An adaptive feedback approach for e-learning systems

E.Kovatcheva, R.Nikolov

Abstract - **The adaptive e-learning systems are a hot topic of educational research. The approach presented is a knowledge-based. There are several types of adaptation of an e-learning system to the learner: content adaptation, interface personalization, etc. This paper dials with a model for adaptation of the learner assessment and the content of one learning system. The model is based on Computer Adaptive Test Theory (CAT) and organization of the learning domains. The learning objects (LO) and the test item ontology play a central role as resource structuring. It supports flexible adaptive strategies for assessment and navigation through the content. Learner knowledge is assessed by CAT and then the system returns the learner to the right leaning material corresponding to the knowledge shown. The congruence between CAT item bank and the LO pool is based on intelligent agents. It supports adaptive feedback to the students depending on the learner evaluation.**

***Index Terms*— Computer Adaptive Test, Item Response Theory, Item Bank, Learning Object, metadata**

I. Introduction

THE traditional educational process has some important phases: content delivery, assessment of student achievement and feedback on the assessment. The e-learning system architecture attempts to follow these steps as well as to use the same players. The adaptive e-learning systems try to adjust the learning process and system features to the learner, namely to provide different opportunities for the learner [1]-[11], such as selecting the level of content difficulty, learning at own manner, pace, “humanizing” student assessment, personalizing the learner interface, receiving proper feedback, etc.

The theory of Computer Adaptive Tests (CAT) based on Item Response Theory (IRT) allows for making accurate assessment without fixed number of items, in less time than with the classic tests. When the learner finishes the test, it can be returned to these content topics where his/her results are low. In that case the content corresponds to the student ability. The Computer Adaptive Tests identify the areas with gaps in student knowledge. The main question is how to go back to the exact content topic where student can improve own knowledge? This paper introduces one possible solution - an adaptive feedback approach based on the congruence between the Learning Object (LO) Pool, and the Item Bank.

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II. ADAPTIVE E-LEARNING SYSTEM

Adaptive e-Learning systems usually contain the following modules [12] learner interface, a learner model, a pedagogical module, and an expert module. The graphical representation of e-learning system is shown on figure 1.

In this paper the terms “student” and “learner” will be use as synonyms.

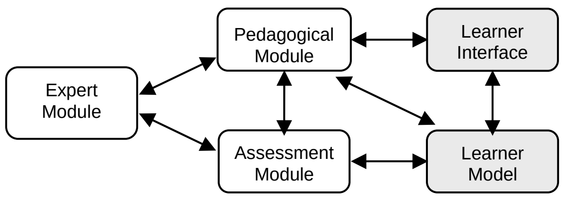

Figure 1: Adaptive e-Learning system Architecture

- **Learner interface** - for channeling computer-user interactions
- **Learner model** - list of facts describing the history of the user interaction and his performance at every step.
- **Pedagogical module** – navigates the user through the learning process: Planning Agent, Curriculum, Dialog System.
- **Expert module** - the domain knowledge base provides the structural description of the subject area, represented as learning objects, concepts and relations between them represented as domain ontology. The learning objects are chunks of basic knowledge in the domain (Table 1). In this system the expert module could be a human (teacher/ trainer) as well as a mentoring engine.

Table 1 LO metadata

Objectives	
	• aims
	• knowledge
Content	
	• declarative type: text, video, audio, ...
	• procedure type: tasks, examples, exercises
Assessment	
	• test, questionnaires, tasks, exercises
	• evaluation criteria
	• Test Aspects

ID number
Authorship
Creation Date

- **Assessment module** - the domain knowledge base provides the structural description like in the expert module. In this model computer adaptive tests are in used. The metadata for the item could be divided into two types [13]: descriptive and psychometric (see Table 2).

Table 2 Item metadata

Descriptive metadata
Objectives
• aims
• knowledge
Characteristic
• type: yes/no, multiple choice, …
• allowed time
• number of attempts
• difficulty level
• item answer
• item mark
ID number
Authorship
Creation Date
Psychometric Metadata
• difficulty parameter
• discrimination parameter
• guess parameter

III. KNOWLEDGE TYPES

As shown in tables 1 and 2, some parts of the Learning Object and the Item metadata are similar. Receptive knowledge points can be categorized using a didactical ontology as defined in [14] (figure 2):

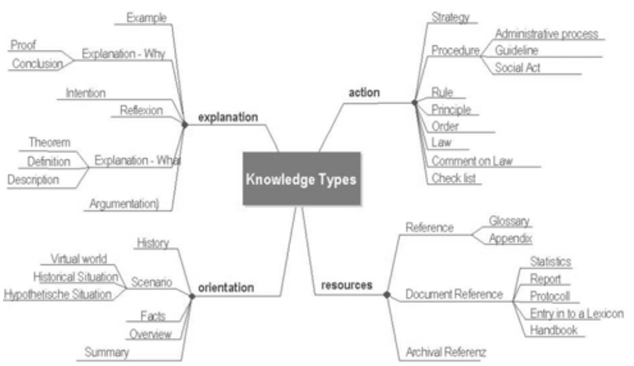

Figure 2: Ontology, Source [14]

- **Orientation knowledge** helps the learner to find their way through a topic without being able to act in a topic-specific manner ("know what").
- **Action knowledge** helps the learner to acquire topic related methods, techniques, or strategies ("skills", "know how").
- **Explanation knowledge** provides the learner with arguments that explain why something is the way it is ("know why").
- **Reference knowledge** teaches the learner where to find additional information on a specific topic ("know where").

These four basic types are further sub-divided into a fine grained ontology.

IV. CAT BASED IRT (ITEMS DETERMINATION)

The adaptive tests, based on the Item Response Theory (IRT) are able to adapt the evaluation to the learners by providing tests suitable for their knowledge level. It is even possible to make accurate assessment with fewer items. The test is given item by item, and the correctness of the answer to an item determines the selection of the next one. The next item is chosen applying the IRT equations that supply the adaptation to the learner's knowledge. The mixture between computers and IRT was a decisive milestone. This research area is known as Computer Adaptive Testing (CAT) [15].

Regarding learners' adaptation, our aim is to develop a tool for generating adaptive assessment using IRT with three parameters (see equation (1) - difficulty, discrimination and pseudo-guessing). The use of one or two parameters does not support the probability of guessing, while four parameters do not lead to improvement in the adaptation level [16]. These three parameters are the psychometric Metadata in table 2.

$$P(\theta) = c + (1-c)\frac{1}{1+e^{-a(\theta-b)}} \tag{1}$$

where:

- b – difficulty parameter
- a – discriminate parameter
- c – guess parameter
- $L = a(\theta - b)$ - logistic deviation
- θ - learner ability level

The learner ability level is calculated during the test and later is used for delivering adequate feedback.

V. LO POOL – ITEM BANK

The common metadata for LO and Items are the relations between the LO pool and the Item Bank. The link from the LO pool to the Item Bank is clear (see figure 3). The assessment task is described in the LO metadata. The opposite congruence is complicated because one learning object can be used in more than one topic, and then the question about it does not lead to one specific topic. This could be solved with the AI methods.

The main feature of the assessment module (figure 1) is to keep the track of each test in collaboration with the learner model. Both have to identify the learner achievement by topic and then to make several intersections including the items with low results. The best way to support this process is using intelligent agents [17]. The procedure will identify the exact topics where the learner has problems.

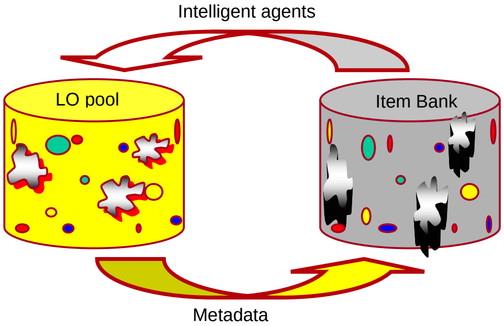

Figure 3: Congruence LO pool – Item Bank

The next step is going to the appropriate content. After identifying the problematic topics, the system returns the learner to them and delivers material corresponding to the student ability level (low, medium, high) as it has been defined in section IV.

VI. CONCLUSION

The attractive field of adaptive e-learning systems opens the opportunities not only for educational researcher but and software engineers. Personalization of the systems allows learners to feel more comfortable across the educational process especially in pure distance education.

Nearly no fully adaptive systems are available at the market.

The adaptive test for learner evaluation and congruence between learning objects pool and item bank are one step ahead in the “humanization” process of the e-learning systems.

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