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Multi-stage mixed rule learning approach for advancing performance of rule-based classification

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Abstract

Rule learning is a special type of machine learning approaches, and its key advantage is the generation of interpretable models, which provides a transparent process of showing how an input is mapped to an output. Traditional rule learning algorithms are typically based on Boolean logic for inducing rule antecedents, which are very effective for training models on data sets that involve discrete attributes only. When continuous attributes are present in a data set, traditional rule learning approaches need to employ crisp intervals. However, in reality, problems usually show shades of grey, which motivated the development of fuzzy rule learning approaches by employing fuzzy intervals for handling continuous attributes. While a data set contains a large portion of discrete attributes or even no continuous attributes, fuzzy approaches cannot be used to learn rules effectively, leading to a drop in the performance. In this paper, a multi-stage approach of mixed rule learning is proposed, which involves strategic combination of both traditional and fuzzy approaches to handle effectively various types of attributes. We compare our proposed approach with existing algorithms of rule learning. Our experimental results show that our proposed approach leads to significant advances in the performance compared with the existing algorithms.

Keywords: Fuzzy classification; Fuzzy rules; Machine learning; Rule learning.

1. Introduction

Rule learning is one of the popular approaches of machine learning, especially given its advantage on interpretation of how a rule based model is used to map an input into an output. In the algorithmic setting, rule learning can be achieved through two main strategies, namely, divide and conquer (DAC) and separate and conquer (SAC). The DAC strategy aims at generating a set of rules automatically represented in the

form of a decision tree [25], i.e., each individual rule can be extracted from a branch of the tree (traversing from the root to a leaf node). Therefore, the DAC strategy is also known as the Top-Down Induction of Decision Trees (TDIDT) [29]. In contrast, the SAC strategy aims at generating a set of rules in the ‘if-then’ form directly from training data in a sequential manner [28], i.e., one rule is generated first and the instances covered by this rule are deleted from the training set before initiating the generation of the next rule on the basis of the remaining instances. Therefore, the SAC strategy is also known as the covering approach [30]. In order to distinguish these two strategies, we use the two terms ‘decision tree learning’ and ‘rule learning’ for referring to the DAC strategy and the SAC strategy, respectively, in the rest of this paper.

In practice, both the decision tree learning and rule learning approaches can be used for classification and regression tasks in the setting of supervised learning, depending on the actual type of data outputs. In particular, when the output is discrete (categorical), the supervised learning task needs to be defined as training of classification models (classifiers). Therefore, the trained decision trees or rules can be referred to as classification trees or classification rules in this context. When the output is continuous (numerical), the supervised learning task needs to be defined as training of regression models. Therefore, the trained decision trees or rules can be referred to as regression trees or regression rules in this context.

In this paper, we focus on classification tasks and investigate effective ways of advancing the performance of rule-based classification. Traditional approaches are typically based on Boolean logic, which indicates that the generated rules involve one or more hard conditions [30], i.e., a rule cannot be used to classify an instance unless some attribute values of the instance are satisfactory (meeting all the conditions). In this setting, the outcome of rule-based classification would be deterministic so the trained rules are usually called deterministic rules [29].

In real word applications, traditional approaches that are used to train deterministic rules can generally result in a high risk of overfitting, due to two main reasons. Firstly, real data usually remain a high level of uncertainty [31]. For example, the data quality is unknown indicating the possible case of noise [24]. Also, real data are likely to be incomplete and it is very uncertain how well the data can be representative of a full population (data distribution) in a specific domain [23]. From the above points of view, deterministic rules trained on real data would be less generalizable, leading to the case that the hard conditions involved in the rules can leave new instances uncovered by any of the rules or make new instances incorrectly covered by one or some of the rules. In other words, due to the low generalizability of the deterministic rules, new instances are likely to be incorrectly classified or unclassified, while the binary truth value (indicating that the joint conditions involved in a rule are fully met or not) is shifted

sharply from 0 to 1 or in the opposite way. On the other hand, the majority of real world problems cannot be simply formulated as black and white, i.e., these problems show some shades of grey [22, 45]. For example, a condition may be partially met to a certain degree although it is not fully met. On the basis of the above argumentation, fuzzy logic has been employed more popularly for reducing the risk of overfitting and advancing the performance of rule-based classification.

Although fuzzy rule learning approaches can be used to deal more effectively with continuous attributes in comparison with traditional rule learning approaches, while a data set contains only discrete attributes or a small portion of continuous attributes, traditional approaches would be more suitable, since fuzzy approaches cannot handle discrete attributes leading to a drop in the classification performance. In this context, it would be very necessary to propose a mixed rule learning approach that is capable of handling more effectively various types of attributes. On the other hand, existing approaches of rule learning typically involve only a single stage of learning. In order to increase the depth of learning, it has become more necessary to let a learning approach involve multiple stages. In this paper, we thus propose a mixed rule learning approach, which involves a multi-stage fuzzy rule learning part for handling continuous attributes in more depth and a traditional rule learning part for handling both discrete attributes and continuous attributes in diverse ways. In this way, we can achieve to take advantages of fuzzy approaches for handling continuous attributes without loss of the effectiveness of dealing with discrete attributes.

The rest of this paper is organized as follows. Section 2 provides a review of rule learning and some existing algorithms are analyzed in details for identifying their key limitations. In Section 3, we present some preliminaries on fuzzy logic and rule-based classification and illustrate our proposed multi-stage approach of mixed rule learning. In Section 4, we provide details on the setting of our experiments and discuss the experimental results. In Section 5, we draw the conclusions by stressing the contributions of our work and suggesting some further directions.

2. Related Work

As mentioned in Section 1, the rule-based models trained through the DAC and SAC strategies are automatically represented in two different forms. In particular, the former strategy leads to the automatic representation of decision trees, whereas the latter directly results in the representation of ‘if-then’ rules. The main reason is due to the essential difference between learning of decision trees and learning of ‘if-then’ rules in terms of algorithmic design [25]. In other words, decision tree learning is achieved essentially through recursive selection of attributes for the nodes of the decision tree

being trained, whereas rule learning is achieved through iterative selection of attribute-value pairs to form the antecedents of the rule being learned [28].

In the context of decision tree learning, the most classic algorithms include ID3 [38], C4.5 [40] and CART [5]. In particular, the ID3 algorithm is designed to employ entropy or information gain as the heuristics for attribute selection, i.e., for each node of the decision tree being trained, the attribute that obtains the minimum entropy or the maximum information gain is selected to show how a training set is split into subsets. The ID3 algorithm has demonstrated the capability of training decision trees that show very high accuracy of classification especially on the chess end game data set [37]. However, the ID3 algorithm can only handle discrete attributes, i.e., when continuous attributes are present in a data set, it is necessary to employ a method of discretization to change the numeric values of each attribute into multiple intervals [8]. In order to achieve direct handling of continuous attributes as part of the decision tree generation process, the C4.5 algorithm was proposed in [40] as a successor of the ID3 algorithm. In addition, the C4.5 algorithm was also enhanced to deal directly with missing values, which usually occur from real data.

On the other hand, the CART algorithm was developed in [5] for generating binary decision trees, which is essentially different from the ID3 and C4.5 algorithms in terms of dealing with multi-valued discrete attributes. In particular, when a discrete attribute A_i involves more than two categorical values, if ID3 or C4.5 is adopted for training a decision tree, the selection of the attribute A_i for a non-leaf node would result in m branches corresponding to the m values of the selected attribute A_i , towards growing the tree. In contrast, if the CART algorithm is adopted, the non-leaf node resulting from the selection of the attribute A_i would only lead to two branches – one showing the positive case (e.g., ‘age= young’) and the other showing the negative case (e.g., ‘age≠ young’). For the above example, if the attribute ‘age’ contains three values, namely, ‘young’, ‘old’ and ‘middle-aged’, then the selected value ‘young’ would be judged as the most effective one to discriminate between different classes. More details on the difference between ID3/C4.5 and CART have been explained in [25].

Since decision tree learning algorithms generally have the risk of producing models that overfit training data, more researchers have been motivated to develop pruning algorithms to simplify decision trees for improving the generalizability. For example, the reduced error pruning (REP) algorithm [10] has been successfully applied to the C4.5 algorithm for simplifying decision trees [39]. Also, the cost complexity pruning (CCP) algorithm [6] has been effectively used for simplifying decision trees that are trained using the CART algorithm [11]. Some other popular pruning algorithms include the pessimistic error pruning (PEP) algorithm [35] and the minimum error pruning (MEP) algorithm [36]. On the other hand, ensemble learning approaches have

been used to boost the effectiveness of decision tree learning. For example, the Bagging [5], Random Subspace [15] and Boosting [12] approaches have been used jointly for creating decision tree ensembles. In addition, several other ways have been taken for advancing the performance of decision tree learning algorithms, namely, incorporating cost functions into the heuristics for attribute selection [20] and employing fuzzy logic [44] for fuzzification of continuous attributes to train fuzzy decision trees [2, 18, 19].

As pointed out in [13], decision tree learning algorithms usually result in the production of complex trees, even if pruning algorithms are used for simplification. On the other hand, it has been pointed out by Cendrowska in [7] that decision tree learning algorithms can lead to the replicated subtree problem, which not only increases the risk of overfitting but also results in high computational complexity. In order to address the above issue, it has been the motivation for some researchers to develop algorithms for learning rules by following the SAC strategy. In particular, the Prism algorithm was developed in [7] as a representative example of rule learning algorithms. Another popular algorithm of rule learning is called Ripper [9].

The nature of the Prism algorithm is to select in turn each of the predefined K classes as the target class and then learn a set of rules from the training set for the target class, i.e., there are totally K sets of rules learned in parallel from the same training set and each rule is learned by discriminating the target class from the other classes. This target class based strategy of learning usually results in a large number of rules that could form a complex rule-based classifier [28]. In order to achieve the complexity reduction, some pruning algorithms have been adopted to simplify rules that are generated using the Prism algorithm, e.g., Jmid-pruning [32]. Also, the PrismCTC algorithm has recently been developed in [28] as a variant of the Prism algorithm through modifying the target class selection strategy, for both improving the classification performance and reducing the complexity of the trained rule-based classifiers. In addition, the Information Entropy based rule generation (IEBRG) [26] and Gini-Index Based Rule Generation (GIBRG) [25] algorithms have been developed by shifting the learning strategy to a non-target class based one, for overcoming the limitations of the Prism algorithm, i.e., the learning of each rule is achieved through discrimination between different classes without the need of selecting a target class.

The nature of the Ripper algorithm is to select iteratively an attribute-value pair as a rule antecedent, based on the FOIL information gain [9]. Since the algorithm involves a pruning action taken as soon as a rule is completely generated and a global optimization stage is involved after the whole rule set has been generated, the algorithm is more robust to noisy data and thus less likely to result in overfitting, in comparison to the Prism algorithm. However, the Ripper algorithm is still based on Boolean logic leading to the production of deterministic rules. When a data set contains a large number

of continuous attributes with high variability on the attribute domains, it would still be difficult to avoid overfitting, due to the case that the binary truth value that shows whether an instance is covered by a rule can be shifted sharply from 0 to 1 (or in the opposite way), even if the values of some attributes are just changed slightly. In order to make the Ripper algorithm more robust, the Fuzzy Unordered Rule Induction Algorithm (FURIA) has been developed in [16] for fuzzifying the antecedents of each rule generated using the Ripper algorithm, which has led to an improvement of the performance of rule-based classification.

FURIA is a fuzzy rule learning algorithm that does not need to consider all continuous attributes for generating rule antecedents, which is different from those earlier fuzzy rule learning algorithms that typically employ all continuous attributes for generating rule antecedents, e.g., the mixed fuzzy rule formation algorithm [4]. However, in reality, it is very likely that a data set contains not only continuous attributes but also discrete attributes. In this case, fuzzy rule learning approaches that only consider continuous attributes for generating rule antecedents would not be capable to perform well on learning rules from the above-mentioned type of data sets. Moreover, existing approaches of fuzzy rule learning typically involve only a single learning stage based on the crisp labels originally assigned to training instances. As mentioned in Section 1, real data may show some shades of grey, which indicates the necessity to include the intensity score (membership degree) for each class as a new continuous attribute (numeric label) of an instance for fuzzy rule learning. In Section 3, we will introduce how to achieve numeric labelling of instances for in-depth learning of fuzzy rules alongside diversified learning of traditional rules, through adopting our proposed multi-stage approach of mixed rule learning.

3. Multi-stage approach of mixed rule learning

In this section, some preliminaries are provided to introduce the theories of fuzzy logic and fuzzy rule-based systems. Furthermore, our proposed multi-stage approach of mixed rule learning is illustrated in details and some theoretical justifications are also given to show how the proposed approach can be more effective to lead to advances in the performance of rule-based classification.

3.1 Preliminaries

Fuzzy logic is based on the fuzzy set theory [44], which employs a fuzzy membership degree $tv_f \in [0, 1]$ instead of a binary membership degree $tv_f \in \{0, 1\}$ for making a judgement. In the context of machine learning, fuzzy classification is achieved by measuring the degree to which an instance x_i belongs to a class c_t , i.e., the membership degree $\mu_{c_t}(x_j)$, where the class c_t is considered as a fuzzy set S and the instance x_j is defined as an element e of the fuzzy set S . In order to determine the membership degree

of an element e to a fuzzy set S , a membership function μ needs to be defined for the fuzzy set S as shown in Fig. 1 as an example of a popularly used trapezoidal membership function, where the horizontal axis indicates the numeric value v of a continuous attribute x (i.e., an element of the fuzzy set S) and the vertical axis indicates the membership degree of the value of attribute x to the fuzzy set S (i.e., $\mu_S(v)$). In machine learning, the purpose of defining a membership function is to fuzzify a continuous attribute, i.e., it is to map the numeric value of a continuous attribute of an instance to the membership degree of this numeric value to a fuzzy set defined for the continuous attribute.

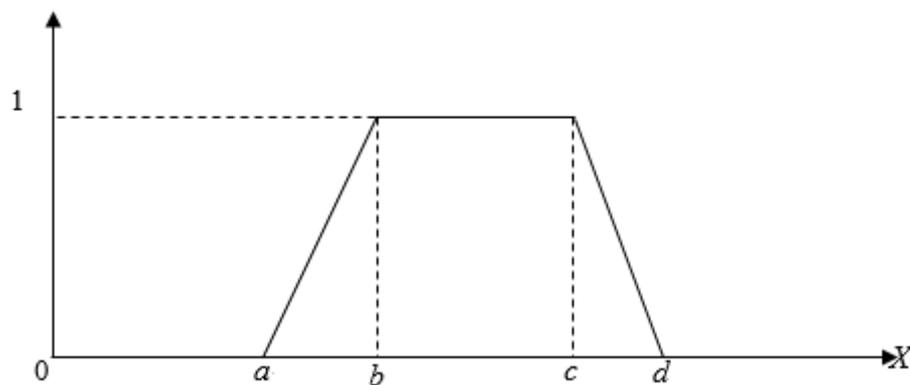


Fig. 1. Trapezoidal membership function [22]

The definition of a membership function can be achieved in practice by using expert knowledge or through inductive reasoning on real data. As shown in Fig. 1, the essence of defining a membership function is to determine the four parameters a , b , c and d for the trapezoidal shape, where b and c are defined, respectively, as the lower bound and the upper bound of the core region $[b, c]$ for an element to obtain a full membership to the fuzzy set, and a and d are defined, respectively, as the lower bound and the upper bound of the support region $(a, b) \cup (c, d)$ for an element to gain a non-zero membership degree to the fuzzy set. When the upper bound and the lower bound of the core region are equal, i.e., $b = c$, then the defined membership function would become triangular and the core region would be represented by a single point at which the membership degree of an element for the fuzzy set is equal to 1. There is another extreme case that the shape of the membership function becomes rectangle and thus there is no support region available for an element of the fuzzy set to obtain a membership degree between 0 and 1, i.e., $\mu_S(v) \in \{0, 1\}$, while $a = b$ and $c = d$.

Fuzzy classification is typically undertaken by constructing a fuzzy-rule based system, which can be represented in the following form:

Rule 1: if A_1 is T_{11} and A_2 is T_{21} and ... and A_d is T_{d1} then class = c_1 ,

Rule 2: if A_1 is T_{12} and A_2 is T_{22} and ... and A_d is T_{d2} then class = c_2 ,

⋮

Rule m : if A_1 is T_{1m} and A_2 is T_{2m} and ... and A_d is T_{dm} then class = c_m .

In the setting of fuzzy rule learning, each antecedent (e.g., A_1 is T_{11}) of a fuzzy rule is generated essentially through defining a fuzzy set T_{ik} for an attribute A_i . The number of antecedents for each rule is the same as the dimensionality of the training data if the fuzzy rule learning algorithm, e.g. the mixed fuzzy rule formation algorithm [4], needs to select all continuous attributes. In contrast, there are also some algorithms that do not need to consider all continuous attributes for generating fuzzy rules, e.g., FURIA [16]. In this case, the number of antecedents for each rule is usually less than (but possibly equal to) the dimensionality of the training data that contain only continuous attributes. The above set of fuzzy rules represents the case that each rule has a unique consequent (class), but it is possible in real world applications that some rules have the same consequent (class), i.e., the number of classes may be less than m .

In the fuzzy rule-based classification stage, there are generally three main operations, namely, fuzzification, inference and defuzzification. The fuzzification operation is to transform the numeric value of each attribute A_i of the instance x_j into the membership degree to a fuzzy set T_{ik} defined for attribute A_i involved in rule R_r . The inference operation is to compute the firing strength of each rule R_r using a T-norm, i.e., to compute the membership degree of the instance x_j to the class c_t shown in the consequent of rule R_r . Based on the firing strength of each rule R_r , we can compute the overall membership degree of the instance x_j to each class c using a T-cornorm, i.e., this is to combine the firing strengths of the rules for each class c_t to obtain the overall membership degree of the instance x_j to c_t .

A T-norm is essentially to conjunct the membership degrees obtained from all the antecedents of rule R_r , which show the degrees to which the values of the attributes of the instance x_j satisfy the antecedents of rule R_r . Some commonly used T-norms include the Min T-norm (Eq. (1)) [44], the Product T-norm (Eq. (2)) [14], Lukasiewicz's T-norm (Eq. (3)) [34] and Yager's T-norm (Eq. (4)) [43] are shown as follows:

$$\top(\mu_{S_1}(v_{1j}), \mu_{S_2}(v_{2j}), \dots, \mu_{S_n}(v_{nj})) = \min_{1 \leq i \leq n} \{\mu_{S_i}(v_{ij})\}, \quad (1)$$

$$\top(\mu_{S_1}(v_{1j}), \mu_{S_2}(v_{2j}), \dots, \mu_{S_n}(v_{nj})) = \prod_{i=1}^n \mu_{S_i}(v_{ij}), \quad (2)$$

$$\top(\mu_{S_1}(v_{1j}), \mu_{S_2}(v_{2j}), \dots, \mu_{S_n}(v_{nj})) = \max\{0, (\sum_{i=1}^n \mu_{S_i}(v_{ij})) - 1\}, \quad (3)$$

$$\top(\mu_{S_1}(v_{1j}), \mu_{S_2}(v_{2j}), \dots, \mu_{S_n}(v_{nj})) = 1 - \min\left\{1, \left[\sum_{i=1}^n (1 - \mu_{S_i}(v_{ij}))\right]^w\right\}^{\frac{1}{w}}. \quad (4)$$

In Eqs. (1)–(4), S_i denotes the fuzzy set defined for the attribute A_i and v_{ij} is the value of attribute A_i of the instance x_j .

A T-cornorm is essentially to combine the membership degrees $\mu_{c_t}^{R_1}(x_j), \mu_{c_t}^{R_2}(x_j), \dots, \mu_{c_t}^{R_m}(x_j)$ obtained from multiple rules R_1, R_2, \dots, R_m for the same class c_t so that we can compute the overall membership degree of the instance x_j to the class c_t . Some commonly used T-cornorms included the Max T-cornorm (Eq. (5)) [44], the Product T-cornorm (Eq. (6)) [14], Lukasiewicz’s T-cornorm (Eq. (7)) [34] and Yager’s T-cornorm (Eq. (8)) [43] are shown as follows:

$$\perp (\mu_{c_t}^{R_1}(x_j), \mu_{c_t}^{R_2}(x_j), \dots, \mu_{c_t}^{R_m}(x_j)) = \max_{1 \leq r \leq m} \{\mu_{c_t}^{R_r}(x_j)\}, \quad (5)$$

$$\perp (\mu_{c_t}^{R_1}(x_j), \mu_{c_t}^{R_2}(x_j), \dots, \mu_{c_t}^{R_m}(x_j)) = \sum_{r=1}^m \mu_{c_t}^{R_r}(x_j) - \prod_{r=1}^m \mu_{c_t}^{R_r}(x_j), \quad (6)$$

$$\perp (\mu_{c_t}^{R_1}(x_j), \mu_{c_t}^{R_2}(x_j), \dots, \mu_{c_t}^{R_m}(x_j)) = \min\{1, \sum_{r=1}^m \mu_{c_t}^{R_r}(x_j)\}, \quad (7)$$

$$\perp (\mu_{c_t}^{R_1}(x_j), \mu_{c_t}^{R_2}(x_j), \dots, \mu_{c_t}^{R_m}(x_j)) = \min\left\{1, \left(\sum_{r=1}^m (\mu_{c_t}^{R_r}(x_j))^w\right)^{\frac{1}{w}}\right\}. \quad (8)$$

Each T-norm has a corresponding T-cornorm (e.g., the Min T-norm is dual to the Max T-cornorm under the order revising operation) and they make up a dual pair that is referred to as fuzzy norm. Therefore, the above four pairs of T-norms and T-cornorms shown in Eqs. (1)–(8) can be referred to as the Min/Max norm, the Product norm, Lukasiewicz’s norm and Yager’s norm. From Eqs. (4) and (8), we can see that Yager’s norm involves a power parameter w . When the value of the parameter w is set to 1, Yager’s norm would be identical to Lukasiewicz’s norm, which indicates that Lukasiewicz’s norm is a special case of Yager’s norm. According to the empirical investigation made in [14], a popular value set for the power parameter w is 2, and we can thus refer it to as Yager’s [2.0] norm, which is the one used in this paper for experimentation (to be reported in Section 4).

After the overall membership degree of the instance x_j to each class c_t is obtained, the final classification is made through the defuzzification operation by assigning the instance x_j the class c_{\max} that obtains the maximum membership degree.

3.2 The proposed multi-stage approach of mixed rule learning

The proposed multi-stage approach of mixed rule learning involves two main parts. The first part is to create a decision tree ensemble that consists of two decision trees as the base classifiers, where the first base classifier is trained on the original feature set using the C4.5 algorithm without pruning and the second base classifier is trained by

discretizing all continuous attributes in the original feature set by using Fayyad and Irani’s MDL method [11] and then using the preprocessed feature set to build a decision tree using C4.5 with reduced error pruning [10]. The second part is to create m^n ($1 \leq n \leq N$) fuzzy ensembles at each of the predefined N stages of fuzzy rule learning, while m shrink heuristics are used for conflict avoidance. In particular, each single fuzzy rule-based classifier is trained using the mixed fuzzy rule formation algorithm [4] with a selected fuzzy norm (e.g., the Min/Max norm) as well as a selected shrink heuristic (e.g., border-based shrink), and then algebraic fusion of the fuzzy rule-based classifiers trained using the same shrink heuristic is taken using a fusion rule. In this section, we describe the whole procedure of the proposed multi-stage approach of mixed rule learning in a step-by-step manner.

The whole procedure is also illustrated in Fig. 2, which shows that a decision tree ensemble is simply created only at the first stage of training but multiple fuzzy ensembles are created at each training stage. In particular, each fuzzy ensemble consists of f fuzzy rule-based classifiers, which are trained using the f selected fuzzy norms, respectively. However, the f fuzzy rule-based classifiers in the same ensemble need to be trained using the same shrink heuristic. According to the empirical investigation in [14], both shrink heuristics and fuzzy norms can have impacts on the performance of the mixed fuzzy rule formation algorithm. Therefore, we adopt m shrink heuristics to achieve effective creation of diversity externally among m fuzzy ensembles and also adopt f fuzzy norms to create diversity internally among f fuzzy rule-based classifiers in the same ensemble.

In terms of training a single fuzzy classifier, the mixed fuzzy rule formation algorithm is designed essentially to learn fuzzy rules sequentially in an instance-by-instance manner, i.e., each instance is checked, and then a new rule is generated or some existing rules are adjusted. In the whole procedure, there may be three possible cases, namely, ‘covered’, ‘commit’ and ‘shrink’. In particular, if an instance x_j is not covered by any existing rules, then the ‘commit’ case is reached and a new rule R_t is generated to cover this instance x_j by setting fuzzy sets involved in the rule antecedents. In order to let the instance x_j obtain the membership degree of 1 to the generated rule R_t , each fuzzy set S_i shown in an antecedent of this rule R_t is defined by initializing the lower and upper bounds (b_i and c_i) of the core region of S_i according to the value v_{ij} of the attribute A_i of this instance x_j and initializing the lower and upper bounds (a_i and d_i) of the support region to cover the entire domain of the attribute A_i . For example, if the value v_{ij} of the attribute A_i is 2.2 and the domain of this attribute is [1.1, 5.6], then the initialized values of a , b , c and d would be 1.1, 2.2, 2.2 and 5.6, respectively. Once a new rule R_t is generated, a so-called anchor $\vec{\lambda}$ is set as a parameter, which remembers the instance x_j that triggered the generation of this rule R_t and will be used in the next

epoch of fuzzy rule learning for further adjusting the set of generated fuzzy rules (to be discussed later in this section).

Input: Initial training set D_{11} , test set D' .

Output: Class label l_j for each instance x_j' .

Initialize: The index (t) of the training stage is initialized to 1, i.e., $t = 1$, the index (i) of a training set used at training stage t is initialized to 1, i.e., $i = 1$;

Create a decision tree ensemble E_0 using training set D_{11} through the two steps below:

Step 1: Train the first unpruned decision tree DT_1 by using the C4.5 algorithm.

Step 2: Discretize all continuous attributes in D_{11} and then train the second pruned decision tree DT_2 by using the C4.5 algorithm alongside the reduced error pruning algorithm;

If the number of continuous attributes $N_c \geq N_{min}$ (the minimum number) **Then**

While $t \leq N_s$ (the number of training stages) **Do**

While $i \leq 2^{t-1}$ **Do**

For the index of shrink heuristic $a = 1, 2, \dots, m$ **Do**

For the index of fuzzy norm $b = 1, 2, \dots, n$ **Do**

Train a fuzzy rule-based classifier h_{tiab} on D_{ti} using the mixed fuzzy rule formation algorithm alongside the selected fuzzy norm b ;

For each training instance x_j **Do**

Predict its numeric label $\mu_{c_k}^{h_{tiab}}(x_j)$ for each class c_k

End For

End For

A fuzzy ensemble is created using shrink heuristic a ;

Fusion of the n fuzzy classifiers to obtain the fused membership degree $\mu_{c_k}^{fuser_{tia}}(x_j)$ by averaging the membership degrees $\mu_{c_k}^{h_{tia1}}(x_j), \mu_{c_k}^{h_{tia2}}(x_j), \dots, \mu_{c_k}^{h_{tiana}}(x_j)$ for each class c_k ;

Use the fused membership degree $\mu_{c_k}^{fuser_{tia}}(x_j)$ as the numeric label (a new continuous attribute added into training set D_{ti}) for each class c_k at the next training stage $t+1$, i.e., D_{ti} is updated to become a new training set used for the next training stage $t+1$;

End For

End While

End While

End If

For each test instance x_j' **Do**

Classify x_j' through algebraic fusion of decision tree ensemble E_0 and all fuzzy ensembles;

End For

Fig. 2. Procedure of the proposed multi-stage mixed rule learning approach.

If an instance x_j is already covered by an existing rule R_k , i.e., the instance x_j has a membership degree $\mu_{R_k}(x_j) \in (0, 1]$ to the rule R_k , then the ‘covered’ case is reached. In this case, the core regions of some fuzzy sets shown in some antecedents of the rule R_k need to be adjusted by letting the values of the corresponding attributes fall into the core regions of these fuzzy sets, such that the instance x_j will obtain a full membership (i.e., $\mu_{R_k}(x_j) = 1$) to the rule R_k . In other words, for each attribute A_i , if its value v_{ij} does not yet fall into the core region $[b_{ik}, c_{ik}]$ of the corresponding fuzzy set S_i , then the lower or upper bound (b_{ik} or c_{ik}) of the core region needs to be modified to ensure $b \leq v_{ij} \leq c$, such that the membership degree of the value v_{ij} of the attribute A_i is equal to 1, i.e., $\mu_{S_i}(v_{ij}) = 1$. Overall, once the ‘covered’ case is reached, the rule R_k that covers the instance x_j must be adjusted to enable that the instance x_j falls into the core region $([b_{1k}, c_{1k}] \wedge [b_{2k}, c_{2k}] \wedge \dots \wedge [b_{nk}, c_{nk}])$ of the rule R_k .

For both the ‘covered’ and ‘commit’ cases, it is necessary to take the shrink action to avoid conflict of classification. In particular, when an instance $x_j \in c_k$ is covered by a rule R_t of class $c_l \neq c_k$, then the rule R_t must be adjusted to let the instance x_j obtain no membership (i.e., $\mu_{R_t}(x_j) = 0$) to the rule. The conflict of classification may involve two possible cases: (1) the instance x_j obtains a partial membership (the membership degree $\mu_{S_i}(v_{ij}) \in (0, 1)$) to the rule R_t ; (2) the instance x_j obtains a full membership (the membership degree $\mu_{S_i}(v_{ij}) = 1$) to the rule R_t . In the first case, the conflict of classification can be avoided without loss of rule coverage (instances of class c_l covered by rule R_t), by adjusting the support regions of the fuzzy sets shown in some antecedents of the rule R_t . In the second case, the conflict of classification cannot be avoided without loss of rule coverage, which means that some instances of c_l covered by rule R_t will be lost due to the adjustments of the core regions of the fuzzy sets shown in some antecedents of the rule R_t . Three shrink heuristics, namely, area-based shrink, anchor-based shrink and rule-based shrink, have been proposed and investigated empirically in [14] with more details on how to achieve conflict avoidance effectively.

Once all the training instances have been checked, the first epoch of fuzzy rule learning is completed and we obtain an initial set of fuzzy rules. At this point, it is necessary to adjust all the rules by turning the core region $([b_{1k}, c_{1k}] \wedge [b_{2k}, c_{2k}] \wedge \dots \wedge [b_{nk}, c_{nk}])$ of each rule R_k back to the original status $([v_{1j}, v_{1j}] \wedge [v_{2j}, v_{2j}] \wedge \dots \wedge [v_{nj}, v_{nj}])$ represented by its anchor $\vec{\lambda}$ (the instance x_j triggering the generation of the rule R_k) but

maintaining the support region $([(a_{1k}, b_{1k}) \vee (c_{1k}, d_{1k})] \wedge [(a_{2k}, b_{2k}) \vee (c_{2k}, d_{2k})] \wedge \dots \wedge [(a_{nk}, b_{nk}) \vee (c_{nk}, d_{nk})])$ of each rule. In other words, for each fuzzy set S_i shown in an antecedent of rule r_k , the core region $[b_{ik}, c_{ik}]$ of S_i needs to be reset to $[v_{ij}, v_{ij}]$, while the support region $(a_{ik}, b_{ik}) \vee (c_{ik}, d_{ik})$ of S_i remains unchanged. In this way, the core regions of the fuzzy rules are adjusted based on the training instances covered by these rules and this process is repeated for several further epochs until no new rule is generated and/or no conflict of classification occurs. As indicated in [4], the above process of resetting and adjusting the generated rules usually needs a small number (less than 10) of epochs. In the worst case, the number of epochs would not exceed a maximum that is equivalent to the total number of training instances. In practice, the maximum number of epochs for training a set of fuzzy rules can also be predefined.

In terms of algebraic fusion of fuzzy classifiers, when different fuzzy norms are used as parameters of the mixed fuzzy rule formation algorithm, multiple fuzzy classifiers with diversity can be trained to make up a fuzzy ensemble. In this context, we can fuse multiple fuzzy classifiers by combining the membership degrees estimated by these classifiers for each class. In other words, each instance x_j would be assigned different membership degrees for each class by using different fuzzy classifiers. In order to reduce the potential estimation error of the membership degree for each class, it has been a popular practice to combine the membership degrees estimated by different classifiers through using a fusion rule [17], such as mean (Eq. (9)), max (Eq. (10)), median (Eq. (11)) and product (Eq. (12)), shown as follows:

$$\mu_{c_k}^{fuser}(x_j) = \frac{1}{m} \sum_{h=1}^m u_{c_k}^h(x_j), \quad (9)$$

$$\mu_{c_k}^{fuser}(x_j) = \max_{1 \leq h \leq m} \{u_{c_k}^h(x_j)\}, \quad (10)$$

$$\mu_{c_k}^{fuser}(x_j) = \text{med}_{1 \leq h \leq m} \{u_{c_k}^h(x_j)\}, \quad (11)$$

$$\mu_{c_k}^{fuser}(x_j) = \prod_{h=1}^m u_{c_k}^h(x_j). \quad (12)$$

In Eqs. (9)–(12), c_k denotes a class with the index of k and x_j represents an unseen instance that is being classified. The denotation $u_{c_k}^h(x_j)$ represents the membership degree of instance x_j estimated by classifier h for class c_k and $u_{c_k}^{fuser}(x_j)$ thus denotes the overall membership degree of instance x_j obtained for each class c_k through combining the membership degrees $u_{c_k}^1(x_j), u_{c_k}^2(x_j), \dots, u_{c_k}^m(x_j)$ estimated by the m classifiers. In this paper, we take the mean rule (shown in Eq. (9)) for algebraic fusion of multiple fuzzy classifiers, since it is the one most popularly used in practice [17].

After fusion of multiple fuzzy classifiers, the combined membership degree $u_{c_k}^{fuser}(x_j)$ of each instance x_j for each class c_k is used as a numeric label (a new continuous attribute) of the instance x_j for the next stage of fuzzy rule learning. Generally speaking, at each stage (except for the first stage) of fuzzy rule learning, multiple fuzzy classifiers are trained separately on the instances that are assigned the numeric labels as new continuous attributes, which are essentially the membership degrees $u_{c_1}^{fuser}(x_j), u_{c_2}^{fuser}(x_j), \dots, u_{c_n}^{fuser}(x_j)$ for the n predefined classes) obtained through taking the outputs of the algebraic fusion of the fuzzy classifiers trained at the previous stage. For example, at the first stage of fuzzy rule learning, there are four classifiers trained on the instances that are assigned the original class labels (ground truth). After fusion of the four classifiers, for each instance x_j , combined membership degrees $u_{c_1}^{fuser}(x_j), u_{c_2}^{fuser}(x_j), \dots, u_{c_n}^{fuser}(x_j)$ are obtained for the n predefined classes and will be used as n numeric labels for training four new classifiers at the next stage. The same operation also applies to each test instance for getting n numeric labels used at the next stage of testing. This process is repeated until the required number of training stages is reached.

The n numeric labels of each instance x_j in a newly created training set for the n predefined classes can be obtained through two ways. In particular, the first way is achieved by using a previously obtained training set for training m fuzzy classifiers and then using each of the m trained fuzzy classifiers to predict the membership degrees $u_{c_1}^h(x_j), u_{c_2}^h(x_j), \dots, u_{c_n}^h(x_j)$ of each instance x_j for the n classes c_1, c_2, \dots, c_n . In this way, for each instance x_j , m membership degrees can be obtained for each class c_k , so a combined membership degree for each class c_k can be obtained through fusing the m fuzzy classifiers. Finally, the combined membership degrees

$u_{c_1}^{fuser}(x_j), u_{c_2}^{fuser}(x_j), \dots, u_{c_n}^{fuser}(x_j)$ for the n classes c_1, c_2, \dots, c_n are used as the n numeric labels of instance x_j in the newly created trained set used for the next stage of fuzzy rule learning and ensemble creation.

The second way of obtaining the n numeric labels of each instance x_j in a newly created training set is to conduct 10-fold cross validation on the training set. In this way, each of the training instances will be treated as an unseen one in a specific one of the 10 folds and will thus obtain n membership degrees for the n classes as predicted by using one of the m fuzzy classifiers trained in the specific fold. Similar to the first way described above, the m trained fuzzy classifiers will be fused to obtain combined

membership degrees $u_{c_1}^{fuser}(x_j), u_{c_2}^{fuser}(x_j), \dots, u_{c_n}^{fuser}(x_j)$ for the n classes c_1, c_2, \dots, c_n , which will be finally used as the n numeric labels of instance x_j in the new created training set used for the next stage of fuzzy rule learning and ensemble creation.

In general, the first way of numeric labelling would be more recommended than the second way, since 10-fold cross validation may result in the case that training instances may not be well representative of test instances in some of the 10 folds. In this case, it is very likely to result in incorrect estimation of the fuzzy membership degrees for the classes, which could introduce noise in the values of the newly added continuous attributes (resulting from numeric labelling of instances). In other words, it is crucial to make sure the numeric labelling of instances is highly confident to avoid noise in values of the newly added continuous attributes. In this case, the newly added continuous attributes can be used as additionally helpful features for learning fuzzy rules of better quality.

The idea of the above multi-stage fuzzy rule learning approach is naturally inspired from the theory of deep neural networks in a layer-by-layer processing manner. For our proposed approach, the depth depends on the number (N) of training stages, whereas the width depends on the number of trained fuzzy classifiers that make up a fuzzy ensemble and the number of fuzzy ensembles. From an ensemble learning perspective, it is crucial that each single classifier trained as a member of an ensemble must not be too weak in terms of its classification performance and different classifiers that make up the ensemble need to be diverse and complementary to each other, such that the fusion of these classifiers in the ensemble can lead to an effective improvement of the overall performance of classification [17]. Similarly, multiple fuzzy ensembles created using different shrink heuristics also need to be diverse and complementary to each other. From this point of view, the increase of depth would aim for improving the overall classification performance, whereas the increase of the width aims to increase the diversity between the trained classifiers to maximize the chance for the classifiers in an ensemble to be more complementary to each other. The main focus of this paper is thus on the increase of both the depth and the width in advancing the performance of rule-based classification.

Finally, all the fuzzy rule ensembles created at the N stages of training are fused in an algebraic rule with a decision tree ensemble created at the first stage of training, in order to avoid the case that fuzzy approaches cannot learn effectively from a data set that contains a very small portion of or even no continuous attributes, leading to low performance of rule-based classification. Also, when a data set contains a large portion of continuous attributes, various ways of handling continuous attributes through both fuzzy and traditional rule learning approaches would be likely to lead to the effective

creation of diversity among different classifiers or ensembles, which again indicates the necessity to adopt fusion of the fuzzy ensembles and the decision tree ensemble, towards advances in the performance of rule-based classification.

4. Experimental results

Some experiments are conducted in this section, by using 20 data sets retrieved from the UCI machine learning repository [21]. Some of the data sets contain both discrete and continuous attributes, whereas the other data sets contain only one type of attributes, i.e., either discrete attributes or continuous attributes. The details of the selected data sets are provided in Table 1 in terms of their characteristics.

Table 1

Data sets used for experiments.

Dataset name	Number of discrete/continuous attributes	Number of instances	Number of classes
Anneal	32/6	898	6
Balance-scale	0/4	625	3
Breast-cancer	9/0	286	2
Breast-w	0/9	699	2
Credit-a	9/6	690	2
Credit-g	13/7	1000	2
Cylinder-bands	21/18	540	2
Dermatology	33/1	366	6
Diabetes	0/8	768	2
Hepatitis	13/6	155	2
Ionosphere	0/34	351	2
Iris	0/4	150	3
Kr-vs-kp	36/0	3196	2
Labor	8/8	57	2
Lymph	15/3	148	4
Sponge	45/0	76	3
Tae	2/3	151	3
Vote	16/0	435	2
Wine	0/13	178	3
Zoo	16/1	101	7

In the setting of the proposed multi-stage approach of mixed rule learning, the creation of the decision tree ensemble is achieved to train two decision trees as base classifiers at the first stage of training only, where the first base classifier is trained simply on the original feature set using the C4.5 algorithm without the simplification

of the trained decision tree through pruning and the second base classifier is trained through first discretizing all the continuous attributes in the feature set and then building the decision tree on the preprocessed feature set with simplification of the trained decision tree using the reduced error pruning algorithm [10].

The creation of fuzzy rule ensembles at each stage of training is achieved to adopt two shrink heuristics (anchor-based shrink and border-based shrink) for creating two fuzzy ensembles on each of the feature sets given at a specific stage of training. For example, at the first stage of training, there is only an original feature set so two ensembles are created on the feature set in total using the anchor-based shrink and the border-based shrink, respectively. At the second stage of training, there are two newly created training sets, since the two fuzzy ensembles created at the first stage of training can assign each instance two different membership degrees for each class, i.e., two different sets of continuous attributes (reflecting the membership degrees for the classes) are separately added to the original feature set to get two new training sets (containing all attributes in the original feature set + newly added continuous attributes). In this context, there are totally four fuzzy ensembles created at the second stage of training on the two new training sets given at this stage, i.e. on each of the two new training sets, there are two fuzzy rule ensembles created using the anchor-based shrink and the border-based shrink, respectively. In our experiments, the number of training stages (N) is set to 2, due to the general small size of each data set. In terms of creation of each of the fuzzy rule ensembles, four fuzzy rule-based classifiers are trained using the four fuzzy norms, namely, the Min/Max Norm, the Product Norm, Lukasiewicz's Norm and Yager's Norm, while the same shrink heuristic is used for avoiding conflict of classification, i.e., the shrink heuristic used for creation of a fuzzy ensemble is either anchor-based shrink or border-based shrink.

In terms of internal fusion of the base classifiers in an ensemble and external fusion of multiple ensembles, the mean rule is used in general. However, when a data set contains a small portion of continuous attributes, it is more likely to result in the case that the performance of the decision tree ensemble could be considerably better than the performance obtained through fusion of all the fuzzy ensembles. In the above case, in order to avoid the drop in the performance of the final fusion of the decision tree ensemble and the ensemble that consists of all the fuzzy ensembles, the max rule is used instead of the mean rule for the final fusion. In addition, when a data set contains only one or even no continuous attribute, the second part of the proposed approach for creation of multiple fuzzy ensembles at multiple stages of training is thus dropped, i.e., only the first part for creation of an decision tree ensemble is involved, in order to avoid the case that fuzzy approaches cannot achieve to learn effectively from such a data set leading to low performance of classification.

For the 20 data sets shown in Table 1, there are six data sets that contain only one or even no continuous attribute, namely, ‘Breast-cancer’, ‘Dermatology’, ‘Kr-vs-kp’, ‘Sponge’, ‘Vote’ and ‘Zoo’. Therefore, on the six data sets, only a decision tree ensemble is created for classifying test instances. Also, there are three data sets that contain a very small number (less than 4) or a very small portion (less 30%) of continuous attributes, namely, ‘Anneal’, ‘Lymph’ and ‘Tae’. Therefore, on the three data sets, the max rule is used instead of the mean rule for the final fusion of a decision tree ensemble and the ensemble that consists of all the fuzzy ensembles.

Table 2
Classification accuracy.

Dataset	C4.5 [40]	Prism [7]	PrismCTC1 [28]	PrismCTC2 [28]	PrismCTC3 [28]	PrismCTC4 [28]	The Proposed method
Anneal	0.98	0.98	0.99	0.99	0.99	0.98	0.97
Balance-scale	0.78	0.83	0.85	0.85	0.84	0.85	0.80
Breast-cancer	0.67	0.67	0.66	0.65	0.64	0.67	0.69
Breast-w	0.94	0.93	0.95	0.95	0.95	0.95	0.96
Credit-a	0.83	0.80	0.77	0.77	0.78	0.81	0.84
Credit-g	0.68	0.74	0.70	0.68	0.68	0.70	0.70
Cylinder-bands	0.58	0.69	0.70	0.70	0.69	0.72	0.69
Dermatology	0.94	0.84	0.90	0.91	0.88	0.85	0.94
Diabetes	0.72	0.70	0.70	0.69	0.70	0.73	0.76
Hepatitis	0.76	0.76	0.82	0.81	0.78	0.83	0.81
Ionosphere	0.89	0.90	0.92	0.92	0.92	0.92	0.93
Iris	0.94	0.88	0.94	0.94	0.93	0.92	0.96
Kr-vs-kp	0.99	0.98	0.98	0.99	0.99	0.98	0.99
Labor	0.80	0.88	0.81	0.85	0.87	0.84	0.84
Lymph	0.76	0.78	0.79	0.77	0.78	0.76	0.76
Sponge	0.93	0.91	0.90	0.93	0.93	0.92	0.93
Tae	0.53	0.49	0.59	0.57	0.58	0.45	0.61
Vote	0.95	0.93	0.94	0.94	0.94	0.90	0.96
Wine	0.91	0.84	0.93	0.93	0.90	0.94	0.96
Zoo	0.92	0.61	0.80	0.86	0.63	0.86	0.92

The experiments on all the 20 data sets are conducted through hold-out testing, i.e., each data set is randomly partitioned into a training set (70%) and a test set (30%). The random partitioning of each data set is repeated 100 times and the average accuracy obtained over the 100 runs on each data set is used for comparison of the performance

of different approaches. Table 2 is presented to show a comparison of the proposed approach with the other algorithms of rule learning in terms of the classification accuracy, where the four columns “PrismSTC1”, “PrismSTC2”, “PrismSTC3” and “PrismSTC4” indicate the performance of the PrismCTC algorithm, while the four different heuristics, namely, ‘confidence’ [28], ‘J-measure’ [28], ‘lift’ [28] and ‘leverage’ [28], are used for rule quality measure, respectively.

Table 3
Number of correctly/incorrectly classified instances.

Dataset	C4.5 [40]	Prism [7]	PrismCTC 1 [28]	PrismCTC 2 [28]	PrismCTC 3 [28]	PrismCTC 4 [28]	The proposed method
Anneal	880/18	880/18	889/9	889/9	889/9	880/18	871/27
Balance-scale	488/137	519/106	531/94	531/94	525/100	531/94	500/125
Breast-cancer	192/94	192/94	189/97	186/100	183/103	192/94	197/89
Breast-w	657/42	650/49	664/35	664/35	664/35	664/35	671/28
Credit-a	573/117	552/138	531/159	531/159	538/152	559/131	580/110
Credit-g	680/320	740/260	700/300	680/320	680/320	700/300	700/300
Cylinder-bands	313/227	373/167	378/162	378/162	373/167	389/151	373/167
Dermatology	344/22	307/59	329/37	333/33	322/44	311/55	344/22
Diabetes	553/215	538/230	538/230	530/238	538/230	561/207	584/184
Hepatitis	118/37	118/37	127/28	126/29	121/34	129/26	126/29
Ionosphere	312/39	316/35	323/28	323/28	323/28	323/28	326/25
Iris	141/9	132/18	141/9	141/9	140/10	138/12	144/6
Kr-vs-kp	3164/32	3132/64	3132/64	3164/32	3164/32	3132/64	3164/32
Labor	46/11	50/7	46/11	48/9	50/7	48/9	48/9
Lymph	112/36	115/33	117/31	114/34	115/33	112/36	112/36
Sponge	71/5	69/7	68/8	71/5	71/5	70/6	71/5
Tae	80/71	74/77	89/62	86/65	88/63	68/83	92/59
Vote	413/22	405/30	409/26	409/26	409/26	392/43	418/17
Wine	162/16	150/28	166/12	166/12	160/18	167/11	171/7
Zoo	93/8	62/39	81/20	87/14	64/37	87/14	93/8

Table 3 is presented to show a comparison of the proposed approach with the other algorithms of rule learning in terms of the number of correctly/incorrectly classified instances for each data set. The number N_{misc} of incorrectly classified instances is approximately estimated for each data set according to Eq. (13), shown as follows:

$$N_{misc} = (1 - avg.Acc) \cdot N_{inst}, \quad (13)$$

where N_{misc} represents the number of misclassified instances, $avg.Acc$ represents the average accuracy and N_{inst} represents the total number of instances in a data set. As mentioned earlier in this section, on each data set, the data partitioning to obtain a training set and a test is repeated 100 times, so the classification accuracy is averaged over the 100 runs on each data set. In this context, the test sets obtained in the 100 runs could have some overlaps, i.e., some instances may be selected more than once for testing, while the same instances may be classified correctly in some runs but may also

be classified incorrectly in other runs. Therefore, it is not achievable to obtain the precise number of misclassified instances for each data set and thus the number of misclassified instances for each data set is estimated according to Eq. (13). Similarly, the number of correctly classified instances is also approximately estimated for each data set by taking the total number of instances minus the number of incorrectly classified instances.

According to the results shown in Table 2 and Table 3, we can see that the proposed approach outperforms all the other approaches or performs the same as the best one of the other approaches in 13 out of the 20 cases. In comparison with the C4.5 algorithm, the proposed approach leads to better performance in 14 out of the 20 cases. In 5 out of the other 6 cases, the proposed approach performs the same as the C4.5 algorithm, i.e., there is only one case in which the proposed approach performs worse than the C4.5 algorithm. In comparison with the Prism algorithm, the proposed approach leads to better performance in 14 out of the 20 cases. In 1 out of the other 6 cases, the proposed approach performs the same as the Prism algorithm, i.e., there are 5 cases where the proposed approach performs worse than the Prism algorithm. In comparison with PrismCTC1, the proposed approach leads to better performance in 14 out of the 20 cases. In 1 out of the other 6 cases, the proposed approach performs the same as PrismCTC1, i.e., there are 5 cases where the proposed approach performs worse than PrismCTC1. In comparison with PrismCTC2, the proposed approach leads to better performance in 12 out of the 20 cases. In 3 out of the other 8 cases, the proposed approach performs the same as PrismCTC2, i.e., there are 5 cases that the proposed approach performs worse than PrismCTC2. In comparison with PrismCTC3, the proposed approach leads to better performance in 13 out of the 20 cases. In 3 out of the other 7 cases, the proposed approach performs the same as PrismCTC3, i.e., there are 4 cases where the proposed approach performs worse than PrismCTC3. In comparison with PrismCTC4, the proposed approach leads to better performance in 13 out of the 20 cases. In 3 out of the other 7 cases, the proposed approach performs the same as PrismCTC4, i.e., there are 4 cases where the proposed approach performs worse than PrismCTC4.

In order to test whether the performance difference between the proposed approach and each of the others is statistically significant (in terms of the classification accuracy and the number of correctly/incorrectly classified instances), we conduct the Wilcoxon rank tests to obtain the p -value resulting from each pairwise comparison shown in the fifth and sixth columns of Table 4. From this table, we can see that statistically significant advances in the classification performance have been achieved through adopting the proposed multi-stage approach of mixed rule learning, in comparison with the other rule learning algorithms, given that the obtained p -value is less than 0.05 for

each pairwise comparison, i.e., as shown in the fifth and sixth columns of this table, the performance difference between the proposed approach and each of the other approaches is statistically significant in terms of both the classification accuracy and the number of correctly/incorrectly classified instances.

Table 4

Statistical analysis using Wilcoxon rank tests.

Compared methods	Number of positive cases	Number of negative cases	Number of ties	p -value (accuracy)	p -value (Number of misclassified instances)	Comments
C4.5 vs the proposed method	14	1	5	0%	0.20%	Significantly better than C4.5
Prism vs the proposed method	14	5	1	0.90%	1.30%	Significantly better than Prism
PrismCTC1 vs the proposed method	14	5	1	1.60%	2.90%	Significantly better than PrismCTC1
PrismCTC2 vs the proposed method	12	5	3	1.70%	3.20%	Significantly better than PrismCTC2
PrismCTC3 vs the proposed method	13	4	3	1.50%	1.20%	Significantly better than PrismCTC3
PrismCTC4 vs the proposed method	13	4	3	2.10%	2.90%	Significantly better than PrismCTC4

The results shown in Tables 2-4 generally indicate that the design of the proposed multi-stage approach of mixed rule learning can lead to advances in the classification performance through involving various ways of handling continuous attributes and avoiding the missing of important information from discrete attributes. In particular, continuous attributes are handled through both discretization to obtain crisp intervals and fuzzification to obtain fuzzy intervals, which lead to effective creation of diversity between decision tree ensembles and fuzzy rule ensembles. Also, when a data set contains discrete attributes in addition to continuous attributes, the inclusion of decision tree ensemble creation as part of the proposed approach can help complement the weakness that fuzzy approaches are unable to handle discrete attributes leading to low performance on the data set. Moreover, the creation of multiple fuzzy ensembles through using different shrink heuristics would help better create further diversity,

while the diversity among fuzzy rule-based classifiers inside each ensemble is already created through using different fuzzy norms for classifiers training.

According to the results shown in Table 2, while a data set contains only continuous attributes, the proposed approach generally leads to an improvement of the classification performance. In particular, on the ‘Breast-w’, ‘Diabetes’, ‘Iris’ and ‘Wine’ data sets, the proposed approach outperforms all the other approaches. On the ‘Balance-scale’, although the proposed approach is not the best performing one, it still outperforms the C4.5 algorithm, which again shows the effectiveness of the proposed approach in improving the performance in comparison with the case that the continuous attributes are handled through a single way involved in the C4.5 algorithm.

On the other hand, while a data set contains only one or even no continuous attributes, the adoption of the proposed approach without the part of fuzzy ensembles creation leads to an improvement of the performance on the ‘Breast-cancer’ and ‘Vote’ data sets, which shows that the creation of a decision tree ensemble that consists of both unpruned and pruned decision trees leads to diversity creation that helps improve the classification performance. On the ‘Dermatology’, ‘Kr-vs-kp’, ‘Sponge’ and ‘Zoo’ data sets, the proposed approach performs the same as the C4.5 algorithm, while C4.5 already shows sufficiently good performance in comparison with the other approaches, i.e., C4.5 either outperforms all the variants of Prism or performs the same as the best one of the variants of Prism. This phenomenon would indicate that the adoption of the proposed approach can effectively keep the performance at the peak without negative impact that leads to a drop in the performance.

Moreover, while a data set contains both discrete and continuous attributes, the adoption of the proposed approach leads to an improvement of the performance in some cases but also leads to a drop in the performance in some other cases, in comparison with the C4.5 algorithm. In particular, on the ‘Credit-a’, ‘Credit-g’, ‘Cylinder-bands’, ‘Hepatitis’, ‘Labor’ and ‘Tae’ data sets, the adoption of the proposed approach leads to an improvement of the performance in comparison with the simple use of the C4.5 algorithm, which supports the argumentation that the inclusion of the part of decision tree ensemble creation into the proposed approach can help better deal with discrete attributes and the involvement of various ways of dealing with continuous attributes leads to better diversity among different ensembles and the classifiers inside each ensemble. However, in some of the cases, the proposed approach performs worse than one or some of the variants of Prism, which could be partially due to the case that the nature of separate and conquer rule learning approaches makes it more suitable to learn rules from the data sets.

In addition, on the ‘Anneal’ and ‘Lymph’ data sets, the adoption of the proposed approach could not lead to an improvement of the performance in comparison with the

simple use of the C4.5 algorithm. This is mainly because the case that the two data sets contain a very small portion of continuous attributes and the inclusion of the fuzzy rule ensembles creation part could not lead to any positive impacts from dealing with continuous attributes, but leads to some negative impacts from being unable to deal with discrete attributes. However, negative impacts are fairly small as shown in Table 2, i.e., the performance either remains the same or drops a little bit through the adoption of the proposed approach.

5. Conclusions

In this paper, the main contribution is that we have proposed a multi-stage approach of mixed rule learning for advancing the performance of rule-based classification. We have compared the proposed multi-stage approach of mixed rule learning with several other existing approaches of rule learning, and the experimental results show that our proposed approach outperforms these existing approaches in most cases in terms of classification accuracy. Furthermore, the results obtained through Wilcoxon rank tests suggest that the degree to which the proposed approach outperforms these existing approaches is statistically significant in terms of both classification accuracy and the number of misclassified instances.

In the future, we will investigate in more depth the mathematical combination of Boolean logic and fuzzy logic towards developing a more generic rule learning approach in the setting of ensemble learning, and will analyze the effectiveness of the diversity creation through fusion of multiple rule-based classifiers towards further advances in the classification performance. We will also explore the combined adoption of multiple ways of membership functions definition [33, 41, 42] towards increasing the diversity of fuzzy classifiers trained at each stage of fuzzy rule learning. Furthermore, we will develop new ways of diversity creation of rule-based classifiers that are trained based on Boolean logic in the case of the absence of continuous attributes. Moreover, we will look to apply the proposed rule learning approach in the context of multi-criteria decision making [46, 49, 50]. In addition, it is worth to conduct in-depth investigation of granular computing techniques [1, 3, 27, 30, 48] to achieve deep learning of fuzzy rules in a multi-granularity manner [24], according to the inspiration of deep neural networks [47].

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