Adaptive Learning and Analytics in Engineering Education

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***Abstract*—The fact that different students have different ability levels and learning patterns limit the effectiveness of traditional one-size-fits-all classroom-based teaching. It is difficult to accomplish a learning methodology tailored to individual students in large classes with traditional teaching methods. In this work-in-progress paper, an adaptive learning system, employing a rule-based logic was developed and tested for three undergraduate student courses. The questions were served to students adaptively by the computer, based on their level of understanding. The analytics from the system can act as a feedback to the instructor. Some limitations and practical issues, as well as suggestions for improvement are discussed.**

***Keywords*—adaptive learning, formative assessment, web application.**

I. Introduction

Students differ in their learning capabilities and it will be difficult to provide a tailored education, especially in large classes. Different technology solutions have been proposed to deal with this challenge [1]. Adaptive learning refers to a learning process in which the user is presented with content that adapts to their level, as inferred from their response to the questions attempted. Such systems take advantage of modern computing to deliver personalized learning to the individual. Studies on the effectiveness of such adaptive learning systems can be found in [2]. Adaptive learning systems can be used for formative or summative assessment. In this work, we focus on formative assessments, and adaptive learning, which has been shown to be very effective in enhancing the learning experience of students [3]. Further, in [4], it was shown that intelligent tutoring systems that provide guidance with respect to students' abilities can help them to become better learners.

Item response theory (IRT) is a popular algorithmic adaptation scheme, which is more popular in the assessment community [5]. IRT focusses on modelling student abilities based on their responses to problems with different difficulty levels. It does not account for temporal aspects of student learning, i.e., how learning has evolved over time. Bayesian knowledge tracing (BKT) is a different approach where the focus is on modelling student learning to assess students' learning based on their response to specific questions which reflects a latent skill [6]. BKT considers temporal aspects, where the skill is honed at every opportunity to apply that skill. There have been works recently which indicate that these models are complementary, and some combined models have been proposed [7]. For computer adaptive tests, Rasch model, which is a special case of IRT, is sufficient, where difficulty is the only parameter used in adaptation and other factors are ignored [8]. In this work, since the focus is on summative assessment which enables the student and the lecturer to get feedback on the students' competence level in a particular topic, we use Rasch model.

A popular adaptive learning system, FastTest [9], implements a platform model system where questions can be added by instructors of the respective course. FastTest provides the whole computer-aided development cycle from the creation of items, to the delivery of fully IRT based adaptive tests. Statistical reports are also provided at the end of tests. One limitation of this system is that the test development is too sophisticated, requiring the expertise of a professional psychometrician in the process to conduct analysis and research. Another popular adaptive learning platform, WileyPlus ORION [10] assess the student's ability level before deciding which instructional material to present to help the student learn. However, this platform uses a publisher model where the content is fully developed by the publisher. As a result, course instructors cannot add new content and content supplied by the publisher is usually limited. In [11], a personalized e-learning system was proposed to estimate the learner's ability using complex artificial neural networks and IRT. This method achieved course material personalization with an 83.3% accuracy which could accelerate learning efficiency.

While adaptive learning systems are not a novel concept, their applicability in engineering courses remains relatively unexplored. This paper details an adaptive learning platform which was implemented from scratch and used for undergraduate courses related to digital systems and computers.

The rest of the paper is organized as follows: Section II provides more details of the adaptive learning platform. Section II details the deployment in various courses, usage details as well as the results of surveys. The paper concludes with section IV, which details future directions and recommendations based on our experience.

II. Adaptive Learning Platform

A. Background Context

We explored the use of adaptive learning in three core second- or third-year undergraduate courses - EE2020 Digital Fundamentals, EE2024 Microcontroller Programming and CG3207 Computer Architecture. All the three courses have large class sizes, typically more than 100 students per semester, where such online learning platforms can be of more value to the instructor. The digital systems / programming nature of these courses make it relatively easy to create multiple choice questions (MCQs), which are the only type of questions supported by our system currently. Hence, we used these courses to conduct a pilot study in our exploration of adaptive learning systems in engineering.

B. Platform Architecture

The platform consists of two parts - the frontend where the user can interact with the platform, and the backend which performs the adaptation and various analytics. The front-end has a separate student view and an instructor view. The instructor view allows the instructor to enter questions for each topic, and set an initial difficulty level. The interface also allows for the creation of tests/polls. It summarizes the information through various analytics, allowing the instructor to gauge the topic-wise understanding of each individual student. In the student view, students can select the topic they want to practice. The practice sessions start with questions of moderate difficulty level, and are gradually increased or decreased as appropriate. Though originally conceived as web interface for conventional computers and mobile apps for portable devices, it was eventually implemented as a bootstrap-based [12] web application which scales well to the display of the device being used. Screenshots of the mobile interface are shown in Fig. 1.

The backend is based on a model view controller model [13], which is the standard for most modern web applications. The language used is PHP, with MySQL as the database. The webserver is Apache, running on a Linux-based operating system. Fig. 2 shows the overall system architecture of the system and Fig. 3 shows the software architecture. The system is linked to the student list and login from the university's online learning system, so that only those students taking a course can log in to the adaptive learning system for that course. A poll feature has also been added, mainly intended to be a clicker like function which will act as additional information to the instructor. The idea of this functionality is to enable the instructor to ask questions during the lecture, and students can respond instantly [14]. The instructor is then able to show the poll results to the class. The data from this poll also gets added to the analytics database.

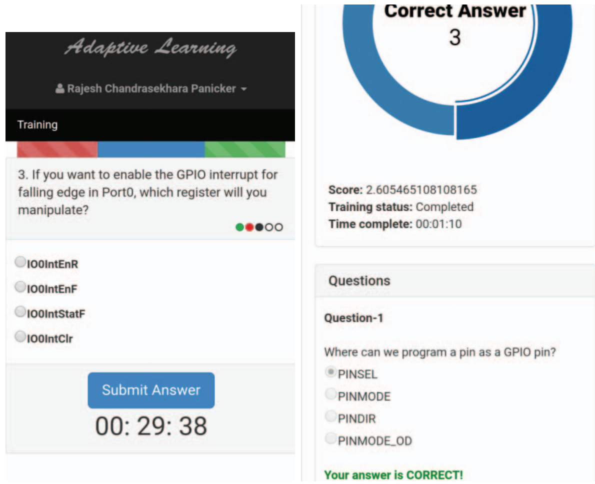

Fig. 1. Screenshots of the mobile interface.

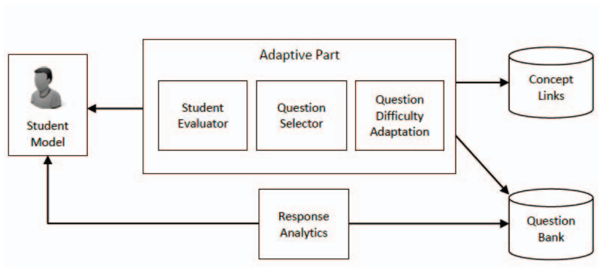

Fig. 2. Overview of the adaptive learning system.

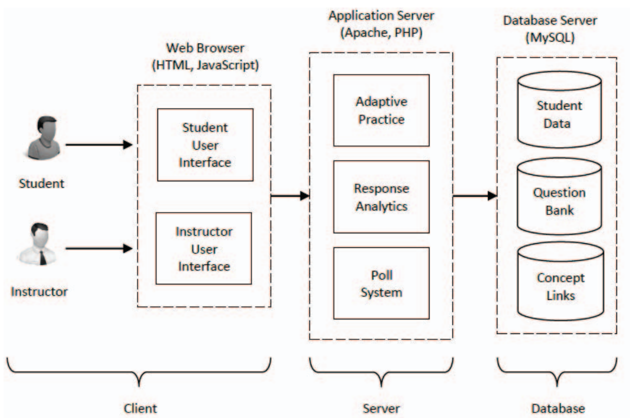

Fig. 3. Overview of the adaptive learning system.

C. Adaptation Scheme

The adaptation could employ either rule-based mechanisms or algorithm-based mechanisms [15]. Rule-based approaches use predetermined branching architectures which the user traverses based on his/her response to questions. If a question is answered correctly, the system could issue a more challenging question which is pre-determined. Similarly, the system can issue an easier question or hints or other assistance if the question is answered wrongly. Algorithmic mechanisms use mathematical models for inferring student's ability level and perform real-time content adaptation. Algorithms range from simple linear models, Bayesian data analysis using inference networks etc. In our system, adaptation is performed at two different levels – student model adaptation and question difficulty adaptation. The questions the student gets on a particular topic depends on the competence of the student in that topic, as given by the student model. The complexity of each question is also adapted based on the fraction of students who are able to solve it successfully. In our system, we have employed a relatively simple rule-based adaptation model for both student model and problem complexity. Every question has a difficulty level associated with it, in the range 1 to 5, with 1 being the easiest and 5 being the hardest. The initial difficulty level is set by the instructor based on their perception of the difficulty level of the question. When a student starts his/her formative assessment session for a particular topic, the system assigns a default mastery level, set to zero. If the student attempts a certain number (a threshold settable via the instructor's interface) of questions correctly, the mastery level is increased, and the student will get questions of higher difficulty, and vice versa. For subsequent sessions on the same topic, the initial questions are based on the student's mastery level in that topic. The question difficulty level is also adapted in a similar manner.

The system is currently designed for formative assessment only – students can attempt it anywhere they like, and sessions are not time restricted, though a time limit can be added easily. After the student goes through the number of questions fixed for the training session, they will be presented with a training review page. This page allows the student to view his/her responses and the overall score. Solutions to questions which the student answered wrongly will also be presented to close the learning loop. Question banks were created with a number of questions from each topic, with difficulty levels rated from 1 to 5. Students can select and practice a topic, and are given a live feedback on the mastery level in that topic as they progress with the questions. At the end of the session, they are given a summary of their answers for each question, along with the correct answers.

D. *Analytics*

The analytics interface allows the instructor to view the performance of any student on any topic. It also allows the instructor to view a histogram of the performance of all the students in the class for a topic. A sample analytic showing the adaptation of difficulty level for a student in a topic is given in Fig. 4. This can act as feedback to the instructor regarding the level of understanding of students in various topics, which will allow them to provide more explanations and additional tutorial problems to help students assimilate the concept better. The instructor can also consider allocating more time and resources to such topics for future semesters. Students can inspect topic-wise score histories and the overall class performance statistics. A scoreboard, which is visible to the whole class is also maintained, indicating their performance relative to the class.

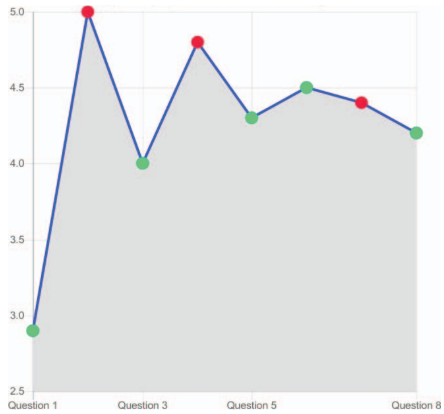

Fig. 4. Screenshot of the analytics page showing the difficulty of questions administered in a training session.

III. Deployment, Usage and Survey Results

A. *Deployment*

The system has been deployed for one semester for each of the courses EE2020, EE2024 and CG3207. The system is currently functional with all the intended features, save for some occasional glitches in certain features. Several usability and functionality issues were fixed incrementally based on feedback from students. The question bank consists of about 200 questions for EE2020, 300 questions for EE2024 and 40 Questions for CG3207, with more questions being added progressively.

B. *Usage and Survey Results*

For CG3207, 50 students out of a class of 91 used the system. 486 questions were attempted over 2 topics. For EE2024, 52 students out of a class of 101 students used the system. 558 attempts over 24 topics were recorded. For EE2020, the numbers of attempts were low as it was released for limited pilot testing in the early phase of this project. The results from a user experience and usefulness survey based on the response from the limited number of students who provided feedback are given in Table 1, which shows that many participants found it good. The relatively low number of respondents (17) despite the large user base is probably due to participation in the survey not being mandatory.

TABLE I. User Experience Survey

Survey Questions	***Average Response (On a Scale of 5)***
Do you think an adaptive learning system will benefit students?	4.2
Rate the User Experience.	3.6
Rate the User Interface.	3.8
Was the system beneficial for your learning?	3.7

The results of a survey on students' perception of adaptation are given in Table 2. 9 out of 17 students could perceive an increase/decrease in the difficulty based on the correctness of their response, while others could not perceive a change in difficulty level. The current number of questions in the question bank is still below what would be required to have a completely successful deployment of this system, which could be the reason for a fair fraction of students not being able to perceive the adaptation behaviour. It is expected that more questions will be added over the subsequent semesters or so, to have a more comprehensive and useful system. The survey also needs to be improved to collect more qualitative and quantitative data to fine-tune the adaptation features and parameters, and to have a better understanding of the effectiveness.

TABLE II. ADAPTATION EXPERIENCE SURVEY

Survey Questions	***Positive Responses***
Do you feel there is a change/ changes in the difficulty level of questions?	12/17
Do you feel the questions are harder when you answer previous questions correctly?	9/17
Do you feel the questions are easier when you answer previous questions incorrectly?	9/17
The system is an adaptive learning system, which can adjust question's difficulty level to the student's ability. Do you think it is helpful to practice on a particular topic?	9/17

C. Challenges and Limitations

The main challenge in deploying such an adaptive learning system is the vast number of questions required to have a meaningful adaptation. There should be a fair number of questions from each topic with varying difficulty levels, which can be challenging. This might be possible only for courses with a relatively big teaching team of instructors and teaching assistants willing to contribute carefully crafted questions. Also, it is only feasible for courses where it is relatively easy and meaningful to evaluate knowledge using multiple choice questions. Courses where conceptual or critical thinking must be evaluated may not benefit from the proposed system. The proposed system was designed with engineering disciplines in mind; disciplines where practical skills on negotiation and creativity are taught might need a different approach and may be worth exploring.

IV. CONCLUSION AND FUTURE DIRECTIONS

The system is currently functional with all the intended features, save for some occasional glitches in certain features. Several usability and functionality issues were fixed incrementally based on the quantitative, qualitative and verbal feedback. Students were generally receptive of the idea of having such a learning platform. Implementing such systems can help address some of the challenges associated with ensuring that students are able to receive formative assessment questions which adapt to their knowledge of the topic. Courses for which multiple-choice questions are easier to create are good candidates for such adaptive learning systems. The system is still being continuously improved based on the feedback and suggestions from students. A provision for an explanation regarding what could be wrong with their thought process, and some hints towards arriving at the correct answers are being added. Work on enhancing the user interface for entering and editing the questions (for the instructor) is in progress. A more fine-grained logging for backend analytics is also being implemented to help analyze the data/adaptation more meaningfully. A mechanism to point out the weak areas/chapters to students based on a number of tests taken for a course and results is also worth considering. It would also be worth exploring other features, such as student motivation, for adaptation.

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