In [1]:
```
# 1. Perform hierarchical clustering using given distance for a given dataset. analyze the performance usin
g CPCC for various linkage measures. Identify optimum number of cluster using Silhouette index.
# (GPS Dataset1.csv). (10 marks)
# a. odd roll numbers (Euclidean distance)
# b. Even roll numbers (Manhattan distance)
# plot the dentogram (5 marks)
# visualize the points using number of clusters identified using Silhouette index (Different colors for differe
nt cluster). (5 marks)

# 2. Perform chi-sqaure analysis for given gss dataset
# a. explore the relationship between job preference and education status.(Job preference and education s
tatus are independent.)- visualize and interpret ( 5 marks) - Odd roll numbers
```

In [2]:
```
import pandas as pd
from sklearn.cluster import KMeans
import numpy as np
import matplotlib.pyplot as plt
from scipy.spatial.distance import cdist,pdist
```

In [3]:
```
df = pd.read_csv("dataset.csv",header=None)
df
```

Out[3]:

| | 0 | 1 |
|---|---|---|
| **0** | 76.95446 | 10.88176 |
| **1** | 76.96292 | 10.85913 |
| **2** | 76.96898 | 10.86515 |
| **3** | 76.97412 | 10.86712 |
| **4** | 76.97384 | 10.86967 |
| **...** | ... | ... |
| **2907** | 79.13229 | 12.91898 |
| **2908** | 79.13190 | 12.92141 |
| **2909** | 79.12957 | 12.92103 |
| **2910** | 76.72108 | 8.08215 |
| **2911** | 80.32030 | 13.21461 |

2912 rows × 2 columns

In [4]:
```
X=df.values
X
```

Out[4]:
```
array([[76.95446, 10.88176],
       [76.96292, 10.85913],
       [76.96898, 10.86515],
       ...,
       [79.12957, 12.92103],
       [76.72108,  8.08215],
       [80.3203 , 13.21461]])
```

# 1. Perform hierarchical clustering using given distance for a given dataset. analyze the performance using CPCC for various linkage measures. Identify optimum number of cluster using Silhouette index.

# (GPS Dataset1.csv). (10 marks)

a. odd roll numbers (Euclidean distance)

plot the dentogram (5 marks)

visualize the points using number of clusters identified using Silhouette index (Different colors for different cluster). (5 marks)

In [5]:
```
from scipy.cluster.hierarchy import dendrogram, linkage,cophenet
```

In [6]:
```
linked1 = linkage(X, 'single')
linked2 = linkage(X, 'complete')
linked3 = linkage(X, 'average')
linked4 = linkage(X, 'median')
linked5 = linkage(X, 'centroid')
```

In [7]:
```
c=[]
for i in [linked1,linked2,linked3,linked4,linked5]:
    c.append(cophenet(i,pdist(X)))
```

In [8]:
```
val = []
met = ['single','complete','average','median','centroid']
for i in c:
    val.append(i[0])
```

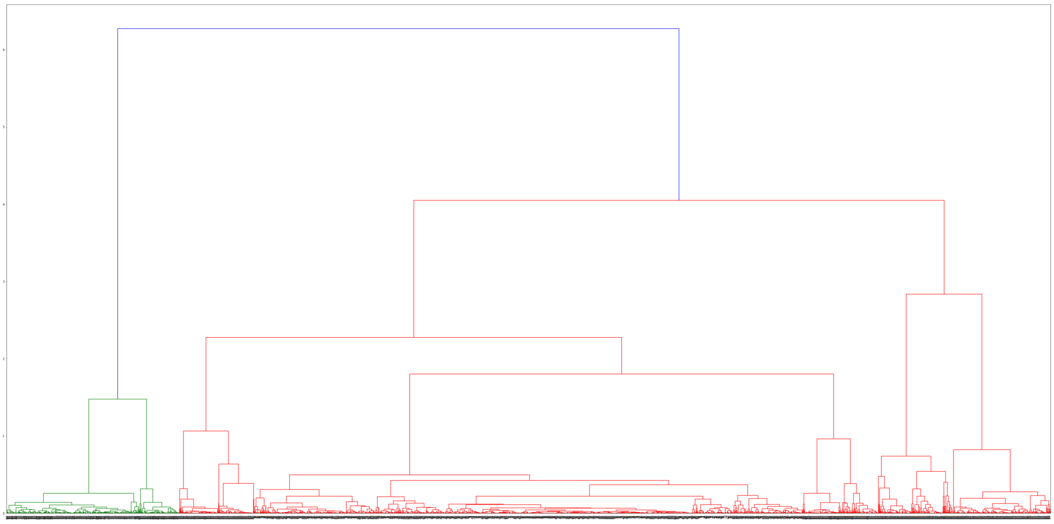
In [9]:
```
data = {'method':met,'Cophenet':val}
pd.DataFrame(data)
```

Out[9]:

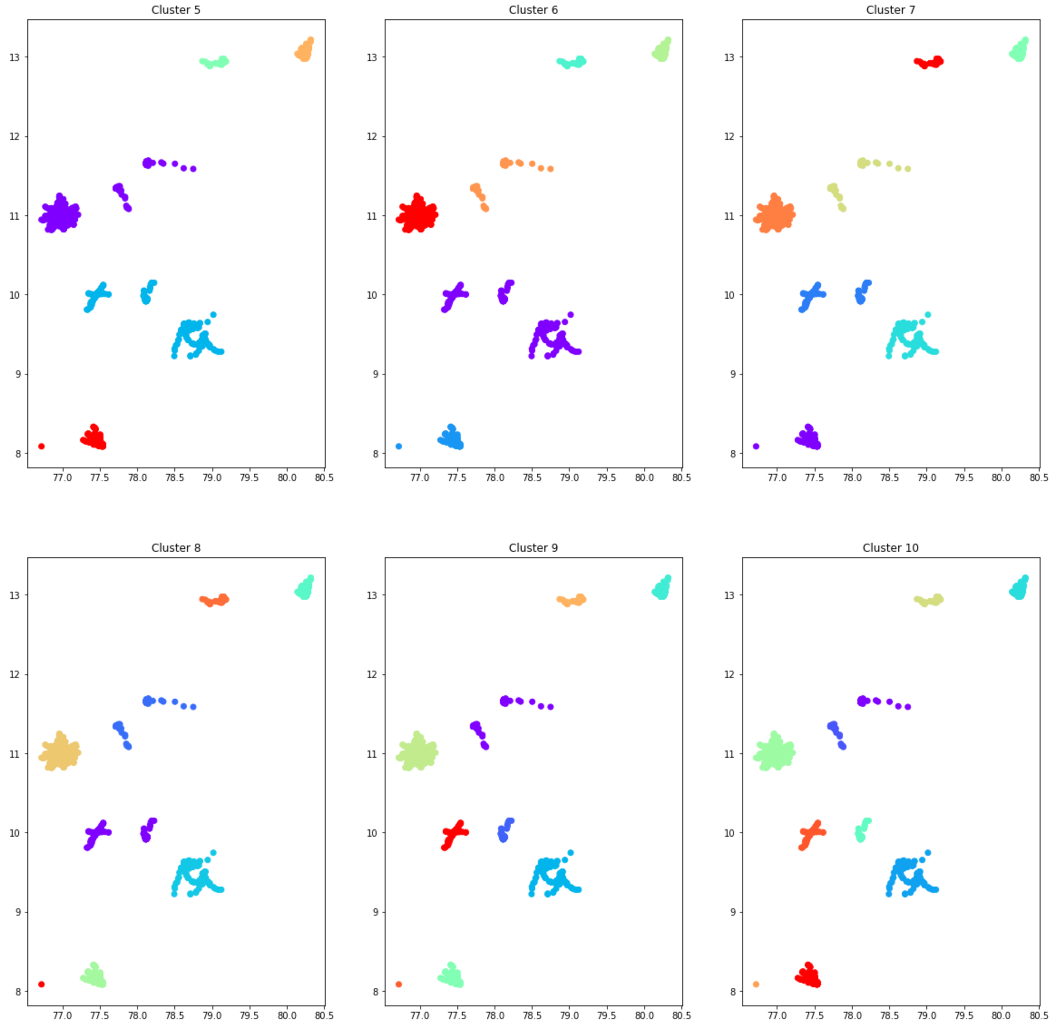
| | method | Cophenet |
|---|---|---|
| **0** | single | 0.911160 |
| **1** | complete | 0.945526 |
| **2** | average | 0.934422 |
| **3** | median | 0.935107 |
| **4** | centroid | 0.934144 |

# Complete Linkage has high cophenet distance

In [10]:
```
labelList = range(len(X))
plt.figure(figsize=(64, 32))
dendrogram(linked2,
        labels = labelList,
        distance_sort = 'descending',
        show_leaf_counts = True)
plt.show()
```



In [11]:
```
from sklearn.cluster import AgglomerativeClustering
fig,axes = plt.subplots(nrows=2,ncols=3,figsize=(20,20))
j=0
k=0
for i in range(5,11):
    clusters=[]
    cluster = AgglomerativeClustering(n_clusters=i, affinity='euclidean', linkage='single')
    clusters.append(cluster.fit_predict(X))
    axes[k,j].title.set_text("Cluster "+str(i))
    axes[k,j].scatter(X[:,0], X[:,1], c=cluster.labels_,cmap='rainbow')
    j+=1
    if(j==3):
        k+=1
        j=0
    if(k==3):
        break
```




In [12]:
```
from sklearn.metrics import silhouette_score
```

In [13]:
```
clusters=[]
ss=[]

for i in range(5,11):
    cluster = AgglomerativeClustering(n_clusters=i, affinity='euclidean', linkage='complete')
    clusters.append(cluster.fit_predict(X))
    ss.append(silhouette_score(X,cluster.labels_))
```

In [14]:
```
pd.DataFrame({"Clusters":range(5,11),"Silhoutte":ss})
```

Out[14]:

| | Clusters | Silhoutte |
|---|---|---|
| **0** | 5 | 0.736492 |
| **1** | 6 | 0.854910 |
| **2** | 7 | 0.877793 |
| **3** | 8 | 0.877986 |
| **4** | 9 | 0.893984 |
| **5** | 10 | 0.887905 |

# Although Silhoutte Score for 9 clusters > 10 clusters . But looking at the plot above. It seems 10 seems a better choice. SO I'm picking 10 as optimum no of clusters

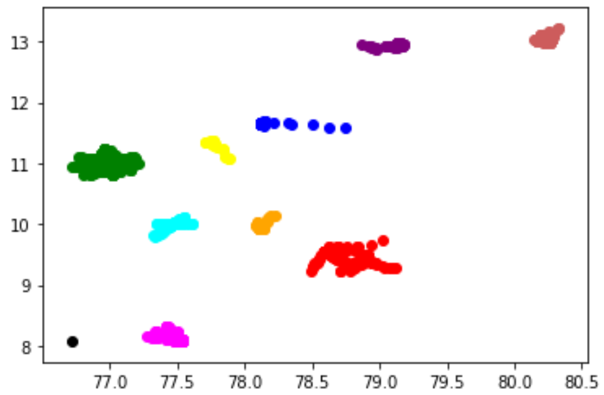
In [15]:
```
cluster = AgglomerativeClustering(n_clusters=10, affinity='euclidean', linkage='complete')
cluster.fit_predict(X)
;
```

Out[15]: ''

In [16]:
```
np.unique(cluster.labels_)
```

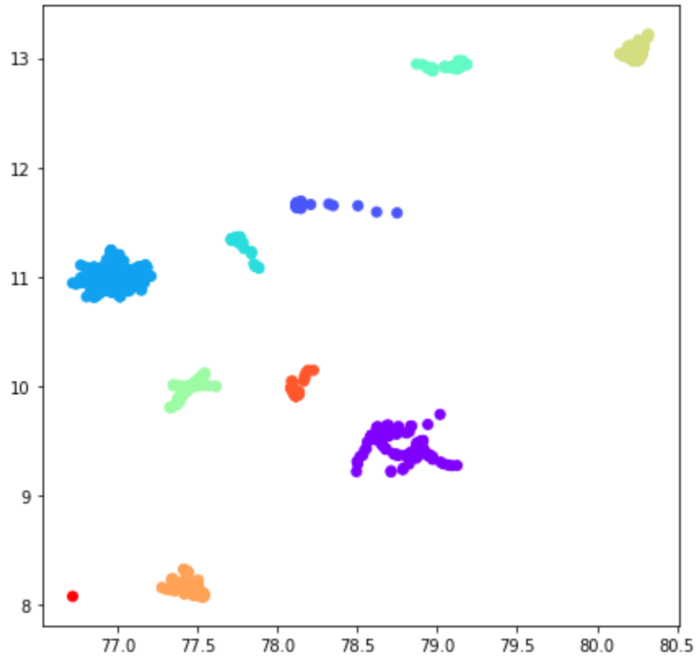
Out[16]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [19]:
```
for i in range(len(cluster.labels_)):
    if cluster.labels_[i]==0:
        plt.scatter(X[i][0], X[i][1],c='red',label='Cluster-1')
    if cluster.labels_[i]==1:
        plt.scatter(X[i][0], X[i][1],c='blue',label='Cluster-2')
    if cluster.labels_[i]==2:
        plt.scatter(X[i][0], X[i][1],c='green',label='Cluster-3')
    if cluster.labels_[i]==3:
        plt.scatter(X[i][0], X[i][1],c='yellow',label='Cluster-4')
    if cluster.labels_[i]==4:
        plt.scatter(X[i][0], X[i][1],c='purple',label='Cluster-5')
    if cluster.labels_[i]==5:
        plt.scatter(X[i][0], X[i][1],c='cyan',label='Cluster-6')
    if cluster.labels_[i]==6:
        plt.scatter(X[i][0], X[i][1],c='indianred',label='Cluster-7')
    if cluster.labels_[i]==7:
        plt.scatter(X[i][0], X[i][1],c='magenta',label='Cluster-8')
    if cluster.labels_[i]==8:
        plt.scatter(X[i][0], X[i][1],c='orange',label='Cluster-9')
    if cluster.labels_[i]==9:
        plt.scatter(X[i][0], X[i][1],c='black',label='Cluster-10')
```



In [98]:
```
from sklearn.cluster import AgglomerativeClustering
cluster = AgglomerativeClustering(n_clusters=10, affinity='euclidean', linkage='complete')
cluster.fit_predict(X)
plt.figure(figsize=(7,7))
plt.scatter(X[:,0], X[:,1], c=cluster.labels_,cmap='rainbow')
```

Out[98]: <matplotlib.collections.PathCollection at 0x7fb3fc1f4210>




In [ ]: