Chapter 15
In Search of Effective Granulization with DTRS for Ternary Classification

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ABSTRACT

Decision-Theoretic Rough Set (DTRS) model provides a three-way decision approach to classification problems, which allows a classifier to make a deferment decision on suspicious examples, rather than being forced to make an immediate determination. The deferred cases must be reexamined by collecting further information. Although the formulation of DTRS is intuitively appealing, a fundamental question that remains is how to determine the class of the deferment examples. In this paper, the authors introduce an adaptive learning method that automatically deals with the deferred examples by searching for effective granulization. A decision tree is constructed for classification. At each level, the authors sequentially choose the attributes that provide the most effective granulization. A subtree is added recursively if the conditional probability lies in between of the two given thresholds. A branch reaches its leaf node when the conditional probability is above or equal to the first threshold, or is below or equal to the second threshold, or the granule meets certain conditions. This learning process is illustrated by an example.

INTRODUCTION

The Decision-Theoretic Rough Set (DTRS) model, proposed by Yao et al. (Yao, Wang, & Lingras, 1990; Yao & Wang, 1992; Yao, 2010) in the early 1990s, is a meaningful and useful generalization of the probabilistic rough set model (Pawlak, 1991). In probabilistic rough set models, three probabilistic regions are defined by considering the degree of overlap between an equivalence class and a set to be approximated. A conditional probability is used to state the degree of overlap and a pair of

DOI: 10.4018/978-1-4666-2476-4.ch015

thresholds is used to define the three regions. An equivalence class is in the probabilistic positive region if its relative overlap with the set is above or equal to a threshold, is in the negative region if its relative overlap is below or equal to another threshold, and is in the boundary region if the relative overlap is between the two parameters. DTRS offers a solid foundation for probabilistic rough sets by systematically calculating the pair of thresholds based on the well-established Bayesian decision theory. Many real world problems can be solved with DTRS. For instance, DTRS provides a three-way decision approach to classification problems by allowing the possibility of indecision to suspicious examples, those examples in the boundary region must be re-examined by collecting additional information. A fundamental question that remains in DTRS is how to determine the classification of these deferred examples.

Cognitive science and cognitive informatics (Wang, 2007; Wang et al., 2009, 2011) study the human intelligence and its computational process. As an effective way of thinking, we typically focus on a particular level of abstraction and ignore irrelevant details. This not only enables us to identify differences between objects in the real world, but also helps us to view different objects as being the same, if low-level detail is ignored. Granular computing (GrC) (Bargiela & Pedrycz, 2002; Liang & Qian, 2008; Qian, Liang, & Dang, 2009; Yao, 2004b, 2007b, 2009) can be seen as a formal way of modeling this human thinking process. GrC is an area of study that explores different levels of granularity in human-centered perception, problem solving, and information processing, as well as their implications and applications in the design and implementation of knowledge intensive intelligent systems. Rough set theory is one of the concrete models of GrC for knowledge representation and data analysis.

In this paper, an adaptive learning method is introduced that classifies the deferred examples by adaptively searching for effective granulization. A decision tree is constructed for classification. At each level, we sequentially choose the attributes that provide the most suitable granulization. A subtree is added if the conditional probability lies in between of the two thresholds. A branch reaches its leaf node when the conditional probability is above or equal to the first threshold, or is below or equal to the second threshold.

The rest of the paper is organized as follows. We briefly review the basic ideas of DTRS. We introduce the interpretations of concepts based on GrC. A new adaptive learning algorithm is introduced for ternary classification. An illustrative example is given. We conclude the paper and explain the future work.

BRIEF INTRODUCTION TO DECISION-THEORETIC ROUGH SET MODEL

Bayesian decision theory is a fundamental statistical approach that makes decisions under uncertainty based on probabilities and costs associated with decisions. Following the discussions given in the book by Duda and Hart (1973), the decision theoretic rough set model is a straightforward application of the Bayesian decision theory.

With respect to the set *C* to be approximated, we have a set of two states $\Omega = \{C, C^C\}$ indicating that an object is in *C* or not in *C*, respectively. We use the same symbol to denote both a set *C* and the corresponding state. With respect to the three regions in the rough set theory, the set of actions is given by $\mathbf{A} = \{a_P, a_B, a_N\}$, where a_P, a_B and a_N represent the three actions in classifying an object *x*, namely, deciding $x \in$ POS(*C*), deciding $x \in$ BND(*C*), and deciding $x \in$ NEG(*C*), respectively. The loss function is given by Matrix 1.

In the matrix, λ_{pp}, λ_{BP} and λ_{NP} denote the losses incurred for taking actions a_P, a_B and a_N respectively, when an object belongs to *C*, and λ_{PN}, λ_{BN}, and λ_{NN} denote the losses incurred for taking these actions when the object does not belong to *C*.