# Improving Prediction of Student Performance in a Blended Course

Sergey Sosnovsky[1(✉)] and Almed Hamzah[1,2]

[1] Utrecht University, Utrecht, The Netherlands
s.a.sosnovsky@uu.nl
[2] Universitas Islam Indonesia, Yogyakarta, Indonesia

**Abstract.** Traditionally, systems supporting blended learning focus only on one portion of the course by tracing students' interaction with learning content at home. In this paper, we argue that in-class activity can be also instrumental in eliciting the true state of students' knowledge and can lead to more accurate models of their performance. Quizitor is an online platform that delivers both the at-home and the in-class assessment. We show that a combination of the two streams of data that Quizitor collects from students can help build more accurate models of students' mastery that help predict their course performance better than models separately trained on either of these two types of activity.

**Keywords:** Self-assessment · Blended learning · Student modelling · Adaptive learning support · Voting tool

## 1 Introduction

Effective learning support in a large blended course can be challenging, especially, when a course population is diverse. An adaptive system aiming to facilitate such support should be able to accurately predict student performance in the course as the first step in administering effective adaptive interventions [1]. Intelligent tutoring systems [2] and adaptive educational hypermedia systems [3] have proven their effectiveness in various subjects and learning contexts. Unfortunately, such systems primarily focus only on one portion of the course by tracing students' interaction with learning content at home. Such a focus on the at-home part of the blended learning 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 learning, engaging in learning activities, reflecting on potential mistakes, etc. In fact, effective regulation of independent studying becomes the biggest challenge for students in blended learning scenarios [4].

Somewhat counter-intuitively, there have not been many effective attempts to propose working solutions for a unified support of the both components of

The research presented in this paper is partially supported by Universitas Islam Indonesia under Doctoral Grant for Lecturer 2019 (grant no 1296).


M. M. Rodrigo et al. (Eds.): AIED 2022, LNCS 13355, pp. 594–599, 2022.
https://doi.org/10.1007/978-3-031-11644-5_54

blended learning: in-class and at-home. Most of the existing literature focused on theoretical frameworks and architectures [5,6]. This paper is trying to make a more practical step in this direction by describing and evaluating an assessment tool that can be used both in class and at home and demonstrating the potential value of blending the two respective data streams.

A combination of in-class and at-home assessment coupled with adaptive support has a potential to significantly improve learning experiences in a blended course. In-class assessment and at-home self-assessment have different purposes, but they both can provide valuable information about student progress and opportunities for targeted interactions. The in-class assessment keeps students engaged and can serve as initial input on their conceptual understanding. The at-home self-assessment helps students practice acquired skills at individual pace and receive adaptive guidance. Combining these two streams of data 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.

This paper presents Quizitor - a system that supports two modes of assessment in a blended course. 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. We have evaluated Quizitor in an undergraduate programming course. An 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. This effect persists when the data are aggregated on the level of the course as well as when we narrow down to topic-based models of student performance. Hence, by tracking students' attempts across the both modes and integrating the both streams of data, Quizitor has a potential to maintain a more accurate model of student performance in a blended course and a more holistic adaptive support of blended learning.

## 2 Quizitor

Quizitor is a hybrid quiz platform that can be used for both in-class and at-home assessments. The main components of its interface are depicted in Fig. 1.

The in-class assessment mode facilitates synchronous assessment where students take a quiz in a class with their teacher. The aims of such assessment can include: taking a short break from a lecture routine, asking students to recall the learning material that has been recently taught, helping students reflect on their understanding of the material, and giving the teacher information on how well students understand the material. A teacher controls when an in-class quiz (and every question within it) starts and finishes. The top-left screen on Fig. 1 shows the teacher interface of an in-class quiz. On this screen, the teacher can see the current question, monitor the time spent on it, the number of submitted answers, and the number of students currently participating in the quiz. Students can see the current question on their devices as well (top-left screen on

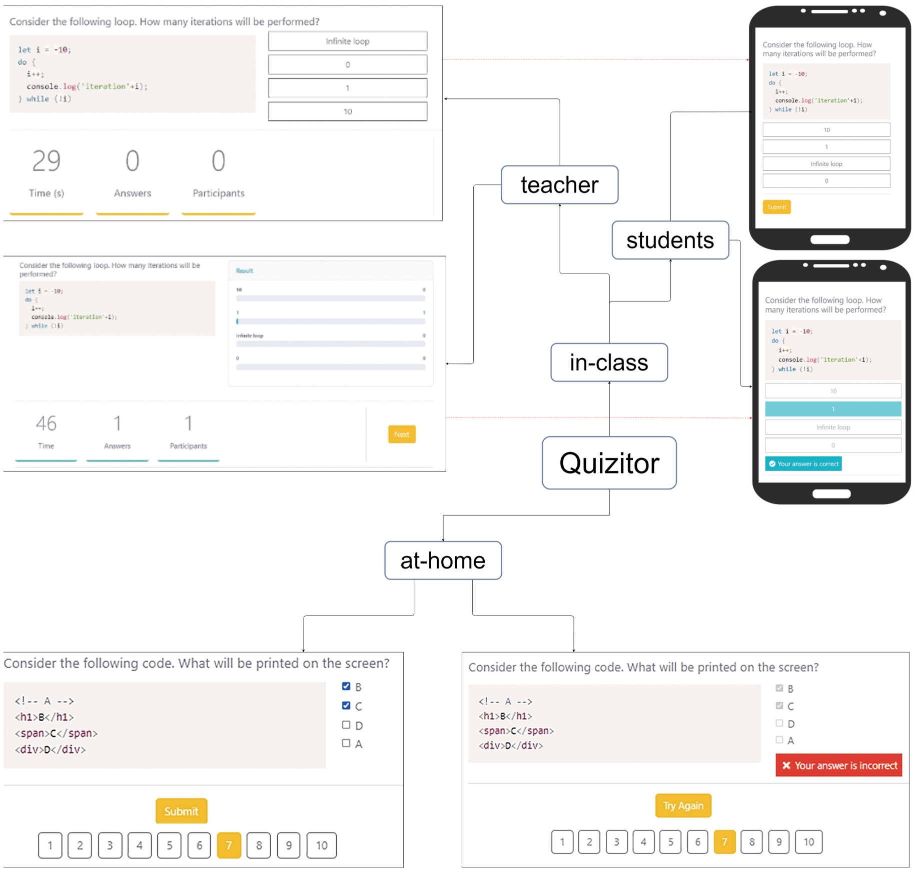


**Fig. 1.** User interfaces of Quizitor.

Fig. 1). They can submit an answer to the question once it is started, but will not move to the next question until the teacher decides to start it for the entire class. Once a teacher stops a question, the summary of its results is presented to the class on both the teacher's screen (middle-left), and individual students' screens (middle-right). The summary shows a distribution of different answers and indicates which answer is correct. After a brief discussion, the teacher can move to the next question.

The at-home mode is designed as a typical tool for individual self-assessment. The primary aims of Quizitor in this mode are to help students practice, reflect, identify knowledge gaps and prepare for exams. In contrast with the in-class questions, the at-home questions can be more complex, as students are not under time pressure when answering them. They can choose the day, time, and location where they want to take the quiz. For each question, students can submit as many attempts as they want. The feedback indicates only the correctness of the attempt and invites a student to repeat the question if the attempt was not correct.

## 3 Evaluation

The main hypothesis of this study is that models of student mastery taking into account the two streams of data coming from students' in-class and at-home assessment activity would be able to predict student course performance better than the models taking into account only individual streams of data.

### 3.1 Data Collection

The data were collected in the undergraduate course on Web technology taught in Utrecht University from February until March 2021. The overall number of students was 198. To participate in the study, students had to sign a consent form. We excluded from the analysis students who did not use the tool actively enough (attempted 75% of at-home questions) and those who did not pass the midterm exam. The resulting number of subjects in this study was 61. The use of Quizitor started during the third lecture and continued for six lectures until the midterm. The topics included basics of HTML, CSS, DOM, and Javascript.

### 3.2 Models of Students' Mastery

To estimate students' mastery based on their activity with Quizitor, we applied Elo Rating System (ERS), which is a relatively easy yet accurate method for modelling an ability. It has been recently gaining popularity in the educational data mining and student modelling community [7]. It can dynamically assess students' ability in a certain field based on the results of their continuous assessment. While assessing student ability, ERS also keeps adjusting the difficulty of questions that students answer. Essentially, ERS constantly balances the "strength" (=ability) of a student vs. the "strength" (=difficulty) of a question.

Two sets of student models have been built: the in-class (IC) models and the at-home (AH) models. The combined IC model is trained based on all students' in-class attempts. The combined AH model represents students' mastery as a result of their overall at-home self-assessment. Individual topical AH and IC models have been trained only based on the data from AH and IC quizzes pertaining to corresponding topics. In order to compute more accurate students' Elo scores, first we have estimated the 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 is estimated by calculating their Elo ratings based on the answers from 80% of students. Then, the obtained question model is used to estimate the Elo scores of the remaining 20% of students. Then, another group of 20% of students is selected and the processes restarts. After five iterations, mastery of all students have been modeled. We have repeated this process separately to compute the IC and AH models.

### 3.3 Results

Simple linear regression models have been used to predict students' midterm performance based on their mastery estimates. There are four pairs of models (AH and IC) for course topics and one more pair of combined models, hence the simple regression has been computed ten times. After that five multiple regression models have been computed to verify the main hypothesis. Significant positive regression coefficients have been found for almost all models (except for IC model for the topic DOM). Table 1 provides the summary of all fifteen regression models. It is easy to see, that the main hypothesis is confirmed. Bigger portions of the variability in the predicted variables are explained by the joint models. Both for the overall case and for each individual topic. The results are consistent across all four target topics and the overall case. This means that both modes of students' work with Quizitor can provide mutually enriching sources of data. An effective "blend" of these data can inform an adaptive tool truly supporting blended learning. The adjusted $R^2$ of the combined models are also much higher compared to individual models indicating absence of overfitting.

**Table 1.** Result from regression model

| Source | Model | $R^2$ | $R^2$-adj | $p$-value |
|---|---|---|---|---|
| Overall | IC | 0.117 | 0.102 | 0.007 |
| | AH | 0.114 | 0.099 | 0.008 |
| | IC-AH | 0.21 | 0.182 | 0.001 |
| HTML | IC | 0.1 | 0.089 | 0.003 |
| | AH | 0.047 | 0.036 | 0.042 |
| | IC-AH | 0.136 | 0.115 | 0.002 |
| CSS | IC | 0.152 | 0.13 | $<$0.001 |
| | AH | 0.113 | 0.09 | 0.03 |
| | IC-AH | 0.237 | 0.198 | 0.005 |
| DOM | IC | 0.073 | 0.051 | 0.079 |
| | AH | 0.142 | 0.11 | 0.044 |
| | IC-AH | 0.218 | 0.157 | 0.041 |
| JS | IC | 0.257 | 0.231 | 0.004 |
| | AH | 0.154 | 0.123 | $<$0.001 |
| | IC-AH | 0.357 | 0.309 | 0.003 |

## 4 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 initial 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.

There are several directions for future research. First, based on the result, there is an evidence that the two streams of data coming from the in-class and at-home activities have an effect on students' grade. We plan to conduct another experiment with different approaches of student modelling where the in-class and at-home activities are merged as an integrated representation of student ability. Second, we plan to add into Quizitor an adaptive functionality that will support students in working with the question material based on their current levels of knowledge. Such an adaptive support can happen not only during students' at-home activity, but also during their in-class question answering in the form of personalised feedback. This can be done at first on the level of coarse-grained topics. The topic-based analysis described in this paper can be viewed as the first step in this direction.

## References

1. Herder, E., Sosnovsky, S., Dimitrova, V.: Adaptive intelligent learning environments. In: Duval, E., Sharples, M., Sutherland, R. (eds.) Technology Enhanced Learning, pp. 109–114. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-02600-8_10
2. Koedinger, K.R., Anderson, J.R., Hadley, W.H., Mark, M.A., et al.: Intelligent tutoring goes to school in the big city. Int. J. Artif. Intell. Educ. **8**(1), 30–43 (1997)
3. Brusilovsky, P., Sosnovsky, S., Yudelson, M.: Addictive links: the motivational value of adaptive link annotation. New Rev. Hypermedia Multimed. **15**(1), 97–118 (2009)
4. Rasheed, R.A., Kamsin, A., Abdullah, N.A.: Challenges in the online component of blended learning: a systematic review. Comput. Educ. **144**, 103701 (2020)
5. Howard, L., Remenyi, Z., Pap, G.: Adaptive blended learning environments. In: International Conference on Engineering Education, pp. 23–28 (2006)
6. Gynther, K.: Design framework for an adaptive MOOC enhanced by blended learning: supplementary training and personalized learning for teacher professional development. Electron. J. e-Learning **14**(1), 15–30 (2016)
7. Yudelson, M.: Elo, i love you won't you tell me your K. In: Scheffel, M., Broisin, J., Pammer-Schindler, V., Ioannou, A., Schneider, J. (eds.) EC-TEL 2019. LNCS, vol. 11722, pp. 213–223. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-29736-7_16