Clustering Based Approach to Cheating Detection

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Preface

Russel Sy is a Computer Science major at New York University of Shanghai, where he is in the process of completing his bachelor's degree. He has taken courses in data structures, algorithms, web design, and object orientated programming. Russel has always been interested in web design and has completed several course projects focused on creating visually appealing and user-friendly websites. Russel is proficient in Java and Python and has experience with C and C++, and SQL databases. He is known for his strong problem-solving and analytical skills.

Sagar Risal is also a Computer Science major at New York University of Shanghai, and is studying for a bachelor's degree in Computer Science as well as a minor in Business. His coursework includes computer networking, object orientated programming, data structures, as well as many other business courses, some even that intersect with Computer Science, such as information technology in business and society. He has interned at an Indian based airline called Akasa air, assisting with the data processing of different financial statements for competitive analysis. He is proficient in Python, C, C++ and has experience with SQL and Javascript. Sagar is known for his strong communication and teamwork skills.

This idea for this project was introduced to us by our advisors: Promethee Nicolas Evangele Spathis and Ratan Dey. We deemed this project particularly interesting and pertinent to our own experience as students who have had to attend university through both an in-person and online approach. We also saw how it related a lot to today's teaching climate, and thought it would be interesting to see what valuable information we could extract from the project to give teaching administration a better idea of how students currently work on these online assessments, and how they could more accurately classify cheaters.

As professors start to rely more and more on online assessments, whether it be due to convenience or physical proximity, the importance of understanding how students interact with the work allows the professor to assign work that is better suited to the needs and abilities of their students. By tracking student engagement and performance on online assignments, professors can identify areas where their students may be struggling and provide targeted support and resources to help them succeed. It is also increasingly important to understand how students collaborate with each other, in order to help professors identify which students may be cheating on an assignment and which students have formed groups to take the assignment together. We feel that this distinction is greatly important in determining whether a student is cheating or not, since accusing someone of cheating is a very serious accusation and should not be done without great care. We understand that when teaching a course remotely it can be difficult to get a good idea of how the students work together as well as interact with the material assigned, which is why we want to show the importance of a better understanding of students in a virtual setting. We feel that this knowledge will be crucial as we continue to evolve and adapt our approach to education in the future.

Acknowledgements

We would like to thank Professor Spathis and Professor Dey for their patience and support during the course of this project. Their guidance and expertise were invaluable in helping us to overcome the challenges we faced, and we are grateful for the time and effort they devoted to working with us. Their encouragement and mentorship were instrumental in helping us to achieve our goals, and we are deeply appreciative of their contributions.

Abstract

The rise of online assessments during the pandemic has made it difficult for professors to ensure the educational integrity of their assessments, as it can be hard to suspect students of cheating when they are not being supervised in person. To address this problem, a non-invasive method was developed to classify cheaters based on data from a dataset that tracks certain metrics in an assignment. Initially, it was thought that students who took a surprisingly short amount of time to complete an assignment and got very high scores were likely cheaters. However, this classification did not take into account students who worked in groups, so the focus shifted to classifying these students and measuring their performance compared to the rest of the class in order to better identify cheaters.

Keywords

Here your keywords: eg. **Cheating; Cheating Detection; Group Collaboration; Online Assessments; Algorithm**

Contents

1 Introduction

Since the beginning of the COVID-19 pandemic, policy makers around the world have implemented the closure either nationwide or localized of schools, colleges, and universities. Following these closures, instructors and students have been faced with the challenges of shifting back and forth between face-to-face teaching and online delivery mode, most often within a few days notice and with no foreseeable limit as to time. Due to universities' short notice closures, instructors and students had little time to adopt and make efficient use of online learning tools and platforms. Assessment and examination were required to be conducted online despite the concerns arising from online cheating. These concerns gave way to the use of cheat detection tools such as online proctoring techniques involving biometric features to verify students' identity or to detect abnormal behaviors during online exams.

Despite the promises of such techniques in terms of accuracy and reliability resulting of combining human trained proctors and artificial intelligence components, their use has been limited due to the hardware requirements of these techniques and the legal concerns they raise. Other tools such as plagiarism detection software and question bank generators have also been considered despite their known limitations regarding the time required for manual interpretation and the simplicity of generated questions, respectively. In this project, the objective is to investigate if the non-invasive analysis of the reports provided by popular learning management systems can help instructors detect cheating or other student studying behaviors.

The overall aim of the present project is to answer the following two questions:

1. When and how do students engage with course materials?

2. How should instructors revise online assessment and evaluation practices?

To answer these questions, we will analyze the log reports collected on a learning management system called Moodle for 11 online quizzes given during the Fall terms of 2020 and 2021 to a cohort of 250 undergraduate students.

The Quiz reports include the following information for each student who took the assignments:

1. The student information (first and last names, student id number, and email address).
2. The state of the attempts (in progress, overdue, finished, or abandoned).
3. The dates the quiz was started and completed.
4. The time taken to complete the attempt.
5. The grade and the details of the points per question.

Using these metrics, we plan on being able to accurately predict whether or not a student has cheated, without the need of privacy invasive methods which can sometimes deter students from performing their best for an exam.

In a study done by Woldeab and Brothen [2019], they found that the students who stated they have anxiety towards test taking, performed significantly worse in the proctored exams compared to the students taking the in person exam. They go on to explain that the difference in exam scores between the students with test anxiety taking the in person exam versus the students with anxiety taking the proctored exam is significant enough that they suggest universities should take extra consideration when selecting their method of maintaining academic integrity during test taking, since certain students can be greatly disadvantaged.

Although a web proctored exam already seems invasive, there are other methods, such as following eyesight, that are even more invasive and could potentially cause more harm to a student's performance. For that reason we want to investigate the non-invasive analysis method of cheating detection that can help instructors detect cheating or other student studying behaviors, without having to negatively affect the performance of students.

2 Related Work

In the realm of cheating detection, we are faced with two different scenarios: prevention and detection during an exam, and detection post-exam. Within the scope of these two scenarios, different cheating detection methods have been developed and/or implemented with varying degrees of efficacy and invasiveness.

During the Exam

The two main avenues institutions can take to prevent and detect cheating can be split into authentication— verifying that the correct person is taking the exam— and proctoring— watching and analyzing examinees throughout the exam to detect suspicious behavior.

Perhaps the most obvious way to verify the identity of an examinee is to use face recognition technology. Arnautovski [2021] proposes an implementation of authenticating an examinee in which a photo of the student and the students personal information are logged into a database and a face recognition technology based "Continuous Authentication Service" validates the identity of an examinee throughout the online exam through the student's webcam. An obvious limitation of this would be the limits of computer vision when conditions are not ideal. This could be issues with the student's lighting, webcam quality, different face angles, data processing and storage, etc. Sabbah [2019] attempts to solve these limitations by including other biometric features in authentication. If an anomaly is detected through webcam face recognition, the examinee will be prompted to scan their finger to verify that the correct student is still taking the exam. This, however, would require specific software to be downloaded and additional hardware apart from a student's pre-existing computer. Both of these methods require students to have sensitive identifying information, such as a photo, fingerprint, first and last names, uploaded to a database. In the event of a data breach, having such sensitive information stolen is, of course, not ideal. So perhaps solely relying on student authentication is not the correct route in cheating prevention and detection.

As is done in in-person examinations, academic institutions have tried proctoring online examinations with human proctors, whether that be the school's faculty or outsourcing proctors from online exam proctoring services. Hylton et al. [2015] conducted an experiment to determine the effectiveness of online proctoring by comparing the performance of a treatment group (monitored by a web-based proctor) and a control group (not monitored). This study found no statistically significant difference in the student's scores. The limits of human proctoring have been apparent even before online learning, as humans can only pay attention to one student at a time.

Automated proctoring has since been developed in order to monitor students one-by-one throughout the examination. Nishchal et al. [2020] attempts to solve this problem by using video surveillance to extract body language indicators from students, as well as processing their facial expressions through a sentiment analyzer to detect whether a student has the intention of cheating. Through examining the student's body language, the researchers were able to detect cheating with 97% accuracy. However, the sentiment analysis method only resulted in 63% accuracy. Although the body language analysis resulted in accurately determining whether a student has cheated, this method faces the same computer vision problems that face recognition has. As a result, approaches have been made to prevent cheating from the start, rather than detecting it. As accessing outside resources has been a problem for online examinations, Chua et al. [2019] suggests implementing a tab locking system to prevent browsing and window navigation functions— however, students circumvent this limitation by referring to secondary devices or other materials. With cheating detection and prevention during online examinations being unreliable, post-exam cheating detection approaches have also been made.

After the Exam

In our review, we were able to categorize post-exam cheating detection methods through either a student's online behavior during the exam, or by employing statistical analyses on a student's other academic information.

Komosny and Rehman [2022] proposed a method of detecting cheaters in unproctored examinations by keeping track of a student's online footprint through their IP addresses, and comparing it with their registered IP address when they submit an exam. A cheating-risk score was then calculated based on their IP address change history. This method of constant IP tracking is an invasion of privacy for the student. Although this method is effective in detecting cheating, it would be hard to convince students to willingly surrender their online movements. Rather than analyzing a student's IP address, Kasliwal [2015] and Migut et al. [2018] try to examine a student's browser behavior during the exam to determine whether a student has cheated, post-exam. Kasliwal [2015] proposed a method to keep track of all student's network activity in order to find links frequently accessed by all students, and so called "secret" links that were accessed infrequently by a few students. In both cases, students who visit either link are deemed cheaters. Although this method allows for accurate cheating detection, as well as possible collusion among students, this method requires additional software on the student's end that could be limited by available hardware. Migut et al. [2018] instead provides a combination of automated during exam proctoring that is then reviewed by humans post-exam. Throughout the exam, the automated proctoring service will take random screenshots of the student's screen, and these screenshots are then reviewed by humans after the exam takes place to check whether any suspicious behavior can be seen in the screenshots. Although this method yields promising results, it still relies on human workload and still invades a student's privacy by recording their screen contents.

An extensive amount of literature exists on cheating detection based on statistical analysis of exam statistics and other previous exam information of a student— a shift away from invasively monitoring the students behavior during an exam.

Kokoç et al. [2021] developed a method to analyze a student's performance throughout the semester in order to predict the student's performance at the end of the semester. Kokoç examined students' behavioral patterns of online assignment submission, as well as how these patterns changed throughout the semester using machine learning methods, such as clustering, Markov Chains, and association rule mining analysis. It was found that this method could accurately predict a student's end of semester performance— however, this method was tested on a small sample size. This method could be used to detect anomalies, such as assignments or exams that far exceed the performance predicted by this method. Kamalov et al. [2021] also uses prior assignment and exam information to predict a student's performance and detect outliers based on a student's continuous assessment results. This method also takes into consideration the sequential nature of assessments throughout the semester through the use of recurrent neural networks and anomaly detection algorithms. The proposed method yields highly accurate results. Although the results of both of these studies are promising, they only rely on a single index pertaining to a student's academic performance (assignment submission or assignment scores).

Li et al. [2019] proposes a method of using multiple indices to detect cheating based on a neural network. Some of the indices used by this method include the student's cognitive diagnosis (produced through linear regression and EM algorithm), seat distribution in an examination room, the student's habit of guessing answers, and the similarity to answers of other student's exams. The accuracy of this method surpassed that of cheating detection methods based on only one indice. Although this method is based on in person learning and relies on questionable metrics, such as a student's cognitive diagnosis, it still demonstrates the potential for multi-index cheating detection. As such, it is clear that catching cheaters based on multiple indices is the way to go.

3 Solution

In order to easily look through and find relationships within the data, we had to process the data given to us regarding each student for each homework, and the related information for that student's submission. We decided to store this information as a JSON object that we outputted and used to retrieve the processed data. The schema is shown in figure 1 is shown below.

```
{Student ID: {
    Homeworks: {
        HW01: {
            Time Taken: minutes,
            Start Time: Date Object,
            Grade Breakdown: array of points per question,
            Total: total score
        },
        HW02: {...},
        ...
    }
}}
```

Figure 1: Schema for JSON object storing student information

Once we processed our data into a more accessible data structure, we decided to plot the data into a Gantt chart showing the time started and time ended for a homework for each student. This allowed us to visually identify grouped clusters of students, as well as students who seem to have cheated.

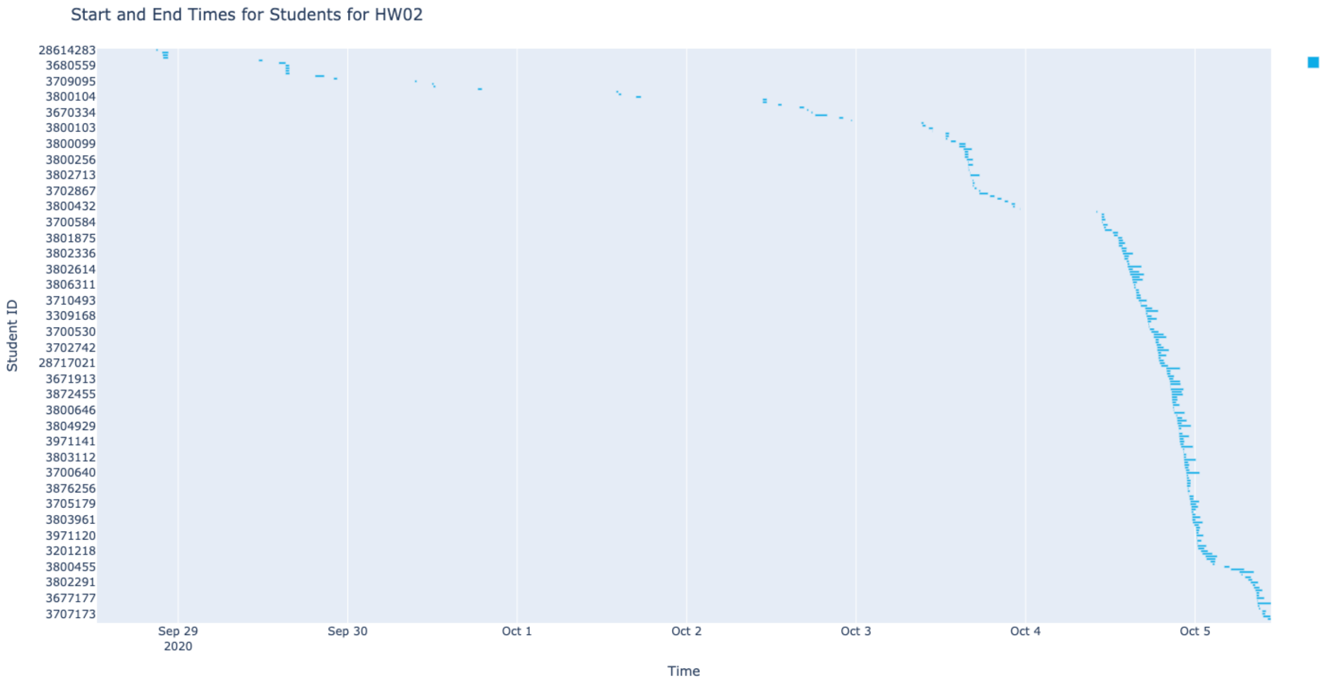

Figure 2: Student submissions throughout the week

Because we used Plotly express in Python to create this chart, we were able to check the grade breakdowns and totals for each bar. We manually classified groups of students by identifying clusters of students with similar grade breakdowns. We also identified cheaters as bars in the graph that were simultaneously much shorter than the rest and had totals that were much higher than other students'. Our goal was to automate the classification of groups and cheaters based on criteria we found from examining the Gantt chart.

Our first priority was to create the distinction between students we classify as being in a group, and students we classify as cheaters. We decided that in order to avoid incorrectly labelling students who worked in a group as a cheater, we would work on classifying the groups first. To do so, we first went through the data we stored in the data structure shown above and found groups per homework. We classified groups by first putting students in groups with other students who have a similar breakdown. We classified a similar breakdown by having 70% of their questions match within 0.5 points. This is to account for slight variation in similar answers. We then went into each group and created sub-groups for students who started and ended at similar times. Students who had similar grade breakdowns, started within 20 minutes of each other, and ended between 10 minutes of each other, are considered a group. After we found all the groups for each homework, we outputted this data as a JSON file where each homework has an associated list of groups found in that homework.

We then wanted to find the frequency that each group appeared throughout all of the homework in order to see how the groups progressed throughout all the homework.

Group Frequency	Group Count
1	235
2	13
3	6
4	4
5	2
6	0
7	0
8	0
9	1
10	0

Table 1: How frequently groups worked together throughout the homework assignments

We found that 90% of the groups that we identified only appeared in one homework and did not repeat throughout any other homework. This suggested to us that our original group classification may have been to generous. In order to correct this, we defined a student to truly be in a group only if that student has been with their group for two or more homework assignments.

Now that we have our final set of groups found in all homework, we began trying to define what a cheater is and find cheaters amongst the students. In order to know what a cheater is, we needed to compare a student's total score and total time taken with the class' average score and average time taken.

Homework	Average Time Taken (mins)	Average Grade (out of 20)
HW01	73.16	14.27
HW02	42.49	17.68
HW03	49.67	15.71
HW04	44.68	17.47
HW05	34.61	18.69
HW06	41.57	16.61
HW07	33.63	18.58
HW09	54.25	11.17
HW10	52.65	16.38
HW011	56.08	10.66

Table 2: Average time taken and average grades for all homework assignments

After testing many different values, we found that we can most accurately find suspected cheaters by finding students who weren't in a group, who finished their homework in less than 25% of the class average time taken, and got more than the class average grade.

Cheating Frequency	Cheater Amount
1	41
2	13
3	10
4	8
5	7
6	3
7	1
8	2
9	0
10	0

Table 3: The breakdown of the frequency of students suspected of cheating

Interestingly, we found that 57% of the students we classified as suspected cheaters only appeared to cheat in one homework. Possible explanations for this result will be discussed in the Results and Discussion section.

After identifying the cheaters and grouped students for each homework, we decided to check whether or not our method worked by comparing the grouped students and suspected cheaters that we classified with our algorithm, compared to the grouped students and suspected cheaters we visually identified at the beginning.

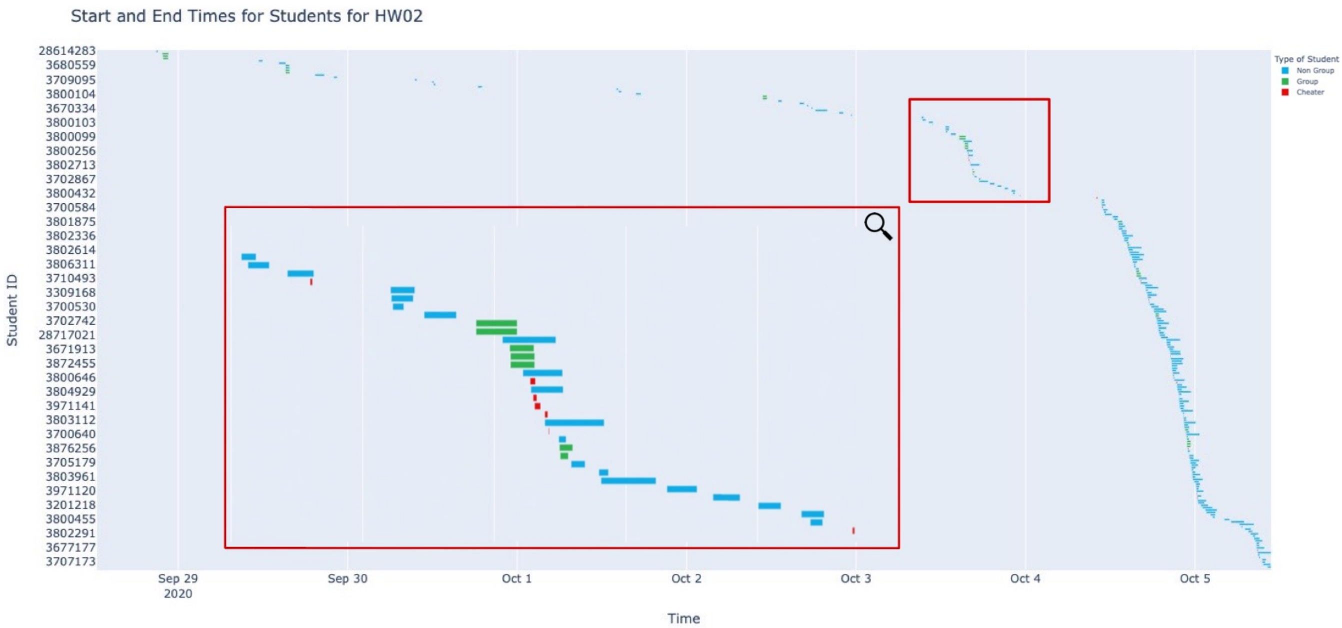

Figure 3: Student submissions throughout the week, now classfying students who worked in groups, students who didn't work in groups and suspected cheaters

In Figure 3, we were able to verify the groups and cheaters classified by our algorithm with our initial categorizations.

4 Results

4.1 Experimentation protocol

Due to the unavailability of the true number of students who worked in groups and students who cheated from the data set, we cannot directly confirm the validity of our results. Although, we still have other ways of confirming the validity of our findings. For example, we can compare our results to previous studies on cheating in online education and see if our results align with what has been found in those studies. Additionally, we can examine the data we have collected and look for patterns or trends that support our conclusions. While it would have been ideal to have direct feedback from students, the lack of this type of data does not necessarily undermine the reliability of our results. In the discussion section of our paper, we will delve deeper into these and other methods for confirming our results and strengthening the overall validity of our study.

4.2 Data tables

Homework	Class	Group	Non Group	Suspected Cheaters
HW01	71.37	78.40	69.91	83.11
HW02	88.40	90.18	87.10	97.63
HW03	78.57	86.27	74.49	97.87
HW04	87.33	93.42	85.57	97.04
HW05	93.44	97.74	92.15	97.74
HW06	82.66	87.61	81.00	91.95
HW07	92.92	95.49	91.26	99.36
HW09	55.60	57.69	50.74	85.15
HW10	81.51	90.12	76.25	95.85
HW011	53.32	63.80	49.86	69.33
Average	78.51	84.07	65.83	91.50

Table 4: Average grades for the class, students who worked in groups, students who didn't work in groups and didn't cheat, and students who are suspected of cheating

In Table 4, we observe how even without the confirmation of our data, just by looking at the table itself we can see that our classification of cheaters makes sense just by a logical standpoint in the sense that they consistently perform better than the rest of the class. Students who worked in groups performing second second best also would make logical sense, since collaboration between the students would lead to collective thought process for each question, thus resulting in a higher grade than if a student were to attempt the questions on their own.

Homework	Cheat Count
HW01	12
HW02	19
HW03	27
HW04	17
HW05	20
HW06	14
HW07	26
HW09	25
HW10	30
HW011	15

Table 5: Number of suspected cheaters per homework assignment

The Table 5 illustrates that the number of students who cheated on their homework assignments remained relatively stable over time. However, it is important to note that this table does not consider the frequency of cheating among individual students. The Table above 3 provides further insight on this issue, as it shows the number of times each student cheated, showing that majority of students don't usually cheat.

4.3 Graphs

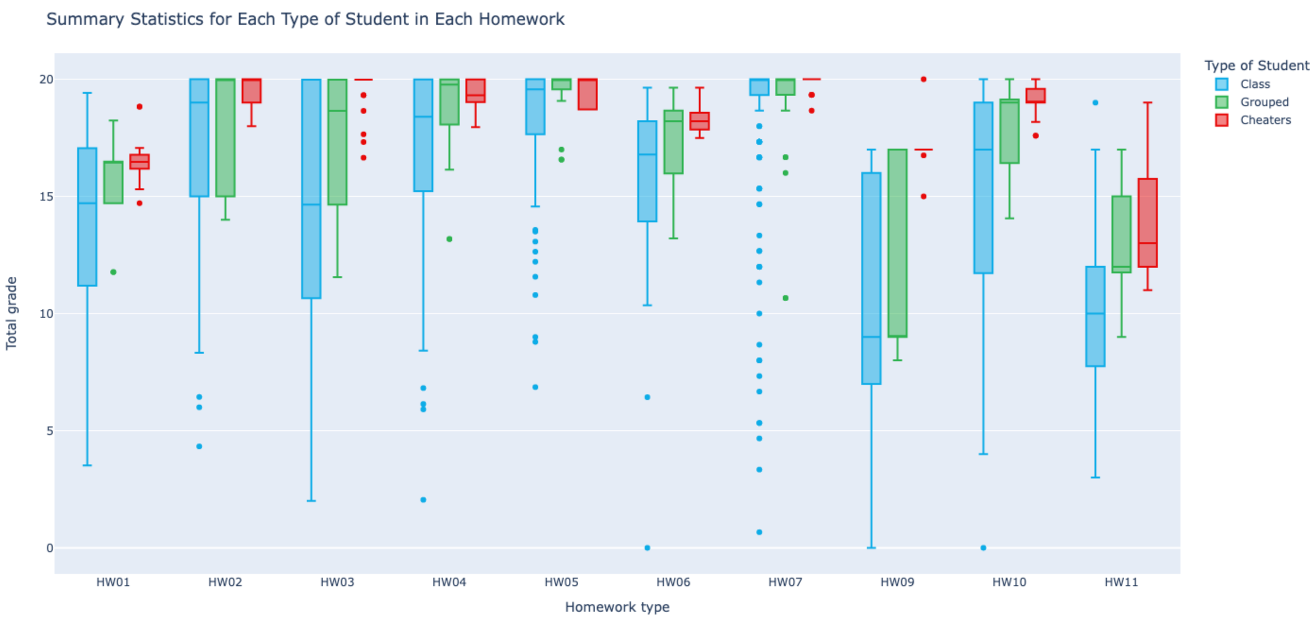

Figure 4: Distribution of student grades, categorized by students who worked in groups, students who didn't work in groups and did not cheat, and students who are suspected of cheating

Figure 4 visualizes the summary statistics for each type of student for each homework. In this graph, we can see that students who work in groups or cheat tend to score higher than students in neither category. We can also see that the range of scores gets tighter as we move from regular students, to grouped students, to cheating students.

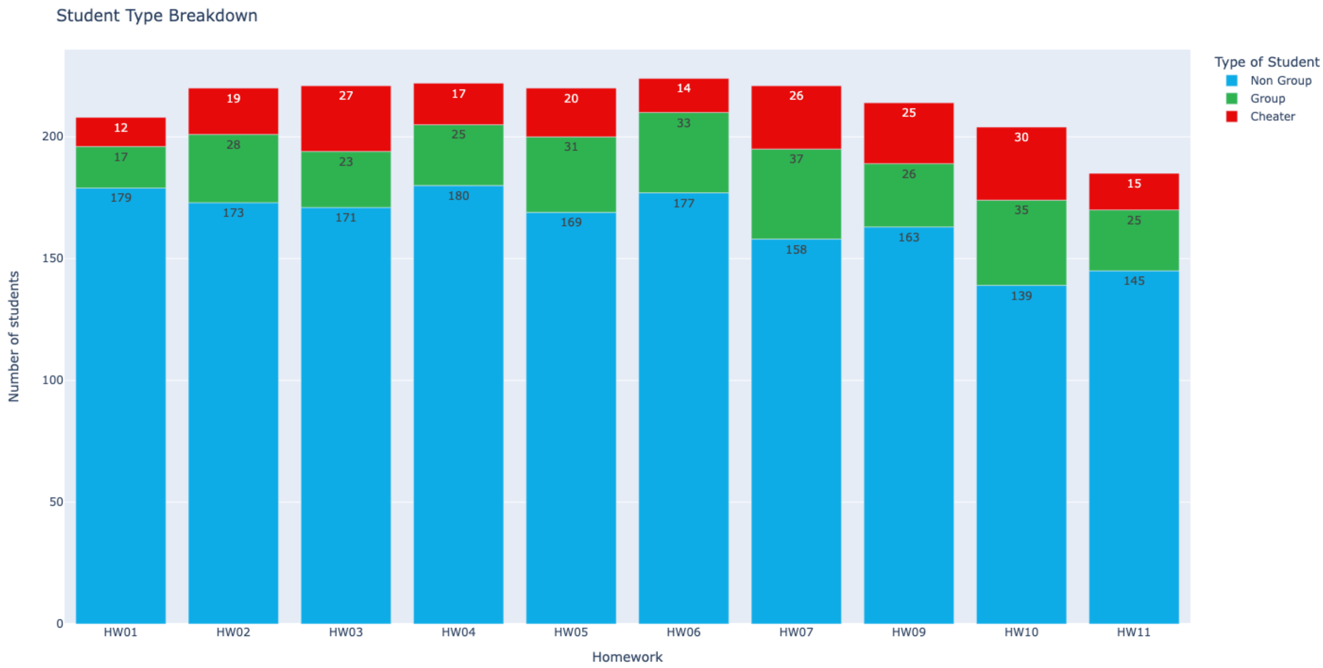

Figure 5: Breakdown of students who did not work in groups and didn't cheat, students who worked in groups, and suspected cheaters

Figure 5 shows the proportion of each type of student for each homework, as well as the number of each student in each of the categories. We can see that the number of grouped students tends to outnumber the number of cheating students per homework. We can also see how these values change throughout the semester as we see the number of groups rising and falling. We can see a peak of grouped students in the middle of the semester, and this led to a trough in students cheating.

5 Discussion

Due to the fact that we are using a non-invasive method to classify cheaters, we have a lot less data to produce results compared to other metrics we could measure by instead using an invasive method. This meant that we had to spend a lot of time understanding how exactly we would organize the data set given to us. Ultimately, we decided that dictionaries were the best choice for us, since it offered easy a way to organize the students with all of their information pertaining to the homework, giving us easy access to their information when iterating through the students.

In our study, we found that 28.92 percent of students cheat on online assessments. However, because of the nature of our dataset, we have no way to 100 percent accurately know if a student suspected of cheating actually cheated, since we were not given a questionnaire or survey of students who did or did not admit to cheating.

Even though we cannot confirm our results, if we look at the paper published by Valizadeh [2022], we see that the paper reports that on average 47.9 percent of undergraduate students admit to cheating. One potential reason for this difference could be that the other paper included colluding, or collaborating with others, as a form of cheating. In our study, we did not classify colluding as cheating, as we saw it as a form of collaboration rather than deception. This difference in definition may have resulted in the discrepancy in the reported rates of cheating between the findings of the paper and our results.

Another method we used to validate our findings was to utilize the final exam scores for this class. Although all of the homework assignments were done online, the final exam was done in person. Our hypothesis was that if our findings were correct, then the average grade for the cheaters would be substantially lower than that of the rest of the students, as the students who repeatedly cheated online would not be prepared for an in person assessment.

Assignment	Class	Group	Non Group	Cheaters
Final	39.35	37.38	41.55	30.55

Table 6: Average final grades for the class, students who worked in groups, students who didn't work in groups and didn't cheat, and students who cheated

Our hypothesis was indeed correct– however, we did not expect the students that worked in groups to also do worse on the final exam compared to the rest of the class. As shown in Table 6, the students who did not cheat throughout the homework assignments and did not work in groups had the highest average grade for the final. The students who worked in a group scored 4.17% lower, while the students we classified as cheaters scored 11% lower. The grouped students scoring lower could be due to students who worked in groups splitting the responsibility for each homework. Therefore, each student in a group did not need to learn as much information as a student doing the homework single handily.

6 Conclusion

We sought out to examine how students engaged with course materials, as well as explore how instructors should revise online assessment and evaluation policies. We were able to do so by analyzing data given through Moodle for homework assignments throughout the semester. By processing this data through out identification algorithm, we were able to classify students who worked in groups and students who cheated in each homework assignment. We found that 9.96% of students who worked in groups continued to work in the same group for more than one homework assignment. We used this metric in order to tighten our definition of a group, that being a group that has worked together for more than one homework. We also found that only 17.67% of students cheated more than once. A possible explanation could be that most students will only cheat on a homework assignment if there are extenuating circumstances preventing the student from completing a particular homework. As a whole class, we found that 28.92% of students have cheated at some point in the semester. This value is lower than values found in other papers– however, a possible explanation could be due to our algorithm not classifying group work as cheating. When taking this into account, as well as the fact that students we assume are repeated cheaters scoring 11% lower on their in person final exam than their non-cheating, non-grouped counterparts, we assume our figures are valid.

Given the nature of cheating and group work derived from the data, we can see that most students generally avoid cheating, as chronic cheating leads to lower retention of class materials and lowered performance in in-person assessments, such as the final exam. From experience, some professors offer to drop the lowest scoring homework in the semester. As most of the derived cheaters have only cheated on one homework assignment, dropping one homework, or even two, could reduce the likelihood that a student will cheat in order to finish their assignment on time.

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