AC 2009-2050: EVALUATING ACADEMIC PROCRASTINATION IN A PERSONALIZED SYSTEM OF INSTRUCTION-BASED CURRICULUM

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Mitch Pryor graduated with a B.S. in Mechanical Engineering from Southern Methodist University in 1993. After teaching high school for two years, he completed his PhD in 2002 at the University of Texas (UT) at Austin where he now works as a Research Scientist in the Robotics Research Group and teaches in the Mechanical Engineering Department. As a researcher, his efforts have focused on software development for robotic systems. Recent research efforts include human/robot interactions, mobile manipulation, and robotic workcell integration including projects funded by NSF, DARPA, DOE/NNSA, and ONR among others. In the ME Department, he has taught graduate and undergraduate courses in programming, numerical methods, and robotics, as well as co-developed a nuclear automation interdisciplinary graduate program. Additionally, he has received academic development funding to study presence and stability in online PSI courses.

Evaluating Academic Procrastination in a Personalized System of Instruction based Curriculum

Abstract

The impact of procrastination on student learning is a common researched topic and correlated with a lack of external/self-regulation, motivation and performance anxiety. Lecture-centric courses provide limited data to measure student procrastination. Projects, homework and midterm deadlines are binary indicators of a tendency to procrastinate. Other evidence is often subjective or anecdotal. In self-paced Personalized System of Instruction (PSI) courses, even these metrics do not exist since students learn material and take tests at their convenience. Yet PSI is an effective teaching strategy in courses such as an introductory programming where students have diverse backgrounds and varied computer literacy. PSI allows individuals to invest the appropriate time without overwhelming new programmers or underwhelming the experienced. Most importantly, a well-designed PSI course can instill time management skills to counter procrastination. Yet, PSI course designs must be evaluated and compared to quantify success. Using a web-based PSI approach, data can be collected and used to quantify procrastination. We present candidate procrastination metrics for comparing student populations, the merits of various teaching strategies, and the impact of course features. Additionally, correlations with traditional metrics (i.e. Grade Point Average (GPA), Scholastic Aptitude Test (SAT), hours completed, etc.) are examined to determine what external factors – if any – impact procrastination and require normalization for comparative evaluation of course designs.

Introduction

Procrastination symbolizes deliberate or intentional deferment of a scheduled task, possibly due to limited time before a deadline. The Webster's dictionary defines procrastination as "*to put off intentionally and habitually.*" Unnecessary and often avoidable anxiety and apprehension are induced when multiple tasks are due. Procrastination amplifies this physical strain if there is fear of failure. While procrastination itself is detrimental in almost all walks of life, it has a more profound impact in academia when students are expected to complete course requirements in a defined amount of time. Potential negative consequences of procrastination are reduced scholastic performance, increased pressure to cheat, mental and physical stress.

Most conventional courses have some indications of procrastination where the concerned instructor relies on test/project/homework performance, attendance, group activity, and personal interactions to gauge an individual's progress on assigned tasks. Based on such indicators and feedback, he/she can take corrective measures deemed necessary to minimize procrastination such as direct communication. However, for a PSI web-based course, the instructor lacks traditional physical presence. Thus, identifying and addressing procrastination is a challenge. In this regard, it is imperative to characterize procrastination using metrics that allow an "online" instructor to evaluate procrastination levels. This paper defines and uses these metrics to evaluate the (hopefully) beneficial impact of various course implementations strategies and features to combat procrastination.

Next, we review the PSI philosophy and our course in particular. We then review relevant research on procrastination. Based on the literature and data collected, the next section defines candidate procrastination metrics. These metrics are then correlated to traditional metric data collected over 15 semesters including H.S. GPA, Univ. GPA, hours completed, long vs. short semester, SAT, etc. This step is necessary to determine preexisting correlations and if metric values must be normalized to compare different course implementations. Finally, course features that may impact procrastination are reviewed for potential benefit and implementation cost.

Personalized System of Instruction: Philosophy and Implementation

The use of computers and computational tools has increased exponentially in science and engineering and computational and numerical methods have become critical components of the engineering curricula. Yet, developing teaching strategies for introductory programming poses some unique challenges. Students enter the University with extremely diverse computational skills. Engineering faculty (outside the computational/electrical departments) typically do not teach programming and abstract concepts taught in Computer Science introductory courses may not match the desired outcomes for, say, a mechanical engineering student. PSI[1], based on the following features, is an approach that helps address this issue.

- Students take tests only when they are comfortable with the material. Thus, each student invests the appropriate time necessary to the course for their unique background.
- There are no midterms and no finals. Instead evaluation is based on periodic proficiency tests. *Programming* is emphasized instead of abstract *programming concepts*.
- All instructional material is online as is the test administration. Lessons are more tutorial than instructional, encouraging students to learn by doing.
- Faculty and proctors are almost always available via chat rooms, email, phone, extended office hours, etc. to answer quick clarifying questions.
- Each unit must be mastered before continuing. This requires students to score perfectly on a test before continuing. Anxiety issues are offset since each test can be taken as many times as necessary. This ensures that each student completes the course with a well-defined, basic competency in programming.
- As with all PSI courses, students earn a mastery grade (A) when they complete the units, or must retake the course if they do not. This ensures that students have the necessary programming tools *before* they enroll in core engineering curriculum courses.

The PSI philosophy is implemented in a 1st year course where students are exposed to three different programming languages - C (compiled), MATLAB™ (interpreted) and JAVA™ (Object-Oriented Programming)[2,3]. By introducing three languages, students learn that programming structure is relatively decoupled from syntax as well as understand the potential application areas of each language. However, the teaching staff is confronted with the task of ensuring that a large and relatively anonymous class with diverse academic backgrounds attains comparable skill in coding. This competence in programming needs to be achieved without overwhelming the novice while challenging the more perceptive. A quick review of our implementation is provided both as an example and to better understand our analysis using the procrastination metrics below.

Figure 1: Course homepage

Specifically, our course implementation includes 18 modules shown in the top navigation menu in Figure 1. Access to each unit requires a password acquired by students who successfully complete the previous unit. Unit 00 familiarizes students with the site layout and test submission system. It is the only unit completed during in class. Unit tests must be completed in 2 hours. Then proctors review the answers and either pass, fail or mark the test for correction. Students who fail the test (i.e. answers are not 100% correct) or do not submit in time retake the test when they feel prepared. Tests may be marked for correction to improve on a technically correct but poor programming technique, or if the error appears to result solely from question interpretation.

Units 1-3 present basic programming concepts in C, followed by a comprehensive Review Test, R1. While unit tests are completed anywhere and graded online, Review Tests are taken during office hours to ensure the course is completed in good faith. Students must also pass a Q&A after each Review Test which provides an opportunity for personal feedback. Units 4-7 cover advanced C concepts. Units 8-10 introduce MATLAB and units 11-13 introduce Object-Oriented Programming in JAVA. The final Review Test, R4, must be completed before the last class day.

This implementation has proven a viable solution to the issues described above. Novices have can learn material at a slower pace while experienced programmers progress faster. Since the course inception, the semester pass rate consistently exceeds 80%. However, significant procrastination is observed in both novice and experienced programmers that unnecessarily burdens course and university resources when they are most needed – the end of the semester. By quantifying procrastination and using data collected, various strategies and their benefit vs. implementation cost can be evaluated. The next section reviews student predisposition to procrastination and examines the notion that it can negatively impact learning.

Procrastination in the Literature

Many researchers have worked to identify the causes of procrastination and methods to minimize its impact. Dietz and others[4] associate procrastination with individual values and learning routines. They assert that people with planned daily tasks deal with procrastination constructively and better than unstructured individuals. Analyzing students' value orientations and interpersonal relationships, the authors present statistical evidence of academic procrastination levels and their dependence on motivational conflicts. They conclude that value orientations and conflicts do affect procrastination levels in an academic setting. Akinsola and others[5] note a statistical correlation between procrastination levels and achievement in mathematics. The authors further deduce that varying levels of procrastination (low, moderate and high) do significantly impact academic accomplishment and no gender differences exist.

Senecal and others[6] offered a different perspective. Similar to the earlier two studies, the authors closely examine student procrastination compared to individual motivation and self-regulation. Relying on statistical inference, they report that academic procrastination is associated with anxiety, depression and low self-esteem. Procrastination is also a consequence of external regulation and lack of motivation. Contrary to above, the authors present statistically significant differences between genders, but did adversely impact GPA.

Elvers *et. al.*[7] describe examined the effect of dilatory behaviors on student performance in both traditional lecture and online courses. In their report, the authors conclude that the two course options do generate different levels of procrastination. Further, they describe that student satisfaction affects procrastination and exam scores. After conducting student interviews, Schraw *et. al.*[8] suggested that laziness, fear of failure impact procrastination. However, cognitive efficiency and peak experience reduce the learning time even though they contribute to increased procrastination. This implies not all aspects of procrastination are necessarily bad. They further state that teacher expectations and lack of incentives influence procrastination. They identified six principles of procrastination that characterize student response to assigned tasks: *minimum time*, *optimum efficiency*, *peak effective experience*, *early assessment*, *open escape routes* and *proximity to reward*.

Chu *et. al.*[9] introduce the concept of active procrastinators where students deliberately work under pressure and produce similar output as non-procrastinators. The authors provide empirical evidence suggesting active procrastinators do considerably better than passive procrastinators in terms of time use, self-efficacy belief, extrinsic motivation, stress-coping strategies, have higher GPA's and lead less stressful lives than passive procrastinators.

The literature has shed light on various concerns that affect procrastination and how we perceive its negative impact on student learning. However, no metrics were found that quantify procrastination in a PSI course. These metrics would give researchers additional insights into student behavior and their response to self-guided teaching strategies.

Proposed Procrastination Metrics

Here we focus on three candidate metrics that give physical insight into the levels of procrastination that occurs in PSI courses.

Margin of Safety Metric (MoS) - The MoS metric is the simplest metric. It is the ratio of the successful final unit (R4 above) submission date and the last class day and is motivated by the scenario of a student who, for example, writes an assigned paper several weeks before it is due, waits until minutes before class to print, and finds the printer is out of paper. It more or less defines "avoiding procrastination" as "robust to last minute complications". If a student turns in R4 on the last class day (assume the last class day is day 67), the MoS for that student is 67/67 = 1. A student turning in R4 before the last class day has a MoS less than 1.

$$0 \le MoS_i = \frac{D_{fin}}{D_{sem} \times N_{sem}} \le 1 \tag{1}$$

where D_{fin} is the day the student completes R4, N_{sem} is the number of enrolled students and D_{sem} is the number of class days in the semester. Some students will not complete the course and stop working prior to the completing R4. These students are also assigned a value of 1. Thus the MoS for each student starts with a value of 0 that linearly approaches 1 until they complete (or fail to complete) the course. This metric addresses the fundamental risk that leaving even small tasks to the last minute can lead to failure. It does not account for the difference between a student methodically progressing through the units and one who completes the majority near the end of the semester.

Pacing Metric(s) - Pacing metrics discern between early and later procrastination by looking at the completion dates for intermediary milestones as well as the date a student completes the last unit. This strategy allows insight into general predisposition towards procrastination during the initial phase of the semester relative to their later efforts.

For example, we could measure a student's pace using the R2 test (about 50% complete) and R4 tests (100% complete). Assuming 67 class days and 18 units need to be completed, a linearly progressing student completes one every 3.72 days. At this O*ptimal Rate* (R_o), R2 (The 10th unit) would be passed on day 37. This leaves a 29.88 ((18 – 10) R_o) days to complete R4.

$$R2_i = \frac{D_{R2}}{n_{R2} \times R_o \times N_{sem}}; R4_i = \frac{D_{R4} - D_{R2}}{(n_{R4} - n_{R2}) \times R_o \times N_{sem}} \tag{2}$$

where D_{R2} and D_{R4} are the days R2 and R4 are completed are respectively. The variables n_{R2} and n_{R4} are the unit numbers for R2 (10) and R4 (18) respectively. For this pacing metric, the bounds are calculated below for a normalized class size where $N_{sem} = 1$,

$$0 \le R2_i = \frac{D_{sem}}{10 \times R_o} = \frac{D_{sem}}{10 \times \frac{D_{sem}}{18}} = 1.8 \tag{3}$$

$$0 \le R4_i = \frac{D_{sem} - 1}{8 \times \frac{D_{sem}}{18}} = 2.25 \tag{4}$$

Evaluating this pacing metric allows teachers to gauge student predisposition to procrastination and their response to approaching yet distant deadlines. Any unit can be used to determine the ratio of progress students during the semester. And more generally, a pacing metric can include more than one intermediate milestone. However, pacing metrics become unwieldy if used for individual unit completion rates. In order to quantify this behavior, the next metric is introduced to provide an average procrastination value over the entire span of the semester.

Cumulative Days to Completion (CDC) Metric - The previous metrics are discrete measures of procrastination. They are fixed values measured at predefined completion points and are thus not indicative of the "average" behavior of the student during the semester. Additionally these metrics cannot be used to quantify short term impact of class events (such as Spring Break or a motivational email from the instructor).

The CDC metric addresses this concern and provides a global average of procrastination. For the CDC metric, we first sum the days elapsed from the beginning of the semester to the completion of *each* unit *i* in the course for every student *j*.

$$D_{tot,j} = \sum_{i=1}^{n_{tot}} D_{ij} \tag{5}$$

In order to compare semesters (or snapshots of performance within a semester), the metric is normalized using the Optimal Rate (R_o) of unit completion.

$$D_{tot,R_o} = \sum_{i=1}^{n_{tot}} \left(i \times R_o\right) \tag{6}$$

$$CDC_j = \frac{D_{tot,j}}{D_{tot,R_o} \times N_{sem}} \tag{7}$$

Using the values from our example semester (i.e. 67 total days, 18 units), we can bound the CDC metric for the semester. But it is worth emphasizing that the CDC metric can be normalized relative to the optimal completion rate at *any* time during the semester, which allows us to compare not only the performance of one semester (or course) to another but also snapshots in time from within the same course. Again, for a normalized class size where $N_{sem} = 1$,

$$0 \le CDC_j = \frac{\sum_{i=1}^{n_{tot}} D_{ij}}{\sum_{i=1}^{n_{tot}} \left(i \times R_o\right)} \le \frac{\sum_{i=1}^{n_{tot}} 67}{\sum_{i=1}^{n_{tot}} \left(i \times \frac{67}{18}\right)} = 1.89 \tag{8}$$

Consider 3 different scenarios where the progression of a student is tracked and measured using the CDC metric and the class size has been normalized to a value of 1. The CDC value is shown in the final column.

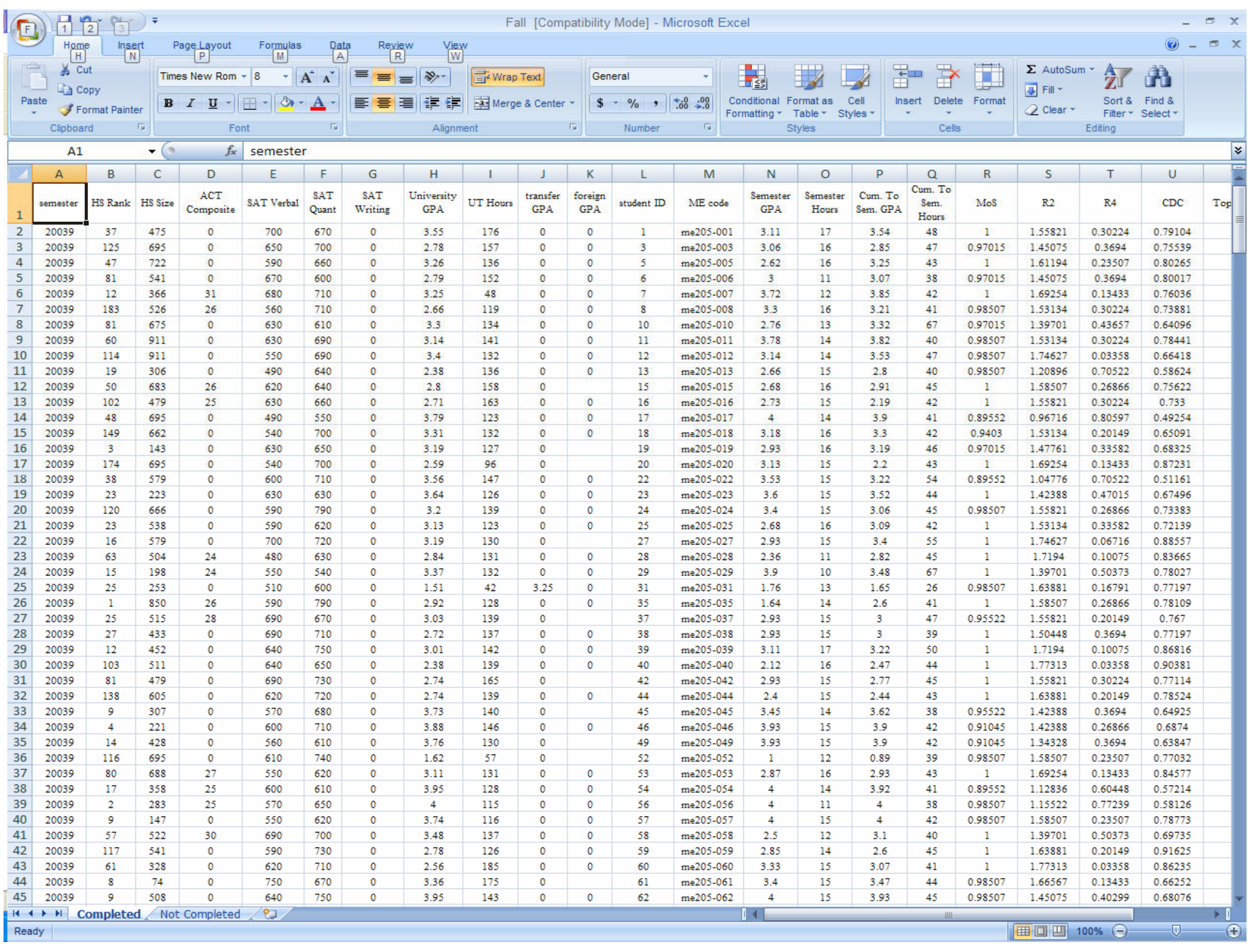
Scenario	Starting Date	Completion Date	CDC
1	First class day	A week from last class day	0.4726
2	First class day	Last class day	0.5277
3	A week since first class day	Last class day	0.5771

Table 1: 3 Students' CDC values relative to their procrastination scenario

If the class CDC average reduces by 0.05, this implies the entire class would complete the course a week ahead of schedule, quantifying a real and measurable impact that course implementation strategies have on procrastination.

Metric Correlation to External Parameters

Before using these parameters, it is important to discern the impact of external factors beyond our control and, if necessary, correct for their presence. For example do students generally procrastinate less in the summer? Do students with more college experience procrastinate less than first-year students? To answer these questions, we have examined data for 15 course offerings and1400 students during a 5 year period. In order to assess student predisposition to procrastination, student performance measured by the metrics above is compared to traditional academic metrics: SAT scores, High School GPA, High School Class Rank, University GPA, hours completed, semester enrolled (spring, fall, or summer), transfer/non-transfer, and number of hours taken in the semester of interest. The student populations varied with an average of 170 students enrolled during long semesters and less than 30 on an average during the summer. Gender and other non-academic profile information were not available. A sample data sheet is shown in Figure 2 and a summary of the available data is listed in Table 2.



	semester	HS Rank	HS Size	ACT Composite	SAT Verbal	SAT Quant	SAT Writing	University GPA	UT Hours	transfer GPA	foreign GPA	student ID	ME code	Semester GPA	Semester Hours	Cum. To Sem. GPA	Cum. To Sem. Hours	MoS	R2	R4	CDC	Top
2	20039	37	475	0	700	670	0	3.55	176	0	0	1	me205-001	3.11	17	3.54	48	1	1.55821	0.30224	0.79104	
3	20039	125	695	0	650	700	0	2.78	157	0	0	3	me205-003	3.06	16	2.85	47	0.97015	1.45075	0.3694	0.75539	
4	20039	47	722	0	590	660	0	3.26	136	0	0	5	me205-005	2.62	16	3.25	43	1	1.61194	0.23507	0.80265	
5	20039	81	541	0	670	600	0	2.79	152	0	0	6	me205-006	3	11	3.07	38	0.97015	1.45075	0.3694	0.80017	
6	20039	12	366	31	680	710	0	3.25	48	0	0	7	me205-007	3.72	12	3.85	42	1	1.69254	0.13433	0.76036	
7	20039	183	526	26	560	710	0	2.66	119	0	0	8	me205-008	3.3	16	3.21	41	0.98507	1.53134	0.30224	0.73881	
8	20039	81	675	0	630	610	0	3.3	134	0	0	10	me205-010	2.76	13	3.32	67	0.97015	1.39701	0.43657	0.64096	
9	20039	60	911	0	630	690	0	3.14	141	0	0	11	me205-011	3.78	14	3.82	40	0.98507	1.53134	0.30224	0.78441	
10	20039	114	911	0	550	690	0	3.4	132	0	0	12	me205-012	3.14	14	3.53	47	0.98507	1.74627	0.03358	0.66418	
11	20039	19	306	0	490	640	0	2.38	136	0	0	13	me205-013	2.66	15	2.8	40	0.98507	1.20896	0.70522	0.58624	
12	20039	50	683	26	620	640	0	2.8	158	0		15	me205-015	2.68	16	2.91	45	1	1.58507	0.26866	0.75622	
13	20039	102	479	25	630	660	0	2.71	163	0	0	16	me205-016	2.73	15	2.19	42	1	1.55821	0.30224	0.733	
14	20039	48	695	0	490	550	0	3.79	123	0	0	17	me205-017	4	14	3.9	41	0.89552	0.96716	0.80597	0.49254	
15	20039	149	662	0	540	700	0	3.31	132	0	0	18	me205-018	3.18	16	3.3	42	0.9403	1.53134	0.20149	0.65091	
16	20039	3	143	0	630	650	0	3.19	127	0		19	me205-019	2.93	16	3.19	46	0.97015	1.47761	0.33582	0.68325	
17	20039	174	695	0	540	700	0	2.59	96	0		20	me205-020	3.13	15	2.2	43	1	1.69254	0.13433	0.87231	
18	20039	38	579	0	600	710	0	3.56	147	0	0	22	me205-022	3.53	15	3.22	54	0.89552	1.04776	0.70522	0.51161	
19	20039	23	223	0	630	630	0	3.64	126	0	0	23	me205-023	3.6	15	3.52	44	1	1.42388	0.47015	0.67496	
20	20039	120	666	0	590	790	0	3.2	139	0	0	24	me205-024	3.4	15	3.06	45	0.98507	1.55821	0.26866	0.73383	
21	20039	23	538	0	590	620	0	3.13	123	0	0	25	me205-025	2.68	16	3.09	42	1	1.53134	0.33582	0.72139	
22	20039	16	579	0	700	720	0	3.19	130	0		27	me205-027	2.93	15	3.4	55	1	1.74627	0.06716	0.88557	
23	20039	63	504	24	480	630	0	2.84	131	0	0	28	me205-028	2.36	11	2.82	45	1	1.7194	0.10075	0.83665	
24	20039	15	198	24	550	540	0	3.37	132	0	0	29	me205-029	3.9	10	3.48	67	1	1.39701	0.50373	0.78027	
25	20039	25	253	0	510	600	0	1.51	42	3.25	0	31	me205-031	1.76	13	1.65	26	0.98507	1.63881	0.16791	0.77197	
26	20039	1	850	26	590	790	0	2.92	128	0	0	35	me205-035	1.64	14	2.6	41	1	1.58507	0.26866	0.78109	
27	20039	25	515	28	690	670	0	3.03	139	0		37	me205-037	2.93	15	3	47	0.95522	1.55821	0.20149	0.767	
28	20039	27	433	0	690	710	0	2.72	137	0	0	38	me205-038	2.93	15	3	39	1	1.50448	0.3694	0.77197	
29	20039	12	452	0	640	750	0	3.01	142	0	0	39	me205-039	3.11	17	3.22	50	1	1.7194	0.10075	0.86816	
30	20039	103	511	0	640	650	0	2.38	139	0	0	40	me205-040	2.12	16	2.47	44	1	1.77313	0.03358	0.90381	
31	20039	81	479	0	690	730	0	2.74	165	0		42	me205-042	2.93	15	2.77	45	1	1.55821	0.30224	0.77114	
32	20039	138	605	0	620	720	0	2.74	139	0	0	44	me205-044	2.4	15	2.44	43	1	1.63881	0.20149	0.78524	
33	20039	9	307	0	570	680	0	3.73	140	0		45	me205-045	3.45	14	3.62	38	0.95522	1.42388	0.3694	0.64925	
34	20039	4	221	0	600	710	0	3.88	146	0	0	46	me205-046	3.93	15	3.9	42	0.91045	1.42388	0.26866	0.6874	
35	20039	14	428	0	560	610	0	3.76	130	0		49	me205-049	3.93	15	3.9	42	0.91045	1.34328	0.3694	0.63847	
36	20039	116	695	0	610	740	0	1.62	57	0		52	me205-052	1	12	0.89	39	0.98507	1.58507	0.23507	0.77032	
37	20039	80	688	27	550	620	0	3.11	131	0	0	53	me205-053	2.87	16	2.93	43	1	1.69254	0.13433	0.84577	
38	20039	17	358	25	600	610	0	3.95	128	0	0	54	me205-054	4	14	3.92	41	0.89552	1.12836	0.60448	0.57214	
39	20039	2	283	25	570	650	0	4	115	0	0	56	me205-056	4	11	4	38	0.98507	1.15522	0.77239	0.58126	
40	20039	9	147	0	550	620	0	3.74	116	0	0	57	me205-057	4	15	4	42	0.98507	1.58507	0.23507	0.78773	
41	20039	57	522	30	690	700	0	3.48	137	0	0	58	me205-058	2.5	12	3.1	40	1	1.39701	0.50373	0.69735	
42	20039	117	541	0	590	730	0	2.78	126	0	0	59	me205-059	2.85	14	2.6	45	1	1.63881	0.20149	0.91625	
43	20039	61	328	0	620	710	0	2.56	185	0	0	60	me205-060	3.33	15	3.07	41	1	1.77313	0.03358	0.86235	
44	20039	8	74	0	750	670	0	3.36	175	0		61	me205-061	3.4	15	3.47	44	0.98507	1.66567	0.13433	0.66252	
45	20039	9	508	0	640	750	0	3.95	143	0	0	62	me205-062	4	15	3.93	45	0.98507	1.45075	0.40299	0.68076	

Figure 2: Sample datasheet

High School Data	College Data	Binary Correlations of Interest
High School Rank High School GPA SAT Verbal Score SAT Quantitative Score	Semester GPA Overall GPA Hours enrolled, overall Hours enrolled, current sem. Semester (F, Sp, Sum.)	Long vs. Short Semester Top 10% HS Class Rank vs. Not First-year Student vs. Not Transfer vs. non-Transfer

Table 2: Data Types in Student Profile

Although a variety of interesting questions can (and should) be addressed using this data and the metrics above, recall our initial objective of is to reduce procrastination and quantify reductions with the proposed metric. Thus, all that needs to be addressed as part of this effort is the impact of (and correction for) external parameters. Due to space constraints not all correlation results can be presented.

Correlation Results

Most external correlations ranked well below 1% and are of little consequence and only data exhibiting at least a 20% correlation is illustrated here. Further, for incomplete students, only the CDC metric was used since the MoS and pacing metrics do not provide any physical insight. To interpret each graph, note the correlation values for R4 will always be the negative of other metrics since the values for R4 are significantly smaller than the other three since procrastinating students tend to have accelerated progress at the end of the semester and hence smaller time intervals elapse between successful submissions.

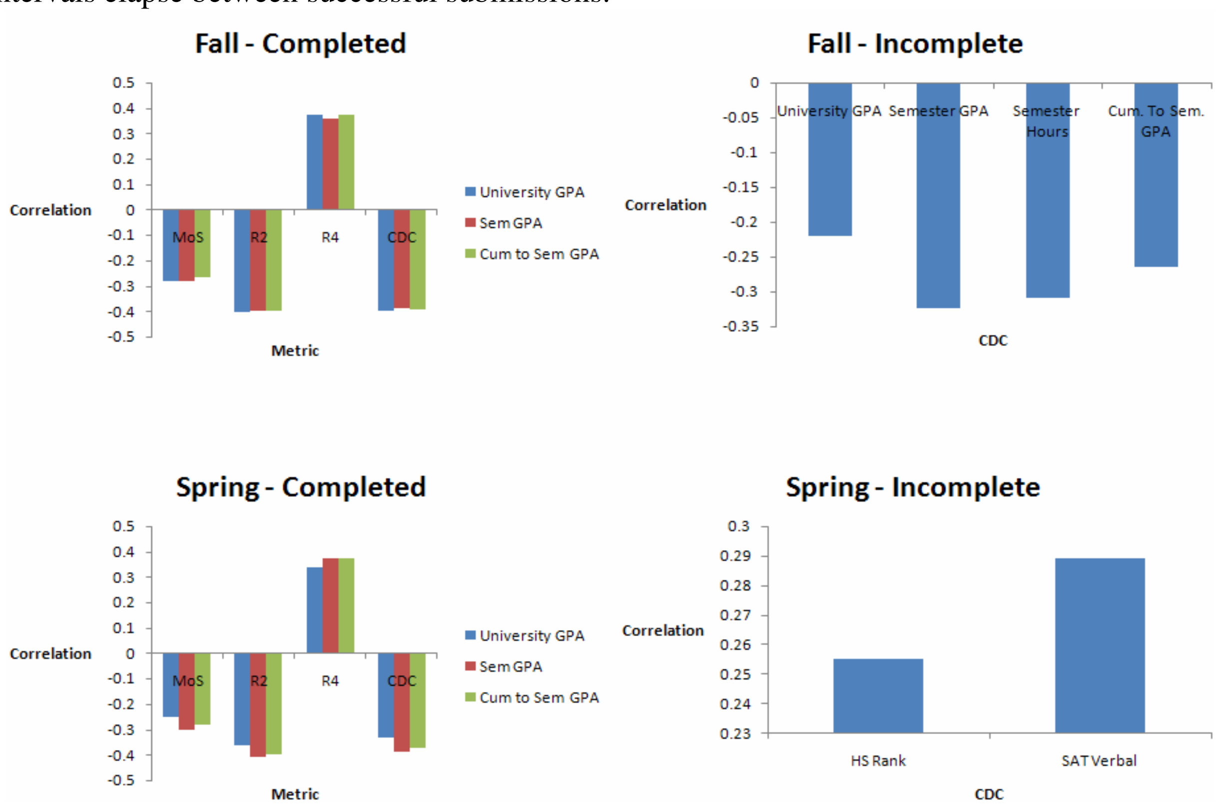


Figure 3: Fall vs. Spring Comparisons

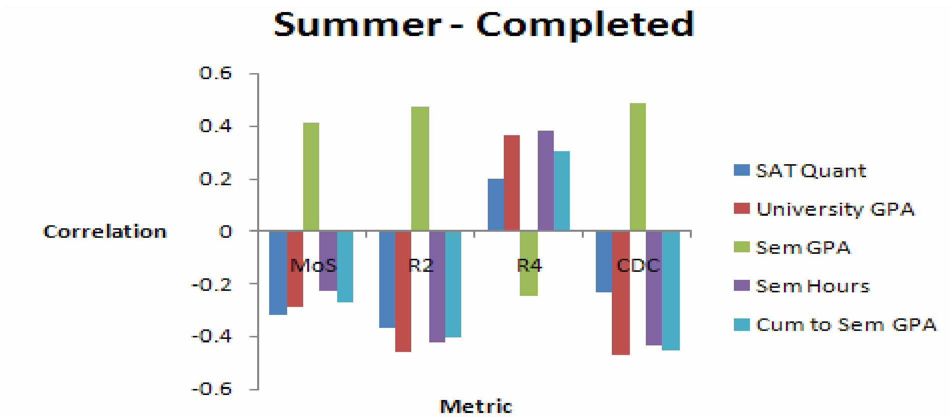


Figure 4: Summer correlations

Notice that (see Figures 3 and 4) the university, semester and cumulative semester GPAs have some correlation with each metric. Procrastination for summer students was affected by SAT quantitative scores and semester hours. The summer semester is significantly less than a regular semester and thus the corresponding procrastination is less. For students who did not complete the course in the long semesters, the most critical parameters were GPA and hours taken in fall, and High School Rank and SAT Verbal in the spring. This is an interesting outcome since the two semesters are comparable in length. One possible explanation for this anomaly could be that more first-year students enrolled in the fall semester with lofty initial expectations. Also, there was insufficient data to statistically examine students who do not complete the course during the summer due to their small population. This may suggest that most students complete the course during a shorter semester due to smaller class sizes and more flexible schedules.

Figure 5: Top 10% High School Rank vs. non-Top 10% High School Rank

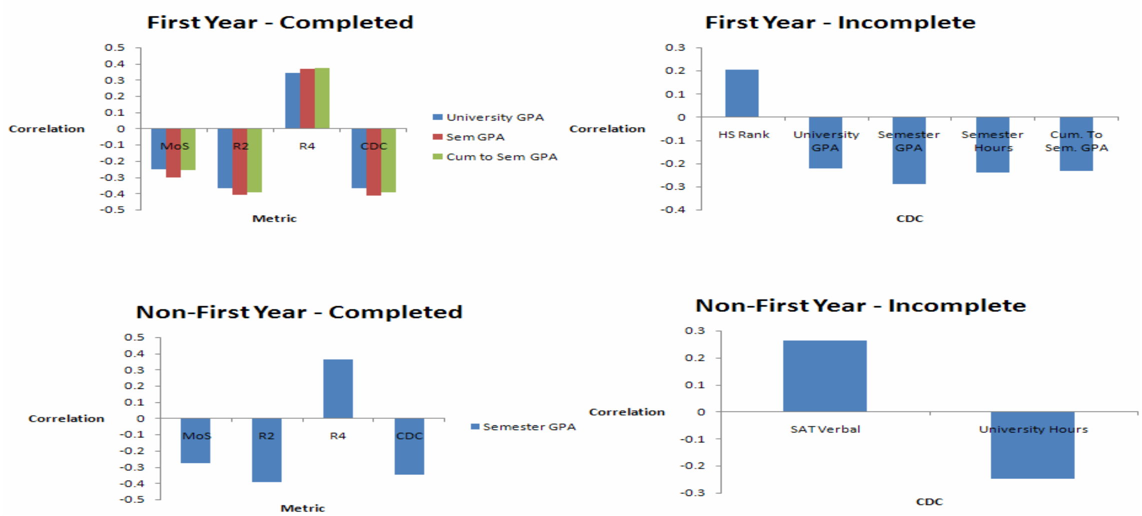


Figure 6: First Year vs. non-First Year Students

The top 10% and first-year student comparison is identical with respect to University GPA, semester GPA and cumulative GPA (see Figures 5 and 6). Semester hours were the only concern for top 10% students who did not complete the course while first-year students who did not complete had some correlation between GPA and associated hours affecting procrastination.

Figure 7: Transfer vs. non-Transfer Students

Transfer students (see Figure 7) had some correlation to semester GPA. For non-transfer students, University GPA, semester GPA and cumulative GPA also had some correlation. There was insufficient data to analyze transfer students who did not finish while SAT verbal scores slightly correlated with procrastination for non-transfer students who did not finish.

One notable conclusion seen in the data is that procrastination does play a role in determining GPA and is correlated with enrollment hours. To minimize this effect and mitigate associated stress levels some improvement measures have been adopted for implementation in the course. These measures are described in the next section. Although not exhaustive, the student profile data examined with respect to the defined procrastination metrics reveal *no significant external predisposition to procrastination that can be correlated with the proposed metrics*. The quantity and quality of the students profile data combined with the potential to collect data on student work rate within the course may yield future insights into the physical significance of traditional students metrics such as GPA, but such efforts are outside our scope and left for future work.

Proposed Course Implementation and Policy Strategies

Both students and instructors do have legitimate concerns about the effect of procrastination on GPA. Thus, PSI instructors have evaluated various techniques that may combat procrastination, and the proposed metrics provide the means to quantify their impact during previous semesters as well as (in the case of CDC) during the course. Some examples of strategies that have been (or will be) implemented are summarized below.

- **Incentive dates –** There are few opportunities to offer carrots instead of sticks. One option is to reward students who complete certain milestones by "deadlines" during the semester. For example, in our course, students who take Review Tests by a certain date may waive one question on the test without penalty.
- **Virtual Study Groups –** One fact of web-based PSI courses is class sizes tend to be large. But the group doesn't have to *seem* large to individuals taking the course. The course can seem to contain only a small subset of students, creating opportunities for personal and positive peer pressure as opposed to the anonymity of a large class.
- **Increased office hours –** Limited office hours may fail to instill a sense of urgency in students who see a closed, unmanned office during their daily routine. An office that is open (and active) creates a sense of urgency and reduces stress in a busy schedule.
- **Increased lab space** - Students tend to work in groups and thus need access to more computing resources when in groups, leading to congestion in undersized labs. The same psychology that leads us to the crowded (but not too crowded) restaurant applies.
- **Dynamic vs. Stale Content –** Web-based instructors may work very hard to set up the course and only to then indefinitely leave the content static. This staleness can also create a lack of urgency. Using a Content Management Systems such as Drupal[10] and others, allows instructors to publish "new" content and features during the semester.
- **Urgency Role Models –** Ungraded tests languishing in the proctors queue and errors in course content left uncorrected show a lack of urgency in the instructor that can be picked up by the student. We suspect semesters with shorter grading times decrease procrastination by more than the time elapsed due to delays in grading.

Of course the opportunities to brainstorm and implement anti-procrastination features and policies are virtually limitless. Our goal in this effort is to define metrics that allow us to quantify their effectiveness. Some initial results are presented briefly in the next section.

Preliminary Results

Here we present the values of the proposed procrastination metrics with respect to policy changes made during the course during the period data was collected: incentive dates, impact of stale content and extended office hours.

Strategy 1: Incentive Dates

Policy: Any student who completes any of the 4 review tests by a milestone date during the course of the semester may waive 1 question on the exam without penalty. The milestones are selected such that students who meet all the milestones finish the course with a week left (should impact MoS value) and the intermediary dates keep the student slightly ahead of the R_o pace for the semester.

Metric Comparison: This policy was implemented in just 2 of the 15 semesters that were studied. Thus metrics for these two semesters are only compared to those for the two previous semesters, to minimize any factor time may have played in the course.

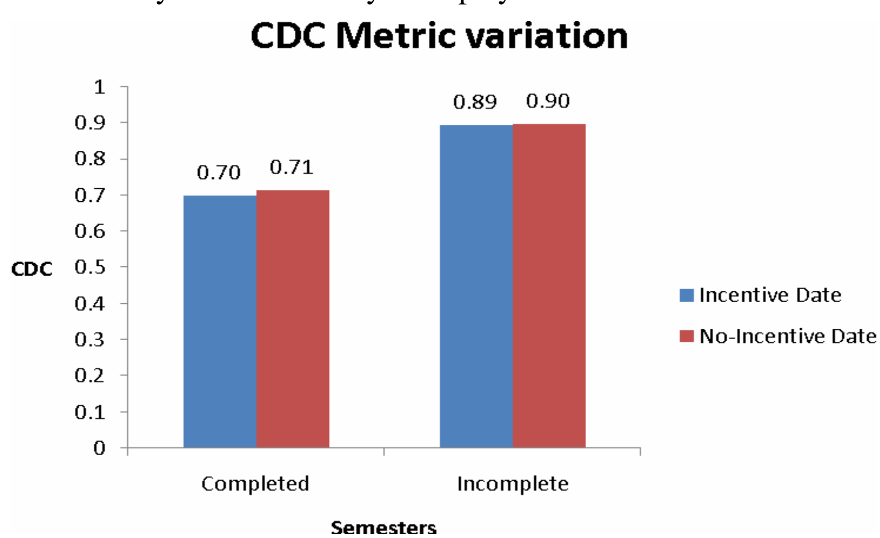


Figure 8: Incentive Date vs. no Incentive Date Policy

Analysis: Notice that the average CDC metric values are slightly smaller implying that the procrastination decreases with incentives. Recall that a decrease of 0.05 in CDC reduces time of completion by 7 days. Hence, a decrease of 0.01 is still significant with corresponding change in time saved. Assuming that tests where one question is omitted properly evaluate the student's ability, the lost cost (i.e. simplicity) of implementing the policy is worth even the nominally observed gain in student performance. Additional trials are necessary to determine the best location of incentive dates relative to optimal rate pace.

Strategy 2: Impact of Stale Content

Policy: During the years data was collected, the course content remained relatively static. This had the long term effect of the web site having a "dated" appearance. Although the web site was updated completely *after* the data collection period, some parts of the website were updated during the course of data collection. We investigate decrease (or not) in student procrastination as the content slowly became "stale".

Metric Comparison: Below is the procrastination metric CDC measured on an average for each semester we have data for in chronological order.

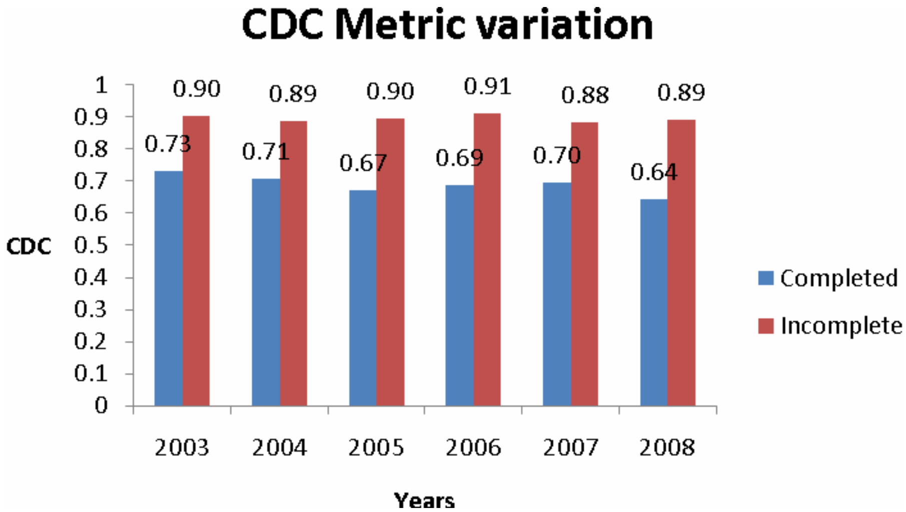


Figure 9: CDC variation with year

Analysis: Notice that the CDC variation with year shows decrease in procrastination as the content was updated (even marginally) for students completing the course. For those that did not, the metric value was more or less remained stagnant. Remember, considerable grading and turnaround time can be reduced with decrease in CDC value which is possible by actively engaging students in constructive technical content.

Strategy 3: Extended Office Hours

Policy: In order to better serve students office hours were increased from 10 hours/week to 18 hours/week. This was done by extending proctor hours from 2 to 3 hours per day and moving the instructor hours into a lab space making it easier for students to seek help in front of a computer.

Metric Comparison: This policy was only in place for one of the 15 examined semesters and is only compared to the previous semester in the graph below.

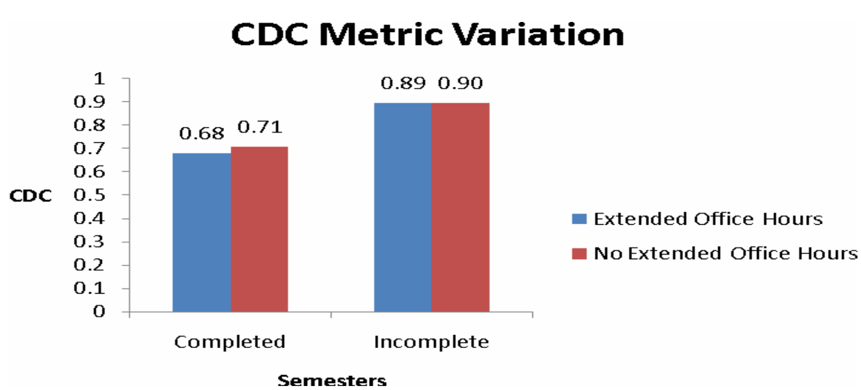


Figure 10: Extended Office Hours vs. no Extended Office Hours

Analysis: Again, notice that a minor extension of 1 hour in the office hours held by the instructors reduced procrastination as defined by the average CDC metric for both complete and incomplete students indicating that more flexibility needs to be shown by the teaching staff to accommodate student schedules. This allows the class on an average to complete well before the deadline and thus more time can be allocated by the teaching staff towards assisting last minute finishers.

Conclusions

This paper reviews the development of three procrastination metrics for a PSI based curriculum. These metrics have been formulated and contrasted with traditional performance indicators to determine the impact of external factors such as HS class rank, GPA, university hours completed, etc. It was found that GPA and enrolled semester hours are the most likely parameters to either affect or be affected by procrastination, however no strong correlations to external factors beyond the instructor's control were identified. Further, based on the outcomes of the analysis, modifications in the course format have been suggested and partially executed to a fair degree of success. Since the data collected to evaluate the value of the procrastination metrics was collected prior to their development and the methodical implementation of procrastination combating policies, only preliminary results of these strategies can be presented. However, results of this paper provide a powerful tool for instructors and proctors to quantify the success (or failure) of the course implementation strategies.

Acknowledgements

The authors gratefully acknowledge the contribution of Lisa Barden and Cengiz Vural in obtaining the relevant data.

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