An Exploratory Study on Student Engagement with Adaptive Notifications in Programming Courses

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Abstract. This paper presents a study on students' engagement and personalized weekly performance notifications. Students were offered to voluntarily opt-in to receive customized notifications regarding their predicted course performances and recommended resources. In addition, the predicted at-risk students were also recommended with code solutions from higher performers in the class. Data was collected from Computer Science programming courses. Students' engagement with the notifications and resources were tracked and have been found to be an indicator of their differential improvement between their exams.

Keywords: Computer Science Education · Learning Analytics · Engagement · Predictive Model · Personalized Notification

1 Introduction

In this work, we explore how predictive analytics models work in distinguishing students struggling with programming courses. We implemented multimodal models for each course that aggregates sources of student data: student characteristics, prior academic history, students' programming laboratory work, and logged interactions between students' offline and online resources. Classification models are built by developing features and extracting patterns of success on these courses, then trained with two years of grountruth data and cross-validated, and finally predictions are generated every week with incoming student data. A report containing whether each student is likely to pass or fail the next formal assessment and their associated confidence is sent to the lecturers for each course. During the second part of the semester, typically after the first laboratory computer-based examination, students are free to opt-in to receive weekly personalized notifications. These notifications are sent via email and contain information regarding their predicted performance, based on the student data modalities gathered such as their progress with laboratory sheets; programming code solutions, from predicted top-ranked students within the same class; and university resources to reach out for help if needed, such as Student Support, the course's lecturer or our system. The accuracy of the predictions generated is crucial as students will receive a customized message regarding their predicted performance and code recommendations for failed submissions from higher performers in the class if they are below a performance threshold. In our work, we measure the engagement with these customized notifications and how that could be an indicator of their performance. The research questions are stated as the following:

RQ1: How accurately are predictive models able to classify students in programming modules for new cohorts of students?

RQ2: What are the effects for students that engage with customized performance and programming feedback notifications?

2 Literature Review: Adaptive Feedback in Learning

Feedback is one of the most effective methods in enhancing student's learning [4]. There is an abundance of factors that affect educational achievement. Some factors are more influential than others. For instance, feedback types and formats, timing of providing feedback, etc. Studies have reported that positive feedback is not always positive for students' growth and achievement; "critical" rather than "confirmatory" is the most beneficial for learning regardless of whether feedback was chosen or assigned [3]; content feedback achieves significantly better learning effects than progress feedback, where the former refers to the qualitative information about the domain content and its accuracy, and the latter describes the quantitative assessment of the student's advancement through the material being covered. Several of the different feedback factors were explored on the intersections with the learner's variables (i.e. skills, affects) and reported to support personalized learning. For instance, cognitive feedback was found to make a significant difference in the outcomes of both student learning gains in an intelligent dialogue tutor; students affects were being adapted to improve motivational outcome (self-efficacy); using student characteristics as tutoring feedback strategies to optimize students' learning in adaptive educational systems. While a large body of empirical studies investigate the feedback impacts in the context of learning, less is focused on researching adaptive notification as feedback in programming courses.

3 Research Methodology

Programming modules in our institution are being delivered through a Virtual Learning Environment that allows students to access the material online and verify their computer-based programming work. The student programming digital footprint gathered is then leveraged using Artificial Intelligence techniques and combining them with other student data modalities to identify students having issues [1] and adapt their learning on this discipline [2]. At the middle of the semester, a feature is enabled for students to opt-in or opt-out of weekly personalized notifications. These include a performance message based on the predictions being run on the incoming class and trained with historical student cohorts' data; recommended material and laboratory sheets resources to review based on their progress; programming code solutions from top-ranked students in the class and additional support resources. A gain index is developed to measure the student's improvement between two examinations, see Equation 1, and normalized to output values between -1 and 1 on Equation 2:

$$gi(e1, e2) = \frac{(e2 - e1)}{e1} \tag{1}$$

$$normgi(e1, e2) = \begin{cases} 1 & e1 = 0 \\ 1 & gi(e1, e2) > 1 \\ gi(e1, e2) & otherwise \end{cases} \tag{2}$$

4 Results

We will now analyse the results obtained by running predictions and sending adaptive feedback on new cohorts of students in 2017/2018 and what this means for the research questions proposed for one of the courses: Shell Scripting for first-year students.

4.1 RQ1: Predictive Modelling

Table 1 shows an increasing accuracy and F1 metrics from the first assessment to the last. That is, as more data is collected around student engagement, we are better able to distinguish students struggling with the material and, thus, giving them more accurate performance notifications.

Table 1. Exam weeks, Model's At-risk Prediction rates, Passing rates, Prediction results and Correlations between the prediction confidence and the actual results

Exam Week	Predicted At-risk	Passing Rate	Accuracy	F1	Precision	Recall	Correlation Coeficient
W7	51.32%	67.11%	65.79%	70.45%	83.78%	60.78%	43%**
W12	40.79%	72.37%	84.21%	88%	97.78%	80%	65%**

** $p - value < 0.01$

4.2 RQ2: Normalized gain for different groups

Table 2 shows the groups analysed: opt-ins vs. opt-outs and engaged-with-the-notifications vs. not-engaged. Students that opted-in in week 7 showed a greater normalized gain compared with students that opted-out between pairs of examinations. Students that engaged with the notifications by clicking on any of the resources (material or laboratory sheets), which were not many, also showed a greater normalized gain compared to students that did not.

Table 2. Normalized gain improvement between student groups created

First Exam Week	Second Exam Week	Group (Number)	Mean (Std.Dev.) Exam-1	Mean (Std.Dev.) Exam-2	Mean (Std.Dev.) *normgi*
W7	W12	Opt-IN (45)	68.33% (34.32%)	77.33% (29.69%)	+27.41% (55.92%)
		Opt-OUT (5)	90% (20%)	92% (16%)	+4% (8%)
W7	W12	Engaged (4)	50% (30.62%)	90% (10%)	+70% (51.96%)
		Did-not-engage (67)	62.31% (38.72%)	64.18% (37.78%)	+20.70% (61.06%)

5 Conclusion & Future work

Engaging with personalized notifications is proven to have a positive effect on the defined normalized gain index between two different examinations. However, this improvement has not yet been found to be significant. In the near future, we are exploring how students engage with the programming code solutions from higher performers and how it affects their programming design learning.

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