In [1]:
```
#Load libraries
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import chi2_contingency
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from random import randrange, uniform
```

In [2]:
```
#Set The Current working directory
os.chdir("C:/Users/Lenovo/Documents/LM/EdWisor/Python")
```

In [3]:
```
os.getcwd()
```

Out[3]:
```
'C:\\Users\\Lenovo\\Documents\\LM\\EdWisor\\Python'
```

In [4]:
```
# Load Data - Train Data
Train_Data=(pd.read_csv('train_cab.csv', header = 0 )).drop(columns="pickup_datetime")
```

In [5]:
```
#Eliminate rows where the pickup and drop location points are same

Train_Data=Train_Data[np.logical_and(Train_Data['pickup_longitude'] != Train_Data['dropoff_longitude'],
                                     Train_Data['pickup_latitude'] != Train_Data['dropoff_latitude'])]
```

In [6]:
```
#replace 0 with NA in the variables and convert the data wherever required for further operations

Train_Data['fare_amount']= Train_Data['fare_amount'].apply(pd.to_numeric, errors='coerce')
Train_Data['fare_amount']= Train_Data['fare_amount'].replace({0:np.nan})
Train_Data['passenger_count']=Train_Data['passenger_count'].fillna(0)
Train_Data['passenger_count']= Train_Data['passenger_count'].astype(int)
Train_Data['passenger_count']=Train_Data['passenger_count'].replace({0: np.nan})
Train_Data['pickup_longitude']= Train_Data['pickup_longitude'].replace({0:np.nan})
Train_Data['pickup_latitude']= Train_Data['pickup_latitude'].replace({0:np.nan})
Train_Data['dropoff_longitude']= Train_Data['dropoff_longitude'].replace({0:np.nan})
Train_Data['dropoff_latitude']= Train_Data['dropoff_latitude'].replace({0:np.nan})
```

In [7]:
```
Train_Data.shape
```

Out[7]:
```
(15603, 6)
```

In [8]:
```
Train_Data.head()
```

Out[8]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	4.5	-73.844311	40.721319	-73.841610	40.712278	1.0
1	16.9	-74.016048	40.711303	-73.979268	40.782004	1.0
2	5.7	-73.982738	40.761270	-73.991242	40.750562	2.0
3	7.7	-73.987130	40.733143	-73.991567	40.758092	1.0
4	5.3	-73.968095	40.768008	-73.956655	40.783762	1.0

Missing Value Analysis

In [9]:
```
#calculate missing values

missing_val = pd.DataFrame(Train_Data.isnull().sum())
#print(missing_val)

#Reset index
missing_val = missing_val.reset_index()
#print(missing_val)

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

#Calculate percentage
missing_val['Missing_percentage'] = (missing_val['count']/len(Train_Data)*100)
#print(missing_val)

#sort in descending order
missing_val = missing_val.sort_values('Missing_percentage', ascending = False).reset_index(drop = True)
print(missing_val)
```

```
          Variables  count  Missing_percentage
0    passenger_count    112            0.717811
1        fare_amount     24            0.153817
2   pickup_longitude     12            0.076908
3    pickup_latitude     12            0.076908
4  dropoff_longitude     10            0.064090
5   dropoff_latitude      9            0.057681
```

Missing Value Imputation

In [10]:
```
#imputation method
#Actual value = -73.99578100000001
#Mean = -73.91159336554888
#Median = -73.9820605
#KNN = -73.890529
```

In [11]:
```
#Create missing value, a small test to identify which method is good for imputation

Train_Data["pickup_longitude"].loc[70]
```

Out[11]:
```
-73.99578100000001
```

In [12]:
```
Train_Data["pickup_longitude"].loc[70] = np.nan
```

In [13]:
```
Train_Data["pickup_longitude"].loc[70]
```

Out[13]: nan

In [14]:
```
#Mean Imputation
#Train_Data['pickup_longitude'] = Train_Data['pickup_longitude'].fillna(Train_Data['pickup_longitude'].mean())

#Train_Data["pickup_longitude"].loc[70]
```

In [15]:
```
#Median Imputation
#Train_Data['pickup_longitude'] = Train_Data['pickup_longitude'].fillna(Train_Data['pickup_longitude'].median())

#Train_Data["pickup_longitude"].loc[70]
```

In [16]:
```
#KNN imputation
#Train_Data = pd.DataFrame(KNN(k = 1).fit_transform(Train_Data), columns = Train_Data.columns)

#Train_Data["pickup_longitude"].loc[70]
```

In [17]:
```
#As it is found Mean is very close to original method we will proceed with imputation via mean
Train_Data['fare_amount'] = Train_Data['fare_amount'].fillna(Train_Data['fare_amount'].mean())
Train_Data['pickup_longitude']= Train_Data['pickup_longitude'].fillna(Train_Data['pickup_longitude'].mean())
Train_Data['pickup_latitude']= Train_Data['pickup_latitude'].fillna(Train_Data['pickup_latitude'].mean())
Train_Data['dropoff_longitude']= Train_Data['dropoff_longitude'].fillna(Train_Data['dropoff_longitude'].mean())
Train_Data['dropoff_latitude']= Train_Data['dropoff_latitude'].fillna(Train_Data['dropoff_latitude'].mean())


#And for category variables imputation is done with mode
Train_Data['passenger_count'] = Train_Data['passenger_count'].fillna(int(Train_Data['passenger_count'].mode()))
```

In [18]:
```
#Imputing the NAs in target variables may hamper the model, so it is preferred to remove NA rows of the data
Train_Data=Train_Data.dropna()
```

In [19]:
```
#conert into proper data type
convert_dic={'fare_amount' : 'float','passenger_count': 'int'}
Train_Data=Train_Data.astype(convert_dic)
```

In [20]:
```
Train_Data.shape
```

Out[20]: (15603, 6)

Outlier Analysis

In [21]:
```
#save the data with in another place with different name

df = Train_Data.copy()
Train_Data = Train_Data.copy()
```

In [22]:
```
# irregular fare_amount are converted to NA

Train_Data.loc[Train_Data['fare_amount']<0 , 'fare_amount']=np.nan
Train_Data.loc[Train_Data['fare_amount'] > 30, 'fare_amount']=np.nan
Train_Data=Train_Data.dropna()
```

In [23]:
```
#irregular passenger counts or those wgich are greater then 8 convertet to NaN
Train_Data.loc[Train_Data['passenger_count'] > 8,'passenger_count'] = np.nan
```

In [27]:
```
#save numeric data names
coutliers = [ 'pickup_longitude', 'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude']
for list in coutliers:
    #Detect and replace with NA
    #Extract quartiles
    q75, q25 = np.percentile(Train_Data[list], [75 ,25])

    #Calculate IQR
    iqr = q75 - q25

    # #Calculate inner and outer fence
    minimum = q25 - (iqr*1.5)
    maximum = q75 + (iqr*1.5)

    # #Replace with NA
    Train_Data.loc[Train_Data[list] < minimum,list] = np.nan
    Train_Data.loc[Train_Data[list] > maximum,list] = np.nan

    # #Calculate missing value
    missing_val = pd.DataFrame(Train_Data.isnull().sum())
```

In [28]:
```
#As Mean is the best method, we impute missing values/ in this case outlier values with mean

Train_Data['pickup_longitude'] = Train_Data['pickup_longitude'].fillna(Train_Data['pickup_longitude'].mean())
Train_Data['pickup_latitude'] = Train_Data['pickup_latitude'].fillna(Train_Data['pickup_latitude'].mean())
Train_Data['dropoff_longitude'] = Train_Data['dropoff_longitude'].fillna(Train_Data['dropoff_longitude'].mean())
Train_Data['dropoff_latitude'] = Train_Data['dropoff_latitude'].fillna(Train_Data['dropoff_latitude'].mean())

#imputed with mode for categorical variables
Train_Data['passenger_count'] = Train_Data['passenger_count'].fillna(int(Train_Data['passenger_count'].mode()))
```

In [29]:
```
#convert the data type of categorical variable passenger count
Train_Data['passenger_count']=Train_Data['passenger_count'].astype('int')
Train_Data['passenger_count']=Train_Data['passenger_count'].astype('category')
```

Feature Selection

In [30]:
```
#haversine function

def haversine(lat1, lon1, lat2, lon2, to_radians=True, earth_radius=6371):

    if to_radians:
        lat1, lon1, lat2, lon2 = np.radians([lat1, lon1, lat2, lon2])

    a = np.sin((lat2-lat1)/2.0)**2 +
        np.cos(lat1) * np.cos(lat2) * np.sin((lon2-lon1)/2.0)**2

    return earth_radius * 2 * np.arcsin(np.sqrt(a))
```

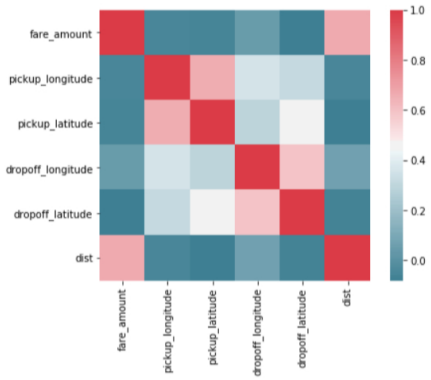
In [31]:
```
Train_Data['dist'] = haversine( Train_Data['pickup_latitude'], Train_Data['pickup_longitude'],
                Train_Data['dropoff_latitude'], Train_Data['dropoff_longitude'])
```

In [32]:
```
##Correlation analysis
#Correlation plot
numeric=['fare_amount','pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_latitude', 'dist']
Train_Data_corr = Train_Data.loc[:,numeric]
```

In [33]:
```
#Set the width and hieght of the plot
f, ax = plt.subplots(figsize=(7, 5))

#Generate correlation matrix
corr = Train_Data_corr.corr()
print(corr)

#Plotted using seaborn library
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(220, 10, as_cmap=True),
            square=True, ax=ax)
```

```
                   fare_amount  pickup_longitude  pickup_latitude  \
fare_amount           1.000000         -0.049298        -0.057861
pickup_longitude     -0.049298          1.000000         0.665421
pickup_latitude      -0.057861          0.665421         1.000000
dropoff_longitude     0.047996          0.356362         0.293342
dropoff_latitude     -0.077377          0.314367         0.442597
dist                  0.667880         -0.050237        -0.079968

                   dropoff_longitude  dropoff_latitude      dist
fare_amount                 0.047996         -0.077377  0.667880
pickup_longitude            0.356362          0.314367 -0.050237
pickup_latitude             0.293342          0.442597 -0.079968
dropoff_longitude           1.000000          0.595164  0.067924
dropoff_latitude            0.595164          1.000000 -0.060560
dist                        0.067924         -0.060560  1.000000
```

Out[33]: `<matplotlib.axes._subplots.AxesSubplot at 0x2c6cae3a320>`



In [35]:
```
#eliminate all data with the pickup and drop location points as same

Train_Data=Train_Data[np.logical_and(Train_Data['pickup_longitude'] != Train_Data['dropoff_longitude'],
                                     Train_Data['pickup_latitude'] != Train_Data['dropoff_latitude'])]
```

Model Development

Decision Tree

In [36]:
```
#Load libraries
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
```

In [37]:
```
# Divide the data into train and test
train1, test1 = train_test_split(Train_Data, test_size=0.2)
```

In [38]:
```
# Decision tree for regression
fit_DT = DecisionTreeRegressor(max_depth=2).fit(train1.iloc[:, 1:7], train1.iloc[:,0])
```

In [39]:
```
fit_DT
```

Out[39]:
```
DecisionTreeRegressor(criterion='mse', max_depth=2, max_features=None,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=None, splitter='best')
```

In [40]:
```
#Apply model on test data
predictions_DT = fit_DT.predict(test1.iloc[:,1:7])
```

In [41]:
```
#Calculate MAPE
def MAPE(y_true, y_pred):
    mape = np.mean(np.abs((y_true - y_pred) / y_true))*100
    return mape
```

In [42]:
```
MAPE(test1.iloc[:,0], predictions_DT)
```

Out[42]: `28.774663291429192`

In [43]:
```
#Error 28.774663291429192
#Accuracy 71.23
```

Random Forest

In [44]:
```
#Random Forest
```

```
from sklearn.ensemble import RandomForestRegressor
```

In [45]:
```
RF_model = RandomForestRegressor(n_estimators = 10).fit(train1.iloc[:, 1:7], train1.iloc[:,0])
```

In [46]:
```
RF_model
```

Out[46]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
```

In [47]:
```
RF_Predictions = RF_model.predict(test1.iloc[:, 1:7])
```

In [48]:
```
MAPE(test1.iloc[:,0], RF_Predictions)
```

Out[48]:
```
25.131668346501414
```

In [49]:
```
#error 25.131668346501414
#accuracy 74.87
```

Linear Regression

In [50]:
```
#Combine all the values in one array
values=['fare_amount', 'pickup_longitude','pickup_latitude', 'dropoff_longitude', 'dropoff_latitude', 'dist']
```

In [51]:
```
linear_Data = Train_Data[values]
```

In [52]:
```
#This function is developed to get columns for specific passenger count. The idea is developed from R linear regression fit,
#which explains all the passenger count individualy contributes in the model

cat_names = ['passenger_count']
for i in cat_names:
    temp = pd.get_dummies(Train_Data[i], prefix= i)
    linear_Data = linear_Data.join(temp)
```

In [53]:
```
linear_Data.shape
```

Out[53]:
```
(14795, 12)
```

In [54]:
```
linear_Data.head()
```

Out[54]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	dist	passenger_count_1	passenger_count_2	passenger_count_3	pa
0	4.5	-73.981697	40.721319	-73.980230	40.712278	1.012886	1	0	0	
1	16.9	-74.016048	40.711303	-73.979268	40.782004	8.450134	1	0	0	
2	5.7	-73.982738	40.761270	-73.991242	40.750562	1.389525	0	1	0	
3	7.7	-73.987130	40.733143	-73.991567	40.758092	2.799270	1	0	0	
4	5.3	-73.968095	40.768008	-73.956655	40.783762	1.999157	1	0	0	

In [55]:
```
#Spliting the newly created data set with passenger count dummies
train1, test1 = train_test_split(linear_Data, test_size=0.2)
```

In [56]:
```
#Import libraries for LR
import statsmodels.api as sm
```

In [57]:
```
# Train the model using the training sets
model = sm.OLS(train1.iloc[:, 0].astype(float), train1.iloc[:, 1:12].astype(float)).fit()
```

In [58]:
```
# Print out the statistics
model.summary()
```

Out[58]:

OLS Regression Results

Dep. Variable:	fare_amount	**R-squared:**	0.451
Model:	OLS	**Adj. R-squared:**	0.450
Method:	Least Squares	**F-statistic:**	971.0
Date:	Thu, 11 Jul 2019	**Prob (F-statistic):**	0.00
Time:	15:20:51	**Log-Likelihood:**	-32642.
No. Observations:	11836	**AIC:**	6.531e+04
Df Residuals:	11825	**BIC:**	6.539e+04
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
pickup_longitude	-8.1153	3.056	-2.655	0.008	-14.106	-2.124
pickup_latitude	6.9690	2.345	2.972	0.003	2.372	11.566
dropoff_longitude	14.7490	2.685	5.492	0.000	9.485	20.013
dropoff_latitude	-16.4963	2.107	-7.828	0.000	-20.627	-12.366
dist	1.9859	0.021	95.766	0.000	1.945	2.027
passenger_count_1	883.5936	341.928	2.584	0.010	213.358	1553.830
passenger_count_2	883.7456	341.930	2.585	0.010	213.506	1553.985
passenger_count_3	883.8646	341.934	2.585	0.010	213.618	1554.111
passenger_count_4	883.8406	341.933	2.585	0.010	213.597	1554.085
passenger_count_5	883.5124	341.928	2.584	0.010	213.277	1553.748
passenger_count_6	884.8060	341.929	2.588	0.010	214.569	1555.043

Omnibus:	5963.342	**Durbin-Watson:**	1.993
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	45147.146
Skew:	2.313	**Prob(JB):**	0.00
Kurtosis:	11.375	**Cond. No.**	2.85e+06

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.85e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [59]:
```
# make the predictions by the model
predictions_LR = model.predict(test1.iloc[:,1:12])
```

In [60]:
```
#Calculate MAPE
MAPE(test1.iloc[:,0], predictions_LR)
```

Out[60]: 27.431370940383022

In [61]:
```
#Error 27.431370940383022
#Accuracy 72.56
```

KNN Imputation

In [62]:
```
#KNN implementation
from sklearn.neighbors import KNeighborsRegressor

KNN_model = KNeighborsRegressor(n_neighbors = 1).fit(train1.iloc[: , 1:7], train1.iloc[:, 0])
```

In [63]:
```
#predict test cases
KNN_Predictions = KNN_model.predict(test1.iloc[: , 1:7])
```

In [64]:
```
MAPE(test1.iloc[:,0], KNN_Predictions)
```

Out[64]: 34.21410560965663

In [65]:
```
#error is 34.21410560965663
#accuracy is 65.80
```

Prediction on original test data

In [66]:
```
pred=(pd.read_csv('test.csv', header = 0 )).drop(columns="pickup_datetime")
```

In [67]:
```
#create Dist variable
pred['dist'] = \
    haversine( pred['pickup_latitude'], pred['pickup_longitude'],
                pred['dropoff_latitude'], pred['dropoff_longitude'])

pred['fare_amount']=0
pred['passenger_count']=pred['passenger_count'].astype('category')
```

In [68]:
```
# Build model on the entire Train data
RF_model = RandomForestRegressor(n_estimators = 10).fit(Train_Data.iloc[:, 1:7], Train_Data.iloc[:,0])

#predict value
pred['fare_amount'] = RF_model.predict(pred.iloc[:, 0:6])
```

In [69]:
```
pred.head()
```

Out[69]:

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	dist	fare_amount
0	-73.973320	40.763805	-73.981430	40.743835	1	2.323259	10.51
1	-73.986862	40.719383	-73.998886	40.739201	1	2.425353	8.43
2	-73.982524	40.751260	-73.979654	40.746139	1	0.618628	5.72
3	-73.981160	40.767807	-73.990448	40.751635	1	1.961033	7.58
4	-73.966046	40.789775	-73.988565	40.744427	1	5.387301	14.54

In [70]:
```
#write output to csv

pred.to_csv("Predicted_Values.csv", index = False)
```

In [ ]:

In [ ]: