USER MODELING APPROACHES IN ADAPTIVE LEARNING SYSTEMS

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Abstract. *Adaptive learning systems have potential for accommodating student differences in a diverse population. Adaptive learning can be used both in blended learning settings and flexible learning methods by adjusting to the pace of student, allowing the flexibility in learning styles, different sequence of curriculum and customized presentation. Adaptive system architecture consists of three essential parts; user model, domain model and interaction/adaptation model. As one important feature of any adaptive system is the user model that represents information about each user/student, this paper focuses on user model by overviewing the existing approaches in user modeling in terms of used data types, model initializing methods and implementation of the models.*

Keywords: *Adaptive learning systems (ALS), adaptive eLearning, user modeling, learner model*

1. INTRODUCTION

The popularity of novel technologies such as mobile devices and Internet connections among people from all ages drives the researchers to focus, among other things, on usability of technology in the education. Technology can be integrated into face-to-face teaching, blended teaching, virtual teaching and distance education. Technology Enhanced learning (TEL) can be used to provide flexibility in the mode of learning for both formal and informal settings. It can be used as a tool in the classroom, by utilizing smart boards, media and games, and as support for learning outside the classroom, in form of web applications, mobile applications and games.

The "One-size-fits-all" approach is not appropriate when each user has unique cognitive processes and abilities. Adaptive learning systems address demographic variability of the learners by customizing course content or presentation according to differences in student skills [11]. They may provide individualized learning in a flexible environment and content for the learners, with the support of learning analytics [18]. An adaptive learning environment facilitates the learning process dynamically by monitoring the activities of the users; interprets them to create basic domain-specific models; considering the user requirements and preferences out of the interpreted activities, represents these in associated models; and acts upon the available knowledge on the users and the subject. [38]

The studies in the literature contain many examples of adaptive learning systems also with different names i.e. Intelligent Tutoring Systems (ITS)[46], Adaptive Intelligent Learning Environments (AILE) [23], Adaptive Educational Hypermedia Systems (AEHS)[10] or Personalized Learning Environments (PLE) [14]. Generally, all of them can be called as adaptive learning systems as they all have adaptation according to the learner characteristics.

Early computer aided adaptive learning systems developed for teaching purposes were Intelligent Tutoring Systems (ITS) which are closer to a tutor-centered paradigm[47]. Traditional ITSs provide adaptive sequencing of curricula and support through adaptive feedback and scaffolding. With the development of the web, adaptive hypermedia techniques have become more popular [5]. ELM-ART- an interactive textbook with adaptive curriculum sequencing, tests and exercises for programming in LISP [22, 45] and AHA! (Adaptive Hypermedia Architecture) [8] could be given as examples of early web based adaptive learning systems. In the 90's, server-based www applications were not interactive enough to support following the student actions and provide online help. After the support of real interactivity; online behavior can be monitored and used for evaluation of their performance and providing help. Later on, many adaptive learning systems are proposed considering different user characteristics such as AEHS-LS (Adaptive E-Learning Hypermedia System based on Learning Style) [19] which determines the learning styles of the users and adopts the system accordingly.

Adaptive system architecture consists of three essential parts; the user model, domain model and the interaction/adaptation model. The user model that represents information about each user/learner is an important feature of any adaptive system. The aim of this paper is to overview existing methods utilized for user modelling in adaptive learning systems and to provide a survey on current research in this field. The paper is organized as follows; the second section of the paper explains the user model and its importance by giving user characteristics and model initialization techniques, while the third section explains user knowledge models. The Fourth section analysis recent research for each of the different ways of user modelling in case of uncertainty containing machine learning methods, and finally the fifth and sixth sections give a discussion and conclusion respectively.

1.1. User model

Adaptive systems mainly consist of three essential components; the user model, domain model and the interaction/adaptation model.

The User Model describes the information about each user; such as knowledge level, preferences, learning style etc. Upon the evaluation of data collected from the user, the system draws conclusions on the user characteristics and acts accordingly.

The Domain Model represents the domain concepts and provides a structure for the representation of the user domain knowledge. In different adaptive learning systems, these concepts can have different functions, weights and meanings. Commonly, each concept is connected or related with other concepts.

The Adaptation/Interaction Model represents and defines the interaction between the user and the system. It includes evaluation, adaptation and inference mechanisms as the data stored in the Adaptation/Interaction Model is used to infer user characteristics with the objective of updating and validating the user model.

According to [32], adaptation can be implemented in an e-learning system by using four elements; content aggregation, presentation, navigation and collaboration support. Adaptive content aggregation means, depending on the learning and teaching style or domain background knowledge the system could offer different types of content, in terms of different background domains, levels of detail or in different multimedia formats. In adaptive presentation, the content can be adopted with additional, prerequisite, comparative explanations and sorting content units regarding criteria like relevance to background knowledge, knowledge level, etc. Adaptive navigation is the adaptation of global or local guidance. An e-learning environment could offer direct guidance as well as link sorting, link hiding, link disabling and link annotating [11]. A network-based educational system that uses the system's knowledge about learners to form a collaborating group can offer this support and suggest communication with the other learners to provide adaptive collaboration support.

The user model is also referred as student model or learner model in different studies. The user model is required in an adaptive system because it can adopt aspects of the system according to given, or inferred, user characteristics. The model can be separated by the system from the rest of its knowledge and contains explicit assumptions about the user. The current trend favors user centric approaches instead of tutor centric approaches.

Koch in [39], gives seven key features of the user models which are user-centric:

- Assisting the user during the learning of a specific subject.
- Providing information to adjust the user.
- Adapting the interface to the user.
- Helping users find information.
- Giving immediate feedback to the user on his level of knowledge.
- Supporting collaborative work.
- Assisting the user during the use of the system.

In user modelling there are two basic questions to be addressed; the first one is how to initialize the new user model and the second is how this model will be updated. Generally, this process involves diagnosis, classification, and control of the user parameters or characteristics. To diagnose the new user, firstly significance of the user characteristics should be evaluated.

1.2. User characteristics

In adaptive/ personalized learning systems, student's individual characteristics have a more significant role than in the traditional learning and can become a reason of student's success or failure. In different adaptive learning systems different user characteristics are taken into consideration. What characteristics of the user should be considered to create a user model, to provide a successful and pleasant learning experience?

Novel adaptive learning systems introduce the new development and deployment of adaptive mechanisms by using different attributes for user modelling. The structure of the user models constantly changes over time. Some of them consider learning styles [17, 19, 20, 33, 40, 43] and some use hybrid models [2] to present user characteristics. Even the same authors over the years recommend different sets of user model attributes; as an example [11] and [22]. In [34] authors selected 22 user model attributes from the research performed in between 2001-2013. The given set of variables includes: age, gender, cognitive abilities (perceptual speed, processing speed, working memory capacity, reasoning ability, verbal ability, spatial ability and other cognitive abilities), meta-cognitive abilities, psychomotor skills, personality, anxiety, emotions and affect, cognitive styles, learning styles, experience, background knowledge, motivation, expectations, preferences, and interaction styles. Other user characteristics in a user model can be objectives/goals/tasks, personality traits, stereotypes, geographic data, demographic data, behavior, social/ group, environment/ work.

Data used in user modelling is categorized in two main classes; Domain Independent Data and Domain Dependent Data. Domain Dependent Data or Domain-specific information model is referred to as the student knowledge model. It describes the students' knowledge level, their understanding of domain knowledge or curriculum elements, the errors that the students made, the students' knowledge development process, records of learning behaviors, records of evaluation or assessment, and so forth.

The domain-independent information is information about the skills of students, so it is based on their behavior. It may include learning goals and objectives to compare with the learners' achievements, cognitive capabilities such as inductive reasoning skill and associative learning skill, motivational states, background and experience, and preferences.

The data collected from users can be categorized like in [2], as demographical data through the registration process, explicit ratings for a subset of the available items, and implicit data from the user's online behavior.

The users' engagement level, motivation state, study time and study habits can be discovered by examining system usage data and online behavior. This information would help the system discover which user is about to quit, and to prevent this; the system could send remainders or offer different content to keep their progress.

Requirements on User Profiling given in [32] are defining static and dynamic information attributes about the users, providing management (like storage, deletion or update) of attributes in real-time and supporting learner tracking (e.g. observing the learning process, the paths through the courses, all learning objects viewed)

1.3. Initialization of the user model

A common feature of various adaptive Web systems is the application of user models (also known as profiles) to adapt the systems' behavior to individual users. User models are essential part of adaptive learning systems which represent the information about users.

In [1], three approaches are explained for initializing the student model.

1. The system may assume that a new user knows nothing about the domain.
2. The user's prior knowledge may be discovered by using a pre-test during the registration process to the system.
3. The system may use patterns among students in order to group similar students into categories.

The first approach can be preferred for the simplicity, but it is not reliable as it assumes the user knows nothing about the domain, although the user may already have some initial knowledge. A great number of educational systems initialize the models of new students by assuming that they know nothing or that they have some standard prior knowledge of the domain being taught. This causes the boredom of the users which already have initial knowledge about the domain and decreases their motivation.

The second approach, applying a pre-test to measure the prior knowledge of the students is a more appropriate solution, but it contains a trade-off between the number of questions and accuracy. If the number of questions in the pre-test is too high it would frustrate the user and decrease the motivation from the starting point. On the other side not having enough number of questions couldn't give the real level of the user. To recover this trade-off, adaptive pre-test is suggested by [5], which can select the next question according to previous answers.

The third initialization way does not require a pre-test, it groups similar users into the same categories, in other words stereotypes. Stereotypes allow the system to start the customized interaction in a quicker way, often based upon a short initial interaction with the user or a short period observing the user. A system might ask the user just a few questions or it might set the student an initial task to assess their level. From this small base of information, the system estimates the values of a large number of components of the student model.[26]

2. User Knowledge Models

A knowledge model represents a reflection of the student's state and level of knowledge and skills in term of a particular subject domain [11]. User knowledge models can be categorized according to their coverage as Overlay models and Perturbation models.

Overlay models keep the user/student knowledge only a subset of the entire domain knowledge and do not allow representing the incorrect knowledge that the student acquired or the misconceptions. This solution demands great flexibility in the student knowledge model for each topic [22]. Many researchers have adopted overlay student models to represent the learner's knowledge for each concept independently, focusing on the comparison between the student model and the expert domain knowledge as in [12]-[36]. A certain measure is assigned to each curriculum element based on the estimated student's understanding on that element. The measure can be a scalar (an integer, or probability measure, or a flag such as initial acquisition/assimilation/mastery) or a vector estimate.

Stereotypic inference also can be used in any modeling method. Users can be categorized i.e. as novices, intermediates, experts and others [26]. The stereotype and overlay techniques of student modeling are often combined in adaptive systems for education. The disadvantage of this technique is that it does not consider incorrect behavior of the user or the reason of that behavior.

Perturbation models assume one or more perturbations (misconceptions) exist for each knowledge domain element. Incorrect user behavior may be caused by the application of one of misconceptions in place of the related correct knowledge element. Therefore the student knowledge is represented by a union of a subset of the domain model and another subset of the misconception set with all misconceptions that the learner may have [9]. Keeping the misconceptions or the errors in the students' knowledge is a more realistic way for a better learning.

3. Uncertainty Based User Models

In user modelling, there is often uncertain or imprecise information; rather it is not sure that the available information is absolutely true or the values are completely defined. In this case, several statistical prediction methods are used.

There are several Artificial Intelligence techniques used in adaptive educational systems for predicting missing information, such as Fuzzy Logic (FL), Decision Trees, Bayesian Networks (BN), Neural Networks, Genetic Algorithms and Markov Models.

3.1. Fuzzy logic

Fuzzy logic methods are used in many adaptive learning systems in user modelling taking into consideration many different user characteristics as in [2–4, 13, 41, 44, 48, 49]. In some studies fuzzy logic methods are commonly used for examining and assessing learning outcomes as in [44]. Learning and teaching behavior can be presented by the fuzzy rules in a human readable and linguistically interpretable manner.

Student modelling is performed by fuzzy models with a multi-agent approach in [48]. Profiling system stores the learning activities and interaction history of each student into the student profile database which is abstracted into a student model. Student model contains fuzzy values of the students' behaviors.

In[30], eight stereotypes for representing the knowledge level of a learner from novice to expert. In this study fuzzy sets are combined with user stereotypes and the overlay model to give appropriate domain concepts that correspond to the learner's knowledge level and educational needs.

The study [4] demonstrates the proposed zSlices type-2 fuzzy-logic-based system's capability for uncertainties produce better performance, in terms of student performance and improved success rates compared with interval type-2 fuzzy logic, type-1 fuzzy systems and non-adaptive systems.

In [3], system gathers input and output information of the user during the learning process including head pose direction and face expressions and the state of the e-learning environment. An interval type-2 fuzzy logic-based system that can learn different teacher's pedagogical decisions based on the content difficulty level as well as the students' average level of engagements and the variation between the engagements in a dynamic real online teaching environment.

3.2. Decision Trees

Decision trees are commonly used for gaining information for decision making. A decision tree is a tree structure such that each branch node represents a choice between a number of alternatives, and each leaf node represents decision.

Decision tree starts with a root node and users split each node recursively according to decision tree learning algorithm. The final result is a decision tree where each branch represents a scenario of decision and its outcome. [27]

One of the methods for user categorization is proposed in [1] is CLARISSE. It identifies the categories among students for an ITS for teaching of quantum information processing. CLARISSE generates an adaptive pre-test to identify the learner's category after very few questions by using decision tree and classify new students according to their cognitive level.

3.3. Bayesian Networks

Bayesian Networks (BN) are a probabilistic graphical model in which each node represents a random variable and each link represents probabilistic dependencies among the corresponding random variables [7]. BNs have been widely used for the purpose of modelling learner skills as they offer probability computations of unobserved nodes from evidence of observed nodes. [16]

In [21] Bayesian Networks is used to detect the learning style of a student in a Web-based education system. The system models perception, processing and understanding of the students by evaluating their participation in forums, chats, mail systems and access patterns. Participation in forums, chats, and mail systems is used to detect whether the student prefers to work alone or in groups. Access patterns to information determine how students understand, sequentially or not.

Dynamic Bayesian Networks (DBNs) have the potential to increase the representational power of the student model and increase prediction accuracy [25], by modelling skill hierarchies. Hierarchical models improve prediction accuracy significantly. A domain expert employing a more detailed skill topology and more complex constraint sets could probably obtain an even higher accuracy on data sets.

The study [35] proposes a user modeling system named Zebra which manipulates students' characteristics by a Triangular Learner Model which is consist of knowledge, learning style and learning history sub-models. Zebra has two engines: mining engine (ME) and belief network engine (BNE). Mining engine (ME) is responsible for collecting learners' data, monitoring their actions, structuring and updating the model while Belief network engine (BNE) is responsible for inferring new personal traits by using Bayesian network and hidden Markov model into inference mechanism.

3.4. Neural Networks

Artificial neural networks are one of the main machine learning methods designed for finding patterns in data. They are brain-inspired systems which are intended to replicate the way that humans learn. They are used for classification, clustering and prediction.

SQL-Tutor is one of the Intelligent Tutoring Systems (ITS), which was developed to teach university students SQL using an Artificial Neural Network (ANN) for decision-making. Inputs of the system were time needed to solve the problem, the level of help provided to the student, the complexity of the problem and the knowledge level of the student. In the output, the ANN attempted to predict the number of errors or constraints violations committed by the student. The system employs this prediction to make the next teaching decision such as selecting the next problem from the problem database. [31]

Another study [40] uses 32 different attributes which can be used to infer the learning style and preferred learning mode of the learner in accordance with Gardner's theory of multiple intelligences by using two different feedforward-backpropagation neural networks, one for the learning style and another for preferred learning mode.

3.5. Learning analytics and educational data mining techniques

Currently, data mining techniques and learning analytics techniques such as clustering, classification, collaborative filtering and association rule mining are used in e-learning platforms [6, 15, 24, 28–30, 37, 42]. In recent studies these methods are more often used.

Learning analytics is the automatic analysis of educational data to enhance the learning experience.

In [42], authors proposed an Adaptive web-based English tutor which uses an online pre-questionnaire to model each student's learning style according to pre-defined Jackson learning styles. At the end, system classifies students according to the learning styles by using k-means clustering.

In the study [37], behavior mining techniques were used to extract the students' access patterns, preferences, learning styles to discover a method for delivering suitable and personalized contents to students based on their special characteristics. FP-Tree association rule mining technique was used for exploring the relationships between characteristics.

4. Discussion

In an e-learning system it is crucial to consider the individual traits to take the attention of the user and increase the engagement level. Adaptive learning systems contain a user model which represents the essential information about the user. This information is used to adapt the system's behavior according to individual traits of the users. E-learning systems may successfully retrieve different learning material and resources that technically match a specific goal. Recent systems are designed in a more user- centric way, allowing users having more choices or more flexibility.

The user modelling is one of the key factors for the success of the e-learning system. Users' achievements will depend to a large extent on the user models to represent the users' actual interests and characteristics. In the literature, the number and type of user characteristics to adapt depending on the design of each system, but relevantly cognitive skills, learning styles and student knowledge are used more commonly as adaptation criteria. The first step in user model design should be defining static and dynamic data attributes about the users. Attributes such as user demographic data (i.e., gender, age), academic background etc. can be entered by the user through the registration process of the system. The system gathers the dynamic data from the user's interactions and online behavior. For unknown information of the user, prediction methods are used. Machine learning and data mining methods are also widely used in recent studies to discover the patterns in user data rather than classic rule-based adaptation methods. Techniques that capture dynamic changes in user information and available user data can increase the adaptivity of user model, so the system can have better performance in individualization.

Student model initialization using patterns among students in order to group similar students into categories seems more practical than assuming that a new user knows nothing about the domain or applying an exhaustive pre-test during the registration process. This allows the system to start the customized interaction in a quicker way. If the assumptions for the user are missing or incorrect, the system should update the user stereotype or change the user group upon the recent data.

Adaptive environments also can adapt to support collaborative and group learning, not just to a single learner. User models are often developed using a combination of methods. For example, when user/student model initialization can be done by machine learning methods (i.e. Bayesian Networks), user model adaptation and prediction can be done by the help of educational data mining techniques such as clustering, classification etc.

5. Conclusion

In this paper we tried to answer the following questions: Which user characteristics are used in adaptive learning systems? Which way of user model initialization is more proper? Which adaptation methods are used? What are the pros and cons of adaptation methods?

In the traditional face to face teaching-learning interaction; teacher/tutor is the center and student is supposed to adopt himself for the different attitudes or teaching methods of teachers. Also, in human tutoring, teacher can notice the students who are not learning well, which mistakes are done by the group of students, what are the misconceptions, what are the different learning styles in the group. In e-learning systems these kinds of knowledge should be extracted from the system. This is where the user modeling becomes critical for the enhancement of learning effectiveness of web-based educational systems. The purpose of user modeling is to understand the user and diagnose the characteristics of the user to be able to perform adaptation accordingly. As it can be seen from the existing studies, all methods employed to predict uncertainty in user modeling are dealing with different aspects of user characteristics. There is no model to take the student as a whole to evaluate all aspects of learning process. Furthermore, extracting data not only from the learning system but from users' other interactions with other systems, web pages etc. to get a proper knowledge of real interests of the user can help improving the adaptation. When user modeling is done with more parameters, in other terms, using more data would increase the accuracy, but on the other side it could cause higher complexity and additional processing time. There is a tradeoff between the amount of data and complexity which should be well balanced. This is why user characteristics or user data should be selected very precisely.

In many researches one of the main problems are defined as the lack of standardization for the design of user models. Existing studies show that each method captures different elements of user characteristics by using different pedagogical theories. Combination of different techniques, in other words, hybrid systems could be the future of user models. The user model can be divided into sub-models such as knowledge model, interaction model, pedagogical model etc. This would contribute to the modularity of the systems or the easier combination of the different methods; such as using different algorithms for different sub-models, combining different machine learning or data mining methods.

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