NYC Taxi Data - Capstone Milestone Report

Problem Definition

The kaggle competition behind this is to build a model that predicts the total ride duration of taxi trips in New York City. The primary dataset is one released by the NYC Taxi and Limousine Commission, which includes pickup time, geo-coordinates, number of passengers, and several other variables.

Source:
https://www.kaggle.com/c/nyc-taxi-trip-duration

Client:

The literal client is Kaggle but the figurative client would be a taxi company looking to optimize their route selection. This kind of service provider could be an Uber/Lyft or traditional taxi company...perhaps even a technologically inclined rickshaw driver.

Data Cleaning/Wrangling:

The data needed to be cleaned to remove the following:

- Extremely long ride times, eliminated data outside +/- 3 std of mean
- Limited passenger count to <=6 as most cabs don't have capacity of a mini-van

Feature engineering was performed to incorporate the following

- Conversion of timestamp data into day, week, month, hour, year, date
- Checking of trip duration & date time values for consistency
- Haversine distances between pickup and drop off latitude & longitude
- Bearings calculated based upon latitude & longitude of pickups
- Generated average speed of trips
- Time series plots

I used a variety of tool bags and libraries to assist in this analysis. These included the following:

- Python 3.6.1 run in Jupyter Notebook
- Plotting capability provided by matplotlib, seaborn
- Analysis capability from pandas, numpy, datetime
- Machine Learning provided by SciKit Learn

Other Potential Datasets:

- Actual direct route information incorporated from an Open Source Routing Machine such as one found at project-osrm.org
- Weather related data could have been incorporated to review outliers for snow storms or flooding

Summary of Initial Findings:

Through my exploratory analysis and statistical investigation I have determined the following:

- The average trip durations between each vendor are similar but statistically different
- The average trip lasts 840 seconds or ~14 minutes.
- The variables are generally independent of each other, meaning there are few pairs that demonstrate strong correlation to each other, save for trip duration and distance.
- Time of day, week, month can impact trip durations
- The lowest amount of traffic in the city occurs in the early morning hours and late evening.
- Machine Learning algorithms for Linear Regression and Clustering were applied to reveal important features and neighbourhoods
- There is a strong response in trip duration based upon the following three variables: distance, month of the year and passenger count.

Statistical Inferences Discussion:
The following represents a few key features about the data.

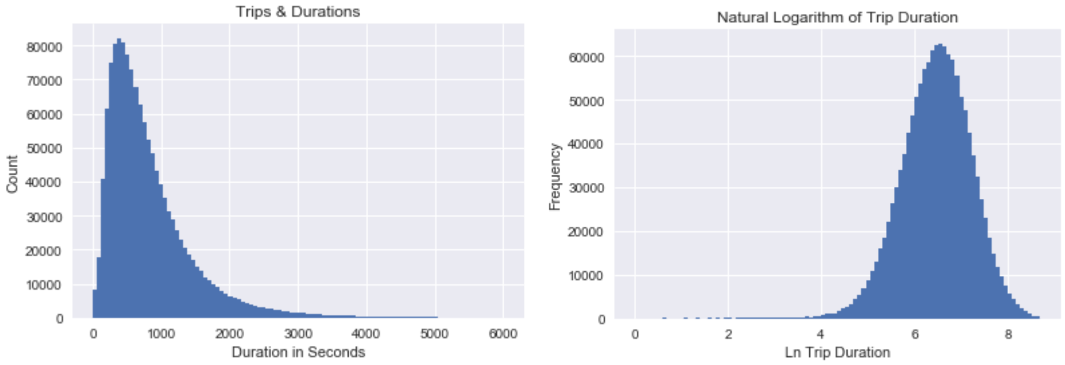


Fig. 1 - Trip Data Distributions

We can see that trip duration is normally distributed around of mean of 840 seconds of 14 minutes.

Split by vendor this makes for an interesting opportunity to test means using hypothesis test for two samples

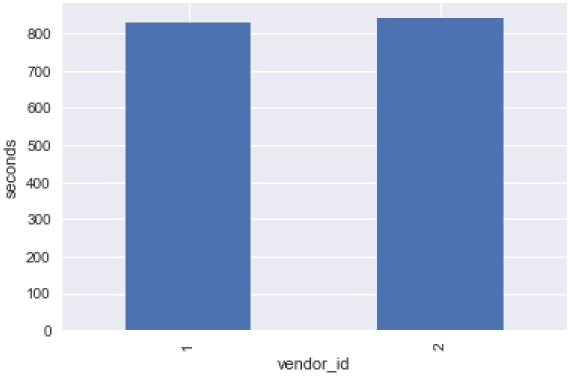


Fig. 2 - Average Trip Time by Vendor

These are huge samples at roughly 600k per vendor. As such we can determine the means and standard deviations to be representative of the populations. The Central Limit Theorem holds that since sample size is >40.

Ho: mu1 - mu2 = deltao
Ha: mu1 - mu2 < deltao

This is to say that for Ha, the mean trip duration of vendor 1 is less than mean trip duration of vendor 2. This inequality indicates a lower tailed test where we reject the null hypothesis if z<= -zalpha

For an alpha value of 0.95 the Zcritical value is 1.65 meaning that in order to reject the null hypothesis our calculated statistic has to be z<= -1.65.

In this case our z statistic is -10.2 which is less than -1.65 and so we must reject the null hypothesis that the mean trip durations are equal and accept that vendor 1 has a lower mean trip duration than vendor 2.

The P-value is also 0 meaning Ho should be rejected for any reasonable significance level.

It is also fair to say that although the means are different, they are not different by much and this will likely not be a significant factor in determining trip duration.

Now we investigate other features of the data including pickup times and distances.

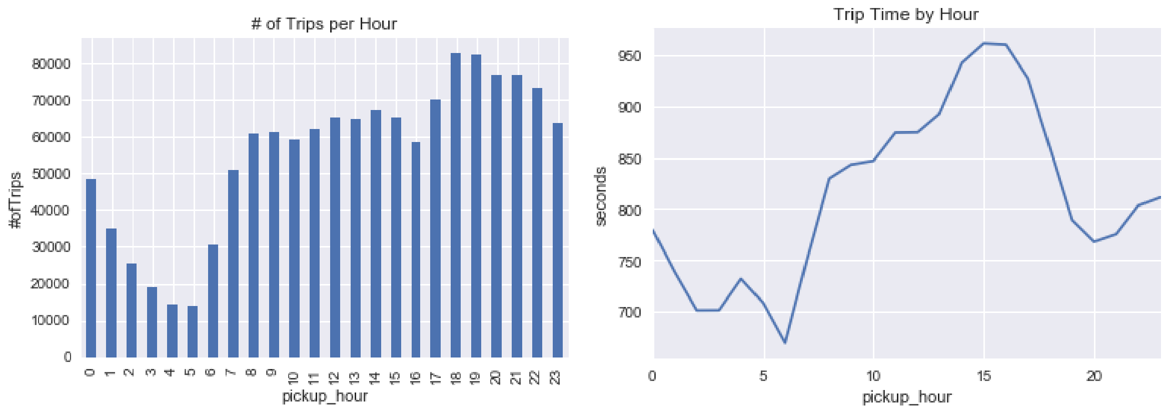


Fig. 3 - Trips & Duration by Hour

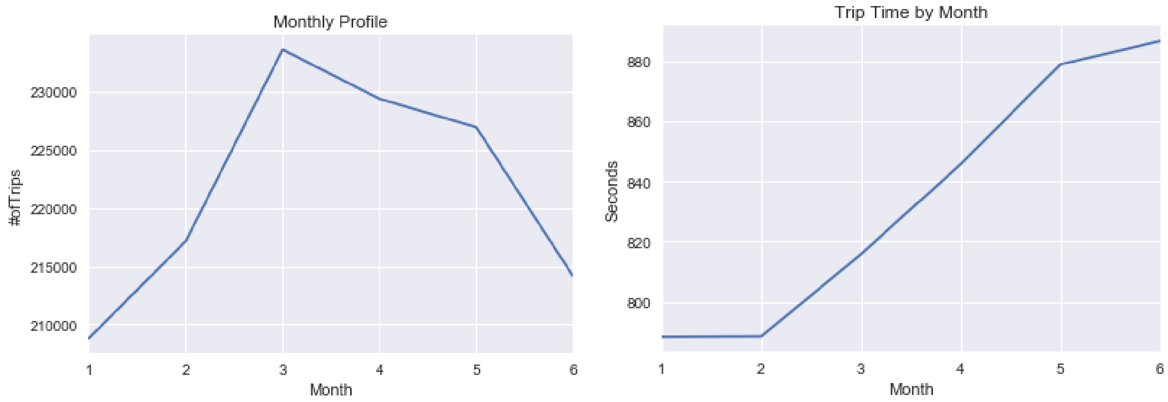


Fig. 4 - Trips & Duration by Month

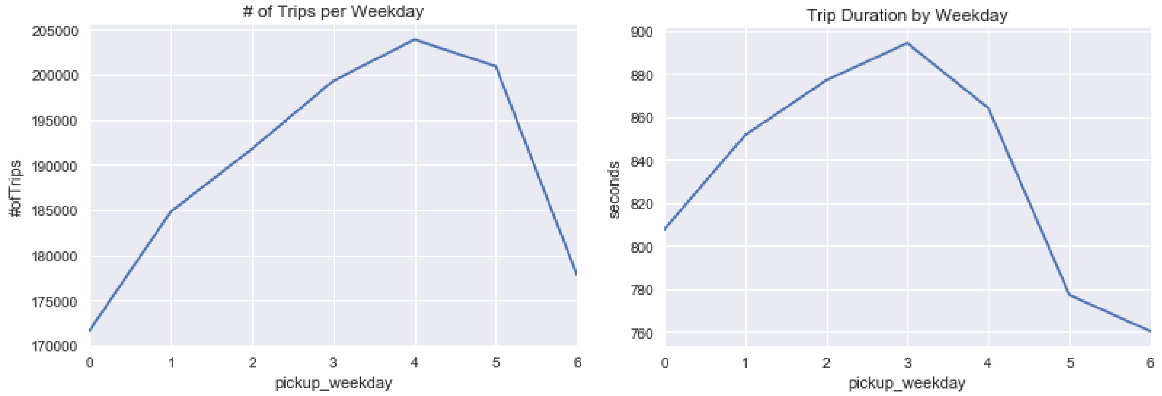


Fig. 5 - Trips & Duration by Weekday

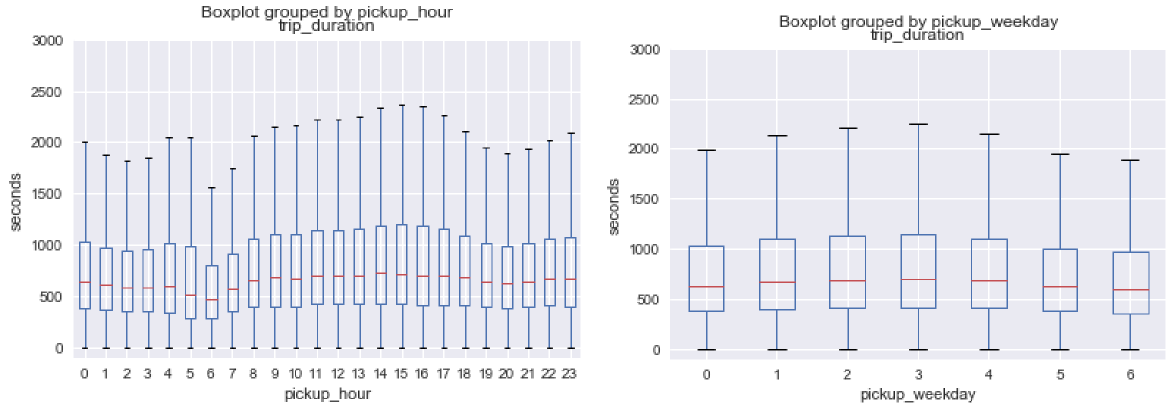


Fig. 6- Trip Duration Boxplots: Hour & Weekday

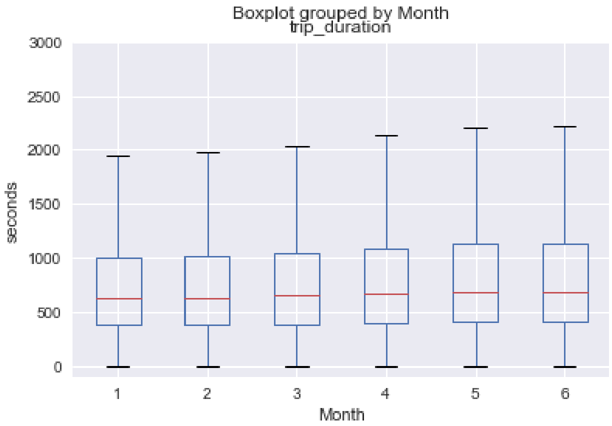


Fig. 7 - Trip Duration Boxplots: Month

In general we see that the profiles of figures 3,4 and 5 are supported by the trends in the boxplots for trip duration. We see an increase in trip duration for the evening hours, the summer months and peak trip durations on Wednesday nights.

As a point of interest, the distance feature is ‘direct distance’ not accounting for one way streets and turns. We obtained the average velocity information.

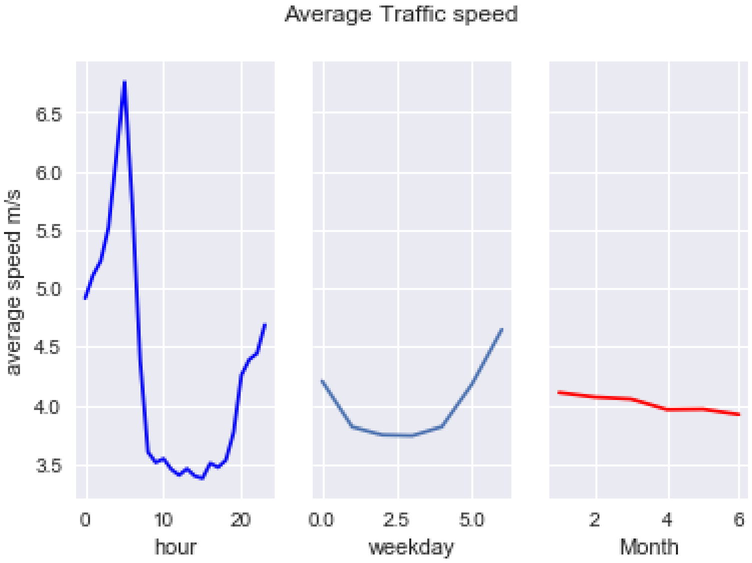
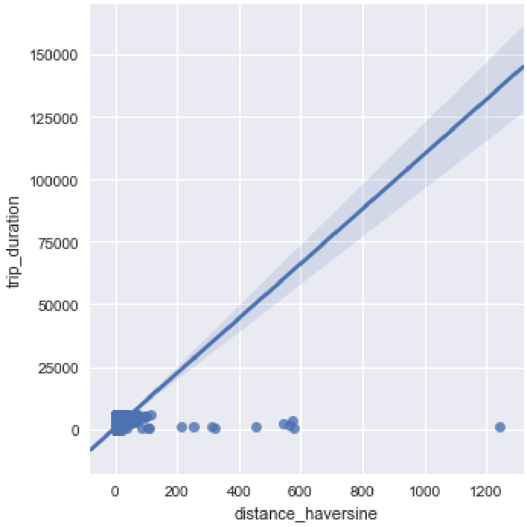


Fig. 8 - Trip Speed

We can then move on to a linear regression model using SciKit Learn. The following parameters were included in the model:

- Month
- Pickup_hour,
- Pickup_weekday,
- Direct Distance,
- Vendor,
- passenger_count

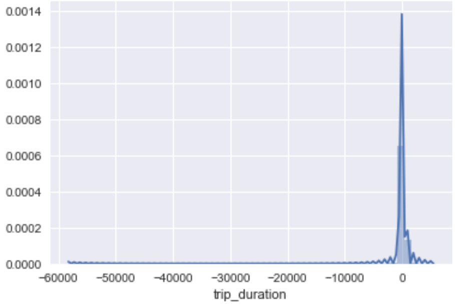
Logically, distance is likely to be the largest contributing factor to trip duration. The following plot demonstrates a strong positive correlation.



A model was created using SciKit Learn's 'TrainTestSplit'. The model produced the following errors and R-squared values:

MAE: 297.663310569
MSE: 185540.117878
RMSE: 430.743680021
R Squared: 0.56

While not impressive, the R-squared value does indicate a degree of fit.
Residual Plot shows Normal Distribution, a positive sign.



The coefficients of the model confirmed suspicions regarding direct distance.

	Coefficient
Distance	105
Month	18
Passenger Count	15
Pickup Hour	4

Vendor	3
Pickup Weekday	-12

Clustering with K-Means Outcomes:
Work in progress

Conclusions:
Inferential Statistics

What is likely to play the biggest role in determining length of the time spent riding in a cab is the total distance travelled. Beyond that obvious conclusion we can expect to take longer rides in the summer months, when we have more passengers, when it is later in the day and if we travel with Vendor 2. As the week goes on the trips generally decrease in duration.

In further analyses I would choose to incorporate more features such as weather and the routes through the city. This would provide greater insight on external factors and also actual distance travelled.

Statistically we can do more investigation also. For example, ANOVA tests could be performed on features to determine correlation with an outcome. We could also perform a clustering algorithm and include the cluster numbers as features for our regression model.

Clustering Outcomes