Hierarchical Clustering

We have two types of Hierarchical Clustering here:

1. **Agglomerative Clustering** (Bottom to Top Clustering)
   - Begins with n clusters and goes till 1 cluster
2. **Divisive Clustering** (Top to Bottom Clustering)
   - Begins with 1 cluster and goes till n clusters

In [63]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, MinMaxScaler

from scipy.cluster import hierarchy

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

In [64]:

```
country = pd.read_csv(r"C:\Users\Bhupendra\Desktop\DataCenter\Clustering\Cou
country.head()
```

Out[64]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

In [65]:
```
df = country.drop('country', axis = 1)
df.head()
```

Out[65]:

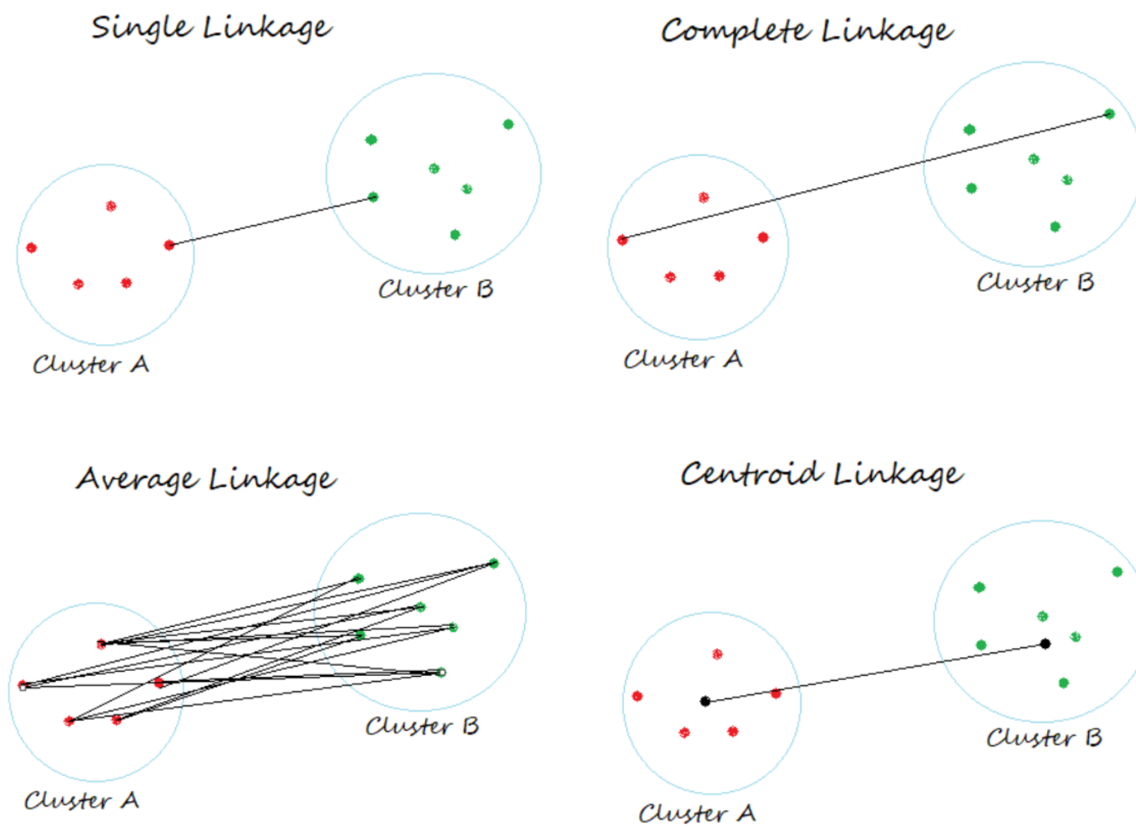
	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

Scaling

In [81]:
```
ss = StandardScaler()
scaled_data = ss.fit_transform(df)
```

Types of Linkages:

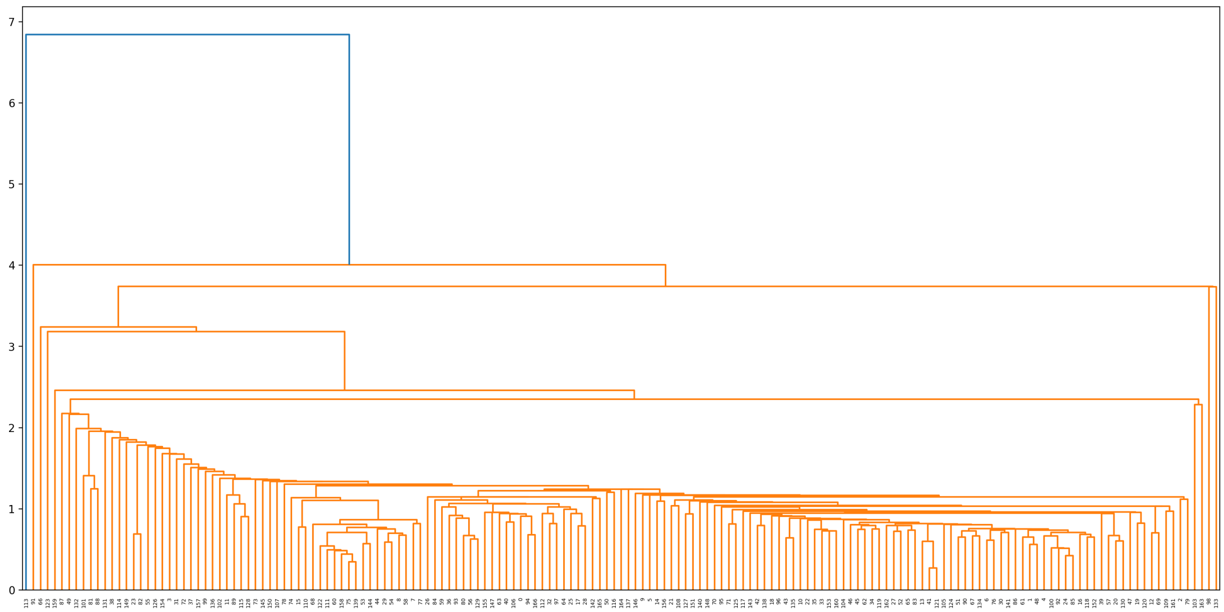
1. **Single Linkage**
2. **Complete Linkage**
3. **Average Linkage**
4. **Centroid Linkage**



Single Linkage Clustering

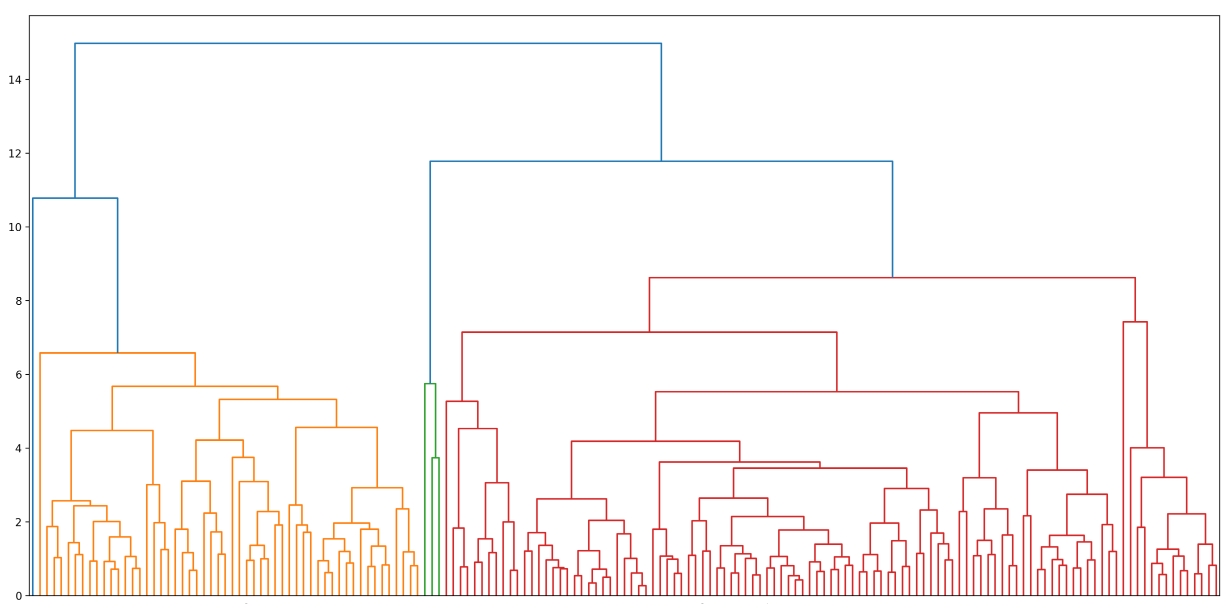
In [82]:
```
# Single Linkage Clustering

plt.figure(figsize = (20,10), dpi = 200)
single = hierarchy.linkage(scaled_data, method = "single", metric = 'euclide
hierarchy.dendrogram(single)
plt.show()
```



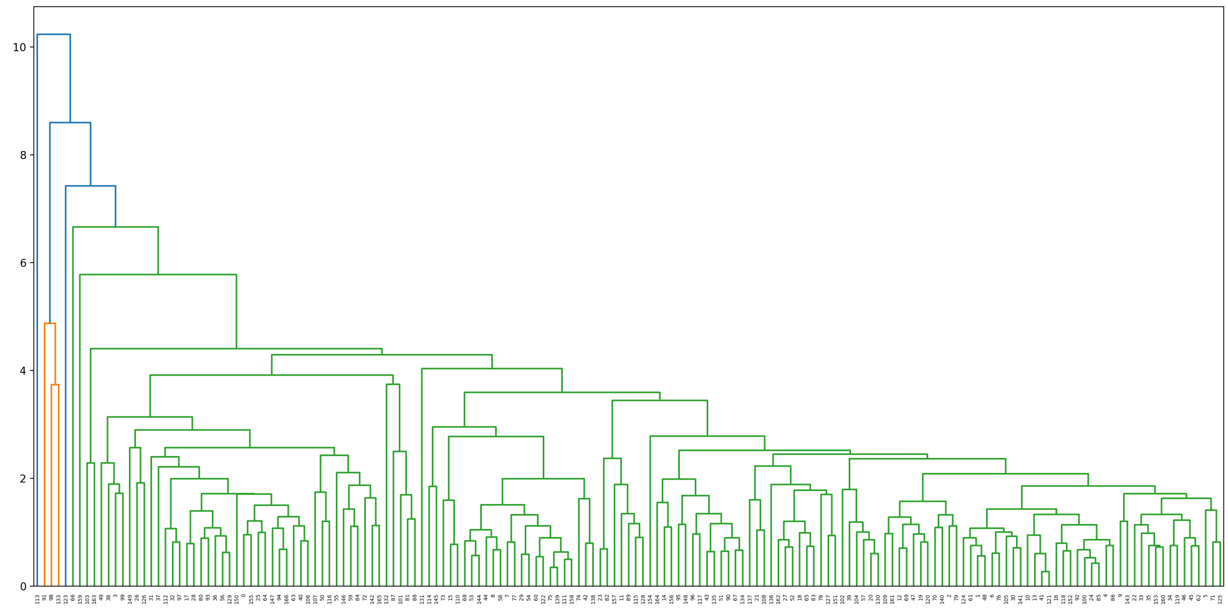
Complete Linkage

In [83]:
```
plt.figure(figsize = (20,10), dpi = 200)
complete = hierarchy.linkage(scaled_data, method = "complete", metric = 'euc
hierarchy.dendrogram(complete)
plt.show()
```



Average Linkage

In [84]:
```
plt.figure(figsize = (20,10), dpi = 200)
avg = hierarchy.linkage(scaled_data, method = "average", metric = 'euclidean
hierarchy.dendrogram(avg)
plt.show()
```



In [85]:
```
scaled_data[0]
```

Out[85]:
```
array([ 1.29153238, -1.13827979,  0.27908825, -0.08245496, -0.8082454 ,
        0.15733622, -1.61909203,  1.90288227, -0.67917961])
```

In [86]:
```
scaled_data[155]
```

Out[86]:
```
array([ 1.06272222, -0.87849025,  0.80125265, -0.75776682, -0.81188739,
        0.26740351, -1.55142162,  2.12152548, -0.67688123])
```

Cut Tree

In [87]:
```
labels = hierarchy.cut_tree(complete, n_clusters = 3).reshape(-1,)
labels
```

Out[87]:
```
array([0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0,
       1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0,
       0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0,
       0, 1, 1, 2, 1, 0, 0, 1, 1, 0, 2, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1,
       1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1,
       0, 2, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0])
```

In [88]:
```
labeled_data = pd.concat([country,pd.DataFrame(labels, columns = ['class'])], axi
```

In [89]:
```
labeled_data.head()
```

Out[89]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gd
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	5
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	40
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	44
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	35
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	122

In [90]:
```
labeled_data['class'].value_counts()
```

Out[90]:
```
1    109
0     55
2      3
Name: class, dtype: int64
```

In [91]:
```
labeled_data[labeled_data['class'] == 2]
```

Out[91]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	g
91	Luxembourg	2.8	175.0	7.77	142.0	91700	3.620	81.3	1.63	105
98	Malta	6.8	153.0	8.65	154.0	28300	3.830	80.3	1.36	21
133	Singapore	2.8	200.0	3.96	174.0	72100	-0.046	82.7	1.15	46

In [92]:
```
labeled_data[labeled_data['class'] == 0].sort_values(by = ['gdpp','income','
```

Out[92]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
26	Burundi	93.6	8.92	11.60	39.2	764	12.30	57.7	6.26	231
88	Liberia	89.3	19.10	11.80	92.6	700	5.47	60.8	5.02	327
37	Congo, Dem. Rep.	116.0	41.10	7.91	49.6	609	20.80	57.5	6.54	334
112	Niger	123.0	22.20	5.16	49.1	814	2.55	58.8	7.49	348
132	Sierra Leone	160.0	16.80	13.10	34.5	1220	17.20	55.0	5.20	399

In [ ]:
```

```