Modelling Student Knowledge in Blended Learning

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ABSTRACT

Blended learning offers a diverse learning experience through multiple activities inside and outside the classroom, which can improve student knowledge, as there are multiple opportunities for learning. However, managing these activities requires an integrated approach to ensure its effectiveness, that is, taking into account learning data from different sources. Disregarding any of these sources may lead to incomplete/incorrect information on the current levels of students' understanding of courses topics. This paper proposes an approach to student modelling that incorporates both streams of student activity performed during both modes of blended learning. To maintain a mode meaningful representation of students' knowledge, reflecting differences in focuses of in-class and at-home assessment, the proposed approach divides student knowledge into three cognitive levels based on Bloom's taxonomy, namely, Remember, Understand, and Apply. The Elo Rating System is used as the main method of student knowledge estimation; it is enriched with knowledge propagation between the Bloom's levels of cognitive activity to account for their inter-dependency. The propagation parameters are optimised. The result shows that the model is capable to distinguish between positive and negative results of student attempts well enough.

CCS CONCEPTS

• **Applied computing** → **E-learning**; **Distance learning**.

KEYWORDS

student modeling, propagation, elo rating, bloom taxonomy

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1 INTRODUCTION

Adaptive support of blended learning has traditionally focused on its online component. This is hardly surprising. First of all, during online, self-regulated learning, students may lack feedback and guidance typically provided by teachers. Without such individual instructional support, some students will struggle with planning their learning actions, staying engaged with learning material, recognising mistakes and gaps in knowledge, and coming up with remedial steps. Additionally, during online learning, students engage with digital material, thus generating activity data and interacting with educational software that can potentially use these data to improve students learning in the course. Hence, implementing adaptive support of the online learning component has been both necessary and opportune.

However, such implementations of learning support completely ignore the face-to-face classroom phase of a blended course, which creates several problems. In blended learning, face-to-face and individual learning activities have different outcomes [9]. Combining them in an integrated way that supports these activities and creates a holistic learning experience can benefit students who often view face-to-face and online components of blended learning as two disjoint processes. Additionally, in larger blended courses, even in a classroom, students cannot receive enough support from teachers, because teachers do not have enough information about individual students and time to provide them with such support. Therefore, we argue, that an effective adaptive educational system for blended learning support should assume a true "blend of learning". It should integrate information from online and face-to-face learning activities; it should use this information to maintain a holistic model of student knowledge; and it should deliver adaptive learning support based on a strategy that helps students throughout their entire learning journey.

In our previous work [10], we have demonstrated that integration of information from the two data streams (one coming from students' in-class activity, and another - from their self-regulated learning at home) significantly increase the accuracy of prediction of student performance. This study proposes a student modeling mechanism to provide a unified representation of student knowledge updated from two types of assessment data corresponding to the two components of blended learning. In-lecture assessment and at-home self-assessment have different purposes and requirements. Questions used in these two modes substantially differ in terms of their objectives and the knowledge they test. We use Bloom's models of educational objectives from [5] to represent student knowledge of various nature in blended learning. Specifically, three levels are used: Remember, Understand, and Apply. We use the Elo Rating System (ERS) to estimate student knowledge. ERS is known to be simple yet effective in student modeling [7], scalable [1], and intuitively explainable [13]. This paper aims specifically to address the following research question: *How to develop and evaluate a student model based on assessment data from multiple contexts in blended learning?*

2 RELATED WORK

Several studies before have explicitly addressed the problem of student modeling in the context of blended learning. Hoic-Bozic [4] studied blended learning design and its implementation at the university level. An adaptive learning system was developed to facilitate various learning activities which, in this study, includes collaborative learning, problem-based learning, and individual learning. To provide adaptive navigation support, the tool modelled student knowledge. The model was developed and updated mostly based on the results of online assessment. However, in addition to online assessment, student performance was also influenced by other factors such as the quality of the final project, seminar work, discussion activity, and presentation skills. Wang [11] used SVM to generate recommendations informed by a student model. In this study, students performed multiple activities in a face-to-face and online environments. Each of the activities contributed to updating the student model. Another study by Zacharis [14] proposed a student modelling method to predict student performance in a blended learning environment, especially its online part. The student modelling method was developed and updated based on various factors characterising students' interactions with learning activities within the main LMS (e.g., quiz performance, content page views, average session lengths, posting comments, contribution to content creation, etc.). The resulting student model was used to make a prediction regarding failing/passing the course by individual students.

The nature of blended learning, in which multiple learning activities are performed in different contexts, makes it important to integrate learning data. Several studies have looked into the ways to effectively combine such data. Predic [8] studied the improvement in the accuracy of the prediction of the final score by combining several classification algorithms to classify student performance based on mixed activities during a blended course. Another research by [12] used multiple linear regression models to predict student performance based on multiple online activities, including video lectures, quizzes, and group discussions. [6] found that combining blended learning activities yields the highest accuracy in predicting student performance. The activities included in this study were video lectures, practice beyond class, quiz and after school lectures. It used principal component regression to predict student performance based on blended datasets.

3 QUIZITOR

To implement the blended learning environment, a tool called Quizitor was developed. It is a hybrid quiz platform that allows two modes of assessment, namely in-class and at-home. The in-class mode refers to class assessment activities managed by a teacher and the at-home mode refers to self-assessment activities managed by students.

The in-class quiz is a teacher-controlled activity. This means that the teacher can determine the start and end of the quiz. It is carried out synchronously during lectures in a classroom. The objective of this type of activity is to interactively assess the student's current knowledge on a particular topic being taught. The assessment technique used in this mode is similar to the so-called voting systems [2]. It starts when the teacher opens a quiz. As shown in Figure 1, after starting a quiz, the teacher can monitor the time, the number of participants, and the number of answers submitted by students. Students can see the question and submit their answers. The in-class activity is designed to be time-constrained. Therefore, only 10 questions were available for each topic. In addition, the questions for the in-class mode are designed as simpler items aimed at recalling concepts, their meanings, and most typical use-cases within 30-60 seconds. Therefore, after around one minute, the teacher usually terminates the current question and displays the results page, which can support a brief discussion of popular responses.

The at-home quizzes, on the other hand, are a student-centered activity. It is carried out asynchronously outside the classroom. The objective is to help students practice their knowledge and prepare for the exam at their own pace. Unlike the in-class quiz, in this mode students are allowed multiple attempts at one particular question. Students can navigate through the questions of a quiz in random order (Figure 2). The numbers of quizzes per topic and questions per quiz in this mode are much larger; and the questions themselves are more complex than in the in-class mode. Topics have between 10 to 40 questions divided into several quizzes.

There are four types of questions available in Quizitor: multiple choice, short answer, ordering, and multiple answer. The Multiple Choice Question (MCQ) is a question with multiple answer options, and the student can choose one option. Short answer question (SAQ) is a question that is answered by typing short word/sentences. The ordering question (ORD) is a question with multiple options in incorrect order and students need to reorder it to make it correct. The Multiple-response question (MAQ) is a question with multiple answer options, and the student can choose more than one option.

Quizitor has been implemented using responsive Web design that makes it accessible across multiple types of devices. On a desktop, the elements of the interface are designed side by side, as shown in Figure 2, while on a mobile, the elements are designed as a stack from the top of the screen. In addition, some elements are removed while they are displayed on the mobile screen, such as the navigational buttons and the title bar. Student access to mobile devices is also easier with a QR code provided on the home screen.

4 MAIN APPROACH

4.1 Modelling student knowledge

We have used ERS to dynamically track the learning progress of students throughout multiple learning activities. There are two steps in this process [7]. First, it computes the probability that the student answers correctly and then updates their knowledge level based on their answer. If the student answers correctly, their knowledge will increase; otherwise, it will decrease. The strength of the update depends on the difference between the original Elo rating of a student and a question. A student with a low Elo score (novice) answering correctly a question with a high Elo score (difficult) will observe a larger increase in knowledge. At the same time, if a student has a high Elo already (expert), it will not change dramatically

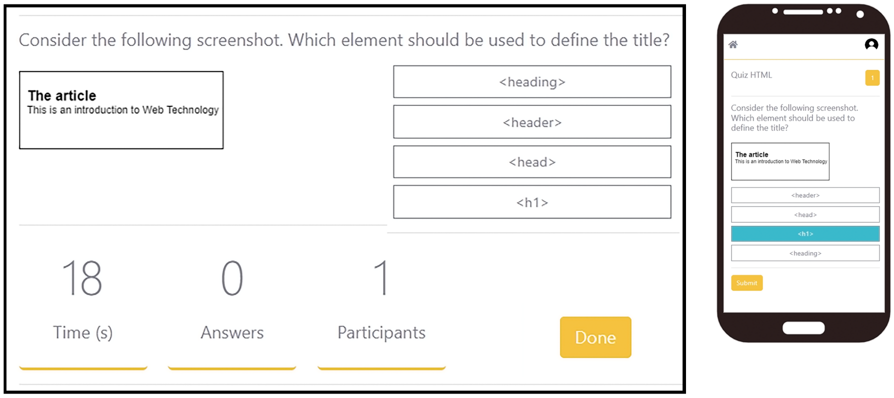


Figure 1: The interface of in-class quiz for the teacher (left) and students (right). Teacher view displays a timer, number of answers, and number of participants.

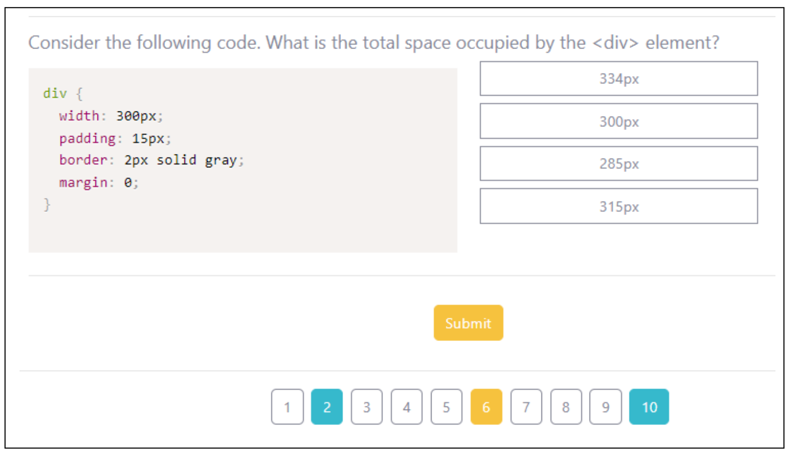


Figure 2: The interface of at-home quiz for the students. It displays the question, submit button, and navigation buttons.

after a correct answer to a low-Elo (i.e. easy) question. An incorrect answer will trigger a reduction of a knowledge score that follows similar rules. At the same time, the difficulty of questions is also balanced after each attempt. If the student answers correctly, the difficulty level of the question will slightly decrease; otherwise, it will slightly increase.

4.2 Bloom's Taxonomy

Bloom taxonomy is a categorization of thinking skills. According to [5], there are six levels of cognitive activity, namely Remember, Understand, Apply, Analyze, Evaluate, and Create. In this study, we focus only on the first three levels, i.e. Remember, Understand, and Apply, to characterize the difficulty and educational objective of the questions and the cognitive processes that students engage when answering them. For the in-class quizzes, most of the questions are designed for Remember and Understand level, while for the at home quizzes, most of the questions are designed for the Understand and Apply level.

4.3 Propagation

As depicted in Figure 3, the steps for propagation are as follows. Correct answers only propagate from higher knowledge level to lower levels. It means that when a student answers a question correctly at the Apply level, it will increase their knowledge at the Understand and Remember level. At the same time, if a student has correctly answered a question on the Remember level, it will have not influence on their knowledge estimates on the levels "above". In contrast, incorrect answers propagate only to higher levels. It means that when a student answers a question incorrectly at the Remember level, it will also decrease their knowledge at the Understand and Apply level. However, the negative evidence will not propagate to the lower levels (i.e. from Apply to Understand, or from Understand to Remember). This ensures that the analysis takes into account the relationship among different cognitive levels. In addition, dedicated weights have been added to the propagation process. We have iterated the weights for forward and backward propagation within the range from 0 to 1 with the step 0.1, to find the optimal combination.

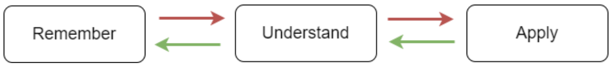


Figure 3: Steps on propagation between cognitive levels.

Table 1: Number of questions in-class and at-home categorized in Bloom's

No.	Topic	In-class			At-home		
		Rem	Und	App	Rem	Und	App
1	HTML	4	4	2	4	7	6
2	CSS	6	4	0	3	7	10
3	JavaScript	3	0	7	0	0	10
4	DOM	1	7	2	1	7	10
5	OOP	4	2	1	1	7	5
	Total	18	17	12	9	28	41

The ERS formula (adopted from [7]) has been modified to account for knowledge propagation between the levels of cognitive activity. First, we compute the probability that the student answers correctly.

$$P(correct_s i = 1) = \frac{1}{1+e^{-(\theta_s - d_i)}}$$

Second, we update the student's knowledge level and the question based on the probability of the expected result.

$$\theta_s := w(\theta_s + K(correct_s i - P(correct_s i = 1)))$$
$$d_i := w(d_i + K(P(correct_s i = 1) - correct_s i))$$

The initial values for θ_s and d_i are 0, K has been set to 0.4, and w represents the weights.

5 EXPERIMENT DESIGN

5.1 Participants

The participants in this study were 176 students enrolled in a university course. 155 students tried system. We excluded students who logged into the system only once. This left 143 students providing data to the analysis. In the beginning of the course, students were introduced to the system and its functions. Informed consent had been collected before the experiment started. The participation was voluntary and students could stop participating at any time.

5.2 Data Collection

The collected data included student attempts characterised by the login time, username, session id, quiz and question id, response time, and the correctness of the answer. Students used Quizitor during the introductory part of a Web Technology course including five lectures on HTML, CSS, JavaScript (JS), DOM, and object-oriented JavaScript (OOP). Each of these lectures had a pair of in-class and at-home quizzes with varying number of questions per quiz. The total number of in-class questions was 47; the total number of at-home questions was 78 (125 in total). Questions were annotated not only in terms of topics, but also in terms of the level of Bloom's taxonomy that they operated on. Table 1 shows the distribution of questions across modes, topics and levels of Bloom's taxonomy.

6 RESULT

143 students used Quizitor to support their learning in the course. 93 of them participated in both in-class and at-home assessment (37 only took at-home quizzes, and 13 participated only in class). The average number of questions attempted in class was 23 (SD = 13.7); the average number of questions attempted at home was 61 (SD = 20.9).

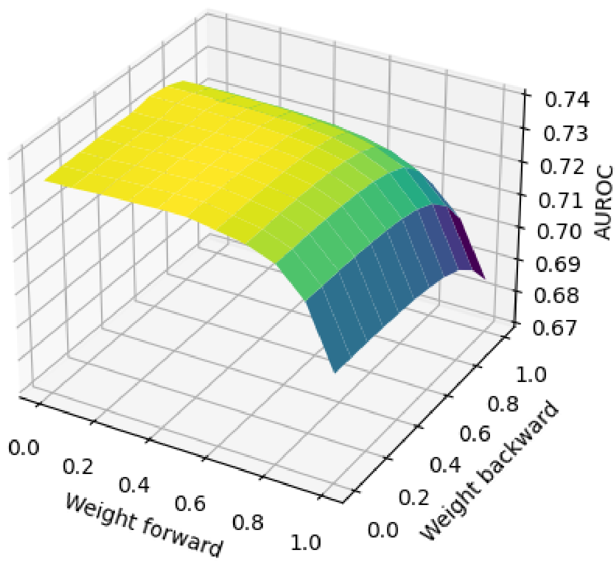
Before we could apply ERS to estimate students' knowledge based on their activity with Quizitor, we needed to estimate Elo scores of all questions, i.e., their levels of difficulty. First, we split all students into two groups of 80% and 20%. The question difficulty was estimated by calculating their Elo ratings based on the answers from 80% of students. Then, the obtained question model was used to estimate the Elo scores of the remaining 20% of students. Next, another group of 20% of students was selected and the processes repeated. After five iterations, Elo scores of all students were modeled. When computing the Elo scores for questions and students' knowledge, we also applied propagation between the three cognitive levels.

To evaluate the predictive validity of the developed student modelling approach, we used the ROC curve analysis - a popular tool from the signal detection theory that became widely used in for evaluating reliability of data-driven models [3]. An ROC curve plots the true positive rate (TPR) against the false positive rate (FPR) of a model at different values of the operating threshold. To numerically estimate the quality of the model, we have computed Area Under ROC (AUROC) value. The AUROC values were computed on an 11 x 11 matrix representing different weights for forward and backward propagation while computing models' predications.

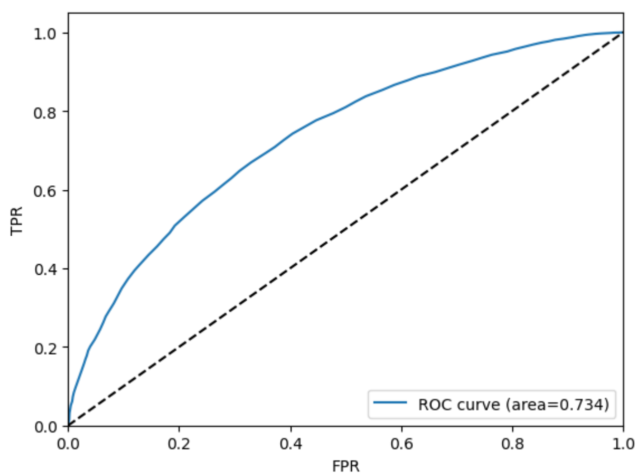
Figure 4a visualises values of AUROC for different weights combinations. The x-axis represents the weight forward, the y-axis represents the weight backward, and the z-axis represents the AUROC value of the corresponding model. The first AUROC value with weights [0.0; 0.0] is 0.732. These values correspond to no-propagation model. It can be seen that the model quality begins to slightly grow from this point, and after around the point [0.5; 0.5], the quality of models drops substantially all the way to the point [1.0; 1.0], which corresponds to propagation without losses. The optimum AUROC value is 0.734 with the weight forward = 0.4 and the weight backward = 0.3. The weight begins to decrease between 0.6 and 1. The smallest AUROC value is 0.684 with the both propagation weights = 1. The right part of Figure 4b visualises the ROC curve of the best model.

7 CONCLUSION

This paper presents evaluation of a student modeling approach that incorporate data coming from various assessment activities in a blended course. It uses the Elo Rating System to track student knowledge and the Bloom's taxonomy to represent students knowledge on different levels of cognitive activity. It shows that the model has a reasonable level of predictive validity. However, in this study, we only used one dataset gathered from one experiment. We plan to test the model across multiple datasets, compare it against other possible approaches and investigate how well can such a model predict students' performance outside Quizitor.



(a)



(b)

Figure 4: A plot showing various AUROC values across different weights (a) and ROC curve with optimum AUROC value (b).

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