Towards Continuity of Personalisation in a Large Blended Course

Sergey Sosnovsky[1], Almed Hamzah[1,2]

[1]Utrecht University, The Netherlands
[2]Universitas Islam Indonesia, Yogyakarta, Indonesia

Abstract
Teaching and learning in a large blended learning course could be quite challenging. Existing adaptive systems mostly focus on supporting students' self-regulated work at home. A few systems also exist to help the instructor conduct in-class assessment. This paper present Quizitor - an assessment system that is capable to deliver both the at-home and the in-class assessment. We believe, that combining these two streams of data can help achieve more accurate student modelling and potentially, more effective adaptive support. The pilot evaluation of Quizitor demonstrates that a model aggregating data from student activity conducted at home and in class predicts students' grades better than models separately trained on either of these two types of activity.

Keywords
self-assessment, blended learning, student modelling, personalisation, voting tool

1. Introduction

Giving a lecture in a large course often lacks interactivity. This is detrimental to the quality of teaching/learning from two standpoints. First, the level of student engagement is directly related to the amount of interaction a learning activity involves [1]. In its absence, a student remains a passive receiver of information, an object (not a subject) of the learning process. She lacks opportunities to monitor her knowledge and self-reflect, has no control over her own learning, and cannot achieve deeper understanding of the material. From another perspective, lack of interactivity results in a shortage of information about learning that occurs (or does not) in a classroom, which brings about less effective instruction. For a teacher, it becomes hard to estimate how much individual students understand, which concepts require additional focus, and where remedial actions are needed. Furthermore, a teacher often remains unaware of individual learning difficulties even after the lecture and cannot address them, hence students are rarely provided with effective tools to catch up on their own.

This problem is magnified when the course population is diverse in terms of relevant background. This is often the case in introductory programming courses. A large portion of students taking them have limited or no programming experience; while other students might have

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s.a.sosnovsky@uu.nl (S. Sosnovsky); a.hamzah@uu.nl (A. Hamzah)
0000-0001-8023-1770 (S. Sosnovsky); 0000-0003-4965-7057 (A. Hamzah)

already developed software on their own. Such a difference in students' initial knowledge of the core concepts makes it very challenging for the instructor to properly cater the course material for all categories of students.

Over the years, a range of technologies has been developed to increase the level of student awareness and engagement during lectures. The least disruptive to the overall flow of the lecture and the most flexible in terms of the subject and context of instruction are the personal response systems [2] or their "close relatives" – voting systems [3]. They allow a teacher to organize real-time in-lecture assessment, immediately display summative results and engage students in a brief remedial discussion. Unfortunately, the data collected from such assessments are not utilized outside of lecture halls to help trace students' progress and guide them to helpful learning material.

Adaptive intelligent learning environments tools have been successfully used to support students' individual work outside of classrooms [4]. For example, intelligent tutoring systems [5] and adaptive educational hypermedia systems [6] have proven their effectiveness in various subjects and learning contexts. More recently, learning analytics technologies have gained wide adoption with a goal to assist both students [7] and teachers [8]. Unfortunately, these systems and technologies mostly focus on supporting independent learning and self-assessment at home or in the lab and are less applicable during lectures, when students have been just exposed to new knowledge and may experience learning difficulties with new material for the first time.

A combination of in-lecture and at-home assessment coupled with adaptive support has a potential to significantly improve learning experiences in a large university course. In-lecture assessment and at-home self-assessment have different purposes, but they both provide valuable information about student progress and opportunities for targeted interactions. The in-lecture assessment keeps students engaged and can serve as initial input on student conceptual understanding. The at-home self-assessment helps the student to practice acquired skills at individual pace and receive adaptive guidance. Combining these two streams of data and two modes of adaptive learning support in a single system could directly benefit students by enabling their reflection on the current progress and building a stronger link between knowledge and skills thus facilitating deeper understanding of the subject. For a teacher, such a system can provide information on individual difficulties and overall performance which should help inform and improve used teaching practices.

This paper presents Quizitor - a system that supports two modes of assessment. It can be used by a teacher during a lecture for a pop-up synchronised assessment of the entire class, and by a student at home for individual self-paced assessment. Quizitor tracks students' attempts across both these modes and can integrate these data for a more holistic adaptive support of blended learning. We have piloted Quizitor in an undergraduate programming course. An initial analysis of the collected data shows that a model integrating student activity from both at-home and in-class assessment can predict students' performance better than models trained on individual streams of activity.

The rest of the paper is structured as follows. First, section one explains the background of the current study. Second, section two describes the state-of-the-art from current literature about the topic. Section three describes the features of Quizitor. Section four describes the design of experiment. Section five describes the results. Section six will end this paper with conclusion.

2. Related Work

In many respects, the blended learning paradigm has emerged as an ad-hoc response to the proliferation of online learning environments and the transition of many educational activities from classroom instruction to individual self-regulated learning. There was no sound methodology for blended learning for the first decade after the term was introduced, and even definitions of blended learning sounded rather vague, simply mentioning that "blended learning" assumes a combination of face-to-face and online instruction [9]. How these component should be combined, how lessons should be orchestrated and how support should be administered was not defined.

In the middle of 2010s, several models of blended learning were proposed [10], a handbook on blended learning has been published [11] and several literature reviews have been written [12, 13]. However, when it comes to the technology-enhanced blended learning, researchers and educators focused primarily on supporting the online learning component, largely disregarding the classroom. This is understandable, as in most models of blended learning, the online component assumes individual, self-regulated work; which means, students may struggle with planning their own learning, engage in the learning activities, reflect on potential mistakes, etc. In fact, this becomes the biggest challenge for students in blended learning [14]. In this regards, a multitude of systems have been designed to help students in blended learning environments, focusing on specific educational approaches, such as gamification [15] or integrated learning experience [16].

However, somewhat counter-intuitively, neither of these methods for blended learning support assumes a true blend of learning. In blended learning environment, face-to-face and individual learning activities have different outcomes [17]. Combining the activity data to gain an integrated outcome will benefit for both students and teacher. According to [14] both teachers and students face several challenges when it comes to blended learning. Students have difficulty in self-regulated learning and learning the new tools. At the same time, teachers view face-to-face and online components of blended learning as two separate activities and as consequence, for them, it is more difficult to manage two rather than one learning activity. There have not been many attempts in the literature to propose working solutions for blending support of the both learning components. Most of them were limited to describing frameworks and architectures [18, 19]. This paper is trying to make a more practical step in this direction by describing and evaluating an assessment tool that can be used by students both on class and at home.

3. Quizitor: Combining In-class and At-home Assessment

This section discusses the design and implementation of Quizitor, an online assessment tool combining in-class and at-home assessment. As of now, Quizitor has been used only in a Web Technology course; however, it is a domain-independent tool that can be used to deliver online questions of several types. Quizitor interface has been designed using a responsive web methodology, hence it can be used with a variety of screen sides from a desktop to mobile phone.

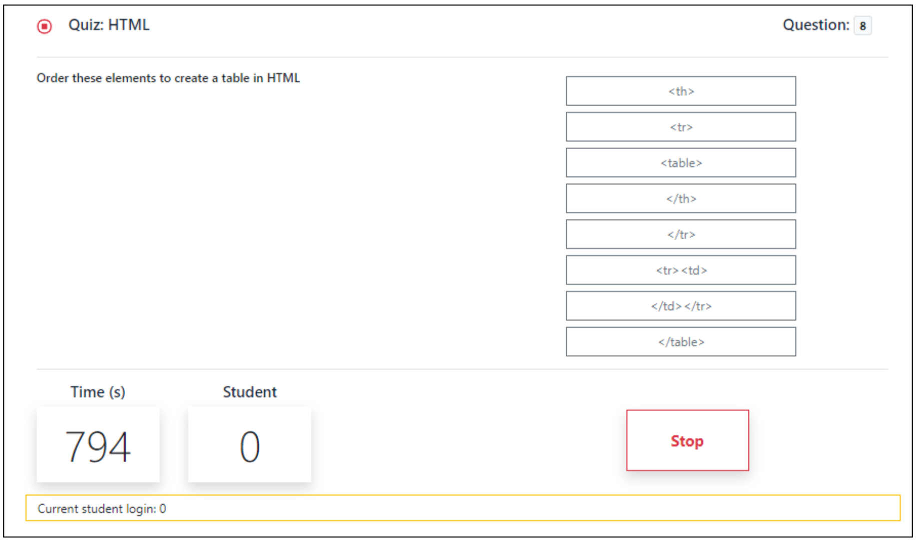

Figure 1: Teacher's view of an in-class ordering question.

The assessment questions in Quizitor are combined into quizzes, which themselves are organised into topics following a course structure. In our current Web technology setup, 6 topics cover 122 at-home questions combined into 14 quizzes and 60 in-class questions combined into 6 quizzes. Currently, four types of question are available in Quizitor, namely: multiple choice questions (MCQ), short answer questions (SAQ), ordering questions (ORD), and multiple answer questions (MAQ). Questions can include graphics and code fragments.

Quizitor supports two assessment modes. The In-class mode is a synchronous assessment where students take a quiz in the class with a teacher. A teacher starts the quiz for all students at the same. A teacher can see, how many students have submitted answers for the current question. A teacher decides when to stop accepting answers and display the results of the current question. The aims of in-class assessment are take a short break from a lecture routine, help students recall the learning material that has been recently taught, help students reflect on their understating of the material, give the teacher information on how well students understand the material. These quizzes usually do not exceed 15 minutes. Figure 1 shows a teacher interface of an in-class question; the student interface looks largely the same, but misses the indicators and controls at the bottom of the page.

The at-home mode supports the asynchronous self-assessment. The aims are to help students practice , reflect, identify knowledge gaps and prepare for exams. In contrast with the in-class mode, the at-home questions can be more complex, as students are not under time pressure when answering them. Students start and stop the questions themselves. They determine the time, the place, and the quiz to take. Students can make as many attempts as they want for each questions. Students can navigate through the quizzes, by clicking on question numbers at the bottom of the page. Figure 2) display an example of an at-home question.

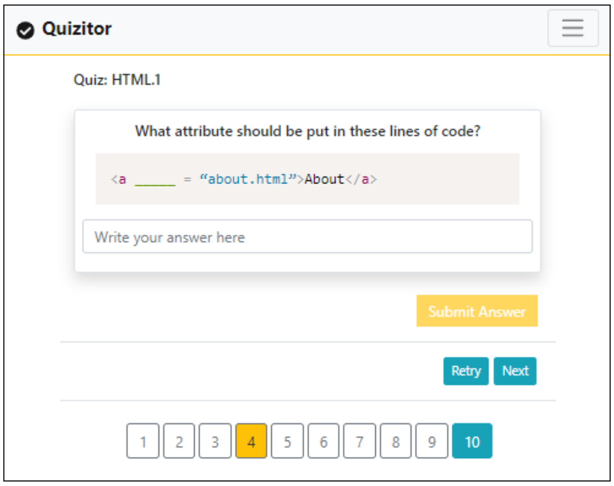

Figure 2: At-home quiz page.

4. The Experiment

In this pilot study, we have tried to investigate the advantages of blending two streams of assessment data coming from two different modes of a blended course. Both data streams have been produced by students using Quizitor: one - in the at-home self-assessment mode and the other - in the in-class assessment mode. Our hypothesis is that a model of student mastery taking into account both these streams of data would be able to predict student course performance better than the models taking into account only individual streams of data. In order to test this, we have computed two models of students' mastery using Elo Rating System. One model was based on their at home assessment results and another - based on their in-class results. After that, we have conducted two simple linear regression analyses, where the obtained students' mastery scores were used as as the predictors of their midterm results. Finally, we have combined the both models and conducted a multiple regression analysis to show that the integrated model can help predict students' grades even better.

4.1. Data collection

The data were collected in the undergraduate course on Web technology taught at in Utrecht University from February until March 2021. The use of Quizitor started at the third lecture and continued for six lectures until the midterm. The topics included basics of HTML, CSS, Javascript and Internet protocols.

This course is offered every year, but this was the first time Quzitor system was used as a learning tool in this course. Students of first, second and third year from computer science, information science and artificial intelligence program take this course. The overall number of students was 198. To participate in the study, students had to sign a consent form. 168 students completed the form. Students who used the tool actively enough (attempted 75% of at-home questions) were given a small extra credit (1% of the course grade). We did not include in the final analysis the activity from 63 students who did not pass the midterm exam.

4.2. Estimating students' mastery

To estimate students' mastery based on their activity with Quizitor, we applied ERS (Elo Rating System). ERS is a relatively easy yet accurate method for modelling ability that has been recently gaining popularity in the educational data mining and student modelling community [20]. It can dynamically assess students' ability in a certain field based on the results of their continuous assessment. While assessing student ability, ERS also keep adjusting the difficulty of questions that students answer. Essentially, ERS constantly balances the "strength" (=ability) of a student vs. a "strength" (=difficulty) of a question. There are two steps of estimating this strength, called Elo ratings ([21]). First, the probability of expected result is calculated.

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

Second, the rating is updated based on the probability of the expected result.

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

The initial value for θ_s and d_i are 0 and K is set to 0.4. Based on these formula, student's rating will decrease if they answer the question incorrectly. On the contrary, their rating will increase if they answer the question correctly.

4.2.1. Student models

In this study, two student model were built: in-class (IC) and at-home (AH). The IC model is trained based on student's in-class assessment. The AH model represents students' mastery as a result of their at-home self-assessment. In order to compute more accurate students' Elo scores, first we estimated Elo scores of the questions, i.e., the levels of difficulty for each question. First, we split all students into two groups of 80% and 20%. The question difficulty was estimated by calculating Elo ratings of each question based on the answers from 80% of students. Then, this question model was used to estimate the Elo score of the rest of 20% of students. Then, another group of 20% of students were selected and the processes repeated. After five iterations, mastery of all students have been modeled. We have repeated this process separately to compute the IC and AH models. Figure 3 and Figure 4 shows the distribution of students' ratings for AH and IC respectively.

5. Results

Table 1 presents the summary of basic statistics characterising students' activity with Quizitor.

A simple linear regression was calculated to predict midterm score based on student's performance with Quizitor reflected as their Elo score. As there are two basic models, the simple regression was calculated two times. After that a combined multiple regression model was calculated to verify the main hypothesis. A significant regression equation was found for all

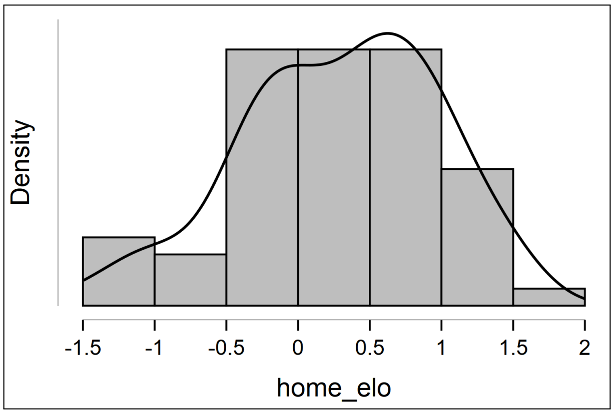

Figure 3: At-home student rating distribution.

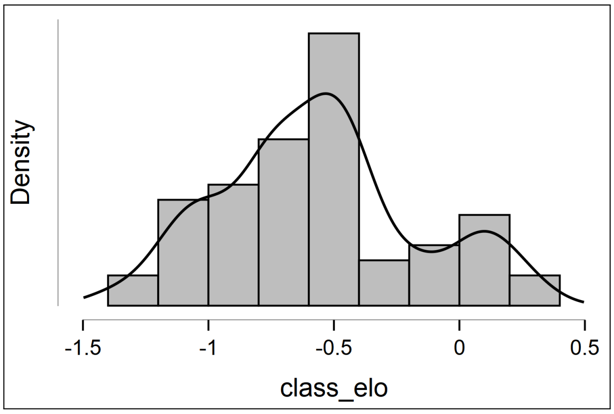

Figure 4: In-class student rating distribution.

Table 1
Summary of students' activity with Quizitor

Modes	At-home(avg)		In-class(avg)	
	M (SD)	%	M (SD)	%
Questions attempted	114.23 (21.22)	93.6	33.44 (14.38)	55.73
Quizzes attempted	12.26 (2.04)	87.58	4.29 (1.71)	71.58
Number of attempts	235.9 (88.73)	-	-	-
Number of attempts per question	2.06 (1.6)			

models and there are positive relationships between the student ability model score and the midterm score. Table 2 presents the summary of the regression models. It is easy to see, that the main hypothesis is confirmed, a much bigger portion of variability in the predicted variable is explained by the joint model.

Table 2
Summary of Coefficient of determination from each model

Model	R^2	Sig.
In_class	0.117	0.007
At-home	0.114	0.008
In_class and At-home	0.210	0.001

5.0.1. Model in-class

Student ability computed based on the in-class activity with Quizitor was found statistically significant as a predictor of the midterm grade, F(1,59) = 7.784, p = .007, accounting for 11.7% of the variability in midterm grade with adjusted R^2 = .102. The correlation between in-class activity and midterm grade was statistically significant, r(59) = .341, p = 0.007. The regression equation for predicting midterm grade based on student in-class rating was y = 7.527 + 0.848x (in-class Elo rating). The confidence interval for the slope to predict midterm grade from student in-class rating was 95% CI [0.240, 1.455]. Therefore, for each one unit of increase of student's rating, the midterm grade will increase as well by about 0.2 to 1.4.

5.0.2. Model at-home

Student ability computed based on the at-home activity with Quizitor was found statistically significant as a predictor of midterm grade, F(1,59) = 7.581, p = .008, accounting for 11.4% of the variability in midterm grade with adjusted R^2 = .099. The correlation between in-class activity and midterm grade was statistically significant, r(59) = .337, p = 0.008. The regression equation for predicting midterm grade from student in-class rating was y = 6.909 + 0.480x (in-class Elo rating). The confidence interval for the slope to predict midterm grade from student in-class rating was 95% CI [0.131, 0.829]. Therefore, for each one unit of increase of student's rating, the midterm grade will increase as well by about 0.1 to 0.8.

5.0.3. Model in-class and at-home

The multiple linear regression model was also significant F(1,59) = 7.687, p = .001, accounting for 21% of the variability in midterm grade with adjusted R^2 = .182. The regression equation for predicting midterm grade from student in-class and at-home rating was y = 7.359 + 0.436x_1 + 0.772x_2.

6. Discussion and Conclusion

In this paper, we have presented Quizitor - an assessment tool that can deliver both in-class and at-home quizzes. Quizitor has been built as the first step in an attempt to organise truly blended adaptive support in a blended course. While Quizitor at the moment does not have any adaptive capabilities, its pilot evaluation has demonstrated that a combination of data coming from the both face-to-face and online components of a blended course can help achieve a more accurate estimation of student ability than models limited to only one of these components.

Several models to predict student's grade are analysed and compared. Based on the R^2 value (Table 2), the r-squared value for the in-class model is mostly similar with the r-squared value for at-home model which is around ($R^2 > 0.11$). The coefficient is increasing while the two models are combined separately as a predictor of midterm score ($R^2 > 0.21$). This indicates that working on Quizitor, to some extent, affecting the exam grade. This kind of effect is one of the required feature that students expect from using a learning tool [22]. By using this kind of integrated approach, the data from in-class activity can be used for at-home activity and vice versa. This will help students to better self-regulate their learning activity. For example, it helps students to select the most appropriate learning contents or tasks. In a class with diverse and large population, this kind of system can help to effectively increase class performance which is beneficial from the teacher's point of view.

There are several directions for future research. First, based on the result, there is an evidence that the two stream of data coming from in-class and at-home have an effect on students' grade. We plan to investigate further to create the fourth model where the in-class and at-home activity are merged into an integrated representation of student ability. Second, we plan to add an adaptive features that will personalize the questions based on the current student's level of knowledge. Lastly, the data gathered from in-class and at-home can be integrated and presented to students or teacher as a real-time feedback for monitoring students' performance.

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