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A multi-objective genetic optimization of interpretability-oriented fuzzy rule-based classifiers

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ABSTRACT

The paper presents a multi-objective genetic approach to design interpretability-oriented fuzzy rule-based classifiers from data. The proposed approach allows us to obtain systems with various levels of compromise between their accuracy and interpretability. During the learning process, parameters of the membership functions, as well as the structure of the classifier's fuzzy rule base (i.e., the number of rules, the number of rule antecedents, etc.) evolve simultaneously using a Pittsburgh-type genetic approach. Since there is no particular coding of fuzzy rule structures in a chromosome (it reduces computational complexity of the algorithm), original crossover and mutation operators, as well as chromosome-repairing technique to directly transform the rules are also proposed. To evaluate both the accuracy and interpretability of the system, two measures are used. The first one – an accuracy measure – is based on the root mean square error of the system's response. The second one – an interpretability measure – is based on the arithmetic mean of three components: (a) the average length of rules (the average number of antecedents used in the rules), (b) the number of active fuzzy sets and (c) the number of active inputs of the system (an active fuzzy set or input means a set or input used by at least one fuzzy rule). Both measures are used as objectives in multi-objective (2-objective in our case) genetic optimization approaches such as well-known SPEA2 and NSGA-II algorithms. Moreover, for the purpose of comparison with several alternative approaches, the experiments are carried out both considering the so-called strong fuzzy partitions (SFPs) of attribute domains and without them. SFPs provide more semantically meaningful solutions, usually at the expense of their accuracy. The operation of the proposed technique in various classification problems is tested with the use of 20 benchmark data sets and compared to 11 alternative classification techniques. The experiments show that the proposed approach generates classifiers of significantly improved interpretability, while still characterized by competitive accuracy.

1. Introduction

An automatic knowledge discovery from data with the use of linguistic fuzzy rule-based systems is currently a rapidly developing research area in the field of computational intelligence. The fundamental problem arising here is the construction of both accurate and interpretable (transparent) systems, i.e. the systems whose behavior is easy to understand and predict on the basis of their knowledge bases.

Effective optimization for the two criteria simultaneously is often impossible [1]. Accuracy-oriented modeling is usually carried out at the expense of transparency and vice versa. Therefore, the research focuses on techniques that determine the suboptimal solution which takes into account the compromise between accuracy and interpretability of the system. The presented paper lines up with this research trend.

The most significant aspect in the modeling process is the method of assessing the quality of a fuzzy system. This method has to comprise simultaneously both the accuracy and interpretability criteria. In particular, the selection of appropriate transparency measure has a significant impact on the performance of the automated knowledge discovery techniques from the data. The interpretability of the system can be considered in two aspects: the complexity and semantics of the system [2,3].

The complexity of the system structure can be expressed by: (a) the number of rules in the rule base, (b) the number of antecedents in the rules, (c) the number of inputs used in the rules (these are the criteria concerning the complexity of the rule base), and (d) the number of fuzzy sets per single input/output, (e) the number of parameters describing the membership function, (f) the number of types of membership functions used in the system (these are the criteria concerning the complexity of the database), etc. Depending upon research needs, the measure of system complexity can include these factors either simultaneously or selectively.

Semantics is expressed in the form of a set of requirements to be met by the system considered to be "interpretable". Thus: (a) the rule base should be consistent, i.e. not contain rules logically contradictory or repetitive, (b) the number of rules with a high degree of activation for a small number of samples of the input data should be as small as possible. On the other hand, the requirements for the collection

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of fuzzy sets are as follows: (a) clear and unambiguous meaning of the fuzzy set labels imaging actual properties of the modeled environment (distinguishability), (b) the correct ordering of location of the membership functions of fuzzy sets (fuzzy ordering) in the domain of input or output attribute (the location of centers of fuzzy membership functions, in order from "the smallest" to "the biggest", taking into account the linguistic relationships "less than", "greater than" between fuzzy sets), (c) the assignment of a given fuzzy set collection to the same input (output) in all rules (rules operate on a common collection of fuzzy sets), (d) complementarity of fuzzy sets (the sum of the values of all membership functions of fuzzy sets assigned to a given input/output calculated for any domain value should be close to unity), etc. More detailed information on interpretability and semantic issues is available, e.g., in [3–8].

In general, the development of universal measures directly assessing the complexity of the system or its semantics is very difficult. The evaluation of the complexity is subjective by nature and often depends on the individual properties of the modeled environment. The evaluation of semantics, for obvious reasons, seems to be even a greater challenge. Currently, the selection of a universal measure of the system transparency for the automation of the modeling process, is still an open issue [3].

In response to these problems, in this paper we apply a multi-objective genetic optimization approach to design interpretability-oriented fuzzy rule-based classification systems from data. The learning process of the system uses a Pittsburgh-type genetic approach [9], in which the parameters of fuzzy set membership functions and the structure of the system's fuzzy rule base evolve at the same time. The paper is a continuation and extension of our earlier research [10–13].

To evaluate both the accuracy and interpretability of the system two measures are used. The measures base upon the error of the system's response to the learning data (accuracy criterion) and the arithmetic mean of three components (interpretability criterion): (a) an average length of a fuzzy rule (in other words the average number of antecedents used in the rule), (b) the number of active fuzzy sets, and (c) the number of the system's active inputs (the active fuzzy set or the system's input is understood as the fuzzy set or the system's input used in at least one fuzzy rule). It is worth noting that unlike most alternative solutions, the proposed measure of interpretability does not directly include the number of rules in the rule base. Both measures are used as objectives in multi-objective (2-objective in our case) genetic optimization approaches such as well-known NSGA-II and SPEA2 algorithms. Moreover, for the purpose of comparison with several alternative approaches, the experiments are carried out with and without considering the so-called strong fuzzy partitions (SFPs) [14,15] of attribute domains. SFPs provide more semantically meaningful solutions, usually at the expense of their accuracy.

In the proposed approach there is no special coding of the fuzzy rule base structure in the chromosome, as is the case of most alternative learning techniques where the rules are represented in the form of binary strings (e.g. [16,17]), integer vectors (e.g. [18]) or are encoded by means of highly specialized schemes (e.g. [19]; more on this can be found in [20]). In our approach, the rules are processed directly and for this reason special genetic crossover and mutation operators are designed. Lack of rule encoding and decoding, reduces computational complexity of the algorithm (in comparison with other learning techniques). In addition, direct analysis of uncoded rules allows easy control of the system's semantics. The paper also proposes chromosome-repairing mechanisms, which support this task as well. In the literature, there are very few similar solutions (e.g. system GIL [21]).

The paper is organized as follows. Section 2 presents a brief review of related works, Section 3 – the components of the fuzzy classification rule base, Section 4 – the details of the proposed learning technique. Finally, in Section 5 the performance of our approach in various classification problems is tested with the use of 20 benchmark data sets and compared to 11 alternative classification techniques.

2. Related works

Most of the earliest publications dealing with the construction techniques of fuzzy rule-based systems from data, focused mainly on methods of obtaining systems with the greatest accuracy. Those methods generated systems with an excessive number of rules, and with a lot of antecedents in the rules. Some improvement of their transparency could be possibly carried out independently, after the completion of the fundamental stage of modeling. For this purpose techniques of the so-called pruning or removal of low active rules or single antecedents in the rules were applied. The number of rules (antecedents) was reduced by an expert, in a way not to significantly impair the accuracy of the system. Obviously, the expert's assessment in this respect was quite subjective. In the considered research area, several neuro-fuzzy approaches were proposed, e.g. [22–27] (see also [28,29] for an alternative approach to combine neural networks and fuzzy systems). Other ways of improving the transparency of the system were based, for example, on orthogonal transformation methods [30], the elimination of the antecedents in the rules by combining similar fuzzy sets (according to specified measures of similarity of fuzzy sets) [31–34] or by connecting compatible clusters of data [35]. A different approach was presented in [36,37], where firstly the systems of the highest possible transparency were obtained by means of data fuzzy clustering techniques and then they were optimized in terms of accuracy.

The above concepts of modeling – conducted in independent stages, directed separately at the accuracy and the transparency of the system – do not guarantee the optimal solution for the both criteria simultaneously. The answer to this problem was provided by researchers using multi-objective optimization methods (a brief review of selected approaches can be found in [38]), among which the methods using genetic algorithms were the most developed (see e.g. [39,20]), including those based on the Michigan [40,41] and Pittsburgh [9] approaches. In particular, the latter case has been commonly used. As mentioned in the introduction, a key and still open issue is the form of a fitness function that assesses the transparency and accuracy of the system at the same time. The next part of this chapter focuses on this aspect.

Initial proposals concerning the fitness functions were based on measures being the weighted sum of numerous components responsible for the accuracy or complexity of the system (a classic case of weighted objectives method, reducing multi-objective optimization task to the task of optimizing a single objective function). The examples are papers [42,43] in which the fitness function is the weighted sum of correct decisions (criterion of accuracy) and the number of rules (transparency criterion). In [44,45] the third component was added to the weighted sum – the number of antecedents in all rules. In [46] the weighted sum of the normalized number of correct decisions and the so-called penalty function were used. The value of the penalty function was dependent upon seven indices: the number of rules and antecedents in rules, the number of system's inputs and the number of linguistic variables describing the inputs, special measures of similarity of rules and fuzzy sets as well as the so-called incompleteness measure. Although these approaches allow to regulate the trade-off between transparency and accuracy of the system by changing the values of the weighting factors for each criterion, their important drawback is relatively large number of the weights and the lack of universal guidelines concerning their appropriate values (the range of acceptable values is often indefinite, and ranges are different for particular weights). Furthermore, the weights must be selected individually for each numerical experiment, which should also be considered as a drawback of these solutions.

A separate group are the Pareto-based multi-objective optimization methods [47–49], including the methods based on evolutionary algorithms (e.g. [50,51]). These methods determine the sub-optimal set of solutions (the approximation of the so-called Pareto front) with different levels of compromise between transparency and accuracy of the system. A typical approach – VEGA (Vector Evaluated Genetic Algorithm) – is based on the division of the population of chromosomes into k parts, where k is equal to the number of criteria. Chromosomes allocated to each part are evaluated using one of k fitness functions, from the point of view of one out of k criteria. The recombination of chromosomes involves the entire population, regardless of division boundaries. This approach has, however, a significant drawback – the tendency to leave out the intermediate solutions. In [52], FFGA (Fonseca's and Fleming's Multiobjective Genetic Algorithm) [53] was applied to model the system in terms of four criteria: the mean square error (accuracy criterion), and three measures (transparency criteria) representing both the complexity of the system and its semantics: the completeness and the distinguishability of fuzzy sets expressed through fuzzy similarity measure, the non-redundancy of fuzzy rules by means of non-redundancy measure as well as the compactness of