#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	dropoff_longitude	dropoff_latitude	passenger_count
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5

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):
Unnamed: 0           200000 non-null int64
key                  200000 non-null object
fare_amount          200000 non-null float64
pickup_datetime      200000 non-null object
pickup_longitude     200000 non-null float64
pickup_latitude      200000 non-null float64
dropoff_longitude    199999 non-null float64
dropoff_latitude     199999 non-null float64
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 required
```

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

Out[7]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5

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
```

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

In [10]:
```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime)
```

In [11]:
```
df.dtypes
```

Out[11]:
```
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
```

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 = True)
```

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
```

To segregate each time of date and time

In [15]:
```
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 [16]:
```
df.head()
```

Out[16]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	40.723217	1	19	7	5	2015	3
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	40.750325	1	20	17	7	2009	4
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	40.772647	1	21	24	8	2009	0
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	40.803349	3	8	26	6	2009	4
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	40.761247	5	17	28	8	2014	3

Here we are going to use Heversine formula to calculate the distance between two points and journey, using longitude and latitude values.

Heversine formula hav(θ) = sin**2(θ/2).

In [19]:
```
from math import *
# function to calculate the travel distance from the longitudes and latitudes
def distance_transform(longitude1, latitude1, longitude2, latitude2):
    travel_dist = []

    for pos in range(len(longitude1)):
        long1,lati1,long2,lati2 = map(radians,[longitude1[pos],latitude1[pos],longitude2[pos],latitude2[pos]])
        dist_long = long2 - long1
        dist_lati = lati2 - lati1
        a = sin(dist_lati/2)**2 + cos(lati1) * cos(lati2) * sin(dist_long/2)**2
        c = 2 * asin(sqrt(a))*6371
        travel_dist.append(c)

    return travel_dist
```

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

Out[21]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek	dist_travel_km
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	40.723217	1	19	7	5	2015	3	1.683323
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	40.750325	1	20	17	7	2009	4	2.457590
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	40.772647	1	21	24	8	2009	0	5.036377
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	40.803349	3	8	26	6	2009	4	1.661683
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	40.761247	5	17	28	8	2014	3	4.475450

```
In [22]: # drop the column 'pickup_daetime' using drop()
         # 'axis = 1' drops the specified column

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

```
In [23]: df.head()
```

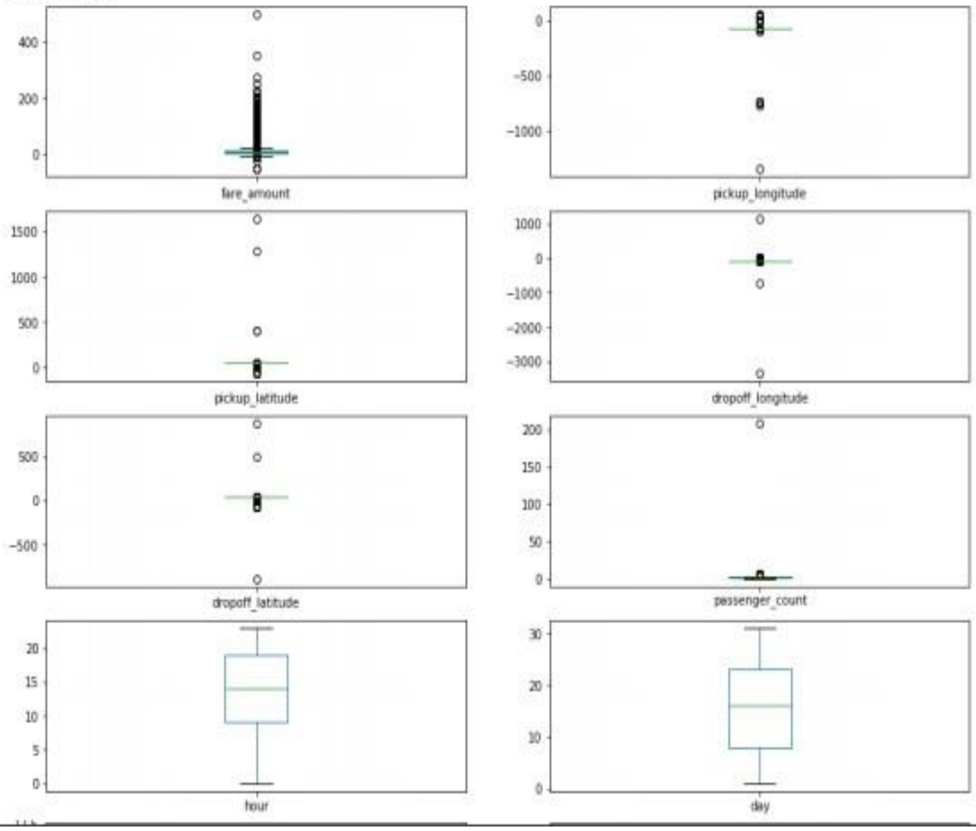
Out[23]:

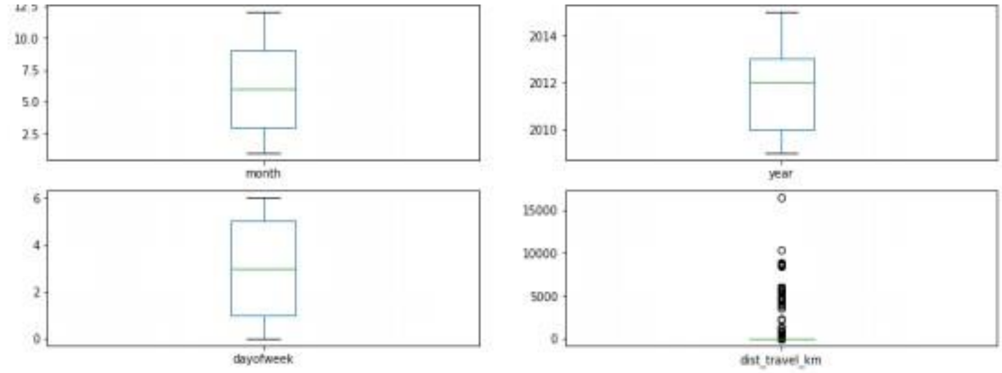
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek	dist_travel_km
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1	19	7	5	2015	3	1.683323
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1	20	17	7	2009	4	2.457590
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1	21	24	8	2009	0	5.036377
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3	8	26	6	2009	4	1.661683
4	16.0	-73.925023	40.744085	-73.973082	40.761247	5	17	28	8	2014	3	4.475450

Checking outliers and filling them

```
In [24]: df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxplot to check the outliers
```

```
Out[24]: 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)
         dist_travel_km       AxesSubplot(0.547727,0.235488;0.352273x0.0920732)
         dtype: object
```



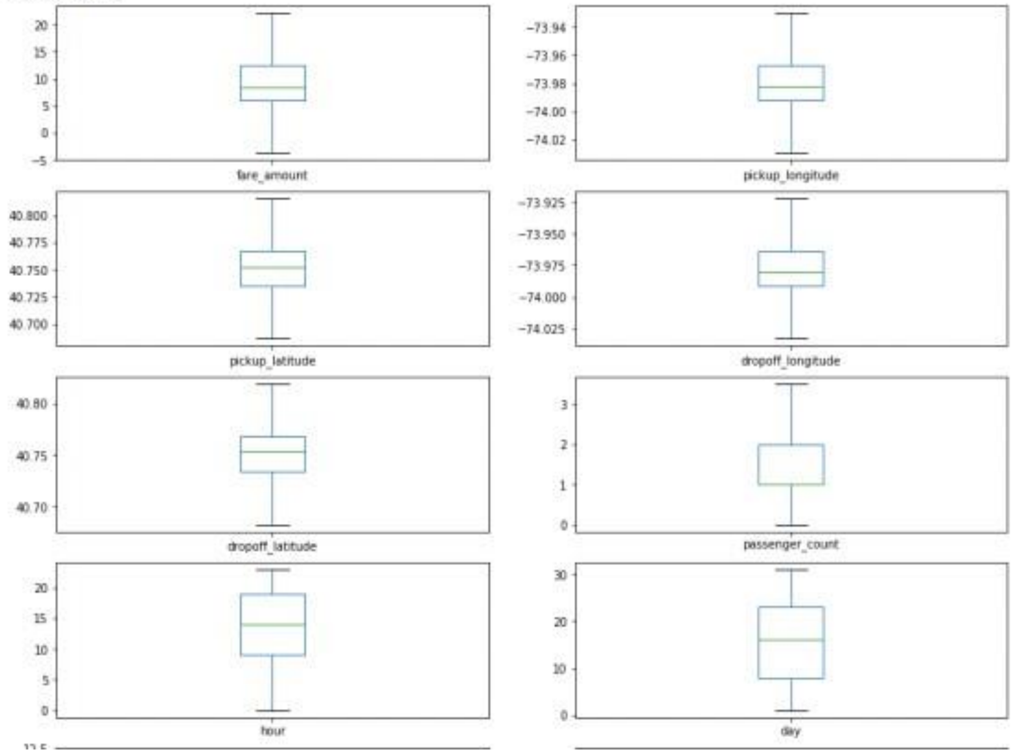


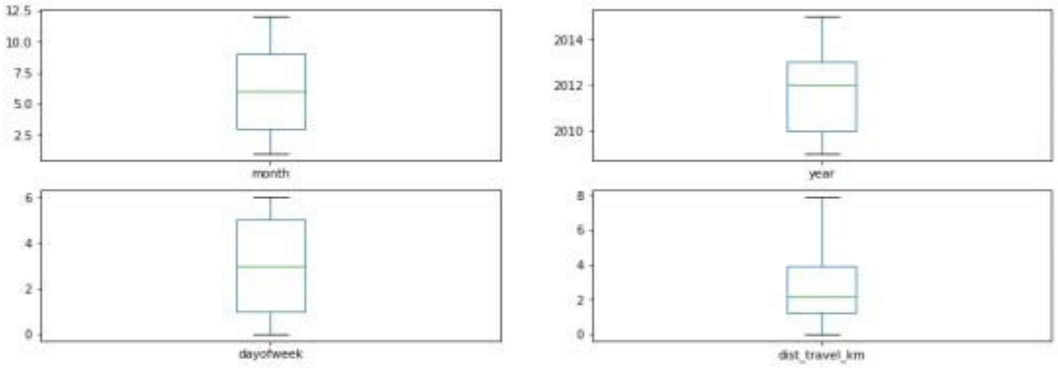
In [25]:
```python
#Using the InterQuartile Range to fill the values
def remove_outlier(df1 , col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    df[col] = np.clip(df1[col] , lower_whisker , upper_whisker)
    return df1

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

In [26]:
```python
df = treat_outliers_all(df , df.iloc[: , 0::])
```

In [27]:
```python
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxplot shows that dataset is free from outliers
```

Out[27]:
```
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)
dist_travel_km       AxesSubplot(0.547727,0.235488;0.352273x0.0920732)
dtype: object
```





n [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)
```

n [29]:
```
#Finding inccorect latitude (Less than or greater than 90) and longitude (greater than or less than 180)
incorrect_coordinates = df.loc[(df.pickup_latitude > 90) |(df.pickup_latitude < -90) |
                                   (df.dropoff_latitude > 90) |(df.dropoff_latitude < -90) |
                                   (df.pickup_longitude > 180) |(df.pickup_longitude < -180) |
                                   (df.dropoff_longitude > 90) |(df.dropoff_longitude < -90)
                                    ]
```

n [30]:
```
df.drop(incorrect_coordinates, inplace = True, errors = 'ignore')
```

n [31]:
```
df.head()
```

ut[31]:

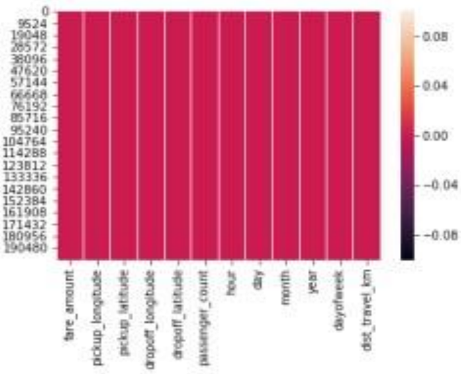
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek	dist_travel_km
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1.0	19	7	5	2015	3	1.683323
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1.0	20	17	7	2009	4	2.457590
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1.0	21	24	8	2009	0	5.036377
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3.0	8	26	6	2009	4	1.661683
4	16.0	-73.929786	40.744085	-73.973082	40.761247	3.5	17	28	8	2014	3	4.475450

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

ut[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
```

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

ut[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x8d8af2a080>
```



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

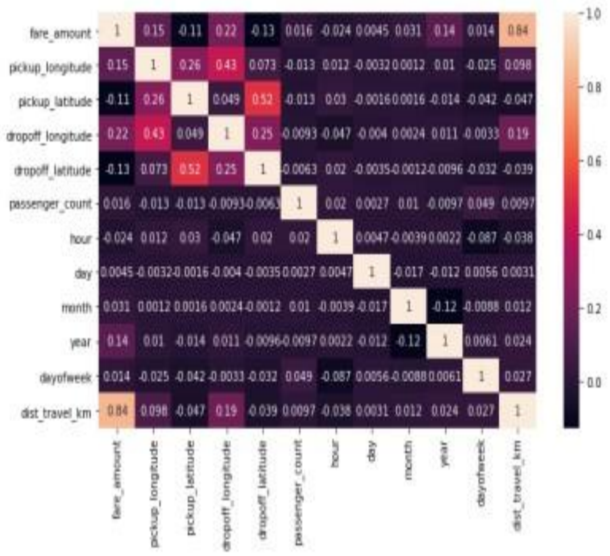
In [35]:
```
corr
```

Out[35]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofweek	dist_travel_km
fare_amount	1.000000	0.154069	-0.110842	0.218675	-0.125898	0.015778	-0.023623	0.004534	0.030817	0.141277	0.013652	0.844374
pickup_longitude	0.154069	1.000000	0.259497	0.425619	0.073290	-0.013213	0.011579	-0.003204	0.001169	0.010198	-0.024652	0.098094
pickup_latitude	-0.110842	0.259497	1.000000	0.048889	0.515714	-0.012889	0.029681	-0.001553	0.001562	-0.014243	-0.042310	-0.046812
dropoff_longitude	0.218675	0.425619	0.048889	1.000000	0.245667	-0.009303	-0.046558	-0.004007	0.002391	0.011346	-0.003336	0.186531
dropoff_latitude	-0.125898	0.073290	0.515714	0.245667	1.000000	-0.006308	0.019783	-0.003479	-0.001193	-0.009603	-0.031919	-0.038900
passenger_count	0.015778	-0.013213	-0.012889	-0.009303	-0.006308	1.000000	0.020274	0.002712	0.010351	-0.009749	0.048550	0.009709
hour	-0.023623	0.011579	0.029681	-0.046558	0.019783	0.020274	1.000000	0.004677	-0.003926	0.002156	-0.086947	-0.038366
day	0.004534	-0.003204	-0.001553	-0.004007	-0.003479	0.002712	0.004677	1.000000	-0.017360	-0.012170	0.005617	0.003062
month	0.030817	0.001169	0.001562	0.002391	-0.001193	0.010351	-0.003926	-0.017360	1.000000	-0.115859	-0.008786	0.011628
year	0.141277	0.010198	-0.014243	0.011346	-0.009603	-0.009749	0.002156	-0.012170	-0.115859	1.000000	0.006113	0.024278
dayofweek	0.013652	-0.024652	-0.042310	-0.003336	-0.031919	0.048550	-0.086947	0.005617	-0.008786	0.006113	1.000000	0.027053
dist_travel_km	0.844374	0.098094	-0.046812	0.186531	-0.038900	0.009709	-0.038366	0.003062	0.011628	0.024278	0.027053	1.000000

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

Out[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x8d8affc588>
```



Dividing the dataset into feature and target values

In [37]:
```
x = df[['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_latitude','passenger_count','hour','day','month','year','dayofweek','dist_travel_km']]
```

In [38]:
```
y = df['fare_amount']
```

Dividing the dataset into training and testing dataset

In [39]:
```
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 [40]:
```
from sklearn.linear_model import LinearRegression
regression = LinearRegression()
```

In [41]:
```
regression.fit(X_train,y_train)
```

Out[41]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [42]:
```
regression.intercept_ #To find the linear intercept
```

Out[42]:
```
2809.192377415925
```

In [43]:
```
regression.coef_ #To find the linear coeeficient
```

In [44]:
```
prediction = regression.predict(X_test) #To predict the target values
```

In [45]:
```
print(prediction)
```

```
[10.80422002  4.74707896  9.95283165 ...  5.89597937 17.00144322
  5.38487972]
```

In [46]:
```
y_test
```

Out[46]:
```
16850      8.50
181076     4.10
70798      9.30
87421     12.90
169443    22.25
18976     11.00
50921     13.70
199564    14.50
125215     5.30
67510      8.50
85217     22.25
156903    21.50
116795     4.10
112179    16.90
124459     3.70
173299    22.25
51448     19.70
99502     22.25
174467    10.90
78880     20.50
26798     22.25
38501      4.50
63091     12.90
171207    22.25
142238     8.50
101106     7.30
120177     4.50
154585    14.50
75840      5.50
85918     14.00
          ...
104227    10.10
14172     19.70
49985      3.70
183045     6.50
11927     12.90
93684      4.50
101795    13.70
21444      6.10
85147      8.50
81311      8.00
157686    11.70
194074     6.50
132558    10.50
132616    11.70
188536     5.70
179629     8.90
11277      3.70
147880     7.30
116553     5.70
157394     6.50
103519    13.30
41348     12.90
12608      4.50
6820       5.50
84612      5.00
168836     3.70
39719     21.00
124536     4.90
90432     22.10
12543      4.90
Name: fare_amount, Length: 66000, dtype: float64
```

```
147880     7.30
116553     5.70
157394     6.50
103519    13.30
41348     12.90
12608      4.50
6820       5.50
84612      5.00
168836     3.70
39719     21.00
124536     4.90
90432     22.10
12543      4.90
Name: fare_amount, Length: 66000, dtype: float64
```

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

In [47]:
```python
from sklearn.metrics import r2_score
```

In [48]:
```python
r2_score(y_test,prediction)
```

Out[48]:
```
0.7471032194200018
```

In [49]:
```python
from sklearn.metrics import mean_squared_error
```

In [50]:
```python
MSE = mean_squared_error(y_test,prediction)
```

In [51]:
```python
MSE
```

Out[51]:
```
7.464818887848474
```

In [52]:
```python
RMSE = np.sqrt(MSE)
```

In [53]:
```python
RMSE
```

Out[53]:
```
2.7321820744321696
```

Random Forest Regression

In [54]:
```python
from sklearn.ensemble import RandomForestRegressor
```

In [55]:
```python
rf = RandomForestRegressor(n_estimators=100) #Here n_estimators means number of trees you want to build before making the prediction
```

In [56]:
```python
rf.fit(X_train,y_train)
```

Out[56]:
```
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=100,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
```

In [57]:
```python
y_pred = rf.predict(X_test)
```

In [58]:
```python
y_pred
```

Out[58]:
```
array([ 9.7025,  4.744 ,  9.202 , ...,  6.468 , 16.2802,  4.47  ])
```

Metrics evaluatin for Random Forest

In [59]:
```python
R2_Random = r2_score(y_test,y_pred)
```

In [60]:
```python
R2_Random
```

Out[60]:
```
0.8024361566950065
```

In [64]:
```python
MSE_Random = mean_squared_error(y_test,y_pred)
MSE_Random
```

Out[64]:
```
5.831542440662031
```

In [65]:
```python
RMSE_Random = np.sqrt(MSE_Random)
RMSE_Random
```

Out[65]:
```
2.4148586792319815
```

Assignment 2

1. 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 [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 [9]:
```
df=pd.read_csv("C:\\Users\\Shree\\Downloads\\archive\\emails.csv")
```

In [11]:
```
df.head()
```

Out[11]:

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

5 rows × 3002 columns

In [12]:
```
df.columns
```

Out[12]:
```
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 [13]:
```
df.isnull().sum()
```

Out[13]:
```
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 [14]:
```
df.isnull().sum()
```

Out[14]:
```
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 [15]:
```
df.drop(['Email No.'],axis=1,inplace=True)
X = df.drop(['Prediction'],axis = 1)
```

In [ ]: KNN classifier

In [16]:
```python
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_state = 42)
```

In [17]:
```python
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [18]:
```python
print("Prediction",y_pred)
```

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

In [20]:
```python
print("KNN accuracy = ",metrics.accuracy_score(y_test,y_pred))
```

```
KNN accuracy =  0.8009020618556701
```

In [21]:
```python
 print("Confusion matrix",metrics.confusion_matrix(y_test,y_pred))
```

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

In [ ]: SVM classifier

In [22]:
```python
# cost C = 1
model = SVC(C = 1)
# fit
model.fit(X_train, y_train)
# predict
y_pred = model.predict(X_test)
```

In [23]:
```python
metrics.confusion_matrix(y_true=y_test, y_pred=y_pred)
```

Out[23]:
```
array([[1091,    6],
       [  90,  365]], dtype=int64)
```

In [24]:
```python
 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	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSala
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.8
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.5
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.5
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.6
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.1

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

Out[49]: (10000, 14)

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

Out[50]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000

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

Out[51]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedS
0	False	False	False	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	False	False	F

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

Out[51]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSa
0	False	False	False	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	False	False	False	F
...	...	...	...	...	...	...	...	...	...	...	...	...	
9995	False	False	False	False	False	False	False	False	False	False	False	False	F
9996	False	False	False	False	False	False	False	False	False	False	False	False	F
9997	False	False	False	False	False	False	False	False	False	False	False	False	F
9998	False	False	False	False	False	False	False	False	False	False	False	False	F
9999	False	False	False	False	False	False	False	False	False	False	False	False	F

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]:
```
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]:
```
df.dtypes
```

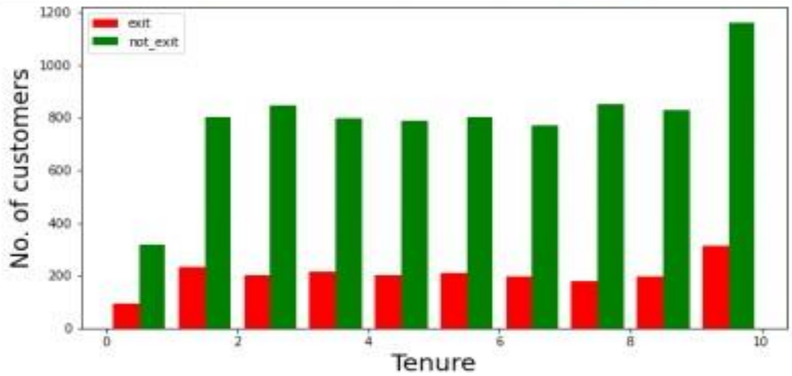
Out[54]:
```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard        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

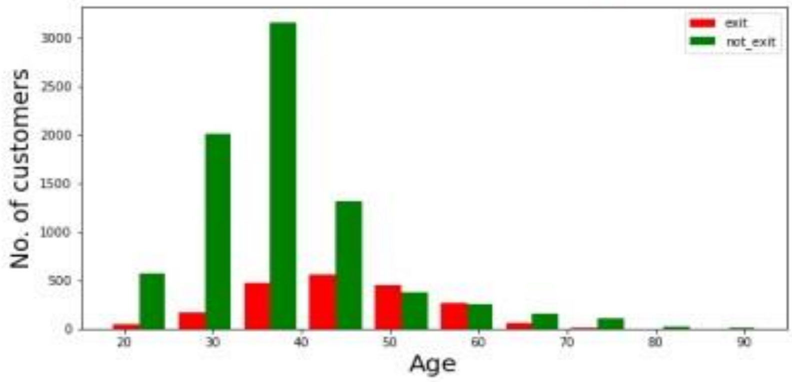
In [55]:
```
df.columns
```

In [55]:
```
df.columns
```
Out[55]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```
In [56]:
```
df = df.drop(['RowNumber', 'Surname', 'CustomerId'], axis= 1) #Dropping the unnecessary columns
```
In [57]:
```
df.head()
```
Out[57]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

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")
```


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

In [76]:
```
classifier.add(Dense(activation = "sigmoid",units = 1,kernel_initializer = "uniform")) #Final neuron will be having siigmoid function
```

In [77]:
```
classifier.compile(optimizer="adam",loss = 'binary_crossentropy',metrics = ['accuracy']) #To compile the Artificial Neural Network. Ussed Binary crossentropy as we just have only two output
```

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

```
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 training dataset
```

```
Epoch 1/50
700/700 [==============================] - 0s 674us/step - loss: 0.4293 - accuracy: 0.7947
Epoch 2/50
700/700 [==============================] - 0s 647us/step - loss: 0.4239 - accuracy: 0.7947
Epoch 3/50
700/700 [==============================] - 0s 657us/step - loss: 0.4203 - accuracy: 0.8067
Epoch 4/50
700/700 [==============================] - 0s 664us/step - loss: 0.4167 - accuracy: 0.8260
Epoch 5/50
700/700 [==============================] - 0s 674us/step - loss: 0.4153 - accuracy: 0.8287
Epoch 6/50
700/700 [==============================] - 0s 653us/step - loss: 0.4137 - accuracy: 0.8310
Epoch 7/50
700/700 [==============================] - 0s 658us/step - loss: 0.4125 - accuracy: 0.8317
Epoch 8/50
700/700 [==============================] - 1s 842us/step - loss: 0.4116 - accuracy: 0.8306
Epoch 9/50
700/700 [==============================] - 0s 671us/step - loss: 0.4103 - accuracy: 0.8331
Epoch 10/50
700/700 [==============================] - 0s 682us/step - loss: 0.4100 - accuracy: 0.8326
Epoch 11/50
700/700 [==============================] - 0s 690us/step - loss: 0.4093 - accuracy: 0.8337
Epoch 12/50
700/700 [==============================] - 0s 688us/step - loss: 0.4087 - accuracy: 0.8339
Epoch 13/50
700/700 [==============================] - 0s 675us/step - loss: 0.4081 - accuracy: 0.8341
Epoch 14/50
700/700 [==============================] - 1s 722us/step - loss: 0.4071 - accuracy: 0.8331
Epoch 15/50
700/700 [==============================] - 1s 811us/step - loss: 0.4065 - accuracy: 0.8341
Epoch 16/50
700/700 [==============================] - 0s 711us/step - loss: 0.4056 - accuracy: 0.8356
Epoch 17/50
700/700 [==============================] - 0s 702us/step - loss: 0.4046 - accuracy: 0.8366
Epoch 18/50
700/700 [==============================] - 0s 688us/step - loss: 0.4035 - accuracy: 0.8343
Epoch 19/50
700/700 [==============================] - 1s 715us/step - loss: 0.4024 - accuracy: 0.8363
Epoch 20/50
700/700 [==============================] - 0s 714us/step - loss: 0.4020 - accuracy: 0.8337
Epoch 21/50
700/700 [==============================] - 0s 705us/step - loss: 0.4010 - accuracy: 0.8374
Epoch 22/50
700/700 [==============================] - 1s 720us/step - loss: 0.4003 - accuracy: 0.8370
Epoch 23/50
700/700 [==============================] - 0s 692us/step - loss: 0.3993 - accuracy: 0.8374
Epoch 24/50
700/700 [==============================] - 0s 709us/step - loss: 0.3990 - accuracy: 0.8356
Epoch 25/50
700/700 [==============================] - 1s 871us/step - loss: 0.3984 - accuracy: 0.8366
Epoch 26/50
700/700 [==============================] - 1s 719us/step - loss: 0.3984 - accuracy: 0.8367
Epoch 27/50
700/700 [==============================] - 1s 719us/step - loss: 0.3980 - accuracy: 0.8366
Epoch 28/50
700/700 [==============================] - 0s 695us/step - loss: 0.3981 - accuracy: 0.8366
Epoch 29/50
700/700 [==============================] - 0s 667us/step - loss: 0.3976 - accuracy: 0.8374
Epoch 30/50
700/700 [==============================] - 0s 669us/step - loss: 0.3972 - accuracy: 0.8373
```

```
700/700 [==============================] - 1s 771us/step - loss: 0.3960 - accuracy: 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 - accuracy: 0.8373
Epoch 39/50
700/700 [==============================] - 1s 823us/step - loss: 0.3950 - accuracy: 0.8384
Epoch 40/50
700/700 [==============================] - 1s 759us/step - loss: 0.3956 - accuracy: 0.8361
Epoch 41/50
700/700 [==============================] - 1s 773us/step - loss: 0.3949 - accuracy: 0.8366
Epoch 42/50
700/700 [==============================] - 0s 695us/step - loss: 0.3953 - accuracy: 0.8369
Epoch 43/50
700/700 [==============================] - 0s 701us/step - loss: 0.3952 - accuracy: 0.8369
Epoch 44/50
700/700 [==============================] - 0s 707us/step - loss: 0.3952 - accuracy: 0.8366
Epoch 45/50
700/700 [==============================] - 0s 680us/step - loss: 0.3955 - accuracy: 0.8376
Epoch 46/50
700/700 [==============================] - 0s 665us/step - loss: 0.3947 - accuracy: 0.8373
Epoch 47/50
700/700 [==============================] - 0s 708us/step - loss: 0.3947 - accuracy: 0.8371
Epoch 48/50
700/700 [==============================] - 0s 681us/step - loss: 0.3944 - accuracy: 0.8371
Epoch 49/50
700/700 [==============================] - 0s 678us/step - loss: 0.3947 - accuracy: 0.8383
Epoch 50/50
700/700 [==============================] - 1s 869us/step - loss: 0.3944 - accuracy: 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)
```

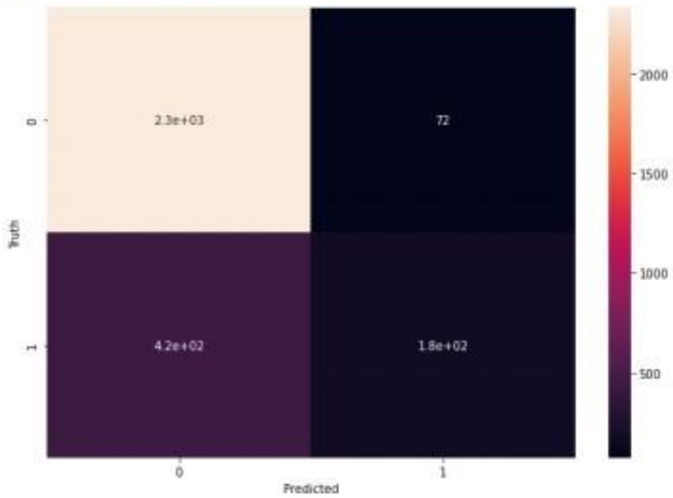
In [94]:
```
accuracy = accuracy_score(y_test,y_pred)
```

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
```

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	STATUS	QTR_ID	MONTH_ID	YEAR_ID	...	ADDRESSLINI
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped	1	2	2003	...	897 Long Airp Aven
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped	2	5	2003	...	59 rue l'Abba
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped	3	7	2003	...	27 rue Colonel Pier Av
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped	3	8	2003	...	78934 Hillsi I
4	10159	49	100.00	14	5205.27	10/10/2003 0:00	Shipped	4	10	2003	...	7734 Strong S

5 rows × 25 columns

In [202]:
```
df.shape
```

Out[202]: (2823, 25)

In [203]:
```
df.describe()
```

Out[203]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	QTR_ID	MONTH_ID	YEAR_ID	MSRP
count	2823.000000	2823.000000	2823.000000	2823.000000	2823.000000	2823.000000	2823.000000	2823.00000	2823.000000
mean	10258.725115	35.092809	83.658544	6.466171	3553.889072	2.717676	7.092455	2003.81509	100.715551
std	92.085478	9.741443	20.174277	4.225841	1841.865106	1.203878	3.656633	0.69967	40.187912
min	10100.000000	6.000000	26.880000	1.000000	482.130000	1.000000	1.000000	2003.00000	33.000000
25%	10180.000000	27.000000	68.860000	3.000000	2203.430000	2.000000	4.000000	2003.00000	68.000000
50%	10262.000000	35.000000	95.700000	6.000000	3184.800000	3.000000	8.000000	2004.00000	99.000000
75%	10333.500000	43.000000	100.000000	9.000000	4508.000000	4.000000	11.000000	2004.00000	124.000000
max	10425.000000	97.000000	100.000000	18.000000	14082.800000	4.000000	12.000000	2005.00000	214.000000

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
```

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', 'TERRITORY', 'PHONE', 'STATE', 'CONTACTFIRSTNAME', 'CONTACTLASTNAME', 'CUSTOMERNAME', 'ORDERNUMBER']
df = df.drop(df_drop, axis=1) #Dropping the categorical uneccessary columns along with columns having null values. Can't fill the null values are there are alot of null values.
```

In [208]:
```
df.isnull().sum()
```

Out[208]:
```
QUANTITYORDERED    0
PRICEEACH          0
ORDERLINENUMBER    0
SALES              0
ORDERDATE          0
QTR_ID             0
MONTH_ID           0
```

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 alot of countries.
df = df.drop(df_drop, axis=1)
```

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

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

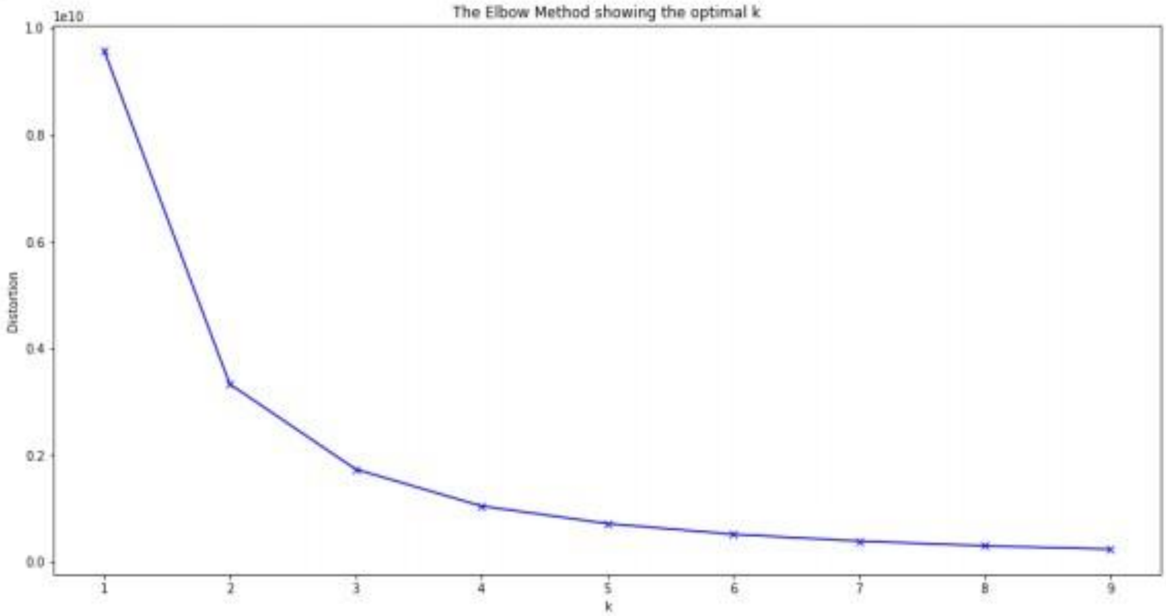
In [218]:
```
df.dtypes #All the datatypes are converted into numeric
```

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 Distortions
```

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 easy to visualize using Principal C
Omponent Analysis.
```

Visualization

In [229]:
```
pca = PCA(n_components=2) #Converting all the features into 2 columns to make it easy to visualize using Principal C
Omponent Analysis.
```

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

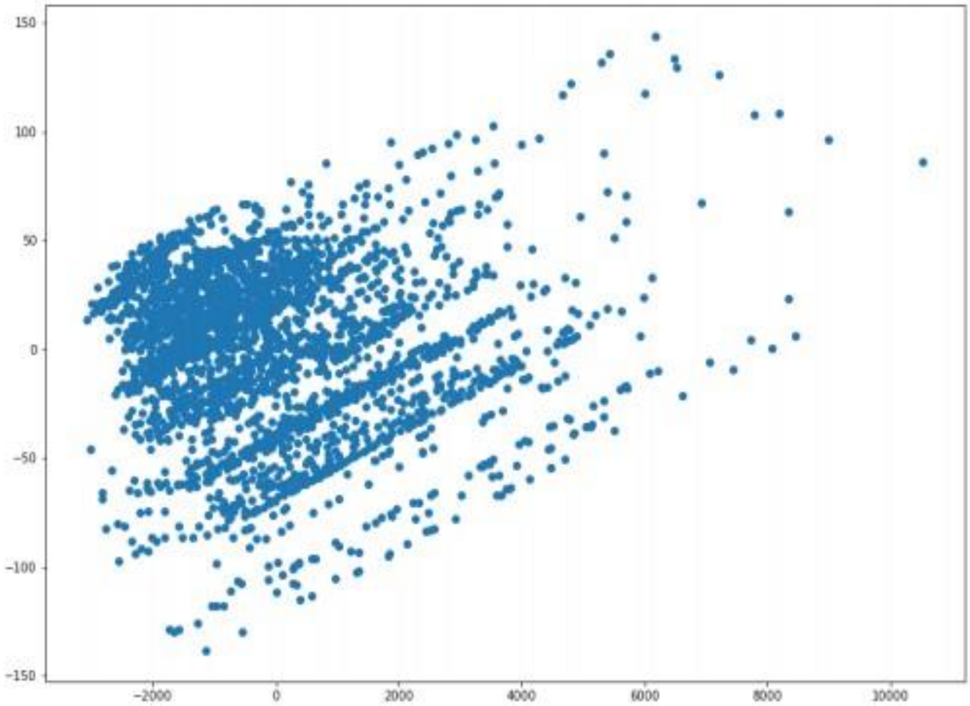
In [231]:
```
reduced_X.head()
```

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 contains a centroids for particular
feature )
```

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,  6.24871902e+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]])
```

```
         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]])
```

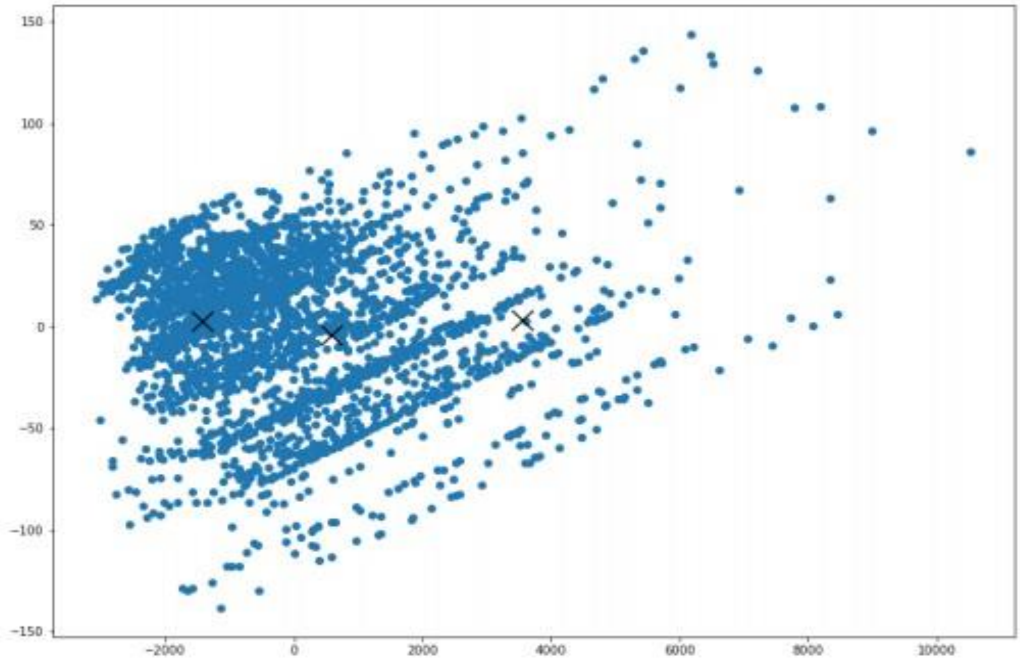
In [234]:
```
reduced_centers = pca.transform(model.cluster_centers_) #Transforming the centroids into 3 in x and y coordinates
```

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=300) #Plotting the centroids
```

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 the same cluster number and second
column     Assigning the color
plt.scatter(reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA2'],
color='slateblue')
plt.scatter(reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA2'],
color='springgreen')
plt.scatter(reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA2'],
color='indigo')


plt.scatter(reduced_centers[:,0],reduced_centers[:,1],color='black',marker='x',s=300)
```

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 the same cluster number and second column      Assigning the color
plt.scatter(reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA2'],color='slateblue')
plt.scatter(reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA2'],color='springgreen')
plt.scatter(reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA2'],color='indigo')


plt.scatter(reduced_centers[:,0],reduced_centers[:,1],color='black',marker='x',s=300)
```

Out[239]: <matplotlib.collections.PathCollection at 0x218dce9e1f0>