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CHARACTERIZATION OF LEARNING STYLES AS STUDENT MODELING TO DETERMINE THE ZONE OF PROXIMAL DEVELOPMENT FOR CONTENT SELECTION IN AN INTELLIGENT TUTORIAL SYSTEM

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Abstract: Student modeling in an intelligent tutorial system has been approached through knowledge tracking; however, one challenge is integrating pedagogical models into the construction of intelligent tutorials. Machine learning allows students to be modeled using historical data to predict learning outcomes. Neural networks within machine learning perform classification through a training process. This work characterizes student modeling with historical data on learning styles to model students and determine their Zone of Proximal Development (ZPD). The ZPD is determined using a Kohonen neural network model, which generates a self-organizing map (SOM) that allows us to classify a type of student modeled by their learning style. The Kohonen network was trained with a 6 x 6 grid, giving a total of 36 neurons and 803 vectors, of which 70% = 562 were used for training and 30% = 241 for testing. The self-organizing map generated four classes of ZPD into which the learning style can fall.

Keywords: Intelligent tutoring systems, Student modeling, Learning styles, Neural networks, Zone of Proximal Development

Student modeling in an intelligent tutoring system is built on knowledge tracking; however, the integration of pedagogical models represents a challenge. Machine learning provides tools for student modeling with historical data to predict learning outcomes. Neural networks, as part of machine learning, perform clustering through a training process. This article works on determining groups of students with the same zone of proximal development (ZPD) through historical data on their learning styles. The Kohonen neural network allows the construction of a Self-Organizing Map (SOM) that performs the clustering of learning styles. Learning styles were obtained by applying the Honey and Alonzo Learning Styles Questionnaire (CHAEA). The questionnaire was administered to 803 students studying Information and Communications Technology Engineering at the Apizaco Institute of Technology. The Kohonen neural network was trained with a 6x6 node grid, using 70% of the data for training and the remaining 30% for testing. The Self-Organizing Map produced four types of Zones of Proximal Development.

INTRODUCTION

Intelligent tutoring systems enhance student participation and engagement, with positive effects on the teaching-learning process, by adapting strategies to students' abilities.[1] . The use of ICT is increasingly common in the development of skills in higher education. However, technology alone does not guarantee this development; techno-pedagogical mediation is required to establish appropriate learning strategies that ensure the intervention is successful. Information and communication technologies are increasingly used in the development of skills in higher education. However, technology alone does not guarantee this; techno-pedagogical scaffolding is needed to establish appropriate learning strategies that enable success.[2] . Machine learning techniques applied to student modeling improve learning performance when implemented in intelligent tutorial systems [3] . The integration of Vygotsky's Zone of Proximal Development allows us to build scaffolding through the integration of artificial intelligence to customize lear-

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ning content. The zone of proximal development allows us to build scaffolding through artificial intelligence that personalizes learning.[2] . This work proposes the characterization of students' zone of proximal development through a Kohonen neural network that receives as input the learning styles of Information Technology Engineering students at the Technological Institute of Apizaco. The characterization process is developed in the article in the following sections. Section 2 reviews the theoretical framework, the learning styles model, the zone of proximal development, and the neural network that allows us to construct the Self-Organizing Map (SOM). Section 3 discusses the methodology, the application of the Honey-Alonzo Learning Styles Questionnaire (CHAEA), the architecture established for the Kohonen neural network, and the obtaining of the Self-Organizing Map (SOM). Finally, section 4 reviews the results and draws conclusions. This work proposes the characterization of the Zone of Proximal Development (ZPD) of students through the Kohonen neural network, which reflects the learning styles of students in the Information and Communication Technologies (ICT) Engineering program at the Apizaco Institute of Technology. This characterization process is developed in the following sections: Section 2: review of basic concepts: learning styles model, ZPD, Kohonen neural network, and Self-Organizing Map (SOM). Section 3: methodology: application of the Honey Alonzo learning styles questionnaire, Kohonen neural network, and Self-Organizing Map (SOM). Section 4: review of results and, finally, the conclusions section.

THEORETICAL FRAMEWORK

Learning Styles

Catalina M. Alonso reviews different authors on what a learning style is and considers Keefe's (1988) definition to be the most comprehensive, which states that:

"Learning styles are the cognitive, affective, and physiological traits that serve as relatively stable indicators of how learners perceive, interact with, and respond to their learning environments."

She believes that learning styles can provide teachers with relevant data on individual and group learning, enabling them to guide the development of skills in the classroom in an appropriate manner.

She reviews Honey and Mumford's questionnaire and the learning styles they describe as:

- Active: spontaneous people who enthusiastically take on new tasks. They are people of the here and now and like to have new experiences. They believe that everything should be tried at least once.
- Reflective: they like to consider experiences and observe them from different perspectives. They gather data and analyze it carefully before reaching any conclusions. They break problems down into their constituent parts and their philosophy is to be prudent.
- Theoretical: they review problems in logical stages, like to keep track of things with formal notation, and are deep in their thought systems to establish principles, theo-

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ries, and models. They seek to be rational and objective.

- Pragmatists: They like the practical application of ideas. They like to experiment, and their philosophy is that you can always do better by applying theories and principles, and if it works, it's good.

With this, Catalina evaluates the Honey-Alonso Learning Styles Questionnaire (CHAEA) in order to validate it, which is why it was chosen to carry out our application as a mediation model, combining it with activities from David Kolb's experiential learning cycle.

Catalina Alonso has reviewed different authors on learning styles and considers a complete definition to be: "Learning styles are cognitive, affective, and physiological traits that allow us to establish relatively stable indicators of how students perceive, interact with, and respond to their learning environment."

She believes that learning styles can provide teachers with data on individual and group learning, enabling them to correctly promote skill development in the classroom.

She reviews Honey and Mumford's questionnaire on learning styles, which they describe as [4] :

- Active: Spontaneous people who enthusiastically take on new tasks. They live in the present and enjoy new experiences. They believe that everything should be tried at least once.
- Reflective: They like to consider experiences and differences observed from different perspectives. They collect data and analyze it carefully before reaching a conclusion. They break problems down into their parts, and their philosophy is prudence.
- Theoretical: They analyze problems in logical stages. They like to express problems using formal notation and delve deeply into their ideas to establish principles, theories, and models. They seek to be rational and objective.
- Pragmatic: They like the practical application of their ideas. They like experimentation, and their philosophy is to apply theories and principles best if they work well.

The Honey-Alonso Learning Styles Questionnaire (CHAEA) provides us with a vector of four values corresponding to the dominant level of each of the styles, which we will use to determine the content and how it should be presented in order to achieve better skills development.

The zone of proximal development

The Zone of Proximal Development developed by Lev Vigotsky describes what a student can do without help and what they can achieve with the guidance and support of a mediator. These are the different activities that they can perform independently and what they can achieve with the scaffolding provided by the mediator. In smart tutorials, it is useful for establishing strategies and promoting student learning in the following areas[2] :

- Differentiation: The potential of each student is identified in order to establish learning strategies according to their needs and abilities.

- Scaffolding: Appropriate activities and support are developed to form a scaffolding that allows students to move from their current level to the required skill development.
- Responsibility: We move from specific guidance to giving them confidence to take on increasing responsibilities until they achieve competence. The aim is for their growing confidence to make them independent.
- Formative assessment: Continuous reinforcement is carried out based on the results of the assessment of progress achieved, promoting deep learning.

With the Zone of Proximal Development, activities can be established that are appropriate to the characteristics of the students, allowing for the growth and development of each student.

Kohonen's Neural Network

Teuvo Kohonen designed a neural network with two layers: the first input layer and the second competence layer. The input layer has a number of nodes equal to the input data of the attributions. Each input is defined with a vector E = (e1, e2, ... en). Each node is connected to all nodes in the competition layer. If there are m nodes in the competition layer, the weights are defined as the matrix:

$$\begin{vmatrix} u11, & u12, .., u1m \\ u21, & u22, .., u2m \\ .., & .., \quad .., \quad .. \\ un1, & un2, .., unm \end{vmatrix}$$

Where uij is the weight of the connection between node i in the input layer and node j in the competition layer. These connections start with random values at the beginning of the learning phase and are modified throughout the process.

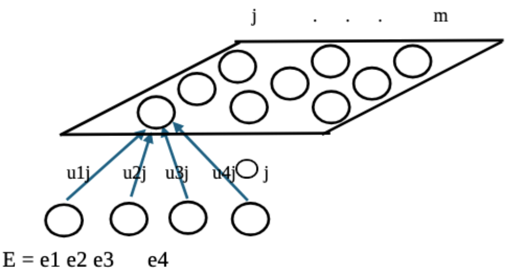

Figure 1. Kohonen neural network architecture

For the training process, it is necessary to compare the vector of the input layer with the weights of the competition layer to determine the shortest distance. In this case, the Euclidean distance was applied, which is defined by:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

All outputs from the competition layer are compared with each other to obtain the one that produces the smallest output.

If a reaction occurs in a neuron in the competition layer, the neighboring neurons are stimulated positively, while those further away are stimulated negatively. The lateral interaction function has a Mexican hat shape. The activation level of a neuron in the second layer depends on the input it receives and the lateral connections with other neurons.

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Lateral interaction is carried out on a winner-takes-all basis. Represented by the equation.

$$\frac{d\mu_{ij}}{dt} = \begin{cases} \propto(t)\left(\varepsilon_i(t) - \mu_{ij}(t)\right) & y \\ 0 & \end{cases}$$

$$si \;\; Ci \;\; Ganadora$$

$$d(c_i, c_j) < \theta$$

$$en \;\; caso \;\; contrario$$

Where $\propto$ is the learning rate and θ is the neighborhood limit.

In this way, the winning neuron is drawn toward the pattern and the neighbors marked by θ.

The increase in connection is proportional ($\propto$) to the distance between the pattern and the winning neuron and is greater if it is larger ($\propto$). It starts with a large value for ($\propto$) and decreases over time.

The general algorithm for Kohonen's self-organizing maps is:

1. Initialize weights with small random values
2. Present an input.
   a. The set of patterns is presented cyclically until convergence is reached.
   b. Update $\propto$
3. Propagate the pattern to the competition layer.
4. Select the neuron with the shortest distance.
5. ε Update the connection between the input layer and the neuron, as well as those in its neighborhood within .
6. $\propto$ If the input is above the threshold, return to step 2, otherwise finish.

METHODOLOGY

Formation of the data group with learning styles.

In the subjects taught in the semesters from January-June 2018 to August-December 2024, students of the Information and Communications Technology Engineering degree at the Apizaco Technological Institute of the National Technological Institute of Mexico were given the Honey-Alonso Learning Styles Questionnaire (CHAEA). A total of 803 vectors of 4 attributes were obtained, where each attribute has a value between 2 and 20, representing the level of mastery of the Active, Reflective, Theoretical, and Pragmatic styles, as shown in Table 1.

Active	*Reflective*	*Theoretical*	*Pragmatic*
10	*12*	*12*	*11*
12	*14*	*11*	*17*

Table 1. Learning styles obtained.

Implementation of the Kohonen neural network

To obtain better results, the data is first normalized by applying the following function to each of the attributes:

$$xn_i = \frac{x_i - min(x[\ ])}{max(x[\ ]) - min(x[\ ])}$$

1. The data set E is loaded.
2. The competition layer is set to 6X6 neurons.
3. Weights w are generated randomly for each node in the competition layer with the number of input attributes, in this case 4.
4. Take an input vector E(i).

a. Iterate for each neuron in the map

i. Calculate the distance between the vector and the neuron weights

ii. Keep the neuron with the smallest distance

b. Update the weights of the neuron and those close to the BMU

5. Increase the epoch while it is less than the number of steps set Return to step 4.

RESULTS AND DISCUSSION

Figure 2 shows the histogram of the learning style data from the set of 562 patterns, corresponding to 70% of the 803 patterns in total and the first data. It should be noted that they behave like a normal distribution.

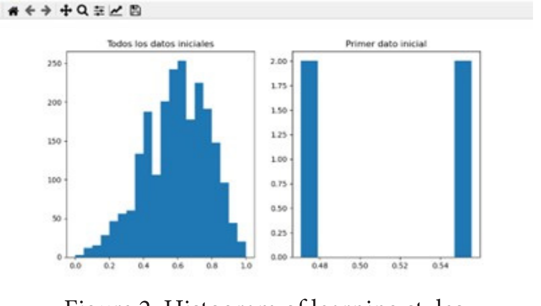

Figure 2. Histogram of learning styles.

Figure 3 shows the data on the composition of learning styles, with blue corresponding to Active, yellow to Reflective, green to Theoretical, and red to Pragmatic. Only the first 10 patterns are shown.

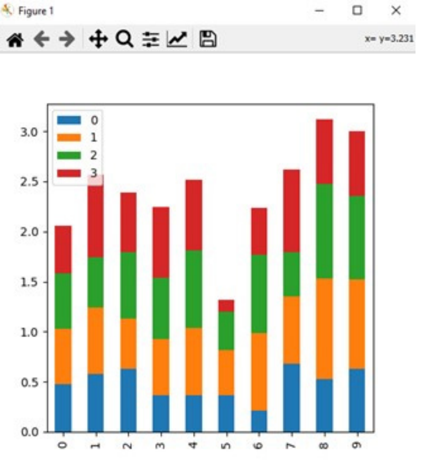

Figure 3. Composition of learning styles

Figure 4 shows the means and standard deviations of the data by style and by data. It should be noted that the highest average corresponds to the Reflective style, followed by Theoretical, then Pragmatic, and the lowest average is for the Active style, with a very similar deviation in all four styles.

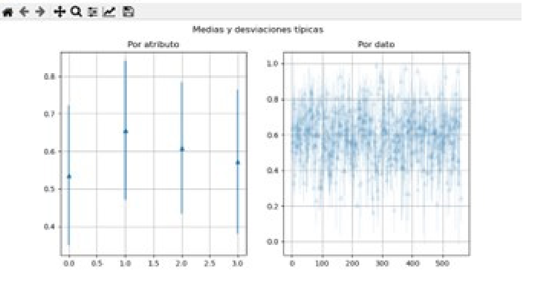

Figure 4. Mean and standard deviation of learning styles

Figure 5 shows the decay rates that allow increasingly smaller modifications to be made to the weights and which stabilize in the first 100 epochs. The total number was 200 epochs, processing all the data in each epoch.

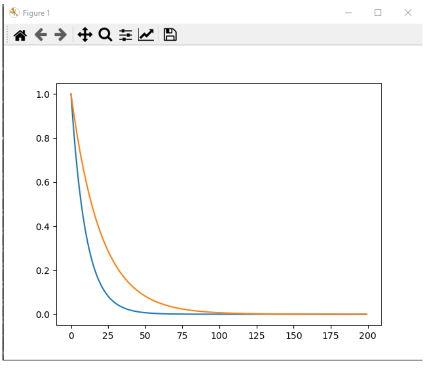

Figure 5. Decay functions.

Figure 6 shows the four groups corresponding to the dominant styles that are grouped in neurons 0, 5, 30, and 35. The classification was performed with a 6x6 neuron cell, and it should be noted that in this case, it is more defined when all patterns are processed.

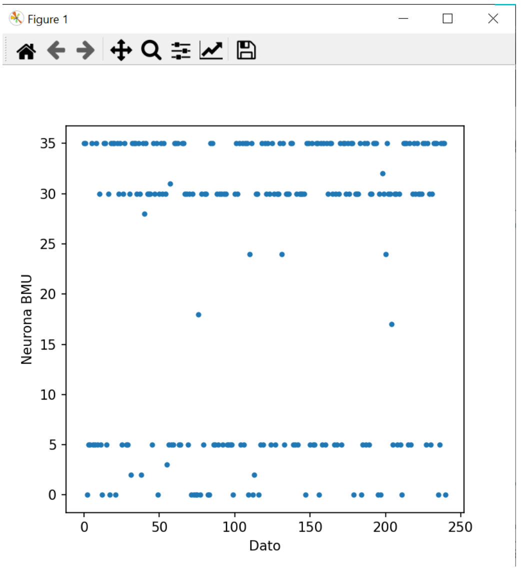

Figure 6. Classification of learning styles

CONCLUSION

The development of the SOM made it possible to characterize the zones of proximal development, finding four groups where students are located according to their learning style and providing guidelines for the content of the learning objects to be developed for the intelligent tutorial system, with the distribution of activities in the four areas of David Kolb's learning cycle: concrete experience, reflective , abstract conceptualization, and active experimentation. thus providing a vector that describes the level of activation of the learning objects.

The user stories specified for the development of learning objects will establish the characteristics of the objects that cover the areas of proximal development found, thus obtaining personalized learning objects for a specific student.

Once their activation vector has been determined, the learning objects are classified with the SOM obtained and labeled so that they can be applied in the corresponding zone of proximal development.

The SOM found will be used as a pedagogical module of the intelligent tutorial system for the subject of Object-Oriented Programming in the Information and Communications Technology Engineering degree program at the Apizaco Institute of Technology.

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