DSA Assignment

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In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
%matplotlib inline
import scipy.cluster.hierarchy as sch
from sklearn.preprocessing import power_transform
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import KMeans
from sklearn import metrics

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
'''Perform clustering (hierarchical,K means clustering and DBSCAN) for the airlines data to obtain optimum number of clusters.
Draw the inferences from the clusters obtained.'''
```

In [3]:
```
df = pd.read_excel(r'DSA\Assignment 3\EastWestAirlines.xlsx', sheet_name='data')
df.head()
```

Out[3]:

	ID#	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo	Flight_trans_12	Days_since_enroll	Award?
0	1	28143	0	1	1	1	174	1	0	0	7000	0
1	2	19244	0	1	1	1	215	2	0	0	6968	0
2	3	41354	0	1	1	1	4123	4	0	0	7034	0
3	4	14776	0	1	1	1	500	1	0	0	6952	0
4	5	97752	0	4	1	1	43300	26	2077	4	6935	1

In [4]:
```
df.describe()
```

Out[4]:

	ID#	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo	Flight_trans_12	Days_since_enroll	Award?
count	3999.000000	3.999000e+03	3999.000000	3999.000000	3999.000000	3999.000000	3999.000000	3999.00000	3999.000000	3999.000000	3999.00000	3999.000000
mean	2014.819455	7.360133e+04	144.114529	2.059515	1.014504	1.012253	17144.846212	11.60190	460.055764	1.373593	4118.55939	0.370343
std	1160.764358	1.007757e+05	773.663804	1.376919	0.147650	0.195241	24150.967826	9.60381	1400.209171	3.793172	2065.13454	0.482957
min	1.000000	0.000000e+00	0.000000	1.000000	1.000000	1.000000	0.000000	0.00000	0.000000	0.000000	2.00000	0.000000
25%	1010.500000	1.852750e+04	0.000000	1.000000	1.000000	1.000000	1250.000000	3.00000	0.000000	0.000000	2330.00000	0.000000
50%	2016.000000	4.309700e+04	0.000000	1.000000	1.000000	1.000000	7171.000000	12.00000	0.000000	0.000000	4096.00000	0.000000
75%	3020.500000	9.240400e+04	0.000000	3.000000	1.000000	1.000000	23800.500000	17.00000	311.000000	1.000000	5790.50000	1.000000
max	4021.000000	1.704838e+06	11148.000000	5.000000	3.000000	5.000000	263685.000000	86.00000	30817.000000	53.000000	8296.00000	1.000000

In [5]:
```
df.columns
```

Out[5]:
```
Index(['ID#', 'Balance', 'Qual_miles', 'cc1_miles', 'cc2_miles', 'cc3_miles',
       'Bonus_miles', 'Bonus_trans', 'Flight_miles_12mo', 'Flight_trans_12',
       'Days_since_enroll', 'Award?'],
      dtype='object')
```

In [6]:
```
df1 =df.drop('ID#',axis=1)
```

In [7]:
```
#checking for null values
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3999 entries, 0 to 3998
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Balance            3999 non-null   int64
 1   Qual_miles         3999 non-null   int64
 2   cc1_miles          3999 non-null   int64
 3   cc2_miles          3999 non-null   int64
 4   cc3_miles          3999 non-null   int64
 5   Bonus_miles        3999 non-null   int64
 6   Bonus_trans        3999 non-null   int64
 7   Flight_miles_12mo  3999 non-null   int64
 8   Flight_trans_12    3999 non-null   int64
 9   Days_since_enroll  3999 non-null   int64
 10  Award?             3999 non-null   int64
dtypes: int64(11)
memory usage: 343.8 KB
```

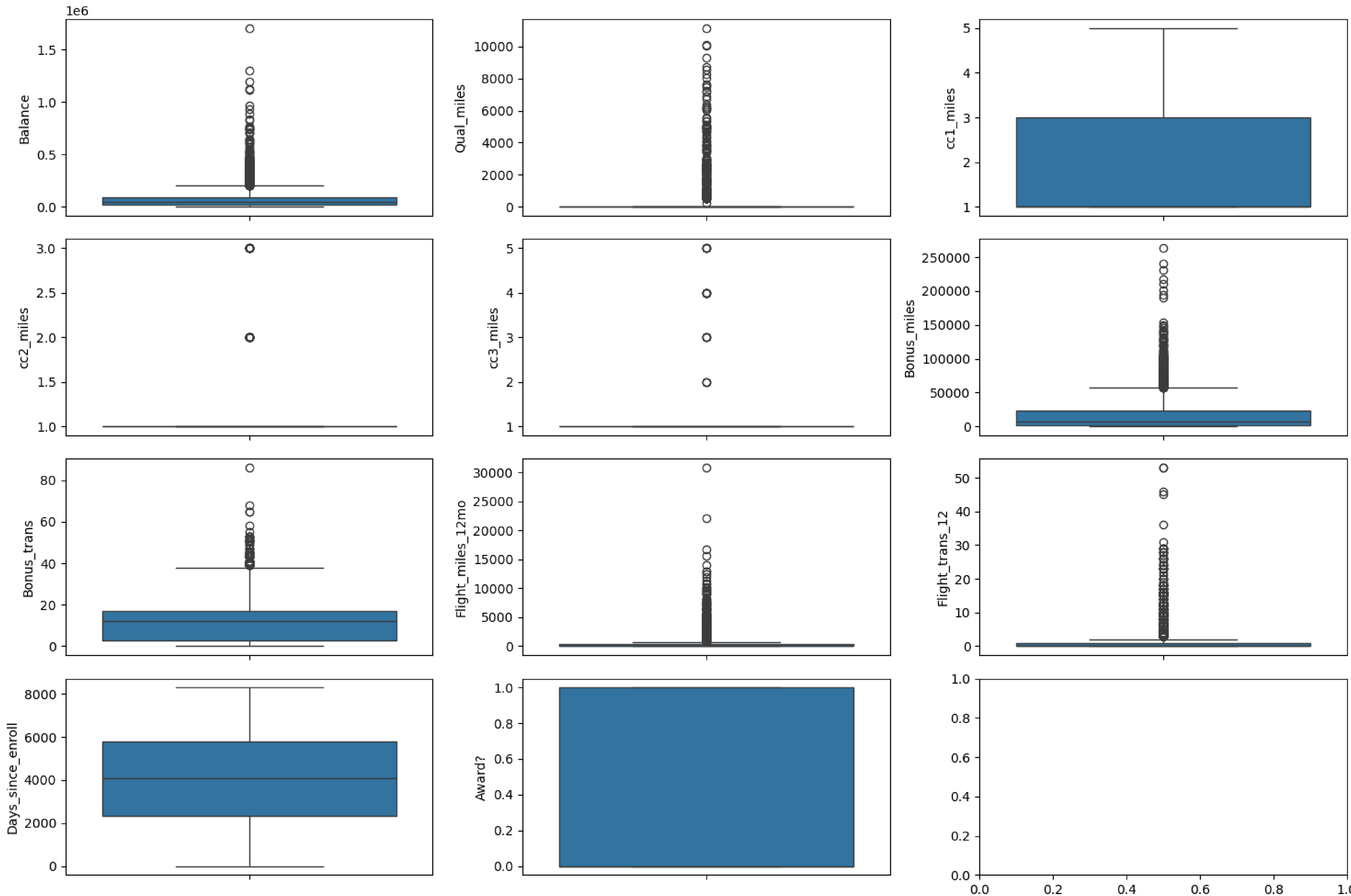
In [8]:
```
# checking for duplicates
df1[df.duplicated(keep=False)]
```

Out[8]:

Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo	Flight_trans_12	Days_since_enroll	Award?

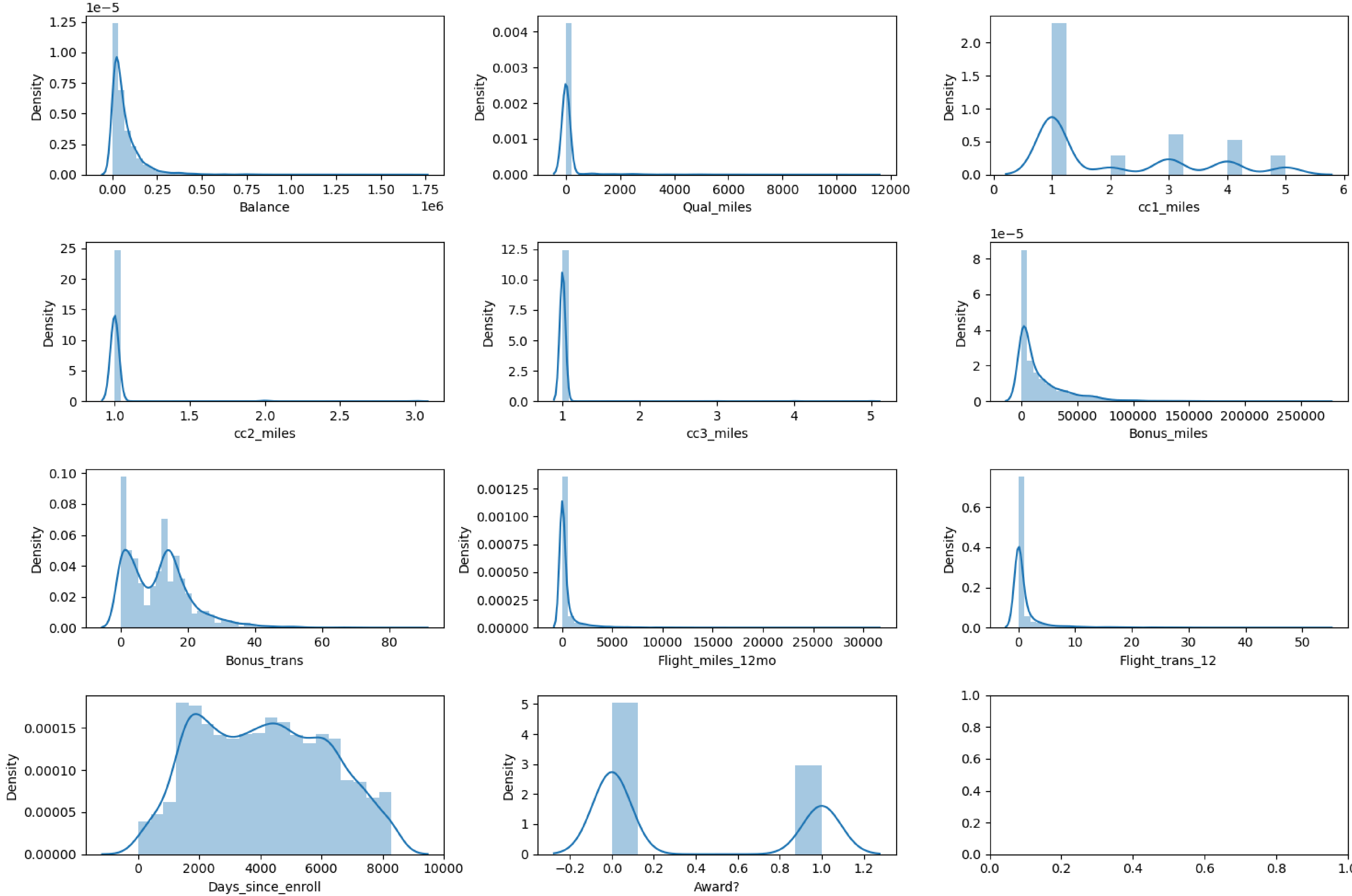
Outliers detection

In [9]:
```python
# using box plot
fig, ax = plt.subplots(4,3,figsize=(15,10))
sns.boxplot(df1.Balance,ax=ax[0,0])
sns.boxplot(df1.Qual_miles,ax=ax[0,1])
sns.boxplot(df1.cc1_miles,ax=ax[0,2])
sns.boxplot(df1.cc2_miles,ax=ax[1,0])
sns.boxplot(df1.cc3_miles,ax=ax[1,1])
sns.boxplot(df1.Bonus_miles,ax=ax[1,2])
sns.boxplot(df1.Bonus_trans,ax=ax[2,0])
sns.boxplot(df1.Flight_miles_12mo,ax=ax[2,1])
sns.boxplot(df1.Flight_trans_12,ax=ax[2,2])
sns.boxplot(df1.Days_since_enroll,ax=ax[3,0])
sns.boxplot(df1['Award?'],ax=ax[3,1])

plt.tight_layout()
plt.show()
```



1e6
Balance
Qual_miles
cc1_miles
cc2_miles
cc3_miles
Bonus_miles
Bonus_trans
Flight_miles_12mo
Flight_trans_12
Days_since_enroll
Award?

In [10]:
```python
#using distplot
fig, ax = plt.subplots(4,3,figsize=(15,10))
sns.distplot(df1.Balance,ax=ax[0,0])
sns.distplot(df1.Qual_miles,ax=ax[0,1])
sns.distplot(df1.cc1_miles,ax=ax[0,2])
sns.distplot(df1.cc2_miles,ax=ax[1,0])
sns.distplot(df1.cc3_miles,ax=ax[1,1])
sns.distplot(df1.Bonus_miles,ax=ax[1,2])
sns.distplot(df1.Bonus_trans,ax=ax[2,0])
sns.distplot(df1.Flight_miles_12mo,ax=ax[2,1])
sns.distplot(df1.Flight_trans_12,ax=ax[2,2])
sns.distplot(df1.Days_since_enroll,ax=ax[3,0])
sns.distplot(df1['Award?'],ax=ax[3,1])

plt.tight_layout()
plt.show()
```


1e−5
Density
Balance
1e6
Density
Qual_miles
Density
cc1_miles
Density
cc2_miles
Density
cc3_miles
1e−5
Density
Bonus_miles
Density
Bonus_trans
Density
Flight_miles_12mo
Density
Flight_trans_12
Density
Days_since_enroll
Density
Award?

Using power transform for standardizing distribution

In [11]:
```
df2 = df1[['Balance','Qual_miles','cc1_miles','cc2_miles','cc3_miles','Bonus_miles','Bonus_trans','Flight_miles_12mo','Flight_trans_12','Days_since_enroll','Award?']]
df2_transformed = power_transform(df2,method='yeo-johnson')
```

In [12]:
```
df2 =pd.DataFrame(df2_transformed,columns=['Balance','Qual_miles','cc1_miles','cc2_miles','cc3_miles','Bonus_miles','Bonus_trans','Flight_miles_12mo','Flight_trans_12','Days_since_enro
df2
```

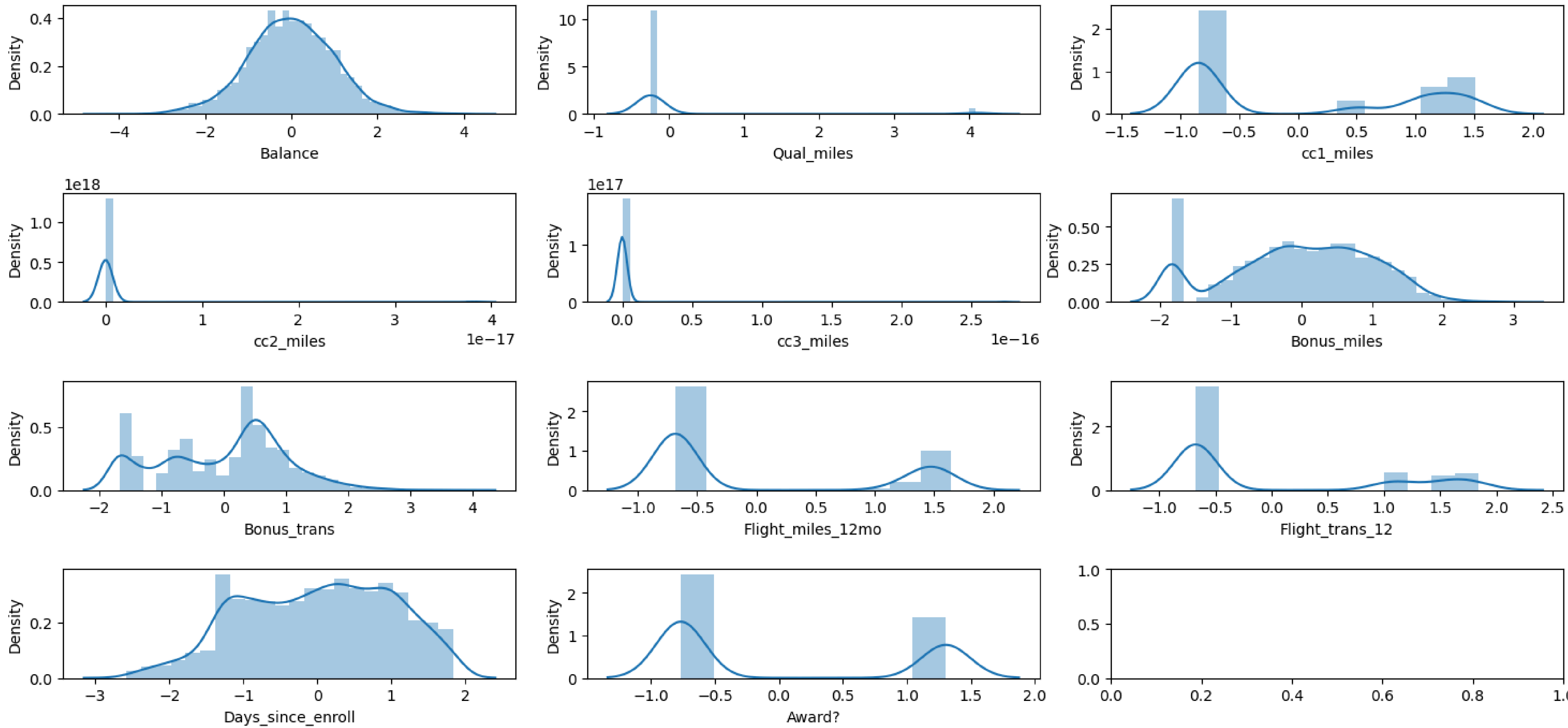
Out[12]:

	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo	Flight_trans_12	Days_since_enroll	Award?
0	-0.346816	-0.244743	-0.844766	0.0	0.0	-1.178402	-1.329671	-0.683308	-0.674970	1.321776	-0.766919
1	-0.633084	-0.244743	-0.844766	0.0	0.0	-1.132416	-1.074960	-0.683308	-0.674970	1.308873	-0.766919
2	-0.038549	-0.244743	-0.844766	0.0	0.0	-0.191941	-0.688822	-0.683308	-0.674970	1.335468	-0.766919
3	-0.821989	-0.244743	-0.844766	0.0	0.0	-0.924946	-1.329671	-0.683308	-0.674970	1.302415	-0.766919
4	0.723596	-0.244743	1.343165	0.0	0.0	1.169363	1.329711	1.549026	1.685925	1.295549	1.303918
...	...	...	...	...	...	...	...	...	...	...	...
3994	-0.662730	-0.244743	-0.844766	0.0	0.0	0.153811	-0.688822	1.346970	1.081077	-1.364712	1.303918
3995	0.340486	-0.244743	-0.844766	0.0	0.0	-0.727886	-0.530613	-0.683308	-0.674970	-1.369774	1.303918
3996	0.460388	-0.244743	1.058591	0.0	0.0	0.795077	-0.134235	-0.683308	-0.674970	-1.365345	1.303918
3997	0.200904	-0.244743	-0.844766	0.0	0.0	-0.924946	-1.329671	1.446453	1.081077	-1.365977	-0.766919
3998	-1.803321	-0.244743	-0.844766	0.0	0.0	-1.826245	-1.679465	-0.683308	-0.674970	-1.367875	-0.766919

3999 rows × 11 columns

visualization after transformation

In [13]:
```
#using distplot
fig, ax = plt.subplots(4,3,figsize=(15,7))
sns.distplot(df2.Balance,ax=ax[0,0])
sns.distplot(df2.Qual_miles,ax=ax[0,1])
sns.distplot(df2.cc1_miles,ax=ax[0,2])
sns.distplot(df2.cc2_miles,ax=ax[1,0])
sns.distplot(df2.cc3_miles,ax=ax[1,1])
sns.distplot(df2.Bonus_miles,ax=ax[1,2])
sns.distplot(df2.Bonus_trans,ax=ax[2,0])
sns.distplot(df2.Flight_miles_12mo,ax=ax[2,1])
sns.distplot(df2.Flight_trans_12,ax=ax[2,2])
sns.distplot(df2.Days_since_enroll,ax=ax[3,0])
sns.distplot(df2['Award?'],ax=ax[3,1])

plt.tight_layout()
plt.show()
```

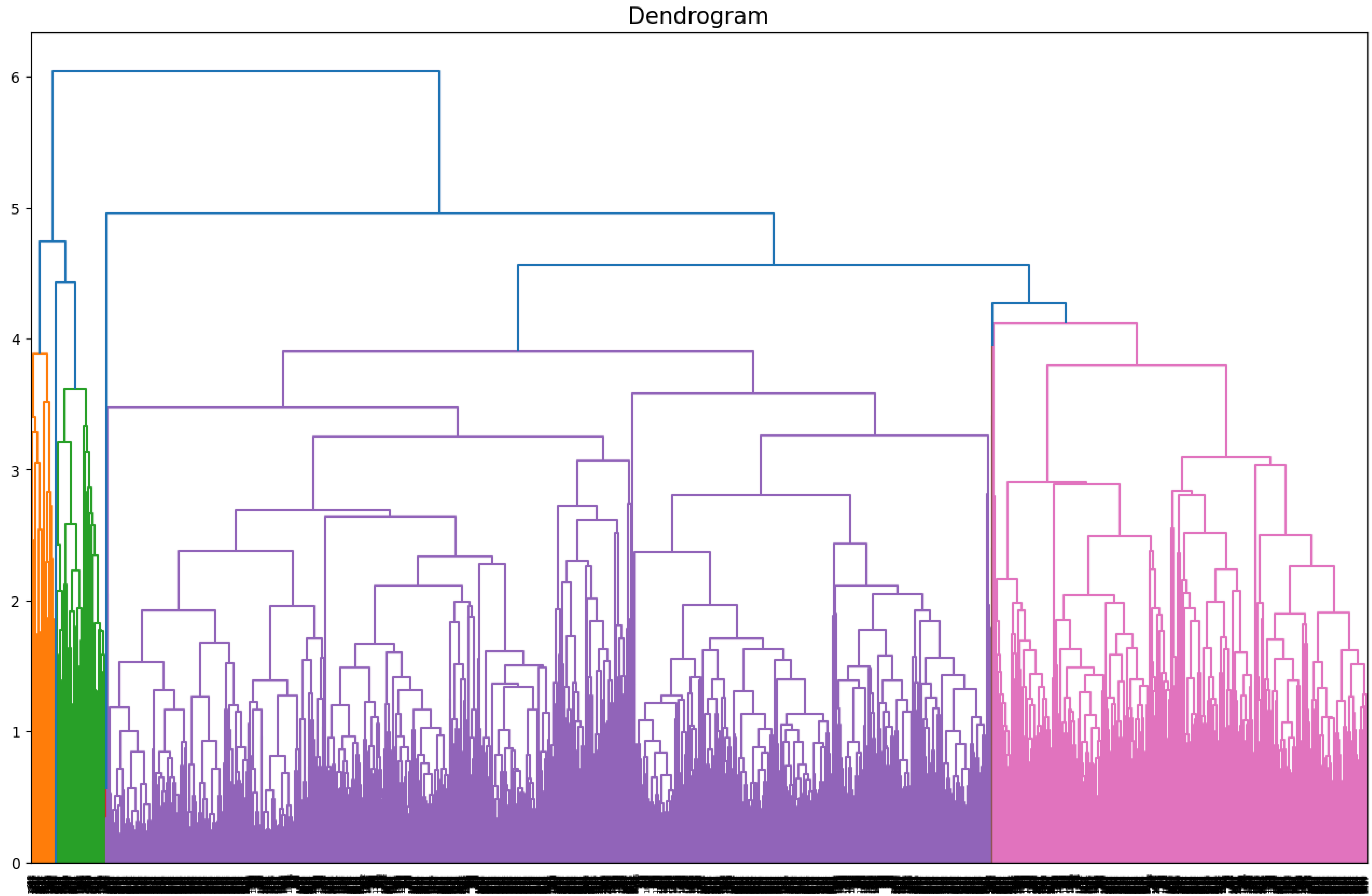

Balance
Qual_miles
cc1_miles
cc2_miles
cc3_miles
Bonus_miles
Bonus_trans
Flight_miles_12mo
Flight_trans_12
Days_since_enroll
Award?
Density

Cluster formation

using average linkage method

In [14]:
```
fig = plt.figure(figsize=(16,10))
dendrogram = sch.dendrogram(sch.linkage(df2_transformed,method='average'))
plt.title('Dendrogram',size=15)
```

Out[14]:
```
Text(0.5, 1.0, 'Dendrogram')
```



Agglomerative hierarchical clustering

In [15]:
```
hc = AgglomerativeClustering(n_clusters=5,affinity='euclidean',linkage='average')
```

In [16]:
```
# Fitting data on model
hc_fit = hc.fit_predict(df2_transformed)
Clusters = pd.DataFrame(hc_fit,columns=['Clusters'])
```

In [17]:
```
df['cluster']=hc_fit
df.groupby('cluster').agg(['mean']).reset_index()
```

Out[17]:

	cluster	ID#	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo	Flight_trans_12	Days_since_enroll	Award?
		mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean
0	0	1799.350993	170339.198675	2508.019868	2.278146	1.013245	1.013245	28717.337748	18.344371	2574.390728	7.768212	4478.728477	0.768212
1	1	1891.090828	104075.087266	0.000000	2.290294	1.017809	1.016919	23897.578807	15.159394	1291.878896	3.845058	4368.430098	0.547640
2	2	1425.000000	125.000000	0.000000	1.000000	1.000000	1.000000	125.000000	1.000000	125.000000	1.000000	5163.500000	0.000000
3	3	2028.933333	57973.546667	2634.706667	2.000000	1.000000	1.000000	15002.626667	10.026667	0.000000	0.000000	4111.026667	0.400000
4	4	2079.624622	55659.328172	0.000000	1.951662	1.013595	1.010574	13694.672961	9.761329	0.000000	0.000000	3991.476586	0.271903

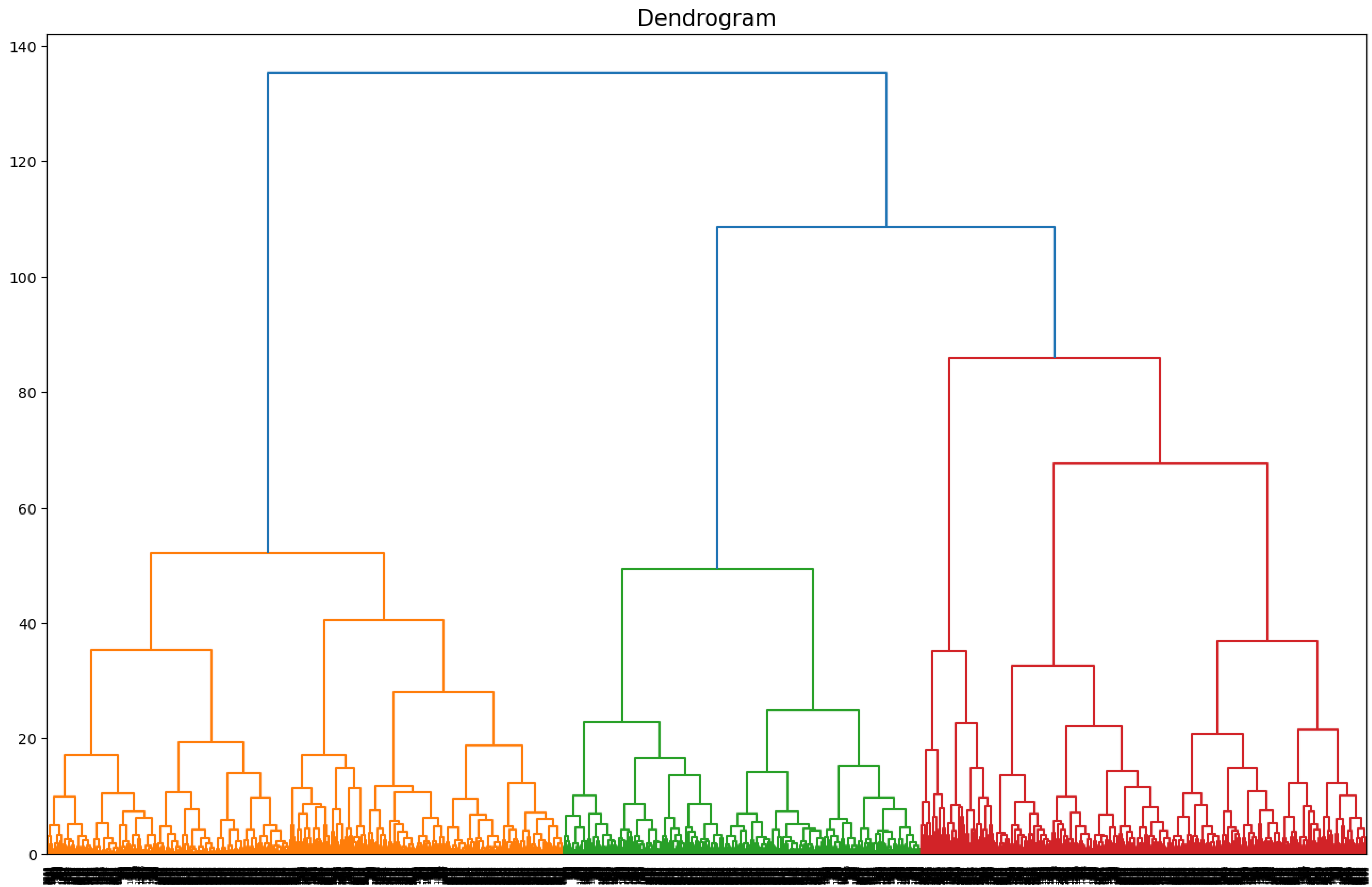
In [18]:
```
for i in range(5):
    print('cluster',i)
    print('Total Members in hierarchy:',len(list(df[df['cluster']==i]['ID#'].values)))
    print()
```

```
cluster 0
Total Members in hierarchy: 151

cluster 1
Total Members in hierarchy: 1123

cluster 2
Total Members in hierarchy: 2

cluster 3
Total Members in hierarchy: 75

cluster 4
Total Members in hierarchy: 2648
```

Using Centroid Linkeage method

In [19]:
```
fig = plt.figure(figsize=(16,10))
dendrogram = sch.dendrogram(sch.linkage(df2_transformed,method='ward'))
plt.title('Dendrogram',size=15)
```

Out[19]: `Text(0.5, 1.0, 'Dendrogram')`



In [20]:
```python
#cluster formation
hc1 = AgglomerativeClustering(n_clusters=5,affinity='euclidean',linkage='ward')
```

In [21]:
```python
# fitting data on model
hc1_fit = hc1.fit_predict(df2_transformed)
Clusters1 = pd.DataFrame(hc1_fit,columns=['Clusters'])
```

In [22]:
```python
df['cluster']=hc1_fit
```

In [23]:
```python
df.groupby('cluster').agg(['mean']).reset_index()
```

Out[23]:

	cluster	ID#	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo	Flight_trans_12	Days_since_enroll	Award?
		mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean
0	0	2270.985322	33419.559030	0.000000	1.000000	1.022336	1.005105	2837.693044	5.463944	0.000000	0.000000	3631.267390	0.151883
1	1	2113.270270	77788.952703	0.000000	1.000000	1.030405	1.000000	6038.932432	8.885135	1403.608108	4.155405	3981.564189	0.429054
2	2	1802.231267	87897.735430	0.000000	3.331175	1.000925	1.018501	29432.774283	15.990749	0.000000	0.000000	4513.629972	0.445883
3	3	1875.539823	133049.712389	2550.061947	2.185841	1.008850	1.008850	24165.995575	15.584071	1720.057522	5.190265	4356.703540	0.646018
4	4	1642.568480	132880.887430	0.000000	3.718574	1.003752	1.035647	43643.870544	22.075047	1163.403377	3.489681	4801.103189	0.677298

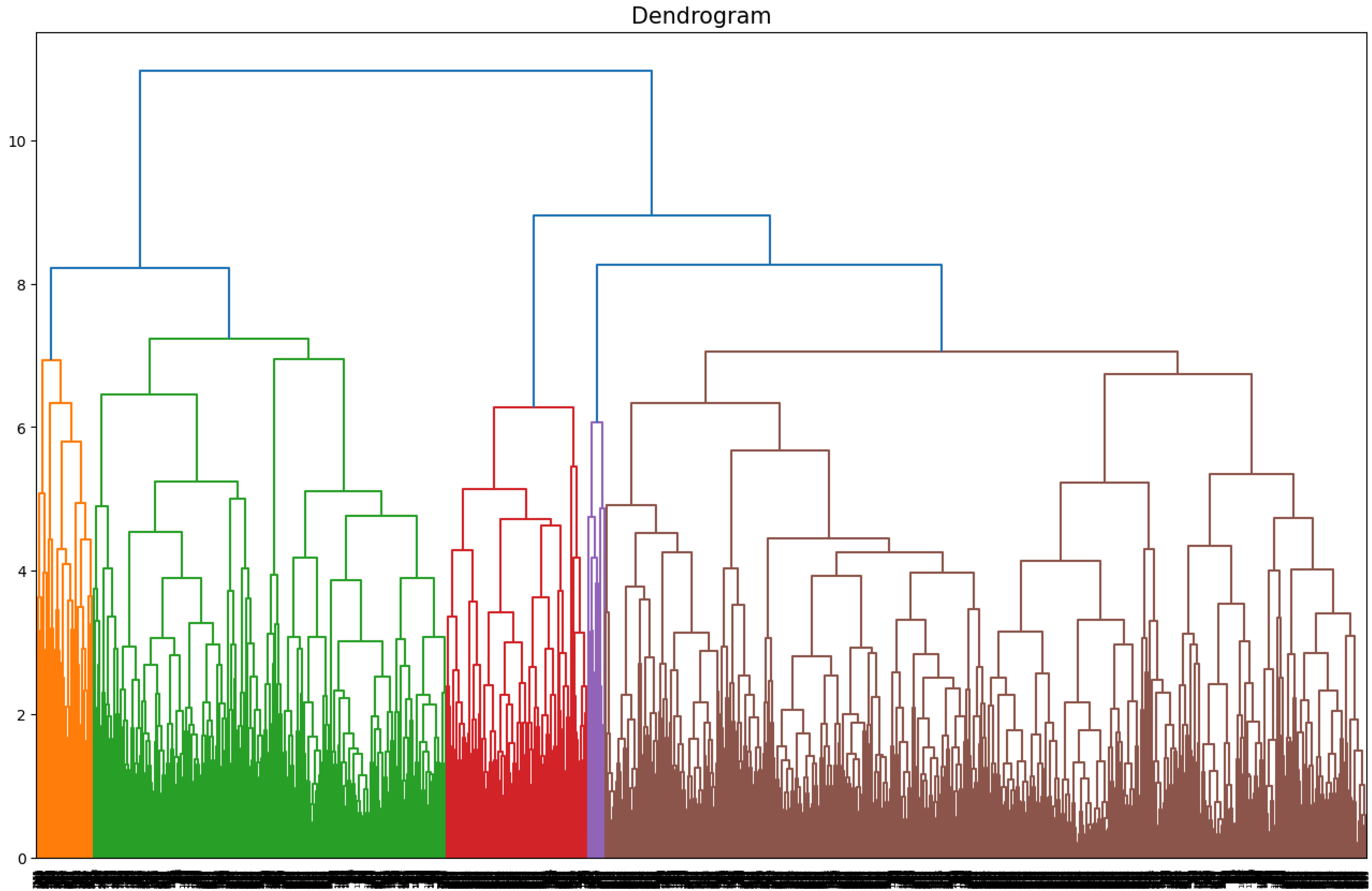
In [24]:
```python
for i in range(5):
    print('cluster',i)
    print('Total Members in hierarchy:',len(list(df[df['cluster']==i]['ID#'].values)))
    print()
```

```
cluster 0
Total Members in hierarchy: 1567

cluster 1
Total Members in hierarchy: 592

cluster 2
Total Members in hierarchy: 1081

cluster 3
Total Members in hierarchy: 226

cluster 4
Total Members in hierarchy: 533
```

using complete linkage method

In [25]:
```
fig = plt.figure(figsize=(16,10))
dendrogram = sch.dendrogram(sch.linkage(df2_transformed,method='complete'))
plt.title('Dendrogram',size=15)
```

Out[25]:
```
Text(0.5, 1.0, 'Dendrogram')
```



In [26]:
```
#cluster formation
hc2 = AgglomerativeClustering(n_clusters=5,affinity='euclidean',linkage='complete')
```

In [27]:
```python
# fitting data on model
hc2_fit = hc2.fit_predict(df2_transformed)
Clusters2 = pd.DataFrame(hc2_fit,columns=['Clusters'])
```

In [28]:
```python
df['cluster']=hc2_fit
df.groupby('cluster').agg(['mean']).reset_index()
```

Out[28]:

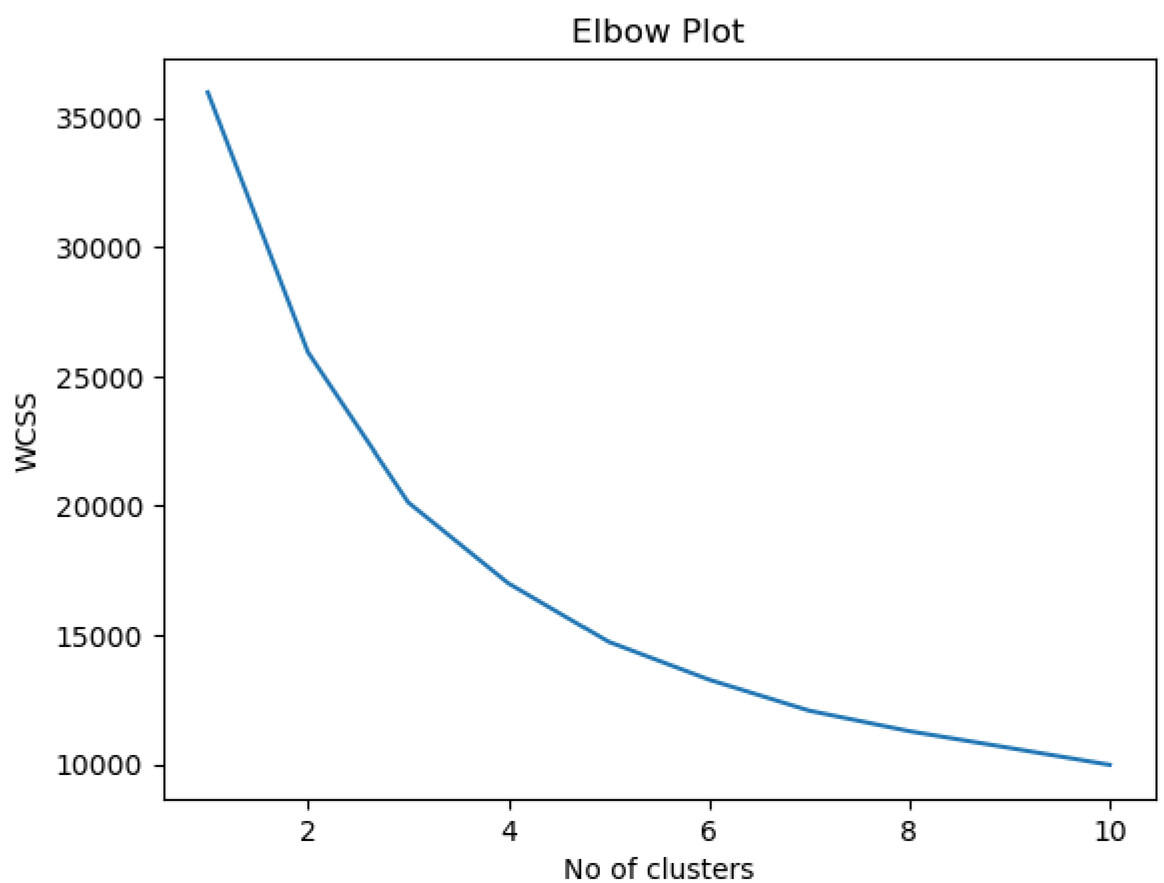
	cluster	ID#	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo	Flight_trans_12	Days_since_enroll	Award?
		mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean
0	0	1475.911404	145838.029218	0.000000	3.541942	1.004713	1.032045	39928.083883	19.713478	809.139491	2.377003	5095.663525	0.553252
1	1	2168.733392	39231.260927	0.000000	1.506119	1.016608	1.005682	7506.878497	7.910839	53.164773	0.161713	3831.724213	0.220717
2	2	2607.044811	46620.754717	0.000000	1.268868	1.030660	1.000000	8399.268868	9.099057	1110.594340	3.367925	3094.386792	0.573113
3	3	2367.264151	46202.320755	2805.528302	1.000000	1.000000	1.000000	2909.528302	3.962264	188.245283	0.566038	3446.471698	0.264151
4	4	1724.895954	159656.138728	2471.797688	2.549133	1.011561	1.011561	30678.092486	19.144509	2189.341040	6.606936	4635.560694	0.763006

In [29]:
```python
for i in range(5):
    print('cluster',i)
    print('Total Members in hierarchy:',len(list(df[df['cluster']==i]['ID#'].values)))
    print()
```

```
cluster 0
Total Members in hierarchy: 1061

cluster 1
Total Members in hierarchy: 2288

cluster 2
Total Members in hierarchy: 424

cluster 3
Total Members in hierarchy: 53

cluster 4
Total Members in hierarchy: 173
```

Elbow plot

In [35]:
```
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i,random_state=0)
    kmeans.fit(df2_transformed)
    wcss.append(kmeans.inertia_)

plt.plot(range(1,11),wcss)
plt.title('Elbow Plot')
plt.xlabel('No of clusters')
plt.ylabel('WCSS')
plt.show()
```



Creating 5 group cluster with k means

In [36]:
```
from sklearn.cluster import KMeans

# Create KMeans object with 5 clusters and random_state=42
new_clusters = KMeans(n_clusters=5, random_state=42)

# Fit KMeans to the transformed DataFrame
new_clusters.fit(df2_transformed)
```

Out[36]:
```
KMeans(n_clusters=5, random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [37]:
```
# Get the cluster labels assigned by KMeans
KM_labels = new_clusters.labels_

# Assign cluster labels to a new column in the DataFrame
df['cluster'] = new_clusters.labels_

# Get the cluster centers
new_clusters.cluster_centers_
```

Out[37]:
```
array([[ 5.95617244e-01,  4.08591363e+00,  6.27073775e-02,
         1.71909534e-19,  1.23462301e-18,  3.71406537e-01,
         4.00741007e-01,  7.95774742e-01,  8.51260285e-01,
         1.51964211e-01,  5.94982813e-01],
       [-6.76230385e-01, -2.32975213e-01, -8.35577978e-01,
         4.66678326e-19,  5.77778983e-34, -9.10280190e-01,
        -8.20207305e-01, -6.82082524e-01, -6.73777367e-01,
        -3.12181555e-01, -5.16505530e-01],
       [ 7.54505594e-01, -2.44743303e-01,  1.11374957e+00,
         2.77052025e-19,  2.98460591e-18,  1.03665259e+00,
         1.04603128e+00,  1.45646102e+00,  1.41053352e+00,
         3.58290326e-01,  6.72519442e-01],
       [ 3.71108591e-01, -2.44743303e-01,  9.07534146e-01,
         2.90834249e-19,  2.55287841e-18,  7.16521541e-01,
         5.91044806e-01, -6.83308041e-01, -6.74970335e-01,
         2.39594007e-01,  1.83456571e-01],
       [ 1.60074522e-02, -2.44743303e-01, -8.19239258e-01,
         7.32640630e-19, -3.85185989e-34, -2.79105284e-01,
        -2.72262658e-01,  1.45172819e+00,  1.43587521e+00,
        -9.52588092e-02,  7.15349601e-02]])
```

In [38]:
```
for i in range(5):
    print('cluster',i)
    print('Total Members in hierarchy:',len(list(df[df['cluster']==i]['ID#'].values)))
    print()
```

```
cluster 0
Total Members in hierarchy: 222

cluster 1
Total Members in hierarchy: 1474

cluster 2
Total Members in hierarchy: 551

cluster 3
Total Members in hierarchy: 1179

cluster 4
Total Members in hierarchy: 573
```

In [ ]:
```
'''Perform Clustering(Hierarchical, Kmeans & DBSCAN) for the crime data and identify the number of clusters formed and draw inferences.
Data Description:
Murder -- Muder rates in different places of United States
Assualt- Assualt rate in different places of United States
UrbanPop - urban population in different places of United States
Rape - Rape rate in different places of United States'''
```

In [65]:
```
data = pd.read_csv(r'DSA\Assignment 3\crime_data.csv')
data.head()
```

Out[65]:

	Unnamed: 0	Murder	Assault	UrbanPop	Rape
0	Alabama	13.2	236	58	21.2
1	Alaska	10.0	263	48	44.5
2	Arizona	8.1	294	80	31.0
3	Arkansas	8.8	190	50	19.5
4	California	9.0	276	91	40.6

In [66]:
```
#renaming column
data.rename(columns={'Unnamed: 0': 'Country'}, inplace=True)
```

In [67]:
```
#checking for null values
data.sum().isnull()
```

Out[67]:
```
Country     False
Murder      False
Assault     False
UrbanPop    False
Rape        False
dtype: bool
```

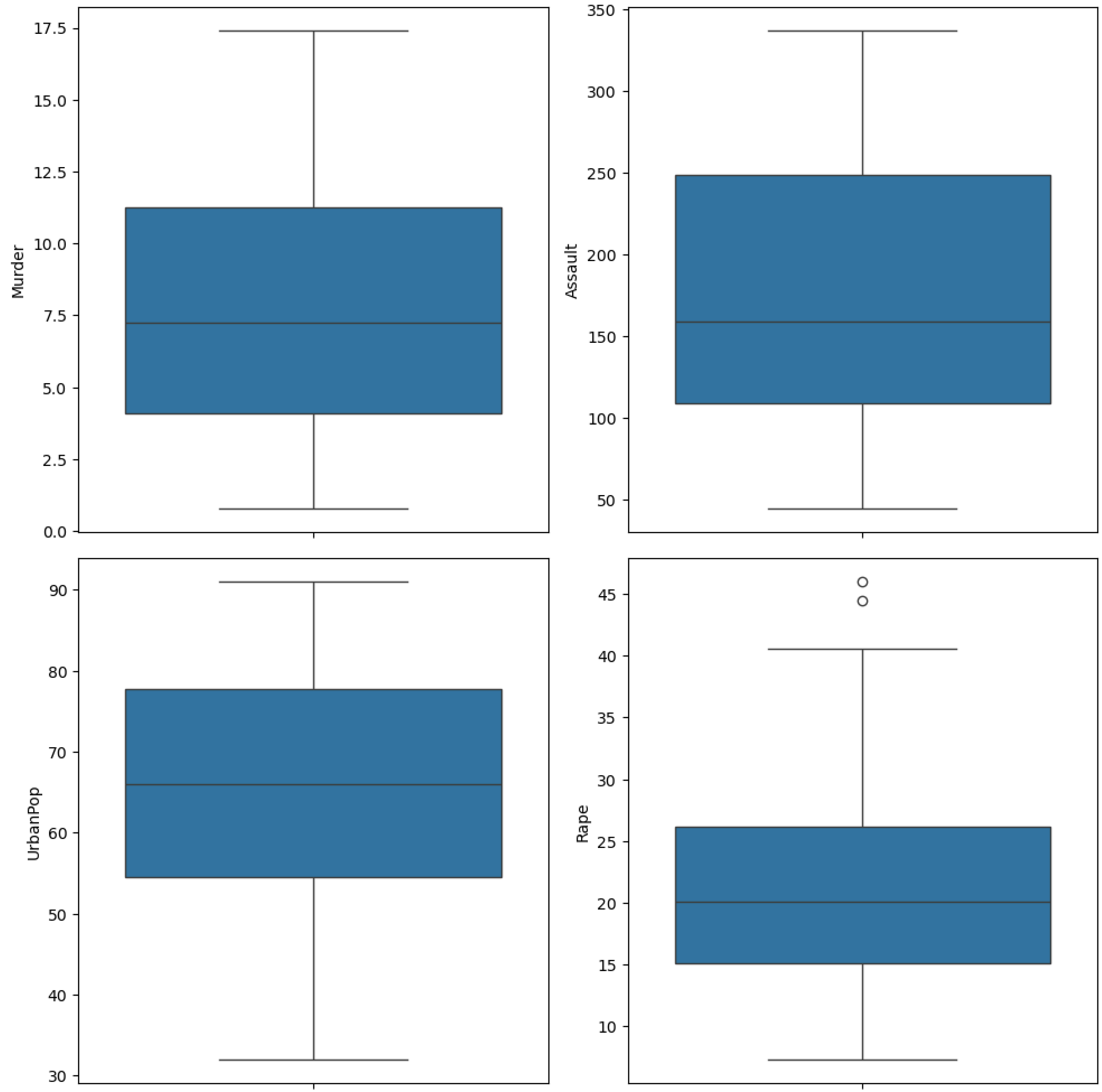
In [68]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Country   50 non-null     object 
 1   Murder    50 non-null     float64
 2   Assault   50 non-null     int64  
 3   UrbanPop  50 non-null     int64  
 4   Rape      50 non-null     float64
dtypes: float64(2), int64(2), object(1)
memory usage: 2.1+ KB
```

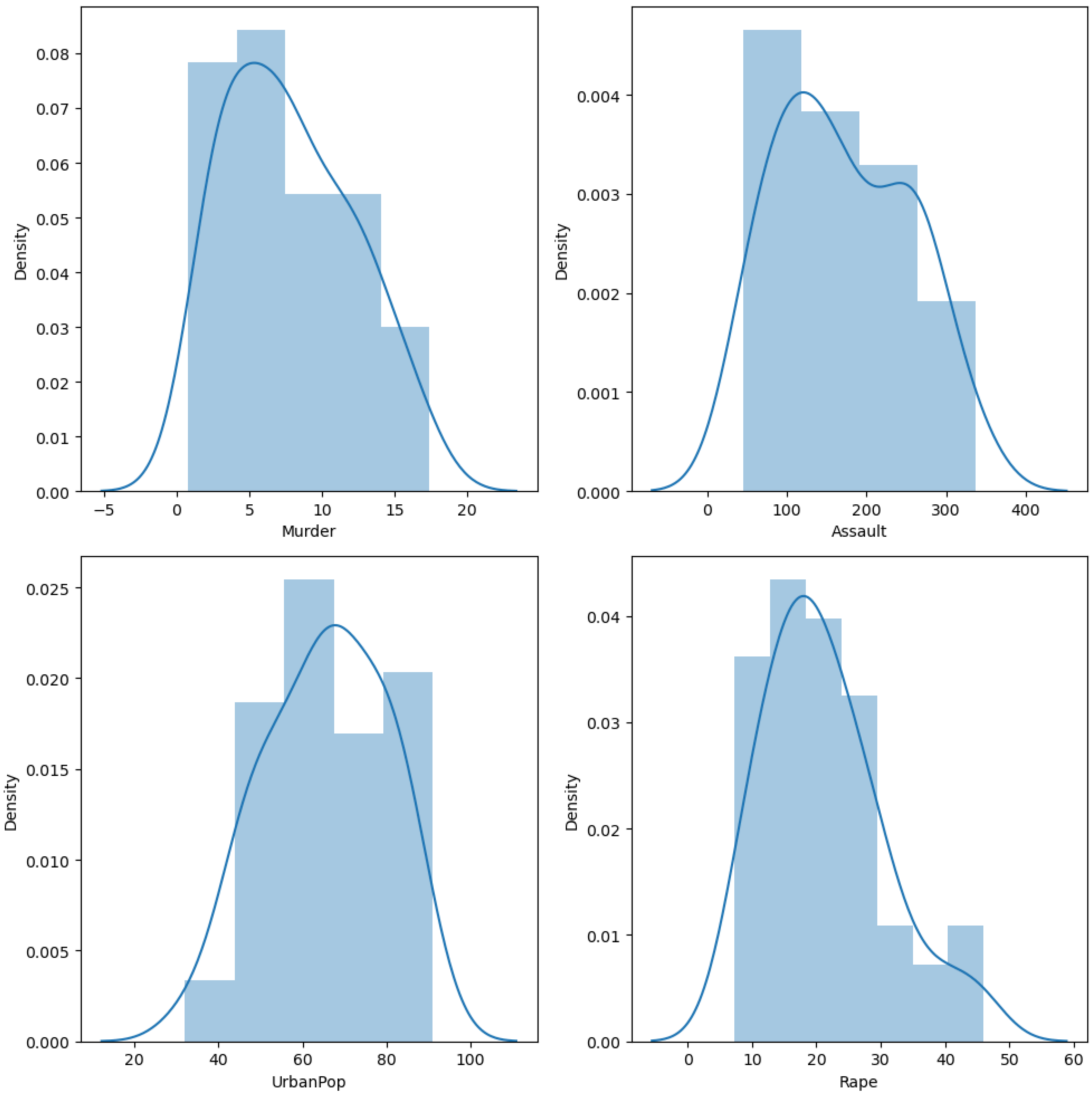
In [69]:
```
#removing duplicated rows
data = data[~data.duplicated(keep=False)]
```

Outliers detection

In [70]:
```
# using box plot
fig, ax = plt.subplots(2,2,figsize=(10,10))
sns.boxplot(data.Murder,ax=ax[0,0])
sns.boxplot(data.Assault,ax=ax[0,1])
sns.boxplot(data.UrbanPop,ax=ax[1,0])
sns.boxplot(data.Rape,ax=ax[1,1])

plt.tight_layout()
plt.show()
```


Murder
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Assault
50
100
150
200
250
300
350
UrbanPop
30
40
50
60
70
80
90
Rape
10
15
20
25
30
35
40
45

In [71]:
```
# using dist plot
fig, ax = plt.subplots(2,2,figsize=(10,10))
sns.distplot(data.Murder,ax=ax[0,0])
sns.distplot(data.Assault,ax=ax[0,1])
sns.distplot(data.UrbanPop,ax=ax[1,0])
sns.distplot(data.Rape,ax=ax[1,1])

plt.tight_layout()
plt.show()
```


Density
Murder
Density
Assault
Density
UrbanPop
Density
Rape

Using power transform to standardize distribution

In [75]:
```
data1 = data[['Murder','Assault','UrbanPop','Rape']]
data1_transformed = power_transform(data1,method='yeo-johnson')
```

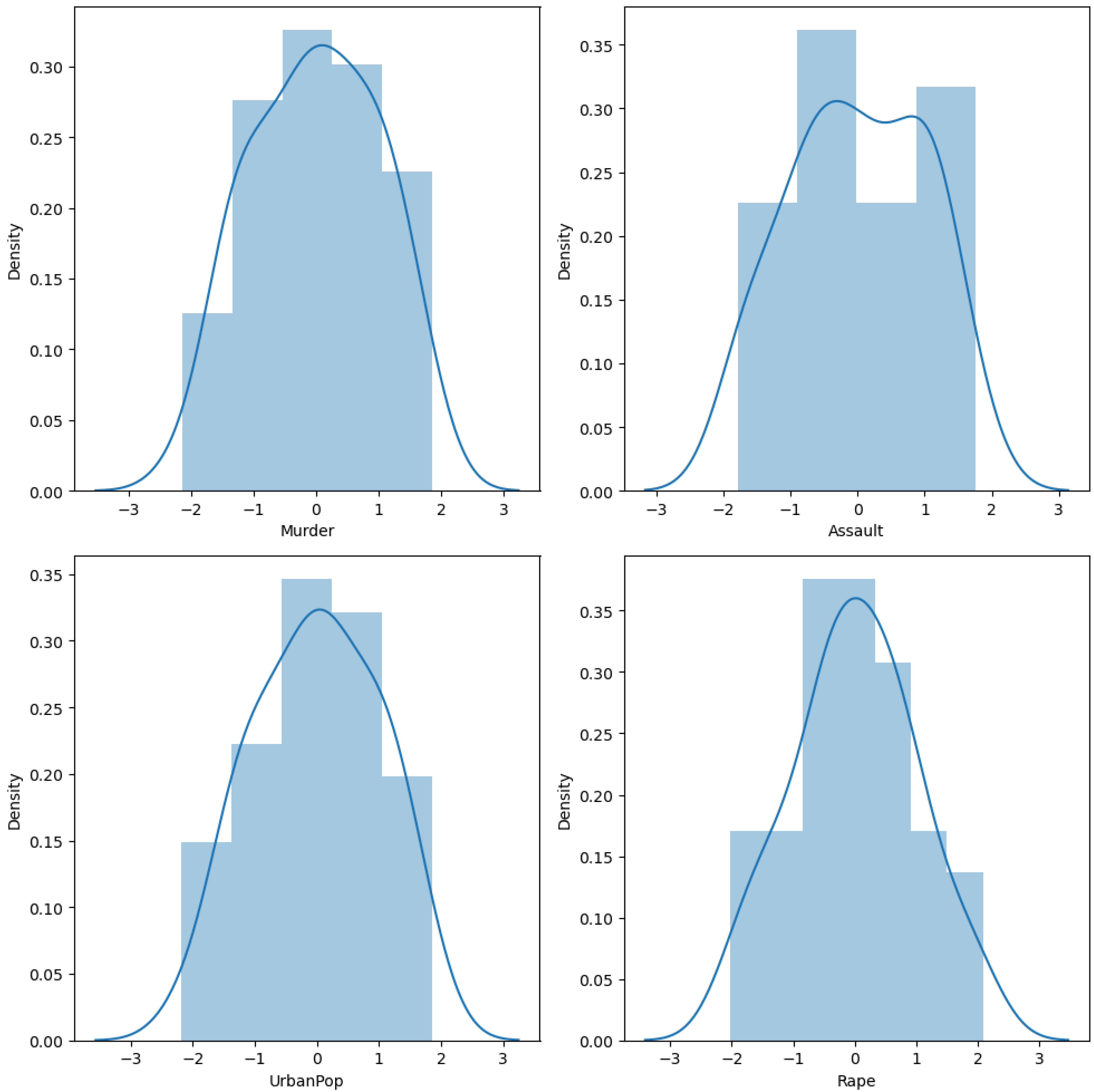
In [76]:
```
data1 = pd.DataFrame(data1_transformed,columns=['Murder','Assault','UrbanPop','Rape'])
data1.head()
```

Out[76]:

	Murder	Assault	UrbanPop	Rape
0	1.193980	0.823923	-0.558080	0.171772
1	0.612467	1.088030	-1.217271	1.991841
2	0.218738	1.376029	1.018593	1.074267
3	0.368945	0.338847	-1.088646	-0.018283
4	0.410700	1.210644	1.863606	1.753540

Visualization after transformation

In [77]:
```
# using dist plot
fig, ax = plt.subplots(2,2,figsize=(10,10))
sns.distplot(data1.Murder,ax=ax[0,0])
sns.distplot(data1.Assault,ax=ax[0,1])
sns.distplot(data1.UrbanPop,ax=ax[1,0])
sns.distplot(data1.Rape,ax=ax[1,1])

plt.tight_layout()
plt.show()
```



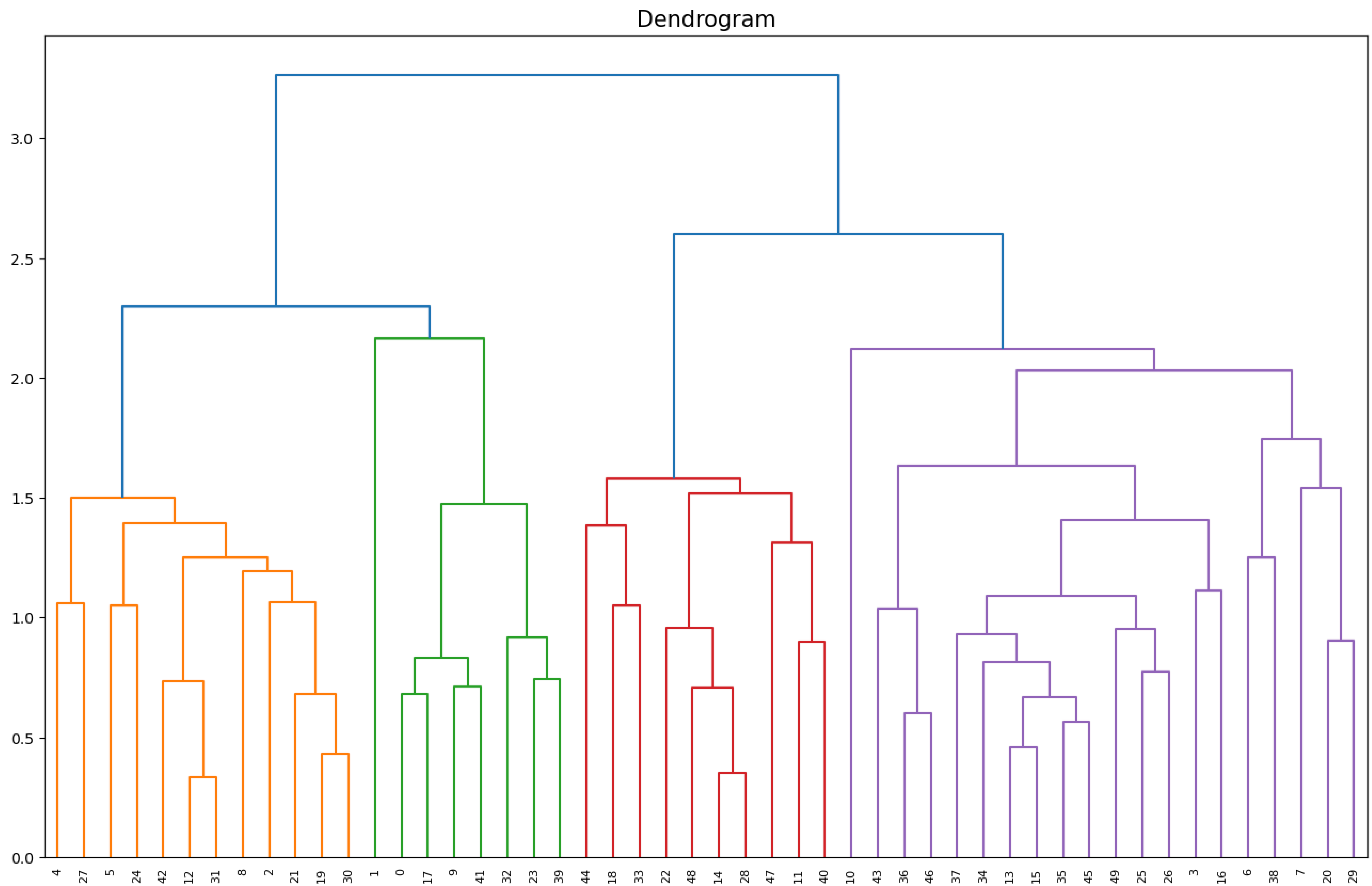
Density
Murder
Density
Assault
Density
UrbanPop
Density
Rape

Cluster formation

average linkage method

In [83]:
```
fig = plt.figure(figsize=(16,10))
dendrogram = sch.dendrogram(sch.linkage(data1_transformed,method='average'))
plt.title('Dendrogram',size=15)
```

Out[83]:
```
Text(0.5, 1.0, 'Dendrogram')
```


Dendrogram
3.0
2.5
2.0
1.5
1.0
0.5
0.0
4 27 5 24 42 12 31 8 2 21 19 30 1 0 17 9 41 32 23 39 44 18 33 22 48 14 28 47 11 40 10 43 36 46 37 34 13 15 35 45 49 25 26 3 16 6 38 7 20 29

Agglomerative hierarchical clustering

In [85]:
```
dc = AgglomerativeClustering(n_clusters=5,affinity='euclidean',linkage='average')
```

In [90]:
```
# Fitting data on model
dc_fit = dc.fit_predict(data1_transformed)
Clusters = pd.DataFrame(dc_fit,columns=['Clusters'])
```

In [98]:
```
data['cluster'] = dc_fit

# Selecting only numeric columns
numeric_columns = data.select_dtypes(include=['number'])

# Calculating mean values for each cluster
cluster_means = numeric_columns.groupby('cluster').mean().reset_index()
data.head()
```

Out[98]:

	Country	Murder	Assault	UrbanPop	Rape	cluster
0	Alabama	13.2	236	58	21.2	3
1	Alaska	10.0	263	48	44.5	4
2	Arizona	8.1	294	80	31.0	1
3	Arkansas	8.8	190	50	19.5	0
4	California	9.0	276	91	40.6	1

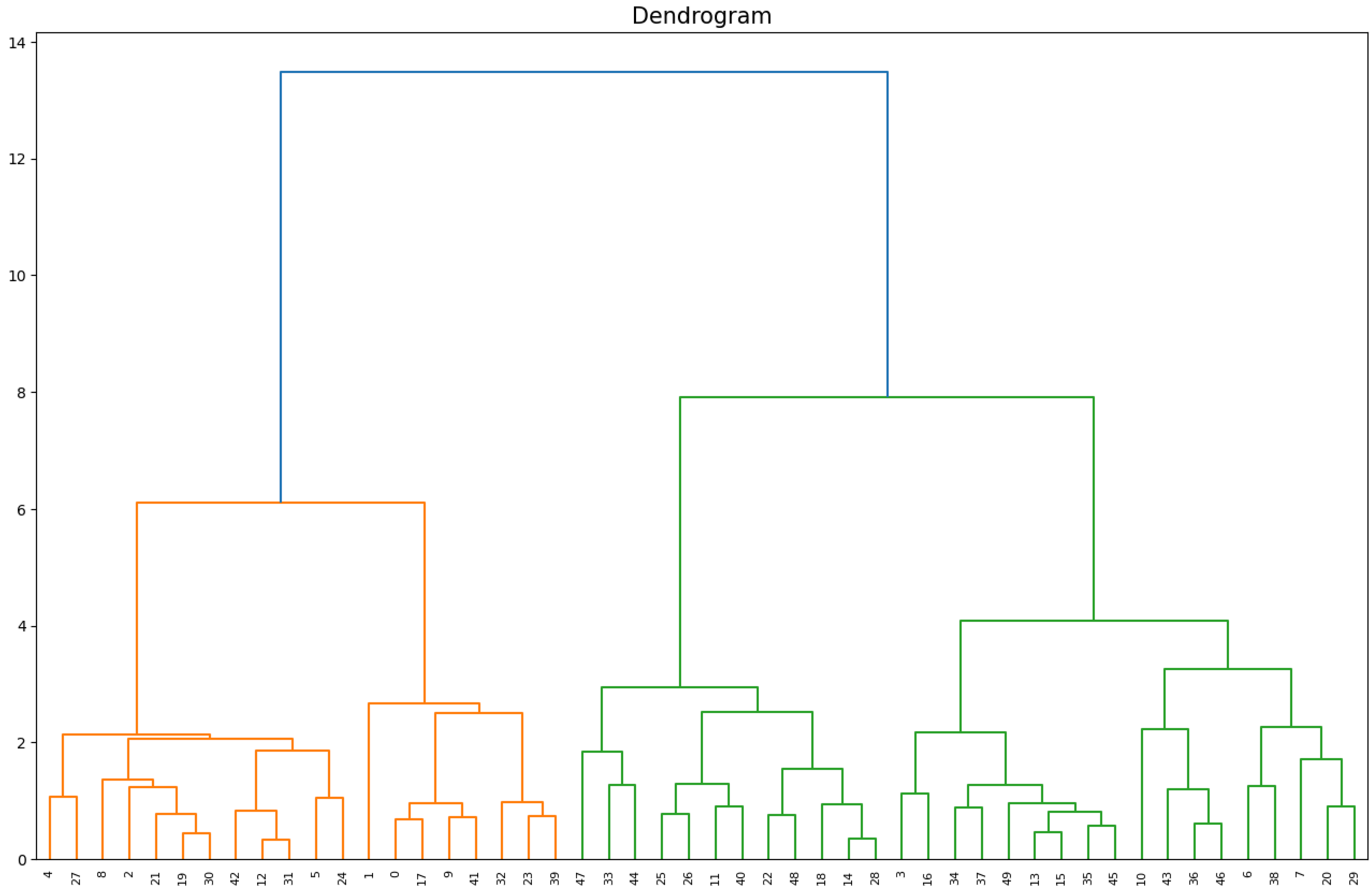
In [99]:
```
for i in range(5):
 print('cluster',i)
 print('Total Members in hierarchy:',len(list(data[data['cluster']==i]['Country'].values)))
 print()
```

```
cluster 0
Total Members in hierarchy: 20

cluster 1
Total Members in hierarchy: 12

cluster 2
Total Members in hierarchy: 10

cluster 3
Total Members in hierarchy: 7

cluster 4
Total Members in hierarchy: 1
```

Using Centroid linkage method

In [100]:
```
fig = plt.figure(figsize=(16,10))
dendrogram = sch.dendrogram(sch.linkage(data1_transformed,method='ward'))
plt.title('Dendrogram',size=15)
```

Out[100]:
```
Text(0.5, 1.0, 'Dendrogram')
```



In [101]:
```
dc1 = AgglomerativeClustering(n_clusters=5,affinity='euclidean',linkage='ward')
```

In [102]:
```
# Fitting data on model
dc1_fit = dc1.fit_predict(data1_transformed)
Clusters1 = pd.DataFrame(dc1_fit,columns=['Clusters'])
```

In [108]:
```
data['cluster'] = dc1_fit

numeric_columns = data.select_dtypes(include=['number'])

cluster_means = numeric_columns.groupby('cluster').mean().reset_index()
data.head()
```

Out[108]:

	Country	Murder	Assault	UrbanPop	Rape	cluster
0	Alabama	13.2	236	58	21.2	1
1	Alaska	10.0	263	48	44.5	1
2	Arizona	8.1	294	80	31.0	3
3	Arkansas	8.8	190	50	19.5	4
4	California	9.0	276	91	40.6	3

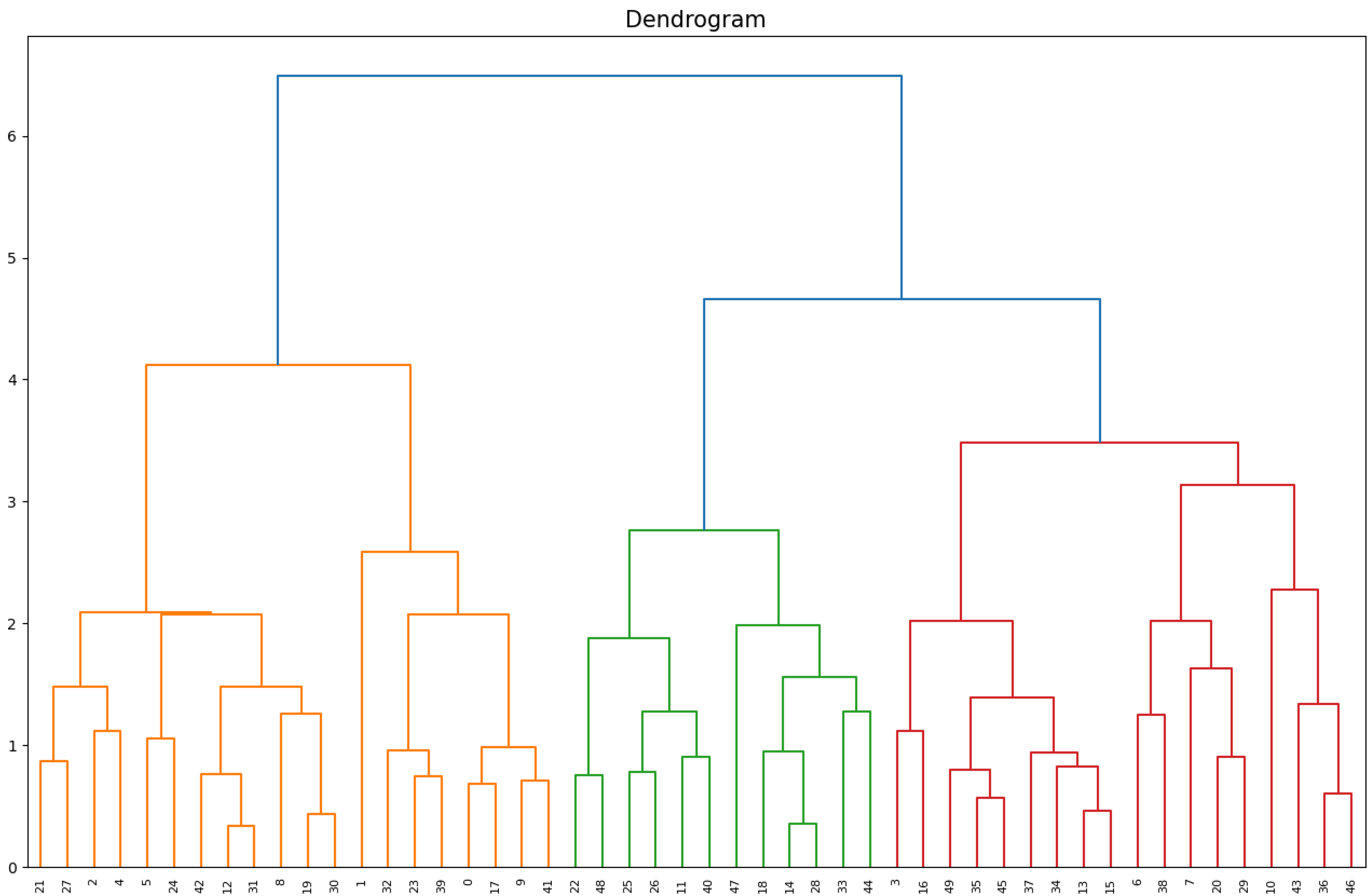
In [109]:
```
for i in range(5):
 print('cluster',i)
 print('Total Members in hierarchy:',len(list(data[data['cluster']==i]['Country'].values)))
 print()
```

```
cluster 0
Total Members in hierarchy: 9

cluster 1
Total Members in hierarchy: 8

cluster 2
Total Members in hierarchy: 12

cluster 3
Total Members in hierarchy: 12

cluster 4
Total Members in hierarchy: 9
```

Using complete linkage

In [110]:
```
fig = plt.figure(figsize=(16,10))
dendrogram = sch.dendrogram(sch.linkage(data1_transformed,method='complete'))
plt.title('Dendrogram',size=15)
```

Out[110]:
```
Text(0.5, 1.0, 'Dendrogram')
```




```
In [111]: dc2 = AgglomerativeClustering(n_clusters=5,affinity='euclidean',linkage='complete')
```

In [113]:
```
# Fitting data on model
dc2_fit = dc2.fit_predict(data1_transformed)
Clusters2 = pd.DataFrame(dc2_fit,columns=['Clusters'])
```

In [114]:
```
data['cluster'] = dc2_fit

numeric_columns = data.select_dtypes(include=['number'])

cluster_means = numeric_columns.groupby('cluster').mean().reset_index()
data.head()
```

Out[114]:

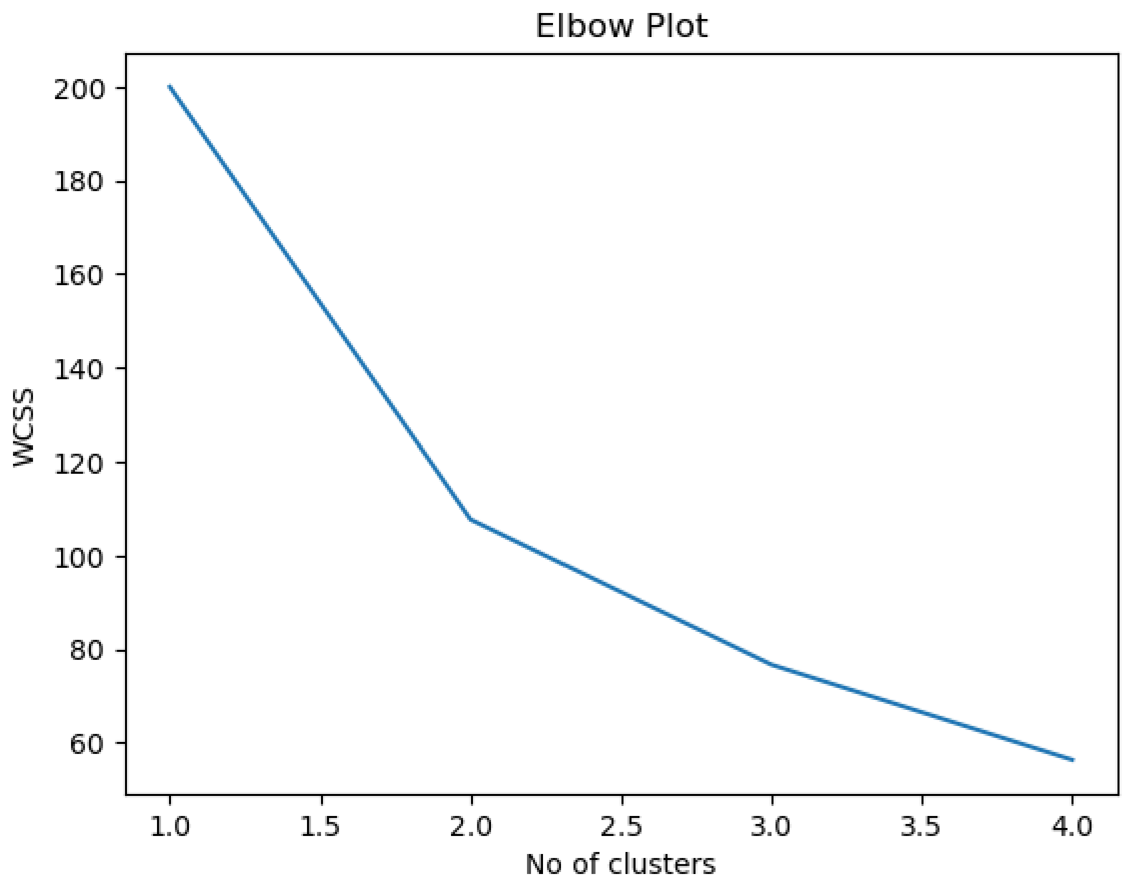
	Country	Murder	Assault	UrbanPop	Rape	cluster
0	Alabama	13.2	236	58	21.2	1
1	Alaska	10.0	263	48	44.5	1
2	Arizona	8.1	294	80	31.0	3
3	Arkansas	8.8	190	50	19.5	4
4	California	9.0	276	91	40.6	3

In [115]:
```
for i in range(5):
 print('cluster',i)
 print('Total Members in hierarchy:',len(list(data[data['cluster']==i]['Country'].values)))
 print()
```

```
cluster 0
Total Members in hierarchy: 9

cluster 1
Total Members in hierarchy: 8

cluster 2
Total Members in hierarchy: 12

cluster 3
Total Members in hierarchy: 12

cluster 4
Total Members in hierarchy: 9
```

Elbow Plot

In [138]:
```
wcss = []
for i in range(1,5):
 kmeans = KMeans(n_clusters=i,random_state=0)
 kmeans.fit(data1_transformed)
 wcss.append(kmeans.inertia_)
plt.plot(range(1,5),wcss)
plt.title('Elbow Plot')
plt.xlabel('No of clusters')
plt.ylabel('WCSS')
plt.show()
```



Kmeans

In [146]:
```
new_clusters = KMeans(n_clusters=5, random_state=42)

# Fit KMeans to the transformed DataFrame
new_clusters.fit(data1_transformed)
KM_labels = new_clusters.labels_
```

In [148]:
```python
data['cluster'] = new_clusters.labels_
new_clusters.cluster_centers_
```

Out[148]:
```
array([[-0.72022398, -0.49175571,  1.28609276, -0.51801769],
       [-0.19347093, -0.31715294, -0.04944974, -0.06958072],
       [ 0.7623321 ,  1.01239549,  0.90058428,  1.13313467],
       [-1.32911053, -1.32029361, -1.00077956, -1.29242127],
       [ 1.219954  ,  0.9030792 , -0.87476952,  0.37102801]])
```

In [150]:
```python
for i in range(5):
    print('Cluster', i)
    print('Total Members in cluster:', len(data[data['cluster'] == i]))
    print()
```

```
Cluster 0
Total Members in cluster: 6

Cluster 1
Total Members in cluster: 13

Cluster 2
Total Members in cluster: 12

Cluster 3
Total Members in cluster: 10

Cluster 4
Total Members in cluster: 9
```