Validating Automated Triggers and Notifications @ Scale in Blackboard Learn

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ABSTRACT
Prior research on individual courses has demonstrated a significant relationship between use of the Learning Management System (LMS) and student course grade. Blackboard has created rule-based algorithms in a new LMS interface to notify students and faculty of students who may be at risk based on relative activity and grades received, and recognize positive behavior and grade achievement. This research project investigated the relationships underlying these algorithms against a large data set of LMS activity (1.2M student course weeks, 34,519 courses, 788 institutions). Findings included a small effect size in the relationship between time spent in the LMS and student grade; however, a small set of courses had a strong relationship that merits further research and consideration.

Keywords
Learning Analytics, Student Persistence, Student Retention, Higher Education, Learning Management Systems, LMS

1. INTRODUCTION
Multiple research studies on individual courses have found a significant relationship between use of the LMS and student grade [8, 7, 2, 3, 9, 10]. The value of LMS data in these courses has been larger than what is found in conventional demographic or academic experience variables in explaining variation in course grades. However, when analysis is expanded to all courses at an institution, several studies have found no relationship or an extremely small effect size in this relationship [1, 5, 4]. Does Learning Analytics only apply to only a small number of courses, or is it broadly applicable? What is the magnitude of this relationship, and is sufficiently large to include algorithms based on this relationship as a core functionality in academic technology platforms?

This question is of great practical significance for academic technology providers. Analytics functionality has typically been provided through custom data warehouses and analytics tools that include multiple data sources and systems, with custom integrations and algorithms. While useful and with accuracy that can be proven, these applications require significant resources to create and maintain, whether procured from a vendor or built in-house. They also require significant time to implement and deploy.

As part of Blackboard's new "Ultra" LMS course interface, rule-based triggers and notifications were created. For example, these rules would analyze course use and send the student and instructor a notification if a student's LMS activity dropped more than 10% from one week to the next. In addition to alerts of potentially at-risk students, positive encouragement alerts were also created to recognize outstanding achievement relative to self and others in the same course.

The rules were created based in prior research findings and an initial small data sample. However, additional validation with a larger data sample was required to ensure that the rules were meaningful predictors of student grade. This poster presents findings from this research on the question of accuracy and draws broader conclusions about the potential utility and generalizability of LMS activity data.

2. DATA SET AND ANALYSIS
The data analyzed for this project was sampled from log data recorded by Blackboard Learn. These logs were transformed into normalized data sets, and calculations made to estimate duration of time spent in the LMS by calculating the difference between start end end times for sessions. The data was aggregated at the institution-course-week-user level (e.g. one row per user per week per course per institution). The data sample included a complete set of students active for each course week, but did not include all weeks for each course. Each row also contained final course duration and final grade. A z-score of duration was calculated to provide a course-specific measure of student activity.

Given the importance of analyzing grade triggers and the relationship between activity and grade, only course-weeks with a graded entry for that week were included in the sample. Further, students with no activity have no logs and are therefore missing. This biases the sample toward courses making more intensive use of the LMS than a random sample.

Exploratory data analysis revealed a large number of rows with invalid grades and duration. The data was filtered to include courses with valid data and a potential for instructional use, namely: grade range between 0% and 120%, a minimum of 60 average minutes in the course, and a maximum of 5,040 minutes in the course per week, and enrollment more than 10 student and less than 500 students.

The final data set analyzed had the following profile:

Table 1. Data Set Characteristics

Records	Courses	Institutions
1.2M	34,591	788

Exploratory data analysis and distributions were conducted to ensure that the data was normally distributed and ensure other assumptions required for linear regression analysis were met. A linear regression of final course grade on course duration and a logistic regression of course pass/fail on duration was run. Next, a separate linear regression was run for each course.

3. FINDINGS

As indicated in the scatterplot in Figure 1, there was a significant relationship between duration and grade. However, the effect size was extremely small (adjusted R^2=0.01537). Further, most of this effect was created by the intercept value; the coefficient for duration was 5.74e-04. Converted into practical effect, this coefficient indicates that for each additional hour spent in the LMS, students would gain 0.034% in their final course grade. Using course-relative measures of duration (e.g. z-scores by course) only increased the effect slightly (R^2=0.017). Logistic regression led to similar results.

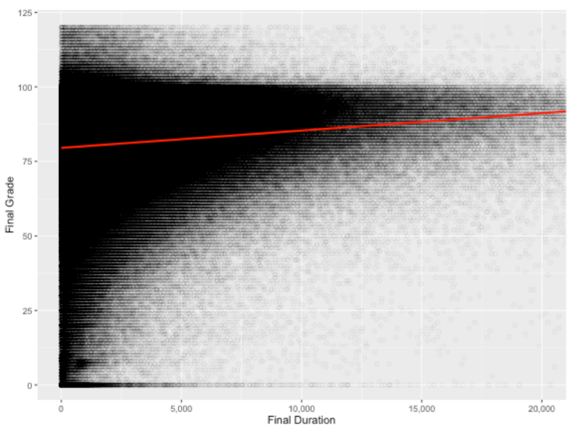

Figure 1. Duration vs. Grade across all Courses

When this regression was re-run at the course level, a high variation in this effect size was found. There were 7,648 (22%) courses with $p < 0.05$; the distribution in effect size is plotted below. Although skewed toward low values, there are a substantial number of courses with low to moderate effect sizes.

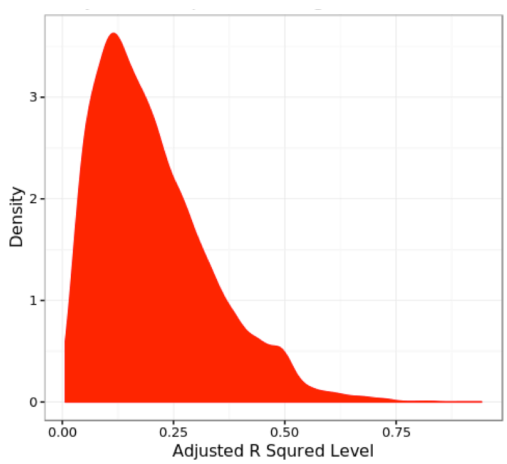

Figure 2. Adjusted R^2 Levels for Courses with Significant Duration vs. Grade Regressions

Initial data subsetting by available criteria (e.g. enrollment size, institution, average activity) did not identify a factor strongly related to this difference in effect.

4. IMPLICATIONS

These findings indicate that while rule-based triggers may not be predictive of student course achievement for all LMS courses, they are predictive for a substantial number of courses. Given known variability in how the LMS is used for instruction, these results provide an encouraging indication of potential value in this data. However, the reasons for this strong relationship among some courses and not among others is an important area for further research. We anticipate investigating issues in course design and early participation as identifiers of higher effect size.

As a result of this research, multiple modifications to the existing triggers in Blackboard Ultra have been made to refine and reduce the number of notifications sent. Further, a new configuration setting will be provided to disable these algorithms by course.

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