Understanding impact of life experiences on performance and learning behavior in an Introductory Computer Science MOOC

by

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Abstract

In this thesis, we attempt to understand the impact of life experiences on performance and learning behavior in an introductory computer science MOOC (Massive Open Online Course). Through data analysis work, this thesis identifies that some life experiences have an impact on a student's performance and learning behaviors in the course. When it came to a student's academic/career life experiences, exposure to the concept of induction in math positively impacts a student's performance in the final exam, while experience in management negatively affects performance in all graded portions of the class except for problem sets. In terms of learning behavior, students without management experience tend to have performed a higher number of solution submissions and watched a larger fraction of the course videos, while students without extensive experience in writing lengthy reports (20+ pages) show greater engagement in the course forum. In regards to a student's non-academic life experiences, students with over 50 hours of experience in open-world strategy games tend to perform better in overall grades and problem sets. Lastly, in analyzing day-to-day behaviors, a positive correlation was observed between regular engagement in riddles, brainteasers, or sudoku and overall grades and performance in the final exam, although no significant correlation is found between day-to-day behaviors and learning behaviors in the course.

Thesis Supervisor: Ana Bell
Title: Senior Lecturer, edX Instructor

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- My roommate Luann - for our amazing undergrad journey together

- My ILBC friends - for continuing to be a great group of friends after 15+ years and for being my family away from home

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Chapter 1

Introduction

Computer science is an increasingly important field, with demand for skilled professionals outpacing the supply of qualifed candidates. Massive open online courses (MOOCs) have become a popular way for individuals to gain new skills and knowledge in this field, offering a flexible and cost-effective way to learn. With this increase in popularity for computer science MOOCs, it is important to understand the factors that influence student performance and retention in these courses.

This thesis aims to examine the potential impact of life experiences on performance and learning behavior in an introductory computer science MOOC, specifically 6.00.1x, Introduction to Computer Science and Programming Using Python, an MOOC offered by MITx on the edX platform. The thesis investigates whether certain life experiences (e.g. previous experience in studying music theory, experience playing open-world strategy games, etc.) are correlated to students' performance and engagement in the course. By understanding the factors that influence behavior in MOOCs, educators can develop targeted strategies to improve retention and success for all students with different backgrounds and experiences.

1.1 Related work

Previously, work has been done to understand learning behavior of students in two MOOCs offered by MITx on the edX platform: 6.00.1x, Introduction to Computer

Science and Programming Using Python, and 6.00.2x, Introduction to Computational Thinking and Data Science.

Some interesting prior work in the area include analyzing student code trajectories [1] and impact of the covid pandemic on student participation in the MOOC.[2] A particularly interesting paper is the paper 'How Student Background and Topic Impact the Doer Effect in Computational Thinking MOOCs' [3].

The paper studies the relationship between a student's background and the "doer effect", which implies a strong correlation between doing practice questions and learning outcomes. The paper concludes that the doer effect is relatively present among students without prior experience as well as among those familiar with the material. The paper focuses on one particular life experience of the student which is on their experience with programming and computational topics. The paper analyzes the learning outcome through final course grades and problem set grades and does not focus on retention of students in the course. This provided a potential direction for my thesis research to take as a potential area to look into would be the performance and completion status of students taking the MOOC based on their life experience.

1.2   Research questions

This thesis will discuss the hypothesis and results of the following three research questions related to the relationship between student life background and behavior, and their performance and behavior in the course.

1. Is there a correlation between a student's career/academic background and their performance and/or behavior in an introductory computer science MOOC?

2. Is there a correlation between a student's previous non-academic life experiences and their performance and/or behavior in an introductory computer science MOOC?

3. Is there a correlation between a student's day-to-day behaviors and their performance and/or behavior in an introductory computer science MOOC?

1.3 Course Background

This thesis's research was conducted on students enrolled in an MOOC offered on the edX platform since 2013, *6.00.1x Introduction to Computer Science and Programming using Python.* For this thesis, we are looking at four runs of the course across two years 2021-2022.

The course runs over a period of nine weeks and is divided into fourteen topics, each of which contains multiple lecture videos, notes, and graded finger exercises for students to solve. Students also solve six graded problem sets covering two topics each (with the exception of the last two topics) which are due at the end of each week with no extensions and take two graded exams (a midterm and a final) during the course.

Week	Topic	Graded assignment due
1	Introduction to Python Core Elements of Programs	Problem Set 1
2	Simple Algorithms Functions	Problem Set 2
3	Tuples and Lists Dictionaries	Problem Set 3
4	Material from Week 1-3	Midterm
5	Testing and Debugging Assertions and Exceptions	Problem Set 4
6	Classes and Inheritance An Extended Example	Problem Set 5
7	Computational Complexity Searching and Sorting Algorithms	Problem Set 6
8	Plotting Summary and Wrap-up	
9	Covers Material from all weeks	Final

Table 1.1: A breakdown of the 6.00.1x course

The students are allowed to take the course in two different enrollment tracks:

1. Audit: Students who registered for the course free of charge

2. Verified: Students who paid a fee of $75 to receive a certificate if they pass the course with a total grade of at least 55%.

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Chapter 2

Research methodology

2.1 Data collection

As previously explained in section 1.3, the thesis relies on data collected from the four runs of the course *6.00.1x* from 2021 - 2022. The thesis analyzes the grades data of students in the different graded parts of the course as well as click stream data generated by students' actions on the website, including watching lecture videos, accessing notes, solving finger exercises, and completing problem sets and assessments. For the purposes of this thesis, we focused on students on the verified enrollment track, since the monetary fee provided incentive for completion of the course, providing us with more complete data of students who actually complete the course since MOOCs do have a very high dropout rate. This leaves us to mainly look at the performance and behavior of 240 students over the four runs.

Term	Total number of students	Total number of verified students	Total number of survey takers	Total number of verified survey takers
2T-2021	6342	1922	115	50
1T-2022	6777	2402	89	43
2T-2022	5492	1897	142	62
2T-2022a	3721	1134	228	85
	22332	**7355**	**574**	**240**

Table 2.1: Table showing the number of students during four runs of MITx 6.00.1x between 2021 to 2022

The content of data can be primarily divided into three categories:

1. Life experience and behavior data

2. Student performance data

3. Student behavior data

2.1.1 Life experience and behavior data

In order to gain more insight into student life experiences and day-to-day behavior, we added an optional survey to the online course. Participants have the flexibility to answer only certain sections or parts of the survey based on their preference. Due to the optional nature of the survey, the response rate was low as listed in Table 2.1. The content of the survey questions can be divided into three categories as follows:

Career/academic background

- Do you have financial experience, such as managing personal assets, buying/selling stock, or working for a financial firm?

- Do you have a background or extensive experience in psychology, medicine, or the life sciences (such as biology, botany, zoology, etc)?

- Do you have experience managing people?

- Have you ever written a report or essay for school/work that was more than 20 pages long?

- Have you studied music theory before?

- Have you ever been exposed to the idea of induction in math?

- Do you have a background or extensive experience in English (or another language) or History?

Non-academic experiences

- Have you spent more than 50 hours playing any open-world strategy game like Minecraft or The Sims?

- At any point in your life, did you actively build structures with Legos, play strategic board games (chess, monopoly, etc), or solve puzzles (rubix cubes also count)?

- Are you familiar with how to quickly look up a topic in the index of a physical textbook or to quickly look up a word in a physical dictionary?

- Have you ever tinkered with robotics or done your own engineering project (such as building a bridge out of toothpicks, building a wooden mini catapult, etc.)?

Day-to-day behaviors

- Have you ever followed a recipe to cook a meal, dessert, or dish? Do you routinely try out new recipes?

- If you were unsure how to do a manual task (for example, tie a tie or fix a bike), would you first try the task by yourself and then watch an instructional video, or would you watch a video first and then try the task?

- Do you enjoy regularly doing riddles, brainteasers, or sudokus?

- When you go shopping for a particular item, how likely are you to wander around the store looking for this item vs. immediately asking a store employee where it is?

Student answers to the survey questions above, together with their personal information collected by edX, specifically their year of birth, level of education, and gender, made up the students' life experience and behavior data analyzed in this thesis.

2.1.2 Student performance data

Student performance data relied on the graded portions of the course which are as described in table 2.2.

Type of assignment	Percent of final grade
Finger exercises (available within each lecture video sequence)	10%
Problem sets	40%
Midterm	25%
Final exam	25%

Table 2.2: Grade breakdown for 6.00.1x

However, it is to note that students can submit their answers for an unlimited number of times for finger exercises and are able to view the answers to the finger exercises before a submission. Students are also given an unlimited number of attempts for problem set submissions but the problem set solutions are not readily available on the website. Midterm and final exam submissions are limited to 10 submissions per problem for every student. Therefore, student performance in problem set, midterm and the final exam might be more indicative of a student's actual performance in the class than their performance in finger exercises.

2.1.3 Student behavior data

As for a student's learning behavior in the course, we were able to collect click stream data generated by students' actions on the website, including watching lecture videos, accessing the course forum, solving finger exercises, and submitting problem sets and assessments. The daily learning behaviors explored in the thesis includes:

- The number of all events a student triggered on the course website per day

- The number of times a student submitted an assessment (problem set, midterm, or final) on the course website per day

Other student learning behavior was also analyzed after aggregating a student's behavior over the complete run of the course. The analyzed behaviors for each student include:

- **Course video statistics**: the total number of videos a student watched, the fraction of course videos a student watched

- **Forum statistics**: number of posted forum threads, number of forum comments, number of endorsed threads posted by the student on the forum.

- **Problem answering strategies**: The total number of attempts to answer the problem, total number of problems answered.

2.2 Data preparation

All data described in section 2.1 is available via edX for each run of the course. The following datasets were used for the analysis performed in this thesis: `grade_report`, `survey_answers`, `person_course_day`, `pc_video_watched` and `person_course`. These datasets were available for each run of the course and were aggregated after data cleaning and preparation.

2.2.1 `grade_report`

This data set included information on student's grades in all graded portions of the course: finger exercises, problem set, midterm, and the final exam. Each row in the data set contained of a student's grades, a unique identifier (ID), email, username, and enrollment track information. We initialized a dictionary mapping students' usernames to their emails since there were other data sets which mapped a student's username with their corresponding data. Then, the data set was filtered for verified students only and all grades data was attached to a student's unique identifier prefixed with the term they took the class, stripping the data of the students' email and username to preserve anonymity.

2.2.2 `survey_answers`

This data set included information on a student's survey answers to the optional survey described in section 2.1.1. Each row in the dataset included `username`, `Answer`,

`Question`, and additional record keeping fields. First, all `username` was replaced with the corresponding `student_id`. Then, the data set was processed by aggregating the data such that each row represented a student with the survey questions as the column titles and the student's answers as the corresponding values. While there was an option for "Prefer not to say" as an answer to all the survey questions, there was still missing data for students who opted to only answer part of the survey and this data was simply represented as a nan value.

2.2.3 `person_course_day`

This data set included information on a student's activity in the course for each day in which they accessed the course. This was a very dense dataset reaching up to 195681 rows for the 1T2022 term alone with 36 columns tracking different available activities on the course website. Each row included `username`, `date`, and student activity tracking variables. The variables I explored are as follows:

- *nevents*: The total number of events a student performed

- *nproblem_ check*: The total number of times a student submitted a solution to a problem for grading by the system

- *nproblem_ answered*: The total number of problems a student has had actually graded

- *nproblem_ attempted*: The total number of problems a student has attempted

This data set was analyzed as it is but `username` was replaced by `student_id` instead to preserve anonymity.

2.2.4 `pc_video_watched`

This data set included video watching statistics of students with each row representing a student, including information on the fraction of total course videos watched by the student.

2.2.5 `person_course`

This data set is the aggregated version of `person_course_day` but included additional biographic information of the students. Each row represented a student, including the aggregate of their activities throughout the course and biographic information including but not limited to, level of education (`LoE`), year of birth (`YoB`) and gender, which are the three variables included in the data analysis. Since this data set included sensitive identifiable information such as `username`, `IP`, and the location of students, all these information were stripped to preserve anonymity. The data set was processed such that each row only comprised of `student_id`, `LoE`, `YoB`, and gender after processing. For level of education, I chose to simplify the encoding provided by edX into the four categories (Elementary, High School, Undergraduate studies, Graduate Studies) instead as described in table 2.2.5 below:

Value	Description	Encoding used in thesis
p	Doctorate	Graduate studies
m	Master's or professional degree.	Graduate studies
b	Bachelor's degree.	Undergraduate studies
a	Associate degree.	Undergraduate studies
hs	Secondary/high school.	High school
jhs	Junior secondary/junior high/middle school.	Elementary
el	Elementary/primary school.	Elementary
other	Other Education.	(omitted)
p_se	Doctorate in science or engineering (no longer used).	Graduate studies
p_oth	Doctorate in another field (no longer used).	Graduate studies

Table 2.3: Table showing level of education encoding in edX and this thesis

As for the aggregates included in the table, the thesis analyzes the following aggregates to examine student learning behaviors over the course:

- *ndays_act*: Total number of days student is active in the course

- *nshow_answer*: Total number of times student click on "Show Answer" for finger exercises

- *nforum_posts*: Total number of forum posts made by student

- *nforum_votes*: Total number of forum votes made by student

- *nforum_threads*: Total number of forum threads the student engaged with

- *nforum_comments*: Total number of forum comments made by student

- *nforum_events*: Total number of the student's forum events

2.3 Data Analysis

2.3.1 Correlation analysis

After data collection and preparation, data analysis was performed to investigate whether a student's life experiences and day-to-day behavior are correlated to students' performance and learning behavior during the course. For each of the survey questions described in section 2.1.1, correlation between the answers to each of the questions and the variables corresponding to student grades and behavior was calculated. Most questions (except for two) had three options as an answer: "Yes", "No", and "Prefer not to answer".

The question "If you were unsure how to do a manual task (for example, tie a tie or fix a bike), would you first try the task by yourself and then watch an instructional video, or would you watch a video first and then try the task?" had the answer options:

- "Either one."

- "I first try the task by myself."

- "I first watch an instructional video."

- "Prefer not to answer."

The question "Have you ever followed a recipe to cook a meal, dessert, or dish? Do you routinely try out new recipes?" had the answer options:

- "Yes I've followed a recipe, and yes I routinely try new ones."

- "Yes I've followed a recipe, but no I don't routinely try new ones."

- "No I haven't followed a recipe before."

- "Prefer not to answer."

Since the answers to the survey questions were categorical within the provided options, they were encoded using one-hot encoding with missing answers encoded as a zero for correlation calculations.

For results signaling correlation between factors and outcomes, the significance of the correlation is further examined with the help of a T-test where the null hypothesis is that there is no relationship between the two variables of interest.

2.3.2   Procrastination habit analysis

Another aspect of learning behavior the thesis analyzed was whether or not a student engaged in procrastination as part of their learning habits. To do this, I plotted a student's `nevents` and `nproblem_check` over the course to see whether a student's activity levels would peak on the day of the deadlines. Then, we opted to look at the number of peaks to signal a student's tendency to procrastinate. However, this analysis did not yield significant correlation results with respect to student life experiences since all density histograms resulting from this analysis were similarly left skewed with the means for the distribution being relatively similar between 1 - 1.6 as the examples show in figure 2-2
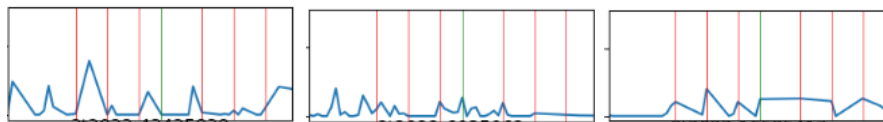
Figure 2-1: Activity peaks for students with the lowest procrastination (peaks before deadlines) to most procrastination (multiple peaks on deadlines) from left to right. The deadlines for assessments can be seen as vertical lines with red lines for problem sets, green for midterm and the right border for the final exam
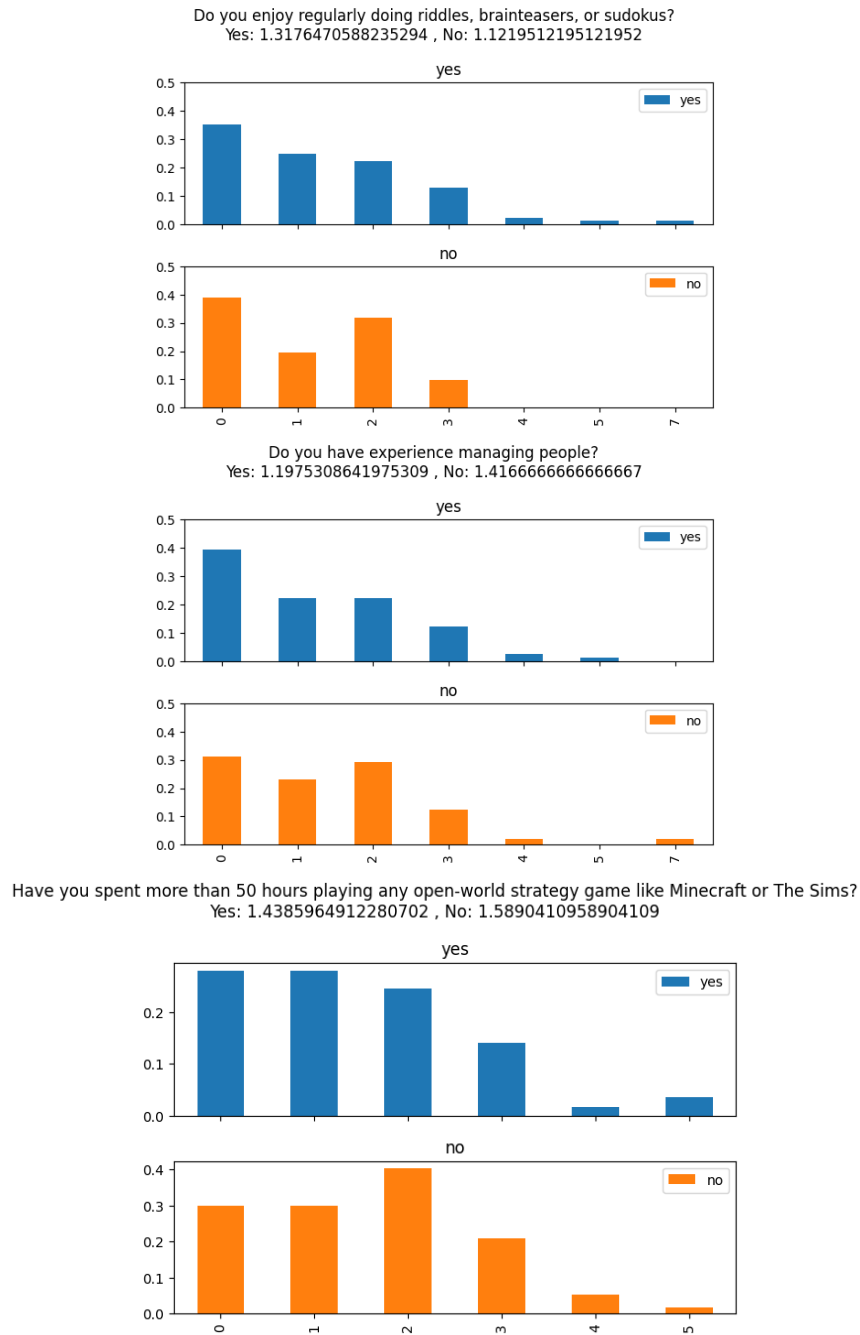
Figure 2-2: Examples of an activity peak count plot on `n_events` for students with/without experience in life sciences with the number of average peaks for each group answering either "Yes" or "No" shown in the title of each plot following the survey question.

Chapter 3

Student career/academic experiences

The survey questions targeted towards understanding a student's career/academic background are as described in section 2.1.1. We explored correlations between a student's answers to these questions and their performance and behavior in the course to answer the first research question listed in section 1.2: "Is there a correlation between a student's career/academic background and their performance and/or behavior in an introductory computer science MOOC?"

3.1 Performance

Using one-hot encoding for the answers to the survey questions, we were able to calculate correlation matrices for relationships between a student's answer to each of the survey question and their performance in the class. There were very little to no correlation between the answers to four of the seven questions and a student's performance in class. We observed some weak correlation around answers for three of the seven questions which were targeted towards students with backgrounds in induction math, management, and music theory.
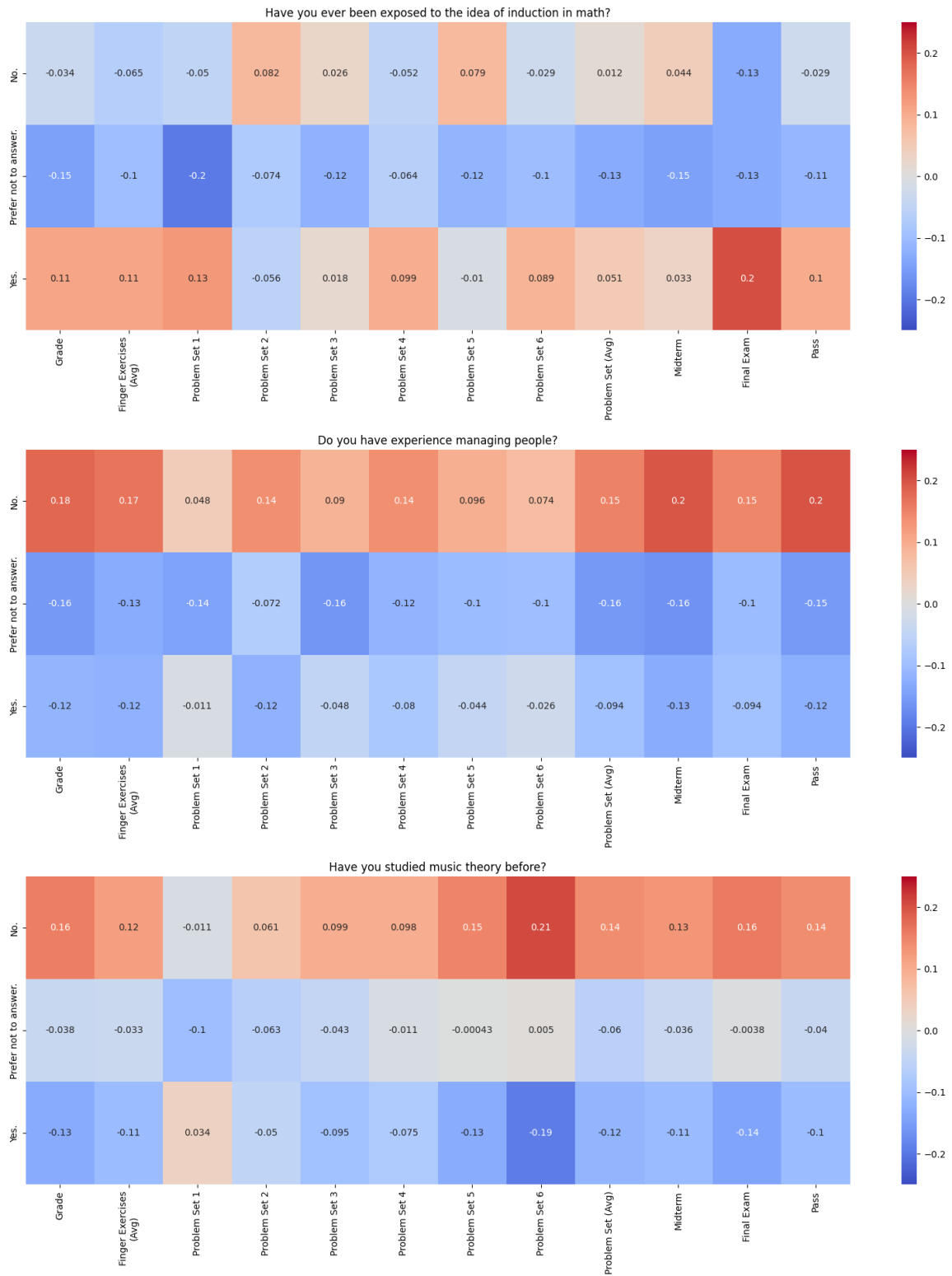
Figure 3-1: Correlation matrices for students with backgrounds in induction math, management, and music theory

3.1.1 Exposure to the idea of induction in math

As seen in figure 3-1, there is a weak positive correlation between student performance and their previous exposure to the idea of induction to math. Upon further investigation, we observe that students who have prior exposure to induction possess a slight advantage in their performance over those who do not. This advantage is observed across all graded components of the course, with the exception of the midterm where both groups of students demonstrate nearly equal performance.
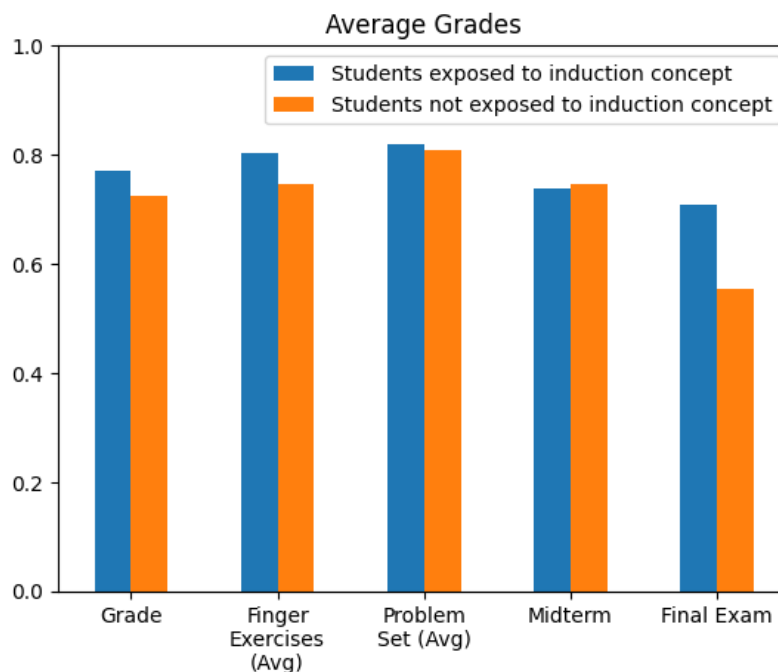
Figure 3-2: Performance of students with/without exposure to induction

However, the correlation between exposure and performance is only significant for the difference in performance in the final exam as evidenced by a p-value of 0.03475427 after performing a T-test. This is an interesting observation since the final exam is arguably the hardest graded assessment of the course. Firstly, it can be contended that both the midterm and final exam hold greater significance in assessing a student's true comprehension of the course compared to problem sets and finger exercises due to the limited number of submissions allowed (10 per problem) for these assessments, compared to the unlimited submissions permitted for finger exercises

and problem sets. Secondly, the final exam encompasses all the material covered throughout the course, making it a comprehensive evaluation that reflects a student's overall understanding of the subject matter taught over the course. Hence, we could potentially say that students with an exposure to induction are likely to end up with a better understanding of the overall course material as evidenced by their better performance in the final exam.

To find potential explanations for the correlation, we took a further look at the students' biographic information. The age and gender distribution of the students with/without correlation did not have significant differences but it was observed that people exposed to induction as a concept were more likely to have completed a higher level of education than those who were not. This could potentially be because while induction as a mathematical concept could be first introduced in secondary or high school education, it is more commonly taught in college level mathematics.
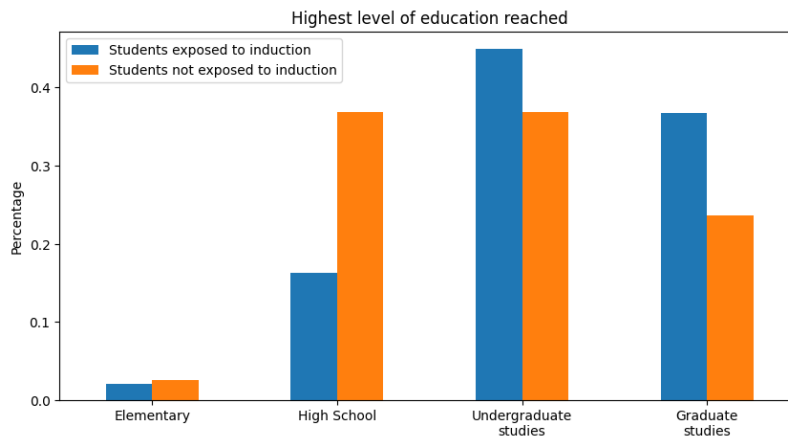
Figure 3-3: Highest level of education completed by students with/without exposure to induction

Hence, potential reasons for the correlation observed between a student's performance in the final exam and their exposure to induction could be attributed to several factors. Firstly, the concept of induction might help students understand certain computer science principles covered in the course, such as recursion. Secondly, students exposed to induction may have an increased familiarity with the course structure and format of *6.00.1x*, which itself is a college-level introductory computer science course,

given their higher likelihood of having completed undergraduate and graduate studies, distinguishing them from those who were not exposed to induction.

3.1.2 Management experience

Another observation made with regards to correlation between a student's career experience and their performance in *6.00.1x* was that students with management experience tend to score lower grades than their counterparts without management experience.
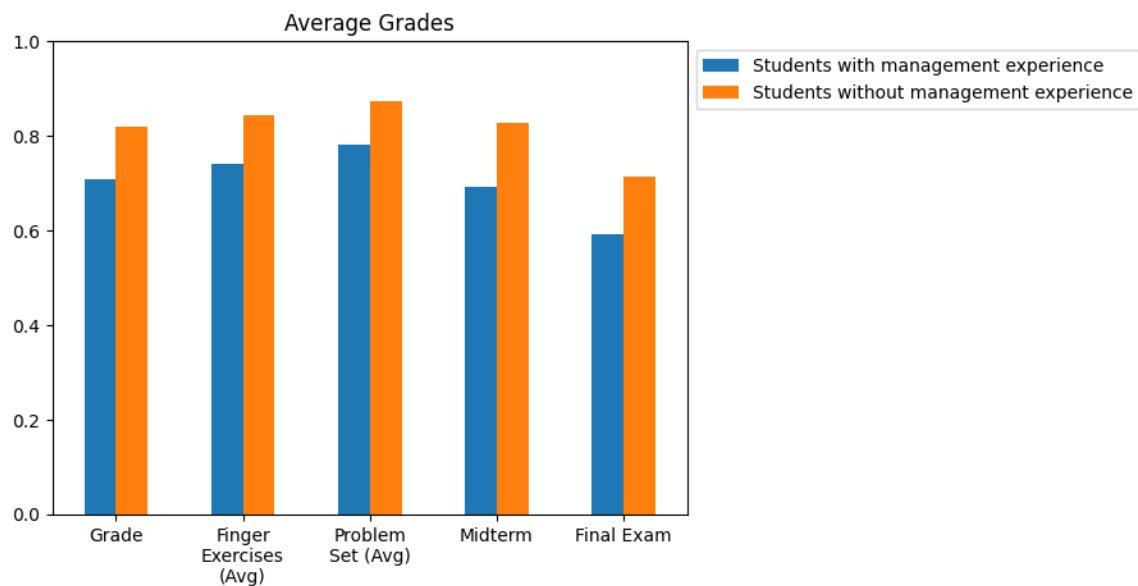
Figure 3-4: Performance of students with/without management experience

The significance of the correlation is again tested using a T-test to obtain the p-values: 0.02772189, 0.03363112, 0.06784234, 0.0178771 , 0.09433969 for the graded portions shown in figure 3-4 from left to right. There is moderate evidence that the correlation is significant for the overall grade, average grade for finger exercises, and the midterm, and weak evidence for the average problem set grade and the final exam.

Again, to find potential explanations for the correlation, we turned to the biographic information of the student. Surprisingly, the students with management experience, although under-performing in our introductory computer science course, were more likely to have completed higher levels of educations than those who do

not have management experience. The average age for people with management experience was also higher with the average year of birth at 1986 compared to those without management experience at 1993.
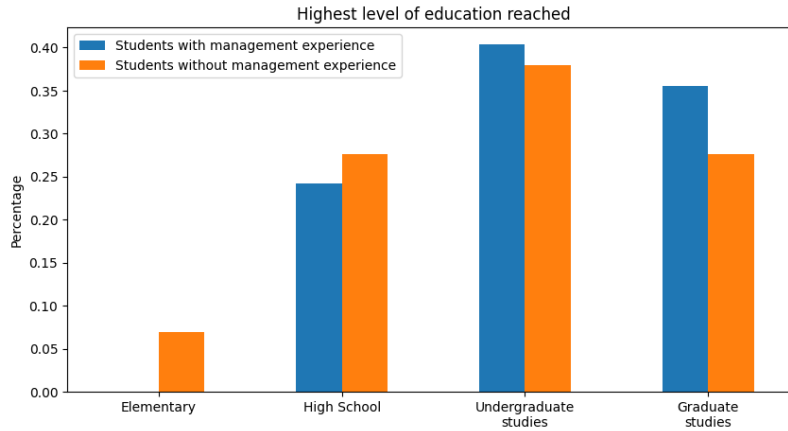
Figure 3-5: Highest level of education completed by students with/without management experience
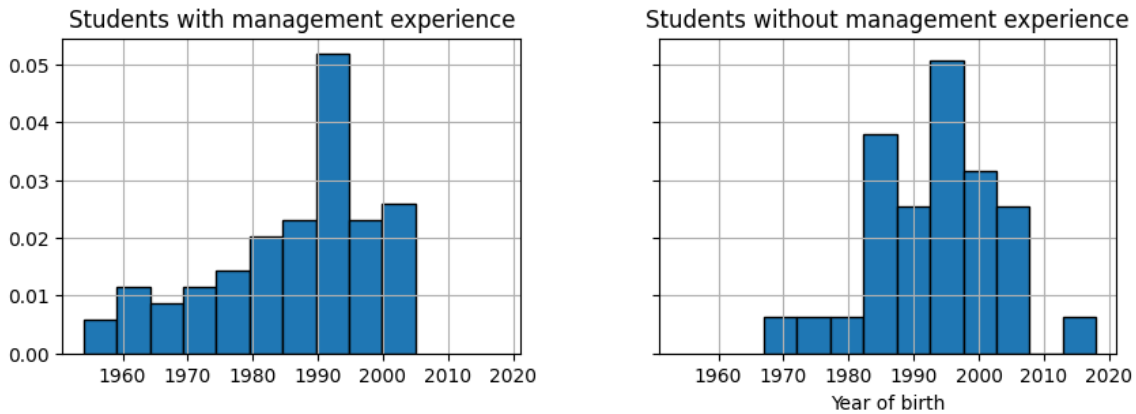
Figure 3-6: Density histogram of the year of birth of students with/without management experience

The exact reason behind the negative correlation between student performance and their management experience remains unclear. However, considering their higher level of education and relatively older age, it is possible that these students may approach the course with less seriousness compared to their counterparts. This could be attributed to the fact that they might not have the same need to acquire the course content for career advancement or to enhance their academic knowledge.

3.1.3   Music theory experience

As seen in figure 3-1, there is a weak negative correlation between student performance and their previous experience in studying music theory. However, this correlation does not seem to be significant given the p-values of 0.08322026, 0.17549506, 0.12220652, 0.16155556, 0.06998799 for overall grade, average finger exercises grade, average problem set grade, midterm grade and final grades. The age, level of education, and gender distribution for the two groups are also similar as well. Hence, while the student performance for these four runs of the course seems to be negatively correlated with their experience studying music theory, little conclusions can be made.

Figure 3-7: Performance of students with/without experience in studying music theory

3.2 Learning behavior

3.2.1 Student overall engagement levels
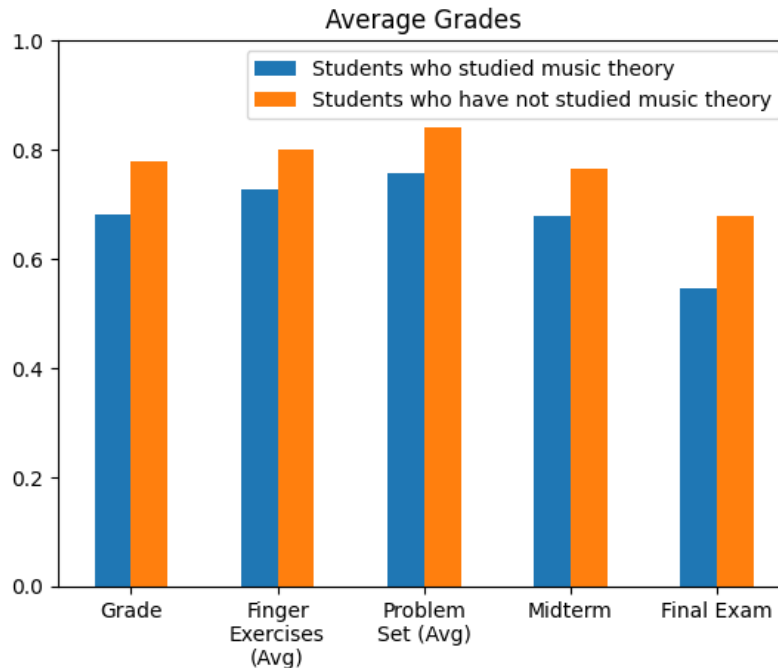
To look at student engagement levels throughout the course, we analyzed the correlations with the number of events a student performed throughout the course, the number of active days throughout the course, and the number of times a student submitted a solution to a problem to be graded by the system. The results are as show in figure 3-8.

The results do confirm our suspicion from the performance analysis that people without management and music theory were more likely to take the course seriously. With a p-value of 0.05304416, it is confirmed that there is a significant positive correlation between lack of management experience and actually submitting solutions to the course system. A student without management experience makes an average of 653 submissions to the system in comparison to 563 of those with management experience. The evidence for the engagement levels of the students with music theory study experience is weaker with p-values of [0.07837126, 0.05051061, 0.06347124] for the three categories we are looking at but we note a significant difference for the averages of these values across two student groups (with / without music study experience): *nevents* - (3130.949153, 3703.741573), *ndays_ act* - (33.101695, 38.292135), and *nproblem_ check* - (540.593220, 624.348315).

The surprise finding in this analysis is that people who do not have an experience of writing a report or essay for schoolwork that was more than 20 pages long were more likely to be more engaged in the class. With p-values of [0.06224447, 0.04770412, 0.0502799] for the three categories, the averages of these values across two student groups (with / without experience in writing long reports): *nevents* - (3304.009615, 3947.636364), *ndays_ act* - (34.730769, 40.295455), and *nproblem_ check* - (567.788462, 661.045455). Perhaps, students more inclined towards STEM in schoolwork and less towards humanities subjects were likely to have lacked this experience and would have more interest in *6.00.1x* although increased engagement levels did not lead to a better performance in the class.
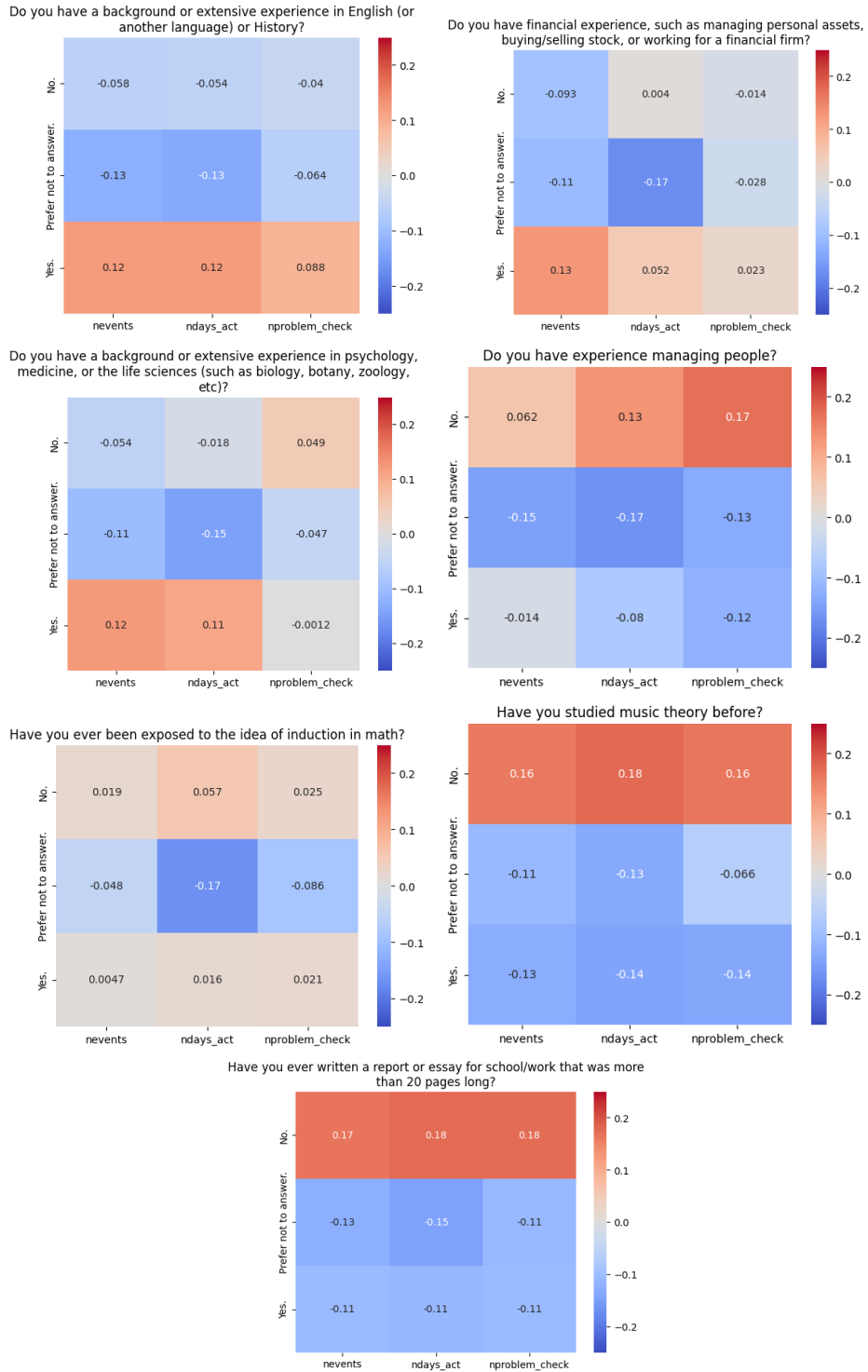
Figure 3-8: Correlations between student academic/career experiences and their engagement levels

3.2.2 Course video watching statistics

We observe a correlation between the fraction of course videos watched and a student's academic/career background in two particular cases: students with/without management experience and students with/without the experience of studying music theory. In both cases, students without the experience were more likely to have watched a larger fraction of the course videos.
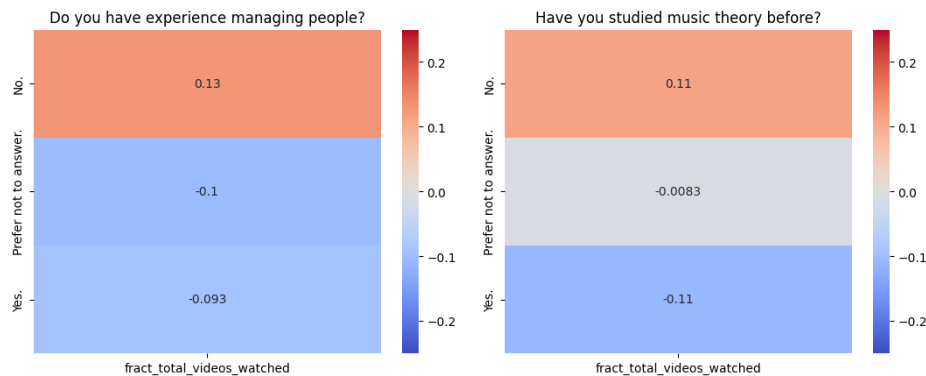
Figure 3-9: Correlation between fraction of course video watched and a student's prior academic/career experience

The average fraction of videos watched by a student without management experience is 78.5% compared to 70.4% of those with management experience, and the average fraction of videos watched by a student without music theory experience is 75.7% compared to 68.4% of those with music theory experience. This finding reinforces the potential conclusion that perhaps the students without management/music theory experience were more likely to approach the course with more seriousness since they might have a need to acquire skills and knowledge taught by the course for career advancement or for academic purposes.

3.2.3 Forum behavior

While no significant correlation was found between a student's forum behaviors and most of their academic/career experiences, we observed a significant positive correlation between the lack of experience of writing a 20+ page report and their likelihood to engage with the course forum.
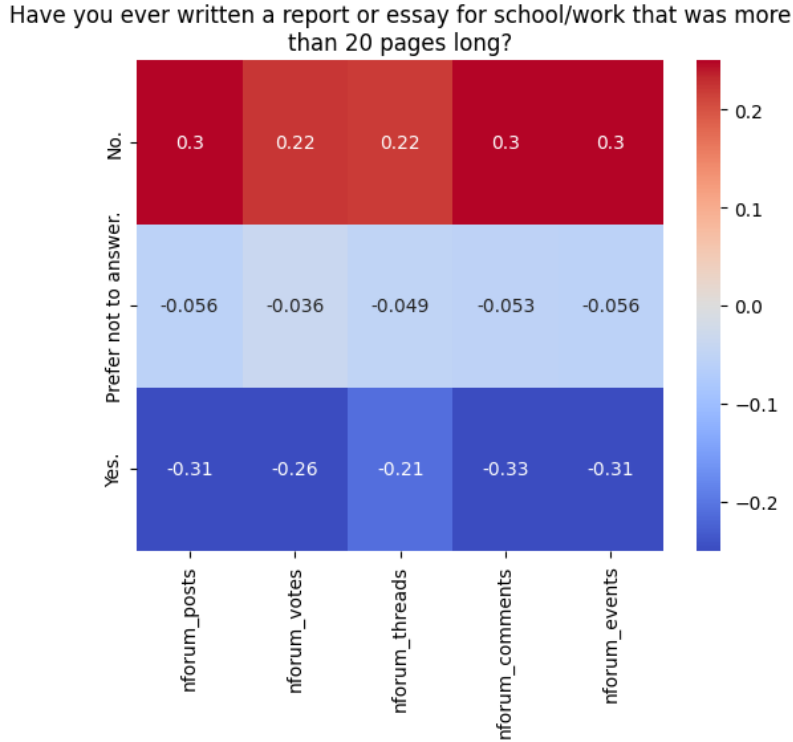
Figure 3-10: Correlation between the lack of experience of writing a 20+ page report and likelihood to engage with the course forum.

While the exact reason behind the correlation is unclear, we observe significant differences in the average numbers which indicate that there is strong evidence for correlation for all categories other than *nforum_threads.*

	With 20+ page report experience	Without 20+ page report experience	p-value
nforum_posts	4.44	10.44	0.00268479
nforum_votes	1.58	5.19	0.02064978
nforum_threads	1.58	2.89	0.07968898
nforum_comments	2.86	7.56	0.00137325
nforum_events	4.44	10.44	0.00268479

Table 3.1: Table showing p-values and difference in average values for forum engagement levels for students with/without the experience of writing a 20+ page long report

3.2.4 Procrastination behavior

There was no noted correlation between a student's academic/career experiences and their procrastination behaviors.

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Chapter 4

Student's non-academic life experiences

To explore a student's non-academic life experiences, the survey questions looked into their experiences around playing open-world strategy games, strategic board games, and puzzles, tinkering with robotics, working on their own engineering projects, and their familiarity with looking up topics in textbooks and words in physical dictionaries as described in section 2.1.1.

4.1 Performance

Again, by utilizing one-hot encoding to represent the survey question responses, correlation matrices were computed to examine the correlation between a student's answers to each question and their performance in the class. Among the four questions assessed, there was minimal to no correlation observed between a student's performance in `6.00.1x` and their experience in constructing structures with Legos, playing strategic board games, or solving puzzles. However, the correlation results for the remaining three questions indicated a potential connection between student performance in the class and the corresponding non-academic life experience.

At any point in your life, did you actively build structures with Legos, play strategic board games (chess, monopoly, etc), or solve puzzles (rubix cubes also count)?

Are you familiar with how to quickly look up a topic in the index of a physical textbook or to quickly look up a word in a physical dictionary?

Have you spent more than 50 hours playing any open-world strategy game like Minecraft or The Sims?

Have you ever tinkered with robotics or done your own engineering project (such as building a bridge out of toothpicks, building a wooden mini catapult, etc.)?
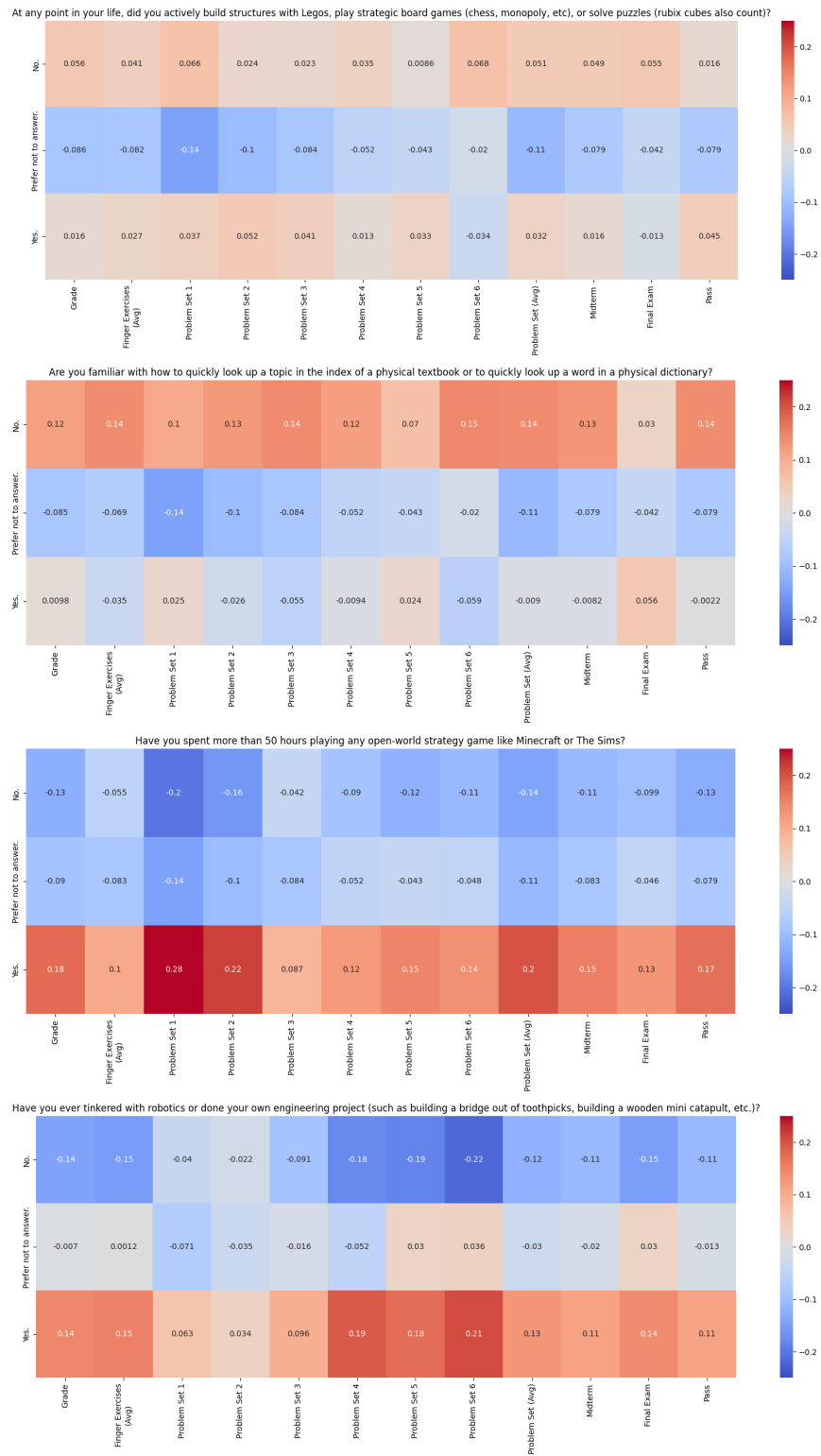
Figure 4-1: Correlation matrices for student performance and their non-academic life experiences

4.1.1 Ability in quickly looking up topics/words

Interestingly, we observe that students who answered "No" to the question "Are you familiar with how to quickly look up a topic in the index of a physical textbook or to quickly look up a word in a physical dictionary?" performed significantly better than those who answered "Yes". In fact, the p-values signalling this difference in performance were all significant with values less than 0.05 except for the final exam: [2.04889678e-02, 9.28162746e-03, 1.16277675e-06, 1.85562454e-03, 7.88821504e-01].

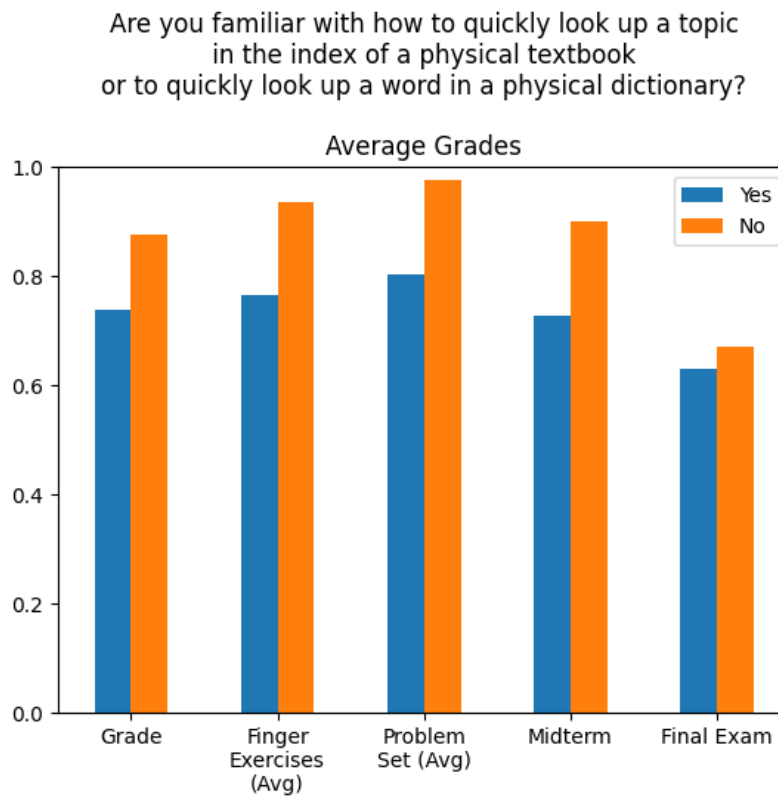Figure 4-2: Performance of students familiar/unfamiliar with word/topic lookup

However, upon further investigation, it was noted that out of 152 verified students who answered this question, 138 answered "Yes", only 10 answered "No", and 4 answered "Prefer not to answer". Therefore, the data available for this question seems to be inadequate for conclusive results although the p-values might suggest otherwise.

4.1.2 Experience in open-world strategy game

There seem to be a strong positive correlation between student performance in *6.00.1x* and experience of playing more than 50 hours in an open-world strategy game such as Minecraft and the Sims. Based on a simple T-test, the positive correlations observed between this experience and a student's overall grade, as well as between this experience and their average problem set grade, are statistically significant.

Have you spent more than 50 hours playing any open-world strategy game like Minecraft or The Sims?
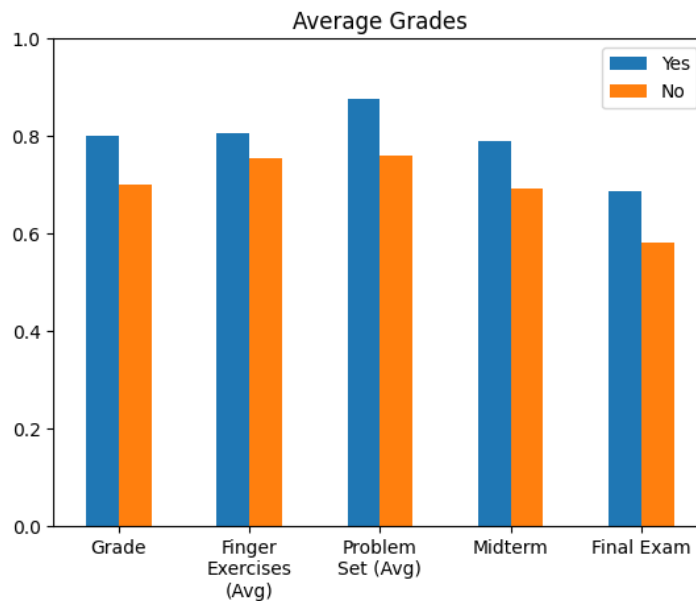

Figure 4-3: Performance of students with/without the experience of playing more than 50 hours in an open-world strategy game. The p-values for the correlation for the categories from left to right is [0.04453636, 0.29343158, 0.01954365, 0.08496997, 0.14493823]

Here, it is important to note that the problem set component of the course is solely dedicated to evaluating a student's coding proficiency and only contains coding questions whereas finger exercises, midterms, and final exams incorporate multiple-choice questions to assess a student's conceptual understanding. The finding that students with the experience of playing 50+ hours in an open-world strategy game such as Minecraft and the Sims do better in terms of their average problem set grades indicate their enhanced performance in coding portions of the class.

After a quick analysis on the biographic information of these students, it is discov-

ered that the distributions in terms of age, level of education, and gender were similar for both groups of students with and without open-world strategy gaming experience. Therefore, the significant distinguishing factor for these two groups' difference in performance in the coding portions of the class could potentially be attributed to their prior experience with open-world strategy games or the lack thereof. Furthermore, existing research has explored the connection between critical thinking and gamers, and it has been found that individuals who engage in strategy games are more likely to have an actively open-minded thinking approach compared to gamers who prefer other genres. [4] Hence, it is possible that transferable skills such as problem solving skills, open-minded critical thinking and adaptability acquired through playing open-world strategy games could have effectively translated into the context of learning introductory computer science coding skills.

4.1.3 Experience in robotics/engineering projects

Unsurprisingly, it was noted that experience in robotics/engineering projects has positive correlation with a student's performance in an introductory computer science MOOC.
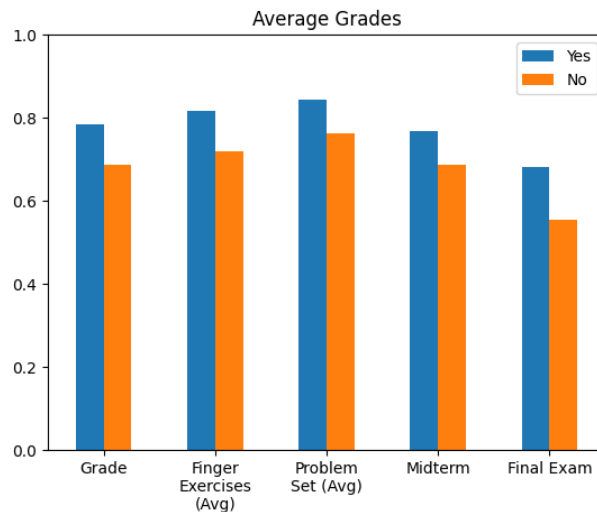

Figure 4-4: Performance of students with/without experience in robotics/engineering

The p-values of [0.07156058, 0.05489916, 0.1196263 , 0.1659525 , 0.0741308] tell us that there is weak evidence that there is a positive correlation between a student's experience in robotics/engineering and their overall course performance, average finger exercise grade, and their final exam grade.

The biographic information analysis yielded no significant difference between the distributions in age, level of education, and gender. Hence, it is possible that transferable skills such as problem solving skills from having tinkered with robotics or having done one's own engineering project could have effectively translated into the context of learning introductory computer science.Moreover, while the survey question did not make a distinction between experience in robotics and more hands-on engineering projects, it is possible that students coming in with prior robotics experience might have had prior coding experience or at least some knowledge around certain computer science concepts, giving them an advantage over those who do not.

4.2   Learning behavior

4.2.1   Student overall engagement levels

While we observed high engagement levels for high performing groups in section 3.2.1, we do not note significantly high engagement levels for groups we have identified to perform better in the class based on their non-academic life experiences. However, we note a high engagement level in terms of *nevents* and *nproblem_check* for students who answered "No" to the question "Are you familiar with how to quickly look up a topic in the index of a physical textbook or to quickly look up a word in a physical dictionary?". However, as we mentioned in section 4.1.1, it is hard to draw conclusions regarding these two groups given the ratio of respondents between the two groups.

4.2.2   Course video watching statistics

We observe a positive correlation between the fraction of course video watched and a students non-academic experiences in three cases: students with experience in open-

world strategy games, those with experience in robotics/engineering projects, and those with experiences in strategy board games/puzzles/building block games.
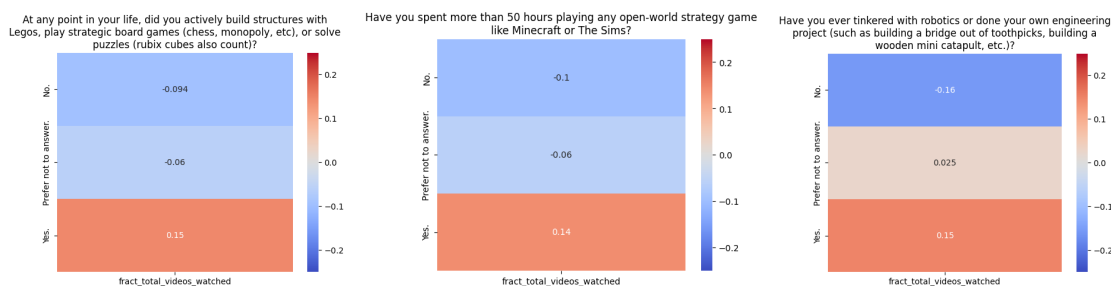

Figure 4-5: Correlation between fraction of videos watched and a student's non-academic life experience

This signals that students with these non-academic life experiences are more likely to have an interest in course content than those without these experiences. These groups are also more likely to be self-selecting, leading to such an outcome. After T-test analysis, there is strong evidence that the correlation between the experience of robotics/engineering and likelihood of watching a higher fraction of course videos is significant, but we couldn't say the same for the other two experiences. Nevertheless, we do observe a higher fraction of course videos watched for those with said experiences.

	With experience	Without experience	p-value
Open-world strategy game experience	77.7%	69.8%	0.11809839
Robotics/engineering experience	77.4%	67.4%	0.05360285
Strategic board games/puzzles/Legos experience	74.6%	64.9%	0.27549065

Table 4.1: Fraction of total videos watched by students with/without the corresponding non-academic life experience and the p-values signaling significance of the correlation

4.2.3 Other behavior

There was no noted correlation between a student's non-academic experiences and their forum or procrastination behaviors.

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Chapter 5

Student's day-to-day behaviors

5.1 Performance

Among the four day-to-day behaviors touched on by the survey questions, a positive correlation was observed between the performance of students and their regular habit of doing riddles, brainteasers, or sudoku.
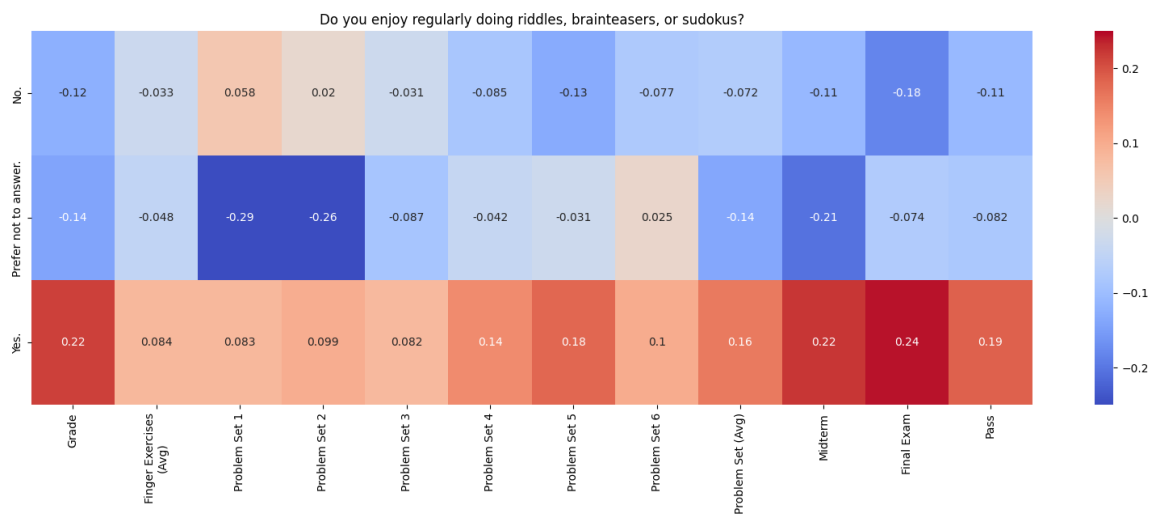

Figure 5-1: Correlation between performance of students and their regular habit of doing riddles, brainteasers, or sudoku.

From the analysis, it is noted that there is strong evidence suggesting a significant positive correlation between a student's habit of doing riddles, brainteasers or sudoku and their performance in *6.00.1x*, particularly for their overall grades and their

performance in the final exam. There is no notable differences in the distribution of demographics (age, level of education, gender) of the two groups.

Again, for reasons explained in section 3.1.1, the final exam is arguably the hardest graded assessment of the course encompassing all topics covered in the course, and it can be argued that students with a habit of doing riddles, brainteasers or sudoku are having a better understanding of the overall course content compared to their counterparts without the habit. This could be due to honed problem solving skills one acquires through regularly doing riddles, brainteasers or sudoku, which could be transferable to the context of studying an introductory computer science course which involves a good amount of problem solving.
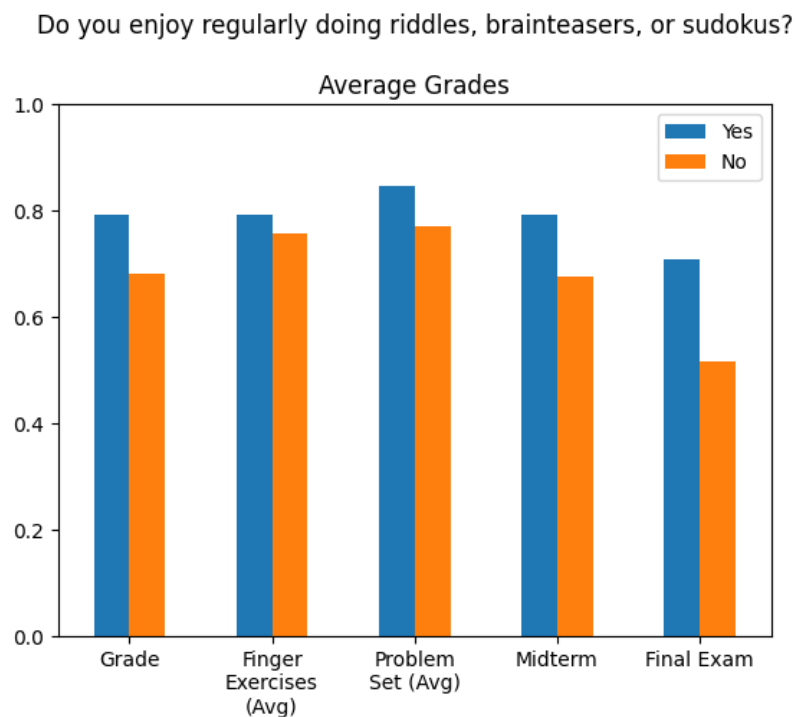

Figure 5-2: Performance of students with/without a regular habit of doing riddles, brainteasers, or sudoku with p-values being [0.0497357 , 0.50750985, 0.18477574, 0.05743962, 0.0123122] for grade categories from left to right.

5.2   Learning behavior

5.2.1   Course video watching statistics

It is observed that students who regularly doing riddles, brainteasers or sudokus were likely to have watched a higher fraction (76.0%) of total videos than their counterparts (0.697988). However, the p-value for this correlation is at 0.26012264, signalling no evidence for the significance of the correlation.

It is also observed that students who have followed a recipe and routinely try new ones tend to watch a larger fraction of instructional videos in the course (77.1% compared to 68.8%). The p-value for this correlation is at 0.10676435, signaling very weak evidence for the significance of the correlation.

Surprisingly, it was also observed that students who usually watch an instructional video before a manual task did not continue this behavior in the context of a computer science course.
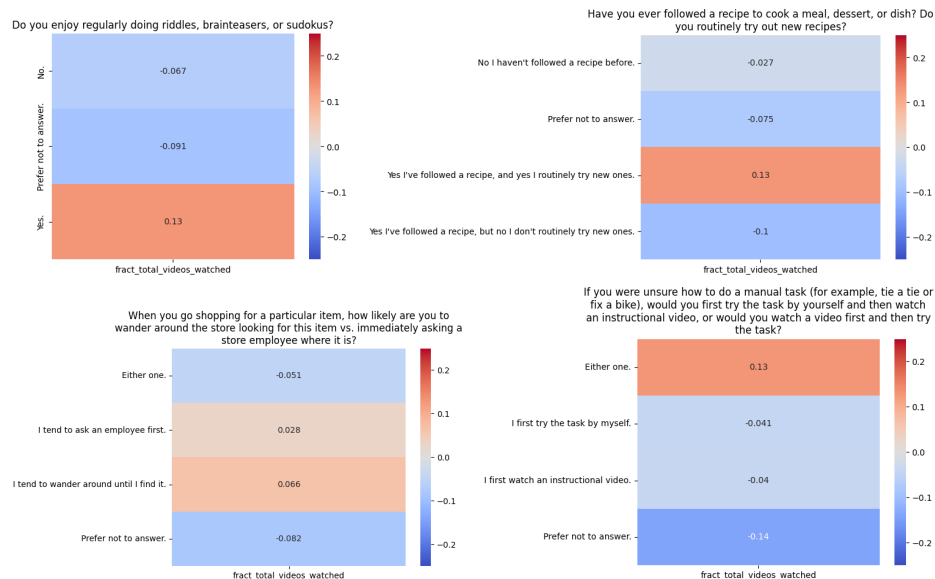

Figure 5-3: Correlation between student day-to-day behaviors and fraction of course videos watched by the student

5.2.2 Other behaviors

There was no noted correlation between a student's day-to-day behaviors and their overall engagement levels in the course, and their forum and procrastination behaviors.

Chapter 6

Conclusion

6.1 Summary of findings

Through a detailed analysis carried out in this thesis research, it is discovered that some of the life experiences of a student can be correlated to their performance and learning behaviors during the class.

Amongst a student's career/academic experiences, it was discovered that exposure to the idea of induction in math was positively correlated to a student's performance in the final exam whereas a student's experience in management is negatively correlated to a student's performance in all graded portions of the class except for the problem sets. Regarding the relationship between learning behavior and career/academic experiences, it was observed that students without management experience were more likely to have performed more solution submissions for the course and have watched a higher fraction of the course videos, indicating a higher level of interest in the class. Also, students who do not have an experience of writing a report or essay for schoolwork that was more than 20 pages long (suspected to be students more inclined towards STEM and not humanities in school work) were more likely to be engaged in the course with higher numbers of active days in the course and higher engagement numbers in the course forum with more posts, votes, and comments by these students. However, the higher levels of engagement did not correlate to a better performance in the course itself.

When it came to a student's non-academic life experiences, the study found that students who have previously spent more than 50 hours in an open-world strategy game were more likely to perform better in terms of overall grade and average problem set grades. As the problem set component of the course is solely dedicated to coding problems, it can be concluded that students with this experience tend to perform better in coding portions of the class.

The thesis also investigated on potential correlation between some of the day-to-day behaviors and a student's performance/behavior in the course. The results showed that there was significant positive correlation between a student's habit of doing riddles, brainteasers or sudoku regularly and their overall grades and their performance in the final exam. However, there were no noted significant correlations between a student's day-to-day behaviors and their learning behaviors in the course.

6.2   Future work

While this thesis explored on several of a student's life experiences, the survey questions were not of the best design to really encapsulate the full clear extent of a student's life experiences especially when it comes to a student's day-to-day behaviors. There is a potential to analyze similar performance and learning behaviors with better designed, less general survey questions targeting more specific life experiences and day-to-day behaviors.

After identifying correlations between life experiences and a student's performance and learning behavior in this scope of this thesis, a potential next step would involve building a predictive model based on these findings. This predictive model can be designed to forecast student performance, engagement level, and course behavior to provide valuable insights for personalized guidance, instructional design improvements, and targeted support to enhance student performance in the course. We could even extend the model such that after a student opts to take a survey, the course present them a guide to topics they might struggle with by using the predicted performance in different graded portions of the class.

Chapter 7

Resources

The survey questions targeting student life experiences were designed by Bill Wu, a former TA for MIT 6.100 course. The thesis data analysis was done in Python with the help of the following python packages: pandas, matplotlib, seaborn, numpy, and scipy. The thesis composition was written on Overleaf with proofreading help from ChatGPT. All of the data was stored online on an MIT dropbox instance and processed and analyzed locally to preserve anonymity in handling sensitive personal information of students.

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Bibliography

[1] Bajwa, Ayesha & Bell, Ana & Hemberg, Erik & O'Reilly, Una-May. (2019). Analyzing Student Code Trajectories in an Introductory Programming MOOC. 53-58. 10.1109/LWMOOCS47620.2019.8939666.

[2] Roy, Anindya & Yee, Michael & Perdue, Meghan & Stein, Julius & Bell, Ana & Carter, Ronisha & Miyagawa, Shigeru. (2022). How COVID-19 Affected Computer Science MOOC Learner Behavior and Achievements: A Demographic Study. 345-349. 10.1145/3491140.3528328.

[3] Maiyuran, Jitesh & Bajwa, Ayesha & Bell, Ana & Hemberg, Erik & O'Reilly, Una-May. (2019). How Student Background and Topic Impact the Doer Effect in Computational Thinking MOOCs. 47-52. 10.1109/LWMOOCS47620.2019.8939643.

[4] Gerber, S. and Scott, L. (2011), Gamers and gaming context: Relationships to critical thinking. British Journal of Educational Technology, 42: 842-849. https://doi.org/10.1111/j.1467-8535.2010.01106.x