Technical Assignment 3

Ying Du (Amelia)

Faculty of Information, University of Toronto

INF2178 LEC0101

Shion Guha

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Introduction

For this analysis report, I have focused on the data from a longitudinal study conducted on young children in 1998-99. The data includes continuous variables, the reading, math, and general knowledge scores of Kindergarten students during fall 1998 and spring 1999 measurements taken over several months.

The report aims to comprehensively analyze the various factors that could influence the students' reading and math score improvements over time. It also attempts to determine whether different factors have interactive effects on the students' score improvements.

Research Questions

I have noticed that students have varying levels of general knowledge. As a result, I planned to use their fall general knowledge as a baseline to compare how their math and reading scores improve over time based on their income group. My research question is:

- How does income status affect the improvement of reading and math scores among kindergarten students, considering their varying general knowledge levels?

To answer this question, I employed a rigorous methodology. I began with exploratory data analysis to understand the distribution of score improvements across income groups. Next, I plotted an interaction plot to determine if different factors have interactive effects. Finally, I used ANCOVA to confirm the findings from the plot and to examine how reading and math scores change over time by income group in-depth, using general knowledge scores as a covariate. This comprehensive approach ensures the reliability and validity of the findings.

Exploratory Data Analysis (EDA)

The boxplots visualize the improvements in reading, math, and general knowledge scores from fall to spring across different income groups.

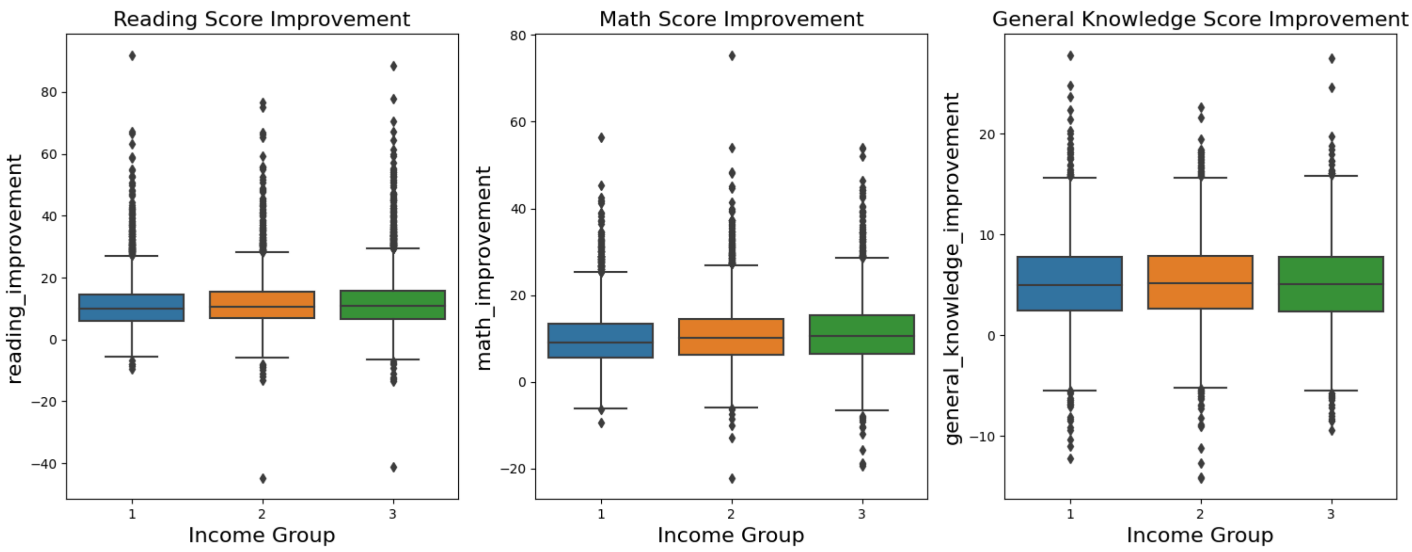

Figure 1. Boxplots for Score Improvements

Figure 1 above shows the variability in score improvements across income groups for different subjects. Given that 3 represents the highest income group based on the dataset, we notice that the boxplot for math score improvement indicates that higher income groups might have slightly larger improvements. However, this trend is not shown for reading and general knowledge improvements, and the improvements in math scores for all three income groups are less than both reading and general knowledge improvements. Moreover, The century tendency line of income group 1(lowest income) of the math score improvement boxplot towards the lower quartile indicates that the majority of the students' score improvements in that group are lower than the overall median.

I also noticed that the boxplot for general knowledge improvement shows broader interquartile ranges (IQR) among different income groups compared to the others, suggesting that the middle 50% of the score improvements are spread out over a wide range of values. The spread suggests a various set of score improvements in terms of general knowledge. The reading boxplot shows the opposite, with a narrower IQR, which indicates uniformity in reading score improvements.

In general, the above boxplots show no significant differences in score improvement among different income groups for the three subjects.

Interaction Plot

According to the EDA, income groups themselves do not have a significant impact on score improvements in different subjects. So, I decided to look at the interaction plots to explore the relationship between income groups and general knowledge levels on score improvements.

To make the interaction clear, I categorized the fall general knowledge scores into three quantile-based groups:

Reading Score Improvement Interaction

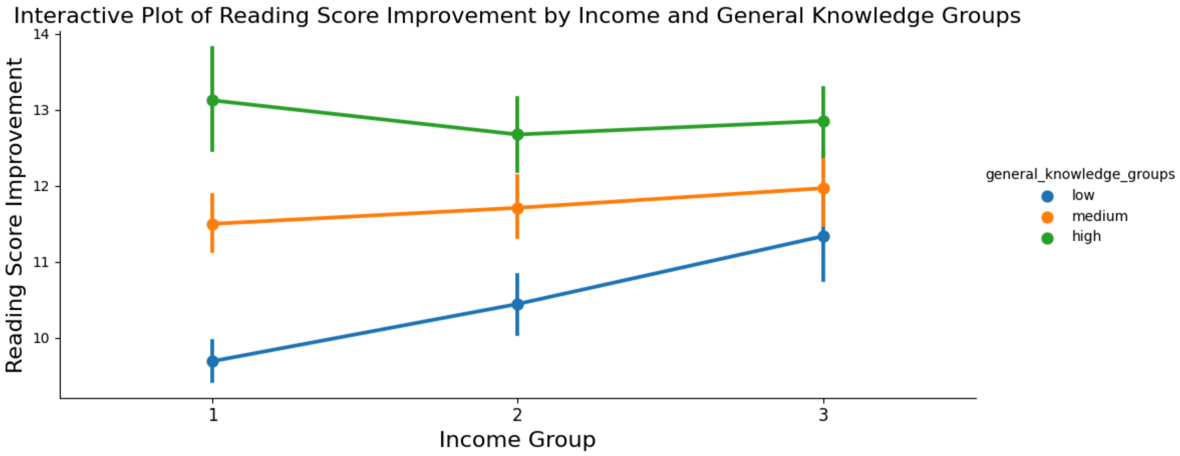

Figure 3. Interactive Plot of Reading Score Improvement

Figure 3 indicates variability in reading score improvement across income groups and general knowledge categories. The differences in improvements suggest that both the income group and the level of general knowledge in the fall can influence how much students improve in reading over time. However, the lines in the plot are very close to each other without significant separation, and their trends are relatively consistent across different income groups, which suggests that **while the plot suggests few interactions between these variables, the interaction effect might not be strong or statistically significant.**

Math Score Improvement Interaction

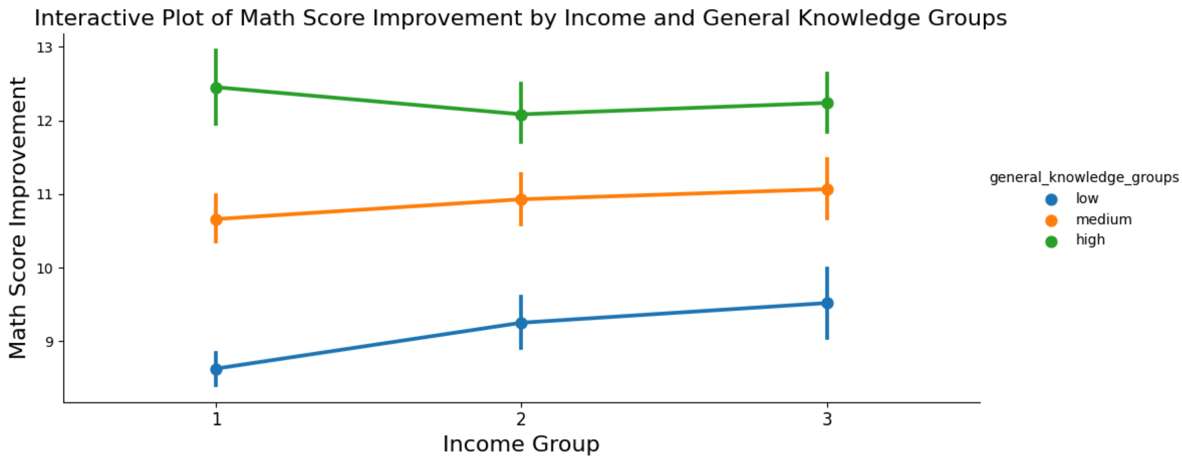

Figure 4. Interactive Plot of Math Score Improvement

Similar to reading scores, the math score improvement interaction plot in Figure 4 shows variability across income groups and general knowledge categories. The pattern of improvements appears to be influenced by the fall general knowledge, but again, the lines are relatively close together with a relatively consistent trend, indicating that **the interaction effect might not be strong or statistically significant.**

Based on the plot, we can infer that students' improvement in reading skills is affected by their income group and level of general knowledge in the fall. However, to determine whether this influence is significant, we need to conduct an ANCOVA test.

ANCOVA Assumptions Testing

Normality of Residuals

To test the normality of the residuals, I conducted the Shapiro-Wilk test.

- Residuals for Reading Scores: p-value < 0.001,
- Residuals for Math Scores: p-value < 0.001,

According to the Shapiro-Wilk test for normality, the residuals of the spring reading scores and math scores are not normally distributed (p-value < 0.001). This indicates that the assumption of normality is not met when predicting the spring reading and math scores from the fall reading, math, and general knowledge scores.

Homogeneity of Variances

- Residuals for Reading Scores: p-value = 2.67e-12 < 0.05
- Residuals for Math Scores: p-value = 1.39e-13 < 0.05

The Levene test for homogeneity of variances indicates that the variances of residuals for reading and math scores are not equal across income groups (p-value < 0.05). Therefore, the assumption of homogeneity of variances has been violated.

Thus, we need to keep in mind that implementing ANCOVA in this dataset may affect the accuracy of the analysis result.

One-way ANCOVA Result

Source	sum_sq	df	F	PR(>F)
C(incomegroup)	287.49	2.0	2.25	1.05e-01
fallgeneralknowledgescore	14054.12	1.0	220.11	2.35e-49
Residual	761671.04	11929.0	NaN	NaN

Figure 2. ANCOVA Result for Reading Score Improvement

Source	sum_sq	df	F	PR(>F)
C(incomegroup)	55.88	2.0	0.62	5.36e-01
fallgeneralknowledgescore	22425.93	1.0	501.08	9.43e-109
Residual	533880.50	11929.0	NaN	NaN

Figure 3. ANCOVA Result for Math Score Improvement

Reading Score Improvement

Based on the data presented in Figure 2, it can be concluded that when the baseline fall general knowledge scores are taken into account, the impact of income groups on improvement in reading scores is not statistically significantly different(p-value = 0.105).

The results also show that a student's general knowledge score in the fall has a significant impact on their reading score improvement (p-value < 0.05). This suggests that students who have higher general knowledge scores in the fall tend to show greater improvement in their reading scores (coef > 0). The findings emphasize the significance of general knowledge as a predictor of reading development.

Math Score Improvement

Similar to reading scores, the income group does not have a significant impact on the improvement of math scores (p-value = 0.536). This indicates that there are no significant differences in math score improvement between different income groups after the fall general knowledge is accounted for.

However, the baseline fall general knowledge score has a significant impact on the improvement of math scores (p-value < 0.05). The analysis indicates that students who had higher general knowledge scores in the fall generally showed greater improvement in their math scores (coef > 0).

Conclusion

Based on the comprehensive analysis results of this dataset, it appears that good general knowledge in the fall is a vital factor affecting improvements in students' reading and math scores, which is more significant than the income group classification. However, since the assumptions of ANCOVA are not fully met, the violation could affect the validity of the ANCOVA results, and these findings should be interpreted with caution. Moreover, there might be other factors not captured in this analysis that might influence academic improvements over time, which would need further data collection.

Data Reference

Joshi, A. (2023, April 23). *Understanding Ancova and implementing it with python: A comprehensive guide*. Medium. https://anuragjoshi70.medium.com/understanding-ancova-and-implementing-it-with-python-a-comprehensive-guide-6e3895c90ecc

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