Association for Information Systems
AIS Electronic Library (AISeL)

AMCIS 1995 Proceedings

Americas Conference on Information Systems (AMCIS)

8-25-1995

A Structural Analysis of Inductive Decision-Making Models

Michael H. Chung
California State University at Long Beach, hmchung@csulb.edu

A Structural Analysis of Inductive Decision-Making Models

H. Michael Chung
Department of Information Systems
School of Business Administration
California State University at Long Beach
Long Beach, CA 90840-8506
INTERNET hmchung@csulb.edu

Abstract

This study explores a relationship between task characteristics and the performance of inductive learning models. The paper investigating an internal structure of domain tasks as represented by attributes and their respective values as well as typical inductive learning algorithms. A potential mapping between a problem space and a solution space is predicted to enhance the predictive accuracy of human decision-making models.

1. Introduction

The growth in the amount of data sources faroutstrips the increase in corresponding knowledge. This creates both a need and an opportunity for eliciting and discovering knowledge from existing databases and environmental phenomena. To discover knowledge, such inductive machine learning algorithms as information theoretic methods (Hunt, 1966; Quinlan, 1979, 1983; Michalski and Chilauski, 1980), genetic algorithms (Holland, 1975; Forsyth and Rada, 1986), and lately, neural networks (Rumelhart and McCelland, 1986; Lippman, 1987) have been applied.

Inductive machine learning endeavors to learn decision rules or patterns underlying the given example cases in database. More importantly, inductive machine learning approaches have been employed to build models of human decision making with rules/patterns (Braun and Chandler, 1987; Messier and Hansen, 1988; Remus and Hill, 1990; Chung and Silver, 1992).

How good is the quality of discovered rules/patterns? The performance of elicited knowledge, its effectiveness, and predictive accuracy as measured against normative criteria in the environment, are unfortunately inconsistent and varies widely. Even the same machine learning method often performs differently at different task domains. While "is my model A better than your model B?" has been a popular research theme in many comparative studies, there was no systematic study that investigates such difference.

Why the same induction machine learning method produces different results? What are the exogenous factors that affect model performance? Human decision makers are often under the influence of various cognitive factors (Dawes and Corrigan, 1974; Payne, 1976, 1982). Do certain domain characteristics affect the model performance (Chandrasekaran, 1989)? These are also some of the questions that motivate this study. While the relative performance of an inductive machine learning method depends on problem domains (Chung and Silver, 1992), details are not clear yet.

2. Research Questions

We hypothesize that the quality of elicited knowledge is affected by the structural mapping of the model with the task domains. When a problem space does not match a given solution space, the quality of knowledge discovered by the algorithmgenerating a solution space tends to be, we assume, poor. The solution space is a coordinate system containing all possible combinations of attributes and attribute values that are relevant to knowledge about solutions for a given domain. The problem space is an unidentified structure of the given sources of data. Each space is represented by a set of attributes and their values.

The primary research theme addressed in this study is to investigate the possible interaction among inductive learning model performance, the task domain, and the human decision maker.

Specific research questions are:

- How do we characterize the problem space of a task domain?
- How do we characterize the solution space produced by an inductive machine learning method?
- Can we map the problem space on the solution space?
- How do the human cognitive factors affect the mapping of the two spaces?
- Can we explain different model performance at different task domains?

From a geometric point of view, this mapping generates certain decision regions in the space defined by the Cartesian product of the attributes. Decision regions in the solution space differ in how they partition the space (Chung and Tam, 1992).

3. Research Methodology and Significance

The research methodology applied to this study is field data collection with controlled experiments.

Multidimensional visualization technology can provide an innovative way of discovering the essence of the structure of the problem space and the solution space (Schoukens and Pintelon, 1991; Therrien, 1992). Furthermore, it can guide the appropriate representation of data and algorithmic model structures.

With three dimensional visualization, task domains and models are graphically projected. Major inductive learning methods and several task domains are employed. The quality of discovered knowledge is cross validated.

In addressing the research questions, search efficiency through the problem space is considered for a practical purpose. Unanticipated discoveries are prevented. Incremental algorithms and dealing with changing and temporal data are also to be taken into account.

The research results are intended to demonstrate that developing a learning model merely based on an algorithmic approach and claiming how to squeeze out the last one percent of predictive performance does not merit any more and should be taken cautiously. It is out objective to provide a structural view of the characteristics of the models and task domains.

Theoretically, this research will provide a new paradigm for constructing a generalized methodology for inductive machine learning models for human decision making. Practically, it addresses whether different task domains can be best modeled by different inductive learning approaches. Future research would involve other knowledge representation schemes to cater for different data types, interpretation, and contextual requirements across different task domains.

The general research framework of this study is summarized in the figure. The study aims at investigating the areas marked with *. The other numbers represent some of the prior research performed by the author and the others.

References

-Braun, H., and Chandler, J., "Predicting Stock Market Behavior Through Rule Induction: An Application of the LearningFromExample Approach," Decision Sciences, 18, 3, 1987, pp. 415429.

-Chandrasekaran, B., "Task-structures, Knowledge Acquisition, and Learning," Machine Learning, 4, 1989, pp.339-345.

-Chung, H.M. and M. Silver, "RuleBased Expert Systems and Linear Models: An Empirical Comparison of LearningByExamples Methods," Decision Sciences, 23, 3, 1992, pp. 687707.

-Chung, H. M. and K. Y. Tam, "A Comparative Analysis of Inductive- Learning Algorithms," Intelligent Systems in Accounting, Finance, and Management, 2, 3, 1992, pp. 3-18.

-Dawes, R. and B. Corrigan, "Linear Models in Decision Making," Psychological Bulletin, 81, 2, 1974, pp. 95106.

-Forsyth, R. and Rada, R., Machine Learning: Applications in Expert System and Information Retrieval, Ellis Horwood, New York, 1986.

-Holland, J, Adaptation in Natural and Artificial Systems, University of Michigan Press, 1975.

-Hunt, E., Marvin, J., and Stone, P., Experiments in Induction, Academic Press, New York, 1966.

-Lippman, R., "An Introduction to Computing with Neural Nets," IEEE ASSP Magazine, 4, 1987, pp. 422.

-Messier, F. and Hansen, J., "Inducing Rules for Expert System Development: An Example Using Default and Bankruptcy Data," Management Science, 34, 12, 1988, pp. 14031415.

-Michalski, R. and Chilauski, R., "Knowledge Acquisition by Encoding Expert Rules versus Computer Induction from Examples: A Case Study Involving Soybean Pathology," International Journal of ManMachine Studies, 12, 1980, pp. 6387.

-Payne, J. W., "Task Complexity and Contingent Processing in Decision Making," Organizational Behavior Human Performance, 16, 2, 1976, pp. 366-387.

-Payne, J. W., "Contingent Decision Behavior," Psychological Bulletin, 92, 2, 1982, pp. 382-402.

-Quinlan, J., "Discovering Rules by Induction from Large Collection of Examples," in Expert Systems in Microelectronic Age, D. Michie (Ed.), Edinburgh University Press, Edinburgh, 1979, pp. 169201.

-Quinlan, J., "Learning Efficient Classification Procedures and Their Application to ChessEnd Games," in Machine Learning: An AI Approach, R. Michalski, T. Mitchell, and J. Carbonell (Eds.),Tioga Publishing, Palo Alto, 1, 1983, pp. 463482.

-Remus, W. and Hill, T., "Neural Network Models of Management Judgment," Proceedings of Hawaii International Conference in System Sciences, 3, 1990, pp. 340344.

-Rumelhart, D. and J. McClelland, Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Volume 1: Foundation, The MIT Press, Cambridge, Massachusetts, 1986.

-Shoukens, J. and R. Pintelon, Identification of Linear Systems: A Practical Guideline to Accurate Modeling, Pergamon Press, Oxford, 1991.

-Therrien, C., Discrete Random Signals and Statistical Signal Processing, Prentice Hall, 1992.