Capstone Project

NYC TAXI TRIP TIME PREDICTION.

Individual Project

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Problem Statement

We have the data which was originally published by the NYC Taxi and limousine Commision (TLC), for the year 2016. This dataset consists of various trip related feature and our aim is to predict the trip duration based on these features.

Introduction

In today's world it has become a race to gain more and more number of customers.

To gain more number of customers companies/vendors usually try to provide their customers with more comfort to attract them.

So here we will be predicting the time of trip duration our customers will take and which algorithm is best suited for that time prediction.

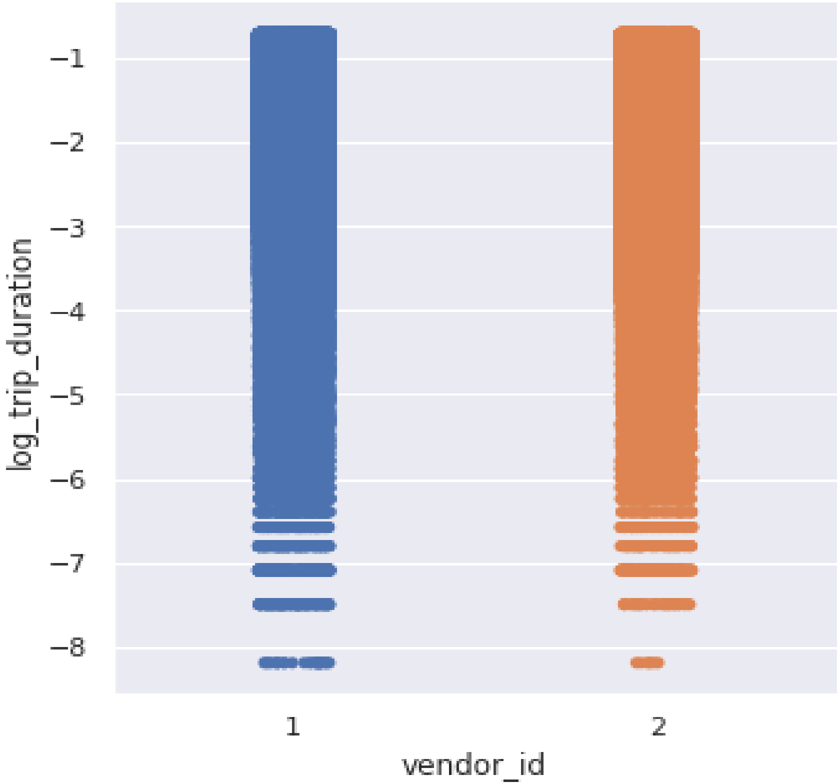
Data Summary

- 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

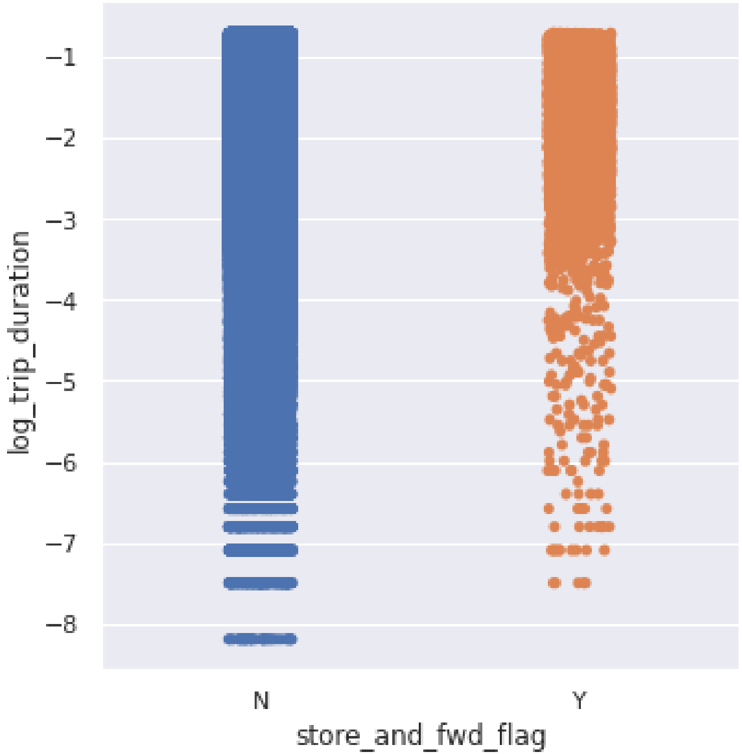
Basic Exploration

- The dataset contains 1458644 rows and 11 features(columns)
- Two categorical features 'store_and_fwd_flag' and 'vendor_id'
- Outlier present in all numerical features
- Data cleaning steps required for datetime features
- No null values present

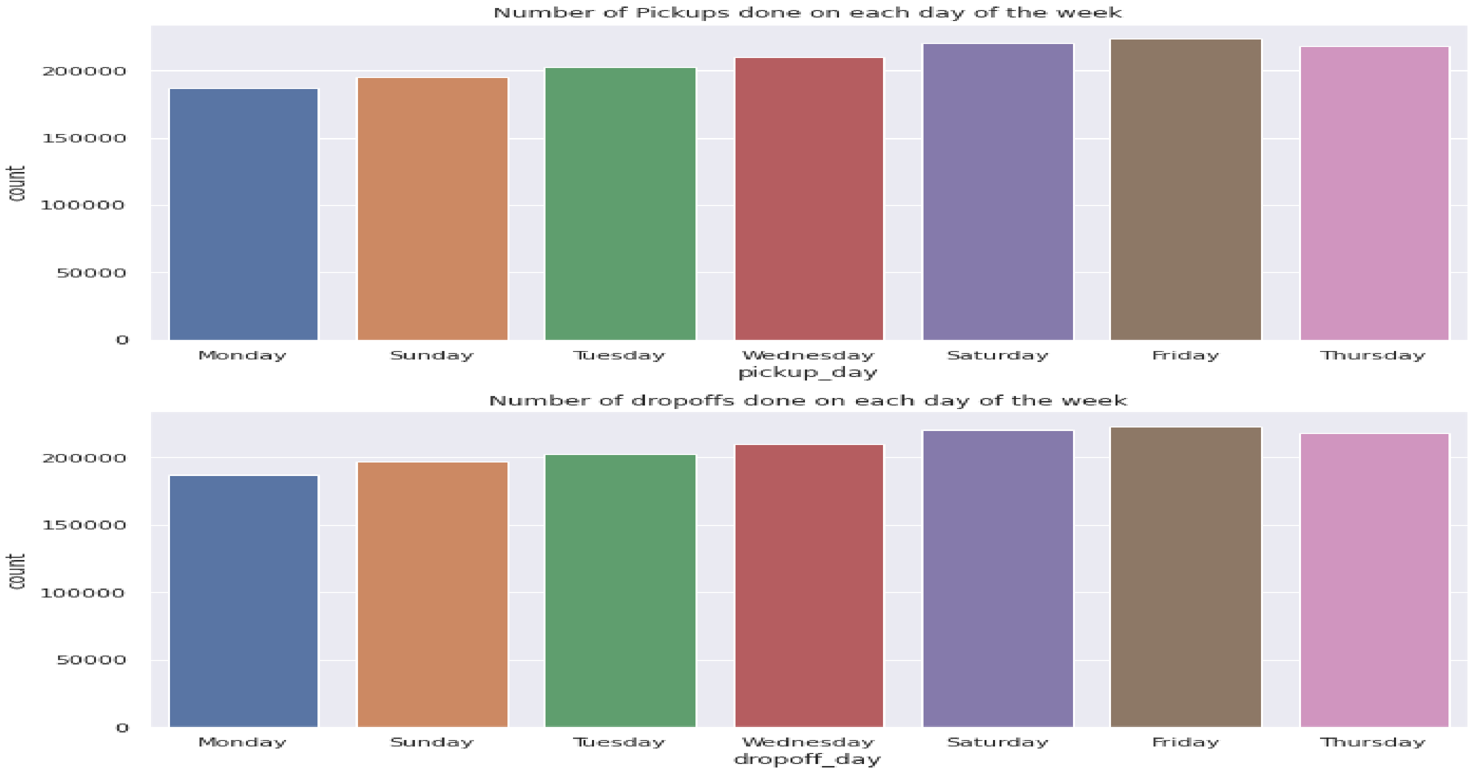
Vendor ID Analysis



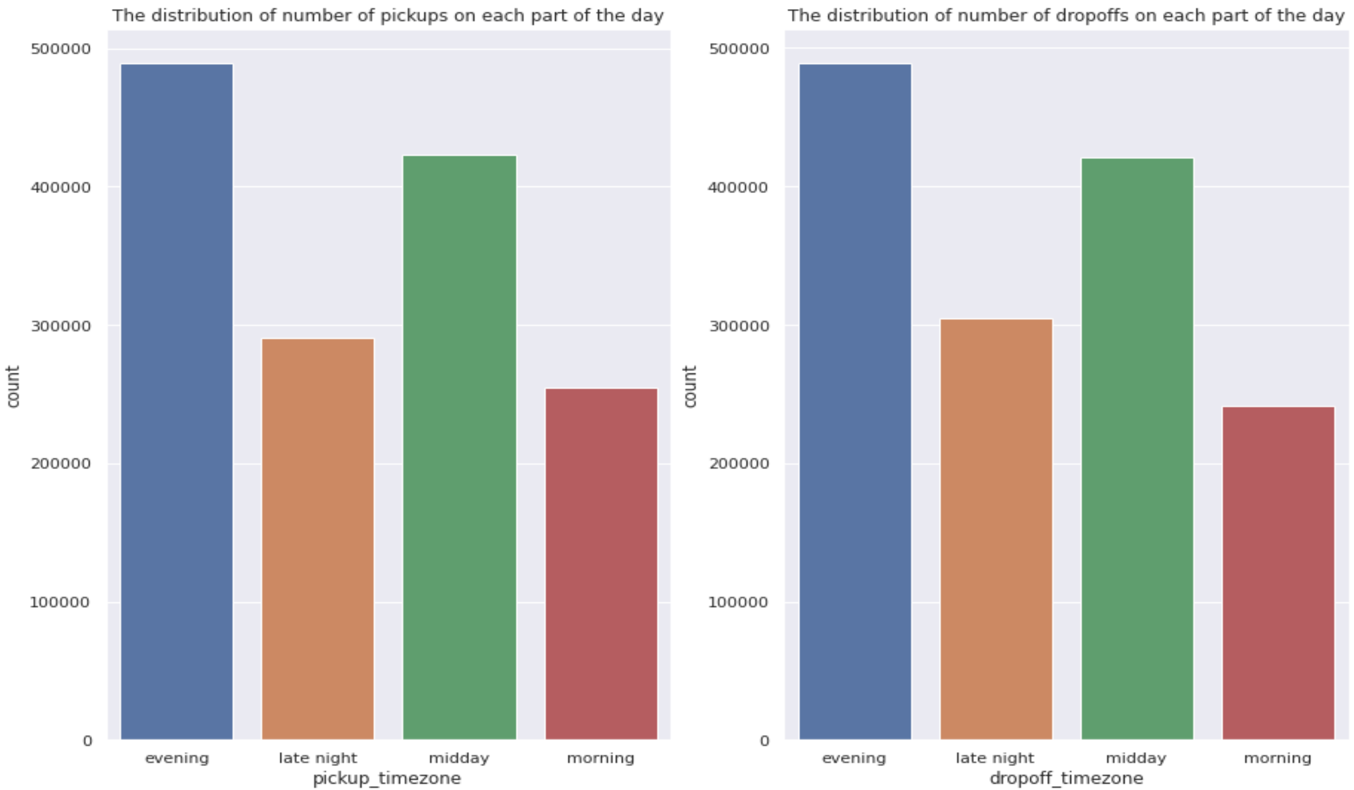
Store and forward flag



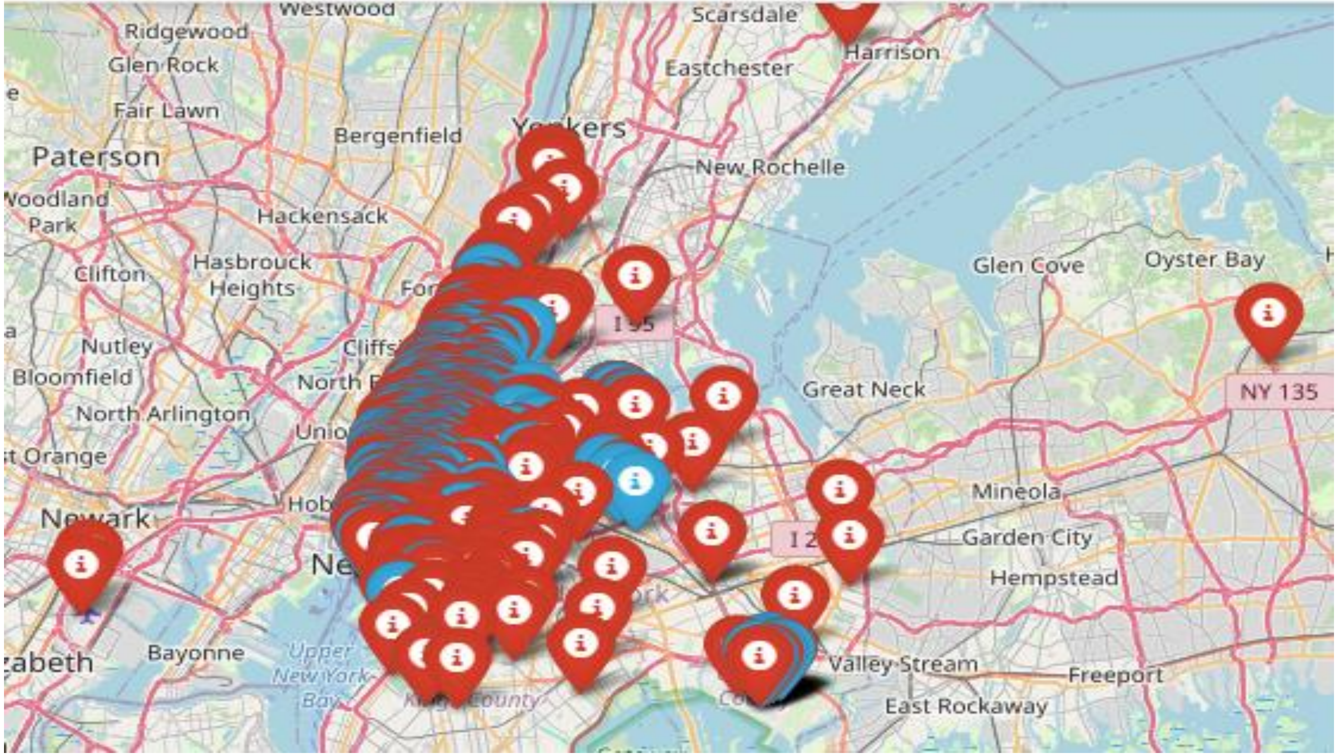
Days of the week



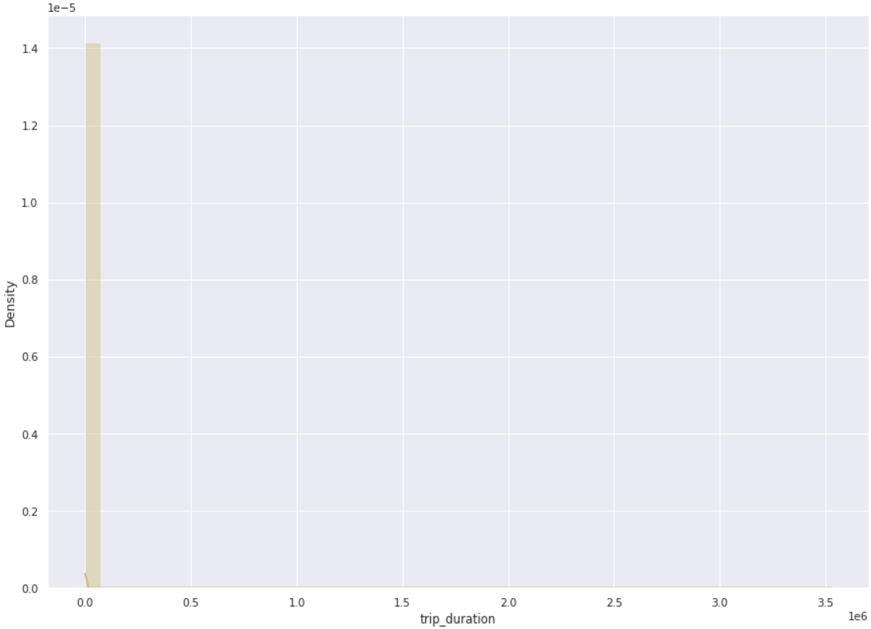
Day Segmentation

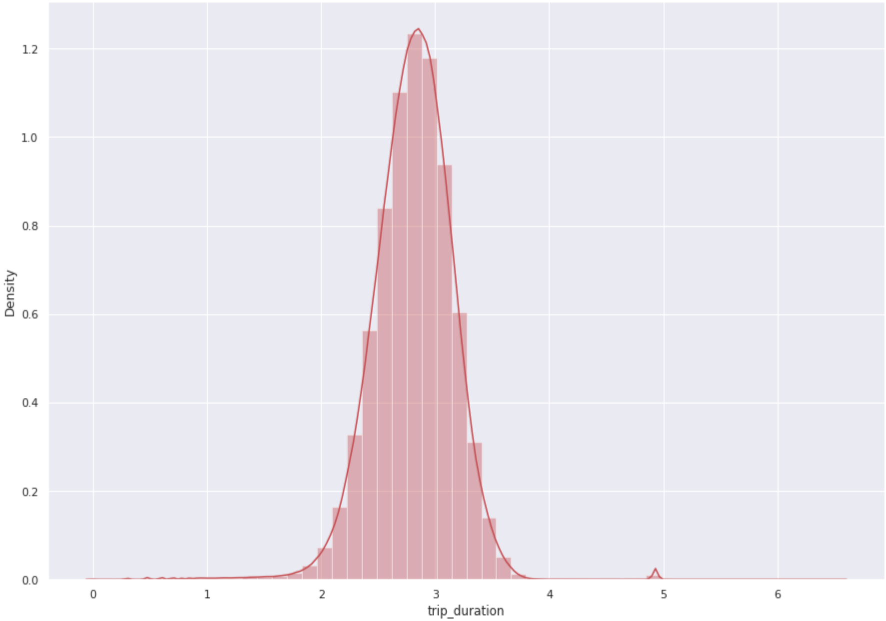


Plotting longitude and latitude

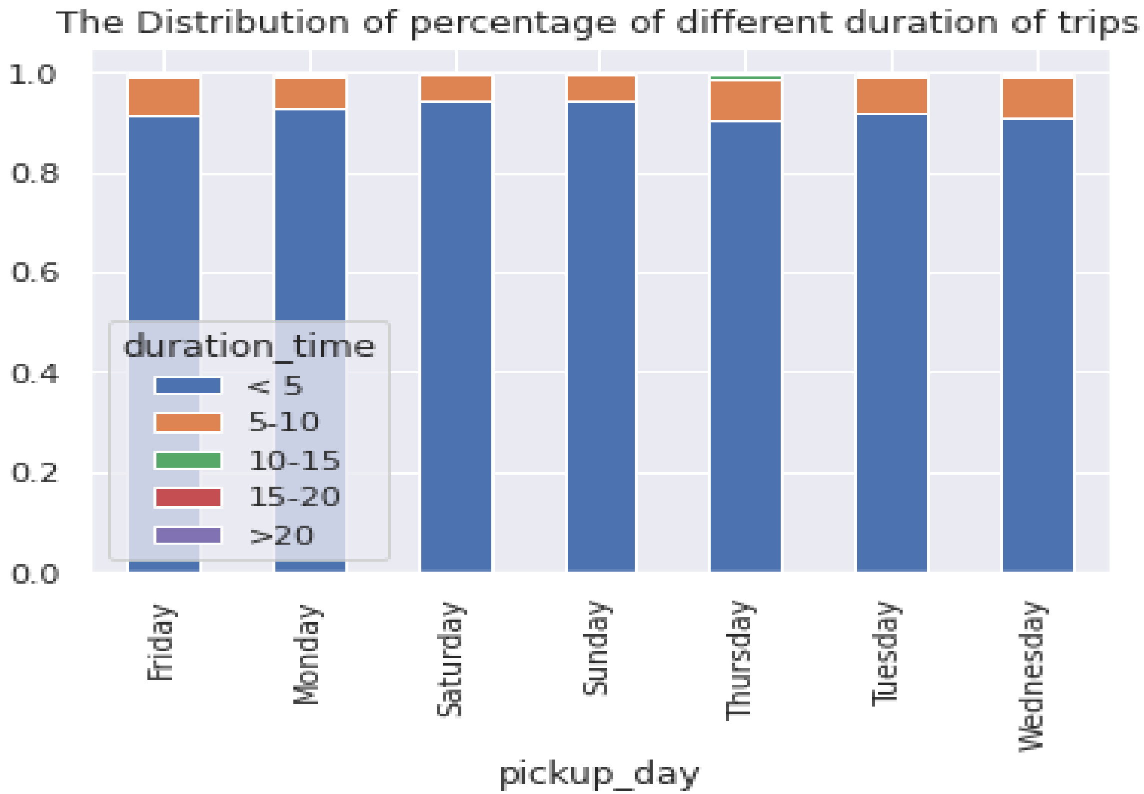


Trip Duration (dependent variable) Data Analysis



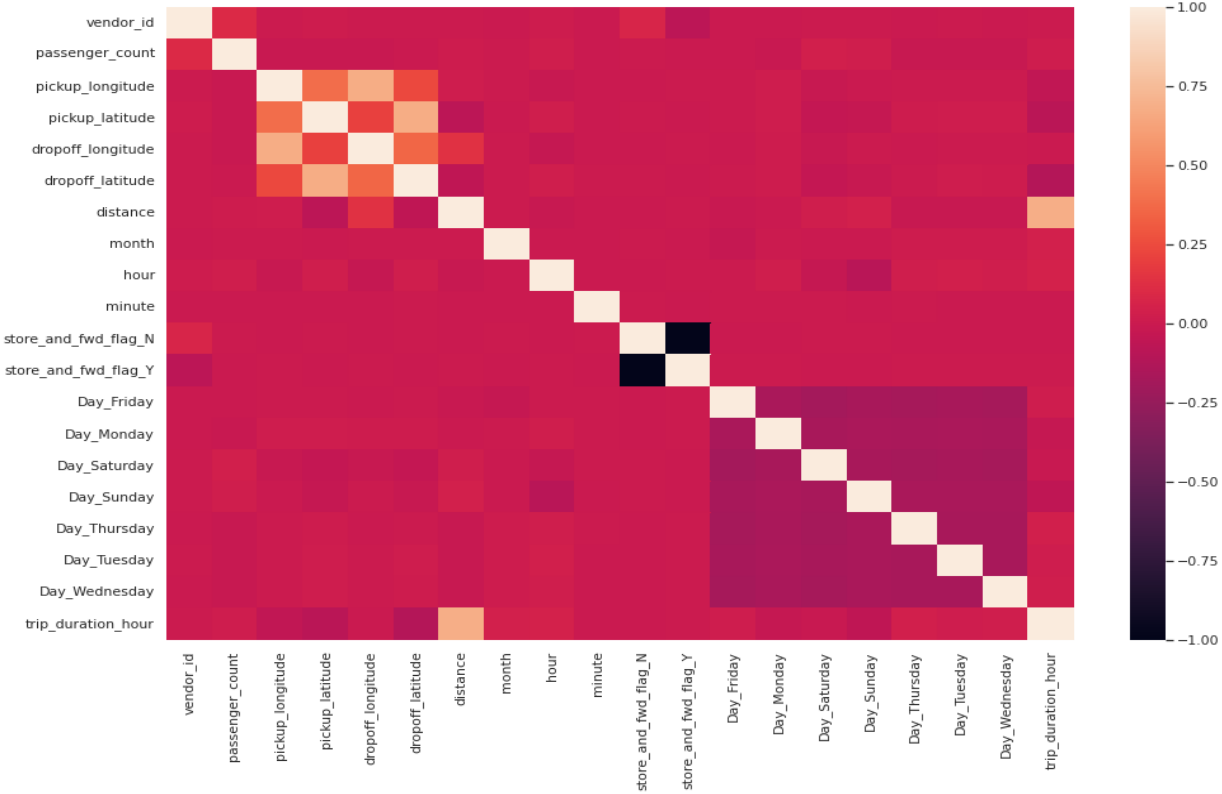


Trip Duration/Day of the week



Analysis Details

Correlation



Lasso Regression

Train set metrics

```
Train MSE : 0.00552025815855849
Train RMSE : 0.0742984398124112
Train R2 : 0.4971655712177893
Train Adjusted R2 :  0.4970461181776832
```

Test set metrics

```
Test MSE : 0.00554725477502239
Test RMSE : 0.0744798951061452
Test R2 : 0.4983934824098727
Test Adjusted R2 :  0.497916479214967
```

Ridge Regression

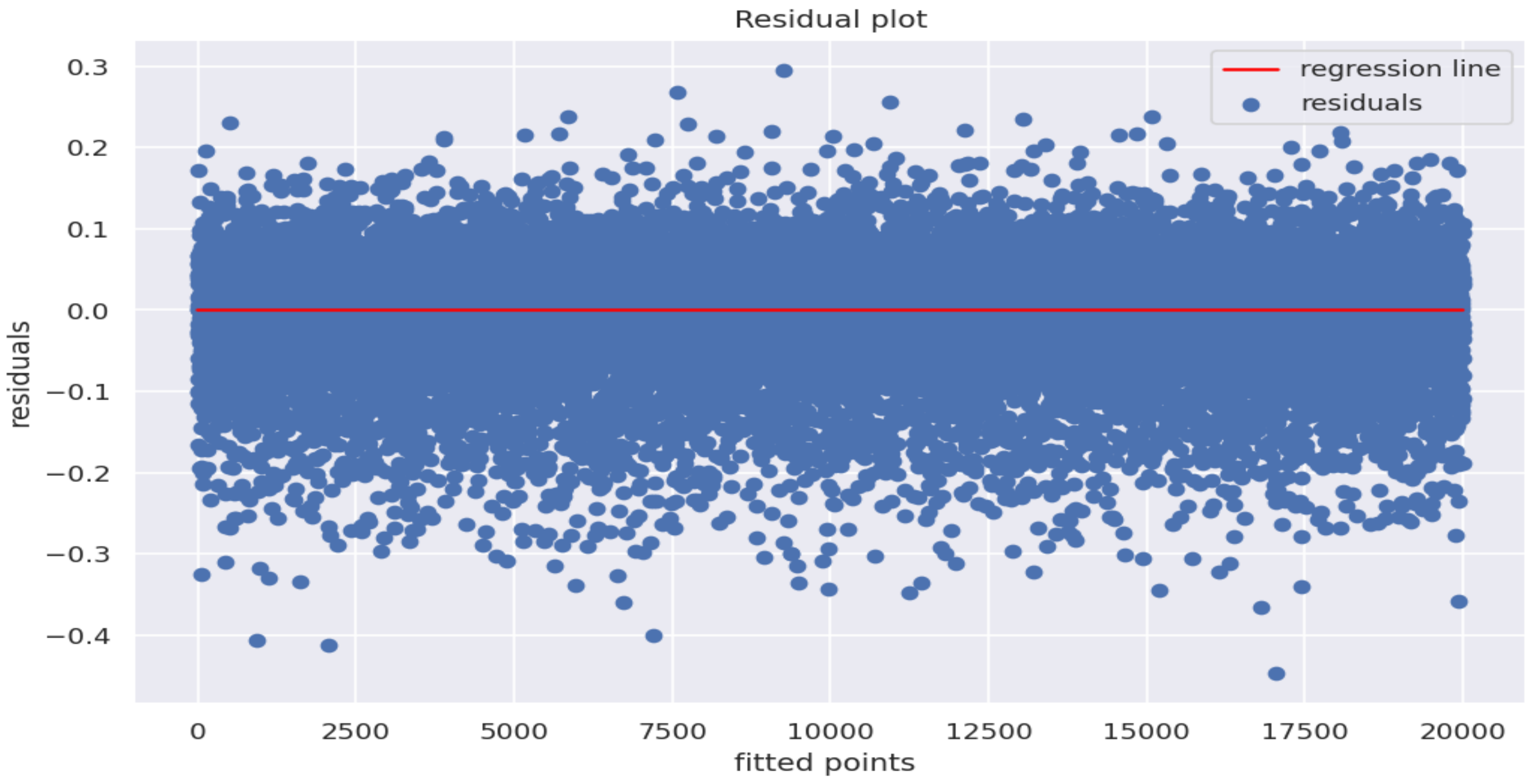
Train set metrics

```
Train MSE : 0.00552025690875150
Train RMSE : 0.0742984314016891
Train R2 : 0.4971656850613645
Train Adjusted R2 :  0.4970462320483133
```

Test set metrics

```
Test MSE : 0.00554725927427578
Test RMSE : 0.0744799253106216
Test R2 : 0.4983930755681258
Test Adjusted R2 :  0.497916071986333
```

Homoscedasticity check



Decision Tree

Train set metrics

```
Train MSE : 0.003903026546923643
Train RMSE : 0.062474207053180З
Train R2 : 0.6444774740830809
Train Adjusted R2 :  0.644393016368747
```

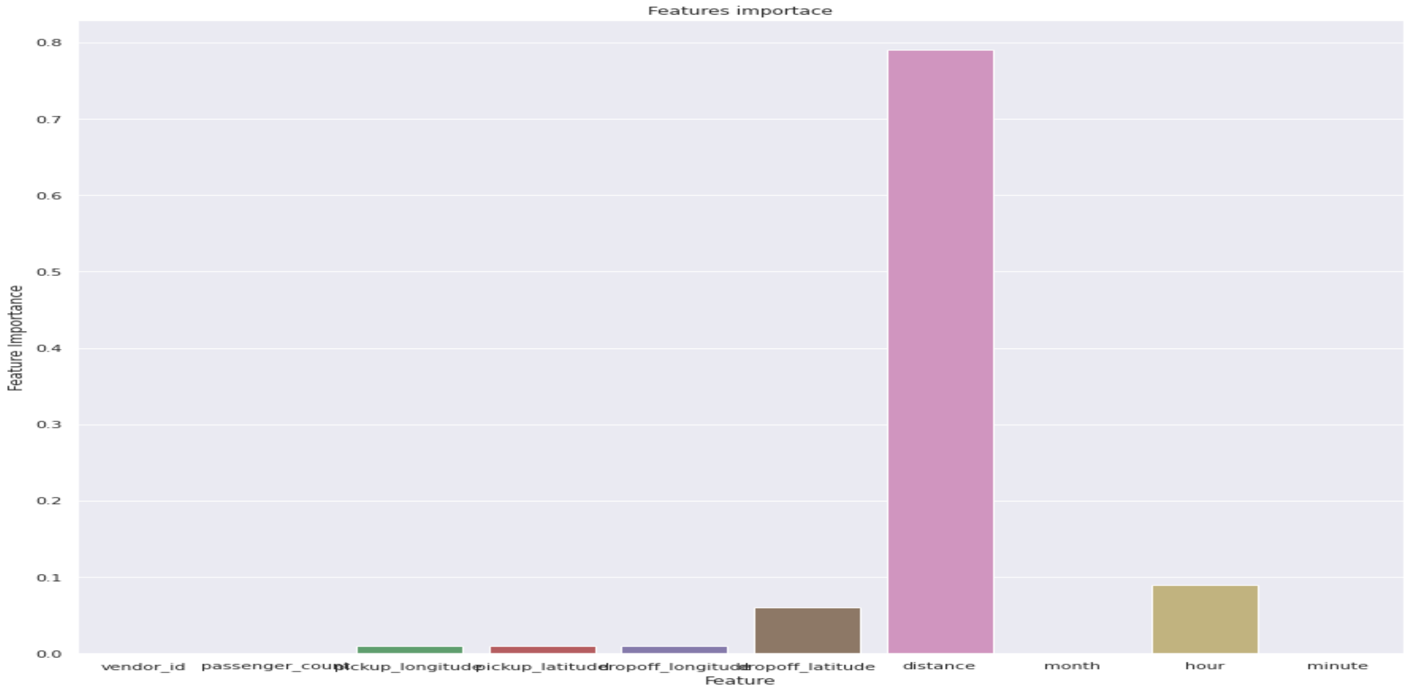
Test set metrics

```
Test MSE : 0.004354489573938102
Test RMSE : 0.065988556386225В
Test R2 : 0.606248416622113В
Test Adjusted R2 :  0.605873978179462Z
```

Parameters:

- Criterion=mse
- Max_depth =10
- Min_sample_leaf=20
- Min_sample_split=10

Decision Tree Feature Importance



Gradient Boosting

Train set metrics

```
Train MSE : 0.002323670139456396
Train RMSE : 0.048204461821043036
Train R2 : 0.7883393649914061
Train Adjusted R2 :  0.7882890830200988
```

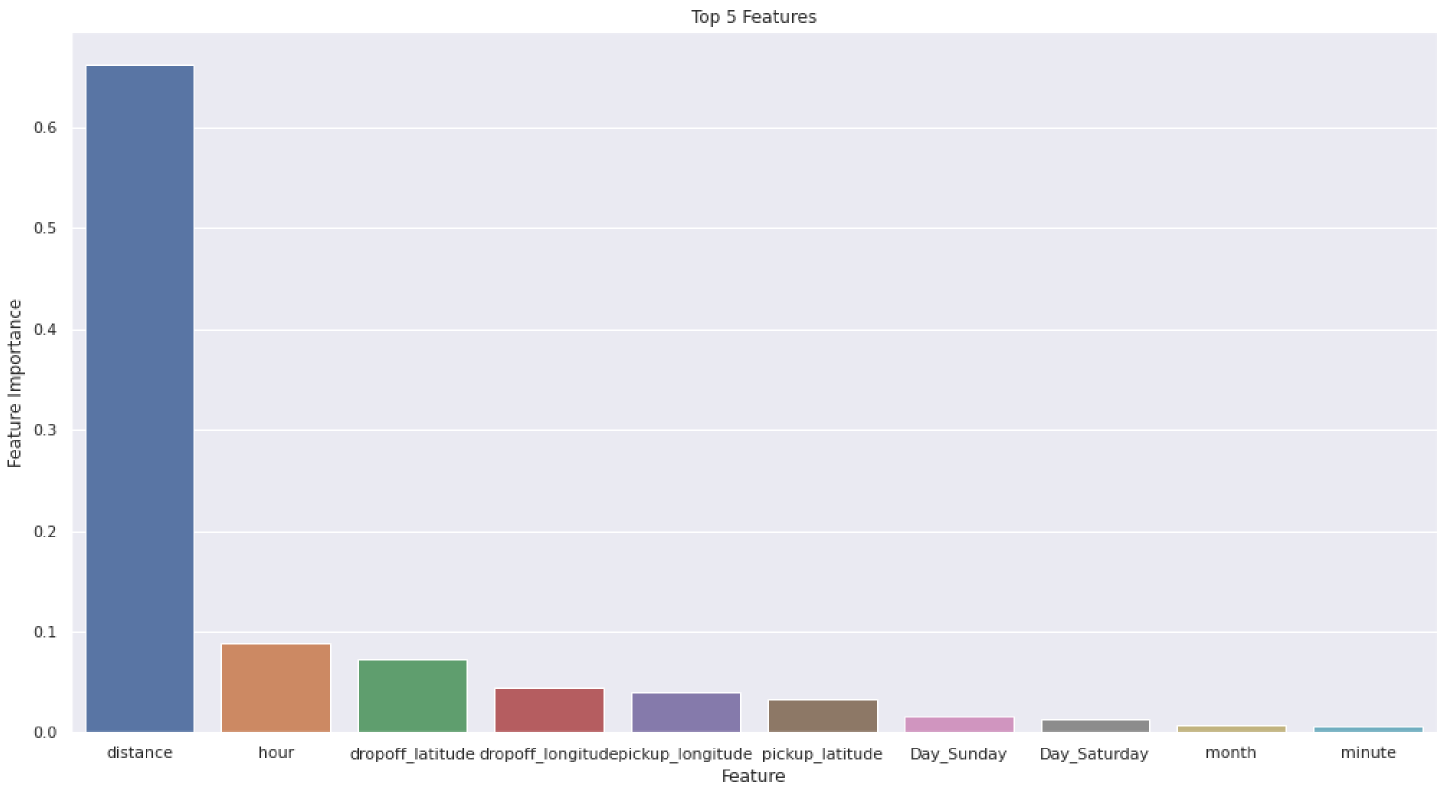
Test set metrics

```
Test MSE : 0.003268332446055223
Test RMSE : 0.05716933134168374
Test R2 : 0.704463392600178
Test Adjusted R2 :  0.7041823517823304
```

Parameters:

- alpha=0.9
- Max_depth =10
- Min_sample_leaf=50
- Min_sample_split=80
- N_estimators=120

GBoost feature importance



XGBOOST

Train set metrics

Train MSE : 0.001990850702399407

Train RMSE : 0.044618950036945146

Train R2 : 0.8186555325896028

Train Adjusted R2 : 0.8186124525085725

Test set metrics

Test MSE : 0.003263916896506688

Test RMSE : 0.05713070012267195

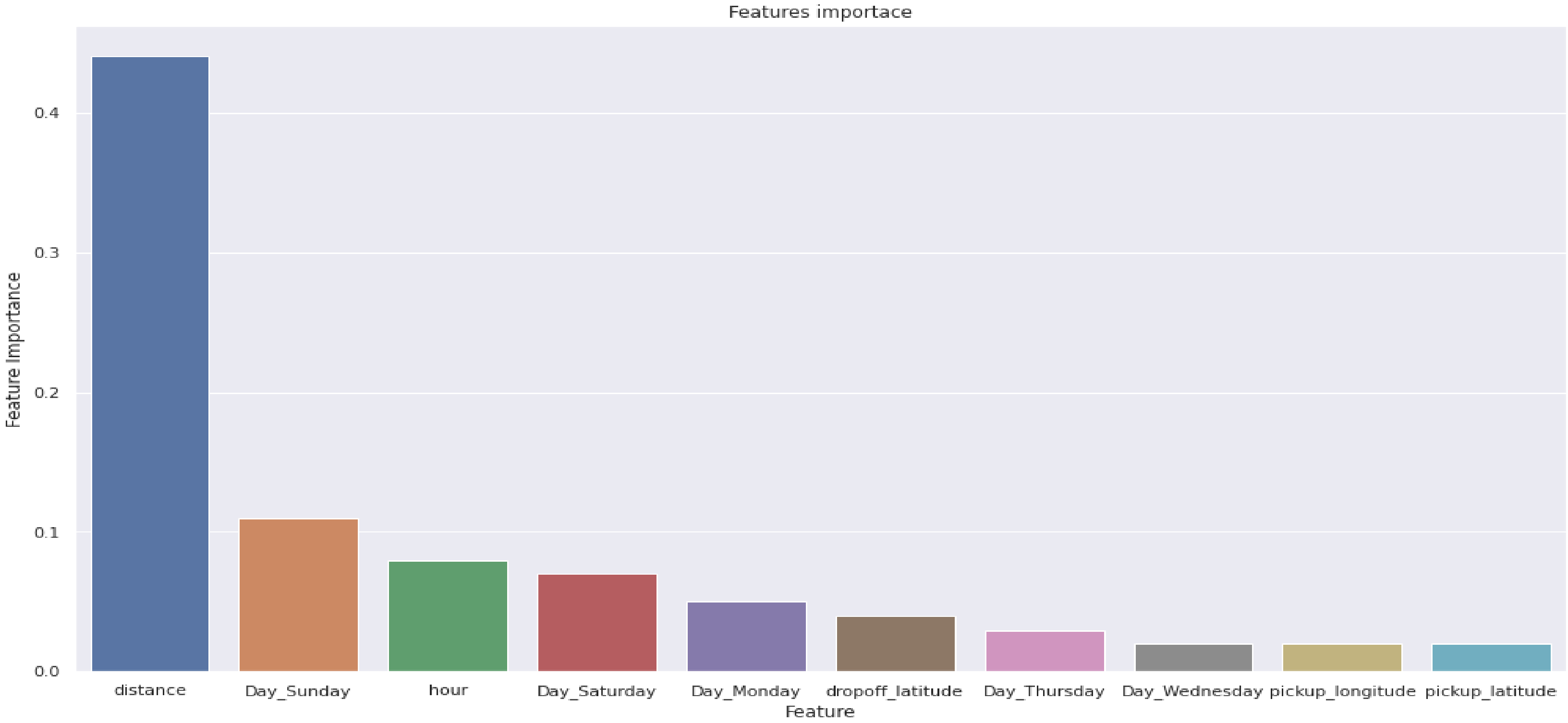
Test R2 : 0.7048626654877816

Test Adjusted R2 : 0.7045820043588662

Parameters:

- gamma=0
- Learning_rate=0.1
- Max_depth =9
- Min_sample_leaf=50
- Min_sample_split=40
- N_estimators=120

XGBoost feature importance



Final metric conclusion

SL NO	MODEL_NAME	Test MSE	Test RMSE	Test R^2	Test Adjusted R^2
1	Linear Regression	0.005539358995881834	0.07442687012015105	0.48551298500777995	0.48502373309162117
2	Lasso Regression	0.005448974432213879	0.07381716895285187	0.5030970331831028	0.502624502834278
3	Ridge Regression	0.005449008499105121	0.07381739970430495	0.5030939265545915	0.5026213932515153
4	DecisionTree Regressor	0.004203945325941736	0.06483783868962426	0.6166337480963826	0.6162691855945723
5	XGBRegressor	0.0031306995630522444	0.0559526546559879	0.7145051935101532	0.7142337019524301
6	GradientBoosting	0.00311712671404449	0.05583123421566543	0.7157429289820318	0.7154726144500327

SL NO	MODEL_NAME	Train MSE	Train RMSE	Train R^2	Train Adjusted R^2
1	Linear Regression	0.005467021181864388	0.07393930742077848	0.5042456435975543	0.5041278724951332
2	Lasso Regression	0.005494826110976565	0.07412709431089665	0.49994898506301866	0.4998301932490177
3	Ridge Regression	0.005494824127596807	0.07412708093265785	0.4999491655584595	0.49983037378733686
4	DecisionTree Regressor	0.003908733073695245	0.06251986143374956	0.6442897552818683	0.6442052529731706
5	XGBRegressor	0.001996779863964856	0.044685342831457114	0.8182850963041854	0.8182419282225373
6	GradientBoosting	0.002278863599313375	0.04773744441539969	0.7926143552635426	0.7925650888563159

Challenges

- **Handling Large Dataset.**
- **Feature Engineering.**

Click to add text

- **Computation Time.**
- **Optimising the Model.**

Conclusion

- In this project, we tried to predict the trip duration of a taxi I NYC.
- We are mostly concerned with the information of pick up latitude and longitude, to get the distance of the trip.
- Gradient Boosting will be the best model to predict the trip duration for a particular taxi.

Thank You!

Q&A