

Prediction of Learning Improvement in Mathematics through a Video Game using Neurocomputational Models

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Abstract: Learning math is important for the academic life of students: the development of mathematical skills is influenced by different characteristics of students such as geographical position, economic level, parents' education, achievement level, teacher objectives, social level, use of information and communication technologies by teachers, learner motivation, gender, age, preferences for playing video games, and the school year of the students. In this work, these previously mentioned characteristics were considered as the attributes (inputs) of a multilayer neural network that uses a backpropagation algorithm to predict the percentage of improvement in mathematics through a 2D mathematical video game that was developed to allow the children to practice addition and subtraction operations. After applying the neural model, using the twelve attributes mentioned before and the backpropagation algorithm, there was a network of one layer with ten neurons and another network of two layers with 5 neurons in the first layer and 20 neurons in the second layer. Both architectures produced a mean squared error smaller than 0.0069 in the prediction of the student's percentage of improvement in mathematics, being the best configurations found in this study for the neural model. These results lead to the conclusion that we are able to predict the percentage of improvement in math that the students could achieve after playing the game, and therefore, claiming if the video game is recommendable or not for certain students.

1 INTRODUCTION

Mathematics can be described as a science that investigates abstract structures in order to create by itself logical definitions using properties and patterns (Ziegler and Loos, 2016). Different studies agree that learning math is difficult for students (Stoica, 2015)(Hurst and Cordes, 2017). Furthermore, the way students describe their identity towards this subject, such as that of being a "math hater" is related to their learning opportunities. Therefore, teaching mathematics in a way that students enjoy learning concepts and solving exercises has become a challenge, making it necessary to find a new technique to promote the study of this science (Andersson et al., 2015).

Information Communication Technologies (ICT) have gained an important role in teaching; many countries have invested in the acquisition and maintenance of devices used in education (Comi et al., 2017a). Of course, the effective use of ICT will de-

pend on the practice that teachers make of it (Comi et al., 2017a). One improvement in the teaching of mathematics is the use of ICT through mobile technologies, virtual learning environments (VLE), personal learning environments (PLE) (Borba et al., 2016), and video games. Computer-based interactive educational methods in teaching allow students to increase their mathematical performance and reduce failures at solving a task (Comi et al., 2017b; Pachemska et al., 2014).

Video games are an innovative approach to improve the cognitive abilities and mathematical skills of the students (Boot et al., 2008). A study had shown that educational math games like "Monkey Tales: The Museum of Anything" have a positive effect on the mathematical performance during gameplay (Vander-cruysse et al., 2015). In another study, the arithmetic performance between a math game and paper exercises were tested with 52 children divided into two groups with a time stamp of three weeks. The first group adopted the game "Monkey Tales": the second

one used paper exercises. Through a series of measures in working memory, visuomotor skills, affective and cognitive learning, it was shown that game training has a better affective response, and the students' scores were higher in the game training than paper exercises; however, future research in the use of games for educational purposes is in continuous development (Castellar et al., 2015).

An artificial neural network (ANN) is a system based on perceptrons interconnections, it tries to simulate neural connections that exist in the brain in order to resolve classification, pattern recognition, and optimization problems. The multilayer perceptron (MLP) is a neural set that is connected between adjacent layers, this process adapts the weight in order to minimize the output respect the real values through back-propagation (Ramchoun and Ettaouil, 2016; Sankar et al., 1992; Silva et al., 2008). The MLP was used because statistical analysis cannot always classify and predict the desired outcomes. Moreover, MLP has been used in some fields as meteorology, economy, business, and learning (Musso et al., 2013).

Due to the predictive capabilities of back propagation (BP) and learning improvement in children through video games, this work used 360 children and a neural network in order to predict the percentage of improvement in their mathematical skills after playing a 2D mathematical video game.

2 METHODOLOGY

Artificial neural networks were used to analyze data gathered to predict the influence of playing a game and its relation to the percentage improvement in mathematics of a group of children. To get permission to test the game and collect student information we sent authorization letters to different schools from Imbabura, Ecuador. The data collected corresponds to 360 students in eighth and ninth grades of primary education.

We developed a 2D mathematical video game using the Unity 3D engine, C# programming language, PHP, MySQL, and models from Unity Technologies (Technologies, 2014). The goal of the game is to solve sums by making a spaceship shoot up toward a green symbol if the answer is correct, and the red symbol otherwise (see Fig.1). Depending on the answer, students gain points or lose them. The objective is to engage the student through an enjoyable learning experience in a time-sensitive game to solve obstacles and math problems. The game stimulates students to progress by increasing the difficulty in the math problems and obstacles (rocks) through three levels: easy,

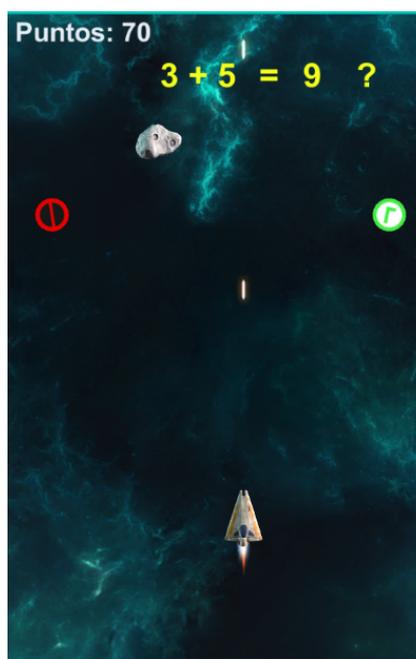


Figure 1: Screen shot of the mathematical educational video game.

medium, and difficult. Students can exceed each level by acquiring a score of 100. In the game, the collected data was each student's name, score, and session time.

The data used in the ANN include the results of math test each student took before and after playing the game. The data also includes information obtained from a questionnaire applied to each student before participating in the activities. The following is a list of the attributes collected gathered by the questionnaire:

1. Geographical position
2. Economic level
3. Parents' education
4. Achievement level
5. Teacher objectives
6. Social level
7. Use of ICT by teachers
8. Learner motivation
9. Gender
10. Age
11. Preferences for playing video games
12. School year

The qualitative nature of some of the attribute items on the questionnaire required a scale from 1 to 5, whereas yes or no items required a scale from 1 or 0; all of the quantitative answers were then summed



Figure 2: Students taking the tests and playing the video game.

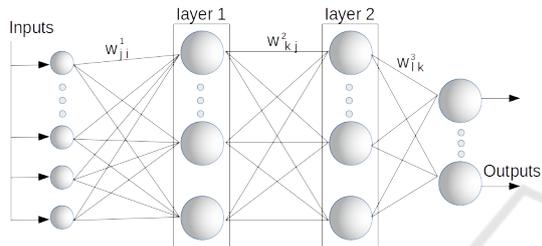


Figure 3: Back propagation architecture of two layers and n inputs.

to obtain a final result for each attribute for each of the students.

The math test consisted of 30 addition problems divided into three categories. The easy category involved sums of numbers between 0 and 20, the medium category involved sums of numbers between -40 and 40, and the difficult category involved numbers between -100 and 100.

The students took a 30 item addition test before they played the video game to establish a database of scores by item difficulty. Then, after the students played the game, they retook a 30 item addition test to see whether there was an improvement in their scores.

A total number of 360 students from different schools of Urcuquí and Ibarra participated in the pre-test, the video game play, and the post-test (see Fig. 2). The collected data was input into the multiple layer neuronal network that implements the BP algorithm to predict the percentage of improvement in math skills using a video game.

The neural networks of multiple layers have the BP algorithm as a method of learning, Fig. 3 shows a diagram of this architecture. The main equations of this algorithm are summarized.

Let n, i be the entire numbers, the activation of the neurons through its synaptic potential y_i belonging to the hidden n_i is given by (1),

$$y_i = g\left(\sum_{j=1}^L w_{ij} \cdot s_j\right) = g(h) \quad (1)$$

where h represents the synaptic potential, w_{ij} are the synaptic weights between neuron i in the current layer and the neurons of the previous layer with activation s_j . Furthermore, the sigmoid activation function is given by (2),

$$g(x) = \frac{1}{1 - e^{-\beta x}} \quad (2)$$

The primary objective of BP is to reduce the error obtained by modifying the synaptic weights, to obtain a minimum difference between targets (given outputs) and network outputs. The error is given in (3),

$$E = \frac{1}{2} \sum_{k=1}^p \sum_{i=1}^M (z_i(k) - y_i(k))^2 \quad (3)$$

where the first sum is on the p patterns of the data set and the second sum is on the M output neurons. $z_i(k)$ is the target value for output neuron i for pattern k and $y_i(k)$ is the corresponding response output of the network. The synaptic weights between two last layers of neurons are given by (4),

$$\Delta w_{ij}(k) = -\eta \frac{\partial E}{\partial w_{ij}(k)} = \eta [z_i(k) - y_i(k)] g'_i(h_i) s_j(k) \quad (4)$$

where η is the learning rate and g' is the derivative of the sigmoid function y_i , and the other weights are modified according to deltas (δ) that propagate the error.

Training and Validation Processes: The training was executed on a controlled form. The weights in the first epoch were obtained with random numbers adjusting the synaptic weights in an on-line manner. To alleviate overfitting, we split the set of available training patterns, into training, validation, and test sets. The training set adjusted the synaptic weights as shown in (4) and the validation set was used to control overfitting effects.

3 RESULTS

We obtained questionnaire and math tests data of 360 students of both genders between the ages of 12 and 14, used as the ANN attributes (inputs) and target value.

The resulting dataset consists of twelve attributes representing the inputs of our neurocomputational model, and the only output of the model is the students' percentage of improvement as seen in Fig. 4, calculated by the difference between the grades on

Table 1: MSE for different architecture neural network models.

Architecture Models	MSE
5	0.006998
10	0.006853
20	0.007218
5-10	0.006900
5-20	0.006854
10-20	0.006869

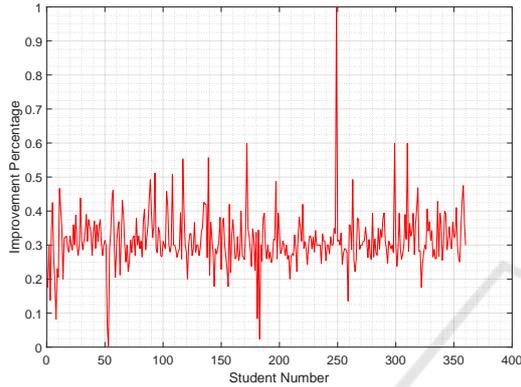


Figure 4: Improvement percentage calculated by the difference between the grades on the post- and pre- tests.

the post- and pre- tests divided by the grade on the pre-test. The BP model training was done with the normalized data set using a ten-fold cross-validation procedure to predict student improvement after playing the game.

Standard parameter values were used for training and testing the neural network model, using 1000 for the maximum number of iterations, $\eta = 0.1$ and $\beta = 1/2$. A validation procedure was performed to avoid the overfitting problems. The training dataset was divided into two sub-dataset with a percentage of 70% to the training dataset and 30% to the validation dataset.

Table 1 shows the mean squared error (MSE) obtained from the prediction of the learning percentage when using the BP algorithm in the neural network with different architectures models and twelve attributes. The architectures used had one and two layers, with a respective number of neurons used in each layer.

Table 2 shows the MSE obtained in the prediction of the improvement percentage of each student in performing sums of integer numbers after playing the video game when one of the twelve attributes is removed. This approach was done using a ten-fold cross-validation procedure with the two best architecture models found in Table 1. The first column of Table 2 indicates the removed attribute, the next col-

Table 2: MSE of best architecture neural network models from Table 1 without one attribute.

Attribute	Architecture Models	MSE
Geographical position	10	0.007125
	5-20	0.006811
Economic level	10	0.006840
	5-20	0.006833
Parents education	10	0.006832
	5-20	0.007019
Achievement level	10	0.006944
	5-20	0.006873
Teacher objectives	10	0.006871
	5-20	0.006893
Social level	10	0.006851
	5-20	0.007027
Use of ICT by teachers	10	0.006953
	5-20	0.006861
Learning motivation	10	0.006870
	5-20	0.006864
Gender	10	0.006907
	5-20	0.007137
Age	10	0.006964
	5-20	0.006842
Liking for video games	10	0.006865
	5-20	0.006833
School year	10	0.007063
	5-20	0.006826

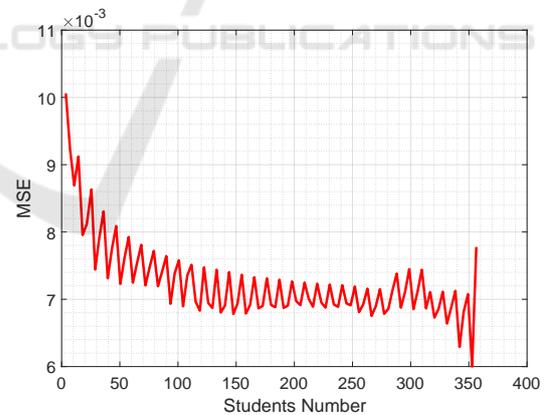


Figure 5: MSE as a function obtained from the percentage training data using twelve attributes in the BP algorithm.

umn shows the architecture used, and the last one the MSE associated to that architecture respectively.

Fig. 5 illustrates the MSE using a BP neural network model with different number of students in the training set, which represent a percentage in the range 1% and 99%. Also, the BP algorithm was run 100 times using the twelve attributes, and an architecture model of two layers with 5 and 20 neurons in each layer respectively.

4 DISCUSSION AND CONCLUSIONS

The experiment was run to test for math improvement in eighth and ninth grade students using the educational video game. In this sense, a BP model was used to predict the percentage of learning growth of students with specific characteristics.

The resulting characteristics (or attributes) gathered were those that may show a significant relationship with the performance of the students in mathematics which may determine the efficiency of the game in such students. As such, the BP algorithm can be used to predict how much the students are able to improve their skills in mathematics by playing the video game.

The characteristics of each student were used to train an artificial neural network model using a normalization of the data and a cross-validation procedure in order to obtain the MSE of the prediction with different architectures.

The MSE obtained in Table 1 and Table 2 is lower than 0.0069 in most of the cases, therefore, we obtained an efficient predictor. As shown in Table 1, the one layer 10 neurons and two layers 5 and 20 neurons architecture models have better results (smaller MSE) in the prediction of the percentage of improvement in comparison with the other ones used, when using the twelve attributes.

From the results obtained in Table 2, the model that gets better predictions is the one that uses an architecture of two layers with 5 and 20 neurons, with the geographical attribute position removed. We were able to remove the geographical attribute because it increased the MSE with this architecture.

Fig. 5 shows how as the training dataset (students number) increases the MSE diminishes and then starts to have a decrease in the 1%, reaching the smallest MSE when the training dataset was 98% equivalent to approximately 353 students, to then obtain an overfitting problem when the training dataset was 99%.

For future work, the data collected can be used to do a classification of the percentage learning rate using the BP algorithm taking a multi-class output depending on an interval learning rate. The attributes that were evaluated can be studied in more detail with the use of a Self-Organizing Map (SOM), to establish what attribute or combination of attributes can enhance the prediction in student learning.

As an overall conclusion, the results presented in this work show that when the BP algorithm with all the attributes was used, the best neurocomputational model was one layer with 10 neurons, in comparison when the geographical position was deleted, the best

architecture was two layers with 5 and 20 neurons, to predict the student percentage of improvement in mathematics after the use of a video game, and therefore, claiming if the video game is recommendable or not for certain students.

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