Adaptation Engine for Intelligent Tutoring Systems

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Abstract

This paper discusses the design for an intelligent and adaptive tutoring system offering pedagogical support that deviates from the traditional chalk and talk form of teaching for online courses. The design proposed utilizes the system's data to create models which recognizes when a user is struggling or falling behind. A novel method of assessing effectiveness of pedagogy using system interaction logs and MOOC data is put forward. The system also provides room for manual intervention by the course administrators in case of at-risk participants. Educational data mining and learning analytics techniques have been applied to understand user behavior and course effectiveness. The design proposed allows the system to personalize the learning experience and supports the instructor in administering the course to a huge number of participants.

Key Words: machine learning, intelligent systems, statistical learning, learning models
1 Introduction

In India a combination of recitation and lecture has had adverse effects. At 15, pupils in Tamil Nadu and Himachal Pradesh are five years behind the average pupil [20]. Teachers need to be well-versed in different learning theories to engage and bolster a student's curiosity and learning. Teachers versed in learning theories can reach out to millions of aspiring learners through Mass Online Open Courses or MOOCs. However managing such a huge class can be quite difficult. This necessitates a support system that assess each student performance, his preferred pedagogy, his learning curve and areas where he is struggling. This system must be able to provide feedback to the course administrator on the effectiveness of course content and details of at-risk students so he/she can take appropriate action. Such a computer system that provides immediate and customized instruction or feedback to learners can be described as an Intelligent tutoring system [16]. Its goal is to solve the over-dependency of students on quality teachers for quality education.

Intelligent tutoring system (ITS) consist of four basic components [17]. These are the domain model, student model, tutoring model and user-interface model. The domain model contains the concepts or strategies to tackle a problem. It is used to detect errors and evaluate a student's performance. The student model is responsible for tracking the student's cognitive state and their evolution. When their actions are detrimental to learning they are given proper directions (via feedback). The tutor model accepts information from the above two and makes a decision on the method for tutoring. Each step by the student is analyzed and an estimate probability is calculated on the student having mastered the skill. This knowledge tracing profiles the student's weaknesses and strengths. This then determines whether the student is ready to move on or requires more practice. The user-interface model carries out the interaction with the student.

The proposed system builds on the standard ITS, making use of a combination of the student information and interactions logs with the system to create a model that predicts not only student mastery of a skill but also the amount of effort he makes, where he is struggling, the type of support or instruction he needs and his future performance.
The major contribution of the paper are as follows -

1. A brief discussion of requisite elements in an adaptive tutoring system.

2. A detailed overview of different models to be developed to build an effective adaptation engine.

3. A novel approach to decide when to trigger a change in content and decide on type of content for a user.

The paper is organized into different sections. Section II discusses the work done in this area and projects ongoing. Section III introduces the design of the system and later delves into the focused areas through which the system can adapt to student needs. Section IV proposes a new approach to build an adaptation engine. Section V discussed the work done and Section VI discusses the future work that can be done. Section VII is the conclusion.

2 Related work

The earliest use of intelligent system was in 1924, when Sidney Pressey of Ohio State University created a mechanical teaching machine [16]. It resembled a typewriter with several keys and a window for asking questions. Pressey was influenced by Edward L. Thorndike [16], a learning theorist and educational psychologist at Columbia University Teacher College. Several techniques have been adapted from such areas and prominent fields such as learning analytics and educational data mining developed leading to huge advances in learning systems.

Educational data mining looks for patterns in data to understand how a student learns [18]. It reduces learning to small components that can be analyzed. For example consider the work of [1] Baker et al. who stated analysis can be carried out in a five ways. Prediction phase in which data is used to build models and estimate the specific sequence and amount of practice that best enable learning. Clustering phase in which users can be grouped and suggestion made to group as whole or a learning philosophy used in an earlier group can be suggested to a new similar student group. Relationship Mining [11] in which Association rule mining can be
used to find things like mistakes that co-occur, and Sequential Pattern mining which can be used to model how students understand a concept by following the sequence in which that concept was developed. Distillation phase breaks down all of the above data into human interpretable formats like graphs, charts and performance statistics. Once the analysis has been carried and data is distilled we can build models on how learning actually takes places and whether it quality and speed is satisfactory. Once an ideal sequence of events that produces required learning has been identified, then we can use that model on future participants [6] i.e. a model developed by prediction or relationship mining can be field-tested on a new student group to estimate success rate of designed learning methods. In this way, Educational data mining helps determine which sequence of topics is effective and which instructional styles are most helpful.

Learning analytics involves interpreting data to assess academic progress, predict future performance and spotting potential issues [18]. Learning analytics includes social network analysis i.e. analysis of student-student or student-system interactions to understand how the student is responding to the content and where he is struggling [4]. Learning analytics can also use attention metadata i.e. amount a student is engaged with the system so as to know if a student is just not putting in the effort or if he is simply gaming the system [5]. Learning analytics helps identify which students are falling behind and those who are ready to move on to the next topic.

Visual Data analytics is another technique by which data can be broken down into easily interpretable formats. It helps expose trends, patterns and exceptions in large and heterogeneous datasets. It can attack certain problems whose size, complexity, and need for closely coupled human and machine analysis may make them otherwise intractable. This technique becomes especially helpful when interaction logs have to be analyzed for courses open for long periods of time. [15].

Such techniques have been utilized in many initiatives especially in the open source field, by universities and companies for improving the learning experience in MOOCs. Open Learning Initiative at Carnegie Mellon University is an online educational system open to all which uses predictive analysis to guide students. Its unique Did
I Get This? section after each topic helps ensure students that they have mastered the skill without it affecting their grade. Worcester Polytechnic Institute and Carnegie Mellon University have also joined hands to introduce an initiative ASSISTment which uses information on how individual students respond to problems and how much support they need from the system. This helps track the students mastery of skill i.e. whether he is falling behind or whether he is ready to move on. This process of detecting and modelling the amount of information a user has under his belt is an important task. [3] Baker et al. used a Bayesian network to estimate the probability that a student knows the skill based on him performing the skill. As a student performs the steps required to attain the answer his methodology is analyzed and an estimate is calculated to determine his chances of success. [20] Baker et al. also used a probability based method to decide whether a student has guessed or slipped based on his prior performance and interactions with the system. Modelling user behavior helps identify actions that correspond to positive learning [7]. [14] Macfayden et al. analyzed several learning management system and found that less than five behavior variables correspond to 30 percentage of the variation in the final grade of students. Such actions that lead to positive learning can be used to restructure the course or to suggest the same approach to students with like-minded learning habits. Other ways of checking the user experience is by carrying out follow-up surveys or questionnaires. Zygna, a learning management company is developing a system to analyze the free-text comments of students so as to identify their levels of satisfaction.

The domain of knowledge can also be adapted according to the most suitable pedagogical support identified for the student over time. This can be identified by carrying out A/B testing on groups of students like distinguishing between the effects of mass practice (repeated examples in short span of time) and spaced practice (examples spaced over time). The one that seems more effective for the group can be applied. This can be extended by identifying the behavioral characteristics of the group for whom this type of learning is effective. Once the type of student the instruction seems most effective for is realized clustering techniques can be used to identify which category a new user would fall into. All such methods focus on a data-rich feedback loop.
3 System Design

The following details the traditional models that are built for a decision support system for course administrators. It gives insight to course administrators on how to better structure the course and adapt the pedagogy for students.

3.1 User Knowledge Modelling

This involves understanding what a user knows i.e. skill, concepts or procedural knowledge. The common data points that are required are student responses, time spent, hints used, repetitions of wrong answer and errors made. This gives an idea of how strong the concepts of a user are [2]. Further data points can also be used like:

The skill that a student practiced and total times a student has practiced a skill helps us identify situations in which a student could be gaming the system [9][10]. It also helps identify students who are not putting in effort and students who are putting in effort but still struggling to apply the concept.

Students performance level inferred from the system or collected from standardized test can give an estimate of the student learning curve. If this learning curve seems to be dipping beyond a threshold (determined by the course administrators), indicating that the current method of instruction is not proving useful then the instructional method may need to be altered.

Free-text analysis and sentiment analysis of the interactions in discussion forums helps identify the areas in which a student needs more material or support. If the skill is deemed to be complete the student can be directed to the next topic [8].

3.2 User Behavior Modelling

This involves understanding the behavior of student, the way he develops concepts, the type of instructional method he responds well too and the category of pedagogical support he needs. The data that is required consists of student responses, time spent, hints used, repetitions of wrong answer and errors made. This gives
an idea of how well he is responding to the current instructional method and how suited he is to it.

Further data can also be used such as

The time he spends on different pedagogical support could help identify which type of material he focuses on.

Analyzing his social interactions [13] such as amount of conversation with teachers and students gives an estimate on how much effort he puts in. This helps identify those student who are not trying and those who are trying but not succeeding.

Analyzing the interaction logs can also help identify those behaviors that are conducive to learning, like certain segment of user follow textual content then practice the skill. Such patterns can be recommended to future users.

3.3 User Experience Modelling

This is to analyze how satisfied the user is with the current system such as instructional methods or pedagogical support. The data points that are required are the responses to surveys which can be conducted from time to time. Sentiment analysis of comments in such surveys can help understand the areas the user is satisfied with and those which the user feels is lacking.

An alternate method would be to generate a statistical report on the type of instructional methods used, support material provided against their respective popularity and effectiveness. This indicates if users are consistently using a pedagogy or dropping out because they are not satisfied.

User experience models can be used to understand if the user is satisfied with the current pedagogy or if it needs to be changed.

3.4 Domain Modelling

This involves finding out at which level to divide topics into modules and how these modules should be arranged. The data that are required are student responses, time spent, hints used, repetitions of wrong answer and errors made. This gives an idea of how the students are faring with the current allocation of the system. Further data points and analysis that can be used are -
Tracking the learning curve of the user, i.e. how fast he is picking up skills, and monitoring the rise/dip in it can help understand if a domain needs be broken down or drilled into simpler modules.

Sentiment analysis of surveys and discussion forums help understand how students feel about particular topic or domains.

### 3.5 User Profiling

This involves identifying which group a user can be clustered into, based on the type of support/instructional method a user would need and how he performs in response to it. The data points that are required are student responses, time spent, hints used, repetitions of wrong answer and errors made which can be used to assess his performance in relation to the pedagogy he has used. Further data points can be used such as

The time students spent on practicing skills and how engaged he is with the discussion forums, which helps identify those students who use intensive practice to gain a skill as opposed to those students to use spaced practice.

### 3.6 Trend Analysis

This attempts to understand what changes over time and patterns that emerge. Certain topics require definite kinds of pedagogical support that all kinds of students respond to. The effectiveness of such support may not seem significant to an experienced instructor but patterns start to emerge as students engage with the system and this is revealed on doing trend analysis. The kind of data required varies depending on what information is of interest. Since this is the case we combine several data points such as system interaction logs, enrollment records, previous performance records, degrees and completion so as to identify the trends in pedagogy and student performance.

The requirement of a huge amount of data and having to extract patterns from it makes it a task suited for applying visual data analytics.
However traditional decision support system involves considerable participation from the course administrators. An adaptive tutoring system however takes the input from the aforementioned traditional models to dynamically change the content with minimal participation from the course administrator. The design of an adaptive tutoring system has been shown below (Fig.1). The components involved are a MOOC Interface which is responsible for displaying information and assessments to support student learning. The next is Student Interaction Logs which is a database tracking and logging interaction between the student and the system. A Predictive Model uses interaction logs and profile infor-
mation (from the Students Information Database) to build models on the users knowledge, behavior, experience etc. From this the system can predict performance, course outcomes and dropouts. This feeds into the Analytics Dashboard which is utilized by both teachers and other course administrators. They can then use Intervention Engine to help at-risk students, which can override any system-generated actions. The predictive model also feeds into the Adaptation Engine so as to change the content depending on the students performance and his requirements.

The drawback with this adaptive system is that the models provide compartmentalized results which may result in losing the big picture. Having both a modularized analysis along with combining the data in an integrated analysis helps to connect the dots and improve delivery of content. The next section put forwards a novel approach to carry out an integrated analysis.

4 Unified Models for Personalization

To tailor-fit the course to a user the system must be able to recognize when the user is doing well and the pedagogy used is successful as opposed to when the user is not doing well due to unsuitable pedagogy. This require integrating user models. The proposed approach build two models - a user activity model combining knowledge, behavior and experience and a user profile model which builds on traditional user profiling.

Phase 1: User Segmentation

Using the amount of content the user interacts with and his/her performance we can build the user activity model. Based on this model we can divide users into four categories. Users that join the course but drop early without engaging with the content the hype group. Those that do not engage with the content but complete tasks by cheating the gamers group. Those that engage with the content, however drop out later on either because the course content gets too dense and unsuitable or they are feel they are not leaning enough the concern group. Then there are those who engage with the content, acquire the skill and complete the course the ideal group.

Phase 2: Adaptive Action for Users
Once a user segment has been identified specific actions have to be taken to aid them.

Those users in the hype category often lack the motivation to engage with the course. Email notification regarding the uses of the field, latest advance often help inspire many of those users.

To combat the gamers the system must include punishments. Those who are identified as gaming the system would undergo separate testing (unique questions) in a controlled environment (i.e. the webcam will be on and question will be timed to prevent cheating). Those identified as gaming the system will be barred from taking the course.

Those users in the ideal category are those who are responding well to the pedagogy provided. They act as data points to improve our system i.e. these users are clustered and their unique traits are stored. These traits constitute the user profile model which is continuously modified with data. For the next set of users, once their traits have been identified, they will assigned the pedagogy of the nearest cluster they belong to.

Those users in the concern category are those for whom the current pedagogy is not effective. Again the traits of the users are collected and they will be assigned the pedagogy the nearest cluster they belong to (besides the one they have previously belonged to).

This approach helps combine data across models to segment users, cluster them further into groups, understand traits of the group and use this to better the tailor the course for users.

5 Work Done

Edx released a dataset pertaining to few of its Harvardx-MITx courses for the year, 2013 (de-identified data). The datasets contains activity statistics in terms of the number of clicks. The number of clicks is operationalized as the number of events (e.g. video plays, e-text page accesses, problem attempts, forum posts) in the server log files [21]. This serves as a rough indicator of how much of the content the user has interacted with. The data also contains the students grades. This serves to evaluate the performance of the proposed model.
On the data we build the user activity model. To define the four categories we define two thresholds. The student performance threshold - has the user passed the course (grade is above 60%) and the user-system engagement threshold - has the user engaged with at least half (50%) the content. Fig. 4 represent a scatter plot where the X-axis is the number of chapters accessed and Y-axis is the number percentage-grade. Using two threshold for them i.e. 60% passing grade and 50% of course content accessed we can divide this plot into four quadrants. Quadrant 1 represent the hype group, Quadrant 2 gamers, Quadrant 3 Concern and Quadrant 4 Ideal. We now focus on the data within quadrants 3 and 4 to develop the user profile model.

Figure 2: User data (10% unidentifiable) - activity statistics for forum posts, and median total numbers of active days, disaggregated by viewed vs. explored or certified registrants. [21]

Figure 3: User segmentation using user activity model (in terms of the percentage of chapters accessed and course grade)
The data contains two variables of interest: number of videos played and number of chapters. This constitutes the students' interaction logs. In addition, we also have student age and educational qualification. Based on these, we can cluster the users into groups.

The assumption is that the cluster formed will help guide the new users to their most suited pedagogy. The data, however, contains only the final snapshot of user activity. We need several snapshots over time.

However, it can be seen when a new user comes in; the user profile model will assign him to a cluster based on his initial interaction with the system. The user activity model keeps track of further interactions, like the course grade and amount of content accessed. If, according to the user activity model, the user is in quadrant 4, he/she is following pedagogy most suited to them and will do well. If the user moves out into quadrant 2 or 1, the system will take adaptive action as stated earlier (mails or controlled tests). If the user moves into quadrant 3, then the user profile model kicks in again, takes the most up-to-date data regarding the user and reassesses. It finds a new cluster, with different pedagogical support that the user would be more suited to.

6 Future Work

Courses that extend over a long period of time may have students that evolve beyond the comprehension of the system as a student can be exposed to various other venues for learning. Such a system would need to incorporate probabilistic models to account for such outside influences.

Furthermore, gaming in such systems is another issue. It is quite hard to actually measure how much effort a user puts in. Even with gaze-tracking systems, it is hard to detect if a student is engaging with the system correctly. A diverse question bank with controlled environments would have to be put forward to ensure that students do not cheat the system.

Other areas include development of the content itself. A lot of the content required is already available across the internet. Attempts are being made to automate the process of content generation by combining such sources to provide the user with a roadmap.
This cutting-edge research field has seen improvements in the past few years with active research ongoing.

7 Conclusion

The novel design proposed unifies the traditional models of user and domain to adapt and deliver content more effectively. The prototype on Edx-MITx courseware indicates that the personalization would help students pick up skills without having to spend time on pedagogy that is not suited to them. Hence specific user and domain models combined with integrated analysis helps improve adaptive tutoring systems to provide better suited content for each user.

References


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