International Journal of Engineering & Technology, 7 (3.13) (2018) 76-78

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Online Learning Styles Identification Model, Based on the Analysis of User Interactions Within an E-Learning Platforms, Using Neural Networks and Fuzzy Logic

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Abstract

Individual Learning Style identification is an essential aspect in the development of intelligent or adaptive e-Learning platforms. Traditional methods are based on the application of questionnaires or psychological tests, which may not be the most appropriate in all cases. The proposed model is based on the analysis of user behavior through the study of their interactions within an e-Learning platform, using a multilayer Backpropagation Neural Network and Fuzzy Logic concepts, for the preprocessing of the inputs and the categorization of the outputs.

Keywords: *Backpropagation Neural Network; e-Learning; Fuzzy Logic; Learning Styles.*

1. Introduction

According to Lo [1], most researchers in the area agree that carrying out the teaching process considering the learning styles, can significantly increase the effectiveness and efficiency of learning. In this regard, various classifications have been proposed for learning styles. According to Herrera [2], the application of TIC's in education, virtual learning environments and e-Learning platforms, have fostered online learning, breaking the barriers of traditional education, however, many proposals and available tools affect the quality of educational services, requiring new models that improve the quality and effectiveness of online tools in the learning process.

The model proposed in the present work, has the objective of online identification of individual learning styles, through the analysis of user's behavior and interactions, within an e-Learning platform, radically differentiating from the traditional methods. A modified version of the Open Source Moodle platform has been developed and used for its application.

2. Background

2.1. Learning Styles

The learning styles were proposed by Kolb [3], who defines them as the preferred ways of learning that a certain subject uses. According to Schmek [4], there is a constant and general predisposition in the individual to adopt the same strategy or way of learning in different situations and independently of the specific objectives or tasks to be solved. There are different approaches to categorize learning styles, such as those proposed by Pask [5], Kolb [3], Fleming [6], Honey [7], etc. This study uses as a reference the model proposed by Honey, which consists in a questionnaire from whose answers each individual can be categorized into four learning styles: reflective, theoretical, active and pragmatic.

Adaptive Hypermedia technology represents an effective strategy to solve many of the learning problems involved in online platforms [8]. The idea behind this technology focuses on adapting the contents of a course, according to the particular characteristics of a user. According to Carver [9], any Web-based learning system should also include information about users, to optimally adapt instructional materials, with the identification of learning styles being a key aspect. Another possible approach is the definition of a personalized student model, where Herrera [2] propose the use of Multi-Agent Systems.

2.2. Neural Networks and Learning Styles Identification

According to Lo [1], the problem of recognizing individual characteristics of a user involves the classification of a number of categories, starting from a potentially infinite number of entries, which is why many researchers point to neural networks as the best approach to solve this problem due to the following advantages of this technique:

1. The ability to recognize patterns departing from inaccurate or poorly understood data.
2. The ability to generalize and learn from specific examples.
3. The ability to quickly update with additional parameters.
4. Speed of execution, which makes it ideal for applications in real time.

According to these premises, various proposals have been developed with different approaches. Some examples of this are: the use of competitive neural networks to find categories of users with interests and attitudes similar from the responses of traditional questionnaires [10]; the integration of neural networks with Case Based Reasoning to recognize the intentions of the users during their navigation [11], and more recently, the use of Multilayer

Feed-Forward Neural Networks and Conceptual Maps for observing the user's navigational behaviour [1], Intelligent Diffuse Models for the characterization of student profiles [12], Fuzzy Cognitive Maps for learner's style and profile recognition [13], Performance Evaluation of Learning Styles Based on Fuzzy Logic Inference System [14], etc.
As an alternative approach, Herrera [2] propose the use of Multi-Agent Systems, combined with other Artificial Intelligence techniques, such as Case Based Reasoning, Genetic Algorithms and other hybrid techniques, embedded in an intelligent e-Learning system, with the purpose of each resource, activity and educational service being flexible to the learning style of each student and encouraging collaborative learning online.
The approach proposed in this paper uses Backpropagation Neural Networks, whose main advantage consists in the ability to learn from the association that exists between the input patterns and the corresponding classes, using several levels of neurons, by propagating the error towards back, based on the generalization of the delta rule. The use of this approach is possible given that there is a training set, product of the logs and the application of the learning styles questionnaire at the beginning of the semester.

2.3. Fuzzy Logic

According to Gonzales [15], Fuzzy Logic theory provides a mathematical framework that allows modelling the uncertainty of human cognitive processes, so that it can be treated by a computer, resulting in a better adaptation to the real world, and therefore to the interpretation of learning styles, in addition to handling uncertainty and lack of precision or clarity. The implementation of this technique provides an inference mechanism that allows to simulate the procedures of human reasoning [15] [16].
Some of the applications of fuzzy logic in this field are: analysis of collaborative learning experiences within e-Learning environments [17], construction of customized e-Learning systems using genetic algorithms, Fuzzy Logic and Case Based Reasoning [18], etc.

3. The Proposed Model

The proposed model is based on the analysis of user behaviour through the study of their interactions within an e-Learning platform, using a multilayer Backpropagation Neural Network and Fuzzy Logic concepts, for the pre-processing of the inputs and the categorization of the outputs.

3.1. Test Data

For the collection of test data, we applied the learning styles questionnaire proposed by Honey [7], to a group of 70 higher education students of the National University of San Augustin during the first semester of the year 2017, so that the Learning Style of each student was known in advance according to a traditional method.
In order to obtain the entries for the Neural Network, according to the proposed online detection method, a modified version of the Open Source Moodle platform was used, applying the following changes:

- A list of categories or types of resources to be used within the course was defined, establishing 20 categories.
- Fuzzy sets were defined, to correlate each category or type of resource with each of the four learning styles proposed by Honey [7].
- A model course was established, ensuring that each course content has alternative presentations corresponding to types of resources with fuzzy sets without intersections.
- The source code of the platform was modified, in order to save a log with the selections (clicks) made by each student, which represent the user's behaviour, according to the previously established categories.

In this way, it was possible to obtain the inputs and outputs of the proposed model, dividing the data into two sets of the same cardinality (a training set and a test set). For the division of the data, the criterion of representativeness of learning styles was used, so each sub-set there is approximately the same proportion of learning styles with respect to the total set.

3.2. Input Pre-Processing

Due to the amount of resource categories, and the fact that some content within the platform, could not always have alternative presentations with non-similar learning styles, the initial tests using all “Clicks” or user selections were not satisfactory, since some sets of inputs were very noisy and made it difficult to train the neural network or distort the output.
To solve this problem, it was decided to define a second group of fuzzy sets, which would better categorize a user's preference for a certain category of resources, according to the percentage of interactions in each category, as shown in Figure 1. This fuzzyfication of the data obtained through the log of the e-Learning platform, has been considered as a stage of pre-processing of the entries.

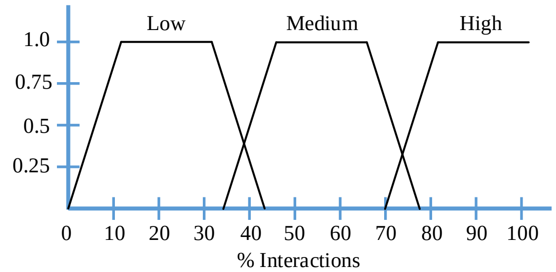

Fig. 1: Fuzzy sets for representing the user preference for a certain resource category.

For example, a user whose learning style is predominantly defined as "active" might have selected a few times resources primarily related to the "reflexive" or "theoretical" styles, because the information contained in these resources was indispensable for other activities within the course or the evaluation of the same, although they were not of their preference, nevertheless these "few" interactions should not be determinant for the model application.

3.3. Neural Network Model

The objective of the Neural Network model is to identify the learning style of a specific individual, based on their interactions and behaviour, within an e-Learning platform, for this, a Backpropagation Neural Network was used, composed of a layer of input, a hidden layer, with the Sigmoidal activation function, and an output layer, as shown in figure 02.

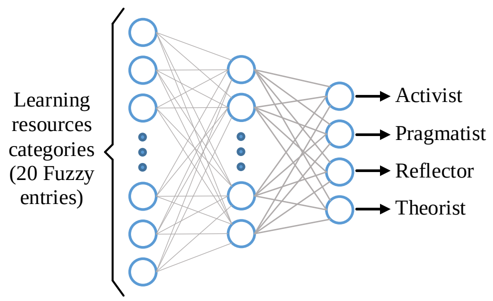

Fig. 2: Neuronal Network Architecture.

Input neurons represent user’s interactions in the e-Learning platform, previously fuzzified, as was described in the pre-processing stage; therefore, 20 neurons have been considered in the input layer, corresponding to each one of the previously defined resource categories.

The hidden layers provide the processing power of the neural network, where the number of neurons in the hidden layer directly affects the Neural Network ability to learn. However, in the particular case proposed, tests were made with different numbers of neurons in the hidden layer, however, as good results were not obtained due to the amount of noise in the inputs, it was decided to pre-process the inputs.
The output layer consists of four output neurons, corresponding to the four learning styles proposed by Honey [7], indicating the predominant learning style for each student.

4. Results and Discussion

For the experimentation and testing of the model, the students followed the course through a modified version of the Moodle platform. In this modified version was possible to obtain a record of all their interactions within the course over a semester.
It is important to note that it is not possible to identify a student's learning style in a single week or learning session, since their interactions with the platform may vary according to the topic developed, the type of resources available, the availability of time in a particular moment, among other factors, as shown in figure 03 for some model cases.

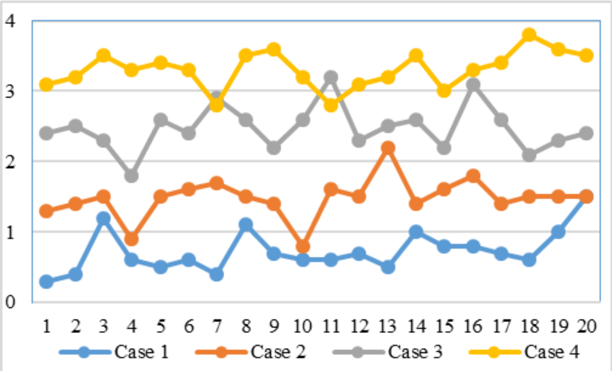

Fig. 3: Fuzzy sets for representing the user preference for a certain resource category

According to this approach, it would be necessary to identify the learning style during an introductory course such as the "Study Methodology", and then adapt the contents of the following courses. It is necessary to monitor and validate the relevance to that learning style each semester.
Taking the data relates to student interactions and student test data (traditional method), we used half of this data as a training set and the other half as a test set to compare the results obtained with the Network Neuronal under this approach. The neural network and the proposed model reached a 77% effectiveness or coincidences in the identification of the learning style with respect to the Honey test.
The importance of online detection of the learning style is that, using the modified version of the Moodle platform developed, the contents of each course will be personalized based on the styles of each student, which will improve the efficiency of the teaching / learning process throughout the process, which will be analyzed in subsequent works.

5. Conclusion

A Backpropagation Network model was proposed, whose input data was fuzzified in a pre-processing stage, which allows learning styles to be identified online, based on the students' interaction with the e-Learning platform.
The identification of learning styles cannot be based on a single session or user access, which can lead to errors of interpretation, but must be made over several sessions to achieve an adequate accuracy in the identification.
The use of neural networks associated with fuzzy logic, made it possible to propose a novel approach, for the resolution of a complex problem, in the line of research of e-Learning platforms.

Acknowledgement

The authors would like to thanks to the National University of San Agustin (UNSA) for supporting this research.

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