A Soft Computing Approach for User Preference in Web based Learning

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ABSTRACT

The web-based learning system has emerged as a new means of skill training and knowledge acquisition, encouraging both academia and industry to invest resources in the adoption of this system. Users have been widely recognized as being a key group in influencing the adoption of such systems. Thus, their attitudes toward this system are pivotal. It is required to design the web layout to user satisfaction based on the fields of human–computer interaction and information systems. Cognitive theory is widely used to predict the effectiveness of the web based and multimedia learning. Questionnaires are one common form of measuring cognition. This study investigates to identify a user's need based on the cognitive behavior of the user based on the questionnaire. The cognitive attributes are used as the training input for the Multilayer Perceptions and proposed parallel Neural Network.

Keywords: Online Learning, User interface design, Multilayer Perceptron (MLP), Parallel Neural Network.

1. INTRODUCTION

In the recent years, exponential growth of Internet-based learning is seen. The transition to online technologies in education provides the opportunities to use new learning methodology and more effective methods of teaching [1]. E-learning is defined as the use of network technology, namely the Internet, to design, deliver, select, administer and extend learning [2]. The other perspectives of using e-learning can be generalized as follows: an opportunity for overcoming the limitations of traditional learning, such as large distance, time, budget or busy program; equal opportunities for getting education, better quality and a variety of lecture materials. Educational institutions, where a lot of specialists work in collaboration, use shared resources and the students get freedom to receive knowledge, skills and experience from other universities [1]. Due to the flexibilities that mentioned above many universities, corporations and educational organizations are developing e-learning programs to provide course materials for web-based learning. Also e-learning can be used for online employee training in business [3].

In web-based educational systems the structure of the domain and the content presented are important. Personalization is an issue that needs further attention, especially when it comes to web-based instruction, where the learners' population is usually characterized by considerable heterogeneity with respect to background knowledge, age, experiences, cultural backgrounds, professions, motivation, and goals, and where learners take the main responsibility for their own learning [4]. Learners enjoyed greater success in learning environments that adapted to and supported their individual learning orientation [5].In general, features like information content, font, navigability, links influence the user's ease of use and satisfaction of the website. In web based learning systems, the cognitive load is the key for the effectiveness of the instructional and multimedia learning. Basically, cognitive load theory asserts that learning is hampered when working memory capacity is exceeded in a learning task. Providing individualized feedback according to student's cognitive states has been shown to be effective for learning [6, 7].Thus the cognitive load and the students website preferences forms the basis of user's satisfaction.

Cognitive load theory research field finds its roots in work by Sweller and colleagues in the late 1980s and early 1990s [8, 9, 10]. Their cognitive load theory has subsequently had a great impact on researchers and designers in the field of education. According to cognitive theory, the learning process comes out of experience, perception, memory and overtly verbal thinking [11]. Cognitive load theory fundamentals are used to explain the cognitive process of learning in web based instructions and multimedia methods [12, 13]. To effectively enhance web-based instruction, the graphical user interface and multimedia formats must be developed in consideration of cognitive load principles [14]. The basic premise of cognitive load theory is that the focus of an instructional module must be the instruction itself. Information that is close to the instruction must be designed to lower cognitive load and improve working memory. Because the mental resources of working memory can be overloaded, any information that ignores cognitive load may interfere with the process of acquiring knowledge and skills. Instruction that effectively presents learning to the working memory has an impact on the ability to store knowledge and skills in long-term memory. A graphical user interface and multimedia formats can increase extraneous cognitive load and have a negative impact on learning.

Based on different sources for cognitive load, Sweller (1999) [15] distinguished three types of load: intrinsic cognitive load type is attributed to the inherent structure and complexity of the instructional materials and cannot be influenced by the instructional designer, and extraneous cognitive load and germane cognitive load are imposed by the requirements of the instruction and can, therefore, be manipulated by the instructional designer. Cognitive load imposed by the format and manner in which information is presented and by the working memory requirements of the instructional activities is referred to as extraneous cognitive load, a term that highlights the fact that this load is a form of overhead that does not contribute to an understanding of the materials. Finally, the load induced by learners' efforts to process and comprehend the material is called germane cognitive load [16, 17].

In this paper, we propose to identify the relation between the cognitive load and the student's web layout preferences. A questionnaire is prepared to identify the cognitive load of the student and his website preferences in a web learning environment. User's learning problems via learner responses is studied by using an artificial neural network (ANN) approach and then areas for improvement in layout of the web learning system are identified.

2. Related Works

Jan L. Plass [18] proposed a hybrid model that combines cognitive and software engineering approaches regarding the criteria for the design and evaluation of the user interface of foreign language multimedia software. The proposed approach involves a three step design which includes selection of instructional activity that supports cognitive processes of competence, selection of feature attributes and selection of designs features. It is still pragmatic to be practical. Based on this proposal, contextualized model of interface design, domain specific evaluation criteria are developed to describe how well the user interface is able to support the cognitive processes involved in the development of linguistic and pragmatic skills and competencies in SLA.

Mihalca, et al [19] used a cognitive load framework to examine the role of learner control on performance and instructional efficiency using agenetics training program. In their study comparing three types of instruction (i.e., non-adaptive program control, adaptive program control, and learner control), they predicted that adaptive control would be more effective than both other groups as it better met the needs of learners than program control and was less load bearing than learner controlled environments. While there is some evidence that adaptive control was effective in terms of instructional efficiency the results did not generalize to test-performance measures (near or far transfer). While the study showed considerable promise for embedding adaptive program control into technology based instruction.

Baylari et al [20] proposed a personalized multi agent e-learning system based on item response theory (IRT) and artificial neural network (ANN) which presents adaptive tests (based on IRT) and personalized recommendations (based on ANN). These agents add adaptivity and interactivity to the learning environment and act as a human instructor which guides the learners in a friendly and personalized teaching environment. The framework constructs adaptive tests that will be used as a post-test in the system. Thus a multi-agent system is proposed which has the capability of estimating the learners' ability based on explicit responses on these tests and presents him/her a personalized and adaptive test based on that ability. Also the system can discover learner's learning problems via learner responses on review tests by using an artificial neural network (ANN) approach and then recommends appropriate learning materials to the student. Experimental results showed that the proposed system can provide personalized and appropriate course material recommendations with the precision of 83.3%, adaptive tests based on learner's ability, and therefore, can accelerate learning efficiency and effectiveness.

3. Methodologies

3.1 Neural Network

Neural networks are made up of multiple layers of computational units, usually interconnected with each other based on the design of the network [21]. The inputs are fed on the input layer and propagated through the layers to get the output. Output signal is computed using weights, bias and activation function. The propagation rule is used to train the network by back propagating the errors and changing the weights of nodes. The difference between the output obtained and the desired output is the error. A BPNN is one of the most frequently utilized neural network techniques for classification and prediction [22].

BPNNs often use the back-propagation algorithm for training, and can require large training times especially for large networks, but there are many other types of ANNs. Once the network is trained for a particular problem, however, it can produce results in a very short time. Parallelization of BPNNs could drastically reduce the training time.

In the proposed Parallel neural network, the network is divided into blocks of adjacent neurons and each is allocated to separate processing. For simplicity, it is assumed that these blocks are non-overlapping and rectangular. This approach to parallelization attempts to take advantage of the locality that exists between adjacent neurons. Gaussian and sigmoid activation functions are used in the proposed network

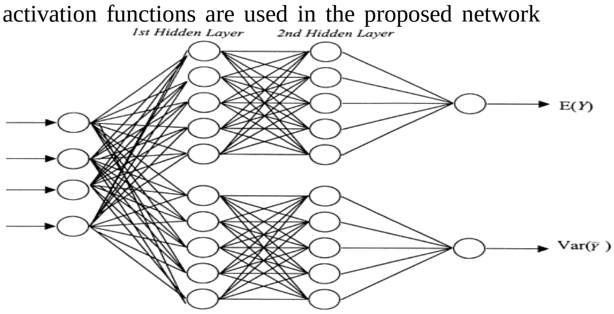

Figure 1: A typical Parallel Neural Network Model

The net input to y_k to the output layer is computed by

$$y(in)_k = w_{0k} + \sum_i x_i w_{ik}$$

The output is given by

$$y_k = f(y(in)_k)$$

Each output unit $y_k \left(k = 1 \text{ to } m \right)$ whose target is t_k, the error correction is given by

$$\delta_k = (t_k - y_k) f'(y(in)_k)$$

Based on the error obtained, the weights and bias are updated such that

$$\Delta\omega_{ik} = \alpha\delta_k n_j$$

$$\Delta\omega_{0k} = \alpha\delta_k$$

δ_k is sent to all the hidden layers and

x_i =*input of neuron i at input layer*

t_i =*target output vector* $\left(t_1, \ \ldots.., \ t_k, \ \ldots\ldots, \ t_m \right)$

$$\alpha = learning\ rate$$

$$w_{0j} = bias\ on\ j^{th}\ hidden\ unit$$

$$w_{ij} = weight\ on\ i^{th}\ neuron\ at\ hidden\ layer\ j$$

$$n_{ij} = neuron\ i\ in\ j^{th} hidden\ layer$$

Each output unit updates the bias and weights :

$$\omega_{jk}(new) = \omega_{jk}(old) + \Delta\omega_{jk}$$

$$\omega_{0k}(new) = \omega_{0k}(old) + \Delta\omega_{0k}$$

Activation function of sigmoid function is given as follows:

$$g(x) = \frac{1-e^{-x}}{1+e^{-x}}$$

Gaussian activation function:

$$\phi(v_i) = \exp\left(-\frac{\|v_i - c_i\|^2}{2\sigma^2}\right)$$

The above process is continued for the specified number of epochs or when the actual output equals the target output. The learning rate α affects the convergence of the network. A larger value of α may speed up the convergence but might result in overshooting, while a smaller value of α has vice-versa effect. The range generally used is from 0.001 to 10. Thus, a large learning rate leads to rapid learning but there is oscillation of weights, while the lower learning rate leads to slower learning. The gradient descent is very slow if the learning rate α is small and oscillates widely if α is too large. One very efficient and commonly used method that allows a larger learning rate without oscillations is by adding a momentum factor to the normal gradient descent method.

The momentum factor is denoted by $\eta \in [0,1]$ and the value of 0.9 is often used for the momentum factor. Also, this approach is more useful when some training data are very different from the majority of data. A momentum factor can be used with either pattern by pattern updating or batch-mode updating. In case of batch mode, it has the effect of complete averaging over the patterns. Even though the averaging is only partial in the pattern-by-pattern mode, it leaves some useful information for weight updating.

The weight updation formulas used here are,

$$\omega_{jk}(t+1) = \omega_{jk}(t) + \underbrace{\alpha\delta_k z_j + \eta\left[\omega_{jk}(t) - \omega_{jk}(t-1)\right]}_{\Delta\omega_{jk}(t+1)}$$

and

$$w_{ij}(t+1) = w_{ij}(t) + \underbrace{\alpha\delta_j x_i + \eta\left[w_{ij}(t) - w_{ij}(t-1)\right]}_{\Delta w_{ij}(t+1)}$$

The momentum factor also helps in faster convergence.

Table 1 gives the parameters of the proposed Neural network

Table 1: Parameters for the proposed Parallel Neural network

Input Neuron	29
Output Neuron	4
Number of Hidden Layer	2
Number of processing elements -upper	4
Number of processing elements - lower	4
Transfer function of hidden layer - upper	Gaussian
Transfer function of hidden layer - lower	Sigmoid
Learning Rule of hidden layer	Momentum
Step size	0.1
Momentum	0.7
Transfer function of output layer	Sigmoid
Learning Rule of output layer	Momentum
Step size	0.1
Momentum	0.7
Learning Rate	0.2
Number of Iterations	1000

4. Experimental Setup

The cognitive behavior of 82 students studying in undergraduate and postgraduate courses was captured using questionnaires. They were initially subjected to go through a known subject and an unknown subject in a popular online learning website [23]. Typical questions were in the areas of

• Learn ability

• Indication about meaningfulness of error messages

• Preference to read text rather than to listen to a lecture

• Interest level in deciphering graphs, charts, and diagrams

• Visualization of content read as a mental picture

• Depth of study in the subject area.

Class labels indicating the type of online learning system preferred is assigned to all the 82 students obtained from the questionnaire. Typical questions in the questionnaire are as follows:

- It is important for me to learn what is being taught in this website
- I like what I am learning in this website
- I'm certain I can understand the ideas taught in this course
- I expect to do very well in this online course
- When I take a test I think about how poorly I am doing

- When I study for a test, I try to put together the information from the course content
- Before I begin studying I think about the things I will need to do to learn
- I find that when the audio tutorial is running I think of other things and don't really listen to what is being said

The distribution of answers for some of the queries is given in Figure 2. This research focuses on the dependency of the preference of delivery method over the cognitive behavior of the person.

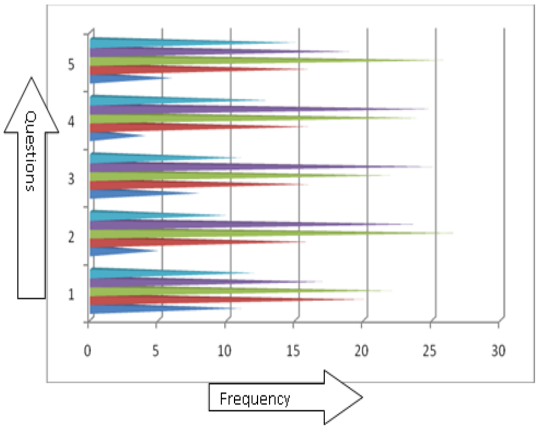

Figure 2: Frequency of answers for some of the questions.

The cognitive attributes are used as the training input for BPNN and the proposed Parallel Neural Network. Of the data acquired, 70% was used for training the neural networks and 30% was used as test data. The classification accuracy of the various classifiers for the cognitive input is tabulated in Table 1 and shown in Figure 3.

Table 1: Classification Accuracy

Technique Used	Classification Accuracy %
BPNN	76
Proposed Parallel Neural Network	92

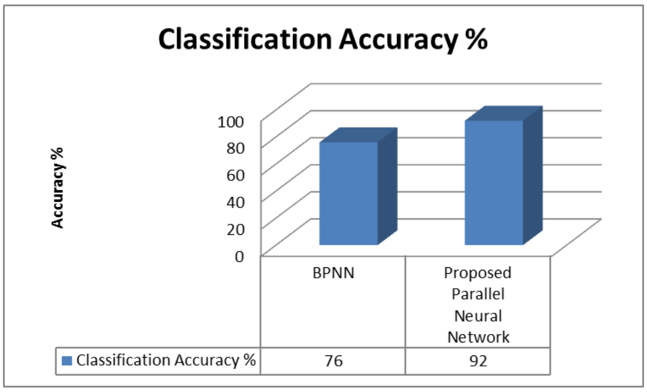

Figure 3: Classification Accuracy for various classifiers

Figures 4, Figure 5 and Table 2 show the precision, recall for both the techniques.

Technique Used	BPNN				Proposed Parallel Neural Network			
Class	a	b	c	d	a	b	c	d
Precision	1	1	0.625	0.727	1	1	0.714	1
Recall	1	0.5	1	0.8	1	0.875	1	0.9

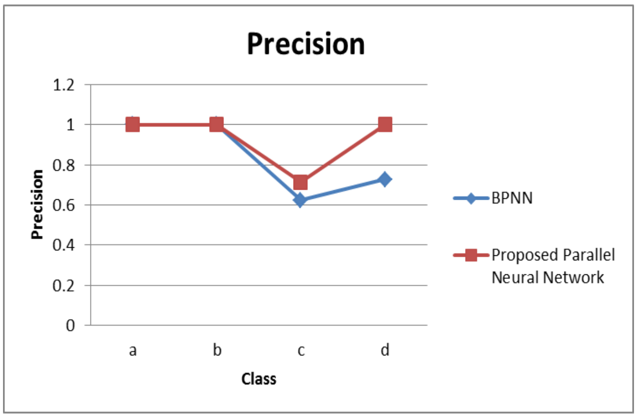

Figure 4: Precision

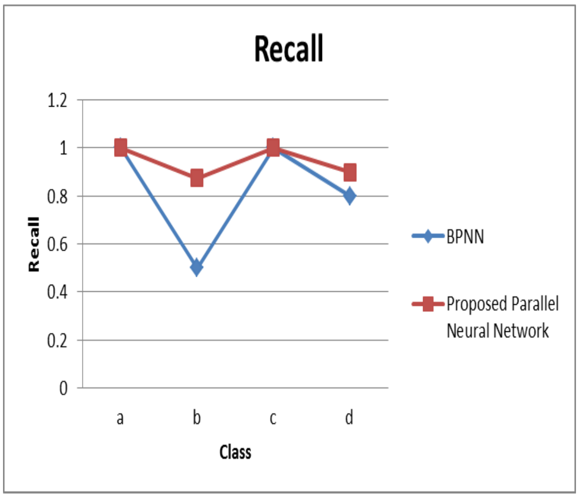

Figure 5: Recall

From Figures 4 and 5, it is observed that the precision and recall of the proposed Parallel Neural Network is higher.

5. Conclusion

The user experience in web based learning environment depends upon the cognitive aspects such as motivation level, likes and dislikes. It is also very important to study about the learners' activities and personal characteristics. In this paper, a questionnaire is used to identify the cognition of the student and his website layout preference in a web learning environment. The cognitive behavior of the user is captured through questionnaire. The questionnaire helps identify the areas for improvement in layout of the web learning system which is used as the class label for the proposed Parallel Neural Network. Experimental results are satisfactory. Cognition aspects can be used as a tool to design a better user interface.

6. REFERENCES

[1] Georgieva, G., Todorov, G., &Smrikarov, A. (2003). A model of a Virtual University some problems during its development. In Proceedings of the 4th international conference on Computer systems and technologies: e-Learning. Bulgaria: ACM Press.

[2] Hamdi, M. S. (2007). MASACAD: A multi-agent approach to information customization for the purpose of academic advising of students. Applied Soft Computing, 7, 746–771.

[3] Chen, C. M., Lee, H. M., & Chen, Y. H. (2005). Personalized e-learning system using item response theory. Computers & Education, 44, 237–255.

[4] Huang, M. J., Huang, H. S., & Chen, M. Y. (2007). Constructing a personalized elearning system based on genetic algorithm and case-based reasoning approach. Expert Systems with Applications, 33, 551–564

[5] Xu, D., & Wang, H. (2006). Intelligent agent supported personalization for virtual learning environments. Decision Support Systems, 42, 825–843.

[6] Economides, A. A. (2005). Personalized feedback in CAT (computer adaptive testing). WSEAS Transactions on Advances in Engineering Education, 3(2), 174–181.

[7] Economides, A. A. (2006). Emotional feedback in CAT (computer adaptive testing). International Journal of Instructional Technology and Distance Learning 3(2).

[8] Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12, 257–285.

[9] Chandler, P., &Sweller, J. (1991). Cognitive load theory and the format of instruction. Cognition and Instruction, 8, 293–332.

[10] Chandler, P., &Sweller, J. (1996). Cognitive load while learning to use a computer program. Applied Cognitive Psychology, 10, 151–170.

[11] Chen, S.Y. ,Magoulas, G. D. &Dimakopoulos, D.(2004). Cognitive styles and users' responses to structured information representation. Journal of the American Society for Information Science and Technology, 56(1), 70–83.

[12] Mayer, R. E. (2001). Multimedia learning. New York: Cambridge University Press.

[13] Niegemann, H. M. (2001). Neuelernmedien: Konzipieren, entwickeln, einsetzen [New instructional media: Conceptualize, develop, implement]. Bern, Switzerland: Huber.

[14] Susan Feinberg and Margaret Murphy; Applying Cognitive Load Theory to the Design of Web-Based Instruction; Usability Testing and Evaluation Center, Illinois Institute of Technology, Illinois. US.

[15] Sweller, J. (1999). Instructional design in technical areas. Camberwell, Australia: ACER Press.

[16] Gerjets, P.,&Scheiter, K. (2003). Goal configurations and processing strategies as moderators between instructional design and cognitive load: Evidence from hypertext-based instruction. Educational Psychologist, 38, 33–41.

[17] Renkl, A., & Atkinson, R. K. (2003). Structuring the transition from example study to problem solving in cognitive skill acquisition: A cognitive load perspective. Educational Psychologist, 38, 15–22.

[18] Jan L Plass; Design and Evaluation of the User Interface of Foreign Language Multimeda software: A Cognitive Approach; Language Learning & Technology, Volume 2, Number 1, July 1998.

[19] Mihalca, L., Salden, R. J., Corbalan, G., Paas, F., &Miclea, M. (2011). Effectiveness of cognitive-load based adaptive instruction in genetics education. Computers in Human Behavior, 27(1), 82-88.

[20] Baylari, A., &Montazer, G. A. (2009). Design a personalized e-learning system based on item response theory and artificial neural network approach. Expert Systems with Applications, 36(4), 8013-8021.

[21] Fausett, L. (1994). Fundamentals of neural networks. Englewood Cliffs, NJ: Prentice-Hall.

[22] Wu, D., Yang, Z., & Liang, L. (2006). Using DEA-neural network approach to evaluate branch efficiency of a large Canadian bank. Expert Systems with Applications, 31, 108-115.

[23] Reiterer, H. The development of design aid tools for a human factor based user interface design. International Conference on Man and Cybernetics Systems, 1993. page 361