

Capstone Project: Ride BigApple (=)





Problem Statement

- **Premise:** Can yellow cab fares be predicted within New York City's five boroughs based on time of the day, time of the year and certain high passenger areas?
 - Scenario: Dataset of rides with just the fare, coordinates, number of passengers and a time stamp.
 - Aim: Engineer new features and build a model that takes user inputs and predicts the ride's fare and distance.



Dataset

• 55.4 million rows



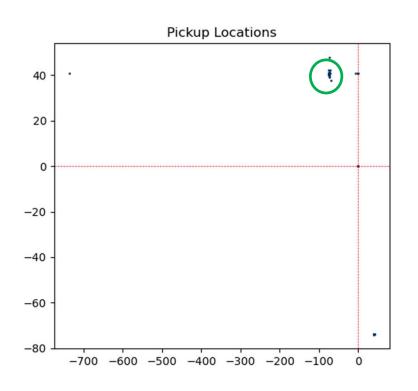
• Sampled 60 thousand observations

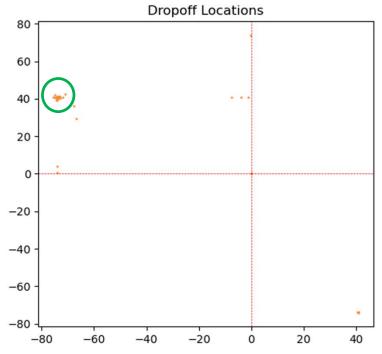


	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	$drop off_longitude$	dropoff_latitude	passenger_count
0	2010-10-31 03:32:00.000000130	3.7	2010-10-31 03:32:00 UTC	-73.982163	40.762762	-73.987518	40.760543	1
1	2014-11-20 22:50:22.0000002	14.5	2014-11-20 22:50:22 UTC	-73.995560	40.759405	-73.968201	40.804051	1
2	2010-01-26 19:27:55.0000002	11.7	2010-01-26 19:27:55 UTC	-74.001313	40.736943	-73.994137	40.699002	1
3	2010-03-22 19:00:00.000000191	4.5	2010-03-22 19:00:00 UTC	-74.005897	40.770640	-74.008753	40.769735	1
4	2011-02-26 08:57:11.0000002	4.9	2011-02-26 08:57:11 UTC	-73.984917	40.749153	-74.000801	40.757591	1



Pickup and Dropoff Coordinates





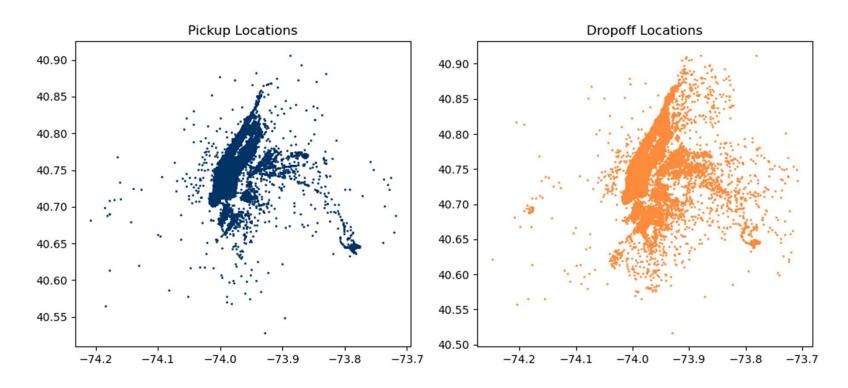


- Pickup and Dropoff Coordinates
 - Northernmost point: 40.915 degrees N latitude
 - Southernmost point: 40.496 degrees N latitude
 - Westernmost point: -74.256 degrees W longitude
 - Easternmost point: -73.702 degrees W longitude



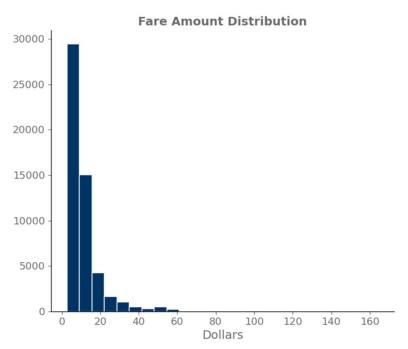


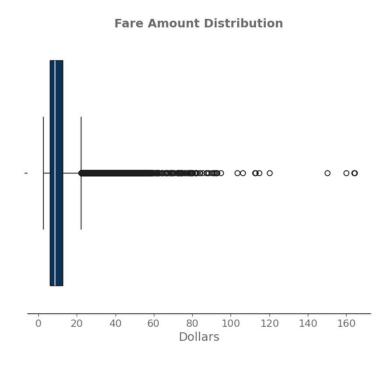
Pickup and Dropoff Coordinates





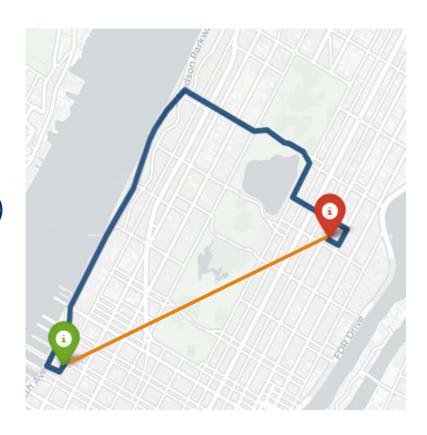
- Target Variable: Fare Amount
 - Right-skewed
 - Mean: 11.16 USD





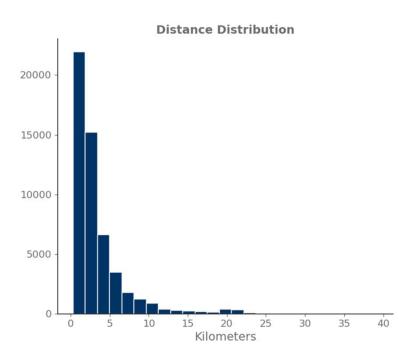


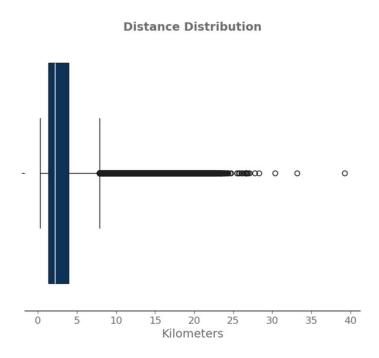
- Dominant feature: Distance, 0.9 corr.
 - 1st: Geodesic Distance (from coordinates)
 - Straight orange line
 - 2nd: Estimated Distance (after applying factors)
 - Aims to approximate blue line
 - 1.15 under 10 kms
 - 1.2 otherwise





- Dominant feature: Distance, 0.9 corr.
 - Also, right-skewed
 - Mean: 3.37 kms

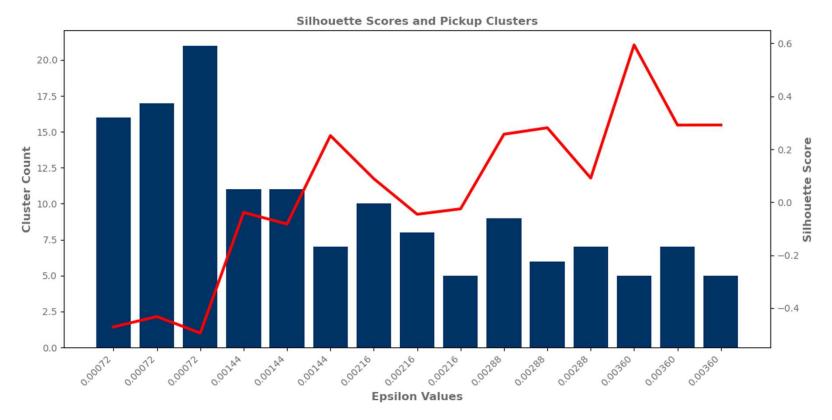






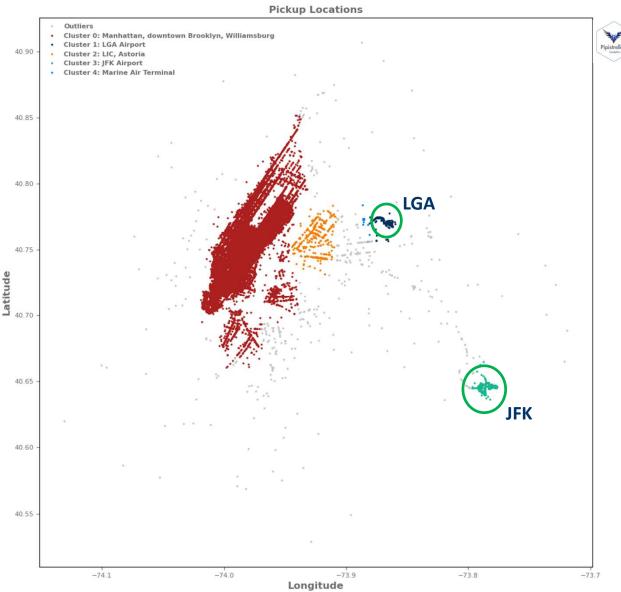
Modeling: Geospatial Clusters

Pickup Coordinates



Modeling: Geospatial Clusters

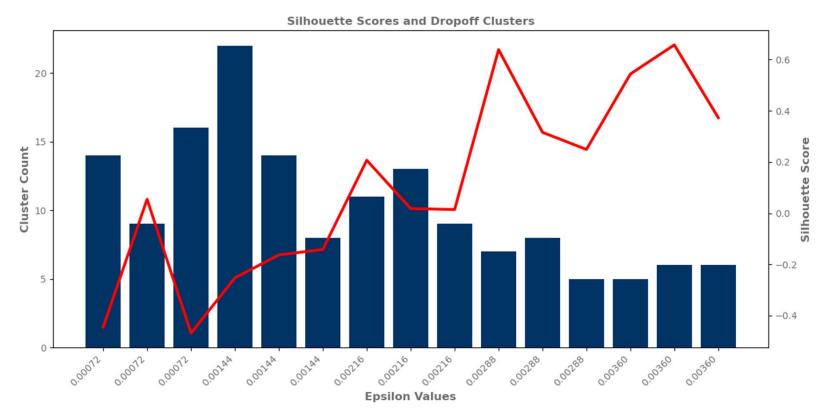
Pickup Clusters





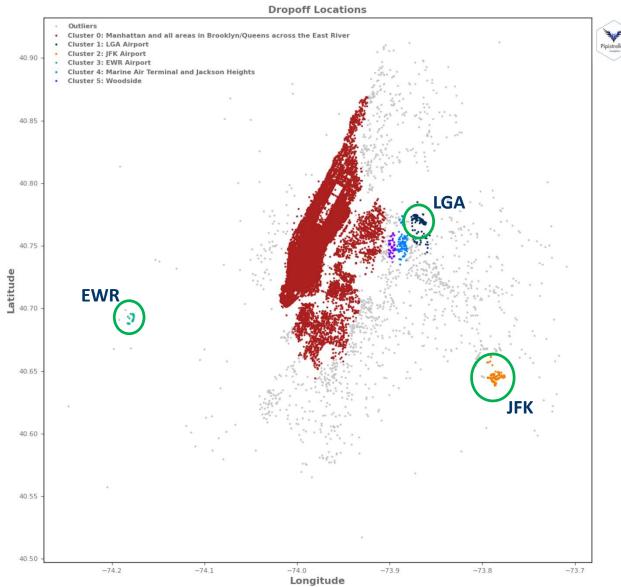
Modeling: Geospatial Clusters

Dropoff Coordinates



Modeling: Geospatial Clusters

Dropoff Clusters





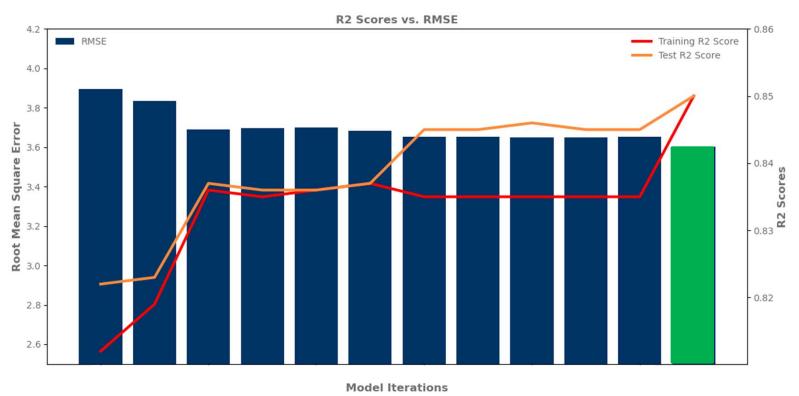
Modeling: XGBRegressor

- Engineered Features
 - **p_0**: pickups, Manhattan+
 - **p_1**: pickups, LGA
 - p_3: pickups, JFK
 - **p_4:** pickups, Marine Air Terminal
 - **d_0**: dropoffs, Manhattan+
 - **d_1**: dropoffs, LGA
 - d_2: dropoffs, JFK
 - **d_3**: dropoffs, EWR

- Engineered Features
 - **estimated_distance:** from coordinates
 - distance_hour: distance/hour interaction
 - **JFK:** rides to/from JFK
 - LGA: rides to/from LGA
 - weekend_rides: rides on Sat. or Sun.
 - holiday_rides: rides in Nov. or Dec.



Modeling: XGBRegressor



MODEL ITERATIONS

First nine: Linear Regression

Next two: Lasso

Last: XGBRegressor

RMSE: 3.602

• R2 Training: 0.85

R2 Test: 0.85



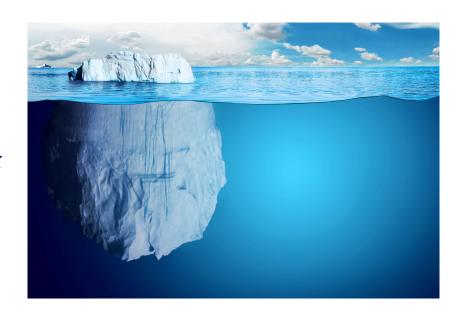
Next Steps: Project

- More EDA,
 - Explore identified relationships at deeper level (better granularity)
 - Discover new relationships
 - Tweak engineered features
- Aim for more, smaller, localized clusters, specially in Manhattan
- Upgrade Streamlit App
 - Accept landmark names instead of addresses
 - Yankee Stadium, Columbus Circle, etc.



Next Steps: Myself

- Bootcamp got me to the tip of the iceberg
- Future Focus
 - Feature Engineering
 - Python Feature Engineering Cookbook by Soledad Galli
 - Visualizations
 - Storytelling with Data by Cole Nussbaumer Knaflic







Questions?