

# Exploratory Data Analysis of Math 1020/1021

Using Machine Learning and Statistical  
Analysis to Estimate a Student's Chance  
of Success in College Algebra



# Goals

1. Analyze the averages across both sections and compare.
2. Determine if correlations between any grade categories differ across the semesters.
3. Determine specific problematic areas of student performance by time in the semester.
4. Speculate a student's end course grade using a small amount of data.
5. Use machine learning and statistical methods (e.g. regression) to determine a student's chance for success in the course by a specific time frame.
6. Use Bayesian statistical methods to determine likelihood of success or failure in the course.
7. Answer any other questions that appear as they come.
8. Provide a framework for administrators of other courses to give an in-depth analysis of their respective courses.

# 1021 Structure

The grade of a student in Math 1021 is determined by the following.

| Category      | Weight | Notes  |
|---------------|--------|--|
| Participation | 10%    | 5% Lab Participation, 5% Class Participation     |
| Homework      | 10%    | 2 Assignments Dropped                            |
| Quizzes       | 10%    | 1 Quiz Dropped                                   |
| Tests         | 45%    | Lowest replaced with final exam grade, if higher |
| Final Exam    | 25%    | Cumulative, never replaced                       |

For students who are unable to qualify for Math 1021, they instead take Math 1020/1021 with corequisite material. Follows same grading scale.

# 1021 Differences in 2022/2024

In 2022, Math 1020 and 1021 were treated as a 5-hour course. They were not separated in Moodle. By 2024, these two courses are treated somewhat independently, as 2- and 3-hour credit courses respectively. Differences?

## Fall 2022

- 1021 homework assignments were locked behind prerequisite assignments. Must complete prerequisites before doing the assignments.
- 3 hours of lab credit each week
- 28 class meetings counted (varies due to holidays, cancellations)
- Older UI for MyLab (mostly similar to current UI)

## Fall 2024

- Assignments are not locked behind prerequisites. Students can choose to not engage with 1020 assignments.
- 1 hour of lab credit for 1020, 2 hours of lab credit for 1021, 3 hours gives credit for both.
- 14 class meetings in 1020. 14 in 1021.
- Newer UI for MyLab (homework platform)

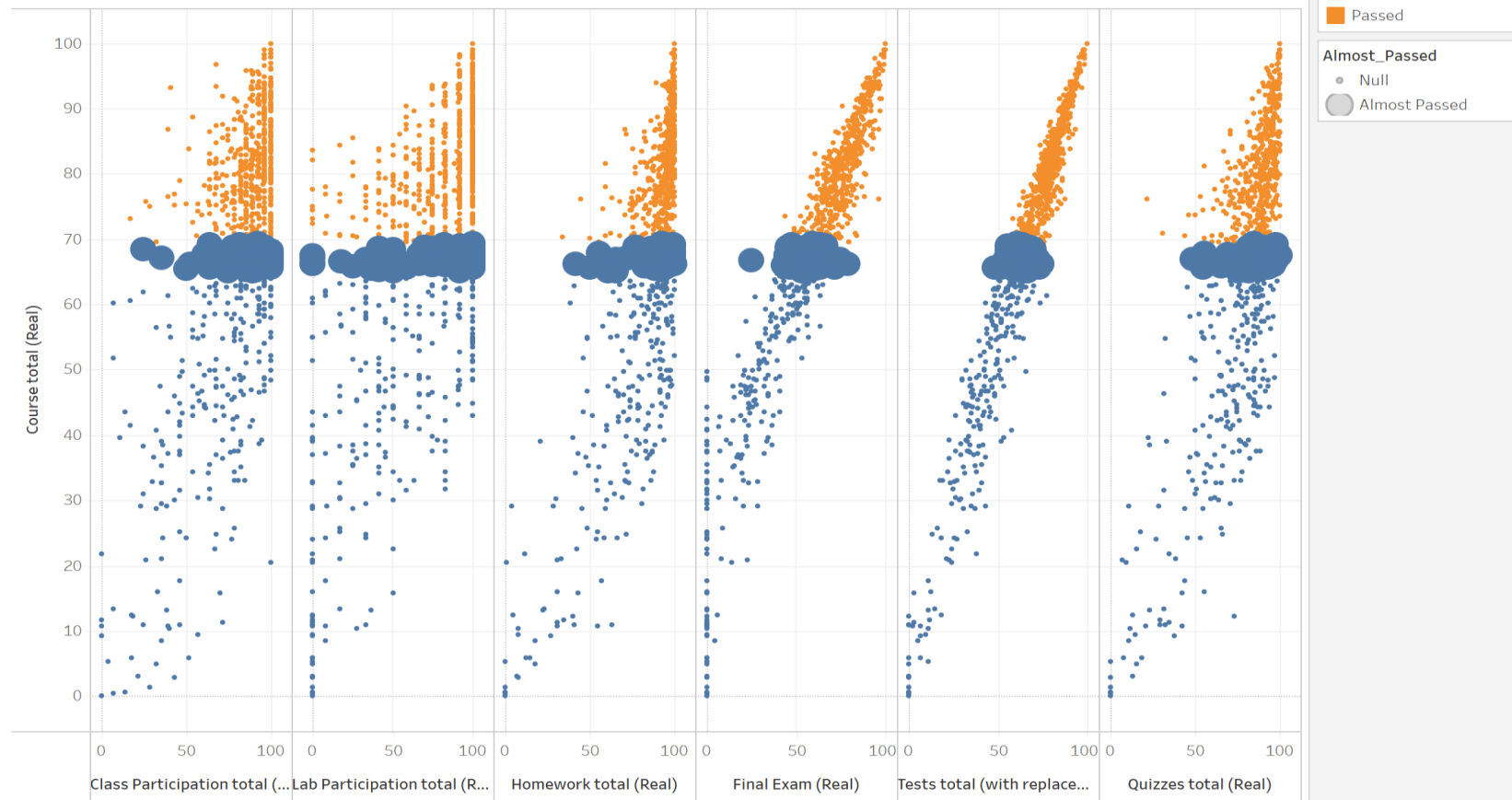


# Initial Visualizations

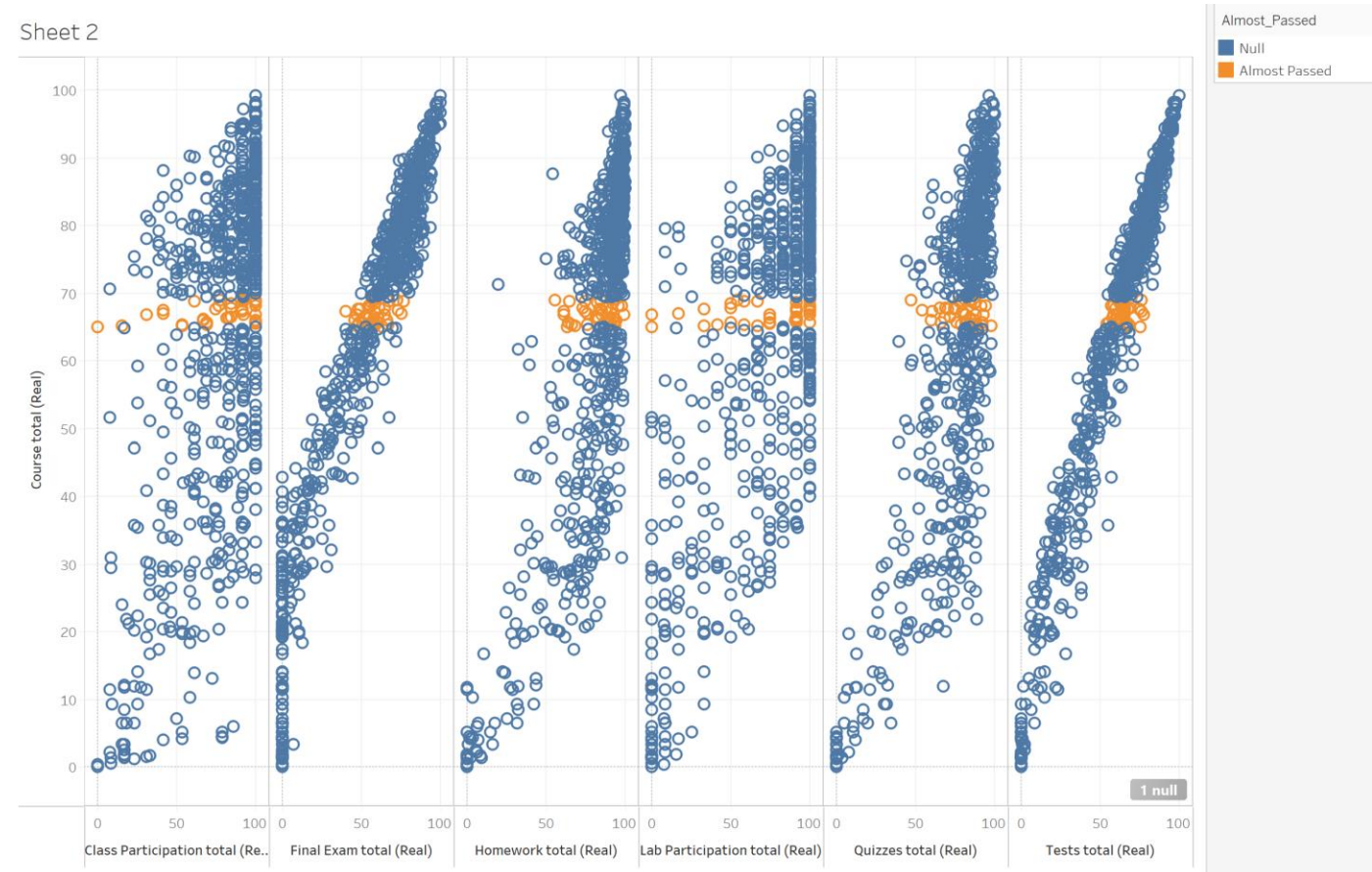


# 2022 Grade Calculation Factors vs Course Total

Grade Calculation Factors vs Course Total



# 2024 Grade Calculation Factors vs Course Total

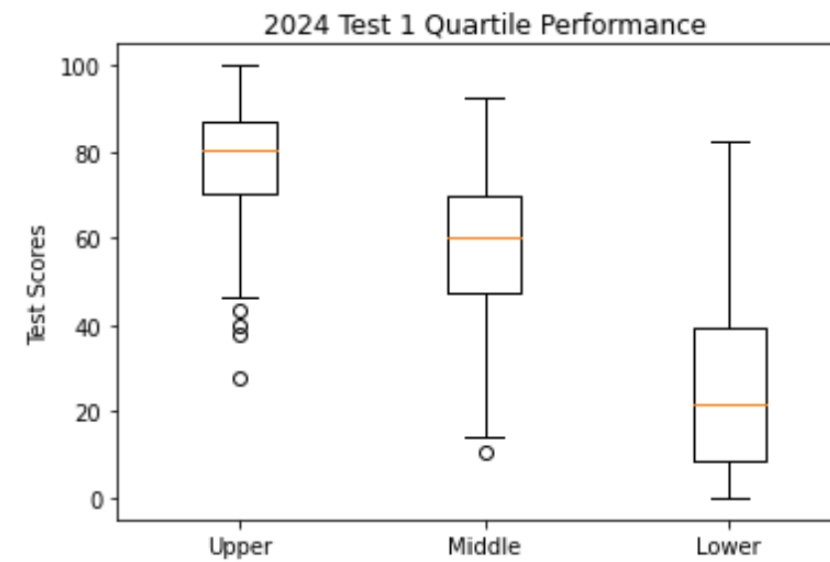
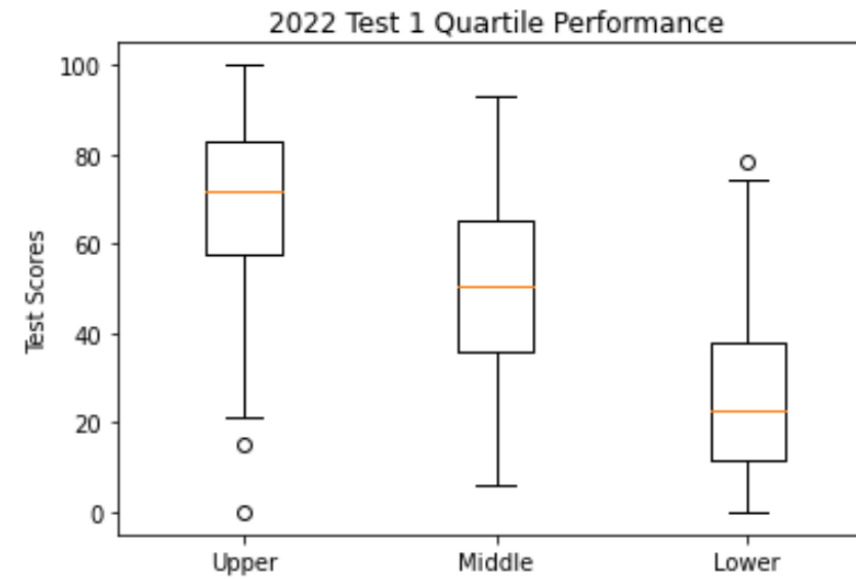


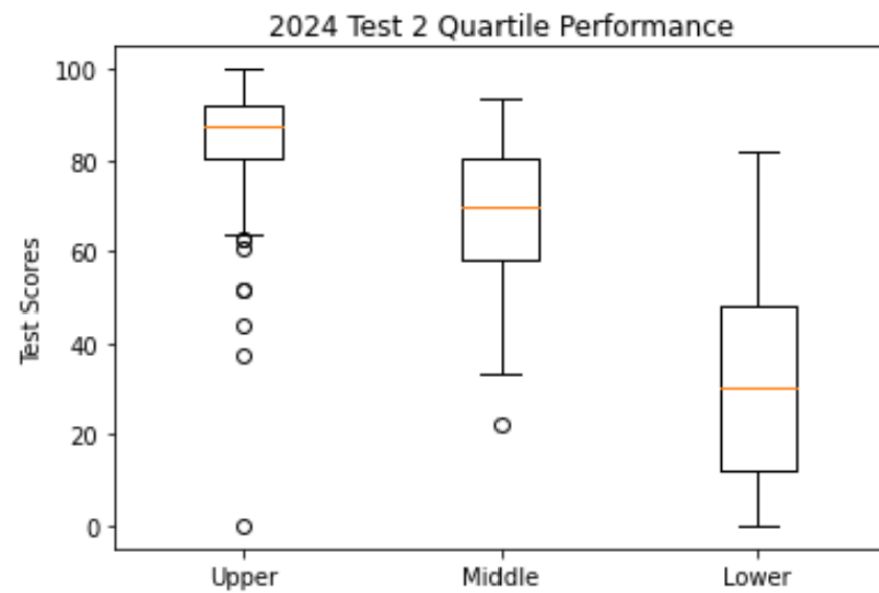
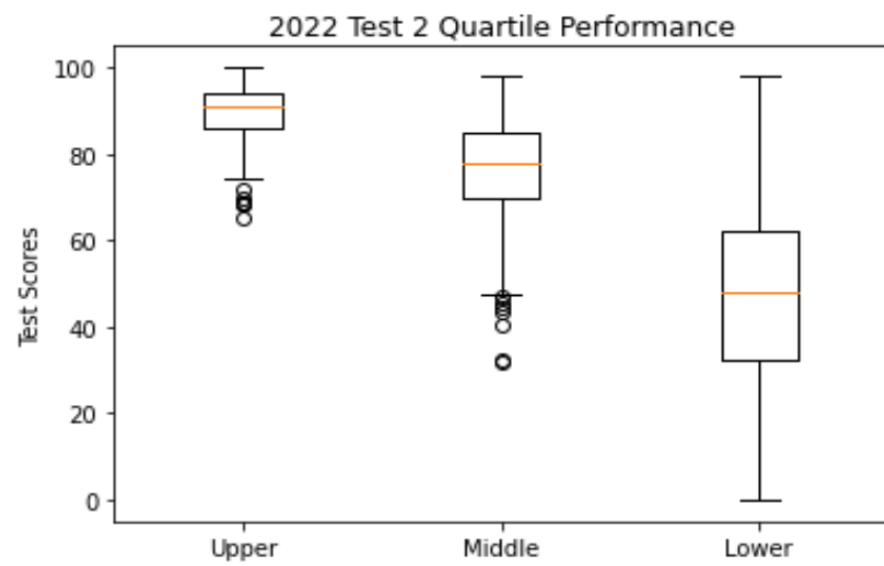


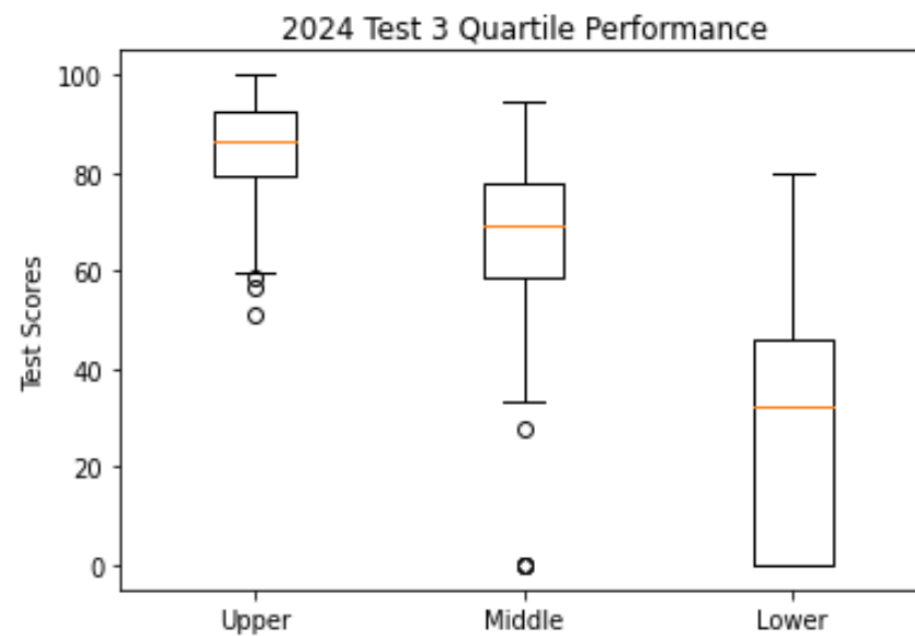
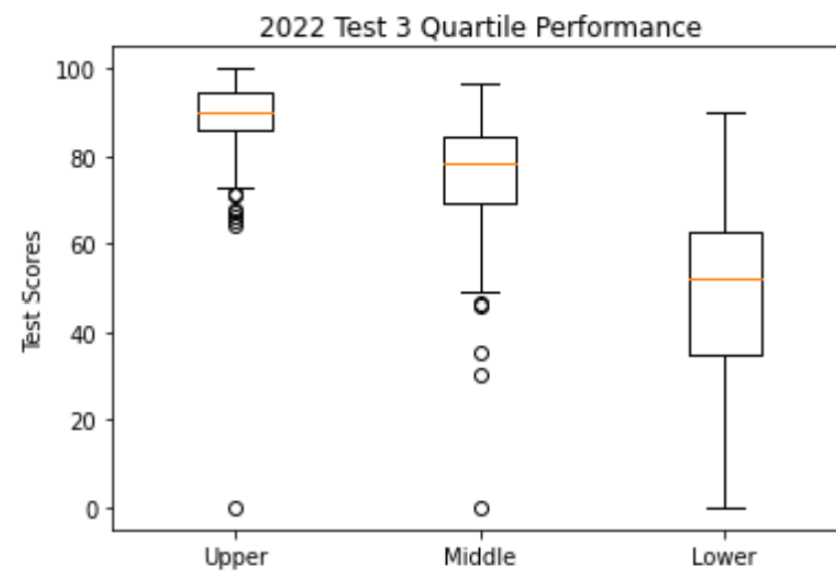
# Student Performance Quartile Visualizations

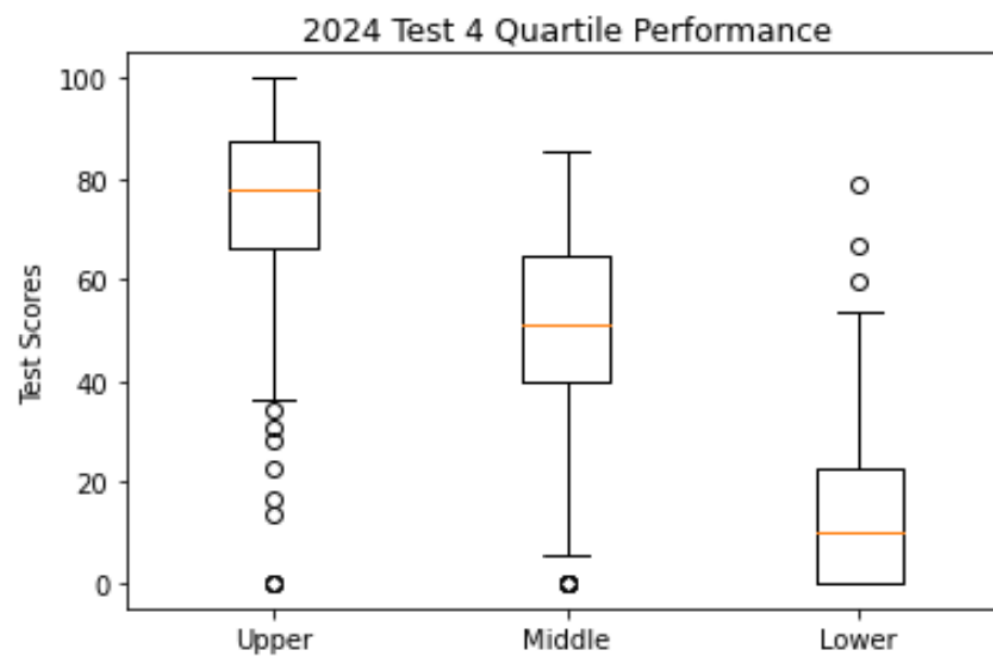
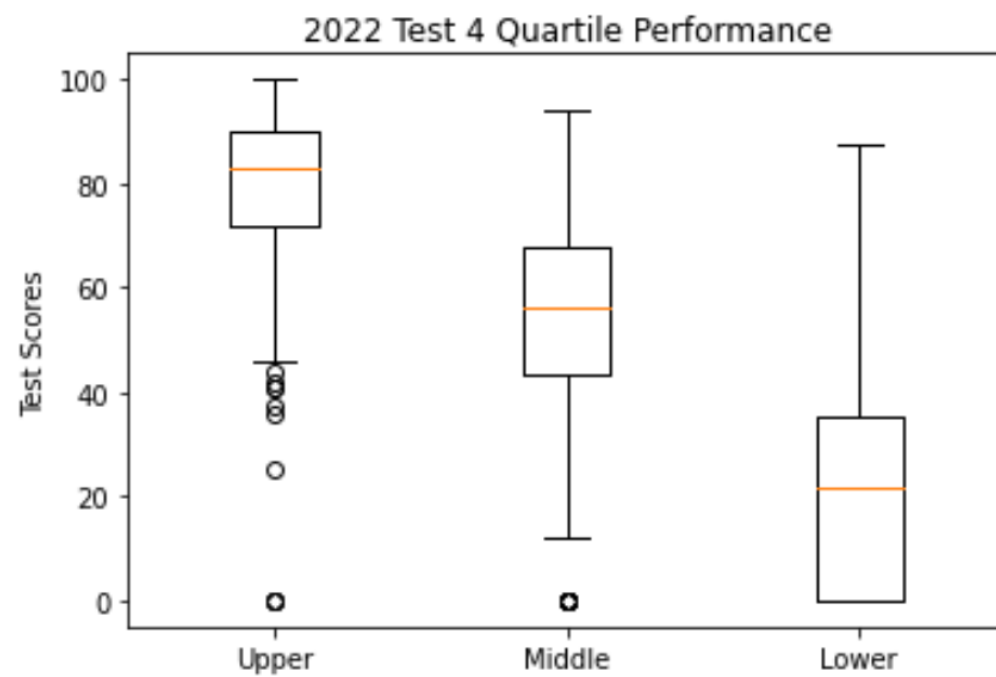




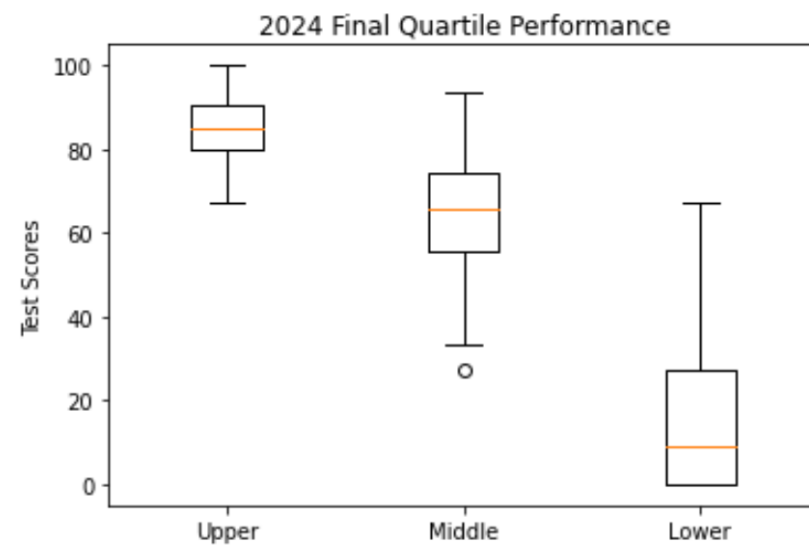
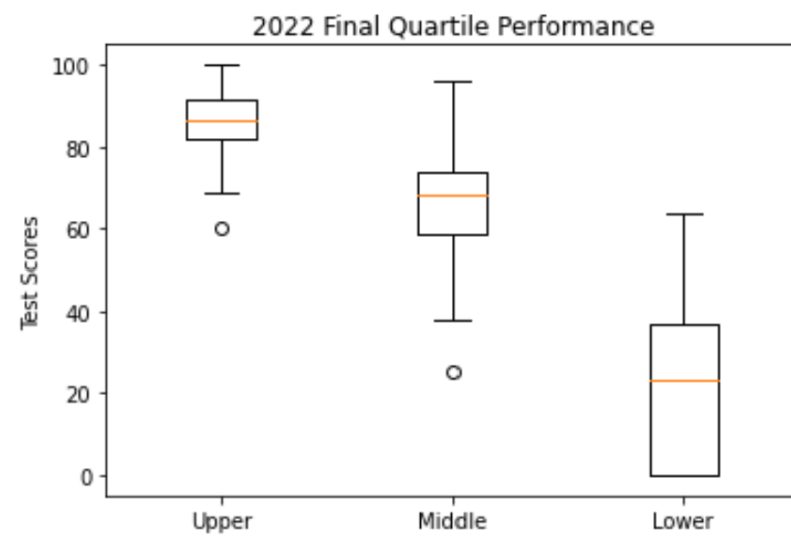




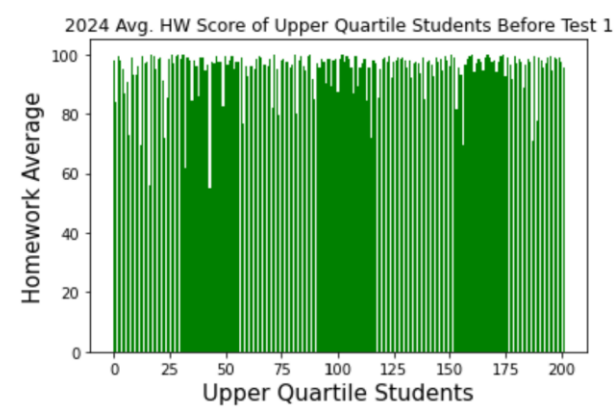
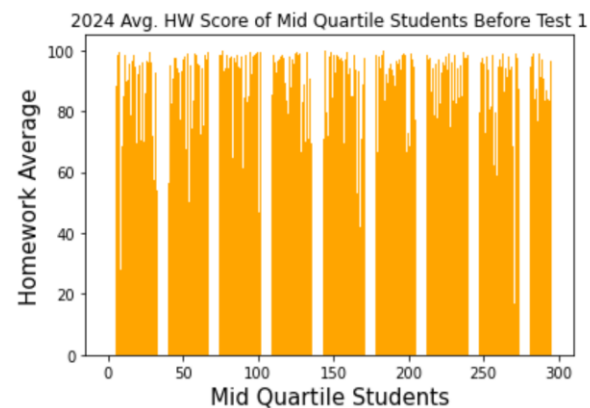
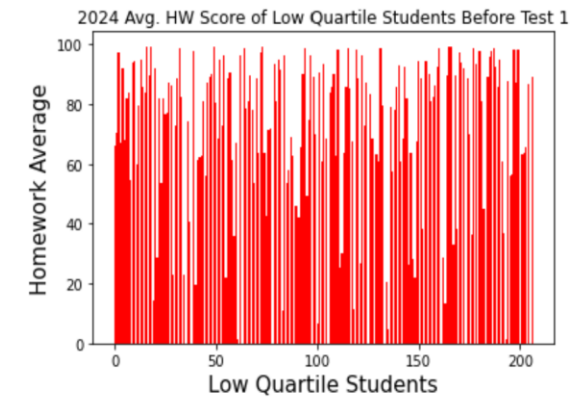
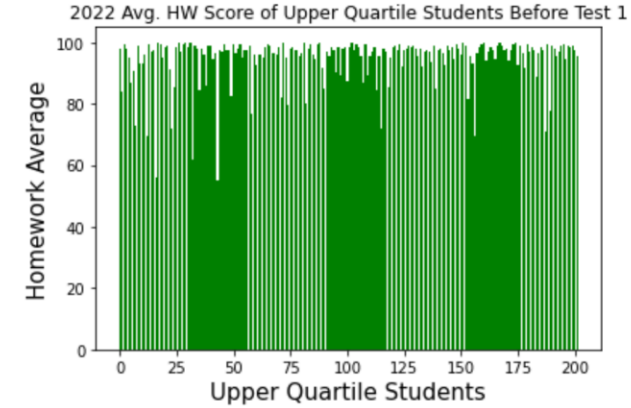
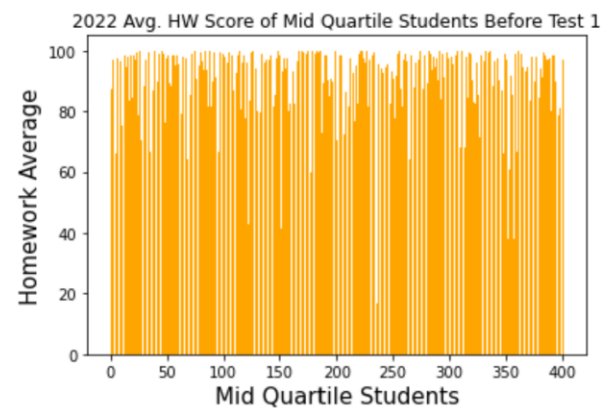
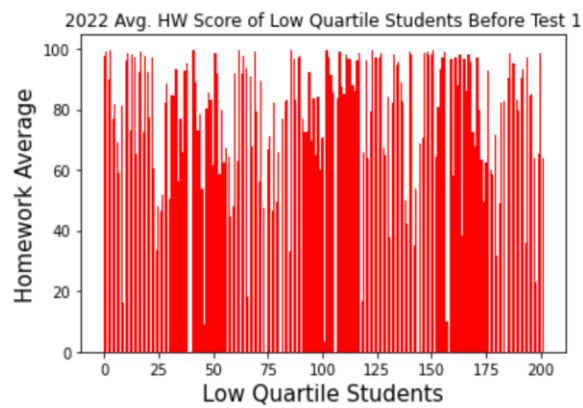






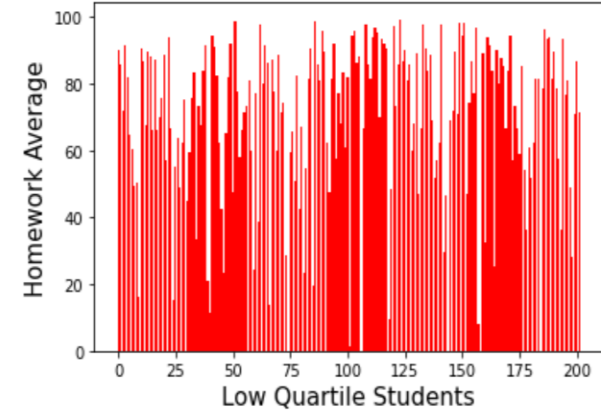


# 2022 vs 2024 Avg HW Scores Before Test 1

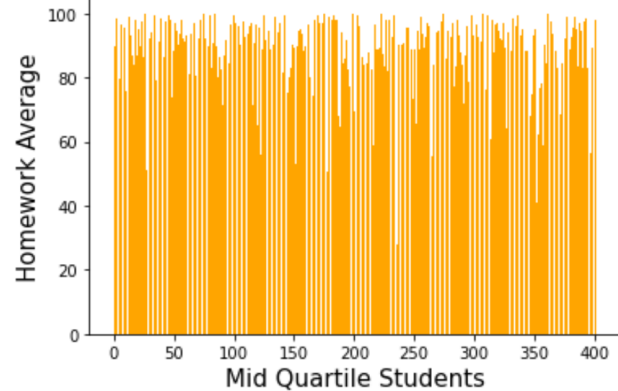


# 2022 vs 2024 Avg HW Scores Before Test 2

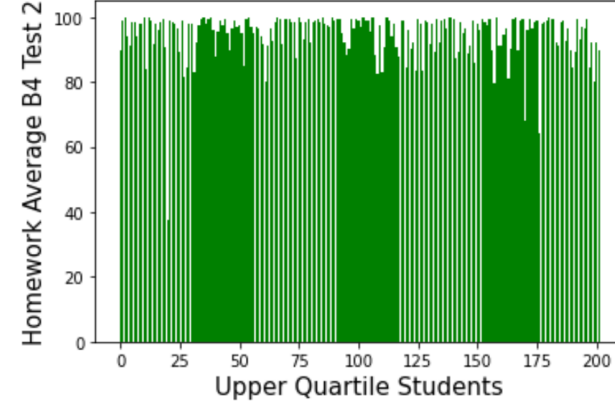
2022 Avg. HW Score of Low Quartile Students Before Test 2



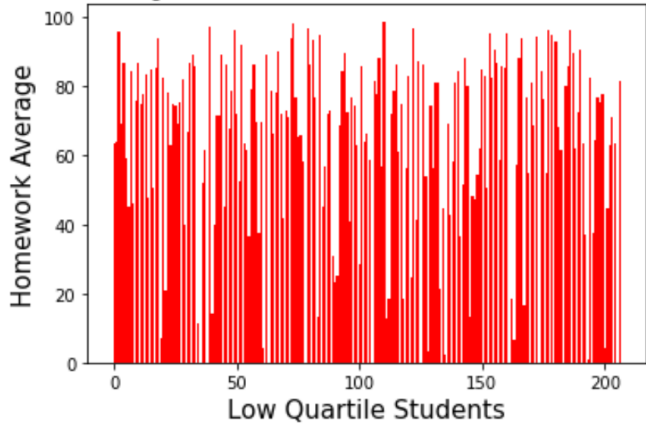
2022 Avg. HW Score of Mid Quartile Students Before Test 2



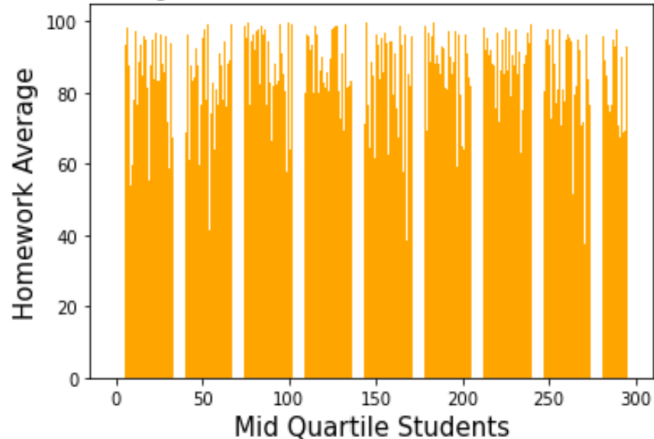
2022 Avg. HW Score of Upper Quartile Students Before Test 2



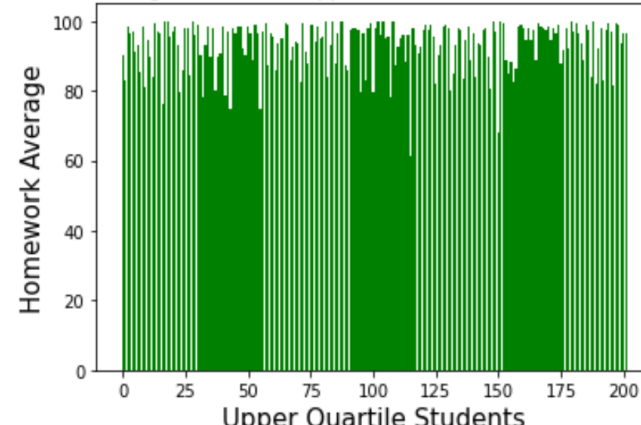
2024 Avg. HW Score of Low Quartile Students Before Test 2



2024 Avg. HW Score of Mid Quartile Students Before Test 2

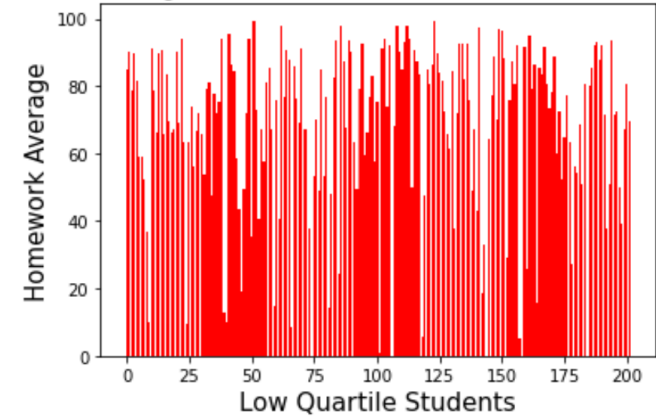


2024 Avg. HW Score of Upper Quartile Students Before Test 2

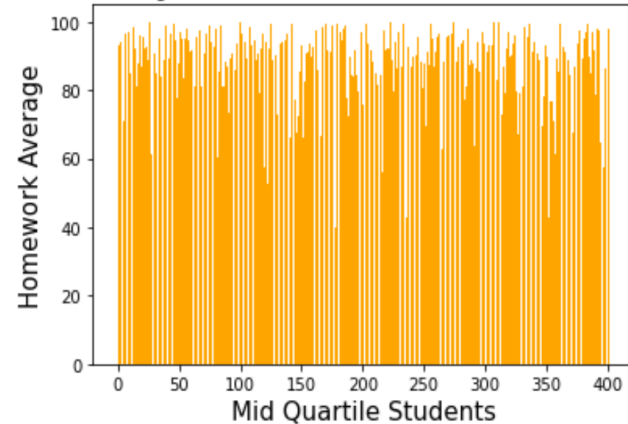


# 2022 vs 2024 Avg. HW Scores Before Test 3

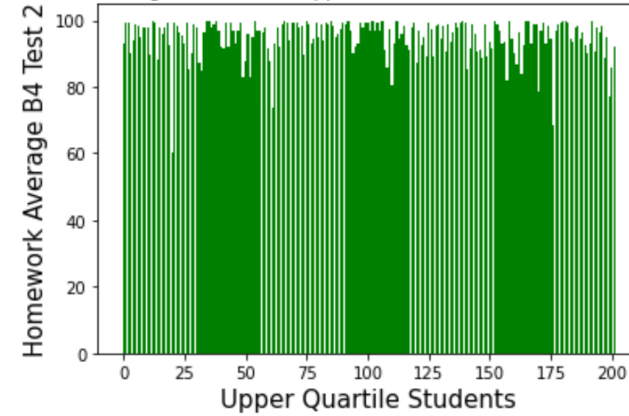
2022 Avg. HW Score of Low Quartile Students Before Test 3



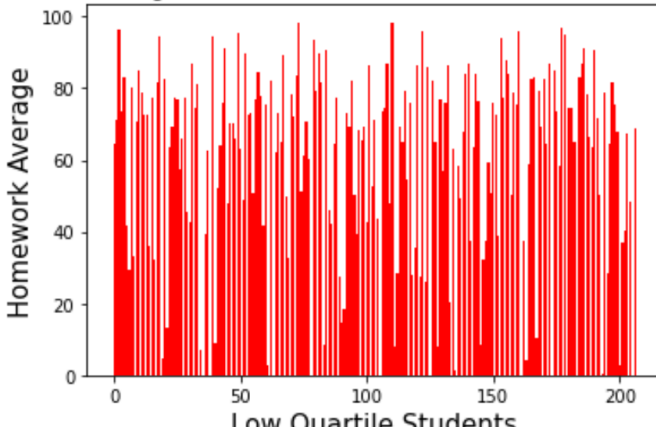
2022 Avg. HW Score of Mid Quartile Students Before Test 3



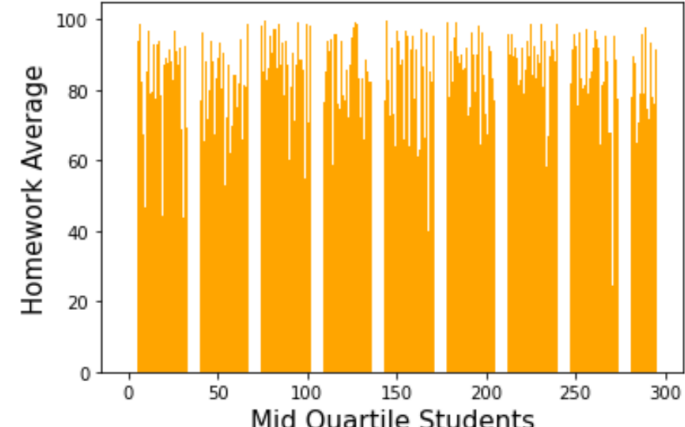
2022 Avg. HW Score of Upper Quartile Students Before Test 3



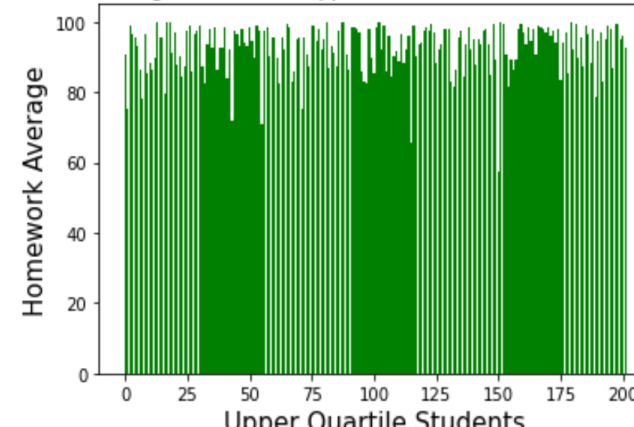
2024 Avg. HW Score of Low Quartile Students Before Test 3



2024 Avg. HW Score of Mid Quartile Students Before Test 3

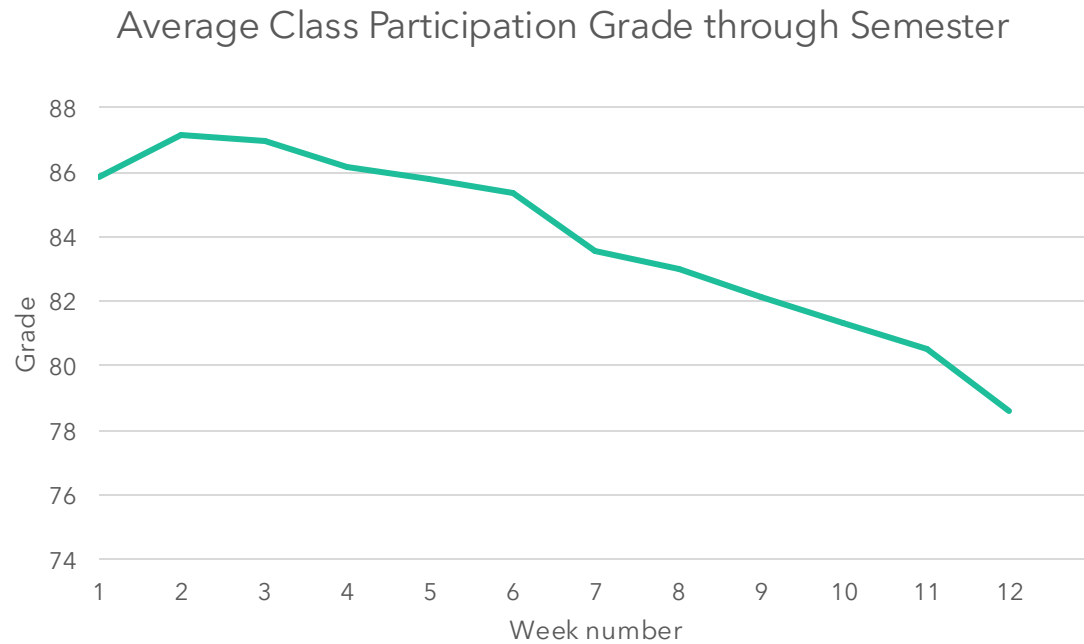


2024 Avg. HW Score of Upper Quartile Students Before Test 3

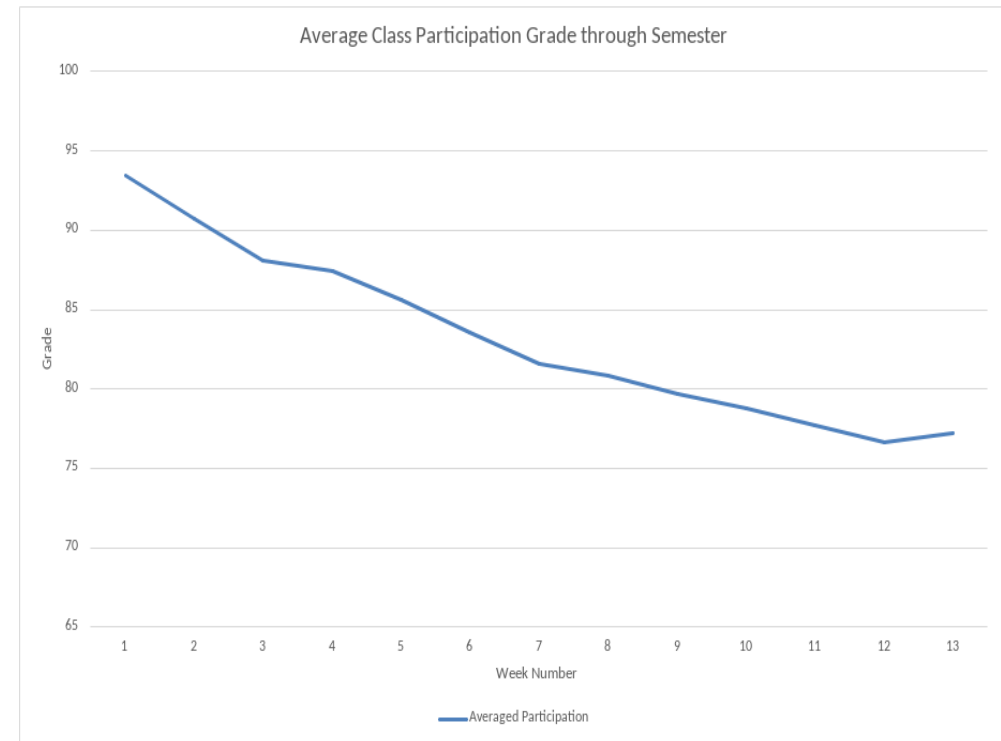




# Average Class Participation Per Week

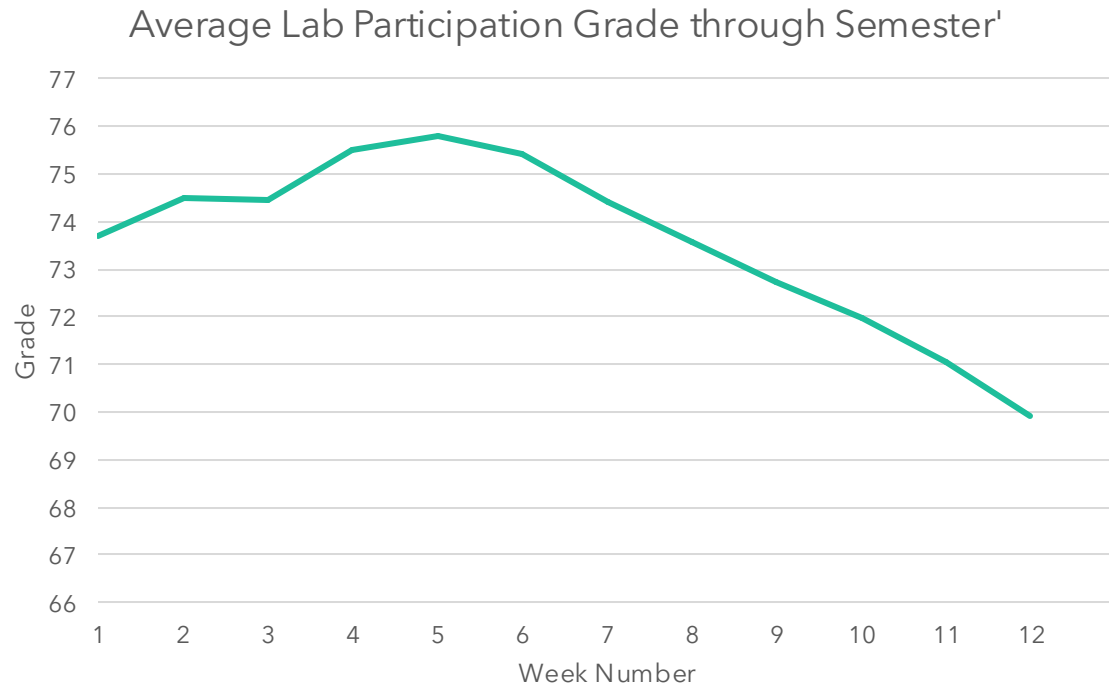


2022

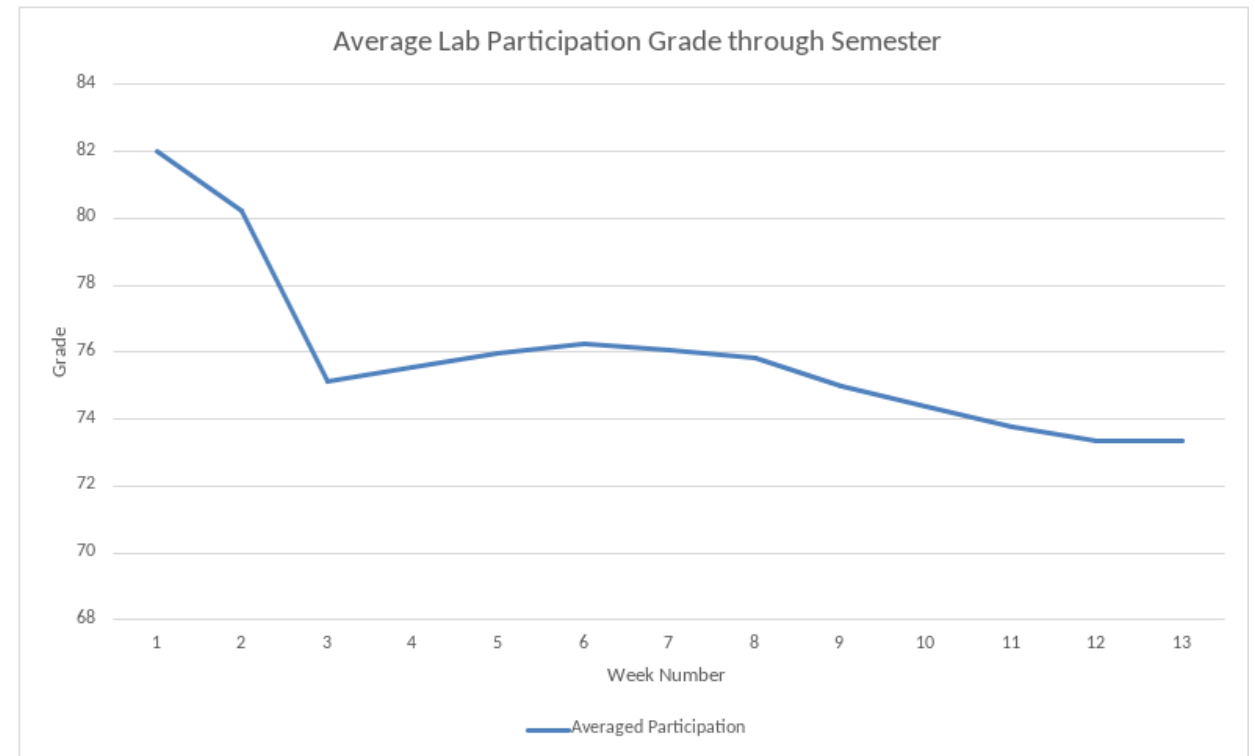


2024

# Average Lab Participation Per Week

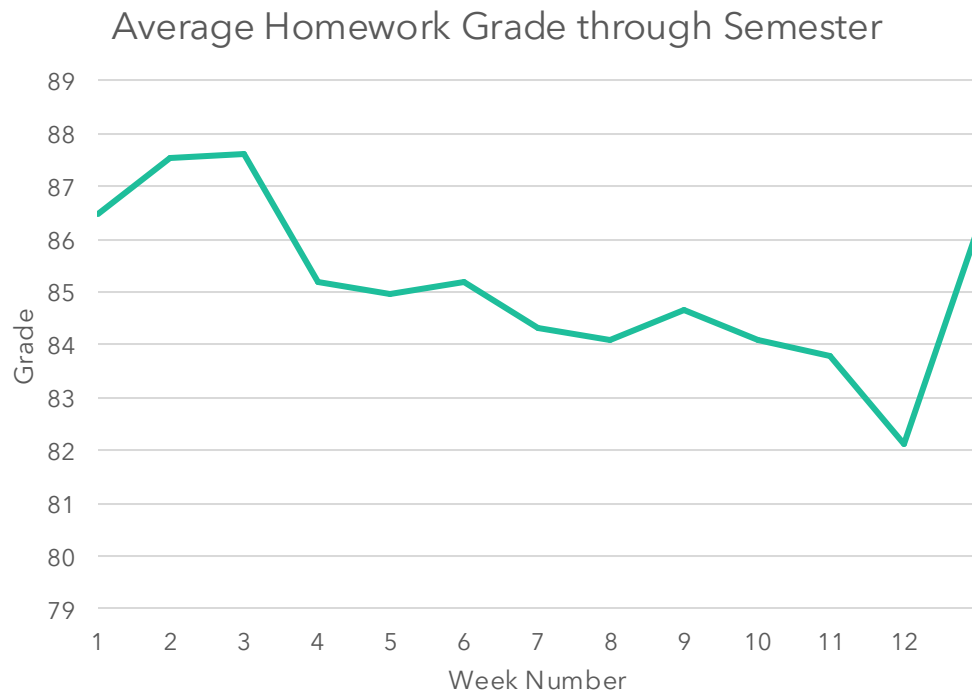


2022

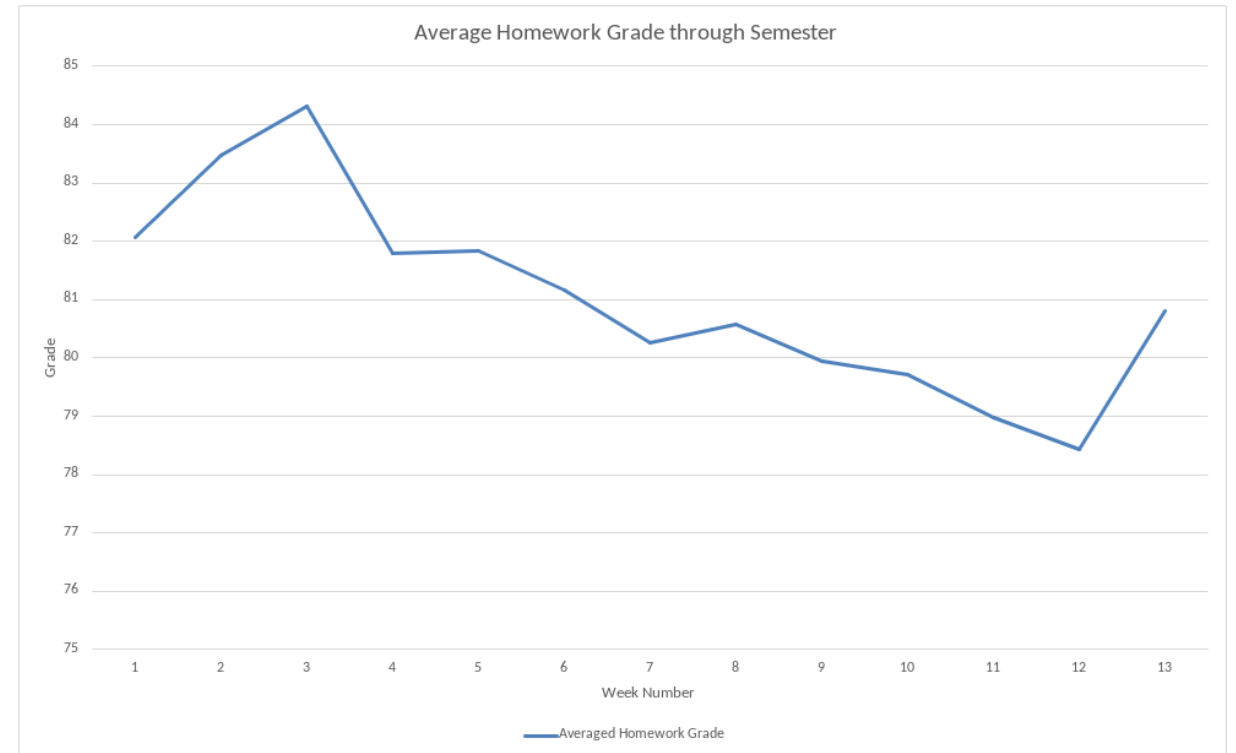


2024

# Average Homework Grade Per Week

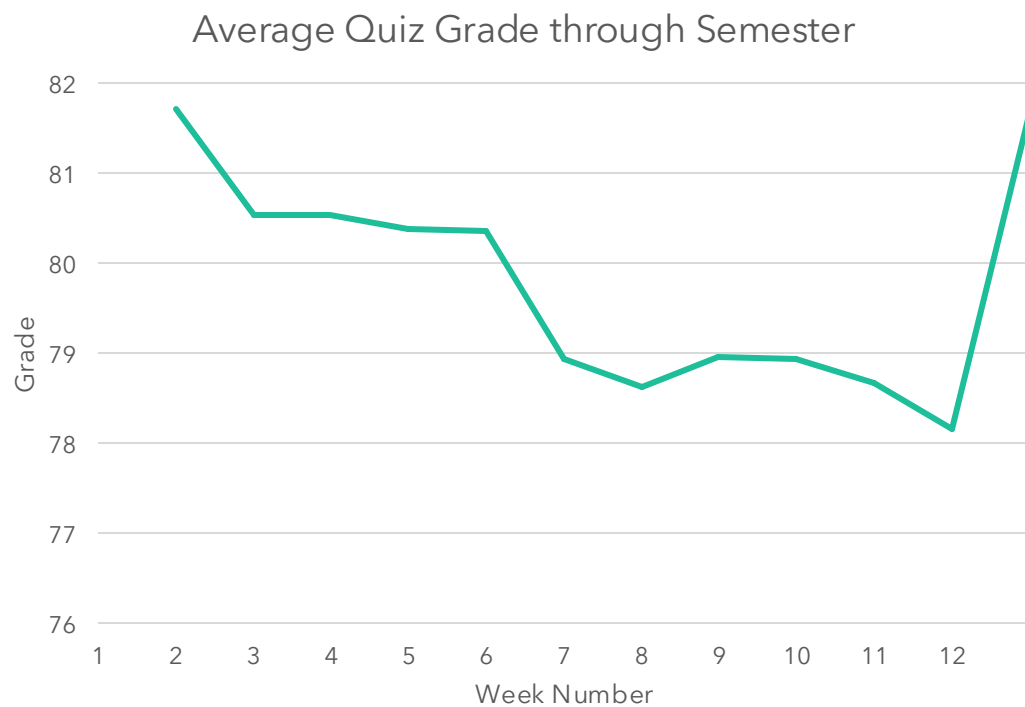


2022

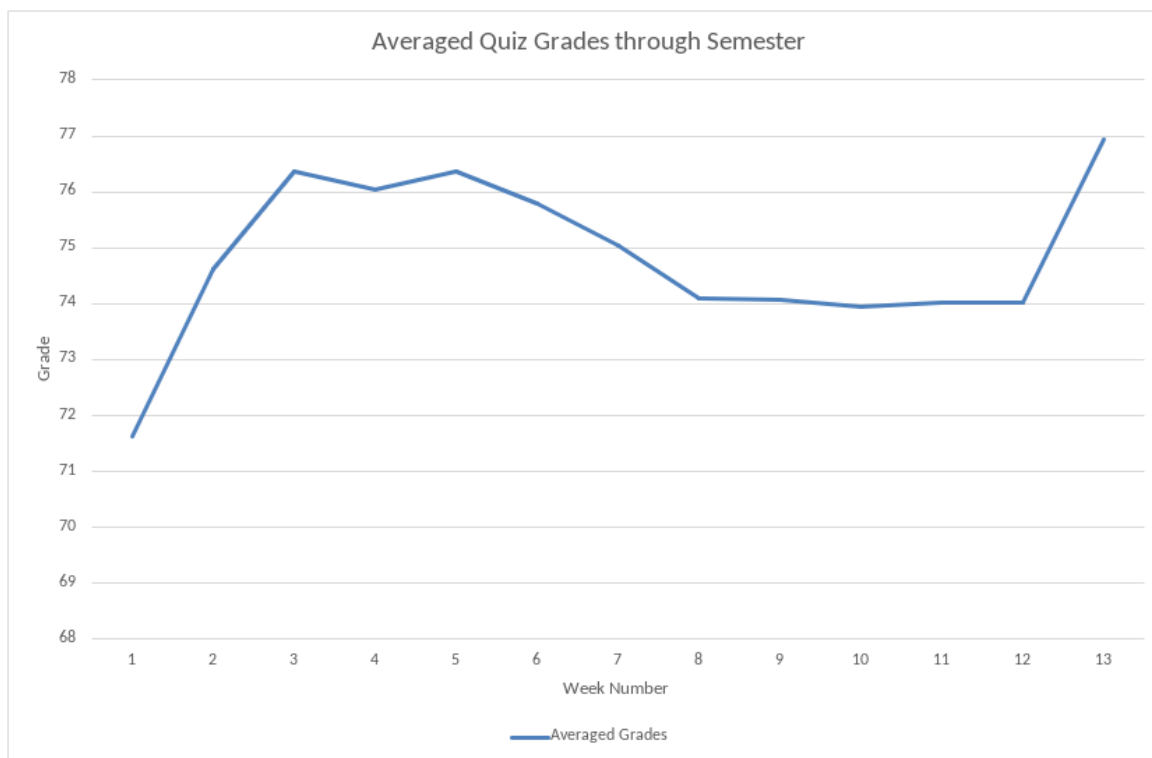


2024

# Average Quiz Grade Per Week



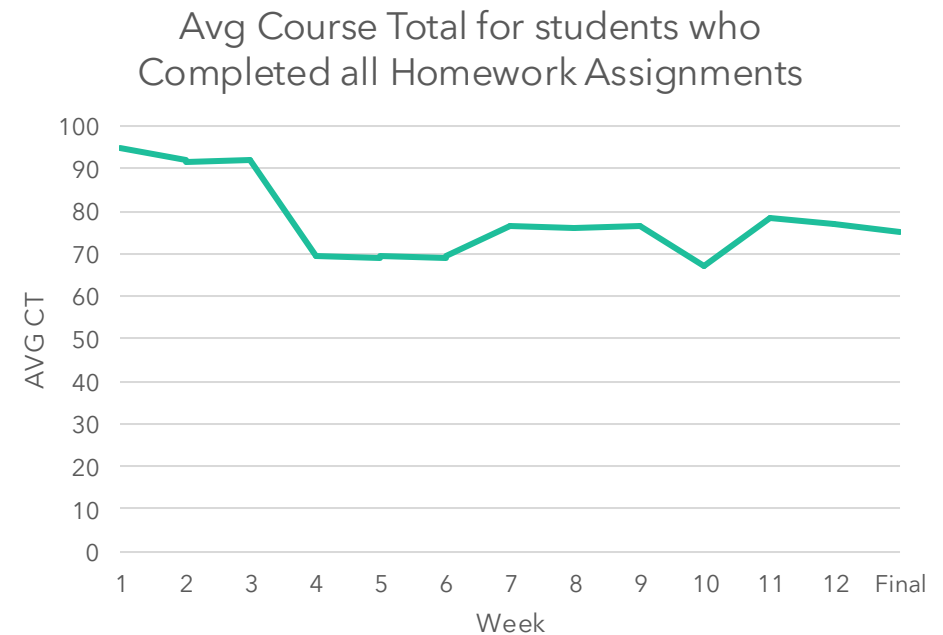
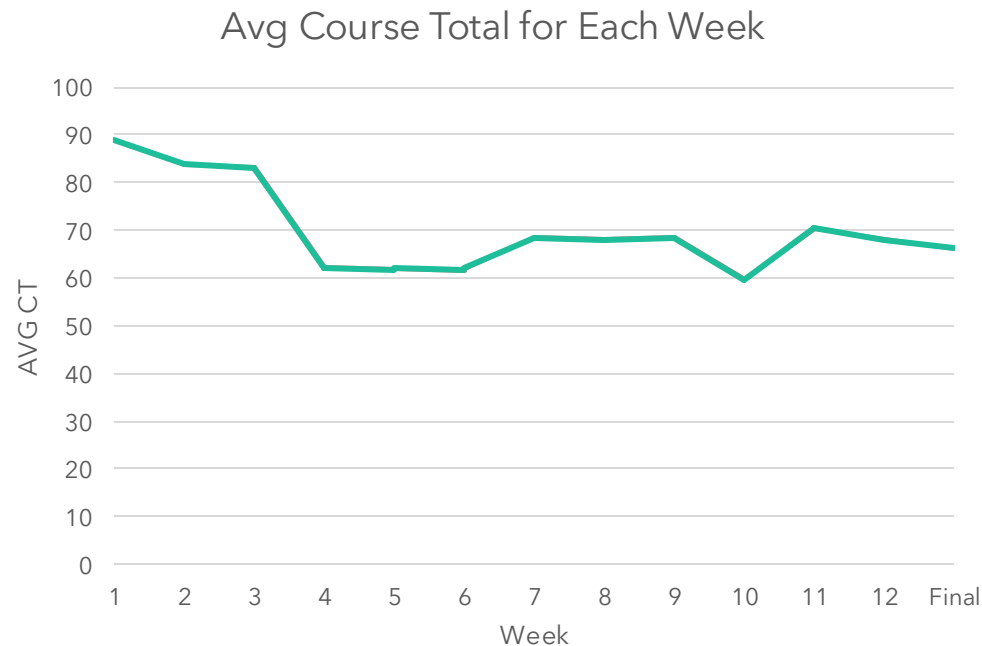
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2024



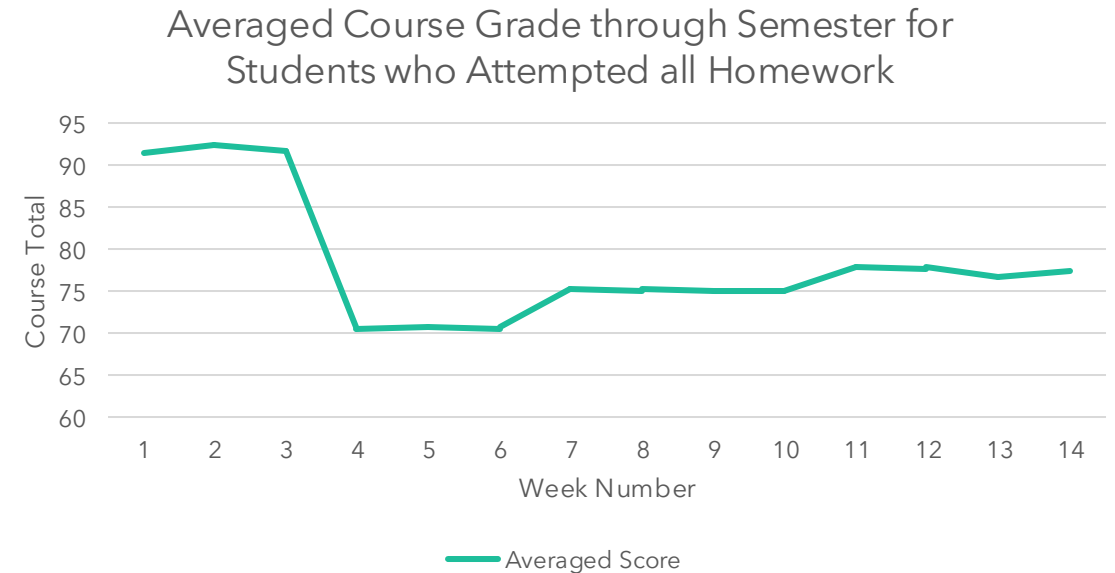
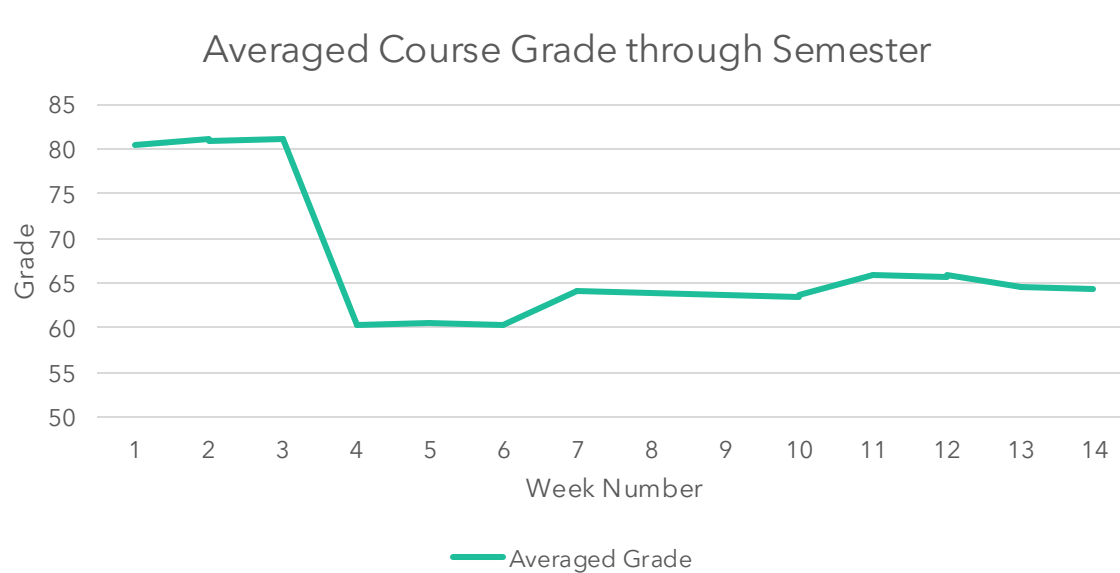
# 2022 Time Series Analysis



Using 2022 data, we generated the above time series of averaged course grades.

- We can see around a 5-7% increase in the course total average for the students who completed all assignments

# 2024 Time Series Analysis

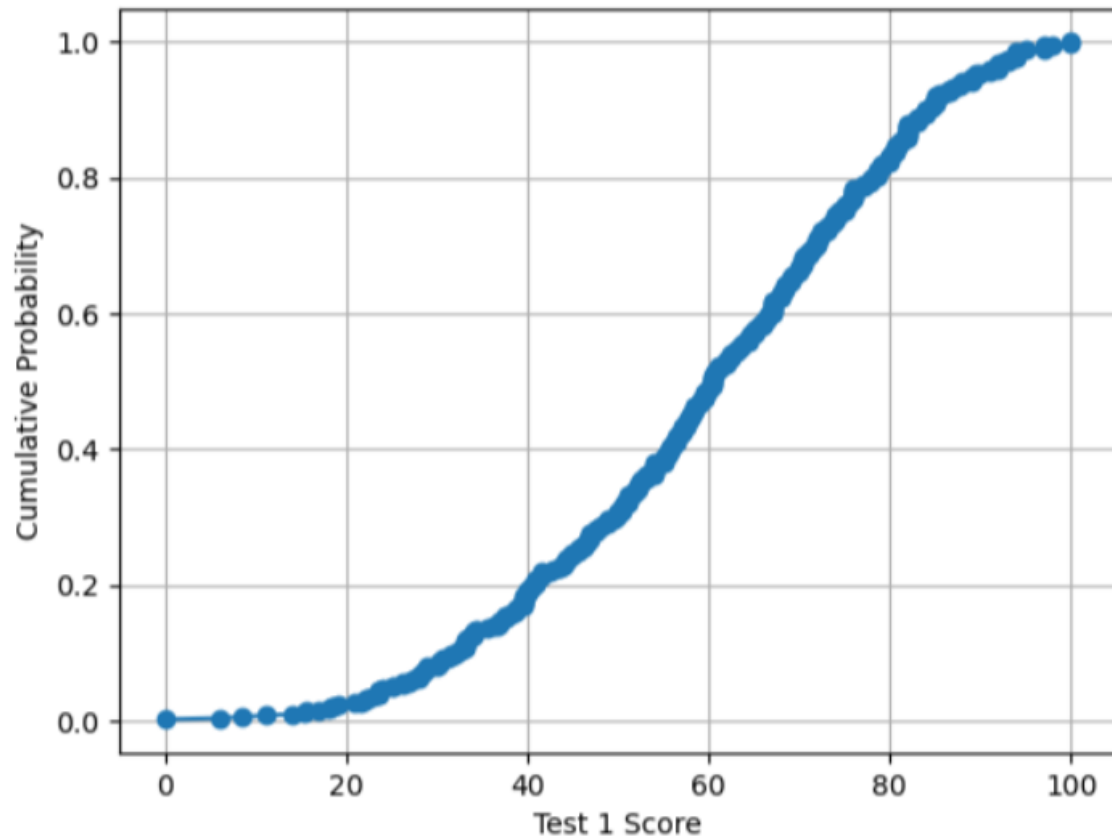


Using 2024 data, we generated the above time series of averaged course grades.

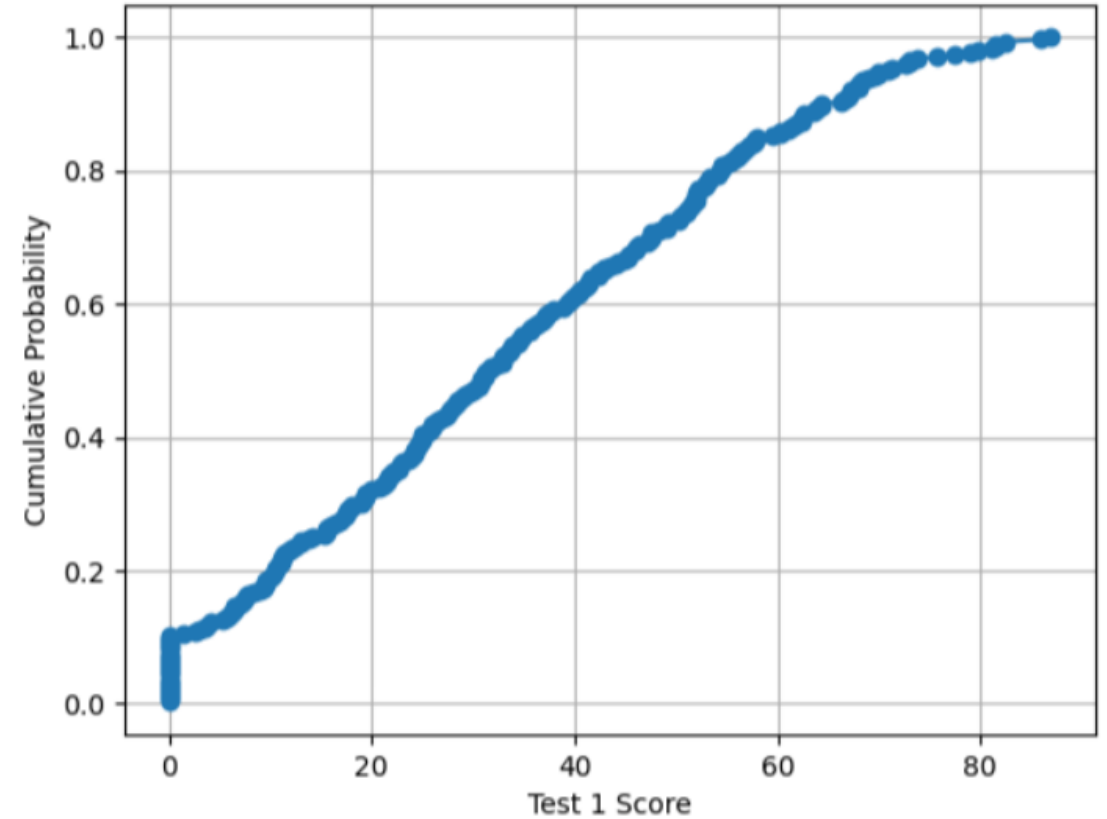
- Week 3 shows a 20 point drop (Test 1).
- Small regains in the semester.
- Consistent with those who did all homework assignments.

# 2022 CDF Test 1

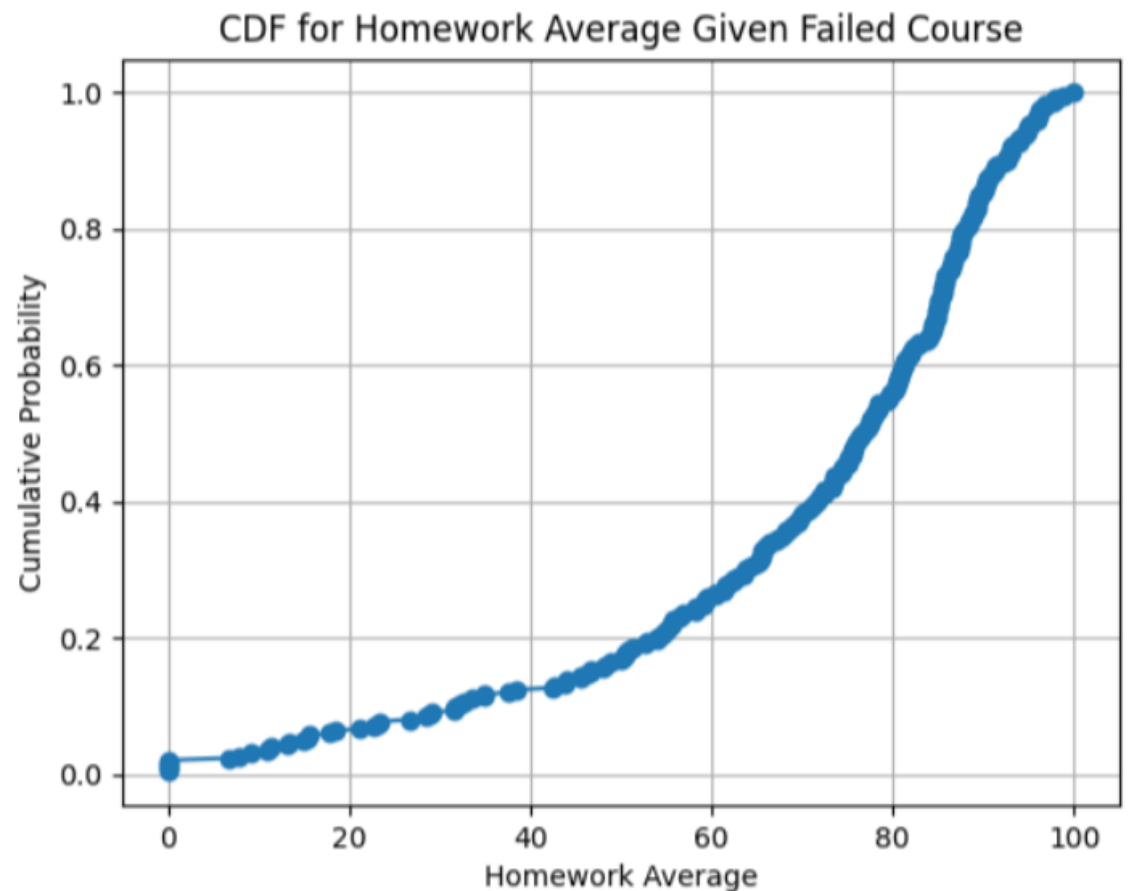
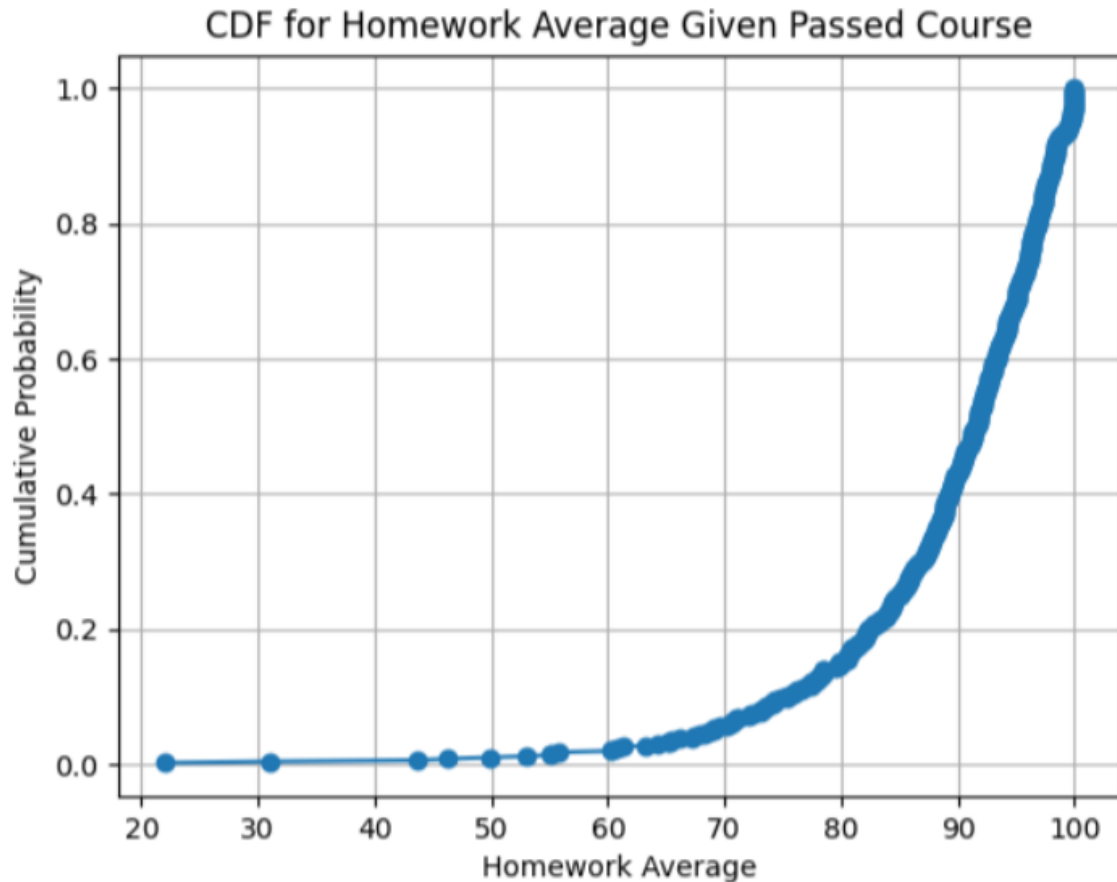
CDF for Test 1 Score Given Passed Course



CDF for Test 1 Score Given Failed Course

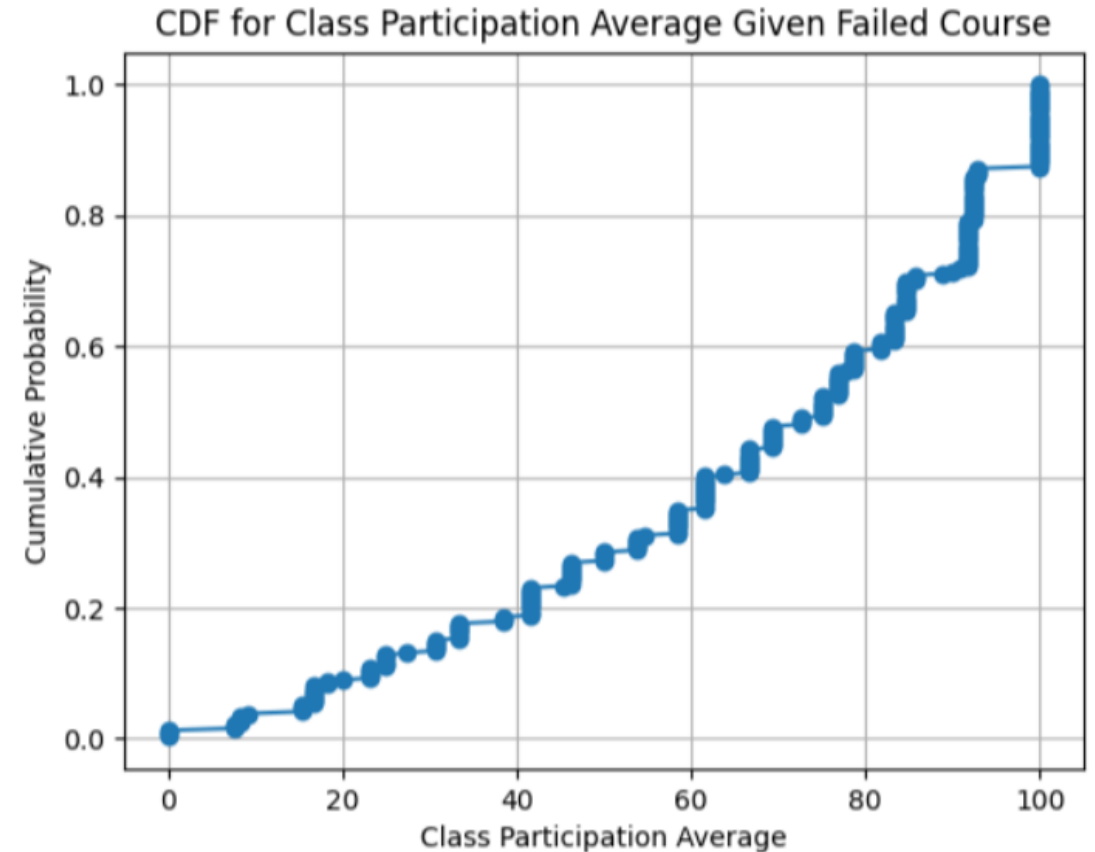
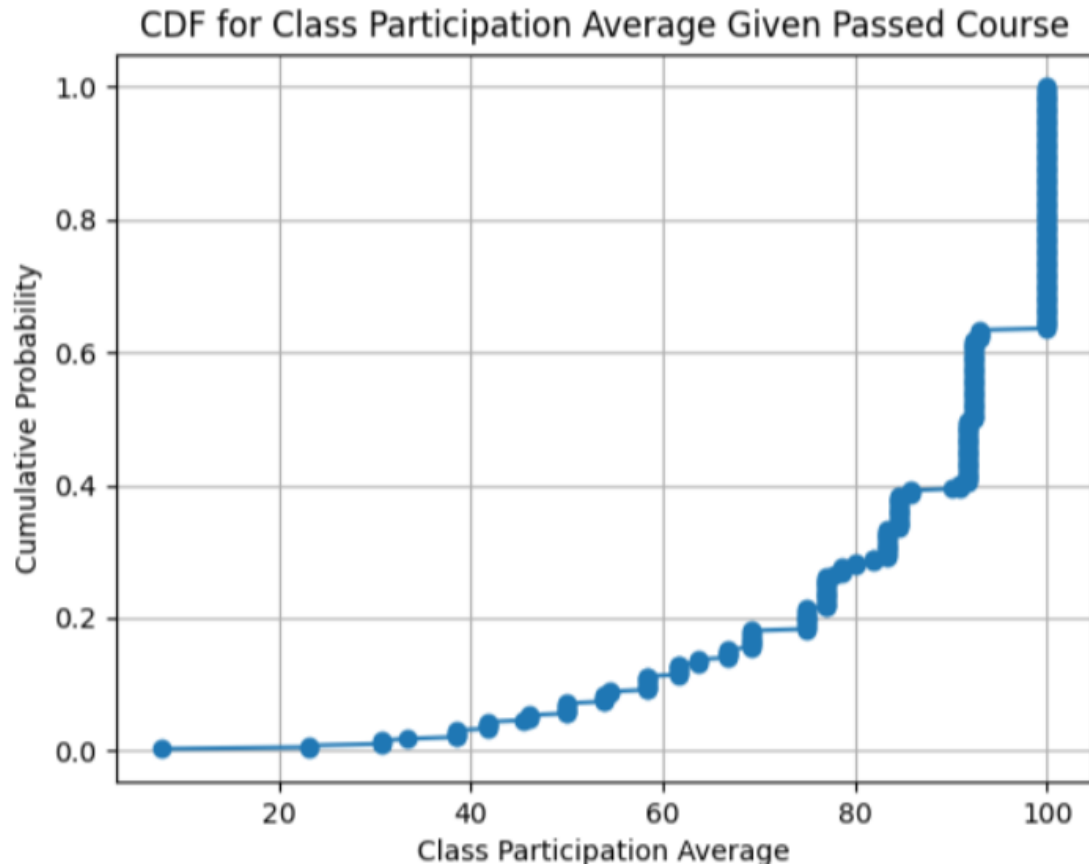


# 2022 CDF Homework Average



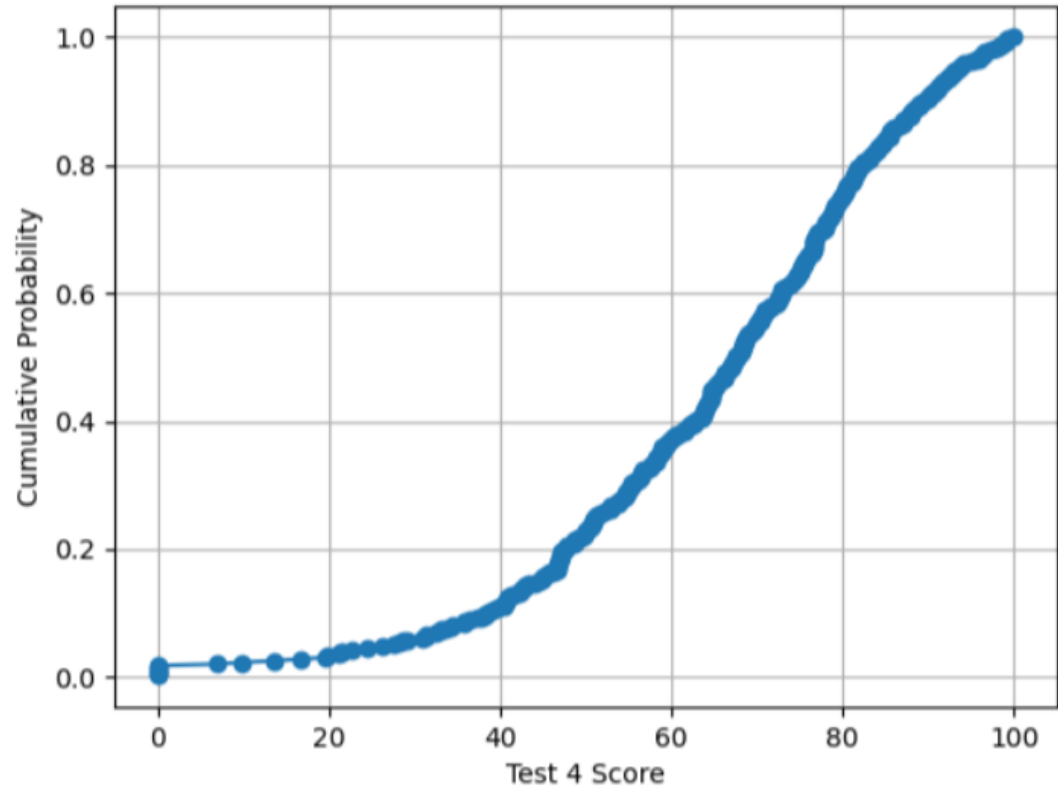


# 2024 CDF Class Participation

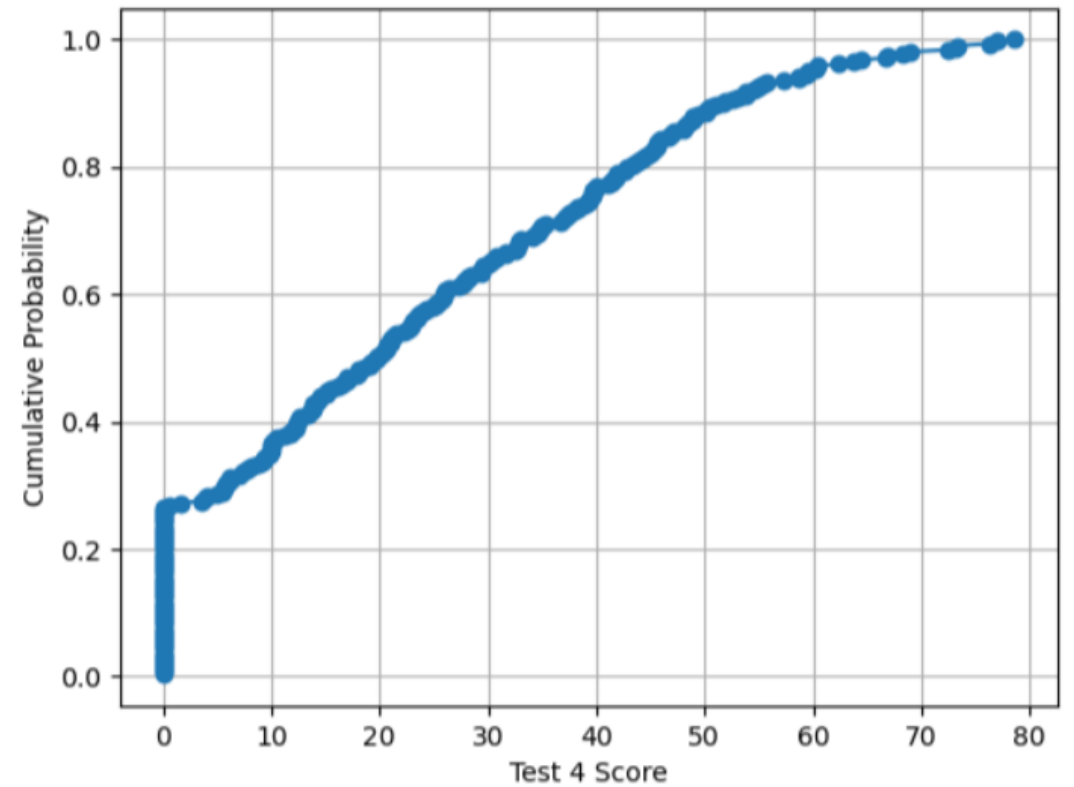


# 2024 CDF Test 4

CDF for Test 4 Score Given Passed Course



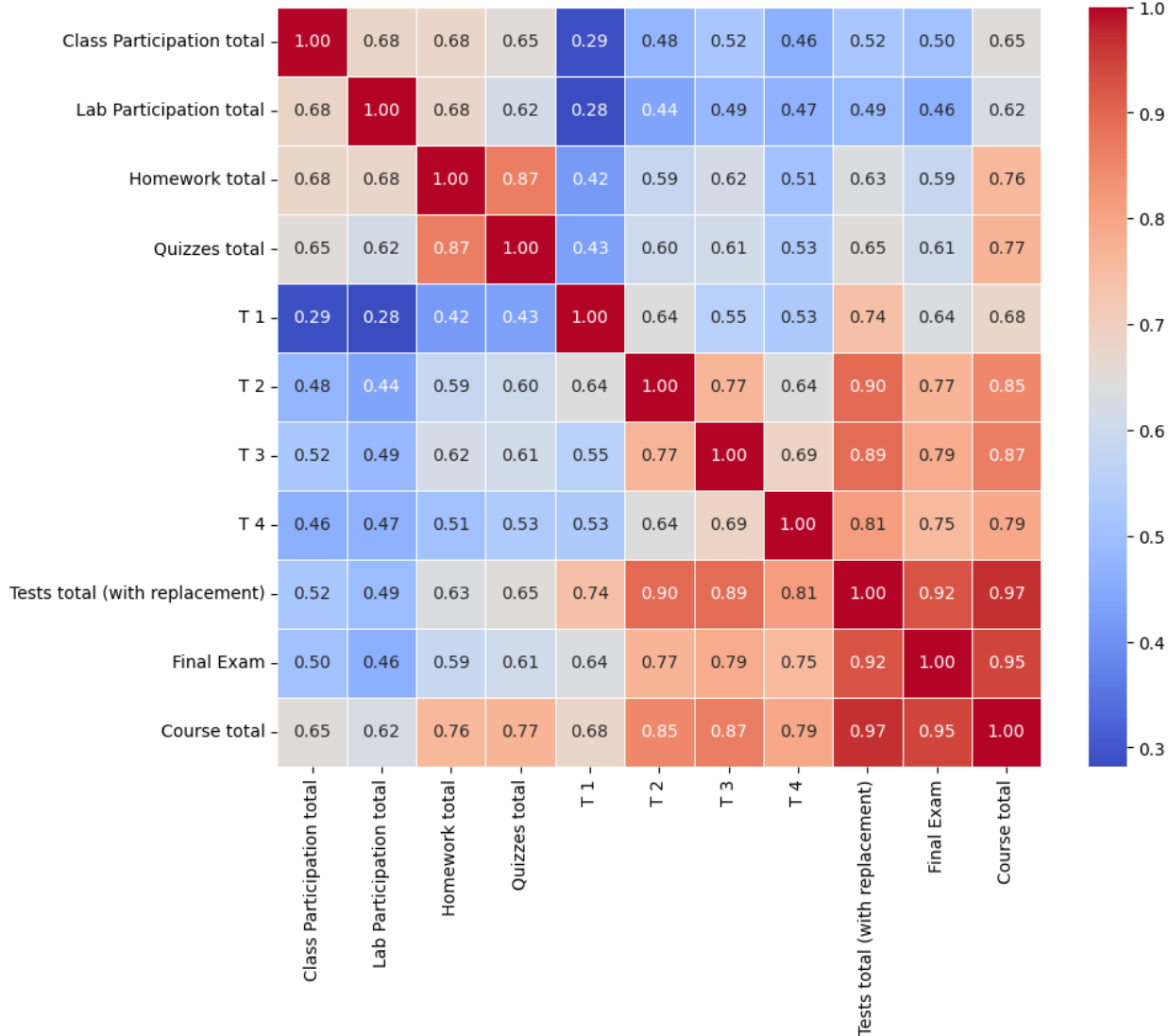
CDF for Test 4 Score Given Failed Course



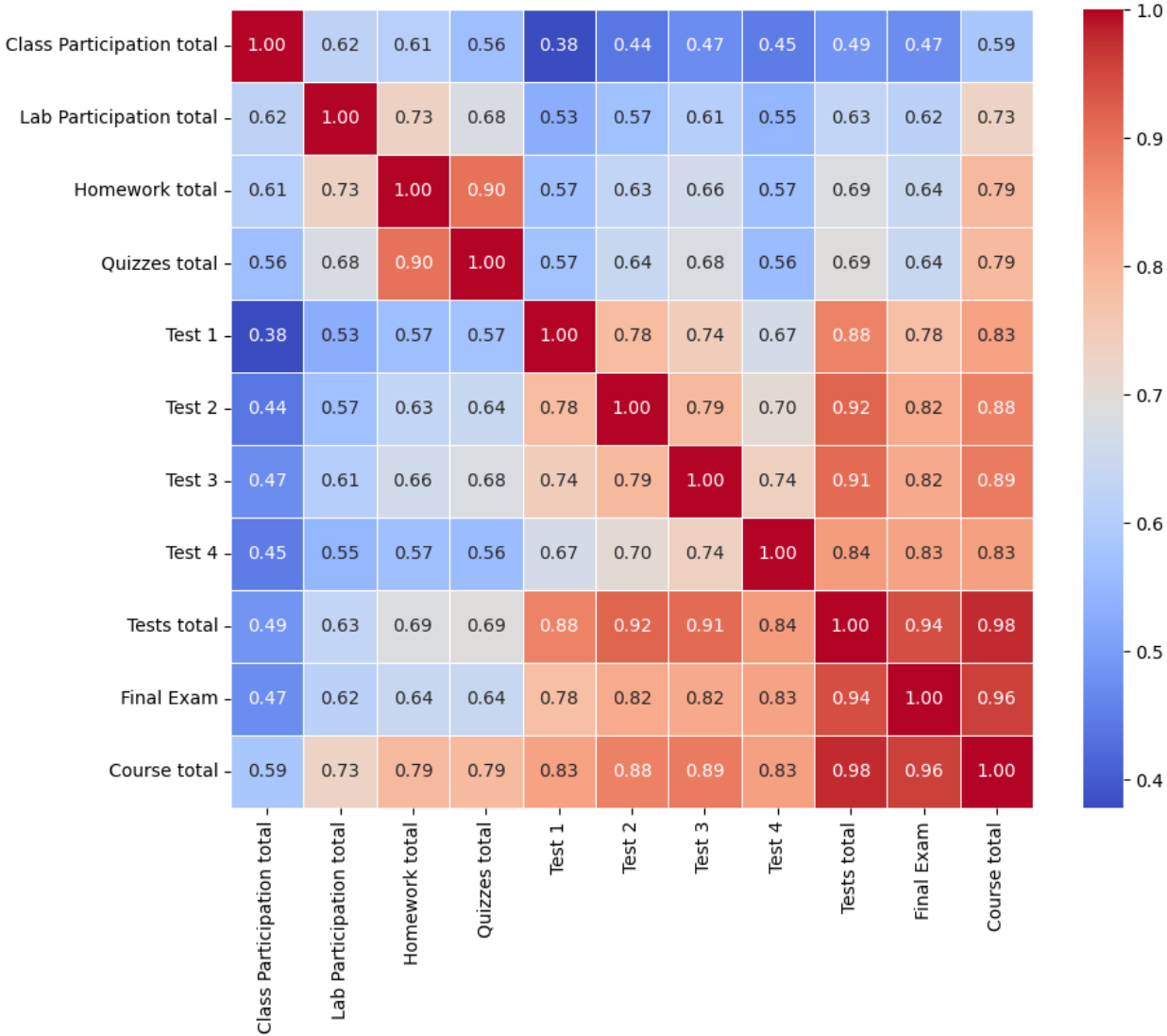
# Heat Maps



Correlation Matrix of MATH 1021 Fall '22 Course Data



Correlation Matrix of MATH 1021 Fall '24 Course Data



# Machine Learning – Background

- Now trained on 2024 Fall Semester
- Test Size – 25% of Data
  - Using data from before Test 1 and before Test 2
- Classification – Pass or Fail, doesn't consider final grade.
  - From last time we found that Logistic Regression to be best option.
- Regression – Course total prediction

# Classification – Preventing False Negatives

- Using Logistic Regression (found to have best performance)
- Added class weights (3 - 1)
  - o Class weights help the model prioritize reducing false negatives or false positives by adjusting the importance of each class during training.
  - o In this case were trying to minimize False Positives

| Key   |  |
|---|--|
| <b>True Negative</b> -<br>Correctly<br>predicted<br>failures    | <b>False Positive</b> -<br>Incorrectly<br>predicted passes |
| <b>False Negative</b> -<br>Incorrectly<br>predicted<br>failures | <b>True Positive</b> -<br>Correctly<br>predicted passes    |

| Logistic Regression<br>Equal Weights |           |
|--------------------------------------|-----------|
| 67                                   | <b>13</b> |
| 14                                   | 8         |

Accuracy: 85%  
Failure Accuracy: 89%  
Pass Accuracy: 84%

| Logistic Regression<br>3-1 Weights |          |
|------------------------------------|----------|
| 70                                 | <b>7</b> |
| 16                                 | 84       |

Accuracy: 87%  
Failure Accuracy: 81%  
Pass Accuracy: 92%



# Classification – Different Checkpoints

- Using Logistic Regression and Class weights (3-1)
- Found marginal increase in accuracy as semester progresses

| Up to Test I |    |
|--------------|----|
| 70           | 7  |
| 16           | 84 |

Accuracy: 87%  
Failure Accuracy: 81%  
Pass Accuracy: 92%

| Up to Test II |    |
|---------------|----|
| 70            | 4  |
| 18            | 85 |

Accuracy: 88%  
Failure Accuracy: 80%  
Pass Accuracy: 96%

| Pre Final Exam |    |
|----------------|----|
| 78             | 7  |
| 11             | 81 |

Accuracy: 90%  
Failure Accuracy: 88%  
Pass Accuracy: 92%

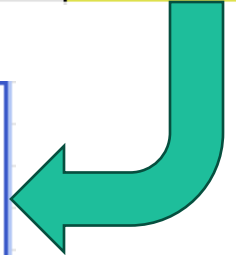


# Classification – Conclusions

| Student's Name | CI 1 | CI 2 | CI 4 | Wk 1 | Wk 2 | Wk 3 | Wk 4 | 1.1a | 1.7   | 1.4a  | 1.4b | 1.1b  | 1.8   | 1.6a | 1.6b | Q 01 | Q 02 | Q 03 | Test 1 | Prediction   |
|----------------|------|------|------|------|------|------|------|------|-------|-------|------|-------|-------|------|------|------|------|------|--------|--------------|
| Student a      | 1    | 1    | 0    | 100  | 100  | 100  | 0    | 100  | 98.29 | 100   | 100  | 100   | 100   | 100  | 90   | 100  | 98   | 100  | 55.1   | 0.3056218723 |
| Student b      | 1    | 1    | 1    | 100  | 100  | 100  | 100  | 100  | 98.29 | 96.88 | 100  | 96.77 | 93.75 | 97.3 | 100  | 100  | 100  | 70   | 89.5   | 0.9289520517 |

- Once the model weight are found, were able to create dynamic predictions using only Excel Spread Sheets
- This is done by adding the equation for the gradebook.
- If the model's prediction is **0.5 or higher**, it classifies the student as likely to **pass** – meaning the model is more than 50% confident in that outcome.

```
=1 / (1 + EXP(-(
-1.272
+ ((B3 - 0.939) / 0.239) * -0.06
+ ((C3 - 0.881) / 0.324) * 0.307
+ ((D3 - 0.837) / 0.369) * 0.004
+ ((E3 - 82.008) / 38.412) * 0.291
+ ((F3 - 78.409) / 41.145) * 0.338
+ ((G3 - 65.152) / 47.649) * -0.016
+ ((H3 - 75.568) / 42.968) * 0.318
+ ((I3 - 85.653) / 27.949) * -0.358
+ ((J3 - 76.27) / 35.74) * 0.548
+ ((K3 - 87.555) / 29.29) * -0.087
+ ((L3 - 79.634) / 33.944) * -0.083
+ ((M3 - 84.617) / 29.24) * 0.491
+ ((N3 - 87.716) / 27.828) * -0.182
+ ((O3 - 86.491) / 26.214) * -0.029
+ ((P3 - 80.232) / 30.364) * 0.588
+ ((Q3 - 71.842) / 35.41) * 0.001
+ ((R3 - 77.54) / 31.318) * -0.353
+ ((S3 - 79.579) / 28.127) * 0.429
+ ((T3 - 53.698) / 26.963) * 2.295
)))
```



# Regression – Feature Engineering

- Features used before Test 1:
  - CP before T1, HW before T1, LP before T1, QT before T1, and Test 1 Scores
- Features used before Test 2:
  - CP before T2, HW before T2, LP before T2, QT before T2, Test 1 Scores and Test 2 Scores
- Target: Final Course Grade ("Course total")

# Regression – Results

- Tested data over 100 random seeds and averaged all metrics

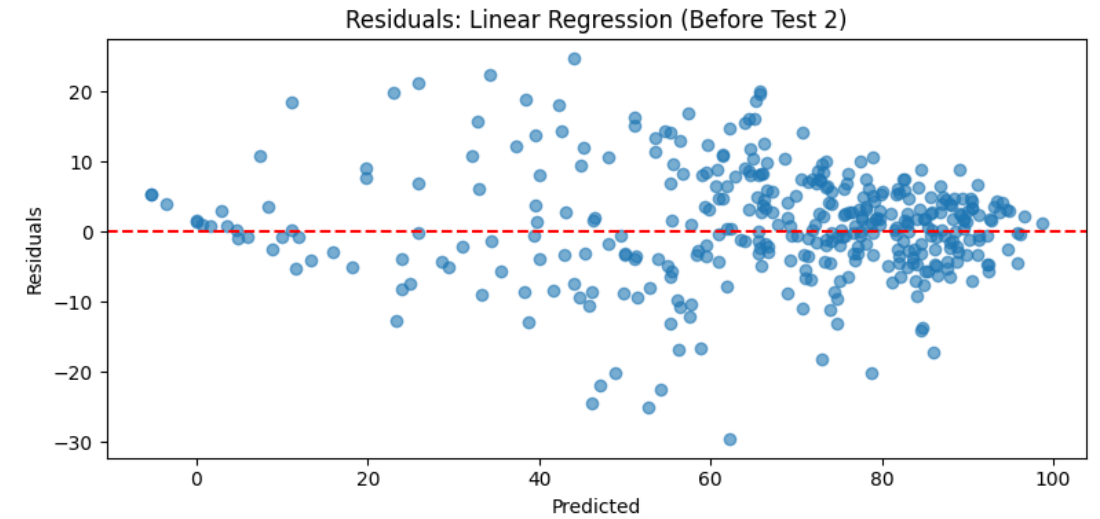
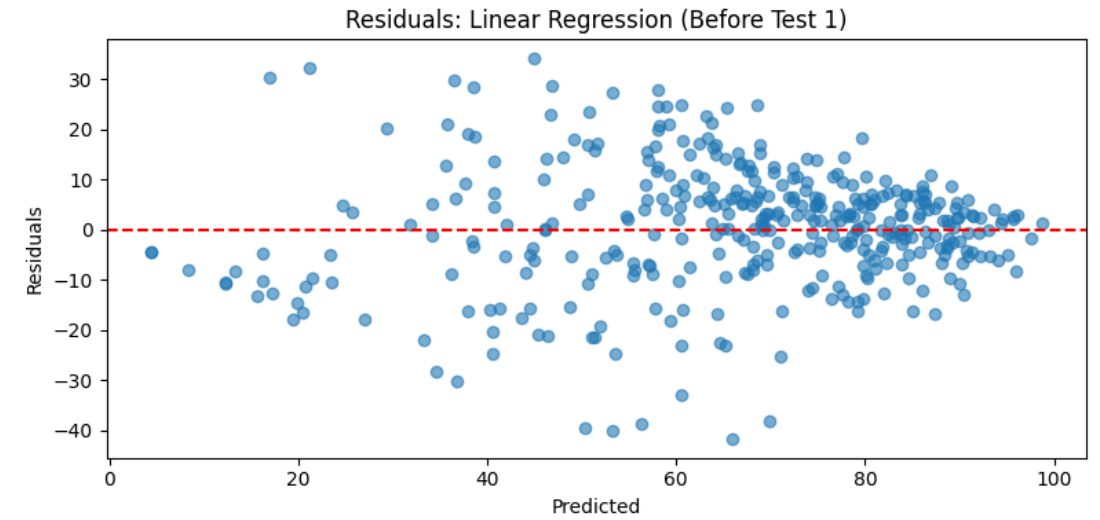
| Up to Test 1       |                    |
|--------------------|--------------------|
| Pass/Fail Accuracy | 78.34% $\pm$ 1.91% |
| MAE                | 9.61 $\pm$ 0.40    |
| RMSE               | 12.63 $\pm$ 0.54   |
| R <sup>2</sup>     | 0.671 $\pm$ 0.033  |

Correct Pass/Fail Predictions: 297 / 378

| Up to Test 2       |                    |
|--------------------|--------------------|
| Pass/Fail Accuracy | 85.55% $\pm$ 1.59% |
| MAE                | 6.35 $\pm$ 0.25    |
| RMSE               | 8.54 $\pm$ 0.37    |
| R <sup>2</sup>     | 0.849 $\pm$ 0.016  |

Correct Pass/Fail Predictions: 325 / 378

# Regression – Residual Plots



# Regression – Risk Flag Forecasting

| Prediction Categories |                    |                                |
|-----------------------|--------------------|--------------------------------|
| Likely Pass           | $\geq 75$          | High confidence of passing     |
| At Risk               | $69.5 \leq x < 75$ | Needs monitoring or support    |
| Likely Fail           | $< 69.5$           | High likelihood of not passing |

- Early flags let instructors target support before final grades are locked in
- "At Risk" students can benefit from tutoring, office hours, or check-in
- Forecasts can guide advisors in academic interventions or schedule adjustments.

# Regression – Conclusions

- Model accuracy improves over time
- Model is stable across random splits
  - Low variance in MAE, MSE, and  $R^2$  show that our model is robust
- Residual plots show better fit after Test 2
  - Before Test 1: Residuals show heteroscedasticity—larger errors for lower-performing students
  - Before Test 2: Residuals are tighter and more balanced, indicating improved fit
- Risk forecasting enables actionable insight

# Retake Policy and Average Gain

In the Fall 2024 semester, a retake policy was used for the first test.

- Students had the option for a second attempt at Test 1. If better, it replaced their original score. If
- If they did worse, it did not replace the original score.
- Did this improve student success? If so, would such a policy have been beneficial in 2022?

## Important Counts

Students who took the retake: 365

Students who did **not** take the retake and failed the course: 142



# For The Non-Retakers

Average gain for students who improved their score: 16 points

- For the 142 students who did not take the retake option, adding the average increase to their test 1 score allowed 6 students who did not take the retake to pass.
- This was the only change done.

For Fall 2022, no retake option was done.

- Out of 300 students who failed, 13 would have passed if their Test 1 score increased by the average gain seen in 2024.
- Thus, we could save approximately 4% of students who failed in 2022.
- This, once more, is even under the assumption that no other behaviors changed aside from a score increase.

# Summary of Findings

- Retake = large individual gains
- But minimal effect on failure rate
- Most failing students struggled beyond Test 1
- Test 1 can be an early warning
- Retakes help, but broader support is needed
- Focus on full-course performance

| Students who Participated in the Optional Test 1 Retake |        |
|---|--------|
| Category  | Counts |
| Total   | 365    |
| Passed the Course                                       | 195    |
| Less than C- on First Attempt                           | 322    |
| Less than C- on First Attempt and Passed                | 161    |
| Less than D- on First Attempt                           | 268    |
| Less than D- on First Attempt and Passed                | 116    |

# More We Hope to Find

- Identify the highest and lowest performing quarters for Math 1021 students, analyzing whether these performance patterns are consistent across both 2022 and 2024 semesters. Explore possible reasons for observed trends or discrepancies.
- **Initial Findings:**

| 2024 Averages of Grade Categories by Test Block (Removing 0's) |       |              |       |              |       |              |       |
|--|-------|--------------|-------|--------------|-------|--------------|-------|
| Test 1 Block   |       | Test 2 Block |       | Test 3 Block |       | Test 4 Block |       |
| Test 1   | 56.42 | Test 2       | 65.60 | Test 3       | 66.56 | Test 4       | 53.03 |
| HW   | 92.31 | HW           | 86.49 | HW           | 88.07 | HW           | 86.03 |
| Q  | 87.85 | Q            | 83.71 | Q            | 82.81 | Q            | 86.10 |
- Interestingly, higher test averages on a collection of assignments don't reflect a higher performance on assignments relevant to these tests, even when removing 0's.
- Though homework averages are positively correlated with test performance (heatmaps).

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