Cab Fare Prediction

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Chapter 1

Introduction

1.1 Problem Statement

The objective of this project is to predict Cab Fare amount.
You are a cab rental start-up company. You have successfully run the pilot project and now want to launch your cab service across the country. You have collected the historical data from your pilot project and now have a requirement to apply analytics for fare prediction. You need to design a system that predicts the fare amount for a cab ride in the city.

1.2 Data

Attributes: ·

- pickup_datetime - timestamp value indicating when the cab ride started.
- pickup_longitude - float for longitude coordinate of where the cab ride started.
- pickup_latitude - float for latitude coordinate of where the cab ride started.
- dropoff_longitude - float for longitude coordinate of where the cab ride ended.
- dropoff_latitude - float for latitude coordinate of where the cab ride ended.
- passenger_count - an integer indicating the number of passengers in the cab ride.

Chapter 2

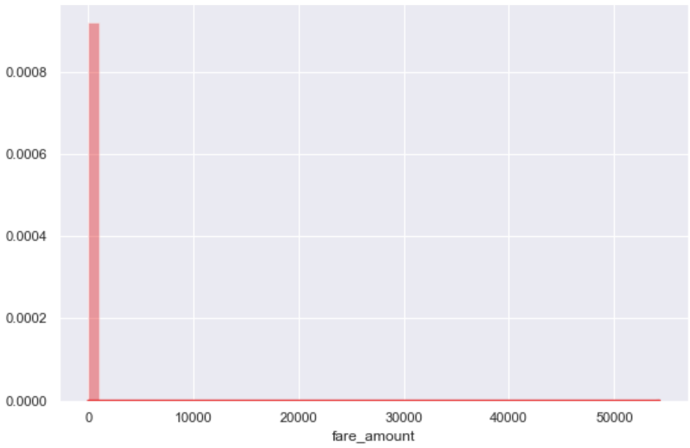
Methodology

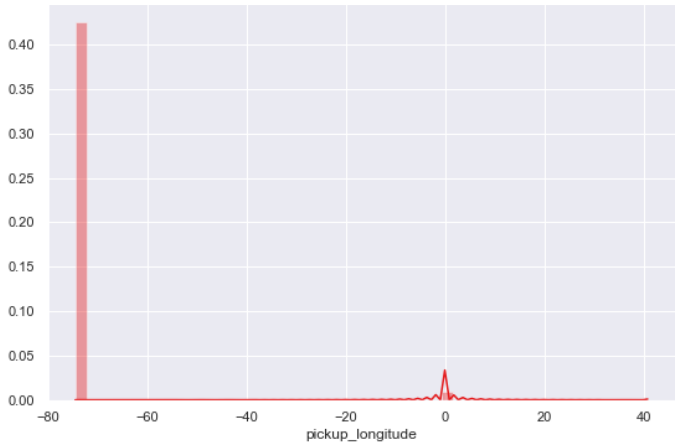
2.1 Pre-Processing

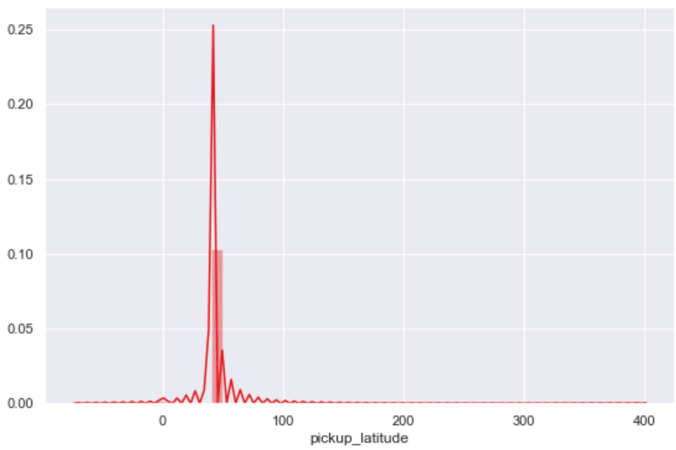
Data pre-processing is the first stage of any type of project. In this stage we get the feel of the data. We do this by looking at plots of independent variables vs target variables. If the data is messy, we try to improve it by sorting deleting extra rows and columns. This stage is called as Exploratory Data Analysis. This stage generally involves data cleaning, merging, sorting, looking for outlier analysis, looking for missing values in the data, imputing missing values if found by various methods such as mean, median, mode, KNN imputation, etc.
Further we will look into what Pre-Processing steps do this project

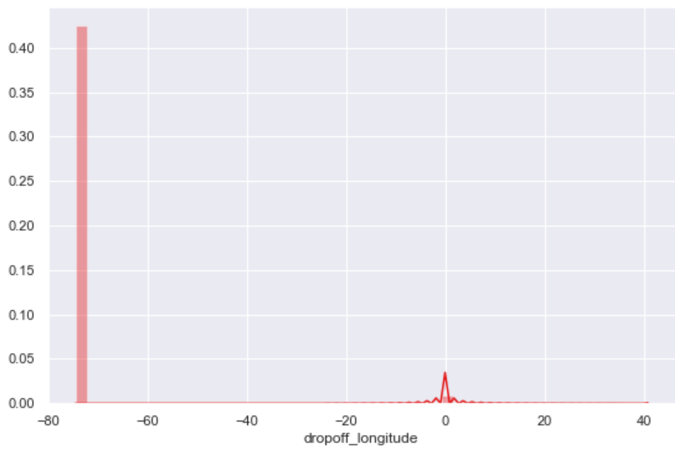
was involved in. Getting feel of data via visualization:

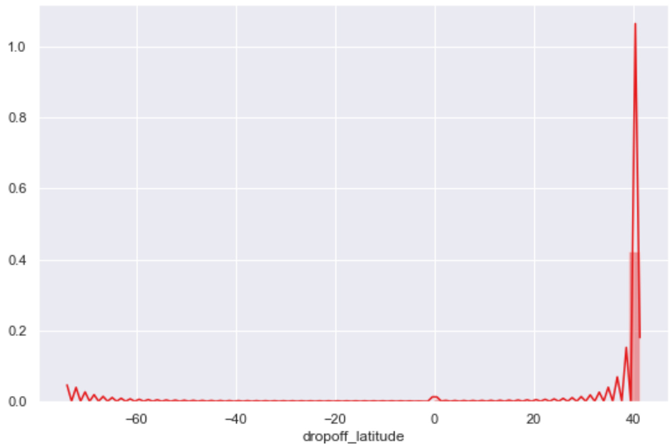
Some Histogram plots from seaborn library for each individual variable created using distplot() method.





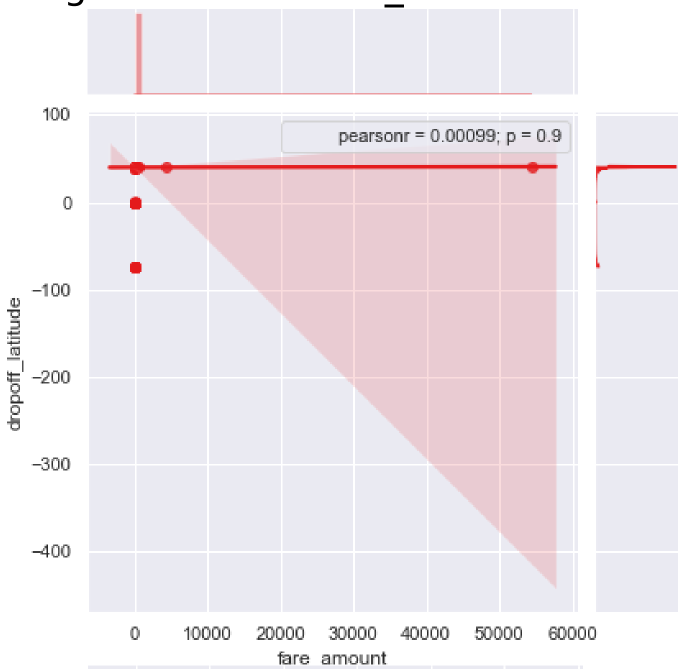


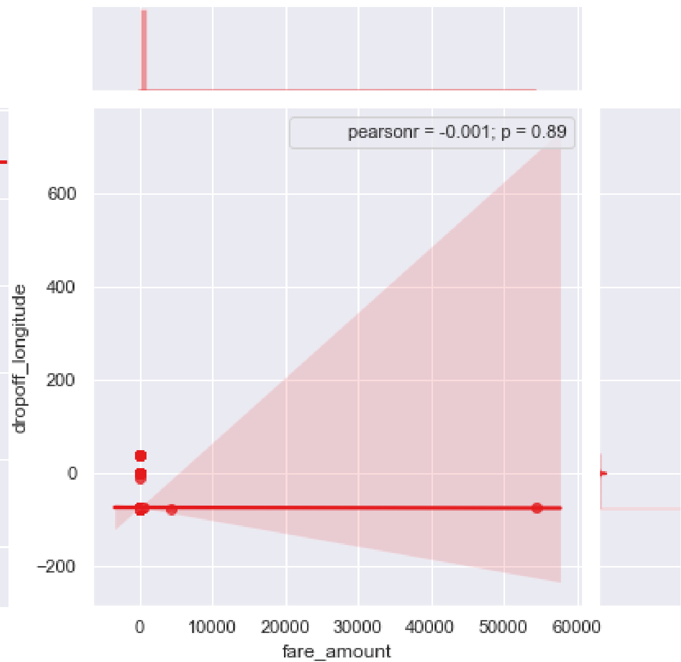


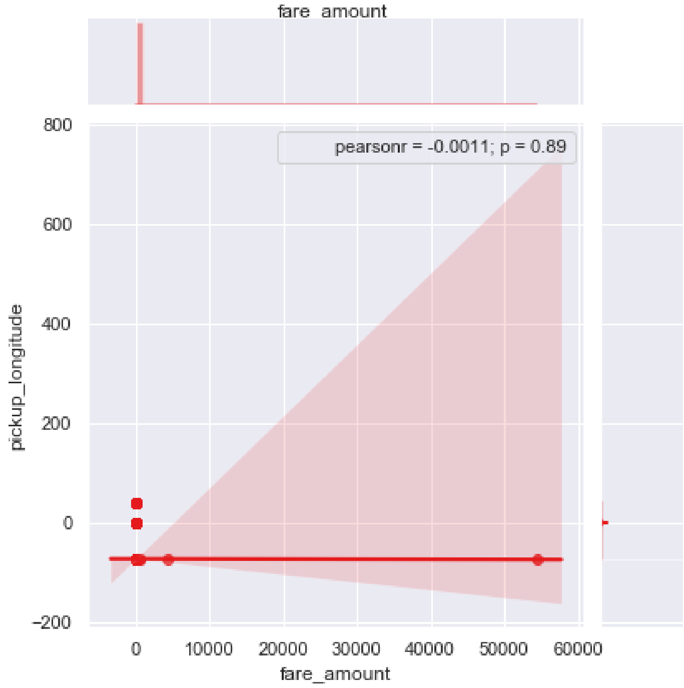


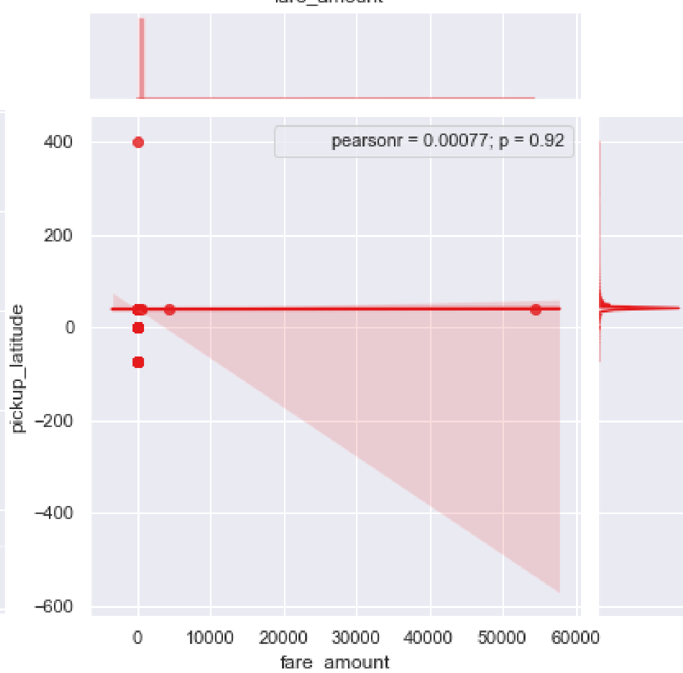
Some Jointplots:

- They are used for BivariateAnalysis.
- Here we have plotted Scatter plot with Regression line between 2 variables along with separate Bar plots of bothvariables.
- Also, we have annotated Pearson correlation coefficient and pvalue.
- Plotted only for numerical/continuousvariables
- Target variable ‘fare_amount’ Vs each numericalvariable.

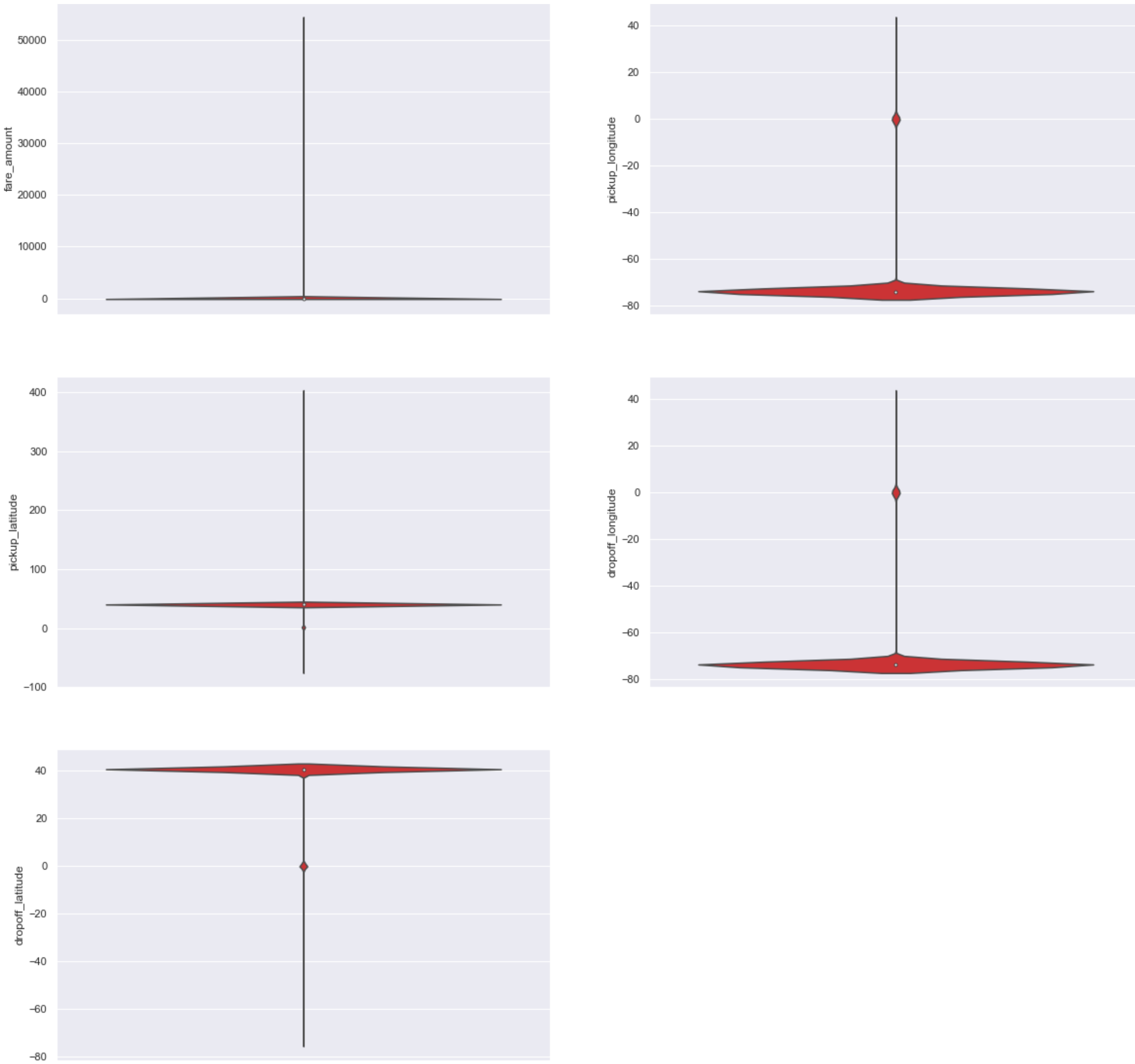




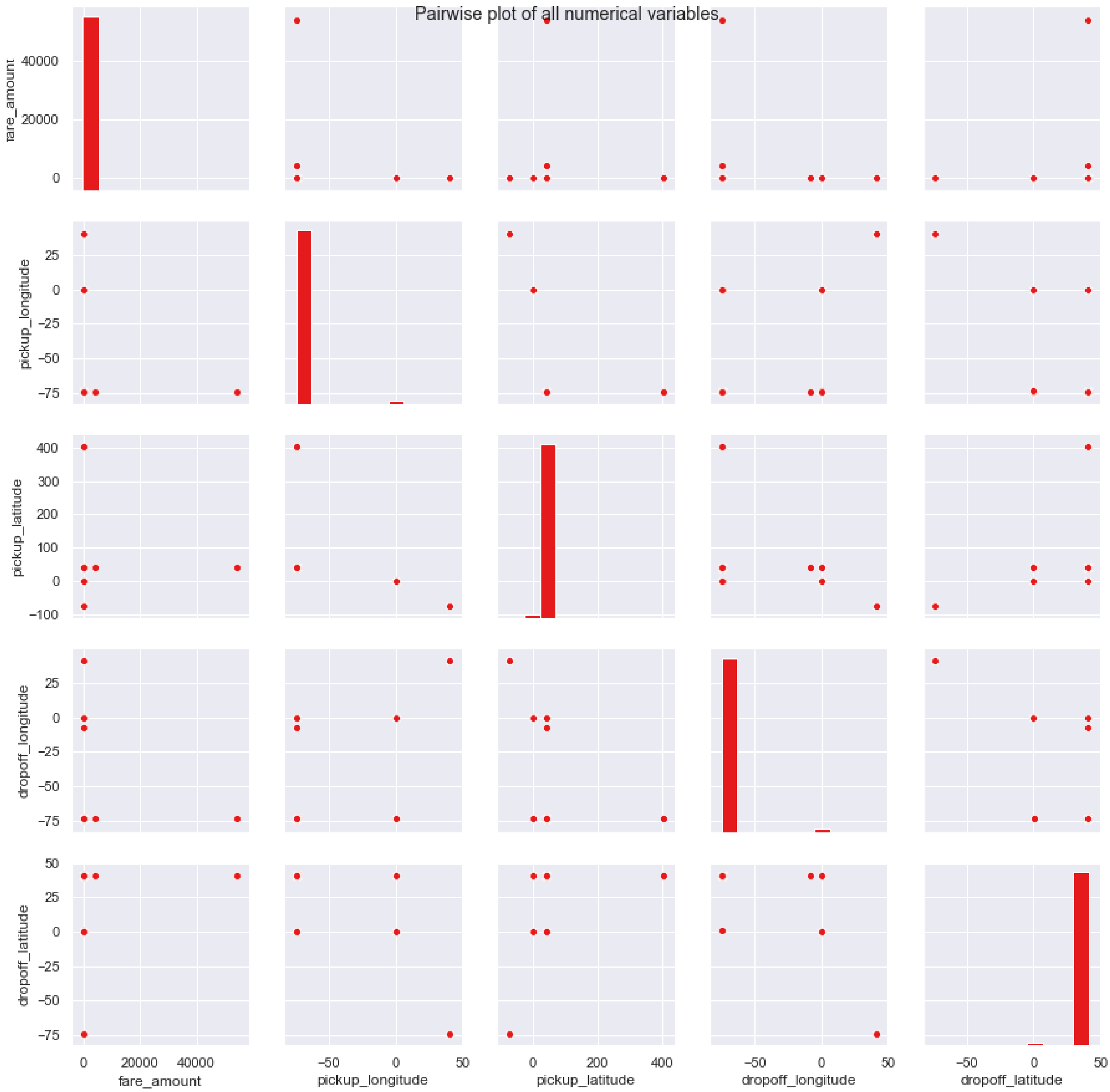




Some Violin Plots to get the idea about till what range is the variables is spread.



Pairwise Plots for all Numerical variables:



2.1.1 Removing values which are not within desired range(outlier) depending upon basic understanding ofdataset.

In this step we will remove values in each variable which are not within desired range and we will consider them as outliers depending upon basic understanding of all the variables.
You would think why haven't made those values NA instead of removing them well I did made them NA but it turned out to be a lot of missing values(NA's) in the dataset. Missing values percentage becomes very much high and then there will be no point of using that imputed data. Take a look at below 3 scenarios--

- If everything beyond range is made nan also except latitudes and longitudesthen:

Variables	Missing_percentage	
0	passenger_count	29.563702
1	pickup_latitude	1.966764
2	pickup_longitude	1.960540
3	dropoff_longitude	1.954316
4	dropoff_latitude	1.941868
5	fare_amount	0.186718
6	pickup_datetime	0.006224

After imputing above mentioned missing values kNN algorithm imputes every value to 0 at a particular row which was made nan using np.nan method:

fare_amount	0.0
pickup_longitude	0.0
pickup_latitude	0.0
dropoff_longit	0.0

ude
dropoff_latitud 0.0
e
passenger_cou 0.0
nt
Name: 1000, dtype: float64

- ➢ And If everything is dropped which are beyond range then below are the missing percentages for eachvariable:

Variables	Missing_percentage	
0	passenger_count	0.351191
1	fare_amount	0.140476

Variables	Missing_percentage	
2	pickup_datetime	0.006385
3	pickup_longitude	0.000000
4	pickup_latitude	0.000000
5	dropoff_longitude	0.000000
6	dropoff_latitude	0.000000

After imputing above mentioned missing values kNN algorithm values at a particular row which was made nan using np.nan method

fare_amount	7.3698
pickup_longitude	-73.9954
pickup_latitude	40.7597
dropoff_longitude	-73.9876
dropoff_latitude	40.7512
passenger_count	2

Name: 1000, dtype: object

- If everything beyond range is made nan exceptpassenger_count:

Variables	Missing_percentag e	
0	pickup_latitude	1.951342
1	dropoff_longitude	1.951342
2	pickup_longitude	1.945087
3	dropoff_latitude	1.938833
4	passenger_count	0.343986

5	fare_amount	0.181375
6	pickup_datetime	0.006254

After imputing above mentioned missing values kNN algorithm imputes every value to 0 at a particular row which was made nan using np.nan method:

fare_amount 0.0
pickup_longitude 0.0
pickup_latitude0.0
dropoff_longitude 0.0
dropoff_latitude 0.0

passenger_count 0.0
Name: 1000,
dtype:float64

2.1.2 Missing valueAnalysis

In this step we look for missing values in the dataset like empty row column cell which was left after removing special characters and punctuation marks. Some missing values are in form of NA. missing values left behind after outlier analysis; missing values can be in any form. Unfortunately, in this dataset we have found some missing values. Therefore, we will do some missing value analysis. Before imputed we selected random row no-1000 and made it NA, so that we will compare original value with imputed value and choose best method which will impute value closer to actual value.

	index	0
0	fare_amount	22
1	pickup_datetime	1
2	pickup_longitude	0
3	pickup_latitude	0
4	dropoff_longitude	0
5	dropoff_latitude	0
6	passenger_count	55

We will impute values for fare_amount and passenger_count both of them has missing values 22 and 55 respectively. We will drop 1 value in pickup_datetime i.e it will be an entire row to drop.

Below are the missing value percentage for each variable:

Variables	Missing_percentage	
0	passenger_count	0.351191
1	fare_amount	0.140476

2	pickup_datetime	0.006385
3	pickup_longitude	0.000000
4	pickup_latitude	0.000000
5	dropoff_longitude	0.000000
6	dropoff_latitude	0.000000

And below is the Standard deviation of particular variable which has missing values in them: fare_amount 435.982171 passenger_count

1.266096dtype:float64

We'd tried central statistical methods and algorithmic method--KNN to impute missing values in the dataset:

1. **For**

   Passenger_cou

   nt: Actual value

   = 1 Mode =1

   KNN = 2

We will choose the KNN method here because it maintains the standard deviation of variable. We will not use Mode method because whole variable will be more biased towards 1 passenger_count also passenger_count has maximum value equals to 1

2. **For**

   fare_amount:

   Actual value

   =7.0,Mean =

   15.117,

   Median = 8.5,

   KNN

   =7.369801

We will Choose KNN method here because it imputes value closest to actual value also it maintains the Standard deiviation of the variable.

Standard deviation for passenger_count and fare_amount after KNN imputation: fare_amount 435.661995
passenger_count 1.264322
dtype: float64

2.1.3 OutlierAnalysis

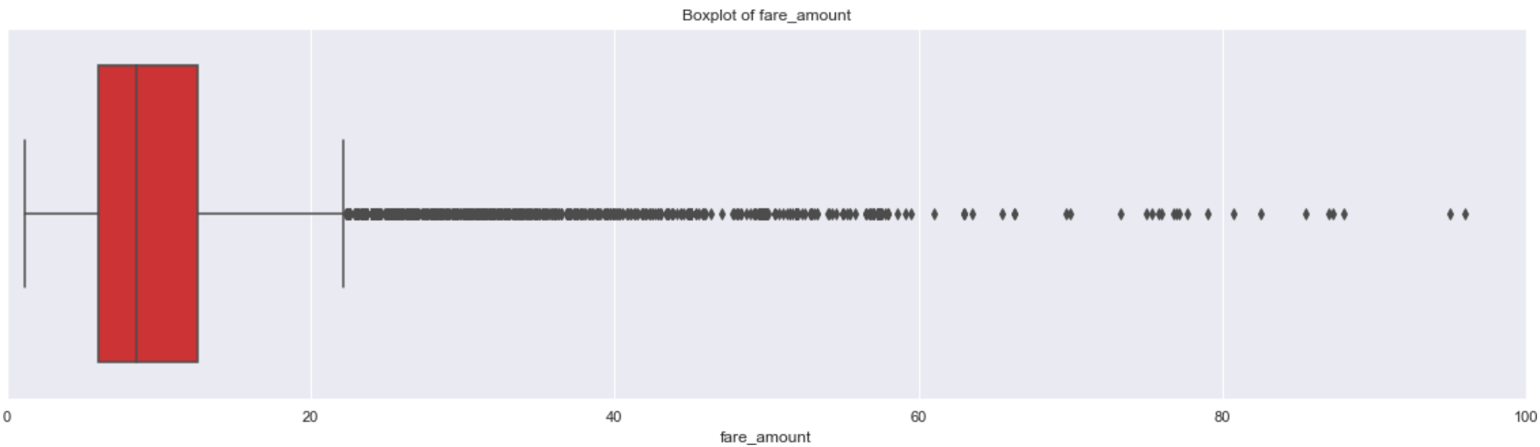
We look for outlier in the dataset by plotting Boxplots. There are outliers present in the data. we have removed these outliers. This is how we done,

I. We replaced them with Nan values or we can say created missingvalues.
II. Then we imputed those missing values with KNNmethod.

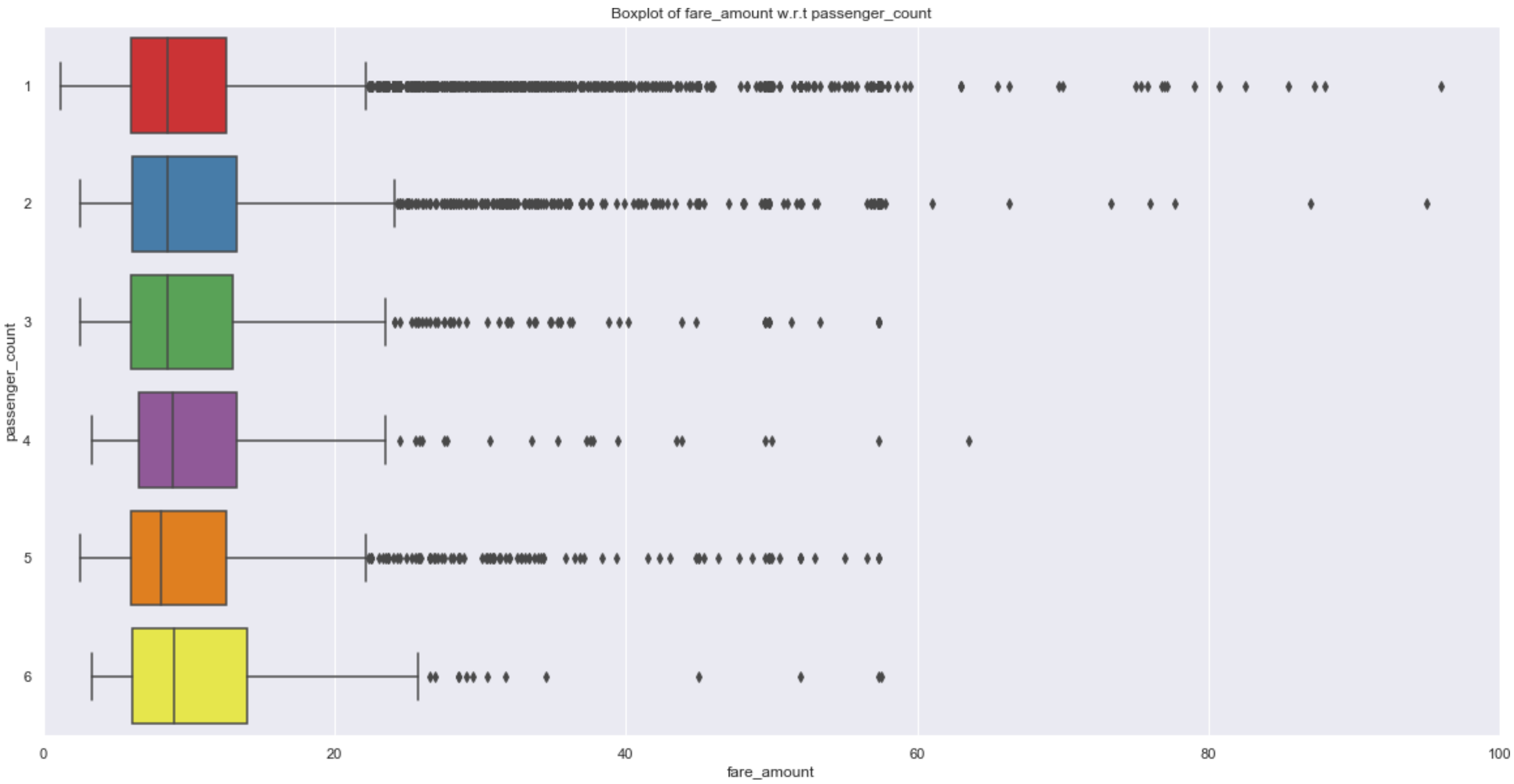
- We Will do Outlier Analysis only on Fare_amount just for now and we will do outlier analysis after feature engineering laitudes andlongitudes.

- Univariate Boxplots: Boxplots for targetvariable.

Univariate Boxplots: Boxplots for all Numerical Variables also for target variable



Bivariate Boxplots: Boxplots for all fare_amount Variables Vs all passenger_count variable.



From above Boxplots we see that ‘fare_amount’have outliers in it:

‘fare_amount’ has 1359 outliers.

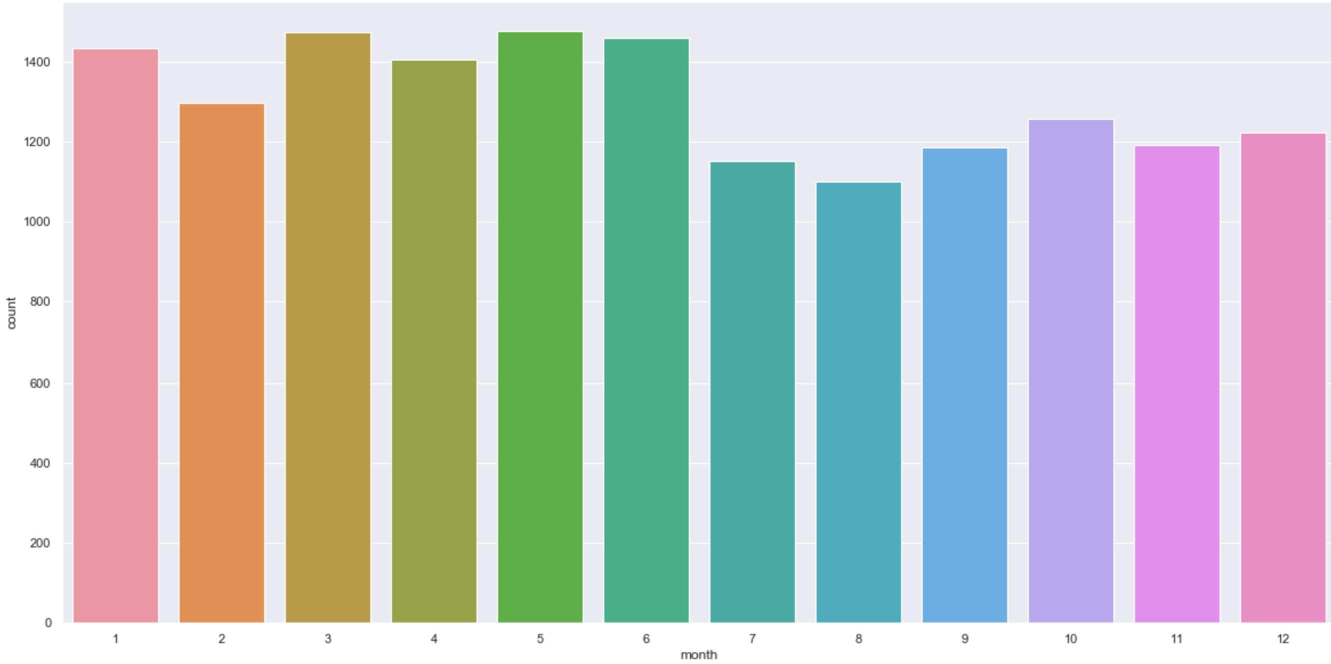
We successfully imputed these outliers with KNN and K value is 3

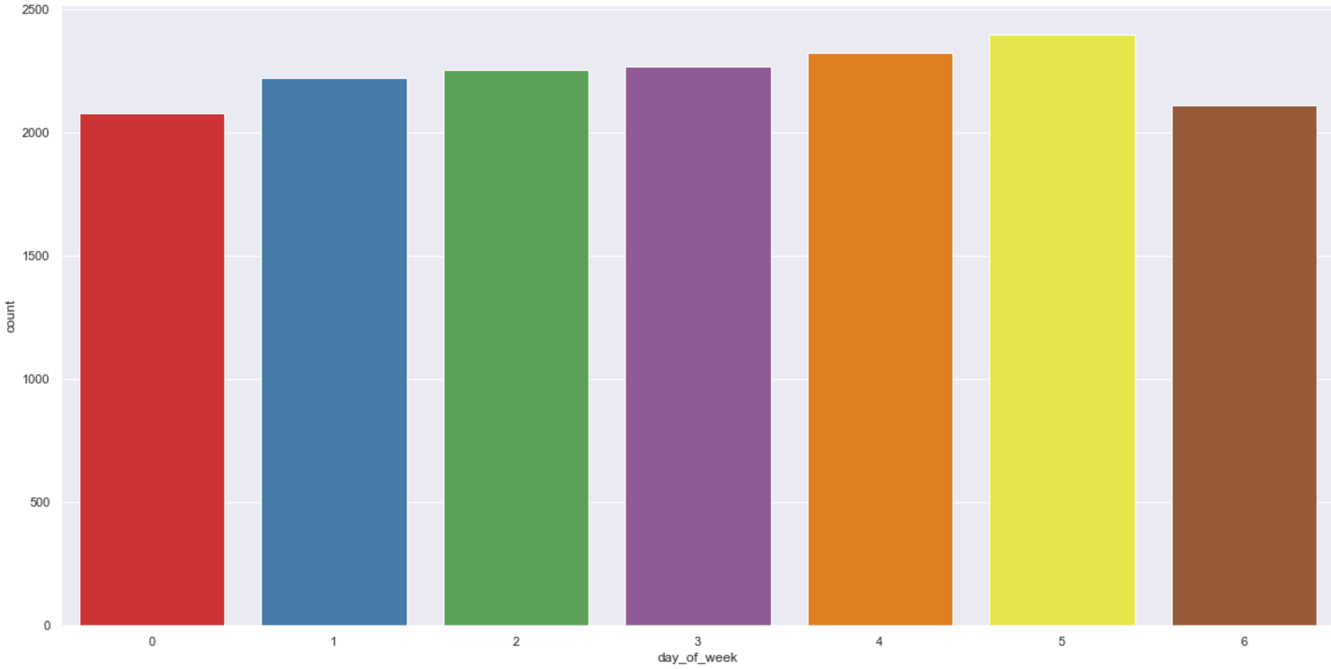
2.1.4 FeatureEngineering

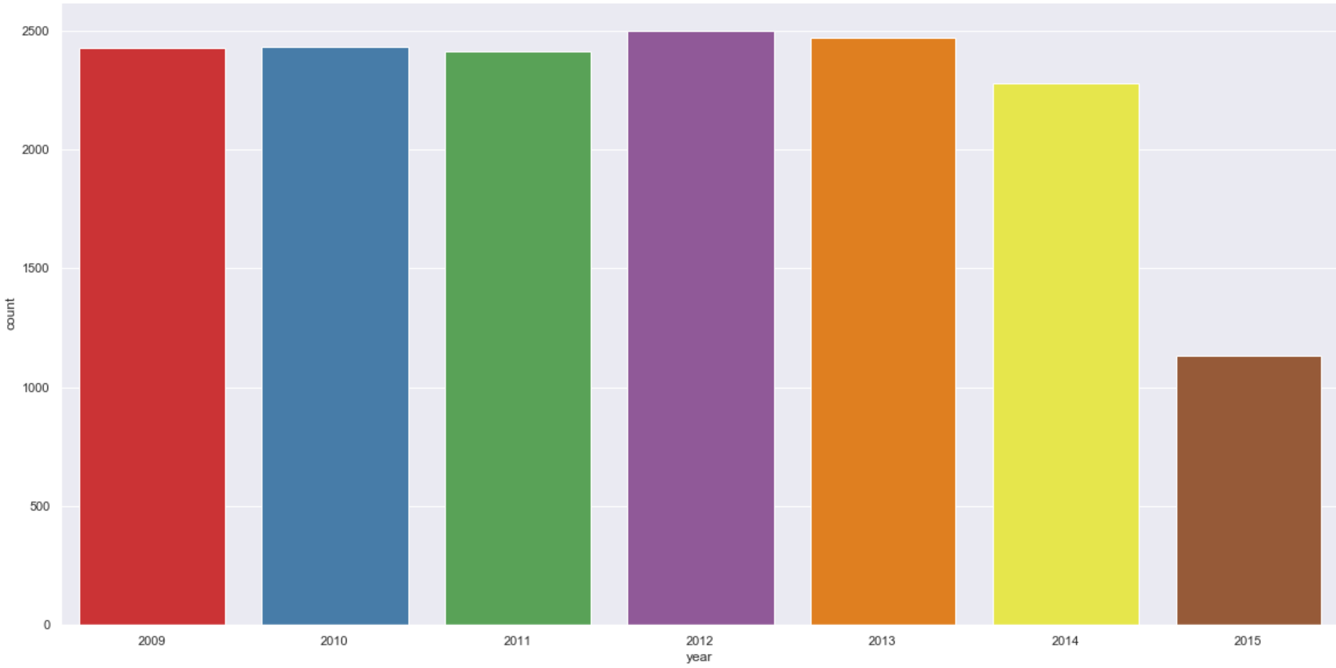
Feature Engineering is used to drive new features from existing features.

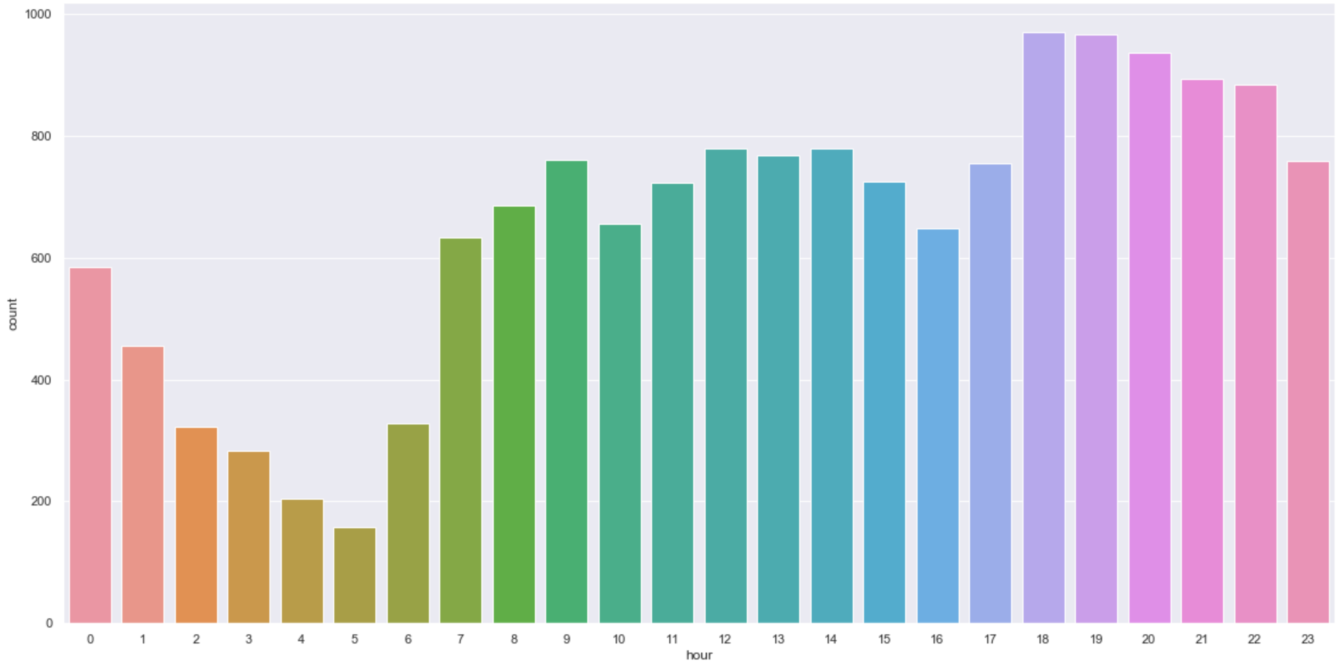
1. **For 'pickup_datetime' variable:**

We will use this timestamp variable to create
new variables. New features will be year,
month, day_of_week, hour.
'year' will contain only years from pickup_datetime. For ex. 2009, 2010, 2011, etc.
'month' will contain only months from pickup_datetime. For ex. 1 for January, 2 for February,
etc.
'day_of_week' will contain only week from pickup_datetime. For ex. 1 which is for Monday,2
for Tuesday,etc.
'hour' will contain only hours from pickup_datetime. For ex. 1, 2, 3, etc.


count
1400
1200
1000
800
600
400
200
0
1
2
3
4
5
6
7
8
9
10
11
12
month


count
2500
2000
1500
1000
500
0
0
1
2
3
4
5
6
day_of_week





As we have now these new variables we will categorize them to new variables like Session from hour column, seasons from month column, week:weekday/weekend from day_of_week variable.

So, session variable which will contain categories—morning, afternoon, evening, night_PM, night_AM.

Seasons variable will contain categories—spring, summer, fall, winter. Week will contain categories—weekday, weekend.

We will one-hot-encode session, seasons, week variable.

2. <u>For ‘passenger_count’ variable</u>:

As passenger_count is a categorical variable we will one-hot-encode it.

3. For ‘Latitudes’ and ‘Longitudes’ variables:

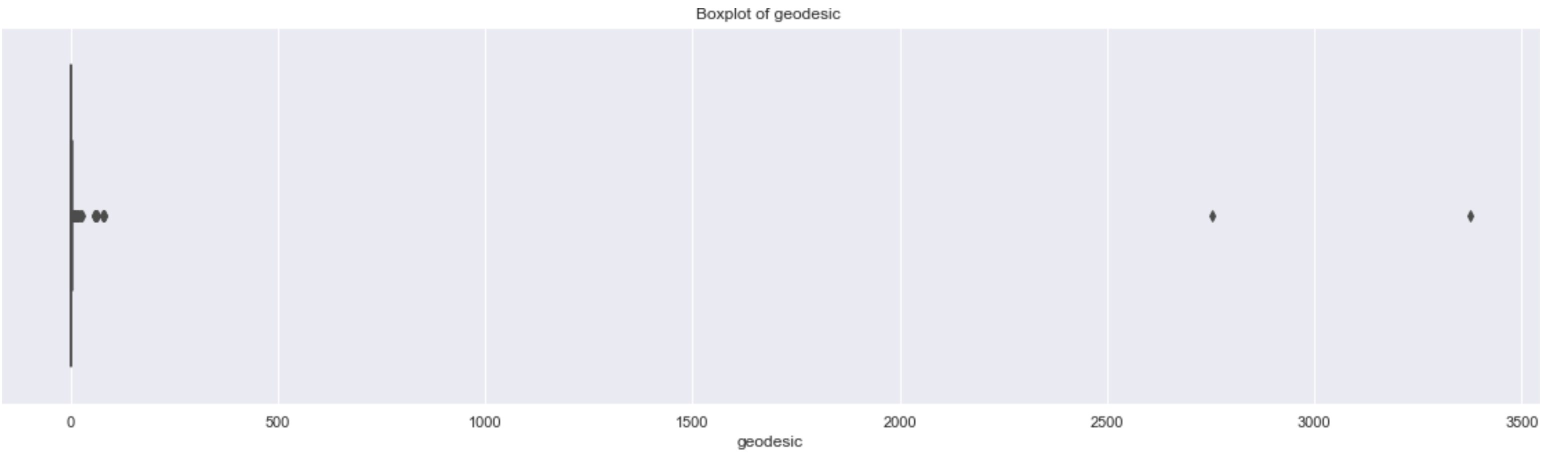
As we have latitude and longitude data for pickup and dropoff, we will find the distance the cab travelled from pickup and dropoff location.
We will use both haversine and vincenty methods to calculate distance. For haversine, variable
name will be ‘great_circle’ and for vincenty, new variable name will be ‘geodesic’.
As Vincenty is more accurate than haversine. Also, vincenty is prefered for short distances. Therefore, we will drop great_circle.
Columns in training data after feature engineering:

```
Index(['fare_amount', 'passenger_count_2',
'passenger_count_3',
      'passenger_count_4', 'passenger_count_5',
      'passenger_count_6', 'season_spring', 'season_summer',
      'season_winter', 'week_weekend', 'session_evening',
      'session_morning', 'session_night_AM',
      'session_night_PM', 'year_2010', 'year_2011', 'year_2012',
      'year_2013', 'year_2014', 'year_2015', 'geodesic'],
     dtype='object')
```

Columns in testing data after feature engineering:

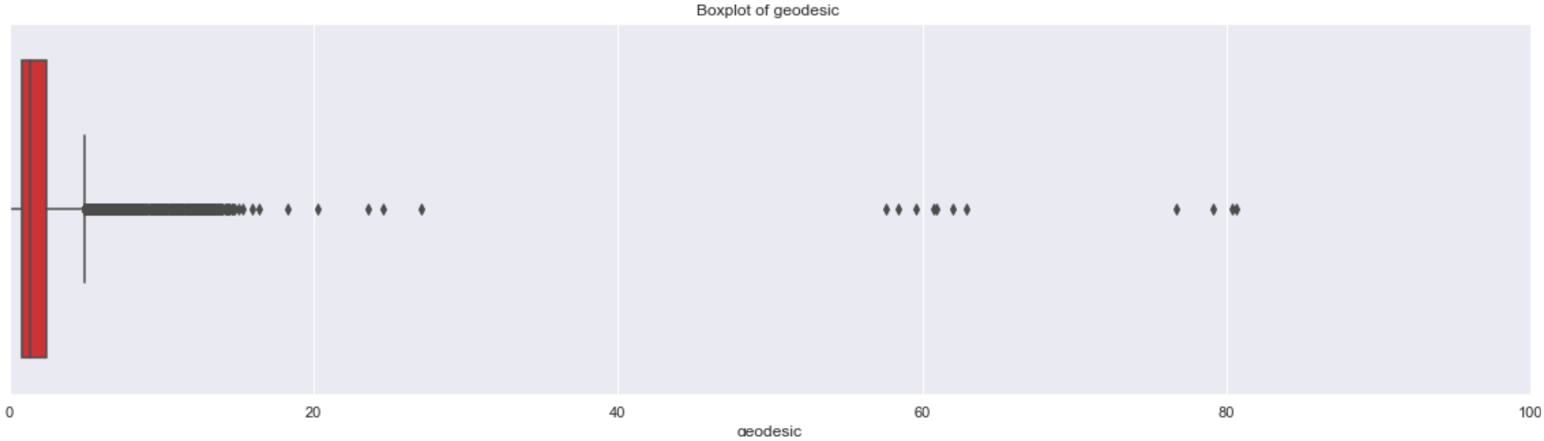
```
Index(['passenger_count_2', 'passenger_count_3',
'passenger_count_4',
      'passenger_count_5', 'passenger_count_6',
      'season_spring', 'season_summer', 'season_winter',
      'week_weekend', 'session_evening', 'session_morning',
      'session_night_AM', 'session_night_PM', 'year_2010',
      'year_2011', 'year_2012', 'year_2013', 'year_2014',
      'year_2015', 'geodesic'],
     dtype='object')
```

we will plot boxplot for our new variable ‘geodesic’:



We see that there are outliers in ‘geodesic’ and also a cab cannot go upto 3400 miles

Boxplot of ‘geodesic’ for range 0 to 100 miles.



We will treat these outliers like we previously did.

2.1.5 FeatureSelection

In this step we would allow only to pass relevant features to further steps. We remove irrelevant features from the dataset. We do this by some statistical techniques, like we look for features which will not be helpful in predicting the target variables. In this dataset we have to predict the fare_amount.

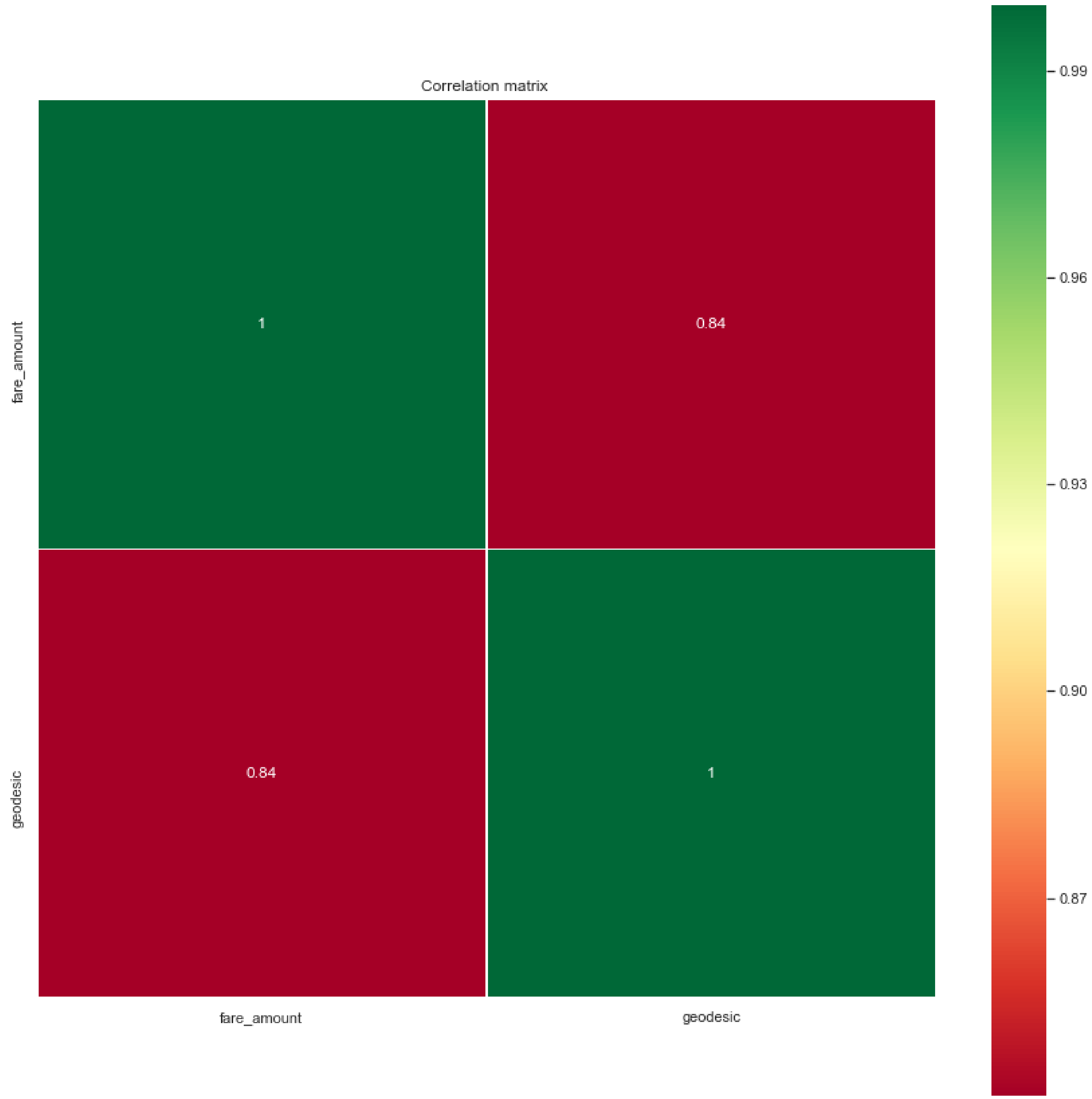
Further below are some types of test involved for feature selection:

1. **Correlation analysis**– This requires only numerical variables. Therefore, we will filter out only numerical variables and feed it to correlation analysis. We do this by plotting correlation plot for all numerical variables. There should be no correlation between independent variables but there should be high correlation between independent variable and dependent variable. So, we plot the correlation plot. we can see that in correlation plot faded colour like skin colour indicates that 2 variables are highly correlated with each other. As the colour fades correlation valuesincreases.

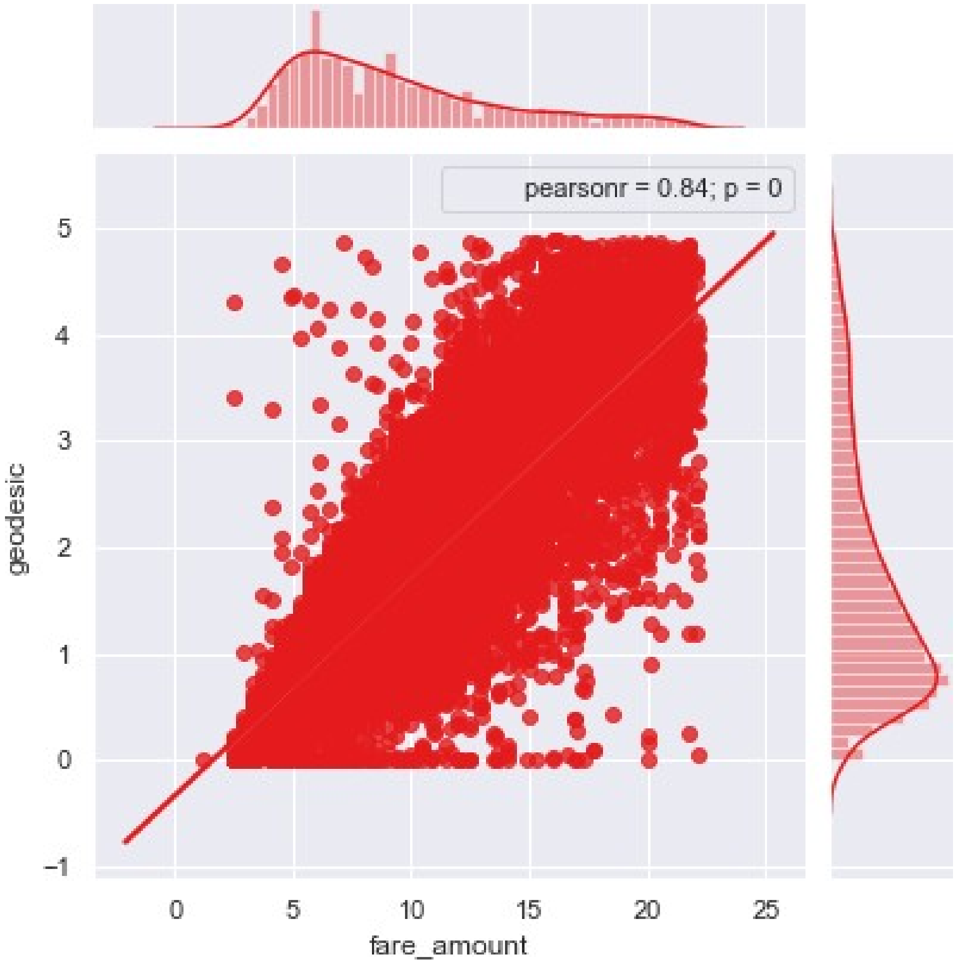
   From below correlation plot we see that:

   - 'fare_amount' and 'geodesic' are very highly correlated with eachother.
   - As fare_amount is the target variable and ‘geodesic’ is independent variable we will keep ‘geodesic’ because it will help to explain variation infare_amount.

Correlation Plot:



Jointplot between ‘geodesic’ and ‘fare_amount’:



2 **Chi-Square test of independence**– Unlike correlation analysis we will filter out only categorical variables and pass it to Chi-Square test. Chi-square test compares 2 categorical variables in a contingency table to see if they are related ornot.

I. Assumption for chi-square test: Dependency between Independent variable and dependent variable should be high and there should be no dependency among independentvariables.

II. Before proceeding to calculate chi-square statistic, we do the hypothesis testing: Null hypothesis: 2 variables areindependent. Alternate hypothesis: 2 variables are not independent. The interpretation of chi-square test:

I. For theorical or excel sheet purpose: If chi-square statistics is greater than critical value then reject the null hypothesis saying that 2 variables are dependent and if it’s less, then accept the null hypothesis saying that 2 variables areindependent.

II. While programming: If p-value is less than 0.05 then we reject the null hypothesis saying that 2 variables are dependent and if p-value is greater than 0.05 then we accept the null hypothesis saying that 2 variables areindependent.

Here we did the test between categorical independent variables pairwise.

- If p-value<0.05 then remove thevariable,

- If p-value>0.05 then keep thevariable.

3 **Analysis of Variance(Anova) Test–**

I. It is carried out to compare between each group in a categoricalvariable.

II. ANOVA only lets us know the means for different groups are same or not.It doesn't help us identify which mean is different.

Hypothesis testing:

- **Null Hypothesis**: mean of all categories in a variable aresame.
- **Alternate Hypothesis**: mean of at least one category in a variable isdifferent.

- If p-value is less than 0.05 then we reject the nullhypothesis.
- And if p-value is greater than 0.05 then we accept the null hypothesis. Below is the anova analysis table for each categoricalvariable:

	df	sum_sq	mean_sq	F	PR(>F)
C(passenger_count_2)	1.0	10.881433	10.881433	0.561880	4.535152e-01
C(passenger_count_3)	1.0	17.098139	17.098139	0.882889	3.474262e-01
C(passenger_count_4)	1.0	63.987606	63.987606	3.304099	6.912635e-02
C(passenger_count_5)	1.0	21.227640	21.227640	1.096122	2.951349e-01
C(passenger_count_6)	1.0	145.904989	145.904989	7.534030	6.061341e-03
C(season_spring)	1.0	28.961298	28.961298	1.495461	2.213894e-01
C(season_summer)	1.0	26.878639	26.878639	1.387920	2.387746e-01
C(season_winter)	1.0	481.664803	481.664803	24.871509	6.193822e-07
C(week_weekend)	1.0	130.676545	130.676545	6.747686	9.395730e-03
C(session_night_AM)	1.0	2130.109284	2130.109284	109.991494	1.197176e-25
C(session_night_PM)	1.0	185.382247	185.382247	9.572500	1.978619e-03
C(session_evening)	1.0	0.972652	0.972652	0.050224	8.226762e-01
C(session_morning)	1.0	48.777112	48.777112	2.518682	1.125248e-01
C(year_2010)	1.0	1507.533635	1507.533635	77.843835	1.231240e-18
C(year_2011)	1.0	1332.003332	1332.003332	68.780056	1.189600e-16
C(year_2012)	1.0	431.018841	431.018841	22.256326	2.406344e-06
C(year_2013)	1.0	340.870175	340.870175	17.601360	2.738958e-05
C(year_2014)	1.0	1496.882424	1496.882424	77.293844	1.624341e-18
C(year_2015)	1.0	2587.637234	2587.637234	133.616659	8.839097e-31
Residual	15640.0	302886.232626	19.366127	NaN	NaN

Looking at above table every variable has p value less than 0.05 so reject the null hypothesis.

4 **Multicollinearity**– In regression, "multicollinearity" refers to predictors that are correlated with other predictors. Multicollinearity occurs when your modelincludes

multiple factors that are correlated not just to your response variable, but also to each other.

I. Multicollinearity increases the standard errors of thecoefficients.
II. Increased standard errors in turn means that coefficients for some independent variables may be found not to be significantly different from0.
III. In other words, by overinflating the standard errors, multicollinearity makes some variables statistically insignificant when they should be significant. Without multicollinearity (and thus, with lower standard errors), those coefficients might besignificant.
IV. VIF is always greater or equal to1.
 if VIF is 1 --- Not correlated to any of the variables. if VIF is between 1-5 --- Moderately correlated.
 if VIF is above 5 --- Highly correlated.
 If there are multiple variables with VIF greater than 5, only remove the variable with the highest VIF.
V. And if the VIF goes above 10, you can assume that the regression coefficients are poorly estimated due tomulticollinearity.

Below is the table for VIF analysis for each independent variable:

	VIF	features
0	15.268789	Intercept
1	1.040670	passenger_count_2[T.1.0]
2	1.019507	passenger_count_3[T.1.0]
3	1.011836	passenger_count_4[T.1.0]
4	1.024990	passenger_count_5[T.1.0]
5	1.017206	passenger_count_6[T.1.0]
6	1.642247	season_spring[T.1.0]
7	1.552411	season_summer[T.1.0]
8	1.587588	season_winter[T.1.0]
9	1.050786	week_weekend[T.1.0]
10	1.376197	session_night_AM[T.1.0]
11	1.423255	session_night_PM[T.1.0]
12	1.524790	session_evening[T.1.0]
13	1.559080	session_morning[T.1.0]
14	1.691361	year_2010[T.1.0]
15	1.687794	year_2011[T.1.0]
16	1.711100	year_2012[T.1.0]
17	1.709348	year_2013[T.1.0]
18	1.665000	year_2014[T.1.0]
19	1.406916	year_2015[T.1.0]
20	1.025425	geodesic

We have checked for multicollinearity in our Dataset and all VIF values are below 5.

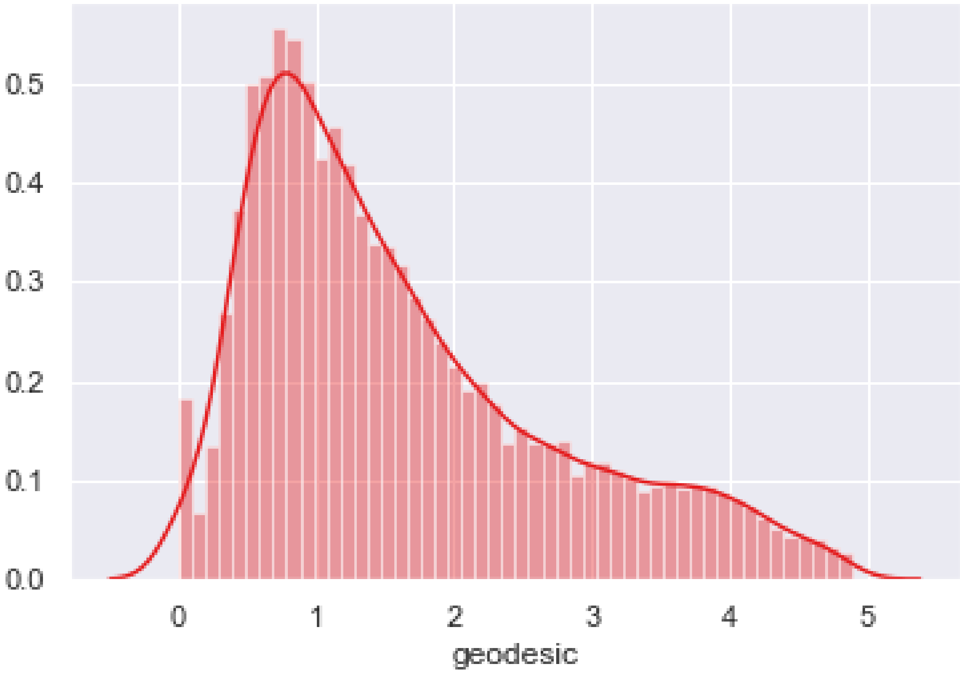
2.1.6 FeatureScaling

Data Scaling methods are used when we want our variables in data to scaled on common ground. It is performed only on continuous variables.

- **Normalization**: Normalization refer to the dividing of a vector by its length. normalization normalizes the data in the range of 0 to 1. It is generally used when we are planning to use distance method for our model development purpose such as KNN. Normalizing the data improves convergence of such algorithms. Normalisation of data scales the data to a very small interval, where outliers can beloosed.
- **Standardization**: Standardization refers to the subtraction of mean from individual point and then dividing by its SD. Z is negative when the raw score is below the mean and Z is positive when above mean. When the data is distributed normally you should go for standardization.

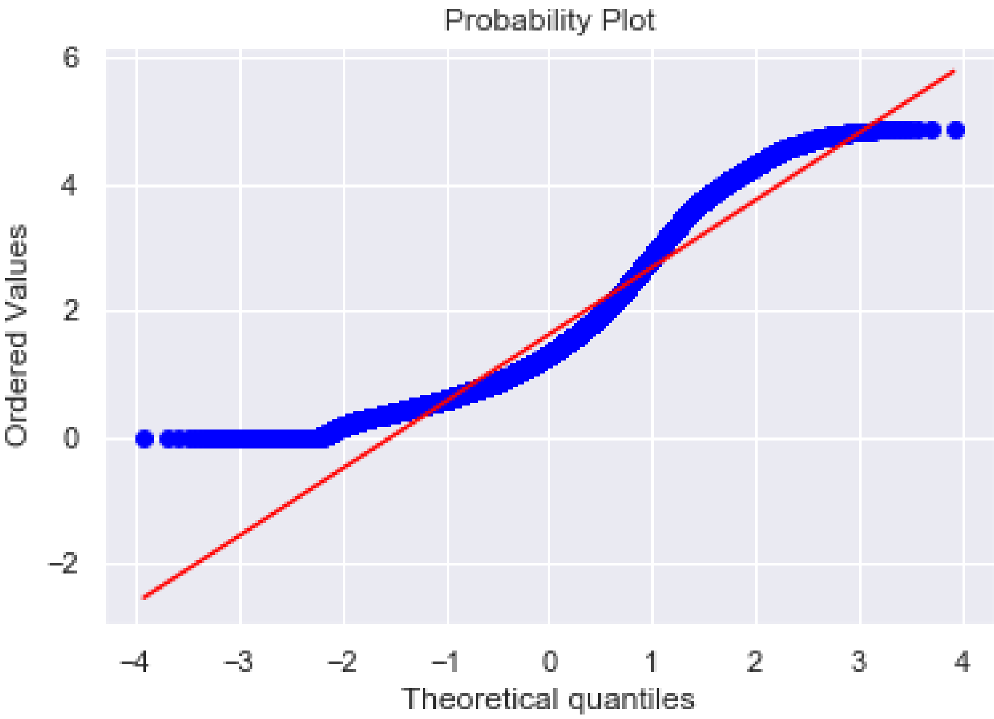
Linear Models assume that the data you are feeding are related in a linear fashion, or can be measured with a linear distance metric.
Also, our independent numerical variable 'geodesic' is not distributed normally so we had chosen normalization over standardization.
- We have checked variance for each column in dataset beforeNormalisation
- High variance will affect the accuracy of the model. So, we want to normalise that variance. Graphs based on which standardization waschosen:
Note: It is performed only on Continuous variables.

distplot() for 'geodesic' feature before normalization:

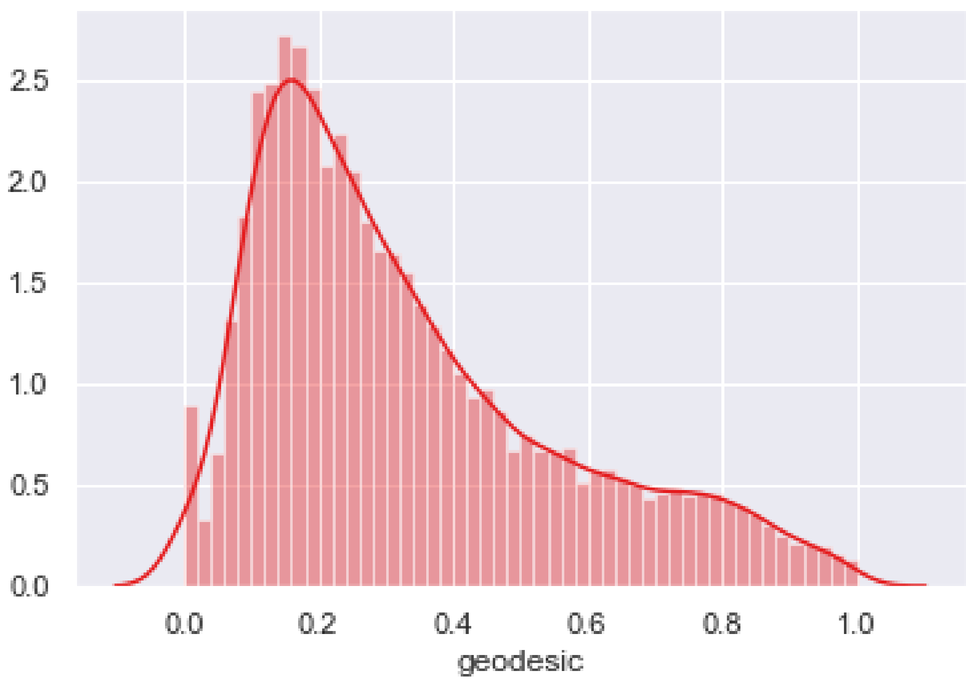


0.5
0.4
0.3
0.2
0.1
0.0
0
1
2
3
4
5
geodesic

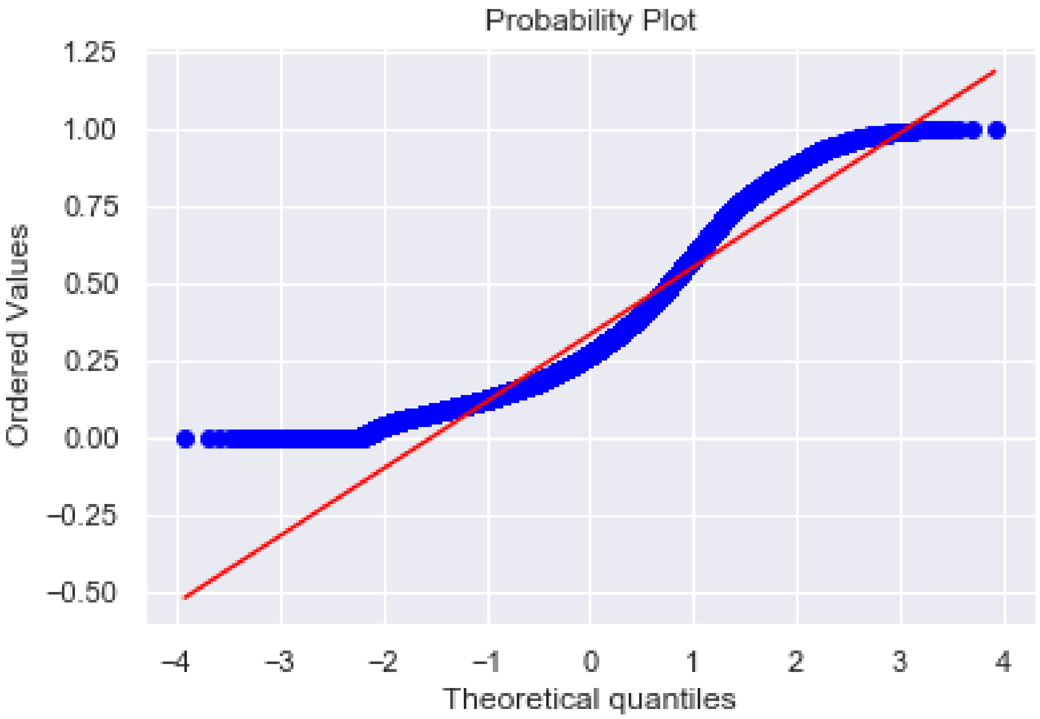
qq probability plot before normalization:



distplot() for ‘geodesic’ feature after normalization:



qq probability plot after normalization:



Chapter 3

Splitting train and Validation Dataset

a) Wehaveusedsklearn'strain_test_split()methodtodividewholeDatasetintotrain andvalidationdatset.
b) 25% is in validation dataset and 75% is in trainingdata.
c) 11745 observations in training and 3915 observations in validationdataset.
d) We will test the performance of model on validationdatset.
e) The model which performs best will be chosen to perform on test dataset provided along with original traindataset.
f) X_train y_train--are trainsubset.
g) X_test y_test--are validationsubset.

Chapter 4

Hyperparameter Optimization

---

a. To find the optimal hyperparameter we have used sklearn.model_selection.GridSearchCV. and sklearn.model_selection.RandomizedSearchCV
b. GridSearchCV tries all the parameters that we provide it and then returns the best suited parameter fordata.
c. We gave parameter dictionary to GridSearchCV which contains keys which are parameter names and values are the values of parameters which we want to tryfor.

Below are best hyperparameter we found for different models:

I. Multiple LinearRegression:
Tuned Decision reg Parameters: {'copy_X': True, 'fit_intercept': True} Best score is 0.7354470072210966

II. RidgeRegression:
Tuned Decision ridge Parameters: {'alpha': 0.0005428675439323859, 'max_iter': 500, 'normalize': True} Best score is 0.7354637543642097

III. LassoRegression:
Tuned Decision lasso Parameters: {'alpha': 0.00021209508879201905, 'max_iter': 1000, 'normalize': False} Best score is 0.40677751497154

IV. Decision TreeRegression:
Tuned Decision Tree Parameters: {'max_depth': 6, 'min_samples_split': 2} Best score is 0.7313489270203365

V. Random ForestRegression:

Tuned Decision Forest Parameters: {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 4, 'max_features': 'auto', 'max_depth': 9, 'bootstrap': True}
Best score is 0.7449373558797026

VI. Xgboostregression:
Tuned Xgboost Parameters: {'subsample': 0.1, 'reg_alpha': 0.08685113737513521, 'n_estimators': 200, 'max_depth': 3, 'learning_rate':
0.05, 'colsample_bytree': 0.7000000000000001, 'colsample_bynode': 0.7000000000000001, 'colsample_bylevel': 0.9000000000000001}

Best score is 0.7489532917329004

Chapter 5

Model Development

Our problem statement wants us to predict the fare_amount. This is a Regression problem. So, we are going to build regression models on training data and predict it on test data. In this project I have built models using 5 Regression Algorithms:

I. LinearRegression
II. RidgeRegression
III. LassoRegression
IV. DecisionTree
V. RandomForest
VI. XgboostRegression

We will evaluate performance on validation dataset which was generated using Sampling. We will deal with specific error metrics like –
Regression metrics for our Models:
- rsquare
- Adjusted rsquare
- MAPE(Mean Absolute PercentageError)
- MSE(Mean squareError)
- RMSE(Root Mean SquareError)
- RMSLE(Root Mean Squared LogError)

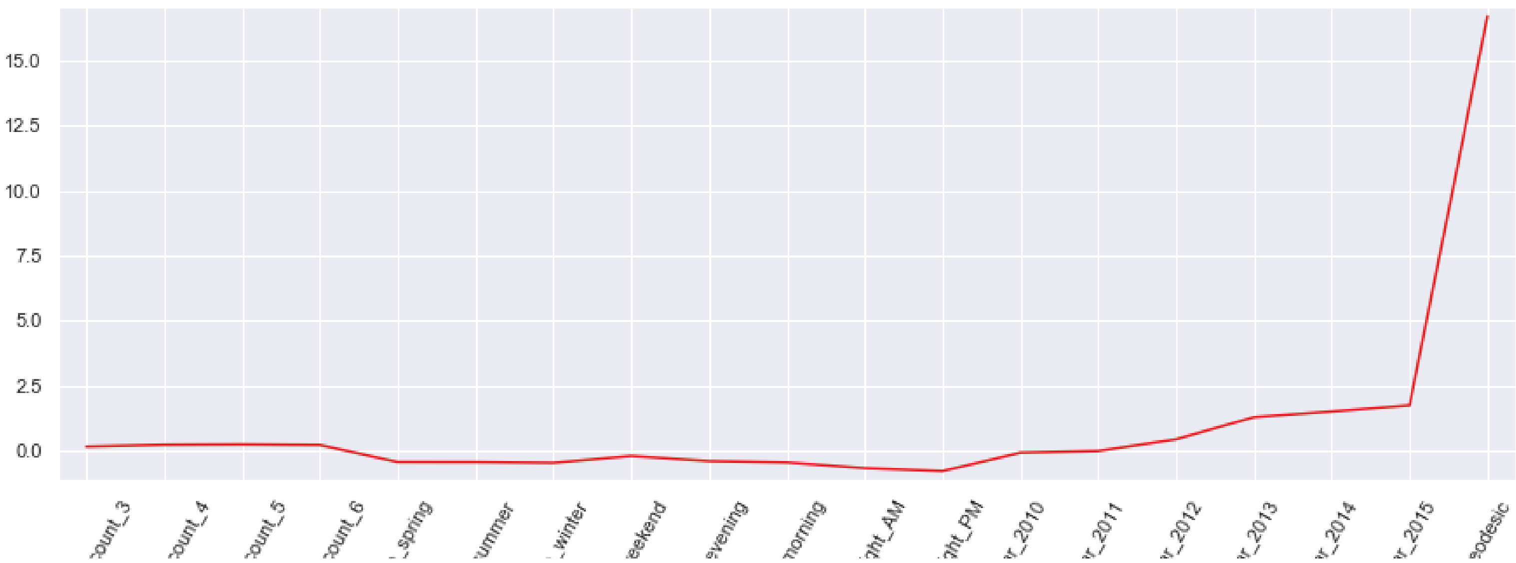
2.3.1 ModelPerformance

Here, we will evaluate the performance of different Regression models based on different Error Metrics

I. Multiple LinearRegression:

Error Metrics	r square	Adj r sq	MAPE	MSE	RMSE	RMSLE
Train	0.734	0.733	18.73	5.28	2.29	0.21
Validation	0.719	0.7406	18.96	5.29	2.30	0.21

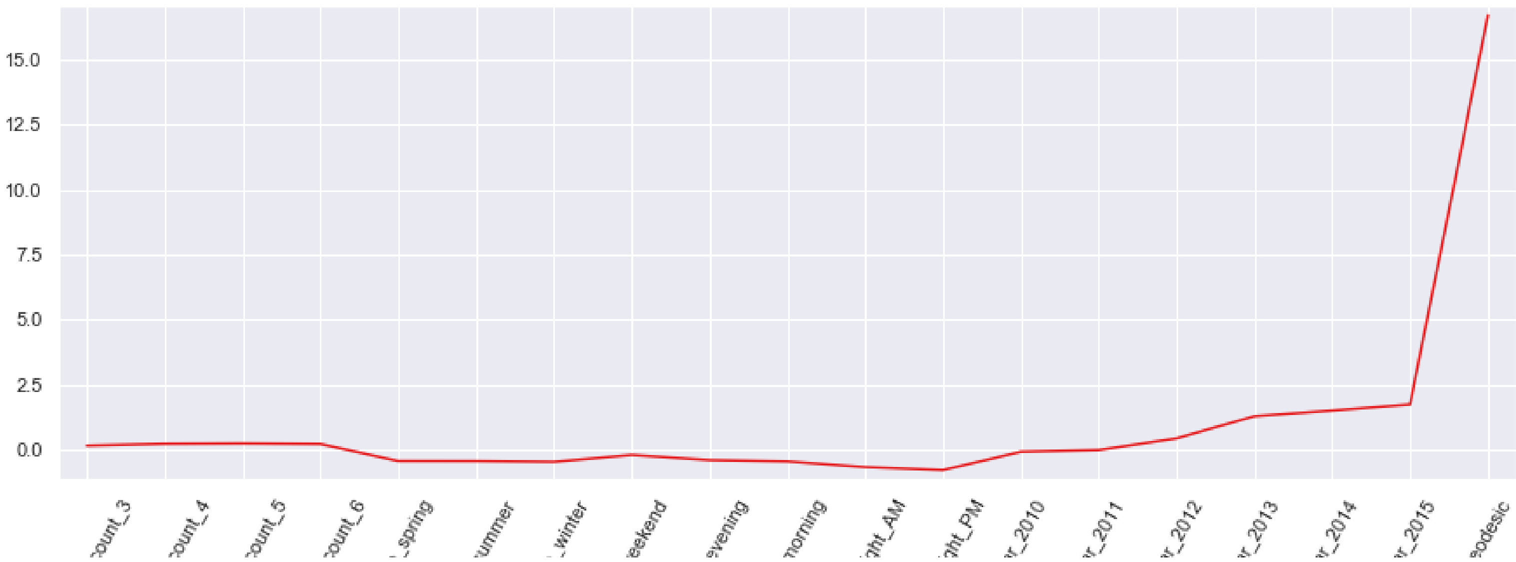
Line Plot for Coefficients of Multiple Linear regression:



II. RidgeRegression:

Error Metrics	r square	Adj r sq	MAPE	MSE	RMSE	RMSLE
Train	0.7343	0.733	18.74	5.28	2.29	0.21
validation	0.7419	0.7406	18.96	5.29	2.3	0.21

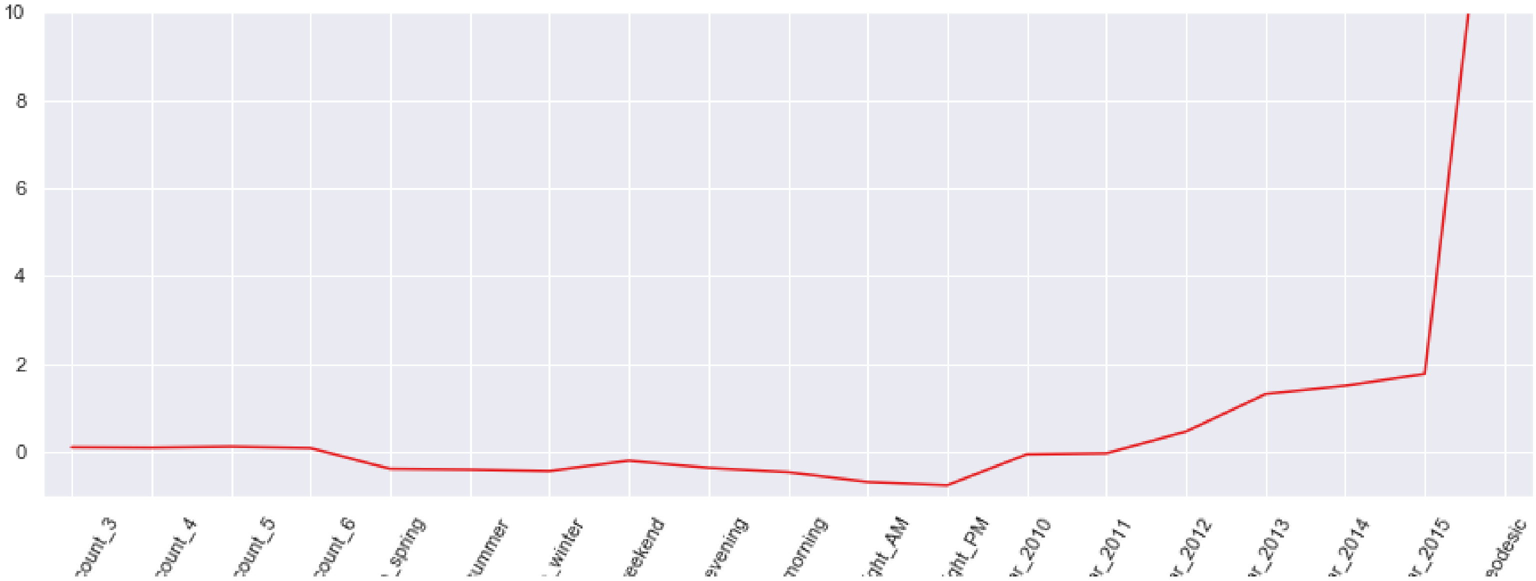
Line Plot for Coefficients of Ridge regression:



III. LassoRegression:

Error Metrics	r square	Adj r sq	MAPE	MSE	RMSE	RMSLE
Train	0.7341	0.7337	18.75	5.28	2.29	0.21
Validation	0.7427	0.7415	18.95	5.27	2.29	0.21

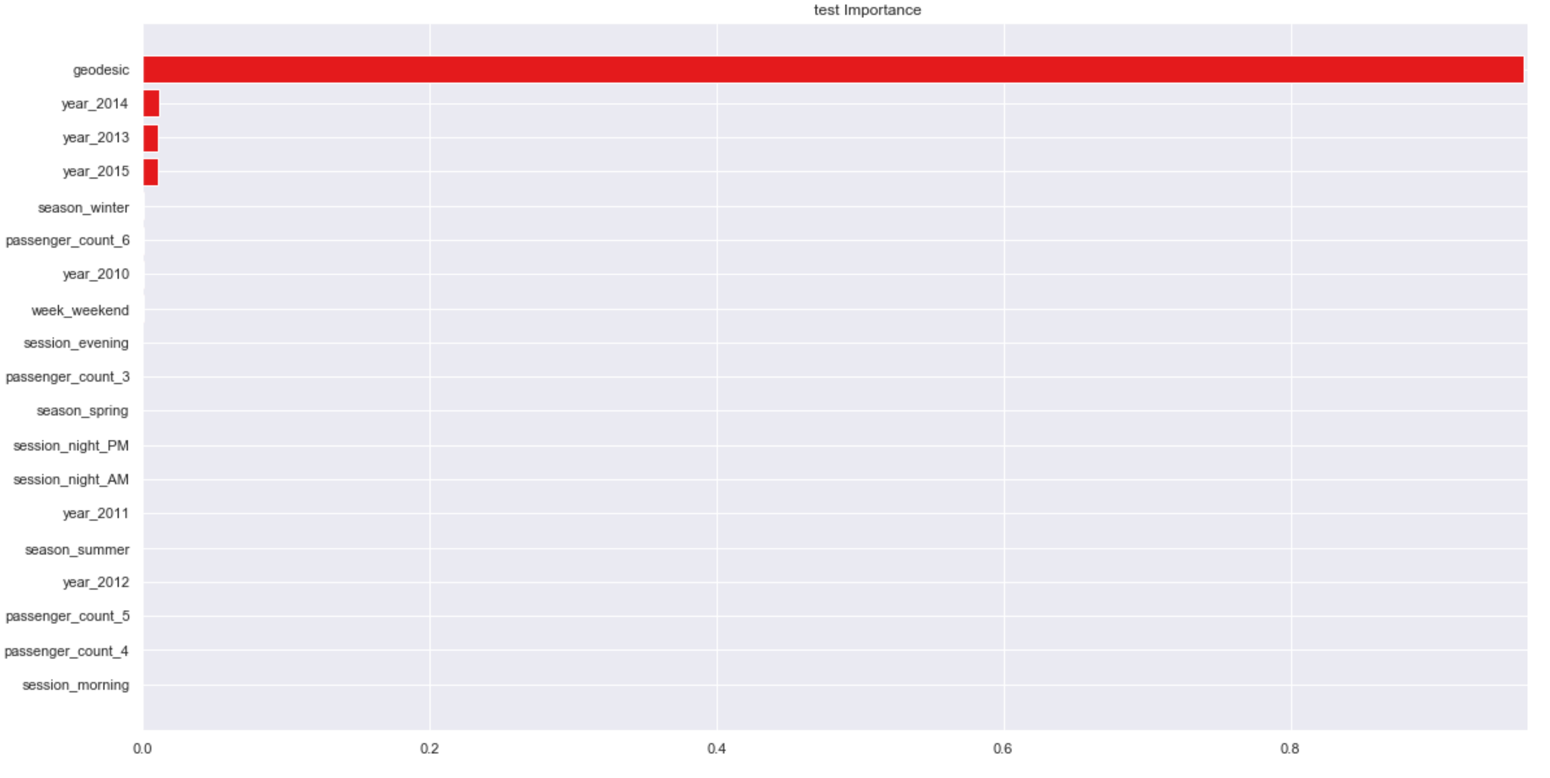
Line Plot for Coefficients of Lasso regression:



IV. Decision TreeRegression:

Error Metrics	r square	Adj r sq	MAPE	MSE	RMSE	RMSLE
Train	0.7471	0.7467	18.54	5.02	2.24	0.20
Validation	0.7408	0.7396	19.07	5.31	2.30	0.21

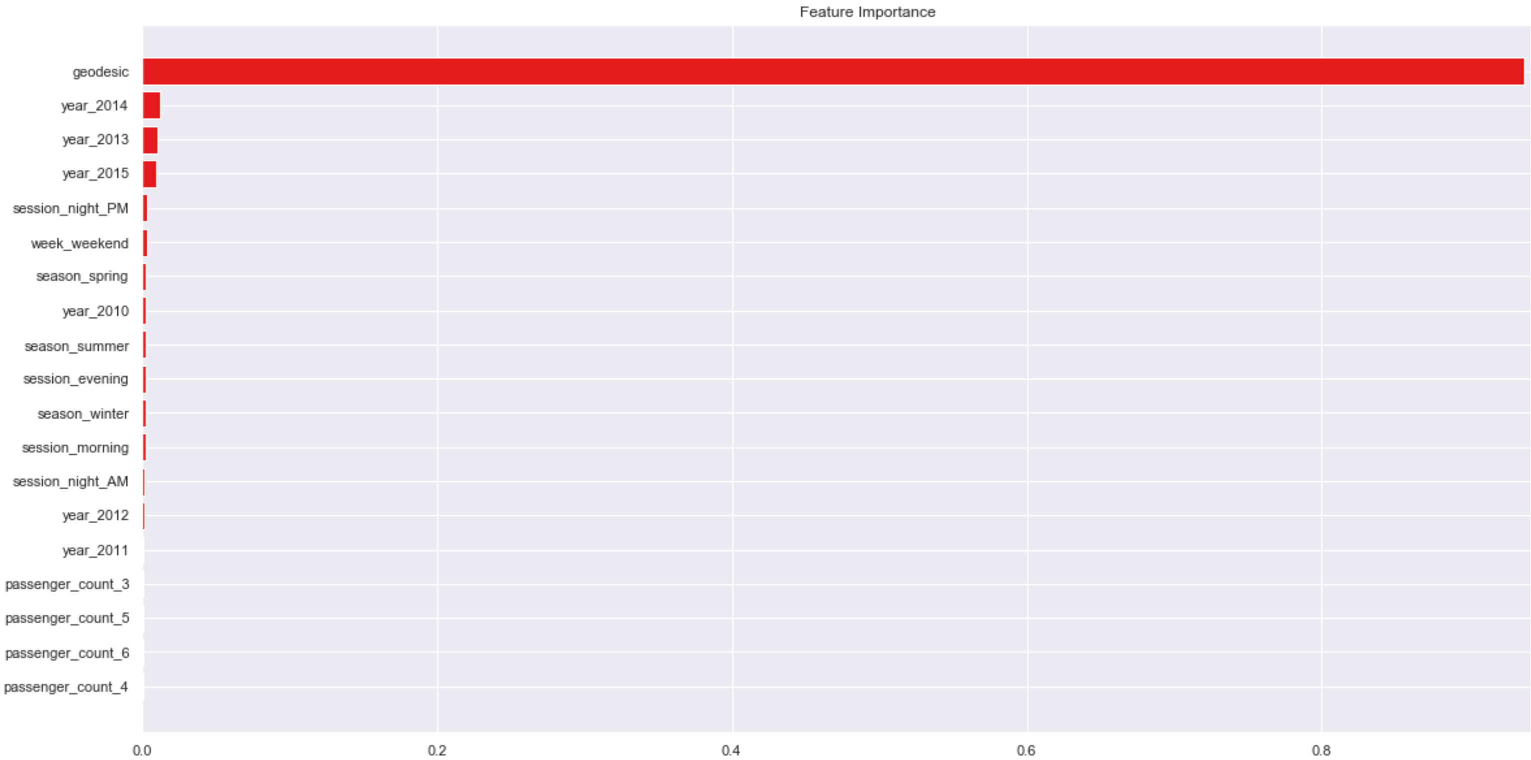
Bar Plot of Decision tree Feature Importance:



V. Random ForestRegression:

Error Metrics	r square	Adj r sq	MAPE	MSE	RMSE	RMSLE
Train	0.7893	0.7889	16.95	4.19	2.04	0.19
Validation	0.7542	0.7530	18.56	5.09	2.24	0.20

Bar Plot of Random Forest Feature Importance:



Cross validation scores: [-5.19821639 -5.18058997 -5.11306209 -5.15194135 -5.14644304]
Average 5-Fold CV Score: -5.158050568861664

Chapter 6

Improving accuracy

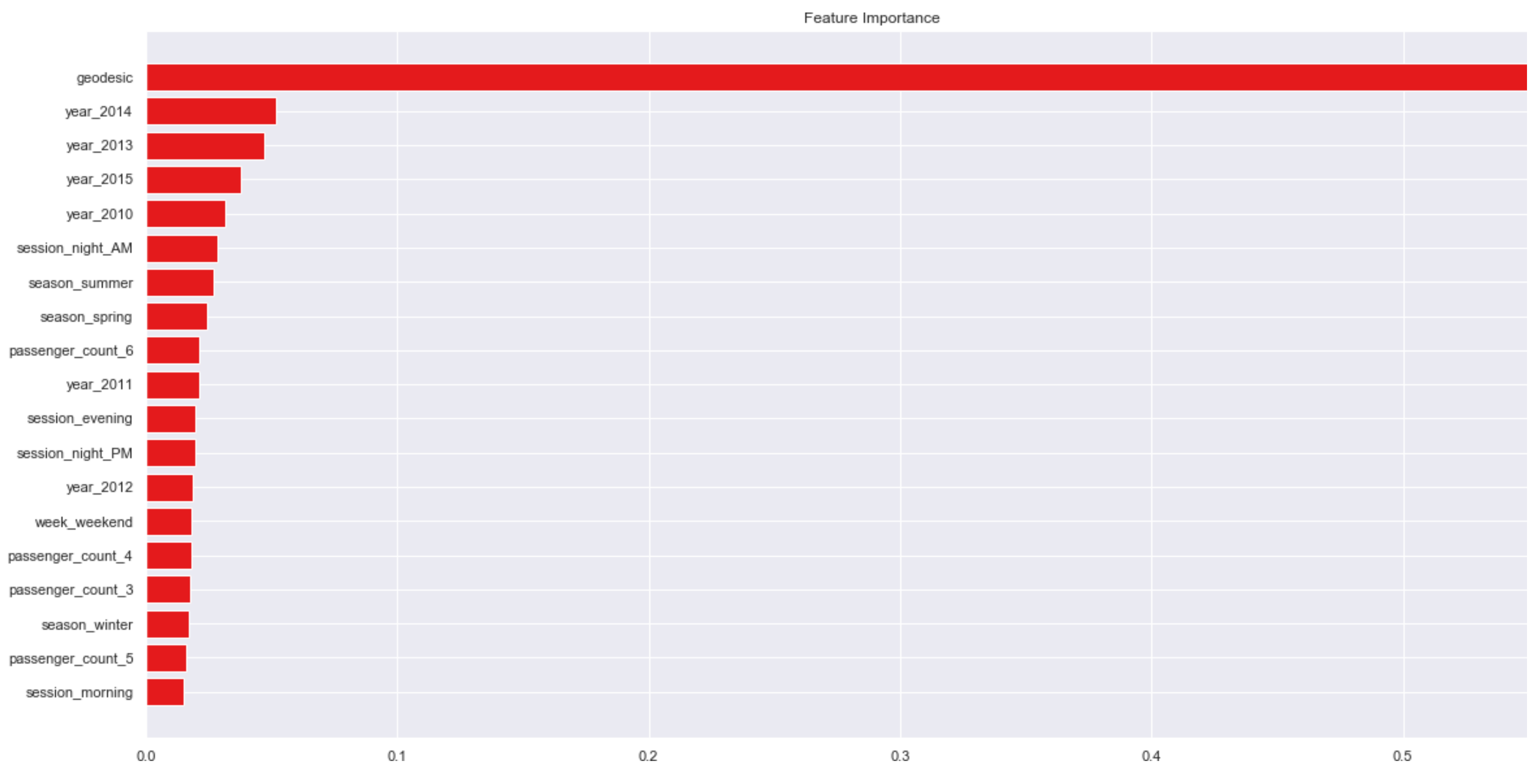
- Improve Accuracy a) Algorithm Tuning b)Ensembles
- We have used xgboost as a ensembletechnique.

<u>Xgboost hyperparameters tuned parameters:</u>Tuned Xgboost Parameters: {'subsample': 0.1, 'reg_alpha': 0.08685113737513521, 'n_estimators': 200, 'max_depth': 3, 'learning_rate': 0.05,
'colsample_bytree': 0.7000000000000001, 'colsample_bynode': 0.7000000000000001,
'colsample_bylevel': 0.9000000000000001}

Xgboost Regression:

Error Metrics	r square	Adj r sq	MAPE	MSE	RMSE	RMSLE
Train	0.7542	0.7538	18.15	4.88	2.21	0.20
Validation	0.7587	0.7575	18.37	4.96	2.22	0.20

Bar Plot of Xgboost Feature Importance:


Feature Importance
geodesic
year_2014
year_2013
year_2015
year_2010
session_night_AM
season_summer
season_spring
passenger_count_6
year_2011
session_evening
session_night_PM
year_2012
week_weekend
passenger_count_4
passenger_count_3
season_winter
passenger_count_5
session_morning
0.0
0.1
0.2
0.3
0.4
0.5

Chapter 7
Finalize model

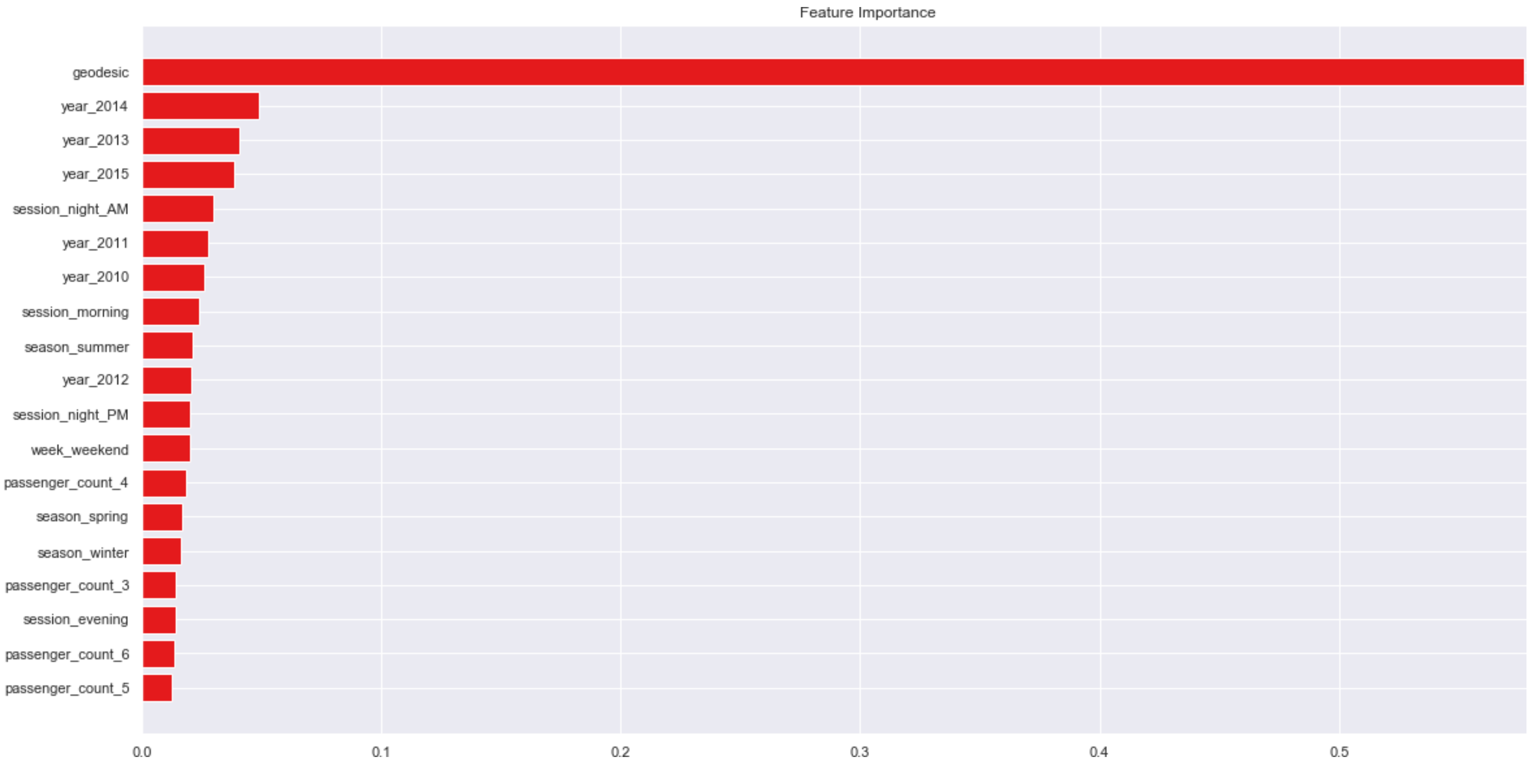
- Create standalone model on entire trainingdataset
- Save model for lateruse

We have trained a Xgboost model on entire training dataset and used that model to predict on test data.Also, we have saved model for later use.

<<<------------------- TrainingDataScore--------->

r square0 . 7 5 6 4 2 9 2 9 5 2 1 8 2 6 6 6
Adjusted r
square:0.7561333973032505
MAPE:18.100202501103993
MSE: 4.881882644209386
RMSE: 2.2094982788428204
RMSLE: 0.2154998534679604
RMSLE: 0.20415655796958632

Feature importance:



Chapter 8

Python-Code

ProblemStatement-
You are a cab rental start-up company. You have successfully run the pilot project and now want to launch your cab service across the country. You have collected thehistorical data from your pilot project and now have a requirement to apply analytics forfare prediction. You need to design a system that predicts the fare amount for a cab ride in the city.

```
# loading the required
libraries import os
import pandas
as pd import
numpy as np
import matplotlib.pyplot
as plt import seaborn as
sns
import matplotlib.pyplot
as plt import scipy.stats
as stats from
fancyimpute import KNN
importwarnings
warnings.filterwarnings('ignor
e') from geopy.distance
import geodesic
from geopy.distance import
great_circle from scipy.stats
import chi2_contingency import
statsmodels.api as sm
from statsmodels.formula.api
import ols from patsy import
dmatrices
from statsmodels.stats.outliers_influence import
variance_inflation_factor from sklearn.model_selection
import train_test_split
from sklearn.metrics import
mean_squared_error from sklearn
import metrics
from sklearn.linear_model import
LinearRegression,Ridge,Lasso from
sklearn.model_selection import GridSearchCV
```

```
from sklearn.model_selection import
RandomizedSearchCV from
sklearn.model_selection import cross_val_score
from sklearn.ensemble import
RandomForestRegressor from sklearn.tree
import DecisionTreeRegressor
from xgboost import
XGBRegressor import
xgboost as xgb
```

from sklearn.externals import joblib

set the working directory
os.chdir('C:/Users/admin/Documents/Pyth
on Files') os.getcwd()

The details of data attributes in the dataset are as follows:
- pickup_datetime - timestamp value indicating when the cab ridestarted.
- pickup_longitude - float for longitude coordinate of where the cab ridestarted.
- pickup_latitude - float for latitude coordinate of where the cab ridestarted.
- dropoff_longitude - float for longitude coordinate of where the cab rideended.
- dropoff_latitude - float for latitude coordinate of where the cab rideended.
- passenger_count - an integer indicating the number of passengers in the cabride.

predictive modeling machine learning project can be broken down into below workflow:
1.PrepareProblem
a) Load libraries b) Load dataset
2.Summarize Data a) Descriptive statistics b) Datavisualizations
3.Prepare Data a) Data Cleaning b) Feature Selection c) DataTransforms
4.Evaluate Algorithms a) Split-out validation dataset b) Test options and evaluation metric c) Spot Check Algorithms d) CompareAlgorithms
5.Improve Accuracy a) Algorithm Tuning b)Ensembles
6.FinalizeModela)Predictionsonvalidationdatasetb)Create standalonemodelonentiretrainingdatasetc)Savemodel for lateruse

Importing data
train =
pd.read_csv('train_cab.csv',dtype={'fare_amount':np.float64},na_values={'fare_a
mount':'430-'}) test = pd.read_csv('test.csv')
data=[train,t
est] for i in
data:
   i['pickup_datetime'] =
pd.to_datetime(i['pickup_datetime'],errors='coerce') train.head(5)

   # (Q) how many data-points and features?
   print (train.shape)

   #Getting the column names of the dataset
   train.columns

train.info()

test.head(5)

test.info()

test.describ

e()

train.descri

be() ##

EDA

- we will convert passenger_count into a categorical variable because passenger_count is not a continuousvariable.

- passenger_count cannot take continous values. and also they are limited in number if its a cab.

```
cat_var=['passenger_count']
num_var=['fare_amount','pickup_longitude','pickup_latitude','dropoff_longitude','
dropoff_latitude']
```

Graphical EDA - Data Visualization

```
# setting up the sns for plots
sns.set(style='darkgrid',palett
e='Set1')
```

Some histogram plots from seaborn library

```
plt.figure(figsize=(20,20))pl
t.subplot(321)
_ =
sns.distplot(train['fare_amount'],bin
s=50) plt.subplot(322)
_ =
sns.distplot(train['pickup_longitude'],bin
s=50) plt.subplot(323)
_ =
sns.distplot(train['pickup_latitude'],bin
s=50) plt.subplot(324)
_ =
sns.distplot(train['dropoff_longitude'],bin
s=50) plt.subplot(325)
_ =
sns.distplot(train['dropoff_latitude'],bin
s=50) # plt.savefig('hist.png')
plt.show()
```

- Jointplots for BivariateAnalysis.
- Here Scatter plot has regression line between 2 variables along with separate Bar plots of both variables.
- Also its annotated with pearson correlation coefficient and pvalue.

```
_ = sns.jointplot(x='fare_amount',y='pickup_longitude',data=train,kind = 'reg')
_.annotate(stats.pear
sonr)                         #
plt.savefig('jointfplo.p
ng') plt.show()

_ = sns.jointplot(x='fare_amount',y='pickup_latitude',data=train,kind = 'reg')
_.annotate(stats.pear
sonr)                         #
plt.savefig('jointfpla.p
ng') plt.show()

_ = sns.jointplot(x='fare_amount',y='dropoff_longitude',data=train,kind = 'reg')
_.annotate(stats.pear
sonr)                         #
plt.savefig('jointfdlo.p
ng') plt.show()

_ = sns.jointplot(x='fare_amount',y='dropoff_latitude',data=train,kind = 'reg')
_.annotate(stats.pear
sonr)                         #
plt.savefig('jointfdla.p
ng') plt.show()
```

Some Violinplots to see spread of

variables

```
plt.figure(figsize=(20,20))
plt.subplot(321)
```

```
_ =
sns.violinplot(y='fare_amount',data
=train) plt.subplot(322)
_ =
sns.violinplot(y='pickup_longitude',data
=train) plt.subplot(323)
```

_ =
sns.violinplot(y='pickup_latitude',data
=train) plt.subplot(324)
_ =
sns.violinplot(y='dropoff_longitude',data
=train) plt.subplot(325)
_ =
sns.violinplot(y='dropoff_latitude',data
=train) plt.savefig('violin.png')
plt.show()

Pairplot for all numerical variables

_ =sns.pairplot(data=train[num_var],kind='scatter',dropna=True)
_.fig.suptitle('Pairwise plot of all numerical
variables') # plt.savefig('Pairwise.png')
plt.show()

Removing values which are not within desired range(outlier) depending upon basic understanding of dataset.

1.Fare amount has a negative value, which doesn't make sense. A price amount cannot be -ve and also cannot be 0. So we will remove these fields.

sum(train['fare_amount

']<1)

train[train['fare_amoun

t']<1]

train =

train.drop(train[train['fare_amount']<1].index,

axis=0) # train.loc[train['fare_amount'] <

1,'fare_amount'] = np.nan 2.Passenger_count

variable

```
for i in range(4,11):
   print('passenger_count above' +str(i)+'={}'.format(sum(train['passenger_count']>i)))
```

so 20 observations of passenger_count is consistenly above from 6,7,8,9,10

passenger_counts, let's check them. train[train['passenger_count']>6]

Also we need to see if there are any

passenger_count<1

train[train['passenger_count']<1]

len(train[train['passenger_count']<1])

test['passenger_count'].unique()

- passenger_count variable conatins values which are equal to0.
- And test data does not contain passenger_count=0 . So if we feature engineer passenger_count of train dataset then it will create a dummy variable for passenger_count=0 which will be an extra feature compared to testdataset.
- So, we will remove those 0values.
- Also, We will remove 20 observation which are above 6 value because a cab cannot hold these number of passengers.

```
train =
train.drop(train[train['passenger_count']>6].index,
axis=0) train =
train.drop(train[train['passenger_count']<1].index,
axis=0)

# train.loc[train['passenger_count'] >6,'passenger_count'] = np.nan
```

train.loc[train['passenger_count']

>1,'passenger_count'] = np.nan

sum(train['passenger_count']>6)

3.Latitudes range from -90 to 90.Longitudes range from -180 to 180.
 Removing which does not satisfy these ranges

```
print('pickup_longitude above
180={}'.format(sum(train['pickup_longitude']>180)))
print('pickup_longitude below -
180={}'.format(sum(train['pickup_longitude']<-180)))
print('pickup_latitude above
90={}'.format(sum(train['pickup_latitude']>90)))
print('pickup_latitude below -
90={}'.format(sum(train['pickup_latitude']<-90)))
print('dropoff_longitude above
180={}'.format(sum(train['dropoff_longitude']>180)))
print('dropoff_longitude below -
180={}'.format(sum(train['dropoff_longitude']<-180)))
print('dropoff_latitude below -
90={}'.format(sum(train['dropoff_latitude']<-90)))
print('dropoff_latitude above
90={}'.format(sum(train['dropoff_latitude']>90)))
```

- There's only one outlier which is in variable pickup_latitude.So we will remove it with nan.
- Also we will see if there are any values equal to 0.

```
for i in
   ['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_l
   atitude']: print(i,'equal to 0={}'.format(sum(train[i]==0)))
```

there are values which are equal to 0. we will

remove them. train =

train.drop(train[train['pickup_latitude']>90].index,ax

is=0)

```
for i in ['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_latitude']:
   train = train.drop(train[train[i]==0].index, axis=0)

# for i in
['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_latit
ude']: #      train.loc[train[i]==0,i] =np.nan
#

train.loc[train['pickup_latitude']>90,'pickup_latitude

'] = np.nan train.shape
```

So, we lossed 16067-15661=406 observations because of non-sensical values.

```
df=train.cop
y()
#train=df.co
py()
```

Missing Value Analysis

#Create dataframe with missing
percentage missing_val =
pd.DataFrame(train.isnull().sum())
#Reset index
missing_val =
missing_val.reset_index()
missing_val

- As we can see there are some missing values in thedata.
- Also pickup_datetime variable has 1 missingvalue.
- We will impute missing values for fare_amount,passenger_count variables exceptpickup_datetime.
- And we will drop that 1 row which has missing value inpickup_datetime.

#Rename variable
missing_val = missing_val.rename(columns = {'index': 'Variables', 0:
'Missing_percentage'}) missing_val

#Calculate percentage
missing_val['Missing_percentage'] =
(missing_val['Missing_percentage']/len(train))*100 #descending order
missing_val = missing_val.sort_values('Missing_percentage', ascending =
False).reset_index(drop = True) missing_val

1.For Passenger_count:
- Actual value =1
- Mode =1
- KNN =2

Choosing a random values to
replace it as NA
train['passenger_count'].loc[1000]

Replacing 1.0 with NA
train['passenger_count'].loc[1000]
= np.nan
train['passenger_count'].loc[1000]

Impute with mode
train['passenger_count'].fillna(train['passenger_count'].mode(
)[0]).loc[1000]

We can't use mode method because data will be more biased towards

passenger_count=1 2.For fare_amount:
- Actual value =7.0,
- Mean = 15.117,
- Median =8.5,
- KNN = 7.369801

for i in
['fare_amount','pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_la
titude']: #   # Choosing a random values to replace it asNA
a=train[i].loc[1000]
print(i,'at loc-1000:
{}'.format(a)) #   #
Replacing 1.0 withNA
train[i].loc[1000] =np.nan
print('Value after replacing with nan:
{}'.format(train[i].loc[1000])) #   # Impute
withmean
print('Value if imputed with mean:
{}'.format(train[i].fillna(train[i].mean()).loc[1000])) #   # Impute
withmedian
print('Value if imputed withmedian:{}\n'.format(train[i].fillna(train[i].median()).loc[1000]))

Choosing a random values to
replace it as NA
a=train['fare_amount'].loc[1000]
print('fare_amount at loc-1000:
{}'.format(a))
Replacing 1.0 with NA
train['fare_amount'].loc[1000]
= np.nan
print('Value after replacing with nan:
{}'.format(train['fare_amount'].loc[1000])) # Impute with mean

```
print('Value if imputed with mean:
{}'.format(train['fare_amount'].fillna(train['fare_amount'].mean()).loc[1000])) # Impute
with median
print('Value if imputed with median:

{}'.format(train['fare_amount'].fillna(train['fare_amount'].median()).loc[1000])) train.std()

columns=['fare_amount', 'pickup_longitude', 'pickup_latitude','dropoff_longitude', 'dropoff_latitude',
'passenger_count']
```

we will separate pickup_datetime into a different dataframe and then merge with train in

feature engineering step. pickup_datetime=pd.DataFrame(train['pickup_datetime'])

# Imputing with missing values using KNN
# Use 19 nearest rows which have a feature to fill in each row's missing features
train = pd.DataFrame(KNN(k =
19).fit_transform(train.drop('pickup_datetime',axis=1)),columns=columns,
index=train.index)

train.std()

train.loc[10

00]

train['passenger_count'].head()

train['passenger_count']=train['passenger_count']

.astype('int') train.std()

train['passenger_count'].unique()

train['passenger_count']=train['passenger_count'].round().astype('object').astype('cat

egory',ordered=True) train['passenger_count'].unique()

train.loc[1000]

- Now about missing value in

pickup_datetime

pickup_datetime.head()

#Create dataframe with missing percentage
missing_val =
pd.DataFrame(pickup_datetime.isnull().sum())
#Reset index
missing_val =
missing_val.reset_index()
missing_val

pickup_datetime.shapetr

ain.shape

- We will drop 1 row which has missing value for pickup_datetime variable after feature engineering step because if we drop now, pickup_datetime dataframe will have 16040 rows and our train has 1641 rows, then if we merge these 2 dataframes then pickup_datetime variable will gain 1 missingvalue.
- And if we merge and then drop now then we would require to split again before outlier analysis and then merge again in feature engineeringstep.
- So, instead of doing the work 2 times we will drop 1 time i.e. after feature engineeringprocess.

# df1 =
train.copy()

```
train=df1.copy
()

train['passenger_count'].des

cribe() train.describe()
```

Outlier Analysis using Boxplot
- We Will do Outlier Analysis only on Fare_amount just for now and we will do outlier analysis after feature engineering laitudes andlongitudes.

- Univariate Boxplots: Boxplots for all Numerical Variables including

```
target variable. plt.figure(figsize=(20,5))
plt.xlim(0,100)
sns.boxplot(x=train['fare_amount'],data=trai
n,orient='h') plt.title('Boxplot of
fare_amount')
# plt.savefig('bp of
fare_amount.png') plt.show()

# sum(train['fare_amount']<22.5)/len(train['fare_amount'])*100
```

- Bivariate Boxplots: Boxplot for Numerical Variable Vs

```
Categorical Variable. plt.figure(figsize=(20,10))
plt.xlim(0,100)
_ =
sns.boxplot(x=train['fare_amount'],y=train['passenger_count'],data=tr
ain,orient='h') plt.title('Boxplot of fare_amount w.r.t passenger_count')
# plt.savefig('Boxplot of fare_amount w.r.t
passenger_count.png') plt.show()

train.describe()

train['passenger_count'].des

cribe() ## Outlier
```

Treatment
- As we can see from the above Boxplots there are outliers in the traindataset.
- Reconsiderpickup_longitude,etc.

```
def outlier_treatment(col):
  ''' calculating outlier indices and replacing them
  with NA ''' #Extract quartiles
  q75, q25 = np.percentile(train[col],
  [75 ,25]) print(q75,q25)
  #CalculateI
  QRiqr =
  q75 -q25
  #Calculate inner and
  outer fence minimum =
  q25 - (iqr*1.5) maximum
  = q75 + (iqr*1.5)
  print(minimum,maximum)
  #Replace with NA
  train.loc[train[col] < minimum,col]
  = np.nan train.loc[train[col] >
  maximum,col] = np.nan

# for i in num_var:
  outlier_treatment('fare_am
  ount')
```

```
#

outlier_treatment('pickup_longitu
de')#

outlier_treatment('pickup_latitude
')
#

outlier_treatment('dropoff_longitud
e')#

outlier_treatment('dropoff_latitude
')
```

```
pd.DataFrame(train.isnull().

sum()) train.std()

#Imputing with missing values using KNN
train = pd.DataFrame(KNN(k = 3).fit_transform(train), columns =

train.columns, index=train.index) train.std()

train['passenger_count'].describe()

train['passenger_count']=train['passenger_count'].astype('int').round().astype('objec

t').astype('category') train.describe()

train.head()

df2 =
train.copy() #
train=df2.cop
y()

train.shape

## Feature Engineering

#### 1.Feature Engineering for timestamp variable
- we will derive new features from pickup_datetimevariable
- new features will beyear,month,day_of_week,hour

# we will Join 2 Dataframes pickup_datetime and train
train =
pd.merge(pickup_datetime,train,right_index=True,left_inde
x=True) train.head()

train.shape

train=train.reset_index(drop

=True)

As we discussed in Missing value imputation step about dropping missing

value, we will do it now. pd.DataFrame(train.isna().sum())

train=train.dropna()

data =
[train,test] for
i in data:
   i["year"] = i["pickup_datetime"].apply(lambda row:
   row.year) i["month"] =
   i["pickup_datetime"].apply(lambda row: row.month)
#   i["day_of_month"] = i["pickup_datetime"].apply(lambda row:
   row.day) i["day_of_week"] =
   i["pickup_datetime"].apply(lambda row: row.dayofweek)
   i["hour"] = i["pickup_datetime"].apply(lambda row:row.hour)
```

```
#
train_nodummies=train.c
opy() #
train=train_nodummies.c
opy()

plt.figure(figsize=(20
,10))
sns.countplot(train['y
ear'])
```

```
# plt.savefig('year.png')

plt.figure(figsize=(20,1
0))
sns.countplot(train['mo
nth']) #
plt.savefig('month.png'
)

plt.figure(figsize=(20,10))
sns.countplot(train['day_of_
week']) #
plt.savefig('day_of_week.png
')

plt.figure(figsize=(20,
10))
sns.countplot(train['h
our']) #
plt.savefig('hour.png')
```

Now we will use month,day_of_week,hour to derive new features like sessions in a day,seasons in a year,week:weekend/weekday

```
def f(x):
  ''' for sessions in a day using hour
  column ''' if (x >=5) and (x <=
  11):
    return 'morning'
  elif (x >=12) and (x <=16 ):
    return 'afternoon'
  elif (x >= 17) and (x <= 20):
    return'evening'
  elif (x >=21) and (x <= 23) :
    return
  'night_PM' elif (x
  >=0) and (x
  <=4):
    return'night_AM'

def g(x):
  ''' for seasons in a year using month
  column''' if (x >=3) and (x <= 5):
    return 'spring'
  elif (x >=6) and (x <=8 ):
    return 'summer'
  elif (x >= 9) and (x <= 11):
    return'fall'
  elif (x >=12)|(x <= 2) :
    return 'winter'

def h(x):
  ''' for week:weekday/weekend in a day_of_week
  column ''' if (x >=0) and (x <= 4):
    return 'weekday'
  elif (x >=5) and (x <=6 ):
    return 'weekend'
```

```
train['session'] =
train['hour'].apply(f)
test['session'] =
test['hour'].apply(f)
# train_nodummies['session'] = train_nodummies['hour'].apply(f)

train['seasons'] =
train['month'].apply(g)
test['seasons'] =
test['month'].apply(g)
# train['seasons'] = test['month'].apply(g)
```

train['week'] =
train['day_of_week'].apply(h)
test['week'] =
test['day_of_week'].apply(h)

train.sha

pe

test.shap

e

2.Feature Engineering for passenger_count variable

- Because models in scikit learn require numerical input,if dataset contains categorical variables then we have to encode them.
- We will use one hot encoding technique for

passenger_count variable.

train['passenger_count'].describe()

#Creating dummies for each variable in passenger_count and merging dummies dataframe to both train and test dataframe
temp = pd.get_dummies(train['passenger_count'], prefix =
'passenger_count') train = train.join(temp)
temp = pd.get_dummies(test['passenger_count'], prefix =
'passenger_count') test = test.join(temp)
temp = pd.get_dummies(train['seasons'],
prefix = 'season') train = train.join(temp)
temp = pd.get_dummies(test['seasons'],
prefix = 'season') test = test.join(temp)
temp = pd.get_dummies(train['week'],
prefix = 'week') train = train.join(temp)
temp = pd.get_dummies(test['week'],
prefix = 'week') test = test.join(temp)
temp = pd.get_dummies(train['session'], prefix
= 'session') train = train.join(temp)
temp = pd.get_dummies(test['session'], prefix
= 'session') test = test.join(temp)
temp = pd.get_dummies(train['year'],
prefix = 'year') train = train.join(temp)
temp = pd.get_dummies(test['year'],
prefix = 'year') test = test.join(temp)

train.hea

d()

test.head

()

we will drop one column from each one-hot-

encoded variables train.columns

```
train=train.drop(['passenger_count_1','season_fall','week_weekday','session_afternoon',
'year_2009'],axis=1)
test=test.drop(['passenger_count_1','season_fall','week_weekday','session_afternoon','y
ear_2009'],axis=1)
```

3.Feature Engineering for latitude and longitude variable
- As we have latitude and longitude data for pickup and dropoff, we will find the distance the cab travelled from pickup and dropofflocation.

```
# train.sort_values('pickup_datetime')
```

def haversine(coord1, coord2):
'''Calculate distance the cab travelled from pickup and dropoff location using the Haversine Formula''' #   data = [train,test]
for i indata:
lon1, lat1 =coord1
lon2, lat2 =coord2
R = 6371000 # radius of Earth
in meters #   phi_1
=np.radians(i[lat1])
#   phi_2 =np.radians(i[lat2])
#   delta_phi = np.radians(i[lat2] -i[lat1])
#   delta_lambda = np.radians(i[lon2] -i[lon1])
#   a = np.sin(delta_phi / 2.0) ** 2 + np.cos(phi_1) * np.cos(phi_2) *
np.sin(delta_lambda / 2.0) ** 2 #   c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1 -a))
#   meters = R * c # output distance inmeters
#   km = meters / 1000.0 # output distance in
kilometers #   miles =
round(km,3)/1.609344
i['distance'] =miles
print(f"Distance: {miles}
miles") # #   returnmiles

haversine(['pickup_longitude','pickup_latitude'],['dropoff_longitude','dropoff_latitude'])

# Calculate distance the cab travelled from pickup and dropoff location using great_circle from geopy library data = [train, test]
for i in data:
   i['great_circle']=i.apply(lambda x: great_circle((x['pickup_latitude'],x['pickup_longitude']), (x['dropoff_latitude'], x['dropoff_longitude'])).miles, axis=1)
   i['geodesic']=i.apply(lambda x: geodesic((x['pickup_latitude'],x['pickup_longitude']), (x['dropoff_latitude'], x['dropoff_longitude'])).miles, axis=1)

train.hea

d()

test.head

()

As Vincenty is more accurate than haversine. Also vincenty is prefered for short distances.Therefore we will drop great_circle. we will drop them together with other variables which were used to feature engineer.

pd.DataFrame(train.isna().

sum())

pd.DataFrame(test.isna().

sum())

We will remove the variables which were used to feature engineer new variables

#
train_nodummies=train_nodummies.drop(['pickup_datetime','pickup_longitude', 'pickup_latitude', #   'dropoff_longitude', 'dropoff_latitude','great_circle'],axis =1)
# test_nodummies=test.drop(['pickup_datetime','pickup_longitude', 'pickup_latitude',

```
#     'dropoff_longitude', 'dropoff_latitude','passenger_count_1', 'passenger_count_2',
'passenger_count_3', #   'passenger_count_4', 'passenger_count_5','passenger_count_6',
#     'season_fall', 'season_spring', 'season_summer','season_winter',
#     'week_weekday', 'week_weekend', 'session_afternoon',
'session_evening', #        'session_morning', 'session_night (AM)',
'session_night(PM)',
#     'year_2009', 'year_2010', 'year_2011', 'year_2012',
'year_2013', #      'year_2014', 'year_2015',
'great_circle'],axis =1)

train=train.drop(['pickup_datetime','pickup_longitude', 'pickup_latitude',
```

```
     'dropoff_longitude', 'dropoff_latitude', 'passenger_count', 'year',
     'month', 'day_of_week', 'hour', 'session', 'seasons',
'week','great_circle'],axis=1)
test=test.drop(['pickup_datetime','pickup_longitude',
'pickup_latitude',
     'dropoff_longitude', 'dropoff_latitude', 'passenger_count', 'year',
     'month', 'day_of_week', 'hour', 'session', 'seasons',

'week','great_circle'],axis=1) train.shape,test.shape

#

test_nodummies.colum

ns #

train_nodummies.colu

mns train.columns

test.colum

ns

train.head

()

test.head(

)

plt.figure(figsize=(20,5))
sns.boxplot(x=train['geodesic'],data=train
,orient='h') plt.title('Boxplot of geodesic ')
# plt.savefig('bp
geodesic.png')
plt.show()

plt.figure(figsize=(
20,5))
plt.xlim(0,100)
sns.boxplot(x=train['geodesic'],data=train
,orient='h') plt.title('Boxplot of geodesic ')
# plt.savefig('bp
geodesic.png')
plt.show()

outlier_treatment('geodesic')

pd.DataFrame(train.isnull().sum(

)) #Imputing with missing values

using KNN
train = pd.DataFrame(KNN(k = 3).fit_transform(train), columns = train.columns, index=train.index)

## Feature
Selection
```

1.Correlation
Analysis

Statistically correlated: features move together directionally. Linear models assume feature independence.
And if features are correlated that could introduce bias into our models.

```
cat_var=['passenger_count_2',
     'passenger_count_3', 'passenger_count_4',
     'passenger_count_5', 'passenger_count_6',
     'season_spring', 'season_summer', 'season_winter',
     'week_weekend',
     'session_evening', 'session_morning',
     'session_night_AM', 'session_night_PM',
     'year_2010', 'year_2011', 'year_2012',
     'year_2013', 'year_2014','year_2015']
num_var=['fare_amount','geodesic']
```

train[cat_var]=train[cat_var].apply(lambda x:
x.astype('category'))
test[cat_var]=test[cat_var].apply(lambda x:
x.astype('category'))

- We will plot a Heatmap of correlation whereas, correlation measures how strongly 2 quantities are related to each other.

heatmap using
correlation matrix
plt.figure(figsize=(15,15))
_ = sns.heatmap(train[num_var].corr(), square=True,
cmap='RdYlGn',linewidths=0.5,linecolor='w',annot=True) plt.title('Correlation matrix ')
#
plt.savefig('correlation.p
ng') plt.show()

As we can see from above correlation plot fare_amount and geodesic is correlated to each other.

- Jointplots for BivariateAnalysis.
- Here Scatter plot has regression line between 2 variables along with separate Bar plots of both variables.
- Also its annotated with pearson correlation coefficient and pvalue.

_ = sns.jointplot(x='fare_amount',y='geodesic',data=train,kind = 'reg')
_.annotate(stats.pear
sonr) #
plt.savefig('jointct.pn
g') plt.show()

Chi-square test of Independence for Categorical Variables/Features

- Hypothesis testing:
  - Null Hypothesis: 2 variables areindependent.
  - Alternate Hypothesis: 2 variables are notindependent.
- If p-value is less than 0.05 then we reject the null hypothesis saying that 2 variables are dependent.
- And if p-value is greater than 0.05 then we accept the null hypothesis saying that 2 variables areindependent.
- There should be no dependencies between Independentvariables.
- So we will remove that variable whose p-value with other variable is low than 0.05.
- And we will keep that variable whose p-value with other variable is high than 0.05

```
#loop for chi square
values for i in
cat_var:
   for j in cat_var:
      if(i != j):
         chi2, p, dof, ex =
         chi2_contingency(pd.crosstab(train[i], train[j])) if(p
         < 0.05):
            print(i,"and",j,"are dependent on eachotherwith",p,'        Remove')
         else:
            print(i,"and",j,"are independent on eachotherwith",p,'      Keep')
```

Analysis of Variance(Anova) Test
- It is carried out to compare between each groups in a categorical variable.
- ANOVA only lets us know the means for different groups are same or not. It doesn’t help us identify which meanis
different.
- Hypothesis testing:

- Null Hypothesis: mean of all categories in a variable are same.
- Alternate Hypothesis: mean of at least one category in a variable is different.

- If p-value is less than 0.05 then we reject the null hypothesis.
- And if p-value is greater than 0.05 then we accept the null hypothesis.

train.columns

#ANOVA
_1)+C(passenger_count_2)+C(passenger_count_3)+C(passenger_count_4)+C(passenger_count_5)
+C(passenger_count_6) model = ols('fare_amount ~
C(passenger_count_2)+C(passenger_count_3)+C(passenger_count_4)+C(passenger_count_5)+C(
passenger_count_6)+C(s eason_spring)+C(season_summer)+C(season_winter)
+C(week_weekend)+C(session_night_AM)+C(session_night_PM)+C(s ession_evening)
+C(session_morning)
+C(year_2010)+C(year_2011)+C(year_2012)+C(year_2013)+C(year_2014)+C(year_20
15)',data=train).fit()

aov_table =
sm.stats.anova_lm(model)
aov_table

Every variable has p-value less than 0.05 therefore we reject the

null hypothesis. ## Multicollinearity Test
- VIF is always greater or equal to1.
- if VIF is 1 --- Not correlated to any of thevariables.
- if VIF is between 1-5 --- Moderatelycorrelated.
- if VIF is above 5 --- Highlycorrelated.
- If there are multiple variables with VIF greater than 5, only remove the variable with the highestVIF.

#
_1+passenger_count_2+passenger_count_3+passenger_count_4+passenger_count_5+
passenger_count_6 outcome, predictors = dmatrices('fare_amount ~
geodesic+passenger_count_2+passenger_count_3+passenger_count_4+passenger_count_5+passenger
_count_6+season
_spring+season_summer+season_winter+week_weekend+session_night_AM+session_night_PM+
session_evening+sessio
n_morning+year_2010+year_2011+year_2012+year_2013+year_2014+year_2015',train,
return_type='dataframe')
# calculating VIF for each individual
Predictors vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(predictors.values, i) for i in
range(predictors.shape[1])] vif["features"] = predictors.columns
vif

So we have no or very low multicollinearity

Feature Scaling Check with or without normalization

of standarscalar train[num_var].var()

sns.distplot(train['geodesic'],b
ins=50) #
plt.savefig('distplot.png')

plt.figure()
stats.probplot(train['geodesic'], dist='norm',
fit=True,plot=plt) # plt.savefig('qq prob
plot.png')

#Normalization
train['geodesic'] = (train['geodesic'] - min(train['geodesic']))/(max(train['geodesic']) -
min(train['geodesic'])) test['geodesic'] = (test['geodesic'] -
min(test['geodesic']))/(max(test['geodesic']) - min(test['geodesic']))

```
train['geodesic'].var()

sns.distplot(train['geodesic'],b
ins=50)
plt.savefig('distplot.png')
```

```
plt.figure()
stats.probplot(train['geodesic'], dist='norm',
fit=True,plot=plt) # plt.savefig('qq prob
plot.png')

train.columns

#
df4=train.cop
y()
train=df4.cop
y()  #
f4=test.copy()
test=f4.copy()

train=train.drop(['passenger_count_2
'],axis=1)
test=test.drop(['passenger_count_2'],
axis=1)

train.columns

## Splitting train into train and validation subsets
- X_train y_train--are trainsubset
- X_test y_test--are validationsubset

X =
train.drop('fare_amount',axis=1).v
alues y =
train['fare_amount'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,
random_state=42) print(train.shape, X_train.shape,
X_test.shape,y_train.shape,y_test.shape)

def rmsle(y,y_):
   log1 = np.nan_to_num(np.array([np.log(v + 1)
   for v in y])) log2 =
   np.nan_to_num(np.array([np.log(v + 1) for v in
   y_])) calc = (log1 - log2) ** 2
   return
np.sqrt(np.mean(calc))
def scores(y, y_):
   print('r square ', metrics.r2_score(y, y_))
   print('Adjusted r square:{}'.format(1 - (1-metrics.r2_score(y, y_))*(len(y)-1)/(len(y)-
   X_train.shape[1]-1))) print('MAPE:{}'.format(np.mean(np.abs((y - y_) / y))*100))
   print('MSE:', metrics.mean_squared_error(y,
   y_)) print('RMSE:',
   np.sqrt(metrics.mean_squared_error(y, y_)))
def test_scores(model):
   print('<<<------------------- TrainingDataScore------->')
   print()
   #Predicting result on Training
   data y_pred =
   model.predict(X_train)
   scores(y_train,y_pred)print('RM
   SLE:',rmsle(y_train,y_pred))prin
   t()
   print('<<<------------------- TestDataScore-------->')
   print()
```

```
# Evaluating on Test Set
y_pred =
model.predict(X_test)
scores(y_test,y_pred)
print('RMSLE:',rmsle(y_test,y
```

_pred)) ## Multiple Linear

Regression

Setup the parameters and distributions to sample
from: param_dist param_dist = {'copy_X':[True, False],

```
    'fit_intercept':[True,False]}
# Instantiate a Decision reg
classifier: reg reg =
LinearRegression()

# Instantiate the gridSearchCV object: reg_cv
reg_cv = GridSearchCV(reg, param_dist, cv=5,scoring='r2')

# Fit it to the
data
reg_cv.fit(X,
y)

# Print the tuned parameters and score
print("Tuned Decision reg Parameters:
{}".format(reg_cv.best_params_)) print("Best score is
{}".format(reg_cv.best_score_))

# Create the regressor: reg_all
reg_all = LinearRegression(copy_X= True, fit_intercept=True)

# Fit the regressor to the
training data
reg_all.fit(X_train,y_train)

# Predict on the test data:
y_pred y_pred =
reg_all.predict(X_test)

# Compute and print R^2 and RMSE
print("R^2:
{}".format(reg_all.score(X_test, y_test)))
rmse =
np.sqrt(mean_squared_error(y_test,y_pred
)) print("Root Mean Squared Error:
{}".format(rmse)) test_scores(reg_all)

# Compute and print the
coefficients reg_coef =
reg_all.coef_ print(reg_coef)

# Plot the coefficients
plt.figure(figsize=(15,5))
plt.plot(range(len(test.columns)),
reg_coef)
plt.xticks(range(len(test.columns)),
test.columns.values, rotation=60) plt.margins(0.02)
plt.savefig('linear
coefficients') plt.show()

from sklearn.model_selection import
cross_val_score # Create a linear
regression object: reg
reg = LinearRegression()

# Compute 5-fold cross-validation scores: cv_scores
cv_scores = cross_val_score(reg,X,y,cv=5,scoring='neg_mean_squared_error')
```

```
# Print the 5-fold cross-
validation scores
print(cv_scores)

print("Average 5-Fold CV Score:

{}".format(np.mean(cv_scores))) ## Ridge

Regression
```

```
# Setup the parameters and distributions to sample
from: param_dist param_dist = {'alpha':np.logspace(-4,
0, 50),
       'normalize':[True,False],
         'max_iter':range(500,500
         0,500)}
# Instantiate a Decision ridge
classifier: ridge ridge = Ridge()

# Instantiate the gridSearchCV object: ridge_cv
ridge_cv = GridSearchCV(ridge, param_dist, cv=5,scoring='r2')

# Fit it to the
data
ridge_cv.fit(X,
y)

# Print the tuned parameters and score
print("Tuned Decision ridge Parameters:
{}".format(ridge_cv.best_params_)) print("Best score is
{}".format(ridge_cv.best_score_))

# Instantiate a ridge regressor: ridge
ridge = Ridge(alpha=0.0005428675439323859, normalize=True,max_iter = 500)

# Fit the regressor to
the data
ridge.fit(X_train,y_train)

# Compute and print the
coefficients ridge_coef =
ridge.coef_ print(ridge_coef)

# Plot the coefficients
plt.figure(figsize=(15,5))
plt.plot(range(len(test.columns)),
ridge_coef)
plt.xticks(range(len(test.columns)),
test.columns.values, rotation=60) plt.margins(0.02)
# plt.savefig('ridge
coefficients') plt.show()
test_scores(ridge)

lasso can be used feature

selection ## Lasso

Regression

# Setup the parameters and distributions to sample
from: param_dist param_dist = {'alpha':np.logspace(-4,
0, 50),
       'normalize':[True,False],
         'max_iter':range(500,500
         0,500)}
# Instantiate a Decision lasso
classifier: lasso lasso = Lasso()

# Instantiate the gridSearchCV object: lasso_cv
```

```
lasso_cv = GridSearchCV(lasso, param_dist, cv=5,scoring='r2')

# Fit it to the
data
lasso_cv.fit(X,
y)

# Print the tuned parameters and score
print("Tuned Decision lasso Parameters: {}".format(lasso_cv.best_params_))
```

```
print("Best score is {}".format(lasso_cv.best_score_))

# Instantiate a lasso regressor: lasso
lasso = Lasso(alpha=0.00021209508879201905, normalize=False,max_iter = 500)

# Fit the regressor to
the data lasso.fit(X,y)

# Compute and print the
coefficients lasso_coef =
lasso.coef_ print(lasso_coef)

# Plot the
coefficients
plt.figure(figsize=(
15,5)) plt.ylim(-
1,10)
plt.plot(range(len(test.columns)), lasso_coef)
plt.xticks(range(len(test.columns)),
test.columns.values, rotation=60) plt.margins(0.02)
plt.savefig('lasso
coefficients') plt.show()
test_scores(lasso)

## Decision Tree

Regression train.info()

# Setup the parameters and distributions to sample
from: param_dist param_dist = {'max_depth':
range(2,16,2),
          'min_samples_split': range(2,16,2)}

# Instantiate a Decision Tree
classifier: tree tree =
DecisionTreeRegressor()

# Instantiate the gridSearchCV object:
tree_cv tree_cv = GridSearchCV(tree,
param_dist, cv=5)

# Fit it to the
data
tree_cv.fit(X,
y)

# Print the tuned parameters and score
print("Tuned Decision Tree Parameters:
{}".format(tree_cv.best_params_)) print("Best score is
{}".format(tree_cv.best_score_))

# Instantiate a tree regressor: tree
tree = DecisionTreeRegressor(max_depth= 6, min_samples_split=2)

# Fit the regressor to
the data
tree.fit(X_train,y_train)
```

```
# Compute and print the
coefficients tree_features =
tree.feature_importances_
print(tree_features)

# Sort test importances in
descending order indices =
np.argsort(tree_features)[::1]
```

```
# Rearrange test names so they match the sorted
test importances names = [test.columns[i] for i in
indices]

# Creating plot
fig =
plt.figure(figsize=(20,10
)) plt.title("test
Importance")

# Add horizontal bars
plt.barh(range(pd.DataFrame(X_train).shape[1]),tree_features[indices
],align = 'center') plt.yticks(range(pd.DataFrame(X_train).shape[1]),
names)
plt.savefig('tree test
importance') plt.show()
# Make predictions and
cal error test_scores(tree)

## Random Forest

Regression # Create

the random grid
random_grid = {'n_estimators':
          range(100,500,100), 'max_depth':
          range(5,20,1),
          'min_samples_leaf':range(2,5,1),
          'max_features':['auto','sqrt','log2'],
          'bootstrap': [True, False],
          'min_samples_split': range(2,5,1)}
# Instantiate a Decision Forest
classifier: Forest Forest =
RandomForestRegressor()

# Instantiate the gridSearchCV object: Forest_cv
Forest_cv = RandomizedSearchCV(Forest, random_grid, cv=5)

# Fit it to the
data
Forest_cv.fit(X
, y)

# Print the tuned parameters and score
print("Tuned Random Forest Parameters:
{}".format(Forest_cv.best_params_)) print("Best score is
{}".format(Forest_cv.best_score_))

# Instantiate a Forest regressor: Forest
Forest = RandomForestRegressor(n_estimators=100, min_samples_split= 2,
min_samples_leaf=4, max_features='auto', max_depth=9, bootstrap=True)

# Fit the regressor to
the data
Forest.fit(X_train,y_train
)
```

```
# Compute and print the coefficients
Forest_features =
Forest.feature_importances_
print(Forest_features)

# Sort feature importances in
descending order indices =
np.argsort(Forest_features)[::1]

# Rearrange feature names so they match the sorted
feature importances names = [test.columns[i] for i in
indices]
```

```
# Creating plot
fig =
plt.figure(figsize=(20,10
)) plt.title("Feature
Importance")

# Add horizontal bars
plt.barh(range(pd.DataFrame(X_train).shape[1]),Forest_features[indices
],align = 'center') plt.yticks(range(pd.DataFrame(X_train).shape[1]),
names)
plt.savefig('Random forest feature
importance') plt.show()# Make
predictions test_scores(Forest)

from sklearn.model_selection import
cross_val_score # Create a random forest
regression object: Forest
Forest = RandomForestRegressor(n_estimators=400, min_samples_split= 2,
min_samples_leaf=4, max_features='auto', max_depth=12, bootstrap=True)

# Compute 5-fold cross-validation scores: cv_scores
cv_scores = cross_val_score(Forest,X,y,cv=5,scoring='neg_mean_squared_error')

# Print the 5-fold cross-
validation scores
print(cv_scores)

print("Average 5-Fold CV Score:

{}".format(np.mean(cv_scores))) ## Improving

accuracy using XGBOOST
- Improve Accuracy a) Algorithm Tuning b)Ensembles

data_dmatrix                              =
xgb.DMatrix(data=X,label=y)
dtrain      =      xgb.DMatrix(X_train,
label=y_train)           dtest           =
xgb.DMatrix(X_test)

dtrain,dtest,data_dmatrix

params = {"objective":"reg:linear",'colsample_bytree':
          0.3,'learning_rate': 0.1, 'max_depth': 5, 'alpha': 10}

cv_results = xgb.cv(dtrain=data_dmatrix, params=params, nfold=5,
            num_boost_round=50,early_stopping_rounds=10,metrics="rmse",
            as_pandas=True, seed=123)
cv_results.head()

#  the  final  boosting  round  metric
print((cv_results["test-rmse-
mean"]).tail(1))

Xgb =
XGBRegressor()
Xgb.fit(X_train,y_t
rain)
```

```
# pred_xgb =
model_xgb.predict(X_test)
test_scores(Xgb)

# Create the random grid
para = {'n_estimators':
          range(100,500,100),
          'max_depth': range(3,10,1),
     'reg_alpha':np.logspace(-4, 0, 50),
     'subsample':
     np.arange(0.1,1,0.2),
     'colsample_bytree':
     np.arange(0.1,1,0.2),
     'colsample_bylevel':
     np.arange(0.1,1,0.2),
```

```
     'colsample_bynode':
    np.arange(0.1,1,0.2),
    'learning_rate': np.arange(.05,
    1, .05)}
# Instantiate a Decision Forest
classifier: Forest Xgb =
XGBRegressor()

# Instantiate the gridSearchCV object:
Forest_cv xgb_cv =
RandomizedSearchCV(Xgb, para,
cv=5)

# Fit it to the
data
xgb_cv.fit(X,
y)

# Print the tuned parameters and score
print("Tuned Xgboost Parameters:
{}".format(xgb_cv.best_params_)) print("Best score is
{}".format(xgb_cv.best_score_))


# Instantiate a xgb regressor: xgb
Xgb = XGBRegressor(subsample= 0.1, reg_alpha= 0.08685113737513521,
n_estimators= 200, max_depth= 3, learning_rate=0.05, colsample_bytree=
0.7000000000000001, colsample_bynode=0.7000000000000001,
colsample_bylevel=0.9000000000000001)

# Fit the regressor to
the data
Xgb.fit(X_train,y_train)

# Compute and print the
coefficients xgb_features =
Xgb.feature_importances_
print(xgb_features)

# Sort feature importances in
descending order indices =
np.argsort(xgb_features)[::1]

# Rearrange feature names so they match the sorted
feature importances names = [test.columns[i] for i in
indices]

# Creating plot
fig =
plt.figure(figsize=(20,10
)) plt.title("Feature
Importance")

# Add horizontal bars
plt.barh(range(pd.DataFrame(X_train).shape[1]),xgb_features[indices
],align = 'center') plt.yticks(range(pd.DataFrame(X_train).shape[1]),
names)
plt.savefig(' xgb feature
importance') plt.show()#
```

Make predictions
test_scores(Xgb)

Finalize model
- Create standalone model on entire trainingdataset
- Save model for lateruse

```
def rmsle(y,y_):
   log1 = np.nan_to_num(np.array([np.log(v + 1)
   for v in y])) log2 =
   np.nan_to_num(np.array([np.log(v + 1) for v in
   y_])) calc = (log1 - log2) ** 2
   return
np.sqrt(np.mean(calc))
def score(y, y_):
```

```
    print('r square ', metrics.r2_score(y, y_))
    print('Adjusted r square:{}'.format(1 - (1-metrics.r2_score(y, y_))*(len(y)-1)/(len(y)-
    X_train.shape[1]-1))) print('MAPE:{}'.format(np.mean(np.abs((y - y_) / y))*100))
    print('MSE:', metrics.mean_squared_error(y,
    y_)) print('RMSE:',
    np.sqrt(metrics.mean_squared_error(y, y_)))
    print('RMSLE:',rmsle(y_test,y_pred))
def scores(model):
    print('<<<------------------- TrainingDataScore------->')
    print()
    #Predicting result on
    Training data y_pred =
    model.predict(X)
    score(y,y_pred)
    print('RMSLE:',rmsle(y,y_pr
    ed))

test.colum

ns

train.colu

mns

train.shap

e

test.shape

a=pd.read_csv('test.csv')

test_pickup_datetime=a['pickup_da

tetime']

# Instantiate a xgb regressor: xgb
Xgb = XGBRegressor(subsample= 0.1, reg_alpha= 0.08685113737513521,
n_estimators= 200, max_depth= 3, learning_rate=0.05, colsample_bytree=
0.7000000000000001, colsample_bynode=0.7000000000000001,
colsample_bylevel=0.9000000000000001)

# Fit the regressor to
the data Xgb.fit(X,y)

# Compute and print the
coefficients xgb_features =
Xgb.feature_importances_
print(xgb_features)

# Sort feature importances in
descending order indices =
np.argsort(xgb_features)[::1]

# Rearrange feature names so they match the sorted
feature importances names = [test.columns[i] for i in
indices]
```

```
# Creating plot
fig =
plt.figure(figsize=(20,10
)) plt.title("Feature
Importance")

# Add horizontal bars
plt.barh(range(pd.DataFrame(X_train).shape[1]),xgb_features[indices
],align = 'center') plt.yticks(range(pd.DataFrame(X_train).shape[1]),
names)
plt.savefig(' xgb1 feature
importance') plt.show()
scores(Xgb)
```

```
# Predictions
pred = Xgb.predict(test.values)
pred_results_wrt_date =
pd.DataFrame({"pickup_datetime":test_pickup_datetime,"fare_amount" : pred})
pred_results_wrt_date.to_csv("predictions_xgboost.csv",index=False)

pred_results_wrt_date

# Save the model as a pickle in a file
joblib.dump(Xgb,
'cab_fare_xgboost_model.pkl')

# # Load the model from the file
# Xgb_from_joblib = joblib.load('cab_fare_xgboost_model.pkl')
```