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Classifying User Preferences of Web Learning System with Genetic Optimization

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ABSTRACT
Web learning system content can be in the form of tutorials, online discussion group or virtual platform for hands on training. Most of the Web learning system is enhanced using multimedia followed by self-assessment tools. A well designed user interface in the web learning system improves performance of the students learning. In web based learning systems, the cognitive load is the key for the effectiveness of the instructional and multimedia learning, thus the cognition, cognitive load and the students' website preferences form the basis of user's satisfaction. Based on the questionnaire, the likes and dislikes of the user are found. The data mining Classifier are trained based on cognitive based feedback questionnaire. A Multi-Layer Perceptron (MLP) neural network was proposed to classify the user preferences of Web Learning system. Thus helps to identify the areas for improvement in layout of the web learning system. To further improve the performance of the proposed MLP, the parameters of the neural network is optimized using Genetic Algorithm (GA). Then all the user preferences are classified using proposed neural network classifiers with an optimization technique. The cognitive attributes are used as the training input for the proposed genetically optimized neural network.
Keywords Web Learning System, Classification Accuracy, Genetic Optimization, Parallel Multi Layer Perceptron,NeuralNetwork. -

I. INTRODUCTION

Cognitive development refers to a mental process by which knowledge is acquired, stored, and retrieved to solve problems. Therefore, cognitive developmental theories attempt to explain cognitive activities that contribute to children's intellectual development. Cognitive theory holds that human memory comprises a very limited working memory[1], and effectively an unlimited long-term memory. Associative processes and organizational processes play an important role in learning and memory. It is well known that humans exploit relationships among items being memorized, and that material being recalled tends to reflect these relationships regardless of whether or not the material was organized when presented [2].

Web-based courses and programs have increasingly been developed by many academic institutions, organizations, and companies worldwide due to their benefits for both learners and educators. However, many of the developmental approaches lack two important considerations needed for implementing Web-based learning applications [3].

User-Centered Design (UCD) is a design philosophy and a process in which the needs, wants and limitations of the end user of a product are the focus of each stage of the design process. By involving the user at each phase of the development process, it ensures that the end product responds to the users' characteristics and, therefore, provides students a positive learning experience. Moreover, it ensures that students do not need to learn new competences in order to learn how to use the environment again. Both the positive learning experience and the maximization of the acquired competences are key for promoting lifelong learning.

Heo and Chow et al[4] conducted a study to determine the impact of an online learning tool on learning and assessment, by minimizing cognitive load. As a point of reference, cognitive load may be intrinsic, extraneous, or germane. The intrinsic cognitive load is related to the complexity of the material. The extraneous cognitive load is due to the design of the instructional materials. Germane cognitive load is the mental processing that allows learning to take place. It is desirable to decrease intrinsic and extraneous cognitive load, while increasing germane cognitive load [4].

Norol et al., [5] explored user characteristics, user's cognitive styles, their current views about e-learning usability and perceived importance of its usability design features. Though the use of e-learning has been a de facto solution for almost all higher learning institutions and its adoption has been proven to successfully aid students in their learning activities, there has been lack of study in further understanding the usability of e-learning courseware and its significance in the instructional design process. A survey was conducted in one of the universities in Malaysia where e-learning courseware is extensively deployed. Based on the analysis it was found that there was a relationship between users' current view and users' perceived importance of interface design. This could result Cognitive load in considering the usability characteristic in designing features. The result is also consistent with the study as most of respondents agreed that the usability characteristic in designing the system is based on certain criteria and it was also found that most of the respondents believe the importance of the criteria in designing the interface. However, although the cognitive style has been found to influence usability in other studies, it does not contribute to the e-learning usability and perceived importance features in the current study. A comparison between genders reveals that there are significant differences between males and females in their views on e-learning usability and perceived importance e-learning features.

Cognitive load theory (CLT) is gaining increasing importance in the design and evaluation of instruction, both traditional and technology based. Although it is well understood as a theoretical construct, the measurement of cognitive load induced by instructional materials in general, and by multimedia instruction in particular, mainly relies on methods that are either indirect, subjective, or both. Integrating aspects of CLT, working memory research, and cognitive theories of multimedia learning, we describe the conceptual basis and practical implementation of a dual-task approach to the direct measurement of cognitive load in multimedia learning. This computer-based instrument provides a direct and objective measure that overcomes many of the shortcomings of other indirect and subjective methods that will enable researchers to validate empirically theoretical predictions of CLT Based on different sources for cognitive load, Sweller (1999) distinguished three types of load: one type that is attributed to the inherent structure and complexity of the instructional materials and cannot be influenced by the instructional designer, and two types that are imposed by the requirements of the instruction and can, therefore, be manipulated by the instructional designer.

II. RELATED WORKS

Mustafa et al [7] GA is based on biological evolution. In GA natural selection mechanics and genetics are emulated artificially to search for a global optimum for a problem. The algorithm starts with a population which is an initial solution randomly selected. The global optimum search is conducted by moving from initial individual's population to a new population using genetics-like operators like selection, crossover and mutation, inspired by natural selection mechanics and real life genetics. Every individual is a candidate for optimization solution and modeled by a value called chromosome. Starting with a population selected randomly, GA operators perform tasks on chromosome, in a reproduction process, to produce new generations ensuring a solution for a global optimum.

Web-based learning's individual difference issues which are also called online training, online instruction or distance education[8]. Distance education design implications were also discussed. Though the purpose was to identify learner's characteristics differences like cognitive, affective, physiological and social factors affecting web-enhanced environment's learning, questions about how web reinforces learning, what development ideas, theories and models presently design/deliver online instruction, and lastly evidence of effectiveness in using World Wide Web (WWW) for learning/instruction was reported. It was also analyzed to extend web-based learning's theoretical and epistemological understanding.

GA with a neural network to determine the suitable network architecture and parameters set from restricted space. The multilayer neural-GA was applied to image processing for pattern recognition and to determine object orientation. A library to cover object views was built from (10×10) pixels real images, the smallest image size used by this algorithm to recognize aircraft type with its direction. The multilayer perceptron neural network integrated with GA showed good optimization, reducing hidden nodes required to train a neural network (number of the epoch's reduced to less than 50%). An important result of the implemented algorithm was time reduction needed to train a neural network.

III. METHODOLOGY

One type of network sees the nodes as 'artificial neurons'. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or the membrane of the neuron. When the signals received are strong enough (surpasses a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons. The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes independence of a certain threshold). ANNs combine artificial neurons in order to process information.

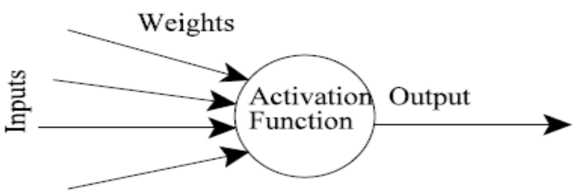

Fig 1 Artificial Neuron

The higher a weight of an artificial neuron is, the stronger the input which is multiplied by it will be. Weights can also be negative, so we can say that the signal is inhibited by the negative weight. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron we can obtain the output we want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. But we can find algorithms which can adjust the weights of the ANN in order to obtain the desired output from the network. This process of adjusting the weights is called learning or training.

The number of types of ANNs and their uses is very high. Since the first neural model by McCulloch and Pitts (1943) there have been developed hundreds of different models considered as ANNs. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc. Also there are many hybrid models where each neuron has more properties than the ones we are reviewing here. Because of matters of space, we will present only an ANN which learns using the backpropagation algorithm[9] for learning the appropriate weights, since it is one of the most common models used in ANNs, and many others are based on it. Since the function of ANNs is to process information, they are used mainly in fields related with it. There are a wide variety of ANNs that are used to model real neural networks, and study behaviour and control in animals and machines, but also there are ANNs which are used for engineering purposes, such as pattern recognition, forecasting, and data compression.

ANN architecture is known as a multilayer perceptron (MLP). Neural networks operational principle is simple. Each input layer neuron has a value, so that the input layer holds input vector. Each neuron connects to other neurons in the next neuron layer.

Artificial Neural Networks' architecture is a neuron layout grouped in layers. ANN's main parameters include: layer numbers, neuron number per layer, connectivity level and neurons interconnector types. A multilayer Perceptron (MLP) is an original Perceptron model variant proposed by Rosenblatt in 1950 [10]. It has one/more hidden layers between input and output layers, neurons are in layers, connections are always directed from lower to upper layers, same layer neurons are not interconnected.

The neural network's first layer is the input layer containing n neurons; the last network layer is the output layer, containing m neurons. In the Perceptron model, a neuron with a linear weighted net function and threshold activation function are used. Input to neuron $x=(x1,x2,x3\ldots x_n)$ is a feature vector in n-dimensional feature space. The net function is a weighted sum of inputs:

$$f(x) = w_0 + \sum_{i=1}^{n} w_i x_i$$

Input Layer

A predictor variable vector of values (x1, x2, x3.. xn) presented to the input layer. The input layer distributes values to each neuron in the hidden layer. In addition to the predictor variables, a constant input of 1.0, called bias is fed to each hidden layer; the bias is multiplied by a weight and added to sum going into the neuron.

Hidden Layer

Neurons between an input and output layers are the hidden layer neurons. Outputs from hidden layer are distributed to the output layer. First hidden layer neurons are directly connected to input layer (data layer) of neural network.

Output Layer

Reaching an output layer neuron, value from every hidden layer neuron is multiplied by a weight (wkj), and resulting weighted values are added producing a combined value vj. The weighted sum (vj) is fed to a transfer function σ, which outputs value yk. The y values are network outputs.
The logistic function defined by:

$$\sigma(s) = 1/(\exp(-a * s)$$

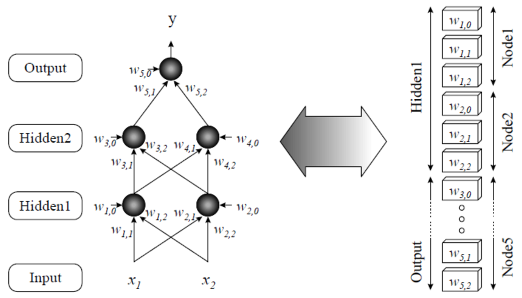

Fig 2. Neural Network Architecture

Genetic Algorithms (GAs)

GAs finds approximate solutions to difficult problems through application of evolutionary biology principles to computer science. GAs views learning as a competition between the populations of evolving candidate problem solutions. A fitness function evaluates every solution to decide if it can contribute to next generation solutions. By operations analogous to gene transfer in sexual reproduction, the algorithm generates a new candidate solution [12] problem.
The 3 important aspects of using GA are:
- Definition of objective function.

- Definition/implementation of genetic representation, and
- Definition/implementation of genetic operators.

Procedure genetic algorithm

begin
t←0
initialise P(t)
evaluate P(t)
while (not termination condition) do
begin
t←0
select P(t) from P(t − 1)
alter P(t)
evaluate P(t)
end
end.

Steps for the genetic algorithm:

1) Generation of Population: Initial population generated with 10 chromosomes and population size maintained over generations.
2) Evaluation: Each chromosome evaluated to find fitness. Parents selection: Here among top 5 chromosomes with better fitness, 4 are chosen randomly to an empty parent chromosomes set. Among 5 with worst fitness, 2 are chosen to same set.
3) Passage of genes from parents to children: The principle is that identical characteristics between parents should pass on to children.
4) Mutation: probability of inherited gene mutation in children was considered 0.1 (gene value is modified to random value).
5) Generation of new Population: The previous population's fittest chromosomes and 6 children generated form a new population for next generation.
6) Steps 2 to 6 are performed till number of iterations corresponds to predefined time or maximum generations.

Experimental setup

The cognitive behavior of 182 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.

The typical questions were in the areas of 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

1. I prefer content that is challenging so I can learn new things.
2. I like what I am learning in this website
3. How is the mental demand to understand the content of the website
4. Was the learning content very high in the web page
5. Do you think the effort required to learn is higher compared to the mental demand.
6. Do you think the dissatisfaction to learn is higher than mental demand

Table 1 Neural network parameters

Input Neurons	29,15
Output Neurons	4,3
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
Number of Iterations	1000

Table 2 Classification Accuracy

Data Mining Algorithm	General Cognition	Cognitive Load
MLP	75.6%	72%
PMLP	92%	76%
GO PMLP	92.68%	85%

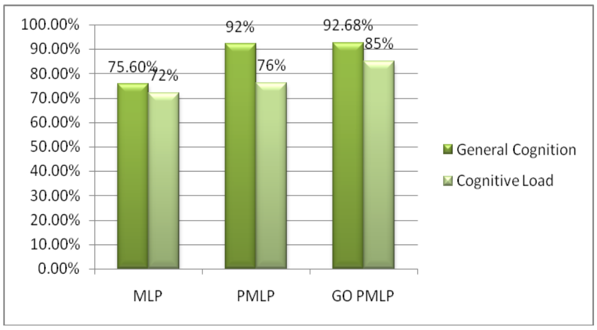

Fig 3. Classification Accuracy

IV. Conclusion

Web Learning system encompasses all tools that make use of the internet for delivery of learning content. A cognitive based feedback questionnaire is used to capture the likes and dislikes of the user which are classified through the classification algorithms. This research work concentrated on enhancing the classification accuracy through neural network based approaches. The GO PMLP algorithms are proposed and validated. These algorithms classify the user preferences of web learning system with enhanced classification accuracy. The proposed Genetic Optimized PMLP achieves classification accuracy for cognition 92.68% and 85% for cognitive load, for web learning data set.

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