Evaluating a Heavily-Instrumented Python CS1 Course

Anonymous1, Anonymous2, Anonymous3
Anonymous Institution
anonymous@anonymous.edu, anonymous@anonymous.edu, anonymous@anonymous.edu

ABSTRACT

The CS1 course is a critical experience for most novice programmers, requiring significant time and effort to overcome the inherent challenges. Ever-increasing enrollments mean that instructors have less insight into their students and can provide less individualized instruction. Automated programming environments and grading systems are one mechanism to scale CS1 instruction, but these new technologies can sometimes make it difficult for the instructor to gain insight into their learners. However, learning analytics collected by these systems can be used to make up some of the difference. This paper describes the process of mining a heavily-instrumented CS1 course to leverage fine-grained evidence of student learning. The existing Python-based curriculum was already heavily integrated with a web-based programming environment that captured keystroke-level student coding snapshots, along with various other forms of automated analyses. A Design-Based Research approach was taken to collect, analyze, and evaluate the data, with the intent to derive meaningful conclusions about the student experience and develop evidence-based improvements for the course. In addition to modeling our process, we report on a number of results regarding the persistence of student mistakes, measurements of student learning and errors, the association between student learning and student effort and procrastination, and places where we might be able to accelerate our curriculum's pacing. We hope that these results, as well as our generalized approach, can guide larger community efforts around systematic course analysis and revision.

Categories and Subject Descriptors

Social and professional topics [**Professional topics**]: Computing education; Information systems [**Information systems applications**]: Data mining

Keywords

cs1, modeling, dbr, python, procrastination

1. INTRODUCTION

The first Computer Science course (CS1) can be a challenging experience for novices given the constraints of a semester [19], but success in CS1 is critical for computer science students, as it sets a foundation for subsequent classes. Large amounts of practice and feedback are critical to this experience, so that learners can overcome programming misconceptions [14, 17] and develop effective schema. Instructors have a key role in developing materials to support learners' productive struggle. Recently, however, scaling enrollments [23] and the move to remote/hybrid learning environments has shifted much of this work away from interacting with individual students towards interacting with systems (which in turn interact with the students directly). For example, programming autograders [16] remove the instructor from the grading process, automatically assessing and sometimes even providing feedback directly to the learner.

Although these systems scale the learning process, they can inhibit the evaluation and revising of course materials. Instructors do not have as many first-hand interactions with students or the artifacts that they produce. When homeworks and exams are no longer hand-graded, teachers may not be as directly motivated to review each submission. Similarly, when automated feedback systems are effectively supporting students, teachers will have fewer opportunities to get direct insight into what issues students are encountering. This knowledge of the students' experience is critical to gauge the effectiveness of the course materials. Instructors need a new model to guide their revision decisions.

We propose instructors follow a Design-Based Research (DBR) approach [6, 3] to iteratively improve their course. In particular, course development should be seen as an iterative and statistical Instructional Design process; each semester, a curriculum is built and presented to learners as an intervention, data is generated and collected as learners interact, that data is analyzed to discover shortcomings and successes of the intervention, and then modifications to the "protocol" are identified for the next iteration of the study. Instructional Design models provide a systematic framework for this development process, but the DBR approach augments this to emphasize the statistical and theory-driven nature of the evaluation process. Fortunately, the same autograding tools that scale practice and feedback opportunities for students can also be used to collect many kinds of learning analytics, permitting the use of educational data mining to garner insights into learning [2].

In this paper, we present our experience of evaluating a CS1 course that has been heavily instrumented to provide rich data on student actions. Our goal is not to prove that our curriculum was a "success" or "failure" as a whole, but to empirically judge specific pieces and identify components that should be modified or maintained. We draw upon programming snapshot data, non-programming autograded question logs, surveys, exam data, and human assessments to produce a diverse dataset. In addition to sharing our conclusions about the state of our course, we believe that we present a formative model for other instructors who wish to evaluate their courses systematically. In fact, our specific analyses are recorded in a Jupyter Notebook[1]. Our hope is that others will use our own analyses as a baseline to develop their own questions, and to motivate others to approach their courses with a more systematic, empirical method.

2. THEORIES AND RELATED WORK

The central premise of our approach is inspired by Design-Based Research, which has been well established in the education literature for decades. Those interested in an introduction to DBR can refer to [6]. Briefly, there are several key tenets: 1) Development is an iterative process of design, intervention, collection, and analysis. 2) Educational interventions cannot be decontextualized from their setting. 3) Processes from all phases of development must be captured and provided sufficient context to ensure reproducibility and replication. 4) Developing learning experiences cannot be separated from developing theories about learning. 5) Results from an intervention must inform the next iteration and communicated out to broader stakeholders.

Messy authenticity is inherent in this process, and naturally limits the theoretical extent of findings in a DBR process. Therefore, any conclusions derived should not be seen as broadly applicable, but only meaningful for the context in which they were developed. Although theories of learning are generated from DBR, this is less true for early iterations. True success for a course is a moving target. As the curriculum improves and students overcome misconceptions faster, more material can be added. Over time, the curriculum necessarily needs to be updated and assignments refreshed. Further, courses often need to be adapted for new audiences with different demographics and prior experiences. Given the DBR model strongly incorporates context, these realities can be accounted for at some level.

DBR has been somewhat underused in Computing Education Research (CER). Recently, Neslon and Ko (2018) made a strong argument that CE research should almost *exclusively* follow Design-Based Research methodologies [24], for three reasons: 1) avoid splitting attention between advancing theory vs. design, 2) the field has not generated enough domain-specific theories, and 3) theory has sometimes been used to impede effective design-based research in the peer review process. Many of the recommendations made in the paper echo the tenets of DBR listed above and are consistent with our vision for communicating our course designs. In fact, their paper was a major guiding inspiration.

Another major inspiration for our approach is Guzdial's 2013 paper evaluating their decade-long Computational Thinking course ("MediaComp") [13]. Although a longer time scale, this paper takes a scientific, cohesive look at their course using a DBR lens. They critically evaluate what worked and contextualize all their findings by their design. They begin with a set of hypotheses about what aspects of the course will be effective, and then systematically review data collected from the offerings to accept or reject those hypotheses. Their conclusions, while not transcendent, are impactful for anyone modeling themselves after their context.

In computing education, programming log data has been used to make various kinds of predictions and evaluations of student learning. Applications include predicting student performance in subsequent courses [8], identifying learners who need additional support [29], modelling student strategies as they work on programming problems [20], evaluating students over the course of a semester [4, 21]. These approaches tend to rely on vast datasets or seek to derive conclusions that are predictive, highly transferable, or are about individual students. Although such research work is valuable, the goal is distinctive. We recognize that each course offering has an important local context that cannot be factored out, and that collecting sufficient evidence over time inhibits the process of iterative course design. Rather than developing generalizable theories or predicting performance, we seek actionable data from a single semester an instructor can use to evaluate and redesign their course.

Effenberger et al [9] are perhaps an example more closely aligned with our own research goals. Rather than evaluating students, their work sought to evaluate four programming problems in a course. Their results suggest that despite commonalities in the tasks, the problems' characteristics were considerably different, underscoring the danger of treating questions as interchangeable in course evaluation.

The process of systematic course revision is similar to the ID+KC model by Gusukuma (2018), which combines formal Instructional Design methodology with a cognitive student model based on Knowledge Components [12]. Instead of focusing on a student model, however, we focus on components of the instruction such as the learning objectives. Still, the systematic process of data collection and analysis to inform revision is common between our methods.

3. CURRICULUM AND TECHNOLOGY

In this section, we describe the course's curriculum and technology. DBR necessitates a clear enough description of the curriculum to understand the evaluation conducted, so we cannot avoid low-level details —the context matters. We have attempted to separate, however, the specific experiential details of our intervention (i.e., the course offering), which are described in Section 3.

As a starting point, we based our course on the [REDACTED] curriculum [2]. This curriculum has students move through a large sequence of almost 50 lessons over the course of a semester, with each lesson focused on a particular introductory programming topic. Each lesson is composed of a set of learning objectives, the lesson presentation, a mastery-

[1]REDACTED URL

[2]URL REDACTED

based quiz, and a set of programming problems. We have made a number of modifications to the materials reported in [27], such as the introduction of static typing and increasing the emphasis on functional design to better suit CS1 for Computer Science majors. A full listing of all the learning objectives covered is available [3].

Learning Management System: The course was delivered through Canvas, which was our university's Learning Management System. All material, including quizzes, programming assignments, and exams, were directly available in Canvas (either natively or through LTI).

Lesson Presentation: The lessons were PowerPoint slides with a recorded voice-over, embedded as a YouTube video directly into a Canvas Page. The content of these slides are transcribed directly below the video, including any code with proper syntax highlighting. Finally, PDF versions of all the slides with their transcriptions are also available.

Mastery Quizzes: After the presentations, students are presented with a Canvas Quiz containing a series of True/False, Matching, Multiple Choice, and Fill-in-the-blank questions. This assignment is presented in a mastery style, where learners can make repeated attempts until they earn a satisfactory grade. Each of the 200+ questions are annotated with a specific identifier. These quizzes are 10% of students' grade.

Although Canvas provides an interface to visualize statistics about individual quiz questions, this is obfuscated by the students multiple attempts–only the final grade is shown, so instructors cannot see how difficult a question was for a student. To provide greater detail in an instructor-friendly report, the Canvas API was used to pull all submission attempts for each student. The scripts used in analysis [4] and an example of the instructor report [5] are publicly available.

Programming Problems: Additionally, most lessons contain two-eight programming problems through a web-based Python coding environment [26]. These problems were also presented in a mastery style, allowing learners to spend as much time as they want until the deadline. These problems are 15% of students' final course grade. The environment has a dual block/text interface, although students were discouraged from using the block interface past the first two weeks of programming activities. The environment naturally records all student interactions in ProgSnap2 format [25], making it readily accessible for our evaluation.

Students were also required to install (and eventually use) a desktop Python programming environment, Thonny [1]. Students largely used Thonny for their programming projects, particularly the final project, although a small number chose to use the environment to write code for other assignments. The Thonny environment was not instrumented to collect log data, but students were required to submit their projects through the autograder in Canvas–therefore, submission data should not be affected by the relatively small number of students who used Thonny.

[3]https://pastebin.com/raw/qKhZgtS9 (anonymized)
[4]REDACTED URL
[5]https://tinyurl.com/ydgsyopl

When students submitted a solution to a programming problem, the system evaluated their work using an instructor-authored script written using the Pedal autograding framework [11]. This system generates feedback to learners and calculates a correctness grade (usually 0 or 1, although partial credit was possible on exams). The existing curriculum had a large quantity of autograded programming problems, some of which needed to be updated based on our changes.

Exams: There were two midterm exams and a final exam. These exams were all divided into two parts: 1) multiple-choice/true-false/matching/etc. questions, and 2) autograded programming questions. For the latter, students were given five-six programming problems that they could move freely between. These problems were automatically graded and given partial credit (20% for correctly specifying the header, and the remaining points allocated based on the percentage of passing instructor unit tests). Both parts were presented in Canvas through the systems students were already familiar with, but students were not allowed to use the internet or to Google. Students took the exam at a proctored testing center and had two hours. They were only allowed to bring a single sheet of hand-written notes. Multiple versions of each exam question were created and drawn from a pool at random, so that no two students had the exact same exam.

Projects: There were six projects throughout the semester, although the first two were very small and heavily scaffolded. The final project was relatively open-ended and meant to be summative, but the middle three projects allowed more mixed forms of support. Although students were largely expected to produce their own code, they were encouraged to seek help as needed from the instructional staff. For the final project, students used the Python Arcade library [6] to create a game. Because students were not previously taught Arcade, two weeks were allocated for students to work collaboratively on extending sample games with new functionality. Then, they individually built one of 12 games.

4. INTERVENTION

In this section, we describe the specific intervention context in more detail. The curriculum and technology was used in the Fall 2019 semester at an R1 university in the eastern United States for a CS1 course that was required for Computer Science majors in their first semester. An IRB-approved research protocol was followed. At the beginning of the semester, students were asked to provide consent via a survey, with 103 students agreeing out of 136 (for a 75.7% consent rate). A separate survey was also administered at the beginning of the semester to collect various demographic data (summarized in Table 1, only for consenting students) relating to gender, race, and prior coding experience.

	Percentage	Number
Identifies as Woman	19%	20
Black Student	6%	6
No Prior Coding Experience	37%	38
Total number of students	100%	103

Table 1: Demographic Data for Intervention

[6]https://arcade.academy/

Instructional Staff: The course was taught by a single instructor. He managed a team of 12 undergraduate teaching assistants. These TAs varied from CS sophomores to seniors, and not all of them had taken the curriculum before. However, they were all selected by the instructor for both for their knowledge and amiability. All members of the instructional staff hosted office hours. The TAs were also responsible for grading certain aspects of the projects (e.g., test quality, documentation quality, code quality), although this amounted to relatively little of the students' final course grade. The instructor met with these TAs every other week for an hour to discuss the state of the course and provide training on pedagogy, inclusivity, etc.

Structure: The lecture met Monday-Wednesday-Friday for 50 minutes across three separate sections. The sections were led by the same instructor, but were taught at different times of day (mid-morning, noon, and afternoon). The instructor did not attempt to provide the exact same experience to all three sections–if a mistake was made in the morning section, they attempted to avoid that mistake later. Typically, the first lecture session of a module started with 15-30 minutes of review of the material guided by clickers, and then students spent the rest of the module's class time working on assignments. There were several special in-class assignments such as worksheets, coding challenges, and readings. The lab met on Thursdays for 1.5 hours. Students worked on open assignments with the support of two TAs, who would actively walk around and answer questions.

5. RESULTS AND ANALYSIS

Our ultimate goal is to evaluate the course and identify aspects that were successful and unsuccessful. First, we consider basic course final course outcomes. Then, we use the programming log data to analyze students' behavioral outcomes from the semester. We dive deeper into this data to characterize the feedback that was delivered to students over the semester. We look at fine-grained data from both parts of the final exam to develop a list of problematic subskills, and then review more of the programming log data in light of these results. We particularly focus our efforts on subskills related to defining functions, to tighten our analysis.

The instructor's naive perception of the course was that things were largely successful, except for the final project. Insufficient time was given to the students to learn the game development API, and instructor expectations were a bit high (which was adjusted for in the grading, but may have caused students undue stress). However, the material prior to the final project went smoothly. Office hours were rarely overfilled, with the exception of week 4 (the module introducing Functions), which had one lesson too many–this was resolved by making the last programming assignment optional (Programming 25: Functional Decomposition).

5.1 Basic Course Outcomes

As a starting point, we consider basic course-level outcomes, the kind that could be determined even without the extra instrumentation. This will include the overall course grades, the major grade categories, and the university-administered course evaluations. As a starting point, the total number of failing grades and course withdrawals (DFW rate) was 14.5%, considered acceptable by the instructor.

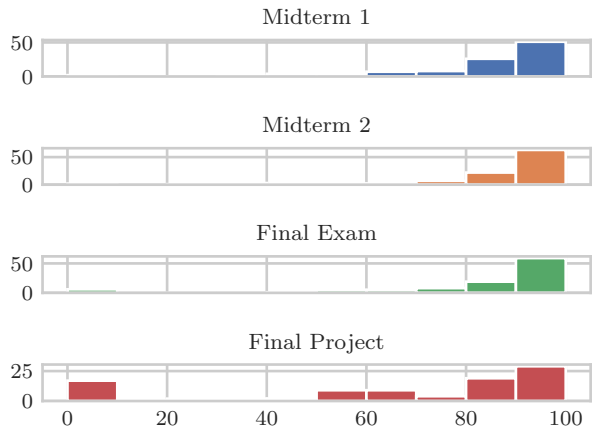


Figure 1: Exam and Final Project Grade Distributions

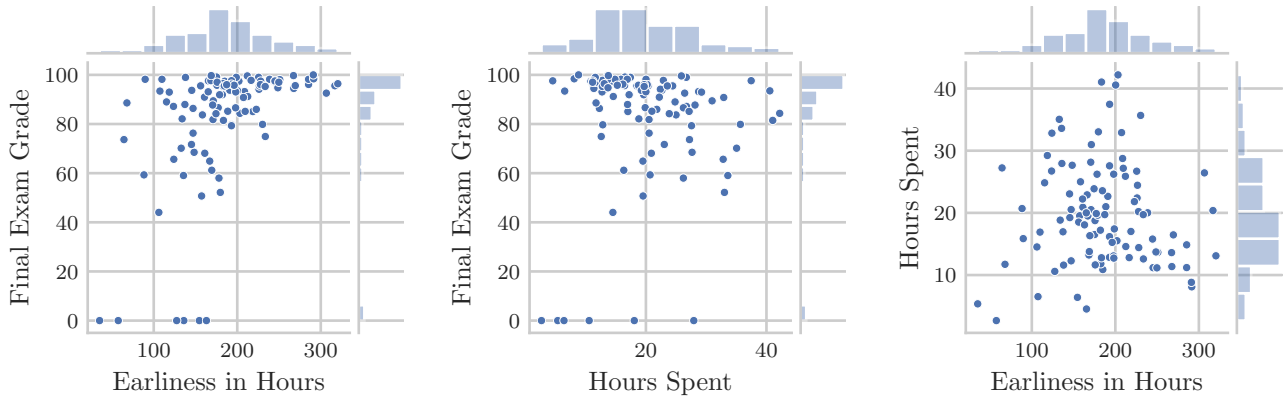
Figure 1 gives histograms for Midterm 1 and 2, Final Exam, and Final Project scores. There was considerably more variance in the final project scores than the exams, possibly due to the issues outlined before. The fact that many students were failed to produce a final project may be evidence that the assignment had unreasonable expectations.

A Kruskal-Wallis test was used to analyze final exam scores by demographics. There were no significant differences for gender, but a large difference for black students ($H(1)=6.39$, $p=.01$) and a smaller difference for prior programming experience ($H(1)=5.51$, $p=0.02$). The students without prior experience scored about 12% lower on average, while the black students scored about 41% lower. Given the concerning spread here, we review this data with more context in the next section before drawing any conclusions.

The university-run course evaluations from students yielded positive but simplistic results. Both the course and the instructor were separately rated on a 5-point likert scale (Poor... Excellent). Both the course (Mdn=5, M=4.62, SD=0.77) and the instructor (Mdn=5, M=4.70, SD=0.67) achieved very high results, but ultimately this tells us little about the students' experience. Course evaluation data is known to contain bias and provide limited data [5, 22]; these results must be taken in context with other sources of data. Note that because the course evaluations are anonymous, they cannot be cross-referenced with other data. A review of the students' free response answers reveals many were unhappy with the Final Project. In fact, the word "Arcade" appears in 41 of the 86 text responses, often as their only comment. Although this helps us see a major point of failure in our curriculum, it highlights the need for alternative evaluation mechanisms. Relying solely on student final perceptions leaves us vulnerable to student biases.

5.2 Time Spent Programming

The keystroke-level log data allows us to determine a number of interesting metrics beyond what is available from our grading spreadsheet. As a simple starting point, using the timestamps of the programming logs we can get a measure of how early students started working on assignments and total time spent. `Earliness` was measured by taking each



(a) Earliness vs. Final Exam Score (b) Hours Spent vs. Final Exam Score (c) Earliness vs. Hours Spent

Figure 2: Comparison of Earliness, Time Spent, and Final Exam Score

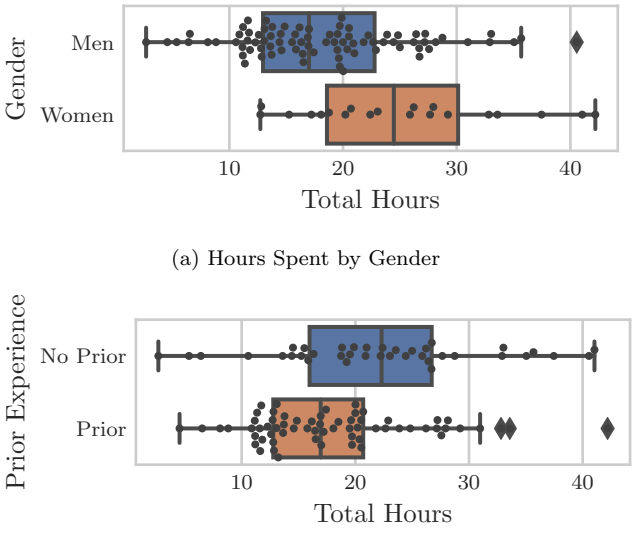
submission event across the entire course, finding the difference between this and the relevant assignment's deadline, and averaging those durations together within each student. `Hours Spent` was measured by grouping all the events in the logs by student, finding the difference with the next adjacent event (clipping to a maximum of 30 seconds, to consider breaks), and summing these durations.

Figures 2a, 2b, and 2c show a marginal plot between earliness, hours spent, and final exam grade. Spearman's Rho was used to calculate the correlation between each outcome. Consistent with Kazerouni [15], earliness (a measure of procrastination) had a significant medium correlation with exam scores ($r_s = .49, p < .001$), while time spent was only modestly correlated ($r_s = -.32, p = .001$). Interestingly, there was no significant correlation between student's time spent and their procrastination ($r_s = -0.09, p = .36$).

Analyzing behavioral outcomes by demographics indicated no differences, with the exception of total hours spent between women vs. men (H(1)=9.77, p=0.002) and between students with vs. without prior experience (H(1)=7.28, p=0.007). This comparison is visualized in Figures 3a and 3b. Women and students with no prior experience spent, on average, about 8 and 5 hours more than their counterparts. Importantly, this means that there was no significant difference in how early students started between subgroups.

Given the difference in final exam scores, black students appear poorly served by the current curriculum. On average, these students spent as much time as their peers on assignments, but their final exam scores were lower than students outside of this category. Given the evidence for the continued education debt owed to non-White students (Ladson-Billings, 2006) [18], more work is needed to identify both potentially problematic structural elements of the course and how the course can better draw on student strengths to produce more equitable outcomes.

Figure 4 visualizes the total time spent by students per week on the programming problems. The data collected raises an interesting question–how many hours should we ideally expect students to spend on our courses? At our institution,



(a) Hours Spent by Gender

(b) Hours Spent by Prior Experience

Figure 3: Hours Spent by Demographics

the guidance from the administration[7] is that in a three-credit course like this one, students should spend 45 hours in class and 90 hours outside of class over the course of the 15-week semester. The median time spent in our course by a given student on all the programming assignments was 19 hours, while the highest time spent by any individual student was just over 42 hours. This does not take into account time spent outside the coding environment (e.g., working on projects in Thonny), working on quizzes, and reading/watching the lesson presentations. However, some students did complete their projects in the online environment, and we expect most of those activities to take considerably less time than the programming activities. This may suggest that we are not asking our students to dedicate as much time as we might.

[7]REDACTED URL

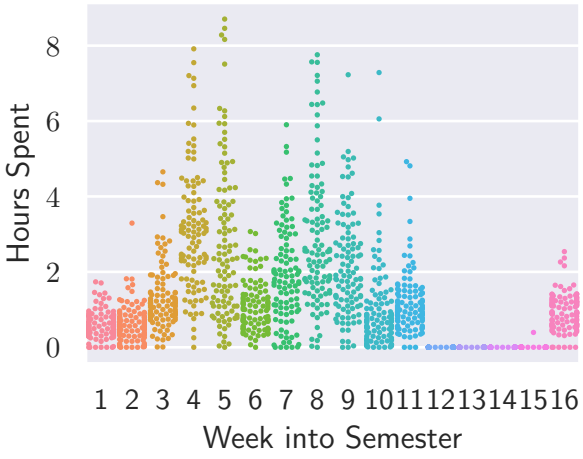


Figure 4: Time Spent per Week of Semester

Looking at specific time periods within the data, we see that students spent less time programming in the first weeks of the course, around the midpoint, and near the end of the programming problems (the last few weeks took place outside of the online coding environment). Especially for the earlier material, it is likely that the pace can be accelerated.

5.3 Error Classification

Table 2 gives the percentage of different feedback messages that students received on programming problems as a percentage of all the feedback events received. Our numbers vary from those reported by Smith and Rixner (2019) [28], possibly because of our very different approach to feedback and the affordances of our programming environment.

One of the most notable departures is the Analyzer and Problem-specific Instructor feedback categories. Our autograding system is capable of overriding error messages. In particular, one of its key features is a type inferencer and flow analyzer that automatically provides more readable and targeted error messages. The subcategories give examples of the kinds of errors produced: `Initialization Problem` (using a variable that was not previously defined) frequently supersedes the classic `NameError`, for example. Meanwhile, some issues have no corresponding runtime error, such as `Unused Variable` (never reading a variable that was previously written to). The Analyzer gives more than a fifth of all feedback delivered to students, suggesting its role is significant. Further work is needed to evaluate the quality of this feedback and the impact on students' learning.

The Problem-specific Instructor feedback category is opaque. Given that this represents almost a third of the feedback, it is unhelpful that the category cannot be easily broken down further. Sampling the logs' text, we see examples like students failing instructor unit tests, a reminder to call a function just once, and a suggestion to avoid a specific subscript index. Although the autograder is a powerful mechanism for delivering contextualized help to students, the lack of organization severely limits our automated analysis possible. As part of our process in the future, we intend to annotate feedback in our autograding scripts with identifiers.

Category	Subcategory	Percentage
Instructor		37.8%
	Problem Specific	32.1%
	Not Enough Student Tests	1.0%
	Not Printing Answer	.8%
Analyzer		22.1%
	Initialization Problem	6.9%
	Unused Variable	5.9%
	Multiple Return Types	2.9%
	Incompatible Types	1.4%
	Parameter Type Mismatch	1.0%
	Overwritten Variable	.6%
	Read out of scope	.5%
Correct		17.8%
Syntax		11.4%
	No Source Code	.3%
Runtime		7.8%
	TypeError	3.7%
	NameError	1.0%
	AttributeError	.8%
	ValueError	.4%
	KeyError	.4%
	IndexError	.4%
Student	Student Tests Failing	2.9%
Instructions		2.4%
System Error		.8%

Table 2: Frequency of Error Messages by Category

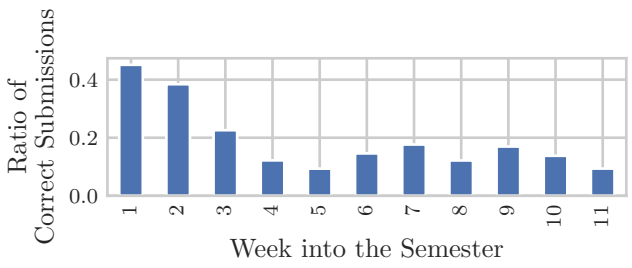
Figure 5a gives the ratio of correct submission events in the log data over each week of the semester. Early on, students complete problems with fewer attempts. This might explain the steady growth in ratios of different kinds of feedback over time, as evidenced by Figures 5b and 5c. It is interesting to observe that the runtime error frequency grows almost linearly over the course of the semester, with the exception of week 7 (a peak week for the Analyzer feedback). We hypothesize this is the result of some more carefully-refined instructor feedback available during that week.

5.4 Final Exam Conceptual Questions

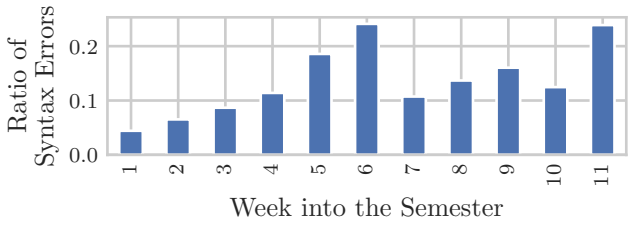
The first part of the final exam was composed of conceptual questions for topics across the curriculum, drawn largely from the quiz questions students had already seen. In this section, we review the quiz report to determine the topics that students struggled with. Most students performed relatively well across the questions, so we focus on errors where more than 80% of the students had incorrect answers.

Students largely had no issues with questions involving evaluating expressions. A small exception to this is students' struggle with Equality vs. Order of different types. In Python, as in many languages, it is not an error to check if two things of different types are equal (although that comparison will always produce false); however, it is an error to compare their order (less than/greater than operators). In fact, 58% of students got this specific question wrong.

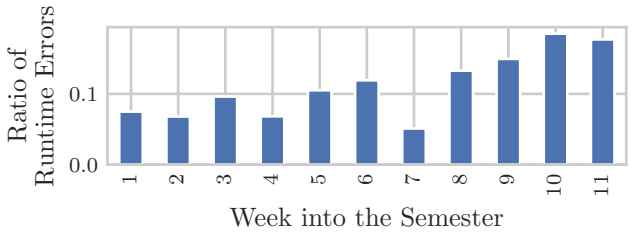
There were three questions related to tracing complex control flow for loops, `if` statements, and functions. Tracing seemed to pose difficulties, with between 25-40% of the students getting these questions wrong. We believe that more



(a) Ratio of Correct Submissions by Week of Semester



(b) Ratio of Syntax Errors by Week of Semester



(c) Ratio of Runtime Errors by Week of Semester

Figure 5: Ratio of Feedback Types by Week of Semester

emphasis should be placed on tracing in the curriculum; there are quiz questions and a worksheet dedicated to the topic, but there are opportunities to expand this material. Tracing has been a recent area of focus within the literature, with promising approaches by Xie [30] and Cunningham [7].

Dictionaries also posed significant trouble for students. Dictionaries come up later in the course, represent more complex reality, and conflate syntactic operations with lists. In fact, this last point is evidenced by data. In a question comparing the relative speed of traversing lists and dictionaries, 50% of the students got one variant of a True/False question incorrect (so they might as well have been guessing).

Again, the point of our analysis is not to necessarily develop a validated examination instrument or to distill an authoritative set of misconceptions. Instead, we seek to demonstrate the insight we have garnered from reviewing our exam. With these simple percentages, we have found targets.

5.5 Deeper Dive on Functions

In looking over the second part of the final exam questions, we are faced with a tremendous number of concepts integrated into each problem. In fact, with over 261 learning objectives in the course, analyzing the entire set is an overwhelming prospect. To scope our analysis for this paper, we decided to focus on a subset of skills just related to Functions that we felt we could clearly identify with computational analysis and that the instructor felt, a-priori, they had seen students struggle with over the course of the semester. Table 3 gives the percentages and quantity of students who successfully demonstrated the subskill on each exam.

Header Definition: Even though we had not observed many students struggling with syntax during the semester, we felt it critical to analyze the incidence of submitted code that had malformed headers. Although the numbers were a little higher than expected, we are not terribly concerned - reviewing the submissions, many seemed like simple typos (e.g., a missing colon) that were relatively easily fixed.

Provided Types: Students were not required or encouraged to provide types in their headers during the exam. In fact, since the advanced feedback features were turned off, their feedback would not actually reference any parameter or return types they specified (as long as they were syntactically correct code). We did not assess the correctness of their provided types - merely their existence. In the final exam, the number of students who annotated their parameter types falls off sharply after the first three questions (moving from about 50% down to 20%). We offer two explanations: first, the fourth question is one of the most difficult in the entire course, so students may have been distracted by its difficulty. Second, the last questions all involve more complicated nested data types (e.g., lists of dictionaries) that were too troublesome for the students to specify.

Parameter Overwriting: This misconception is one that the instructors were very concerned with, having observed it repeatedly among certain students early in the semester (and concerned with its persistence). Applying the parameter overwriting pattern to the rest of the submissions over the entire semester, we found that the behavior trails off over the course of the semester. By the final exam, almost no students were making this particular mistake. Although the instructor believes that more can be done up front to avoid this critical misconception, it is comforting that the existing curriculum seems to largely address this by the end.

Return/Print: We observed that some students struggle to differentiate between the concepts of return statements and print calls. However, largely students were successful with this subskill, despite a quarter of students getting a related (more abstract rendering) version of this subskill wrong on part 1 of the final exam. It seems that although troublesome for a small clutch of students, most are able to eventually separate this concept in their code.

Parameters/Input: Similar to students' issues with returning vs. printing, some students were observed in individual sessions mixing up parameters and the input function (which was presented as a very distinctive way that data could enter a function). However, it appears that this was truly isolated to just a few students.

Functional Decomposition: Largely inspired by Fisler et al's [10] success in overcoming the difficulties of the Rainfall problem, Functional Decomposition was taught as a method for complex processing data. Students had previously been

Subskill	Description	1st Exam	2nd Exam	Final Exam
Header Definition	Defined the function header with correct syntax	83.5% (86)	84.5% (87)	91.3% (94)
Provided Types	Provided types for all parameters and the return	40.8% (42)	45.6% (47)	37.9% (39)
Parameter Overwrite	Did not assign literal values to parameters in the body	88.3% (91)	98.1% (101)	99.0% (102)
Return/Print	Did not print without returning	80.6% (83)	89.3% (92)	91.3% (94)
Parameters/Input	Did not use the input function instead of parameters	96.1% (99)	100.0% (103)	99.0% (102)
Unit Testing	Wrote unit tests	88.3% (91)	79.6% (82)	67.0% (69)
Decomposition	Separated work into a helper function	1.0% (1)	17.5% (18)	19.4% (20)

Table 3: Percentage of Students Demonstrating Subskill across Exams

taught 8 different looping patterns (e.g., accumulating, mapping, filtering). A number of assignments required students to decompose problems. Therefore, it is somewhat disappointing that so few students chose to leverage decomposition (particularly since the harder final exam problems were naturally susceptible to a decomposition approach). In addition to the midterm 2 and final exam questions, we also took a closer look at an earlier open-ended programming problem that was particularly complex and well-suited to decomposition. In these problems, there seemed to be a pattern of students being more successful when they leverage decomposition. Although not conclusive, this supports the hypothesis that decomposition may be an effective strategy.

	Decomposed		Monolithic	
	Pass	Fail	Pass	Fail
Earlier Problem	37	8	29	27
Midterm 2 Question 5	13	5	40	43
Final Exam Question 4	7	8	42	44
Total	57	21	111	114
	18.8%	6.9%	36.6%	37.6%

Table 4: Student Use's of Decomposition over Time

Unit Testing: Given that students were not required to unit test their code on the final exam, we were pleased to find that many students wrote unit tests anyway. Interestingly, though, the percentage of students who used this strategy decreased over the course of the semester, even as the programming problems became more difficult. We hypothesize that since the later exam problems involve complex nested data, students either did not feel comfortable generating test data or they felt that it would not be an efficient use of their time. We believe that we need to sell the concept more - rather than thinking that writing test cases would be a detriment to their success, students should see tests as one of the most direct paths to completion.

6. DISCUSSION

Reviewing our findings, we made several decisions about places to modify our curriculum. The log data suggests that some of the earlier material can be accelerated, so that more time can ultimately be allocated to week 4 (critical material covering functions). We also believe we need to spend more time throughout the semester convincing students that subskills like decomposition and unit testing can help them solve challenging questions, although follow-up analyses will be needed to confirm this theory. Finally, we must come up with new ways to support some of our demographic subgroups, given that outcomes in that area are not yet equal.

Better structure to our existing data sources might help in future analyses. For example, although each quiz question was labeled with a unique identifier, we realized during analysis that we really needed every quiz *answer* (and in some cases, sets of answers) to have a unique identifier as well. In particular, some questions had multiple parts, or different answers yielded information about different misconceptions. In a similar vein, annotating instructor feedback for the programming problems would have substantially increased the differentiation of our feedback messages.

More metadata about each identifier would also help efforts to cross-reference and cluster related problems (especially over time). This is a non-trivial effort, given the quantity of course materials present in the curriculum. As a starting point, we believe this effort should probably be focused on certain major learning objectives and topics (e.g., functions) that are particularly worthy of attention based on the formative evaluation conducted here.

We expect that before our next iteration of our analyses, we need to develop more hypotheses up front for guidance. A considerable amount of time was spent performing exploratory analyses, trying different approaches and seeing what emerged from the data. Although helpful as we oriented ourselves, the data dredging that can emerge may yield false conclusions that are not actually worth investing in. Finally, while we attempted to follow a replicable process in our data collection and analysis, we believe more should be done to streamline and package our data pipeline to encourage replication and reproduction.

7. CONCLUSION

In this paper, we have described our evaluation of data from a heavily-instrumented CS1 course. Our goal was less about judging the course overall, and more about finding specific areas of improvement and success. We feel that course evaluation is less about the end-goal and more about small iterative augmentations that collect over time. To structure our approach, we followed a loose Design-Based Research model supported by educational data mining. In our experience, the high volume and variety of data sources can be very helpful in understanding the successes and failures of the course, although it does pose difficulties for analysis. As always, a better pipeline could help make sense of these data and results more quickly, possibly even during the semester. However, in the immediate term, our data analysis contributes to the community's knowledge of students and ideally provides a model for others to follow along. In general, we hope to encourage increased rigor in course evaluation as we integrate data-rich tools into our courses.

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APPENDIX

A. FIRST ONE