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Using Fuzzy Algorithms for Modular Rules Induction

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***Abstract* – The goal of this research is to explore and compare two fuzzy algorithms that extract modular IF-THEN rules – Fuzzy PRISM and Fuzzy AQR learning strategy. The article describes the historical need for algorithms obtained in a different induction process – it points out the weak spots of ID3 algorithm and the necessity for improvements. PRISM algorithm is proposed as an improvement to ID3 algorithm changing its principal induction strategy. Both algorithms examined in this article are modifications of PRISM algorithm. This paper provides step-by-step descriptions of both algorithms, a comparison of the results acquired by both algorithms in working with real data as well as conclusions and directions of future research.**

***Keywords* – fuzzy IF – THEN rules, modular rules, MPG data, FAQR**

I. Introduction

In 1979 Ross Quinlan published his research (Quinlan [1]) about ID3 algorithm (Dunham [2]), starting an extensive use of decision trees in classification and taking the first place in a research (Wu et al. [3]) about ten most popular data mining algorithms. Initially ID3 was used to describe chess game but soon this algorithm was fitted for various fields. The extraction of classification rules from decision trees is a widely used technique. But also this approach has its deficiencies – acquired classification rules do not always match the initial training data. The main shortcoming of ID3 is its inability to handle noise in input data, which leads to ever new improved versions of ID3. Scientists have put forward a hypothesis that the visualization of ID3 results using decision tree is the main defect of this algorithm and it can be perfected by radically changing the principal induction strategy. Therefore some algorithms have been proposed that induce modular classification rules directly from the training set without the use of decision trees (Cendrowska [4]).

In 1987 Jadzia Cendrowska publishes her research about algorithm PRISM that describes results as modular rules although it is based on ID3 algorithm (Cendrowska [4]). The main goal of the algorithm is to acquire classification rules directly from the training data set. To use a data set with PRISM algorithm, it has to meet the following criteria: *classification is mutually exclusive* (there are no records with equal values and different classes); *there is no noise*, that is, every record is complete and correct; *every record can be uniquely classified*; *there are no duplicate values*; *the training set is complete*, i.e., there are all possible combinations for pairs of attribute values; *data is categorical* (if the data are continuous then they are categorized). Both methods inspected in this article – Fuzzy PRISM (Wang et al. [5]) and Fuzzy AQR learning strategy (Wang et al. [6]) are based on PRISM algorithm by (Cendrowska[4]).

The remainder of the paper is organized as follows. Section II examines both methods used in the research – Fuzzy PRISM and Fuzzy inductive learning strategy. Section III describes the data used in experiments. Section IV discusses conducted experiments and their results. The last section gives conclusions about capabilities of the algorithms and the aspects of their working process as well as outlines directions of future research.

II. Methods

This section describes both studied algorithms - Fuzzy Prism and Fuzzy AQR learning strategy step by step. This gives an idea about induction process of each algorithm that provides rules.

A. Fuzzy PRISM

The fuzzy inductive algorithm for learning modular rules consists of eight steps. Next we will describe the algorithm in detail. If the training set contains instances of more than one class, then for each classification δ_k :

1. Initiate a complex $\tilde{C}$ or initial rule set, which is filled with zero values that are replaced with the established rules in the course of the algorithm execution.
2. Measure the fuzzy information gain, $I(\delta_k \mid s_i)$, of the classification δ_k for each possible selector s_i from the training set:

$$I(\delta_k \mid S_i) = \log_2\left(\frac{H(\delta_k \mid S_i)}{H(\delta_k)}\right) = \log_2(H(\delta_k \mid S_i)) - \log_2(H(\delta_k)), \tag{1}$$

where

$H(\delta_k)$ antecedent fuzzy information;

$H(\delta_k \mid S_i)$ subsequent fuzzy information defined as follows:

$$H(\delta_k \mid S_i) = \frac{\sum_{j=1}^{n} u_{\delta k}(e_j)\,\tau u_{si}(e_j)}{\sum_{j=1}^{n} u_{si}(e_j)}, \quad H(\delta_k) = \frac{1}{n}\sum_{j=1}^{n} u_{\delta k}(e_j), \tag{2}$$

where

n is the size of the training set;

e_j is the j -the instance in the training set;

$u_{\delta k}(e_j)$ is the class membership value specifying to whatdegree instance e_j belongs to event δ_k .

3. Choose a selector s_i for which $I(\delta_k \mid s_i)$ is maximum.
4. Add selector s_i to $\tilde{C}$ and calculate $B(\delta_k \mid \tilde{C})$ which is defined as follows:

$$B(\delta_k \mid \tilde{C}) = \frac{\sum_{j=1}^{n} u_{\tilde{C}}(e_j) \tau u_{\delta k i}(e_j)}{\sum_{j=1}^{n} u_{\tilde{C}}(e_j)},$$

where

$\tilde{C}$ - condition of the induced rule;

δ_k - conclusion of the induced rule.

5. If $B(\delta_k \mid \tilde{C})$ is above the predefined truth level β , then execute Step 6; otherwise, create a new training set in which each instance is $\alpha - covered$ by the selector s_i , and go to Step 2.
6. Form the rule „IF $\tilde{C}$ THEN δ_k ".
7. Remove all instances $\alpha - covered$ by the rule „IF $\tilde{C}$ THEN δ_k " from the original training set.
8. Repeat Step 1 to Step 7 until all instances α-*belonging* to class δ_k in the original training set have been removed.

When the rules for one classification have been induced, the training set is restored to its initial state and the algorithm is applied again to induce a set of rules covering the next classification (Wang et al.[5]).

B. Fuzzy AQR Learning strategy

Input data – fuzzy positive and negative records. Output data – a fuzzy description $\tilde{R}$ that $\alpha - covers$ almost all positive records in the $\tilde{P}_\beta$ set and almost none of the negative records in $\tilde{N}_\beta$.

Then the fuzzy training algorithm AQR is described step-by-step to assess its capabilities:

Step 1. The initial empty set $\tilde{R}$ is introduced.

Step 2. The following steps of the algorithm should be taken until $\tilde{R}$ $\alpha - cover$ all positive records from training set $\tilde{P}_\beta$ (where $\exists \tilde{e} \in \tilde{P}_\beta, \tilde{e} \tilde{\not\subset}_\alpha \tilde{R}$) with rules. When all records are covered, the algorithm stops and returns the calculated value of $\tilde{R}$.

Step 3. Choose SEED that is a positive record which is not $\alpha -$covered by $\tilde{R}$ and that has the highest $U_{\tilde{P}}(\tilde{e})$ of all positive records.

Step 4. Return to procedure GEN_COMPLEX to obtain $\tilde{C}_{set}$, which is a set of complexes that $\alpha - cover$ SEED and $\alpha - cover$ no negative records $\tilde{N}_\beta$ (where $\forall \tilde{C}_i \in \tilde{C}_{set}, \forall \tilde{e} \in \tilde{N}_\beta, SEED \tilde{\subset}_\alpha \tilde{C}_i \ \& \tilde{e} \tilde{\not\subset}_\alpha \tilde{C}_i$).

Step 5. Choose a complex $\tilde{C}_{best}$, which has the highest $U_{\tilde{\forall}+\tilde{\forall}-}$ values in the set $\tilde{C}_{set}$.

Step 6. Add $\tilde{C}_{best}$ as an addition disjunction to $\tilde{R}$ (where $\tilde{R} = \tilde{R} \vee \tilde{C}_{best}$) and then go to Step 2.

Next, a step-by-step description of procedure GEN_COMPLEX is given; as a result of this procedure the $\tilde{C}_{set}$ is acquired.

Step 1. $\tilde{C}_{set}$ is assumed to be a set of simple selectors that $\alpha - cover$ SEED.

Step 2. Until at least one complex $\tilde{C}_{set}$ $\alpha - covers$ negative records $\tilde{N}_\beta$ (where $\exists \tilde{C}_j \in \tilde{C}_{set}, \exists \tilde{e} \in \tilde{N}_\beta, \tilde{e} \tilde{\subset}_\alpha \tilde{C}_j$) continue with the following steps.

Step 3. Choose the $\tilde{C}_j$ with the least $U_{exclude}(\tilde{C}_j)$ value in the set $\tilde{C}_{set}$.

Step 4. Choose negative instance $\tilde{e}$, which has the highest possible $U_{\tilde{N}}(\tilde{e})$ among those $\alpha - covered$ by $\tilde{C}_j$.

Step 5. Specialize all complexes in the $\tilde{C}_{set}$ data set to $\alpha - not\ cover$ negative records $\tilde{e}$ using the following sub-steps:

a) Let $\tilde{S}$ be a data selector set that $\alpha - cover$ SEED, but does not cover $\tilde{e}$.

b) Let $\tilde{C}_{set}$ be a data set $\{\tilde{C}_j \wedge \tilde{S}_k \mid \tilde{C}_j \in old\ \tilde{C}_{set}, \tilde{S}_k \in \tilde{S}\}$.

c) All complexes that are included in other complexes are removed from $\tilde{C}_{set}$ (if $\tilde{C}i$ is included in $\tilde{C}_j$ and $U_{\tilde{\forall}-\forall-(\tilde{C}_i)} \geq U_{\tilde{\forall}+\forall-(\tilde{C}_j)}$ then remove $\tilde{C}_j$ from $\tilde{C}_{set}$).

Step 6. Remove the worst complexes from $\tilde{C}_{set}$ until size $\tilde{C}_{set} \leq \theta$ - level defined by user (Wang et al. [6]).

III. USED DATA SET

Miles per gallon data set is also frequently used in solving classification tasks. When an algorithm is applied to each record (car), it is necessary to identify its membership class to good or bad fuel economy, i.e. determine whether a car is fuel-efficient or it is not. Another thing to examine is miles traveled using one gallon of fuel.

TABLE I
DATA SET DESCRIPTION

Number of records:	398	**Number of attributes:**	**9**	**Attribute name**	**Value**
Missing values?	Yes			Miles per gallon	Numeric value
Number of records used in research:	392			Cylinders	Predefined categorical value
Field:	Nature			Displacement	Numeric value
Attribute data:	Real			Horsepower	Numeric value
Data added:	07.07.1993.			Weight	Numeric value
Class	L - (good)[1]			Acceleration	Numeric value
Class	S - (bad)[2]			Model Year	Finitecategorical value
[1] - 22 and more miles per gallon [2] - 21 and less miles per gallon				Origin	Finitecategorical value
				Name	String of symbols, unique for each record

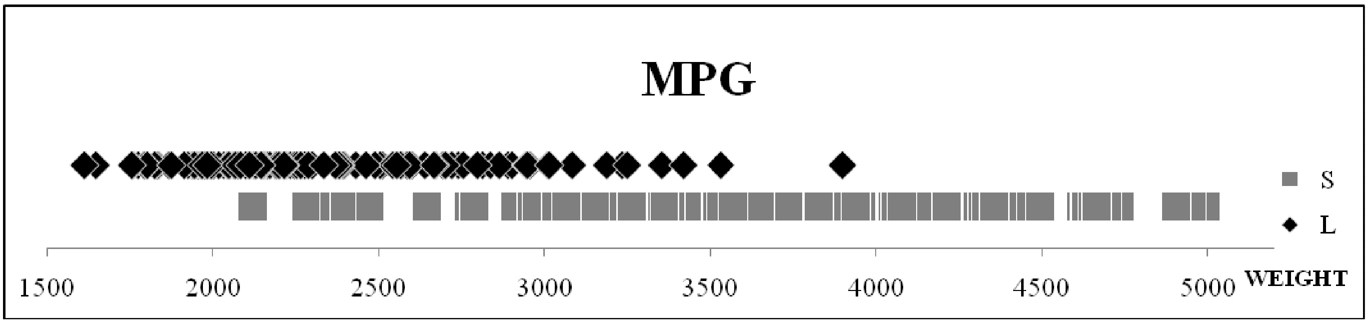

Fig. 1. Miles per gallon data set

Analogical measure in Latvia would bethe amount of fuel (in liters) that is needed to travel 100 kilometers. The original data set does not contain separate class labels but a number is given that represents the number of miles traveled using one gallon of fuel. Fuel consumption when travelling 100 km was calculated using data conversion tool.

As a result, two classes were identified – L for good fuel consumption level that is 22 miles per gallon and more (10 liters per 100 km and less) and S for bad fuel consumption level meaning 21 miles per gallon and less (11 liters per 100 km and more). A detaileddescription of this data set is given in Table 1.

Researches that were done previously (Gasparovica et al. [8], [9]) give a more thorough inspection of the MPG data set and determine the most relevant attribute in this set – the Weight attribute. The depiction of the data set according to this relevant attribute can be seen in Fig.1,which shows that in this resolution both classes significantly overlap and fuzzy techniques that can process fuzzy data are required to work with such data.

IV. PRACTICAL EXPERIMENTS

This section describes the experiments performed and their results as well as provides conclusions about capabilities of both algorithms working with the type of data that have one relevant attribute as Miles per gallon.

A. Fuzzy PRISM

All experiments carried out using this algorithm are summarized in Table II. It shows that the experiments can be divided into two groups based on the number of intervals the attribute was split into. Many experiments were conducted using the data set that has the attribute split into two intervals to determine the changes in results that arise from changing the parameter β, which is the truth level defined by user, and that is compared to fitnessof a rule. Experiments that used 342 records for training and 50 records for testing were carried out with the following β values –0.95;0.9;0.8;07. When comparing the results one can see that the best result was obtained when β =0.9 resulting in 0.54 accuracy.

The next experiments were conducted using a slightly different split into training and test sets – accordingly 277 and 117. Two experiments were conducted dividing each attribute into two intervals and two using the attributes divided into up to six intervals. The best result 0.33 for two intervals was achieved with $\beta = 0.8$, which of course is not a good result for classification. Therefore, each attribute was divided even more – into three to six intervals. As can be seen from the results, the performance was improved significantly reaching 0.918 in three-fold cross-validation, which is considerably higher than the previous accuracy 0.54 that was achieved using the data set with all attributes split into two intervals.

TABLE II

FUZZY PRISM ALGORITHM WITH MPG DATA

Intervals	**α**	**β**	**Training set**	**Testing set**	**Incorrectly classified examples**	**Not classified at all**	**Correctly classified examples**	**Accuracy**	**Comments**
Two	0.5	0.95	342	50	8	24	18	0.360	
	0.5	0.9	342	50	13	3	27	0.540	Using importance
	0.5	0.8	342	50	21	3	26	0.520	Using importance
	0.5	0.7	342	50	22	3	25	0.500	Using importance
	0.5	0.9	277	117	16	77	24	0.205	
	0.5	0.8	277	117	33	46	39	0.333	
Five	0.5	0.7	277	117	11	0	106	0.906	
	0.5	0.7	262(260)	130(132)	8	0	122	0.918	Three – fold cross validation

The overall conclusion is that although this method allows choosing various levels of β, its value should not be less than 0.7 because it would decrease validityof a rule and the accuracy would suffer from several rules classifying the same record, resulting in additional classification work to determine the rule whose classification is more important

B. Fuzzy AQR Learning strategy

This strategy has four different parameters whose values can affect the result – $\alpha, \beta, \theta, \gamma$. All results from the experiments using this strategy are summarized in Table III.

TABLE III

FUZZY AQR LEARNING STRATEGY WITH MPG DATA

α	**β**	**θ**	**γ**	**Train-ing**	**Test**	**In-correct**	**Correct**	**Accuracy**
0.5	0.5	5	5	50	344	38	306	0.890
0.4	0.5	5	5	50	344	39	305	0.887
0.6	0.5	5	5	50	344	45	299	0.869
0.7	0.5	5	5	50	344	54	290	0.843
0.5	0.4	5	5	50	344	38	306	0.890
0.5	0.6	5	5	50	344	38	306	0.890
0.5	0.7	5	5	50	344	38	306	0.890
0.5	0.5	4	5	50	344	38	306	0.890
0.5	0.5	6	5	50	344	38	306	0.890
0.5	0.5	5	4	50	344	38	306	0.890
0.5	0.5	5	6	50	344	38	306	0.890
0.5	0.5	5	5	60	334	38	296	0.886
0.5	0.5	5	5	70	324	36	288	0.889
0.5	0.5	5	5	100	294	31	294	0.905
0.5	0.5	5	5	150	245	138	107	0.437
0.5	0.5	5	5	200	195	28	167	0.856
0.5	0.5	5	5	277	117	15	103	0.873
0.5	0.5	5	5	300	95	5	90	0.947

They can be divided into five groups. The experiments of the first group examine the influence of parameter α values on results; experiments were performed using values 0.4, 0.5, 0.6, and 0.7. The best result was achieved using value 0.5 making it the best choice for further experiments.

The second group inspects various values of coefficient β showing that changing this coefficient does not influence the end result; further experiments used β value 0.5.

The third and the fourth groups of experiments examine changes in values of coefficients θ, γ and their effect on accuracy. Such effect was not observed, therefore values of these coefficients were left unchanged, i.e. equal to 5.

The fifth group includes experiments with different sizes of training and test sets beginning with 50 records for training and ending with 300. The obtained results are adequate; the only surprise is that the classification accuracy with 150 records for training was so low – 0.437. It could be explained by many complicated records falling into test set not allowing the classifier to learn how to classify them. The best result of this group of experiments was achieved using 300 records for training leaving 95 for testing, 5 of which were misclassified, making the overall accuracy so high – 0.947.

V. CONCLUSIONS

In this work a data set for experiments was found – the Miles per Gallon data set; it was analyzed in detail so as to determine its structure and composition and to predict possible problems (overlapping in some intervals). It describes working principles of each algorithm step-by-step. Voluminous comparative experiments were carried out using both algorithms.

As a result, one can conclude that FAQR shows higher accuracy results than Fuzzy PRISM in the case of two classes and two intervals for each attribute. Therefore, to improve the results, the initial attributes were divided into narrower intervals,which can be seen in the lower part of the Table I, where the split into up to five intervals gives a significant increase in accuracy.

But for such a complex data set as MPG is, where values in different intervals overlap a lot, the best results are achieved using FAQR algorithm, although its computation time is a lot higher than that of Fuzzy PRISM algorithm, where calculations are made in a second, whereas FAQR needs up to half a minute for calculations. Thus, the requirements for computational resources and possibilities of using the algorithms in a specific area should be taken into account.

VI. Future research

Directions for future research are related to using other data in work with both explored algorithms. This would allow testing and defining capabilities of the algorithms and their specific features that can emerge when they are applied to different data sets. Experiments using bioinformatics data sets are planned; the data sets are very complex because they hold a large number of attributes and a small number of records at the same time, complicating the classification process (Golub et al. [10]).

Investigation of related methods that are able to classify fuzzy data can also be included in future research.

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Madara Gasparoviča, Ludmila Aleksejeva.Izplūdušo algoritmu pielietošanamodulāro likumu iegūšanā
Šī darba mērķis ir izpētīt un salīdzināt divus izplūdušos algoritmus, kas iegūst modulāros JA – TAD likumus – Izplūdušais PRISM and Izplūdušais induktīvās apmācības algoritms. Darbā aprakstīta arī vēsturiskā nepieciešamība pēc citādākā indukcijas procesā iegūtiem algoritmiem – aprakstītas ID3 algoritma vājās vietas un nepieciešamība pēc uzlabojumiem - PRISM algoritms tiek piedāvāts kā ID3 algoritma uzlabojums, mainot pamata indukcijas stratēģiju. Abi šajā darbā aprakstītie algoritmi ir PRISM algoritma modifikācijas. Šajā darbā dots abu algoritmu apraksts, pa soļiem, aprakstīta darbā izmantojamā MPG (Nobrauktās jūdzes ar galonu benzīna) datu kopa. Veikti eksperimenti ar abiem algoritmiem un salīdzināti to iegūtie rezultāti darbā ar MPG datu kopu.Veikti padziļināti pētījumi par dažādo lietotāja koeficientu izmaiņu ietekmi uz gala rezultātu. Secināts, ka vismaz MPG datu kopai vērā ņemamu rezultāta uzlabojumu dod tikai viena koeficienta – β izmaiņas. Rezultātā redzams, ka FAQR uzrāda augstākas precizitātes rezultātu, nekā Fuzzy PRISM divu klāšu un divu intervālu gadījumā. Tāpēc, lai uzlabotu rezultātu, sākotnējie atribūti jādala lielākā skaitā intervālu. Tomēr šādai sarežģītai datu kopai, kā MPG, kur vērtības dažos intervālos ir diezgan pārklājošas, tomēr labākus rezultātus uzrāda FAQR, lai gan arī skaitļošanas laiks krietni lielāks, kā Fuzzy PRISM algoritmam, kur aprēķini notiek sekundes laikā, turpretī FAQR rēķina līdz par pus minūtei. Tādējādi, jāņem vērā arī algoritmu ātrdarbība un iespējas tos pielietot konkrētai problēmsfērai. Izdarīti secinājumi un doti nākamie iespējamie pētījumu attīstības virzieni.

Мадара Гаспаровича, Людмила Алексеева. Применение нечётких алгоритмов для вывода модульных правил
Целью данной работы является исследование и сравнение двух нечётких алгоритмов, позволяющих получать модульные правила "Если ... то": нечёткого алгоритма PRISM и нечёткого алгоритма индуктивного обучения AQR. В работе описана исторически обоснованная потребность в другом подходе к процессу индукции – определены слабые стороны алгоритма ID3 и требования по его улучшению. Алгоритм предложен как усовершенствование алгоритма ID3 путём принципиального изменения стратегии индукции. Оба алгоритма являются модификациями алгоритма PRISM. Дана характеристика алгоритмов и описание их действий по шагам, а также описание множества данных MPG (расстояние в милях на галлон). Проведены эксперименты с обоими алгоритмами и сравнены результаты, полученные на множестве данных MPG. Выполнены дополнительные исследования по выявлению влияния изменений пользователем различных коэффициентов на конечный результат. Констатировано, что, по крайней мере для множества данных MPG, существенное улучшение результатов дает изменение только одного коэффициента β. В результате доказано, что в случае двух классов и двух интервалов нечёткий алгоритм AQR дает более точный результат, чем нечёткий алгоритм PRISM. Поэтому для улучшения результата исходные атрибуты необходимо разделять на большее число интервалов. Однако для столь сложного множества данных, как MPG, где оценки в различных интервалах в значительной степени перекрываются, лучшие результаты дает все-таки нечёткий алгоритм AQR, несмотря на то, что время вычисления значительно больше (до полуминуты), чем у нечёткого алгоритма PRISM, где расчеты выполняются в течение секунды. Таким образом, при подборе алгоритма следует учитывать их быстродействие и возможность применения в конкретной проблемной области. Сформулированы выводы, рекомендации и возможные направления дальнейших исследований.