

Springboard Capstone Project One Predicting Taxi Ride Duration in NYC

Author: Anshul Dikshit

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Outline

- Introduction & Problem Statement
- Dataset
- Analysis & Findings
- Statistical Inference
- Machine Learning
- Conclusions



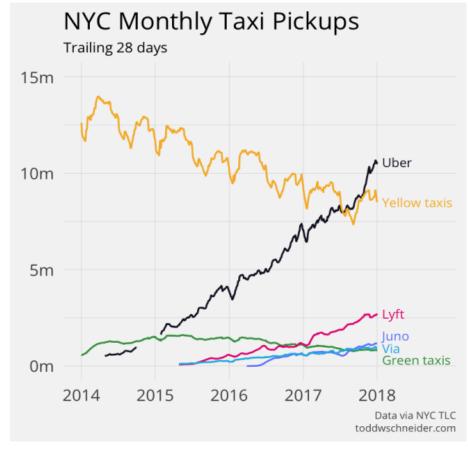


Introduction & PROBLEM STATEMENT

With almost 1.5 million trips in 2016, riding through taxi at any time of the year across New York City is a big deal.

THE PROBLEM

Given the increase in number of taxi rides in NYC in recent years, there needs to be an estimates of taxi trip durations can improve the taxi utilization and the satisfaction of drivers and passengers



Data Set

The data has been taken from Kaggle which provides a starting point dataset consisting of the records of ~1.5 million taxi trips that took place in 2016. I've tried to go through the process of understanding the individual variables in the data by presenting beautiful, clear, and interactive data visualizations along with some approaches to their interpretation

Test dataset:

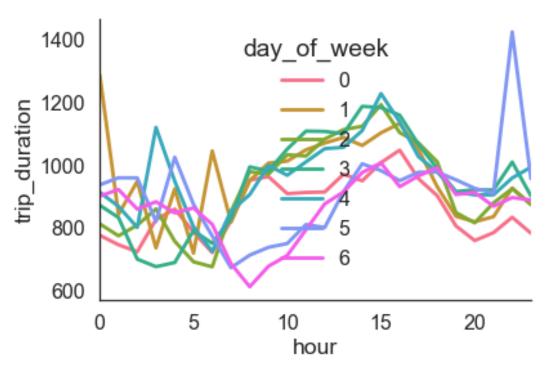
| Variable name | Variable description |
|--------------------|--|
| id | A unique identifier for each trip |
| vendor_id | A code indicating the provider associated with the trip record |
| pickup_datetime | Date and time when the meter was engaged |
| passenger_count | The number of passengers in the vehicle (driver entered value) |
| pickup_longitude | The longitude where the meter was engaged |
| pickup_latitude | The latitude where the meter was engaged |
| dropoff_longitude | The longitude where the meter was disengaged |
| dropoff_latitude | The latitude where the meter was disengaged |
| store_and_fwd_flag | This flag indicates whether the trip record was held in vehicle memory before sending to the vendor because the vehicle did not have a connection to the server. |
| | Y=store and forward; N=not a store and forward trip |

Train dataset:

| Variable name | Variable description |
|--------------------|---|
| id | A unique identifier for each trip |
| vendor_id | A code indicating the provider associated with the trip record |
| pickup_datetime | Date and time when the meter was engaged |
| dropoff_datetime | Date and time when the meter was disengaged |
| passenger_count | The number of passengers in the vehicle (driver entered value) |
| pickup_longitude | The longitude where the meter was engaged |
| pickup_latitude | The latitude where the meter was engaged |
| dropoff_longitude | The longitude where the meter was disengaged |
| dropoff_latitude | The latitude where the meter was disengaged |
| store_and_fwd_flag | This flag indicates whether the trip record was held in vehicle memory before sending to the vendor because the vehicle did not have a connection to the server. Y=store and forward; N=not a store and forward trip |
| trip_duration | Duration of the trip in seconds |

Initial Analysis

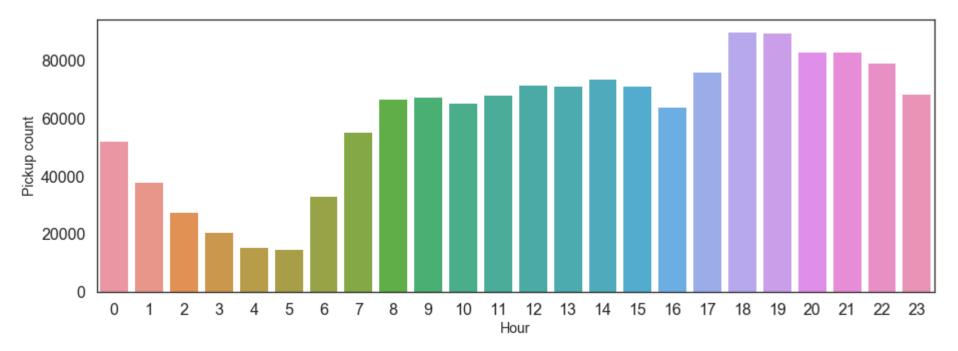
On day 0, that is Sunday and day 6 that is Saturday, the trip duration is very less that all the weekdays at 5 AM to 15 AM time. See this, on Saturday around midnight, the rides are taking far more than usual time, this is obvious through now verified using given data



Initial Analysis (cont.)

How many pickups/hr

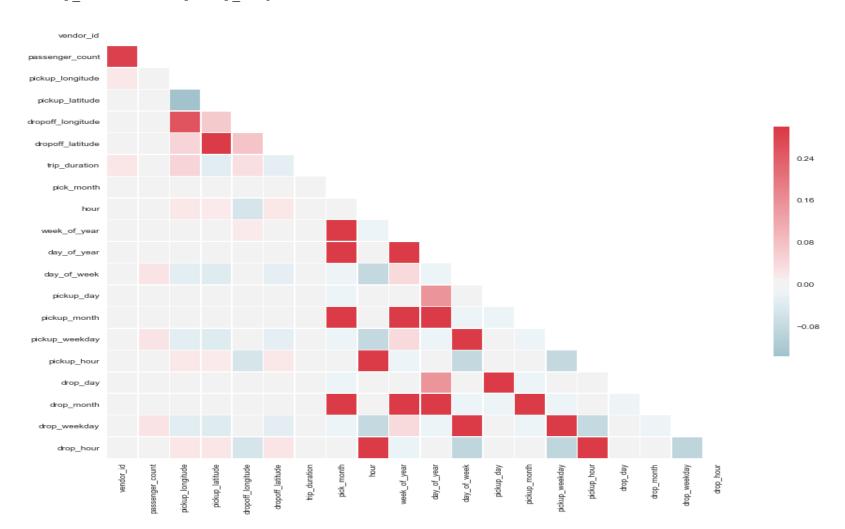
As expected, the number of pickups gradually decreases after mid-night. The highest number of pickups are around 6pm and 7pm in the evening which makes sense as many people are on their way to home from office.



Correlation between the different variables

The highest correlation is observed with the gollowing variables:

- Week of year and pick month
- day of year and pick month
- trip duration and pickup longitude



Training and testing the model using XGBoost

```
[0]
        train-rmse:3.0237
                                valid-rmse:3.02175
Multiple eval metrics have been passed: 'valid-rmse' will be used for early stopping.
Will train until valid-rmse hasn't improved in 2 rounds.
[1]
        train-rmse:1.55838
                                valid-rmse:1.55558
[2]
        train-rmse:0.861315
                                valid-rmse:0.859258
[3]
                                valid-rmse:0.564487
        train-rmse:0.563039
[4]
                                valid-rmse:0.461999
        train-rmse:0.456612
[5]
                                valid-rmse:0.430632
        train-rmse:0.423083
[6]
        train-rmse:0.41285
                                valid-rmse:0.422282
[7]
                                valid-rmse:0.419009
        train-rmse:0.407927
[8]
        train-rmse:0.404263
                                valid-rmse:0.416805
[9]
        train-rmse:0.401599
                                valid-rmse:0.415815
Modeling RMSLE 0.41581
```