

An adaptive feedback approach for e-learning systems

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Abstract— The adaptive e-learning systems are hot topics of research. The present approach is knowledge-based. The domain ontology for the learning objects (LO) and the test items play a central role as resources structuring the learning content and supporting flexible adaptive strategies for assessment and navigation through the content. The congruence between computer adaptive tests (CAT) item banks and the LO pool is based on intelligent agents. This supports better feedback to the students.

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 of assessment. The e-learning system architecture attempts to follow them as well as using and same players. The adaptive e-learning systems try to adjust the learning process and system features to the learner, namely to provide different possibilities to the learner such as selecting the level of content difficulty, learning in own curriculum, “humanizing” student assessment, personalizing the learner interface, receiving proper feedback and so on.

The theory of Computer Adaptive Tests (CAT) based on Item Response Theory (IRT) offer the possibility to make an accurate assessment without fixed number of items, in less time than with the classic tests. When learner finishes the test it can be return to the content topics where his/her results are low. In that case content will be corresponding to the student ability. The main question is how to identify the less achieved topics. This paper introduces one possible decision - an adaptive feedback approach according the congruence between Learning Object (LO) Pool and Item Bank.

II. ADAPTIVE E-LEARNING SYSTEM

Adaptive e-Learning systems usually contain the following modules [1] learner interface, learner model, pedagogical module and expert module. For precisely description of the learning process the assessment module could be separate (figure 1). In this paper the terms “student” and “learner” will be use as synonyms.

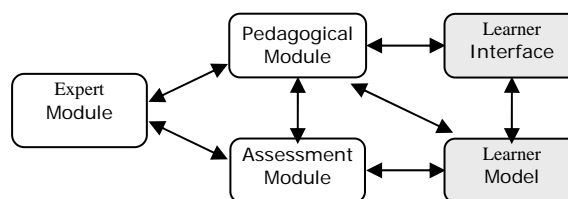


Figure 1: Adaptive e-Learning system Architecture

- **Learner interface** - for channeling computer-user interactions
- **Learner model** - list of facts describing the history of user interaction and his performance in every step.
- **Pedagogical module** – navigates user thru 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. Learning objects (LO) are chunks of elementary knowledge in the domain (Table 1). In this system the expert module could be human (teacher / trainer) as well as mentoring engine.
- **Assessment module** - the domain knowledge base provides the structural description as in the expert module, the computer adaptive test. In this model computer adaptive tests

are in used. The metadata for the item could be separate in to types [2]: descriptive and psychometric (see Table 2).

Table 1 LO metadata

Objectives	<ul style="list-style-type: none"> • aims • knowledge
Content	<ul style="list-style-type: none"> • declarative type: text, video, audio, ... • procedure type: tasks, examples, exercises
Assessment	<ul style="list-style-type: none"> • test, questionnaires, tasks, exercises • evaluation criteria • Test Aspects
ID number	
Authorship	
Creation Date	

Table 2 Item metadata

Descriptive metadata	
Objectives	<ul style="list-style-type: none"> • aims • knowledge
Characteristic	<ul style="list-style-type: none"> • type: yes/no, multiple choice, ... • allowed time • number of attempts • difficulty level • item answer • item mark
ID number	
Authorship	
Creation Date	
Psychometric Metadata	
	<ul style="list-style-type: none"> • difficulty parameter • discrimination parameter • guess parameter

III. KNOWLEDGE TYPES

As it is shown in tables 1 and 2 some parts of Learning Object and Item metadata are similar. Receptive knowledge points can be categorized using a didactical ontology defined in [3]:

- **Orientation knowledge** helps a learner to find her way through a topic without being able to act in a topic-specific manner (“know what”).
- **Action knowledge** helps a learner to acquire topic related methods, techniques, or strategies (“skills”, “know how”).
- **Explanation knowledge** provides a learner with arguments that explain why something is the way it is (“know why”).
- **Reference knowledge** teaches a 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 providing tests suitable for their knowledge level. Even, it is possible to make an accurate assessment with fewer items. The test is given item by item, and the answer to the previous 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) [4].

Regarding learners' adaptation, our aim is to develop a tool for generating adaptive assessment using IRT with three parameters (see (1)- difficulty, discrimination and pseudo-guessing), because the use of one, two parameters do not support the probability of guessing and four parameters does not cause a big improvement in the adaptation level [5]. These three parameters are the psychometric Metadata in table 2.

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

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 calculating during the test and later is used for delivering of adequate feedback.

V. LO POOL – ITEM BANK

The common metadata for LO and Items are the relations between the LO pool and Item Bank. From LO pool to Item Bank the link is clear (see figure 2). In the LO metadata is described the assessment task. The opposite congruence is complicate because one learning object can be used in more than one topic, then the question about it does not lead to one special topic. This could be solved with the AI methods.

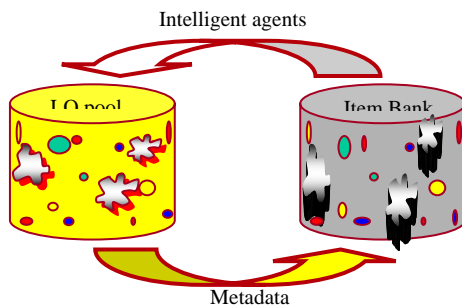


Figure 2: Congruence LO pool – Item Bank

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 for topics and then to make several intersections including the items with low results. Best way to support this process is using of intelligent agents [6]. This procedure will identify exact topics where learner has problems.

The next step is going to the appropriate content. After identification of the topics with problem the system returns the learner to the problematic topics and deliver material according the student ability level (low, medium, high) as it was define in section IV.

VI. CONCLUSION

The attractive field of adaptive e-learning systems is a hot research field at present. 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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Manuscript received 14 November 2007. This work was supported in part by the UNESCO/ Keizo Obuchi grant.

Published as submitted by the author.