In [1071]:
```
import numpy as np
# Numpy is used in organizing the data into arrays
import pandas as pd
# Pandas is used to read the dataset
import scipy.cluster.hierarchy as sch
# Scipy is used to visualize the hierarchial cluster as a dendrogram
import matplotlib.pyplot as plt
# Matplotlib is used to plot and data visualizing
from sklearn.cluster import AgglomerativeClustering as AC
# Sklearn is used to apply the Hierarchial clustering
from sklearn_extra.cluster import KMedoids
# Sklearn_extra is used to apply KMedoids clustering
```

In [1072]:
```
File=pd.read_csv('Mall_customers.csv')
File
```

Out[1072]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

In [1073]:
```
# First HIERARCHIAL CLUSTERING
# Preprocessing
# Numpy was very useful here to create the array that will be clustered
X = np.array([File['Annual Income (k$)']])
Y = np.array([File['Spending Score (1-100)']])
for i in range(len(X)):
    Data=np.array([X[i],Y[i]])
# To Make sure that Data is correct
Data[:,10]
```

Out[1073]:
```
array([19, 14], dtype=int64)
```

In [1074]:
```
# Some preprocessing on the data
C = np.array([File['CustomerID']])
G = np.array([File['Gender']])
NewG = np.zeros(200)
# This NewG is an array that converted string to Numbers
# To be able to cluster it so Num 1 = Male & Num 2 =Female
for i in range(200):
    if G[:,i] == "Male":
        # 1 for Male
        NewG[i] = 1
    elif G[:,i] == "Female":
        # 2 for Female
        NewG[i] = 2
    else:
            break
# NewG shape is (200,) but I will use NG which shapes is (1,200)
NG = NewG.reshape((1, 200))
for i in range(len(C)):
    Data1 = np.array([C[i],NG[i]])

# Test our result
#This result is True as 2 is the CustomerID & 1 = Male
Data1[:,1]
```

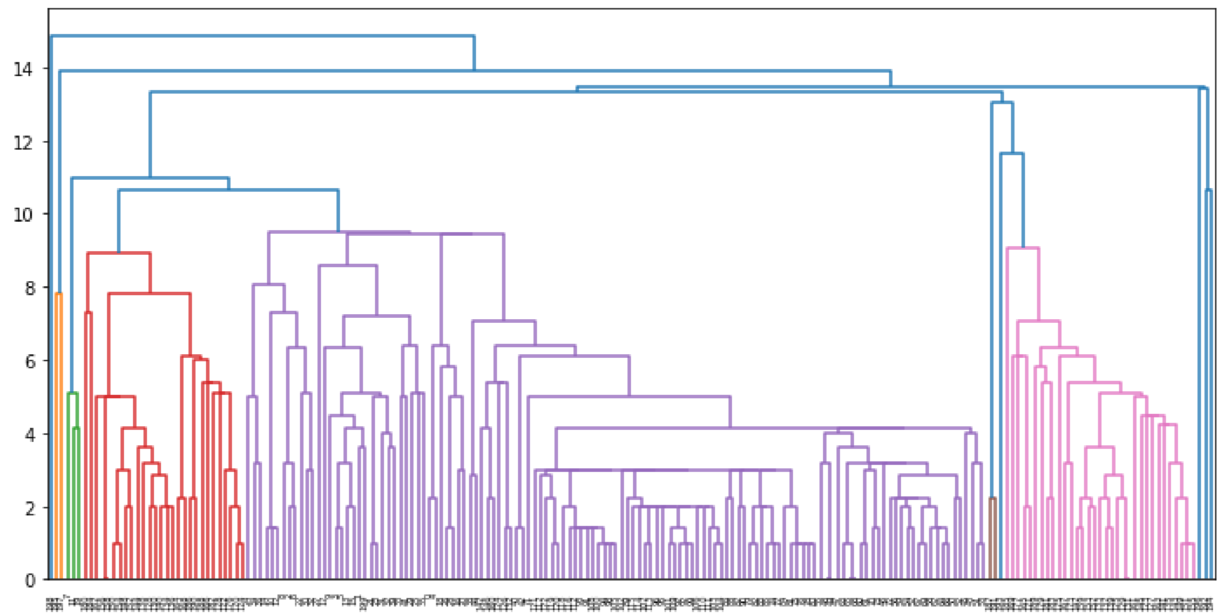
Out[1074]:
```
array([2., 1.])
```

In [1075]:
```
# Visualizing the data as a dendrogram
A = np.array(File['Age'])
NA = A.reshape((1, 200))
NG = NewG.reshape((1, 200))
for i in range(len(NA)):
    Data2 = np.array([NG[i],NA[i]])
NZ = np.concatenate((Z,Data2),axis=0)
#fig = plt.subplots(1,figsize=(12,6))
#HierDend = sch.dendrogram(sch.linkage(NZ,'single'))
```

In [1076]:
```
# Tests
for i in range(len(C)):
    Data3=np.array([Y[i],NA[i]])
TNZ=np.concatenate((NZ,Data3),axis=0)
#HierDend = sch.dendrogram(sch.linkage(TNZ,'single'))
for i in range(len(C)):
    Data4=np.array([NG[i],Y[i]])
TTNZ=np.concatenate((TNZ,Data4),axis=0)
#HierDend = sch.dendrogram(sch.linkage(TTNZ,'single'))
```

In [1077]:
```python
# Hierarchial Cluster WITH K 5 Clusters , Euclidean Distance , Single Linkage
# from the dendrogram K = 5 clusters
Final=np.resize(Data, (200,2))
for i in range(200):
    if i==199:
        break
    else:
        Final[i][1]=Y[0][i]
for i in range(200):
    if i==199:
        break
    else:
        Final[i][0]=X[0][i]
```

In [1078]:
```python
plt.figure(figsize=(12, 6))
HierDend = sch.dendrogram(sch.linkage(Final,'single'))
```



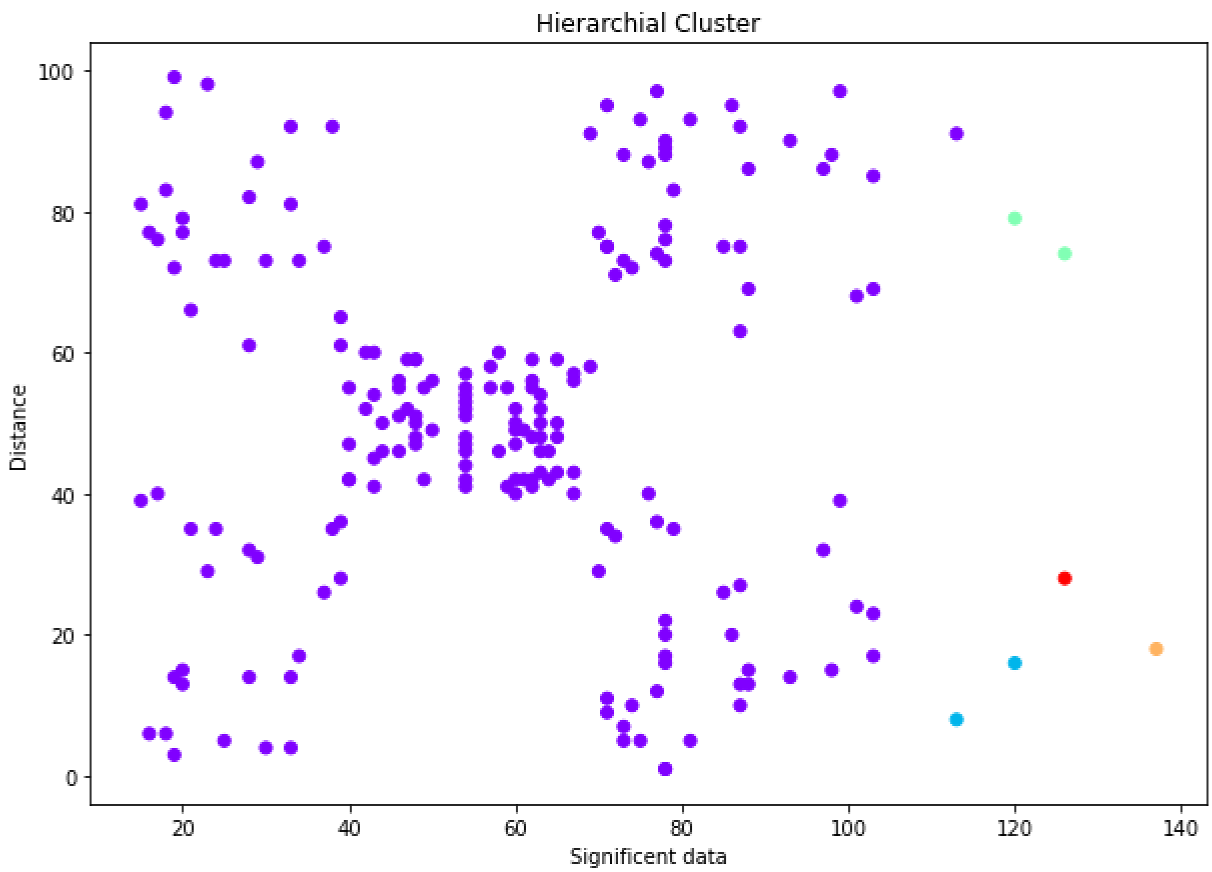
In [1079]:
```python
HierarchialCluster = AC(n_clusters =5,affinity ='euclidean',linkage ='single')
HierarchialCluster.fit_predict(Final)
```

Out[1079]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 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, 1, 2, 4, 2,
       3, 0], dtype=int64)
```

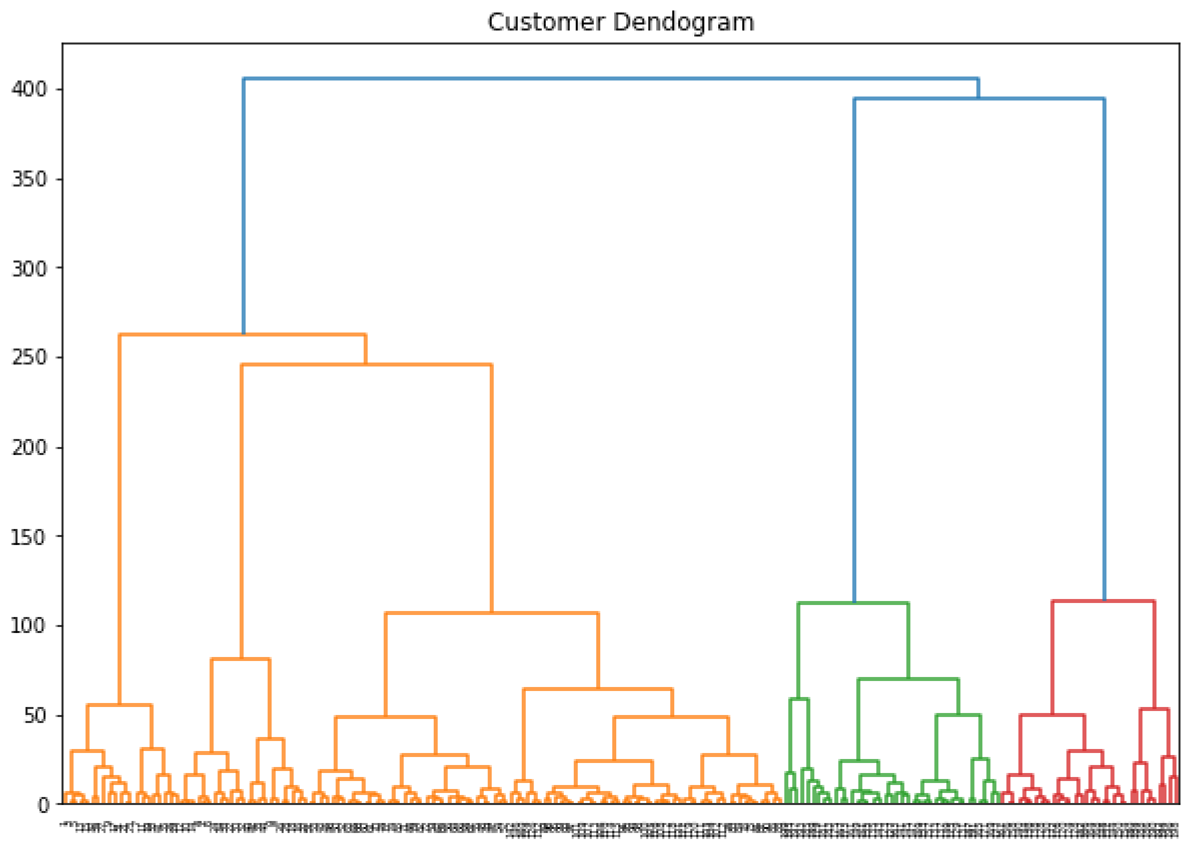
In [1080]:
```
plt.figure(figsize=(10, 7))
plt.scatter(Final[:,0],Final[:,1],c=HierarchialCluster.labels_,cmap='rainbow')

plt.title('Hierarchial Cluster')
plt.xlabel('Significent data')
plt.ylabel('Distance')
```

Out[1080]: Text(0, 0.5, 'Distance')



In [1081]:
```
# Using ward linkage strategy to test the Hierarchial Clustering
# Using ward linkage was excellent for Hierarchial Clustering
data = File.iloc[:, 3:5].values
plt.figure(figsize=(10, 7))
plt.title("Customer Dendogram")
dend = sch.dendrogram(sch.linkage(data, method='ward'))
```

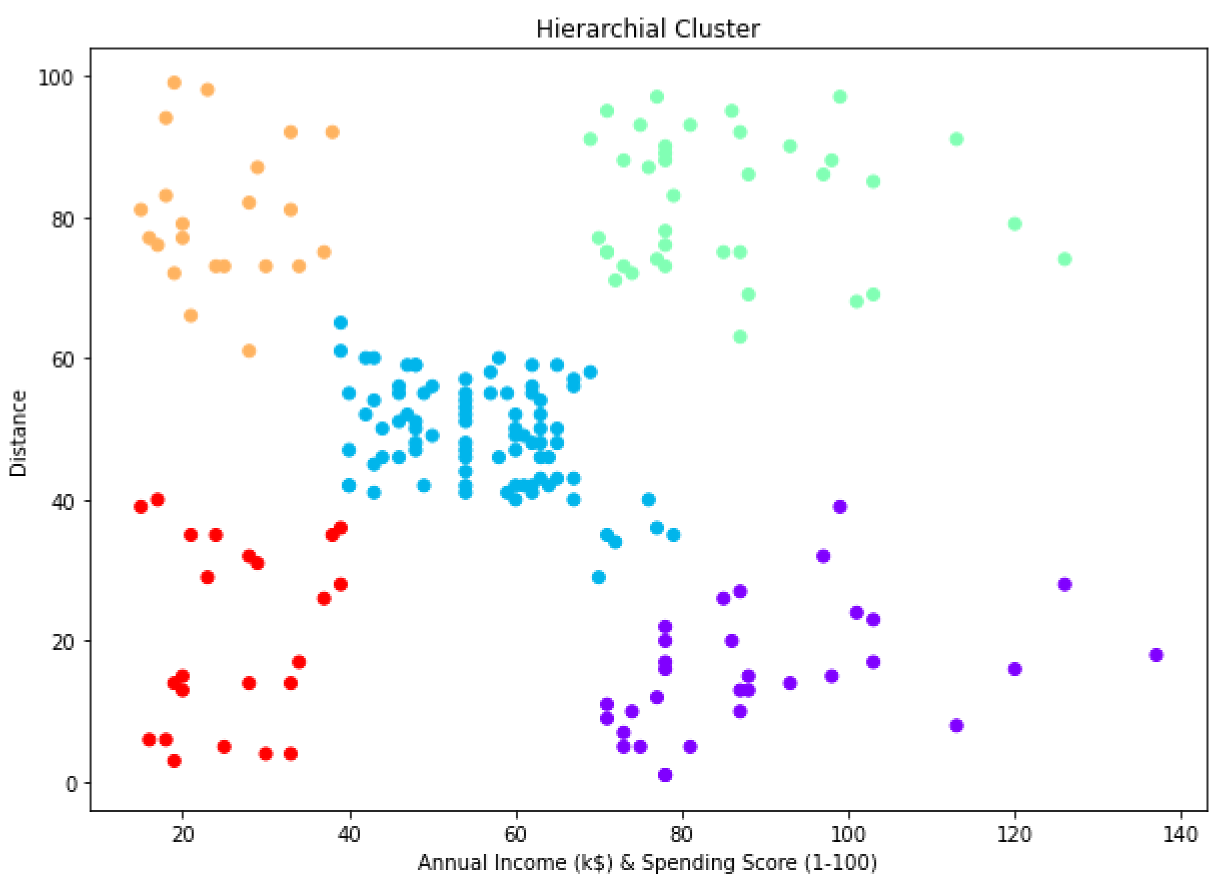


In [1082]:
```
# Using ward linkage strategy to test the Hierarchial Clustering
# Using ward linkage was excellent for Hierarchial Clustering
HierarchialCluster1 = AC(n_clusters =5,affinity ='euclidean',linkage ='ward')
HierarchialCluster1.fit_predict(Final)
```

Out[1082]:
```
array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
       4, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1, 2, 0, 2, 0, 2,
       1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 3], dtype=int64)
```

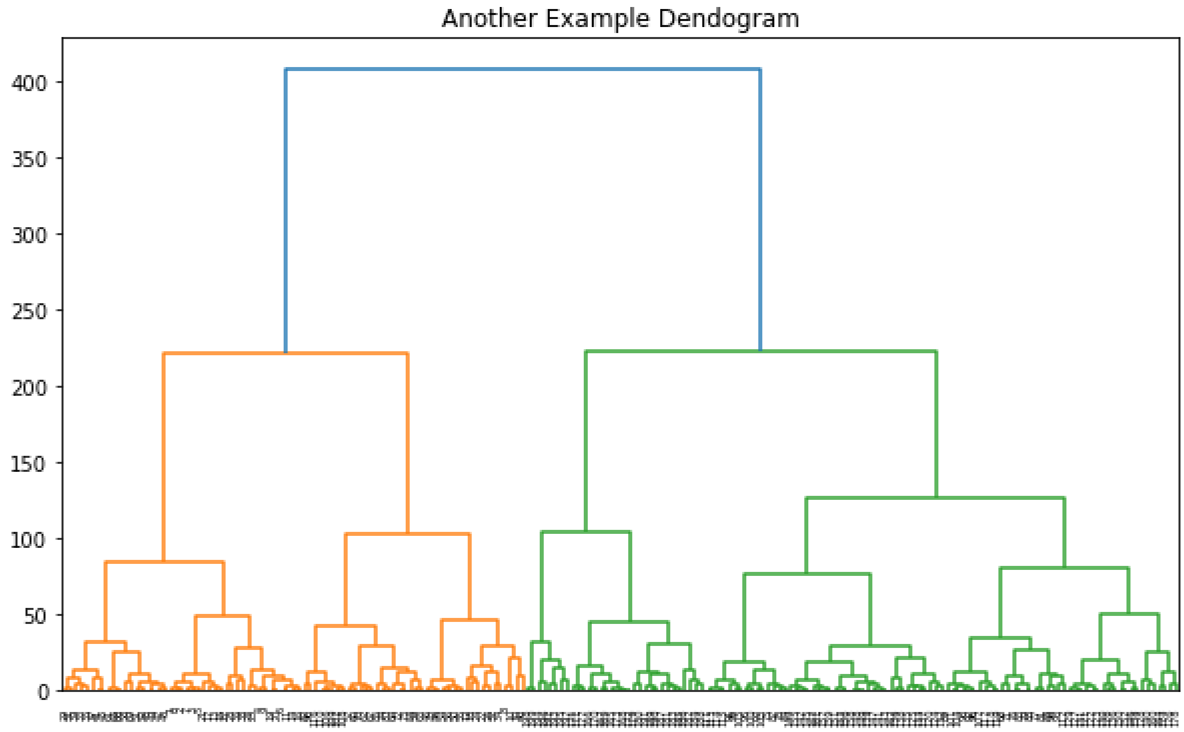
In [1083]:
```
# Here Hierarchial Clustering is more accurate and better than KMedoids cluster
plt.figure(figsize=(10, 7))
plt.scatter(Final[:,0],Final[:,1],c=HierarchialCluster1.labels_,cmap='rainbow')
plt.title('Hierarchial Cluster')
plt.xlabel('Annual Income (k$) & Spending Score (1-100)')
plt.ylabel('Distance')
```

Out[1083]:
```
Text(0, 0.5, 'Distance')
```



In [1084]:
```
data1 = File.iloc[:, 2:4].values
```

In [1085]:
```
# Another Example
plt.figure(figsize=(10, 6))
plt.title("Another Example Dendogram")
dend1 = sch.dendrogram(sch.linkage(data1, method='ward'))
```

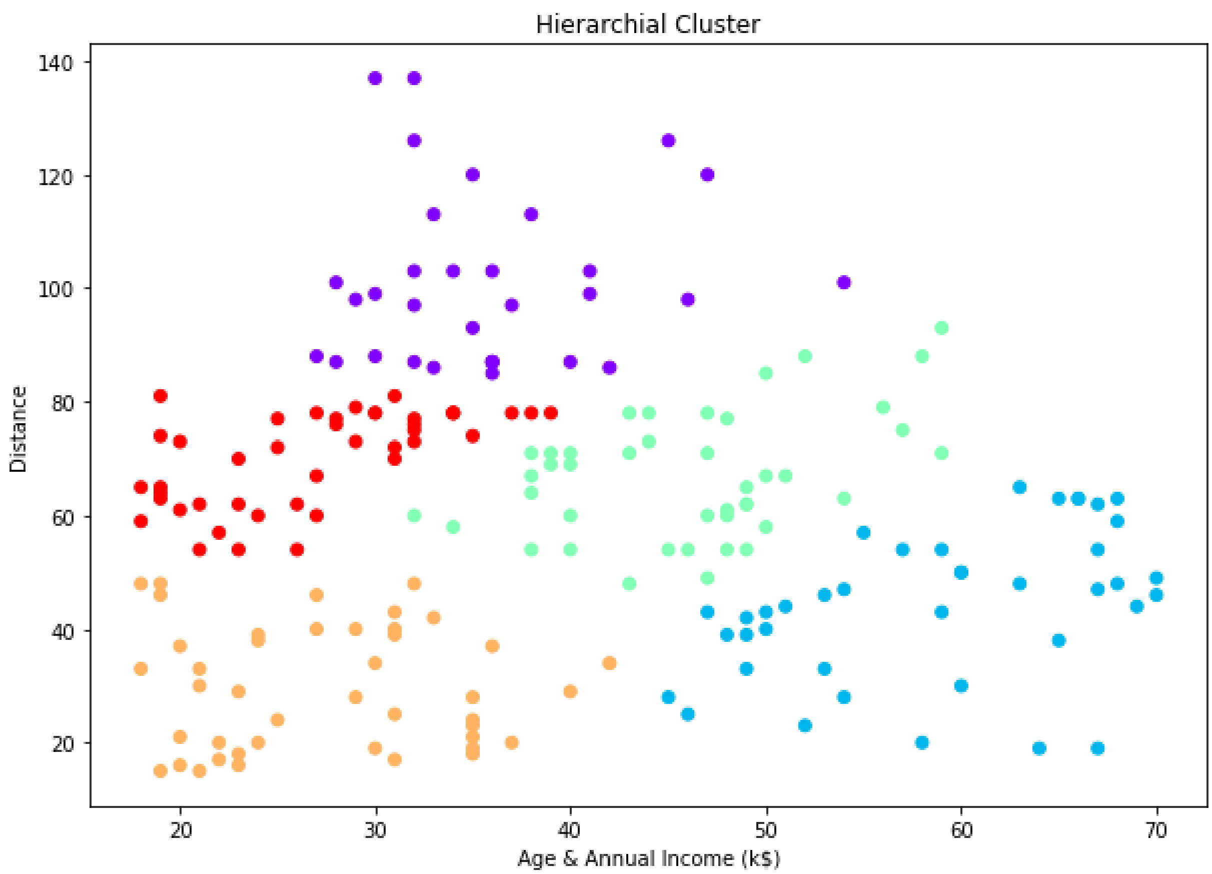


In [1086]:
```
HierarchialCluster2 = AC(n_clusters =5,affinity ='euclidean',linkage ='ward')
HierarchialCluster2.fit_predict(data1)
```

Out[1086]:
```
array([3, 3, 3, 3, 3, 3, 3, 3, 1, 3, 1, 3, 1, 3, 3, 3, 3, 3, 1, 3, 3, 3,
       1, 3, 1, 3, 1, 3, 3, 3, 1, 3, 1, 3, 1, 3, 3, 3, 3, 3, 1, 3, 1, 3,
       1, 3, 1, 3, 3, 3, 1, 3, 3, 1, 1, 1, 1, 1, 3, 1, 1, 3, 1, 1, 1, 3,
       2, 1, 3, 3, 1, 2, 1, 1, 1, 4, 2, 2, 4, 2, 1, 2, 1, 2, 4, 2, 1, 4,
       2, 2, 1, 4, 2, 2, 2, 4, 2, 4, 2, 4, 4, 2, 1, 4, 2, 4, 1, 2, 1, 1,
       1, 4, 2, 4, 4, 4, 1, 2, 2, 2, 4, 2, 2, 2, 4, 4, 2, 2, 2, 2, 2, 2,
       4, 4, 4, 4, 2, 4, 4, 4, 2, 4, 4, 4, 4, 4, 2, 4, 4, 4, 2, 4, 2, 4,
       2, 4, 4, 4, 4, 4, 2, 4, 4, 4, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0,
       2, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0], dtype=int64)
```

In [1087]:
```
# More accurate result here at Hierarchial Clustering
plt.figure(figsize=(10, 7))
plt.scatter(data1[:,0],data1[:,1],c=HierarchialCluster2.labels_,cmap='rainbow')
plt.title('Hierarchial Cluster')
plt.xlabel('Age & Annual Income (k$)')
plt.ylabel('Distance')
```

Out[1087]: Text(0, 0.5, 'Distance')



In [1088]:

```
# Secondly KMedoids WITH K=5 Clusters and Manhattan distance
clu = KMedoids(n_clusters=5,metric="manhattan",init='random',random_state=33)
clu.fit_predict(data)
```

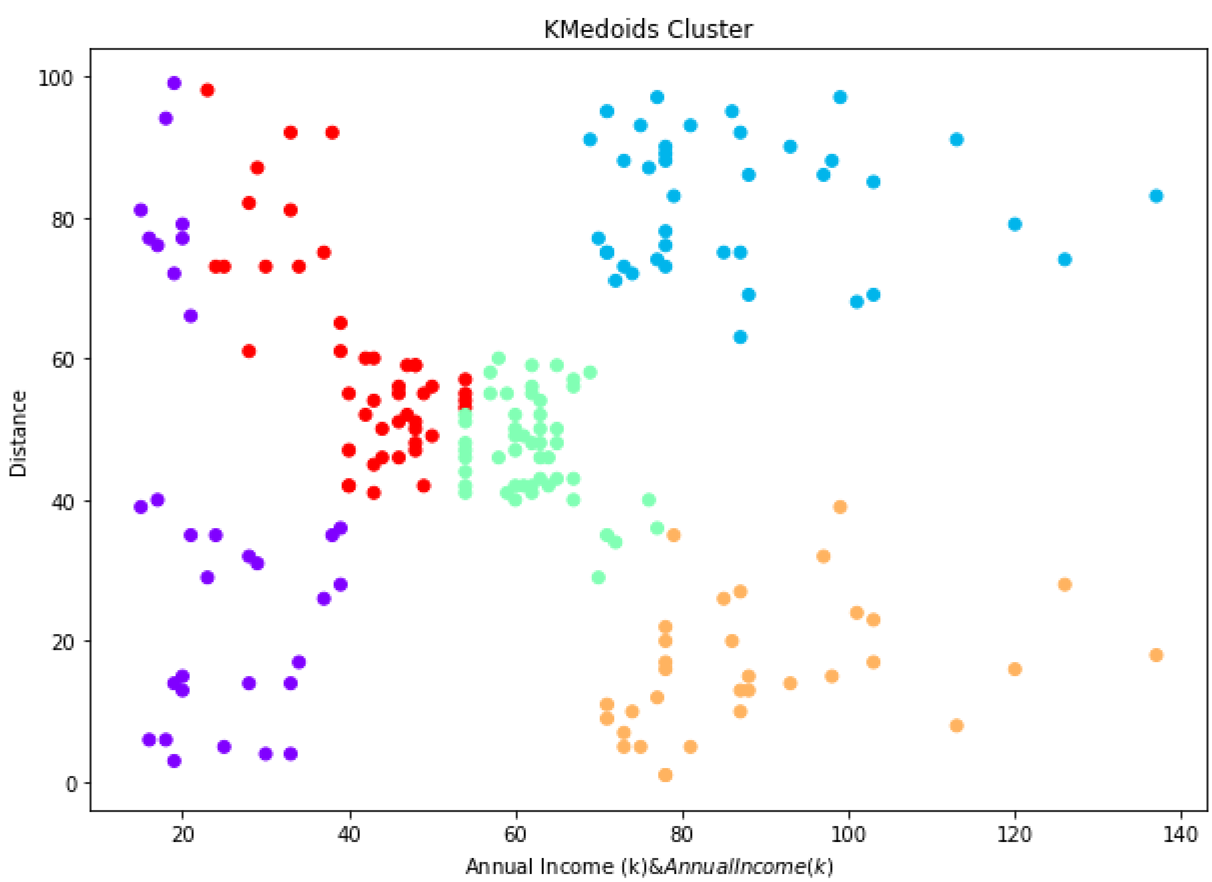
Out[1088]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 4,
       0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4,
       0, 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, 2, 4, 4, 2, 2, 2, 2, 4, 2, 2, 4, 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, 2, 1, 2, 1, 3, 1, 3, 1,
       2, 1, 3, 1, 3, 1, 3, 1, 3, 1, 2, 1, 3, 1, 2, 1, 3, 1, 3, 1, 3, 1,
       3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1,
       3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1,
       3, 1], dtype=int64)
```

In [1089]:

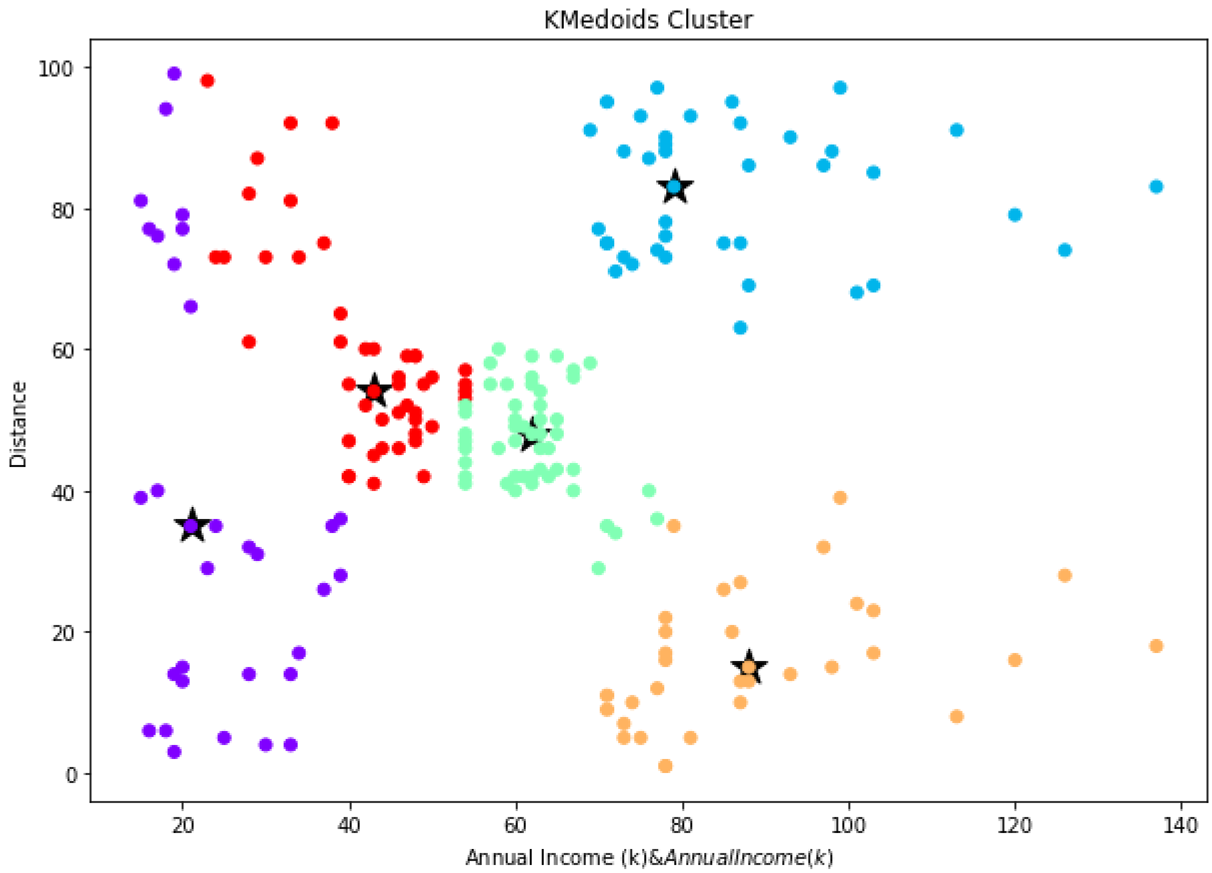
```
# Kmedoid is better here only if we compare it with hierarchal clustering using s
# The green & red are a mess as well as red & purple
# Hierarchial is better in case of using ward linkage only
plt.figure(figsize=(10, 7))
plt.scatter(data[:,0],data[:,1],c=clu.labels_,cmap='rainbow')
plt.title('KMedoids Cluster')
plt.xlabel('Annual Income (k$) & Annual Income (k$)')
plt.ylabel('Distance')
```

Out[1089]: Text(0, 0.5, 'Distance')



In [1090]:
```
plt.figure(figsize=(10, 7))
plt.scatter(clu.cluster_centers_[:,0],clu.cluster_centers_[:,1],c='black',s=350,r
plt.scatter(data[:,0],data[:,1],c=clu.labels_,cmap='rainbow')
plt.title('KMedoids Cluster')
plt.xlabel('Annual Income (k$) & Annual Income (k$)')
plt.ylabel('Distance')
```

Out[1090]:
```
Text(0, 0.5, 'Distance')
```



In [1091]:
```
print('INDICES : ',clu.medoid_indices_)
print('Cluster Centers : \n',clu.cluster_centers_)
```

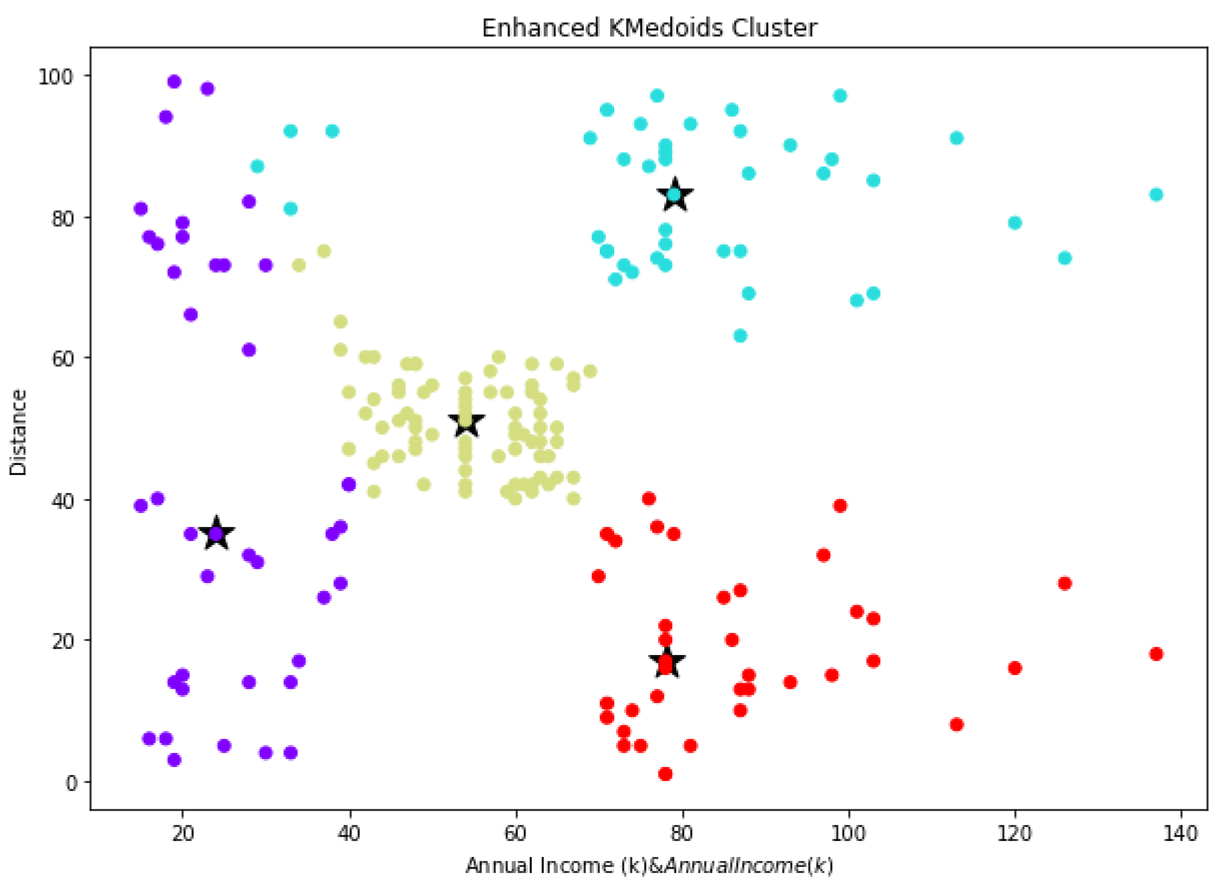
```
INDICES :  [ 16 161 101 176  52]
Cluster Centers :
 [[21 35]
 [79 83]
 [62 48]
 [88 15]
 [43 54]]
```

In [1092]:
```
cluENH = KMedoids(n_clusters=4,metric="manhattan",init='random',random_state=33)
cluENH.fit_predict(data)
```

Out[1092]:
```
array([0, 0, 0, 0, 0, 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, 1, 0, 1, 0, 2, 0, 2, 0, 1, 0, 2,
       0, 2, 2, 2, 0, 0, 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, 3, 1, 3, 1, 3, 1, 3, 1,
       3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1,
       3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1,
       3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1,
       3, 1], dtype=int64)
```

In [1093]:
```
plt.figure(figsize=(10, 7))
plt.scatter(cluENH.cluster_centers_[:,0],cluENH.cluster_centers_[:,1],c='black',s
plt.scatter(data[:,0],data[:,1],c=cluENH.labels_,cmap='rainbow')
plt.title('Enhanced KMedoids Cluster')
plt.xlabel('Annual Income (k$) & Annual Income (k$)')
plt.ylabel('Distance')
```

Out[1093]:
```
Text(0, 0.5, 'Distance')
```

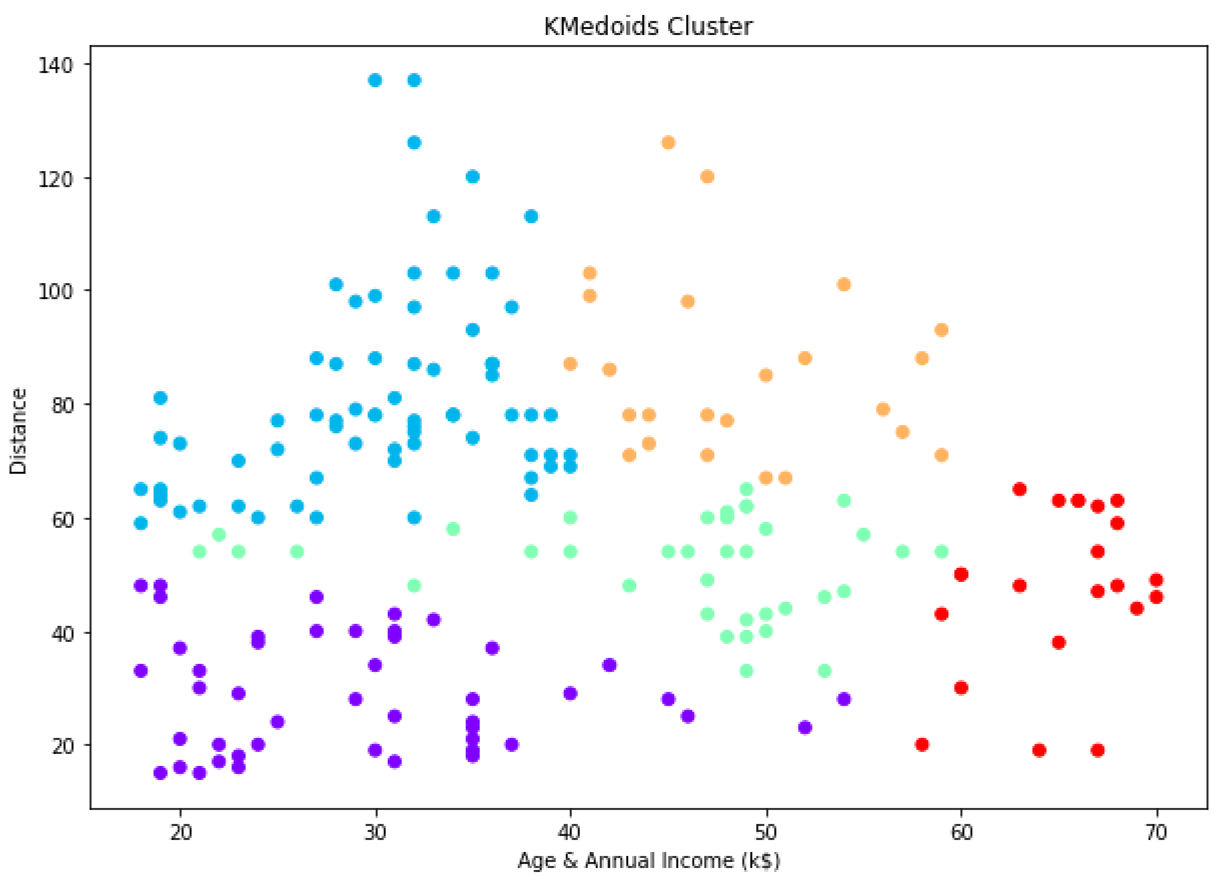


In [1094]:
```
# Another Example Using Kmedoids
clu1 = KMedoids(n_clusters=5,metric="manhattan",init='random',random_state=33)
clu1.fit_predict(data1)
```

Out[1094]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 4, 0, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 4, 0, 2, 0, 2, 0, 0, 0, 0, 0, 4, 0, 2, 0,
       2, 0, 2, 0, 0, 0, 2, 0, 0, 4, 2, 2, 2, 4, 0, 2, 4, 0, 4, 2, 4, 0,
       2, 4, 0, 2, 4, 2, 4, 4, 2, 2, 2, 2, 2, 2, 2, 2, 4, 2, 2, 2, 2, 2,
       2, 2, 4, 1, 2, 2, 1, 1, 2, 1, 2, 1, 1, 2, 4, 1, 2, 1, 4, 2, 4, 4,
       4, 1, 1, 1, 1, 1, 4, 2, 3, 3, 1, 1, 1, 1, 1, 1, 3, 1, 3, 1, 3, 1,
       1, 1, 1, 1, 3, 1, 1, 1, 3, 1, 1, 1, 1, 1, 3, 1, 1, 1, 3, 1, 3, 1,
       3, 1, 1, 1, 1, 1, 3, 1, 1, 1, 3, 1, 3, 1, 1, 1, 3, 1, 1, 1, 3, 1,
       3, 1, 3, 1, 1, 1, 3, 1, 3, 1, 3, 1, 3, 1, 1, 1, 1, 1, 3, 1, 3, 1,
       1, 1], dtype=int64)
```

In [1095]:
```
# Here we can see clearly that Agglomarative Hierarchial Clustering is MUCH bette
plt.figure(figsize=(10, 7))
plt.scatter(data1[:,0],data1[:,1],c=clu1.labels_,cmap='rainbow')
plt.title('KMedoids Cluster')
plt.xlabel('Age & Annual Income (k$)')
plt.ylabel('Distance')
```

Out[1095]:
```
Text(0, 0.5, 'Distance')
```



In [1096]:
```
print('INDICES : ',clu1.medoid_indices_)
print('Cluster Centers : \n',clu1.cluster_centers_)
```

```
INDICES :  [ 25 147  85 154  62]
Cluster Centers :
 [[29 28]
 [32 77]
 [48 54]
 [47 78]
 [67 47]]
```

In [1097]:
```
plt.figure(figsize=(10, 7))
# The simple ( * ) represent Cluster centers
# Which created more accuracy & more clear visual representation
plt.scatter(clu1.cluster_centers_[:,0],clu1.cluster_centers_[:,1],c='black',s=35(
plt.scatter(data1[:,0],data1[:,1],c=clu1.labels_,cmap='rainbow')
plt.title('KMedoids Cluster')
plt.xlabel('Age & Annual Income (k$)')
plt.ylabel('Distance')
```

Out[1097]:
```
Text(0, 0.5, 'Distance')
```