TOWARDS THE USE OF REPORTING TOOLS FOR LEARNING ADAPTABILITY LEVEL IN AN E-LEARNING SYSTEM

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Abstract

The e-learning maintains specific features, as long as it is based on the use of new technologies. They can bring a lot of automation in the evaluation, and consequently help tutors in taking decisions concerning the levels of learners.

The reporting tools, in many existing e-learning platforms can then be applied effectively, to bring out all the explicit and implicit aspects which fall within the learner's behavior during the test, and must be taken into account to better adapt his or her level.

These aspects can be expressed as parameters which, for a treatment implemented, will lead to a level reassessment algorithm, which will accompany the tutor in taking decisions.

Keywords: e-learning system, Adaptability, reporting tools, re-assessment.

1 INTRODUCTION

The e-learning systems [4], highly developed today, provide robustness ensured by the use of new technologies [4], and flexibility in learning since learners can join virtual classrooms regardless of place and time dimensions. These systems are capable, in a virtual context, and through the wealth of content, to offer didactics close enough to reality. However, certain points such as evaluation, which can be described by several categories, are still under discussion [11] [6]:

- Diagnostic: usually at the beginning of a training;

- Formative: regulation at the beginning or the middle of a training;

- Summative: at the end of a training.

An assessment may reveal that a learner is at a level N. This may not be an absolute value, but rather on the basis of certain parameters that have characterized the evaluation and its context as well as the behavior of the student during the test. This level may be revised upwards or downwards.

The purpose of this article is to provide a rehabilitative approach to the student's level, based on certain parameters that may exist beforehand in the reports generated by the e-learning platforms [7].

Firstly, we will make a presentation of the general context of adaptability problem [14] [5] as part of a comprehensive online education system; then we continue by making a state of the art on adaptability in e-learning. Finally, we will give a detailed description of the approach we propose.

2 CONTEXT OF THE PROBLEM

A multitude of existing solutions in e-learning provide an opportunity to develop analytical and reporting tools [2]. These tools aim to have a synthetic view on the progress of the learning process, for example, time elapsed on a course, evolution in activities, resources consulted, and when they were consulted among others.

Apart from the incompleteness of the information provided in reports, they do not present advantages for the evaluation and assessment of a learner's skills, as the tutor is required to do it manually, and the process stops at the stage of observation without allowing to automatically generating correction level proposals, or adaptation of the following learning steps.

3 REVIEW OF LITERATURE ON EVALUATION TECHNIQUES IN E-LEARNING

When we talk about adaptation in e-learning systems, several aspects can be treated:

- Adaptation of the content of education [14]
- Adaptation of the assessment to the learner [11]
- Adaptation of the level of the learner [13]

The previous studies conducted on adaptation were interested mainly in customizing the navigation mode, and guiding the learner through hypermedia [3]. These researches consisted primarily of adapting the content to the learner.

Other systems based on artificial intelligence helped to propose more "smart" approaches to provide systems adapted to the needs of the learner [14].

As far as evaluation is concerned, several studies have been conducted to examine more closely the theories of this difficult imposing and decisive operation for educational purposes, and propose adaptive techniques [11] [10]. These studies have compared conventional (classic) assessments [10], which consisted of providing the same exam with the same set of questions, having the same difficulty, for the same period to a group of learners, and adaptive assessments [10], offering questions tailored to each learner. One of the theories presented is the Item Response Theory **IRT**, which deals with the relationship between the test items and examinee through his or her ability and proficiency to answer [1] [8].

The LCI model (Learning Cautions Indexes) [12] is also used to determine any abnormal situation which accompanies the learner's assessment, as if the learner completes a tough test and fails in an easy one.

4 STATEMENT OF THE PROBLEM

In the global schemata of an e-learning solution shown in Fig. 1, the analysis and reporting tools [2] are an essential part in the monitoring of a learner. The information collected by an e-learning system can be an important source to evaluate or review the level of a learner upwards or downwards.

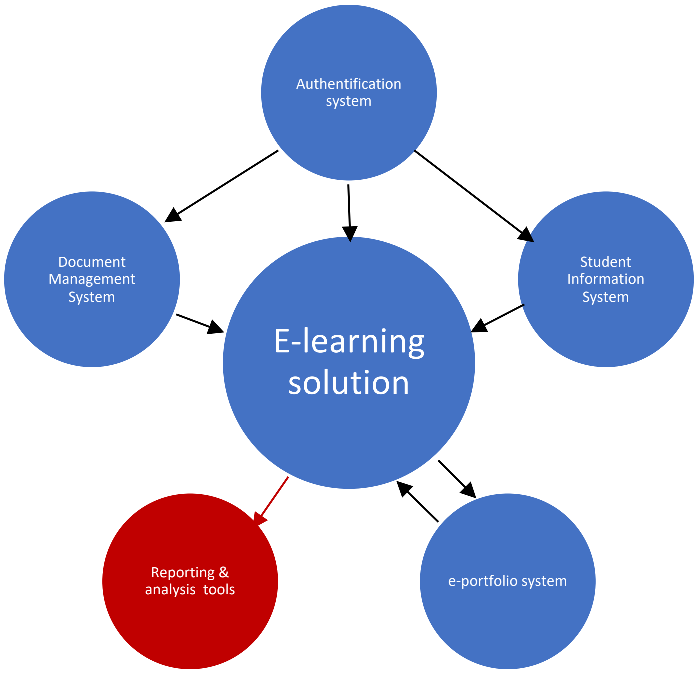

Fig. 1: Global schemata of e-learning solution [9]

Our contribution offers therefore, an approach to ensure, after collection of different indicators related to the learning process, an automatic adaptation of the level of a learner.

$$L_{\text{adapted}} = f(L_{\text{obtained}}, pi)$$

Where:

L_{adapted}: the final level of the evaluated after adaptation

L_{obtained}: the level of the evaluated before adaptation

pi: indicators recovered in the reporting tools

The recovered indicators may be enriched and refined so as to have the best calculated adaptation. As indicators we can, among others, mention the following:

- The elapsed time spent on an issue
- The number of attempts
- The number of wrong responses compared to the difficulty of the question
- The number of correct answers compared to the difficulty of the question

5 FINDINGS

When we consider the learning assessment process, we note that the parameters such as those mentioned in the IRR approach are defined a priori, such as the difficulty of a question. Many other parameters that can be recognized a posteriori are as follows:

- The total number of right answers (quantitatively, it is an unreliable indicator);
- The total number of false answers (quantitatively, it is an unreliable indicator);
- The elapsed time (spent) on a question;
- The number of attempts;
- The number of correct responses compared to the difficulty of the question (reliable indicator);
- The number of wrong responses compared to the difficulty of the question (reliable indicator).

These criteria can give an assessment on the behavior of the student during an evaluation process, and can give an accurate idea of his level. We can have, for example, two students who had the same score in an evaluation, but with different testing parameters.

Here's an example scenario:

Score of the student 1: 4

Total time for answers = 15mn

Score of the student 2: 4

Total time for answers = 10mn

The student 1 may be undervalued.

Some e-learning platforms such as Moodle allow generating reports [15] that can be analyzed to get out important information about the evaluation and learner behavior during the test. This information can be stored in his or her profile, and participate in an adaptation of his or her level.

Figure 2 shows the steps of the adaptation level of the learner, based on information collected at the reporting tools of the e-learning platform.

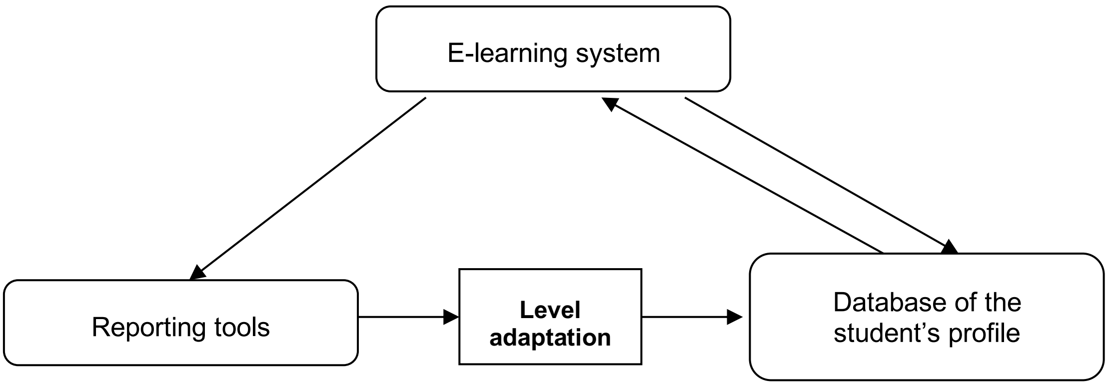

Fig. 2: Using Reports to adapt the level of student in global schemata of an e-learning platform

Time is a decisive parameter for adaptation. The question that will be asked next is that of the reference. A fast or slow response will be defined relative to the average time of learners' responses to the same question. This average time must be calculated dynamically throughout the evaluation process.

The time must be calculated dynamically, with an initial value estimated by the tutor, discarding extreme values that are supposed to be insignificant.

The learner will be undervalued increasingly it moves away from the calculated average, because we can consider that a high time due to hesitation, and that time is too fast due to a thoughtless response.

6 DESCRIPTION OF THE PROPOSED APPROACH

In section 5, we cited the criteria whereby we can decide to review the level of a learner during a test.

As for the study hypothesis, we will assume that we are in a linear, stable and an ideal environment for the evaluation and without any particular constraint.

We will start by listing the criteria considered by combining their labels:

Criterion	Description	Label
The total number of right answers	Unreliable quantitative	TNRA
The total number of false answers	Unreliable quantitative	TNFA
The Elapsed time on a question	Unreliable quantitative	ETQ
The number of attempts for each question	Reliable qualitative	NA
The number of wrong responses compared to the difficulty of the question	Reliable qualitative	NWRDQ
The number of correct responses compared to the difficulty of the question	Reliable qualitative	NCRDQ

Tab.1: Criteria influencing the evaluation process of a learner

Here is a description of each criterion:

- Total number of right answers:

Unreliable quantitative criterion, calculated at the end of the test, and affects the final grade.

- Total number of false answers:

Unreliable quantitative criterion, calculated at the end of the test, and affects the final grade.

- Elapsed time on a question:

Unreliable quantitative criterion, calculated for each question, and affects the grade of the issue.

The mark may be revised as follows:

$$\text{Mark}_{\text{final}}=\text{Mark}_{\text{Initial}} - (Ac*|ETQ-At|)$$

We will subtract from the initial mark, an amount which represents the distance of the estimated average time (in seconds), multiplied by a coefficient **Ac** to adjust this decrease.

To each question, the tutor initially provides an estimated time **Te**, and after each test taking, the average time **At** is calculated.

Knowing that:

- **Ti** : time spent on the question by each learner i;
- **n** : the number of learners who responded to the question;

Two formulae can be selected:

$$\textbf{At} = \frac{Te+\frac{\sum_{i=1}^{n} Ti}{n}}{2}$$

Or

$$\textbf{At} = \frac{Te+\sum_{i=1}^{n} Ti}{n+1}$$

The first formula is the one that will be retained because it gives more importance to **Te**.

To improve the approach, we can ignore singular values (not significant), which are estimated far from the average.

- The number of attempts for each question

A reliable qualitative criterion determines the degree of hesitation of the learner in relation to his or her response. Several online assessment platforms offer the possibility of marking questions for a subsequent return. A candidate, who returns several times to an issue, will see his or her mark for the question decrease by multiplying it by a coefficient **Coef**, initially equal to 1.

After each attempt Na:

Coef = 1 / (Le*Na)

Le (Level Assessment) is a coefficient which represents the level of the assessment. The higher the level is, the greater **Le** should be. This coefficient must be different from zero.

Each question will be multiplied by its respective coefficient at the end of the test.

In the absence of marking responses option, the coefficient **Coef** should remain equal to 1.

- The number of wrong responses compared to the difficulty of the question, and the number of correct responses compared to the difficulty of the question:

Both indicators are used to determine in the form of **reports,** the **reaction** of the learner **facing** the difficulty of the questions. Note that these two criteria are complementary since **knowledge** of one implies the deduction of the other.

The tutor can estimate the respective difficulties of the various questions of a given test. Learners' responses should logically follow the growing degree of difficulties. If we consider, for example, that there are two levels of difficulty (easy and difficult), learners should be able to answer the easy questions first and then the hard questions. If not, the tutor may make observations for prerequisites and possibly review the educational content.

7 ALGORITHM FOR THE TRANSFORMATION OF THE SCORE

Table 2 presents the criteria as variables:

Criteria	Appellation	Description	Scope
1	**TNRA**	Total number of right answers	At the end of evaluation
2	**TNFA**	Total number of false answers	At the end of evaluation
3	**ETQ**	Elapsed time on a question	At the end of each question
	Te	*Time estimated by the tutor*	To initialize on the creation of the test
	N	*Number of learners who answered the question*	At the end of evaluation
	At	*Average time*	To calculate
4	**NA**	Number of attempts for each question	At the end of evaluation
	Coef	*Coefficient of reduction of Note*	To calculate
	Le	*Level of evaluation*	To initialize at the beginning of the evaluation
	Ac	*Adjustment coefficient*	To initialize at the beginning of the evaluation
5	**NWRDQ**	Number of wrong responses compared to the difficulty of questions	At the end of evaluation
	Dq	*Difficulty of the question*	To initialize on the creation of the test
6	**NCRDQ**	Number of correct responses compared to the difficulty of questions	At the end of evaluation

Tab.2: Presentation of criteria as variables

The sequencing boots and calculations of the criteria can be used to define the following algorithm:

creation of test:

For each question :

- Initialize Dq[i]
- Initialize Te[i]
- At[i] = Te[i]

Test activation :

- Define N
- Initialize Le
- Initialize Ac

Before launching the test for a learner:

- Initialize NA at 0 (NA array, size : number of question)
- Initialize TNRA à 0
- Initialize TNFA à 0

- Initialize Coef[i] à 1 (Coef array, size : number of question)

Starting test for a learner j :

For each response

- Recover ETQ[j][i] (ETQ two dimensional array, rows : number of learners, columns : number of questions)
- Increment NA[i]

If correct answer

- Increment TNRA

Else

- Increment TNFA

End if

At the end of the test :

If test with a marking option

- For each question Calculate Coef[i]=1/(Le*NA[i])

End if

- Update Mark[i]=Mark[i]* Coef[i]
- Update Mark[i]=Mark[i]- absolute_value(ETQ[j][i]-At[i])
- Calculate the final score for learner

At the end of all tests for all learners :

- recover all ETQ[j][i] and Calculate At[i] (vertically for all learners)

8 CONCLUSION

Adaptability in the context of e-learning is a vast and complex subject and presents several aspects of study such as the adaptation of the content, the adaptation of levels of learners and tests adapting.

We have presented, through this contribution, a first approach that could contribute to the efficiency and streamlining of the adaptability process, for a better evaluation in e-learning platforms. This approach will also give tutors measures and indicators on which some important instructional decisions can be taken.

The criteria used in our approach can be enriched for having more informed decisions.

This work may lead to an implementation, in order to demonstrate the suitability of the selected criteria.

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