Fuzzy Student Modeling for Personalization of e-Learning Courses

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Abstract. In the context of e-learning courses, personalization is a more and more studied issue, being its advantage in terms of time and motivations widely proved. Course personalization basically means to understand student's needs: to this aim several Artificial Intelligence methodologies have been used to model students for tailoring e-learning courses and to provide didactic strategies, such as planning, case based reasoning, or fuzzy logic, just to cite some of them. Moreover, in order to disseminate personalised e-learning courses, the use of known and available Learning Management System is mandatory.

In this paper we propose a fine-grained student model, embedded into an Adaptive Educational Hypermedia, LS_Plan provided as plug-in for Moodle. In this way we satisfy the two most important requirements: a fine-grained personalization and a large diffusion. In particular, the substantial modification proposed in this contribution regards the methodology to evaluate the knowledge of the single student which currently has a low granularity level. The experiments showed that the new system has improved the evaluation mechanism by adding information that students and teachers can use to keep track of learning progress.

1 Introduction

Distance learning is a mode of teaching/learning more and more required, used in education and working contexts. Research in this field has dramatically increased in different directions: human-computer interfaces, design of Learning Management Systems (LMSs), social context [14], students' modeling [20], teachers' background and teaching styles [18].

In this context,the use of known and available LMSs is mandatory and essential to create and to spread content, but a LMS that provides all these features is difficult to find.

Moreover, the personalization of the learning experience is closely related to the efficiency and effectiveness of the learning process itself: personalized content is more easily assimilated and the learner is more motivated. However student diagnosis is uncertain, and a possible approach to face this problem is a fine-grained student modeling, that several researchers (e.g. [24]) assessed

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as adequate to carry out the student's assessment and pedagogical strategies. Fuzzy logic techniques have been used to improve the performance of intelligent educational systems due to their ability to handle uncertain information, such as students actions, and to provide human descriptions of knowledge and of students cognitive abilities [11].

In this paper we focus on the definition of a fine grained student model, taking inspiration from the work reported in [20], that allows to create and customize courses basing on student's learning styles according to the Felder-Silverman model. We integrate into this model Kosba's studies ([11]) on the application of fuzzy logic for the description of the cognitive level of the students with respect to certain topics. We propose a plugin for the most world-widespread LMS: Moodle. In particular, our aim is to modify and improve the existing student model, that is the set of acquired information from student learning style and needs, and from the interactions with the system during her own personalized learning material fruition. The current student model provides a student adaptive component, and evaluates students' needs according to their knowledge and learning preferences. In this proposal, the substantial modification regards the knowledge representation of the student, which currently has a low granularity level. LS_Plan basically uses two values to estimate the knowledge: acquired or not acquired. We introduce in the new student model a fine-grained Cognitive State with four different levels of knowledge acquisition. This improvement brings a great advantage to the end user that has her personalized course carefully tailored on her personal knowledge and learning goals, avoiding waste of time and motivations in studying topics that could reveals trivial or too much difficult in a "one-size-fits-all" course, or in a course not carefully personalized.

In the following section we report about some meaningful related work, in Sec. 3 we describe the fine-grained Student Model. In Sec. 4 we show an example of application. Conclusions and future work are drawn in Sec. 5.

2 Related Work

Fuzzy approach is a widely applied technique in user modeling, in particular it is used to model different aspects of student's characteristics such as the degree of knowledge the student has or acquires in a given subject. It allows natural description of knowledge and inference in the form of imprecise concepts, operators, and rules.

For example in [24] is proposed BSS1 that is an ITS with a general fuzzy logic engine for supporting the intelligent features of the ITS. In [2], ABITS defines the domain knowledge where Learning Objects (LO) and related metadata are the basic elements of the system. Its student model is represented by Cognitive state, student's preferences, and curricula. Fuzzy logic is applied here to represent the uncertainty of the student's score that can be obtained by different kind of assessments and with different degree of reliability, as we also consider. Following a similar approach, in [12] the author presents TADV that is a famous framework for web distance education characterized by the Advice Generator that communicates with the student, during her didactic path, about results gained over time. Its student model is represented by four main aspects that, on the whole, contribute to the overall student evaluation. They are: general information, behaviour, preferences, knowledge. The last one is represented by fuzzy logic, where the knowledge of a student about a certain topic is modeled by the following variables: Certainty Factor (CF), Measure of Belief (MB), Measure of Disbelief (MD). The Certainty Factor is a variable that takes on values between -1 and 1, and is directly influenced by the other two variables MB and MD. MB and MD are variables extrapolated from the results of the assessment quiz that the student takes for each concept of a specific course. Both MD and MB range between 0 and 1. The first increases with each correct answer given by the student to a specific quiz. The second one is increased if the student responds incorrectly or skips the quiz. The result of the two values is combined giving the final value of CF. Kosba defines three levels of learning: completely learned, learned and unlearned. The CF is compared with the intervals that define the learning levels and stores the result obtained by the student for the specific concept. Not only quizzes modify the degree of understanding assigned to each student, but also the time variable that contributes to define the Belief Graph. On the other way TADV gives suggestion to students, but does not provide a personalized didactic strategy.

The work presented in [10] proposes an educational hypermedia where for each domain concept the user model saves a corresponding value using a linguistic variable concept knowledge, which takes three possible values which estimates user knowledge of that concept: unknown, known, and learned. More recently, [3] proposes an adaptive learning environment for computer programming based on hybrid student model, which combines an overlay model with stereotype and fuzzy logic techniques. In a perspective of technology enhanced learning, there is research work [5], [4], [6], [21] aiming to integrate more traditional individualized e-learning [23] and social-collaborative e-learning [22], [1] and [7]. Many personalized e-learning systems do not use fuzzy approach to model students. They rather insist to suitably represent student's learning styles, such as [9] or [20],[8], and also teachers' teaching styles ([13], [15], [17],[16]).

We start from the work presented in [20], [19] and improve it with some aspects of the student model that can be made more realistic by means fine-grained modeling. Being inspired by the work of Kosba, we integrate into LS_Plan a student model that will provide more realistic assessment of the students and the subsequent re-planning of the learning that the student must follow. Unlike other Adaptive Educational Systems like [10] and [3] that are "problem oriented", LS_Plan provides a personalization engine that can be plugged in any educational system being, therefore, problem independent.

3 The Student Model

In this section we present the Student Model (SM) and its relation with the adaptive system in which it is involved. Fig. 1 shows some relations among the

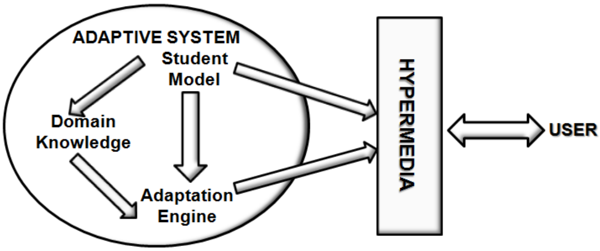

Fig. 1. Coarse-grained relations among components into Adaptive Systems. On the bases of a given SM, the Adaptation Engine configures a personalized course extracted from the Domain Knowledge. The course is presented to the student through a Hypermedia.

main components of an adaptive system. Before describing more in detail the characteristics of the new student model we will introduce some definitions about the elements we are going to work with, then we show new mechanisms defined in the Adaptation Engine, which exploit the new model.

Definition 1. (Knowledge Item). *A knowledge item KI is an atomic element of knowledge about a given topic. KI is a set: $KI = \{KI_K, KI_A, KI_E\}$ where KI_ℓ, with $\ell \in \{K, A, E\}$, represents a cognitive level taken from Bloom's Taxonomy: Knowledge, Application and Evaluation.*

We have chosen only three out of the six levels of Bloom's taxonomy: it is easy, but heavy, to provide the KI with all the six levels.

Definition 2. (Learning Style). *A Learning Style LS is a 4-tuple: $LS = \langle D_1, D_2, D_3, D_4 \rangle$, with*
$D_i \in [-11, +11]$, $i = 1, \ldots, 4$ where each D_i is a Felder and Silverman Learning Style Dimension, i.e., D_1: active-reflective, D_2: sensing-intuitive, D_3: visual-verbal, D_4: sequential-global.

We used the range $[-11, +11]$ according to the Felder-Soloman ILS scale.

Definition 3. (Cognitive State). *The Cognitive State CS is the set of all the KI_ℓ possessed by the student with respect to the given topic: $CS \subseteq DK$.*

Definition 4. (Student Model). *The student model SM is a pair: $SM = (CS, LS)$ where, CS is given in Definition 3 and LS is given in Definition 2.*

This is the original Student Model definition presented in [20]. In the following we will not consider LS, because they will stay unchanged. Rather, we refine KIs, which contribute to CS, with fuzzy aspects taking inspiration from the work reported in [11].

Definition 5. (Fuzzy Knowledge Item). *A fuzzy knowledge item KI is an atomic element of knowledge about a given topic. KI is a set: $KI = \{KI_K, KI_A, KI_E\}$ where KI_ℓ, with $\ell \in \{K, A, E\}$ is a real number. Each $KI_\ell \in [0, \ldots, 1]$. The less the value, the less is the knowledge acquired for that item. KI is divided in four evaluation classes:* $[0, 0.4)$ *not sufficient,* $[0.4, 0.6)$ *sufficient,* $[0.6, 0.8)$ *good,* $[0.8, 1]$ *excellent.*

With this definitions we will represent always all the KI the student will deal with, even if they are equal to 0 (see the outcome of the two SM in Fig. 3). On the other hand in the previous SM in CS there were only KI (fully) acquired.

The use of fuzzy logic is highlighted in the evaluation mechanism, in particular when a student is assigned a score to the end of a quiz. In order to describe these mechanisms we have to introduce the Learning Node which is strictly related to the quiz.

Definition 6. (Learning Node). *A Learning Node LN is a 5-tuple: $LN = \langle LM, AK, RK, LS, T \rangle$* where

- LM *is the Learning Material, i.e., any instructional digital resource.*
- AK *Acquired Knowledge. It is a KI_ℓ that represents the knowledge that the student acquires at a given level as specified in Definition 1, after having passed the assessment test related to the KI_ℓ of the node. If such a test is not present in the node the AK is considered acquired anyway.*
- RK *Required Knowledge. It is the set of KI_ℓ necessary for studying the material of the node, i.e., the cognitive prerequisites required by the AK associated to the node.*
- LS *is given in Definition 2.*
- T *is a pair of reals $T = (t_{min}, t_{max})$ that represents the estimated time interval for studying the material of the node, as prefixed by the teacher.*

Let us consider a quiz related to a given LN. The mechanism for computing scores related to quizzes are normalized, for each quiz, between 0 and 1. Let us consider a LN having N questions related to it. The set of all the questions $Q_{LN} = \{q_1, \ldots, q_N\}$ forms the quiz for that LN. Each q_i has a weight w associated to it, i.e. the score obtained in case of correct answer. The maximum score a student can get in a quiz is 1.

$$\sum_{k=1}^{N} w(q_i) = 1$$

In this way, the score is directly related to the degree of knowledge acquired for that LN. In case the teacher does not specify weights, the weight computation is given by

$$w(q_i) = \frac{1}{N}$$

In particular, the new aspects of the student model will be the following: new representation of the student's knowledge; new representation of the score tests; new management of time variable associated to quizzes.

According to it, the learner's knowledge will be classified within one of these four classes.

Timing are also considered in a different way: time computation is no more related to material fruition (that is difficult to estimate), but to the time the student needs to take the quiz at the end of each Learning Node. This is actually more realistic evaluation than the time spent for studying the lesson itself. Obviously it is not possible to know if the fruition time (t_f) of a Learning Node is actually spent on studying or if it is affected by other factors. However, the thresholds t_{min} and t_{max} that we consider, allow to eliminate at least two student behaviors: the so-called "coffee break" effect, when the fruition time t_f is greater than t_{max}, and a casual browsing of a given material, when t_f is less than t_{min}.

This kind of knowledge representation provides also more flexibility for the teacher that can fix different thresholds for different LN, depending on the importance that LN has in the context of a given course. For example if a LN explains a very important concept that the student must acquire, the teacher can fix threshold to 0.7 and if less that LN will be proposed again to the student.

4 Experiments with Moodle

The new student model and the related management has been implemented into LS_Plan and Moodle 1.9. The experimentation has been carried out with the purpose of verifying if the new student model is more refined than the previous one, highlighting the differences between the same two courses, the one running with improved LS_Plan and the other one with the original plug-in. The experimental course is very small, but enough to show the difference with the previous system. Fig.2 shows the platform and the conceptual map of the experimental course. In this experiment all the concepts are at the same level K.

We consider two courses with 5 Learning Nodes which represent the concepts related to the course on neorealist cinema: intro C_1, themes C_2, movies C_3, desica C_4, rossellini C_5. For the sake of readability in the table we show labels associated to the topics. 5 students attended the course. They first answered to the initial questionnaire. For each concept the system selected a number of questions between 3 and 6. The overall initial questionnaire was composed by 15 questions. The old system memorized the Cognitive State reported in the following table:

The new system memorized also the level of knowledge that students got for each concept in the KI Score section of the LS_Plan Data Base.

We follow the student $s2$ whose initial situation is depicted in Fig. 2. The figure is a snapshot of the system after the initial questionnaire. Let us note that only C_2, C_4 and C_5 are proposed to the student, because he proved to know already concepts C_1 and C_3 in the initial questionnaire. $s2$ studies the first lesson proposed by the system, $C_2 themes$, obtaining a score of 0.7 as reported in Tab. 3.

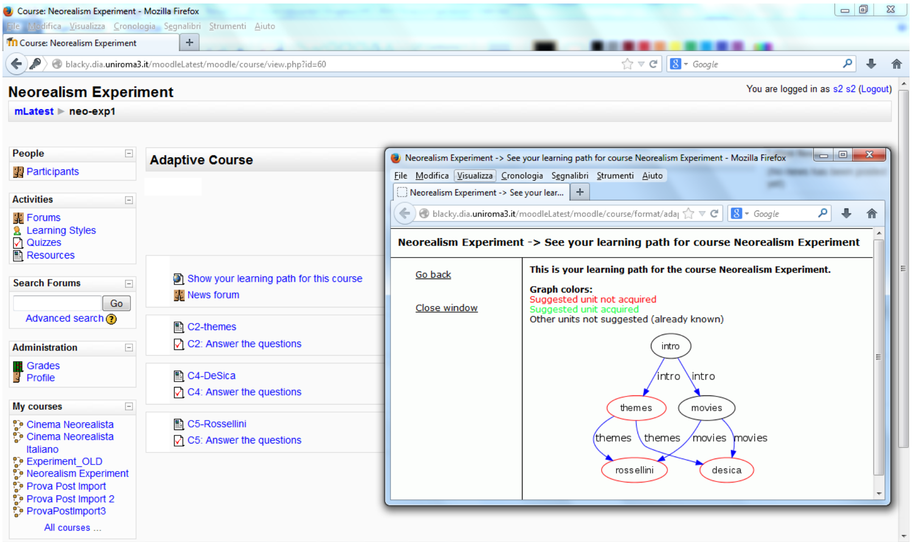

Fig. 2. The experimental course. The interface of the old system and the new one is exactly the same, the difference is in the internal user knowledge representation and in the adaptation mechanism at the initial stage.

Table 1. Cognitive state of the students after the initial questionnaire

Student	Course	Cognitive State	CS Level
s1	id1	C_1,C_2,C_5	K,K,K
s2	id1	C_1,C_3	K,K
s3	id1	C_2,C_4	K,K
s4	id1	C_2	K
s5	id1	C_2,C_3,C_5	K,K,K

Table 2. Cognitive state of the students after the initial questionnaire with the new student model. Bold numbers in the rightmost column represents the acquired concepts.

Student	Course	Cognitive State	CS Level	KI score ($C_1,\ldots,C_5$)
s1	id1	C_1,C_2,C_5	K,K,K	**0.5**, **0.4**, 0.2, 0, **0.5**
s2	id1	C_1,C_3	K,K	**0.5**, 0.1, **0.5**, 0.2, 0.2
s3	id1	C_2,C_4	K,K	0.2, **0.4**, 0.1, **0.5**, 0.2
s4	id1	C_2	K	0.1, **0.5**, 0.2, 0.2, 0.1
s5	id1	C_2,C_3,C_5	K,K,K	0.1, **0.4**, **0.4**, 0.2, **0.5**

The visible effect of the updating mechanism is an indication of the knowledge acquired during the course (together with the learning preference that can be tuned during the fruition of a course) as indicated by the system, like in Fig. 3.

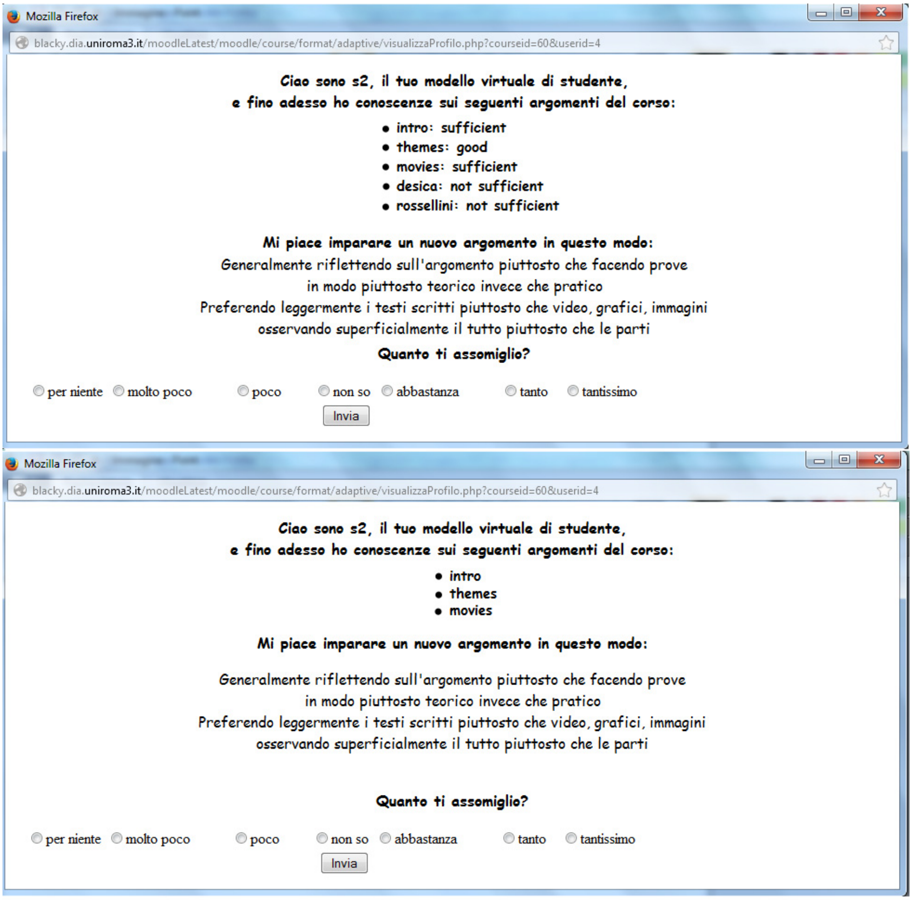

Fig. 3. The outcome of the two advices. On the top there is an dialogue window that describe user's knowledge with the new model: all the KI are listed with their respective degree of acquisition. In the dialogue window below, the previous SM indicates only the list of acquired KI.

Table 3. KI score updating for concept C_2 of student $s2$

Student	Course	Cognitive State	CS Level	KI score $(C_1, \ldots, C_5)$
s2	id1	C_1,C_3,C_5	K,K	$\mathbf{0.5}, \mathbf{0.7}, \mathbf{0.5}, 0.2, 0.2$

5 Conclusions

In this work we adopted fuzzy representation for a student model used into the Adaptive Educational System LS_Plan. Starting form the student model proposed in [20] and taking inspiration from the work presented in [12] we introduced a fuzzy representation of the Cognitive State of the student model and, consequently, all the related adaptation rules. These rules act mainly at the quiz level, in particular fuzzy CS modeling allows to give a more fine grained evaluation about the knowledge acquired by the student and a consequent freedom for the teacher to apply possible different didactic strategies.

In fact, with this new personalization process, not only teachers can estimate in a more precise way how much a student knows about a given topic, but also the student can have more appropriate suggestions about her/his way of learning.

The adaptation has been carried out with a plug-in for Moodle 1.9. We are going to adapt it to Moodle 2.5 in order to perform wider experiments.

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