TECHNICAL UNIVERSITY OF CRETE
SCHOOL OF PRODUCTION AND ENGINEERING MANAGEMENT
MASTER IN TECHNOLOGY AND INNOVATION MANAGEMENT

MASTER'S THESIS

BUSINESS DECISION ANALYSIS BASED ON DATA ANALYTICS

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Supervisor

Professor Matsatsinis Nikolaos

Chania, 2022

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A thesis submitted in partial fulfillment of the requirements for the degree in Master in Technology and Innovation Management.

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Biography

Antonia Trikounaki is a Business Administration graduate of the Management School of Athens University of Economics and Business, majoring in business administration.

After graduating from the Management School in 2020, she enrolled at the Master in Technology and Innovation Management, at the School of Production Engineering and Management in Technical University of Crete.

Her educational background, also includes knowledge of Business Software Systems, Robotic Process Automation Software Systems and Business Process and Notation Systems.

She has attended numerous seminars on various topics such as Industry 4.0, Artificial Intelligence, Artificial Intelligence& Data Analytics, E-business, Leadership, Digital Marketing, Customer Engagement, Google Ads and SEO, Social Media Marketing, Digital Transformation, Digital PR, Online Targeting Strategies, IT trends, Enterprise Crisis Management, Digital Nomads & Strategies to Restart the Tourism Sector in Crete, Hotel Megatrends and Health & Security in the Workplace.

She has attended trading seminars and she has participated in negotiating tournaments and mediation simulations. She has also participated in various workshops concerning Public Spaces, Smart Technologies and Urban Health.

She has an experience as a Real Estate Assistant and as a Guest Relations officer in a 5-Star Hotel.

Abstract

Despite the continuous and exponential technological evolution, a common phenomenon observed in the service and retail industry is the lack of pattern recognition in a dataset and thus the inability to create predictions on business issues. This, makes them even more susceptible to uncertainty and risk, as they are not able to focus on the key variables that influence their companies' attributes.

This thesis, highlights three different case studies of companies operating in the service and retail industry. Specifically, the paper focuses on the case of a hotel company based in Chania of Crete, a multinational insurance company and a big Greek Super Market chain, that seek to use data analysis along with data science to extract the necessary information and make the predictions needed in order to take effective decisions and improve their business performance.

The aforementioned, can be achieved by using the methods of categorization, clustering and association rule mining through the usage of machine learning software, WEKA. Through algorithms' implementation, it is possible to make predictions, check their accuracy, create patterns of interrelated sales/purchases and group features, based on the data provided by the companies.

In each of these three cases, the dataset is examined, and through WEKA'S assistance, the data is analyzed in order to obtain results, capable of assisting or improving decision-making, increasing competitiveness and possibly increasing the sales of the firms in question.

The first chapter presents the concept of data mining, the purpose it serves and the ways through which it helps in business problem solving. Then the data mining software- WEKA is presented, which is used in each of the cases, to analyze the data given and to provide meaningful patterns, rules and results for the issues addressed. The presentation, analysis and explanation of the different regression and classification algorithms follows, which will be used in the use cases of the following chapters and the different clusterers that will be applied through WEKA’s software. Additionally, the concept of association rule mining is presented and explained, as well as the various metrics that will be used to analyze and interpret WEKA’s results.

The second chapter presents the Creta Palm Hotel's case. For this case, a certain amount of data, concerning the hotel's bookings from the different travel agencies as well as the different booking sources was collected, for the years 2019 and 2020. This data is about to be analyzed through classification algorithms' implementations and clustering method developments, with the assistance of the machine learning software WEKA. This aims in generating predictions for the total bookings of the different travel agencies and the different booking pages, in checking the accuracy of the total bookings' predictions as well as in grouping the different co-operative booking sources' characteristics based on the years of 2019 and 2020. Total bookings' predictions concern all those travel agencies and booking sources that have the same, or similar characteristics to the agencies/sources given for analysis, that is the training data. The agencies/sources whose data have the same or similar characteristics to the training data, are expected to behave in the same way and have similar number of sales.

The third chapter is about the multinational insurance company NN. In this case, the company created a questionnaire for its customers and collected their responses, in order to examine their intentions and preferences concerning the insurance products she promotes. These responses, are being processed and then analyzed, in order to predict the customers' interest for insurance estimating, to test the predictions' accuracy and to cluster the customers' characteristics, based on the data provided by the company. The aforementioned are accomplished, through classification algorithms' implementation and clustering methods' development, with the assistance of WEKA machine learning software. WEKA's predictions for the customers' interest in retirement estimation, concern customers who display the same or similar characteristics as those of the customers answering the questionnaire. Therefore, customers with the same or similar characteristics as the training data are expected to behave in the same way and have a similar response.

The forth chapter presents the case of a large Super Market in Greece. For this use case, a database with transactional and demographic data was collected from the Supermarket for a period of eight months during 2021. This database included the customers' gender, age, card code and all of their purchases with its dates, the shop and area from which the customers made each purchase, the products each customer chose along with their product category and the amount of money that they spent on each product. The collection and analysis of these data, gives us the opportunity to find useful information about the customers, through association rule mining and clustering. Weka Machine Learning Software, transforms the dataset into meaningful patterns with the assistance of integrated algorithms, aiming to find the products that appear an association with each other and are usually purchased together (association rule mining) as well as to group the customers depending on their purchase frequency of the various product categories. Association rule mining- in other words- market basket analysis, discovers the correlations between the different items in customers' shopping cart and clustering segregates groups with similar traits. These methods help the company to have a better understanding of the customers' profile and thus, create value for them. This leads to a better customer experience and creates a stronger sentiment or loyalty towards the company. The methods of association rule mining and clustering helps the company to better predict the results of a new oncoming dataset that has similar characteristics with our already existing dataset and make the necessary marketing campaigns depending on the customers' gender, age and area of shopping.

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Chapter 1

1.1 Data Mining

Data mining is a process that turns raw data into useful information. Through data mining software systems, businesses are able to look for patterns in large batches of data, so they can learn more about their customers and thus develop more effective marketing strategies, increase sales and decrease costs. Data mining depends on effective data collection, warehousing, and computer processing.[1]

Data mining is the process of extracting useful information from a large amount of data, often from a data warehouse or collection of linked data sets. Data mining tools include powerful statistical, mathematical, and analytics capabilities whose primary purpose is to sift through large sets of data to identify trends, patterns, and relationships to support informed decision-making and planning.[2]

Data Mining can be directed or undirected. Directed Data Mining attempts to explain a particular situation or field such as customer response or house price in a certain area, using predefined classes, whereas undirected data mining attempts to find similarities among groups, without the need of a predefined classes or the need of certain target fields.[3]

The process of sorting through large data sets and identifying patterns through data analysis can help solve business problems. Data mining techniques and tools enable enterprises to turn data into useful information and knowledge, to make predictions and take better business decisions. Data mining is a key part of data analytics and data science.

According to Fayyad et al., (1996) [1]:
The knowledge discovery in databases (KDD) is the overall process of discovering useful knowledge from data, and data mining refers to a particular step in this process. Data mining is the application of specific algorithms for extracting patterns from data.

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[1] Source: https://www.sap.com/mena-ar/insights/what-is-data-mining.html
[2] Source: https://www.investopedia.com/terms/d/datamining.asp
[3] Source: https://www.coursehero.com/file/p479j4o/Directed-vs-Undirected-data-mining-Directed-data-mining-attempts-to-explain-or/

The information that data mining generates can be used in business intelligence (BI) and advanced analytics applications that involve analysis of historical data, as well as real-time analytics applications.

Data mining aims in effective business strategies' planning and managing operations. That includes market analysis, advertising, marketing, sales, business management, decision support, customer support, manufacturing, supply chain management, finance and HR.

Data mining supports fraud detection and cybersecurity planning. It also plays an important role in risk management, healthcare, government, scientific research, mathematics etc.[4]

Data mining attempts to extract potentially useful knowledge from data. Let us consider transactions (market baskets) that are obtained from a supermarket. Data mining can be used to discover useful information from data like 'when a customer buys spaghetti, he/she also buys cheese" and 'customers of this supermarket department in X area like to buy Y products and they usually associate them with Z products'.

Different kinds of knowledge require different kinds of representation e.g. classification, clustering, association rule mining.

Classification analysis is a type of Predictive Data Mining, which helps to know what may possibly happen in the future in business, whereas Clustering and Association Rule Mining analysis are types of Descriptive Data Mining, which converts given data into useful information.

1.2 Data Mining Software: WEKA

The University of Waikato in New Zealand developed WEKA (Waikato Environment for Knowledge Analysis), an open-source, data mining software package written in Java, issued under General Public International Journal of Pure and Applied Mathematics. Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your

[4] Source: https://searchbusinessanalytics.techtarget.com/definition/data-mining

own Java code. Weka is fully implemented in Java Programming Language and it fits with almost any computing platform.

You can download the relevant software from: http://www.cs.waikato.ac.nz/~ml/weka/index.html, and then install it on your Personal Computer.

Weka Software is supported from various Operating Systems such as Windows, Mac OS X and Linux.

If you do not already have a version of java installed you should download the version that will also contain the java VM. You can choose between Version for 32 bits or Version for 64 bits.

Machine learning (ML) techniques and their application to real-world data mining problems can be done using WEKA. The software package supports several standard data mining tasks, such as data pre-processing, clustering, classification, regressing, visualization and feature selection. The Graphic User Interface allows us to try out different data preparation, transformation and modeling algorithms on data set and contains a collection of visualization tools for data analysis and predictive modeling coupled with graphical user interface.

Weka is a software tool with integrated Machine Learning algorithms that can develop machine learning models which may provide meaningful patterns, rules and results. That is, Weka does not require knowledge of algorithm programming and coding in order to provide results of the inspected data and thus, it speeds-up the procedures. In order to use Weka, someone has to pre-process and pre-label the data to train a classifier (the variable we want to predict). After training, the dataset must usually be saved in csv format and then loaded in Weka Software. After the dataset has been loaded in Weka, someone can make further data preparations in order to bring it in a suitable format and therefore, be able to create prediction models, clustering models and association rules.

Machine Learning is a part of data-driven Intelligent Automation through which machines must learn themselves to do tasks instead of us, understand the human brain function and mimic them.

According to Agrawal, et l., (2019) [2], "Machine learning is a subset of AI that involves techniques that enable machines to learn from the given data for pattern detection and future prediction".

Artificial intelligence uses machine learning algorithms to perform data analytics by building learning models to be used in "intelligent" ways. The learning models are based on the idea that machines can learn from data, identify patterns, and predict future states that help in decision-making with little human intervention.

The algorithm models and rules can be used to predict future behavior or choice, to improve business revenues, to confirm something already known or to just find new information that was not identified before.

WEKA with the help of the Apriori Algorithm helps in mining association rules in the dataset. Apriori is a frequent pattern mining algorithm that counts the number of occurrences of an item set in the transaction.

Cluster Analysis is a technique to find out clusters of data that represent similar characteristics. WEKA provides many algorithms to perform cluster analysis out of which simple k means are highly used.

Data Visualization in WEKA can be performed on all datasets in the WEKA directory. The raw dataset can be viewed as well as other resultant datasets of other algorithms such as classification, clustering, and association can be visualized using WEKA.

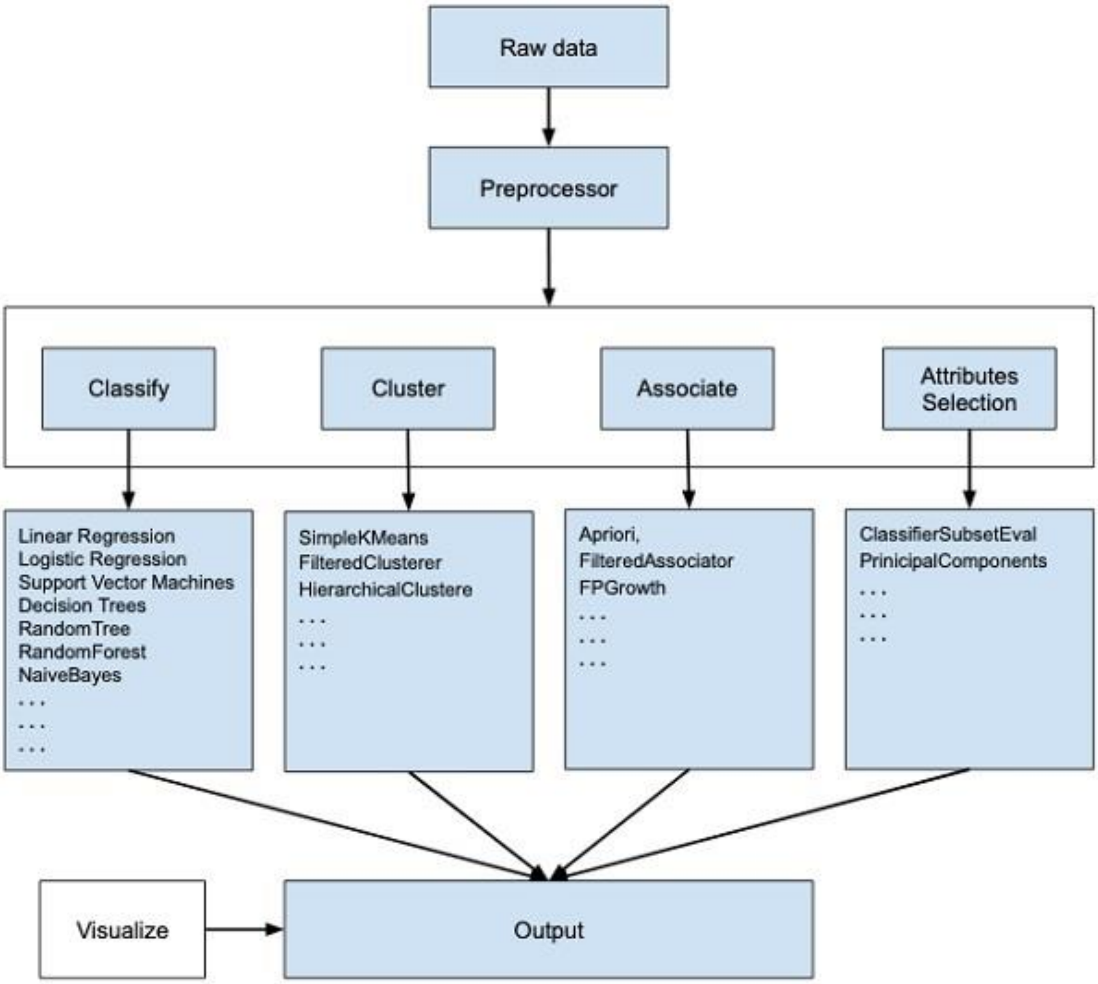

Figure 1: Weka visualization [5]

The above picture helps us to understand more about WEKA tool. There are many stages in dealing with Big Data to make it suitable for machine learning.

1.3 Regression

Regression analysis consists of a set of machine learning methods that allow us to predict a continuous outcome variable (y) based on the value of one or multiple predictor variables (x).[6] That is, Regression is a process of finding the correlations between dependent and independent variables.

[5] Source: https://www.tutorialspoint.com/weka/what_is_weka.htm

[6] Source: http://www.sthda.com/english/wiki/regression-analysis-essentials-for-machine-learning

Regression algorithms are Supervised Learning algorithms that are used for prediction in Machine learning and they work with the labeled datasets. Regression algorithms are used to predict the continuous values/quantities such as price, salary, age, etc. In Regression, the algorithms are used with continuous data and the output variable must be of real value.[7]

Regression predictions can be evaluated using root mean squared error and adjusted R- square. The best model is defined as the model that has the lowest prediction error. The most popular metric for comparing regression models, is Root Mean Squared Error. It measures the model prediction error. It corresponds to the average difference between the observed known values of the outcome and the predicted value by the model. RMSE is computed as RMSE = mean((observed - predicted)^2). The lower the RMSE, the better the model[8]

For numeric/continuous values, WEKA's regression models, detect correlation coefficient, mean absolute error, root mean squared error, relative absolute error and root relative squared error.

- Correlation coefficient implies what percentage of the variance in your data is explained by your model. The greater the correlation coefficient value, the stronger the model's predictions are. A high correlation coefficient (greater than 0.95) depicts that there is a strong relation between our data values and the values of the algorithm's prediction model and that our data do get close to the predictions of the model. This practically means that, we can better predict the results of a new oncoming dataset that has similar characteristics with an already existing dataset and there is a high probability that the dataset values are similar to those predicted from the algorithm.

- Mean absolute error is the average distance the models' predictions are from the actual data points. Absolute in the title indicates that predictions below data points ate not treated as negative distances.

- Root mean squared error (RMSE) is another way of calculating the mean absolute error. It measures the model prediction error. It corresponds to the average difference between the observed known values of the outcome and the

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[7] Source: https://www.javatpoint.com/regression-vs-classification-in-machine-learning?fbclid=IwAR0MJoSS1zxED1LmJnEJy0TY3XIpTszCeJGkV2_Rdz_AVMo8ByCPp5cdgjo
[8] Source: http://www.sthda.com/english/wiki/regression-analysis-essentials-for-machine-learning

predicted value by the model. RMSE is computed as RMSE = mean((observed - predicted)^2). In other words, RMSE is the standard deviation of the residuals (prediction errors). The Residuals is a measure of how far/spread out are the data points from the regression line or how concentrated are the data around the line of the best fit.[9] The lower the RMSE, the better the model.

- Relative absolute error and root relative squared error scale the error to the mean. This enables the comparison between models constructed with larger/smaller valued data.
- Total number of instances is the number of data points in the data set.

The regression Algorithm can be further divided into Linear and Non-linear Regression.

Six Types of Rression Algorithms:

1. Functions (Gaussian Process, SMOreg, Multilayer Perceptron, Linear Regression, Voted Perception)
2. Lazy (K Star, LWL, IBk)
3. Meta (Bagging, Randomizable Filtered Classifier, Stacking, Vote, Additive Regression, Instances Handler Wrapper, Regression By Discretization, Random SubSpace, CV Parameter Selection, Multi Scheme, Random Committee)
4. Misc (Input Mapped Classifier)
5. Rules (M5Rules, Decision Table, Zero R)
6. Trees (Decision Stump, Random Forest, Random Tree, RepTree, M5P)

1.3.1 Linear Regression

Linear regression is a very simple regression algorithm that only supports regression type problems and is issued for prediction. The model uses the Akaike criterion for model selection, and is able to deal with weighted instances. Linear Regression can only deal with numeric attributes. [10]

[9] Source: https://www.statisticshowto.com/probability-and-statistics/regression-analysis/rmse-root-mean-square-error/
[10] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/LinearRegression.html

1.3.2 *Gaussian Process*

Gaussian Process implements regression without hyper parameter-tuning. This implementation applies normalization/standardization to the target attribute as well as the other attributes (if normalization/standardization is turned on). Missing values are replaced by the global mean/mode. Nominal attributes are converted to binary ones.[11]

1.3.3 *Multilayer Perceptron*

The Multi-Layer Perceptron algorithms supports both regression and classification problems. It is also called artificial neural networks or simply neural networks for short. Neural networks are a complex algorithm to use for predictive modeling because there are so many configuration parameters that can only be tuned effectively through intuition and a lot of trial and error.[12] This is a classifier that uses backpropagation to learn a multi-layer perceptron to classify instances. The network can be built by hand or set up using a simple heuristic. The network parameters can also be monitored and modified during training time. The nodes in this network are all sigmoid, except for when the class is numeric, in which case the output nodes become unthresholded linear units.[13]

1.3.4 *SMOreg*

"SMOreg implements the "sequential minimal optimization" algorithm for support vector machines, which are an important paradigm in machine learning". Burges, (1998) [4].

Sequential Minimal Optimization (SMO) method breaks the problem down into sub-problems that can be solved analytically (by calculating) rather than numerically (by searching or optimizing).[14]

1.3.5 *Lazy IBk*

This is a K-nearest neighbor's (KNN) classifier which attempts to predict the correct class for the test data by calculating the distance between the test data and all the training points. Then, it selects the K number of points which is closest to the test data. The K-Nearest Neighbours (KNN) algorithm is one of the most simple

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[11] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/GaussianProcesses.html
[12] Source: https://machinelearningmastery.com/use-regression-machine-learning-algorithms-weka/?fbclid=IwAR3PWrbfejBgXpV4YmADPnKm7F5h1Ubxh8zNCSa75EfYoDL3s_qmVYL-V4E
[13] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/MultilayerPerceptron.html
[14] Source:https://machinelearningmastery.com/support-vector-machines-for-machine-learning/

supervised machine learning algorithms that is used to solve both classification and regression problems. KNN is also known as an instance-based model or a lazy learner because it doesn't construct an internal model. For regression problems, it will find the k nearest neighbors and predict the value by calculating the mean value of the nearest neighbors.[15]

When making predictions on regression problems, KNN will take the mean of the k most similar instances in the training dataset. [16]

1.3.6 LWL

According to Atkenson, et al., (1997) [9], "LWL is an implementation of a more sophisticated learning scheme for numeric prediction, using locally weighted regression".

1.3.7 Lazy K Star

According to Sharma and Jain (2013) [8]: *K-Star algorithm can be defined as a method of cluster analysis which mainly aims at the partition of "n" observation into "k" clusters in which each observation belongs to the cluster with the nearest mean. We can describe K-Star algorithm as an instance-based learner which uses entropy as a distance measure. The benefits are that it provides a consistent approach to handling of real valued attributes, symbolic attributes and missing values.*

"K- Star is a simple, instance-based classifier, similar to K-Nearest Neighbour (K-NN)" (Vijayarani and Muthulakshimi (2013) [5])

1.3.8 Decision Table

According to Kalmegh (2018) [3]: *Decision Table is an accurate method for numeric prediction from decision trees and it is an ordered set of If-Then rules that have the potential to be more compact and therefore more understandable than the decision trees. Selection to explore decision tables because it is a simpler, less compute intensive algorithm than the decision-tree-based approach.*

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[15] Source: https://towardsdatascience.com/an-introduction-to-k-nearest-neighbours-algorithm-3ddc99883acd
[16] Source: https://machinelearningmastery.com/use-regression-machine-learning-algorithms-weka/?fbclid=IwAR3PWrbfejBgXpV4YmADPnKm7F5h1Ubxh8zNCSa75EfYoDL3s_qmVYL-V4E

1.3.9 M5Rules

M5Rules generates a decision list for regression problems using separate-and-conquer. In each iteration it builds a model tree using M5 and makes the "best" leaf into a rule.[17]

1.3.10 Zero R

Zero R predicts the mean (for a numeric class) or the mode (for a nominal class).[18]

1.3.11 Decision Stump Tree

Decision Stump trees can support both classification and regression problems. Decision Stump is a decision tree learner. According to Witten, et al., (1999) [10]: *Decision Stump builds simple binary decision "stumps" (one-level decision trees) for both numeric and nominal classification problems. It copes with missing values by extending a third branch from the stump- in other words by treating "missing" as a separate attribute value.*

1.3.12 M5P trees

M5P trees can support both classification and regression problems. According to [17]"The M5P model tree is based on conventional decision tree associated to linear regression function at the leaves nodes".

1.3.13 Random Forest

Random Forest trees can support both classification and regression problems. According to E. Kleinberg (n.d) [31]: *Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. Random forests are an ensemble learning method for classification (and regression) that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees. The algorithm for inducing a random forest was developed by Leo Breiman and Adele Cutler.*

It is called 'Random' Forest as it is using two random processes: bootstrapping and random feature selection. Bootstrapping ensures that we are not using the same data for every tree, so it helps the model to be less sensitive to our training data. The

[17] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/M5Rules.html
[18] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/ZeroR.html

random feature selection helps to reduce the correlation between the trees (if we use every feature, then the decision trees will have the same decision nodes and they will act very similarly, which will increase the variance). [19]

1.3.14 Random Tree

Random trees can support both classification and regression problems. A Random tree is a decision tree learner. Random Tree considers K randomly chosen attributes at each node and performs no pruning. It has also an option to allow estimation of class probabilities (or target mean in the regression case) based on a hold-out set (back fitting). [20]

1.3.15 RepTree

Rep trees can support both classification and regression problems. Rep Tree is a fast decision tree learner. It builds a decision/regression tree using information gain/variance and prunes it using reduced-error pruning (with back fitting). Rep Tree only sorts values for numeric attributes once. Missing values are dealt with by splitting the corresponding instances into pieces (i.e. as in C4.5). [21]

1.3.16 Meta Additive Regression

Meta Additive Classifier enhances the performance of a regression base classifier. Each iteration fits a model to the residuals left by the classifier on the previous iteration. Prediction is accomplished by adding the predictions of each classifier. Reducing the shrinkage (learning rate) parameter helps prevent overfitting and has a smoothing effect but increases the learning time.[22]

1.3.17 Meta Regression By Discretization

This is a regression scheme that employs any classifier on a copy of the data that has the class attribute (equal-width) discretized. The predicted value is the expected value of the mean class value for each discretized interval (based on the predicted probabilities for each interval). [23]

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[19] Source: https://www.youtube.com/watch?v=v6VJ2RO66Ag
[20] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/trees/RandomTree.html
[21] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/trees/REPTree.html
[22] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/AdditiveRegression.html
[23] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RegressionByDiscretization.html

1.3.18 Meta Randomizable Filtered Classifier

Meta Randomizable Filtered Classifier runs an arbitrary classifier on data that has been passed through an arbitrary filter. Like the classifier, the structure of the filter is based exclusively on the training data and test instances will be processed by the filter without changing their structure. [24]

1.3.19 Meta Vote

Occasionally meta-analyses use 'vote counting' to compare the number of positive studies with the number of negative studies. Vote counting might be considered as a last resort in situations when standard meta-analytical methods cannot be applied (such as when there is no consistent outcome measure).[25]

1.3.20 Meta Stacking

Meta Stacking combines several classifiers using the stacking method and can do classification or regression.[26]

1.3.21 Meta Instances Handler Wrapper

This is a generic wrapper around any classifier to enable weighted instances support. and uses resampling with weights if the base classifier is not implementing the weka core. By default, the training data is passed through to the base classifier if it can handle instance weights. However, it is possible to force the use of resampling with weights as well.[27]

1.3.22 Meta Random Sub Space

This method constructs a decision tree based classifier that maintains highest accuracy on training data and improves on generalization accuracy as it grows in complexity. The classifier consists of multiple trees constructed systematically by pseudorandomly selecting subsets of components of the feature vector, that is, trees constructed in randomly chosen subspaces.[28]

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[24] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomizableFilteredClassifier.html

[25] Source: https://handbook-5-1.cochrane.org/chapter_9/9_4_11_use_of_vote_counting_for_meta_analysis.htm

[26] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/Stacking.html

[27] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/WeightedInstancesHandlerWrapper.html

[28] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomSubSpace.html

1.3.23 Meta CV Parameter Selection

Meta CV Parameter Selection performs parameter selection by cross-validation for any classifier.[29]

1.3.24 Meta Bagging

Meta Bagging is a classifier that reduces variance and can do classification and regression depending on the base learner. [30]

1.3.25 Meta Multischeme

Meta Multischeme classifier uses cross validation on the training data or the performance on the training data. The performance is measured based on percent correct (classification) or mean-squared error (regression). [31]

1.3.26 Meta Random Committee

Meta Random Committee builds an ensemble of randomizable base classifiers. Each base classifier is built using a different random number seed (but based on the same data). The final prediction is a straight average of the predictions generated by the individual base classifiers. [32]

1.3.27 Misc Input Mapped Classifier

This is a wrapper classifier that addresses incompatible training and test data by building a mapping between the training data that a classifier has been built with and the incoming test instances' structure.[33]

1.4 Classification

According to[23] [23]: *Classification is a data mining task that maps the data into predefined groups and classes. It is also called as supervised learning. It consists of two steps:*

1. ***Model construction:*** *It consists of set of predetermined classes. Each tuple is assumed to belong to a predefined class. The set of tuples used for model*

[29] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/CVParameterSelection.html
[30] Source: https://weka.sourceforge.io/doc.stable/weka/classifiers/meta/Bagging.html
[31] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/MultiScheme.html
[32] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomCommittee.html
[33] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/misc/InputMappedClassifier.html

construction, is training set. The model is represented as classification rules, decision trees, or mathematical formulas.

2. ***Model usage:*** *This model is used for classifying future or unknown objects. The known label of test sample is compared with the classified result from the model. Accuracy rate is the percentage of test set samples that are correctly classified by the model. Test set is independent of training set, otherwise over-fitting will occur.*

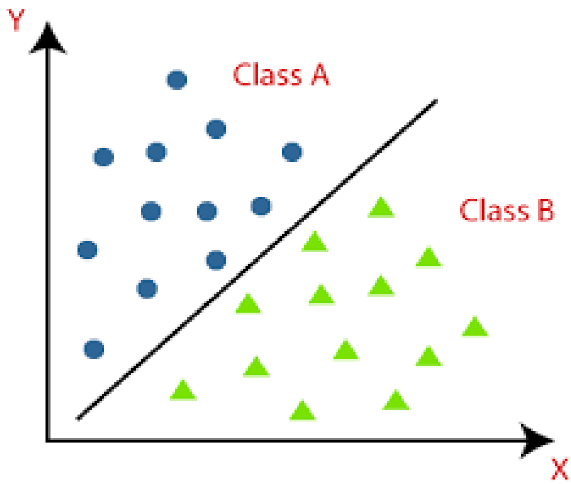

Figure 2: Classification [34]

Classification algorithms can be better understood using the above diagram. In the diagram, there are two classes, class A and class B. Each class has features that are similar to each other and dissimilar to other classes.

Classification algorithms are also Supervised Learning algorithms that are used for prediction in Machine learning and they work with the labeled datasets. Unlike regression, classification algorithms are used to predict or classify the discrete values/ class labels such as Male or Female, True or False, Spam or Not Spam, etc. Classification is a process of finding a function which helps in dividing the dataset into classes based on different parameters. In Classification, a computer program is trained on the training dataset and based on that training, it categorizes the data into

[34] Source: https://www.javatpoint.com/classification-algorithm-in-machine-learning

different classes. The algorithms in classification, are used with discrete data and the output variable must be a discrete value.[35]

A common way to estimate Classification predictions is to calculate accuracy. The classification accuracy is the percentage of correctly classified examples out of all predictions made. For example, if a classification predictive model made 5 predictions and 3 of them were correct and 2 of them were incorrect, then the classification accuracy of the model based on just these predictions would be: [36]

accuracy = correct predictions / total predictions * 100 ⇒

accuracy = 3 / 5 * 100 ⇒

accuracy = 60%

For nominal/discrete values, WEKA's classification models detect Correctly Classified Instances, Incorrectly Classified Instances, Kappa statistic, Mean absolute error, Root mean squared error, Relative absolute error, Root relative squared error, Total Number of Instances, TP Rate, FP Rate, Precision, Recall, F-Measure.

- Correctly Classified Instances depict how many relevant instances were predicted correctly as true
- Incorrectly Classified Instances depict how many irrelevant instances were falsely predicted as true.
- Kappa statistic is a chance-corrected measure of agreement between the classifications and the true classes. Specifically, K statistic is a value which estimates how well the model will perform, considering the chance that you randomly guessed correctly, without having any knowledge. It is calculated by taking the agreement expected by chance away from the observed agreement and dividing by the maximum possible agreement. A zero value equals to random guessing, but a value greater than zero means that your classifier is doing better than chance. The further the value above zero, the better it performs.

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[35] Source: https://www.javatpoint.com/regression-vs-classification-in-machine-learning?fbclid=IwAR0MJoSS1zxED1LmJnEJy0TY3XIpTszCeJGkV2_Rdz_AVMo8ByCPp5cdgjo

[36] Source: https://machinelearningmastery.com/classification-versus-regression-in-machine-learning/?fbclid=IwAR2bkzuaIYkl8YkQcKhm2ie5yiYs3O9-Ybt4VhVquc4vlJG2yfDq3H52duw#:~:text=Classification%20is%20the%20task%20of,of%20predicting%20a%20continuous%20quantity

K statistic= $\frac{\mathrm{P(A)-P(E)}}{1-P(E)}$ (Source: Kinge & Gaikwad, (2018). [13])

P(A): Agreement percentage, P(E): Agreement chances.

If K = 1, Agreement is in tolerable range

- Mean absolute error is the average distance the models' predictions are from the actual data points. Absolute in the title indicates that predictions below data points ate not treated as negative distances.

MAE= $\frac{\sum_{i=1}^{n} Actual - Forecast\ i}{n}$ (Source: Kinge & Gaikwad, (2018). [13])

- Root mean squared error is another way of calculating the mean absolute error. It follows an assumption that error are unbiased and follow a normal distribution.

RMS= $\sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n}}$ (Source: Kinge & Gaikwad, (2018). [13])

- Relative absolute error and root relative squared error scale the error to the mean. This enables the comparison between models constructed with larger/smaller valued data.
- Total number of instances is the number of data points in the data set.
- True Positive (TP) Rate: rate of true positives (instances correctly classified as positive)
- False Positive (FP) Rate: rate of false positives (instances incorrectly classified as positive)
- True Negative (TN) Rate: rate of true negatives (instances correctly classified as negative)
- False Negative (FN) Rate: rate of false negatives (instances that were incorrectly classified as negative)
- Precision: proportion of instances that are truly of a class divided by the total instances classified as that class.

Precision =$\frac{\mathrm{TP}}{\mathrm{P}} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$ (Source: Kinge & Gaikwad, (2018). [13])

- Recall: proportion of instances classified as a given class divided by the actual total in that class (equivalent to TP rate).

  Recall $=\frac{\mathrm{TP}}{\mathrm{T}} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$ (Source: Kinge & Gaikwad, (2018). [13])

- F-Measure: A combined measure for precision and recall calculated as:

  F-Measure $= \frac{2 * Precision * Recall}{(\mathrm{Precision + Recall})}$ (Source: Kinge & Gaikwad, (2018). [13])

- Accuracy: The ability of the model to correctly predict the class label of new or previously unseen data.

  Accuracy$= \frac{\mathrm{N}}{\mathrm{T}} = \frac{\mathrm{TP}+TN}{\mathrm{TP}+TN+FP+\mathrm{FN}}$ (Source: Kinge & Gaikwad, (2018). [13])

Precision, Recall, F-Measure and ROC Area give a really good picture of how well things are performing. [37]

[37] Source-Interpreting Results and Accuracy in Weka: https://www.youtube.com/watch?v=gfhGfnkypCY

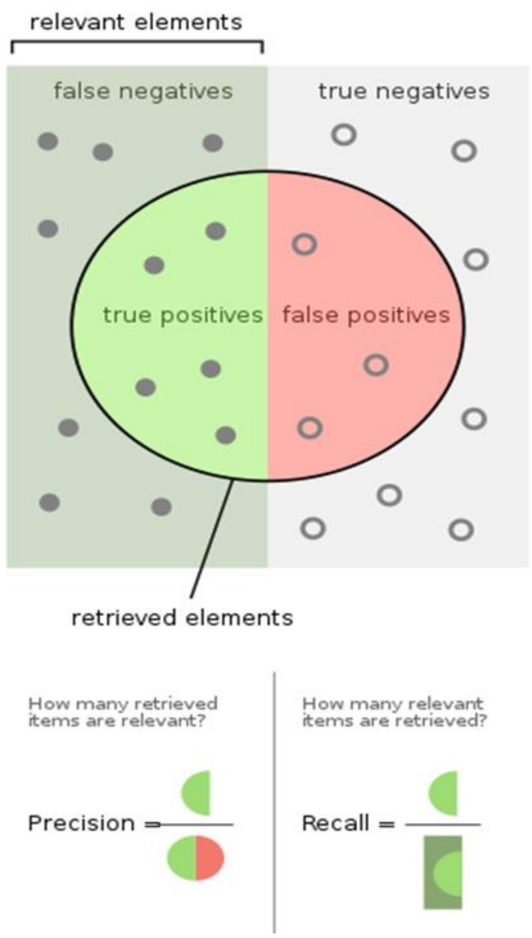

Figure 3: Interpretation of Precision and Recall [38]

As mentioned above, the percentage of correctly classified instances is often called accuracy or sample accuracy. It does have some disadvantages as a performance estimate, so someone can look at some of the other numbers such as ROC Area.

ROC Area (Receiver Operating Characteristic-Area Under the Curve) shows us which items are correctly put in their classes (For example, if you had one item from each class, what percentage of the time are you going to correctly put them in their classes). An "optimal" classifier will have ROC area values approaching 1, with 0.5 being comparable to "random guessing" (similar to a Kappa statistic of 0). A value above 0.8 is considered a strong and accurate result. ROC uses True Positives and False Positive Rates as the axes that we are looking out, to draw a curve.

[38] Source: https://commons.wikimedia.org/w/index.php?curid=36926283

PRC (Precision on Recall): Works better for unbalanced data. ROC tends to be in general a better choice, because PRC do not really count the true positives.

Kappa is a chance-corrected measure of agreement between the classifications and the true classes. K switches on kernel density estimation numerical attributes which often improves performance. It is calculated by taking the agreement expected by chance away from the observed agreement and dividing by the maximum possible agreement. A value greater than zero, means that your classifier is doing better than chance.

The error rates are used for numeric prediction rather than classification. In numeric prediction, predictions are not just right or wrong, the error has a magnitude, and these measures reflect that.

The Confusion Matrix is another way of detecting how well a model is doing.

Confusion Matrix

```
  a  b   <-- classified as
 aa  ba|  a = 0
 ab  bb|  b = 1
```

The correctly and incorrectly classified instances show the percentage of test instances that were correctly and incorrectly classified. The raw numbers are shown in the confusion matrix, with a and b representing the class labels.

For instance:

```
  a    b   <-- classified as
 50   5 |  a = 0
 27  13|  b = 1
```

aa=50, ba=5, ab=27, bb=13.

- 50 elements of class a are classified as class a
- 5 elements of class a were incorrectly classified as class b
- 13 elements of class b were correctly classified as class b
- 27 elements of class b were incorrectly classified as class a

Assuming that we have 100 instances, we can detect that 50 out of 55 a’s were predicted correctly (TP Rate) and 13 out of 40 b’s were predicted correctly (TP Rate).

The percentages and raw numbers add up, so that we have aa + bb = 50 + 13 = 63, ab + ba = 27 + 5 =32.

According to Kalmegh, (2018) [3], classification may refer to categorization and the process in which ideas and objects are recognized, differentiated, and understood. An algorithm that implements classification is known as a classifier. Classification is an important technique with broad applications. It classifies data of various kinds.

Classification Algorithms can be divided into these two categories[39]:

- Indicative Linear Models
    - Logistic Regression
    - SMO Reg
- Indicative Non-linear Models
    - Naïve Bayes
    - Random Forest
    - Random Tree

Classifiers can be also divided into these two categories:

- Binary classifiers: They work with only two classes or possible outcomes (example: positive or negative sentiment; whether a customer will want a retirement estimation or not),
- Multiclass classifiers: They work with multiple classes (ex: whether an image is a cat, dog or a rabbit). Multiclass assumes that each sample is assigned to one and only one label.

[39] Source: https://www.javatpoint.com/classification-algorithm-in-machine-learning

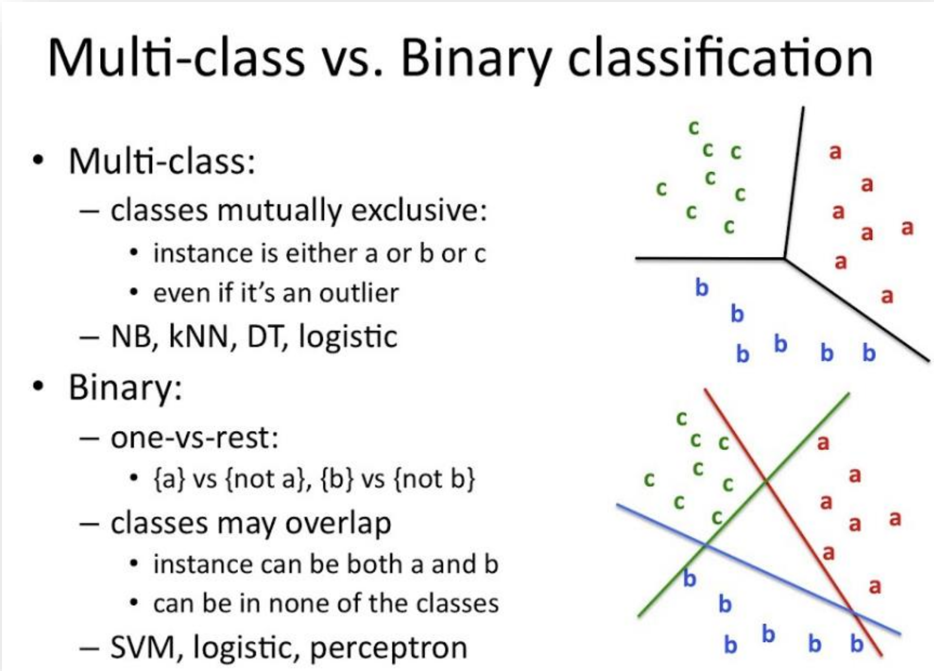

Figure 4: Binary and Multi-class Classifiers [40]

Seven Types of Classifiers:

1. Functions (SMO, Multilayer Perceptron, Logistic, Voted Perception)
2. Bayes (Bayes Net, Naive Bayes, Naive Bayes Multinomial Text)
3. Lazy (K Star, LWL, IBk)
4. Meta (Bagging, Randomizable Filtered Classifier, Stacking, Vote, Multi Class Classifier, Multiclass Classifier Updateable, Instances Handler Wrapper, Random SubSpace, CV Parameter Selection, Multi Scheme, Random Committee)
5. Misc (Input Mapped Classifier)
6. Rules (Decision Table, One R, J Rip, Part, Zero R)
7. Trees (J48, Decision Stump, Random Forest, Random Tree, RepTree, Hoeffding Tree, LMT)

1.4.1 SMO

SMO implements John Platt's sequential minimal optimization algorithm for training a support vector classifier.

[40] Source: https://medium.com/@jorgesleonel/classification-methods-in-machine-learning-58ce63173db8

This implementation globally replaces all missing values and transforms nominal attributes into binary ones. It also normalizes all attributes by default. (In that case the coefficients in the output are based on the normalized data, not the original data --- this is important for interpreting the classifier). Multi-class problems are solved using pairwise classification (1-vs-1). To obtain proper probability estimates, use the option that fits calibration models to the outputs of the support vector machine. In the multi-class case, the predicted probabilities are coupled using Hastie and Tibshirani's pairwise coupling method.[41]

1.4.2 Multilayer Perceptron

This is a classifier that uses backpropagation to learn a multi-layer perceptron to classify instances. The network can be built by hand or set up using a simple heuristic. The network parameters can also be monitored and modified during training time. The nodes in this network are all sigmoid, except for when the class is numeric, in which case the output nodes become unthresholded linear units.[42]

1.4.3 Logistic

The logistic classification model (or logit model) is a binary classification model in which the conditional probability of one of the two possible realizations of the output variable is assumed to be equal to a linear combination of the input variables, transformed by the logistic function.[43]

Logistic class is for building and using a multinomial logistic regression model with a ridge estimator. There are some modifications, however, compared to the paper of leCessie and van Houwelingen (1992):
If there are k classes for n instances with m attributes, the parameter matrix B to be calculated will be an m(k-1) matrix.*

The probability for class j with the exception of the last class is:

Pj(Xi) = exp(XiBj)/((sum[j=1..(k-1)]exp(Xi*Bj))+1)

The last class has probability:

1-(sum[j=1..(k-1)]Pj(Xi))

---

41 Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/SMO.html
42 Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/MultilayerPerceptron.html
43 Source:https://www.statlect.com/fundamentals-of-statistics/logistic-classification-model

= 1/((sum[j=1..(k-1)]exp(Xi*Bj))+1)

The (negative) multinomial log-likelihood is thus:

L = -sum[i=1..n]{sum[j=1..(k-1)](Yij * ln(Pj(Xi)))+(1 - (sum[j=1..(k-1)]Yij)) * ln(1 - sum[j=1..(k-1)]Pj(Xi))} + ridge * (B^2)

In order to find the matrix B for which L is minimized, a Quasi-Newton Method is used to search for the optimized values of the m*(k-1) variables. Note that before we use the optimization procedure, we 'squeeze' the matrix B into a m*(k-1) vector.

Although original Logistic Regression does not deal with instance weights, we modify the algorithm a little bit to handle the instance weights.[44]

1.4.4 SGD

A simple yet efficient optimization algorithm, used to find the values of parameters/coefficients of functions that minimize a cost function. In other words, it is used for discriminative learning of linear classifiers under convex loss functions such as SVM and Logistic regression. SGD has been successfully applied to large-scale datasets because the update to the coefficients is performed for each training instance, rather than at the end of instances.[45]

1.4.5 SGD Text

SDG Text implements stochastic gradient descent for learning various linear models (binary class SVM, binary class logistic regression, squared loss, Huber loss and epsilon-insensitive loss linear regression). SGD Text Globally replaces all missing values and transforms nominal attributes into binary ones. It also normalizes all attributes, so the coefficients in the output are based on the normalized data. For numeric class attributes, the squared, Huber or epsilon-insensitive loss function must be used. Epsilon-insensitive and Huber loss may require a much higher learning rate.[46]

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[44] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/Logistic.html
[45] Source:https://www.tutorialspoint.com/scikit_learn/scikit_learn_stochastic_gradient_descent.htm
[46] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/SGD.html

1.4.6 Voted Perceptron

Voted Perceptron implements the voted perceptron algorithm. The classifier replaces all missing values and transforms nominal attributes into binary ones.[47]

1.4.7 Naive Bayes

The Naive Bayes algorithm is based on conditional probabilities (Vijayarani, et. al., (2013) [5].

Before moving to Naive Bayes' explanation, it is important to know about Bayes' theorem.

"Bayes' Theorem finds the probability of an event occurring given the probability of another event that has already occurred" Vijayarani, et. al., (2013) [5].

Bayes' theorem is stated mathematically as the following equation:

$$\Pr(A|B) = \frac{\Pr(A \cap B)}{\Pr(B)} = \frac{\Pr(B|A)\Pr(A)}{\Pr(B)} =$$

$$\{Pr(A \cap B) = Pr(A) * Pr(B|A) = Pr(B) * Pr(A|B)\}$$

where A and B are events and $P(B) \neq 0$.

Basically, we are trying to find probability of event A, given the event B is true. Event B is also termed as evidence. P(A) is the priori of A (Probability of event before evidence is seen). The evidence is an attribute value of an unknown instance (here, it is event B). P(A|B) is a posteriori probability of B (Probability of event after evidence is seen).

So, in a certain dataset:

$$\Pr(y|X) = \frac{\Pr(y \cap X)}{\Pr(X)} = \frac{\Pr(X|y)\Pr(y)}{\Pr(X)} =$$

y is class variable and X is a dependent feature vector (of size *n*) where:

$X = (x_1, x_2, x_3, \ldots x_n)$.

According to Vijayarani, et. al., (2013) [5]:
Naive Bayes uses the normal distribution to model numeric attributes and assumes

[47] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/VotedPerceptron.html

independence of variables. Naive Bayes can use kernel density estimators, which develop performance if the normality assumption if grossly correct; it can also handle numeric attributes using supervised discretization. Naive Bayes Updateable is an incremental version that processes one request at a time. It can use a kernel estimator but not discretization.

According to Al-Hyari, et al., (2013) [6], “Naive Bayes classifier is one of the efficient and highly scalable inductive learning algorithms which is trained in a supervised learning strategy”.

All naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable. For example, a fruit may be considered to be an apple if it has certain characteristics. A naive Bayes classifier considers each of these characteristics to contribute independently to the probability that this fruit is an apple, regardless of any possible correlations between the characteristics.[48]

In many practical applications, parameter estimation for naive Bayes models uses the method of maximum likelihood. In other words, one can work with the naive Bayes model without accepting Bayesian Probability or using any Bayesian methods.

Below is an example for a naive Bayes classifier, using 10-fold cross-validation.

=== Summary ===

Correctly Classified Instances	71	71	%
Incorrectly Classified Instances	29	29	%
Kappa statistic	0.3108		
Mean absolute error	0.3333		
Root mean squared error	0.4662		
Relative absolute error	69.9453 %		
Root relative squared error	95.5466 %		
Total Number of Instances	100		

=== Detailed Accuracy By Class ===

[48] Source: https://en.wikipedia.org/wiki/Naive_Bayes_classifier

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.967	0.692	0.686	0.967	0.803	0.709	0
	0.308	0.033	0.857	0.308	0.453	0.708	1
W.A	0.71	0.435	0.753	0.71	0.666	0.709	

Table 1: Detailed Accuracy by Class- An example

*W.A: Weighted Average

=== Confusion Matrix ===

a b <-- classified as

59 2 | a = 0

27 12| b = 1

The correctly and incorrectly classified instances show the percentage of test instances that were correctly and incorrectly classified. The raw numbers are shown in the confusion matrix, with a and b representing the class labels. Here there were 100 instances, so the percentages and raw numbers add up, aa + bb = 59 + 12 = 71, ab + ba = 27 + 2 = 29. It also means that 59 out of 61 a's were predicted correctly (TP Rate) and 12 out of 39 b's were predicted correctly (TN Rate).

1.4.8 Bayes Net

A Bayesian network (also known as a Bayes network, Bayes net, belief network, or decision network), is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG). Bayesian networks are ideal for taking an event that occurred and predicting the likelihood that any one of several possible known causes was the contributing factor. For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases.[49]

The classifier assumes strong (Naive) independence assumptions and is based on Bayes' Theorem. A more descriptive term for the underlying probability model would be "independent feature model". In simple terms, a naive Bayes classifier assumes

[49] Source: https://en.wikipedia.org/wiki/Bayesian_network

that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. [50]

Bayes Net classifier usually provides better attribute results than Naïve Bayes classifier.

1.4.9 Naïve Bayes Multinomial Text

The Multinomial naive bayes for text data, operates directly on String attributes. Other types of input attributes are accepted but ignored during training and classification.[51]

1.4.10 Lazy K Star

According to Sharma and Jain (2013) [8]: *K-Star algorithm can be defined as a method of cluster analysis which mainly aims at the partition of "n" observation into "k" clusters in which each observation belongs to the cluster with the nearest mean. We can describe K-Star algorithm as an instance-based learner which uses entropy as a distance measure. The benefits are that it provides a consistent approach to handling of real valued attributes, symbolic attributes and missing values.*

"K- Star is a simple, instance-based classifier, similar to K-Nearest Neighbour (K-NN)" (Vijayarani and Muthulakshimi (2013) [5]).

K-Star can be guided using heuristic functions.[52]

1.4.11 Lazy IBk

This is a K-nearest neighbor's (KNN) classifier which attempts to predict the correct class for the test data by calculating the distance between the test data and all the training points. Then, it selects the K number of points, which are closest to the test data. [53]The K-Nearest Neighbours (KNN) algorithm is one of the simplest supervised machine learning algorithms that is used to solve both classification and regression problems. KNN is also known as an instance-based model or a lazy learner because it

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[50] Source: https://medium.com/@analyttica/what-is-bayesian-network-classifier-4d2771f91f63
[51]Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/bayes/NaiveBayesMultinomialText.html

[52] Source: https://www.sen.uni-konstanz.de/research/research/tools/k-star-algorithm/
[53] Source: https://medium.com/swlh/k-nearest-neighbor-ca2593d7a3c4

doesn't construct an internal model. For classification problems, it will find the k nearest neighbors and predict the class by the majority vote of the nearest neighbors.[54]

Usually, it is observed that the lazy IBK classifier provides better results than those of lazy K Star classifier.

1.4.12 Meta Multi Class Classifier

In machine learning, multiclass or multinomial classification is the problem of classifying instances into one of three or more classes (classifying instances into one of two classes is called binary classification). While many classification algorithms (i.e multinomial logistic regression) naturally permit the use of more than two classes, some are by nature binary algorithms; these can, however, be turned into multinomial classifiers by a variety of strategies.[55]

According to Witten, et al., (1999) [10], "Meta Multi Class Classifier transforms the multiclass problem into several two-class ones and combine the results".

Each training point belongs to one of the n different classes. The goal is to construct a function which, given a new data point, will correctly predict the class to which the new point belongs.[56]

1.4.13 Meta Multi Class Classifier Updateable

This is a meta classifier for handling multi-class datasets with 2-class classifiers and it has more than two outcomes. This classifier is also capable of applying error correcting output codes for increased accuracy. The base classifier must be an updateable classifier.[57]

1.4.14 Meta Randomizable Filtered Classifier

Meta Randomizable Filtered Classifier runs an arbitrary classifier on data that has been passed through an arbitrary filter. Like the classifier, the structure of the filter is based exclusively on the training data and test instances will be processed by the filter without changing their structure. [58]

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[54] Source: https://towardsdatascience.com/an-introduction-to-k-nearest-neighbours-algorithm-3ddc99883acd
[55] Source: https://en.wikipedia.org/wiki/Multiclass_classification
[56] Source: https://www.mit.edu/~9.520/spring09/Classes/multiclass.pdf
[57]Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/MultiClassClassifierUpdateable.html
[58] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomizableFilteredClassifier.html

1.4.15 Meta Vote

Occasionally meta-analyses use ‘vote counting’ to compare the number of positive studies with the number of negative studies. Vote counting might be considered as a last resort in situations when standard meta-analytical methods cannot be applied (such as when there is no consistent outcome measure).[59]

1.4.16 Meta Stacking

Combines several classifiers using the stacking method and can do classification or regression.[60]

1.4.17 Meta Instances Handler Wrapper

This is a generic wrapper around any classifier to enable weighted instances support. and uses resampling with weights if the base classifier is not implementing the weka core. By default, the training data is passed through to the base classifier if it can handle instance weights. However, it is possible to force the use of resampling with weights as well.[61]

1.4.18 Meta Random Sub Space

This method constructs a decision tree based classifier that maintains highest accuracy on training data and improves on generalization accuracy as it grows in complexity. The classifier consists of multiple trees constructed systematically by pseudorandomly selecting subsets of components of the feature vector, that is, trees constructed in randomly chosen subspaces.[62]

1.4.19 Meta CV Parameter Selection

Meta CV Parameter Selection performs parameter selection by cross-validation for any classifier.[63]

1.4.20 Meta Bagging

Meta Bagging is a classifier that reduces variance and can do classification and regression depending on the base learner. [64]

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[59] Source: https://handbook-5-1.cochrane.org/chapter_9/9_4_11_use_of_vote_counting_for_meta_analysis.htm
[60] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/Stacking.html
[61] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/WeightedInstancesHandlerWrapper.html
[62] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomSubSpace.html
[63] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/CVParameterSelection.html

1.4.21 Meta Multischeme

Meta Multischeme classifier uses cross validation on the training data or the performance on the training data. Performance is measured based on percent correct (classification) or mean-squared error (regression). [65]

1.4.22 Meta Random Committee

Meta Random Committee builds an ensemble of randomizable base classifiers. Each base classifier is built using a different random number seed (but based one the same data). The final prediction is a straight average of the predictions generated by the individual base classifiers. [66]

1.4.23 Misc Input Mapped Classifier

This is a wrapper classifier that addresses incompatible training and test data by building a mapping between the training data that a classifier has been built with and the incoming test instances' structure.[67]

1.4.24 JRip

This implements a propositional rule learner, Repeated Incremental Pruning to Produce Error Reduction (RIPPER), which was proposed by William W. Cohen as an optimized version of IREP.[68]

1.4.25 Zero R

Zero R predicts the mean (for a numeric class) or the mode (for a nominal class).[69]

1.4.26 One R Rules

One R is a rule learner that uses the minimum-error attribute for prediction, discretizing numeric attributes. [70]

1.4.27 Rules Part

This is a Rule learner that uses separate-and-conquer method. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule. [71]

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[64] Source: https://weka.sourceforge.io/doc.stable/weka/classifiers/meta/Bagging.html
[65] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/MultiScheme.html
[66] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomCommittee.html
[67] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/misc/InputMappedClassifier.html
[68] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/JRip.html
[69] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/ZeroR.html
[70] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/OneR.html
[71] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/PART.html

1.4.28 Decision Table

According to Kalmegh (2018) [3]:
Decision Table is an accurate method for numeric prediction from decision trees and it is an ordered set of If-Then rules that have the potential to be more compact and therefore more understandable than the decision trees. Selection to explore decision tables because it is a simpler, less compute intensive algorithm than the decision-tree-based approach.

1.4.29 Random Forest

According to E. Kleinberg (n.d) [31]:
Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. Random forests are an ensemble learning method for classification (and regression) that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees. The algorithm for inducing a random forest was developed by Leo Breiman and Adele Cutler.

As Kinge and Gaikwad indicate in their survey [13]:
Random Forest builds a randomized decision tree in each iteration of the algorithm and often produces excellent predictors. Every subtree gives a classification and provides the tree votes for that class.

It is called 'Random' Forest as it is using two random processes: bootstrapping and random feature selection. Bootstrapping ensures that we are not using the same data for every tree, so it helps the model to be less sensitive to our training data. The random feature selection helps to reduce the correlation between the trees (if we use every feature, then the decision trees will have the same decision nodes and they will act very similarly, which will increase the variance). [72]

1.4.30 J48 Tree

According to Vaithiyanathan, et al., (2014) [15]:
J48 Tree is an optimized implementation of the C4.5 or improved version of the C4.5. J48 Tree is a decision tree learner. The output given by J48 is the Decision tree. A Decision tree is same as that of the tree structure having different nodes, such as root node, intermediate nodes and leaf node. Each node in the tree contains a decision and

[72] Source: https://www.youtube.com/watch?v=v6VJ2RO66Ag

that decision leads to our result as name is decision tree. Decision tree divide the input space of a data set into mutually exclusive areas, where each area having a label, a value or an action to describe or elaborate its data points. Splitting criterion is used in decision tree to calculate which attribute is the best to split that portion tree of the training data that reaches a particular node.

1.4.31 Decision Stump Tree

Decision Stump is a decision tree learner. According to Witten, et al., (1999) [10]: *Decision Stump builds simple binary decision "stumps" (one-level decision trees) for both numeric and nominal classification problems. It copes with missing values by extending a third branch from the stump- in other words by treating "missing" as a separate attribute value.*

1.4.32 Random Tree

Random tree is a decision tree learner. Random Tree considers K randomly chosen attributes at each node and performs no pruning. It has also an option to allow estimation of class probabilities (or target mean in the regression case) based on a hold-out set (backfitting). [73]

1.4.33 RepTree

Rep Tree is a fast decision tree learner. It builds a decision/regression tree using information gain/variance and prunes it using reduced-error pruning (with back fitting). Rep Tree only sorts values for numeric attributes once. Missing values are dealt with by splitting the corresponding instances into pieces (i.e. as in C4.5). [74]

1.4.34 Hoeffding Tree

[18] [18]:

A Hoeffding tree (VFDT) is an incremental, anytime decision tree induction algorithm that is capable of learning from massive data streams, assuming that the distribution generating examples does not change over time. Hoeffding trees exploit the fact that a small sample can often be enough to choose an optimal splitting attribute. This idea is supported mathematically by the Hoeffding bound, which quantifies the number of observations (in our case, examples) needed to estimate some statistics within a prescribed precision (in our case, the goodness of an attribute). A theoretically

[73] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/trees/RandomTree.html
[74] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/trees/REPTree.html

appealing feature of Hoeffding Trees not shared by other incremental decision tree learners is that it has sound guarantees of performance. Using the Hoeffding bound one can show that its output is asymptotically nearly identical to that of a non-incremental learner using infinitely many examples.

1.4.35 Tree LMT

Classifier for building 'logistic model trees', which are classification trees with logistic regression functions at the leaves. The algorithm can deal with binary and multi-class target variables, numeric and nominal attributes and missing values. [75]

Linear/Logistic Regression Models, Rules' Models and Decision Tree Models are interpretable and can be easily comprehended by a human, by looking only at the model summary/ parameters, without any techniques. Interpretable models provide their own explanation. On the other hand, Voted Perceptron model, SMO Reg model and Random Forest are not interpretable and are quite difficult to be comprehended or explained by just looking at the model/summary, as they are more complicated (as their algorithms are separated into levels). For that reason, additional techniques/ tools are required in order to understand the predictions made from the algorithms.

The classifiers in WEKA are designed to be trained to predict a single 'class' attribute, which is the target for prediction. Some classifiers can only learn nominal classes, others can only learn numeric classes and others can learn both. By default, the class is taken to be the last attribute in the data.

1.5 Clustering

Clustering is a method og grouping similar things together and is considered one of the most important unsupervised learning techniques as it does not need labeling. According to Alam, (2016) [30]:
Clustering is an unsupervised learning problem and collection of objects in such a way that similar objects in the same group and dissimilar objects are in other groups.

[75] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/trees/LMT.html

In other words, we can say that clustering is a process of portioning a data set into a set of meaningful subclasses, known as clusters. Clustering is the same as classification in which data is grouped. [76]

Though, unlike classification, clustering does not seek rules that predict a particular class, but rather try to divide the data into groups/clusters, that are not previously defined, by determining similarities between data according to characteristics found in the real data.

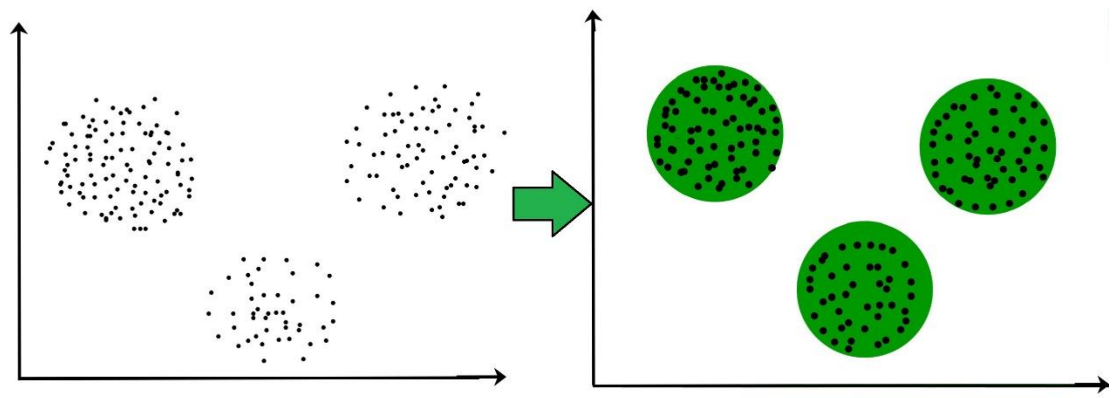

Figure 5: Clustering [77]

Eight Different Types of Clustering Algorithms in Weka Tool:

1.5.1 Simple K-Means

Let us explain how Simple K-Means clusterer works in a given dataset:

[76] Source: https://www.javatpoint.com/classification-vs-clustering-in-data-mining
[77] Source: https://www.geeksforgeeks.org/ml-classification-vs-clustering/

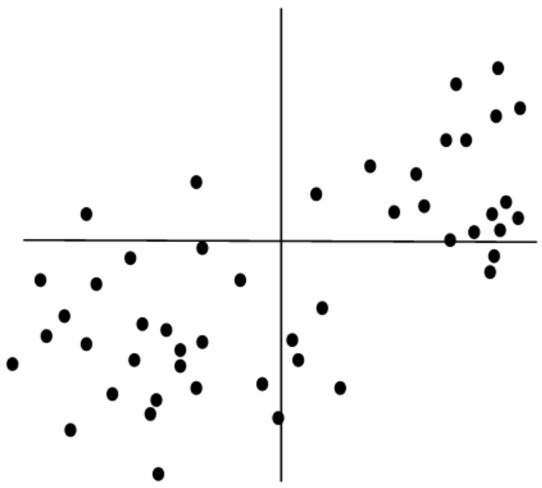

Figure 6: Pointed Data

The technique begins by randomly sprinkling some labels throughout our data (let us assume we have pink cluster and blue cluster. After labelling the data, Simple K-Means computes the centroids.

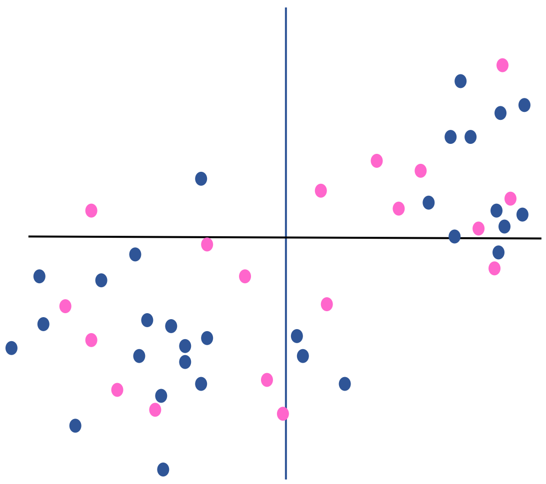

Figure 7: Data Labeling

Next, Simple K-Means randomly selects the cluster centroids, which might be close with each other.

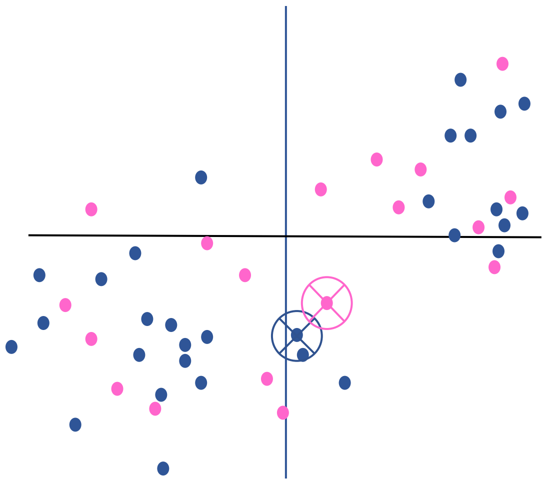

Figure 8: Finding Cluster Centroids

Now, let us forger about the previous data labeling.

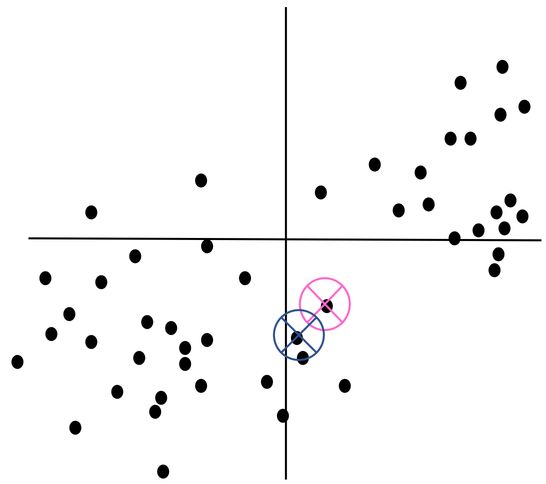

Figure 9: Centroids with no data labeling

Now, each point gets a label from the nearest centroid. For those points that are near both centroids, the machine finds the best answer. Euclidian distance is the most common way to calculate the distance of a pair of objects and it examines the root of square differences between coordinates.

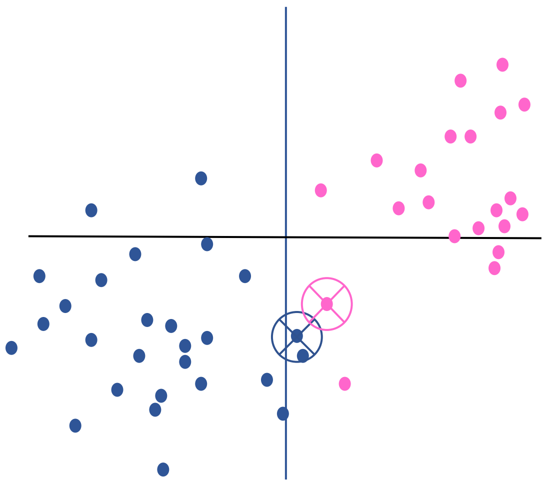

Figure 10: Clustering

Next, Simple K-Means re-computes the centers. Now the centroids should be far apart:

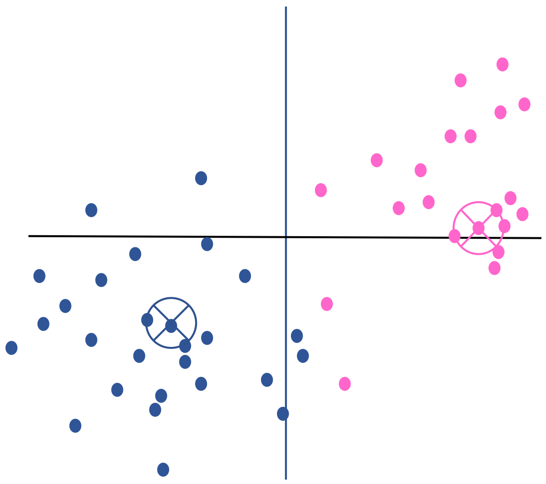

Figure 11: Recomputing the centers

Again, the clusterer forgets about the labels:

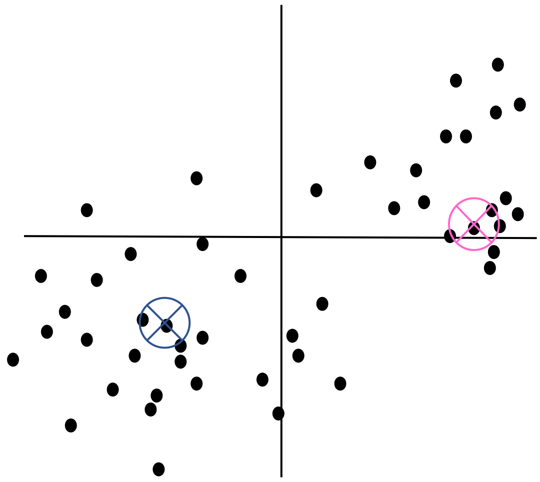

Figure 12: Centroids with no data labeling

Now, each point gets a label from the closest centroid.

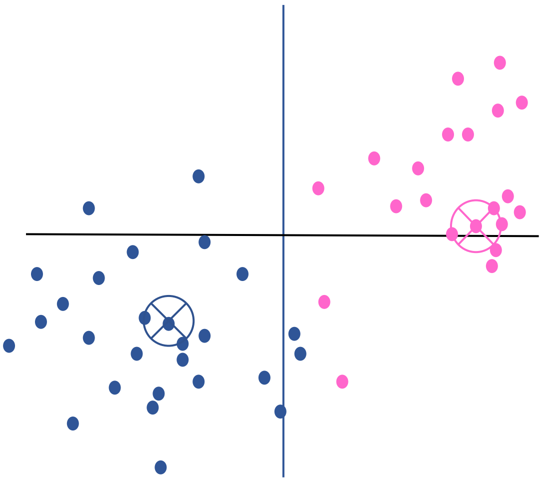

Figure 13: Clustering

Simple K-Means repeats the same procedure, until the cluster labels stop changing.

Nothing changes the next round, so the final clusters are these two:

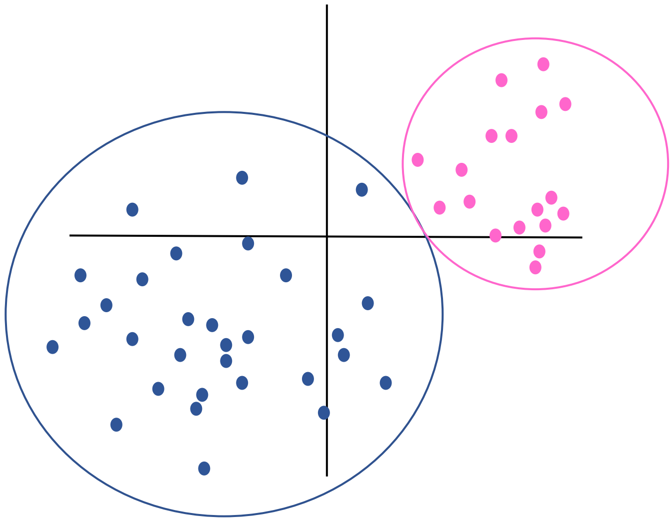

Figure 14: Final Clusters

Let us assume that a point that is equally distanced between the two centroids. After several rounds of flipping from the one cluster to the other, it finally stops and gives us one final answer (about the cluster chosen).

Something that should be pointed out is that we usually get different results from clustering each time.[78]

So, Simple K-Means is a distant-based clusterer that minimizes the squared distance from each instance to their cluster center, after defining k centroids. It is one of the best unsupervised algorithms. For each different number of seeds, there is different clustering results.[79] [80]

K in K-means stands for the number of clusters we want to create.

"This technique is iterated till there is no change in gravity centers" ([21]) [21].

1.5.2 EM

"EM (Expectation Maximization) is a probabilistic clusterer and can be used for unsupervised learning. Like Naive Bayes, it makes the assumption that all attributes are independent random variables." (Witten I.H., et al., (1999)) [10].

---

[78] Source: https://www.youtube.com/watch?v=lQ39ZRFfYbI&t=10s
[79] Source: https://www.youtube.com/watch?v=4b5d3muPQmA
[80] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

EM assigns a probability distribution to each instance which indicates the probability of it belonging to each of the clusters. EM can decide how many clusters to create by cross validation, or you may specify apriori how many clusters to generate.[81]

Let us assume we want two clusters a and b respectively.

EM starts by placing the Gaussians (μ_a, σ_a^2), (μ_b, σ_b^2) randomly on space somewhere. Then, for each point $P(b|x_i)$ it asks: is it more likely that the point belongs to the group/cluster a or b?[82]

Unlike K-Means that takes one point and places it to the one cluster or the other, EM computes the probability that it goes into a or b cluster. This probability never gets zero or one, it is always a number between zero and one (0<probability EM<1).

Once it has computed the probability that it came from a or b cluster, EM uses Gaussian numbers (μ_a, σ_a^2), (μ_b, σ_b^2), to re-estimate the means and the variances to fit the points assigned to them. Repeating, the clusters are continuing to separate and we can see very different groups of data. This procedure iterates until convergence.[83]

The model just finds that there are distinguished groups in the dataset that behave differently.

EM works for both numeric and nominal attributes providing mean and standard deviation results and value probability results respectively. Log likelihood is an overall quality measure and is increased by each iteration.[84]

1.5.3 Hierarchical Clustering

Hierarchical Clustering is often associated with heatmaps. Hierarchical Clustering orders the rows and the columns based on similarity, in order to see the correlations in the data.

Let us see an example:[85]

---

[81] Source: https://weka.sourceforge.io/doc.dev/weka/clusterers/EM.html

[82] Normal or Gaussian distribution is the most common distribution for independent, randomly generated variables. A random variable is a normally distributed variable with mean μ=0 and standard deviation σ=1.

[83] Source: https://www.youtube.com/watch?v=REypj2sy_5U

[84] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

[85] Source: https://www.youtube.com/watch?v=7xHsRkOdVwo

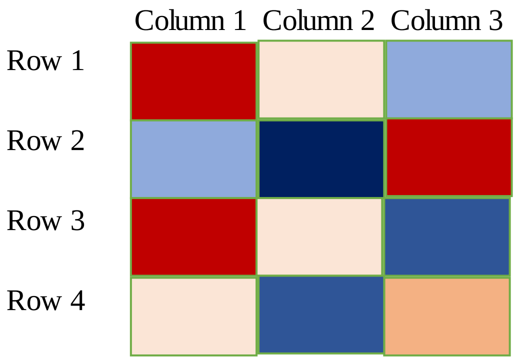

Figure 15: Heatmap

Hierarchical Clustering figures which rows are similar to row 1. Row1 and row 3 are quite similar as in column 1, both row 1 and row 3 are red, in column 2 both row 1 and row 3 are pink and in column 3 both row 1 and row 3 are blue. Row 1 and row 2 are also quite similar, but not as much as row 1 and row 2.

Now hierarchical clustering figures which row is most similar to row 2. Doing all the comparisons we can detect that row 2 is most similar to row 4.

The same procedure happens for row 3 and raw 4.

After this, hierarchical clustering figures which of the different combinations are the most similar and then merges them into clusters.

In this case rows 1 and 3 are the most similar than any other combination. So raw1 and raw 3 are now cluster 1. Cluster 1 is now treated like it is a single raw.

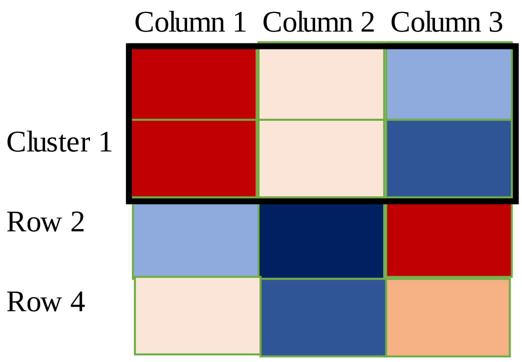

Figure 16: Clustering

Now the model tries to figure out which raw is similar to cluster 1. Cluster 1 is most similar to raw 4.

Finally, raw 2 is most similar to raw 4.

Of the different combinations, the model figures which two rows are the most similar and it merges them into a cluster. In our case, rows 2 and 4 are the most similar, so we merge them into a cluster.

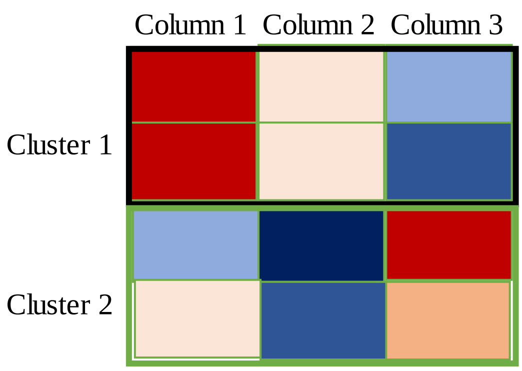

Figure 17: Clustering

Now the clusters can be all merged together.

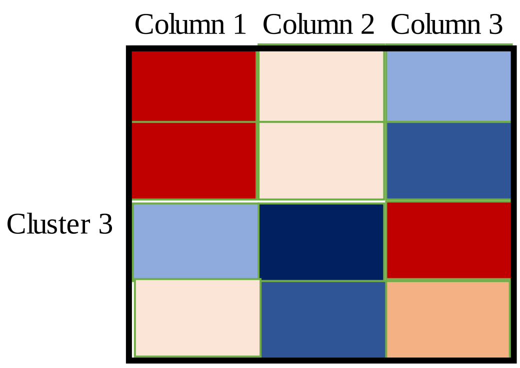

Figure 18: Clustering

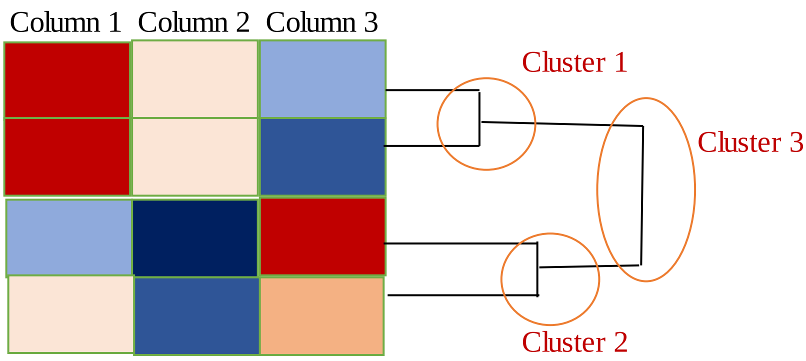

Figure 19: Dendrogram in hierarchical clustering

Hierarchical clustering is often accompanied by a dendrogram that indicates the order that the clusters were formed and the homogeneity that they presented.

Cluster 1 was formed first, had high homogeneity and has the shortest branch.

Cluster 2 was formed second, had the second best homogeneity and has the second shortest branch.

Cluster 3 has all the rows merged together and was formed last. It also has the longest branch.

According to[22] [22]:
Hierarchical cluster divides the clusters in a sequential manner with nested portions. It consists of the agglomerative approach and divisive approach. (i) Agglomerative: This is a "bottom-up" method, every analysis starts its individual cluster, and similar clusters integrated collectively move over the hierarchy until every data from at intervals one cluster. (ii) Divisive: This is a "top-down" approach, and this hierarchical clustering having all its objects into one cluster then split the cluster into the cluster. In its splitting process needs minimum relation for the different cluster and maximum relation in the same cluster.

1.5.4 Filtered Clusterer

This is a clusterer that has been passed through an arbitrary filter. Like the clusterer, the structure of the filter is based exclusively on the training data and test instances will be processed by the filter without changing their structure.[86]

According to [20] [20]: *This algorithm is primarily based completely on storing the multidimensional data points within a tree. The process regarding the tree is like a binary tree method, as represents a hierarchical subdivision on its data point set's bounding box the usage of their axis after which splitting is aligned by way on hyper planes. Each node on the tree is related with a closed field, referred to as the cell.*

1.5.5 Farthest First

According to[24] [24]: *Farthest first finds its variant of K-means. Each cluster center point furthermost from the existing cluster center is placed by the K-mean, and this point must be positioned within the data area. So that it greatly speeds up the clustering in most cases, but it needs less move and adjustment for their fast performance.*

1.5.6 Cobweb

"Cobweb is an incremental system for hierarchical conceptual clustering." (Fisher, D.H. (1987)) [25] [26]. Cobweb was invented by Professor Douglas H. Fisher, currently at Vanderbilt University.

According to [27] [27]: *Cobweb incrementally organizes observations into a classification tree. Each node in a classification tree represents a class (concept) and is labeled by a probabilistic concept that summarizes the attribute-value distributions of objects classified under the node. This classification tree can be used to predict missing attributes or the class of a new object.*

1.5.7 Make A Density Based

This is a class for wrapping a Clusterer to make it return a distribution and density. It fits normal distributions and discrete distributions within each cluster produced by the wrapped clusterer.[87]

[86] Source: https://weka.sourceforge.io/doc.dev/weka/clusterers/FilteredClusterer.html

We only have two hyperparameters:

- Eps(ilon): A “neighborhood’s” radius around a point x
- MinPts: The minimum number of neighbors within “eps” radius

Let us consider of a MinPts=5

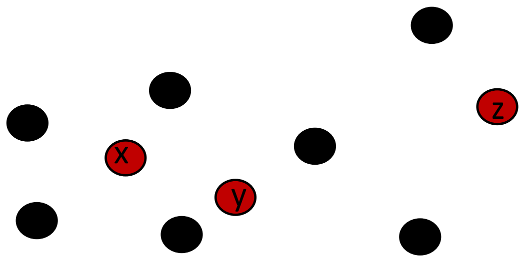

Figure 20: Data points

The clusterer randomly chooses point X. This point, is not already in a cluster, so it creates a new cluster. X and is also rounded by five other points, so we call X a core point.

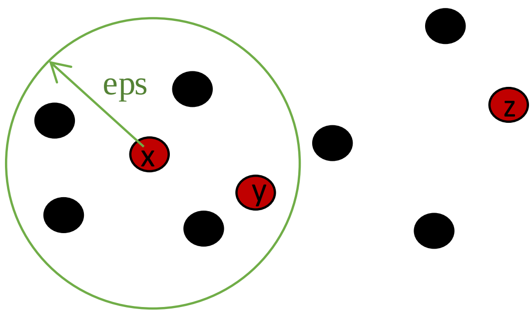

Figure 21: Corepoint X and hyperparameters

If we do the same analysis for y, we would see that it is already in cluster 1. Y is rounded by four points but one of these points is a core point. So we will call y a border point.

[87] Source: https://weka.sourceforge.io/doc.dev/weka/clusterers/MakeDensityBasedClusterer.html

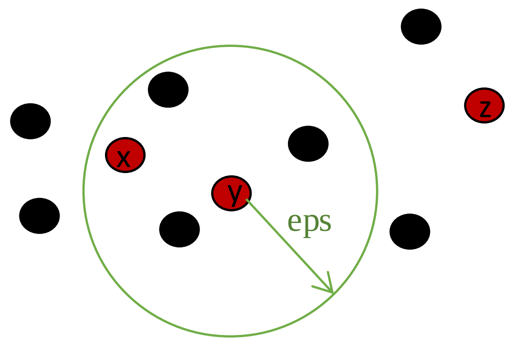

Figure 22: Borderpoint Y and hyperparameters

Except for one point, all the other points already exist in cluster 1 as well.

We re-do the same procedure for z, which is not in another cluster. Z has two neighbors, but none of them is a core point. Thus, we call z a noise point.

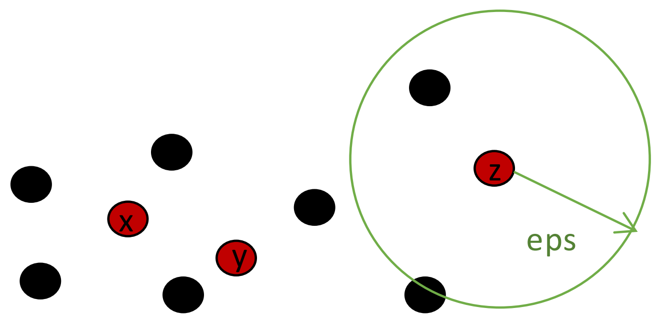

Figure 23: Noisepoint z and hyperparameters

Thus, removing the remaining-noise points, we have 1 final cluster.

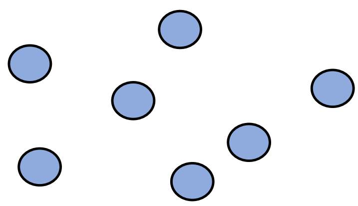

Figure 24: Final cluster

So:

- The clusterer randomly chooses the core points and then for each core point that is not already assigned to a cluster, creates a new cluster.
- The clusterer finds all its density connected points and assigns them to the same cluster as the core point.
- Then it iterates through the remaining unvisited points in the dataset.
- The core points that do not belong to any cluster are treated as outliers or noise points.[88]

According to [29] [29]: *Density-Based Clustering refers to unsupervised learning methods that identify distinctive groups/clusters in the data, based on the idea that a cluster in a data space is a contiguous region of high point density, separated from other such clusters by contiguous regions of low point density. The data points in the separating regions of low point density are typically considered noise/outliers.*

1.5.8 Canopy

According to Mai and Cheng (2016) [33]: *Canopy is one of the improved K-means algorithm, can be used to determine the number of clusters. With the introduction of Canopy clustering, the data set is divided into k sub-sets by setting the radius, and the sub-sets can be selected as the initial centers of K-means. Because the Canopy algorithm can reduce the running time of the clustering by reduce the count of comparisons, it will improve the computational efficiency. The Canopy algorithm's steps as follows:*

Step1: Put all data into a List, and initialize two distance radius about the loose threshold T1 and the tight threshold T2 (T1> T2).

Step2: Randomly select a point as the first initial center of the Canopy cluster, and delete this node from the List.

Step3: Get a point from the List, and calculate the distance d to each Canopy clusters. If d < T2, the point belongs to this cluster; if T2≤d≤T1, this point will be marked with

[88] Source: https://www.youtube.com/watch?v=f4pZ9PHNdcM

a weak label; If the distance d to all Canopy center is greater than T1, then the point will be a new Canopy cluster center. Finally, this point should be deleted from the List;

Step4: Run the step3 repeatedly until the list is empty, and recalculate the cluster center. But the execution efficiency of Canopy algorithm is affected by the radius about T1 and T2. When T1 is too large, it will makes one point belongs to multiple Canopy cluster, which will increase the computing time; when the T2 is too large, it will reduce the clustering count. So the initial radius about T1 and T2 is generally set based on the experience or experimental test, which will influence the accuracy and efficiency of classification. In order to solve the above problems, an improved Canopy-K means algorithm is proposed.

Capopy clustering algorithm can run in either batch or incremental mode. Results are generally not as good when running incrementally, as the min/max for each numeric attribute is not known in advance.[89]

According to [28] [28]: *Canopy clustering algorithm is an unsupervised pre-clustering algorithm and it is often used as preprocessing step for the K-means algorithm or the Hierarchical clustering algorithm. It is intended to speed up clustering operations on large data sets, where using another algorithm directly may be impractical due to the size of the data set.*

1.6 Association Rule Mining

According to Kaur and Madan (2015) **Error! Reference source not found.**: *Association rule mining is one of an important technique of data mining for knowledge discovery. The knowledge of the correlation between the items in the data transaction can use association rule mining*.

“It is a very famous technique for discovering correlations between variables in the huge databases” (Karthikeyan and Ravikumar, (2014) **Error! Reference source not found.**).

[89] Source: https://weka.sourceforge.io/doc.dev/weka/clusterers/Canopy.html

Association rule mining is a kind of supervised learning that has been mainly developed to identify the strongly associated relationships among item sets that have high-frequency and strong-correlation. Association rules enable us to detect the items that frequently occur together in an application and have correlations among a set of items. They are often expressed in the rule form showing attribute-value conditions that occur frequently together in a given set of data. An association rule in the form of X → Y is interpreted as 'database tuples that satisfy X are likely to satisfy Y '. Association analysis is widely used in transaction data analysis for business decision making process.

Rules can predict any attribute, or indeed any combination of attributes. To find them we need a different kind of algorithm. "Support" and "confidence" are two measures of a rule that are used to evaluate them and rank them. The most popular association rule learner, and the one used in Weka, is called Apriori.

From a given dataset with adjusted number of rules to find and adjusted minimum metric (minmetric) score/ confidence, Weka's associator model exports the best association rules/results. These results have certain confidence level, lift, leverage and conviction.

Confidence c, essentially describes the level of interrelation between two elements or sets of elements. Confidence measures the reliability of the results emerged from a rule. For a given rule, X ⇒ Y, the higher the confidence level, the more likely Y is to engage in transactions containing X. Confidence also provides an estimation of the conditional probability of Y given that X has already occurred. Confidence for the correlation rule X ⇒ Y, is calculated from the ratio of the number of transactions containing both X and Y (XUY) to the number of transactions containing the element X. It is defined by the relation:

$$Confidence = C\ (X \Rightarrow Y) = \frac{\sigma(XUY)}{\sigma X}$$

σ: support count

So, confidence is the conditional probability, that a transaction that contains a certain item X, also contains another item Y. For instance, a transaction that contains the item 'Diapers' should also contain the item 'Beer'.

According to probability theory, confidence for the correlation rule X⇒ Y, is calculated as follows:

$$\mathrm{P}(X \Rightarrow Y) = \frac{P(XUY)}{P(Y)}$$

Support count (σ(X)) of a set of elements, is the number of times that the element X appears. That is, that the support count of an element set X, can be stated as:

$$\sigma(X) = |\{t_i / X \subseteq t_i,\ t_i \in T\}|$$

i: the number of elements in a set.

Lift, is another known metric that is calculated as follows:

$$\mathrm{Lift}(X \Rightarrow Y) = \frac{c(X\mathrm{U}Y)}{s(Y)}$$

This metric calculates the correlation between the Rule's Confidence and the set of elements' support in the subsequent (second) part of the Rule (Y).

The Lift measures the degree and type of correlation between the elements of the rule and can be used to measure the relationship or independence of the elements of a rule. The statistical measure Lift (lift ratio) is used to assess the degree of confidence of a rule and is described as the confidence of the rule divided by the confidence, assuming the independence of the entailed from the previous one:

$$Lift(X \Rightarrow Y) = \frac{P(X,Y)}{P(X)P(Y)}$$

So, given a rule A ⇒ B, lift is the ratio of the probability that X and Y occur together to the multiple of the two individual probabilities for X and Y. This indicates how likely is for the product Y to be purchased given that product X is purchased, while checking how popular product Y is.

If this value is 1, then X and Y are independent. The higher this value, the more likely that the existence of X and Y together in a transaction is not just a random occurrence, but because of some relationship between them. [90]

Lift and Leverage measure similar things, except that leverage measures the difference between the probability of co-occurrence of X and Y as the independent probabilities of each of X and Y.[91]

$$\text{Leverage}(X \Rightarrow Y) = P(X \cup Y) - P(X)P(Y) = P(X,Y) - P(X) \cdot P(Y)$$

Leverage measures the difference between the probability of co-occurrence of X and Y in the data set, compared to what would be expected if X and Y were statistically independent.

In other words, leverage measures the proportion of additional cases covered by both X and Y above those expected if X and Y were independent of each other. If the value of the leverage is zero, then X and Y are statistically independent. A leverage value greater than zero, means that X and Y are related. The higher the leverage value, the stronger the correlation between X and Y.

Thus, for leverage, values above zero are desirable, whereas for lift, we want to see values greater than 1.[92]

Finally, *conviction* is similar to lift, but it measures the effect of the right-hand-side not being true. It also inverts the ratio. So, convictions is measured as:

$$Conviction = \frac{P(X)P(not\ Y)}{P(X \cup Y)} = \frac{P(X)P(not\ Y)}{P(X,Y)}$$

[90] Source: DePaul University's website: http://facweb.cs.depaul.edu/mobasher/classes/ect584/weka/associate.html

[91] Source: DePaul University's website: http://facweb.cs.depaul.edu/mobasher/classes/ect584/weka/associate.html

[92] Source: DePaul University's website: http://facweb.cs.depaul.edu/mobasher/classes/ect584/weka/associate.html

Thus, conviction, in contrast to lift is not symmetric (and also has no upper bound). In most cases, it is sufficient to focus on a combination of support, confidence, and either lift or leverage to quantitatively measure the "quality" of the rule. However, the real value of a rule, in terms of usefulness is subjective and depends heavily of the particular domain and business objectives. [93]

[93] Source: DePaul University's website: http://facweb.cs.depaul.edu/mobasher/classes/ect584/weka/associate.html

Chapter 2

*Use Case: Creta Palm Hotel 4**

Creta Palm is a four-starred hotel in Chania, Crete, Greece. For this use case, two datasets were collected from 2019 and 2020 respectively, concerning the booking source, the country of the booking source, whether the booking source is a Tour Operator or Online Travel Agency (TO/OTA), the month that each booking source made a booking in Creta Palm, the average daily rate (ADR) each booking source made in Creta Palm that month, the total bookings that the booking source made in Creta Palm that month, the total overnight stays (total pax nights) the booking source made in Creta Palm that month as well as the average number of people per room (average pax/room), the total overnight stays per room (total room nights), the number of overnight stays with breakfast (BB) and its percentage (BB%), the number of overnight stays with dinner (HB) and its percentage (HB%) and the number of "all inclusive" overnight stays (AI) and its percentage (AI%) each booking source made in Creta Palm this certain month.

Each booking source can be shown multiple times in the same year, but in different months.

In 2019, the hotel accommodated its customers from April to October whereas in 2020, the hotel accommodated its customers from July to October due to COVID-19 pandemic.

The COVID-19 outbreak has had pernicious impacts on tourism industry worldwide, so that it is considered one of the most damaged global industries. As the COVID-19 cases and deaths increased at an exponential rate, the transportation of international tourists presented a severe decline since March 2020 due to the fear of infection from the contagious virus and the worldwide health restrictions each country had imposed. As a consequence, Creta Palm presented less total bookings than those expected under normal conditions.

A real problem that the enterprises in the tourism industry are facing is that they cannot easily make predictions, nor can they identify useful patterns and rules from a certain amount of data. This, makes them more susceptible to uncertainty and risk, as they are not able to focus on the key variables that influence their companies' attributes.

This issue can be solved, through collecting and analyzing data, in order to collect the necessary information from the travel agencies, analyze their profile and make certain predictions and clusterings about them. Weka Machine Learning Software, can transform the dataset into meaningful patterns with the assistance of integrated algorithms and help us make predictions on certain variables as well as clusterings for these travel agencies or future travel agencies with a similar profile. WEKA, helps us to better predict the results of a new oncoming dataset that has similar characteristics with our already existing dataset and there is a high probability that the dataset values are similar to those predicted from the algorithm.

Creta Palm's dataset needed a further data preparation/ training in order to bring it in a suitable format and train a classifier (the variable we want to predict). In this case, the classifier is total bookings.

After training, the dataset is loaded in Weka, where further data preparations were made in order to bring it in a suitable format and therefore, prediction models and clustering models are created. These models are developed through the integrated machine learning algorithms that are chosen each time. These algorithms provide patterns and consequently, useful prediction results for the hotel.

Cross-validation method is used in order to value the classifiers, by using the number of folds entered in the corresponding field. In our 10-fold cross-validation, the original sample is randomly partitioned into 10 subsamples. Of the 10 subsamples, a single subsample is retained as the test set, and the remaining 9 subsamples are used as training set[94]. The cross-validation process is repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds then can be averaged (or otherwise combined) to produce a single estimation.

Supplied test set is used in order to make predictions for new unseen data from the set of instances loaded from the file.

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[94] A training set is a subset of a dataset that is used to train a model and a test set is a subset of a dataset that is used to test the trained model. Source: https://developers.google.com/machine-learning/crash-course/training-and-test-sets/splitting-data

For clustering outputs, the training set is used, so that, the cluster is the same set that the clusterer is trained on.

Chapter 2 presents the total bookings of each booking source based on the hotel's data for the years 2019 and 2020 (see chapter WEKA ***Regression 2019*** for the year 2019 and chapter WEKA **Regression 2020** for the year 2020 respectively) as well as the clusterings created for the years 2019 and 2020 (see chapter 2.2 for the year 2019 and chapter 2.4 for the year 2020 respectively) through weka software system.

Creta Palm data sets' sizes were not satisfactory, so the results may not be as good as they should be.

2.1 WEKA Regression 2019

WEKA Algorithms

As mentioned above, for numeric values, WEKA regression algorithms detect correlation coefficient, mean absolute error, root mean squared error, relative absolute error and root relative squared error.

- Correlation coefficient implies what percentage of the variance in your data is explained by your model. The greater the correlation coefficient value, the more accurate the model's predictions are. A high correlation coefficient (greater than 0.95) depicts that there is a strong relation between our data values and the values of the algorithm's prediction model and that our data do get close to the predictions of the model.
- Mean absolute error is the average distance the models' predictions are from the actual data points. Absolute in the title indicates that predictions below data points ate not treated as negative distances.
- Root mean squared error is another way of calculating the mean absolute error.
- Relative absolute error and root relative squared error scale the error to the mean. This enables the comparison between models constructed with larger/smaller valued data.

- Total number of instances is the number of data points in the data set.

Correlation coefficient and mean absolute error give a really good picture of how well things are performing. A high correlation coefficient (above 0.9) and a low mean absolute error depict that our predictions are close to the expected values, which indicate high accuracy in our results..

This chapter presents the algorithms that are performing well considering all the values as well as the predictions of the algorithms concerning the hotel's Total Bookings.

2.1.1 M5Rules

See Appendix: M5Rules Algorithm| Creta Palm 2019

=== Summary ===

Correlation coefficient	0.9788
Mean absolute error	3.9186
Root mean squared error	5.7585
Relative absolute error	20.4949 %
Root relative squared error	20.3659 %
Total Number of Instances	91

M5 Rules Algorithm provides the best results from all the algorithms. The high correlation coefficient (0.9788>0.95) depicts that there is a strong relation between our data values and the values of the (M5Rules) algorithm's prediction model and that our data do get close to the predictions of the model.

We can better predict the results of a new oncoming dataset that has similar characteristics with our already existing dataset and there is a high probability that the dataset values are similar to those predicted from the algorithm.

M5Rules generates a decision list for regression problems using separate-and-conquer. In each iteration, it builds a model tree using M5 and makes the "best" leaf into a rule.[95]

M5Rules is an interpretable, quite simple algorithm model. The model is understandable and explainable, as it is clear of how it arrived at a specific decision.

Let us interpret the patterns and conclusions that M5P rules regression's model tells us: Booking Sources and countries have different type of influence in total bookings each time (either positive or negative depending on the sign of the number in front of each booking source or country). However, as we can see, the total overnight stays (total PAX nights), the total overnight stays with dinner (HB) and the total room nights are having a positive correlation to the total bookings. Specifically, the positive coefficient in front of these variables depict that the higher the values of total PAX nights, total overnight stays with dinner and total room nights, the higher the number of the total bookings. On the other hand, all-inclusive overnight stays (AI), seem to have a negative correlation to the total bookings as the variable has a negative coefficient in front of it. That is, that the more overnight stays with dinner (HB) may lead to less total bookings.

High values of HB may lead to in overall less total bookings, but that does not mean that they are not profitable. The hotel may examine the situation and can possibly raise the prices for overnight stays with dinner, or confine the availability of them, in order to have a higher number of total bookings.

According to the algorithm's results, June , July and September of 2019 seem to have a positive correlation with the total bookings, which means that in these months the total bookings of Creta Palm increased.

M5Rules' Algorithm predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

"Actual" represents the actual total bookings of Creta Palm in 2019. "Predicted" represents the hotel's predicted bookings for each travel agency according to the respective algorithm. "Error" represents the accuracy of the predicted booking results. The higher the deviation between the actual and the predicted booking results, the lower the accuracy.

[95] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/M5Rules.html

=== Predictions on test data ===

inst#	actual	predicted	error
TUI DEUTSCHLAND	14	16.561	2.561
EXPEDIA	32	27.472	-4.528
AURINKOMATKAT	125	113.653	-11.347
TUI UK	8	7.951	-0.049
ARHUS CHARTER	25	34.889	9.889
JET2HOLIDAYS	28	25.491	-2.509
ARHUS CHARTER	40	32.647	-7.353
EXPEDIA	45	39.657	-5.343
AURINKOMATKAT	92	101.22	9.22
AURINKOMATKAT	132	131.206	-0.794
AURINKOMATKAT	78	92.685	14.685
ITAKA	42	49.487	7.487
SUNWEB	19	17.322	-1.678
JET2HOLIDAYS	35	34.279	-0.721
TUI NL	6	7.1	1.1
ITAKA	56	41.326	-14.674
AURINKOMATKAT	82	93.822	11.822
EXPEDIA	26	31.83	5.83
SUNWEB	21	30.36	9.36
EXPEDIA	46	35.05	-10.95
AURINKOMATKAT	135	116.425	-18.575
BOOKING. COM	11	10.472	-0.528

Table 2: Predictions on test data- M5 Rules

2.1.2 M5P trees

M5 pruned model tree: (using smoothed linear models)

LM1 (91/16.644%)

See Appendix: M5P Trees Algorithm| Creta Palm 2019

=== Summary ===

Correlation coefficient	0.9768
Mean absolute error	4.0039
Root mean squared error	5.9966
Relative absolute error	20.9406 %
Root relative squared error	21.208 %
Total Number of Instances	91

M5P Trees' Algorithm provides the second best result from all algorithms. The high correlation coefficient (0.9768>0.95) depicts that there is a strong relation between our data values and the values of the (M5P Trees) algorithm's prediction model and that our data do get close to the predictions of the model.

According to [17]"The M5P model tree is based on conventional decision tree associated to linear regression function at the leaves nodes".

M5P Trees is an interpretable, quite simple algorithm model. The model is understandable and explainable, as it is clear of how it arrived at a specific decision.

M5P Trees provide the same algorithm results as those of M5Rules.

Booking Sources and countries have different type of influence in total bookings each time (either positive or negative depending on the sign of the number in front of each booking source or country). However, as we can see, the total overnight stays (total PAX nights), the total overnight stays with dinner (HB) and the total room nights are having a positive correlation to the total bookings. Specifically, the positive coefficient in front of these variables depict that the higher the values of total PAX nights, total overnight stays with dinner and total room nights, the higher the number of the total bookings. On the other hand, all-inclusive overnight stays (AI), seem to have a negative correlation to the total bookings as the variable has a negative coefficient in front of it. That is, that the more overnight stays with dinner (HB) may lead to less total bookings.

High values of HB may lead to in overall less total bookings, but that does not mean that they are not profitable. The hotel may examine the situation and can possibly raise the prices for overnight stays with dinner, or confine the availability of them, in order to have a higher number of total bookings.

According to the algorithm's results, June, July and September of 2019 seem to have a positive correlation with the total bookings, which means that in these months the total bookings of Creta Palm increased.

M5P Trees Algorithm's predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

=== Predictions on user test set ==

inst#	actual	predicted	error

EXPEDIA	14	31.947	-0.053
AURINKOMATKAT	32	108.374	-16.626
TUI UK	125	7.951	-0.049
TUI DEUTSCHLAND	8	17.476	3.476
ARHUS CHARTER	25	34.889	9.889
JET2HOLIDAYS	28	25.491	-2.509
ARHUS CHARTER	40	32.647	-7.353
EXPEDIA	45	39.657	-5.343
AURINKOMATKAT	92	101.22	9.22
AURINKOMATKAT	132	131.206	-0.794
AURINKOMATKAT	78	92.685	14.685
ITAKA	42	49.487	7.487
SUNWEB	19	18.835	-0.165
JET2HOLIDAYS	35	33.886	-1.114
TUI NL	6	7.1	1.1
ITAKA	56	38.252	-17.748
AURINKOMATKAT	82	93.822	11.822
EXPEDIA	26	31.83	5.83
SUNWEB	21	30.807	9.807
EXPEDIA	46	35.242	-10.758
AURINKOMATKAT	135	117.105	-17.895
BOOKING.COM	11	10.472	-0.528

Table 3: Predictions on user test set- M5P Trees

2.1.3 SMO Reg

See Appendix: SMOreg Algorithm| Creta Palm 2019

=== Summary ===

Correlation coefficient 0.9712

Mean absolute error 5.219

Root mean squared error 6.6622

Relative absolute error 27.2957 %

Root relative squared error 23.5618 %

Total Number of Instances 91

Number of kernel[96] evaluations: 4186 (99.697% cached)

SMO Reg Algorithm also provides a high correlation coefficient (0.9712>0.95). This means that there is a strong relation between our data values and the values of the (SMO Reg) algorithm's prediction model and that our data do get close to the predictions of the model.

Sequential Minimal Optimization (SMO) method breaks the problem down into sub-problems that can be solved analytically (by calculating) rather than numerically (by searching or optimizing).[97]

SMO Reg is neither interpretable nor simple algorithm model. This means, that one who does not have the necessary expertise in the field of technology or analytics cannot fundamentally understand how the model arrived in a certain output or how the output influences the output, by just reading the algorithm.

SMO Reg's Algorithm predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
EXPEDIA	14	10.463	-3.537
AURINKOMATKAT	32	28.704	-3.296
TUI UK	125	109.383	-15.617
TUI DEUTSCHLAND	8	7.741	-0.259
ARHUS CHARTER	25	36.617	11.617
JET2HOLIDAYS	28	26.181	-1.819
ARHUS CHARTER	40	31.028	-8.972
EXPEDIA	45	35.884	-9.116
AURINKOMATKAT	92	96.418	4.418
AURINKOMATKAT	132	137.243	5.243
AURINKOMATKAT	78	93.971	15.971
ITAKA	42	48.435	6.435
SUNWEB	19	19.374	0.374
JET2HOLIDAYS	35	32.115	-2.885
TUI NL	6	10.302	4.302
ITAKA	56	36.596	-19.404
AURINKOMATKAT	82	89.021	7.021

[96] A "kernel" is usually used to refer to a method of using a linear classifier to solve a non-linear problem.
[97] Source:https://machinelearningmastery.com/support-vector-machines-for-machine-learning/

EXPEDIA	26	39.009	13.009
SUNWEB	21	29.428	8.428
EXPEDIA	46	39.046	-6.954
AURINKOMATKAT	135	130.624	-4.376
BOOKING.COM	11	16.079	5.079

Table 4: Predictions on test data- SMO Reg

2.1.4 Linear Regression

See Appendix: Linear Regression Model Algorithm

=== Summary ===

Correlation coefficient 0.9695

Mean absolute error 4.7712

Root mean squared error 6.8744

Relative absolute error 24.954 %

Root relative squared error 24.3122 %

Total Number of Instances 91

Linear Regression provides a high correlation coefficient (0.9695>0.95) as well. As a consequence, there is a strong relation between our data values and the values of the algorithm's prediction model and that our data do get close to the predictions of the model.

Linear regression is a very simple regression algorithm that only supports regression type problems and is issued for prediction. The model uses the Akaike criterion for model selection, and is able to deal with weighted instances. Linear Regression can only deal with numeric attributes. [98]

The model is understandable and explainable, as it is clear of how it arrived at a specific decision.

As far as the patterns and conclusions that linear regression's model are concerned: Booking Sources and countries have different type of influence in total bookings each time (either positive or negative depending on the sign of the number in front of each booking source or country). However, as we can see, Average Daily Rate (ADR), total overnight stays (total PAX nights) and total room nights are having a positive

[98] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/LinearRegression.html

correlation to the total bookings. Specifically, the positive coefficient in front of these variables depict that the higher the values of ADR, total PAX nights and total room nights, the higher the number of the total bookings, which is something expected. On the other hand, overnight stays with breakfast (BB) and all-inclusive overnight stays (AI), seem to have a negative correlation to the total bookings as these variables have a negative coefficient in front of them. That is, that the more overnight stays with breakfast (BB) as well as the more all-inclusive overnight stays (AI), may lead to less total bookings.

According to the algorithm's results, June and July seem to have a positive correlation with the total bookings, which means that in June and July the total bookings increased. This is confirmed through the original dataset.

High values of BB and AI may lead to in overall less total bookings, but that does not mean that they are not profitable. The hotel may examine the situation and can possibly raise the prices for overnight stays with breakfast or all-inclusive overnight stays, or confine the availability of those two, in order to have a higher number of total bookings.

Linear Regression's predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
EXPEDIA	14	12.259	-1.741
AURINKOMATKA	32	31.243	-0.757
TUI UK	125	117.443	-7.557
TUI DEUTSCHLAND	8	10.173	2.173
ARHUS CHARTER	25	33.709	8.709
JET2HOLIDAYS	28	25.192	-2.808
ARHUS CHARTER	40	34.862	-5.138
EXPEDIA	45	37.768	-7.232
AURINKOMATKAT	92	94.726	2.726
AURINKOMATKAT	132	135.551	3.551
AURINKOMATKAT	78	94.647	16.647
ITAKA	42	55.068	13.068
SUNWEB	19	19.481	0.481
JET2HOLIDAYS	35	33.772	-1.228
TUI NL	6	8.04	2.04

ITAKA	56	40.695	-15.305
AURINKOMATKAT	82	92.631	10.631
EXPEDIA	26	37.602	11.602
SUNWEB	21	30.232	9.232
EXPEDIA	46	39.935	-6.065
AURINKOMATKAT	135	120.129	-14.871
BOOKING.COM	11	14.332	3.332

Table 5: Predictions on test data- Linear Regression

2.1.5 Gaussian Process

Kernel used:[99]
Linear Kernel: K(x,y) = <x,y>

All values shown based on: Normalize training data.

Average Target Value : 0.16
Inverted Covariance Matrix:
  Lowest Value = -0.23
  Highest Value = 0.80
Inverted Covariance Matrix * Target-value Vector:
  Lowest Value = -0.07
  Highest Value = 0.14

=== Summary ===

Correlation coefficient 0.9674

Mean absolute error 5.4531

Root mean squared error 7.1561

Relative absolute error 28.5204 %

Root relative squared error 25.3086 %

Total Number of Instances 91

[99] A "kernel" is usually used to refer to a method of using a linear classifier to solve a non-linear problem.

Gaussian Process provides a high correlation coefficient (0.9674>0.95) as well. As a consequence, there is a strong relation between our data values and the values of the algorithm's prediction model and that our data do get close to the predictions of the model.

Gaussian Process is a simple and interpretable model but it has not too many parameters. Gaussian Process implements regression without hyper parameter tuning. This implementation applies normalization/standardization to the target attribute as well as the other attributes (if normalization/standardization is turned on). Missing values are replaced by the global mean/mode. Nominal attributes are converted to binary ones.[100]

Gaussian Processes' predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
EXPEDIA	14	14.662	0.662
AURINKOMATKAT	32	28.203	-3.797
TUI UK	125	99.79	-25.21
TUI DEUTSCHLAND	8	10.393	2.393
ARHUS CHARTER	25	31.42	6.42
JET2HOLIDAYS	28	24.124	-3.876
ARHUS CHARTER	40	34.074	-5.926
EXPEDIA	45	38.173	-6.827
AURINKOMATKAT	92	92.942	0.942
AURINKOMATKAT	132	129.598	-2.402
AURINKOMATKAT	78	86.816	8.816
ITAKA	42	53.013	11.013
SUNWEB	19	17.918	-1.082
JET2HOLIDAYS	35	30.582	-4.418
TUI NL	6	12.375	6.375
ITAKA	56	35.378	-20.622
AURINKOMATKAT	82	94.342	12.342
EXPEDIA	26	38.622	12.622
SUNWEB	21	25.842	4.842
EXPEDIA	46	36.575	-9.425
AURINKOMATKAT	135	122.617	-12.383

[100] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/GaussianProcesses.html

BOOKING.COM	11	16.95	5.95

Table 6: Predictions on test data- Gaussian Process

2.1.6 Random Forest

=== Summary ===

Correlation coefficient 0.9655

Mean absolute error 5.9985

Root mean squared error 8.3188

Relative absolute error 31.3731 %

Root relative squared error 29.4205 %

Total Number of Instances 91

Random Forest is bagging with 100 iteration and provides a high correlation coefficient (0.9674>0.95) as well. As a consequence, there is a strong relation between our data values and the values of the algorithm's prediction model and that our data do get close to the predictions of the model.

According to E. Kleinberg (n.d) [31]: *Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. Random forests are an ensemble learning method for regression that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees.*

Random Forest is not an interpretable model, and it has not too many parameters for analysis. So, one who does not have the necessary expertise in the field of technology or analytics cannot fundamentally understand how the model arrived in a certain output or how the output influences the output, by just reading the algorithm.

Random Forest's predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
EXPEDIA	14	16.088	2.088
AURINKOMATKAT	32	28.787	-3.213
TUI UK	125	92.079	-32.921
TUI DEUTSCHLAND	8	10.704	2.704
ARHUS CHARTER	25	35.69	10.69
JET2HOLIDAYS	28	25.833	-2.167
ARHUS CHARTER	40	31.636	-8.364
EXPEDIA	45	32.956	-12.044
AURINKOMATKAT	92	87.222	-4.778
AURINKOMATKAT	132	106.129	-25.871
AURINKOMATKAT	78	83.944	5.944
ITAKA	42	42.417	0.417
SUNWEB	19	21.884	2.884
JET2HOLIDAYS	35	25.092	-9.908
TUI NL	6	10.205	4.205
ITAKA	56	41.017	-14.983
AURINKOMATKAT	82	81.03	-0.97
EXPEDIA	26	34.859	8.859
SUNWEB	21	22.201	1.201
EXPEDIA	46	33.427	-12.573
AURINKOMATKAT	135	110.976	-24.024
BOOKING.COM	11	11.026	0.026

Table 7: Predictions on test data- Random Forest

2.1.7 Meta Randomizable Filtered Classifier

=== Summary ===

Correlation coefficient 0.9448

Mean absolute error 6.0989

Root mean squared error 9.4001

Relative absolute error 31.898 %

Root relative squared error 33.245 %

Total Number of Instances 91

Meta Randomizable Filtered Classifier provides lower correlation coefficient results. However, there is still a positive relation between our data values and the values of the algorithm's prediction model and our data do get close to the predictions of the model.

This is a metaclassifier for handling multi-class datasets with two-class classifiers and it has more than two outcomes. This classifier is also capable of applying error correcting output codes for increased accuracy. The base classifier must be an updateable classifier.[101]

Meta Randomizable Filtered Classifier's predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
EXPEDIA	14	24	10
AURINKOMATKAT	32	28	-4
TUI UK	125	92	-33
TUI DEUTSCHLAND	8	18	10
ARHUS CHARTER	25	39	14
JET2HOLIDAYS	28	34	6
ARHUS CHARTER	40	25	-15
EXPEDIA	45	34	-11
AURINKOMATKAT	92	125	33
AURINKOMATKAT	132	135	3
AURINKOMATKAT	78	82	4
ITAKA	42	41	-1
SUNWEB	19	23	4
JET2HOLIDAYS	35	16	-19
TUI NL	6	4	-2
ITAKA	56	41	-15
AURINKOMATKAT	82	92	10
EXPEDIA	26	45	19
SUNWEB	21	23	2
EXPEDIA	46	35	-11
AURINKOMATKAT	135	132	-3
BOOKING.COM	11	9	-2

Table 8: Predictions on test data- Meta Randomizable Filtered Classifier

[101] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/MultiClassClassifierUpdateable.html

2.1.8 Meta Random Committee

Meta Random Committee's Classifier model contributes to the total bookings' predictions through the decision tree model that is presented in the appendix. The total bookings' number depends on parameters such as the booking sources and whether it is Tour Operators or Online Travel Agencies (TO/OTA), the customer's countries, the average daily rate (ADR), the total overnight stays per room (total room nights), the average number of people per room (average pax/room), the total overnight stays (total pax nights), the number of overnight stays with breakfast (BB) and its percentage (BB%), the number of overnight stays with dinner (HB) and its percentage (HB%) and the "all inclusive" overnight stays (AI) and its percentage (AI%) and the month of the lodging.

See Appendix: Meta Random Committee Algorithm| Creta Palm 2019

=== Summary ===

Correlation coefficient	0.9429
Mean absolute error	6.6512
Root mean squared error	9.6551
Relative absolute error	34.7865 %
Root relative squared error	34.1466 %
Total Number of Instances	91

Meta Random Committee provides lower correlation coefficient results. However, there is still a positive relation between our data values and the values of the algorithm's prediction model and our data do get close to the predictions of the model.

This is a classifier for building an ensemble of randomizable base classifiers. Each base classifier is built using a different random number seed (but based on the same data). The final prediction is a straight average of the predictions generated by the individual base classifiers. [102]

Meta Random Committee's predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

[102] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomCommittee.html

=== Predictions on test data ===

inst#	actual	predicted	error
EXPEDIA	14	9.271	-4.729
AURINKOMATKA	32	28.04	-3.96
TUI UK	125	81.214	-43.786
TUI	8	12.52	4.52
ARHUS CHARTER	25	36.546	11.546
JET2HOLIDAYS	28	24.12	-3.88
ARHUS CHARTER	40	25.45	-14.55
EXPEDIA	45	37.307	-7.693
AURINKOMATKAT	92	66.011	-25.989
AURINKOMATKAT	132	120.05	-11.95
AURINKOMATKAT	78	95.255	17.255
ITAKA	42	46.533	4.533
SUNWEB	19	23.167	4.167
JET2HOLIDAYS	35	22.049	-12.951
TUI NL	6	6.533	0.533
ITAKA	56	53.183	-2.817
AURINKOMATKAT	82	93.457	11.457
EXPEDIA	26	32.547	6.547
SUNWEB	21	32.183	11.183
EXPEDIA	46	37.983	-8.017
AURINKOMATKAT	135	105.313	-29.687
BOOKING.COM	11	11.933	0.933

Table 9: Predictions on test data- Meta Random Committee

See in the Appendix:

Classifiers with low or negative correlation coefficient (2019):

A lower or negative correlation coefficient depicts that there is a weak relation (or negative relation) between our data and the algorithm’s prediction model and that the data do not get close to the predictions of the model. This practically means that for the new oncoming agencies that have similar characteristics as those 2019’s agencies, there is a low probability that the total bookings are similar as those predicted from the algorithm (or that the total bookings depict opposite results from those predicted from the algorithm – as far as negative correlation coefficient results are concerned-).

2.2 WEKA Clustering 2019

WEKA Clusterers

Clustering is a method of grouping similar things together. As mentioned in the first chapter, clustering is a process of portioning a data set into a set of meaningful subclasses, known as clusters. Clustering is the same as classification in which data is grouped. [103]

Though, unlike classification, clustering does not seek rules that predict a particular class, but rather try to divide the data into groups/clusters, that are not previously defined, by determining similarities between data according to characteristics found in the real data.

Like regression's procedure, two datasets were collected from 2019 and 2020 respectively, concerning the booking source, the country of the booking source, whether the booking source is a Tour Operator or Online Travel Agency (TO/OTA), the month that each booking source made a booking in Creta Palm, the average daily rate (ADR) each booking source made in Creta Palm that month, the total bookings that the booking source made in Creta Palm that month, the total overnight stays (total pax nights) the booking source made in Creta Palm that month as well as the average number of people per room (average pax/room), the total overnight stays per room (total room nights), the number of overnight stays with breakfast (BB) and its percentage (BB%), the number of overnight stays with dinner (HB) and its percentage (HB%) and the number of "all inclusive" overnight stays (AI) and its percentage (AI%) each booking source made in Creta Palm this certain month. These datasets are loaded to WEKA software system in order to make the clusterings.

According to these data, WEKA created several clustering options depending on the clusterer chosen (Simple K- Means, EM, Make a Density, Farthest First, Canopy, Filtered) in order to group the travel agencies that presented similarities and disjoin those that displayed dissimilarities. The aim of clustering is to find distinct groups within a given dataset. Clustering also helps us discern the characteristics between data elements that would otherwise have been unlabeled and uncategorized.

[103] Source: https://www.javatpoint.com/classification-vs-clustering-in-data-mining

For clustering outputs, the same dataset is used as those of classification.

Chapters 2.2 and 2.4 present the clusterings made according to the hotel's data for the years 2019 and 2020 (see chapter 2.2 for the year 2019 and chapter 2.4 for the year 2020 respectively).

2.2.1 Simple K Means

As mentioned in the first chapter (an analytical explanation is presented in chapter 60), Simple Means is a distant-based clusterer that minimizes the squared distance from each instance to their cluster center, after defining k centroids. It is one of the best unsupervised algorithms. For each different number of seeds, there are different clustering results.[104] [105]

Simple K Means uses random numbers and by using the same seed, we will always get the same random numbers. If we run Simple K Means over the same data twice, with the same seed, we will get exactly the same results. For different number of seeds, the results will vary each time we run Simple K Means.

In our dataset we use the same seed.

Simple K Means Clusterer, presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings, depending on their number of clusters are presented below.

<u>Simple K Means with 2 Clusters</u>

Number of iterations: 7

Within cluster sum of squared errors: 278.35

Missing values globally replaced with mean/mode.

[104] Source: https://www.youtube.com/watch?v=4b5d3muPQmA
[105] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

	Final Cluster Centroids		
Attribute	Full Data (91.0)	0 (54.0)	1 (37.0)
Booking Source	ARHUS CHARTER	BLUE AEGEAN	RAINBOW
Country	Denmark	Vary	Poland
Average pax/room	2.4126	2.4121	2.4133
TO/ OTA	TO	TO	TO
ADR	82.1023	74.4252	93.3067
Total Bookings	22.1868	14.2222	93.3067
Total PAX Nights	491.0659	236.3333	862.8378
Total Room Nights	195.9231	101.1296	334.2703
BB	238.8	149.0704	369.7568
BB%	0.4559	0.555	0.3112
HB	77.6	75.7519	80.2973
HB%	0.2866	0.3741	0.1588
AI	180.4333	21.2302	412.7838
AI%	0.2728	0.0964	0.5303
Month	April 2019	April 2019	August 2019

Table 10: Final Cluster Centroids- Simple K Means

Clustered Instances (number of instances detected in each cluster):

0 54 (59%)

1 37 (41%)

Simple K Means divides Cretan Palm’s booking sources into two clusters. The first cluster’s centroid is BLUE AEGEAN and the second cluster’s centroid is RAINBOW.

Centroids of cluster 0 depict that the customers in cluster 0 have as dominant characteristics that they come from various different countries (Vary), that they choose BLUE AEGEAN as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1 have as dominant characteristics that they come from Poland, that they choose RAINBOW as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

Simple K Means uses random numbers and by using the same seed, we will always get the same random numbers. If we run Simple K Means over the same data twice, with the same seed, we will get exactly the same results. For different number of seeds, the results will vary each time we run Simple K Means.

In our dataset we use the same seed.

Simple K Means Clusterer, presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings, depending on their number of clusters are presented below.

Simple K Means with 3 Clusters

See the clustering results in the appendix: ***Simple K Means with 3 Clusters| Creta Palm 2019***

Within cluster sum of squared errors: 255.64

Number of iterations: 5

Missing values globally replaced with mean/mode.

Clustered Instances

0 41 (45%)

1 24 (26%)

2 26 (29%)

Simple K Means with 4 Clusters

See the clustering results in the appendix: ***Simple K Means with 4 Clusters| Creta Palm 2019***

Within cluster sum of squared errors: 235.03

Number of iterations: 7

Missing values globally replaced with mean/mode.

Clustered Instances

0 41 (45%)

1 24 (26%)

2 26 (29%)

Simple K Means with 5 Clusters

See the clustering results in the appendix: ***Simple K Means with 5 Clusters| Creta Palm 2019***

Within cluster sum of squared errors: 235.03

Number of iterations: 7

Missing values globally replaced with mean/mode.

Clustered Instances

0 21 (23%)

1 14 (15%)

2 18 (20%)

3 30 (33%)

4 8 (9%)

2.2.2 EM

"EM (Expectation Maximization) is a probabilistic clusterer and can be used for unsupervised learning. Like Naive Bayes, it makes the assumption that all attributes are independent random variables." (Witten I.H., et al., (1999))

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.2), unlike K-Means that takes one point and places it to the one cluster or the other, EM computes the probability that it goes into a or b cluster. This probability never gets zero or one, it is always a number between zero and one (0<probability EM<1).

The model just finds that there are distinguished groups in the dataset that behave differently. EM run alternative number of clusters and then chooses automatically the number of the clusters it shall create.

EM works for numeric attributes providing mean and standard deviation results and value probability results respectively. Log likelihood is an overall quality measure and is increased by each iteration. [106]

Number of clusters selected by cross validation: 6
Number of iterations performed: 2

	0 (0.25)	1 (0.14)	2 (0.18)	3 (0.09)	4 (0.16)	5 (0.17)
Booking Source						
ARHUS CHARTER	1.9645	1	6	1.1962	1.798	1.0413
AURINKOMATKAT	1	8	1	1	1	1
BLUE AEGEAN	5.9625	1	1	1.861	1.1185	2.058
BOOKING.COM	1	1	1	8	8	1
BRAVO TOURS	8	1	1	1	1	1
EXPEDIA	1	1	1	1	8	1
ITAKA	1	2	6	1.0036	1.9964	1
Jet2Holidays	1.0233	1	1	1.0427	1.8145	7.1194
RAINBOW	3.9457	1	4	1.2826	1.7107	1.0609
SUNWEB	1	1	1	7.9973	1	1.0027
TUI Deutschland	8	1	1	1	1	1
TUI NL	1	1	1	6.3393	1.6418	2.0189
TUI UK	1	1	1	1.5546	1.9216	6.5003

[106] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

[total]	35.9196	21	26	27.2773	32.0015	26.8016
Country						
Denmark	8.9645	1	6	1.1962	1.798	1.0413
Finland	1	8	1	1	1	1
Romania	5.9625	1	1	1.861	1.1185	2.058
Vary	1	1	1	1	15	1
Poland	3.9457	2	9	1.2863	2.7071	1.0609
UK	1.0468	1	1	1.5973	2.7361	12.6197
Netherlands	1	1	1	13.3366	1.6418	2.0216
Germany	8	1	1	1	1	1
[total]	30.9196	16	21	22.2773	27.0015	21.8016

Table 11: Clustering- EM

See the rest of the results in the Appendix: EM Clusterer| Creta Palm 2019

EM divides Cretan Palm's booking sources into six clusters. For each of the attributes, there is a probability that the output is going to be this certain attribute. This probability is calculated if you divide the number of the attribute by the total attributes in each of the clusters. For example:

ARHUS CHARTER in cluster 0 (1.9645) has a 5.4% probability (1.9645/35.9196*) of being cluster's 0 centroid.

*[total: 35.9196]

BLUE AEGEAN in cluster 0, (5.9625) has the highest probability (16.5%=5.9625/35.9196*) of being cluster's 0 centroid. That is, BLUE AEGEAN has a higher probability that it is chosen among the customers of the first cluster.

The same procedure applies to the other clusters as well.

AURINKOMATKAT in cluster 1 (8) has by far the highest probability (38%= 8/21) of being cluster's 1 centroid. That is, AURINKOMATKAT has a higher probability that it is chosen among the customers of the second cluster.

ARHUS CHARTER in cluster 2 (6) has the highest probability (23%= 6/ 26) of being cluster's 2 centroids. So, this agency has a higher probability that are chosen among the customers of the third cluster.

SUNWEB in cluster 3 (7.9973) has the highest probability (29.3%=7.9973/27.2773) of being cluster's 3 centroid. That is, SUNWEB has a higher probability that it is chosen among the customers of the second cluster.

ITAKA in cluster 4 (1.9964) has the highest probability (6.2%=1.9964/32.0015) of being cluster's 4 centroid. That is, ITAKA has a higher probability that it is chosen among the customers of the second cluster.

Jet2holidays in cluster 5 (7.1194) has the highest probability (26.5%=7.1194/26.8016) of being cluster's 5 centroid. That is, this agency has a higher probability that it is chosen among the customers of the second cluster.

Additionally, it is 28% probable that cluster's 0 centroid is Denmark (8.9645/30.9196= 28%), 50% probable that cluster's 1 centroid is Finland (8/16=50%), 42.8% probable that cluster's 2 centroid is Poland (9/21= 42.8%), 59.8% probable that cluster's 3 centroid is Netherlands (13.3366/22.2773=59.8%), 55.5% probable that cluster's 4 centroid is Varying (15/27.0015=55.5%) and 57.8% that cluster's 5 centroid is UK (12.6197/21.8016=57.8%).

Clustered Instances (number of instances detected in each cluster):

0 25 (27%)
1 8 (9%)
2 13 (14%)
3 12 (13%)
4 22 (24%)
5 11 (12%)

Log likelihood: -33.71

2.2.3 Filtered Clusterer

According to [20][20]:
This algorithm is primarily based completely on storing the multidimensional data points within a tree. The process regarding the tree is like a binary tree method, as represents a hierarchical subdivision on its data point set's bounding box the usage of their axis after which splitting is aligned by way on hyper planes. Each node on the tree is related with a closed field, referred to as the cell.

The results are the same as those of Simple K Means for all the number of clusters, which is expected, as Filtered Clusterer uses Simple K Means in order to proceed to the outcome.

Filtered Clusterer with 2 Clusters

Number of iterations: 7

Within cluster sum of squared errors: 278.35

Missing values globally replaced with mean/mode.

	Final Cluster Centroids		
Attribute	Full Data (91.0)	0 (54.0)	1 (37.0)
Booking Source	ARHUS CHARTER	BLUE AEGEAN	RAINBOW
Country	Denmark	Vary	Poland
Average pax/room	2.4126	2.4121	2.4133
TO/ OTA	TO	TO	TO
ADR	82.1023	74.4252	93.3067
Total Bookings	22.1868	14.2222	93.3067
Total PAX Nights	491.0659	236.3333	862.8378
Total Room Nights	195.9231	101.1296	334.2703
BB	238.8	149.0704	369.7568
BB%	0.4559	0.555	0.3112
HB	77.6	75.7519	80.2973
HB%	0.2866	0.3741	0.1588
AI	180.4333	21.2302	412.7838
AI%	0.2728	0.0964	0.5303
Month	April 2019	April 2019	August 2019

Table 12: Final Cluster Centroids- Filtered Clusterer

Clustered Instances (number of instances detected in each cluster):

0 54 (59%)

1 37 (41%)

Filtered Clusterer divides Cretan Palm's booking sources into two clusters. The first cluster's centroid is BLUE AEGEAN and the second cluster's centroid is RAINBOW.

Centroids of cluster 0 depict that the customers in cluster 0 have as dominant characteristics that they come from various different countries (Vary), that they choose BLUE AEGEAN as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1 have as dominant characteristics that they come from Poland, that they choose RAINBOW as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

2.2.4 Farthest First

According to[24]:
Farthest first finds its variant of K-means. Each cluster center point furthermost from the existing cluster center is placed by the K-mean, and this point must be positioned within the data area. So that it greatly speeds up the clustering in most cases, but it needs less move and adjustment for their fast performance.

In order to examine Farthest First Clusterer's accuracy, we choose different number of clusters manually.

<u>Farthest First Clusterer with 2 Clusters</u>

	Cluster Centroids	
	Cluster 0	**Cluster 1**
Booking Source	BRAVO TOURS	AURINKOMATKAT
Country	Denmark	Finland
Average pax/room	2.0	3.06
TO/ OTA	TO	TO
ADR	51.04	132.97
Total Bookings	1	135

Total PAX Nights	10.0	3700
Total Room Nights	5	1210
BB	0	1859
BB%	0	0.5
HB	10	540
HB%	1.0	0.15
AI	0	1301
AI%	0	0.35
Month	April 2019	July 2019

Table 13: Cluster Centroids- Farthest First

Clustered Instances (number of instances detected in each cluster):

0 81 (89%)

1 10 (11%)

Farthest First divides Cretan Palm's booking sources into two clusters. The first cluster's centroid is BRAVO TOURS and the second cluster's centroid is AURINKOMATKAT.

Centroids of cluster 0 depict that the customers in cluster 0 have as dominant characteristics that they choose BRAVO TOURS as their travel agency, that they come from Denmark and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1, have as dominant characteristics that they come from Finland, that they choose AURINKOMATKAT as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies (OTA). Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

Below are presented the other clusterings' results.

Farthest First Clusterer with 3 Clusters

Appendix: ***Farthest First with 3 Clusters| Creta Palm 2019***

Farthest First Clusterer with 4 Clusters

Appendix: ***Farthest First with 4 Clusters| Creta Palm 2019***

Farthest First Clusterer with 5 Clusters

Appendix: ***Farthest First with 5 Clusters| Creta Palm 2019***

2.2.5 Make A Density

According to [29]:
Density-Based Clustering refers to unsupervised learning methods that identify distinctive groups/clusters in the data, based on the idea that a cluster in a data space is a contiguous region of high point density, separated from other such clusters by contiguous regions of low point density. The data points in the separating regions of low point density are typically considered noise/outliers.

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.7),

- The clusterer randomly chooses the core points and then for each core point that is not already assigned to a cluster, creates a new cluster.
- The clusterer finds all its density connected points and assigns them to the same cluster as the core point.
- Then it iterates through the remaining unvisited points in the dataset.
- The core points that do not belong to any cluster are treated as outliers or noise points.[107]

Make A Density Clusterer, also presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings depending on their number of clusters are presented below.

Make A Density Clusterer with 2 Clusters

[107] Source: https://www.youtube.com/watch?v=f4pZ9PHNdcM

See the clustering results in the appendix: ***Make A Density Clusterer, Fitted estimators (with ML estimates of variance) | Creta Palm 2019***

Within cluster sum of squared errors: 278.35

Number of iterations: 7

Missing values globally replaced with mean/mode.

Wrapped clusterer: kMeans

Clustered Instances (number of instances detected in each cluster):

	Final Cluster Centroids		
Attribute	Full Data (91.0)	0 (54.0)	1 (37.0)
Booking Source	ARHUS CHARTER	BLUE AEGEAN	RAINBOW
Country	Denmark	Vary	Poland
Average pax/room	2.4126	2.4121	2.4133
TO/ OTA	TO	TO	TO
ADR	82.1023	74.4252	93.3067
Total Bookings	22.1868	14.2222	93.3067
Total PAX Nights	491.0659	236.3333	862.8378
Total Room Nights	195.9231	101.1296	334.2703
BB	238.8	149.0704	369.7568
BB%	0.4559	0.555	0.3112
HB	77.6	75.7519	80.2973
HB%	0.2866	0.3741	0.1588
AI	180.4333	21.2302	412.7838
AI%	0.2728	0.0964	0.5303
Month	April 2019	April 2019	August 2019

Table 14: Final Cluster Centroids- Make A Density Based Clusterer

Clustered Instances (number of instances detected in each cluster):

0 63 (69%)

1 28 (31%)

Log likelihood: -49.94

Make A Density Based Clusterer divides Cretan Palm's booking sources into two clusters. The first cluster's centroid is BLUE AEGEAN and the second cluster's centroid is RAINBOW.

Centroids of cluster 0 depict that the customers in cluster 0 have as dominant characteristics that they come from various different countries (Vary), that they choose they BLUE AEGEAN travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to the their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1 have as dominant characteristics that they come from Poland, that they choose RAINBOW as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

Make A Density Clusterer has the same cluster centroids as Simple K Means Clusterer and Filtered Clusterer. The only difference this Clusterer has from Filtered Clusterer and Simple K Means Clusterer is that they have different number of instances in each cluster. Filtered Clusterer and Simple K Means have 54 instances in Cluster 0 and 37 instances in Cluster 1, whereas Make A Density Clusterer has 63 instances in Cluster 0 and 28 instances in Cluster 1.

<u>**Make A Density Clusterer with 3 Clusters**</u>

Within cluster sum of squared errors: 255.64

Number of iterations: 5

Missing values globally replaced with mean/mode.

Wrapped clusterer: kMeans

Clustered Instances

0 56 (62%)

1 23 (25%)

2 12 (13%)

Log likelihood: -49.78718

Make A Density Clusterer with 4 Clusters

Within cluster sum of squared errors: 235.03

Number of iterations: 7

Missing values globally replaced with mean/mode.

Wrapped clusterer: kMeans

Clustered Instances

0 20 (22%)

1 15 (16%)

2 15 (16%)

3 41 (45%)

Log likelihood: -48.82826

Make A Density Clusterer with 5 Clusters

Within cluster sum of squared errors: 212.91

Number of iterations: 9

Missing values globally replaced with mean/mode.

Wrapped clusterer: kMeans

Clustered Instances

0 21 (23%)
1 8 (9%)
2 17 (19%)
3 38 (42%)
4 7 (8%)

Log likelihood: -46.80844

2.2.6 Canopy

According to Mai and Cheng (2016)[33]: *Canopy is one of the improved K-means algorithm, can be used to determine the number of clusters. With the introduction of Canopy clustering, the data set is divided into k sub-sets by setting the radius, and the sub-sets can be selected as the initial centers of K-means. Because the Canopy algorithm can reduce the running time of the clustering by reduce the count of comparisons, it will improve the computational efficiency.*
The Canopy algorithm's analytical explanation of the steps are presented in chapter 1.5.8.

Canopy runs alternative number of clusters and then chooses automatically the number of the clusters it shall create.

Number of canopies (cluster centers) found: 16
T2 radius: 1,536
T1 radius: 1,919

Canopy divides Cretan Palm's booking sources into sixteen clusters. The characteristics (Country origin, Total Bookings, ADR TO/OTA, Average PAX/room BB, BB%, etc.) of each cluster centroids are presented in the appendix. Each cluster has a centroid which is dominant and has similar characteristics with the other elements of the cluster. The elements present Attribute, Booking Source, Country, Average pax/room, TO/ OTA, ADR, Total Bookings, Total PAX Nights, Total Room Nights, BB, BB%, HB, HB%, AI, AI% and Month as shown in the appendix: Canopy Clusterer| Creta Palm 2019

Note: The numbers in these brackets: **Error! Reference source not found.** show the instances that are appeared in the cluster.

2.3 WEKA Regression 2020
WEKA Algorithms

This chapter presents the algorithms that are performing well considering all the values as well as the predictions of the algorithms concerning the hotel's Total Bookings.

2.3.1 M5P trees

See Appendix: M5P Trees Algorithm| Creta Palm 2020

=== Summary ===

Correlation coefficient	0.9782
Mean absolute error	2.9395
Root mean squared error	4.0306
Relative absolute error	21.653 %
Root relative squared error	20.5785 %
Total Number of Instances	52
Ignored Class Unknown Instances	4

M5P Trees Algorithm provides the best results from all algorithms. The high correlation coefficient (0.9782>0.95) depicts that there is a strong relation between our data values and the values of the (M5P Trees) algorithm's prediction model and that our data do get close to the predictions of the model.

According to [17] "The M5P model tree is based on conventional decision tree associated to linear regression function at the leaves nodes".

M5P Trees is an interpretable, quite simple algorithm model. The model is understandable and explainable, as it is clear of how it arrived at a specific decision.

As far as the patterns and conclusions that M5P Trees' model are concerned for the year 2020: Booking Sources and countries have different type of influence in total bookings each time (either positive or negative depending on the sign of the number in front of each booking source or country). However, as we can see, the total overnight stays (total PAX nights) and the total room nights are having a positive correlation to the total bookings. Specifically, the positive coefficient in front of these variables depict that the higher the values of total PAX nights and total room nights, the higher the number of the total bookings.

M5P Trees' Algorithm predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
ITAKA	26	26.882	0.882
BOOKING.COM	109	112.126	3.126
RAINBOW	13	9.022	-3.978
BOOKING.COM	27	26.096	-0.904
BOOKING.COM	56	48.765	-7.235
BRAVO TOURS	42	46.575	4.575
AURINKOMATKAT	29	26.306	-2.694
RAINBOW	31	36.464	5.464
EXPEDIA	32	19.268	-12.732
ITAKA	7	2.693	-4.307
SUNWEB	12	8.857	-3.143
ITAKA	47	53.013	6.013
TUI UK	2	1.344	-0.656
BRAVO TOURS	14	14.852	0.852
BLUE AEGEAN	15	10.339	-4.661
TUI DEUTSCHLAND	16	13.974	-2.026
AURINKOMATKAT	17	19.531	2.531
ITAKA	23	26.284	3.284
RAINBOW	25	20.637	-4.363
SUNWEB	20	19.123	-0.877
EXPEDIA	52	48.853	-3.147
ARHUS CHARTER	30	19.021	-10.979

Table 15: Predictions on test data- M5P trees

2.3.2 M5Rules

See Appendix: M5Rules Algorithm| Creta Palm 2020

=== Summary ===

Correlation coefficient 0.978

Mean absolute error 2.9492

Root mean squared error 4.0424

Relative absolute error 21.7249 %

Root relative squared error 20.639 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

M5Rules Algorithm provides the second best results from all algorithms. The high correlation coefficient (0.978>0.95) depicts that there is a strong relation between our data values and the values of the (M5Rules) algorithm's prediction model and that our data do get close to the predictions of the model.

M5Rules generates a decision list for regression problems using separate-and-conquer. In each iteration, it builds a model tree using M5 and makes the "best" leaf into a rule.[108]

M5Rules is an interpretable, quite simple algorithm model. The model is understandable and explainable, as it is clear of how it arrived at a specific decision.

As far as the patterns and conclusions that M5Rules' model are concerned for the year 2020: Booking Sources and countries have different type of influence in total bookings each time (either positive or negative depending on the sign of the number in front of each booking source or country). However, as we can see, the total overnight stays (total PAX nights) and the total room nights are having a positive correlation to the total bookings. Specifically, the positive coefficient in front of these variables depict that the higher the values of total PAX nights and total room nights, the higher the number of the total bookings.

M5Rules' Algorithm predictions of the Total Bookings of some of the 2019 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
ITAKA	26	26.882	0.882
BOOKING.COM	109	112.126	3.126
RAINBOW	13	9.022	-3.978
BOOKING.COM	27	26.096	-0.904
BOOKING.COM	56	48.765	-7.235
BRAVO TOURS	42	46.575	4.575
AURINKOMATKAT	29	26.306	-2.694
RAINBOW	31	36.464	5.464
EXPEDIA	32	19.268	-12.732
ITAKA	7	2.693	-4.307
SUNWEB	12	8.857	-3.143

[108] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/M5Rules.html

ITAKA	47	53.013	6.013
TUI UK	2	1.344	-0.656
BRAVO TOURS	14	14.852	0.852
BLUE AEGEAN	15	10.339	-4.661
TUI DEUTSCHLAND	16	13.974	-2.026
AURINKOMATKAT	17	19.531	2.531
ITAKA	23	26.284	3.284
RAINBOW	25	20.637	-4.363
SUNWEB	20	19.123	-0.877
EXPEDIA	52	48.853	-3.147
ARHUS CHARTER	30	19.021	-10.979

Table 16: Predictions on test data- M5Rules

2.3.3 Linear Regression

See Appendix: Linear Regression Algorithm| Creta Palm 2020

=== Summary ===

Correlation coefficient 0.9701

Mean absolute error 3.8488

Root mean squared error 4.7515

Relative absolute error 28.3516 %

Root relative squared error 24.259 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Linear Regression provides a high correlation coefficient (0.9701>0.95) as well. As a consequence, there is a strong relation between our data values and the values of the algorithm's prediction model and that our data do get close to the predictions of the model.

Linear regression is a very simple regression algorithm that only supports regression type problems and is issued for prediction. The model uses the Akaike criterion for model selection, and is able to deal with weighted instances. Linear Regression can only deal with numeric attributes. [109]

The model is understandable and explainable, as it is clear of how it arrived at a specific decision.

As far as the patterns and conclusions that linear regression's model are concerned for the year 2020: Booking Sources and countries have different type of influence in total bookings each time (either positive or negative depending on the sign of the number in front of each booking source or country). However, as we can see, the total overnight stays (total PAX nights) and total room nights are having a positive correlation to the total bookings. Specifically, the positive coefficient in front of these variables depict that the higher the values of total PAX nights and total room nights, the higher the number of the total bookings, which is something expected. On the other hand, overnight stays with breakfast (BB) and all-inclusive overnight stays (AI), seem to have a negative correlation to the total bookings as these variables have a negative coefficient in front of them. That is, that the more overnight stays with breakfast (BB) as well as the more all-inclusive overnight stays (AI), may lead to less total bookings.

High values of BB and AI may lead to in overall less total bookings, but that does not mean that they are not profitable. The hotel may examine the situation and can possibly raise the prices for overnight stays with breakfast or all-inclusive overnight stays, or confine the availability of those two, in order to have a higher number of total bookings.

According to the algorithm's results, August of 2020 seem to have a negative correlation with the total bookings, which means that in August the total bookings decreased. This is disproved from the original dataset, as August seems to have the highest number of total bookings in 2020. This depicts that the algorithm has its weaknesses and does not always provide the most accurate results.

Linear Regression's predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

[109] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/LinearRegression.html

inst#	actual	predicted	error
ITAKA	26	20.678	-5.322
BOOKING.COM	109	105.515	-3.485
RAINBOW	13	9.492	-3.508
BOOKING.COM	27	25.894	-1.106
BOOKING.COM	56	48.979	-7.021
BRAVO TOURS	42	53.509	11.509
AURINKOMATKAT	29	26.846	-2.154
RAINBOW	31	39.184	8.184
EXPEDIA	32	23.564	-8.436
ITAKA	7	-2.12	-9.12
SUNWEB	12	4.849	-7.151
ITAKA	47	55.995	8.995
TUI UK	2	0.135	-1.865
BRAVO TOURS	14	9.008	-4.992
BLUE AEGEAN	15	10.967	-4.033
TUI DEUTSCHLAND	16	17.029	1.029
AURINKOMATKAT	17	17.968	0.968
ITAKA	23	28.564	5.564
RAINBOW	25	16.139	-8.861
SUNWEB	20	21.542	1.542
EXPEDIA	52	55.352	3.352
ARHUS CHARTER	30	22.895	-7.105

Table 17: Predictionss on test data- Linear Regession

2.3.4 SMO Reg

See Appendix: SMO Reg Algorithm| Creta Palm 2020

=== Summary ===

Correlation coefficient 0.9577

Mean absolute error 4.658

Root mean squared error 5.7122

Relative absolute error 34.3121 %

Root relative squared error 29.164 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

SMO Reg Algorithm also provides a high correlation coefficient (0.9577>0.95). This means that there is a strong relation between our data values and the values of the (SMO Reg) algorithm's prediction model and that our data do get close to the predictions of the model.

As mentioned above, Sequential Minimal Optimization (SMO) method breaks the problem down into sub-problems that can be solved analytically (by calculating) rather than numerically (by searching or optimizing).[110]

SMO Reg is neither interpretable nor simple algorithm model, which means that one who does not have the necessary expertise in the field of technology or analytics cannot fundamentally understand how the model arrived in a certain output or how the output influences the output, by just reading the algorithm.

SMO Reg's Algorithm predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
ITAKA	26	19.128	-6.872
BOOKING.COM	109	105.993	-3.007
RAINBOW	13	8.852	-4.148
BOOKING.COM	27	24.249	-2.751
BOOKING.COM	56	46.352	-9.648
BRAVO TOURS	42	53.009	11.009
AURINKOMATKAT	29	29.454	0.454
RAINBOW	31	41.94	10.94
EXPEDIA	32	21.759	-10.241
ITAKA	7	-4.945	-11.945
SUNWEB	12	7.574	-4.426
ITAKA	47	58.902	11.902
TUI UK	2	0.869	-1.131
BRAVO TOURS	14	11.427	-2.573
BLUE AEGEAN	15	7.027	-7.973
TUI DEUTSCHLAND	16	11.713	-4.287
AURINKOMATKAT	17	16.475	-0.525
ITAKA	23	30.089	7.089
RAINBOW	25	13.382	-11.618
SUNWEB	20	12.87	-7.13
EXPEDIA	52	55.743	3.743
ARHUS CHARTER	30	24.616	-5.384

Table 18: Predictions on test data- SMO Reg

[110] Source:https://machinelearningmastery.com/support-vector-machines-for-machine-learning/

2.3.5 Gaussian Processes

=== Classifier model (full training set) ===

Kernel used:[111]

Linear Kernel: K(x,y) = <x,y>

All values shown based on: Normalize training data

Average Target Value : 0.1379675370501059

Inverted Covariance Matrix:

Lowest Value = -0.26844055814504447

Highest Value = 0.71814875178401

Inverted Covariance Matrix * Target-value Vector:

Lowest Value = -0.08407454635891383

Highest Value = 0.1197270118367203

=== Summary ===

Correlation coefficient	0.9463
Mean absolute error	5.3462
Root mean squared error	6.7355
Relative absolute error	39.3818 %
Root relative squared error	34.3884 %
Total Number of Instances	52
Ignored Class Unknown Instances	4

Gaussian Process provides lower correlation coefficient results (0.9463< 0.95). However, there is still a positive relation between our data values and the values of the algorithm's prediction model and our data do get close to the predictions of the model.

Gaussian Process is a simple and interpretable model but it has not too many parameters. Gaussian Process is a simple and interpretable model but it has not too many parameters. Gaussian Process implements regression without hyper parameter-

[111] A "kernel" is usually used to refer to a method of using a linear classifier to solve a non-linear problem.

tuning. This implementation applies normalization/standardization to the target attribute as well as the other attributes (if normalization/standardization is turned on). Missing values are replaced by the global mean/mode. Nominal attributes are converted to binary ones.[112]

Gaussian Processes' predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
ITAKA	26	26.485	0.485
BOOKING.COM	109	93.201	-15.799
RAINBOW	13	10.278	-2.722
BOOKING.COM	27	33.033	6.033
BOOKING.COM	56	48.686	-7.314
BRAVO TOURS	42	30.058	-11.942
AURINKOMATKAT	29	24.359	-4.641
RAINBOW	31	26.331	-4.669
EXPEDIA	32	19.681	-12.319
ITAKA	7	9.608	2.608
SUNWEB	12	6.254	-5.746
ITAKA	47	39.457	-7.543
TUI UK	2	1.91	-0.09
BRAVO TOURS	14	16.222	2.222
BLUE AEGEAN	15	11.632	-3.368
TUI DEUTSCHLAND	16	14.309	-1.691
AURINKOMATKAT	17	19.118	2.118
ITAKA	23	29.013	6.013
RAINBOW	25	17.296	-7.704
SUNWEB	20	11.729	-8.271
EXPEDIA	52	48.222	-3.778
ARHUS CHARTER	30	21.006	-8.994

Table 19: Predictions on test set- Gaussian Process

2.3.6 Meta Random Committee

[112] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/GaussianProcesses.html

Meta Random Committee's Classifier model contributes to the total bookings' predictions through the decision tree model that is presented in the appendix. The total bookings' number depends on parameters such as the booking sources and whether it is Tour Operators or Online Travel Agencies (TO/OTA), the customer's countries, the average daily rate (ADR), the total overnight stays per room (total room nights), the average number of people per room (average pax/room), the total overnight stays (total pax nights), the number of overnight stays with breakfast (BB) and its percentage (BB%), the number of overnight stays with dinner (HB) and its percentage (HB%) and the "all inclusive" overnight stays (AI) and its percentage (AI%) and the month of the lodging.

See Appendix: Meta Random Committee Algorithm| Creta Palm 2020

=== Summary ===

Correlation coefficient	0.9142
Mean absolute error	5.2402
Root mean squared error	9.5939
Relative absolute error	38.6006 %
Root relative squared error	48.9824 %
Total Number of Instances	52
Ignored Class Unknown Instances	4

Meta Random Committee provides lower correlation coefficient results. However, there is still a positive relation between our data values and the values of the algorithm's prediction model and our data do get close to the predictions of the model.

This is a classifier for building an ensemble of randomizable base classifiers. Each base classifier is built using a different random number seed (but based on the same data). The final prediction is a straight average of the predictions generated by the individual base classifiers. [113]

Meta Random Committee's predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

[113] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomCommittee.html

inst#	actual	predicted	error
ITAKA	26	23.55	-2.45
BOOKING.COM	109	55.1	-53.9
RAINBOW	13	10.078	-2.922
BOOKING.COM	27	23.502	-3.498
BOOKING.COM	56	30.756	-25.244
BRAVO TOURS	42	34.748	-7.252
AURINKOMATKAT	29	18.3	-10.7
RAINBOW	31	23.091	-7.909
EXPEDIA	32	19.85	-12.15
ITAKA	7	6.667	-0.333
SUNWEB	12	7.467	-4.533
ITAKA	47	50.6	3.6
TUI UK	2	1.087	-0.913
BRAVO TOURS	14	15.5	1.5
BLUE AEGEAN	15	8.079	-6.921
TUI DEUTSCHLAND	16	14.877	-1.123
AURINKOMATKAT	17	14.722	-2.278
ITAKA	23	25	2
RAINBOW	25	13.06	-11.94
SUNWEB	20	14.894	-5.106
EXPEDIA	52	49.745	-2.255
ARHUS CHARTER	30	22.378	-7.622

Table 20: Predictions on test data-Meta Random Cmmittee

2.3.7 Lazy K Star

=== Summary ===

Correlation coefficient 0.9106

Mean absolute error 4.8774

Root mean squared error 9.3287

Relative absolute error 35.9285 %

Root relative squared error 47.6283 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Lazy K Star provides lower correlation coefficient results. However, there is still a positive relation between our data values and the values of the algorithm's prediction model and our data do get close to the predictions of the model.

Lazy K Star has not too many parameters. According to Sharma and Jain (2013): "*K-Star algorithm as an instance-based learner which uses entropy as a distance measure. The benefits are that it provides a consistent approach to handling of real valued attributes, symbolic attributes and missing values*".

K- Star is a simple classifier, similar to K-Nearest Neighbour (K-NN).

For regression problems, it will find the k nearest neighbors and predict the value by calculating the mean value of the nearest neighbors.[114]

Lazy K Star's predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
ITAKA	26	23.017	-2.983
BOOKING.COM	109	55.992	-53.008
RAINBOW	13	10.004	-2.996
BOOKING.COM	27	32	5
BOOKING.COM	56	46.354	-9.646
BRAVO TOURS	42	23.499	-18.501
AURINKOMATKAT	29	19.954	-9.046
RAINBOW	31	22.999	-8.001
EXPEDIA	32	27	-5
ITAKA	7	3.009	-3.991
SUNWEB	12	14.98	2.98
ITAKA	47	50.485	3.485
TUI UK	2	0.015	-1.985
BRAVO TOURS	14	14.575	0.575
BLUE AEGEAN	15	17.206	2.206
TUI DEUTSCHLAND	16	8.983	-7.017
AURINKOMATKAT	17	11.392	-5.608
ITAKA	23	29.928	6.928
RAINBOW	25	18.323	-6.677
SUNWEB	20	24.542	4.542

[114] Source: https://towardsdatascience.com/an-introduction-to-k-nearest-neighbours-algorithm-3ddc99883acd

EXPEDIA	52	31.888	-20.112
ARHUS CHARTER	30	17.975	-12.025

Table 21: Predictions on test set- Lazy K Star

2.3.8 Random Forest

=== Summary ===

Correlation coefficient 0.9011

Mean absolute error 6.0915

Root mean squared error 10.8418

Relative absolute error 44.8714 %

Root relative squared error 55.3535 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Random Forest is bagging with 100 iterations and provides lower correlation coefficient results as well. However, there is still a positive relation between our data values and the values of the algorithm's prediction model and our data do get close to the predictions of the model.

According to E. Kleinberg (n.d) [31]: *Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. Random forests are an ensemble learning method for classification (and regression) that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees.*

Random Forest is not an interpretable model and it has not too many parameters for analysis. So, one who does not have the necessary expertise in the field of technology or analytics cannot fundamentally understand how the model arrived in a certain output or how the output influences the output, by just reading the algorithm.

Random Forest's predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
ITAKA	26	25.066	-0.934
BOOKING.COM	109	45.244	-63.756
RAINBOW	13	12.045	-0.955
BOOKING.COM	27	30.985	3.985
BOOKING.COM	56	44.259	-11.741
BRAVO TOURS	42	28.863	-13.137
AURINKOMATKAT	29	17.04	-11.96
RAINBOW	31	23.128	-7.872
EXPEDIA	32	18.216	-13.784
ITAKA	7	14.132	7.132
SUNWEB	12	9.581	-2.419
ITAKA	47	37.477	-9.523
TUI UK	2	1.816	-0.184
BRAVO TOURS	14	14.832	0.832
BLUE AEGEAN	15	7.985	-7.015
TUI DEUTSCHLAND	16	14.674	-1.326
AURINKOMATKAT	17	13.412	-3.588
ITAKA	23	25.884	2.884
RAINBOW	25	17.065	-7.935
SUNWEB	20	17.344	-2.656
EXPEDIA	52	35.752	-16.248
ARHUS CHARTER	30	24.263	-5.737

Table 22: Predictions on test data- Random Forest

2.3.9 Multilayer Perceptron

See Appendix: Multilayer Perceptron Algorithm| Creta Palm 2020

=== Summary ===

Correlation coefficient 0.9049

Mean absolute error 5.4974

Root mean squared error 8.3199

Relative absolute error 40.4953 %

Root relative squared error 42.478 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Multilayer Perceptron provides low correlation coefficient results as well. However, there is still a positive relation between our data values and the values of the algorithm's prediction model and our data do get close to the predictions of the model.

Multilayer Perceptron is neither interpretable nor simple algorithm model so, one who does not have the necessary expertise in the field of technology or analytics cannot fundamentally understand how the model arrived in a certain output or how the output influences the output, by just reading the algorithm.

The Multi-Layer Perceptron algorithm is also called artificial neural network and is a complex algorithm to use for predictive modeling because there are so many configuration parameters that can only be tuned effectively through intuition and a lot of trial and error.[115] As mentioned in the first chapter, this is a classifier that uses backpropagation to learn a multi-layer perceptron to classify instances. The nodes in this network are all sigmoid, except for when the class is numeric, in which case the output nodes become unthresholded linear units.[116]

Multilayer Perceptron's Algorithm predictions of the Total Bookings of some of the 2020 Booking Sources are presented below.

=== Predictions on test data ===

inst#	actual	predicted	error
ITAKA	26	21.989	-4.011
BOOKING.COM	109	65.167	-43.833
RAINBOW	13	8.583	-4.417
BOOKING.COM	27	20.91	-6.09
BOOKING.COM	56	51.337	-4.663
BRAVO TOURS	42	47.227	5.227
AURINKOMATKAT	29	27.209	-1.791
RAINBOW	31	25.555	-5.445
EXPEDIA	32	23.341	-8.659
ITAKA	7	12.797	5.797

[115] Source: https://machinelearningmastery.com/use-regression-machine-learning-algorithms-weka/?fbclid=IwAR3PWrbfejBgXpV4YmADPnKm7F5h1Ubxh8zNCSa75EfYoDL3s_qmVYL-V4E

[116] Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/functions/MultilayerPerceptron.html

SUNWEB	12	10.571	-1.429
ITAKA	47	53.93	6.93
TUI UK	2	6.141	4.141
BRAVO TOURS	14	20.899	6.899
BLUE AEGEAN	15	7.29	-7.71
TUI DEUTSCHLAND	16	17.466	1.466
AURINKOMATKAT	17	25.118	8.118
ITAKA	23	29.706	6.706
RAINBOW	25	11.194	-13.806
SUNWEB	20	7.703	-12.297
EXPEDIA	52	65.968	13.968
ARHUS CHARTER	30	31.41	1.41

Table 23: Predictions on test data- Multilayer Perceptron

See in the Appendix: ***Classifiers with low or negative correlation coefficient (2020)***: A lower or negative correlation coefficient depicts that there is a weak relation (or negative relation) between our data and the algorithm’s prediction model and that the data do not get close to the predictions of the model. This practically means that for the new oncoming agencies that have similar characteristics as those 2020’s agencies, there is a low probability that the total bookings are similar as those predicted from the algorithm (or that the total bookings depict opposite results from those predicted from the algorithm – as far as negative correlation coefficient results are concerned-).

2.4 WEKA Clustering 2020
WEKA Clusterers

As mentioned before, Simple K-Means, EM, Make a Density, Farthest First, Canopy, Filtered are the clusterers that are used in order to group the travel agencies that presented similarities and disjoin those that displayed dissimilarities. The aim of clustering is to find distinct groups within a given dataset.

2.4.1 Simple K Means

As mentioned in the first chapter (an analytical explanation is presented in chapter 60), Simple Means is a distant-based clusterer that minimizes the squared distance from each instance to their cluster center, after defining k centroids. It is one of the best unsupervised algorithms. For each different number of seeds, there are different clustering results.[117] [118]

Simple K Means uses random numbers and by using the same seed, we will always get the same random numbers. If we run Simple K Means over the same data twice, with the same seed, we will get exactly the same results. For different number of seeds, the results will vary each time we run Simple K Means.

In our dataset we use the same seed.

Simple K Means Clusterer, presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings, depending on their number of clusters are presented below.

Simple K Means with 2 Clusters

Number of iterations: 4

Within cluster sum of squared errors: 159.36

Missing values globally replaced with mean/mode.

	Final Cluster Centroids		
Attribute	Full Data (56.0)	0 (35.0)	1 (21.0)
Booking Source	ARHUS CHARTER	SELF BOOKINGS	TUI Deutschland
Country	Vary	Vary	Germany
Average pax/room	2.3586	2.3561	2.2937
TO/ OTA	TO	TO	TO
ADR	73.5381	65.7399	86.5352

[117] Source: https://www.youtube.com/watch?v=4b5d3muPQmA
[118] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

Total Bookings	15.0385	13.2615	18
Total PAX Nights	270.2642	220.8226	352.6667
Total Room Nights	108.3774	91.8609	135.9048
BB	142.16	83.4846	239.9524
BB%	0.4362	0.379	0.5315
HB	38.9184	17.4146	74.758
HB%	0.1671	0.0913	0.2935
AI	105.98	145.968	39.3333
AI%	0.3901	0.5243	0.1664
Month	JULY 2020	SEPTEMBER 2020	AUGUST 2020

Table 24: Final Cluster Centroids- Simple K- Means

Clustered Instances (number of instances detected in each cluster):

0 35 (63%)

1 21 (38%)

Simple K Means divides Cretan Palm's booking sources into two clusters. The first cluster's centroid is SELF BOOKINGS and the second cluster's centroid is TUI Deutschland.

Centroids of cluster 0 depict that the customers in cluster 0 have as dominant characteristics that they come from various different countries (Vary), that they make their own bookings (SELF BOOKINGS) and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to the their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1 have as dominant characteristics that they come from Germany, that they choose TUI Deutschland as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

<u>Simple K Means with 3 Clusters</u>

See the clustering results in the appendix: ***Simple K Means with 3 Clusters| Creta Palm 2020***

Number of iterations: 4

Within cluster sum of squared errors: 143.02

Missing values globally replaced with mean/mode.

Clustered Instances

0 25 (45%)
1 13 (23%)
2 18 (32%)

Simple K Means with 4 Clusters

See the clustering results in the appendix: ***Simple K Means with 4 Clusters| Creta Palm 2020***

Number of iterations: 6

Within cluster sum of squared errors: 125.29

Missing values globally replaced with mean/mode.

Clustered Instances

0 17 (30%)
1 12 (21%)
2 16 (29%)
3 11 (20%)

Simple K Means with 5 Clusters

See the clustering results in the appendix: ***Simple K Means with 5 Clusters| Creta Palm 2020***

Number of iterations: 7

Within cluster sum of squared errors: 115.67

Missing values globally replaced with mean/mode.

Clustered Instances

0 16 (29%)
1 9 (16%)
2 13 (23%)
3 7 (13%)

4 11 (20%)

2.4.2 EM

"EM (Expectation Maximization) is a probabilistic clusterer and can be used for unsupervised learning. Like Naive Bayes, it makes the assumption that all attributes are independent random variables." (Witten I.H., et al., (1999))

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.2), unlike K-Means that takes one point and places it to the one cluster or the other, EM computes the probability that it goes into the a or b cluster. This probability never gets zero or one, it is always a number between zero and one (0<probability EM<1).

The model just finds that there are distinguished groups in the dataset that behave differently. EM run alternative number of clusters and then chooses automatically the number of the clusters it shall create.

EM works for numeric attributes providing mean and standard deviation results and value probability results respectively. Log likelihood is an overall quality measure and is increased by each iteration. [119]

Number of clusters selected by cross validation: 3
Number of iterations performed: 4

	0 (0.28)	1 (0.55)	2 (0.17)
Booking Source			
ARHUS CHARTER	3	3	1
AURINKOMATKAT	2	4	1
BLUE AEGEAN	2	4	1
BOOKING.COM	1	1.983	4.017
BRAVO TOURS	4.0041	1.9539	1.042
EXPEDIA	1	1.7907	4.2093
ITAKA	3.0004	1.9877	2.0119
Jet2Holidays	1.0093	3.9984	1.9923

[119] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

RAINBOW	4.0002	1	1.9998
SELF BOOKINGS	1	5	1
SUNWEB	4	2	1
TUI Deutschland	1	5	1
TUI NL	1.8652	4.1343	1.0006
TUI UK	1	4.9996	1.0004
[total]	29.8792	44.8476	23.2732
Country			
Denmark	6.0041	3.9539	1.042
Finland	2	4	1
Romania	2	4	1
Vary	1	6.7737	7.2263
Poland	6.0006	1.9877	3.0117
UK	1.0093	7.998	1.9927
Netherlands	4.8652	5.1343	1.0006
Germany	1	5	1
[total]	23.8792	38.8476	17.2732

Table 25: Clustering-EM

See Appendix: EM Clustering Model (continued)| Creta Palm 2020

EM divides Cretan Palm's booking sources into three clusters. For each of the attributes, there is a probability that the output is going to be this certain attribute. This probability is calculated if you divide the number of the attribute by the total attributes in each of the clusters. For example:

ARHUS CHARTER in cluster 0, (3) have a 10% probability (3/29.8792*) of being cluster's 0 centroid.

*[total: 29.8792]

BRAVO TOURS in cluster 0 (4.0041) has the highest probability (13.4% = 4.0041 / 29.8792) of being cluster's 0 centroid. That is, BRAVO TOURS has a higher probability that it is chosen among the customers of the first cluster.

The same procedure applies to the other clusters as well.

TUI UK in cluster 1 (4.9996) has the highest probability (11.14%= 4.9996/ 44.8476) of being cluster's 1 centroid. That is, TUI UK has a higher probability that it is chosen among the customers of the second cluster.

EXPEDIA in cluster 2 (4.2093) has the highest probability (18%= 4.2093/ 23.2732) of being cluster's 2 centroid. That is, EXPEDIA has a higher probability that it is chosen among the customers of the third cluster.

Additionally, it is 25% probable that cluster's 0 centroid is Denmark (6.0041/23.8792= 25%), 20.5% probable that cluster's 1 centroid is UK (7.998/38.8476=20.5%) and 41.8% probable that cluster's 2 centroid is Varying (7.2263/17.2732= 41.8%).

Clustered Instances (number of instances detected in each cluster):

0 16 (29%)

1 31 (55%)

2 9 (16%)

Log likelihood: -42.06695

2.4.3 Make A Density

According to [29]:
Density-Based Clustering refers to unsupervised learning methods that identify distinctive groups/clusters in the data, based on the idea that a cluster in a data space is a contiguous region of high point density, separated from other such clusters by contiguous regions of low point density. The data points in the separating regions of low point density are typically considered noise/outliers.

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.7),

- The clusterer randomly chooses the core points and then for each core point that is not already assigned to a cluster, creates a new cluster.
- The clusterer finds all its density connected points and assigns them to the same cluster as the core point.
- Then it iterates through the remaining unvisited points in the dataset.

- The core points that do not belong to any cluster are treated as outliers or noise points.[120]

Make A Density Clusterer, also presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings depending on their number of clusters are presented below.

Make A Density Clusterer has the same cluster centroids as Simple K Means Clusterer.

Make A Density Clusterer with 2 Clusters

See the clustering results in the appendix: ***Make A Density Based Clusterer fitted estimators| Creta Palm 2020***

Number of iterations: 4

Within cluster sum of squared errors: 159.367

Missing values globally replaced with mean/mode.

	Final Cluster Centroids		
Attribute	Full Data (56.0)	0 (35.0)	1 (21.0)
Booking Source	ARHUS CHARTER	SELF BOOKINGS	TUI Deutschland
Country	Vary	Vary	Germany
Average pax/room	2.3586	2.3561	2.3627
TO/ OTA	TO	TO	TO
ADR	73.5381	65.7399	86.5352
Total Bookings	15.0385	13.2615	18
Total PAX Nights	270.2642	220.8226	352.6667
Total Room Nights	108.3774	91.8609	135.9048

[120] Source: https://www.youtube.com/watch?v=f4pZ9PHNdcM

BB	142.16	83.4846	239.9524
BB%	0.4362	0.379	0.5315
HB	38.9184	17.4146	74.758
HB%	0.1671	0.0913	0.2935
AI	105.98	145.968	39.3333
AI%	0.3901	0.5243	0.1664
Month	JULY 2020	SEPTEMBER 2020	AUGUST 2020

Table 26: Final Cluster Centroids- Make A Density Based Clusterer

Clustered Instances (number of instances detected in each cluster):

0 40 (71%)

1 17 (29%)

Log likelihood: -47.15

Make A Density Based Clusterer divides Cretan Palm's booking sources into two clusters. The first cluster's centroid is SELF BOOKINGS and the second cluster's centroid is TUI Deutschland.

Centroids of cluster 0 depict that the customers in cluster 0 have as dominant characteristics that they come from various different countries (Vary), that they make their own bookings (SELF BOOKINGS) and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to the their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1 have as dominant characteristics that they come from Germany, that they choose TUI Deutschland as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

The only difference this Clusterer has from Simple K Means Clusterer is that they have different number of instances in each cluster. Simple K Means Clusterer have 35 instances in Cluster 0 and 21 instances in Cluster 1, whereas Make A Density Clusterer has 40 instances in Cluster 0 and 17 instances in Cluster 1.

<u>Make A Density Clusterer with 3 Clusters</u>

Within cluster sum of squared errors: 143.02

Number of iterations: 4

Missing values globally replaced with mean/mode.

Wrapped clusterer: kMeans

Clustered Instances

0 36 (64%)

1 11 (20%)

2 9 (16%)

Log likelihood: -46.90959

<u>Make A Density Clusterer with 4 Clusters</u>

Within cluster sum of squared errors: 125.29

Number of iterations: 6

Missing values globally replaced with mean/mode.

Wrapped clusterer: kMeans

Clustered Instances

0 23 (41%)

1 14 (25%)

2 8 (14%)

3 11 (20%)

Log likelihood: -45.37988

<u>Make A Density Clusterer with 5 Clusters</u>

Within cluster sum of squared errors: 115.67

Number of iterations: 7

Missing values globally replaced with mean/mode.

Wrapped clusterer: kMeans

Clustered Instances

0 19 (34%)
1 9 (16%)
2 7 (13%)
3 9 (16%)
4 12 (21%)

Log likelihood: -42.89493

2.4.4 Filtered Clusterer

According to [20][20]:
This algorithm is primarily based completely on storing the multidimensional data points within a tree. The process regarding the tree is like a binary tree method, as represents a hierarchical subdivision on its data point set's bounding box the usage of their axis after which splitting is aligned by way on hyper planes. Each node on the tree is related with a closed field, referred to as the cell.

The results are the same as those of Simple K Means for all the number of clusters, which is expected, as Filtered Clusterer uses Simple K Means in order to proceed to the outcome.

<u>Filtered Clusterer with 2 Clusters</u>

Number of iterations: 4
Within cluster sum of squared errors: 159.36
Missing values globally replaced with mean/mode.

	Final Cluster Centroids		
Attribute	Full Data (56.0)	0 (35.0)	1 (21.0)
Booking Source	ARHUS CHARTER	SELF BOOKINGS	TUI Deutschland

Country	Vary	Vary	Germany
Average pax/room	2.3586	2.3561	2.2937
TO/ OTA	TO	TO	TO
ADR	73.5381	65.7399	86.5352
Total Bookings	15.0385	13.2615	18
Total PAX Nights	270.2642	220.8226	352.6667
Total Room Nights	108.3774	91.8609	135.9048
BB	142.16	83.4846	239.9524
BB%	0.4362	0.379	0.5315
HB	38.9184	17.4146	74.758
HB%	0.1671	0.0913	0.2935
AI	105.98	145.968	39.3333
AI%	0.3901	0.5243	0.1664
Month	JULY 2020	SEPTEMBER 2020	AUGUST 2020

Table 27: Final Cluster Centroids- Filtered Clusterer

Clustered Instances (number of instances detected in each cluster):

0 35 (63%)

1 21 (38%)

Filtered Clusterer divides Cretan Palm's booking sources into two clusters. The first cluster's centroid is SELF BOOKINGS and the second cluster's centroid is TUI Deutschland.

Centroids of cluster 0 depict that the customers in cluster 0 have as dominant characteristics that they come from various different countries (Vary), that they make their own bookings (SELF BOOKINGS) and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to the their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1 have as dominant characteristics that they come from Germany, that they choose TUI Deutschland as a travel agency and that they choose Tour Operators (TO) over Online travel Agencies.

Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

Filtered Clusterer provides the same cluster centroids as Simple K Means Clusterer and Make A Density Clusterer.

2.4.5 Farthest First

According to[24]:
Farthest first finds its variant of K-means. Each cluster center point furthermost from the existing cluster center is placed by the K-mean, and this point must be positioned within the data area. So that it greatly speeds up the clustering in most cases, but it needs less move and adjustment for their fast performance.

In order to examine Farthest First Clusterer's accuracy, we choose different number of clusters manually.

Farthest First Clusterer with 2 Clusters

	Cluster centroids	
	Cluster 0	**Cluster 1**
Booking Source	TUI Deutschland	BOOKING.COM
Country	Germany	Vary
Average pax/room	2.28	3.11
TO/ OTA	TO	OTA
ADR	117.18	123.27
Total Bookings	9	109
Total PAX Nights	194	2155
Total Room Nights	85	691
BB	0	1652
BB%	0	0.76
HB	148	503
HB%	0.76	0.23
AI	46	10
AI%	0.23	0.004

Month	August 2020	August 2020

Table 28: Cluster Centroids- Farthest First

Clustered Instances (number of instances detected in each cluster):

0 52 (93%)

1 5 (7%)

Farthest First divides Cretan Palm's booking sources into two clusters. The first cluster's centroid is TUI Deutschland and the second cluster's centroid is BOOKING.COM.

Centroids of cluster 0 depicts that the customers in cluster 0 have as dominant characteristics that they choose TUI Deutschland as their travel agency, that they come from Germany and that they choose Tour Operators (TO) over Online travel Agencies. Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

The second cluster's centroids depict that the customers in cluster 1, have as dominant characteristics that they come from various different countries, that they choose Booking.com as a travel agency and that they choose Online travel Agencies (OTA) over Tour Operators (TO). Additionally, their characteristics (Total Bookings, ADR, Average PAX/room BB, BB%, etc.), are similar to their cluster's centroids characteristics.

Farthest First Clusterer with 3 Clusters

Appendix: ***Farthest First with 3 Clusters| Creta Palm 2020***

Farthest First Clusterer with 4 Clusters

Appendix: ***Farthest First with 4 Clusters| Creta Palm 2020***

Farthest First Clusterer with 5 Clusters

Appendix: ***Farthest First with 5 Clusters| Creta Palm 2020***

2.4.6 Canopy

According to Mai and Cheng (2016)[33]: *Canopy is one of the improved K-means algorithm, can be used to determine the number of clusters. With the introduction of Canopy clustering, the data set is divided into k sub-sets by setting the radius, and the sub-sets can be selected as the initial centers of K-means. Because the Canopy algorithm can reduce the running time of the clustering by reduce the count of comparisons, it will improve the computational efficiency.*

The Canopy algorithm's analytical explanation of the steps are presented in chapter 1.5.8.

Canopy runs alternative number of clusters and then chooses automatically the number of the clusters it shall create.

Number of canopies (cluster centers) found: 14

T2 radius: 1,504

T1 radius: 1,880

Canopy divides Cretan Palm's booking sources into fourteen clusters. The characteristics (Country origin, Total Bookings, ADR TO/OTA, Average PAX/room BB, BB%, etc.) of each cluster's centroids are presented in the appendix. Each cluster its dominant centroids. The elements in each cluster, have similar characteristics with these centroids. The elements present Attribute, Booking Source, Country, Average pax/room, TO/ OTA, ADR, Total Bookings, Total PAX Nights, Total Room Nights, BB, BB%, HB, HB%, AI, AI% and Month as shown in the appendix: Canopy Clusterer| Creta Palm 2020.

Note: The numbers in these brackets: **Error! Reference source not found.** show the instances that are appeared in the cluster.

Conclusions

M5Rules, M5P Trees and SMO Reg are the algorithms that provide the best results for the year 2019. M5Trees, M5Rules and Linear Regression Reg are the algorithms that provide the best results for the year 2020.

These algorithms provided a high correlation coefficient (>0.97) which depicts a strong relation between our data values and the values of the algorithms' prediction model. So, our data do get close to the predictions of these models.

WEKA as well other machine learning software systems, provide us the opportunity to predict the results of a new oncoming dataset that has similar characteristics with our already existing dataset and there is a high probability that the dataset values are similar to those predicted from the algorithm.

Chapter 3

Use Case: NN Hellas

NN Hellas is part of the NN Group and is a private health and life insurance provider. NN Hellas created questionnaire in order to gather information and have a better understanding of its customers' attitude, perception and awareness of insurances (life, health and house insurances).

A hundred and eighty-two (182) NN customers gave answers about their superseding ability, their insurance type, the significance of their insurance package, the safety offered from their insurance package, the level of satisfaction from the public insurance health benefits, their wish for extra benefits from their health insurance and their wish for covering certain expenditures after they receive their pension.

Specifically, the questionnaire includes the following alternative answers:

- I have a car superseding ability
- I have a motorbike superseding ability
- I have a house superseding ability
- I have a business superseding ability
- I do not have superseding ability
- I have/had Business Insurance
- I have/had Civil Liability Insurance
- I have/had Vessel Insurance
- I have/had Health Insurance
- I have/had everyday needs Insurance
- I have/had Business House Insurance
- I have/had Family Insurance
- I have/had Cash Insurance
- I have/had Child Insurance
- I have/had Car Insurance
- I have/had Motorbike Insurance
- I have never had Insurance

- The Fixed Costs would not be covered in case of a possible loss of mine
- The Loans would not be covered in case of a possible loss of mine
- Children studies would not be covered in case of a possible loss of mine
- Tax obligations would not be covered in case of a possible loss of mine
- No needs to leave behind in case of a possible loss of mine
- Happiness would not be covered in case of a possible loss of mine
- Purchases in non-basic necessities would not be covered in case of a possible loss of mine
- I want a risk protection
- A satisfying amount of money for the support of my beloved ones
- I am not at all satisfied from the public insurance health benefits
- I am kind of satisfied from the public insurance health benefits
- I am quite satisfied from the public insurance health benefits
- I am absolutely satisfied from the public insurance health benefits
- I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue
- I would choose a big private hospital in Athens or Thessaloniki for a mild health issue
- I would choose a local private hospital for a mild health issue
- I would choose a local public hospital for a mild health issue
- I would choose a public hospital in Athens or Thessaloniki for serious health issues
- I would choose a big private hospital of Athens or Thessaloniki for serious health issues
- I would choose a local private hospital for serious health issues
- I would choose a local public hospital for serious health issues
- I would choose a foreign hospital for serious health issues
- I wish for private health services coupled with my insurance
- I would like diagnostic tests to be included to my private insurance
- I would like doctor visits to be included to my private insurance
- I would like hospital care to be included to my private insurance
- I would like Annual check up to be included to my private insurance

- I would like to go abroad to be included to my private insurance
- I would like ambulance to be included to my private insurance
- I would like a team insurance
- I will not get a pension
- I will get a small pension
- I will get a satisfying pension
- I have managed for a lump sum or supplementary pension
- I have managed for a lump sum or supplementary pension through my bank savings
- I have managed for a lump sum or supplementary pension through Pension scheme purchase
- I have managed for a lump sum or supplementary pension through Life insurance program and savings plan
- I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation
- I am about to take immediate care of a lump sum or supplementary pension
- I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase
- Even if I wanted it I cannot take care of a lump sum or supplementary pension
- It is of a major importance to support my children and grandchildren after I receive my pension
- It is of a major importance to cover my healthcare after I receive my pension
- It is of a major importance to cover my pleasure trips after I receive my pension
- It is of a major importance to cover my house purchases after I receive my pension
- It is of a major importance to cover my fixed costs after I receive my pension
- It is of a major importance to cover my everyday needs after I receive my pension
- I am interested in estimating my retirement

A real problem that the insurance sector is addressing in Greece is that, Greeks do not have developed the so-called ‘insurance consciousness in contrast to the other European citizens. This means, that the percentage of Greece’s GDP that is concerning the insurance sector is much lower than that of other European countries (Greece’s GDP concerning insurances is about 2%, whereas the average percentage of GDP in other European countries is approximately 7%).

This means that companies do not pay attention to the data they select from their customers, or they do not even select quality data, make predictions, nor can they identify useful patterns and rules from a certain amount of data. This, makes them more susceptible to uncertainty and risk, as they are not able to focus on the key variables that influence their companies’ attributes.

This issue can be solved through collecting and analyzing data, in order to collect the necessary information from the customers, analyze their profile and make certain predictions and clusterings about them. Weka Machine Learning Software, can transform the dataset into meaningful patterns with the help of integrated algorithms and help us make predictions on certain variables as well as clusterings for these customers or future customers with a similar profile. WEKA, helps us to better predict the results of a new oncoming dataset that has similar characteristics with our already existing dataset and there is a high probability that the dataset values are similar to those predicted from the algorithm.

NN’s dataset needed a further data preparation/training in order to bring it in a suitable format and train a classifier (the variable we want to predict). In this case, the classifier is the customers’ interest to estimate their retirement.

After training, the dataset is loaded in Weka, where further data preparations is made in order to bring it in a suitable format and therefore, to create prediction and clustering models. These models are developed through the integrated machine learning algorithms that are chosen each time. These algorithms provide patterns and consequently, useful prediction results for NN. The results depict that a new upcoming dataset, with similar characteristics with our already existing dataset, can be better predicted and there is a high probability that the new dataset values are similar to those predicted from the algorithms.

Cross-validation method is used in order to value the classifiers, by using the number of folds entered in the corresponding field. In our 10-fold cross-validation, the original sample is randomly partitioned into 10 subsamples. Of the 10 subsamples, a single subsample is retained as the test set, and the remaining 9 subsamples are used as training set[121]. The cross-validation process is repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds then can be averaged (or otherwise combined) to produce a single estimation.

Supplied test set is used in order to make predictions for new unseen data from the set of instances loaded from the file.

For clustering outputs, the training set is used, so that, the cluster is the same set that the clusterer is trained on.

Chapter 3 presents the predictions made about the customers' interest for retirement estimation as well as the clusterings made through weka software system based on the dataset given.

3.1 WEKA Classification
WEKA Algorithms

As mentioned above, for nominal values, WEKA detects Correctly Classified Instances, Incorrectly Classified Instances, Kappa statistic, Mean absolute error, Root mean squared error, Relative absolute error, Root relative squared error, Total Number of Instances, TP Rate, FP Rate, Precision, Recall, F-Measure.

Precision, Recall, F-Measure and ROC Area give a really good picture of how well things are performing.

ROC Area (Receiver Operating Characteristic-Area Under the Curve) shows us which items are correctly put in their classes. An "optimal" classifier will have ROC area values approaching 1, with 0.5 being comparable to "random guessing" (similar to a Kappa statistic of 0). A value above 0.8 is considered a strong and accurate result.

[121] A training set is a subset of a dataset that is used to train a model and a test set is a subset of a dataset that is used to test the trained model. Source: https://developers.google.com/machine-learning/crash-course/training-and-test-sets/splitting-data

ROC uses True Positives and False Positive Rates as the axes that we are looking out, to draw a curve.

PRC (Precision on Recall): Works better for unbalanced data. ROC tends to be in general a better choice, because PRC do not really count the true positives.

The Confusion Matrix is another way of detecting how well a model is doing.

Confusion Matrix

a b <-- classified as

aa ba| a = 0

ab bb| b = 1

Correctly Classified Instances is a good measurement of our model's performance, but kappa statistic value, detailed accuracy by class and confusion matrix should also be taken into consideration in order to depict how well the model is performing.

So, we prefer algorithms with high correctly classified instances and positive kappa statistic. It is of a major importance that every element is classified and not all instances are in one class. If we have 90% of the instances in one class, then we are right 90% of the times, but the model is not reliable. Furthermore, if ba=0 and bb=0, this means that nothing is classified as b and that the model is performing really poor in class b. So, we suggest that the company that brought the results do something about it in order to get better results.

This chapter presents the algorithms that are performing well considering all the values as well as the predictions of the algorithms concerning the customers' willingness to estimate their retirement. The error predictions indicate that the dataset is unbalanced and there is no great diversity on customers' answers.

In the appendix are presented the algorithms that presented poor performance.

3.1.1 Random Tree

See Appendix: Random Tree Algorithm| NN

The algorithm rules found, that the customers' interest of retirement estimation depends on factors such as the need of covering their fixed costs after they receive their pension, their car superseding ability, the need of including doctor visits in their private insurance, the choose of a local, public hospital for serious or mild health issues, the need of covering their healthcare after they receive their pension, the interest for private health services to be coupled with their insurance, the need of hospital care inclusion to their private insurance, the amount of satisfactions from their public insurance health benefits, the need of covering pleasure trips after they receive their retirement, the supplementary pension management, the interest for risk protection, the fixed costs', tax obligations' and children' studies coverage estimation, the already existing insurance ownership and the estimation for a satisfactory pension.

Specifically, customers presented an interest in estimating their retirement in those cases:

- They do have a car superseding ability but it is not of a major importance to cover their fixed costs after they receive their pension.
- They do not prefer a local, public hospital for serious health issues and it is of a major importance to cover their fixed costs after they receive their pension.
- They do not prefer a local, public hospital for serious health issues and they want doctor visits to be included to their private insurance. Additionally, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They do not think of healthcare as in need to be covered from their pension and they do not need doctor visits to be included to their private insurance. Additionally, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They want healthcare to be covered from their pension and they do not necessarily want private health services to be coupled with their insurance. They would choose a local public hospital for mild health issues and they want doctor visits to be included to their private insurance. Additionally, they do not have a car

superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.

- They are not quite satisfied from their public insurance healthcare benefits and they want hospital care to be included to their private insurance and private health services to be coupled with their insurance. They would choose a local, public hospital for mild health issues and they want doctor visits to be included to their private insurance. Additionally, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They want to cover their pleasure trips after they receive their retirement and they are quite satisfied from their public insurance healthcare benefits. They want hospital care to be included to their private insurance and private health services to be coupled with their insurance. They would choose a local, public hospital for mild health issues and they want doctor visits to be included to their private insurance. Additionally, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They have not managed for a supplementary pension and they do not want to cover their pleasure trips after they receive their retirement. They are quite satisfied from their public insurance healthcare benefits. They want hospital care to be included to their private insurance and private health services to be coupled with their insurance. They would choose a local, public hospital for mild health issues and they want doctor visits to be included to their private insurance. Additionally, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They do not want to include hospital care to their private insurance but they want private health services to be coupled with their insurance. They would choose a local, public hospital for mild health issues and they want doctor visits to be included to their private insurance. Additionally, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They can cover tax obligation and fixed costs in a possible loss of theirs and they would not choose a local, public hospital for serious health issues. They want a risk protection and is of a major importance to cover their healthcare after they

receive their pension. They do not want to include doctor visits to their private insurance, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.

- They cannot cover fixed costs in a possible loss of theirs and they would not choose a local, public hospital for serious health issues. They want a risk protection and is of a major importance to cover their healthcare after they receive their pension. They do not want to include doctor visits to their private insurance, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They do not believe they will get a satisfying pension, they had never had insurance but they believe that children studies will be covered in a possible loss of theirs. They do not want a risk protection but it is of a major importance to cover their healthcare after they receive their pension. They do not want to include doctor visits to their private insurance, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.
- They had had insurance before and they believe that children studies will be covered in a possible loss of theirs. They do not want a risk protection but it is of a major importance to cover their healthcare after they receive their pension. They do not want to include doctor visits to their private insurance, they do not have a car superseding ability and it is not of a major importance to cover their fixed costs after they receive their pension.

=== Summary ===

Correctly Classified Instances	172	94.5055 %
Incorrectly Classified Instances	10	5.4945 %
Kappa statistic	0.1415	
Mean absolute error	0.0532	
Root mean squared error	0.2273	
Relative absolute error	59.6934 %	
Root relative squared error	110.7167 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,983	0,875	0,961	0,983	0,972	0,151	0,524	0,958	Yes
	0,125	0,017	0,250	0,125	0,167	0,151	0,527	0,080	No
W.A	0,945	0,837	0,945	0,929	0,945	0,151	0,527	0,920	

Table 29: Detailed Accuracy by Class- Random Tree

=== Confusion Matrix ===

```
  a    b   <-- classified as
 171   3 |   a = Yes
   7   1 |   b = No
```

Random Tree provides the best performance of all the algorithms. The high percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that Random Tree is a high-performance algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Random Tree is a quite simple and interpretable model.

In the Confusion Matrix "a=Yes" means that they are interested in estimating their retirement, whereas the prediction "b=No" means that they are not interested in estimating their retirement. The correctly and incorrectly classified instances show the percentage of test instances that were correctly and incorrectly classified. The raw numbers are shown in the confusion matrix, with a and b representing the class labels. Here there were 182 instances, so the percentages and raw numbers add up, aa + bb = 171 + 1 = 172 and ab + ba = 7 + 3 = 10. It also means that 171 out of 174 a's were predicted correctly (TP Rate-out of 174 customers that were predicted to want a retirement estimation, only 171 truly wanted to estimate their retirement) and 1 out of 8 b's were predicted correctly (TN Rate-out of 8 customers that were predicted to reject a retirement estimation, only 1 of them truly rejected the retirement estimation).

Some of the Random Trees' Model predictions about the customers' willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement. Here, the instances 1 through 10 are predicted to be of class 1, whose value is “Yes” (Yes= I am interested in estimating my retirement). Class 2, whose value is “No” (No= I am not interested in estimating my retirement) is not predicted in the first 10 instances.

The rest of the results are presented in the appendix: Random Tree Predictions| NN

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	1
5	1:Yes	1:Yes	1
6	1:Yes	1:Yes	1
7	1:Yes	1:Yes	1
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	1
10	1:Yes	1:Yes	1

Table 30:Predictions on test set- Random Tree

3.1.2 Lazy IBK

=== Classifier model (full training set) ===

IB1 instance-based classifier
using 1 nearest neighbor(s) for classification

=== Summary ===

Correctly Classified Instances	172	94.5055 %
Incorrectly Classified Instances	10	5.4945 %
Kappa statistic	0.1415	
Mean absolute error	0.0627	
Root mean squared error	0.236	
Relative absolute error	70.2979 %	
Root relative squared error	114.9252 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,983	0,875	0,961	0,983	0,972	0,151	0,634	0,968	Yes
	0,125	0,017	0,250	0,125	0,167	0,151	0,634	0,092	No
W.A	0,945	0,837	0,929	0,945	0,936	0,151	0,634	0,930	

Table 31: Detailed Accuracy by Class- Lazy IBk

=== Confusion Matrix ===

```
  a    b   ← classified as
171    3 |  a = Yes
  7    1 |  b = No
```

Lazy IBK provides the second best performance of all the algorithms. The high percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that Lazy IBK is a high-performance algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Lazy IBK is a K-nearest neighbor's (KNN) classifier which attempts to predict the correct class for the test data by calculating the distance between the test data and all the training points. Then, it selects the K number of points which is closest to the test data. The K-Nearest Neighbours (KNN) algorithm is one of the most simple supervised machine learning algorithms that is used to solve both classification and regression problems. KNN is also known as an instance-based model or a lazy learner because it doesn’t construct an internal model. For classification problems, it will find the k nearest neighbors and predict the class by the majority vote of the nearest neighbors.[122]

Some of the Lazy IBK’s Model predictions about each customers’ willingness to estimate their retirement are presented below. The prediction “1.Yes” means that they are interested in estimating their retirement, whereas the prediction “2.No” means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Lazy IBK Predictions| NN

=== Predictions on user test set ===

[122] Source: https://towardsdatascience.com/an-introduction-to-k-nearest-neighbours-algorithm-3ddc99883acd

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	0.995
2	1:Yes	1:Yes	0.995
3	1:Yes	1:Yes	0.995
4	1:Yes	1:Yes	0.995
5	1:Yes	1:Yes	0.995
6	1:Yes	1:Yes	0.995
7	1:Yes	1:Yes	0.995
8	1:Yes	1:Yes	0.995
9	1:Yes	1:Yes	0.995
10	1:Yes	1:Yes	0.995

Table 32: Predictions on user test set- Lazy IBk

3.1.3 Naive Bayes Updateable

Naive Bayes and Naive Bayes Updateable provide the same results.

See Appendix: Naive Bayes Updatable Classifier| NN

=== Summary ===

Correctly Classified Instances 171 93.956 %

Incorrectly Classified Instances 11 6.044 %

Kappa statistic 0.1242

Mean absolute error 0.0663

Root mean squared error 0.2246

Relative absolute error 74.3306 %

Root relative squared error 109.3955 %

Total Number of Instances 182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,977	0,875	0,960	0,977	0,969	0,128	0,746	0,983	Yes
	0,125	0,023	0,200	0,125	0,154	0,128	0,746	0,152	No
W.A	0,940	0,838	0,927	0,940	0,933	0,128	0,746	0,946	

Table 33: Detailed Accuracy by Class- Naïve Bayes Updateable

=== Confusion Matrix ===

a b ← classified as
170 4 | a = Yes

7 1 | b = No

Naïve Bayes Updateable provides a good performance as well. The percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that Naïve Bayes Updateable is a high-performance algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Naïve Bayes Updateable is a quite simple and interpretable model. For each of the classes, there is a probability that the attribute of the class (i.e car superseding ability) is true for the customers and a probability that the attribute is not true.

Example (taken from the model in the appendix):

The classes are divided to two: Class 1= Yes and Class 2=No.

	Class	
Attribute	Yes	No
	(0.95)	(0.05)
Car superseding ability		
Yes	36.0	1.0
No	140.0	9.0
[total]	176.0	10.0

Table 34: Example of Naive Bayes Updateabe

- True Positives= 36.0
- False Positives= 140.0
- True Negatives= 9.0
- False Negatives= 1.0

The correctly and incorrectly classified instances show the percentage of test instances that were correctly and incorrectly classified. The raw numbers are shown in the confusion matrix, with Yes and No representing the class labels. Here there were 186 instances, so the percentages and raw numbers add up 36 + 9 = 45 and 1+140 = 141. It also means that 36 out of 176 Yes's were predicted correctly (TP Rate-out of 176 customers that were predicted to have a car superseding ability, only 36 of them truly had) and 9 out of 10 No's were predicted correctly (TN Rate-out of 10 customers that were predicted to reject a retirement estimation, 9 of them indeed rejected the retirement estimation).

A visible problem is that 95% of the instances are in class “Yes”, which means that we receive right answers 95% of the times for these predictions, so the model is not that much reliable. This happens because the customers’ answers were quite similar.

Precision (how many selected items are relevant)= TP/(TP=+FP)= 36/(36+140)= 0.20

Recall (how many relevant items are selected)= TP/(TP+FN)= 36/(36+1)= 0.97

The same applies to the other attibutes as well.

Some of the Naïve Bayes Updateable’s model predictions about each customers’ willingness to estimate their retirement are presented below. The prediction “1.Yes” means that they are interested in estimating their retirement, whereas the prediction “2.No” means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Naive Bayes Updateable Predictions| NN

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	0.997
5	1:Yes	1:Yes	0.992
6	1:Yes	1:Yes	0.994
7	1:Yes	1:Yes	0.999
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	0.995
10	1:Yes	1:Yes	1

Table 35: Predictions on user test set- Naive Bayes Updateable

3.1.4 Bayes Net

=== Summary ===

Correctly Classified Instances	171	93.956 %
Incorrectly Classified Instances	11	6.044 %
Kappa statistic	0.2353	

Mean absolute error	0.0715
Root mean squared error	0.2293
Relative absolute error	80.2176 %
Root relative squared error	111.6498 %
Total Number of Instances	182

See Appendix: Bayes Net Classifier Model| NN

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,971	0,750	0,966	0,971	0,968	0,236	0,759	0,982	Yes
	0,250	0,029	0,286	0,250	0,267	0,236	0,759	0,271	No
W.A	0,940	0,718	0,936	0,940	0,938	0,236	0,759	0,951	

Table 36: Detailed Accuracy by Class- Bayes Net

(W.A= Weighted Average)

=== Confusion Matrix ===

```
  a   b   ← classified as
169  5 |   a = Yes
  6   2 |   b = No
```

Bayes Net provides a good performance as well. The percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that Bayes Net is a high-performance algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Bayes Net is a quite simple and interpretable model.

Example (taken from the algorithm in the appendix):

Bayes Network Classifier (full training set), not using ADTree:

#attributes=65 #classindex=6: This lines list the number of attributes and the number of the class variables for which the classifier was trained.

Network structure sample (nodes followed by parents)

.

.

Have or Had Car Insurance(1): I am interested in estimating my retirement

Have or Had Motorbike Insurance(2): I am interested in estimating my retirement

Have never had Insurance(2): I am interested in estimating my retirement

.

.

I am interested in estimating my retirement(2):

Each of the variables is followed by a parent, which is “I am interested in estimating my retirement”. So, the variables “Have or Had Car Insurance”, “Have or Had Motorbike Insurance” and “Have or Had Motorbike Insurance” has as a parent the class “I am interested in estimating my retirement”. The number in brackets is the cardinality of the variable. It shows that there are two class variables.

LogScore Bayes: -4584.11

LogScore BDeu: -4694.39

LogScore MDL: -4813.55

LogScore ENTROPY: -4483.1

LogScore AIC: -4610.1

These lines list the logarithmic score of the network structure for various methods of scoring. The logarithmic scoring rule is a scoring rule used to measure how well a given assignment of probabilities to values of a random variable performs on some real-world instances of the random variable. The smaller the value of the score with the logarithmic scoring rule, the better the assignment of probabilities has performed according to the rule.[123]

[123] Source: https://calculus.subwiki.org/wiki/Logarithmic_scoring_rule

In decision theory, a scoring rule, measures the accuracy of probabilistic predictions. It is applicable to tasks in which predictions must assign probabilities to a set of mutually exclusive outcomes or classes. The set of possible outcomes can be either binary (or categorical in nature), and the probabilities assigned to this set of outcomes must sum to one (where each individual probability is in the range of 0 to 1). A score can be thought of as either a measure of the "calibration" of a set of probabilistic predictions, or as a "cost function" or "loss function". [124]

Some of the Bayes Net model predictions about each customers' willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Bayes Net Predictions| NN

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	0.997
5	1:Yes	1:Yes	0.994
6	1:Yes	1:Yes	0.996
7	1:Yes	1:Yes	0.999
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	0.994
10	1:Yes	1:Yes	1

Table 37: Predictions on user test set- Bayes Net

3.1.5 Naive Bayes

Naive Bayes and Naive Bayes Updateable provide the same results.

=== Summary ===

Correctly Classified Instances	171	93.956 %
Incorrectly Classified Instances	11	6.044 %
Kappa statistic	0.1242	
Mean absolute error	0.0663	
Root mean squared error	0.2246	

[124] Source: https://en.wikipedia.org/wiki/Scoring_rule

Relative absolute error 74.3306 %

Root relative squared error 109.3955 %

Total Number of Instances 182

See Appendix: Naive Bayes Classifier Model| NN

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,977	0,875	0,960	0,977	0,969	0,128	0,746	0,983	Yes
	0,125	0,023	0,200	0,125	0,154	0,128	0,746	0,152	No
W.A	0,940	0,838	0,927	0,940	0,933	0,128	0,746	0,946	

Table 38: Detailed Accuracy by Class- Naive Bayes

=== Confusion Matrix ===

```
  a    b   <- classified as
170    4 |  a = Yes
  7    1 |  b = No
```

Naïve Bayes provides a good performance. The percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that Naïve Bayes Updateable is a high-performance algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Naïve Bayes Updateable is a quite simple and interpretable model. The classifier model's results as well as the predictions for the customers' willingness of retirement estimation are the same as those of Naïve Bayes Updateable.

Some of the Naïve Bayes' model predictions about each customers' willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Naive Bayes Predictions| NN

=== Predictions on user test set ===

Inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	0.997
5	1:Yes	1:Yes	0.992
6	1:Yes	1:Yes	0.994
7	1:Yes	1:Yes	0.999
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	0.995
10	1:Yes	1:Yes	1

Table 39: Predictions on user test set- Naive Bayes

3.1.6 Lazy K Star

=== Summary ===

Correctly Classified Instances	170	93.4066 %
Incorrectly Classified Instances	12	6.5934 %
Kappa statistic	0.1093	
Mean absolute error	0.0688	
Root mean squared error	0.2479	
Relative absolute error	77.143 %	
Root relative squared error	120.7316 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,971	0,875	0,960	0,971	0,966	0,111	0,524	0,958	Yes
	0,125	0,029	0,167	0,125	0,143	0,111	0,524	0,116	No
W.A	0,945	0,934	0,838	0,925	0,9364	0,111	0,524	0,921	

Table 40: Detailed Accuracy by Class- Lazy K Star

=== Confusion Matrix ===

```
  a    b   <- classified as
169    5 |   a = Yes
  7    1 |   b = No
```

Lazy K Star provides a good performance of all the algorithms. The high percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that Random Tree is a high-performance algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Lazy K Star does not have many parameters. According to Sharma and Jain (2013): "*K-Star algorithm as an instance-based learner which uses entropy as a distance measure. The benefits are that it provides a consistent approach to handling of real valued attributes, symbolic attributes and missing values*".

K- Star is a simple classifier, similar to K-Nearest Neighbour (K-NN).

For classification problems, it will find the k nearest neighbors and predict the class by the majority vote of the nearest neighbors.[125]

Some of the Lazy K Star's Model predictions about the customers' willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Lazy K Star Predictions| NN

The predictions found for Lazy K Star are the same as those of Random Tree.

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	1
5	1:Yes	1:Yes	1
6	1:Yes	1:Yes	1
7	1:Yes	1:Yes	1
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	1
10	1:Yes	1:Yes	1

Table 41: Predictions on user test set- Lazy K Star

[125] Source: https://towardsdatascience.com/an-introduction-to-k-nearest-neighbours-algorithm-3ddc99883acd

3.1.7 Meta Randomizable Filtered Classifier

=== Summary ===

Correctly Classified Instances 169 92.8571 %

Incorrectly Classified Instances 13 7.1429 %

Kappa statistic 0.0963

Mean absolute error 0.0766

Root mean squared error 0.2657

Relative absolute error 85.9134 %

Root relative squared error 129.4034 %

Total Number of Instances 182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,966	0,875	0,960	0,966	0,963	0,096	0,575	0,963	Yes
	0,125	0,034	0,143	0,125	0,133	0,096	0,575	0,062	No
W.A	0,929	0,838	0,924	0,929	0,926	0,096	0,575	0,923	

Table 42: Detailed Accuracy by Class- Meta Randomizable Filtered Classifier

=== Confusion Matrix ===

```
  a   b   <-- classified as
168   6 |   a = Yes
  7   1 |   b = No
```

Randomizable Filtered Classifier provides a satisfactory percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that this is a high-performance algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Randomizable Filtered Classifier does not have many parameters. As mentioned in the first chapter, it runs an arbitrary classifier on data that has been passed through an arbitrary filter. Like the classifier, the structure of the filter is based exclusively on the training data and test instances will be processed by the filter without changing their structure. [126]

Some of the model's predictions about each customers' willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Randomizable Filtered Classifier Predictions| NN

The predictions found for Randomizable Filtered Classifier are the same as those of Lazy IBK classifier.

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	0.995
2	1:Yes	1:Yes	0.995
3	1:Yes	1:Yes	0.995
4	1:Yes	1:Yes	0.995
5	1:Yes	1:Yes	0.995
6	1:Yes	1:Yes	0.995
7	1:Yes	1:Yes	0.995
8	1:Yes	1:Yes	0.995
9	1:Yes	1:Yes	0.995
10	1:Yes	1:Yes	0.995

Table 43: Predictions in user test set- Meta Randomizable Filtered Classifier

3.1.8 SMO

=== Summary ===

Correctly Classified Instances	169	92.8571 %
Incorrectly Classified Instances	13	7.1429 %
Kappa statistic	0.0963	
Mean absolute error	0.0714	
Root mean squared error	0.2673	
Relative absolute error	80.1144 %	
Root relative squared error	130.1572 %	

[126] Source: https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/RandomizableFilteredClassifier.html

Total Number of Instances 182

See Appendix: SMO Reg Classifier| NN

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,966	0,875	0,960	0,966	0,963	0,096	0,545	0,960	Yes
	0,125	0,034	0,143	0,125	0,133	0,096	0,545	0,056	No
W.A	0,929	0,838	0,924	0,929	0,926	0,096	0,545	0,920	

Table 44: Detailed Accuracy by Class- SMO

=== Confusion Matrix ===

```
  a    b   <-- classified as
168    6 |   a = Yes
  7    1 |   b = No
```

SMO Reg provides a satisfactory percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that this is a well-functioning algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

SMO Reg is neither interpretable nor simple algorithm model, which means that one who does not have the necessary expertise in the field of technology or analytics cannot fundamentally understand how the model arrived in a certain output or how the output influences the output, by just reading the algorithm.

As mentioned in the first chapter, the implementation of SMO globally replaces all missing values and transforms nominal attributes into binary ones. It also normalizes all attributes by default. (In that case the coefficients in the output are based on the normalized data, not the original data --- this is important for interpreting the classifier). Multi-class problems are solved using pairwise classification (1-vs-1).

Some of the model's predictions about each customer's willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: SMO Reg Predictions| NN

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	1
5	1:Yes	1:Yes	1
6	1:Yes	1:Yes	1
7	1:Yes	1:Yes	1
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	1
10	1:Yes	1:Yes	1

Table 45:Predictions in user test set- SMO

3.1.9 Multi Class Classifier Updateable

See Appendix: Multi Class Classifier Updateable| NN

=== Summary ===

Correctly Classified Instances 166 91.2088 %

Incorrectly Classified Instances 16 8.7912 %

Kappa statistic 0.1555

Mean absolute error 0.0879

Root mean squared error 0.2965

Relative absolute error 98.6023 %

Root relative squared error 144.3965 %

Total Number of Instances 182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,943	0,750	0,965	0,943	0,950	0,159	0,596	0,964	Yes
	0,250	0,057	0,167	0,250	0,200	0,159	0,596	0,075	No
W.A	0,912	0,720	0,930	0,912	0,920	0,159	0,596	0,925	

Table 46: Detailed Accuracy by Class- Multi Class Classifier Updateable

=== Confusion Matrix ===

```
  a    b   <-- classified as
164  10 |   a = Yes
  5    2 |   b = No
```

Multi Class Classifier Updateable provides a satisfactory percentage of correctly classified instances and a high kappa statistic, which, along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that it is a well-functioning algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

The final results are presented in the appendix, however this is a description of how it works.

This is a metaclassifier for handling multi-class datasets with 2-class classifiers and it has more than two outcomes. This classifier is also capable of applying error correcting output codes for increased accuracy. The base classifier must be an updateable classifier.[127]

Multi Class Classifier Updateable is using SVM algorithm model, so it is neither interpretable nor simple model. That is, one who does not have the necessary expertise in the field of technology or analytics cannot fundamentally understand how the model arrived in a certain output or how the output influences the output, by just reading the algorithm.

For our dataset's evaluation, we need to take into consideration the loss function as well, apart from the metrics.

Loss function: Hinge loss[128] (SVM)

I am interested in estimating my retirement =

0.8597 (normalized) Car superseding ability=No

[127]Source:https://weka.sourceforge.io/doc.dev/weka/classifiers/meta/MultiClassClassifierUpdateable.html

[128] *The hinge loss is a type of cost function that penalizes misclassified samples and correctly classified ones that are within a defined margin from the decision boundary. The hinge loss function is most commonly employed to regularize soft margin support vector machines. The degree of regularization determines how aggressively the classifier tries to prevent misclassifications and can be controlled with an additional parameter C. Hard margin SVMs do not allow for misclassifications and do not require regularization.* Source: https://programmathically.com/understanding-hinge-loss-and-the-svm-cost-function/

\+ 0.5898 (normalized) Motorbike superseding ability=Yes

\+ -0.2799 (normalized) House superseding ability=Yes

\+ -0.1399 (normalized) Business superseding ability=Yes

\+ 0.4298 (normalized) No superseding ability=Yes

\+ -0.4098 (normalized) Have or had Business Insurance=Yes

.

.

SVM or Support Vector Machine is a supervised, linear, machine learning model that uses classification algorithms for two-group classification and regression problems. It can solve linear and non-linear problems and work well for many practical problems.[129] [130]

For datasets with linear relationships, SVM algorithm creates a line or a hyperplane (a line whose distance to the nearest element of each tag is the largest) that separates data into classes. For data with non-linear relationships, SVM algorithm use kernels[131] to make non-separable data into separable data and fit them into classes.[132] In our case, it seems we have data of linear relationships; however both cases are presented below.

So, SVMs define the boundary between areas belonging to different categories, which is not necessarily the categories we want.

SVM does not assume normality, but it minimizes some symmetric loss function using hyperplanes or kernels for linear and non-linear problems respectively.

Let us see how Support Vector Machines work example.

<u>Linear relationship in dataset</u>:

Let us suppose we have two tags: pink and blue, and our data has two features: x and y. We want a classifier that, given a pair of (x,y) coordinates, outputs if it's either pink or blue.

---

[129] Source: https://towardsdatascience.com/https-medium-com-pupalerushikesh-svm-f4b42800e989
[130] Source: https://monkeylearn.com/blog/introduction-to-support-vector-machines-svm/
[131] A "kernel" is usually used to refer to a method of using a linear classifier to solve a non-linear problem.
[132] Source: https://www.aitude.com/svm-difference-between-linear-and-non-linear-models/

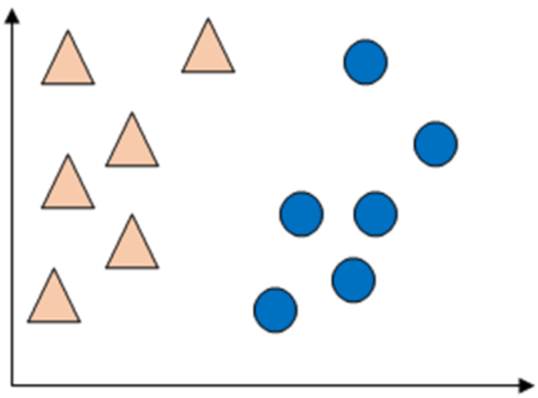

Figure 25: Labeled data

A support vector machine takes these data points and outputs the hyperplane, which is a line that best separates the tags and consequently maximizes the margins from both tags. This line is our decision boundary: anything that falls to one side of the line will be classified as pink, and anything that falls to the other side of the line will be classified as blue.

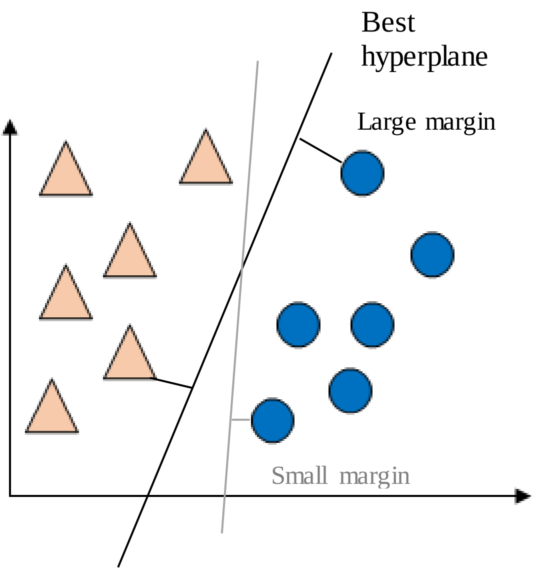

Figure 26: Best hyperplane for our labeled data

<u>Nonlinear data:</u>

Let us consider an example in which data are not linearly separable:

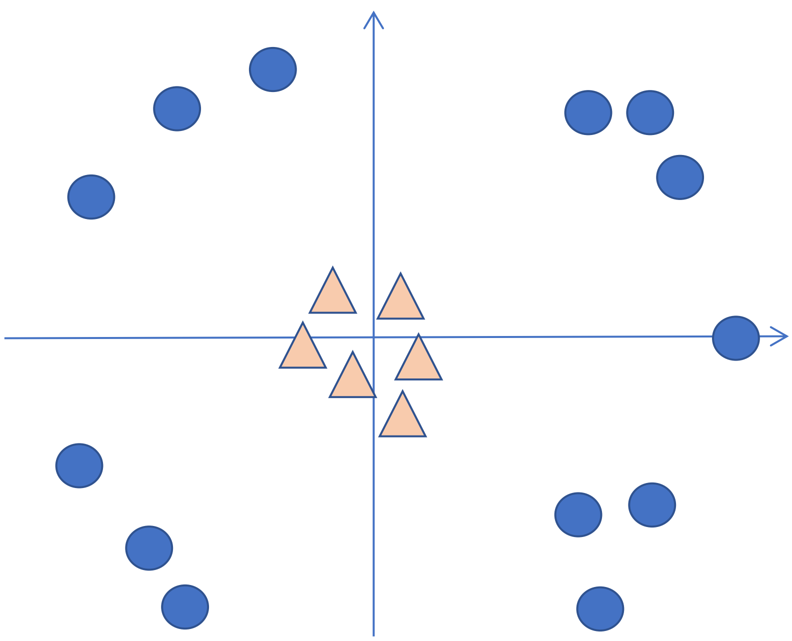

Figure 27: Complex Dataset

In this case, there is not a linear decision boundary (a single straight line that separates both tags). However, the vectors are very clearly segregated and it looks as though it should be easy to separate them.

For that reason, we will add a third dimension z (let us say z=1), which is a hyperplane, parallel to the x axis in order to be calculated a certain way that is convenient for us: $z = x^2 + y^2$ (you'll notice that's the equation for a circle).

This will give us a three-dimensional space:

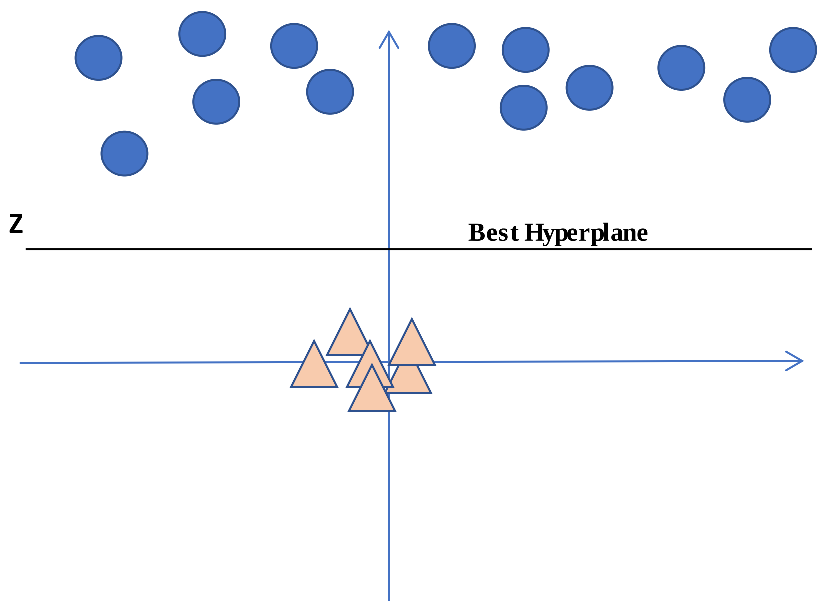

Figure 28: Best hyperplane for three-dimension mapping

Now the last step is mapping it back to two dimensions.

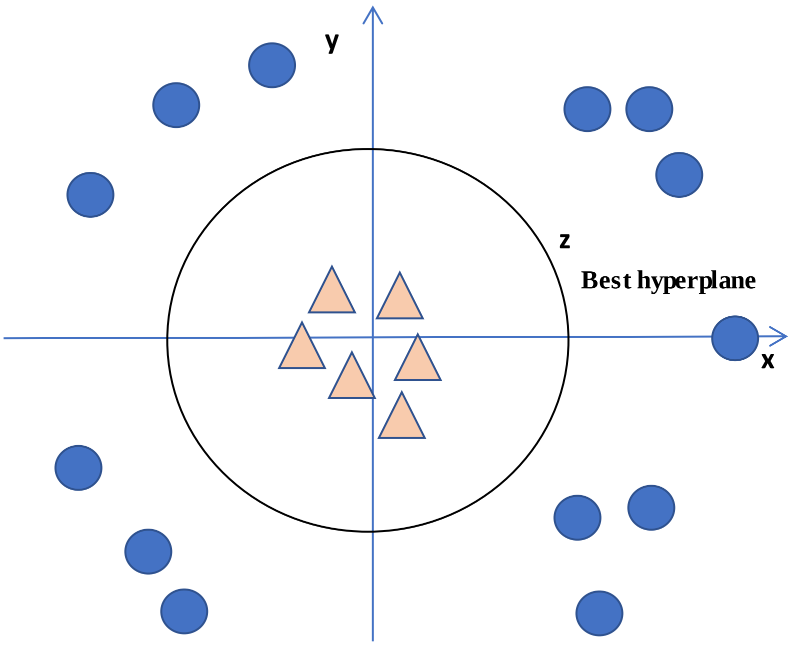

Figure 29: Best hyperplane for two dimentions in a non-linear dataset

So, our decision boundary is a circumference of radius, which separates both tags using SVM.[133]

<u>The kernel trick:</u>

As we can detect from the previous example, there is a way to classify nonlinear data by mapping our space to a higher dimension. However, there can be a lot of new dimensions, each one of them possibly involving a complicated calculation. Doing this for every vector in the dataset can be a lot of work. However, SVM does not need the actual vectors to work; it actually can get by only with the dot products between them.

Let us assume the new space we want:

$z = x^2 + y^2$

Figure out what the dot product in our space looks like:

[133] Source: https://monkeylearn.com/blog/introduction-to-support-vector-machines-svm/

$a * b = xa * xb + ya * yb + za * zb \Rightarrow$

$a * b = xa * xb + ya * yb + (xa^2 + ya^2) * (xb^2 + yb^2)$

That's the kernel trick, which allows us to ease complex calculations. Normally, the kernel is linear, and we get a linear classifier. However, by using a nonlinear kernel we can get a nonlinear classifier by just changing the dot product to that of the space that we want.

The kernel trick can be used with other linear classifiers as well such as logistic regression. A support vector machine only takes care of finding the decision boundary.

Compared to newer algorithms like neural networks, they have two main advantages: higher speed and better performance with a limited number of samples (in the thousands). This makes the algorithm very suitable for text classification problems, where it's common to have access to a dataset of thousands of tagged samples.[134]

Some of the model's predictions about each customers' willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Multi Class Classifier Updeateable Predictions| NN.

The predictions found for Multi Class Classifier Updateable are the same as those of Lazy K Star and Random Tree.

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	1
5	1:Yes	1:Yes	1
6	1:Yes	1:Yes	1

[134] Source: https://monkeylearn.com/blog/introduction-to-support-vector-machines-svm/

7	1:Yes	1:Yes	1
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	1
10	1:Yes	1:Yes	1

Table 47: Predictions on user test set- Multi Class Classifier Updateable

3.1.10 Multi Class Classifier

See Appendix: Multi Class Classifier| NN

=== Summary ===

Correctly Classified Instances 165 90.6593 %

Incorrectly Classified Instances 17 9.3407 %

Kappa statistic 0.2159

Mean absolute error 0.0952

Root mean squared error 0.3044

Relative absolute error 106.8283 %

Root relative squared error 148.264 %

Total Number of Instances 182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,931	0,625	0,970	0,931	0,950	0,228	0,624	0,967	Yes
	0,375	0,069	0,200	0,375	0,261	0,228	0,681	0,222	No
W.A	0,907	0,601	0,936	0,907	0,920	0,228	0,627	0,934	

Table 48: Detailed Accuracy by Class- Multi Class Classifier

=== Confusion Matrix ===

```
  a   b   <-- classified as
 162  12 |   a = Yes
  5    3 |   b = No
```

Multi Class Classifier provides a satisfactory percentage of correctly classified instances and a high kappa statistic, which, along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that it is a well-functioning algorithm model. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

In machine learning, multiclass or multinomial classification is the problem of classifying instances into one of three or more classes (classifying instances into one of two classes is called binary classification). While many classification algorithms (i.e multinomial logistic regression) naturally permit the use of more than two classes, some are by nature binary algorithms; these can, however, be turned into multinomial classifiers by a variety of strategies.[135]

Each training point belongs to one of the n different classes. The goal is to construct a function which, given a new data point, will correctly predict the class to which the new point belongs.[136]

Multi Class Classifier is interpretable and simple algorithm model. The final results are presented in the appendix; however this is a description of how it works.

Logistic Regression with ridge parameter of 1.0E-8

Coefficients...

	Class
Variable	Yes
==	
Car superseding ability=No	-26.2427
Motorbike superseding ability=Yes	-4.39
House superseding ability=Yes	5.3858
Business superseding ability=Yes	44.8751
No superseding ability=Yes	3.3551
Have or Had Business Insurance=Yes	18.2946

Odds Ratios...

[135] Source: https://en.wikipedia.org/wiki/Multiclass_classification
[136] Source: https://www.mit.edu/~9.520/spring09/Classes/multiclass.pdf

	Class
Variable	Yes
==	
Car superseding ability=No	0
Motorbike superseding ability=Yes	0.0124
House superseding ability=Yes	218.2802
Business superseding ability=Yes	3.08
No superseding ability=Yes	28.6496
Have or Had Business Insurance=Yes	88150280.8

Coefficients are the weights that are applied to each attribute plugged into the logistic function to obtain probabilities. The results illustrate the probability/odd that the instance belongs to class yes (Yes= I am interested in estimating my retirement) . The criterion which depicts that an instance belongs to class "yes" is that this probability is greater than 0.5 [137].

Odds ratios are the exponential of the weights we have found. For example, the first coefficient we have is: "Car superseding ability=No": -26.2427. By calculating $\exp(-26.2427)$ we get a value really close to 0. This is the corresponding value in the odds ratio table and means that there is almost zero probability that a customer who has no car superseding ability, is interested in estimating his/her retirement.

From the second coefficient we have: "Motorbike superseding ability=Yes": -4.39. By calculating $\exp(-4.39)$ we get a value of $0.0124 (< 0.5)$. This means that although a customer may have a motorbike superseding ability, that does not mean that he/she is interested in estimating his/her retirement.

[137] Source: https://stackoverflow.com/questions/19136213/how-to-interpret-weka-logistic-regression-output

The relation between the coefficient for "Car superseding ability=No" and its odds ratio is, the logarithm of the odds of "Car superseding ability=No", over the odds of "Car superseding ability=Yes":

$$\log \frac{\text{Odds (Car superseding ability=No)}}{\text{Odds (Car superseding ability=Yes)}}$$ [138]

Example: The odds of "House superseding ability=Yes" is the probability of a customer having a house superseding ability when they are interested in estimating their retirement over the probability of having a house superseding ability when they are not interested in estimating their retirement. Similarly, you can calculate the odds for "House superseding ability=No".

The log of this ratio is the value of the coefficient attached to the variable "House superseding ability=Yes" in the logistic regression.

It is also observed that, the odds for "Have or Had Business Insurance=Yes" are extremely favorable to the yes outcome, producing a high positive value. This means that the customers that have or has business insurance are really interested in estimating their retirement.

Some of the model's predictions about each customer's willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Multi Class Classifier Predictions| NN

The predictions found for Multi Class Classifier Updateable are the same as those of Lazy K Star and Random Tree.

=== Predictions on user test set ===

inst#	Actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1

[138] Source: https://stats.stackexchange.com/questions/71684/how-to-interpret-weka-logistic-regression-output

4	1:Yes	1:Yes	1
5	1:Yes	1:Yes	1
6	1:Yes	1:Yes	1
7	1:Yes	1:Yes	1
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	1
10	1:Yes	1:Yes	1

Table 49: Predictions on user test set- Multi Class Classifier

3.1.11 Logistic

See Appendix: Logistic Classification Model| NN

=== Summary ===

Correctly Classified Instances	165	90.6593 %
Incorrectly Classified Instances	17	9.3407 %
Kappa statistic	0.2159	
Mean absolute error	0.0952	
Root mean squared error	0.3044	
Relative absolute error	106.8283 %	
Root relative squared error	148.264 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,931	0,625	0,970	0,931	0,950	0,228	0,624	0,967	Yes
	0,375	0,069	0,200	0,375	0,261	0,228	0,681	0,222	No
W.A	0,907	0,601	0,936	0,907	0,920	0,228	0,627	0,934	

Table 50: Detailed Accuracy by Class- Logistic

== Confusion Matrix ===

```
  a   b   <-- classified as
 162  12 |  a = Yes
   5   3 |  b = No
```

Logistic classification provides a satisfactory percentage of correctly classified instances and a high kappa statistic, which, along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that it is a well-functioning algorithm model.

This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

The logistic classification model (or logit model) is a binary classification model in which the conditional probability of one of the two possible realizations of the output variable is assumed to be equal to a linear combination of the input variables, transformed by the logistic function.[139]

Logistic class is for building and using a multinomial logistic regression model with a ridge estimator.

Logistic Classification is interpretable and simple algorithm model and it provides the same results as those of Multi Class Classifier.

Some of the model's predictions about each customers' willingness to estimate their retirement are presented below. The prediction "1.Yes" means that they are interested in estimating their retirement, whereas the prediction "2.No" means that they are not interested in estimating their retirement.

The rest of the results are presented in the appendix: Logistic Regression Predictions| NN

The predictions found for Logistic Classifier are the same as those of Multi Class Classifier, Multi Class Classifier Updateable, Lazy K Star and Random Tree.

=== Predictions on user test set ===

inst#	actual	predicted	error prediction
1	1:Yes	1:Yes	1
2	1:Yes	1:Yes	1
3	1:Yes	1:Yes	1
4	1:Yes	1:Yes	1
5	1:Yes	1:Yes	1
6	1:Yes	1:Yes	1
7	1:Yes	1:Yes	1
8	1:Yes	1:Yes	1
9	1:Yes	1:Yes	1
10	1:Yes	1:Yes	1

Table 51: Predictions on user test set- Logistic

[139] Source:https://www.statlect.com/fundamentals-of-statistics/logistic-classification-model

The algorithms Zero R, One R and J-Rip usually are the simplest algorithms with the best results given for predictability. However in our case these algorithms do not provide satisfying (low accuracy, negative kappa statistic, negative MCC).

See in the Appendix: Classifiers with low accuracy| NN

These are the algorithms with negative kappa statistic or negative MCC, which are a bad- functioning models.

3.2 WEKA Clustering

WEKA Clusterers

Clustering is a method of grouping similar things together. As mentioned in the first chapter, clustering is a process of portioning a data set into a set of meaningful subclasses, known as clusters. Clustering is the same as classification in which data is grouped. [140]

Though, unlike classification, clustering does not seek rules that predict a particular class, but rather try to divide the data into groups/clusters, that are not previously defined, by determining similarities between data according to characteristics found in the real data.

The objective of our clustering procedure is to group the customers who presented similarities in their insurance interests and to disjoin those who displayed dissimilarities. We proceed to the implementation of different clusterers (Simple K-Means, EM, Make a Density, Farthest First, Canopy, Filtered Clusterer) to the same dataset, in order to see how they behave and maybe to point possible similarities between the clustering results.

Below are the clusterers' results, which give information about the cluster centroids of the customers' answers. These, present the different clusters that are created, based on same characteristics observed in a set of elements.

Centroids are those characteristics that are dominant in the cluster and are similar (have similar characteristics) with the objects in the same cluster.

[140] Source: https://www.javatpoint.com/classification-vs-clustering-in-data-mining

The dataset used for the creation of the clustering results was the answers of a hundred and eighty-two (182) NN customers concerning their superseding ability, their insurance type, the significance of their insurance package, the safety offered from their insurance package, the level of satisfaction from the public insurance health benefits, their wish for extra benefits from their health insurance and their wish for covering certain expenditures after they receive their pension were loaded to WEKA software system in order to make the clusterings.

According to these data, WEKA created several clustering options depending on the clusterer chosen (Simple K-Means, EM, Make a Density, Farthest First, Canopy, Filtered) in order to group the travel agencies that presented similarities and disjoin those that displayed dissimilarities. The aim of clustering is to find distinct groups within a given dataset. Clustering also helps us discern the characteristics between data elements that would otherwise have been unlabeled and uncategorized.

3.2.1 Simple K Means

As mentioned in the first chapter (an analytical explanation is presented in chapter 60), Simple Means is a distant-based clusterer that minimizes the squared distance from each instance to their cluster center, after defining k centroids. It is one of the best unsupervised algorithms. For each different number of seeds, there are different clustering results.[141] [142]

Simple K Means uses random numbers and by using the same seed, we will always get the same random numbers. If we run Simple K Means over the same data twice, with the same seed, we will get exactly the same results. For different number of seeds, the results will vary each time we run Simple K Means.

In our dataset we use the same seed.

Simple K Means Clusterer, presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

[141] Source: https://www.youtube.com/watch?v=4b5d3muPQmA
[142] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings, depending on their number of clusters are presented below.

Simple K Means with 2 Clusters

See the clustering results in the appendix: ***Simple K Means Clustering| NN***

Within cluster sum of squared errors: 1889.54

Number of iterations: 5

Missing values globally replaced with mean/mode.

Clustered Instances (number of instances detected in each cluster):

0 60 (33%)

1 122 (67%)

Simple K Means divides NN customers into two clusters, Cluster 0 and Cluster 1. 67% of the instances are in Cluster 1 (122 customers out of 182 are included in this cluster). The two clusters present differentiations in the fields of insurance owning, the satisfactory amount of money for family support, the satisfaction from public insurance health benefits, the selection of a big private hospital in a big city of Greece over public hospitals for serious health issues, the willingness to include traveling to the private insurance, the management of supplementary pension and the importance of covering pleasure trips after pension receiving.

	Cluster 0	Cluster 1
Have never had Insurance	No	Yes
Tax obligations would not be covered in case of a possible loss of mine	Yes	No
A satisfying amount of money for the support of my beloved ones	99.57	79.57
Kind of satisfied from the public insurance health benefits	No	Yes
I would choose a big private hospital of Athens or Thessaloniki for serious health issues	Yes	No
I would like going abroad to be included to my private insurance	Yes	No

I have managed for a lump sum or supplementary pension	Yes	No
It is of a major importance to cover my pleasure trips after I receive my pension	Yes	No

Table 52: Cluster Centroids- Simple K- Means

Centroids of cluster 0 depicts that the certain characteristics of Cluster 0, are dominant in the cluster and are similar with the objects in the same cluster. The second cluster's centroid depicts that the certain characteristics of Cluster 1 are dominant in the second cluster and are similar with the objects in the same cluster.

Simple K Means with 3 clusters:

Within cluster sum of squared errors: 1824.91

Clustered Instances

0 36 (20%)

1 100 (55%)

2 46 (25%)

Simple K Means with 4 clusters:

Within cluster sum of squared errors: 1716.16

Clustered Instances

0 45 (25%)

1 71 (39%)

2 22 (12%)

3 44 (24%)

Simple K Means with 5 clusters:

See the clustering results in the appendix:

Within cluster sum of squared errors: 1651.43

Clustered Instances

0 45 (25%)

1 71 (39%)

2 22 (12%)

3 44 (24%)

It is clear that a higher number of clusters, leads to a lower squared error, meaning that, the dataset is closer to finding the line of best fit.

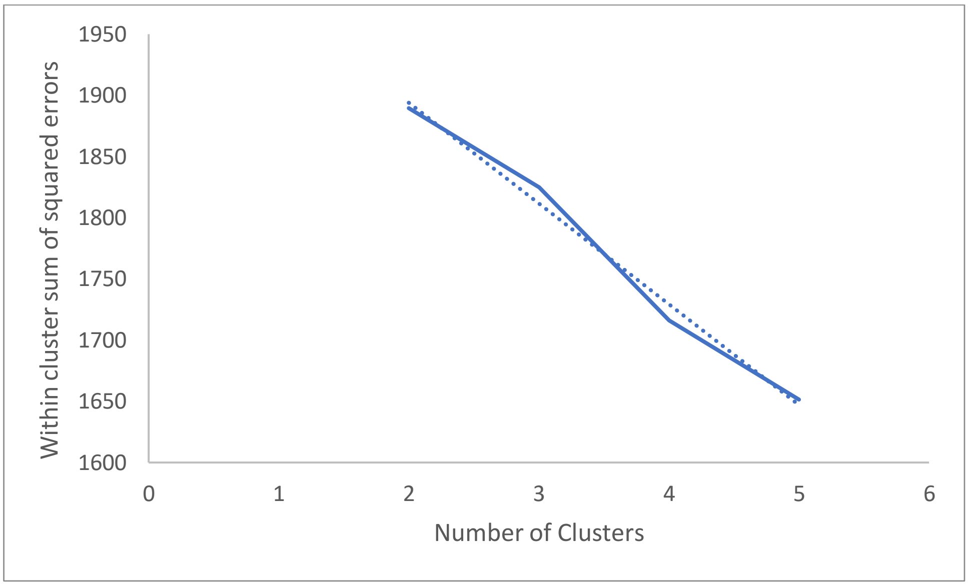

Figure 30: Within cluster sum of squared errors and number of clusters

3.2.2 EM

"EM (Expectation Maximization) is a probabilistic clusterer and can be used for unsupervised learning. Like Naive Bayes, it makes the assumption that all attributes are independent random variables." (Witten I.H., et al., (1999))

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.2), unlike K-Means that takes one point and places it to the one cluster or the other, EM computes the probability that it goes into a or b cluster. This probability never gets zero or one, it is always a number between zero and one (0<probability EM<1).

The model just finds that there are distinguished groups in the dataset that behave differently.

EM works for numeric attributes providing mean and standard deviation results and value probability results respectively. Log likelihood is an overall quality measure and is increased by each iteration. [143]

EM run alternative number of clusters and then chooses automatically the number of the clusters it shall create.

=== Model and evaluation on training set ===

See Appendix: ***EM Clusterer| NN***

Number of clusters selected by cross validation: 3

Number of iterations performed: 9

EM divides Cretan Palm's booking sources into three clusters.

43% of the customers are included in Cluster 0, 21% of the customers are included in Cluster 1 and 35% of the customers are included in Cluster 2.

Here is an example of how it works (all the rest clustering results are in the appendix):

- Customers in Cluster 0 have a 30% probability (24.1773/80.4633) to choose a big private hospital in a big city of Greece (Athens or Thessaloniki) over public hospitals for serious health issues (and a 70% probability (56.286/80.4633) not to choose a big private hospital in a big city of Greece (Athens or Thessaloniki) over public hospitals for serious health issues).
- Customers in Cluster 1 have a 66.5% probability (27.3252/41.0313) to choose a big private hospital in a big city of Greece (Athens or Thessaloniki) over public hospitals for serious health issues (and a 33.5% probability (27.3252/41.0313) not to choose a big private hospital in a big city of Greece (Athens or Thessaloniki) over public hospitals for serious health issues).
- Customers in Cluster 2 have a 42.8% probability (28.4974/66.5054) to choose a big private hospital in a big city of Greece (Athens or Thessaloniki) over public hospitals for serious health issues (and a 57.2% probability (38.0079/66.5054) not to choose a big private hospital in a big city of Greece (Athens or Thessaloniki) over public hospitals for serious health issues).

[143] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

	Cluster 0 (0.43)	Cluster 1 (0.21)	Cluster 2 (0.35)
I would choose a big private hospital of Athens or Thessaloniki for serious health issues			
Yes	24.1773	27.3252	28.4974
No	56.286	13.7061	38.0079
[total]	80.4633	41.0313	66.5054

Table 53: Cluster Centroids- EM

Clustered Instances (number of instances detected in each cluster):

0 79 (43%)

1 38 (21%)

2 65 (36%)

Log likelihood: -27.88

3.2.3 Farthest First

According to[24]:
Farthest first finds its variant of K-means. Each cluster center point furthermost from the existing cluster center is placed by the K-mean, and this point must be positioned within the data area. So that it greatly speeds up the clustering in most cases, but it needs less move and adjustment for their fast performance.

In order to examine Farthest First Clusterer's accuracy, we choose different number of clusters manually.

Farthest First Clusterer with 2 Clusters

See Appendix for the clustered centroids: ***Farthest First Clusterer | NN***

Farthest First divides NN's customer answers into two clusters. Each cluster's centroids are presented in the appendix. The elements "Yes" and "No" represent the centroid answers to the questionnaires' statements: "I have a car superseding ability, I have a motorbike superseding ability, I have a house superseding ability, I have a business superseding ability, I do not have superseding ability, I have/had Business Insurance, I have/had Civil Liability Insurance, It is of a major importance to cover my everyday needs after I receive my pension,…….,I am interested in estimating my retirement". Each "Yes/No" answer in each question is the centroid of all the answers that the customers have answered (in that specific question).

The clusters differentiate in these fields:

- business superseding ability
- general superseding ability
- business insurance ability
- civil liability insurance ability
- risk protection interest
- satisfying amount of money for the support of beloved ones
- importance of supporting children and grandchildren after pension
- immediate care of supplementary pension interest
- retirement estimation interest

	Cluster 0	Cluster 1
Business superseding ability	Yes	No
General superseding ability	No	Yes
Business insurance ability	Yes	No
Civil liability insurance ability	No	Yes
Risk protection interest	Yes	No
Satisfying amount of money for the support of beloved ones	100	86.6
Importance of supporting children and grandchildren after pension	No	Yes
Immediate care of supplementary pension interest	No	Yes
Retirement estimation interest	Yes	No

Table 54: Cluster Centroids – Farthest First

Clustered Instances (number of instances detected in each cluster):

0 148 (81%)

1 34 (19%)

Farthest First clusterer divides the data into two groups/clusters, with the first one having 81% of the instances and the second one having 19% of the instances.

According to centroids, the first cluster (Cluster 0) concerns customers who are interested in estimating their retirement, whereas the second cluster (Cluster 1) concerns customers who are not interested in estimating their retirement. The two clusters have similar characteristics (similar centroids) except for these written on the table. The rest of the characteristics are presented in the appendix.

Farthest First Clusterer with 3 Clusters

Clustered Instances

0 93 (51%)

1 23 (13%)

2 66 (36%)

Farthest First Clusterer with 4 Clusters

Clustered Instances

0 85 (47%)

1 18 (10%)

2 49 (27%)

3 30 (16%)

Farthest First Clusterer with 5 Clusters

Clustered Instances

0 72 (40%)

1 15 (8%)

2 45 (25%)

3 26 (14%)

4 24 (13%)

3.2.4 Make A Density Based Clusterer

According to [29]:
Density-Based Clustering refers to unsupervised learning methods that identify distinctive groups/clusters in the data, based on the idea that a cluster in a data space is a contiguous region of high point density, separated from other such clusters by contiguous regions of low point density. The data points in the separating regions of low point density are typically considered noise/outliers.

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.7),

- The clusterer randomly chooses the core points and then for each core point that is not already assigned to a cluster, creates a new cluster.
- The clusterer finds all its density connected points and assigns them to the same cluster as the core point.
- Then it iterates through the remaining unvisited points in the dataset.
- The core points that do not belong to any cluster are treated as outliers or noise points.[144]

Make A Density Clusterer, also presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings depending on their number of clusters are presented below.

Make A Density Clusterer with 2 Clusters

See the clustering results in the appendix: ***Make A Density Fitted Estimators| NN***

Within cluster sum of squared errors: 1889.5

[144] Source: https://www.youtube.com/watch?v=f4pZ9PHNdcM

Wrapped clusterer: kMeans

Number of iterations: 5

Missing values globally replaced with mean/mode.

Clustered Instances (number of instances detected in each cluster):

0 59 (32%)

1 123 (68%)

Log likelihood: -28.64

Make a density clusterer divides the data into two groups/clusters, with the first one having 32% of the instances and the second one having 68% of the instances.

<u>Make A Density Clusterer with 3 Clusters</u>

Wrapped clusterer: kMeans

Number of iterations: 5

Within cluster sum of squared errors: 1824.91

Clustered Instances

0 32 (18%)

1 102 (56%)

2 48 (26%)

Log likelihood: -28.45069

<u>Make A Density Clusterer with 4 Clusters</u>

Wrapped clusterer: kMeans

Number of iterations: 7

Within cluster sum of squared errors: 1716.16

Clustered Instances

0 43 (24%)

1 73 (40%)

2 21 (12%)

3 45 (25%)

Log likelihood: -28.10392

Make A Density Clusterer with 5 Clusters

Wrapped clusterer: kMeans

Number of iterations: 13

Within cluster sum of squared errors: 1651.43

Clustered Instances

0 42 (23%)

1 34 (19%)

2 20 (11%)

3 44 (24%)

4 42 (23%)

Log likelihood: -28.0086

It is clear that a higher number of clusters, leads to a lower squared error, meaning that, the dataset is closer to finding the line of best fit.

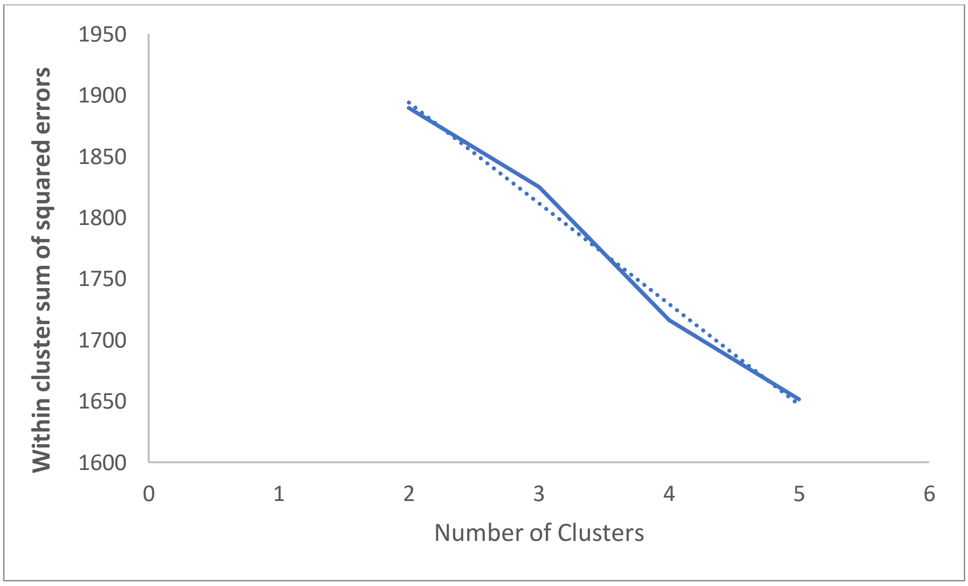

Figure 31: Within cluster sum of squared errors and number of clusters

3.2.5 Canopy

According to Mai and Cheng (2016)[33]: *Canopy is one of the improved K-means algorithm, can be used to determine the number of clusters. With the introduction of Canopy clustering, the data set is divided into k sub-sets by setting the radius, and the sub-sets can be selected as the initial centers of K-means. Because the Canopy algorithm can reduce the running time of the clustering by reduce the count of comparisons, it will improve the computational efficiency.*

The Canopy algorithm's analytical explanation of the steps, are presented in chapter 1.5.8.

Canopy runs alternative number of clusters and then chooses automatically the number of the clusters it shall create.

See Appendix: ***Canopy Clustering| NN***

Number of canopies (cluster centers) found: 7

T2 radius: 4,020

T1 radius: 5,026

Clustered Instances (number of instances detected in each cluster):

0 61 (34%)

1 50 (27%)

2 6 (3%)

3 20 (11%)

4 6 (3%)

5 33 (18%)

6 6 (3%)

Canopy divides NN's customer answers into seven clusters. Each cluster's elements are presented in the appendix. The elements "Yes" and "No" represent the answers to the questionnaires' statements: "I have a car superseding ability, I have a motorbike superseding ability, I have a house superseding ability, I have a business superseding ability, I do not have superseding ability, I have/had Business Insurance, I have/had Civil Liability Insurance, It is of a major importance to cover my everyday needs after

I receive my pension,…….,I am interested in estimating my retirement”. An obvious difference between the clusters is the amount of money that is satisfactory for the support of the customer’s beloved ones.

According to centroids, all the clusters concern customers who are interested in estimating their retirement. These clusters differ in other characteristics and are presented in the appendix.

Note: The numbers in these brackets: **Error! Reference source not found.** show the instances that are appeared in the cluster.

3.2.6 Filtered Clusterer

According to [20][20]:
This algorithm is primarily based completely on storing the multidimensional data points within a tree. The process regarding the tree is like a binary tree method, as represents a hierarchical subdivision on its data point set’s bounding box the usage of their axis after which splitting is aligned by way on hyper planes. Each node on the tree is related with a closed field, referred to as the cell.

These results are the same as those of Simple K Means for all the clusterings, which is expected, as Filtered Clusterer uses Simple K Means in order to proceed to the outcome.

Conclusions

95% of the customers that answered the questionnaire (174 out of 182) are interested in estimating their retirement.

According to the Random Tree algorithm- which presents an interpretable decision tree model- there is a correlation between certain factors (that influence the variable) and the variable (interest of retirement estimation).

It is recommended that the company adopts a marketing strategy focused on the customers that are interested in estimating their retirement.

Random Tree, Lazy IBK, Naïve Bayes Updateable and Bayes Net, are the algorithms that provide the most accurate results. The high percentage of correctly classified instances and the positive kappa statistic along with the high accuracy of the estimators (ROC Area (>0,5)) indicate that these are high-performance algorithm models. This practically means that, the predictions made by the algorithm were correct and better than a random guessing. So, there is a high probability that the dataset values are similar to those predicted from the algorithm.

Below there is a table providing all the algorithms' results as well as a table providing all algorithms' ranking. The second table ranks the algorithms and depicts which one of these is the best, based on the number of times a particular algorithm defeats others.

	Random Tree	Lazy IBK	Naive Bayes Updateable	Bayes Net	Naive Bayes	Lazy K Star	Meta Randomizable Filtered Classifier	SMO	Multi Class Classifier Updateable	Multi Class Classifier	Logistic Regression
Correctly Classified Instances	172	172	171	171	171	170	169	169	166	165	165
Incorrectly Classified Instances	10	10	11	11	11	12	13	13	16	7	17
Kappa statistic	0,1415	0,1415	0,1242	0,2353	0,1242	0,1093	0,0963	0,0963	0,15555	0,2159	0,2159
Mean absolute error	0,0532	0,0627	0,0663	0,0715	0,0663	0,0688	0,0766	0,0714	0,0879	0,0952	0,0952
Root mean squared error	0,2273	0,236	0,2246	0,2293	0,2246	0,2479	0,2657	0,2673	0,2965	0,3044	0,3044
Relative absolute error	59,69%	70,30%	74,33%	80,22%	74,33%	77,14%	85,91%	80,11%	98,60%	106,83%	106,83%
Root relative squared error	110,71%	114,93%	109,39%	111,65%	109,39%	120,73%	129,40%	13,16%	144,40%	148,26%	148,26%
Total Number of Instances	182	182	182	182	182	182	182	182	182	182	182
TP Rate	0,945	0,945	0,94	0,94	0,94	0,945	0,929	0,929	0,912	0,907	0,907
FP Rate	0,837	0,837	0,838	0,718	0,838	0,934	0,838	0,838	0,72	0,601	0,601
Precision	0,945	0,929	0,927	0,936	0,927	0,838	0,924	0,924	0,93	0,936	0,936
Recall	0,929	0,945	0,94	0,94	0,94	0,925	0,929	0,929	0,912	0,907	0,907
F-Measure	0,945	0,936	0,933	0,938	0,933	0,9364	0,926	0,926	0,92	0,92	0,92
MCC	0,151	0,151	0,128	0,236	0,128	0,111	0,096	0,096	0,159	0,228	0,228
ROC Area	0,527	0,634	0,746	0,759	0,746	0,524	0,575	0,545	0,596	0,627	0,627
PRC Area	0,92	0,93	0,946	0,951	0,946	0,921	0,923	0,92	0,925	0,934	0,934

Figure 32: Algorithms' results

Dataset	SMO	Random Tree	Lazy IBK	Naive Bayes	Bayes Net	Lazy K Star	Meta Randomizable Filtered Classifier	Multi Class Classifier Updateable	Multi Class Classifier	Logistic
NN	93,81	92,03	93,64	93,91	93,91	93,64	92,37	92,38	89,41*	89,41*
	(v/ /*)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/0/1)	(0/0/1)
Ranking	2	0	0	0	0	0	0	0	-1	-1

Figure 33: Algorithms' ranking

The ranking table shows the number of statistically significant victories (we set level of significance: 0.05) of each algorithm versus all other algorithms for the data set (except Naïve Bayes Updateable which is binary). A victory (v) means an accuracy that is better than the accuracy of another algorithm and that this difference is statistically significant.[145]

We can see that SMO has two victories, which means that this is potentially the best one. Logistic and Multi Class Classifier, have 1 loss each. The accuracy of these two algorithms compared to SMO is low, so SMO algorithm is potentially the best one outperforming Logistic and Multiclass Classifier.

We can see that Logistic and Multiclass Classifier algorithms have an '*' next to its results, meaning its results with respect to SMO are statistically different.

The rating scores of Logistic and Multiclass Classifier is the same. Putting Logistic and Multi Class Classifier to the test base, we confirm the already known results, that is, SMO outperforms these two algorithms.

[145] Statistical significance is achieved when the p-value is lower than the level of significance (which is usually 0.05).
A p-value, or probability value, is a number describing how likely it is that your data would have occurred by random chance (i.e. that the null hypothesis is true). A p-value less than 0.05 (typically ≤ 0.05) is statistically significant. It indicates strong evidence against the null hypothesis, as there is less than a 5% probability the null is correct (and the results are random). Therefore, we reject the null hypothesis, and accept the alternative hypothesis. A p-value higher than 0.05 (> 0.05) is not statistically significant and indicates strong evidence for the null hypothesis. This means we retain the null hypothesis and reject the alternative hypothesis. Source: McLeod, S. A. (2019, May 20). What a p-value tells you about statistical significance. Simply Psychology. www.simplypsychology.org/p-value.html

Dataset	Logistic	Random Tree	Lazy IBK	Naive Bayes	Bayes Net	Lazy K Star	Meta Randomizable Filtered Classifier	SMO	Multi Class Classifier Updateable	Multi Class Classifier
NN	89,41	92,03	93,64	93,91	93,91	93,64	92,37	93,81 v	92,38	89,41
	(v/ /*)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(1/0/0)	(0/1/0)	(0/1/0)
Ranking	-1	0	0	0	0	0	0	2	0	-1

Figure 34: Algorithms' ranking

Dataset	Multi Class Classifier	Random Tree	Lazy IBK	Naive Bayes	Bayes Net	Lazy K Star	Meta Randomizable Filtered Classifier	SMO	Multi Class Classifier Updateable	Logistic
NN	89,41	92,03	93,64	93,91	93,91	93,64	92,37	93,81 v	92,38	89,41
	(v/ /*)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(0/1/0)	(1/0/0)	(0/1/0)	(0/1/0)
Ranking	-1	0	0	0	0	0	0	2	0	-1

Figure 35: Algorithms' ranking

We can see that SMO has a small 'v' next to its results. This means that the difference in accuracy for this algorithm compared to Logistic and Multiclass Classifier is statistically significant. We can also see that the accuracy of SMO algorithms compared to these algorithms is high, so we can say that SMO achieved a statistically significantly better result than Logistic’s and Multiclass Classifier's base lines.

So, we will probably choose SMO to make predictions about this problem.

If we wanted to report the results, we would say that the SMO algorithm achieved a classification accuracy of 93.81% (+/- 5.47%).

Chapter 4

Use Case: Large Super Market in Greece

4.1 WEKA Association Rule Mining

In this chapter, we are going to make an analysis for a Super Market chain in Greece, using Association Rule Mining (also known as market basket analysis) to discover the correlations between the different items in customers' shopping cart, as well as Clustering to segregate groups with similar traits. The findings of these correlations may help the Super Market better understand the purchase behavior of the buyers, make the correct decisions and hence, establish a profitable sales strategy by considering items frequently purchased together by customers.

For a supermarket with multiple stores, finding purchasing patterns can be useful in forming sales, marketing, service, and operation strategies. However, there are some problems arisen from the existing traditional strategic methods for a supermarket environment such as the nature of purchasing patterns.

To address these problems, the Apriori algorithm is used for automated extraction of association rules in a supermarket's environment.

The rules can be used for sales, marketing and operation strategies, for product procurement and inventory as well as for distribution of the entire Supermarket chain. (Chen et. al., 2005. Market basket analysis in a multiple store environment, Decision Support Systems) [34]

For this use case, a database with transactional and demographic data was collected from the Supermarket for a period of eight months (January to August of 2021). This database includes the customers' gender, age, card code and all of their purchases with its dates, the shop and area from which the customers made each purchase, the products each customer chose along with their product category and the amount of money that they spent on each product. The total number of the customers is 467, the different product categories are 431 and the different shops are 41.

The collection and analysis of these data, gives us the opportunity to find useful information about the customers, analyze their profile and make certain predictions and clusterings about them. Weka Machine Learning Software, can transform the dataset into meaningful patterns with the assistance of integrated algorithms and help us make predictions on certain variables as well as clusterings. WEKA, helps us to better predict the results of a new oncoming dataset that has similar characteristics with our already existing dataset.

To proceed to these analyses, the original dataset was subjected to data preparation/ training in order to become in a suitable format and make the necessary associations and clusterings.

Association Rule Mining preparation includes sorting all customers by card code, gender, age, shopping area, and shopping dates and then for each shopping date and each shopping area[146] chosen by each customer, we recorded if there was a purchase for each of the product categories with the assistance of Pivot Tables. Then, different sub-datasets were made; two for the different genders, six for the various age groups and fourteen for the different shopping areas (all around Crete) that customers choose for their purchases. Each one sub-dataset, is loaded to Weka and is being analyzed using Apriori algorithm in order to extract the necessary rules and discover the correlations between the different items in customers' shopping cart. Through data mining processing, useful information is extracted from a database aiming to make crucial business decisions. Data mining combined with artificial intelligence techniques, discovers various correlations and maybe unexpected patterns between two or more variables. As far as the Super Market Analysis is concerned, Association Rule Mining is used to discover the correlation between one item to another and to depict which items are frequently purchased together.

According to Solanki and Patel (2015) **Error! Reference source not found.**:
An association rule is one of the forms, where A is an "antecedent" (if part) and B is the "consequent" (then part). Here variables A and B are the item sets and the rule ( ) means that customer who purchase an item set A are expected to purchase an item set B with the probability % c, where c is called confidence.

Clustering preparation, included sorting all customers by gender, age and then for each customer, the purchase frequency was recorded for each of the product

[146] A shopping area may has one or more different shops.

categories, with the assistance of Pivot Tables. Then, the dataset was loaded to Weka in order to segregate the customers with similar characteristics. In our case, the purpose is to find the groups that are similar as per their purchase frequencies.

Association Rule Mining /Market Basket Analysis is presented below, by adducing the correlations between the different items in customers' shopping cart for each gender (women and men of every age group and every area of purchase), each shopping area[147] from the different prefectures of Crete (regardless of gender and age group) and each age group (of all genders and areas of purchase).

To evaluate the performance of Apriori's results, we use the following metrics:

As denoted in the first chapter, for a given rule X ⇒ Y, <conf:(w)> lift:(z) lev:(t) conv:(j) :

- Confidence (<conf>) measures the reliability of the results emerged from a rule. The higher the confidence level, the more likely Y is to engage in transactions containing X.
- Lift is about how likely is for the product Y to be purchased given that product X is purchased, while checking how popular product Y is. Values greater than 1 are desirable.
- Leverage (lev) measures the proportion of additional cases covered by both X and Y above those expected if X and Y were independent of each other. If the value of the leverage is zero, then X and Y are statistically independent. A leverage value greater than zero, means that X and Y are related. The higher the leverage value, the stronger the correlation between X and Y.
- Conviction (conv) is the effect of the right-hand-side not being true.

Associator model (full training set): Apriori

[147] These areas are: Chania, Kounoupidiana, Heraclion, Kokkini Chani, Gazi, Malia, LImenas Chersonissou, Mires, Nea Alikarnassos, Tympaki, Ierapetra, Neapoli, Siteia, Agios Nikolaos.

4.1.1 Best results found for Women

1. CURED MEAT PRODUCTS (DRAINING BENCHES)=t 2439 ==> CHEESE (DRAINING BENCHES)=t 2203 <conf:(0.9)> lift:(2.55) lev:(0.09) [1340] conv:(6.65)[148]

2. FRUITS, GROCERY=t CHEESE (DRAINING BENCHES)=t 2320 ==> VEGETABLES, GROCERY=t 1685 <conf:(0.73)> lift:(1.53) lev:(0.04) [583] conv:(1.92)[149]

3. FRUITS, GROCERY=t XM CODE (OUT OF CATEGORY), BAZAAR=t 2691 ==> VEGETABLES, GROCERY=t 1875 <conf:(0.7)> lift:(1.47) lev:(0.04) [597] conv:(1.73)

4. FRUITS, GROCERY=t 5639 ==> VEGETABLES, GROCERY=t 3768 <conf:(0.67)> lift:(1.41) lev:(0.07) [1090] conv:(1.58)

5. PASTA, CONSUMABLES=t 2800 ==> VEGETABLES, GROCERY=t 1605 <conf:(0.57)> lift:(1.21) lev:(0.02) [275] conv:(1.23)

6. VEGETABLES, GROCERY=t CHEESE (DRAINING BENCHES)=t 3005 ==> FRUITS, GROCERY=t 1685 <conf:(0.56)> lift:(1.56) lev:(0.04) [604] conv:(1.46)

7. BREAD, CONSUMABLES=t 3895 ==> CHEESE (DRAINING BENCHES)=t 2159 <conf:(0.55)> lift:(1.57) lev:(0.05) [781] conv:(1.45)

8. YOGURT, CONSERVATION=t 3831 ==> VEGETABLES, GROCERY=t 2103 <conf:(0.55)> lift:(1.16) lev:(0.02) [284] conv:(1.16)

9. CHEESE (DRAINING BENCHES)=t 5546 ==> VEGETABLES, GROCERY=t 3005 <conf:(0.54)> lift:(1.14) lev:(0.02) [371] conv:(1.15)

[148] This rule depicts that there is a correlation between the purchase of cured meat products and cheese by women. That is, that the purchase of cured meat products, usually lead to the purchase of cheese and with a confidence of 0,9 it is very likely that cheese is to engage in transactions containing cured meat products. The lift 2.25 (>1) also depicts that it is very likely for the cheese to be purchased given that cured meat products are purchased. The leverage 0.09 (>0) depicts that these two products are statistically dependent and related with each other.

[149] This rule depicts that there is a correlation between the purchase of fruits and cheese with vegetables by women. That is, that the purchase of fruits and cheese, usually lead to the purchase of vegetables. Fruits and cheese along with vegetables are frequently purchased together with a confidence of 0.73.

10. VEGETABLES, GROCERY=t XM CODE (OUT OF CATEGORY), BAZAAR=t 3475 ==> FRUITS, GROCERY=t 1875 <conf:(0.54)> lift:(1.5) lev:(0.04) [625] conv:(1.39)

The results show that women's purchases of fruits, consumables (pasta, bread), cheese and conserved products (yogurt), usually lead to the purchase of vegetables. Furthermore, the purchase of cured meat products usually lead to the purchase of cheese and the purchase of bazaar products usually lead to the purchase of fruits or vegetables. Vegetables lead to the purchase of fruits and vice versa.

These rules present high levels of confidence (>0,5) which is a metric of reliability of the results emerged from a rule, high levels of lift (>1) which is a metric of relation between the items. The rules' leverages are also greater than zero, which depicts that these products are statistically dependent and related with each other.

4.1.2 Best results found for Men

1. CURED MEAT PRODUCTS (DRAINING BENCHES)=t 630 ==> CHEESE (DRAINING BENCHES)=t 567 <conf:(0.9)> lift:(2.68) lev:(0.09) [355] conv:(6.54)
2. FRUITS, GROCERY=t 1287 ==> VEGETABLES, GROCERY=t 735 <conf:(0.57)> lift:(1.43) lev:(0.05) [222] conv:(1.4)
3. BREAD, CONSUMABLES=t 1014 ==> CHEESE (DRAINING BENCHES)=t 541 <conf:(0.53)> lift:(1.59) lev:(0.05) [201] conv:(1.42)
4. YOGURT, CONSERVATION=t 953 ==> VEGETABLES, GROCERY=t 469 <conf:(0.49)> lift:(1.24) lev:(0.02) [89] conv:(1.18)
5. VEGETABLES, GROCERY=t 1616 ==> FRUITS, GROCERY=t 735 <conf:(0.45)> lift:(1.43) lev:(0.05) [222] conv:(1.25)
6. BREAD, CONSUMABLES=t 1014 ==> VEGETABLES, GROCERY=t 454 <conf:(0.45)> lift:(1.12) lev:(0.01) [50] conv:(1.09)

7. MILK, CONSERVATION=t 1087 ==> CHEESE (DRAINING BENCHES)=t 484 <conf:(0.45)> lift:(1.33) lev:(0.03) [119] conv:(1.2)
8. CHEESE (DRAINING BENCHES)=t 1361 ==> VEGETABLES, GROCERY=t 599 <conf:(0.44)> lift:(1.11) lev:(0.01) [57] conv:(1.07)
9. BREAD, CONSUMABLES=t 1014 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 445 <conf:(0.44)> lift:(1.14) lev:(0.01) [56] conv:(1.1)
10. YOGURT, CONSERVATION=t 953 ==> CHEESE (DRAINING BENCHES)=t 411 <conf:(0.43)> lift:(1.29) lev:(0.02) [91] conv:(1.17)

The high levels of confidence (0.9) and lift (2.68) depict that men's purchases of cured meat products usually lead to the purchase of cheese.

Fruits usually lead to the purchase of vegetables and bread usually leads to the purchase of cheese. These rules have lower confidence and lift levels but they still considered to have a quite strong co-relation.

The other rules present a lower confidence level (0.5), which depict a weaker engagement between the related products.

Propositions concerning both male and female target audience:

Since we have found which products with a high correlation factor, that go well together, we can proceed to certain in-store and/or online targeting activities, in order to enhance the cross-selling purchasing and maximize customer engagement and sales.

– It is recommended that fruits, vegetables, consumables (pasta, bread) and dairy products to be placed next to each other or within accessible reach to facilitate cross-selling.

  Furthermore, cured meat products can be placed next to cheeses or within accessible reach.
– In the consumables' section can be placed a dairy products' promotion panel (for instance, in the pasta section can be placed a panel promoting the various types of cheese that may go well with the various types of pasta).

- Simultaneous discounts and offers can also be put from time to time to the highly correlated products, such as to the bazaar items and the fruits/ vegetables, to the consumables and the dairy products and/or the cured meat products and the cheeses.
- In-store digital signage is a form of dynamic advertising and can placed all around the aisles and activate the clients during their purchases. For example, pasta section can promote a healthy spaghetti receipt with cheese and vegetables. That way, visitors can identify a checklist of ingredients easily and shall consider again their purchase needs. Moreover, the usage of digital signage, is a useful reminder and an interactive counselor to the customers, as they can directly emphasize in suggesting other products that are going well with the one that the customer is standing in front. For instance, a digital signage in the cured meat product section can also suggest cheeses' section for a more complete shopping list.

  Digital signage may also promote the high-related products' offers and discounts. That way, customers can be directly informed and better engaged with the purchase activities.
- Website as well as mobile applications may also promote a cross-selling tactic by showcasing the correlated products when a customer is searching for a certain product category. For example, when a customer is scrolling through the pasta section, a message shall appear at the end of the page, such as "Customers that searched for pasta, also searched for mozzarella cheese. Take a look at our dairy section!" and then by clicking the respective button, customers shall be redirected to the certain section.

Simple moves like the aforementioned, might be used to increase the sales of whatever correlated category needs to be promoted and will lead to higher sales.

4.1.3 Best results found for Chania Area

1. BREAD, CONSUMABLES=t 127 ==> VEGETABLES, GROCERY=t 97 <conf:(0.76)> lift:(1.55) lev:(0.05) [34] conv:(2.08)
2. FRUITS, GROCERY=t 227 ==> VEGETABLES, GROCERY=t 146 <conf:(0.64)> lift:(1.31) lev:(0.05) [34] conv:(1.41)
3. CHEESE (DRAINING BENCHES)=t 202 ==> VEGETABLES, GROCERY=t 126 <conf:(0.62)> lift:(1.27) lev:(0.04) [26] conv:(1.33)
4. CAVA, NON-ALCOHOLIC/SOFT DRINKS=t 142 ==> VEGETABLES, GROCERY=t 76 <conf:(0.54)> lift:(1.09) lev:(0.01) [6] conv:(1.08)
5. YOGURT, CONSERVATION=t 147 ==> VEGETABLES, GROCERY=t 77 <conf:(0.52)> lift:(1.07) lev:(0.01) [4] conv:(1.05)
6. PASTRIES/ SWEETS, CONSUMABLES=t 152 ==> VEGETABLES, GROCERY=t 76 <conf:(0.5)> lift:(1.02) lev:(0) [1] conv:(1)
7. XM CODE (OUT OF CATEGORY), BAZAAR=t 200 ==> VEGETABLES, GROCERY=t 93 <conf:(0.47)> lift:(0.95) lev:(-0.01) [-5] conv:(0.94)
8. VEGETABLES, GROCERY=t 362 ==> FRUITS, GROCERY=t 146 <conf:(0.4)> lift:(1.31) lev:(0.05) [34] conv:(1.15)
9. MILK, CONSERVATION=t 198 ==> VEGETABLES, GROCERY=t 76 <conf:(0.38)> lift:(0.78) lev:(-0.03) [-21] conv:(0.82)
10. CHEESE (DRAINING BENCHES)=t 202 ==> FRUITS, GROCERY=t 77 <conf:(0.38)> lift:(1.24) lev:(0.02) [14] conv:(1.11)

The results show that in the area of Chania purchases of bread, conserved products (yoghurt), consumables, drinks, beverages, cheese and fruits usually lead to the purchase of vegetables which means that it is very likely that vegetables are about to engage in transactions containing the aforementioned. These rules present high levels of confidence (>0,5) which is a metric of reliability of the results emerged from a rule, high levels of lift (>1) which is a metric of relation between the items. The rules' leverages are also greater than zero, which depicts that these products are statistically dependent and related with each other.

The other rules present a low confidence level (<0.5), which depict a weaker engagement between the related products. For example, the purchase of cheese seems to lead to the purchase of fruits; however, it has a lower confidence and lift level, which depict that the rule is not that reliable.

4.1.4 Best results found for Kounoupidiana Area

1. CURED MEAT PRODUCTS (DRAINING BENCHES)=t 92 ==> CHEESE (DRAINING BENCHES)=t 85 <conf:(0.92)> lift:(2.45) lev:(0.08) [50] conv:(7.16)

2. CAVA NON-ALCOHOLICS/WATER=t 91 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 70 <conf:(0.77)> lift:(1.46) lev:(0.04) [22] conv:(1.96)

3. CHEESE, CONSERVATION=t XM CODE (OUT OF CATEGORY), BAZAAR=t 86 ==> VEGETABLES, GROCERY=t 66 <conf:(0.77)> lift:(1.52) lev:(0.04) [22] conv:(2.03)

4. FRUITS, GROCERY=t CHEESE (DRAINING BENCHES)=t 116 ==> VEGETABLES, GROCERY=t 89 <conf:(0.77)> lift:(1.52) lev:(0.05) [30] conv:(2.05)

5. FRUITS, GROCERY=t XM CODE (OUT OF CATEGORY), BAZAAR=t 155 ==> VEGETABLES, GROCERY=t 118 <conf:(0.76)> lift:(1.51) lev:(0.06) [39] conv:(2.02)

6. CHEESE, CONSERVATION=t 134 ==> VEGETABLES, GROCERY=t 95 <conf:(0.71)> lift:(1.4) lev:(0.04) [27] conv:(1.66)

7. FRUITS, GROCERY=t 247 ==> VEGETABLES, GROCERY=t 172 <conf:(0.7)> lift:(1.38) lev:(0.08) [47] conv:(1.61)

8. VEGETABLES, GROCERY=t CHEESE, CONSERVATION=t 95 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 66 <conf:(0.69)> lift:(1.32) lev:(0.03) [16] conv:(1.5)

9. VEGETABLES, GROCERY=t FRUITS, GROCERY=t 172 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 118 <conf:(0.69)> lift:(1.31) lev:(0.04) [27] conv:(1.48)

10. VEGETABLES, GROCERY=t CHEESE (DRAINING BENCHES)=t 135 ==> FRUITS, GROCERY=t 89 <conf:(0.66)> lift:(1.68) lev:(0.06) [35] conv:(1.74)

All the rules present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

The results show that in the area of Kounoupidiana and as it is presented from the high confidence (0.92>0.5) and lift (2.45>1) levels, there is a high probability that purchases of cured meat products shall lead to the purchase of cheese.

Furthermore, purchases of non-alcoholic drinks, fruits, cheeses (conserved and from draining benches), bazaar items and other uncategorized products usually lead to the purchase of vegetables.

Vegetables on the other hand, usually lead to the purchase of uncategorized products and fruits. From the last rule, we can detect that a customer who has vegetables and cheese in his cart, will usually purchase fruits as well.

The Prefecture of Chania displays a correlation between non-alcoholic drinks/beverages with vegetables as well as between cheese and vegetables. That is, the purchase of beverages and/ or cheese, lead to the purchase of vegetables.

4.1.5 Best results found for Heraclion Area(City)

1. CURED MEAT PRODUCTS (DRAINING BENCHES)=t 2435 ==> CHEESE (DRAINING BENCHES)=t 2215 <conf:(0.91)> lift:(2.51) lev:(0.09) [1331] conv:(7.02)

2. FRUITS, GROCERY=t CHEESE (DRAINING BENCHES)=t 2166 ==> VEGETABLES, GROCERY=t 1548 <conf:(0.71)> lift:(1.56) lev:(0.04) [558] conv:(1.9)

3. FRUITS, GROCERY=t XM CODE (OUT OF CATEGORY), BAZAAR=t 2314 ==> VEGETABLES, GROCERY=t 1611 <conf:(0.7)> lift:(1.52) lev:(0.04) [554] conv:(1.79)

4. FRUITS, GROCERY=t 5092 ==> VEGETABLES, GROCERY=t 3339 <conf:(0.66)> lift:(1.44) lev:(0.07) [1013] conv:(1.58)

5. BREAD, CONSUMABLES=t 3735 ==> CHEESE (DRAINING BENCHES)=t 2117 <conf:(0.57)> lift:(1.56) lev:(0.05) [761] conv:(1.47)

6. VEGETABLES, GROCERY=t CHEESE (DRAINING BENCHES)=t 2768 ==> FRUITS, GROCERY=t 1548 <conf:(0.56)> lift:(1.62) lev:(0.04) [590] conv:(1.48)

7. YOGURT, CONSERVATION=t 3604 ==> VEGETABLES, GROCERY=t 1916 <conf:(0.53)> lift:(1.16) lev:(0.02) [269] conv:(1.16)

8. BREAD, CONSUMABLES=t 3735 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 1972 <conf:(0.53)> lift:(1.22) lev:(0.02) [357] conv:(1.2)

9. BREAD, CONSUMABLES=t 3735 ==> VEGETABLES, GROCERY=t 1969 <conf:(0.53)> lift:(1.15) lev:(0.02) [263] conv:(1.15)

10. PASTRIES/ SWEETS, CONSUMABLES=t 2873 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 1500 <conf:(0.52)> lift:(1.21) lev:(0.02) [257] conv:(1.19)

The results show that in Heraclion Area and as it is presented from the high confidence (0.91>0.5) and lift (2.51>1) levels, there is a high probability that purchases of cured meat products shall lead to the purchase of cheese.

Furthermore, purchases of fruits and/or cheeses (from draining benches) as well as fruits and bazaar items, usually lead to the purchase of vegetables.

Purchases of vegetables also lead to the purchase of fruits.

Also, bread presents a high correlation with cheese (from the draining benches) as well as with bazaar items and vegetables.

Purchases of conserved yoghurt lead to the purchases of vegetables as well and pastry purchases usually lead to the purchase of bazaar items.

4.1.6 Best results found for Gazi Area

1. MILK, CONSERVATION=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 43 ==> CHEESE (DRAINING BENCHES)=t 42 <conf:(0.98)> lift:(2.01) lev:(0.06) [21] conv:(11.07)

2. YOGURT, CONSERVATION=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 38 ==> CHEESE (DRAINING BENCHES)=t 37 <conf:(0.97)> lift:(2.01) lev:(0.05) [18] conv:(9.78)

3. BREAD, CONSUMABLES=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t XM CODE (OUT OF CATEGORY), BAZAAR=t 40 ==> CHEESE (DRAINING BENCHES)=t 38 <conf:(0.95)> lift:(1.96) lev:(0.05) [18] conv:(6.86)

4. CURED MEAT PRODUCTS (DRAINING BENCHES)=t XM CODE (OUT OF CATEGORY), BAZAAR=t 68 ==> CHEESE (DRAINING BENCHES)=t 64 <conf:(0.94)> lift:(1.94) lev:(0.08) [31] conv:(7)

5. BREAD, CONSUMABLES=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 51 ==> CHEESE (DRAINING BENCHES)=t 48 <conf:(0.94)> lift:(1.94) lev:(0.06) [23] conv:(6.56)

6. CURED MEAT PRODUCTS (DRAINING BENCHES)=t 109 ==> CHEESE (DRAINING BENCHES)=t 102 <conf:(0.94)> lift:(1.93) lev:(0.13) [49] conv:(7.01)

7. FRUITS, GROCERY=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 49 ==> CHEESE (DRAINING BENCHES)=t 45 <conf:(0.92)> lift:(1.89) lev:(0.06) [21] conv:(5.05)

8. CAVA, NON ALCOHOLIC/TEA/JUICES=t 41 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 37 <conf:(0.9)> lift:(1.73) lev:(0.04) [15] conv:(3.93)

9. VEGETABLES, GROCERY=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 51 ==> CHEESE (DRAINING BENCHES)=t 46 <conf:(0.9)> lift:(1.86) lev:(0.06) [21] conv:(4.38)

10. TEA/JUICES, CONSERVATION=t 43 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 38 <conf:(0.88)> lift:(1.7) lev:(0.04) [15] conv:(3.44)

All the rules present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

The results show that in the area of Gazi and as it is presented from the high confidence and lift levels, there is a high probability that purchases of conserved milk and yoghurt along with cured meat products will lead to the purchase of cheese.

Also purchases of bread along with cured milk products and bazaar lead to the purchase of cheese.

Purchases of fruits or vegetables along with cured meat products may also lead to the purchase of cheese.

Moreover, purchases of non-alcoholic drinks usually leads to the purchase of bazaar products.

4.1.7 Best results found for Malia Area

1. CAVA ALCOHOL/WINES=t BAKE OFF «ZESTI GONIA»=t 11 ==> SMOKERS’ ITEMS=t 11 <conf:(1)> lift:(2.3) lev:(0.07) [6] conv:(6.21)
2. OIL, CONSUMABLES=t 10 ==> VEGETABLES, GROCERY=t 10 <conf:(1)> lift:(1.7) lev:(0.05) [4] conv:(4.12)
3. OIL, CONSUMABLES=t 10 ==> SMOKERS’ ITEMS=t 10 <conf:(1)> lift:(2.3) lev:(0.07) [5] conv:(5.65)
4. OIL, CONSUMABLES=t SMOKERS’ ITEMS=t 10 ==> VEGETABLES, GROCERY=t 10 <conf:(1)> lift:(1.7) lev:(0.05) [4] conv:(4.12)
5. VEGETABLES, GROCERY=t OIL, CONSUMABLES=t 10 ==> SMOKERS’ ITEMS=t 10 <conf:(1)> lift:(2.3) lev:(0.07) [5] conv:(5.65)
6. OIL, CONSUMABLES=t 10 ==> VEGETABLES, GROCERY=t SMOKERS’ ITEMS=t 10 <conf:(1)> lift:(3.27) lev:(0.08) [6] conv:(6.94)
7. FRUITS, GROCERY=t CORN PUFF SNACK/CHIPS=t 10 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 10 <conf:(1)> lift:(2.83) lev:(0.08) [6] conv:(6.47)
8. OIL, CONSUMABLES=t BAKE OFF «ZESTI GONIA»=t 9 ==> VEGETABLES, GROCERY=t 9 <conf:(1)> lift:(1.7) lev:(0.04) [3] conv:(3.71)

9. VEGETABLES, GROCERY=t CORN PUFF SNACK/CHIPS=t 9 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 9 <conf:(1)> lift:(2.83) lev:(0.07) [5] conv:(5.82)

10. CAVA, NON-ALCOHOLIC/SOFT DRINKS=t BAKE OFF «ZESTI GONIA»=t 9 ==> VEGETABLES, GROCERY=t 9 <conf:(1)> lift:(1.7) lev:(0.04) [3] conv:(3.71)

35. FRESH PORK MEAT=t 11 ==> VEGETABLES, GROCERY=t 9 <conf:(0.82)> lift:(1.39) lev:(0.03) [2] conv:(1.51)

All the rules for Malia Area (except the last one) present the highest confidence level, and a high lift and leverage level as well, which is an evidence of strong output reliability and strong relation between the products.

Purchases of alcohol and consumables usually lead to the purchase of smokers' items and vegetables. Purchases of oils lead to the purchase of vegetables and/or smoker's items.

Fruits or vegetables along with corn puff snacks usually lead to the purchase of bazaar items.

Furthermore, vegetables are about to engage in transactions containing pork meat.

The purchase of non-alcoholic drinks and bake-offs usually lead to the purchase of vegetables.

4.1.8 Best results found for Nea Alikarnassos Area

1. BREAD, CONSUMABLES=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 62 ==> CHEESE (DRAINING BENCHES)=t 59 <conf:(0.95)> lift:(2.49) lev:(0.09) [35] conv:(9.57)

2. CURED MEAT PRODUCTS (DRAINING BENCHES)=t 91 ==> CHEESE (DRAINING BENCHES)=t 81 <conf:(0.89)> lift:(2.33) lev:(0.11) [46] conv:(5.11)

3. FRUITS, GROCERY=t CHEESE, CONSERVATION=t 71 ==> VEGETABLES, GROCERY=t 62 <conf:(0.87)> lift:(1.69) lev:(0.06) [25] conv:(3.44)

4. BREAD, CONSUMABLES=t CHEESE, CONSERVATION=t 55 ==> VEGETABLES, GROCERY=t 46 <conf:(0.84)> lift:(1.62) lev:(0.04) [17] conv:(2.66)

5. VEGETABLES, GROCERY=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 51 ==> CHEESE (DRAINING BENCHES)=t 42 <conf:(0.82)> lift:(2.15) lev:(0.06) [22] conv:(3.15)

6. YOGURT, CONSERVATION=t FRUITS, GROCERY=t 74 ==> VEGETABLES, GROCERY=t 60 <conf:(0.81)> lift:(1.57) lev:(0.05) [21] conv:(2.39)

7. YOGURT, CONSERVATION=t CHEESE, CONSERVATION=t 58 ==> VEGETABLES, GROCERY=t 46 <conf:(0.79)> lift:(1.54) lev:(0.04) [16] conv:(2.16)

8. RUSKS, CONSUMABLES=t 52 ==> VEGETABLES, GROCERY=t 41 <conf:(0.79)> lift:(1.53) lev:(0.03) [14] conv:(2.1)

9. CHEESE, CONSERVATION=t 112 ==> VEGETABLES, GROCERY=t 88 <conf:(0.79)> lift:(1.52) lev:(0.07) [30] conv:(2.17)

10. BREAD, CONSUMABLES=t FRUITS, GROCERY=t 72 ==> VEGETABLES, GROCERY=t 56 <conf:(0.78)> lift:(1.51) lev:(0.05) [18] conv:(2.05)

All the rules of Nea Alikarnassos Area, present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

There is a high probability that purchases of bread along with cured meat products will lead to the purchase of cheese.

Also vegetables along with cured meat products also lead to the purchase of cheese.

Purchases of cheese along with fruits or bread lead to the purchase of vegetables.

Conserved yoghurt purchases along with fruits or cheese may also lead to the purchase of vegetables.

4.1.9 Best results found for Limenas Chersonissou

1. PASTRIES/ SWEETS, CONSUMABLES=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 7 <conf:(1)> lift:(2.29) lev:(0.06) [3] conv:(3.94)
2. CHOCOLATES, CONSUMABLES=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 7 <conf:(1)> lift:(2.29) lev:(0.06) [3] conv:(3.94)
3. FRUITS, GROCERY=t CAVA, NON-ALCOHOLIC/SOFT DRINKS=t 6 ==> CAVA NON-ALCOHOLICS/WATER=t 6 <conf:(1)> lift:(2.46) lev:(0.06) [3] conv:(3.56)
4. MILK, CONSERVATION=t 12 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 11 <conf:(0.92)> lift:(2.1) lev:(0.09) [5] conv:(3.38)
5. CHEESE (DRAINING BENCHES)=t 8 ==> VEGETABLES, GROCERY=t 7 <conf:(0.88)> lift:(2.07) lev:(0.06) [3] conv:(2.31)
6. CHEESE (DRAINING BENCHES)=t 8 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 7 <conf:(0.88)> lift:(2) lev:(0.05) [3] conv:(2.25)
7. BAKE OFF «ZESTI GONIA»=t 8 ==> CAVA ALCOHOL BEERS=t 7 <conf:(0.88)> lift:(2.33) lev:(0.06) [4] conv:(2.5)
8. PASTA, CONSUMABLES=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 6 <conf:(0.86)> lift:(1.96) lev:(0.05) [2] conv:(1.97)
9. CAVA, NON ALCOHOLIC/TEA/JUICES=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 6 <conf:(0.86)> lift:(1.96) lev:(0.05) [2] conv:(1.97)
10. HOUSEHOLD, BAZAAR=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 6 <conf:(0.86)> lift:(1.96) lev:(0.05) [2] conv:(1.97)

All the rules for the Area of Limenas Chersonissou present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

The results show that, purchases of pastries, chocolates, conserved milk, cheese, pasta and non- alcoholic beverages usually lead to the purchase of bazaar items and the purchase of bake-offs usually lead to the purchase of alcohol beers.

4.1.10 Best results found for Kokkini Chani Area

1. MILK, CONSERVATION=t SMOKERS' ITEMS=t 31 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 30 <conf:(0.97)> lift:(1.41) lev:(0.04) [8] conv:(4.83)

2. BREAKFAST CEREALS, CONSUMABLES=t MILK, CONSERVATION=t 28 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 27 <conf:(0.96)> lift:(1.4) lev:(0.03) [7] conv:(4.36)

3. SMOKERS' ITEMS=t 40 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 38 <conf:(0.95)> lift:(1.38) lev:(0.04) [10] conv:(4.16)

4. MILK, CONSERVATION=t TOMATO JUICE/COMPOSTERS/PRESERVES=t 36 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 34 <conf:(0.94)> lift:(1.37) lev:(0.04) [9] conv:(3.74)

5. MILK, CONSERVATION=t YOGURT, CONSERVATION=t FRUITS, GROCERY=t 34 ==> VEGETABLES, GROCERY=t 32 <conf:(0.94)> lift:(1.48) lev:(0.04) [10] conv:(4.13)

6. MILK, CONSERVATION=t YOGURT, CONSERVATION=t VEGETABLES, GROCERY=t 34 ==> FRUITS, GROCERY=t 32 <conf:(0.94)> lift:(1.8) lev:(0.06) [14] conv:(5.41)

7. RUSKS, CONSUMABLES=t FRUITS, GROCERY=t 30 ==> VEGETABLES, GROCERY=t 28 <conf:(0.93)> lift:(1.47) lev:(0.04) [8] conv:(3.64)

8. RUSKS, CONSUMABLES=t VEGETABLES, GROCERY=t 30 ==> FRUITS, GROCERY=t 28 <conf:(0.93)> lift:(1.79) lev:(0.05) [12] conv:(4.78)

9. YOGURT, CONSERVATION=t FRUITS, GROCERY=t 42 ==> VEGETABLES, GROCERY=t 39 <conf:(0.93)> lift:(1.46) lev:(0.05) [12] conv:(3.83)

10. YOGURT, CONSERVATION=t VEGETABLES, GROCERY=t 42 ==> FRUITS, GROCERY=t 39 <conf:(0.93)> lift:(1.78) lev:(0.07) [17] conv:(5.02)

All the rules for Kokkini Chani Area present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

Purchases of conserved milk along with smoking items tomato juices, may lead to the purchase of bazaar items. Also breakfast items' purchases along with conserved milk may lead to the purchase of bazaar items as well.

Moreover, purchases of conserved milk and yoghurt along with fruits or rusks along with fruits, can lead to the purchase of vegetables.

Purchases of conserved milk and yoghurt along with vegetables or rusks along with vegetables, can lead to the purchase of fruits.

4.1.11 Best results found for Mires Area

1. FRUITS, GROCERY=t CAVA, NON-ALCOHOLIC/SOFT DRINKS=t 12 ==> VEGETABLES, GROCERY=t 11 <conf:(0.92)> lift:(2.1) lev:(0.05) [5] conv:(3.38)
2. FRUITS, GROCERY=t CAVA, NON-ALCOHOLIC/SOFT DRINKS=t 12 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 11 <conf:(0.92)> lift:(2.28) lev:(0.06) [6] conv:(3.59)
3. FRUITS, GROCERY=t CHEESE (DRAINING BENCHES)=t XM CODE (OUT OF CATEGORY), BAZAAR=t 12 ==> VEGETABLES, GROCERY=t 11 <conf:(0.92)> lift:(2.1) lev:(0.05) [5] conv:(3.38)
4. PASTRIES/ SWEETS, CONSUMABLES=t VEGETABLES, GROCERY=t 13 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 11 <conf:(0.85)> lift:(2.11) lev:(0.05) [5] conv:(2.59)
5. VEGETABLES, GROCERY=t FRUITS, GROCERY=t CHEESE (DRAINING BENCHES)=t 13 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 11 <conf:(0.85)> lift:(2.11) lev:(0.05) [5] conv:(2.59)
6. YOGURT, CONSERVATION=t FRUITS, GROCERY=t 14 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 11 <conf:(0.79)> lift:(1.96) lev:(0.05) [5] conv:(2.09)

7. VEGETABLES, GROCERY=t CHEESE (DRAINING BENCHES)=t XM CODE (OUT OF CATEGORY), BAZAAR=t 14 ==> FRUITS, GROCERY=t 11 <conf:(0.79)> lift:(2.75) lev:(0.06) [7] conv:(2.5)

8. FRUITS, GROCERY=t CHEESE (DRAINING BENCHES)=t 17 ==> VEGETABLES, GROCERY=t 13 <conf:(0.76)> lift:(1.75) lev:(0.05) [5] conv:(1.91)

9. DETERGENT=t 19 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 14 <conf:(0.74)> lift:(1.83) lev:(0.06) [6] conv:(1.89)

10. CHEESE (DRAINING BENCHES)=t XM CODE (OUT OF CATEGORY), BAZAAR=t 19 ==> VEGETABLES, GROCERY=t 14 <conf:(0.74)> lift:(1.68) lev:(0.05) [5] conv:(1.78)

The rules for Mires Area present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

The results show that purchases of fruits along with soft drinks usually lead to the purchase of vegetables and bazaar items. Pastry purchases along with vegetables also lead to the purchase of bazaar items.

Furthermore, fruits, cheese, bazaar items and vegetables seem to have a high correlation with each other.

Purchases of cheese along with fruits or bazaar items may lead to the purchase of vegetables.

4.1.12 Best results found for Tympaki Area

1. VEGETABLES, GROCERY=t 11 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 11 <conf:(1)> lift:(1.08) lev:(0.07) [0] conv:(0.85)

2. CAVA ALCOHOL BEERS=t 9 ==> VEGETABLES, GROCERY=t 9 <conf:(1)> lift:(1.18) lev:(0.11) [1] conv:(1.38)

3. CAVA ALCOHOL BEERS=t 9 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 9 <conf:(1)> lift:(1.08) lev:(0.05) [0] conv:(0.69)

4. CAVA ALCOHOL BEERS=t XM CODE (OUT OF CATEGORY), BAZAAR=t 9 ==> VEGETABLES, GROCERY=t 9 <conf:(1)> lift:(1.18) lev:(0.11) [1] conv:(1.38)

5. VEGETABLES, GROCERY=t CAVA ALCOHOL BEERS=t 9 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 9 <conf:(1)> lift:(1.08) lev:(0.05) [0] conv:(0.69)

6. CAVA ALCOHOL BEERS=t 9 ==> VEGETABLES, GROCERY=t XM CODE (OUT OF CATEGORY), BAZAAR=t 9 <conf:(1)> lift:(1.18) lev:(0.11) [1] conv:(1.38)

7. CHEESE, CONSERVATION=t 8 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 8 <conf:(1)> lift:(1.08) lev:(0.05) [0] conv:(0.62)

8. VEGETABLES, GROCERY=t CHEESE, CONSERVATION=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 7 <conf:(1)> lift:(1.08) lev:(0.04) [0] conv:(0.54)

9. RUSKS, CONSUMABLES=t 6 ==> VEGETABLES, GROCERY=t 6 <conf:(1)> lift:(1.18) lev:(0.07) [0] conv:(0.92)

10. RUSKS, CONSUMABLES=t 6 ==> CAVA ALCOHOL BEERS=t 6 <conf:(1)> lift:(1.44) lev:(0.14) [1] conv:(1.85)

The rules for Tympaki Area present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

Purchases of alcohol beers usually lead to the purchase of bazaar items and vegetables, usually lead to the purchase of vegetables and bazaar items and the purchase of consumables usually lead to the purchase of vegetables and alcohol beers.

Also purchases of conserved cheese also lead to the purchase of bazaar items.

4.1.13 Best results found for Neapoli Area

1. CHOCOLATES, CONSUMABLES=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 7 <conf:(1)> lift:(1.24) lev:(0.06) [1] conv:(1.33)

2. DETERGENTS=t 7 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 7 <conf:(1)> lift:(1.24) lev:(0.06) [1] conv:(1.33)

3. FRUITS, GROCERY=t DETERGENTS=t 5 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 5 <conf:(1)> lift:(1.24) lev:(0.05) [0] conv:(0.95)

4. RUSKS, CONSUMABLES=t 4 ==> CHOCOLATES, CONSUMABLES=t 4 <conf:(1)> lift:(3) lev:(0.13) [2] conv:(2.67)

5. RUSKS, CONSUMABLES=t 4 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 4 <conf:(1)> lift:(1.24) lev:(0.04) [0] conv:(0.76)

6. RICE/ LESUME, PASTRY=t 4 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 4 <conf:(1)> lift:(1.24) lev:(0.04) [0] conv:(0.76)

7. HYGIENE PRODUCTS=t 4 ==> HYGIENE PRODUCTS=t 4 <conf:(1)> lift:(2.63) lev:(0.12) [2] conv:(2.48)

8. STATIONERY=t 4 ==> DETERGENTS=t 4 <conf:(1)> lift:(3) lev:(0.13) [2] conv:(2.67)

9. STATIONERY=t 4 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 4 <conf:(1)> lift:(1.24) lev:(0.04) [0] conv:(0.76)

10. RUSKS, CONSUMABLES=t XM CODE (OUT OF CATEGORY), BAZAAR=t 4 ==> CHOCOLATES, CONSUMABLES=t 4 <conf:(1)> lift:(3) lev:(0.13) [2] conv:(2.67)

784. FRESH BEEF, MEAT=t DETERGENTS=t 2 ==> FRUITS, GROCERY=t 2 <conf:(1)> lift:(1.91) lev:(0.05) [0] conv:(0.95)

785. FRUITS, GROCERY=t FRESH BEEF, MEAT=t 2 ==> DETERGENTS=t 2 <conf:(1)> lift:(3) lev:(0.06) [1] conv:(1.33)

786. FRESH BEEF, MEAT=t 2 ==> FRUITS, GROCERY=t DETERGENTS=t 2 <conf:(1)> lift:(4.2) lev:(0.07) [1] conv:(1.52)

787. FRESH BEEF, MEAT=t XM CODE (OUT OF CATEGORY), BAZAAR=t 2 ==> FRUITS, GROCERY=t 2 <conf:(1)> lift:(1.91) lev:(0.05) [0] conv:(0.95)

788. FRUITS, GROCERY=t FRESH BEEF, MEAT=t 2 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 2 <conf:(1)> lift:(1.24) lev:(0.02) [0] conv:(0.38)

789. FRESH BEEF, MEAT=t 2 ==> FRUITS, GROCERY=t XM CODE (OUT OF CATEGORY), BAZAAR=t 2 <conf:(1)> lift:(2.1) lev:(0.05) [1] conv:(1.05)

836. FRESH BEEF, MEAT=t XM CODE (OUT OF CATEGORY), BAZAAR=t 2 ==> DETERGENTS=t 2 <conf:(1)> lift:(3) lev:(0.06) [1] conv:(1.33)

837. FRESH BEEF, MEAT=t DETERGENTS=t 2 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 2 <conf:(1)> lift:(1.24) lev:(0.02) [0] conv:(0.38)

838. FRESH BEEF, MEAT=t 2 ==> DETERGENTS=t XM CODE (OUT OF CATEGORY), BAZAAR=t 2 <conf:(1)> lift:(3) lev:(0.06) [1] conv:(1.33)

839. FRESH PORK MEAT=t XM CODE (OUT OF CATEGORY), BAZAAR=t 2 ==> CORN PUFF SNACK/CHIPS=t 2 <conf:(1)> lift:(5.25) lev:(0.08) [1] conv:(1.62)

840. FRESH PORK MEAT=t CORN PUFF SNACK/CHIPS=t 2 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 2 <conf:(1)> lift:(1.24) lev:(0.02) [0] conv:(0.38)

All rules for Neapoli Area present a high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

In the Area of Neapoli purchases of consumables, detergents, stationery, pastry and fruits along with fresh beer, usually lead to the purchase of bazaar items.

Furthermore, the purchase of fresh beef meat, usually leads to the purchase of fruits, detergents and bazaar items. Also, the purchases of fresh pork meat usually leads to the purchase of corn puff snacks and bazaar items.

4.1.14 Best results found for Sitia Area

1. FRUITS, GROCERY=t 449 ==> VEGETABLES, GROCERY=t 264 <conf:(0.59)> lift:(1.23) lev:(0.04) [50] conv:(1.26)

2. XM CODE (OUT OF CATEGORY), BAZAAR=t 416 ==> VEGETABLES, GROCERY=t 229 <conf:(0.55)> lift:(1.16) lev:(0.03) [30] conv:(1.16)

3. YOGURT, CONSERVATION=t 271 ==> VEGETABLES, GROCERY=t 149 <conf:(0.55)> lift:(1.15) lev:(0.02) [19] conv:(1.15)

4. CHEESE (DRAINING BENCHES)=t 337 ==> VEGETABLES, GROCERY=t 176 <conf:(0.52)> lift:(1.1) lev:(0.01) [15] conv:(1.09)

5. CAVA NON-ALCOHOLICS/WATER=t 272 ==> VEGETABLES, GROCERY=t 139 <conf:(0.51)> lift:(1.07) lev:(0.01) [9] conv:(1.06)

6. YOGURT, CONSERVATION=t 271 ==> FRUITS, GROCERY=t 135 <conf:(0.5)> lift:(1.32) lev:(0.03) [33] conv:(1.23)

7. CAVA NON-ALCOHOLICS/WATER=t 272 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 130 <conf:(0.48)> lift:(1.37) lev:(0.03) [35] conv:(1.24)

8. MILK, CONSERVATION=t 284 ==> VEGETABLES, GROCERY=t 134 <conf:(0.47)> lift:(0.99) lev:(-0) [-1] conv:(0.99)

9. PASTRIES/ SWEETS, CONSUMABLES=t 274 ==> VEGETABLES, GROCERY=t 129 <conf:(0.47)> lift:(0.99) lev:(-0) [-1] conv:(0.98)

10. VEGETABLES, GROCERY=t 568 ==> FRUITS, GROCERY=t 264 <conf:(0.46)> lift:(1.23) lev:(0.04) [50] conv:(1.16)

All rules for Sitia Area present quite low confidence, lift and leverage levels, which is an evidence of low reliability and weak relation between the products.

The best results show that, purchases such as fruits, bazaar items, conserved cheese and yoghurt and non-alcoholic drinks, lead to the purchase of vegetables.

4.1.15 Best results found for Ierapetra Area

1. BREAD, CONSUMABLES=t CURED MEAT PRODUCTS (DRAINING BENCHES)=t 14 ==> CHEESE (DRAINING BENCHES)=t 12 <conf:(0.86)> lift:(2.85) lev:(0.08) [7] conv:(3.26)

2. COFFEE, CONSUMABLES=t CHEESE (DRAINING BENCHES)=t 13 ==> BREAD, CONSUMABLES=t 11 <conf:(0.85)> lift:(2.08) lev:(0.06) [5] conv:(2.57)

3. MILK, CONSERVATION=t FRESH POULTRY, MEAT=t 12 ==> BREAD, CONSUMABLES=t 10 <conf:(0.83)> lift:(2.04) lev:(0.05) [5] conv:(2.37)

4. COFFEE, CONSUMABLES=t VEGETABLES, GROCERY=t 12 ==> BREAD, CONSUMABLES=t 10 <conf:(0.83)> lift:(2.04) lev:(0.05) [5] conv:(2.37)

5. MILK, CONSERVATION=t TOMATO JUICES/ COMPOSTERS/ PRESERVES=t 14 ==> BREAD, CONSUMABLES=t 11 <conf:(0.79)> lift:(1.93) lev:(0.05) [5] conv:(2.07)

6. BREAD, CONSUMABLES=t TOMATO JUICES/ COMPOSTERS/ PRESERVES=t 14 ==> MILK, CONSERVATION=t 11 <conf:(0.79)> lift:(1.97) lev:(0.05) [5] conv:(2.11)

7. CURED MEAT PRODUCTS (DRAINING BENCHES)=t 23 ==> CHEESE (DRAINING BENCHES)=t 18 <conf:(0.78)> lift:(2.6) lev:(0.11) [11] conv:(2.68)

8. BREAD, CONSUMABLES=t FRESH POULTRY, MEAT=t 13 ==> MILK, CONSERVATION=t 10 <conf:(0.77)> lift:(1.93) lev:(0.05) [4] conv:(1.96)

9. TOMATO JUICES/ COMPOSTERS/ PRESERVES=t CHEESE (DRAINING BENCHES)=t 13 ==> BREAD, CONSUMABLES=t 10 <conf:(0.77)> lift:(1.89) lev:(0.05) [4] conv:(1.92)

10. COFFEE, CONSUMABLES=t CHEESE (DRAINING BENCHES)=t 13 ==> MILK, CONSERVATION=t 10 <conf:(0.77)> lift:(1.93) lev:(0.05) [4] conv:(1.96)

11. FRESH POULTRY, MEAT=t 17 ==> BREAD, CONSUMABLES=t 13 <conf:(0.76)> lift:(1.88) lev:(0.06) [6] conv:(2.01)

15. FRESH POULTRY, MEAT=t 17 ==> MILK, CONSERVATION=t 12 <conf:(0.71)> lift:(1.77) lev:(0.05) [5] conv:(1.71)

21. FRESH POULTRY, MEAT=t 17 ==> COFFEE, CONSUMABLES=t 11 <conf:(0.65)> lift:(2.15) lev:(0.06) [5] conv:(1.7)

31. FRESH POULTRY, MEAT=t 17 ==> BREAD, CONSUMABLES=t MILK, CONSERVATION=t 10 <conf:(0.59)> lift:(2.42) lev:(0.06) [5] conv:(1.61)

80. COFFEE, CONSUMABLES=t 31 ==> FRESH POULTRY, MEAT=t 11 <conf:(0.35)> lift:(2.15) lev:(0.06) [5] conv:(1.23)

100. BREAD, CONSUMABLES=t 42 ==> FRESH POULTRY, MEAT=t 13 <conf:(0.31)> lift:(1.88) lev:(0.06) [6] conv:(1.17)

108. MILK, CONSERVATION=t 41 ==> FRESH POULTRY, MEAT=t 12 <conf:(0.29)> lift:(1.77) lev:(0.05) [5] conv:(1.14)

123. MILK, CONSERVATION=t 41 ==> BREAD, CONSUMABLES=t FRESH POULTRY, MEAT=t 10 <conf:(0.24)> lift:(1.93) lev:(0.05) [4] conv:(1.12)

The rules for Ierapetra Area present a quite high confidence, lift and leverage level, which is an evidence of strong output reliability and strong relation between the products.

Purchases of coffee, cheese, milk, tomato juices/composters and bread, usually lead to the purchase of bread. Additionally, fresh poultry meat is found to have a positive correlation with bread, milk and coffee which means that the purchase of fresh poultry meat usually leads to the purchase of milk bread and coffee and vice versa.

4.1.16 Best results found for Agios Nikolaos Area

1. PASTRIES/ SWEETS, CONSUMABLES=t CORN PUFF SNACK/CHIPS=t 27 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 26 <conf:(0.96)> lift:(1.75) lev:(0.05) [11] conv:(6.07)

2. CHOCOLATES, CONSUMABLES=t CAVA, NON-ALCOHOLIC/SOFT DRINKS=t 25 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 24 <conf:(0.96)> lift:(1.74) lev:(0.05) [10] conv:(5.62)

3. CORN PUFF SNACK/CHIPS=t 26 ==> CORN PUFF SNACK/CHIPS=t 24 <conf:(0.92)> lift:(3.55) lev:(0.08) [17] conv:(6.41)

4. CHOCOLATES, CONSUMABLES=t CORN PUFF SNACK/CHIPS=t 30 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 27 <conf:(0.9)> lift:(1.63) lev:(0.05) [10] conv:(3.37)

5. CHOCOLATES, CONSUMABLES=t COFFEE, CONSUMABLES=t 28 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 25 <conf:(0.89)> lift:(1.62) lev:(0.04) [9] conv:(3.15)

6. FRESH POULTRY, MEAT=t 33 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 29 <conf:(0.88)> lift:(1.6) lev:(0.05) [10] conv:(2.97)

7. PASTRIES/ SWEETS, CONSUMABLES=t CHOCOLATES, CONSUMABLES=t 37 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 32 <conf:(0.86)> lift:(1.57) lev:(0.05) [11] conv:(2.77)

8. FRUITS, GROCERY=t CORN PUFF SNACK/CHIPS=t 29 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 25 <conf:(0.86)> lift:(1.57) lev:(0.04) [9] conv:(2.61)

9. CHOCOLATES, CONSUMABLES=t FRUITS, GROCERY=t 36 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 30 <conf:(0.83)> lift:(1.51) lev:(0.04) [10] conv:(2.31)

10. COFFEE, CONSUMABLES=t FRUITS, GROCERY=t 29 ==> XM CODE (OUT OF CATEGORY), BAZAAR=t 24 <conf:(0.83)> lift:(1.5) lev:(0.04) [8] conv:(2.17)

130. XM CODE (OUT OF CATEGORY), BAZAAR=t 125 ==> FRESH POULTRY, MEAT=t 29 <conf:(0.23)> lift:(1.6) lev:(0.05) [10] conv:(1.1)

137. XM CODE (OUT OF CATEGORY), BAZAAR=t 125 ==> FRESH PORK MEAT=t 25 <conf:(0.2)> lift:(1.34) lev:(0.03) [6] conv:(1.05)

Most of Agios Nikolaos results present a quite high confidence, lift and leverage level, which is an evidence of strong reliability and strong relation between the products.

Purchases of pastries/sweets/chocolates (consumables), soft drinks, corn puff snacks and other snacks lead to the purchase of bazaar items. Furthermore, the purchase of bazaar items seems to lead to the purchase of fresh poultry and fresh pork meat, but also fresh poultry meat usually lead to the purchase of bazaar items.

4.1.17 Best results found for the <=18 Age Group

1. CHEESE, CONSERVATION=t 6 ==> VEGETABLES, GROCERY=t 6 <conf:(1)> lift:(1.91) lev:(0.14) [2] conv:(2.86)
2. MILK, CONSERVATION=t TEA/ JUICES, CONSERVATION=t 6 ==> VEGETABLES, GROCERY=t 6 <conf:(1)> lift:(1.91) lev:(0.14) [2] conv:(2.86)
3. MILK, CONSERVATION=t VEGETABLES, GROCERY=t 6 ==> TEA/ JUICES, CONSERVATION=t 6 <conf:(1)> lift:(1.5) lev:(0.1) [2] conv:(2)
4. CORN PUFF SNACK/CHIPS, CONSUMABLES=t 5 ==> CHEESE (DRAINING BENCHES)=t 5 <conf:(1)> lift:(1.62) lev:(0.09) [1] conv:(1.9)
5. MILK, CONSERVATION=t CHEESE, CONSERVATION=t 5 ==> VEGETABLES, GROCERY=t 5 <conf:(1)> lift:(1.91) lev:(0.11) [2] conv:(2.38)
6. CHEESE, CONSERVATION=t TEA/ JUICES, CONSERVATION=t 5 ==> MILK, CONSERVATION=t 5 <conf:(1)> lift:(2.63) lev:(0.15) [3] conv:(3.1)
7. MILK, CONSERVATION=t CHEESE, CONSERVATION=t 5 ==> TEA/ JUICES, CONSERVATION=t 5 <conf:(1)> lift:(1.5) lev:(0.08) [1] conv:(1.67)
8. CHEESE, CONSERVATION=t TEA/ JUICES, CONSERVATION=t 5 ==> VEGETABLES, GROCERY=t 5 <conf:(1)> lift:(1.91) lev:(0.11) [2] conv:(2.38)
9. CHEESE, CONSERVATION=t FOOD, CONSERVATION=t 5 ==> VEGETABLES, GROCERY=t 5 <conf:(1)> lift:(1.91) lev:(0.11) [2] conv:(2.38)
10. VEGETABLES, GROCERY=t CHEESE, CONSERVATION=t TEA/ JUICES, CONSERVATION=t 5 ==> MILK, CONSERVATION=t 5 <conf:(1)> lift:(2.63) lev:(0.15) [3] conv:(3.1)

The results show that, for the ages under 18, the purchase of conserved cheese, milk and juices leads to the purchase of vegetables. In addition, the purchase of snacks usually leads to the purchase of cheese. The results for this age group present really high confidence, lift and leverage levels which is an evidence of strong reliability and strong relation between the products.

4.1.18 Best results found for the Age Group 18-25

1. CHEESE, CONSERVATION=t 13 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 13 <conf:(1)> lift:(1.24) lev:(0.04) [2] conv:(2.48)

2. YOGURT, CONSERVATION=t FRUITS, GROCERIES=t 13 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 13 <conf:(1)> lift:(1.24) lev:(0.04) [2] conv:(2.48)

3. YOGURT, CONSERVATION=t VEGETABLES, GROCERY=t 12 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 12 <conf:(1)> lift:(1.24) lev:(0.04) [2] conv:(2.29)

4. FRUITS, GROCERIES=t CHEESE (DRAINING BENCHES)=t 12 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 12 <conf:(1)> lift:(1.24) lev:(0.04) [2] conv:(2.29)

5. MILK, CONSERVATION=t FRUITS, GROCERIES=t 11 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 11 <conf:(1)> lift:(1.24) lev:(0.03) [2] conv:(2.1)

6. YOGURT, CONSERVATION=t CHEESE, CONSERVATION=t 11 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 11 <conf:(1)> lift:(1.24) lev:(0.03) [2] conv:(2.1)

7. FRUITS, GROCERIES=t CHEESE, CONSERVATION=t 11 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 11 <conf:(1)> lift:(1.24) lev:(0.03) [2] conv:(2.1)

8. CURED MEAT (DRAINING BENCHES)=t 10 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 10 <conf:(1)> lift:(1.24) lev:(0.03) [1] conv:(1.9)

9. BREAD, CONSUMABLES=t FRUITS, GROCERIES=t 10 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 10 <conf:(1)> lift:(1.24) lev:(0.03) [1] conv:(1.9)

10. BREAD, CONSUMABLES=t CHEESE, CONSERVATION=t 10 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 10 <conf:(1)> lift:(1.24) lev:(0.03) [1] conv:(1.9)

286. VEGETABLES, GROCERY=t FRESH BEEF, MEAT=t 6 ==> XM CODE OUT OF CATEGORY=t 6 <conf:(1)> lift:(1.24) lev:(0.02) [1] conv:(1.14)

According to the results, for the ages 18 to 25, the purchases of fruits along with conserved cheese lead to the purchase of bazaar items. In addition, the purchases of conserved milk, yogurt, cheese, cured meat as well as the purchases of consumables like bread and vegetables/groceries lead to the purchase of bazaar items. The results for this age group present high confidence, lift and leverage levels which is an evidence of strong reliability and strong relation between the products.

4.1.19 Best results found for the Age Group 26-35

1. CURED MEAT, CONSERVATION=t 105 ==> CHEESE (DRAINING BENCHES)=t 81 <conf:(0.77)> lift:(2.92) lev:(0.08) [53] conv:(3.09)
2. MILK, CONSERVATION=t FRUITS, GROCERIES=t 97 ==> VEGETABLES, GROCERY=t 66 <conf:(0.68)> lift:(1.6) lev:(0.04) [24] conv:(1.74)
3. MILK, CONSERVATION=t VEGETABLES, GROCERY=t 97 ==> FRUITS, GROCERIES=t 66 <conf:(0.68)> lift:(1.9) lev:(0.05) [31] conv:(1.94)
4. FRUITS, GROCERIES=t 228 ==> VEGETABLES, GROCERY=t 148 <conf:(0.65)> lift:(1.53) lev:(0.08) [51] conv:(1.62)
5. CHEESE, CONSERVATION=t 115 ==> VEGETABLES, GROCERY=t 66 <conf:(0.57)> lift:(1.35) lev:(0.03) [17] conv:(1.32)
6. VEGETABLES, GROCERY=t 270 ==> FRUITS, GROCERIES=t 148 <conf:(0.55)> lift:(1.53) lev:(0.08) [51] conv:(1.41)
7. YOGURT, CONSERVATION=t 161 ==> MILK, CONSERVATION=t 85 <conf:(0.53)> lift:(1.48) lev:(0.04) [27] conv:(1.35)
8. YOGURT, CONSERVATION=t 161 ==> VEGETABLES, GROCERY=t 85 <conf:(0.53)> lift:(1.24) lev:(0.03) [16] conv:(1.2)
9. CHEESE (DRAINING BENCHES)=t 168 ==> MILK, CONSERVATION=t 84 <conf:(0.5)> lift:(1.4) lev:(0.04) [24] conv:(1.27)

10. CHEESE (DRAINING BENCHES)=t 168 ==> CURED MEAT, CONSERVATION=t 81 <conf:(0.48)> lift:(2.92) lev:(0.08) [53] conv:(1.59)

For the ages 18 to 25, the purchase of conserved, cheese, yogurt as well as conserved milk along with fruits, lead to the purchase of vegetables. Moreover, the purchases of conserved milk and vegetables lead to the purchase of fruits. Furthermore, purchases of cheese lead to the purchase of conserved milk or conserved cured meat. The results for this age group present lower confidence, lift and leverage levels, which might be an evidence of not that strong reliability and relation between the products.

4.1.20 Best results found for the Age Group 36-45

1. BREAD, CONSUMABLES=t CURED MEAT, CONSERVATION=t 582 ==> CHEESE (DRAINING BENCHES)=t 554 <conf:(0.95)> lift:(2.53) lev:(0.07) [335] conv:(12.53)
2. VEGETABLES, GROCERY=t CURED MEAT, CONSERVATION=t 524 ==> CHEESE (DRAINING BENCHES)=t 491 <conf:(0.94)> lift:(2.5) lev:(0.06) [294] conv:(9.62)
3. CURED MEAT, CONSERVATION=t XMCODE OUT OF CATEGORIES, BAZAAR=t 616 ==> CHEESE (DRAINING BENCHES)=t 575 <conf:(0.93)> lift:(2.49) lev:(0.08) [343] conv:(9.16)
4. CURED MEAT, CONSERVATION=t 976 ==> CHEESE (DRAINING BENCHES)=t 900 <conf:(0.92)> lift:(2.46) lev:(0.12) [533] conv:(7.92)
5. FRUITS, GROCERIES=t CHEESE (DRAINING BENCHES)=t 699 ==> VEGETABLES, GROCERY=t 532 <conf:(0.76)> lift:(1.69) lev:(0.05) [217] conv:(2.29)
6. FRUITS, GROCERIES=t XMCODE OUT OF CATEGORIES, BAZAAR=t 964 ==> VEGETABLES, GROCERY=t 694 <conf:(0.72)> lift:(1.6) lev:(0.06) [259] conv:(1.95)

7. CORN PUFF SNACK/CHIPS, CONSUMABLES=t 706 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 504 <conf:(0.71)> lift:(1.23) lev:(0.02) [93] conv:(1.46)

8. BREAD, CONSUMABLES=t CHEESE (DRAINING BENCHES)=t 786 ==> CURED MEAT, CONSERVATION=t 554 <conf:(0.7)> lift:(3.28) lev:(0.08) [385] conv:(2.65)

9. CHEESE, CONSERVATION=t 789 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 553 <conf:(0.7)> lift:(1.21) lev:(0.02) [94] conv:(1.39)

The results show that, for the ages 36 to 45, purchases of conserved cured meat, along with bread or vegetables lead to the purchase of cheese. In addition, the purchases of snacks and conserved cheese lead to the purchase bazaar items. Purchases of conserved cured meat lead to the purchase of cheese. Fruit purchases, along with cheese of bazaar items, usually lead to the purchase of vegetables. The results for this age group present high confidence, lift and leverage levels, which is an evidence of strong reliability and strong relation between the products.

4.1.21 Best results found for the Age Group 46-55

1. CURED MEAT, CONSERVATION=t 1271 ==> CHEESE (DRAINING BENCHES)=t 1139 <conf:(0.9)> lift:(2.43) lev:(0.09) [669] conv:(6.03)

2. FRUITS, GROCERIES=t CHEESE (DRAINING BENCHES)=t 1116 ==> VEGETABLES, GROCERY=t 784 <conf:(0.7)> lift:(1.48) lev:(0.03) [256] conv:(1.77)

3. FRUITS, GROCERIES=t XMCODE OUT OF CATEGORIES, BAZAAR=t 1142 ==> VEGETABLES, GROCERY=t 800 <conf:(0.7)> lift:(1.48) lev:(0.03) [259] conv:(1.75)

4. FRUITS, GROCERIES=t 2513 ==> VEGETABLES, GROCERY=t 1661 <conf:(0.66)> lift:(1.4) lev:(0.06) [472] conv:(1.55)

5. PASTA, CONSUMABLES=t 1426 ==> VEGETABLES, GROCERY=t 798 <conf:(0.56)> lift:(1.18) lev:(0.02) [123] conv:(1.19)

6. PASTA, CONSUMABLES=t 1426 ==> CHEESE (DRAINING BENCHES)=t 790 <conf:(0.55)> lift:(1.5) lev:(0.03) [263] conv:(1.41)

7. BREAD, CONSUMABLES=t 2217 ==> VEGETABLES, GROCERY=t 1197 <conf:(0.54)> lift:(1.14) lev:(0.02) [148] conv:(1.14)

8. YOGURT, CONSERVATION=t 1941 ==> VEGETABLES, GROCERY=t 1044 <conf:(0.54)> lift:(1.14) lev:(0.02) [125] conv:(1.14)

9. BREAD, CONSUMABLES=t 2217 ==> CHEESE (DRAINING BENCHES)=t 1190 <conf:(0.54)> lift:(1.45) lev:(0.05) [370] conv:(1.36)

10. VEGETABLES, GROCERY=t CHEESE (DRAINING BENCHES)=t 1478 ==> FRUITS, GROCERIES=t 784 <conf:(0.53)> lift:(1.59) lev:(0.04) [291] conv:(1.42)

For the ages 46 to 55, purchases of fruits as well as pasta, bread and conserved yogurt lead to the purchase of vegetables. Moreover, the purchases of conserved cured meat and bread lead to the purchase of cheese.

4.1.22 Best results found for the Age Group 56-65

1. CURED MEAT, CONSERVATION=t 484 ==> CHEESE (DRAINING BENCHES)=t 437 <conf:(0.9)> lift:(2.84) lev:(0.07) [282] conv:(6.87)

2. FRUITS, GROCERIES=t XMCODE OUT OF CATEGORIES, BAZAAR=t 678 ==> VEGETABLES, GROCERY=t 439 <conf:(0.65)> lift:(1.46) lev:(0.03) [138] conv:(1.57)

3. FRUITS, GROCERIES=t 1465 ==> VEGETABLES, GROCERY=t 899 <conf:(0.61)> lift:(1.38) lev:(0.06) [248] conv:(1.44)

4. VEGETABLES, GROCERY=t XMCODE OUT OF CATEGORIES, BAZAAR=t 809 ==> FRUITS, GROCERIES=t 439 <conf:(0.54)> lift:(1.49) lev:(0.04) [143] conv:(1.38)

5. YOGURT, CONSERVATION=t 928 ==> VEGETABLES, GROCERY=t 483 <conf:(0.52)> lift:(1.17) lev:(0.02) [71] conv:(1.16)

6. VEGETABLES, GROCERY=t 1780 ==> FRUITS, GROCERIES=t 899 <conf:(0.51)> lift:(1.38) lev:(0.06) [248] conv:(1.28)

7. MILK, CONSERVATION=t 1013 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 499 <conf:(0.49)> lift:(1.15) lev:(0.02) [63] conv:(1.12)

8. CHEESE (DRAINING BENCHES)=t 1276 ==> VEGETABLES, GROCERY=t 628 <conf:(0.49)> lift:(1.11) lev:(0.02) [61] conv:(1.09)

9. VEGETABLES, GROCERY=t FRUITS, GROCERIES=t 899 ==> XMCODE OUT OF CATEGORIES, BAZAAR=t 439 <conf:(0.49)> lift:(1.14) lev:(0.01) [52] conv:(1.11)

10. YOGURT, CONSERVATION=t 928 ==> FRUITS, GROCERIES=t 448 <conf:(0.48)> lift:(1.32) lev:(0.03) [108] conv:(1.22)

For the ages 56 to 65, purchases of conserved cured meat lead to the purchased of cheese. The purchases of conserved yogurt lead to the purchase of fruits or vegetables. Furthermore, the purchases of vegetables and/or bazaar items lead to the purchase of fruits and vice versa. The results for this age group present medium confidence, lift and leverage levels, except the first rule that presents high levels of these metrics.

4.1.23 Best results found for the Age Group 66+

1. FRUITS, GROCERIES=t CHEESE (DRAINING BENCHES)=t 433 ==> VEGETABLES, GROCERY=t 299 <conf:(0.69)> lift:(1.49) lev:(0.03) [97] conv:(1.72)

2. FRUITS, GROCERIES=t 1164 ==> VEGETABLES, GROCERY=t 738 <conf:(0.63)> lift:(1.36) lev:(0.07) [197] conv:(1.46)

3. VEGETABLES, GROCERY=t CHEESE (DRAINING BENCHES)=t 484 ==> FRUITS, GROCERIES=t 299 <conf:(0.62)> lift:(1.55) lev:(0.04) [106] conv:(1.57)

4. VEGETABLES, GROCERY=t 1360 ==> FRUITS, GROCERIES=t 738 <conf:(0.54)> lift:(1.36) lev:(0.07) [197] conv:(1.31)

5. CHEESE (DRAINING BENCHES)=t 930 ==> VEGETABLES, GROCERY=t 484 <conf:(0.52)> lift:(1.12) lev:(0.02) [51] conv:(1.11)

6. YOGURT, CONSERVATION=t 676 ==> VEGETABLES, GROCERY=t 334 <conf:(0.49)> lift:(1.06) lev:(0.01) [19] conv:(1.06)

7. CHEESE (DRAINING BENCHES)=t 930 ==> FRUITS, GROCERIES=t 433 <conf:(0.47)> lift:(1.17) lev:(0.02) [63] conv:(1.12)

8. MILK, CONSERVATION=t 749 ==> VEGETABLES, GROCERY=t 346 <conf:(0.46)> lift:(0.99) lev:(-0) [-2] conv:(0.99)

9. YOGURT, CONSERVATION=t 676 ==> FRUITS, GROCERIES=t 311 <conf:(0.46)> lift:(1.16) lev:(0.01) [42] conv:(1.11)

10. XMCODE OUT OF CATEGORIES, BAZAAR=t 742 ==> VEGETABLES, GROCERY=t 327 <conf:(0.44)> lift:(0.95) lev:(-0.01) [-17] conv:(0.95)

For customers above the age of 66, the purchase of vegetables leads to the purchase of fruits. Additionally, the purchases of conserved milk, yogurt, cheese as well as the purchases of cheese usually lead to the purchase of fruits and groceries. Lastly, purchases of bazaar items may lead of the purchases of vegetables. The results for this age group present medium confidence, lift and leverage levels.

Propositions concerning all target audiences:

The findings of these correlations may help the Super Market find the purchase behavior of its buyers, understand what they want, make the correct decisions and hence establish a profitable sales strategy by considering items frequently purchased together by customers.

Market basket analysis applies to bricks-and-mortar stores as well as in websites.

Since we have found which products with a high correlation factor, that go well together, we can proceed to certain in-store and/or online targeting activities, in order to enhance the cross-selling purchasing and maximize customer engagement and sales.

- Concerning the bricks-and-mortar stores it is recommended that products that present a correlation (the purchase of the product A leads to (or include) the purchase of the product B) to be placed on nearby shelves (even if it is an unexpected combination such as cheese and vegetables). Each store in the different areas of Crete, may present differentiations on its product placements depending on its customers' frequent purchasing patterns. For example, the stores in Tympaki area and Malia area provide different product correlations. In Tympaki area purchases of vegetables usually lead to the purchase of bazaar items and whereas in Malia area vegetables are about to engage in transactions containing pork meat.
- Promotion panels can be placed throughout the isles of interest (for instance, for correlations between pasta and cheese, a promotion panel can be placed near the pasta shelves regarding the various types of cheese that may go well with the various types of pasta).
- Simultaneous discounts and offers can also be put from time to time to the highly correlated products.
- In-store digital signage is a form of dynamic advertising and can placed all around the aisles and activate the clients during their purchases. For example, pasta section can promote a healthy spaghetti receipt with cheese and vegetables. That way, visitors can identify a checklist of ingredients easily and shall consider again their purchase needs. Moreover, the usage of digital signage, is a useful reminder and an interactive counselor to the customers, as they can directly emphasize in suggesting other products that are going well with the one that the customer is standing in front. For instance, a digital signage in the cured meat product section can also suggest cheeses' section for a more complete shopping list. Digital signage may also promote the high-related products' offers and discounts. That way, customers can be directly informed and better engaged with the purchase activities. Digital signage,

apart from assisting in cross-selling strategy, may reduce the perception of a long waiting-time. This will lead to a more enjoyable experience.

– Website as well as mobile applications can implement a cross-selling tactic by presenting to the users the products that are likely to be purchased together and by making the best recommendations on product matchings. For example, when a customer is scrolling through the pasta section, a message shall appear at the end of the page, such as "Customers who bought pasta, also bought mozzarella cheese. Take a look at our dairy section!" and then by clicking the respective button, customers shall be redirected to the certain section. These recommendations can be made depending on the customer's profile (gender, age, area) which they have created online through this website. Thus, the website may provide different recommendations and offers, based on the algorithms' combinations of data concerning the customers' gender, age group and area. For example, a woman in the age group 26-35 in Chania area, has different purchasing profile than that of a woman (or a man) in the age group 56-65, in Malia area and a man in the age group 18-25 in Mires area, has different purchasing profile than that of a man (or a woman) in the age group 46-55, in Ierapetra area. In each case, the recommendations and the offers may differ.

4.2 WEKA Clustering
WEKA Clusterers

Clustering is a method of grouping similar things together. As mentioned in the first chapter, clustering is a process of portioning a data set into a set of meaningful subclasses, known as clusters. Clustering is the same as classification in which data is grouped. [150]

Though, unlike classification, clustering does not seek rules that predict a particular class, but rather try to divide the data into groups/clusters, that are not previously

[150] Source: https://www.javatpoint.com/classification-vs-clustering-in-data-mining

defined, by determining similarities between data according to characteristics found in the real data.

The objective of our clustering procedure is to group the customers who presented similarities in their purchase frequency of the different product categories depending on their gender and age and to disjoin those who displayed dissimilarities. We proceed to the implementation of different clusterers (Simple K-Means, EM, Make a Density, Farthest First, Canopy, Filtered Clusterer) to the same dataset, in order to see how they behave and maybe to point possible similarities between the clustering results.

Below are the clusterers' results, which give information about the cluster centroids of gender, age and product category. These, present the different clusters that are created, based on same characteristics observed in a set of elements.

Centroids are those characteristics that are dominant in the cluster and are similar (have similar characteristics) with the objects in the same cluster.

The dataset used for the creation of the clustering results, was made by sorting the original dataset's information through a pivot table. Specifically, we sorted the data for gender, age and product category and we got a table with all the purchase frequencies of the customers that were distinguished between their gender (male, female) and their age (each gender's age is presented one time, instead of many and this is why in overall we end-up with a total of only 108 customers). In this case, we are searching for the purchase frequency of the customers depending on their gender and age, not their place of origin.

4.2.1 Simple K Means

As mentioned in the first chapter (an analytical explanation is presented in chapter 60), Simple Means is a distant-based clusterer that minimizes the squared distance from each instance to their cluster center, after defining k centroids. It is one of the best unsupervised algorithms. For each different number of seeds, there are different clustering results.[151] [152]

[151] Source: https://www.youtube.com/watch?v=4b5d3muPQmA

Simple K Means uses random numbers and by using the same seed, we will always get the same random numbers. If we run Simple K Means over the same data twice, with the same seed, we will get exactly the same results. For different number of seeds, the results will vary each time we run Simple K Means.

In our dataset we use the same seed.

Simple K Means Clusterer, presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings depending on their number of clusters are presented below.

Simple K Means with 2 Clusters

See the clustering results in the appendix: ***Simple K Means with 2 Clusters***

Within cluster sum of squared errors: **11112.0**

Clustered Instances:

0 7 (6%)

1 101 (94%)

Simple K Means divides customers into two clusters, Cluster 0 and Cluster 1. 94% of the instances are in Cluster 1 (101 customers out of 108 are included in this cluster) and 6% of the instances are in Cluster 0 (7 customers out of 108 are included in this cluster). The two clusters present differentiations in the purchase frequency of the product categories'.

To be more precise, the centroids of the two clusters, concerning the gender are the same (women), however they differ as per the age (38 and 32 respectively) and the purchase frequency of the various product categories. Cluster 1 includes most of the samples (94% of the total samples) whereas Cluster 0 includes just a few samples (6% of the total samples). That means, that customers in cluster 1, mostly characterized as women, aged 32, are the typical ones, who choose all product categories at the same rate, whereas the customers in cluster 0, mostly characterized as women aged 38, tend

[152] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

to choose certain product categories much more frequently than the other cluster's customers do.

These frequently purchased products are fruits, vegetables, milk, bread, chocolates, rice/pulses, fresh beef, dump poultry, water, yoghurt as well as uncategorized products.

<u>Simple K Means with 3 clusters:</u>

See the clustering results in the appendix: ***Simple K Means with 3 Clusters***

Within cluster sum of squared errors: 11051.0

Clustered Instances:

0 7 (6%)

1 99 (92%)

2 2 (2%)

Simple K Means divides customers into three clusters, Cluster 0, Cluster 1 and Cluster 2. 92% of the instances are in Cluster 1 (99 customers out of 108 are included in this cluster), 6% of the instances are in Cluster 0 (7 customers out of 108 are included in this cluster) and 2% of the instances are in Cluster 2 (2 customers out of 108 are included in this cluster). The three clusters present differentiations in the purchase frequency of the product categories'.

The centroids of the three clusters, concerning the gender are the same (women), however they differ as per the age (38, 32, 41) and the purchase frequency of the various product categories. Cluster 1 includes most of the samples (92% of the total samples) whereas, Cluster 0 and Cluster 2 include just a few samples (6% and 2% of the total samples respectively). That means, that customers in cluster 1, mostly characterized as women aged 32, are the typical ones, who choose all product categories at the same rate, whereas the customers in cluster 0, mostly characterized as women aged 38, tend to choose certain product categories much more frequently than the other clusters' customers do.

These frequently purchased products are fruits, vegetables, milk, bread, chocolates, rice/pulses, fresh beef, dump poultry, water, yoghurt as well as paper, household, detergents and uncategorized products.

<u>Simple K Means with 4 clusters:</u>

See the clustering results in the appendix: ***Simple K Means with 4 Clusters***

Within cluster sum of squared errors: 10605.0

Clustered Instances:

0 8 (7%)

1 87 (81%)

2 12 (11%)

3 1 (1%)

Simple K Means divides customers into four clusters, Cluster 0, Cluster 1, Cluster 2 and Cluster 3. 81% of the instances are in Cluster 1 (87 customers out of 108 are included in this cluster), 11% of the instances are in Cluster 2 (12 customers out of 108 are included in this cluster), 7% of the instances are in Cluster 0 (8 customers out of 108 are included in this cluster) and 1% of the customers are in Cluster 3 (1 customer out of 108 is in this cluster). The four clusters present differentiations in the purchase frequency of the product categories'.

The centroids of cluster 0, cluster 2 and cluster 3, concerning the gender, are the same (women), unlike the centroid of Cluster 1 (which is male). The clusters' centroids differ as per the age (38, 32, 37, 52 for Clusters 0, 1, 2, 3, 4 respectively) and the purchase frequency of the various product categories. Cluster 1 includes most the samples whereas, cluster 3, cluster 0 and cluster 2 include just a few samples. That means, that customers in cluster 1, mostly characterized as men, aged 32, are the typical ones, who choose a wide variety of all product categories at the same rate, whereas the customers in cluster 3, mostly characterized as women, aged 52, tend to choose certain product categories much more frequently than the other clusters' customers do.

These frequently purchased products are pasta, bread, rusks, rice/pulses, biscuits, chocolates, pastries/sweets, frozens, breakfast cereals, shelf stable milk, coffee, fruits, sausages, preserved cheeses, fresh beef, dump pork, dump poultry, non- alcoholic drinks/water, tea/juices, beers, household, detergents, animal food, paper, bath foams, smoker's items and uncategorized products.

<u>Simple K Means with 5 clusters:</u>

See the clustering results in the appendix: ***Simple K Means with 5 Clusters***

Within cluster sum of squared errors: 10458.0

Clustered Instances

0	8 (7%)
1	87 (81%)
2	7 (6%)
3	1 (1%)
4	5 (5%)

Simple K Means divides customers into five clusters, Cluster 0, Cluster 1, Cluster 2, Cluster 3 and Cluster 4. 81% of the instances are in Cluster 1 (87 customers out of 108 are included in this cluster), 7% of the instances are in Cluster 0 (8 customers out of 108 are included in this cluster), 6% of the instances are in Cluster 2 (7 customers out of 108 are included in this cluster) and 5% of the customers are in Cluster 4 (5 customer out of 108 are included in this cluster) and 1% of the customers are in Cluster 3 (1 customer out of 108 is included in this cluster). The five clusters present differentiations in the purchase frequency of the product categories'.

The centroids of cluster 0, cluster 2, cluster 3 and cluster 4 concerning the gender, are the same (women), unlike the centroid of Cluster 1 (which is male). The clusters' centroids differ as per the age (38, 32, 37, 52, 39 for Clusters 0, 1, 2, 3, 4,5 respectively) and the purchase frequency of the various product categories. Cluster 1 includes most the samples whereas cluster 3, cluster 0, cluster 2 and cluster 4 include just a few samples. That means, that customers in cluster 1, mostly characterized as men, aged 32, are the typical ones, who choose a wide variety of all product categories at the same rate, whereas the customers in cluster 3, mostly characterized as women, aged 52, tend to choose certain product categories much more frequently than the other clusters' customers do.

These frequently purchased products are pasta, bread, rusks, rice/pulses, biscuits, chocolates, pastries/sweets, frozens, breakfast cereals, shelf stable milk, coffee, fruits, sausages, preserved cheeses, fresh beef, dump pork, dump poultry, non- alcoholic drinks/water, tea/juices, beers, household, detergents, animal food, paper, bath foams, smoker's items and uncategorized products.

This clustering is similar to the one with 4 clusters, but it also adds an extra cluster to expand the options.

It is clear that a higher number of clusters, leads to a lower squared error, meaning that, the dataset is closer to finding the line of best fit.

Figure 36: Within cluster sum of squared errors and Number of clusters

4.2.2 Make A Density

According to [29]:
Density-Based Clustering refers to unsupervised learning methods that identify distinctive groups/clusters in the data, based on the idea that a cluster in a data space is a contiguous region of high point density, separated from other such clusters by contiguous regions of low point density. The data points in the separating regions of low point density are typically considered noise/outliers.

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.7),

- The clusterer randomly chooses the core points and then for each core point that is not already assigned to a cluster, creates a new cluster.
- The clusterer finds all its density connected points and assigns them to the same cluster as the core point.
- Then it iterates through the remaining unvisited points in the dataset.
- The core points that do not belong to any cluster are treated as outliers or noise points.[153]

Make A Density Clusterer, also presents a different squared error depending on the number of clusters we wish to create. The bigger the number of clusters, the lower the value of squared errors within the clusters.

In order to cross-validate this, we choose different number of clusters manually. The results of each of the clusterings depending on their number of clusters are presented below.

<u>Make A Density Clusterer with 2 Clusters</u>

See the clustering results in the appendix: ***Make A Density Based Clusterer with 2 Clusters***

Wrapped clusterer: kMeans

Number of iterations: 2

Within cluster sum of squared errors: 11112.0

Missing values globally replaced with mean/mode

Clustered Instances:

0 14 (13%)

1 94 (87%)

Log likelihood: -416.07815

Make A Density Clusterer divides customers into two clusters, Cluster 0 and Cluster 1. 87% of the instances are in Cluster 1 (94 customers out of 108 are included in this

[153] Source: https://www.youtube.com/watch?v=f4pZ9PHNdcM

cluster) and 13% of the instances are in Cluster 0 (14 customers out of 108 are included in this cluster). The two clusters present differentiations in the purchase frequency of the product categories'.

To be more precise, the centroids of the two clusters, concerning the gender are the same (women), however they differ as per the age (38 and 32 respectively) and the purchase frequency of the various product categories. Cluster 1 includes most of the samples (94% of the total samples) whereas Cluster 0 includes just a few samples (6% of the total samples). That means, that customers in cluster 1, mostly characterized as women, aged 32, are the typical ones, who choose all product categories at the same rate, whereas the customers in cluster 0, mostly characterized as women aged 38, tend to choose certain product categories much more frequently than the other cluster's customers do.

These frequently purchased products are fruits, vegetables, milk, bread, chocolates, rice/pulses, fresh beef, dump poultry, water, yoghurt as well as uncategorized products.

These results are the same as those of Simple K Means, which is expected, as Simple K Means is wrapped to Make A Density Based Clusterer.

Make A Density Clusterer with 3 Clusters

See the clustering results in the appendix: ***Make A Density Based Clusterer with 3 Clusters***

Wrapped clusterer: kMeans

Number of iterations: 2

Within cluster sum of squared errors: 11051.0

Missing values globally replaced with mean/mode

Clustered Instances:

0 8 (7%)
1 91 (84%)
2 9 (8%)

Log likelihood: -413.54478

Make A Density Clusterer divides customers into three clusters, Cluster 0, Cluster 1 and Cluster 2. 84% of the instances are in Cluster 1 (91 customers out of 108 are included in this cluster), 8% of the instances are in Cluster 2 (9 customers out of 108 are included in this cluster) and 7% of the instances are in Cluster 0 (8 customers out of 108 are included in this cluster). The three clusters present differentiations in the purchase frequency of the product categories'.

The centroids of the three clusters, concerning the gender are the same (women), however they differ as per the age (38, 32, 41) and the purchase frequency of the various product categories. Cluster 1 includes most of the samples (92% of the total samples) whereas, Cluster 0 and Cluster 2 include just a few samples (6% and 2% of the total samples respectively). That means, that customers in cluster 1, mostly characterized as women aged 32, are the typical ones, who choose all product categories at the same rate, whereas the customers in cluster 0, mostly characterized as women aged 38, tend to choose certain product categories much more frequently than the other clusters' customers do.

These frequently purchased products are fruits, vegetables, milk, bread, chocolates, rice/pulses, fresh beef, dump poultry, water, yoghurt as well as paper, household, detergents and uncategorized products.

These results are the same as those of Simple K Means, which is expected, as Simple K Means is wrapped to Make A Density Based Clusterer.

<u>Make A Density Clusterer with 4 clusters:</u>

See the clustering results in the appendix: *Make A Density Based Clusterer with 4 Clusters*

Within cluster sum of squared errors: 10605.0

Clustered Instances:

0 8 (7%)

1 86 (80%)

2 13 (12%)

3 1 (1%)

Log likelihood: -390.05324

Make A Density Based Clusterer divides customers into four clusters, Cluster 0, Cluster 1, Cluster 2 and Cluster 3. 80% of the instances are in Cluster 1 (86 customers out of 108 are included in this cluster), 12% of the instances are in Cluster 2 (13 customers out of 108 are included in this cluster), 7% of the instances are in Cluster 0 (8 customers out of 108 are included in this cluster) and 1% of the customers are in Cluster 3 (1 customer is included in this cluster). The four clusters present differentiations in the purchase frequency of the product categories'.

The centroids of cluster 0, cluster 2 and cluster 3, concerning the gender, are the same (women), unlike the centroid of Cluster 1 (which is male). The clusters' centroids differ as per the age (38, 32, 37, 52 for Clusters 0, 1, 2, 3, 4 respectively) and the purchase frequency of the various product categories. Cluster 1 includes most the samples whereas, cluster 3, cluster 0 and cluster 2 include just a few samples. That means, that customers in cluster 1, mostly characterized as men, aged 32, are the typical ones, who choose a wide variety of all product categories at the same rate, whereas the customers in cluster 3, mostly characterized as women, aged 52, tend to choose certain product categories much more frequently than the other clusters' customers.

These frequently purchased products are pasta, bread, rusks, rice/pulses, biscuits, chocolates, pastries/sweets, frozens, breakfast cereals, shelf stable milk, coffee, fruits, sausages, preserved cheeses, fresh beef, dump pork, dump poultry, non- alcoholic drinks/water, tea/juices, beers, household, detergents, animal food, paper, bath foams, smoker's items and uncategorized products.

These results are the same as those of Simple K Means, which is expected, as Simple K Means is wrapped to Make A Density Based Clusterer.

Make A Density Clusterer with 5 clusters:

See the clustering results in the appendix: ***Make A Density Based Clusterer with 5 Clusters***

Within cluster sum of squared errors: 10458.0

0 8 (7%)

1 85 (79%)

2 8 (7%)

3 1 (1%)

4 6 (6%)

Log likelihood: -389.75263

Make A Density Clusterer Simple K Means divides customers into five clusters, Cluster 0, Cluster 1, Cluster 2, Cluster 3 and Cluster 4. 81% of the instances are in Cluster 1 (87 customers out of 108 are included in this cluster), 7% of the instances are in Cluster 0 (8 customers out of 108 are included in this cluster), 6% of the instances are in Cluster 2 (7 customers out of 108 are included in this cluster) and 5% of the customers are in Cluster 4 (5 customer out of 108 are included in this cluster) and 1% of the customers are in Cluster 3 (1 customer is included in this cluster). The five clusters present differentiations in the purchase frequency of the product categories'.

The centroids of cluster 0, cluster 2, cluster 3 and cluster 4 concerning the gender, are the same (women), unlike the centroid of Cluster 1 (which is male). The clusters' centroids differ as per the age (38, 32, 37, 52, 39 for Clusters 0, 1, 2, 3, 4, 5 respectively) and the purchase frequency of the various product categories. Cluster 1 includes most the samples whereas cluster 3, cluster 0, cluster 2 and cluster 4 include just a few samples. That means, that customers in cluster 1, mostly characterized as men, aged 32, are the typical ones, who choose a wide variety of all product categories at the same rate, whereas the customers in cluster 3, mostly characterized as women, aged 52, tend to choose certain product categories much more frequently than the other clusters' customers do.

These frequently purchased products are pasta, bread, rusks, rice/pulses, biscuits, chocolates, pastries/sweets, frozens, breakfast cereals, shelf stable milk, coffee, fruits, sausages, preserved cheeses, fresh beef, dump pork, dump poultry, non- alcoholic drinks/water, tea/juices, beers, household, detergents, animal food, paper, bath foams, smoker's items and uncategorized products.

These results are the same as those of Simple K Means, which is expected, as Simple K Means is wrapped to Make A Density Based Clusterer.

It is clear that a higher number of clusters, leads to a lower squared error, meaning that, the dataset is closer to finding the line of best fit.

Figure 37: Within cluster sum of squared errors and Number of clusters

4.2.3 Filtered Clusterer

According to [20][20]:

This algorithm is primarily based completely on storing the multidimensional data points within a tree. The process regarding the tree is like a binary tree method, as represents a hierarchical subdivision on its data point set's bounding box the usage of their axis after which splitting is aligned by way on hyper planes. Each node on the tree is related with a closed field, referred to as the cell.

These results are the same as those of Simple K Means for all the clusterings, which is expected, as Filtered Clusterer uses Simple K Means in order to proceed to the outcome.

4.2.4 Farthest First

According to[24]:
Farthest first finds its variant of K-means. Each cluster center point furthermost from the existing cluster center is placed by the K-mean, and this point must be positioned within the data area. So that it greatly speeds up the clustering in most cases, but it needs less move and adjustment for their fast performance.

In order to examine Farthest First Clusterer's accuracy, we choose different number of clusters manually.

<u>Farthest First Clusterer with 2 Clusters:</u>

See the clustering results in the appendix: ***Farthest First with 2 Clusters***

Clustered Instances:

0 107 (99%)

1 1 (1%)

Simple K Means divides customers into two clusters, Cluster 0 and Cluster 1. 99% of the instances are in Cluster 0 (107 customers out of 108 are included in this cluster) and 1% of the instances are in Cluster 1 (1 is included in this cluster). The two clusters present differentiations in the purchase frequency of the product categories'.

To be more precise, the centroids of the two clusters, concerning the gender are the same (women), however they differ as per the age (82 and 52 respectively) and the purchase frequency of the various product categories. Cluster 1 includes most of the samples (99% of the total samples) whereas Cluster 0 includes just a one sample. This seems to be inaccurate results, as it is not that possible 99% of the customers to have similar consuming behavior concerning the purchase frequency as of 82 year-old women.

The same applies to the clusterings with a higher number of clusters as well, in which Cluster 0 has the higher rate of samples.

Farthest First seems to give inaccurate results for this case, however it shall be presented as well in the appendix:

Farthest First with 3 Clusters

Farthest First with 4 Clusters

Farthest First with 5 Clusters

4.2.5 EM

"EM (Expectation Maximization) is a probabilistic clusterer and can be used for unsupervised learning. Like Naive Bayes, it makes the assumption that all attributes are independent random variables." (Witten I.H., et al., (1999))

As mentioned in the first chapter (an analytical explanation is presented in chapter 1.5.2), unlike K-Means that takes one point and places it to the one cluster or the other, EM computes the probability that it goes into a or b cluster. This probability never gets zero or one, it is always a number between zero and one (0<probability EM<1).

The model just finds that there are distinguished groups in the dataset that behave differently.

EM works for numeric attributes providing mean and standard deviation results and value probability results respectively. Log likelihood is an overall quality measure and is increased by each iteration. [154]

EM run alternative number of clusters and then chooses automatically the number of the clusters it shall create.

=== Model and evaluation on training set ===

See Appendix: ***EM Clusterer***

Clustered Instances:

0 1 (1%)

1 2 (2%)

2 85 (79%)

3 1 (1%)

4 1 (1%)

5 13 (12%)

6 5 (5%)

[154] Source: https://www.youtube.com/watch?v=HCA0Z9kL7Hg

Log likelihood: -384.06072

Each cluster has the attributes of Gender, Age and Product Category. For each of the attributes, there is a probability that the output is going to be this certain attribute. This probability is calculated if you divide the number of the attribute by the total attributes in each of the clusters.

Cluster 2 seems to include most of the samples (79% of the total samples) and its customers are the typical ones (42,5% possibility of its centroid to be a woman and 57,5% possibility of its centroid to be a man).

4.2.6 Canopy

According to Mai and Cheng (2016)[33]: *Canopy is one of the improved K-means algorithm, can be used to determine the number of clusters. With the introduction of Canopy clustering, the data set is divided into k sub-sets by setting the radius, and the sub-sets can be selected as the initial centers of K-means. Because the Canopy algorithm can reduce the running time of the clustering by reduce the count of comparisons, it will improve the computational efficiency.*

The Canopy algorithm's analytical explanation of the steps is presented in chapter 1.5.8.

We choose different number of clusters manually. The results of each of the clusterings, depending on their number of clusters are presented below.

Canopy Clustering with 2 Clusters

See the appendix***: Canopy clustering with 2 clusters***

Clustered Instances

0 107 (99%)

1 1 (1%)

First we divide customers into two clusters, Cluster 0 and Cluster 1. 99% of the instances are in Cluster 0 (107 customers out of 108 are included in this cluster) and

1% of the instances are in Cluster 1 (1 customer is included in this cluster). The two clusters present differentiations in the purchase frequency of the product categories'.

To be more precise, the centroids of the two clusters, concerning the gender are the same (men), however they differ as per the age (32 and 49 respectively) and the purchase frequency of the various product categories. Cluster 0 includes most of the samples whereas Cluster 1 includes just a one sample. That means, that customers in cluster 0, mostly characterized as men, aged 32, are the typical ones, who choose all product categories at the same rate, whereas the customers in cluster 1, mostly characterized as men aged 49, tend to choose certain product categories much more frequently than the other cluster's customers do.

These frequently purchased products are pasta, bread, rusks, rice/pulses, biscuits, chocolates, pastries/sweets, frozens, breakfast cereals, shelf stable milk, coffee, fruits, sausages, preserved cheeses, fresh beef, dump pork, dump poultry, non- alcoholic drinks/water, tea/juices, beers, household, detergents, animal food, paper, bath foams, smoker's items and uncategorized products.

Canopy Clustering with 3 Clusters

See the appendix***: Canopy clustering with 3 clusters***

Clustered Instances

0 94 (87%)
1 1 (1%)
2 13 (12%)

We divide customers into 3 clusters but the first two clusters remain the same and we just introduce a new one, the centroids of which are men aged 72. The number of samples in each cluster now renumbers, with Cluster 1 remaining the same as it was. Still, Cluster 0 includes the most samples and characterizes the typical customer.

Canopy Clustering with 4 Clusters

See the appendix***: Canopy clustering with 4 clusters***

Clustered Instances

0 93 (86%)
1 1 (1%)

2 13 (12%)

3 1 (1%)

We divide customers into 4 clusters but the first three clusters remain the same and we just introduce a new one, the centroids of which are women aged 40. The number of samples in each cluster now renumbers, with Cluster 1 remaining the same as it was. Still, Cluster 0, followed by Cluster 2 includes the most samples and characterizes the typical customer. Cluster 1 and Cluster 2 tend to choose certain product categories much more frequently than the other cluster's customers do.

These frequently purchased products are the same as those mentioned above and these are pasta, bread, rusks, rice/pulses, biscuits, chocolates, pastries/sweets, frozens, breakfast cereals, shelf stable milk, coffee, fruits, sausages, preserved cheeses, fresh beef, dump pork, dump poultry, non- alcoholic drinks/water, tea/juices, beers, household, detergents, animal food, paper, bath foams, smoker's items and uncategorized products.

Canopy Clustering with 5 Clusters

See the appendix***: Canopy clustering with 5 clusters***

Clustered Instances

0 88 (81%)

1 1 (1%)

2 12 (11%)

3 1 (1%)

4 6 (6%)

Lastly, we divide customers into 5 clusters but the first four clusters remain the same and we just introduce a new one, the centroids of which are women aged 81. The number of samples in each cluster now renumbers, with Cluster 1 remaining the same as it was.

In each of the 5 cases, Cluster 0 (the centroids of which are men, aged 32), includes the most samples and characterizes the typical customer who chooseσ all product categories at the same rate.

Conclusions

Association rule mining or market basket analysis is a data mining technique used to increase sales by better understanding customer purchasing patterns. Through analyzing large databases, we can detect the products that are likely to be purchased together. Implementation of market basket analysis requires a background in statistics and data science.

In this chapter, we used the WEKA Machine Learning Software System Tool for association rule mining and clustering. We discovered the correlations between the different items in customers' shopping cart and we grouped customers who displayed similar characteristics.

These, shall help the Super Market find the purchase behavior of its buyers, understand what they want, make the correct decisions and hence establish a profitable sales strategy by considering items frequently purchased together by customers. For a supermarket with multiple stores, finding purchasing patterns can be useful in forming the best cross- selling actions as well as the best marketing, service, and operation strategies.

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APPENDIX

APPENDIX 1: Creta Palm Hotel

M5Rules Algorithm| Creta Palm 2019

=== Classifier model (full training set) ===

pruned model rules (using smoothed linear models) :Number of Rules : 1

<u>Rule: 1</u>

TOTAL BOOKINGS =

2.3818 * Booking Source=TUI NL,BLUEAEGEAN,SUNWEB,Jet2Holidays,ARHUS CHARTER,ITAKA,EXPEDIA,AURINKOMATKAT

- 5.4481

*BookingSource=SUNWEB,Jet2Holidays,ARHUSCHARTER,ITAKA,EXPEDIA,AURINKOMATKAT

+ 6.033
* BookingSource=Jet2Holidays,ARHUSCHARTER,ITAKA,EXPEDIA,AURINKOMATKAT

+ 6.8512
* BookingSource=ARHUSCHARTER,ITAKA,EXPEDIA,AURINKOMATKAT

- 4.2256 * Booking Source=ITAKA,EXPEDIA,AURINKOMATKAT

+ 4.4683 * Booking Source=EXPEDIA,AURINKOMATKAT

+ 0.008 * TOTAL PAX Nights

+ 0.0735 * Total Room Nights

+ 0.0149 * HB

- 0.0085 * AI

+ 3.3041 * MONTH=September 2019,July 2019,June 2019

- 0.2915 [91/16.644%]

M5P Trees Algorithm| Creta Palm 2019

LM num: 1

TOTAL BOOKINGS = 2.3818 * Booking Source
= TUI NL,BLUE
AEGEAN,SUNWEB,Jet2Holidays,ARHUS
CHARTER,ITAKA,EXPEDIA,AURINKOMATKAT
- 5.4481 * Booking Source
=SUNWEB,Jet2Holidays,ARHUS
CHARTER,ITAKA,EXPEDIA,AURINKOMATKAT
+ 6.033 * Booking Source
=Jet2Holidays,ARHUS
CHARTER,ITAKA,EXPEDIA,AURINKOMATKAT
+ 6.8512 * Booking Source
=ARHUS
CHARTER,ITAKA,EXPEDIA,AURINKOMATKAT
- 4.2256 * Booking Source
=ITAKA,EXPEDIA,AURINKOMATKAT
+ 4.4683 * Booking Source
=EXPEDIA,AURINKOMATKAT
+ 0.008 * TOTAL PAX Nights
+ 0.0735 * Total Room Nights
+ 0.0149 * HB
- 0.0085 * AI
+ 3.3041 * MONTH
=September 2019,July 2019,June 2019
- 0.2915

SMOreg Algorithm| Creta Palm 2019

weights (not support vectors):

+ 0.0793 * (normalized) Booking Source=ARHUS CHARTER

- 0.0049 * (normalized) Booking Source=AURINKOMATKAT

+ 0.0087 * (normalized) Booking Source=BLUE AEGEAN

- 0.0348 * (normalized) Booking Source=BOOKING.COM

- 0.0549 * (normalized) Booking Source=BRAVO TOURS

+ 0.0472 * (normalized) Booking Source=EXPEDIA

+ 0.0104 * (normalized) Booking Source=ITAKA

+ 0.0084 * (normalized) Booking Source=Jet2Holidays

- 0.0134 * (normalized) Booking Source=RAINBOW

- 0.0198 * (normalized) Booking Source=SUNWEB

- 0.0245 * (normalized) Booking Source=TUI Deutschland

+ 0.0048 * (normalized) Booking Source=TUI NL

- 0.0064 * (normalized) Booking Source=TUI UK

+ 0.0244 * (normalized) Country=Denmark

- 0.0049 * (normalized) Country=Finland

+ 0.0087 * (normalized) Country=Romania

+ 0.0124 * (normalized) Country=Vary

- 0.0031 * (normalized) Country=Poland

+ 0.002 * (normalized) Country=UK

- 0.015 * (normalized) Country=Netherlands

- 0.0245 * (normalized) Country=Germany

- 0.0418 * (normalized) Average pax/room

+ 0.0124 * (normalized) TO/ OTA=OTA

+ 0.0815 * (normalized) ADR

+ 0.2293 * (normalized) TOTAL PAX Nights

+ 0.4811 * (normalized) Total Room Nights

+ 0.1714 * (normalized) BB

- 0.015 * (normalized) BB%

+ 0.1306 * (normalized) HB

+ 0.0058 * (normalized) HB%

- 0.0177 * (normalized) AI

- 0.0024 * (normalized) AI%

+ 0.0153 * (normalized) MONTH=April 2019

\+ 0.0126 * (normalized) MONTH=May 2019

\+ 0.0113 * (normalized) MONTH=June 2019

\+ 0.0014 * (normalized) MONTH=July 2019

\- 0.0297 * (normalized) MONTH=August 2019

\- 0.0188 * (normalized) MONTH=September 2019

\+ 0.0079 * (normalized) MONTH=October 2019

\- 0.0058

Linear Regression Model Algorithm| Creta Palm 2019

TOTAL BOOKINGS =

-7.8096 * Booking Source=
BOOKING.COM,BRAVO TOURS,TUI Deutschland,TUI UK,TUI NL,BLUE AEGEAN,SUNWEB,Jet2Holidays,ARHUS CHARTER,ITAKA,EXPEDIA, AURINKOMATKAT
+7.6327 * Booking Source=
TUI UK,TUI NL,BLUE AEGEAN,SUNWEB,Jet2Holidays,ARHUS CHARTER,ITAKA,EXPEDIA,AURINKOMATKAT +
-6.6557 * Booking Source=SUNWEB,Jet2Holidays,ARHUS CHARTER,ITAKA,EXPEDIA,AURINKOMATKAT +
7.1524 * Booking Source=
Jet2Holidays,ARHUSCHARTER,ITAKA,EXPEDIA,AURINKOMATKAT +
-7.9784 * Booking Source=
AURINKOMATKAT-6.6556*Country=
Netherlands,UK,Poland,Denmark,Vary,Finland +
7.8617 * Country=
Denmark,Vary,Finland +
-7.9782 * Country=Finland +
0.0478 * ADR +
0.0103 * TOTAL PAX Nights +
0.1078 * Total Room Nights +
-0.0071 * BB +
-0.0185 * AI +
-4.0717 * MONTH=
August 2019,September 2019,July 2019,June 2019 +
4.7388 * MONTH=
July 2019,June 2019 +4.1779

Meta Random Committee Algorithm| Creta Palm 2019

=== Classifier model (full training set) ===

All the base classifiers:

RandomTree

==========

Booking Source = ARHUS CHARTER

| Total Room Nights < 103 : 0 (1/0)

| Total Room Nights >= 103

| | Average pax/room < 2.27

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 34 (1/0)

| | | MONTH = June 2019 : 40 (1/0)

| | | MONTH = July 2019 : 39 (1/0)

| | | MONTH = August 2019 : 25 (1/0)

| | | MONTH = September 2019 : 39 (1/0)

| | | MONTH = October 2019 : 0 (0/0)

| | Average pax/room >= 2.27 : 22 (1/0)

Booking Source = AURINKOMATKAT

| BB% < 0.61

| | HB% < 0.13 : 92 (1/0)

| | HB% >= 0.13

| | | TOTAL PAX Nights < 3032 : 125 (1/0)

| | | TOTAL PAX Nights >= 3032

| | | | ADR < 120.78 : 132 (1/0)

| | | | ADR >= 120.78 : 135 (1/0)

| BB% >= 0.61

| | Average pax/room < 2.51

| | | Total Room Nights < 839 : 78 (1/0)

| | | Total Room Nights >= 839 : 82 (1/0)

| | Average pax/room >= 2.51 : 63 (1/0)

Booking Source = BLUE AEGEAN

| TOTAL PAX Nights < 89.5 : 0.33 (3/0.22)

| TOTAL PAX Nights >= 89.5

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 24 (1/0)

| | MONTH = July 2019 : 27 (1/0)

| | MONTH = August 2019 : 18 (1/0)

| | MONTH = September 2019 : 20 (1/0)

| | MONTH = October 2019 : 0 (0/0)

Booking Source = BOOKING.COM

| BB% < 0.81

| | TOTAL PAX Nights < 100.5 : 9 (1/0)

| | TOTAL PAX Nights >= 100.5

| | | Average pax/room < 2.83 : 13 (1/0)

| | | Average pax/room >= 2.83 : 11 (1/0)

| BB% >= 0.81 : 2.5 (4/0.25)

Booking Source = BRAVO TOURS

| AI < 40

| | TOTAL PAX Nights < 85.5

| | | Total Room Nights < 16.5 : 1 (1/0)

| | | Total Room Nights >= 16.5 : 3.67 (3/0.22)

| | TOTAL PAX Nights >= 85.5

| | | ADR < 84.92 : 7 (1/0)

| | | ADR >= 84.92 : 5 (1/0)

| AI >= 40 : 24 (1/0)

Booking Source = EXPEDIA

| MONTH = April 2019 : 41 (1/0)

| MONTH = May 2019 : 22 (1/0)

| MONTH = June 2019 : 45 (1/0)

| MONTH = July 2019 : 46 (1/0)

| MONTH = August 2019 : 27 (1/0)

| MONTH = September 2019 : 26 (1/0)

| MONTH = October 2019 : 32 (1/0)

Booking Source = ITAKA

| MONTH = April 2019 : 2 (1/0)

| MONTH = May 2019 : 15 (1/0)

| MONTH = June 2019 : 63 (1/0)

| MONTH = July 2019 : 42 (1/0)

| MONTH = August 2019 : 41 (1/0)

| MONTH = September 2019 : 56 (1/0)

| MONTH = October 2019 : 13 (1/0)

Booking Source = Jet2Holidays

| TOTAL PAX Nights < 155.5 : 0 (1/0)

| TOTAL PAX Nights >= 155.5

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 28 (1/0)

| | MONTH = June 2019 : 20 (1/0)

| | MONTH = July 2019 : 35 (1/0)

| | MONTH = August 2019 : 22 (1/0)

| | MONTH = September 2019 : 34 (1/0)

| | MONTH = October 2019 : 18 (1/0)

Booking Source = RAINBOW : 0.86 (7/0.12)

Booking Source = SUNWEB

| MONTH = April 2019 : 4 (1/0)

| MONTH = May 2019 : 21 (1/0)

| MONTH = June 2019 : 24 (1/0)

| MONTH = July 2019 : 23 (1/0)

| MONTH = August 2019 : 19 (1/0)

| MONTH = September 2019 : 23 (1/0)

| MONTH = October 2019 : 12 (1/0)

Booking Source = TUI Deutschland

| TOTAL PAX Nights < 94 : 2 (3/0.67)

| TOTAL PAX Nights >= 94

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 12 (1/0)

| | MONTH = July 2019 : 13 (1/0)

| | MONTH = August 2019 : 7 (1/0)

| | MONTH = September 2019 : 14 (1/0)

| | MONTH = October 2019 : 0 (0/0)

Booking Source = TUI NL

| TOTAL PAX Nights < 237.5

| | ADR < 72.11 : 1.5 (2/0.25)

| | ADR >= 72.11

| | | TOTAL PAX Nights < 175.5 : 6 (1/0)

| | | TOTAL PAX Nights >= 175.5 : 9 (1/0)

| TOTAL PAX Nights >= 237.5 : 15.67 (3/0.22)

Booking Source = TUI UK

| MONTH = April 2019 : 0 (1/0)

| MONTH = May 2019 : 1 (1/0)

| MONTH = June 2019 : 18 (1/0)

| MONTH = July 2019 : 5 (1/0)

| MONTH = August 2019 : 7 (1/0)

| MONTH = September 2019 : 8 (1/0)

| MONTH = October 2019 : 16 (1/0)

Size of the tree : 112 Binary and Multi-class Classifiers

RandomTree

==========

Booking Source = ARHUS CHARTER

| MONTH = April 2019 : 0 (1/0)

| MONTH = May 2019 : 34 (1/0)

| MONTH = June 2019 : 40 (1/0)

| MONTH = July 2019 : 39 (1/0)

| MONTH = August 2019 : 25 (1/0)

| MONTH = September 2019 : 39 (1/0)

| MONTH = October 2019 : 22 (1/0)

Booking Source = AURINKOMATKAT

| MONTH = April 2019 : 78 (1/0)

| MONTH = May 2019 : 125 (1/0)

| MONTH = June 2019 : 132 (1/0)

| MONTH = July 2019 : 135 (1/0)

| MONTH = August 2019 : 92 (1/0)

| MONTH = September 2019 : 82 (1/0)

| MONTH = October 2019 : 63 (1/0)

Booking Source = BLUE AEGEAN

| ADR < 43.99 : 0.33 (3/0.22)

| ADR >= 43.99

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 24 (1/0)

| | MONTH = July 2019 : 27 (1/0)

| | MONTH = August 2019 : 18 (1/0)

| | MONTH = September 2019 : 20 (1/0)

| | MONTH = October 2019 : 0 (0/0)

Booking Source = BOOKING.COM

| BB < 65 : 2.5 (4/0.25)

| BB >= 65

| | BB% < 0.71

| | | TOTAL PAX Nights < 160 : 13 (1/0)

| | | TOTAL PAX Nights >= 160 : 11 (1/0)

| | BB% >= 0.71 : 9 (1/0)

Booking Source = BRAVO TOURS

| HB% < 0.91

| | AI% < 0.21 : 24 (1/0)

| | AI% >= 0.21 : 7 (1/0)

| HB% >= 0.91

| | Total Room Nights < 16.5 : 1 (1/0)

| | Total Room Nights >= 16.5 : 4 (4/0.5)

Booking Source = EXPEDIA

| BB < 492.5

| | TOTAL PAX Nights < 353 : 22 (1/0)

| | TOTAL PAX Nights >= 353

| | | TOTAL PAX Nights < 471.5 : 32 (1/0)

| | | TOTAL PAX Nights >= 471.5 : 26.5 (2/0.25)

| BB >= 492.5

| | TOTAL PAX Nights < 566.5 : 41 (1/0)

| | TOTAL PAX Nights >= 566.5 : 45.5 (2/0.25)

Booking Source = ITAKA

| ADR < 100.16

| | BB% < 0.5

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 15 (1/0)

| | | MONTH = June 2019 : 0 (0/0)

| | | MONTH = July 2019 : 0 (0/0)

| | | MONTH = August 2019 : 0 (0/0)

| | | MONTH = September 2019 : 0 (0/0)

| | | MONTH = October 2019 : 13 (1/0)

| | BB% >= 0.5 : 2 (1/0)

| ADR >= 100.16

| | AI < 1489

| | | Average pax/room < 2.71 : 56 (1/0)

| | | Average pax/room >= 2.71 : 63 (1/0)

| | AI >= 1489 : 41.5 (2/0.25)

Booking Source = Jet2Holidays

| ADR < 25.75 : 0 (1/0)

| ADR >= 25.75

| | ADR < 70.31

| | | BB < 339.5

| | | | Average pax/room < 2.11 : 20 (1/0)

| | | | Average pax/room >= 2.11 : 18 (1/0)

| | | BB >= 339.5 : 28 (1/0)

| | ADR >= 70.31

| | | TOTAL PAX Nights < 602 : 22 (1/0)

| | | TOTAL PAX Nights >= 602 : 34.5 (2/0.25)

Booking Source = RAINBOW : 0.86 (7/0.12)

Booking Source = SUNWEB

| TOTAL PAX Nights < 454.5

| | BB < 82 : 4 (1/0)

| | BB >= 82 : 12 (1/0)

| TOTAL PAX Nights >= 454.5

| | HB < 22 : 19 (1/0)

| | HB >= 22

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 21 (1/0)

| | | MONTH = June 2019 : 24 (1/0)

| | | MONTH = July 2019 : 23 (1/0)

| | | MONTH = August 2019 : 0 (0/0)

| | | MONTH = September 2019 : 23 (1/0)

| | | MONTH = October 2019 : 0 (0/0)

Booking Source = TUI Deutschland

| TOTAL PAX Nights < 94 : 2 (3/0.67)

| TOTAL PAX Nights >= 94

| | TOTAL PAX Nights < 208

| | | TOTAL PAX Nights < 152 : 12 (1/0)

| | | TOTAL PAX Nights >= 152 : 7 (1/0)

| | TOTAL PAX Nights >= 208 : 13.5 (2/0.25)

Booking Source = TUI NL

| MONTH = April 2019 : 1 (1/0)

| MONTH = May 2019 : 16 (1/0)

| MONTH = June 2019 : 15 (1/0)

| MONTH = July 2019 : 6 (1/0)

| MONTH = August 2019 : 9 (1/0)

| MONTH = September 2019 : 16 (1/0)

| MONTH = October 2019 : 2 (1/0)

Booking Source = TUI UK

| TOTAL PAX Nights < 216

| | MONTH = April 2019 : 0 (1/0)

| | MONTH = May 2019 : 1 (1/0)

| | MONTH = June 2019 : 0 (0/0)

| | MONTH = July 2019 : 5 (1/0)

| | MONTH = August 2019 : 7 (1/0)

| | MONTH = September 2019 : 8 (1/0)

| | MONTH = October 2019 : 0 (0/0)

| TOTAL PAX Nights >= 216

| | TOTAL PAX Nights < 255.5 : 18 (1/0)

| | TOTAL PAX Nights >= 255.5 : 16 (1/0)

Size of the tree : 119

RandomTree

==========

Country = Denmark

| Total Room Nights < 88

| | ADR < 58.92 : 0.5 (2/0.25)

| | ADR >= 58.92

| | | Average pax/room < 1.94 : 7 (1/0)

| | | Average pax/room >= 1.94 : 4 (4/0.5)

| Total Room Nights >= 88

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 34 (1/0)

| | MONTH = June 2019 : 40 (1/0)

| | MONTH = July 2019

| | | Average pax/room < 2.52 : 39 (1/0)

| | | Average pax/room >= 2.52 : 24 (1/0)

| | MONTH = August 2019 : 25 (1/0)

| | MONTH = September 2019 : 39 (1/0)

| | MONTH = October 2019 : 22 (1/0)

Country = Finland

| BB < 1541.5

| | MONTH = April 2019 : 78 (1/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 0 (0/0)

| | MONTH = July 2019 : 0 (0/0)

| | MONTH = August 2019 : 92 (1/0)

| | MONTH = September 2019 : 82 (1/0)

| | MONTH = October 2019 : 63 (1/0)

| BB >= 1541.5

| | Average pax/room < 2.55 : 125 (1/0)

| | Average pax/room >= 2.55

| | | HB < 557.5 : 135 (1/0)

| | | HB >= 557.5 : 132 (1/0)

Country = Romania

| AI < 6

| | Total Room Nights < 44.5 : 0.4 (2.5/0.24)

| | Total Room Nights >= 44.5 : 20 (1/0)

| AI >= 6

| | TOTAL PAX Nights < 85.5 : 0 (0.5/0)

| | TOTAL PAX Nights >= 85.5

| | | Average pax/room < 3.2

| | | | Average pax/room < 2.75 : 24 (1/0)

| | | | Average pax/room >= 2.75 : 27 (1/0)

| | | Average pax/room >= 3.2 : 18 (1/0)

Country = Vary

| HB < 10 : 2.5 (4/0.25)

| HB >= 10

| | TOTAL PAX Nights < 353

| | | Average pax/room < 2.16 : 22 (1/0)

| | | Average pax/room >= 2.16

| | | | HB < 28.5 : 9 (1/0)

| | | | HB >= 28.5

| | | | | TOTAL PAX Nights < 160 : 13 (1/0)

| | | | | TOTAL PAX Nights >= 160 : 11 (1/0)

| | TOTAL PAX Nights >= 353

| | | Total Room Nights < 227

| | | | MONTH = April 2019 : 0 (0/0)

| | | | MONTH = May 2019 : 0 (0/0)

| | | | MONTH = June 2019 : 0 (0/0)

| | | | MONTH = July 2019 : 0 (0/0)

| | | | MONTH = August 2019 : 27 (1/0)

| | | | MONTH = September 2019 : 26 (1/0)

| | | | MONTH = October 2019 : 32 (1/0)

| | | Total Room Nights >= 227

| | | | MONTH = April 2019 : 41 (1/0)

| | | | MONTH = May 2019 : 0 (0/0)

| | | | MONTH = June 2019 : 45 (1/0)

| | | | MONTH = July 2019 : 46 (1/0)

| | | | MONTH = August 2019 : 0 (0/0)

| | | | MONTH = September 2019 : 0 (0/0)

| | | | MONTH = October 2019 : 0 (0/0)

Country = Poland

| TOTAL PAX Nights < 777.5

| | Total Room Nights < 57 : 1 (8/0.25)

| | Total Room Nights >= 57

| | | AI < 280.5 : 13 (1/0)

| | | AI >= 280.5 : 15 (1/0)

| TOTAL PAX Nights >= 777.5

| | Total Room Nights < 533.5

| | | BB < 780.5 : 56 (1/0)

| | | BB >= 780.5 : 63 (1/0)

| | Total Room Nights >= 533.5 : 41.5 (2/0.25)

Country = UK

| TOTAL PAX Nights < 216

| | ADR < 70.78 : 0.33 (3/0.22)

| | ADR >= 70.78

| | | Average pax/room < 1.84 : 5 (1/0)

| | | Average pax/room >= 1.84 : 7.5 (2/0.25)

| TOTAL PAX Nights >= 216

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 28 (1/0)

| | MONTH = June 2019

| | | ADR < 67.94 : 20 (1/0)

| | | ADR >= 67.94 : 18 (1/0)

| | MONTH = July 2019 : 35 (1/0)

| | MONTH = August 2019 : 22 (1/0)

| | MONTH = September 2019 : 34 (1/0)

| | MONTH = October 2019

| | | Average pax/room < 2.05 : 16 (1/0)

| | | Average pax/room >= 2.05 : 18 (1/0)

Country = Netherlands

| TOTAL PAX Nights < 237.5

| | MONTH = April 2019

| | | ADR < 55.51 : 1 (1/0)

| | | ADR >= 55.51 : 4 (1/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 0 (0/0)

| | MONTH = July 2019 : 6 (1/0)

| | MONTH = August 2019 : 9 (1/0)

| | MONTH = September 2019 : 0 (0/0)

| | MONTH = October 2019 : 2 (1/0)

| TOTAL PAX Nights >= 237.5

| | Total Room Nights < 243

| | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | Booking Source = BOOKING.COM : 0 (0/0)

| | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | Booking Source = EXPEDIA : 0 (0/0)

| | | Booking Source = ITAKA : 0 (0/0)

| | | Booking Source = Jet2Holidays : 0 (0/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SUNWEB : 12 (1/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 15.67 (3/0.22)

| | | Booking Source = TUI UK : 0 (0/0)

| | Total Room Nights >= 243

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 21 (1/0)

| | | MONTH = June 2019 : 24 (1/0)

| | | MONTH = July 2019 : 23 (1/0)

| | | MONTH = August 2019 : 19 (1/0)

| | | MONTH = September 2019 : 23 (1/0)

| | | MONTH = October 2019 : 0 (0/0)

Country = Germany

| Average pax/room < 2.39

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 12 (1/0)

| | MONTH = July 2019 : 13 (1/0)

| | MONTH = August 2019 : 7 (1/0)

| | MONTH = September 2019 : 14 (1/0)

| | MONTH = October 2019 : 1 (1/0)

| Average pax/room >= 2.39 : 2.5 (2/0.25)

Size of the tree : 142

RandomTree

==========

TOTAL PAX Nights < 1867

| Total Room Nights < 176.5

| | HB < 12

| | | Total Room Nights < 88

| | | | BB < 65

| | | | | AI < 29

| | | | | | Country = Denmark : 0.5 (2/0.25)

| | | | | | Country = Finland : 0 (0/0)

| | | | | | Country = Romania : 0.42 (2.39/0.24)

| | | | | | Country = Vary : 2.5 (4/0.25)

| | | | | | Country = Poland : 1 (7/0.29)

| | | | | | Country = UK : 0.33 (3/0.22)

| | | | | | Country = Netherlands : 1.5 (2/0.25)

| | | | | | Country = Germany : 0 (0/0)

| | | | | AI >= 29 : 4.9 (1.02/0.47)

| | | | BB >= 65

| | | | | TOTAL PAX Nights < 119.5 : 3.78 (1.06/0.84)

| | | | | TOTAL PAX Nights >= 119.5 : 6.5 (2/0.25)

| | | Total Room Nights >= 88

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA

| | | | | TOTAL PAX Nights < 280.5 : 13 (1/0)

| | | | | TOTAL PAX Nights >= 280.5 : 15 (1/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 16 (1/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| | HB >= 12

| | | TOTAL PAX Nights < 145.5

| | | | BB < 35

| | | | | HB < 94

| | | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | | Booking Source = BLUE AEGEAN : 0 (0.35/0)

| | | | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | | | Booking Source = BRAVO TOURS

| | | | | | | MONTH = April 2019 : 0 (0/0)

| | | | | | | MONTH = May 2019 : 7 (1/0)

| | | | | | | MONTH = June 2019 : 0 (0/0)

| | | | | | | MONTH = July 2019 : 0 (0/0)

| | | | | | | MONTH = August 2019 : 3 (1/0)

| | | | | | | MONTH = September 2019 : 4 (1/0)

| | | | | | | MONTH = October 2019 : 4 (1/0)

| | | | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | | | Booking Source = ITAKA : 0 (0/0)

| | | | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | | | Booking Source = RAINBOW : 1 (1/0)

| | | | | | Booking Source = SUNWEB : 0 (0/0)

| | | | | | Booking Source = TUI Deutschland : 2 (3/0.67)

| | | | | | Booking Source = TUI NL : 0 (0/0)

| | | | | | Booking Source = TUI UK : 0 (0/0)

| | | | | HB >= 94

| | | | | | Average pax/room < 2.71 : 11.5 (1.04/5.8)

| | | | | | Average pax/room >= 2.71 : 4.79 (1.04/1.01)

| | | | BB >= 35

| | | | | ADR < 34.3 : 0 (0.09/0)

| | | | | ADR >= 34.3 : 11 (2/4)

| | | TOTAL PAX Nights >= 145.5

| | | | HB < 296

| | | | | TOTAL PAX Nights < 237.5

| | | | | | HB% < 0.98

| | | | | | | Country = Denmark : 0 (0/0)

| | | | | | | Country = Finland : 0 (0/0)

| | | | | | | Country = Romania : 18 (1/0)

| | | | | | | Country = Vary : 11 (1/0)

| | | | | | | Country = Poland : 0 (0/0)

| | | | | | | Country = UK : 8 (1/0)

| | | | | | | Country = Netherlands : 9 (1/0)

| | | | | | | Country = Germany : 7 (1/0)

| | | | | | HB% >= 0.98

| | | | | | | Average pax/room < 2.23 : 20 (1/0)

| | | | | | | Average pax/room >= 2.23 : 13 (1/0)

| | | | | TOTAL PAX Nights >= 237.5

| | | | | | Average pax/room < 2.42

| | | | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | | | Booking Source = BLUE AEGEAN : 24 (1/0)

| | | | | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | | | | Booking Source = EXPEDIA : 22 (1/0)

| | | | | | | Booking Source = ITAKA : 0 (0/0)

| | | | | | | Booking Source = Jet2Holidays

| | | | | | | | BB% < 0.69 : 18 (1/0)

| | | | | | | | BB% >= 0.69 : 20 (1/0)

| | | | | | | Booking Source = RAINBOW : 0 (0/0)

| | | | | | | Booking Source = SUNWEB : 0 (0/0)

| | | | | | | Booking Source = TUI Deutschland : 14 (1/0)

| | | | | | | Booking Source = TUI NL : 15 (1/0)

| | | | | | | Booking Source = TUI UK

| | | | | | | | Average pax/room < 1.94 : 16 (1/0)

| | | | | | | | Average pax/room >= 1.94 : 18 (1/0)

| | | | | | Average pax/room >= 2.42 : 12 (1/0)

| | | | HB >= 296

| | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | Booking Source = BLUE AEGEAN : 27 (1/0)

| | | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | | Booking Source = BRAVO TOURS : 24 (1/0)

| | | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | | Booking Source = ITAKA : 0 (0/0)

| | | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | | Booking Source = RAINBOW : 0 (0/0)

| | | | | Booking Source = SUNWEB : 0 (0/0)

| | | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | | Booking Source = TUI NL : 0 (0/0)

| | | | | Booking Source = TUI UK : 0 (0/0)

| Total Room Nights >= 176.5

| | Country = Denmark

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 34 (1/0)

| | | MONTH = June 2019 : 40 (1/0)

| | | MONTH = July 2019 : 39 (1/0)

| | | MONTH = August 2019 : 25 (1/0)

| | | MONTH = September 2019 : 39 (1/0)

| | | MONTH = October 2019 : 22 (1/0)

| | Country = Finland : 63 (1/0)

| | Country = Romania : 0 (0/0)

| | Country = Vary

| | | Total Room Nights < 227

| | | | MONTH = April 2019 : 0 (0/0)

| | | | MONTH = May 2019 : 0 (0/0)

| | | | MONTH = June 2019 : 0 (0/0)

| | | | MONTH = July 2019 : 0 (0/0)

| | | | MONTH = August 2019 : 27 (1/0)

| | | | MONTH = September 2019 : 26 (1/0)

| | | | MONTH = October 2019 : 32 (1/0)

| | | Total Room Nights >= 227

| | | | ADR < 65.59 : 41 (1/0)

| | | | ADR >= 65.59 : 45.5 (2/0.25)

| | Country = Poland

| | | BB < 780.5

| | | | TOTAL PAX Nights < 1489 : 56 (1/0)

| | | | TOTAL PAX Nights >= 1489 : 41.5 (2/0.25)

| | | BB >= 780.5 : 63 (1/0)

| | Country = UK

| | | TOTAL PAX Nights < 602

| | | | Average pax/room < 2.43 : 28 (1/0)

| | | | Average pax/room >= 2.43 : 22 (1/0)

| | | TOTAL PAX Nights >= 602 : 34.5 (2/0.25)

| | Country = Netherlands

| | | TOTAL PAX Nights < 533 : 16 (1/0)

| | | TOTAL PAX Nights >= 533

| | | | MONTH = April 2019 : 0 (0/0)

| | | | MONTH = May 2019 : 21 (1/0)

| | | | MONTH = June 2019 : 24 (1/0)

| | | | MONTH = July 2019 : 23 (1/0)

| | | | MONTH = August 2019 : 19 (1/0)

| | | | MONTH = September 2019 : 23 (1/0)

| | | | MONTH = October 2019 : 0 (0/0)

| | Country = Germany : 0 (0/0)

TOTAL PAX Nights >= 1867

| TOTAL PAX Nights < 2480.5

| | BB% < 0.6 : 92 (1/0)

| | BB% >= 0.6

| | | Average pax/room < 2.4 : 78 (1/0)

| | | Average pax/room >= 2.4 : 82 (1/0)

| TOTAL PAX Nights >= 2480.5

| | Total Room Nights < 1176 : 125 (1/0)

| | Total Room Nights >= 1176

| | | BB < 1912 : 135 (1/0)

| | | BB >= 1912 : 132 (1/0)

Size of the tree : 169

RandomTree

==========

TOTAL PAX Nights < 1867

| Total Room Nights < 176.5

| | ADR < 133.47

| | | Booking Source = ARHUS CHARTER : 0 (1/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN

| | | | HB% < 0.42 : 0.6 (1.67/0.24)

| | | | HB% >= 0.42

| | | | | Total Room Nights < 42.5 : 0 (1.33/0)

| | | | | Total Room Nights >= 42.5

| | | | | | Average pax/room < 2.26 : 20 (1/0)

| | | | | | Average pax/room >= 2.26 : 24 (1/0)

| | | Booking Source = BOOKING.COM

| | | | MONTH = April 2019 : 13 (1/0)

| | | | MONTH = May 2019 : 3 (1/0)

| | | | MONTH = June 2019 : 11 (1/0)

| | | | MONTH = July 2019 : 2 (1/0)

| | | | MONTH = August 2019 : 9 (1/0)

| | | | MONTH = September 2019 : 3 (1/0)

| | | | MONTH = October 2019 : 2 (1/0)

| | | Booking Source = BRAVO TOURS

| | | | MONTH = April 2019 : 1 (1/0)

| | | | MONTH = May 2019 : 7 (1/0)

| | | | MONTH = June 2019 : 5 (1/0)

| | | | MONTH = July 2019 : 0 (0/0)

| | | | MONTH = August 2019 : 3 (1/0)

| | | | MONTH = September 2019 : 4 (1/0)

| | | | MONTH = October 2019 : 4 (1/0)

| | | Booking Source = EXPEDIA : 22 (1/0)

| | | Booking Source = ITAKA

| | | | MONTH = April 2019 : 2 (1/0)

| | | | MONTH = May 2019 : 15 (1/0)

| | | | MONTH = June 2019 : 0 (0/0)

| | | | MONTH = July 2019 : 0 (0/0)

| | | | MONTH = August 2019 : 0 (0/0)

| | | | MONTH = September 2019 : 0 (0/0)

| | | | MONTH = October 2019 : 13 (1/0)

| | | Booking Source = Jet2Holidays

| | | | BB < 113.5 : 0 (1/0)

| | | | BB >= 113.5

| | | | | Total Room Nights < 157.5 : 20 (1/0)

| | | | | Total Room Nights >= 157.5 : 18 (1/0)

| | | Booking Source = RAINBOW : 0.86 (7/0.12)

| | | Booking Source = SUNWEB

| | | | BB% < 0.47 : 12 (1/0)

| | | | BB% >= 0.47 : 4 (1/0)

| | | Booking Source = TUI Deutschland

| | | | MONTH = April 2019 : 3 (1/0)

| | | | MONTH = May 2019 : 2 (1/0)

| | | | MONTH = June 2019 : 12 (1/0)

| | | | MONTH = July 2019 : 13 (1/0)

| | | | MONTH = August 2019 : 7 (1/0)

| | | | MONTH = September 2019 : 14 (1/0)

| | | | MONTH = October 2019 : 1 (1/0)

| | | Booking Source = TUI NL

| | | | Total Room Nights < 105.5

| | | | | MONTH = April 2019 : 1 (1/0)

| | | | | MONTH = May 2019 : 0 (0/0)

| | | | | MONTH = June 2019 : 0 (0/0)

| | | | | MONTH = July 2019 : 6 (1/0)

| | | | | MONTH = August 2019 : 9 (1/0)

| | | | | MONTH = September 2019 : 0 (0/0)

| | | | | MONTH = October 2019 : 2 (1/0)

| | | | Total Room Nights >= 105.5 : 15.5 (2/0.25)

| | | Booking Source = TUI UK

| | | | BB < 140

| | | | | MONTH = April 2019 : 0 (1/0)

| | | | | MONTH = May 2019 : 1 (1/0)

| | | | | MONTH = June 2019 : 0 (0/0)

| | | | | MONTH = July 2019 : 5 (1/0)

| | | | | MONTH = August 2019 : 7 (1/0)

| | | | | MONTH = September 2019 : 8 (1/0)

| | | | | MONTH = October 2019 : 0 (0/0)

| | | | BB >= 140

| | | | | BB < 152.5 : 16 (1/0)

| | | | | BB >= 152.5 : 18 (1/0)

| | ADR >= 133.47

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 0 (0/0)

| | | MONTH = June 2019 : 0 (0/0)

| | | MONTH = July 2019

| | | | HB < 321.5 : 24 (1/0)

| | | | HB >= 321.5 : 27 (1/0)

| | | MONTH = August 2019 : 18 (1/0)

| | | MONTH = September 2019 : 0 (0/0)

| | | MONTH = October 2019 : 0 (0/0)

| Total Room Nights >= 176.5

| | TOTAL PAX Nights < 1040.5

| | | Country = Denmark

| | | | Average pax/room < 2.27

| | | | | Average pax/room < 2.12

| | | | | | AI < 641 : 40 (1/0)

| | | | | | AI >= 641 : 25 (1/0)

| | | | | Average pax/room >= 2.12

| | | | | | AI% < 0.5 : 34 (1/0)

| | | | | | AI% >= 0.5 : 39 (2/0)

| | | | Average pax/room >= 2.27 : 22 (1/0)

| | | Country = Finland : 0 (0/0)

| | | Country = Romania : 0 (0/0)

| | | Country = Vary

| | | | Total Room Nights < 227

| | | | | MONTH = April 2019 : 0 (0/0)

| | | | | MONTH = May 2019 : 0 (0/0)

| | | | | MONTH = June 2019 : 0 (0/0)

| | | | | MONTH = July 2019 : 0 (0/0)

| | | | | MONTH = August 2019 : 27 (1/0)

| | | | | MONTH = September 2019 : 26 (1/0)

| | | | | MONTH = October 2019 : 32 (1/0)

| | | | Total Room Nights >= 227

| | | | | HB% < 0.07 : 41 (1/0)

| | | | | HB% >= 0.07 : 45.5 (2/0.25)

| | | Country = Poland : 0 (0/0)

| | | Country = UK

| | | | TOTAL PAX Nights < 602

| | | | | TOTAL PAX Nights < 545.5 : 28 (1/0)

| | | | | TOTAL PAX Nights >= 545.5 : 22 (1/0)

| | | | TOTAL PAX Nights >= 602 : 34.5 (2/0.25)

| | | Country = Netherlands

| | | | Average pax/room < 2.08 : 16 (1/0)

| | | | Average pax/room >= 2.08

| | | | | HB < 22 : 19 (1/0)

| | | | | HB >= 22

| | | | | | BB < 348.5 : 23.33 (3/0.22)

| | | | | | BB >= 348.5 : 21 (1/0)

| | | Country = Germany : 0 (0/0)

| | TOTAL PAX Nights >= 1040.5

| | | TOTAL PAX Nights < 1639.5

| | | | Average pax/room < 2.5 : 56 (1/0)

| | | | Average pax/room >= 2.5 : 63 (2/0)

| | | TOTAL PAX Nights >= 1639.5 : 41.5 (2/0.25)

TOTAL PAX Nights >= 1867

| TOTAL PAX Nights < 2480.5

| | Average pax/room < 2.51

| | | ADR < 77.03 : 78 (1/0)

| | | ADR >= 77.03 : 82 (1/0)

| | Average pax/room >= 2.51 : 92 (1/0)

| TOTAL PAX Nights >= 2480.5

| | Total Room Nights < 1176 : 125 (1/0)

| | Total Room Nights >= 1176

| | | Average pax/room < 2.96 : 132 (1/0)

| | | Average pax/room >= 2.96 : 135 (1/0)

Size of the tree : 142

RandomTree

==========

TOTAL PAX Nights < 1867

| TOTAL PAX Nights < 338.5

| | TOTAL PAX Nights < 93.5

| | | ADR < 66.69 : 0.58 (12/0.41)

| | | ADR >= 66.69

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 2.5 (4/0.25)

| | | | Booking Source = BRAVO TOURS

| | | | | ADR < 71.4 : 7 (1/0)

| | | | | ADR >= 71.4 : 3.67 (3/0.22)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA : 2 (1/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 1 (5/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 2 (3/0.67)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 5 (1/0)

| | TOTAL PAX Nights >= 93.5

| | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN

| | | | MONTH = April 2019 : 0 (0/0)

| | | | MONTH = May 2019 : 0 (0/0)

| | | | MONTH = June 2019 : 24 (1/0)

| | | | MONTH = July 2019 : 0 (0/0)

| | | | MONTH = August 2019 : 18 (1/0)

| | | | MONTH = September 2019 : 20 (1/0)

| | | | MONTH = October 2019 : 0 (0/0)

| | | Booking Source = BOOKING.COM

| | | | Average pax/room < 2.53 : 9 (1/0)

| | | | Average pax/room >= 2.53

| | | | | ADR < 97.15 : 13 (1/0)

| | | | | ADR >= 97.15 : 11 (1/0)

| | | Booking Source = BRAVO TOURS : 5 (1/0)

| | | Booking Source = EXPEDIA : 22 (1/0)

| | | Booking Source = ITAKA

| | | | Average pax/room < 2.7 : 13 (1/0)

| | | | Average pax/room >= 2.7 : 15 (1/0)

| | | Booking Source = Jet2Holidays : 20 (1/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SUNWEB

| | | | TOTAL PAX Nights < 202.5 : 4 (1/0)

| | | | TOTAL PAX Nights >= 202.5 : 12 (1/0)

| | | Booking Source = TUI Deutschland

| | | | MONTH = April 2019 : 0 (0/0)

| | | | MONTH = May 2019 : 0 (0/0)

| | | | MONTH = June 2019 : 12 (1/0)

| | | | MONTH = July 2019 : 13 (1/0)

| | | | MONTH = August 2019 : 7 (1/0)

| | | | MONTH = September 2019 : 14 (1/0)

| | | | MONTH = October 2019 : 0 (0/0)

| | | Booking Source = TUI NL

| | | | TOTAL PAX Nights < 237.5

| | | | | Average pax/room < 2.38 : 6 (1/0)

| | | | | Average pax/room >= 2.38 : 9 (1/0)

| | | | TOTAL PAX Nights >= 237.5 : 15.5 (2/0.25)

| | | Booking Source = TUI UK

| | | | Total Room Nights < 110.5 : 7.5 (2/0.25)

| | | | Total Room Nights >= 110.5

| | | | | BB < 152.5 : 16 (1/0)

| | | | | BB >= 152.5 : 18 (1/0)

| TOTAL PAX Nights >= 338.5

| | MONTH = April 2019 : 41 (1/0)

| | MONTH = May 2019

| | | TOTAL PAX Nights < 612.5

| | | | Country = Denmark : 34 (1/0)

| | | | Country = Finland : 0 (0/0)

| | | | Country = Romania : 0 (0/0)

| | | | Country = Vary : 0 (0/0)

| | | | Country = Poland : 0 (0/0)

| | | | Country = UK : 28 (1/0)

| | | | Country = Netherlands : 0 (0/0)

| | | | Country = Germany : 0 (0/0)

| | | TOTAL PAX Nights >= 612.5 : 21 (1/0)

| | MONTH = June 2019

| | | Booking Source = ARHUS CHARTER : 40 (1/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | Booking Source = BOOKING.COM : 0 (0/0)

| | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | Booking Source = EXPEDIA : 45 (1/0)

| | | Booking Source = ITAKA : 63 (1/0)

| | | Booking Source = Jet2Holidays : 0 (0/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SUNWEB : 24 (1/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 0 (0/0)

| | | Booking Source = TUI UK : 0 (0/0)

| | MONTH = July 2019

| | | Booking Source = ARHUS CHARTER : 39 (1/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 27 (1/0)

| | | Booking Source = BOOKING.COM : 0 (0/0)

| | | Booking Source = BRAVO TOURS : 24 (1/0)

| | | Booking Source = EXPEDIA : 46 (1/0)

| | | Booking Source = ITAKA : 42 (1/0)

| | | Booking Source = Jet2Holidays : 35 (1/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SUNWEB : 23 (1/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 0 (0/0)

| | | Booking Source = TUI UK : 0 (0/0)

| | MONTH = August 2019

| | | Average pax/room < 3.05

| | | | Country = Denmark : 25 (1/0)

| | | | Country = Finland : 0 (0/0)

| | | | Country = Romania : 0 (0/0)

| | | | Country = Vary : 27 (1/0)

| | | | Country = Poland : 0 (0/0)

| | | | Country = UK : 22 (1/0)

| | | | Country = Netherlands : 19 (1/0)

| | | | Country = Germany : 0 (0/0)

| | | Average pax/room >= 3.05 : 41 (1/0)

| | MONTH = September 2019

| | | Booking Source = ARHUS CHARTER : 39 (1/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | Booking Source = BOOKING.COM : 0 (0/0)

| | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | Booking Source = EXPEDIA : 26 (1/0)

| | | Booking Source = ITAKA : 56 (1/0)

| | | Booking Source = Jet2Holidays : 34 (1/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SUNWEB : 23 (1/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 16 (1/0)

| | | Booking Source = TUI UK : 0 (0/0)

| | MONTH = October 2019

| | | Average pax/room < 2.46

| | | | Country = Denmark : 22 (1/0)

| | | | Country = Finland : 0 (0/0)

| | | | Country = Romania : 0 (0/0)

| | | | Country = Vary : 32 (1/0)

| | | | Country = Poland : 0 (0/0)

| | | | Country = UK : 18 (1/0)

| | | | Country = Netherlands : 0 (0/0)

| | | | Country = Germany : 0 (0/0)

| | | Average pax/room >= 2.46 : 63 (1/0)

TOTAL PAX Nights >= 1867

| AI% < 0.18

| | ADR < 77.03 : 78 (1/0)

| | ADR >= 77.03 : 82 (1/0)

| AI% >= 0.18

| | TOTAL PAX Nights < 2480.5 : 92 (1/0)

| | TOTAL PAX Nights >= 2480.5

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 125 (1/0)

| | | MONTH = June 2019 : 132 (1/0)

| | | MONTH = July 2019 : 135 (1/0)

| | | MONTH = August 2019 : 0 (0/0)

| | | MONTH = September 2019 : 0 (0/0)

| | | MONTH = October 2019 : 0 (0/0)

Size of the tree : 156

RandomTree

==========

Average pax/room < 2

| TOTAL PAX Nights < 216

| | TOTAL PAX Nights < 55 : 1.14 (12.27/0.49)

| | TOTAL PAX Nights >= 55

| | | ADR < 75.48 : 7.5 (2/0.25)

| | | ADR >= 75.48 : 4.5 (2/0.25)

| TOTAL PAX Nights >= 216

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 22 (1/0)

| | MONTH = June 2019 : 18 (1/0)

| | MONTH = July 2019 : 0 (0/0)

| | MONTH = August 2019 : 0 (0/0)

| | MONTH = September 2019 : 0 (0/0)

| | MONTH = October 2019 : 16 (1/0)

Average pax/room >= 2

| HB% < 0.28

| | Country = Denmark

| | | Total Room Nights < 103 : 0 (0.58/0)

| | | Total Room Nights >= 103

| | | | Average pax/room < 2.27

| | | | | BB% < 0.5

| | | | | | Total Room Nights < 306 : 39.5 (2/0.25)

| | | | | | Total Room Nights >= 306

| | | | | | | Average pax/room < 2.12 : 25 (1/0)

| | | | | | | Average pax/room >= 2.12 : 39 (1/0)

| | | | | BB% >= 0.5 : 34 (1/0)

| | | | Average pax/room >= 2.27 : 22 (1/0)

| | Country = Finland

| | | Total Room Nights < 1040.5

| | | | Total Room Nights < 699 : 63 (1/0)

| | | | Total Room Nights >= 699

| | | | | MONTH = April 2019 : 78 (1/0)

| | | | | MONTH = May 2019 : 0 (0/0)

| | | | | MONTH = June 2019 : 0 (0/0)

| | | | | MONTH = July 2019 : 0 (0/0)

| | | | | MONTH = August 2019 : 92 (1/0)

| | | | | MONTH = September 2019 : 82 (1/0)

| | | | | MONTH = October 2019 : 0 (0/0)

| | | Total Room Nights >= 1040.5

| | | | Total Room Nights < 1176 : 125 (1/0)

| | | | Total Room Nights >= 1176

| | | | | Total Room Nights < 1217.5 : 135 (1/0)

| | | | | Total Room Nights >= 1217.5 : 132 (1/0)

| | Country = Romania : 0 (1.15/0)

| | Country = Vary

| | | Total Room Nights < 106.5 : 2.33 (3/0.22)

| | | Total Room Nights >= 106.5

| | | | HB% < 0.23

| | | | | TOTAL PAX Nights < 501 : 32 (1/0)

| | | | | TOTAL PAX Nights >= 501

| | | | | | ADR < 65.59 : 41 (1/0)

| | | | | | ADR >= 65.59 : 45.5 (2/0.25)

| | | | HB% >= 0.23 : 26.5 (2/0.25)

| | Country = Poland

| | | TOTAL PAX Nights < 777.5

| | | | Total Room Nights < 57 : 1.27 (1.58/0.93)

| | | | Total Room Nights >= 57

| | | | | Total Room Nights < 104.5 : 15 (1/0)

| | | | | Total Room Nights >= 104.5 : 13 (1/0)

| | | TOTAL PAX Nights >= 777.5

| | | | Average pax/room < 3.07

| | | | | TOTAL PAX Nights < 1410.5 : 56 (1/0)

| | | | | TOTAL PAX Nights >= 1410.5 : 63 (1/0)

| | | | Average pax/room >= 3.07 : 41.5 (2/0.25)

| | Country = UK

| | | BB < 149

| | | | BB% < 0.7 : 4.44 (1.58/11.37)

| | | | BB% >= 0.7 : 0.63 (1.58/0.23)

| | | BB >= 149

| | | | Total Room Nights < 225

| | | | | TOTAL PAX Nights < 475

| | | | | | TOTAL PAX Nights < 332.5 : 20 (1/0)

| | | | | | TOTAL PAX Nights >= 332.5 : 18 (1/0)

| | | | | TOTAL PAX Nights >= 475 : 22 (1/0)

| | | | Total Room Nights >= 225

| | | | | MONTH = April 2019 : 0 (0/0)

| | | | | MONTH = May 2019 : 28 (1/0)

| | | | | MONTH = June 2019 : 0 (0/0)

| | | | | MONTH = July 2019 : 35 (1/0)

| | | | | MONTH = August 2019 : 0 (0/0)

| | | | | MONTH = September 2019 : 34 (1/0)

| | | | | MONTH = October 2019 : 0 (0/0)

| | Country = Netherlands

| | | BB < 201.5

| | | | BB < 90.5

| | | | | HB < 3

| | | | | | ADR < 55.51 : 1 (1/0)

| | | | | | ADR >= 55.51 : 4 (1/0)

| | | | | HB >= 3 : 6 (1/0)

| | | | BB >= 90.5

| | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | | Booking Source = ITAKA : 0 (0/0)

| | | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | | Booking Source = RAINBOW : 0 (0/0)

| | | | | Booking Source = SUNWEB : 12 (1/0)

| | | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | | Booking Source = TUI NL : 9 (1/0)

| | | | | Booking Source = TUI UK : 0 (0/0)

| | | BB >= 201.5

| | | | TOTAL PAX Nights < 533 : 16 (2/0)

| | | | TOTAL PAX Nights >= 533

| | | | | Total Room Nights < 272 : 24 (1/0)

| | | | | Total Room Nights >= 272

| | | | | | ADR < 114.13

| | | | | | | BB < 294 : 19 (1/0)

| | | | | | | BB >= 294

| | | | | | | | Average pax/room < 2.17 : 23 (1/0)

| | | | | | | | Average pax/room >= 2.17 : 21 (1/0)

| | | | | | ADR >= 114.13 : 23 (1/0)

| | Country = Germany : 0 (0/0)

| HB% >= 0.28

| | Total Room Nights < 43

| | | TO/ OTA = TO

| | | | Total Room Nights < 14 : 0 (1.27/0)

| | | | Total Room Nights >= 14

| | | | | Average pax/room < 2.98 : 3 (4/0.5)

| | | | | Average pax/room >= 2.98 : 5 (1/0)

| | | TO/ OTA = OTA

| | | | ADR < 100.75 : 13 (1/0)

| | | | ADR >= 100.75 : 9 (1/0)

| | Total Room Nights >= 43

| | | AI < 10

| | | | Average pax/room < 2.19 : 20 (1/0)

| | | | Average pax/room >= 2.19

| | | | | AI% < 0.02 : 12 (3/0.67)

| | | | | AI% >= 0.02 : 7 (1/0)

| | | AI >= 10

| | | | Country = Denmark : 24 (1/0)

| | | | Country = Finland : 0 (0/0)

| | | | Country = Romania

| | | | | MONTH = April 2019 : 0 (0/0)

| | | | | MONTH = May 2019 : 0 (0/0)

| | | | | MONTH = June 2019 : 24 (1/0)

| | | | | MONTH = July 2019 : 27 (1/0)

| | | | | MONTH = August 2019 : 18 (1/0)

| | | | | MONTH = September 2019 : 0 (0/0)

| | | | | MONTH = October 2019 : 0 (0/0)

| | | | Country = Vary : 0 (0/0)

| | | | Country = Poland : 0 (0/0)

| | | | Country = UK : 0 (0/0)

| | | | Country = Netherlands : 15 (1/0)

| | | | Country = Germany : 14 (1/0)

Size of the tree : 148

RandomTree

==========

Booking Source = ARHUS CHARTER

| AI < 542.5

| | TOTAL PAX Nights < 244 : 0 (1/0)

| | TOTAL PAX Nights >= 244

| | | ADR < 44.02 : 34 (1/0)

| | | ADR >= 44.02 : 22 (1/0)

| AI >= 542.5

| | Total Room Nights < 306 : 39.5 (2/0.25)

| | Total Room Nights >= 306

| | | Average pax/room < 2.12 : 25 (1/0)

| | | Average pax/room >= 2.12 : 39 (1/0)

Booking Source = AURINKOMATKAT

| TOTAL PAX Nights < 2480.5

| | MONTH = April 2019 : 78 (1/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 0 (0/0)

| | MONTH = July 2019 : 0 (0/0)

| | MONTH = August 2019 : 92 (1/0)

| | MONTH = September 2019 : 82 (1/0)

| | MONTH = October 2019 : 63 (1/0)

| TOTAL PAX Nights >= 2480.5

| | TOTAL PAX Nights < 3032 : 125 (1/0)

| | TOTAL PAX Nights >= 3032

| | | Total Room Nights < 1217.5 : 135 (1/0)

| | | Total Room Nights >= 1217.5 : 132 (1/0)

Booking Source = BLUE AEGEAN

| ADR < 43.99 : 0.33 (3/0.22)

| ADR >= 43.99

| | TOTAL PAX Nights < 227.5

| | | HB < 168 : 18 (1/0)

| | | HB >= 168 : 20 (1/0)

| | TOTAL PAX Nights >= 227.5

| | | ADR < 116.24 : 24 (1/0)

| | | ADR >= 116.24 : 27 (1/0)

Booking Source = BOOKING.COM

| Total Room Nights < 29 : 2.5 (4/0.25)

| Total Room Nights >= 29

| | ADR < 97.15 : 13 (1/0)

| | ADR >= 97.15

| | | TOTAL PAX Nights < 156.5 : 9 (1/0)

| | | TOTAL PAX Nights >= 156.5 : 11 (1/0)

Booking Source = BRAVO TOURS

| ADR < 129.51

| | Total Room Nights < 32

| | | Average pax/room < 2.4 : 1 (1/0)

| | | Average pax/room >= 2.4 : 3 (1/0)

| | Total Room Nights >= 32

| | | Average pax/room < 1.94 : 7 (1/0)

| | | Average pax/room >= 1.94 : 4.33 (3/0.22)

| ADR >= 129.51 : 24 (1/0)

Booking Source = EXPEDIA

| MONTH = April 2019 : 41 (1/0)

| MONTH = May 2019 : 22 (1/0)

| MONTH = June 2019 : 45 (1/0)

| MONTH = July 2019 : 46 (1/0)

| MONTH = August 2019 : 27 (1/0)

| MONTH = September 2019 : 26 (1/0)

| MONTH = October 2019 : 32 (1/0)

Booking Source = ITAKA

| ADR < 100.16

| | BB < 24

| | | Average pax/room < 2.7 : 13 (1/0)

| | | Average pax/room >= 2.7 : 15 (1/0)

| | BB >= 24 : 2 (1/0)

| ADR >= 100.16

| | Total Room Nights < 533.5

| | | TOTAL PAX Nights < 1410.5 : 56 (1/0)

| | | TOTAL PAX Nights >= 1410.5 : 63 (1/0)

| | Total Room Nights >= 533.5 : 41.5 (2/0.25)

Booking Source = Jet2Holidays

| MONTH = April 2019 : 0 (1/0)

| MONTH = May 2019 : 28 (1/0)

| MONTH = June 2019 : 20 (1/0)

| MONTH = July 2019 : 35 (1/0)

| MONTH = August 2019 : 22 (1/0)

| MONTH = September 2019 : 34 (1/0)

| MONTH = October 2019 : 18 (1/0)

Booking Source = RAINBOW : 0.86 (7/0.12)

Booking Source = SUNWEB

| MONTH = April 2019 : 4 (1/0)

| MONTH = May 2019 : 21 (1/0)

| MONTH = June 2019 : 24 (1/0)

| MONTH = July 2019 : 23 (1/0)

| MONTH = August 2019 : 19 (1/0)

| MONTH = September 2019 : 23 (1/0)

| MONTH = October 2019 : 12 (1/0)

Booking Source = TUI Deutschland

| AI < 28

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 2 (1/0)

| | MONTH = June 2019 : 12 (1/0)

| | MONTH = July 2019 : 13 (1/0)

| | MONTH = August 2019 : 7 (1/0)

| | MONTH = September 2019 : 14 (1/0)

| | MONTH = October 2019 : 1 (1/0)

| AI >= 28 : 3 (1/0)

Booking Source = TUI NL

| Total Room Nights < 105.5

| | Total Room Nights < 36.5 : 1.5 (2/0.25)

| | Total Room Nights >= 36.5

| | | TOTAL PAX Nights < 175.5 : 6 (1/0)

| | | TOTAL PAX Nights >= 175.5 : 9 (1/0)

| Total Room Nights >= 105.5 : 15.67 (3/0.22)

Booking Source = TUI UK

| TOTAL PAX Nights < 216

| | AI% < 0.06 : 0.8 (1.25/0.16)

| | AI% >= 0.06

| | | MONTH = April 2019 : 0 (0.75/0)

| | | MONTH = May 2019 : 0 (0/0)

| | | MONTH = June 2019 : 0 (0/0)

| | | MONTH = July 2019 : 5 (1/0)

| | | MONTH = August 2019 : 7 (1/0)

| | | MONTH = September 2019 : 8 (1/0)

| | | MONTH = October 2019 : 0 (0/0)

| TOTAL PAX Nights >= 216

| | ADR < 72.12 : 16 (1/0)

| | ADR >= 72.12 : 18 (1/0)

Size of the tree : 118

RandomTree

==========

Country = Denmark

| HB% < 0.36

| | MONTH = April 2019 : 0 (0.46/0)

| | MONTH = May 2019 : 34 (1/0)

| | MONTH = June 2019 : 40 (1/0)

| | MONTH = July 2019 : 39 (1/0)

| | MONTH = August 2019 : 25 (1/0)

| | MONTH = September 2019 : 39 (1/0)

| | MONTH = October 2019 : 22 (1/0)

| HB% >= 0.36

| | TOTAL PAX Nights < 246

| | | ADR < 58.92 : 0.65 (1.54/0.23)

| | | ADR >= 58.92

| | | | ADR < 71.4 : 7 (1/0)

| | | | ADR >= 71.4 : 4 (4/0.5)

| | TOTAL PAX Nights >= 246 : 24 (1/0)

Country = Finland

| MONTH = April 2019 : 78 (1/0)

| MONTH = May 2019 : 125 (1/0)

| MONTH = June 2019 : 132 (1/0)

| MONTH = July 2019 : 135 (1/0)

| MONTH = August 2019 : 92 (1/0)

| MONTH = September 2019 : 82 (1/0)

| MONTH = October 2019 : 63 (1/0)

Country = Romania

| Total Room Nights < 28 : 0.33 (3/0.22)

| Total Room Nights >= 28

| | Average pax/room < 3.2

| | | AI < 6 : 20 (1/0)

| | | AI >= 6

| | | | AI < 27 : 27 (1/0)

| | | | AI >= 27 : 24 (1/0)

| | Average pax/room >= 3.2 : 18 (1/0)

Country = Vary

| HB < 10 : 2.5 (4/0.25)

| HB >= 10

| | BB < 492.5

| | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | Booking Source = BOOKING.COM

| | | | TOTAL PAX Nights < 100.5 : 9 (1/0)

| | | | TOTAL PAX Nights >= 100.5

| | | | | BB < 110.5 : 13 (1/0)

| | | | | BB >= 110.5 : 11 (1/0)

| | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | Booking Source = EXPEDIA

| | | | BB < 303 : 22 (1/0)

| | | | BB >= 303

| | | | | MONTH = April 2019 : 0 (0/0)

| | | | | MONTH = May 2019 : 0 (0/0)

| | | | | MONTH = June 2019 : 0 (0/0)

| | | | | MONTH = July 2019 : 0 (0/0)

| | | | | MONTH = August 2019 : 27 (1/0)

| | | | | MONTH = September 2019 : 26 (1/0)

| | | | | MONTH = October 2019 : 32 (1/0)

| | | Booking Source = ITAKA : 0 (0/0)

| | | Booking Source = Jet2Holidays : 0 (0/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SUNWEB : 0 (0/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 0 (0/0)

| | | Booking Source = TUI UK : 0 (0/0)

| | BB >= 492.5

| | | TOTAL PAX Nights < 566.5 : 41 (1/0)

| | | TOTAL PAX Nights >= 566.5 : 45.5 (2/0.25)

Country = Poland

| TOTAL PAX Nights < 777.5

| | AI < 146 : 1 (8/0.25)

| | AI >= 146

| | | Average pax/room < 2.7 : 13 (1/0)

| | | Average pax/room >= 2.7 : 15 (1/0)

| TOTAL PAX Nights >= 777.5

| | MONTH = April 2019 : 0 (0/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 63 (1/0)

| | MONTH = July 2019 : 42 (1/0)

| | MONTH = August 2019 : 41 (1/0)

| | MONTH = September 2019 : 56 (1/0)

| | MONTH = October 2019 : 0 (0/0)

Country = UK

| TOTAL PAX Nights < 216

| | Total Room Nights < 31 : 0.33 (3/0.22)

| | Total Room Nights >= 31

| | | ADR < 79.73 : 8 (1/0)

| | | ADR >= 79.73

| | | | ADR < 103.68 : 5 (1/0)

| | | | ADR >= 103.68 : 7 (1/0)

| TOTAL PAX Nights >= 216

| | Average pax/room < 2.06

| | | Average pax/room < 1.94 : 16 (1/0)

| | | Average pax/room >= 1.94

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA : 0 (0/0)

| | | | Booking Source = Jet2Holidays : 20 (1/0)

| | | | Booking Source = RAINBOW : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 18 (1/0)

| | Average pax/room >= 2.06

| | | BB < 283 : 18 (1/0)

| | | BB >= 283

| | | | Total Room Nights < 246

| | | | | ADR < 81.69 : 28 (1/0)

| | | | | ADR >= 81.69 : 22 (1/0)

| | | | Total Room Nights >= 246 : 34.5 (2/0.25)

Country = Netherlands

| Total Room Nights < 105.5

| | MONTH = April 2019

| | | Average pax/room < 2.87 : 4 (1/0)

| | | Average pax/room >= 2.87 : 1 (1/0)

| | MONTH = May 2019 : 0 (0/0)

| | MONTH = June 2019 : 0 (0/0)

| | MONTH = July 2019 : 6 (1/0)

| | MONTH = August 2019 : 9 (1/0)

| | MONTH = September 2019 : 0 (0/0)

| | MONTH = October 2019 : 2 (1/0)

| Total Room Nights >= 105.5

| | TOTAL PAX Nights < 533

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 16 (1/0)

| | | MONTH = June 2019 : 15 (1/0)

| | | MONTH = July 2019 : 0 (0/0)

| | | MONTH = August 2019 : 0 (0/0)

| | | MONTH = September 2019 : 16 (1/0)

| | | MONTH = October 2019 : 12 (1/0)

| | TOTAL PAX Nights >= 533

| | | ADR < 91.61

| | | | MONTH = April 2019 : 0 (0/0)

| | | | MONTH = May 2019 : 21 (1/0)

| | | | MONTH = June 2019 : 24 (1/0)

| | | | MONTH = July 2019 : 0 (0/0)

| | | | MONTH = August 2019 : 0 (0/0)

| | | | MONTH = September 2019 : 23 (1/0)

| | | | MONTH = October 2019 : 0 (0/0)

| | | ADR >= 91.61

| | | | BB < 258 : 23 (1/0)

| | | | BB >= 258 : 19 (1/0)

Country = Germany

| MONTH = April 2019 : 3 (1/0)

| MONTH = May 2019 : 2 (1/0)

| MONTH = June 2019 : 12 (1/0)

| MONTH = July 2019 : 13 (1/0)

| MONTH = August 2019 : 7 (1/0)

| MONTH = September 2019 : 14 (1/0)

| MONTH = October 2019 : 1 (1/0)

Size of the tree : 153

RandomTree

==========

Total Room Nights < 569.5

| Booking Source = ARHUS CHARTER

| | BB < 244

| | | Total Room Nights < 103 : 0 (1/0)

| | | Total Room Nights >= 103

| | | | Average pax/room < 2.26

| | | | | MONTH = April 2019 : 0 (0/0)

| | | | | MONTH = May 2019 : 0 (0/0)

| | | | | MONTH = June 2019 : 40 (1/0)

| | | | | MONTH = July 2019 : 39 (1/0)

| | | | | MONTH = August 2019 : 25 (1/0)

| | | | | MONTH = September 2019 : 39 (1/0)

| | | | | MONTH = October 2019 : 0 (0/0)

| | | | Average pax/room >= 2.26 : 22 (1/0)

| | BB >= 244 : 34 (1/0)

| Booking Source = AURINKOMATKAT : 0 (0/0)

| Booking Source = BLUE AEGEAN

| | MONTH = April 2019 : 0 (1/0)

| | MONTH = May 2019 : 1 (1/0)

| | MONTH = June 2019 : 24 (1/0)

| | MONTH = July 2019 : 27 (1/0)

| | MONTH = August 2019 : 18 (1/0)

| | MONTH = September 2019 : 20 (1/0)

| | MONTH = October 2019 : 0 (1/0)

| Booking Source = BOOKING.COM

| | TOTAL PAX Nights < 81.5 : 2.5 (4/0.25)

| | TOTAL PAX Nights >= 81.5

| | | Average pax/room < 2.53 : 9 (1/0)

| | | Average pax/room >= 2.53

| | | | Average pax/room < 2.83 : 13 (1/0)

| | | | Average pax/room >= 2.83 : 11 (1/0)

| Booking Source = BRAVO TOURS

| | Total Room Nights < 88

| | | MONTH = April 2019 : 1 (1/0)

| | | MONTH = May 2019 : 7 (1/0)

| | | MONTH = June 2019 : 5 (1/0)

| | | MONTH = July 2019 : 0 (0/0)

| | | MONTH = August 2019 : 3 (1/0)

| | | MONTH = September 2019 : 4 (1/0)

| | | MONTH = October 2019 : 4 (1/0)

| | Total Room Nights >= 88 : 24 (1/0)

| Booking Source = EXPEDIA

| | BB < 492.5

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 22 (1/0)

| | | MONTH = June 2019 : 0 (0/0)

| | | MONTH = July 2019 : 0 (0/0)

| | | MONTH = August 2019 : 27 (1/0)

| | | MONTH = September 2019 : 26 (1/0)

| | | MONTH = October 2019 : 32 (1/0)

| | BB >= 492.5

| | | TOTAL PAX Nights < 566.5 : 41 (1/0)

| | | TOTAL PAX Nights >= 566.5 : 45.5 (2/0.25)

| Booking Source = ITAKA

| | ADR < 100.16

| | | TOTAL PAX Nights < 157 : 2 (1/0)

| | | TOTAL PAX Nights >= 157

| | | | Average pax/room < 2.7 : 13 (1/0)

| | | | Average pax/room >= 2.7 : 15 (1/0)

| | ADR >= 100.16

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 0 (0/0)

| | | MONTH = June 2019 : 63 (1/0)

| | | MONTH = July 2019 : 42 (1/0)

| | | MONTH = August 2019 : 41 (1/0)

| | | MONTH = September 2019 : 56 (1/0)

| | | MONTH = October 2019 : 0 (0/0)

| Booking Source = Jet2Holidays

| | TOTAL PAX Nights < 155.5 : 0 (1/0)

| | TOTAL PAX Nights >= 155.5

| | | Total Room Nights < 225

| | | | ADR < 88.71

| | | | | ADR < 61.23 : 20 (1/0)

| | | | | ADR >= 61.23 : 18 (1/0)

| | | | ADR >= 88.71 : 22 (1/0)

| | | Total Room Nights >= 225

| | | | ADR < 63.28 : 28 (1/0)

| | | | ADR >= 63.28 : 34.5 (2/0.25)

| Booking Source = RAINBOW : 0.86 (7/0.12)

| Booking Source = SUNWEB

| | MONTH = April 2019 : 4 (1/0)

| | MONTH = May 2019 : 21 (1/0)

| | MONTH = June 2019 : 24 (1/0)

| | MONTH = July 2019 : 23 (1/0)

| | MONTH = August 2019 : 19 (1/0)

| | MONTH = September 2019 : 23 (1/0)

| | MONTH = October 2019 : 12 (1/0)

| Booking Source = TUI Deutschland

| | MONTH = April 2019 : 3 (1/0)

| | MONTH = May 2019 : 2 (1/0)

| | MONTH = June 2019 : 12 (1/0)

| | MONTH = July 2019 : 13 (1/0)

| | MONTH = August 2019 : 7 (1/0)

| | MONTH = September 2019 : 14 (1/0)

| | MONTH = October 2019 : 1 (1/0)

| Booking Source = TUI NL

| | Total Room Nights < 105.5

| | | ADR < 72.11 : 1.5 (2/0.25)

| | | ADR >= 72.11

| | | | ADR < 99.22 : 9 (1/0)

| | | | ADR >= 99.22 : 6 (1/0)

| | Total Room Nights >= 105.5 : 15.67 (3/0.22)

| Booking Source = TUI UK

| | Total Room Nights < 110.5

| | | MONTH = April 2019 : 0 (1/0)

| | | MONTH = May 2019 : 1 (1/0)

| | | MONTH = June 2019 : 0 (0/0)

| | | MONTH = July 2019 : 5 (1/0)

| | | MONTH = August 2019 : 7 (1/0)

| | | MONTH = September 2019 : 8 (1/0)

| | | MONTH = October 2019 : 0 (0/0)

| | Total Room Nights >= 110.5

| | | Average pax/room < 1.94 : 16 (1/0)

| | | Average pax/room >= 1.94 : 18 (1/0)

Total Room Nights >= 569.5

| MONTH = April 2019 : 78 (1/0)

| MONTH = May 2019 : 125 (1/0)

| MONTH = June 2019 : 132 (1/0)

| MONTH = July 2019 : 135 (1/0)

| MONTH = August 2019 : 92 (1/0)

| MONTH = September 2019 : 82 (1/0)

| MONTH = October 2019 : 63 (1/0)

Size of the tree : 123

Classifiers with low or negative correlation coefficient (2019):

Lazy K Star

=== Summary ===

Correlation coefficient 0.9327

Mean absolute error 5.6405

Root mean squared error 10.2027

Relative absolute error 29.5003 %

Root relative squared error 36.0832 %

Total Number of Instances 91

Multilayer Perceptron

=== Classifier model (full training set) ===

Linear Node 0

Inputs Weights

Threshold 0.07109771693061714

Node 1 -0.40296824691080807

Node 2 -0.6621335013310197

Node 3 -0.15864620365909546

Node 4 0.48608176152571403

Node 5 0.320017054944052

Node 6 -0.015398430701580727

Node 7 0.2678088365511743

Node 8 0.789022850752216

Node 9 0.0650264845432003

Node 10 -0.2576120577691362

Node 11 -0.10638092361038676

Node 12 -0.11877718270766281

Node 13 -0.43654228984554383

Node 14 0.043836947271253576

Node 15 -0.9001252189528062

Node 16 -0.004790221125993978

Node 17 -0.0012769329858275688

Node 18 0.06708084280419196

Node 19 0.7755129240131697

Node 20 0.5500903953235246

Sigmoid Node 1

Inputs Weights

Threshold -0.11326154146273766

Attrib Booking Source=ARHUS CHARTER -0.09418668469134503

Attrib Booking Source=AURINKOMATKAT -0.13467906112452732

Attrib Booking Source=BLUE AEGEAN -0.07189096692433342

Attrib Booking Source=BOOKING.COM 0.15133623162093096

Attrib Booking Source=BRAVO TOURS 0.44790692359303674

Attrib Booking Source=EXPEDIA -0.11927389893708984

Attrib Booking Source=ITAKA 0.1074193640614443

Attrib Booking Source=Jet2Holidays 0.012858384779396978

Attrib Booking Source=RAINBOW 0.35564479553726697

Attrib Booking Source=SUNWEB -0.366487876317349

Attrib Booking Source=TUI Deutschland 0.08323600411299704

Attrib Booking Source=TUI NL 0.3489859546182458

Attrib Booking Source=TUI UK -0.01940903138333248

Attrib Country=Denmark 0.28153762835641666

Attrib Country=Finland -0.2167262882646323

Attrib Country=Romania -0.14061327106561472

Attrib Country=Vary -0.017729858490741324

Attrib Country=Poland 0.434843453491475

Attrib Country=UK -0.0135769428443448

Attrib Country=Netherlands   -0.03816091862488667

Attrib Country=Germany   0.10735182934668279

Attrib Average pax/room   0.1514516521674497

Attrib TO/ OTA=OTA   -0.04595987161277557

Attrib ADR   -0.522669379038609

Attrib TOTAL PAX Nights   -0.7573891157291729

Attrib Total Room Nights   -1.033735878799182

Attrib BB   -0.22437045590270988

Attrib BB%   0.29573039967030723

Attrib HB   -0.21383402033083415

Attrib HB%   0.07587841944809334

Attrib AI   -0.15949481654894643

Attrib AI%   0.10878341562462213

Attrib MONTH=April 2019   0.18947180010603956

Attrib MONTH=May 2019   0.6932856731289202

Attrib MONTH=June 2019   0.29329771764356277

Attrib MONTH=July 2019   0.09335836708842352

Attrib MONTH=August 2019   -0.16581612258471282

Attrib MONTH=September 2019   -0.4713727079555084

Attrib MONTH=October 2019   -0.23470146813953838

Sigmoid Node 2

Inputs   Weights

Threshold   -0.14500373283323176

Attrib Booking Source=ARHUS CHARTER   -0.03331361622882429

Attrib Booking Source=AURINKOMATKAT   -0.050257277986903395

Attrib Booking Source=BLUE AEGEAN   0.25077196701663534

Attrib Booking Source=BOOKING.COM 0.31491757630579437

Attrib Booking Source=BRAVO TOURS 0.08827509041325324

Attrib Booking Source=EXPEDIA 0.1741498039085636

Attrib Booking Source=ITAKA 0.20222158513442773

Attrib Booking Source=Jet2Holidays 0.3104616636897445

Attrib Booking Source=RAINBOW -0.15953860368312195

Attrib Booking Source=SUNWEB 0.18851968172914688

Attrib Booking Source=TUI Deutschland 0.3851747861321432

Attrib Booking Source=TUI NL 0.3975115053101002

Attrib Booking Source=TUI UK -0.0870111750124361

Attrib Country=Denmark -0.11896972740448301

Attrib Country=Finland 0.0016599969185305513

Attrib Country=Romania 0.20774224545505507

Attrib Country=Vary 0.2040632841462182

Attrib Country=Poland -0.13266945629881008

Attrib Country=UK 0.061278986377222226

Attrib Country=Netherlands 0.37922647718146596

Attrib Country=Germany 0.3712168573446193

Attrib Average pax/room 0.08396269769215998

Attrib TO/ OTA=OTA 0.28356162492548515

Attrib ADR -0.04366042223209534

Attrib TOTAL PAX Nights -0.32948438932977686

Attrib Total Room Nights -0.4574275192442581

Attrib BB -0.10296993828844121

Attrib BB% 0.28674763733448444

Attrib HB 0.06408662386547005

Attrib HB%   0.01615493029088179

Attrib AI   0.0431817059589975

Attrib AI%   -0.10708461864550932

Attrib MONTH=April 2019   -0.260440029308215

Attrib MONTH=May 2019   -0.13095152958028575

Attrib MONTH=June 2019   -0.0728121516901253

Attrib MONTH=July 2019   0.6454272112242992

Attrib MONTH=August 2019   -0.20993254309204723

Attrib MONTH=September 2019   0.2109052653367657

Attrib MONTH=October 2019   0.6825318512200114

Sigmoid Node 3

Inputs   Weights

Threshold   -0.12187370738606022

Attrib Booking Source=ARHUS CHARTER   0.1579850297321055

Attrib Booking Source=AURINKOMATKAT   -8.478095328921116E-4

Attrib Booking Source=BLUE AEGEAN   0.1665869454257261

Attrib Booking Source=BOOKING.COM   0.09882429479270258

Attrib Booking Source=BRAVO TOURS   0.25773140197123395

Attrib Booking Source=EXPEDIA   0.08012593829802178

Attrib Booking Source=ITAKA   0.04357791897886238

Attrib Booking Source=Jet2Holidays   0.1666253739275713

Attrib Booking Source=RAINBOW   0.1203040290683847

Attrib Booking Source=SUNWEB   0.1253543807304496

Attrib Booking Source=TUI Deutschland   0.17851238115079268

Attrib Booking Source=TUI NL   0.09825808810535806

Attrib Booking Source=TUI UK   0.10133062696379672

Attrib Country=Denmark   0.1651785357083922

Attrib Country=Finland   0.007046427690325411

Attrib Country=Romania   0.18432658830673

Attrib Country=Vary   0.04198507177425412

Attrib Country=Poland   0.018369906920388642

Attrib Country=UK   0.07314959404029829

Attrib Country=Netherlands   0.1306865205368309

Attrib Country=Germany   0.19483778081901262

Attrib Average pax/room   0.005997231960752283

Attrib TO/ OTA=OTA   0.049008831157464475

Attrib ADR   -0.15509921459295542

Attrib TOTAL PAX Nights   -0.11164756926562847

Attrib Total Room Nights   -0.15925007238156058

Attrib BB   0.07263935241845097

Attrib BB%   0.0029110989607911888

Attrib HB   0.07176523537098872

Attrib HB%   0.12606596516987986

Attrib AI   0.07789109621684301

Attrib AI%   0.14204831239639912

Attrib MONTH=April 2019   0.2308082482521892

Attrib MONTH=May 2019   0.12092533153187415

Attrib MONTH=June 2019   0.0577454251000822

Attrib MONTH=July 2019   0.04297433848554704

Attrib MONTH=August 2019   0.11058058330616923

Attrib MONTH=September 2019   0.0426026414696721

Attrib MONTH=October 2019   0.06859656265485663

Sigmoid Node 4

Inputs   Weights

Threshold   -0.08829822544965715

Attrib Booking Source=ARHUS CHARTER   0.12324177977207927

Attrib Booking Source=AURINKOMATKAT   0.05397160950919729

Attrib Booking Source=BLUE AEGEAN   0.02466583249074063

Attrib Booking Source=BOOKING.COM   0.2665267928628154

Attrib Booking Source=BRAVO TOURS   -0.015150610277449116

Attrib Booking Source=EXPEDIA   0.13232030705877357

Attrib Booking Source=ITAKA   0.1068392553903618

Attrib Booking Source=Jet2Holidays   0.0907827192582196

Attrib Booking Source=RAINBOW   0.10329601189558947

Attrib Booking Source=SUNWEB   -0.01175395798822746

Attrib Booking Source=TUI Deutschland   0.028340793469234515

Attrib Booking Source=TUI NL   0.22416398532423068

Attrib Booking Source=TUI UK   0.06586345195569884

Attrib Country=Denmark   -0.03501608603358452

Attrib Country=Finland   0.06770683768503061

Attrib Country=Romania   0.05080125104070624

Attrib Country=Vary   0.3213045376069354

Attrib Country=Poland   0.11296256321750293

Attrib Country=UK   0.10990510339007457

Attrib Country=Netherlands   0.07305686378831382

Attrib Country=Germany   0.005457208305791118

Attrib Average pax/room   -0.16492836728381124

Attrib TO/ OTA=OTA   0.326247630937099

Attrib ADR   -0.07977152307546563

Attrib TOTAL PAX Nights   0.15618008664858826

Attrib Total Room Nights   0.22156951930064672

Attrib BB   0.03540490664427582

Attrib BB%   0.09310832691938212

Attrib HB   -0.14455010044267458

Attrib HB%   0.06661855672301585

Attrib AI   -0.04354004068407641

Attrib AI%   -0.10010928668837105

Attrib MONTH=April 2019   0.5946432116872858

Attrib MONTH=May 2019   0.08527148761822016

Attrib MONTH=June 2019   -0.07278774733945576

Attrib MONTH=July 2019   0.04033662719437262

Attrib MONTH=August 2019   0.0072897256959839115

Attrib MONTH=September 2019   -0.15781161348577807

Attrib MONTH=October 2019   0.05901007650322424

Sigmoid Node 5

Inputs   Weights

Threshold   -0.15252077397233652

Attrib Booking Source=ARHUS CHARTER   0.07401385666454594

Attrib Booking Source=AURINKOMATKAT   0.10590777355772074

Attrib Booking Source=BLUE AEGEAN   0.28090170282948274

Attrib Booking Source=BOOKING.COM   0.08912340454683429

Attrib Booking Source=BRAVO TOURS   -0.0976316151695189

Attrib Booking Source=EXPEDIA   0.08856501750543637

Attrib Booking Source=ITAKA   0.03856946851896069

Attrib Booking Source=Jet2Holidays   0.09233877121714698

Attrib Booking Source=RAINBOW   0.05904657225748539

Attrib Booking Source=SUNWEB   0.1678598277695587

Attrib Booking Source=TUI Deutschland   0.06913468165382287

Attrib Booking Source=TUI NL   0.2422502933503587

Attrib Booking Source=TUI UK   0.11185535211524558

Attrib Country=Denmark   -0.15242381945352576

Attrib Country=Finland   0.0752424399344786

Attrib Country=Romania   0.2609179095939755

Attrib Country=Vary   0.04468291498004096

Attrib Country=Poland   0.08237861016730219

Attrib Country=UK   0.11486401225167099

Attrib Country=Netherlands   0.2547513638153792

Attrib Country=Germany   0.06550378845086255

Attrib Average pax/room   -0.08472214449184247

Attrib TO/ OTA=OTA   0.03789259208746756

Attrib ADR   0.03685042924024216

Attrib TOTAL PAX Nights   0.1417816890393352

Attrib Total Room Nights   0.26792828752813647

Attrib BB   -0.0035004408384894442

Attrib BB%   -0.0914152732424823

Attrib HB   -0.06418134428561187

Attrib HB%   0.16115265563585196

Attrib AI   0.010943896463538716

Attrib AI%   -0.009691757867903376

Attrib MONTH=April 2019   0.09981967302232046

Attrib MONTH=May 2019   0.11883214384665779

Attrib MONTH=June 2019   0.20430824304867956

Attrib MONTH=July 2019   -0.020896928155150353

Attrib MONTH=August 2019   0.20915303451748152

Attrib MONTH=September 2019   -0.16155611842254664

Attrib MONTH=October 2019   0.231854245626138

Sigmoid Node 6

Inputs   Weights

Threshold   -0.1331528029674265

Attrib Booking Source=ARHUS CHARTER   0.057719189522516125

Attrib Booking Source=AURINKOMATKAT   -0.00755653730202173

Attrib Booking Source=BLUE AEGEAN   0.11929231068087226

Attrib Booking Source=BOOKING.COM   0.19856521682600506

Attrib Booking Source=BRAVO TOURS   0.16002439343823102

Attrib Booking Source=EXPEDIA   0.08968829936887909

Attrib Booking Source=ITAKA   0.13920970548733022

Attrib Booking Source=Jet2Holidays   0.08076861742413488

Attrib Booking Source=RAINBOW   0.13703068942672747

Attrib Booking Source=SUNWEB   0.14826069569889974

Attrib Booking Source=TUI Deutschland   0.15330433641868735

Attrib Booking Source=TUI NL   0.18576930489477836

Attrib Booking Source=TUI UK   0.15452186540542778

Attrib Country=Denmark   0.08466908100126325

Attrib Country=Finland   -0.011150216516441198

Attrib Country=Romania   0.19677612653771606

Attrib Country=Vary   0.09351783980625879

Attrib Country=Poland   0.15482882627369693

Attrib Country=UK   0.1163396795356653

Attrib Country=Netherlands   0.13512225230901656

Attrib Country=Germany   0.19961592020180285

Attrib Average pax/room   0.031111085009333697

Attrib TO/ OTA=OTA   0.11355168501362091

Attrib ADR   -0.08567324738980296

Attrib TOTAL PAX Nights   -0.044722261896475116

Attrib Total Room Nights   -0.1491737867134942

Attrib BB   -0.013378285846881973

Attrib BB%   0.06480063688733026

Attrib HB   -0.024653772906461577

Attrib HB%   0.06668995276620447

Attrib AI   0.036221882192291006

Attrib AI%   0.096547497715648

Attrib MONTH=April 2019   0.09692835002447044

Attrib MONTH=May 2019   0.1974239837379522

Attrib MONTH=June 2019   0.04000687818621975

Attrib MONTH=July 2019   0.20210575617104287

Attrib MONTH=August 2019   0.055327977811591614

Attrib MONTH=September 2019   0.11261169649761638

Attrib MONTH=October 2019   0.0425271153334509

Sigmoid Node 7

Inputs   Weights

Threshold   -0.08709508579313097

Attrib Booking Source=ARHUS CHARTER   0.06588302998863553

Attrib Booking Source=AURINKOMATKAT 0.12253460643975338

Attrib Booking Source=BLUE AEGEAN 0.1316971857888071

Attrib Booking Source=BOOKING.COM 0.05861057483807775

Attrib Booking Source=BRAVO TOURS 0.00418370598448621

Attrib Booking Source=EXPEDIA 0.22126166670689487

Attrib Booking Source=ITAKA 0.0565947799275185

Attrib Booking Source=Jet2Holidays 0.1848860561517084

Attrib Booking Source=RAINBOW 0.04802908010320675

Attrib Booking Source=SUNWEB 0.12701080415354205

Attrib Booking Source=TUI Deutschland 0.11214537715672059

Attrib Booking Source=TUI NL 0.16140945726636838

Attrib Booking Source=TUI UK 0.018877026669084085

Attrib Country=Denmark 0.03053721393371835

Attrib Country=Finland 0.07452490166248364

Attrib Country=Romania 0.22624186839247698

Attrib Country=Vary 0.12943000299358196

Attrib Country=Poland -0.023511461281392296

Attrib Country=UK 0.04673892821822464

Attrib Country=Netherlands 0.13767228636925216

Attrib Country=Germany 0.195345691233857

Attrib Average pax/room -0.08286989185835227

Attrib TO/ OTA=OTA 0.18029770223191074

Attrib ADR 0.11723222957911775

Attrib TOTAL PAX Nights 0.20596881193382388

Attrib Total Room Nights 0.3327879055783564

Attrib BB 0.10967251216957664

Attrib BB%   -0.05420167376164751

Attrib HB   0.07141335828869727

Attrib HB%   0.13071471077430902

Attrib AI   0.031109448601938854

Attrib AI%   -0.11222835020664951

Attrib MONTH=April 2019   0.16143321262169172

Attrib MONTH=May 2019   0.16351418315928837

Attrib MONTH=June 2019   0.23817872755847866

Attrib MONTH=July 2019   0.2049335936850878

Attrib MONTH=August 2019   0.051725714814472266

Attrib MONTH=September 2019   -0.204749546646595

Attrib MONTH=October 2019   0.021864781332978346

Sigmoid Node 8

Inputs   Weights

Threshold   -0.1257970545635837

Attrib Booking Source=ARHUS CHARTER   0.458846828909564

Attrib Booking Source=AURINKOMATKAT   0.10396951699049099

Attrib Booking Source=BLUE AEGEAN   0.10441191825811097

Attrib Booking Source=BOOKING.COM   -0.059259106172731335

Attrib Booking Source=BRAVO TOURS   0.07187103732713496

Attrib Booking Source=EXPEDIA   0.2173253588397431

Attrib Booking Source=ITAKA   -0.19598892953686287

Attrib Booking Source=Jet2Holidays   0.5104869320221894

Attrib Booking Source=RAINBOW   -0.05477962180439255

Attrib Booking Source=SUNWEB   -0.1367860868267929

Attrib Booking Source=TUI Deutschland   0.07548100866379165

Attrib Booking Source=TUI NL   0.19622170517724513

Attrib Booking Source=TUI UK   -0.46384423517039125

Attrib Country=Denmark   0.5198640341784722

Attrib Country=Finland   0.1424707748378368

Attrib Country=Romania   0.13983155694943605

Attrib Country=Vary   0.06304545799262137

Attrib Country=Poland   -0.3827710401433516

Attrib Country=UK   -0.006528953528970396

Attrib Country=Netherlands   0.060342755651172454

Attrib Country=Germany   0.06747508043009698

Attrib Average pax/room   0.17063137358209032

Attrib TO/ OTA=OTA   0.08565245634439483

Attrib ADR   0.38291042059179237

Attrib TOTAL PAX Nights   0.47496039204414275

Attrib Total Room Nights   0.6687622992720236

Attrib BB   0.37918494887068455

Attrib BB%   -0.11970134305524115

Attrib HB   0.2703121395780883

Attrib HB%   -0.05092913360004239

Attrib AI   0.02564300623921458

Attrib AI%   -0.2165638664802037

Attrib MONTH=April 2019   -0.13939038874107237

Attrib MONTH=May 2019   0.5308305053126212

Attrib MONTH=June 2019   -0.01928179974833053

Attrib MONTH=July 2019   0.9379797474326447

Attrib MONTH=August 2019   -0.054991228350805076

Attrib MONTH=September 2019   -0.5454788854676752

Attrib MONTH=October 2019   -0.38448404825814786

Sigmoid Node 9

Inputs   Weights

Threshold   -0.1363888447903936

Attrib Booking Source=ARHUS CHARTER   0.10097419844350917

Attrib Booking Source=AURINKOMATKAT   0.08804793716986287

Attrib Booking Source=BLUE AEGEAN   0.15380042523153908

Attrib Booking Source=BOOKING.COM   0.1537942430536753

Attrib Booking Source=BRAVO TOURS   0.07562240608683088

Attrib Booking Source=EXPEDIA   0.11275259921941003

Attrib Booking Source=ITAKA   0.12194531953384458

Attrib Booking Source=Jet2Holidays   0.09776452895589681

Attrib Booking Source=RAINBOW   0.14043398836588145

Attrib Booking Source=SUNWEB   0.13513082088890316

Attrib Booking Source=TUI Deutschland   0.15163582939129688

Attrib Booking Source=TUI NL   0.10336200407629272

Attrib Booking Source=TUI UK   0.14235125761181291

Attrib Country=Denmark   0.08226214889195387

Attrib Country=Finland   0.02630167876723207

Attrib Country=Romania   0.1366709143783275

Attrib Country=Vary   0.055267973757146

Attrib Country=Poland   0.10097707138180811

Attrib Country=UK   0.07816455167222211

Attrib Country=Netherlands   0.06765662211059766

Attrib Country=Germany   0.15303213503963886

Attrib Average pax/room   0.05387344304422825

Attrib TO/ OTA=OTA   0.07225772583556413

Attrib ADR   -0.07845596643669012

Attrib TOTAL PAX Nights   0.06782605856246231

Attrib Total Room Nights   0.025264974406370922

Attrib BB   -0.01614466156678523

Attrib BB%   0.016947590520749983

Attrib HB   0.007604283697366847

Attrib HB%   0.05888674208815257

Attrib AI   0.04116845052457511

Attrib AI%   0.045116396304026536

Attrib MONTH=April 2019   0.169161907451603

Attrib MONTH=May 2019   0.04202427006369376

Attrib MONTH=June 2019   0.011676093488940987

Attrib MONTH=July 2019   0.03872856569434875

Attrib MONTH=August 2019   0.06288169336227316

Attrib MONTH=September 2019   0.10533191740867846

Attrib MONTH=October 2019   0.13272661962666357

Sigmoid Node 10

Inputs   Weights

Threshold   -0.1479529865406293

Attrib Booking Source=ARHUS CHARTER   0.11166945747509623

Attrib Booking Source=AURINKOMATKAT   -0.05796395706386043

Attrib Booking Source=BLUE AEGEAN   0.24198951815188224

Attrib Booking Source=BOOKING.COM   0.08106355828585772

Attrib Booking Source=BRAVO TOURS   0.19960448739456865

Attrib Booking Source=EXPEDIA   0.108236054582306

Attrib Booking Source=ITAKA   0.14797463920497547

Attrib Booking Source=Jet2Holidays   0.11915272434972801

Attrib Booking Source=RAINBOW   0.029137381904747094

Attrib Booking Source=SUNWEB   0.3221162499109217

Attrib Booking Source=TUI Deutschland   0.3508306052003681

Attrib Booking Source=TUI NL   0.061948889617785594

Attrib Booking Source=TUI UK   0.1977849429779874

Attrib Country=Denmark   0.09169274715908388

Attrib Country=Finland   -0.04878273664216448

Attrib Country=Romania   0.2150320615893737

Attrib Country=Vary   0.09480374182847663

Attrib Country=Poland   0.00671504926705343

Attrib Country=UK   0.12310093910522323

Attrib Country=Netherlands   0.2281102325809599

Attrib Country=Germany   0.31594924348616954

Attrib Average pax/room   0.033965796379352965

Attrib TO/ OTA=OTA   0.028691438428517728

Attrib ADR   -0.17661374391066015

Attrib TOTAL PAX Nights   -0.29674151710350927

Attrib Total Room Nights   -0.3325354028078236

Attrib BB   -0.02003469170603024

Attrib BB%   0.16846523952604903

Attrib HB   0.016185274563194622

Attrib HB%   0.08667972959651282

Attrib AI   0.06245618366277375

Attrib AI% 0.20895229848430177

Attrib MONTH=April 2019 0.2621826932031723

Attrib MONTH=May 2019 0.3481055531367439

Attrib MONTH=June 2019 -0.013893840598901412

Attrib MONTH=July 2019 0.17978170743015123

Attrib MONTH=August 2019 0.117623741208433

Attrib MONTH=September 2019 0.08495306502572793

Attrib MONTH=October 2019 0.0566750424235328

Sigmoid Node 11

Inputs Weights

Threshold -0.1046368306475034

Attrib Booking Source=ARHUS CHARTER 0.13805635835217248

Attrib Booking Source=AURINKOMATKAT 0.04138567430032936

Attrib Booking Source=BLUE AEGEAN 0.133033081011269

Attrib Booking Source=BOOKING.COM 0.12630208986270725

Attrib Booking Source=BRAVO TOURS 0.11626243566881996

Attrib Booking Source=EXPEDIA 0.13059791884435212

Attrib Booking Source=ITAKA 0.06640664670477883

Attrib Booking Source=Jet2Holidays 0.12175966174489797

Attrib Booking Source=RAINBOW 0.14087511641437436

Attrib Booking Source=SUNWEB 0.08762736696503368

Attrib Booking Source=TUI Deutschland 0.11351651000446977

Attrib Booking Source=TUI NL 0.07639739142486357

Attrib Booking Source=TUI UK 0.18424566409654494

Attrib Country=Denmark 0.06053828364752289

Attrib Country=Finland 0.020464307178890542

Attrib Country=Romania   0.10549059736923652

Attrib Country=Vary   0.03693805566850185

Attrib Country=Poland   0.05193381523230864

Attrib Country=UK   0.18364483051067088

Attrib Country=Netherlands   0.0885980233465479

Attrib Country=Germany   0.14538280919844285

Attrib Average pax/room   0.046588907207822716

Attrib TO/ OTA=OTA   0.08164635229926205

Attrib ADR   -0.07921270589624796

Attrib TOTAL PAX Nights   -0.06846822446991845

Attrib Total Room Nights   -0.09402438192672431

Attrib BB   0.06917134089552159

Attrib BB%   0.034468556591493615

Attrib HB   0.09572893871532921

Attrib HB%   0.12115413977552143

Attrib AI   0.08893536119763679

Attrib AI%   0.1011930705792736

Attrib MONTH=April 2019   0.14225093715449863

Attrib MONTH=May 2019   0.12012336029057548

Attrib MONTH=June 2019   0.11159981956735232

Attrib MONTH=July 2019   0.11969741522670341

Attrib MONTH=August 2019   0.0832911057093754

Attrib MONTH=September 2019   0.1253657396855563

Attrib MONTH=October 2019   -0.017529764545586933

Sigmoid Node 12

Inputs   Weights

Threshold   -0.10376818940306982

Attrib Booking Source=ARHUS CHARTER   0.12377295168144976

Attrib Booking Source=AURINKOMATKAT   9.36550377229498E-4

Attrib Booking Source=BLUE AEGEAN   0.1504833560471242

Attrib Booking Source=BOOKING.COM   0.08091500272386506

Attrib Booking Source=BRAVO TOURS   0.18912365331068037

Attrib Booking Source=EXPEDIA   0.0361218560999875

Attrib Booking Source=ITAKA   0.06455371773210085

Attrib Booking Source=Jet2Holidays   0.11972958428188056

Attrib Booking Source=RAINBOW   0.18328696970661243

Attrib Booking Source=SUNWEB   0.20326929454367082

Attrib Booking Source=TUI Deutschland   0.22062842029794813

Attrib Booking Source=TUI NL   0.11979771075669969

Attrib Booking Source=TUI UK   0.20030210679392968

Attrib Country=Denmark   0.11574371486422529

Attrib Country=Finland   0.010464898174932704

Attrib Country=Romania   0.09097538983979073

Attrib Country=Vary   0.0760392839563745

Attrib Country=Poland   0.09447383606645256

Attrib Country=UK   0.1508938630440705

Attrib Country=Netherlands   0.10387419898971226

Attrib Country=Germany   0.1642134399451636

Attrib Average pax/room   -0.003761394221586533

Attrib TO/ OTA=OTA   0.007072651426213641

Attrib ADR   -0.07826956727126017

Attrib TOTAL PAX Nights   -0.10389152664853052

Attrib Total Room Nights   -0.16195228859343383

Attrib BB   0.0329797907895684

Attrib BB%   0.017237860867849217

Attrib HB   -0.03233175815595289

Attrib HB%   0.17858318874231346

Attrib AI   0.06997066090027922

Attrib AI%   0.08483129670979074

Attrib MONTH=April 2019   0.17198471537909737

Attrib MONTH=May 2019   0.17388502730438052

Attrib MONTH=June 2019   0.06678441293697533

Attrib MONTH=July 2019   0.12396268266611378

Attrib MONTH=August 2019   0.15649248392649054

Attrib MONTH=September 2019   0.11136596147492343

Attrib MONTH=October 2019   4.12091588471187E-4

Sigmoid Node 13

Inputs   Weights

Threshold   -0.0946963087575667

Attrib Booking Source=ARHUS CHARTER   0.0889564839324552

Attrib Booking Source=AURINKOMATKAT   -0.010035591160551761

Attrib Booking Source=BLUE AEGEAN   0.2854951983703372

Attrib Booking Source=BOOKING.COM   -0.06522530998679167

Attrib Booking Source=BRAVO TOURS   0.25293967808766105

Attrib Booking Source=EXPEDIA   0.10396583420348915

Attrib Booking Source=ITAKA   -0.040498819326266096

Attrib Booking Source=Jet2Holidays   0.04900367343792238

Attrib Booking Source=RAINBOW   0.022443222559516418

Attrib Booking Source=SUNWEB   0.2985469129836817

Attrib Booking Source=TUI Deutschland   0.23483693056498847

Attrib Booking Source=TUI NL   0.027260036834836663

Attrib Booking Source=TUI UK   0.13999019575386712

Attrib Country=Denmark   0.18590695992669704

Attrib Country=Finland   -0.05159269924971623

Attrib Country=Romania   0.338620949348999

Attrib Country=Vary   -0.07546127990452739

Attrib Country=Poland   -0.07584043942571046

Attrib Country=UK   8.591788038928249E-4

Attrib Country=Netherlands   0.2276923287867788

Attrib Country=Germany   0.24480706751433354

Attrib Average pax/room   0.0032739252316809487

Attrib TO/ OTA=OTA   -0.08108319432575198

Attrib ADR   -0.2658843388623676

Attrib TOTAL PAX Nights   -0.2482641181862449

Attrib Total Room Nights   -0.2387332758031298

Attrib BB   0.042241653238975316

Attrib BB%   0.12397616831259141

Attrib HB   0.09657438346173008

Attrib HB%   0.11448068643848237

Attrib AI   0.12200702672537686

Attrib AI%   0.14909020329143974

Attrib MONTH=April 2019   0.41767510973659333

Attrib MONTH=May 2019   0.15625225970167514

Attrib MONTH=June 2019   -0.07728240446113788

Attrib MONTH=July 2019   0.04762581338922958

Attrib MONTH=August 2019   0.0369961318987717

Attrib MONTH=September 2019   0.19608982124469743

Attrib MONTH=October 2019   0.01052640987006035

Sigmoid Node 14

Inputs   Weights

Threshold   -0.16131919852015117

Attrib Booking Source=ARHUS CHARTER   0.07312454705767092

Attrib Booking Source=AURINKOMATKAT   0.04139808242839088

Attrib Booking Source=BLUE AEGEAN   0.10639819565126121

Attrib Booking Source=BOOKING.COM   0.15978701154114847

Attrib Booking Source=BRAVO TOURS   0.06853116385698058

Attrib Booking Source=EXPEDIA   0.09750579555191514

Attrib Booking Source=ITAKA   0.1288563748416659

Attrib Booking Source=Jet2Holidays   0.11656873795990447

Attrib Booking Source=RAINBOW   0.11229489922462414

Attrib Booking Source=SUNWEB   0.14564722508557085

Attrib Booking Source=TUI Deutschland   0.112596418775315 39

Attrib Booking Source=TUI NL   0.0911733279905308

Attrib Booking Source=TUI UK   0.10835152900856779

Attrib Country=Denmark   0.12623590849878988

Attrib Country=Finland   0.07728377556419387

Attrib Country=Romania   0.14633845817486632

Attrib Country=Vary   0.11769798081375156

Attrib Country=Poland   0.06354684927440406

Attrib Country=UK   0.055138746739384244

Attrib Country=Netherlands 0.10936050459589791

Attrib Country=Germany 0.16865021399035496

Attrib Average pax/room 0.001041645938739338

Attrib TO/ OTA=OTA 0.060212410712161

Attrib ADR -0.034183803323064595

Attrib TOTAL PAX Nights 0.022491637768155395

Attrib Total Room Nights 0.03812508421122355

Attrib BB -0.015710863201808613

Attrib BB% 0.011013247043542234

Attrib HB 0.004520158812315304

Attrib HB% 0.04155851370524105

Attrib AI 0.10171684489083517

Attrib AI% 0.040976137728615365

Attrib MONTH=April 2019 0.143231860017455

Attrib MONTH=May 2019 0.10529144896515866

Attrib MONTH=June 2019 0.08207156601998966

Attrib MONTH=July 2019 0.07899185644225974

Attrib MONTH=August 2019 0.0904086792443873

Attrib MONTH=September 2019 0.0835534110140994

Attrib MONTH=October 2019 0.07856017776378883

Sigmoid Node 15

Inputs Weights

Threshold 0.08627377609237893

Attrib Booking Source=ARHUS CHARTER -0.23875721061985217

Attrib Booking Source=AURINKOMATKAT -0.37717269043909274

Attrib Booking Source=BLUE AEGEAN -0.06357113721433791

Attrib Booking Source=BOOKING.COM   0.29954294329425424

Attrib Booking Source=BRAVO TOURS   0.0039969329619432645

Attrib Booking Source=EXPEDIA   -0.10177222083592012

Attrib Booking Source=ITAKA   -0.5842497031348396

Attrib Booking Source=Jet2Holidays   -0.23654426445262297

Attrib Booking Source=RAINBOW   0.47249848859598864

Attrib Booking Source=SUNWEB   0.015367095319731653

Attrib Booking Source=TUI Deutschland   -0.0542764577802904

Attrib Booking Source=TUI NL   0.048213881423111118

Attrib Booking Source=TUI UK   0.3371382911118146

Attrib Country=Denmark   -0.1825092568630062

Attrib Country=Finland   -0.3641028636735545

Attrib Country=Romania   -0.11195056316776195

Attrib Country=Vary   0.22033198052019787

Attrib Country=Poland   -0.03620108662138396

Attrib Country=UK   0.15874188437455614

Attrib Country=Netherlands   0.12139269624402012

Attrib Country=Germany   -0.1219479723299893

Attrib Average pax/room   -0.05130473951260568

Attrib TO/ OTA=OTA   0.2059250095454292

Attrib ADR   -0.21211258563016905

Attrib TOTAL PAX Nights   -0.6710399301330281

Attrib Total Room Nights   -0.9435869402410023

Attrib BB   -0.46019775273566904

Attrib BB%   0.08743042052674287

Attrib HB   0.03138652952795913

Attrib HB%   0.1797351174258127

Attrib AI   -0.35552507340819844

Attrib AI%   0.12460838277919911

Attrib MONTH=April 2019   0.3575822899041137

Attrib MONTH=May 2019   -0.2413720368059171

Attrib MONTH=June 2019   -0.5460549756412101

Attrib MONTH=July 2019   0.43176996694817843

Attrib MONTH=August 2019   0.3066535986023676

Attrib MONTH=September 2019   -0.6496451444843252

Attrib MONTH=October 2019   0.10636208562883474

Sigmoid Node 16

Inputs   Weights

Threshold   -0.10729758149168733

Attrib Booking Source=ARHUS CHARTER   0.13731114880243384

Attrib Booking Source=AURINKOMATKAT   0.05884114443950078

Attrib Booking Source=BLUE AEGEAN   0.1459046080830644

Attrib Booking Source=BOOKING.COM   0.10608562518741818

Attrib Booking Source=BRAVO TOURS   0.1655870520544009

Attrib Booking Source=EXPEDIA   0.055665093844449433

Attrib Booking Source=ITAKA   0.0667447101253541

Attrib Booking Source=Jet2Holidays   0.058420326939913864

Attrib Booking Source=RAINBOW   0.06990041859135547

Attrib Booking Source=SUNWEB   0.09762494694779064

Attrib Booking Source=TUI Deutschland   0.14314141918870937

Attrib Booking Source=TUI NL   0.16995218578086355

Attrib Booking Source=TUI UK   0.09143851565335569

Attrib Country=Denmark   0.08194262848956356

Attrib Country=Finland   0.06419503507702952

Attrib Country=Romania   0.16743064571239877

Attrib Country=Vary   0.09707378838754258

Attrib Country=Poland   0.08410070172710438

Attrib Country=UK   0.08751415123817873

Attrib Country=Netherlands   0.09814097913951654

Attrib Country=Germany   0.11175551222454819

Attrib Average pax/room   0.08812071283473287

Attrib TO/ OTA=OTA   0.13265238378374572

Attrib ADR   -0.07592939125136626

Attrib TOTAL PAX Nights   0.04808450020204058

Attrib Total Room Nights   -0.01633844856521662

Attrib BB   0.02598216468220472

Attrib BB%   0.003457752368601739

Attrib HB   0.079896012535177

Attrib HB%   0.05173755506407564

Attrib AI   0.1289611965375111

Attrib AI%   0.09410824929857683

Attrib MONTH=April 2019   0.12803628603326286

Attrib MONTH=May 2019   0.07105638628867884

Attrib MONTH=June 2019   0.046617789078525304

Attrib MONTH=July 2019   0.052252614651873384

Attrib MONTH=August 2019   0.07514135797774185

Attrib MONTH=September 2019   0.12023328309374857

Attrib MONTH=October 2019   0.09006737219937161

Sigmoid Node 17

Inputs Weights

Threshold -0.1192316391407173

Attrib Booking Source=ARHUS CHARTER 0.05727325960202926

Attrib Booking Source=AURINKOMATKAT 0.08034739626934438

Attrib Booking Source=BLUE AEGEAN 0.1723698864306009

Attrib Booking Source=BOOKING.COM 0.13297866924664

Attrib Booking Source=BRAVO TOURS 0.12785431221537535

Attrib Booking Source=EXPEDIA 0.06892782865090363

Attrib Booking Source=ITAKA 0.12486412040260744

Attrib Booking Source=Jet2Holidays 0.1243786095131842

Attrib Booking Source=RAINBOW 0.11716601699041312

Attrib Booking Source=SUNWEB 0.1322848562468597

Attrib Booking Source=TUI Deutschland 0.09157271941889569

Attrib Booking Source=TUI NL 0.10221724195436054

Attrib Booking Source=TUI UK 0.12166771725047497

Attrib Country=Denmark 0.09774954705672201

Attrib Country=Finland 0.0801685704700489

Attrib Country=Romania 0.08687603848127137

Attrib Country=Vary 0.09871334543391781

Attrib Country=Poland 0.13431534019585192

Attrib Country=UK 0.0616010634650774

Attrib Country=Netherlands 0.10520727867843208

Attrib Country=Germany 0.15528060161083296

Attrib Average pax/room 0.0135889886464766

Attrib TO/ OTA=OTA 0.05082999981578145

Attrib ADR   -0.030416787686220928

Attrib TOTAL PAX Nights   0.03251047574389115

Attrib Total Room Nights   7.15566003048551E-4

Attrib BB   0.09158025880176072

Attrib BB%   0.005847082527404315

Attrib HB   0.04946653158551159

Attrib HB%   0.06942810076761279

Attrib AI   0.09213272268367574

Attrib AI%   0.11439995537859739

Attrib MONTH=April 2019   0.19023318593115138

Attrib MONTH=May 2019   0.05193665105918128

Attrib MONTH=June 2019   0.07862631237609473

Attrib MONTH=July 2019   0.058827975006347004

Attrib MONTH=August 2019   0.07219263309325431

Attrib MONTH=September 2019   0.05979988328256532

Attrib MONTH=October 2019   0.027582075872239178

Sigmoid Node 18

Inputs   Weights

Threshold   -0.09719128665717423

Attrib Booking Source=ARHUS CHARTER   0.05425184921386771

Attrib Booking Source=AURINKOMATKAT   0.028741355581596233

Attrib Booking Source=BLUE AEGEAN   0.12478204898380336

Attrib Booking Source=BOOKING.COM   0.10298678895347409

Attrib Booking Source=BRAVO TOURS   0.05734510130187418

Attrib Booking Source=EXPEDIA   0.05185213255610612

Attrib Booking Source=ITAKA   0.12906343983637705

Attrib Booking Source=Jet2Holidays   0.11619866303364934

Attrib Booking Source=RAINBOW   0.1275910108245811

Attrib Booking Source=SUNWEB   0.07001311651179035

Attrib Booking Source=TUI Deutschland   0.09491699844589271

Attrib Booking Source=TUI NL   0.1676679075383375

Attrib Booking Source=TUI UK   0.15688609379412619

Attrib Country=Denmark   0.060435514382605546

Attrib Country=Finland   0.05574380992925237

Attrib Country=Romania   0.08779362770283487

Attrib Country=Vary   0.07154491545824056

Attrib Country=Poland   0.09431259995242677

Attrib Country=UK   0.079608136221246

Attrib Country=Netherlands   0.13657682089270953

Attrib Country=Germany   0.16587930384480204

Attrib Average pax/room   0.06864395372420765

Attrib TO/ OTA=OTA   0.13992524954914234

Attrib ADR   -0.020690498322432225

Attrib TOTAL PAX Nights   0.08604274652120697

Attrib Total Room Nights   0.061110441374099614

Attrib BB   0.021362386474221683

Attrib BB%   0.01496342756722587

Attrib HB   0.05868796789280961

Attrib HB%   0.04660994535226006

Attrib AI   0.09944895606222533

Attrib AI%   0.04246146640255664

Attrib MONTH=April 2019   0.1695776742438388

Attrib MONTH=May 2019   0.04475223001571981

Attrib MONTH=June 2019   0.08959687013615607

Attrib MONTH=July 2019   0.08530013303431776

Attrib MONTH=August 2019   0.083935949634467

Attrib MONTH=September 2019   0.09797974342545664

Attrib MONTH=October 2019   0.11216352287901772

Sigmoid Node 19

Inputs   Weights

Threshold   -0.12302728582125275

Attrib Booking Source=ARHUS CHARTER   -0.02290637191682181

Attrib Booking Source=AURINKOMATKAT   -8.962819793780499E-4

Attrib Booking Source=BLUE AEGEAN   0.07463017208902967

Attrib Booking Source=BOOKING.COM   -0.2881219853163261

Attrib Booking Source=BRAVO TOURS   0.0685793895483629

Attrib Booking Source=EXPEDIA   0.5931169334982721

Attrib Booking Source=ITAKA   0.13176357072629283

Attrib Booking Source=Jet2Holidays   -0.15377507004261004

Attrib Booking Source=RAINBOW   0.026787444386056652

Attrib Booking Source=SUNWEB   0.13750762516167164

Attrib Booking Source=TUI Deutschland   0.14037168280793902

Attrib Booking Source=TUI NL   0.1098058371080899

Attrib Booking Source=TUI UK   0.3227513203254333

Attrib Country=Denmark   -0.10592000116244385

Attrib Country=Finland   0.09164757655845934

Attrib Country=Romania   0.08677632713386588

Attrib Country=Vary   0.2264643738013373

Attrib Country=Poland   -0.018864783818074823

Attrib Country=UK   0.11025034381715573

Attrib Country=Netherlands   0.17828162447436557

Attrib Country=Germany   0.08122887736334923

Attrib Average pax/room   -0.4068033989108904

Attrib TO/ OTA=OTA   0.25583982742032907

Attrib ADR   -0.1831929783500107

Attrib TOTAL PAX Nights   0.2510565144622139

Attrib Total Room Nights   0.37142907669905284

Attrib BB   0.16195485537442397

Attrib BB%   -0.09259441170787973

Attrib HB   -0.0914366907836561

Attrib HB%   0.2261289051686077

Attrib AI   -0.032121730590823856

Attrib AI%   -0.1462912811908819

Attrib MONTH=April 2019   0.47641803898736207

Attrib MONTH=May 2019   -0.24594015567810737

Attrib MONTH=June 2019   0.4893802256917139

Attrib MONTH=July 2019   0.23468932920895197

Attrib MONTH=August 2019   -0.34667415498844567

Attrib MONTH=September 2019   -0.4007469876618807

Attrib MONTH=October 2019   0.4891084029651396

Sigmoid Node 20

Inputs   Weights

Threshold   -0.09955480296163897

Attrib Booking Source=ARHUS CHARTER   0.15505166476747623

Attrib Booking Source=AURINKOMATKAT 0.04703939373314027

Attrib Booking Source=BLUE AEGEAN 0.09922743898154979

Attrib Booking Source=BOOKING.COM 0.0489742772437892

Attrib Booking Source=BRAVO TOURS -0.17990012841764758

Attrib Booking Source=EXPEDIA 0.03313484743319637

Attrib Booking Source=ITAKA -0.012061432781360487

Attrib Booking Source=Jet2Holidays 0.3299006322858109

Attrib Booking Source=RAINBOW 0.1699993423299534

Attrib Booking Source=SUNWEB -0.13073479467289437

Attrib Booking Source=TUI Deutschland 0.06679888800723244

Attrib Booking Source=TUI NL 0.47772412958443544

Attrib Booking Source=TUI UK -0.0645616545373109

Attrib Country=Denmark -0.009356781531836816

Attrib Country=Finland 0.014248931596833974

Attrib Country=Romania 0.1463550292985704

Attrib Country=Vary -0.09630337754270897

Attrib Country=Poland 0.17357859459113825

Attrib Country=UK 0.09787099146026873

Attrib Country=Netherlands 0.15651382478067488

Attrib Country=Germany 0.10483225175035624

Attrib Average pax/room -0.10449800107708898

Attrib TO/ OTA=OTA -0.07400210240178949

Attrib ADR -0.09722157890291633

Attrib TOTAL PAX Nights 0.19106613460995148

Attrib Total Room Nights 0.2923047926762347

Attrib BB 0.13661917335104412

Attrib BB%   0.0033679713482861807

Attrib HB   0.010499784941871709

Attrib HB%   -0.018247991724779557

Attrib AI   -0.0013360866665371976

Attrib AI%   0.10470101783993127

Attrib MONTH=April 2019   -0.049816209785018536

Attrib MONTH=May 2019   0.5211222435611422

Attrib MONTH=June 2019   -0.08508676634167955

Attrib MONTH=July 2019   -0.03867066067277948

Attrib MONTH=August 2019   0.12093141218739785

Attrib MONTH=September 2019   -0.25876536670541744

Attrib MONTH=October 2019   0.3046738408866307

Class

Input

Node 0

=== Summary ===

Correlation coefficient	0.927
Mean absolute error	7.2876
Root mean squared error	10.5483
Relative absolute error	38.1148 %
Root relative squared error	37.3055 %
Total Number of Instances	91

Meta Regression By Discretization

=== Classifier model (full training set) ===
Class attribute discretized into 10 values
J48 pruned tree

```
Total Room Nights <= 120: '(-inf-13.5]' (50.0/6.0)
Total Room Nights > 120
|   BB <= 597
|   |   Country = Denmark
|   |   |   Average pax/room <= 2.25: '(27-40.5]' (5.0/1.0)
|   |   |   Average pax/room > 2.25: '(13.5-27]' (2.0)
|   |   Country = Finland: '(13.5-27]' (0.0)
|   |   Country = Romania: '(13.5-27]' (0.0)
|   |   Country = Vary
|   |   |   Total Room Nights <= 226: '(13.5-27]' (4.0/1.0)
|   |   |   Total Room Nights > 226: '(40.5-54]' (3.0)
|   |   Country = Poland: '(40.5-54]' (3.0/1.0)
|   |   Country = UK
|   |   |   Total Room Nights <= 224: '(13.5-27]' (5.0)
|   |   |   Total Room Nights > 224: '(27-40.5]' (3.0)
|   |   Country = Netherlands: '(13.5-27]' (7.0)
|   |   Country = Germany: '(13.5-27]' (1.0)
|   BB > 597
|   |   HB% <= 0.14
|   |   |   TOTAL PAX Nights <= 1813: '(54-67.5]' (2.0)
|   |   |   TOTAL PAX Nights > 1813: '(81-94.5]' (2.0)
|   |   HB% > 0.14: '(121.5-inf)' (4.0/1.0)

Number of Leaves  :   15

Size of the tree :    23
=== Summary ===

Correlation coefficient          0.9221
Mean absolute error              7.7887
Root mean squared error         11.2044
Relative absolute error         40.736  %
Root relative squared error     39.6259 %
Total Number of Instances       91
```

Meta Additive Regression

=== Classifier model (full training set) ===

Additive Regression

Base classifier weka.classifiers.trees.DecisionStump

10 models generated

Model number 0

Decision Stump

Classifications

BB <= 769.0 : -6.95510586974002

BB > 769.0 : 74.06318681318677

BB is missing : -22.186813186813186

Model number 1

Decision Stump

Classifications

Total Room Nights <= 104.0 : -10.226558265582662

Total Room Nights > 104.0 : 10.004241781548252

Total Room Nights is missing : -1.5616323862859344E-15

Model number 2

Decision Stump

Classifications

AI <= 843.0 : -1.5060026753720124

AI > 843.0 : 23.556733828207864

AI is missing : 10.226558265582662

Model number 3

Decision Stump

Classifications

Total Room Nights <= 519.0 : 1.638231502595407

Total Room Nights > 519.0 : -13.269675171022792

Total Room Nights is missing : 7.027345738286705E-16

Model number 4

Decision Stump

Classifications

AI <= 573.5 : -1.586992381078663

AI > 573.5 : 11.546420873437249

AI is missing : -1.638231502595407

Model number 5

Decision Stump

Classifications

Booking Source = EXPEDIA : 10.361671598090993

Booking Source != EXPEDIA : -0.8634726331742496

Booking Source is missing : 5.465713352000771E-16

<u>Model number 6</u>

Decision Stump

Classifications

Total Room Nights <= 1040.5 : -0.40215898257489857

Total Room Nights > 1040.5 : 11.7966634888637

Total Room Nights is missing : 1.5616323862859346E-16

<u>Model number 7</u>

Decision Stump

Classifications

Total Room Nights <= 425.5 : 1.1447801332530734

Total Room Nights > 425.5 : -8.325673696385994

Total Room Nights is missing : -8.393774076286898E-16

<u>Model number 8</u>

Decision Stump

Classifications

MONTH = October 2019 : -5.312662995204634

MONTH != October 2019 : 0.8854438325341064

MONTH is missing : 5.319310315786464E-16

<u>Model number 9</u>

Decision Stump

Classifications

Average pax/room <= 2.1100000000000003 : -2.465666200366835

Average pax/room > 2.1100000000000003 : 1.0188559419205916

Average pax/room is missing : -1.65

=== Summary ===

Correlation coefficient	0.913
Mean absolute error	7.8356
Root mean squared error	11.7053
Relative absolute error	40.9813 %
Root relative squared error	41.3974 %
Total Number of Instances	91

Meta Random Sub Space

=== Classifier model (full training set) ===

All the base classifiers:

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R6,8,9,3,14,13,5,15'

@attribute 'TOTAL PAX Nights' numeric

@attribute BB numeric

@attribute 'BB\%' numeric

@attribute 'Average pax/room' numeric

@attribute MONTH {'April 2019','May 2019','June 2019','July 2019','August 2019','September 2019','October 2019'}

@attribute 'AI\%' numeric

@attribute ADR numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

TOTAL PAX Nights < 1040.5

| TOTAL PAX Nights < 233.5

| | TOTAL PAX Nights < 89.5

| | | TOTAL PAX Nights < 23 : 0.57 (9/0.25) [5/0.24]

| | | TOTAL PAX Nights >= 23 : 2.53 (10/1.21) [5/1.61]

| | TOTAL PAX Nights >= 89.5 : 9.93 (9/15.14) [6/27.44]

| TOTAL PAX Nights >= 233.5

| | BB < 481 : 23.06 (21/44.75) [10/83.99]

| | BB >= 481 : 40 (3/29.56) [2/29.61]

TOTAL PAX Nights >= 1040.5 : 82.64 (8/1049.61) [3/1184.77]

Size of the tree : 11

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R1,13,11,2,9,3,8,15'

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute 'AI\%' numeric

@attribute 'HB\%' numeric

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute 'BB\%' numeric

@attribute 'Average pax/room' numeric

@attribute BB numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Booking Source = ARHUS CHARTER : 28.43 (6/186.56) [1/152.11]

Booking Source = AURINKOMATKAT : 101 (6/835.58) [1/110.25]

Booking Source = BLUE AEGEAN : 12.86 (3/104) [4/142.5]

Booking Source = BOOKING.COM : 6.14 (5/11.76) [2/50.24]

Booking Source = BRAVO TOURS : 6.86 (4/2.25) [3/130.92]

Booking Source = EXPEDIA : 34.14 (3/46.89) [4/122.36]

Booking Source = ITAKA : 33.14 (4/293.5) [3/849.67]

Booking Source = Jet2Holidays : 22.43 (6/141.92) [1/0.25]

Booking Source = RAINBOW : 0.86 (4/0) [3/0.33]

Booking Source = SUNWEB : 18 (4/63.69) [3/24.56]

Booking Source = TUI Deutschland : 7.43 (5/27.04) [2/25.36]

Booking Source = TUI NL : 9.29 (4/29.5) [3/49.67]

Booking Source = TUI UK

| BB < 140 : 4.2 (4/7.19) [1/27.56]

| BB >= 140 : 17 (2/1) [0/0]

Size of the tree : 16

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R12,5,7,9,10,1,11,15'

@attribute AI numeric

@attribute ADR numeric

@attribute 'Total Room Nights' numeric

@attribute 'BB\%' numeric

@attribute HB numeric

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute 'HB\%' numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Booking Source = ARHUS CHARTER : 28.43 (6/186.56) [1/152.11]

Booking Source = AURINKOMATKAT : 101 (5/540.64) [2/1673.36]

Booking Source = BLUE AEGEAN

| ADR < 49.2 : 0.33 (3/0.22) [0/0]

| ADR >= 49.2 : 22.25 (2/9) [2/18.5]

Booking Source = BOOKING.COM

| Total Room Nights < 27 : 2.5 (2/0.25) [2/0.25]

| Total Room Nights >= 27 : 11 (3/2.67) [0/0]

Booking Source = BRAVO TOURS

| AI < 2 : 3 (2/1) [2/4]

| AI >= 2 : 12 (2/1) [1/324]

Booking Source = EXPEDIA

| Total Room Nights < 221 : 26.75 (2/9) [2/26.5]

| Total Room Nights >= 221 : 44 (2/6.25) [1/2.25]

Booking Source = ITAKA : 33.14 (3/392.67) [4/566.5]

Booking Source = Jet2Holidays : 22.43 (6/135.92) [1/42.25]

Booking Source = RAINBOW : 0.86 (7/0.12) [0/0]

Booking Source = SUNWEB : 18 (3/67.56) [4/69.44]

Booking Source = TUI Deutschland : 7.43 (5/32.24) [2/14.66]

Booking Source = TUI NL

| AI < 43.5 : 3 (2/4) [1/9]

| AI >= 43.5 : 14 (2/0.25) [2/21.25]

Booking Source = TUI UK : 7.86 (3/10.89) [4/85.28]

Size of the tree : 24

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R2,11,5,4,3,9,14,15'

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute 'HB\%' numeric

@attribute ADR numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute 'Average pax/room' numeric

@attribute 'BB\%' numeric

@attribute MONTH {'April 2019','May 2019','June 2019','July 2019','August 2019','September 2019','October 2019'}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Country = Denmark : 17.64 (8/149.75) [6/402.25]

Country = Finland : 101 (3/878) [4/793.5]

Country = Romania : 12.86 (4/12.19) [3/480.56]

Country = Vary : 20.14 (11/295.32) [3/78.13]

Country = Poland : 17 (9/606.1) [5/313.99]

Country = UK : 15.14 (11/133.79) [3/149.79]

Country = Netherlands

| MONTH = April 2019 : 2.5 (1/0) [1/9]

| MONTH = May 2019 : 18.5 (2/6.25) [0/0]

| MONTH = June 2019 : 19.5 (1/0) [1/81]

| MONTH = July 2019 : 14.5 (0/0) [2/72.25]

| MONTH = August 2019 : 14 (1/0) [1/100]

| MONTH = September 2019 : 19.5 (2/12.25) [0/0]

| MONTH = October 2019 : 7 (1/0) [1/100]

Country = Germany : 7.43 (6/30.92) [1/0.25]

Size of the tree : 16

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R13,12,9,6,5,8,1,15'

@attribute 'AI\%' numeric

@attribute AI numeric

@attribute 'BB\%' numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute ADR numeric

@attribute BB numeric

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO

TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Booking Source = ARHUS CHARTER : 28.43 (4/263.69) [3/88.56]

Booking Source = AURINKOMATKAT

| TOTAL PAX Nights < 2480.5 : 78.75 (2/210.25) [2/10.25]

| TOTAL PAX Nights >= 2480.5 : 130.67 (3/17.56) [0/0]

Booking Source = BLUE AEGEAN

| TOTAL PAX Nights < 89.5 : 0.33 (3/0.22) [0/0]

| TOTAL PAX Nights >= 89.5 : 22.25 (3/14.89) [1/5.44]

Booking Source = BOOKING.COM

| BB% < 0.81 : 11 (2/4) [1/0]

| BB% >= 0.81 : 2.5 (3/0.22) [1/0.44]

Booking Source = BRAVO TOURS : 6.86 (4/66.5) [3/55.33]

Booking Source = EXPEDIA : 34.14 (3/64.67) [4/121.25]

Booking Source = ITAKA

| TOTAL PAX Nights < 763 : 10 (2/30.25) [1/56.25]

| TOTAL PAX Nights >= 763 : 50.5 (3/84.22) [1/128.44]

Booking Source = Jet2Holidays : 22.43 (6/115.92) [1/182.25]

Booking Source = RAINBOW : 0.86 (3/0.22) [4/0.11]

Booking Source = SUNWEB : 18 (3/84.67) [4/20.25]

Booking Source = TUI Deutschland : 7.43 (4/19.25) [3/38.92]

Booking Source = TUI NL

| AI < 51 : 4.5 (4/10.25) [0/0]

| AI >= 51 : 15.67 (2/0.25) [1/0.25]

Booking Source = TUI UK

| TOTAL PAX Nights < 216 : 4.2 (4/12.5) [1/1]

| TOTAL PAX Nights >= 216 : 17 (2/1) [0/0]

Size of the tree : 26

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R12,10,11,6,9,5,3,15'

@attribute AI numeric

@attribute HB numeric

@attribute 'HB\%' numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute 'BB\%' numeric

@attribute ADR numeric

@attribute 'Average pax/room' numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

```
REPTree
============
TOTAL PAX Nights < 1040.5
|   TOTAL PAX Nights < 363
|   |   TOTAL PAX Nights < 149
|   |   |   TOTAL PAX Nights < 62.5 : 1 (15/0.46) [7/1.02]
|   |   |   TOTAL PAX Nights >= 62.5 : 5.71 (4/2.19) [10/19.61]
|   |   TOTAL PAX Nights >= 149
|   |   |   Average pax/room < 2.23
|   |   |   |   Average pax/room < 1.96 : 12 (2/16) [0/0]
|   |   |   |   Average pax/room >= 1.96
|   |   |   |   |   AI < 28 : 20.67 (2/0) [1/4]
|   |   |   |   |   AI >= 28 : 16.75 (3/0.89) [1/5.44]
|   |   |   Average pax/room >= 2.23
|   |   |   |   Average pax/room < 2.71
|   |   |   |   |   TOTAL PAX Nights < 208 : 7 (2/0) [0/0]
|   |   |   |   |   TOTAL PAX Nights >= 208 : 14.17 (5/2.96) [1/139.24]
|   |   |   |   Average pax/room >= 2.71 : 17.75 (2/2.25) [2/70.25]
|   TOTAL PAX Nights >= 363
|   |   BB% < 0.78
|   |   |   AI < 573.5 : 23.5 (8/9.61) [4/40.95]
|   |   |   AI >= 573.5 : 35.75 (4/38.69) [0/0]
|   |   BB% >= 0.78 : 37.14 (6/45.56) [1/13.44]
TOTAL PAX Nights >= 1040.5 : 82.64 (7/780.78) [4/1672.83]

Size of the tree : 23
```

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R11,4,5,9,1,2,13,15'

@attribute 'HB\%' numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute ADR numeric

@attribute 'BB\%' numeric

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute 'AI\%' numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Booking Source = ARHUS CHARTER : 28.43 (5/213.84) [2/93.96]

Booking Source = AURINKOMATKAT : 101 (3/17.56) [4/2804.03]

Booking Source = BLUE AEGEAN : 12.86 (3/110.22) [4/141.28]

Booking Source = BOOKING.COM : 6.14 (3/26.89) [4/13.44]

Booking Source = BRAVO TOURS : 6.86 (6/58.89) [1/11.11]

Booking Source = EXPEDIA

| HB% < 0.23 : 37.2 (2/49) [3/109.67]

| HB% >= 0.23 : 26.5 (2/0.25) [0/0]

Booking Source = ITAKA : 33.14 (6/531.14) [1/84.03]

Booking Source = Jet2Holidays : 22.43 (4/156.69) [3/98.56]

Booking Source = RAINBOW : 0.86 (6/0.14) [1/0.03]

Booking Source = SUNWEB : 18 (3/22.89) [4/65.61]

Booking Source = TUI Deutschland : 7.43 (4/18.5) [3/43]

Booking Source = TUI NL : 9.29 (6/42.56) [1/0.11]

Booking Source = TUI UK : 7.86 (7/40.98) [0/0]

Size of the tree : 16

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R12,5,8,1,14,3,13,15'

@attribute AI numeric

@attribute ADR numeric

@attribute BB numeric

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute MONTH {'April 2019','May 2019','June 2019','July 2019','August 2019','September 2019','October 2019'}

@attribute 'Average pax/room' numeric

@attribute 'AI\%' numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Booking Source = ARHUS CHARTER : 28.43 (4/226.19) [3/166.06]

Booking Source = AURINKOMATKAT : 101 (3/874.89) [4/653.69]

Booking Source = BLUE AEGEAN : 12.86 (3/94.89) [4/150.86]

Booking Source = BOOKING.COM : 6.14 (3/18.67) [4/33.5]

Booking Source = BRAVO TOURS : 6.86 (3/84.67) [4/57.25]

Booking Source = EXPEDIA : 34.14 (6/67.14) [1/200.69]

Booking Source = ITAKA : 33.14 (6/354.56) [1/1320.11]

Booking Source = Jet2Holidays : 22.43 (5/168.8) [2/5]

Booking Source = RAINBOW : 0.86 (4/0.19) [3/0.06]

Booking Source = SUNWEB : 18 (7/46.86) [0/0]

Booking Source = TUI Deutschland : 7.43 (6/22.92) [1/56.25]

Booking Source = TUI NL : 9.29 (5/43.36) [2/23.44]

Booking Source = TUI UK : 7.86 (5/57.2) [2/0.5]

Size of the tree : 14

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R11,10,9,5,6,3,1,15'

@attribute 'HB\%' numeric

@attribute HB numeric

@attribute 'BB\%' numeric

@attribute ADR numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute 'Average pax/room' numeric

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Booking Source = ARHUS CHARTER : 28.43 (5/53.2) [2/536.5]

Booking Source = AURINKOMATKAT

| TOTAL PAX Nights < 2480.5 : 78.75 (4/108.69) [0/0]

| TOTAL PAX Nights >= 2480.5 : 130.67 (2/25) [1/4]

Booking Source = BLUE AEGEAN

| ADR < 43.99 : 0.33 (2/0) [1/1]

| ADR >= 43.99 : 22.25 (4/12.19) [0/0]

Booking Source = BOOKING.COM

| HB% < 0.16 : 2.5 (2/0.25) [2/0.25]

| HB% >= 0.16 : 11 (3/2.67) [0/0]

Booking Source = BRAVO TOURS : 6.86 (2/9) [5/80.4]

Booking Source = EXPEDIA : 34.14 (3/100.67) [4/74.25]

Booking Source = ITAKA

| ADR < 100.16 : 10 (2/42.25) [1/20.25]

| ADR >= 100.16 : 50.5 (3/84.22) [1/128.44]

Booking Source = Jet2Holidays : 22.43 (6/115.92) [1/182.25]

Booking Source = RAINBOW : 0.86 (6/0.14) [1/0.03]

Booking Source = SUNWEB : 18 (4/63.69) [3/24.56]

Booking Source = TUI Deutschland : 7.43 (5/25.04) [2/30.26]

Booking Source = TUI NL : 9.29 (2/0.25) [5/105.05]

Booking Source = TUI UK

| TOTAL PAX Nights < 216 : 4.2 (3/8.22) [2/13.61]

| TOTAL PAX Nights >= 216 : 17 (2/1) [0/0]

Size of the tree : 24

Filtered Header

@relation 'Creta Palm Data 2019 class TB-weka.filters.unsupervised.attribute.Remove-V-R11,13,9,4,2,14,6,15'

@attribute 'HB\%' numeric

@attribute 'AI\%' numeric

@attribute 'BB\%' numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute MONTH {'April 2019','May 2019','June 2019','July 2019','August 2019','September 2019','October 2019'}

@attribute 'TOTAL PAX Nights' numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Country = Denmark

| HB% < 0.93 : 26.29 (6/44.25) [2.75/609.52]

| HB% >= 0.93 : 3.24 (2/0) [3.25/4.62]

Country = Finland : 101 (5/609.76) [2/1057.04]

Country = Romania : 12.86 (4/114.75) [3/150.92]

Country = Vary

| TOTAL PAX Nights < 237 : 6.14 (5/13.44) [2/33.86]

| TOTAL PAX Nights >= 237 : 34.14 (4/51.19) [3/158.73]

Country = Poland

| TOTAL PAX Nights < 654 : 3.6 (6/0.33) [4/85]

| TOTAL PAX Nights >= 654 : 50.5 (3/46.89) [1/277.78]

Country = UK

| TOTAL PAX Nights < 216 : 3.5 (5/10.16) [1/17.64]

| TOTAL PAX Nights >= 216 : 23.88 (4/54.69) [4/66.31]

Country = Netherlands

| TOTAL PAX Nights < 237.5 : 4.4 (2/12.25) [3/7.58]

| TOTAL PAX Nights >= 237.5

| | TOTAL PAX Nights < 533 : 14.75 (4/2.69) [0/0]

| | TOTAL PAX Nights >= 533 : 22 (3/4.67) [2/1]

Country = Germany : 7.43 (7/26.53) [0/0]

Size of the tree : 21

=== Summary ===

Correlation coefficient	0.9124
Mean absolute error	8.0427
Root mean squared error	11.6649
Relative absolute error	42.0642 %
Root relative squared error	41.2546 %
Total Number of Instances	91

Lazy IBK

=== Classifier model (full training set) ===

IB1 instance-based classifier

using 1 nearest neighbour(s) for classification

=== Summary ===

Correlation coefficient	0.8847
Mean absolute error	8.4505
Root mean squared error	13.0236
Relative absolute error	44.1974 %

Root relative squared error 46.06 %

Total Number of Instances 91

REPTree

=== Classifier model (full training set) ===

Booking Source = ARHUS CHARTER : 28.43 (5/218.16) [2/88.74]

Booking Source = AURINKOMATKAT : 101 (5/881.2) [2/382.5]

Booking Source = BLUE AEGEAN : 12.86 (5/135.36) [2/101.14]

Booking Source = BOOKING.COM : 6.14 (4/17.19) [3/37.23]

Booking Source = BRAVO TOURS : 6.86 (6/3.33) [1/400]

Booking Source = EXPEDIA : 34.14 (5/87.44) [2/79.46]

Booking Source = ITAKA : 33.14 (4/219.25) [3/860.92]

Booking Source = Jet2Holidays : 22.43 (4/200.19) [3/17.06]

Booking Source = RAINBOW : 0.86 (6/0.14) [1/0.03]

Booking Source = SUNWEB : 18 (4/17.19) [3/87.73]

Booking Source = TUI Deutschland : 7.43 (3/13.56) [4/36.28]

Booking Source = TUI NL : 9.29 (7/36.49) [0/0]

Booking Source = TUI UK : 7.86 (2/12.25) [5/79.05]

Size of the tree : 14

=== Summary ===

Correlation coefficient 0.8709

Mean absolute error 9.9758

Root mean squared error 13.7176

Relative absolute error 52.1747 %

Root relative squared error 48.5141 %

Total Number of Instances	91

Meta Bagging

=== Classifier model (full training set) ===

Bagging with 10 iterations and base learner

=== Summary ===

Correlation coefficient	0.8699
Mean absolute error	9.8428
Root mean squared error	13.7439
Relative absolute error	51.4791 %
Root relative squared error	48.6074 %
Total Number of Instances	91

Lazy LWL

=== Classifier model (full training set) ===

Locally weighted learning

Using classifier: weka.classifiers.trees.DecisionStump

Using linear weighting kernels

Using all neighbours

=== Summary ===

Correlation coefficient	0.835
Mean absolute error	12.4952
Root mean squared error	15.4648
Relative absolute error	65.3511 %
Root relative squared error	54.6936 %
Total Number of Instances	91

Decision Table

=== Classifier model (full training set) ===

Number of training instances: 91

Number of Rules : 10

Non matches covered by Majority class.

Best first.

Start set: no attributes

Search direction: forward

Stale search after 5 node expansions

Total number of subsets evaluated: 87

Merit of best subset found: 9.319

Evaluation (for feature selection): CV (leave one out)

Feature set: 4,6,15

=== Summary ===

Correlation coefficient	0.8247
Mean absolute error	9.2794
Root mean squared error	15.9439
Relative absolute error	48.5324 %
Root relative squared error	56.3878 %
Total Number of Instances	91

Random Tree

=== Classifier model (full training set) ===

RandomTree

==========

TOTAL PAX Nights < 1867

| TOTAL PAX Nights < 338.5

| | Total Room Nights < 37.5

| | | TOTAL PAX Nights < 28 : 0.6 (15/0.24)

| | | TOTAL PAX Nights >= 28

| | | | TOTAL PAX Nights < 62.5 : 1.86 (7/0.41)

| | | | TOTAL PAX Nights >= 62.5 : 3.17 (6/0.47)

| | Total Room Nights >= 37.5

| | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN

| | | | TOTAL PAX Nights < 227.5

| | | | | Average pax/room < 2.71 : 20 (1/0)

| | | | | Average pax/room >= 2.71 : 18 (1/0)

| | | | TOTAL PAX Nights >= 227.5 : 24 (1/0)

| | | Booking Source = BOOKING.COM

| | | | TOTAL PAX Nights < 100.5 : 9 (1/0)

| | | | TOTAL PAX Nights >= 100.5

| | | | | ADR < 97.15 : 13 (1/0)

| | | | | ADR >= 97.15 : 11 (1/0)

| | | Booking Source = BRAVO TOURS

| | | | BB% < 0.58 : 7 (1/0)

| | | | BB% >= 0.58 : 5 (1/0)

| | | Booking Source = EXPEDIA : 22 (1/0)

| | | Booking Source = ITAKA

| | | | AI < 280.5 : 13 (1/0)

| | | | AI >= 280.5 : 15 (1/0)

| | | Booking Source = Jet2Holidays : 20 (1/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SUNWEB

| | | | TOTAL PAX Nights < 202.5 : 4 (1/0)

| | | | TOTAL PAX Nights >= 202.5 : 12 (1/0)

| | | Booking Source = TUI Deutschland

| | | | MONTH = April 2019 : 0 (0/0)

| | | | MONTH = May 2019 : 0 (0/0)

| | | | MONTH = June 2019 : 12 (1/0)

| | | | MONTH = July 2019 : 13 (1/0)

| | | | MONTH = August 2019 : 7 (1/0)

| | | | MONTH = September 2019 : 14 (1/0)

| | | | MONTH = October 2019 : 0 (0/0)

| | | Booking Source = TUI NL

| | | | TOTAL PAX Nights < 237.5

| | | | | ADR < 99.22 : 9 (1/0)

| | | | | ADR >= 99.22 : 6 (1/0)

| | | | TOTAL PAX Nights >= 237.5 : 15.5 (2/0.25)

| | | Booking Source = TUI UK

| | | | BB < 140

| | | | | TOTAL PAX Nights < 129.5 : 5 (1/0)

| | | | | TOTAL PAX Nights >= 129.5 : 7.5 (2/0.25)

| | | | BB >= 140

| | | | | ADR < 72.12 : 16 (1/0)

| | | | | ADR >= 72.12 : 18 (1/0)

| TOTAL PAX Nights >= 338.5

| | Country = Denmark

| | | MONTH = April 2019 : 0 (0/0)

| | | MONTH = May 2019 : 34 (1/0)

| | | MONTH = June 2019 : 40 (1/0)

| | | MONTH = July 2019

| | | | HB% < 0.42 : 39 (1/0)

| | | | HB% >= 0.42 : 24 (1/0)

| | | MONTH = August 2019 : 25 (1/0)

| | | MONTH = September 2019 : 39 (1/0)

| | | MONTH = October 2019 : 22 (1/0)

| | Country = Finland : 63 (1/0)

| | Country = Romania : 27 (1/0)

| | Country = Vary

| | | HB% < 0.23

| | | | Average pax/room < 2.45

| | | | | Total Room Nights < 214 : 32 (1/0)

| | | | | Total Room Nights >= 214

| | | | | | TOTAL PAX Nights < 566.5 : 41 (1/0)

| | | | | | TOTAL PAX Nights >= 566.5 : 45 (1/0)

| | | | Average pax/room >= 2.45 : 46 (1/0)

| | | HB% >= 0.23 : 26.5 (2/0.25)

| | Country = Poland

| | | BB < 780.5

| | | | Average pax/room < 2.79 : 56 (1/0)

| | | | Average pax/room >= 2.79 : 41.5 (2/0.25)

| | | BB >= 780.5 : 63 (1/0)

| | Country = UK

| | | TOTAL PAX Nights < 602

| | | | BB < 449

| | | | | Average pax/room < 2.46 : 18 (1/0)

| | | | | Average pax/room >= 2.46 : 22 (1/0)

| | | | BB >= 449 : 28 (1/0)

| | | TOTAL PAX Nights >= 602 : 34.5 (2/0.25)

| | Country = Netherlands

| | | BB% < 0.54

| | | | TOTAL PAX Nights < 643 : 24 (1/0)

| | | | TOTAL PAX Nights >= 643

| | | | | Average pax/room < 2.17 : 23 (1/0)

| | | | | Average pax/room >= 2.17

| | | | | | MONTH = April 2019 : 0 (0/0)

| | | | | | MONTH = May 2019 : 21 (1/0)

| | | | | | MONTH = June 2019 : 0 (0/0)

| | | | | | MONTH = July 2019 : 23 (1/0)

| | | | | | MONTH = August 2019 : 19 (1/0)

| | | | | | MONTH = September 2019 : 0 (0/0)

| | | | | | MONTH = October 2019 : 0 (0/0)

| | | BB% >= 0.54 : 16 (1/0)

| | Country = Germany : 0 (0/0)

TOTAL PAX Nights >= 1867

| MONTH = April 2019 : 78 (1/0)

| MONTH = May 2019 : 125 (1/0)

| MONTH = June 2019 : 132 (1/0)

| MONTH = July 2019 : 135 (1/0)

| MONTH = August 2019 : 92 (1/0)

| MONTH = September 2019 : 82 (1/0)

| MONTH = October 2019 : 0 (0/0)

Size of the tree : 110

=== Summary ===

Correlation coefficient 0.821

Mean absolute error 8.7104

Root mean squared error 16.1906

Relative absolute error 45.5563 %

Root relative squared error 57.2604 %

Total Number of Instances 91

Decision Stump

=== Classifier model (full training set) ===

Decision Stump

Classifications

BB <= 769.0 : 15.231707317073171

BB > 769.0 : 96.25

BB is missing : 0.0

=== Summary ===

Correlation coefficient 0.8058

Mean absolute error 13.2695

Root mean squared error 16.4947

Relative absolute error 69.401 %

Root relative squared error 58.3358 %

Total Number of Instances 91

Classifiers **“CV Parameter Selection”, “Meta Multi Scheme”, “Meta Stacking”, “Meta Vote”, “Meta Weighted Instances Handler Wrapper”, “Meta Input Mapped Classifier”** and **“ZeroR”** provide the same algorithm results, with a correlation coefficient: **-0.3669**.

=== Summary ===

Correlation coefficient -0.3669

Mean absolute error 19.12

Root mean squared error 28.2754

Relative absolute error 100 %

Root relative squared error 100 %

Total Number of Instances 91

ZeroR predicts class value: 22.18

Simple K Means with 3 Clusters| Creta Palm 2019

```
Final cluster centroids:
                                         Cluster#
Attribute                Full Data              0              1              2
                            (91.0)         (41.0)         (24.0)         (26.0)
===============================================================================
Booking Source   ARHUS CHARTER   BLUE AEGEAN ARHUS CHARTER          ITAKA
Country                    Denmark           Vary        Denmark         Poland
Avarage pax/room            2.4126         2.4466         2.2539         2.5055
TO/ OTA                         TO             TO             TO             TO
ADR                        82.1023        74.4385          85.23        91.3004
TOTAL PAX Nights          491.0659       250.0488       429.0417       928.3846
Total Room Nights         195.9231       105.1951       186.8333       347.3846
BB                           238.8       166.4829       154.0833       431.0385
BB%                         0.4559         0.5947         0.2819         0.3975
HB                            77.6        75.9415        53.2917       102.6538
HB%                         0.2866         0.3284         0.2715         0.2345
AI                        180.4333        19.7423       222.8333       394.6923
AI%                         0.2728         0.0786         0.4526         0.4132
MONTH                   April 2019     April 2019    August 2019      June 2019
TOTAL BOOKINGS             22.1868        14.7073        19.5833        36.3846
```

Simple K Means with 4 Clusters| Creta Palm 2019

```
Final cluster centroids:
                                       Cluster#
```

Attribute	Full Data	0	1	2	3
	(91.0)	(25.0)	(16.0)	(18.0)	(32.0)
Booking Source	ARHUS CHARTER	BRAVO TOURS	RAINBOW	ITAKA	Jet2Holidays
Country	Denmark	Denmark	Poland	Poland	UK
Avarage pax/room	2.4126	2.4418	2.2883	2.6722	2.3059
TO/ OTA	TO	TO	TO	TO	TO
ADR	82.1023	75.6138	95.722	100.179	70.1934
TOTAL PAX Nights	491.0659	273.44	228.125	1351.7222	308.4375
Total Room Nights	195.9231	116.64	96.5	502.6111	135.0625
BB	238.8	104.112	86.125	623.3333	204.0625
BB%	0.4559	0.2801	0.3047	0.4322	0.6821
HB	77.6	112.264	39.5625	128.9444	40.6563
HB%	0.2866	0.5989	0.3023	0.085	0.1481
AI	180.4333	76.9373	102.4375	599.4444	64.5938
AI%	0.2728	0.169	0.3946	0.4817	0.1756
MONTH	April 2019	April 2019	August 2019	June 2019	October 2019
TOTAL BOOKINGS	22.1868	16.48	9.375	53.1111	15.6563

Simple K Means with 5 Clusters| Creta Palm 2019

Final cluster centroids:

Attribute	Full Data	Cluster# 0	1	2	3	4
	(91.0)	(21.0)	(14.0)	(18.0)	(30.0)	(8.0)
Booking Source	ARHUS CHARTER	BRAVO TOURS	RAINBOW	ITAKA	Jet2Holidays	AURINKOMATKAT
Country	Denmark	Denmark	Poland	Poland	UK	Finland
Avarage pax/room	2.4126	2.4783	2.3195	2.5411	2.2899	2.5737
TO/ OTA	TO	TO	TO	TO	TO	TO
ADR	82.1023	74.5529	95.8794	96.3187	68.4807	96.9038
TOTAL PAX Nights	491.0659	161.2857	208.3571	685.3889	259.1667	2283.875
Total Room Nights	195.9231	66.0952	85.7857	262.4444	116.6333	877.125
BB	238.8	67.6095	76	179.2222	169.2333	1368
BB%	0.4559	0.3039	0.3168	0.2911	0.6793	0.6313
HB	77.6	99.5048	43.3571	29.5	32.4	357.75
HB%	0.2866	0.6606	0.3426	0.095	0.1467	0.1625
AI	180.4333	17.8302	89	476.6667	58.4667	558.125
AI%	0.2728	0.0926	0.3416	0.6139	0.1799	0.2063
MONTH	April 2019	April 2019	August 2019	June 2019	October 2019	July 2019
TOTAL BOOKINGS	22.1868	11.0476	9	28.6667	13.0667	94.125

EM Clusterer| Creta Palm 2019

Number of clusters selected by cross validation: 6

Number of iterations performed: 2

Attribute	Cluster 0 (0.25)	1 (0.09)	2 (0.14)	3 (0.16)	4 (0.21)	5 (0.15)
Booking Source						
ARHUS CHARTER	1.9645	1	6	1.1962	1.798	1.0413
AURINKOMATKAT	1	8	1	1	1	1
BLUE AEGEAN	5.9625	1	1	1.861	1.1185	2.058
BOOKING.COM	1	1	1	1	8	1
BRAVO TOURS	8	1	1	1	1	1
EXPEDIA	1	1	1	1	8	1
ITAKA	1	2	6	1.0036	1.9964	1
Jet2Holidays	1.0233	1	1	1.0427	1.8145	7.1194
RAINBOW	3.9457	1	4	1.2826	1.7107	1.0609
SUNWEB	1	1	1	7.9973	1	1.0027
TUI Deutschland	8	1	1	1	1	1
TUI NL	1	1	1	6.3393	1.6418	2.0189
TUI UK	1.0235	1	1	1.5546	1.9216	6.5003
[total]	35.9196	21	26	27.2773	32.0015	26.8016
Country						
Denmark	8.9645	1	6	1.1962	1.798	1.0413
Finland	1	8	1	1	1	1
Romania	5.9625	1	1	1.861	1.1185	2.058
Vary	1	1	1	1	15	1
Poland	3.9457	2	9	1.2863	2.7071	1.0609
UK	1.0468	1	1	1.5973	2.7361	12.6197
Netherlands	1	1	1	13.3366	1.6418	2.0216
Germany	8	1	1	1	1	1
[total]	30.9196	16	21	22.2773	27.0015	21.8016
Average pax/room						
mean	2.4112	2.63	2.3869	2.3397	2.5613	2.1836
std. dev.	0.4005	0.2832	0.4229	0.275	0.4782	0.2477
TO/ OTA						
TO	23.9196	9	14	15.2773	6.0015	14.8016
OTA	1	1	1	1	15	1
[total]	24.9196	10	15	16.2773	21.0015	15.8016
ADR						
mean	84.9945	95.7125	96.0338	74.2696	82.628	63.6668
std. dev.	40.0007	22.2281	13.1838	30.2916	33.8575	38.5206
TOTAL BOOKINGS						
mean	8.3335	96.25	25.7692	13.1435	17.7131	14.4021
std. dev.	8.6207	28.2212	17.7511	8.5626	15.7915	11.3081
TOTAL PAX Nights						
mean	123.1261	2399	648.6154	374.6268	270.1771	272.3284
std. dev.	110.6516	776.995	579.5326	278.0052	237.0828	224.4275
Total Room Nights						
mean	49.1283	910.875	251.5385	161.3676	111.4095	124.997
std. dev.	41.9332	254.8821	193.7709	118.9394	98.925	97.5841
BB						
mean	0	1499.125	0	182.1568	228.9783	201.8723
std. dev.	0.005	311.291	0.0009	122.6681	201.2768	166.6418
BB%						
mean	0.1087	0.6563	0	0.6072	0.8826	0.6017
std. dev.	0.2709	0.1441	0	0.2227	0.1161	0.1346
HB						
mean	113.6146	341.75	0	18.9981	41.1989	48.5101
std. dev.	101.8571	181.5625	121.4626	19.4071	51.9163	35.6939
HB%						
mean	0.8524	0.1375	0	0.0458	0.1174	0.1853
std. dev.	0.2427	0.0644	0.3631	0.0415	0.1161	0.0877
AI						
mean	9.5115	558.125	648.6154	173.9444	0	59.4841
std. dev.	15.966	400.59	579.5326	167.2705	0.0001	56.3886
AI%						
mean	0.0915	0.2062	1	0.3479	0	0.2255
std. dev.	0.1302	0.1066	0	0.2117	0.3429	0.1403
MONTH						
April 2019	4.0114	2	1	2.9054	5.0986	3.9846
May 2019	3	2	3	4.1278	5.6526	1.2195

June 2019	4	3	3	2.0342	3	3.9658
July 2019	5	2	3	3.0125	3	2.9875
August 2019	4	2	4	3.421	3	2.579
September 2019	5	2	3	3.0024	3	2.9976
October 2019	4.9082	2	3	2.7739	3.2503	3.0676
[total]	29.9196	15	20	21.2773	26.0015	20.8016

Farthest First with 3 Clusters| Creta Palm 2019

```
]
Cluster centroids:

Cluster 0:
BRAVO TOURS Denmark 2.0 TO 51.04 10.0 5.0 0.0 0.0 10.0 1.0 0.0
0.0 April 2019 1.0

Cluster 1:
AURINKOMATKAT Finland 3.06 TO 132.97 3700.0 1210.0 1859.0 0.5
540.0 0.15 1301.0 0.35 July 2019 135.0

Cluster 2:
BOOKING.COM Vary 3.69 OTA 132.24 59.0 16.0 57.0 0.97 2.0 0.03 0.0
0.0 July 2019 2.0

=== Model and evaluation on training set ===

Clustered Instances

0      61 ( 67%)
1       9 ( 10%)
2      21 ( 23%)
```

Farthest First with 4 Clusters| Creta Palm 2019

```
Cluster centroids:

Cluster 0:
BRAVO TOURS Denmark 2.0 TO 51.04 10.0 5.0 0.0 0.0 10.0 1.0 0.0
0.0 April 2019 1.0

Cluster 1:
AURINKOMATKAT Finland 3.06 TO 132.97 3700.0 1210.0 1859.0 0.5
540.0 0.15 1301.0 0.35 July 2019 135.0

Cluster 2:
BOOKING.COM Vary 3.69 OTA 132.24 59.0 16.0 57.0 0.97 2.0 0.03 0.0
0.0 July 2019 2.0

Cluster 3:
ITAKA Poland 3.15 TO 115.77 1718.0 545.0 0.0 0.0 0.0 0.0 1718.0
1.0 August 2019 41.0


=== Model and evaluation on training set ===

Clustered Instances
```

```
0      45 ( 49%)
1       7 (  8%)
2      18 ( 20%)
3      21 ( 23%)
```

Farthest First with 5 Clusters| Creta Palm 2019

```
Cluster centroids:

Cluster 0:
BRAVO TOURS Denmark 2.0 TO 51.04 10.0 5.0 0.0 0.0 10.0 1.0 0.0
0.0 April 2019 1.0

Cluster 1:
AURINKOMATKAT Finland 3.06 TO 132.97 3700.0 1210.0 1859.0 0.5
540.0 0.15 1301.0 0.35 July 2019 135.0

Cluster 2:
BOOKING.COM Vary 3.69 OTA 132.24 59.0 16.0 57.0 0.97 2.0 0.03 0.0
0.0 July 2019 2.0

Cluster 3:
ITAKA Poland 3.15 TO 115.77 1718.0 545.0 0.0 0.0 0.0 0.0 1718.0
1.0 August 2019 41.0

Cluster 4:
BLUE AEGEAN Romania 2.0 TO 0.0 8.0 4.0 8.0 1.0 0.0 0.0 0.0 0.0
May 2019 1.0

=== Model and evaluation on training set ===

Clustered Instances

0      22 ( 24%)
1       7 (  8%)
2      15 ( 16%)
3      17 ( 19%)
4      30 ( 33%)
```

Canopy Clusterer| Creta Palm 2019

Cluster 0: 'BRAVOTOURS', Denmark, 2.7625, TO, 113.8375, 9, 162.75, 57.75, 0, 0.29, 147.75, 0.955, 15, 0.045, 'June 2019',{4} <0,6,8,9,11,15>

Cluster 1: Jet2Holidays,UK, 2.165584, TO, 77.209231, 16.692308, 318.538462, 145.615385, 225.153846, 0.650452, 43.692308, 0.139738, 51.846154, 0.221756, 'July 2019',{13} <1,2,3,7,8,9,13>

Cluster 2: RAINBOW, Poland, 2.653147, TO, 47.845, 1,17. 75, 6.25, 17.75, 0.863971, 0, 0.071647, 0, 0.068206, 'April 2019',{4} <1,2,3,5,7,8,9,13,14,15>

Cluster 3: SUNWEB, Netherlands, 2.344545, TO, 80.927273, 16.545455, 474.727273, 204.909091, 222.181818, 0.507273, 29.818182, 0.071818, 222.727273, 0.420909, 'May 2019',{11} <1,2,3,7,10,11,12,13,14>

Cluster 4:
AURINKOMATKAT,Finland,2.498333,TO,88.43,95.333333,2321.833333,925.833333,1428.833333,0.625,365.666667,0.158333,527.333333,0.216667,'April 2019',{6} <4>

Cluster 5: EXPEDIA, Vary, 2.421111, OTA, 78.018889, 28.222222, 417.666667, 171.333333, 346.333333, 0.843333, 71.333333, 0.156667, 0, 0, 'April 2019',{9} <2,5,7,10>

Cluster 6:
'BLUEAEGEAN', Romania, 2.500647, TO, 81.34875, 13, 158.625, 62,29.85, 0.113971, 157.825, 0.780397, 33.054167, 0.109456, 'September 2019',{8} <0,6,8,9,15>

Cluster 7: 'TUI UK', UK, 2.646294, TO, 3.3, 0.5, 23, 8, 23, 0.727941, 0, 0.143294, 0, 0.136412, 'April 2019',{2} <1,2,3,5,7,8,13,15>

Cluster 8:
'BRAVOTOURS', Denmark, 2.073147, TO, 48.4575, 3, 43, 22.25, 0, 0.113971, 37, 0.754147, 6, 0.135706, 'April 2019',{4} <0,1,2,6,7,8,9,11,13,15>

Cluster 9: RAINBOW, Poland, 2.17, TO, 100.61, 7, 109.5, 47, 0, 0, 109.5, 1, 0, 0, 'July 2019',{2} <0,1,2,6,8,9,14,15>

Cluster 10: BOOKING.COM, Vary, 2.844, OTA, 121.024, 5.6, 93.6, 33.4, 72.8, 0.856, 20.8, 0.144, 0, 0, 'May 2019',{5} <3,5,10>

Cluster 11: 'ARHUSHARTER', Denmark, 2.17, TO, 83.287839, 33, 605.2, 281, 0, 0, 0, 0, 605.2, 1, 'June 2019',{5} <0,3,8,11,12,13,14>

Cluster 12: ITAKA, Poland, 2.836, TO, 103.606, 33.4, 1070.4, 367.6, 0, 0, 0, 0, 1070.4, 1, 'May 2019',{5} <3,11,12,14>

Cluster 13: 'ARHUS CHARTER', Denmark, 2.08, TO, 0, 17.5, 248, 115, 248, 1, 0, 0 ,0, 0, 'May 2019',{2} <1,2,3,7,8,11,13>

Cluster 14: RAINBOW, Poland, 2, TO, 104.656667, 1, 18, 9, 0, 0, 0, 0, 18, 1, 'May2019',{3} <2,3,9,11,12,14>

Cluster 15: 'TUIDeutschland', Germany, 2.354, TO, 89.37, 5, 102.2, 43.2, 0, 0, 92.2, 0.896, 10, 0.104, 'April 2019',{5} <0,2,6,7,8,9,15>

Clustered Instances

0	3	(3%)
1	8	(9%)
2	5	(5%)
3	12	(13%)
4	7	(8%)
5	8	(9%)
6	6	(7%)
7	7	(8%)
8	4	(4%)
9	2	(2%)
10	6	(7%)
11	5	(5%)
12	5	(5%)
13	3	(3%)
14	3	(3%)
15	7	(8%)

Make A Density Clusterer, Fitted estimators (with ML estimates of variance) | Creta Palm 2019

Cluster 0:
Prior probability: 0.5914

Attribute: Booking Source
Discrete Estimator. Counts = 3 2 8 8 7 8 2 6 1 2 7 6 7 (Total = 67)
Attribute: Country
Discrete Estimator. Counts = 9 2 8 15 2 12 7 7 (Total = 62)
Attribute: Average pax/room
Normal Distribution. Mean = 2.4121 StdDev = 0.4301
Attribute: TO/ OTA
Discrete Estimator. Counts = 41 15 (Total = 56)
Attribute: ADR
Normal Distribution. Mean = 74.4252 StdDev = 37.9721
Attribute: TOTAL BOOKINGS

Normal Distribution. Mean = 14.2222 StdDev = 15.2518
Attribute: TOTAL PAX Nights
Normal Distribution. Mean = 236.3333 StdDev = 300.9303
Attribute: Total Room Nights
Normal Distribution. Mean = 101.1296 StdDev = 129.5958
Attribute: BB
Normal Distribution. Mean = 149.0704 StdDev = 224.6238
Attribute: BB%
Normal Distribution. Mean = 0.555 StdDev = 0.3818
Attribute: HB
Normal Distribution. Mean = 75.7519 StdDev = 99.247
Attribute: HB%
Normal Distribution. Mean = 0.3741 StdDev = 0.3745
Attribute: AI
Normal Distribution. Mean = 21.2302 StdDev = 45.6064
Attribute: AI%
Normal Distribution. Mean = 0.0964 StdDev = 0.1353
Attribute: MONTH
Discrete Estimator. Counts = 13 10 9 8 4 8 9 (Total = 61)

Cluster 1:
Prior probability: 0.4086

Attribute: Booking Source
Discrete Estimator. Counts = 6 7 1 1 2 1 7 3 8 7 2 3 2 (Total = 50)
Attribute: Country
Discrete Estimator. Counts = 7 7 1 1 14 4 9 2 (Total = 45)
Attribute: Average pax/room
Normal Distribution. Mean = 2.4133 StdDev = 0.35
Attribute: TO/ OTA
Discrete Estimator. Counts = 38 1 (Total = 39)
Attribute: ADR
Normal Distribution. Mean = 93.3067 StdDev = 24.5645
Attribute: TOTAL BOOKINGS
Normal Distribution. Mean = 33.8108 StdDev = 36.6015
Attribute: TOTAL PAX Nights
Normal Distribution. Mean = 862.8378 StdDev = 946.7349
Attribute: Total Room Nights
Normal Distribution. Mean = 334.2703 StdDev = 341.4076
Attribute: BB
Normal Distribution. Mean = 369.7568 StdDev = 596.6422
Attribute: BB%
Normal Distribution. Mean = 0.3112 StdDev = 0.3184
Attribute: HB

Normal Distribution. Mean = 80.2973 StdDev = 146.6225
Attribute: HB%
Normal Distribution. Mean = 0.1588 StdDev = 0.2975
Attribute: AI
Normal Distribution. Mean = 412.7838 StdDev = 467.9476
Attribute: AI%
Normal Distribution. Mean = 0.5303 StdDev = 0.384
Attribute: MONTH
Discrete Estimator. Counts = 2 5 6 7 11 7 6 (Total = 44)

M5P Trees Algorithm| Creta Palm 2020

== Classifier model (full training set) ===

M5 pruned model tree:

(using smoothed linear models)

LM1 (52/17.057%)

LM num: 1

TOTAL BOOKINGS =

-3.2594 * Booking Source=SUNWEB,ARHUS CHARTER,AURINKOMATKAT,RAINBOW,BRAVO TOURS,EXPEDIA,ITAKA,BOOKING.COM

+ 5.7916 * Booking Source=ARHUS CHARTER,AURINKOMATKAT,RAINBOW,BRAVO TOURS,EXPEDIA,ITAKA,BOOKING.COM

+ 5.4911 * Booking Source=BOOKING.COM

+ 0.0311 * TOTAL PAX Nights

+ 0.0461 * Total Room Nights

- 0.1135

M5Rules Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

M5 pruned model rules

(using smoothed linear models) :

Number of Rules : 1

Rule: 1

TOTAL BOOKINGS =

-3.2594 * Booking Source=SUNWEB,ARHUS CHARTER,AURINKOMATKAT,RAINBOW,BRAVO TOURS,EXPEDIA,ITAKA,BOOKING.COM

+ 5.7916 * Booking Source=ARHUS CHARTER,AURINKOMATKAT,RAINBOW,BRAVO TOURS,EXPEDIA,ITAKA,BOOKING.COM

+ 5.4911 * Booking Source=BOOKING.COM

+ 0.0311 * TOTAL PAX Nights

+ 0.0461 * Total Room Nights

- 0.1135 [52/17.057%]

Linear Regression Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Linear Regression Model

TOTAL BOOKINGS =

-4.0586 * Booking Source=Jet2Holidays,BLUE AEGEAN,TUI Deutschland,SUNWEB,ARHUS CHARTER,AURINKOMATKAT,RAINBOW,BRAVO TOURS,EXPEDIA,ITAKA,BOOKING.COM +

3.6465 * Booking Source=BLUE AEGEAN,TUI Deutschland,SUNWEB,ARHUS CHARTER,AURINKOMATKAT,RAINBOW,BRAVO TOURS,EXPEDIA,ITAKA,BOOKING.COM +

-3.7908 * Booking Source=ITAKA,BOOKING.COM +

4.961 * Booking Source=BOOKING.COM +

-2.6084 * Country=Netherlands,Germany,Finland,Denmark,Poland,Vary +

4.9457 * Country=Denmark,Poland,Vary +

-3.0723 * MONTH=AUGUST 2020 +

0.0196 * TOTAL PAX Nights +

0.1122 * Total Room Nights +

-0.0083 * BB +

-0.0212 * AI + 1.977

SMO Reg Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

weights (not support vectors):

+ 0.0118 * (normalized) Booking Source=ARHUS CHARTER

+ 0.0003 * (normalized) Booking Source=AURINKOMATKAT

- 0.0016 * (normalized) Booking Source=BLUE AEGEAN

+ 0.0135 * (normalized) Booking Source=BOOKING.COM

+ 0.0029 * (normalized) Booking Source=BRAVO TOURS

- 0.0053 * (normalized) Booking Source=EXPEDIA

+ 0 * (normalized) Booking Source=ITAKA

- 0.0043 * (normalized) Booking Source=Jet2Holidays

+ 0.005 * (normalized) Booking Source=RAINBOW

- 0.0036 * (normalized) Booking Source=SELF BOOKINGS

- 0.0096 * (normalized) Booking Source=SUNWEB

- 0.0117 * (normalized) Booking Source=TUI Deutschland
+ 0 * (normalized) Booking Source=TUI NL
+ 0.0026 * (normalized) Booking Source=TUI UK
+ 0.0146 * (normalized) Country=Denmark
+ 0.0003 * (normalized) Country=Finland
- 0.0016 * (normalized) Country=Romania
+ 0.0046 * (normalized) Country=Vary
+ 0.005 * (normalized) Country=Poland
- 0.0017 * (normalized) Country=UK
- 0.0096 * (normalized) Country=Netherlands
- 0.0117 * (normalized) Country=Germany
- 0.0229 * (normalized) Average pax/room
+ 0.0082 * (normalized) TO/ OTA=OTA
+ 0.0455 * (normalized) ADR
- 0.0077 * (normalized) MONTH=JULY 2020
- 0.0123 * (normalized) MONTH=AUGUST 2020
+ 0.0044 * (normalized) MONTH=SEPTEMBER 2020
+ 0.0156 * (normalized) MONTH=OCTOBER 2020
+ 0.3325 * (normalized) TOTAL PAX Nights
+ 0.4042 * (normalized) Total Room Nights
+ 0.15 * (normalized) BB
- 0.0021 * (normalized) BB%
+ 0.1003 * (normalized) HB
+ 0.0058 * (normalized) HB%
+ 0.0069 * (normalized) AI
+ 0.0075 * (normalized) AI%

- 0.0088

Meta Random Committee Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

All the base classifiers:

RandomTree

==========

TOTAL PAX Nights < 737

| Country = Denmark

| | ADR < 147.39

| | | AI < 161

| | | | ADR < 45.22 : 0 (1.6/0)

| | | | ADR >= 45.22 : 10 (2/0)

| | | AI >= 161

| | | | TOTAL PAX Nights < 101.5 : 0 (0.4/0)

| | | | TOTAL PAX Nights >= 101.5

| | | | | Average pax/room < 2.17 : 18 (1/0)

| | | | | Average pax/room >= 2.17 : 14 (1/0)

| | ADR >= 147.39 : 30 (1/0)

| Country = Finland

| | ADR < 42.74 : 0 (1/0)

| | ADR >= 42.74

| | | Total Room Nights < 185.5 : 17 (1/0)

| | | Total Room Nights >= 185.5 : 29 (1/0)

| Country = Romania

| | MONTH = JULY 2020 : 3 (1/0)

| | MONTH = AUGUST 2020 : 10 (1/0)

| | MONTH = SEPTEMBER 2020 : 15 (1/0)

| | MONTH = OCTOBER 2020 : 0 (1/0)

| Country = Vary

| | HB < 53.5

| | | ADR < 64.38 : 0.63 (1.6/0.23)

| | | ADR >= 64.38

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 8 (1/0)

| | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | Booking Source = EXPEDIA : 6 (1/0)

| | | | Booking Source = ITAKA : 0 (0/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 0 (0/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| | HB >= 53.5

| | | Total Room Nights < 82 : 0 (0.4/0)

| | | Total Room Nights >= 82

| | | | Average pax/room < 2.4 : 32 (1/0)

| | | | Average pax/room >= 2.4 : 27 (1/0)

| Country = Poland

| | AI < 332

| | | MONTH = JULY 2020 : 1 (1/0)

| | | MONTH = AUGUST 2020 : 25 (1/0)

| | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | MONTH = OCTOBER 2020

| | | | BB% < 0.5 : 13 (1/0)

| | | | BB% >= 0.5 : 7 (1/0)

| | AI >= 332

| | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | Booking Source = BOOKING.COM : 0 (0/0)

| | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | Booking Source = EXPEDIA : 0 (0/0)

| | | Booking Source = ITAKA

| | | | TOTAL PAX Nights < 554 : 26 (1/0)

| | | | TOTAL PAX Nights >= 554 : 23 (1/0)

| | | Booking Source = Jet2Holidays : 0 (0/0)

| | | Booking Source = RAINBOW : 31 (1/0)

| | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | Booking Source = SUNWEB : 0 (0/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 0 (0/0)

| | | Booking Source = TUI UK : 0 (0/0)

| Country = UK

| | TOTAL PAX Nights < 262.5

| | | MONTH = JULY 2020 : 0.5 (2/0.25)

| | | MONTH = AUGUST 2020 : 0 (1/0)

| | | MONTH = SEPTEMBER 2020 : 2.5 (2/0.25)

| | | MONTH = OCTOBER 2020 : 0 (2/0)

| | TOTAL PAX Nights >= 262.5 : 18 (1/0)

| Country = Netherlands

| | BB < 189

| | | ADR < 41.63 : 0 (1/0)

| | | ADR >= 41.63

| | | | MONTH = JULY 2020

| | | | | Average pax/room < 2.36 : 3 (1/0)

| | | | | Average pax/room >= 2.36 : 6 (1/0)

| | | | MONTH = AUGUST 2020

| | | | | Average pax/room < 2.3 : 5 (1/0)

| | | | | Average pax/room >= 2.3 : 9 (1/0)

| | | | MONTH = SEPTEMBER 2020 : 8 (1/0)

| | | | MONTH = OCTOBER 2020 : 12 (1/0)

| | BB >= 189 : 20 (1/0)

| Country = Germany

| | MONTH = JULY 2020 : 16 (1/0)

| | MONTH = AUGUST 2020 : 9 (1/0)

| | MONTH = SEPTEMBER 2020 : 5 (1/0)

| | MONTH = OCTOBER 2020 : 3 (1/0)

TOTAL PAX Nights >= 737

| ADR < 117.03

```
| | TO/ OTA = TO
| | | Country = Denmark : 42 (1/0)
| | | Country = Finland : 0 (0/0)
| | | Country = Romania : 0 (0/0)
| | | Country = Vary : 0 (0/0)
| | | Country = Poland : 47 (1/0)
| | | Country = UK : 0 (0/0)
| | | Country = Netherlands : 0 (0/0)
| | | Country = Germany : 0 (0/0)
| | TO/ OTA = OTA
| | | Booking Source = ARHUS CHARTER : 0 (0/0)
| | | Booking Source = AURINKOMATKAT : 0 (0/0)
| | | Booking Source = BLUE AEGEAN : 0 (0/0)
| | | Booking Source = BOOKING.COM : 56 (1/0)
| | | Booking Source = BRAVO TOURS : 0 (0/0)
| | | Booking Source = EXPEDIA : 52 (1/0)
| | | Booking Source = ITAKA : 0 (0/0)
| | | Booking Source = Jet2Holidays : 0 (0/0)
| | | Booking Source = RAINBOW : 0 (0/0)
| | | Booking Source = SELF BOOKINGS : 0 (0/0)
| | | Booking Source = SUNWEB : 0 (0/0)
| | | Booking Source = TUI Deutschland : 0 (0/0)
| | | Booking Source = TUI NL : 0 (0/0)
| | | Booking Source = TUI UK : 0 (0/0)
| ADR >= 117.03 : 109 (1/0)
```

Size of the tree : 123

RandomTree

==========

Booking Source = ARHUS CHARTER

| MONTH = JULY 2020 : 0 (1/0)

| MONTH = AUGUST 2020 : 0 (1/0)

| MONTH = SEPTEMBER 2020 : 30 (1/0)

| MONTH = OCTOBER 2020 : 18 (1/0)

Booking Source = AURINKOMATKAT

| MONTH = JULY 2020 : 17 (1/0)

| MONTH = AUGUST 2020 : 29 (1/0)

| MONTH = SEPTEMBER 2020 : 0 (0/0)

| MONTH = OCTOBER 2020 : 0 (1/0)

Booking Source = BLUE AEGEAN

| TOTAL PAX Nights < 111

| | HB < 24.5 : 0 (1/0)

| | HB >= 24.5 : 3 (1/0)

| TOTAL PAX Nights >= 111

| | ADR < 87.31 : 15 (1/0)

| | ADR >= 87.31 : 10 (1/0)

Booking Source = BOOKING.COM

| MONTH = JULY 2020 : 56 (1/0)

| MONTH = AUGUST 2020 : 109 (1/0)

| MONTH = SEPTEMBER 2020 : 27 (1/0)

| MONTH = OCTOBER 2020 : 8 (1/0)

Booking Source = BRAVO TOURS

| MONTH = JULY 2020 : 42 (1/0)

| MONTH = AUGUST 2020 : 10 (1/0)

| MONTH = SEPTEMBER 2020 : 14 (1/0)

| MONTH = OCTOBER 2020 : 10 (1/0)

Booking Source = EXPEDIA

| MONTH = JULY 2020 : 32 (1/0)

| MONTH = AUGUST 2020 : 52 (1/0)

| MONTH = SEPTEMBER 2020 : 6 (1/0)

| MONTH = OCTOBER 2020 : 1 (1/0)

Booking Source = ITAKA

| Average pax/room < 2.78

| | BB < 36

| | | ADR < 99.42 : 23 (1/0)

| | | ADR >= 99.42 : 26 (1/0)

| | BB >= 36 : 7 (1/0)

| Average pax/room >= 2.78 : 47 (1/0)

Booking Source = Jet2Holidays

| TOTAL PAX Nights < 262.5

| | MONTH = JULY 2020 : 1 (1/0)

| | MONTH = AUGUST 2020 : 0 (0/0)

| | MONTH = SEPTEMBER 2020 : 3 (1/0)

| | MONTH = OCTOBER 2020 : 0 (1/0)

| TOTAL PAX Nights >= 262.5 : 18 (1/0)

Booking Source = RAINBOW

| AI% < 0.5 : 25 (1/0)

| AI% >= 0.5

| | Average pax/room < 2.12 : 31 (1/0)

| | Average pax/room >= 2.12

| | | Average pax/room < 2.58 : 13 (1/0)

| | | Average pax/room >= 2.58 : 1 (1/0)

Booking Source = SELF BOOKINGS : 0 (1/0)

Booking Source = SUNWEB

| BB < 189

| | TOTAL PAX Nights < 214 : 12 (1/0)

| | TOTAL PAX Nights >= 214

| | | Average pax/room < 2.54 : 9 (1/0)

| | | Average pax/room >= 2.54 : 6 (1/0)

| BB >= 189 : 20 (1/0)

Booking Source = TUI Deutschland

| ADR < 119.28

| | ADR < 98.34

| | | TOTAL PAX Nights < 78.5 : 3 (1/0)

| | | TOTAL PAX Nights >= 78.5 : 5 (1/0)

| | ADR >= 98.34 : 9 (1/0)

| ADR >= 119.28 : 16 (1/0)

Booking Source = TUI NL

| TOTAL PAX Nights < 88.5

| | ADR < 43.49 : 0 (1/0)

| | ADR >= 43.49 : 3 (1/0)

| TOTAL PAX Nights >= 88.5

| | TOTAL PAX Nights < 130.5 : 5 (1/0)

| | TOTAL PAX Nights >= 130.5 : 8 (1/0)

Booking Source = TUI UK

| MONTH = JULY 2020 : 0 (1/0)

| MONTH = AUGUST 2020 : 0 (1/0)

| MONTH = SEPTEMBER 2020 : 2 (1/0)

| MONTH = OCTOBER 2020 : 0 (1/0)

Size of the tree : 81

RandomTree

==========

BB < 489.5

| TOTAL PAX Nights < 235

| | TOTAL PAX Nights < 105

| | | TO/ OTA = TO

| | | | Country = Denmark : 0 (1.92/0)

| | | | Country = Finland : 0 (1/0)

| | | | Country = Romania

| | | | | HB < 24.5 : 0 (1/0)

| | | | | HB >= 24.5 : 3 (1/0)

| | | | Country = Vary : 0 (0.79/0)

| | | | Country = Poland

| | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | | Booking Source = ITAKA : 7 (1/0)

| | | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | | Booking Source = RAINBOW : 1 (1/0)

| | | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | | Booking Source = SUNWEB : 0 (0/0)

| | | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | | Booking Source = TUI NL : 0 (0/0)

| | | | | Booking Source = TUI UK : 0 (0/0)

| | | | Country = UK

| | | | | Total Room Nights < 3.5 : 0 (3.92/0)

| | | | | Total Room Nights >= 3.5

| | | | | | BB < 7 : 1 (1/0)

| | | | | | BB >= 7 : 2.5 (2/0.25)

| | | | Country = Netherlands

| | | | | AI < 13

| | | | | | Total Room Nights < 21 : 0 (1/0)

| | | | | | Total Room Nights >= 21 : 3 (1/0)

| | | | | AI >= 13 : 5 (1/0)

| | | | Country = Germany

| | | | | Average pax/room < 2.06 : 3 (1/0)

| | | | | Average pax/room >= 2.06 : 5 (1/0)

| | | TO/ OTA = OTA

| | | | ADR < 64.38 : 0.89 (1.13/0.1)

| | | | ADR >= 64.38

```
| | | | |  Average pax/room < 2.15 : 6 (1/0)
| | | | |  Average pax/room >= 2.15 : 8 (1/0)
| |  TOTAL PAX Nights >= 105
| | |  AI% < 0.76
| | | |  MONTH = JULY 2020 : 6 (1/0)
| | | |  MONTH = AUGUST 2020 : 9.67 (3/0.22)
| | | |  MONTH = SEPTEMBER 2020 : 8 (1/0)
| | | |  MONTH = OCTOBER 2020 : 0 (0/0)
| | |  AI% >= 0.76
| | | |  Average pax/room < 2.13 : 10 (1/0)
| | | |  Average pax/room >= 2.13
| | | | |  AI < 189.5 : 12.5 (2/0.25)
| | | | |  AI >= 189.5 : 14.5 (2/0.25)
|  TOTAL PAX Nights >= 235
| |  TOTAL PAX Nights < 381.5
| | |  Country = Denmark : 18 (1/0)
| | |  Country = Finland : 17 (1/0)
| | |  Country = Romania : 0 (0/0)
| | |  Country = Vary : 0 (0/0)
| | |  Country = Poland : 25 (1/0)
| | |  Country = UK : 0 (0/0)
| | |  Country = Netherlands : 9 (1/0)
| | |  Country = Germany : 16 (1/0)
| |  TOTAL PAX Nights >= 381.5
| | |  AI < 737
| | | |  Country = Denmark : 30 (1/0)
```

| | | | Country = Finland : 29 (1/0)

| | | | Country = Romania : 0 (0/0)

| | | | Country = Vary

| | | | | Average pax/room < 2.4 : 32 (1/0)

| | | | | Average pax/room >= 2.4 : 27 (1/0)

| | | | Country = Poland

| | | | | TOTAL PAX Nights < 576

| | | | | | ADR < 99.42 : 23 (1/0)

| | | | | | ADR >= 99.42 : 26 (1/0)

| | | | | TOTAL PAX Nights >= 576 : 31 (1/0)

| | | | Country = UK : 18 (1/0)

| | | | Country = Netherlands : 20 (1/0)

| | | | Country = Germany : 0 (0/0)

| | | AI >= 737 : 42 (1/0)

BB >= 489.5

| Booking Source = ARHUS CHARTER : 0 (0.08/0)

| Booking Source = AURINKOMATKAT : 0 (0/0)

| Booking Source = BLUE AEGEAN : 0 (0/0)

| Booking Source = BOOKING.COM

| | TOTAL PAX Nights < 1556.5 : 56 (1/0)

| | TOTAL PAX Nights >= 1556.5 : 109 (1/0)

| Booking Source = BRAVO TOURS : 0 (0/0)

| Booking Source = EXPEDIA : 52 (1/0)

| Booking Source = ITAKA : 47 (1/0)

| Booking Source = Jet2Holidays : 0 (0/0)

| Booking Source = RAINBOW : 0 (0/0)

| Booking Source = SELF BOOKINGS : 0 (0.08/0)

| Booking Source = SUNWEB : 0 (0/0)

| Booking Source = TUI Deutschland : 0 (0/0)

| Booking Source = TUI NL : 0 (0/0)

| Booking Source = TUI UK : 0 (0.08/0)

Size of the tree : 99

RandomTree

==========

Total Room Nights < 297.5

| TOTAL PAX Nights < 235

| | Total Room Nights < 49

| | | Total Room Nights < 17.5

| | | | Total Room Nights < 1.5 : 0 (10/0)

| | | | Total Room Nights >= 1.5 : 1.25 (4/0.19)

| | | Total Room Nights >= 17.5

| | | | Country = Denmark : 0 (0/0)

| | | | Country = Finland : 0 (0/0)

| | | | Country = Romania : 3 (1/0)

| | | | Country = Vary

| | | | | ADR < 70.08 : 6 (1/0)

| | | | | ADR >= 70.08 : 8 (1/0)

| | | | Country = Poland : 7 (1/0)

| | | | Country = UK : 3 (1/0)

| | | | Country = Netherlands

| | | | | Average pax/room < 2.13 : 3 (1/0)

| | | | | Average pax/room >= 2.13 : 5 (1/0)

| | | | Country = Germany

| | | | | Average pax/room < 2.06 : 3 (1/0)

| | | | | Average pax/room >= 2.06 : 5 (1/0)

| | Total Room Nights >= 49

| | | BB% < 0.17

| | | | MONTH = JULY 2020 : 0 (0/0)

| | | | MONTH = AUGUST 2020 : 9.5 (2/0.25)

| | | | MONTH = SEPTEMBER 2020 : 14.5 (2/0.25)

| | | | MONTH = OCTOBER 2020

| | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | | Booking Source = BRAVO TOURS : 10 (1/0)

| | | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | | Booking Source = ITAKA : 0 (0/0)

| | | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | | Booking Source = RAINBOW : 13 (1/0)

| | | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | | Booking Source = SUNWEB : 12 (1/0)

| | | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | | Booking Source = TUI NL : 0 (0/0)

| | | | | Booking Source = TUI UK : 0 (0/0)

| | | BB% >= 0.17

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | Booking Source = BRAVO TOURS : 10 (1/0)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA : 0 (0/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 0 (0/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB : 6 (1/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 8 (1/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| TOTAL PAX Nights >= 235

| | Booking Source = ARHUS CHARTER

| | | TOTAL PAX Nights < 318.5 : 18 (1/0)

| | | TOTAL PAX Nights >= 318.5 : 30 (1/0)

| | Booking Source = AURINKOMATKAT

| | | TOTAL PAX Nights < 385 : 17 (1/0)

| | | TOTAL PAX Nights >= 385 : 29 (1/0)

| | Booking Source = BLUE AEGEAN : 0 (0/0)

| | Booking Source = BOOKING.COM : 27 (1/0)

| | Booking Source = BRAVO TOURS : 0 (0/0)

| | Booking Source = EXPEDIA : 32 (1/0)

| | Booking Source = ITAKA

| | | ADR < 99.42 : 23 (1/0)

| | | ADR >= 99.42 : 26 (1/0)

| | Booking Source = Jet2Holidays : 18 (1/0)

| | Booking Source = RAINBOW

| | | BB < 162 : 31 (1/0)

| | | BB >= 162 : 25 (1/0)

| | Booking Source = SELF BOOKINGS : 0 (0/0)

| | Booking Source = SUNWEB

| | | MONTH = JULY 2020 : 0 (0/0)

| | | MONTH = AUGUST 2020 : 9 (1/0)

| | | MONTH = SEPTEMBER 2020 : 20 (1/0)

| | | MONTH = OCTOBER 2020 : 0 (0/0)

| | Booking Source = TUI Deutschland : 16 (1/0)

| | Booking Source = TUI NL : 0 (0/0)

| | Booking Source = TUI UK : 0 (0/0)

Total Room Nights >= 297.5

| ADR < 117.03

| | TO/ OTA = TO

| | | Average pax/room < 2.66 : 42 (1/0)

| | | Average pax/room >= 2.66 : 47 (1/0)

| | TO/ OTA = OTA

| | | MONTH = JULY 2020 : 56 (1/0)

| | | MONTH = AUGUST 2020 : 52 (1/0)

| | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | MONTH = OCTOBER 2020 : 0 (0/0)

| ADR >= 117.03 : 109 (1/0)

Size of the tree : 95

RandomTree

```
==========
BB < 489.5
|   Total Room Nights < 88
|   |   Booking Source = ARHUS CHARTER : 0 (1.92/0)
|   |   Booking Source = AURINKOMATKAT : 0 (1/0)
|   |   Booking Source = BLUE AEGEAN
|   |   |   Total Room Nights < 46
|   |   |   |   ADR < 43.55 : 0 (1/0)
|   |   |   |   ADR >= 43.55 : 3 (1/0)
|   |   |   Total Room Nights >= 46 : 10 (1/0)
|   |   Booking Source = BOOKING.COM : 8 (1/0)
|   |   Booking Source = BRAVO TOURS : 10 (2/0)
|   |   Booking Source = EXPEDIA
|   |   |   Average pax/room < 2.54 : 6 (1/0)
|   |   |   Average pax/room >= 2.54 : 1 (1/0)
|   |   Booking Source = ITAKA : 7 (1/0)
|   |   Booking Source = Jet2Holidays
|   |   |   BB < 28 : 0.5 (2/0.25)
|   |   |   BB >= 28 : 3 (1/0)
|   |   Booking Source = RAINBOW
|   |   |   Average pax/room < 2.58 : 13 (1/0)
|   |   |   Average pax/room >= 2.58 : 1 (1/0)
```

| | Booking Source = SELF BOOKINGS : 0 (0.92/0)

| | Booking Source = SUNWEB

| | | MONTH = JULY 2020 : 6 (1/0)

| | | MONTH = AUGUST 2020 : 0 (0/0)

| | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | MONTH = OCTOBER 2020 : 12 (1/0)

| | Booking Source = TUI Deutschland

| | | AI < 29

| | | | MONTH = JULY 2020 : 0 (0/0)

| | | | MONTH = AUGUST 2020 : 0 (0/0)

| | | | MONTH = SEPTEMBER 2020 : 5 (1/0)

| | | | MONTH = OCTOBER 2020 : 3 (1/0)

| | | AI >= 29 : 9 (1/0)

| | Booking Source = TUI NL

| | | TOTAL PAX Nights < 88.5

| | | | MONTH = JULY 2020 : 3 (1/0)

| | | | MONTH = AUGUST 2020 : 0 (0/0)

| | | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | | MONTH = OCTOBER 2020 : 0 (1/0)

| | | TOTAL PAX Nights >= 88.5

| | | | ADR < 93.64 : 5 (1/0)

| | | | ADR >= 93.64 : 8 (1/0)

| | Booking Source = TUI UK

| | | TOTAL PAX Nights < 7 : 0 (2.92/0)

| | | TOTAL PAX Nights >= 7 : 2 (1/0)

| Total Room Nights >= 88

| | Total Room Nights < 159.5

| | | Booking Source = ARHUS CHARTER : 18 (1/0)

| | | Booking Source = AURINKOMATKAT : 17 (1/0)

| | | Booking Source = BLUE AEGEAN : 15 (1/0)

| | | Booking Source = BOOKING.COM : 0 (0/0)

| | | Booking Source = BRAVO TOURS : 14 (1/0)

| | | Booking Source = EXPEDIA : 0 (0/0)

| | | Booking Source = ITAKA : 0 (0/0)

| | | Booking Source = Jet2Holidays : 0 (0/0)

| | | Booking Source = RAINBOW : 25 (1/0)

| | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | Booking Source = SUNWEB : 9 (1/0)

| | | Booking Source = TUI Deutschland : 16 (1/0)

| | | Booking Source = TUI NL : 0 (0/0)

| | | Booking Source = TUI UK : 0 (0/0)

| | Total Room Nights >= 159.5

| | | Country = Denmark

| | | | TOTAL PAX Nights < 641 : 30 (1/0)

| | | | TOTAL PAX Nights >= 641 : 42 (1/0)

| | | Country = Finland : 29 (1/0)

| | | Country = Romania : 0 (0/0)

| | | Country = Vary

| | | | ADR < 91.19 : 32 (1/0)

| | | | ADR >= 91.19 : 27 (1/0)

| | | Country = Poland

| | | | Average pax/room < 2.25 : 31 (1/0)

| | | | Average pax/room >= 2.25

| | | | | Average pax/room < 2.54 : 23 (1/0)

| | | | | Average pax/room >= 2.54 : 26 (1/0)

| | | Country = UK : 18 (1/0)

| | | Country = Netherlands : 20 (1/0)

| | | Country = Germany : 0 (0/0)

BB >= 489.5

| TO/ OTA = TO : 39.63 (1.19/292.19)

| TO/ OTA = OTA

| | TOTAL PAX Nights < 1556.5

| | | ADR < 44.03 : 0 (0.06/0)

| | | ADR >= 44.03 : 54 (2/4)

| | TOTAL PAX Nights >= 1556.5 : 109 (1/0)

Size of the tree : 87

RandomTree

==========

BB < 489.5

| Booking Source = ARHUS CHARTER

| | MONTH = JULY 2020 : 0 (0.92/0)

| | MONTH = AUGUST 2020 : 0 (1/0)

| | MONTH = SEPTEMBER 2020 : 30 (1/0)

| | MONTH = OCTOBER 2020 : 18 (1/0)

| Booking Source = AURINKOMATKAT

| | ADR < 42.74 : 0 (1/0)

| | ADR >= 42.74

| | | Average pax/room < 2.1 : 29 (1/0)

| | | Average pax/room >= 2.1 : 17 (1/0)

| Booking Source = BLUE AEGEAN

| | TOTAL PAX Nights < 111

| | | ADR < 43.55 : 0 (1/0)

| | | ADR >= 43.55 : 3 (1/0)

| | TOTAL PAX Nights >= 111

| | | Average pax/room < 2.31 : 15 (1/0)

| | | Average pax/room >= 2.31 : 10 (1/0)

| Booking Source = BOOKING.COM

| | Average pax/room < 2.33 : 8 (1/0)

| | Average pax/room >= 2.33 : 27 (1/0)

| Booking Source = BRAVO TOURS

| | TOTAL PAX Nights < 549

| | | ADR < 102.41 : 10 (2/0)

| | | ADR >= 102.41 : 14 (1/0)

| | TOTAL PAX Nights >= 549 : 42 (1/0)

| Booking Source = EXPEDIA

| | ADR < 78.41

| | | ADR < 64.38 : 1 (1/0)

| | | ADR >= 64.38 : 6 (1/0)

| | ADR >= 78.41 : 32 (1/0)

| Booking Source = ITAKA

| | MONTH = JULY 2020 : 26 (1/0)

| | MONTH = AUGUST 2020 : 0 (0/0)

| | MONTH = SEPTEMBER 2020 : 23 (1/0)

| | MONTH = OCTOBER 2020 : 7 (1/0)

| Booking Source = Jet2Holidays

| | MONTH = JULY 2020 : 1 (1/0)

| | MONTH = AUGUST 2020 : 18 (1/0)

| | MONTH = SEPTEMBER 2020 : 3 (1/0)

| | MONTH = OCTOBER 2020 : 0 (1/0)

| Booking Source = RAINBOW

| | TOTAL PAX Nights < 226.5

| | | Total Room Nights < 33.5 : 1 (1/0)

| | | Total Room Nights >= 33.5 : 13 (1/0)

| | TOTAL PAX Nights >= 226.5

| | | Average pax/room < 2.24 : 31 (1/0)

| | | Average pax/room >= 2.24 : 25 (1/0)

| Booking Source = SELF BOOKINGS : 0 (0.92/0)

| Booking Source = SUNWEB

| | BB% < 0.47

| | | MONTH = JULY 2020 : 6 (1/0)

| | | MONTH = AUGUST 2020 : 9 (1/0)

| | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | MONTH = OCTOBER 2020 : 12 (1/0)

| | BB% >= 0.47 : 20 (1/0)

| Booking Source = TUI Deutschland

| | ADR < 119.28

| | | Average pax/room < 2.2

| | | | Average pax/room < 2.06 : 3 (1/0)

| | | | Average pax/room >= 2.06 : 5 (1/0)

| | | Average pax/room >= 2.2 : 9 (1/0)

| | ADR >= 119.28 : 16 (1/0)

| Booking Source = TUI NL

| | MONTH = JULY 2020 : 3 (1/0)

| | MONTH = AUGUST 2020 : 5 (1/0)

| | MONTH = SEPTEMBER 2020 : 8 (1/0)

| | MONTH = OCTOBER 2020 : 0 (1/0)

| Booking Source = TUI UK

| | TOTAL PAX Nights < 7 : 0 (2.92/0)

| | TOTAL PAX Nights >= 7 : 2 (1/0)

BB >= 489.5

| ADR < 117.03

| | ADR < 44.03 : 0 (0.24/0)

| | ADR >= 44.03

| | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | Booking Source = BOOKING.COM : 56 (1/0)

| | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | Booking Source = EXPEDIA : 52 (1/0)

| | | Booking Source = ITAKA : 47 (1/0)

| | | Booking Source = Jet2Holidays : 0 (0/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | Booking Source = SUNWEB : 0 (0/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 0 (0/0)

| | | Booking Source = TUI UK : 0 (0/0)

| ADR >= 117.03 : 109 (1/0)

Size of the tree : 91

RandomTree

==========

BB < 489.5

| Total Room Nights < 88

| | Booking Source = ARHUS CHARTER : 0 (1.92/0)

| | Booking Source = AURINKOMATKAT : 0 (1/0)

| | Booking Source = BLUE AEGEAN

| | | ADR < 89.95

| | | | MONTH = JULY 2020 : 3 (1/0)

| | | | MONTH = AUGUST 2020 : 0 (0/0)

| | | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | | MONTH = OCTOBER 2020 : 0 (1/0)

| | | ADR >= 89.95 : 10 (1/0)

| | Booking Source = BOOKING.COM : 8 (1/0)

| | Booking Source = BRAVO TOURS : 10 (2/0)

| | Booking Source = EXPEDIA

| | | TOTAL PAX Nights < 41 : 1 (1/0)

| | | TOTAL PAX Nights >= 41 : 6 (1/0)

| | Booking Source = ITAKA : 7 (1/0)

| | Booking Source = Jet2Holidays

| | | ADR < 45.04 : 0 (1/0)

| | | ADR >= 45.04

| | | | TOTAL PAX Nights < 63 : 1 (1/0)

| | | | TOTAL PAX Nights >= 63 : 3 (1/0)

| | Booking Source = RAINBOW

| | | Total Room Nights < 33.5 : 1 (1/0)

| | | Total Room Nights >= 33.5 : 13 (1/0)

| | Booking Source = SELF BOOKINGS : 0 (0.92/0)

| | Booking Source = SUNWEB

| | | ADR < 103.91 : 12 (1/0)

| | | ADR >= 103.91 : 6 (1/0)

| | Booking Source = TUI Deutschland

| | | ADR < 98.34

| | | | ADR < 74.59 : 3 (1/0)

| | | | ADR >= 74.59 : 5 (1/0)

| | | ADR >= 98.34 : 9 (1/0)

| | Booking Source = TUI NL

| | | AI < 13

| | | | ADR < 43.49 : 0 (1/0)

| | | | ADR >= 43.49 : 3 (1/0)

| | | AI >= 13

| | | | Average pax/room < 2.19 : 8 (1/0)

| | | | Average pax/room >= 2.19 : 5 (1/0)

| | Booking Source = TUI UK

| | | TOTAL PAX Nights < 7 : 0 (2.92/0)

| | | TOTAL PAX Nights >= 7 : 2 (1/0)

| Total Room Nights >= 88

| | Country = Denmark

| | | MONTH = JULY 2020 : 42 (1/0)

| | | MONTH = AUGUST 2020 : 0 (0/0)

| | | MONTH = SEPTEMBER 2020

| | | | Total Room Nights < 137 : 14 (1/0)

| | | | Total Room Nights >= 137 : 30 (1/0)

| | | MONTH = OCTOBER 2020 : 18 (1/0)

| | Country = Finland

| | | TOTAL PAX Nights < 385 : 17 (1/0)

| | | TOTAL PAX Nights >= 385 : 29 (1/0)

| | Country = Romania : 15 (1/0)

| | Country = Vary

| | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | Booking Source = BOOKING.COM : 27 (1/0)

| | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | Booking Source = EXPEDIA : 32 (1/0)

| | | Booking Source = ITAKA : 0 (0/0)

| | | Booking Source = Jet2Holidays : 0 (0/0)

| | | Booking Source = RAINBOW : 0 (0/0)

| | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | Booking Source = SUNWEB : 0 (0/0)

| | | Booking Source = TUI Deutschland : 0 (0/0)

| | | Booking Source = TUI NL : 0 (0/0)

| | | Booking Source = TUI UK : 0 (0/0)

| | Country = Poland

| | | MONTH = JULY 2020 : 26 (1/0)

| | | MONTH = AUGUST 2020 : 25 (1/0)

| | | MONTH = SEPTEMBER 2020

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA : 23 (1/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 31 (1/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| | | MONTH = OCTOBER 2020 : 0 (0/0)

| | Country = UK : 18 (1/0)

| | Country = Netherlands

| | | Average pax/room < 2.32 : 20 (1/0)

| | | Average pax/room >= 2.32 : 9 (1/0)

| | Country = Germany : 16 (1/0)

BB >= 489.5

| Average pax/room < 3.06

| | Total Room Nights < 158.5 : 0 (0.18/0)

| | Total Room Nights >= 158.5

| | | BB < 954

| | | | ADR < 99.44 : 52 (1/0)

| | | | ADR >= 99.44 : 56 (1/0)

| | | BB >= 954 : 47 (1/0)

| Average pax/room >= 3.06 : 102.71 (1.06/645.9)

Size of the tree : 105

RandomTree

==========

Total Room Nights < 297.5

| Total Room Nights < 88

| | Total Room Nights < 27

| | | TOTAL PAX Nights < 4.5 : 0 (10/0)

| | | TOTAL PAX Nights >= 4.5

| | | | HB < 45.5 : 1.25 (4/0.19)

| | | | HB >= 45.5 : 3 (1/0)

| | Total Room Nights >= 27

| | | Country = Denmark : 10 (2/0)

| | | Country = Finland : 0 (0/0)

| | | Country = Romania : 10 (1/0)

| | | Country = Vary

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 8 (1/0)

| | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | Booking Source = EXPEDIA : 6 (1/0)

| | | | Booking Source = ITAKA : 0 (0/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 0 (0/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| | | Country = Poland

| | | | Total Room Nights < 46.5 : 7 (1/0)

| | | | Total Room Nights >= 46.5 : 13 (1/0)

| | | Country = UK : 3 (1/0)

| | | Country = Netherlands

| | | | ADR < 85.13 : 12 (1/0)

| | | | ADR >= 85.13

| | | | | Total Room Nights < 60

| | | | | | TOTAL PAX Nights < 88.5 : 3 (1/0)

| | | | | | TOTAL PAX Nights >= 88.5 : 5 (1/0)

| | | | | Total Room Nights >= 60

| | | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | | | Booking Source = ITAKA : 0 (0/0)

| | | | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | | | Booking Source = RAINBOW : 0 (0/0)

| | | | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | | | Booking Source = SUNWEB : 6 (1/0)

| | | | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | | | Booking Source = TUI NL : 8 (1/0)

| | | | | | Booking Source = TUI UK : 0 (0/0)

| | | Country = Germany

| | | | MONTH = JULY 2020 : 0 (0/0)

| | | | MONTH = AUGUST 2020 : 9 (1/0)

| | | | MONTH = SEPTEMBER 2020 : 5 (1/0)

| | | | MONTH = OCTOBER 2020 : 3 (1/0)

| Total Room Nights >= 88

| | Average pax/room < 2.09

| | | Total Room Nights < 256 : 29 (1/0)

| | | Total Room Nights >= 256 : 31 (1/0)

| | Average pax/room >= 2.09

| | | Country = Denmark

| | | | ADR < 147.39

| | | | | ADR < 95.55 : 18 (1/0)

| | | | | ADR >= 95.55 : 14 (1/0)

| | | | ADR >= 147.39 : 30 (1/0)

| | | Country = Finland : 17 (1/0)

| | | Country = Romania : 15 (1/0)

| | | Country = Vary

| | | | MONTH = JULY 2020 : 32 (1/0)

| | | | MONTH = AUGUST 2020 : 0 (0/0)

| | | | MONTH = SEPTEMBER 2020 : 27 (1/0)

| | | | MONTH = OCTOBER 2020 : 0 (0/0)

| | | Country = Poland

| | | | ADR < 99.42 : 23 (1/0)

| | | | ADR >= 99.42 : 25.5 (2/0.25)

| | | Country = UK : 18 (1/0)

| | | Country = Netherlands

| | | | TOTAL PAX Nights < 389 : 9 (1/0)

| | | | TOTAL PAX Nights >= 389 : 20 (1/0)

| | | Country = Germany : 16 (1/0)

Total Room Nights >= 297.5

| TOTAL PAX Nights < 1619

| | TOTAL PAX Nights < 925.5 : 42 (1/0)

| | TOTAL PAX Nights >= 925.5

| | | Country = Denmark : 0 (0/0)

| | | Country = Finland : 0 (0/0)

| | | Country = Romania : 0 (0/0)

| | | Country = Vary

| | | | ADR < 99.44 : 52 (1/0)

| | | | ADR >= 99.44 : 56 (1/0)

| | | Country = Poland : 47 (1/0)

| | | Country = UK : 0 (0/0)

| | | Country = Netherlands : 0 (0/0)

| | | Country = Germany : 0 (0/0)

| TOTAL PAX Nights >= 1619 : 109 (1/0)

Size of the tree : 97

RandomTree

==========

BB < 489.5

| TOTAL PAX Nights < 235

| | AI < 37

| | | Total Room Nights < 27

| | | | ADR < 29.86 : 0 (9.02/0)

| | | | ADR >= 29.86

| | | | | Country = Denmark : 0 (0/0)

| | | | | Country = Finland : 0 (0/0)

| | | | | Country = Romania : 3 (1/0)

| | | | | Country = Vary : 1 (1/0)

| | | | | Country = Poland : 1 (1/0)

| | | | | Country = UK : 1.5 (2/0.25)

| | | | | Country = Netherlands : 0 (0/0)

| | | | | Country = Germany : 0 (0/0)

| | | Total Room Nights >= 27

| | | | ADR < 91.94

| | | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | | Booking Source = BOOKING.COM : 8 (1/0)

| | | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | | Booking Source = EXPEDIA : 6 (1/0)

| | | | | Booking Source = ITAKA : 7 (1/0)

| | | | | Booking Source = Jet2Holidays : 3 (1/0)

| | | | | Booking Source = RAINBOW : 0 (0/0)

| | | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | | Booking Source = SUNWEB : 0 (0/0)

| | | | | Booking Source = TUI Deutschland

| | | | | | Average pax/room < 2.06 : 3 (1/0)

| | | | | | Average pax/room >= 2.06 : 5 (1/0)

| | | | | Booking Source = TUI NL

| | | | | | Average pax/room < 2.13 : 3 (1/0)

| | | | | | Average pax/room >= 2.13 : 5 (1/0)

| | | | | Booking Source = TUI UK : 0 (0/0)

| | | | ADR >= 91.94 : 10 (2/0)

| | AI >= 37

| | | ADR < 39.73 : 0 (0.73/0)

| | | ADR >= 39.73

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 15 (1/0)

| | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | Booking Source = BRAVO TOURS

| | | | | Total Room Nights < 73.5 : 10 (1/0)

| | | | | Total Room Nights >= 73.5 : 14 (1/0)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA : 0 (0/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 13 (1/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB

| | | | | ADR < 103.91 : 12 (1/0)

| | | | | ADR >= 103.91 : 6 (1/0)

| | | | Booking Source = TUI Deutschland : 9 (1/0)

| | | | Booking Source = TUI NL : 8 (1/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| TOTAL PAX Nights >= 235

| | Country = Denmark

| | | TOTAL PAX Nights < 318.5 : 18 (1/0)

| | | TOTAL PAX Nights >= 318.5

| | | | MONTH = JULY 2020 : 42 (1/0)

| | | | MONTH = AUGUST 2020 : 0 (0/0)

| | | | MONTH = SEPTEMBER 2020 : 30 (1/0)

| | | | MONTH = OCTOBER 2020 : 0 (0/0)

| | Country = Finland

| | | Average pax/room < 2.1 : 29 (1/0)

| | | Average pax/room >= 2.1 : 17 (1/0)

| | Country = Romania : 0 (0/0)

| | Country = Vary

| | | ADR < 91.19 : 32 (1/0)

| | | ADR >= 91.19 : 27 (1/0)

| | Country = Poland

| | | Total Room Nights < 256.5

| | | | ADR < 99.42 : 23 (1/0)

| | | | ADR >= 99.42 : 25.5 (2/0.25)

| | | Total Room Nights >= 256.5 : 31 (1/0)

| | Country = UK : 18 (1/0)

| | Country = Netherlands

| | | ADR < 93.81 : 20 (1/0)

| | | ADR >= 93.81 : 9 (1/0)

| | Country = Germany : 16 (1/0)

BB >= 489.5

| ADR < 117.03

| | ADR < 44.03 : 0 (0.24/0)

| | ADR >= 44.03

| | | Country = Denmark : 0 (0/0)

| | | Country = Finland : 0 (0/0)

| | | Country = Romania : 0 (0/0)

| | | Country = Vary

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 56 (1/0)

| | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | Booking Source = EXPEDIA : 52 (1/0)

| | | | Booking Source = ITAKA : 0 (0/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 0 (0/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| | | Country = Poland : 47 (1/0)

| | | Country = UK : 0 (0/0)

| | | Country = Netherlands : 0 (0/0)

| | | Country = Germany : 0 (0/0)

| ADR >= 117.03 : 109 (1/0)

Size of the tree : 109

RandomTree

==========

ADR < 97.41

| Booking Source = ARHUS CHARTER

| | ADR < 41.14 : 0 (2/0)

| | ADR >= 41.14 : 18 (1/0)

| Booking Source = AURINKOMATKAT

| | Total Room Nights < 68.5 : 0 (1/0)

| | Total Room Nights >= 68.5

| | | Average pax/room < 2.1 : 29 (1/0)

| | | Average pax/room >= 2.1 : 17 (1/0)

| Booking Source = BLUE AEGEAN

| | Total Room Nights < 46

| | | ADR < 43.55 : 0 (1/0)

| | | ADR >= 43.55 : 3 (1/0)

| | Total Room Nights >= 46

| | | Average pax/room < 2.31 : 15 (1/0)

| | | Average pax/room >= 2.31 : 10 (1/0)

| Booking Source = BOOKING.COM

| | Average pax/room < 2.33 : 8 (1/0)

| | Average pax/room >= 2.33 : 27 (1/0)

| Booking Source = BRAVO TOURS : 10 (2/0)

| Booking Source = EXPEDIA

| | MONTH = JULY 2020 : 32 (1/0)

| | MONTH = AUGUST 2020 : 52 (1/0)

| | MONTH = SEPTEMBER 2020 : 6 (1/0)

| | MONTH = OCTOBER 2020 : 1 (1/0)

| Booking Source = ITAKA

| | MONTH = JULY 2020 : 0 (0/0)

| | MONTH = AUGUST 2020 : 0 (0/0)

| | MONTH = SEPTEMBER 2020 : 23 (1/0)

| | MONTH = OCTOBER 2020 : 7 (1/0)

| Booking Source = Jet2Holidays

| | BB < 231

| | | AI < 14 : 0.5 (2/0.25)

| | | AI >= 14 : 3 (1/0)

| | BB >= 231 : 18 (1/0)

| Booking Source = RAINBOW

| | ADR < 85.19 : 13 (1/0)

| | ADR >= 85.19 : 1 (1/0)

| Booking Source = SELF BOOKINGS : 0 (1/0)

| Booking Source = SUNWEB

| | MONTH = JULY 2020 : 0 (0/0)

| | MONTH = AUGUST 2020 : 0 (0/0)

| | MONTH = SEPTEMBER 2020 : 20 (1/0)

| | MONTH = OCTOBER 2020 : 12 (1/0)

| Booking Source = TUI Deutschland

| | MONTH = JULY 2020 : 0 (0/0)

| | MONTH = AUGUST 2020 : 0 (0/0)

| | MONTH = SEPTEMBER 2020 : 5 (1/0)

| | MONTH = OCTOBER 2020 : 3 (1/0)

| Booking Source = TUI NL

| | MONTH = JULY 2020 : 3 (1/0)

| | MONTH = AUGUST 2020 : 5 (1/0)

| | MONTH = SEPTEMBER 2020 : 8 (1/0)

| | MONTH = OCTOBER 2020 : 0 (1/0)

| Booking Source = TUI UK

| | ADR < 35 : 0 (3/0)

| | ADR >= 35 : 2 (1/0)

ADR >= 97.41

| BB < 1367.5

| | Country = Denmark

| | | AI < 295 : 14 (1/0)

| | | AI >= 295

| | | | Booking Source = ARHUS CHARTER : 30 (1/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | Booking Source = BRAVO TOURS : 42 (1/0)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA : 0 (0/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 0 (0/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| | Country = Finland : 0 (0/0)

| | Country = Romania : 0 (0/0)

| | Country = Vary : 56 (1/0)

| | Country = Poland

| | | BB% < 0.5

| | | | ADR < 102.14 : 31 (1/0)

| | | | ADR >= 102.14 : 26 (1/0)

| | | BB% >= 0.5

| | | | Booking Source = ARHUS CHARTER : 0 (0/0)

| | | | Booking Source = AURINKOMATKAT : 0 (0/0)

| | | | Booking Source = BLUE AEGEAN : 0 (0/0)

| | | | Booking Source = BOOKING.COM : 0 (0/0)

| | | | Booking Source = BRAVO TOURS : 0 (0/0)

| | | | Booking Source = EXPEDIA : 0 (0/0)

| | | | Booking Source = ITAKA : 47 (1/0)

| | | | Booking Source = Jet2Holidays : 0 (0/0)

| | | | Booking Source = RAINBOW : 25 (1/0)

| | | | Booking Source = SELF BOOKINGS : 0 (0/0)

| | | | Booking Source = SUNWEB : 0 (0/0)

| | | | Booking Source = TUI Deutschland : 0 (0/0)

| | | | Booking Source = TUI NL : 0 (0/0)

| | | | Booking Source = TUI UK : 0 (0/0)

| | Country = UK : 0 (0/0)

| | Country = Netherlands

| | | TOTAL PAX Nights < 299 : 6 (1/0)

| | | TOTAL PAX Nights >= 299 : 9 (1/0)

| | Country = Germany

| | | Average pax/room < 2.35 : 9 (1/0)

| | | Average pax/room >= 2.35 : 16 (1/0)

| BB >= 1367.5 : 109 (1/0)

Size of the tree : 107

Multilayer Perceptron Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Linear Node 0

Inputs Weights

Threshold -0.35220722928027764

Node 1 0.7068336793168924

Node 2 -0.013147412294212868

Node 3 -0.3600576130557452

Node 4 0.2625684872935586

Node 5 -0.20049201520802387

Node 6 0.5020969459777488

Node 7 -0.1607713922400183

Node 8 0.020298920989118313

Node 9 -0.00869032593719303

Node 10 -8.788576605409771E-5

Node 11 -0.3239302288546291

Node 12 0.6945851771843676

Node 13 -0.5866254154459591

Node 14 -0.657429677571837

Node 15 0.002093448409455931

Node 16 0.10797855195831878

Node 17 -0.03758542503939778

Node 18 0.303927612688793

Node 19 -0.05647774504642454

Sigmoid Node 1

Inputs   Weights

Threshold   -0.0443585314448995

Attrib Booking Source=ARHUS CHARTER   -0.034098816062567726

Attrib Booking Source=AURINKOMATKAT   0.024779310379166104

Attrib Booking Source=BLUE AEGEAN   0.06805491113679517

Attrib Booking Source=BOOKING.COM   0.06383501972347144

Attrib Booking Source=BRAVO TOURS   -0.007822264952454864

Attrib Booking Source=EXPEDIA   0.15629077016656634

Attrib Booking Source=ITAKA   0.024021262720210525

Attrib Booking Source=Jet2Holidays   0.17461271780531198

Attrib Booking Source=RAINBOW   0.31888248557098486

Attrib Booking Source=SELF BOOKINGS   -0.003807688945055579

Attrib Booking Source=SUNWEB   -0.16884717049793854

Attrib Booking Source=TUI Deutschland   0.0729242887229587

Attrib Booking Source=TUI NL   0.0830083264127876

Attrib Booking Source=TUI UK   0.08823520832260652

Attrib Country=Denmark   -0.12951537127835255

Attrib Country=Finland   0.048284723468535455

Attrib Country=Romania   0.13850850018623662

Attrib Country=Vary   0.11404344554149286

Attrib Country=Poland   0.2604761524223664

Attrib Country=UK   0.12409763756800672

Attrib Country=Netherlands   -0.21636327243270223

Attrib Country=Germany   0.022478522707113546

Attrib Average pax/room   -0.15517657087450804

Attrib TO/ OTA=OTA   0.17531749379198808

Attrib ADR   0.16749487085431902

Attrib MONTH=JULY 2020   0.37635100535554084

Attrib MONTH=AUGUST 2020   0.2948596649618947

Attrib MONTH=SEPTEMBER 2020   -0.39902489803063806

Attrib MONTH=OCTOBER 2020   -0.16738064347325685

Attrib TOTAL PAX Nights   0.44629621172338163

Attrib Total Room Nights   0.47659433148588815

Attrib BB   0.22306382097878474

Attrib BB%   0.25224812177621

Attrib HB   0.13879855779743175

Attrib HB%   -0.1018132915097763

Attrib AI   0.07257651585138526

Attrib AI%   -0.20385284670738527

Sigmoid Node 2

Inputs   Weights

Threshold   -0.07535668297107032

Attrib Booking Source=ARHUS CHARTER   0.10549851870107949

Attrib Booking Source=AURINKOMATKAT   0.05799223261922426

Attrib Booking Source=BLUE AEGEAN   0.15576298231715238

Attrib Booking Source=BOOKING.COM   0.04708994579071747

Attrib Booking Source=BRAVO TOURS   0.1465294865171615

Attrib Booking Source=EXPEDIA   0.09343493340614416

Attrib Booking Source=ITAKA   0.10610878314339864

Attrib Booking Source=Jet2Holidays   0.16321733160670707

Attrib Booking Source=RAINBOW   0.118197623489446

Attrib Booking Source=SELF BOOKINGS 0.14909280574752146

Attrib Booking Source=SUNWEB 0.05620711847931745

Attrib Booking Source=TUI Deutschland 0.10729933654484294

Attrib Booking Source=TUI NL 0.11774314674655122

Attrib Booking Source=TUI UK 0.095982204978741

Attrib Country=Denmark 0.07230639623048242

Attrib Country=Finland 0.11025931896167926

Attrib Country=Romania 0.10135372447982136

Attrib Country=Vary 0.05386450416967181

Attrib Country=Poland 0.11265997073436297

Attrib Country=UK 0.08986550748966533

Attrib Country=Netherlands 0.09189118409182312

Attrib Country=Germany 0.07897277876153017

Attrib Average pax/room 0.0012907602473205347

Attrib TO/ OTA=OTA 0.055594421278198886

Attrib ADR -0.04896951454333076

Attrib MONTH=JULY 2020 0.1027062313099135

Attrib MONTH=AUGUST 2020 0.004667695616470775

Attrib MONTH=SEPTEMBER 2020 0.10643704310124076

Attrib MONTH=OCTOBER 2020 0.09126084196756612

Attrib TOTAL PAX Nights -0.0647004940814029

Attrib Total Room Nights -0.006332379156993063

Attrib BB 0.06673549527877987

Attrib BB% 0.010958618651479613

Attrib HB 0.043401524389213735

Attrib HB% 0.055729540811212945

Attrib AI   0.07688246305666971

Attrib AI%   -0.024989830002110476

Sigmoid Node 3

Inputs   Weights

Threshold   -0.13070146853302914

Attrib Booking Source=ARHUS CHARTER   0.047516175121149924

Attrib Booking Source=AURINKOMATKAT   0.24627538008456057

Attrib Booking Source=BLUE AEGEAN   0.14171979862927642

Attrib Booking Source=BOOKING.COM   0.11713916091015036

Attrib Booking Source=BRAVO TOURS   0.19508737601585427

Attrib Booking Source=EXPEDIA   0.16497819116325607

Attrib Booking Source=ITAKA   0.10240350517300624

Attrib Booking Source=Jet2Holidays   0.11143421146766486

Attrib Booking Source=RAINBOW   0.1356168045120526

Attrib Booking Source=SELF BOOKINGS   0.2895757394409267

Attrib Booking Source=SUNWEB   -0.042797696032496925

Attrib Booking Source=TUI Deutschland   0.03452322272541273

Attrib Booking Source=TUI NL   0.13065570184532335

Attrib Booking Source=TUI UK   0.027943390382273822

Attrib Country=Denmark   0.18931698333296626

Attrib Country=Finland   0.24477978544371193

Attrib Country=Romania   0.11335100452162104

Attrib Country=Vary   0.2868267685961481

Attrib Country=Poland   0.07931124866385031

Attrib Country=UK   -0.003302629960025442

Attrib Country=Netherlands   -0.09321493152317169

Attrib Country=Germany   0.098145127561625

Attrib Average pax/room   0.06122208111530044

Attrib TO/ OTA=OTA   0.20488966191171876

Attrib ADR   -0.07494757354441724

Attrib MONTH=JULY 2020   0.3467549078318984

Attrib MONTH=AUGUST 2020   -0.12382349020594795

Attrib MONTH=SEPTEMBER 2020   0.06725688839201678

Attrib MONTH=OCTOBER 2020   -0.10245461007321777

Attrib TOTAL PAX Nights   -0.4346589094296057

Attrib Total Room Nights   -0.6250903544940348

Attrib BB   -0.07895161578047494

Attrib BB%   0.24878729408756484

Attrib HB   0.020662193519758548

Attrib HB%   0.03907831949735876

Attrib AI   0.00418327612903968

Attrib AI%   -0.09246573898974307

Sigmoid Node 4

Inputs   Weights

Threshold   -0.12177517066719586

Attrib Booking Source=ARHUS CHARTER   0.1425102639914988

Attrib Booking Source=AURINKOMATKAT   0.10356495418335518

Attrib Booking Source=BLUE AEGEAN   0.1537592269367017

Attrib Booking Source=BOOKING.COM   0.15326793405172734

Attrib Booking Source=BRAVO TOURS   -0.004071850446200693

Attrib Booking Source=EXPEDIA   0.02634879235242209

Attrib Booking Source=ITAKA   0.06644867954975704

Attrib Booking Source=Jet2Holidays   0.13822759990515326

Attrib Booking Source=RAINBOW   0.06954837259799761

Attrib Booking Source=SELF BOOKINGS   0.03290141568400705

Attrib Booking Source=SUNWEB   0.0227696262504487

Attrib Booking Source=TUI Deutschland   0.025276630229300257

Attrib Booking Source=TUI NL   0.050699880224836805

Attrib Booking Source=TUI UK   0.14417047437616579

Attrib Country=Denmark   0.05362148331715693

Attrib Country=Finland   0.1242215807023514

Attrib Country=Romania   0.09865398777070548

Attrib Country=Vary   0.007479236081582394

Attrib Country=Poland   0.06826002044838911

Attrib Country=UK   0.1988278694055645

Attrib Country=Netherlands   -0.02536924605038882

Attrib Country=Germany   0.0389053107067417

Attrib Average pax/room   0.09987723386523821

Attrib TO/ OTA=OTA   0.048599794646004404

Attrib ADR   0.04623702331329077

Attrib MONTH=JULY 2020   0.01688018610408994

Attrib MONTH=AUGUST 2020   0.10958327914075525

Attrib MONTH=SEPTEMBER 2020   -0.0014471217717948958

Attrib MONTH=OCTOBER 2020   0.1475066873372439

Attrib TOTAL PAX Nights   0.21151295841784917

Attrib Total Room Nights   0.14660234547732873

Attrib BB   0.1326572783198153

Attrib BB%   0.0317341941113038

Attrib HB 0.08610014103228872

Attrib HB% 0.10624360930252622

Attrib AI 0.01479844031941715

Attrib AI% -0.013542008940754

Sigmoid Node 5

Inputs Weights

Threshold -0.15108966611352828

Attrib Booking Source=ARHUS CHARTER 0.13540843356568646

Attrib Booking Source=AURINKOMATKAT 0.13981719985977886

Attrib Booking Source=BLUE AEGEAN 0.12812179411472413

Attrib Booking Source=BOOKING.COM 0.08437359969299492

Attrib Booking Source=BRAVO TOURS 0.165627420273853

Attrib Booking Source=EXPEDIA 0.0999995076513826

Attrib Booking Source=ITAKA 0.10979555429044296

Attrib Booking Source=Jet2Holidays 0.1327729272492991

Attrib Booking Source=RAINBOW 0.13136189031216775

Attrib Booking Source=SELF BOOKINGS 0.20513476701729236

Attrib Booking Source=SUNWEB 0.13014421273967292

Attrib Booking Source=TUI Deutschland 0.07768010831706469

Attrib Booking Source=TUI NL 0.061924637269400076

Attrib Booking Source=TUI UK 0.07683006929847813

Attrib Country=Denmark 0.16161678471922983

Attrib Country=Finland 0.15007425681835923

Attrib Country=Romania 0.08545972637846173

Attrib Country=Vary 0.05807692327470757

Attrib Country=Poland 0.06664464801965071

Attrib Country=UK   0.007110490161630729

Attrib Country=Netherlands   0.09868359523128331

Attrib Country=Germany   0.09938145719556936

Attrib Average pax/room   -0.01749675234937621

Attrib TO/ OTA=OTA   0.06725008709536581

Attrib ADR   -0.049394860671629216

Attrib MONTH=JULY 2020   0.1684857091065976

Attrib MONTH=AUGUST 2020   0.06699569978303532

Attrib MONTH=SEPTEMBER 2020   0.041154935515578625

Attrib MONTH=OCTOBER 2020   -0.11346621939837633

Attrib TOTAL PAX Nights   -0.19608769519684627

Attrib Total Room Nights   -0.24794075181194528

Attrib BB   -0.010337606315456797

Attrib BB%   0.08596046742264778

Attrib HB   0.030710640855660602

Attrib HB%   0.11363505355090757

Attrib AI   0.06673399327824088

Attrib AI%   -0.045744475462397155

Sigmoid Node 6

Inputs   Weights

Threshold   -0.0913384174273276

Attrib Booking Source=ARHUS CHARTER   0.06753244595732237

Attrib Booking Source=AURINKOMATKAT   0.14297999327795083

Attrib Booking Source=BLUE AEGEAN   0.19185055676934018

Attrib Booking Source=BOOKING.COM   0.18494527668065655

Attrib Booking Source=BRAVO TOURS   0.12156914965801599

Attrib Booking Source=EXPEDIA   0.12839836890824305

Attrib Booking Source=ITAKA   0.0565680761607219

Attrib Booking Source=Jet2Holidays   0.1844639070874336

Attrib Booking Source=RAINBOW   0.11243551915623728

Attrib Booking Source=SELF BOOKINGS   0.07264628237353044

Attrib Booking Source=SUNWEB   -0.10322947742866422

Attrib Booking Source=TUI Deutschland   0.008347192060936615

Attrib Booking Source=TUI NL   0.09809764373856221

Attrib Booking Source=TUI UK   0.11150337174833076

Attrib Country=Denmark   0.087596864012537

Attrib Country=Finland   0.09981629245787273

Attrib Country=Romania   0.17772890602093042

Attrib Country=Vary   0.10331696441100681

Attrib Country=Poland   0.05529598102793342

Attrib Country=UK   0.13390068596206411

Attrib Country=Netherlands   -0.08026086168025809

Attrib Country=Germany   0.03509959521987222

Attrib Average pax/room   0.013030828204777313

Attrib TO/ OTA=OTA   0.14950741609404805

Attrib ADR   0.14850318142789612

Attrib MONTH=JULY 2020   0.20156851217769536

Attrib MONTH=AUGUST 2020   0.16908106732543848

Attrib MONTH=SEPTEMBER 2020   -0.09144400774374231

Attrib MONTH=OCTOBER 2020   -0.07934188950034711

Attrib TOTAL PAX Nights   0.4243119881126081

Attrib Total Room Nights   0.47590925144138446

Attrib BB 0.29348658631000213

Attrib BB% 0.04993602868558195

Attrib HB 0.14107487571572133

Attrib HB% 0.07447261853878043

Attrib AI 0.09369601498672318

Attrib AI% -0.015313020969768026

Sigmoid Node 7

Inputs Weights

Threshold -0.16913466824932255

Attrib Booking Source=ARHUS CHARTER 0.09813162810813773

Attrib Booking Source=AURINKOMATKAT 0.12091785658795137

Attrib Booking Source=BLUE AEGEAN 0.10162575378489905

Attrib Booking Source=BOOKING.COM 0.05996951817929735

Attrib Booking Source=BRAVO TOURS 0.05481822357508535

Attrib Booking Source=EXPEDIA 0.1308124662715472

Attrib Booking Source=ITAKA 0.04597581502416891

Attrib Booking Source=Jet2Holidays 0.12423412811343026

Attrib Booking Source=RAINBOW 0.11626098574504445

Attrib Booking Source=SELF BOOKINGS 0.21197697930143444

Attrib Booking Source=SUNWEB 0.04369227331752699

Attrib Booking Source=TUI Deutschland 0.10475382925575645

Attrib Booking Source=TUI NL 0.1046972729668376

Attrib Booking Source=TUI UK 0.13296283570961043

Attrib Country=Denmark 0.13307270453243505

Attrib Country=Finland 0.17734026313854168

Attrib Country=Romania 0.1417435324418222

Attrib Country=Vary   0.07641800685834974

Attrib Country=Poland   0.11063876074352354

Attrib Country=UK   0.11819960610594468

Attrib Country=Netherlands   0.034643412143747686

Attrib Country=Germany   0.09428198764750588

Attrib Average pax/room   -0.04569518906989207

Attrib TO/ OTA=OTA   0.014975952879521923

Attrib ADR   -0.05631169131432615

Attrib MONTH=JULY 2020   0.19856676945996274

Attrib MONTH=AUGUST 2020   0.006836781410568524

Attrib MONTH=SEPTEMBER 2020   0.14426839530616678

Attrib MONTH=OCTOBER 2020   -0.041347576850074626

Attrib TOTAL PAX Nights   -0.12854351379627074

Attrib Total Room Nights   -0.18329172034594382

Attrib BB   0.023538408712542737

Attrib BB%   0.03386716683255277

Attrib HB   0.06647604807196034

Attrib HB%   0.031235889829098393

Attrib AI   0.0229353761379585

Attrib AI%   0.029769024538213694

Sigmoid Node 8

Inputs   Weights

Threshold   -0.13817596093537104

Attrib Booking Source=ARHUS CHARTER   0.14865099273079135

Attrib Booking Source=AURINKOMATKAT   0.11918192829394306

Attrib Booking Source=BLUE AEGEAN   0.1029214176846807

Attrib Booking Source=BOOKING.COM   0.029838138830058

Attrib Booking Source=BRAVO TOURS   0.08989059629144017

Attrib Booking Source=EXPEDIA   0.035326980121631345

Attrib Booking Source=ITAKA   0.10701854705823231

Attrib Booking Source=Jet2Holidays   0.13682139292953996

Attrib Booking Source=RAINBOW   0.11981175181493137

Attrib Booking Source=SELF BOOKINGS   0.09885835781527731

Attrib Booking Source=SUNWEB   0.08504111226478249

Attrib Booking Source=TUI Deutschland   0.12660260705142387

Attrib Booking Source=TUI NL   0.07677767236046533

Attrib Booking Source=TUI UK   0.13678316692867265

Attrib Country=Denmark   0.09277331489249588

Attrib Country=Finland   0.07103108261492835

Attrib Country=Romania   0.12286619474852316

Attrib Country=Vary   0.02183288760219848

Attrib Country=Poland   0.05660151782026134

Attrib Country=UK   0.08681655847398773

Attrib Country=Netherlands   0.06415451049829757

Attrib Country=Germany   0.1416591419099702

Attrib Average pax/room   -0.02531975417610194

Attrib TO/ OTA=OTA   -0.018638091498302322

Attrib ADR   -0.05781510493836422

Attrib MONTH=JULY 2020   0.0474037826358191

Attrib MONTH=AUGUST 2020   0.02360538973173462

Attrib MONTH=SEPTEMBER 2020   0.07746304896688043

Attrib MONTH=OCTOBER 2020   0.0438906023799886

Attrib TOTAL PAX Nights 0.04148926914648341

Attrib Total Room Nights 0.02696216243953585

Attrib BB 0.06373620240689566

Attrib BB% 0.05286914582971879

Attrib HB 0.04530064155212853

Attrib HB% 0.11354794564064902

Attrib AI 0.08146450294599734

Attrib AI% 0.03200456757046585

Sigmoid Node 9

Inputs Weights

Threshold -0.13735927815813867

Attrib Booking Source=ARHUS CHARTER 0.1142062167127564

Attrib Booking Source=AURINKOMATKAT 0.040893478718821506

Attrib Booking Source=BLUE AEGEAN 0.15849579626124458

Attrib Booking Source=BOOKING.COM 0.06241497427973921

Attrib Booking Source=BRAVO TOURS 0.13688698547433148

Attrib Booking Source=EXPEDIA 0.05381103890182279

Attrib Booking Source=ITAKA 0.11232274301712379

Attrib Booking Source=Jet2Holidays 0.1063748839307315

Attrib Booking Source=RAINBOW 0.08256863240964896

Attrib Booking Source=SELF BOOKINGS 0.1627949533521751

Attrib Booking Source=SUNWEB 0.14332661167611674

Attrib Booking Source=TUI Deutschland 0.10920155469720282

Attrib Booking Source=TUI NL 0.07817365884217917

Attrib Booking Source=TUI UK 0.1199320444129233

Attrib Country=Denmark 0.07798263796590661

Attrib Country=Finland 0.12241057145681095

Attrib Country=Romania 0.08187249984673216

Attrib Country=Vary 0.04207027331018536

Attrib Country=Poland 0.03318595536834471

Attrib Country=UK 0.13710935775153216

Attrib Country=Netherlands 0.04573488242801416

Attrib Country=Germany 0.1091163137128016

Attrib Average pax/room 0.026603606707018487

Attrib TO/ OTA=OTA 0.08495660971094747

Attrib ADR 0.024162499525052283

Attrib MONTH=JULY 2020 0.024931354415516013

Attrib MONTH=AUGUST 2020 0.03234953533012723

Attrib MONTH=SEPTEMBER 2020 0.10844938305071589

Attrib MONTH=OCTOBER 2020 0.030130762090018966

Attrib TOTAL PAX Nights 0.010581268974912907

Attrib Total Room Nights -0.0022934886233687423

Attrib BB 0.028959587723221877

Attrib BB% -0.013715186102039957

Attrib HB 0.04724668899339332

Attrib HB% 0.07218669268359423

Attrib AI 0.0744044871739882

Attrib AI% -0.012828689954054107

Sigmoid Node 10

Inputs Weights

Threshold -0.10395933206891955

Attrib Booking Source=ARHUS CHARTER 0.12152709066802773

Attrib Booking Source=AURINKOMATKAT   0.060519663468126685

Attrib Booking Source=BLUE AEGEAN   0.14435096489678778

Attrib Booking Source=BOOKING.COM   0.07285451574033466

Attrib Booking Source=BRAVO TOURS   0.11633378199128447

Attrib Booking Source=EXPEDIA   0.039327236520914265

Attrib Booking Source=ITAKA   0.1184797046578443

Attrib Booking Source=Jet2Holidays   0.07773524367818542

Attrib Booking Source=RAINBOW   0.08215149165044057

Attrib Booking Source=SELF BOOKINGS   0.16333526994347855

Attrib Booking Source=SUNWEB   0.08975656116644189

Attrib Booking Source=TUI Deutschland   0.09178830495207162

Attrib Booking Source=TUI NL   0.11662525423746914

Attrib Booking Source=TUI UK   0.07393896742023938

Attrib Country=Denmark   0.10064131681747936

Attrib Country=Finland   0.09899668869894869

Attrib Country=Romania   0.1014768346919674

Attrib Country=Vary   0.017955352468231038

Attrib Country=Poland   0.09202764048578146

Attrib Country=UK   0.14564303933522657

Attrib Country=Netherlands   0.11471726554566519

Attrib Country=Germany   0.1546231804235821

Attrib Average pax/room   -0.01963858069356034

Attrib TO/ OTA=OTA   0.035842537028030474

Attrib ADR   -0.0468399476395823

Attrib MONTH=JULY 2020   0.1062781798029032

Attrib MONTH=AUGUST 2020   0.04899022513701145

Attrib MONTH=SEPTEMBER 2020   0.022282917722422392

Attrib MONTH=OCTOBER 2020   0.049415969337957846

Attrib TOTAL PAX Nights   0.013332409554774775

Attrib Total Room Nights   -0.019704648955313014

Attrib BB   0.00382802602316993

Attrib BB%   0.025525037591730193

Attrib HB   0.10246671688537559

Attrib HB%   0.07472839046293554

Attrib AI   0.08965846650237415

Attrib AI%   0.048037953929688654

Sigmoid Node 11

Inputs   Weights

Threshold   -0.11899192519441092

Attrib Booking Source=ARHUS CHARTER   0.032906887169651775

Attrib Booking Source=AURINKOMATKAT   0.1925862627203965

Attrib Booking Source=BLUE AEGEAN   0.09680745009116434

Attrib Booking Source=BOOKING.COM   0.07828396365432423

Attrib Booking Source=BRAVO TOURS   0.2277197228324353

Attrib Booking Source=EXPEDIA   0.25043535233332484

Attrib Booking Source=ITAKA   0.05907693869722906

Attrib Booking Source=Jet2Holidays   0.048124960331698934

Attrib Booking Source=RAINBOW   0.08623035148302181

Attrib Booking Source=SELF BOOKINGS   0.2880351615127983

Attrib Booking Source=SUNWEB   -0.012137820953059075

Attrib Booking Source=TUI Deutschland   0.13326984978381573

Attrib Booking Source=TUI NL   0.08110101492223158

Attrib Booking Source=TUI UK   0.07028140540240334

Attrib Country=Denmark   0.1650195783796354

Attrib Country=Finland   0.20865090711114262

Attrib Country=Romania   0.0624112585365286

Attrib Country=Vary   0.2988131101078037

Attrib Country=Poland   0.05789879664020744

Attrib Country=UK   0.014523154041807589

Attrib Country=Netherlands   -0.118085969544410458

Attrib Country=Germany   0.12345019899951763

Attrib Average pax/room   0.045966907352806875

Attrib TO/ OTA=OTA   0.18241107639410822

Attrib ADR   -0.0506554139768775 34

Attrib MONTH=JULY 2020   0.3458243835600519

Attrib MONTH=AUGUST 2020   -0.021471441695918605

Attrib MONTH=SEPTEMBER 2020   0.06877151408601456

Attrib MONTH=OCTOBER 2020   -0.10772524364545065

Attrib TOTAL PAX Nights   -0.4486680207271173

Attrib Total Room Nights   -0.5991194199620518

Attrib BB   -0.08196039523382312

Attrib BB%   0.2497535442787267

Attrib HB   0.039187410435214454

Attrib HB%   0.012555448680394923

Attrib AI   -0.005709587668437713

Attrib AI%   -0.09650212771140183

Sigmoid Node 12

Inputs   Weights

Threshold 0.008923858289018994

Attrib Booking Source=ARHUS CHARTER -0.05705805057723772

Attrib Booking Source=AURINKOMATKAT 0.06701941979036737

Attrib Booking Source=BLUE AEGEAN 0.07790644425258736

Attrib Booking Source=BOOKING.COM 0.12272537544578214

Attrib Booking Source=BRAVO TOURS 0.18177688526254418

Attrib Booking Source=EXPEDIA 0.19105480836380737

Attrib Booking Source=ITAKA 0.06657796310235517

Attrib Booking Source=Jet2Holidays -0.1090049252165471

Attrib Booking Source=RAINBOW -0.10454436692336351

Attrib Booking Source=SELF BOOKINGS 0.03701272019012146

Attrib Booking Source=SUNWEB -0.3193648287452197

Attrib Booking Source=TUI Deutschland 0.1324897184100106

Attrib Booking Source=TUI NL -0.05953961442321127

Attrib Booking Source=TUI UK -0.018996593663351345

Attrib Country=Denmark 0.03875928508293106

Attrib Country=Finland 0.10048175435394653

Attrib Country=Romania 0.12781076015143142

Attrib Country=Vary 0.3148926993574691

Attrib Country=Poland 0.04019503461070003

Attrib Country=UK -0.1369831682585527

Attrib Country=Netherlands -0.40232033801004846

Attrib Country=Germany 0.09604991802439197

Attrib Average pax/room -0.09816535662082507

Attrib TO/ OTA=OTA 0.34389195708256737

Attrib ADR 0.3597547393933265

Attrib MONTH=JULY 2020   0.7299210365445803

Attrib MONTH=AUGUST 2020   -0.06395349842040343

Attrib MONTH=SEPTEMBER 2020   -0.1989701667646899

Attrib MONTH=OCTOBER 2020   -0.45522387139662684

Attrib TOTAL PAX Nights   0.5243098739602359

Attrib Total Room Nights   0.6744682943409593

Attrib BB   0.12901885863265336

Attrib BB%   0.15229536313935785

Attrib HB   0.06032599193185318

Attrib HB%   -0.19798586532103013

Attrib AI   0.25279365425874945

Attrib AI%   -0.13130268023064676

Sigmoid Node 13

Inputs   Weights

Threshold   -0.13631632563690432

Attrib Booking Source=ARHUS CHARTER   0.12999309702209494

Attrib Booking Source=AURINKOMATKAT   0.3544147613051819

Attrib Booking Source=BLUE AEGEAN   0.30455901603601665

Attrib Booking Source=BOOKING.COM   0.12748138313979634

Attrib Booking Source=BRAVO TOURS   0.11576079720716445

Attrib Booking Source=EXPEDIA   0.02765901839123922

Attrib Booking Source=ITAKA   -0.017212815583781172

Attrib Booking Source=Jet2Holidays   -0.017540199260141213

Attrib Booking Source=RAINBOW   0.3796689532996641

Attrib Booking Source=SELF BOOKINGS   0.20285454162730243

Attrib Booking Source=SUNWEB   -0.13323594452909804

Attrib Booking Source=TUI Deutschland   -0.02139743192761791

Attrib Booking Source=TUI NL   0.12131010688348078

Attrib Booking Source=TUI UK   0.168195683820399

Attrib Country=Denmark   0.11127479414105415

Attrib Country=Finland   0.33647693954898317

Attrib Country=Romania   0.2807336135608056

Attrib Country=Vary   0.03234224651814814

Attrib Country=Poland   0.1888215246992415

Attrib Country=UK   0.06679269257225832

Attrib Country=Netherlands   -0.16126495963010543

Attrib Country=Germany   -0.005320400252885884

Attrib Average pax/room   0.02694312678487512

Attrib TO/ OTA=OTA   -0.006047553183000557

Attrib ADR   -0.17494149470971804

Attrib MONTH=JULY 2020   0.5313337548962764

Attrib MONTH=AUGUST 2020   -0.3934137099439581

Attrib MONTH=SEPTEMBER 2020   0.10687392910839895

Attrib MONTH=OCTOBER 2020   0.008086401499414662

Attrib TOTAL PAX Nights   -0.28507161001170006

Attrib Total Room Nights   -0.3586958578969481

Attrib BB   0.10923244854733527

Attrib BB%   0.17470331064693653

Attrib HB   0.057516659064525646

Attrib HB%   0.06242569994371022

Attrib AI   0.026806010639939724

Attrib AI%   0.06136523883818108

Sigmoid Node 14

Inputs   Weights

Threshold   0.03284992617594235

Attrib Booking Source=ARHUS CHARTER   -0.2644229889796864

Attrib Booking Source=AURINKOMATKAT   -0.2619805229850532

Attrib Booking Source=BLUE AEGEAN   -0.13191751162037324

Attrib Booking Source=BOOKING.COM   -0.09926325463378156

Attrib Booking Source=BRAVO TOURS   0.046162273230422955

Attrib Booking Source=EXPEDIA   0.09851981604695036

Attrib Booking Source=ITAKA   0.16301731065283026

Attrib Booking Source=Jet2Holidays   0.2579816349446593

Attrib Booking Source=RAINBOW   -0.26610781072130973

Attrib Booking Source=SELF BOOKINGS   0.16383064171076595

Attrib Booking Source=SUNWEB   -0.1552891853077426

Attrib Booking Source=TUI Deutschland   0.27360885037136407

Attrib Booking Source=TUI NL   0.13943479367607167

Attrib Booking Source=TUI UK   0.0611718835535817

Attrib Country=Denmark   -0.21500674068582906

Attrib Country=Finland   -0.29640257706783707

Attrib Country=Romania   -0.13860306049810633

Attrib Country=Vary   0.13780635956148377

Attrib Country=Poland   -0.06290593335449002

Attrib Country=UK   0.2976195706484944

Attrib Country=Netherlands   0.009077748648998024

Attrib Country=Germany   0.23475202744259308

Attrib Average pax/room   0.0778667231230654

Attrib TO/ OTA=OTA   0.09479824076412202

Attrib ADR   -0.31757973173728904

Attrib MONTH=JULY 2020   0.3566194652307629

Attrib MONTH=AUGUST 2020   0.5005686321200872

Attrib MONTH=SEPTEMBER 2020   -0.4707677121759187

Attrib MONTH=OCTOBER 2020   -0.21819976781023

Attrib TOTAL PAX Nights   -0.7047400877368926

Attrib Total Room Nights   -0.8548996657527919

Attrib BB   -0.3000308233227895

Attrib BB%   0.11785462901122491

Attrib HB   -0.08318188002153738

Attrib HB%   0.09846934926065623

Attrib AI   -0.058568949355139385

Attrib AI%   0.23286938837726248

Sigmoid Node 15

Inputs   Weights

Threshold   -0.09755851347687959

Attrib Booking Source=ARHUS CHARTER   0.0760210071104531

Attrib Booking Source=AURINKOMATKAT   0.11680903933930553

Attrib Booking Source=BLUE AEGEAN   0.09121180371882515

Attrib Booking Source=BOOKING.COM   0.05127741710904949

Attrib Booking Source=BRAVO TOURS   0.1319079997311859

Attrib Booking Source=EXPEDIA   0.05929978502463564

Attrib Booking Source=ITAKA   0.06638466455606833

Attrib Booking Source=Jet2Holidays   0.07230293015687629

Attrib Booking Source=RAINBOW   0.07062321361142114

Attrib Booking Source=SELF BOOKINGS   0.16961004025288007

Attrib Booking Source=SUNWEB   0.14732510154059722

Attrib Booking Source=TUI Deutschland   0.0809019746025792

Attrib Booking Source=TUI NL   0.09441537854792352

Attrib Booking Source=TUI UK   0.1450675000267229

Attrib Country=Denmark   0.05290766710438923

Attrib Country=Finland   0.15036047975283326

Attrib Country=Romania   0.1345192115604981

Attrib Country=Vary   0.06637097501233923

Attrib Country=Poland   0.07024825731283386

Attrib Country=UK   0.1491116724786122

Attrib Country=Netherlands   0.09362466736656705

Attrib Country=Germany   0.1407849316268908

Attrib Average pax/room   0.040067913141351406

Attrib TO/ OTA=OTA   0.010853125254077277

Attrib ADR   -0.027104054126848482

Attrib MONTH=JULY 2020   0.14809648866253003

Attrib MONTH=AUGUST 2020   0.023842892768332923

Attrib MONTH=SEPTEMBER 2020   0.06370005436336221

Attrib MONTH=OCTOBER 2020   0.051439604278156977

Attrib TOTAL PAX Nights   -0.023877997158620788

Attrib Total Room Nights   -0.03561910455196841

Attrib BB   -0.009056180026315622

Attrib BB%   0.0029168999498376137

Attrib HB   0.07368560622781907

Attrib HB%   0.11508601076813985

Attrib AI 0.09267332527797299

Attrib AI% 0.048020470650251314

Sigmoid Node 16

Inputs Weights

Threshold -0.11317015660074953

Attrib Booking Source=ARHUS CHARTER 0.07932409916475332

Attrib Booking Source=AURINKOMATKAT 0.07518964832913173

Attrib Booking Source=BLUE AEGEAN 0.12642565674136585

Attrib Booking Source=BOOKING.COM 0.10524082763229062

Attrib Booking Source=BRAVO TOURS 0.05469970016652741

Attrib Booking Source=EXPEDIA 0.055978581817591494

Attrib Booking Source=ITAKA 0.08947238691269963

Attrib Booking Source=Jet2Holidays 0.12992817918284577

Attrib Booking Source=RAINBOW 0.13321848065898959

Attrib Booking Source=SELF BOOKINGS 0.08006543464003249

Attrib Booking Source=SUNWEB 0.13911909388290628

Attrib Booking Source=TUI Deutschland 0.05216203548217172

Attrib Booking Source=TUI NL 0.0881677819696682

Attrib Booking Source=TUI UK 0.118805336811160822

Attrib Country=Denmark 0.1047774966199159

Attrib Country=Finland 0.08209659093611892

Attrib Country=Romania 0.08962255402820478

Attrib Country=Vary 0.0626882123922402

Attrib Country=Poland 0.06392445972484427

Attrib Country=UK 0.15988869851030707

Attrib Country=Netherlands 0.025592614982989287

Attrib Country=Germany   0.048456084825804054

Attrib Average pax/room   0.046728291353927164

Attrib TO/ OTA=OTA   0.10046769628922154

Attrib ADR   0.04908592279710585

Attrib MONTH=JULY 2020   0.057495414152290564

Attrib MONTH=AUGUST 2020   0.020382633117494962

Attrib MONTH=SEPTEMBER 2020   0.0718882836686056

Attrib MONTH=OCTOBER 2020   0.0631645959281579

Attrib TOTAL PAX Nights   0.10066130778686234

Attrib Total Room Nights   0.11169956926392921

Attrib BB   0.06136675767452667

Attrib BB%   0.043676505053017435

Attrib HB   0.10546002863556246

Attrib HB%   0.11405493468177653

Attrib AI   0.09944922107119979

Attrib AI%   0.05203212134868179

Sigmoid Node 17

Inputs   Weights

Threshold   -0.17085478376769692

Attrib Booking Source=ARHUS CHARTER   0.14498842785376703

Attrib Booking Source=AURINKOMATKAT   0.12670873230348126

Attrib Booking Source=BLUE AEGEAN   0.09190773361236915

Attrib Booking Source=BOOKING.COM   0.08565045188817398

Attrib Booking Source=BRAVO TOURS   0.09679327580610168

Attrib Booking Source=EXPEDIA   0.08912830967855682

Attrib Booking Source=ITAKA   0.07422776262715547

Attrib Booking Source=Jet2Holidays   0.14512901638720163

Attrib Booking Source=RAINBOW   0.10479713366684126

Attrib Booking Source=SELF BOOKINGS   0.16406600345679573

Attrib Booking Source=SUNWEB   0.12563092229823647

Attrib Booking Source=TUI Deutschland   0.10385510084060581

Attrib Booking Source=TUI NL   0.0431204895791828

Attrib Booking Source=TUI UK   0.09187050111961752

Attrib Country=Denmark   0.06992110557586734

Attrib Country=Finland   0.12828440593516252

Attrib Country=Romania   0.08397234923716809

Attrib Country=Vary   0.06571682750670696

Attrib Country=Poland   0.057588962897883074

Attrib Country=UK   0.09828886794625723

Attrib Country=Netherlands   0.09800818077628937

Attrib Country=Germany   0.09131609007560351

Attrib Average pax/room   0.019020955776399864

Attrib TO/ OTA=OTA   0.041093912597144774

Attrib ADR   -0.026991023247396065

Attrib MONTH=JULY 2020   0.07118410686501807

Attrib MONTH=AUGUST 2020   0.03591112252127608

Attrib MONTH=SEPTEMBER 2020   0.04576411720236792

Attrib MONTH=OCTOBER 2020   -0.019140000992184904

Attrib TOTAL PAX Nights   -0.027107936535711957

Attrib Total Room Nights   -0.05376934973840479

Attrib BB   0.06450671592230209

Attrib BB%   -0.028377766329981534

Attrib HB 0.08318438299816966

Attrib HB% 0.0781622175675319

Attrib AI 0.05890210730477784

Attrib AI% 0.07993397133438253

Sigmoid Node 18

Inputs Weights

Threshold -0.10672993236693175

Attrib Booking Source=ARHUS CHARTER 0.09999366726438302

Attrib Booking Source=AURINKOMATKAT 0.09611395328370759

Attrib Booking Source=BLUE AEGEAN 0.08849272249109041

Attrib Booking Source=BOOKING.COM 0.10442835884725121

Attrib Booking Source=BRAVO TOURS 0.09042516937973

Attrib Booking Source=EXPEDIA -0.029267698764101263

Attrib Booking Source=ITAKA 0.006854899539011768

Attrib Booking Source=Jet2Holidays 0.13297477221884904

Attrib Booking Source=RAINBOW 0.05768366313899758

Attrib Booking Source=SELF BOOKINGS 0.046082957625755115

Attrib Booking Source=SUNWEB 0.1810645054798091

Attrib Booking Source=TUI Deutschland 0.06026951569224879

Attrib Booking Source=TUI NL 0.031130747102789104

Attrib Booking Source=TUI UK 0.09722363058811223

Attrib Country=Denmark 0.0733664674866501

Attrib Country=Finland 0.038343481017556476

Attrib Country=Romania 0.06225862575441235

Attrib Country=Vary 0.006276124717432812

Attrib Country=Poland 0.05085794696814359

Attrib Country=UK   0.12019517661824049

Attrib Country=Netherlands   0.07831346911216852

Attrib Country=Germany   0.056279654031173625

Attrib Average pax/room   0.10126637795294302

Attrib TO/ OTA=OTA   0.020415861942336574

Attrib ADR   0.025456788576361564

Attrib MONTH=JULY 2020   0.04763634072687759

Attrib MONTH=AUGUST 2020   -0.14234672132616222

Attrib MONTH=SEPTEMBER 2020   0.09362468419042735

Attrib MONTH=OCTOBER 2020   0.220622666215035

Attrib TOTAL PAX Nights   0.23679755729253213

Attrib Total Room Nights   0.2435991180832139

Attrib BB   0.1410247034655608

Attrib BB%   -0.017998300764572803

Attrib HB   0.08515918751570904

Attrib HB%   0.10825975866238528

Attrib AI   0.06450566432350655

Attrib AI%   -0.011529841464190435

Sigmoid Node 19

Inputs   Weights

Threshold   -0.15282388740626424

Attrib Booking Source=ARHUS CHARTER   0.1219182333379638

Attrib Booking Source=AURINKOMATKAT   0.07905870732684044

Attrib Booking Source=BLUE AEGEAN   0.12980481259020948

Attrib Booking Source=BOOKING.COM   0.04127531306433957

Attrib Booking Source=BRAVO TOURS   0.0770841030425281

Attrib Booking Source=EXPEDIA   0.0584141641843902

Attrib Booking Source=ITAKA   0.10878242606605891

Attrib Booking Source=Jet2Holidays   0.10358770890273891

Attrib Booking Source=RAINBOW   0.11715206794957717

Attrib Booking Source=SELF BOOKINGS   0.1240742339245748

Attrib Booking Source=SUNWEB   0.0718850539345562

Attrib Booking Source=TUI Deutschland   0.13117691014497146

Attrib Booking Source=TUI NL   0.12150239329955598

Attrib Booking Source=TUI UK   0.11020868418967777

Attrib Country=Denmark   0.12179633871637312

Attrib Country=Finland   0.12370439773635943

Attrib Country=Romania   0.09048199185002846

Attrib Country=Vary   0.08918197397284922

Attrib Country=Poland   0.06272770383369916

Attrib Country=UK   0.12882243886765626

Attrib Country=Netherlands   0.04154296646278616

Attrib Country=Germany   0.11674148825047839

Attrib Average pax/room   0.031043416654808354

Attrib TO/ OTA=OTA   0.01303926528350667

Attrib ADR   0.007813555534130278

Attrib MONTH=JULY 2020   0.1300837927378734

Attrib MONTH=AUGUST 2020   0.018761426369225405

Attrib MONTH=SEPTEMBER 2020   0.0994693751649831

Attrib MONTH=OCTOBER 2020   0.0408669871588251

Attrib TOTAL PAX Nights   -0.06993214498184884

Attrib Total Room Nights   -0.08953237985309832

Attrib BB 0.07250053445969222

Attrib BB% 0.03234956960804703

Attrib HB 0.09700070771662139

Attrib HB% 0.03082228517572309

Attrib AI 0.09086306183897391

Attrib AI% 0.013113146303164808

Class

Input

Node 0

Classifiers with low or negative correlation coefficient (2020):

Meta Random Sub Space Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R3,14,2,6,13,4,1,15'

@attribute 'Average pax/room' numeric

@attribute 'AI\%' numeric

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute MONTH {'JULY 2020','AUGUST 2020','SEPTEMBER 2020','OCTOBER 2020'}

@attribute AI numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,'SELF BOOKINGS',SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Booking Source = ARHUS CHARTER : 12 (1/0) [3/408]

Booking Source = AURINKOMATKAT : 15.33 (2/72.25) [1/420.25]

Booking Source = BLUE AEGEAN : 7 (2/6.25) [2/123.25]

Booking Source = BOOKING.COM : 50 (3/389.56) [1/6188.44]

Booking Source = BRAVO TOURS : 19 (2/4) [2/452]

Booking Source = EXPEDIA : 22.75 (4/423.69) [0/0]

Booking Source = ITAKA : 25.75 (3/69.56) [1/802.78]

Booking Source = Jet2Holidays : 5.5 (3/62) [1/36]

Booking Source = RAINBOW : 17.5 (2/36) [2/234]

Booking Source = SELF BOOKINGS : 0 (0/0) [1/177.52]

Booking Source = SUNWEB : 11.75 (4/27.19) [0/0]

Booking Source = TUI Deutschland : 8.25 (3/20.67) [1/49]

Booking Source = TUI NL : 4 (2/6.25) [2/15.25]

Booking Source = TUI UK : 0.5 (3/0.89) [1/0.44]

Size of the tree : 15

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R13,14,1,10,9,4,6,15'

@attribute AI numeric

@attribute 'AI\%' numeric

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,'SELF BOOKINGS',SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute 'BB\%' numeric

@attribute BB numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute MONTH {'JULY 2020','AUGUST 2020','SEPTEMBER 2020','OCTOBER 2020'}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

BB < 489.5

| Booking Source = ARHUS CHARTER : 12.3 (2.9/148.25) [1/273.35]

| Booking Source = AURINKOMATKAT : 15.33 (3/141.56) [0/0]

| Booking Source = BLUE AEGEAN : 7 (1/0) [3/131.33]

| Booking Source = BOOKING.COM : 17.5 (2/90.25) [0/0]

| Booking Source = BRAVO TOURS : 19 (3/3.56) [1/940.44]

| Booking Source = EXPEDIA : 13 (3/184.67) [0/0]

| Booking Source = ITAKA : 18.67 (1/0) [2/132.5]

| Booking Source = Jet2Holidays : 5.5 (2/72.25) [2/66.25]

| Booking Source = RAINBOW : 17.5 (3/152) [1/100]

| Booking Source = SELF BOOKINGS : 0 (0.9/0) [0/0]

| Booking Source = SUNWEB : 11.75 (2/2.25) [2/88.25]

| Booking Source = TUI Deutschland : 8.25 (4/24.69) [0/0]

| Booking Source = TUI NL : 4 (1/0) [3/12.67]

| Booking Source = TUI UK : 0.51 (1.9/0) [2/2]

BB >= 489.5 : 61.53 (3.29/227.12) [1/3830.64]

Size of the tree : 17

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R5,7,10,2,13,14,8,15'

@attribute ADR numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute 'BB\%' numeric

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

```
@attribute AI numeric
@attribute 'AI\%' numeric
@attribute 'Total Room Nights' numeric
@attribute 'TOTAL BOOKINGS' numeric

@data
```

Classifier Model

```
REPTree
============
TOTAL PAX Nights < 768.5
|   Total Room Nights < 88
|   |   TOTAL PAX Nights < 60.5 : 0.53 (13/0.71) [2/1.29]
|   |   TOTAL PAX Nights >= 60.5
|   |   |   BB% < 0.1 : 9.4 (4/2.25) [1/30.25]
|   |   |   BB% >= 0.1 : 6.45 (2/0.25) [9/9.58]
|   Total Room Nights >= 88
|   |   TOTAL PAX Nights < 382.5 : 16.29 (7/19.92) [0/0]
|   |   TOTAL PAX Nights >= 382.5 : 26.22 (5/15.44) [4/32.71]
TOTAL PAX Nights >= 768.5 : 61.2 (3/748.22) [2/585.11]

Size of the tree : 11
```

Filtered Header

```
@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R14,4,3,2,5,7,9,15'
```

@attribute 'AI\%' numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute 'Average pax/room' numeric

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute ADR numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute BB numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

TOTAL PAX Nights < 737

| TOTAL PAX Nights < 235

| | TOTAL PAX Nights < 102.5

| | | TOTAL PAX Nights < 45.5 : 0.36 (10/0.45) [4/0.25]

| | | TOTAL PAX Nights >= 45.5 : 4.78 (6/3.89) [3/2.67]

| | TOTAL PAX Nights >= 102.5 : 10.7 (5/10.24) [5/4.76]

| TOTAL PAX Nights >= 235

| | Country = Denmark : 24 (2/36) [0/0]

| | Country = Finland : 23 (2/36) [0/0]

| | Country = Romania : 22.93 (0/0) [0/0]

| | Country = Vary : 29.5 (1/0) [1/25]

| | Country = Poland : 26.25 (1/0) [3/41.67]

| | Country = UK : 18 (1/0) [0/0]

| | Country = Netherlands : 14.5 (1/0) [1/121]

| | Country = Germany : 16 (1/0) [0/0]

TOTAL PAX Nights >= 737 : 61.2 (4/678.69) [1/315.06]

Size of the tree : 17

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R11,3,10,7,4,5,6,15'

@attribute HB numeric

@attribute 'Average pax/room' numeric

@attribute 'BB\%' numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute ADR numeric

@attribute MONTH {'JULY 2020','AUGUST 2020','SEPTEMBER 2020','OCTOBER 2020'}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

: 15.04 (34/432.11) [18/261.13]

Size of the tree : 1

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R9,10,5,12,8,11,2,15'

@attribute BB numeric

@attribute 'BB\%' numeric

@attribute ADR numeric

@attribute 'HB\%' numeric

@attribute 'Total Room Nights' numeric

@attribute HB numeric

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Total Room Nights < 259.5

| Total Room Nights < 88

| | Total Room Nights < 23.5 : 0.53 (10/0.21) [5/2.09]

| | Total Room Nights >= 23.5

| | | Total Room Nights < 49 : 5 (5/3.04) [3/4.56]

| | | Total Room Nights >= 49 : 9.75 (5/2.16) [3/10.51]

| Total Room Nights >= 88 : 21.27 (11/37.06) [4/56.85]

Total Room Nights >= 259.5 : 56.17 (3/748.22) [3/914.56]

Size of the tree : 9

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R1,3,5,10,7,4,2,15'

@attribute 'Booking Source' {'ARHUS CHARTER',AURINKOMATKAT,'BLUE AEGEAN',BOOKING.COM,'BRAVO TOURS',EXPEDIA,ITAKA,Jet2Holidays,RAINBOW,'SELF BOOKINGS',SUNWEB,'TUI Deutschland','TUI NL','TUI UK'}

@attribute 'Average pax/room' numeric

@attribute ADR numeric

@attribute 'BB\%' numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute 'TO/ OTA' {TO,OTA}

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

TOTAL PAX Nights < 765.5

| TOTAL PAX Nights < 201

| | TOTAL PAX Nights < 61

| | | ADR < 29.86 : 0 (7/0) [3/0]

| | | ADR >= 29.86 : 1.6 (5/0.64) [0/0]

| | TOTAL PAX Nights >= 61 : 7.14 (8/4.94) [6/14.73]

| TOTAL PAX Nights >= 201

| | Booking Source = ARHUS CHARTER : 24 (2/36) [0/0]

| | Booking Source = AURINKOMATKAT : 23 (1/0) [1/144]

| | Booking Source = BLUE AEGEAN : 15 (1/0) [0/0]

| | Booking Source = BOOKING.COM : 27 (0/0) [1/45.56]

| | Booking Source = BRAVO TOURS : 14 (0/0) [1/39.06]

| | Booking Source = EXPEDIA : 32 (1/0) [0/0]

| | Booking Source = ITAKA : 24.5 (2/2.25) [0/0]

| | Booking Source = Jet2Holidays : 18 (0/0) [1/5.06]

| | Booking Source = RAINBOW : 28 (1/0) [1/36]

| | Booking Source = SELF BOOKINGS : 20.44 (0/0) [0/0]

| | Booking Source = SUNWEB : 11.75 (3/21.56) [1/58.78]

| | Booking Source = TUI Deutschland : 16 (1/0) [0/0]

| | Booking Source = TUI NL : 20.44 (0/0) [0/0]

| | Booking Source = TUI UK : 20.44 (0/0) [0/0]

TOTAL PAX Nights >= 765.5 : 61.2 (2/702.25) [3/1276.92]

Size of the tree : 23

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R5,7,3,13,10,6,4,15'

@attribute ADR numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute 'Average pax/room' numeric

@attribute AI numeric

@attribute 'BB\%' numeric

@attribute MONTH {'JULY 2020','AUGUST 2020','SEPTEMBER 2020','OCTOBER 2020'}

@attribute 'TO/ OTA' {TO,OTA}

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

TOTAL PAX Nights < 764.5

| TOTAL PAX Nights < 382.5

| | TOTAL PAX Nights < 102.5

| | | TOTAL PAX Nights < 45.5 : 0.36 (9/0.44) [5/0.24]

| | | TOTAL PAX Nights >= 45.5

| | | | ADR < 86.31 : 5.8 (3/2.89) [2/3.61]

| | | | ADR >= 86.31 : 3.5 (3/0) [1/4]

| | TOTAL PAX Nights >= 102.5 : 12.8 (9/9.06) [6/52.03]

| TOTAL PAX Nights >= 382.5 : 26.22 (6/17) [3/46]

TOTAL PAX Nights >= 764.5 : 61.2 (4/626.5) [1/576]

Size of the tree : 11

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R13,8,3,11,12,9,14,15'

@attribute AI numeric

@attribute 'Total Room Nights' numeric

@attribute 'Average pax/room' numeric

@attribute HB numeric

@attribute 'HB\%' numeric

@attribute BB numeric

@attribute 'AI\%' numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

Total Room Nights < 159.5

| Total Room Nights < 88.5

| | Total Room Nights < 27 : 0.53 (11/0.79) [4/0.77]

| | Total Room Nights >= 27 : 7.38 (10/4.49) [6/21.81]

| Total Room Nights >= 88.5 : 16.29 (5/26.64) [2/3.46]

Total Room Nights >= 159.5

| Total Room Nights < 259.5 : 25.63 (5/29.76) [3/7.51]

| Total Room Nights >= 259.5 : 56.17 (3/13.56) [3/1269.22]

Size of the tree : 9

FilteredClassifier using weka.classifiers.trees.REPTree -M 2 -V 0.001 -N 3 -S 1158800660 -L -1 -I 0.0 on data filtered through weka.filters.unsupervised.attribute.Remove -V -R 9,7,2,13,3,8,11,15

Filtered Header

@relation 'Creta Palm Data 2020 ()-weka.filters.unsupervised.attribute.Remove-V-R9,7,2,13,3,8,11,15'

@attribute BB numeric

@attribute 'TOTAL PAX Nights' numeric

@attribute Country {Denmark,Finland,Romania,Vary,Poland,UK,Netherlands,Germany}

@attribute AI numeric

@attribute 'Average pax/room' numeric

@attribute 'Total Room Nights' numeric

@attribute HB numeric

@attribute 'TOTAL BOOKINGS' numeric

@data

Classifier Model

REPTree

============

```
TOTAL PAX Nights < 768.5
|   Total Room Nights < 88
|   |   TOTAL PAX Nights < 102.5
|   |   |   TOTAL PAX Nights < 35 : 0.31 (6/0.14) [7/0.6]
|   |   |   TOTAL PAX Nights >= 35 : 4.4 (6/3.89) [4/4.78]
|   |   TOTAL PAX Nights >= 102.5 : 9.75 (6/2.14) [2/13.69]
|   Total Room Nights >= 88 : 21.88 (13/48.56) [3/32.67]
TOTAL PAX Nights >= 768.5 : 61.2 (3/748.22) [2/585.11]
```

Size of the tree : 9

=== Summary ===

Correlation coefficient 0.875

Mean absolute error 6.3925

Root mean squared error 10.6306

Relative absolute error 47.0885 %

Root relative squared error 54.2753 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Meta Randomizable Filtered Classifier| Creta Palm 2020

=== Classifier model (full training set) ===

IB1 instance-based classifier

using 1 nearest neighbour(s) for classification

=== Summary ===

Correlation coefficient	0.8399
Mean absolute error	5.9423
Root mean squared error	11.0026
Relative absolute error	43.7726 %
Root relative squared error	56.1748 %
Total Number of Instances	52
Ignored Class Unknown Instances	4

Rules Decision Table Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Decision Table:

Number of training instances: 52

Number of Rules : 7

Non matches covered by Majority class.

Best first.

Start set: no attributes

Search direction: forward

Stale search after 5 node expansions

Total number of subsets evaluated: 74

Merit of best subset found: 14.863

Evaluation (for feature selection): CV (leave one out)

Feature set: 8,15

=== Summary ===

Correlation coefficient	0.8395
Mean absolute error	6.5878

Root mean squared error 12.1645

Relative absolute error 48.5274 %

Root relative squared error 62.1067 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Meta Additive Regression Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Additive Regression

Initial prediction: 15.03

10 models generated.

Model number 0

Decision Stump

Classifications

TOTAL PAX Nights <= 737.0 : -4.9108019639934595

TOTAL PAX Nights > 737.0 : 46.16153846153846

TOTAL PAX Nights is missing : -5.943963270300838E-15

Model number 1

Decision Stump

Classifications

Average pax/room <= 3.065 : 1.304307213284903

Average pax/room > 3.065 : 47.800000000000026

Average pax/room is missing : -10.127659574468082

Model number 2

Decision Stump

Classifications

Total Room Nights <= 88.0 : -3.67971943686449238

Total Room Nights > 88.0 : 5.431966787752982

Total Room Nights is missing : -2.391249591500337E-16

Model number 3

Decision Stump

Classifications

Total Room Nights <= 297.5 : 1.7058949530192467

Total Room Nights > 297.5 : -16.035412558380912

Total Room Nights is missing : 7.173748774501012E-16

Model number 4

Decision Stump

Classifications

Total Room Nights <= 159.5 : -1.8124090327177127

Total Room Nights > 159.5 : 4.91939594594808

Total Room Nights is missing : 4.782499183000674E-16

Model number 5

Decision Stump

Classifications

AI <= 737.0 : 0.07211576747739341

AI > 737.0 : -14.82025738860505

AI is missing : 3.786233516563391

Model number 6

Decision Stump

Classifications

Average pax/room <= 2.795 : -0.018679579795516488

Average pax/room > 2.795 : -4.221059895160568

Average pax/room is missing : 2.5998824243601986

Model number 7

Decision Stump

Classifications

HB <= 426.0 : 0.056719633608277725

HB > 426.0 : 9.832993952363008

HB is missing : -3.1247041829880158

Model number 8

Decision Stump

Classifications

Booking Source = RAINBOW : 4.555911629386115

Booking Source != RAINBOW : -0.3796593024488432

Booking Source is missing : -2.391249591500337E-16

Model number 9

Decision Stump

Classifications

Average pax/room <= 1.9849999999999999 : 4.202024608327246

Average pax/room > 1.9849999999999999 : -0.5294429338712259

Average pax/room is missing : 1.277366813819454

=== Summary ===

Correlation coefficient	0.8342
Mean absolute error	6.4298
Root mean squared error	11.6181
Relative absolute error	47.3635 %
Root relative squared error	59.3169 %
Total Number of Instances	52
Ignored Class Unknown Instances	4

Random Tree Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

RandomTree

==========

Total Room Nights < 297.5

| Booking Source = ARHUS CHARTER

| | MONTH = JULY 2020 : 0 (1/0)

| | MONTH = AUGUST 2020 : 0 (1/0)

| | MONTH = SEPTEMBER 2020 : 30 (1/0)

| | MONTH = OCTOBER 2020 : 18 (1/0)

| Booking Source = AURINKOMATKAT
| | ADR < 42.74 : 0 (1/0)
| | ADR >= 42.74
| | | Average pax/room < 2.1 : 29 (1/0)
| | | Average pax/room >= 2.1 : 17 (1/0)
| Booking Source = BLUE AEGEAN
| | MONTH = JULY 2020 : 3 (1/0)
| | MONTH = AUGUST 2020 : 10 (1/0)
| | MONTH = SEPTEMBER 2020 : 15 (1/0)
| | MONTH = OCTOBER 2020 : 0 (1/0)
| Booking Source = BOOKING.COM
| | BB < 182 : 8 (1/0)
| | BB >= 182 : 27 (1/0)
| Booking Source = BRAVO TOURS
| | AI < 161 : 10 (2/0)
| | AI >= 161 : 14 (1/0)
| Booking Source = EXPEDIA
| | MONTH = JULY 2020 : 32 (1/0)
| | MONTH = AUGUST 2020 : 0 (0/0)
| | MONTH = SEPTEMBER 2020 : 6 (1/0)
| | MONTH = OCTOBER 2020 : 1 (1/0)
| Booking Source = ITAKA
| | TOTAL PAX Nights < 303.5 : 7 (1/0)
| | TOTAL PAX Nights >= 303.5
| | | TOTAL PAX Nights < 554 : 26 (1/0)
| | | TOTAL PAX Nights >= 554 : 23 (1/0)
| Booking Source = Jet2Holidays
| | Total Room Nights < 115.5
| | | TOTAL PAX Nights < 63 : 0.5 (2/0.25)
| | | TOTAL PAX Nights >= 63 : 3 (1/0)
| | Total Room Nights >= 115.5 : 18 (1/0)
| Booking Source = RAINBOW

| | TOTAL PAX Nights < 226.5

| | | ADR < 85.19 : 13 (1/0)

| | | ADR >= 85.19 : 1 (1/0)

| | TOTAL PAX Nights >= 226.5

| | | ADR < 102.15 : 31 (1/0)

| | | ADR >= 102.15 : 25 (1/0)

| Booking Source = SELF BOOKINGS : 0 (1/0)

| Booking Source = SUNWEB

| | ADR < 81.25 : 20 (1/0)

| | ADR >= 81.25

| | | MONTH = JULY 2020 : 6 (1/0)

| | | MONTH = AUGUST 2020 : 9 (1/0)

| | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | MONTH = OCTOBER 2020 : 12 (1/0)

| Booking Source = TUI Deutschland

| | ADR < 119.28

| | | Total Room Nights < 62

| | | | Average pax/room < 2.06 : 3 (1/0)

| | | | Average pax/room >= 2.06 : 5 (1/0)

| | | Total Room Nights >= 62 : 9 (1/0)

| | ADR >= 119.28 : 16 (1/0)

| Booking Source = TUI NL

| | MONTH = JULY 2020 : 3 (1/0)

| | MONTH = AUGUST 2020 : 5 (1/0)

| | MONTH = SEPTEMBER 2020 : 8 (1/0)

| | MONTH = OCTOBER 2020 : 0 (1/0)

| Booking Source = TUI UK

| | Total Room Nights < 3.5 : 0 (3/0)

| | Total Room Nights >= 3.5 : 2 (1/0)

Total Room Nights >= 297.5

| Average pax/room < 3.06

| | Country = Denmark : 42 (1/0)

| | Country = Finland : 0 (0/0)

| | Country = Romania : 0 (0/0)

| | Country = Vary

| | | MONTH = JULY 2020 : 56 (1/0)

| | | MONTH = AUGUST 2020 : 52 (1/0)

| | | MONTH = SEPTEMBER 2020 : 0 (0/0)

| | | MONTH = OCTOBER 2020 : 0 (0/0)

| | Country = Poland : 47 (1/0)

| | Country = UK : 0 (0/0)

| | Country = Netherlands : 0 (0/0)

| | Country = Germany : 0 (0/0)

| Average pax/room >= 3.06 : 109 (1/0)

Size of the tree : 83

=== Summary ===

Correlation coefficient 0.8035

Mean absolute error 7.5063

Root mean squared error 11.6473

Relative absolute error 55.2936 %

Root relative squared error 59.466 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Meta Bagging Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Bagging with 10 iterations and base learner

=== Summary ===

Correlation coefficient 0.7682

Mean absolute error 7.8863

Root mean squared error 13.0864

Relative absolute error 58.0927 %

Root relative squared error 66.8134 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Meta Regression by Discretization Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Class attribute discretized into 10 values

Classifier spec: weka.classifiers.trees.J48 -C 0.25 -M 2

J48 pruned tree

Total Room Nights <= 85: '(-inf-10.9]' (31.0/2.0)

Total Room Nights > 85

| BB <= 406: '(21.8-32.7]' (17.0/9.0)

| BB > 406

| | Average pax/room <= 2.91: '(43.6-54.5]' (2.0)

| | Average pax/room > 2.91: '(54.5-65.4]' (2.0/1.0)

Number of Leaves : 4

Size of the tree : 7

=== Summary ===

Correlation coefficient 0.7575

Mean absolute error 8.4383

Root mean squared error 12.8237

Relative absolute error 62.1588 %

Root relative squared error 65.4725 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Lazy LWL Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

Locally weighted learning

Using classifier: weka.classifiers.trees.DecisionStump

Using linear weighting kernels

Using all neighbours

=== Summary ===

Correlation coefficient	0.6917
Mean absolute error	9.4686
Root mean squared error	14.0376
Relative absolute error	69.7484 %
Root relative squared error	71.6703 %
Total Number of Instances	52
Ignored Class Unknown Instances	4

REP Tree Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

REPTree

============

TOTAL PAX Nights < 737

| Total Room Nights < 87

| | TOTAL PAX Nights < 102.5 : 2.09 (15/5.98) [8/6.52]

| | TOTAL PAX Nights >= 102.5 : 9.75 (6/5.47) [2/0.36]

| Total Room Nights >= 87 : 21.88 (8/59.48) [8/31.11]

TOTAL PAX Nights >= 737 : 61.2 (5/593.36) [0/0]

Size of the tree : 7

=== Summary ===

Correlation coefficient 0.6909

Mean absolute error 9.4218

Root mean squared error 14.1754

Relative absolute error 69.4032 %

Root relative squared error 72.3738 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Decision Stump Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

REPTree

============

TOTAL PAX Nights < 737

| Total Room Nights < 87

| | TOTAL PAX Nights < 102.5 : 2.09 (15/5.98) [8/6.52]

| | TOTAL PAX Nights >= 102.5 : 9.75 (6/5.47) [2/0.36]

| Total Room Nights >= 87 : 21.88 (8/59.48) [8/31.11]

TOTAL PAX Nights >= 737 : 61.2 (5/593.36) [0/0]

Size of the tree : 7

=== Summary ===

Correlation coefficient 0.6589

Mean absolute error 11.4081

Root mean squared error 17.1056

Relative absolute error 84.0353 %

Root relative squared error 87.3339 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Lazy IBK Algorithm| Creta Palm 2020

=== Classifier model (full training set) ===

IB1 instance-based classifier

using 1 nearest neighbour(s) for classification

=== Summary ===

Correlation coefficient 0.5753

Mean absolute error 12.0577

Root mean squared error 15.7816

Relative absolute error 88.8201 %

Root relative squared error 80.574 %

Total Number of Instances 52

Ignored Class Unknown Instances 4

Classifiers "Meta CV Parameter Selection", "Meta Multi Scheme", "Meta Stacking", "Meta Vote", "Meta Weighted Instances Handler Wrapper", "Misc Input Mapped Classifier" and **"Zero R"**, provide the same algorithm results, with a correlation coefficient: **-0.3543**, as shown below:

Cross-validated Parameter selection.

Classifier: weka.classifiers.rules.ZeroR

Classifier Options:

ZeroR predicts class value: 15.03

=== Summary ===

Correlation coefficient -0.3543

Mean absolute error	13.5754
Root mean squared error	19.5864
Relative absolute error	100 %
Root relative squared error	100 %
Total Number of Instances	52
Ignored Class Unknown Instances	4

Simple K Means with 3 Clusters| Creta Palm 2020

Final cluster centroids:

Attribute	Full Data (56.0)	Cluster# 0 (25.0)	1 (13.0)	2 (18.0)
Booking Source	ARHUS CHARTER	SELF BOOKINGS	TUI Deutchland	AURINKOMATKAT
Country	Vary	Vary	Germany	Finland
Avarage pax/room	2.3586	2.3295	2.4344	2.3441
TO/ OTA	TO	TO	TO	TO
ADR	73.5381	69.0307	82.6585	73.2117
MONTH	JULY 2020	OCTOBER 2020	JULY 2020	AUGUST 2020
TOTAL PAX Nights	270.2642	225.2717	192.3846	389
Total Room Nights	108.3774	94.4053	78.6923	149.2222
BB	142.16	92.6656	36.7169	287.0556
BB%	0.4362	0.3988	0.2233	0.6419
HB	38.9184	20.3069	45.9812	59.6667
HB%	0.1671	0.0971	0.3549	0.1288
AI	105.98	125.7968	156.8431	41.7222
AI%	0.3901	0.4992	0.4162	0.2197
TOTAL BOOKINGS	15.0385	14.2446	8.8462	20.6132

Simple K Means with 4 Clusters| Creta Palm 2020

Final cluster centroids:

Attribute	Full Data (56.0)	Cluster# 0 (17.0)	1 (12.0)	2 (16.0)	3 (11.0)
Booking Source	ARHUS CHARTER	SELF BOOKINGS	TUI Deutchland	AURINKOMATKAT	BRAVO TOURS
Country	Vary	Vary	Germany	Finland	Denmark
Avarage pax/room	2.3586	2.4005	2.4364	2.3721	2.1891
TO/ OTA	TO	TO	TO	TO	TO
ADR	73.5381	52.2639	81.19	71.78	100.6264
MONTH	JULY 2020	OCTOBER 2020	JULY 2020	AUGUST 2020	SEPTEMBER 2020
TOTAL PAX Nights	270.2642	184.8701	133.8333	407.375	351.6364
Total Room Nights	108.3774	72.1254	54.4167	154.125	156.7273
BB	142.16	131.3906	39.7767	302.0625	37.9091
BB%	0.4362	0.5582	0.2419	0.6378	0.1664
HB	38.9184	29.8631	49.8129	67.125	0
HB%	0.1671	0.1428	0.3845	0.1449	0
AI	105.98	43.4659	95.33	37.5625	313.7273
AI%	0.3901	0.2924	0.3675	0.2078	0.8309
TOTAL BOOKINGS	15.0385	12.1833	6.0833	21.7524	19.4545

Simple K Means with 5 Clusters| Creta Palm 2020

Final cluster centroids:

Attribute	Full Data (56.0)	Cluster# 0 (16.0)	1 (9.0)	2 (13.0)	3 (7.0)	4 (11.0)
Source	ARHUS CHARTER	SELF BOOKINGS	TUI Deutchland	AURINKOMATKAT	RAINBOW	ARHUS CHARTER
Country	Vary	Vary	Germany	Finland	Poland	Denmark
Av. pax/room	2.3586	2.4162	2.3321	2.3974	2.4843	2.1706
TO/ OTA	TO	TO	TO	TO	TO	TO

ADR	73.5381	50.5635	82.8844	75.82	98.9471	80.4427
MONTH	JULY 2020	OCTOBER 2020	JULY 2020	AUGUST 2020	JULY 2020	SEPTEMBER 2020
TOTAL PAX	270.2642	188.362	111.4444	487	421.7143	166.8182
Total Room N.	108.3774	72.8833	48.1111	183.6923	176.2857	77.0909
BB	142.16	139.6025	32.24	370.6923	6.4286	52.1055
BB%	0.4362	0.5931	0.2518	0.6745	0.0286	0.3366
HB	38.9184	31.7296	76.3152	70.9231	3.4286	3.538
HB%	0.1671	0.1517	0.5797	0.0986	0.0143	0.0304
AI	105.98	38.12	39.1089	44.6154	411.8571	137.2709
AI%	0.3901	0.2482	0.1622	0.2165	0.9543	0.6291
TOTAL BOOKINGS	15.0385	12.1322	5.5556	25.8491	20.2857	10.9091

EM Clustering Model (continued)| Creta Palm 2020

	Cluster		
Attribute	0	1	2
	(0.28)	(0.55)	(0.17)
Booking Source			
ARHUS CHARTER	3	3	1
AURINKOMATKAT	2	4	1
BLUE AEGEAN	2	4	1
BOOKING.COM	1	1.983	4.017
BRAVO TOURS	4.0041	1.9539	1.042
EXPEDIA	1	1.7907	4.2093
ITAKA	3.0004	1.9877	2.0119
Jet2Holidays	1.0093	3.9984	1.9923
RAINBOW	4.0002	1	1.9998
SELF BOOKINGS	1	5	1
SUNWEB	4	2	1
TUI Deutchland	1	5	1
TUI NL	1.8652	4.1343	1.0006
TUI UK	1	4.9996	1.0004
[total]	29.8792	44.8476	23.2732
Country			
Denmark	6.0041	3.9539	1.042
Finland	2	4	1
Romania	2	4	1
Vary	1	6.7737	7.2263

Poland	6.0006	1.9877	3.0117
UK	1.0093	7.998	1.9927
Nederlands	4.8652	5.1343	1.0006
Germany	1	5	1
[total]	23.8792	38.8476	17.2732
Avarage pax/room			
mean	2.2972	2.2975	2.6667
std. dev.	0.2519	0.2068	0.318
TO/ OTA			
TO	16.8792	30.0739	4.0469
OTA	1	2.7737	7.2263
[total]	17.8792	32.8476	11.2732
ADR			
mean	98.1323	54.3313	95.316
std. dev.	24.7663	45.2436	17.7772
MONTH			
JULY 2020	4	9.9994	3.0006
AUGUST 2020	3.0145	7.9514	6.0341
SEPTEMBER 2020	7.8642	6.9111	2.2247
OCTOBER 2020	5.0004	9.9857	2.0139
[total]	19.8792	34.8476	13.2732
TOTAL PAX Nights			
mean	346.2423	93.5928	727.8619
std. dev.	218.9589	102.9212	601.8411
Total Room Nights			
mean	152.0379	40.1846	260.4587
std. dev.	93.078	42.6628	188.5728
BB			
mean	50.167	53.846	593.4631

```
  std. dev.           97.9618  59.9082 476.2931


BB%

  mean                 0.1385   0.4653    0.849

  std. dev.             0.241   0.3055   0.1343


HB

  mean                 1.1336  32.2179 125.9087

  std. dev.            4.3725  43.0547 167.8338


HB%

  mean                 0.0019    0.263   0.1314

  std. dev.            0.0073   0.3066   0.1286


AI

  mean               294.9417  38.3408   7.4118

  std. dev.          230.6609  52.2848  10.9021


AI%

  mean                 0.8559   0.2645   0.0101

  std. dev.            0.2507   0.1901   0.0211


TOTAL BOOKINGS

  mean                18.8993   5.6153  39.7735

  std. dev.           10.3394   5.7736  29.3252
```

Make A Density Based Clusterer fitted estimators| Creta Palm 2020

Fitted estimators (with ML estimates of variance):

Cluster: 0 Prior probability: 0.6207

Attribute: ï»¿Booking Source

Discrete Estimator. Counts = 4 3 3 4 4 4 3 3 4 5 4 1 3 4 (Total = 49)

Attribute: Country

Discrete Estimator. Counts = 7 3 3 11 6 6 6 1 (Total = 43)

Attribute: Avarage pax/room

Normal Distribution. Mean = 2.3561 StdDev = 0.2526

Attribute: TO/ OTA

Discrete Estimator. Counts = 30 7 (Total = 37)

Attribute: ADR

Normal Distribution. Mean = 65.7399 StdDev = 46.3358

Attribute: MONTH

Discrete Estimator. Counts = 10 2 14 13 (Total = 39)

Attribute: TOTAL PAX Nights

Normal Distribution. Mean = 220.8226 StdDev = 246.7839

Attribute: Total Room Nights

Normal Distribution. Mean = 91.8609 StdDev = 97.6317

Attribute: BB

Normal Distribution. Mean = 83.4846 StdDev = 155.2409

Attribute: BB%

Normal Distribution. Mean = 0.379 StdDev = 0.3137

Attribute: HB

Normal Distribution. Mean = 17.4146 StdDev = 30.8339

Attribute: HB%

Normal Distribution. Mean = 0.0913 StdDev = 0.0946

Attribute: AI

Normal Distribution. Mean = 145.968 StdDev = 205.4665

Attribute: AI%

Normal Distribution. Mean = 0.5243 StdDev = 0.3715

Attribute: TOTAL BOOKINGS

Normal Distribution. Mean = 13.2615 StdDev = 13.3537

Cluster: 1 Prior probability: 0.3793

Attribute: ï»¿Booking Source

Discrete Estimator. Counts = 2 3 3 2 2 2 3 3 2 1 2 5 3 2 (Total = 35)

Attribute: Country

Discrete Estimator. Counts = 3 3 3 3 4 4 4 5 (Total = 29)

Attribute: Avarage pax/room

Normal Distribution. Mean = 2.3627 StdDev = 0.3152

Attribute: TO/ OTA

Discrete Estimator. Counts = 20 3 (Total = 23)

Attribute: ADR

Normal Distribution. Mean = 86.5352 StdDev = 31.1497

Attribute: MONTH

Discrete Estimator. Counts = 6 14 2 3 (Total = 25)

Attribute: TOTAL PAX Nights

Normal Distribution. Mean = 352.6667 StdDev = 492.0075

Attribute: Total Room Nights

Normal Distribution. Mean = 135.9048 StdDev = 162.215

Attribute: BB

Normal Distribution. Mean = 239.9524 StdDev = 406.2404

Attribute: BB%

Normal Distribution. Mean = 0.5315 StdDev = 0.3923

Attribute: HB

Normal Distribution. Mean = 74.758 StdDev = 126.5836

Attribute: HB%

Normal Distribution. Mean = 0.2935 StdDev = 0.3737

Attribute: AI

Normal Distribution. Mean = 39.3333 StdDev = 69.5792

Attribute: AI%

Normal Distribution. Mean = 0.1664 StdDev = 0.2042

Attribute: TOTAL BOOKINGS

Normal Distribution. Mean = 18 StdDev = 24.702

Farthest First with 3 Clusters| Creta Palm 2020

```
Cluster centroids:

Cluster 0:
TUI Deutchland Germany 2.28 TO 117.18 AUGUST 2020 194.0 85.0 0.0
0.0 148.0 0.76 46.0 0.23 9.0

Cluster 1:
BOOKING.COM Vary 3.11 OTA 123.27 AUGUST 2020 2155.0 691.0 1652.0
0.76 503.0 0.23 10.0 0.004 109.0

Cluster 2:
EXPEDIA Vary 3.0 OTA 59.71 OCTOBER 2020 9.0 3.0 9.0 1.0 0.0 0.0
0.0 0.0 1.0


=== Model and evaluation on training set ===

Clustered Instances

0      38 ( 68%)
1       3 (  5%)
2      15 ( 27%)
```

Farthest First with 4 Clusters| Creta Palm 2020

```
Cluster centroids:

Cluster 0:
TUI Deutchland Germany 2.28 TO 117.18 AUGUST 2020 194.0 85.0 0.0
0.0 148.0 0.76 46.0 0.23 9.0
```

```
Cluster 1:
BOOKING.COM Vary 3.11 OTA 123.27 AUGUST 2020 2155.0 691.0 1652.0
0.76 503.0 0.23 10.0 0.004 109.0

Cluster 2:
EXPEDIA Vary 3.0 OTA 59.71 OCTOBER 2020 9.0 3.0 9.0 1.0 0.0 0.0
0.0 0.0 1.0

Cluster 3:
BRAVO TOURS Denmark 2.41 TO 100.28 JULY 2020 895.0 370.0 0.0 0.0
0.0 0.0 895.0 1.0 42.0

=== Model and evaluation on training set ===

Clustered Instances

0      24 ( 43%)
1       3 (  5%)
2      15 ( 27%)
3      14 ( 25%)
```

Farthest First with 5 Clusters| Creta Palm 2020

```
Cluster centroids:

Cluster 0:
TUI Deutchland Germany 2.28 TO 117.18 AUGUST 2020 194.0 85.0 0.0
0.0 148.0 0.76 46.0 0.23 9.0

Cluster 1:
BOOKING.COM Vary 3.11 OTA 123.27 AUGUST 2020 2155.0 691.0 1652.0
0.76 503.0 0.23 10.0 0.004 109.0

Cluster 2:
EXPEDIA Vary 3.0 OTA 59.71 OCTOBER 2020 9.0 3.0 9.0 1.0 0.0 0.0
0.0 0.0 1.0

Cluster 3:
BRAVO TOURS Denmark 2.41 TO 100.28 JULY 2020 895.0 370.0 0.0 0.0
0.0 0.0 895.0 1.0 42.0

Cluster 4:
ITAKA Poland 2.91 TO 108.52 AUGUST 2020 1083.0 372.0 1083.0 1.0
0.0 0.0 0.0 0.0 47.0

=== Model and evaluation on training set ===

Clustered Instances

0      18 ( 32%)
1       3 (  5%)
2      13 ( 23%)
3      14 ( 25%)
4       8 ( 14%)
```

Canopy Clusterer| Creta Palm 2020

Number of canopies (cluster centers) found: 14

Cluster 0: ITAKA, Poland, 2.5375, TO, 97.0825, 'JULY2020', 427, 180.5, 0, 0, 0, 0, 427, 1, 20.25, {4} <0,3,4,5,10,12,13>

Cluster 1: Jet2Holidays, UK, 2.208163, TO, 70.611164, 'SEPTEMBER2020', 197.037736, 86.053908, 139.88, 0.66034, 5.559767, 0.047755, 53.997143, 0.284313, 9.434066,{7} <1,2,3,7,9,11,13>

Cluster 2: 'ARHUS CHARTER', Denmark, 2.240714, TO, 29.713333, 'AUGUST2020', 108.877358, 49.396226, 69.553333, 0.45746, 12.972789, 0.111429, 76.993333, 0.42673, 7.173077, {6} <1,2,3,4,7,9,10,12,13>

Cluster 3: ITAKA, Poland, 2.09, TO, 77.645, 'OCTOBER2020', 73, 35, 67, 0.915, 19.459184, 0, 6, 0.08, 5, {2} <0,1,2,3,7,9,12>

Cluster 4: 'BRAVO TOURS', Denmark, 2.256667, TO, 84.39, 'OCTOBER2020', 152, 66.333333, 10.666667, 0.05, 0, 0, 141.333333, 0.946667, 11.666667,{3} <0,2,4,9,10>

Cluster 5: 'TUI Deutchland', Germany, 2.276667, TO, 106.02, 'JULY2020', 193, 82.666667, 0, 0, 122, 0.726667, 71, 0.263333, 10,{3} <0,5,6,10,13>

Cluster 6: 'BLUEAEGEAN', Romania, 2.372857, TO, 59.97, 'JULY2020', 74, 30.666667, 0, 0.145397, 67, 0.679048, 7, 0.170032, 4.333333, {3} <5,6,9,13>

Cluster 7:'TUINL', Nederlands, 2.195714, TO, 74.382, 'AUGUST 2020', 203.4, 94.4, 112.4, 0.615238, 3.6, 0.039429, 87.4, 0.336019, 9.2, {5} <1,2,3,7,9,12,13>

Cluster 8: EXPEDIA, Vary, 2.48, OTA, 87.92, 'JULY2020', 670.5, 264, 438.5, 0.685, 215, 0.285, 7, 0.005, 42, {2} <8,11,13>

Cluster 9: AURINKOMATKAT, Finland, 2.334857, TO, 33.50763, 'OCTOBER2020', 115.65283, 49.075472, 62.832, 0.458952, 18.183673, 0.165714, 37.996, 0.366076, 9.415385,{5} <1,2,3,4,6,7,9,13>

Cluster 10: 'BRAVOTOURS', Denmark, 2.32, TO, 104.55, 'JULY2020', 549, 230.5, 0, 0, 0, 0, 549, 1, 28,{2} <0,2,4,5,10,13>

Cluster 11: BOOKING.COM, Vary, 2.4375, OTA, 73.6225, 'SEPTEMBER2020', 145, 61, 108, 0.8025, 37, 0.19, 0, 0, 10.5,{4} <1,8,11,13>

Cluster 12: ITAKA, Poland, 2.655, TO, 107.115, 'AUGUST2020', 703.5, 253.5, 703.5, 1, 0 ,0, 0, 0, 36,{2} <0,2,3,7,12>

Cluster 13: 'SELFBOOKINGS', Vary, 2.358571, TO, 0, 'JULY2020', 0, 0, 142.16, 0.43619, 38.918367, 0.167143, 105.98, 0.390095, 0,{2} <0,1,2,5,6,7,8,9,10,11,13>

Clustered Instances:

0	5 (9%)
1	4 (7%)
2	4 (7%)
3	2 (4%)
4	5 (9%)
5	3 (5%)
6	5 (9%)
7	6 (11%)
8	5 (9%)
9	5 (9%)
10	2 (4%)
11	3 (5%)
12	2 (4%)
13	5 (9%)

APPENDIX 2: NN

Random Tree Algorithm| NN

Note: The number in the parenthesis (i.e. 35/0) denotes that the respective rule had been correctly applied in 35 cases.

It is of a major importance to cover my fixed costs after I receive my pension = No

| Car superseding Ability = Yes : Yes (35/0)

| Car superseding Ability = No

| | I would like doctor visits to be included to my private insurance = Yes

| | | I would choose a local public hospital for a mild health issue = No : Yes (65/0)

| | | I would choose a local public hospital for a mild health issue = Yes

| | | | I wish for private health services coupled with my insurance = Yes

| | | | | I would like hospital care to be included to my private insurance = Yes

| | | | | | Quite satisfied from the public insurance health benefits = No : Yes (10/0)

| | | | | | Quite satisfied from the public insurance health benefits = Yes

| | | | | | | It is of a major importance to cover my pleasure trips after I receive my pension = Yes : Yes (4/0)

| | | | | | | It is of a major importance to cover my pleasure trips after I receive my pension = No

| | | | | | | | I have managed for a lump sum or supplementary pension = Yes : No (1/0)

| | | | | | | | I have managed for a lump sum or supplementary pension = No : Yes (1/0)

| | | | | I would like hospital care to be included to my private insurance = No : Yes (7/0)

| | | | I wish for private health services coupled with my insurance = No

| | | | | It is of a major importance to cover my healthcare after I receive my pension = Yes : Yes (2/0)

| | | | | It is of a major importance to cover my healthcare after I receive my pension = No : No (1/0)

| | I would like doctor visits to be included to my private insurance = No

| | | It is of a major importance to cover my healthcare after I receive my pension = Yes

| | | | Want a risk protection = Yes

| | | | | I would choose a local public hospital for serious health issues = No

| | | | | | Fixed Costs would not be covered in case of a possible loss of mine = Yes : Yes (19/0)

| | | | | | Fixed Costs would not be covered in case of a possible loss of mine = No

| | | | | | | Tax obligations would not be covered in case of a possible loss of mine = No : Yes (5/0)

| | | | | | | Tax obligations would not be covered in case of a possible loss of mine = Yes : No (1/0)

| | | | | I would choose a local public hospital for serious health issues = Yes : No (1/0)

| | | | Want a risk protection = No

| | | | | Children Studies would not be covered in case of a possible loss of mine = No

| | | | | | Have never had Insurance = Yes

| | | | | | | I will get a satisfying pension = No : Yes (2/0)

| | | | | | | I will get a satisfying pension = Yes : No (1/0)

| | | | | | Have never had Insurance = No : Yes (3/0)

| | | | | Children Studies would not be covered in case of a possible loss of mine = Yes : No (2/0)

| | | It is of a major importance to cover my healthcare after I receive my pension = No : Yes (15/0)

| | I would like doctor visits to be included to my private insurance = Yes : Yes (5/0)

It is of a major importance to cover my fixed costs after I receive my pension = Yes

| I would choose a local public hospital for serious health issues = No : Yes (1/0)

| I would choose a local public hospital for serious health issues = Yes : No (1/0)

Random Tree Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	1
12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	1
14	1:Yes	1:Yes	1
15	1:Yes	1:Yes	1
16	1:Yes	1:Yes	1
17	1:Yes	1:Yes	1
18	1:Yes	1:Yes	1
19	1:Yes	1:Yes	1
20	1:Yes	1:Yes	1
21	1:Yes	1:Yes	1
22	1:Yes	1:Yes	1
23	1:Yes	1:Yes	1
24	1:Yes	1:Yes	1
25	1:Yes	1:Yes	1
26	1:Yes	1:Yes	1
27	1:Yes	1:Yes	1
28	1:Yes	1:Yes	1
29	1:Yes	1:Yes	1
30	1:Yes	1:Yes	1
31	1:Yes	1:Yes	1
32	1:Yes	1:Yes	1
33	1:Yes	1:Yes	1
34	1:Yes	1:Yes	1
35	1:Yes	1:Yes	1
36	1:Yes	1:Yes	1
37	1:Yes	1:Yes	1
38	1:Yes	1:Yes	1
39	1:Yes	1:Yes	1
40	1:Yes	1:Yes	1
41	1:Yes	1:Yes	1
42	1:Yes	1:Yes	1
43	1:Yes	1:Yes	1
44	1:Yes	1:Yes	1
45	1:Yes	1:Yes	1
46	1:Yes	1:Yes	1
47	1:Yes	1:Yes	1
48	1:Yes	1:Yes	1
49	1:Yes	1:Yes	1
50	1:Yes	1:Yes	1
51	1:Yes	1:Yes	1
52	1:Yes	1:Yes	1
53	1:Yes	1:Yes	1
54	1:Yes	1:Yes	1
55	1:Yes	1:Yes	1
56	1:Yes	1:Yes	1

57	1:Yes	1:Yes	1
58	1:Yes	1:Yes	1
59	1:Yes	1:Yes	1
60	1:Yes	1:Yes	1
61	1:Yes	1:Yes	1
62	1:Yes	1:Yes	1
63	1:Yes	1:Yes	1
64	1:Yes	1:Yes	1
65	1:Yes	1:Yes	1
66	1:Yes	1:Yes	1
67	1:Yes	1:Yes	1
68	1:Yes	1:Yes	1
69	1:Yes	1:Yes	1
70	1:Yes	1:Yes	1
71	1:Yes	1:Yes	1
72	1:Yes	1:Yes	1
73	1:Yes	1:Yes	1
74	1:Yes	1:Yes	1
75	1:Yes	1:Yes	1
76	1:Yes	1:Yes	1
77	1:Yes	1:Yes	1
78	1:Yes	1:Yes	1
79	1:Yes	1:Yes	1
80	1:Yes	1:Yes	1
81	1:Yes	1:Yes	1
82	1:Yes	1:Yes	1
83	1:Yes	1:Yes	1
84	1:Yes	1:Yes	1
85	1:Yes	1:Yes	1
86	1:Yes	1:Yes	1
87	1:Yes	1:Yes	1
88	1:Yes	1:Yes	1
89	1:Yes	1:Yes	1
90	1:Yes	1:Yes	1
91	1:Yes	1:Yes	1
92	1:Yes	1:Yes	1
93	1:Yes	1:Yes	1
94	1:Yes	1:Yes	1
95	1:Yes	1:Yes	1
96	1:Yes	1:Yes	1
97	1:Yes	1:Yes	1
98	1:Yes	1:Yes	1
99	1:Yes	1:Yes	1
100	1:Yes	1:Yes	1
101	1:Yes	1:Yes	1
102	1:Yes	1:Yes	1
103	1:Yes	1:Yes	1
104	1:Yes	1:Yes	1

105	1:Yes	1:Yes	1
106	1:Yes	1:Yes	1
107	1:Yes	1:Yes	1
108	1:Yes	1:Yes	1
109	1:Yes	1:Yes	1
110	1:Yes	1:Yes	1
111	1:Yes	1:Yes	1
112	1:Yes	1:Yes	1
113	1:Yes	1:Yes	1
114	1:Yes	1:Yes	1
115	1:Yes	1:Yes	1
116	1:Yes	1:Yes	1
117	1:Yes	1:Yes	1
118	1:Yes	1:Yes	1
119	1:Yes	1:Yes	1
120	1:Yes	1:Yes	1
121	1:Yes	1:Yes	1
122	1:Yes	1:Yes	1
123	1:Yes	1:Yes	1
124	1:Yes	1:Yes	1
125	1:Yes	1:Yes	1
126	1:Yes	1:Yes	1
127	1:Yes	1:Yes	1
128	1:Yes	1:Yes	1
129	1:Yes	1:Yes	1
130	1:Yes	1:Yes	1
131	1:Yes	1:Yes	1
132	1:Yes	1:Yes	1
133	1:Yes	1:Yes	1
134	1:Yes	1:Yes	1
135	1:Yes	1:Yes	1
136	1:Yes	1:Yes	1
137	1:Yes	1:Yes	1
138	1:Yes	1:Yes	1
139	1:Yes	1:Yes	1
140	1:Yes	1:Yes	1
141	1:Yes	1:Yes	1
142	1:Yes	1:Yes	1
143	1:Yes	1:Yes	1
144	1:Yes	1:Yes	1
145	1:Yes	1:Yes	1
146	1:Yes	1:Yes	1
147	1:Yes	1:Yes	1
148	1:Yes	1:Yes	1
149	1:Yes	1:Yes	1
150	1:Yes	1:Yes	1
151	1:Yes	1:Yes	1
152	1:Yes	1:Yes	1

153	1:Yes	1:Yes	1
154	1:Yes	1:Yes	1
155	1:Yes	1:Yes	1
156	1:Yes	1:Yes	1
157	1:Yes	1:Yes	1
158	1:Yes	1:Yes	1
159	1:Yes	1:Yes	1
160	1:Yes	1:Yes	1
161	1:Yes	1:Yes	1
162	2:No	2:No	1
163	1:Yes	1:Yes	1
164	1:Yes	1:Yes	1
165	1:Yes	1:Yes	1
166	1:Yes	1:Yes	1
167	1:Yes	1:Yes	1
168	2:No	2:No	1
169	2:No	2:No	1
170	1:Yes	1:Yes	1
171	2:No	2:No	1
172	1:Yes	1:Yes	1
173	1:Yes	1:Yes	1
174	2:No	2:No	1
175	1:Yes	1:Yes	1
176	1:Yes	1:Yes	1
177	1:Yes	1:Yes	1
178	2:No	2:No	1
179	2:No	2:No	1
180	1:Yes	1:Yes	1
181	2:No	2:No	1
182	1:Yes	1:Yes	1

Lazy IBK Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	0.995
12	1:Yes	1:Yes	0.995
13	1:Yes	1:Yes	0.995
14	1:Yes	1:Yes	0.995
15	1:Yes	1:Yes	0.995
16	1:Yes	1:Yes	0.995
17	1:Yes	1:Yes	0.995
18	1:Yes	1:Yes	0.995
19	1:Yes	1:Yes	0.995
20	1:Yes	1:Yes	0.995
21	1:Yes	1:Yes	0.995
22	1:Yes	1:Yes	0.995

23	1:Yes	1:Yes	0.995
24	1:Yes	1:Yes	0.995
25	1:Yes	1:Yes	0.995
26	1:Yes	1:Yes	0.995
27	1:Yes	1:Yes	0.995
28	1:Yes	1:Yes	0.995
29	1:Yes	1:Yes	0.995
30	1:Yes	1:Yes	0.995
31	1:Yes	1:Yes	0.995
32	1:Yes	1:Yes	0.995
33	1:Yes	1:Yes	0.995
34	1:Yes	1:Yes	0.995
35	1:Yes	1:Yes	0.995
36	1:Yes	1:Yes	0.995
37	1:Yes	1:Yes	0.995
38	1:Yes	1:Yes	0.995
39	1:Yes	1:Yes	0.995
40	1:Yes	1:Yes	0.995
41	1:Yes	1:Yes	0.995
42	1:Yes	1:Yes	0.995
43	1:Yes	1:Yes	0.995
44	1:Yes	1:Yes	0.995
45	1:Yes	1:Yes	0.995
46	1:Yes	1:Yes	0.995
47	1:Yes	1:Yes	0.995
48	1:Yes	1:Yes	0.995
49	1:Yes	1:Yes	0.995
50	1:Yes	1:Yes	0.995
51	1:Yes	1:Yes	0.995
52	1:Yes	1:Yes	0.995
53	1:Yes	1:Yes	0.995
54	1:Yes	1:Yes	0.995
55	1:Yes	1:Yes	0.995
56	1:Yes	1:Yes	0.995
57	1:Yes	1:Yes	0.995
58	1:Yes	1:Yes	0.995
59	1:Yes	1:Yes	0.995
60	1:Yes	1:Yes	0.995
61	1:Yes	1:Yes	0.995
62	1:Yes	1:Yes	0.995
63	1:Yes	1:Yes	0.995
64	1:Yes	1:Yes	0.995
65	1:Yes	1:Yes	0.995
66	1:Yes	1:Yes	0.995
67	1:Yes	1:Yes	0.995
68	1:Yes	1:Yes	0.995
69	1:Yes	1:Yes	0.995
70	1:Yes	1:Yes	0.995

71	1:Yes	1:Yes	0.995
72	1:Yes	1:Yes	0.995
73	1:Yes	1:Yes	0.995
74	1:Yes	1:Yes	0.995
75	1:Yes	1:Yes	0.995
76	1:Yes	1:Yes	0.995
77	1:Yes	1:Yes	0.995
78	1:Yes	1:Yes	0.995
79	1:Yes	1:Yes	0.995
80	1:Yes	1:Yes	0.995
81	1:Yes	1:Yes	0.995
82	1:Yes	1:Yes	0.995
83	1:Yes	1:Yes	0.995
84	1:Yes	1:Yes	0.995
85	1:Yes	1:Yes	0.995
86	1:Yes	1:Yes	0.995
87	1:Yes	1:Yes	0.995
88	1:Yes	1:Yes	0.995
89	1:Yes	1:Yes	0.995
90	1:Yes	1:Yes	0.995
91	1:Yes	1:Yes	0.995
92	1:Yes	1:Yes	0.995
93	1:Yes	1:Yes	0.995
94	1:Yes	1:Yes	0.995
95	1:Yes	1:Yes	0.995
96	1:Yes	1:Yes	0.995
97	1:Yes	1:Yes	0.995
98	1:Yes	1:Yes	0.995
99	1:Yes	1:Yes	0.995
100	1:Yes	1:Yes	0.995
101	1:Yes	1:Yes	0.995
102	1:Yes	1:Yes	0.995
103	1:Yes	1:Yes	0.995
104	1:Yes	1:Yes	0.995
105	1:Yes	1:Yes	0.995
106	1:Yes	1:Yes	0.995
107	1:Yes	1:Yes	0.995
108	1:Yes	1:Yes	0.995
109	1:Yes	1:Yes	0.995
110	1:Yes	1:Yes	0.995
111	1:Yes	1:Yes	0.995
112	1:Yes	1:Yes	0.995
113	1:Yes	1:Yes	0.995
114	1:Yes	1:Yes	0.995
115	1:Yes	1:Yes	0.995
116	1:Yes	1:Yes	0.995
117	1:Yes	1:Yes	0.995
118	1:Yes	1:Yes	0.995

119	1:Yes	1:Yes	0.995
120	1:Yes	1:Yes	0.995
121	1:Yes	1:Yes	0.995
122	1:Yes	1:Yes	0.995
123	1:Yes	1:Yes	0.995
124	1:Yes	1:Yes	0.995
125	1:Yes	1:Yes	0.995
126	1:Yes	1:Yes	0.995
127	1:Yes	1:Yes	0.995
128	1:Yes	1:Yes	0.995
129	1:Yes	1:Yes	0.995
130	1:Yes	1:Yes	0.995
131	1:Yes	1:Yes	0.995
132	1:Yes	1:Yes	0.995
133	1:Yes	1:Yes	0.995
134	1:Yes	1:Yes	0.995
135	1:Yes	1:Yes	0.995
136	1:Yes	1:Yes	0.995
137	1:Yes	1:Yes	0.995
138	1:Yes	1:Yes	0.995
139	1:Yes	1:Yes	0.995
140	1:Yes	1:Yes	0.995
141	1:Yes	1:Yes	0.995
142	1:Yes	1:Yes	0.995
143	1:Yes	1:Yes	0.995
144	1:Yes	1:Yes	0.995
145	1:Yes	1:Yes	0.995
146	1:Yes	1:Yes	0.995
147	1:Yes	1:Yes	0.995
148	1:Yes	1:Yes	0.995
149	1:Yes	1:Yes	0.995
150	1:Yes	1:Yes	0.995
151	1:Yes	1:Yes	0.995
152	1:Yes	1:Yes	0.995
153	1:Yes	1:Yes	0.995
154	1:Yes	1:Yes	0.995
155	1:Yes	1:Yes	0.995
156	1:Yes	1:Yes	0.995
157	1:Yes	1:Yes	0.995
158	1:Yes	1:Yes	0.995
159	1:Yes	1:Yes	0.995
160	1:Yes	1:Yes	0.995
161	1:Yes	1:Yes	0.995
162	2:No	2:No	0.995
163	1:Yes	1:Yes	0.995
164	1:Yes	1:Yes	0.995
165	1:Yes	1:Yes	0.995
166	1:Yes	1:Yes	0.997

167	1:Yes	1:Yes	0.997
168	2:No	2:No	0.995
169	2:No	2:No	0.995
170	1:Yes	1:Yes	0.995
171	2:No	2:No	0.995
172	1:Yes	1:Yes	0.995
173	1:Yes	1:Yes	0.995
174	2:No	2:No	0.995
175	1:Yes	1:Yes	0.995
176	1:Yes	1:Yes	0.995
177	1:Yes	1:Yes	0.995
178	2:No	2:No	0.995
179	2:No	2:No	0.995
180	1:Yes	1:Yes	0.995
181	2:No	2:No	0.995
182	1:Yes	1:Yes	0.995

Bayes Net Classifier Model| NN

Bayes Network Classifier (full training set)

not using ADTree

#attributes=65 #classindex=64

Network structure (nodes followed by parents)

Car superseding Ability(2): I am interested in estimating my retirement

Motorbike superseding Ability(2): I am interested in estimating my retirement

House superseding Ability(2): I am interested in estimating my retirement

Business superseding Ability(2): I am interested in estimating my retirement

No superseding ability(2): I am interested in estimating my retirement

Have or Had Business Insurance(2): I am interested in estimating my retirement

Have or Had Civil Liability Insurance(2): I am interested in estimating my retirement

Have or Had Vessel Insurance(2): I am interested in estimating my retirement

Have or Had Health Insurance(2): I am interested in estimating my retirement

Have or Had Everyday needs Insurance(2): I am interested in estimating my retirement

Have or Had Business House Insurance(2): I am interested in estimating my retirement

Have or Had Family Insurance(2): I am interested in estimating my retirement

Have or Had Cash Insurance(2): I am interested in estimating my retirement

Have or Had Child Insurance(2): I am interested in estimating my retirement

Have or Had Car Insurance(1): I am interested in estimating my retirement

Have or Had Motorbike Insurance(2): I am interested in estimating my retirement

Have never had Insurance(2): I am interested in estimating my retirement

Fixed Costs would not be covered in case of a possible loss of mine(2): I am interested in estimating my retirement

Loans would not be covered in case of a possible loss of mine(2): I am interested in estimating my retirement

Children Studies would not be covered in case of a possible loss of mine(2): I am interested in estimating my retirement

Tax obligations would not be covered in case of a possible loss of mine(2): I am interested in estimating my retirement

No needs to leave behind in case of a possible loss of mine(2): I am interested in estimating my retirement

Happiness would not be covered in case of a possible loss of mine(2): I am interested in estimating my retirement

Purchases in non basic necessities would not be covered in case of a possible loss of mine(2): I am interested in estimating my retirement

Want a risk protection(2): I am interested in estimating my retirement

A satisfying amount of money for the support of my beloved ones(1): I am interested in estimating my retirement

Not at all satisfied from the public insurance health benefits(2): I am interested in estimating my retirement

Kind of satisfied from the public insurance health benefits(2): I am interested in estimating my retirement

Quite satisfied from the public insurance health benefits(2): I am interested in estimating my retirement

Absolutely satisfied from the public insurance health benefits(2): I am interested in estimating my retirement

I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue(2): I am interested in estimating my retirement

I would choose a big private hospital in Athens or Thessaloniki for a mild health issue(2): I am interested in estimating my retirement

I would choose a local private hospital for a mild health issue(2): I am interested in estimating my retirement

I would choose a local public hospital for a mild health issue(2): I am interested in estimating my retirement

I would choose a public hospital in Athens or Thessaloniki for serious health issues(2): I am interested in estimating my retirement

I would choose a big private hospital of Athens or Thessaloniki for serious health issues(2): I am interested in estimating my retirement

I would choose a local private hospital for serious health issues(2): I am interested in estimating my retirement

I would choose a local public hospital for serious health issues(2): I am interested in estimating my retirement

I would choose a foreign hospital for serious health issues(2): I am interested in estimating my retirement

I wish for private health services coupled with my insurance(2): I am interested in estimating my retirement

I would like diagnostic tests to be included to my private insurance(2): I am interested in estimating my retirement

I would like doctor visits to be included to my private insurance(3): I am interested in estimating my retirement

I would like hospital care to be included to my private insurance(2): I am interested in estimating my retirement

I would like Annual check up to be included to my private insurance(2): I am interested in estimating my retirement

I would like going abroad to be included to my private insurance(2): I am interested in estimating my retirement

I would like ambulance to be included to my private insurance (2): I am interested in estimating my retirement

Team insurance (2): I am interested in estimating my retirement

I will not get a pension(2): I am interested in estimating my retirement

I will get a small pension(2): I am interested in estimating my retirement

I will get a satisfying pension(2): I am interested in estimating my retirement

I have managed for a lump sum or supplementary pension(2): I am interested in estimating my retirement

I have managed for a lump sum or supplementary pension through Bank Savings(2): I am interested in estimating my retirement

I have managed for a lump sum or supplementary pension through Pension scheme purchase(2): I am interested in estimating my retirement

I have managed for a lump sum or supplementary pension through Life insurance program and savings plan(2): I am interested in estimating my retirement

I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation(2): I am interested in estimating my retirement

I am about to take immediate care of a lump sum or supplementary pension(2): I am interested in estimating my retirement

I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase (2): I am interested in estimating my retirement

Even if I wanted it I cannot take care of a lump sum or supplementary pension(2): I am interested in estimating my retirement

It is of a major importance to support my children and grandchildren after I receive my pension(2): I am interested in estimating my retirement

It is of a major importance to cover my healthcare after I receive my pension(2): I am interested in estimating my retirement

It is of a major importance to cover my pleasure trips after I receive my pension(2): I am interested in estimating my retirement

It is of a major importance to cover my house purchases after I receive my pension(2): I am interested in estimating my retirement

It is of a major importance to cover my fixed costs after I receive my pension(2): I am interested in estimating my retirement

It is of a major importance to cover my everyday needs after I receive my pension(2): I am interested in estimating my retirement

I am interested in estimating my retirement(2):

LogScore Bayes: -4584.11

LogScore BDeu: -4694.39

LogScore MDL: -4813.55

LogScore ENTROPY: -4483.1

LogScore AIC: -4610.1

Bayes Net Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	1
12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	0.999
14	1:Yes	1:Yes	1
15	1:Yes	1:Yes	0.999
16	1:Yes	1:Yes	1
17	1:Yes	1:Yes	0.996
18	1:Yes	1:Yes	0.999
19	1:Yes	1:Yes	0.987
20	1:Yes	1:Yes	0.999
21	1:Yes	1:Yes	0.934
22	1:Yes	1:Yes	1
23	1:Yes	1:Yes	0.991

24	1:Yes	1:Yes	0.999
25	1:Yes	1:Yes	1
26	1:Yes	1:Yes	1
27	1:Yes	1:Yes	0.962
28	1:Yes	1:Yes	0.853
29	1:Yes	1:Yes	1
30	1:Yes	1:Yes	0.932
31	1:Yes	1:Yes	1
32	1:Yes	1:Yes	1
33	1:Yes	1:Yes	1
34	1:Yes	1:Yes	1
35	1:Yes	1:Yes	1
36	1:Yes	1:Yes	1
37	1:Yes	1:Yes	1
38	1:Yes	1:Yes	1
39	1:Yes	1:Yes	1
40	1:Yes	1:Yes	1
41	1:Yes	1:Yes	1
42	1:Yes	1:Yes	0.997
43	1:Yes	1:Yes	1
44	1:Yes	1:Yes	1
45	1:Yes	1:Yes	0.939
46	1:Yes	1:Yes	0.653
47	1:Yes	1:Yes	1
48	1:Yes	1:Yes	1
49	1:Yes	1:Yes	1
50	1:Yes	1:Yes	1
51	1:Yes	1:Yes	0.999
52	1:Yes	1:Yes	1
53	1:Yes	1:Yes	1
54	1:Yes	1:Yes	0.999
55	1:Yes	1:Yes	1
56	1:Yes	1:Yes	1
57	1:Yes	1:Yes	0.989
58	1:Yes	1:Yes	0.999
59	1:Yes	1:Yes	1
60	1:Yes	1:Yes	0.999
61	1:Yes	1:Yes	1
62	1:Yes	1:Yes	1
63	1:Yes	1:Yes	1
64	1:Yes	1:Yes	0.999
65	1:Yes	1:Yes	1
66	1:Yes	1:Yes	1
67	1:Yes	1:Yes	1
68	1:Yes	1:Yes	1
69	1:Yes	1:Yes	1
70	1:Yes	1:Yes	1
71	1:Yes	1:Yes	0.998

72	1:Yes	1:Yes	1
73	1:Yes	1:Yes	1
74	1:Yes	1:Yes	1
75	1:Yes	2:No	0.516
76	1:Yes	1:Yes	1
77	1:Yes	1:Yes	1
78	1:Yes	1:Yes	0.916
79	1:Yes	1:Yes	0.984
80	1:Yes	1:Yes	0.998
81	1:Yes	1:Yes	1
82	1:Yes	1:Yes	0.973
83	1:Yes	1:Yes	1
84	1:Yes	1:Yes	1
85	1:Yes	1:Yes	1
86	1:Yes	1:Yes	1
87	1:Yes	1:Yes	1
88	1:Yes	1:Yes	0.999
89	1:Yes	1:Yes	1
90	1:Yes	1:Yes	1
91	1:Yes	1:Yes	0.984
92	1:Yes	1:Yes	0.812
93	1:Yes	1:Yes	1
94	1:Yes	1:Yes	0.969
95	1:Yes	1:Yes	1
96	1:Yes	1:Yes	1
97	1:Yes	1:Yes	1
98	1:Yes	1:Yes	0.983
99	1:Yes	1:Yes	0.983
100	1:Yes	1:Yes	0.938
101	1:Yes	1:Yes	1
102	1:Yes	1:Yes	0.999
103	1:Yes	1:Yes	1
104	1:Yes	1:Yes	0.99
105	1:Yes	1:Yes	1
106	1:Yes	1:Yes	1
107	1:Yes	1:Yes	1
108	1:Yes	1:Yes	1
109	1:Yes	1:Yes	1
110	1:Yes	1:Yes	1
111	1:Yes	2:No	0.567
112	1:Yes	1:Yes	0.852
113	1:Yes	1:Yes	1
114	1:Yes	1:Yes	0.995
115	1:Yes	1:Yes	1
116	1:Yes	1:Yes	1
117	1:Yes	1:Yes	1
118	1:Yes	1:Yes	1
119	1:Yes	1:Yes	1

120	1:Yes	1:Yes	0.995
121	1:Yes	1:Yes	1
122	1:Yes	1:Yes	1
123	1:Yes	1:Yes	0.939
124	1:Yes	1:Yes	0.994
125	1:Yes	1:Yes	0.998
126	1:Yes	1:Yes	0.722
127	1:Yes	1:Yes	1
128	1:Yes	1:Yes	0.99
129	1:Yes	1:Yes	1
130	1:Yes	1:Yes	0.963
131	1:Yes	1:Yes	0.997
132	1:Yes	1:Yes	0.884
133	1:Yes	1:Yes	1
134	1:Yes	1:Yes	1
135	1:Yes	2:No	0.724
136	1:Yes	1:Yes	0.999
137	1:Yes	1:Yes	1
138	1:Yes	1:Yes	0.988
139	1:Yes	1:Yes	0.996
140	1:Yes	1:Yes	0.999
141	1:Yes	1:Yes	1
142	1:Yes	1:Yes	0.999
143	1:Yes	1:Yes	0.993
144	1:Yes	1:Yes	1
145	1:Yes	1:Yes	1
146	1:Yes	1:Yes	1
147	1:Yes	1:Yes	1
148	1:Yes	1:Yes	1
149	1:Yes	1:Yes	0.924
150	1:Yes	1:Yes	0.878
151	1:Yes	1:Yes	1
152	1:Yes	1:Yes	1
153	1:Yes	1:Yes	0.995
154	1:Yes	1:Yes	1
155	1:Yes	1:Yes	1
156	1:Yes	1:Yes	0.857
157	1:Yes	1:Yes	1
158	1:Yes	1:Yes	0.987
159	1:Yes	1:Yes	0.999
160	1:Yes	1:Yes	1
161	1:Yes	1:Yes	1
162	2:No	1:Yes	0.601
163	1:Yes	1:Yes	0.893
164	1:Yes	1:Yes	0.998
165	1:Yes	1:Yes	0.999
166	1:Yes	1:Yes	1
167	1:Yes	1:Yes	1

168	2:No	2:No	0.982
169	2:No	2:No	0.999
170	1:Yes	1:Yes	1
171	2:No	2:No	1
172	1:Yes	1:Yes	1
173	1:Yes	1:Yes	0.932
174	2:No	1:Yes	0.994
175	1:Yes	1:Yes	1
176	1:Yes	1:Yes	0.996
177	1:Yes	2:No	0.845
178	2:No	2:No	0.864
179	2:No	1:Yes	0.831
180	1:Yes	2:No	0.754
181	2:No	1:Yes	0.619
182	1:Yes	1:Yes	0.981

Naive Bayes Classifier Model| NN

=== Classifier model (full training set) ===

Naive Bayes Classifier

	Class	
Attribute	Yes	No
	(0.95)	(0.05)
==		
Car superseding Ability		
Yes	36.0	1.0
No	140.0	9.0
[total]	176.0	10.0
Motorbike superseding Ability		
No	150.0	8.0
Yes	26.0	2.0
[total]	176.0	10.0
House superseding Ability		
No	164.0	9.0

Yes	12.0	1.0
[total]	176.0	10.0
Business superseding Ability		
No	170.0	9.0
Yes	6.0	1.0
[total]	176.0	10.0
No superseding ability		
No	66.0	2.0
Yes	110.0	8.0
[total]	176.0	10.0
Have or Had Business Insurance		
No	148.0	9.0
Yes	28.0	1.0
[total]	176.0	10.0
Have or Had Civil Liability Insurance		
No	149.0	9.0
Yes	27.0	1.0
[total]	176.0	10.0
Have or Had Vessel Insurance		
No	168.0	9.0
Yes	8.0	1.0
[total]	176.0	10.0
Have or Had Health Insurance		
No	173.0	9.0
Yes	3.0	1.0
[total]	176.0	10.0

Have or Had Everyday needs Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Business House Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Family Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Cash Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Child Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Car Insurance		
No	175.0	9.0
[total]	175.0	9.0
Have or Had Motorbike Insurance		
No	174.0	9.0
Yes	2.0	1.0

[total]	176.0	10.0
Have never had Insurance		
Yes	104.0	7.0
No	72.0	3.0
[total]	176.0	10.0
Fixed Costs would not be covered in case of a possible loss of mine		
Yes	127.0	6.0
No	48.0	4.0
[total]	175.0	10.0
Loans would not be covered in case of a possible loss of mine		
No	123.0	6.0
Yes	52.0	4.0
[total]	175.0	10.0
Children Studies would not be covered in case of a possible loss of mine		
No	130.0	7.0
Yes	45.0	3.0
[total]	175.0	10.0
Tax obligations would not be covered in case of a possible loss of mine		
No	102.0	8.0
Yes	73.0	2.0
[total]	175.0	10.0
No needs to leave behind in case of a possible loss of mine		
No	173.0	9.0
Yes	2.0	1.0
[total]	175.0	10.0
Happiness would not be covered in case of a possible loss of mine		

No	173.0	9.0
Yes	2.0	1.0
[total]	175.0	10.0
Purchases in non basic necessities would not be covered in case of a possible loss of mine		
No	173.0	9.0
Yes	2.0	1.0
[total]	175.0	10.0
Want a risk protection		
Yes	151.0	4.0
No	25.0	6.0
[total]	176.0	10.0
A satisfying amount of money for the support of my beloved ones		
mean	72.31	43.33
std. dev.	44.52	35.38
weight sum	151	3
precision	43.33	43.33
Not at all satisfied from the public insurance health benefits		
No	146.0	8.0
Yes	30.0	2.0
[total]	176.0	10.0
Kind of satisfied from the public insurance health benefits		
Yes	100.0	3.0
No	76.0	7.0
[total]	176.0	10.0
Quite satisfied from the public insurance health benefits		

No	132.0	4.0
Yes	44.0	6.0
[total]	176.0	10.0
Absolutely satisfied from the public insurance health benefits		
No	172.0	9.0
Yes	4.0	1.0
[total]	176.0	10.0
I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue		
Yes	28.0	1.0
No	148.0	9.0
[total]	176.0	10.0
I would choose a big private hospital in Athens or Thessaloniki for a mild health issue		
No	119.0	9.0
Yes	57.0	1.0
[total]	176.0	10.0
I would choose a local private hospital for a mild health issue		
No	129.0	7.0
Yes	47.0	3.0
[total]	176.0	10.0
I would choose a local public hospital for a mild health issue		
No	130.0	3.0
Yes	46.0	7.0
[total]	176.0	10.0
I would choose a public hospital in Athens or Thessaloniki for serious health issues		
No	141.0	7.0
Yes	35.0	3.0

[total]	176.0	10.0
I would choose a big private hospital of Athens or Thessaloniki for serious health issues		
Yes	76.0	3.0
No	100.0	7.0
[total]	176.0	10.0
I would choose a local private hospital for serious health issues		
No	150.0	8.0
Yes	26.0	2.0
[total]	176.0	10.0
I would choose a local public hospital for serious health issues		
No	166.0	6.0
Yes	10.0	4.0
[total]	176.0	10.0
I would choose a foreign hospital for serious health issues		
No	144.0	9.0
Yes	32.0	1.0
[total]	176.0	10.0
I wish for private health services coupled with my insurance		
Yes	167.0	6.0
No	9.0	4.0
[total]	176.0	10.0
I would like diagnostic tests to be included to my private insurance		
Yes	104.0	6.0
No	72.0	4.0
[total]	176.0	10.0

I would like doctor visits to be included to my private insurance		
Yes	113.0	3.0
No	58.0	7.0
Yes	6.0	1.0
[total]	177.0	11.0
I would like hospital care to be included to my private insurance		
Yes	124.0	6.0
No	52.0	4.0
[total]	176.0	10.0
I would like Annual check up to be included to my private insurance		
Yes	105.0	7.0
No	71.0	3.0
[total]	176.0	10.0
I would like going abroad to be included to my private insurance		
Yes	78.0	2.0
No	98.0	8.0
[total]	176.0	10.0
I would like ambulance to be included to my private insurance		
No	172.0	9.0
Yes	4.0	1.0
[total]	176.0	10.0
Team insurance		
No	130.0	7.0
Yes	46.0	3.0
[total]	176.0	10.0
I will not get a pension		

Yes	37.0	2.0
No	139.0	8.0
[total]	176.0	10.0
I will get a small pension		
No	67.0	4.0
Yes	109.0	6.0
[total]	176.0	10.0
I will get a satisfying pension		
No	145.0	7.0
Yes	31.0	3.0
[total]	176.0	10.0
I have managed for a lump sum or supplementary pension		
Yes	61.0	4.0
No	115.0	6.0
[total]	176.0	10.0
I have managed for a lump sum or supplementary pension through Bank Savings		
Yes	43.0	4.0
No	61.0	3.0
[total]	104.0	7.0
I have managed for a lump sum or supplementary pension through Pension scheme purchase		
No	102.0	6.0
Yes	2.0	1.0
[total]	104.0	7.0
I have managed for a lump sum or supplementary pension through Life insurance program and savings plan		
No	102.0	6.0

Yes	2.0	1.0
[total]	104.0	7.0
I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation		
No	82.0	6.0
Yes	22.0	1.0
[total]	104.0	7.0
I am about to take immediate care of a lump sum or supplementary pension		
No	73.0	4.0
Yes	31.0	3.0
[total]	104.0	7.0
I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase		
No	80.0	5.0
Yes	24.0	2.0
[total]	104.0	7.0
Even if I wanted it I cannot take care of a lump sum or supplementary pension		
No	102.0	5.0
Yes	2.0	2.0
[total]	104.0	7.0
It is of a major importance to support my children and grandchildren after I receive my pension		
Yes	116.0	6.0
No	60.0	4.0
[total]	176.0	10.0
It is of a major importance to cover my healthcare after I receive my pension		
Yes	135.0	7.0

No	41.0	3.0
[total]	176.0	10.0

It is of a major importance to cover my pleasure trips after I receive my pension

Yes	72.0	3.0
No	104.0	7.0
[total]	176.0	10.0

It is of a major importance to cover my house purchases after I receive my pension

No	161.0	9.0
Yes	15.0	1.0
[total]	176.0	10.0

It is of a major importance to cover my fixed costs after I receive my pension

No	174.0	8.0
Yes	2.0	2.0
[total]	176.0	10.0

It is of a major importance to cover my everyday needs after I receive my pension

No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0

Naive Bayes Predictions| NN

#inst	actual	predicted	error
10	1:Yes	1:Yes	1
11	1:Yes	1:Yes	1
12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	1
14	1:Yes	1:Yes	1
15	1:Yes	1:Yes	0.999
16	1:Yes	1:Yes	1
17	1:Yes	1:Yes	0.999
18	1:Yes	1:Yes	0.999
19	1:Yes	1:Yes	0.98

20	1:Yes	1:Yes	1
21	1:Yes	1:Yes	0.979
22	1:Yes	1:Yes	1
23	1:Yes	1:Yes	0.999
24	1:Yes	1:Yes	1
25	1:Yes	1:Yes	1
26	1:Yes	1:Yes	1
27	1:Yes	1:Yes	0.984
28	1:Yes	1:Yes	0.918
29	1:Yes	1:Yes	1
30	1:Yes	1:Yes	0.981
31	1:Yes	1:Yes	1
32	1:Yes	1:Yes	1
33	1:Yes	1:Yes	1
34	1:Yes	1:Yes	1
35	1:Yes	1:Yes	1
36	1:Yes	1:Yes	1
37	1:Yes	1:Yes	1
38	1:Yes	1:Yes	1
39	1:Yes	1:Yes	1
40	1:Yes	1:Yes	1
41	1:Yes	1:Yes	1
42	1:Yes	1:Yes	0.995
43	1:Yes	1:Yes	1
44	1:Yes	1:Yes	0.999
45	1:Yes	1:Yes	0.991
46	1:Yes	1:Yes	0.732
47	1:Yes	1:Yes	1
48	1:Yes	1:Yes	1
49	1:Yes	1:Yes	1
50	1:Yes	1:Yes	1
51	1:Yes	1:Yes	1
52	1:Yes	1:Yes	1
53	1:Yes	1:Yes	0.998
54	1:Yes	1:Yes	1
55	1:Yes	1:Yes	1
56	1:Yes	1:Yes	1
57	1:Yes	1:Yes	0.986
58	1:Yes	1:Yes	0.999
59	1:Yes	1:Yes	1
60	1:Yes	1:Yes	1
61	1:Yes	1:Yes	1
62	1:Yes	1:Yes	0.999
63	1:Yes	1:Yes	1
64	1:Yes	1:Yes	1
65	1:Yes	1:Yes	1
66	1:Yes	1:Yes	1
67	1:Yes	1:Yes	0.999

68	1:Yes	1:Yes	1
69	1:Yes	1:Yes	1
70	1:Yes	1:Yes	1
71	1:Yes	1:Yes	1
72	1:Yes	1:Yes	1
73	1:Yes	1:Yes	1
74	1:Yes	1:Yes	1
75	1:Yes	1:Yes	0.551
76	1:Yes	1:Yes	1
77	1:Yes	1:Yes	1
78	1:Yes	1:Yes	0.975
79	1:Yes	1:Yes	0.986
80	1:Yes	1:Yes	0.998
81	1:Yes	1:Yes	1
82	1:Yes	1:Yes	0.981
83	1:Yes	1:Yes	1
84	1:Yes	1:Yes	1
85	1:Yes	1:Yes	1
86	1:Yes	1:Yes	1
87	1:Yes	1:Yes	1
88	1:Yes	1:Yes	0.999
89	1:Yes	1:Yes	1
90	1:Yes	1:Yes	1
91	1:Yes	1:Yes	0.97
92	1:Yes	1:Yes	0.697
93	1:Yes	1:Yes	1
94	1:Yes	1:Yes	0.955
95	1:Yes	1:Yes	1
96	1:Yes	1:Yes	1
97	1:Yes	1:Yes	1
98	1:Yes	1:Yes	0.979
99	1:Yes	1:Yes	0.995
100	1:Yes	1:Yes	0.996
101	1:Yes	1:Yes	1
102	1:Yes	1:Yes	0.999
103	1:Yes	1:Yes	1
104	1:Yes	1:Yes	0.984
105	1:Yes	1:Yes	1
106	1:Yes	1:Yes	1
107	1:Yes	1:Yes	1
108	1:Yes	1:Yes	1
109	1:Yes	1:Yes	1
110	1:Yes	1:Yes	1
111	1:Yes	1:Yes	0.529
112	1:Yes	1:Yes	0.956
113	1:Yes	1:Yes	1
114	1:Yes	1:Yes	0.996
115	1:Yes	1:Yes	0.999

116	1:Yes	1:Yes	1
117	1:Yes	1:Yes	1
118	1:Yes	1:Yes	1
119	1:Yes	1:Yes	1
120	1:Yes	1:Yes	0.996
121	1:Yes	1:Yes	1
122	1:Yes	1:Yes	1
123	1:Yes	1:Yes	0.965
124	1:Yes	1:Yes	0.998
125	1:Yes	1:Yes	1
126	1:Yes	1:Yes	0.861
127	1:Yes	1:Yes	1
128	1:Yes	1:Yes	0.992
129	1:Yes	1:Yes	1
130	1:Yes	1:Yes	0.968
131	1:Yes	1:Yes	0.997
132	1:Yes	1:Yes	0.951
133	1:Yes	1:Yes	1
134	1:Yes	1:Yes	1
135	1:Yes	2:No	0.743
136	1:Yes	1:Yes	0.999
137	1:Yes	1:Yes	1
138	1:Yes	1:Yes	0.986
139	1:Yes	1:Yes	0.999
140	1:Yes	1:Yes	0.998
141	1:Yes	1:Yes	1
142	1:Yes	1:Yes	0.999
143	1:Yes	1:Yes	0.996
144	1:Yes	1:Yes	1
145	1:Yes	1:Yes	1
146	1:Yes	1:Yes	1
147	1:Yes	1:Yes	1
148	1:Yes	1:Yes	1
149	1:Yes	1:Yes	0.978
150	1:Yes	1:Yes	0.946
151	1:Yes	1:Yes	1
152	1:Yes	1:Yes	1
153	1:Yes	1:Yes	0.999
154	1:Yes	1:Yes	0.999
155	1:Yes	1:Yes	1
156	1:Yes	1:Yes	0.937
157	1:Yes	1:Yes	0.999
158	1:Yes	1:Yes	0.994
159	1:Yes	1:Yes	1
160	1:Yes	1:Yes	1
161	2:No	1:Yes	1
162	1:Yes	1:Yes	0.92
163	1:Yes	1:Yes	0.916

164	1:Yes	1:Yes	0.998
165	1:Yes	1:Yes	0.999
166	1:Yes	1:Yes	1
167	2:No	1:Yes	1
168	2:No	2:No	0.958
169	1:Yes	2:No	0.995
170	2:No	1:Yes	1
171	1:Yes	2:No	0.998
172	1:Yes	1:Yes	1
173	2:No	1:Yes	0.966
174	1:Yes	1:Yes	0.998
175	1:Yes	1:Yes	1
176	1:Yes	1:Yes	0.996
177	2:No	2:No	0.736
178	2:No	2:No	0.517
179	1:Yes	1:Yes	0.899
180	2:No	2:No	0.894
181	1:Yes	1:Yes	0.768
182	1:Yes	1:Yes	0.999

Naive Bayes Updatable Classifier| NN

Naive Bayes Classifier (full training set)

Class

Attribute Yes No

(0.95) (0.05)

===

Car superseding Ability

Yes 36.0 1.0

No 140.0 9.0

[total] 176.0 10.0

Motorbike superseding Ability

No 150.0 8.0

Yes 26.0 2.0

[total] 176.0 10.0

House superseding Ability

No	164.0	9.0
Yes	12.0	1.0
[total]	176.0	10.0
Business superseding Ability		
No	170.0	9.0
Yes	6.0	1.0
[total]	176.0	10.0
No superseding ability		
No	66.0	2.0
Yes	110.0	8.0
[total]	176.0	10.0
Have or Had Business Insurance		
No	148.0	9.0
Yes	28.0	1.0
[total]	176.0	10.0
Have or Had Civil Liability Insurance		
No	149.0	9.0
Yes	27.0	1.0
[total]	176.0	10.0
Have or Had Vessel Insurance		
No	168.0	9.0
Yes	8.0	1.0
[total]	176.0	10.0
Have or Had Health Insurance		
No	173.0	9.0
Yes	3.0	1.0

[total]	176.0	10.0
Have or Had Everyday needs Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Business House Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Family Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Cash Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Child Insurance		
No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0
Have or Had Car Insurance		
No	175.0	9.0
[total]	175.0	9.0
Have or Had Motorbike Insurance		
No	174.0	9.0

Yes	2.0	1.0
[total]	176.0	10.0
Have never had Insurance		
Yes	104.0	7.0
No	72.0	3.0
[total]	176.0	10.0
Fixed Costs would not be covered in case of a possible loss of mine		
Yes	127.0	6.0
No	48.0	4.0
[total]	175.0	10.0
Loans would not be covered in case of a possible loss of mine		
No	123.0	6.0
Yes	52.0	4.0
[total]	175.0	10.0
Children Studies would not be covered in case of a possible loss of mine		
No	130.0	7.0
Yes	45.0	3.0
[total]	175.0	10.0
Tax obligations would not be covered in case of a possible loss of mine		
No	102.0	8.0
Yes	73.0	2.0
[total]	175.0	10.0
No needs to leave behind in case of a possible loss of mine		
No	173.0	9.0
Yes	2.0	1.0
[total]	175.0	10.0

Happiness would not be covered in case of a possible loss of mine		
No	173.0	9.0
Yes	2.0	1.0
[total]	175.0	10.0
Purchases in non-basic necessities would not be covered in case of a possible loss of mine		
No	173.0	9.0
Yes	2.0	1.0
[total]	175.0	10.0
Want a risk protection		
Yes	151.0	4.0
No	25.0	6.0
[total]	176.0	10.0
A satisfying amount of money for the support of my beloved ones		
mean	72.31	43.33
std. dev.	44.52	35.38
weight sum	151	3
precision	43.33	43.33
Not at all satisfied from the public insurance health benefits		
No	146.0	8.0
Yes	30.0	2.0
[total]	176.0	10.0
Kind of satisfied from the public insurance health benefits		
Yes	100.0	3.0
No	76.0	7.0
[total]	176.0	10.0

Quite satisfied from the public insurance health benefits		
No	132.0	4.0
Yes	44.0	6.0
[total]	176.0	10.0
Absolutely satisfied from the public insurance health benefits		
No	172.0	9.0
Yes	4.0	1.0
[total]	176.0	10.0
I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue		
Yes	28.0	1.0
No	148.0	9.0
[total]	176.0	10.0
I would choose a big private hospital in Athens or Thessaloniki for a mild health issue		
No	119.0	9.0
Yes	57.0	1.0
[total]	176.0	10.0
I would choose a local private hospital for a mild health issue		
No	129.0	7.0
Yes	47.0	3.0
[total]	176.0	10.0
I would choose a local public hospital for a mild health issue		
No	130.0	3.0
Yes	46.0	7.0
[total]	176.0	10.0
I would choose a public hospital in Athens or Thessaloniki for serious health issues		
No	141.0	7.0

Yes	35.0	3.0
[total]	176.0	10.0

I would choose a big private hospital of Athens or Thessaloniki for serious health issues

Yes	76.0	3.0
No	100.0	7.0
[total]	176.0	10.0

I would choose a local private hospital for serious health issues

No	150.0	8.0
Yes	26.0	2.0
[total]	176.0	10.0

I would choose a local public hospital for serious health issues

No	166.0	6.0
Yes	10.0	4.0
[total]	176.0	10.0

I would choose a foreign hospital for serious health issues

No	144.0	9.0
Yes	32.0	1.0
[total]	176.0	10.0

I wish for private health services coupled with my insurance

Yes	167.0	6.0
No	9.0	4.0
[total]	176.0	10.0

I would like diagnostic tests to be included to my private insurance

Yes	104.0	6.0
No	72.0	4.0

[total]	176.0	10.0
I would like doctor visits to be included to my private insurance		
Yes	113.0	3.0
No	58.0	7.0
Yes	6.0	1.0
[total]	177.0	11.0
I would like hospital care to be included to my private insurance		
Yes	124.0	6.0
No	52.0	4.0
[total]	176.0	10.0
I would like Annual check up to be included to my private insurance		
Yes	105.0	7.0
No	71.0	3.0
[total]	176.0	10.0
I would like going abroad to be included to my private insurance		
Yes	78.0	2.0
No	98.0	8.0
[total]	176.0	10.0
I would like ambulance to be included to my private insurance		
No	172.0	9.0
Yes	4.0	1.0
[total]	176.0	10.0
Team insurance		
No	130.0	7.0
Yes	46.0	3.0
[total]	176.0	10.0

I will not get a pension		
Yes	37.0	2.0
No	139.0	8.0
[total]	176.0	10.0
I will get a small pension		
No	67.0	4.0
Yes	109.0	6.0
[total]	176.0	10.0
I will get a satisfying pension		
No	145.0	7.0
Yes	31.0	3.0
[total]	176.0	10.0
I have managed for a lump sum or supplementary pension		
Yes	61.0	4.0
No	115.0	6.0
[total]	176.0	10.0
I have managed for a lump sum or supplementary pension through Bank Savings		
Yes	43.0	4.0
No	61.0	3.0
[total]	104.0	7.0
I have managed for a lump sum or supplementary pension through Pension scheme purchase		
No	102.0	6.0
Yes	2.0	1.0
[total]	104.0	7.0
I have managed for a lump sum or supplementary pension through Life insurance program and savings plan		

No	102.0	6.0
Yes	2.0	1.0
[total]	104.0	7.0

I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation

No	82.0	6.0
Yes	22.0	1.0
[total]	104.0	7.0

I am about to take immediate care of a lump sum or supplementary pension

No	73.0	4.0
Yes	31.0	3.0
[total]	104.0	7.0

I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase

No	80.0	5.0
Yes	24.0	2.0
[total]	104.0	7.0

Even if I wanted it I cannot take care of a lump sum or supplementary pension

No	102.0	5.0
Yes	2.0	2.0
[total]	104.0	7.0

It is of a major importance to support my children and grandchildren after I receive my pension

Yes	116.0	6.0
No	60.0	4.0
[total]	176.0	10.0

It is of a major importance to cover my healthcare after I receive my pension

Yes	135.0	7.0
No	41.0	3.0
[total]	176.0	10.0

It is of a major importance to cover my pleasure trips after I receive my pension

Yes	72.0	3.0
No	104.0	7.0
[total]	176.0	10.0

It is of a major importance to cover my house purchases after I receive my pension

No	161.0	9.0
Yes	15.0	1.0
[total]	176.0	10.0

It is of a major importance to cover my fixed costs after I receive my pension

No	174.0	8.0
Yes	2.0	2.0
[total]	176.0	10.0

It is of a major importance to cover my everyday needs after I receive my pension

No	174.0	9.0
Yes	2.0	1.0
[total]	176.0	10.0

Naive Bayes Updateable Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	1
12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	1
14	1:Yes	1:Yes	1
15	1:Yes	1:Yes	0.999
16	1:Yes	1:Yes	1
17	1:Yes	1:Yes	0.999
18	1:Yes	1:Yes	0.999

19	1:Yes	1:Yes	0.98
20	1:Yes	1:Yes	1
21	1:Yes	1:Yes	0.979
22	1:Yes	1:Yes	1
23	1:Yes	1:Yes	0.999
24	1:Yes	1:Yes	1
25	1:Yes	1:Yes	1
26	1:Yes	1:Yes	1
27	1:Yes	1:Yes	0.984
28	1:Yes	1:Yes	0.918
29	1:Yes	1:Yes	1
30	1:Yes	1:Yes	0.981
31	1:Yes	1:Yes	1
32	1:Yes	1:Yes	1
33	1:Yes	1:Yes	1
34	1:Yes	1:Yes	1
35	1:Yes	1:Yes	1
36	1:Yes	1:Yes	1
37	1:Yes	1:Yes	1
38	1:Yes	1:Yes	1
39	1:Yes	1:Yes	1
40	1:Yes	1:Yes	1
41	1:Yes	1:Yes	1
42	1:Yes	1:Yes	0.995
43	1:Yes	1:Yes	1
44	1:Yes	1:Yes	0.999
45	1:Yes	1:Yes	0.991
46	1:Yes	1:Yes	0.732
47	1:Yes	1:Yes	1
48	1:Yes	1:Yes	1
49	1:Yes	1:Yes	1
50	1:Yes	1:Yes	1
51	1:Yes	1:Yes	1
52	1:Yes	1:Yes	1
53	1:Yes	1:Yes	0.998
54	1:Yes	1:Yes	1
55	1:Yes	1:Yes	1
56	1:Yes	1:Yes	1
57	1:Yes	1:Yes	0.986
58	1:Yes	1:Yes	0.999
59	1:Yes	1:Yes	1
60	1:Yes	1:Yes	1
61	1:Yes	1:Yes	1
62	1:Yes	1:Yes	0.999
63	1:Yes	1:Yes	1
64	1:Yes	1:Yes	1
65	1:Yes	1:Yes	1
66	1:Yes	1:Yes	1

67	1:Yes	1:Yes	0.999
68	1:Yes	1:Yes	1
69	1:Yes	1:Yes	1
70	1:Yes	1:Yes	1
71	1:Yes	1:Yes	1
72	1:Yes	1:Yes	1
73	1:Yes	1:Yes	1
74	1:Yes	1:Yes	1
75	1:Yes	1:Yes	0.551
76	1:Yes	1:Yes	1
77	1:Yes	1:Yes	1
78	1:Yes	1:Yes	0.975
79	1:Yes	1:Yes	0.986
80	1:Yes	1:Yes	0.998
81	1:Yes	1:Yes	1
82	1:Yes	1:Yes	0.981
83	1:Yes	1:Yes	1
84	1:Yes	1:Yes	1
85	1:Yes	1:Yes	1
86	1:Yes	1:Yes	1
87	1:Yes	1:Yes	1
88	1:Yes	1:Yes	0.999
89	1:Yes	1:Yes	1
90	1:Yes	1:Yes	1
91	1:Yes	1:Yes	0.97
92	1:Yes	1:Yes	0.697
93	1:Yes	1:Yes	1
94	1:Yes	1:Yes	0.955
95	1:Yes	1:Yes	1
96	1:Yes	1:Yes	1
97	1:Yes	1:Yes	1
98	1:Yes	1:Yes	0.979
99	1:Yes	1:Yes	0.995
100	1:Yes	1:Yes	0.996
101	1:Yes	1:Yes	1
102	1:Yes	1:Yes	0.999
103	1:Yes	1:Yes	1
104	1:Yes	1:Yes	0.984
105	1:Yes	1:Yes	1
106	1:Yes	1:Yes	1
107	1:Yes	1:Yes	1
108	1:Yes	1:Yes	1
109	1:Yes	1:Yes	1
110	1:Yes	1:Yes	1
111	1:Yes	1:Yes	0.529
112	1:Yes	1:Yes	0.956
113	1:Yes	1:Yes	1
114	1:Yes	1:Yes	0.996

115	1:Yes	1:Yes	0.999
116	1:Yes	1:Yes	1
117	1:Yes	1:Yes	1
118	1:Yes	1:Yes	1
119	1:Yes	1:Yes	1
120	1:Yes	1:Yes	0.996
121	1:Yes	1:Yes	1
122	1:Yes	1:Yes	1
123	1:Yes	1:Yes	0.965
124	1:Yes	1:Yes	0.998
125	1:Yes	1:Yes	1
126	1:Yes	1:Yes	0.861
127	1:Yes	1:Yes	1
128	1:Yes	1:Yes	0.992
129	1:Yes	1:Yes	1
130	1:Yes	1:Yes	0.968
131	1:Yes	1:Yes	0.997
132	1:Yes	1:Yes	0.951
133	1:Yes	1:Yes	1
134	1:Yes	1:Yes	1
135	1:Yes	2:No	0.743
136	1:Yes	1:Yes	0.999
137	1:Yes	1:Yes	1
138	1:Yes	1:Yes	0.986
139	1:Yes	1:Yes	0.999
140	1:Yes	1:Yes	0.998
141	1:Yes	1:Yes	1
142	1:Yes	1:Yes	0.999
143	1:Yes	1:Yes	0.996
144	1:Yes	1:Yes	1
145	1:Yes	1:Yes	1
146	1:Yes	1:Yes	1
147	1:Yes	1:Yes	1
148	1:Yes	1:Yes	1
149	1:Yes	1:Yes	0.978
150	1:Yes	1:Yes	0.946
151	1:Yes	1:Yes	1
152	1:Yes	1:Yes	1
153	1:Yes	1:Yes	0.999
154	1:Yes	1:Yes	0.999
155	1:Yes	1:Yes	1
156	1:Yes	1:Yes	0.937
157	1:Yes	1:Yes	0.999
158	1:Yes	1:Yes	0.994
159	1:Yes	1:Yes	1
160	1:Yes	1:Yes	1
161	1:Yes	1:Yes	1
162	2:No	1:Yes	0.92

163	1:Yes	1:Yes	0.916
164	1:Yes	1:Yes	0.998
165	1:Yes	1:Yes	0.999
166	1:Yes	1:Yes	1
167	1:Yes	1:Yes	1
168	2:No	2:No	0.958
169	2:No	2:No	0.995
170	1:Yes	1:Yes	1
171	2:No	2:No	0.998
172	1:Yes	1:Yes	1
173	1:Yes	1:Yes	0.966
174	2:No	1:Yes	0.998
175	1:Yes	1:Yes	1
176	1:Yes	1:Yes	0.996
177	1:Yes	2:No	0.736
178	2:No	2:No	0.517
179	2:No	1:Yes	0.899
180	1:Yes	2:No	0.894
181	2:No	1:Yes	0.768
182	1:Yes	1:Yes	0.999

Lazy K Star Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	1
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31	1:Yes	1:Yes	1
32	1:Yes	1:Yes	1
33	1:Yes	1:Yes	1
34	1:Yes	1:Yes	1

35	1:Yes	1:Yes	1
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37	1:Yes	1:Yes	1
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160	1:Yes	1:Yes	1
161	1:Yes	1:Yes	1
162	2:No	2:No	1
163	1:Yes	1:Yes	1
164	1:Yes	1:Yes	1
165	1:Yes	1:Yes	1
166	1:Yes	1:Yes	1
167	1:Yes	1:Yes	1
168	2:No	2:No	1
169	2:No	2:No	1
170	1:Yes	1:Yes	1
171	2:No	2:No	1
172	1:Yes	1:Yes	1
173	1:Yes	1:Yes	1
174	2:No	2:No	1
175	1:Yes	1:Yes	1
176	1:Yes	1:Yes	1
177	1:Yes	1:Yes	1
178	2:No	2:No	1

179	2:No	2:No	1
180	1:Yes	1:Yes	1
181	2:No	2:No	1
182	1:Yes	1:Yes	1

Randomizable Filtered Classifier Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	0.995
12	1:Yes	1:Yes	0.995
13	1:Yes	1:Yes	0.995
14	1:Yes	1:Yes	0.995
15	1:Yes	1:Yes	0.995
16	1:Yes	1:Yes	0.995
17	1:Yes	1:Yes	0.995
18	1:Yes	1:Yes	0.995
19	1:Yes	1:Yes	0.995
20	1:Yes	1:Yes	0.995
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25	1:Yes	1:Yes	0.995
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31	1:Yes	1:Yes	0.995
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40	1:Yes	1:Yes	0.995
41	1:Yes	1:Yes	0.995
42	1:Yes	1:Yes	0.995
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44	1:Yes	1:Yes	0.995
45	1:Yes	1:Yes	0.995
46	1:Yes	1:Yes	0.995
47	1:Yes	1:Yes	0.995
48	1:Yes	1:Yes	0.995
49	1:Yes	1:Yes	0.995
50	1:Yes	1:Yes	0.995

51	1:Yes	1:Yes	0.995
52	1:Yes	1:Yes	0.995
53	1:Yes	1:Yes	0.995
54	1:Yes	1:Yes	0.995
55	1:Yes	1:Yes	0.995
56	1:Yes	1:Yes	0.995
57	1:Yes	1:Yes	0.995
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59	1:Yes	1:Yes	0.995
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93	1:Yes	1:Yes	0.995
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95	1:Yes	1:Yes	0.995
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98	1:Yes	1:Yes	0.995

99	1:Yes	1:Yes	0.995
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135	1:Yes	1:Yes	0.995
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141	1:Yes	1:Yes	0.995
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155	1:Yes	1:Yes	0.995
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157	1:Yes	1:Yes	0.995
158	1:Yes	1:Yes	0.995
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160	1:Yes	1:Yes	0.995
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162	2:No	2:No	0.995
163	1:Yes	1:Yes	0.995
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166	1:Yes	1:Yes	0.997
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168	2:No	2:No	0.995
169	2:No	2:No	0.995
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171	2:No	2:No	0.995
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175	1:Yes	1:Yes	0.995
176	1:Yes	1:Yes	0.995
177	1:Yes	1:Yes	0.995
178	2:No	2:No	0.995
179	2:No	2:No	0.995
180	1:Yes	1:Yes	0.995
181	2:No	2:No	0.995
182	1:Yes	1:Yes	0.995

Logistic Classification Model| NN

Logistic classification with ridge parameter of 1.0E-8

Coefficients...

	Class
Variable	Yes

==

Car superseding Ability=No	-26.2427
Motorbike superseding Ability=Yes	-4.39
House superseding Ability=Yes	5.3858
Business superseding Ability=Yes	44.8751
No superseding ability=Yes	3.3551
Have or Had Business Insurance=Yes	18.2946
Have or Had Civil Liability Insurance=Yes	42.4228
Have or Had Vessel Insurance=Yes	-33.1193
Have or Had Health Insurance=Yes	-37.0265
Have or Had Everyday needs Insurance=Yes	-31.7624
Have or Had Business House Insurance=Yes	-44.8548
Have or Had Family Insurance=Yes	-49.4047
Have or Had Cash Insurance=Yes	-53.9398
Have or Had Child Insurance=Yes	12.6073
Have or Had Motorbike Insurance=Yes	-1.6668
Have never had Insurance=No	-10.1612
Fixed Costs would not be covered in case of a possible loss of mine=No	11.1234
Loans would not be covered in case of a possible loss of mine=Yes	-28.2996
Children Studies would not be covered in case of a possible loss of mine=Yes	-1.3838
Tax obligations would not be covered in case of a possible loss of mine=Yes	-4.141
No needs to leave behind in case of a possible loss of mine=Yes	-2.9381
Happiness would not be covered in case of a possible loss of mine=Yes	-18.9965
Purchases in non-basic necessities would not be covered in case of a possible loss of mine=Yes	24.0523

Want a risk protection=No	-32.7197
A satisfying amount of money for the support of my beloved ones	0.0216
Not at all satisfied from the public insurance health benefits=Yes	-26.4691
Kind of satisfied from the public insurance health benefits=No	-8.1841
Quite satisfied from the public insurance health benefits=Yes	9.0859
Absolutely satisfied from the public insurance health benefits=Yes	-8.7435
I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue=No	-5.5799
I would choose a big private hospital in Athens or Thessaloniki for a mild health issue=Yes	20.0535
I would choose a local private hospital for a mild health issue=Yes	-4.9704
I would choose a local public hospital for a mild health issue=Yes	-19.8892
I would choose a public hospital in Athens or Thessaloniki for serious health issues=Yes	-17.0709
I would choose a big private hospital of Athens or Thessaloniki for serious health issues=No	-4.0864
I would choose a local private hospital for serious health issues=Yes	5.0078
I would choose a local public hospital for serious health issues=Yes	6.0193
I would choose a foreign hospital for serious health issues=Yes	5.1473
I wish for private health services coupled with my insurance=No	-13.6774
I would like diagnostic tests to be included to my private insurance=No	8.8833
I would like doctor visits to be included to my private insurance=Yes	24.7004
I would like doctor visits to be included to my private insurance=No	-19.3459
I would like doctor visits to be included to my private insurance=Yes	-52.4769
I would like hospital care to be included to my private insurance=No	33.9022
I would like Annual check up to be included to my private insurance=No	19.2363

I would like going abroad to be included to my private insurance=No	-2.5301
I would like ambulance to be included to my private insurance =Yes	1.4932
Team insurance =Yes	-8.6958
I will not get a pension=No	-12.6141
I will get a small pension=Yes	-2.1184
I will get a satisfying pension=Yes	-10.6577
I have managed for a lump sum or supplementary pension=No	6.6073
I have managed for a lump sum or supplementary pension through Bank Savings=No	30.2287
I have managed for a lump sum or supplementary pension through Pension scheme purchase=Yes	-54.3474
I have managed for a lump sum or supplementary pension through Life insurance program and savings plan=Yes	12.6073
I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation=Yes	-11.2331
I am about to take immediate care of a lump sum or supplementary pension=Yes	-25.3673
I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase =Yes	-14.2421
Even if I wanted it I cannot take care of a lump sum or supplementary pension=Yes	-44.301
It is of a major importance to support my children and grandchildren after I receive my pension=No	-11.5925
It is of a major importance to cover my healthcare after I receive my pension=No	-3.646
It is of a major importance to cover my pleasure trips after I receive my pension=No	-10.7943

It is of a major importance to cover my house purchases after I receive my pension=Yes -14.7902

It is of a major importance to cover my fixed costs after I receive my pension=Yes -43.8113

It is of a major importance to cover my everyday needs after I receive my pension=Yes -31.7624

Intercept 81.5235

Odds Ratios...

	Class
Variable	Yes
==	
Car superseding Ability=No	0
Motorbike superseding Ability=Yes	0.0124
House superseding Ability=Yes	218.2802
Business superseding Ability=Yes	3.08
No superseding ability=Yes	28.6496
Have or Had Business Insurance=Yes	88150280.86
Have or Had Civil Liability Insurance=Yes	2.65
Have or Had Vessel Insurance=Yes	0
Have or Had Health Insurance=Yes	0
Have or Had Everyday needs Insurance=Yes	0
Have or Had Business House Insurance=Yes	0
Have or Had Family Insurance=Yes	0
Have or Had Cash Insurance=Yes	0
Have or Had Child Insurance=Yes	298733.29
Have or Had Motorbike Insurance=Yes	0.1888

Have never had Insurance=No	0
Fixed Costs would not be covered in case of a possible loss of mine=No	67736.35
Loans would not be covered in case of a possible loss of mine=Yes	0
Children Studies would not be covered in case of a possible loss of mine=Yes	0.2506
Tax obligations would not be covered in case of a possible loss of mine=Yes	0.0159
No needs to leave behind in case of a possible loss of mine=Yes	0.053
Happiness would not be covered in case of a possible loss of mine=Yes	0
Purchases in non basic necessities would not be covered in case of a possible loss of mine=Yes	2.79
Want a risk protection=No	0
A satisfying amount of money for the support of my beloved ones	1.0218
Not at all satisfied from the public insurance health benefits=Yes	0
Kind of satisfied from the public insurance health benefits=No	0.0003
Quite satisfied from the public insurance health benefits=Yes	8829.5989
Absolutely satisfied from the public insurance health benefits=Yes	0.0002
I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue=No	0.0038
I would choose a big private hospital in Athens or Thessaloniki for a mild health issue=Yes	511817009.01
I would choose a local private hospital for a mild health issue=Yes	0.0069
I would choose a local public hospital for a mild health issue=Yes	0
I would choose a public hospital in Athens or Thessaloniki for serious health issues=Yes	0
I would choose a big private hospital of Athens or Thessaloniki for serious health issues=No	0.0168
I would choose a local private hospital for serious health issues=Yes	149.5731
I would choose a local public hospital for serious health issues=Yes	411.2982

I would choose a foreign hospital for serious health issues=Yes	171.96
I wish for private health services coupled with my insurance=No	0
I would like diagnostic tests to be included to my private insurance=No	7210.64
I would like doctor visits to be included to my private insurance=Yes	5.33
I would like doctor visits to be included to my private insurance=No	0
I would like doctor visits to be included to my private insurance=Yes	0
I would like hospital care to be included to my private insurance=No	5.29
I would like Annual check up to be included to my private insurance=No	226063771.49
I would like going abroad to be included to my private insurance=No	0.0797
I would like ambulance to be included to my private insurance =Yes	4.4515
Team insurance =Yes	0.0002
I will not get a pension=No	0
I will get a small pension=Yes	0.1202
I will get a satisfying pension=Yes	0
I have managed for a lump sum or supplementary pension=No	740.4793
I have managed for a lump sum or supplementary pension through Bank Savings=No	1.34
I have managed for a lump sum or supplementary pension through Pension scheme purchase=Yes	0
I have managed for a lump sum or supplementary pension through Life insurance program and savings plan=Yes	298733.2066
I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation=Yes	0
I am about to take immediate care of a lump sum or supplementary pension=Yes	0

I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase =Yes 0

Even if I wanted it I cannot take care of a lump sum or supplementary pension=Yes 0

It is of a major importance to support my children and grandchildren after I receive my pension=No 0

It is of a major importance to cover my healthcare after I receive my pension=No 0.0261

It is of a major importance to cover my pleasure trips after I receive my pension=No 0

It is of a major importance to cover my house purchases after I receive my pension=Yes 0

It is of a major importance to cover my fixed costs after I receive my pension=Yes 0

It is of a major importance to cover my everyday needs after I receive my pension=Yes 0

Logistic Regression Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	1
12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	1
14	1:Yes	1:Yes	1
15	1:Yes	1:Yes	1
16	1:Yes	1:Yes	1
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18	1:Yes	1:Yes	1
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21	1:Yes	1:Yes	1
22	1:Yes	1:Yes	1
23	1:Yes	1:Yes	1
24	1:Yes	1:Yes	1
25	1:Yes	1:Yes	1
26	1:Yes	1:Yes	1

27	1:Yes	1:Yes	1
28	1:Yes	1:Yes	1
29	1:Yes	1:Yes	1
30	1:Yes	1:Yes	1
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32	1:Yes	1:Yes	1
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39	1:Yes	1:Yes	1
40	1:Yes	1:Yes	1
41	1:Yes	1:Yes	1
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178	2:No	2:No	1
179	2:No	2:No	1
180	1:Yes	1:Yes	1
181	2:No	2:No	1
182	1:Yes	1:Yes	1

SMO Reg Classifier| NN

Kernel used: Linear Kernel: K(x,y) = <x,y>

Classifier for classes: Yes, No

BinarySMO

Machine linear: showing attribute weights, not support vectors.

0.5581 * (normalized) Car superseding Ability=No

+ 0.3858 * (normalized) Motorbike superseding Ability=Yes

+ -0.1487 * (normalized) House superseding Ability=Yes

+ -0.0192 * (normalized) Business superseding Ability=Yes

+ 0.2542 * (normalized) No superseding ability=Yes

+ -0.0702 * (normalized) Have or Had Business Insurance=Yes

+ -0.4933 * (normalized) Have or Had Civil Liability Insurance=Yes

+ -0 * (normalized) Have or Had Vessel Insurance=Yes

+ 0.044 * (normalized) Have never had Insurance=No

+ -0.0314 * (normalized) Fixed Costs would not be covered in case of a possible loss of mine=No

+ 0.4173 * (normalized) Loans would not be covered in case of a possible loss of mine=Yes

+ 0.0743 * (normalized) Children Studies would not be covered in case of a possible loss of mine=Yes

+ -0.3094 * (normalized) Tax obligations would not be covered in case of a possible loss of mine=Yes

+ -0.0751 * (normalized) Purchases in non basic necessities would not be covered in case of a possible loss of mine=Yes

+ 0.8043 * (normalized) Want a risk protection=No

+ 0.101 * (normalized) A satisfying amount of money for the support of my beloved ones

+ 0.4458 * (normalized) Not at all satisfied from the public insurance health benefits=Yes

+ 0.4266 * (normalized) Kind of satisfied from the public insurance health benefits=No

+ 0.0098 * (normalized) Quite satisfied from the public insurance health benefits=Yes

+ -0.0291 * (normalized) Absolutely satisfied from the public insurance health benefits=Yes

+ 0.1453 * (normalized) I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue=No

+ -0.6878 * (normalized) I would choose a big private hospital in Athens or Thessaloniki for a mild health issue=Yes

+ 0.1451 * (normalized) I would choose a local private hospital for a mild health issue=Yes

+ 0.6879 * (normalized) I would choose a local public hospital for a mild health issue=Yes

+ 0.4222 * (normalized) I would choose a public hospital in Athens or Thessaloniki for serious health issues=Yes

+ -0.0536 * (normalized) I would choose a big private hospital of Athens or Thessaloniki for serious health issues=No

+ -0.1972 * (normalized) I would choose a local private hospital for serious health issues=Yes

+ 0.1199 * (normalized) I would choose a local public hospital for serious health issues=Yes

+ -0.3986 * (normalized) I would choose a foreign hospital for serious health issues=Yes

+ 0.3267 * (normalized) I wish for private health services coupled with my insurance=No

+ -0.594 * (normalized) I would like diagnostic tests to be included to my private insurance=No

+ -0.569 * (normalized) I would like doctor visits to be included to my private insurance=Yes

+ 0.569 * (normalized) I would like doctor visits to be included to my private insurance=No

+ 0 * (normalized) I would like doctor visits to be included to my private insurance=Yes

+ -0.6324 * (normalized) I would like hospital care to be included to my private insurance=No

+ -0.4584 * (normalized) I would like Annual check up to be included to my private insurance=No

+ 0.0573 * (normalized) I would like going abroad to be included to my private insurance=No

+ -0.0751 * (normalized) I would like ambulance to be included to my private insurance =Yes

+ 0.1281 * (normalized) Team insurance =Yes

+ 0.4074 * (normalized) I will not get a pension=No

+ 0.2487 * (normalized) I will get a small pension=Yes

+ 0.1588 * (normalized) I will get a satisfying pension=Yes

+ 0.1512 * (normalized) I have managed for a lump sum or supplementary pension=No

+ -0.6477 * (normalized) I have managed for a lump sum or supplementary pension through Bank Savings=No

+ -0.0751 * (normalized) I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation=Yes

+ 0.5914 * (normalized) I am about to take immediate care of a lump sum or supplementary pension=Yes

+ 0.0162 * (normalized) I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase =Yes

+ 0.4028 * (normalized) Even if I wanted it I cannot take care of a lump sum or supplementary pension=Yes

+ 0.0601 * (normalized) It is of a major importance to support my children and grandchildren after I receive my pension=No

+ -0.0389 * (normalized) It is of a major importance to cover my healthcare after I receive my pension=No

+ 0.567 * (normalized) It is of a major importance to cover my pleasure trips after I receive my pension=No

+ 0 * (normalized) It is of a major importance to cover my house purchases after I receive my pension=Yes

+ 0.7332 * (normalized) It is of a major importance to cover my fixed costs after I receive my pension=Yes

- 3.2305

Number of kernel evaluations: 5192 (92.48% cached)

SMO Reg Predictions| NN

#inst	actual	predicted	error
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12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	1
14	1:Yes	1:Yes	1

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177	1:Yes	1:Yes	1
178	2:No	2:No	1
179	2:No	1:Yes	1
180	1:Yes	1:Yes	1
181	2:No	2:No	1
182	1:Yes	1:Yes	1

Multi Class Classifier| NN

=== Classifier model (full training set) ===

Classifier 1

Logistic Regression with ridge parameter of 1.0E-8

Coefficients...

Variable	Class Yes
Car superseding Ability=No	-26.2427
Motorbike superseding Ability=Yes	-4.39
House superseding Ability=Yes	5.3858
Business superseding Ability=Yes	44.8751

No superseding ability=Yes	3.3551
Have or Had Business Insurance=Yes	18.2946
Have or Had Civil Liability Insurance=Yes	42.4228
Have or Had Vessel Insurance=Yes	-33.1193
Have or Had Health Insurance=Yes	-37.0265
Have or Had Everyday needs Insurance=Yes	-31.7624
Have or Had Business House Insurance=Yes	-44.8548
Have or Had Family Insurance=Yes	-49.4047
Have or Had Cash Insurance=Yes	-53.9398
Have or Had Child Insurance=Yes	12.6073
Have or Had Motorbike Insurance=Yes	-1.6668
Have never had Insurance=No	-10.1612
Fixed Costs would not be covered in case of a possible loss of mine=No	11.1234
Loans would not be covered in case of a possible loss of mine=Yes	-28.2996
Children Studies would not be covered in case of a possible loss of mine=Yes	-1.3838
Tax obligations would not be covered in case of a possible loss of mine=Yes	-4.141
No needs to leave behind in case of a possible loss of mine=Yes	-2.9381
Happiness would not be covered in case of a possible loss of mine=Yes	-18.9965
Purchases in non-basic necessities would not be covered in case of a possible loss of mine=Yes	24.0523
Want a risk protection=No	-32.7197
A satisfying amount of money for the support of my beloved ones	0.0216
Not at all satisfied from the public insurance health benefits=Yes	-26.4691
Kind of satisfied from the public insurance health benefits=No	-8.1841

Quite satisfied from the public insurance health benefits=Yes	9.0859
Absolutely satisfied from the public insurance health benefits=Yes	-8.7435
I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue=No	-5.5799
I would choose a big private hospital in Athens or Thessaloniki for a mild health issue=Yes	20.0535
I would choose a local private hospital for a mild health issue=Yes	-4.9704
I would choose a local public hospital for a mild health issue=Yes	-19.8892
I would choose a public hospital in Athens or Thessaloniki for serious health issues=Yes	-17.0709
I would choose a big private hospital of Athens or Thessaloniki for serious health issues=No	-4.0864
I would choose a local private hospital for serious health issues=Yes	5.0078
I would choose a local public hospital for serious health issues=Yes	6.0193
I would choose a foreign hospital for serious health issues=Yes	5.1473
I wish for private health services coupled with my insurance=No	-13.6774
I would like diagnostic tests to be included to my private insurance=No	8.8833
I would like doctor visits to be included to my private insurance=Yes	24.7004
I would like doctor visits to be included to my private insurance=No	-19.3459
I would like doctor visits to be included to my private insurance=Yes	-52.4769
I would like hospital care to be included to my private insurance=No	33.9022
I would like Annual check up to be included to my private insurance=No	19.2363
I would like going abroad to be included to my private insurance=No	-2.5301
I would like ambulance to be included to my private insurance =Yes	1.4932
Team insurance =Yes	-8.6958
I will not get a pension=No	-12.6141
I will get a small pension=Yes	-2.1184

I will get a satisfying pension=Yes -10.6577

I have managed for a lump sum or supplementary pension=No 6.6073

I have managed for a lump sum or supplementary pension through Bank Savings=No 30.2287

I have managed for a lump sum or supplementary pension through Pension scheme purchase=Yes -54.3474

I have managed for a lump sum or supplementary pension through Life insurance program and savings plan=Yes 12.6073

I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation=Yes -11.2331

I am about to take immediate care of a lump sum or supplementary pension=Yes -25.3673

I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase =Yes -14.2421

Even if I wanted it I cannot take care of a lump sum or supplementary pension=Yes -44.301

It is of a major importance to support my children and grandchildren after I receive my pension=No -11.5925

It is of a major importance to cover my healthcare after I receive my pension=No -3.646

It is of a major importance to cover my pleasure trips after I receive my pension=No -10.7943

It is of a major importance to cover my house purchases after I receive my pension=Yes -14.7902

It is of a major importance to cover my fixed costs after I receive my pension=Yes -43.8113

It is of a major importance to cover my everyday needs after I receive my pension=Yes -31.7624

Intercept 81.5235

Odds Ratios...

Variable	Class Yes
Car superseding Ability=No	0
Motorbike superseding Ability=Yes	0.0124
House superseding Ability=Yes	218.2802
Business superseding Ability=Yes	3.08
No superseding ability=Yes	28.6496
Have or Had Business Insurance=Yes	88150280.8
Have or Had Civil Liability Insurance=Yes	2.65
Have or Had Vessel Insurance=Yes	0
Have or Had Health Insurance=Yes	0
Have or Had Everyday needs Insurance=Yes	0
Have or Had Business House Insurance=Yes	0
Have or Had Family Insurance=Yes	0
Have or Had Cash Insurance=Yes	0
Have or Had Child Insurance=Yes	298733.29
Have or Had Motorbike Insurance=Yes	0.1888
Have never had Insurance=No	0
Fixed Costs would not be covered in case of a possible loss of mine=No	67736.35
Loans would not be covered in case of a possible loss of mine=Yes	0
Children Studies would not be covered in case of a possible loss of mine=Yes	0.2506
Tax obligations would not be covered in case of a possible loss of mine=Yes	0.0159

No needs to leave behind in case of a possible loss of mine=Yes 0.053

Happiness would not be covered in case of a possible loss of mine=Yes 0

Purchases in non basic necessities would not be covered in case of a possible loss of mine=Yes 2.79

Want a risk protection=No 0

A satisfying amount of money for the support of my beloved ones 1.0218

Not at all satisfied from the public insurance health benefits=Yes 0

Kind of satisfied from the public insurance health benefits=No 0.0003

Quite satisfied from the public insurance health benefits=Yes 8829.59

Absolutely satisfied from the public insurance health benefits=Yes 0.0002

I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue=No 0.0038

I would choose a big private hospital in Athens or Thessaloniki for a mild health issue=Yes 511817009.01

I would choose a local private hospital for a mild health issue=Yes 0.0069

I would choose a local public hospital for a mild health issue=Yes 0

I would choose a public hospital in Athens or Thessaloniki for serious health issues=Yes 0

I would choose a big private hospital of Athens or Thessaloniki for serious health issues=No 0.0168

I would choose a local private hospital for serious health issues=Yes 149.5731

I would choose a local public hospital for serious health issues=Yes 11.2982

I would choose a foreign hospital for serious health issues=Yes 171.9687

I wish for private health services coupled with my insurance=No 0

I would like diagnostic tests to be included to my private insurance=No 7210.64

I would like doctor visits to be included to my private insurance=Yes 5.33

I would like doctor visits to be included to my private insurance=No 0

I would like doctor visits to be included to my private insurance=Yes 0

I would like hospital care to be included to my private insurance=No 0
5.29

I would like Annual check up to be included to my private insurance 226063771.49

I would like going abroad to be included to my private insurance=No 0.0797

I would like ambulance to be included to my private insurance =Yes 4.4515

Team insurance =Yes 0.0002

I will not get a pension=No 0

I will get a small pension=Yes 0.1202

I will get a satisfying pension=Yes 0

I have managed for a lump sum or supplementary pension=No 740.4793

I have managed for a lump sum or supplementary pension through

Bank Savings=No 1.34

I have managed for a lump sum or supplementary pension through Pension scheme purchase=Yes 0

I have managed for a lump sum or supplementary pension through Life insurance program and savings plan=Yes 298733.2066

I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation=Yes 0

I am about to take immediate care of a lump sum or supplementary pension=Yes 0

I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase =Yes 0

Even if I wanted it I cannot take care of a lump sum or supplementary pension=Yes

0

It is of a major importance to support my children and grandchildren after I receive my pension=No 0

It is of a major importance to cover my healthcare after I receive my pension 0.0261

It is of a major importance to cover my pleasure trips after I receive my pension=No 0

It is of a major importance to cover my house purchases after I receive my pension=Yes 0

It is of a major importance to cover my fixed costs after I receive my pension=Yes 0

It is of a major importance to cover my everyday needs after I receive my pension=Yes 0

Multi Class Classifier Predictions| NN

#inst	actual	predicted	error
10	1:Yes	1:Yes	1
11	1:Yes	1:Yes	1
12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	1
14	1:Yes	1:Yes	1
15	1:Yes	1:Yes	1
16	1:Yes	1:Yes	1
17	1:Yes	1:Yes	1
18	1:Yes	1:Yes	1
19	1:Yes	1:Yes	1
20	1:Yes	1:Yes	1
21	1:Yes	1:Yes	1
22	1:Yes	1:Yes	1
23	1:Yes	1:Yes	1
24	1:Yes	1:Yes	1
25	1:Yes	1:Yes	1
26	1:Yes	1:Yes	1
27	1:Yes	1:Yes	1
28	1:Yes	1:Yes	1
29	1:Yes	1:Yes	1
30	1:Yes	1:Yes	1
31	1:Yes	1:Yes	1
32	1:Yes	1:Yes	1
33	1:Yes	1:Yes	1
34	1:Yes	1:Yes	1
35	1:Yes	1:Yes	1
36	1:Yes	1:Yes	1
37	1:Yes	1:Yes	1

38	1:Yes	1:Yes	1
39	1:Yes	1:Yes	1
40	1:Yes	1:Yes	1
41	1:Yes	1:Yes	1
42	1:Yes	1:Yes	1
43	1:Yes	1:Yes	1
44	1:Yes	1:Yes	1
45	1:Yes	1:Yes	1
46	1:Yes	1:Yes	1
47	1:Yes	1:Yes	1
48	1:Yes	1:Yes	1
49	1:Yes	1:Yes	1
50	1:Yes	1:Yes	1
51	1:Yes	1:Yes	1
52	1:Yes	1:Yes	1
53	1:Yes	1:Yes	1
54	1:Yes	1:Yes	1
55	1:Yes	1:Yes	1
56	1:Yes	1:Yes	1
57	1:Yes	1:Yes	1
58	1:Yes	1:Yes	1
59	1:Yes	1:Yes	1
60	1:Yes	1:Yes	1
61	1:Yes	1:Yes	1
62	1:Yes	1:Yes	1
63	1:Yes	1:Yes	1
64	1:Yes	1:Yes	1
65	1:Yes	1:Yes	1
66	1:Yes	1:Yes	1
67	1:Yes	1:Yes	1
68	1:Yes	1:Yes	1
69	1:Yes	1:Yes	1
70	1:Yes	1:Yes	1
71	1:Yes	1:Yes	1
72	1:Yes	1:Yes	1
73	1:Yes	1:Yes	1
74	1:Yes	1:Yes	1
75	1:Yes	1:Yes	1
76	1:Yes	1:Yes	1
77	1:Yes	1:Yes	1
78	1:Yes	1:Yes	1
79	1:Yes	1:Yes	1
80	1:Yes	1:Yes	1
81	1:Yes	1:Yes	1
82	1:Yes	1:Yes	1
83	1:Yes	1:Yes	1
84	1:Yes	1:Yes	1
85	1:Yes	1:Yes	1

86	1:Yes	1:Yes	1
87	1:Yes	1:Yes	1
88	1:Yes	1:Yes	1
89	1:Yes	1:Yes	1
90	1:Yes	1:Yes	1
91	1:Yes	1:Yes	1
92	1:Yes	1:Yes	1
93	1:Yes	1:Yes	1
94	1:Yes	1:Yes	1
95	1:Yes	1:Yes	1
96	1:Yes	1:Yes	1
97	1:Yes	1:Yes	1
98	1:Yes	1:Yes	1
99	1:Yes	1:Yes	1
100	1:Yes	1:Yes	1
101	1:Yes	1:Yes	1
102	1:Yes	1:Yes	1
103	1:Yes	1:Yes	1
104	1:Yes	1:Yes	1
105	1:Yes	1:Yes	1
106	1:Yes	1:Yes	1
107	1:Yes	1:Yes	1
108	1:Yes	1:Yes	1
109	1:Yes	1:Yes	1
110	1:Yes	1:Yes	1
111	1:Yes	1:Yes	1
112	1:Yes	1:Yes	1
113	1:Yes	1:Yes	1
114	1:Yes	1:Yes	1
115	1:Yes	1:Yes	1
116	1:Yes	1:Yes	1
117	1:Yes	1:Yes	1
118	1:Yes	1:Yes	1
119	1:Yes	1:Yes	1
120	1:Yes	1:Yes	1
121	1:Yes	1:Yes	1
122	1:Yes	1:Yes	1
123	1:Yes	1:Yes	1
124	1:Yes	1:Yes	1
125	1:Yes	1:Yes	1
126	1:Yes	1:Yes	1
127	1:Yes	1:Yes	1
128	1:Yes	1:Yes	1
129	1:Yes	1:Yes	1
130	1:Yes	1:Yes	1
131	1:Yes	1:Yes	1
132	1:Yes	1:Yes	1
133	1:Yes	1:Yes	1

134	1:Yes	1:Yes	1
135	1:Yes	1:Yes	1
136	1:Yes	1:Yes	1
137	1:Yes	1:Yes	1
138	1:Yes	1:Yes	1
139	1:Yes	1:Yes	1
140	1:Yes	1:Yes	1
141	1:Yes	1:Yes	1
142	1:Yes	1:Yes	1
143	1:Yes	1:Yes	1
144	1:Yes	1:Yes	1
145	1:Yes	1:Yes	1
146	1:Yes	1:Yes	1
147	1:Yes	1:Yes	1
148	1:Yes	1:Yes	1
149	1:Yes	1:Yes	1
150	1:Yes	1:Yes	1
151	1:Yes	1:Yes	1
152	1:Yes	1:Yes	1
153	1:Yes	1:Yes	1
154	1:Yes	1:Yes	1
155	1:Yes	1:Yes	1
156	1:Yes	1:Yes	1
157	1:Yes	1:Yes	1
158	1:Yes	1:Yes	1
159	1:Yes	1:Yes	1
160	1:Yes	1:Yes	1
161	2:No	1:Yes	1
162	1:Yes	2:No	1
163	1:Yes	1:Yes	1
164	1:Yes	1:Yes	1
165	1:Yes	1:Yes	1
166	1:Yes	1:Yes	1
167	2:No	1:Yes	1
168	2:No	2:No	1
169	1:Yes	2:No	1
170	2:No	1:Yes	1
171	1:Yes	2:No	1
172	1:Yes	1:Yes	1
173	2:No	1:Yes	1
174	1:Yes	2:No	1
175	1:Yes	1:Yes	1
176	1:Yes	1:Yes	1
177	2:No	1:Yes	1
178	2:No	2:No	1
179	1:Yes	2:No	1
180	2:No	1:Yes	1
181	1:Yes	2:No	1

182	1:Yes	1:Yes	1

Multi Class Classifier Updateable| NN

=== Classifier model (full training set) ===

Classifier 1

Loss function: Hinge loss (SVM)

I am interested in estimating my retirement =

0.8597 (normalized) Car superseding Ability=No

\+ 0.5898 (normalized) Motorbike superseding Ability=Yes

\+ -0.2799 (normalized) House superseding Ability=Yes

\+ -0.1399 (normalized) Business superseding Ability=Yes

\+ 0.4298 (normalized) No superseding ability=Yes

\+ -0.4098 (normalized) Have or Had Business Insurance=Yes

\+ -1.7394 (normalized) Have or Had Civil Liability Insurance=Yes

\+ -0.02 (normalized) Have or Had Vessel Insurance=Yes

\+ -0.01 (normalized) Have or Had Health Insurance=Yes

\+ 0 (normalized) Have or Had Everyday needs Insurance=Yes

\+ 0 (normalized) Have or Had Business House Insurance=Yes

\+ -0.01 (normalized) Have or Had Family Insurance=Yes

\+ -0.01 (normalized) Have or Had Cash Insurance=Yes

\+ 0 (normalized) Have or Had Child Insurance=Yes

\+ 0 (normalized) Have or Had Car Insurance

\+ 0 (normalized) Have or Had Motorbike Insurance=Yes

\+ 0.2099 (normalized) Have never had Insurance=No

\+ -0.12 (normalized) Fixed Costs would not be covered in case of a possible loss of mine=No

+ 1.3795 (normalized) Loans would not be covered in case of a possible loss of mine=Yes

+ -0.09 (normalized) Children Studies would not be covered in case of a possible loss of mine=Yes

+ -0.3199 (normalized) Tax obligations would not be covered in case of a possible loss of mine=Yes

+ -0.07 (normalized) No needs to leave behind in case of a possible loss of mine=Yes

+ -0.05 (normalized) Happiness would not be covered in case of a possible loss of mine=Yes

+ -0.1 (normalized) Purchases in non-basic necessities would not be covered in case of a possible loss of mine=Yes

+ 1.4794 (normalized) Want a risk protection=No

+ -0.3727 (normalized) A satisfying amount of money for the support of my beloved ones

+ 0.7797 (normalized) Not at all satisfied from the public insurance health benefits=Yes

+ 0.3998 (normalized) Kind of satisfied from the public insurance health benefits=No

+ -0.3099 (normalized) Quite satisfied from the public insurance health benefits=Yes

+ -0.07 (normalized) Absolutely satisfied from the public insurance health benefits=Yes

+ -0.1499 (normalized) I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue=No

+ -1.5794 (normalized) I would choose a big private hospital in Athens or Thessaloniki for a mild health issue=Yes

+ 0.3499 (normalized) I would choose a local private hospital for a mild health issue=Yes

+ 1.0796 (normalized) I would choose a local public hospital for a mild health issue=Yes

+ 0.7597 (normalized) I would choose a public hospital in Athens or Thessaloniki for serious health issues=Yes

+ -0.2199 (normalized) I would choose a big private hospital of Athens or Thessaloniki for serious health issues=No

+ -0.2799 (normalized) I would choose a local private hospital for serious health issues=Yes

+ -0.14 (normalized) I would choose a local public hospital for serious health issues=Yes

+ -0.5598 (normalized) I would choose a foreign hospital for serious health issues=Yes

+ 0.7597 (normalized) I wish for private health services coupled with my insurance=No

+ -1.4594 (normalized) I would like diagnostic tests to be included to my private insurance=No

+ -2.4391 (normalized) I would like doctor visits to be included to my private insurance=Yes

+ 0.7997 (normalized) I would like doctor visits to be included to my private insurance=No

+ -0.03 (normalized) I would like doctor visits to be included to my private insurance=Yes

+ -1.8294 (normalized) I would like hospital care to be included to my private insurance=No

+ -1.3495 (normalized) I would like Annual check up to be included to my private insurance=No

+ -0.2599 (normalized) I would like going abroad to be included to my private insurance=No

+ -0.1 (normalized) I would like ambulance to be included to my private insurance =Yes

+ 0.1699 (normalized) Team insurance =Yes

+ 0.3699 (normalized) I will not get a pension=No

+ 0.01 (normalized) I will get a small pension=Yes

+ 0.3599 (normalized) I will get a satisfying pension=Yes

+ -0.03 (normalized) I have managed for a lump sum or supplementary pension=No

+ -1.1595 (normalized) I have managed for a lump sum or supplementary pension through Bank Savings=No

+ 0 (normalized) I have managed for a lump sum or supplementary pension through Pension scheme purchase=Yes

+ 0 (normalized) I have managed for a lump sum or supplementary pension through Life insurance program and savings plan=Yes

+ -0.2499 (normalized) I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation=Yes

+ 1.4095 (normalized) I am about to take immediate care of a lump sum or supplementary pension=Yes

+ -0.03 (normalized) I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase =Yes

+ 0.4798 (normalized) Even if I wanted it I cannot take care of a lump sum or supplementary pension=Yes

+ 0.4299 (normalized) It is of a major importance to support my children and grandchildren after I receive my pension=No

+ -0.0799 (normalized) It is of a major importance to cover my healthcare after I receive my pension=No

+ 0.6597 (normalized) It is of a major importance to cover my pleasure trips after I receive my pension=No

+ -0.2499 (normalized) It is of a major importance to cover my house purchases after I receive my pension=Yes

+ 1.4694 (normalized) It is of a major importance to cover my fixed costs after I receive my pension=Yes

+ 0 (normalized) It is of a major importance to cover my everyday needs after I receive my pension=Yes

- 1.67

Multi Class Classifier Updeateable Predictions| NN

#inst	actual	predicted	error
11	1:Yes	1:Yes	1
12	1:Yes	1:Yes	1
13	1:Yes	1:Yes	1
14	1:Yes	1:Yes	1
15	1:Yes	1:Yes	1
16	1:Yes	1:Yes	1
17	1:Yes	1:Yes	1
18	1:Yes	1:Yes	1
19	1:Yes	1:Yes	1
20	1:Yes	1:Yes	1
21	1:Yes	1:Yes	1
22	1:Yes	1:Yes	1
23	1:Yes	1:Yes	1
24	1:Yes	1:Yes	1
25	1:Yes	1:Yes	1
26	1:Yes	1:Yes	1
27	1:Yes	1:Yes	1
28	1:Yes	1:Yes	1
29	1:Yes	1:Yes	1
30	1:Yes	1:Yes	1
31	1:Yes	1:Yes	1
32	1:Yes	1:Yes	1
33	1:Yes	1:Yes	1
34	1:Yes	1:Yes	1
35	1:Yes	1:Yes	1
36	1:Yes	1:Yes	1
37	1:Yes	1:Yes	1
38	1:Yes	1:Yes	1
39	1:Yes	1:Yes	1
40	1:Yes	1:Yes	1
41	1:Yes	1:Yes	1
42	1:Yes	1:Yes	1

43	1:Yes	1:Yes	1
44	1:Yes	1:Yes	1
45	1:Yes	1:Yes	1
46	1:Yes	1:Yes	1
47	1:Yes	1:Yes	1
48	1:Yes	1:Yes	1
49	1:Yes	1:Yes	1
50	1:Yes	1:Yes	1
51	1:Yes	1:Yes	1
52	1:Yes	1:Yes	1
53	1:Yes	1:Yes	1
54	1:Yes	1:Yes	1
55	1:Yes	1:Yes	1
56	1:Yes	1:Yes	1
57	1:Yes	1:Yes	1
58	1:Yes	1:Yes	1
59	1:Yes	1:Yes	1
60	1:Yes	1:Yes	1
61	1:Yes	1:Yes	1
62	1:Yes	1:Yes	1
63	1:Yes	1:Yes	1
64	1:Yes	1:Yes	1
65	1:Yes	1:Yes	1
66	1:Yes	1:Yes	1
67	1:Yes	1:Yes	1
68	1:Yes	1:Yes	1
69	1:Yes	1:Yes	1
70	1:Yes	1:Yes	1
71	1:Yes	1:Yes	1
72	1:Yes	1:Yes	1
73	1:Yes	1:Yes	1
74	1:Yes	1:Yes	1
75	1:Yes	1:Yes	1
76	1:Yes	1:Yes	1
77	1:Yes	1:Yes	1
78	1:Yes	1:Yes	1
79	1:Yes	1:Yes	1
80	1:Yes	1:Yes	1
81	1:Yes	1:Yes	1
82	1:Yes	1:Yes	1
83	1:Yes	1:Yes	1
84	1:Yes	1:Yes	1
85	1:Yes	1:Yes	1
86	1:Yes	1:Yes	1
87	1:Yes	1:Yes	1
88	1:Yes	1:Yes	1
89	1:Yes	1:Yes	1
90	1:Yes	1:Yes	1

91	1:Yes	1:Yes	1
92	1:Yes	1:Yes	1
93	1:Yes	1:Yes	1
94	1:Yes	1:Yes	1
95	1:Yes	1:Yes	1
96	1:Yes	1:Yes	1
97	1:Yes	1:Yes	1
98	1:Yes	1:Yes	1
99	1:Yes	1:Yes	1
100	1:Yes	1:Yes	1
101	1:Yes	1:Yes	1
102	1:Yes	1:Yes	1
103	1:Yes	1:Yes	1
104	1:Yes	1:Yes	1
105	1:Yes	1:Yes	1
106	1:Yes	1:Yes	1
107	1:Yes	1:Yes	1
108	1:Yes	1:Yes	1
109	1:Yes	1:Yes	1
110	1:Yes	1:Yes	1
111	1:Yes	1:Yes	1
112	1:Yes	1:Yes	1
113	1:Yes	1:Yes	1
114	1:Yes	1:Yes	1
115	1:Yes	1:Yes	1
116	1:Yes	1:Yes	1
117	1:Yes	1:Yes	1
118	1:Yes	1:Yes	1
119	1:Yes	1:Yes	1
120	1:Yes	1:Yes	1
121	1:Yes	1:Yes	1
122	1:Yes	1:Yes	1
123	1:Yes	1:Yes	1
124	1:Yes	1:Yes	1
125	1:Yes	1:Yes	1
126	1:Yes	1:Yes	1
127	1:Yes	1:Yes	1
128	1:Yes	1:Yes	1
129	1:Yes	1:Yes	1
130	1:Yes	1:Yes	1
131	1:Yes	1:Yes	1
132	1:Yes	1:Yes	1
133	1:Yes	1:Yes	1
134	1:Yes	1:Yes	1
135	1:Yes	1:Yes	1
136	1:Yes	1:Yes	1
137	1:Yes	1:Yes	1
138	1:Yes	1:Yes	1

139	1:Yes	1:Yes	1
140	1:Yes	1:Yes	1
141	1:Yes	1:Yes	1
142	1:Yes	1:Yes	1
143	1:Yes	1:Yes	1
144	1:Yes	1:Yes	1
145	1:Yes	1:Yes	1
146	1:Yes	1:Yes	1
147	1:Yes	1:Yes	1
148	1:Yes	1:Yes	1
149	1:Yes	1:Yes	1
150	1:Yes	1:Yes	1
151	1:Yes	1:Yes	1
152	1:Yes	1:Yes	1
153	1:Yes	1:Yes	1
154	1:Yes	1:Yes	1
155	1:Yes	1:Yes	1
156	1:Yes	1:Yes	1
157	1:Yes	1:Yes	1
158	1:Yes	1:Yes	1
159	1:Yes	1:Yes	1
160	1:Yes	1:Yes	1
161	1:Yes	1:Yes	1
162	2:No	2:No	1
163	1:Yes	1:Yes	1
164	1:Yes	1:Yes	1
165	1:Yes	1:Yes	1
166	1:Yes	1:Yes	1
167	1:Yes	1:Yes	1
168	2:No	2:No	1
169	2:No	2:No	1
170	1:Yes	1:Yes	1
171	2:No	2:No	1
172	1:Yes	1:Yes	1
173	1:Yes	1:Yes	1
174	2:No	2:No	1
175	1:Yes	1:Yes	1
176	1:Yes	1:Yes	1
177	1:Yes	1:Yes	1
178	2:No	2:No	1
179	2:No	2:No	1
180	1:Yes	1:Yes	1
181	2:No	2:No	1
182	1:Yes	1:Yes	1

Classifiers with low accuracy| NN

SGD| NN

SGDText:

Loss function: Hinge loss (SVM)

Dictionary size: 0

I am interested in estimating my retirement = - 1

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.044	
Root mean squared error	0.2097	
Relative absolute error	49.3012 %	
Root relative squared error	102.1037 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,500	0,956	Yes
	0,000	0,000	?	0,000	?	?	0,500	0,044	No
W.A	0,956	0,956	?	0,956	?	?	0,500	0,916	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 174   0 |   a = Yes
   8   0 |   b = No
```

Decision Table| NN

Correctly Classified Instances	173	95.0549 %
Incorrectly Classified Instances	9	4.9451 %
Kappa statistic	-0.0099	
Mean absolute error	0.0934	
Root mean squared error	0.2135	
Relative absolute error	104.774 %	

Root relative squared error 103.9543 %
Total Number of Instances 182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,994	1,000	0,956	0,994	0,975	-0,016	0,450	0,954	Yes
	0,000	0,006	0,000	0,000	0,000	-0,016	0,450	0,042	No
W.A	0,951	0,956	0,914	0,951	0,932	-0,016	0,450	0,914	

=== Confusion Matrix ===

a	b		<-- classified as
173	1	|	a = Yes
8	0	|	b = No

JRIP rules| NN

(I would choose a local public hospital for a mild health issue = Yes) and (Want a risk protection = No) and (I will get a small pension = Yes) and (I would like Annual check up to be included to my private insurance = Yes) => I am interested in estimating my retirement=No (3.0/0.0)

(I would like doctor visits to be included to my private insurance = No) and (I would choose a local public hospital for serious health issues = Yes) and (Kind of satisfied from the public insurance health benefits = No) => I am interested in estimating my retirement=No (3.0/0.0)

I am interested in estimating my retirement=Yes (176.0/2.0)

Number of Rules : 3

=== Summary ===

Correctly Classified Instances 169 92.8571 %
Incorrectly Classified Instances 13 7.1429 %
Kappa statistic -0.035

Mean absolute error	0.0921
Root mean squared error	0.2499
Relative absolute error	103.2467 %
Root relative squared error	121.7182 %
Total Number of Instances	182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,971	1,000	0,955	0,971	0,963	-0,036	0,506	0,960	Yes
	0,000	0,029	0,000	0,000	0,000	-0,036	0,506	0,046	No
W.A	0,929	0,957	0,913	0,929	0,921	-0,036	0,506	0,920	

=== Confusion Matrix ===

a	b	<-- classified as
169	5 |	a = Yes
8	0 |	b = No

Rules OneR| NN

Car superseding Ability:

Yes -> Yes

No -> Yes

(174/182 instances correct)

=== Summary ===

Correctly Classified Instances	172	94.5055 %
Incorrectly Classified Instances	10	5.4945 %
Kappa statistic	-0.0179	
Mean absolute error	0.0549	
Root mean squared error	0.2344	
Relative absolute error	61.6265 %	
Root relative squared error	114.1555 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,989	1,000	0,956	0,989	0,972	-0,023	0,494	0,956	Yes
	0,000	0,011	0,000	0,000	0,000	-0,023	0,494	0,044	No
W.A.	0,945	0,957	0,914	0,945	0,929	-0,023	0,494	0,915	

=== Confusion Matrix ===

```
  a   b   <-- classified as
172   2 |   a = Yes
  8   0 |   b = No
```

Rules PART| NN

PART decision list:

It is of a major importance to cover my fixed costs after I receive my pension = No

AND

I wish for private health services coupled with my insurance = Yes

AND

Want a risk protection = Yes: Yes (146.0/1.0)

Tax obligations would not be covered in case of a possible loss of mine = Yes: Yes (13.37)

Kind of satisfied from the public insurance health benefits = Yes: Yes (11.0/1.0)

It is of a major importance to cover my pleasure trips after I receive my pension = No

AND

I would choose a local public hospital for a mild health issue = Yes: No (5.0)

: Yes (6.63/1.0)

Number of Rules :   5

=== Summary ===

Correctly Classified Instances	169	92.8571 %
Incorrectly Classified Instances	13	7.1429 %
Kappa statistic	-0.035	
Mean absolute error	0.0864	
Root mean squared error	0.2704	
Relative absolute error	96.8912 %	
Root relative squared error	131.6686 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,971	1,000	0,955	0,971	0,963	-0,036	0,249	0,921	Yes
	0,000	0,029	0,000	0,000	0,000	-0,036	0,249	0,036	No
W.A	0,929	0,957	0,913	0,929	0,921	-0,036	0,249	0,882	

=== Confusion Matrix ===

a	b	<-- classified as
169	5 |	a = Yes
8	0 |	b = No

Rules ZeroR| NN

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %

Kappa statistic	0
Mean absolute error	0.0892
Root mean squared error	0.2053
Relative absolute error	100%
Root relative squared error	100%
Total Number of Instances	182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,392	0,947	Yes
	0,000	0,000	?	0,000	?	?	0,392	0,040	No
W.A	0,956	0,956	?	0,956	?	?	0,392	0,907	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 174   0 |   a = Yes
   8   0 |   b = No
```

Trees Decision Stump| NN

Classifications

A satisfying amount of money for the support of my beloved ones <= 125.0005 : Yes

A satisfying amount of money for the support of my beloved ones > 125.0005 : Yes

A satisfying amount of money for the support of my beloved ones is missing : Yes

Class distributions

A satisfying amount of money for the support of my beloved ones <= 125.0005

Yes No

0.97 0.025

A satisfying amount of money for the support of my beloved ones > 125.0005

Yes No

1.0 0.0

A satisfying amount of money for the support of my beloved ones is missing

Yes No

0.82 0.17

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.0794	
Root mean squared error	0.2045	
Relative absolute error	89.043 %	
Root relative squared error	99.6095 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,573	0,963	Yes
	0,000	0,000	?	0,000	?	?	0,573	0,082	No
W.A.	0,956	0,956	?	0,956	?	?	0,573	0,924	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 174   0 |   a = Yes
   8   0 |   b = No
```

Trees Hoeffding Tree| NN

Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Yes (175,000) NB1 NB adaptive1

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.0892	
Root mean squared error	0.2053	
Relative absolute error	100 %	
Root relative squared error	100 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,392	0,947	Yes
	0,000	0,000	?	0,000	?	?	0,392	0,040	No
W.A.	0,956	0,956	?	0,956	?	?	0,392	0,907	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 174   0 |   a = Yes
   8   0 |   b = No
```

Trees J48| NN

=== Classifier model (full training set) ===

J48 pruned tree

: Yes (182.0/8.0)

Number of Leaves : 1

Size of the tree : 1

=== Summary ===

Correctly Classified Instances	171	93.956 %
Incorrectly Classified Instances	11	6.044 %
Kappa statistic	-0.0246	
Mean absolute error	0.0965	
Root mean squared error	0.2415	
Relative absolute error	108.2033 %	
Root relative squared error	117.6141 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,983	1,000	0,955	0,983	0,969	-0,028	0,582	0,965	Yes
	0,000	0,017	0,000	0,000	0,000	-0,028	0,582	0,052	No
W.A.	0,940	0,957	0,913	0,940	0,926	-0,028	0,582	0,925	

=== Confusion Matrix ===

```
  a   b   <-- classified as
171   3 |   a = Yes
  8   0 |   b = No
```

Trees LMT| NN

Logistic model tree

: LM_1:0/0 (182)

Number of Leaves : 1

Size of the Tree : 1

LM_1:

Class Yes :

0 +

Class No :

0 +

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.4618	
Root mean squared error	0.4822	
Relative absolute error	518.0072 %	
Root relative squared error	234.836 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,482	0,953	Yes
	0,000	0,000	?	0,000	?	?	0,482	0,043	No
W.A.	0,956	0,956	?	0,956	?	?	0,482	0,913	

=== Confusion Matrix ===

a	b		<-- classified as
174	0	|	a = Yes
8	0	|	b = No

Trees RandomForest| NN

Bagging with 100 iterations and base learner

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	

Mean absolute error	0.0763
Root mean squared error	0.197
Relative absolute error	85.6312 %
Root relative squared error	95.934 %
Total Number of Instances	182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,770	0,985	Yes
	0,000	0,000	?	0,000	?	?	0,770	0,267	No
W.A.	0,956	0,956	?	0,956	?	?	0,770	0,953	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 174   0 |   a = Yes
   8   0 |   b = No
```

REPTree| NN

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.0804	
Root mean squared error	0.2053	
Relative absolute error	90.2187 %	
Root relative squared error	99.9629 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
1,000	1,000	0,956	1,000	0,978	?	0,407	0,955	Yes
0,000	0,000	?	0,000	?	?	0,407	0,040	No

W.A	0,956	0,956	?	0,956	?	?	0,407	0,915

=== Confusion Matrix ===

a	b	<-- classified as
174	0 |	a = Yes
8	0 |	b = No

Naive Bayes Multinomial Text| NN

The independent frequency of a class

Yes 175.0

No 9.0

The frequency of a word given the class

Yes No

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.0892	
Root mean squared error	0.2053	
Relative absolute error	100 %	
Root relative squared error	100 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
1,000	1,000	0,956	1,000	0,978	?	0,392	0,947	Yes
0,000	0,000	?	0,000	?	?	0,392	0,040	No

W.A.	0,956	0,956	?	0,956	?	?	0,392	0,907

=== Confusion Matrix ===

a b <-- classified as

174 0 | a = Yes

8 0 | b = No

SGDText| NN

I am interested in estimating my retirement = - 1

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.044	
Root mean squared error	0.2097	
Relative absolute error	49.3012 %	
Root relative squared error	102.1037 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,500	0,956	Yes
	0,000	0,000	?	0,000	?	?	0,500	0,044	No
W.A	0,956	0,956	?	0,956	?	?	0,500	0,916	

=== Confusion Matrix ===

a b <-- classified as

174 0 | a = Yes

8 0 | b = No

Voted Perceptron| NN

VotedPerceptron: Number of perceptrons=16

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.044	
Root mean squared error	0.2097	
Relative absolute error	49.3012 %	
Root relative squared error	102.1037 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,500	0,956	Yes
	0,000	0,000	?	0,000	?	?	0,451	0,053	No
W.A	0,956	0,956	?	0,956	?	?	0,498	0,916	

=== Confusion Matrix ===

```
  a   b   <-- classified as
 174   0 |   a = Yes
   8   0 |   b = No
```

Lazy LWL| NN

Locally weighted learning

===========================

Using classifier: weka.classifiers.trees.DecisionStump

Using linear weighting kernels

Using all neighbours

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %

Kappa statistic	0
Mean absolute error	0.0814
Root mean squared error	0.2156
Relative absolute error	91.3454 %
Root relative squared error	104.9973 %
Total Number of Instances	182

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,469	0,954	Yes
	0,000	0,000	?	0,000	?	?	0,466	0,047	No
W.A.	0,956	0,956	?	0,956	?	?	0,469	0,914	

=== Confusion Matrix ===

a	b	<-- classified as
174	0 |	a = Yes
8	0 |	b = No

Meta.MultiScheme| NN

ZeroR predicts class value: Yes

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.0892	
Root mean squared error	0.2053	
Relative absolute error	100 %	
Root relative squared error	100 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,392	0,947	Yes
	0,000	0,000	?	0,000	?	?	0,392	0,040	No
W.A.	0,956	0,956	?	0,956	?	?	0,392	0,907	

=== Confusion Matrix ===

a b <-- classified as

174 0 | a = Yes

8 0 | b = No

Misc Input Mapped Classifier|NN

ZeroR predicts class value.

Model attributes → Incoming attributes

=== Summary ===

Correctly Classified Instances	174	95.6044 %
Incorrectly Classified Instances	8	4.3956 %
Kappa statistic	0	
Mean absolute error	0.0892	
Root mean squared error	0.2053	
Relative absolute error	100 %	
Root relative squared error	100 %	
Total Number of Instances	182	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	1,000	0,956	1,000	0,978	?	0,392	0,947	Yes
	0,000	0,000	?	0,000	?	?	0,392	0,040	No
W.A.	0,956	0,956	?	0,956	?	?	0,392	0,907	

=== Confusion Matrix ===

```
  a   b   <-- classified as
174   0 |   a = Yes
  8   0 |   b = No
```

Simple K Means Clustering| NN

Simple K Means with 2 Clusters

	Final cluster centroids		
Attribute	Full Data (182.0)	0 (60.0)	1 (122.0)
Car superseding Ability	No	No	No
Motorbike superseding Ability	No	No	No
House superseding Ability	No	No	No
Business superseding Ability	No	No	No
No superseding ability	Yes	Yes	Yes
Have or Had Business Insurance	No	No	No
Have or Had Civil Liability Insurance	No	No	No
Have or Had Vessel Insurance	No	No	No
Have or Had Health Insurance	No	No	No
Have or Had Everyday needs Insurance	No	No	No
Have or Had Business House Insurance	No	No	No
Have or Had Family Insurance	No	No	No
Have or Had Cash Insurance	No	No	No
Have or Had Child Insurance	No	No	No
Have or Had Car Insurance	No	No	No
Have or Had Motorbike Insurance	No	No	No
Have never had Insurance	Yes	No	Yes
Fixed Costs would not be covered in case of a possible loss of mine	Yes	Yes	Yes

Loans would not be covered in case of a possible loss of mine	No	No	No
Children Studies would not be covered in case of a possible loss of mine	No	No	No
Tax obligations would not be covered in case of a possible loss of mine	No	Yes	No
No needs to leave behind in case of a possible los	No	No	No
Happiness would not be covered in case of a possible loss of mine	No	No	No
Purchases in non-basic necessities would not be covered in case of a possible loss of mine	No	No	No
Want a risk protection	Yes	Yes	Yes
A satisfying amount of money for the support of my beloved ones	86.16	99.57	79.57
Not at all satisfied from the public insurance health benefits	No	No	No
Kind of satisfied from the public insurance health benefits	Yes	No	Yes
Quite satisfied from the public insurance health benefits	No	No	No
Absolutely satisfied from the public insurance health benefits	No	No	No
I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue	No	No	No
I would choose a big private hospital in Athens or Thessaloniki for a mild health issue	No	No	No
I would choose a local private hospital for a mild health issue	No	No	No
I would choose a local public hospital for a mild health issue	No	No	No
I would choose a public hospital in Athens or Thessaloniki for serious health issues	No	No	No
I would choose a big private hospital of Athens or Thessaloniki for serious health issues	No	Yes	No
I would choose a local private hospital for serious health issues	No	No	No
I would choose a local public hospital for serious health issues	No	No	No
I would choose a foreign hospital for serious health issues	No	No	No
I wish for private health services coupled with my insurance	Yes	Yes	Yes
I would like diagnostic tests to be included to my private insurance	Yes	Yes	Yes

I would like doctor visits to be included to my private insurance	Yes	Yes	Yes
I would like hospital care to be included to my private insurance	Yes	Yes	Yes
I would like Annual check up to be included to my private insurance	Yes	Yes	Yes
I would like to go abroad to be included to my private insurance	No	Yes	No
I would like ambulance to be included to my private insurance	No	No	No
Team insurance	No	No	No
I will not get a pension	No	No	No
I will get a small pension	Yes	Yes	Yes
I will get a satisfying pension	No	No	No
I have managed for a lump sum or supplementary pension	No	Yes	No
I have managed for a lump sum or supplementary pension through Bank Savings	No	No	No
I have managed for a lump sum or supplementary pension through Pension scheme purchase	No	No	No
I have managed for a lump sum or supplementary pension through Life insurance program and savings plan	No	No	No
I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation	No	No	No
I am about to take immediate care of a lump sum or supplementary pension	No	No	No
I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase	No	No	No
Even if I wanted it I cannot take care of a lump sum or supplementary pension	No	No	No
It is of a major importance to support my children and grandchildren after I receive my pension	Yes	Yes	Yes
It is of a major importance to cover my healthcare after I receive my pension	Yes	Yes	Yes
It is of a major importance to cover my pleasure trips after I receive my pension	No	Yes	No
It is of a major importance to cover my house purchases	No	No	No

after I receive my pension			
It is of a major importance to cover my fixed costs after I receive my pension	No	No	No
It is of a major importance to cover my everyday needs after I receive my pension	No	No	No
I am interested in estimating my retirement	Yes	Yes	Yes

EM Clusterer| NN

	Cluster		
Attribute	0 (0.43)	1 (0.21)	2 (0.35)
Car superseding Ability			
Yes	18.35	11.05	8.58
No	62.10	29.97	57.92
[total]	80.46	41.03	66.50
Motorbike superseding Ability			
No	67.93	30.83	60.23
Yes	12.53	10.19	6.26
[total]	80.46	41.03	66.50
House superseding Ability			
No	72.78	38.99	62.22
Yes	7.68	2.03	4.28
[total]	80.46	41.03	66.50
Business superseding Ability			
No	78.32	37.14	64.52
Yes	2.13	3.88	1.97
[total]	80.46	41.03	66.50
No superseding ability			
No	34.70	20.19	14.09

Yes	45.75 20.83 52.41
[total]	80.46 41.03 66.50
Have or Had Business Insurance	
No	75.65 21.65 60.68
Yes	4.80 19.37 5.81
[total]	80.46 41.03 66.50
Have or Had Civil Liability Insurance	
No	78.29 22.03 58.66
Yes	2.16 18.99 7.84
[total]	80.46 41.03 66.50
Have or Had Vessel Insurance	
No	78.71 35.78 63.50
Yes	1.74 5.25 3.00
[total]	80.46 41.03 66.50
Have or Had Health Insurance	
No	79.46 39.03 64.49
Yes	1.00 1.99 2.0
[total]	80.46 41.03 66.50
Have or Had Everyday needs Insurance	
No	79.46 39.95 64.57
Yes	1.00 1.07 1.92
[total]	80.46 41.03 66.50
Have or Had Business House Insurance	
No	79.46 40.01 64.51
Yes	1 1.01 1.98
[total]	80.46 41.03 66.50
Have or Had Family Insurance	

No	79.46	39.03	65.50
Yes	1	2	1
[total]	80.46	41.03	66.50
Have or Had Cash Insurance			
No	78.46	40.03	65.50
Yes	2	1	1
[total]	80.46	41.03	66.50
Have or Had Child Insurance			
No	79.45	39.04	65.50
Yes	1.01	1.98	1.0
[total]	80.46	41.03	66.50
Have or Had Car Insurance			
No	79.46	40.03	65.50
[total]	79.46	40.03	65.50
Have or Had Motorbike Insurance			
No	78.48	40.02	65.48
Yes	1.9	1.00	1.02
[total]	80.46	41.03	66.50
Have never had Insurance			
Yes	63.66	4.20	44.12
No	16.79	36.82	22.37
[total]	80.46	41.03	66.50
Fixed Costs would not be covered in case of a possible loss of mine			
Yes	56.29	27.89	50.80
No	24.16	13.13	15.69
[total]	80.46	41.03	66.50
Loans would not be covered in case of a possible loss of mine			

No	59.12	27.72	44.15
Yes	21.34	13.30	22.35
[total]	80.46	41.03	66.50
Children Studies would not be covered in case of a possible loss of mine			
No	67.77	31.72	39.50
Yes	12.69	9.31	26.99
[total]	80.46	41.03	66.50
Tax obligations would not be covered in case of a possible loss of mine			
No	62.87	17.49	31.62
Yes	17.58	23.53	34.87
[total]	80.46	41.03	66.50
No needs to leave behind in case of a possible loss of mine			
No	79.44	40.02	64.52
Yes	1.01	1.00	1.97
[total]	80.46	41.03	66.50
Happiness would not be covered in case of a possible loss of mine			
No	78.46	40.03	65.50
Yes	1.99	1	1.00
[total]	80.46	41.03	66.50
Purchases in non-basic necessities would not be covered in case of a possible loss of mine			
No	79.46	39.03	65.50
Yes	1.00	1.99	1.00
[total]	80.46	41.03	66.50
Want a risk protection			
Yes	63.86	36.01	56.11
No	16.59	5.01	10.38
[total]	80.46	41.03	66.50

A satisfying amount of money for the support of my beloved ones	
mean	75.79 93.35 94.43
std. dev.	40.43 41.12 43.18
Not at all satisfied from the public insurance health benefits	
No	64.11 37.49 53.39
Yes	16.34 3.53 13.11
[total]	80.46 41.03 66.50
Kind of satisfied from the public insurance health benefits	
Yes	36.56 31.11 36.32
No	43.90 9.91 30.18
[total]	80.46 41.03 66.50
Quite satisfied from the public insurance health benefits	
No	51.91 34.75 50.32
Yes	28.54 6.27 16.18
[total]	80.46 41.03 66.50
Absolutely satisfied from the public insurance health benefits	
No	79.45 38.92 63.61
Yes	1.00 2.10 2.88
[total]	80.46 41.03 66.50
I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue	
Yes	11.00 8.04 10.95
No	69.46 32.98 55.55
[total]	80.46 41.03 66.50
I would choose a big private hospital in Athens or Thessaloniki for a mild health issue	
No	61.86 21.89 45.23
Yes	18.596 19.13 21.26

[total]	80.46	41.03	66.50
I would choose a local private hospital for a mild health issue			
No	58.1	29.17	49.72
Yes	22.36	11.85	16.77
[total]	80.46	41.03	66.50
I would choose a local public hospital for a mild health issue			
No	49.95	37.04	46.99
Yes	30.50	3.98	19.50
[total]	80.46	41.03	66.50
I would choose a public hospital in Athens or Thessaloniki for serious health issues			
No	60.3	34.13	54.56
Yes	20.16	6.89	11.94
[total]	80.46	41.03	66.50
I would choose a big private hospital of Athens or Thessaloniki for serious health issues			
Yes	24.17	27.32	28.49
No	56.2	13.70	38.00
[total]	80.46	41.03	66.50
I would choose a local private hospital for serious health issues			
No	65.61	37.56	55.82
Yes	14.85	3.46	10.68
[total]	80.46	41.03	66.50
I would choose a local public hospital for serious health issues			
No	71.45	38.03	63.51
Yes	9.00	2.99	2.99
[total]	80.46	41.03	66.50
I would choose a foreign hospital for serious health issues			
No	65.20	37.68	51.11

Yes	15.26 3.34 15.39
[total]	80.46 41.03 66.50
I wish for private health services coupled with my insurance	
Yes	69.96 40.00 64.0
No	10.49 1.02 2.47
[total]	80.46 41.03 66.50
I would like diagnostic tests to be included to my private insurance	
Yes	20.86 25.13 64.99
No	59.59 15.89 1.50
[total]	80.46 41.03 66.50
I would like doctor visits to be included to my private insurance	
Yes	28.96 22.63 65.408
No	46.51 18.39 1.09
Yes	5.99 1.00 1.00
[total]	81.46 42.03 67.50
I would like hospital care to be included to my private insurance	
Yes	31.97 35.21 63.81
No	48.48 5.81 2.69
[total]	80.46 41.03 66.50
I would like Annual check up to be included to my private insurance	
Yes	26.41 28.47 58.11
No	54.05 12.55 8.38
[total]	80.46 41.03 66.50
I would like going abroad to be included to my private insurance	
Yes	17.20 18.35 45.44
No	63.26 22.67 21.05
[total]	80.46 41.03 66.50

I would like ambulance to be included to my private insurance			
No	79.46	38.05	64.48
Yes	1.00	2.97	2.02
[total]	80.46	41.03	66.50
Team insurance			
No	56.52	32.79	48.68
Yes	23.93	8.24	17.82
[total]	80.46	41.03	66.50
I will not get a pension			
Yes	19.20	5.26	15.52
No	61.25	35.76	50.97
[total]	80.46	41.03	66.50
I will get a small pension			
No	33.94	15.21	22.84
Yes	46.52	25.81	43.66
[total]	80.46	41.031	66.50
I will get a satisfying pension			
No	64.72	30.08	58.18
Yes	15.73	10.94	8.316
[total]	80.46	41.03	66.50
I have managed for a lump sum or supplementary pension			
Yes	20.133	33.39	12.47
No	60.32	7.63	54.0
[total]	80.46	41.03	66.50
I have managed for a lump sum or supplementary pension through Bank Savings			
Yes	16.62	16.62	14.75
No	63.83	24.40	51.75

[total]	80.46 41.03 66.50
I have managed for a lump sum or supplementary pension through Pension scheme purchase	
No	79.27 39.38 65.33
Yes	1.18 1.64 1.16
[total]	80.46 41.03 66.50
I have managed for a lump sum or supplementary pension through Life insurance program and savings plan	
No	79.45 39.04 65.50
Yes	1.011 1.98 1.00
[total]	80.46 41.03 66.50
I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation	
No	75.43 23.28 65.28
Yes	5.03 17.74 1.21
[total]	80.46 41.03 66.50
I am about to take immediate care of a lump sum or supplementary pension	
No	62.87 37.98 52.13
Yes	17.58 3.04 14.37
[total]	80.46 41.03 66.505
I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase	
No	73.89 22.65 64.45
Yes	6.57 18.37 2.05
[total]	80.46 41.03 66.50
Even if I wanted it I cannot take care of a lump sum or supplementary pension	
No	78.46 40.03 64.50
Yes	1.99 1 2
[total]	80.46 41.03 66.50
It is of a major importance to support my children and grandchildren after I receive my	

pension	
Yes	44.52 28.39 50.081
No	35.93 12.64 16.42
[total]	80.463 41.03 66.50
It is of a major importance to cover my healthcare after I receive my pension	
Yes	46.15 35.45 61.38
No	34.30 5.57 5.12
[total]	80.46 41.03 66.50
It is of a major importance to cover my pleasure trips after I receive my pension	
Yes	23.24 20.41 32.33
No	57.21 20.61 34.16
[total]	80.46 41.03 66.50
It is of a major importance to cover my house purchases after I receive my pension	
No	74.01 37.83 59.15
Yes	6.44 3.20 7.35
[total]	80.46 41.03 66.50
It is of a major importance to cover my fixed costs after I receive my pension	
No	78.44 40.03 64.52
Yes	2.01 1 1.98
[total]	80.46 41.03 66.50
It is of a major importance to cover my everyday needs after I receive my pension	
No	79.46 39.95 64.57
Yes	1 1.07 1.9267
[total]	80.46 41.03 66.50
I am interested in estimating my retirement	
Yes	72.88 40 64.10
No	7.57 1.02 2.40

[total]	80.46 41.03 66.50

Farthest First Clusterer | NN

Cluster centroids:

Cluster 0:

No No No Yes No Yes Yes No No No No No No No No No No Yes No No No No No No Yes 100 No Yes No No No No Yes No No Yes No No No Yes No No Yes No No No No No Yes No No No No No No Yes No No Yes No No No No No Yes

Cluster 1:

No No No No Yes No No No No No No No No No No No No No No Yes No No No No No 86.16 No No Yes No No No No Yes No No No Yes No No Yes No No No No No Yes No No Yes Yes Yes No No No No Yes No Yes Yes No No No No No

Each "Yes/No" answer in each question (Car superseding ability, motorbike superseding ability etc..) is the centroid of all the answers that the customers have answered (in that specific question).

Make A Density Fitted Estimators| NN

Fitted estimators (with ML estimates of variance):

Cluster 0:
Prior probability= 0.3315

Attribute: Car superseding Ability
Discrete Estimator. Counts = 10 52 (Total = 62)
Attribute: Motorbike superseding Ability
Discrete Estimator. Counts = 50 12 (Total = 62)
Attribute: House superseding Ability
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: Business superseding Ability
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: No superseding ability
Discrete Estimator. Counts = 18 44 (Total = 62)

Attribute: Have or Had Business Insurance
Discrete Estimator. Counts = 46 16 (Total = 62)
Attribute: Have or Had Civil Liability Insurance
Discrete Estimator. Counts = 40 22 (Total = 62)
Attribute: Have or Had Vessel Insurance
Discrete Estimator. Counts = 54 8 (Total = 62)
Attribute: Have or Had Health Insurance
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: Have or Had Everyday needs Insurance
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: Have or Had Business House Insurance
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: Have or Had Family Insurance
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: Have or Had Cash Insurance
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: Have or Had Child Insurance
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: Have or Had Car Insurance
Discrete Estimator. Counts = 61 (Total = 61)
Attribute: Have or Had Motorbike Insurance
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: Have never had Insurance
Discrete Estimator. Counts = 19 43 (Total = 62)
Attribute: Fixed Costs would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 46 16 (Total = 62)
Attribute: Loans would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 41 21 (Total = 62)
Attribute: Children Studies would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 44 18 (Total = 62)
Attribute: Tax obligations would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 17 45 (Total = 62)
Attribute: No needs to leave behind in case of a possible loss of mine
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: Happiness would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: Purchases in non basic necessities would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: Want a risk protection
Discrete Estimator. Counts = 54 8 (Total = 62)
Attribute: A satisfying amount of money for the support of my beloved ones
Normal Distribution. Mean = 99.5782 StdDev = 40.5907
Attribute: Not at all satisfied from the public insurance health benefits

Discrete Estimator. Counts = 48 14 (Total = 62)
Attribute: Kind of satisfied from the public insurance health benefits
Discrete Estimator. Counts = 27 35 (Total = 62)
Attribute: Quite satisfied from the public insurance health benefits
Discrete Estimator. Counts = 43 19 (Total = 62)
Attribute: Absolutely satisfied from the public insurance health benefits
Discrete Estimator. Counts = 58 4 (Total = 62)
Attribute: I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue
Discrete Estimator. Counts = 9 53 (Total = 62)
Attribute: I would choose a big private hospital in Athens or Thessaloniki for a mild health issue
Discrete Estimator. Counts = 32 30 (Total = 62)
Attribute: I would choose a local private hospital for a mild health issue
Discrete Estimator. Counts = 49 13 (Total = 62)
Attribute: I would choose a local public hospital for a mild health issue
Discrete Estimator. Counts = 50 12 (Total = 62)
Attribute: I would choose a public hospital in Athens or Thessaloniki for serious health issues
Discrete Estimator. Counts = 55 7 (Total = 62)
Attribute: I would choose a big private hospital of Athens or Thessaloniki for serious health issues
Discrete Estimator. Counts = 38 24 (Total = 62)
Attribute: I would choose a local private hospital for serious health issues
Discrete Estimator. Counts = 54 8 (Total = 62)
Attribute: I would choose a local public hospital for serious health issues
Discrete Estimator. Counts = 58 4 (Total = 62)
Attribute: I would choose a foreign hospital for serious health issues
Discrete Estimator. Counts = 54 8 (Total = 62)
Attribute: I wish for private health services coupled with my insurance
Discrete Estimator. Counts = 60 2 (Total = 62)
Attribute: I would like diagnostic tests to be included to my private insurance
Discrete Estimator. Counts = 45 17 (Total = 62)
Attribute: I would like doctor visits to be included to my private insurance
Discrete Estimator. Counts = 43 19 1 (Total = 63)
Attribute: I would like hospital care to be included to my private insurance
Discrete Estimator. Counts = 52 10 (Total = 62)
Attribute: I would like Annual check up to be included to my private insurance
Discrete Estimator. Counts = 47 15 (Total = 62)
Attribute: I would like going abroad to be included to my private insurance
Discrete Estimator. Counts = 45 17 (Total = 62)
Attribute: I would like ambulance to be included to my private insurance
Discrete Estimator. Counts = 59 3 (Total = 62)
Attribute: Team insurance

Discrete Estimator. Counts = 47 15 (Total = 62)
Attribute: I will not get a pension
Discrete Estimator. Counts = 12 50 (Total = 62)
Attribute: I will get a small pension
Discrete Estimator. Counts = 25 37 (Total = 62)
Attribute: I will get a satisfying pension
Discrete Estimator. Counts = 48 14 (Total = 62)
Attribute: I have managed for a lump sum or supplementary pension
Discrete Estimator. Counts = 36 26 (Total = 62)
Attribute: I have managed for a lump sum or supplementary pension through Bank Savings
Discrete Estimator. Counts = 17 45 (Total = 62)
Attribute: I have managed for a lump sum or supplementary pension through Pension scheme purchase
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: I have managed for a lump sum or supplementary pension through Life insurance program and savings plan
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation
Discrete Estimator. Counts = 48 14 (Total = 62)
Attribute: I am about to take immediate care of a lump sum or supplementary pension
Discrete Estimator. Counts = 55 7 (Total = 62)
Attribute: I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase
Discrete Estimator. Counts = 43 19 (Total = 62)
Attribute: Even if I wanted it I cannot take care of a lump sum or supplementary pension
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: It is of a major importance to support my children and grandchildren after I receive my pension
Discrete Estimator. Counts = 43 19 (Total = 62)
Attribute: It is of a major importance to cover my healthcare after I receive my pension
Discrete Estimator. Counts = 54 8 (Total = 62)
Attribute: It is of a major importance to cover my pleasure trips after I receive my pension
Discrete Estimator. Counts = 40 22 (Total = 62)
Attribute: It is of a major importance to cover my house purchases after I receive my pension
Discrete Estimator. Counts = 55 7 (Total = 62)
Attribute: It is of a major importance to cover my fixed costs after I receive my pension
Discrete Estimator. Counts = 60 2 (Total = 62)

Attribute: It is of a major importance to cover my everyday needs after I receive my pension
Discrete Estimator. Counts = 61 1 (Total = 62)
Attribute: I am interested in estimating my retirement
Discrete Estimator. Counts = 61 1 (Total = 62)

Cluster 1:
Prior probability= 0.6685

Attribute: Car superseding Ability
Discrete Estimator. Counts = 27 97 (Total = 124)
Attribute: Motorbike superseding Ability
Discrete Estimator. Counts = 108 16 (Total = 124)
Attribute: House superseding Ability
Discrete Estimator. Counts = 113 11 (Total = 124)
Attribute: Business superseding Ability
Discrete Estimator. Counts = 119 5 (Total = 124)
Attribute: No superseding ability
Discrete Estimator. Counts = 50 74 (Total = 124)
Attribute: Have or Had Business Insurance
Discrete Estimator. Counts = 111 13 (Total = 124)
Attribute: Have or Had Civil Liability Insurance
Discrete Estimator. Counts = 118 6 (Total = 124)
Attribute: Have or Had Vessel Insurance
Discrete Estimator. Counts = 123 1 (Total = 124)
Attribute: Have or Had Health Insurance
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: Have or Had Everyday needs Insurance
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: Have or Had Business House Insurance
Discrete Estimator. Counts = 123 1 (Total = 124)
Attribute: Have or Had Family Insurance
Discrete Estimator. Counts = 123 1 (Total = 124)
Attribute: Have or Had Cash Insurance
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: Have or Had Child Insurance
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: Have or Had Car Insurance
Discrete Estimator. Counts = 123 (Total = 123)
Attribute: Have or Had Motorbike Insurance
Discrete Estimator. Counts = 123 1 (Total = 124)
Attribute: Have never had Insurance
Discrete Estimator. Counts = 92 32 (Total = 124)
Attribute: Fixed Costs would not be covered in case of a possible loss of mine

Discrete Estimator. Counts = 88 36 (Total = 124)
Attribute: Loans would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 89 35 (Total = 124)
Attribute: Children Studies would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 94 30 (Total = 124)
Attribute: Tax obligations would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 94 30 (Total = 124)
Attribute: No needs to leave behind in case of a possible loss of mine
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: Happiness would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: Purchases in non basic necessities would not be covered in case of a possible loss of mine
Discrete Estimator. Counts = 123 1 (Total = 124)
Attribute: Want a risk protection
Discrete Estimator. Counts = 101 23 (Total = 124)
Attribute: A satisfying amount of money for the support of my beloved ones
Normal Distribution. Mean = 79.5744 StdDev = 41.9303
Attribute: Not at all satisfied from the public insurance health benefits
Discrete Estimator. Counts = 106 18 (Total = 124)
Attribute: Kind of satisfied from the public insurance health benefits
Discrete Estimator. Counts = 76 48 (Total = 124)
Attribute: Quite satisfied from the public insurance health benefits
Discrete Estimator. Counts = 93 31 (Total = 124)
Attribute: Absolutely satisfied from the public insurance health benefits
Discrete Estimator. Counts = 123 1 (Total = 124)
Attribute: I would choose a Public Hospital in Athens or Thessaloniki for a mild health issue
Discrete Estimator. Counts = 20 104 (Total = 124)
Attribute: I would choose a big private hospital in Athens or Thessaloniki for a mild health issue
Discrete Estimator. Counts = 96 28 (Total = 124)
Attribute: I would choose a local private hospital for a mild health issue
Discrete Estimator. Counts = 87 37 (Total = 124)
Attribute: I would choose a local public hospital for a mild health issue
Discrete Estimator. Counts = 83 41 (Total = 124)
Attribute: I would choose a public hospital in Athens or Thessaloniki for serious health issues
Discrete Estimator. Counts = 93 31 (Total = 124)
Attribute: I would choose a big private hospital of Athens or Thessaloniki for serious health issues
Discrete Estimator. Counts = 41 83 (Total = 124)
Attribute: I would choose a local private hospital for serious health issues
Discrete Estimator. Counts = 104 20 (Total = 124)

Attribute: I would choose a local public hospital for serious health issues
Discrete Estimator. Counts = 114 10 (Total = 124)
Attribute: I would choose a foreign hospital for serious health issues
Discrete Estimator. Counts = 99 25 (Total = 124)
Attribute: I wish for private health services coupled with my insurance
Discrete Estimator. Counts = 113 11 (Total = 124)
Attribute: I would like diagnostic tests to be included to my private insurance
Discrete Estimator. Counts = 65 59 (Total = 124)
Attribute: I would like doctor visits to be included to my private insurance
Discrete Estimator. Counts = 73 46 6 (Total = 125)
Attribute: I would like hospital care to be included to my private insurance
Discrete Estimator. Counts = 78 46 (Total = 124)
Attribute: I would like Annual check up to be included to my private insurance
Discrete Estimator. Counts = 65 59 (Total = 124)
Attribute: I would like going abroad to be included to my private insurance
Discrete Estimator. Counts = 35 89 (Total = 124)
Attribute: I would like ambulance to be included to my private insurance
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: Team insurance
Discrete Estimator. Counts = 90 34 (Total = 124)
Attribute: I will not get a pension
Discrete Estimator. Counts = 27 97 (Total = 124)
Attribute: I will get a small pension
Discrete Estimator. Counts = 46 78 (Total = 124)
Attribute: I will get a satisfying pension
Discrete Estimator. Counts = 104 20 (Total = 124)
Attribute: I have managed for a lump sum or supplementary pension
Discrete Estimator. Counts = 29 95 (Total = 124)
Attribute: I have managed for a lump sum or supplementary pension through Bank Savings
Discrete Estimator. Counts = 30 94 (Total = 124)
Attribute: I have managed for a lump sum or supplementary pension through Pension scheme purchase
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: I have managed for a lump sum or supplementary pension through Life insurance program and savings plan
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: I have managed for a lump sum or supplementary pension through Real estate purchase for rent or exploitation
Discrete Estimator. Counts = 115 9 (Total = 124)
Attribute: I am about to take immediate care of a lump sum or supplementary pension
Discrete Estimator. Counts = 97 27 (Total = 124)
Attribute: I have managed for a lump sum or supplementary pension through Pension scheme or savings plan purchase

Discrete Estimator. Counts = 117 7 (Total = 124)
Attribute: Even if I wanted it I cannot take care of a lump sum or supplementary pension
Discrete Estimator. Counts = 121 3 (Total = 124)
Attribute: It is of a major importance to support my children and grandchildren after I receive my pension
Discrete Estimator. Counts = 79 45 (Total = 124)
Attribute: It is of a major importance to cover my healthcare after I receive my pension
Discrete Estimator. Counts = 88 36 (Total = 124)
Attribute: It is of a major importance to cover my pleasure trips after I receive my pension
Discrete Estimator. Counts = 35 89 (Total = 124)
Attribute: It is of a major importance to cover my house purchases after I receive my pension
Discrete Estimator. Counts = 115 9 (Total = 124)
Attribute: It is of a major importance to cover my fixed costs after I receive my pension
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: It is of a major importance to cover my everyday needs after I receive my pension
Discrete Estimator. Counts = 122 2 (Total = 124)
Attribute: I am interested in estimating my retirement
Discrete Estimator. Counts = 115 9 (Total = 124)

Canopy Clustering| NN

Cluster 0: No,No,No,No,Yes,No,No,No,No,No,No,No,No,No,No,No,No,Yes,No,No,Yes,No,No,No,Yes,85.444184,No,Yes,No,No,No,No,No,No,No,Yes,No,No,No,Yes,Yes,Yes,Yes,Yes,Yes,No,No,No,Yes,No,No,No,No,No,No,No,No,No,Yes,Yes,Yes,No,No,No,Yes,{80} <0,1,2,3,4,5,6>
Cluster 1: No,No,No,No,Yes,No,No,No,No,No,No,No,No,No,No,No,Yes,Yes,No,No,No,No,No,No,Yes,82.623013,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,Yes,Yes,Yes,Yes,No,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,Yes,No,No,No,No,Yes,{64} <0,1,2,3,4,5,6>
Cluster 2: No,No,No,No,No,Yes,No,No,No,No,No,No,No,No,No,No,No,Yes,No,No,No,No,No,No,Yes,68.0002,No,Yes,No,No,No,No,No,No,No,No,No,No,Yes,Yes,No,Yes,No,Yes,No,No,No,No,Yes,No,No,Yes,No,No,No,No,No,No,No,Yes,No,No,No,No,Yes,{5} <0,1,2,3,4,5,6>

<u>Cluster 3:</u> No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,No,Yes,No,No,No,No, No,Yes,73.152483,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,No,No,No,No ,No,No,No,Yes,No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,{11} <0,1,2,3,4,5,6>
<u>Cluster 4:</u> No,No,No,No,No,No,Yes,Yes,No,No,No,No,No,No,No,No,No,No,Yes,Yes,No,No,N o,No,Yes,150.001,Yes,No,No,No,No,Yes,No,No,No,No,No,No,Yes,Yes,Yes,Yes,Ye s,Yes,Yes,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,Yes,Yes,No,No,No,Ye s,{4} <0,1,2,3,4,5,6>
<u>Cluster 5:</u> No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,Yes,No,No,No,No,No, No,Yes,94.042603,No,Yes,No,No,No,No,No,Yes,No,No,No,No,No,Yes,No,No,No,N o,No,No,No,No,Yes,No,No,No,No,No,No,No,No,No,Yes,No,No,No,No,No,Yes,{12 } <0,1,2,3,4,5,6>
<u>Cluster 6:</u> No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,No,Yes,Yes,No,No,No,No,No, No,Yes,109.042519,No,Yes,No,No,No,No,No,Yes,No,No,No,Yes,No,Yes,Yes,Yes,Y es,No,Yes,No,No,Yes,No,No,Yes,Yes,No,No,No,No,No,No,Yes,Yes,No,No,No,No, Yes,{4} <0,1,2,3,4,5,6>

Each “Yes/No” answer in each question (Car superseding ability, motorbike superseding ability etc..) is the centroid of all the answers that the customers have answered (in that specific question).

APPENDIX 3: Large Super Market in Greece

Product Categories’ Codes Translated

Product Categories’ Codes	Product Categories’ Names
011A01	PASTA
011A02	FOOD
011A03	BREADS
011A04	PASTRIES/SWEETS
011AAY	BREADS
011AAF	BREADS
011AAX	RUSKS/RUSKS
011AAC	RUSKS/RUSKS
011AAV	RUSKS/RUSKS

012G01	OTHER - MAINTENANCE
012GZ5	OTHER - MAINTENANCE
012D04	FROZENS
012DBA	FROZENS
012DBB	FROZENS
012DZ5	FROZENS
012DF0	FROZENS
012DF3	FROZENS
021A05	RICE/PULSES
021A06	RICE/PULSES
021E05	RICE/PULSES
021E06	RICE/PULSES
031A07	FOOD
031A68	FOOD
031A73	FOOD
031A74	FOOD
041A08	BISCUITS
041A09	PASTRIES/SWEETS
041A16	BREAKFAST ITEMS
041A17	BREAKFAST ITEMS
041A18	PASTRIES/SWEETS
041A19	PASTRIES/SWEETS
041A20	PASTRIES/SWEETS
041A21	PASTRIES/SWEETS
041A22	PASTRIES/SWEETS
041A23	PASTRIES/SWEETS
041A25	CHOCOLATES
041A26	CHOCOLATES
041A27	CANDIES/GUMS
041A28	CANDIES/GUMS
041AC2	PASTRIES/SWEETS
042G19	OTHER - MAINTENANCE
042D21	FROZENS
042DZ3	FROZENS
042E20	OTHER - DRAINING BENCHES
051A10	BREAKFAST CEREALS
051A29	BREAKFAST ITEMS
051A30	BREAKFAST ITEMS
051A33	TEAS/JUICES - SHELF
051A34	BREAKFAST ITEMS
061A11	SHELF STABLE MILK
062G11	MILK - MAINTENANCE
062G12	YOGHURTS

062G14	DESSERTS/CREAMS GAL.
062GX0	DESSERTS/CREAMS GAL.
062GC5	DESSERTS/CREAMS GAL.
062GC9	DESSERTS/CREAMS GAL.
062E12	YOGHURTS
071A15	FOOD
081A24	FOOD
082G24	OTHER - MAINTENANCE
091A31	COFFEE
091BBN	HOUSEHOLD
092G31	COFFEE
092E31	COFFEE
101A37	COMPOSTERS/PRESERVES/TOMATOES
102D35	FROZENS
102E35	VEGETABLES
111A36	COMPOSTERS/PRESERVES/TOMATOES
112E40	FRUITS
121A38	FOOD
121A39	KETCHUP/MAYONEZA/MUSTARD
121A64	KETCHUP/MAYONEZA/MUSTARD
121A65	KETCHUP/MAYONEZA/MUSTARD
121A67	FOOD
121AZ4	FOOD
122G63	OTHER - MAINTENANCE
122G67	OTHER - MAINTENANCE
131A41	COMPOSTERS/PRESERVES/TOMATOES
132G41	OTHER - MAINTENANCE
132D41	FROZENS
141A42	OILS
141A43	BUTTER/MARGARINES
141ABG	OILS
141ABD	OILS
142G44	BUTTER/MARGARINES
142G45	BUTTER/MARGARINES
142E45	BUTTER/MARGARINES
152G46	SAUSAGES
152GY0	SAUSAGES
152E46	SAUSAGES
162G50	CHEESES - PRESERVATION
162EJ2	CHEESES - DRAINING BENCHES
172G51	OTHER - MAINTENANCE
172GM6	OTHER - MAINTENANCE
172E51	OTHER - DRAINING BENCHES

172EJ3	OTHER - DRAINING BENCHES
182G52	OTHER - MAINTENANCE
182E52	OTHER - DRAINING BENCHES
191A53	FOOD
192E53	OTHER - DRAINING BENCHES
201A54	FOOD
202G54	OTHER - MAINTENANCE
202E54	OTHER - DRAINING BENCHES
212D55	FROZENS
212D56	FROZENS
212E55	FRESH FISH/MOLLUSCS
212E56	FRESH FISH/MOLLUSCS
222G59	DAMP POULTRY
222D58	FROZENS
222D59	FROZENS
222D62	FROZENS
222E57	FRESH BEEF
222E58	DAMP PORK
222E59	DAMP POULTRY
222E60	DAMP POULTRY
222E61	DAMPMEAT- LAMBS/OTHER
222E62	DAMPS MEAT- LAMBS/OTHER
222EY1	DAMP POULTRY
231A66	EGGS
241A08	BISCUITS
241A70	CORN PUFF SNACK/CHIPS
241A71	CORN PUFF SNACK/CHIPS
241A72	FOOD
242E72	OTHER - DRAINING BENCHES
251A33	KAVA NON-ALCOHOLIC/TEA/JUICES
251A75	KAVA NON-ALCOHOLIC/WATER
251A76	KAVA NON-ALCOHOLIC/SOFT DRINKS
251AX3	KAVA NON-ALCOHOLIC/SOFT DRINKS
251AX4	KAVA NON-ALCOHOLIC/SOFT DRINKS
251AX5	KAVA NON-ALCOHOLIC/TEA/JUICES
252G33	TEAS/JUICES - MAINTENANCE
252G76	OTHER - MAINTENANCE
252GX5	TEAS/JUICES - MAINTENANCE
261A77	KAVA ALCOHOL/BEERS
261A78	KAVA ALCOHOL/WINES
261A79	KAVA ALCOHOL/DRINKS
261A80	KAVA ALCOHOL/DRINKS
261A81	KAVA ALCOHOL/DRINKS

261A82	KAVA ALCOHOL/DRINKS
261A83	KAVA ALCOHOL/DRINKS
261A84	KAVA ALCOHOL/DRINKS
261A85	KAVA ALCOHOL/DRINKS
261A86	KAVA ALCOHOL/DRINKS
261A88	KAVA ALCOHOL/DRINKS
261AZ7	KAVA ALCOHOL/DRINKS
261AX4	KAVA ALCOHOL/DRINKS
281BB1	TYPES OF PHYSICAL HEALTH
281BD9	TYPES OF PHYSICAL HEALTH
281BE1	TYPES OF PHYSICAL HEALTH
281BS7	TYPES OF PHYSICAL HEALTH
281BS8	TYPES OF PHYSICAL HEALTH
281BS9	TYPES OF PHYSICAL HEALTH
281BT0	TYPES OF PHYSICAL HEALTH
281BT3	TYPES OF PHYSICAL HEALTH
291BA4	TYPES OF PHYSICAL HEALTH
291BA8	TYPES OF PHYSICAL HEALTH
291BC4	TYPES OF PHYSICAL HEALTH
301BB2	DETERGENTS
301BB3	DETERGENTS
301BB4	DETERGENTS
301BB5	DETERGENTS
301BG1	DETERGENTS
301BT2	DETERGENTS
311BA8	DETERGENTS
311BB6	DETERGENTS
321BB7	DETERGENTS
321BB8	DETERGENTS
331BB9	HOUSEHOLD
331BY5	HOUSEHOLD
341BG3	HOUSEHOLD
341BG4	HOUSEHOLD
351BG8	HOUSEHOLD
351BG9	HOUSEHOLD
351BD1	HOUSEHOLD
351BD2	HOUSEHOLD
351BD3	HOUSEHOLD
351BD5	HOUSEHOLD
361BBL	HOUSEHOLD
361BG2	DETERGENTS
361BG5	HOUSEHOLD
361BG6	HOUSEHOLD

361BG7	HOUSEHOLD
361BD4	HOUSEHOLD
361BD6	BAZAAR
361BD8	HOUSEHOLD
361BM5	HOUSEHOLD
361BY4	HOUSEHOLD
361BY6	HOUSEHOLD
371AE2	ANIMAL FEEDS-ACCESSORIES
371BE3	ANIMAL FEEDS-ACCESSORIES
381BE4	PAPER
381BE5	PAPER
381BE6	PAPER
381BE7	PAPER
391BE8	SMOKER'S ITEMS
401BE9	BAZAAR
401BZ1	HOUSEHOLD
411A14	BABY FOOD
411AZ2	BABY FOOD
423ZH1	BAZAAR
423ZH2	BAZAAR
433ZBM	BAZAAR
433ZH1	BAZAAR
433ZH2	BAZAAR
433ZH3	BAZAAR
433ZH5	BAZAAR
463HH1	BAZAAR
463HH2	BAZAAR
463HH3	BAZAAR
463HH4	BAZAAR
463HH5	BAZAAR
473UH1	BAZAAR
473UH2	BAZAAR
473UH3	BAZAAR
473UH4	BAZAAR
483IH6	BAZAAR
483IH7	BAZAAR
483IH8	BAZAAR
483IH9	BAZAAR
493KU1	BAZAAR
493KU2	BAZAAR
503KU4	HOUSEHOLD
503KU5	BAZAAR
503KU6	BAZAAR

503KU7	BAZAAR
513KU8	BAZAAR
513KU9	HOUSEHOLD
533LI1	GAMES
543LI3	GAMES
553LH4	GAMES
563LI5	GAMES
563LI6	GAMES
573LI7	GAMES
573LI8	GAMES
583LI9	GAMES
583LK1	GAMES
603MK6	BAZAAR
613MK7	BAZAAR
623MK8	BAZAAR
633NK9	BAZAAR
633NX7	HOUSEHOLD
643NL1	BAZAAR
653NL2	BAZAAR
663NL3	BAZAAR
673NL4	BAZAAR
673NL5	BAZAAR
673NN9	BAZAAR
683JL5	BAZAAR
693JL5	BAZAAR
693JL7	BAZAAR
693JL8	BAZAAR
703JL5	BAZAAR
723PM2	BAZAAR
733PM3	BAZAAR
733PN8	HOUSEHOLD
743PM4	BAZAAR
751BT8	XMCODE OUT OF CATEGORIES
761AN1	FOOD
762GN1	OTHER - MAINTENANCE
771BN2	BAZAAR
783RN5	BAZAAR
783RN6	BAZAAR
793SB0	BAZAAR
793SG0	BAZAAR
793SD0	BAZAAR
803TA0	BAZAAR
803TBJ	XMCODE OUT OF CATEGORIES

811BAP	BODY/HAND COSMETICS
811BAS	TYPES OF PHYSICAL HEALTH
811BJ4	BATH FOAMS/SHAMPOO/SOFTENERS
811BJ6	BATH FOAMS/SHAMPOO/SOFTENERS
811BJ7	BATH FOAMS/SHAMPOO/SOFTENERS
811BJ9	BATH FOAMS/SHAMPOO/SOFTENERS
811BO1	BODY/HAND COSMETICS
811BO2	BODY/HAND COSMETICS
811BO3	BODY/HAND COSMETICS
811BO4	BODY/HAND COSMETICS
811BO5	BODY/HAND COSMETICS
811BO6	BODY/HAND COSMETICS
811BO8	BODY/HAND COSMETICS
811BO9	BODY/HAND COSMETICS
811BP0	BODY/HAND COSMETICS
811BP1	BODY/HAND COSMETICS
811BP2	TYPES OF PHYSICAL HEALTH
811BP3	TYPES OF PHYSICAL HEALTH
821BA5	FACE/HEAD COSMETICS
821BO4	FACE/HEAD COSMETICS
821BP6	FACE/HEAD COSMETICS
821BP7	FACE/HEAD COSMETICS
831B90	BATH FOAMS/SHAMPOO/SOFTENERS
831BA7	FACE/HEAD COSMETICS
831BP8	BATH FOAMS/SHAMPOO/SOFTENERS
831BP9	BATH FOAMS/SHAMPOO/SOFTENERS
831BR1	FACE/HEAD COSMETICS
831BR2	FACE/HEAD COSMETICS
831BC8	FACE/HEAD COSMETICS
841BO4	BODY/HAND COSMETICS
841BR4	TYPES OF PHYSICAL HEALTH
841BR5	TYPES OF PHYSICAL HEALTH
841BR6	BODY/HAND COSMETICS
851BR7	TYPES OF ORAL HEALTH
851BR8	TYPES OF ORAL HEALTH
851BR9	TYPES OF ORAL HEALTH
851BS0	TYPES OF ORAL HEALTH
851BS1	FACE/HEAD COSMETICS
851BS2	TYPES OF ORAL HEALTH
851BS3	TYPES OF ORAL HEALTH
851BX2	TYPES OF ORAL HEALTH
861B98	FACE/HEAD COSMETICS
861BS4	FACE/HEAD COSMETICS

861BS6	FACE/HEAD COSMETICS
861BT6	HOUSEHOLD
861BC0	BODY/HAND COSMETICS
873TY8	BAZAAR
902DX6	FROZENS
913HX8	BAZAAR
923JC1	BAZAAR
933JC6	BAZAAR
943XC7	BAZAAR
943XV1	BAZAAR
951A01	PASTA
951A02	FOOD
951A04	PASTRIES/SWEETS
951A05	RICE/PULSES
951A06	RICE/PULSES
951A07	FOOD
951A10	BREAKFAST CEREALS
951A15	FOOD
951A16	BREAKFAST ITEMS
951A22	PASTRIES/SWEETS
951A23	PASTRIES/SWEETS
951A26	CHOCOLATES
951A37	COMPOSTERS/PRESERVES/TOMATOES
951A38	FOOD
951A39	KETCHUP/MAYONEZA/MUSTARD
951A41	COMPOSTERS/PRESERVES/TOMATOES
951A42	OILS
951A52	FOOD
951A53	FOOD
951A54	FOOD
951A64	KETCHUP/MAYONEZA/MUSTARD
951A67	FOOD
951A69	FOOD
951A71	FOOD
951A72	FOOD
951A77	KAVA ALCOHOL/WINES
951A78	KAVA ALCOHOL/WINES
951AN1	BREAKFAST ITEMS
951AX4	ALOE VERA BEVERAGE
952G11	MILK - MAINTENANCE
952G12	YOGHURTS
952G44	BUTTER/MARGARINES
952G45	BUTTER/MARGARINES

952G46	SAUSAGES
952G50	CHEESES - PRESERVATION
952G77	TEAS/JUICES - MAINTENANCE
952GX5	FROZENS
952D35	FROZENS
952EJ2	CHEESES - DRAINING BENCHES
963CV0	XMCODE OUT OF CATEGORIES
AA1A54	FOOD
AA1A72	FOOD
AB1A05	RICE/PULSES
AB1A11	SHELF STABLE MILK
AB1A35	COMPOSTERS/PRESERVES/TOMATOES
AB1A38	FOOD
AB1AAR	PASTA
AB1AT6	FOOD
AH1BBC	SMOKER'S ITEMS
AK2E04	BAKE OFF / HOT CORNER
AK2E59	BAKE OFF / HOT CORNER
AK2EBH	BAKE OFF / HOT CORNER
AK2EBU	BAKE OFF / HOT CORNER
AK2EBI	BAKE OFF / HOT CORNER
AK2EBV	BAKE OFF / HOT CORNER
AT1AAT	XMCODE OUT OF CATEGORIES

Error! Reference source not found.

=== Clustering model (full training set) ===

Simple K Means with 2 Clusters

Number of iterations: 2
Within cluster sum of squared errors: **11112.0**

Missing values globally replaced with mean/mode

Final cluster centroids:

```
                           Cluster#
Attribute     Full Data          0          1
                (108.0)      (7.0)    (101.0)
 ============================================
GENDER            WOMAN      WOMAN      WOMAN
AGE                  32         38         32
011A01                2         81          2
011A02                1         33          1
011A03                1          1          1
```

011A04	1	1	1
011AAY	1	45	1
011AAF	1	96	1
011AAX	3	13	3
011AAC	2	15	2
011AAV	2	2	2
012G01	1	1	1
012GZ5	1	1	1
012D04	1	1	1
012DBA	1	11	1
012DBB	1	1	1
012DZ5	1	2	1
012DF0	1	2	1
012DF3	1	8	1
021A05	2	31	2
021A06	1	14	1
021E05	1	2	1
021E06	1	1	1
031A07	1	27	1
031A68	1	17	1
031A73	1	26	1
031A74	1	1	1
041A08	3	69	3
041A09	1	1	1
041A16	1	1	1
041A17	1	3	1
041A18	1	1	1
041A19	1	1	1
041A20	1	1	1
041A21	1	56	1
041A22	1	1	1
041A23	1	14	1
041A25	1	72	1
041A26	1	12	1
041A27	1	12	1
041A28	2	19	2
041AC2	2	5	2
042G19	1	1	1
042D21	1	1	1
042DZ3	1	14	1
042E20	1	1	1
051A10	1	35	1
051A29	1	10	1
051A30	1	1	1
051A33	1	1	1
051A34	1	8	1
061A11	4	13	4
062G11	3	119	3
062G12	1	84	1
062G14	1	10	1
062GX0	1	1	1
062GC5	1	37	1
062GC9	1	1	1
062E12	2	2	2
071A15	1	29	1
081A24	5	42	5
082G24	1	5	1
091A31	2	61	2

091BBN	1	1	1
092G31	1	1	1
092E31	2	17	2
101A37	4	52	4
102D35	1	18	1
102E35	1	214	1
111A36	1	1	1
112E40	11	120	11
121A38	1	3	1
121A39	1	6	1
121A64	1	16	1
121A65	1	9	1
121A67	1	8	1
121AZ4	1	2	1
122G63	2	2	2
122G67	1	1	1
131A41	2	24	2
132G41	1	1	1
132D41	1	14	1
141A42	1	1	1
141A43	1	8	1
141ABG	1	1	1
141ABD	1	14	1
142G44	1	17	1
142G45	2	15	2
142E45	1	1	1
152G46	2	41	2
152GY0	1	1	1
152E46	4	74	4
162G50	1	66	1
162EJ2	1	142	1
172G51	1	1	1
172GM6	1	1	1
172E51	1	2	1
172EJ3	1	1	1
182G52	1	5	1
182E52	1	5	1
191A53	1	1	1
192E53	1	4	1
201A54	1	1	1
202G54	1	1	1
202E54	2	2	2
212D55	1	7	1
212D56	1	7	1
212E55	1	2	1
212E56	2	2	2
222G59	1	2	1
222D58	1	1	1
222D59	1	9	1
222D62	1	1	1
222E57	1	35	1
222E58	1	26	1
222E59	5	35	5
222E60	2	2	2
222E61	2	5	2
222E62	1	1	1
222EY1	1	2	1
231A66	2	51	2

241A08	1	19	1
241A70	1	8	1
241A71	2	40	2
241A72	1	12	1
242E72	1	5	1
251A33	1	8	1
251A75	8	108	8
251A76	1	10	1
251AX3	2	4	2
251AX4	3	54	3
251AX5	1	21	1
252G33	1	1	1
252G76	1	1	1
252GX5	1	9	1
261A77	1	21	1
261A78	1	18	1
261A79	1	1	1
261A80	1	1	1
261A81	1	1	1
261A82	1	1	1
261A83	1	1	1
261A84	1	1	1
261A85	1	1	1
261A86	1	1	1
261A88	1	1	1
261AZ7	1	1	1
261AX4	1	1	1
281BB1	2	9	2
281BD9	1	1	1
281BE1	1	6	1
281BS7	1	8	1
281BS8	1	3	1
281BS9	1	8	1
281BT0	1	1	1
281BT3	1	1	1
291BA4	1	5	1
291BA8	1	22	1
291BC4	1	1	1
301BB2	1	37	1
301BB3	1	22	1
301BB4	2	38	2
301BB5	1	19	1
301BG1	1	1	1
301BT2	1	1	1
311BA8	1	1	1
311BB6	1	3	1
321BB7	1	1	1
321BB8	1	6	1
331BB9	1	1	1
331BY5	1	1	1
341BG3	1	14	1
341BG4	1	6	1
351BG8	1	6	1
351BG9	1	4	1
351BD1	1	2	1
351BD2	1	1	1
351BD3	1	6	1
351BD5	1	11	1

361BBL	1	5	1
361BG2	1	1	1
361BG5	1	15	1
361BG6	1	1	1
361BG7	3	25	3
361BD4	1	1	1
361BD6	1	1	1
361BD8	1	2	1
361BM5	1	15	1
361BY4	1	1	1
361BY6	1	2	1
371AE2	1	9	1
371BE3	1	2	1
381BE4	2	21	2
381BE5	1	28	1
381BE6	2	23	2
381BE7	1	25	1
391BE8	1	27	1
401BE9	1	7	1
401BZ1	1	1	1
411A14	1	1	1
411AZ2	1	1	1
423ZH1	1	1	1
423ZH2	1	1	1
433ZBM	1	1	1
433ZH1	1	1	1
433ZH2	1	4	1
433ZH3	1	1	1
433ZH5	1	1	1
463HH1	1	1	1
463HH2	1	1	1
463HH3	1	8	1
463HH4	1	1	1
463HH5	1	1	1
473UH1	1	1	1
473UH2	1	3	1
473UH3	1	1	1
473UH4	1	1	1
483IH6	1	9	1
483IH7	1	2	1
483IH8	1	1	1
483IH9	1	4	1
493KU1	1	1	1
493KU2	1	1	1
503KU4	1	22	1
503KU5	1	1	1
503KU6	1	1	1
503KU7	1	3	1
513KU8	1	1	1
513KU9	1	3	1
533LI1	1	1	1
543LI3	1	1	1
553LH4	1	1	1
563LI5	1	1	1
563LI6	1	1	1
573LI7	1	1	1
573LI8	1	1	1
583LI9	1	1	1

583LK1	1	1	1
603MK6	1	1	1
613MK7	1	1	1
623MK8	1	1	1
633NK9	1	4	1
633NX7	2	11	2
643NL1	1	5	1
653NL2	1	5	1
663NL3	2	8	2
673NL4	1	5	1
673NL5	1	1	1
673NN9	1	4	1
683JL5	1	1	1
693JL5	1	1	1
693JL7	1	1	1
693JL8	1	1	1
703JL5	1	5	1
723PM2	1	1	1
733PM3	1	1	1
733PN8	1	1	1
743PM4	1	1	1
751BT8	1	1	1
761AN1	1	23	1
762GN1	1	21	1
771BN2	1	1	1
783RN5	1	1	1
783RN6	1	1	1
793SB0	1	1	1
793SG0	1	1	1
793SD0	1	3	1
803TA0	1	1	1
803TBJ	1	1	1
811BAP	1	4	1
811BAS	1	2	1
811BJ4	1	8	1
811BJ6	1	1	1
811BJ7	2	4	2
811BJ9	1	1	1
811BO1	1	4	1
811BO2	1	9	1
811BO3	1	1	1
811BO4	1	7	1
811BO5	1	1	1
811BO6	1	1	1
811BO8	1	1	1
811BO9	1	1	1
811BP0	1	2	1
811BP1	1	1	1
811BP2	2	4	2
811BP3	1	1	1
821BA5	1	1	1
821BO4	1	2	1
821BP6	1	13	1
821BP7	1	1	1
831B90	2	15	2
831BA7	1	10	1
831BP8	1	4	1
831BP9	1	11	1

831BR1	1	5	1
831BR2	1	1	1
831BC8	1	1	1
841BO4	1	1	1
841BR4	1	2	1
841BR5	1	7	1
841BR6	1	1	1
851BR7	1	21	1
851BR8	1	1	1
851BR9	1	1	1
851BS0	1	1	1
851BS1	1	1	1
851BS2	1	7	1
851BS3	1	1	1
851BX2	1	1	1
861B98	1	2	1
861BS4	1	3	1
861BS6	1	4	1
861BT6	1	3	1
861BC0	1	1	1
873TY8	1	1	1
902DX6	1	1	1
913HX8	1	1	1
923JC1	1	1	1
933JC6	1	1	1
943XC7	1	2	1
943XV1	1	1	1
951A01	1	1	1
951A02	1	1	1
951A04	1	1	1
951A05	1	1	1
951A06	1	1	1
951A07	1	1	1
951A10	1	1	1
951A15	1	1	1
951A16	1	1	1
951A22	1	1	1
951A23	1	1	1
951A26	1	1	1
951A37	1	1	1
951A38	2	2	2
951A39	1	1	1
951A41	1	1	1
951A42	1	1	1
951A52	1	1	1
951A53	2	2	2
951A54	1	1	1
951A64	1	1	1
951A67	1	1	1
951A69	5	5	5
951A71	1	1	1
951A72	1	3	1
951A77	1	1	1
951A78	1	1	1
951AN1	1	1	1
951AX4	1	1	1
952G11	1	9	1
952G12	1	1	1

952G44	1	1	1
952G45	1	1	1
952G46	1	1	1
952G50	1	1	1
952G77	1	1	1
952GX5	1	1	1
952D35	1	2	1
952EJ2	1	1	1
963CV0	3	200	3
AA1A54	1	1	1
AA1A72	1	1	1
AB1A05	1	1	1
AB1A11	1	1	1
AB1A35	1	1	1
AB1A38	1	2	1
AB1AAR	1	1	1
AB1AT6	1	1	1
AH1BBC	1	8	1
AK2E04	1	1	1
AK2E59	1	1	1
AK2EBH	1	1	1
AK2EBU	1	1	1
AK2EBI	1	1	1
AK2EBV	1	1	1
AT1AAT	1	1	1

=== Model and evaluation on training set ===

Clustered Instances

0 7 (6%)
1 101 (94%)

Simple K Means with 3 Clusters

Number of iterations: 2
Within cluster sum of squared errors: 11051.0

Missing values globally replaced with mean/mode

Final cluster centroids:

		Cluster#		
Attribute	Full Data (108.0)	0 (7.0)	1 (99.0)	2 (2.0)
GENDER	WOMAN	WOMAN	WOMAN	WOMAN
AGE	32	38	32	41
011A01	2	81	2	4
011A02	1	33	1	9
011A03	1	1	1	1
011A04	1	1	1	1
011AAY	1	45	1	8
011AAF	1	96	1	1

011AAX	3	13	3	2
011AAC	2	15	2	4
011AAV	2	2	2	2
012G01	1	1	1	3
012GZ5	1	1	1	1
012D04	1	1	1	1
012DBA	1	11	1	1
012DBB	1	1	1	1
012DZ5	1	2	1	1
012DF0	1	2	1	1
012DF3	1	8	1	1
021A05	2	31	2	3
021A06	1	14	1	1
021E05	1	2	1	1
021E06	1	1	1	1
031A07	1	27	1	2
031A68	1	17	1	1
031A73	1	26	1	1
031A74	1	1	1	1
041A08	3	69	3	4
041A09	1	1	1	1
041A16	1	1	1	1
041A17	1	3	1	1
041A18	1	1	1	1
041A19	1	1	1	1
041A20	1	1	1	1
041A21	1	56	1	1
041A22	1	1	1	1
041A23	1	14	1	1
041A25	1	72	1	8
041A26	1	12	1	1
041A27	1	12	1	1
041A28	2	19	2	2
041AC2	2	5	2	3
042G19	1	1	1	1
042D21	1	1	1	1
042DZ3	1	14	1	2
042E20	1	1	1	1
051A10	1	35	1	1
051A29	1	10	1	1
051A30	1	1	1	1
051A33	1	1	1	1
051A34	1	8	1	1
061A11	4	13	4	7
062G11	3	119	3	20
062G12	1	84	1	17
062G14	1	10	1	2
062GX0	1	1	1	1
062GC5	1	37	1	1
062GC9	1	1	1	1
062E12	2	2	2	1
071A15	1	29	1	8
081A24	5	42	5	10
082G24	1	5	1	4
091A31	2	61	2	3
091BBN	1	1	1	1
092G31	1	1	1	1
092E31	2	17	2	2

101A37	4	52	4	4
102D35	1	18	1	7
102E35	1	214	1	34
111A36	1	1	1	1
112E40	11	120	11	39
121A38	1	3	1	1
121A39	1	6	1	1
121A64	1	16	1	1
121A65	1	9	1	1
121A67	1	8	1	3
121AZ4	1	2	1	1
122G63	2	2	2	2
122G67	1	1	1	1
131A41	2	24	2	7
132G41	1	1	1	1
132D41	1	14	1	1
141A42	1	1	1	1
141A43	1	8	1	1
141ABG	1	1	1	1
141ABD	1	14	1	1
142G44	1	17	1	1
142G45	2	15	2	2
142E45	1	1	1	1
152G46	2	41	2	10
152GY0	1	1	1	1
152E46	4	74	4	8
162G50	1	66	1	6
162EJ2	1	142	1	22
172G51	1	1	1	1
172GM6	1	1	1	1
172E51	1	2	1	2
172EJ3	1	1	1	1
182G52	1	5	1	1
182E52	1	5	1	1
191A53	1	1	1	1
192E53	1	4	1	4
201A54	1	1	1	1
202G54	1	1	1	1
202E54	2	2	2	2
212D55	1	7	1	7
212D56	1	7	1	2
212E55	1	2	1	1
212E56	2	2	2	2
222G59	1	2	1	1
222D58	1	1	1	1
222D59	1	9	1	1
222D62	1	1	1	1
222E57	1	35	1	10
222E58	1	26	1	10
222E59	5	35	5	15
222E60	2	2	2	2
222E61	2	5	2	1
222E62	1	1	1	1
222EY1	1	2	1	1
231A66	2	51	2	8
241A08	1	19	1	1
241A70	1	8	1	3
241A71	2	40	2	13

241A72	1	12	1	4
242E72	1	5	1	1
251A33	1	8	1	1
251A75	8	108	8	21
251A76	1	10	1	1
251AX3	2	4	2	2
251AX4	3	54	3	17
251AX5	1	21	1	19
252G33	1	1	1	1
252G76	1	1	1	1
252GX5	1	9	1	2
261A77	1	21	1	1
261A78	1	18	1	1
261A79	1	1	1	1
261A80	1	1	1	1
261A81	1	1	1	1
261A82	1	1	1	1
261A83	1	1	1	1
261A84	1	1	1	1
261A85	1	1	1	1
261A86	1	1	1	1
261A88	1	1	1	1
261AZ7	1	1	1	1
261AX4	1	1	1	1
281BB1	2	9	2	2
281BD9	1	1	1	1
281BE1	1	6	1	1
281BS7	1	8	1	2
281BS8	1	3	1	1
281BS9	1	8	1	1
281BT0	1	1	1	1
281BT3	1	1	1	1
291BA4	1	5	1	1
291BA8	1	22	1	1
291BC4	1	1	1	1
301BB2	1	37	1	2
301BB3	1	22	1	1
301BB4	2	38	2	4
301BB5	1	19	1	1
301BG1	1	1	1	1
301BT2	1	1	1	1
311BA8	1	1	1	1
311BB6	1	3	1	1
321BB7	1	1	1	1
321BB8	1	6	1	6
331BB9	1	1	1	1
331BY5	1	1	1	1
341BG3	1	14	1	1
341BG4	1	6	1	1
351BG8	1	6	1	1
351BG9	1	4	1	1
351BD1	1	2	1	1
351BD2	1	1	1	1
351BD3	1	6	1	1
351BD5	1	11	1	1
361BBL	1	5	1	1
361BG2	1	1	1	1
361BG5	1	15	1	2

361BG6	1	1	1	1
361BG7	3	25	3	3
361BD4	1	1	1	1
361BD6	1	1	1	1
361BD8	1	2	1	1
361BM5	1	15	1	1
361BY4	1	1	1	1
361BY6	1	2	1	1
371AE2	1	9	1	2
371BE3	1	2	1	1
381BE4	2	21	2	2
381BE5	1	28	1	5
381BE6	2	23	2	5
381BE7	1	25	1	1
391BE8	1	27	1	1
401BE9	1	7	1	1
401BZ1	1	1	1	1
411A14	1	1	1	1
411AZ2	1	1	1	1
423ZH1	1	1	1	1
423ZH2	1	1	1	1
433ZBM	1	1	1	1
433ZH1	1	1	1	1
433ZH2	1	4	1	1
433ZH3	1	1	1	1
433ZH5	1	1	1	1
463HH1	1	1	1	1
463HH2	1	1	1	1
463HH3	1	8	1	1
463HH4	1	1	1	1
463HH5	1	1	1	1
473UH1	1	1	1	1
473UH2	1	3	1	1
473UH3	1	1	1	1
473UH4	1	1	1	1
483IH6	1	9	1	1
483IH7	1	2	1	1
483IH8	1	1	1	1
483IH9	1	4	1	1
493KU1	1	1	1	1
493KU2	1	1	1	1
503KU4	1	22	1	2
503KU5	1	1	1	1
503KU6	1	1	1	1
503KU7	1	3	1	1
513KU8	1	1	1	1
513KU9	1	3	1	1
533LI1	1	1	1	1
543LI3	1	1	1	1
553LH4	1	1	1	1
563LI5	1	1	1	1
563LI6	1	1	1	1
573LI7	1	1	1	1
573LI8	1	1	1	1
583LI9	1	1	1	1
583LK1	1	1	1	1
603MK6	1	1	1	1
613MK7	1	1	1	1

623MK8	1	1	1	1
633NK9	1	4	1	1
633NX7	2	11	2	2
643NL1	1	5	1	1
653NL2	1	5	1	1
663NL3	2	8	2	2
673NL4	1	5	1	1
673NL5	1	1	1	1
673NN9	1	4	1	1
683JL5	1	1	1	1
693JL5	1	1	1	1
693JL7	1	1	1	1
693JL8	1	1	1	1
703JL5	1	5	1	1
723PM2	1	1	1	1
733PM3	1	1	1	1
733PN8	1	1	1	1
743PM4	1	1	1	1
751BT8	1	1	1	1
761AN1	1	23	1	1
762GN1	1	21	1	1
771BN2	1	1	1	1
783RN5	1	1	1	1
783RN6	1	1	1	1
793SB0	1	1	1	1
793SG0	1	1	1	1
793SD0	1	3	1	1
803TA0	1	1	1	1
803TBJ	1	1	1	1
811BAP	1	4	1	1
811BAS	1	2	1	1
811BJ4	1	8	1	1
811BJ6	1	1	1	1
811BJ7	2	4	2	2
811BJ9	1	1	1	1
811BO1	1	4	1	1
811BO2	1	9	1	1
811BO3	1	1	1	1
811BO4	1	7	1	1
811BO5	1	1	1	1
811BO6	1	1	1	1
811BO8	1	1	1	1
811BO9	1	1	1	1
811BP0	1	2	1	1
811BP1	1	1	1	1
811BP2	2	4	2	2
811BP3	1	1	1	1
821BA5	1	1	1	1
821BO4	1	2	1	1
821BP6	1	13	1	1
821BP7	1	1	1	1
831B90	2	15	2	2
831BA7	1	10	1	1
831BP8	1	4	1	1
831BP9	1	11	1	1
831BR1	1	5	1	1
831BR2	1	1	1	1
831BC8	1	1	1	1

841BO4	1	1	1	1
841BR4	1	2	1	1
841BR5	1	7	1	1
841BR6	1	1	1	1
851BR7	1	21	1	2
851BR8	1	1	1	1
851BR9	1	1	1	1
851BS0	1	1	1	1
851BS1	1	1	1	1
851BS2	1	7	1	1
851BS3	1	1	1	1
851BX2	1	1	1	1
861B98	1	2	1	1
861BS4	1	3	1	1
861BS6	1	4	1	1
861BT6	1	3	1	1
861BC0	1	1	1	1
873TY8	1	1	1	1
902DX6	1	1	1	1
913HX8	1	1	1	1
923JC1	1	1	1	1
933JC6	1	1	1	1
943XC7	1	2	1	1
943XV1	1	1	1	1
951A01	1	1	1	1
951A02	1	1	1	1
951A04	1	1	1	1
951A05	1	1	1	1
951A06	1	1	1	1
951A07	1	1	1	1
951A10	1	1	1	1
951A15	1	1	1	1
951A16	1	1	1	1
951A22	1	1	1	1
951A23	1	1	1	1
951A26	1	1	1	1
951A37	1	1	1	1
951A38	2	2	2	2
951A39	1	1	1	1
951A41	1	1	1	1
951A42	1	1	1	1
951A52	1	1	1	1
951A53	2	2	2	2
951A54	1	1	1	1
951A64	1	1	1	1
951A67	1	1	1	1
951A69	5	5	5	5
951A71	1	1	1	1
951A72	1	3	1	1
951A77	1	1	1	1
951A78	1	1	1	1
951AN1	1	1	1	1
951AX4	1	1	1	1
952G11	1	9	1	1
952G12	1	1	1	1
952G44	1	1	1	1
952G45	1	1	1	1
952G46	1	1	1	1

952G50	1	1	1	1
952G77	1	1	1	1
952GX5	1	1	1	1
952D35	1	2	1	1
952EJ2	1	1	1	1
963CV0	3	200	3	6
AA1A54	1	1	1	1
AA1A72	1	1	1	1
AB1A05	1	1	1	1
AB1A11	1	1	1	1
AB1A35	1	1	1	1
AB1A38	1	2	1	1
AB1AAR	1	1	1	1
AB1AT6	1	1	1	1
AH1BBC	1	8	1	1
AK2E04	1	1	1	1
AK2E59	1	1	1	1
AK2EBH	1	1	1	1
AK2EBU	1	1	1	1
AK2EBI	1	1	1	1
AK2EBV	1	1	1	1
AT1AAT	1	1	1	1

=== Model and evaluation on training set ===

Clustered Instances

0 7 (6%)
1 99 (92%)
2 2 (2%)

<u>Simple K Means with 4 Clusters</u>

Number of iterations: 7
Within cluster sum of squared errors: 10605.0

Missing values globally replaced with mean/mode

Final cluster centroids:

		Cluster#			
Attribute	Full Data	0	1	2	3
	(108.0)	(8.0)	(87.0)	(12.0)	(1.0)
GENDER	WOMAN	WOMAN	MAN	WOMAN	WOMAN
AGE	32	38	32	37	52
011A01	2	81	2	14	153
011A02	1	22	1	8	109
011A03	1	1	1	1	1
011A04	1	1	1	1	17
011AAY	1	45	1	26	89
011AAF	1	96	1	20	324
011AAX	3	27	3	36	69
011AAC	2	15	2	22	47
011AAV	2	2	2	6	24

012G01	1	1	1	1	1
012GZ5	1	2	1	1	8
012D04	1	1	1	1	1
012DBA	1	11	1	1	10
012DBB	1	1	1	1	1
012DZ5	1	7	1	6	14
012DF0	1	3	1	1	11
012DF3	1	7	1	1	20
021A05	2	31	2	43	100
021A06	1	14	1	23	53
021E05	1	2	1	1	6
021E06	1	1	1	1	1
031A07	1	19	1	2	49
031A68	1	17	1	7	38
031A73	1	26	1	27	37
031A74	1	1	1	1	2
041A08	3	69	3	75	221
041A09	1	1	1	1	11
041A16	1	1	1	1	18
041A17	1	8	1	7	58
041A18	1	1	1	1	2
041A19	1	1	1	1	1
041A20	1	5	1	2	11
041A21	1	56	1	25	80
041A22	1	3	1	6	8
041A23	1	14	1	6	39
041A25	1	72	1	24	198
041A26	1	12	1	5	87
041A27	1	10	1	8	14
041A28	2	19	2	8	49
041AC2	2	5	2	2	7
042G19	1	1	1	1	1
042D21	1	1	1	1	1
042DZ3	1	14	1	8	52
042E20	1	1	1	1	1
051A10	1	35	1	7	124
051A29	1	4	1	1	10
051A30	1	4	1	1	7
051A33	1	1	1	1	1
051A34	1	13	1	2	14
061A11	4	6	4	4	60
062G11	3	119	3	23	315
062G12	1	84	1	91	208
062G14	1	10	1	12	41
062GX0	1	1	1	1	1
062GC5	1	37	1	15	38
062GC9	1	1	1	1	20
062E12	2	2	2	2	2
071A15	1	15	1	26	81
081A24	5	42	5	51	140
082G24	1	3	1	1	5
091A31	2	51	2	12	229
091BBN	1	1	1	1	2
092G31	1	1	1	1	1
092E31	2	3	2	5	17
101A37	4	50	4	3	108
102D35	1	18	1	5	86
102E35	1	214	1	176	478
111A36	1	1	1	1	1
112E40	11	120	11	61	344
121A38	1	17	1	1	13

121A39	1	14	1	5	16
121A64	1	16	1	2	16
121A65	1	5	1	5	20
121A67	1	2	1	5	18
121AZ4	1	1	1	1	1
122G63	2	9	2	2	12
122G67	1	1	1	1	3
131A41	2	74	2	8	62
132G41	1	1	1	1	1
132D41	1	14	1	2	24
141A42	1	1	1	1	1
141A43	1	8	1	9	4
141ABG	1	1	1	1	1
141ABD	1	14	1	3	16
142G44	1	15	1	14	87
142G45	2	13	2	4	11
142E45	1	1	1	1	1
152G46	2	41	2	8	130
152GY0	1	1	1	1	1
152E46	4	74	4	17	162
162G50	1	66	1	14	144
162EJ2	1	142	1	123	323
172G51	1	10	1	1	6
172GM6	1	1	1	1	1
172E51	1	8	1	7	12
172EJ3	1	1	1	1	1
182G52	1	17	1	10	30
182E52	1	5	1	11	25
191A53	1	1	1	1	1
192E53	1	4	1	3	10
201A54	1	1	1	2	1
202G54	1	1	1	1	1
202E54	2	2	2	2	3
212D55	1	13	1	3	24
212D56	1	7	1	13	26
212E55	1	2	1	1	3
212E56	2	2	2	2	2
222G59	1	2	1	1	19
222D58	1	1	1	1	12
222D59	1	5	1	1	9
222D62	1	1	1	1	1
222E57	1	35	1	3	116
222E58	1	26	1	25	107
222E59	5	35	5	3	108
222E60	2	2	2	2	2
222E61	2	2	2	4	7
222E62	1	1	1	1	1
222EY1	1	1	1	1	2
231A66	2	51	2	21	126
241A08	1	19	1	11	21
241A70	1	8	1	13	35
241A71	2	40	2	54	116
241A72	1	12	1	19	38
242E72	1	5	1	5	13
251A33	1	8	1	5	25
251A75	8	108	8	19	133
251A76	1	7	1	8	41
251AX3	2	2	2	2	4
251AX4	3	89	3	72	155
251AX5	1	21	1	11	76
252G33	1	1	1	1	6

252G76	1	1	1	1	1
252GX5	1	9	1	10	44
261A77	1	21	1	8	61
261A78	1	5	1	8	18
261A79	1	1	1	1	1
261A80	1	1	1	1	4
261A81	1	1	1	1	1
261A82	1	1	1	1	1
261A83	1	1	1	1	7
261A84	1	1	1	1	1
261A85	1	1	1	1	1
261A86	1	1	1	1	1
261A88	1	1	1	1	3
261AZ7	1	1	1	1	1
261AX4	1	1	1	1	1
281BB1	2	9	2	29	75
281BD9	1	1	1	1	2
281BE1	1	6	1	1	41
281BS7	1	29	1	3	27
281BS8	1	3	1	1	9
281BS9	1	9	1	1	29
281BT0	1	1	1	1	7
281BT3	1	1	1	1	1
291BA4	1	5	1	7	20
291BA8	1	22	1	7	36
291BC4	1	1	1	1	1
301BB2	1	37	1	18	91
301BB3	1	22	1	47	73
301BB4	2	38	2	22	128
301BB5	1	19	1	31	56
301BG1	1	1	1	1	1
301BT2	1	1	1	1	2
311BA8	1	1	1	1	17
311BB6	1	3	1	1	10
321BB7	1	1	1	1	2
321BB8	1	6	1	8	24
331BB9	1	1	1	1	3
331BY5	1	1	1	1	1
341BG3	1	14	1	10	26
341BG4	1	6	1	5	20
351BG8	1	4	1	4	8
351BG9	1	4	1	1	4
351BD1	1	2	1	1	7
351BD2	1	1	1	1	1
351BD3	1	11	1	11	29
351BD5	1	13	1	7	16
361BBL	1	10	1	1	5
361BG2	1	1	1	2	2
361BG5	1	18	1	13	43
361BG6	1	1	1	1	1
361BG7	3	25	3	29	61
361BD4	1	1	1	1	1
361BD6	1	1	1	2	2
361BD8	1	2	1	1	3
361BM5	1	5	1	2	9
361BY4	1	1	1	1	1
361BY6	1	2	1	1	33
371AE2	1	9	1	3	76
371BE3	1	4	1	1	18
381BE4	2	18	2	31	44
381BE5	1	28	1	53	146

381BE6	2	23	2	54	121
381BE7	1	25	1	41	89
391BE8	1	1	1	1	6
401BE9	1	6	1	1	7
401BZ1	1	4	1	2	9
411A14	1	1	1	1	1
411AZ2	1	1	1	1	1
423ZH1	1	1	1	1	1
423ZH2	1	1	1	1	3
433ZBM	1	1	1	1	1
433ZH1	1	1	1	1	3
433ZH2	1	4	1	3	11
433ZH3	1	1	1	1	1
433ZH5	1	1	1	1	1
463HH1	1	1	1	1	1
463HH2	1	1	1	1	1
463HH3	1	7	1	4	8
463HH4	1	1	1	1	1
463HH5	1	1	1	1	3
473UH1	1	1	1	1	2
473UH2	1	1	1	1	3
473UH3	1	1	1	1	1
473UH4	1	1	1	1	1
483IH6	1	3	1	1	9
483IH7	1	1	1	1	6
483IH8	1	1	1	1	6
483IH9	1	4	1	2	6
493KU1	1	1	1	1	1
493KU2	1	1	1	1	1
503KU4	1	5	1	6	22
503KU5	1	1	1	1	1
503KU6	1	1	1	1	1
503KU7	1	3	1	1	6
513KU8	1	1	1	1	1
513KU9	1	2	1	1	4
533LI1	1	1	1	1	1
543LI3	1	1	1	1	2
553LH4	1	1	1	1	1
563LI5	1	1	1	1	5
563LI6	1	1	1	1	1
573LI7	1	1	1	1	2
573LI8	1	1	1	1	1
583LI9	1	1	1	1	2
583LK1	1	1	1	1	1
603MK6	1	1	1	3	3
613MK7	1	1	1	1	1
623MK8	1	3	1	3	5
633NK9	1	9	1	12	19
633NX7	2	3	2	7	22
643NL1	1	2	1	1	9
653NL2	1	6	1	8	13
663NL3	2	7	2	10	26
673NL4	1	5	1	3	8
673NL5	1	1	1	1	1
673NN9	1	4	1	2	7
683JL5	1	1	1	1	1
693JL5	1	1	1	1	1
693JL7	1	1	1	1	1
693JL8	1	1	1	1	1
703JL5	1	5	1	2	5
723PM2	1	1	1	1	1

733PM3	1	1	1	1	5
733PN8	1	1	1	1	1
743PM4	1	1	1	1	1
751BT8	1	1	1	1	8
761AN1	1	17	1	2	40
762GN1	1	21	1	1	80
771BN2	1	1	1	1	1
783RN5	1	1	1	1	1
783RN6	1	1	1	1	1
793SB0	1	1	1	1	4
793SG0	1	1	1	1	2
793SD0	1	1	1	1	3
803TA0	1	1	1	1	1
803TBJ	1	1	1	1	1
811BAP	1	4	1	3	7
811BAS	1	2	1	1	5
811BJ4	1	8	1	6	25
811BJ6	1	1	1	1	1
811BJ7	2	4	2	2	14
811BJ9	1	1	1	1	2
811BO1	1	5	1	1	19
811BO2	1	14	1	2	9
811BO3	1	1	1	1	5
811BO4	1	7	1	1	7
811BO5	1	1	1	1	1
811BO6	1	1	1	1	1
811BO8	1	1	1	1	1
811BO9	1	1	1	1	4
811BP0	1	2	1	1	2
811BP1	1	1	1	1	1
811BP2	2	4	2	4	11
811BP3	1	1	1	1	1
821BA5	1	1	1	1	2
821BO4	1	2	1	1	7
821BP6	1	13	1	1	15
821BP7	1	1	1	1	2
831B90	2	15	2	2	13
831BA7	1	6	1	1	30
831BP8	1	1	1	2	11
831BP9	1	11	1	8	46
831BR1	1	1	1	4	21
831BR2	1	1	1	1	6
831BC8	1	1	1	1	1
841BO4	1	1	1	1	4
841BR4	1	4	1	1	2
841BR5	1	7	1	8	20
841BR6	1	1	1	3	10
851BR7	1	21	1	9	40
851BR8	1	1	1	1	1
851BR9	1	1	1	1	4
851BS0	1	1	1	1	1
851BS1	1	1	1	1	10
851BS2	1	7	1	3	12
851BS3	1	1	1	1	1
851BX2	1	1	1	1	1
861B98	1	2	1	1	12
861BS4	1	3	1	1	4
861BS6	1	11	1	5	17
861BT6	1	3	1	1	5
861BC0	1	1	1	1	1
873TY8	1	1	1	1	1

902DX6	1	1	1	1	1
913HX8	1	1	1	1	1
923JC1	1	1	1	1	1
933JC6	1	1	1	1	1
943XC7	1	1	1	1	2
943XV1	1	1	1	1	1
951A01	1	1	1	1	1
951A02	1	1	1	1	1
951A04	1	1	1	1	1
951A05	1	1	1	1	1
951A06	1	1	1	1	1
951A07	1	1	1	1	1
951A10	1	1	1	1	1
951A15	1	1	1	1	1
951A16	1	1	1	1	2
951A22	1	1	1	1	1
951A23	1	1	1	1	14
951A26	1	1	1	1	1
951A37	1	1	1	1	6
951A38	2	2	2	2	2
951A39	1	1	1	1	1
951A41	1	1	1	1	1
951A42	1	1	1	1	1
951A52	1	1	1	1	2
951A53	2	2	2	2	2
951A54	1	1	1	1	1
951A64	1	1	1	1	1
951A67	1	1	1	1	2
951A69	5	5	5	5	5
951A71	1	1	1	1	1
951A72	1	3	1	1	4
951A77	1	1	1	1	1
951A78	1	1	1	1	1
951AN1	1	1	1	1	1
951AX4	1	1	1	1	1
952G11	1	26	1	5	9
952G12	1	1	1	1	3
952G44	1	1	1	1	1
952G45	1	1	1	1	1
952G46	1	1	1	1	1
952G50	1	1	1	1	1
952G77	1	1	1	1	1
952GX5	1	1	1	1	1
952D35	1	2	1	1	4
952EJ2	1	1	1	1	1
963CV0	3	200	3	66	423
AA1A54	1	1	1	1	1
AA1A72	1	1	1	1	1
AB1A05	1	1	1	1	1
AB1A11	1	1	1	1	1
AB1A35	1	1	1	1	1
AB1A38	1	2	1	1	5
AB1AAR	1	1	1	1	65
AB1AT6	1	1	1	1	1
AH1BBC	1	9	1	2	96
AK2E04	1	1	1	6	10
AK2E59	1	1	1	1	1
AK2EBH	1	1	1	1	1
AK2EBU	1	1	1	1	1
AK2EBI	1	1	1	1	2
AK2EBV	1	1	1	1	1

AT1AAT	1	1	1	1	1

=== Model and evaluation on training set ===

Clustered Instances

0 8 (7%)
1 87 (81%)
2 12 (11%)
3 1 (1%)

Simple K Means with 5 Clusters

Number of iterations: 6
Within cluster sum of squared errors: 10458.0

Missing values globally replaced with mean/mode

Final cluster centroids:

		Cluster#				
Attribute	Full Data	0	1	2	3	4
	(108.0)	(8.0)	(87.0)	(7.0)	(1.0)	5.0)
GENDER	WOMAN	WOMAN	MAN	WOMAN	WOMAN	WOMAN
AGE	32	38	32	37	52	39
011A01	2	81	2	14	153	47
011A02	1	22	1	8	109	33
011A03	1	1	1	1	1	1
011A04	1	1	1	1	17	4
011AAY	1	45	1	7	89	24
011AAF	1	96	1	20	324	41
011AAX	3	27	3	36	69	17
011AAC	2	15	2	22	47	8
011AAV	2	2	2	3	24	2
012G01	1	1	1	1	1	1
012GZ5	1	2	1	1	8	4
012D04	1	1	1	1	1	1
012DBA	1	11	1	1	10	1
012DBB	1	1	1	1	1	1
012DZ5	1	7	1	6	14	1
012DF0	1	3	1	1	11	1
012DF3	1	7	1	1	20	11
021A05	2	31	2	43	100	20
021A06	1	14	1	7	53	18
021E05	1	2	1	1	6	1
021E06	1	1	1	1	1	1
031A07	1	19	1	2	49	7
031A68	1	17	1	1	38	10
031A73	1	26	1	4	37	13
031A74	1	1	1	1	2	1
041A08	3	69	3	75	221	62
041A09	1	1	1	2	11	4
041A16	1	1	1	1	18	1
041A17	1	8	1	7	58	1
041A18	1	1	1	1	2	1
041A19	1	1	1	1	1	1
041A20	1	5	1	1	11	2
041A21	1	56	1	39	80	7
041A22	1	3	1	2	8	3
041A23	1	14	1	18	39	7
041A25	1	72	1	24	198	34
041A26	1	12	1	9	87	13
041A27	1	10	1	8	14	8

041A28	2	19	2	8	49	5
041AC2	2	5	2	1	7	2
042G19	1	1	1	1	1	1
042D21	1	1	1	1	1	1
042DZ3	1	14	1	8	52	27
042E20	1	1	1	1	1	1
051A10	1	35	1	7	124	9
051A29	1	4	1	1	10	1
051A30	1	4	1	1	7	3
051A33	1	1	1	1	1	1
051A34	1	13	1	2	14	1
061A11	4	6	4	4	60	28
062G11	3	119	3	23	315	39
062G12	1	84	1	91	208	70
062G14	1	10	1	17	41	11
062GX0	1	1	1	1	1	1
062GC5	1	37	1	1	38	11
062GC9	1	1	1	1	20	1
062E12	2	2	2	2	2	2
071A15	1	15	1	37	81	20
081A24	5	42	5	7	140	32
082G24	1	3	1	1	5	1
091A31	2	51	2	12	229	37
091BBN	1	1	1	3	2	1
092G31	1	1	1	1	1	1
092E31	2	3	2	5	17	2
101A37	4	50	4	3	108	30
102D35	1	18	1	5	86	16
102E35	1	214	1	176	478	121
111A36	1	1	1	1	1	1
112E40	11	120	11	61	344	88
121A38	1	17	1	1	13	8
121A39	1	14	1	5	16	8
121A64	1	16	1	2	16	3
121A65	1	5	1	5	20	5
121A67	1	2	1	1	18	3
121AZ4	1	1	1	1	1	1
122G63	2	9	2	2	12	3
122G67	1	1	1	1	3	1
131A41	2	74	2	8	62	14
132G41	1	1	1	1	1	1
132D41	1	14	1	1	24	3
141A42	1	1	1	1	1	1
141A43	1	8	1	3	4	3
141ABG	1	1	1	1	1	1
141ABD	1	14	1	2	16	3
142G44	1	15	1	32	87	13
142G45	2	13	2	2	11	2
142E45	1	1	1	1	1	1
152G46	2	41	2	8	130	24
152GY0	1	1	1	1	1	1
152E46	4	74	4	17	162	18
162G50	1	66	1	14	144	55
162EJ2	1	142	1	123	323	85
172G51	1	10	1	1	6	1
172GM6	1	1	1	1	1	1
172E51	1	8	1	2	12	2
172EJ3	1	1	1	1	1	1
182G52	1	17	1	3	30	2
182E52	1	5	1	11	25	14
191A53	1	1	1	1	1	1
192E53	1	4	1	3	10	11
201A54	1	1	1	2	1	1
202G54	1	1	1	1	1	1
202E54	2	2	2	1	3	2
212D55	1	13	1	3	24	9
212D56	1	7	1	13	26	3
212E55	1	2	1	2	3	1
212E56	2	2	2	2	2	2
222G59	1	2	1	1	19	7
222D58	1	1	1	1	12	1
222D59	1	5	1	1	9	1

222D62	1	1	1	1	1	1
222E57	1	35	1	3	116	14
222E58	1	26	1	25	107	36
222E59	5	35	5	3	108	21
222E60	2	2	2	2	2	2
222E61	2	2	2	2	7	3
222E62	1	1	1	1	1	1
222EY1	1	1	1	1	2	1
231A66	2	51	2	21	126	31
241A08	1	19	1	11	21	2
241A70	1	8	1	3	35	6
241A71	2	40	2	7	116	54
241A72	1	12	1	19	38	9
242E72	1	5	1	8	13	7
251A33	1	8	1	6	25	7
251A75	8	108	8	19	133	25
251A76	1	7	1	2	41	6
251AX3	2	2	2	2	4	2
251AX4	3	89	3	72	155	37
251AX5	1	21	1	11	76	47
252G33	1	1	1	1	6	1
252G76	1	1	1	1	1	1
252GX5	1	9	1	22	44	18
261A77	1	21	1	8	61	11
261A78	1	5	1	8	18	1
261A79	1	1	1	1	1	2
261A80	1	1	1	1	4	1
261A81	1	1	1	1	1	1
261A82	1	1	1	1	1	1
261A83	1	1	1	1	7	1
261A84	1	1	1	1	1	1
261A85	1	1	1	1	1	1
261A86	1	1	1	1	1	1
261A88	1	1	1	1	3	1
261AZ7	1	1	1	1	1	1
261AX4	1	1	1	1	1	1
281BB1	2	9	2	14	75	8
281BD9	1	1	1	1	2	1
281BE1	1	6	1	1	41	1
281BS7	1	29	1	5	27	3
281BS8	1	3	1	1	9	1
281BS9	1	9	1	1	29	4
281BT0	1	1	1	1	7	1
281BT3	1	1	1	1	1	1
291BA4	1	5	1	2	20	7
291BA8	1	22	1	7	36	7
291BC4	1	1	1	1	1	1
301BB2	1	37	1	18	91	17
301BB3	1	22	1	47	73	33
301BB4	2	38	2	22	128	40
301BB5	1	19	1	10	56	9
301BG1	1	1	1	1	1	1
301BT2	1	1	1	1	2	1
311BA8	1	1	1	1	17	4
311BB6	1	3	1	1	10	1
321BB7	1	1	1	1	2	1
321BB8	1	6	1	3	24	4
331BB9	1	1	1	1	3	1
331BY5	1	1	1	1	1	1
341BG3	1	14	1	3	26	2
341BG4	1	6	1	1	20	2
351BG8	1	4	1	4	8	1
351BG9	1	4	1	1	4	1
351BD1	1	2	1	1	7	2
351BD2	1	1	1	1	1	1
351BD3	1	11	1	11	29	9
351BD5	1	13	1	4	16	1
361BBL	1	10	1	1	5	1
361BG2	1	1	1	1	2	1
361BG5	1	18	1	6	43	11
361BG6	1	1	1	1	1	1
361BG7	3	25	3	29	61	20

361BD4	1	1	1	1	1	1
361BD6	1	1	1	2	2	2
361BD8	1	2	1	1	3	1
361BM5	1	5	1	2	9	5
361BY4	1	1	1	1	1	1
361BY6	1	2	1	1	33	4
371AE2	1	9	1	7	76	1
371BE3	1	4	1	1	18	1
381BE4	2	18	2	31	44	14
381BE5	1	28	1	21	146	19
381BE6	2	23	2	4	121	54
381BE7	1	25	1	41	89	15
391BE8	1	1	1	3	6	1
401BE9	1	6	1	1	7	6
401BZ1	1	4	1	1	9	1
411A14	1	1	1	1	1	1
411AZ2	1	1	1	1	1	1
423ZH1	1	1	1	1	1	1
423ZH2	1	1	1	1	3	1
433ZBM	1	1	1	1	1	1
433ZH1	1	1	1	1	3	2
433ZH2	1	4	1	1	11	4
433ZH3	1	1	1	1	1	1
433ZH5	1	1	1	1	1	1
463HH1	1	1	1	1	1	1
463HH2	1	1	1	1	1	1
463HH3	1	7	1	3	8	1
463HH4	1	1	1	1	1	1
463HH5	1	1	1	1	3	1
473UH1	1	1	1	1	2	1
473UH2	1	1	1	1	3	2
473UH3	1	1	1	1	1	1
473UH4	1	1	1	1	1	1
483IH6	1	3	1	1	9	2
483IH7	1	1	1	1	6	3
483IH8	1	1	1	1	6	1
483IH9	1	4	1	2	6	1
493KU1	1	1	1	1	1	1
493KU2	1	1	1	1	1	1
503KU4	1	5	1	6	22	8
503KU5	1	1	1	1	1	1
503KU6	1	1	1	1	1	1
503KU7	1	3	1	1	6	2
513KU8	1	1	1	1	1	1
513KU9	1	2	1	1	4	4
533LI1	1	1	1	1	1	1
543LI3	1	1	1	1	2	1
553LH4	1	1	1	1	1	1
563LI5	1	1	1	6	5	2
563LI6	1	1	1	1	1	1
573LI7	1	1	1	1	2	1
573LI8	1	1	1	1	1	1
583LI9	1	1	1	1	2	1
583LK1	1	1	1	1	1	1
603MK6	1	1	1	3	3	1
613MK7	1	1	1	1	1	1
623MK8	1	3	1	3	5	3
633NK9	1	9	1	12	19	10
633NX7	2	3	2	7	22	2
643NL1	1	2	1	1	9	1
653NL2	1	6	1	11	13	1
663NL3	2	7	2	14	26	7
673NL4	1	5	1	3	8	3
673NL5	1	1	1	1	1	1
673NN9	1	4	1	1	7	1
683JL5	1	1	1	1	1	1
693JL5	1	1	1	1	1	1
693JL7	1	1	1	1	1	1
693JL8	1	1	1	1	1	1
703JL5	1	5	1	4	5	3
723PM2	1	1	1	1	1	1
733PM3	1	1	1	1	5	1

733PN8	1	1	1	1	1	1
743PM4	1	1	1	1	1	1
751BT8	1	1	1	1	8	1
761AN1	1	17	1	2	40	4
762GN1	1	21	1	1	80	2
771BN2	1	1	1	1	1	1
783RN5	1	1	1	1	1	1
783RN6	1	1	1	1	1	1
793SB0	1	1	1	1	4	1
793SG0	1	1	1	1	2	1
793SD0	1	1	1	1	3	1
803TA0	1	1	1	1	1	1
803TBJ	1	1	1	1	1	1
811BAP	1	4	1	2	7	2
811BAS	1	2	1	1	5	1
811BJ4	1	8	1	6	25	8
811BJ6	1	1	1	1	1	1
811BJ7	2	4	2	2	14	2
811BJ9	1	1	1	1	2	1
811BO1	1	5	1	1	19	12
811BO2	1	14	1	1	9	2
811BO3	1	1	1	1	5	1
811BO4	1	7	1	1	7	1
811BO5	1	1	1	1	1	1
811BO6	1	1	1	1	1	1
811BO8	1	1	1	1	1	1
811BO9	1	1	1	1	4	1
811BP0	1	2	1	1	2	1
811BP1	1	1	1	1	1	1
811BP2	2	4	2	2	11	2
811BP3	1	1	1	1	1	1
821BA5	1	1	1	1	2	1
821BO4	1	2	1	1	7	2
821BP6	1	13	1	1	15	1
821BP7	1	1	1	1	2	1
831B90	2	15	2	2	13	4
831BA7	1	6	1	8	30	1
831BP8	1	1	1	2	11	1
831BP9	1	11	1	8	46	8
831BR1	1	1	1	3	21	8
831BR2	1	1	1	1	6	1
831BC8	1	1	1	1	1	1
841BO4	1	1	1	1	4	1
841BR4	1	4	1	1	2	1
841BR5	1	7	1	8	20	6
841BR6	1	1	1	1	10	1
851BR7	1	21	1	9	40	10
851BR8	1	1	1	1	1	1
851BR9	1	1	1	1	4	1
851BS0	1	1	1	1	1	1
851BS1	1	1	1	1	10	1
851BS2	1	7	1	3	12	1
851BS3	1	1	1	1	1	1
851BX2	1	1	1	1	1	1
861B98	1	2	1	1	12	1
861BS4	1	3	1	1	4	1
861BS6	1	11	1	5	17	7
861BT6	1	3	1	1	5	1
861BC0	1	1	1	1	1	1
873TY8	1	1	1	1	1	1
902DX6	1	1	1	1	1	1
913HX8	1	1	1	1	1	1
923JC1	1	1	1	1	1	1
933JC6	1	1	1	1	1	1
943XC7	1	1	1	1	2	1
943XV1	1	1	1	1	1	1
951A01	1	1	1	1	1	1
951A02	1	1	1	1	1	1
951A04	1	1	1	1	1	1
951A05	1	1	1	1	1	1
951A06	1	1	1	1	1	1
951A07	1	1	1	1	1	1

951A10	1	1	1	1	1	1
951A15	1	1	1	1	1	1
951A16	1	1	1	1	2	1
951A22	1	1	1	1	1	1
951A23	1	1	1	1	14	1
951A26	1	1	1	1	1	1
951A37	1	1	1	1	6	1
951A38	2	2	2	2	2	2
951A39	1	1	1	1	1	1
951A41	1	1	1	1	1	1
951A42	1	1	1	1	1	1
951A52	1	1	1	1	2	1
951A53	2	2	2	2	2	2
951A54	1	1	1	1	1	1
951A64	1	1	1	1	1	1
951A67	1	1	1	1	2	1
951A69	5	5	5	5	5	5
951A71	1	1	1	1	1	1
951A72	1	3	1	1	4	2
951A77	1	1	1	1	1	1
951A78	1	1	1	1	1	1
951AN1	1	1	1	1	1	1
951AX4	1	1	1	1	1	1
952G11	1	26	1	4	9	9
952G12	1	1	1	1	3	1
952G44	1	1	1	1	1	1
952G45	1	1	1	1	1	1
952G46	1	1	1	1	1	1
952G50	1	1	1	1	1	1
952G77	1	1	1	1	1	1
952GX5	1	1	1	1	1	1
952D35	1	2	1	1	4	1
952EJ2	1	1	1	1	1	1
963CV0	3	200	3	66	423	101
AA1A54	1	1	1	1	1	1
AA1A72	1	1	1	1	1	1
AB1A05	1	1	1	1	1	1
AB1A11	1	1	1	1	1	1
AB1A35	1	1	1	1	1	1
AB1A38	1	2	1	1	5	1
AB1AAR	1	1	1	1	65	1
AB1AT6	1	1	1	1	1	1
AH1BBC	1	9	1	7	96	8
AK2E04	1	1	1	6	10	2
AK2E59	1	1	1	1	1	1
AK2EBH	1	1	1	1	1	1
AK2EBU	1	1	1	1	1	1
AK2EBI	1	1	1	1	2	1
AK2EBV	1	1	1	1	1	1
AT1AAT	1	1	1	1	1	1

=== Model and evaluation on training set ===

Clustered Instances

0 8 (7%)
1 87 (81%)
2 7 (6%)
3 1 (1%)
4 5 (5%)

Error! Reference source not found.

Make A Density Based Clusterer with 2 Clusters

```
Final cluster centroids:
                              Cluster#
Attribute      Full Data             0            1
                 (108.0)         (7.0)      (101.0)
===================================================
GENDER          WOMAN        WOMAN        WOMAN
AGE                   32            38           32
011A01                 2            81            2
011A02                 1            33            1
011A03                 1             1            1
011A04                 1             1            1
011AAY                 1            45            1
011AAF                 1            96            1
011AAX                 3            13            3
011AAC                 2            15            2
011AAV                 2             2            2
012G01                 1             1            1
012GZ5                 1             1            1
012D04                 1             1            1
012DBA                 1            11            1
012DBB                 1             1            1
012DZ5                 1             2            1
012DF0                 1             2            1
012DF3                 1             8            1
021A05                 2            31            2
021A06                 1            14            1
021E05               1             2            1
021E06               1             1            1
031A07                 1            27            1
031A68                 1            17            1
031A73                 1            26            1
031A74                 1             1            1
041A08                 3            69            3
041A09                 1             1            1
041A16                 1             1            1
041A17                 1             3            1
041A18                 1             1            1
041A19                 1             1            1
041A20                 1             1            1
041A21                 1            56            1
041A22                 1             1            1
041A23                 1            14            1
041A25                 1            72            1
041A26                 1            12            1
041A27                 1            12            1
041A28                 2            19            2
041AC2                 2             5            2
042G19                 1             1            1
042D21                 1             1            1
042DZ3                 1            14            1
042E20                 1             1            1
051A10                 1            35            1
```

051A29	1	10	1
051A30	1	1	1
051A33	1	1	1
051A34	1	8	1
061A11	4	13	4
062G11	3	119	3
062G12	1	84	1
062G14	1	10	1
062GX0	1	1	1
062GC5	1	37	1
062GC9	1	1	1
062E12	2	2	2
071A15	1	29	1
081A24	5	42	5
082G24	1	5	1
091A31	2	61	2
091BBN	1	1	1
092G31	1	1	1
092E31	2	17	2
101A37	4	52	4
102D35	1	18	1
102E35	1	214	1
111A36	1	1	1
112E40	11	120	11
121A38	1	3	1
121A39	1	6	1
121A64	1	16	1
121A65	1	9	1
121A67	1	8	1
121AZ4	1	2	1
122G63	2	2	2
122G67	1	1	1
131A41	2	24	2
132G41	1	1	1
132D41	1	14	1
141A42	1	1	1
141A43	1	8	1
141ABG	1	1	1
141ABD	1	14	1
142G44	1	17	1
142G45	2	15	2
142E45	1	1	1
152G46	2	41	2
152GY0	1	1	1
152E46	4	74	4
162G50	1	66	1
162EJ2	1	142	1
172G51	1	1	1
172GM6	1	1	1
172E51	1	2	1
172EJ3	1	1	1
182G52	1	5	1
182E52	1	5	1
191A53	1	1	1
192E53	1	4	1
201A54	1	1	1
202G54	1	1	1
202E54	2	2	2

212D55	1	7	1
212D56	1	7	1
212E55	1	2	1
212E56	2	2	2
222G59	1	2	1
222D58	1	1	1
222D59	1	9	1
222D62	1	1	1
222E57	1	35	1
222E58	1	26	1
222E59	5	35	5
222E60	2	2	2
222E61	2	5	2
222E62	1	1	1
222EY1	1	2	1
231A66	2	51	2
241A08	1	19	1
241A70	1	8	1
241A71	2	40	2
241A72	1	12	1
242E72	1	5	1
251A33	1	8	1
251A75	8	108	8
251A76	1	10	1
251AX3	2	4	2
251AX4	3	54	3
251AX5	1	21	1
252G33	1	1	1
252G76	1	1	1
252GX5	1	9	1
261A77	1	21	1
261A78	1	18	1
261A79	1	1	1
261A80	1	1	1
261A81	1	1	1
261A82	1	1	1
261A83	1	1	1
261A84	1	1	1
261A85	1	1	1
261A86	1	1	1
261A88	1	1	1
261AZ7	1	1	1
261AX4	1	1	1
281BB1	2	9	2
281BD9	1	1	1
281BE1	1	6	1
281BS7	1	8	1
281BS8	1	3	1
281BS9	1	8	1
281BT0	1	1	1
281BT3	1	1	1
291BA4	1	5	1
291BA8	1	22	1
291BC4	1	1	1
301BB2	1	37	1
301BB3	1	22	1
301BB4	2	38	2
301BB5	1	19	1

301BG1	1	1	1
301BT2	1	1	1
311BA8	1	1	1
311BB6	1	3	1
321BB7	1	1	1
321BB8	1	6	1
331BB9	1	1	1
331BY5	1	1	1
341BG3	1	14	1
341BG4	1	6	1
351BG8	1	6	1
351BG9	1	4	1
351BD1	1	2	1
351BD2	1	1	1
351BD3	1	6	1
351BD5	1	11	1
361BBL	1	5	1
361BG2	1	1	1
361BG5	1	15	1
361BG6	1	1	1
361BG7	3	25	3
361BD4	1	1	1
361BD6	1	1	1
361BD8	1	2	1
361BM5	1	15	1
361BY4	1	1	1
361BY6	1	2	1
371AE2	1	9	1
371BE3	1	2	1
381BE4	2	21	2
381BE5	1	28	1
381BE6	2	23	2
381BE7	1	25	1
391BE8	1	27	1
401BE9	1	7	1
401BZ1	1	1	1
411A14	1	1	1
411AZ2	1	1	1
423ZH1	1	1	1
423ZH2	1	1	1
433ZBM	1	1	1
433ZH1	1	1	1
433ZH2	1	4	1
433ZH3	1	1	1
433ZH5	1	1	1
463HH1	1	1	1
463HH2	1	1	1
463HH3	1	8	1
463HH4	1	1	1
463HH5	1	1	1
473UH1	1	1	1
473UH2	1	3	1
473UH3	1	1	1
473UH4	1	1	1
483IH6	1	9	1
483IH7	1	2	1
483IH8	1	1	1
483IH9	1	4	1

493KU1	1	1	1
493KU2	1	1	1
503KU4	1	22	1
503KU5	1	1	1
503KU6	1	1	1
503KU7	1	3	1
513KU8	1	1	1
513KU9	1	3	1
533LI1	1	1	1
543LI3	1	1	1
553LH4	1	1	1
563LI5	1	1	1
563LI6	1	1	1
573LI7	1	1	1
573LI8	1	1	1
583LI9	1	1	1
583LK1	1	1	1
603MK6	1	1	1
613MK7	1	1	1
623MK8	1	1	1
633NK9	1	4	1
633NX7	2	11	2
643NL1	1	5	1
653NL2	1	5	1
663NL3	2	8	2
673NL4	1	5	1
673NL5	1	1	1
673NN9	1	4	1
683JL5	1	1	1
693JL5	1	1	1
693JL7	1	1	1
693JL8	1	1	1
703JL5	1	5	1
723PM2	1	1	1
733PM3	1	1	1
733PN8	1	1	1
743PM4	1	1	1
751BT8	1	1	1
761AN1	1	23	1
762GN1	1	21	1
771BN2	1	1	1
783RN5	1	1	1
783RN6	1	1	1
793SB0	1	1	1
793SG0	1	1	1
793SD0	1	3	1
803TA0	1	1	1
803TBJ	1	1	1
811BAP	1	4	1
811BAS	1	2	1
811BJ4	1	8	1
811BJ6	1	1	1
811BJ7	2	4	2
811BJ9	1	1	1
811BO1	1	4	1
811BO2	1	9	1
811BO3	1	1	1
811BO4	1	7	1

811BO5	1	1	1
811BO6	1	1	1
811BO8	1	1	1
811BO9	1	1	1
811BP0	1	2	1
811BP1	1	1	1
811BP2	2	4	2
811BP3	1	1	1
821BA5	1	1	1
821BO4	1	2	1
821BP6	1	13	1
821BP7	1	1	1
831B90	2	15	2
831BA7	1	10	1
831BP8	1	4	1
831BP9	1	11	1
831BR1	1	5	1
831BR2	1	1	1
831BC8	1	1	1
841BO4	1	1	1
841BR4	1	2	1
841BR5	1	7	1
841BR6	1	1	1
851BR7	1	21	1
851BR8	1	1	1
851BR9	1	1	1
851BS0	1	1	1
851BS1	1	1	1
851BS2	1	7	1
851BS3	1	1	1
851BX2	1	1	1
861B98	1	2	1
861BS4	1	3	1
861BS6	1	4	1
861BT6	1	3	1
861BC0	1	1	1
873TY8	1	1	1
902DX6	1	1	1
913HX8	1	1	1
923JC1	1	1	1
933JC6	1	1	1
943XC7	1	2	1
943XV1	1	1	1
951A01	1	1	1
951A02	1	1	1
951A04	1	1	1
951A05	1	1	1
951A06	1	1	1
951A07	1	1	1
951A10	1	1	1
951A15	1	1	1
951A16	1	1	1
951A22	1	1	1
951A23	1	1	1
951A26	1	1	1
951A37	1	1	1
951A38	2	2	2
951A39	1	1	1

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951A41                  1           1           1
951A42                  1           1           1
951A52                  1           1           1
951A53                  2           2           2
951A54                  1           1           1
951A64                  1           1           1
951A67                  1           1           1
951A69                  5           5           5
951A71                  1           1           1
951A72                  1           3           1
951A77                  1           1           1
951A78                  1           1           1
951AN1                  1           1           1
951AX4                  1           1           1
952G11                  1           9           1
952G12                  1           1           1
952G44                  1           1           1
952G45                  1           1           1
952G46                  1           1           1
952G50                  1           1           1
952G77                  1           1           1
952GX5                  1           1           1
952D35                  1           2           1
952EJ2                  1           1           1
963CV0                  3         200           3
AA1A54                  1           1           1
AA1A72                  1           1           1
AB1A05                  1           1           1
AB1A11                  1           1           1
AB1A35                  1           1           1
AB1A38                  1           2           1
AB1AAR                  1           1           1
AB1AT6                  1           1           1
AH1BBC                  1           8           1
AK2E04                  1           1           1
AK2E59                  1           1           1
AK2EBH                  1           1           1
AK2EBU                  1           1           1
AK2EBI                  1           1           1
AK2EBV                  1           1           1
AT1AAT                  1           1           1
```

Make A Density Based Clusterer with 3 Clusters

```
Final cluster centroids:
                           Cluster#
Attribute     Full Data           0           1           2
                (108.0)       (7.0)      (99.0)       (2.0)
===========================================================
GENDER            WOMAN       WOMAN       WOMAN       WOMAN
AGE                  32          38          32          41
011A01                2          81           2           4
011A02                1          33           1           9
011A03                1           1           1           1
011A04                1           1           1           1
011AAY                1          45           1           8
011AAF                1          96           1           1
```

011AAX	3	13	3	2
011AAC	2	15	2	4
011AAV	2	2	2	2
012G01	1	1	1	3
012GZ5	1	1	1	1
012D04	1	1	1	1
012DBA	1	11	1	1
012DBB	1	1	1	1
012DZ5	1	2	1	1
012DF0	1	2	1	1
012DF3	1	8	1	1
021A05	2	31	2	3
021A06	1	14	1	1
021E05	1	2	1	1
021E06	1	1	1	1
031A07	1	27	1	2
031A68	1	17	1	1
031A73	1	26	1	1
031A74	1	1	1	1
041A08	3	69	3	4
041A09	1	1	1	1
041A16	1	1	1	1
041A17	1	3	1	1
041A18	1	1	1	1
041A19	1	1	1	1
041A20	1	1	1	1
041A21	1	56	1	1
041A22	1	1	1	1
041A23	1	14	1	1
041A25	1	72	1	8
041A26	1	12	1	1
041A27	1	12	1	1
041A28	2	19	2	2
041AC2	2	5	2	3
042G19	1	1	1	1
042D21	1	1	1	1
042DZ3	1	14	1	2
042E20	1	1	1	1
051A10	1	35	1	1
051A29	1	10	1	1
051A30	1	1	1	1
051A33	1	1	1	1
051A34	1	8	1	1
061A11	4	13	4	7
062G11	3	119	3	20
062G12	1	84	1	17
062G14	1	10	1	2
062GX0	1	1	1	1
062GC5	1	37	1	1
062GC9	1	1	1	1
062E12	2	2	2	1
071A15	1	29	1	8
081A24	5	42	5	10
082G24	1	5	1	4
091A31	2	61	2	3
091BBN	1	1	1	1
092G31	1	1	1	1
092E31	2	17	2	2

101A37	4	52	4	4
102D35	1	18	1	7
102E35	1	214	1	34
111A36	1	1	1	1
112E40	11	120	11	39
121A38	1	3	1	1
121A39	1	6	1	1
121A64	1	16	1	1
121A65	1	9	1	1
121A67	1	8	1	3
121AZ4	1	2	1	1
122G63	2	2	2	2
122G67	1	1	1	1
131A41	2	24	2	7
132G41	1	1	1	1
132D41	1	14	1	1
141A42	1	1	1	1
141A43	1	8	1	1
141ABG	1	1	1	1
141ABD	1	14	1	1
142G44	1	17	1	1
142G45	2	15	2	2
142E45	1	1	1	1
152G46	2	41	2	10
152GY0	1	1	1	1
152E46	4	74	4	8
162G50	1	66	1	6
162EJ2	1	142	1	22
172G51	1	1	1	1
172GM6	1	1	1	1
172E51	1	2	1	2
172EJ3	1	1	1	1
182G52	1	5	1	1
182E52	1	5	1	1
191A53	1	1	1	1
192E53	1	4	1	4
201A54	1	1	1	1
202G54	1	1	1	1
202E54	2	2	2	2
212D55	1	7	1	7
212D56	1	7	1	2
212E55	1	2	1	1
212E56	2	2	2	2
222G59	1	2	1	1
222D58	1	1	1	1
222D59	1	9	1	1
222D62	1	1	1	1
222E57	1	35	1	10
222E58	1	26	1	10
222E59	5	35	5	15
222E60	2	2	2	2
222E61	2	5	2	1
222E62	1	1	1	1
222EY1	1	2	1	1
231A66	2	51	2	8
241A08	1	19	1	1
241A70	1	8	1	3
241A71	2	40	2	13

241A72	1	12	1	4
242E72	1	5	1	1
251A33	1	8	1	1
251A75	8	108	8	21
251A76	1	10	1	1
251AX3	2	4	2	2
251AX4	3	54	3	17
251AX5	1	21	1	19
252G33	1	1	1	1
252G76	1	1	1	1
252GX5	1	9	1	2
261A77	1	21	1	1
261A78	1	18	1	1
261A79	1	1	1	1
261A80	1	1	1	1
261A81	1	1	1	1
261A82	1	1	1	1
261A83	1	1	1	1
261A84	1	1	1	1
261A85	1	1	1	1
261A86	1	1	1	1
261A88	1	1	1	1
261AZ7	1	1	1	1
261AX4	1	1	1	1
281BB1	2	9	2	2
281BD9	1	1	1	1
281BE1	1	6	1	1
281BS7	1	8	1	2
281BS8	1	3	1	1
281BS9	1	8	1	1
281BT0	1	1	1	1
281BT3	1	1	1	1
291BA4	1	5	1	1
291BA8	1	22	1	1
291BC4	1	1	1	1
301BB2	1	37	1	2
301BB3	1	22	1	1
301BB4	2	38	2	4
301BB5	1	19	1	1
301BG1	1	1	1	1
301BT2	1	1	1	1
311BA8	1	1	1	1
311BB6	1	3	1	1
321BB7	1	1	1	1
321BB8	1	6	1	6
331BB9	1	1	1	1
331BY5	1	1	1	1
341BG3	1	14	1	1
341BG4	1	6	1	1
351BG8	1	6	1	1
351BG9	1	4	1	1
351BD1	1	2	1	1
351BD2	1	1	1	1
351BD3	1	6	1	1
351BD5	1	11	1	1
361BBL	1	5	1	1
361BG2	1	1	1	1
361BG5	1	15	1	2

361BG6	1	1	1	1
361BG7	3	25	3	3
361BD4	1	1	1	1
361BD6	1	1	1	1
361BD8	1	2	1	1
361BM5	1	15	1	1
361BY4	1	1	1	1
361BY6	1	2	1	1
371AE2	1	9	1	2
371BE3	1	2	1	1
381BE4	2	21	2	2
381BE5	1	28	1	5
381BE6	2	23	2	5
381BE7	1	25	1	1
391BE8	1	27	1	1
401BE9	1	7	1	1
401BZ1	1	1	1	1
411A14	1	1	1	1
411AZ2	1	1	1	1
423ZH1	1	1	1	1
423ZH2	1	1	1	1
433ZBM	1	1	1	1
433ZH1	1	1	1	1
433ZH2	1	4	1	1
433ZH3	1	1	1	1
433ZH5	1	1	1	1
463HH1	1	1	1	1
463HH2	1	1	1	1
463HH3	1	8	1	1
463HH4	1	1	1	1
463HH5	1	1	1	1
473UH1	1	1	1	1
473UH2	1	3	1	1
473UH3	1	1	1	1
473UH4	1	1	1	1
483IH6	1	9	1	1
483IH7	1	2	1	1
483IH8	1	1	1	1
483IH9	1	4	1	1
493KU1	1	1	1	1
493KU2	1	1	1	1
503KU4	1	22	1	2
503KU5	1	1	1	1
503KU6	1	1	1	1
503KU7	1	3	1	1
513KU8	1	1	1	1
513KU9	1	3	1	1
533LI1	1	1	1	1
543LI3	1	1	1	1
553LH4	1	1	1	1
563LI5	1	1	1	1
563LI6	1	1	1	1
573LI7	1	1	1	1
573LI8	1	1	1	1
583LI9	1	1	1	1
583LK1	1	1	1	1
603MK6	1	1	1	1
613MK7	1	1	1	1

623MK8	1	1	1	1
633NK9	1	4	1	1
633NX7	2	11	2	2
643NL1	1	5	1	1
653NL2	1	5	1	1
663NL3	2	8	2	2
673NL4	1	5	1	1
673NL5	1	1	1	1
673NN9	1	4	1	1
683JL5	1	1	1	1
693JL5	1	1	1	1
693JL7	1	1	1	1
693JL8	1	1	1	1
703JL5	1	5	1	1
723PM2	1	1	1	1
733PM3	1	1	1	1
733PN8	1	1	1	1
743PM4	1	1	1	1
751BT8	1	1	1	1
761AN1	1	23	1	1
762GN1	1	21	1	1
771BN2	1	1	1	1
783RN5	1	1	1	1
783RN6	1	1	1	1
793SB0	1	1	1	1
793SG0	1	1	1	1
793SD0	1	3	1	1
803TA0	1	1	1	1
803TBJ	1	1	1	1
811BAP	1	4	1	1
811BAS	1	2	1	1
811BJ4	1	8	1	1
811BJ6	1	1	1	1
811BJ7	2	4	2	2
811BJ9	1	1	1	1
811BO1	1	4	1	1
811BO2	1	9	1	1
811BO3	1	1	1	1
811BO4	1	7	1	1
811BO5	1	1	1	1
811BO6	1	1	1	1
811BO8	1	1	1	1
811BO9	1	1	1	1
811BP0	1	2	1	1
811BP1	1	1	1	1
811BP2	2	4	2	2
811BP3	1	1	1	1
821BA5	1	1	1	1
821BO4	1	2	1	1
821BP6	1	13	1	1
821BP7	1	1	1	1
831B90	2	15	2	2
831BA7	1	10	1	1
831BP8	1	4	1	1
831BP9	1	11	1	1
831BR1	1	5	1	1
831BR2	1	1	1	1
831BC8	1	1	1	1

841BO4	1	1	1	1
841BR4	1	2	1	1
841BR5	1	7	1	1
841BR6	1	1	1	1
851BR7	1	21	1	2
851BR8	1	1	1	1
851BR9	1	1	1	1
851BS0	1	1	1	1
851BS1	1	1	1	1
851BS2	1	7	1	1
851BS3	1	1	1	1
851BX2	1	1	1	1
861B98	1	2	1	1
861BS4	1	3	1	1
861BS6	1	4	1	1
861BT6	1	3	1	1
861BC0	1	1	1	1
873TY8	1	1	1	1
902DX6	1	1	1	1
913HX8	1	1	1	1
923JC1	1	1	1	1
933JC6	1	1	1	1
943XC7	1	2	1	1
943XV1	1	1	1	1
951A01	1	1	1	1
951A02	1	1	1	1
951A04	1	1	1	1
951A05	1	1	1	1
951A06	1	1	1	1
951A07	1	1	1	1
951A10	1	1	1	1
951A15	1	1	1	1
951A16	1	1	1	1
951A22	1	1	1	1
951A23	1	1	1	1
951A26	1	1	1	1
951A37	1	1	1	1
951A38	2	2	2	2
951A39	1	1	1	1
951A41	1	1	1	1
951A42	1	1	1	1
951A52	1	1	1	1
951A53	2	2	2	2
951A54	1	1	1	1
951A64	1	1	1	1
951A67	1	1	1	1
951A69	5	5	5	5
951A71	1	1	1	1
951A72	1	3	1	1
951A77	1	1	1	1
951A78	1	1	1	1
951AN1	1	1	1	1
951AX4	1	1	1	1
952G11	1	9	1	1
952G12	1	1	1	1
952G44	1	1	1	1
952G45	1	1	1	1
952G46	1	1	1	1

952G50	1	1	1	1
952G77	1	1	1	1
952GX5	1	1	1	1
952D35	1	2	1	1
952EJ2	1	1	1	1
963CV0	3	200	3	6
AA1A54	1	1	1	1
AA1A72	1	1	1	1
AB1A05	1	1	1	1
AB1A11	1	1	1	1
AB1A35	1	1	1	1
AB1A38	1	2	1	1
AB1AAR	1	1	1	1
AB1AT6	1	1	1	1
AH1BBC	1	8	1	1
AK2E04	1	1	1	1
AK2E59	1	1	1	1
AK2EBH	1	1	1	1
AK2EBU	1	1	1	1
AK2EBI	1	1	1	1
AK2EBV	1	1	1	1
AT1AAT	1	1	1	1

Make A Density Based Clusterer with 4 Clusters

Final cluster centroids:

		Cluster#			
Attribute	Full Data	0	1	2	3
	(108.0)	(8.0)	(87.0)	(12.0)	(1.0)
GENDER	WOMAN	WOMAN	MAN	WOMAN	WOMAN
AGE	32	38	32	37	52
011A01	2	81	2	14	153
011A02	1	22	1	8	109
011A03	1	1	1	1	1
011A04	1	1	1	1	17
011AAY	1	45	1	26	89
011AAF	1	96	1	20	324
011AAX	3	27	3	36	69
011AAC	2	15	2	22	47
011AAV	2	2	2	6	24
012G01	1	1	1	1	1
012GZ5	1	2	1	1	8
012D04	1	1	1	1	1
012DBA	1	11	1	1	10
012DBB	1	1	1	1	1
012DZ5	1	7	1	6	14
012DF0	1	3	1	1	11
012DF3	1	7	1	1	20
021A05	2	31	2	43	100
021A06	1	14	1	23	53
021E05	1	2	1	1	6
021E06	1	1	1	1	1
031A07	1	19	1	2	49
031A68	1	17	1	7	38
031A73	1	26	1	27	37
031A74	1	1	1	1	2
041A08	3	69	3	75	221

041A09	1	1	1	1	11
041A16	1	1	1	1	18
041A17	1	8	1	7	58
041A18	1	1	1	1	2
041A19	1	1	1	1	1
041A20	1	5	1	2	11
041A21	1	56	1	25	80
041A22	1	3	1	6	8
041A23	1	14	1	6	39
041A25	1	72	1	24	198
041A26	1	12	1	5	87
041A27	1	10	1	8	14
041A28	2	19	2	8	49
041AC2	2	5	2	2	7
042G19	1	1	1	1	1
042D21	1	1	1	1	1
042DZ3	1	14	1	8	52
042E20	1	1	1	1	1
051A10	1	35	1	7	124
051A29	1	4	1	1	10
051A30	1	4	1	1	7
051A33	1	1	1	1	1
051A34	1	13	1	2	14
061A11	4	6	4	4	60
062G11	3	119	3	23	315
062G12	1	84	1	91	208
062G14	1	10	1	12	41
062GX0	1	1	1	1	1
062GC5	1	37	1	15	38
062GC9	1	1	1	1	20
062E12	2	2	2	2	2
071A15	1	15	1	26	81
081A24	5	42	5	51	140
082G24	1	3	1	1	5
091A31	2	51	2	12	229
091BBN	1	1	1	1	2
092G31	1	1	1	1	1
092E31	2	3	2	5	17
101A37	4	50	4	3	108
102D35	1	18	1	5	86
102E35	1	214	1	176	478
111A36	1	1	1	1	1
112E40	11	120	11	61	344
121A38	1	17	1	1	13
121A39	1	14	1	5	16
121A64	1	16	1	2	16
121A65	1	5	1	5	20
121A67	1	2	1	5	18
121AZ4	1	1	1	1	1
122G63	2	9	2	2	12
122G67	1	1	1	1	3
131A41	2	74	2	8	62
132G41	1	1	1	1	1
132D41	1	14	1	2	24
141A42	1	1	1	1	1
141A43	1	8	1	9	4
141ABG	1	1	1	1	1
141ABD	1	14	1	3	16
142G44	1	15	1	14	87
142G45	2	13	2	4	11
142E45	1	1	1	1	1

152G46	2	41	2	8	130
152GY0	1	1	1	1	1
152E46	4	74	4	17	162
162G50	1	66	1	14	144
162EJ2	1	142	1	123	323
172G51	1	10	1	1	6
172GM6	1	1	1	1	1
172E51	1	8	1	7	12
172EJ3	1	1	1	1	1
182G52	1	17	1	10	30
182E52	1	5	1	11	25
191A53	1	1	1	1	1
192E53	1	4	1	3	10
201A54	1	1	1	2	1
202G54	1	1	1	1	1
202E54	2	2	2	2	3
212D55	1	13	1	3	24
212D56	1	7	1	13	26
212E55	1	2	1	1	3
212E56	2	2	2	2	2
222G59	1	2	1	1	19
222D58	1	1	1	1	12
222D59	1	5	1	1	9
222D62	1	1	1	1	1
222E57	1	35	1	3	116
222E58	1	26	1	25	107
222E59	5	35	5	3	108
222E60	2	2	2	2	2
222E61	2	2	2	4	7
222E62	1	1	1	1	1
222EY1	1	1	1	1	2
231A66	2	51	2	21	126
241A08	1	19	1	11	21
241A70	1	8	1	13	35
241A71	2	40	2	54	116
241A72	1	12	1	19	38
242E72	1	5	1	5	13
251A33	1	8	1	5	25
251A75	8	108	8	19	133
251A76	1	7	1	8	41
251AX3	2	2	2	2	4
251AX4	3	89	3	72	155
251AX5	1	21	1	11	76
252G33	1	1	1	1	6
252G76	1	1	1	1	1
252GX5	1	9	1	10	44
261A77	1	21	1	8	61
261A78	1	5	1	8	18
261A79	1	1	1	1	1
261A80	1	1	1	1	4
261A81	1	1	1	1	1
261A82	1	1	1	1	1
261A83	1	1	1	1	7
261A84	1	1	1	1	1
261A85	1	1	1	1	1
261A86	1	1	1	1	1
261A88	1	1	1	1	3
261AZ7	1	1	1	1	1
261AX4	1	1	1	1	1
281BB1	2	9	2	29	75
281BD9	1	1	1	1	2

281BE1	1	6	1	1	41
281BS7	1	29	1	3	27
281BS8	1	3	1	1	9
281BS9	1	9	1	1	29
281BT0	1	1	1	1	7
281BT3	1	1	1	1	1
291BA4	1	5	1	7	20
291BA8	1	22	1	7	36
291BC4	1	1	1	1	1
301BB2	1	37	1	18	91
301BB3	1	22	1	47	73
301BB4	2	38	2	22	128
301BB5	1	19	1	31	56
301BG1	1	1	1	1	1
301BT2	1	1	1	1	2
311BA8	1	1	1	1	17
311BB6	1	3	1	1	10
321BB7	1	1	1	1	2
321BB8	1	6	1	8	24
331BB9	1	1	1	1	3
331BY5	1	1	1	1	1
341BG3	1	14	1	10	26
341BG4	1	6	1	5	20
351BG8	1	4	1	4	8
351BG9	1	4	1	1	4
351BD1	1	2	1	1	7
351BD2	1	1	1	1	1
351BD3	1	11	1	11	29
351BD5	1	13	1	7	16
361BBL	1	10	1	1	5
361BG2	1	1	1	2	2
361BG5	1	18	1	13	43
361BG6	1	1	1	1	1
361BG7	3	25	3	29	61
361BD4	1	1	1	1	1
361BD6	1	1	1	2	2
361BD8	1	2	1	1	3
361BM5	1	5	1	2	9
361BY4	1	1	1	1	1
361BY6	1	2	1	1	33
371AE2	1	9	1	3	76
371BE3	1	4	1	1	18
381BE4	2	18	2	31	44
381BE5	1	28	1	53	146
381BE6	2	23	2	54	121
381BE7	1	25	1	41	89
391BE8	1	1	1	1	6
401BE9	1	6	1	1	7
401BZ1	1	4	1	2	9
411A14	1	1	1	1	1
411AZ2	1	1	1	1	1
423ZH1	1	1	1	1	1
423ZH2	1	1	1	1	3
433ZBM	1	1	1	1	1
433ZH1	1	1	1	1	3
433ZH2	1	4	1	3	11
433ZH3	1	1	1	1	1
433ZH5	1	1	1	1	1
463HH1	1	1	1	1	1
463HH2	1	1	1	1	1
463HH3	1	7	1	4	8

463HH4	1	1	1	1	1
463HH5	1	1	1	1	3
473UH1	1	1	1	1	2
473UH2	1	1	1	1	3
473UH3	1	1	1	1	1
473UH4	1	1	1	1	1
483IH6	1	3	1	1	9
483IH7	1	1	1	1	6
483IH8	1	1	1	1	6
483IH9	1	4	1	2	6
493KU1	1	1	1	1	1
493KU2	1	1	1	1	1
503KU4	1	5	1	6	22
503KU5	1	1	1	1	1
503KU6	1	1	1	1	1
503KU7	1	3	1	1	6
513KU8	1	1	1	1	1
513KU9	1	2	1	1	4
533LI1	1	1	1	1	1
543LI3	1	1	1	1	2
553LH4	1	1	1	1	1
563LI5	1	1	1	1	5
563LI6	1	1	1	1	1
573LI7	1	1	1	1	2
573LI8	1	1	1	1	1
583LI9	1	1	1	1	2
583LK1	1	1	1	1	1
603MK6	1	1	1	3	3
613MK7	1	1	1	1	1
623MK8	1	3	1	3	5
633NK9	1	9	1	12	19
633NX7	2	3	2	7	22
643NL1	1	2	1	1	9
653NL2	1	6	1	8	13
663NL3	2	7	2	10	26
673NL4	1	5	1	3	8
673NL5	1	1	1	1	1
673NN9	1	4	1	2	7
683JL5	1	1	1	1	1
693JL5	1	1	1	1	1
693JL7	1	1	1	1	1
693JL8	1	1	1	1	1
703JL5	1	5	1	2	5
723PM2	1	1	1	1	1
733PM3	1	1	1	1	5
733PN8	1	1	1	1	1
743PM4	1	1	1	1	1
751BT8	1	1	1	1	8
761AN1	1	17	1	2	40
762GN1	1	21	1	1	80
771BN2	1	1	1	1	1
783RN5	1	1	1	1	1
783RN6	1	1	1	1	1
793SB0	1	1	1	1	4
793SG0	1	1	1	1	2
793SD0	1	1	1	1	3
803TA0	1	1	1	1	1
803TBJ	1	1	1	1	1
811BAP	1	4	1	3	7
811BAS	1	2	1	1	5
811BJ4	1	8	1	6	25

811BJ6	1	1	1	1	1
811BJ7	2	4	2	2	14
811BJ9	1	1	1	1	2
811BO1	1	5	1	1	19
811BO2	1	14	1	2	9
811BO3	1	1	1	1	5
811BO4	1	7	1	1	7
811BO5	1	1	1	1	1
811BO6	1	1	1	1	1
811BO8	1	1	1	1	1
811BO9	1	1	1	1	4
811BP0	1	2	1	1	2
811BP1	1	1	1	1	1
811BP2	2	4	2	4	11
811BP3	1	1	1	1	1
821BA5	1	1	1	1	2
821BO4	1	2	1	1	7
821BP6	1	13	1	1	15
821BP7	1	1	1	1	2
831B90	2	15	2	2	13
831BA7	1	6	1	1	30
831BP8	1	1	1	2	11
831BP9	1	11	1	8	46
831BR1	1	1	1	4	21
831BR2	1	1	1	1	6
831BC8	1	1	1	1	1
841BO4	1	1	1	1	4
841BR4	1	4	1	1	2
841BR5	1	7	1	8	20
841BR6	1	1	1	3	10
851BR7	1	21	1	9	40
851BR8	1	1	1	1	1
851BR9	1	1	1	1	4
851BS0	1	1	1	1	1
851BS1	1	1	1	1	10
851BS2	1	7	1	3	12
851BS3	1	1	1	1	1
851BX2	1	1	1	1	1
861B98	1	2	1	1	12
861BS4	1	3	1	1	4
861BS6	1	11	1	5	17
861BT6	1	3	1	1	5
861BC0	1	1	1	1	1
873TY8	1	1	1	1	1
902DX6	1	1	1	1	1
913HX8	1	1	1	1	1
923JC1	1	1	1	1	1
933JC6	1	1	1	1	1
943XC7	1	1	1	1	2
943XV1	1	1	1	1	1
951A01	1	1	1	1	1
951A02	1	1	1	1	1
951A04	1	1	1	1	1
951A05	1	1	1	1	1
951A06	1	1	1	1	1
951A07	1	1	1	1	1
951A10	1	1	1	1	1
951A15	1	1	1	1	1
951A16	1	1	1	1	2
951A22	1	1	1	1	1
951A23	1	1	1	1	14

951A26	1	1	1	1	1
951A37	1	1	1	1	6
951A38	2	2	2	2	2
951A39	1	1	1	1	1
951A41	1	1	1	1	1
951A42	1	1	1	1	1
951A52	1	1	1	1	2
951A53	2	2	2	2	2
951A54	1	1	1	1	1
951A64	1	1	1	1	1
951A67	1	1	1	1	2
951A69	5	5	5	5	5
951A71	1	1	1	1	1
951A72	1	3	1	1	4
951A77	1	1	1	1	1
951A78	1	1	1	1	1
951AN1	1	1	1	1	1
951AX4	1	1	1	1	1
952G11	1	26	1	5	9
952G12	1	1	1	1	3
952G44	1	1	1	1	1
952G45	1	1	1	1	1
952G46	1	1	1	1	1
952G50	1	1	1	1	1
952G77	1	1	1	1	1
952GX5	1	1	1	1	1
952D35	1	2	1	1	4
952EJ2	1	1	1	1	1
963CV0	3	200	3	66	423
AA1A54	1	1	1	1	1
AA1A72	1	1	1	1	1
AB1A05	1	1	1	1	1
AB1A11	1	1	1	1	1
AB1A35	1	1	1	1	1
AB1A38	1	2	1	1	5
AB1AAR	1	1	1	1	65
AB1AT6	1	1	1	1	1
AH1BBC	1	9	1	2	96
AK2E04	1	1	1	6	10
AK2E59	1	1	1	1	1
AK2EBH	1	1	1	1	1
AK2EBU	1	1	1	1	1
AK2EBI	1	1	1	1	2
AK2EBV	1	1	1	1	1
AT1AAT	1	1	1	1	1

Make A Density Based Clusterer with 5 Clusters

```
Final cluster centroids:
                            Cluster#
Attribute      Full Data          0          1          2          3          4
                 (108.0)      (8.0)     (87.0)      (7.0)      (1.0)      (5.0)
========================================================================
GENDER            WOMAN      WOMAN        MAN      WOMAN      WOMAN      WOMAN
AGE                  32         38         32         37         52         39
011A01                2         81          2         14        153         47
011A02                1         22          1          8        109         33
011A03                1          1          1          1          1          1
011A04                1          1          1          1         17          4
011AAY                1         45          1          7         89         24
011AAF                1         96          1         20        324         41
```

011AAX	3	27	3	36	69	17
011AAC	2	15	2	22	47	8
011AAV	2	2	2	3	24	2
012G01	1	1	1	1	1	1
012GZ5	1	2	1	1	8	4
012D04	1	1	1	1	1	1
012DBA	1	11	1	1	10	1
012DBB	1	1	1	1	1	1
012DZ5	1	7	1	6	14	1
012DF0	1	3	1	1	11	1
012DF3	1	7	1	1	20	11
021A05	2	31	2	43	100	20
021A06	1	14	1	7	53	18
021E05	1	2	1	1	6	1
021E06	1	1	1	1	1	1
031A07	1	19	1	2	49	7
031A68	1	17	1	1	38	10
031A73	1	26	1	4	37	13
031A74	1	1	1	1	2	1
041A08	3	69	3	75	221	62
041A09	1	1	1	2	11	4
041A16	1	1	1	1	18	1
041A17	1	8	1	7	58	1
041A18	1	1	1	1	2	1
041A19	1	1	1	1	1	1
041A20	1	5	1	1	11	2
041A21	1	56	1	39	80	7
041A22	1	3	1	2	8	3
041A23	1	14	1	18	39	7
041A25	1	72	1	24	198	34
041A26	1	12	1	9	87	13
041A27	1	10	1	8	14	8
041A28	2	19	2	8	49	5
041AC2	2	5	2	1	7	2
042G19	1	1	1	1	1	1
042D21	1	1	1	1	1	1
042DZ3	1	14	1	8	52	27
042E20	1	1	1	1	1	1
051A10	1	35	1	7	124	9
051A29	1	4	1	1	10	1
051A30	1	4	1	1	7	3
051A33	1	1	1	1	1	1
051A34	1	13	1	2	14	1
061A11	4	6	4	4	60	28
062G11	3	119	3	23	315	39
062G12	1	84	1	91	208	70
062G14	1	10	1	17	41	11
062GX0	1	1	1	1	1	1
062GC5	1	37	1	1	38	11
062GC9	1	1	1	1	20	1
062E12	2	2	2	2	2	2
071A15	1	15	1	37	81	20
081A24	5	42	5	7	140	32
082G24	1	3	1	1	5	1
091A31	2	51	2	12	229	37
091BBN	1	1	1	3	2	1
092G31	1	1	1	1	1	1
092E31	2	3	2	5	17	2
101A37	4	50	4	3	108	30
102D35	1	18	1	5	86	16
102E35	1	214	1	176	478	121
111A36	1	1	1	1	1	1
112E40	11	120	11	61	344	88
121A38	1	17	1	1	13	8
121A39	1	14	1	5	16	8
121A64	1	16	1	2	16	3
121A65	1	5	1	5	20	5
121A67	1	2	1	1	18	3
121AZ4	1	1	1	1	1	1
122G63	2	9	2	2	12	3
122G67	1	1	1	1	3	1
131A41	2	74	2	8	62	14

132G41	1	1	1	1	1	1
132D41	1	14	1	1	24	3
141A42	1	1	1	1	1	1
141A43	1	8	1	3	4	3
141ABG	1	1	1	1	1	1
141ABD	1	14	1	2	16	3
142G44	1	15	1	32	87	13
142G45	2	13	2	2	11	2
142E45	1	1	1	1	1	1
152G46	2	41	2	8	130	24
152GY0	1	1	1	1	1	1
152E46	4	74	4	17	162	18
162G50	1	66	1	14	144	55
162EJ2	1	142	1	123	323	85
172G51	1	10	1	1	6	1
172GM6	1	1	1	1	1	1
172E51	1	8	1	2	12	2
172EJ3	1	1	1	1	1	1
182G52	1	17	1	3	30	2
182E52	1	5	1	11	25	14
191A53	1	1	1	1	1	1
192E53	1	4	1	3	10	11
201A54	1	1	1	2	1	1
202G54	1	1	1	1	1	1
202E54	2	2	2	1	3	2
212D55	1	13	1	3	24	9
212D56	1	7	1	13	26	3
212E55	1	2	1	2	3	1
212E56	2	2	2	2	2	2
222G59	1	2	1	1	19	7
222D58	1	1	1	1	12	1
222D59	1	5	1	1	9	1
222D62	1	1	1	1	1	1
222E57	1	35	1	3	116	14
222E58	1	26	1	25	107	36
222E59	5	35	5	3	108	21
222E60	2	2	2	2	2	2
222E61	2	2	2	2	7	3
222E62	1	1	1	1	1	1
222EY1	1	1	1	1	2	1
231A66	2	51	2	21	126	31
241A08	1	19	1	11	21	2
241A70	1	8	1	3	35	6
241A71	2	40	2	7	116	54
241A72	1	12	1	19	38	9
242E72	1	5	1	8	13	7
251A33	1	8	1	6	25	7
251A75	8	108	8	19	133	25
251A76	1	7	1	2	41	6
251AX3	2	2	2	2	4	2
251AX4	3	89	3	72	155	37
251AX5	1	21	1	11	76	47
252G33	1	1	1	1	6	1
252G76	1	1	1	1	1	1
252GX5	1	9	1	22	44	18
261A77	1	21	1	8	61	11
261A78	1	5	1	8	18	1
261A79	1	1	1	1	1	2
261A80	1	1	1	1	4	1
261A81	1	1	1	1	1	1
261A82	1	1	1	1	1	1
261A83	1	1	1	1	7	1
261A84	1	1	1	1	1	1
261A85	1	1	1	1	1	1
261A86	1	1	1	1	1	1
261A88	1	1	1	1	3	1
261AZ7	1	1	1	1	1	1
261AX4	1	1	1	1	1	1
281BB1	2	9	2	14	75	8
281BD9	1	1	1	1	2	1
281BE1	1	6	1	1	41	1
281BS7	1	29	1	5	27	3

281BS8	1	3	1	1	9	1
281BS9	1	9	1	1	29	4
281BT0	1	1	1	1	7	1
281BT3	1	1	1	1	1	1
291BA4	1	5	1	2	20	7
291BA8	1	22	1	7	36	7
291BC4	1	1	1	1	1	1
301BB2	1	37	1	18	91	17
301BB3	1	22	1	47	73	33
301BB4	2	38	2	22	128	40
301BB5	1	19	1	10	56	9
301BG1	1	1	1	1	1	1
301BT2	1	1	1	1	2	1
311BA8	1	1	1	1	17	4
311BB6	1	3	1	1	10	1
321BB7	1	1	1	1	2	1
321BB8	1	6	1	3	24	4
331BB9	1	1	1	1	3	1
331BY5	1	1	1	1	1	1
341BG3	1	14	1	3	26	2
341BG4	1	6	1	1	20	2
351BG8	1	4	1	4	8	1
351BG9	1	4	1	1	4	1
351BD1	1	2	1	1	7	2
351BD2	1	1	1	1	1	1
351BD3	1	11	1	11	29	9
351BD5	1	13	1	4	16	1
361BBL	1	10	1	1	5	1
361BG2	1	1	1	1	2	1
361BG5	1	18	1	6	43	11
361BG6	1	1	1	1	1	1
361BG7	3	25	3	29	61	20
361BD4	1	1	1	1	1	1
361BD6	1	1	1	2	2	2
361BD8	1	2	1	1	3	1
361BM5	1	5	1	2	9	5
361BY4	1	1	1	1	1	1
361BY6	1	2	1	1	33	4
371AE2	1	9	1	7	76	1
371BE3	1	4	1	1	18	1
381BE4	2	18	2	31	44	14
381BE5	1	28	1	21	146	19
381BE6	2	23	2	4	121	54
381BE7	1	25	1	41	89	15
391BE8	1	1	1	3	6	1
401BE9	1	6	1	1	7	6
401BZ1	1	4	1	1	9	1
411A14	1	1	1	1	1	1
411AZ2	1	1	1	1	1	1
423ZH1	1	1	1	1	1	1
423ZH2	1	1	1	1	3	1
433ZBM	1	1	1	1	1	1
433ZH1	1	1	1	1	3	2
433ZH2	1	4	1	1	11	4
433ZH3	1	1	1	1	1	1
433ZH5	1	1	1	1	1	1
463HH1	1	1	1	1	1	1
463HH2	1	1	1	1	1	1
463HH3	1	7	1	3	8	1
463HH4	1	1	1	1	1	1
463HH5	1	1	1	1	3	1
473UH1	1	1	1	1	2	1
473UH2	1	1	1	1	3	2
473UH3	1	1	1	1	1	1
473UH4	1	1	1	1	1	1
483IH6	1	3	1	1	9	2
483IH7	1	1	1	1	6	3
483IH8	1	1	1	1	6	1
483IH9	1	4	1	2	6	1
493KU1	1	1	1	1	1	1
493KU2	1	1	1	1	1	1
503KU4	1	5	1	6	22	8

503KU5	1	1	1	1	1	1
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503KU7	1	3	1	1	6	2
513KU8	1	1	1	1	1	1
513KU9	1	2	1	1	4	4
533LI1	1	1	1	1	1	1
543LI3	1	1	1	1	2	1
553LH4	1	1	1	1	1	1
563LI5	1	1	1	6	5	2
563LI6	1	1	1	1	1	1
573LI7	1	1	1	1	2	1
573LI8	1	1	1	1	1	1
583LI9	1	1	1	1	2	1
583LK1	1	1	1	1	1	1
603MK6	1	1	1	3	3	1
613MK7	1	1	1	1	1	1
623MK8	1	3	1	3	5	3
633NK9	1	9	1	12	19	10
633NX7	2	3	2	7	22	2
643NL1	1	2	1	1	9	1
653NL2	1	6	1	11	13	1
663NL3	2	7	2	14	26	7
673NL4	1	5	1	3	8	3
673NL5	1	1	1	1	1	1
673NN9	1	4	1	1	7	1
683JL5	1	1	1	1	1	1
693JL5	1	1	1	1	1	1
693JL7	1	1	1	1	1	1
693JL8	1	1	1	1	1	1
703JL5	1	5	1	4	5	3
723PM2	1	1	1	1	1	1
733PM3	1	1	1	1	5	1
733PN8	1	1	1	1	1	1
743PM4	1	1	1	1	1	1
751BT8	1	1	1	1	8	1
761AN1	1	17	1	2	40	4
762GN1	1	21	1	1	80	2
771BN2	1	1	1	1	1	1
783RN5	1	1	1	1	1	1
783RN6	1	1	1	1	1	1
793SB0	1	1	1	1	4	1
793SG0	1	1	1	1	2	1
793SD0	1	1	1	1	3	1
803TA0	1	1	1	1	1	1
803TBJ	1	1	1	1	1	1
811BAP	1	4	1	2	7	2
811BAS	1	2	1	1	5	1
811BJ4	1	8	1	6	25	8
811BJ6	1	1	1	1	1	1
811BJ7	2	4	2	2	14	2
811BJ9	1	1	1	1	2	1
811BO1	1	5	1	1	19	12
811BO2	1	14	1	1	9	2
811BO3	1	1	1	1	5	1
811BO4	1	7	1	1	7	1
811BO5	1	1	1	1	1	1
811BO6	1	1	1	1	1	1
811BO8	1	1	1	1	1	1
811BO9	1	1	1	1	4	1
811BP0	1	2	1	1	2	1
811BP1	1	1	1	1	1	1
811BP2	2	4	2	2	11	2
811BP3	1	1	1	1	1	1
821BA5	1	1	1	1	2	1
821BO4	1	2	1	1	7	2
821BP6	1	13	1	1	15	1
821BP7	1	1	1	1	2	1
831B90	2	15	2	2	13	4
831BA7	1	6	1	8	30	1
831BP8	1	1	1	2	11	1
831BP9	1	11	1	8	46	8
831BR1	1	1	1	3	21	8

831BR2	1	1	1	1	6	1
831BC8	1	1	1	1	1	1
841BO4	1	1	1	1	4	1
841BR4	1	4	1	1	2	1
841BR5	1	7	1	8	20	6
841BR6	1	1	1	1	10	1
851BR7	1	21	1	9	40	10
851BR8	1	1	1	1	1	1
851BR9	1	1	1	1	4	1
851BS0	1	1	1	1	1	1
851BS1	1	1	1	1	10	1
851BS2	1	7	1	3	12	1
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861B98	1	2	1	1	12	1
861BS4	1	3	1	1	4	1
861BS6	1	11	1	5	17	7
861BT6	1	3	1	1	5	1
861BC0	1	1	1	1	1	1
873TY8	1	1	1	1	1	1
902DX6	1	1	1	1	1	1
913HX8	1	1	1	1	1	1
923JC1	1	1	1	1	1	1
933JC6	1	1	1	1	1	1
943XC7	1	1	1	1	2	1
943XV1	1	1	1	1	1	1
951A01	1	1	1	1	1	1
951A02	1	1	1	1	1	1
951A04	1	1	1	1	1	1
951A05	1	1	1	1	1	1
951A06	1	1	1	1	1	1
951A07	1	1	1	1	1	1
951A10	1	1	1	1	1	1
951A15	1	1	1	1	1	1
951A16	1	1	1	1	2	1
951A22	1	1	1	1	1	1
951A23	1	1	1	1	14	1
951A26	1	1	1	1	1	1
951A37	1	1	1	1	6	1
951A38	2	2	2	2	2	2
951A39	1	1	1	1	1	1
951A41	1	1	1	1	1	1
951A42	1	1	1	1	1	1
951A52	1	1	1	1	2	1
951A53	2	2	2	2	2	2
951A54	1	1	1	1	1	1
951A64	1	1	1	1	1	1
951A67	1	1	1	1	2	1
951A69	5	5	5	5	5	5
951A71	1	1	1	1	1	1
951A72	1	3	1	1	4	2
951A77	1	1	1	1	1	1
951A78	1	1	1	1	1	1
951AN1	1	1	1	1	1	1
951AX4	1	1	1	1	1	1
952G11	1	26	1	4	9	9
952G12	1	1	1	1	3	1
952G44	1	1	1	1	1	1
952G45	1	1	1	1	1	1
952G46	1	1	1	1	1	1
952G50	1	1	1	1	1	1
952G77	1	1	1	1	1	1
952GX5	1	1	1	1	1	1
952D35	1	2	1	1	4	1
952EJ2	1	1	1	1	1	1
963CV0	3	200	3	66	423	101
AA1A54	1	1	1	1	1	1
AA1A72	1	1	1	1	1	1
AB1A05	1	1	1	1	1	1
AB1A11	1	1	1	1	1	1
AB1A35	1	1	1	1	1	1
AB1A38	1	2	1	1	5	1

AB1AAR	1	1	1	1	65	1
AB1AT6	1	1	1	1	1	1
AH1BBC	1	9	1	7	96	8
AK2E04	1	1	1	6	10	2
AK2E59	1	1	1	1	1	1
AK2EBH	1	1	1	1	1	1
AK2EBU	1	1	1	1	1	1
AK2EBI	1	1	1	1	2	1
AK2EBV	1	1	1	1	1	1
AT1AAT	1	1	1	1	1	1

Farthest First Clusterer

Farthest First with 2 Clusters

Cluster centroids:

Cluster 0: WOMAN 82 4 9 1 1 8 1 2 4 2 3 1 1 1 1 1 1 1 3 1 1 1 2 1 1 1 4 1 1 1 1 1 1 1 1 1 8 1 1 2 3 1 1 2 1 1 1 1 1 1 7 20 17 2 1 1 1 1 8 10 4 3 1 1 2 4 7 34 1 39 3 1 1 1 3 1 2 1 7 1 1 1 1 1 1 1 2 1 10 1 8 6 22 1 1 2 1 1 1 1 6 1 1 2 7 2 1 2 1 1 1 1 10 10 15 2 8 1 1 8 1 3 13 4 1 1 21 1 2 17 19 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 2 1 1 1 1 1 1 1 2 1 4 1 1 1 1 1 1 6 1 1 1 1 1 1 1 1 1 1 1 1 2 1 3 1 1 1 1 1 1 2 1 2 5 5 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 6 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 2 1 1 1 5 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 6 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Cluster 1: WOMAN 52 153 109 1 17 89 324 69 47 24 1 8 1 10 1 14 11 20 100 53 6 1 49 38 37 2 221 11 18 58 2 1 11 80 8 39 198 87 14 49 7 1 1 52 1 124 10 7 1 14 60 315 208 41 1 38 20 2 81 140 5 229 2 1 17 108 86 478 1 344 13 16 16 20 18 1 12 3 62 1 24 1 4 1 16 87 11 1 130 1 162 144 323 6 1 12 1 30 25 1 10 1 1 3 24 26 3 2 19 12 9 1 116 107 108 2 7 1 2 126 21 35 116 38 13 25 133 41 4 155 76 6 1 44 61 18 1 4 1 1 7 1 1 1 3 1 1 75 2 41 27 9 29 7 1 20 36 1 91 73 128 56 1 2 17 10 2 24 3 1 26 20 8 4 7 1 29 16 5 2 43 1 61 1 2 3 9 1 33 76 18 44 146 121 89 6 7 9 1 1 1 3 1 3 11 1 1 1 1 8 1 3 2 3 1 1 9 6 6 6 1 1 22 1 1 6 1 4 1 2 1 5 1 2 1 2 1 3 1 5 19 22 9 13 26 8 1 7 1 1 1 1 5 1 5 1 1 8 40 80 1 1 1 4 2 3 1 1 7 5 25 1 14 2 19 9 5 7 1 1 1 4 2 1 11 1 2 7 15 2 13 30 11 46 21 6 1 4 2 20 10 40 1 4 1 10 12 1 1 12 4 17 5 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 2 1 14 1 6 2 1 1 1 2 2 1 1 2 5 1 4 1 1 1 1 9 3 1 1 1 1 1 1 4 1 423 1 1 1 1 1 5 65 1 96 10 1 1 1 2 1 1

Farthest First with 3 Clusters

Cluster centroids:

Cluster 0: WOMAN 82 4 9 1 1 8 1 2 4 2 3 1 1 1 1 1 1 1 3 1 1 1 2 1 1 1 4 1 1 1 1 1 1 1 1 1 8 1 1 2 3 1 1 2 1 1 1 1 1 1 7 20 17 2 1 1 1 1 8 10 4 3 1 1 2 4 7 34 1 39 3 1 1 1 3 1 2 1 7 1 1 1 1 1 1 1 2 1 10 1 8 6 22 1 1 2 1 1 1 1 6 1 1 2 7 2 1 2 1 1 1 1 10 10 15 2 8 1 1 8 1 3 13 4 1 1 21 1 2 17 19 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 2 1 1 1 1 1 1 1 2 1 4 1 1 1 1 1 1 6 1 1 1 1 1 1 1 1 1 1 1 1 2 1 3 1 1 1 1 1 1 2 1 2 5 5 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 1 1 1 1 1 1 1 1 1

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Clustered Instances

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<u>Farthest First with 4 Clusters</u>

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Clustered Instances

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1   1 (1%)

2   1 (1%)

3   1 (1%)

Farthest First with 5 Clusters

Cluster centroids:

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Clustered Instances

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2 1 (1%)

3 1 (1%)

4 1 (1%)

EM Clusterer

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Number of clusters selected by cross validation: 7
Number of iterations performed: 3


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  21             1    1    2    1    1    1    1
  22             1    1    2    1    1    3    1
  24             1    2    1    1    1    2    1
  25             1    1    1    1    1    2    1
  26             1    1    2    1    1    2    2
  29             1    1    2    1    1    2    1
  30             1    1    2    1    1    1    1
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34	1	1	2	1	1	1	1
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39	1	1	1	1	1	2	1
45	1	1	1	1	1	3	2
47	1	1	2	1	1	1	1
52	1	1	1	1	1	1	2
60	1	1	1	1	1	1	2
62	1	1	1	1	1	1	2
63	1	1	2	1	1	1	1
68	2	1	1	1	1	1	1
82	1	1	2	1	1	1	1
89	1	1	1	1	1	2	1
[total]	38	39	122	38	38	50	42
011AAF							
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4	1	1	3	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	7	1	1	1	1
7	1	1	7	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	5	1	1	1	1
14	1	1	2	1	1	1	1
16	1	1	3	1	1	1	1
17	1	1	2	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	4	1	1	1	1
20	1	1	4	1	1	1	1
22	1	1	3	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	3	1	1	1	1
27	1	1	2	1	1	1	1
30	1	1	2	1	1	1	1
34	1	1	3	1	1	1	1
39	1	1	3	1	1	1	1
40	1	1	2	1	1	1	1
41	1	1	4	1	1	2	1
45	1	1	2	1	1	1	1
46	1	1	2	1	1	1	1
47	1	1	2	1	1	1	1
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61	1	1	2	1	1	1	1
65	1	1	2	1	1	1	1
66	1	1	1	1	1	2	1
69	1	1	1	1	1	2	1
77	1	1	2	1	1	1	1
80	1	1	2	1	1	1	1
86	1	1	2	1	2	2	1
87	1	1	1	1	1	2	1
88	2	1	1	1	1	1	1
96	1	1	1	1	1	2	1

97	1	1	2	1	1	1	1
100	1	1	2	1	1	1	1
106	1	1	1	1	1	1	2
111	1	2	1	1	1	1	1
118	1	1	1	1	1	1	2
124	1	1	1	1	1	2	1
137	1	1	1	1	1	1	2
147	1	1	1	1	1	2	1
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151	1	1	1	1	1	1	2
162	1	1	1	1	1	2	1
163	1	1	1	1	1	1	2
184	1	1	1	1	1	2	1
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204	1	1	1	1	1	2	1
265	1	1	1	2	1	1	1
324	1	1	1	1	1	2	1
[total]	59	60	143	59	59	71	63
011AAX							
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7	1	1	5	1	1	1	1
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10	1	1	2	1	1	1	1
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12	1	1	3	1	1	1	1
13	1	1	3	1	1	2	1
15	1	1	2	1	1	1	1
16	1	1	3	1	1	1	1
17	1	2	3	1	1	1	1
20	1	1	2	1	1	1	1
21	1	1	1	1	1	2	1
24	1	1	1	1	1	2	1
26	1	1	2	1	1	1	1
27	1	1	1	1	1	3	1
28	1	1	1	1	1	2	1
31	1	1	1	1	1	2	1
32	1	1	1	1	1	1	2
33	1	1	2	1	1	1	1
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35	1	2	1	1	1	1	1
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47	1	1	2	1	1	1	1
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49	1	1	1	1	1	2	2
50	1	1	1	1	1	1	2
59	1	1	1	1	1	2	1
64	1	1	1	1	1	1	2
66	1	1	1	2	1	1	1

68	1	1	1	1	1	2	1
69	1	1	1	1	1	2	1
76	1	1	2	1	1	1	1
[total]	43	44	127	43	43	55	47
011AAC							
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4	1	1	5	1	1	1	1
5	1	1	6	1	1	1	1
6	1	1	6	1	1	1	1
7	1	1	2	1	1	1	1
8	1	2	6	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	6	1	1	2	1
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17	1	1	3	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	3	1	1	2	1
20	1	1	2	1	1	2	1
21	1	1	2	1	1	2	1
22	1	1	3	1	1	1	2
23	1	1	1	1	1	2	1
24	1	1	3	1	1	2	1
26	1	1	1	1	2	1	2
27	1	2	1	1	1	2	1
28	2	1	2	1	1	1	1
29	1	1	1	1	1	1	2
34	1	1	2	1	1	1	1
40	1	1	2	1	1	1	1
42	1	1	2	1	1	1	1
44	1	1	1	1	1	2	1
45	1	1	1	1	1	2	1
47	1	1	1	1	1	2	1
51	1	1	1	1	1	1	2
52	1	1	1	1	1	1	2
53	1	1	1	2	1	1	1
[total]	37	38	121	37	37	49	41
011AAV							
1	1	1	10	1	1	1	2
2	1	1	57	1	1	4	1
3	2	1	4	1	1	1	1
4	1	1	8	1	1	1	1
5	1	1	4	1	1	1	1
6	1	1	2	1	2	2	2
7	1	1	2	1	1	2	1
8	1	2	4	1	1	2	1
10	1	1	3	1	1	2	1
11	1	1	1	1	1	2	1
18	1	1	1	1	1	2	1
19	1	1	1	1	1	2	2
24	1	1	1	1	1	2	1
27	1	1	1	1	1	1	2
30	1	1	1	1	1	2	1

31	1	2	1	1	1	1	1
38	1	1	1	1	1	2	1
47	1	1	1	2	1	1	1
54	1	1	1	1	1	1	2
[total]	20	21	104	20	20	32	24
012G01							
1	2	3	83	2	2	13	5
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3	1	1	2	1	1	2	2
4	1	1	2	1	1	1	1
[total]	5	6	89	5	5	17	9
012GZ5							
1	1	2	77	1	2	4	3
2	1	1	4	1	1	2	3
3	1	1	4	2	1	2	1
4	1	1	2	1	1	4	1
5	1	1	3	1	1	2	1
6	1	1	1	1	1	2	1
7	1	2	1	1	1	1	1
8	2	1	1	1	1	2	1
12	1	1	1	1	1	2	2
17	1	1	1	1	1	2	1
[total]	11	12	95	11	11	23	15
012D04							
1	1	2	84	2	1	11	6
2	2	1	1	1	2	3	1
3	1	1	2	1	1	2	1
6	1	2	2	1	1	1	1
[total]	5	6	89	5	5	17	9
012DBA							
1	1	1	63	1	1	4	1
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3	1	1	4	1	1	2	1
4	2	1	5	1	1	2	1
5	1	1	3	1	1	1	2
6	1	2	2	1	2	1	2
7	1	1	2	1	1	1	1
8	1	1	1	1	1	1	2
9	1	1	2	2	1	2	1
10	1	1	1	1	1	2	2
11	1	2	1	1	1	2	2
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16	1	1	1	1	1	2	1
19	1	1	1	1	1	2	1
[total]	15	16	99	15	15	27	19
012DBB							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
012DZ5							
1	1	1	62	1	1	2	1
2	2	1	9	2	1	1	1
3	1	1	7	1	1	4	1
4	1	1	5	1	1	1	1
5	1	1	2	1	1	2	1
6	1	2	3	1	1	1	2
7	1	2	1	1	2	3	1
8	1	1	2	1	1	1	1
9	1	1	3	1	1	1	3

11	1	1	1	1	1	1	2
12	1	1	1	1	1	3	1
13	1	1	1	1	1	3	1
14	1	1	1	1	1	2	1
22	1	1	1	1	1	1	2
23	1	1	1	1	1	2	1
[total]	16	17	100	16	16	28	20
012DF0							
1	1	2	74	1	2	5	3
2	1	1	7	2	1	2	2
3	1	2	5	1	1	5	1
4	1	1	2	1	1	2	2
5	2	1	1	1	1	2	1
6	1	1	1	1	1	2	1
7	1	1	2	1	1	1	2
11	1	1	1	1	1	2	1
[total]	9	10	93	9	9	21	13
012DF3							
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3	1	1	6	1	1	1	1
4	1	1	6	1	1	1	1
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7	1	2	2	1	1	2	1
8	1	1	3	2	1	2	2
9	1	1	2	1	1	1	1
10	1	1	1	1	2	1	1
11	1	1	2	1	1	2	2
12	1	1	1	1	1	5	1
13	1	1	2	1	1	1	1
14	1	1	1	1	1	2	2
15	1	1	1	1	1	2	2
16	1	2	1	1	1	1	1
17	2	1	1	1	1	1	1
20	1	1	1	1	1	2	1
24	1	1	1	1	1	2	2
[total]	20	21	104	20	20	32	24
021A05							
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4	1	1	5	1	1	1	1
5	1	1	3	1	1	1	1
6	1	1	8	1	1	1	1
7	1	1	3	1	1	1	1
8	1	1	4	1	1	1	1
9	1	1	6	1	1	1	1
10	1	1	6	1	1	1	1
11	1	1	3	1	1	1	1
12	1	1	2	1	1	1	1
13	1	1	3	1	1	1	1
14	1	1	2	1	1	1	1
15	1	1	2	1	1	1	1
16	1	1	2	1	1	1	1
17	1	1	2	1	1	1	1
18	1	1	2	1	1	1	1
20	1	2	1	1	1	2	1

21	1	1	2	1	1	1	1
24	1	1	1	1	1	3	1
25	1	1	1	1	2	1	1
26	1	1	4	1	1	1	1
27	1	1	2	1	1	2	1
31	1	1	1	1	1	2	1
32	1	1	1	1	1	2	2
34	1	1	1	1	1	1	2
38	1	2	1	1	1	1	1
39	1	1	1	1	1	2	1
43	2	1	1	1	1	3	1
45	1	1	1	1	1	2	1
49	1	1	1	1	1	1	2
53	1	1	1	1	1	2	1
54	1	1	1	1	1	1	2
56	1	1	1	1	1	1	2
68	1	1	1	1	1	2	1
98	1	1	1	2	1	1	1
100	1	1	1	1	1	2	1
[total]	39	40	123	39	39	51	43
021A06							
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4	1	1	2	1	1	1	1
5	1	1	6	1	1	1	1
6	1	1	8	1	1	1	1
7	1	1	7	1	1	1	1
8	1	1	5	1	1	1	1
9	1	1	3	1	1	1	1
11	1	1	2	1	1	1	1
13	1	1	3	1	1	1	1
14	1	1	3	1	1	2	1
15	1	1	6	1	1	1	1
17	1	1	3	1	1	1	1
18	1	2	1	1	1	1	1
21	1	1	2	1	1	1	1
23	1	1	2	1	2	2	1
24	1	1	1	1	1	2	1
25	1	1	1	1	1	1	2
28	1	1	1	1	1	3	1
29	1	2	1	1	1	1	1
31	1	1	1	1	1	3	1
35	1	1	2	1	1	1	2
37	1	1	1	1	1	2	1
38	1	1	1	1	1	1	2
40	1	1	1	1	1	2	2
42	2	1	1	1	1	1	1
43	1	1	2	1	1	1	1
46	1	1	1	1	1	1	2
49	1	1	1	1	1	2	1
53	1	1	1	1	1	3	1
56	1	1	1	1	1	2	1
62	1	1	1	2	1	1	1
[total]	34	35	118	34	34	46	38
021E05							
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2	1	1	3	1	1	5	2

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7	2	1	2	1	1	1	1
9	1	1	1	1	1	2	1
14	1	1	2	1	1	1	1
18	1	1	1	1	1	1	2
[total]	10	11	94	10	10	22	14
021E06							
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4	2	1	1	1	1	1	2
7	1	1	2	1	1	2	1
16	1	1	1	1	2	1	1
[total]	6	7	90	6	6	18	10
031A07							
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3	1	1	10	1	1	1	1
4	1	1	8	1	1	1	1
5	1	1	6	1	1	1	1
6	1	1	5	1	1	1	1
7	1	2	5	1	1	1	1
8	1	1	5	1	1	2	1
9	1	1	3	1	1	2	1
10	1	1	4	1	1	1	1
11	1	1	2	1	1	2	1
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13	1	2	1	1	1	1	1
15	2	1	1	1	1	2	1
16	1	1	2	1	1	1	2
17	1	1	2	1	1	1	1
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19	1	1	1	1	1	4	1
23	1	1	1	1	1	2	1
25	1	1	1	1	1	1	2
27	1	1	1	2	1	2	1
28	1	1	1	1	1	1	2
32	1	1	1	1	2	1	1
34	1	1	1	1	1	2	1
39	1	1	1	1	1	1	2
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[total]	27	28	111	27	27	39	31
031A68							
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11	1	1	6	1	1	1	1
13	1	2	2	1	1	1	2
16	1	1	1	1	1	1	2
17	1	1	2	1	1	2	1

18	1	1	2	1	1	1	1
19	1	1	1	1	1	2	1
20	1	1	1	1	1	2	1
22	1	2	1	1	1	1	1
23	1	1	1	1	1	2	1
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32	1	1	1	1	1	1	2
33	1	1	1	1	1	2	1
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38	1	1	1	1	1	2	1
43	1	1	1	1	1	2	1
44	1	1	1	1	1	2	1
45	1	1	1	1	1	1	2
[total]	32	33	116	32	32	44	36
031A73							
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3	1	1	10	1	1	1	1
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5	1	1	9	1	1	1	1
6	1	1	5	1	1	1	1
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9	1	1	3	1	1	2	1
10	1	1	2	1	1	1	2
11	1	1	3	1	1	1	1
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13	1	1	2	1	1	2	1
14	1	1	1	1	2	2	1
15	1	1	1	1	1	2	1
16	1	2	1	1	1	1	1
17	1	1	2	1	1	1	1
18	1	1	1	1	1	3	1
19	1	1	1	1	1	1	2
22	2	1	1	1	1	1	1
25	1	1	1	1	1	2	1
26	1	1	1	1	1	3	1
27	1	1	1	1	1	3	1
30	1	1	1	2	1	1	2
31	1	1	1	1	1	2	1
37	1	1	1	1	1	2	1
38	1	1	1	1	1	1	2
39	1	1	1	1	1	1	2
[total]	28	29	112	28	28	40	32
031A74							
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3	1	1	2	1	1	1	1
4	1	1	3	1	2	1	1
[total]	5	6	89	5	5	17	9
041A08							
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3	1	1	19	1	1	1	1
4	1	1	4	1	1	1	1

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6	1	1	5	1	1	1	1
7	1	1	2	1	1	1	1
8	1	1	2	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	3	1	1	1	1
12	1	1	2	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	3	1	1	1	1
15	1	1	2	1	1	1	1
19	1	1	3	1	1	1	1
21	1	1	3	1	1	1	1
23	1	1	3	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	5	1	1	1	1
26	1	1	4	1	1	1	1
28	1	1	3	1	1	1	1
33	1	1	3	1	1	1	1
35	1	1	2	1	1	1	1
36	1	1	3	1	1	1	1
37	1	1	2	1	1	1	1
39	1	1	3	1	1	1	1
40	1	1	2	1	1	1	1
42	1	1	2	1	1	1	1
43	1	1	2	1	1	1	1
44	1	1	2	1	1	1	1
47	1	1	2	1	1	1	1
50	1	1	2	1	1	1	1
62	1	1	1	1	1	2	1
64	1	1	2	1	1	2	1
66	1	1	2	1	1	2	1
69	1	1	1	1	1	2	1
75	2	2	1	1	1	2	1
77	1	1	2	1	1	1	1
89	1	1	1	1	1	2	1
90	1	1	1	1	1	2	1
92	1	1	1	1	1	2	1
96	1	1	1	1	2	1	1
97	1	1	1	1	1	2	1
98	1	1	1	1	1	2	1
99	1	1	1	1	1	1	2
106	1	1	1	1	1	1	2
111	1	1	1	1	1	2	1
112	1	1	1	1	1	1	2
113	1	1	1	1	1	1	2
121	1	1	2	1	1	1	1
127	1	2	1	1	1	1	1
159	1	1	1	2	1	1	1
164	1	1	1	1	1	2	1
168	1	1	1	1	1	1	2
221	1	1	1	1	1	2	1
[total]	57	58	141	57	57	69	61
041A09							
1	1	1	70	2	1	6	1
2	1	1	6	1	1	3	2
3	1	1	6	1	1	2	2
4	1	2	2	1	1	1	2

5	1	1	2	1	2	1	1
6	1	1	3	1	1	1	1
7	1	1	1	1	1	2	2
8	1	1	1	1	1	2	1
9	2	1	1	1	1	1	1
10	1	2	1	1	1	1	1
11	1	1	1	1	1	2	1
12	1	1	1	1	1	1	2
13	1	1	1	1	1	2	1
16	1	1	1	1	1	2	1
26	1	1	2	1	1	1	1
41	1	1	2	1	1	1	1
[total]	17	18	101	17	17	29	21
041A16							
1	2	1	69	1	1	8	2
2	1	1	7	1	2	2	2
3	1	1	6	1	1	1	1
4	1	1	3	1	1	1	3
6	1	2	3	2	1	3	2
7	1	1	3	1	1	1	1
8	1	1	1	1	1	3	1
11	1	2	1	1	1	1	1
18	1	1	1	1	1	2	1
[total]	10	11	94	10	10	22	14
041A17							
1	1	1	65	1	1	2	1
2	1	1	6	1	1	1	1
3	1	1	4	1	1	3	3
4	1	1	5	1	1	3	1
5	2	1	3	1	1	1	1
6	1	2	3	1	1	1	1
7	1	1	4	1	2	2	1
8	1	2	2	1	1	3	1
9	1	1	2	1	1	1	2
10	1	1	1	1	1	1	2
12	1	1	1	1	1	1	2
13	1	1	1	1	1	2	1
14	1	1	1	1	1	2	1
15	1	1	1	1	1	2	1
18	1	1	1	1	1	2	1
21	1	1	1	2	1	1	1
58	1	1	1	1	1	2	1
[total]	18	19	102	18	18	30	22
041A18							
1	2	3	83	2	1	13	4
2	1	1	4	1	2	2	1
5	1	1	1	1	1	1	2
8	1	1	1	1	1	1	2
[total]	5	6	89	5	5	17	9
041A19							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
041A20							
1	2	1	71	1	1	3	1
2	1	2	7	1	2	3	3
3	1	1	5	1	1	2	1
4	1	1	3	1	1	2	2
5	1	1	2	2	1	2	2

6	1	1	2	1	1	3	1
7	1	1	1	1	1	2	1
8	1	1	1	1	1	2	1
9	1	2	1	1	1	1	1
10	1	1	1	1	1	2	1
11	1	1	1	1	1	2	2
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[total]	13	14	97	13	13	25	17
041A21							
1	1	1	43	1	1	1	1
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3	1	1	5	1	1	1	1
4	1	1	7	1	1	1	1
5	1	1	2	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	4	1	1	2	2
9	1	1	7	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	1	1	1	2	1
13	1	1	2	1	1	1	1
14	1	1	2	1	1	1	1
15	1	2	2	1	1	1	2
16	1	1	2	1	1	1	1
17	1	1	1	1	1	2	1
19	1	1	2	1	1	1	1
23	1	1	1	1	1	2	1
25	2	1	1	1	1	2	1
29	1	1	1	1	1	2	1
30	1	1	2	1	1	1	1
31	1	1	1	1	1	2	1
32	1	1	1	1	1	2	2
36	1	1	1	1	1	2	1
38	1	1	1	1	2	3	1
39	1	1	2	1	1	1	2
41	1	1	1	1	1	2	1
44	1	1	2	1	1	1	1
45	1	2	1	1	1	1	1
56	1	1	1	2	1	1	2
80	1	1	1	1	1	2	1
[total]	31	32	115	31	31	43	35
041A22							
1	1	2	74	1	1	2	1
2	1	1	3	1	2	1	3
3	1	2	4	1	1	5	1
4	1	1	2	1	1	1	1
5	2	1	2	1	1	1	1
6	1	1	3	1	1	5	2
7	1	1	2	1	1	2	3
8	1	1	1	1	1	2	1
10	1	1	1	1	1	2	1
11	1	1	1	1	1	2	1
12	1	1	3	1	1	1	1
13	1	1	1	2	1	1	1
[total]	13	14	97	13	13	25	17
041A23							
1	1	1	39	1	1	1	1
2	1	1	11	1	1	1	1
3	1	1	7	1	1	1	1

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  12           1   1   2   1   1   2   1
  14           1   2   2   1   1   3   1
  15           1   1   1   1   1   1   2
  16           1   2   1   1   1   2   1
  17           1   1   1   1   1   1   2
  18           2   1   1   1   2   1   1
  19           1   1   1   1   1   3   1
  22           1   1   1   1   1   1   2
  24           1   1   1   1   1   2   1
  30           1   1   1   1   1   1   2
  34           1   1   1   1   1   2   1
  36           1   1   1   1   1   1   2
  39           1   1   1   1   1   2   1
  49           1   1   1   2   1   1   1
  [total]     26  27 110  26  26  38  30
041A25
  1            1   1  20   1   1   1   1
  2            1   1   7   1   1   1   1
  3            1   1   4   1   1   1   1
  4            1   1  11   1   1   1   1
  5            1   1   3   1   1   1   1
  6            1   1   2   1   1   1   1
  7            1   1   2   1   1   1   1
  8            1   1   3   1   1   1   1
  9            1   1   3   1   1   1   1
  10           1   1   2   1   1   1   1
  12           1   1   4   1   1   1   1
  13           1   1   3   1   1   1   1
  14           1   1   3   1   1   1   1
  18           1   1   3   1   1   1   1
  19           1   1   4   1   1   1   1
  20           1   1   3   1   1   1   1
  23           1   1   2   1   1   1   1
  24           1   1   5   1   1   1   1
  25           1   1   3   1   1   1   1
  26           1   1   3   1   1   1   1
  27           1   1   2   1   1   1   1
  28           1   1   2   1   1   1   1
  29           1   1   2   1   1   1   1
  30           1   1   2   1   1   1   1
  32           1   1   2   1   1   1   1
  34           1   1   1   1   1   2   1
  36           1   1   2   1   1   1   1
  38           1   1   3   1   1   1   1
  39           1   1   2   1   1   1   1
  42           1   1   2   1   1   1   1
  43           2   1   1   1   1   1   1
  46           1   1   2   1   1   1   1
  47           1   1   2   1   1   1   1
  53           1   1   2   1   1   1   1
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54	1	1	1	1	2	1	1
56	1	1	2	1	1	1	1
59	1	1	1	1	1	1	2
63	1	2	1	1	1	1	1
69	1	1	1	1	1	2	1
71	1	1	1	1	1	2	1
72	1	1	1	1	1	2	1
74	1	1	1	1	1	2	1
77	1	1	1	1	1	2	1
79	1	1	1	1	1	2	1
80	1	1	1	1	1	2	1
81	1	1	1	1	1	3	1
85	1	1	1	1	1	2	1
87	1	1	1	1	1	1	2
102	1	2	1	1	1	1	1
114	1	1	1	1	1	1	2
120	1	1	1	1	1	2	2
125	1	1	2	1	1	1	1
136	1	1	1	1	1	1	2
145	1	1	1	2	1	1	1
198	1	1	1	1	1	2	1
[total]	56	57	140	56	56	68	60
041A26							
1	1	1	48	1	1	1	1
2	1	1	14	1	1	1	1
3	1	1	5	1	1	1	1
4	1	1	2	1	1	1	1
5	1	1	5	1	1	3	1
6	1	1	2	1	1	2	1
7	1	1	2	1	1	2	1
8	1	1	5	1	1	1	1
9	2	1	4	1	2	1	1
10	1	1	2	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	2	1	1	2	1
13	1	2	2	1	1	2	1
15	1	1	2	1	1	1	1
17	1	1	2	1	1	2	3
18	1	1	2	1	1	1	1
21	1	1	1	1	1	2	2
23	1	1	1	1	1	2	2
25	1	1	1	1	1	2	1
27	1	2	1	1	1	1	1
28	1	1	1	1	1	2	1
34	1	1	1	1	1	1	2
41	1	1	1	1	1	2	1
64	1	1	1	2	1	1	1
87	1	1	1	1	1	2	1
[total]	26	27	110	26	26	38	30
041A27							
1	1	1	53	1	1	1	1
2	1	1	10	1	1	1	1
3	1	1	6	1	1	1	1
4	1	1	5	1	1	2	1
5	1	1	2	1	1	1	1
6	1	1	3	1	1	2	1
7	1	1	3	1	1	1	1
8	2	1	2	1	2	2	2

9	1	1	4	1	1	3	1
10	1	3	1	1	1	2	1
12	1	1	2	1	1	2	2
13	1	1	3	1	1	1	1
14	1	1	2	1	1	2	1
16	1	1	1	1	1	2	2
18	1	1	2	1	1	1	1
20	1	1	1	1	1	2	1
21	1	1	1	2	1	1	1
23	1	1	1	1	1	2	1
24	1	1	1	1	1	1	2
25	1	1	1	1	1	2	1
30	1	1	1	1	1	1	2
31	1	1	2	1	1	1	1
38	1	1	1	1	1	2	1
[total]	24	25	108	24	24	36	28
041A28							
1	1	1	8	1	1	1	1
2	1	1	51	1	1	1	1
3	1	1	5	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	4	1	1	2	1
6	1	1	2	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	3	1	2	2	1
9	1	2	4	1	1	1	1
10	1	1	4	1	1	1	1
11	1	1	2	1	1	1	1
12	2	1	2	1	1	1	1
13	1	1	2	1	1	2	1
15	1	1	2	1	1	1	2
17	1	1	1	1	1	2	1
19	1	1	1	1	1	2	1
21	1	1	2	1	1	2	1
26	1	1	1	1	1	2	2
29	1	1	1	1	1	2	1
30	1	1	1	1	1	2	1
37	1	1	1	1	1	3	1
40	1	1	1	1	1	1	3
41	1	1	2	1	1	1	1
42	1	1	1	1	1	1	2
43	1	2	1	1	1	1	1
49	1	1	1	1	1	2	1
61	1	1	1	1	1	2	1
83	1	1	1	2	1	1	1
[total]	29	30	113	29	29	41	33
041AC2							
1	1	1	9	1	1	1	1
2	1	1	60	1	1	4	1
3	1	1	4	1	1	1	1
4	1	1	5	1	1	1	2
5	1	1	5	2	1	2	1
6	1	1	1	1	1	2	2
7	1	1	1	1	2	2	2
8	1	1	1	1	1	3	1
9	1	1	3	1	1	1	1
10	2	1	2	1	1	1	1
11	1	3	3	1	1	1	1

12	1	1	2	1	1	2	1
13	1	1	1	1	1	2	1
16	1	1	1	1	1	2	1
17	1	1	1	1	1	1	2
19	1	1	1	1	1	2	1
23	1	1	1	1	1	2	1
25	1	1	1	1	1	1	2
27	1	1	2	1	1	1	1
[total]	20	21	104	20	20	32	24
042G19							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
042D21							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
042DZ3							
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3	1	1	3	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	8	1	1	1	1
7	1	1	2	1	1	1	1
8	2	1	3	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	8	1	1	2	1
11	1	1	2	1	1	1	1
12	1	1	3	1	1	1	1
13	1	1	3	1	1	1	1
14	1	1	3	1	1	2	1
16	1	1	1	1	1	2	2
18	1	1	1	1	1	1	2
19	1	1	1	2	1	1	1
20	1	1	1	1	1	2	2
21	1	2	1	1	1	2	1
22	1	1	1	1	2	3	1
23	1	1	1	1	1	3	1
24	1	1	1	1	1	3	1
27	1	1	1	1	1	2	2
29	1	1	2	1	1	1	1
32	1	2	1	1	1	1	1
45	1	1	1	1	1	1	2
52	1	1	1	1	1	2	1
[total]	28	29	112	28	28	40	32
042E20							
1	2	3	85	2	2	14	6
12	1	1	2	1	1	1	1
[total]	3	4	87	3	3	15	7
051A10							
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4	1	1	5	1	1	1	1
5	1	1	7	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	3	1	1	1	1
8	1	1	3	1	1	1	1
9	1	1	2	1	1	2	1

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  10             1   1   3   1   1   1   1
  12             1   1   2   1   1   1   1
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  23             1   1   3   1   1   2   1
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  26             1   1   4   1   1   1   1
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  35             1   1   2   1   1   3   1
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  41             1   1   2   1   1   1   1
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  43             2   2   1   1   1   1   1
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  124            1   1   1   1   1   2   1
  137            1   2   1   1   1   1   1
  143            1   1   1   1   1   2   1
  222            1   1   1   2   1   1   1
  [total]       43  44 127  43  43  55  47
051A29
  1              2   2  77   1   1   5   1
  2              1   2   6   1   1   2   1
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  4              1   1   2   1   1   3   2
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  10             1   1   1   1   1   3   1
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  19             1   1   1   2   1   1   1
  [total]       12  13  96  12  12  24  16
051A30
  1              1   1  70   1   1   2   4
  2              2   1   9   2   1   4   1
  3              1   2   5   1   2   1   2
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  5              1   1   3   1   1   4   1
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  7              1   1   1   1   1   2   1
  8              1   1   1   1   1   2   1
  9              1   1   1   1   1   2   1
  11             1   2   1   1   1   1   1
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12	1	1	1	1	1	1	2
18	1	1	2	1	1	1	1
[total]	13	14	97	13	13	25	17
051A33							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
051A34							
1	1	2	61	1	1	1	1
2	1	1	12	1	1	1	3
3	1	1	7	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	2	1	1	4	1
6	1	1	1	1	1	3	1
7	1	1	3	1	1	1	1
8	1	1	2	2	2	1	1
9	1	1	1	1	1	2	1
10	1	1	1	1	1	2	2
11	1	1	1	1	1	2	1
12	1	1	1	1	1	2	1
13	1	2	1	1	1	2	1
14	1	1	1	1	1	2	1
16	2	1	1	1	1	1	1
19	1	1	1	1	1	1	2
20	1	1	1	1	1	1	2
23	1	1	1	1	1	2	1
24	1	1	1	1	1	2	1
[total]	20	21	104	20	20	32	24
061A11							
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6	1	2	3	1	1	1	1
7	1	1	5	1	1	1	1
8	1	1	4	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	3	1	1	1	1
12	1	1	4	1	1	1	1
13	1	1	4	1	1	2	1
16	1	1	2	1	1	1	1
17	1	1	2	1	1	1	1
18	1	1	4	1	1	1	1
20	1	1	3	1	1	1	1
21	1	1	2	1	2	1	1
24	2	1	2	1	1	1	1
26	1	1	2	1	1	1	1
27	1	1	2	1	1	1	1
28	1	1	1	1	1	3	1
31	1	1	1	1	1	2	1
32	1	1	1	1	1	2	1
33	1	2	1	1	1	1	1
35	1	1	1	1	1	1	2
36	1	1	1	1	1	1	2
38	1	1	2	1	1	2	1
42	1	1	1	1	1	2	1
43	1	1	2	1	1	1	1

44	1	1	1	2	1	1	1
46	1	1	1	1	1	2	1
52	1	1	1	1	1	1	2
59	1	1	1	1	1	2	1
60	1	1	1	1	1	3	2
63	1	1	1	1	1	2	1
67	1	1	1	1	1	1	2
73	1	1	1	1	1	2	1
[total]	39	40	123	39	39	51	43
062G11							
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3	1	1	16	1	1	1	1
4	1	1	3	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	2	1	1	1	1
8	1	1	3	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	4	1	1	1	1
12	1	1	3	1	1	1	1
13	1	1	4	1	1	1	1
14	1	1	2	1	1	1	1
16	1	1	3	1	1	1	1
17	1	1	2	1	1	1	1
20	1	1	3	1	1	1	1
21	1	1	2	1	1	1	1
22	1	1	3	1	1	1	1
23	1	1	2	1	1	1	1
27	1	1	3	1	1	1	1
29	1	1	2	1	1	1	1
30	1	1	2	1	1	1	1
33	1	1	4	1	1	1	1
35	1	1	4	1	1	1	1
36	1	1	2	1	1	1	1
39	1	1	1	1	1	2	1
41	1	1	3	1	1	1	1
45	1	1	2	1	1	1	1
48	1	1	2	1	1	1	1
49	1	1	2	1	1	1	1
51	1	1	2	1	1	1	1
53	1	1	1	1	1	2	1
56	1	1	2	1	1	1	1
57	1	1	2	1	1	1	1
62	1	1	3	1	1	1	1
64	1	1	2	1	1	1	1
69	1	1	2	1	1	1	1
70	1	1	1	1	1	2	1
75	1	1	2	1	1	1	1
76	1	1	2	1	1	1	1
77	1	1	3	1	1	1	1
80	1	1	2	1	1	1	1
81	1	1	2	1	1	1	1
93	1	1	2	1	1	1	1
95	1	2	1	1	1	1	1
101	1	1	2	1	1	1	1
103	1	1	1	1	2	1	1
109	1	1	1	1	1	1	2

110	1	1	2	1	1	1	1
116	1	1	2	1	1	1	1
119	1	1	1	1	1	2	1
123	1	1	1	1	1	2	1
132	1	1	1	1	1	2	1
138	1	1	1	1	1	2	1
141	2	1	1	1	1	1	1
148	1	1	1	1	1	2	1
154	1	1	1	1	1	1	2
164	1	1	1	1	1	1	2
169	1	2	1	1	1	1	1
171	1	1	1	1	1	1	2
182	1	1	1	1	1	2	1
191	1	1	1	1	1	2	1
197	1	1	1	1	1	1	2
204	1	1	1	1	1	2	1
223	1	1	1	1	1	2	1
297	1	1	1	2	1	1	1
315	1	1	1	1	1	2	1
[total]	68	69	152	68	68	80	72
062G12							
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5	1	1	5	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	2	1	1	1	1
9	1	1	4	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	2	1	1	1	1
13	1	1	2	1	1	1	1
15	1	1	5	1	1	1	1
16	1	1	2	1	1	1	1
17	1	1	3	1	1	1	1
18	1	1	3	1	1	1	1
20	1	1	2	1	1	1	1
21	1	1	4	1	1	1	1
22	1	1	3	1	1	1	1
23	1	1	2	1	1	1	1
24	1	1	3	1	1	1	1
25	1	1	3	1	1	1	1
26	1	1	2	1	1	1	1
28	1	1	5	1	1	1	1
30	1	1	4	1	1	1	1
32	1	1	4	1	1	1	1
33	1	1	2	1	1	1	1
36	1	1	2	1	1	1	1
38	1	1	3	1	1	1	1
39	1	1	2	1	1	1	1
40	1	1	3	1	1	1	1
45	1	1	2	1	1	1	1
46	1	1	3	1	1	1	1
47	1	1	2	1	1	1	1
49	1	1	2	1	1	1	1
52	1	1	2	1	1	1	1
55	1	1	2	1	1	1	1
57	1	1	2	1	1	1	1

59	1	1	2	1	1	1	1
64	1	1	3	1	1	1	1
70	1	1	1	1	1	2	1
74	1	1	2	1	1	1	1
76	1	1	1	1	1	2	1
80	1	1	1	1	1	2	1
84	1	1	2	1	1	2	1
86	1	1	1	1	1	2	1
89	1	2	1	1	1	2	1
91	1	1	1	1	1	1	3
98	1	1	1	1	2	1	1
100	1	1	1	1	1	2	1
111	2	1	1	1	1	2	1
125	1	1	1	1	1	2	1
132	1	1	1	1	1	2	1
138	1	1	1	1	1	2	1
150	1	1	1	1	1	1	2
160	1	2	1	1	1	1	1
163	1	1	1	1	1	1	2
192	1	1	1	1	1	1	2
205	1	1	1	1	1	2	1
208	1	1	1	1	1	2	1
268	1	1	1	2	1	1	1
[total]	61	62	145	61	61	73	65
062G14							
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4	1	1	7	1	1	1	1
5	1	1	3	1	1	1	1
6	1	1	1	1	1	2	1
7	1	1	1	1	1	2	1
8	1	1	2	1	1	2	1
9	2	1	4	1	1	1	1
10	1	1	2	1	1	2	2
11	1	1	2	1	1	2	1
12	1	1	2	1	1	1	3
13	1	1	2	1	1	1	1
14	1	1	1	1	1	2	1
15	1	1	2	1	1	2	2
16	1	1	1	1	2	2	1
17	1	1	2	1	1	2	1
20	1	2	1	1	1	1	1
29	1	1	1	1	1	2	1
33	1	1	1	2	1	1	2
38	1	2	1	1	1	1	1
41	1	1	1	1	1	2	1
56	1	1	1	1	1	2	1
[total]	24	25	108	24	24	36	28
062GX0							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
062GC5							
1	1	1	51	1	1	1	1
2	1	1	10	1	1	1	1
3	1	1	8	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	3	1	1	1	1

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  6             1    1    5    1    1    1    1
  7             1    1    3    1    1    1    1
  8             1    1    4    1    1    1    1
  10            2    1    1    1    1    2    1
  11            1    1    1    1    1    4    1
  13            1    1    1    1    1    1    2
  14            1    1    2    1    1    1    2
  15            1    1    2    1    2    2    2
  16            1    1    1    1    1    2    1
  17            1    1    3    1    1    1    1
  18            1    2    1    1    1    1    1
  19            1    1    1    1    1    2    1
  21            1    2    2    1    1    1    1
  23            1    1    1    1    1    2    1
  27            1    1    1    1    1    1    2
  37            1    1    1    2    1    2    1
  38            1    1    1    1    1    3    1
  41            1    1    1    1    1    2    1
  64            1    1    1    1    1    2    1
  68            1    1    1    1    1    1    2
  [total]      26   27  110   26   26   38   30
062GC9
  1             1    1   72    2    1    4    3
  2             1    1    7    1    1    3    3
  3             2    2    7    1    1    1    1
  4             1    1    1    1    1    3    1
  5             1    1    2    1    1    2    1
  6             1    1    1    1    2    1    2
  8             1    2    1    1    1    1    1
  9             1    1    1    1    1    2    1
  10            1    1    2    1    1    2    1
  20            1    1    1    1    1    2    1
  24            1    1    1    1    1    2    1
  25            1    1    1    1    1    2    1
  [total]      13   14   97   13   13   25   17
062E12
  1             1    1    6    1    1    1    1
  2             1    3   74    2    2   12    5
  3             1    1    4    1    1    2    1
  4             2    1    2    1    1    2    2
  5             1    1    3    1    1    1    1
  6             1    1    2    1    1    1    1
  [total]       7    8   91    7    7   19   11
071A15
  1             1    1   30    1    1    1    1
  2             1    1    4    1    1    1    1
  3             1    1    5    1    1    1    1
  4             1    1   11    1    1    1    1
  5             1    1    8    1    1    1    1
  6             1    1    5    1    1    1    1
  7             1    1    3    1    1    1    1
  8             1    1    6    1    1    1    1
  9             1    1    2    1    1    1    1
  11            1    1    3    1    1    1    1
  13            1    1    3    1    1    1    1
  14            1    1    6    1    1    1    1
  15            1    2    2    1    1    1    1
  16            1    1    3    1    1    1    1
```

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  17           1   1   2   1   1   1   1
  18           1   1   3   1   1   1   1
  19           1   1   2   1   1   1   1
  20           1   2   2   1   1   1   1
  21           1   1   2   1   1   1   1
  24           1   1   2   1   1   2   1
  26           1   1   1   1   1   3   1
  27           1   1   1   1   1   2   1
  28           1   1   1   1   2   1   1
  29           1   1   1   1   1   2   1
  31           1   1   1   1   1   2   1
  33           1   1   1   1   1   2   2
  35           1   1   1   1   1   2   1
  36           1   1   1   1   1   2   1
  37           1   1   2   1   1   1   2
  41           1   1   1   2   1   1   1
  43           2   1   1   1   1   1   1
  47           1   1   1   1   1   1   2
  49           1   1   1   1   1   2   1
  50           1   1   1   1   1   1   2
  59           1   1   1   1   1   1   2
  66           1   1   1   1   1   2   1
  68           1   1   1   1   1   2   1
  81           1   1   1   1   1   2   1
  [total]     39  40 123  39  39  51  43
081A24
  1            1   1   7   1   1   1   1
  2            1   1   6   1   1   1   1
  3            1   1   9   1   1   1   1
  4            1   1   3   1   1   1   1
  5            1   1  28   1   1   1   1
  7            1   1   4   1   1   1   1
  8            1   1   6   1   1   1   1
  9            1   1   4   1   1   1   1
  10           1   1   3   1   1   1   1
  11           1   1   5   1   1   1   1
  12           1   1   3   1   1   1   1
  13           1   1   2   1   1   1   1
  14           1   1   4   1   1   1   1
  16           1   1   3   1   1   1   1
  17           1   1   2   1   1   1   1
  18           1   1   3   1   1   1   1
  20           1   1   2   1   1   1   1
  21           1   1   2   1   1   1   1
  22           1   1   2   1   1   1   1
  23           1   1   3   1   1   1   1
  24           1   1   2   1   1   1   1
  25           1   1   3   1   1   1   1
  28           1   1   1   1   1   2   1
  31           1   1   1   1   1   2   1
  32           1   1   1   1   1   2   1
  36           1   1   1   1   1   2   1
  38           1   1   1   1   2   1   1
  39           1   1   1   1   1   2   1
  40           1   2   1   1   1   1   1
  41           1   2   2   1   1   2   1
  42           1   1   1   1   1   3   1
  44           1   1   1   1   1   1   2
```

47	1	1	1	1	1	2	1
48	2	1	1	1	1	1	1
51	1	1	1	1	1	1	3
57	1	1	1	1	1	2	1
58	1	1	1	1	1	2	1
69	1	1	1	2	1	1	2
89	1	1	1	1	1	1	2
98	1	1	1	1	1	2	1
140	1	1	1	1	1	2	1
[total]	42	43	126	42	42	54	46
082G24							
1	2	2	76	1	2	6	2
2	1	1	5	1	1	1	2
3	1	2	5	1	1	3	1
4	1	1	3	1	1	2	2
5	1	1	1	1	1	3	1
7	1	1	1	1	1	3	1
9	1	1	1	2	1	2	1
10	1	1	1	1	1	1	2
13	1	1	1	1	1	1	2
[total]	10	11	94	10	10	22	14
091A31							
1	1	1	8	1	1	1	1
2	1	1	15	1	1	1	1
3	1	1	5	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	3	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	5	1	1	1	1
8	1	1	3	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	3	1	1	1	1
12	1	1	5	1	1	1	1
14	1	1	3	1	1	1	1
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17	1	1	2	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	2	1	1	1	1
20	1	1	3	1	1	1	1
21	1	1	2	1	1	1	1
22	1	1	3	1	1	1	1
23	1	1	2	1	1	1	1
24	1	1	3	1	1	1	1
25	1	1	2	1	1	1	1
27	1	1	2	1	1	1	1
30	1	1	2	1	1	1	1
31	1	1	2	1	1	1	1
32	1	1	3	1	1	1	1
33	1	1	2	1	1	1	1
36	1	1	2	1	1	1	1
37	1	1	2	1	1	2	1
39	1	1	2	1	2	1	1
43	1	1	2	1	1	1	1
44	1	1	2	1	1	1	1
45	1	2	1	1	1	1	1
51	1	1	1	1	1	3	1

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54	1	1	2	1	1	1	1
56	1	1	1	1	1	2	1
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61	1	1	1	1	1	2	1
62	1	1	1	1	1	2	1
63	1	1	1	1	1	1	2
69	1	1	2	1	1	1	1
72	1	1	1	1	1	1	2
74	1	1	2	1	1	1	1
79	1	1	1	1	1	2	1
80	1	1	1	1	1	2	1
81	1	1	1	1	1	2	1
86	1	1	1	1	1	2	1
88	2	1	1	1	1	1	1
103	1	2	1	1	1	1	1
117	1	1	1	1	1	1	2
134	1	1	1	1	1	1	2
142	1	1	1	1	1	2	1
147	1	1	1	1	1	1	2
178	1	1	1	2	1	1	1
229	1	1	1	1	1	2	1
[total]	59	60	143	59	59	71	63
091BBN							
1	1	3	74	2	1	6	2
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3	1	1	5	1	2	2	1
4	1	1	3	1	1	4	2
5	1	1	3	1	1	2	2
6	1	1	2	1	1	1	2
20	1	1	1	1	1	1	2
[total]	8	9	92	8	8	20	12
092G31							
1	2	3	83	2	2	13	6
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6	1	1	2	1	1	1	1
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[total]	5	6	89	5	5	17	9
092E31							
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3	1	2	6	1	1	1	1
4	1	1	3	1	1	1	1
5	1	1	6	1	1	2	2
6	1	1	2	1	1	1	1
7	1	1	1	1	1	2	2
9	1	1	2	1	1	1	1
11	1	1	2	1	1	2	1
12	1	1	3	1	1	1	1
13	2	1	2	1	1	1	2
14	1	2	2	1	1	1	2
15	1	1	3	1	1	1	1
17	1	1	1	1	1	2	2
18	1	1	1	1	1	3	1
22	1	1	2	2	1	1	1
23	1	1	1	1	1	2	1
29	1	1	2	1	1	1	1
33	1	1	1	1	1	2	1

38	1	1	2	1	1	2	1
40	1	1	2	1	1	1	1
42	1	1	1	1	1	2	1
52	1	1	1	1	1	2	1
[total]	24	25	108	24	24	36	28
101A37							
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4	1	1	24	1	1	1	1
5	1	1	8	1	1	1	1
6	1	1	5	1	1	1	1
7	1	1	6	1	1	1	1
8	1	1	2	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	4	1	1	1	1
16	1	1	4	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	2	1	1	1	1
20	1	1	2	1	1	1	1
21	1	1	3	1	1	1	1
22	1	1	3	1	1	1	1
23	1	1	4	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	2	1	1	1	1
26	1	1	2	1	1	1	1
30	1	2	1	1	1	1	1
31	1	1	2	1	1	1	1
33	1	1	2	1	1	1	1
34	1	1	2	1	1	1	1
41	2	1	2	1	1	2	1
42	1	1	1	1	2	2	1
47	1	1	1	1	1	2	1
49	1	1	2	1	1	2	1
50	1	2	1	1	1	2	1
51	1	1	1	1	1	2	1
52	1	1	1	1	1	2	1
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63	1	1	1	1	1	1	2
64	1	1	1	1	1	1	2
65	1	1	1	1	1	2	1
67	1	1	1	1	1	2	1
88	1	1	1	2	1	1	1
89	1	1	1	1	1	1	2
90	1	1	1	1	1	2	1
107	1	1	1	1	1	1	3
108	1	1	1	1	1	2	1
[total]	44	45	128	44	44	56	48
102D35							
1	1	1	30	1	1	1	1
2	1	1	6	1	1	1	1
3	1	1	8	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	6	1	1	1	1
6	1	1	9	1	1	1	1
7	1	1	6	1	1	1	1

8	1	1	4	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	6	1	1	1	1
12	1	1	2	1	1	1	1
13	1	1	3	1	1	1	1
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16	1	1	1	1	1	2	1
17	1	1	2	1	1	1	1
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21	1	1	2	1	1	2	1
22	1	1	1	1	1	3	1
23	1	1	3	1	1	1	1
24	1	1	2	1	1	1	1
26	1	1	1	1	1	2	1
28	1	1	1	1	1	2	1
29	1	1	1	1	1	2	1
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33	1	1	1	1	2	1	1
35	1	1	1	1	1	2	1
36	1	1	1	2	1	2	1
38	1	1	1	1	1	1	2
39	1	1	1	1	1	1	2
40	1	1	1	1	1	2	1
41	1	2	1	1	1	1	1
54	1	1	1	1	1	1	2
58	1	1	1	1	1	1	2
74	1	1	1	1	1	2	1
86	1	1	1	1	1	2	1
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102E35							
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4	1	1	3	1	1	1	1
8	1	1	2	1	1	1	1
9	1	1	2	1	1	1	1
10	1	1	4	1	1	1	1
11	1	1	3	1	1	1	1
12	1	1	4	1	1	1	1
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15	1	1	2	1	1	1	1
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21	1	1	2	1	1	1	1
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23	1	1	3	1	1	1	1
24	1	1	3	1	1	1	1
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31	1	1	3	1	1	1	1
34	1	1	3	1	1	1	1
35	1	1	4	1	1	1	1

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37	1	1	2	1	1	1	1
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55	1	1	2	1	1	1	1
61	1	1	2	1	1	1	1
62	1	1	3	1	1	1	1
66	1	1	3	1	1	1	1
67	1	1	2	1	1	1	1
69	1	1	4	1	1	1	1
72	1	1	2	1	1	1	1
74	1	1	2	1	1	1	1
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83	1	1	3	1	1	1	1
92	1	1	2	1	1	1	1
96	1	1	2	1	1	1	1
102	1	1	3	1	1	1	1
111	1	1	2	1	1	1	1
119	1	1	2	1	1	1	1
121	1	1	2	1	1	2	1
137	1	1	1	1	1	2	1
147	1	1	2	1	1	1	1
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157	1	1	1	1	1	2	1
161	1	2	1	1	1	1	1
162	1	1	2	1	1	1	1
176	1	1	1	1	1	1	3
202	1	1	1	1	1	2	1
214	1	1	1	1	1	2	1
216	1	1	1	1	1	2	1
226	1	1	1	1	1	2	1
229	2	1	1	1	1	1	1
231	1	1	1	1	1	2	1
238	1	1	1	1	1	1	2
249	1	1	1	1	1	2	1
275	1	2	1	1	1	1	1
278	1	1	1	1	1	2	1
282	1	1	1	1	1	1	2
303	1	1	1	1	1	2	1
356	1	1	1	1	1	2	1
388	1	1	1	2	1	1	1
453	1	1	1	1	1	1	2
478	1	1	1	1	1	2	1
[total]	73	74	157	73	73	85	77
111A36							
1	2	2	85	2	2	12	4
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[total]	5	6	89	5	5	17	9
112E40							
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4	1	1	3	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	2	1	1	1	1
8	1	1	2	1	1	1	1
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14	1	1	4	1	1	1	1
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17	1	1	2	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	3	1	1	1	1
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21	1	1	3	1	1	1	1
22	1	1	2	1	1	1	1
23	1	1	2	1	1	1	1
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27	1	1	2	1	1	1	1
28	1	1	3	1	1	1	1
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34	1	1	2	1	1	1	1
35	1	1	4	1	1	1	1
39	1	1	2	1	1	1	1
40	1	1	2	1	1	1	1
41	1	1	2	1	1	1	1
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45	1	1	2	1	1	1	1
46	1	1	2	1	1	1	1
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63	1	1	2	1	1	1	1
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68	1	1	2	1	1	1	1
70	1	1	2	1	1	1	1
72	1	1	2	1	1	1	1
79	1	1	2	1	1	1	1
81	1	1	1	1	2	1	1
83	1	1	2	1	1	1	1
85	1	1	3	1	1	1	1
86	1	1	2	1	1	1	1
88	1	1	1	1	1	2	1
89	1	1	2	1	1	1	1
90	1	1	1	1	1	2	1
95	1	1	2	1	1	1	1
104	1	1	2	1	1	1	1
110	1	1	2	1	1	1	1
120	1	1	1	1	1	2	1
125	1	1	1	1	1	1	2

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  134          1    1    1    1    1    2    1
  142          1    2    1    1    1    1    1
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  155          1    1    1    1    1    1    2
  169          1    1    1    1    1    2    1
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  191          1    1    1    1    1    1    2
  192          1    1    1    1    1    2    1
  203          1    1    1    1    1    2    1
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  216          1    1    1    1    1    2    1
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  236          1    1    1    1    1    1    2
  246          1    1    1    1    1    2    1
  254          1    1    1    1    1    2    1
  339          1    1    1    2    1    1    1
  344          1    1    1    1    1    2    1
  [total]     79   80  163   79   79   91   83
121A38
  1            1    1   68    1    1    1    2
  2            1    1    6    1    1    1    1
  3            1    1    5    1    1    3    1
  4            1    1    5    1    1    1    2
  5            1    1    2    1    2    2    1
  8            1    2    2    1    1    4    1
  9            1    1    1    1    1    2    1
  10           1    1    3    1    1    4    1
  13           1    1    2    1    1    2    1
  15           2    1    1    1    1    1    1
  17           1    2    1    1    1    2    2
  18           1    1    1    2    1    2    1
  21           1    1    1    1    1    1    2
  24           1    1    1    1    1    1    2
  [total]     15   16   99   15   15   27   19
121A39
  1            1    1   65    1    1    2    1
  2            1    1    9    1    1    1    1
  3            1    1    6    1    1    1    1
  4            1    1    3    1    1    1    1
  5            2    1    2    1    1    1    3
  6            1    1    2    1    1    5    2
  7            1    1    2    1    1    2    1
  8            1    2    1    1    1    2    2
  9            1    1    1    1    2    2    1
  10           1    1    2    1    1    2    1
  11           1    1    2    1    1    3    1
  13           1    1    1    1    1    1    2
  14           1    2    1    2    1    1    1
  16           1    1    1    1    1    2    1
  17           1    1    2    1    1    1    1
  22           1    1    1    1    1    2    1
  [total]     17   18  101   17   17   29   21
121A64
  1            1    1   63    1    1    1    1
  2            1    1   10    1    2    2    1
  3            1    2    8    1    1    2    1
  4            1    1    4    1    1    3    1
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7	1	1	2	1	1	2	1
9	1	1	1	1	1	3	2
10	1	1	1	1	1	2	1
11	2	1	1	1	1	3	1
13	1	1	1	1	1	1	2
16	1	2	1	1	1	3	3
18	1	1	1	2	1	1	1
19	1	1	2	1	1	1	1
20	1	1	1	1	1	2	1
[total]	15	16	99	15	15	27	19
121A65							
1	1	1	60	1	1	1	1
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3	1	1	6	1	1	1	1
4	1	1	3	1	1	2	1
5	1	2	5	1	1	2	1
6	1	1	8	1	1	2	1
7	1	1	2	1	1	1	1
8	1	1	2	1	1	1	2
9	1	1	2	1	1	4	1
10	1	1	1	1	2	1	2
11	1	1	1	1	1	2	1
12	1	2	2	1	1	2	1
14	2	1	1	1	1	1	1
15	1	1	1	1	1	2	1
16	1	1	2	1	1	1	3
19	1	1	1	1	1	2	1
20	1	1	1	1	1	2	1
25	1	1	1	1	1	2	1
29	1	1	1	1	1	2	1
40	1	1	1	2	1	1	1
46	1	1	1	1	1	1	2
[total]	22	23	106	22	22	34	26
121A67							
1	1	1	58	1	1	1	1
2	1	2	10	1	1	1	1
3	1	2	6	1	1	2	1
4	1	1	4	1	1	2	1
5	1	1	6	1	1	2	2
6	1	1	2	1	1	1	1
7	1	1	1	1	1	1	2
8	1	1	1	1	1	3	1
9	1	1	5	1	1	2	1
10	1	1	2	1	1	1	1
12	1	1	1	1	1	3	1
13	1	1	1	1	1	3	2
14	1	1	1	1	2	1	1
15	1	1	1	1	1	1	2
16	1	1	1	1	1	2	1
17	2	1	1	1	1	1	1
18	1	1	1	1	1	2	1
23	1	1	1	1	1	1	2
26	1	1	1	1	1	2	1
30	1	1	1	2	1	1	1
[total]	21	22	105	21	21	33	25
121AZ4							
1	2	2	81	1	2	8	4

```
  2             1    2    3    1    1    3    3
  3             1    1    1    2    1    1    1
  4             1    1    3    1    1    1    1
  5             1    1    2    1    1    3    1
  8             1    1    1    1    1    2    1
  10            1    1    1    1    1    2    1
  [total]       8    9   92    8    8   20   12
122G63
  1             1    1   11    1    1    1    1
  2             2    1   55    1    1    2    1
  3             1    1   10    1    1    2    1
  4             1    1    4    1    2    4    2
  5             1    1    2    1    1    2    1
  6             1    1    6    1    1    2    1
  7             1    1    2    1    1    2    1
  9             1    1    1    1    1    3    2
  10            1    2    1    1    1    1    1
  11            1    1    2    1    1    1    1
  12            1    1    1    1    1    2    1
  13            1    1    1    1    1    1    2
  14            1    1    2    1    1    2    1
  15            1    1    1    1    1    1    2
  16            1    2    1    1    1    1    1
  17            1    1    1    2    1    2    1
  20            1    1    1    1    1    1    2
  [total]      18   19  102   18   18   30   22
122G67
  1             2    3   80    2    1    6    3
  2             1    1    6    1    1    1    2
  3             1    1    1    1    1    4    1
  4             1    1    2    1    1    2    2
  6             1    1    1    1    2    2    1
  8             1    1    1    1    1    3    1
  10            1    1    1    1    1    1    2
  11            1    1    1    1    1    2    1
  [total]       9   10   93    9    9   21   13
131A41
  1             1    1    6    1    1    1    1
  2             1    1   28    1    1    1    1
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  8             1    1    4    1    1    1    1
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  17            1    1    3    1    1    1    1
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  24            1    1    1    1    1    2    1
  25            1    1    1    1    1    2    1
```

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56	1	1	1	1	1	2	1
57	1	1	1	1	1	1	2
62	1	1	1	1	1	2	1
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74	1	2	1	1	1	2	1
76	1	1	1	2	1	1	1
77	1	1	1	1	1	2	1
136	1	1	1	1	1	1	2
[total]	40	41	124	40	40	52	44
132G41							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
132D41							
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8	1	1	1	1	1	2	1
9	1	1	3	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	1	1	1	2	1
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24	1	1	1	1	1	2	1
27	1	1	1	1	1	1	2
[total]	17	18	101	17	17	29	21
141A42							
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4	1	1	2	1	1	1	1
[total]	4	5	88	4	4	16	8
141A43							
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3	1	1	7	1	1	4	2
4	2	1	2	1	1	3	1
5	1	1	4	1	1	1	1
6	1	1	2	1	1	1	1
8	1	1	1	2	2	2	1
9	1	1	1	1	1	2	3
13	1	1	1	1	1	2	1
17	1	1	1	1	1	2	1
22	1	1	1	1	1	1	2
[total]	12	13	96	12	12	24	16

141ABG							
1	2	2	81	1	1	11	4
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4	1	1	2	1	1	1	1
7	1	1	2	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	1	2	1	1	1
19	1	1	1	1	1	2	1
21	1	1	1	1	1	2	1
24	1	1	1	1	1	1	2
[total]	12	13	96	12	12	24	16
141ABD							
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3	1	2	7	1	1	4	1
4	1	1	3	1	2	1	1
5	1	1	1	1	1	2	1
6	1	1	4	1	1	2	2
7	2	2	1	1	1	3	1
8	1	1	2	1	1	1	2
10	1	1	2	1	1	1	2
11	1	1	3	1	1	1	1
12	1	1	1	1	1	1	2
14	1	1	1	2	1	2	1
16	1	1	1	1	1	3	1
27	1	1	1	1	1	3	1
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[total]	16	17	100	16	16	28	20
142G44							
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10	1	1	4	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	2	1	1	1	1
13	1	1	2	1	1	2	1
14	1	1	3	1	1	2	1
15	1	2	1	1	1	1	1
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17	1	1	1	1	1	2	1
18	1	1	2	1	1	1	1
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21	1	1	2	1	1	2	2
23	1	1	1	1	1	2	1
26	1	1	2	1	1	1	2
29	1	1	1	1	1	2	1
31	1	1	1	1	1	2	2
32	1	1	2	1	2	2	1
33	1	1	1	1	1	2	2
35	1	1	1	1	1	2	1

36	1	1	1	2	1	1	1
37	1	1	1	1	1	2	2
55	1	1	1	1	1	2	1
87	1	1	1	1	1	2	1
[total]	32	33	116	32	32	44	36
142G45							
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5	1	1	2	1	1	1	2
6	1	1	5	1	1	1	1
7	1	1	4	1	2	1	1
9	1	1	2	1	1	1	1
10	1	1	1	1	1	2	1
11	1	1	2	1	1	3	1
12	1	1	1	1	1	2	1
13	1	2	1	2	1	1	1
15	1	1	1	1	1	3	1
16	1	1	1	1	1	2	1
17	1	1	2	1	1	1	1
19	1	1	1	1	1	1	2
20	1	2	1	1	1	2	1
21	1	1	1	1	1	2	1
22	1	1	1	1	1	1	2
25	1	1	1	1	1	1	2
27	1	1	2	1	1	1	1
31	2	1	1	1	1	1	1
32	1	1	1	1	1	2	1
35	1	1	1	1	1	1	2
[total]	25	26	109	25	25	37	29
142E45							
1	2	3	84	2	2	13	4
2	1	1	2	1	1	2	2
3	1	1	2	1	1	1	1
5	1	1	1	1	1	1	2
[total]	5	6	89	5	5	17	9
152G46							
1	1	1	5	1	1	1	1
2	1	1	27	1	1	1	1
3	1	1	8	1	1	1	1
4	1	1	3	1	1	1	1
5	1	1	2	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	3	1	1	1	1
8	1	1	8	1	1	1	1
9	1	1	5	1	1	1	1
10	1	1	5	1	1	1	1
11	1	1	4	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	4	1	1	1	1
16	1	1	4	1	1	1	1
18	1	1	4	1	1	1	1
19	1	1	2	1	1	1	1
20	1	1	2	1	1	1	1
23	1	1	4	1	1	1	1
24	1	1	2	1	1	1	2
25	1	1	2	1	1	2	1

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  27          1   1   1   1   1   2   1
  30          1   1   2   1   1   1   1
  31          1   1   2   1   1   2   1
  32          1   1   2   1   1   1   1
  35          1   1   1   1   1   1   2
  36          1   1   1   1   1   2   1
  41          2   1   1   1   1   3   1
  44          1   1   2   1   2   2   1
  45          1   1   1   1   1   1   2
  48          1   2   1   1   1   1   1
  51          1   1   1   1   1   2   1
  54          1   1   2   1   1   1   1
  57          1   1   1   1   1   3   1
  60          1   1   1   1   1   2   1
  62          1   1   1   1   1   1   2
  68          1   2   1   1   1   1   1
  71          1   1   1   1   1   2   1
  114         1   1   1   1   1   1   2
  119         1   1   1   2   1   1   1
  130         1   1   1   1   1   2   1
  [total]    41  42 125  41  41  53  45
152GY0
  1           2   3  85   2   2  14   4
  2           1   1   2   1   1   1   2
  6           1   1   1   1   1   1   2
  [total]     4   5  88   4   4  16   8
152E46
  1           1   1   9   1   1   1   1
  2           1   1   7   1   1   1   1
  3           1   1   3   1   1   1   1
  4           1   1  24   1   1   1   1
  5           1   1   3   1   1   1   1
  6           1   1   4   1   1   1   1
  7           1   1   2   1   1   1   1
  8           1   1   4   1   1   1   1
  9           1   1   2   1   1   1   1
  10          1   1   4   1   1   1   1
  11          1   1   2   1   1   1   1
  12          1   1   2   1   1   1   1
  14          1   1   3   1   1   1   1
  15          1   1   3   1   1   1   1
  17          1   1   5   1   1   1   1
  18          1   1   2   1   1   2   2
  19          1   1   2   1   1   1   1
  20          1   1   2   1   1   1   1
  22          1   1   4   1   1   1   1
  23          1   1   2   1   1   2   1
  25          1   1   2   1   1   1   1
  26          1   1   2   1   1   1   1
  27          1   1   3   1   1   1   1
  31          1   1   4   1   1   1   1
  38          1   1   3   1   1   1   1
  39          1   1   2   1   1   1   1
  42          2   1   1   1   1   1   1
  49          1   1   1   1   2   1   1
  50          1   1   1   1   1   1   2
  52          1   1   3   1   1   1   1
  54          1   1   1   1   1   2   1
```

56	1	1	3	1	1	1	1
57	1	1	1	1	1	2	1
60	1	1	2	1	1	1	1
65	1	1	1	1	1	2	1
67	1	1	2	1	1	1	1
74	1	1	1	1	1	2	1
76	1	1	1	1	1	2	1
80	1	1	1	1	1	2	1
86	1	1	1	1	1	1	2
94	1	1	1	1	1	1	2
99	1	1	1	1	1	1	2
100	1	1	1	1	1	2	1
101	1	2	1	1	1	1	1
104	1	1	1	1	1	2	1
114	1	2	1	1	1	1	1
130	1	1	1	1	1	2	1
162	1	1	1	1	1	2	1
163	1	1	1	1	1	2	1
199	1	1	1	2	1	1	1
[total]	51	52	135	51	51	63	55
162G50							
1	1	1	20	1	1	1	1
2	1	1	6	1	1	1	1
3	1	1	4	1	1	1	1
4	1	1	3	1	1	1	1
5	1	1	2	1	1	1	1
6	1	1	5	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	5	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	4	1	1	1	1
12	1	1	3	1	1	1	1
14	1	1	2	1	1	1	1
15	1	1	3	1	1	1	1
16	1	1	3	1	1	1	1
17	1	1	4	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	3	1	1	1	1
20	1	1	2	1	1	1	1
21	1	1	4	1	1	1	1
22	1	1	2	1	1	1	1
23	1	1	2	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	2	1	1	1	1
26	1	1	2	1	1	1	1
27	1	1	2	1	1	2	1
28	1	1	2	1	1	1	1
30	1	1	2	1	1	1	1
31	1	1	2	1	1	1	1
32	1	1	2	1	1	1	1
33	1	1	2	1	1	2	1
34	1	1	2	1	1	1	1
36	1	1	4	1	1	1	1
41	1	1	2	1	1	1	1
45	1	1	2	1	1	1	1
48	1	1	2	1	1	1	1
52	1	1	1	1	2	1	1

55	1	1	1	1	1	3	1
56	1	1	2	1	1	1	1
62	1	2	1	1	1	1	1
63	1	1	1	1	1	2	1
66	1	1	1	1	1	2	1
67	1	1	1	1	1	2	1
71	1	1	1	1	1	1	2
72	1	1	1	1	1	2	1
73	1	1	2	1	1	1	1
74	1	1	1	1	1	1	2
77	1	1	1	1	1	1	2
79	1	1	1	1	1	2	1
81	2	1	1	1	1	1	1
84	1	1	1	1	1	2	1
99	1	1	1	1	1	2	1
103	1	1	1	1	1	1	2
115	1	1	1	2	1	1	1
129	1	1	1	1	1	2	1
134	1	2	1	1	1	1	1
144	1	1	1	1	1	2	1
157	1	1	1	1	1	1	2
[total]	59	60	143	59	59	71	63
162EJ2							
1	1	1	10	1	1	1	1
2	1	1	3	1	1	1	1
3	1	1	2	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	3	1	1	1	1
6	1	1	2	1	1	1	1
7	1	1	2	1	1	1	1
8	1	1	5	1	1	1	1
9	1	1	5	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	4	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	2	1	1	1	1
15	1	1	4	1	1	1	1
16	1	1	2	1	1	1	1
17	1	1	2	1	1	1	1
18	1	1	3	1	1	1	1
21	1	1	2	1	1	1	1
22	1	1	2	1	1	1	1
23	1	1	2	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	2	1	1	1	1
26	1	1	3	1	1	1	1
27	1	1	3	1	1	1	1
31	1	1	3	1	1	1	1
32	1	1	2	1	1	1	1
33	1	1	2	1	1	1	1
35	1	1	2	1	1	1	1
36	1	1	5	1	1	1	1
44	1	1	2	1	1	1	1
46	1	1	3	1	1	1	1
48	1	1	4	1	1	1	1
57	1	1	2	1	1	1	1
58	1	1	2	1	1	1	1

60	1	1	4	1	1	1	1
62	1	1	3	1	1	1	1
68	1	1	2	1	1	1	1
69	1	1	2	1	1	1	1
75	1	1	2	1	1	1	1
77	1	1	2	1	1	1	1
78	1	1	2	1	1	1	1
81	1	1	2	1	1	1	1
85	1	1	2	1	1	2	1
87	1	1	2	1	1	1	1
90	1	1	2	1	1	1	1
101	1	1	2	1	1	1	1
102	1	1	2	1	1	2	1
103	1	1	2	1	1	1	1
116	1	1	2	1	1	1	1
123	1	1	1	1	2	1	2
124	2	1	1	1	1	1	1
129	1	1	1	1	1	2	1
142	1	1	1	1	1	2	1
146	1	1	1	1	1	2	1
152	1	1	1	1	1	2	1
158	1	1	1	1	1	1	2
165	1	1	1	1	1	3	2
167	1	2	1	1	1	1	1
176	1	1	1	1	1	2	1
192	1	2	1	1	1	1	1
215	1	1	1	1	1	2	1
224	1	1	1	1	1	1	2
229	1	1	1	1	1	2	1
269	1	1	1	1	1	2	1
287	1	1	1	1	1	1	2
323	1	1	1	1	1	2	1
375	1	1	1	2	1	1	1
[total]	69	70	153	69	69	81	73
172G51							
1	2	1	79	1	1	8	4
2	1	2	5	1	1	1	1
3	1	1	2	1	2	2	2
4	1	1	3	1	1	3	1
5	1	1	1	1	1	1	2
6	1	1	1	1	1	2	1
8	1	1	1	1	1	2	1
10	1	2	1	2	1	2	1
[total]	9	10	93	9	9	21	13
172GM6							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
172E51							
1	1	1	46	1	1	2	1
2	1	1	12	2	1	3	2
3	1	1	10	1	1	1	1
4	1	1	10	1	1	2	1
5	1	1	5	1	1	1	1
6	1	2	3	1	1	2	3
7	1	2	3	1	1	4	1
8	1	1	2	1	2	4	1
10	1	1	2	1	1	1	1
12	1	1	2	1	1	2	1

13	1	1	1	1	1	1	2
15	1	1	1	1	1	1	2
17	2	1	1	1	1	1	1
20	1	1	1	1	1	2	1
[total]	15	16	99	15	15	27	19
172EJ3							
1	1	3	86	2	2	14	5
2	2	1	1	1	1	1	2
[total]	3	4	87	3	3	15	7
182G52							
1	1	1	47	1	1	1	1
2	1	1	7	1	1	2	1
3	1	1	5	1	1	1	2
4	1	1	6	1	1	1	2
5	1	1	7	1	1	3	1
6	1	1	2	1	1	1	1
7	1	1	5	1	1	2	1
8	1	1	3	1	1	1	1
9	1	2	3	1	2	1	1
10	1	1	3	1	1	3	1
11	1	1	3	1	1	2	1
12	1	1	3	1	1	1	2
13	1	1	2	1	1	2	1
14	1	1	2	1	1	2	1
15	1	1	1	1	1	2	1
17	1	2	1	1	1	3	1
18	1	1	1	1	1	1	2
19	1	1	2	1	1	1	1
20	1	1	1	1	1	1	2
29	2	1	1	1	1	1	1
30	1	1	1	1	1	2	1
51	1	1	1	2	1	1	1
[total]	23	24	107	23	23	35	27
182E52							
1	1	1	41	1	1	1	1
2	1	1	13	1	1	1	1
3	1	1	9	1	1	1	1
4	1	1	12	1	1	2	1
5	1	1	5	1	1	2	1
6	1	1	3	1	1	1	1
7	2	1	2	1	1	1	1
8	1	1	3	1	1	1	1
9	1	2	3	1	1	3	1
10	1	2	1	1	1	1	1
11	1	1	2	1	2	1	3
12	1	1	2	1	1	2	1
13	1	1	2	1	1	2	1
14	1	1	1	1	1	4	2
16	1	1	1	1	1	3	1
20	1	1	1	1	1	2	1
21	1	1	1	1	1	1	2
22	1	1	1	2	1	1	1
23	1	1	1	1	1	1	2
25	1	1	1	1	1	2	1
[total]	21	22	105	21	21	33	25
191A53							
1	2	2	81	2	2	10	5
2	1	2	1	1	1	1	1

3	1	1	5	1	1	2	1
4	1	1	2	1	1	1	2
5	1	1	1	1	1	3	1
6	1	1	1	1	1	2	1
[total]	7	8	91	7	7	19	11
192E53							
1	1	1	57	1	1	2	1
2	1	1	8	1	1	1	1
3	2	1	8	1	2	1	1
4	1	1	7	1	1	3	3
5	1	1	2	1	1	1	1
6	1	1	4	1	1	4	1
9	1	2	2	1	1	2	1
10	1	1	2	1	1	3	1
11	1	2	1	1	1	2	2
12	1	1	1	1	1	2	1
13	1	1	2	1	1	1	1
14	1	1	1	1	1	2	2
15	1	1	2	1	1	1	1
17	1	1	2	2	1	1	1
21	1	1	1	1	1	2	1
23	1	1	1	1	1	1	2
[total]	17	18	101	17	17	29	21
201A54							
1	1	1	77	1	1	7	2
2	1	1	6	1	2	5	2
3	2	1	4	2	1	2	3
4	1	1	2	1	1	2	1
5	1	2	1	1	1	1	1
7	1	1	1	1	1	2	1
22	1	2	1	1	1	1	1
41	1	1	1	1	1	1	2
[total]	9	10	93	9	9	21	13
202G54							
1	2	3	82	1	1	10	4
2	1	1	2	2	2	4	3
3	1	1	3	1	1	2	1
16	1	1	2	1	1	1	1
[total]	5	6	89	5	5	17	9
202E54							
1	2	1	11	1	1	2	1
2	1	3	74	2	1	9	5
3	1	1	3	1	2	2	2
4	1	1	1	1	1	2	1
6	1	1	1	1	1	2	1
8	1	1	1	1	1	2	1
[total]	7	8	91	7	7	19	11
212D55							
1	1	1	52	1	1	1	1
2	1	1	13	1	1	1	1
3	1	1	7	1	1	1	1
4	1	1	7	1	1	1	1
5	1	1	4	1	1	3	1
6	1	1	1	1	2	1	1
7	1	1	3	2	1	1	1
8	1	1	3	1	1	1	1
9	1	2	1	1	1	3	1
10	1	1	2	1	1	1	1

```
  11            1   1   1   1   1   1   2
  12            1   1   2   1   1   2   1
  13            1   1   1   1   1   3   1
  14            1   1   1   1   1   1   2
  15            1   1   1   1   1   3   1
  16            1   2   1   1   1   1   1
  17            1   1   2   1   1   2   1
  20            1   1   1   1   1   1   3
  22            1   1   1   1   1   2   2
  24            1   1   1   1   1   2   1
  27            2   1   1   1   1   2   1
  [total]      22  23 106  22  22  34  26
212D56
  1             1   1  50   1   1   1   1
  2             1   1   9   1   1   1   1
  3             1   2  10   1   1   1   1
  4             1   1   6   1   1   2   1
  5             1   1   6   1   1   1   1
  6             1   1   3   1   1   1   1
  7             1   1   2   1   1   4   1
  8             1   1   4   1   1   3   2
  9             1   1   2   1   1   2   1
  10            2   1   1   1   1   1   1
  11            1   1   2   1   1   1   1
  12            1   1   1   1   1   2   1
  13            1   1   1   1   2   2   2
  14            1   1   2   2   1   2   1
  17            1   1   1   1   1   1   3
  19            1   1   1   1   1   2   1
  20            1   2   1   1   1   1   1
  23            1   1   1   1   1   2   1
  26            1   1   1   1   1   2   1
  29            1   1   1   1   1   1   2
  [total]      21  22 105  21  21  33  25
212E55
  1             1   1  72   1   1   6   1
  2             1   3   6   2   1   2   3
  3             1   1   3   1   1   2   1
  4             2   1   4   1   1   2   1
  5             1   1   2   1   1   2   1
  6             1   1   2   1   1   2   2
  7             1   1   2   1   1   2   1
  8             1   1   2   1   1   1   1
  11            1   1   1   1   1   2   2
  14            1   1   1   1   1   1   2
  15            1   1   1   1   1   2   1
  17            1   1   1   1   2   1   1
  [total]      13  14  97  13  13  25  17
212E56
  1             1   1   1   1   1   1   3
  2             2   3  85   2   2  14   3
  4             1   1   2   1   1   1   1
  8             1   1   1   1   1   1   2
  [total]       5   6  89   5   5  17   9
222G59
  1             2   1  64   1   2   2   1
  2             1   1   8   1   1   3   2
  3             1   1   4   1   1   2   1
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4	1	1	4	1	1	2	2
5	1	1	3	1	1	2	1
6	1	2	3	1	1	1	2
7	1	2	2	1	1	3	1
8	1	1	3	1	1	2	1
10	1	1	3	1	1	1	1
11	1	1	1	2	1	2	1
18	1	1	1	1	1	1	2
19	1	1	1	1	1	2	1
20	1	1	1	1	1	1	2
21	1	1	1	1	1	2	1
27	1	1	1	1	1	2	1
[total]	16	17	100	16	16	28	20
222D58							
1	1	2	82	2	1	8	3
2	1	1	2	1	1	3	2
3	1	2	2	1	2	4	1
4	2	1	1	1	1	1	2
6	1	1	2	1	1	1	1
7	1	1	1	1	1	1	2
12	1	1	1	1	1	2	1
13	1	1	2	1	1	1	1
[total]	9	10	93	9	9	21	13
222D59							
1	1	1	76	1	2	8	3
2	2	2	4	1	1	2	1
3	1	1	2	1	1	1	2
4	1	1	3	1	1	1	2
5	1	1	3	1	1	3	1
6	1	1	2	1	1	2	1
7	1	1	1	2	1	1	1
9	1	1	1	1	1	3	2
12	1	1	2	1	1	1	1
13	1	2	1	1	1	1	1
[total]	11	12	95	11	11	23	15
222D62							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
222E57							
1	1	1	27	1	1	1	1
2	1	1	7	1	1	1	1
3	1	1	6	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	4	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	8	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	4	1	1	1	1
13	1	1	4	1	1	1	1
14	1	2	4	1	1	1	1
15	1	1	3	1	1	1	1
17	1	1	3	1	1	2	1
18	1	1	2	1	1	1	1
19	1	1	4	1	1	1	1
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25	1	1	2	1	1	1	1

26	1	1	2	1	1	1	1
28	2	1	3	1	1	1	1
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34	1	1	1	1	1	2	1
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37	1	1	2	1	1	2	2
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53	1	1	1	1	1	2	1
55	1	2	1	1	1	1	1
56	1	1	1	1	1	2	1
57	1	1	1	1	1	1	2
62	1	1	1	1	1	1	3
71	1	1	1	1	1	2	1
74	1	1	1	1	1	2	1
109	1	1	1	2	1	1	1
116	1	1	1	1	1	2	1
[total]	40	41	124	40	40	52	44
222E58							
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3	1	1	6	1	1	1	1
4	1	1	7	1	1	1	1
5	1	1	4	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	3	1	1	1	1
9	1	1	5	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	5	1	1	1	1
12	1	1	4	1	1	1	1
13	1	1	4	1	1	1	1
14	1	1	2	1	1	1	1
15	1	1	3	1	1	1	1
20	1	1	3	1	1	2	1
21	1	1	2	1	2	1	1
22	1	1	2	1	1	1	1
23	1	1	3	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	2	1	1	1	3
26	1	1	1	1	1	2	1
27	1	1	3	1	1	2	1
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33	1	1	1	1	1	2	1
34	1	1	3	1	1	1	1
36	1	1	1	1	1	3	1
37	1	2	2	1	1	1	1
38	1	1	1	1	1	2	1
39	1	1	1	1	1	1	2
43	1	2	1	1	1	1	1
47	1	1	1	1	1	2	1
56	1	1	2	1	1	1	1
62	1	1	1	1	1	2	1
64	1	1	1	1	1	2	1
66	1	1	1	1	1	1	3

76	1	1	1	1	1	2	1
95	1	1	1	2	1	1	1
107	1	1	1	1	1	2	1
[total]	40	41	124	40	40	52	44
222E59							
1	1	1	8	1	1	1	1
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4	1	1	8	1	1	1	1
5	1	1	25	1	1	1	1
6	1	1	2	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	5	1	1	1	1
10	1	1	5	1	1	1	1
11	1	1	3	1	1	1	1
12	1	1	2	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	4	1	1	1	1
15	1	1	4	1	1	1	1
17	1	1	3	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	2	1	1	1	1
20	1	1	3	1	1	1	1
21	1	2	2	1	1	1	1
22	1	1	3	1	1	1	1
23	1	1	2	1	1	1	1
24	1	1	1	1	1	2	1
27	1	1	2	1	1	1	1
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31	1	1	2	1	2	1	1
32	1	1	3	1	1	1	1
33	1	1	1	1	1	1	2
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39	1	1	1	1	1	1	2
42	1	1	1	1	1	2	1
46	1	1	1	1	1	2	1
51	1	2	1	1	1	1	1
52	1	1	1	1	1	2	1
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59	1	1	2	1	1	2	1
61	1	1	1	1	1	1	2
72	1	1	1	1	1	2	1
78	1	1	1	1	1	2	1
81	1	1	1	1	1	2	1
85	1	1	1	1	1	1	2
108	1	1	1	1	1	2	1
134	1	1	1	2	1	1	1
146	1	1	1	1	1	1	2
[total]	46	47	130	46	46	58	50
222E60							
2	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
222E61							
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3	1	1	3	1	1	2	2

4	1	1	3	1	1	5	1
5	1	1	4	1	1	3	2
6	1	1	5	1	1	1	1
7	1	1	4	1	1	3	1
8	1	1	3	1	1	1	2
9	2	1	2	1	1	1	1
10	1	2	2	1	1	2	1
11	1	1	2	1	1	1	1
13	1	1	1	1	1	2	2
20	1	1	1	2	1	1	1
[total]	14	15	98	14	14	26	18
222E62							
1	2	3	81	1	2	11	3
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5	1	1	2	1	1	2	3
7	1	1	1	1	1	1	2
[total]	6	7	90	6	6	18	10
222EY1							
1	2	2	84	1	2	8	4
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4	1	1	1	1	1	2	1
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8	1	1	2	1	1	1	1
9	1	1	1	1	1	2	1
19	1	2	1	1	1	1	1
[total]	10	11	94	10	10	22	14
231A66							
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7	1	1	4	1	1	1	1
8	1	1	5	1	1	1	1
9	1	1	6	1	1	1	1
10	1	1	4	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	4	1	1	1	1
13	1	1	5	1	1	1	1
15	1	1	4	1	1	1	1
17	1	1	2	1	1	1	1
19	1	1	3	1	1	1	1
21	1	1	3	1	2	1	1
25	1	1	2	1	1	1	1
26	1	1	3	1	1	1	1
27	1	1	2	1	1	1	1
28	1	1	2	1	1	1	1
30	1	1	2	1	1	1	1
31	1	1	2	1	1	2	1
33	1	1	2	1	1	1	1
35	1	1	2	1	1	1	1
40	1	1	2	1	1	1	1
41	1	1	2	1	1	1	1
43	1	1	2	1	1	2	1
47	1	1	2	1	1	1	1

49	1	1	2	1	1	1	1
50	1	2	1	1	1	1	1
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53	1	1	1	1	1	1	2
55	1	1	2	1	1	1	1
57	1	1	1	1	1	2	1
59	2	1	1	1	1	3	1
60	1	1	1	1	1	2	1
65	1	1	1	1	1	2	1
66	1	1	2	1	1	1	1
75	1	1	1	1	1	1	2
76	1	1	1	1	1	1	2
84	1	2	1	1	1	1	1
85	1	1	1	1	1	2	1
98	1	1	1	1	1	1	2
126	1	1	1	1	1	2	1
128	1	1	1	1	1	2	1
176	1	1	1	2	1	1	1
[total]	48	49	132	48	48	60	52
241A08							
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3	1	1	6	1	1	1	1
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5	1	1	3	1	1	2	2
6	1	1	3	1	1	1	1
7	1	1	2	1	1	1	1
8	1	2	3	1	1	1	2
9	1	1	1	1	1	3	1
10	1	1	1	1	2	1	1
11	2	1	1	1	1	3	2
12	1	1	3	1	1	1	1
13	1	1	2	1	1	2	1
14	1	1	2	1	1	1	1
16	1	1	1	1	1	1	2
19	1	1	1	2	1	2	1
20	1	1	2	1	1	1	1
21	1	1	1	1	1	2	1
22	1	2	1	1	1	2	1
23	1	1	1	1	1	3	1
32	1	1	1	1	1	1	2
[total]	22	23	106	22	22	34	26
241A70							
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3	1	1	10	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	3	1	1	1	1
6	1	1	4	1	1	2	1
8	1	1	2	1	1	2	1
9	1	1	1	1	2	1	1
10	1	1	2	1	1	1	1
11	1	2	4	1	1	1	1
13	1	1	1	1	1	2	3
14	1	1	3	1	1	1	1
15	1	1	2	1	1	2	1
19	1	1	1	1	1	2	1

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  35            1    1    2    1    1    2    1
  39            1    1    1    1    1    2    1
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241A71
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  7             1    1    5    1    1    1    1
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  9             1    1    2    1    1    1    1
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  14            1    1    4    1    1    1    1
  15            1    1    2    1    1    1    1
  16            1    1    2    1    1    1    1
  18            1    1    2    1    1    1    1
  19            1    1    2    1    1    1    1
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  23            1    1    2    1    1    1    1
  24            1    1    2    1    1    1    1
  30            1    1    2    1    1    1    1
  31            1    1    2    1    1    1    1
  32            1    1    1    1    1    2    1
  33            1    1    1    1    2    1    1
  34            1    1    3    1    1    1    1
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  37            1    1    1    1    1    2    1
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  43            1    1    2    1    1    2    1
  44            1    1    1    1    1    3    1
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  56            1    1    1    1    1    2    1
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  64            1    1    1    1    1    2    1
  66            1    1    1    1    1    1    2
  73            1    1    1    1    1    1    2
  74            1    1    2    1    1    1    1
  76            1    2    1    1    1    1    1
  88            1    1    1    1    1    2    1
  89            1    1    1    1    1    2    1
  104           1    1    1    1    1    2    1
  115           1    1    1    1    1    1    2
  116           1    1    1    1    1    2    1
```

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  [total]      44   45 128   44   44   56   48
241A72
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  5             1    1    6    1    1    1    1
  6             1    1    4    1    1    2    1
  7             1    1    5    1    1    1    1
  8             1    1    3    1    2    1    1
  9             1    1    3    1    1    2    1
  10            1    1    4    1    1    1    1
  11            1    1    3    1    1    2    1
  12            1    1    3    1    1    2    1
  13            1    1    2    1    1    1    1
  14            1    1    3    1    1    1    1
  15            1    1    1    1    1    2    1
  16            1    2    1    1    1    2    1
  17            1    1    1    1    1    2    1
  19            2    1    1    1    1    1    3
  21            1    1    1    1    1    2    2
  23            1    1    1    1    1    2    1
  25            1    1    1    1    1    1    2
  27            1    1    1    1    1    1    2
  29            1    1    1    2    1    1    1
  32            1    1    1    1    1    2    1
  33            1    2    1    1    1    1    1
  36            1    1    1    1    1    2    1
  38            1    1    1    1    1    2    1
  39            1    1    1    1    1    2    1
  [total]      29   30 113   29   29   41   33
242E72
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  2             1    1    7    1    1    1    1
  3             1    1    6    1    1    1    1
  4             1    1    6    1    2    1    1
  5             1    1    4    1    1    3    2
  6             1    1    3    1    1    1    2
  7             1    1    1    1    1    4    1
  8             1    1    2    1    1    2    2
  9             1    2    1    1    1    2    1
  10            1    1    3    1    1    2    1
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  [total]      21   22 105   21   21   33   25
251A33
  1             1    1   61    1    1    1    1
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  4             1    1    3    1    1    2    1
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6	2	1	2	1	2	1	1
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9	1	1	2	1	1	2	1
10	1	1	3	1	1	2	1
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15	1	1	2	1	1	2	1
16	1	1	2	1	1	3	1
23	1	1	1	1	1	2	1
25	1	1	1	1	1	2	1
26	1	2	1	1	1	1	1
31	1	1	1	2	1	1	1
34	1	1	1	1	1	1	2
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[total]	21	22	105	21	21	33	25
251A75							
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4	1	1	2	1	1	1	1
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12	1	1	2	1	1	1	1
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14	1	1	3	1	1	1	1
15	1	1	2	1	1	1	1
16	1	1	2	1	1	1	1
17	1	1	2	1	1	1	1
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19	1	1	6	1	1	1	1
21	1	1	2	1	1	1	1
22	1	1	1	1	1	2	1
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25	1	1	1	1	1	2	1
26	1	1	2	1	1	1	1
27	1	1	2	1	1	1	1
29	1	1	2	1	1	1	1
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39	1	1	2	1	1	1	1
40	1	1	3	1	1	1	1
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49	1	1	2	1	1	1	1
51	1	1	1	1	1	2	1
53	1	1	1	1	1	2	1
54	1	1	2	1	1	2	1
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63	1	1	2	1	1	1	1
64	1	1	1	1	1	2	1

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79	1	1	2	1	1	1	2
96	1	1	1	1	1	2	1
97	1	1	1	1	1	1	2
107	1	1	1	1	1	2	1
108	1	1	1	1	1	3	1
113	1	1	1	1	1	1	2
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131	1	1	2	1	1	1	1
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149	1	2	1	1	1	1	1
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[total]	58	59	142	58	58	70	62
251A76							
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7	1	1	2	1	1	2	1
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14	1	1	1	1	1	2	1
16	1	1	1	1	1	1	2
17	1	1	3	1	1	1	1
18	1	1	1	1	1	2	1
19	1	1	2	1	1	1	1
21	1	2	2	1	1	1	1
22	1	1	1	2	1	1	1
23	1	1	1	1	1	1	2
24	1	1	2	1	1	1	1
25	1	1	1	1	1	1	2
29	1	1	1	1	2	2	1
37	1	1	2	1	1	1	1
41	1	1	1	1	1	2	1
49	1	2	1	1	1	1	1
63	1	1	1	1	1	2	1
75	1	1	1	1	1	1	2
[total]	30	31	114	30	30	42	34
251AX3							
1	1	1	8	1	1	2	1
2	1	3	73	1	1	5	3
3	2	1	3	1	1	1	1
4	1	1	1	1	1	4	1
5	1	1	1	2	1	1	1
6	1	1	3	1	1	2	1
7	1	1	1	1	1	1	2
8	1	1	2	1	1	1	1

```
  9            1    1    2    1    1    1    1
  12           1    1    1    1    2    1    1
  13           1    1    1    1    1    2    2
  16           1    1    1    1    1    2    1
  24           1    1    1    1    1    2    1
  29           1    1    1    1    1    2    1
  30           1    1    1    1    1    1    2
  [total]     16   17  100   16   16   28   20
251AX4
  1            1    1    6    1    1    1    1
  2            1    1    4    1    1    1    1
  3            1    1   19    1    1    1    1
  4            1    1    4    1    1    1    1
  5            1    1    2    1    1    1    1
  6            1    1    5    1    1    1    1
  7            1    1    4    1    1    1    1
  8            1    1    4    1    1    1    1
  9            1    1    6    1    1    1    1
  11           1    1    3    1    1    1    1
  12           1    1    6    1    1    1    1
  14           1    1    2    1    1    1    1
  15           1    1    4    1    1    1    1
  17           1    1    3    1    1    1    1
  21           1    1    3    1    1    1    1
  22           1    1    2    1    1    1    1
  23           1    1    3    1    1    1    1
  24           1    1    2    1    1    1    1
  25           1    1    2    1    1    1    1
  27           1    1    2    1    1    1    1
  28           1    1    2    1    1    1    1
  29           1    1    3    1    1    1    1
  30           1    1    2    1    1    1    1
  31           1    1    3    1    1    1    1
  32           1    1    2    1    1    1    1
  36           1    1    2    1    1    1    1
  37           1    1    2    1    1    2    1
  41           1    1    2    1    1    1    1
  42           1    1    2    1    1    1    1
  43           1    1    2    1    1    1    1
  44           1    1    2    1    1    1    1
  51           1    1    2    1    1    1    1
  54           1    1    1    1    1    2    1
  55           2    1    1    1    1    1    1
  60           1    1    2    1    1    1    1
  61           1    1    1    1    1    2    1
  62           1    2    1    1    1    1    1
  64           1    1    1    1    1    2    1
  66           1    1    2    1    1    1    1
  69           1    1    2    1    1    2    1
  71           1    1    1    1    1    2    1
  72           1    1    1    1    2    1    2
  73           1    1    1    1    1    1    2
  75           1    1    1    1    1    2    1
  76           1    1    1    1    1    1    2
  81           1    1    2    1    1    1    1
  82           1    1    1    1    1    2    1
  84           1    2    1    1    1    1    1
  89           1    1    1    1    1    2    2
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90	1	1	1	1	1	2	1
113	1	1	2	1	1	1	2
135	1	1	1	1	1	2	1
141	1	1	1	1	1	2	1
155	1	1	1	1	1	2	1
156	1	1	1	2	1	1	1
[total]	56	57	140	56	56	68	60
251AX5							
1	1	1	26	1	1	1	1
2	1	1	11	1	1	1	1
3	1	1	5	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	4	1	1	1	1
6	1	1	6	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	2	1	1	1	1
9	1	1	2	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	3	1	1	1	1
12	1	1	5	1	1	2	1
13	1	1	4	1	1	1	1
14	1	1	2	1	1	1	1
15	1	1	4	1	1	1	1
16	1	1	3	1	1	1	1
19	1	1	4	1	1	1	1
20	1	1	3	1	1	1	1
21	1	1	1	1	1	2	1
23	1	1	2	1	1	1	1
25	1	1	2	1	2	1	1
29	1	1	2	1	1	1	2
32	1	1	1	1	1	2	1
34	1	2	1	1	1	1	2
35	1	1	2	1	1	1	1
38	1	1	1	1	1	2	1
41	1	1	1	1	1	2	1
42	2	1	2	1	1	2	1
43	1	1	2	1	1	1	1
46	1	1	1	1	1	2	1
47	1	2	1	1	1	2	1
48	1	1	1	1	1	1	2
55	1	1	2	1	1	1	1
57	1	1	1	1	1	2	1
59	1	1	1	1	1	1	2
65	1	1	2	1	1	2	1
72	1	1	1	1	1	2	1
76	1	1	1	1	1	2	1
78	1	1	1	1	1	2	1
79	1	1	1	1	1	1	2
94	1	1	1	2	1	1	1
[total]	42	43	126	42	42	54	46
252G33							
1	2	1	82	2	2	11	5
2	1	2	3	1	1	1	2
3	1	1	1	1	1	2	1
6	1	1	1	1	1	3	1
7	1	1	2	1	1	1	1
15	1	2	1	1	1	1	1
29	1	1	2	1	1	1	1

[total]	8	9	92	8	8	20	12
252G76							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
252GX5							
1	1	1	46	1	1	1	1
2	1	1	6	1	1	1	1
3	1	1	4	1	1	1	1
4	1	1	3	1	1	1	1
5	1	1	6	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	6	1	1	1	1
8	1	1	4	1	1	1	1
9	1	1	3	1	1	2	1
10	1	1	3	1	1	2	1
11	1	1	2	1	1	1	1
14	1	1	3	1	1	1	1
16	1	1	2	1	1	1	1
18	1	1	1	1	1	2	1
20	1	1	1	1	1	2	1
21	1	1	1	1	1	2	1
22	1	1	1	1	2	1	1
23	1	1	2	1	1	2	1
24	1	1	3	1	1	1	1
25	1	1	1	1	1	1	2
27	1	1	2	1	1	1	2
31	1	1	1	1	1	2	1
32	1	1	1	1	1	2	1
33	1	1	2	1	1	2	2
35	1	1	1	1	1	2	1
37	1	1	2	1	1	2	1
39	1	1	1	1	1	2	1
41	1	1	1	1	1	1	2
44	1	1	1	1	1	2	1
45	1	2	1	1	1	1	1
47	2	1	1	1	1	1	1
77	1	2	1	1	1	1	1
99	1	1	1	1	1	1	2
113	1	1	1	2	1	1	1
[total]	35	36	119	35	35	47	39
261A77							
1	1	1	29	1	1	1	1
2	1	1	10	1	1	1	1
3	1	1	9	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	6	1	1	1	1
6	1	1	2	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	4	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	4	1	1	1	1
11	1	1	2	1	1	2	1
12	1	1	3	1	1	1	1
13	1	1	4	1	1	1	1
14	1	1	2	1	1	3	1
15	1	1	2	1	1	1	1
16	1	1	2	1	1	1	1
17	1	1	2	1	1	1	1

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  18            1   1   3   1   1   2   1
  19            1   1   3   1   1   1   1
  20            1   2   1   1   2   1   1
  21            1   1   1   1   1   2   1
  23            1   1   2   1   1   2   1
  25            1   2   1   1   1   1   1
  26            1   1   1   1   1   2   1
  29            1   1   2   1   1   1   2
  30            2   1   1   1   1   1   1
  33            1   1   2   1   1   1   1
  34            1   1   1   1   1   2   2
  35            1   1   1   1   1   1   2
  38            1   1   1   1   1   1   2
  39            1   1   2   1   1   1   1
  40            1   1   2   1   1   2   1
  45            1   1   1   1   1   2   1
  49            1   1   1   2   1   1   1
  57            1   1   1   1   1   2   1
  61            1   1   1   1   1   2   1
  62            1   1   1   1   1   2   2
  [total]      38  39 122  38  38  50  42
261A78
  1             1   1  55   1   1   2   1
  2             1   1  10   1   1   1   1
  3             1   1   7   1   1   2   1
  4             1   1   2   1   1   2   1
  5             1   1   4   1   1   2   1
  6             1   1   5   1   1   2   2
  7             1   1   2   1   1   1   2
  8             1   2   2   1   2   1   2
  9             1   1   3   1   1   1   1
  10            1   1   2   1   1   2   1
  11            1   1   3   1   1   2   1
  12            2   1   1   1   1   2   1
  14            1   1   2   1   1   2   1
  15            1   1   1   1   1   2   1
  18            1   1   1   2   1   2   1
  22            1   1   1   1   1   1   2
  24            1   1   1   1   1   2   1
  34            1   1   1   1   1   1   2
  42            1   1   1   1   1   2   1
  45            1   2   1   1   1   1   1
  [total]      21  22 105  21  21  33  25
261A79
  1             2   2  83   2   2  10   4
  2             1   2   3   1   1   3   2
  3             1   1   2   1   1   3   1
  9             1   1   1   1   1   1   2
  [total]       5   6  89   5   5  17   9
261A80
  1             2   3  84   2   2  12   6
  2             1   1   2   1   1   2   1
  3             1   1   2   1   1   1   1
  4             1   1   1   1   1   2   1
  [total]       5   6  89   5   5  17   9
261A81
  1             2   3  84   2   2  14   5
  2             1   1   2   1   1   1   2
```

3	1	1	2	1	1	1	1
[total]	4	5	88	4	4	16	8
261A82							
1	1	3	82	2	1	11	3
2	1	1	3	1	2	3	1
3	2	1	2	1	1	1	3
4	1	1	2	1	1	2	2
[total]	5	6	89	5	5	17	9
261A83							
1	2	3	82	2	1	9	6
2	1	1	4	1	2	4	1
4	1	1	2	1	1	2	1
7	1	1	1	1	1	2	1
[total]	5	6	89	5	5	17	9
261A84							
1	2	3	86	2	2	14	5
2	1	1	1	1	1	1	2
[total]	3	4	87	3	3	15	7
261A85							
1	2	3	85	2	2	13	6
2	1	1	2	1	1	2	1
[total]	3	4	87	3	3	15	7
261A86							
1	2	3	86	2	2	13	6
2	1	1	1	1	1	2	1
[total]	3	4	87	3	3	15	7
261A88							
1	2	2	85	1	2	9	6
2	1	1	1	1	1	2	1
3	1	1	1	1	1	5	1
4	1	2	1	1	1	1	1
5	1	1	2	2	1	1	1
[total]	6	7	90	6	6	18	10
261AZ7							
1	2	2	86	2	2	11	6
2	1	1	1	1	1	2	1
3	1	1	1	1	1	2	1
4	1	1	1	1	1	2	1
5	1	2	1	1	1	1	1
[total]	6	7	90	6	6	18	10
261AX4							
1	1	2	86	2	2	13	6
2	2	1	1	1	1	1	1
4	1	2	1	1	1	2	1
[total]	4	5	88	4	4	16	8
281BB1							
1	1	1	9	1	1	1	1
2	1	1	35	1	1	1	1
3	1	1	6	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	5	1	1	2	1
9	1	1	6	1	1	2	1
10	1	1	2	1	1	1	1
11	1	1	2	1	1	1	1
13	1	1	3	1	1	1	1

14	1	1	1	1	1	2	1
16	1	1	3	1	1	1	1
17	1	1	3	1	1	2	1
18	1	1	2	1	1	1	1
19	1	1	2	1	1	1	1
21	1	1	1	1	1	2	1
22	1	1	3	1	2	1	1
24	2	1	3	1	1	1	1
26	1	1	1	1	1	2	1
29	1	1	1	1	1	1	4
31	1	1	1	1	1	2	1
32	1	1	1	1	1	1	2
34	1	1	1	1	1	2	1
41	1	1	1	1	1	2	1
46	1	1	1	1	1	1	2
47	1	1	2	1	1	1	1
49	1	2	1	1	1	1	1
53	1	2	1	1	1	1	1
55	1	1	1	1	1	2	1
60	1	1	1	2	1	1	1
75	1	1	1	1	1	2	1
77	1	1	1	1	1	2	1
84	1	1	1	1	1	2	1
[total]	36	37	120	36	36	48	40
281BD9							
1	1	2	76	2	1	6	4
2	1	1	3	1	1	3	1
3	1	1	3	1	1	2	1
4	1	1	2	1	1	2	2
5	1	1	3	1	1	1	1
6	2	1	1	1	1	2	1
8	1	1	2	1	1	1	1
9	1	1	2	1	1	2	1
11	1	1	1	1	2	1	1
14	1	1	1	1	1	2	1
18	1	2	1	1	1	1	1
22	1	1	1	1	1	1	2
24	1	1	2	1	1	1	1
37	1	1	1	1	1	2	1
[total]	15	16	99	15	15	27	19
281BE1							
1	1	1	67	2	2	4	3
2	1	2	8	1	1	1	1
3	1	1	3	1	1	1	1
4	1	1	5	1	1	2	1
5	1	1	4	1	1	1	1
6	1	1	1	1	1	3	1
7	1	1	3	1	1	3	2
8	1	2	1	1	1	2	1
9	1	1	1	1	1	1	2
15	1	1	1	1	1	2	1
17	1	1	1	1	1	2	1
21	1	1	2	1	1	1	1
25	1	1	1	1	1	1	2
31	2	1	1	1	1	1	1
41	1	1	1	1	1	3	1
[total]	16	17	100	16	16	28	20
281BS7							

1	1	1	56	1	1	1	1
2	1	1	9	1	1	1	1
3	1	1	5	1	1	3	1
4	1	1	4	1	1	1	1
5	1	1	5	1	2	1	1
6	1	1	3	1	1	1	2
7	2	1	1	1	1	1	1
8	1	1	3	1	1	2	1
9	1	2	3	1	1	2	1
10	1	1	2	1	1	1	1
13	1	1	5	1	1	1	3
14	1	1	1	1	1	2	1
15	1	1	1	1	1	1	2
17	1	1	1	1	1	2	1
20	1	1	1	1	1	3	2
22	1	1	1	1	1	2	1
26	1	2	1	1	1	1	1
27	1	1	1	1	1	2	1
29	1	1	1	1	1	3	1
35	1	1	1	1	1	2	1
53	1	1	1	2	1	1	1
[total]	22	23	106	22	22	34	26
281BS8							
1	1	2	77	1	1	4	4
2	2	1	4	1	1	3	3
3	1	1	2	1	1	5	1
4	1	2	2	2	2	1	1
5	1	1	4	1	1	1	1
7	1	1	1	1	1	2	1
8	1	1	2	1	1	1	1
9	1	1	1	1	1	3	1
13	1	1	1	1	1	2	1
[total]	10	11	94	10	10	22	14
281BS9							
1	1	1	54	1	1	1	1
2	1	1	9	1	1	2	1
3	1	1	7	1	1	1	1
4	1	1	5	1	1	1	2
5	1	1	2	1	1	1	1
6	2	1	6	1	1	1	1
7	1	1	4	1	1	2	1
8	1	1	2	1	1	1	2
9	1	3	2	1	1	2	1
10	1	1	2	1	1	3	1
11	1	1	1	1	1	2	1
12	1	1	2	1	1	2	2
13	1	1	1	1	1	2	1
14	1	1	1	1	1	3	1
15	1	1	1	2	1	2	1
16	1	1	1	1	1	2	1
17	1	1	1	1	1	1	2
20	1	1	2	1	1	1	1
22	1	1	1	1	1	1	2
28	1	1	1	1	2	1	1
29	1	1	1	1	1	2	1
[total]	22	23	106	22	22	34	26
281BT0							
1	1	1	81	2	1	9	4

2	1	2	5	1	1	2	1
3	1	2	1	1	1	3	2
4	2	1	1	1	1	1	1
5	1	1	1	1	2	2	1
6	1	1	2	1	1	1	1
7	1	1	1	1	1	2	2
[total]	8	9	92	8	8	20	12
281BT3							
1	2	2	81	1	2	12	3
2	1	1	4	2	1	2	2
3	1	2	2	1	1	1	2
4	1	1	2	1	1	1	2
5	1	1	1	1	1	2	1
[total]	6	7	90	6	6	18	10
291BA4							
1	1	1	69	1	1	3	1
2	1	1	6	1	1	1	1
3	1	1	9	1	1	2	1
4	1	2	3	1	1	2	3
5	1	1	1	1	1	4	2
6	1	1	1	1	2	1	2
7	2	1	1	1	1	3	2
8	1	2	2	1	1	1	1
9	1	1	2	1	1	2	1
10	1	1	1	1	1	2	1
11	1	1	1	1	1	2	1
12	1	1	1	2	1	1	1
20	1	1	1	1	1	2	1
[total]	14	15	98	14	14	26	18
291BA8							
1	1	1	44	1	1	1	1
2	1	1	12	1	1	1	1
3	1	1	10	1	1	2	1
4	1	1	4	1	1	1	1
5	1	1	2	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	4	1	2	2	1
8	1	1	1	1	1	1	2
9	1	2	3	1	1	1	1
10	1	1	4	1	1	2	1
11	1	1	3	1	1	1	1
12	1	1	2	1	1	1	2
13	2	1	1	1	1	1	2
14	1	1	1	1	1	1	2
15	1	1	2	1	1	2	1
16	1	1	2	1	1	1	1
18	1	1	2	1	1	2	1
20	1	1	3	1	1	3	1
22	1	1	1	1	1	3	1
23	1	1	1	1	1	2	2
24	1	1	1	2	1	2	1
31	1	1	1	1	1	2	1
34	1	2	1	1	1	1	1
36	1	1	1	1	1	2	1
[total]	25	26	109	25	25	37	29
291BC4							
1	2	3	85	2	2	13	6
2	1	1	1	1	1	2	1

```
  3           1   1   2   1   1   1   1
  [total]     4   5  88   4   4  16   8
301BB2
  1           1   1  27   1   1   1   1
  2           1   1  10   1   1   1   1
  3           1   1   4   1   1   1   1
  4           1   1   4   1   1   1   1
  5           1   1  10   1   1   1   1
  6           1   1   3   1   1   1   1
  7           1   1   3   1   1   1   1
  8           1   1   2   1   1   1   1
  9           1   1   3   1   1   1   1
  10          1   1   4   1   1   1   1
  11          1   1   5   1   1   1   1
  12          1   1   6   1   1   1   1
  13          1   1   4   1   1   1   1
  14          1   1   2   1   1   1   1
  16          1   1   5   1   1   1   1
  17          1   2   2   1   1   1   1
  18          1   1   3   1   1   1   1
  19          1   1   2   1   1   1   1
  22          1   1   1   1   1   2   1
  23          1   1   1   1   1   2   1
  24          1   1   1   1   1   3   1
  26          1   1   3   1   1   1   1
  27          1   1   1   1   1   2   1
  33          1   1   2   1   1   2   1
  34          1   1   1   1   2   1   1
  37          1   1   1   1   1   3   1
  39          1   1   1   1   1   2   2
  44          1   1   1   1   1   1   2
  45          2   1   1   1   1   1   1
  47          1   2   1   1   1   1   1
  48          1   1   1   1   1   1   2
  49          1   1   1   1   1   2   1
  54          1   1   2   1   1   1   1
  55          1   1   1   1   1   2   1
  62          1   1   1   1   1   1   2
  71          1   1   1   2   1   1   2
  91          1   1   1   1   1   2   1
  94          1   1   1   1   1   2   1
  [total]    39  40 123  39  39  51  43
301BB3
  1           1   1  24   1   1   1   1
  2           1   1   7   1   1   1   1
  3           1   1  11   1   1   1   1
  4           1   1   9   1   1   1   1
  5           1   1   3   1   1   1   1
  6           1   1   4   1   1   1   1
  7           1   1   5   1   1   1   1
  8           1   1   4   1   1   1   1
  9           1   1   6   1   1   1   1
  10          1   1   3   1   1   1   1
  11          1   1   2   1   1   1   1
  13          1   1   3   1   1   1   1
  14          1   1   4   1   1   1   1
  15          1   1   3   1   1   1   1
  16          1   1   3   1   1   1   1
```

17	1	1	2	1	1	1	1
19	1	1	4	1	1	1	1
22	1	1	2	1	1	2	1
23	1	1	2	1	1	2	1
25	1	1	2	1	1	1	1
26	1	1	2	1	1	1	1
28	1	1	1	1	1	2	1
30	1	1	1	1	1	2	1
33	1	2	1	1	1	2	1
34	1	1	1	1	1	1	2
36	1	1	1	1	1	2	2
37	1	1	1	1	1	2	1
39	1	1	1	1	1	2	1
45	2	1	1	1	1	1	1
46	1	1	1	1	1	2	1
47	1	1	2	1	1	2	1
48	1	1	1	1	1	1	2
49	1	1	1	1	1	1	2
52	1	1	1	1	1	2	1
54	1	2	1	1	2	1	1
67	1	1	1	1	1	1	2
73	1	1	1	1	1	2	1
76	1	1	1	2	1	1	1
78	1	1	1	1	1	2	1
[total]	40	41	124	40	40	52	44
301BB4							
1	1	1	7	1	1	1	1
2	1	1	19	1	1	1	1
3	1	1	5	1	1	1	1
4	1	1	7	1	1	1	1
5	1	1	3	1	1	1	1
6	1	1	6	1	1	1	1
7	1	1	3	1	1	1	1
8	1	1	3	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	4	1	1	1	1
12	1	1	4	1	1	1	1
14	1	1	4	1	1	1	1
15	1	1	4	1	1	1	1
16	1	1	2	1	1	1	1
17	1	1	2	1	1	1	1
21	1	1	2	1	1	1	1
22	1	1	5	1	1	1	1
23	1	1	4	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	3	1	1	1	1
26	1	1	3	1	1	1	1
27	1	1	2	1	1	1	1
28	1	1	2	1	1	1	1
29	1	1	2	1	1	1	1
32	1	1	2	1	1	1	1
35	1	1	2	1	1	1	1
36	1	1	2	1	1	1	1
37	1	1	2	1	1	1	1
38	1	1	2	1	1	2	1
40	1	2	2	1	1	1	1
42	1	1	1	1	1	2	1

44	1	1	1	1	1	2	1
47	1	1	1	1	1	2	2
53	1	1	1	1	1	1	2
56	1	1	1	1	1	2	1
59	2	1	1	1	1	1	1
62	1	1	1	1	1	2	1
63	1	1	1	1	1	2	1
64	1	1	1	1	2	1	1
66	1	1	1	1	1	2	1
73	1	1	1	1	1	2	2
78	1	1	1	1	1	1	2
79	1	1	1	1	1	2	1
81	1	1	1	1	1	2	1
85	1	1	1	1	1	1	2
114	1	1	1	1	1	2	1
120	1	2	1	1	1	1	1
124	1	1	1	2	1	1	1
128	1	1	1	1	1	2	1
[total]	51	52	135	51	51	63	55
301BB5							
1	1	1	42	1	1	1	1
2	1	1	7	1	1	1	1
3	1	1	2	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	5	1	1	2	1
6	1	1	9	1	1	1	1
7	1	1	2	1	1	1	1
8	1	1	5	1	1	1	1
9	1	1	4	1	1	2	1
10	1	1	2	1	1	1	1
11	1	1	4	1	1	1	1
12	1	1	3	1	1	1	1
13	1	1	3	1	1	1	1
14	1	1	2	1	1	2	1
15	1	1	2	1	1	1	1
17	1	1	2	1	1	1	1
19	1	1	2	1	1	2	1
20	1	2	1	1	1	1	1
21	1	1	1	1	1	2	1
22	1	2	1	1	1	1	1
24	2	1	1	1	1	2	1
26	1	1	1	1	1	2	1
29	1	1	1	1	1	2	1
31	1	1	1	1	1	2	2
34	1	1	1	1	1	1	2
36	1	1	1	1	1	2	1
37	1	1	1	1	1	2	1
38	1	1	2	1	1	1	1
47	1	1	1	2	1	1	1
48	1	1	1	1	1	1	2
56	1	1	1	1	1	2	2
59	1	1	1	1	2	2	1
60	1	1	1	1	1	1	2
[total]	34	35	118	34	34	46	38
301BG1							
1	2	1	86	1	2	14	5
2	1	2	1	1	1	1	2
7	1	2	1	2	1	1	1

```
  [total]       4    5   88    4    4   16    8
301BT2
  1             2    2   86    2    2   13    6
  2             1    2    1    1    1    2    1
  [total]       3    4   87    3    3   15    7
311BA8
  1             1    2   63    2    1    5    3
  2             1    2    8    1    1    1    1
  3             2    1    7    1    1    3    1
  4             1    1    4    1    1    3    1
  5             1    1    4    1    1    4    1
  6             1    1    2    1    1    1    2
  7             1    1    2    1    1    2    1
  8             1    1    1    1    2    1    1
  9             1    1    1    1    1    1    2
  10            1    1    2    1    1    1    1
  12            1    1    1    1    1    1    2
  17            1    1    1    1    1    2    1
  26            1    1    2    1    1    1    1
  [total]      14   15   98   14   14   26   18
311BB6
  1             2    1   66    1    1    2    2
  2             1    1   11    1    1    1    1
  3             1    2    5    1    1    5    2
  4             1    2    5    2    2    1    1
  5             1    1    2    1    1    1    1
  6             1    1    2    1    1    2    2
  7             1    1    1    1    1    3    2
  8             1    1    1    1    1    3    2
  9             1    1    1    1    1    2    1
  10            1    1    1    1    1    2    1
  11            1    1    1    1    1    2    1
  [total]      12   13   96   12   12   24   16
321BB7
  1             1    1   79    1    1    7    3
  2             1    3    6    1    1    3    1
  3             2    1    2    1    1    1    3
  4             1    1    1    1    2    3    2
  5             1    1    1    2    1    2    1
  8             1    1    2    1    1    1    1
  9             1    1    1    1    1    2    1
  13            1    1    1    1    1    2    1
  [total]       9   10   93    9    9   21   13
321BB8
  1             1    1   54    1    1    1    1
  2             1    1   12    1    1    1    1
  3             1    1    4    1    1    1    1
  4             1    2    8    1    1    1    1
  5             1    1    4    1    1    2    1
  6             1    1    5    1    1    3    1
  7             1    1    1    1    1    1    2
  8             1    1    3    1    1    4    1
  9             1    1    1    1    1    2    2
  10            1    1    3    1    1    2    2
  12            1    1    1    1    1    1    2
  15            1    1    1    1    1    2    1
  16            1    1    1    1    2    1    1
  17            1    1    1    1    1    2    1
```

18	1	1	1	2	1	1	1
19	1	1	1	1	1	1	2
20	1	1	1	1	1	2	1
21	1	2	1	1	1	1	1
23	1	1	1	1	1	2	1
24	1	1	1	1	1	2	1
25	2	1	1	1	1	1	1
[total]	22	23	106	22	22	34	26
331BB9							
1	2	3	85	2	2	11	4
2	1	1	2	1	1	3	3
3	1	1	1	1	1	2	1
[total]	4	5	88	4	4	16	8
331BY5							
1	2	3	84	2	2	14	6
2	1	1	3	1	1	1	1
[total]	3	4	87	3	3	15	7
341BG3							
1	1	1	50	1	1	1	1
2	1	2	10	1	1	1	1
3	1	1	11	1	1	1	1
4	1	1	8	1	1	1	2
5	1	1	7	1	1	2	1
6	1	1	4	1	1	2	1
7	2	1	1	1	1	1	1
8	1	1	2	1	1	2	1
9	1	1	1	1	1	1	2
10	1	1	1	1	2	3	1
12	1	1	1	1	1	1	2
13	1	1	1	1	1	2	1
14	1	2	1	1	1	4	1
16	1	1	1	1	1	1	2
17	1	1	1	1	1	2	1
18	1	1	1	1	1	2	1
19	1	1	1	2	1	1	2
25	1	1	1	1	1	2	1
26	1	1	1	1	1	2	1
[total]	20	21	104	20	20	32	24
341BG4							
1	1	1	65	1	1	1	1
2	1	2	12	1	1	1	1
3	1	1	2	1	1	2	1
4	1	1	2	1	1	2	1
5	2	1	6	1	1	3	2
6	1	1	1	1	1	3	1
7	1	1	1	2	1	2	2
8	1	1	1	1	1	3	1
9	1	1	1	1	1	1	2
10	1	1	3	1	1	1	1
11	1	1	2	1	1	2	1
13	1	1	1	1	1	2	1
14	1	2	1	1	1	1	1
15	1	1	1	1	2	1	1
16	1	1	1	1	1	1	2
19	1	1	1	1	1	2	1
20	1	1	1	1	1	2	1
22	1	1	1	1	1	1	2
[total]	19	20	103	19	19	31	23

351BG8							
1	1	2	68	1	1	2	1
2	1	1	6	1	1	3	1
3	1	1	7	1	1	2	1
4	1	1	4	1	1	3	2
5	2	1	3	1	2	2	1
6	1	1	3	2	1	3	1
7	1	1	1	1	1	2	3
8	1	2	1	1	1	2	2
14	1	1	1	1	1	2	2
19	1	1	1	1	1	2	1
[total]	11	12	95	11	11	23	15
351BG9							
1	1	1	73	1	1	2	1
2	1	1	8	1	1	1	2
3	1	1	5	1	1	3	1
4	1	2	2	1	1	4	2
5	2	1	2	1	1	2	2
6	1	2	1	1	1	2	2
7	1	1	1	1	1	4	1
9	1	1	1	1	1	2	1
10	1	1	1	2	1	1	1
11	1	1	1	1	2	1	2
13	1	1	1	1	1	2	1
[total]	12	13	96	12	12	24	16
351BD1							
1	1	1	64	1	1	1	2
2	2	1	10	1	1	7	1
3	1	2	4	1	1	1	2
4	1	1	7	1	1	1	3
5	1	1	2	1	1	3	1
6	1	1	2	1	1	1	1
7	1	1	2	2	1	3	1
8	1	1	2	1	1	1	1
9	1	1	1	1	1	2	1
14	1	2	1	1	1	1	1
17	1	1	1	1	1	2	1
18	1	1	1	1	1	2	1
25	1	1	1	1	2	1	1
26	1	1	1	1	1	1	2
[total]	15	16	99	15	15	27	19
351BD2							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
351BD3							
1	1	1	54	1	1	1	1
2	1	1	14	1	1	1	1
3	1	1	10	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	4	1	1	1	1
6	2	1	3	1	1	2	1
7	1	1	1	1	1	3	1
8	1	1	2	1	1	3	1
9	1	2	1	1	1	3	2
11	1	2	1	1	2	4	3
12	1	1	1	1	1	2	1
17	1	1	1	1	1	1	2
21	1	1	1	1	1	1	2

```
  23           1   1   1   2   1   1   1
  26           1   1   1   1   1   2   1
  29           1   1   1   1   1   2   1
  [total]     17  18 101  17  17  29  21
351BD5
  1            1   2  47   1   1   1   1
  2            1   1  14   1   1   1   1
  3            1   1   6   1   1   1   1
  4            1   1   8   1   1   1   2
  5            1   1   6   1   1   2   1
  6            1   1   4   1   1   2   1
  7            1   1   4   1   1   2   3
  11           1   1   3   1   2   2   1
  13           1   2   1   1   1   3   1
  15           1   1   1   1   1   2   2
  16           1   1   1   1   1   4   1
  17           1   1   1   2   1   1   1
  18           1   1   1   1   1   2   1
  19           1   1   1   1   1   1   2
  23           1   1   1   1   1   2   1
  26           2   1   1   1   1   2   1
  30           1   1   2   1   1   1   1
  [total]     18  19 102  18  18  30  22
361BBL
  1            1   1  64   1   2   2   2
  2            1   1   8   1   1   3   2
  3            1   1   6   1   1   3   1
  4            2   1   5   1   1   4   1
  5            1   1   4   1   1   3   1
  6            1   1   3   1   1   1   1
  7            1   1   2   1   1   1   1
  8            1   1   1   1   1   2   2
  9            1   3   1   1   1   1   1
  10           1   1   1   1   1   2   2
  12           1   1   1   1   1   1   2
  14           1   1   1   2   1   1   1
  17           1   1   1   1   1   2   1
  [total]     14  15  98  14  14  26  18
361BG2
  1            2   1  76   1   2   7   2
  2            1   3   4   1   1   5   3
  3            1   1   5   1   1   3   1
  4            1   1   1   1   1   2   3
  5            1   1   2   1   1   1   1
  6            1   1   2   1   1   1   1
  7            1   1   2   1   1   1   1
  10           1   1   1   2   1   1   1
  [total]      9  10  93   9   9  21  13
361BG5
  1            1   1  39   1   1   1   1
  2            1   1  14   1   1   1   1
  3            1   1  11   1   1   1   1
  4            1   1   7   1   1   1   1
  5            1   1   3   1   1   1   1
  6            1   1  10   1   1   1   1
  7            1   1   4   1   1   1   1
  9            1   1   4   1   1   1   2
  11           2   2   1   1   1   1   1
```

12	1	1	1	1	1	2	1
13	1	1	2	1	1	3	1
14	1	1	1	1	1	3	1
15	1	1	1	1	1	2	1
16	1	1	1	1	2	1	2
17	1	1	1	1	1	2	1
18	1	2	1	1	1	3	2
19	1	1	1	1	1	1	2
22	1	1	1	2	1	1	1
23	1	1	1	1	1	1	2
25	1	1	1	1	1	2	1
33	1	1	1	1	1	2	1
43	1	1	1	1	1	2	1
49	1	1	1	1	1	2	1
[total]	24	25	108	24	24	36	28
361BG6							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
361BG7							
1	1	1	10	1	1	1	1
2	1	1	8	1	1	1	1
3	1	1	37	1	1	1	1
4	1	1	6	1	1	1	1
5	1	1	2	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	5	1	1	1	1
8	1	1	2	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	3	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	5	1	1	1	1
13	1	1	3	1	1	1	1
14	1	1	2	1	1	1	1
16	1	1	3	1	1	2	1
17	1	1	2	1	1	1	1
20	1	1	1	1	1	2	1
21	1	2	1	1	1	2	1
25	1	1	1	1	1	2	1
27	1	1	1	1	1	2	1
29	1	1	1	1	1	1	3
30	1	1	2	1	1	1	1
31	1	1	2	1	1	1	1
32	1	1	1	1	1	3	1
33	1	1	1	1	1	1	2
34	2	1	1	1	1	1	1
36	1	1	1	1	2	1	1
37	1	1	2	1	1	1	1
39	1	1	1	1	1	3	2
42	1	1	1	1	1	2	1
56	1	2	1	1	1	1	1
61	1	1	1	1	1	3	1
66	1	1	1	2	1	1	1
75	1	1	1	1	1	1	2
77	1	1	1	1	1	2	1
[total]	36	37	120	36	36	48	40
361BD4							
1	1	2	83	2	2	10	5
2	1	1	3	1	1	3	1

```
  3            1   1   2   1   1   2   2
  4            2   2   1   1   1   1   1
  6            1   1   1   1   1   2   1
  [total]      6   7  90   6   6  18  10
361BD6
  1            1   1  75   1   2   3   4
  2            2   1   9   1   1   7   1
  3            1   2   3   2   1   3   1
  5            1   1   1   1   1   2   2
  6            1   2   2   1   1   1   1
  7            1   1   1   1   1   2   2
  8            1   1   1   1   1   2   1
  [total]      8   9  92   8   8  20  12
361BD8
  1            1   3  83   1   2   5   4
  2            2   1   3   1   1   7   2
  3            1   1   1   1   1   2   1
  4            1   1   2   2   1   2   1
  5            1   1   1   1   1   2   2
  [total]      6   7  90   6   6  18  10
361BM5
  1            1   1  63   1   1   1   1
  2            1   1   7   1   1   3   1
  3            1   1  10   1   1   1   1
  4            2   1   3   1   1   2   2
  5            1   1   4   1   1   5   1
  6            1   2   2   1   1   1   1
  7            1   1   3   1   1   1   2
  8            1   1   1   1   1   1   3
  9            1   1   1   1   1   3   1
  10           1   1   1   1   1   2   1
  12           1   1   1   1   1   1   2
  14           1   1   1   1   1   2   1
  15           1   1   1   2   1   2   1
  17           1   1   1   1   1   2   1
  18           1   1   1   1   2   1   1
  21           1   2   1   1   1   1   1
  [total]     17  18 101  17  17  29  21
361BY4
  1            2   3  84   2   2  14   6
  2            1   1   3   1   1   1   1
  [total]      3   4  87   3   3  15   7
361BY6
  1            1   1  69   1   1   3   2
  2            1   1   5   1   1   2   2
  3            1   1   6   1   2   1   1
  4            1   2   4   1   1   3   1
  5            1   2   2   1   1   1   1
  6            1   1   3   1   1   2   2
  7            1   1   2   1   1   1   1
  8            2   1   2   2   1   1   1
  9            1   1   1   1   1   2   1
  11           1   1   1   1   1   3   1
  13           1   1   1   1   1   1   2
  15           1   1   1   1   1   2   1
  16           1   1   1   1   1   1   2
  18           1   1   1   1   1   2   1
  30           1   1   1   1   1   2   1
```

33	1	1	1	1	1	2	1
[total]	17	18	101	17	17	29	21
371AE2							
1	1	1	50	1	1	3	1
2	1	1	7	1	1	1	1
3	1	1	4	1	1	2	1
4	1	1	6	1	1	1	1
5	1	1	3	1	1	2	1
6	1	1	2	1	1	1	1
7	1	1	2	1	1	1	2
8	1	2	1	1	1	1	1
9	1	1	1	1	1	2	1
10	1	1	4	1	1	2	1
11	1	1	3	1	1	1	1
12	1	2	1	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	3	1	1	1	1
15	1	1	3	1	1	1	1
19	1	1	3	1	1	2	1
21	1	1	3	1	1	1	1
24	1	1	3	1	1	1	1
25	1	1	2	1	2	1	1
32	1	1	1	1	1	2	1
36	2	1	1	1	1	1	1
38	1	1	1	1	1	2	1
40	1	1	1	1	1	1	2
44	1	1	1	1	1	1	2
46	1	1	2	1	1	1	1
51	1	1	1	1	1	1	2
54	1	1	1	1	1	2	1
61	1	1	1	1	1	2	1
70	1	1	1	1	1	2	1
71	1	1	1	2	1	1	1
76	1	1	1	1	1	2	1
104	1	1	1	1	1	1	2
[total]	33	34	117	33	33	45	37
371BE3							
1	2	1	76	1	1	6	2
2	1	2	4	1	1	5	1
3	1	1	3	1	1	1	1
4	1	2	1	1	1	3	1
5	1	1	2	1	1	1	1
6	1	1	1	1	2	1	1
7	1	1	1	1	1	2	1
8	1	1	2	1	1	1	2
9	1	1	3	1	1	1	1
12	1	1	1	1	1	1	2
14	1	1	1	2	1	1	1
18	1	1	2	1	1	2	1
19	1	1	1	1	1	1	2
24	1	1	1	1	1	1	2
[total]	15	16	99	15	15	27	19
381BE4							
1	1	1	5	1	1	1	1
2	1	1	43	1	1	1	1
3	1	1	8	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	4	1	1	1	1

6	1	1	4	1	1	1	1
7	1	1	2	1	1	1	1
8	1	1	3	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	6	1	1	2	1
11	1	1	2	1	1	1	1
14	1	1	1	1	1	2	1
15	1	1	3	1	1	1	1
16	1	1	4	1	1	1	2
17	1	2	2	1	1	1	1
18	1	1	1	1	1	2	1
19	1	1	2	1	1	1	1
21	1	1	1	1	1	3	1
22	1	1	2	1	1	1	1
23	1	1	1	1	1	3	1
26	1	1	2	1	1	1	1
28	1	1	1	1	2	1	1
29	1	1	2	1	1	3	1
31	2	1	1	1	1	1	2
33	1	1	1	1	1	1	2
34	1	1	1	1	1	2	1
36	1	1	1	1	1	1	2
39	1	1	2	1	1	1	1
41	1	1	1	1	1	1	2
42	1	1	1	2	1	1	1
44	1	1	1	1	1	2	1
48	1	2	1	1	1	1	1
49	1	1	1	1	1	2	1
50	1	1	1	1	1	2	1
[total]	35	36	119	35	35	47	39
381BE5							
1	1	1	30	1	1	1	1
2	1	1	6	1	1	1	1
3	1	1	4	1	1	1	1
4	1	1	3	1	1	1	1
5	1	1	4	1	1	1	1
6	1	1	9	1	1	1	1
7	1	1	2	1	1	1	1
8	1	1	3	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	5	1	1	1	1
13	1	1	3	1	1	1	1
14	1	1	4	1	1	1	1
15	1	1	3	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	2	1	1	2	1
21	1	1	3	1	1	1	1
26	1	1	4	1	1	1	1
27	1	2	1	1	1	1	1
28	1	1	1	1	1	3	1
30	1	1	3	1	1	1	1
32	1	1	2	1	1	1	1
33	1	1	1	1	1	2	1
34	1	1	2	2	1	1	1
35	1	1	2	1	1	1	1
36	1	1	1	1	2	1	1

```
  37           1   1   1   1   1   2   1
  42           1   1   1   1   1   2   1
  44           1   1   2   1   1   1   2
  45           1   1   1   1   1   2   1
  47           1   1   2   1   1   3   1
  51           2   1   2   1   1   1   1
  53           1   1   1   1   1   2   2
  61           1   1   2   1   1   1   1
  69           1   1   1   1   1   1   2
  78           1   1   1   1   1   1   2
  82           1   2   1   1   1   1   1
  84           1   1   1   1   1   2   1
  87           1   1   1   1   1   2   1
  105          1   1   1   1   1   1   2
  146          1   1   1   1   1   2   1
  [total]     43  44 127  43  43  55  47
381BE6
  1            1   1   8   1   1   1   1
  2            1   1  31   1   1   1   1
  3            1   1   5   1   1   1   1
  4            1   1   4   1   1   1   1
  5            1   1   9   1   1   1   1
  6            1   1   6   1   1   1   1
  7            1   1   3   1   1   1   1
  8            1   1   2   1   1   1   1
  9            1   1   2   1   1   1   1
  10           1   1   2   1   1   1   1
  12           1   1   4   1   1   1   1
  14           1   1   4   1   1   1   1
  15           1   1   2   1   1   1   1
  17           1   1   4   1   1   1   1
  18           1   1   5   1   1   1   1
  20           1   1   3   1   1   1   1
  21           1   1   2   1   1   1   1
  23           1   1   1   1   1   3   1
  24           1   1   1   1   2   1   1
  25           1   1   1   1   1   2   1
  26           1   2   3   1   1   1   1
  28           1   1   2   1   1   1   1
  29           1   1   1   1   1   2   1
  32           1   1   2   1   1   1   1
  34           1   1   1   1   1   2   1
  35           1   1   2   1   1   1   2
  39           1   1   1   1   1   2   1
  41           1   1   1   1   1   3   1
  42           1   1   1   1   1   1   2
  44           1   1   1   1   1   2   1
  45           2   1   1   1   1   1   1
  48           1   1   1   1   1   2   1
  54           1   1   1   1   1   2   2
  56           1   1   1   2   1   1   1
  59           1   1   2   1   1   2   1
  62           1   1   1   1   1   1   2
  63           1   2   1   1   1   1   1
  86           1   1   1   1   1   1   2
  121          1   1   1   1   1   2   1
  [total]     40  41 124  40  40  52  44
381BE7
```

1	1	1	23	1	1	1	1
2	1	1	7	1	1	1	1
3	1	1	10	1	1	1	1
4	1	1	7	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	6	1	1	1	1
8	1	1	4	1	1	1	1
9	1	1	4	1	1	1	1
10	1	1	2	1	1	1	1
11	1	1	4	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	4	1	1	1	1
15	1	2	3	1	1	1	1
16	1	1	3	1	1	1	1
17	1	1	3	1	1	2	1
18	1	1	3	1	1	1	1
20	1	1	3	1	1	2	1
21	1	1	3	1	1	1	1
22	1	1	2	1	1	1	1
24	1	1	1	1	1	1	2
25	1	1	1	1	1	3	1
26	1	1	1	1	1	2	1
27	1	1	2	1	1	1	1
31	1	1	1	1	1	2	1
32	1	1	1	1	1	1	2
33	1	1	1	1	1	2	1
34	1	1	2	1	1	1	1
35	1	1	1	1	1	1	2
37	1	1	1	1	2	1	1
41	2	1	1	1	1	3	1
45	1	1	2	1	1	2	2
47	1	1	1	2	1	1	1
48	1	1	1	1	1	2	1
51	1	2	1	1	1	1	1
64	1	1	1	1	1	2	1
66	1	1	1	1	1	1	2
89	1	1	1	1	1	2	1
[total]	39	40	123	39	39	51	43
391BE8							
1	1	1	76	1	1	5	1
2	1	1	5	1	1	4	1
3	1	1	3	1	1	3	1
4	1	1	2	1	2	2	2
5	1	3	1	1	1	1	1
6	1	1	2	1	1	3	2
7	1	1	2	1	1	1	1
8	1	1	1	1	1	1	2
9	1	1	1	1	1	1	2
11	1	1	2	1	1	1	1
21	1	1	1	1	1	2	1
27	1	1	1	2	1	1	2
29	2	1	1	1	1	1	1
[total]	14	15	98	14	14	26	18
401BE9							
1	1	1	56	1	1	2	1
2	1	1	11	1	1	2	3
3	1	1	10	1	1	2	2

4	1	1	5	1	1	1	2
5	2	1	4	1	1	3	1
6	1	2	2	1	1	4	1
7	1	1	3	2	1	3	1
9	1	2	2	1	1	2	1
10	1	1	1	1	2	2	1
11	1	1	1	1	1	2	2
[total]	11	12	95	11	11	23	15
401BZ1							
1	1	1	71	1	2	5	1
2	2	1	10	1	1	4	3
3	1	2	4	1	1	1	2
4	1	2	2	1	1	2	2
5	1	1	2	2	1	1	1
6	1	1	2	1	1	3	2
7	1	1	1	1	1	2	1
9	1	1	1	1	1	2	1
11	1	1	1	1	1	2	1
[total]	10	11	94	10	10	22	14
411A14							
1	2	3	86	2	2	13	6
2	1	1	1	1	1	2	1
[total]	3	4	87	3	3	15	7
411AZ2							
1	1	3	78	1	1	6	3
2	1	1	3	1	1	2	2
3	2	1	4	1	1	2	2
4	1	1	3	2	1	1	1
5	1	1	1	1	2	2	2
7	1	1	1	1	1	2	1
8	1	1	2	1	1	2	1
12	1	1	1	1	1	2	1
32	1	1	1	1	1	2	1
51	1	1	1	1	1	2	1
[total]	11	12	95	11	11	23	15
423ZH1							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
423ZH2							
1	2	3	86	1	2	12	4
2	1	1	1	1	1	1	3
3	1	1	1	2	1	3	1
[total]	4	5	88	4	4	16	8
433ZBM							
1	2	3	79	1	1	8	4
2	1	1	5	1	2	3	2
3	1	1	4	2	1	3	2
5	1	1	1	1	1	2	1
6	1	1	1	1	1	2	1
[total]	6	7	90	6	6	18	10
433ZH1							
1	1	2	79	2	1	7	3
2	1	1	4	1	2	4	2
3	2	2	4	1	1	4	2
4	1	1	1	1	1	2	2
5	1	1	2	1	1	1	1
[total]	6	7	90	6	6	18	10
433ZH2							

1	1	1	78	1	2	3	1
2	1	3	8	1	1	1	1
3	2	1	2	1	1	5	3
4	1	1	1	1	1	5	1
5	1	1	1	2	1	2	2
6	1	1	1	1	1	2	2
7	1	1	1	1	1	1	2
11	1	1	1	1	1	2	1
[total]	9	10	93	9	9	21	13
433ZH3							
1	2	2	85	2	2	14	5
2	1	2	2	1	1	1	2
[total]	3	4	87	3	3	15	7
433ZH5							
1	2	3	86	2	2	13	5
2	1	1	1	1	1	2	2
[total]	3	4	87	3	3	15	7
463HH1							
1	2	3	85	2	2	12	3
2	1	1	2	1	1	2	3
3	1	1	1	1	1	2	2
[total]	4	5	88	4	4	16	8
463HH2							
1	2	3	86	2	2	13	6
2	1	1	1	1	1	2	1
[total]	3	4	87	3	3	15	7
463HH3							
1	1	1	74	1	1	5	1
2	1	1	7	1	1	2	1
3	1	1	4	1	1	2	2
4	1	1	1	1	1	2	3
5	1	1	4	1	1	3	2
6	1	2	1	1	1	3	1
7	1	2	1	2	1	1	1
8	1	1	1	1	2	3	2
11	2	1	1	1	1	1	1
[total]	10	11	94	10	10	22	14
463HH4							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
463HH5							
1	2	3	81	2	2	9	5
2	1	1	3	1	1	3	1
3	1	1	3	1	1	3	1
4	1	1	2	1	1	1	2
5	1	1	1	1	1	2	1
[total]	6	7	90	6	6	18	10
473UH1							
1	1	1	81	1	2	7	1
2	2	1	6	1	1	4	2
3	1	2	1	1	1	2	2
4	1	2	1	1	1	2	3
5	1	1	1	1	1	2	1
7	1	1	1	2	1	1	1
8	1	1	1	1	1	1	2
9	1	1	1	1	1	2	1
[total]	9	10	93	9	9	21	13
473UH2							

```
  1            2   2  83   1   1   4   2
  2            1   1   4   1   2   4   3
  3            1   2   1   1   1   4   2
  4            1   1   1   1   1   4   1
  5            1   1   1   2   1   2   2
  [total]      6   7  90   6   6  18  10
473UH3
  1            2   3  84   1   2  14   5
  2            1   1   3   2   1   1   2
  [total]      3   4  87   3   3  15   7
473UH4
  1            2   3  86   2   2  14   6
  [total]      2   3  86   2   2  14   6
483IH6
  1            1   1  76   1   2   3   2
  2            1   1   3   1   1   3   2
  3            1   3   6   1   1   3   1
  4            1   1   3   1   1   2   1
  5            1   1   2   2   1   1   1
  6            1   1   1   1   1   2   1
  9            1   1   1   1   1   3   2
  10           1   1   1   1   1   1   2
  11           1   1   1   1   1   2   1
  12           1   1   1   1   1   1   2
  14           2   1   1   1   1   2   1
  17           1   1   1   1   1   2   1
  [total]     13  14  97  13  13  25  17
483IH7
  1            1   2  78   1   1   7   2
  2            1   1   7   1   1   2   3
  3            1   1   3   1   1   5   1
  4            1   2   1   2   2   1   3
  5            1   1   1   1   1   2   1
  6            1   1   1   1   1   2   1
  7            2   1   1   1   1   1   1
  [total]      8   9  92   8   8  20  12
483IH8
  1            2   3  83   1   2  10   4
  2            1   1   1   1   1   1   2
  3            1   1   2   2   1   1   1
  4            1   1   1   1   1   2   1
  5            1   1   3   1   1   2   2
  6            1   1   1   1   1   2   1
  7            1   1   1   1   1   2   1
  [total]      8   9  92   8   8  20  12
483IH9
  1            1   2  76   1   1   2   1
  2            1   1   8   1   1   3   2
  3            1   1   3   1   2   3   1
  4            1   1   2   1   1   4   1
  5            1   1   1   1   1   2   1
  6            2   2   1   1   1   3   3
  7            1   1   1   2   1   1   2
  8            1   1   1   1   1   2   2
  11           1   1   1   1   1   2   1
  [total]     10  11  94  10  10  22  14
493KU1
  1            2   1  83   1   2   9   4
```

2	1	3	4	1	1	4	2
3	1	1	1	1	1	2	1
4	1	1	1	1	1	2	1
5	1	1	1	2	1	1	2
[total]	6	7	90	6	6	18	10
493KU2							
1	1	3	86	2	2	13	6
2	1	1	1	1	1	2	1
4	2	1	1	1	1	1	1
[total]	4	5	88	4	4	16	8
503KU4							
1	1	1	45	1	1	1	1
2	1	1	10	1	1	1	2
3	1	2	10	1	1	2	1
4	1	1	7	1	1	1	1
5	1	1	3	1	1	3	1
6	1	1	5	1	2	2	2
7	1	1	5	1	1	1	1
8	1	1	3	1	1	3	1
9	1	1	3	1	1	1	1
10	1	1	1	1	1	2	1
12	2	1	2	1	1	1	1
13	1	1	1	1	1	1	2
14	1	1	2	1	1	4	1
15	1	1	2	1	1	1	1
16	1	2	1	1	1	2	1
22	1	1	1	1	1	3	2
27	1	1	1	1	1	1	2
46	1	1	1	2	1	1	1
[total]	19	20	103	19	19	31	23
503KU5							
1	1	3	86	2	2	12	6
2	2	1	1	1	1	2	1
3	1	1	1	1	1	2	1
[total]	4	5	88	4	4	16	8
503KU6							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
503KU7							
1	1	1	71	1	2	1	3
2	2	3	9	1	1	4	1
3	1	1	5	1	1	3	2
4	1	1	3	1	1	2	2
5	1	1	2	1	1	4	1
6	1	1	1	1	1	3	1
7	1	1	1	1	1	3	1
12	1	1	1	2	1	1	2
[total]	9	10	93	9	9	21	13
513KU8							
1	2	3	86	2	2	14	5
2	1	1	1	1	1	1	2
[total]	3	4	87	3	3	15	7
513KU9							
1	2	1	70	1	2	3	2
2	1	2	11	1	1	2	1
3	1	1	5	1	1	4	1
4	1	2	1	1	1	4	1
5	1	1	1	1	1	2	2

6	1	1	2	2	1	2	1
7	1	1	1	1	1	2	2
8	1	1	2	1	1	1	1
11	1	1	1	1	1	2	2
16	1	1	1	1	1	1	2
[total]	11	12	95	11	11	23	15
533LI1							
1	2	3	85	1	1	14	6
2	1	1	2	2	1	1	1
3	1	1	1	1	2	1	1
[total]	4	5	88	4	4	16	8
543LI3							
1	2	2	81	2	2	8	4
2	1	1	4	1	1	5	1
3	1	1	3	1	1	2	3
4	1	1	1	1	1	2	1
5	1	2	1	1	1	1	1
[total]	6	7	90	6	6	18	10
553LH4							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
563LI5							
1	1	1	72	2	1	6	1
2	1	1	4	1	1	5	4
3	1	1	6	1	1	2	1
4	1	2	3	1	1	2	1
5	1	2	3	1	1	2	1
6	1	1	1	1	2	1	3
7	2	1	1	1	1	1	1
8	1	1	1	1	1	2	1
9	1	1	3	1	1	1	1
[total]	10	11	94	10	10	22	14
563LI6							
1	2	3	86	2	1	14	6
5	1	1	1	1	2	1	1
[total]	3	4	87	3	3	15	7
573LI7							
1	1	1	83	2	2	8	6
2	2	2	4	1	1	4	1
3	1	1	1	1	1	2	1
4	1	2	1	1	1	1	1
5	1	1	1	1	1	2	1
7	1	1	1	1	1	2	1
[total]	7	8	91	7	7	19	11
573LI8							
1	2	2	83	2	1	10	3
2	1	1	3	1	2	3	3
3	1	1	1	1	1	2	2
4	1	2	2	1	1	1	1
5	1	1	1	1	1	2	1
[total]	6	7	90	6	6	18	10
583LI9							
1	2	3	85	2	2	13	5
2	1	1	2	1	1	2	2
[total]	3	4	87	3	3	15	7
583LK1							
1	1	1	80	1	2	13	4
2	1	1	5	1	1	1	2

3	2	1	2	2	1	1	2
4	1	1	2	1	1	2	1
5	1	3	1	1	1	1	1
[total]	6	7	90	6	6	18	10
603MK6							
1	1	1	76	1	1	8	1
2	1	1	6	1	1	3	4
3	1	2	4	1	1	4	2
4	2	1	1	1	1	1	1
5	1	2	2	1	2	1	1
6	1	1	2	2	1	2	2
[total]	7	8	91	7	7	19	11
613MK7							
1	1	3	80	2	1	9	4
2	1	1	3	1	1	3	3
3	1	1	3	1	1	2	1
5	1	1	2	1	1	1	1
6	1	1	1	1	2	2	1
7	2	1	1	1	1	1	1
8	1	1	1	1	1	2	1
55	1	1	2	1	1	1	1
[total]	9	10	93	9	9	21	13
623MK8							
1	1	1	67	1	1	3	1
2	1	1	10	1	1	3	1
3	1	1	4	1	1	4	3
4	1	1	6	1	1	1	1
5	1	1	2	1	2	3	1
6	1	1	2	1	1	2	2
8	2	1	1	1	1	1	1
9	1	1	1	1	1	2	1
10	1	2	1	1	1	1	2
11	1	1	1	1	1	1	2
12	1	1	1	1	1	2	1
14	1	2	1	1	1	2	1
18	1	1	1	2	1	1	1
[total]	14	15	98	14	14	26	18
633NK9							
1	1	1	61	1	1	1	1
2	1	1	9	1	1	1	1
3	1	1	5	1	1	1	1
4	1	1	7	1	1	3	1
5	1	1	6	1	1	1	2
6	1	1	1	1	1	3	1
7	1	2	1	1	2	1	1
8	1	1	2	1	1	2	2
9	1	1	1	1	1	4	1
10	1	1	2	1	1	2	2
11	1	2	1	1	1	2	1
12	2	1	1	1	1	2	1
14	1	1	1	1	1	2	1
15	1	1	1	1	1	1	2
19	1	1	1	1	1	2	1
20	1	1	1	2	1	1	1
23	1	1	1	1	1	1	2
[total]	18	19	102	18	18	30	22
633NX7							
1	1	1	13	1	1	1	1

```
  2              1    2   57    1    1    1    1
  3              1    1    7    1    1    3    1
  4              1    1    3    1    1    2    1
  5              1    1    4    1    1    2    2
  6              2    1    2    1    1    1    1
  7              1    1    4    1    1    2    1
  8              1    1    1    1    1    2    1
  9              1    2    1    1    1    1    1
  11             1    1    2    1    1    2    3
  12             1    1    1    2    1    2    1
  13             1    1    2    1    1    2    1
  14             1    1    1    1    1    2    1
  16             1    1    1    1    1    1    2
  18             1    1    1    1    2    1    1
  20             1    1    1    1    1    2    1
  21             1    1    1    1    1    2    1
  22             1    1    1    1    1    2    1
  23             1    1    1    1    1    1    2
  [total]       20   21  104   20   20   32   24
643NL1
  1              2    1   77    1    2    3    4
  2              1    2    5    1    1    4    2
  3              1    1    5    1    1    3    1
  4              1    2    2    1    1    2    1
  5              1    1    1    2    1    3    1
  6              1    1    1    1    1    3    1
  8              1    1    1    1    1    1    2
  9              1    1    1    1    1    2    1
  [total]        9   10   93    9    9   21   13
653NL2
  1              1    1   58    1    1    3    1
  2              1    1   12    1    1    1    1
  3              1    1    4    1    1    1    1
  4              1    1    5    1    1    1    1
  5              1    1    4    1    1    2    1
  6              1    1    1    1    1    3    2
  7              1    1    4    1    1    2    2
  8              1    1    2    1    1    4    1
  9              2    2    1    1    1    2    1
  10             1    1    2    1    1    2    2
  11             1    1    1    1    2    2    2
  12             1    1    3    2    1    1    1
  13             1    2    1    1    1    2    1
  14             1    1    1    1    1    1    2
  [total]       15   16   99   15   15   27   19
663NL3
  1              1    1    9    1    1    1    1
  2              1    1   44    1    1    1    1
  3              1    1   11    1    1    1    1
  4              1    1    2    1    1    1    1
  5              1    1   10    1    1    1    1
  6              1    1    6    1    1    1    1
  7              1    2    4    1    1    3    1
  8              1    1    3    1    1    2    1
  10             1    1    3    1    1    2    2
  11             1    1    2    1    1    3    1
  12             1    1    1    1    1    2    1
  14             1    1    2    1    1    2    2
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15	2	1	1	1	1	1	1
20	1	1	1	1	1	1	2
21	1	1	1	1	1	2	1
23	1	1	1	1	2	1	2
24	1	1	1	1	1	2	1
26	1	2	1	1	1	3	1
29	1	1	1	1	1	1	2
30	1	1	1	1	1	2	1
31	1	1	1	2	1	1	1
[total]	22	23	106	22	22	34	26
673NL4							
1	1	1	72	1	1	2	1
2	1	1	11	1	1	3	1
3	1	1	3	1	1	2	4
4	1	1	3	1	1	3	2
5	1	3	1	1	1	3	1
7	2	1	1	1	1	4	1
8	1	1	1	1	1	3	1
9	1	1	1	1	1	1	2
10	1	1	1	1	2	1	1
11	1	1	1	2	1	1	1
[total]	11	12	95	11	11	23	15
673NL5							
1	2	3	85	2	2	14	6
2	1	1	2	1	1	1	1
[total]	3	4	87	3	3	15	7
673NN9							
1	1	3	63	1	1	3	3
2	1	1	8	1	1	3	1
3	2	1	5	1	1	2	1
4	1	1	3	1	1	4	1
5	1	1	4	1	1	3	4
6	1	1	2	1	1	1	1
7	1	1	2	1	1	2	1
8	1	1	3	1	2	1	1
9	1	1	2	1	1	1	1
10	1	1	1	2	1	1	1
11	1	1	2	1	1	1	1
13	1	1	1	1	1	2	1
16	1	1	1	1	1	2	1
35	1	1	2	1	1	1	1
[total]	15	16	99	15	15	27	19
683JL5							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
693JL5							
1	2	2	86	1	1	13	5
2	1	1	1	1	1	2	2
3	1	1	1	2	1	1	1
4	1	2	1	1	2	1	1
[total]	5	6	89	5	5	17	9
693JL7							
1	1	3	86	2	2	14	6
2	2	1	1	1	1	1	1
[total]	3	4	87	3	3	15	7
693JL8							
1	1	3	86	2	2	14	4
2	2	1	1	1	1	1	3

[total]	3	4	87	3	3	15	7
703JL5							
1	1	1	76	1	1	2	1
2	2	2	6	1	1	2	1
3	1	2	6	1	1	4	2
4	1	1	1	1	2	3	2
5	1	1	1	1	1	6	1
6	1	1	1	1	1	2	1
7	1	1	1	1	1	1	4
8	1	1	1	2	1	1	1
[total]	9	10	93	9	9	21	13
723PM2							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
733PM3							
1	1	2	77	1	1	8	3
2	1	1	5	1	1	2	2
3	1	1	5	2	2	1	1
4	1	2	2	1	1	2	1
5	1	1	1	1	1	4	2
6	1	1	1	1	1	2	1
7	2	1	1	1	1	1	2
[total]	8	9	92	8	8	20	12
733PN8							
1	1	3	81	2	1	9	3
2	2	1	4	1	2	3	3
3	1	1	2	1	1	1	1
4	1	1	1	1	1	1	2
5	1	1	1	1	1	3	1
6	1	1	2	1	1	2	1
[total]	7	8	91	7	7	19	11
743PM4							
1	2	3	82	1	2	9	4
2	1	1	3	2	1	2	2
3	1	1	2	1	1	4	2
4	1	1	2	1	1	1	1
6	1	1	1	1	1	2	1
[total]	6	7	90	6	6	18	10
751BT8							
1	1	2	75	2	2	8	3
2	1	1	3	1	1	3	1
3	1	1	2	1	1	2	1
4	1	2	3	1	1	1	2
6	2	1	1	1	1	2	1
7	1	1	2	1	1	1	1
8	1	1	2	1	1	2	1
10	1	1	2	1	1	1	2
12	1	1	2	1	1	1	1
13	1	1	2	1	1	1	1
15	1	1	2	1	1	1	1
24	1	1	1	1	1	1	2
47	1	1	1	1	1	2	1
[total]	14	15	98	14	14	26	18
761AN1							
1	1	1	57	1	1	1	1
2	1	1	12	1	1	2	1
3	1	1	4	1	1	2	1
4	1	1	4	1	1	2	1

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  5           1   1   4   1   1   1   3
  6           1   1   3   1   1   1   1
  7           1   1   2   1   1   1   1
  8           1   1   1   1   1   2   1
  9           2   1   2   1   1   1   1
  10          1   1   2   1   1   1   1
  11          1   1   2   1   1   1   2
  12          1   1   1   1   2   2   1
  13          1   1   1   1   1   1   2
  14          1   1   2   1   1   2   1
  15          1   1   2   1   1   1   1
  17          1   2   1   1   1   2   1
  19          1   1   1   1   1   2   1
  23          1   1   1   1   1   2   2
  25          1   2   1   1   1   1   1
  27          1   1   1   1   1   2   1
  29          1   1   1   1   1   2   1
  34          1   1   1   1   1   2   1
  38          1   1   2   1   1   1   1
  40          1   1   1   1   1   2   1
  51          1   1   1   2   1   1   1
  [total]    26  27 110  26  26  38  30
762GN1
  1           1   1  58   1   1   1   1
  2           1   1   2   1   1   3   1
  3           1   1   4   1   1   1   1
  4           1   1   3   1   1   2   1
  5           1   1   3   1   1   2   2
  6           1   1   2   1   1   1   1
  7           1   1   5   1   1   2   1
  8           1   1   5   1   1   1   1
  9           1   1   3   1   1   1   1
  10          1   1   2   1   1   1   1
  11          1   1   2   1   1   1   1
  12          1   2   1   1   1   1   1
  13          1   1   2   1   1   2   1
  14          1   1   1   1   1   2   2
  15          1   1   1   1   2   1   1
  16          1   1   2   1   1   1   1
  17          1   1   2   1   1   3   1
  19          1   1   1   1   1   1   2
  21          1   1   1   1   1   3   1
  23          1   1   2   1   1   1   1
  24          1   1   1   2   1   1   1
  25          1   1   1   1   1   1   2
  27          1   1   1   1   1   2   1
  29          1   2   2   1   1   1   1
  31          1   1   2   1   1   1   1
  33          1   1   2   1   1   1   1
  34          2   1   1   1   1   1   1
  37          1   1   1   1   1   1   2
  80          1   1   1   1   1   2   1
  [total]    30  31 114  30  30  42  34
771BN2
  1           2   3  86   2   2  13   6
  2           1   1   1   1   1   2   1
  [total]     3   4  87   3   3  15   7
783RN5
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  1           1   3  86   2   2  13   6
  2           2   1   1   1   1   2   1
  [total]     3   4  87   3   3  15   7
783RN6
  1           2   3  85   2   2  14   6
  2           1   1   2   1   1   1   1
  [total]     3   4  87   3   3  15   7
793SB0
  1           2   3  86   1   2  13   6
  2           1   1   1   2   1   1   1
  4           1   1   1   1   1   2   1
  [total]     4   5  88   4   4  16   8
793SG0
  1           2   3  83   2   2  11   5
  2           1   1   4   1   1   2   2
  3           1   1   1   1   1   2   1
  5           1   1   1   1   1   2   1
  [total]     5   6  89   5   5  17   9
793SD0
  1           2   3  85   2   2   7   2
  2           1   1   1   1   1   3   2
  3           1   1   1   1   1   4   3
  4           1   1   1   1   1   3   2
  5           1   1   2   1   1   1   1
  [total]     6   7  90   6   6  18  10
803TA0
  1           2   3  86   2   2  14   6
  [total]     2   3  86   2   2  14   6
803TBJ
  1           2   2  76   2   2   8   6
  2           1   2   3   1   1   1   1
  3           1   1   4   1   1   1   1
  4           1   1   3   1   1   1   1
  5           1   1   3   1   1   2   1
  6           1   1   1   1   1   3   1
  10          1   1   1   1   1   2   1
  12          1   1   1   1   1   2   1
  13          1   1   2   1   1   1   1
  20          1   1   1   1   1   2   1
  [total]    11  12  95  11  11  23  15
811BAP
  1           1   1  68   1   1   2   1
  2           2   2   4   1   1   2   2
  3           1   1   7   1   2   4   1
  4           1   1   6   1   1   4   1
  5           1   1   3   1   1   1   1
  6           1   1   1   1   1   3   1
  7           1   1   1   1   1   3   3
  8           1   1   1   1   1   1   2
  9           1   1   1   1   1   1   2
  11          1   1   1   1   1   2   1
  12          1   1   2   1   1   1   1
  13          1   1   1   2   1   1   1
  15          1   1   2   1   1   1   1
  22          1   2   1   1   1   1   1
  [total]    15  16  99  15  15  27  19
811BAS
  1           1   1  78   1   1   5   2
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2	1	1	4	1	1	3	2
3	1	1	3	1	1	2	2
4	1	3	1	1	1	1	1
5	1	1	3	1	1	4	2
6	1	1	1	1	1	2	2
7	1	1	1	1	2	1	1
8	1	1	2	2	1	2	1
9	2	1	1	1	1	1	1
11	1	1	1	1	1	2	1
[total]	11	12	95	11	11	23	15
811BJ4							
1	1	1	54	1	1	1	1
2	1	1	9	1	1	1	1
3	1	1	5	1	1	1	1
4	1	1	10	1	1	1	1
5	1	1	5	1	1	3	1
6	1	1	3	1	1	1	2
7	1	1	3	1	1	1	1
8	1	1	3	1	2	5	1
9	1	1	1	1	1	2	1
10	1	1	2	1	1	1	1
11	1	2	1	1	1	1	2
13	1	1	1	1	1	2	1
14	1	1	1	1	1	3	1
15	1	1	1	1	1	1	3
17	1	1	1	1	1	2	1
18	2	1	1	1	1	2	1
20	1	1	1	1	1	1	2
23	1	2	1	1	1	1	1
25	1	1	1	1	1	2	1
45	1	1	1	2	1	1	1
[total]	21	22	105	21	21	33	25
811BJ6							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
811BJ7							
1	1	1	15	1	1	2	1
2	1	1	68	1	1	3	1
3	1	2	1	1	2	2	1
4	2	1	2	1	1	2	2
5	1	1	2	1	1	4	1
6	1	1	2	1	1	1	3
7	1	1	2	1	1	1	3
8	1	1	1	1	1	2	1
9	1	2	1	1	1	2	1
10	1	1	1	1	1	2	1
12	1	1	1	2	1	2	1
14	1	1	1	1	1	2	1
[total]	13	14	97	13	13	25	17
811BJ9							
1	2	1	83	1	2	9	3
2	1	2	2	1	1	3	2
3	1	2	3	2	1	2	1
4	1	1	1	1	1	1	2
6	1	1	1	1	1	3	2
[total]	6	7	90	6	6	18	10
811BO1							
1	1	1	69	1	1	3	2

2	1	1	6	1	1	1	1
3	1	2	5	1	1	2	1
4	2	1	5	1	1	3	1
5	1	2	2	1	1	2	2
7	1	1	2	1	1	1	1
9	1	1	2	1	2	2	2
10	1	1	2	1	1	3	1
11	1	1	1	2	1	1	2
12	1	1	1	1	1	3	1
13	1	1	1	1	1	2	1
17	1	1	1	1	1	1	2
19	1	1	1	1	1	2	1
[total]	14	15	98	14	14	26	18
811BO2							
1	2	1	69	1	1	3	1
2	1	1	9	1	1	3	3
3	1	1	4	1	1	2	1
4	1	2	4	1	1	1	1
5	1	1	1	1	2	2	2
6	1	1	2	1	1	1	1
7	1	1	1	1	1	2	1
8	1	1	2	1	1	2	1
9	1	1	1	1	1	3	1
10	1	1	1	1	1	1	2
11	1	2	2	1	1	2	1
12	1	1	1	1	1	1	2
14	1	1	1	2	1	3	1
[total]	14	15	98	14	14	26	18
811BO3							
1	1	1	82	1	2	8	3
2	1	1	2	1	1	2	1
3	1	1	2	1	1	1	2
4	1	1	1	1	1	5	1
5	2	3	2	1	1	2	1
8	1	1	2	1	1	1	2
11	1	1	1	2	1	1	2
[total]	8	9	92	8	8	20	12
811BO4							
1	1	2	75	1	2	5	2
2	2	1	8	1	1	3	3
3	1	1	4	1	1	3	2
5	1	1	2	1	1	1	1
6	1	1	1	1	1	3	1
7	1	2	1	1	1	3	2
8	1	1	1	2	1	1	1
9	1	1	1	1	1	2	1
[total]	9	10	93	9	9	21	13
811BO5							
1	2	3	86	2	2	12	5
2	1	1	1	1	1	2	2
5	1	1	1	1	1	2	1
[total]	4	5	88	4	4	16	8
811BO6							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
811BO8							
1	2	3	84	2	2	13	6
2	1	1	1	1	1	2	1

3	1	1	2	1	1	1	1
6	1	1	2	1	1	1	1
[total]	5	6	89	5	5	17	9
811BO9							
1	2	1	78	1	2	10	6
2	1	1	6	1	1	1	1
3	1	2	3	2	1	4	1
4	1	2	2	1	1	2	1
[total]	5	6	89	5	5	17	9
811BP0							
1	2	2	81	1	2	6	2
2	1	1	4	1	1	4	4
3	1	1	1	1	1	3	1
4	1	1	1	1	1	3	1
5	1	1	2	1	1	2	1
6	1	2	1	1	1	1	2
8	1	1	1	2	1	1	1
9	1	1	2	1	1	1	1
[total]	9	10	93	9	9	21	13
811BP1							
1	2	3	84	2	2	13	6
2	1	1	2	1	1	1	1
3	1	1	2	1	1	2	1
[total]	4	5	88	4	4	16	8
811BP2							
1	1	1	9	1	1	2	1
2	1	2	60	1	2	5	1
3	1	1	4	1	1	4	1
4	1	1	6	2	1	1	5
5	1	1	4	1	1	2	2
6	1	1	2	1	1	3	1
7	1	1	2	1	1	1	1
8	1	1	1	1	1	2	1
9	2	2	1	1	1	1	1
11	1	1	1	1	1	2	1
12	1	1	2	1	1	1	1
15	1	1	2	1	1	1	1
23	1	1	2	1	1	1	1
26	1	1	2	1	1	1	1
34	1	1	2	1	1	1	1
[total]	16	17	100	16	16	28	20
811BP3							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
821BA5							
1	2	2	74	1	2	8	4
2	1	2	9	1	1	5	1
3	1	1	3	2	1	1	2
4	1	1	2	1	1	1	2
5	1	1	1	1	1	2	1
6	1	1	2	1	1	2	1
[total]	7	8	91	7	7	19	11
821BO4							
1	1	3	80	1	2	5	3
2	2	1	5	1	1	6	3
3	1	1	2	1	1	1	1
4	1	1	1	1	1	1	2
5	1	1	1	1	1	2	1

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  6            1   1   1   2   1   2   1
  7            1   1   1   1   1   2   1
  9            1   1   1   1   1   2   1
  12           1   1   2   1   1   1   1
  [total]     10  11  94  10  10  22  14
821BP6
  1            1   1  73   1   2   6   1
  2            2   1   4   1   1   1   1
  3            1   1   7   1   1   3   1
  4            1   2   2   1   1   1   1
  6            1   2   1   1   1   2   2
  7            1   1   2   1   1   2   1
  8            1   1   3   1   1   1   2
  10           1   1   1   1   1   1   2
  12           1   1   1   1   1   2   2
  13           1   1   1   2   1   3   1
  15           1   1   1   1   1   2   1
  23           1   1   1   1   1   1   2
  [total]     13  14  97  13  13  25  17
821BP7
  1            2   3  84   2   2  13   4
  2            1   1   3   1   1   2   3
  [total]      3   4  87   3   3  15   7
831B90
  1            1   1  10   1   1   2   1
  2            2   1  68   1   1   2   1
  3            1   2   4   1   1   3   1
  4            1   1   2   1   1   5   3
  5            1   1   5   1   1   2   1
  6            1   1   1   1   1   2   1
  7            1   1   2   1   2   1   2
  8            1   1   1   1   1   2   1
  10           1   1   1   1   1   1   2
  13           1   2   1   1   1   2   1
  15           1   1   1   2   1   2   1
  18           1   1   1   1   1   1   2
  [total]     13  14  97  13  13  25  17
831BA7
  1            1   2  66   1   1   2   1
  2            1   1   8   1   1   1   1
  3            1   1   4   1   1   1   1
  4            1   1   3   1   2   4   1
  5            1   1   4   1   1   1   2
  6            1   2   3   1   1   2   1
  7            1   1   1   1   1   2   1
  8            2   1   3   1   1   2   1
  9            1   1   2   1   1   2   1
  10           1   1   1   2   1   2   2
  11           1   1   1   1   1   2   2
  12           1   1   1   1   1   1   2
  14           1   1   1   1   1   1   2
  15           1   1   1   1   1   2   1
  16           1   1   1   1   1   2   1
  30           1   1   1   1   1   2   1
  [total]     17  18 101  17  17  29  21
831BP8
  1            1   2  72   1   1   5   3
  2            2   1   7   1   2   3   2
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3	1	2	2	1	1	2	1
4	1	1	3	2	1	3	1
5	1	1	6	1	1	2	1
6	1	1	1	1	1	2	1
7	1	1	1	1	1	1	2
8	1	1	1	1	1	2	1
11	1	1	1	1	1	2	1
12	1	1	1	1	1	1	2
[total]	11	12	95	11	11	23	15
831BP9							
1	1	1	48	1	1	1	1
2	1	1	5	1	1	1	1
3	1	1	11	1	1	1	1
4	1	1	6	1	1	1	1
5	1	1	7	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	4	1	1	1	1
8	1	1	3	1	2	2	1
9	1	1	3	1	1	1	1
11	1	1	1	1	1	2	1
12	1	1	2	1	1	2	1
13	1	2	3	1	1	1	1
14	1	1	1	1	1	1	2
15	1	1	1	1	1	3	2
17	1	2	1	1	1	1	1
18	2	1	1	1	1	3	1
19	1	1	2	1	1	1	1
20	1	1	1	1	1	2	1
21	1	1	1	1	1	2	2
24	1	1	1	1	1	1	2
25	1	1	1	1	1	2	1
27	1	1	1	1	1	3	1
29	1	1	1	1	1	1	2
41	1	1	1	2	1	1	1
46	1	1	1	1	1	2	1
[total]	26	27	110	26	26	38	30
831BR1							
1	2	2	63	1	1	2	1
2	1	1	9	1	1	1	1
3	1	1	10	1	2	2	2
4	1	1	3	1	1	4	1
5	1	1	2	1	1	2	2
6	1	1	1	1	1	2	1
7	1	1	3	1	1	1	1
8	1	2	1	2	1	3	3
9	1	1	1	1	1	2	2
10	1	1	1	1	1	2	1
12	1	1	1	1	1	2	1
13	1	1	2	1	1	1	1
21	1	1	1	1	1	2	1
[total]	14	15	98	14	14	26	18
831BR2							
1	1	2	84	1	2	9	3
2	1	1	2	1	1	1	3
3	1	2	1	1	1	2	2
4	1	1	1	1	1	3	1
5	1	1	2	1	1	2	1
6	1	1	1	1	1	2	1

7	2	1	1	1	1	1	1
8	1	1	1	2	1	1	1
[total]	9	10	93	9	9	21	13
831BC8							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
841BO4							
1	2	2	80	1	1	9	3
2	1	2	3	2	1	2	3
3	1	1	3	1	2	2	2
4	1	1	3	1	1	2	1
5	1	1	1	1	1	2	1
6	1	1	1	1	1	2	1
[total]	7	8	91	7	7	19	11
841BR4							
1	2	1	73	1	1	3	2
2	1	1	7	1	1	4	2
3	1	2	5	1	2	1	2
4	1	2	2	2	1	5	1
5	1	1	2	1	1	2	1
6	1	1	2	1	1	4	1
7	1	1	1	1	1	1	2
28	1	1	1	1	1	1	2
[total]	9	10	93	9	9	21	13
841BR5							
1	1	1	47	1	1	1	1
2	1	1	14	1	1	1	1
3	1	1	8	1	1	1	1
4	1	1	4	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	5	1	1	2	1
7	1	2	5	1	1	4	1
8	1	1	1	1	1	1	3
10	1	1	1	1	1	2	1
11	1	1	1	1	2	1	1
12	1	1	1	1	1	3	1
13	1	1	1	1	1	3	2
14	1	1	2	1	1	1	1
16	1	2	1	1	1	1	2
19	1	1	2	1	1	1	1
20	2	1	1	1	1	2	1
23	1	1	2	1	1	1	1
24	1	1	2	1	1	1	1
25	1	1	1	2	1	1	1
26	1	1	1	1	1	1	2
27	1	1	1	1	1	2	1
29	1	1	1	1	1	2	1
33	1	1	1	1	1	2	1
[total]	24	25	108	24	24	36	28
841BR6							
1	1	2	84	1	1	7	2
2	1	2	3	1	1	3	3
3	2	1	1	2	2	5	2
8	1	1	1	1	1	1	2
10	1	1	1	1	1	2	1
[total]	6	7	90	6	6	18	10
851BR7							
1	1	1	33	1	1	1	1

2	1	1	12	1	1	1	1
3	1	1	8	1	1	1	1
4	1	1	5	1	1	1	1
5	1	1	5	1	1	1	1
6	1	1	4	1	1	1	1
7	1	1	6	1	1	1	1
8	1	1	2	1	1	1	1
9	1	1	3	1	2	1	1
10	1	2	2	1	1	1	2
11	1	1	4	1	1	1	1
12	1	1	4	1	1	1	1
13	1	1	3	1	1	2	1
14	1	1	2	1	1	1	1
15	1	1	2	1	1	1	2
16	1	1	3	1	1	3	1
17	1	1	1	1	1	1	2
18	1	1	2	1	1	3	1
19	1	1	1	1	1	2	1
21	2	1	1	1	1	3	1
26	1	1	2	1	1	2	1
28	1	1	1	1	1	3	1
29	1	1	2	1	1	1	1
30	1	2	1	1	1	1	2
38	1	1	1	1	1	1	2
40	1	1	1	1	1	2	1
51	1	1	1	1	1	2	1
68	1	1	1	2	1	1	1
[total]	29	30	113	29	29	41	33
851BR8							
1	2	1	81	2	2	11	4
2	1	1	3	1	1	3	2
3	1	2	1	1	1	2	2
5	1	1	3	1	1	1	1
6	1	1	2	1	1	1	1
13	1	2	1	1	1	1	1
[total]	7	8	91	7	7	19	11
851BR9							
1	2	1	79	2	2	8	2
2	1	1	5	1	1	2	2
3	1	1	2	1	1	3	1
4	1	1	2	1	1	3	1
5	1	3	2	1	1	1	1
6	1	1	1	1	1	1	2
8	1	1	1	1	1	2	1
10	1	1	1	1	1	1	2
12	1	1	1	1	1	1	2
[total]	10	11	94	10	10	22	14
851BS0							
1	2	3	84	2	2	14	5
2	1	1	1	1	1	1	2
4	1	1	2	1	1	1	1
5	1	1	2	1	1	1	1
[total]	5	6	89	5	5	17	9
851BS1							
1	2	3	85	2	2	10	4
2	1	1	2	1	1	2	3
3	1	1	1	1	1	3	1
10	1	1	1	1	1	2	1

[total]	5	6	89	5	5	17	9
851BS2							
1	1	2	58	1	1	1	1
2	1	1	13	1	1	3	1
3	2	1	9	1	2	2	2
4	1	1	5	1	1	1	1
5	1	1	4	1	1	3	2
6	1	1	1	1	1	2	2
7	1	2	1	1	1	4	1
8	1	1	2	1	1	2	1
9	1	1	1	1	1	1	2
10	1	1	1	1	1	1	2
11	1	1	1	2	1	1	1
12	1	1	1	1	1	2	1
13	1	1	1	1	1	3	1
[total]	14	15	98	14	14	26	18
851BS3							
1	2	1	84	2	2	11	4
2	1	2	1	1	1	2	3
3	1	2	3	1	1	2	1
6	1	1	1	1	1	2	1
[total]	5	6	89	5	5	17	9
851BX2							
1	2	3	84	2	2	14	6
2	1	1	2	1	1	1	1
4	1	1	2	1	1	1	1
[total]	4	5	88	4	4	16	8
861B98							
1	2	2	82	1	2	5	3
2	1	2	4	2	1	5	2
3	1	1	2	1	1	2	2
4	1	1	1	1	1	3	1
5	1	1	1	1	1	2	1
12	1	1	1	1	1	2	1
13	1	1	1	1	1	1	2
[total]	8	9	92	8	8	20	12
861BS4							
1	1	1	83	1	2	5	4
2	1	2	4	1	1	2	2
3	1	1	1	2	1	5	1
4	1	1	1	1	1	5	1
5	2	1	1	1	1	1	1
6	1	1	1	1	1	1	2
8	1	2	1	1	1	1	1
[total]	8	9	92	8	8	20	12
861BS6							
1	1	1	56	1	2	1	1
2	2	1	8	1	1	1	1
3	1	1	8	1	1	1	1
4	1	2	7	1	1	4	1
5	1	1	5	1	1	2	2
6	1	1	4	1	1	2	1
7	1	2	2	1	1	3	1
8	1	1	2	1	1	2	1
9	1	1	1	1	1	1	2
10	1	1	2	1	1	1	1
11	1	1	1	1	1	4	1
14	1	1	1	1	1	1	3

15	1	1	1	1	1	2	1
16	1	1	1	2	1	1	1
17	1	1	1	1	1	2	1
21	1	1	1	1	1	1	2
[total]	17	18	101	17	17	29	21
861BT6							
1	1	3	83	1	2	5	5
2	2	1	4	1	1	6	1
3	1	1	1	2	1	3	2
4	1	1	1	1	1	2	1
5	1	1	1	1	1	2	1
[total]	6	7	90	6	6	18	10
861BC0							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
873TY8							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
902DX6							
1	2	3	80	1	2	10	6
2	1	1	4	1	1	3	1
3	1	1	3	1	1	2	1
11	1	1	1	2	1	1	1
13	1	1	2	1	1	1	1
18	1	1	1	1	1	2	1
[total]	7	8	91	7	7	19	11
913HX8							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
923JC1							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
933JC6							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
943XC7							
1	2	3	84	1	2	9	4
2	1	1	3	1	1	6	3
3	1	1	1	2	1	1	1
[total]	4	5	88	4	4	16	8
943XV1							
1	2	3	84	2	2	13	4
2	1	1	3	1	1	1	2
3	1	1	1	1	1	2	2
[total]	4	5	88	4	4	16	8
951A01							
1	2	2	83	1	2	13	5
2	1	1	3	1	1	1	2
3	1	1	1	1	1	2	1
6	1	1	1	2	1	1	1
7	1	1	2	1	1	1	1
8	1	2	1	1	1	1	1
[total]	7	8	91	7	7	19	11
951A02							
1	2	2	83	1	2	13	6
2	1	1	2	1	1	2	1
4	1	2	2	2	1	1	1
8	1	1	2	1	1	1	1

[total]	5	6	89	5	5	17	9
951A04							
1	2	1	83	2	2	10	6
2	1	1	2	1	1	5	1
3	1	2	1	1	1	1	1
6	1	1	3	1	1	1	1
31	1	2	1	1	1	1	1
[total]	6	7	90	6	6	18	10
951A05							
1	1	2	81	2	2	12	5
2	1	1	2	1	1	1	1
3	2	2	1	1	1	2	1
4	1	1	3	1	1	1	1
5	1	1	2	1	1	1	1
7	1	1	1	1	1	2	1
10	1	1	1	1	1	1	2
15	1	1	2	1	1	1	1
[total]	9	10	93	9	9	21	13
951A06							
1	1	2	80	2	2	9	5
2	1	1	2	1	1	1	2
3	2	1	3	1	1	1	1
4	1	1	2	1	1	2	1
5	1	2	1	1	1	3	1
6	1	1	2	1	1	1	1
8	1	1	1	1	1	2	1
10	1	1	2	1	1	1	1
12	1	1	1	1	1	2	1
[total]	10	11	94	10	10	22	14
951A07							
1	2	3	84	2	2	13	6
2	1	1	2	1	1	2	1
4	1	1	2	1	1	1	1
[total]	4	5	88	4	4	16	8
951A10							
1	1	3	83	1	2	9	5
2	1	1	3	1	1	2	1
3	1	1	1	1	1	2	1
4	1	1	1	1	1	3	1
5	2	1	2	1	1	2	1
8	1	1	1	1	1	1	2
9	1	1	1	2	1	1	1
[total]	8	9	92	8	8	20	12
951A15							
1	2	2	84	1	2	11	5
2	1	1	1	1	1	3	2
3	1	2	2	2	1	1	1
5	1	1	1	1	1	2	1
7	1	1	2	1	1	1	1
[total]	6	7	90	6	6	18	10
951A16							
1	2	2	85	1	2	13	6
2	1	1	1	1	1	2	1
3	1	1	1	2	1	1	1
4	1	2	2	1	1	1	1
[total]	5	6	89	5	5	17	9
951A22							
1	1	3	86	2	2	14	6

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  2            2   1   1   1   1   1   1
  [total]      3   4  87   3   3  15   7
951A23
  1            1   1  82   1   2  11   5
  2            2   3   4   1   1   2   1
  3            1   1   1   1   1   1   2
  6            1   1   2   1   1   2   1
  11           1   1   1   2   1   1   1
  14           1   1   1   1   1   2   1
  [total]      7   8  91   7   7  19  11
951A26
  1            2   3  85   1   2  13   6
  2            1   1   1   1   1   2   1
  4            1   1   2   1   1   1   1
  5            1   1   1   2   1   1   1
  [total]      5   6  89   5   5  17   9
951A37
  1            1   2  79   2   2  11   5
  2            1   1   3   1   1   2   2
  3            1   1   2   1   1   1   1
  4            1   2   2   1   1   1   1
  5            1   1   2   1   1   1   1
  6            1   1   1   1   1   2   1
  7            1   1   2   1   1   1   1
  8            2   1   1   1   1   1   1
  10           1   1   1   1   1   2   1
  11           1   1   2   1   1   1   1
  [total]     11  12  95  11  11  23  15
951A38
  2            2   3  86   2   2  14   6
  [total]      2   3  86   2   2  14   6
951A39
  1            2   3  85   2   2  14   5
  2            1   1   2   1   1   1   1
  3            1   1   1   1   1   1   2
  [total]      4   5  88   4   4  16   8
951A41
  1            2   3  86   2   2  14   6
  [total]      2   3  86   2   2  14   6
951A42
  1            2   3  86   2   2  13   6
  2            1   1   1   1   1   2   1
  [total]      3   4  87   3   3  15   7
951A52
  1            2   2  84   1   2  12   6
  2            1   1   2   1   1   3   1
  4            1   1   2   1   1   1   1
  6            1   1   1   2   1   1   1
  7            1   2   1   1   1   1   1
  [total]      6   7  90   6   6  18  10
951A53
  2            2   3  86   2   2  14   6
  [total]      2   3  86   2   2  14   6
951A54
  1            2   3  86   1   2  14   6
  4            1   1   1   2   1   1   1
  [total]      3   4  87   3   3  15   7
951A64
```

1	2	3	85	2	2	14	6
3	1	1	2	1	1	1	1
[total]	3	4	87	3	3	15	7
951A67							
1	2	3	84	2	2	13	5
2	1	1	1	1	1	2	1
4	1	1	2	1	1	1	1
5	1	1	2	1	1	1	1
10	1	1	1	1	1	1	2
[total]	6	7	90	6	6	18	10
951A69							
5	2	3	86	2	2	13	6
10	1	1	1	1	1	2	1
[total]	3	4	87	3	3	15	7
951A71							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
951A72							
1	1	1	72	1	2	5	3
2	1	1	7	1	1	3	2
3	1	2	2	1	1	3	3
4	2	1	3	1	1	3	1
5	1	2	3	1	1	2	1
6	1	1	1	1	1	2	1
7	1	1	1	1	1	2	1
12	1	1	2	2	1	1	1
13	1	1	2	1	1	1	1
15	1	1	2	1	1	1	1
[total]	11	12	95	11	11	23	15
951A77							
1	2	3	86	2	2	13	6
2	1	1	1	1	1	2	1
[total]	3	4	87	3	3	15	7
951A78							
1	2	3	81	2	2	12	5
2	1	1	3	1	1	1	1
3	1	1	3	1	1	1	2
5	1	1	1	1	1	3	1
6	1	1	2	1	1	1	1
[total]	6	7	90	6	6	18	10
951AN1							
1	2	2	82	1	1	13	6
2	1	1	1	2	1	1	1
3	1	1	2	1	1	1	1
4	1	1	3	1	2	1	1
5	1	1	2	1	1	2	1
9	1	2	1	1	1	1	1
[total]	7	8	91	7	7	19	11
951AX4							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
952G11							
1	1	1	54	1	1	1	2
2	1	1	2	1	1	1	1
3	1	1	5	1	1	1	1
4	2	1	4	1	1	1	1
5	1	1	3	1	1	3	1
6	1	1	4	1	1	2	1

7	1	1	1	1	2	1	1
8	1	1	3	1	1	1	1
9	1	2	2	1	1	3	2
10	1	1	2	1	1	1	1
12	1	1	3	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	2	1	1	1	1
17	1	1	2	1	1	1	2
18	1	1	3	1	1	2	1
20	1	1	2	1	1	1	1
21	1	1	1	1	1	2	2
26	1	1	1	1	1	2	1
27	1	1	3	1	1	2	1
29	1	2	1	1	1	1	1
32	1	1	2	1	1	1	1
34	1	1	2	1	1	1	1
38	1	1	1	1	1	2	1
40	1	1	1	1	1	2	1
42	1	1	2	1	1	1	1
44	1	1	2	1	1	1	1
51	1	1	2	1	1	1	1
52	1	1	1	1	1	1	2
55	1	1	1	1	1	2	1
58	1	1	1	1	1	2	1
124	1	1	1	2	1	1	1
[total]	32	33	116	32	32	44	36
952G12							
1	1	1	75	1	1	12	3
2	1	2	2	1	1	1	3
3	2	1	2	1	1	2	1
4	1	1	2	2	2	1	1
8	1	1	3	1	1	1	2
9	1	1	2	1	1	1	1
11	1	2	1	1	1	1	1
12	1	1	1	1	1	2	1
13	1	1	2	1	1	1	1
16	1	1	3	1	1	1	1
25	1	1	2	1	1	1	1
33	1	1	2	1	1	1	1
[total]	13	14	97	13	13	25	17
952G44							
1	2	3	86	2	2	14	5
5	1	1	1	1	1	1	2
[total]	3	4	87	3	3	15	7
952G45							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
952G46							
1	2	3	85	2	2	13	6
2	1	1	1	1	1	2	1
3	1	1	2	1	1	1	1
[total]	4	5	88	4	4	16	8
952G50							
1	2	3	83	2	2	13	4
2	1	1	1	1	1	2	2
3	1	1	2	1	1	1	1
11	1	1	2	1	1	1	1
12	1	1	1	1	1	1	2

14	1	1	2	1	1	1	1
[total]	7	8	91	7	7	19	11
952G77							
1	2	3	86	2	2	14	5
2	1	1	1	1	1	1	2
[total]	3	4	87	3	3	15	7
952GX5							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
952D35							
1	2	1	71	1	2	7	4
2	1	2	5	1	1	3	3
3	1	1	4	1	1	1	1
4	1	1	2	1	1	3	1
5	1	1	2	1	1	1	1
6	1	1	3	1	1	2	1
7	1	2	2	2	1	2	1
8	1	1	2	1	1	1	1
13	1	1	2	1	1	1	1
14	1	1	2	1	1	1	1
18	1	1	1	1	1	2	1
[total]	12	13	96	12	12	24	16
952EJ2							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
963CV0							
1	1	1	3	1	1	1	1
2	1	1	5	1	1	1	1
3	1	1	11	1	1	1	1
4	1	1	2	1	1	1	1
5	1	1	6	1	1	1	1
6	1	1	5	1	1	1	1
7	1	1	3	1	1	1	1
8	1	1	2	1	1	1	1
9	1	1	3	1	1	1	1
10	1	1	2	1	1	1	1
14	1	1	2	1	1	1	1
15	1	1	2	1	1	1	1
16	1	1	2	1	1	1	1
17	1	1	4	1	1	1	1
18	1	1	2	1	1	1	1
19	1	1	2	1	1	1	1
21	1	1	4	1	1	1	1
22	1	1	3	1	1	1	1
25	1	1	2	1	1	1	1
29	1	1	2	1	1	1	1
30	1	1	2	1	1	1	1
32	1	1	3	1	1	1	1
33	1	1	4	1	1	1	1
35	1	1	4	1	1	1	1
38	1	1	3	1	1	1	1
39	1	1	2	1	1	1	1
43	1	1	2	1	1	1	1
44	1	1	3	1	1	1	1
48	1	1	2	1	1	1	1
51	1	1	2	1	1	1	1
52	1	1	2	1	1	1	1
54	1	1	2	1	1	1	1

57	1	1	2	1	1	1	1
62	1	1	2	1	1	1	1
63	1	1	2	1	1	1	1
66	1	1	2	1	1	1	1
70	1	1	3	1	1	1	1
71	1	1	2	1	1	1	1
77	1	1	2	1	1	1	1
80	1	1	2	1	1	1	1
81	1	1	2	1	1	1	1
83	1	1	2	1	1	1	1
86	1	1	2	1	1	1	1
89	1	1	3	1	1	1	1
101	1	1	1	1	1	2	1
107	1	1	2	1	1	1	1
118	1	1	2	1	1	1	1
121	1	1	1	1	1	2	1
147	1	1	1	1	1	2	1
148	1	1	2	1	1	1	1
151	1	1	2	1	1	1	1
157	1	1	1	1	1	2	1
165	1	1	1	1	1	1	2
169	1	1	1	1	1	2	1
199	1	1	1	1	2	1	1
200	1	1	1	1	1	2	1
201	1	1	1	1	1	2	1
211	1	2	1	1	1	1	1
212	1	1	1	1	1	1	2
215	1	1	2	1	1	1	1
216	1	1	1	1	1	2	1
232	2	1	1	1	1	1	1
243	1	1	1	1	1	1	2
245	1	1	1	1	1	2	1
269	1	1	1	1	1	1	2
276	1	1	1	1	1	2	1
315	1	2	1	1	1	1	1
316	1	1	1	1	1	1	2
352	1	1	1	1	1	2	1
366	1	1	1	1	1	2	1
376	1	1	1	2	1	1	1
423	1	1	1	1	1	2	1
[total]	73	74	157	73	73	85	77
AA1A54							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
AA1A72							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
AB1A05							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
AB1A11							
1	2	3	86	2	2	12	6
2	1	1	1	1	1	2	1
3	1	1	1	1	1	2	1
[total]	4	5	88	4	4	16	8
AB1A35							
1	2	3	85	2	2	14	5
2	1	1	2	1	1	1	2

[total]	3	4	87	3	3	15	7
AB1A38							
1	2	1	83	1	2	7	5
2	1	2	4	1	1	4	1
3	1	1	1	1	1	3	1
4	1	2	1	2	1	1	1
5	1	1	1	1	1	2	1
6	1	1	1	1	1	2	1
13	1	1	1	1	1	1	2
[total]	8	9	92	8	8	20	12
AB1AAR							
1	2	1	70	1	2	5	2
2	1	1	3	1	1	1	2
3	1	1	5	1	1	2	1
4	1	1	3	1	1	2	1
5	1	1	2	1	1	3	1
6	1	2	2	1	1	1	1
7	1	1	2	1	1	2	2
8	1	1	4	1	1	1	2
9	1	1	2	1	1	3	1
10	1	1	1	2	1	1	1
13	1	2	1	1	1	1	1
14	1	1	2	1	1	1	2
16	1	1	1	1	1	2	1
65	1	1	1	1	1	2	1
[total]	15	16	99	15	15	27	19
AB1AT6							
1	2	3	86	2	2	14	6
[total]	2	3	86	2	2	14	6
AH1BBC							
1	1	1	65	1	1	1	1
2	1	1	2	1	1	2	1
3	1	1	3	1	1	2	1
4	1	1	4	1	1	1	1
6	1	1	3	1	1	1	1
7	1	1	3	1	1	1	1
8	1	1	1	1	1	3	2
9	1	2	2	1	1	2	1
10	1	1	1	1	1	2	2
11	1	1	1	1	1	1	2
14	1	1	2	1	1	1	1
16	1	2	2	1	1	1	2
17	1	1	1	1	1	2	1
19	1	1	2	1	1	2	1
22	1	1	3	1	1	1	1
24	1	1	1	1	1	2	1
34	1	1	2	1	1	1	1
40	1	1	1	1	1	2	1
44	1	1	2	1	1	1	1
46	1	1	3	1	1	1	1
49	2	1	1	1	1	1	1
50	1	1	1	1	1	2	1
59	1	1	1	1	1	1	2
60	1	1	1	1	2	1	1
65	1	1	2	1	1	1	1
96	1	1	1	1	1	2	1
103	1	1	1	1	1	2	1
105	1	1	1	2	1	1	1

```
  [total]      29   30 113   29   29   41   33
AK2E04
  1             1    1  63    2    2    2    1
  2             1    1   6    1    1    2    1
  3             1    1   3    1    1    3    1
  4             1    1   2    1    1    2    1
  5             1    2   8    1    1    2    1
  6             1    1   3    1    1    1    2
  7             1    1   2    1    1    1    1
  9             1    1   2    1    1    2    1
  10            2    1   1    1    1    3    1
  11            1    1   1    1    1    2    2
  13            1    1   2    1    1    1    2
  16            1    1   1    1    1    2    1
  19            1    1   1    1    1    1    2
  21            1    1   1    1    1    2    1
  23            1    1   2    1    1    1    1
  24            1    1   1    1    1    2    1
  34            1    1   2    1    1    1    1
  35            1    1   2    1    1    1    1
  38            1    2   1    1    1    1    1
  60            1    1   1    1    1    1    2
  [total]      21   22 105   21   21   33   25
AK2E59
  1             1    3  82    1    2   10    6
  2             1    1   2    1    1    2    1
  3             1    1   2    2    1    1    1
  4             2    1   3    1    1    2    1
  5             1    1   1    1    1    2    1
  9             1    1   1    1    1    2    1
  [total]       7    8  91    7    7   19   11
AK2EBH
  1             2    3  86    2    2   14    6
  [total]       2    3  86    2    2   14    6
AK2EBU
  1             2    3  86    2    2   14    6
  [total]       2    3  86    2    2   14    6
AK2EBI
  1             2    3  85    2    2   10    6
  2             1    1   2    1    1    4    1
  4             1    1   1    1    1    2    1
  [total]       4    5  88    4    4   16    8
AK2EBV
  1             2    3  86    2    2   14    6
  [total]       2    3  86    2    2   14    6
AT1AAT
  1             2    3  86    2    2   14    6
  [total]       2    3  86    2    2   14    6
```

Canopy Clusterer

Note: The numbers in these brackets: **Error! Reference source not found.** show the instances that are appeared in the cluster.

<u>Canopy clustering with 2 clusters</u>

T2 radius: 9,721

T1 radius: 12,151

Cluster 0:

MAN,32,2,1,1,1,1,1,3,2,2,1,1,1,1,1,1,1,2,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,2,2,1,1,1,1,1,
1,1,1,1,4,3,1,1,1,1,1,2,1,5,1,2,1,1,2,4,1,1,1,11,1,1,1,1,1,1,2,1,2,1,1,1,1,1,1,2,1,2,1,4,1,1,1,1,1
,1,1,1,1,1,1,1,2,1,1,1,2,1,1,1,1,1,1,5,2,2,1,1,2,1,1,2,1,1,1,8,1,2,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,
1,2,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,2,1,2,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,2,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,2,1,1,1,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,{52} <0>

Cluster 1:

MAN,49,39,10,1,40,22,80,7,8,1,1,1,1,2,1,2,1,11,17,15,1,1,4,1,2,1,121,41,2,2,2,1,15,44,1,8,12
5,4,9,10,5,1,1,11,12,35,1,2,1,1,43,62,59,4,1,8,5,2,13,14,1,24,1,6,2,20,21,74,1,89,2,6,1,1,1,1,6,
1,20,1,10,1,1,11,1,5,6,1,23,1,15,73,60,1,1,2,1,4,12,1,2,1,1,3,7,1,1,2,6,1,5,1,10,8,5,2,2,1,1,43,2
0,8,24,14,1,6,115,5,6,113,42,1,1,14,18,7,1,1,1,1,1,1,1,1,1,1,1,47,2,5,9,1,6,1,2,4,16,1,19,19,32,
19,1,1,2,1,1,5,1,1,6,5,2,2,1,1,3,6,2,5,4,1,9,1,1,1,2,1,3,5,2,39,32,15,27,1,3,1,1,1,1,1,1,3,1,1,1,1,
1,5,1,4,1,1,1,1,1,1,1,1,1,1,6,1,1,2,1,2,1,1,1,2,1,1,1,1,1,1,1,1,1,2,1,4,5,1,1,1,1,1,1,1,1,1,1,1,1,3,
11,13,1,1,1,1,1,1,1,1,5,1,7,1,6,1,1,2,1,1,1,1,1,2,1,1,23,1,1,1,1,1,2,1,5,13,1,1,1,1,1,19,1,26,6,1,
1,1,2,3,1,1,2,7,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,4,1,1,1,1,27,8,1,1
,1,1,1,1,8,1,57,1,1,1,1,1,1,6,1,46,1,1,1,1,1,1,1 <1>

=== Model and evaluation on training set ===

Clustered Instances

0 107 (99%)
1 1 (1%)

<u>Canopy clustering with 3 clusters</u>

T2 radius: 9,721

T1 radius: 12,151

Cluster 0:

MAN,32,2,1,1,1,1,1,3,2,2,1,1,1,1,1,1,1,2,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,2,2,1,1,1,1,1,
1,1,1,1,4,3,1,1,1,1,1,2,1,5,1,2,1,1,2,4,1,1,1,11,1,1,1,1,1,1,2,1,2,1,1,1,1,1,1,2,1,2,1,4,1,1,1,1,1
,1,1,1,1,1,1,2,1,1,1,2,1,1,1,1,1,1,5,2,2,1,1,2,1,1,2,1,1,1,8,1,2,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,
1,2,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,2,1,2,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,2,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,2,1,1,1,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,{52} <0,2>

Cluster 1:

MAN,49,39,10,1,40,22,80,7,8,1,1,1,1,2,1,2,1,11,17,15,1,1,4,1,2,1,121,41,2,2,2,1,15,44,1,8,12
5,4,9,10,5,1,1,11,12,35,1,2,1,1,43,62,59,4,1,8,5,2,13,14,1,24,1,6,2,20,21,74,1,89,2,6,1,1,1,1,6,
1,20,1,10,1,1,11,1,5,6,1,23,1,15,73,60,1,1,2,1,4,12,1,2,1,1,3,7,1,1,2,6,1,5,1,10,8,5,2,2,1,1,43,2
0,8,24,14,1,6,115,5,6,113,42,1,1,14,18,7,1,1,1,1,1,1,1,1,1,1,1,47,2,5,9,1,6,1,2,4,16,1,19,19,32,
19,1,1,2,1,1,5,1,1,6,5,2,2,1,1,3,6,2,5,4,1,9,1,1,1,2,1,3,5,2,39,32,15,27,1,3,1,1,1,1,1,1,3,1,1,1,1,
1,5,1,4,1,1,1,1,1,1,1,1,1,1,6,1,1,2,1,2,1,1,1,2,1,1,1,1,1,1,1,1,1,2,1,4,5,1,1,1,1,1,1,1,1,1,1,1,1,3,
11,13,1,1,1,1,1,1,1,1,5,1,7,1,6,1,1,2,1,1,1,1,1,2,1,1,23,1,1,1,1,1,2,1,5,13,1,1,1,1,1,19,1,26,6,1,
1,1,2,3,1,1,2,7,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,4,1,1,1,1,27,8,1,1
,1,1,1,1,8,1,57,1,1,1,1,1,1,6,1,46,1,1,1,1,1,1,1 <1>

Cluster 2:

MAN,72,12,9,1,1,1,14,3,2,2,1,1,1,1,1,1,1,1,7,8,1,1,6,3,1,1,3,1,1,1,1,1,1,2,1,1,23,1,1,2,2,1,1,5,
1,1,1,1,1,1,7,3,18,1,1,1,1,2,3,7,1,15,1,1,1,16,6,24,1,19,1,1,1,1,1,1,2,1,9,1,1,1,2,1,1,6,2,1,11,1,
1,21,24,1,1,5,1,1,1,1,1,1,1,2,1,3,1,2,1,1,1,1,9,11,3,2,2,1,1,15,1,1,8,1,1,1,8,1,2,28,12,1,1,1,3,2,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,8,5,6,1,1,1,1,1,1,2,1,1,2,1,1,1,1,1,1,1,2,1,4,1,3,1,1,1,
1,1,1,1,1,2,10,12,4,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,
1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,6,1,2,1,1,1,1,1,1,1,1,1,1,2,
1,1,1,1,1,2,5,1,4,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,4,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,
1,1,1,1,2,1,1,1,5,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,14,3,1,1,1,1,1,1 <0,2>

=== Model and evaluation on training set ===

Clustered Instances

0 94 (87%)

1 1 (1%)

2 13 (12%)

Canopy clustering with 4 clusters

T2 radius: 9,721

T1 radius: 12,151

Cluster 0:

MAN,32,2,1,1,1,1,1,3,2,2,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,2,2,1,1,1,1,1,1,1,1,1,4,3,1,1,1,1,1,2,1,5,1,2,1,1,2,4,1,1,1,11,1,1,1,1,1,1,2,1,2,1,1,1,1,1,1,1,2,1,2,1,4,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,2,1,1,1,1,1,1,5,2,2,1,1,2,1,1,2,1,1,1,8,1,2,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,2,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,{52} <0,2>

Cluster 1:

MAN,49,39,10,1,40,22,80,7,8,1,1,1,1,2,1,2,1,11,17,15,1,1,4,1,2,1,121,41,2,2,2,1,15,44,1,8,125,4,9,10,5,1,1,11,12,35,1,2,1,1,43,62,59,4,1,8,5,2,13,14,1,24,1,6,2,20,21,74,1,89,2,6,1,1,1,1,6,1,20,1,10,1,1,11,1,5,6,1,23,1,15,73,60,1,1,2,1,4,12,1,2,1,1,3,7,1,1,2,6,1,5,1,10,8,5,2,2,1,1,43,20,8,24,14,1,6,115,5,6,113,42,1,1,14,18,7,1,1,1,1,1,1,1,1,1,1,1,47,2,5,9,1,6,1,2,4,16,1,19,19,32,19,1,1,2,1,1,5,1,1,6,5,2,2,1,1,3,6,2,5,4,1,9,1,1,1,2,1,3,5,2,39,32,15,27,1,3,1,1,1,1,1,1,3,1,1,1,1,1,5,1,4,1,1,1,1,1,1,1,1,1,1,6,1,1,2,1,2,1,1,1,2,1,1,1,1,1,1,1,1,1,2,1,4,5,1,1,1,1,1,1,1,1,1,1,1,1,3,11,13,1,1,1,1,1,1,1,1,5,1,7,1,6,1,1,2,1,1,1,1,1,2,1,1,23,1,1,1,1,1,2,1,5,13,1,1,1,1,1,19,1,26,6,1,1,1,2,3,1,1,2,7,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,4,1,1,1,1,27,8,1,1,1,1,1,1,8,1,57,1,1,1,1,1,1,6,1,46,1,1,1,1,1,1,1 <1>

Cluster 2:

MAN,72,12,9,1,1,1,14,3,2,2,1,1,1,1,1,1,1,1,7,8,1,1,6,3,1,1,3,1,1,1,1,1,1,2,1,1,23,1,1,2,2,1,1,5,1,1,1,1,1,1,7,3,18,1,1,1,1,2,3,7,1,15,1,1,1,16,6,24,1,19,1,1,1,1,1,1,2,1,9,1,1,1,2,1,1,6,2,1,11,1,1,21,24,1,1,5,1,1,1,1,1,1,1,2,1,3,1,2,1,1,1,1,9,11,3,2,2,1,1,15,1,1,8,1,1,1,8,1,2,28,12,1,1,1,3,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,8,5,6,1,1,1,1,1,1,2,1,1,2,1,1,1,1,1,1,1,2,1,4,1,3,1,1,1,1,1,1,1,1,2,10,12,4,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,6,1,2,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,2,5,1,4,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,4,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,14,3,1,1,1,1,1,1 <0,2>

Cluster 3:

WOMAN,40,89,39,1,15,33,162,49,20,38,1,1,1,16,1,3,3,8,45,40,1,1,15,6,9,1,111,13,8,3,1,1,10
,29,3,19,85,25,38,61,12,1,1,22,1,86,7,2,1,6,31,182,100,14,1,64,10,2,24,47,1,62,1,1,2,42,40,15
7,1,131,10,6,7,4,4,5,4,1,37,1,14,1,1,1,7,21,11,1,51,1,104,55,152,1,1,1,1,17,9,6,6,1,1,2,5,14,1,
2,21,1,1,1,37,20,42,2,2,2,1,43,22,59,88,36,9,5,54,11,2,64,78,1,1,31,23,3,2,2,1,1,1,1,1,1,3,1,1,
41,9,17,20,1,12,1,1,7,20,1,27,36,73,26,1,1,5,6,13,8,1,1,10,4,6,5,2,1,9,15,2,3,14,1,21,1,1,5,10,
1,11,32,7,21,47,29,41,6,5,2,1,1,1,1,2,1,1,1,1,1,2,6,1,1,9,4,1,1,1,1,1,4,4,2,14,1,1,4,1,1,1,1,1,8,1
,3,2,1,4,6,6,14,8,20,5,1,14,8,1,1,1,1,1,1,5,1,1,1,1,1,27,5,1,1,1,1,5,1,1,1,11,5,17,1,5,6,13,3,4,1,
1,1,1,3,1,3,2,1,1,1,6,1,8,4,3,21,10,5,1,5,6,10,3,16,3,1,1,3,6,2,1,1,2,4,2,1,1,1,1,1,1,1,1,1,1,1,1,1
,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,10,1,1,1,1,1,1,21,1,1,1,1,1,1,1,1,1,245,1,1,1,1,1,1,5,1,17,1,1,1
,1,1,1,1 <3>

=== Model and evaluation on training set ===

Clustered Instances

0	93 (86%)
1	1 (1%)
2	13 (12%)
3	1 (1%)

<u>Canopy clustering with 5 clusters</u>

T2 radius: 9,721

T1 radius: 12,151

Cluster 0:
MAN,32,2,1,1,1,1,1,3,2,2,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,2,2,1,1,1,1,1,
1,1,1,1,4,3,1,1,1,1,1,2,1,5,1,2,1,1,2,4,1,1,1,11,1,1,1,1,1,1,2,1,2,1,1,1,1,1,1,1,2,1,2,1,4,1,1,1,1,1
,1,1,1,1,1,1,1,2,1,1,1,2,1,1,1,1,1,1,5,2,2,1,1,2,1,1,2,1,1,1,8,1,2,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,
1,2,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,2,1,2,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,2,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,2,1,1,1,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,{52} <0,2,4>

Cluster 1:
MAN,49,39,10,1,40,22,80,7,8,1,1,1,1,2,1,2,1,11,17,15,1,1,4,1,2,1,121,41,2,2,2,1,15,44,1,8,12
5,4,9,10,5,1,1,11,12,35,1,2,1,1,43,62,59,4,1,8,5,2,13,14,1,24,1,6,2,20,21,74,1,89,2,6,1,1,1,1,6,
1,20,1,10,1,1,11,1,5,6,1,23,1,15,73,60,1,1,2,1,4,12,1,2,1,1,3,7,1,1,2,6,1,5,1,10,8,5,2,2,1,1,43,2
0,8,24,14,1,6,115,5,6,113,42,1,1,14,18,7,1,1,1,1,1,1,1,1,1,1,1,47,2,5,9,1,6,1,2,4,16,1,19,19,32,
19,1,1,2,1,1,5,1,1,6,5,2,2,1,1,3,6,2,5,4,1,9,1,1,1,2,1,3,5,2,39,32,15,27,1,3,1,1,1,1,1,1,3,1,1,1,1,
1,5,1,4,1,1,1,1,1,1,1,1,1,1,6,1,1,2,1,2,1,1,1,2,1,1,1,1,1,1,1,1,1,2,1,4,5,1,1,1,1,1,1,1,1,1,1,1,1,3,
11,13,1,1,1,1,1,1,1,1,5,1,7,1,6,1,1,2,1,1,1,1,1,2,1,1,23,1,1,1,1,1,2,1,5,13,1,1,1,1,1,19,1,26,6,1,

1,1,2,3,1,1,2,7,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,5,1,4,1,1,1,1,27,8,1,1
,1,1,1,1,8,1,57,1,1,1,1,1,1,6,1,46,1,1,1,1,1,1,1 <1>

Cluster 2:
MAN,72,12,9,1,1,1,14,3,2,2,1,1,1,1,1,1,1,1,7,8,1,1,6,3,1,1,3,1,1,1,1,1,1,2,1,1,23,1,1,2,2,1,1,5,
1,1,1,1,1,1,7,3,18,1,1,1,1,2,3,7,1,15,1,1,1,16,6,24,1,19,1,1,1,1,1,1,2,1,9,1,1,1,2,1,1,6,2,1,11,1,
1,21,24,1,1,5,1,1,1,1,1,1,1,2,1,3,1,2,1,1,1,1,9,11,3,2,2,1,1,15,1,1,8,1,1,1,8,1,2,28,12,1,1,1,3,2,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,8,5,6,1,1,1,1,1,1,2,1,1,2,1,1,1,1,1,1,1,2,1,4,1,3,1,1,1,
1,1,1,1,1,2,10,12,4,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,
1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,6,1,2,1,1,1,1,1,1,1,1,1,1,1,2,
1,1,1,1,1,2,5,1,4,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,4,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,
1,1,1,1,2,1,1,1,5,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,14,3,1,1,1,1,1,1 <0,2,4>

Cluster 3:
WOMAN,40,89,39,1,15,33,162,49,20,38,1,1,1,16,1,3,3,8,45,40,1,1,15,6,9,1,111,13,8,3,1,1,10
,29,3,19,85,25,38,61,12,1,1,22,1,86,7,2,1,6,31,182,100,14,1,64,10,2,24,47,1,62,1,1,2,42,40,15
7,1,131,10,6,7,4,4,5,4,1,37,1,14,1,1,1,7,21,11,1,51,1,104,55,152,1,1,1,1,17,9,6,6,1,1,2,5,14,1,
2,21,1,1,1,37,20,42,2,2,2,1,43,22,59,88,36,9,5,54,11,2,64,78,1,1,31,23,3,2,2,1,1,1,1,1,1,3,1,1,
41,9,17,20,1,12,1,1,7,20,1,27,36,73,26,1,1,5,6,13,8,1,1,10,4,6,5,2,1,9,15,2,3,14,1,21,1,1,5,10,
1,11,32,7,21,47,29,41,6,5,2,1,1,1,1,2,1,1,1,1,1,2,6,1,1,9,4,1,1,1,1,1,4,4,2,14,1,1,4,1,1,1,1,1,8,1
,3,2,1,4,6,6,14,8,20,5,1,14,8,1,1,1,1,1,1,5,1,1,1,1,1,27,5,1,1,1,1,5,1,1,1,11,5,17,1,5,6,13,3,4,1,
1,1,1,3,1,3,2,1,1,1,6,1,8,4,3,21,10,5,1,5,6,10,3,16,3,1,1,3,6,2,1,1,2,4,2,1,1,1,1,1,1,1,1,1,1,1,1,1
,1,1,1,1,1,1,1,1,2,1,1,1,1,2,1,1,1,10,1,1,1,1,1,1,21,1,1,1,1,1,1,1,1,245,1,1,1,1,1,1,5,1,17,1,1,1
,1,1,1,1 <3>

Cluster 4:
WOMAN,81,12,12,1,1,12,7,11,4,2,1,1,1,1,1,1,1,2,1,1,1,1,4,7,1,1,11,1,1,1,1,1,1,4,1,2,4,1,1,2,4
,1,1,1,1,5,1,2,1,1,11,4,15,1,1,1,1,2,2,9,1,12,1,1,2,2,3,20,1,14,1,1,1,1,9,1,2,1,2,1,1,1,1,1,1,8,2,1
,2,1,4,1,18,1,1,1,1,3,2,1,1,1,1,2,1,1,1,2,1,1,2,1,7,5,5,2,2,2,1,12,4,1,2,6,1,1,13,1,2,6,9,1,1,1,3,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,3,8,2,1,1,1,6,1,1,1,1,1,2,1,1,1,1,1,5,1,1,1,1,4,1,1,1,
1,1,5,1,1,2,13,2,8,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,1,1,1,1
,1,2,1,1,1,2,1,1,2,1,1,8,1,1,1,1,1,1,1,1,1,1,1,8,1,1,1,1,1,1,1,1,1,1,1,1,2,1,2,1,1,1,1,1,1,1,1,1,1,1,
1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1,2,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,1,
1,1,1,2,1,1,1,5,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,14,1,1,1,1,1,1,3,1,1,1,1,1,1,1,1,1 <0,2,4>

=== Model and evaluation on training set ===

Clustered Instances

0 88 (81%)

1 1 (1%)

2 12 (11%)

3 1 (1%)

4 6 (6%)