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Multi-attribute search framework for optimizing extended belief rule-based systems

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ABSTRACT

The advantages and applications of rule-based systems have caused them to be widely recognized as one of the most popular systems in human decision-making, due to their accuracy and efficiency. To improve the performance of rule-based systems, there are several issues proposed to be focused. First, it is unnecessary to take the entire rule base into consideration during each decision-making process. Second, there is no need to visit the entire rule base to search for the key rules. Last, the key rules for each decision-making process should be different. This paper focuses on an advanced extended belief rule base (EBRB) system and proposes a multi-attribute search framework (MaSF) to reconstruct the relationship between rules in the EBRB to form the MaSF-based EBRB. MaSFs can be divided into *k*-dimensional tree (KDT)-based MaSFs and Burkhard–Keller (BKT)-based MaSFs. The former is targeted at decision-making problems with small-scale attribute datasets, while the latter is for those with large-scale attribute datasets. Based on the MaSF-based EBRB, the *k*-neighbor search and the best activated rule set algorithms are further proposed to find both the unique and the desired rules for each decision-making process without visiting the entire EBRB, especially when handling classification problems with large attribute datasets. Two sets of experiments based on benchmark datasets with different numbers of attributes are performed to analyze the difference between KDT-based MaSFs and BKT-based MaSFs, and to demonstrate how to use MaSFs to improve the accuracy and efficiency of EBRB systems. MaSFs and their corresponding algorithms are also regarded as a general optimization framework that can be used with other rule-based systems.

1. Introduction

Among all knowledge representation forms that can be used in artificial intelligence [43], rules are the most common scheme for expressing numerous types of knowledge, and rule-based systems has been the fastest growing branch of decision-support systems [3,42]. In many cases, a rule-based system consists of two essential components; namely, a large number of IF-THEN rules and a suitable reasoning approach. For IF-THEN rules, it is inevitably necessary to represent information that contains different varieties of uncertainty, as fuzzy, incomplete, or incorrect information, as a result of imprecision or incompleteness of human knowledge and the vagueness intrinsic to human knowledge [36,56]. In the development and implementation of knowledge reasoning mechanisms, uncertainty has already drawn considerable attention.

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Acronyms

BKT	Burkhard-Keller tree
BKTSF	algorithm of constructing BKT-based MaSF
BRB	belief rule base
CRR	combination rule rate
DRA	method of dynamic rule activation
DST	Dempster-Shafer theory
EBRB	extended belief rule base
ER	evidential reasoning
KDT	*k*-dimensional tree
KDTSF	algorithm of constructing KDT-based MaSF
KSKDT	*k*-neighbor search in KDT-based MaSF
KSBKT	*k*-neighbor search in BKT-based MaSF
MaSF	multi-attribute search framework
RIMER	belief rule-base inference methodology using the evidential reasoning
SBR	algorithm of searching for best activated rule set
VRR	visitation rule rate

Notations

$A_{i,j}$	j^{th} referential value of the i^{th} antecedent attribute
$a_{i,j}$	j^{th} quantitative referential value in the i^{th} antecedent attribute
$\bar{a}_{i,j}$	j^{th} non-dimensional referential value in the i^{th} antecedent attribute
C_i^k	common form of referential value in the i^{th} antecedent attribute of thek^{th} rule
$C(Q)$	assessment of the best activated rule set
D_j	j^{th} consequent in rule base
$d(\bullet,\bullet)$	distance of rule
node	index-unit in the KDT/BKT-based MaSF
node.cns	set of sub-index-unit in *node*
node.lsn	index of left sub-index-unit in *node*
node.r	index of extended belief rule in *node*
node.rsn	index of right sub-index-unit in *node*
node.sa	splitting attribute in *node*
node.sv	splitting value in *node*
p	percentage to tune η
Q	set of activated rule
R_k	k^{th} rule in rule base
$SRA(\bullet,\bullet)$	similarity of rule antecedent
$SRC(\bullet,\bullet)$	similarity of rule consequent
U_i	i^{th} antecedent attribute in rule base
$x_q=(x_{q,1},x_{q,2},...,x_{q,T})$	q^{th} input data vector
$y_q=(y_1^q,y_2^q,...,y_T^q)$	non-dimensional value of $x_q=(x_{q,1},x_{q,2},...,x_{q,T})$
$\alpha_{i,j}$	individual matching degree of the j^{th} referential value in the i^{th} antecedent attribute
$\beta_{j,k}$	belief degree assessed to D_j in the k^{th} rule
δ_i	antecedent attribute weight of the i^{th} antecedent attribute
η	number of rules need to be activated
θ_k	rule weight of the k^{th} belief rule
ξ	maximum distance between query y_q and R_k
$\tau(j,k)$	relationship between the j^{th} consequent and the k^{th} belief rule
Φ	set of extended belief rule

Three of the most widely applied approaches for reasoning with uncertain information include Bayesian probability theory [6], the Dempster–Shafer theory (DST) of evidence [18,40], and fuzzy set theory [57]. However, each of these theories, due to its own features and limitations, is only suitable for specific applications [17,22,24,32,35,67]. In the example of DST, researchers were plagued by the Zadeh paradox [58]. Suppose that three people A, B, and C were murder suspects with guilt probabilities of 1%, 99%, and 0% from witness D, respectively; according to witness E, the guilt probabilities for A, B, and C are 1%, 0% and 99%, respectively. It is inconceivable that A is the murderer with guilt probability 100% using DST's combination rule. Hence, there is a need to develop a powerful knowledge reasoning mechanism to handle different kinds of information under uncertainty.