On the Influence of Grades on Learning Behavior of Students in MOOCs

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Abstract
MOOCs (Massive Open Online Courses) frequently use grades to calculate whether a student passes the course. To better understand how student behavior is influenced by grade feedback, we conduct a study on the changes of certified students' behavior before and after they have received their grade. We use observational student data from two MITx MOOCs to examine student behavior before and after a grade is released and calculate the difference (the delta-activity). We then analyze the changes in the delta-activity distributions across all graded assignments a we observe that the variation in delta-activity decreases as grade decreases, with students who have the lowest grade exhibiting little or no change in weekly activity. This trend persists throughout each course, in all course offerings, suggesting that a change in grade does not correlate with a change in the behavior of certified MOOC students.

Author Keywords
MOOCs; Data Analysis; Statistics; Feedback

Introduction
Massive open online courses (MOOCs) are courses on online platforms that support traditional lesson plans and/or teaching with emerging technologies. They create widely available learning opportunities that students can frequently take at no cost [1]. Because MOOCs are not conducted in a

Data Set
We use the click events on students who received certificates from three offerings of the two EdX MOOCs *6.00.1x Introduction to Computer Science and Programming Using Python* and *6.00.2x Introduction to Computational Thinking and Data Science*, offered in 2016 and 2017. 6.00.1x and 6.00.2x are introductory course in programming and computational thinking and data science. Students who received certificates are called "certified" students because they completed the course with a passing grade and paid for a certification. The courses are somewhat similar in their structure, technical content and learning through application.
6.00.1x had 946, 1971, 1511 certified students in the Spring 2016, Fall 2016, and Spring 2017 offerings. 6.00.2x had 512, 528, 322 certified students in the same offerings.

traditional classroom, MOOC students have more opportunity to self-regulate their learning experience than traditional students. In this observational study, we are interested in the *impact of knowing one's grade on one's behavior*. We investigate this by analyzing the change in student activity after a grade is received and how this change in activity correlates to changes in grade. For our analysis we use activity data from three course offerings of two different programming and computer science courses on the EdX MOOC platform [6].

Related Work
The impact of grade feedback on self-regulated learning is widely studied and important in successful course design [2]. Carver and Scheier created a model of how students change their learning behavior after receiving feedback. They state that students will evaluate their feedback and adjust their learning behavior to reach their course goals [3]. For example, if a student receives a lower grade on an exam, then student will work harder to improve their next exam score to end with their desired grade. Other studies have shown that this model is inconsistent for different types of feedback [4], while other models suggest that it would depend on the student information or misinformation [2]. Main and Ost applied and found consistent results to the Carver and Scheier model in their observation and analysis of student behavior in a traditional course setting [5]. Following the work in this field, we will connect these traditional learning models to student behavior in MOOCs.

Study Design and Definitions
We hypothesize that certified students will noticeably adjust their behavior to the grades that they receive. Specifically, our initial belief is that students with lower grades will raise their activity levels to improve their grades and students with high grades will maintain their activity and grades in order to obtain their certification.
For each offering of each course, we define the *cumulative activity* of a student as the total number of click events the student triggers with a 7-day period. This is because assignments are released and mostly due on a weekly basis. We define the *grade state* of a student as the current cumulative grade (we normalize the total points earned by dividing it by total points possible to get a value between 0.0 and 1.0) at the time a grade is finalized and released. All finalized grades are released at 23:30:00 UTC on each due date. We define the cumulative activity after the grade is disclosed as the *after activity* and the cumulative activity before the grade is given out as the *before activity*. We define the *delta activity* of a student as the difference between the after activity and before activity of a state. Finally, we define *delta grade* as the change in grade from the previous grade to the current grade state.

Activity Analysis
We analyze the before activity and after activity of students to better understand how much activity students typically have and how much variation there is among students. For each grade state of each course offering, we calculate the before and after activity by summing the total daily click events triggered for the 7 days before and after the next grade state. Because we are looking at the change in behavior after transitioning to a new grade state, we keep the activity calculation conditions the same for all grade states.

We find that before and after activity means stay close together in the beginning and middle of the course hovering at or above 500 click events. Afterwards, after activity consistently falls towards the end of the course. Finally there is a large gap between the last before activity and after activity points. This is due to the increase of activity to study for finals and the lack of necessary activity once the final

Qualitative Analysis of Delta Activity vs. Grade
Concretely, points on the the delta activity vs. grade scatter plot can be split into two sections: points to the left of the x=0 line (the "left" section) and points to the right of the x=0 line (the "right" section). The significance of the left section is that it shows the students who became less active after receiving their grade and what grade caused them to do so. Similarly, the right section shows the students who became more active after receiving their grade and the grade that they received.
In Figure 1, we can see a general trend of decreasing activity as the course progresses, indicated by the more populated left sections of the delta activity vs. grade plots. We can also see many students doing drastically more or drastically less activity after receiving a high grade. However, we do not see many instances increasing or decreasing activity after receiving a lower grade, which contradicts our hypothesis. In fact, the lowest scoring students, in general, have close to 0 change in their activity after receiving their grade.

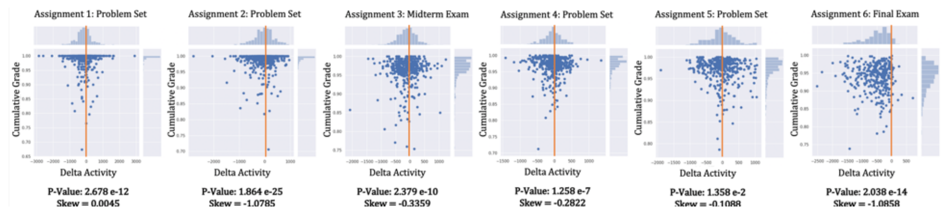

Figure 1: Spring 2016 6.00.2x Grade vs. Delta Activity

assessment score is given and the course is over.

Analysis on Delta Activity

Following our initial data analysis, we focus our study on how behavior before and after a grade is released compares to the grade received. After we find all before and after activity for all grade states, we calculate the delta activity by taking the difference between the after activity and the before activity. For most grade states, we find distribution of delta activity is centered at or below 0, indicating that on average, students do less activity as the course progresses. We perform a normality test for each of the delta activity distributions with null hypothesis: the sample is from a normal distribution. We use the `scipy.stats.normaltest` function[1] in our analysis. We find that the distributions of delta activity are significantly (p-value less than 0.05) not normal. Figure 1 shows the distribution and skew of the Spring 2016 offering of 6.00.2x.

Delta Activity vs. Delta Grade

To further understand the implications of grade on activity, we investigate the how delta activity correlates to changes in grade (delta grade). We calculate the delta grade by taking the difference between the grade at some grade state s_t and the grade at s_{t-1}. Figure 2 shows delta activity vs. delta grade scatter plots, for all assignments in the Fall 2016 offering of 6.00.1x and Fall 2016 offering of 6.00.2x.

[1] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.normaltest.html

Differences Between 6.00.1x and 6.00.2x

The major difference between 6.00.1x and 6.00.2x data sets occur with the delta activity vs. delta grade graphs. As seen in the Fall 2016 offerings in Figure 2, 6.00.1x has very defined "star" shapes for nearly all delta activity vs. delta grade graphs. This means that for every change in grade, the largest grade change occurred for students who minimally changed in activity, while the largest changes in activity occurred for students who had minimal changes in grade.

Though this "star" shape is also apparent in some 6.00.2x plots, we notice that the shape is not as defined, and mostly not centered at x=0, y=0. This trait is present in all three offerings of 6.00.2x, making it more likely that these traits are systematic rather than coincidental.

Conclusion

There are confounding variables when one observe behavior before and after an assessment. First, if the course material changes, i.e. flips in difficulty or underlying nature of knowledge (e.g. theoretical to procedural to analytical) or topic (mathematically oriented to language oriented).

Qualitative Significance of Delta Activity vs. Delta Grade Using our plots of delta activity vs. delta grade, we can observe more implications about student behaviors. We can divide the delta activity vs. delta grade graphs into four sections along $x = 0$ and $y = 0$. The upper-left section shows students who raised their overall grade while having less activity. The upper-right sections shows students who raised their overall grade while having more activity. The lower-left shows students who dropped in grades while having less activity. Lastly, lower-right shows students who dropped in grades despite increasing their activity.
The 11 scatter plots in Figure 2, show that all 4 extremes of the 4 sections are uncommon and rarely occur. Moreover, the largest changes on one axis are often along the 0 line of the other axis (we will refer to this as the "star" formation). This observation then supports the claims that the largest variations in activity occur for students with little or no change in grade and while the largest variations in grade occur when students have little or no change in activity.

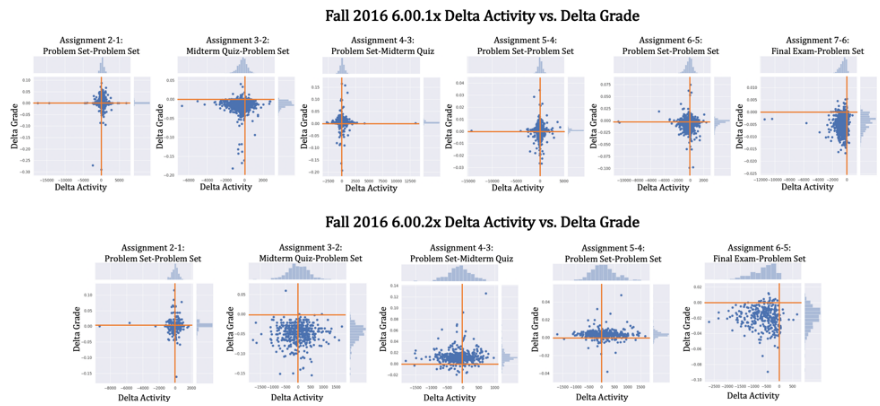

Figure 2: Spring 2016 Delta Grade vs. Delta Activity

Setting these aside for future consideration, all in all, in our study on the EdX MOOCs 6.00.1x and 6.00.2x, we were not able to find evidence to support that people change their behavior in accordance with their grades in the ways that we expect. Instead we find more observations to the contrary and open the field to more investigations on lack of correlation between grades and learning behavior.

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