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Dynamic Learning Modeler

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Abstract

Constructive approach to learning focuses on the learner's behavior, enabling a self-adapted exposure to knowledge that is precisely tailored to the learner's needs and background. The building blocks for such adaptive knowledge construction are the evolving learning objects (LOs) which are self-contained entities that encapsulate a segment of knowledge as well as some metadata attributes and procedures. In addition to complementing the standard specification of learning objects to incorporate self- adaptive learning features within the LO construct, the paper also proposes a learner-modeling technique which learns from the learners about the learners. In this dynamic learner modeling approach, past learning experiences are reused to stereotype future learners. The proposed adaptive learning architecture in this paper supports both navigation and presentation learning adaptivity.

Keywords

Adaptive learning, E-learning, multimedia material for education, Learning objects, Learner modeling, Hypermedia courseware.

1. Introduction

Web-based education and training is currently a hot research and development area (Khan 1997). Most of the progress made in this field has been influenced by the evolving technological infrastructure, the need for competitive workforce, the availability of learning material in cyberspace**,** and the progress made towards standards for learning architectures to ensure knowledge reuse and interoperability of learning management systems (Koidl 2002). One of the most important features which has not been fully explored in this area is the ability of the learning system to adapt to the learner's profile.

Unlike conventional learning practices, adaptive e-learning should address both the curriculum requirements and strategies for knowledge delivery to suit individual learners. The objective of adaptive e-learning is to offer personalized learning, taking into account the learner's goals, background, learning styles, presentation preferences and performance requirements. In addition, adaptive e-learning systems should be able to identify skill gaps and prescribe the necessary learning material. They should also allow individuals to monitor their own progress and guide them completing the remaining learning tasks in an efficient way. Many research efforts were made to achieve these goals. As a result, a number of e-learning systems have been developed (Karagiannidis et al., 2001; Castro et al., 2001; Dufresne 2000; Brusilovsky 1998 & 1999). These are mainly based on technologies in the area of adaptive hypermedia. Most of these systems are platform development rather content development.

The shift to content development based systems is recent, nevertheless, significant work have been undertaken to develop e-learning standards and specifications by such groups as the Instructional Management Systems (IMS Global Consortium 2003), the IEEE Learning Technology Standards Committee (IEEE-LTSC 2003), and the Advanced Distributed Learning (ADL Co-Labs 2001). The aim is to develop standards and specifications capable to support open, widely distributed, reusable, content sharable, interchangeable, and intensely interactive learning infrastructures. In this context many concepts such as Learning Objects (LO), Meta-Data, Document Object Model (DOM), Computer Managed Instruction (CMI), and Data Interchange Protocol (DIP) have emerged to address important issues such as those related to: i) interoperability of content from multiple sources; ii) interchangeability of content for transfer between sources; iii) reusability of content within the same source; and iv) accessibility of content to search object repositories (Theorix 2003). However, there has been limited emphasis on the need for introducing adaptive learning features within the learning object. Under the current version of these standards, the LO is treated as an opaque entity that cannot yet be adapted to learners' profiles (Rodriguez et al. 2002).

In previous work (Atif et al. 2003), we addressed the lack of adaptability in the learning object by expanding semantically the learning object metadata to accommodate individual learner's needs, and to enable dynamic generation of personalized learning routes. In this work, two other fundamental aspects of adaptive e-learning systems were investigated. These are the problems related to difficulties encountered while profiling learners and courseware design issues respectively. As far as the learner profiling process is concerned, we believe that many learners do not properly contribute in the pre-assessment given to them in order to build their profile. In fact, many learners do not seriously fill in the required questionnaires nor answer properly test questions, which usually results in an unreliable and incomplete learner model. As for the courseware design, not all authors have the required pedagogical skills and knowledge to properly plan different versions of a course to suit all kind of learners. Based on these assumptions, the proposed system is designed so that both the learner and the courseware author are relieved from these tedious tasks.

The remaining sections of this paper are organized as follows. Section 2 presents the background and related work. Section 3 describes learning resources construction framework. In Section 4, we present the adaptive learning architecture. Finally, the proposed work in this paper is summarized and further research work is suggested.

2. Background and Related Work

A major current focus in designing modern e-learning systems is the actual concentration on efficient production of instructional components or objects which are interoperable and reusable (Najjar, 1996; Redeker, 2002). With no doubt the concept of reusability has become a key issue for new e-learning initiatives. The reusability of learning objects provides a framework that builds on past experience and creates new mechanisms for producing and exchanging knowledge. There is an actual need to discover new techniques for the exchange and integration of various sources of knowledge from different institutions. The shift from platform-development to content-development of e-learning systems will have a significant impact on developing such techniques (Koidl 2002). An important implication of this shift is to allow learners to take control of their own learning process in an active mode rather than in a massive, receiving way (Fung and Yeung 2000). Unfortunately, these goals are not yet achieved and most available e-learning systems are still tutor or author centered and not learner centered.

Leaner centered systems should adapt to the learner's goals, background, skills, presentation preferences and learning styles. Developing a system that can deal with all of these learning aspects is one of the most challenging tasks facing the research community today. This is mainly due to the fact that we do not really know how the human really learns (Koidl 2002). Moreover, the process of adapting content to different learners, based on their profile and behavior, is not a straightforward task. So far, the majority of existing adaptive web-based learning systems are based on hypermedia (Brusilovsky 1998). Adaptive hypermedia systems build a model of the individual learner. This model is used throughout the interaction to adapt the hypermedia document to the learner needs (De Bra et al. 1999). The learner's model is usually initiated from a questionnaire at the beginning of the course. Typical questionnaires are based on stereotype like beginner, intermediate, and advanced (Brusilovsky 1998). Tests during a learning session can also be used for further adaptation. These assessment tools are used to check the learner's knowledge and to predict their learning modalities and the learning style that suits them most. Consequently, most of the focus for these systems is on the learner's model that is a kind of repository about the learner and forms the heart of the learner centric system.

Adaptive learning in hypermedia systems was dealt with from different perspectives (Brusilovsky 1998 & 1999). A good review of the different adaptive techniques can be found in (Brusilovsky 1998). The main approaches have been adaptive curriculum sequencing, adaptive presentation, and adaptive navigation support (Brusilovsky 1998). In adaptive curriculum sequencing, the learner is provided with the most suitable individually planned sequence of learning objects to learn from, and a sequence of learning tasks to work with. This is done by showing and hiding of content based on information extracted from the learner's model ((Brusilovsky et al., 1997; Specht et al., 1997). Adaptive presentation techniques, on the other hand, adapt the content of a learning object accessed by the learner to the current knowledge level, goals, and other characteristics of the learner. Thus, different learners may get different content for the same learning object (Calvi and De Bra, 1997; Eliot et al., 1997). Finally, adaptive navigation support can be considered as an extension of adaptive curriculum sequencing into a hypermedia context. However, it is less directive than traditional sequencing in the sense that it guides learners implicitly and leaves the choice of the next learning item to the learners. This is based on the idea that if the learner navigates from one item to the other, the system can for example hide, sort and annotate the links to provide best guidance to the learner ((Brusilovsky and Schwarz 1997).

The feature shared by most of the above mentioned adaptive learning techniques, is that they all heavily rely on the pre-assessment based learner model. The proposed system does not require such a model. Also, the courseware author is not requested to design different versions of the same course to suit all kind of learners. The author rather focuses on the learning object metadata (LOM) which empowers the learning objects' dynamic. The proposed system combines adaptive navigation support and adaptive presentation technique in an orthogonal way. The system follows the adaptive navigation support model whereby new learners are matched with previous learning-path profiles in order to either: i) adhere to a known learning model; ii) to confirm and consolidate an existing learning experience which might be added to the learning models repository; or iii) to enrich the system with a new learning experience not mature enough to be included in the learning models repository but which must be kept in a database of candidate learning models. Before applying the adaptive presentation technique, the system dynamically classifies the learner based on categories such as beginner, intermediate and advanced. The classification process depends mainly on the number of visited prerequisite learning objects during a learning session. Unlike most existing systems, this classification is not permanent, but contextual, and may even change many times during a learning session. This is mainly due to the fact that a learner might possess the skills in dealing with some concepts and lacks knowledge when dealing with others. Consequently, this classification reflects the knowledge level of a particular learner dealing with a specific concept. This fine grain adaptation is dealt with using adaptive presentation technique. This is carried out by the LO adaptor which dynamically adapts the content of the learning object accessed by the learner based on the category allocated to that learner.

3. Learning Construction Framework

In this paper, we proposes a hierarchical, incremental framework for packaging learning content into learning objects and a web connectivity of learning objects through which a personalized learning route is identified. The learning object design forces a certain e-pedagogy discipline in order for instruction designers to operate under a well defined framework that prevent the design of lengthy and discursive material which may not benefit learners.

As shown in Figure 1, the learning objects are self-contained instructional units which content accommodates heterogeneous learning sources (text, presentation, audio or video) or a combination of any of these media. Moreover, learning objects are inter-linked to form a network of learning resources through which learners navigate to build a personalized learning path. They can also be reused a number of times in different contexts and can be delivered over the Internet in an open system framework free from any vendor-specific container. Hence, learning objects appear as modular building blocks, which can be easily integrated to manage e-learning content according to a specific learning strategy. The e-learning system presented in this paper promotes such generic object-based learning which has the ability to capture any learning source.

The proposed framework consists of three conceptual layers (see Figure1): authoring layer, LO production layer and LO deployment layer. The authoring layer allows courseware authors to build LO content. The system uses industry standards for learning resource authoring and management. This ensures LO interoperability and thus allows LO export/import from/to other learning systems. The LO production layer is crucial to adapt LO content to the targeted learners. This is done by the LO adaptor which adjusts the LO content based on the LO metadata and the learner's category provided by the learner modeler. Finally, the LO deployment layer deals with the process of constructing personalized learning paths. At this layer, a courseware structure is represented as a web of learning objects for a particular course, representing the various concepts interdependencies among learning objects. However, a learning path is a subset of the courseware web represented by a sequence of instance-LOs to which a particular learner get exposed during a learning session.

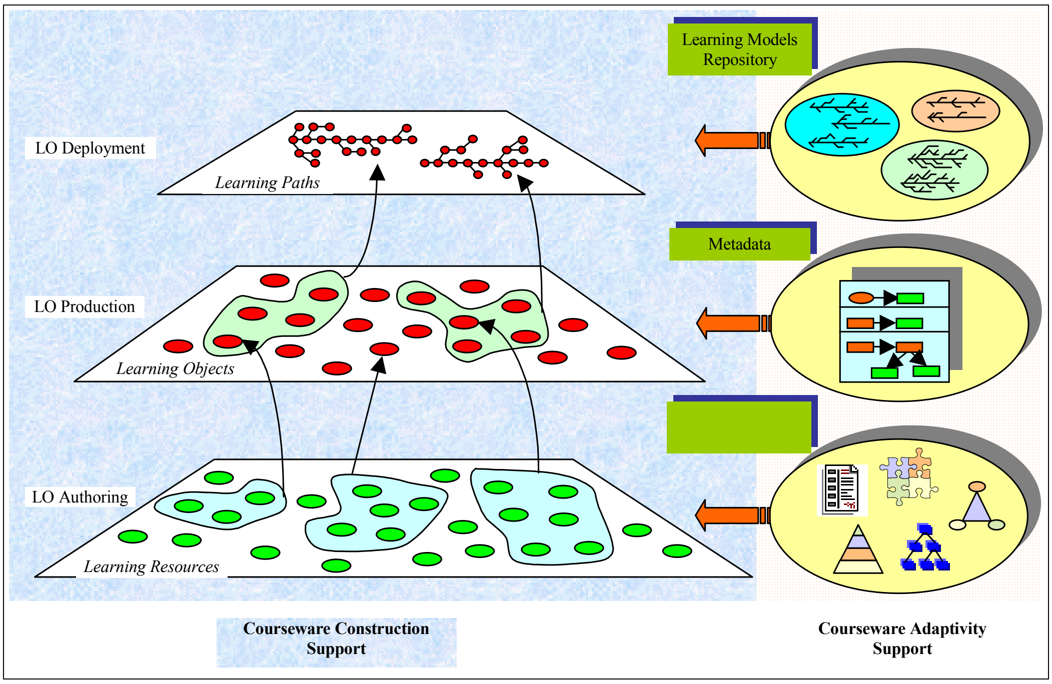

Figure 1. Learning Construction Framework

3.1. Learning Objects

To allow the deployment of LOs in an adaptive way, extensions to the existing IEEE/IMS LOM (IEEE-LTSC LOM 2003) specification were introduced to dynamically allow LO integration, LO correlation, media selection and learner-LO interaction. Thus, the proposed metadata structure describes a multimedia rich interactive LO. The LO structure used in this paper is based on the LOM specification which includes elements such as general, rights, lifecycle, classification and annotation to describe the static features of the learning object. However, additional features extend standard elements such as educational, technical and relation to dynamically adapt the LO to learners' profiles. The proposed structure of learning object attributes is depicted in Figure 2.

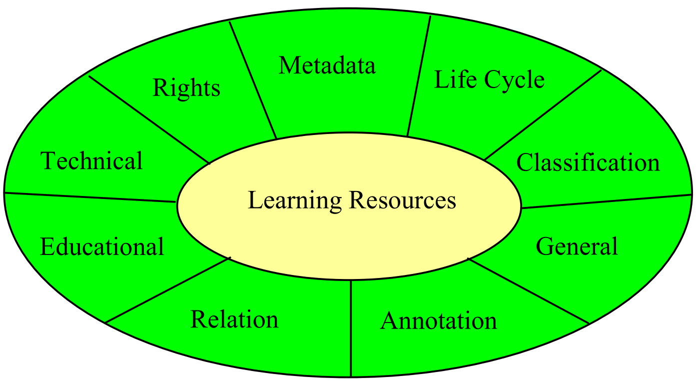

Figure 2. Learning Object Attributes

Learning object resources construct is rather *media-centric* which captures both tangible and intangible formats of learning. Learning resources such as text script, video, animations and images represent the static attributes of the learning object. These are the attributes which cannot be modified when reused. On the other hand, relation, technical and educational related features (IEEE-LTSC LOM 2003) represent the dynamic attributes which can modify some aspects of the LO when reused. Below, we summarize the educational, technical, and relation attributes. However, we provide a detailed description of the metadata attribute due to its dominant role in the LO adaptation. The remaining attributes are similar to the LOM specification.

- The educational element is enhanced with features related to media selection, analogy, assessment and customization. Below we provide a description of each if these features:

- Media selection allows a learner to customize the object to zoom on a particular media in case the learning object is a combination of multiple media.
- Analogy facilitates learning by analogy and offers learners alternatives to comprehend further the subject imbedded in the LO.
- Assessment enables problem-based learning and corresponds to a particular assessment strategy by which the learner can assess his understanding of the material embedded in the learning object.
- Customization provides learners with the opportunity to augment learning content during instruction by taking their own personal notes. The customization assumes an authentication process for learners who may then take notes through the system at playback time to reflect their own understanding of the presented material. These notes are attached to the profile of the learner for the currently being played object.

- The technical attributes represent the synchronization and layout features describing respectively the level of synchronization involved in combining multiple media, and the actual time and space distribution of the learning media.

- Relation corresponds to the *"correlation"* feature which reflects the self-adaptability nature of the LO. As a response to a learner state, the learner modeler suggests a learning sequence of LOs, and individual LOs are adapted and connected accordingly. Thus, this attribute contributes in self-adjusting the proposed learning material based on the behavior of the learners as dictated by the constructivist approach (Duffy and Jonassen 1991). Different learners follow different learning routes suitable to their background level and understanding pace.

- Metadata attribute enables further intra-LO adaptation by providing five LO functionalities. These are LO sequencing, LO structure, LO presentation, LO navigation support and LO interactivity. These are briefly described below.

a) *LOs Sequence*: Different techniques can be used to track learners' behaviour in order to invoke the appropriate LO sequence that provides personalized learning content. As learners interact with the e-learning content, results are communicated to the interaction manager which adapts the LO sequence accordingly. For example, learners might be sent to different places in the content based on user-initiated request for clarification of prerequisite knowledge, or user requests for supportive knowledge expressed in terms of examples, case studies or procedural information. In the proposed system, each learning object has semantic connections with other objects. Different users navigate across the learning web composing the learning objects interconnectivity following different paths. The learning path-building process, which contains the sequence of objects exposed to a learner, is performed dynamically based on past learning experiences.

b) *LO Structure:* The LO structure reflects the educational effectiveness and pedagogic features of the LO. It consists of a sequence of learning tasks to accomplish the goals and objectives set up by the courseware author to understand the concepts presented in the LO. These are combination of learning resources similar to those listed in the educational component of the LOM specification (IEEE-LTSC LOM 2003), and can be: slideshows, examples, questions, problems, simulations, case studies, experiments, diagrams, graphs and so forth.

c) *LO Presentation*: LO presentation describes the way individualized learning materials embedded into the LO are dynamically presented to the learner. Multimedia contributes further to learning when instructional designers use the most effective medium to present specific information. Hence, there is a need for instructional designer to map a learning content to an appropriate media. A number of empirical studies suggest how to select specific media or a combination of media for successfully presenting specific kinds of learning content as summarized in Table 1.

The content-to-media mapping shown in table 1 has been confirmed through empirical experiments to provide the best media allocation for learning content (Najjar 1996). Assembly instructions are best comprehended when an assembly task is presented using a combination of illustrations and text highlighting the major steps. Procedural information for operating a particular device for instance, appears to be more helpful for learners to acquire when a combination of animation or video and text is presented to learners. For problem-based learning, an animation with verbal narration was shown to be effective. For instance, solving a mathematical equation may be better illustrated through a graphical illustration. Pictures increase recognition accuracy especially when combined with text to drive the learner to focus on specific features of the pictures. Sound appears to be an effective way to communicate. For instance, in learning a particular foreign language, it would be more helpful for a learner to hear the words. But some words are context dependent and the context may be better understood if shown through video. And to help the language-learner further, a textual version of the words' phonetic would reinforce the learning process of such verbal information. Finally, recalling story details would be more effective with a video or a soundtrack. The e-learning system presented in this paper provides opportunities to map knowledge imbedded in LOs in any of the above formats or a combination of the above formats.

Learning Content	Media
Assembly instructions	Text with supportive pictures
Procedural information	Text with animation or video
Problem Solving	Animation with explanatory verbal narration
Recognition	Pictures with text or verbal narration
Verbal	Sound or video and text
Story details	Video with a soundtrack

Table 1. Media Allocation

d) *LO Navigation*: LO navigation functionality ensures that different LO's are allocated different navigation alternatives, depending on their type, role, content and structure. Here we describe the possible ways of navigating within a LO. For instance, a learner starting a problem solving LO is recommended to go through all problem solving steps, however, it is not recommended to explore all alternatives in a LO consisting of a number of examples/case studies describing the same concept. By doing so, the system guides learners implicitly and leaves the choice of the next knowledge item to be learnt and next problem to be solved, to the learners.

e) *LO Interactivity*: LO interactivity is an important aspect in the learning process. It may also differ from one LO to another depending on its type and role. The system allows learners to interact with most LOs, and especially with those LOs related to problem solving, questionnaires and self-assessment.

3.2. Courseware Structure

A courseware represents a particular course designed by the author. An example of a courseware is shown in Figure 3. The courseware is constructed by the author simply by identifying the sequence of learning objects references which participate in the courseware. Learning objects are classified as *mandatory learning objects* (MLOs) and *secondary learning objects* (SLOs). The mandatory learning objects are recommended objects in the sense that the learner should normally visit them to fulfill the courseware understanding requirements. However, secondary objects are those learning objects describing prerequisite knowledge. For the recommended path, that is the path formed by the MLOs, the courseware author considers each mandatory learning object individually to identify its correlative sequence of references to possible SLOs. The process of building a correlative sequences is re-iterated on each SLO. Secondary learning objects might be added to the learning path dynamically based on the learner interactions with the learning objects.

The above courseware structure represents a body of knowledge, which is highly structured. Full comprehension of a topic may be dependent on the understanding of one or several other concepts. In a properly organized course, a particular concept is presented only after all concepts, on which it depends, have already been presented. Furthermore, a competent instructor will not proceed before insuring that the majority of the students have mastered or at least have been exposed to the prerequisite concepts otherwise, the instructional process will not be very effective. However, since we are dealing with individuals and not a group of learners, there should be some flexibility in presenting the course material to meet personal abilities of learners. All this leads us to the conclusion that the organization of knowledge within a subject matter has the form of a directed graph, not unlike the PERT charts used in project management. The graph structure will give learners the choice to either follow the recommended leaning path, or to request an SLO.

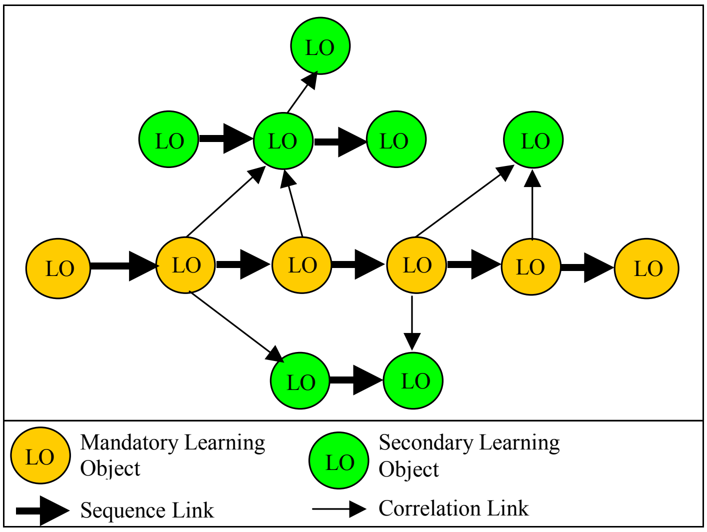

Figure 3. Courseware Structure

4. Adaptive Learning Architecture

Instead of relying solely on the learner's behavior and the acquired knowledge throughout a learning session, a learner modeler utilizes the *specific* knowledge of previously experienced learning sessions. A learning path experienced by a previous learner whose learning behavior matches the current learner is predicted to be pursued in the current learning session as well. A Learning Models Repository (LMR) stores a set of learning-models categories which are based on previously validated learning experiences. LMR is incrementally augmented to reach a maturity level where it covers a large scope of models used to dynamically profile an actual learner. The initial experiences are constructed by the learners themselves. At this stage, the learning construction process requires frequent interactions with the learning system to adjust the learning path and the learning content. At a later stage, the interaction frequency decreases with the maturity of LMR as learners are clustered apriori to specific learning categories in which the sequence of LOs is automatically proposed to the learner.

As illustrated in Figure 4, an effective integration of the abovementioned case-based technique to adaptive learning requires a well worked out set of methods in order to: i) extract relevant models from the memory of experiences (LMR); ii) integrate a model into that memory; and iii) index the inserted models for later matching with similar learning experiences. Central tasks that our case-based learning approach has to deal with are to identify the current learning session, find a similar past case, and use that case to elaborate an adjusted learning plan. To satisfy these roles, the system features three functional modules as shown in Figure 4. These modules are: the Interaction Manager (IM) which listens to learners' initiated events, the Learner Modeler (LM) which plans a learning-path, and the Learning Object Adapter (LOA) which adjusts the depth and the style of the learning content of the LOs within the inferred learning path based on the learning category.

The architecture presented in Figure 4 targets two levels of adaptive learning: adaptive navigation and adaptive presentation. Adaptive navigation is performed by LM module following a case-based learner modeling technique which will be further elaborated in later sections of this paper. Adaptive presentation on the other hand is carried out by LOA based on an automatic learner-categorization approach which given a learning-path delivered by LM, it adjusts the content of the constituting LOs based on the actual learner category. This category is revealed to IM when a learner interacts with the learning unit map (or courseware). IM intercepts particularly correlation links invocations and interprets this invocation as an opportunity to adapt or to revise the learner model and to adjust the LO presentation based on the current learner state. The architecture proposed in Figure 4 features also two data repositories: Learner Models Repository (LMR) and Learning Objects Database (LOD). While LMR contains learning-paths which representatives of classes of learners, LOD provides various categories of each intervening LO in the learning paths maintained by LMR. This is a deliberate strategy to provide a horizontal learning adaptivity by selecting the appropriate sequence of LOs identified by their IDs. These IDs are used to index a class of LOs in the LOD which represent a vertical adaptivity level by selecting the intervening LO which matches the current learner skill or category. This is because learners have different backgrounds which require different learning sequences but also different skills and learning styles which require different types of presentations. The proposed architecture in Figure 4 aims at accommodating such bidimensional learners' heterogeneity. Next, we provide an in-depth description of the modules constituting this adaptive learning architecture.

4.1 Learning Models Repository

Learning by re-using past experiences is a powerful and frequent way used by humans for learning. This claim is also supported by results from cognitive psychological research (Osborne 1999)**.** Several studies have given empirical evidence for the dominating role of specific, previously experienced situations in human learning based on retaining of experiences in a dynamic and evolving repository. Past learning experiences are used as learner models to dynamically profile current learners. A very important feature of this strategy is its coupling to learn from the learners. The proposed case-based learning approach does not only denote a dynamic learner profiling technique, irrespective of how the cases are acquired, it also denotes a paradigm that enables sustained learning by updating the learning paths database after a learning session has been completed. To be able to achieve this objective, the system needs to track the learner behavior and build a personalized learning model. Since no pre-assessment is required in our system, personalized learner modeling relies mainly on the route traversed by learners in the courseware map. Actually, the main assumption underlying the learner modeling is based on the fact that a learner level can be inferred according to the volume of additional material he/she requires to fully comprehend the courseware concepts. This volume is intercepted by the system to categorize learners into levels.

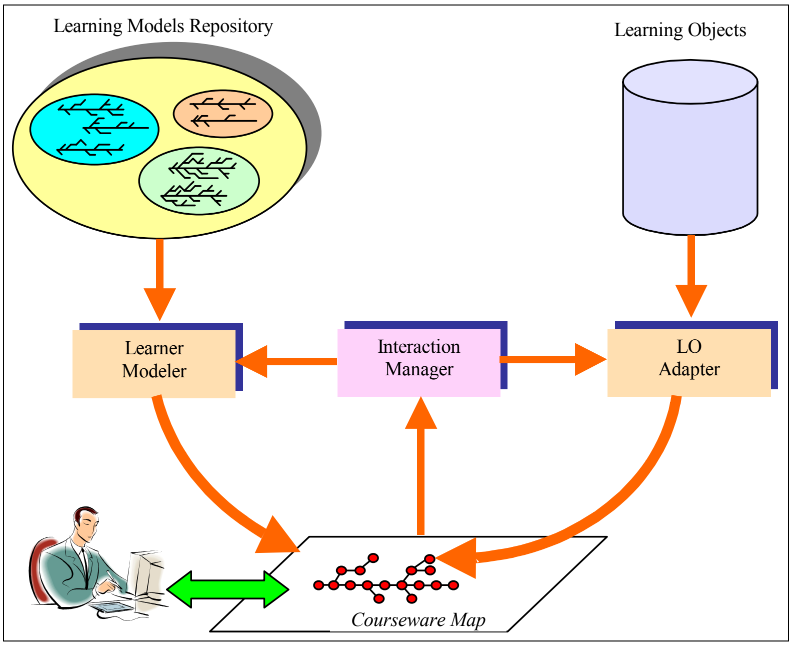

Figure 4. Adaptive Learning Architecture

a) Learner category

Learners are classified into categories based on the volume of visited SLOs. The number of categories is a paramemter in our system which may depend on criteria related to the nature of the courseware such as whether it is theoretical or practical oriented, whether or not it requires some prerequisite knowledge, etc. The courseware author decides a categorization scheme for learners of that courseware as well as thresholds used to upgrade learners from one category to another. This is done at authoring time. At learning time, learners are categorized according to the additional knowledge they request during the learning process. Learner categories are quantified as the proportion of SLOs over MLOs. To illustrate how learner categorization works let us consider a courseware with three sample learner categories: *advanced*, *intermediate* and *beginner*. Table 2 shows how the system identifies the different learner categories:

Learner Category	G(t)
Beginner	More than 50%
Intermediate	Between 50% and 10%
Advanced	Less than 10%

Table 2. Example of A Learner Categorization Scheme

Where `G(t)` represents the ratio `SO(t)/MO(t)`, `t` is the current time within a learning session, `So` and `Mo` are respectively the number of SLO and MLO visited at time `t`. An interesting feature of `G(t)` is its ability to dynamically adjust the learner category according to the number of SLOs and MLOs visited so far by a learner. Actually, during the learning process the learner category is evaluated at each invocation of a learning object by computing `G(t)`. This allows the system to upgrade or downgrade the learner category at each correlation invocation accordingly to adapt the learning-path construction process. The last computed G(t) value when the learner has completed the learning session (i.e. he has reached the last mandatory LO) represents the actual learner category which is going to be used to link the learning-path traversed by that learner to a specific learner category.

b) Learning Models Repository Construction

A learner model is mainly a learning-path that has been validated for a specific learner category. Its validation comes from the frequency of learners within the same category who visited the same sequence of learning objects for a given courseware. As learners complete a courseware and reveal a specific category, the system increments the frequency of visiting that traversed path within that category. Whenever the frequency of visiting the same path within a category goes beyond a certain predefined threshold, a learner model is validated and added to LMR. This model becomes representative for a class of learners and will be considered as candidate in modeling future learners.

Learner models pending validation are temporarily stored in the Learning Models Database (LMD) structured according to learner categories (see Figure 5). As learners complete a courseware learning session, a category is inferred for each learner as well as a new learning model which is going to reinforce the validity of existing learning models within the inferred category. Hence, the system learns from new experiences to either reinforce an existing learning model pending validation, or to add a new learning experience in the LMD which could be further consolidated by future learners.

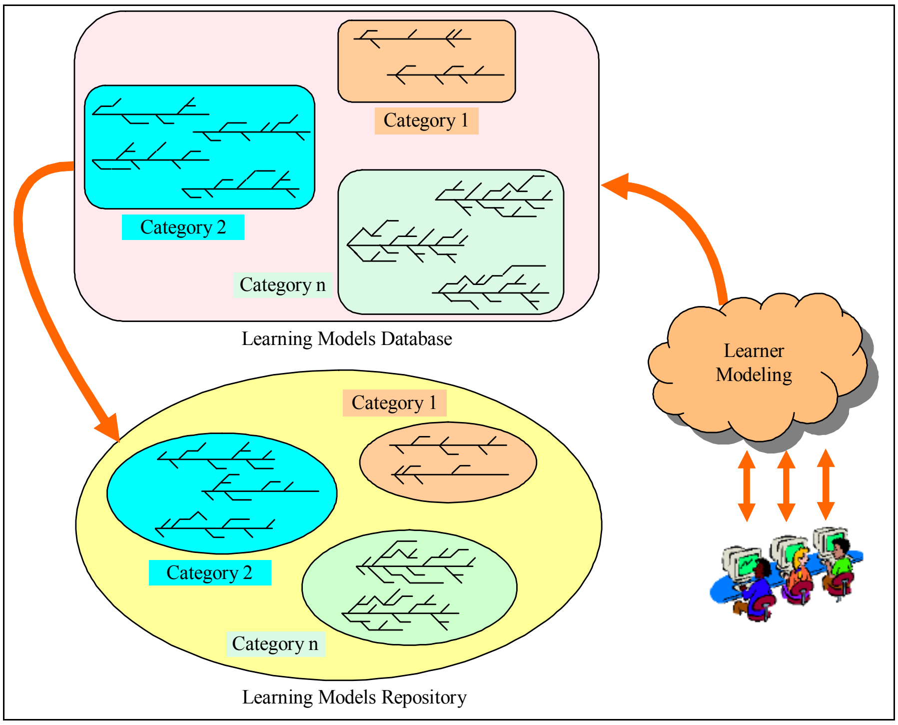

Figure 5. Learning Models Repository Construction

4.2 Learner Modeler

In this section, we describe the learning-path planning process which represents the core function of LM. The general cycle of LM is described by the following three processes given the current stage of a learning session for a particular learner (see Figure 6):
1. RETRIEVE the most similar learning models
2. SELECT the model which has the shortest learning path among the similar models
3. REVISE the proposed model according to the learner constraints, as shown later in Table 3.

In case no path is found, the learning process relies exclusively on the LOA adaptivity level to expose learners to self-adjusted LOs based on their current category. However, the LMR grows as *it learns* more from the learners themselves. At this stage, every courseware map may have been explored differently by multiple learners leading to a range of validated learning models for the same courseware. The first task of LM when invoked by IM is to retrieve similar cases. This is done by querying LMR for learning paths associated with the same courseware, and which include a contiguous segment of LOs similar to the segment of LOs explored (i.e. in the currently being constructed learning path). In other words, the retrieved models from LMR are profiles which share a common learning history with the current learner.

Once, LM has retrieved a set of candidate paths from LMR, it selects the candidate which has the shortest learning path. In doing so, LM assumes that the current learner matches the model of the most advanced learner who has a similar past learning experience. This statement is gradually revised by LM when the learner deviates from the proposed elaborated path allowing LM to incrementally build a tailored learning path for the learner.

In the process of revising a qualifying learning model, user-defined constraints are considered to provide opportunities to learners to intervene explicitly in the learning adaptivity process. These constraints are mainly subjective and may largely differ contextually among learners. For instance, the revision of a successful learning model match may consist in removing from that model a set of LOs, the learner may wish to exclude. These constraints are communicated to LM the form of a message being exchanged among the three functional modules of system architecture shown in Figure 4. The message being exchanged among these modules is structured as a 5-tuple data-structure $\{R, P, E_P, G, C, D\}$ described in Table 3.

Label	Legend
P	A sequence of references to mandatory learning objects representing the targeted learning concepts initially containing the mandatory learning objects for the courseware. ($P=[p_1, p_2, \ldots, p_n]$)
R	The actual learning path for the current courseware object containing initially an empty set (R=[]) but will be updated during a learning session by the visited learning objects and their sequence.
E_P	Path constraints; i.e. a list of learning objects to be excluded from the learning path
G	Current Learner Category
C	Cost constraints; i.e. constraints such as the number of learning objects on the path or the maximum time the learner can afford to allocate to a learning session.
D	Accumulated cost along the learning path.

Table 3. Message Structure

A major field of the message being collaboratively exchanged among the system functional modules is the learning path *R* which is continuously updated by LM to ensure an adaptive navigation process. G represents the current learner category and is calculated as mentioned in Section 4.a. The learning-path planning process is subject to the following conditions which affect the selection process of candidate learning models performed by LM as well the selection of the constituent LOs performed by LOA:
1. The learning objects should not be in the path constraint E_P
2. The learning object has not already been visited
3. The learning object does not violate the cost or time constraints function C.

The first condition is user-defined to explicitly exclude specific LOs from the learning path. For instance a learner is aware about some concepts and therefore he does not wish the corresponding LOs to be exposed throughout a learning session. The second condition above is maintained by the learning system to avoid cycles in the learning-path construction process. Finally, the last condition is set by the learner to optimize the learning process. The optimization process can be expressed in the form of the cardinality of the intervening LOs in the learning path or even the maximum duration of a learning session. This unique feature self-adjusts the sequence of the presented learning objects as well as their content based on the time a learner can afford to allocate to a learning session. The time attribute corresponding to each learning object is calculated based on the length of the continuous media attribute if any (i.e. video-clip time). This media play time is part of the standard LO attributes as described by the LOM specification (IEEE-LTSC LOM 2003). All of these constraints serve as pruning opportunities throughout the construction process of a learning path.

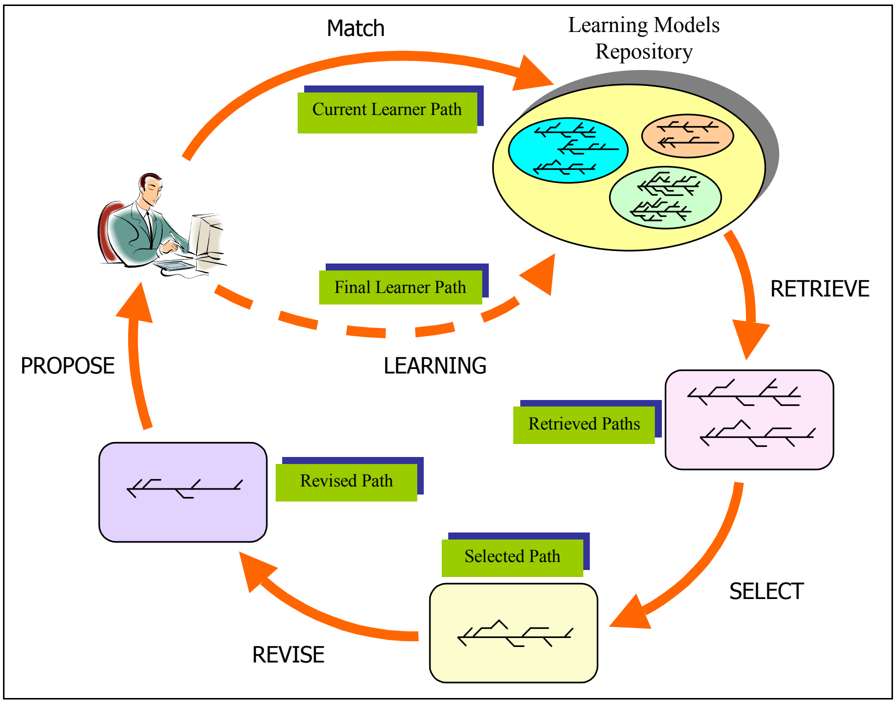

Figure 6. General cycle of the learner modeler

4.3 Learning Object Adapter

The next adaptivity level of the learning architecture presented in this paper consists in adjusting the LO content within the learning path recommended by LM by instantiating the LO metadata according to the current learner category. This intra-object personalization of the learning process represents the adaptive presentation dimension of the learning process. This dimension of adaptive learning adds to the adaptive navigation dimension provided by LM introduced in the previous section. LOA focuses on the content of the LOs to be presented to the learner. As shown in Figure 4 earlier LOD stores several versions of LOs. Each class of LO presents the same concepts but with different level of depth and learning style depending on the category an LO is associated with.

LOA is triggered by IM (see Figure 4) prior to play each LO in the learning path. IM may be invoked implicitly when a learner activates a correlation or automatically when transiting from one LO to the next one in the learning path. Basically, LOA runs whenever a new LO is about to be presented to the learner. At this stage, IM passes to LOA the message that contains the current learner category which is going to be used by LOA to retrieve from LOD the version of LO to be presented to the learner.

5. Conclusions

In this paper we have mainly proposed an extension to the LOM specification for learning objects to integrate learning adaptivity features. We have also shown a procedural methodology for LO construction as well as a hierarchy of learning units involving LOs. We also provided a procedural architecture to exploit these additions in order to root-out automatically learning deficiencies which may differ from one learner to another although they may be involved in the same courseware. The proposed architecture makes use of a learner modeler which learns about learners from the learners. The result of this process is a learning models repository which is used to profile dynamically learners as they interact with the system. We have shown in this paper two levels of supported learning adaptivity namely navigation and presentation adaptivity. The navigation adaptivity relies on an incremental strategy that progressively builds a repository of learning models based on past learning experiences. Existing learning models are re-used to guide current learners. Presentation adaptivity complements the navigational adaptivity by adjusting the constituting LOs.

6. References

Advanced Distributed Learning Co-labs (2001). SCORM Version 1.2, retrieved February 10, 2003 from http://www.adlnet.org/

Atif, Y. Benlamri, R. and Berri J., (2003). Learning Objects Based Framework for Self-Adaptive Learning. Submitted for publication.

Brusilovsky, P. and Schwarz, E. (1997). User as student: Towards an adaptive interface for advanced Web-based applications. *Proc. of 6th Int. Conf. on User Modeling*, Sardinia, Italy, June 2-5, 177-188.

Brusilovsky, P., Eklund, J., and Schwarz, E. (1997). Adaptive Navigation Support in Educational Hypermedia on the World Wide Web. *Proc. of The 6th IFIP World Conf. on Human-Computer Interaction.* Sydney, Australia, July 14-18, 278-285.

Brusilovsky, P. (1998). Adaptive Educational Systems on the World-Wide-Web: A Review of Available Technologies. *Proc. of Workshop WWW-Based Tutoring at 4th Int. Conf. on Intelligent Tutoring Systems (ITS'98)*, San Antonio, TX, August 6-19.

Brusilovsky, P. (1999). Adaptive and Intelligent Technologies for Web-based Education. In Rollinger, C. and Peylo, C. Eds, *Special Issue on Intelligent Systems and Teleteaching, Künstliche Intelligenz*, 4, 19-25.

Calvi, L. and De Bra, P. (1997). Using dynamic hypertext to create multi-purpose textbooks. *Proc. of World Conference on Educational Multimedia/Hypermedia and World Conference on Educational Telecommunications*, Calgary, Canada, June 14-19, 130-135.

Castro, M. et al. (2001). Examples of Distance Learning Projects in the European Community, *IEEE Transaction on Education*, 44 (4), 406-411.

De Bra, P., Brusilovsky, P., and Houben, G.-J. (1999). Adaptive Hypermedia: From Systems to Framework, *ACM Computing Surveys*, 31 (4es), December 1999.

Duffy T. M. and Jonassen D. H. (1991). Constructivism: New Implications for Educational Technology. *Educational Technology*, 31 (5), 7-12.

Dufresne, A. (2000). Model of an Adaptive Support Interface for Distance learning, *Proc of the 5th Int. Conf. On Intelligent Tutoring Systems ITS'2000,* Montreal, Canada, June, 334-343.

Eliot, C., Neiman, D., and Lamar, M. (1997). Medtec: A Web-based intelligent tutor for basic anatomy. *Proc. of WebNet'97, World Conference of the WWW, Internet and Intranet.* Toronto, Canada, November 1-5, 161-165.

Fung, A.C.W. and Yeung, J.C.F., (2000). An Object Model For a Web-Based Adaptive Educational System. *Proc of the IFIP International Conference on Educational Use of Technologies (ICEUT'2000),* China, August, 420-426.

IEEE-LTSC (2003). Learning Technology Standards Committee website: http://ltsc.ieee.org/

IEEE-LTSC LOM specification (2001), IEEE 1484.12/D6.1, May 2001. retrieved February 3, 2003 from http://ltsc.ieee.org/doc/wg12/LOM-WD6-1-1.pdf

IMS Global Learning Consortium (2003), retrieved February 6, 2003 from IMS Learner Information Package Specification: http://www.imsglobal.org/profiles/index.html and IMS Content Packaging Specification: http://www.imsproject.org/content/packaging/index.html

Karagiannidis, C., Sampson, D. and Cardinali, F. (2001). Integrating Adaptive Educational Content into Different Courses and Curricula, *Educational Technology & Society*, 4 (3), 37-44.

Khan B. H. (1997). *Web-Based Instruction*, Englewood Cliffs, New Jersey: Educational Technology Publication.

Koidl, K. (2002). Adaptive Hypermedia Systems for e-Learning, *Proc of Seminar Telekooperation*, Germany, retrieved February 6, 2003 from http://www.tk.informatik.tu-darmstadt.de/Lehre/ss02/semtele/

Najjar, L. J. (1996). Multimedia Information and Learning. *Journal of Educational Multimedia and Hypermedia*, 5, 129-150.

Osborne, J. W. (1999). Behavioral measure of metacognition for teachers, *Paper presented at the national meeting of the American Education Research Association (AERA)*, Montreal, Quebec, April 1999.

Redeker, G. (2002), Learning Objects - Instructional Metadata and Sequencing. *World Conference on E-Learning in Corp., Govt., Health., & Higher Ed.* (1), 798-805.

Rodriguez, O., et al., (2002). Open Learning Objects: The case of inner metadata. *Proc of the 11th World Wide Web Conference - www'2002,* Honolulu, May 2002.

Specht, M., et al., (1997). AST: Adaptive WWW-Courseware for Statistics. In: Brusilovsky, P., *Proc. of Workshop: Adaptive Systems and User Modeling on the World Wide Web. 6th Int. Conf. on User Modeling,* Sardinia, Italy, June 2, 91-95,

Theorix, (2003), Specifications and Standards in eLearning Systems: Overview of Seven Models, Publication of e-com inc., January 2003. retrieved March 3, 2003 from http://demo.flexsite.net/templates/theorix_13_02_2002/download/T4StandardsOverview.pdf