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Volume I
A–Des
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
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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.

**NEW PERSPECTIVE FOR STUDENT MODELING**

The goal of CTM is to have a student model that can be persistent over a long period of time and consistent across a variety of domains. Thus, the CTM is perfectly suitable for those students who aim to proceed in life-
long learning. It is not essential for CTM to be able to predict the student behaviour the very first time the students use the system, but instead, what the students need is a student model that can grow to know them very well over time.

This changes the traditional idea of the student model that is thought of as just a database sitting on the server and full of numbers for only a particular task. The CTM offers the role of “learning companion,” which can be consulted by and interact with different learning environments about a particular student. The CTM can still be valid after a long period of time due to the more or less persistent nature of cognitive traits of human beings. When a student encounters a new learning environment, the learning environment can directly use the CTM of the particular student, and does not need to “relearn the student” from scratch. The CTM can also be saved to portable electronic media, such as a flash drive, and accessed every time the student starts up a learning session. In this sense, the CTM is like a learning companion who, even though does not know “what” is to be learned, knows “how” the learning content can be best presented to the student. The CTM also stands as a cognitive facilitator between the student and the learning management system (LMS).

NEW APPROACH FOR STUDENT MODELING

CTM could enable the learning environments to provide fine-grained adaptivity that takes each individual student’s cognitive abilities and resources into account. Traits are relatively stable over a long period of time and persistent across different domains.

The new approach to model cognitive traits raises a novel issue: that is, how can cognitive traits be modeled? One could use explicit questioning techniques to elicit information from the learners, but using questionnaires has been argued as bringing cultural bias (Heine & Lehman, 1995), acquiescent responses (participants simply accept all propositions put in front of them; Ray, 1983), intergroup bias (Navarrete, Kurzban, Fessler, & Kirkpatrick, 2003), and so forth. Decisions need to be very carefully made to avoid biases if the questionnaire approach is used to obtain the student attributes.

Learners’ behaviours (interaction paths) in the VLEs are guided by their beliefs regarding what they perceive as the most suitable way for them to learn for achieving the best learning result, or what is the most comfortable path to finish the learning task at hand. These decisions mostly depend on their learning attitude. Their beliefs are in turn guided by their cognitive capabilities. Thus, if the cognitive attributes of the learners are sought, analysing learner behaviours would be a simpler and more reliable approach than the questionnaire approach.

A trait, working memory, will be used as an example to illustrate the modeling approach taken by the CTM. The example below starts with a theoretical analysis of working memory in order to find its characteristics.

ANALYSIS OF WORKING MEMORY

Working memory is also referred to as short-term memory. It denotes the memory capable of transient preservation of information and is functionally different from the memory that stores historical information (long-term memory). Richards-Ward (1996) named it the short-term store (STS) to emphasise its role as the temporal storage of recently perceived information. STS allows us to keep active a limited amount of information (roughly five to nine items) for a brief period of time (Miller, 1956).

The term working memory refers to the same construct as the STS in terms of the capacity of transient storage. In addition, it also acknowledges that cognitive processes take place in working memory. Cognitive scientist Baddeley (1986) assumed that the major function of working memory is to temporarily store the outcomes of intermediate computations when solving a problem, and to allow operations of further computations on these temporary outcomes.

Baddeley (1992) studied working memory and tried to understand it by decomposing it into components. The structure of working memory was described as a control-slave system comprised of the central executive (controlling component), phonological loop (slave component for verbal information), and a visual-spatial sketch pad (slave component for graphical information). The central executive takes the role to monitor and to control the output of the two slave systems and to select what is relevant for potential processing (Richards-Ward, 1996). Metaphors used for working memory include “blackboard of the mind” (Reddy, 1980), “mental sketch pad” (Baddeley, 1986), and “online memory” (Goldman-Rakic, 1987). Although
these metaphors capture the essential idea of the transient storage capacity of working memory, they still suggestively emphasise the role of the storage functionality of working memory. The central executive, which is conceptualised as very active and responsible for the selection, initiation, and termination of processing routines (e.g., selecting, encoding, storing, and retrieving), is still the least understood aspect of working memory.

As Baddeley (1986, 1992) defined working memory structurally, others defined it as a process (Daneman, & Carpenter, 1980; Salthouse, Mitcheel, Skovronek, & Babcock, 1989). Salthouse et al. proposed that working memory consists of (a) a storage capacity sensitive to the number of items presented and (b) an operational capacity sensitive to the number of operations performed on items. Salthouse et al. found that young adults have a higher operational capacity than older adults, especially among the highly capable participants. Little or no difference was reported on the storage capacity across the age differences. Therefore, they concluded, at that time, that it was the operational capacity that causes age-related working-memory decline. A further study of the operational efficiency of working memory showed that it was not the operational capacity (number of operations allowed) that contributed the most to the efficiency of working memory, but it was actually the speed of execution (e.g., comparison speed) that determined the performance of the overall system of working memory (Salthouse & Babcock, 1991). Even though these two points of view do not agree on a common structure of working memory, they both agree that working memory consists of both storage and operational subsystems (Richards-Ward, 1996).

In addition to the storage capacity, Atkinson and Shiffrin (1968) defined working memory functionally as the gateway allowing information to be transferred to long-term memory. This definition stresses the ability to channel the incoming isolated information (as received by our senses) to the semantically networked structure in long-term memory. This involves a great degree of cognitive efforts such as interpretation, translation, association, memorisation, and so on. This functionality is comparable to the central execution unit mentioned above, and essentially it transforms and transfers the messages from the short-term storage system into the long-term one. The transformation process invokes the formation of rules (data with operational application) from pure data (in the form of incoming messages), and the transfer process filters which rules and data are to be stored for long term and which are to be discarded.

Several studies have shown that age-related performance of young children and old adults compared with young adults can be characterized by the inability to retain information in working memory while simultaneously processing other information (Case, 1995; Salthouse & Babcock, 1991; Verhaeghen & Salthouse, 1997). Deficiencies in working-memory capacity result in different performances in a variety of tasks. Examples of tasks affected could include natural language use (comprehension, production, etc.), recognition of declarative memory, skill acquisition, and so on (Byrne, 1996).

An empirical study by Huai (2000) showed that students with a holistic learning style also have a significantly smaller short-term working memory but have a remarkably higher learning effect in the long run, whereas the students with a serial learning style (highly capable of following and remembering sequentially fixed information) have better short-term working-memory capacity but a poorer learning result in the long run. This point shows the intricate relationship between humans’ inbuilt abilities and how different learning styles are adopted to circumvent any deficiencies in those abilities. The navigational strategies adopted by serial learners are linear, whereas holists sometimes do better by jumping directly to complex concepts (Felder, 1988).

**MANIFEST**

Each of the points mentioned in the analysis of working memory gives sign and indication about the student’s working-memory capacity. However, in order to enable a learning environment to make judgement about a student’s working-memory capacity, each of the points has to be translated into more definite terms. These terms are called manifests in this discussion. A manifest is defined as a student’s behaviour pattern or attribute, observable during the student’s learning process. A manifest can be a single observable student action (e.g., comparison speed), or it can be a complex pattern comprised of a long sequence of observable student actions (e.g., frequently revisiting learned materials). A manifest can also be a student attribute.
Table 1. Summary of manifests for working-memory capacity

<table>
<thead>
<tr>
<th>Low Working Memory Capacity</th>
<th>High Working Memory Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>non-linear navigational pattern</td>
<td>linear navigational pattern</td>
</tr>
<tr>
<td>constantly reverse navigation</td>
<td>rare (or none) reverse navigation</td>
</tr>
<tr>
<td>frequently revisit learned materials</td>
<td>infrequent (or none) revisit learned material</td>
</tr>
<tr>
<td>unable to absorb side information while still remain progressing</td>
<td>able to learn side information while still remain progressing in the main tract</td>
</tr>
<tr>
<td>unable to perform tasks simultaneously</td>
<td>able to perform tasks simultaneously</td>
</tr>
<tr>
<td>low comparison speed</td>
<td>high comparison speed</td>
</tr>
<tr>
<td>unable to retrieve information effectively from long-term memory</td>
<td>able to retrieve information from long-term memory effectively</td>
</tr>
<tr>
<td>in long sequence of calculation or procedural, frequently missing steps or lost components</td>
<td>performing long sequence of calculation or procedural, without missing steps or lost components</td>
</tr>
<tr>
<td>unable to comprehend highly demanding text or concepts</td>
<td>able to comprehend highly demanding text or concepts</td>
</tr>
</tbody>
</table>

The implications of the analysis of working memory can be translated into the following manifests summarised in Table 1.

During a learning session, many manifests may be activated. How can the activations be interpreted by the VLE about a learner’s cognitive traits? To solve this question, a mechanism called individualised temperament network (ITN) has been designed.

**INDIVIDUALISED TEMPERAMENT NETWORK**

An individualised temperament network is a neural-network-like structure representing a particular cognitive trait (e.g., working-memory capacity) of the learner. Each node in the ITN has a weight and corresponds to a manifest. Once a manifest is detected from the learner’s actions, the corresponding node is activated. The execution of the ITN involves polling of all the nodes in the network. One of two groups (low or high) is selected as the prevailing group that wins in the polling, and the other becomes the recessive group. The weights of the manifests in the prevailing group are increased by the gradient constant, which is a constant determining the speed of change of the value of weights, whereas the weights of the manifests in the recessive group are decreased by the gradient constant (Lin, 2003). The polling result of the ITN is then updated to the CTM representing the VLE’s current belief of a particular cognitive trait (working-memory capacity in this case) of the learner.

**ARCHITECTURE OF EMBODIMENT OF COGNITIVE TRAIT MODEL**

CTM can be implemented in many forms; the architecture of a possible embodiment is discussed in this section to provide the reader an idea of how CTM could be implemented. The architecture of the cognitive trait model is represented in Figure 1. The learner interface (LI) provides a presentation of the learning environment to interact with the learner. In Web-based systems, the learner interface is generally implemented inside a Web browser. Due to the stateless nature of the http (hypertext transfer protocol) used by Web browsers, it is necessary to embed a mechanism that can monitor...
Figure 1. Architecture of an embodiment of the cognitive trait model

- **Trait Model (TM)**: Persistent storage of the values of the cognitive traits of the learners.
- **Trait Model Gateway (TMG)**: Provide an interface of the TM for updates.
- **Individualized Temperament Networks Component (ITNC)**: Provides procedures to run the individualised temperament network (ITN) based on the input of the MDC. An ITN is a neural network-like structure representing a particular cognitive trait (e.g., working memory capacity) of the learner.
- **Manifest Detector Component (MDC)**: Provide procedures to detect manifests from the history of learners’ actions. A manifest is a piece of interaction pattern that manifests a kind of learner’s characteristic (e.g., low working memory capacity).
- **Stores learner actions**
- **External Performance Based Model**
- **Action History Component (AHC)**
- **Action History History (AH)**
- **Interface Listener Component (ILC)**: Provides user interface of the virtual learning environment to the learners.
- **Learner Interface (LI)**
events created by a learner’s interactions with a learning environment. The mechanism is represented by the interface listener component (ILC) in Figure 1. Learner interactions are interpreted as a series of learner actions performed on knowledge objects. Actions are passed on to the action history components (AHCs) and are stored in the action history (AH).

The performance-based model presents a learner’s domain competence and models the problem-solving process that the learner undertakes. Certain information in the performance-based model, such as the passing or failing of a unit, can be useful for detecting manifests (indications) of some cognitive traits, and therefore data in the performance-based model is used as a source by the manifest detector component (MDC).

Various manifests are defined on the basis of cognitive traits. Each manifest is a piece of an interaction pattern that manifests a learner characteristic (e.g., low working-memory capacity). The manifest detector component has knowledge of a number of manifests and detects those manifests within a series of actions that are requested from the action history component. Each manifest belongs to one of the two groups (low or high) of a particular cognitive trait, and each manifest belongs to only one particular individualised temperament network.

The ITNC in Figure 1 can have more than one individualised temperament network. Each ITN represents a particular cognitive trait (e.g., working-memory capacity) of the learner. Each node in the ITN has a weight and corresponds to a manifest. Once a manifest is detected from the learner’s actions, the corresponding node is activated. The result of the execution of an ITN determines how the nodes in the ITN should be updated. The results of the execution of the ITNs are then sent to the trait model gateway, which is responsible for all the transactions to the trait model, and then saved to the trait model.

**BENEFITS OF COGNITIVE TRAIT MODEL**

Research on the cognitive trait model will provide significant benefits to the way e-learning is conducted. Some of the benefits are listed as, but not limited to, the following.

- The CTM will greatly benefit the students when they start using a new learning system because the new system will not need to remodel the students again. It means that the students can receive the right level of adaptivity from the system immediately.
- The CTM will be very suitable for students who intend to or are required to pursue lifelong learning due to the persistent nature of the model. The longer the cognitive trait model is used, the better its effectiveness and accuracy would be, and the model will not be outdated by discoveries of new knowledge.
- The use of CTM will encourage students to actively engage in learning because learning systems will have the possibility to provide the right information to the learners according to their cognitive capacity.
- The CTM will integrate the research fields of cognitive science and e-learning, and will bring the best of both areas directly to the students.

**FUTURE TRENDS**

Since most of the current student models are only competence oriented, the adaptation can only be provided in a performance-based manner, which means that the VLE must adapt itself in those areas where the student’s performance is identified (or predicted) to be suboptimal.

The cognitive trait model aims to provide a supplementary module to any existing VLE that needs to support adaptation at the cognitive level. CTM can be integrated into an existing framework of VLE by the addition of the specification of learning-object relations and trait-analysing facilities. The existing competence model can be used for performance-based adaptivity, while CTM can supply the adaptivity that addresses the differences of each individual’s cognitive abilities. CTM can also be used alone in VLEs that are not performance oriented (e.g., learning a subject of interest or learning as a means of self-enrichment).

**FUTURE IMPROVEMENT**

The work on the cognitive trait model is the beginning of a new era in which adaptation is geared toward lifelong
learning and learner profiling is treated as a long-term activity to support the continuum of the learning process. A number of research areas are open for further improvement of cognitive trait modeling.

More research is required to identify a student’s navigational patterns and their implications. Nelson et al. (1993) researched quantitative and qualitative techniques for collecting and analyzing user-interaction data in hypermedia systems. Beasley & Vila (1992) developed a system called LinkWay folder, and measured how the linearity and nonlinearity of students’ navigational patterns related to their gender and their ability. Their results show that low-ability students tended to navigate in a more linear manner. However, according to Andris and Stueber (1994, p. 21), “the literature does not reveal any standard measures of navigational patterns, and most especially such measures whose reliability and validity have been established.” Other aspects of the navigational pattern including reverse navigation and excursion also require more efforts in order to acquire stronger rationale and justification.

So far, the CTM approach focuses only on quantitative techniques for trait analysis. Further research on experimental cognitive psychology (Reisberg, 1997; Richards-Ward, 1996) and psychometrics (Revelle, 1995), which is the branch of psychology concerned with the design and analysis of research and the measurement of human characteristics, is required in order to provide qualitative and explicit techniques for the trait analysis in CTM.

More advanced techniques to collect student data or analysis could increase the accuracy of the CTM. Calvo (2001) used an online eye-movement-monitoring facility to examine elaborative inference, which is an ability that is heavily dependent on the resources available in working memory. The evaluation of this technique showed improved accuracy of the measurement (Calvo, 2001). Similar techniques can be used when this kind of technology is mature enough and has widespread usability.

Another area that requires more effort is the study about the temporal information of a student’s action. Recording a student’s actions by a time stamp could allow the system to find out the duration of a task, which could be learning a concept in a learning object or performing a procedure that is represented by a series of learning objects. The question needs to be asked whether the temporal information has any value to the system or if it is just an overhead, and how it can be best adopted in CTM.

It is also suspected that learning style is a result of a human’s adoption of a certain learning strategy or preference based on the individual’s cognitive capacity. For example, the holistic learning strategy allows the individual to build concepts around one or few main concepts, and therefore the general retrieval path of a concept is shorter during the recall process (think of a concept as a node in a semantic network). Therefore, one possible way to interpret the experiment results of holistic learners having smaller short-term memory (Huai, 2000) is that because these individuals have smaller short-term memory, they are forced to adopt the holistic learning strategy, which their capacity can cope with. However, more research is certainly required in this area.

Another area that needs to be looked at is the cultural, ethnical, and gender-related differences in cognitive profiling. The above-mentioned factors may pose a certain degree of influence on an individual’s cognitive processes. More study is required to identify the factors and to address the differences accordingly.

REFERENCES


Miller, G. (1956). The magic number seven, plus or minus two: Some limit of our capacity for processing information. Psychology Review, 63(2), 81-96.


KEY TERMS

**Cognitive Trait Model:** A model representing one or more cognitive traits of learners.

**Cognitive Traits:** The abilities humans possess for cognition. Working memory is an example.

**Individualised Temperament Network:** A neural-network-like structure representing a particular cognitive trait (e.g., working-memory capacity) of the learner.

**Manifest:** A defined student behaviour pattern or attribute, observable during the student’s learning process.
**Performance-Based Models:** Student models that profile the learners according to their performance.

**Student Model:** A profile of a learner including a chosen set of attributes or characteristics related to the learning process.

**Working Memory:** Denotes the memory capable of transient preservation of information, which is functionally different from the memory that stores historical information (long-term memory).

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