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Student modeling: Recognizing the individual needs of users in e-learning environments

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Abstract
Along with numerous universities and large trading companies heavily relying on e-learning environments to train their students and employees, the design and development of adaptive educational hypermedia that customize the content and navigation for each student has gained importance and priority all around the world. This study aims to describe the concept of student modeling, heart of the adaptive learning systems, and analyze the information collection, construction and updating phases of a student modeling process. In the study, the classification of student models in numerous ways is explained, and the different methods employed in the representation of information in the student model are addressed. Moreover, the problem of uncertainty, which is one of the most important challenges in the student modeling process, is mentioned, and the trends in student modeling are discussed.

Keywords: Student modeling, inference, modeling techniques, adaptive educational hypermedia systems

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Öğrenci modelleme: E-öğrenme ortamlarında kullanıcıların bireysel gereksinimlerinin ayırt edilmesi

Sibel Somyürek*

Özet
Pek çok üniversite ve büyük ticari şirketin öğrencilerini ve çalışanlarını eğitmek için internet temelli eğitim ortamlarını tercih etmesiyle birlikte, her bir öğrenci için içerik ve gezinmeyi kişiselleştiren uyarlanabilir eğitsel hiper ortamların tasarlanması ve geliştirilmesi tüm dünyada önem kazanmıştır. Bu çalışma, uyarlanabilir öğrenme sistemlerinin merkezinde yer alan öğrenci modelleme kavramını tanımlayarak, öğrenci modeli oluşturma sürecindeki öğrenci hakkında bilgi toplama, öğrenci modelini yapılandırma ve öğrenci modelini güncelleme aşamalarını ayrıntılı bir şekilde ele almak amacıyla gerçekleştirilmiştir. Çalışmada öğrenci modellerinin çeşitli şekillerde sınıflandırılmasına ilişkin bilgi verilerek, bilgi gösteriminde kullanılan farklı yöntemler üzerinde durulmuştur. Ayrıca öğrenci modelleme sürecindeki en önemli zorluklardan birini oluşturan belirsizlik probleminden bahsedilmiş ve öğrenci modellerinin sahip olması gereken standartlar tartışılmıştır.

Anahtar Kelimeler: Öğrenci modelleme, sonuç çıkarma, modelleme teknikleri, uyarlanabilir eğitsel hiper ortam

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Introduction

Today, along with the huge rise in the amount of information required to be learned and the developments in digital technology, numerous universities and large trading companies all around the world began offer internet-based education to train their students and employees (Ebner, et al., 1999; De Bra, 1996). Due to the accessibility of internet-based education environments in terms of number and diversity of education programs, students who take classes over the Internet tend to be more heterogenously distributed than the students in the traditional class setting. Therefore, the need to personalize the learning material for each student becomes of more importance in internet-based education environment. This problem is attempted to be eliminated by developing adaptive educational hypermedia (Surjono and Maltby, 2003).

Adaptive educational hypermedia are advanced hypermedia systems that structure the learning environment by building a model of the student's goals, interests, and preferences and customize the education for each student (Brusilovsky, 1998). In educational hypermedia, according to the prior knowledge of students or the relations between topics, it is possible make adaptations such as suggesting relevant topics for studying, offering extra information for those who would like further information, listing down the topics preferred the most by students, presenting of other subjects about which different students interested in while studying the current subject, presenting the links in a different order for each students, etc. In order to provide different services to different users, an adaptive system needs to define and distinguish a user or user groups (Zhang and Ghorbani, 2007). Without knowing anything about the user, an educational hypermedia application will offer the same learning content and pedagogic methods to each student (Fröschl, 2005, p:10). Therefore, a user model that recognizes the individual learning needs and preferences is the key element for personalization in adaptive systems.

User Model

A model is an abstract presentation of something that exists in the real world (Koch, 2000, p:35). A user model, on the other hand, is the presentation of a mental status (such as knowledge, preference, background, and experience) related to a context in the real world (De Bra, 1999). Stated differently, the user model mean the systems set of beliefs about the user's (Kay, 2000).

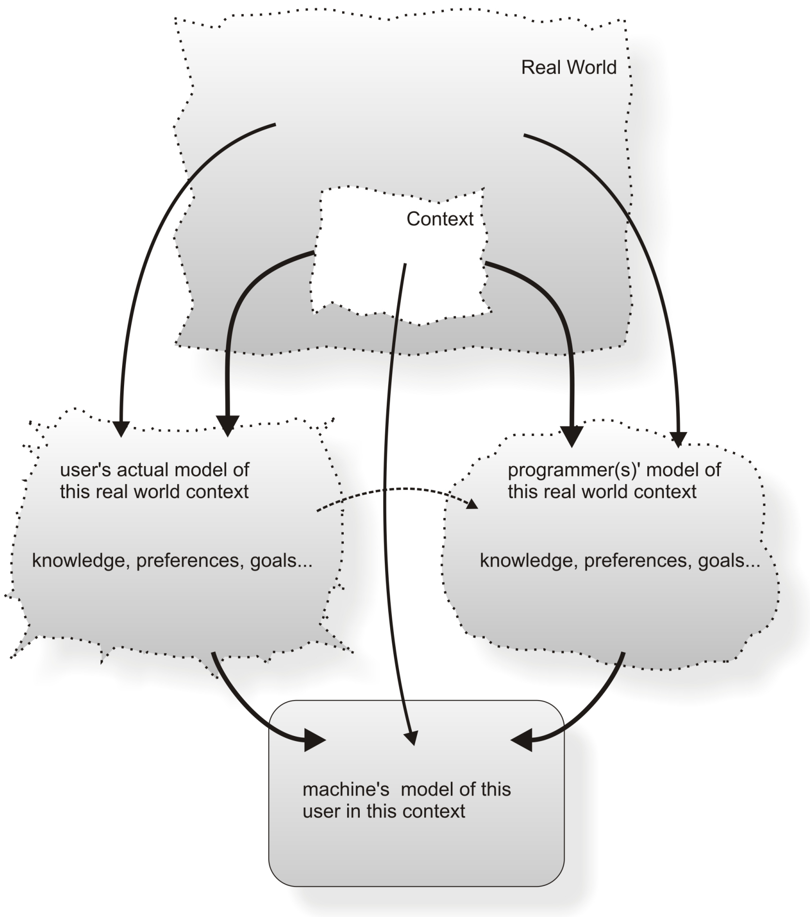

Figure 1. User Model (Kay, 2000)

In adaptive systems, the user model stores the specific information on each individual, and in this way enables the system to identify different users (Butz, Hua, and Maquire, 2006). The entire user model building/updating process is called user modeling. The fundamental goals of user modeling may be listed as follows (Jameson et al., 1997):

- To assist the user in locating information;
- To customize the information presented to the user;
- To modify an interface according to the user;
- To select appropriate instructional exercises or interventions;
- To provide feedback to the user on the level of their knowledge;
- To reinforce collaboration,
- To predict future behavior of users.

Since the core task for any user modeling system is predicting future behavior of users, there exist numerous user models which automatically identify user patterns and give suggestions to users on what to do (White, Bailey and Chen, 2009; Bohnert, 2008; Sas et al., 2003; Barra, Malandrino, Scarano, 2003; Trousse, 2000).

The user in adaptive learning systems is the student. Therefore, in adaptive learning systems, the concept of "student model" is used instead of user model.

Student Model

One of the most important features that differentiate intelligent learning systems from traditional learning systems is the ability to interpret student behavior that make modeling of learning and thinking processes of student possible (Shute and Psotka, 1996). The student model is one of the four dimensions that intelligent learning systems must include and student modeling constitutes the essence of researches on intelligent learning systems such as adaptive systems (Holt et al., 1994).

Classification of Student Models

Student models vary widely and may be classified in different ways depending on their different features. For instance, student models can be divided in two groups according to the structure of the information as "field dependent" and "field independent" on the subject. Information that is field dependent indicate the knowledge and capability level of the student related to the course content offered within the adaptive learning system, while field independent information contain information independent of content such as skills, motivational status, preferences, and learning styles (Brusilovsky, 1994; Shareef and Kinshuk, 2003).

Another classification is made based on the the information gathering source (single user – group of users) in the inference mechanism of the student models as "content based" and "collaborative". Content-based student models are used in situations where past behavior of the user may give an idea on his future behavior. For instance, if there is previous information indicating that a user likes movies such as "Star Wars", "Raiders of the Lost Ark", "Air Force One", a similar movie such as "The Eyewitness" may be suggested to that user. On the other hand, collaborative models are used when a user's behavior is similar to that of other users. In this approach, the student model is constructed in the light of information collected from a group of students, and this model is used to make estimations about one user. For instance, where the favorite movies of a user are similar to those of a group of users, other favorite movies of the users in this group may be suggested to that user (Zukerman and Albrecht, 2001).

Student models may be addressed in two different groups as “visible and opak”. If the student can see and/or change the student model, the student model is called “visible”; otherwise, it is called “opaque”. Visibility requires the user interface to ask questions and gather information about certain features from the student and display a part of or the whole of the model to the student (Höök, 1998; Kay, 1995). In visible student models, a more correct model can be constructed with the partnership of the user and the system. However, the users may want to define themselves as an expert to the system or a playful or curious user may want to see how system responses would change when she acts differently. So, the users being able to view the model and make changes may lead to gathering incorrect information from time to time (Kay, 2000).

Student models may be addressed in two different groups as “dynamic and static”. Dynamic student models entail obtaining dynamic information about the user based on the user’s interaction with the system. The student model is constantly updated with the information obtained in this way. In static student models, the information is obtained from queries or observations. Information obtained in this way is gathered either the first time the user uses the system (in the initial phase) or periodically (Koch, 2000, p:38).

Student models may be classified in four groups as “prediction, recommendation, classification and filtering” based on the type of task for which the model is going to be used. Prediction is the capability of anticipating future needs of student using past student behavior. Recommendation is the capability of suggesting interesting elements to a student according to some extra information not based on the past behavior of the user. Classification builds a model that classifies items into one of several predefined classes. Filtering is the selection of subset items from the original set of items to provide each student with information corresponding to her/his preferences (Frias-Martinez et al., 2005).

Student Modeling Process

The first decision to be made when building a student model is what aspects of the student should model (Zhou and Evens, 1999). The student model should be constructed with students’ goals, knowledge, capabilities, preferences, multimedia experience, interests, personality in mind, which are effective in their learning (Kobsa, 2001). The student modeling process can be seen in figure 2.

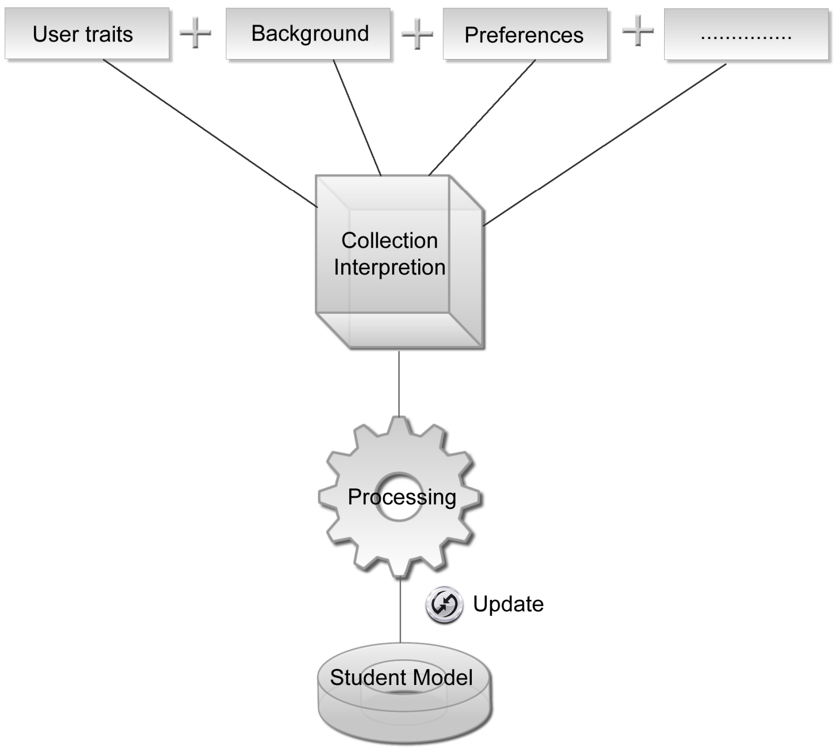

Figure 2. Student Modeling Process

The student modeling process has three basic phases:

- Gathering data related to the student characteristics
- Constructing the student model, and
- Updating the student model.

Gathering data related to the student characteristics

In order to construct the appropriate adaptations on the adaptive systems, the system should obtain some information on the user and the user context (Herder, 2006, p:28). To begin constructing the student model, information about the student (goals, plans, attitudes, capabilities, knowledge, beliefs of the learner, etc.) should be gathered up and transferred to this model (Fröschl, 2005, p:36). In the student information gathering process, both static and dynamic information is collected. Static information, including personality, cognitive style, etc., is obtained from student records and is quite stable. However, dynamic information that shows student performance and improvement throughout the student's interaction with the system is dependent on the field and changes in the learning process. Dynamic information is obtained from the results of the reaction and behavior of the student while using the system (Alotaiby, 2005).

The methods of gathering data related to the student characteristics may be listed as three main topics:

a. **Direct questions:** The initial information needed to construct the student modeling may be obtained via direct questions to the user. This method is an effective way to gather general information on the user. It may be used to determine the demographic data, interests, preferences, etc. of students. Questionnaires, forms, pre-tests, psychological tests may use in gathering data. However, it is difficult to determine the right number of questions, and too many questions may disturb the user (Beaumont, 1994; Tsiriga and Virvou, 2003; Nielsen, 1998). In the initialisation of the student model of existing adaptive systems, self-report measures through questionnaires or tests are commonly used (Limongelli et al, 2009; Somyürek, 2008; Surjono, 2007; Triantafyllou, Demetriadis and Pomportsis, 2003).

b. **Assumptions:** In situations where more information on the student is needed but it cannot be obtained in any other way, one may make assumptions. For instance, if it is unknown that the student has background information on the subject, it can be hypothesized that he has no knowledge on the subject in the beginning. Furthermore, in this method, similar students may be stereotyped and therefore group-specific options may be employed. For instance, the system may offer the help option to inexperienced users visible when they first log in to the system (Fröschl, 2005, p:37; Koch, 2000, p:47).

c. **User-system interaction:** The usage information obtained throughout the interaction of the user with the system is the most important information obtained about the user. This way, the pages that the user visits, access length and frequency, system log out time, answers given to the questions in the system, searches conducted, etc. may be determined. However, information gathered in this way may not be completely reliable. For instance, the fact that a user browses a page does not mean that she paid substantial attention to that page (Zhang and Ghorbani, 2007). A typical user exhibits patterns when accessing a hypermedia system and the set of interactions of the user with the system containing those patterns can be stored in a log database in the server. In this context, data mining and other machine learning techniques make it possible to to recognize regularities in user trails and to integrate them as part of the user model (Frias-Martinez, Magoulas, Chen, Macredie, 2005).

The information obtained using the methods above should be transferred to the variables properly that constitute a student model. Information may exist in three ways in the variables that make up the student model: boolean, discrete, and continuous. Variables stored in boolean form may take two values for each situation, right and wrong. For instance, the situation of a student knowing a concept may be stored as “knows” or “doesn’t know”. Discretely stored variables may take limited number of values for each situation. For instance, the situation of a student knowing a concept may be stored and classified as “knows well”, “knows”, or “doesn’t know”. Variables stored in continuum may take values between 0 and 1 for each situation. For instance, the situation of a student knowing a concept may be composed of values that vary between 0 and 1. In this case, 0 indicates completely unknown, 1 indicates completely known, and the values between 0 and 1 (0.2, 0.35, 0.82, etc.) indicate the status of knowing. In an adaptive learning environment, the possibilities for adaptation of the system to each student are greater in the continuous storage of variables as opposed to boolean and discrete storage. However, working with continuous variables requires system developers to deal with more complicated data (De Bra, 1998).

Constructing the student model

When constructing a student model, it is not sufficient to collect information merely on the student. The collected information should be used to represent the learning process of a student and to make decisions like determining the path which a student will follow during his/her learning process or choosing the most adequate pedagogical strategy for the next subject which will be presented (Wenger, 1987).

This topic focuses on uncertainty problem and student modeling techniques.

Uncertainty problem

One of the most important problems encountered when constructing a student model is uncertainty (Butz, Hua and Maguire, 2006). In order to construct the student model, it is required to obtain some information such as the student's behaviors' around the system, interests, personal characteristics, and in the light of this information, some facts such as the student's learning speed and learning preferences should be divulged. However, it is generally not possible to figure out exact information by using the data to interpret on how much the student knows on a certain subject, how the student's learning preferences will change in the study process, etc., as individual behaviors are complicated, and may change instantly with situation, environment and time. For instance, a student may prefer to study a content using captured videos while he may prefer to study a similar content using interactive examples. Furthermore, the same student may desire to study the same subject in different ways at different times. Therefore, in the student modeling process, coming up with correct estimations on the user based on uncertain information is an important problem that should be addressed (Butz, Hua and Maguire, 2006). The first student modeling systems attempted to make decisions using manually constructed rules reached by analyzing various situations about the problem, in order to make deductions from observations on the user. These systems have not been able to attain the desired performance due to heavy dependence on the source and not being able to generate solutions under uncertain conditions (Zukerman and Albrecht, 2001). Furthermore, serious problems occurred in the construction and updating of these systems. First modeling approaches worked with a system based on accepting an absolute right or wrong, also known as Boolean logic. In Boolean logic, any situation has to be assigned one of the two values such as "yes" or "no", "1" or "0", or "knows" or "doesn't know". Therefore, no matter how detailed the models constructed using this logic, they do not completely reflect the truth. The reason is that the real world is complicated, generally due to uncertainty and the lack of certain judgements (Baykal and Beyan, 2004).

As traditional information presentation methods proved insufficient in modeling human behavior, the question of how to deal with uncertainty has been a rapidly spreading and increasing research topic from early 1990's on (Jameson, 1996, Butz, Hua and Maguire, 2006). In uncertain situations, the systematic pre-planned numeric forecasts can only be made after certain acceptance and assumptions (Baykal and Beyan, 2004). Due the possibility of accessing large quantities of electronically available data and by advances in machine learning of artificial intelligence, the predictive statistical models constructed on these acceptance and assumptions gained momentum and began to be used in student modeling (Zukerman and Albrecht, 2001). Artificial neural networks, Demster Shafer approach, and

Bayesian networks may be given as primary examples to these models (Jameson, 1996; Zukerman and Albrecht, 2001). These models make it possible to construct and update student models composed of complicated and extensive data, and to make numeric forecasts on students' behaviors.

Student modeling techniques

In constructing student models, stereotype model, overlay model, perturbation model, fuzzy logic and machine learning techniques such as Bayesian network are predominantly used.

Stereotype model

Stereotype model is a model predominantly used in student modeling due to its ease of construction. Forming groups based on common characteristics of individuals (beginner/expert, field dependent/field independent, etc.) constitutes the core of this model (Figure 3). In the light of initial information gathered, students are assigned to groups (stereotypes) where they have similar characteristics.

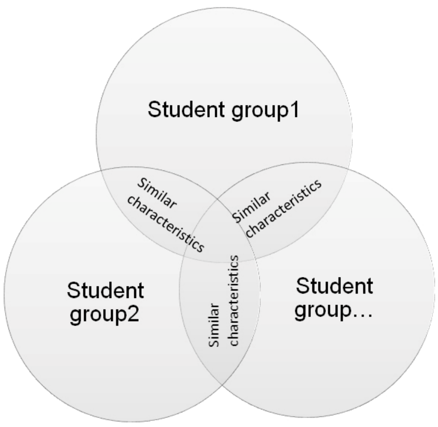

Figure 3. Stereotype Model

People frequently make assumptions based on simple observations (Rich, 1979). For instance, faced with the knowledge that a person is a judge, it may be deducted that this person is over the age of forty, has a good education and is well respected. Though not all of these assumptions are true, unless day-to-day experience proves to the contrary, they are made. In constructing a stereotype model, similar to daily life assumptions, groups are formed based on certain assumptions. Stereotype model is convenient in situations where it is possible to obtain sufficient information on the users. For instance, this model may be used when constructing packaged content about university students. Suppose we have evidence that Bob is a first-year computer science student who uses the piano hall of the university. It would be appropriate if a page with Computer Science and music events on campus content appears when he opens up the university web page. In addition to this, it may be expected that Bob is interested in general culture topics. Also, the information that Bob is not interested in theatre may be obtained with a questionnaire and added to Bob's stereotype model, and hence avoiding the generation of a long list of news of theatre events for Bob (Herder, 2006, p:30).

In situations where the user interface or learning type is going to be adapted, it is sufficient to use a stereotype model. However, when individual adaptations are required or guidance specific to individuals or suggestion systems will be active, stereotype model might fall short (Koch, 2000, p: 51).

Overlay model

Overlay models fundamentally regard student information as a subset of expert information (Figure 4). Overlay models are based on the premise that the materials presented by intelligent learning systems will ensure complete correlation between the student's knowledge and the expert's knowledge. One of the downsides of this approach is its disregard to the fact that students may have beliefs that may not be included in experts' information (Beck, Stern and Haugsjaa, 1996).

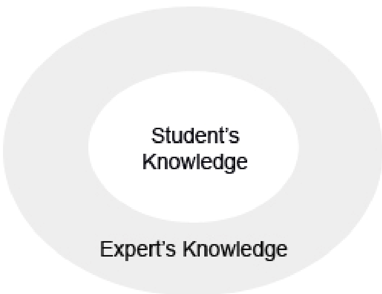

Figure 4. Overlay Model (Beck, Stern, and Haugsjaa, 1996)

The success of the overlay model tightly depends on dividing the expert information into as small elements as possible. In the overlay model, what the student knows and does not know may be specifically shown. The information level the student has on each information unit may be shown as "1-0", or "knows-does not know". More advanced overlay models may indicate the knowledge status of the students by grades (an integer or probability measure)

(Brusilovsky, 1994). The decision that the system makes on the knowledge level of the student in relation to each knowledge unit is the basis of the overlay model. The use of probability techniques is generally preferred in making this decision. Since it is the approach that deals with uncertainty best, Bayesian Networks are the most widely used probability technique (Özmert Büğrü, 2003; p:23,24).

Perturbation model

The overlay model has a disadvantage in that it does not contain the mistakes and misconceptions of students. However, students have misconceptions about subject fields in general. For that reason, overlay models have been expanded to allow representation of the false information students might have (Figure 5), and perturbation model has been constructed (Beck, Stern and Haugsjaa, 1996). The perturbation model differs the overlay model since it doesn't perceive students knowledge as a simplification of expert knowledge, but rather like perturbations over the expert knowledge (Webber, 2004, s.711). The perturbation model may contain users' errors or bugs and the reasons why users encounter these errors. The adaptive system can present learning material, concepts, subjects or topics with which users don't know by obtaining information from the perturbation model. Adaptive systems can also provide users with explanations, annotations to learn accurately, or assist users in correcting errors (Nguyen and Do, 2008). In other words, perturbation model make it possible to better evaluate student errors and transform students' false information pedagogically meaningful data (Beck, Stern and Haugsjaa, 1996).

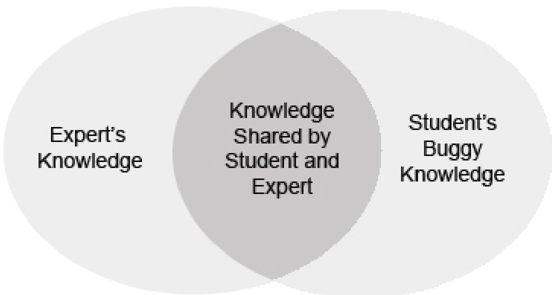

Figure 5. Perturbation Model (Beck, Stern and Haugsjaa, 1996)

Fuzzy logic

At the center of using overlay model for student modeling lies the idea of encoding the information of the expert relevant to the situation and making decisions using this information. In first student models, expert information was stated by dual codes based on the if-then structure. For instance, let us consider the statement “The room will be dark unless the lights are on.” The interpretation of a statement as absolute right or wrong in this way is known as classic logic. However, the daylight coming in through the window may also have an effect on the darkness of the room. As seen in this example, in some cases, more than one variable may have an effect on a consequence. The experts’ need to support their explanations on certain information (if-then) with “else” revealed the inadequacy of the 0-1 coding. However, the fact that the strength of the light through the window determines the darkness level of a room will be proved the “else” coding inadequate as well, and created the need for a fuzzy logic. Fuzzy logic is based on the acceptance that a value of any situation can be any continuous value between 0 and 1 (Baykal and Beyan, 2004; Jensen, 1997, Kadie, Hovel and Horvitz, 2001).

Fuzzy logic may be defined as a strict mathematical order to communicate and work with uncertainties. As is known, in statistics and probability theory, we work with certainties as opposed to uncertainties, but the environment we live in is rather full of uncertainties. Hence, in order to understand the deduction capability of humans, it is necessary to work with uncertainties. The mathematics only allows extreme values, and that is the reason why it is difficult to model complicated systems with classis mathematical methods, since the data has to be complete. Fuzzy logic removes this obligation,allows for a more qualitative definition (Constantin, 1996; Aktaran: Yavuz and Karaman, 2003), and provides a mechanism to mimic human decision-making (Frias-Martinez, Magoulas, Chen, Macredie, 2005). Fuzzy logic defines a framework in which the inherent ambiguity of real information can be captured, modeled and used to reason under uncertainty. Fuzzy Clustering, Fuzzy Association Rules, etc. are the combination of fuzzy logic and machine learning techniques to produce user models. It is also possible to capture user models with a machine learning technique and use fuzzy logic inference to implement the personalization engine (Frias-Martinez, Magoulas, Chen, Macredie, 2005).

Machine learning techniques

The field of machine learning, a sub category of the broader field of artificial intelligence, deals with the design and development of algorithm and techniques that help computers learn (Knight, 2004, p.4). Many successful applications from face recognition systems (Ergezer, 2003) to risk assessment in medical interventions (Toprak et al., 2003) have been developed in the field of machine learning, which seeks to answer the question of how computer programs that automatically improve their own performance based on experience and expand their database may be constructed (Mitchell, 1997). As information and communication technologies become more integrated into daily life and the need to develop systems that can solve the complicated problems encountered becomes more apparent, machine learning has become more critical. Machine learning is predominantly used in the data mining process where previously unknown but meaningful data is attempted to be obtained from within extensive mass data (Gopal, 2000, p:18; Mitchell, 1997).

The focus of the researches made in the field of machine learning is extracting meaningful information out of large data masses using numeric and statistical methods (Vrakas and Vlahavas, 2008). The general goal of machine learning is to obtain the same results in a more efficient, correct and less costly way by automating the steps people follow in a decision-making process, using computers (Jordan, 2008). By directly observing user's interaction with the system and allowing the systems to make decisions based on these, machine learning is quite functional in student modeling (Alessandro, 2006, p:27). Machine learning enables to model the uncertainities in complex problems and to inference meaningful results from the modeled information. Various techniques called as predictive statistical models are developed to deal with these uncertainties in the field of machine learning. Predictive statistical models enable the estimation of certain directions of human behavior such as goals, actions, and preferences (Zukerman and Albrecht, 2001). Markov models, artifical neural networks, and Bayesian networks are some of predictive statistical models.

Bayesian Networks

Probability, among the various ways suggested to model uncertainty, is a mathematical structure that may act in harmony with certain rules (Nokelainen et al., 2001). The probability theory is interested in events and their probability of happening. Bayesian networks are derived from Bayesian probability theory that enables to compute the posterior probabilities from uncertainties, prior probabilities, and casual relations (Niedermayer, 1998). In classic statistics, the frequency value is required, which is derived from the (observable) occurence number of a certain event divided by the total number of observations throughout a long period. In Bayesian interpretation, however, the degree of subjective beliefs regarding the probability of happening of an event is important (Nokelainen et al., 2001).

Bayesian networks are directed non-cyclical graphs where variables are shown with nodes, and conditional probabilities are shown with links (Jameson, 1998). Bayesian method is one of the basic methods used to overcome uncertainty in student model systems (Jameson, 1996) and has been used in the student modeling process of many adaptive learning environment (Kelly, 2005; Özmert Büğrü, 2003; Stern, 2001). Using the Bayesian algorithm, dynamically updated data sets may be used and customized inference mechanisms for each students may be created (Witten and Frank, 2000). While both fuzzy logic and bayesian network can be used to handle uncertainty (represent subjective belief), fuzzy logic focus on the degree of membership of an element in that set, bayesian network focus on degree of belief of a certain person that a variable is in a set (Frias-Martinez, Magoulas, Chen, Macredie, 2005; Heckerman and Shortcliffe, 1992).

Techniques used in constructing a student model, such as bayesian network, fuzzy logic, perturbation model, overlay model, and stereotype model, may be used separately as well as handled together in the student model. For instance, a student model based on the misconceptions of students about "web design" subject can be constructed with fuzzy logic and perturbation model duo.

Updating the student model

The student model is constructed prior to the student using the system and is updated in the light of the data obtained in the learning process of the student (Shareef and Kinshuk, 2003). The methods used in updating the student model may be summarized under two titles; performance measures and student activity analysis.

Performance measures

When a student answers a question, the answer is analyzed by the system and this process is called performance measurement (Brusilovsky, 1994). For instance, in a practice and drill software, depending on the student's right or wrong answer related to a certain learning objective, the variable indicating the knowledge status of that student is updated. This way, decisions can be made if the system should pose any more questions on the same learning objective or move on to questions concerning a new learning objective.

Student activity analysis

By analyzing the activities like the nodes clicked on, the duration spent on the nodes, the selected features of the system like help, note taking, the queries made while a student uses a system, the information like which subjects are studied or explanation types are selected etc., can be updated.

In order to update a student model, both performance measures and the student activity analysis may be used at the same time.

Student Model Trends

One of the most important features of student models is the fact that they are accessible and usable by different applications. An valuable database may be created with the characteristics brought together in a user model and the interpretation of these characteristics. When a different application requires some of these characteristics of the user, recollecting similar data leads to wasted effort, time, and money. For this reason, it is important that the information in a student model can be reusable. When a reusable student model is constructed, it should go with certain standards (Kay, 2000). The IMS Learner Information Package Information Model (IMS LIP) portrays the structure of user data to allow interoperability between different systems. The core structures of the IMS LIP are based upon: accessibilities, activities, affiliations, competencies, goals, identifications, interests, qualifications, certifications and licenses, relationship, security keys, and transcripts (IMS, 2009). The Learning Technology Standards Committee (LTSC) has defined specifications like P1484 and P1484.2 for student data. While the purpose of P1484 is to specify common architecture for CAI systems (LTSC, 2001), the purpose of P1484.2 is to describe portable learner records (IEEE, 2000). P1484.2 (The Public and Private Information for Learners Standard) is a data interchange specification and used for communication among cooperating systems (IEEE, 2000). In addition to these, in order for the e-learning environment to offer appropriate content for different students in accordance with the information in the student model, the contents need to be designed as learning objects and metadata that defines each learning object should be created. It is the only way to determine by the learning system which contents are suitable for student characteristics (Kay, 2000).

Conclusion

Since the behaviors of an adaptive educational hypermedia largely depend on the individual learning needs and preferences of students, student modeling is the key element for personalization. This study is conducted to explain the major concepts/steps in student modeling by focusing on the student model issue using a holistic approach. Therefore, the concept of student model is defined, and gathering data related to the student characteristics, model constructing, and updating phases in the student modeling process are addressed in detail.

A student model is designed and developed in the direction of decisions on the various aspects of the system, which will be adapted to the user. Student models intended for a variety of purposes may be constructed, such as determining preferences of students in the learning process, recognizing their plans and solutions, evaluating their performances and problem-solving skills, etc. The degree of addressing real world complexities and the ability of the techniques to handle missing/uncertain information about student and context indicate the level of success of the student model. Another important feature of student models is their accessibility by and availability to different learning applications.

In conclusion, in order to improve the performance of adaptive educational hypermedia, the student model process should be carefully designed and constructed. Therefore, it is of importance to analyze in detail all the elements of the student model process and compare the efficiency of alternative methods/techniques for the same learning conditions. Also, the case studies and experimental studies aiming to determine which modeling techniques appropriate for different student/context characteristics and available data will contribute to more value for implementation of adaptive educational hypermedia.

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