A Fuzzy Classification System for Prediction of the Results of the Basketball Games

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Abstract— **Prediction of the sports game results is an interesting topic that has gained attention lately. Mostly there are used stochastical methods of uncertainty description. In this work it is presented a preliminary approach to build a fuzzy model to basketball game results prediction. Ten fuzzy rule learning algorithms are selected, conducted and compared against standard linear regression with use of the KEEL system. Feature selection algorithms are applied and a majority voting is used in order to select the most representative features.**

I. Introduction

For many years gambling has been a part of human life. It has attracted many people as it offers a chance to get wealthy in a very short time. One of the main fields of gambling is a sports betting, what in many countries is absolutely legal nowadays. It is defined as "the general activity of predicting sports results by making a wager on the outcome of a sporting event." [1]. There are several types of bets. In sports such as basketball or American football betting on the point spread is very typical. In such case not only the result is important, but the difference of the points scored by the teams. Up to my knowledge there is no system for doing so. In this work, I would like to make a trial to anticipate this phenomenon, that is to build a system for a prediction of the result of the sport game. In this first approximation, I will restrict the scenario to the determination of the team wining the game (that is, no information on the score will be considered). Thus, the system will provide as an output information about which of the two teams will win the game, so the area of the problem will be reduced to binary classification. To do so, there will be used several fuzzy rule-based classification systems.

A motivation behind using fuzzy rules is following. They are a generalization of the standard crisp rules and the "soft" decision boundaries are the main advantage of the fuzzy rules over the crisp ones, which define only two possible options "full" (among the rule) and "zero" (everywhere outside of the rule). Thus, such boundaries provide a "sharp" transition between classes. Furthermore, those "soft boundaries" could become a crisp ones if it is needed. Finally, the use of the aggregation operators makes the boundaries of fuzzy rules not always axis-parallel, thus increases their flexibility.

The area of the problem will be reduced to the basketball games only, due to my previous experience with that sport and due to the high complexity of the problem.

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This paper is set up as follows. In the next section all objectives and assumptions will be described. Sec. III briefly introduces fuzzy logic and sports game results prediction literature is reviewed. In Sec. IV feature selection algorithms and fuzzy rule learning approaches are presented. Sec. V shows experiments conducted and their analysis. Finally, in Sec. VI collects some concluding remarks and future research lines.

II. Objectives and Assumptions

The objective of this work is to build a fuzzy rule-based system (FRBS) to predict results of the basketball games from the ACB (Asociación de Clubes de Baloncesto) league. Due to the complexity of the problem several techniques to automatically generate FRBS were used i.e. ad-hoc data-driven models and genetic fuzzy systems (GFS). While the first group is based on learning the system behaviour from the input-output dataset resulting in fast, however not always precise models, the second group treats learning of a fuzzy system, precisely parameters of that system, as an optimization problem and uses a genetic algorithm (GA) to proceed that task.

The system modeling process is divided into three parts. First step encloses a data retrieval, that is obtaining a data and from it all necessary/significant attributes. The next move is a data preprocessing, which includes missing values handling, feature selection, and data scaling. The last step is to run selected learning algorithms in order to learn models.

In this work, there are used two well-known data mining system WEKA [2], [3] and KEEL [4]. The first one is used to provide a feature selection and the latter one to run the main part of experiment, that is to learn fuzzy models.

III. Preliminaries

This section introduces fuzzy logic, fuzzy systems, and explores the current literature related to sports game results prediction.

A. Fuzzy Systems

Fuzzy systems in engineering, based on fuzzy logic introduced by Zadeh [5], [6], have their origin in seventies when Mamdami [7], [8] provided a first fuzzy controller. Since then, fuzzy systems have gained acceptance in many fields, among others in control and automation, pattern recognition, medical diagnosis and forecasting. The fuzzy systems developed are mostly treated as black boxes, therefore an analytical theory for fuzzy systems is needed to eliminate the misunderstanding and controversy. An important role is

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played by investigation and optimization of fuzzy models created and comparative analysis of different approaches [9], [10], [11].

B. Sports game results prediction

Systems for the sports game results prediction have been developed for many years. Most of them were invented with intention to serve rather in a commercial area than for educational purposes. We may find some publications regarding that topic in the literature, though. Most of those systems use stochastical methods of uncertainty description: regressive and autoregressive analysis, Bayessian networks combined with Markov chains and method MonteCarlo [12], [13], [14], [15], [16]. Machine learning techniques, however not for a wide scale, have been also applied to sports (football) results prediction. Tsakonas et al. [17] investigated fuzzy models, neural networks (NN) and genetic programming (GP) separately. In conclusion GP obtained better results than the other two ones and the fuzzy system outperformed NN. However, the results were ambiguous. Rotshtein et al. [18] used fuzzy model with genetic and neural optimization technique combination. That approach obtained accurate results.

Up to my knowledge, there was not developed any system to the basketball games prediction based on fuzzy logic. In this work I would like to build a fuzzy system providing correct results of the basketball games.

IV. Algorithms used in the experiment

The next subsections will respectively provide a brief description of feature selection techniques and fuzzy system generation algorithms.

A. Feature Selection

For the feature selection WEKA (Waikato Environment for Knowledge Analysis) have been used, a non-commercial and open-source data mining system [2], [3]. WEKA contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes. The eight following algorithms for feature selection process were selected.

- CfsSubsetEval [19] - It evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them.
- ChiSquaredAttributeEval [20] - It evaluates the worth of an attribute by computing the value of the chi-squared statistic with respect to the class.
- ConsistencySubsetEval [21] - It evaluates the worth of a subset of attributes by the level of consistency in the class values when the training instances are projected onto the subset of attributes.
- GainRatioAttributeEval [19] - It evaluates the worth of an attribute by measuring the gain ratio with respect to the class.
- OneRAttributeEval [22] - It evaluates the worth of an attribute by using the OneR classifier.
- ReliefFAttributeEval [19], [23] - It evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class.
- SVMAttributeEval [24] - It evaluates the worth of an attribute by using an SVM classifier.
- SymmetricalUncertAttributeEval [19] - It evaluates the worth of an attribute by measuring the symmetrical uncertainty with respect to the class.

B. Fuzzy Systems

In order to perform a core part of the experiment KEEL (Knowledge Extraction based on Evolutionary Learning), which is a non-commercial Java software tool designed to assess different algorithms for regression, classification, clustering, pattern mining problems [4], was used. KEEL contains several dozen of algorithms for data pre-processing, designing and conducting the experiments, data post-processing and evaluating and visualizing the results obtained, which have been bound into one flexible and user friendly system. Ten algorithms to build a fuzzy rule-based system (FRBS) for the classification problem were proposed.

- Clas-Fuzzy-Chi-RW [25] - This algorithm proposed by Chi et al. provides FRBS with rule weights. This FRBS design method determines the relationship between the variables of the problem and establishes an association between the space of the features and the space of the classes by means of the following steps. Firstly, it establishes of the linguistic partitions. Once determined the domain of variation of each feature, the fuzzy partitions are computed. Secondly, it generates a fuzzy rule for each example by assign the example to the fuzzy region with the greatest membership degree a nd the label of class of the example in the consequent. Then, it computes the rule weight.
- Clas-Fuzzy-Ishib-Weighted [26] - This algorithm proposed by Ishibuchi et al. provides FRBS with rule weights. It uses an incremental approach to adjust the weights of each rule generated from data in the previous step rule.
- Clas-Fuzzy-Ishib-Hybrid [27] - This process includes a combination between the Pittsburgh and Michigan approches in order to build a fuzzy rule base for a classification problem. Firstly, a population of rule sets is generated (Pittsburgh approach) and one iteration is run including selection, crossover and mutation. Then, a pre-specified probability is applied to each rule set in order to perform a single Michigan iteration for the whole rule set. Those new rules generated in the michigan search step replace the rule set and finally all the rules sets generated during the Pittsburgh process replace the whole population by an elitist approach.
- Clas-Fuzzy-SGERD [28] - SGERD is a steady-state genetic algorithm, where its generations are finite and bounded to the problem dimension. Individual selection in this algorithm is nonrandom, and only the best ones

can survive. Each parent produces a finite number of offspring through reproduction, whereas the crossover and mutation operators are very specific, and a few crossovers might be replaced by mutations. The fitness function used in SGERD is based on a rule evaluation criterion, very determinant in featuring the best rules among all candidates. SGERD stoppes when no new offspring are included in the population.

- Clas-Fuzzy-AdaBoost - [29] Boosting algorithms are statistical additive modeling techniques that combine different low-quality classifiers to obtain a compound classifier that performs better than any of its components. Adaboost is a boosting algorithm, which repeatedly invokes a learning algorithm to successively generate a committee of simple, low-quality classifiers. Each time a new simple classifier is added to the compound one, the examples in the training set are re-weighted (so that future classifiers will focus on the most difficult examples,) and a voting strength is assigned to the classifier. The number of votes a classifier is given depends on the confidence in its classification accuracy, as measured on the training set. Adaboost generates a compound classifier which decision is a linear threshold of the outputs of the simple classifiers. In this algorithm, each of the weak hypothesis is a Fuzzy rule extracted from data.
- Clas-Fuzzy-LogitBoost - [30] Boosting algorithms are statistical additive modeling techniques that combine different low-quality classifiers to obtain a compound classifier that performs better than any of its components. Logitboost or logistic extended additive model is a backfitting algorithm, which repeatedly invokes a learning algorithm to successively generate a committee of simple, low-quality classifiers. In this algorithm, each of the weak hypothesis is a Fuzzy rule extracted from data. Those fuzzy rules are extracted from data by means of a genetic algorithm. Each time a new simple classifier is added to the compound one, the examples in the training set are re-weighted (so that future classifiers will focus on the most difficult examples).
- Clas-Fuzzy-GAP - [31] In this algorithm an instance is classified by means of a linear combination of its features. The method uses the least mean squares (LMS) to produce a cuadratic discriminant. An instance is classified with the class that happens to have the better value for the cuadratic combination of its features.
- Clas-Fuzzy-GP - [31] This algorithm uses a genetic programming (GP) algorithm to learn a fuzzy classifier. For each hypothesis, the number of labels and number of rules must be given. In same way, as it is possible to manage any combination of conjunction and/or disjunctions in the antecedent part of a fuzzy rule, a maximum deep tree size must be given too. Those parameters are, in conjunction with GP typical parameters, of capital importance in the evolution of this method.
- Clas-Fuzzy-MaxLogitBoost - [32] Boosting algorithms are statistical additive modeling techniques that combine different low-quality classifiers to obtain a compound classifier that performs better than any of its components. Logitboost or logistic extended additive model is a backfitting algorithm, which repeatedly invokes a learning algorithm to successively generate a committee of simple, low-quality classifiers. In this case, the inference is done by combining the votes with the max operator instead of the arithmetic sum. In this algorithm, each of the weak hypothesis is a Fuzzy rule extracted from data. Those fuzzy rules are extracted from data by means of a genetic algorithm. Each time a new simple classifier is added to the compound one, the examples in the training set are re-weighted (so that future classifiers will focus on the most difficult examples).
- Clas-Fuzzy-SAP - [31] A Simulated Annealing algorithm is used to learn a fuzzy classifier. For each hypothesis, the number of labels and number of rules must be given. In same way, as it is possible to manage any combination of conjunction and/or disjunctions in the antecedent part of a fuzzy rule, a maximum deep tree size must be given too. Those parameters are, in conjunction with Simulated Annealing typical parameters, of capital importance in the evolution of this method.

V. Experiments and analysis of results

This section is devoted to validate algorithms introduced in KEEL to predict basketball games results. While the first subsection describes the data retrieval process, the second one introduces a first approach of developed experiments, and the third one shows the experiments and the results obtained in the second part of experiments. Furthermore, the two last sections provide statistical analysis of the results and the interpretability/complexity discussion.

A. Data retrieval

In order to obtain the data, Internet webpages regarding basketball were explored. The only one source containing such information was the ACB league official webpage. Previous games including all statistics since 2000 were gathered into PDF format files for each game period. The most recent season, 2008-2009 was selected from among the whole data, as the entire season expresses the behaviour of the each team and moreover big changes do not arise inside of the team e.g. changing of the coach and players, new sponsors etc. Including a king's tournament (Copa del Rey) there were obtained 245 instances.

Later on, PDF format files were transformed into .txt format files and then the other set of variables was obtained using shell scripts.

Moreover, in the second step, it turned out that some of the text among the PDF files were saved as the images. In order to obtain a set of variables from that a use of an OCR (Optical Character Recognition) program was necessary. Furthermore, a set of scripts in order to clean the data were applied. Due to the lack of detailed information for king's tournament the dataset was reduced to 238 instances.

B. First step - An intuitive approach

1) Experimental setup: A very intuitive and basic approach derived from [18] is to consider results of 3 previous games of each team as the variables. The reasoning behind that is following. If one team has won all recent games, it means that it has a good tendency to win and it is very probable that this team will not loose the current game. This approach, however promising, has some disadvantages as it does not consider overall situation between teams e.g. there might be a case that both teams have winning tendency, thus the prediction of the result would be rather ambiguous. Nevertheless, it is a good choice for the first attempt as the aim of the model is to be simple, accurate, and interpretable.

The resulting dataset contains 6 variables, that is a difference of scored points between considered team and the opponent in 3 previous games of the one team and for another. The output is a binary value, where 0 means that a first team won and 1 concerns winning of the second team.

To evaluate the performance of ten different models, an experiment in KEEL was setup. The data was transformed using a decimal scaling ranging within a range [-1;1]. In order to compare the accuracy of the considered classifiers, it was used 10-fold cross-validation. Obtained results of FRBSs are compared against standard linear regression.

2) Results: The results of the ten FRBSs and the linear regression are presented in the table I and II. They represent train and test sets respectively. The table is designed as follows. First column represents the algorithms used, the three next ones shows global measures i.e. global error, standard deviation of the global error, and accuracy respectively. The best global result is emphasized with the bold font.

The best accuracy over train set was obtained by Clas-Fuzzy-Ishib-Weighted, whereas Clas-Fuzzy-Chi-RW outperformed other algorithms in terms of standard deviation. Furthermore, a training error is not the best metric as it does not express generalization of the model and very often high accuracy over training set leads to overfitting. Considering test set results Clas-Fuzzy-Ishib-Weighted outperformed other algorithms in terms of accuracy, whereas Clas-Fuzzy-Chi-RW obtained the best result in terms of standard deviation.

The results obtained were not satisfactory. As mentioned before that was a preliminary, naive approach and did not consider many factors. Thus, in order to increase accuracy there were applied improvements.

C. Second step - An advanced approach

1) Experimental setup: The next step is to consider more sophisticated variables. Previous approach does not describe the whole domain of the problem. Here, a trial to deeply describe a basketball game phenomenon is performed.

An important issue considering a current state of the basketball team is statistics of the team in the given period i.e. an average of scored points, an average of lost points, etc. A new set of features with use of OCR program and additional scripts was obtained to reflect better the current state of the team. Following features for each team were extracted: average of scored points per game, average of lost points per game, average of gained assists per game, and average valuation per game. Moreover, place of the game plays a crucial role, hence this attribute is considered as well. Due to the lack of such information for king's tournament (Copa del Rey) the dataset was reduced to 238 instances.

Finally, 15 features (6+8+1) were obtained. As fuzzy systems suffers from the so-called curse of dimensionality, which usually leads to the explosion of fuzzy rules, a feature selection method was performed. Seven algorithms from WEKA were performed in order to provide robust results. Then, the most valuable attributes were selected. The first five features obtained relatively high score, so that those ones will be considered in further experiments. The table III presents a code\number assigned to each feature and table IV feature selection algorithms and features obtained, whereas table V shows the number of votes of each selected feature. Any of the provided features in Sec. V-B appeared, what means that those features do not provide enough information about the output. Thus, it may be concluded that results of the previous games do not influence the result of the current game.

TABLE I

RESULTS FOR THE TEN KEEL ALGORITHMS OBTAINED FROM THE TRAIN SET IN THE FIRST STEP

Algorithm	Glob. Err.	stddev Glob. Err.	Acc.
LinearLMS	0.296	0.014	0.704
Clas-Fuzzy-Chi-RW	0.337	**0.010**	0.663
Clas-Fuzzy-Ishib-Weighted	0.245	0.015	0.755
Clas-Fuzzy-Ishib-Hybrid	0.295	0.009	0.705
Clas-Fuzzy-SGERD	0.347	0.016	0.653
Class-Fuzzy-SAP	0.341	0.013	0.695
Class-Fuzzy-MaxLogitBoost	0.257	0.012	0.743
Class-Fuzzy-LogitBoost	**0.180**	0.014	**0.820**
Class-Fuzzy-GP	0.351	0.012	0.649
Class-Fuzzy-GAP	0.336	0.011	0.663
Class-Fuzzy-AdaBoost	0.331	0.014	0.669

TABLE II

RESULTS FOR THE TEN KEEL ALGORITHMS OBTAINED FROM THE TEST SET IN THE FIRST STEP

Algorithm	Glob. Err.	stddev Glob. Err.	Acc.
LinearLMS	**0.333**	0.089	**0.667**
Clas-Fuzzy-Chi-RW	0.375	0.040	0.625
Clas-Fuzzy-Ishib-Weighted	0.358	0.087	0.642
Clas-Fuzzy-Ishib-Hybrid	0.363	0.063	0.637
Clas-Fuzzy-SGERD	0.367	0.066	0.633
Class-Fuzzy-SAP	0.366	0.069	0.634
Class-Fuzzy-MaxLogitBoost	0.425	0.071	0.575
Class-Fuzzy-LogitBoost	0.417	0.102	0.583
Class-Fuzzy-GP	0.395	**0.039**	0.605
Class-Fuzzy-GAP	0.378	0.070	0.622
Class-Fuzzy-AdaBoost	0.425	0.064	0.575

TABLE III

CODE ASSGINED TO EACH OF THE 15 FEATURES

Feature name.	assigned nr
home/away game	1
last game result of the first team	2
second previous game result of the first team	3
third previous game result of the first team	4
last game result of the second team	5
second previous game result of the second team	6
third previous game result of the second team	7
average scored points of the first team	8
average lost points of the first team	9
average nr of assists of the first team	10
evaluation of the first team	11
average scored points of the second team	12
average lost points of the second team	13
average nr of assists of the second team	14
evaluation of the second team	15

TABLE IV

THE RESULTS OF FEATURE SELECTION ALGORITHMS

Feature sel.	sel. feat.
CfsSubsetEval	8, 9, 10, 11, 14, 15
ChiSquaredAttributeEval	11, 10, 14, 15, 8
ConsistencySubsetEval	8, 9, 10, 11, 12, 14, 15
GainRatioAttributeEval	11, 10, 14, 8, 15
OneRAttributeEval	14, 8, 10, 13, 11
ReliefFAttributeEval	11, 10, 9, 8, 13
SVMAttributeEval	14, 8, 9, 15, 4
SymmetricalUncertAttributeEval	11, 10, 14, 8, 15

TABLE V

RANKING OF THE FEATURES

Feature code	nr of votes
8	8
10	7
11	7
14	7
15	7
9	4
12	1
13	1
4	1

TABLE VI

RESULTS FOR THE TEN KEEL ALGORITHMS OBTAINED FROM THE TRAIN SET IN THE SECOND STEP

Algorithm	Glob. Err.	stddev Glob. Err.	Acc.
LinearLMS	0.293	0.017	0.707
Clas-Fuzzy-Chi-RW	0.272	**0.007**	0.728
Clas-Fuzzy-Ishib-Weighted	0.286	0.010	0.714
Clas-Fuzzy-Ishib-Hybrid	**0.248**	0.010	**0.752**
Clas-Fuzzy-SGERD	0.326	0.016	0.674
Class-Fuzzy-SAP	0.295	0.009	0.705
Class-Fuzzy-MaxLogitBoost	0.223	0.011	0.777
Class-Fuzzy-LogitBoost	0.210	0.014	0.790
Class-Fuzzy-GP	0.274	0.009	0.726
Class-Fuzzy-GAP	0.276	0.008	0.724
Class-Fuzzy-AdaBoost	0.268	0.016	0.732

TABLE VII

RESULTS FOR THE TEN KEEL ALGORITHMS OBTAINED FROM THE TEST SET IN THE SECOND STEP

Algorithm	Glob. Err.	stddev Glob. Err.	Acc.
LinearLMS	0.311	0.082	0.689
Clas-Fuzzy-Chi-RW	**0.285**	0.075	**0.715**
Clas-Fuzzy-Ishib-Weighted	0.341	**0.063**	0.659
Clas-Fuzzy-Ishib-Hybrid	0.332	**0.063**	0.668
Clas-Fuzzy-SGERD	0.365	0.072	0.635
Class-Fuzzy-SAP	0.332	0.097	0.668
Class-Fuzzy-MaxLogitBoost	0.358	0.073	0.642
Class-Fuzzy-LogitBoost	0.332	0.074	0.668
Class-Fuzzy-GP	0.286	0.085	0.714
Class-Fuzzy-GAP	0.311	0.045	0.689
Class-Fuzzy-AdaBoost	0.328	0.057	0.672

To evaluate the performance of ten different models, an experiment in KEEL was setup. The data was transformed using a decimal scaling ranging within a range [-1;1]. In order to compare the accuracy of the considered classifiers, it was used 10-fold cross-validation. Obtained results of FRBSs are compared against standard linear regression.

2) Results: The results of the used algorithms are presented in the table VI and VII. They represent train and test sets respectively. The table is designed as follows. First column represents the algorithms used, the three next ones shows global measures i.e. global error, standard deviation of the global error, and accuracy respectively. The best global result is emphasized with the bold font.

The best accuracy over train set was obtained by Clas-Fuzzy-Ishib-Hybrid, whereas Clas-Fuzzy-Chi-RW outperformed other algorithms in terms of standard deviation. Furthermore, a training error is not the best metric as it does not express generalization of the model and very often high accuracy over training set leads to overfitting. Considering test set results Clas-Fuzzy-Chi-RW outperformed other algorithms, whereas Clas-Fuzzy-Ishib-Weighted and Clas-Fuzzy-Ishib-Hybrid obtained the best result in terms of standard deviation. It may be concluded that Clas-Fuzzy-Ishib-Weighted, Clas-Fuzzy-Ishib-Hybrid, and Clas-Fuzzy-SGERD tends to overfitting while obtaining a high accuracy over train set and lower accuracy over test set. Clas-Fuzzy-Chi-RW obtained the highest accuracy over test set and furthermore accuracy for train and test sets are almost similar, thus this algorithm should be selected for basketball game results prediction.

3) Statistical tests: The last part of the experiments aims to evaluate statistical tests over the generated systems. There was used Wilcoxon signed rank test. This test was set as follows. Obtained FRBSs were compared against the Linear regression model. The results of the analysis are placed in Tables IX and VIII, where N denotes that there is no evidence against the H0 hypothesis and Y that there is evidence against the H0 hypothesis with the 0.95 significance level. The H0 hypothesis in the case of Wilcoxon test stated that true difference in means was equal to 0.

Considering experiments in the first step three out of ten algorithms were considered having significant difference with respect to the accuracy (means not equal to 0) in comparison to linear regression. From all algorithms used in the second step there was any that showed significant difference with respect to the accuracy (means not equal to 0) in comparison to linear regression.

TABLE VIII
RESULTS FOR THE WILCOXON TEST FOR KEEL FUZZY ALGORITHMS COMPARED AGAINST LINEAR REGRESSION IN THE FIRST STEP

Algorithm	Result
Clas-Fuzzy-Chi-RW	N
Clas-Fuzzy-Ishib-Weighted	N
Clas-Fuzzy-Ishib-Hybrid	N
Clas-Fuzzy-SGERD	N
Class-Fuzzy-SAP	N
Class-Fuzzy-MaxLogitBoost	Y
Class-Fuzzy-LogitBoost	Y
Class-Fuzzy-GP	N
Class-Fuzzy-GAP	N
Class-Fuzzy-AdaBoost	Y

TABLE IX
RESULTS FOR THE WILCOXON TEST FOR KEEL FUZZY ALGORITHMS COMPARED AGAINST LINEAR REGRESSION IN THE SECOND STEP

Algorithm	Result
Clas-Fuzzy-Chi-RW	N
Clas-Fuzzy-Ishib-Weighted	N
Clas-Fuzzy-Ishib-Hybrid	N
Clas-Fuzzy-SGERD	N
Class-Fuzzy-SAP	N
Class-Fuzzy-MaxLogitBoost	N
Class-Fuzzy-LogitBoost	N
Class-Fuzzy-GP	N
Class-Fuzzy-GAP	N
Class-Fuzzy-AdaBoost	N

4) Interpretability issue: Interpretability of fuzzy systems has started getting an attention in the fuzzy community lately. At the beginning fuzzy systems were abstracted from human experts or heuristics and they were usually well understandable for humans. However, during a time fuzzy systems have been automatically generated, which are not necessarily comprehensible to human beings. In addition, it is well-known to improve the fuzzy systems that are abstracted from experts using different learning methods in order to improve their performance.

Comparison of given fuzzy systems is still ambiguous in terms of interpretability. Let consider a complexity instead, as it can be numerically expressed. Table X presents complexity metrics such as average nr of rules and granularity (nr of fuzzy terms). Clas-Fuzzy-SGERD outperformed other algorithms in terms of average number of rules, whereas low and stable amount of fuzzy terms are obtained by Clas-Fuzzy-Chi-RW and Clas-Fuzzy-Ishib-Weighted.

Let consider Clas-Fuzzy-Chi-RW, which was the one that obtained the best accuracy. The example rule of this system is following: $IF\ 1team\_avg\_pts\ IS\ HighAND1team\_avg\_ast\ IS\ High\ AND\ 1team_val\ IS\ High\ AND\ 2team_ast\ IS\ Low\ AND\ 2team_val\ IS\ Low\ Then\ 0\ ; withRuleWeight : 0.935$ The generated rule could be understood in the following way. If the first team has a good current statistics, that is has a good tendency and the second team did not play very well by now, then first team is going to win. As it can be seen above obtained rules are readable, what in consequence improves transparency of the system. Thus, it may be concluded that the obtained system ensures an appropriate accuracy-complexity trade-off to some extent.

TABLE X
COMPLEXITY OF THE FOUR KEEL ALGORITHMS.

Algorithm	Granularity	Avg nr of rules
Clas-Fuzzy-Chi-RW	3	39.5
Clas-Fuzzy-Ishib-Weighted	3	218.6
Clas-Fuzzy-Ishib-Hybrid	2-5	8.8
Clas-Fuzzy-SGERD	2-5	2.5

VI. CONCLUDING REMARKS AND FUTURE WORKS

In this work it has been proposed an attempt to build a fuzzy system to basketball game results prediction. The data was obtained from Internet and several attributes were extracted. Experiment was conducted using four fuzzy models, including genetic fuzzy systems and ad-hoc data driven approach, presented in KEEL.

The preliminary experiments developed clearly showed the new proposal is very promising, however there is a lot of space for improvement. The next step should aim to try different and more sophisticated fuzzy models e.g. neuro-fuzzy systems or classifier ensembles, extract larger datasets i.e. more than one season with features better reflecting the current problem, and finally present that obtained system is interpretable.

REFERENCES

[1] “wikipedia,” http://www.wikipedia.org.
[2] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, “The weka data mining software: an update,” *SIGKDD Explor. Newsl.*, vol. 11, no. 1, pp. 10–18, 2009.
[3] I. H. Witten and E. Frank, *Data Mining: Practical Machine Learning Tools and Techniques*, 2nd ed. San Francisco: Morgan Kaufmann, 2005.
[4] J. Alcalá-Fdez, F. Berlanga, L. Sánchez, S. García, M. del Jesus, A. Fernández, and F. Herrera., “Keel: A data mining software tool integrating genetic fuzzy systems,” in *3rd International Workshop on Genetic and Evolving Fuzzy Systems(GEFS08)*, 2008, pp. 83–88.
[5] L. Zadeh, “Fuzzy sets,” *Information Control*, vol. 8, pp. 338–353, 1965.

[6] ——, “The concept of a linguistic variable and its application to approximate reasoning,” *Information Sciences*, vol. 1, pp. 119–249, 1975.

[7] E. H. Mamdani and S. Assilian, “An experiment in linguistic synthesis with a fuzzy logic controller,” *International Journal of Man-Machine Studies*, vol. 7, no. 1, pp. 1–13, 1975.

[8] E. H. Mamdani, “Application of fuzzy logic to approximate reasoning using linguistic synthesis,” in *Proceedings of the sixth international symposium on Multiple-valued logic*. Los Alamitos, CA, USA: IEEE Computer Society Press, 1976, pp. 196–202.

[9] O. Cordón, G. F., H. F., H. F., and M. L., “Ten years of genetic fuzzy systems: current framework and new trends,” *Fuzzy Sets and Systems*, vol. 141, pp. 5–31, July 2004.

[10] F. Herrera, “Genetic fuzzy systems: Status, critical consideration and future directions,” *International Journal of Computational Intelligence Research*, vol. 1, no. 1, pp. 59–67, September 2005.

[11] ——, “Genetic fuzzy systems: taxonomy, current research trends and prospects,” *Evolutionary Intelligence*, vol. 1, no. 1, pp. 27–46, January 2008.

[12] M. J. Dixon and S. G. Coles, “Modelling association football scores and inefficiencies in the football betting market,” *Journal of Applied Statistics*, vol. 46, no. 2, pp. 265–??, 1997.

[13] R. H. Koning, “Balance in competition in dutch soccer,” *The Statistician*, vol. 49, pp. 419–431, 2000.

[14] H. Stern, “On the probability of winning a football game,” *The American Statistician*, vol. 45, no. 3, pp. 179–??, Aug. 1991.

[15] B. Min, J. Kim, C. Choe, H. Eom, and R. I. (Bob) McKay, “A compound framework for sports results prediction: A football case study,” *Know.-Based Syst.*, vol. 21, no. 7, pp. 551–562, 2008.

[16] H. Rue and yvind Salvesen, “Prediction and retrospective analysis of soccer matches in a league,” pp. 399–418, 2000.

[17] A. Tsakonas, G. Dounias, S. Shtovba, and V. Vivdyuk, “Soft computing-based result prediction of football games,” in *The Ist International Conference on Inductive Modelling (ICIM’2002)*, V. Hrytsyk, Ed., Lviv, Ukraine, 20-25 May 2002, pp. 15–23. [Online]. Available: http://www2.ba.aegean.gr/members/tsakonas/Lvov2002.pdf

[18] A. P. Rotshtein, M. Posner, and A. B. Rakityanskaya, “Football predictions based on a fuzzy model with genetic and neural tuning,” *Cybernetics and Sys. Anal.*, vol. 41, no. 4, pp. 619–630, 2005.

[19] L. A. Hall, M. A.and Smith, “Practical feature subset selection for machine learning,” in *Australian Computer Science Conference*, 1998, pp. 181–191.

[20] H. Liu and R. Setiono, “Chi2: Feature selection and discretization of numeric attributes,” *Tools with Artificial Intelligence, IEEE International Conference on*, vol. 0, p. 388, 1995.

[21] M. Dash and H. Liu, “Consistency-based search in feature selection,” *Artif. Intell.*, vol. 151, no. 1-2, pp. 155–176, 2003.

[22] R. Holte, “Very simple classification rules perform well on most commonly used datasets,” *Machine Learning*, vol. 11, no. 0, pp. 63–91, 1993.

[23] “A practical approach to feature selection,” in *9th International Workshop on Machine Learning(ML’92)*, 1992, pp. 249–256.

[24] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, “Gene selection for cancer classification using support vector machines,” *Mach. Learn.*, vol. 46, no. 1-3, pp. 389–422, 2002.

[25] Z. Chi, H. Yan, and T. Pham, *Fuzzy Algorithms: With Applications To Image Processing and Pattern Recognition*. World Scientific, 1996.

[26] T. Nakashima, G. Schaefer, Y. Yokota, and H. Ishibuchi, “A weighted fuzzy classifier and its application to image processing tasks,” *Fuzzy Sets and Systems*, vol. 158, pp. 284–294, 2007.

[27] H. Ishibuchi, T. Yamamoto, and T. Nakashima, “Hybridization of fuzzy gbml approaches for pattern classification problems,” *IEEE Transactions on Systems and Man and Cybernetics - Part B: Cybernetics*, vol. 35, no. 2, pp. 359–365, 2005.

[28] E. Mansoori, M. Zolghadri, and S. Katebi, “Sgerd: A steady-state genetic algorithm for extracting fuzzy classification rules from data,” *IEEE Transactions on Fuzzy Systems*, vol. 16, no. 4, pp. 1061–1071, 2008.

[29] M. del Jesus, F. Hoffmann, L. Junco, and L. Sánchez, “Induction of fuzzy-rule-based classifiers with evolutionary boosting algorithms,” *IEEE Transactions on Fuzzy Systems*, vol. 12, no. 3, pp. 296–308, 2004.

[30] J. Otero and L. Sánchez, “Induction of descriptive fuzzy classifiers with the logitboost algorithm,” *Soft Computing*, vol. 10, no. 9, pp. 825–835, 2006.

[31] L. Sánchez, I. Couso, and J. Corrales, “Combining gp operators with sa search to evolve fuzzy rule based classifiers,” *Information Sciences*, vol. 136, no. 1-4, pp. 175–192, 2001.

[32] L. Sánchez and J. Otero, “Boosting fuzzy rules in classification problems under single-winner inference,” *International Journal of Intelligent Systems*, vol. 22, no. 9, pp. 1021–1034, 2007.