

Cognitive Profiling in Life-Long Learning

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INTRODUCTION

Statistics indicate that the information stored in the world doubles every 2.8 years (Keegan, 2000). The problem every country faces now is not how to create more information, but how to locate and utilise the available information. This amazing phenomenon brings on the dawn of a so-called knowledge economy within which market transactions are facilitated or even driven by knowledge that is acquiring more of the properties of a commodity (Houghton & Sheehan, 2000).

Corporations like General Electric (GE) spend \$500 million on training and education every year, and overall \$62.5 billion was budgeted for formal training by U.S. organisations in 1999 alone (Keegan, 2000). Corporations and individuals are more and more required to absorb and keep updated the new information through on-the-job or private training in order to stay competitive. Thus, lifelong learning has become a common practice for a wide range of careers ranging from engineers to sales representatives and doctors to farmers.

Technology-based instruction, within which electronic learning, e-learning, is the largest component, was predicted to have 60 to 75% of share attributed to the corporate training market in 2004 (Keegan, 2000). One of the main advantages of e-learning over traditional instructor-led training is its ability to provide individualisation and adaptivity to suit the learner's need. Adaptive learning systems can adapt the learning content and presentation according to the characteristics of the learners (Beaumont, 1994; Costa, et al., 1991; Jonassen & Wang, 1990), and they aim at providing individualised courses similar to having the one-to-one privilege from a private tutor.

However, in order for the virtual learning environment (VLE) to provide adaptivity, the profile of

the learner needs to be acquired. The process of learner profiling is commonly known as student modeling (El-Sheikh & Sticklen, 1998; Hume, 1995; Zhou & Evens, 1999). A student model representing a chosen set of attributes of the learners is the result of the student-modeling process. Adaptive VLEs can then provide adaptivity based on the data in the student models.

Most of the existing student models focus on the performance of the learner on specific domain content (Brusilovsky et al., 1998; Staff, 2001); for example, they model which unit and/or skill has been learned to what degree. Adaptation based on performance models can be in the form of guiding the learner to the next most suitable learning task. Interbook, a tool for authoring and delivering adaptive electronic textbooks, used performance-based adaptation (Brusilovsky et al., n.d.).

In this entry, a rather different approach to student modeling is discussed. The new approach focuses on the cognitive profile of the learners. The cognitive attributes of the learners are called cognitive traits that are used as the basic tools for cognition. Working-memory capacity is an example of a cognitive trait. The model created, therefore, is named the cognitive trait model (CTM).

Before the discussion of the cognitive trait model, the current existing student-modeling approach is discussed in order to provide a background understanding of the purposes and techniques used for student modeling.

PERFORMANCE-BASED STUDENT MODEL

Two major types of performance-based models have been used in existing systems: state models and process models. In state models, a learner's domain

competence, which is identified as the most important feature in the existing systems, has to be constantly updated to reflect the progress in the student's understanding. This is often accomplished by recording the nodes or concepts visited by the students and the result of the learning from some form of assessment. For example, the state model in CIRCSIM-Tutor is used to guide the planning of the tutoring dialogue, switch the tutoring protocols, and, in large, adjust the curriculum (Zhou & Evens, 1999).

Process models are oriented to model the problem-solving process the students undertake. A process model represents the students in terms of both the knowledge they learned in the domain and inference procedures. According to El Sheikh (1997), "Such a model would be an executable process model, and could thus predict what the learner will do next, as well as work backwards from learner behavior to generate explanations." For enumerative modeling, the system developers analyse the model and determine possible errors students can make or are prone to make (Smith, 1998). An error can either be a primitive error or a composite error, which is the combination of primitive errors. An example of the process model is DEBUGGY (Burton, 1982), which used the enumerative technique and catered to both primitive and composite errors.

LIMITATION OF PERFORMANCE-BASED MODELS

However, performance-based models, no matter if they are state models or process models, have the following limitations.

1. **Domain dependency:** The result and effort of the modeling process cannot be reused in other domains.
2. **Lack of cognitive support:** Focus on domain content results in lack of support for the cognitive resources of the learner.
3. **Fluidity of the domain knowledge:** The discovery of new scientific theories or new technologies replacing the old ones rapidly requires the domain content to be updated accordingly, thus, the previous modeling result could be rendered useless.

If the first limitation can be overcome, the instructional institutions would benefit greatly in terms of costs, while at the same time the learners would enjoy the right level of adaptation at the beginning of every new course. The second and third limitations can be overcome by modeling the attributes of the learners relating to human cognition, which are quite stable over one's lifetime. A different approach of student modeling is thereby introduced; it is called the cognitive trait model.

COGNITIVE TRAIT MODEL

In the field of instructional science today, new and innovative learning practices are getting more and more attention. Some examples are exploratory-based learning, problem-based learning, and constructivist learning (Brooks & Brooks, 1993). For these student-oriented learning practices, the role of students has taken more responsibility in the learning process, and the teachers are becoming the facilitators of the process. The ability of a computer-assisted learning system to provide cognitive support is thus becoming more important as those cognitive traits and abilities are the tools the students have to use to construct their own knowledge. Without appropriate support, students may be discouraged due to cognitive overload or bored because the content is simply too easy.

The aim of the cognitive trait model is to provide fine-tuned system adaptivity to support the cognitive processes of learners during learning. It has to be clearly understood that the purpose of CTM is not to replace performance-based student models, but to complement them. Student performance models (state models and process models) record dynamic student-domain-specific data, whereas CTM stores those student attributes (cognitive traits) that could be multidimensional or stochastic, and are relatively persistent over time and transferable across different domains. The combination of two models therefore provides two different kinds of adaptations: One is based on performance, another is based on cognitive resources. Both types of adaptation can be used alone or in conjunction with each other depending on their availabilities.

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