An explainable evolving fuzzy neural network in position identification of basketball players

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Abstract
Evolving fuzzy neural networks have the adaptive capacity to solve complex problems. They can facilitate understanding the behavior of the analyzed problem as they can extract knowledge from an analyzed data set. Thus, this work proposes applying an evolving fuzzy neural network capable of solving pattern classification problems with considerable interpretability in the position identification of basketball players. The models used in these tests were compared to the state-of-the-art on the subject, and their results were superior (87.50 % of accuracy) and interpretable. In addition to being accurate in solving the problems, the model presented relevant information on data stream processing, allowing a complete evaluation of the data behavior during its evaluation.

Keywords
Evolving fuzzy neural networks, Evolving fuzzy systems, Interpretability, Data streams, Position identification of basketball players

1. Introduction

Evolving Fuzzy neural networks are hybrid methods combining the notions of artificial neural networks and fuzzy logic [1]. Consequently, these models can solve complex problems while extracting knowledge from the data, making them expert systems [2]. The association of a fuzzy inference system and artificial intelligence training methodologies streamlines the performance of these models [3], making them applicable, for example, to dynamical systems.

Evolving fuzzy neural networks are models with a high capacity for solving complex problems, adding interpretability to the results. However, many proposed models do not present alternative ways of interpreting the results, especially when confronted with the evaluation of stream data or surveying the model's behavior over time [4]. To bridge this interpretability gap, models were proposed in the literature with the ability to extract knowledge about the analyzed data, in addition to exploring the joint interpretability of the functioning of these models as they evaluate new data [5, 6, 7, 8]. These interpretation factors in the evaluation of streaming data can identify outliers in the data, garner new insight, and new situations that can add knowledge

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to the users of these systems.

This paper aims to present the functioning of an evolving fuzzy neural network (ENFS-Uni0) [7] in solving pattern classification problems. In this work, we intend to explain how the interpretability of the results with the interpretability of the model's behavior can help in the complex analyses to be carried out in a data set. ENFS-Uni0 is an evolving model with three layers, with the first one being composed of the data fuzzification process. This procedure is performed by an evolving fuzzification technique based on data density and is responsible for constructing Gaussian neurons to represent the data of a problem. The second layer is composed of fuzzy logic neurons, which aggregate the neurons formed in the first layer with their respective weights. Finally, the third layer of the model is represented by an aggregation artificial neural network, responsible for the defuzzification process. Aspects of interpretability about the evolution of Gaussian neurons, evaluation of the features of the problem, and training that defines consequents of interpretable rules are present in the model to reach an advanced level of interpretation of the results. The interpretability of evolving fuzzy systems models meets different criteria from traditional models of artificial neural networks. Therefore, it is intended to present practical examples of action in solving problems in an interpretable way following the interpretability criteria proposed by Lughofer [9] for this category of models. These examples will be provided by analyzing the model's manners as it performs the task of pattern classification problems. The interpretability obtained by the model through fuzzy rules will be compared with the approach of fuzzy systems that are also capable of extracting knowledge about an analyzed data set. Thus, it may be possible to measure the degrees of interpretability achieved by the ENFS-Uni0.

This article proposes to work with the resolution of a multiclass problem of basketball players' position profiles on the court by comparing the results obtained with fuzzy solutions that also can extract knowledge. The highlights of this paper are to present the main features of interpretation of the problems that the evolving fuzzy neural networks have. In addition to this element, it also proposes solving a complex classification problem, that has been published recently, along with the interpretation of its results. Thus, the reader can appreciate the characteristics of accuracy and interpretability, reach an understanding of evolving fuzzy systems and identify how hybrid methods could be combined to exploit their benefits for online (evolving) learning.

In addition to the introduction, the paper presents a theoretical reference section (section 2) related to the concept of evolving fuzzy models and their respective interpretability capabilities. Section 3 shows the reader the layers and training of the model. Experiments and their discussions are highlighted in the Sec. 4 and section 5 sections respectively. Finally, in the 6 section, conclusions about the activities carried out for this paper are given.

2. Evolving fuzzy systems and interpretability

2.1. Evolving Fuzzy Systems

Evolving fuzzy systems (EFS) are to bet set apart from traditional neural network models mainly by their ability to combine the advantages of fuzzy inference systems with the training of artificial neural network devices, operating to adapt the parameters according to the dynamics of the data. Thus, the knowledge extraction can be helpful to others while the model has an advanced and assertive problem-solving capacity [10].

They are models which build upon the concept of fuzzy logic (truth values are fuzzified in [0,1] by membership functions [11]). They have a tradeoff between universal approximation (models with a high-handed degree of non-linearity by piece-wise local approximation) and interpretability (understandable linguistic terms and rules) [10].

The main concepts about evolving fuzzy systems are their ability to process samples or data blocks step by step for model building, omitting time-consuming retraining (incrementality), performing recursive parameter adaptation (adaptability), and adding structural elements (evolving) as the system deals with newly loaded samples or has new states. EFS also is a fuzzy system in a single-pass incremental and evolving manner with online recordings/data streams with similarities between specific architectures with certain types of neural networks. Evolving fuzzy systems are considered (dark) gray-box models with knowledge-based input and data-driven learning [10]. Its main requirements for real applications are linked to quick online identification of models from scratch, updating and extending existing models, bringing reliability and security to the process, avoiding extrapolation, and working with model adjustments based on the knowledge extracted from the data [12]. EFS can also work on extracting models from massive databases since, in most fundamental problems [12], it is not possible to load all the data at once. Its ability to improve the human-machine interaction by monitoring deviations/changes in data flow (gradual forgetting, smoothing over time) is also highlighted [10].

Evolving fuzzy neural networks (EFNN) are EFS and have an input and an output layer as the main element. The hidden layers of these models vary, depending on the number of features in the fuzzy inference systems and the aggregations performed by the neural networks [1]. This ability provided by the fuzzy inference system, that makes up the evolving fuzzy neural network, enables it to build fuzzy rules and demonstrate knowledge over time. Thus, it is possible to analyze the results of knowledge evolution as new samples are presented for the training and evaluation of the model [3].

2.2. On-line assurance of interpretability

Evaluating the interpretability of intelligent models has been exhaustively addressed in the literature, mainly in the XAI (Explainable AI) [13] research area, where humans can understand the solution results. A general definition of interpretability is that it can be seen as how a human being can understand the cause of a decision or the degree to which a human being can consistently predict the model's outcome. It is an established factor that, the greater the interpretability of a machine learning model, the easier it is for users to understand why certain decisions or predictions were made [14].

Interpretable machine learning is an embracing term that captures extracting relevant knowledge from a machine learning model about relationships contained in data or learned by the model. In the context of evolving learning, some characteristics are necessary to be adapted so that the evaluation of these models is done in a way that humans understand them, mainly because of their adaptive behavior [14]. Lughofer [9] addressed the criteria of transparency, readability, and interpretability of the EFS fuzzy rule bases (which, consequently, also cover the EFNN). For this purpose, some essential criteria for evaluating these models were defined, which are listed below [9]:

- **Distinguishability and simplicity:** Simplicity demands models with a tradeoff between low complexity and high precision, while distinguishability requires using structural components (rules, fuzzy sets) in a separable way (non-overlapping and non-redundant).
- **Consistency:** Consistency in a rule base is given when two rules do not overlap in antecedents and consequents. Such occurrences lead to a more remarkable case of conflict within an evolving classification context as classes overlap within the same local region. A fuzzy rule is consistent with another fuzzy rule if the similarity of its antecedents is less than the similarity of its consequents.
- **Coverage and completeness:** Coverage refers to the specific characteristics of fuzzy partitions and rules that do not allow any holes in the resource space, hence undefined input states. Completeness is the evaluation of the contribution of rules with a significant distance to the sample. It can be seen as a generalization of coverage.
- **Feature importance levels:** This ability assesses the importance of features in the final output of the model, allowing an assessment of their influence to bring interpretability to the process and reduce the rule length.
- **Rule importance levels:** Criteria for evaluating importance levels of rules defined by numerical values (weights or rule consequents) to assess the relevance of the rule for the analyzed context.
- **Interpretation of consequents:** Possibility to evaluate the consequents of the model through distinguishability, simplicity, and completeness for fuzzy Mamdani systems and rule confidence for single-model fuzzy classifiers that have the form of a rule.
- **Knowledge expansion:** Evaluation of results beyond just accuracy. Criteria for incorporating new knowledge, evaluations, and operations with the rules serve as parameters for this criterion. Rule evolution criteria also allow the identification of an assessment of the knowledge acquired by the model.

Studies on the interpretability of models based on fuzzy rules have found a conflict between the precision of the model and its interpretability- two objectives that are at odds with each other. Preserving the interpretation of a fuzzy system during adaptation is a difficult task that has received much attention in the fuzzy system modeling community [15]. Therefore, to be considered interpretable, an EFNN model must meet high accuracy criteria (to guarantee the efficiency of the results) and must also meet the criteria listed above. These listed criteria will be used to evaluate the evolving fuzzy neural network model results in this paper. The following section will present the model architecture, training, and interpretability techniques.

3. Evolving Fuzzy neural network

This section presents the architectural and training features of the ENFS-Uni0 [7]. The aspects of its operation help in the interpretability of online problems, allowing the behavior of the evaluation of the model as it analyzes the data set samples. The architecture of ENFS-Uni0 is composed of three layers. The first two are a fuzzy inference system (responsible for extracting knowledge from the data set through IF-THEN rules). A neural network represents the last layer capable of aggregating all the consequents of fuzzy rules and transforming them into the expected output (defuzzification process) [7].

The model parameters are established during a fuzzification process, which determines the number of fuzzy rules that the system can extract from the data. This process results in the Gaussian neurons formed with the centers and the standard deviation of the clusters found by means of an autonomous data clustering technique [16]. These clusters are defined through data density concepts and empirical data operators [17]. Therefore, these Gaussian neurons generated by the fuzzification process are responsible for the composition of the antecedent terms of the fuzzy rules [7]. Each of these neurons has a weight determined by an online technique for determining the class separability criterion of the problem (feature weight separability criteria (FWSC)) [18]. This approach brings benefits of interpretability to the dimensions of the problem (identifying those with greater relevance to find the analyzed classes) and allowing the rules' reducibility, generating a compact knowledge about the problem in question [7]. These neurons and their respective weights are aggregated in the second layer of the models through fuzzy logic neurons. These neurons use fuzzy aggregators to aggregate the weights and Gaussian neurons and transform them into a single value [7]. For this, the EFNS-Uni0 uses the uni-nullneuron [19], composed of uni-nullnorms [20]. These special fuzzy operators allow that there are different connectives of the antecedents in a group of fuzzy rules formed by the models. For instance, when only one t-norm is used to aggregate neurons, all the generated connectives are of the AND type. When using a t-conorm, the whole set of generated rules uses the OR connective [21]. The use of uni-nullnorm derives from the concepts of n-uninorms [20], which allow fuzzy operators to vary between uninorms [22, 23] or nullnorms [24] (two particular types of fuzzy operators that allow the use of t-norms and t-conorms together) [7].

Thus, a set of rules that expresses knowledge about a data set may contain rules either with AND or with OR connectors. This skill facilitates the dynamic resolution of complex problems, allowing for knowledge extraction with flexibility. This process performed by the uni-nullneuron uses three parameters to determine what type of operator the neuron will use to perform a given aggregation [7]. The rule consequents are determined differently according to the stage in which the model is executing its activities to complete the formation of fuzzy rules. The Extreme Learning Machine concept [25] (using pseudo-inverse of the Moore-Penrose matrix [26]) is applied in the offline stage. In the evolving phase of the model, the rule consequents are updated by a technique inspired by a version of recursive weighted least squares [27] called indicator-based recursive weighted least squares (I-RWLS) for each class [7], where there is a value for each of the analyzed classes. The process of obtaining the model output is performed by a neural aggregation network that uses all the consequents of the rules as weights of the artificial neuron (Singleton concept). This neuron, which has a linear activation function, is responsible for the model result [7].

The original EFNS-Uni0 technique also uses a pruning technique to select the most relevant neurons for the model. However, this approach will not be used in this paper, as we want to see the impacts and evolution of all the knowledge acquired during the tests. The model has abilities to extract knowledge and interpret the results. The fuzzy rules formed by EFNS-Uni0 can be represented by [7]:

$$
\begin{aligned}
Rule_1 : \ If \ x_1 \ is \ A_1^1 \ with \ impact \ w_{11}... \\
and/or_{(g,u,\beta)} \ x_2 \ is \ A_1^2 \ with \ impact \ w_{21}... \\
Then \ y_1 \ is \ [v_{11}...v_{1C}] \\
Rule_2 : \ If \ x_1 \ is \ A_2^1 \ with \ impact \ w_{12}... \\
and/or_{(g,u,\beta)} \ x_2 \ is \ A_2^2 \ with \ impact \ w_{22}... \\
Then \ y_2 \ is \ [v_{21}...v_{2C}] \\
....Rule_L : \ If \ x_1 \ is \ A_L^1 \ with \ impact \ w_{1L}... \\
and/or_{(g,u,\beta)} \ x_2 \ is \ A_L^2 \ with \ impact \ w_{2L}... \\
Then \ y_L \ is \ [v_{L1}...v_{LC}]
\end{aligned}
\tag{1}
$$

where C is the number of classes in the problem, **A** are the Gaussian neurons (where the membership functions of fuzzy sets, formed by the input data density through an evolving clustering method, are the activation functions of the corresponding neurons i.e., $a_{jl} = \mu_l^A$ for j = 1... N and l = 1 ... L, where N is the number of inputs and L is the number of fuzzy sets for each input) and **w** is its respective weight (w_{il} (for i = 1... N and l = 1... L). $\vec{v}_i = [v_{i1}, ..., v_{iC}]$ is calculated in two different ways. The offline phase is based on Eq. 2 and the evolving step uses Eq. 5 related below.

$$\vec{v}_k = Z^{+}\vec{y}_k \quad \forall k = 1, ..., C \tag{2}$$

$$\eta = \vec{z}^t Q^{t-1} \left(\psi + (\vec{z}^t)^T Q^{t-1} \vec{z}^t\right)^{-1} \tag{3}$$

$$Q^t = (\mathrm{I}_{L^t} - \eta^T \vec{z}^t)\psi^{-1} Q^{t-1} \tag{4}$$

$$\vec{v}_k^t = \vec{v}_k^{t-1} + \eta^T (y_k^t - \vec{z}^t \vec{v}_k^{t-1}) \tag{5}$$

$Z^{+} = Z^T Z$ is the pseudo-inverse of the Moore-Penrose matrix [26] of Z (uninull-neurons (Eq. 6)) and y_k denotes the column indicator vector containing 1s at the row positions for samples belonging to class k and 0 for all samples belonging not to class k. η is the current kalman gain (row) vector, $I_{L_s^t}$ is an identity matrix based on the number of neurons in the second layer, $L_s^t \times L_s^t; \psi \in]0, 1]$ denotes a possible forgetting factor, but is to 1 per default (no forgetting). Q denotes the inverse Hessian matrix $Q = (Z^T Z)^{-1}$ and is set initially as $\omega I_{L_s^t}$, where ω=1000. The Z is a uni-nullneuron vector, and this fuzzy neuron can be represented by:

$$z = UNI^{NUL}(w, a, \beta, g, u) = N^{un}{}_{i=1}^{n} p(w_i, a_i, \beta, g, u) \tag{6}$$

$$p(w, a, \beta, g, u) = \begin{cases} wa + \bar{w}\frac{g}{\beta}, \ if \ U_1 \\ wa + \bar{w}\frac{u-\beta}{1-\beta}, \ if \ U_2 \end{cases} \tag{7}$$

$$N^{un}(x, y, \beta, g, u) = \begin{cases} \beta U_1(\frac{x}{\beta}, \frac{y}{\beta}), \ if \ x, y \in [0, \beta] \\ \beta \ + \ (1-\beta) \ U_2 \ (\frac{x-\beta}{1-\beta}, \frac{y-\beta}{1-\beta}), \ if \ x, y \ \in \ (\beta, 1] \end{cases} \tag{8}$$

where p is a conditional transformation of the values of the uni-nullnorm (Eq. (8)- commutative binary function N^{un}: $[0,1]^2 \rightarrow [0,1]$, with $g, u, \beta \in$ [0,1] with $0 \leq g \leq \beta \leq u \leq 1$ and $0 < \beta < 1$)). U_1 is a uninorm with a neutral element (identity) = $\frac{g}{\beta}$ and U_2 is a uninorm using $(\frac{u-\beta}{1-\beta})$ like as neutral element.

The assessment of the changes of Gaussian neurons in the first layer can measure how the rule antecedents change over time [28]. Other interpretable factors that the model can also measure are identifying the evolution of fuzzy rules and their respective consequents. This overview allows the model's user to identify moments of change in the model's efficiency or even to measure moments in which the technique acquired new knowledge [7]. Details on how the techniques work can be seen in depth at [7].

The process carried out in the third layer is also seen as defuzzification process with an aggregation neural network composed of a single neuron.

$$y = \Omega \left(\sum_{j=0}^{l} f_{\Gamma}(z_j, v_j) \right) \tag{9}$$

where z_0 = 1, v_0 is the bias, and z_j and v_j, j = 1, ..., l are the output of each fuzzy neuron of the second layer and their corresponding weight, respectively and f_{Γ} represents the neuron activation function. When the model acts in solving problems with multiple classification outputs, $\sum_{j=0}^{l} f_{\Gamma}(z_j, \vec{v}_j)$ delivers an output vector $\vec{o}$ (as v_j turns into a vector of outputs $\vec{v}_j$ for the jth neuron), where each entry is the overall certainty (among all neurons/rules) that the sample belongs to the corresponding class. Therefore, when the model has C class outputs, Ω is given by:

$$\Omega = argmax_{i=1,\ldots,C} \;\; o_i \tag{10}$$

The architecture of the model can be seen in Fig. 1 and the flow of its operation can be visited in Fig. 2. A pseudo-code of ENFS-Uni0 is presented in Algorithm 1.

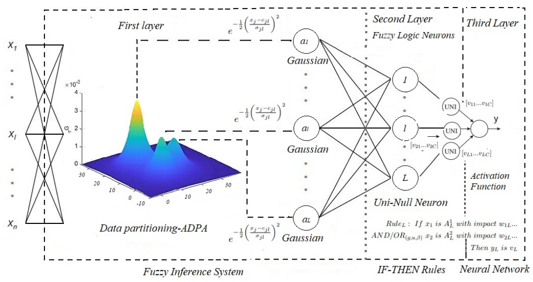

Figure 1: ENFS-Uni0.

4. Experiments

This paper aspires to demonstrate the ability of evolving fuzzy neural networks in the interpretability of pattern classification problems. To this end, some experiments and comparisons

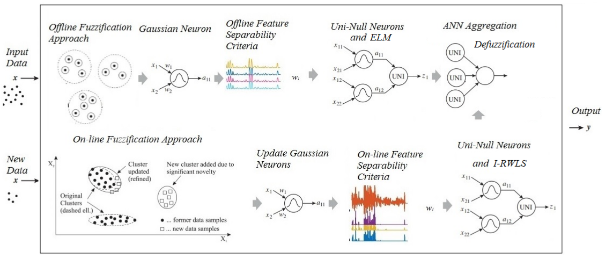

Figure 2: Algorithm execution steps.

Algorithm 1 ENFS-Uni0 Training and Update Algorithm

Initial Batch Learning Phase (Input: data matrix X with K samples):

(1) Extract L clouds in the first layer using the ADPA approach (L is automatically estimated therein).
(2) Estimate center values $\vec{c}$ and widths $\vec{\sigma}$ for the L clouds derived from ADPA.
(3) Calculate the combination (feature) weights $\vec{w}$ for neuron construction using FWSC.
(4) Construct L logic neurons on the second layer of the network by welding the L fuzzy neurons of the first layer, using uni-nullnorms concept and the centers $\vec{c}$ and widths $\vec{\sigma}$.
(5)
for $i = 1, ..., K$ **do**
  (5.1) Calculate the regression vector $z(x_i)$.
  (5.2) Store it as one row entry into the activation level matrix Z.
end for
(6) Extract reduced activation level matrix Z according to the L neurons.
(7) Estimate the weights of the output layer for all classes $k = 1, ..., C$ by ELM approach using Z and indicator vectors $\vec{y}_k$.

Update Phase (Input: single data sample $\vec{x}_t$):
(8) Update L clouds and evolving new one on demand (due to rule evolution conditions) in the first layer using extended evolving ADPA approach ($\rightarrow L_{s,upd}$ clouds).
(9) Update the feature weights $\vec{w}$ by updating the within- and between-class scatter matrix and recalculating FWSC.
(10) Perform Steps (2) and (4).
(11) Calculate the degree of change of all neurons.
(12) Calculate the regression vector $z(\vec{x}_t)$.
(13) Update the weights of the output layer by I-RWLS.

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with state-of-the-art models will be carried out and discussed. The quality measure evaluated in this paper is the accuracy (ACC):

$$ACC = \frac{TP + TN}{TP + FN + TN + FP} * 100. \tag{11}$$

where TP = true positive, TN = true negative, FN = false negative and FP = false positive.

Another method of analyzing accuracy using EFNN is combined with the trend-line method of the stream mining case. In these cases, the accuracy is cumulatively updated by:

$$ACC(K+1) = \frac{ACC(K) * K + I_{\hat{y}=y}}{K+1}, \tag{12}$$

Where I represents the indicator function, if the prediction is correct, it is 1, that is, $\hat{y} = y$; otherwise, it is 0 ($ACC(0) = 0$); after updating the accuracy, the model will be updated, so that produces an interleaved test-then-train protocol that is widely used in the data stream mining community [29] to exploit the predictive power of incremental adaptive (and evolving) models.

All tests were run on a computer with the following settings: Intel(R) Core(TM) i7-6700 CPU 3.40GHz, 16GB RAM.

4.1. data set

The data set [1] used in the experiments is the **Spanish Basketball League ACB data set**: The data set consists of 80 samples (perfectly balanced with 20 samples per class) corresponding to the four classes (point guard, shooting guard, small forward, center) that are associated with 13 attributes (height, blocks (Fig. 3 -a), rebounds, assists, points, personal fouls committed, personal fouls received, free throw percentage (Fig. 3 -b), 2-point field goal percentage, 3-point field goal percentage, turnover, steals, and global assessment). The numerical values associated with each sample correspond to the statistics available online at the website of the Spanish Basketball League ACB. The authors have collected statistics from each player's 2017-2018 season [30].

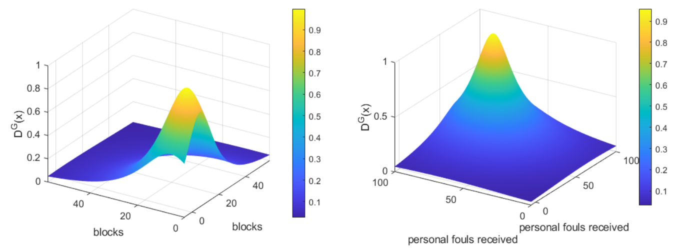

Figure 3: Density evaluation in dimension (a) block and (b) free throw.

This data set has already been addressed in another academic research [31] with a maximum accuracy of 63%.

4.2. Models used in the experiments

The models used in the test are presented below. Except for the models provided by the online solution, which already have predefined parameters, the other models previously underwent a 10-fold procedure with cross-validation of 70%-30% for the definition of parameters.

[1]https://citius.usc.es/investigacion/datasets/basketballplayers

Evolving Neuro-Fuzzy System based on Uni-Nullneurons (ENFS-Uni0) –The evolving fuzzy neural network is used as a reference in this study. It uses uni-nullneurons, and the non-regularized approach was adopted to analyze all rules.

Autonomous Learning Multimodel (ALMMo) — A model is a neuro-fuzzy technique for autonomous zero-order multiple learning with pre-processing that improves the classifier and the approximation model accuracy by creating stable models. The parameter is radius = 2-cos(30°) [32].

Fuzzy Hoeffding Decision Tree (FHDT)— Approach for incremental learning of multi-way in classification tasks with uniform fuzzy partitions for each input attribute: selecting the best input attribute to be used for the splitting at each node is performed by using the fuzzy information gain defined [33]. The configuration is based on the online solution [2]

Fuzzy Unordered Rule Induction Algorithm -(FURIA) — Fuzzy rule-based classification is a method for classifying items using fuzzy rules with fuzzy sets of trapezoidal shapes in the antecedent of each rule. FURIA uses fuzzy logic to learn how to operate instead of relying on rigid rules and ordered rule sets. The configuration is based on the online solution [34]. [3]

Self-Adaptive Fuzzy learning (SAFL) — A novel self-adaptive fuzzy learning (SAFL) system is proposed for streaming data prediction with a set of prototype-based fuzzy rules. The parameters are γ_0=0.5, $\Omega_0 = 1000$, $M_0 = 0.05$[4]

4.3. Results

The results of classification experiments is presented in Table 1. As for the pattern-classification tests were 50% for training and 50% for testing. In the evaluation of stream data, 20% of the samples were destined for training and the rest for testing. This facilitates the evaluation of the data in trendlines presented in the Fig. 4. In addition to the results in trendlines of the model, the evolution criteria of the first layer Gaussian neurons are also presented (Fig. 5), and the evolution and changes over time of the relevance of the features to the problem impact directly on the weights of Gaussian neurons (Fig. 7) and the behavior of fuzzy neurons relative to their evolution during the experiment (Fig. 6).

Table 1
Result of Positions of Basketball Players data set.

Model	ACC.
ENFS-Uni0	87.50
ALMMo	47.50
SAFL	17.50
FURIA	69.44
FHDT	75.00

[2]https://demos.citius.usc.es/ExpliClas
[3]https://demos.citius.usc.es/ExpliClas
[4]defined according to the experiments performed in [35].

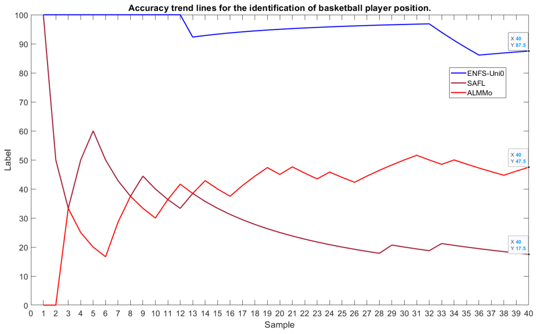

Figure 4: Trendlines for the accuracy of the test in identifying the position of basketball players.

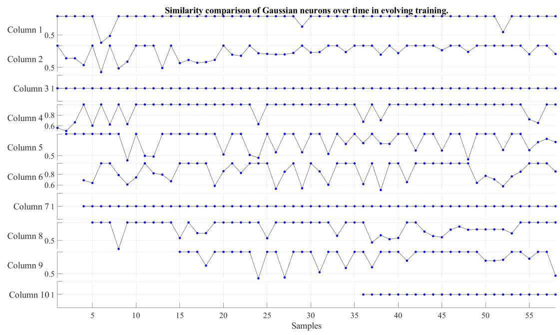

Figure 5: Similarity comparison of Gaussian neurons over time.

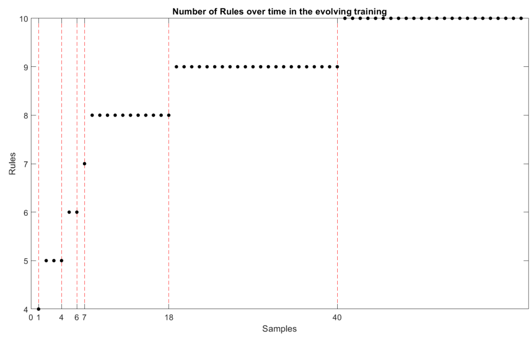

Figure 6: Number of fuzzy rules over time in the evolving training.

5. Discussions

The discussions carried out in this paper seek to bring a relationship between the main interpretability characteristics of an evolving fuzzy system model and the results obtained in the experiments performed.

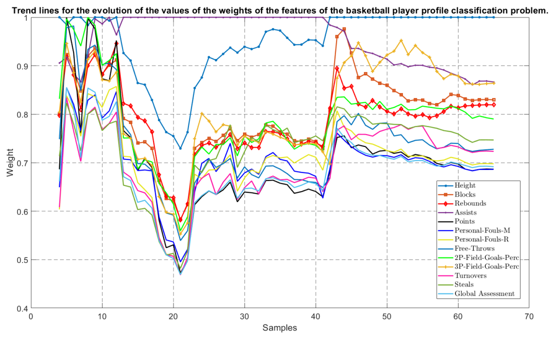

Figure 7: Online feature weight separability criterion for the dimensions of the position identification problem of basketball players.

5.1. Distinguishability and simplicity

The simplicity of the ENFS-Uni0 model in solving the problem of identifying the position of basketball players showed in the form of obtaining the best results in the evaluation of trendlines (Fig. 4) when compared to state-of-the-art models with a rule evolution that goes from 4 initial rules to a total of 10 fuzzy rules for solving the problem (Fig. 6). The distinguishability aspects can be seen in Fig. 5, where it is possible to identify during the analysis when the Gaussian neurons obtained changes as the model evaluated new samples. This behavior facilitates the understanding of how the architecture changed as new significant samples were evaluated by the model and, at the same time, identifies how the distinction provided by the Gaussian neurons originated in the fuzzification process helped the adaptation of the model in the identification of basketball player profiles. The centers of the clusters initially formed by the algorithm with the two dimensions most relevant to the problem according to Fig. 7 can be seen in Fig. 8. The final version with the first layer of Gaussian neurons can be seen in Fig. 9. In both cases, no overlapping was identified, despite the centers of rules 2 and 5 being very close.

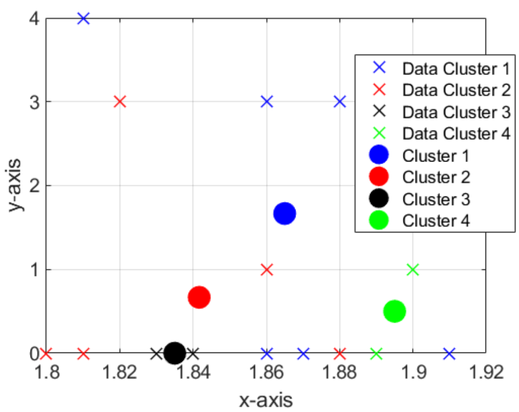

Figure 8: Initial clustering with 4 fuzzy rules (4 centers)- height versus blocks.

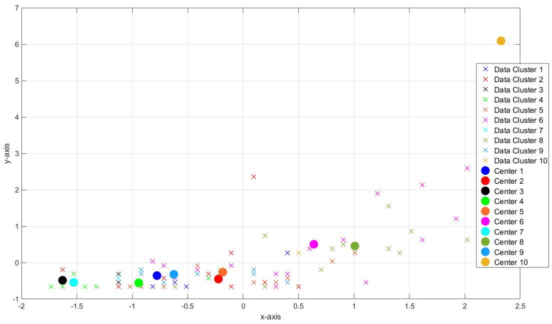

Figure 9: Final clustering with 10 fuzzy rules (10 centers)- height versus blocks.

Table 2
Comparison of Rule 3's initial behavior with the addition of a new class

changes mf.	Simil.	Point guard	shooting guard	small forward	center
10	1	small	small	small	small
7	1	very small	medium	small	small

Table 3
Comparison of Rule 7's initial behavior with the addition of a new class

changes mf.	Simil.	Point guard	shooting guard	small forward	center
6	1	medium	very small	medium	small
9	1	very small	small	very small	medium

5.2. Consistency

The analysis of the antecedents of fuzzy rules in this context varies according to the value of the Gaussian membership functions elaborated by the fuzzification method and the respective weight generated by the feature weight technique. In the context of evolving classification, it is essential to analyze whether, after training, the rules received the impact of the evaluation of a new sample. Fig. 7 presents a dynamic variation of the weight values for the neurons of the first layer, thus altering the similarity of the antecedents when compared to the rule in its previous format. The dynamics of evaluating the similarity of Gaussian neurons can be seen in Fig. 5. A factor that should also be highlighted in this figure is that rules 3, 7, and 10 maintain a high degree of similarity in their antecedents throughout the evaluation. Therefore, these rules can be evaluated on their consistency. Table 2 presents an evaluation obtained during the experiment comparing rule 3 and Table 3 for the rule 7 in the first moment of evolution with regard to their respective changes when a new class appears (for rule 3 when the shooting guard class appears and for rule 7 when the small forward class is presented to the model). It is noted that membership functions change, but the similarity of antecedents does not change. At the same time, there is a change in the consequents of the rules.

Therefore, the aforementioned rules are considered consistent because even with the similarity

Table 4
Interpretability of fuzzy neurons' output during the first evolving step.

Rule	Point guard	shooting guard	small forward	center
1	large	small	small	small
2	small	small	small	small
3	small	small	small	small
4	small	small	small	small

Table 5
Probability of fuzzy neurons' output in the last evolving step.

Rule	Point guard	shooting guard	small forward	center
1	very small	high	very small	high
2	high	very small	small	very small
3	very small	high	high	high
4	high	very small	very small	very small
5	very small	high	small	high
6	very small	high	very small	high
7	high	very small	small	very small
8	high	very small	very small	very small
9	high	medium	small	very small
10	very small	very small	very small	high

of the Gaussian neurons equal 1, the weights strongly impact the construction of the rule antecedents, generating assertive results at the end of the evaluation.

5.3. Coverage and completeness

In evaluating this criterion, rule consequents allow an assessment that, for all samples, at least one rule is triggered to a significant degree. The model proved to be able to activate at least one rule for each group formed by the model. The initial evaluation situation, where only one rule is activated (because only one class was presented to the model), is presented in Table 4. The other rules always activated evaluations of a class of the problem throughout the experiment. The interpretability of the rule consequents at the end of the experiment is presented in Table5, demonstrating the relevance of each rule for a particular class of problem. For these tables, a rule that has no relation to the class in question is considered very small (0% probability). The one with the highest probability of belonging to that class is considered high (between 85% and 100%). This evaluation is completed by the values small (between 1 and 15% of probability) and medium (between 16 and 84% of probability).

5.4. Feature importance levels

The importance of the features of the problem brings several evaluations of interpretability to the results. First, as can be seen in Fig. 7, it is possible to evaluate the evolution of features as new data is analyzed. This allows a dynamic assessment of how specific samples change the separability of classes as they are analyzed. A key factor in the interpretability of this model was the identification of the most relevant features to correctly identify the problem classes, namely height, blocks, rebounds, and 3P Fields goals percentage. This evaluation demonstrates that the model can correctly differentiate the classes and is consistent with accurate evaluations of a basketball game. A player's height is a determining factor for his position on the court. His ability to block, rebound and shoot three-pointers can also facilitate his on-court functionality. These characteristics found by the model are also highlighted in studies in the literature on the positions of players on the court [36].

Another point to be highlighted in this context is connected to the reducibility of fuzzy rules generated according to the features of the problem. The features that contribute the least to the problem can be eliminated, thus creating more compact rules. The following is an example of a fuzzy rule generated by the model:

IF *height* is mf5 with impact 1.00 OR **blocks** is mf8 with impact 0.82 OR **rebounds** is mf7 with impact 0.81 OR **assists** is mf6 with impact 0.86 OR **points** is mf5 with impact 0.68 OR **personal fouls committed** is mf10 with impact 0.69 OR **personal fouls received** is mf10 with impact 0.69 OR **free throw percentage** is mf10 with impact 0.72 OR 2-point field goal percentage is mf9 with impact 0.79 OR **3-point field goal percentage** is mf8 with impact 0.86 OR **turnover** is mf7 with impact 0.72 OR **steals** is mf7 with impact 0.74 OR **global assessment** is mf5 with impact 0.69 **THEN position is** point guard: **very small probability**, shooting guard: **high probability**, small forward: **small probability**, center: **high probability**.

Let us consider a relevance criterion (for example, weights below 0.70 are considered irrelevant) and replace the membership functions with linguistic terms. We can build a more compact and interpretable fuzzy rule, as shown below [5].

IF *height* is medium with impact 1.00 OR **blocks** is large with impact 0.82 OR **rebounds** is large with impact 0.81 OR **assists** is medium with impact 0.86 OR **free throw percentage** is very large with impact 0.72 OR 2-point field goal percentage is very large with impact 0.79 OR **3-point field goal percentage** is large with impact 0.86 OR **turnover** is large with impact 0.72 OR **steals** is large with impact 0.74 **THEN position is** point guard: **very small probability**, shooting guard: **high probability**, small forward: **small probability**, center: **high probability**.

5.5. Rule importance levels

The criteria for evaluating the relevance of rules are given in this experiment by evaluating the weights of their consequents concerning each of the classes. Some rules have greater relevance to determining one class over others. It is even possible to identify if there is duality in

[5]the linguistic terms were converted following the following criteria mf1 and mf2 = very small (short), mf3 and mf4=small, mf5 and mf6=medium, mf7 and mf8=large(tall), mf9 and mf10= very large(tall).

Table 6
Rule consequent values at the end of the experiment.

Rule	Point guard	shooting guard	small forward	center
1	0	1	0	1
2	1	0	0.03	0
3	0	1	1	1
4	1	0	0	0
5	0	1	0.01	1
6	0	1	0	1
7	1	0	0.01	0
8	1	0	0	0
9	1	0.55	0.01	0
10	0	0	0	1

Table 7
Rule 1 consequent values in the first 4 evaluations of the evolving model.

Interaction	Point guard	shooting guard	small forward	center
1	large	small	small	small
2	small	small	small	small
3	very small	medium	small	small
4	very small	medium	small	small

identifying the rule if it has similar values for the identification of a class. The values presented in Table 6 exemplify this context.

Table 7 presents the changing behavior of the relevance of a first rule throughout the evaluation of the model's behavior as new samples are submitted to the model.

As seen in Table7, as new samples are evaluated, the relevance of a rule for the determination of specific class changes. Rule 1 corresponded to identifying the point guard profile in the first evolving iteration. In the second iteration, this rule started to have a small probability of identifying the classes involved. In the third and fourth iterations, the rule started to act in identifying the shooting guard class.

5.6. Interpretation of consequents

The evaluation of the consequents of this model allows us to identify the rules that best collaborate in identifying a basketball player's position. In this contextual evaluation, it is possible to identify (based on the Tables 5 and 6) that for the point guard position, for example, the rules that most contribute to identifying it are 2, 4, 7, 8 and 9. As for the shooting guard position, rules 1, 3, 5, and 6 best classify this class in the model. In evaluating a small forward, only rule 3 allows a high identification of this profile. Finally, the fuzzy rules of classifying correctly for the center position are 1, 3, 5, 6, and 10. We can also infer the relevance of a rule to find a specific class on the evaluation of consequents. The rules that clearly define a basketball player's position are 4 and 8 for the point guard and 10 for the center position. This is due to the probability of the other classes involved in the problem for these rules to be null. Rules 2 and 7 are also considered in identifying a point guard with a high probability for this position. A study can also be carried out on the shooting guard position. All rules that can identify this profile with high precision are also linked to identifying the center position. Rule 3 can belong to characteristics of 3 groups.

This evaluation even differs from the FURIA and FHDT models, which concluded that there is confusion in the classifier between types of point guard and shooting guard positions (models with 69.44% and 75.00% accuracy, respectively). One way of evaluating the consequents can also be seen as an indirect pruning of neurons. When a rule has all its consequents come out as zero, it can no longer represent a class. As the neural network works with the aggregation of all fuzzy rules to perform the defuzzification process, a rule with zero weights will not contribute to obtaining the answers.

5.7. Knowledge expansion

The assessment of the knowledge acquired by the model comprises some factors listed in previous subtopics. The evolution of the rules (Fig. 6) indicating that the model acquired knowledge about new data strongly evidences that this model was able to learn from the samples. The interpretability of rule antecedents, features weights, and rule consequents allow for a complete analysis of the problem, thus enabling a rule generated on a problem to provide the most diverse information about a context. Another factor that evidences the expansion of knowledge of the model is how several operational elements can compose the complete extraction of knowledge about a data set. The explanation of the FURIA (Fig. 10) and FHDT (Fig.11) models present graphical information about the problem, but they fail to analyze changes sample by sample. Another difference in knowledge gain compared to these two models is the final number of rules extracted: the FURIA model obtained 69.44% accuracy with seven rules, the FHDT achieved 75.00% accuracy with only five, and the ENFS -Uni0 achieved 87.50% accuracy with ten fuzzy rules. The models used in the trend line test only presented an accuracy of their results, not identifying any interpretable evaluation of them. The use of ENFS-Uni0 allows a comprehensive analysis, including behavioral data. Thus, researchers in the field can even understand how a specific sample can facilitate or complicate the classifier's conclusions. A solid interpretability criterion is the ability to translate data into fuzzy rules, which show logical relationships between rule antecedents.

By solving the same problem addressed in this paper, the FURIA model generated a graphical (Fig. 10) and contextual analysis of the assessments of the position of basketball players. The classifier was quite confusing as a global assessment because correctly classified instances represent a 69.44%. As explained earlier, there may be confusion related to some classes. Regarding the interpretability over some samples, the model concluded, for example, that an analyzed sample was small forward because height is medium. However, this does not seem right because the type should be a shooting guard instead of a small forward, according to the information in the data set. Another action was classifying a sample as a center because

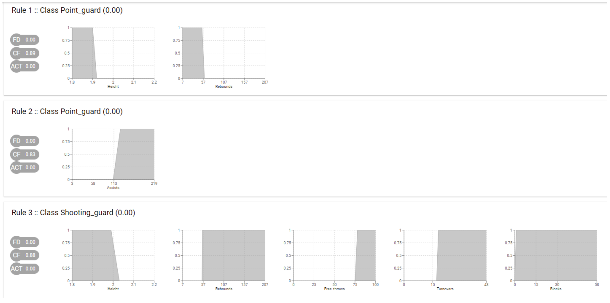

Figure 10: Graphical Resolution FURIA algorithm (7 rules)

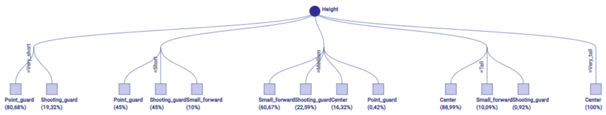

Figure 11: Fuzzy Hoeffding Decision Tree (FHDT)- Tree resolution (5 rules).

height is tall. Already the FHDT model (Fig. 11), on the other hand, presented the same global description (except for the accuracy of 75.00%) and an evaluation of the interpretability of samples where the model classified a player as being small forward. However, it highlighted the medium chance probability that it is a point guard. Another evaluation concluded that the player was a small forward because his height is medium, following rule 3 of the FHDT model. However, this classification is also wrong because the type should be Shooting guard instead of Small forward, according to the information in the data set.

6. Conclusion

This paper presented the functioning of an evolving fuzzy neural network acting in an interpretable way in the identification of basketball players' positions on the court. The model obtained expressive results compared to state-of-the-art evolving fuzzy systems models and presented a complete explanation of the model's functioning and its results. The ENFS-Uni0 presented an interpretable evaluation that ranged from the evaluation of antecedents, feature weights, and evaluation of rule consequents. Such an approach facilitates the understanding of researchers on the topic addressed, providing insights and evaluations that other interpretable fuzzy models were not able to do. The use of models with a high degree of interpretability helps respond to the challenges of emerging research on how explainability can be handled in online learning. In future work, this paper's extension is left to measure better the impact of weights on the similarity of antecedents regarding the weight of the respective neurons.

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