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

```
1 import pandas as pd
2 import numpy as np
3 import seaborn as sns
4 import matplotlib.pyplot as plt
5 #Importing the required libraries.
```

```
1 from sklearn.cluster import KMeans, k_means #For clustering
2 from sklearn.decomposition import PCA #Linear Dimensionality reduction.
```

```
1 df = pd.read_csv('sales_data_sample.csv', encoding = "Latin-1")
2 #df = pd.read_csv("sales_data_sample.csv") #Loading the dataset.
```

Preprocessing

```
1 df.head()
```

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

5 rows × 25 columns

```
1 df.shape
```

```
(2823, 25)
```

```
1 df.describe()
```

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	2
count	2823.000000	2823.000000	2823.000000	2823.000000	2823.000000	
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	

```
1 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
```

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

```
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
```

```
df.dtypes
```

```
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
```

```
df_drop  = ['ADDRESSLINE1', 'ADDRESSLINE2', 'STATUS','POSTALCODE', 'CITY', 'TERRITORY', 'PHONE', 'STATE', 'CONTA
df = df.drop(df_drop, axis=1) #Dropping the categorical uneccessary columns along with columns having null value
```

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

```
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
```

```
1 df.dtypes
```

```
    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
```

```
1 # Checking the categorical columns.
```

```
1 df['COUNTRY'].unique()
```

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

```
1 df['PRODUCTLINE'].unique()
```

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

```
1 df['DEALSIZE'].unique()
```

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

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

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

```
1 df_drop  = ['COUNTRY','PRODUCTLINE','DEALSIZE'] #Dropping Country too as there are alot of countries.
2 df = df.drop(df_drop, axis=1)
```

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

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

```
1 df.dtypes #All the datatypes are converted into numeric
```

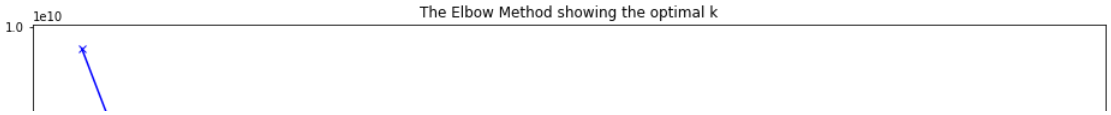
```
    QUANTITYORDERED       int64
    PRICEEACH           float64
    ORDERLINENUMBER       int64
```

```
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.

```
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
```

```
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.

```
1 X_train = df.values #Returns a numpy array.
```

```
1 X_train.shape
```

```
(2823, 19)
```

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

```
1 unique,counts = np.unique(predictions,return_counts=True)
```

```
1 counts = counts.reshape(1,3)
```

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

```
1 counts_df.head()
```

	Cluster1	Cluster2	Cluster3
0	1083	1367	373

Visualization

```
1 pca = PCA(n_components=2) #Converting all the features into 2 columns to make it easy to visualize using Princip
```

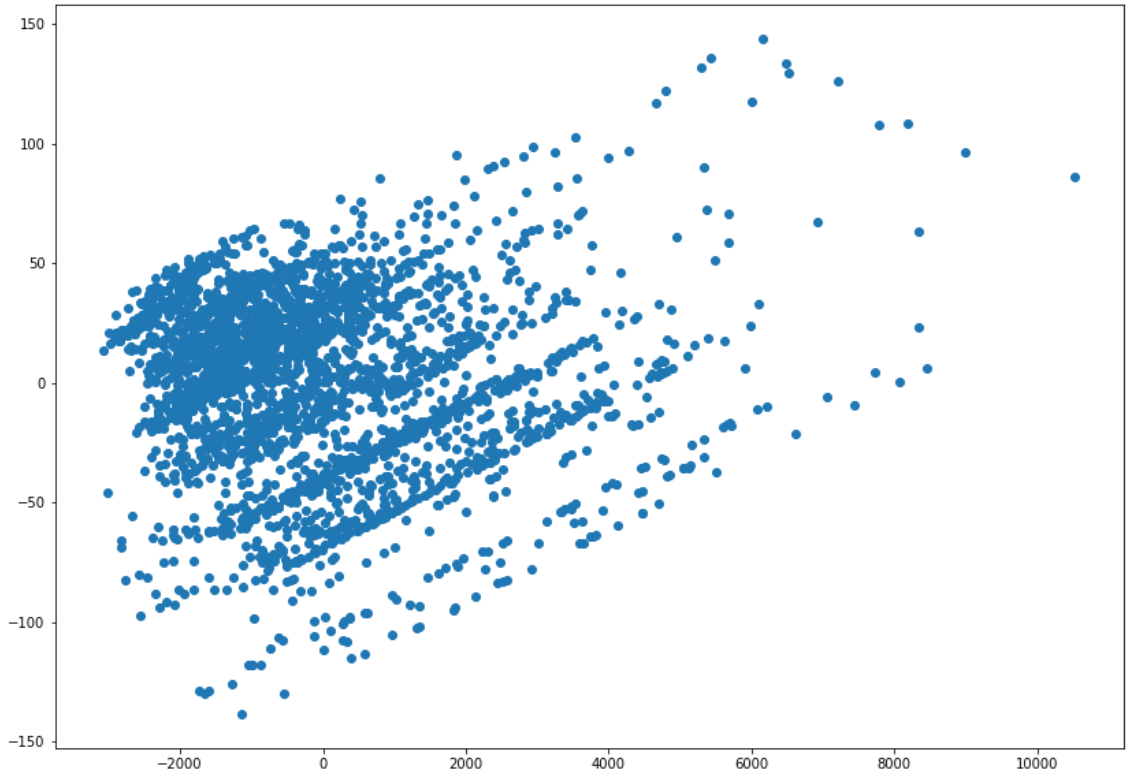
```
1 reduced_X = pd.DataFrame(pca.fit_transform(X_train),columns=['PCA1','PCA2']) #Creating a DataFrame.
```

```
1 reduced_X.head()
```

	PCA1	PCA2

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

```
<matplotlib.collections.PathCollection at 0x7f0fe6fad810>
```




```
1 model.cluster_centers_ #Finding the centriods. (3 Centriods in total. Each Array contains a centroids for partic
```

```
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,
        -3.38618023e-15],
       [ 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,
        -1.99840144e-15]])
```

```
1 reduced_centers = pca.transform(model.cluster_centers_) #Transforming the centroids into 3 in x and y coordinate
```

+ Code + Text

```
1 reduced_centers
```

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

```
1 plt.figure(figsize=(14,10))
2 plt.scatter(reduced_X['PCA1'],reduced_X['PCA2'])
3 plt.scatter(reduced_centers[:,0],reduced_centers[:,1],color='black',marker='x',s=300) #Plotting the centriods
```

```
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```
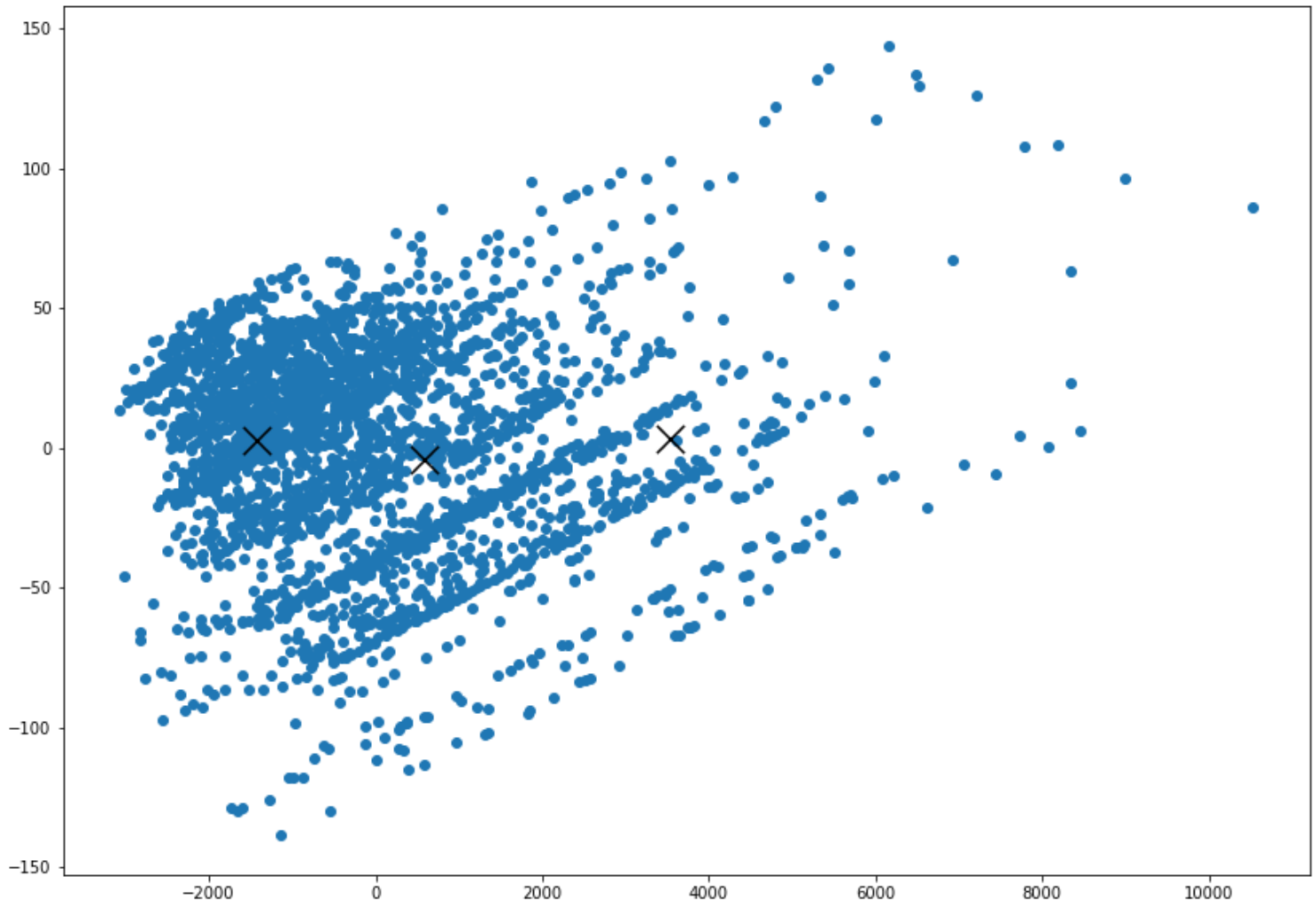



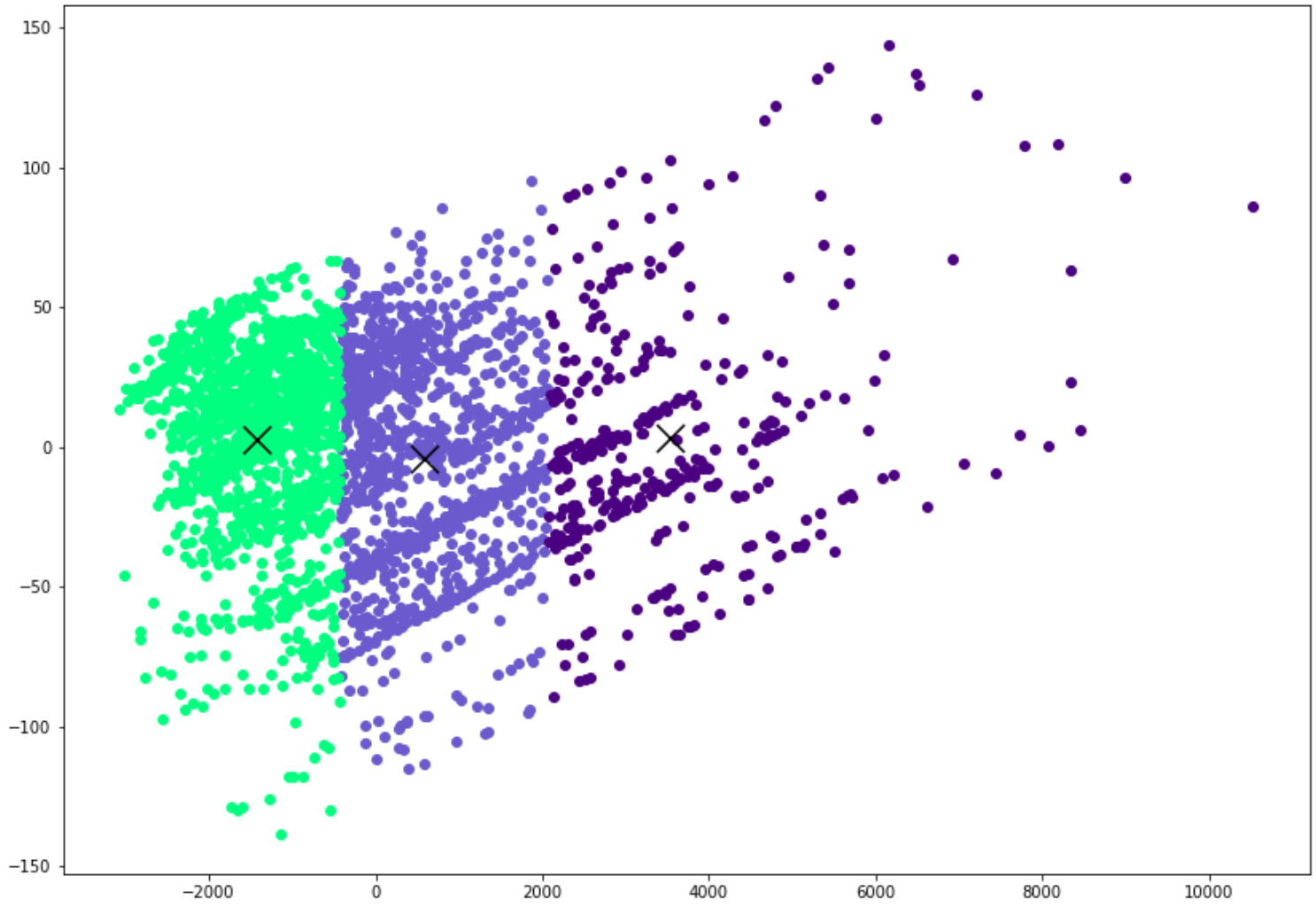

```
1 reduced_X['Clusters'] = predictions #Adding the Clusters to the reduced dataframe.
```

```
1 reduced_X.head()
```

	PCA1	PCA2	Clusters
0	-682.488323	-42.819535	1
1	-787.665502	-41.694991	1
2	330.732170	-26.481208	0

```
#Plotting the clusters
plt.figure(figsize=(14,10))
#                     taking the cluster number and first column          taking the same cluster number and se
plt.scatter(reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA
plt.scatter(reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA
plt.scatter(reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA


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

```
<matplotlib.collections.PathCollection at 0x7f0fe700c1d0>
```



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