# Tracking students engagement with OER resources and online homework

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As education uses online and digital learning tools and resources more, an opportunity arises to study students' learning behaviors and outcomes through data analytics. In this study we perform correlation data mining of individual student's click-stream on both an Open Educational Resource site, BoxSand.org, and online homework on Mastering Physics. Exploratory analysis can used to inform a model-based approach with long-term goals of creating inferential and predictive models.

## I. INTRODUCTION

In the fall of 2014 the Oregon State University (OSU) introductory algebra-based physics sequence underwent a drastic pedagogical change away from lecture-based instruction towards a student-centered, actively engaged, peer instruction model with the goals of improving learning outcomes [1,2]. A flipped classroom approach [3–5] was adopted where more than 300 pre-lecture videos were created along with corresponding pre and post lecture assignments through the online homework system Mastering Physics [6]. A website was created to host the videos and other Open Education Resources (OER). Students are guided through their out-of-class study by a daily learning guide that parses the subject into small digestible modules centered on the flipped classroom lectures. We are motived to understand the effects of pedagogical changes from the lens of data analytics to inform future reform and better understand factors influencing student success.

### A. Research questions

The students in this course are non-physics science majors, primarily in their junior and senior year. Interest in physics varies widely. Will they prepare for class? Will they watch the pre-lecture videos? What began as a concern about students' motivation has presented itself as an opportunity to study engagement behavior. Our exploratory research cast a wide net. In broad terms, we want to know *what can learning analytics* [7] *tell us about students' engagement with OER and online homework, and how does that engagement correlate with performance in the class*? More directed emergent questions have come after initial analysis: (1) What engagement behaviors correlate and may be predictors of student success? (2) What are beneficial engagement behaviors leading up to an exam? (3) Can changing engagement behaviors influence course grade?

Our final question was not exploratory but rather model-based. (4) Can we create a model to quantify and predict students' final grades based on their engagement with (i) pre-lecture videos, (ii) attempts at pre/post lecture online homework, and (iii) correctness in online homework? We feel this helps to address the PERC 2016 call for methodical approaches to PER, including predicting and generalizing learning outcomes [8].

We feel it's important for the reader to understand this is an exploratory project and does not claim to identify underlying causations. While our long-term goals are to create predictive analytics and design intervention protocols, we felt a need to contribute our work-in-progress to support similar reports presented within the PER community [9–11].

## II. METHODS

The study is ongoing but most of the data presented here will be from the 2017-2018 academic year. Students were presented with the study during the second day of class in fall term and consent was acquired via in-class signatures. In fall quarter 55.6% of the class agreed to the study, which drops to 49.5% and 47.7% in the subsequent winter and spring quarters. We believe this constitutes a representative sample of the entire class as the female/male ratio (1.40) and average grade (71.0%) of the cohort are nearly identical to the class as a whole.

### A. Data collected

The website BoxSand.org [12] was created to host traditional course specific materials such as the syllabus, calendar, assignments, class templates, problem solutions, etc. It is also filled with thousands of OER including videos both from OSU and YouTube, textbooks like OpenStax, infographics, concept maps, simulations, practice problem sets, and much more. These resources are organized by topic in a menu driven system and students are guided to the best resources. The goal is to provide curated sets of primary and supplementary resources and study students' interactions with both. Students' click-stream is tracked where each data point represents a clickable interaction with some piece of content on the site. The site has aggregate tracking via Google Analytics and individualized click-stream tracking via a number of custom Drupal modules. The database reports when they start and stop a video, along with when they complete each quartile. During the 2017-2018 academic year over 1.4 million data entries were collected from roughly 450 students in the study on BoxSand.org.

The publishing company Pearson owns and hosts the Mastering Physics online homework system. They provided click-stream data of our students while on their site, including site navigation as well as all attempts on answering questions or accessing hints. During the 2017-2018 academic year nearly 1.3 million clicks were made by students in the study on Mastering Physics.

Grades on in-class clicker questions, online homework, recitation, lab, hand-written homework, midterm 1, midterm 2, final exam, and overall grade percentage are collected. This paper will focus on exam grades, which constitute 65% of the overall grade, as well as the final grade.

### B. Exploratory analysis

Analysis began with visual exploratory statistics. To get a feel for the data, plots were generated for a wide range of data slices, far too many to present in this paper. An example is BoxSand sessions (logins) vs. time (see Fig 1).

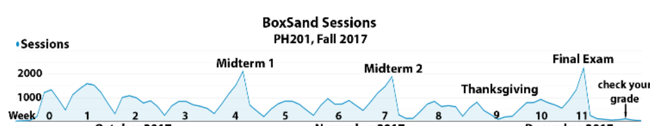


FIG 1. BoxSand sessions vs. time [13] for fall quarter 2017.

We looked at subsets of the BoxSand data, including watching pre-lecture videos, accessing homework and exam solutions, fundamental examples, the syllabus, and other non-OSU OER like the OpenStax textbook, Khan Academy videos, and PhET simulations. Engagement with these resources was plotted vs. final grade along with a weekly grade using a running exam average. Linear fits helped understand possible correlations and effect sizes. This can help inform a model-based analysis.

### C. Model-based analysis

To quantify the effect that watching videos and interacting with online homework have on a student's final grade, we fit a linear mixed model [14] of the form:

$$y = \beta_0 + \beta_1 v + \beta_2 P + \beta_3 C + \beta_4 W + \beta_5 S + \tau + \epsilon, \quad (1)$$

where $y$ is the course grade, $v$ is the proportion of quartiles of videos a student watched in a term, $P$ is proportion of all homework problems attempted in a term, C is the proportion of correct answers on homework problems in a term, $W$ is an indicator variable for winter term (1 if term = winter term, 0 otherwise), and $S$ is an indicator variable for spring term. $\beta_0$ is the overall intercept representing the expected course grade for a student watching no videos, attempting no homework, and getting no homework problems correct. $\beta_1$, $\beta_2$, $\beta_3$ are the expected grade increases for engaging in an additional 10% of the total number of course video quartiles watched, homework problems attempted, and correct homework answers, respectively. $\beta_4$ and $\beta_5$ are the expected intercept shifts in course grades for winter and spring term, respectively. We expect students to randomly deviate around the average trends described in Equation (1). These random deviations are modeled by $\tau$, is the random student to student error, and $\epsilon$ , the within student random term to term error.

The model in Equation (1) assumes that $\tau$ is a mean-zero, normal random variable with variance $\sigma_\tau^2$, which captures how much we expect course grades to deviate from the average between students. $\epsilon$ is a mean-zero normal random variable with variance $\sigma_\epsilon^2$, which captures how much we expect course grades for a unique student to deviate from the average between terms. The sum of these two $\sigma^2$ parameters captures the overall variability in course grades. We assume that the between student errors ($\tau$) and between term (for a given student) errors ($\epsilon$), do not depend on one another. The model formulation in Equation (1) allows us to capture the correlation between term-to-term grades for a unique student, given by: $\sigma_\tau^2/(\sigma_\tau^2 + \sigma_\epsilon^2)$. This ratio also represents the proportion of variability attributable to term to term variation within a particular student.

The model is fit using the *lme4* package [15] in R and the $\beta$ and $\sigma^2$ parameters are estimated with Restricted Maximum Likelihood (REML) [16,17]. In Section III, we estimate the $\beta, \sigma_\tau^2$ , and $\sigma_\epsilon^2$ parameters to obtain a fitted model. We used this fitted model to assess the significance of our explanatory variables (videos watched, homework problems attempted, correct homework submissions, term) and make predictions of the average course grade for students with different combinations of these explanatory variables. We performed diagnostic checks on the model assumptions following guidelines from [14].

## III. RESULTS

This manuscript serves to report on a subset of the results found using data visualization and statistical analyses.

### A. Exploratory results

The exploratory results fit mostly into two categories, performing correlation calculations of certain engagements vs. grade and using plots to visualize distributions and trends. There were far too many plots generated to report on here and each hints at an interesting effect that in its own right constitute deeper study. We report on the most interesting results found during our exploratory work here and will talk about future plans with these results and those from the larger exploratory work at the end of the paper.

#### 1. *Correlation matrix*

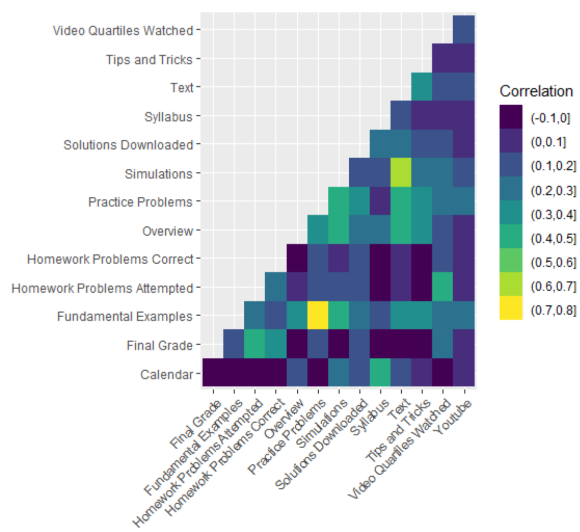


FIG 2. Correlation between several BoxSand click-stream data sources, online homework, and grades.

We see a plot (see Fig 2) quantifying the Pearson correlation between several variables in the 2017-2018 academic year. The variables include *Final Grade %*, *Homework Attempted %*, and *Homework Correct %*. There are also BoxSand click-stream numbers for: the *Calendar*, *Syllabus*, *Overview* (short topic introduction), *Text* (full textbook chapters), *Tips & Tricks* (expert advice for each topic), *Practice Problems* (non-graded), *Fundamental Examples*, *Simulations*, *Solutions Downloaded* (hand-written homework and exams), *YouTube*, and *Video*

*Quartiles Watched* (OSU pre-lecture videos). We noticed (see Fig 2) that the number of video quartiles watched, homework problems attempted, and number of video quartiles watched are the three most highly correlated variables with a student's final course grade. The positive nature of this correlation indicates that as the number of homework problems attempted, correct solutions answered, or video quartiles watched, so does the course final grade. We also see several other interesting patterns in the data and can use this to inform future research. For example, we see high correlation between *Fundamental Examples* and *Practice Problems*. It is likely that there are groups of students who learn well by working through problems and therefore visit both sections. We hope to categorize students into groups in the future as a way to identify common patterns exhibited by certain "types" of students and use this information to reach these target groups in unique ways in an effort to improve their course grade and engagement. These group characterizations could also be helpful in identifying "at-risk" students early in the term.

### 2. *Cramming behaviors*

One of the most interesting exploratory results is students' engagement with videos vs. current grade on a weekly basis. For the weeks leading up to the first midterm we considered their current grade to be what they received on the first midterm. For the weeks between the 1$^{st}$ and 2$^{nd}$ midterm we averaged the two midterm grades. For the weeks after the 2$^{nd}$ midterm we used a weighted average of their midterm and final exam grades. We found that during most off exam weeks the correlation between watching more videos resulted in higher grades on exams, denoted by a more positive slope in a linear fit of videos watched versus grade. During the week of the exam though, this correlation would flip (see Fig 3), and watching videos leading up to the exam correlated with lower performance.

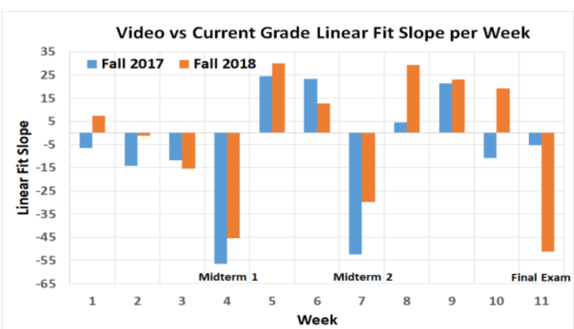


FIG 3. Videos watched vs. current grade linear fit slope in units of videos vs. 100% grade difference.

The videos, which constitute the traditional content delivery lecture portion of the class, are intended to be early in the learning cycle. So it is no surprise that watching videos right before the exam is not effective exam preparation.

In contrast when looking at online homework practice vs. grades on a per week basis, this flip of correlation on exam weeks does not typically occur. The take away is students should watch videos early when first introduced to a topic and by the time exam preparation rolls around, they should be practicing problems.

### 3. *Online homework engagement*

Online homework has been shown to be an effective tool when learning physics [18]. To visualize the distribution of students' engagement with online homework and how that correlates with course grade, a 3-D bar plot was created (see Fig 4). Front and to the left indicates lower course grade and lower homework engagement while back and to the right are higher grades and more homework engagement. Here you see that the students that tend to have lower course grades tend to do less of their homework.

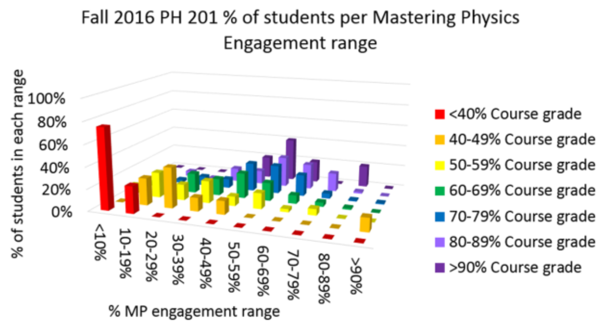


FIG. 4. Percentage of each student in a given online homework engagement range vs. course grade.

It's important to note that due to the large number of problems assigned, full credit was set at 66.6% completion.

### 4. *Changing behavior changes outcome*

We wanted to know if a student changes their behavior around watching videos, would it change their exam grades. We looked at the change in exam grade percentage between two subsequent exams vs. the change in video watching percentage in those two time periods. Both percentages are standardized, the exam grades centered to the class average and the videos to the total number of required videos for that time period.

We found that students that increased their engagement with videos from one exam period to the next saw an increase in exam score. If a student watched none of the videos during one period and then all of them the next, they saw an average gain of ~5% on the exam. This trend of increasing engagement with videos correlates with increasing exam scores does continue throughout the year but the effect gets smaller. We believe this is due to less variability in how much students change their behavior.

### B. Model-based results

The results from our model-based analysis confirmed our original hypothesis; that video quartiles watched, homework problems attempted, and correct homework solutions have positive effects on a student's course grade. For the 2017-2018 academic year, the $\beta$ estimates are summarized in Table 1.

Table 1: Model Output

| Variable | Estimate | P-value |
|---|---|---|
| Intercept ($\beta_0$) | *58.76 %* | *< 0.0001* |
| Quartiles ($\beta_1$) | *0.25 %* | *0.0044* |
| HW Attempted ($\beta_2$) | *1.35 %* | *< 0.0001* |
| HW Correct ($\beta_3$) | *1.15 %* | *0.0006* |
| Winter term ($\beta_4$) | *- 6.17 %* | *< 0.0001* |
| Spring term ($\beta_5$) | *- 9.17 %* | *< 0.0001* |

We first notice that the slope estimates for winter and spring term are negative, implying that the average grades in these two terms are lower than in fall term. This is not always the case, there are a number of confounding variables that go into where average grades lie from term to term. An increase of ten percentage points of total video quartiles watched, homework problems attempted, and correct solutions increases the expected course grade by 0.25%, 1.35%, and 1.15%, respectively, while holding all variables except the one in question constant. Additionally, none of the regression assumptions outlined in [14] appeared to be violated, giving us confidence in the validity of our model inference. It is important to note that online homework contributes ~5% to a student's grade. Just attempting all homework increases the average course grade by 13.5%, meaning students get a great deal of return on investment, presumably showing up largely in improved exam scores that contribute the most to their final grade. It is also interesting that attempting homework had a larger effect than whether it was correct or not. We believe this could be due to the ease and prevalence of cheating on online homework.

A student who watches all videos, attempts all homework problems, and gets half of the homework problems correct is expected to have a 21.75% higher course grade than a student who does not participate at all in these activities. All estimates from Table 1 had very small p-values, indicating that we have a lot of statistical certainty that these variables significantly impact course grade. Lastly, our model suggests that approximately 86% of the variability in course grades is attributable to student-to-student variation. The remaining variability in course grades is attributable to term-to-term variation within a unique student. These variability results are not surprising, as we expect different students make up a wide range of course grades, but unique students rarely have large changes in their term to term grades.

## IV. CONCLUSIONS

We found in our exploratory analysis that watching pre-lecture videos, attempting online homework, and answering online homework correctly are strongly correlated with final grade. Additionally, watching videos early in the learning cycle correlates with higher grades in the class. Leading up to an exam, students should be practicing physics and not still familiarizing themselves with the topic. Lastly, students are not destined to a certain grade and changing engagement with pre-lecture videos can improve their outcome on exams.

Our model-based analysis confirmed some of our exploratory work and general intuitions. While holding all other variables constant, watching videos could have a maximum effect of 2.5% on expected course grade. Similarly, just attempting online homework had a maximum effect of 13.5% on expected course grade, larger than the 11.5% effect of answering correctly. That is nearly a 3-fold return on investment when compared to how many points the online homework directly contributes to the final grade.

Most of the results presented in this work match what we believe most teachers already know. Engaging with the resources and practice provided by the instructor will help you learn physics better. What this research provides is hard evidence of these claims. We now use these data to encourage our students to follow the flipped classroom model. We have found it to be a strong motivator for learning assistants, teaching assistants, and instructors to use when convincing students proper engagement behaviors. After all we are teaching future scientists and rather than have them default to authority about what correlates with success in physics, we would prefer them to use data and draw their own conclusions.

#### *1. Future work*

We hope this work will evolve into more sophisticated models that encapsulate a clearer picture of what engagement behaviors correlate with success in physics, including in-class engagement and hand-written homework. Additionally, a thorough demographic breakdown is essential in future studies. The ultimate goal is to create predictive models so that struggling students can be identified as early as possible and interventions created to help them back on track. We plan to use artificial intelligence to identify patterns not obvious in the data that will help classify the types of behaviors students undergo. This can then be a platform to base true adaptive learning practices and provide students individualized learning paths. Lastly, we want to move beyond correlation by using learning analytics to inform cognitive PER scientists of interesting questions so that they can delve deeper into the root causes of these effects.


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