PREDICTING NYC TAXI FARES

Supervised Learning Capstone

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Thinkful Data Science Bootcamp
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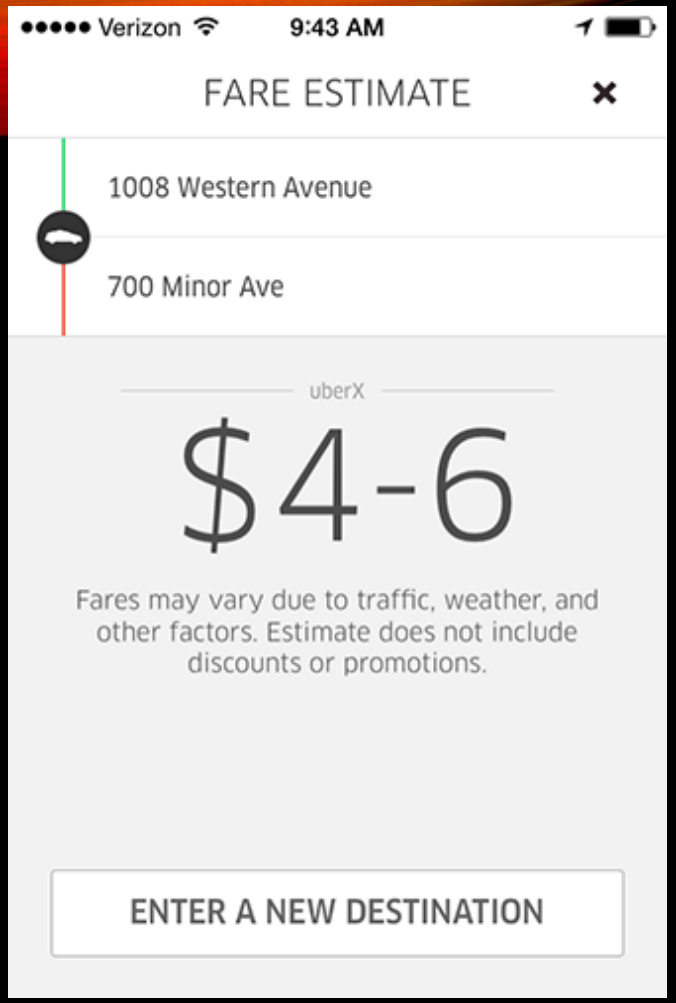


THE PROBLEM

Background:

- Ride hailing is competitive in NYC
- 800,000 rides are hailed per day
- Yellow Cabs are losing to Uber and Lyft
- Yellow Cab share is 35%

Current Situation:

- Passengers want fare transparency
- Uber/Lyft provide Fare Estimates to potential passengers
- Yellow Cabs do not

Project Goal:

- Develop a machine learning model to allow Yellow Cabs to quote fares, just like Uber and Lyft

THE APPROACH

- Data was collected for 55,000 million NY cab rides from 2010—2015

- Data includes:
  - Date/Time of pickup
  - Pickup Location Coord (Lat, Long)
  - Drop off Location Coord (Lat, Long)
  - Fare Amount

The Goal

Create model to predict Fare Amount

Given: Date/Time, pickup location, drop off location

WHAT MAKES UP A CAB FARE?

Base Fare
- Min Fare: $2.50

Distance
- $0.50 per 1/5 mile

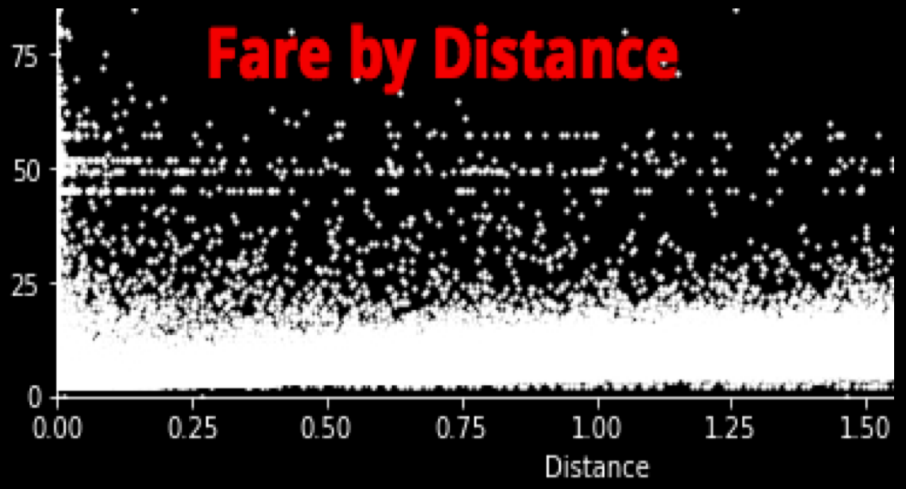
Tolls

Tax
- $0.50 Taxes

Peak/Off Peak Fees
- $0.50 night fee: 8pm to 6am
- $1.00 peak fee: 4pm to 8pm

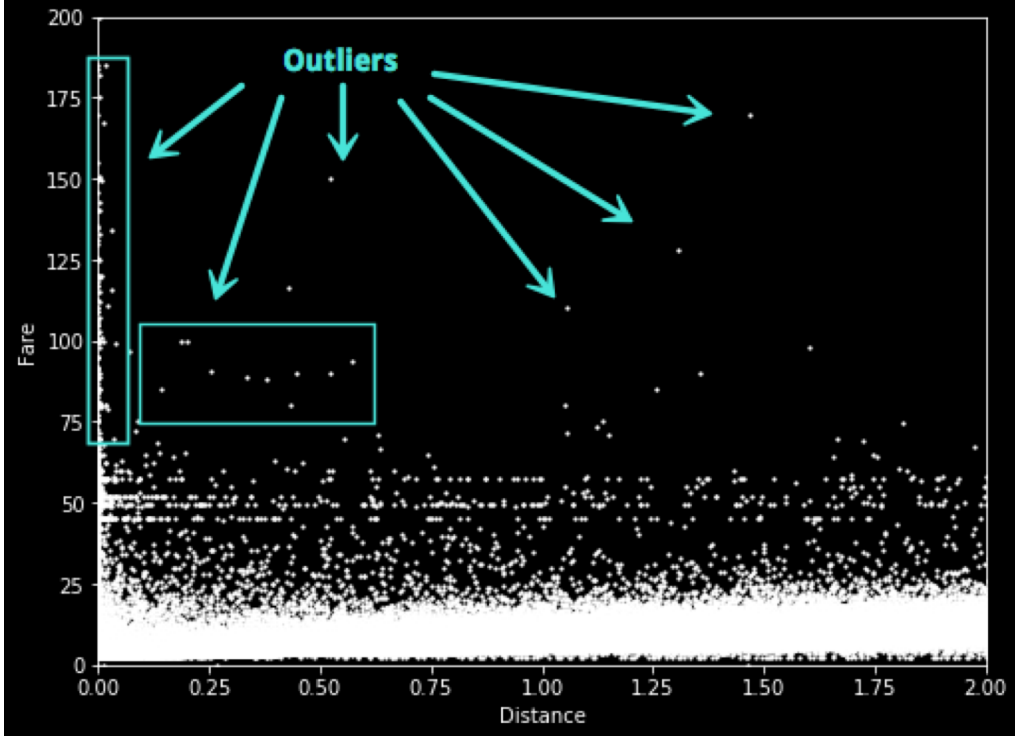
Waiting Time
- $0.50 per minute waiting
(moving < 12.5mph)

WHY CAN'T WE JUST USE DISTANCE?



- Waiting time is the main problem
- Hard to predict traffic
- Trips less than 2 miles can have fares ranging all the way up to $50!

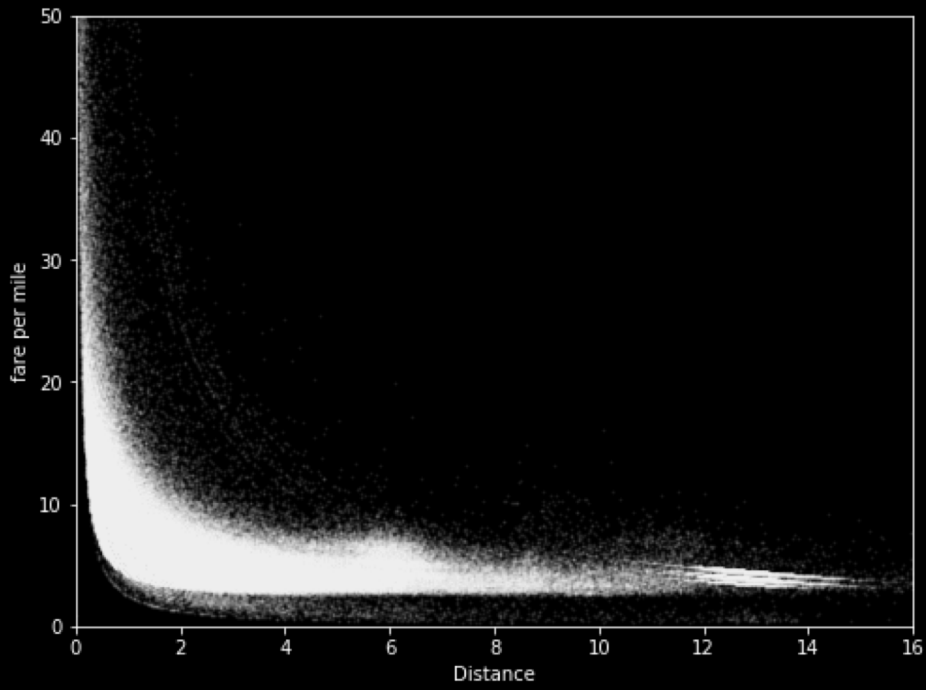
DATA CLEANSING

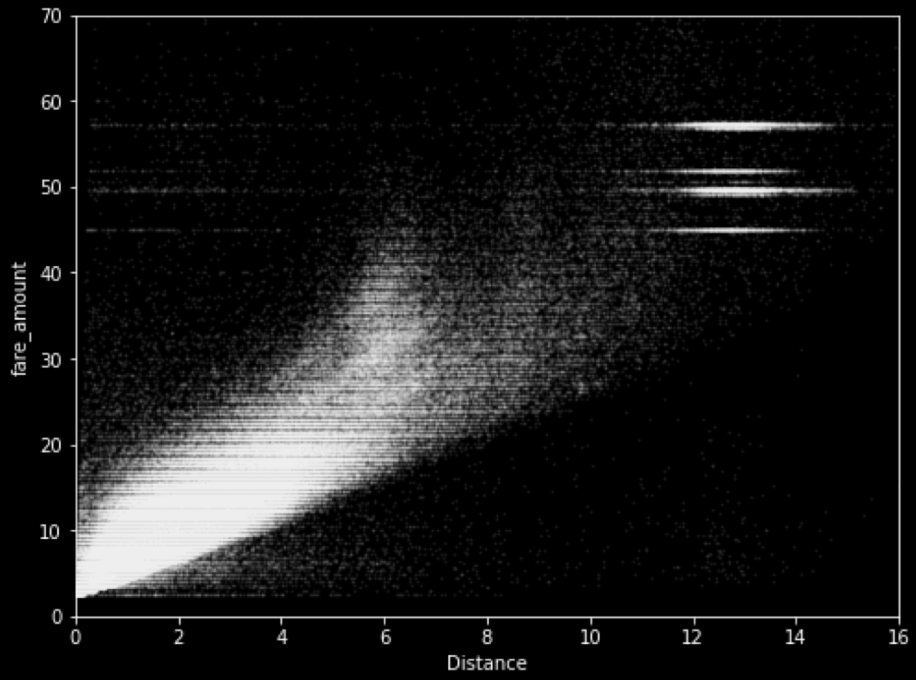


Removed:

- Trips costing more than $100 per mile
- Trips with Distance of 0
- Trips with Fare of $0
- Locations out of Range

EXPLORING THE DATA





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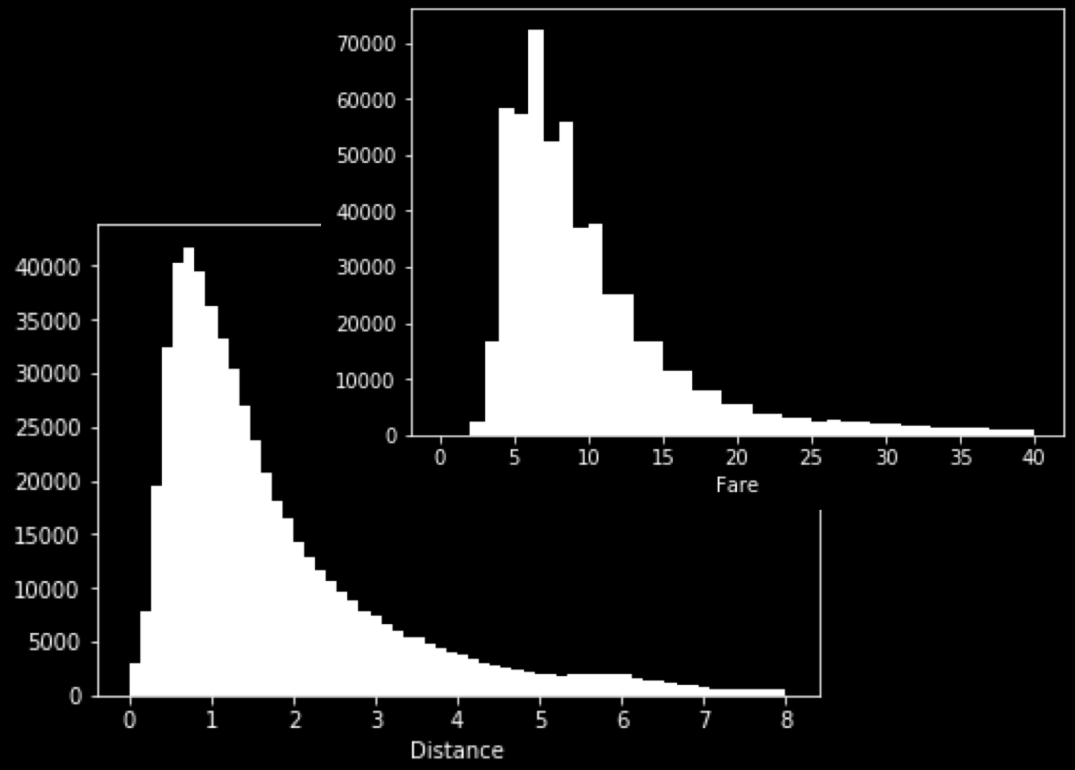
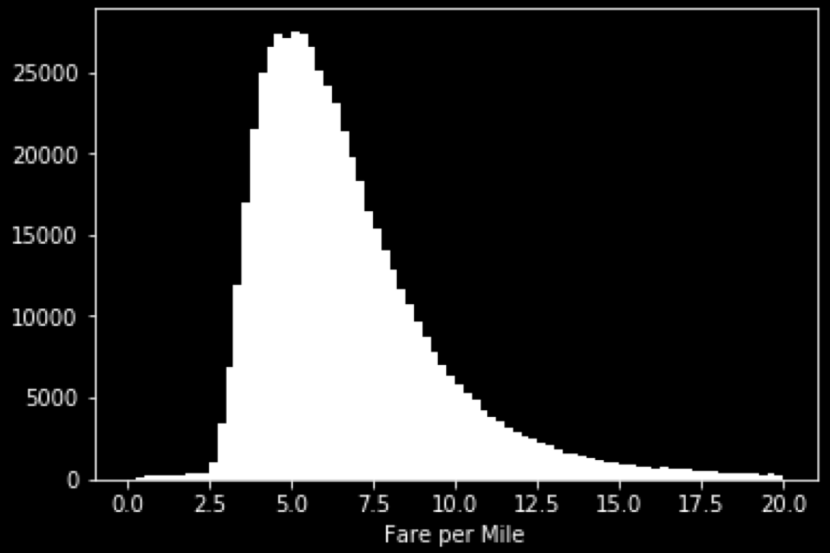




PREDICTING FARE WITH MACHINE LEARNING

Predict Fare via Distance Calculator

An intelligent calculation for fare would be:

Fare = $5 + $0.67 per 1/5 mile

This model predicts the fare with

75% accuracy

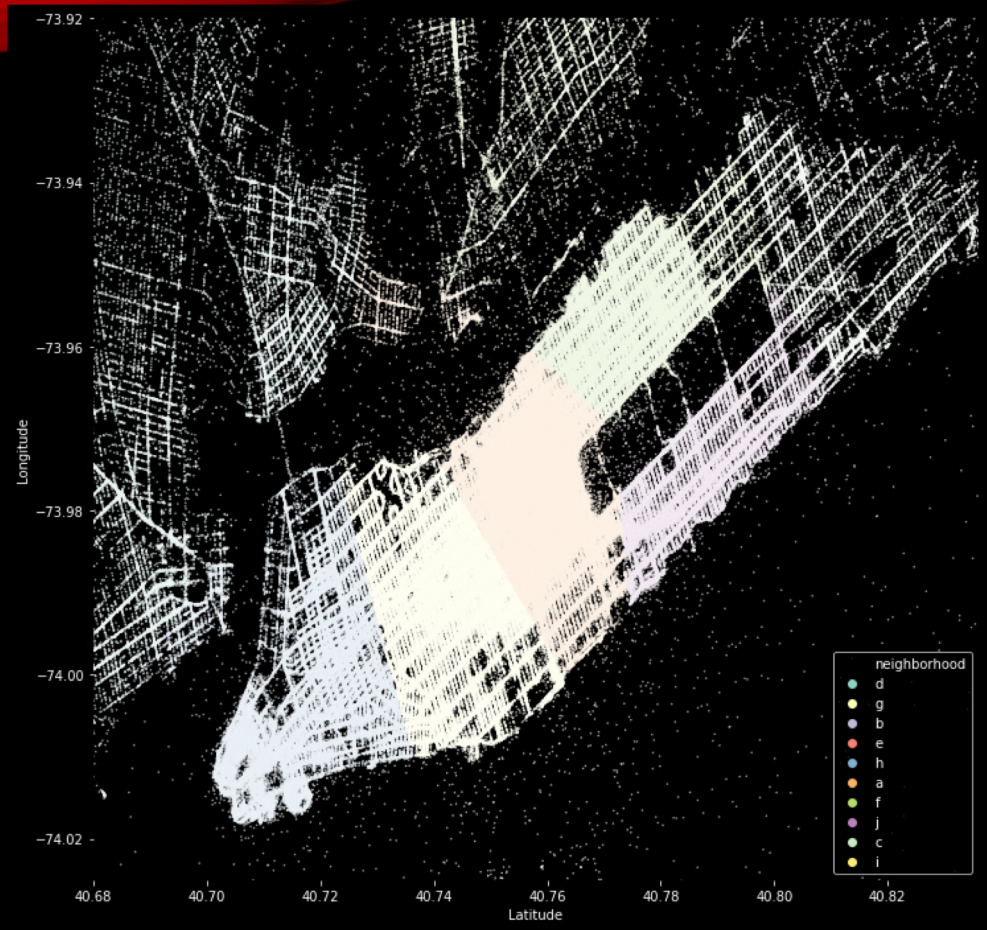
Predict Fare via Machine Learning

By analyzing 100k trips and various variables, machine learning improves the fare prediction.

A machine learning model predicts fare with

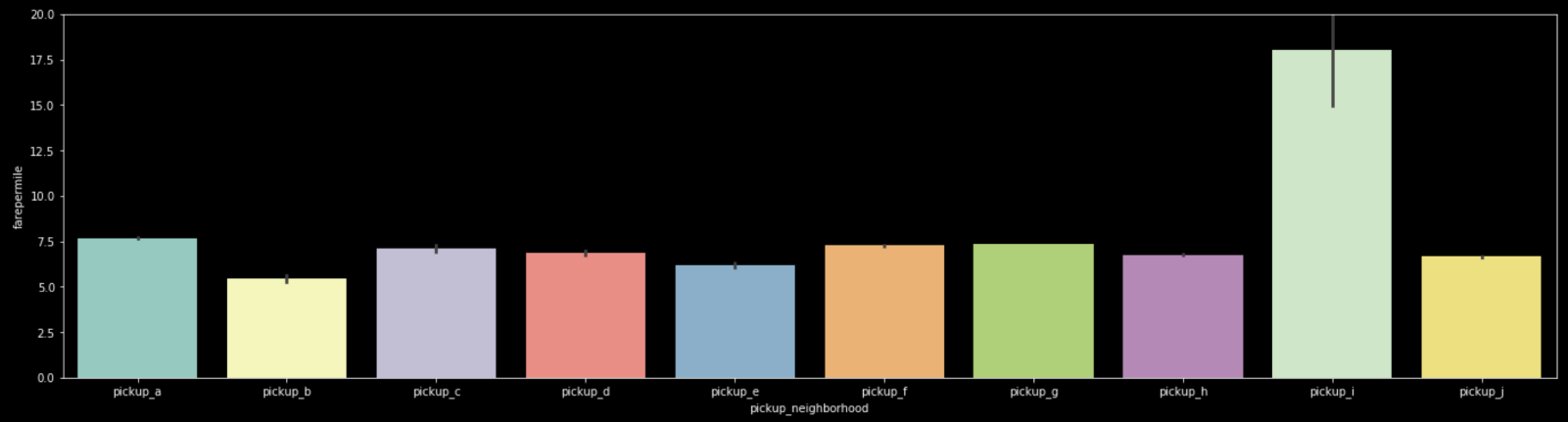
85% accuracy

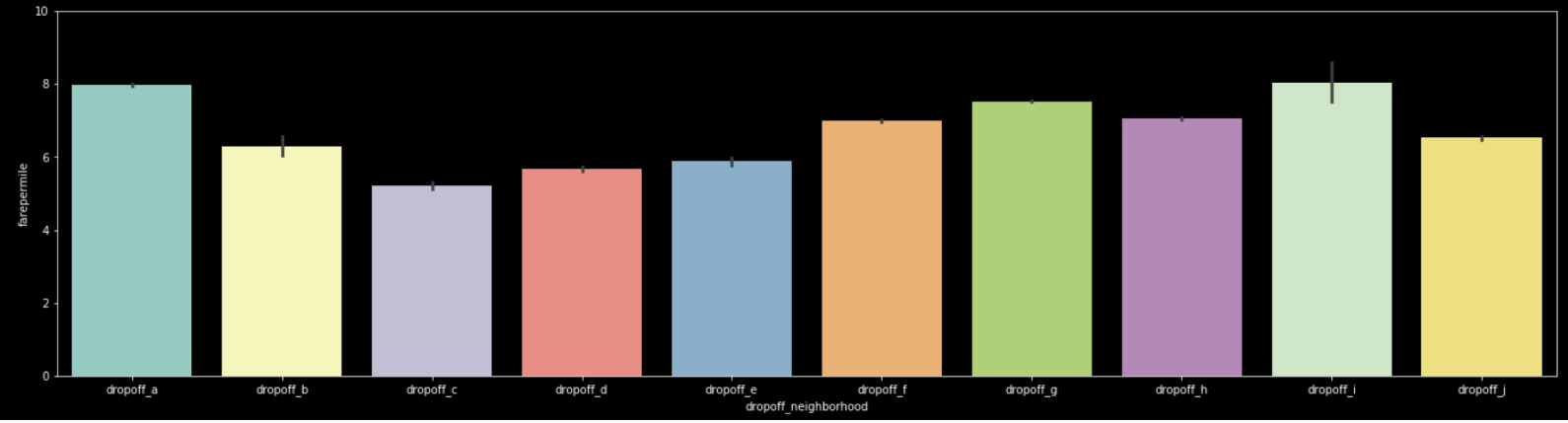
IN WHAT NEIGHBORHOOD IS THE TRIP?



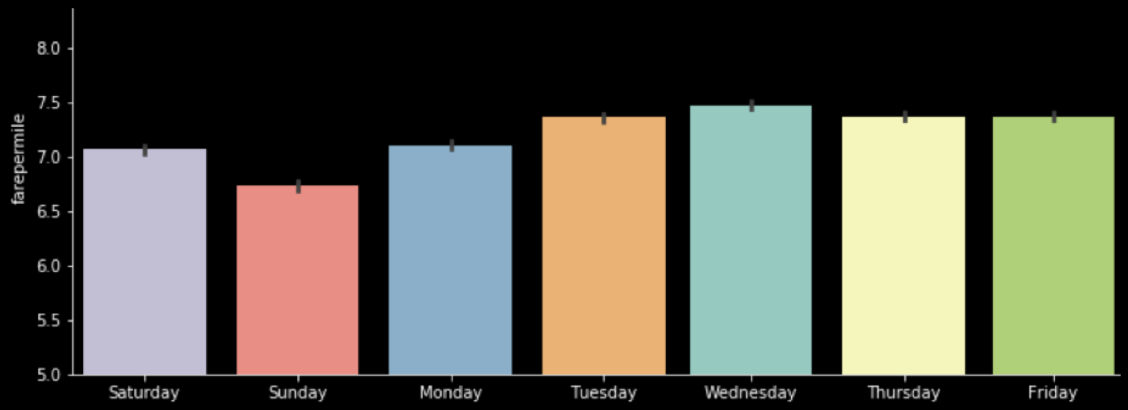
- Raw data did not include neighborhood
- It had latitude/longitude of pickups and drop offs
- Used K-Means clustering to classify each location into a neighborhood

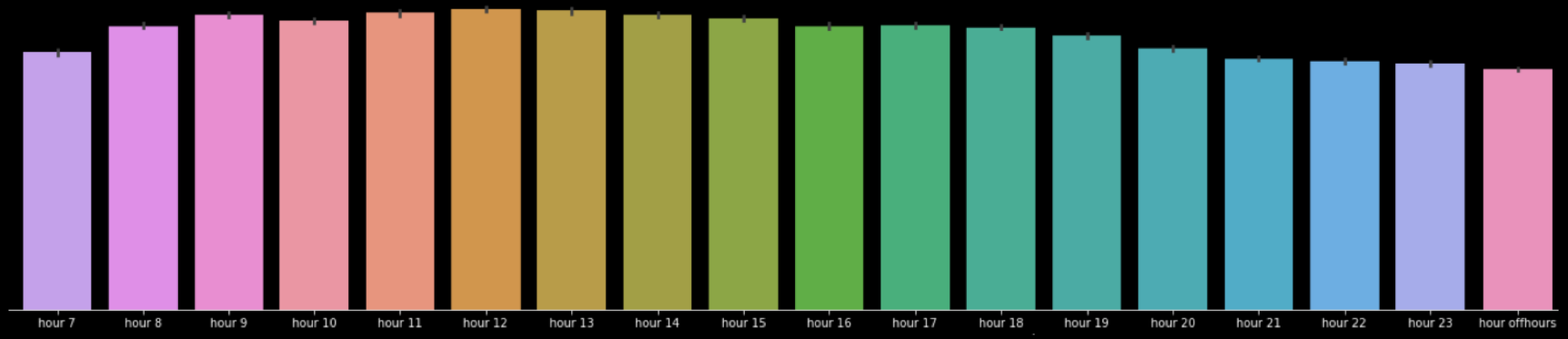
IN WHAT NEIGHBORHOOD IS THE TRIP?



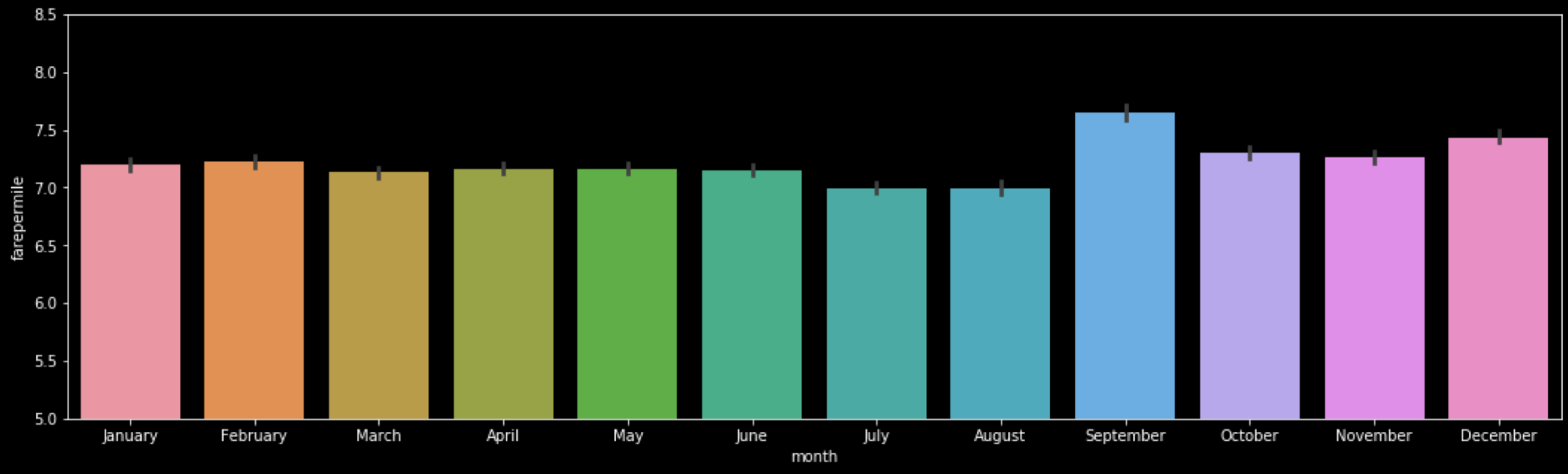


WHAT DAY/TIME IS THE TRIP?

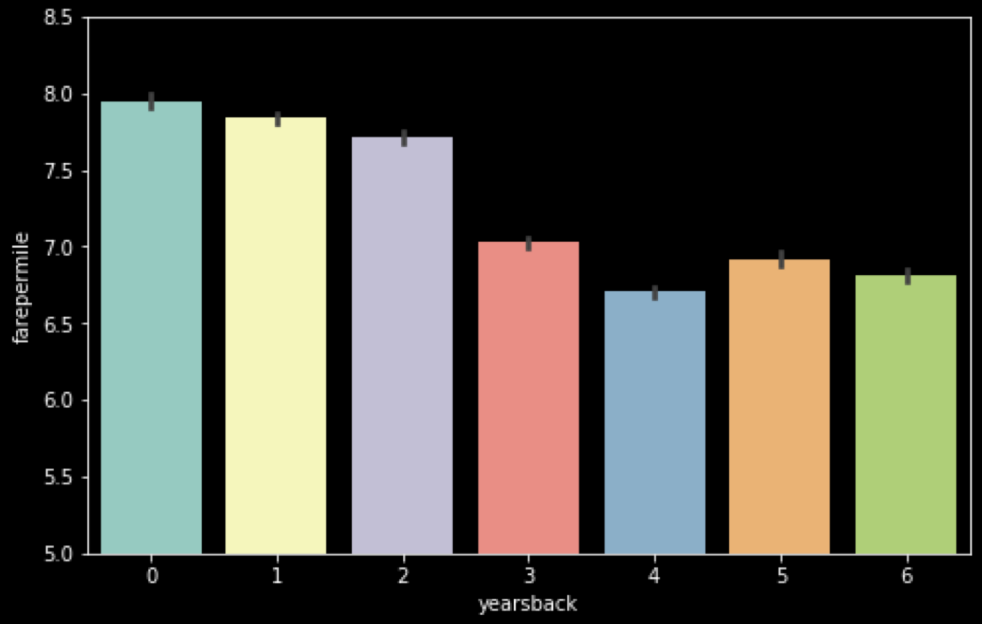




IN WHAT MONTH IS THE TRIP?



ADJUSTING FOR YEAR



- Preferred to use only current year data
- The problem, current year data did not contain all months
- Used data from all years
- Model considers the year

LINEAR REGRESSION

Parameter	Coeffecient
Distance	3.18766
pickup_f	2.72567
pickup_e	1.80419
dropoff_f	1.7397
dropoff_a	-1.24568
dropoff_e	1.16563
dropoff_d	-1.16297
pickup_i	-0.93435
pickup_h	-0.843274
pickup_d	-0.802747
hour offhours	-0.796381
pickup_g	-0.700399
dropoff_c	0.669987
pickup_a	-0.639254
pickup_c	-0.56551
yearsback	-0.539557
dropoff_g	-0.509957
hour 22	-0.473082
dropoff_i	-0.447837
hour 14	0.428566
hour 7	-0.42768
hour 21	-0.423438
hour 23	-0.405336

hour 20	-0.401007
hour 15	0.399084
hour 11	0.386091
December	0.374973
hour 16	0.36823
September	0.363612
November	0.347777
January	-0.329728
hour 13	0.325502
October	0.320482
hour 12	0.30835
February	-0.287021
March	-0.285356
Sunday	-0.249097
hour 17	0.236832
hour 10	0.233097
April	-0.220042
Thursday	0.19481
hour 9	0.182364
dropoff_h	-0.164548
August	-0.164452

hour 19	-0.163482
July	-0.1503
Wednesday	0.132476
Friday	0.129599
Saturday	-0.122603
hour 8	0.113138
hour 18	0.109152
Monday	-0.0803993
June	0.0476519
dropoff_j	-0.0464079
pickup_j	-0.0464079
May	-0.0175972
Tuesday	-0.0047855
dropoff_b	0.00208805
pickup_b	0.00208805

L1 (Ridge) Regularization helps make coefficients explainable

COMPARING MODEL ACCURACY

100k Sample	Distance Calculator (No ML)	Linear Regression	K Nearest Neighbors Regression
5 NY Neighborhoods	.751 (+/- .055)	.767 .044	.843 .013
10 NY Neighborhoods	.751 (+/- .055)	.777 .057	.847 .013
15 NY Neighborhoods	.751 (+/- .055)	.793 .053	.843 .012

Other Models attempted but were too slow:

- Support Vector Machine Regression
- Random Forest Regression

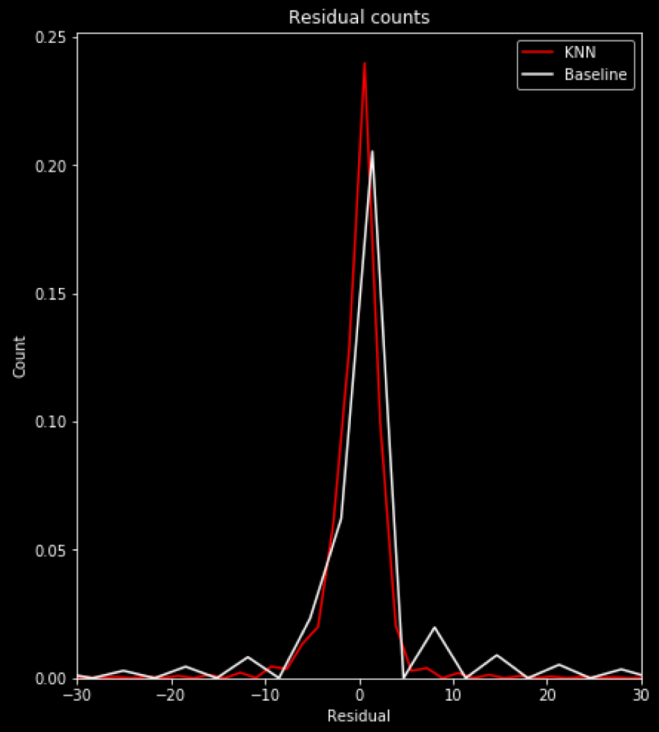
FINAL MODEL TUNING

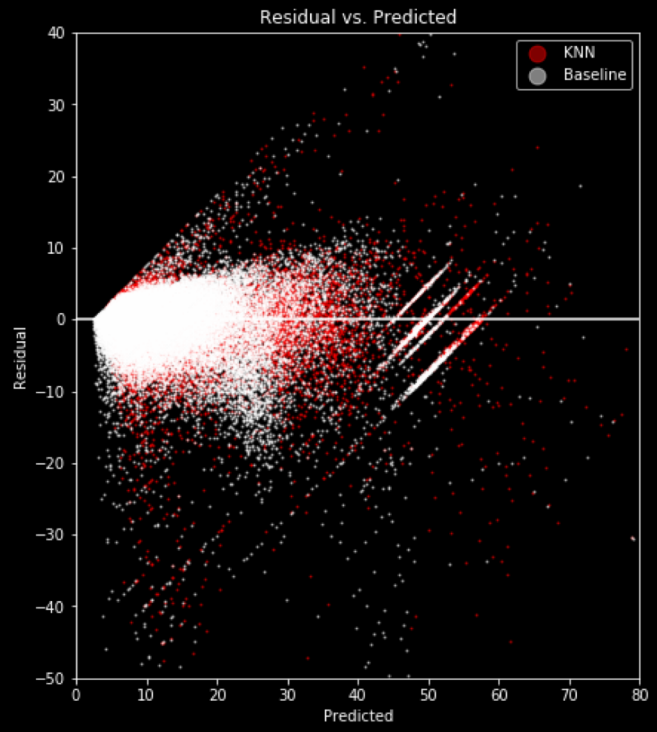
Used sklearn GridSearchCV to fine tune the model

Find the optimal number of K neighbors.

	10 Neighbors	15 Neighbors	20 Neighbors	30 Neighbors	40 Neighbors
Cross Validation Accuracy	.846 (+/- .014)	.847 (+/-.013)	.847 (+/-.013)	.846 (+/-.012)	.845 (+/-.012)

T-TEST: IS KNN MODEL BETTER THAN USING A SIMPLE DISTANCE CALCULATOR?





	Accuracy
KNN	.847 (+/- .013)
Distance Calculator	.751 (+/- .055)

	T Test
Hypothesis	KNN model improves accuracy over Baseline model
P-Value	1.53e-05
Result	99.9% confident that KNN does improves accuracy

KAGGLE RESULTS

- This was also a Kaggle competition
- My first submission: 750th place out of 1500
- My limitations
  - Limited Compute power
  - Could analyze only 600k of the 55mill records
  - Spent 1 week