A Procrastination Index for Online Learning Based on Assignment Start Time

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ABSTRACT

Despite decades of evidence on the impacts of procrastination on learner outcomes, the educational data mining community has procrastinated in applying measures of procrastination based on learner behavior. We advance a new measure of habitual procrastination within online learning, the *Procrastination Index,* which represents a learner's degree of procrastinating in when they start learning assignments (rather than when they complete assignments), relative to other learners within the same assignment (recognizing that different assignments may need different amounts of time). We apply this measure to data from over 100,000 students in 3,700 course sections from a large online learning platform. We find that students who habitually delay starting assignments have 21 times the risk of failing their courses than students who start on time. The result of this work is a straightforward and reliable Procrastination Index that generalizes across multiple academic disciplines, takes the individual features of assignments into account, is a strong predictor of academic performance, and provides an early signal to enable educators to design appropriate interventions for at-risk students.

Keywords

Procrastination, educational data mining, at-risk prediction

1. INTRODUCTION

Everyone procrastinates sometimes – even psychological researchers studying procrastination [8]. Despite procrastination's near-universality as a phenomenon, though, understanding is still incomplete as to what the full effects of procrastination are, where it emerges from, and how it can be combatted.

The relationship between procrastination and academic performance has been studied extensively. A meta-analysis by van Eerde [20] found that students who procrastinate generally receive worse course grades, a result seen in online learning environments as well [7, 12, 23]. On the other hand, other researchers have found evidence that students who procrastinate experience less stress and have better health than students who do not procrastinate [19].

A range of procrastination behaviors appear to be associated with poorer outcomes. Although procrastination has been defined rather broadly as "the tendency to postpone an activity under one's control to the last possible minute, or even not to perform it at all" [6], most studies of procrastination involve homework or studying. However, even procrastinating on accessing course materials is associated with worse course outcomes [1]. Several factors appear to be associated with the decision to procrastinate, from anxiety and depression [3] (though see [19] for contrasting evidence), to self-handicapping [20], to poor self-regulation [12] or a lack of scaffolding for self-regulation [16].

However, there are key limitations to past research on procrastination. Importantly, most published papers on the topic assess procrastination through self-report measures [11,18]. While these self-report measures correlate to behavioral measures such as whether the student hands in assignments late and total time spent, the correlation is moderate, in the -0.2 to -0.3 range [20]. Furthermore, this is not quite the same as identifying actual procrastination – delaying in starting or working on an assignment. For instance, a student could start early, work hard throughout, but still turn in a difficult assignment late. It is also conceivable that some students may think they are procrastinating more than other students when they are not. Correspondingly, some highly successful students may procrastinate, starting at the last minute, and still turn in high-quality work on time. These students may not see themselves as procrastinators. Therefore, in this paper we attempt to hone more closely in on procrastination as a behavior, using learning system data to see when students start an assignment as well as when they turn it in, following recent work in the EDM community using log data to study procrastination [i.e. 4, 9, 13].

In the remainder of this paper, we begin by offering an operational definition of procrastination at the level of a learning task and then aggregating it to the level of a learner. We study the properties of procrastination according to this definition, and then investigate the empirical relationship between procrastination and academic performance. We embed this into an analysis of the probabilistic risk associated with different levels of procrastination according to our definition. Finally, we present linear and logistic regression models that use procrastination on tasks to predict students' final grade and whether they will pass or fail the course, as a method for applying this paper's findings into prediction-based interventions.

2. METHODS

We used two datasets for the study, Alpha and Beta, that were derived from the online learning system Connect, a web-based learning system actively used by approximately 6000 higher education institutions worldwide. Students use Connect to read a course text and complete assignments. Instructors can compose assignments from a question bank as well as creating their own assignments. Both instructor-created and question bank assignments can be auto-graded. Connect records assignment start and end time, and the grade. Dataset Alpha is a heterogeneous

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dataset spanning multiple institutions. Alpha consists of 2,666,617 assignment submissions by 102,506 students on the platform during the Fall 2018 semester. The assignments span 3,681 courses, 42 disciplines, and 3,681 instructors at 1,216 institutions. Although the platform is used internationally, we restricted the analysis to US institutions to limit regional issues, policy differences in data use, and possible cultural differences in procrastination. The students submitted about 112,025 unique assignments in various courses. The courses are set up by instructors and differ in terms of course length, the number of homework assignments (the sample was restricted to courses with at least 10 assignments), and what percentage of the overall course grade is made up of the assignments on the Connect platform.

Dataset Beta, a more homogeneous data set from a single institution, also contained the final course grade for each student. The dataset, collected in the 2018/2019 academic year, consists of 98,201 assignment submissions on 5,986 assignments by 1,022 unique students in 298 sections of 37 courses in 28 disciplines. Many students were included in more than one course for a total of 3758 student-sections. The courses are designed with a regular spacing of assignments, four per week in each of eight weeks, for a total of approximately 32 assignments per course. In these courses, assignments on Connect are worth 80% of the course grade.

3. OPERATIONAL DEFINITIONS

3.1 Task Procrastination

All procrastination is delay, but not all delay is procrastination [15]. The central concept in procrastination is task delay – i.e. delaying in starting or completing a task that needs to be completed to accomplish some goal. When the student considers when to start an assignment, the student must decide, explicitly or implicitly, how much time they will need and, therefore, when they should start. An error in estimating this correctly places the student at risk of a poor grade. As a first step, let us postulate that for each assignment there is a threshold time to start the assignment, τ_t., a point after which we cannot reasonably expect most students to perform well on the assignment due at time τ_d. Note that this is a simplifying assumption: student knowledge of the topic and general ability likely varies, causing the true threshold start time to vary between students for a given assignment [cf. 10].

Consider two scenarios. In the first, a student begins a task at time τ_s ,before the threshold time τ_t and is therefore likely to complete the task and complete it well.

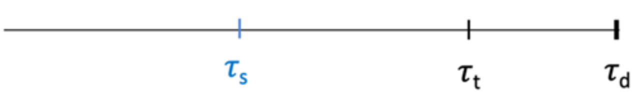

Figure 1 "Safe Zone" for starting an assignment

In the second scenario, a student begins a task after the threshold time, and is not likely to obtain a good grade on the assignment.

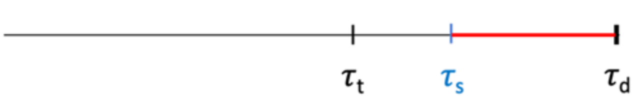

Figure 2 Case when start time is after threshold time

But how does one find τ_t? Or in other words, how do we assess task procrastination for a specific task given that the time needed to complete will vary from task to task? We can answer this question by considering the average z-scores derived based on each assignment rather than the absolute scores. Figure 3 shows the average grade z-scores students achieved based on when they start an assignment. By the 60th percentile, the score is below the mean performance on the homeworks. Near the 75th percentile, the score has dropped to 10% less than the mean and the decrease accelerates.

Based on these findings, we can heuristically set the threshold time τ_t for an assignment to be κ^{75}_s, the start time at which 75% of students have started the assignment. Setting κ^{75}_s as the threshold time, we can assign each student and each assignment a Boolean value to indicate whether the student started their assignment early enough or whether they procrastinated. A value of 0 means the student started their assignment early enough that we can say they did not procrastinate. A value of 1 means the student procrastinated. In other words, if τ_s is before κ^{75}_s, the student started on time. If τ_s is after κ^{75}_s , the student procrastinated. In the unfortunate special case where more than a quarter of students start after the due date, seen in approximately a quarter of assignments, we set τ_t to 0 -- starting after the due date is by definition procrastination, since no one can complete an assignment in less than 0 seconds.

$$\kappa^{75}_{s'} \;= \kappa^{75}_s \text{ if } \kappa^{75}_s \;<= \tau_d$$
$$\tau_d \text{, if } \kappa^{75}_s \;> \tau_d$$

Task procrastination is then is defined as follows. It is set to 0 if the start time is before the fourth quartile threshold $\kappa^{75}_{s'}$ as defined above. It is set to 1 if the start time is after this point or if no start time exists (the student never started the assignment)

$$P = 0 \text{ if } \tau_t < \kappa^{75}_{s'}$$
$$P = 1 \text{ if } \tau_t > \kappa^{75}_{s'} \text{ or } \tau_t \text{ is null}$$

3.2 Learner Procrastination

We can now use this assessment of Task Procrastination t as the basis for creating a Learner Procrastination Index (PI). For example, the following array represents a student S1 and their procrastination pattern (again, 1 represents procrastination and 0 represents not procrastinating). Take a hypothetical student, Chris. Chris started the first two assignments on time, and procrastinated on the remaining ones, until beginning the final assignment on time.

$$P_{Chris} = [0; 0; 1; 1; 1; 1; 1; 1; 1; 0]$$

From this, we compute Chris's Procrastination Index (PI) as the percentage of 1s on a scale from 0 to 1, 0.7 based on the above.

$$PI = mean(P_{Chris})$$

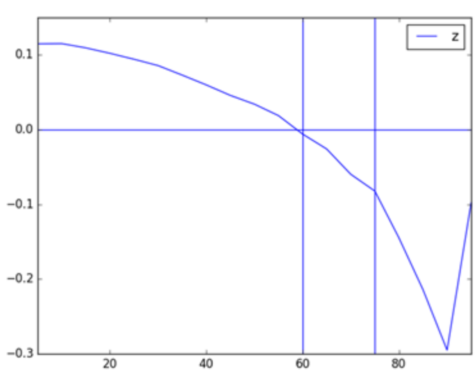

Figure 3 Starting Percentile vs. Z-Scored Grade

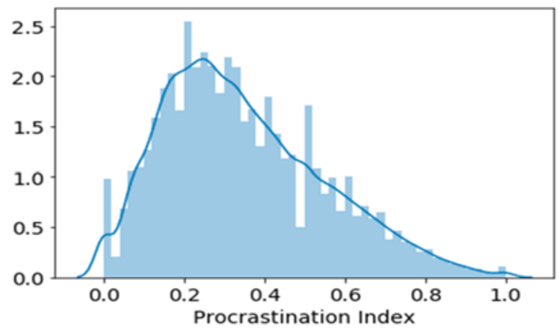

Figure 4 Histogram of PI for the 100k+ students

A PI of 0 means that student began every assignment on time. A PI of 1 means that the student procrastinated on every assignment. Figure 4 represents the distribution of the Procrastination Index for the over 100K students in Dataset Alpha.

4. Analysis of Procrastination, Performance, and Outcomes

With this operational definition of procrastination, we can now examine the relationship between procrastination and performance, shown in Figures 5 and 6. Figure 5 shows the average of the score on assignments in Connect for the dataset Alpha and figure 6 shows the average of the final grade on the course for dataset Beta. The average course grade declines as the Procrastination Index increases. The Pearson correlation between Procrastination Index and grade was found to be -0.67 and -0.69 for the datasets Alpha and Beta respectively, $p<0.001$ for both datasets. It is worth noting that these correlations are double to triple the magnitude of the correlations to grades previously reported for self-report measures of procrastination ($r=-0.2$ to -0.29; [i.e. 20]). Furthermore, as Figure 6 shows, the relationship is fairly consistent. Students who procrastinate under 5% average an A grade; students who procrastinate under 20% of the time have above a B average. Students who procrastinate under half the time receive more Bs and As than Cs. As the graph shows, there is a relatively steep drop-off in grade around a PI of 50%. Students who procrastinate 95% of the time tend to obtain a D or F.

In the remainder of this section, we will analyze the difference in course grades between students who frequently procrastinate (high Procrastination Index; "high PI") and students who procrastinate less often ("low PI"). These cut-offs are somewhat arbitrary, and we set them using course grades; although this creates some circularity, the resultant analysis is correlational rather than causal and therefore should be considered descriptive in nature.

Given the sharp drop-off in grades seen at a Procrastination Index of around 50% (see Figure 6), we can consider students who procrastinate more than half of the time to have high procrastination. There is not quite as clear a cut-off for low procrastination, but given that 20% marks a point where students tend to get Bs or better, we can consider 20% a cutoff for low procrastination. To create a group of students with medium PI for analysis, we chose PI between 0.3 and 0.4 to have values evenly between low PI and high PI while having a gap between groups.

Figure 7 shows the probability distribution function of Dataset Alpha for performance for different PI groups. Students with a high PI (red) are distributed at the lower end of the performance range. Students with low PI (green) tend to have higher performance and have low probability of obtaining an average score of under 60%.

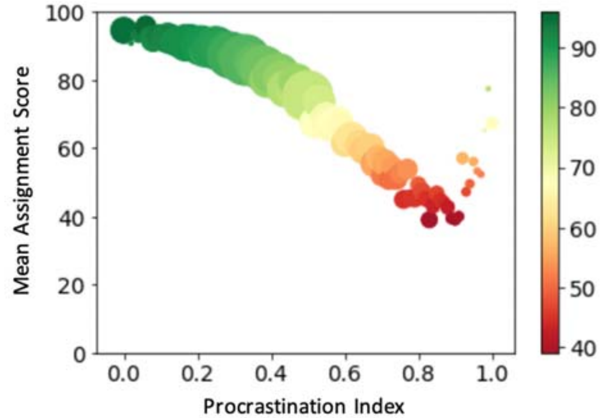

Figure 5 PI vs. Mean Assignment Score

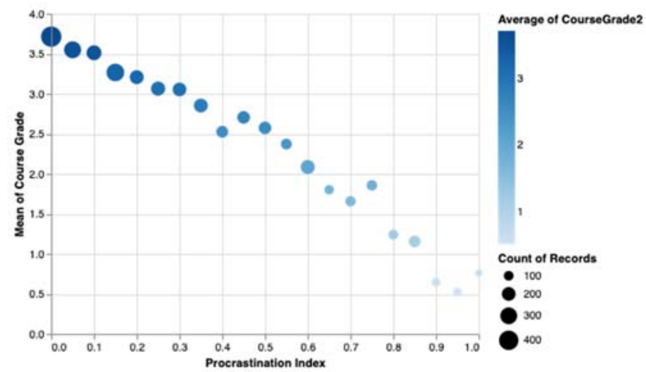

Figure 6 PI vs Mean Course Grade (A: 4, B: 3, C: 2, D: 1, F/W:0)

4.1 Procrastination and the Risk of Failure

Based on these categorizations, we can study the degree to which students with high and low PI are at different levels of risk of failing a course. For Dataset Alpha, we classify a student as passing if they obtain a grade of 70 or higher for the course. For Dataset Beta, we have obtained the actual final grades from the university. A/B/C is defined as pass; D and all other grades (F and a never-completed "incomplete" or withdraw) are treated as a failing grade.

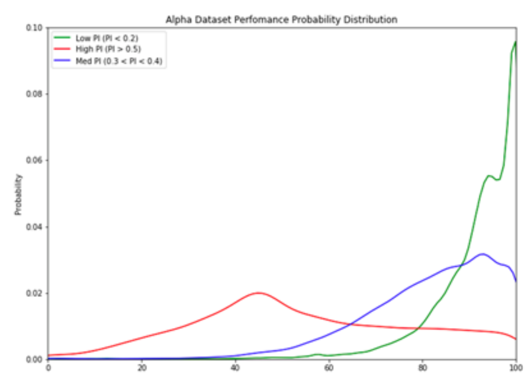

Figure 7 Performance (mean assignment score) Distribution for Different PI ranges for Dataset Alpha

Within Dataset Alpha, high PI students fail 71.5% of the time, while low PI students fail 3.4% of the time (RR= 21). Specifically, we compute the risk ratio (RR) for the likelihood that a student with a high PI will fail the course, compared to the likelihood that low

PI student will fail. We also compare the score distributions with Cliff's Delta, a measure of the degree of overlap between two distributions. Cliff's Delta scales from -1 to +1, where +1 and -1 indicate no overlap (in the two directions), 0 indicates total overlap, and values in between indicate partial overlap.

Dataset Beta, high PI students fail 54.6% of the time, while low PI students fail 1.1% of the time (RR=50). The Cliff's Delta is 0.82 for dataset Alpha is 0.82 (median score 91 vs. 54) and 0.77 for Beta (median score 92 vs. 67), indicating very little overlap between the two distributions. Nearly every student in the low PI group outscores every student in the high PI group.

4.2 Procrastination as a Predictor of Outcomes

In this section, we investigate PI as a potential predictor of final score and course outcome, using linear regression to predict the final score and logistic regression model to predict if a student would pass or fail the course, with a training-test split. We find that PI can be used to predict the final score, with $R^2 = 0.45$ for both datasets, and RMSE of 15 (Alpha)/ 17 (Beta) grade points. Logistic regression obtains a successful AUC ROC of 0.86 for both datasets. Even if we vary the cut-off for task procrastination, considering the 50th, 60th, 75th, 85th, and 95th percentile, and re-fit the model, model performance remains high. As Table 1 shows, the models maintain reasonably high AUC ROC across thresholds, with moderately higher AUC ROC with procrastination cut-offs from the 75th to 95th percentile of time. However, it is probably not useful for intervention to select a threshold where 95% of students have already started the assignment. Note that the recall values in this table do not fit the intuition that recall should go up for lower thresholds; this is because the threshold is at the level of individual assignments, whereas the logistic regression model sets a second cut-off at the level of students across assignments.

Table 1 Performance of logistic regression models that use different start time thresholds for procrastination.

Threshold Percentile	Average Precision	Average Recall	AUC ROC	Precision of Students who fail	Recall of Students who fail
50	69	59	0.8	55	22
60	72	63	0.83	60	31
75	76	67	0.86	65	40
85	78	69	0.87	68	44
95	78	69	0.87	68	43

5. DISCUSSION AND CONCLUSIONS

Though there has been considerable work on procrastination over the last decades, much of this work has looked at self-report measures or submission time. In this paper, we consider when students start assignments, relative to other students' work on the same assignment, which can function across contexts and can be aggregated across a course. Our aggregation, termed the Procrastination Index, is correlated with not only score within the Connect platform, but with the overall grade on the course, and can predict student grades, achieving double to triple the correlation to student outcomes seen for prior self-report measures [i.e. 20].

We can use early detection of procrastination to message students and to help them develop good habits. Even students who are performing well, but frequently procrastinate, may benefit from developing better habits – procrastination may become a bigger problem for these students when they reach more difficult material. Finishing tasks just in time can make sense in specific cases – but if students develop a general strategy of procrastinating, it may mis-serve them later [2]. Several interventions may be successful at helping students to work effectively. [21] have recently published a meta-analysis of different interventions designed to reduce procrastination, looking at which type of intervention leads to the strongest reduction. They investigated interventions involving self-regulated learning strategies (including time management), cognitive-behavioral therapy, and assertiveness training. They found that cognitive-behavioral therapy led to significantly less procrastination, and that assertiveness training actually led to significantly more procrastination. However, all of the interventions investigated in [21] were intensive. By contrast, [2] has proposed a way for students to offer their own deadlines to avoid a last minute rush to complete, leading to improved grades. In an automatic system, we can envision a system enabling students to suggest deadlines or presenting additional deadlines (for, say, a milestone that represents completing half the homework) to help them break down the task and reduce procrastination. It may also be possible to create automated interventions inspired by cognitive-behavioral therapy, although it is unclear whether they will work as well as the full therapeutic approach.

It remains to be seen what interventions are most effective at reducing procrastination and improving outcomes in a scalable fashion. As with other domains such as help-seeking [cf. 17], the relationship between procrastination and outcomes is probably not fully causal and it may be possible to reduce procrastination without improving outcomes. Finding the right intervention(s) to improve outcomes will be beneficial not only in improving outcomes but also in understanding whether – and how – procrastination has causal impacts on learning. More generally, a fuller understanding of procrastination may help us to better alleviate its impacts. Do students procrastinate as a habit or is it an ongoing error in their estimation of their time demands? What role do boredom and lack of engagement play? Better understanding the answers to these questions may ultimately lead to redesign of courses and/or assignments to better keep students engaged in their learning in a steady fashion throughout the semester.

In this paper, we have proposed a way to identify procrastination in students based on their interactions with an online learning system, that accounts for start time relative to other students. The PI indicator seems to generalize well across many different class sections. subject areas, and disciplines. We have been able to apply it to over a hundred thousand student scores in the Connect learning platform as well as with around 3,700 students at a specific institution with their final course grades. The correlation of Procrastination Index to the outcome in the course is around -0.7. The PI on a course can be used in a linear regression model to predict the final score, achieving an R^2 of 0.45, substantially higher than the predictive power of self-report measures of procrastination. For predicting pass or fail using a logistic regression model based solely on procrastination, we are able to achieve an area under the ROC curve of 0.86. We plan to use this research to improve our products – targeting content that is often procrastinated on for improvements -- and develop ways to nudge students to work more effectively and finish their tasks earlier. If we, as a field, stop procrastinating on this important issue, the impact on our students may be profound.

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