

User Profile Modeling in the Context of Web – Based Learning Management Systems

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Abstract: Over the past two decades, great research efforts have been conducted towards the personalization of e-learning platforms. This feature increases remarkably the quality of the provided learning services, since the users' special needs and capabilities are respected. The idea of predicting the users' preferences and adapting the e-learning platform accordingly is the focal point of this paper. In particular, this paper introduces the main requirements of an advanced e-learning system, explains the way a user navigates in such a system, presents the architecture of a novel e-learning system, and describes its main components. Research is focused on the User Model component, its role in the e-learning system and the parameters that comprise it. In this context, Bayesian Networks are used as a tool for the encoding, learning and reasoning of probabilistic relationships, with the aim to effectively predict user preferences. In support of this vision, four different scenarios are presented, in order to test the way Bayesian Networks apply in the e-learning field.

Keywords: Bayesian Networks, E-learning System, User Modeling, User Profile.

1. Introduction

The development of e-learning systems that are able to satisfy the needs of both novice and advanced users is an area of interest which is always under the spotlight of research efforts. Although significant steps have been made towards the direction of providing enhanced, personalized educational services, there is still a great volume of research that needs to be further conducted with a view to rendering these services fully personalized and adaptable. In this context, the user preferences should hold a primary role and should dictate the structure and functionality of the entire educational system.

Thus, one of the issues that must be addressed is the prediction of these preferences and, in general, the modeling of the user's profile, in terms of educational level, familiarity with a specific subject, overall performance etc. This can prove to be a really complex task, since the values of certain attributes and characteristics of the user's profile are unknown, yet follow an implicit logic which we are trying to approximate, based on certain evidence and feedback originating from the user's navigation through the system. A further parameter that also needs to be taken under consideration is the way in which information should be presented to the end-user, since navigating through a system that provides a large and possibly overwhelming volume of information is an issue that poses extra limitations and corresponding challenges for application designers and usability specialists; cognitive overload [16] and disorientation [15] are the main ones [4], [6].

Therefore, the goal is to develop a novel e-learning platform, which will accelerate the learning process and render it more efficient, by diminishing the emerged problems,

thanks to its enhanced functionality to dynamically plan lessons and personalize both the communication and the learning strategy [5].

This paper embraces the idea of the development of such an e-learning platform, capable of adapting to each user group's specific needs. In particular, Section 2 outlines some interesting related work that can be found in the literature, while Section 3 discusses on the structure of an e-learning system and, more specifically, introduces the main requirements of an advanced e-learning system, explains the way a user navigates in such a system, presents the architecture of a novel e-learning system, and describes its main components. Finally, it elaborates on the User Model component and its functionality in the e-learning system. In Section 4, the parameters comprising a typical user profile are presented. Section 5 discusses on User Profile Modeling, by defining a 3-layer model which makes use of Bayesian Networks, with a view to predicting user preferences. Section 6 presents the results of four scenarios revealing the system's performance, while Section 7 concludes the paper.

2. Related work

The field of e-learning systems has received significant research attention over the past years. More specifically, in [6] it is supported that web navigation can be modeled by studying individual differences and behavioral metrics. For this to be achieved, Juvina et al. use Latent Semantic Analysis (LSA) as a method for extracting and representing the contextual-usage meaning of words by statistical computations applied to a large corpus of text [26]. Remarkable progress has also been achieved in [12], where emphasis is given on personalization, learner evaluation and detection mechanisms, in order to achieve the e-learning platform's adaptation. Brusilovsky et al.,

in [27], also support the development of an adaptive e-learning platform, whose main components, for achieving adaptation, are Value-Added Services, Student Modeling Servers, and Topic Based Inference Agents.

As a sequel of the abovementioned research studies, this paper advocates the implementation of an e-learning platform that is able to adapt to the user's personal needs and requirements, using information not only provided directly by the user, but also inferred by his overall behavior during his navigation in the e-learning system. In particular, the proposed system is in position to predict the user's future preferences and interests, making use of Bayesian Networks, which constitute a concrete method for predicting the values of the desired parameters, based on another - much easier to measure - set of parameters. This means that the e-learning system extracts robust and reliable information, by monitoring the user's actions within the system. This makes it more likely for the system to select the most appropriate material in order to present it to the user.

3. E-learning system structure

3.1 *System requirements*

An advanced e-learning system has to comply with the following requirements:

Personalization: This requirement suggests that the learning process needs to take into account the user's preferences and personal needs. This implies either that the user is in position to explicitly specify these preferences or that the system has the ability to infer them through a monitoring process. The latter is far more convenient for the end-user and, thereby, constitutes a highly desirable feature.

Adaptability: The user's preferences change over time and the system must be able to track them and properly adjust to them. By 'properly' it is implied that the whole history of the user's learning behavior must be taken under consideration, and not just his latest (most recent) actions.

Extensibility: An e-learning system has to be extensible in terms of the learning material it provides. The incorporation of new courses and resources must be an easy to accomplish task.

Interoperability: An e-learning system must be able to both access content from and provide content to digital libraries and other e-learning systems. In this way, the provision of enriched and updated content is feasible. Regarding the client side, the interoperability requirement imposes that there should be no need of specific software, in order for a user to gain access to the e-learning platform.

While the latter two requirements can be fulfilled by adopting open, web-based interfaces and following XML standards, the former two ones call for the presence of a robust probabilistic scheme, capable of inferring the user's preferences, at any time, based on monitored data and previous experience.

3.2 User navigation

The goal of an e-learning platform is to effectively interact with users, offering them the appropriate information, while conforming to their preferences and needs, in order to evolve their knowledge and skills on certain topics. To this end, the development of an efficient system, which will contribute to users' effective learning, is a challenging research task.

Within this framework, Fig. 1 represents the way an e-learning system works, and, more specifically, the user navigation procedure.

Fig. 1

In such a system, when the user enters the educational platform, he is asked to participate in a set of questionnaires, cognitive tests and performance measures [1]. These questions aim at extracting some initial clues regarding the user's preferences, skills and personal goals. Using these features, the system forms an initial profile for the user in the system. This profile classifies each user in a particular group of users, assigning him with specific attributes. The socio-cultural status, the interests, the previous experience in working with computers and the expected outcomes of studying the particular material are some indicative attributes that characterize a group of users [6], [14], [17]. A categorical criterion is used, 'user groups' instead of 'individual users', only to reduce variability that is inherently beyond our control [1].

After completing the set of provided questions, and being integrated in a specific group, the user starts his navigation in the system, as depicted in Fig. 1. He explores the available material, studies the courses and the given resources, and takes the correspondent exercises, following the path he finds more interesting and spending time on issues he thinks they worth studying and are likely to enrich his knowledge.

At this point, the system has developed specific mechanisms, so as to detect the user's reactions to the incentives given by the e-learning environment. For instance, in case the system has noticed that the user is viewing a page for a much longer time than expected, it may use a pop-up window to clarify the user's opinion about the specific material. Thus, the system communicates with the user and defines whether he finds it difficult to understand the meaning of the page, or he thinks it is very interesting and

needs further information on the topic. Consequently, the system will have to provide the user with some additional simplified information, so as to make the learning material more comprehensible, or, on the other hand, offer him extra resources for further studying and increasing his knowledge on the subject.

When completing a chapter or a lesson, it is assumed that the user has enhanced his knowledge on the particular field in which he was involved. This can be certified by a test taken at the end of the course. The answers given to the questions reveal the depth in which the user has understood the material he went through, and indicate an evolution or modification in his preferences, skills and expected outcomes for future content. Along with this, the user is provided with some feedback designed from the course tutor, according to the answers he gave to the questions. The role of this feedback is to direct users to further study the lesson's section they did not fully comprehend, as well as emphasize the points they have managed to absorb as expected. By taking into account the questionnaire and test results, the answers provided to the pop-up questions during the lesson, and the feedback from the tutor, it is possible to adapt the material that is to be displayed to the user in the next lesson he is going to virtually attend, as well as update the user's profile. The practical way in which the user's profile is updated, so as to conform to the user's changing needs and skills, will be examined thoroughly in Section 5.

3.3 The proposed e-learning system and its components

In the previous section, the navigation of a user in an e-learning system and the interaction with it during this navigation were described. This section intends to define the architecture of such a system, as well as the components that comprise it, with the

aim to provide users with a compact platform, rich and comprehensible content, and apposite feedback.

Four main components make up the e-learning system proposed in this paper: *User Model (Profiles)*, *Domain Model (Content)*, *User Interface* and *User Monitoring*, as depicted in Fig. 2. Each of these components has an irreplaceable role in this system, rendering its presence mandatory for the system's functionality [9]-[13], [17].

Fig. 2

The *User Model* component stores all user-related data, i.e. the users' profiles, including personal information, preferences, monitored user actions and user performance related data. It enables the system to deliver customized instruction, on the basis of the individual student's, or student group's, learning style [17]. In the forthcoming sections, focus is given on this component, since it plays an integral part in rendering the e-learning system adaptable and user-centric, i.e. truly cognitive.

The *Domain Model* component stores information about the material that is to be delivered to users. In particular, learning theories [19] that have been evolved the last two decades, as well as learning styles [2] that have been identified, have shown that not all users learn in the same way, due to socio-cultural and educational differences and different life experiences. Thus, the educational material will have to be expressed and presented in different ways, aiming at fulfilling the users' special needs. The Domain Model stores the learning segments (learning courses) in XML format and, when notified, provides the appropriate information to the User Interface component, utilizing the instructions sent by the User Model, about each user group's preferences.

The *User Interface* is the component that exploits information from the User Model (Profiles), in which the users' preferences are stored, and the Domain Model

(Content), in which each lesson's structure is stored, and forms the final content to be delivered to the user. This content is formed in pages using Java Servlets [18], and comprises the material to be finally presented to the user.

Finally, the architecture comes full circle with the *User Monitoring* component. This mechanism monitors each user's behavior during his navigation in the e-learning system, detecting the user's interest on certain subjects, or weaknesses of understanding in some others. The data collected in the User Monitoring component are transferred to the User Model, in order to serve as input for the adaptation of the user profile.

Summarizing the above, the proposed e-learning system's architecture consists of four main components, which aim at rendering the system easy to navigate, interesting and attractive to the user, as well as adaptable to particular characteristics and learning style preferences, imposed by each user group.

3.4 Role of the User Model component

In the previous section, the User Model component was briefly outlined. In this section, the User Model's role, the parameters that characterize it, and its function in the system will be analyzed.

The main objective of the User Model is to tailor the learners' information space, by presenting learning material according to each group's cognitive level/progress, socio-cultural attributes, goals, plans, tasks, preferences, and beliefs [3], [7], **Error! Reference source not found..**

In more detail, the user is initially provided with a certain amount of questions and cognitive tests to fill in when entering the system, as also stated in Section 3.3. This set

of tests aims at tracking some primary characteristics regarding the user's preferences. More specifically, the system wants to identify what are the reasons that impelled the user to take the particular course, what he expects to learn, how much he thinks he is familiarized with the content of the course and, thus, whether he thinks himself to be a novice, an intermediate or an expert in the subject. Later on, the way he wishes the material to be presented to him, the level of interactivity he prefers to have with the system, and the depth of content complexity he desires, are also essential information for the system.

In summary, the User Model has to infer the following information: (a) the users' preferences concerning the content of each course; and (b) the users' preferences regarding the structure of the user interface. Furthermore, it has to store the following information: (a) the users' profiles, i.e. personal information about each user; (b) information about each user group, i.e. which members it consists of, what are its main characteristics (e.g., group of novice or expert users); (c) log files about each user's behavior during his navigation in the system; (d) the answers each user provided to the set of questions and tests, when he entered the system for the first time; and (e) the scores in the exercises and evaluation tests, when completing a lesson, as well as the feedback provided by the administrator of the course, for each user.

4. User Profile parameters

A user's preferences are constantly changing, as he progressively studies the offered courses, enhancing his knowledge and viewing different aspects of a subject which he was probably unaware of in the past. This means that the system should revise certain aspects of the offered learning procedure, in order to better meet the

user's evolved needs. Each of these aspects is influenced by one or more factors that reflect the user's behavior within the system. Hence, it is made clear that a user's e-learning profile consists of two types of parameters: the learning procedure preferences, which will be referred to as 'target parameters', and the influential factors, which will be called 'evaluation parameters'.

In what follows, four target parameters and three evaluation parameters are presented, in order to retain the forthcoming analysis both realistic and easy to follow. More complex models may incorporate a higher number of parameters, yet the nature of the analysis does not change.

4.1 Target parameters

The target parameters include *Content Difficulty*, *Content Volume*, *Interactivity*, and *Interface*. By keeping these parameters updated, the system is able to provide the user with the appropriate content, in the most suitable way. The values of these parameters are modified according to the user's behavior in each didactic unit.

Content Difficulty is influenced by the level of the user's knowledge on the subject, being a novice, intermediate or expert. As the user takes more and more courses, his level changes, from novice to intermediate, or from intermediate to expert, and he consequently asks for more complex content, with more detailed information on the subject and more advanced resources to explore. *Content Difficulty* may be attributed to one of the following three values: low, medium, or high.

Content Volume refers to the amount of information the user wishes to explore in the lesson he is about to study. Low, medium, or high are the values that *Content Volume* can be set to.

Interactivity is one of the parameters much appreciated by e-learning users. This is because Interactivity makes the user feel that the system is intelligent and able to adapt to his preferences, as well as in position to understand the difficulties he encounters and to help him solve them. *Interactivity* may also take the values low, medium, or high.

Another important profile parameter is the desired type of *Interface*, which also affects the learning procedure. This parameter is assumed to have four different values: Simple, Normal, Rich, or Advanced.

4.2 Evaluation parameters

Though it may seem as easy, it is in practice rather difficult to properly set the values of the target parameters. In most cases, even the user is not in position to realistically estimate his educational level, the level his familiarity on a subject or the expected outcomes of taking a specific course. Therefore, we need to set a number of evaluation parameters, which aid the system to predict the user's preferences, as he progresses with the study of the provided material. The evaluation parameters are the *Lesson Duration*, the *Test Duration*, and the *Performance*.

More precisely, *Lesson Duration* refers to the time that a user spends for completing a didactic unit/lesson. This time is measured and then compared by the system to a set of (pre-estimated) threshold values, which depend on the particular lesson. The result is the classification of the user's time in one of the following four classes: low, medium, high, or very high. The value of *Lesson Duration* subsequently affects the determination of the target parameters' values. The *Test Duration* parameter

is similar in nature, with the difference that it is related to the time that a user spends to complete a test.

What is also measured and taken into account in the process of user preferences prediction is the *Performance* parameter. By keeping the user's test scores, the system can estimate how well the user has comprehended the concepts of the course. This parameter is assumed to have four possible values: 'A', 'B', 'C', or 'D'.

5. User Profile modeling

5.1 Overview

The functionality of the proposed system for the modeling and adaptation of the user's profile comprises three different functional layers, as depicted in Fig. 3. The role of every layer is described thoroughly in what follows.

Fig. 3

Monitoring Layer: The role of this layer is to collect the values of certain key indicators, which will, in turn, be used for the evaluation and adaptation processes. These indicators are representative of the user's general performance and assist in forming his profile. In other words, this layer is responsible for retrieving the corresponding measurements from the User Monitoring component of Fig. 2.

Modeling and Evaluation Layer: The main functionality of this layer lies in retrieving the information collected from the monitoring layer and in modeling it in an efficient way. For this purpose, this layer makes use of Bayesian Networks, which have proven to be valuable tools for the encoding, learning and reasoning of probabilistic relationships [20]-[23]. Once the values of the monitored parameters (i.e., the evaluation

parameters) are retrieved through the Monitoring Layer, the Modeling and Evaluation Layer caters to providing this evidence to the model, in order to acquire some instantaneous estimation about the target parameters of the user's profile. The application of a specific model must anyhow comply with certain requirements. In particular, the selected model must reflect the actual causal relationships between the different attributes, while taking into account, at the same time, the degree of their dependency, which implies that the way different parameters are affected by the evidence varies.

Adaptation Layer. This layer is responsible for updating the estimated profile attributes according to the evidence received through the indicators of the Monitoring Layer. This evidence serves as feedback in order to acquire knowledge related to the user's behavior. What needs to be highlighted is the necessity to take into account, not only the current feedback, but also the past monitored evidence. In this way, any irregular information or any temporary performance fluctuations will not affect tremendously the estimation process. The need to encompass historical information in an e-learning system, as described in Section 3.4, is more than obvious, since such a system needs to evaluate not only a user's current performance, but also his overall progress.

5.2 Modeling and Evaluation Layer

Fig. 4(a) depicts the Bayesian network employed for the modeling of the relationships between the target and evaluation parameters of a user's profile. As can be observed, the causal relationships between the parameters under consideration are as follows.

Content Difficulty dependencies: This parameter depends directly on the values of all evaluation parameters. The actual lesson duration, the test duration and the user's performance dictate the difficulty level of the content that should be provided in the next lesson to the user.

Content Volume dependencies: The volume of the content that should be provided in the next lesson to the user is affected by the time needed to complete both the previous lesson and the corresponding test. The Content Volume's dependency on the performance can be considered negligible, since large content volume does not necessarily suggest great difficulty.

Interactivity dependencies: It is assumed that the degree of the required interactivity is determined solely by the user's past performance. More specifically, if a user achieves low performance, it is quite probable that he needs further guidance, thus more interactivity, through the lesson.

Lesson Interface dependencies: It is realistic to assume that the only indicator affecting the type of interface needed throughout a lesson is the amount of time that the user has spent in the previous lesson.

With reference to the model of Fig. 4(a), the notations depicted in Table I will be used for estimating the desired probabilities.

Table I

The goal is the determination of the values of the parameters CD , CV , I and LI that maximize the following joint conditional probability:

$$P(CD, CV, I, LI | LD, TD, R)$$

In what follows, we will demonstrate that the calculation of the abovementioned joint conditional probability reduces to the computation of the product of four partial conditional probabilities, which is a computationally easier task.

The joint probability distribution of the network of Fig. 4(a) can be expressed as follows:

$$P(CD, CV, I, LI, LD, TD, R) = P(CD | LD, TD, R) \cdot P(CV | LD, TD) \cdot P(I | R) \cdot P(LI | LD) \cdot P(LD) \cdot P(TD) \cdot P(R) \quad (1)$$

Based on the Bayesian product rule, it also holds that:

$$P(CD, CV, I, LI, LD, TD, R) = P(CD, CV, I, LI | LD, TD, R) \cdot P(LD, TD, R) \quad (2)$$

Equation (2), due to the independence of the parameters LD , TD and R , becomes:

$$P(CD, CV, I, LI, LD, TD, R) = P(CD, CV, I, LI | LD, TD, R) \cdot P(LD) \cdot P(TD) \cdot P(R) \quad (3)$$

From (1) and (3), it can be derived that:

$$P(CD, CV, I, LI | LD, TD, R) = P(CD | LD, TD, R) \cdot P(CV | LD, TD) \cdot P(I | R) \cdot P(LI | LD) \quad (4)$$

The values of the partial conditional probabilities of equation (4), for given $LD=ld$, $TD=td$ and $R=r$, can be retrieved from the model's Conditional Probability Tables (CPTs), which have, a priori, been filled appropriately by a set of experts in the domain of education (i.e., teachers, psychologists, pedagogues). Fig. 4(b) illustrates the model's CPT for the Content Volume parameter. The CPTs for the other target parameters have a similar structure.

The final goal is the determination of the most probable set of values for the target parameters, CD , CV , I and LI , given the evidence $LD=ld$, $TD=td$ and $R=r$. It is relatively easy to observe that the values of the target parameters which maximize the

joint conditional probability $P(CD, CV, I, LI | LD = ld, TD = td, R = r)$ are those that maximize each of the four product factors separately.

As described above, every Bayesian network is associated with a set of probability tables, i.e. the probability distributions of the evaluation parameters and the CPTs of the target parameters. A learning system may employ either a unique (and generic) set of probability tables or several sets of probability tables, each one corresponding to a different user class. The latter presumes that there is an additional parameter, 'User Class', which acts as a contextual parameter [23]-[24]. According to the value of this parameter, a different set of probability tables is used by the underlying Bayesian network. This extended model is depicted in Fig. 4(c), which features the separation of the model into two different layers: the contextual layer and the predictive layer. The former defines the set of probability tables that should be used by the latter.

The class each user belongs to can be defined upon the user's initial entry to the educational platform, via questionnaires, cognitive tests and performance measures. This helps the system classify the user into a particular group, assigning him with specific attributes, as described in Section 3.2.

Fig. 4

5.3 Adaptation Layer

As stated in Section 5.1, the computation of the most probable set of user profile characteristics should also encompass historical information, i.e. past monitored data regarding the user's overall performance. Therefore, a mechanism that updates the instantaneous, i.e. the most recent, estimations, on the basis of past information should

be developed. A simple yet effective approach is the calibration of the estimated probability according to the following formula:

$$p_{\text{adapted},n} = w_{\text{hist}} \cdot p_{\text{adapted},n-1} + w_{\text{instant}} \cdot \left(1 - |p_{\text{adapted},n-1} - p_{\text{instant},n}|\right) \cdot p_{\text{instant},n} \quad (5)$$

where $|x|$ returns the absolute value of x . Assuming that n represents the current time moment, $p_{\text{adapted},n}$ denotes the adapted probability estimation at moment n , $p_{\text{adapted},n-1}$ denotes the adapted probability's previous value, $p_{\text{instant},n}$ stands for the current instantaneous estimation, and w_{hist} and w_{instant} reflect the weights attributed to the historical estimation and the current instantaneous estimation, respectively. As can be observed, the right-hand part of equation (5) comprises two components, one for the employment of historical information and one for the employment of the instantaneous estimation. Thus, the proposed approach consists in modifying the previous estimation (first component) by a factor that is a function of the most recent, instantaneous, estimation (second component). To achieve this, the instantaneous estimation $p_{\text{instant},n}$ is multiplied not only by a weight w_{instant} , but also by a factor that depends on the difference between $p_{\text{adapted},n-1}$ and $p_{\text{instant},n}$. A small difference between these two values results in greater consideration of the second component. In this way, abrupt fluctuations can be smoothed out while the adaptive nature of the overall system is not violated.

The system's ability to adapt to the evidence received by the user, while, at the same time, perform a certain filtering of the outcome is influenced by the ratio $w_{\text{hist}}/w_{\text{instant}}$, which controls the contribution of the two components in formulating the adapted probability estimation. Larger values of the aforementioned ratio suggest slower adaptation rate, but better smoothing ability; whereas, smaller values imply faster

adaptation rate yet more sensitive behavior regarding sharp fluctuations. In Section 6, the impact of the ratio $w_{hist}/w_{instant}$ will additionally be examined in more detail through simulation results.

6. Results

6.1 Scenario 1 – Generic example

In this scenario, we will examine the model's behavior in a random situation. The value of the ratio $w_{hist}/w_{instant}$ has been set equal to 1. Initially (step 0), as depicted in Fig. 5(b), all the possible values of each target parameter are considered equally probable (uniform distribution). Hence, a lesson with random content difficulty, content volume, interactivity and interface is generated and delivered at this step. At the end of this lesson, the model's monitoring mechanism reports the following evidence: *Lesson Duration = Medium, Test Duration = High, Performance = C*. This set of evidence serves as input for the formation of the next lesson, i.e. the lesson of step 1, as depicted in Fig. 5(a). At the beginning of step 1, the aforementioned evidence is utilized in order to produce a set of instantaneous probability estimations concerning the target parameters. This is carried out with the use of equation (4), as described in Section 5.2, after setting $LD=Medium$, $TD=High$ and $R=C$. Subsequently, the instantaneous estimations of this step (step 1), in conjunction with the adapted probability estimations of the previous step (step 0), are utilized for the computation of the adapted probability estimations (Fig. 5(c)) of the current step (step 1), on the basis of the analysis of Section 5.3 (equation (5)). Based on the adapted probability estimations, we come to the conclusion that, at step 1, *Low* is the most probable value for *Content Difficulty*, *Medium* for *Content Volume*, *High*

for *Interactivity*, and *Rich* for *Lesson Interface*. Thus, the lesson of step 1 should comply with these suggestions, in order to best fit the user's preferences. The same method is followed for inferring the most probable values of the target parameters throughout the rest of the steps.

Fig. 5

Based on the results of Fig. 5(c), we construct the diagrams of Fig. 6. As may be observed from the curves of Fig. 6, the adapted estimations smooth out the sharp fluctuations of the instantaneous estimations, which is the desired behavior. Indeed, they tend to moderate the fast oscillations of the instantaneous estimations, by adapting to the evidence at a slower pace. This has the clear advantage of exploiting not only the most recent evidential data, but also knowledge about the past.

Fig. 6

As an indicative example of this behavior, let us observe the estimation results for the *Content Difficulty* parameter, at steps 4 and 5. At step 4, we may observe that the adapted estimation indicates *High* as the most probable value. However, at step 5, a radical change is detected at the evidential data. According to the instantaneous estimations, *Low* is by far the most probable value at step 5. However, the adapted estimation takes into account the historical knowledge, by moderating this oscillation, and suggests again *High* as the most probable value; this time, of course, the probability of value *High* has significantly been decreased. This gradual adaptation to the evidence allows the system to avoid temporary and impulsive oscillations.

6.2 Scenario 2 – Fluctuation smoothing

In this scenario, we examine the oscillation avoidance through a more specific example. As depicted in Fig. 7(a), we assume that the user's performance is very low during the steps 1-4, then that there is a sudden radical improvement at step 5, while at step 6 the user continues to have a very low performance. In this use case scenario, at step 5, it would be wrong to consider that the user has suddenly become an expert. I.e., the system should avoid providing him with content of great difficulty at this point. Examining the estimation results for the *Content Difficulty* parameter, this is exactly what is achieved by the proposed system at step 5, as may be observed in Fig. 7(b). Indeed, at step 4, *Low* is the most probable value for *Content Difficulty*. At step 5, the adapted probability of this value is decreased, yet it is not surpassed by the probabilities of the other candidate values, which constitutes the desired behavior. The results are similar for all the other target parameters, as well.

Fig. 7

6.3 Scenario 3 – Impact of the weights' ratio

In this scenario, we assume that we have the same situation as in Scenario 1, but we set $w_{hist}/w_{instant}=2$, i.e. the historical knowledge weighs twice as much as the current instantaneous knowledge. Fig. 8 illustrates the results for the *Content Difficulty* parameter. Results for the rest of the target parameters can similarly be obtained. As it is clear from this diagram, the degree of normalization is noticeably affected by the value of the ratio under consideration. Compared to Fig. 6(a), we may observe that the fluctuations of the instantaneous estimations are moderated at a larger degree, which is

the expected outcome, since the past estimations now contribute more than the current one in forming the adapted estimations.

The drawback in reinforcing the historical component too much over the current instantaneous component is that the adaptation speed is rendered excessively slow. The latter implies that if a large but permanent change occurs, then the system will be able to adjust to this change only after a considerable number of steps. This is why, in the e-learning context, values greater than 3 are not normally recommended for the ratio $w_{hist}/w_{instant}$. The impact of this ratio on the adaptation speed is further studied in Scenario 4.

Fig. 8

6.4 Scenario 4 – Measuring the adaptation speed

The goal of this scenario is to obtain results about the model's adaptation speed for different values of the ratio $w_{hist}/w_{instant}$. In this scenario, we assume that the user has very low performance in steps 1-4, but exhibits a remarkable and steady performance thereafter, as shown in Fig. 9(a). We will study the estimation results for the *Lesson Interface* parameter, for values 1, 2, and 3 of the ratio (Fig. 9(b), Fig. 9(c), and Fig. 9(d), respectively). The results for the other target parameters are similar. At step 4, *Simple* is the most probable value of *Lesson Interface*. Our goal is to measure the adaptation speed, i.e. how many steps it takes for the model to regard the value *Advanced* as the most probable one, for the three different values of the ratio. As may be observed from Fig. 9(b), for $w_{hist}/w_{instant}=1$, 3 steps are needed by the system to reach this conclusion. For $w_{hist}/w_{instant}=2$ (Fig. 9(c)), 5 steps are needed, while for $w_{hist}/w_{instant}=3$ (Fig. 9(d)), 6 steps

are required. Hence, it is clear that larger values of the ratio result in slower adaptation speed.

Fig. 9

7. Conclusions – Future Work

In this paper, the concept of predicting the users' preferences in an e-learning environment was established and implemented. Modern e-learning systems need to offer personalized experience to their users. To that end, the automatic inference of the users' preferences is a key issue, whose probabilistic nature can be dealt with, as demonstrated, through the utilization of Bayesian Networks.

In particular, this paper presented the central requirements of an advanced e-learning system. Focus was given on the need for personalization and adaptability. The structure of a novel e-learning system complying with these requirements was presented. The parameters comprising a typical user profile within the e-learning context were investigated. The central role of the system's User Model component was explained, and its encompassed functionality was thoroughly analyzed as a 3-layer model, which makes use of Bayesian Networks and appropriate fluctuation smoothing in a consistent manner. Results depicting the system's predicting behavior were demonstrated.

Future work includes the exhaustive trial testing and fine-tuning of the implemented e-learning system with the help of a number of volunteers. The incorporation of additional parameters to the proposed model will also be investigated. For instance, the preferred type of practice (e.g., multiple choice questions, true/false questions, etc.), and the preferred learning structure (e.g., top-to-down approach, down-

to-top approach, etc.) may serve as additional target parameters. Measuring a user's scroll rate (how much time it takes him to scroll to the end of the page, i.e. how fast he reads), or how many times a user is forced to scroll up (in order to search for a piece of information that he neglected at first glance) are examples of additional target parameters. Furthermore, a user's age, origin, or profession can serve as additional contextual parameters.

Another challenging future task is the dynamic determination of the optimal structure for the Bayesian Network of the Modeling and Evaluation Layer. So far, the structure of the Bayesian Network of Fig. 4 has been considered constant and unaltered. However, one could argue that a different set of causal relationships should have been assumed. The development of an efficient algorithm for learning the structure (i.e., causal relationships) of the Bayesian Network that is used for modeling the user preferences involves finding the structure that best suits a given set of pre-defined data, and is an NP-hard problem [25].

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Table I: Parameter Notations

Parameter	Notation
LessonDuration	LD
TestDuration	TD
Performance	R
ContentDifficulty	CD
ContentVolume	CV
Interactivity	I
LessonInterface	LI

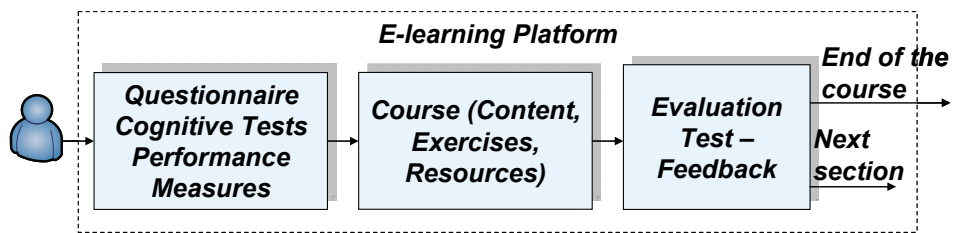


Fig. 1: User's navigation in the e-learning platform

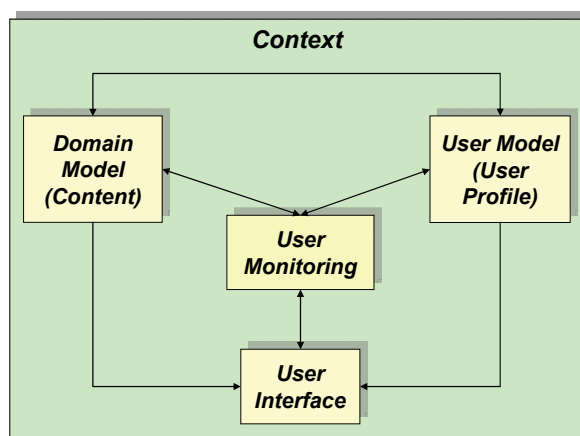


Fig. 2: E-learning system's architecture

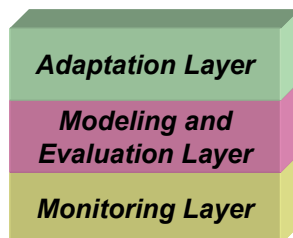
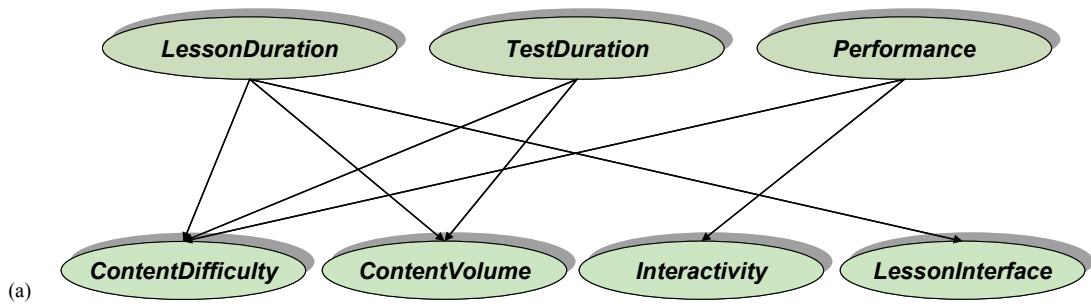


Fig. 3: Functional layers of the user profile model



(b)

Parent Node(s)		ContentVolume			bar charts
TestDuration	LessonDuration	Low	Medium	High	
Low	Low	0,1	0,2	0,7	
	Medium	0,15	0,25	0,6	
	High	0,25	0,35	0,4	
	VeryHigh	0,5	0,3	0,2	
Medium	Low	0,15	0,25	0,6	
	Medium	0,15	0,45	0,4	
	High	0,2	0,5	0,3	
	VeryHigh	0,4	0,45	0,15	
High	Low	0,3	0,45	0,25	
	Medium	0,35	0,5	0,15	
	High	0,5	0,4	0,1	
	VeryHigh	0,6	0,3	0,1	
VeryHigh	Low	0,3	0,55	0,15	
	Medium	0,4	0,5	0,1	
	High	0,65	0,3	0,05	
	VeryHigh	0,75	0,2	0,05	

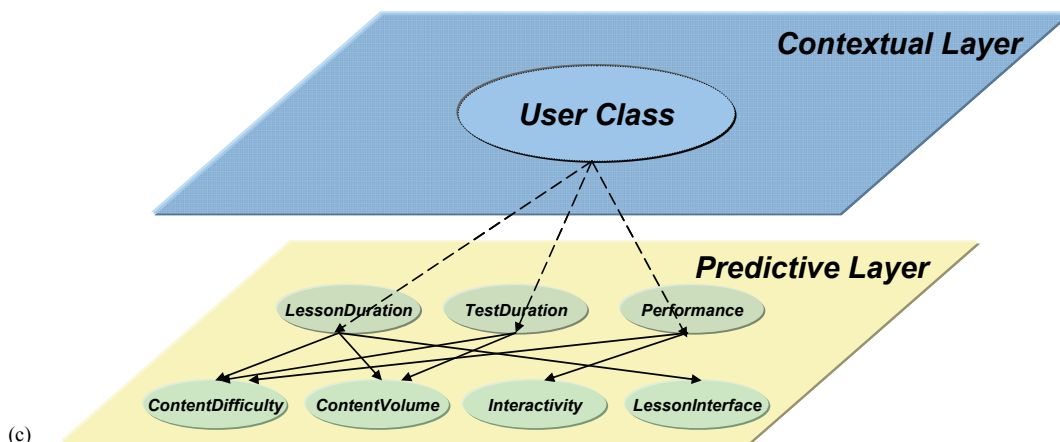


Fig. 4: (a) Bayesian network employed by the Modeling and Evaluation Layer; (b) The CPT for *Content Volume*; (c) Extension of model (a) in a two-level Bayesian network

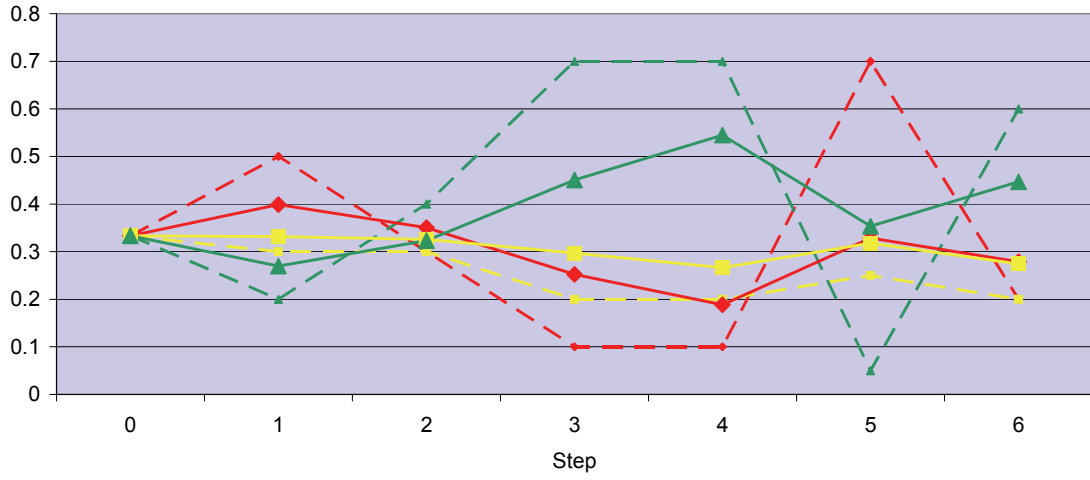
Step	Evidence		
	LessonDuration	TestDuration	Performance
0	-	-	-
1	Medium	High	C
2	Medium	Medium	B
3	Low	Low	A
4	Low	Low	A
5	VeryHigh	VeryHigh	D
(a) 6	Medium	Low	A

Step	Instantaneous Estimations												
	ContentDifficulty			ContentVolume			Interactivity			LessonInterface			
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Simple	Normal	Rich	Advanced
0	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.25	0.25	0.25	0.25
1	0.5	0.3	0.2	0.35	0.5	0.15	0.2	0.3	0.5	0.1	0.3	0.35	0.25
2	0.3	0.3	0.4	0.15	0.45	0.4	0.5	0.3	0.2	0.1	0.3	0.35	0.25
3	0.1	0.2	0.7	0.1	0.2	0.7	0.6	0.3	0.1	0.1	0.25	0.3	0.35
4	0.1	0.2	0.7	0.1	0.2	0.7	0.6	0.3	0.1	0.1	0.25	0.3	0.35
5	0.7	0.25	0.05	0.75	0.2	0.05	0.1	0.2	0.7	0.45	0.35	0.15	0.05
(b) 6	0.2	0.2	0.6	0.15	0.25	0.6	0.6	0.3	0.1	0.1	0.3	0.35	0.25

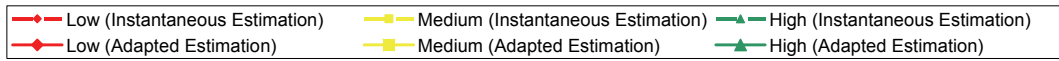
Step	Adapted Estimations												
	ContentDifficulty			ContentVolume			Interactivity			LessonInterface			
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Simple	Normal	Rich	Advanced
0	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.25	0.25	0.25	0.25
1	0.40	0.33	0.27	0.36	0.40	0.24	0.27	0.33	0.40	0.17	0.28	0.29	0.26
2	0.35	0.33	0.32	0.25	0.44	0.31	0.36	0.34	0.30	0.14	0.29	0.32	0.26
3	0.25	0.30	0.45	0.20	0.36	0.44	0.44	0.34	0.21	0.12	0.27	0.31	0.30
4	0.19	0.27	0.55	0.17	0.30	0.54	0.51	0.34	0.16	0.11	0.26	0.31	0.32
5	0.33	0.32	0.35	0.31	0.31	0.37	0.36	0.33	0.31	0.23	0.33	0.24	0.20
(c) 6	0.28	0.27	0.45	0.24	0.30	0.46	0.45	0.34	0.21	0.16	0.32	0.29	0.23

Fig. 5: Scenario 1: (a) Evidence; (b) Instantaneous Estimations; and (c) Adapted Estimations

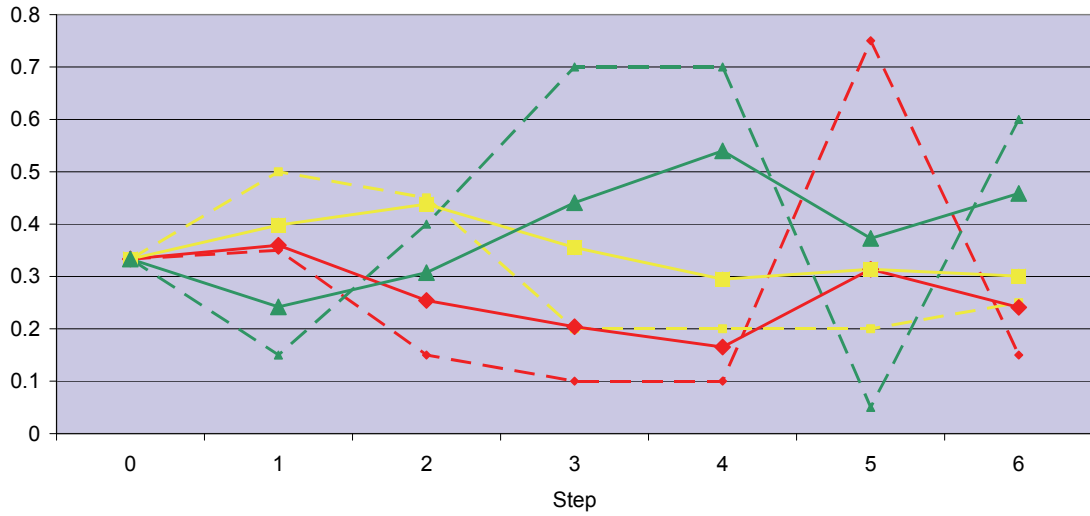
Content Difficulty - Probability Estimation Results



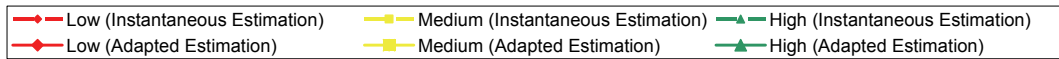
(a)



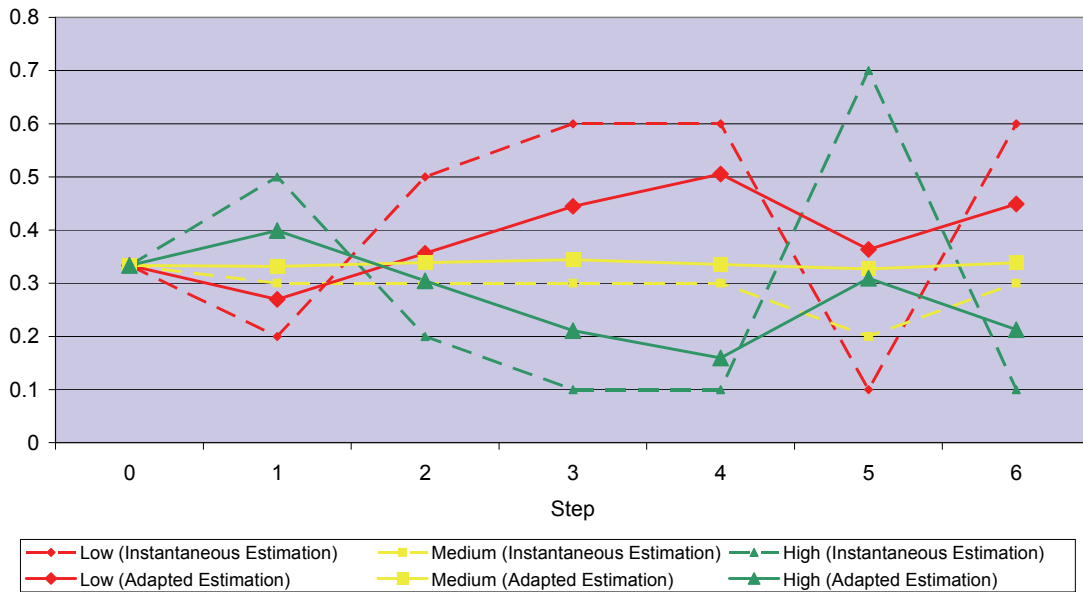
Content Volume - Probability Estimation Results



(b)

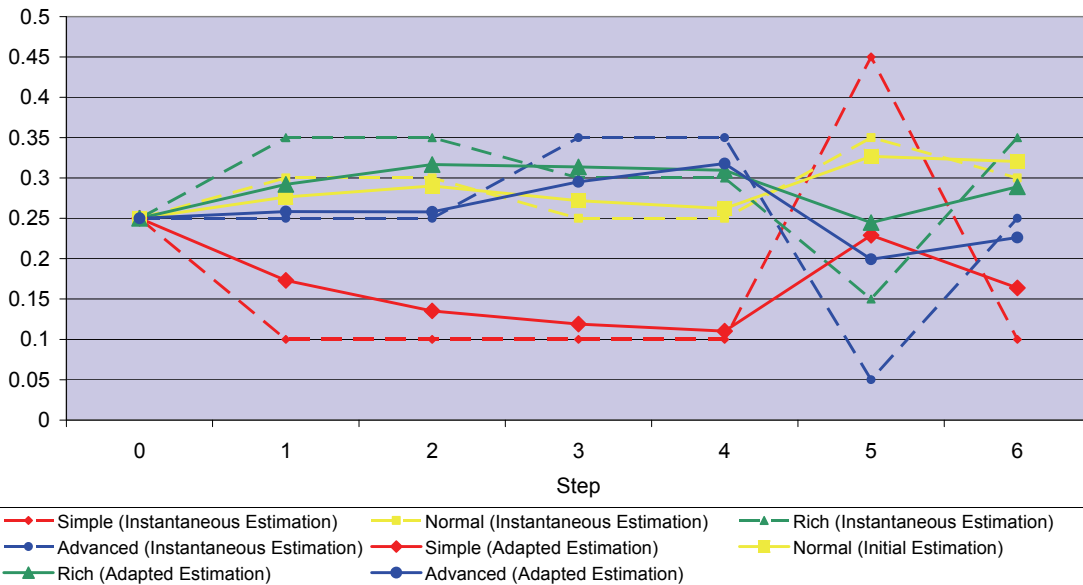


Interactivity - Probability Estimation Results



(c)

Lesson Interface - Probability Estimation Results



(d)

Fig. 6: Scenario 1: Estimation results for the (a) Content Difficulty; (b) Content Volume; (c) Interactivity; and (d) Lesson Interface target parameters

Step	Evidence		
	LessonDuration	TestDuration	Performance
0	-	-	-
1	VeryHigh	VeryHigh	D
2	VeryHigh	VeryHigh	D
3	VeryHigh	VeryHigh	D
4	VeryHigh	VeryHigh	D
5	Low	Low	A
(a) 6	VeryHigh	VeryHigh	D

Content Difficulty - Probability Estimation Results

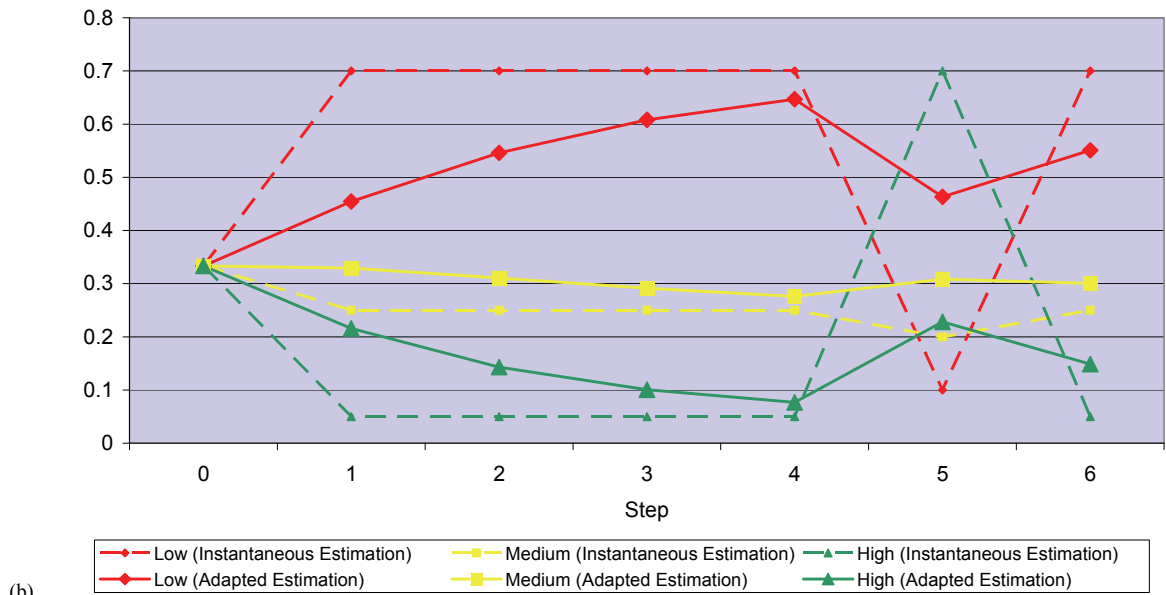


Fig. 7: Scenario 2: (a) Evidence; and (b) Estimation results for the Content Difficulty parameter

Content Difficulty - Probability Estimation Results

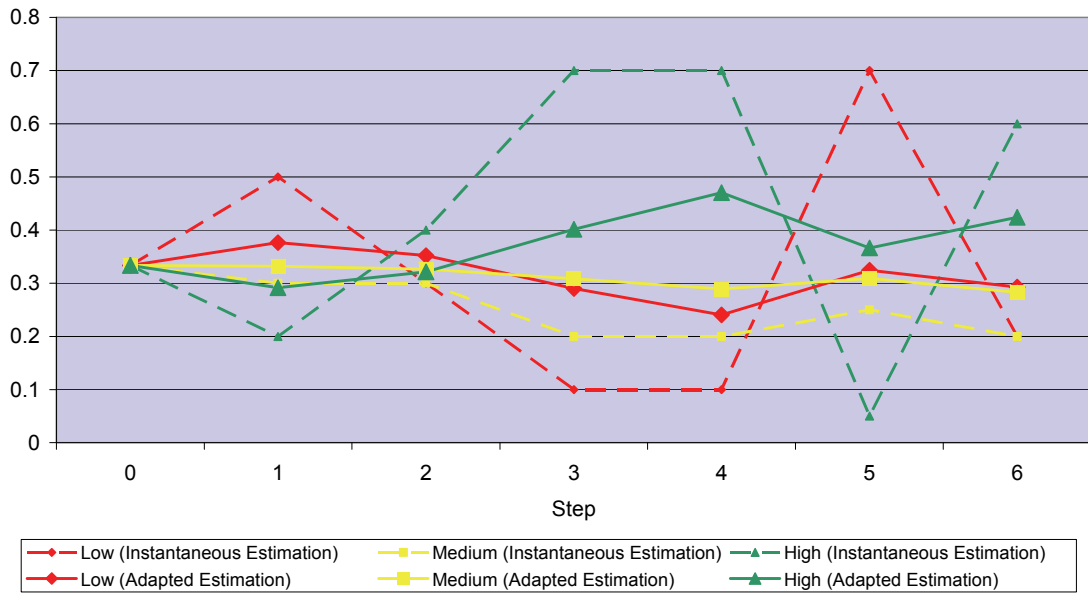
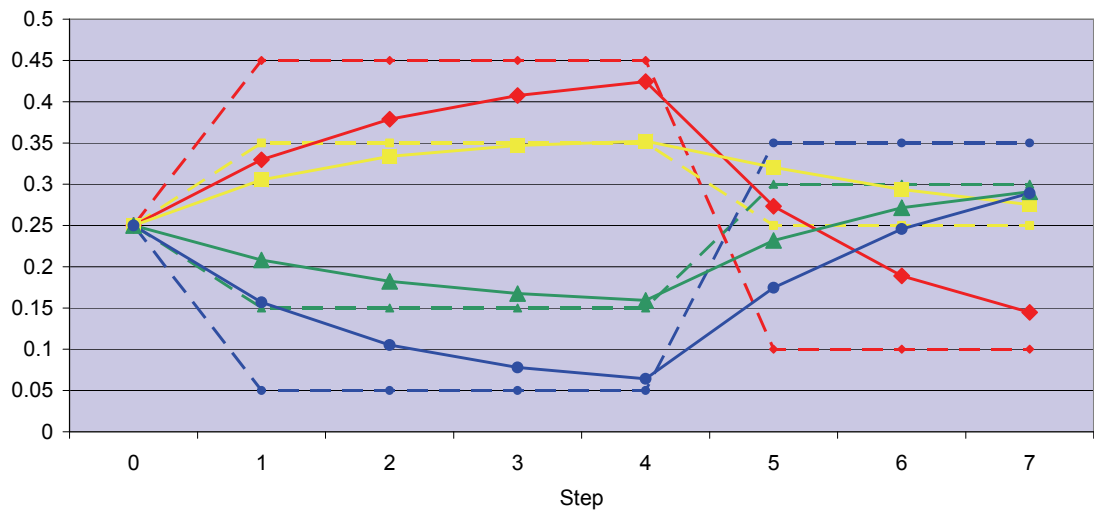


Fig. 8: Scenario 3: Estimation results for the *Content Difficulty* parameter

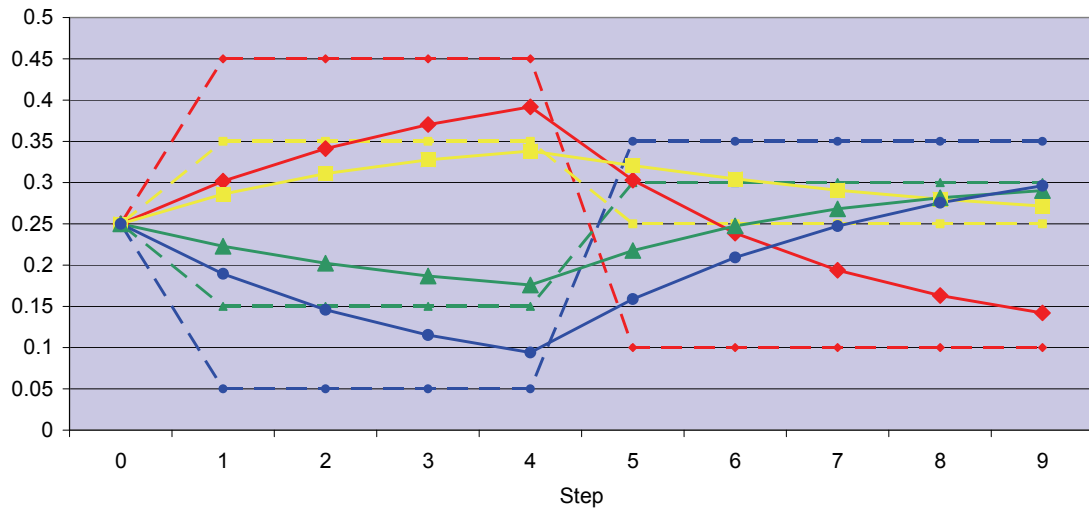
Step	Evidence		
	LessonDuration	TestDuration	Performance
0	-	-	-
1	VeryHigh	VeryHigh	D
2	VeryHigh	VeryHigh	D
3	VeryHigh	VeryHigh	D
4	VeryHigh	VeryHigh	D
5	Low	Low	A
6	Low	Low	A
7	Low	Low	A
(a)

Lesson Interface - Probability Estimation Results



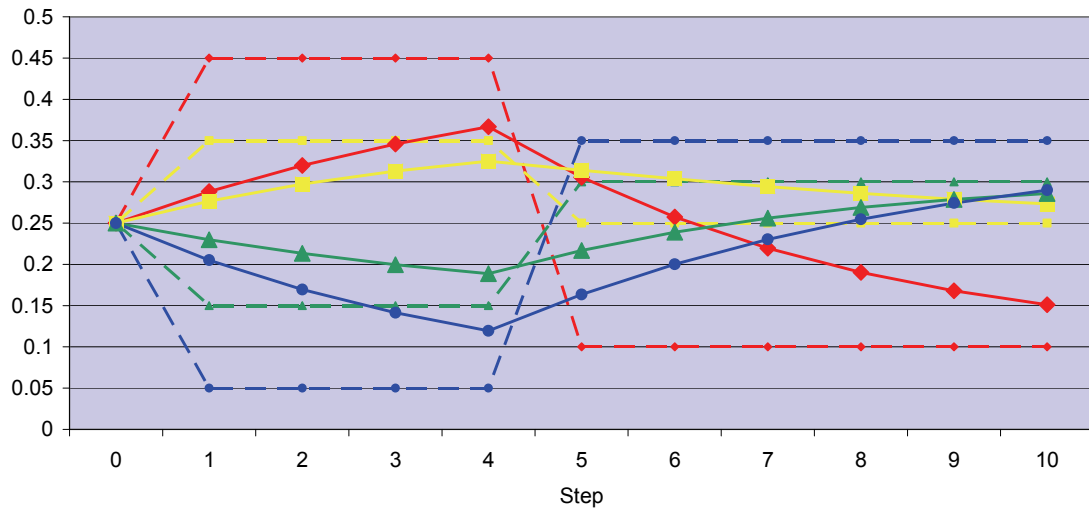
(b)

Lesson Interface - Probability Estimation Results



(c)

Lesson Interface - Probability Estimation Results



(d)

Fig. 9: Scenario 4: (a) Evidence; Estimation results for the *Lesson Interface* parameter, for (b) $w_{hist}/w_{instant}=1$; (c) $w_{hist}/w_{instant}=2$; and (d) $w_{hist}/w_{instant}=3$