"An Overview of Student Modeling Approaches under Uncertain Conditions"

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Abstract – This study presents an overview of student modeling approaches under uncertain conditions prevalent in e-learning environments. The student model plays a vital role in the adaptation of the instruction as per students' current knowledge. A discussion on the most commonly used student modeling approaches is presented. The issue of inexact student modeling and approaches used to deal with uncertainty in student modeling tasks are then explored. Student modeling mechanisms, which is appropriate for interpreting student's interactions with learning objects in order to estimate their knowledge status under uncertain conditions, is discussed.

Keywords— Student model, Adaptive e-learning system, Fuzzy Student modeling

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1. INTRODUCTION

The main objective of an adaptive e-learning system is to provide individualized assistance to students in e-learning environments, so that they may achieve their learning goals effectively and efficiently. The student model plays a vital role in the adaptation of the instruction as per students' current knowledge and is an integral part of any adaptive e-learning systems (Dekson & Suresh, 2010). The adaptation of an e-learning system mainly involves choosing and presenting each successive teaching activity as a function of entire scope of student's knowledge of the subject being taught and other relevant features of the student, which are in turn maintained in a student model. Therefore, the student model is used to modify the interaction between system and student to suit the needs of individual students.

To create and maintain an up-to-date student model, an adaptive system collects data for the student model from various sources that may include implicitly observing student's interaction and explicitly requesting direct input from the student (Thomson & Mitrovic, 2009). This process is known as *student modeling.* However, there is no agreement of what information should be included in a student model. In general, a student model would include the student's *prior relevant learning*, the student's *progress within the course*, the student's preferred *learning style*, as well as other types of student-related information (Mustafa & Sharif, 2011). Implementing such a comprehensive student model would be a computationally challenging and time consuming task. For this reason, most developers of intelligent e-learning systems attempt to model the student only in relation to subject matter representation (Holt et al., 1994). There are many barriers to student modeling resulting from the problem of inferring knowledge about a student from data about his behavior or interaction with the system. Some of these barriers listed by Mazza and Milani (2005) are:

- The student modeling process generally contains a large amount of *uncertainty* due to the interpretive nature of observations and the assumptions were sometimes needed.
- Interpreting interaction data and explaining students' behaviour is *computationally challenging*.
- Students are, many a times, involved in *unanticipated, novel behaviour* that requires much sophistication to interpret.

A review of the common approaches used for student modeling in intelligent computer-based educational systems is presented followed by a discussion on techniques used to handle uncertainty in student modeling.

2. STUDENT MODELING APPROACHES

There are many approaches for student modeling; however, there is generally no one accepted classification developed to systematically compare these approaches. Few studies have attempted to classify student models [e.g., (Brusilovsky & Millán, 2007); (Djordjevic et al., 1996); (Elsom, 1993); (King, 1998)]. These studies seem to agree that the most commonly used basic student modeling approaches are: *Overlay* modeling, *buggy* (error) modeling and *Learner-based* modeling. The descriptions of these approaches are presented in the following subsections.

2.1. Overlay student modeling

The entire domain information consists of a set of knowledge elements or curriculum elements and represents the expert's knowledge in this domain. The overlay model describes the student's knowledge as a subset of the complete domain model. Lack of knowledge is derived by comparing the perceived student knowledge to the expert's knowledge [(Mott & Lester, 2006); (Martins et al., 2008)]. To each knowledge element in the learner's overlay model, a certain measure is assigned representing the estimated knowledge of the learner on that element. The measure can be a scalar (for example an integer, a probability measure or a flag) or a vector estimate (Henze & Nejdl, 2003).

In an overlay student model, the student is represented by a relatively simple mechanism, which supports inferencing about the student's cognitive state relative to an ideal domain expert (Stephen & Hopple, 1992). This gives a chance for an easy comparison between what the student knows and what he should know. The overlay model can be constructed from scratch as a semantic net, with nodes and arcs added as they are taught, or by starting with the expert knowledge base as a student model and interpreting deviations that are subsequently detected (Rickel, 1992). An overlay model allows a flexible model of the learner's knowledge for each topic. The complexity of an overlay model depends on the structure of the domain knowledge, where the granularity is important. Further, the estimation of the learner's knowledge is important and is measured by examining the sections the learner has read and the tests the learner has taken (Dagger, Wade & Conlan, 2004).

Using an overlay model, student errors will be interpreted as a lack of knowledge (Stephen & Hopple, 1992), which means that there is no plan to account and correct the student's misconceptions. This can be considered as a major disadvantage of the overlay modeling because misconceptions are common amongst average students and intelligent educational systems must deal with them regularly. There are many intelligent tutoring systems (ITS) that implement overlay models, for example, SCHOLAR – a geography tutor for South America (Carbonell, 1970), BIP – a problem-solving laboratory for introductory programming (Barr, Beard & Atkinson, 1976), WEST – an electronic board game to teach arithmetic (Burton & Brown, 1978), WUMPUS – an educational game for teaching probabilistic reasoning (Goldstein, 1982), GUIDON – a tutor built on the medical diagnostic system MYCIN for medical student tutoring (Clancey, 1983), TRILL - The Rather Intelligent Little Lisper (Cerri & Elsom, 1990), AST – an Adaptive Statistics Tutor (Specht et al., 1997), PAT Online – a web-base algebra tutor (Brusilovsky et al.,1997), and Virtual Campus PROLOG Tutor (Peylo et al., 2000).

2.2. Buggy (error) student modeling

Burton (1982) introduced the buggy modeling approach, which considers both *correct and buggy rules* that the student may follow. The buggy model attempts to represent the *erroneous beliefs* of the student in terms of a set of bugs or misconceptions (Kumar, 1992). The common technique for implementing a buggy model is to represent explicit knowledge of likely misconceptions beside the representation of the expert knowledge.

The system requires a library of bugs in determining the buggy model of a student. Depending on the incorrect answers of a student to a set of questions, it is possible to determine bugs in the student's understanding by mapping the student's behaviour to bugs in the library (Kumar, 1992). The inclusion of the bugs allows more sophisticated understanding of the student than the understanding accomplished with a simple overlay on the expert model (Holt et al., 1994).

King (1998) indicates that buggy models can be divided into two categories. The first is the *Enumerative model*, which models both correct knowledge and common misconceptions. This normally relies on the reliability of the bug library. In most cases, it is necessary to enumerate all the bugs based on some empirical analysis of students' errors. Other approaches for enumerating bug libraries are informed by studies of human learning that uses concept learning theories to define possible patterns of erroneous reasoning. The second category is the *Reconstructive model*, which determines misconceptions when a student improperly applies operators during some procedural task; there is no need for bug library since misapplied operators will determine misconceptions (King, 1998).

A buggy model is domain independent, and represents both a student's knowledge and some student-expert differences, defined explicitly. The utilization of a bug library provides information that can be used to promote the students' self-reflection and to give hints on context comprehension (Tsinakos & Margaritis, 2000). Unfortunately, there are many disadvantages, for example, buggy models are difficult to design and implement (Stephen, 1992), and in some cases, they do not explain why bugs have occurred (Verdejo, 1994).

Some examples of systems that use buggy models are LMS - a system for testing algebra skills (Sleeman & Smith, 1981), PROUST - a system for teaching PASCAL programming (VanLehn, 1982), MALGEN – which attempts to determine common misconceptions by forming new problem-solving operators that represent incorrect knowledge (Ellery et al., 1990), and INSTRUCT – which models tasks where domain knowledge can be partitioned into a set of operators and a set of applicability conditions (Djordjevic et al., 1996).

2.3. Leaner-based modeling

Learner-based models can explain *misconceptions* in the student's knowledge in terms of their *generation* process (Brown & VanLehn, 1980). This approach, alternatively called *genetic modeling* (Brusilovsky, 1994), is based on the idea that when students construct knowledge over time, they can gradually form misconceptions, which in turn prevent a student from progressing through the course (King, 1998). Using this approach, it is important to explain the mechanisms by which the student acquires knowledge to enable the tutoring system to understand more about a particular student's learning abilities and to justify the problems with his abilities (Elsom, 1993).

Learner-based models are usually implemented using *machine learning* techniques (e.g. neural networks and genetic algorithms) to emulate the generation process. This approach, therefore, brings intelligent educational systems one step closer to human-like performance (King, 1998). A comprehensive review of using machine learning techniques in student modeling can be found in (Sison & Shimura, 1998). Examples of systems that implement learner models are: DEBUGGY – a system that evaluates a student's subtraction performance and describes misconceptions by selecting predefined bug specifications and then iteratively removes, combines or forces elements of the evolving set until a student's answers to a set of subtraction training examples are explained (Burton, 1982); PIXIE/INFER – which attempts to form student models through operator specialization and designed to model a student's problem solving ability and to provide appropriate remediation to improve the student's performance (Ellery et al., 1990), and ASSERT – which attempts to determine commonalties between newly created knowledge bugs through the use of bug generalization procedures (Baffes & Mooney, 1996).

Each of the modeling approaches discussed is applied in different intelligent educational systems and has its pros and cons. The bug models and genetic models are certainly more powerful than the traditional overlay model, but they are also much harder to develop. This restricts the use of these models mostly to problem solving ITS and to experimental systems, thereby limiting the practical use of these models. The overlay model is considered to be simple, flexible and more powerful in reasoning the students' knowledge status (Brusilovsky & Millan, 2007). In web based education systems, the student modeling task is fraught with uncertainty, especially when it depends mainly on the students' interactions with the course. Most of the information included in the models comes from *observations* and *guesses* about the students, which may be proven right or wrong from their later performance (Chrysafiadi & Virvou, 2012). The following sections deal with techniques used to handle such uncertainty in student modeling.

3. STUDENT MODELING AND UNCERTAINTY

Many techniques are used in AI to reason in uncertain environments. Amongst the most popular techniques are statistical (probabilistic) reasoning and fuzzy logic, and both techniques are used widely to reason in uncertain environments (Zadeh, 2005). These AI techniques have also been applied to model the students' cognitive aspects. The aim of the discussion is to explore and identify a suitable approach for estimating the students' knowledge status using the evidence available from web-based learning system's tracking data.

3.1. Student modeling using statistical reasoning

Statistical reasoning in AI is usually based on the Bayes' theorem, which provides a mechanism for combining new and existent evidence usually given as *subjective probabilities*. It is used to revise existing prior probabilities based on a new set of observation made (Turban & Aronson, 2005). Rich and Knight (1993) also demonstrate that the Bayesian statistics provides an attractive basis for uncertain reasoning systems. Several mechanisms for exploiting its power and making it more tractable have been developed, e.g. Bayesian Networks, and Certainty Factors.

Reasoning using Bayesian Networks

Bayesian methods support the use of probabilistic inference to update and improve belief values. The main goal of Bayesian networks is to enable probabilistic inference. According to Li and Ji (2005), Bayesian networks are used for plan recognition, user's needs inference and affective state assessments. To infer the current state and needs of the learner, taken pauses and errors are considered. Further, goals and needs are inferred by using the learner's background, actions and queries. The current emotional and mental aspects of the learner are an important indication of the learner's state, intention and needs (Li & Ji, 2005). Therefore, the affective state is a point of interest and can be generated by using Bayesian networks (Arroyo & woolf, 2005). For example, the emotional states are modeled as consequences of how the current action fits to the learner's goals and preferences.

Bayesian networks are used to model students in many intelligent educational systems. Bayesian networks have been proposed to relate a particular piece of a student's knowledge with the student's observable behavior in a probabilistic way [(Pardos et al., 2007); (Stathacopoulou et al., 2003); (Wei & Blank, 2006)]. Many intelligent systems use Bayesian networks for student modeling, for example, OLAE (Martin & VanLehn, 1995), POLA (Conati & VanLehn, 1996), CAPIT (Mayo & Mitrovic, 2001), Andes (VanLehn & Niu, 2001), ACE (Bunt & Conati, 2003) and ASSISTment (Feng et al., 2006).

Bayesian networks require considerable computational efforts and emphasize the need for sophisticated domain and expert models. Conati *et al.* (2002) admitted that the performance of the computer used became much slower and in some cases they had to direct Andes to use stochastic evaluation of the networks to stop the reconstruction process.

In conclusion, the Bayesian networks prove effectiveness when used to model students in many applications. However, Bayesian networks are not computationally simple. They still depend on the acquiring of conditional probabilities and sophisticated domain and expert models. Significant time and effort are needed to initialize the Bayesian networks and to provide all probabilistic parameters (Pardos et al., 2007). This is not always a straightforward task because people are usually poor probability estimators. Therefore, in many cases Bayesian networks are not the natural choice for the construction process of student models. Instead a simpler, fairly intuitive, technique is required so that the majority of teachers who use web-based learning system can follow it easily or, at least, can participate effectively in providing the necessary metadata required for representing domain knowledge.

Reasoning using certainty factors

Standard statistical reasoning methods assume uncertainty due to the probability that an event may be true or false, whereas the certainty factor theory takes uncertainty as a function of *degree of belief*. The certainty factor model has been used as a method for representing and manipulating of uncertain knowledge in the rule-based medical expert system MYCIN (Shortliffe & Buchanan, 1975). Turban and Aronson (2005) define Certainty Factor (*CF*) as a figure that expresses a degree of belief in an event, fact, or hypothesis based on evidence or an expert's assessment. Several methods can be used to handle *CF* in intelligent systems. Klein and Methlie (1995), Rich and Knight (1993), and Turban and Aronson (2005) agreed that the approach used in MYCIN [(Buchanan & Shortliffe, 1984); (Shortliffe & Buchanan, 1975); (Shortliffe, 1976)] is the most acceptable approach for calculating the certainty factors. In MYCIN, the numbers attached to certainty factors take values in the range (-1, 1). If the value is positive one believes that the fact is true; if it is negative one believes that the fact is not true, with complete knowledge or certainty at each extreme -1 and +1 (Klein & Methlie, 1995). In this approach, certainty factor ($CF\,[h, e]$) is defined in terms of two components:

1. $MB\,[h, e]$- A measure (between 0 and 1) of belief in a hypothesis h given the evidence e; it measures the extent to which the evidence supports the hypothesis.

2. $MD\,[h, e]$- A measure (between 0 and 1) of disbelief in hypothesis h given the evidence e; MD measures the extent to which the evidence supports the negation of the hypothesis.

Using these two measures, CF is defined as:

$$CF[h, e] = MB[h, e] - MD[h, e] \quad \textbf{(1)}$$

When several pieces of evidence are combined to compute the CF of one hypothesis, the measures of belief and disbelief of a hypothesis given observations $s1$ and $s2$ are computed from:

$MB\,[h, s_1 \wedge s_2] = 0$ if $MD\,[h, s_1 \wedge s_2] = 1$

$= MB\,[h, s_1] + MB\,[h, s_2]$.

$(1 - MB\,[h, s_1])$ otherwise **(2)**

$MD\,[h, s_1 \wedge s_2] = 0$

if $MB\,[h, s_1 \wedge s_2] = 1$

$= MD\,[h, s_1] + MD\,[h, s_2]$.

(1- *MD* [h, s_1]) otherwise **(3)**

This can be stated as: the measure of belief in *h* is zero if *h* is disbelieved with certainty. Otherwise, the measure of belief in *h* given two observations is the measure of belief given by the first observation plus some increment added for the second observation. This increment is computed by firstly taking the difference between 1, the complete certainty, and the belief given from the first observation. This difference is the most that can be added by the second observation. The difference is then scaled by the belief in *h* given only the second observation. Similarly, it is possible to give an explanation for the formula of computing disbelief (Rich & Knight, 1993).

The approach of certainty factors appears to mimic quite well the way people manipulate certainties (Shultz et al., 1989). In addition, Rich and Knight (1993) state that this approach makes strong independence assumptions that make it relatively *easy to use*; at the same time these assumptions create *dangers* if the important dependencies are not captured correctly. This will not affect the reliability of the approach especially when individual evidence (antecedent)/hypothesis (consequent) relationships are considered *independently* of the others. In other words, the reliability of the approach will be negatively affected if *chaining* of individual dependent evidences (which lead to a certain hypothesis) is considered while the relationships between these evidences are missed or not correctly defined.

In web-based learning system, a student's interactions captured and maintained by learning system can be considered as evidence for the student's cognitive state. Each individual interaction related to a certain domain concept can be considered as evidence (belief or disbelief) to determine the knowledge level of that concept. In addition, the low mastery level of a domain concept can be explained by the absence of some types of interactions (e.g. the interactions which indicate that the student has visited the learning objects related to the concept do not exist) or by the existence of some interactions (e.g. *interactions which indicate erroneous solution of quizzes related to the concept*). The necessary data (measures of belief and disbelief) required to initialize this approach is relatively easy to acquire when compared with data required by the Bayesian network approach. It is easier to ask teachers specifying their beliefs and disbeliefs than to ask them to state the probabilities of all outcomes. Moreover, certainty factor approach does not require sophisticated schemes to represent domain knowledge. These mentioned factors make the overall computational effort required to estimate a students' knowledge status relatively simple. The following subsection discusses the combination of certainty factors with fuzzy logic and fuzzy set theory to handle uncertainties in student modeling.

3.2. Fuzzy student modeling

The certainty factors approach described above can be used as a mechanism to compute a scalar value (from -1 to 1) to represent the knowledge level of any domain concept represented in the overlay student model. This scalar value depends on the values of measures of belief and disbelief. In some cases, the computing of these measures needs an interpretation mechanism so that it can be reasonably estimated. For example, if the understanding measure of belief assigned to reading a page for five minutes is 0.4, what will be the value of this measure if a student read the page for only two minutes or for 15 minutes? Another issue to be considered is the determination of the knowledge levels of different concepts. For example, if the certainty factor of a concept is 0.3, what will be the status of that concept (i.e. learned or unlearned)? These issues show the need for some concepts of fuzzy logic and fuzzy set theory.

Traditional set theory defines set membership as a Boolean predicate, e.g. one is either tall or not and of course there must be a specific height that defines the boundary. Fuzzy set theory (Zadeh, 1965) allows us to represent set membership as a possibility distribution, i.e. one's tallness increases with one's height until the maximum boundary is reached. Turban and Aronson (2005) point out many advantages of fuzzy logic, e.g. providing flexibility, giving options, and allowing for observation.

In conclusion, fuzzy set theory attempts to capture the notion that items can have varying degrees of membership within a set, as opposed to the standard view that an item either belongs or does not belong to a set. For example, a student might have partial membership within the set of students who are expert in a particular skill, as reflected in teacher comments, e.g. "student S is *fairly good* at two-column multiplication".

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. The students' interactions with the learning system are considered to be the main source of information for judging the students' knowledge status. In fuzzy student modeling, the interpretation from students' interactions to extract useful information is of utmost importance. Papanikolaou *et al.* (2003) propose one such fuzzy logic-based approach to store, interpret and analyze uncertain information in building decision making model which also evaluates students' knowledge status and skills. As the fuzzy logic based methods are more close to and consistent with the human-being decision-making processes, hence to deal with uncertainty many researchers have integrated fuzzy logic into the student model of ITS (Shakouri & Tavassoli, 2012).

In Agent Based Intelligent Tutoring System (ABITS), reading a learning object (e.g. lesson) reasons a slight increase of the student's knowledge of these concepts with a large degree of uncertainty, while answering a test correctly increases the knowledge degree of the concerned concepts but with a lower degree of uncertainty (Capuano et al., 2000). In InterBook, user activities like reading text, looking at examples, or solving multiple-choice tests are tracked by the system in order to determine a score which reasons the user's current state of knowledge in the related concept. These scores are finally projected into a scalar value by applying some simple linear equations, and is used to estimate the educational state of any concept (Brusilovsky et al., 1997). As described by Brusilovsky & Millan (2007), the overlay model is powerful and flexible since it can independently measure the student's knowledge of different topics.

Fuzzy techniques are used in combination with different approaches for building student models. For example, in ATS (Adaptive Tutoring system), the student modeling component uses machine-learning techniques to emulate a student's learning state combined with fuzzy methods to represent uncertainty (Gurer et al., 1995). The Brilliant Scholar Series-1 (BSS1) is used by several thousand home and school users in the learning of curricular subjects such as mathematics and sciences (Warendorf & Tsao, 1997). BSS1 uses heuristics to interact with users and monitor their progress. Fuzzy logic techniques have been used to improve the performance of BSS1. A general fuzzy logic engine was designed and implemented to support development of intelligent features for BSS1 (Warendorf & Tsao, 1997). Tsaganou *et al.* (2002) present FCBRDHTC, a Fuzzy Case-Based Reasoning method for modeling student's Historical Text Comprehension. The fuzzy Case Based Reasoning algorithm handles the uncertainty in the acquisition of the expert's knowledge regarding the student's observable behaviour during historical text comprehension. Stathacopoulou *et al.* (2003) proposed an approach for student modeling based on both neural networks and fuzzy modeling approach. Fuzzy logic is used to handle the subjective judgments of human tutors with respect to student observable behaviour and their classification of the student's knowledge. The student's knowledge is decomposed into pieces and assessed by combining fuzzy evidence, each one contributing to some degree to the final assessment (Stathacopoulou et al., 2003). Kavcic (2004) proposed a fuzzy user model to deal with vagueness in the user's knowledge description. The proposed model used fuzzy sets for knowledge representation and linguistic rules for model updating. Nikravesh and Takagi (2003) cite many examples that use fuzzy techniques for user modeling. Chrysafiadi & Virvou (2012) used an overlay model and fuzzy logic technique in order to define and update the student's knowledge level of each domain concept, each time the student interacts with the e-learning system.

Based on the above discussions, we argue that the approach of certainty factors can be used along with some ideas from fuzzy logic and fuzzy set theory to reason about a student's knowledge status and this approach can be beneficial if applied to model the uncertainties in student modeling.

4. CONCLUSION

Student models are usually implemented in intelligent educational systems to adapt the learning process according to the student's knowledge and skills. There is no formal classification for student modeling techniques used in intelligent learning environments, and there is no agreement about the information that should be kept in student models and the ways by which this information can be used to diagnose the students' errors and misconceptions. It appears that information kept in student models depends mainly on the domain being represented, the domain knowledge representation technique, and on the student modeling technique being used. Moreover, this information depends on the adaptive and individualization features, the developers aim to implement in the educational system. Web-based intelligent educational systems use student models to support students in navigating through the course and preventing them from being lost in hyperspace. Most adaptive techniques and collaborative features used within these systems primarily depend on information from student models. A review of important student modeling concepts, approaches, and systems is presented. The issue of inexact student modeling and approaches used to deal with uncertainty in student modeling tasks are also discussed. Student modeling mechanism, which is appropriate for interpreting student's interactions with learning objects in Web-based intelligent educational environments, is presented.

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