INTELLIGENT DISTANCE LEARNING SYSTEMS

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Abstract: Models used for creating intelligent systems based on artificial non-chromic networks indicate to the teachers which educational as well as teaching activities should be corrected. Activities that require to be corrected are performed at established distance learning systems and thus can be: lectures, assignments, tests, grading, competitions, directed leisure activities, and case studies. Results regarding data processing in artificial neural networks specifically indicate a specific activity that needs to be maintained, promoted, or changed in order to improve students' abilities and achievements. The developed models are also very useful to students who can understand their achievements much better as well as to develop their skills for future competencies. These models indicate that students' abilities are far more developed in those who use some of the mentioned distance learning systems in comparison with the students who learn due to the traditional classes system.

Keywords: neural networks, distance learning system, achievements, competencies.

INTRODUCTION

Predicting future events is one of the basic areas within artificial application neural networks [1].

Hereby, these future events are necessary abilities as well as students' achievements. Unlike classic methods, based on models, artificial neural networks belong to the class of self-adaptive methods based on data with only a few model assumptions for problems being studied [2]. The research problem is in correlation with activities in the teaching process that can be promoted. Artificial neural networks throughout data testing and training should provide a projection of students' abilities as well as competence [3]. The subject of research in this paper relates to the development and application of algorithms towards the prediction of neural networks use in distance learning systems.

Most research work concerning to the use of artificial neural networks in distance learning systems is one-dimensional just because it focuses on methods and techniques applied to either the electronic learning system only or especially to students and teachers [4-6] while fewer papers and research deal with the problem of learning based on past events [7-8].

So far, this area has not been sufficiently explored, especially the field of e-learning as indicated by the great number of scientific work published in 2019 which refers to the robotics, economy as well as natural phenomena [9-13]. To create intelligent distance learning systems, this paper will display the method of analyzing data using artificial neural networks.

METHOD

Artificial neural networks are an integral part of artificial intelligence primarily used for numerical prediction [14,15], classification [16,17] and pattern recognition [18,19, 20].

The data should be divided into three samples: the one for coaching, cross-validation, and testing [20]. Upon model defined, the input is prepared, the algorithm selected, learning rule, and required functions established, the network should be taught or trained on the basis of prepared data in order to identify the connection among data likewise to be capable of predicting values based on input values. The learning phase is a process of adjusting network weights that take place in multiple iterations or passing through the network. In the cross-validation phase, the network tends to observe the length training, the number of hidden neurons as well as parameters. Network testing is the third phase of neural network operation and it is crucial for network evaluation. The difference relating to the learning and the testing phase is that in this phase the network is no longer in the learning process. Network evaluation is done by calculating the error in a way to compare the network output with the actual outputs [22].

Result

Lectures, assignments, tests, grading, competitions, directed leisure activities are input variables important for in-depth data analyses as well as model creation neural networks [23]. The output variable is a satisfactory level of achievement. Defined variables data refer to 102 elementary school students (eighth graders) analyzed during the school year 2018-2019. The data has been updated into the Neural designer studio database for the purpose of this paper due to further processing and creating an artificial neural network. The statistics regarding defined input variables are important information for designing models since they can alert to the presence of false data. Table 1 displays the minimum, maximum, middle, and standard deviation of all variables in the data set.

Table 1.

	Minimum	Maximum	Mean	Deviation
Lectures	1.00	5.00	4.04	1.09
assignments	1.00	5.00	3.93	1.23
tests	1.00	5.00	4.06	1.19
grading	1.00	5.00	2.96	0.61
competitions	1.00	5.00	2.60	0.94
directed leisure activities	1.00	5.00	2.25	0.88
level of achievement - satisfactory	0.00	1.00	0.51	0.50

Table 2 displays the value of the correlations of all input variables. The minimum correlation is -0.440712 between the lecture and competition variables. The maximum correlation is 0.9555376 between tasks and tests.

Table 2.

	Lectures	assignments	tests	grading	competitions	directed leisure activities
Lectures	1	0.83	0.75	0.24	-0.44	-0.29
assignments		1	0.96	0.56	-0.19	-0.048
tests			1	0.6	-0.0052	0.19
grading				1	0.65	0.33
competitions					1	0.67
directed leisure activities						1

An artificial neural network is defined as a single layer with forwarding propagation while the activation function is a Hyperbolic Tangent function which can be mathematically expressed as follows:

$$tghX = \left(\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}\right) tghX = \left(\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}\right) \qquad (1)$$

Where X represents an independent variable size. Graphic representation of the Hyperbolic Tangent of the function is given in Figure 1.

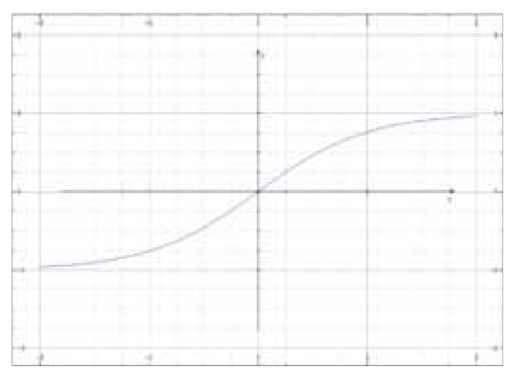

Figure 1. *Graphic representation of Hyperbolic Tangent function*

The total number of variables for a neural network is seven, of which one variable is a target variable referring to a satisfactory level of achievement. The training strategy over the data set is defined by the optimization algorithm using the Quasi-newton method. The optimization process is approximately the same as the ordinary Newton method with Hessian matrix step modification.

The following is a brief numerical example of one type of Quasi-newton method that uses the original Hessian inverse matrix for each iteration.

Target function:

$$\min f(x) = 2x_1^2 + 3x_2^2 \min f(x) = 2x_1^2 + 3x_2^2 \qquad (2)$$

Starting point selection:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}\begin{bmatrix} 1 \\ 1 \end{bmatrix} \qquad (3)$$

Hessian matrix inverse calculation :

$$\nabla\nabla f\,(\mathrm{x}) = \begin{bmatrix} 2x_1 \\ 3x_2 \end{bmatrix}\begin{bmatrix} 2x_1 \\ 3x_2 \end{bmatrix} \qquad (4)$$

$$\nabla^2\,\nabla^2\, f\,(\mathrm{x}) = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}\begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix} \qquad (5)$$

$$\mathrm{H}^{-1} = \begin{bmatrix} 0{,}5 & 0 \\ 0 & 0{,}3 \end{bmatrix}\mathrm{H}^{-1} = \begin{bmatrix} 0{,}5 & 0 \\ 0 & 0{,}3 \end{bmatrix} \qquad (6)$$

Finding a new value for variable x:

$$x^{k+1} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0{,}5 & 0 \\ 0 & 0{,}3 \end{bmatrix} x^{k+1} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0{,}5 & 0 \\ 0 & 0{,}3 \end{bmatrix} (7)$$

Specifying a new value for variable x :

$$x^{k+1}x^{k+1} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \qquad (8)$$

Determining the value in case the function converges:

$$\nabla\nabla f\,(\mathrm{x}) = 0 \ (9)$$

The training of the data set has been performed within a thousand interactions during one hour of testing time. Upon the performed training, Figure 2 displays the training as well as selection error in each iteration. Blue line represents a training error and the orange one represents a selection error. The home value of the training error is 2.33562 and the final value after 135 epochs is 9.72136e-6. The initial value of the selection error is 3.444445 and the final value after 135 epochs is 0,382761.

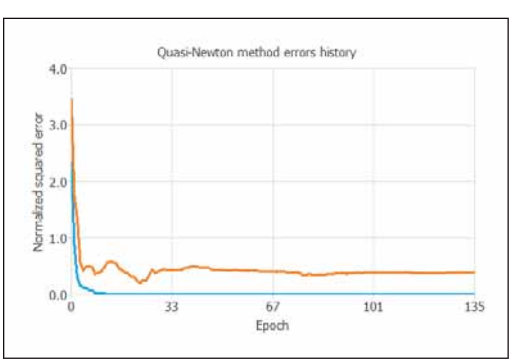

Figure 2. *Graphic representation of error history using the Quasi-newton method*

Figure 3 provides a graphic representation of the resulting deep artificial architecture neural networks. It contains a scaling layer, a neural network as well as a non-scaling layer. The yellow circles represent the scaled neurons, the blue ones represent perceptron neurons and the red ones represent neurons. The number of inputs is 6 and the number of outputs is 1. The number of hidden neurons is 1.

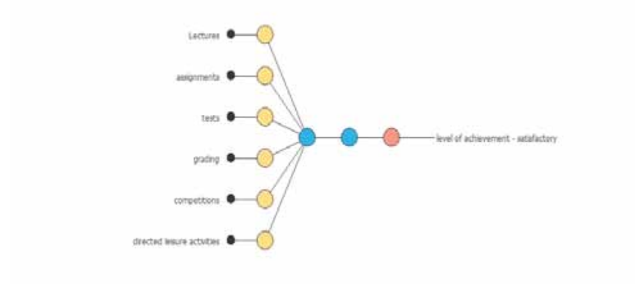

Figure 3 *- Graphic representation of artificial neural network architecture*

The testing has been performed on the data relating to the lecture variable with dedicated value 1. Table 3 displays the value for the target variable with value 0.0911 whose correlation with original values has been proved.

Table 3.

	Value
Lectures	1
assignments	3.93137
tests	4.05882
grading	2.96078
competitions	2.59804
directed leisure activities	2.2451
level of achievement - satisfactory	0.0911282828

Figure 4 displays a graph illustrating the dependence of the target variable with input variables.

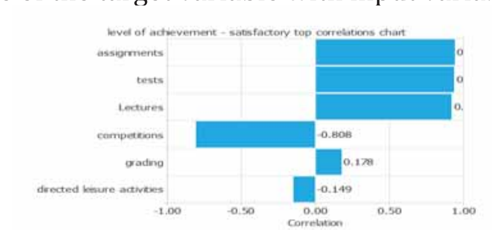

Figure 4- *graph view illustrating the dependency of the target variable with the input variables*

In order to test the model, we have assigned random variables to the input variables by assigning the value 1 to three variables. The value of the target variable is 0.459, which is, closer to 0 than 1, which proves that the model of artificial neural networks provides expected results. Table 4 displays the allocated input values as well as the target variable value.

Table 4.

	Value
Lectures	1
assignments	1
tests	3
grading	2
competitions	1
directed leisure activities	4
level of achievement - satisfactory	0.459540169

Within creating intelligent distance learning systems, based on the results obtained by the data processed within an artificial neural network of the observed input variables: lectures, assignments, tests, grading, competitions as well as directed free activities represent necessary facilities in achieving a satisfactory level of accomplishment.

Discussion

Defined input variables and the data processing results, using artificial neural networks, are the basis of creating a distance learning system that needs to provide users with unhindered access to all available resources on the portal distance learning systems [24].

Content organization on the distance learning platform should provide conditions for that clear, transparent, and logical organization of teaching content through lectures, which in form and content, should be tailored to the target audience. Upon the lectures execution on the platform, tasks related to the completed After-lectures are assigned. Further follow-up of classes is enabled only after tasks have successfully been solved.

Tests represent a separate unit in the distance learning system, periodically organized. Due to their form, they can be classified into self-evaluative and formal ones. Assessment is a constant activity whereby the lecturer monitors all the work as well as students' engagement.

Introducing contest-related content likewise directed leisure activities are innovations within distance learning systems that provide trainees with competency development likewise greater learning motivation.

Due to the analyses including 102 elementary school pupils (eighth graders) who have used the distance learning system as an adjunct to traditional teaching, within the school year of 2018-2019, as well as 85 elementary school pupils within the school year 2017-2018, taught in a traditional way, the greater success of the pupils using the distance learning system is accomplished and evident.

Conclusion

The research presented in this paper indicates that by application of the neural network in creating intelligent distance learning systems, the achievement and competences of primary school pupils can be significantly improved. This paper displays a realized model of artificial neural networks in the function of the development towards organizing teaching content likewise activities on a distance learning platform.

A comparative analysis regarding two-generation eighth-graders at their first year of high school education indicates the implementation efficiency of the above-mentioned contents of distance learning.

The developed distance learning model has been applied at the elementary school level. However, it can be successfully applied both at a high school or at an academic level.

Further development directions for distance learning relate to the application, besides the methods of neural networks likewise other methods of in-depth data analyses.

The aforementioned research results should form the basis for further development of the distance learning systems.

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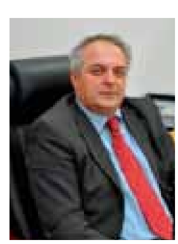

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