Various Rule Pruning Techniques and Accuracy measures for Fuzzy rules

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Abstract
Interpretability is the most desired property for any knowledge based systems. The Fuzzy logic systems are well known for their interpretable results, due to use of linguistic variables. However it has been observed that the fuzzy systems produce a large rule set, thus affecting the interpretability of the system. Also the generated rule base is complex, thus making the overall inference system complex. Many rule pruning techniques have being found by researchers. The main aim of this paper is to make a comparative study of all the techniques for rule pruning. The different accuracy measures used for rating a rule is also studied and compared here.

Keywords: Fuzzy logic, fuzzy rule, rule pruning, interpretability

1. INTRODUCTION
The fuzzy logic systems are used for applications that have high level of human interaction like taking decisions etc, and also used for applications that require interpretable outputs. The plus points of Fuzzy systems are that, it is capable to represent the uncertainties of the human knowledge using linguistic variables. Also it provides simple interaction of the domain expert with the engineer designer of the system. Because of the natural rules representation, the results are easily interpretable. Apart from this the extension of the knowledge base through addition of new rules is possible. However the drawback of fuzzy inference systems is that it depends on the expert knowledge to generate the rules; it is incapable to generalize the concept provided- that is it only answers to what is written in its rule base; it is not robust in relation the topological changes of the system as such changes would demand alterations in the original rule base; and it depends on the expert’s existence to determine the inference logical rules, thus making system more complex.

Rule pruning tends to simplify the rule base. The rules generated can be simplified in number of ways: removing redundant rule, shortening the rule and merging the rules. This way the rules can be simplified thus increasing the interpretability of system.

Study of various rule pruning methods depict that there is a trade-off between the accuracy and the interpretability. Interpretability can be characterized by reduced rule base, simplified rule set, interpretable fuzzy partitions, use of linguistic variables, etc. Various researchers have worked in this field to develop an efficient rule pruning technique. In this paper a comparative study of all such rule pruning techniques is done.

2. FUZZY RULES
The fuzzy inference system is used to classify/predict the patterns. The input variables are firstly fuzzified and the fuzzy rules are poured into the system to classify/predict the data. The pre-knowledge of the rules is required in fuzzy inference system. So thus the less the number of rules, the simpler would be the classification/prediction. The fuzzy rule consists of two parts: A premise/antecedents and result/consequents. The premise may be further made up of partial premises. A sample fuzzy rule is given in figure 2.1. The fuzzy rules can be classified in to two: Simple rule and Compound rule. Simple rule just consists of one antecedent and one consequent. Eg. If weight is heavy then person is healthy. Compound rule consists of more than one antecedent. Eg. If weight is heavy and height is tall then person is healthy.

![Figure2.5: A sample compound fuzzy rule](image)

Here in, the various methods studied, for rule base simplification deals with these antecedents and consequents. The rules are categorized as inconsistent rules if the have same antecedents and different consequents. The rules having similar antecedents and consequents are called identical rules. The rules not used for classifying any single record are considered as redundant rules. The two rules having difference of just one or two antecedent values and rest all other antecedents and the result are same and if the different antecedents can be combined to one resultant antecedent and resultant value are
called candidate rules for merging. In rule pruning process the rules capable of merging are merged and the identical, redundant and inconsistent rules are pruned away, thus simplifying the rule base to increase the interpretability.

3. RULE SIMPLIFICATION METHODS

Researchers have being working since long time to increase the interpretability of fuzzy logic systems by simplifying the rule base. The study of various techniques presented in different papers reveals that the basics of rule simplification were same in all the techniques adopted by researchers. However the only thing that was different was the rule rating technique. Different researchers used different accuracy measures to rate a rule for finding its significance level in the classification. Less significant rules or rule’s antecedents can be pruned. The various methods adopted by researchers for rule pruning are presented in the subsection below.

3.1 Method1

The paper [1] presents the way by which a rule weight of each fuzzy rule can be specified in fuzzy rule-based classification systems. Each fuzzy rule in can be viewed as a fuzzy association rule. The confidence can be defined as measuring the validity of the fuzzy rule. The support can be defined as measuring the coverage of training patterns. The confidence was used as the rule weight of the fuzzy rule. The different variations to the calculation of rule weights are presented in this paper. Based on this rule weight rules significance level can be sensed, and thereby less significant rules or antecedents can be pruned.

3.2 Method2

The paper [2] presents the rule induction and simultaneous rule pruning technique where the examples covered by a rule are just marked instead of being removed as compared to other methods. This leads to a higher level of overlapping as compared to the other covering algorithms because all the examples continue to be used for the purpose of calculating both the accuracy as well as the score of each newly formed rule. As a solution a new specialization heuristic was attempted, which integrates the “New Classified” information of the rule into the evaluation function. The proposed heuristic reduced the average number of rules by 16.83 percent while maintaining the classification accuracy for the 15 data sets tested. However the method is designed to work for noisy data.

3.3 Method3

The paper [3] gives a rule-base self-extraction and simplification method. It is proposed to establish interpretable fuzzy models from numerical data. A fuzzy clustering technique along with the proposed fuzzy partition validity index is used to extract the initial fuzzy rule-base and find out the optimal number of fuzzy rules. Some approximate similarity measures are presented and a parameter fine-tuning mechanism is introduced to improve the accuracy of the simplified model, in order to reduce the complexity of fuzzy models while keeping good model accuracy. The redundant fuzzy rules are removed and similar fuzzy sets are merged to create a common fuzzy set in the rule base by using the similarity measures. The simplified rule base is computationally efficient and linguistically interpretable. But incorporation of a priori physically-based linguistic information into the modeling procedure and the improvement in the model optimization would be beneficial.

3.4 Method4

In the theses [4], the rule shortening procedure is presented, that one by one takes each rule and checks the accuracy of the rule by one by one removing the descriptors of the rules. If the new accuracy more than old value then the descriptor is removed from the rule thus shortening it. Again the rule generalization method is presented that generates the attribute of new generalized rule by taking the intersection of the attribute sets of both rules. The value of attribute is calculated by taking the sum of the corresponding values sets. The input rules are sorted as per the length of the rule, in terms of descending lengths. Another approach called rule group generalization is presented wherein; the group is formed of all the rules whose attributes sets are subsets of the seed rule attribute. Then after the group is generalized by generalizing the descriptors of the rules in the group one at a time.

Performed tests show that tuned classifiers consist of a lower number of more general rules, which increases their legibility with little loss of accuracy. Moreover, the results obtained encouraged the use of different rule tuning methods to find a transformation that not only results in a reduction of the model's size, but also increases its classification ability.

3.5 Method5

In the paper [5] a novel approach to rule representation and simplification is given. Fingrams shows the graphical interaction between rules at the inference level in terms of co-fired rules. Analysis of fingrams lets one to: measure the comprehensibility of fuzzy systems, detect redundancies and/or inconsistencies among fuzzy rules, identify the most significant rules, etc. The rules form the nodes of graph and the distance between the two nodes depict the relation between two rules. The large sized nodes are ones, used frequently. The nodes at the periphery of graph are the least used rules. To retain the most significant rules pathfinder algorithm is used to prune the graph.

3.6 Method6

The rule simplification process presented in the paper [6] is shown in figure 3.1. It consists of four steps. The simplify rule base steps deals with removing the identical rules, removing the most specific rules and retaining the generalized rules. The Merge rules step deals with merging of the rules having the same consequences, and whose premises when
merged attains higher accuracy. The force rule removal step deals with the removal of the rule that is not used or least used. In the force premise removal, for each rule, it begins by removing premises related to those inputs less used in the rule base.

Therefore, a new ordering of the rule base (rules and premises) according to these criteria is needed. First, rules are ordered by number of premises. Second, input variables are ranked regarding the number of times they are used in the rule base. The proposed approach leads not only to a good balance between accuracy and interpretability but also to a simultaneous improvement of both in some cases.

4. COMPARISON
The study carried out on various rule pruning techniques reveals that the basic fundamental of all the methods is same, i.e. all methods provide rank to the rule in some or the other way, and then prune the less significant rule. Just the thing that differs is the rule ranking methodology. The comparison of the studied rule pruning methods is given in table 4.1 below.

![Figure 3.1: Rule simplification process [6]](image)

<table>
<thead>
<tr>
<th>Papers</th>
<th>Remarks</th>
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<tbody>
<tr>
<td>[1]</td>
<td>Fuzzy rules are treated as association rules. Based on the confidence, rules are ranked.</td>
</tr>
<tr>
<td>[3]</td>
<td>Lacks optimization and linguistic information in modeling procedure.</td>
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<tr>
<td>[5]</td>
<td>Deals with co-fired rules. Represents rule base through graph. Shows which rules can be simplified based on the number of instances (+ve or -ve) it is used in.</td>
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<tr>
<td>[6]</td>
<td>Rule simplification method with accurate and interpretable results is given.</td>
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5. CONCLUSION
The study on the different rule tuning methods available so far for fuzzy rules was successfully carried out and useful derivations were derived. Most of the researchers have remarked the trade-off between the accuracy and interpretability. However one author of paper [6] has claimed to attain interpretability without affecting accuracy.

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References

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