Analyzation of Traffic Patterns in Relation to Delays in Boston Public Transit

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Abstract

Do delays in public transit times correlate with increased travel times for uber? What are the most influential weather patterns affecting bus travel time? Based on the delay from weather patterns, how much extra travel time should a Boston commuter account for?

Generally we found that a fair number of trips in the uber data were delayed similarly to bus routes in the mtba data set, but there were also plenty of trips that were actually faster than average suggesting only a slightly positive correlation. Attempts to accurately predict percentage of daily buses on time from weather conditions were unsuccessful.

1. Introduction

The authors of this paper will layout the methods and sources of data for an analysis of traffic, ride sharing, and public transportation in the Boston metro area and how weather plays into the delays . Data will be sources from 2016 to present, and most of the data will serve to provide a baseline for normal travel times between various sectors of the city. By examining the delays in bus transit times we will provide the Massachusetts Bay Transportation Authority (MBTA) with useful information on where to account for extra travel time and wariness of traffic. The city of Boston may also be able to use this information to prioritize or de-prioritize road maintenance in bad weather. This paper will go into the application of knowledge gained, previous work that has been done on the data, details about the data sets and where to download them, methods of evaluation, and data mining tools.

2. Related Work

There has been quite a bit of prior work about traffic prediction and analysis. One such study was done by a group of researchers at the University of Southern California with a goal of accurately predicting and quantifying impact of traffic incidents. This is a pretty good study, as in their conclusion they claim that their model can increase "prediction accuracy of baseline approaches by up to 45% [1]" for the impact of traffic incidents on road networks. Another group did some work on developing a support system for using real time bus location data to accurately estimate arrival times. This study may be useful considering that all the data we intend on using is public transit data or Uber. Perhaps it can give us some ideas of how to use our public transit data in a cleverer way. A way in which our project will be different from the described research above is in a couple of ways. First, the most recent of these projects was done in 2016 so there is potential at least to have more currently relevant results. Second our work is going to try to learn how individual traffic delays affect city-wide transit rather than just providing time estimates for when the next bus will arrive or route prediction for obstruction avoidance. Both projects may be useful to us though by providing different ideas for how to use and view our data as well as what we might avoid. If we find that we are getting stuck in a corner though and neither of these are able to help get us out it seems there is plenty of other research out there which if we searched for we may be able to find our answers. [2]

There is also some work done on analyzing the impact of weather on traffic. We found an article in which writers were researching the relationship between inclement weather and traffic flow in Istanbul. Researchers used Remote Traffic Microwave Sensor (RTMS) and weather data from two highway roads in the Istanbul metropolitan area. The research found that traffic went slower when it was raining, but traffic went a bit faster if the road was wet and it was not raining. Researches also found that snow decrease the total number of cars in the roads by a significant amount. [3]

3. Data Sets

Our team has utilized three data sets: one from Uber, and one from MBTA, and a third from NOAA. The Uber dataset (see *figure 5)* must be downloaded in quarter-year increments from Uber's exclusive data tool, Movement. It can be found at *https://movement.uber.com/*. The MBTA dataset must similarly be downloaded in a few chunks rather than in one file from their dashboard at *http://www.mbtabackOntrack.com/performace/index.html\#/download*. You must select the radio box "Reliability". Our team had difficulty downloading the entire dataset at once, and had to split the download into three time frames: January 1st 2016 - January 1st 2017, January 2nd 2017 - January 1st 2018, and January 2nd 2018 - March 5th 2018.

The MBTA Reliability dataset has 395,130 rows and 9 attributes. The attributes include service date and time, whether the row is for Off-Peak service or Peak service times, the type of transport (including rail, commuter, and bus), the route line, stop station, metric measured (including Passenger Wait Time and Schedule Adherence), and varying numerators and denominators for those metrics.

We primarily used the service date and time, and numerator and denominator attributes. The Peak vs Off-Peak hours attribute was not very helpful for establishing a link between delays in public transit and traffic, and similarly was not effective when training regression models.

The Uber Movement dataset is split into 7 distinct .csv files, each containing 3 months worth of travel times between every Uber-defined source and destination in Boston. Each file has 7 attributes: sourceid, dstid, hod, meanTravelTime, standardDeviationTravelTime, geometricMeanTravelTime, and geometricStandardDeviationTravelTime. We decided to use only the geometric mean travel time attribute in our analysis as it was most relatable to the bus data. This data set turned out to be more difficult to use effectively as we lacked dates for each entry which would have allowed us to more directly compared bus data. This also would have allowed us to do similar or more complex attempts at predicting delays based on weather. We did, in an attempt to get better and more useful data, reach out to Uber who did respond to us, but after making our request did not give us what we asked for.

Our third data set was daily aggregated weather values for the boston area from the National Oceanic and Atmospheric Adminis-tration (NOAA). This data set included 44 attributes, the majority of which were empty. In order to use this data we trimmed those 44 down to 5 which were inches of precipitation, inches of snow, average temperature, max temperature, min temperature. Initial analysis was performed with all of these but later average temperature was removed. Unfortunately it's removal didn't increase performance of the models.

4. Main Techniques Applied

4.1 Correlation Analysis

In order to do our correlation analysis, we had to do these things. Because our Uber data set didn't have any dates for the entries we had to figure out how to compare the Uber and MTBA data another way. What we figured out is that on the website where we got the Uber data, they have a map (see *figure 1*) which lets you specify which zones to go between and over what date range and what direction. The result it gives is an average travel time for those parameters. Using our MBTA data *(figure 4),* we built a function in our Jupyter Notebook to find a threshold of lateness for each unique line, and find 25 days where the line was below this threshold. We then used those specific dates to pull data from Uber's Movement tool to determine average travel times in both directions for those days *(figure 6)*. We would also get the overall average time for the entire time frame starting from 2016 to the present.

Then, comparing the daily travel times in both directions to the overall average we would get some measurable difference which could be positive or negative and a ratio of that difference to the overall time.

As a natural consequence of having to do this by hand through Uber's website rather than through coding, this only supplied us with 736 entries which were not enough to do further analysis with. Had Uber provided greater access to their data, our team could have analyzed and mined the data further.

4.2 Regression

At some point late in our semester we were informed that we were a little off track and still needed to do some data mining. In order to achieve this goal we decided to download the weather data and add another question to answer. We downloaded the NOAA data set (see *figure 2*) and decided that the attributes concerning precipitation, snow and temperature values were the only useful ones in the set that would also not confuse the regression models (see *figure 3*). The question we decided to answer was "to what degree do different weather conditions affect the percentage of buses on time?" In order to do this we first had to combine the MTBA bus data with the newly acquired NOAA weather data. This was done by formatting their date columns to be the same and then using the pandas join method to apply the daily weather entries to the appropriate days in the bus set.

After doing this, we reorganized the newly joined data in Excel so that the columns would include the weather stats, if the entry was during peak hours or off peak hours, and what bus route the entry was for with percent of buses on time as our "score". Dates were removed because they might mudle our results. In order to make the bus route usable we would have had to use one-hot encoding to transform the bus route numbers into categorical data and would have added around 500 new attributes to our data set. Therefore, we decided not to use these in order to preserve good performance. The peak or off peak attribute was binary in nature so it was transformed from string entries into a binary (one or zero) format for simplicity.

Initial attempts for regression were to use this data set above split nearly half and half for training and testing and attempt to train a number of different regression models on them. The regression algorithms we tried were a Multi-Layer Perceptron Neural Network, a Random Forest Regressor, Logistic Regressor, TheilSen Regressor, and a couple others. These were trained on the split data with their default settings from Sci-Kit Learn and tested with only a few metrics to try and identify which would perform better than the others. Once one was identified that would perform the best, it would then be tuned to provide the best results possible. Initially it appeared that the regressors weren't performing well and that it was because the peak or off peak attribute was muddling the performance of the models. When this feature was then removed and training re-attempted and evaluated it seemed that suddenly all of the models were performing quite well but these positive results turned out to be from bugs in code. Where the data was being partitioned for training and testing sets the column indices were off by one and so the models were actually being fit to predict what the minimum temperature would be based on the other weather data. When the bug was fixed, it turned out that the models were unable to accurately predict percentage of buses on time. We were getting on average 13% absolute error with negative r^2 scores and poor explained variance scores, which would suggest that this doesn't work.

5. Key Results

The results of the correlation analysis (see *figures 7-9*) of bus delays and uber delays are generally that there is a slight positive correlation. The number of days where the delays were positively correlated were twice as many as those where they were negatively correlated

The results of our regression attempts unfortunately were that we could not accurately predict percentages of buses on time given weather data.

We attempted to use K-Means, Density-based, and EM clustering with WEKA to find collections of data points in the bus and weather datasets that correlate with each other. EM clustering proved the most effective, and we obtained four clusters. The data split well on average temperature and levels of precipitation, but did not differentiate itself when looking at the percent of buses on-time. Clustering did not provide additional insight into pockets of bus and weather data that may be of interest.

6. Applications

Given a full set of results, there are numerous applications that our research could provide to both the typical consumer and the industry. Unfortunately our data and analysis was incomplete and thus our applications are theoretical.

For the consumer, this research may provide insight on how to account for delays in their typical commute. With the information regarding when to expect delays based on the weather, a consumer will be able to make an informed decision on which mode of transportation (public transit or Uber) is ideal to make it on time. Our research would also be able to account for days in the past that have experienced heavy delays and relay that to the consumer so that they can look out for specific days in which transit is particularly slow.

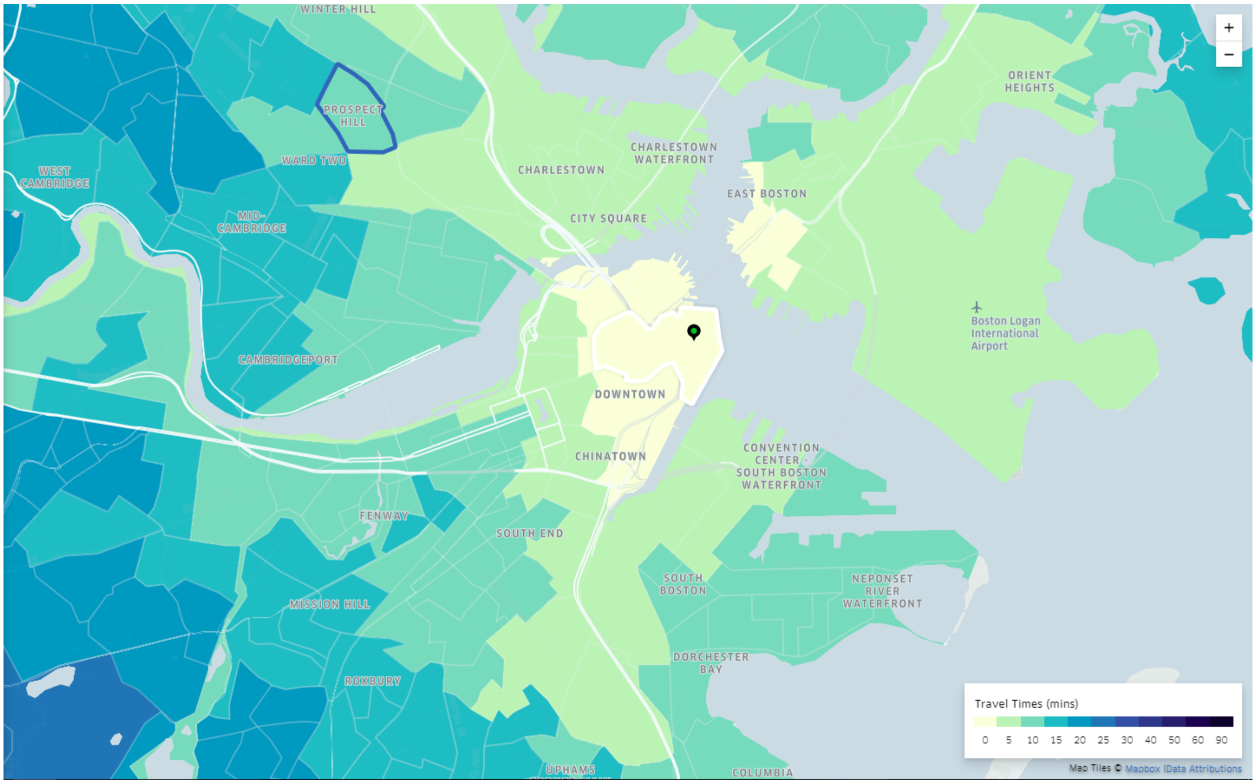
For the industry (or commercial market) our research could be utilized to optimize maintenance as well as transit related business. In the sense of maintenance, the Boston road maintenance department could utilize our analysis between MBTA and weather patterns to predict when to prepare for adequately staffing the roads, and more so specific sections of the roads that experience heavy delays, in order to keep the people of Boston on time for their days. Similarly, a thrifty Uber employee may use our 'results' to find specific zones that are highly traversed and are experiencing delays. This way the driver will be able to maximize their profits by finding passengers easier and increase their travel time. Further, a company that relies on road based deliveries, whether it be a pizza delivery man or a large-scale 18-wheeler shipping truck, could utilize our research for avoiding certain days or zones within Boston that are predicted to experience delays. In a business where timeliness is essential, an algorithm that could predict such delays would be immensely beneficial to companies so that they can preempt a detour and avoid slow traffic by combining our research with Google Maps.

7. Further Research

If our intermediate results of our regression models not been invalidated by faulty coding, we might have had some theories about the information that those results suggested. It appeared that from the results the most effective predictor which was essentially a Decision Tree regressor had figured that the minimum temperature was the most significant of the weather attributes. One theory was that perhaps on days where temperatures dipped pretty low, more people would be wanting to ride the bus, and the added volume increased the time spent at each stop. This theory would have just been conjecture, but MTBA also has a ridership data set which we didn't download. Not having looked at it, we don't know if it would have been useful for this, but it could have been used to perform further research into this finding, had it been correct. The point of including this component, even though based off of invalid results is to illustrate that we were thinking of these things despite our results not being very great.

8.Figures

Figure 1



Uber's tool called *Movement* that provides mean transit times between different zones in the greater Boston area. These zones are the same as the ones demarcated by the census. This tool was essential for aggregating data from Uber.

Figure 2

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	STATION	NAME	LATITUDE	LONGITUD	ELEVATION	DATE	AWND	AWND_ATTRIBUTES	PGTM	PGTM_AT	PRCP	PRCP_ATT	SNOW	SNOW_AT	TAVG	TAVG_A
2	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/1/2016	12.75	,,W			0	,,W,2400	0	T,,W	39	H,,S
3	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/2/2016	13.42	,,W			0	,,W,2400	0	,,W	35	H,,S
4	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/3/2016	11.63	,,W			0	,,W,2400	0	,,W	36	H,,S
5	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/4/2016	12.3	,,W			0	T,,W,2400	0	T,,W	30	H,,S
6	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/5/2016	10.07	,,W			0	,,W,2400	0	,,W	16	H,,S
7	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/6/2016	10.07	,,W			0	,,W,2400	0	,,W	30	H,,S
8	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/7/2016	6.49	,,W			0	,,W,2400	0	,,W	33	H,,S
9	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/8/2016	10.96	,,W			0	,,W,2400	0	,,W	35	H,,S
10	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/9/2016	6.04	,,W			0.01	,,W,2400	0	,,W	40	H,,S
11	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/10/2016	14.99	,,W			1.38	,,W,2400	0	,,W	45	H,,S
12	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/11/2016	19.24	,,W			0	,,W,2400	0	,,W	40	H,,S
13	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/12/2016	9.62	,,W			0.08	,,W,2400	0.3	,,W	29	H,,S
14	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/13/2016	19.69	,,W			0	,,W,2400	0	T,,W	29	H,,S
15	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/14/2016	10.51	,,W			0	T,,W,2400	0	T,,W	24	H,,S
16	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/15/2016	6.49	,,W			0	,,W,2400	0	,,W	31	H,,S
17	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/16/2016	9.4	,,W			1.22	,,W,2400	0	T,,W	39	H,,S
18	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/17/2016	9.4	,,W			0.1	,,W,2400	1.3	,,W	35	H,,S
19	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/18/2016	16.78	,,W			0.11	,,W,2400	1.8	,,W	27	H,,S
20	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/19/2016	21.92	,,W			0	,,W,2400	0	,,W	20	H,,S
21	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/20/2016	18.79	,,W			0	,,W,2400	0	,,W	24	H,,S
22	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/21/2016	13.87	,,W			0	,,W,2400	0	,,W	27	H,,S
23	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/22/2016	11.41	,,W			0	,,W,2400	0	,,W	24	H,,S
24	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/23/2016	20.36	,,W			0.37	,,W,2400	6.1	,,W	29	H,,S
25	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/24/2016	11.18	,,W			0	T,,W,2400	0	T,,W	25	H,,S
26	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/25/2016	7.16	,,W			0	,,W,2400	0	,,W	31	H,,S
27	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/26/2016	14.32	,,W			0	,,W,2400	0	,,W	37	H,,S
28	USW00014739	BOSTON, MA US	42.3606	-71.0097	3.7	1/27/2016	12.08	,,W			0	,,W,2400	0	,,W	43	H,,S

A view of the raw data collected from NOAA regarding their weather readings from the Boston Area. We collected data from the beginning of 2016 to the present day. While this format is very informative, we found a lot of the attributes to be beyond the scope of what we needed.

Figure 3

DATE	PRCP	SNOW	TAVG	TMAX	TMIN
1/1/2016	0	0	39	41	33
1/2/2016	0	0	35	40	31
1/3/2016	0	0	36	44	31
1/4/2016	0	0	30	36	14
1/5/2016	0	0	16	26	8
1/6/2016	0	0	30	45	21
1/7/2016	0	0	33	43	26
1/8/2016	0	0	35	42	30
1/9/2016	0.01	0	40	41	38
########	1.38	0	45	58	38
########	0	0	40	51	25
########	0.08	0.3	29	37	21
########	0	0	29	33	21
########	0	0	24	30	21
########	0	0	31	42	26
########	1.22	0	39	43	34
########	0.1	1.3	35	38	29
########	0.11	1.8	27	29	19
########	0	0	20	25	16
########	0	0	24	33	19
########	0	0	27	33	21
########	0	0	24	32	19

A view of our weather data set collected from NOAA after we cleaned and reduced it in order to only have the essential attributes for our methods.

Figure 4

SERVICE_DATE	PEAK_OFFPEAK_IND	MODE_TYPE	ROUTE_OR_LINE	ROUTE_TYPE	STOP	METRIC_TYPE	OTP_NUMERATOR	OTP_DENOMINATOR
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Lowell Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Middleboro Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Haverhill Line			Headway / Schedule Adherence	9	12
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Fairmount Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Greenbush Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Middleboro Line			Headway / Schedule Adherence	14	16
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Newburyport Line			Headway / Schedule Adherence	10	12
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Franklin Line			Headway / Schedule Adherence	9	18
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Greenbush Line			Headway / Schedule Adherence	16	16
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Providence Line			Headway / Schedule Adherence	14	18
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Franklin Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Needham Line			Headway / Schedule Adherence	15	18
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Fitchburg Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Fairmount Line			Headway / Schedule Adherence	27	34
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Rockport Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Kingston/Plymouth Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Peak Service (Weekdays 6:30-9:30AM, 3:30PM-6:30PM)	Commuter	Providence Line			Headway / Schedule Adherence	0	0
2/15/2016 0:00	Off-Peak Service (All Other Times)	Commuter	Lowell Line			Headway / Schedule Adherence	13	16

The data extracted from the MBTA website, this data was essential for generating a correlation analysis with the Uber data as well as the NOAA data.

Figure 5

	sourceid	dstid	hod	geometric_mean_travel_time	geometric_standard_deviation_travel_time
37966	1	12	10	190.14	1.84
46433	1	12	1	268.45	1.75
173566	1	12	19	182.16	1.86
340456	1	12	23	172.17	1.98
566201	1	12	14	214.99	2.07
626849	1	12	18	247.95	1.97
654506	1	12	0	175.1	1.74
661874	1	12	9	209.82	1.95
947908	1	12	11	184.44	2.04
981259	1	12	20	198.73	2.32
1169032	1	12	2	185.77	1.73
1207241	1	12	17	159.2	1.98
1296465	1	12	8	164.53	1.64
1716807	1	12	12	202.84	1.99
1733221	1	12	21	214.42	2.02
1962223	1	12	15	178.18	1.82

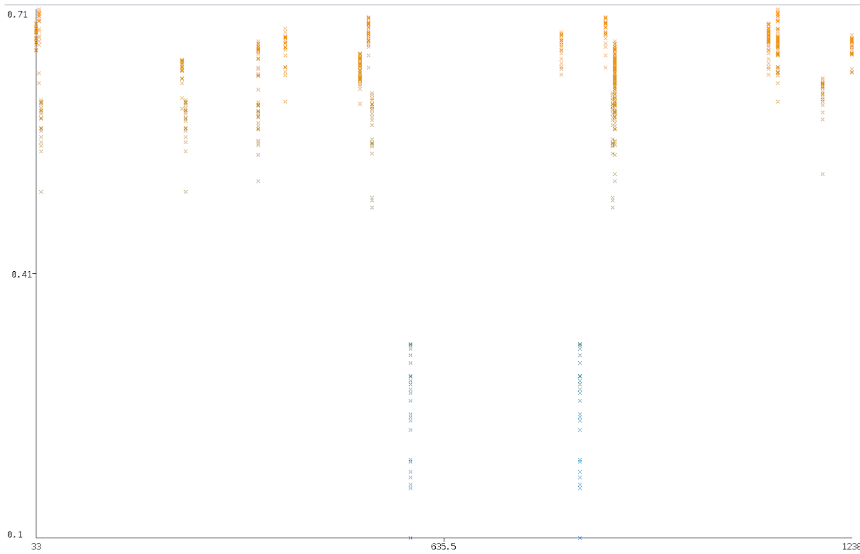
Our Uber data we collected from the *Movement* tool after cleaning and reducing it to optimize it for our purposes. HOD stands for hour of the day.

Figure 6

route id	source	destination	date	% on time (bus)	avg time	actual	diff(avg,actual)	correlation	ratio: delay -> total time
1	362	888	7/4/2016 0:00	0.578894	0:21:11	0:19:24	0:01:47	neg	9.192439863
1	362	888	7/21/2016 0:00	0.59332	0:21:11	0:21:22	0:00:11	pos	0.8580343214
1	362	888	11/24/2016 0:00	0.545145	0:21:11	0:19:38	0:01:33	neg	7.894736842
1	362	888	12/14/2016 0:00	0.596059	0:21:11	0:24:31	0:03:20	pos	13.59619307
1	362	888	12/25/2016 0:00	0.558298	0:21:11	0:18:45	0:02:26	neg	12.97777778
1	362	888	12/26/2016 0:00	0.589461	0:21:11	0:17:25	0:03:46	neg	21.62679426
1	362	888	2/17/2017 0:00	0.588679	0:21:11	0:21:15	0:00:04	pos	0.3137254902
1	362	888	4/12/2017 0:00	0.58209	0:21:11	0:29:22	0:08:11	pos	27.86606129
1	362	888	4/14/2017 0:00	0.606164	0:21:11	0:23:40	0:02:29	pos	10.49295775
1	362	888	4/28/2017 0:00	0.557018	0:21:11	0:20:59	0:00:12	neg	0.9531374106
1	362	888	5/17/2017 0:00	0.602585	0:21:11	0:26:53	0:05:42	pos	21.20272784
1	362	888	5/24/2017 0:00	0.606159	0:21:11	0:22:01	0:00:50	pos	3.785011355
1	362	888	5/25/2017 0:00	0.560284	0:21:11	0:32:15	0:11:04	pos	34.31524548
1	362	888	6/9/2017 0:00	0.602094	0:21:11	0:19:11	0:02:00	neg	10.42571677

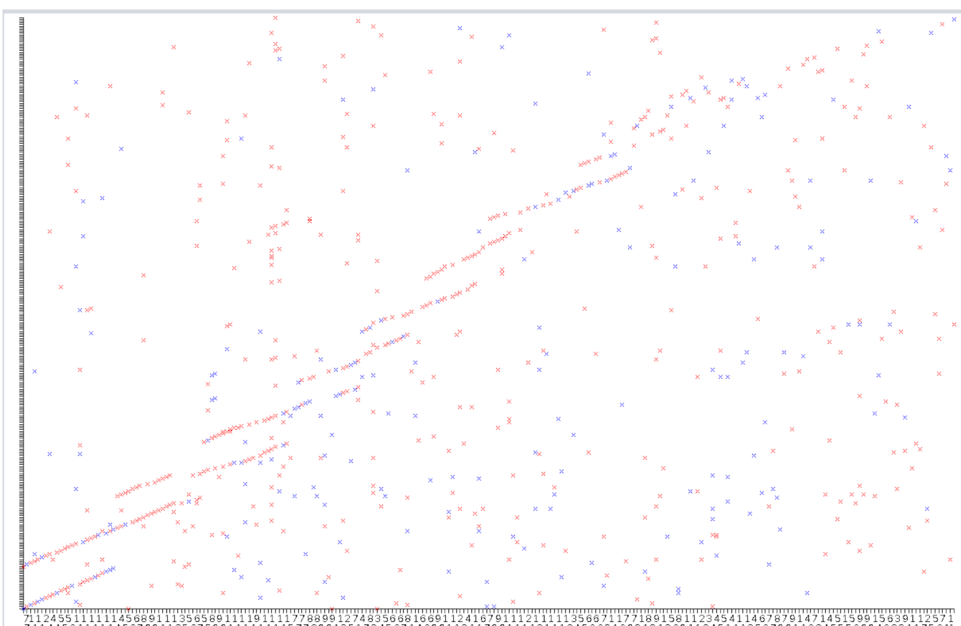
Uber was unable to provide transit times between two specific zones AND include the date (something necessary for our research), so we manually collected nearly 736 data points using the *Movement* tool. Data seen above.

Figure 7



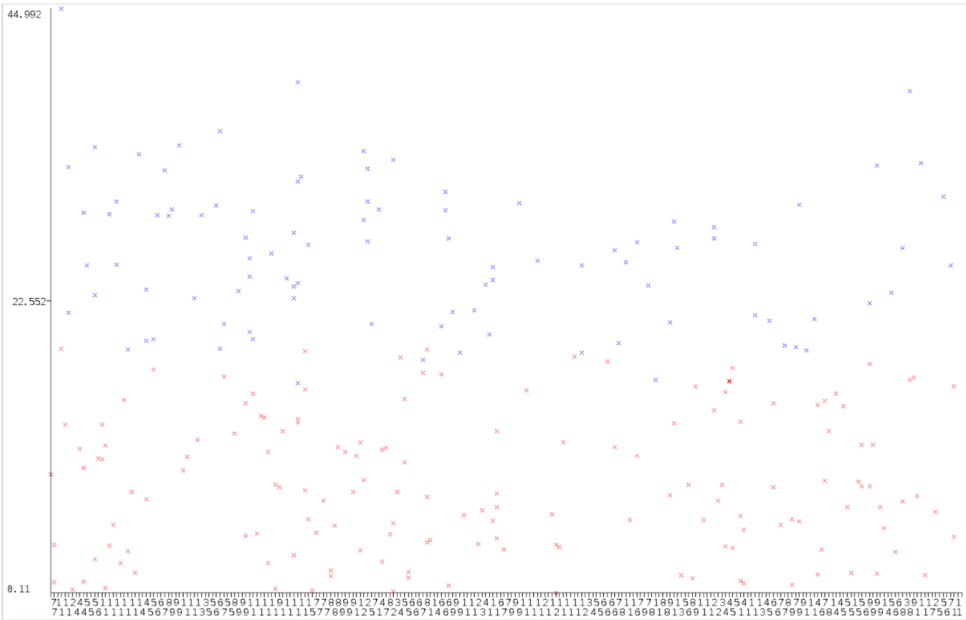
A graph displaying bus route number on the x-axis vs percent on time on the y-axis. Color gradient from blue to orange represents 0% to 100% of buses on time.

Figure 8



A graph displaying dates from 2016 to 2018 on the x-axis, and difference between observed and average Uber travel times.

Figure 9



A graph displaying dates from 2016 to 2018 on the x-axis, and the ratio between the delay in observed and actual travel times for Uber data. Red represents an established positive correlation between travel times on Uber and delays in public transit, and blue represents an established negative correlation.

9. References

[1] B. Pan, U. Demiryurek, C. Shahabi, and C. Gupta, "Forecasting Spatiotemporal Impact of Traffic Incidents on Road Networks," in 2013 IEEE 13th International Conference on Data Mining, 2013, pp. 587–596.

[2] F. Sun, Y. Pan, J. White, and A. Dubey, "Real-Time and Predictive Analytics for Smart Public Transportation Decision Support System," in 2016 IEEE International Conference on Smart Computing (SMARTCOMP), 2016, pp. 1–8

[3] Akin, D., Sisiopiku, V.P., Skabardonis, A., 2011. "Impacts of weather on traffic flow characteristics of urban freeways in istanbul." Procedia: Soc. Behav. Sci. 16.