Chapter 11

Toward New Method for Adaptive Learning

Souhaib Aammou  
Abdelmalek Essaâdi University, Morocco

Youssef Jdidou  
Abdelmalek Essaadi University, Morocco

Kaoutar El Bakkari  
University of Cadiz, Spain

ABSTRACT

This chapter deals with the design, creation, and implementation of the content model of an adaptive system. The authors propose the use of a meta-ontology composed of three conceptual models. They also propose SCORM as a technical means for structuring ontology and resources. They also present the problem of adaptation as the search for the most relevant pedagogical sequence among the available ones. To evaluate this relevance, the authors propose to use an original semantic similarity measure. This allows one to measure a distance between each of the available sequences and the metadata vector returned by the decision engine. Thus, the authors recommend the educational activities that best fit the learner’s learning style, as one would have thought.

INTRODUCTION

The majority of research on adaptive education systems focused on modeling of learners based on their levels of knowledge and preferences (Bull et al. 2007). In parallel, several experimental studies in differential psychology have shown that individual differences play an important role in teaching (Zhang, 2015). Learners acquire and process pedagogical information in different ways; they learn at different rates depending on the learning context (Sternberg, 2015). These results suggest that adapting pedagogical sequences to learning styles allows the learner to retain information longer and to apply it more effectively.
The goal of this research is to describe a suitable learner model, consisting of the cognitive ability and pedagogical preference of a learner that has associated cognitive metrics found within instructional content. Our approach consists to split the learner model into a knowledge model and a preferences model. We try to propose a solution inspired by the statistical theory of learning for the implementation of the model: Bayesian network.

The learner model maintains knowledge and preferences. The decision engine uses the knowledge model and performance obtained by the learner. It determinates the following pedagogical objective to be taught. It also predicted the theoretical performance that the learner can achieve if pedagogical sequence is optimally adapted. It also uses the preference model. It reinforces the estimation of the learning style and inferences the metadata of the ideal sequence to be proposed to the learner. These metadata are then provided to the adaptation module which uses the content model to select the optimal pedagogical sequence and adapt the content.

**Learner Model**

Learner models are usually used to represent their knowledge and behavioral and cognitive characteristics. Despite this common goal, models vary considerably in their content. Most of them focus on knowledge and skills, although some researchers have argued that other characteristics are also addressed (Vassileva, 1990).

The learner model we propose consists of a knowledge model and a preference model. The first is used to predict the next educational goal to study, based on the current level of knowledge. The second specifies the educational content adapted to the learning style of the learner to the objective.

**Knowledge Model**

The literature is full of research on the modeling of learner knowledge. In this work, the model of knowledge that we propose is an overlay model on the content model (Tadlaoui et al., 2016). This means that the entire structure of the content model is represented in the knowledge model and described in the form of educational objectives to be achieved. It indicates, for each learning objective, the level of knowledge of the learner. Indeed, is associated with each learning objective already studied the measured performance \( P^a \), the learner has achieved the summative evaluation of the last corresponding instructional sequence. We have also a model for predicting us to estimate the possible theoretical \( P^b \) performance for a learner in a given objective based on current knowledge in the field. The objective will be achieved only when the \( P^b \) is greater than a fixed threshold \( \varepsilon \). In our case, \( \varepsilon \) is taken as 10.

Our knowledge model is a probabilistic model that uses a Bayesian network. Therefore, we can infer the next educational goal to offer the learner having observed a number of \( P^a \) in dependent objectives. We define the level measurement acquisition of a learning objective as a function of the theoretical \( P^b \) performance and actual \( P^a \). This function presented takes the form shown in Figure 1.

With \( \Phi \in [0,1] \) the level of acquiring a target, \( P^a \in [0,1] \) the measured actual performance of learners and \( P^b \in [0,1] \) the best estimated theoretical performance.

Figure 1 shows the variations of \( \Phi \). It is thus considered that the performance of the learner can improve as long as it is below its theoretical performance. Beyond that, we consider that the objective is achieved.