PCA and Clustering Assignment

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Procedure

1. Data Understanding.
    a. Hint: Don't forget to read the data description properly.
2. Perform PCA.
    a. Data Standardization
    b. Perform PCA and choose the PCs that defines more than 85% variance.
    c. Run the PCA with the chosen number.
3. Perform Clustering.
    a. Data preparation for clustering.
        i. Outlier treatment
        ii. Hopkins check
    b. Clustering
        i. K-MEANS
            1. Run K-Means and choose K using both Elbow and Silhouette score
            2. Run K-Means with the chosen K
            3. Visualize the clusters
            4. Clustering profiling.

Data Understanding

- The data for this assignment was based on a comparison between countries on various parameters like child mortality rate, export, import, income, gdpp, health, inflation and life expectancy.
- Structure of dataframe after importing this csv was as follows:

country 167 non-null object ,child_mort 167 non-null float64

exports 167 non-null float64 ,health 167 non-null float64

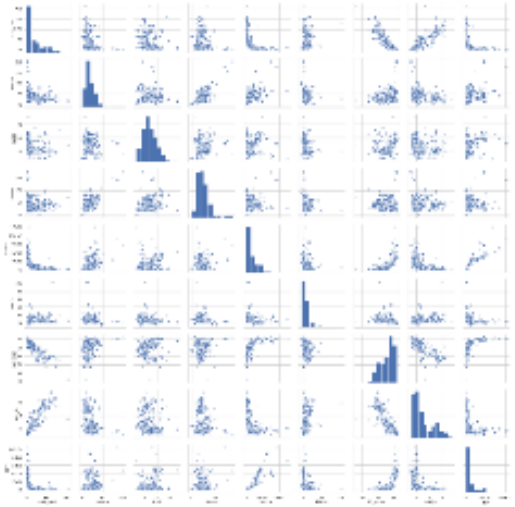
imports 167 non-null float64 ,income 167 non-null int64

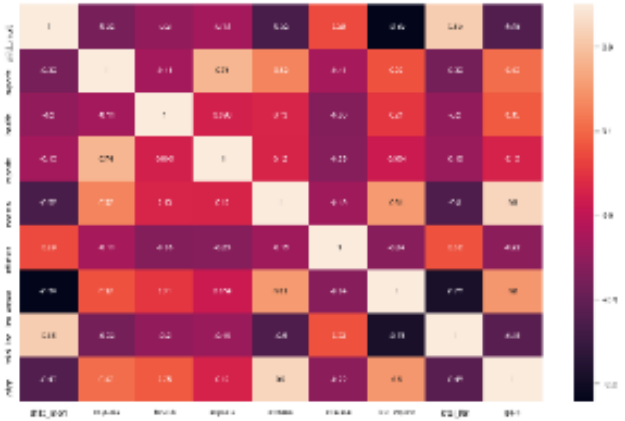
inflation 167 non-null float64 ,life_expec 167 non-null float64

total_fer 167 non-null float64 ,gdpp 167 non-null int64

Data Understanding

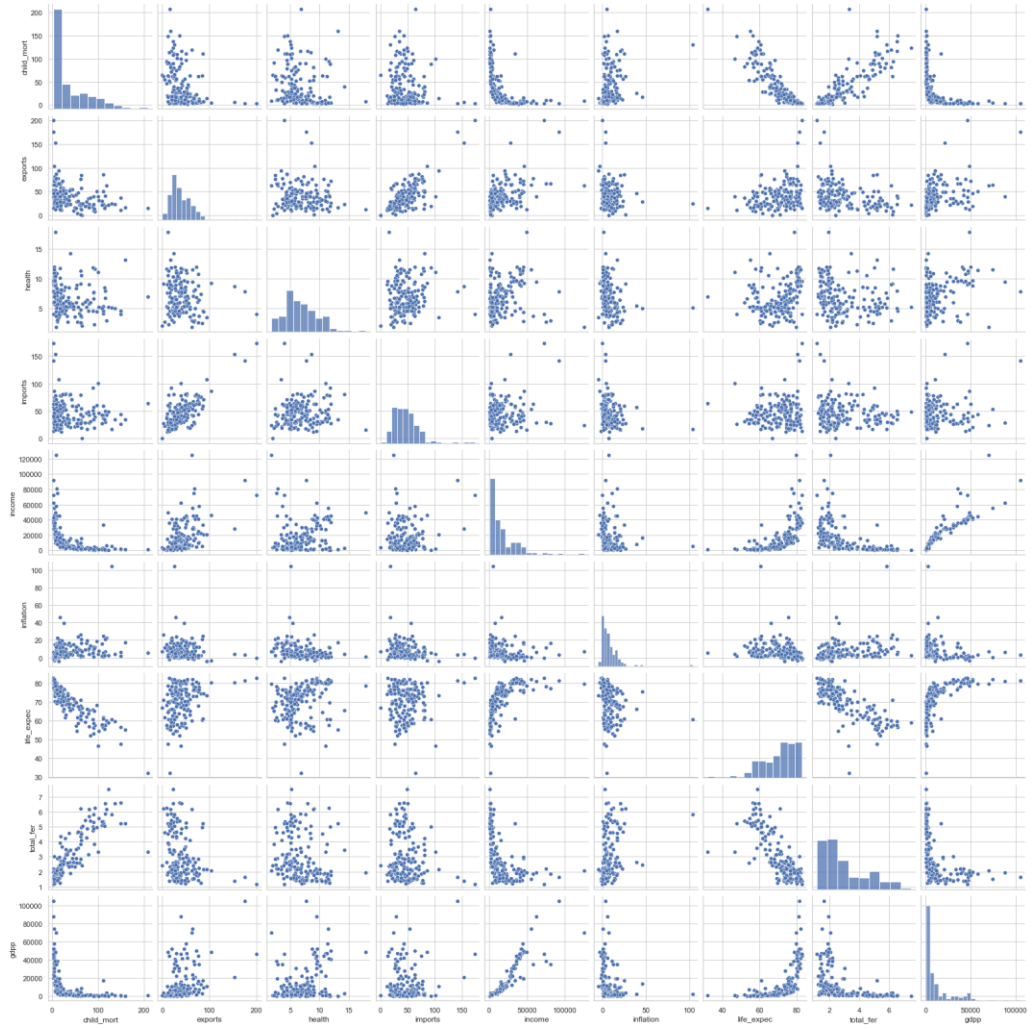
- Null value check
- Set ‘country’ as index.
- Percentile check
- Multiple Bivariate analysis using pairplot.
- Correlation heatmap
- Check for Outliers.



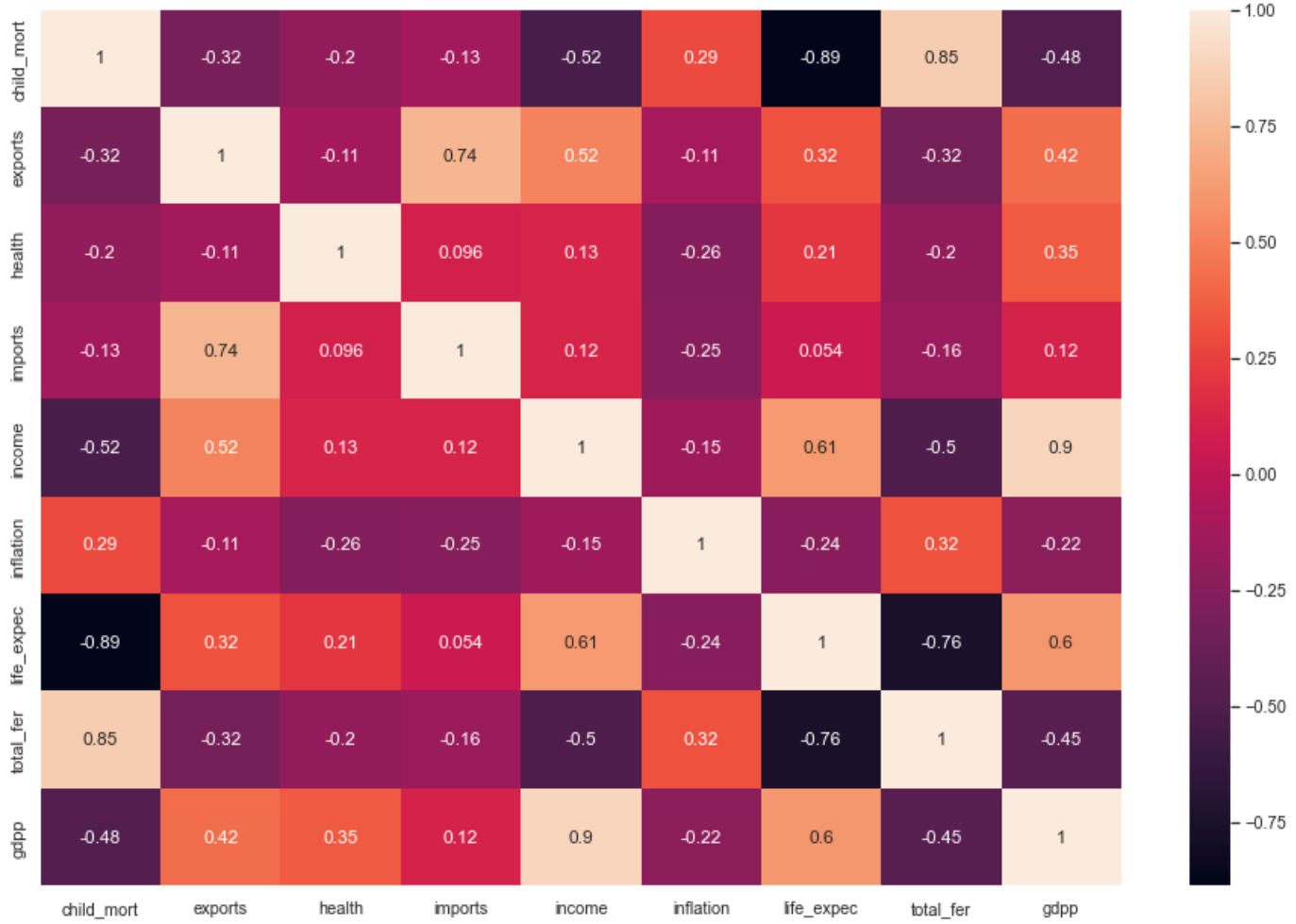


Data Understanding

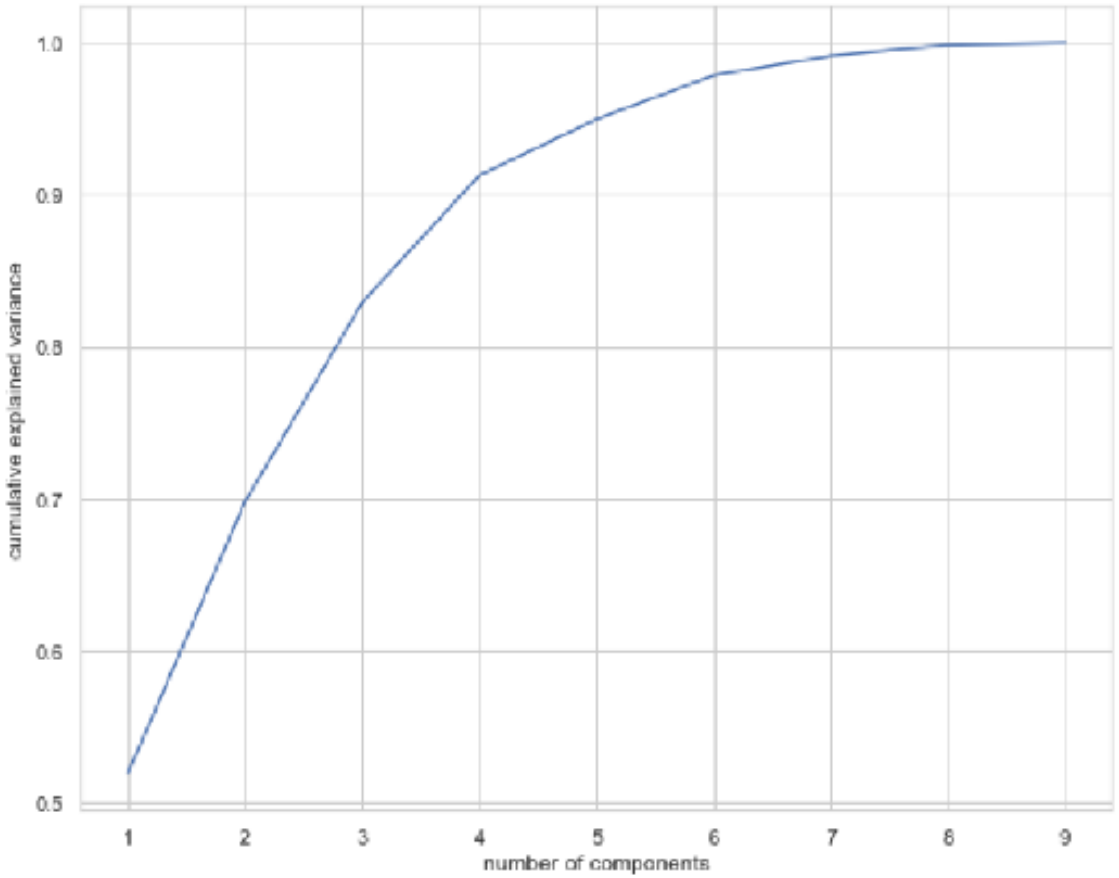
Pairplot



Correlation Heatmap



Principal Clustering Analysis – Dimensionality Reduction



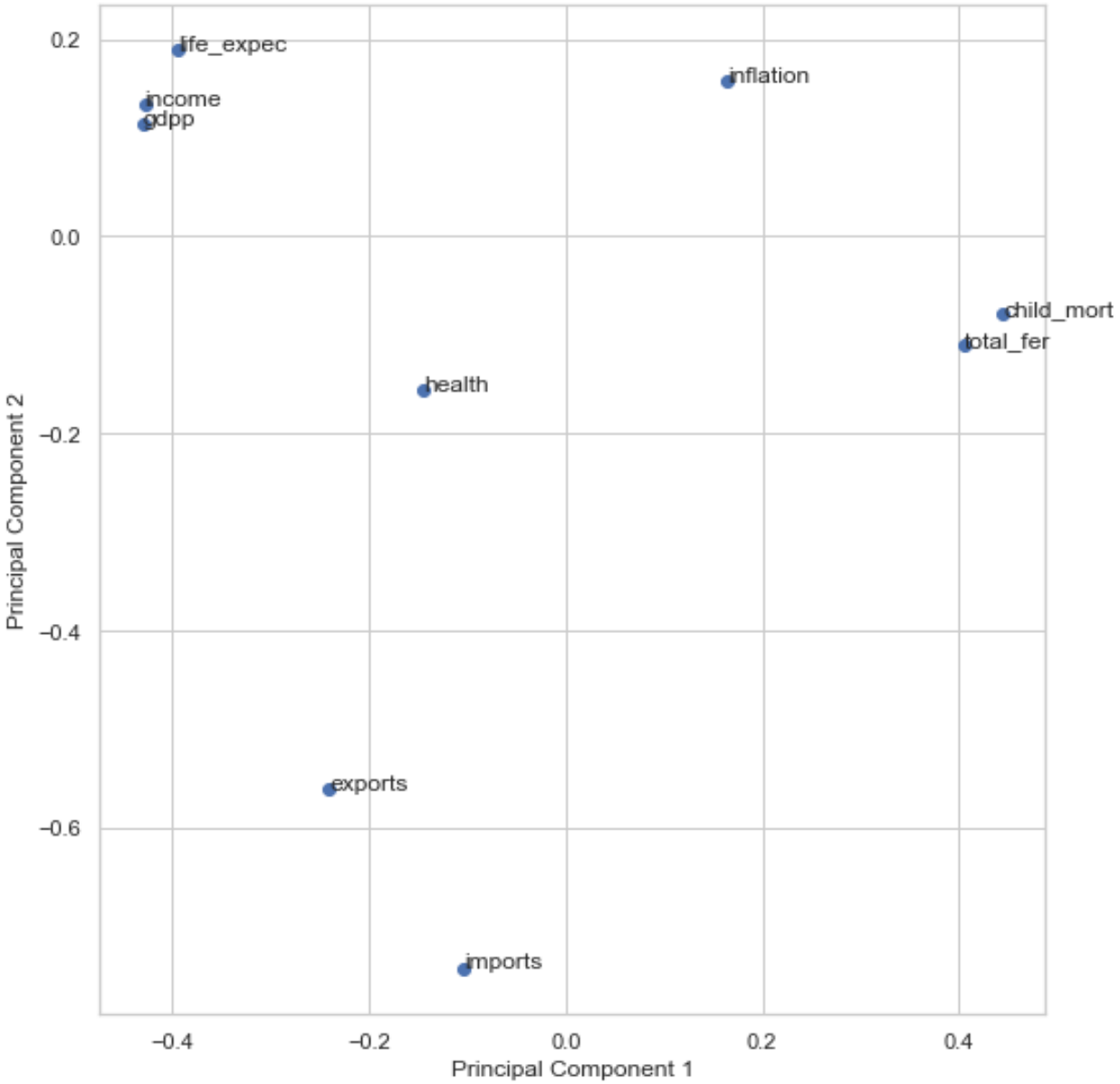
We take 5 cluster at pca(0.94), there is no point of taking 6 clusters at pca(0.96).

And have named these clusters as :

- PC1, PC2, PC3, PC4 AND PC5.

We performed outlier analysis after performing pca and now have 164 countries out of 166(initially).

Principal Clustering Analysis – Dimensionality Reduction



Visualizing the principal components

Check Hopkins Statistics

- The Hopkins statistic, is a statistic which gives a value which indicates the cluster tendency, in other words: how well the data can be clustered.
- If the value is between {0.01, ...,0.3}, the data is regularly spaced.
- If the value is around 0.5, it is random.
- If the value is between {0.7, ..., 0.99}, it has a high tendency to cluster.

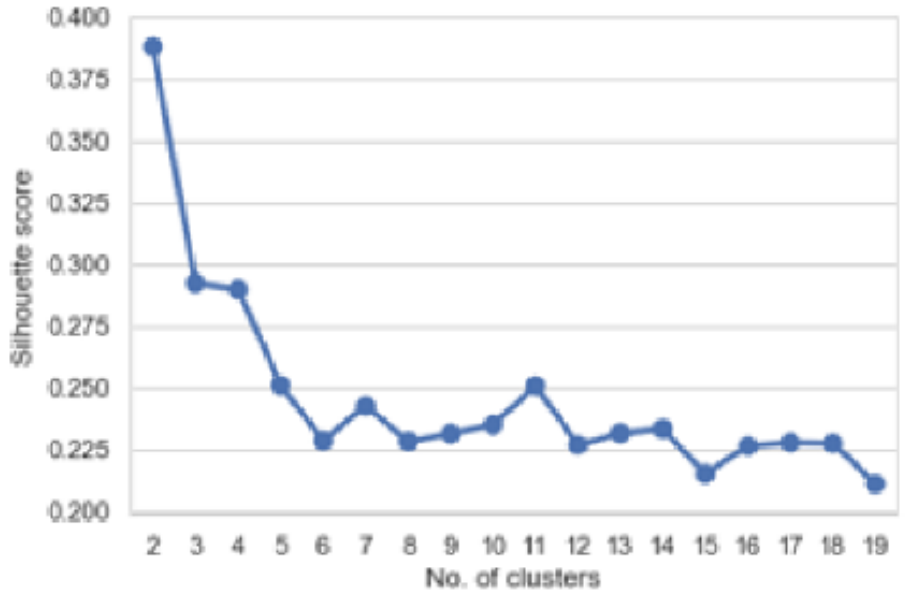
- Print("DF_PCA: ", hopkins(df_pca))
- Print("DF_scaled: ", hopkins(df_scaled))

```
DF_PCA:  0.6841846826361749
DF_scaled:  0.8013886832588535
```

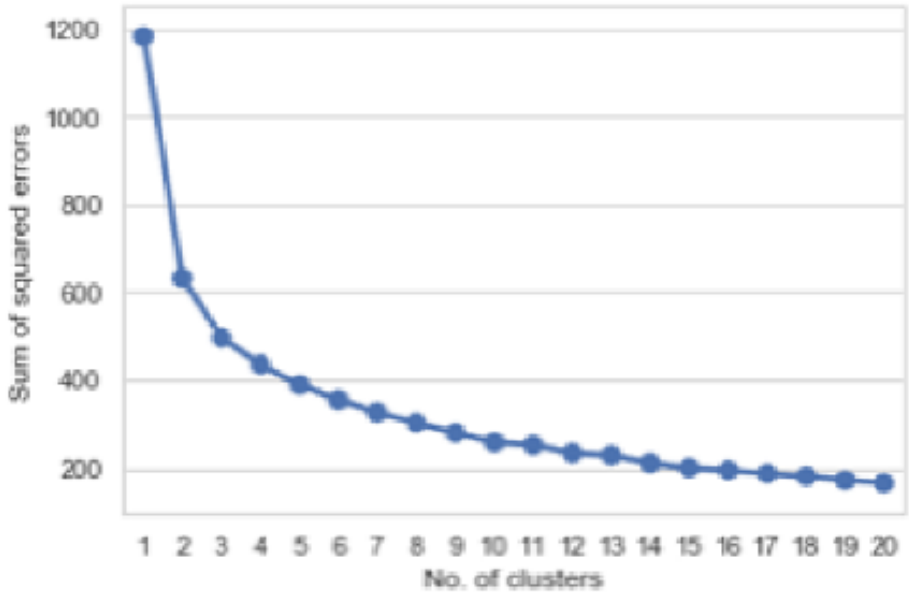
Clustering

- **Select optimum number of clusters using silhouette score, no of squared errors.**

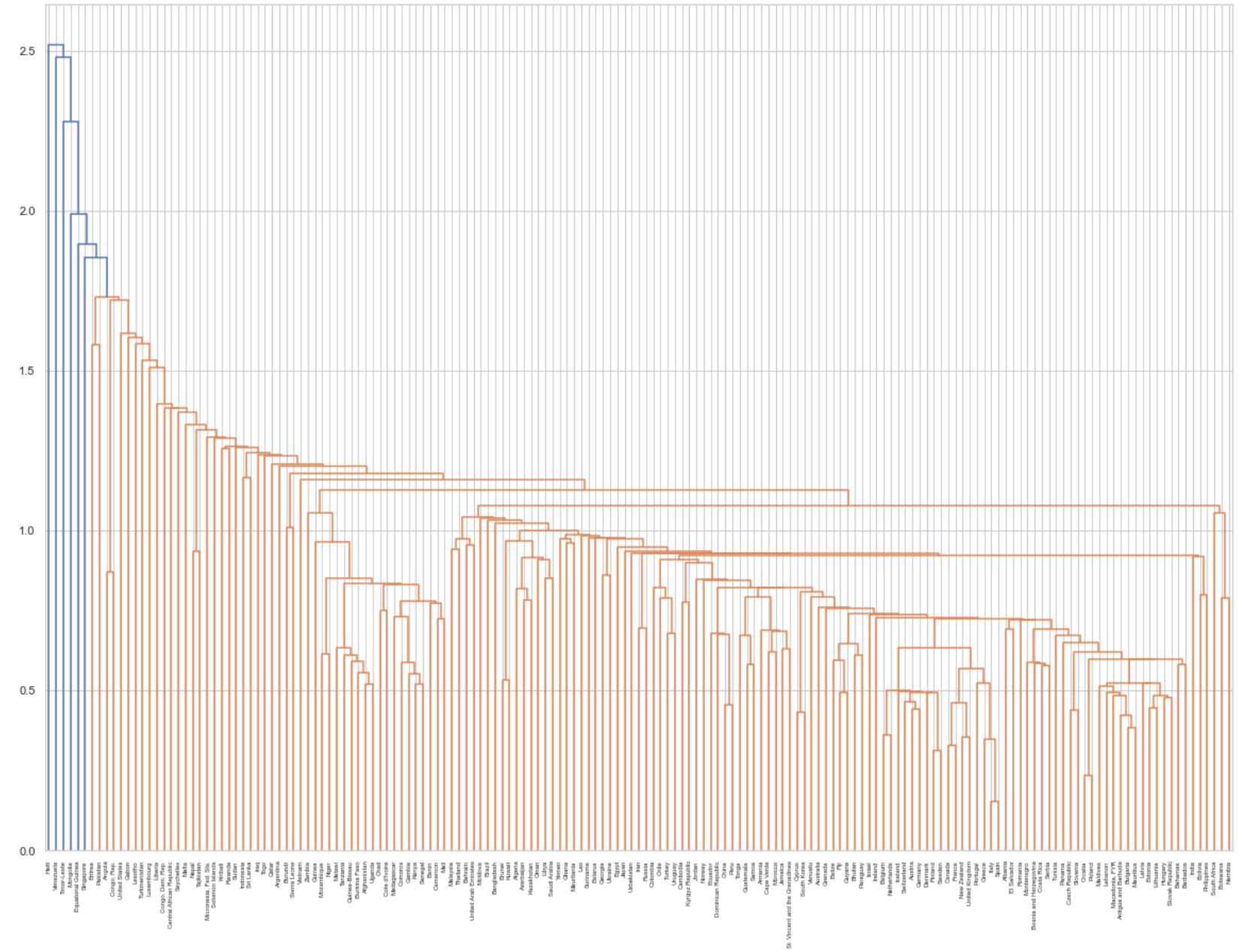
```
Text(0, 0.5, 'Silhouette score')
```




```
Text(0, 0.5, 'Sum of squared errors')
```



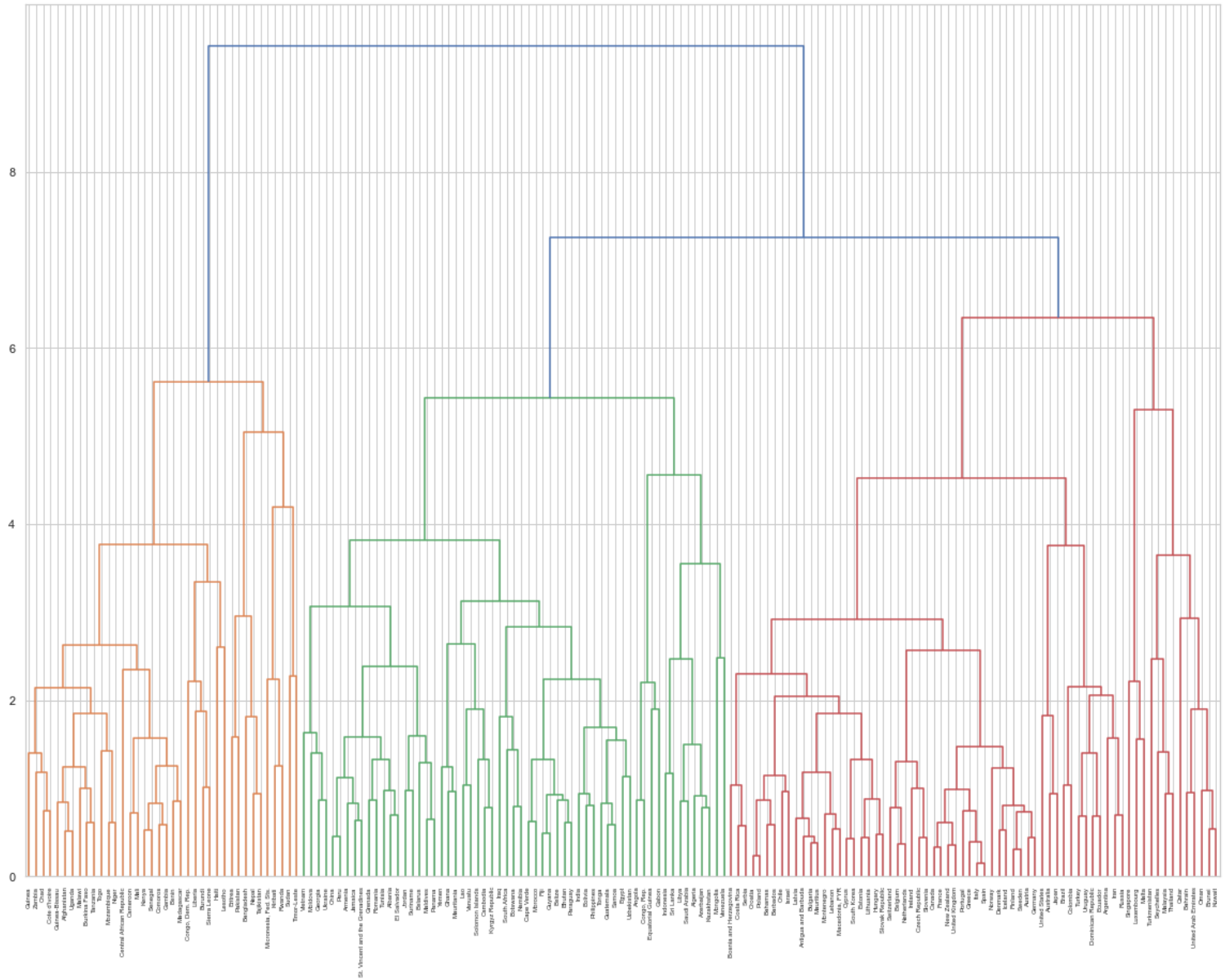
Optimum number of clusters through hierarchical clustering




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

plt.figure(figsize=(20,15))
mergings_s = linkage(df_pca, method = "single",
metric='euclidean')
dendrogram(mergings_s, labels=df_pca.index,
leaf_rotation=90, leaf_font_size=6)
plt.show()
```

Optimum number of clusters through hierarchical clustering




```
plt.figure(figsize=(20,15))
mergings_c = linkage(df_pca, method = "complete",
metric='euclidean')
dendrogram(mergings_c, labels=df_pca.index,
leaf_rotation=90, leaf_font_size=6)
plt.show()
```

We can take the number of clusters o be either 3 or 4

K-Means

```
# Kmeans with K=4
K_means_4 = KMeans(n_clusters = 4, max_iter=50)
K_means_4.fit(df_pca)
```

```
KMeans(max_iter=50, n_clusters=4)
```

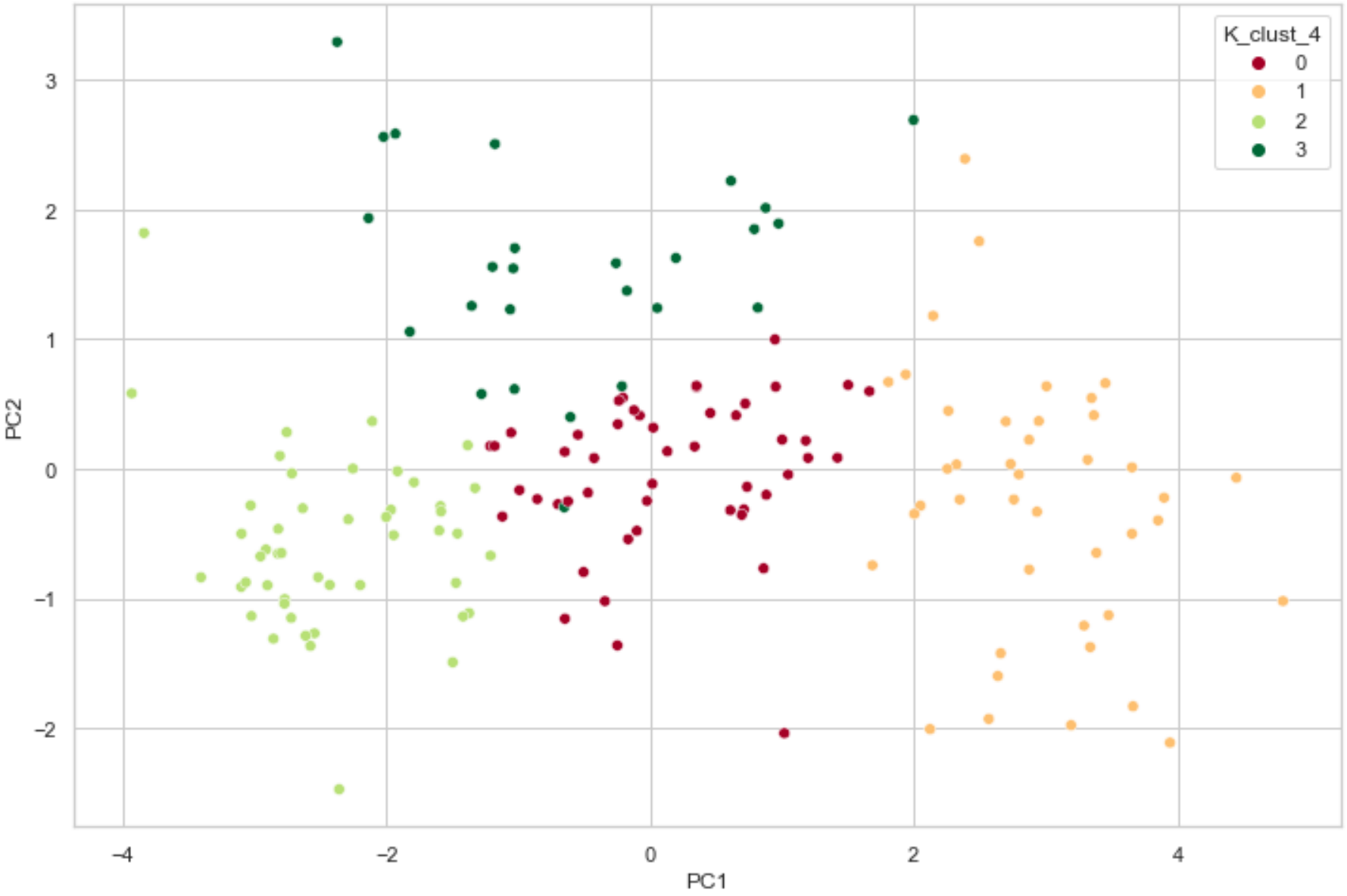
Combining original data, principal components, K-means cluster IDs & Hierarchical clustering cluster IDs

K_clust_4	0	1	2	3
H_clust_4				
0	2	36	0	0
1	40	6	0	13
2	7	0	45	3
3	0	0	3	10

Effectively, K-means clustering has broken down the cluster '1' of Hierarchical clustering - into 2 sub-clusters

We will use the clusters formed by K-means for further analysis

Analysis of cluster data



Scatter Plot of 4 clusters,

We can clearly see that all 4 clusters a distinctly scattered across the space.

Line Plot analysis

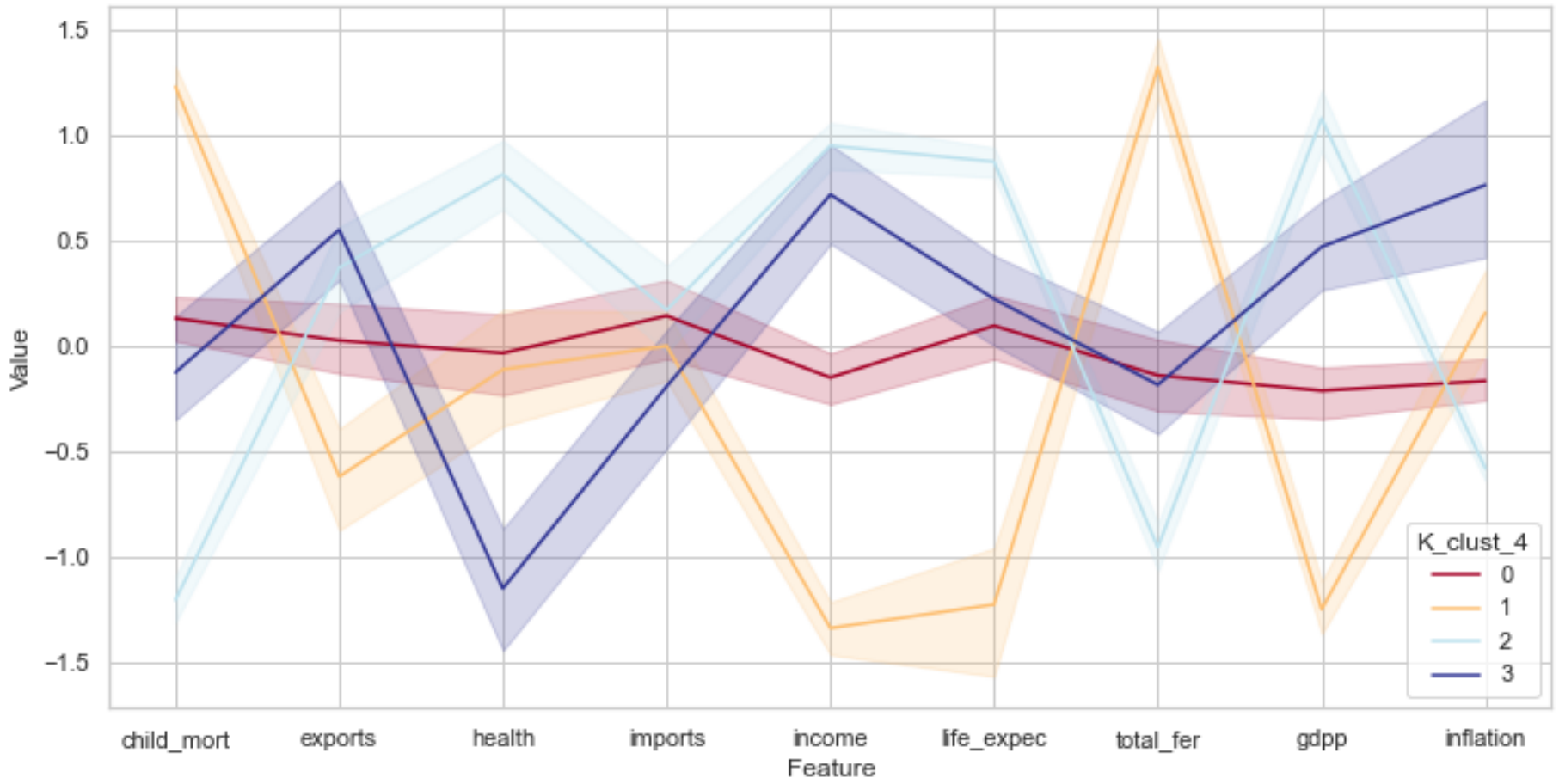
country	child_mort	exports	health	imports	income	life_expec	total_fer	gdpp	inflation	K_clust_4
Afghanistan	1.257285	-1.566676	0.450917	0.146381	-1.413059	-1.580003	1.667924	-1.460560	0.157336	1
Albania	-0.206196	-0.224045	0.105222	0.262136	0.071749	0.630275	-0.962078	-0.122592	-0.312347	0
Algeria	0.223939	0.187829	-0.963592	-0.376408	0.285304	0.649198	0.207329	-0.064683	0.789274	3
Angola	1.496866	0.818843	-1.864462	0.079772	-0.353135	-1.094994	1.786385	-0.221051	1.387054	1
Antigua and Barbuda	-0.618844	0.409060	-0.090571	0.543123	0.605603	0.677491	-0.429314	0.608191	-0.601749	2

Result we get after clustering

	country	K_clust_4	Feature	Value
0	Afghanistan	1	child_mort	1.257285
1	Albania	0	child_mort	-0.206196
2	Algeria	3	child_mort	0.223939
3	Angola	1	child_mort	1.496866
4	Antigua and Barbuda	2	child_mort	-0.618844

We have taken a smaller dataframe with K_clust_4 and Feature with the value

Line Plot analysis



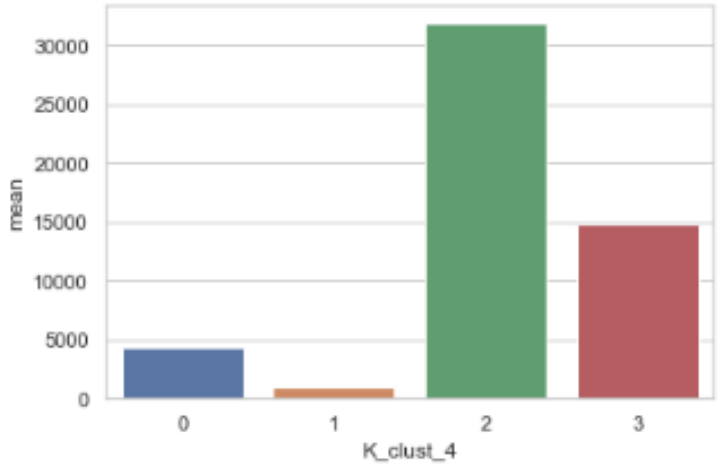
Observation: Cluster #1 contains countries that are in direct need of financial aid, since:

- It has disproportionately high child mortality rate, total_fer & inflation.
- It has lowest gdpp, income & life_expectancy.

Barplots for features Vs Clusters

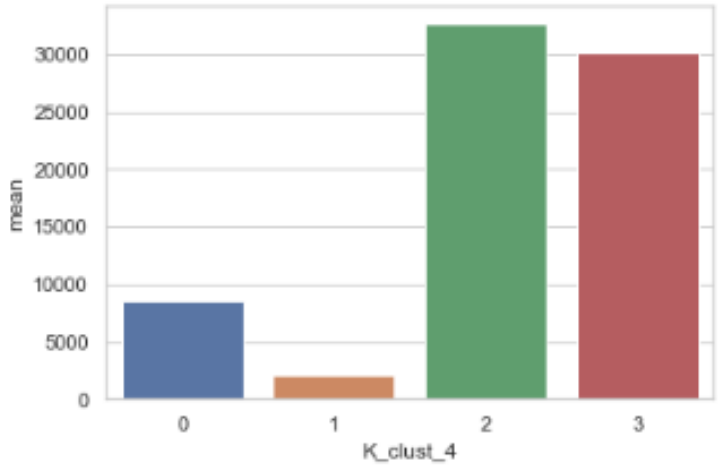
```
sns.barplot(x = cluster_summary.reset_index().K_clust_4, y = cluster_summary['gdpp']['mean'])
```

```
<AxesSubplot:xlabel='K_clust_4', ylabel='mean'>
```




```
sns.barplot(x = cluster_summary.reset_index().K_clust_4, y = cluster_summary['income']['mean'])
```

```
<AxesSubplot:xlabel='K_clust_4', ylabel='mean'>
```

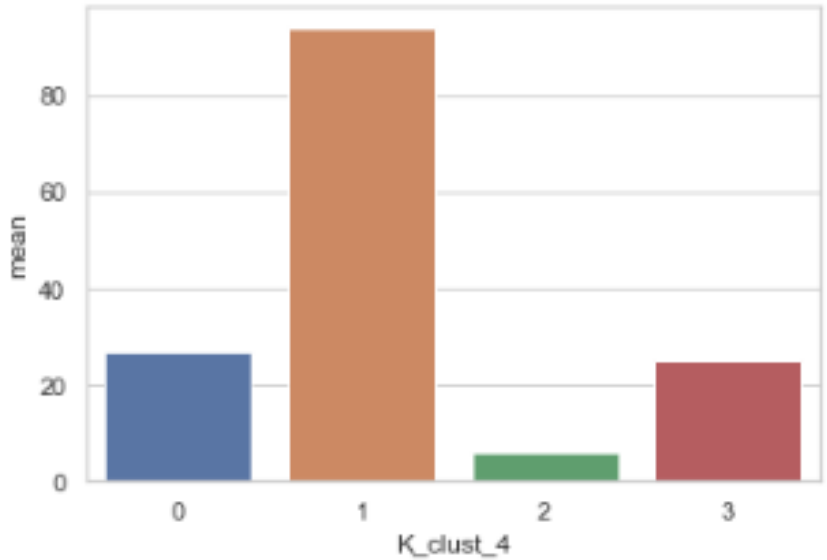


We can infer from barplots that cluster 1 is really suffering

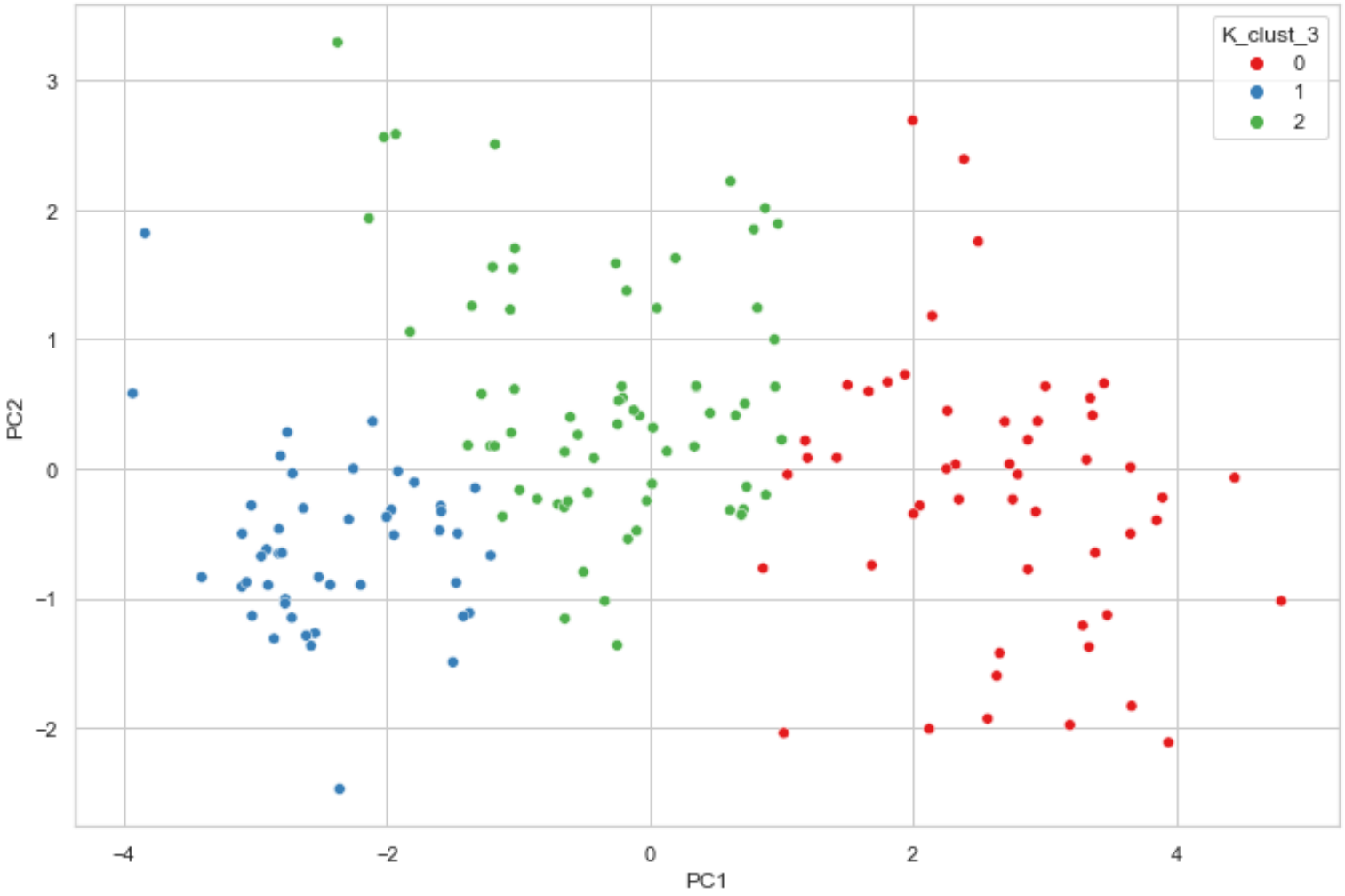
Barplots for features Vs Clusters

```
sns.barplot(x = cluster_summary.reset_index().K_clust_4, y = cluster_summary['child_mort']['mean'])
```

```
<AxesSubplot:xlabel='K_clust_4', ylabel='mean'>
```



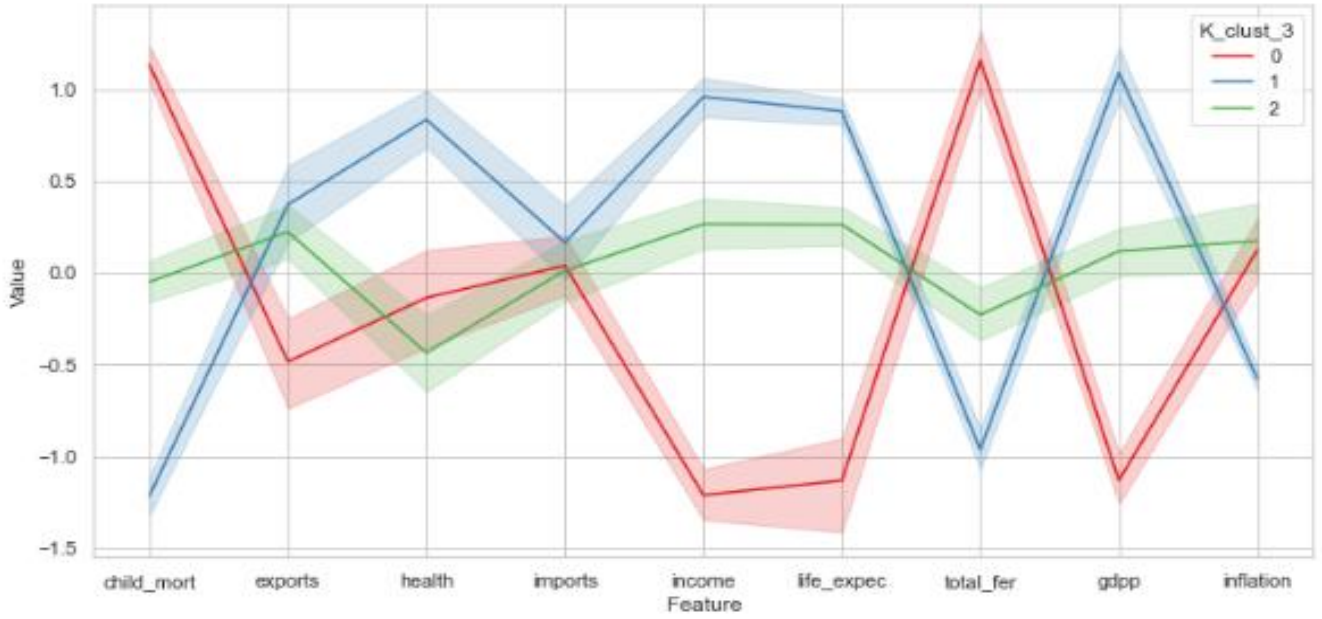
Cluster analysis for # of clusters = 3

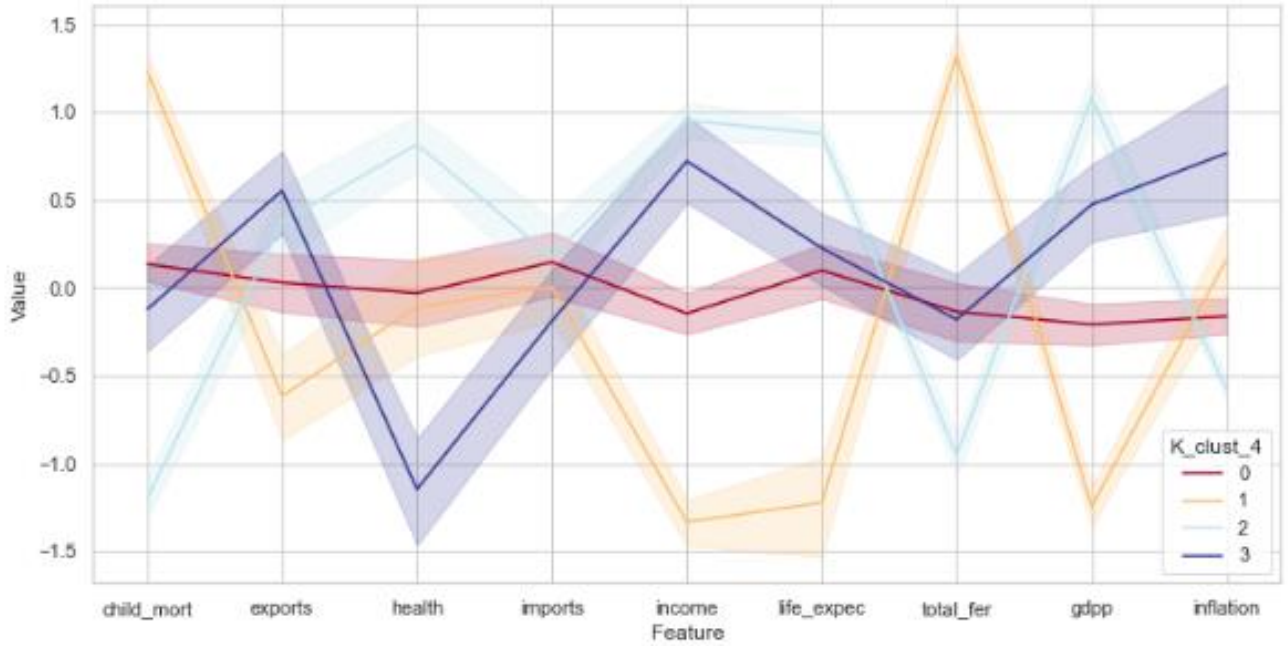


All 3 clusters are scattered distinctly in their own territory

Observation: Cluster #1 of 4-cluster K-means is the same as cluster #1 for 3-cluster K-means; This is the cluster with countries in dire need of financial aid.

Cluster analysis for # of clusters = 3





All 3 clusters are scattered distinctly in their own territory

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Conclusion

Child Mortality

	country	K_clust_4	Feature	Value
66	Haiti	1	child_mort	1.979683
130	Sierra Leone	1	child_mort	1.752837
32	Chad	1	child_mort	1.697036
31	Central African Republic	1	child_mort	1.691253
97	Mali	1	child_mort	1.618654
111	Niger	1	child_mort	1.525451
3	Angola	1	child_mort	1.496866
25	Burkina Faso	1	child_mort	1.474789
37	Congo, Dem. Rep.	1	child_mort	1.474789
64	Guinea-Bissau	1	child_mort	1.459752
17	Benin	1	child_mort	1.436694
40	Cote d'Ivoire	1	child_mort	1.436694
63	Guinea	1	child_mort	1.420973
28	Cameroon	1	child_mort	1.413004
106	Mozambique	1	child_mort	1.355066

Income

	country	K_clust_4	Feature	Value
697	Congo, Dem. Rep.	1	income	-2.206478
748	Liberia	1	income	-2.092822
686	Burundi	1	income	-2.021421
771	Niger	1	income	-1.969684
691	Central African Republic	1	income	-1.898672
766	Mozambique	1	income	-1.871555
754	Malawi	1	income	-1.777605
723	Guinea	1	income	-1.659760
808	Togo	1	income	-1.646157
790	Sierra Leone	1	income	-1.639440
784	Rwanda	1	income	-1.556804
724	Guinea-Bissau	1	income	-1.532974
753	Madagascar	1	income	-1.532974
696	Comoros	1	income	-1.521314
710	Eritrea	1	income	-1.515547

Conclusion

Gdpp

	country	K_clust_4	Feature	Value
1181	Burundi	1	gdpp	-2.044268
1243	Liberia	1	gdpp	-1.811877
1192	Congo, Dem. Rep.	1	gdpp	-1.797714
1266	Niger	1	gdpp	-1.770258
1285	Sierra Leone	1	gdpp	-1.678811
1248	Madagascar	1	gdpp	-1.655752
1261	Mozambique	1	gdpp	-1.646107
1186	Central African Republic	1	gdpp	-1.604350
1249	Malawi	1	gdpp	-1.585138
1205	Eritrea	1	gdpp	-1.552444
1303	Togo	1	gdpp	-1.544172
1219	Guinea-Bissau	1	gdpp	-1.467855
1155	Afghanistan	1	gdpp	-1.460560
1211	Gambia	1	gdpp	-1.449765
1279	Rwanda	1	gdpp	-1.448576

We can clearly see that countries are common in each of these dataframe with respect to (child_mort, income and gdpp).

Some of those countries are:
1. Congo, Dem. Rep.
2. Sierra Leone
3. Niger
4. Mozambique
5. Guinea-Bissau
6. Central African Republic
7. Liberia

- Congo, Dem. Rep., Sierra Leone, Niger, Mozambique, Guinea-Bissau, Central African Republic and Liberia are the countries in dire need of financial aid as these countries are common among all three features.

Thank You