Chapter XXVIII
Applying Fuzzy Logic in Dynamic Causal Mining

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ABSTRACT

This chapter applies fuzzy logic to a dynamic causal mining (DCM) algorithm and argues that DCM, a combination of association mining and system dynamics for discovering causality patterns, needs a potentially more substantive approach for the user to understand the nature of extracted rules and information in a variety of contexts. Furthermore, the author hopes that the use of fuzzy logic will not only assist the user to make better decisions, but also assist in a better understanding of future behaviour of the target system.

INTRODUCTION

Dynamic causal mining (DCM) assists decision makers in controlling a system at decision points by converting data into policies. DCM searches for simultaneous dynamic causal relations in a database and discovers delay and feedback relationships between attributes based on separate time stamps. This makes the algorithm more suitable for dynamic modeling and enables the discovery of hidden dynamic structures, which can be applied to predict the future behaviour of a dynamic system.

Causality, in this chapter, denotes a relationship between two or more entities. There are two types of causality: static and dynamic. In marked basket analysis, an example of static causality could be that purchasing nails might cause the purchase of a hammer. An example of dynamic causality is that an increase in the purchase of chips might cause an increase in the purchase of soft drinks. However, an increase in the purchase of nails might not cause an increase in the purchase of hammers (one hammer is enough to nail all the nails), thus this is not a dynamic causality.
The DCM approach imposes problems such as accuracy and efficiency, and this chapter further suggests using fuzzy sets to solve these problems. Compared to quantitative rules, fuzzy rules correspond better to sharp boundaries between neighbour sets. In most real-life applications, databases contain many other attribute values other than 0 and 1. Quantitative attributes such as production volume and income take values from an ordinal scale. One way of dealing with a quantitative attribute is to divide the range of the original attributes into partitions, such as low, medium, and high. It is more intuitive to allow attribute values to vary from the interval \([0, 1]\) (instead of just 0 or 1), indicating the degree of belonging. Thus, attributes are no longer binary but fuzzy.

This chapter suggests relaxing the strict separation among polarity +, polarity -, and neutrality, and using more flexible linguistic terms like high increase, increase, high decrease, decrease, and neutral. Fuzzy sets can provide a reasonable representation using cognitive concepts in terms of natural language. These linguistic terms use graded statements rather than ones that are strictly true or false, and thus provide an approximate but effective way to describe the dynamic causal behaviour of systems (Zadeh, 1975a, 1975b, 1975c).

This approach obtains not only a more human-understandable knowledge from the database, but also provides more compact and robust representations. The use of fuzzy partitions of the domains of quantitative attributes can avoid some undesirable threshold effects that are usually produced by crisp (nonfuzzy) partitions.

The rest of this chapter is structured as follows. First, a brief description of dynamic causal mining and its component is presented. Second, the fuzzy approach is introduced. Then the detailed fuzzy algorithm is described. An illustrative example is used to show how the fuzzified DCM can be applied. It is followed with a real-life example. At last, the conclusion and future work is presented.

This chapter will not give any detailed introduction about fuzzy data mining; another chapter of this book includes an introduction to fuzzy data mining methods by Feil and Abonyi. Also in this volume, the reader can find one application of fuzzy data mining techniques to tourism by Carrasco, Araque, Salguero, and Vila.

**DYNAMIC CAUSAL MINING**

The DCM algorithm was discovered in 2005 (Pham, Wang, & Dimov, 2005) using only the counting algorithm to integrate with game theory. It was extended in 2006 (Pham, Wang, & Dimov, 2006) with delay and feedback analysis, and was further improved for analysis in game theory with formal concept analysis (Wang, 2007). DCM enables the generation of dynamic causal rules from data sets by integrating the concepts of systems thinking (Senge, Kleiner, Roberts, Ross, & Smith, 1994) and system dynamics (Forrester, 1961) with association mining (Agrawal, Mannila, Srikant, Toivonen, & Inkeri, 1996). The algorithm can process data sets with both categorical and numerical attributes. Compared with other association mining algorithms, DCM rule sets are smaller and more dynamically focused. The pruning is carried out based on polarities. This reduces the size of the pruned data set and still maintains the accuracy of the generated rule sets. The rules extracted can be joined to create dynamic policy, which can be simulated through software for future decision making. The rest of this section gives a brief review of association mining, fuzzy data mining, and system dynamics.

**Association Mining**

Association mining was discovered by Agrawal (Agrawal et al., 1996). It was further improved in various ways, such as in speed (Agrawal et al.; Cheung, Han, Ng, & Fu, 1996) and with parallelism (Zaki, Parthasarathy, Ogihara, & Li, 1997), to find interesting associations and/or correlation relationships among large sets of data items. It shows attribute value conditions that occur frequently together in a given data set. It generates
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