Learning Style Diagnosis as an Adaptivity Parameter in a Unified e-Learning System Architecture

Sotirios Botsios[1], and Dimitrios Georgiou[1]

[1] Department of Electric & Computer Engineering
Democritus Univ. of Thrace, GR 671 00, Xanthi, Greece
smpotsio@ee.duth.gr

Abstract. Adaptation and personalization services in e-learning environments are considered the turning point of recent research efforts, as the "one-size-fits-all" approach has some important drawbacks, from the educational point of view. Adaptive Educational Hypermedia Systems in World Wide Web became a very active research field and the need for standardization arose, as the continually augmenting research efforts lacked the interoperability dimension. To this end, we propose an adaptive hypermedia educational system architecture strongly coupled to existing standards that overcomes the above mentioned weakness. Part of such architecture is the development of diagnostic tools capable to recognize certain learner's characteristics to the purpose of providing learning material tailored to the learner's specific needs in an asynchronous learning environment. This paper describes Learning Style diagnosis which can be approached either by the use of probabilistic expert systems or by the use of fuzzy systems.

Keywords: Learning Management Systems, Adaptive Educational Hypermedia Systems, Standards, Learning Style Diagnosis, Probabilistic Expert Systems, Bayesian Networks, Fuzzy Cognitive Maps.

1 Introduction

A recent research [1] demonstrated that both instructors and learners have very positive perceptions toward using e-learning as a teaching assisted tool. According to Brusilovsky and Miller [2] Adaptive and Intelligent Web-Based Educational Systems provide an alternative to the traditional 'just-put-it-on-the-Web' approach in the development of Web-based educational courseware. In their work Brusilovsky and Pyelo, [3] mention that Adaptive and Intelligent Web-Based Educational Systems attempt to be more adaptive by building a model of the goals, preferences and knowledge of each individual student and using this model throughout the interaction with the system in order to be more intelligent by incorporating and performing some activities traditionally executed by a human teacher – such as coaching students or diagnosing misconceptions.

There exist a wide variety of diverse Adaptive and Intelligent Web-Based Educational Systems. The 'rules' that are used to describe the creation of such systems are not yet fully standardized, and the criteria that need to be used pedagogically effective rule-sets (i.e. adaptation parameters) are, as yet, poorly mentioned [4]. Many experimental Adaptive Educational Hypermedia Systems have been created – each to their own unique specifications. As yet, however, no combined effort has been made to extract the common design paradigms from these systems.

The current research efforts of the authors are concentrated in providing a starting point for the development of a unified architecture for the retrieval of learning objects from disperse Learning Objects Repositories (LOR) to an e-learning environment. Rehak and Mason [5] consider Learning Object (LO) as a digitized entity which can be used, reused or referenced during technology supported learning. Practically, LOs acquisition is achieved by querying LOR distributed over the internet. This LO "journey" must comply with widely accepted standards. The LO query includes "filters" that refer to various adaptation parameters.

These parameters are strongly coupled with various aspects of the learner profile, i.e. cognitive style-cognitive abilities, learning style (LS), learning behavior-motivation, competency level-personal goals-course material difficulty. The authors believe that the accurate estimation of some or all of these parameters in a standardized manner can boost the efficiency of the e-learning process. Therefore, part of the research conducted and main topic of this paper concerns the LS estimation. We describe two techniques for LS estimation that can provide some service to the previously mentioned architecture. Both of the techniques are based on the Kolb's Learning Style Inventory (KLSI) [6]. The first one consists of the Fault Implication Avoidance Algorithm (FIAA) and a Probabilistic Expert System. [7]. The second technique describes an adjustable tool that allows experts to reinforce the system's LS recognition ability. To this end, we developed a three layer Fuzzy Cognitive Map (FCM).

The rest of the paper is structured as follows. Section 2 provides a brief theoretical background of LS, while in section 3 the previously mentioned techniques are described.

2. Learning Style

Learning Theories diverge with respect to the fact that students learn and acquire knowledge in many different ways, which have been classified as LSs. There exists a great variety of models and theories in the literature regarding learning behavior and cognitive characteristics i.e. LSs or Cognitive Styles (CSs) [8]. According to Riding and Rayner, CS refers to an individual's method of processing information [9]. The building up of a repertoire of learning strategies that combine with cognitive style, contribute to an individual's LS. In particular, LSs are applied CSs, removed one more level from pure processing ability usually referring to learners' preferences on how they process information and not to actual ability, skill or processing tendency [10]. LSs classifications have been proposed by Kolb [6] and others [11], [12], [13]. Most of the authors categorize LSs and/or CSs into groups and propose certain inventories and methodologies capable of classifying learners accordingly.

The KLSI is considered as one of the most well known and widely used in research. According to the model students have a preference in the way they learn: a. Concrete Experience or Abstract Conceptualization and b. Active Experimentation or Reflective Observation. [14] The model is represented in a two dimensions graph. The preference is diagnosed by analysing subject's responses in given questions of a questionnaire.

3. Techniques for LS Estimation of this research

3.1 FIAA and Probabilistic Expert System

The first technique consists of the FIAA and a Probabilistic Expert System [7]. Taking into account the structure of KLSI, FIAA dynamically creates a descending shorting of learner's answerers per question, decreases the amount of necessary input for the diagnosis, which in turn can result to limitation of possible controversial answers. The applied Probabilistic Expert System, funded upon Bayesian Networks, analyzes information from responses supplied by the system's antecedent users (users that complete the questionnaire before the present user) to conclude to a LS diagnosis of the present user. One of the primary roles of a Bayesian model is to allow the model creator to use commonsense and real-world knowledge to eliminate needless complexity in the model. Evidence is provided that the effect of some factors, such as cultural environment and lucky guesses or slippery answers, that hinder an accurate estimation, is diminished. This technique produces a "clear" LS estimation (no "grey" estimation areas).

Let us consider the $BN=(\boldsymbol{V},\boldsymbol{A},\boldsymbol{P})$ where $\boldsymbol{V}=\boldsymbol{\pi_v}\cup\boldsymbol{M}$ and $\boldsymbol{\pi_v}=\boldsymbol{LS}=\{C_1, C_2, \ldots, C_v\}$ is the set of LSs. A learner is recognized as being of class C_i, ($i=1,2,\ldots,v$) according to his/her responses to a given set of m questions. Each question can be answered by yes or not. Let $\boldsymbol{Q}=\{Q_1^{(k)},Q_2^{(k)},\ldots,Q_m^{(k)}\}$ be the set of answers where k is a Boolean operator taking the values TRUE or FALSE whenever $Q_l^{(k)}$ represents the answer YES or NOT respectively. There are 2^m different sets of such responses to the questionnaire. Let us consider the index j, where $j\in\{1,2,\ldots,2^m\}$. A learner's responses to the set of questions formulates an element

$$r_j = \bigcup_{l=1}^{m} Q_l^{(k)} \quad \textbf{(1)}$$

where $r_j\subset\boldsymbol{M}$ the set of BN leaves. Obviously, $r_i \neq r_j$ for any pair $(r_i,r_j)\subset\boldsymbol{M}$, with $i\neq j$.

Let n be the number of learners who made use of the system, and n_{ri} be the number of those who responded to the questionnaire with r_i. The a priori probability that the $(n+1)^{th}$ user responded to the questionnaire with an element r_i is

$$P\left(r_i^{(n+1)}\right) = \frac{(n+1)_{r_i}}{n+1} \quad \textbf{(2)}$$

In this case, the BN in use is a weighted and oriented $K_{2^m}^{v}$ graph, i.e. a weighted and oriented complete bipartite graph on n and 2^m nodes. At each edge of the network's graph we adjust the conditional probability $P(r_i^{(n)}/C_j^{(n)})$, i.e. a probability which dynamically changes as a new user enters the system. This probability expresses the ratio of users who responded to the questionnaire with the element r_i and were finally classified in C_j, in terms of the total number of r_i responses. Thus, the measure $P(C_j^{(n+1)})$ is the probability that the LS of the $(n+1)^{th}$ learner belongs to C_j. This probability is given by the relation

$$P\left(C_j^{(n+1)}\right)=\sum_{i=1}^{2^m} P\left(C_j^{(n)} / r_i^{(n)}\right) P\left(r_i^{(n+1)}\right), \quad j=1,2,\ldots,v \tag{3}$$

where

$$P\left(C_j^{(n)} / r_i^{(n)}\right)=\frac{P\left(r_i^{(n)} / C_j^{(n)}\right) P\left(C_j^{(n)}\right)}{\sum_{k=1}^{v} P\left(r_i^{(n)} / C_k^{(n)}\right) P\left(C_k^{(n)}\right)}, \quad \forall (i,j) \in \{1,2,\ldots,n\} \times \left\{1,2,\ldots,2^m\right\} \tag{4}$$

Let $score_j^{(n+1)}$, $j=1,2,\ldots,v$ be the score for the j^{th} LS, that the $(n+1)^{th}$ student gets by responding to the revised inventory. Then, by the contribution of BN, the learner's j^{th} LS final score is given by

$$ls_j = P\left(C_j^{(n+1)}\right)\left(score_j^{(n+1)}\right) \tag{5}$$

Then the dominant LS is the maximum value of ls_j, $j=1,2,\ldots,v$.

3.2 Fuzzy Cognitive Maps

The second technique describes an adjustable tool that allows experts to reinforce the system's LS recognition ability. To this end, we develop a three layer Fuzzy Cognitive Map (FCM). FCM is a soft computing tool which can be considered as a combination of fuzzy logic and neural networks techniques. FCM representation is as simple as an oriented and weighted compact graph consisting of nodes (concepts) and arcs (fuzzy relation between linked concepts). The inner layer contains LSs, the middle one contains Learning Activity Factors (LAFs) and the outer layer refers to the 48 statements one can find in the KLSI [6]. The list of LAFs and their relational links to the LSs are those indicated in Kolb's [14]. Each pair of layers (outer–middle, and middle–inner) consist a complete bipartite oriented and weighted graph. Student's responses to inventory reflect on certain LAFs according to relations which have been pointed out by experts. At a second step LAF reflect on LSs. Unlike the technique of LSs recognition which is based directly to student's response to LS inventory, the proposed schema allows the cognitive scientists or experienced educators to interfere, tuning up the system, in order to contribute on the accuracy of the recognition. For example, a teacher, having its own clear diagnosis on a learner's LAFs, can tune up the system's weights in order to adjust it in situation at hand.

Initially, every concept gets a hypothetic value and as the time proceeds (i.e. new learners use the system), the values of the concepts change, as they are under the influence of the adjacent concepts and their corresponding weights.

At the step n the value $V^n(C_i)$ of the concept C_i is determined by the relation [5]

$$V^{n+1}\left(C_i\right)=f\left(k_1 \sum w_{ji} V^n\left(C_j\right)+k_2 V^n\left(C_i\right)\right) \tag{6}$$

where $V^{n+1}(C_i)$ is the value of the concept C_i at the discrete time step $n+1$, w_{ji} the defuzzified value of the weight between concepts C_i and C_j. The coefficient $0 \leq k_1 \leq 1$ defines the concept's dependence of on its interconnected concepts, while the coefficient $0 \leq k_2 \leq 1$ represent the proportion of contribution of the previous value of the concept in the computation of the new value. In other words, k_2 is the effect of the knowledge the system has gained by the previous users. Function f is a predefined threshold function. We used the unipolar sigmoid function, as we want to restrict values of concepts between 0 and 1. The maximum value between four $V(C_i)$, which represent the four LSs, is considered as the dominant LS of the $(n+1)^{th}$ user.

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