Project 1

Group 19

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```
#importing the necessary libraries to perform the tasks
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Task 1

Dataset 1

```
#creating a dataframe using the first dataset
df1 = pd.read_csv('Data1.csv')
```

```
#displaying the first dataframe
df1
```

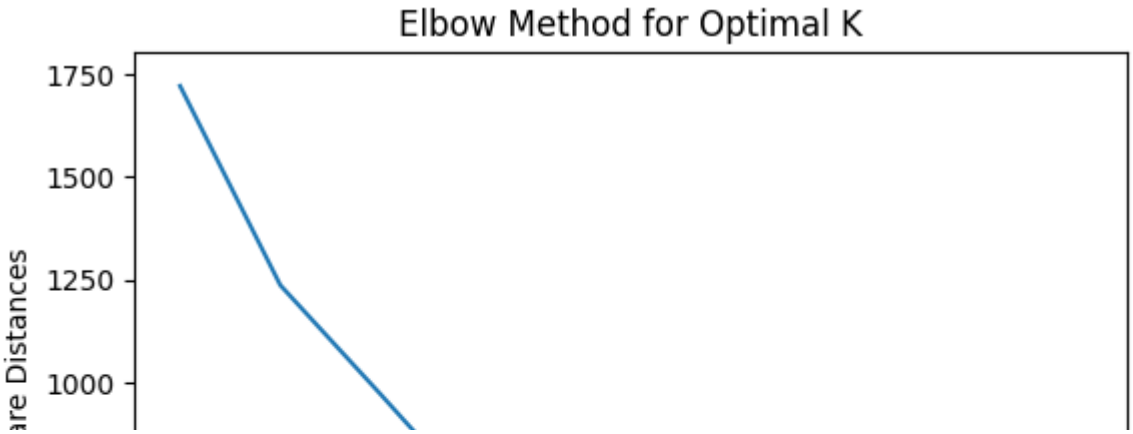
	Unnamed: 0	X1	X2	X3	Class
0	1	-0.063274	0.027734	0.022683	1
1	2	-0.000731	0.048211	0.069198	1

```
#using the head() function to display the first five rows of the dataset
df1.head()
```

	Unnamed: 0	X1	X2	X3	Class
0	1	-0.063274	0.027734	0.022683	1
1	2	-0.000731	0.048211	0.069198	1
2	3	-0.060767	-0.009080	0.053085	1
3	4	0.013252	-0.011876	0.055324	1
4	5	-0.054508	-0.003813	0.001738	1

```
#here, we are implementing the elbow method to determine the optimal number of clusters
k = []
wcss = []
for i in range(1,11):
  mdl = KMeans(n_clusters = i, n_init = 10)
  mdl.fit(df1.iloc[:,1:4])
  k.append(i)
  wcss.append(mdl.inertia_)


#creating an elbow plot to find the number of clusters
#here k denotes the number of clusters and wcss stands for within-cluster sum of squares

sns.lineplot(x = k, y = wcss)
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
#we are now generating labels since we know the optimal number of clusters from the above
KModel = KMeans(n_clusters = 7,
             init = 'k-means++',)
KModel.fit(df1.iloc[:,1:4])
```

```
KMeans
KMeans(n_clusters=7)
```

```
#displaying the array generated
KModel.labels_
```

```
array([3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 6, 6,
       6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6,
       6, 6, 6, 6, 6, 6, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4], dtype=int32)
```

```
#here we are returning the coordinates of the centroids of the clusters
KModel.cluster_centers_
```

```
array([[ 2.27123000e-02, -2.96813597e+00, -1.11774567e-01],
       [ 2.99953830e+00, -1.13086667e-03, -1.40059600e-01],
       [ 1.39986933e-01,  3.08174697e+00,  7.45050000e-02],
       [-4.24071875e-03,  4.75815625e-03,  7.24671875e-03],
       [-4.72621667e-02,  4.58006333e-02, -3.04276190e+00],
       [-2.99518840e+00, -1.37363333e-02,  8.82396000e-02],
       [-6.31190000e-03,  9.19421333e-02,  2.87236200e+00]])
```

```
#in this line, we are assigning the above coordinates to the centroid variable
centroid = KModel.cluster_centers_
```

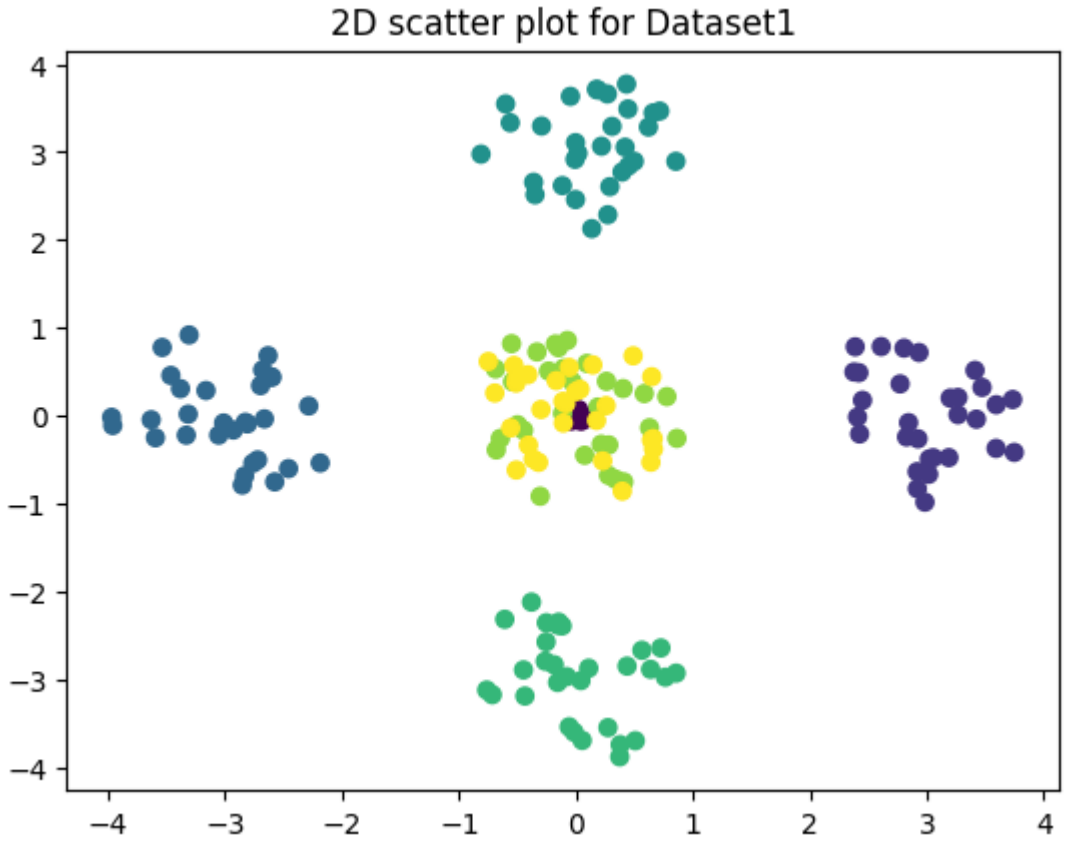
```
#now we are assigning labels to the original dataset based on the values we obtained abov
df1_cluster = df1.copy()
df1_cluster["Cluster"] = KModel.fit_predict(df1)


#displaying the first five rows of the updated dataframe
df1_cluster.head()
```

	Unnamed: 0	X1	X2	X3	Class	Cluster
0	1	-0.063274	0.027734	0.022683	1	6
1	2	-0.000731	0.048211	0.069198	1	6
2	3	-0.060767	-0.009080	0.053085	1	6
3	4	0.013252	-0.011876	0.055324	1	6
4	5	-0.054508	-0.003813	0.001738	1	6

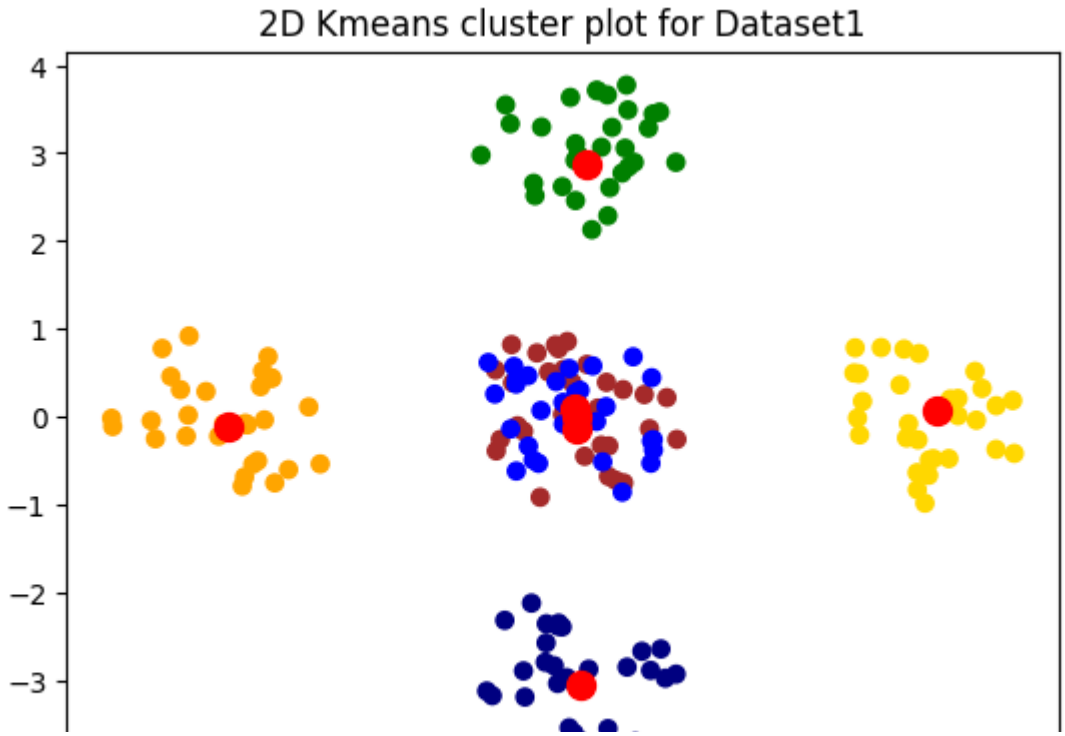
```
#in this line of code, we are creating an list of random colours to be able to visualize
colours = ['Gold','Brown','Navy','Blue','Orange','green','yellow']


#here, a new column called color is being added to the dataframe
#we are also mapping values in the cluster column to their respective colours
df1_cluster['Color'] = df1_cluster['Cluster'].map(lambda p:colours[p])


#viewing the updated dataframe
df1_cluster
```

```
          Unnamed: 0        X1        X2        X3  Class  Cluster  Color
```

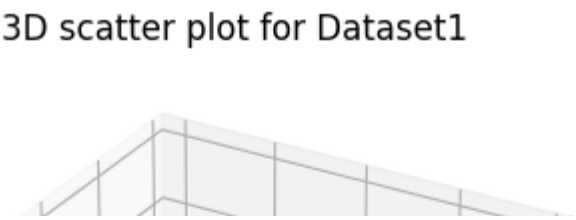
```
#we have created a 2-D scatter plot to visualize our data

%matplotlib inline
#plt.figure(figsize = (10, 10))
plt.title("2D scatter plot for Dataset1")
plt.scatter(df1_cluster['X1'],
            df1_cluster['X2'],
            c = df1_cluster['Class'])
plt.show()
```



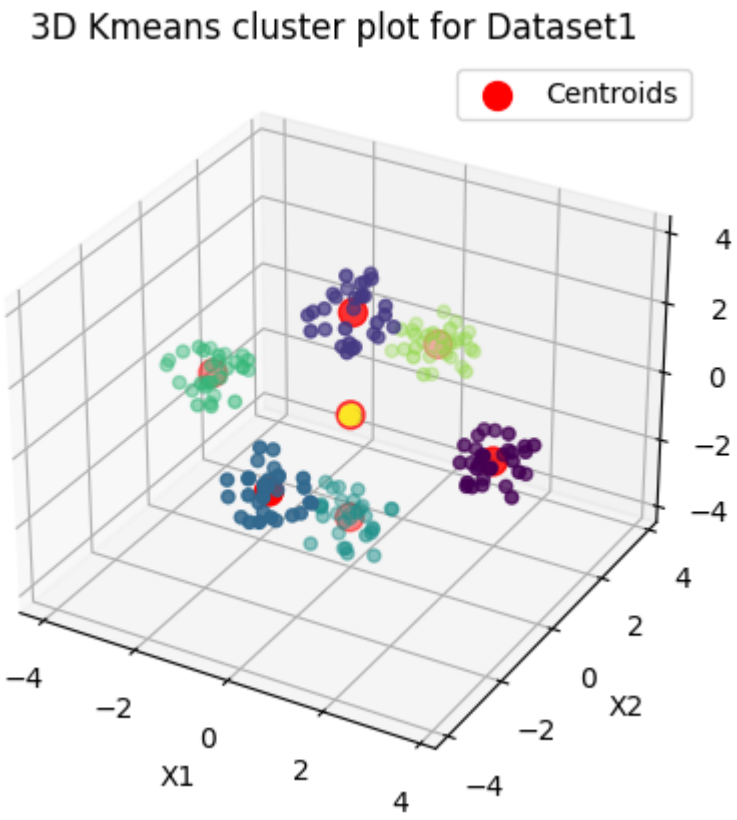

```
#here we are visualizing the various clusters in thier respective colors

%matplotlib inline
#plt.figure(figsize = (10, 10))
plt.title("2D Kmeans cluster plot for Dataset1")
plt.scatter(df1_cluster['X1'],
            df1_cluster['X2'],
            c = df1_cluster['Color'])
plt.scatter(centroid[:, 1], centroid[:, 2], c = 'red', s = 100)
plt.show()
```




```
#in this block, we are creaing a 3-D scatter plot for the first dataset

%matplotlib notebook
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
plt.ion()
plt.title("3D scatter plot for Dataset1")
ax.scatter(df1_cluster['X1'], df1_cluster['X2'], df1_cluster['X3'], c = df1_cluster['Clas
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.show()
```

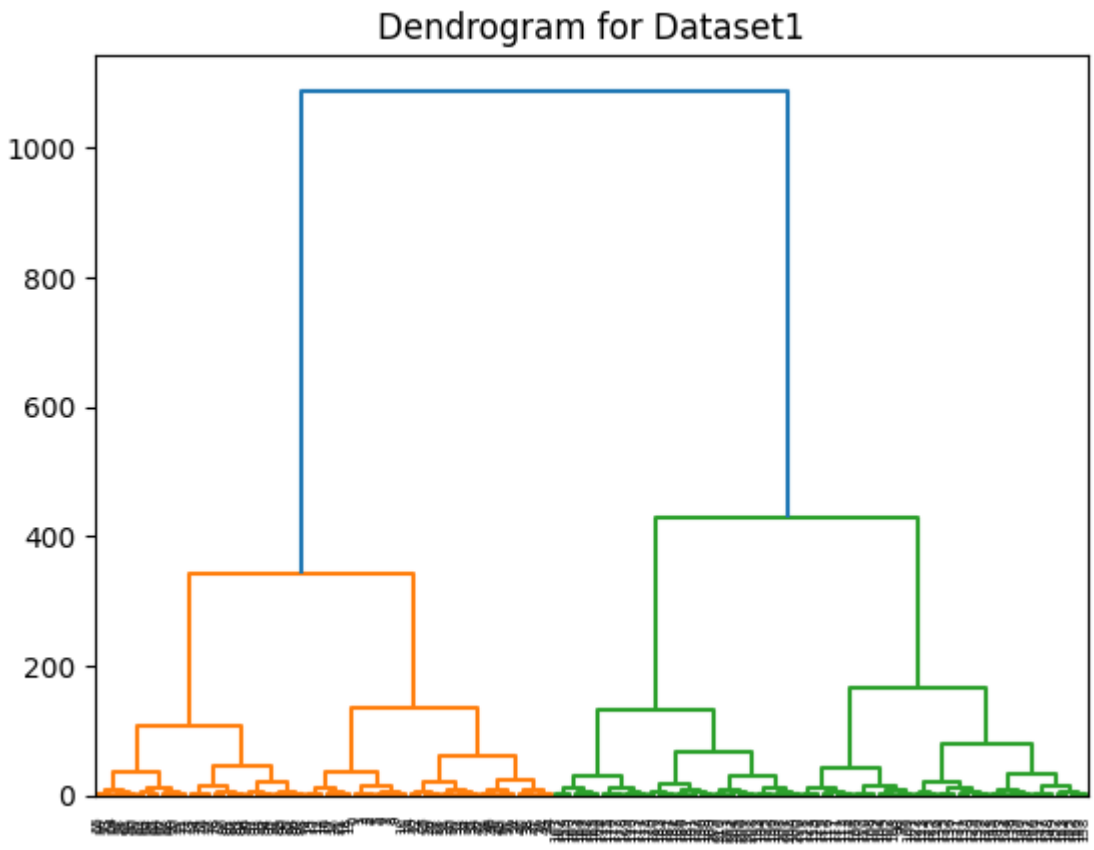



```
#in this segment, we are creating a 3-D cluster plot for the first dataset

%matplotlib notebook
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
plt.ion()
plt.title("3D Kmeans cluster plot for Dataset1")
ax.scatter(df1_cluster['X1'], df1_cluster['X2'], df1_cluster['X3'], c = df1_cluster['Clus
ax.scatter(centroid[:, 0], centroid[:, 1], centroid[:,2], c = 'red', s = 100, label = 'Ce
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.legend()
plt.show()
```




```
#here,we are performing hierarchical clustering through the means of a dendogram

import scipy.cluster.hierarchy as sch
from scipy.cluster.hierarchy import dendrogram, linkage
%matplotlib inline
```

```
dendrogram = sch.dendrogram(sch.linkage(df1_cluster.iloc[:,0:3], method = 'ward'))
plt.title('Dendrogram for Dataset1')
plt.show()
```



Please refer the comments of the operations on the first dataset because we are implementing the same techniques for the further ones

Task 2

```
df2 = pd.read_csv('Data2.csv')
```

```
df2
```

	Unnamed: 0	X	Y	C	Class
0	X1	3.277701	0.814082	0.326574	1
1	X2	0.387577	0.176780	0.888046	1
2	X3	0.268546	0.582963	0.080981	1
3	X4	2.031145	0.244597	0.643921	1
4	X5	0.188677	0.461280	0.496633	1
...	...	...	...	...	...

```
#we are only selecting the columns required to perform appropriate operations
df2_subset = df2[['X','Y','C','Class']]
```

```
df2_subset
```

	X	Y	C	Class
0	3.277701	0.814082	0.326574	1
1	0.387577	0.176780	0.888046	1
2	0.268546	0.582963	0.080981	1
3	2.031145	0.244597	0.643921	1
4	0.188677	0.461280	0.496633	1
...	...	...	...	...
399	3.248655	2.297291	3.388138	3
400	4.100000	5.100000	0.504558	4
401	3.900000	4.900000	0.941634	4
402	4.000000	5.000000	0.702123	4
403	4.100000	5.100000	0.887645	4

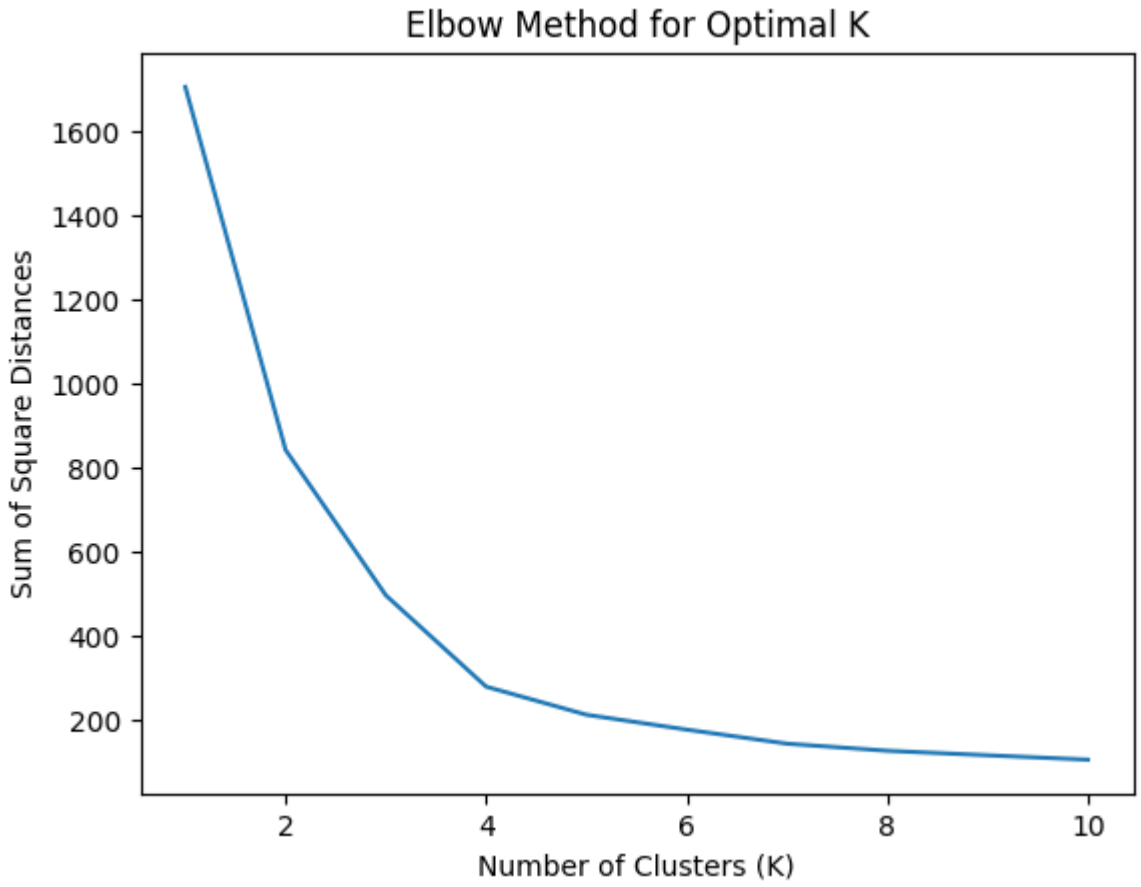
404 rows × 4 columns

```
k2= []
wcss2 = []
for i in range(1,11):
  md2 = KMeans(n_clusters = i, n_init = 10)
  md2.fit(df2_subset.iloc[:,0:3])
  k2.append(i)
  wcss2.append(md2.inertia_)
```

```
sns.lineplot(x = k2, y = wcss2)
plt.xlabel("Number of Clusters (K)")
```

```
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
KModel2 = KMeans(n_clusters = 4,
             init = 'k-means++',)
KModel2.fit(df2.iloc[:,1:4])
```

```
KMeans
KMeans(n_clusters=4)
```

```
KModel2.labels_
```

```
array([0, 2, 2, 0, 2, 0, 0, 0, 0, 2, 2, 0, 0, 2, 2, 0, 2, 2, 2, 2, 2, 0,
       2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 2, 2, 0, 2, 0, 2, 2, 0,
       2, 2, 2, 0, 0, 0, 2, 0, 0, 2, 2, 0, 2, 0, 2, 2, 0, 2, 0, 2, 0, 2,
       2, 2, 2, 2, 2, 2, 2, 0, 2, 0, 0, 2, 2, 2, 0, 2, 2, 2, 0, 0, 0, 2,
       0, 2, 2, 0, 2, 2, 2, 0, 2, 2, 0, 0, 0, 0, 2, 0, 2, 0, 2, 2, 0, 0,
       2, 2, 2, 0, 2, 2, 2, 0, 2, 2, 0, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 0,
       2, 2, 2, 2, 2, 0, 0, 0, 0, 2, 2, 0, 0, 2, 2, 0, 0, 2, 0, 0, 2, 2,
       2, 2, 2, 0, 2, 2, 2, 2, 2, 0, 0, 2, 0, 0, 0, 2, 2, 0, 2, 2, 0, 2,
       2, 0, 0, 2, 0, 0, 2, 0, 2, 0, 2, 2, 2, 2, 0, 0, 2, 2, 2, 0, 2, 2,
       0, 2, 3, 3, 3, 3, 2, 3, 2, 3, 3, 3, 3, 2, 3, 3, 3, 3, 3, 2, 3, 3,
       2, 3, 3, 3, 3, 3, 3, 3, 2, 3, 3, 2, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2,
       3, 3, 3, 3, 3, 3, 3, 3, 2, 3, 3, 3, 3, 3, 3, 3, 2, 3, 2, 2, 3, 3,
```

```
            3, 2, 2, 2, 3, 2, 3, 3, 2, 3, 3, 3, 3, 2, 3, 3, 3, 2, 2, 3, 3, 3,
            2, 3, 3, 3, 3, 3, 3, 2, 3, 3, 3, 2, 2, 3, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 3, 3, 3, 3], dtype=int32)
```

```
KModel2.cluster_centers_
```

```
array([[3.04451388, 0.51152101, 0.48663013],
       [2.9348529 , 2.55931128, 2.55146488],
       [1.0118234 , 0.75530155, 0.5346417 ],
       [1.1534002 , 4.08301554, 1.04313881]])
```

```
centroid2 = KModel2.cluster_centers_
```

```
centroid2
```

```
array([[3.04451388, 0.51152101, 0.48663013],
       [2.9348529 , 2.55931128, 2.55146488],
       [1.0118234 , 0.75530155, 0.5346417 ],
       [1.1534002 , 4.08301554, 1.04313881]])
```

```
#Assigning labels to original dataset
df2_cluster = df2_subset.copy()
df2_cluster["Cluster"] = KModel2.fit_predict(df2_subset)
```

```
df2_cluster.head()
```

	X	Y	C	Class	Cluster
0	3.277701	0.814082	0.326574	1	3
1	0.387577	0.176780	0.888046	1	1
2	0.268546	0.582963	0.080981	1	1
3	2.031145	0.244597	0.643921	1	3
4	0.188677	0.461280	0.496633	1	1

```
colours = ['Navy','Blue','Orange','green']
```

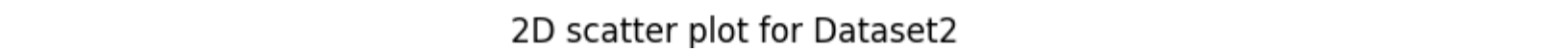
```
df2_cluster['Color'] = df2_cluster['Cluster'].map(lambda p:colours[p])
```

```
df2_cluster
```

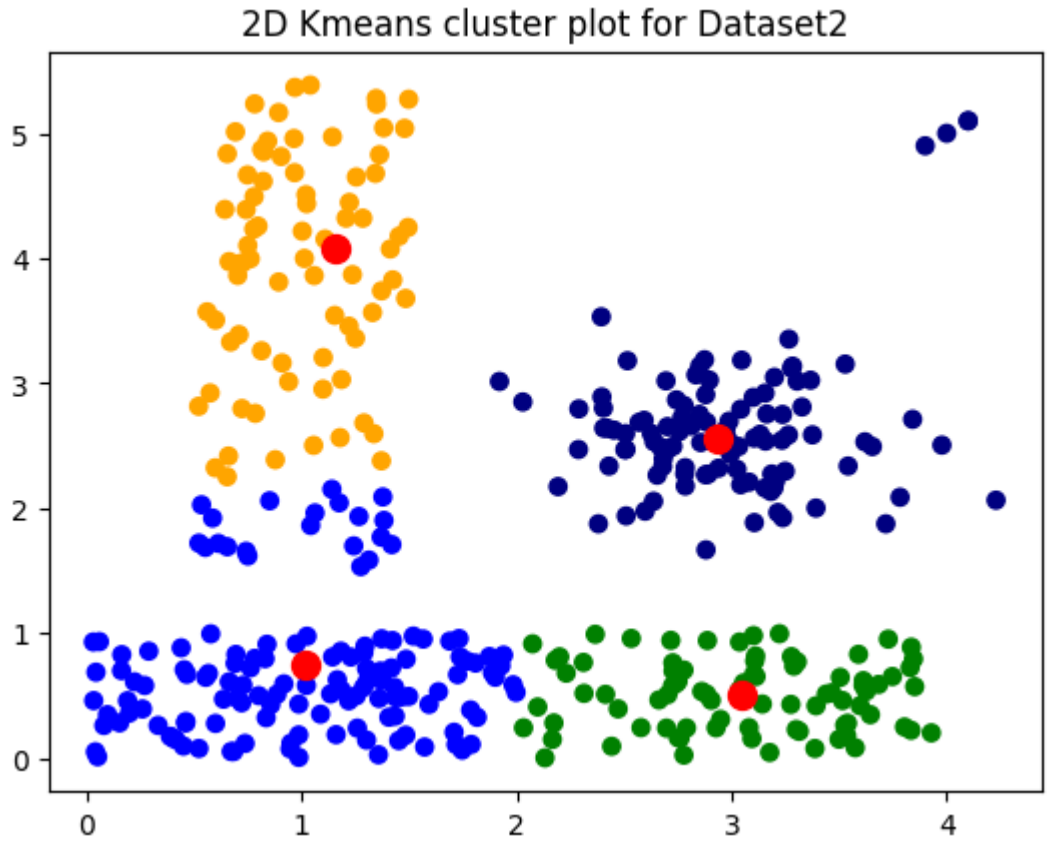
	X	Y	C	Class	Cluster	Color
0	3.277701	0.814082	0.326574	1	3	green
1	0.387577	0.176780	0.888046	1	1	Blue
2	0.268546	0.582963	0.080981	1	1	Blue
3	2.031145	0.244597	0.643921	1	3	green
4	0.188677	0.461280	0.496633	1	1	Blue
...	...	...	...	...	...	...
399	3.248655	2.297291	3.388138	3	0	Navy
400	4.100000	5.100000	0.504558	4	0	Navy
401	3.900000	4.900000	0.941634	4	0	Navy
402	4.000000	5.000000	0.702123	4	0	Navy
403	4.100000	5.100000	0.887645	4	0	Navy

404 rows × 6 columns

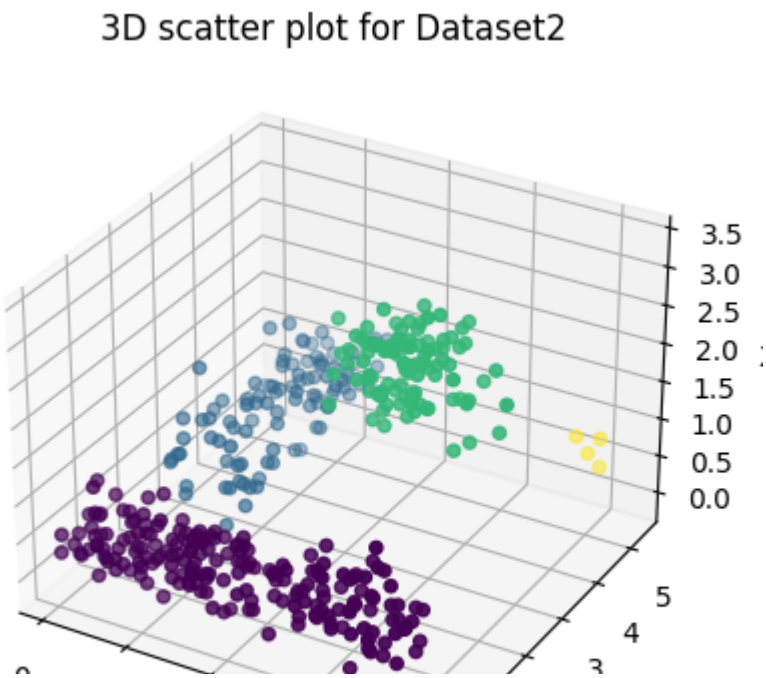
```
%matplotlib inline
plt.title("2D scatter plot for Dataset2")
plt.scatter(df2_cluster['X'],
            df2_cluster['Y'],
            c=df2_cluster['Class'])
plt.show()
```



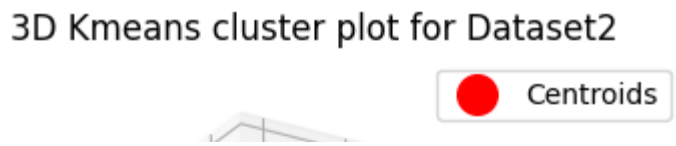

```
%matplotlib inline
plt.title("2D Kmeans cluster plot for Dataset2")
plt.scatter(df2_cluster['X'],
            df2_cluster['Y'],
            c = df2_cluster['Color'])
plt.scatter(centroid2[:,0], centroid2[:,1], c = 'red', s = 100)
plt.show()
```



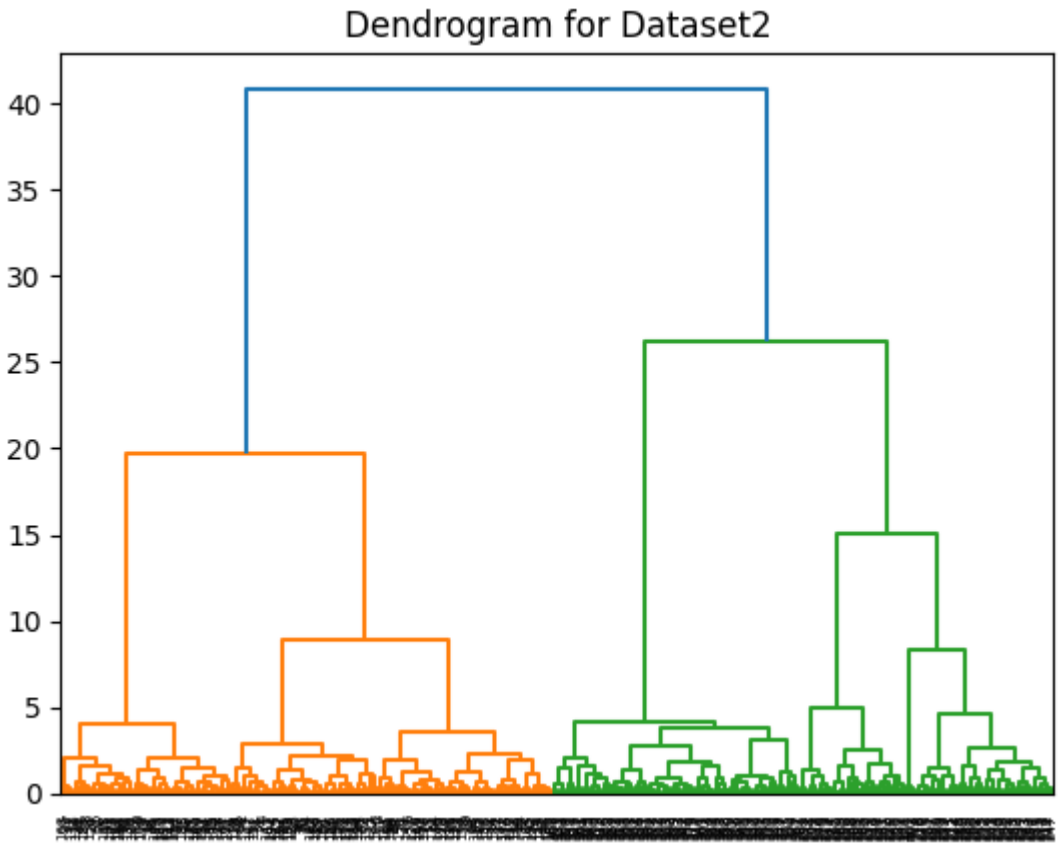

```
%matplotlib notebook
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
plt.title("3D scatter plot for Dataset2")
plt.ion()
ax.scatter(df2_cluster['X'], df2_cluster['Y'], df2_cluster['C'], c = df2_cluster['Class']
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.show()
```




```
%matplotlib notebook
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
plt.title("3D Kmeans cluster plot for Dataset2")
plt.ion()
ax.scatter(df2_cluster['X'], df2_cluster['Y'], df2_cluster['C'], c = df2_cluster['Cluster
ax.scatter(centroid2[:, 0], centroid2[:, 1], centroid2[:,2], c = 'red', s = 200, label =
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.legend()
plt.show()
```




```
%matplotlib inline
dendrogram = sch.dendrogram(sch.linkage(df2_cluster.iloc[:,0:3], method = 'ward'))
plt.title('Dendrogram for Dataset2')
plt.show()
```



Dataset 3

```
df3 = pd.read_csv('Data3.csv')
```

```
df3
```

	Unnamed: 0	X1	X2	X3	Class
0	1	1.295428	0.050829	-0.385217	1
1	2	1.409178	-0.035191	-0.251980	1
2	3	1.096803	0.246365	-0.415011	1
3	4	1.463328	0.265354	-0.513488	1
4	5	1.603284	0.080577	-0.470257	1
...	...	...	...	...	...
395	396	0.795695	0.209456	1.880609	4

```
df3_subset = df3[['X1','X2','X3', 'Class']]
```

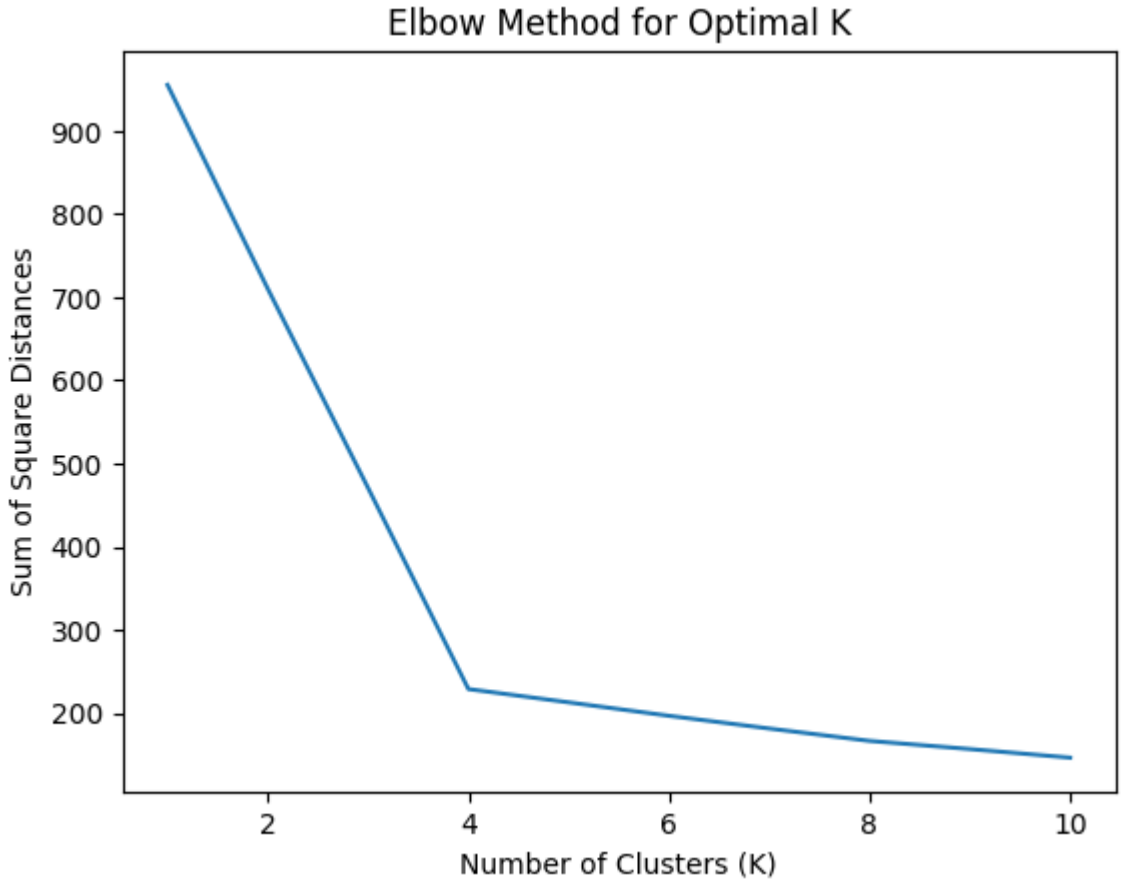
```
df3_subset
```

	X1	X2	X3	Class
0	1.295428	0.050829	-0.385217	1
1	1.409178	-0.035191	-0.251980	1
2	1.096803	0.246365	-0.415011	1
3	1.463328	0.265354	-0.513488	1
4	1.603284	0.080577	-0.470257	1
...	...	...	...	...
395	0.795695	0.209456	1.880609	4
396	0.653127	-0.703156	1.549448	4
397	-0.726249	-0.103244	0.694300	4
398	0.808596	-0.492640	1.649370	4
399	0.749291	-0.447840	0.863555	4

400 rows × 4 columns

```
k3= []
wcss3 = []
for i in range(1,11):
  md3 = KMeans(n_clusters = i, n_init = 10)
  md3.fit(df3_subset.iloc[:,0:3])
  k3.append(i)
  wcss3.append(md3.inertia_)
```

```
sns.lineplot(x = k3, y = wcss3)
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
plt.show()
```




```
KModel3 = KMeans(n_clusters = 4,
             init = 'k-means++',)
KModel3.fit(df3_subset.iloc[:,0:3])
```

```
KMeans
KMeans(n_clusters=4)
```

```
KModel3.labels_
```

```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

```
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3], dtype=int32)
```

```
KModel3.cluster_centers_
```

```
array([[-0.51838252, -1.16526495, -0.42573357],
       [-0.51838252,  1.0347351 , -0.42573357],
       [ 1.3868734 , -0.06526492, -0.42573357],
       [ 0.11670268, -0.06526492,  1.37055896]])
```

```
centroid3 = KModel3.cluster_centers_
```

```
centroid3
```

```
array([[-0.51838252, -1.16526495, -0.42573357],
       [-0.51838252,  1.0347351 , -0.42573357],
       [ 1.3868734 , -0.06526492, -0.42573357],
       [ 0.11670268, -0.06526492,  1.37055896]])
```

```
df3_cluster = df3_subset.copy()
df3_cluster["Cluster"] = KModel3.fit_predict(df3_subset)
```

```
df3_cluster
```

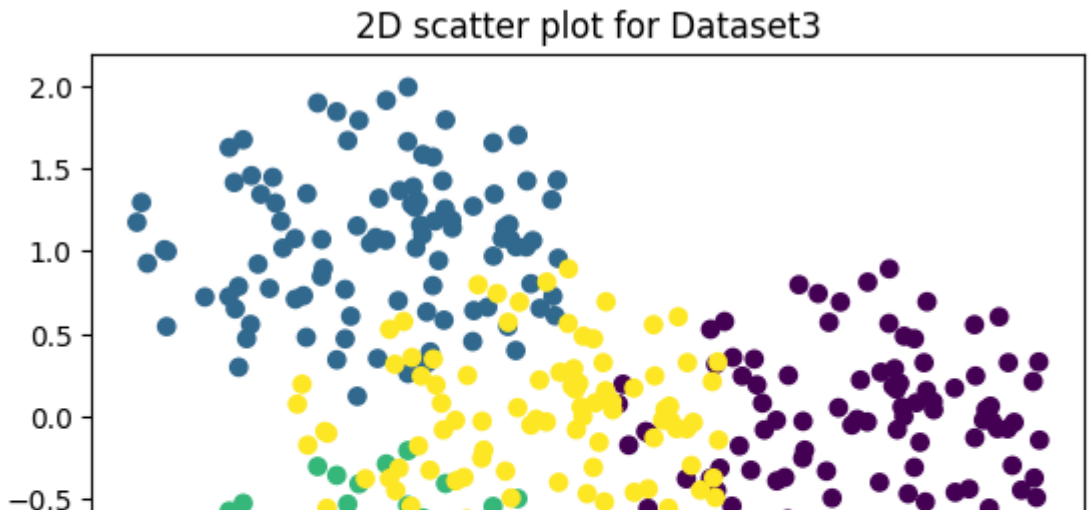
	X1	X2	X3	Class	Cluster
0	1.295428	0.050829	-0.385217	1	1
2	1.096803	0.246365	-0.415011	1	1

```
colours3 = ['Navy','Blue','Orange','green']
df3_cluster['Color'] = df3_cluster['Cluster'].map(lambda p:colours3[p])

df3_cluster
```

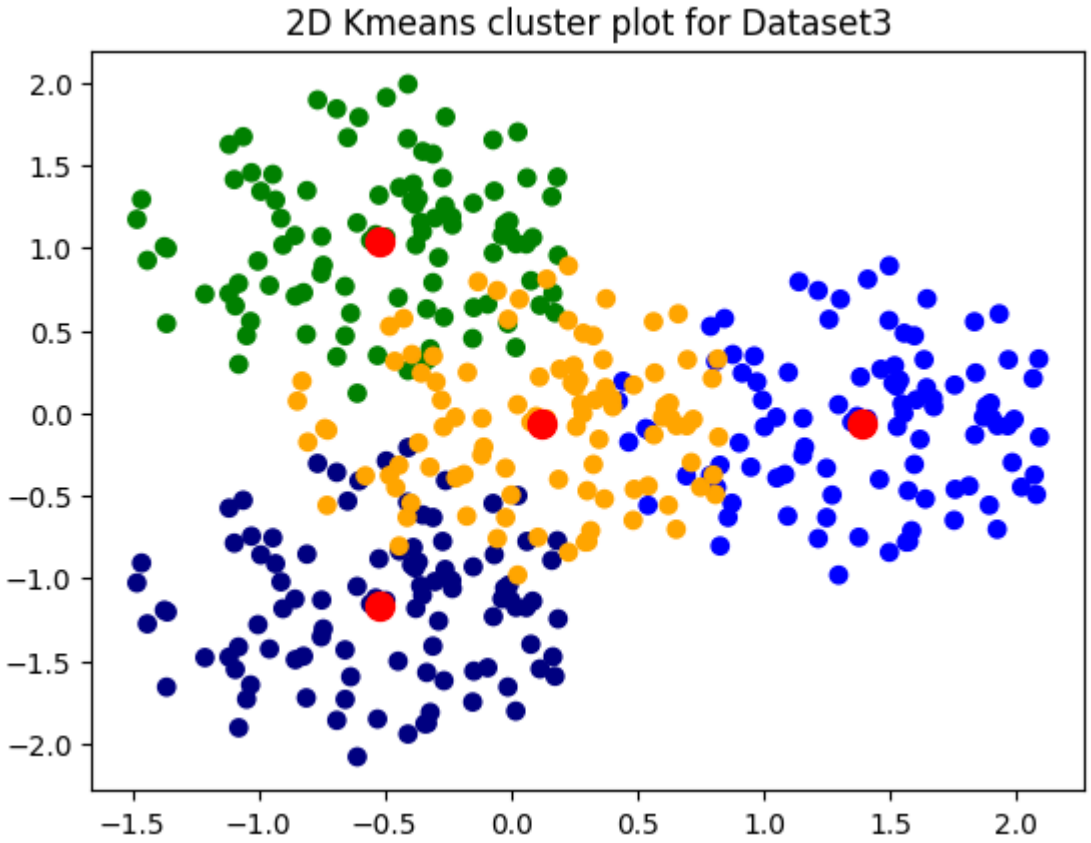
	X1	X2	X3	Class	Cluster	Color
0	1.295428	0.050829	-0.385217	1	1	Blue
1	1.409178	-0.035191	-0.251980	1	1	Blue
2	1.096803	0.246365	-0.415011	1	1	Blue
3	1.463328	0.265354	-0.513488	1	1	Blue
4	1.603284	0.080577	-0.470257	1	1	Blue
...	...	...	...	...	...	...
395	0.795695	0.209456	1.880609	4	2	Orange
396	0.653127	-0.703156	1.549448	4	2	Orange
397	-0.726249	-0.103244	0.694300	4	2	Orange
398	0.808596	-0.492640	1.649370	4	2	Orange
399	0.749291	-0.447840	0.863555	4	2	Orange

400 rows × 6 columns

```
%matplotlib inline
plt.title("2D scatter plot for Dataset3")
plt.scatter(df3_cluster['X1'],
            df3_cluster['X2'],
            c = df3_cluster['Class'])
plt.show()
```

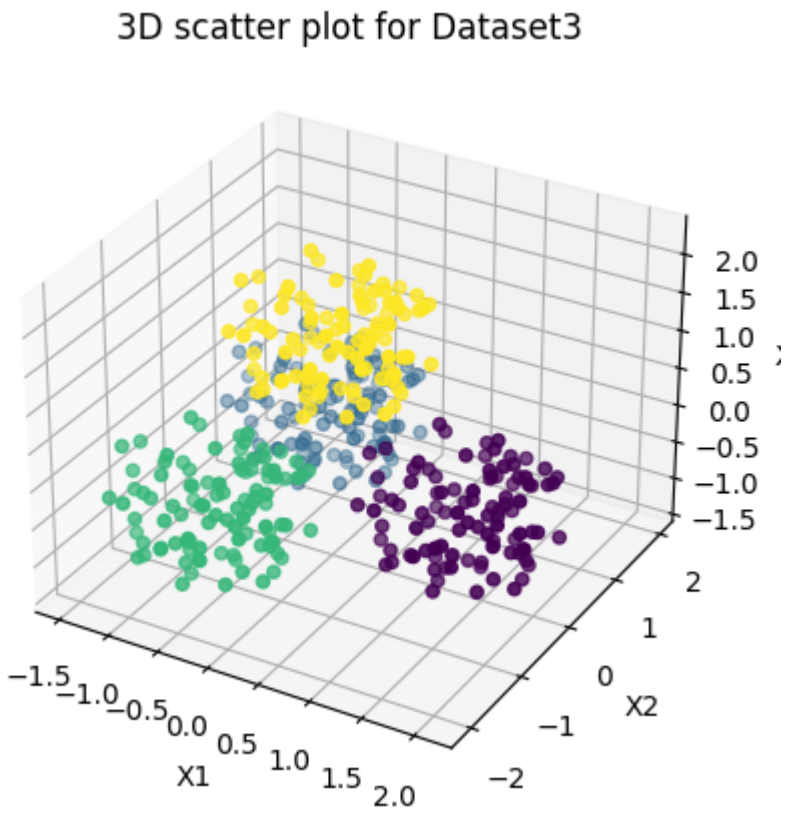



```
%matplotlib inline
plt.title("2D Kmeans cluster plot for Dataset3")
plt.scatter(df3_cluster['X1'],
            df3_cluster['X2'],
            c = df3_cluster['Color'])
plt.scatter(centroid3[:,0], centroid3[:,1], c = 'red', s = 100)
plt.show()
```

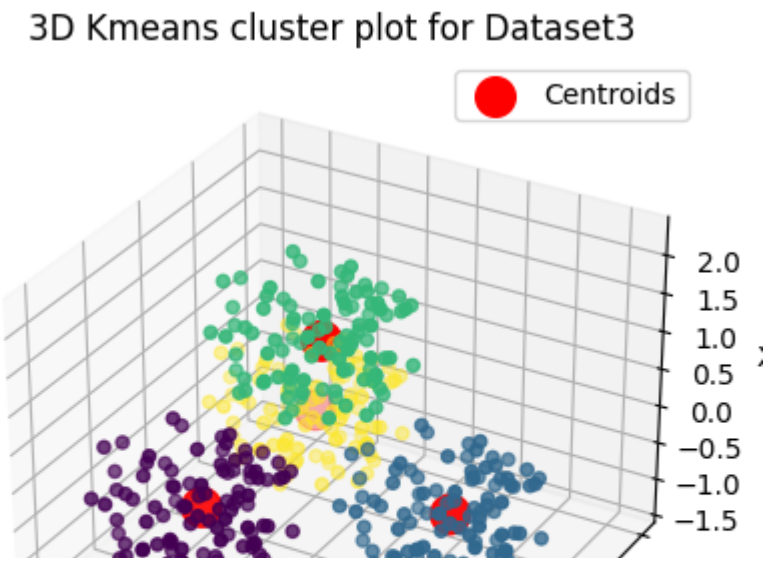



```
%matplotlib notebook
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
```

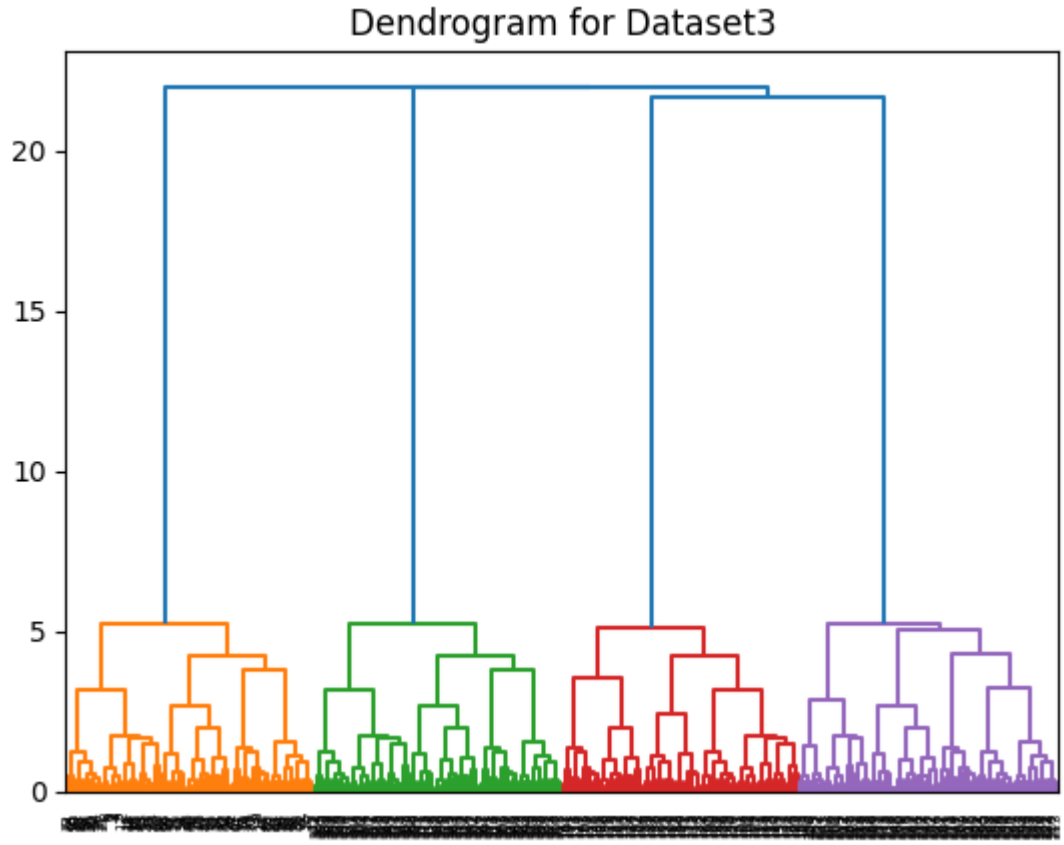
```
plt.title("3D scatter plot for Dataset3")
ax.scatter(df3_cluster['X1'], df3_cluster['X2'], df3_cluster['X3'], c = df3_cluster['Clas
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.show()
```




```
%matplotlib notebook
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
plt.title("3D Kmeans cluster plot for Dataset3")
ax.scatter(df3_cluster['X1'], df3_cluster['X2'], df3_cluster['X3'], c = df3_cluster['Clus
ax.scatter(centroid3[:, 0], centroid3[:, 1], centroid3[:,2], c = 'red', s = 200, label =
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.legend()
plt.show()
```




```
%matplotlib inline
dendrogram = sch.dendrogram(sch.linkage(df3_cluster.iloc[:,0:3], method = 'ward'))
plt.title('Dendrogram for Dataset3')
plt.show()
```



Dataset 4

```
df4 = pd.read_csv('Data4.csv')
```

```
df4
```

	Unnamed: 0	X1	X2	X3	Class
0	1	-0.45300	-0.8910	0.02300	1
1	2	0.65300	-0.8460	0.02110	1
2	3	0.39800	0.9130	-0.00139	1
3	4	0.09520	1.0500	0.00628	1
4	5	0.52400	-0.9410	0.03780	1
...	...	...	...	...	...
995	996	0.01520	0.0531	-0.36100	2
996	997	0.05160	0.6910	0.87500	2
997	998	-0.00511	1.3900	-0.94700	2
998	999	-0.06710	0.7140	0.88100	2
999	1000	-0.05770	0.4280	-0.73000	2

1000 rows × 5 columns

```
df4_subset = df4[['X1','X2','X3', 'Class']]
```

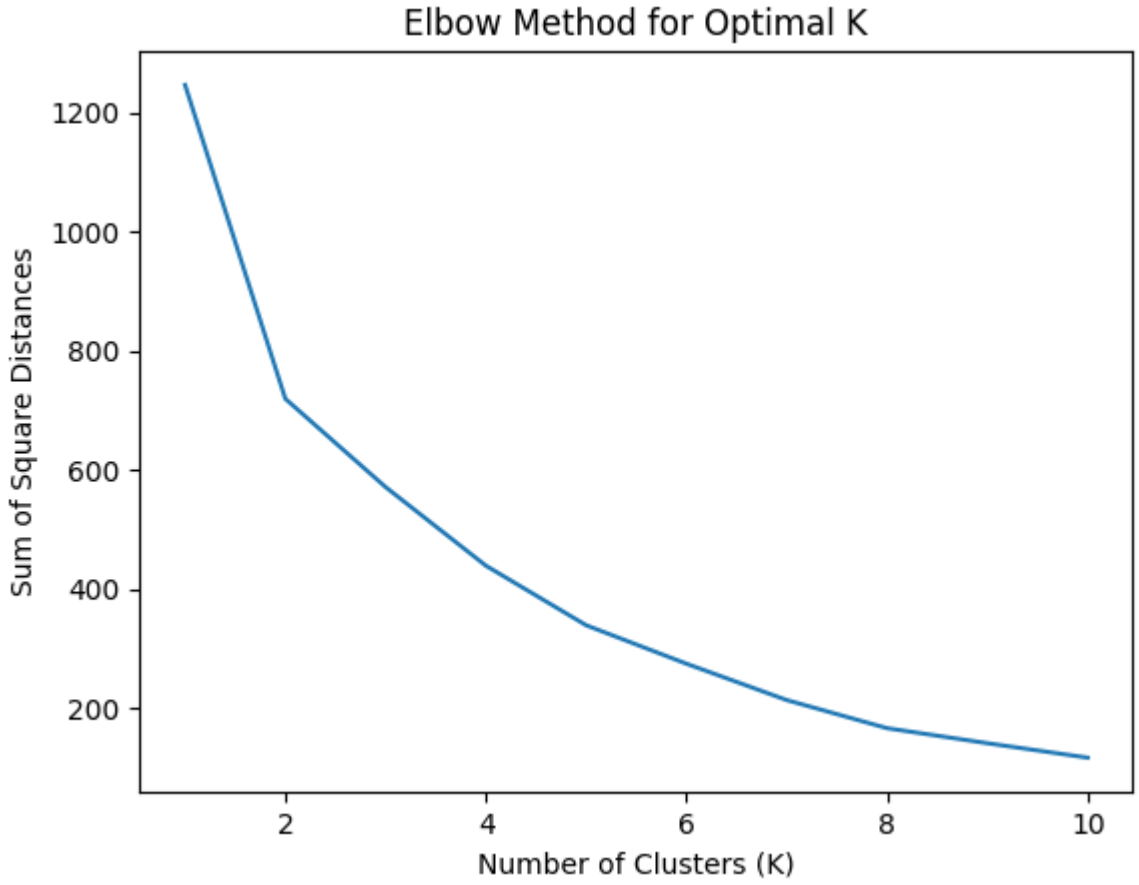
```
df4_subset
```

	X1	X2	X3	Class
0	-0.45300	-0.8910	0.02300	1
1	0.65300	-0.8460	0.02110	1
2	0.39800	0.9130	-0.00139	1
3	0.09520	1.0500	0.00628	1
4	0.52400	-0.9410	0.03780	1
...	...	...	...	...
995	0.01520	0.0531	-0.36100	2
996	0.05160	0.6910	0.87500	2
997	-0.00511	1.3900	-0.94700	2
998	-0.06710	0.7140	0.88100	2
999	-0.05770	0.4280	-0.73000	2

1000 rows × 4 columns

```
k4 = []
wcss4 = []
for i in range(1,11):
  md4 = KMeans(n_clusters = i, n_init = 10)
  md4.fit(df4_subset.iloc[:,0:3])
  k4.append(i)
  wcss4.append(md4.inertia_)


sns.lineplot(x = k4, y = wcss4)
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
#Generating labels
KModel4 = KMeans(n_clusters = 2,
             init = 'k-means++',)
KModel4.fit(df4_subset.iloc[:,0:3])
```

```
KMeans
KMeans(n_clusters=2)
```

```
KModel4.labels_
```

```
array([0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0,
       1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0,
       1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0,
       1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,
       0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0,
       1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1,
       0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1,
       0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1,
       0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1,
       1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1,
       1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1,
       0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1,
       1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0,
       1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1,
       1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1,
       0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1,
       0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 1, 0, 1, 1, 1, 1], dtype=int32)
```

```
KModel4.cluster_centers_
```

```
array([[-1.66176447e-02, -2.94129933e-01,  8.49923812e-03],
       [ 8.84493587e-04,  1.15671543e+00, -2.43330581e-02]])
```

```
centroid4 = KModel4.cluster_centers_
```

```
centroid4
```

```
array([[-1.66176447e-02, -2.94129933e-01,  8.49923812e-03],
       [ 8.84493587e-04,  1.15671543e+00, -2.43330581e-02]])
```

```
df4_cluster = df4_subset.copy()
df4_cluster["Cluster"] = KModel4.fit_predict(df4_subset)
```

```
df4_cluster
```

	X1	X2	X3	Class	Cluster
0	-0.45300	-0.8910	0.02300	1	1
1	0.65300	-0.8460	0.02110	1	1
2	0.39800	0.9130	-0.00139	1	0
3	0.09520	1.0500	0.00628	1	0
4	0.52400	-0.9410	0.03780	1	1
...	...	...	...	...	...
995	0.01520	0.0531	-0.36100	2	0
996	0.05160	0.6910	0.87500	2	0
997	-0.00511	1.3900	-0.94700	2	0
998	-0.06710	0.7140	0.88100	2	0
999	-0.05770	0.4280	-0.73000	2	0

1000 rows × 5 columns

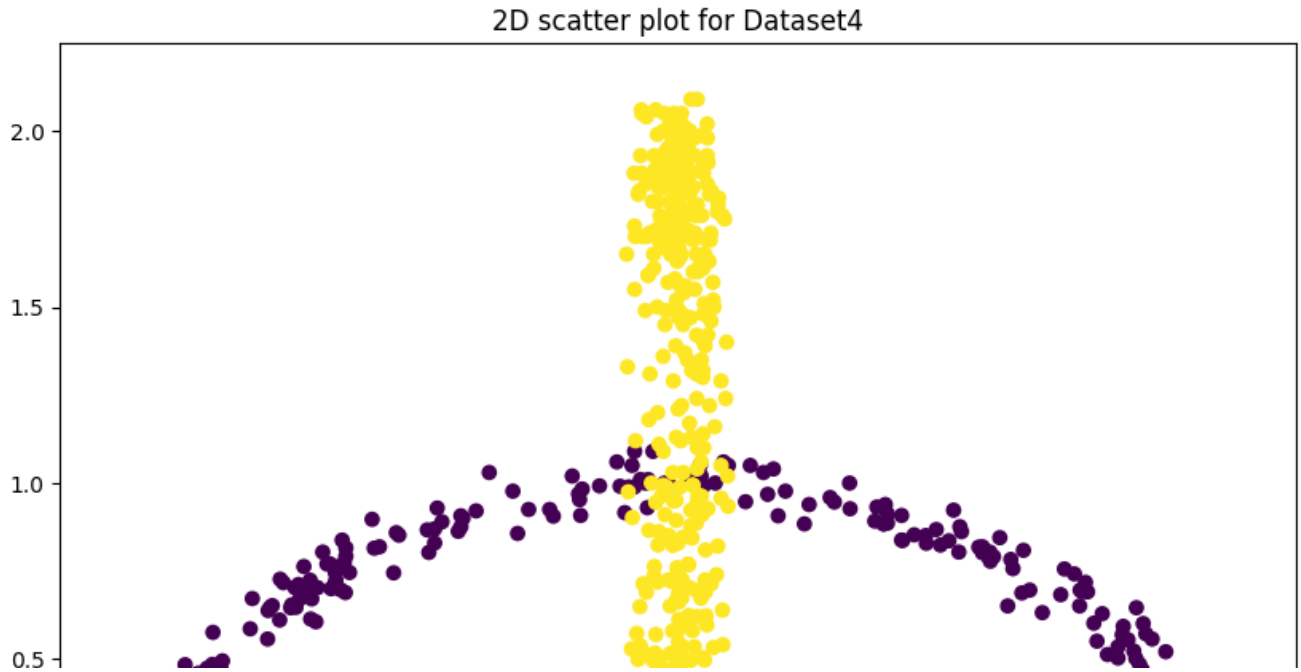
```
colours4 = ['Blue','Orange']
```

```
df4_cluster['Color'] = df4_cluster['Cluster'].map(lambda p:colours4[p])
```

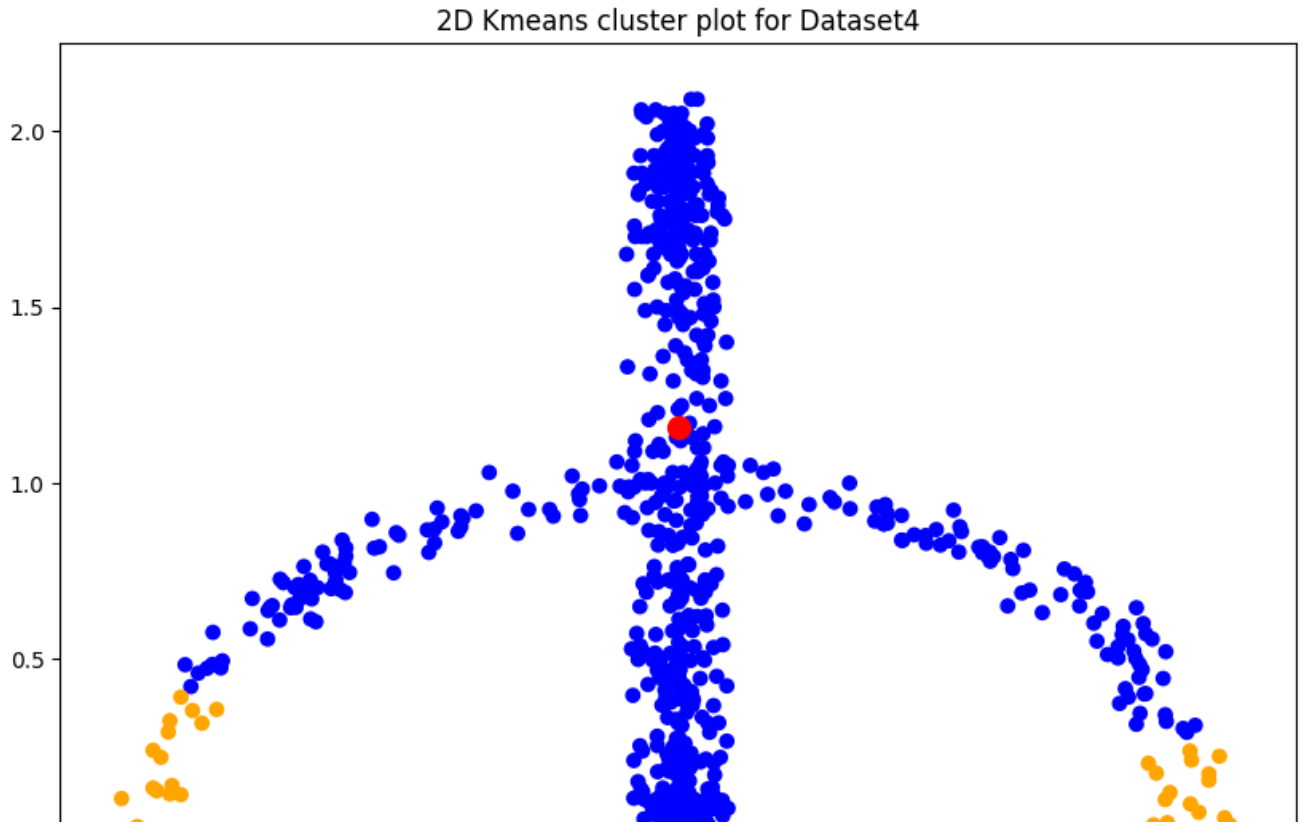
```
df4_cluster
```

	X1	X2	X3	Class	Cluster	Color
0	-0.45300	-0.8910	0.02300	1	1	Orange
1	0.65300	-0.8460	0.02110	1	1	Orange
2	0.39800	0.9130	-0.00139	1	0	Blue
3	0.09520	1.0500	0.00628	1	0	Blue
4	0.52400	-0.9410	0.03780	1	1	Orange
...	...	...	...	...	...	...
995	0.01520	0.0531	-0.36100	2	0	Blue
996	0.05160	0.6910	0.87500	2	0	Blue

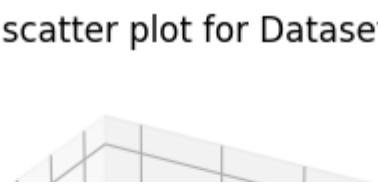
```
%matplotlib notebook
%matplotlib inline
plt.figure(figsize = (10, 10))
plt.title("2D scatter plot for Dataset4")
plt.scatter(df4_cluster['X1'],
            df4_cluster['X2'],
            c = df4_cluster['Class'])
plt.show()
```



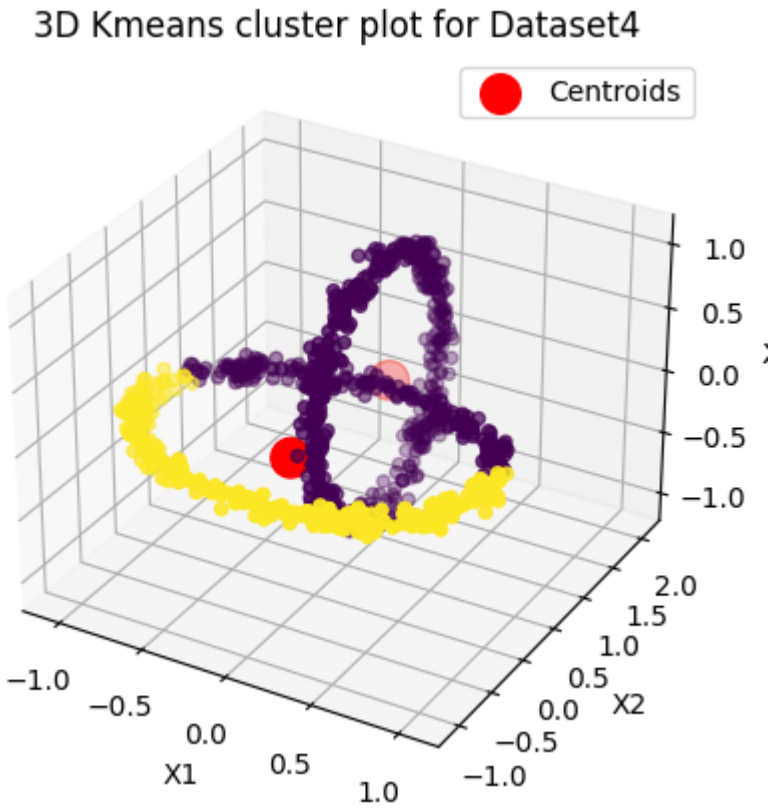

```
%matplotlib notebook
%matplotlib inline
plt.figure(figsize = (10, 10))
plt.title("2D Kmeans cluster plot for Dataset4")
plt.scatter(df4_cluster['X1'],
            df4_cluster['X2'],
            c = df4_cluster['Color'])
plt.scatter(centroid4[:,0], centroid4[:,1], c = 'red', s = 100)
plt.show()
```



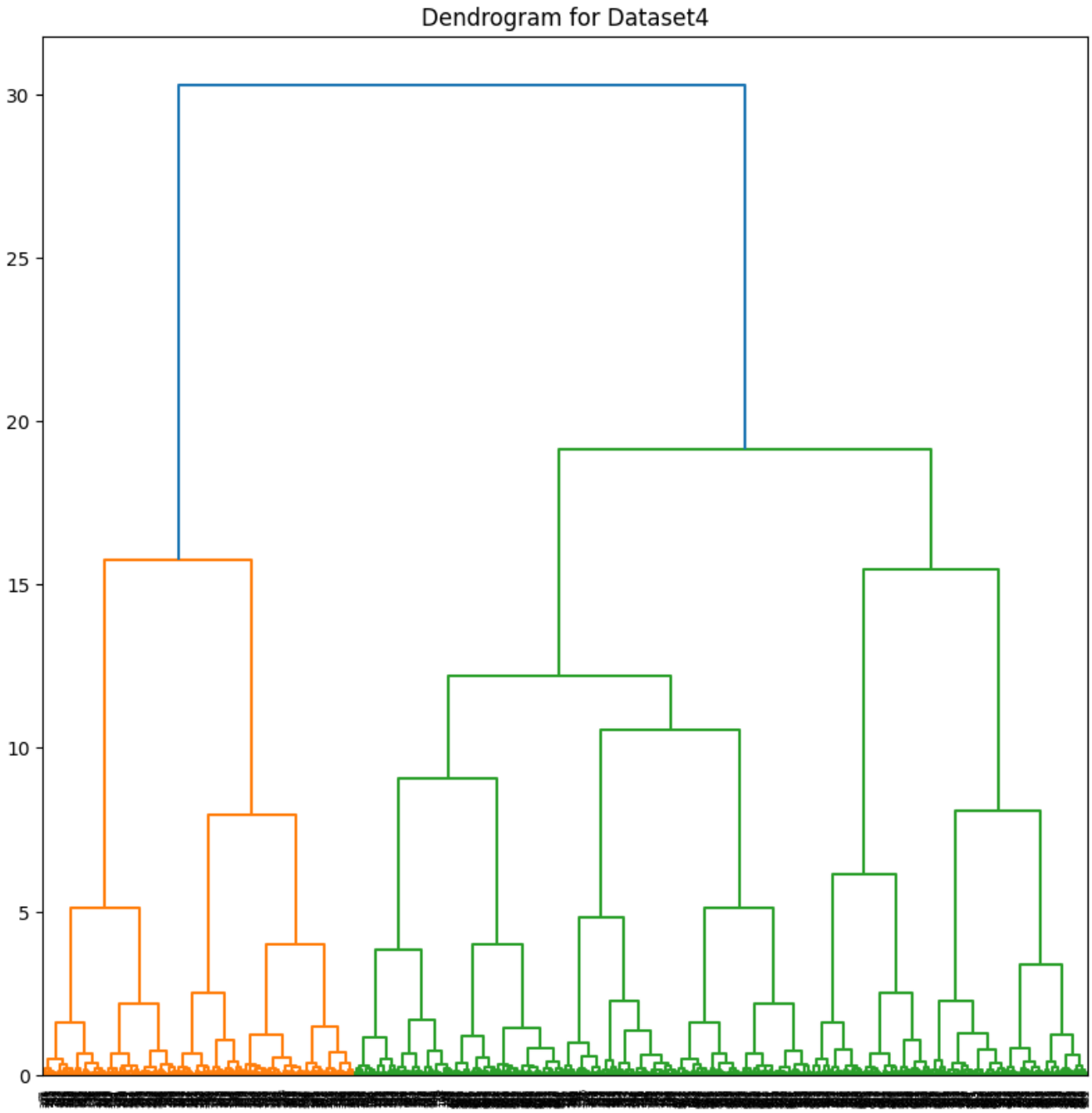

```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
plt.title("3D scatter plot for Dataset4")
ax.scatter(df4_cluster['X1'], df4_cluster['X2'], df4_cluster['X3'], c = df4_cluster['Clas
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.ion()
plt.show()
```




```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
plt.title("3D Kmeans cluster plot for Dataset4")
ax.scatter(df4_cluster['X1'], df4_cluster['X2'], df4_cluster['X3'], c = df4_cluster['Clus
ax.scatter(centroid4[:, 0], centroid4[:, 1], centroid4[:,2], c = 'red', s = 200, label =
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.legend()
plt.ion()
plt.show()
```




```
import scipy.cluster.hierarchy as sch
from scipy.cluster.hierarchy import dendrogram, linkage
%matplotlib inline
plt.figure(figsize = (10, 10))
dendrogram = sch.dendrogram(sch.linkage(df4_cluster.iloc[:,0:3], method = 'ward'))
plt.title('Dendrogram for Dataset4')
plt.show()
```



Dataset 5

```
df5 = pd.read_csv('Data5.csv')
```

```
df5
```

	Unnamed: 0	X1	X2	X3	Class
0	1	-4.822490	-50.402170	4.020861	1
1	2	-44.460120	20.964670	-11.492060	1
2	3	50.001020	0.780748	9.134460	1
3	4	-41.699080	-22.310060	16.314120	1
4	5	4.425242	-4.666664	50.223740	1
...	...	...	...	...	...
795	796	-1.531027	0.681636	0.543271	2
796	797	0.500754	-1.848209	0.605654	2
797	798	1.089574	-0.246493	-3.355758	2
798	799	-1.907717	4.964502	2.098423	2
799	800	3.415463	4.529521	-1.617736	2

800 rows × 5 columns

```
df5_subset = df5[['X1','X2','X3','Class']]
```

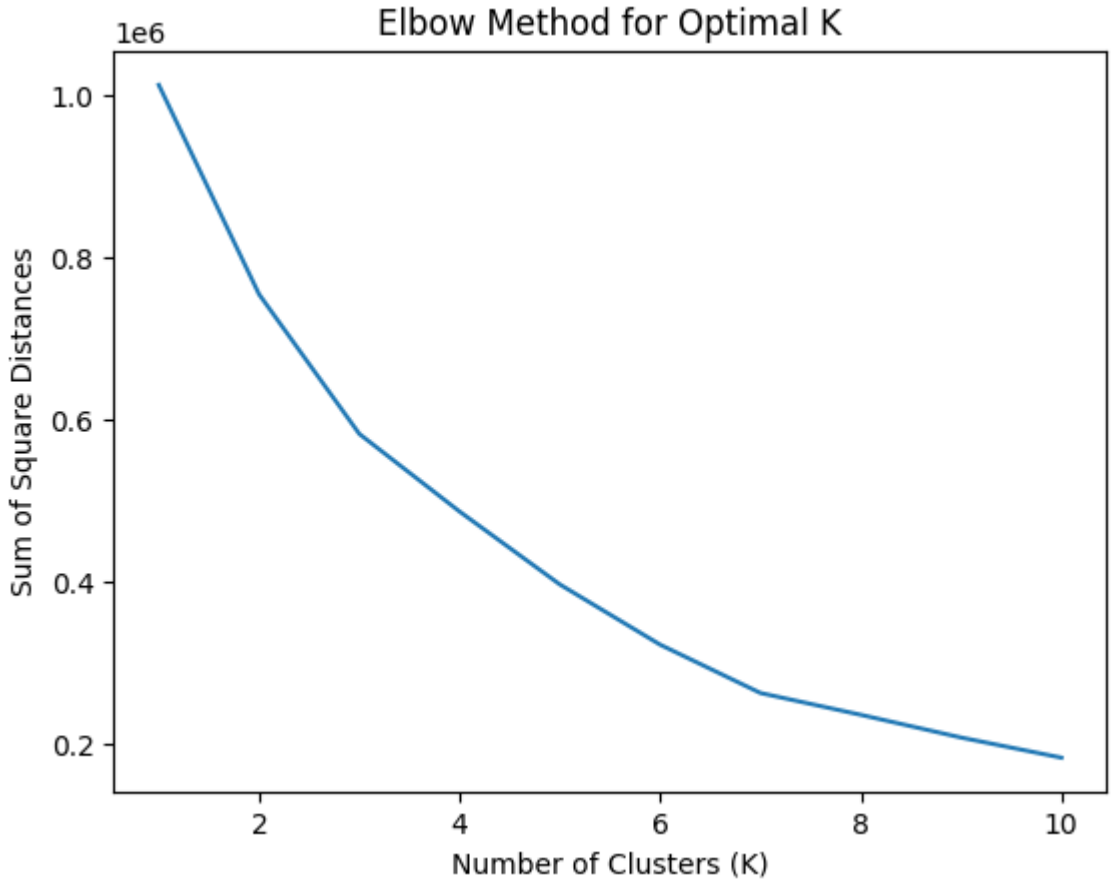
```
df5_subset
```

	X1	X2	X3	Class
0	-4.822490	-50.402170	4.020861	1
1	-44.460120	20.964670	-11.492060	1
2	50.001020	0.780748	9.134460	1
3	-41.699080	-22.310060	16.314120	1
4	4.425242	-4.666664	50.223740	1
...	...	...	...	...
795	-1.531027	0.681636	0.543271	2
796	0.500754	-1.848209	0.605654	2
797	1.089574	-0.246493	-3.355758	2
798	-1.907717	4.964502	2.098423	2
799	3.415463	4.529521	-1.617736	2

800 rows × 4 columns

```
k5= []
wcss5 = []
for i in range(1,11):
  md5 = KMeans(n_clusters = i, n_init = 10)
  md5.fit(df5_subset.iloc[:,0:3])
  k5.append(i)
  wcss5.append(md5.inertia_)


sns.lineplot(x = k5, y = wcss5)
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
KModel5 = KMeans(n_clusters = 2,
             init = 'k-means++',)
KModel5.fit(df5_subset.iloc[:,0:3])
```

```
KMeans
KMeans(n_clusters=2)
```

```
KModel5.labels_
```

```
array([1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1,
       1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1,
       0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1,
       1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1,
       1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0,
       0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1,
       1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
       0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0,
       0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1,
       1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0,
       1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1], dtype=int32)
```

```
KModel5.cluster_centers_
```

```
array([[-9.01628338, -3.77555523, 34.10740302],
       [ 1.67324664, -0.14618357, -8.22394005]])
```

```
centroid5 = KModel5.cluster_centers_
```

```
centroid5
```

```
array([[-9.01628338, -3.77555523, 34.10740302],
       [ 1.67324664, -0.14618357, -8.22394005]])
```

```
df5_cluster = df5_subset.copy()
df5_cluster["Cluster"] = KModel5.fit_predict(df5_subset)
```

```
df5_cluster
```

	X1	X2	X3	Class	Cluster
0	-4.822490	-50.402170	4.020861	1	1
1	-44.460120	20.964670	-11.492060	1	1
2	50.001020	0.780748	9.134460	1	1
3	-41.699080	-22.310060	16.314120	1	0
4	4.425242	-4.666664	50.223740	1	0
...	...	...	...	...	...
795	-1.531027	0.681636	0.543271	2	1
796	0.500754	-1.848209	0.605654	2	1
797	1.089574	-0.246493	-3.355758	2	1
798	-1.907717	4.964502	2.098423	2	1
799	3.415463	4.529521	-1.617736	2	1

800 rows × 5 columns

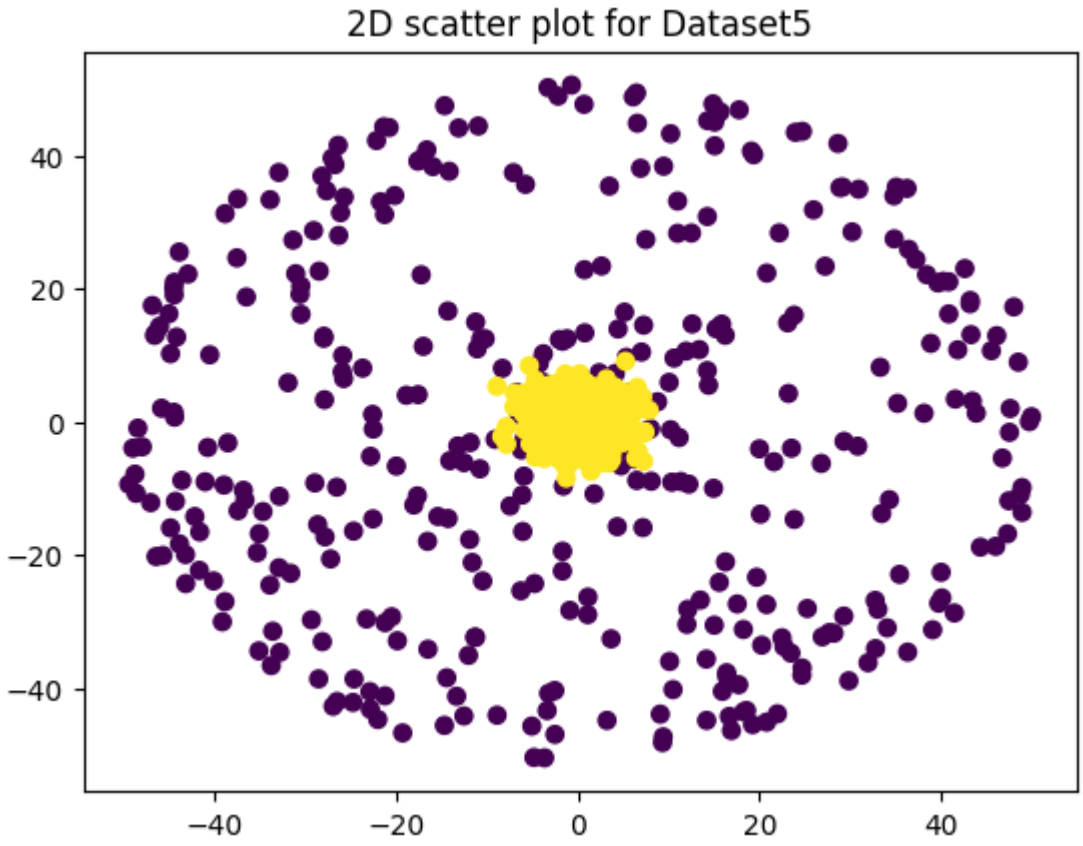
```
colours5 = ['Blue','green']
```

```
df5_cluster['Color'] = df5_cluster['Cluster'].map(lambda p:colours5[p])
```

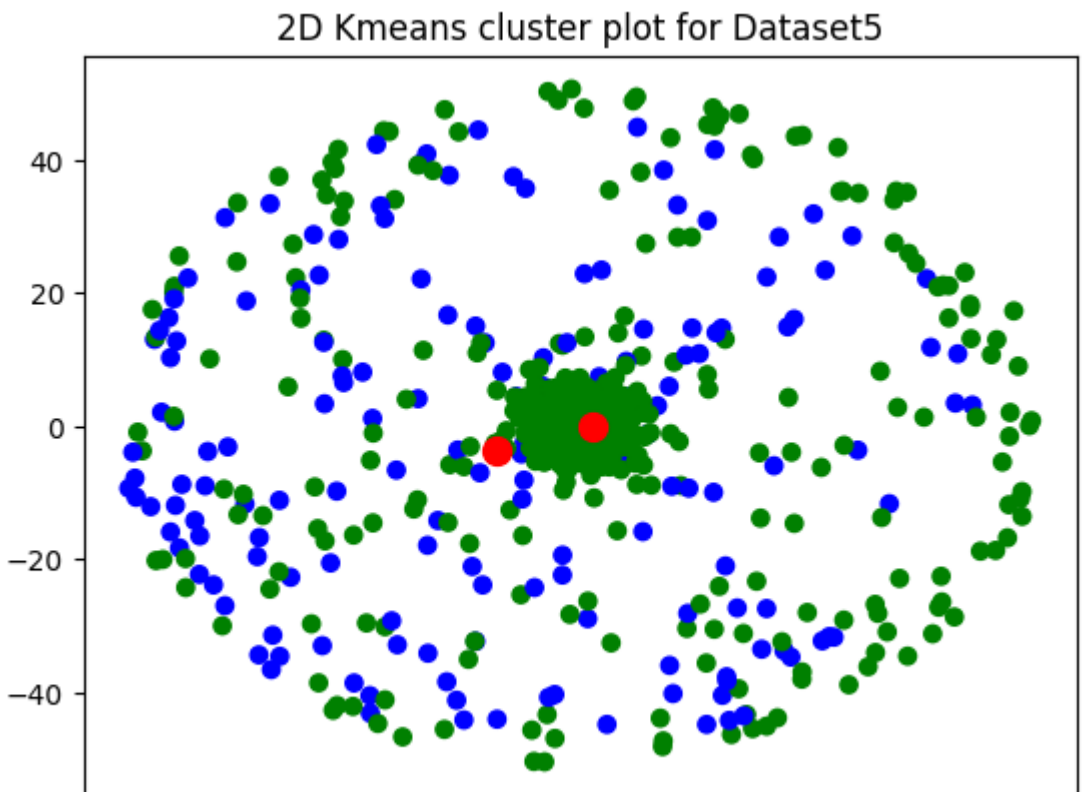
```
df5_cluster
```

	X1	X2	X3	Class	Cluster	Color
0	-4.822490	-50.402170	4.020861	1	1	green
1	-44.460120	20.964670	-11.492060	1	1	green
2	50.001020	0.780748	9.134460	1	1	green

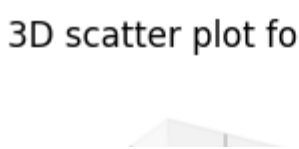
```
%matplotlib notebook
%matplotlib inline
plt.title("2D scatter plot for Dataset5")
plt.scatter(df5_cluster['X1'],
            df5_cluster['X2'],
            c = df5_cluster['Class'])
plt.show()
```



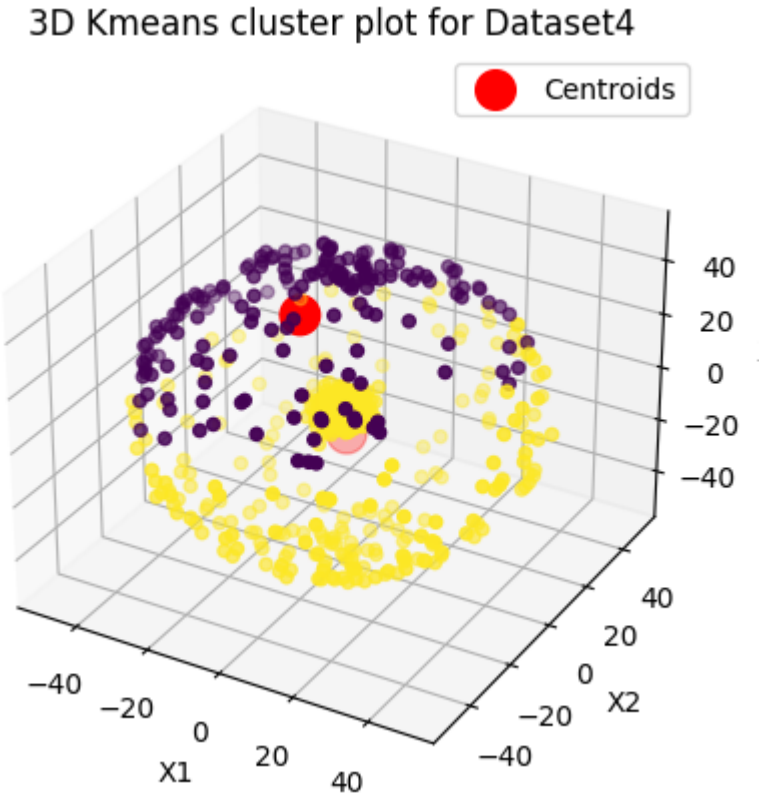

```
%matplotlib notebook
%matplotlib inline
plt.title("2D Kmeans cluster plot for Dataset5")
plt.scatter(df5_cluster['X1'],
            df5_cluster['X2'],
            c = df5_cluster['Color'])
plt.scatter(centroid5[:,0], centroid5[:,1], c = 'red', s = 100)
plt.show()
```



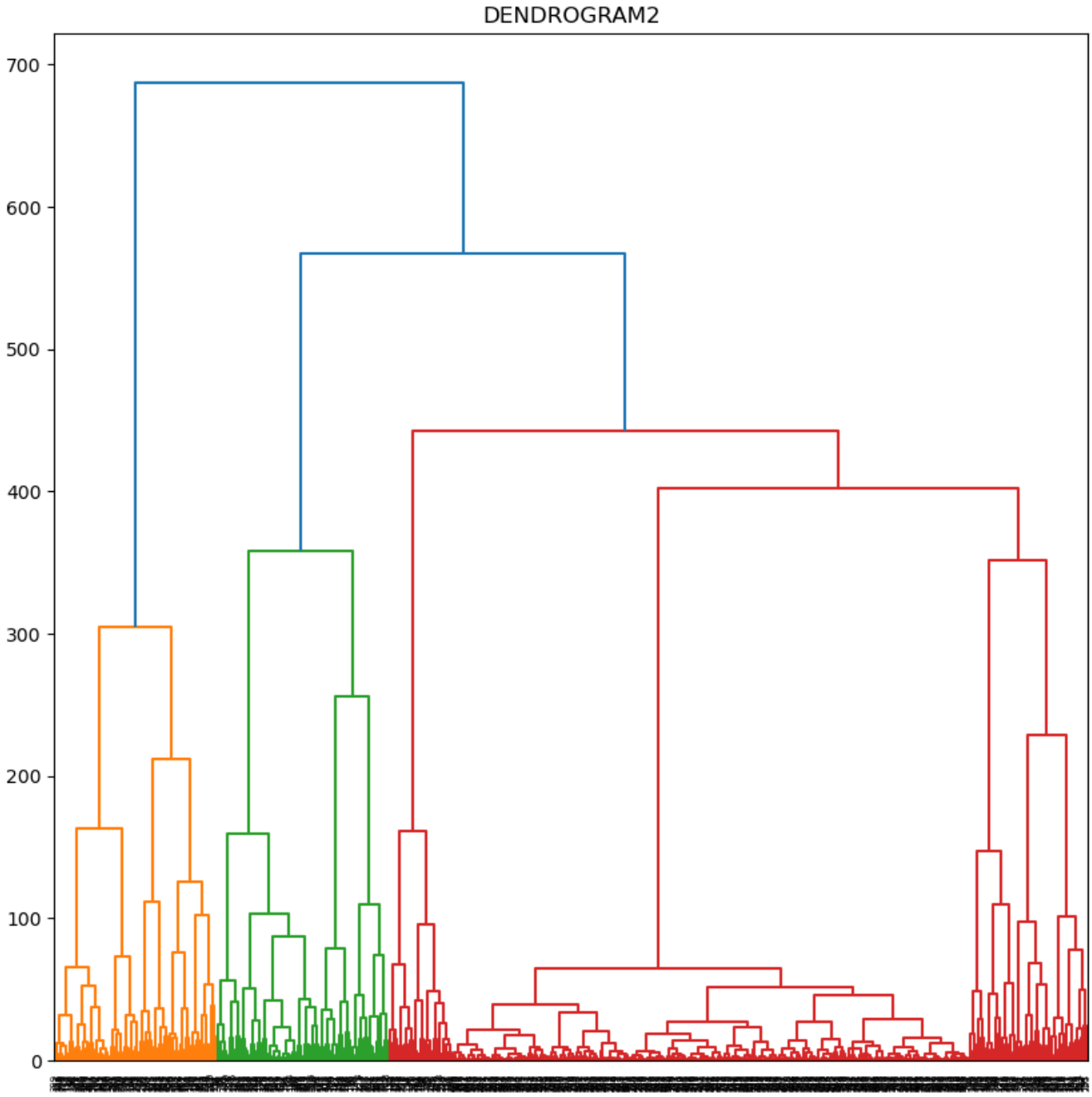

```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
plt.title("3D scatter plot for Dataset5")
ax.scatter(df5_cluster['X1'], df5_cluster['X2'], df5_cluster['X3'], c = df5_cluster['Clas
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.ion()
plt.show()
```




```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
plt.title("3D Kmeans cluster plot for Dataset4")
ax.scatter(df5_cluster['X1'], df5_cluster['X2'], df5_cluster['X3'], c = df5_cluster['Clus
ax.scatter(centroid5[:, 0], centroid5[:, 1], centroid5[:,2], c = 'red', s = 200, label =
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.legend()
plt.ion()
plt.show()
```




```
%matplotlib inline
plt.figure(figsize = (10, 10))
dendrogram = sch.dendrogram(sch.linkage(df5_cluster.iloc[:,0:3], method = 'ward'))
plt.title('DENDROGRAM2')
plt.show()
```



Dataset 6

```
df6 = pd.read_csv('Data6.csv')
```

```
df6
```

	Unnamed: 0	X1	X2	Class
0	1	1.388261	2.076096	1
1	2	2.177247	3.102304	1
2	3	0.378645	5.307610	1
3	4	3.681732	1.622681	1
4	5	2.462861	2.777897	1
...	...	...	...	...
4091	4092	0.909687	0.375763	2
4092	4093	2.698381	0.511262	2
4093	4094	1.078797	1.526153	2
4094	4095	1.974889	-0.649343	2
4095	4096	-0.127192	-0.763974	2

```
df6_subset = df6[['X1','X2','Class']]
```

```
df6_subset
```

	X1	X2	Class
0	1.388261	2.076096	1
1	2.177247	3.102304	1
2	0.378645	5.307610	1
3	3.681732	1.622681	1
4	2.462861	2.777897	1
...	...	...	...
4091	0.909687	0.375763	2
4092	2.698381	0.511262	2
4093	1.078797	1.526153	2
4094	1.974889	-0.649343	2
4095	-0.127192	-0.763974	2

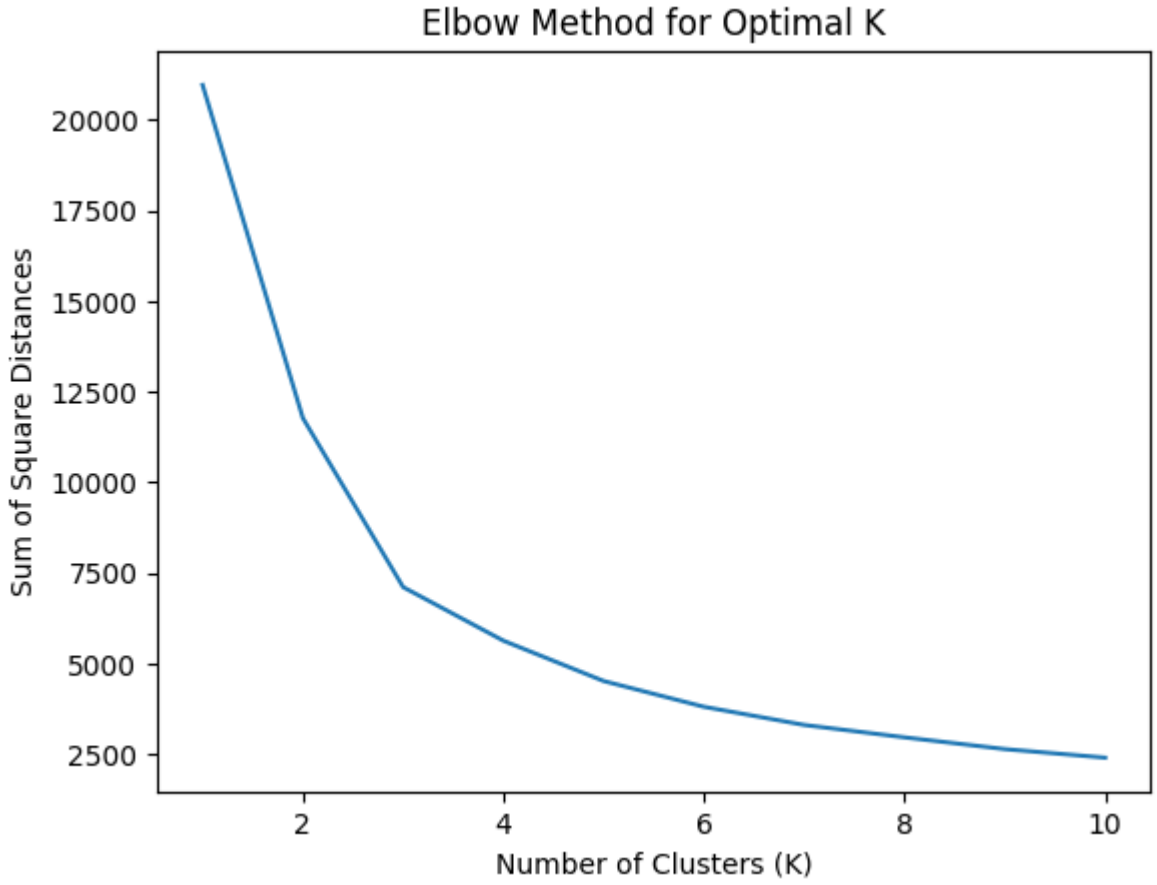
4096 rows × 3 columns

```
k6= []
wcss6 = []
for i in range(1,11):
```

```
  md6 = KMeans(n_clusters = i, n_init = 10)
  md6.fit(df6_subset.iloc[:,0:2])
  k6.append(i)
  wcss6.append(md6.inertia_)
```

```
sns.lineplot(x = k6, y = wcss6)
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
KModel6 = KMeans(n_clusters = 3,
             init = 'k-means++',)
KModel6.fit(df6_subset.iloc[:,0:2])
```

```
KMeans
KMeans(n_clusters=3)
```

```
KModel6.labels_
```

```
array([0, 2, 2, ..., 1, 1, 1], dtype=int32)
```

```
centroid6 = KModel6.cluster_centers_
```

```
centroid6
```

```
array([[2.97112836, 1.73077279],
       [0.33874351, 0.34163007],
       [0.99754282, 3.91330846]])
```

```
df6_cluster = df6_subset.copy()
df6_cluster["Cluster"] = KModel6.fit_predict(df6_subset)
```

```
df6_cluster
```

	X1	X2	Class	Cluster
0	1.388261	2.076096	1	1
1	2.177247	3.102304	1	2
2	0.378645	5.307610	1	2
3	3.681732	1.622681	1	1
4	2.462861	2.777897	1	1
...	...	...	...	...
4091	0.909687	0.375763	2	0
4092	2.698381	0.511262	2	1
4093	1.078797	1.526153	2	0
4094	1.974889	-0.649343	2	0
4095	-0.127192	-0.763974	2	0

4096 rows × 4 columns

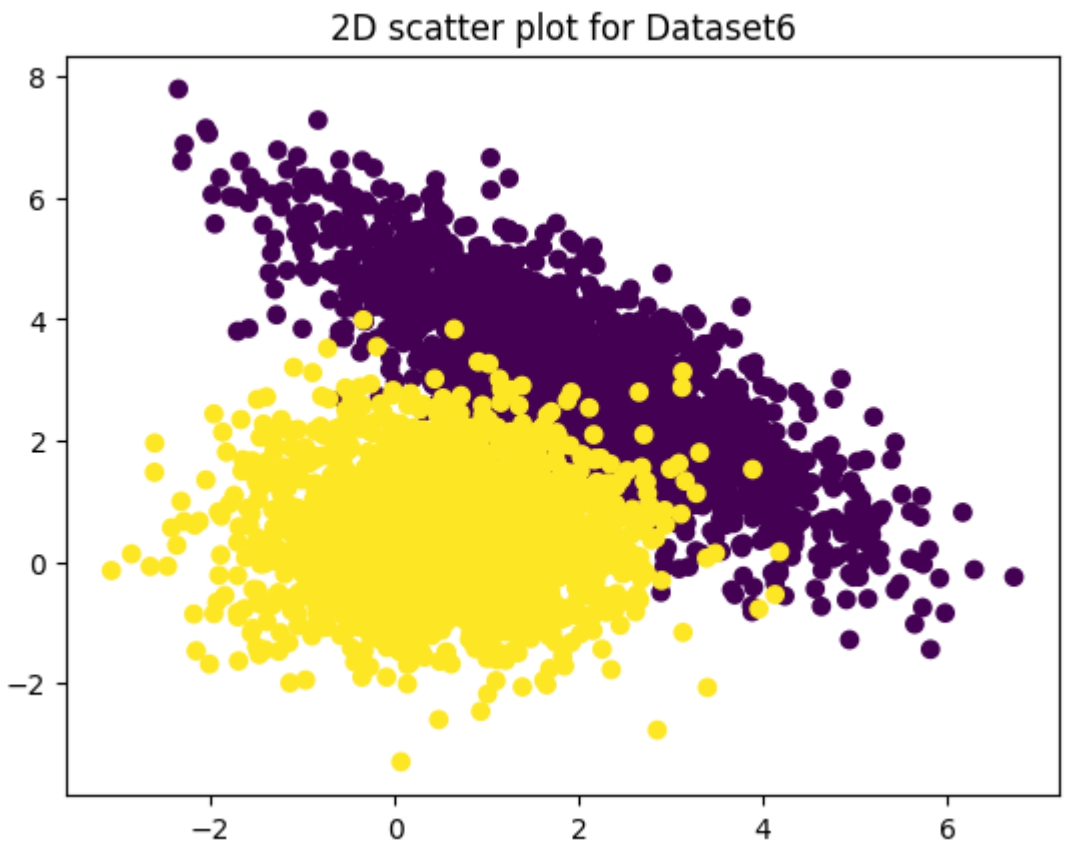
```
colours6 = ['Orange','green','blue']
```

```
df6_cluster['Color'] = df6_cluster['Cluster'].map(lambda p:colours6[p])
```

```
df6_cluster
```

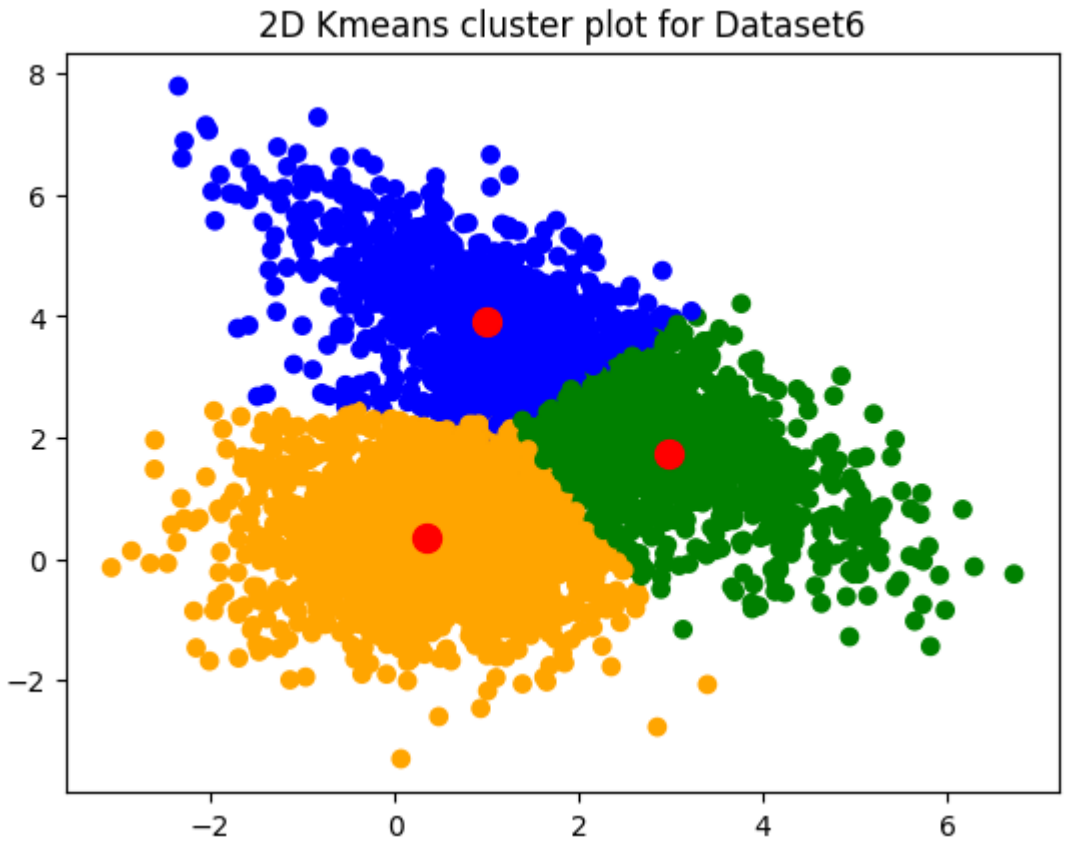
	X1	X2	Class	Cluster	Color
0	1.388261	2.076096	1	1	green
1	2.177247	3.102304	1	2	blue
2	0.378645	5.307610	1	2	blue
3	3.681732	1.622681	1	1	green
4	2.462861	2.777897	1	1	green
...	...	...	...	...	...
4091	0.909687	0.375763	2	0	Orange
4092	2.698381	0.511262	2	1	green

```
%matplotlib notebook
%matplotlib inline
plt.title("2D scatter plot for Dataset6")
plt.scatter(df6_cluster['X1'],
            df6_cluster['X2'],
            c = df6_cluster['Class'])
plt.show()
```

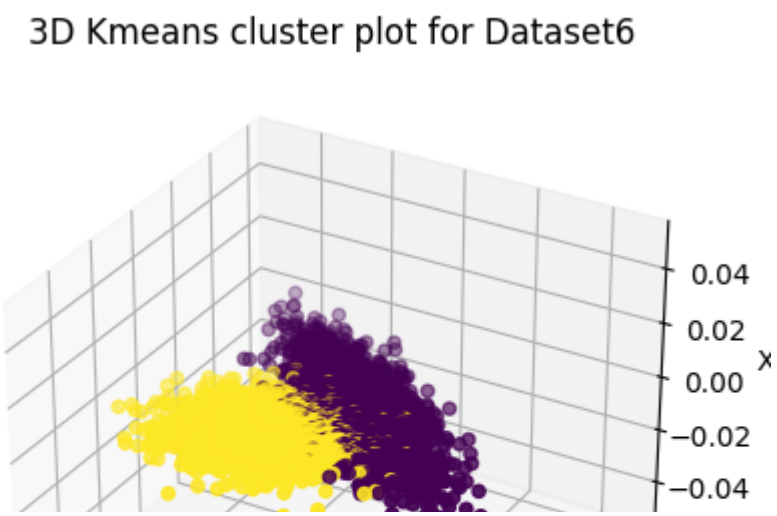



```
%matplotlib notebook
%matplotlib inline
```

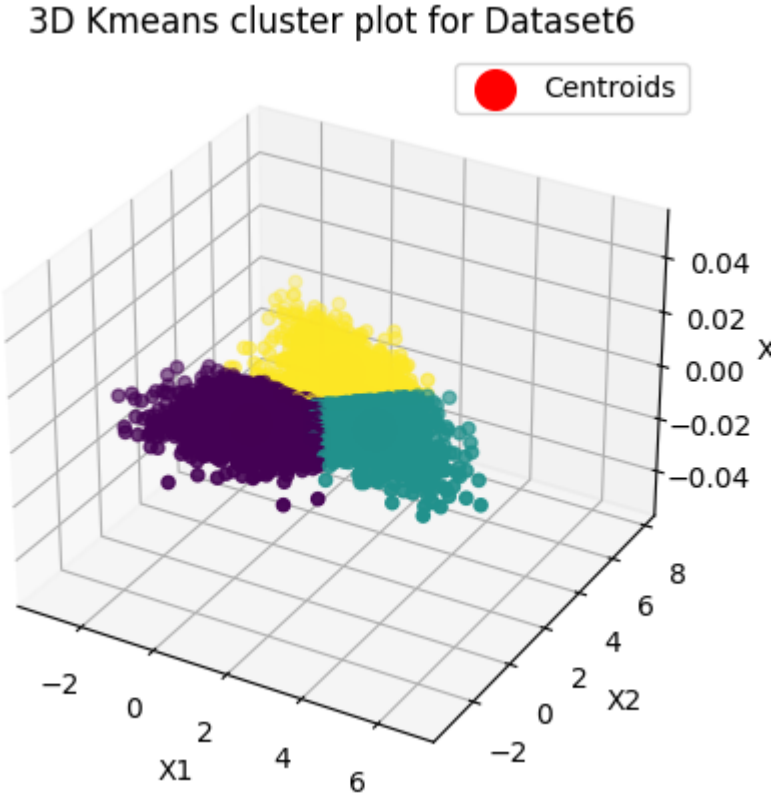
```
plt.title("2D Kmeans cluster plot for Dataset6")
plt.scatter(df6_cluster['X1'],
            df6_cluster['X2'],
            c = df6_cluster['Color'])
plt.scatter(centroid6[:,0], centroid6[:,1], c = 'red', s = 100)
plt.show()
```




```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
plt.title("3D Kmeans cluster plot for Dataset6")
ax.scatter(df6_cluster['X1'], df6_cluster['X2'], c = df6_cluster['Class'], cmap = 'viridi
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.ion()
plt.show()
```

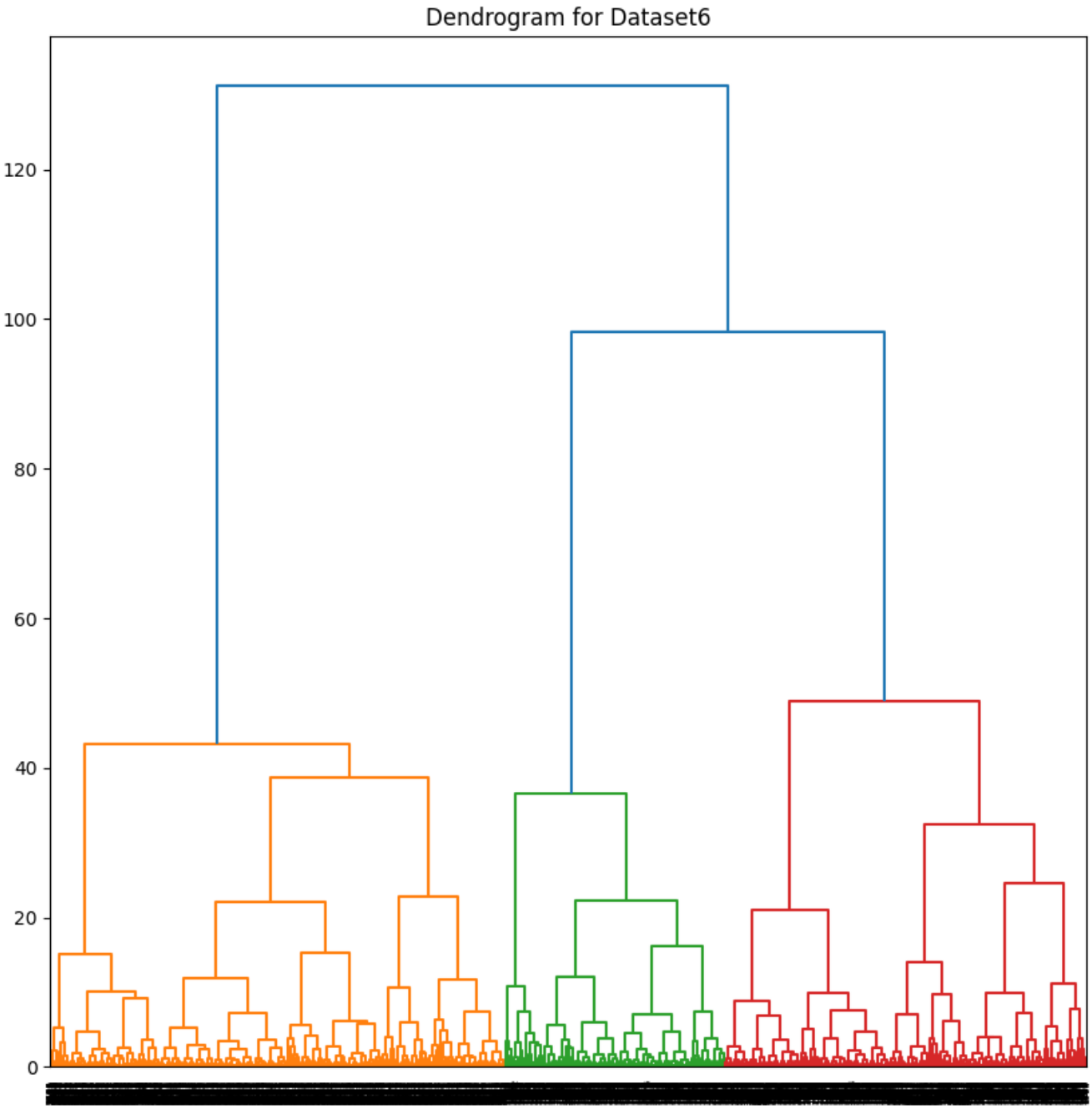



```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
plt.title("3D Kmeans cluster plot for Dataset6")
ax.scatter(df6_cluster['X1'], df6_cluster['X2'],c=df6_cluster['Cluster'],cmap='viridis')
ax.scatter(centroid6[:, 0], centroid6[:, 1], c = 'red', s = 200, label = 'Centroids')
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.legend()
plt.ion()
plt.show()
```




```
%matplotlib inline
```

```
%matplotlib inline
plt.figure(figsize = (10, 10))
dendrogram = sch.dendrogram(sch.linkage(df6_cluster.iloc[:,0:2], method = 'ward'))
plt.title('Dendrogram for Dataset6')
plt.show()
```



Dataset 7

```
df7 = pd.read_csv('Data7.csv')
```

```
df7
```

	Unnamed: 0	X1	X2	Class
0	1	-3.000000	-3.000000	5
1	2	-3.000000	3.000000	4
2	3	3.000000	-3.000000	6
3	4	3.000000	3.000000	3
4	5	-0.417091	0.114782	1
...	...	...	...	...
765	766	-1.604434	-1.118861	2
766	767	-3.050000	-3.050000	5
767	768	-3.050000	2.950000	4
768	769	2.950000	-3.050000	6
769	770	2.950000	2.950000	3

770 rows × 4 columns

```
df7_subset = df7[['X1','X2','Class']]
```

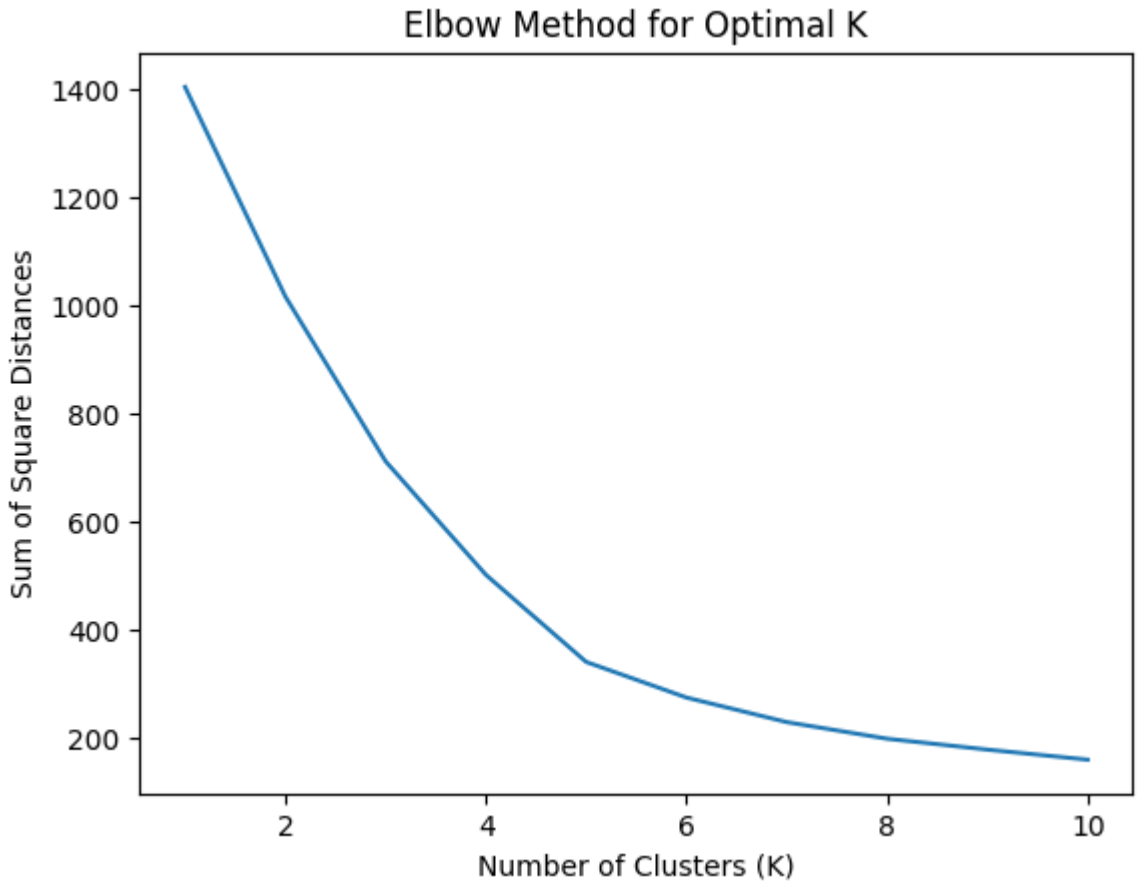
```
df7_subset
```

	X1	X2	Class
0	-3.000000	-3.000000	5
1	-3.000000	3.000000	4
2	3.000000	-3.000000	6

```
k7= []
wcss7 = []
for i in range(1,11):
  md7 = KMeans(n_clusters = i, n_init = 10)
  md7.fit(df7_subset.iloc[:,0:2])
  k7.append(i)
  wcss7.append(md7.inertia_)
```

```
sns.lineplot(x = k7, y = wcss7)
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
#Generating labels
KModel7 = KMeans(n_clusters=5,
            init = 'k-means++',)
```

```
KModel7.fit(df7_subset.iloc[:,0:2])
```

```
▾       KMeans
KMeans(n_clusters=5)
```

```
KModel7.labels_
```

```
array([3, 1, 2, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 3, 1, 2, 4, 3, 1, 3, 2, 3, 1, 3, 2, 3, 2, 3, 2, 1, 2, 1,
       3, 1, 3, 2, 1, 1, 1, 4, 1, 2, 1, 1, 4, 1, 2, 3, 1, 1, 2, 2, 1, 3,
       1, 4, 3, 1, 2, 3, 4, 3, 2, 2, 1, 4, 2, 4, 2, 4, 2, 1, 1, 4, 4, 4,
       3, 2, 3, 2, 3, 4, 2, 1, 3, 4, 2, 4, 4, 3, 2, 4, 1, 1, 1, 3, 1, 1,
       2, 1, 1, 1, 1, 4, 1, 2, 1, 2, 3, 2, 1, 4, 4, 2, 1, 2, 3, 3, 2, 3,
       3, 3, 3, 1, 2, 3, 4, 3, 3, 1, 3, 3, 2, 2, 3, 2, 3, 4, 3, 2, 4, 2,
       1, 3, 3, 4, 2, 3, 2, 4, 2, 4, 4, 2, 1, 3, 2, 1, 4, 3, 4, 4, 4, 2,
       2, 1, 3, 4, 4, 3, 4, 4, 3, 2, 4, 3, 2, 4, 2, 1, 4, 1, 1, 3, 4, 2,
       2, 2, 3, 4, 3, 3, 1, 2, 1, 4, 1, 3, 3, 2, 1, 3, 3, 1, 2, 4, 3, 2,
       4, 4, 2, 2, 4, 4, 2, 1, 2, 1, 3, 1, 4, 4, 4, 1, 2, 2, 1, 1, 4, 1,
       1, 4, 3, 4, 4, 3, 4, 1, 3, 2, 3, 3, 2, 4, 3, 1, 4, 4, 2, 4, 1, 1,
       4, 2, 4, 4, 1, 4, 4, 3, 2, 4, 1, 1, 2, 4, 1, 1, 2, 3, 3, 1, 4, 2,
       4, 3, 2, 3, 4, 4, 4, 1, 2, 3, 1, 3, 1, 1, 2, 3, 2, 1, 4, 3, 2, 1,
       1, 1, 3, 4, 1, 3, 1, 1, 2, 3, 1, 2, 4, 2, 1, 2, 3, 4, 1, 4, 4, 4,
       2, 2, 3, 4, 2, 3, 2, 3, 1, 4, 4, 4, 2, 1, 2, 3, 1, 1, 2, 2, 1, 4,
       2, 1, 1, 3, 2, 2, 2, 2, 1, 3, 4, 2, 1, 3, 3, 3, 4, 2, 3, 2, 3, 1,
       1, 3, 1, 2, 4, 1, 3, 4, 1, 4, 3, 4, 4, 1, 4, 2, 1, 3, 3, 1, 2, 4],
      dtype=int32)
```

```
centroid7 = KModel7.cluster_centers_
```

```
centroid7
```

```
array([[ 0.00909089, -0.02326302],
       [-1.24006227,  1.15081667],
       [ 1.32634626, -1.01080009],
```

```
              [-1.08116062, -1.30840123],
              [ 1.1258747 ,  1.25385075]])
```

```
df7_cluster = df7_subset.copy()
df7_cluster["Cluster"] = KModel7.fit_predict(df7_subset)
```

```
df7_cluster
```

	X1	X2	Class	Cluster
0	-3.000000	-3.000000	5	4
1	-3.000000	3.000000	4	3
2	3.000000	-3.000000	6	1
3	3.000000	3.000000	3	2
4	-0.417091	0.114782	1	0
...	...	...	...	...
765	-1.604434	-1.118861	2	4
766	-3.050000	-3.050000	5	4
767	-3.050000	2.950000	4	3
768	2.950000	-3.050000	6	1
769	2.950000	2.950000	3	2

770 rows × 4 columns

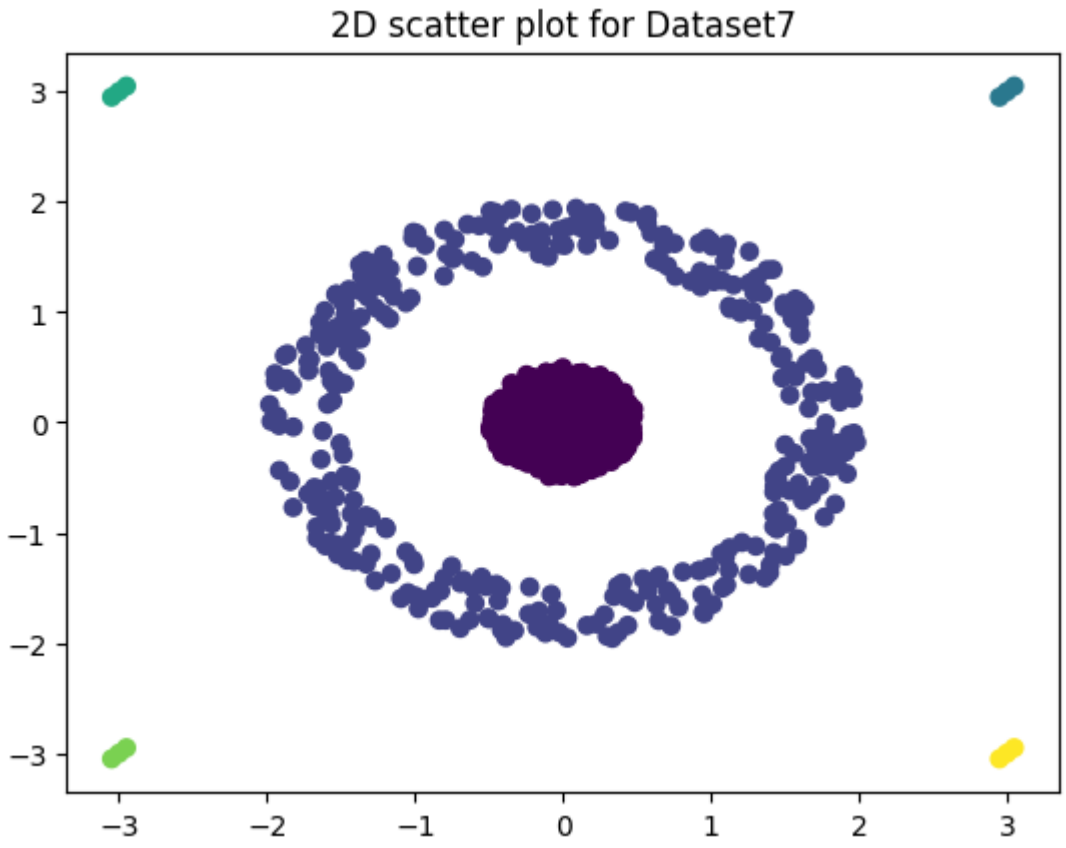
```
colours7 = ['Orange','Yellow','Green','Blue','Navy']
```

```
df7_cluster['Color'] = df7_cluster['Cluster'].map(lambda p:colours7[p])
```

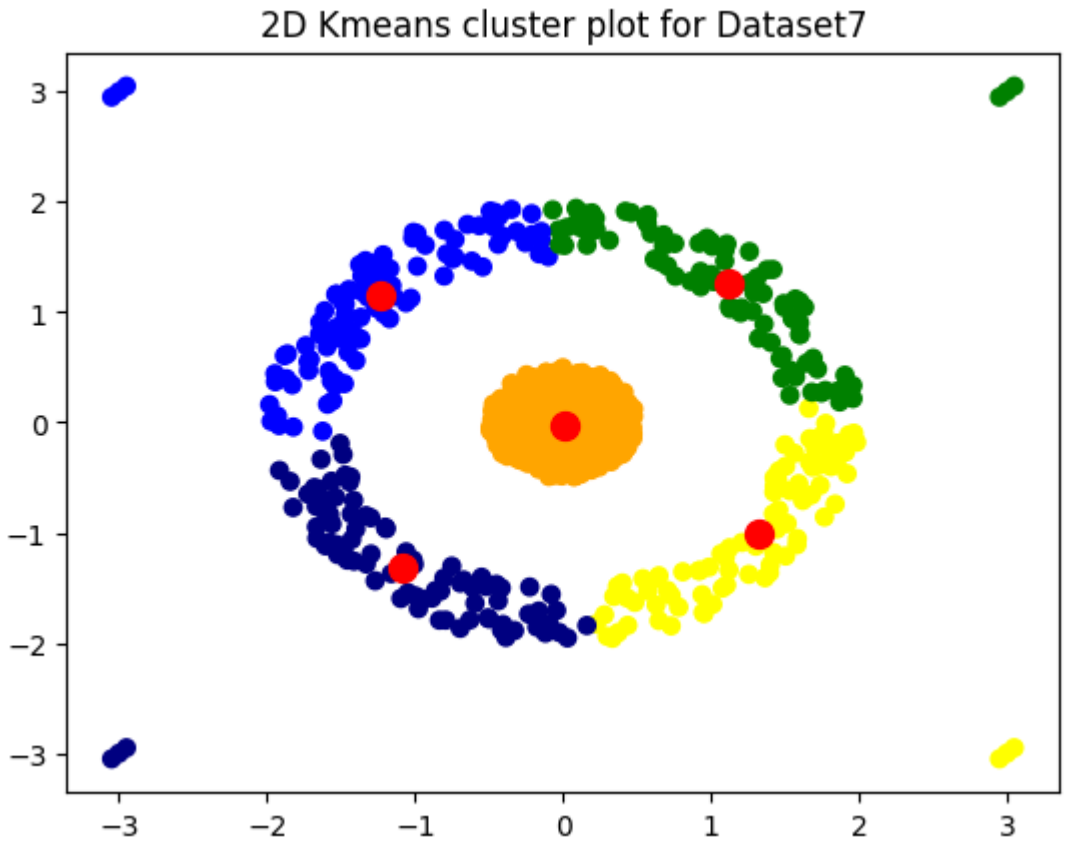
```
df7_cluster
```

	X1	X2	Class	Cluster	Color
0	-3.000000	-3.000000	5	4	Navy
1	-3.000000	3.000000	4	3	Blue
2	3.000000	-3.000000	6	1	Yellow
3	3.000000	3.000000	3	2	Green
4	-0.417091	0.114782	1	0	Orange

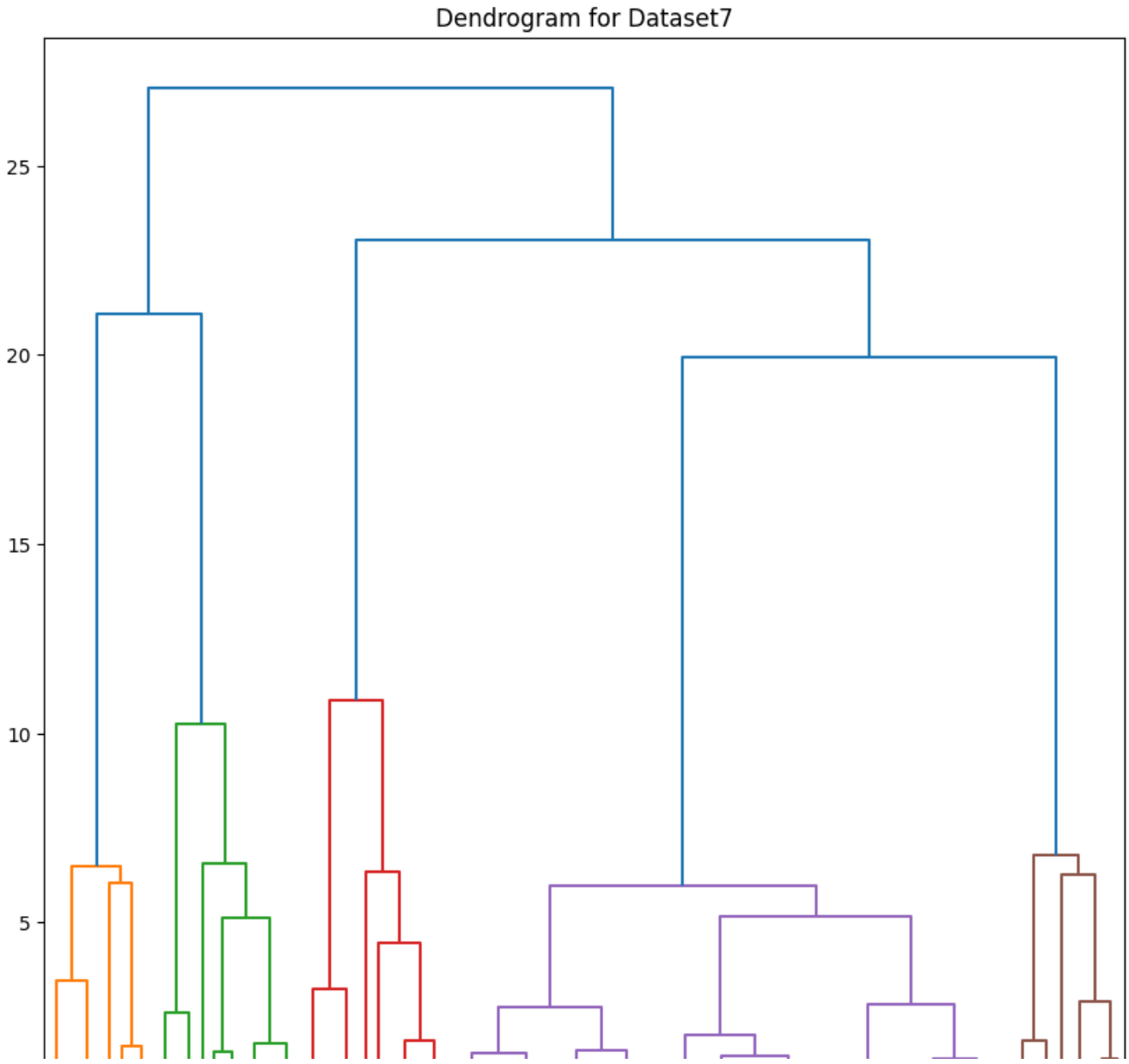
```
%matplotlib notebook
%matplotlib inline
plt.title("2D scatter plot for Dataset7")
plt.scatter(df7_cluster['X1'],
            df7_cluster['X2'],
            c = df7_cluster['Class'])
plt.show()
```



```
%matplotlib notebook
%matplotlib inline
plt.title("2D Kmeans cluster plot for Dataset7")
plt.scatter(df7_cluster['X1'],
            df7_cluster['X2'],
            c = df7_cluster['Color'])
plt.scatter(centroid7[:,0], centroid7[:,1], c = 'red', s = 100)
plt.show()
```




```
%matplotlib inline
plt.figure(figsize = (10, 10))
dendrogram = sch.dendrogram(sch.linkage(df7_cluster.iloc[:,0:2], method = 'ward'))
plt.title('Dendrogram for Dataset7')
plt.show()
```



Dataset 8

```
df8 = pd.read_csv('Data8.csv')
```

```
df8
```

	Unnamed: 0	X1	X2	X3	Class
0	1	0.000000	0.000000	1.00000	1
1	2	0.000000	0.052336	0.99863	1
2	3	0.049774	0.016173	0.99863	1
3	4	0.030762	-0.042341	0.99863	1
4	5	-0.030762	-0.042341	0.99863	1
...	...	...	...	...	...

```
df8_subset = df8[['X1','X2','X3','Class']]
```

3998	3999	0.000000	-0.052336	-0.99863	1

```
df8_subset
```

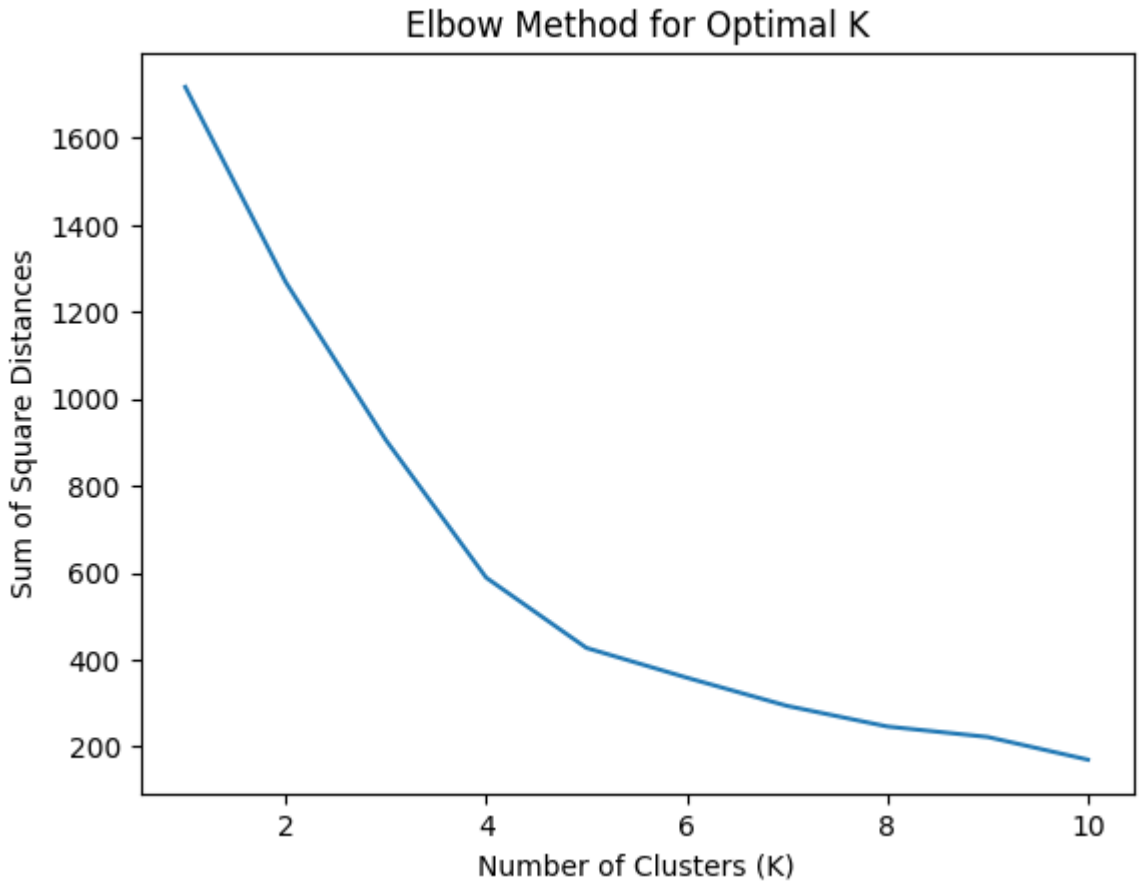
	X1	X2	X3	Class
0	0.000000	0.000000	1.00000	1
1	0.000000	0.052336	0.99863	1
2	0.049774	0.016173	0.99863	1
3	0.030762	-0.042341	0.99863	1
4	-0.030762	-0.042341	0.99863	1
...	...	...	...	...
3997	0.049774	-0.016173	-0.99863	1
3998	0.000000	-0.052336	-0.99863	1
3999	-0.049774	-0.016173	-0.99863	1
4000	-0.030762	0.042341	-0.99863	1
4001	0.000000	0.000000	-1.00000	1

4002 rows × 4 columns

```
k8= []
wcss8 = []
for i in range(1,11):
  md8 = KMeans(n_clusters = i, n_init = 10)
  md8.fit(df7_subset.iloc[:,0:3])
  k8.append(i)
  wcss8.append(md8.inertia_)


sns.lineplot(x = k8, y = wcss8)
plt.xlabel("Number of Clusters (K)")
```

```
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
KModel8 = KMeans(n_clusters=5,
             init = 'k-means++',)
KModel8.fit(df8_subset.iloc[:,0:3])
```

```
▾ KMeans
KMeans(n_clusters=5)
```

```
KModel8.labels_
```

```
array([1, 3, 3, ..., 2, 0, 0], dtype=int32)
```

```
centroid8 = KModel8.cluster_centers_
```

```
centroid8
```

```
array([[ 0.5869387 ,  0.13324775, -0.544568  ],
       [-0.57642499, -0.12393276,  0.55877565],
       [-0.53051364,  0.32847604, -0.47176031],
```

```
              [ 0.39200376,  0.44622627,  0.50523576],
              [ 0.12517378, -0.76384342, -0.04580884]])
```

```
df8_cluster = df8_subset.copy()
df8_cluster["Cluster"] = KModel8.fit_predict(df8_subset)
```

```
df8_cluster
```

	X1	X2	X3	Class	Cluster
0	0.000000	0.000000	1.00000	1	4
1	0.000000	0.052336	0.99863	1	4
2	0.049774	0.016173	0.99863	1	4
3	0.030762	-0.042341	0.99863	1	4
4	-0.030762	-0.042341	0.99863	1	4
...	...	...	...	...	...
3997	0.049774	-0.016173	-0.99863	1	1
3998	0.000000	-0.052336	-0.99863	1	1
3999	-0.049774	-0.016173	-0.99863	1	1
4000	-0.030762	0.042341	-0.99863	1	1
4001	0.000000	0.000000	-1.00000	1	1

4002 rows × 5 columns

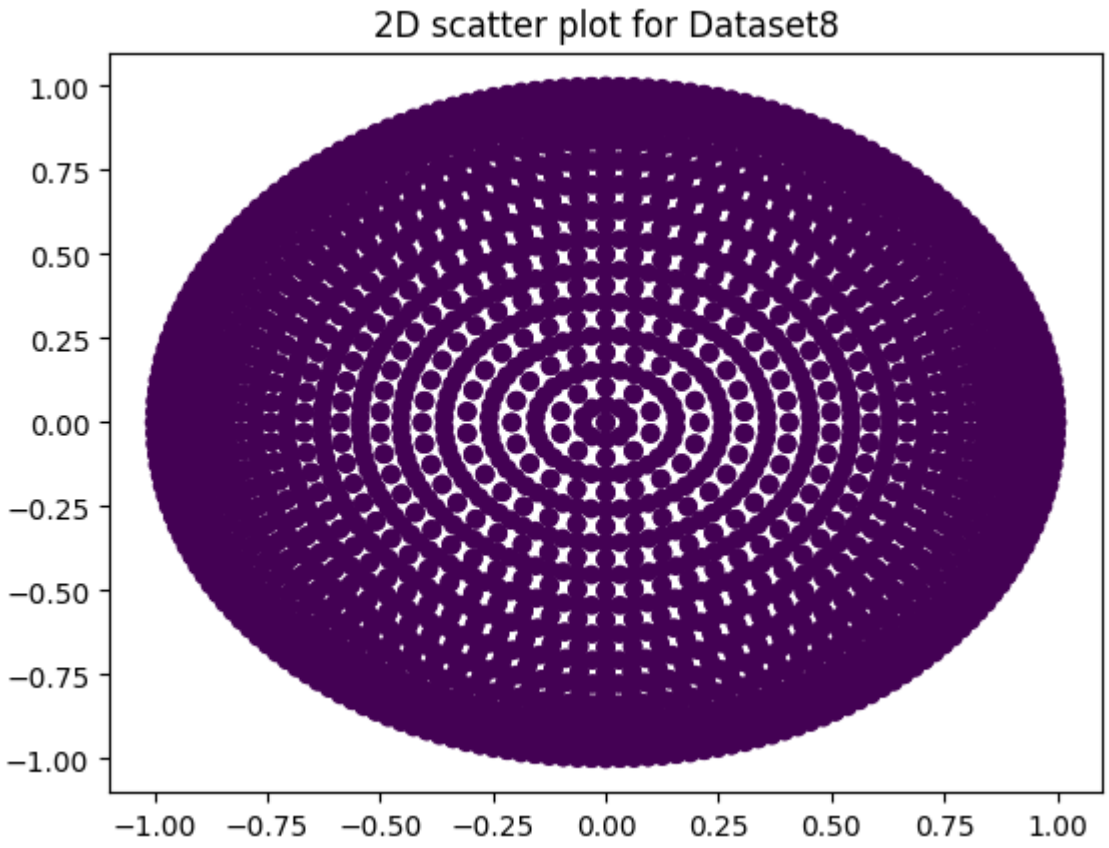
```
colours8 = ['Brown','Green','Gold','Blue','Silver']
```

```
df8_cluster['Color'] = df8_cluster['Cluster'].map(lambda p:colours8[p])
```

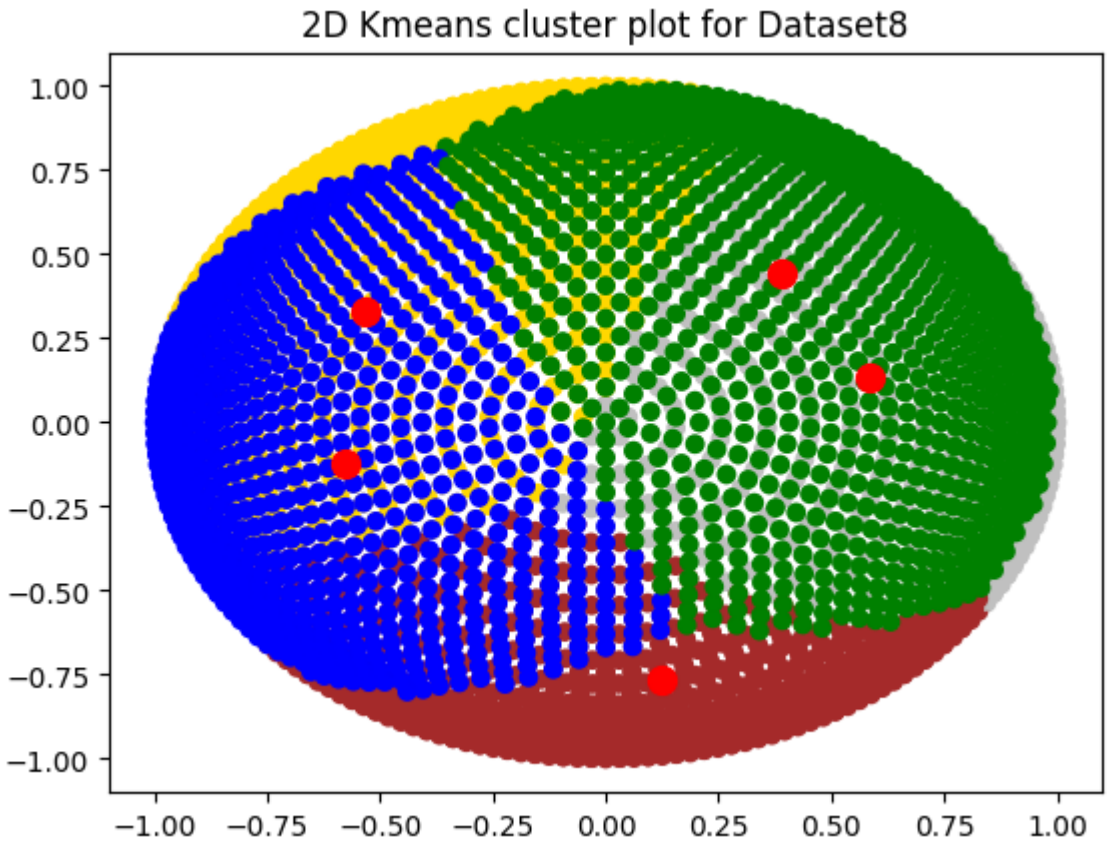
```
df8_cluster
```

	X1	X2	X3	Class	Cluster	Color
0	0.000000	0.000000	1.00000	1	4	Silver
1	0.000000	0.052336	0.99863	1	4	Silver
2	0.049774	0.016173	0.99863	1	4	Silver
3	0.030762	-0.042341	0.99863	1	4	Silver
4	-0.030762	-0.042341	0.99863	1	4	Silver

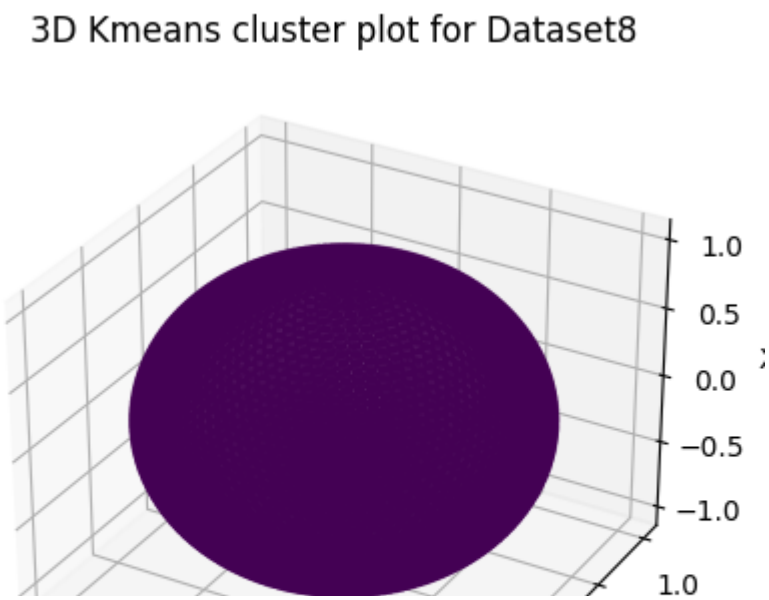
```
%matplotlib notebook
%matplotlib inline
plt.title("2D scatter plot for Dataset8")
plt.scatter(df8_cluster['X1'],
            df8_cluster['X2'],
            c = df8_cluster['Class'])
plt.show()
```



```
%matplotlib notebook
%matplotlib inline
plt.title("2D Kmeans cluster plot for Dataset8")
plt.scatter(df8_cluster['X1'],
            df8_cluster['X2'],
            c = df8_cluster['Color'])
plt.scatter(centroid8[:,0], centroid8[:,1], c = 'red', s = 100)
plt.show()
```



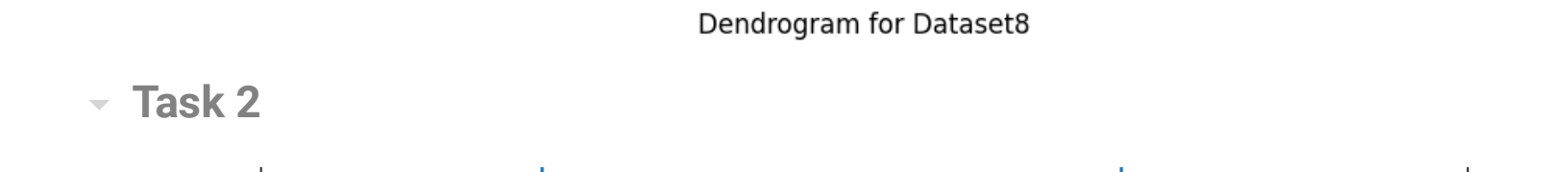

```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
plt.title("3D Kmeans cluster plot for Dataset8")
ax.scatter(df8_cluster['X1'], df8_cluster['X2'], df8_cluster['X3'], c = df8_cluster['Clas
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.ion()
plt.show()
```




```
%matplotlib inline
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
plt.title("3D Kmeans cluster plot for Dataset8")
ax.scatter(df8_cluster['X1'], df8_cluster['X2'], df8_cluster['X3'], c=df8_cluster['Cluste
ax.scatter(centroid8[:, 0], centroid8[:, 1], centroid8[:,2],c = 'red', s = 200, label = '
ax.set_xlabel('X1')
ax.set_ylabel('X2')
ax.set_zlabel('X3')
plt.legend()
plt.ion()
plt.show()
```

3D Kmeans cluster plot for Dataset8

```
%matplotlib inline
plt.figure(figsize = (10, 10))
dendrogram = sch.dendrogram(sch.linkage(df8_cluster.iloc[:,0:3], method = 'ward'))
plt.title('Dendrogram for Dataset8')
plt.show()
```



Task 2

```
#reading the world indicators dataset and creating a dataframe out of it
df9 = pd.read_csv('World Indicators.csv')
```

```
df9
```

	Birth Rate	Business Tax Rate	Days to Start Business	Energy Usage	GDP	Health Exp % GDP	Health Exp/Capita	Hou to T
0	0.025	72.0%	25.0	41852.0	$199,070,864,638	0.044	$233	451
1	0.046	52.1%	66.0	13576.0	$104,115,863,405	0.034	$178	282
2	0.037	65.9%	29.0	3761.0	$7,294,900,431	0.045	$34	270
3	0.024	19.5%	60.0	2215.0	$15,292,424,757	0.052	$404	152
4	0.042	43.5%	13.0	NaN	$10,395,757,480	0.064	$39	270
...	...	...	...	...	...	...	...	
203	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
204	0.013	46.5%	5.0	2191193.0	$15,533,800,000,000	0.177	$8,467	187
205	0.015	41.9%	7.0	4430.0	$47,236,710,623	0.088	$1,213	336
206	0.020	62.8%	141.0	70198.0	$316,482,176,579	0.045	$487	864
207	0.011	NaN	NaN	NaN	NaN	NaN	NaN	Na

208 rows × 20 columns

```
#calculating the total number of null values in every column of the dataset
nulls_per_column = df9.isna().sum(axis = 0)
```

```
print(nulls_per_column)
```

```
Birth Rate                9
Business Tax Rate        27
Days to Start Business   27
Energy Usage             72
GDP                      20
Health Exp % GDP         23
Health Exp/Capita        23
Hours to do Tax          28
Infant Mortality Rate    20
Internet Usage            9
Lending Interest         77
Life Expectancy Female   11
Life Expectancy Male     11
Mobile Phone Usage       12
Population 0-14          17
Population 15-64         17
Population 65+           17
Population Urban          2
Region                    0
Country                   0
dtype: int64
```

```
#Dropping columns energy usage and lending interest since there exists maximum nulls
df9 = df9.drop(columns = 'Energy Usage')
```

```
df9
```

	Birth Rate	Business Tax Rate	Days to Start Business	GDP	Health Exp % GDP	Health Exp/Capita	Hours to do Tax	Infa Mortali Ra
0	0.025	72.0%	25.0	$199,070,864,638	0.044	$233	451.0	0.0
1	0.046	52.1%	66.0	$104,115,863,405	0.034	$178	282.0	0.1
2	0.037	65.9%	29.0	$7,294,900,431	0.045	$34	270.0	0.0
3	0.024	19.5%	60.0	$15,292,424,757	0.052	$404	152.0	0.0
4	0.042	43.5%	13.0	$10,395,757,480	0.064	$39	270.0	0.0

```
df9 = df9.drop(columns = 'Lending Interest')
```

...	...	...	...	...	...	...	...	

```
df9
```

	Birth Rate	Business Tax Rate	Days to Start Business	GDP	Health Exp % GDP	Health Exp/Capita	Hours to do Tax	Infa Mortali Ra
0	0.025	72.0%	25.0	$199,070,864,638	0.044	$233	451.0	0.0
1	0.046	52.1%	66.0	$104,115,863,405	0.034	$178	282.0	0.1
2	0.037	65.9%	29.0	$7,294,900,431	0.045	$34	270.0	0.0
3	0.024	19.5%	60.0	$15,292,424,757	0.052	$404	152.0	0.0
4	0.042	43.5%	13.0	$10,395,757,480	0.064	$39	270.0	0.0
...	...	...	...	...	...	...	...	
203	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
204	0.013	46.5%	5.0	$15,533,800,000,000	0.177	$8,467	187.0	0.0
205	0.015	41.9%	7.0	$47,236,710,623	0.088	$1,213	336.0	0.0
206	0.020	62.8%	141.0	$316,482,176,579	0.045	$487	864.0	0.0
207	0.011	NaN	NaN	NaN	NaN	NaN	NaN	N

208 rows × 18 columns

```
#repeating the above step after dropping the column which was not required for analysis
null_counts = df9.isna().sum(axis = 1)


print(null_counts)
```

```
0       0
1       0
2       0
3       0
4       0
       ..
203    15
204     0
205     0
206     0
207     8
Length: 208, dtype: int64
```

```
#dropping any remaining countries with null data
df9_subset = df9.dropna(subset = df9.columns, thresh=len(df9.columns))


df9_subset
```

	Birth Rate	Business Tax Rate	Days to Start Business	GDP	Health Exp % GDP	Health Exp/Capita	Hours to do Tax	Infa Mortali Ra
0	0.025	72.0%	25.0	$199,070,864,638	0.044	$233	451.0	0.0
1	0.046	52.1%	66.0	$104,115,863,405	0.034	$178	282.0	0.1
3	0.024	19.5%	60.0	$15,292,424,757	0.052	$404	152.0	0.0

```
null_counts = df9_subset.isna().sum(axis=1)
```

```
#now, we can confirm that there are no null values in the dataframe and proceed with the
print(null_counts)
```

```
0      0
1      0
2      0
3      0
4      0
      ..
201    0
202    0
204    0
205    0
206    0
Length: 171, dtype: int64
```

```
#in this block, we are converting values of specific columns into float type
cols_to_convert = ['Health Exp/Capita', 'GDP', 'Business Tax Rate']
df9_subset[cols_to_convert] = df9_subset[cols_to_convert].apply(lambda x: pd.to_numeric(x
```

```
df9_subset
```

	Birth Rate	Business Tax Rate	Days to Start Business	GDP	Health Exp % GDP	Health Exp/Capita	Hours to do Tax	Infant Mortality Rate	Ir
0	0.025	72.0	25.0	1.990709e+11	0.044	233.0	451.0	0.023	
1	0.046	52.1	66.0	1.041159e+11	0.034	178.0	282.0	0.107	
2	0.037	65.9	29.0	7.294900e+09	0.045	34.0	270.0	0.060	
3	0.024	19.5	60.0	1.529242e+10	0.052	404.0	152.0	0.039	
4	0.042	43.5	13.0	1.039576e+10	0.064	39.0	270.0	0.068	
...	...	...	...	...	...	...	...	...	

```
df9_subset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 171 entries, 0 to 206
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Birth Rate              171 non-null    float64
 1   Business Tax Rate       171 non-null    float64
 2   Days to Start Business  171 non-null    float64
 3   GDP                     171 non-null    float64
 4   Health Exp % GDP        171 non-null    float64
 5   Health Exp/Capita       171 non-null    float64
 6   Hours to do Tax         171 non-null    float64
 7   Infant Mortality Rate   171 non-null    float64
 8   Internet Usage          171 non-null    float64
 9   Life Expectancy Female  171 non-null    float64
 10  Life Expectancy Male    171 non-null    float64
 11  Mobile Phone Usage      171 non-null    float64
 12  Population 0-14         171 non-null    float64
 13  Population 15-64        171 non-null    float64
 14  Population 65+          171 non-null    float64
 15  Population Urban        171 non-null    float64
 16  Region                  171 non-null    object 
 17  Country                 171 non-null    object 
dtypes: float64(16), object(2)
memory usage: 25.4+ KB
```

```
#standardizing the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df9_subset.iloc[:,0:16] = scaler.fit_transform(df9_subset.iloc[:,0:16])
```

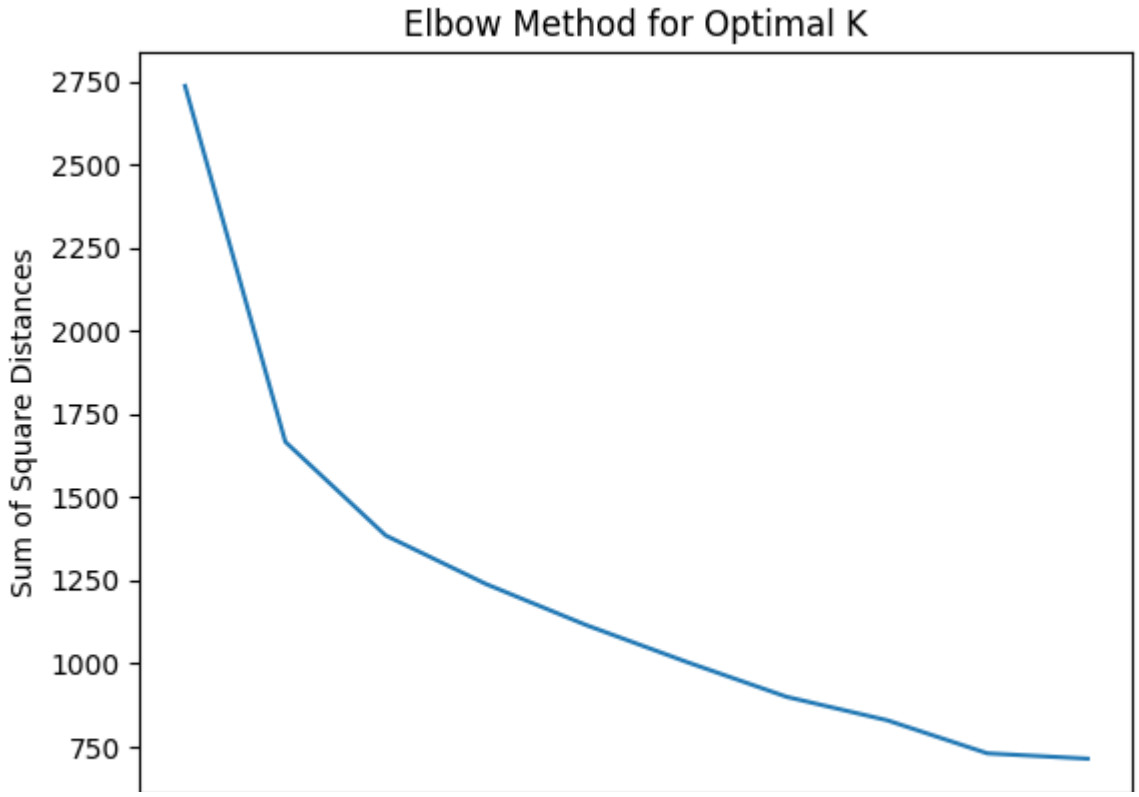
```
df9_subset
```

	Birth Rate	Business Tax Rate	Days to Start Business	GDP	Health Exp % GDP	Health Exp/Capita	Hours to do Tax	Infa Mortali Ra
0	0.241085	0.733673	-0.099269	-0.145350	-0.874226	-0.454207	0.662583	-0.174
1	2.169232	0.189712	0.611634	-0.210537	-1.238575	-0.483635	-0.007818	3.159
2	1.342883	0.566931	-0.029912	-0.277006	-0.837791	-0.560683	-0.055420	1.293
3	0.149269	-0.701399	0.507600	-0.271515	-0.582746	-0.362713	-0.523511	0.460
4	1.801966	-0.045366	-0.307338	-0.274877	-0.145527	-0.558008	-0.055420	1.611
...	...	...	...	...	...	...	...	
201	-0.401630	-0.471787	11.500591	-0.279018	-0.291267	-0.316698	-0.337068	-0.214
202	-0.677080	-0.438986	0.178157	-0.265760	-0.546311	-0.078600	-0.293432	-0.293
204	-0.860713	0.036638	-0.446051	10.382036	3.971623	3.951423	-0.384670	-0.849
205	-0.677080	-0.089102	-0.411373	-0.249585	0.728912	0.070145	0.206393	-0.690
206	-0.217997	0.482194	1.912067	-0.064747	-0.837791	-0.318304	2.300901	-0.531

171 rows × 18 columns


```
#here, we are implementing the elbow method to perform K-means clustering
k9 = []
wcss9 = []
for i in range(1,11):
  md9 = KMeans(n_clusters = i, n_init = 10)
  md9.fit(df9_subset.iloc[:,0:16])
  k9.append(i)
  wcss9.append(md9.inertia_)


sns.lineplot(x = k9, y = wcss9)
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Sum of Square Distances")
plt.title("Elbow Method for Optimal K")
```

```
Text(0.5, 1.0, 'Elbow Method for Optimal K')
```




```
#from the above graph, we can conclude that we have two optimal clusters
KModel9 = KMeans(n_clusters = 2,
             init = 'k-means++',)
KModel9.fit(df9_subset.iloc[:,0:16])
```

```
KMeans
KMeans(n_clusters=2)
```

```
KModel9.labels_
```

```
array([0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0,
       0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0], dtype=int32)
```

```
centroid9 = KModel9.cluster_centers_
```

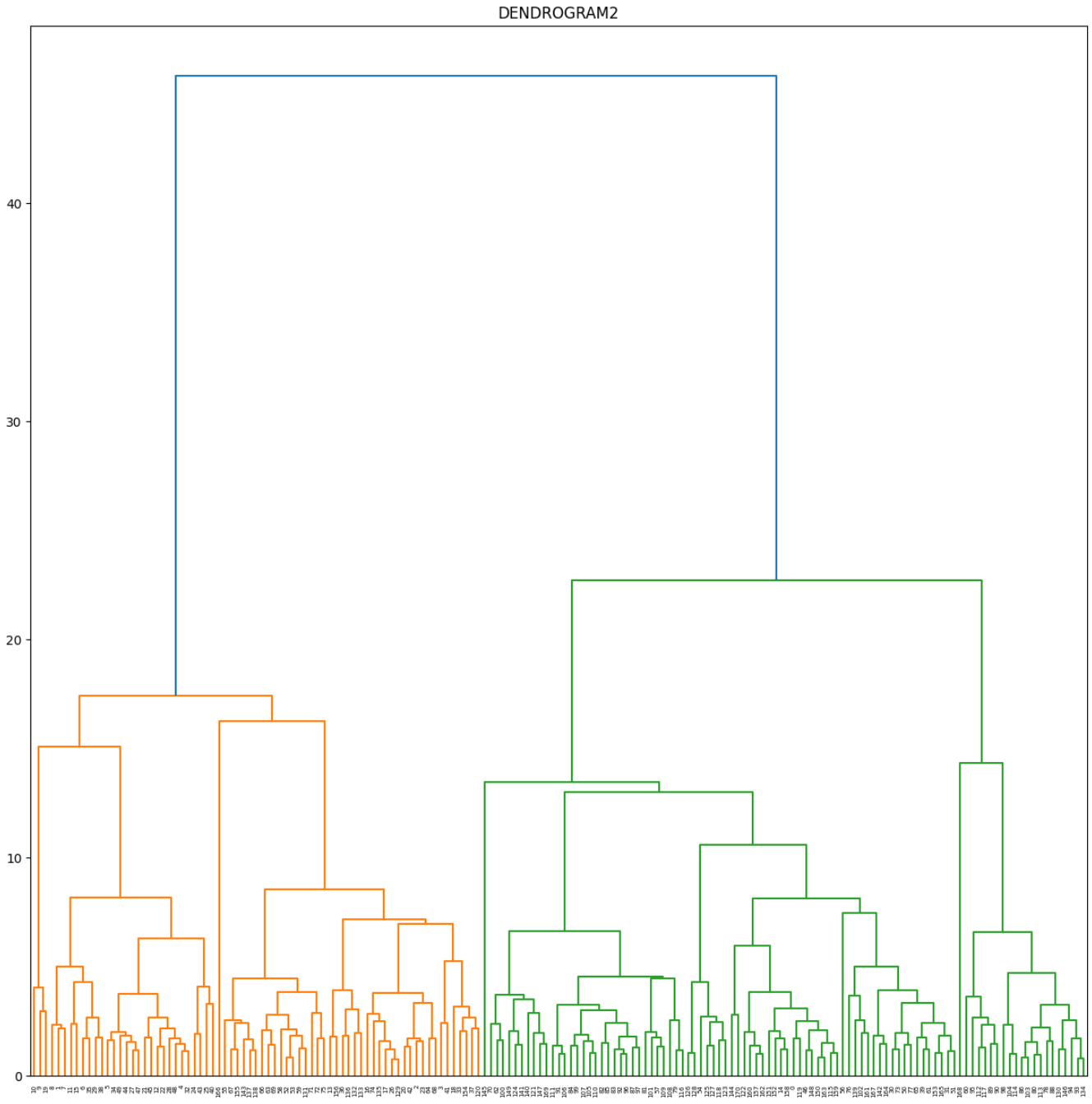
```
#Assigning labels to the original dataset
df9_subset['KMeans Prediction'] = KModel9.labels_
```

```
df9_subset
```

	Birth Rate	Business Tax Rate	Days to Start Business	GDP	Health Exp % GDP	Health Exp/Capita	Hours to do Tax	Infa Mortali Ra
0	0.241085	0.733673	-0.099269	-0.145350	-0.874226	-0.454207	0.662583	-0.174
1	2.169232	0.189712	0.611634	-0.210537	-1.238575	-0.483635	-0.007818	3.159
2	1.342883	0.566931	-0.029912	-0.277006	-0.837791	-0.560683	-0.055420	1.293
3	0.149269	-0.701399	0.507600	-0.271515	-0.582746	-0.362713	-0.523511	0.460
4	1.801966	-0.045366	-0.307338	-0.274877	-0.145527	-0.558008	-0.055420	1.611
...	...	...	...	...	...	...	...	
201	-0.401630	-0.471787	11.500591	-0.279018	-0.291267	-0.316698	-0.337068	-0.214
202	-0.677080	-0.438986	0.178157	-0.265760	-0.546311	-0.078600	-0.293432	-0.293
204	-0.860713	0.036638	-0.446051	10.382036	3.971623	3.951423	-0.384670	-0.849
205	-0.677080	-0.089102	-0.411373	-0.249585	0.728912	0.070145	0.206393	-0.690
206	-0.217997	0.482194	1.912067	-0.064747	-0.837791	-0.318304	2.300901	-0.531

171 rows × 19 columns


```
#performing hierarchical clustering through the means of a dendogram
%matplotlib inline
plt.figure(figsize = (15, 15))
dendrogram = sch.dendrogram(sch.linkage(df9_subset.iloc[:,0:16], method = 'ward'))
plt.title('DENDROGRAM2')
plt.show()
```


DENDROGRAM2
40
30
20
10
0

```
#importing the necessary libraries to perform agglomerative clustering and performing it
from sklearn.cluster import AgglomerativeClustering
cluster = AgglomerativeClustering(n_clusters = 2, linkage = 'ward')
labels = cluster.fit_predict(df9_subset.iloc[:,0:16])
```

```
labels
```

```
array([0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0])
```

```
#here, we are adding the labels column to the original dataset
df9_subset['Hierarchical Prediction'] = cluster.labels_
```

```
df9_subset
```

	Birth Rate	Business Tax Rate	Days to Start Business	GDP	Health Exp % GDP	Health Exp/Capita	Hours to do Tax	Infa Mortal: Ra
0	0.241085	0.733673	-0.099269	-0.145350	-0.874226	-0.454207	0.662583	-0.174

```
#conducting internal validation through different methods

# Determining K-means silhouette score

from sklearn import metrics

print('K-means Silhouette Score:',metrics.silhouette_score(df9_subset.iloc[:,0:16], df9_s
```

```
K-means Silhouette Score: 0.361108968463887
```

```
# Determining K-means Calinski-Harabasz score

import sklearn
print('K-means Calinski-Harabasz Score:',sklearn.metrics.calinski_harabasz_score(df9_subs
```

```
K-means Calinski-Harabasz Score: 108.54562732127647
```

```
#intalling validclust module
!pip install validclust
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/
Requirement already satisfied: validclust in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: seaborn in /usr/local/lib/python3.9/dist-packages (fr
Requirement already satisfied: pandas in /usr/local/lib/python3.9/dist-packages (fro
Requirement already satisfied: matplotlib in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: packaging in /usr/local/lib/python3.9/dist-packages (
Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.9/dist-packag
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.9/dist-packag
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.9/dist
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.9/dist-pac
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: importlib-resources>=3.2.0 in /usr/local/lib/python3.
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.9/dist
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.9/dist-packag
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: zipp>=3.1.0 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/dist-packages (f
```

```
# Determining K-means Dunn Index score
```

```
from validclust import dunn
from sklearn.metrics import pairwise_distances

print('K-means Dunn Index Score:', dunn(pairwise_distances(df9_subset.iloc[:,0:16]), df9_
```

```
K-means Dunn Index Score: 0.06697056305227665
```

```
# Determining hierarchical Silhouette score

print('Hierarchical Silhouette Score:', metrics.silhouette_score(df9_subset.iloc[:,0:16],
```

```
Hierarchical Silhouette Score: 0.35327630525116543
```

```
# Determining hierarchical Calinski-Harabasz score

print('Hierarchical Calinski-Harabasz Score:', sklearn.metrics.calinski_harabasz_score(df
```

```
Hierarchical Calinski-Harabasz Score: 105.43473274338285
```

```
# Determining hierarchical Dunn Index score

print('Hierarchical Dunn Index Score:', dunn(pairwise_distances(df9_subset.iloc[:,0:16]),
```

```
Hierarchical Dunn Index Score: 0.08888902262316713
```

Hence, we can conclude that K-means is the method with the best clustering solution, as two out of three internal validation metrics produce higher scores than those of the hierarchical solution.

```
#K-means
print('K-means Cluster 0:')
print(df9_subset[df9_subset['KMeans Prediction'] == 0]['Country'].values.tolist())
print('K-means Cluster 1:')
print(df9_subset[df9_subset['KMeans Prediction'] == 1]['Country'].values.tolist())
```

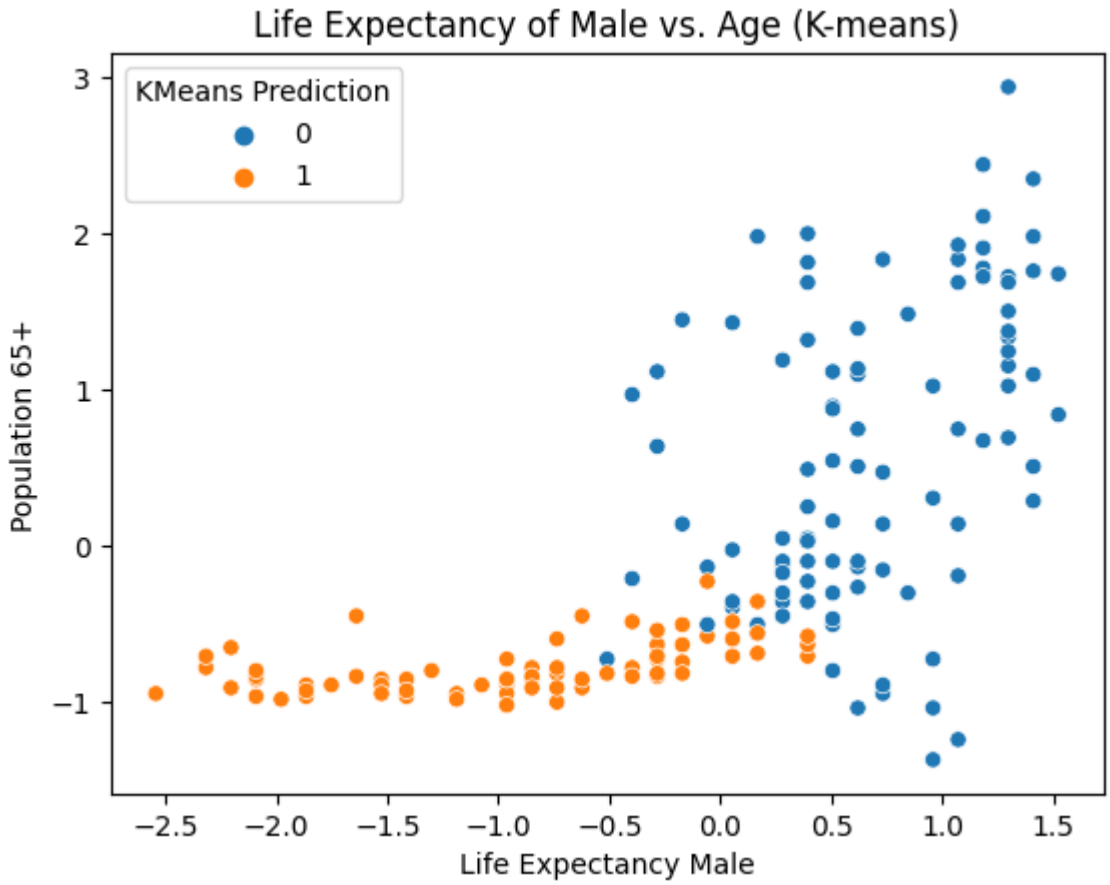
```
K-means Cluster 0:
['Algeria', 'Egypt, Arab Rep.', 'Mauritius', 'Morocco', 'Seychelles', 'Tunisia', 'Ar
K-means Cluster 1:
['Angola', 'Benin', 'Botswana', 'Burkina Faso', 'Burundi', 'Cameroon', 'Central Afri
```

```
#Hierarchical
print('Hierarchical Cluster 0:')
print(df9_subset[df9_subset['Hierarchical Prediction']==0]['Country'].values.tolist())
print('Hierarchical Cluster 1:')
print(df9_subset[df9_subset['Hierarchical Prediction']==1]['Country'].values.tolist())
```

```
Hierarchical Cluster 0:
['Algeria', 'Egypt, Arab Rep.', 'Mauritius', 'Morocco', 'Seychelles', 'Tunisia', 'Ar
Hierarchical Cluster 1:
['Angola', 'Benin', 'Botswana', 'Burkina Faso', 'Burundi', 'Cameroon', 'Central Afri
```

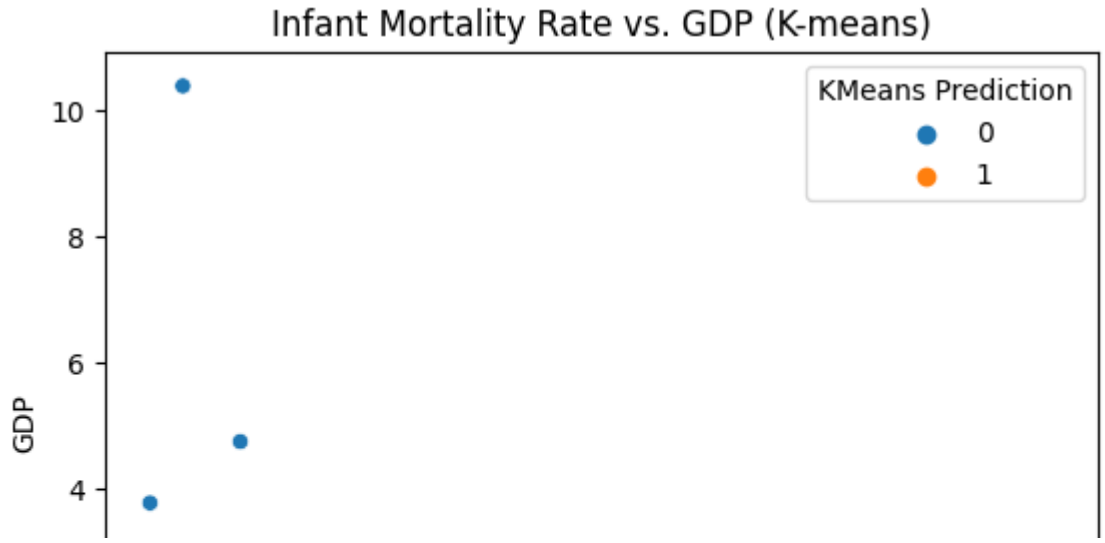
```
#here, we are creating appropriate scatter plots
sns.scatterplot(x = 'Life Expectancy Male', y='Population 65+', hue='KMeans Prediction',
plt.title('Life Expectancy of Male vs. Age (K-means)')
```

```
Text(0.5, 1.0, 'Life Expectancy of Male vs. Age (K-means)')
```



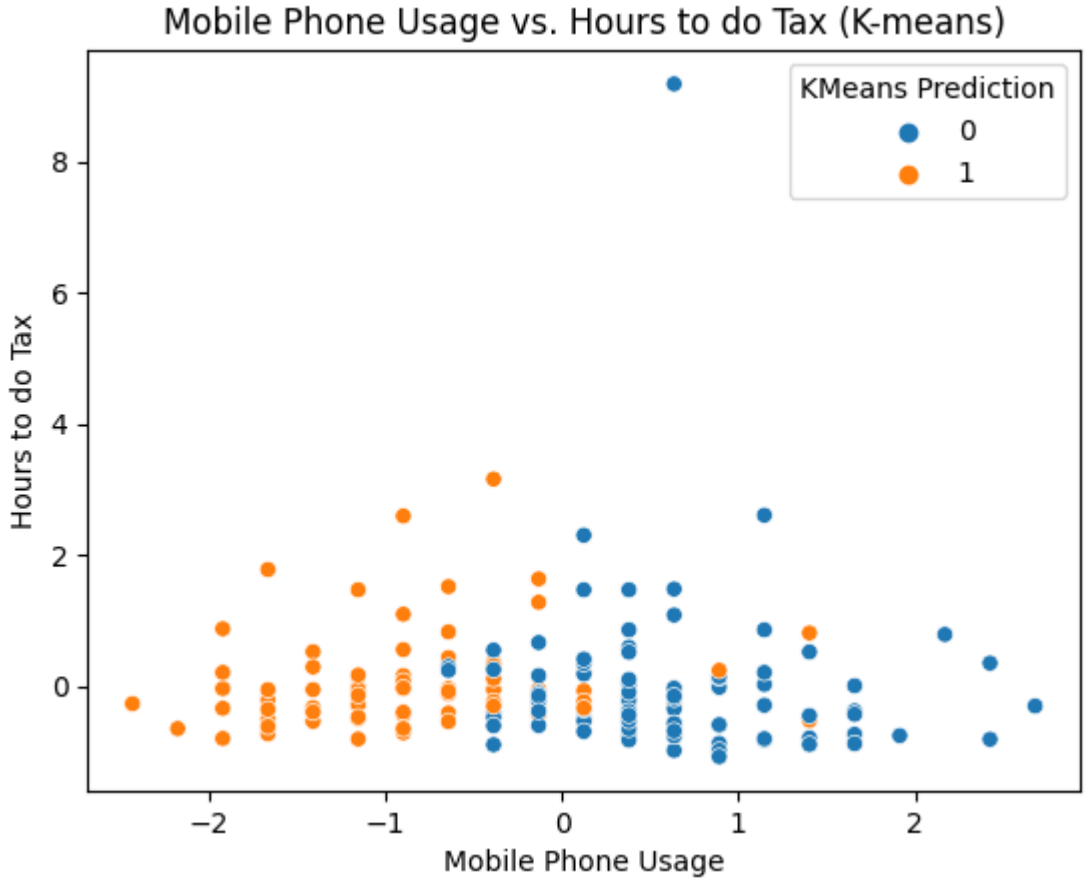

```
sns.scatterplot(x = df9_subset['Infant Mortality Rate'], y = df9_subset['GDP'], hue = df9
plt.title('Infant Mortality Rate vs. GDP (K-means)')
```

```
Text(0.5, 1.0, 'Infant Mortality Rate vs. GDP (K-means)')
```

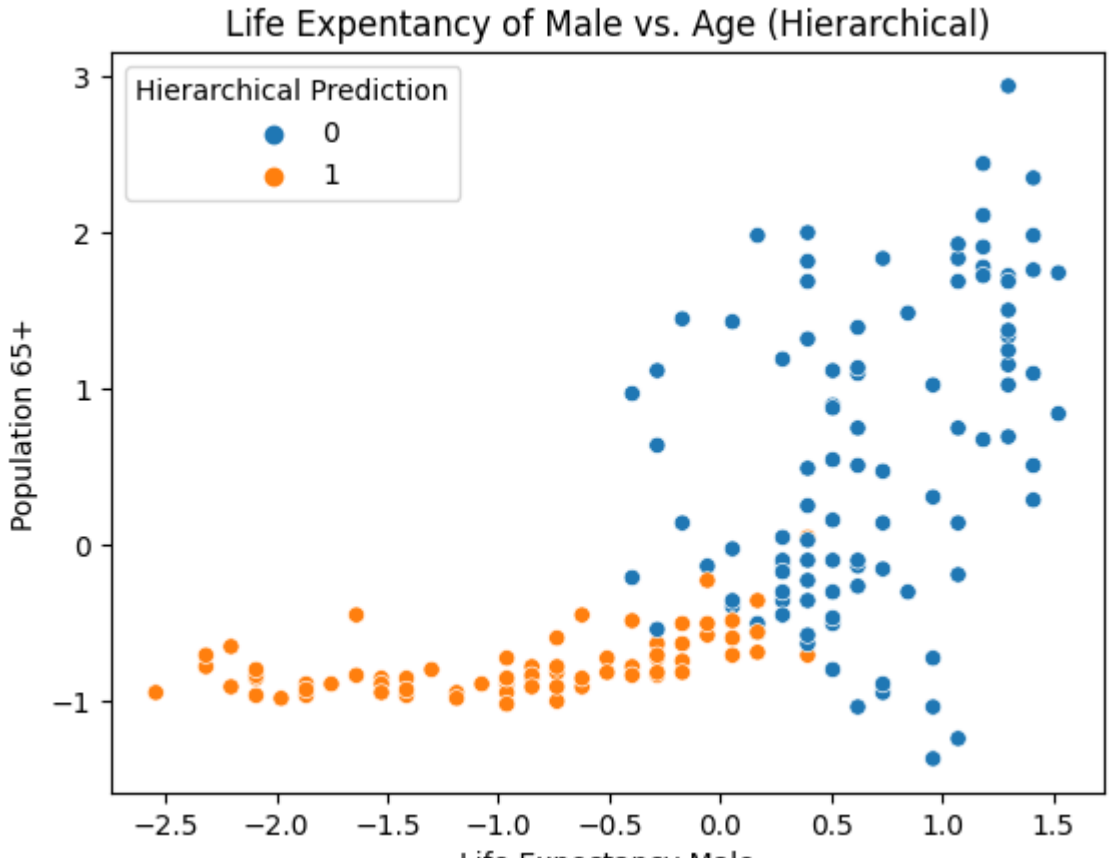



```
sns.scatterplot(x = df9_subset['Mobile Phone Usage'], y = df9_subset['Hours to do Tax'],
plt.title('Mobile Phone Usage vs. Hours to do Tax (K-means)')
```

```
Text(0.5, 1.0, 'Mobile Phone Usage vs. Hours to do Tax (K-means)')
```




```
sns.scatterplot(x = 'Life Expectancy Male', y = 'Population 65+', hue = 'Hierarchical Pre
plt.title('Life Expentancy of Male vs. Age (Hierarchical)')
plt.show()
```

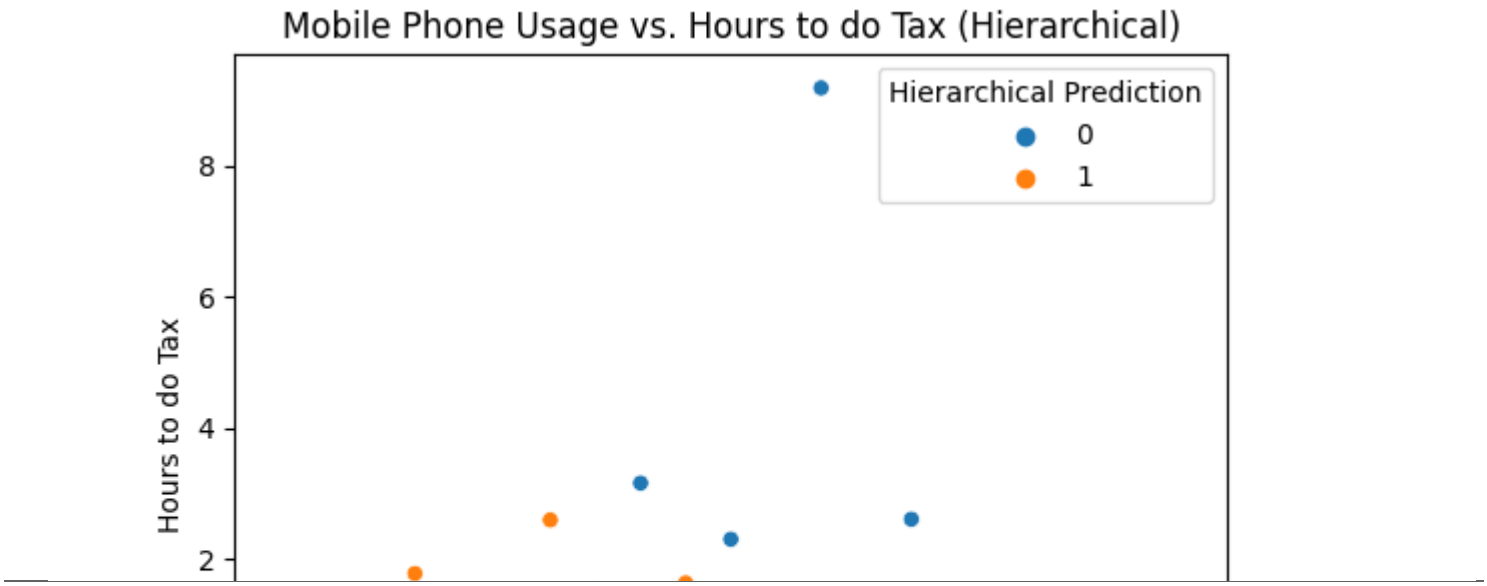



```
sns.scatterplot(x = df9_subset['Infant Mortality Rate'], y = df9_subset['GDP'], hue = df9
plt.title('Infant Mortality Rate vs. GDP (Hierarchical)')
```

```
Text(0.5, 1.0, 'Infant Mortality Rate vs. GDP (Hierarchical)')
```

```
sns.scatterplot(x = df9_subset['Mobile Phone Usage'], y = df9_subset['Hours to do Tax'],
plt.title('Mobile Phone Usage vs. Hours to do Tax (Hierarchical)')
```

```
Text(0.5, 1.0, 'Mobile Phone Usage vs. Hours to do Tax (Hierarchical)')
```



✓ 1s completed at 5:08 PM