```
# Implement K-Means clustering/ hierarchical clustering on sales_data_sample.csv dataset. Determine the number of clusters us

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
#Importing the required libraries.

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

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

```
df.head()
```

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID	...	ADDR
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped	1	2	2003	...	Airp
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped	2	5	2003	...	
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped	3	7	2003	...	Co
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped	3	8	2003	...	78
4	10159	49	100.00	14	5205.27	10/10/2003 0:00	Shipped	4	10	2003	...	773

5 rows × 25 columns

```
df.shape
```

```
(2823, 25)
```

```
df.describe()
```

	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

```
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_drop  = ['ADDRESSLINE1', 'ADDRESSLINE2', 'STATUS','POSTALCODE', 'CITY', 'TERRITORY', 'PHONE', 'STATE', 'CONTACTFIRSTNAME',
df = df.drop(df_drop, axis=1) #Dropping the categorical uneccessary columns along with columns having null values. Can't fill
```

```
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
```

```
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
```

```
# Checking the categorical columns.
df['COUNTRY'].unique()
df['PRODUCTLINE'].unique()
df['DEALSIZE'].unique()
```

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

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

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

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

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

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

```
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
```

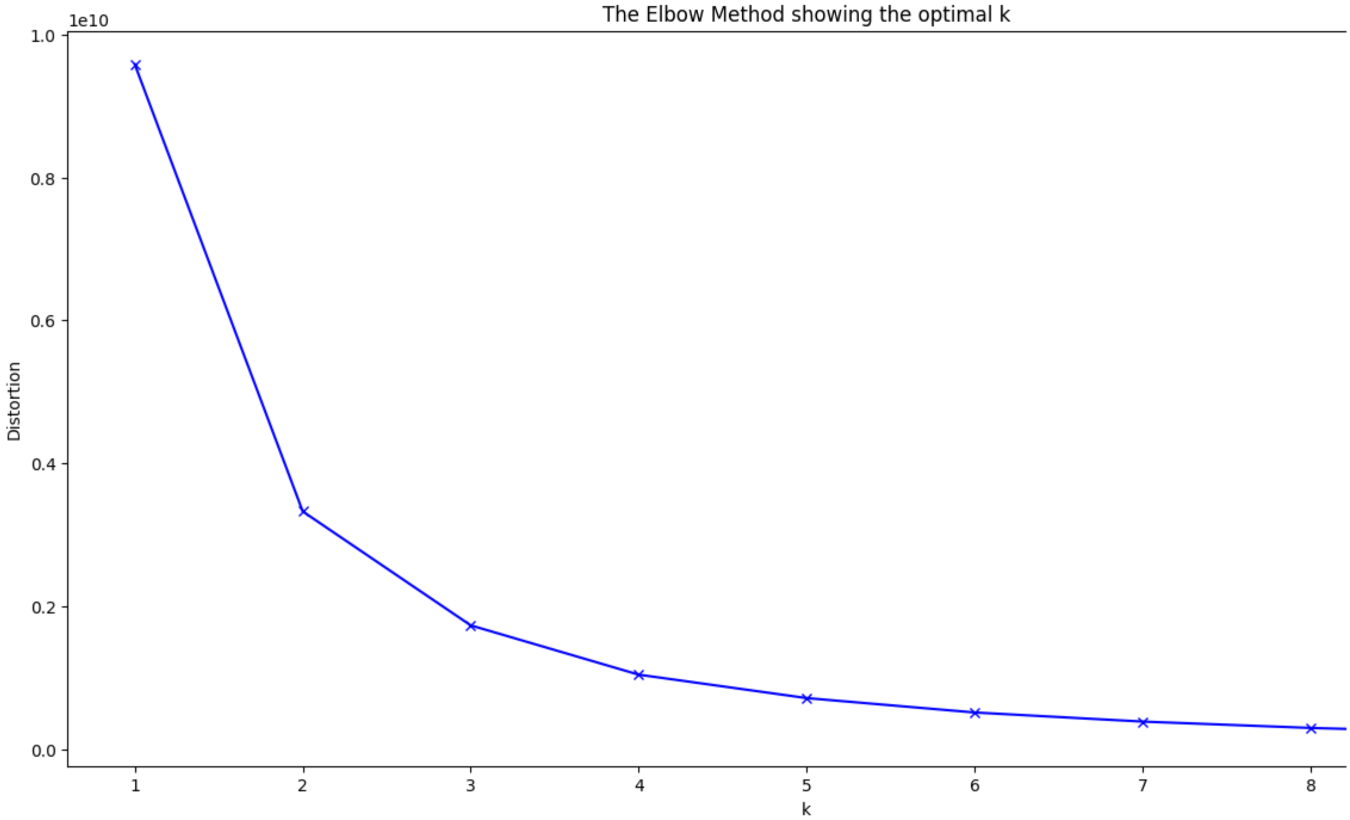
```
Classic Cars          uint8
Motorcycles           uint8
Planes                uint8
Ships                 uint8
Trains                uint8
Trucks and Buses      uint8
Vintage Cars          uint8
Large                 uint8
Medium                uint8
Small                 uint8
dtype: object
```

```
## 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
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
```

```
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.
print("Observations: A Elbow can be observed at 3 and after that the curve decreases gradually. ")

X_train = df.values #Returns a numpy array.

X_train.shape
```

```
Observations: A Elbow can be observed at 3 and after that the curve decreases gradually.
(2823, 19)
```

```
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)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
```

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

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

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

```
counts_df.head()
```

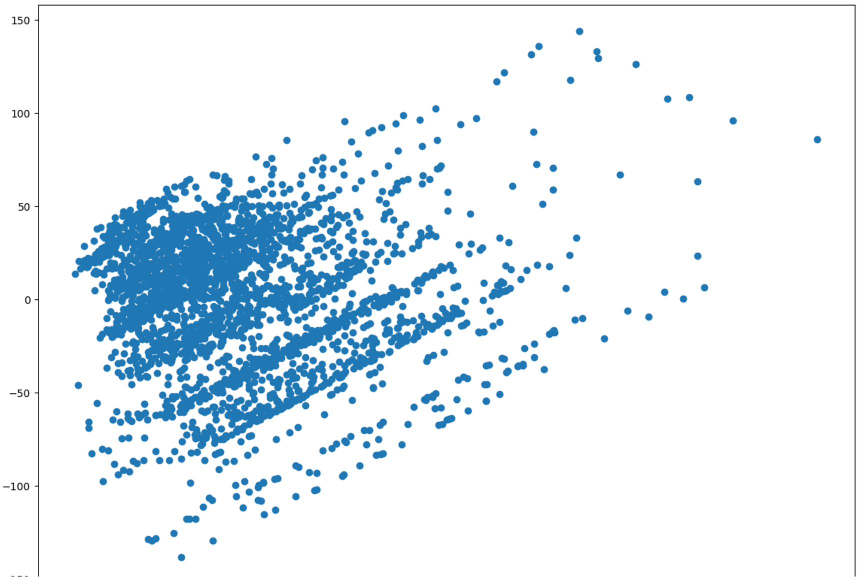
	Cluster1	Cluster2	Cluster3
0	1083	1367	373

```
## Visualization

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

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

reduced_X.head()
```

	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

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

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

```
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]])
```

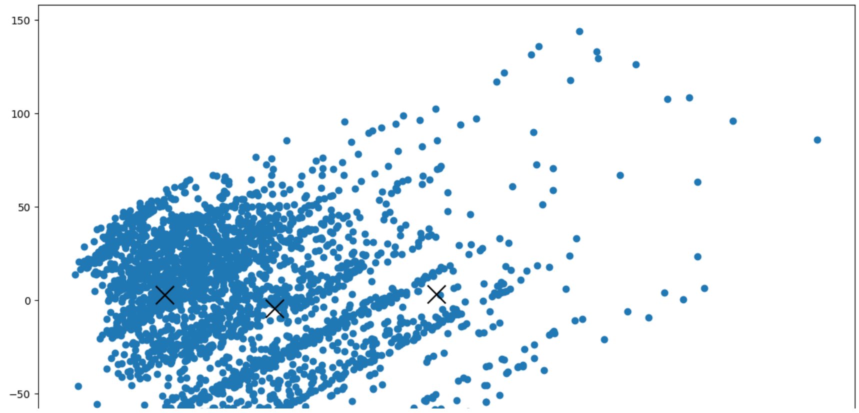



```
reduced_centers = pca.transform(model.cluster_centers_) #Transforming the centroids into 3 in x and y coordinates

reduced_centers
```

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

```
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 centriods
```

```
<matplotlib.collections.PathCollection at 0x7ff0f518d1e0>
```




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

```
reduced_X.head()
```

	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

```
#Plotting the clusters
plt.figure(figsize=(14,10))
#                      taking the cluster number and first column           taking the same cluster number and second column
plt.scatter(reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 0].loc[:,'PCA2'],color='sl
plt.scatter(reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 1].loc[:,'PCA2'],color='sp
plt.scatter(reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA1'],reduced_X[reduced_X['Clusters'] == 2].loc[:,'PCA2'],color='in
```

<matplotlib.collections.PathCollection at 0x7ff0f5cc5240>


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

<matplotlib.collections.PathCollection at 0x7ff0f5d91f00>