In [16]:

```
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.head()
```

Out[3]:

	0	1
0	-10.939341	-37.062742
1	-10.938346	-37.062588
2	-10.938666	-37.061499
3	-10.940389	-37.058291
4	-10.943048	-37.056201

In [26]:

```
df.shape
```

Out[26]:

```
(810, 2)
```

In [4]:

```
df.isnull().sum()
```

Out[4]:

```
0    0
1    0
dtype: int64
```

In [10]:

```
X=df.values
```

In [18]:

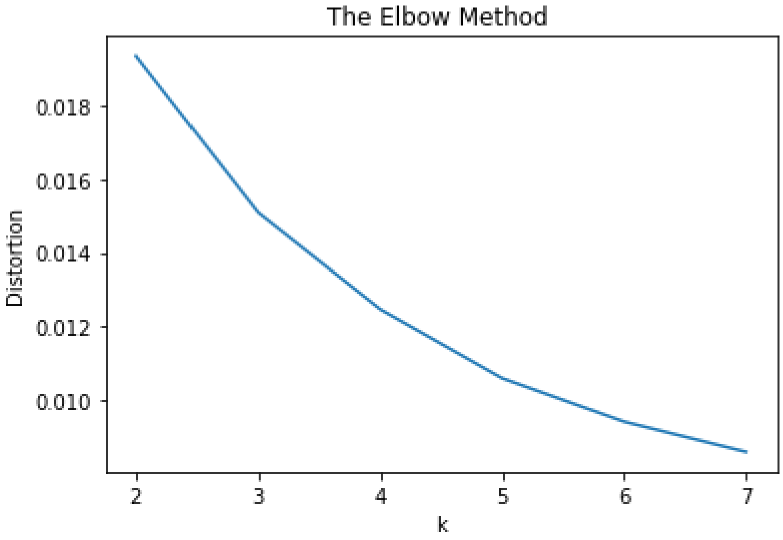
```
X
```

Out[18]:

```
array([[-10.93934139, -37.06274211],
       [-10.93834606, -37.06258756],
       [-10.93866607, -37.06149893],
       ...,
       [-10.96774471, -37.04156872],
       [-10.97922092, -37.04416391],
       [-10.97887015, -37.04730602]])
```

In [19]:

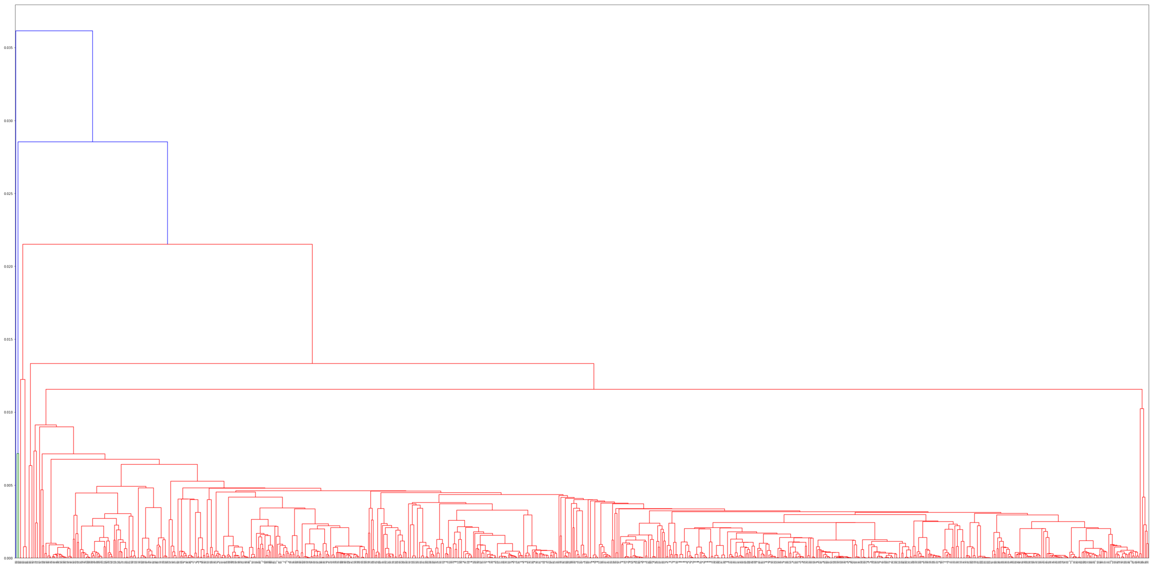
```
distortions = []
Ks = [2, 3, 4, 5, 6, 7]
for k in Ks:
    kmeans = KMeans(n_clusters = k)
    model = kmeans.fit(X)
    centers = model.cluster_centers_
    distortions.append(sum(np.min(cdist(X,centers, 'euclidean'), axis=1)) / X.sh
ape[0])

plt.plot(Ks, distortions)
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method ')
plt.show()
```



SINGLE

In [22]:

```
from scipy.cluster.hierarchy import dendrogram, linkage,cophenet

linked1 = linkage(X, 'single')

labelList = range(len(X))

plt.figure(figsize=(64, 32))
dendrogram(linked1,
           labels = labelList,
           distance_sort = 'descending',
           show_leaf_counts = True)
plt.show()
```



In [23]:

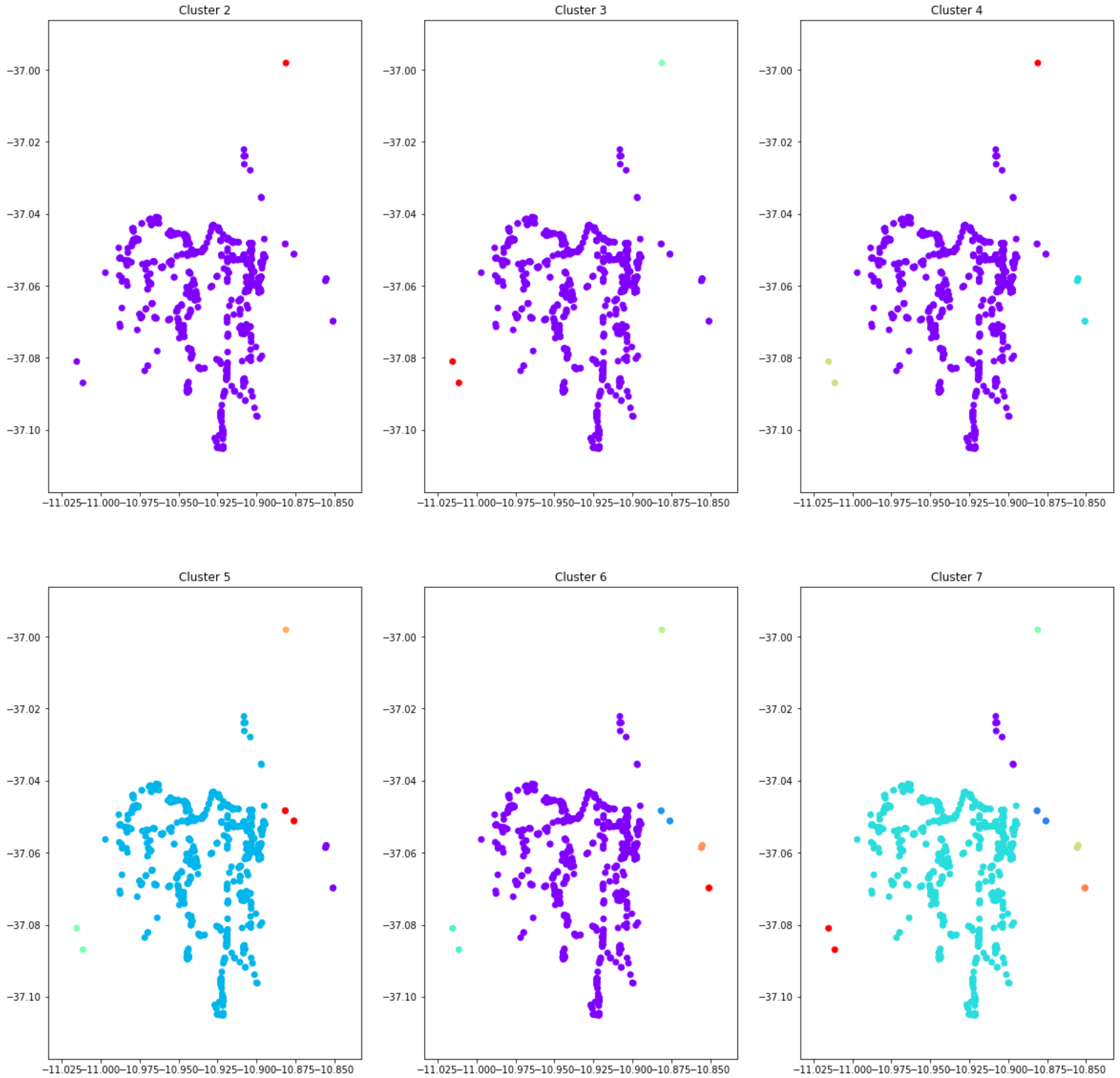
```
c1=cophenet(linked1,pdist(X))
c1
```

Out[23]:

```
(0.501683091756393,
 array([0.00069311, 0.0009498 , 0.00217511, ..., 0.00489925, 0.00489
925,
        0.00218404]))
```

In [55]:

```
from sklearn.cluster import AgglomerativeClustering
fig,axes = plt.subplots(nrows=2,ncols=3,figsize=(20,20))
j=0
k=0
for i in [2,3,4,5,6,7]:

    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 [63]:

```
cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='single')
```

In [66]:

```
cluster.fit_predict(X)
```

Out[66]:

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 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, 1, 1, 1, 1, 1, 1, 1, 2, 2, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 4, 0, 0, 0, 4, 1, 1, 1,
1, 1,
       4, 0, 0, 0, 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, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

Davies Bouldin Index

In [67]:

```
from sklearn.metrics import davies_bouldin_score
db_score = davies_bouldin_score(X,cluster.labels_)
db_score
```

Out[67]:

```
0.4571351972460979
```

Dunn Index

In [70]:

```
import numpy as np
from sklearn.metrics.pairwise import euclidean_distances

def delta(ck, cl):
    values = np.ones([len(ck), len(cl)])*10000

    for i in range(0, len(ck)):
        for j in range(0, len(cl)):
            values[i, j] = np.linalg.norm(ck[i]-cl[j])

    return np.min(values)

def big_delta(ci):
    values = np.zeros([len(ci), len(ci)])

    for i in range(0, len(ci)):
        for j in range(0, len(ci)):
            values[i, j] = np.linalg.norm(ci[i]-ci[j])

    return np.max(values)

def dunn(k_list):
    deltas = np.ones([len(k_list), len(k_list)])*1000000
    big_deltas = np.zeros([len(k_list), 1])
    l_range = list(range(0, len(k_list)))

    for k in l_range:
        for l in (l_range[0:k]+l_range[k+1:]):
            deltas[k, l] = delta(k_list[k], k_list[l])

        big_deltas[k] = big_delta(k_list[k])

    di = np.min(deltas)/np.max(big_deltas)
    return di
```

In [80]:

```
dic = {0:[],1:[],2:[],3:[],4:[],5:[]}
pt=1
for x in cluster.labels_:
    dic[x].append(pt)
    pt+=1
```

In [86]:

```
dunn_score = dunn([dic[0],dic[1],dic[2],dic[3],dic[4]])
dunn_score
```

Out[86]:

```
0.0012360939431396785
```

Silhouette

In [88]:

```
from sklearn.metrics import silhouette_score
```

In [90]:

```
ss = silhouette_score(X,cluster.labels_)
ss
```

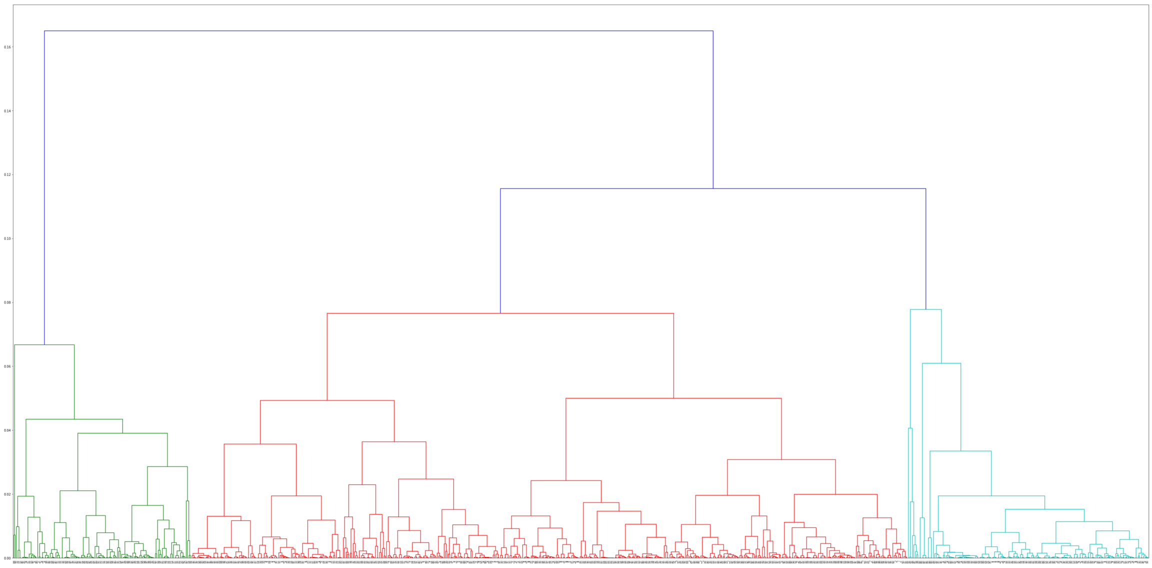
Out[90]:

```
0.17451824982707576
```

COMPLETE

In [24]:

```
linked2 = linkage(X, 'complete')

labelList = range(len(X))

plt.figure(figsize=(64, 32))
dendrogram(linked2,
          labels = labelList,
          distance_sort = 'descending',
          show_leaf_counts = True)
plt.show()
```



In [25]:

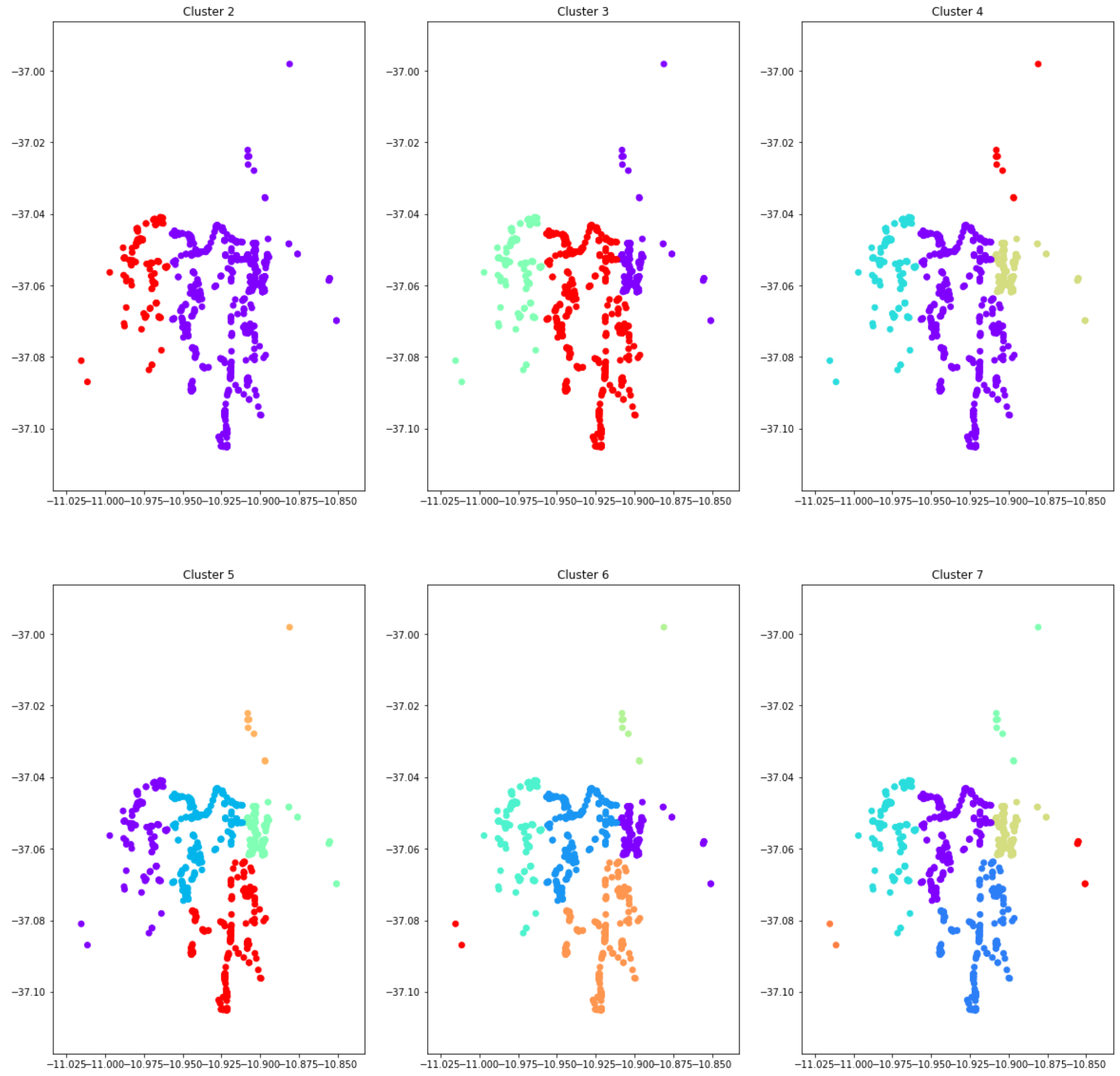
```
c2=cophenet(linked2,pdist(X))
c2
```

Out[25]:

```
(0.6663436788527682,
 array([0.00145305, 0.00145305, 0.01250059, ..., 0.03900114, 0.03900
114,
        0.00508868]))
```

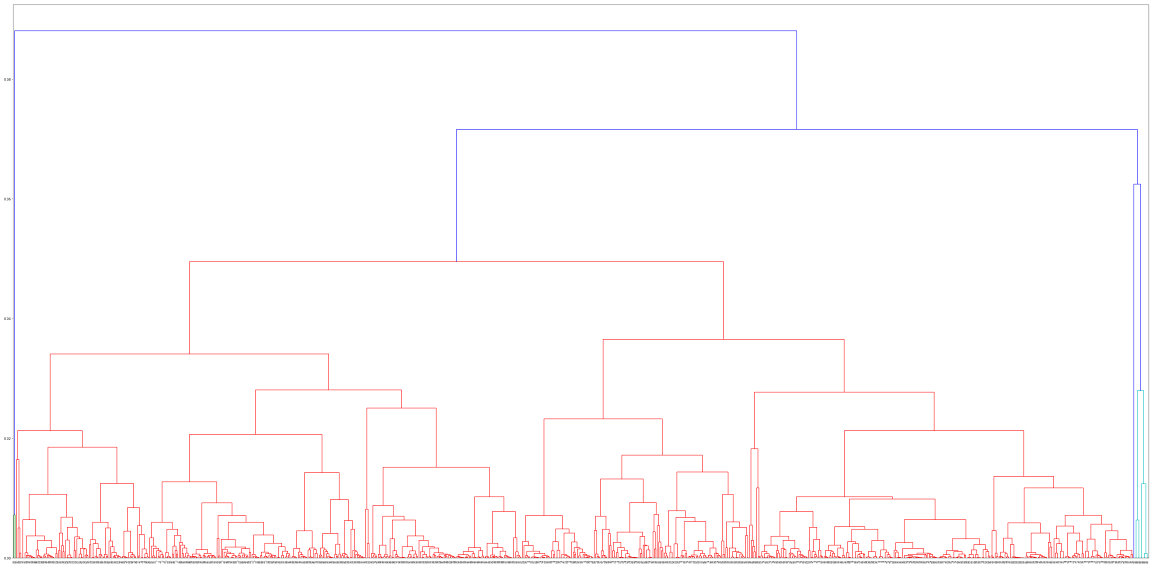
In [44]:

```
from sklearn.cluster import AgglomerativeClustering
fig,axes = plt.subplots(nrows=2,ncols=3,figsize=(20,20))
j=0
k=0
for i in [2,3,4,5,6,7]:

    clusters=[]
    cluster = AgglomerativeClustering(n_clusters=i, affinity='euclidean', linkage='complete')
    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 [56]:

```
from scipy.cluster.hierarchy import dendrogram, linkage

linked4 = linkage(X, 'average')

labelList = range(len(X))

plt.figure(figsize=(64, 32))
dendrogram(linked4,
            labels = labelList,
            distance_sort = 'descending',
            show_leaf_counts = True)
max_d=100
plt.show()
```



In [57]:

```
c4=cophenet(linked4,pdist(X))
c4
```

Out[57]:

```
(0.7373574471821873,
 array([0.00098734, 0.00123228, 0.00594048, ..., 0.03408204, 0.03408
204,
        0.00367309]))
```

In [100]:

```
cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='c
omplete')
cluster.fit_predict(X)
;
```

Out[100]:

```
''
```

Davies Bouldin Index

In [101]:

```
from sklearn.metrics import davies_bouldin_score
db_score = davies_bouldin_score(X,cluster.labels_)
db_score
```

Out[101]:

```
0.7502686829970208
```

Dunn Index

In [102]:

```
import numpy as np
from sklearn.metrics.pairwise import euclidean_distances

def delta(ck, cl):
    values = np.ones([len(ck), len(cl)])*10000

    for i in range(0, len(ck)):
        for j in range(0, len(cl)):
            values[i, j] = np.linalg.norm(ck[i]-cl[j])

    return np.min(values)

def big_delta(ci):
    values = np.zeros([len(ci), len(ci)])

    for i in range(0, len(ci)):
        for j in range(0, len(ci)):
            values[i, j] = np.linalg.norm(ci[i]-ci[j])

    return np.max(values)

def dunn(k_list):
    deltas = np.ones([len(k_list), len(k_list)])*1000000
    big_deltas = np.zeros([len(k_list), 1])
    l_range = list(range(0, len(k_list)))

    for k in l_range:
        for l in (l_range[0:k]+l_range[k+1:]):
            deltas[k, l] = delta(k_list[k], k_list[l])

        big_deltas[k] = big_delta(k_list[k])

    di = np.min(deltas)/np.max(big_deltas)
    return di
```

In [103]:

```
dic = {0:[],1:[],2:[],3:[],4:[],5:[]}
pt=1
for x in cluster.labels_:
    dic[x].append(pt)
    pt+=1
```

In [104]:

```
dunn_score = dunn([dic[0],dic[1],dic[2],dic[3],dic[4]])
dunn_score
```

Out[104]:

```
0.0012422360248447205
```

Silhouette

In [105]:

```
from sklearn.metrics import silhouette_score
```

In [106]:

```
ss = silhouette_score(X,cluster.labels_)
ss
```

Out[106]:

```
0.4036281778559927
```

In [ ]:

```

```

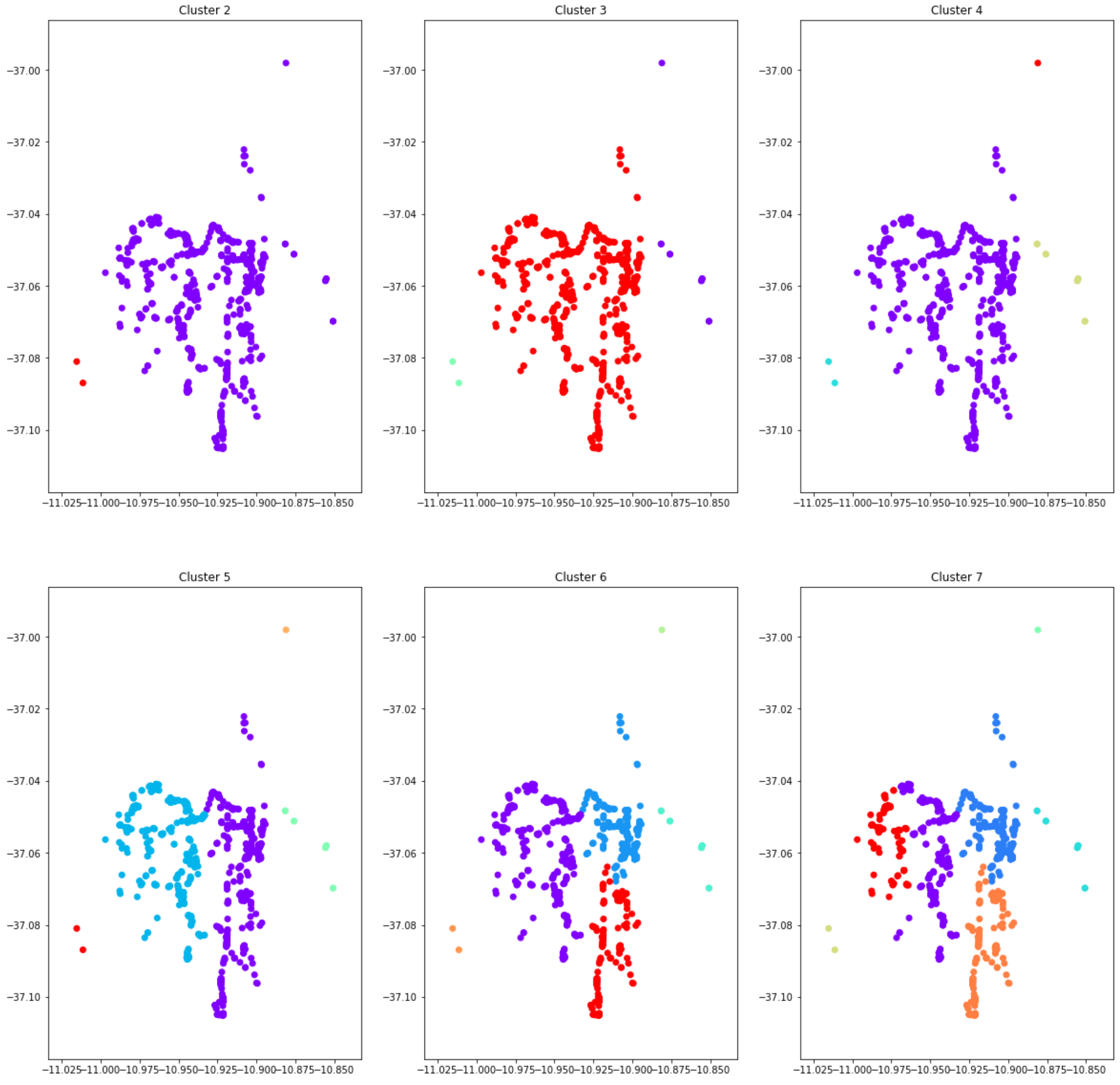
In [ ]:

```

```

Average

In [59]:

```
from sklearn.cluster import AgglomerativeClustering
fig,axes = plt.subplots(nrows=2,ncols=3,figsize=(20,20))
j=0
k=0
for i in [2,3,4,5,6,7]:

    clusters=[]
    cluster = AgglomerativeClustering(n_clusters=i, affinity='euclidean', linkage='average')
    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 [93]:

```
cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='average')
cluster.fit_predict(X)
;
```

Out[93]:

```
''
```

Davies Bouldin Index

In [94]:

```
from sklearn.metrics import davies_bouldin_score
db_score = davies_bouldin_score(X,cluster.labels_)
db_score
```

Out[94]:

```
0.603344711583115
```

Dunn Index

In [95]:

```
import numpy as np
from sklearn.metrics.pairwise import euclidean_distances

def delta(ck, cl):
    values = np.ones([len(ck), len(cl)])*10000

    for i in range(0, len(ck)):
        for j in range(0, len(cl)):
            values[i, j] = np.linalg.norm(ck[i]-cl[j])

    return np.min(values)

def big_delta(ci):
    values = np.zeros([len(ci), len(ci)])

    for i in range(0, len(ci)):
        for j in range(0, len(ci)):
            values[i, j] = np.linalg.norm(ci[i]-ci[j])

    return np.max(values)

def dunn(k_list):
    deltas = np.ones([len(k_list), len(k_list)])*1000000
    big_deltas = np.zeros([len(k_list), 1])
    l_range = list(range(0, len(k_list)))

    for k in l_range:
        for l in (l_range[0:k]+l_range[k+1:]):
            deltas[k, l] = delta(k_list[k], k_list[l])

        big_deltas[k] = big_delta(k_list[k])

    di = np.min(deltas)/np.max(big_deltas)
    return di
```

In [96]:

```
dic = {0:[],1:[],2:[],3:[],4:[],5:[]}
pt=1
for x in cluster.labels_:
    dic[x].append(pt)
    pt+=1
```

In [97]:

```
dunn_score = dunn([dic[0],dic[1],dic[2],dic[3],dic[4]])
dunn_score
```

Out[97]:

```
0.0012360939431396785
```

Silhouette

In [98]:

```
from sklearn.metrics import silhouette_score
```

In [99]:

```
ss = silhouette_score(X,cluster.labels_)
ss
```

Out[99]:

```
0.40384921521212547
```

In [ ]:

```

```