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ANALYSIS OF JOB SATISFACTION OF ACADEMICIANS THROUGH THE USE OF ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The quality of higher education depends on many criteria. One of them is the job satisfaction of the academicians who are working in the universities. The highly satisfied academicians are expected to have better performance in education. There are many different factors that may affect the job satisfaction of the academicians. In this study, we analyzed whether there is a relation between some of these factors and the job satisfaction of the academicians through the use of Back-propagation multilayer perceptron algorithm. The results have shown that the job satisfaction is highly related with the factors analyzed and can be estimated through the use of this model.

Keywords: Back-propagation, multilayer erceptron algorithm, job satisfaction, quality of higher education

INTRODUCTION

In the literature, there are many studies that analyze the quality of higher education (Lacy., Sheehan & Spector, 1997). The main aim of these studies is to analyze how to improve the quality of the education in universities. There are many different factors that can affect the quality of higher education (Santhepparaj & Alam, 2005). One of these factors is the job satisfaction of the academicians who are one of the most important keys in higher education.

Artificial Neural Networks (ANNs) is one of the methods in literature that can establish a relation between input and output variables (Bishop, 1995; Fine, 1999; Haykin, 1998). ANNs are used in many fields of science for different purposes (Ripley, 1996). There are many ANN structures that are designed for different applications. One of them is called as Back-Propagation Multilayer perceptron (BPMLP) algorithm which is used in different areas like recognition, curve fitting, estimation, etc. (Collobert & Bengio, 2004).

In this paper, the goal is to find whether a relation can be established between the job satisfaction of academicians and several factors that may have direct or indirect effect to it or not. In order to model this relation, BPMLP algorithm is used. A questionnaire is formed that has 7 different parts. The first 6 parts are used as an input data which consist of 55 questions. The last part is used as an output data which has 4 questions and used for the evaluation of the overall job satisfaction of the academicians.

This paper is organized as follows; in the next section, the brief explanation of the model, that is used to establish the relation, is presented. Then the experimental results obtained, together with their discussions are given. Lastly, the concluding remarks of this study are given in the conclusion section.

MODEL DESCRIPTION

Artificial Neural Networks are systems that are deliberately constructed to make use of some organizational principles resembling those of a human brain (Chin-Teng & George Lee, 1996). In its most general form , a neural network is a machine that is designed to model the way in which the brain performs a particular task or a function of interest (Simon, 1999).This model can be used in many different problem solutions including nonlinear modeling. Hence we decided to use one of the modeling techniques of ANN approach which is called as Back Propagation Multilayer Perceptron (BPMLP) in Human Resource Management. The BPMLP algorithm is a type of supervised, error correction learning that calculates an error on the output layer and propagates that error backwards through the network to determine how each individual weight factor contributes to the output error.

In this paper, we used a BPMLP algorithm with 2 hidden layers that consist of N1 and N2 neurons respectively. The steepest-descent gradient approach used by the BPMLP to minimize the mean square error function (Cichoclar & Unbehaven, 1993), is defined as:

$$E_p = \frac{1}{2}\sum_{j=1}^{n}(d_{jp} - y_{jp})^2 = \frac{1}{2}\sum_{j=1}^{n} e_{jp}^2$$
(1)

Where , d_{jp} is the desired output signal of the jth output neuron for the pth example, n is the number of output neurons and y_{jp} is the actual output signal.

The total error function is defined as:

$$E_r = \sum_p E_p = \frac{1}{2}\sum_p \sum_j \left(d_{jp} - y_{jp}\right)^2$$
(2)

For each learning example, the synaptic weights w_{ij} are changed by an amount of

$$\Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}} \quad , \eta > 0$$
(3)

$$\Delta w_{ij} = \eta \delta_j o_i$$
(4)

Where η is the learning rate, ∂_j is the local gradient of the hidden neuron j and o_i is the function signal at the output neuron i.

The data from the input neurons is propagated through the network via the interconnections such that every neuron in a layer is connected to every neuron in the adjacent layers. Each interconnection has associated with it a scalar weight, which acts to modify the strength of the signal passing through it. The neurons within the hidden layer perform two tasks: they sum the weighted inputs to the neuron and then pass the resulting summation through a nonlinear activation function.

The unipolar sigmoid activation function with its output in the range (0, 1) used in this study is as follows:

$$y_{j=}\varphi\left(u_j\right) = \frac{1}{1+exp\left(-\gamma_j u_j\right)}$$
(5)

Where $\varphi(.)$ is the unipolar sigmoid activation function and u_j is defined as the weighted sum of inputs together with its bias value θ_j and is obtained using the formula

$$u_j = \sum_{i=1}^{n} w_{ji} x_i + \theta_j \quad (6)$$

In the above equation a bias is included in order to shift the space of the nonlinearity.

In this study, the number of inputs to BPMLP is 56(including bias value) and the number of outputs are 4. The two parameters, namely the learning parameter η and the number of neurons in hidden layer N1, should be selected in such a way that the total error is minimized.

EXPERIMENTAL RESULTS

The job satisfaction is of great importance for academicians in terms of training the well-qualified individuals which the country needs and providing scientific and technical advances (Trivellas, & Dargenidou, 2009). It is one of the main factors that directly affect the quality of higher education (Siddique et al., 2002). In order to collect data for this study, "Satisfaction Survey" is created by forming a questionnaire. Likert scale has been used as a metric scale type and represents answers as 1 "Strongly disagree", 2 "Disagree", 3 "Neutral", 4 "Agree", 5 "Strongly agree".

This questionnaire consists of 59 questions. The first 55 questions which forms the 6 groups that may have a direct or indirect relation to job satisfaction are used for input data and the other 4 questions that shows the level of job satisfaction of the academicians are used for the output data. Input groups consist of "Demographic Information", "Physical, Technical and Sociocultural Infrastructure", "Management Organization", "Organizational Culture", "Educational and Academic Activities" and "Personal Information". The output group consists of "General Fulfillment".

Table 1. Average train and test error for 100 iterations.

ITE 100		*Num of Hidden Neurons (N1)*				
		6	***10***	***15***	***18***	
	0.05	0,168003	0,167464	0,167695	0,167817	avg train error
	0.05	0,174173	0,173212	0,173722	0,17373	avg test error
	0.1	0,167316	0,165787	0,165571	0,165581	avg train error
	0.1	0,172883	0,170697	0,170525	0,170274	avg test error
	0.15	0,166383	0,163016	0,161916	0,161645	avg train error
η	***0.15***	0,171401	0,167146	0,1659	0,165253	avg test error
	0.2	0,164973	0,158878	0,156745	0,156161	avg train error
	0.2	0,169453	0,162158	0,159621	0,15855	avg test error
	0.25	0,162891	0,153769	0,15098	0,150272	avg train error
	0.25	0,166786	0,155867	0,152268	0,150941	avg test error
	0.3	0,160056	0,148607	0,145796	0,145213	avg train error
	0.3	0,16321	0,149038	0,144974	0,143671	avg test error

In this study, our aim is to observe whether a relationship between the job satisfaction of the academicians in Girne American University (GAU) and the 6 groups of input data can be established or not. 112 academicians from GAU have filled this questionnaire. 12 of them are omitted because of missing parts. From the remaining data, 70 of them are used as training data and the rest are used as testing data. BPMLP model is used by selecting the number of inputs as 56(including bias value) and the number of outputs as 4.

Table 2. Average train and test error for 500 iterations.

ITE 500		*Num of hidden neurons (N1)*				
		6	***10***	***15***	***18***	
	0.05	0,161561	0,152015	0,148817	0,147793	avg train error
	0.05	0,167384	0,156706	0,153338	0,152034	avg test error
	0.1	0,144087	0,133426	0,131354	0,131164	avg train error
	0.1	0,145193	0,130082	0,12742	0,12724	avg test error
	0.15	0,134009	0,130557	0,123961	0,123898	avg train error
η	***0.15***	0,131918	0,128961	0,120793	0,122022	avg test error
	0.2	0,119571	0,113408	0,104055	0,102644	avg train error
	0.2	0,124628	0,121871	0,125404	0,127156	avg test error
	0.25	0,103901	0,095493	0,090597	0,089905	avg train error
	0.25	0,143994	0,136686	0,14117	0,141771	avg test error
	0.3	0,091872	0,088126	0,083689	0,083088	avg train error
	0.3	0,154831	0,147706	0,149652	0,148908	avg test error

Table 1-5 show the results obtained for different number of iterations (100, 500, 1000, 10000, 50000) for the training and testing data. In all of these tables, the LP parameter has selected from the set {0.05, 0.1, 0.15, 0.2, 0.25, 0.3} and the number of hidden neurons from the set of {6, 10, 15, 18}.

From these tables, one can observe that LP parameter is affecting the performance of the BPMLP more than the number of the neurons in the hidden layer (N1). Moreover, it can be observed that after 10000 iterations, the training error is decreasing but the corresponding testing error is increasing which indicates that after some point of iteration the learning process turns into a memorizing of the input data.

Table 3. Average train and test error for 1000 iterations.

ITE 000		*Num of hidden neurons (N1)*				
		6	***10***	***15***	***18***	
	0.05	0,143834	0,133015	0,130806	0,130546	avg train error
	0.05	0,145334	0,13018	0,127561	0,127385	avg test error
	0.1	0,118444	0,11216	0,102667	0,101206	avg train error
	0.1	0,124175	0,121437	0,124387	0,126	avg test error
	0.15	0,060158	0,086442	0,081497	0,081078	avg train error
η	***0.15***	0,153164	0,146403	0,148067	0,147999	avg test error
	0.2	0,07923	0,077196	0,072076	0,071647	avg train error
	0.2	0,162866	0,157691	0,159612	0,159256	avg test error
	0.25	0,07498	0,069488	0,064378	0,064143	avg train error
	0.25	0,172314	0,1696	0,178398	0,182178	avg test error
	0.3	0,067715	0,061195	0,058045	0,058122	avg train error
	0.3	0,173483	0,182708	0,202021	0,214241	avg test error

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Table 4. Average train and test error for 10000 iterations.

ITE 10000		*Num of hidden neurons (N1)*				
		6	***10***	***15***	***18***	
	0.05	0,050316	0,038922	0,028965	0,029033	avg train error
	0.05	0,260084	0,249384	0,257247	0,284157	avg test error
	0.1	0,025979	0,014125	0,012248	0,012725	avg train error
	0.1	0,248639	0,301366	0,322108	0,365751	avg test error
	0.15	0,023062	0,013872	0,007478	0,009071	avg train error
η	***0.15***	0,260205	0,400729	0,334284	0,399959	avg test error
	0.2	0,010721	0,006995	0,004007	0,006182	avg train error
	0.2	0,273356	0,372293	0,358356	0,403099	avg test error
	0.25	0,046631	0,003761	0,003073	0,000297	avg train error
	0.25	0,230758	0,343729	0,339389	0,41517	avg test error
	0.3	0,019802	0,002408	0,003331	0,002329	avg train error
	0.3	0,26767	0,33764	0,329667	0,391316	avg test error

Table 5. Average train and test error for 50000 iterations.

ITE 50000		*Num of Hidden Neurons (N1)*				
		6	***10***	***15***	***18***	
	0.05	0,029566	0,00438	0,003224	0,00333	avg train error
	0.05	0,278329	0,433679	0,353412	0,462825	avg test error
	0.1	0,009865	0,002454	0,001931	0,001856	avg train error
	0.1	0,315945	0,474906	0,373108	0,5067	avg test error
	0.15	0,008855	0,002801	0,001938	0,001784	avg train error
η	***0.15***	0,311536	0,746962	0,409796	0,50305	avg test error
	0.2	0,015441	0,001387	0,001854	0,001827	avg train error
	0.2	0,499753	0,560865	0,409322	0,488283	avg test error
	0.25	0,023674	0,001769	0,00061	0,001776	avg train error
	0.25	0,356316	0,447432	0,39104	0,469716	avg test error
	0.3	0,019787	0,001188	0,000675	0,001175	avg train error
	0.3	0,301313	0,375494	0,34245	0,431585	avg test error

The best testing error is obtained when the LP=0.15, N1=15 and the number of iterations is 500. For these values, the testing data is evaluated using the BPMLP model parameters obtained. The results tabulated in Table 6. The first value is obtained when we take into consideration all output questions. That is to say from 30 testing data for how many of them all 4 outputs are recognized correctly. For this calculation, each output is categorized as 0 if the output value is strictly less than 0.6 and 1 if it is greater than 0.6. Hence there are 16 different output groups for these 4 questions. This result has shown that for 26 out of 30 testing data, all 4 questions are correctly predicted through the use of the BPMLP. The other 4 results respectively show the number of correct prediction of each output data separately.

Table 6. The number of correct prediction of the job satisfaction for the test data.

26
28
28
28
30

These results have shown that the model establishes a strong relation between input and output data and it can be used as a prediction of job satisfaction of the academic staff with the known input data.

CONCLUSION

In this paper, our aim is to investigate whether a relation between the job satisfaction of the academic staff in the universities and the 6 group of factors that consist of "Demographic Information", "Physical, Technical and Sociocultural Infrastructure", "Management Organization", "Organizational Culture", "Educational and Academic Activities" and "Personal Information" can be established or not. A BPMLP algorithm is used for this purpose.

From the experimental results, one can summarize the observations as follows;

i. The relation between the job satisfaction of the academic staff and the selected 6 group of factors can be established through the use of BPMLP.
ii. As the number of iteration increases, the training error decreases but the testing error increases which indicates that BPMLP is not learning but memorizing the training data.
iii. For the minimum test error conditions (i.e, LP=0.15, N1=15 and ITE=500), the number of correct decisions of the 4 output questions is 26/30 for the test data which indicates that there is a strong relation between the input and output data. For approximately 86% of the test data, one can predict what will be their job satisfaction for the given input data.

As a future work, the model can be further used in deciding which group of input data has more impact on the output data which show the job satisfaction of the academic staff.

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