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', 'TERRI
          df = df.drop(df_drop, axis=1) #Dropping the categorical uneccessary columns along
```

```
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 colum
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 ar
df = df.drop(df_drop, axis=1)
```

In [216]:

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

In [217]:

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

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
```

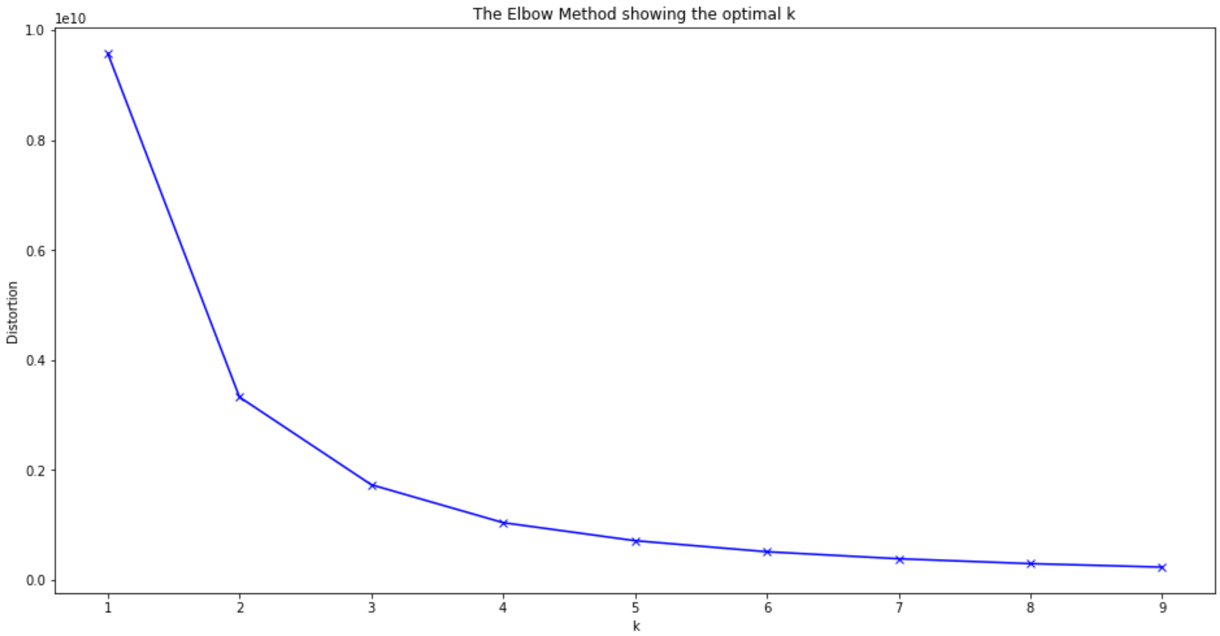
Plotting the Elbow Plot to determine the number of clusters.

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 Disto
```

In [220]:

```python
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]:

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

In [222]:

```python
X_train.shape
```

Out[222]:

```
(2823, 19)
```

In [223]:

```python
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]:

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

In [226]:

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

In [227]:

```python
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
```

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

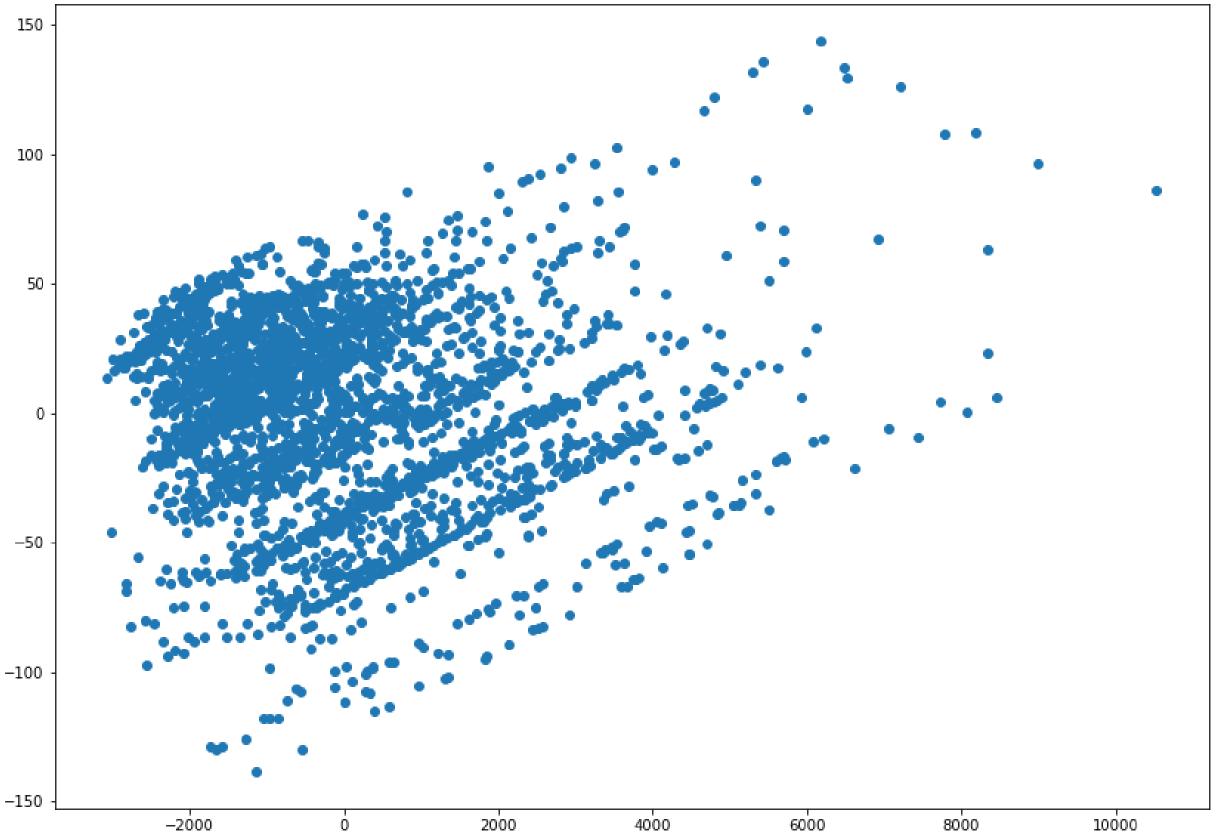
In [231]:
```
reduced_X.head()
```

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

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]])
```

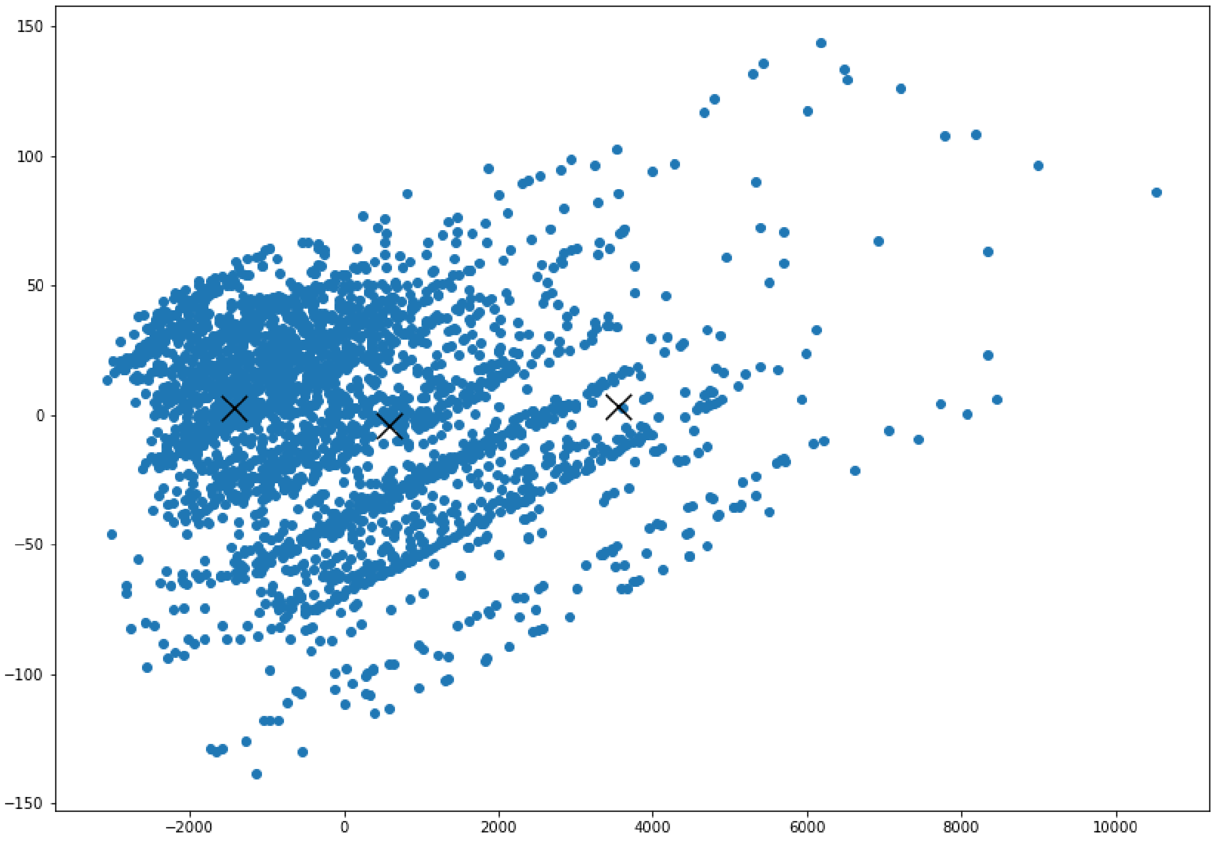
In [234]:
```
reduced_centers = pca.transform(model.cluster_centers_) #Transforming the centro
```

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=
```

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

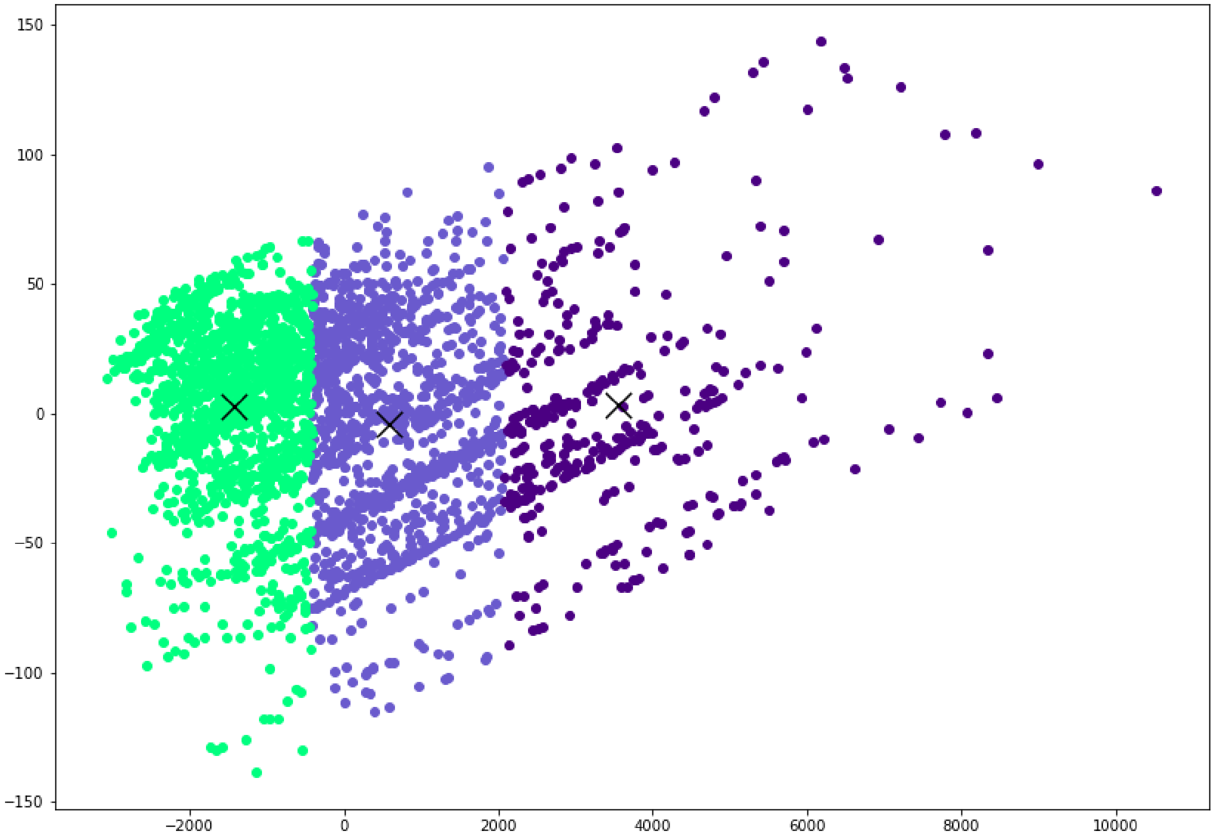
In [239]:

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


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

Out[239]:

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


150
100
50
0
−50
−100
−150
−2000
0
2000
4000
6000
8000
10000