#Predict the price of the Uber ride from a given pickup point to the agreed drop-off location. Perform following tasks:

1. Pre-process the dataset.
2. Identify outliers.
3. Check the correlation.
4. Implement linear regression and random forest regression models.
5. Evaluate the models and compare their respective scores like R2, RMSE, etc. Dataset link: https://www.kaggle.com/datasets/yasserh/uber-fares-dataset

In [1]:
```
#Importing the required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
#importing the dataset
df  = pd.read_csv("uber.csv")
```

1. Pre-process the dataset.

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.73835
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.72822
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.74077
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.79084
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.74408

In [4]:
```
df.info() #To get the required information of the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         200000 non-null  int64
 1   key                200000 non-null  object
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

In [5]:
```
df.columns #TO get number of columns in the dataset
```

Out[5]:
```
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

In [6]:
```
df = df.drop(['Unnamed: 0', 'key'], axis= 1) #To drop unnamed column as it isn't re
```

In [7]:
```
df.head()
```

Out[7]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_la
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.7
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.7
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.7
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.8
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.7

In [8]:
```
df.shape #To get the total (Rows,Columns)
```

Out[8]:
```
(200000, 7)
```

In [9]:
```
df.dtypes #To get the type of each column
```

Out[9]:
```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 7 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   fare_amount        200000 non-null  float64
 1   pickup_datetime    200000 non-null  object 
 2   pickup_longitude   200000 non-null  float64
 3   pickup_latitude    200000 non-null  float64
 4   dropoff_longitude  199999 non-null  float64
 5   dropoff_latitude   199999 non-null  float64
 6   passenger_count    200000 non-null  int64  
dtypes: float64(5), int64(1), object(1)
memory usage: 10.7+ MB
```

In [11]:
```
df.describe() #To get statistics of each columns
```

Out[11]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pas
count	200000.000000	200000.000000	200000.000000	199999.000000	199999.000000	2
mean	11.359955	-72.527638	39.935885	-72.525292	39.923890	
std	9.901776	11.437787	7.720539	13.117408	6.794829	
min	-52.000000	-1340.648410	-74.015515	-3356.666300	-881.985513	
25%	6.000000	-73.992065	40.734796	-73.991407	40.733823	
50%	8.500000	-73.981823	40.752592	-73.980093	40.753042	
75%	12.500000	-73.967154	40.767158	-73.963658	40.768001	
max	499.000000	57.418457	1644.421482	1153.572603	872.697628	

Filling Missing values

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [13]:
```
df['dropoff_latitude'].fillna(value=df['dropoff_latitude'].mean(),inplace = True)
df['dropoff_longitude'].fillna(value=df['dropoff_longitude'].median(),inplace = Tru
```

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

In [15]:
```
df.dtypes
```

Out[15]:
```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

Column pickup_datetime is in wrong format (Object). Convert it to DateTime Format

In [16]:
```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime, errors='coerce')
```

In [17]:
```
df.dtypes
```

Out[17]:
```
fare_amount                      float64
pickup_datetime      datetime64[ns, UTC]
pickup_longitude                 float64
pickup_latitude                  float64
dropoff_longitude                float64
dropoff_latitude                 float64
passenger_count                    int64
dtype: object
```

To segregate each time of date and time

In [18]:
```
df= df.assign(hour = df.pickup_datetime.dt.hour,
             day= df.pickup_datetime.dt.day,
             month = df.pickup_datetime.dt.month,
             year = df.pickup_datetime.dt.year,
             dayofweek = df.pickup_datetime.dt.dayofweek)
```

In [19]:
```
df.head()
```

Out[19]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_la
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	40.7
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	40.7
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	40.7
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	40.8
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	40.7

In [20]:

```
# drop the column 'pickup_daetime' using drop()
# 'axis = 1' drops the specified column

df = df.drop('pickup_datetime',axis=1)
```

In [21]:

```
df.head()
```

Out[21]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger
0	7.5	-73.999817	40.738354	-73.999512	40.723217	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	
4	16.0	-73.925023	40.744085	-73.973082	40.761247	

In [22]:

```
df.dtypes
```

Out[22]:

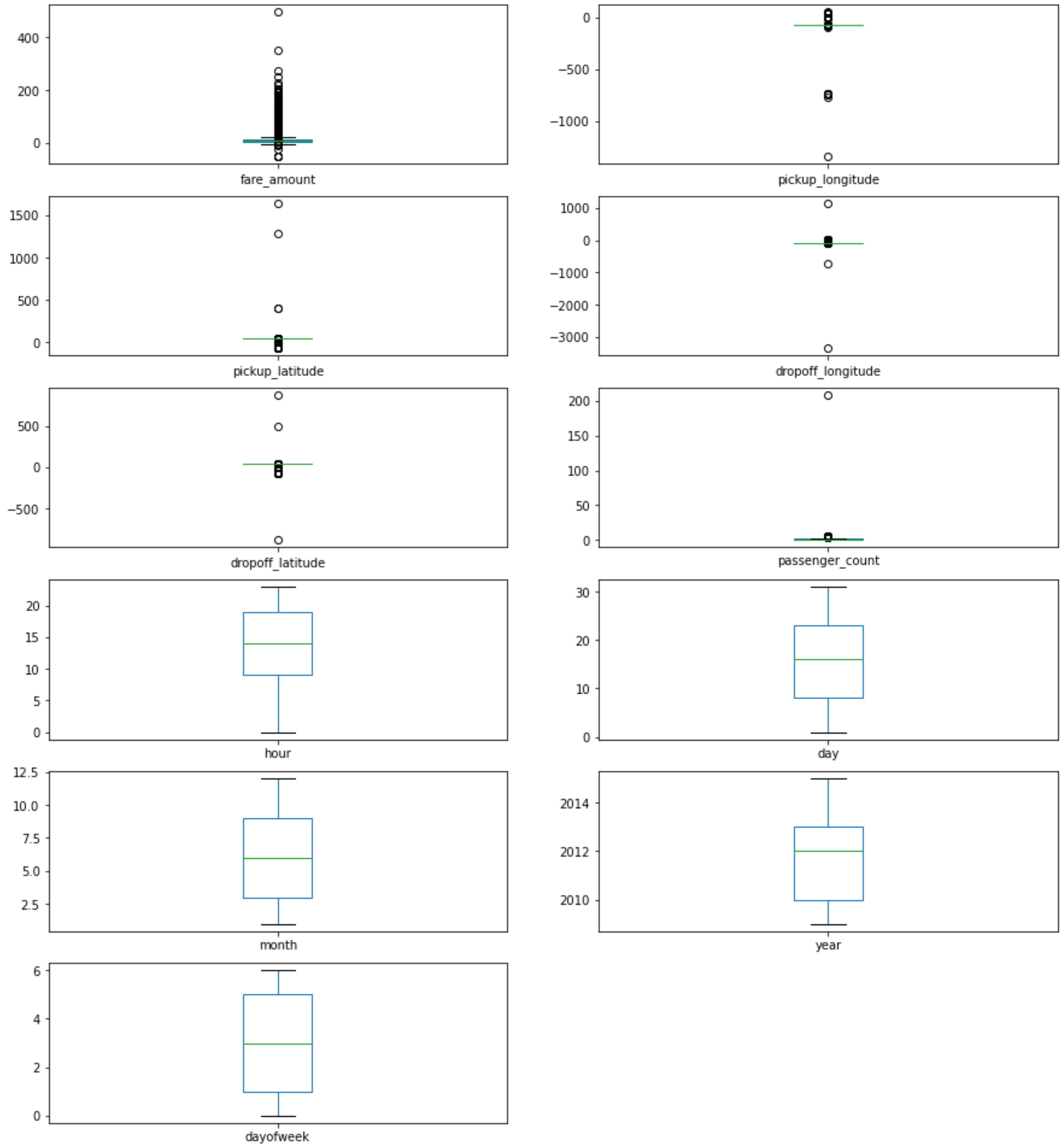
```
fare_amount          float64
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
hour                   int64
day                    int64
month                  int64
year                   int64
dayofweek              int64
dtype: object
```

Checking outliers and filling them

In [23]:

```
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxplot to ch
```

Out[23]:
```
fare_amount          AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude   AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude      AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude  AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude     AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count    AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
hour                 AxesSubplot(0.125,0.456463;0.352273x0.0920732)
day                AxesSubplot(0.547727,0.456463;0.352273x0.0920732)
month                AxesSubplot(0.125,0.345976;0.352273x0.0920732)
year               AxesSubplot(0.547727,0.345976;0.352273x0.0920732)
dayofweek            AxesSubplot(0.125,0.235488;0.352273x0.0920732)
dtype: object
```



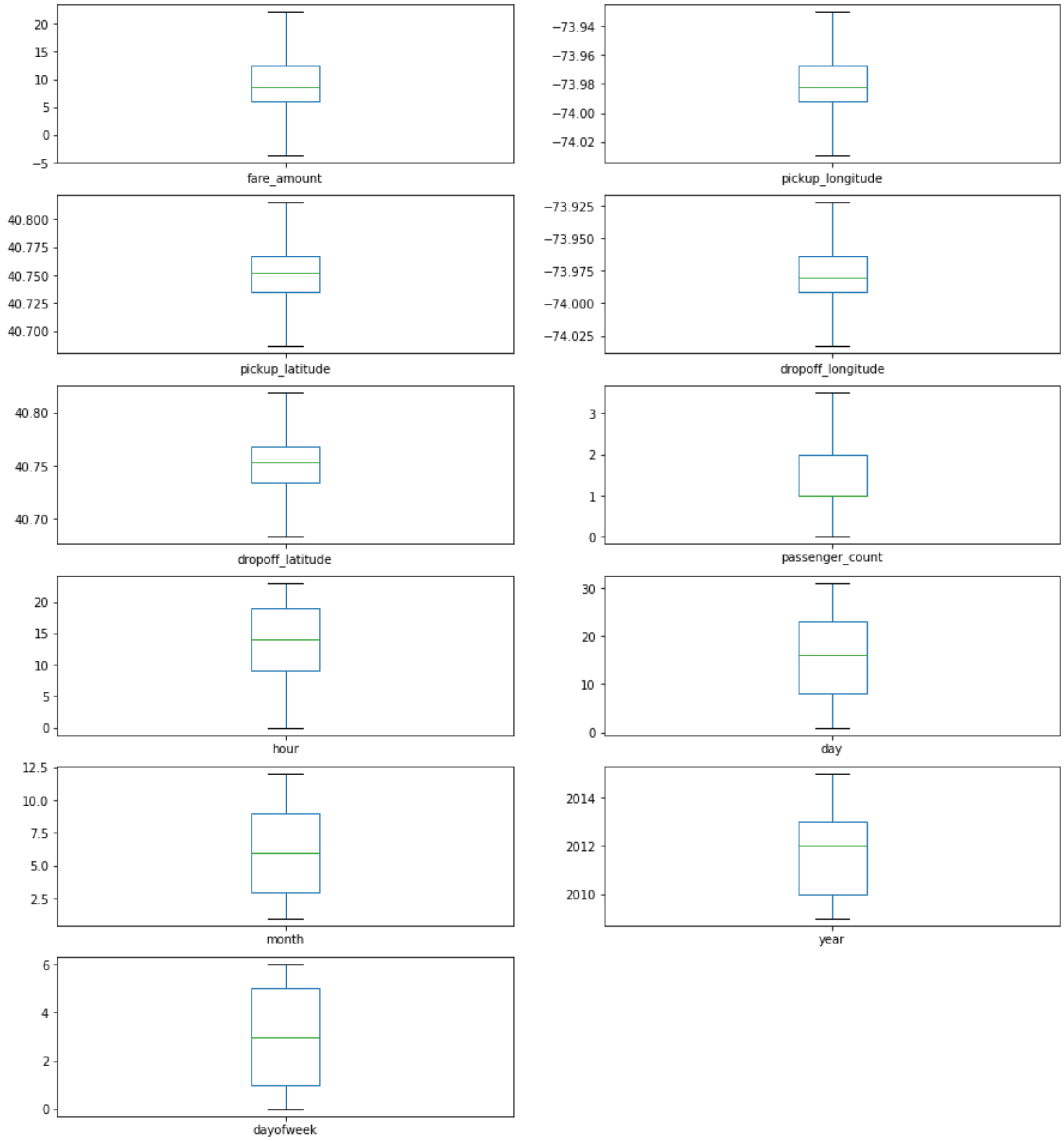
In [24]:
```python
#Using the InterQuartile Range to fill the values
def remove_outlier(df1 , col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    df[col] = np.clip(df1[col] , lower_whisker , upper_whisker)
    return df1
```

```python
def treat_outliers_all(df1 , col_list):
    for c in col_list:
        df1 = remove_outlier(df , c)
    return df1
```

In [25]:
```python
df = treat_outliers_all(df , df.iloc[: , 0::])
```

In [26]:
```python
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxplot shows
```

Out[26]:
```
fare_amount             AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude     AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude         AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude    AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude        AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count      AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
hour                    AxesSubplot(0.125,0.456463;0.352273x0.0920732)
day                  AxesSubplot(0.547727,0.456463;0.352273x0.0920732)
month                   AxesSubplot(0.125,0.345976;0.352273x0.0920732)
year                 AxesSubplot(0.547727,0.345976;0.352273x0.0920732)
dayofweek               AxesSubplot(0.125,0.235488;0.352273x0.0920732)
dtype: object
```



In [27]:
```python
#pip install haversine
```

```
import haversine as hs  #Calculate the distance using Haversine to calculate the di
travel_dist = []
for pos in range(len(df['pickup_longitude'])):
        long1,lati1,long2,lati2 = [df['pickup_longitude'][pos],df['pickup_latitude'
        loc1=(lati1,long1)
        loc2=(lati2,long2)
        c = hs.haversine(loc1,loc2)
        travel_dist.append(c)

print(travel_dist)
df['dist_travel_km'] = travel_dist
df.head()
```

```
IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.

Current values:
NotebookApp.iopub_data_rate_limit=1000000.0 (bytes/sec)
NotebookApp.rate_limit_window=3.0 (secs)
```

Out[27]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger
0	7.5	-73.999817	40.738354	-73.999512	40.723217	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	
4	16.0	-73.929786	40.744085	-73.973082	40.761247	

In [28]:

```
#Uber doesn't travel over 130 kms so minimize the distance
df= df.loc[(df.dist_travel_km >= 1) | (df.dist_travel_km <= 130)]
print("Remaining observastions in the dataset:", df.shape)
```

```
Remaining observastions in the dataset: (200000, 12)
```

In [29]:

```
#Finding inccorect latitude (Less than or greater than 90) and longitude (greater t
incorrect_coordinates = df.loc[(df.pickup_latitude > 90) |(df.pickup_latitude < -90
                                    (df.dropoff_latitude > 90) |(df.dropoff_latitude
                                    (df.pickup_longitude > 180) |(df.pickup_longitud
                                    (df.dropoff_longitude > 90) |(df.dropoff_longitu
                                     ]
```

In [30]:

```
df.drop(incorrect_coordinates, inplace = True, errors = 'ignore')
```

In [31]:

```
df.head()
```

Out[31]:

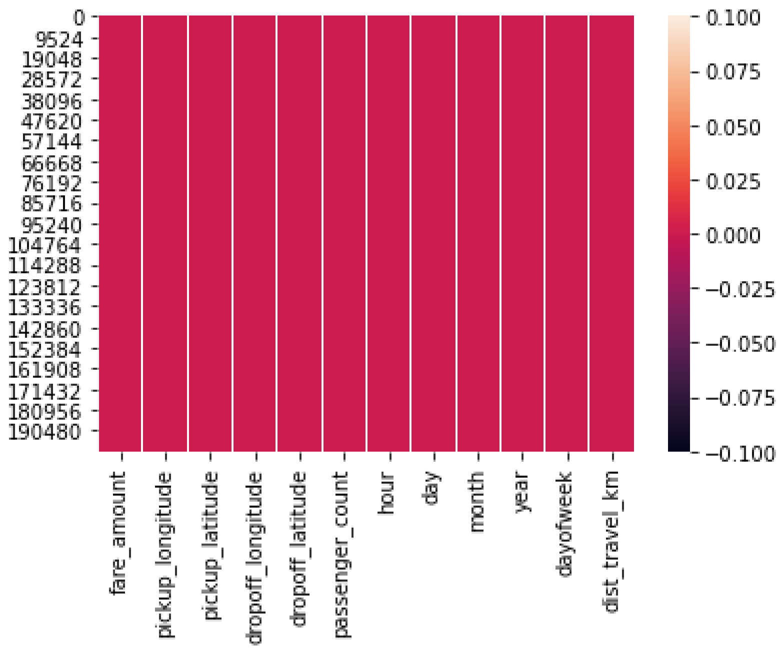
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger
0	7.5	-73.999817	40.738354	-73.999512	40.723217	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	
4	16.0	-73.929786	40.744085	-73.973082	40.761247	

In [32]:
```
df.isnull().sum()
```

Out[32]:
```
fare_amount          0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
hour                 0
day                  0
month                0
year                 0
dayofweek            0
dist_travel_km       0
dtype: int64
```

In [33]:
```
sns.heatmap(df.isnull()) #Free for null values
```

Out[33]: <AxesSubplot:>



In [34]:
```
corr = df.corr() #Function to find the correlation
```

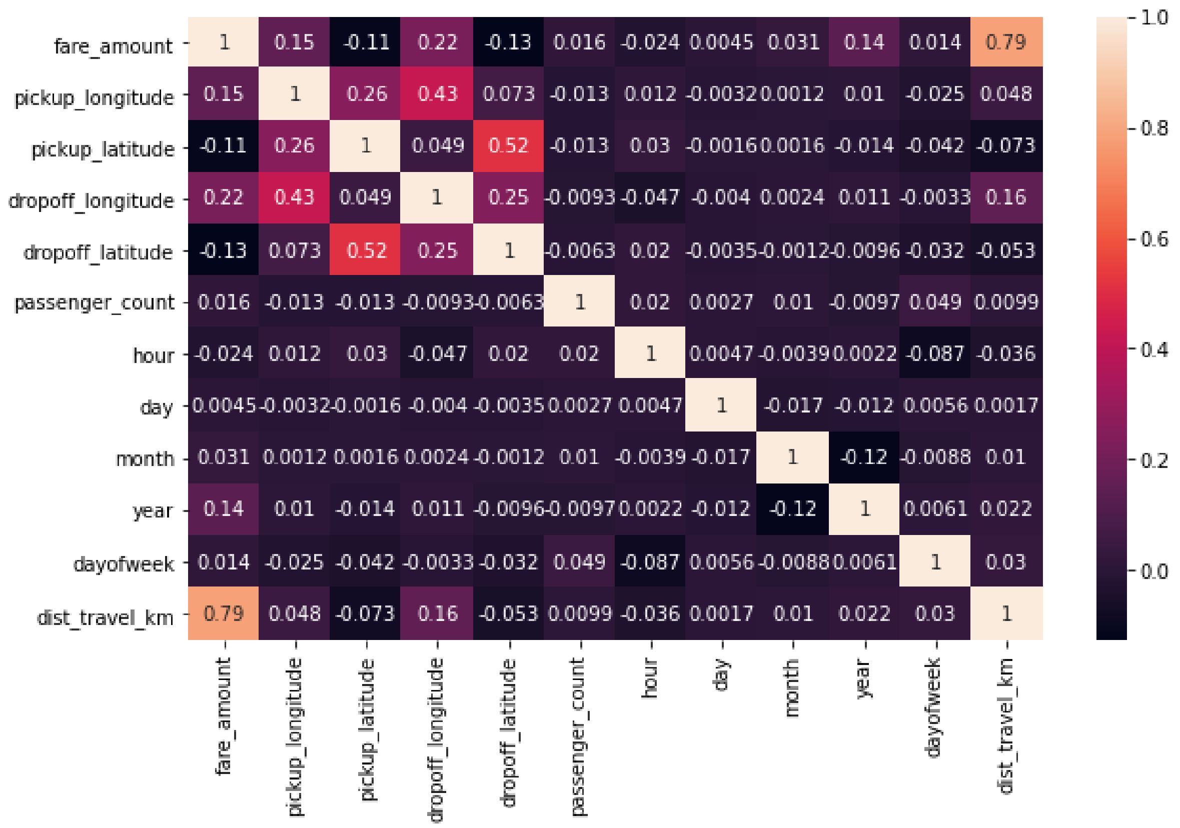
In [35]:
```
corr
```

Out[35]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_lati
fare_amount	1.000000	0.154069	-0.110842	0.218675	-0.12
pickup_longitude	0.154069	1.000000	0.259497	0.425619	0.07
pickup_latitude	-0.110842	0.259497	1.000000	0.048889	0.51
dropoff_longitude	0.218675	0.425619	0.048889	1.000000	0.24
dropoff_latitude	-0.125898	0.073290	0.515714	0.245667	1.00
passenger_count	0.015778	-0.013213	-0.012889	-0.009303	-0.00
hour	-0.023623	0.011579	0.029681	-0.046558	0.01
day	0.004534	-0.003204	-0.001553	-0.004007	-0.00
month	0.030817	0.001169	0.001562	0.002391	-0.00
year	0.141277	0.010198	-0.014243	0.011346	-0.00
dayofweek	0.013652	-0.024652	-0.042310	-0.003336	-0.03
dist_travel_km	0.786385	0.048446	-0.073362	0.155191	-0.05

In [36]:
```
fig,axis = plt.subplots(figsize = (10,6))
sns.heatmap(df.corr(),annot = True) #Correlation Heatmap (Light values means highly
```

Out[36]: <AxesSubplot:>



Dividing the dataset into feature and target values

In [182…
```
x = df[['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_latitude'
```

In [183…
```
y = df['fare_amount']
```

Dividing the dataset into training and testing dataset

In [184…
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(x,y,test_size = 0.33)
```

Linear Regression

In [185…
```
from sklearn.linear_model import LinearRegression
regression = LinearRegression()
```

In [186…
```
regression.fit(X_train,y_train)
```

Out[186]:
```
LinearRegression()
```

In [80]:
```
regression.intercept_ #To find the linear intercept
```

Out[80]:
```
2640.1356169149753
```

In [187…
```
regression.coef_ #To find the linear coeeficient
```

Out[187]:
```
array([ 2.54805415e+01, -7.18365435e+00,  1.96232986e+01, -1.79401980e+01,
        5.48472723e-02,  5.32910041e-03,  4.05930990e-03,  5.74261856e-02,
        3.66574831e-01, -3.03753790e-02,  1.84233728e+00])
```

In [188…
```
prediction = regression.predict(X_test) #To predict the target values
```

In [189…
```
print(prediction)
```

```
[ 5.47848314 10.11016249 12.19490542 ...  7.11952609 20.2482979
  8.82791961]
```

In [190…
```
y_test
```

Out[190]:
```
155740     4.90
47070     10.00
116192    14.50
164589     6.50
154309    11.30
          ...
76552      7.70
27926     10.90
38972      6.50
120341    22.25
178449     8.10
Name: fare_amount, Length: 66000, dtype: float64
```

Metrics Evaluation using R2, Mean Squared Error, Root Mean Sqared Error

In [191…
```
from sklearn.metrics import r2_score
```

In [192…
```
r2_score(y_test,prediction)
```

Out[192]:
```
0.6651880468683617
```

In [193…
```
from sklearn.metrics import mean_squared_error
```

In [194…
```
MSE = mean_squared_error(y_test,prediction)
```

In [195…
```
MSE
```

Out[195]: 9.961516917717704

In [196…
```
RMSE = np.sqrt(MSE)
```

In [197…
```
RMSE
```

Out[197]: 3.156187085348032

Random Forest Regression

In [198…
```
from sklearn.ensemble import RandomForestRegressor
```

In [199…
```
rf = RandomForestRegressor(n_estimators=100) #Here n_estimators means number of tre
```

In [200…
```
rf.fit(X_train,y_train)
```

Out[200]: RandomForestRegressor()

In [201…
```
y_pred = rf.predict(X_test)
```

In [202…
```
y_pred
```

Out[202]: array([5.714 , 10.285 , 12.68 , ..., 6.338 , 19.4685, 7.712])

Metrics evaluatin for Random Forest

In [210…
```
R2_Random = r2_score(y_test,y_pred)
```

In [211…
```
R2_Random
```

Out[211]: 0.7948374920410631

In [205…
```
MSE_Random = mean_squared_error(y_test,y_pred)
```

In [206…
```
MSE_Random
```

Out[206]: 6.104112397417331

In [207…
```
RMSE_Random = np.sqrt(MSE_Random)
```

In [208…
```
RMSE_Random
```

Out[208]: 2.4706501972997574

Assignment 2

2. Classify the email using the binary classification method. Email Spam detection has two states: a) Normal State – Not Spam, b) Abnormal State – Spam. Use K-Nearest Neighbors and Support Vector Machine for classification. Analyze their performance.

Dataset link: The emails.csv dataset on the Kaggle
https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv

In [19]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn import metrics
```

In [20]:
```
df=pd.read_csv('emails.csv')
```

In [21]:
```
df.head()
```

Out[21]:

	Email No.	the	to	ect	and	for	of	a	you	hou	...	connevey	jay	valued	lay	infrastruct
0	Email 1	0	0	1	0	0	0	2	0	0	...	0	0	0	0	
1	Email 2	8	13	24	6	6	2	102	1	27	...	0	0	0	0	
2	Email 3	0	0	1	0	0	0	8	0	0	...	0	0	0	0	
3	Email 4	0	5	22	0	5	1	51	2	10	...	0	0	0	0	
4	Email 5	7	6	17	1	5	2	57	0	9	...	0	0	0	0	

5 rows × 3002 columns

In [22]:
```
df.columns
```

Out[22]:
```
Index(['Email No.', 'the', 'to', 'ect', 'and', 'for', 'of', 'a', 'you', 'hou',
       ...
       'connevey', 'jay', 'valued', 'lay', 'infrastructure', 'military',
       'allowing', 'ff', 'dry', 'Prediction'],
      dtype='object', length=3002)
```

In [23]:
```
df.isnull().sum()
```

Out[23]:
```
Email No.     0
the           0
to            0
ect           0
and           0
             ..
military      0
allowing      0
ff            0
dry           0
Prediction    0
Length: 3002, dtype: int64
```

In [24]:
```
df.dropna(inplace = True)
```

In [25]:
```
df.drop(['Email No.'],axis=1,inplace=True)
X = df.drop(['Prediction'],axis = 1)
y = df['Prediction']
```

In [26]:
```
from sklearn.preprocessing import scale
X = scale(X)
# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_s
```

KNN classifier

In [35]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7)

knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [36]:
```
print("Prediction",y_pred)
```

```
Prediction [0 0 1 ... 1 1 1]
```

In [37]:
```
print("KNN accuracy = ",metrics.accuracy_score(y_test,y_pred))
```

```
KNN accuracy =  0.8009020618556701
```

In [39]:
```
print("Confusion matrix",metrics.confusion_matrix(y_test,y_pred))
```

```
Confusion matrix [[804 293]
 [ 16 439]]
```

SVM classifier

In [27]:
```
# cost C = 1
model = SVC(C = 1)

# fit
model.fit(X_train, y_train)

# predict
y_pred = model.predict(X_test)
```

In [28]:
```
metrics.confusion_matrix(y_true=y_test, y_pred=y_pred)
```

Out[28]:
```
array([[1091,    6],
       [  90,  365]])
```

In [29]:
```
print("SVM accuracy = ",metrics.accuracy_score(y_test,y_pred))
```

```
SVM accuracy =  0.9381443298969072
```

Given a bank customer, build a neural network-based classifier that can determine whether they will leave or not in the next 6 months.

Dataset Description: The case study is from an open-source dataset from Kaggle. The dataset contains 10,000 sample points with 14 distinct features such as CustomerId, CreditScore, Geography, Gender, Age, Tenure, Balance, etc. Link to the Kaggle project: https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling Perform following steps:

1. Read the dataset.
2. Distinguish the feature and target set and divide the data set into training and test sets.
3. Normalize the train and test data.
4. Initialize and build the model. Identify the points of improvement and implement the same.
5. Print the accuracy score and confusion matrix.

In [46]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt #Importing the libraries
```

In [47]:
```
df = pd.read_csv("Churn_Modelling.csv")
```

Preprocessing.

In [48]:
```
df.head()
```

Out[48]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
0	1	15634602	Hargrave	619	France	Female	42	2	0.00
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86
2	3	15619304	Onio	502	France	Female	42	8	159660.80
3	4	15701354	Boni	699	France	Female	39	1	0.00
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82

In [49]:
```
df.shape
```

Out[49]: (10000, 14)

In [50]:
```
df.describe()
```

Out[50]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	Nur
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	1
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	

In [51]:
```
df.isnull()
```

Out[51]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balan
0	False	False	False	False	False	False	False	False	Fal
1	False	False	False	False	False	False	False	False	Fal
2	False	False	False	False	False	False	False	False	Fal
3	False	False	False	False	False	False	False	False	Fal
4	False	False	False	False	False	False	False	False	Fal
...	...	...	...	...	...	...	...	...	
9995	False	False	False	False	False	False	False	False	Fal
9996	False	False	False	False	False	False	False	False	Fal
9997	False	False	False	False	False	False	False	False	Fal
9998	False	False	False	False	False	False	False	False	Fal
9999	False	False	False	False	False	False	False	False	Fal

10000 rows × 14 columns

In [52]:
```
df.isnull().sum()
```

Out[52]:
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

In [53]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [54]:
```python
df.dtypes
```

Out[54]:
```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

In [55]:
```python
df.columns
```

Out[55]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

In [56]:
```python
df = df.drop(['RowNumber', 'Surname', 'CustomerId'], axis= 1) #Dropping the unneces
```

In [57]:
```python
df.head()
```

Out[57]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiv
0	619	France	Female	42	2	0.00	1	1	
1	608	Spain	Female	41	1	83807.86	1	0	
2	502	France	Female	42	8	159660.80	3	1	
3	699	France	Female	39	1	0.00	2	0	
4	850	Spain	Female	43	2	125510.82	1	1	

Visualization

In [101…

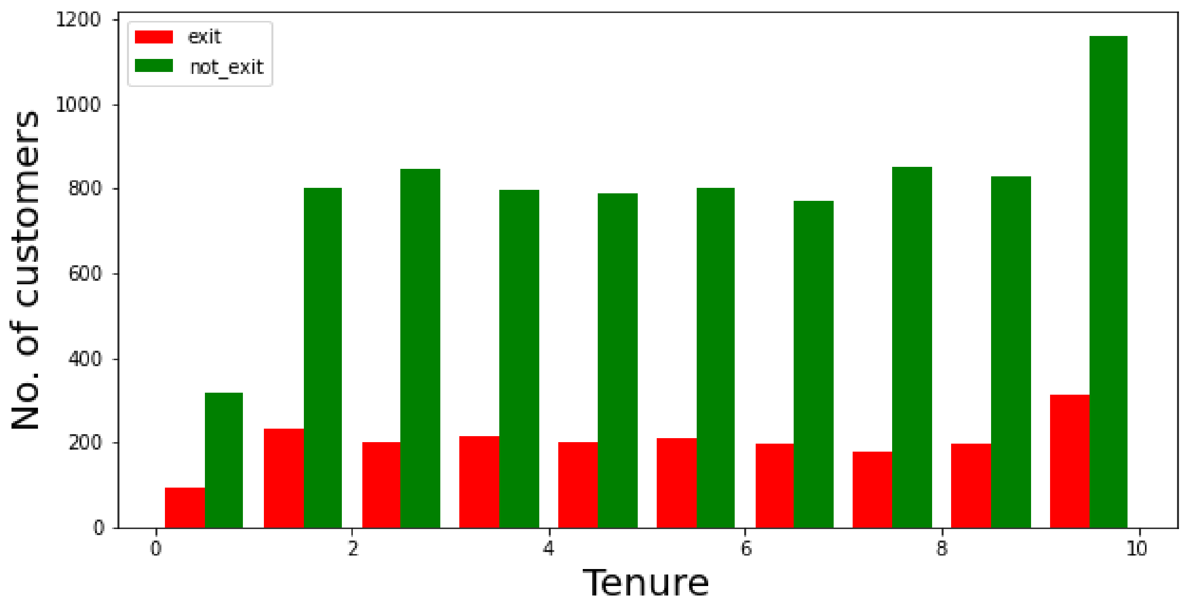
```
def visualization(x, y, xlabel):
    plt.figure(figsize=(10,5))
    plt.hist([x, y], color=['red', 'green'], label = ['exit', 'not_exit'])
    plt.xlabel(xlabel,fontsize=20)
    plt.ylabel("No. of customers", fontsize=20)
    plt.legend()
```

In [102…

```
df_churn_exited = df[df['Exited']==1]['Tenure']
df_churn_not_exited = df[df['Exited']==0]['Tenure']
```

In [103…

```
visualization(df_churn_exited, df_churn_not_exited, "Tenure")
```

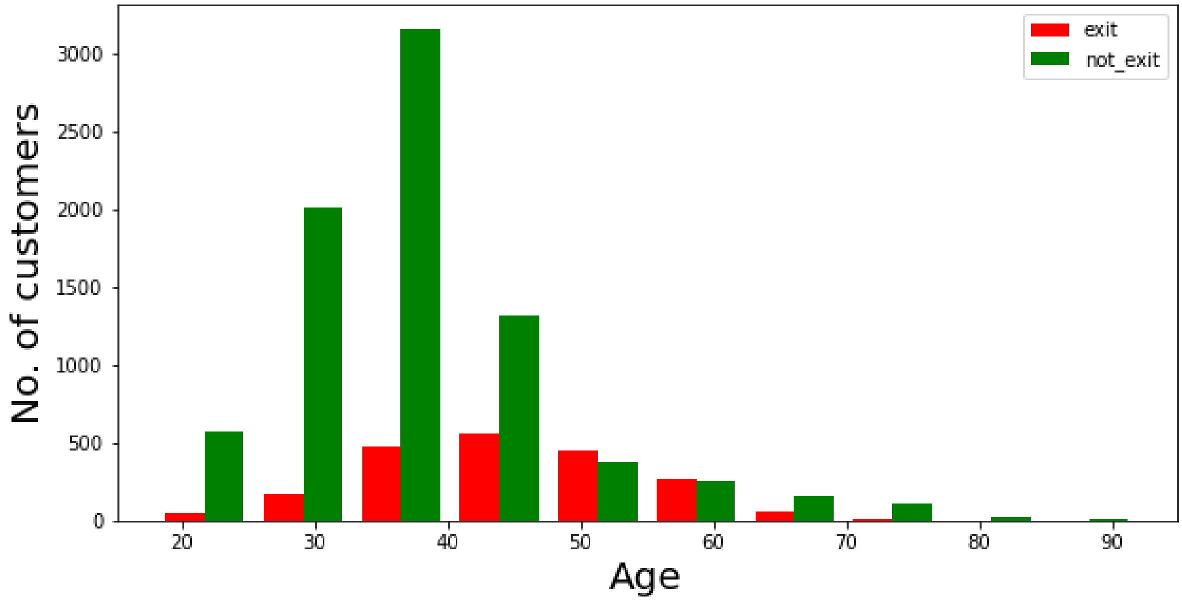


In [105…

```
df_churn_exited2 = df[df['Exited']==1]['Age']
df_churn_not_exited2 = df[df['Exited']==0]['Age']
```

In [106…

```
visualization(df_churn_exited2, df_churn_not_exited2, "Age")
```



Converting the Categorical Variables

In [59]:
```
X = df[['CreditScore','Gender','Age','Tenure','Balance','NumOfProducts','HasCrCard'
states = pd.get_dummies(df['Geography'],drop_first = True)
gender = pd.get_dummies(df['Gender'],drop_first = True)
```

In [61]:
```
df = pd.concat([df,gender,states], axis = 1)
```

Splitting the training and testing Dataset

In [62]:
```
df.head()
```

Out[62]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiv
0	619	France	Female	42	2	0.00	1	1	
1	608	Spain	Female	41	1	83807.86	1	0	
2	502	France	Female	42	8	159660.80	3	1	
3	699	France	Female	39	1	0.00	2	0	
4	850	Spain	Female	43	2	125510.82	1	1	

In [63]:
```
X = df[['CreditScore','Age','Tenure','Balance','NumOfProducts','HasCrCard','IsActiv
```

In [64]:
```
y = df['Exited']
```

In [65]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.30)
```

Normalizing the values with mean as 0 and Standard Deviation as 1

In [66]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

In [67]:
```
X_train  = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [68]:
```
X_train
```

Out[68]:
```
array([[ 4.56838557e-01, -9.45594735e-01,  1.58341939e-03, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-2.07591864e-02, -2.77416637e-01,  3.47956411e-01, ...,
        -1.09507222e+00, -5.81969145e-01,  1.74334114e+00],
       [-1.66115021e-01,  1.82257167e+00, -1.38390855e+00, ...,
        -1.09507222e+00, -5.81969145e-01, -5.73611200e-01],
       ...,
       [-3.63383654e-01, -4.68324665e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [ 4.67221117e-01, -1.42286480e+00,  1.38707539e+00, ...,
         9.13181783e-01, -5.81969145e-01,  1.74334114e+00],
       [-8.82511636e-01,  2.95307447e-01, -6.91162564e-01, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01]])
```

In [69]:
```
X_test
```

Out[69]:
```
array([[ 3.63395520e-01,  1.99853433e-01,  1.58341939e-03, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-4.15243057e-02,  4.86215475e-01,  1.58341939e-03, ...,
        -1.09507222e+00, -5.81969145e-01,  1.74334114e+00],
       [-1.87923736e+00, -3.72870651e-01, -1.38390855e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       ...,
       [-6.02182526e-01, -5.63778679e-01, -1.73028154e+00, ...,
        -1.09507222e+00, -5.81969145e-01, -5.73611200e-01],
       [ 1.51585964e+00, -6.59232693e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-5.19122049e-01,  1.04399419e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01]])
```

Building the Classifier Model using Keras

In [70]:
```
import keras #Keras is the wrapper on the top of tenserflow
#Can use Tenserflow as well but won't be able to understand the errors initially.
```

In [71]:
```
from keras.models import Sequential #To create sequential neural network
from keras.layers import Dense #To create hidden layers
```

In [72]:
```
classifier = Sequential()
```

In [74]:
```
#To add the layers
#Dense helps to contruct the neurons
#Input Dimension means we have 11 features
# Units is to create the hidden layers
#Uniform helps to distribute the weight uniformly
classifier.add(Dense(activation = "relu",input_dim = 11,units = 6,kernel_initialize
```

In [75]:
```
classifier.add(Dense(activation = "relu",units = 6,kernel_initializer = "uniform"))
```

In [76]:
```
classifier.add(Dense(activation = "sigmoid",units = 1,kernel_initializer = "uniforr
```

In [77]:
```
classifier.compile(optimizer="adam",loss = 'binary_crossentropy',metrics = ['accura
```

In [79]:
```
classifier.summary() #3 layers created. 6 neurons in 1st,6neurons in 2nd layer and
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
dense_3 (Dense)             (None, 6)                 72
_________________________________________________________________
dense_4 (Dense)             (None, 6)                 42
_________________________________________________________________
dense_5 (Dense)             (None, 1)                 7
=================================================================
Total params: 121
Trainable params: 121
Non-trainable params: 0
_________________________________________________________________
```

In [89]:
```
classifier.fit(X_train,y_train,batch_size=10,epochs=50) #Fitting the ANN to trainir
```

```
Epoch 1/50
700/700 [==============================] - 0s 674us/step - loss: 0.4293 - accurac
y: 0.7947
Epoch 2/50
700/700 [==============================] - 0s 647us/step - loss: 0.4239 - accurac
y: 0.7947
Epoch 3/50
700/700 [==============================] - 0s 657us/step - loss: 0.4203 - accurac
y: 0.8067
Epoch 4/50
700/700 [==============================] - 0s 664us/step - loss: 0.4167 - accurac
y: 0.8260
Epoch 5/50
700/700 [==============================] - 0s 674us/step - loss: 0.4153 - accurac
y: 0.8287
Epoch 6/50
700/700 [==============================] - 0s 653us/step - loss: 0.4137 - accurac
y: 0.8310
Epoch 7/50
700/700 [==============================] - 0s 658us/step - loss: 0.4125 - accurac
y: 0.8317
Epoch 8/50
700/700 [==============================] - 1s 842us/step - loss: 0.4116 - accurac
y: 0.8306
Epoch 9/50
700/700 [==============================] - 0s 671us/step - loss: 0.4103 - accurac
y: 0.8331
Epoch 10/50
700/700 [==============================] - 0s 682us/step - loss: 0.4100 - accurac
y: 0.8326
Epoch 11/50
700/700 [==============================] - 0s 690us/step - loss: 0.4093 - accurac
y: 0.8337
Epoch 12/50
700/700 [==============================] - 0s 688us/step - loss: 0.4087 - accurac
y: 0.8339
Epoch 13/50
700/700 [==============================] - 0s 675us/step - loss: 0.4081 - accurac
y: 0.8341
Epoch 14/50
700/700 [==============================] - 1s 722us/step - loss: 0.4071 - accurac
y: 0.8331
Epoch 15/50
700/700 [==============================] - 1s 811us/step - loss: 0.4065 - accurac
y: 0.8341
Epoch 16/50
700/700 [==============================] - 0s 711us/step - loss: 0.4056 - accurac
y: 0.8356
Epoch 17/50
700/700 [==============================] - 0s 702us/step - loss: 0.4046 - accurac
y: 0.8366
Epoch 18/50
700/700 [==============================] - 0s 688us/step - loss: 0.4035 - accurac
y: 0.8343
Epoch 19/50
700/700 [==============================] - 1s 715us/step - loss: 0.4024 - accurac
y: 0.8363
Epoch 20/50
700/700 [==============================] - 0s 714us/step - loss: 0.4020 - accurac
y: 0.8337
Epoch 21/50
```

```
700/700 [==============================] - 0s 705us/step - loss: 0.4010 - accurac
y: 0.8374
Epoch 22/50
700/700 [==============================] - 1s 720us/step - loss: 0.4003 - accurac
y: 0.8370
Epoch 23/50
700/700 [==============================] - 0s 692us/step - loss: 0.3993 - accurac
y: 0.8374
Epoch 24/50
700/700 [==============================] - 0s 709us/step - loss: 0.3990 - accurac
y: 0.8356
Epoch 25/50
700/700 [==============================] - 1s 871us/step - loss: 0.3984 - accurac
y: 0.8366
Epoch 26/50
700/700 [==============================] - 1s 719us/step - loss: 0.3984 - accurac
y: 0.8367
Epoch 27/50
700/700 [==============================] - 1s 719us/step - loss: 0.3980 - accurac
y: 0.8366
Epoch 28/50
700/700 [==============================] - 0s 695us/step - loss: 0.3981 - accurac
y: 0.8366
Epoch 29/50
700/700 [==============================] - 0s 667us/step - loss: 0.3976 - accurac
y: 0.8374
Epoch 30/50
700/700 [==============================] - 0s 669us/step - loss: 0.3972 - accurac
y: 0.8373
Epoch 31/50
700/700 [==============================] - 0s 670us/step - loss: 0.3970 - accurac
y: 0.8370
Epoch 32/50
700/700 [==============================] - 1s 720us/step - loss: 0.3972 - accurac
y: 0.8376
Epoch 33/50
700/700 [==============================] - 0s 675us/step - loss: 0.3965 - accurac
y: 0.8367
Epoch 34/50
700/700 [==============================] - 0s 680us/step - loss: 0.3961 - accurac
y: 0.8364
Epoch 35/50
700/700 [==============================] - 0s 685us/step - loss: 0.3962 - accurac
y: 0.8379
Epoch 36/50
700/700 [==============================] - 1s 771us/step - loss: 0.3960 - accurac
y: 0.8370
Epoch 37/50
700/700 [==============================] - 1s 1ms/step - loss: 0.3963 - accuracy:
0.8366
Epoch 38/50
700/700 [==============================] - 1s 764us/step - loss: 0.3962 - accurac
y: 0.8373
Epoch 39/50
700/700 [==============================] - 1s 823us/step - loss: 0.3950 - accurac
y: 0.8384
Epoch 40/50
700/700 [==============================] - 1s 759us/step - loss: 0.3956 - accurac
y: 0.8361
Epoch 41/50
700/700 [==============================] - 1s 773us/step - loss: 0.3949 - accurac
```

```
y: 0.8366
Epoch 42/50
700/700 [==============================] - 0s 695us/step - loss: 0.3953 - accurac
y: 0.8369
Epoch 43/50
700/700 [==============================] - 0s 701us/step - loss: 0.3952 - accurac
y: 0.8369
Epoch 44/50
700/700 [==============================] - 0s 707us/step - loss: 0.3952 - accurac
y: 0.8366
Epoch 45/50
700/700 [==============================] - 0s 680us/step - loss: 0.3955 - accurac
y: 0.8376
Epoch 46/50
700/700 [==============================] - 0s 665us/step - loss: 0.3947 - accurac
y: 0.8373
Epoch 47/50
700/700 [==============================] - 0s 708us/step - loss: 0.3947 - accurac
y: 0.8371
Epoch 48/50
700/700 [==============================] - 0s 681us/step - loss: 0.3944 - accurac
y: 0.8371
Epoch 49/50
700/700 [==============================] - 0s 678us/step - loss: 0.3947 - accurac
y: 0.8383
Epoch 50/50
700/700 [==============================] - 1s 869us/step - loss: 0.3944 - accurac
y: 0.8370
```

Out[89]: <tensorflow.python.keras.callbacks.History at 0x1fb1eb93df0>

In [90]:
```
y_pred =classifier.predict(X_test)
y_pred = (y_pred > 0.5) #Predicting the result
```

In [97]:
```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
```

In [92]:
```
cm = confusion_matrix(y_test,y_pred)
```

In [93]:
```
cm
```

Out[93]:
```
array([[2328,   72],
       [ 425,  175]], dtype=int64)
```

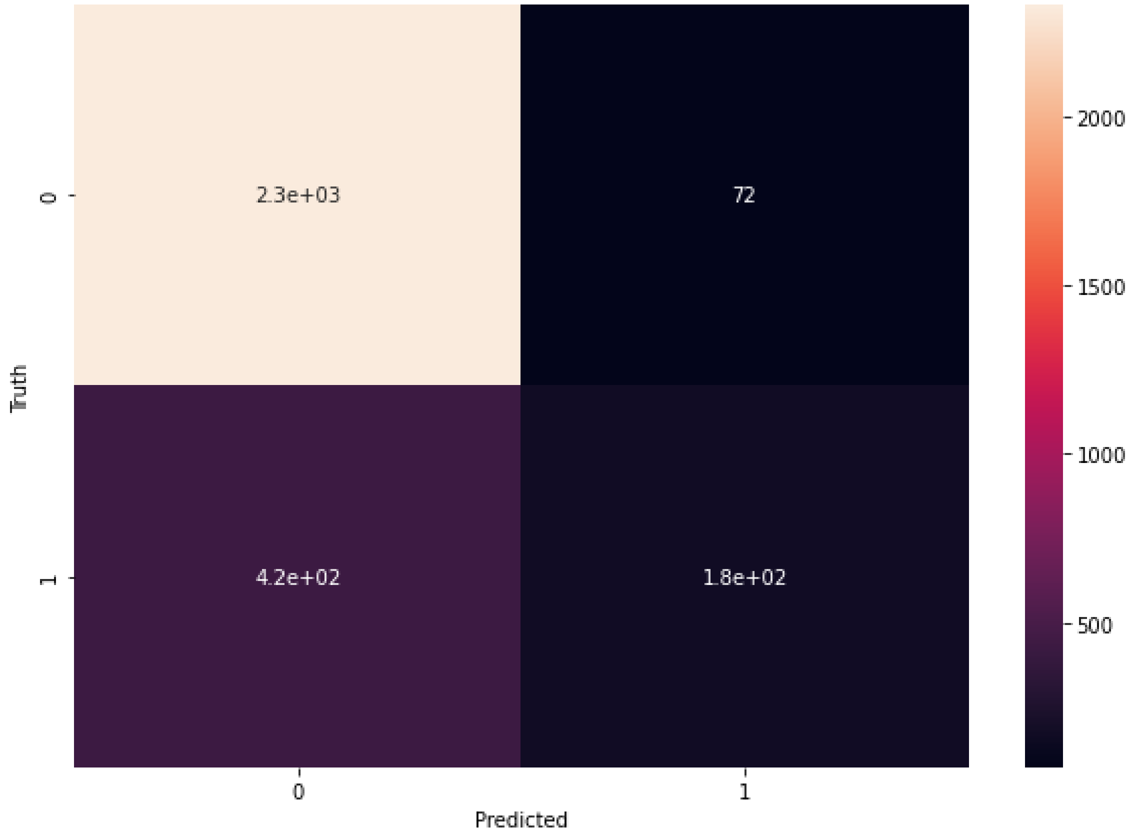
In [94]:
```
accuracy = accuracy_score(y_test,y_pred)
```

In [95]:
```
accuracy
```

Out[95]: 0.8343333333333334

In [98]:
```
plt.figure(figsize = (10,7))
sns.heatmap(cm,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[98]: Text(69.0, 0.5, 'Truth')



In [100…
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.97      0.90      2400
           1       0.71      0.29      0.41       600

    accuracy                           0.83      3000
   macro avg       0.78      0.63      0.66      3000
weighted avg       0.82      0.83      0.81      3000
```

In [ ]:

Assignment 5

KNN algorithm on diabetes dataset

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn import metrics
```

In [2]:
```
df=pd.read_csv('diabetes.csv')
```

In [3]:
```
df.columns
```

Out[3]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'Pedigree', 'Age', 'Outcome'],
      dtype='object')
```

Check for null values. If present remove null values from the dataset

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Pregnancies      0
Glucose          0
BloodPressure    0
SkinThickness    0
Insulin          0
BMI              0
Pedigree         0
Age              0
Outcome          0
dtype: int64
```

In [ ]:

Outcome is the label/target, other columns are features

In [7]:
```
X = df.drop('Outcome',axis = 1)
y = df['Outcome']
```

In [8]:
```
from sklearn.preprocessing import scale
X = scale(X)
# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_s
```

In [9]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7)

knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [17]:
```
print("Confusion matrix: ")
cs = metrics.confusion_matrix(y_test,y_pred)
print(cs)
```

```
Confusion matrix:
[[123  28]
 [ 37  43]]
```

In [12]:
```
print("Acccuracy ",metrics.accuracy_score(y_test,y_pred))
```

```
Acccuracy  0.7186147186147186
```

Classification error rate: proportion of instances misclassified over the whole set of instances. Error rate is calculated as the total number of two incorrect predictions (FN + FP) divided by the total number of a dataset (examples in the dataset.

Also error_rate = 1- accuracy

In [29]:
```
total_misclassified = cs[0,1] + cs[1,0]
print(total_misclassified)
total_examples = cs[0,0]+cs[0,1]+cs[1,0]+cs[1,1]
print(total_examples)
print("Error rate",total_misclassified/total_examples)
print("Error rate ",1-metrics.accuracy_score(y_test,y_pred))
```

```
65
231
Error rate 0.2813852813852814
Error rate  0.2813852813852814
```

In [13]:
```
print("Precision score",metrics.precision_score(y_test,y_pred))
```

```
Precision score 0.6056338028169014
```

In [14]:
```
print("Recall score ",metrics.recall_score(y_test,y_pred))
```

```
Recall score  0.5375
```

In [15]:
```
print("Classification report ",metrics.classification_report(y_test,y_pred))
```

```
Classification report                precision    recall  f1-score   support

           0       0.77      0.81      0.79       151
           1       0.61      0.54      0.57        80

    accuracy                           0.72       231
   macro avg       0.69      0.68      0.68       231
weighted avg       0.71      0.72      0.71       231
```

Implement K-Means clustering/ hierarchical clustering on sales_data_sample.csv dataset. Determine the number of clusters using the elbow method.

In [198…
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
#Importing the required libraries.
```

In [199…
```
from sklearn.cluster import KMeans, k_means #For clustering
from sklearn.decomposition import PCA #Linear Dimensionality reduction.
```

In [200…
```
df = pd.read_csv("sales_data_sample.csv") #Loading the dataset.
```

Preprocessing

In [201…
```
df.head()
```

Out[201]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE
0	10107	30	95.70	2	2871.00	2/24/2003 0:00
1	10121	34	81.35	5	2765.90	5/7/2003 0:00
2	10134	41	94.74	2	3884.34	7/1/2003 0:00
3	10145	45	83.26	6	3746.70	8/25/2003 0:00
4	10159	49	100.00	14	5205.27	10/10/2003 0:00

5 rows × 25 columns

In [202…
```
df.shape
```

Out[202]:
```
(2823, 25)
```

In [203…
```
df.describe()
```

Out[203]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	
count	2823.000000	2823.000000	2823.000000	2823.000000	2823.000000	282
mean	10258.725115	35.092809	83.658544	6.466171	3553.889072	
std	92.085478	9.741443	20.174277	4.225841	1841.865106	
min	10100.000000	6.000000	26.880000	1.000000	482.130000	
25%	10180.000000	27.000000	68.860000	3.000000	2203.430000	
50%	10262.000000	35.000000	95.700000	6.000000	3184.800000	
75%	10333.500000	43.000000	100.000000	9.000000	4508.000000	
max	10425.000000	97.000000	100.000000	18.000000	14082.800000	

In [204…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   ORDERNUMBER       2823 non-null   int64  
 1   QUANTITYORDERED   2823 non-null   int64  
 2   PRICEEACH         2823 non-null   float64
 3   ORDERLINENUMBER   2823 non-null   int64  
 4   SALES             2823 non-null   float64
 5   ORDERDATE         2823 non-null   object 
 6   STATUS            2823 non-null   object 
 7   QTR_ID            2823 non-null   int64  
 8   MONTH_ID          2823 non-null   int64  
 9   YEAR_ID           2823 non-null   int64  
 10  PRODUCTLINE       2823 non-null   object 
 11  MSRP              2823 non-null   int64  
 12  PRODUCTCODE       2823 non-null   object 
 13  CUSTOMERNAME      2823 non-null   object 
 14  PHONE             2823 non-null   object 
 15  ADDRESSLINE1      2823 non-null   object 
 16  ADDRESSLINE2      302 non-null    object 
 17  CITY              2823 non-null   object 
 18  STATE             1337 non-null   object 
 19  POSTALCODE        2747 non-null   object 
 20  COUNTRY           2823 non-null   object 
 21  TERRITORY         1749 non-null   object 
 22  CONTACTLASTNAME   2823 non-null   object 
 23  CONTACTFIRSTNAME  2823 non-null   object 
 24  DEALSIZE          2823 non-null   object 
dtypes: float64(2), int64(7), object(16)
memory usage: 551.5+ KB
```

In [205…

```
df.isnull().sum()
```

Out[205]:
```
ORDERNUMBER            0
QUANTITYORDERED        0
PRICEEACH              0
ORDERLINENUMBER        0
SALES                  0
ORDERDATE              0
STATUS                 0
QTR_ID                 0
MONTH_ID               0
YEAR_ID                0
PRODUCTLINE            0
MSRP                   0
PRODUCTCODE            0
CUSTOMERNAME           0
PHONE                  0
ADDRESSLINE1           0
ADDRESSLINE2        2521
CITY                   0
STATE               1486
POSTALCODE            76
COUNTRY                0
TERRITORY           1074
CONTACTLASTNAME        0
CONTACTFIRSTNAME       0
DEALSIZE               0
dtype: int64
```

In [206…
```
df.dtypes
```

Out[206]:
```
ORDERNUMBER           int64
QUANTITYORDERED       int64
PRICEEACH           float64
ORDERLINENUMBER       int64
SALES               float64
ORDERDATE            object
STATUS               object
QTR_ID                int64
MONTH_ID              int64
YEAR_ID               int64
PRODUCTLINE          object
MSRP                  int64
PRODUCTCODE          object
CUSTOMERNAME         object
PHONE                object
ADDRESSLINE1         object
ADDRESSLINE2         object
CITY                 object
STATE                object
POSTALCODE           object
COUNTRY              object
TERRITORY            object
CONTACTLASTNAME      object
CONTACTFIRSTNAME     object
DEALSIZE             object
dtype: object
```

In [207…
```
df_drop  = ['ADDRESSLINE1', 'ADDRESSLINE2', 'STATUS','POSTALCODE', 'CITY', 'TERRITO
df = df.drop(df_drop, axis=1) #Dropping the categorical uneccessary columns along w
```

In [208…
```
df.isnull().sum()
```

Out[208]:
```
QUANTITYORDERED     0
PRICEEACH           0
ORDERLINENUMBER     0
SALES               0
ORDERDATE           0
QTR_ID              0
MONTH_ID            0
YEAR_ID             0
PRODUCTLINE         0
MSRP                0
PRODUCTCODE         0
COUNTRY             0
DEALSIZE            0
dtype: int64
```

In [209…
```
df.dtypes
```

Out[209]:
```
QUANTITYORDERED       int64
PRICEEACH           float64
ORDERLINENUMBER       int64
SALES               float64
ORDERDATE            object
QTR_ID                int64
MONTH_ID              int64
YEAR_ID               int64
PRODUCTLINE          object
MSRP                  int64
PRODUCTCODE          object
COUNTRY              object
DEALSIZE             object
dtype: object
```

In [ ]:
```
# Checking the categorical columns.
```

In [210…
```
df['COUNTRY'].unique()
```

Out[210]:
```
array(['USA', 'France', 'Norway', 'Australia', 'Finland', 'Austria', 'UK',
       'Spain', 'Sweden', 'Singapore', 'Canada', 'Japan', 'Italy',
       'Denmark', 'Belgium', 'Philippines', 'Germany', 'Switzerland',
       'Ireland'], dtype=object)
```

In [211…
```
df['PRODUCTLINE'].unique()
```

Out[211]:
```
array(['Motorcycles', 'Classic Cars', 'Trucks and Buses', 'Vintage Cars',
       'Planes', 'Ships', 'Trains'], dtype=object)
```

In [212…
```
df['DEALSIZE'].unique()
```

Out[212]:
```
array(['Small', 'Medium', 'Large'], dtype=object)
```

In [213…
```
productline = pd.get_dummies(df['PRODUCTLINE']) #Converting the categorical columns
Dealsize = pd.get_dummies(df['DEALSIZE'])
```

In [214…
```
df = pd.concat([df,productline,Dealsize], axis = 1)
```

In [215…
```
df_drop  = ['COUNTRY','PRODUCTLINE','DEALSIZE'] #Dropping Country too as there are
df = df.drop(df_drop, axis=1)
```

In [216…
```
df['PRODUCTCODE'] = pd.Categorical(df['PRODUCTCODE']).codes #Converting the datatyp
```

In [217…
```
df.drop('ORDERDATE', axis=1, inplace=True) #Dropping the Orderdate as Month is alre
```

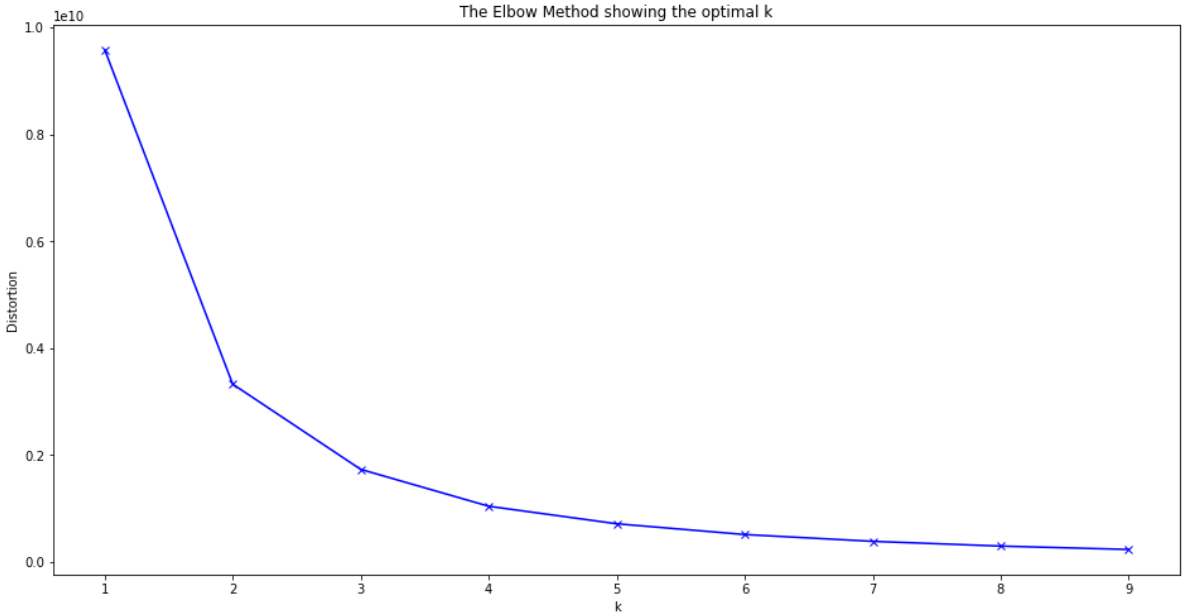
In [218…
```
df.dtypes #All the datatypes are converted into numeric
```

Out[218]:
```
QUANTITYORDERED       int64
PRICEEACH           float64
ORDERLINENUMBER       int64
SALES               float64
QTR_ID                int64
MONTH_ID              int64
YEAR_ID               int64
MSRP                  int64
PRODUCTCODE            int8
Classic Cars          uint8
Motorcycles           uint8
Planes                uint8
Ships                 uint8
Trains                uint8
Trucks and Buses      uint8
Vintage Cars          uint8
Large                 uint8
Medium                uint8
Small                 uint8
dtype: object
```

Plotting the Elbow Plot to determine the number of clusters.

In [219…
```
distortions = [] # Within Cluster Sum of Squares from the centroid
K = range(1,10)
for k in K:
    kmeanModel = KMeans(n_clusters=k)
    kmeanModel.fit(df)
    distortions.append(kmeanModel.inertia_)   #Appeding the intertia to the Distort
```

In [220…
```
plt.figure(figsize=(16,8))
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```



As the number of k increases Inertia decreases.

Observations: A Elbow can be observed at 3 and after that the curve decreases gradually.

In [221…
```
X_train = df.values #Returns a numpy array.
```

In [222…
```
X_train.shape
```

Out[222]: (2823, 19)

In [223…
```
model = KMeans(n_clusters=3,random_state=2) #Number of cluster = 3
model = model.fit(X_train) #Fitting the values to create a model.
predictions = model.predict(X_train) #Predicting the cluster values (0,1,or 2)
```

In [225…
```
unique,counts = np.unique(predictions,return_counts=True)
```

In [226…
```
counts = counts.reshape(1,3)
```

In [227…
```
counts_df = pd.DataFrame(counts,columns=['Cluster1','Cluster2','Cluster3'])
```

In [228…
```
counts_df.head()
```

Out[228]:

	Cluster1	Cluster2	Cluster3
0	1083	1367	373

Visualization

In [229…
```
pca = PCA(n_components=2) #Converting all the features into 2 columns to make it ea
```

In [230…
```
reduced_X = pd.DataFrame(pca.fit_transform(X_train),columns=['PCA1','PCA2']) #Creat
```

In [231…
```
reduced_X.head()
```

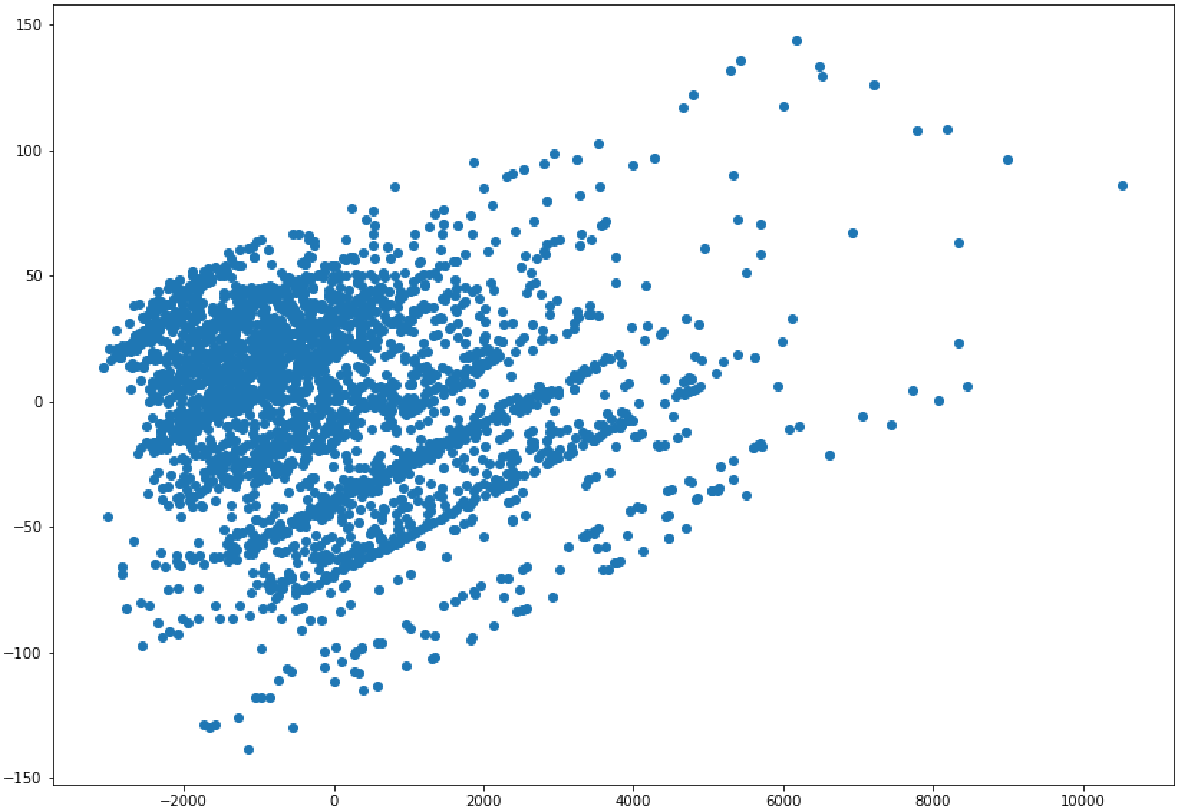
Out[231]:

	PCA1	PCA2
0	-682.488323	-42.819535
1	-787.665502	-41.694991
2	330.732170	-26.481208
3	193.040232	-26.285766
4	1651.532874	-6.891196

In [232…

```
#Plotting the normal Scatter Plot
plt.figure(figsize=(14,10))
plt.scatter(reduced_X['PCA1'],reduced_X['PCA2'])
```

Out[232]: <matplotlib.collections.PathCollection at 0x218dc747880>



In [233…

```
model.cluster_centers_ #Finding the centriods. (3 Centriods in total. Each Array cc
```

Out[233]:
```
array([[ 3.72031394e+01,  9.52120960e+01,  6.44967682e+00,
         4.13868425e+03,  2.72022161e+00,  7.09879963e+00,
         2.00379409e+03,  1.13248384e+02,  5.04469067e+01,
         3.74884580e-01,  1.15420129e-01,  9.41828255e-02,
         8.21791320e-02,  1.84672207e-02,  1.16343490e-01,
         1.98522622e-01,  2.08166817e-17,  1.00000000e+00,
        -6.66133815e-16],
       [ 3.08302853e+01,  7.00755230e+01,  6.67300658e+00,
         2.12409474e+03,  2.71762985e+00,  7.09509876e+00,
         2.00381127e+03,  7.84784199e+01,  6.24871982e+01,
         2.64813460e-01,  1.21433797e-01,  1.29480614e-01,
         1.00219459e-01,  3.87710315e-02,  9.21726408e-02,
         2.53108998e-01,  6.93889390e-18,  6.21799561e-02,
         9.37820044e-01],
       [ 4.45871314e+01,  9.98931099e+01,  5.75603217e+00,
         7.09596863e+03,  2.71045576e+00,  7.06434316e+00,
         2.00389008e+03,  1.45823056e+02,  3.14959786e+01,
         5.33512064e-01,  1.07238606e-01,  7.23860590e-02,
         2.14477212e-02,  1.07238606e-02,  1.31367292e-01,
         1.23324397e-01,  4.20911528e-01,  5.79088472e-01,
         5.55111512e-17]])
```

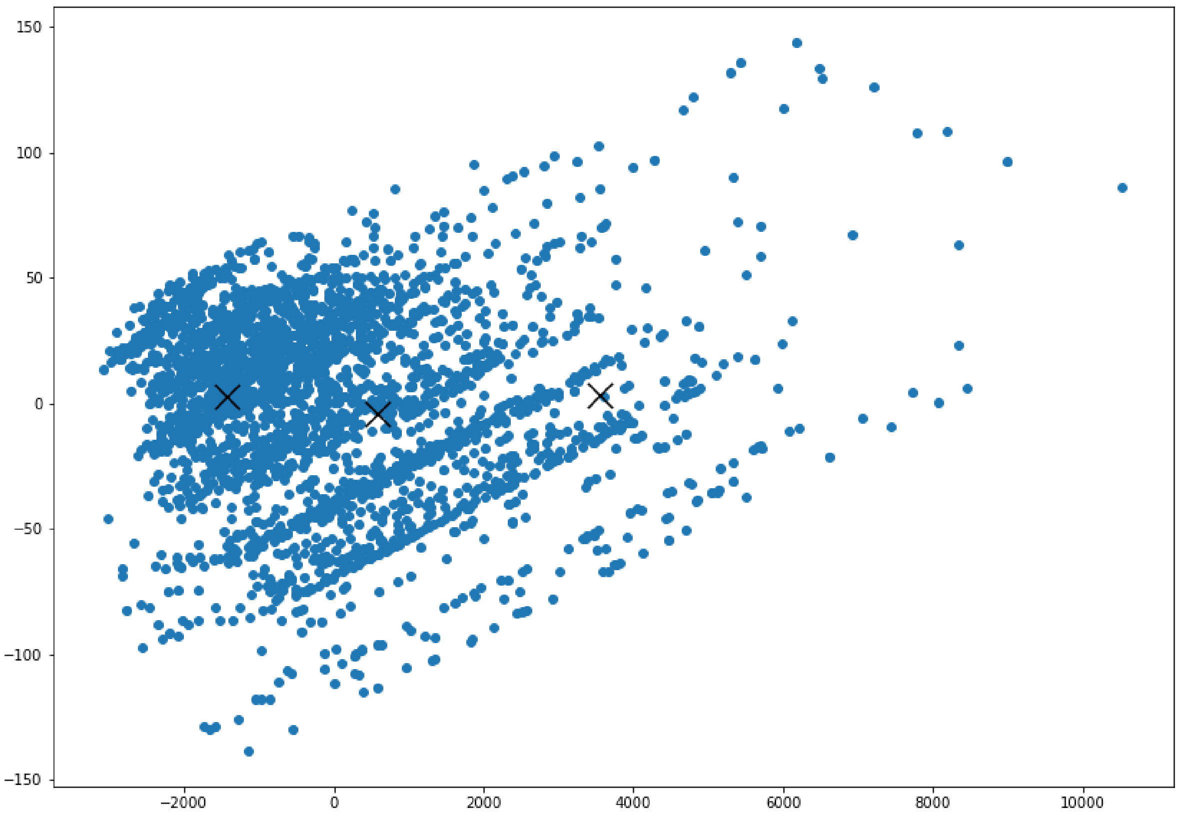
In [234…
```
reduced_centers = pca.transform(model.cluster_centers_) #Transforming the centroids
```

In [235…
```
reduced_centers
```

Out[235]:
```
array([[ 5.84994044e+02, -4.36786931e+00],
       [-1.43005891e+03,  2.60041009e+00],
       [ 3.54247180e+03,  3.15185487e+00]])
```

In [236…
```
plt.figure(figsize=(14,10))
plt.scatter(reduced_X['PCA1'],reduced_X['PCA2'])
plt.scatter(reduced_centers[:,0],reduced_centers[:,1],color='black',marker='x',s=3(
```

Out[236]: <matplotlib.collections.PathCollection at 0x218deb6e220>



In [237…

```
reduced_X['Clusters'] = predictions #Adding the Clusters to the reduced dataframe.
```

In [238…

```
reduced_X.head()
```

Out[238]:

	PCA1	PCA2	Clusters
0	-682.488323	-42.819535	1
1	-787.665502	-41.694991	1
2	330.732170	-26.481208	0
3	193.040232	-26.285766	0
4	1651.532874	-6.891196	0

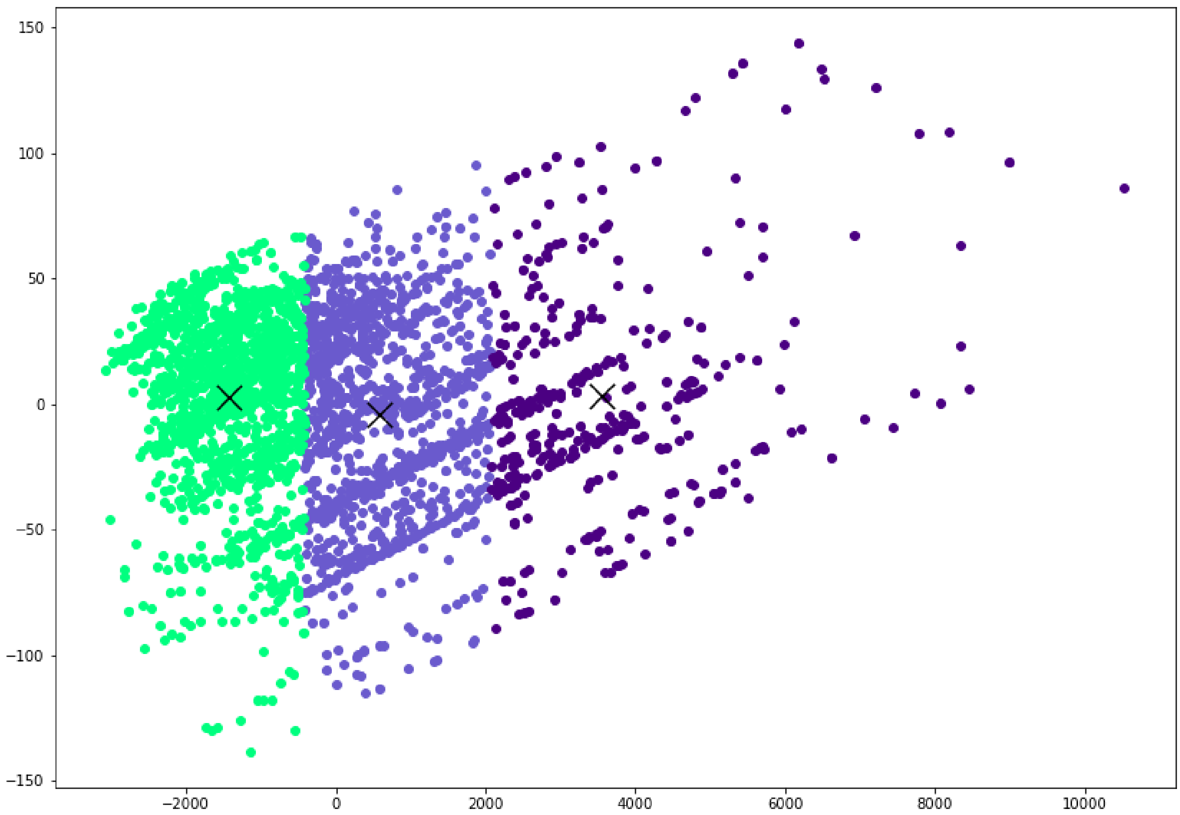
In [239…

```
#Plotting the clusters
plt.figure(figsize=(14,10))
#                       taking the cluster number and first column           taking t
plt.scatter(reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA1'],reduced_X[reduced_X
plt.scatter(reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA1'],reduced_X[reduced_X
plt.scatter(reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA1'],reduced_X[reduced_X


plt.scatter(reduced_centers[:,0],reduced_centers[:,1],color='black',marker='x',s=30
```

Out[239]:

```
<matplotlib.collections.PathCollection at 0x218dce9e1f0>
```



In [ ]: