INDUCTIVE LEARNING SUPPORT FOR DECISION MAKING

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Extended Abstract

In this paper we review the applicability of representative inductive machine learning approaches in multicriteria decision making. We limit our review to four systems. We use SICLA and KBG as representative conceptual clustering systems and ID3 and CN2 as representative learning from examples systems. We demonstrate our results by way of two real world decision making exemplars. The first exemplar concerns the evaluation of retail outlets [15]. The second exemplar concerns venture capital assessment [16]. We discuss the conditions under which inductive learning methodologies can be effectively implemented to support decision making.

Inductive machine learning was pioneered by Michalski [9]. It aims at the derivation of knowledge from a set of observations, or facts. In cases where facts are known to belong to a certain class we speak of concept acquisition or learning from examples. In such an instance we target our inquiry towards the derivation of concept identification rules. Rules may be either discriminant or characteristic. When concept classes underlying fact membership are not known we speak of learning from observations, or conceptual clustering. Accordingly, we look forward toward the partitioning of facts into a meaningful and disjoint set of clusters. A cluster represents a "coming together in space and time so that the density of whatever is clustered contrasts with the density around" [6, p.33]. Generalization and specialization are essential processes when making inductive inferences. The basic premise characterizing any inductive inference is falsity preservation. The derivation of a hypothesis

H from facts E is falsity preserving in the sense that "if some facts falsify E, then they must also falsify H" [9, p.89].

Although inductive machine learning is a rather new field there are several and successful 'fielded' applications [7, 8]. Carter and Catlett [2] propose a methodology for credit card assessment using inductive learning techniques. Also, Shaw and Gentry [14] present an approach for company risk assessment that is based on inductive learning. Both applications are exploratory; they, however, stress the potential of inductive learning in decision making support. We maintain that learning is a trait of decision making: "quite often the decision maker is interested in finding out what his weights are or what they should be under different decision circumstances. In this sense, the weights of importance could be considered as desirable outputs rather than independent inputs of an analysis. Weights must be revealed or **learned** through a careful interactive process", [17, p.22] - emphasis is ours.

In this paper we discuss the methodological issues underlying the application of inductive learning techniques in business decision making. We limit our endeavor to four representative and well-known inductive learning systems, ID3 [12, 11, 13], CN2 [5, 4], KBG [1] and SICLA [3]. These systems are part of the Machine Learning Toolbox [7, 18]. We explore inductive system suitability by way of three decision making exemplars. We draw our exemplars from retail outlet evaluation and venture capital assessment. We target our inquiry toward the evaluation of pros and cons, concerning the application of the selected inductive learning systems, in real world business decision making. Specifically, our research focuses around the following lines:

1. Grouping of alternatives into disjoint cluster groups. We use a Lexicographic Evaluation Functional, LEF, criterion to optimize clustering [10].
2. Identification of the most significant criteria for either alternative discrimination or alternative characterization. Suppose that we have two alternative courses of action, a_1 and a_2. We are interested in differences between a_1 and a_2, or in what a_1 and a_2 are all about. Furthermore, we present a methodology for inducing criteria weights.

3. Identification of relevant and accurate discrimination and recognition rules. We associate this line with the previous one.

4. Identification of the most representative alternative for each decision class. We steer our venture in the direction of deriving a conceptual indexing scheme for alternative courses of action.

5. Identification of bias and error resulting from contextual factors. We define context to represent the decision making environment.

Furthermore, we explore the implications of our research in decision making. We place emphasis upon the expert critiquing and case based reasoning paradigms.

References

[1] G. Bisson. Conceptual clustering in a first order logic representation. In *ECAI '92 Proceedings*, pages 458–462, Wien, Austria, August 1992. Wiley.

[2] C Carter and J Catlett. Assessing credit card applications using machine learning. *IEEE Expert*, pages 71–79, Fall 1987.

[3] G. Celeux, E. Diday, G. Govaert, Y. Lechevallier, and H. Ralambondrainy. *Classifcation automatique des donnees*. Dunod Informatique, 1989.

[4] P Clark and R Boswell. Rule Induction with CN2: Some Recent Improvements. In *Proceedings of the Fifth Working Session on Learning*, pages 151–163, Porto, Portugal, March 1991. Springer Verlag.

[5] P Clark and T Niblett. The CN2 induction algorithm. *Machine Learning*, 3:261–283, 1989.

[6] E de Bono. *Wordpower*. Penguin Books, 1977.

[7] Y Kodratoff, D Sleeman, M Uszynski, K Gausse, and S Craw. Building a machine learning toolbox. In B Le Pape and L Steels, editors, *Enhancing the Knowledge Engineering Process - Contributions from ESPRIT*. Elsevier, 1992.

[8] P Langley. Areas of applications for machine learning. In *Proceedings of the fifth International Symposium on Knowledge Engineering*, Sevilla, Spain, 1992.

[9] RS. Michalski. A theory and methodology of inductive learning. In RS Michalski, JG Carbonell, and TM Mitchell, editors, *Machine Learning: An Artificial Intelligence Approach*, chapter 4, pages 83–132. Tioga, Palo Alto, California, 1983.

[10] RS. Michalski and RE. Stepp. Learning from observation: conceptual clustering. In RS Michalski, JG Carbonell, and TM Mitchell, editors, *Machine Learning: An Artificial Intelligence Approach: Volume I*, chapter 11, pages 331–363. Tioga, Palo Alto, California, 1983.

[11] JR Quinlan. Generating production rules from decision trees. In *IJCAI 1987*, pages 304–307, Milan, August 1987. Morgan Kaufmann.

[12] JR. Quinlan. Decision Trees and Decisionmaking. *IEEE Transactions on Systems, Man and Cybernetics*, 20(2):339–347, March/April 1990.

[13] JR. Quinlan. Decision Trees and Decisionmaking. *IEEE TRans. on Systems, Man, and Cybernetics*, 20(2):339–345, 1990.

[14] MJ Shaw and JA Gentry. Inductive learning for risk classification. *IEEE Expert*, pages 47–53, February 1990.

[15] J. Siskos. Evaluating a system of furniture retails outlets using an interactive ordinal regression method. *European Journal of Operational Research*, 23:179–193, 1986.

[16] J. Siskos and C. Zopounidis. The evaluation criteria for the venture capital investment activity: an interactive assessment. *European Journal of Operational Research*, 31:304–313, 1987.

[17] MK Starr and M Zeleny. MCDM: State and future of the arts. In MK Starr and M Zeleny, editors, *TIMS Studies in Management Sciences 6: Multiple Criteria Decision Making*, pages 5–29. North Holland, 1977.

[18] M Uszynski. Mlt Third Annual Public Report. Public Report D9.3.3, P2154, Alcatel Alsthom Reserche, Marcoussis, France, April 1992.

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