Capstone Project - 1

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 Commission (TLC), for the year 2016. This dataset consists of various trip related features 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.

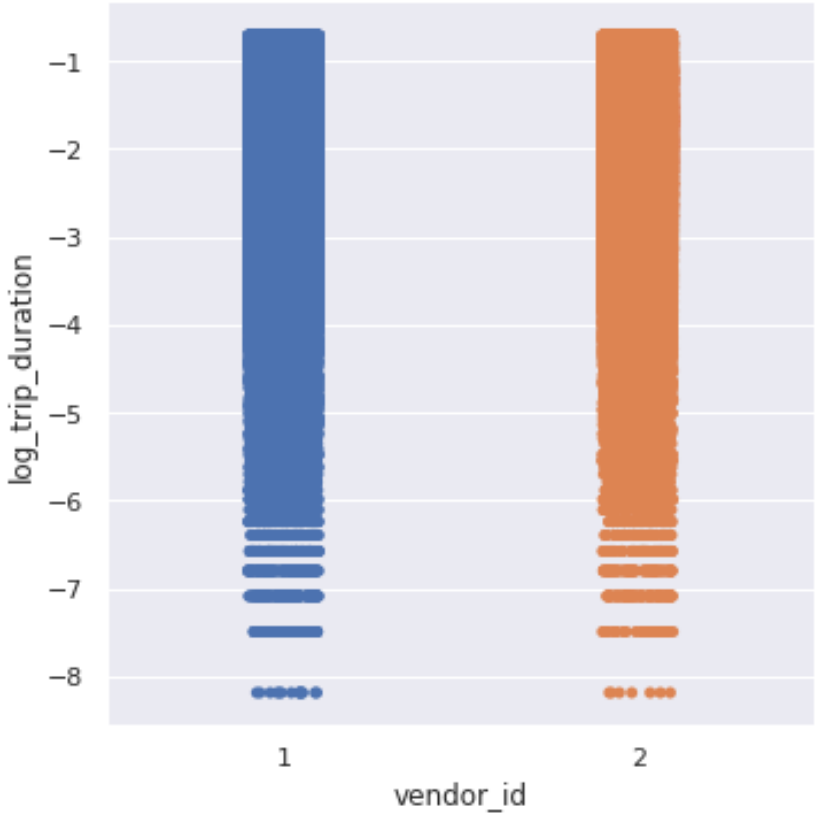
Data Summary

- 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 (Dependent variable)

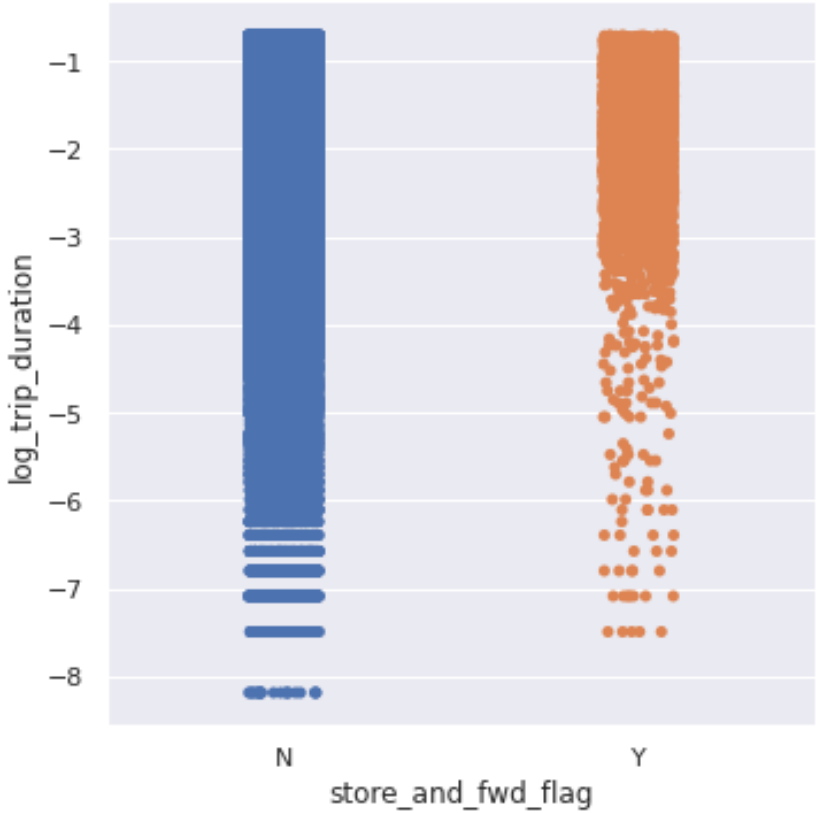
Basic Exploration

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

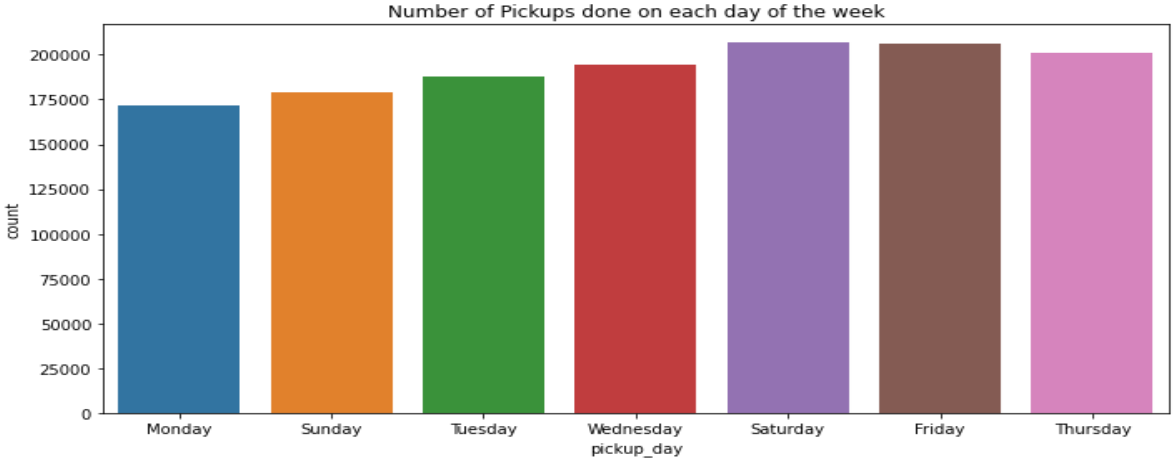
Vendor ID Analysis

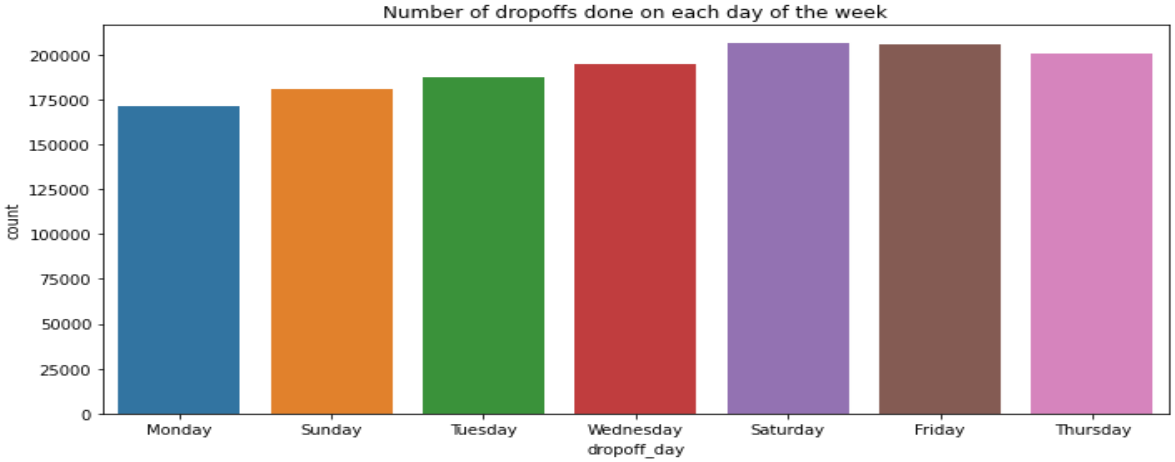


Store and forward flag

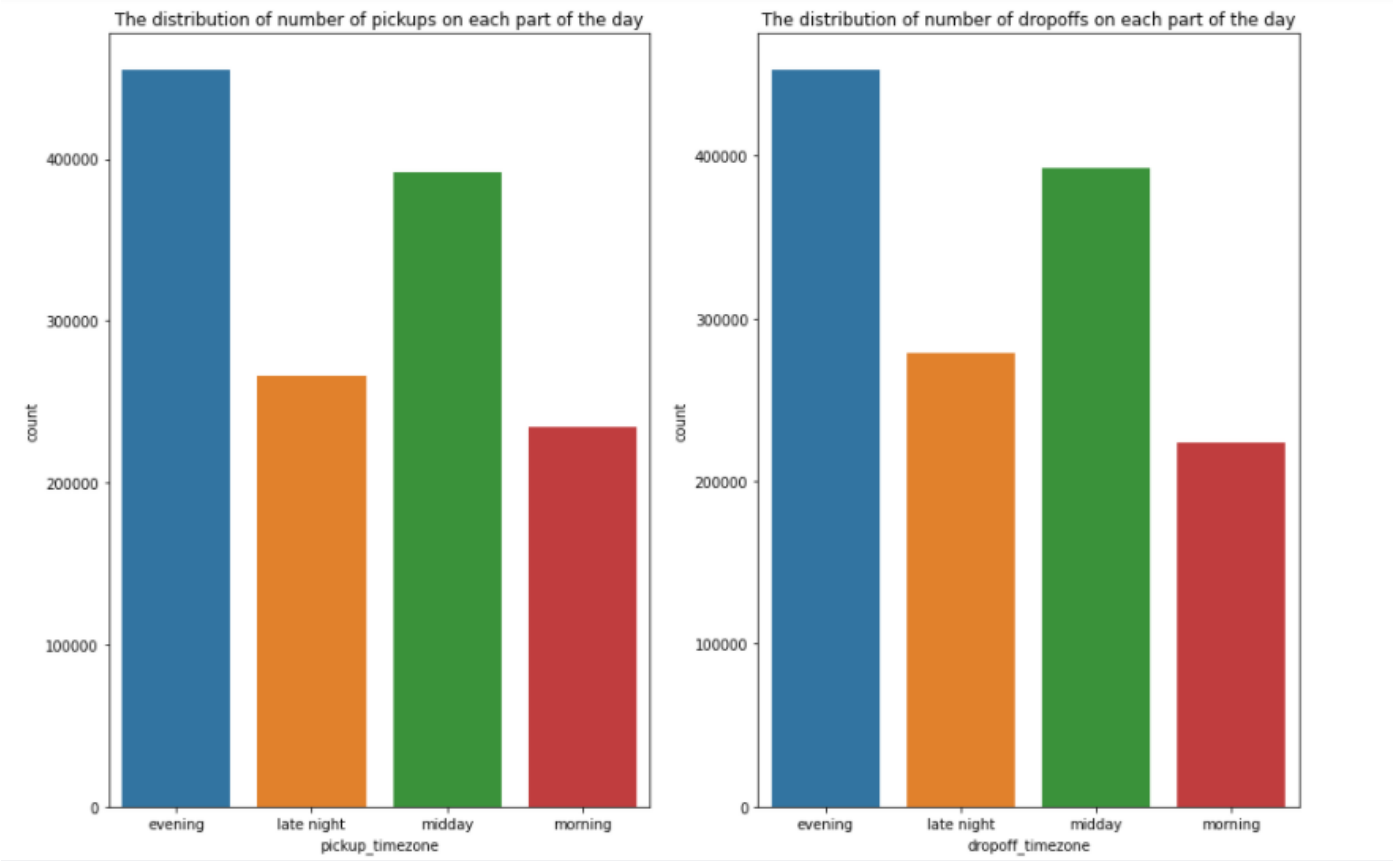


Days of the week

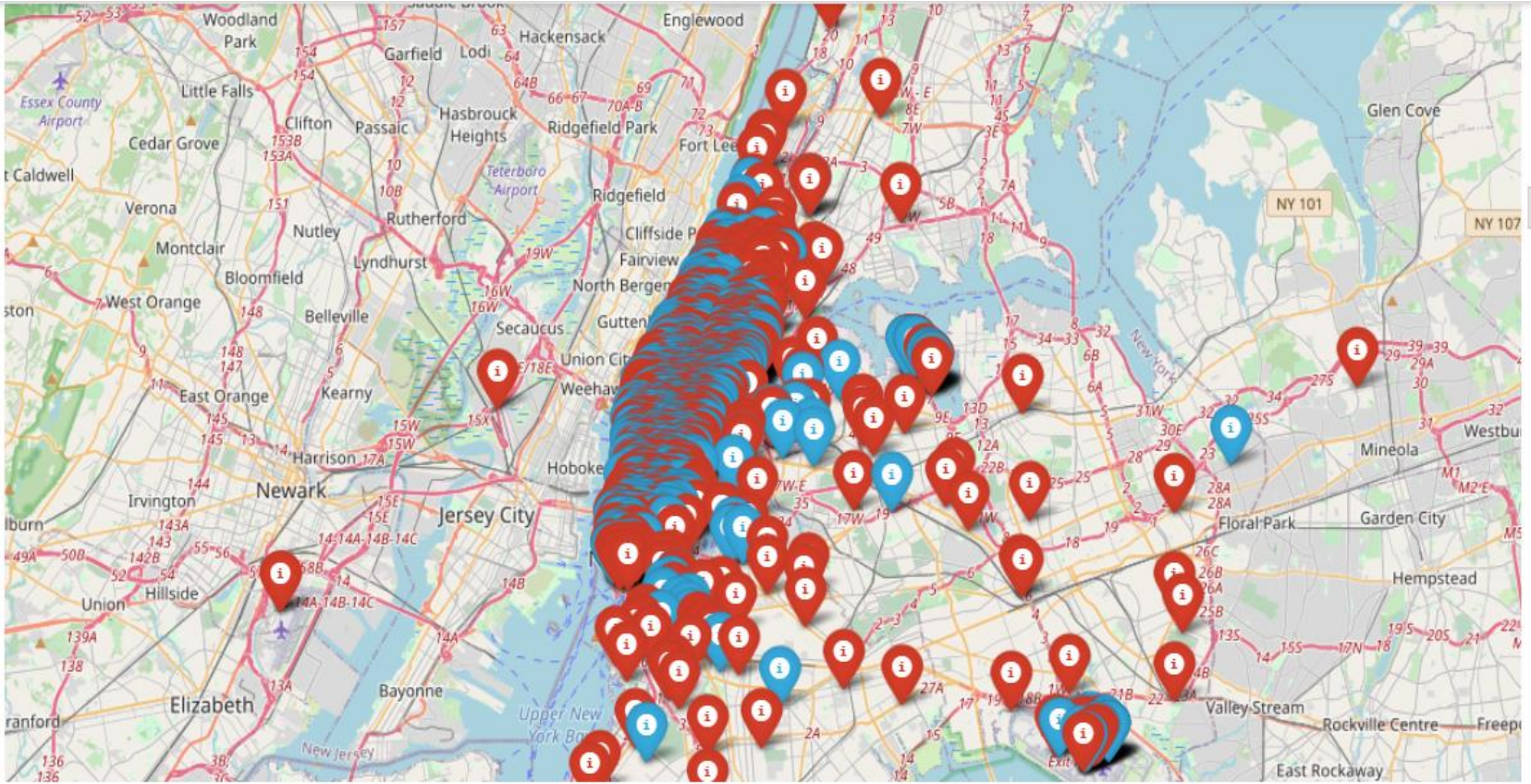




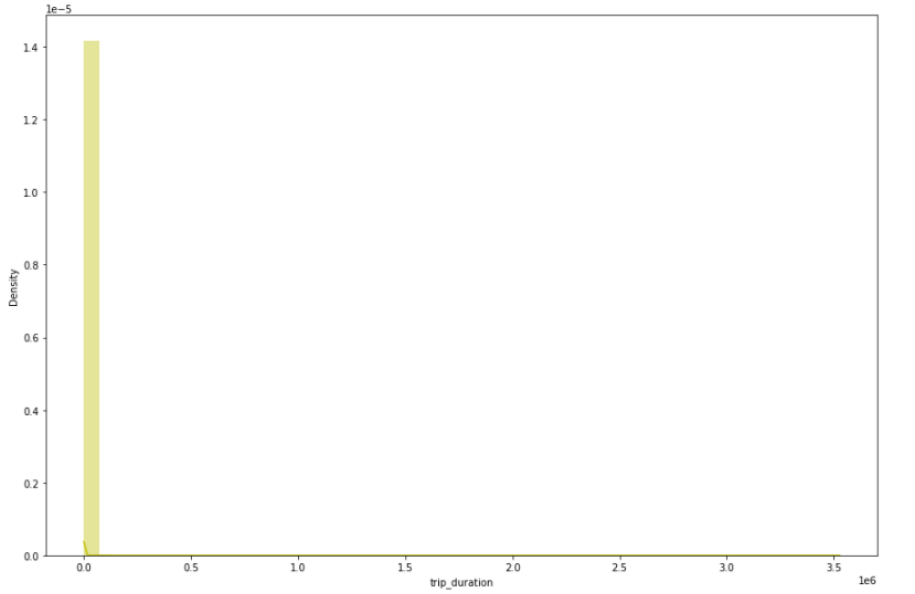
Day Segmentation

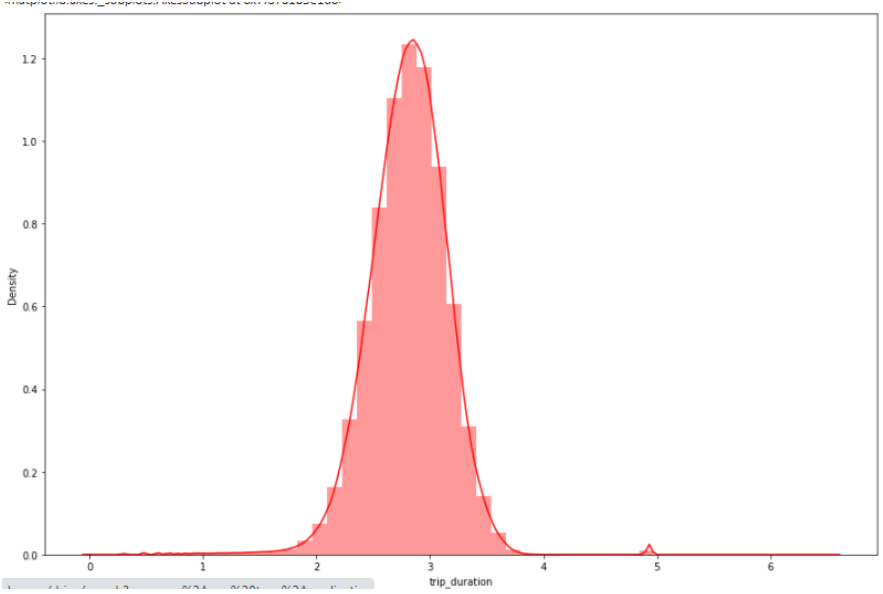


Plotting longitude and latitude

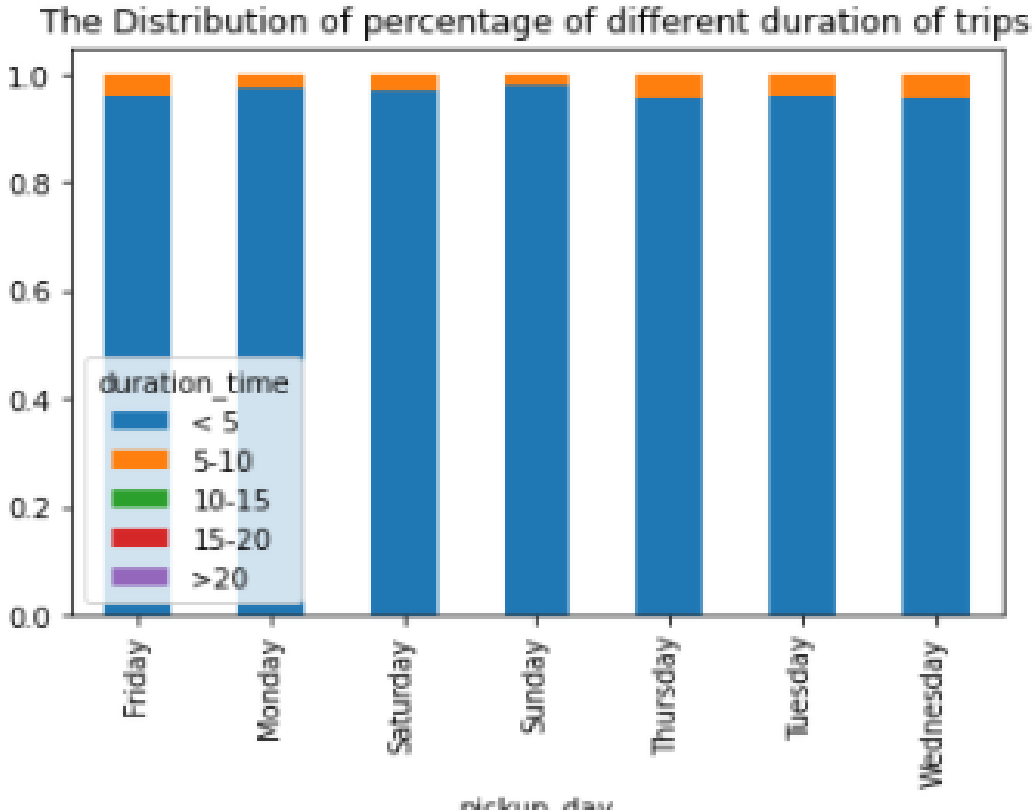


Trip Duration (dependent variable) Data Analysis



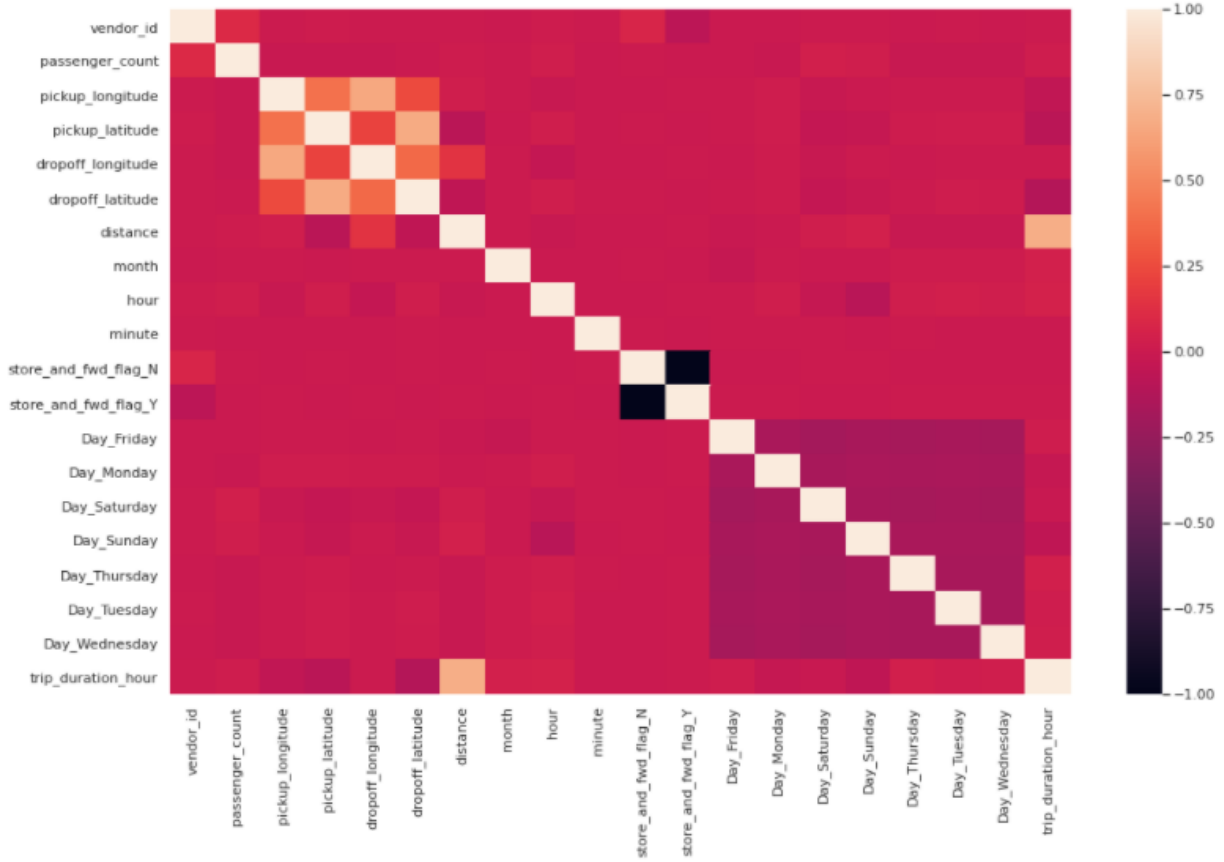


Trip Duration/Day of the week

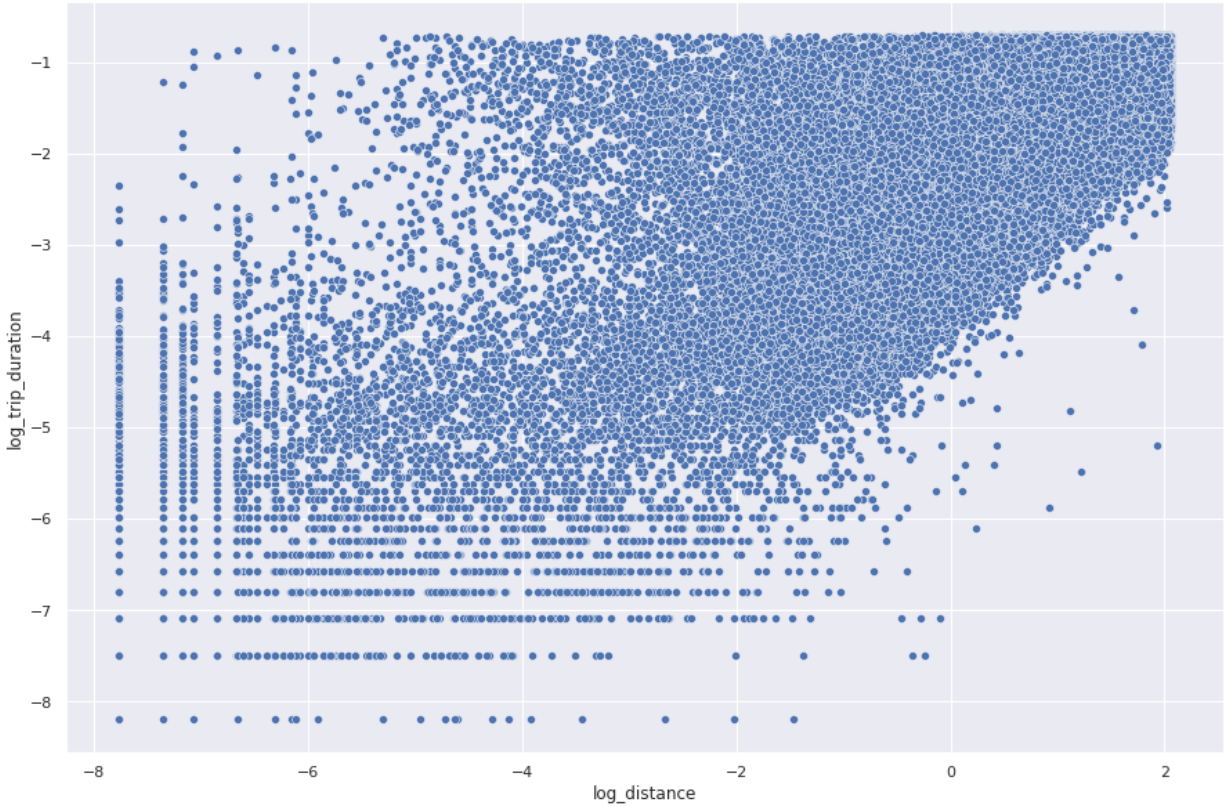


Analysis Details

Correlation



Linear Relationship between Trip Duration & Distance



Lasso Regression

Train set metrics

rics

Train MSE : 0.005494826110976565
Train RMSE : 0.07412709431089665
Train R2 : 0.49994898506301866
Train Adjusted R2 : 0.4998301932490177

Test MSE : 0.005448974432213879
Test RMSE : 0.07381716895285187
Test R2 : 0.5030970331831028
Test Adjusted R2 : 0.502624502834278

Ridge Regression

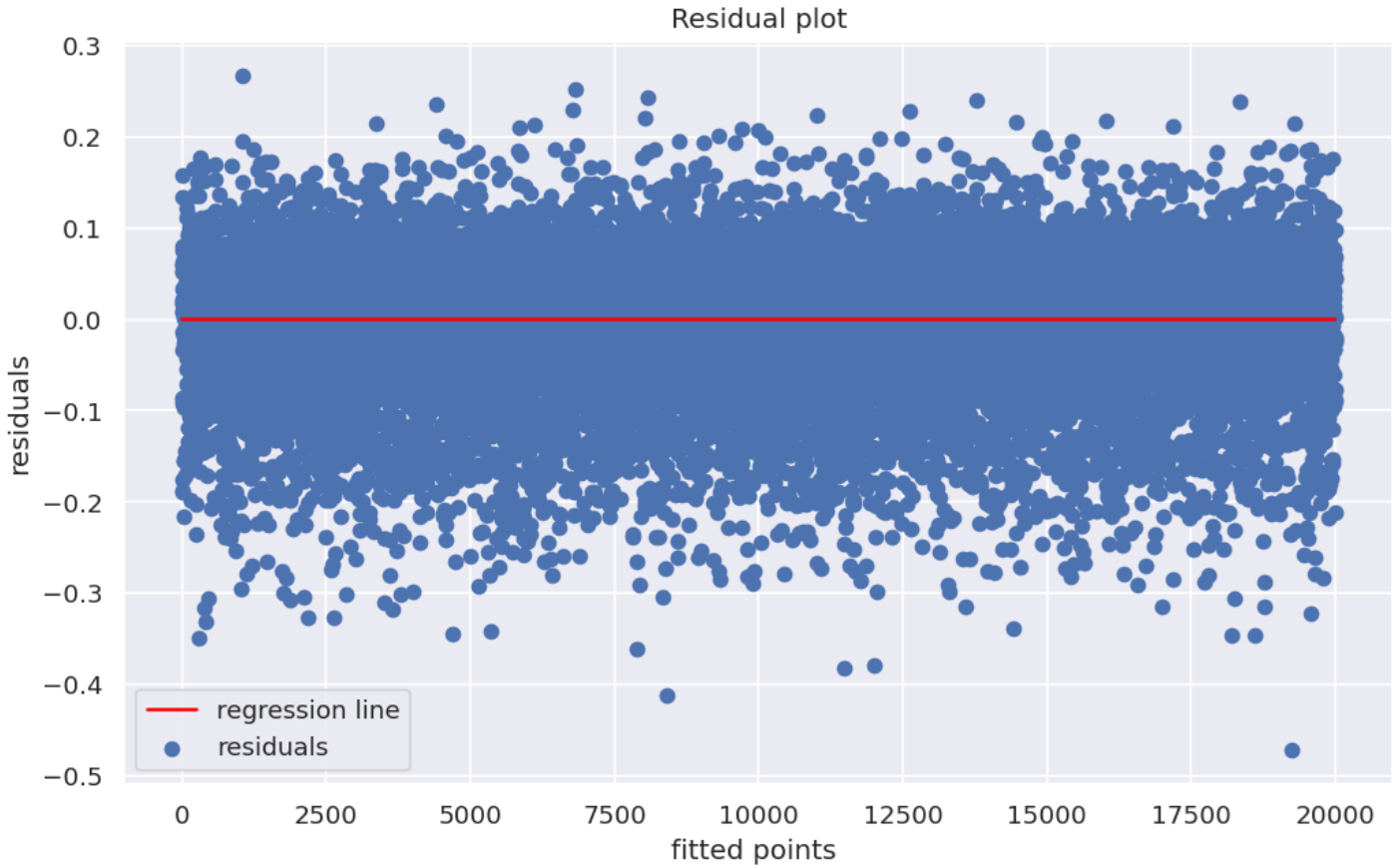
Train set metrics

rics

Train MSE : 0.005494824127596807
Train RMSE : 0.07412708093265785
Train R2 : 0.4999491655584595
Train Adjusted R2 : 0.49983037378733686

Test MSE : 0.005449008499105121
Test RMSE : 0.07381739970430495
Test R2 : 0.5030939265545915
Test Adjusted R2 : 0.5026213932515153

Homoscedasticity Check



Decision Tree

Train set metrics

Train MSE : 0.003908733073695245
Train RMSE : 0.06251986143374956
Train R2 : 0.6442897552818683
Train Adjusted R2 : 0.6442052529731706

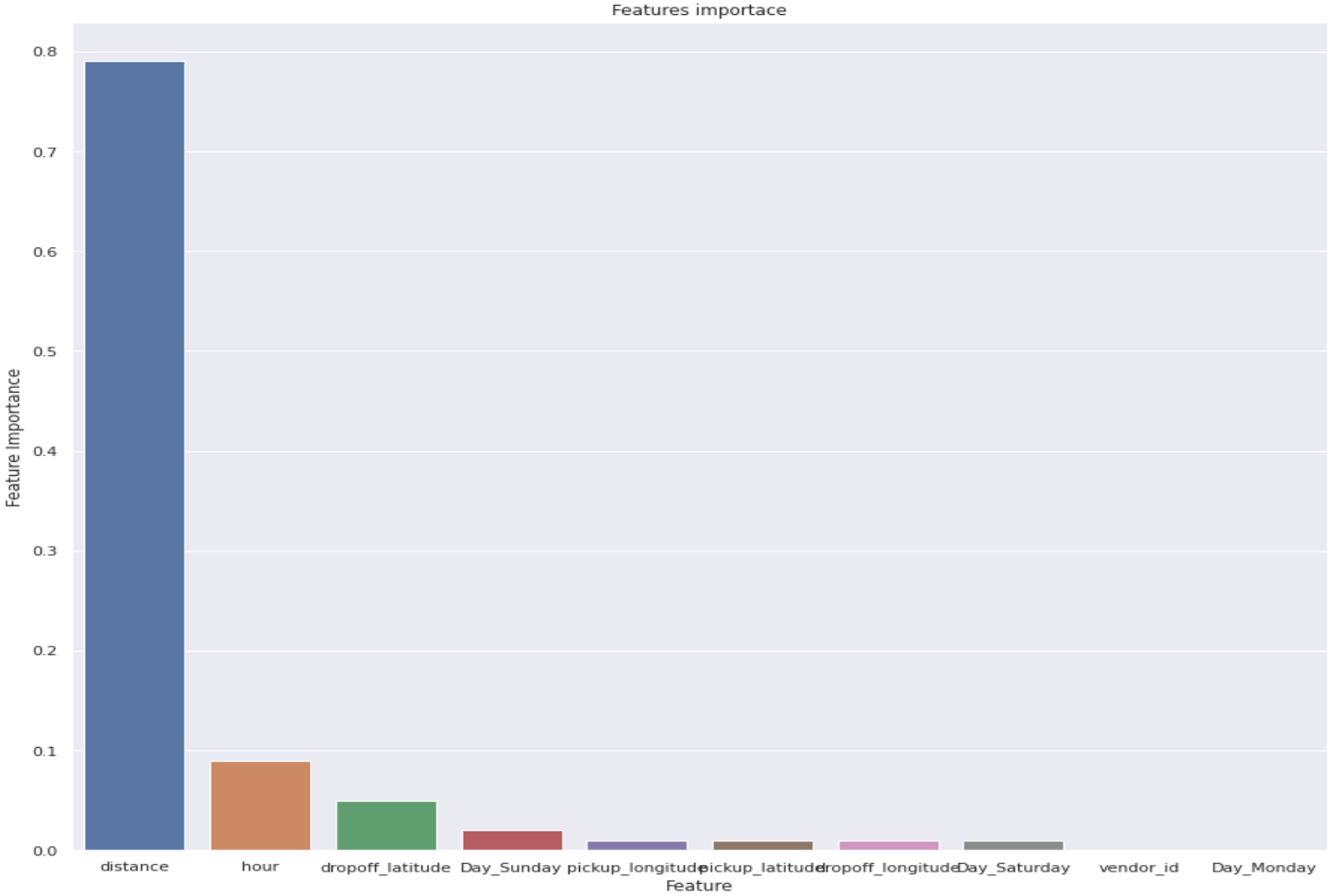
Test set metrics

Test MSE : 0.004203945325941736
Test RMSE : 0.06483783868962426
Test R2 : 0.6166337480963826
Test Adjusted R2 : 0.6162691855945723

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 : 0.002278863599313375
Train RMSE : 0.04773744441539969
Train R2 : 0.7926143552635426
Train Adjusted R2 : 0.7925650888563159

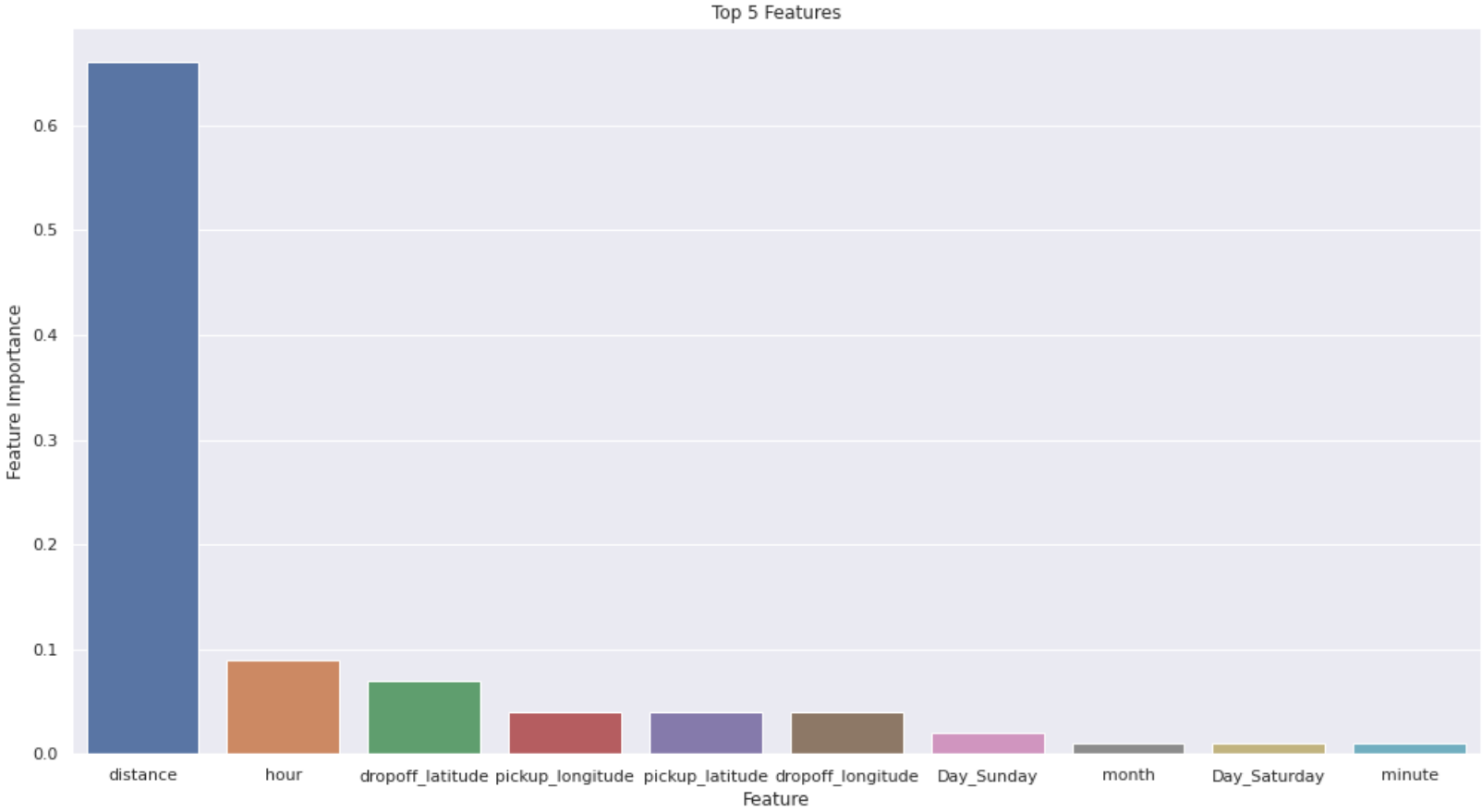
Test set metrics

Test MSE : 0.00311712671404449
Test RMSE : 0.05583123421566543
Test R2 : 0.7157429289820318
Test Adjusted R2 : 0.7154726144500327

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 : 0.001996779863964856
Train RMSE : 0.044685342831457114
Train R2 : 0.8182850963041854
Train Adjusted R2 : 0.8182419282225373

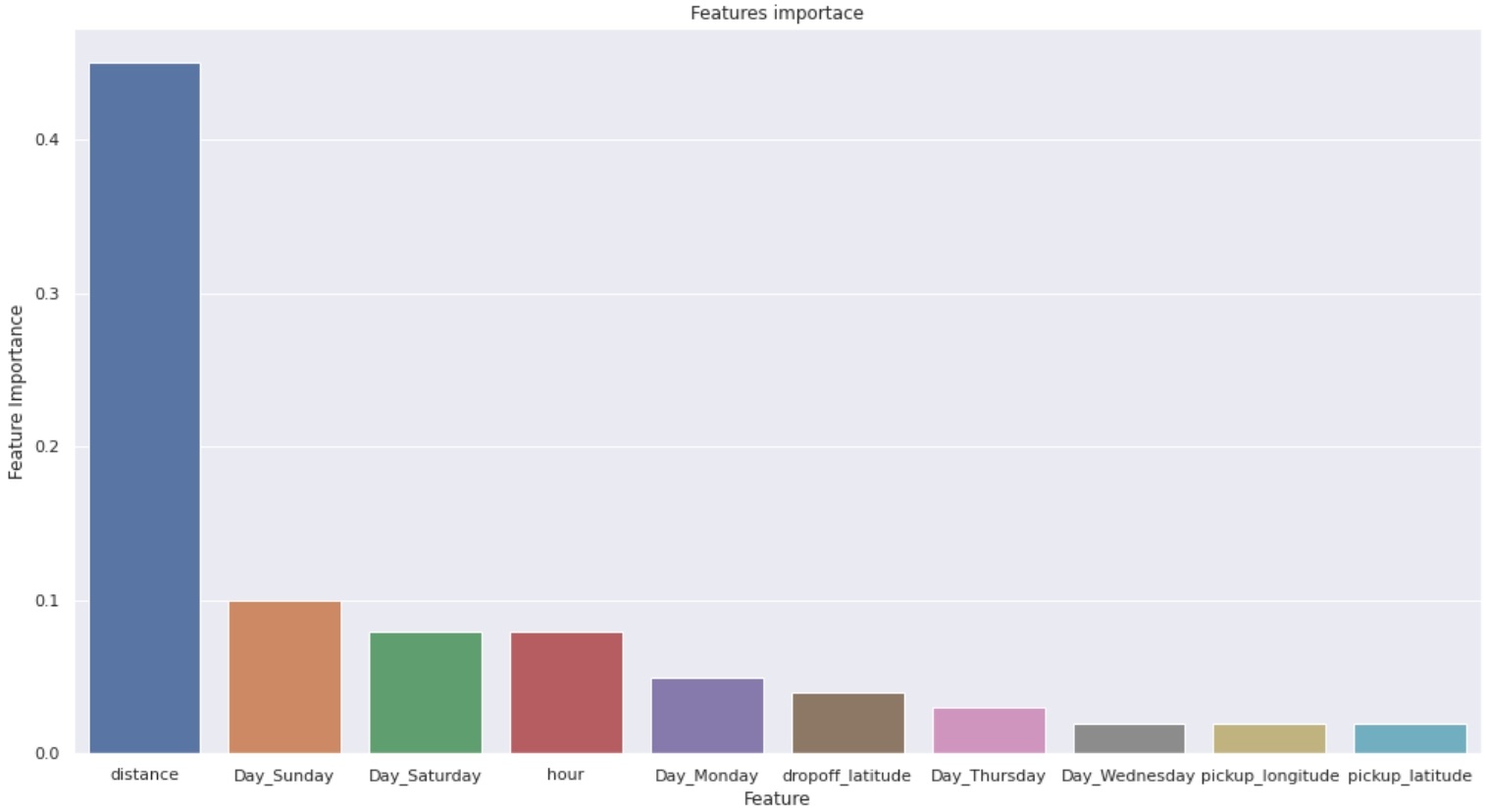
Test set metrics

Test MSE : 0.0031306995630522444
Test RMSE : 0.0559526546559879
Test R2 : 0.7145051935101532
Test Adjusted R2 : 0.7142337019524301

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 metrics 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.
- Computation Time.
- Optimising the Model.

Conclusion

- In this project, we tried to predict the trip duration of a taxi in NYC.
- We are mostly concerned with the information of pick up latitude and longitude and drop off 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