Concept-based Classification for Adaptive Course Sequencing Using Artificial Neural Network

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***Abstract*— The task of presenting an optimal personalized learning path in an educational hypermedia system requires much effort and cost particularly in defining rules for the adaptation of learning materials. This research focuses on the adaptive course sequencing method that uses soft computing techniques as an alternative to a rule-based adaptation for an adaptive learning system. In this paper we present recent work concerning concept-based classification of learning object using artificial neural network (ANN). Self Organizing Map (SOM) and Back Propagation (BP) algorithm were employed to discover the connection between the domain concepts contained in the learning object and the learner's learning need. The experiment result shows that this approach is assuring in determining a suitable learning object for a particular student in an adaptive and dynamic learning environment.**

Keywords-; adaptive learning; course sequencing; learning object; classification; neural network

I. INTRODUCTION

A typical and traditional educational system provides the same resources to all learners even though different learner really needs different information regarding to his goal, level of knowledge, learning style and preferences. Course sequencing is a technology originated in the area of Intelligent Tutoring System (ITS) with the goal to provide student with the most suitable individually planned sequence of knowledge units to learn and sequence of learning tasks (examples, questions, problems, etc) to work with [1]. It is an important adaptive method in ITS and Adaptive Hypermedia for determining learning path through the hyperspace.

To incorporate course sequencing techniques in an educational system, the content selection rules and concept selection rules are required in order for setting the principles of content selection and instructional planning of the system. The content selection rules are designed according to the cognitive style or learning preferences of the learner [2]. Though most of these rules are domain independent, there are still an absence of well defined and commonly accepted rules on the selection and sequencing of the content in a way to produce a sense of instructional value in most educational system ([3],[5],[6]). Furthermore, the complexity of dependencies between the content or learning object characteristics and learners usually requires a complicated and huge set of rules to be defined.

This research attempts to propose an innovative course sequencing method that automate teacher's role in designing the adaptation rules. As an alternative to the tedious work of rules definition, this method will employ soft computing techniques in order to generate and optimize the learning path for a student. In this paper, we addressed the problem of selecting the suitable set of learning objects associated to learner knowledge level as a classification problem. The rest of the paper is organized as follows: in Section II we will give some overview on related works that have employed artificial neural network in learning object selection. Section III will explain our approach toward the problem. The experiments that have been conducted will be presented in Section IV. Section V will discuss the results of the experiment. We will conclude the paper in Section VI along with the further works of the study.

II. ARTIFICIAL NEURAL NETWORK IN E-LEARNING

Artificial Neural Network (ANN) is inspired by the way biological nervous system processing information. It is composed of large numbers of highly interconnected neurons which responsible as a processing elements. ANN models have particular property such as ability to adapt, to learn, or to cluster data. For classification problem, the network needs a training corpus of objects with known category membership. New objects with unknown category can be classified after training the network. Intensive employment of ANN has been seen in multiple fields related to classification task such as pattern and speech recognition, non-linear system and control.

In the e-learning area, ANN has been widely used in classification of students based on their preferences or learning styles. In that case, ANN has been used to build the learner model which consists of personal static data, system usage data and his preferences [7]. Instead of classification, ANN also has been used for predicting student performance as presented in [8][9]. However ANN rarely been employed in educational system in the classification and modeling of the domain knowledge and learning materials. An attempt

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has been done by [4] by combining both user modeling and learning object (LO) classification using ANN.

III. PROPOSED APPROACH

This section discusses the research methodology that will be used in order to achieve the goal of this study. Works reported in this paper is only a part of overall framework of this research. Basically the methodology is based on the conceptual framework as depicted in Fig. 1. The following subsections will explain briefly on the framework.

A. *User Model*

For the design of the User Model, overlay model has been used for representing the student knowledge space. The idea of the overlay model is to represent an individual user's knowledge of the subject as an 'overlay' of the domain model. Profiles of 60 learners are created based on their performance which representing their knowledge level for every concept tested during the pre-test evaluation. The pre-test questions given are corresponding with the learning goal that he has selected. The data for every student is recorded as in Table I. Table II illustrates the classification scheme for student mastery level while Table III shows the finalized concept mastery representation that will be an input for the experiment using artificial neural network as discussed in the following subsection.

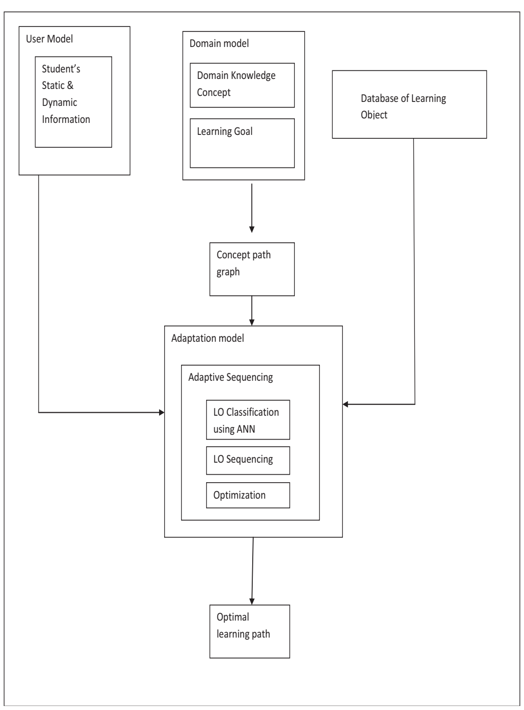

Figure 1. Conceptual framework

TABLE I. RESULT OF PRE-TEST

Concept Id	Concept	Score (Avg)
C1	Primitive data type	80
C2	Array Declaration	60
C3	For- loop	49
C4	Class and Object declaration	35
C5	Initializer list	89

TABLE II. CLASSIFICATION OF MASTERY LEVEL

Score	Level	Representation
80-100	Advance	0
40-79	Normal	0.5
0-39	Poor	1

TABLE III. FINALIZED CONCEPT MASTERY REPRESENTATION

Concept Id	Representation
C1	0
C2	0.5
C3	0.5
C4	1
C5	0

B. *Domain Model*

In this research, the selected domain is Array, one topic of Object Oriented Java Programming course which is currently being taught at FSKSM, Universiti Teknologi Malaysia. We only focused on five learning goals in this topic and to achieve these learning goals, we have identified 25 concepts that must be mastered by the students. Some of the concepts are presented in Table IV. For each learning goal, domain experts have to estimate the weight of each concepts of domain knowledge. The value given to the concept is 1 if the particular concept is important in achieving the learning goal, 0.5 if it is not necessary and 0, if the concept is not relevant.

C. *Adaptation Model*

Adaptation model contains the rules for describing the runtime behavior of the system as well as how the domain model relates to the user model to specify adaptation. In a typical approach to the problem of generating personalized learning path, the rules for adaptive sequencing are defined in this model. In this research, this model will employ soft computing technique in the selection and sequencing of learning objects instead of containing rules definitions.

TABLE IV. PART OF DOMAIN KNOWLEDGE CONCEPTS

Learning Goal	**Main Concept**	**Pre-requisite Concept**
Declare and create an array of primitive types	• Primitive data type • Array declaration • For-loop • Class and object declaration • Initializer list	• Assignment Stmt • Control Structure • Reference variable • Class and object
Declare and create an array of object	• Creation of array of type class • Creation of object in each/ particular index of the array	• Array of primitive type

IV. EXPERIMENTS

Two experiments have been conducted with the objective to select a group of similar learning object for a particular student regarding to his subject knowledge mastery level.

A. Clustering of learning object using Self Organizing Map (SOM)

For the first experiment, a data set comprising of 129 learning objects for the topic have been prepared. Domain expert was then to estimate the weight of each concepts of domain knowledge contained in every LO. The weight value given to the concept is 1, if the concept is very relevant or has been described particularly in that learning object, 0.5 if the concept is slightly described and 0, if the concept is not relevant to the LO. There are 25 concepts to be evaluated by the experts for every LO.

The SOM is an unsupervised neural network that maps a set of n-dimensional vectors to a two-dimensional topographic map. The training of an unsupervised neural network is data-driven, without a target condition that would have to be satisfied (as in a supervised neural network). The SOM combines an analytic and graphical technique to group data onto a low-dimensional (typically 2-dimensional) display and organize the data into clusters by this projection [14].

In our approach, SOM technique is employed to cluster the collections of LO into groups based on concepts similarity of the LO. A network has been created with 25 input neurons and has been trained with different dimension sizes of the map in order to get the best clustering result. Fig. 2 illustrates the architecture of the ANN for this experiment. From the experiments, using our data, the best result was obtained when the size of the map dimension is 5 x 5. The network managed to cluster the LO into 12 groups based on the concepts of the domain knowledge. The output of this experiment is the LOs with their class ID which later will be trained by the neural network in order to classify each student to any groups of the LO in the second experiment.

B. Concept-based classification of learning objects and students using Backpropagation ANN

In the second experiment, profiles of 60 students are created based on their performance in the pre-test evaluation. The input layer represents the concepts of the course, where the input vector is a set of values belonging to the set {0,0.5,1} .The determination of the values is based on the finalized concepts mastery level of the student as in Table 3. For example, if the mastery level for concept C1 is 0 which means that the student has already mastered the concept and categorized as 'advance', the value for the concept C1 is set to 0 in the input layer. This concept C1 is not important for the student to be learnt in his learning path anymore. The output layer is assigned to the groups of learning object that have been identified previously. Three steps have been taken in performing this experiment.

Step 1: Create a neural network to train LO data for classification.

The network used for the experiment is a multi layer perceptron (MLP) network constructed of 25 neurons in the input layer which represent 25 domain knowledge concepts that have been identified by the domain expert. Fig. 3 illustrates the architecture of the network.

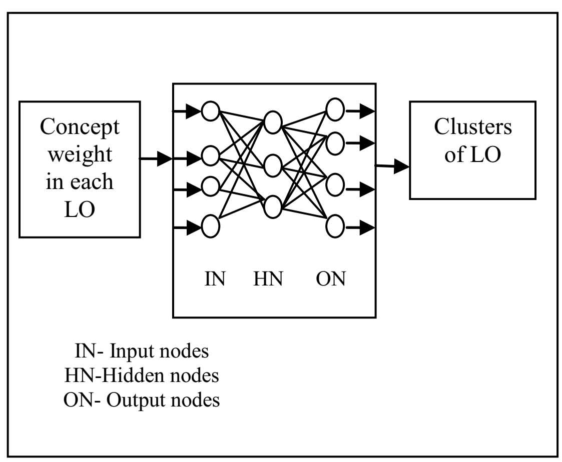

Figure 2. ANN architecture for LO clustering

The output layer represents the group of suitable LO. A group of LO is a set of LO with the same class ID as been identified in the previous experiment. Classification task using ANN requires an already known class that each training instance belongs to, so that the supervised learning can be used.

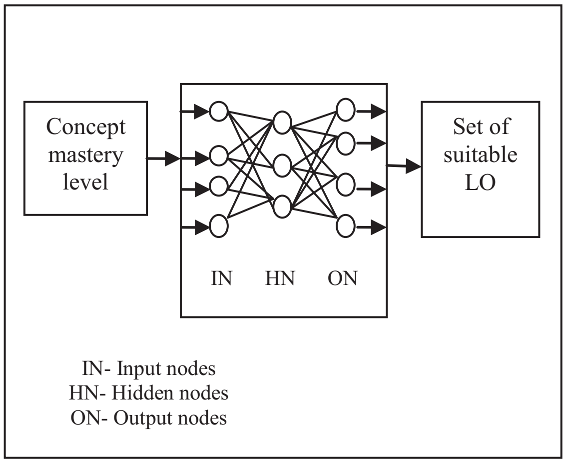

Figure 3. ANN architecture for LO classification

Step 2: Train the network using LO data

In this phase, the MLP network as created in Step1 is trained using a classic Backpropagation(BP) algorithm, Output-Weight-Optimization (OWO). OWO involves solving a set of linear equations using the Conjugate Gradient Technique in order to calculate optimum output weights. Error at each node is calculated and is back propagated to the hidden layer where the hidden weights are calculated so as to minimize mapping error. This experiment has been done with different size of hidden nodes and the performance is measured based on the error rate of each data classification. In our case, the error has been successfully minimized to zero percent (0.000%) after 100 iterations when the hidden layer node is set to 25 neurons.

The weight matrix produced during the training phase will be used for testing the network to classify each student to a suitable LO class in the next phase.

Step 3: Testing the network using student profiles data

The objective of this step is to determine which class or group of LO that matched the profile of a student. The data to be compared was his mastery level upon the domain knowledge concepts. For example, let us consider the profile of a particular student as shown in Table V.

TABLE V. EXAMPLE OF STUDENT DATA

Concept	**C1**	**C2**	**C3**	**C4**
Mastery Level	Advance	Advance	Remedy	Remedy
Value	0	0	1	1

Here, the mastery level regarding four concepts from the topic for the student is presented. The idea is to select any LO that have the same pattern of his value, i.e , 0 0 1 1. Therefore, a suitable LO for the student is LO with same data representation pattern as in Table VI. To identify the LO classes for a student, the created network for training the LO data as well as the weight vector from the previous step are used.

TABLE VI. EXAMPLE OF SUITABLE LO

Concept	**C1**	**C2**	**C3**	**C4**
Relatedness of the concept	Not relevant	Not relevant	High	High
Value	0	0	1	1

V. RESULTS AND DISCUSSION

The neural network has been tested towards 60 students' profiles. The result shows that the classifier had selected the most matching LOs with the student profiles. Table VII presents the results of the classification.

The result shows that most of the good classifications were the samples with bigger size of hidden nodes. The obtained result shows that ANN were able to select up to 100% of learning objects as selected by the domain expert for each student.

TABLE VII. CLASSIFICATION RESULTS

	Hidden Nodes Size	**Mean Squared Error**	**% Correct Classification**
1	13	2.929653	100
2	20	0.779631	100
3	25	0.150094	100
4	50	0.000000	100
5	51	0.000000	100

VI. CONCLUSION

Adaptive course sequencing is an approach that aims to provide learner the most suitable learning materials throughout his learning path in a web based educational system. In this paper, we addressed the learning object selection problem based on learner's mastery level upon the domain concepts. Instead of defining a complex and huge set of rules as normally done in a traditional adaptive learning, domain expert only need to give her estimation and decision on selecting the suitable learning objects.

A neural network has been constructed to identify a group of similar learning object as well as to select a suitable learning object for a particular student. The suitability of the learning object here is meant by the similarity of the domain concept data representation pattern between the student's and the learning object's profiles. The result of this preliminary study shows that the computational intelligence approach is assuring in achieving our goal that is to produce an adaptation model that can imitate the rule-based decision making task of an instructor.

The next stage of this research is to generate the learning paths graph for the domain model through the sequencing of suitable learning objects classified before this. Of all possible generated learning paths, we will identify the most appropriate or optimal learning path for a particular student. Some searching techniques such as Beam Search, Partition Search and Simulated Annealing, as well as nature-inspired techniques, ant colony optimization (ACO) will be considered in this further study.

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