Going the Distance: How Commute Time Affects Performance

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Abstract

A data set combination of student performance and potentially relevant student characteristics from the UCI Machine Learning Repository was used to help identify any relationship between commute time and student performance, which could potentially be extrapolated to influence commute-related educational decisions and public policy. The data sets were manipulated and analyzed using the pandas software library, written in the Python programming language, establishing clear correlations between data attributes. Matplotlib and seaborn, a matplotlib enhancement, were used to visualize the correlations between data set attributes, primarily through the use of pairplots. This report’s analyses established a clear negative correlation between student commute time and performance from the data. However, due to the highly limited data set and statistical limitations of this report, additional research into commuting and human performance is needed to generate more comprehensive conclusions that might help influence public or educational policy.

Motivation

Long commutes are a tremendous problem for society to mitigate. More driving comes with significant hazards, from increased greenhouse gas emissions to a greater number of traffic accidents. As we determine what degree of resources we should allocate to addressing this issue, we need to quantify the relative impact commuting has on us and our surroundings. There are only so many resources we can invest in any of the many challenges our society is facing. Thus we must determine how detrimental commuting is before we can justify allocating limited resources to help mitigate it.

Additionally, as one of the critical suppliers of those public resources is tax revenue, determining how commute times affect our performance seems like a valuable area of study. Education is crucial for allowing individuals to reach their economic potential. Since many students may consider commuting longer distances to save money on housing costs, it seems valuable for them, their advocates, and their educational institutions to analyze whether or not the costs of their increased commute times outweigh the benefits.

To do this, we need a data set that can help determine the relationship between transit time and student performance. Fortunately, UC Irvine’s Machine Learning Repository has a data set combination that can do just that.

Dataset(s)

This is a multivariate data set with integer attribute characteristics. There are 1044 data instances across 33 attributes in two data sets. There are no missing values. The data sets are kept at the UC Irvine Machine Learning Repository and were originally gathered from secondary school students in two Portuguese schools in Portugal's Alentejo region. The data were collected during the 2005-2006 school year. The data consist of various demographic and characteristic values for each student and describe their academic grades in each of two subjects at three different instances. The dataset combination includes an attribute key describing what each attribute name refers to and how the attribute was measured.

Specifically, the dataset was obtained from:
https://archive.ics.uci.edu/ml/datasets/Student+Performance

Data Preparation and Cleaning

Fortunately, the data set had no missing values, and the data was formatted appropriately for analysis through two csv data files.

The only issue was that pandas presumes that the values in a csv file are separated by commas for the read_csv function. However, a quick review of pandas documentation, and adjusting the code accordingly, allowed the data sets csv files with values separated by semicolons to be properly read by pandas.

Research Question(s)

When comparing time spent commuting to student performance measures, do any meaningful trends emerge when focusing on a sample of Portuguese secondary school students? Can these conclusions be extended to the wider population to help influence public policy?

Methods (1/3)

1) A Jupyter notebook was created for this project, which is included alongside this presentation. Pandas, a Python library, was imported into the notebook to analyze the data. Written in the Python programming language, pandas is a software library designed for data manipulation and analysis.

2) Pandas expects csv file data to be separated with commas by default. Thus, as the csv data sets used in this project were separated by semicolons instead, the read_csv function was modified to accommodate this and the data was successfully read with pandas.

3) The data set was then partially reviewed to confirm the csv was properly processed by pandas. An attribute key describing each abbreviated attribute name was linked in the project's Jupyter notebook to make the identities of the data set more accessible to a reviewer.

[The attribute key was originally given here, by UCI: https://archive.ics.uci.edu/ml/datasets/Student+Performance#]

4) The data set was then limited to values that seemed relevant to travel time and performance; namely the student's reason for selecting the school, where distance from home was a given reason for selection; study time for the students, which will be useful in determining how study time relates to performance; and student performance measures at three different course checkpoints. Number of absences were also included to see if they were correlated with travel time.

Methods (2/3)

5) Using pandas .describe(), the descriptive statistics of the values were then displayed and reviewed, where it was noted that very few students experienced significant travel time. This scarcity of data representing higher travel times may significantly reduce the conclusive power of this project.

6) Any initial trends from the descriptive statistics were explored further, in this case via pandas .mode() to confirm that the most frequent travel time value was the value representing the least travel time. It was also noted that the most frequent reason for selecting the school was not the school's distance from the student's home, which suggests that travel time was not highly important to most students.

7) Suspected correlations were then explored further with pandas .corr(), where notable correlative relationships were identified between the analyzed attributes. These relationships will be analyzed more in the Findings section of the project. Notably, it was identified that the number of absences was not significantly correlated with travel time.

8) To visualize the data, matplotlib was imported into the Jupyter notebook, along with seaborn, a matplotlib enhancement.

Methods (3/3)

9) A pairplot was then created using seaborn. Pairplot scatterplots allowed attributes to be visually compared against each other. Regression lines were also added to the pairplots using the kind=”reg” parameter, allowing us to more easily visualize the correlations between attributes in each of the scatterplots. Additionally, histograms were formed when the pairplots caused an attribute to be compared against itself, allowing each attribute's relative frequencies to be compared in the attribute histograms.

Importantly, when the histograms are formed, the labeled y-axes of the pairplots are not accurate for the histograms, and so the y-axes for the histograms should largely be ignored and the height of the bars used instead to determine the relative frequency of these attribute values. [This will be much more apparent in Findings later, and is also evident in the included Jupyter notebook for the project.]

In our Jupyter notebook, sns.histplot() was then used for the travel time attribute, which was one of the histograms in the pairplot, to demonstrate how the true y-axis of the histograms is a measure of the frequency of the attribute values in a given discrete bin. This confirms that the y-axes listed in the seaborn pairplots should not be used for the histograms.

The scatterplot-and-histogram-visualized results will then be used to help identify and describe correlations and frequency distributions in our data set, which will contribute to our findings later in the report.

10) An image for the pairplot visualization was then created for use in reporting our findings.

11) The above procedure was then repeated for the csv file measuring attributes for the Portuguese class data, as this unique data helps provide more context to the trends we observe in the Math class data, allowing us to draw firmer conclusions from our data.

Findings (1/7)

As a result of our analysis, we were able to identify that the data demonstrated that the students' travel time to school was negatively correlated to their grades in the course. In the case of their math performance, the strength of the negative correlation for travel time was greater than the strength of the positive correlation for study time in terms of the student's final course grade, which should help underscore how powerfully negative commuting can be.

Thus, using the data sets in this project, we have been able to answer our research question and demonstrate that student travel time does appear to be related to student performance. In addition, we are able to confirm our suspicion that the relationship between commute and performance would be negative.

Findings (2/7)

We were able to easily identify these findings using the the correlation function on the attributes relevant to our analysis, namely:

traveltime - home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)

studytime - weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)

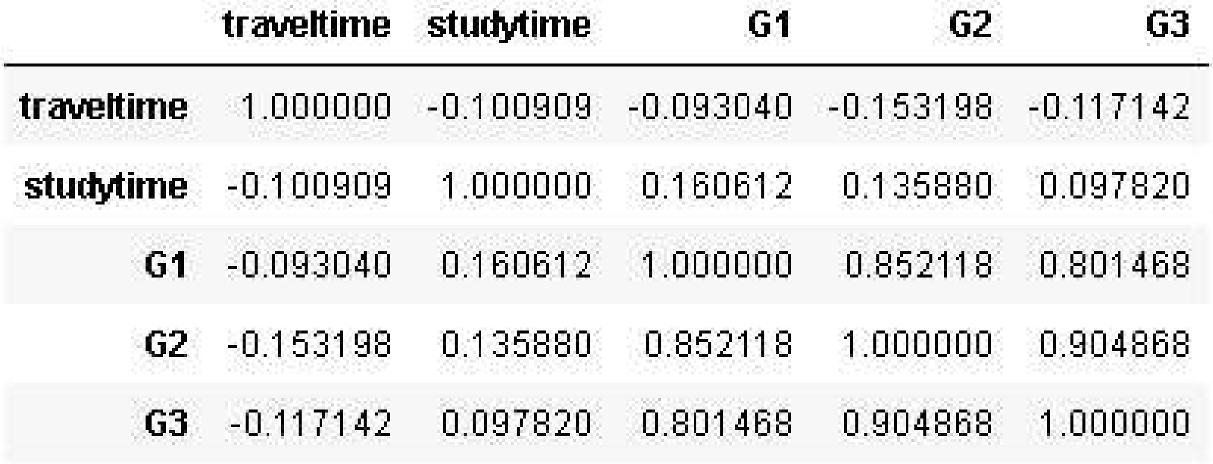
G1 - first period grade (numeric: from 0 to 20)

G2 - second period grade (numeric: from 0 to 20)

G3 - final grade (numeric: from 0 to 20, output target)

Findings (3/7)

Math data set correlations:



	traveltime	studytime	G1	G2	G3
traveltime	1.000000	-0.100909	-0.093040	-0.153198	-0.117142
studytime	-0.100909	1.000000	0.160612	0.135880	0.097820
G1	-0.093040	0.160612	1.000000	0.852118	0.801468
G2	-0.153198	0.135880	0.852118	1.000000	0.904868
G3	-0.117142	0.097820	0.801468	0.904868	1.000000

Please note the negative correlations between travel time (“traveltime”) and the grade score at each of three grade checkpoints (“G1”, “G2”, and “G3”). In the case of the final two grades (“G2” and “G3”), the negative correlation of travel time is greater in magnitude than the associated positive correlation of study time.

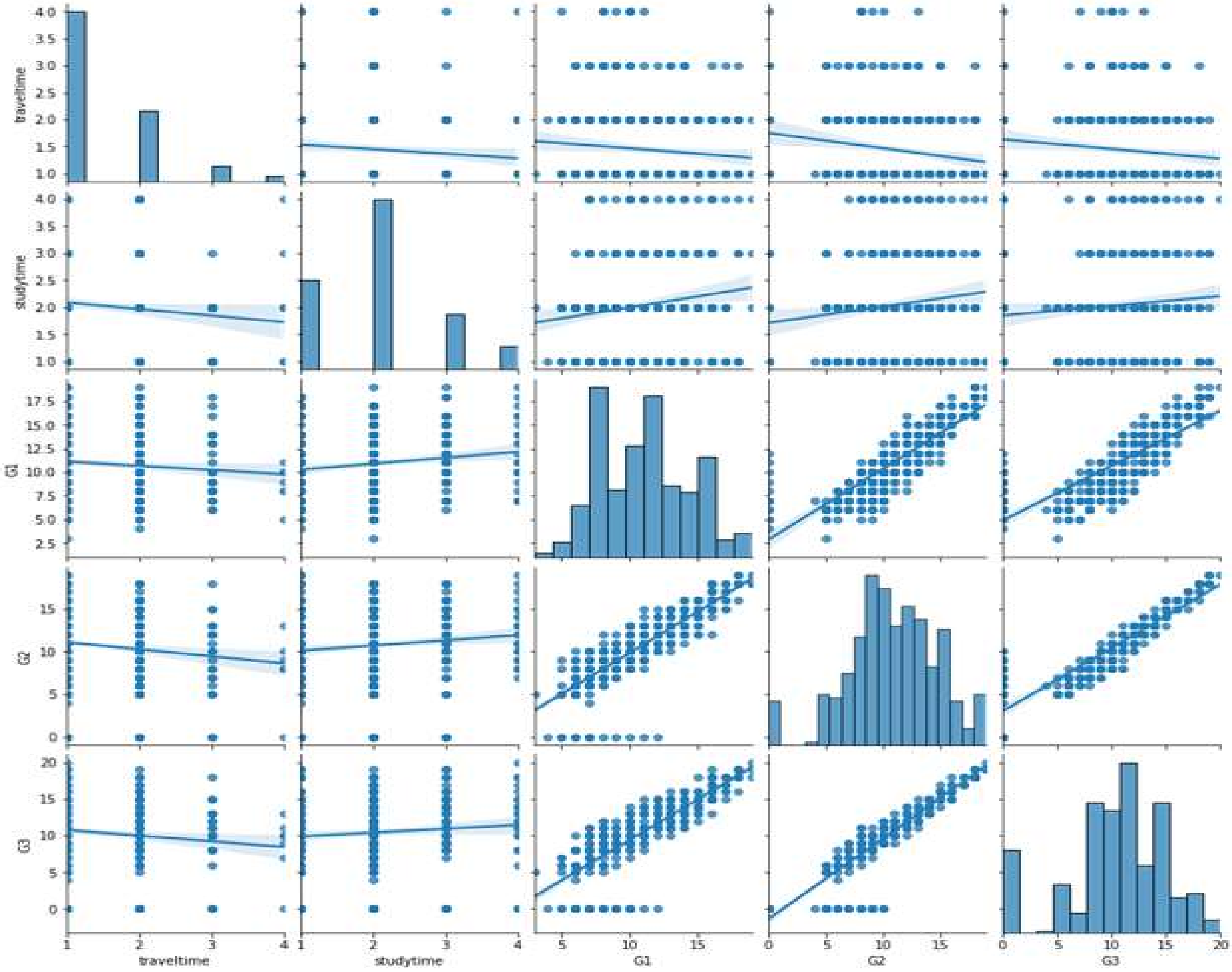
The pairplot on the next slide helps visualize these attribute relationships (in the form of scatterplots) and the frequency of the attribute scores (in the case of the histograms). [Please note, the y-axes of the visualizations only refer to the scatterplots. The y-axes of the histograms are just a general count of the frequency of a given attribute score. (The higher the histogram bar, the more frequently that score was reported.)]

Findings (4/7)

Math Data Set PairPlots (Scatterplots and Histograms)

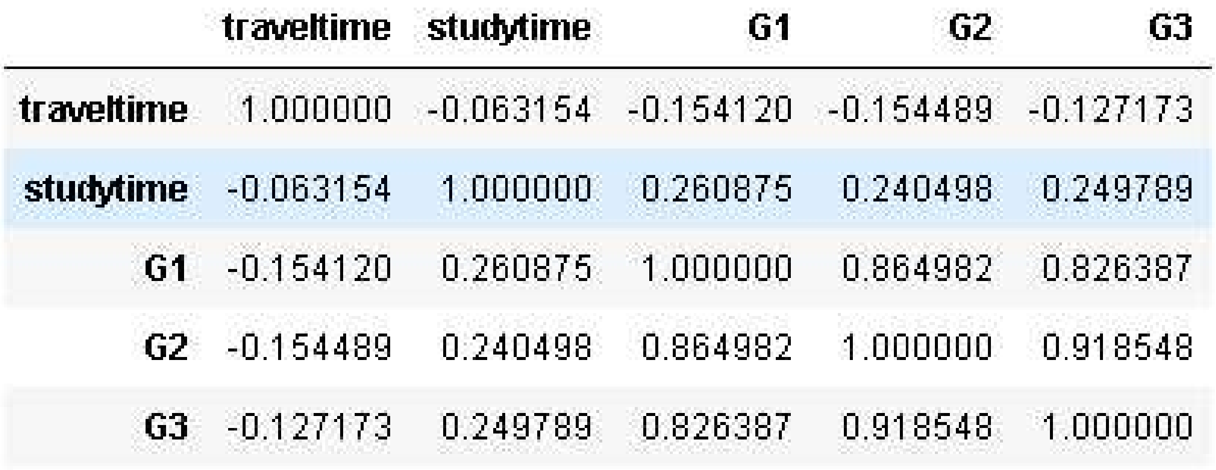
Scatterplot regression lines help identify the correlation between the two attributes being compared.

(Notably, the scatterplots in the upper right show a negative correlation between travel time and the scores at each grade checkpoint.)



Findings (5/7)

Portuguese data set correlations



	traveltime	studytime	G1	G2	G3
traveltime	1.000000	-0.063154	-0.154120	-0.154489	-0.127173
studytime	-0.063154	1.000000	0.260875	0.240498	0.249789
G1	-0.154120	0.260875	1.000000	0.864982	0.826387
G2	-0.154489	0.240498	0.864982	1.000000	0.918548
G3	-0.127173	0.249789	0.826387	0.918548	1.000000

As we can see from the correlations above, travel time is again negatively correlated with performance at each of the grade checkpoints.

Additionally, in the next slide, we can see how the pairplots help illustrate these correlations.

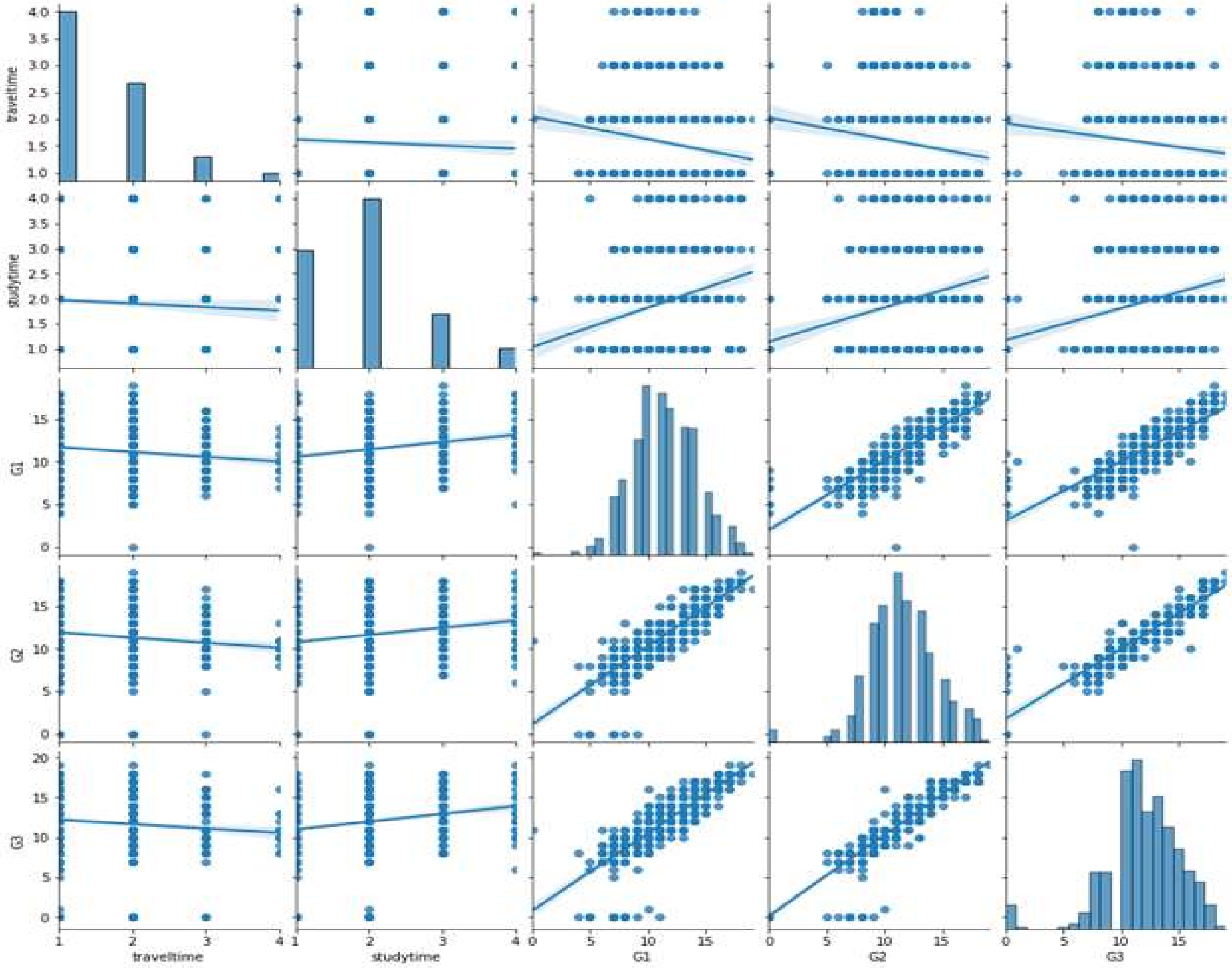
Findings (6/7)

Portuguese Data Set PairPlots

Scatterplot regression lines help identify the correlation between the two attributes being compared.

(Notably, the scatterplots in the upper right show a negative correlation between travel time and the scores at each grade checkpoint.

Visually, we can see that these negative correlations between scores and travel time are more negative for Portuguese scores than for the math scores in the previous data set.)



Findings 7/7

As we can see from the visualizations, the scatterplots' regression lines identify the correlations between the two attributes being compared in each scatterplot.

In the case of both Portuguese and Math courses for these Portuguese students, travel time is negatively correlated with course grades, strongly suggesting that travel time impacts student performance, which is the question we were hoping to answer in our analysis. We were also able to better assess how travel time influenced student performance relative to other factors, like study time. Unfortunately, due to the limited data sets, it won't be easy to extend these conclusions to the broader community or influence public policy without more robust supporting evidence.

The histograms of these visualizations are also valuable, as they help us better identify the frequency of an attribute's scores. Importantly for our analyses, the travel time histograms in the upper left of the pairplots identify that most students in both course data sets have travel time attribute scores reflecting the least amount of travel time. This lack of high travel time data is an unfortunate limitation on our ability to analyze the effect of high commute time on student performance.

We can also identify other findings from the scatterplots and histograms that are less relevant to our research question, such as the visual suggestion that not all students took all the exams based on their resulting scores of zero. These outlier scores represent another limitation of our study that may affect our ability to draw meaningful conclusions from the data.

Limitations (1/2)

Unfortunately, while the data set was very accessible and did not require a significant amount of cleaning for use in our project, some clear limitations prevent us from drawing firm conclusions about how commute time may affect performance.

We must recall that the data set contained data from the 2005-2006 school year. Students were from the Alentejo area of Portugal, attending one of two public schools. This highly specific data set means that it will be challenging to extend the conclusions from our analyses very far. Also, the fact that we only have 1044 records across both data sets suggests the conclusions we can draw are much less powerful than if we had a much larger number of records to work with, especially a larger number of records from a more diverse sample population.

Additionally, as our statistical proficiency is not very developed based on this course's scope, there is likely more we could have done using more advanced statistical methods to improve on our analyses and the resultant conclusions. Another clear limitation based on this lack of statistical prowess is the potential for one of the other attributes to confound the relationship between travel time and performance.

Future research could therefore involve applying more advanced statistical methods to determine if more conclusive results could be obtained from these data sets. However, based on the highly specific nature of the data set, the results may not be particularly meaningful to our wider understanding of commute time and performance

Limitations (2/2)

Additionally, as seen in our Jupyter notebook for the project, absences were notably negatively correlated with grades at each checkpoint. This negative correlation was similar to the negative correlation between travel time and checkpoint grades.

However, absences were only very weakly negatively correlated with travel time. Thus, to draw more firm conclusions about how travel time, checkpoint grades, and other attributes may be related, more elaborate statistical methods are likely needed. It would seem that establishing these more complicated relationships would be necessary to remove their influence on the critical relationship we are looking to study: commute time and performance.

Thus, while this research question represents a valuable starting point, there is obviously much more that would need to be done in order to draw more compelling conclusions that may, in turn, influence public policy and government spending.

Conclusions (1/2)

Through this analysis, we were able to identify that time spent commuting (“traveltime”) had a measurable and consistently negative relationship with student performance in Math and Portuguese courses in our two-school sample of Alentejo-area Portuguese secondary students from the 2005-2006 school year. In fact in the Math course, school commute time appeared to have a stronger relationship with student performance at two of the three grade checkpoints than time spent studying did. However, in both courses, while time spent studying was correlated with higher grades, time spent commuting was associated with lower grades.

While we would likely need to use more advanced statistical methods and use a larger sample set to draw more decisive conclusions, it seems that we have clearly identified a trend in school commute’s relationship with student performance in our sample population. This trend also helped confirm the suspicion that led to our research question: that commute time would be associated with adverse outcomes in student performance.

Conclusions (2/2)

Unfortunately, as mentioned, without a more comprehensive statistical analysis and a much larger data set, it would be difficult to justify extending our conclusions to larger populations, especially in designating public funding. However, our project should help justify the need for additional research into the harmful effects of commute time and how we might work to mitigate those effects.

So, while we might not have definitively answered the research question for society, we hope that this research has helped contribute to the overall discussion of commuting time and performance.

Acknowledgments

The author would like to thank the UC Irvine Machine Learning Repository for hosting the data sets used in this analysis. In addition, we would like to thank the Portuguese researchers who helped obtain the data and consented to have it hosted at the Machine Learning Repository.

Also, we are incredibly grateful to the scientists, especially data scientists, who are kind enough to share their knowledge and expertise with the rest of us. Reviewing the publicly available work of various data scientists, and observing their online discussions, significantly helped inform the direction of this project.

Thank you, as well, to the instructors and participants in this course for allowing the author to become more proficient in data science.

References

UC Irvine Machine Learning Repository:
https://archive.ics.uci.edu/ml/datasets/Student+Performance

Study generating this data set:
P. Cortez and A. Silva. Using Data Mining to Predict Secondary School Student Performance. In A. Brito and J. Teixeira Eds., Proceedings of 5th FUture BUsiness TEChnology Conference (FUBUTEC 2008) pp. 5-12, Porto, Portugal, April, 2008, EUROSIS, ISBN 978-9077381-39-7.
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