# **ASSIGNMENT :** HELP International using K-mean clustering

SUBMITTED BY : Nidhi Sharma

# Overview

- HELP International is an international humanitarian NGO that is committed to fighting poverty and providing the people of backward countries with basic amenities and relief during the time of disasters and natural calamities.After the recent funding programmes, they have been able to raise around $ 10 million. Now the CEO of the NGO needs to decide how to use this money strategically and effectively. The significant issues that come while making this decision are mostly related to choosing the countries that are in the direst need of aid.

- My job is:-

  - To categorise the countries using some socio-economic and health factors that determine the overall development of the country.
  - We need to suggest the countries which the CEO needs to focus on the most.

**AIM/TASK:** Identify top 10 countries that are direst need of aid.

**Job** : Categorise the countries using some socio-economic and health factors that determine the overall development of the country.

Suggestions : atleast 5 countries which the CEO needs to focus on the most.

# Steps followed are:-

- 1. Read and understand the data
- 2. Clean the data
- 3. Visualization of data
- 3. Prepare the data for modelling
- 4. Hopkins Statistics Test
- 5. Modelling
- 6. Final analysis

# 1. Read,Data understanding and representation

Exports : Exports of goods and services per capita. Given as %age of the GDP per capita

Health: Total health spending per capita. Given as %age of GDP per capita

Imports: Imports of goods and services per capita. Given as %age of the GDP per capita

hild_mort: Death of children under 5 years of age per 1000 live births

Income: Net income per person

Inflation:The measurement of the annual growth rate of the Total GDP

life_expec :The average number of years a new born child would live if the current mortality patterns are to remain the same

total_fer:The number of children that would be born to each woman if the current age-fertility rates remain the same.

gdpp :The GDP per capita. Calculated as the Total GDP divided by the total population.

This fig shows the data has 10 columns and 167 rows

| | 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 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 162 | Vanuatu | 29.2 | 46.6 | 5.25 | 52.7 | 2950 | 2.62 | 63.0 | 3.50 | 2970 |
| 163 | Venezuela | 17.1 | 28.5 | 4.91 | 17.6 | 16500 | 45.90 | 75.4 | 2.47 | 13500 |
| 164 | Vietnam | 23.3 | 72.0 | 6.84 | 80.2 | 4490 | 12.10 | 73.1 | 1.95 | 1310 |
| 165 | Yemen | 56.3 | 30.0 | 5.18 | 34.4 | 4480 | 23.60 | 67.5 | 4.67 | 1310 |
| 166 | Zambia | 83.1 | 37.0 | 5.89 | 30.9 | 3280 | 14.00 | 52.0 | 5.40 | 1460 |

167 rows × 10 columns

# Converting the exports, imports and health variables to actual values:-

**Converting imports,exports and health spending from percentage values to actual values of their GDP per capita. Because the percentage values don't give a clear picture of that country. For example Austria and Belarus have almost same exports % (Austria=51.3, Belarus= 51.4) but their gdpp has a huge gap (Austria=46900, Belarus= 6030) which doesn't give an accurate idea of which country is more developed than the other.**

```
# Converting exports,imports and health spending percentages to absolute values.
country['exports'] = country['exports'] * country['gdpp']/100
country['imports'] = country['imports'] * country['gdpp']/100
country['health'] = country['health'] * country['gdpp']/100
country
```

| | country | child_mort | exports | health | imports | income | inflation | life_expec | total_fer | gdpp |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Afghanistan | 90.2 | 55.30 | 41.9174 | 248.297 | 1610 | 9.44 | 56.2 | 5.82 | 553 |
| 1 | Albania | 16.6 | 1145.20 | 267.8950 | 1987.740 | 9930 | 4.49 | 76.3 | 1.65 | 4090 |
| 2 | Algeria | 27.3 | 1712.64 | 185.9820 | 1400.440 | 12900 | 16.10 | 76.5 | 2.89 | 4460 |
| 3 | Angola | 119.0 | 2199.19 | 100.6050 | 1514.370 | 5900 | 22.40 | 60.1 | 6.16 | 3530 |
| 4 | Antigua and Barbuda | 10.3 | 5551.00 | 735.6600 | 7185.800 | 19100 | 1.44 | 76.8 | 2.13 | 12200 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 162 | Vanuatu | 29.2 | 1384.02 | 155.9250 | 1565.190 | 2950 | 2.62 | 63.0 | 3.50 | 2970 |
| 163 | Venezuela | 17.1 | 3847.50 | 662.8500 | 2376.000 | 16500 | 45.90 | 75.4 | 2.47 | 13500 |
| 164 | Vietnam | 23.3 | 943.20 | 89.6040 | 1050.620 | 4490 | 12.10 | 73.1 | 1.95 | 1310 |
| 165 | Yemen | 56.3 | 393.00 | 67.8580 | 450.640 | 4480 | 23.60 | 67.5 | 4.67 | 1310 |
| 166 | Zambia | 83.1 | 540.20 | 85.9940 | 451.140 | 3280 | 14.00 | 52.0 | 5.40 | 1460 |

# EDA correlation (Visualization of the data)

Inference:

- imports and exports are highly correlated with correlation of 0.99

- health and gdpp are highly correlated with correlation of 0.92

- income and gdpp are highly correlated with correlation of 0.9

- child_mortality and life_expentency are highly correlated with correlation of -0.89

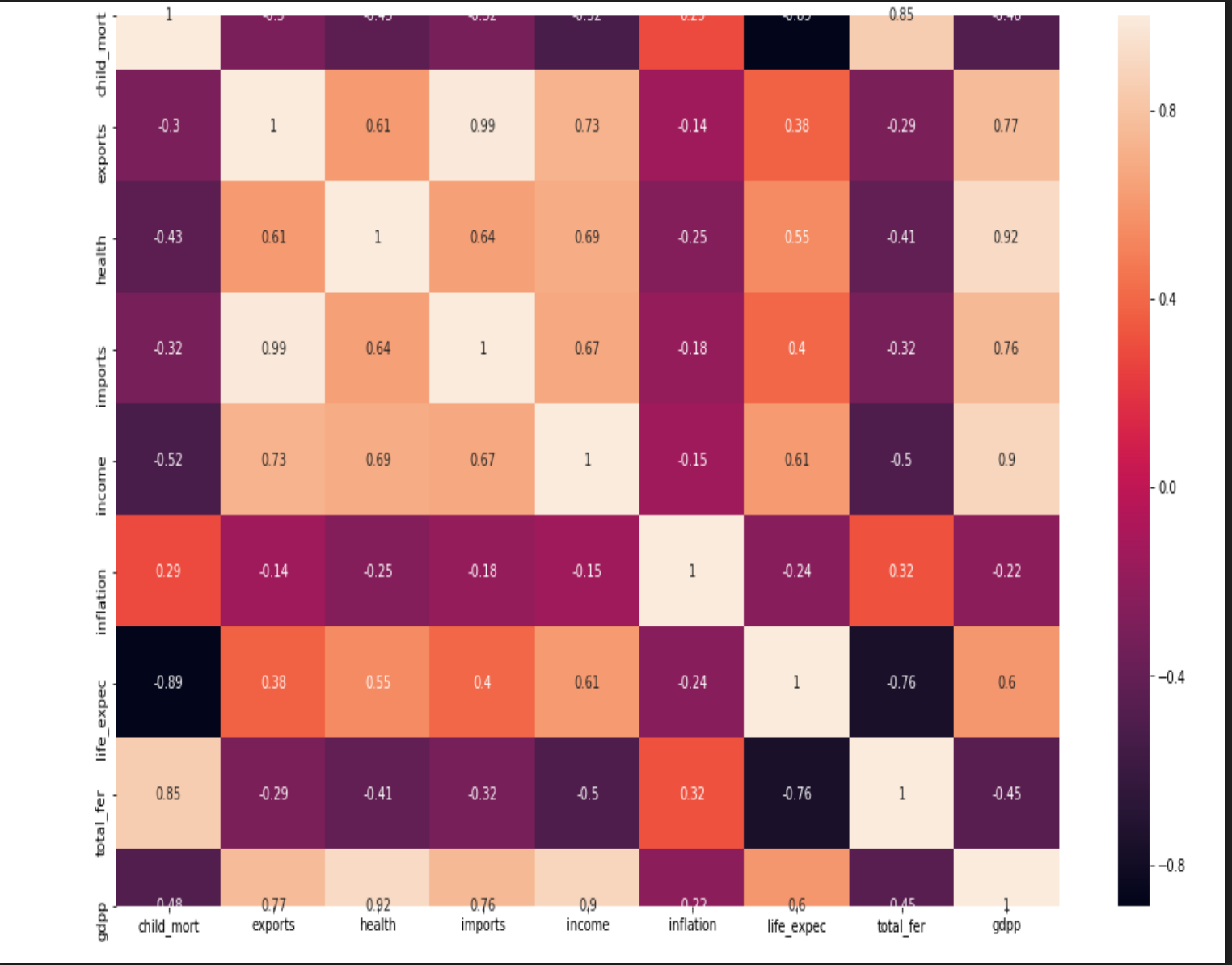
- child_mortality and total_fertility are highly correlated with correlation of 0.85

- gdpp and exports are highly correlated with correlation of 0.77

- gdpp and imports are highly correlated with correlation of 0.76

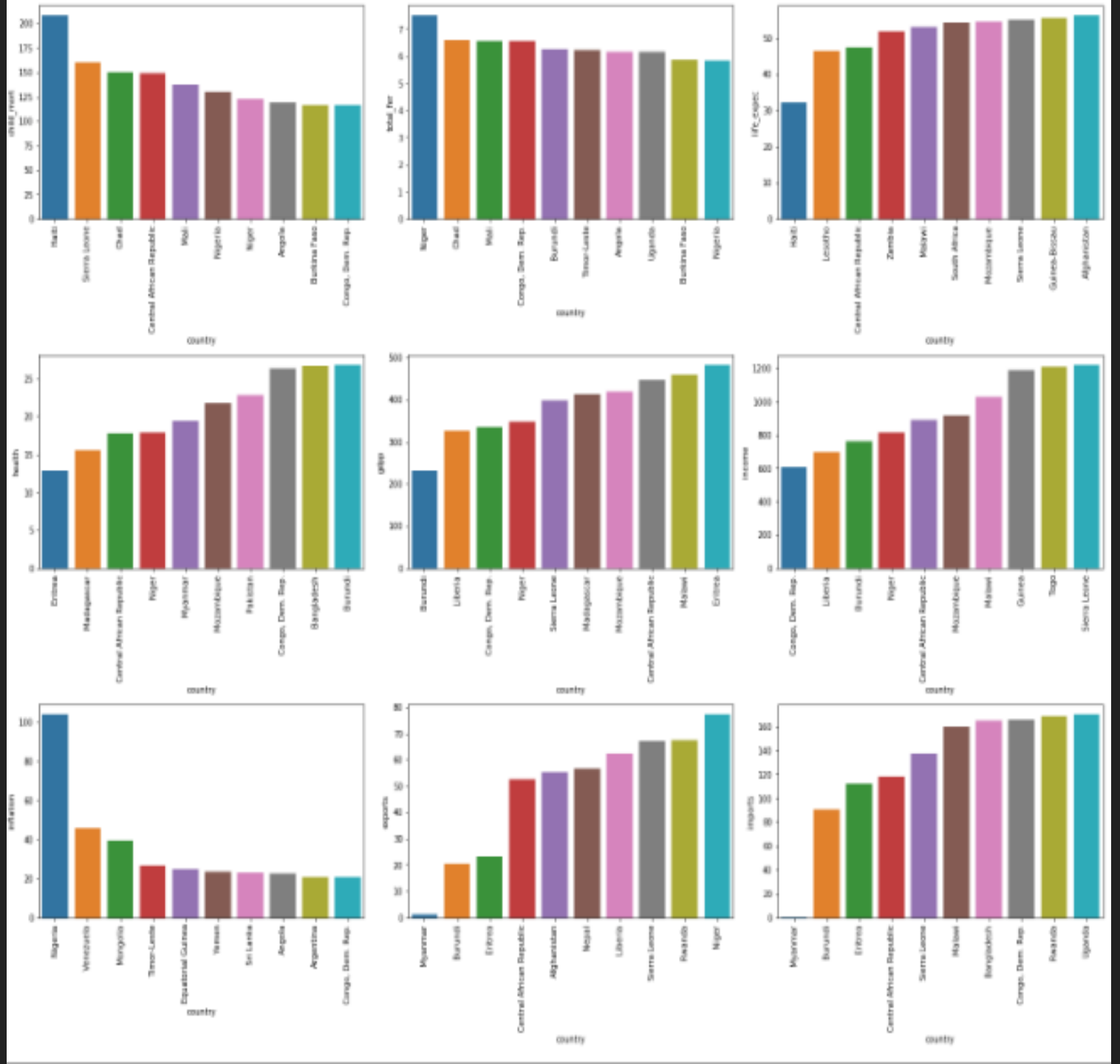
- life_expentency and total_fertility are highly correlated with correlation of -0.76

- income and exports are highly correlated with correlation of 0.73



# Univariate analysis of the data

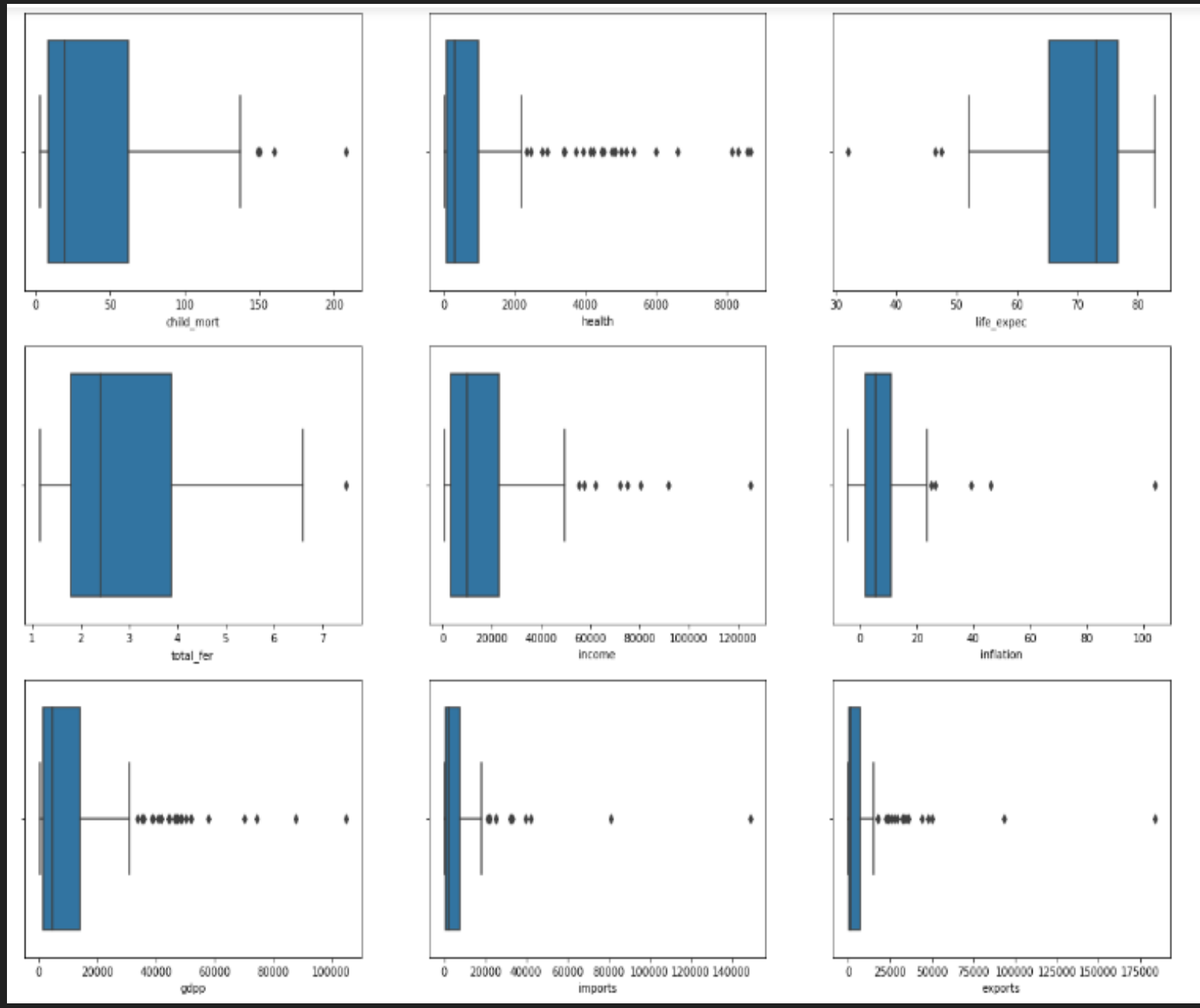
We need to choose the countries that are in the direct need of aid. Hence, we need to identify those countries with using some socio-economic and health factors that determine the overall development of the country. T**op 10 countries based on every column**



# Univariate analysis of the data

BOX PLOT

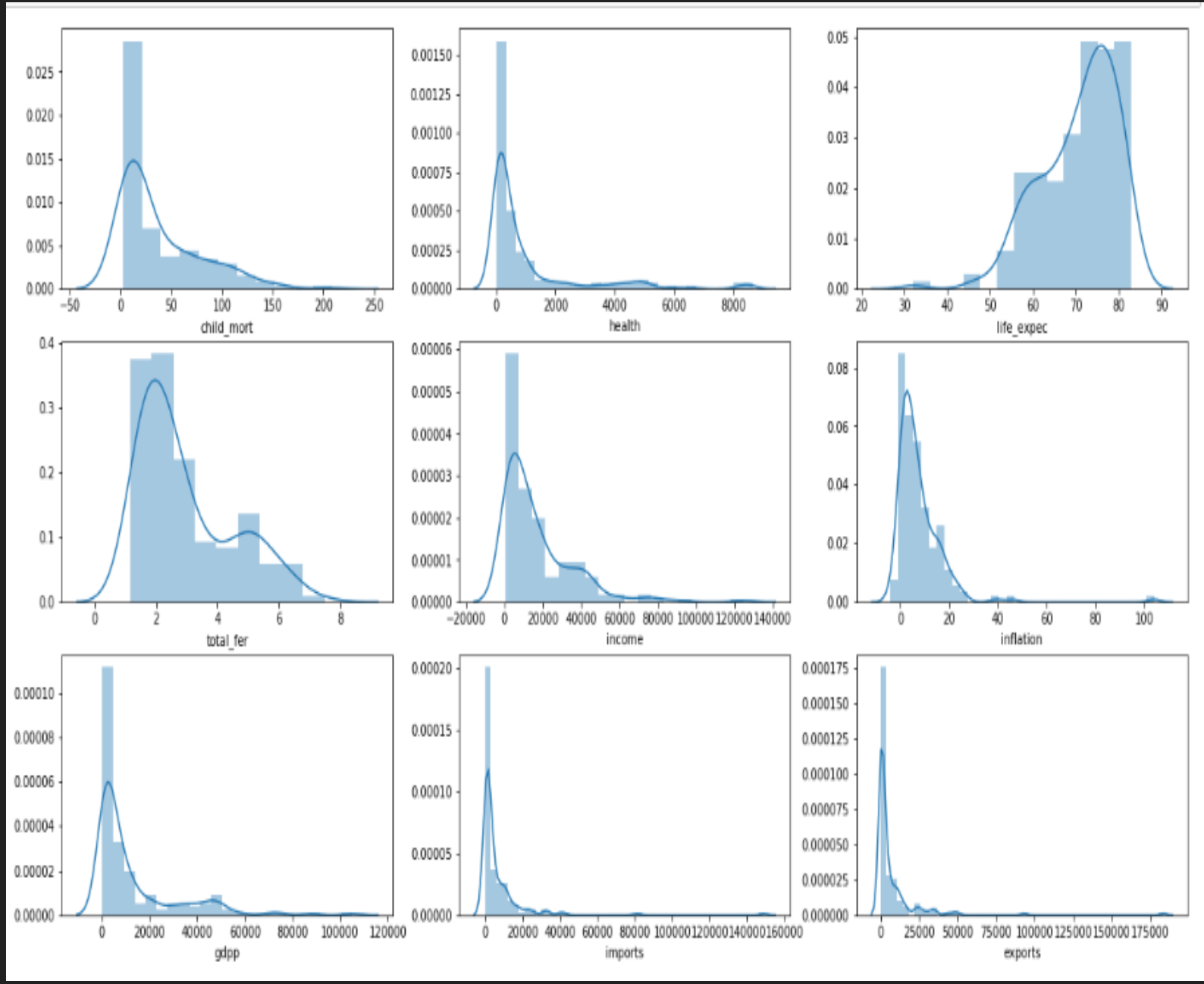
We can see outliers



# Univariate analysis of the data

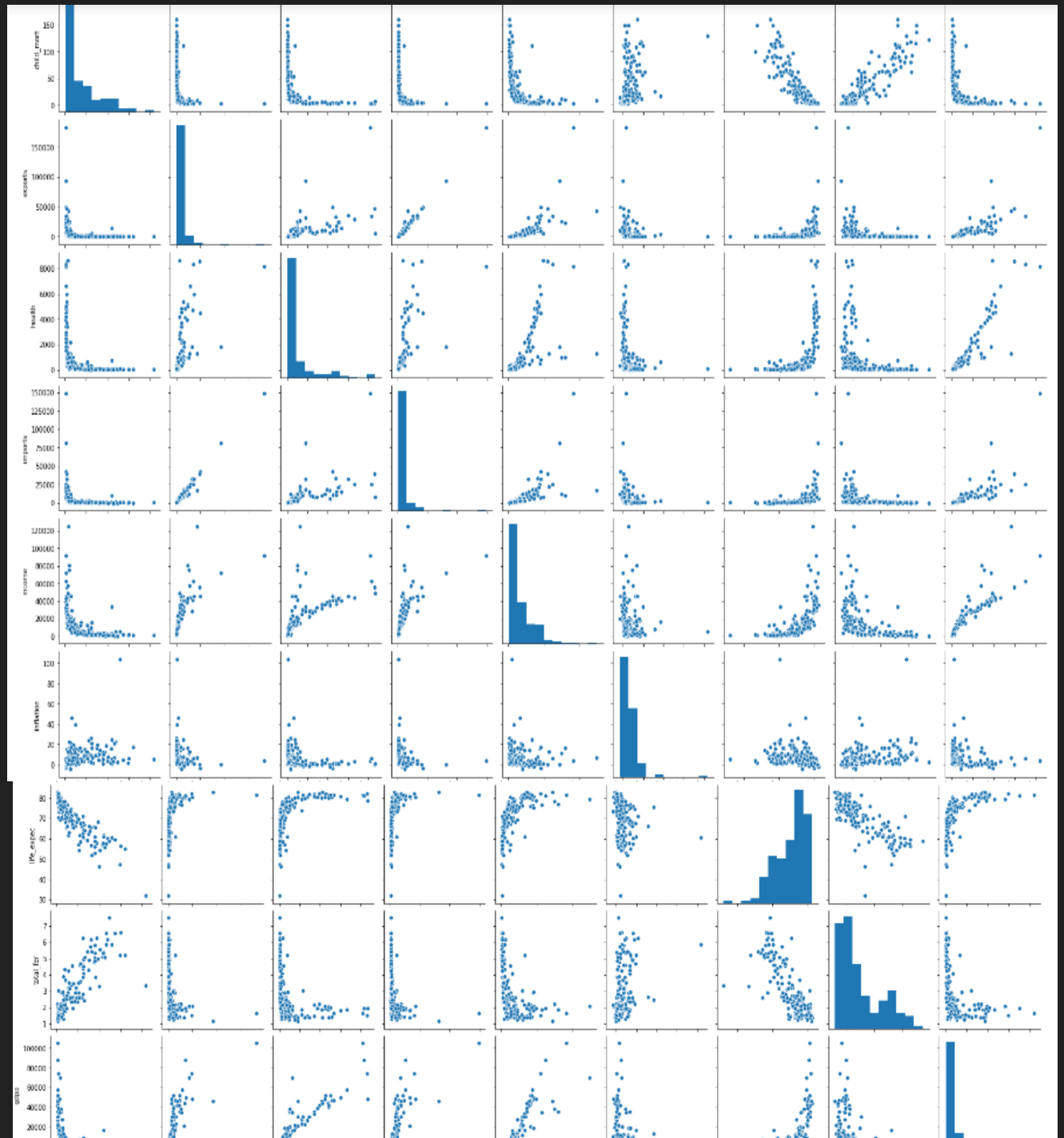
DIST PLOT

We can see distribution of data



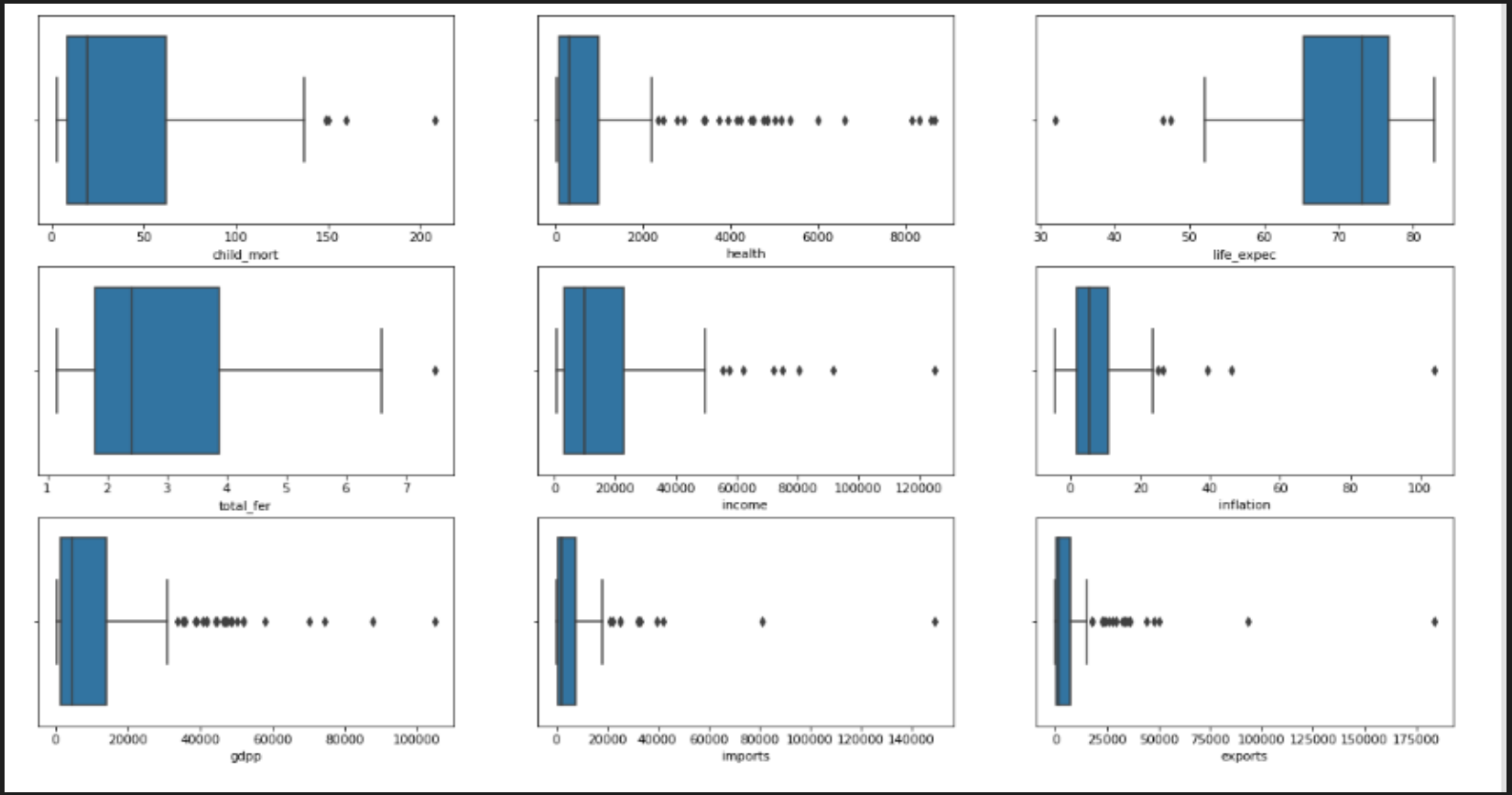
## Bivariate analysis of the data

PAIR PLOT



# Checking Outliers in the data

- Using capping technique

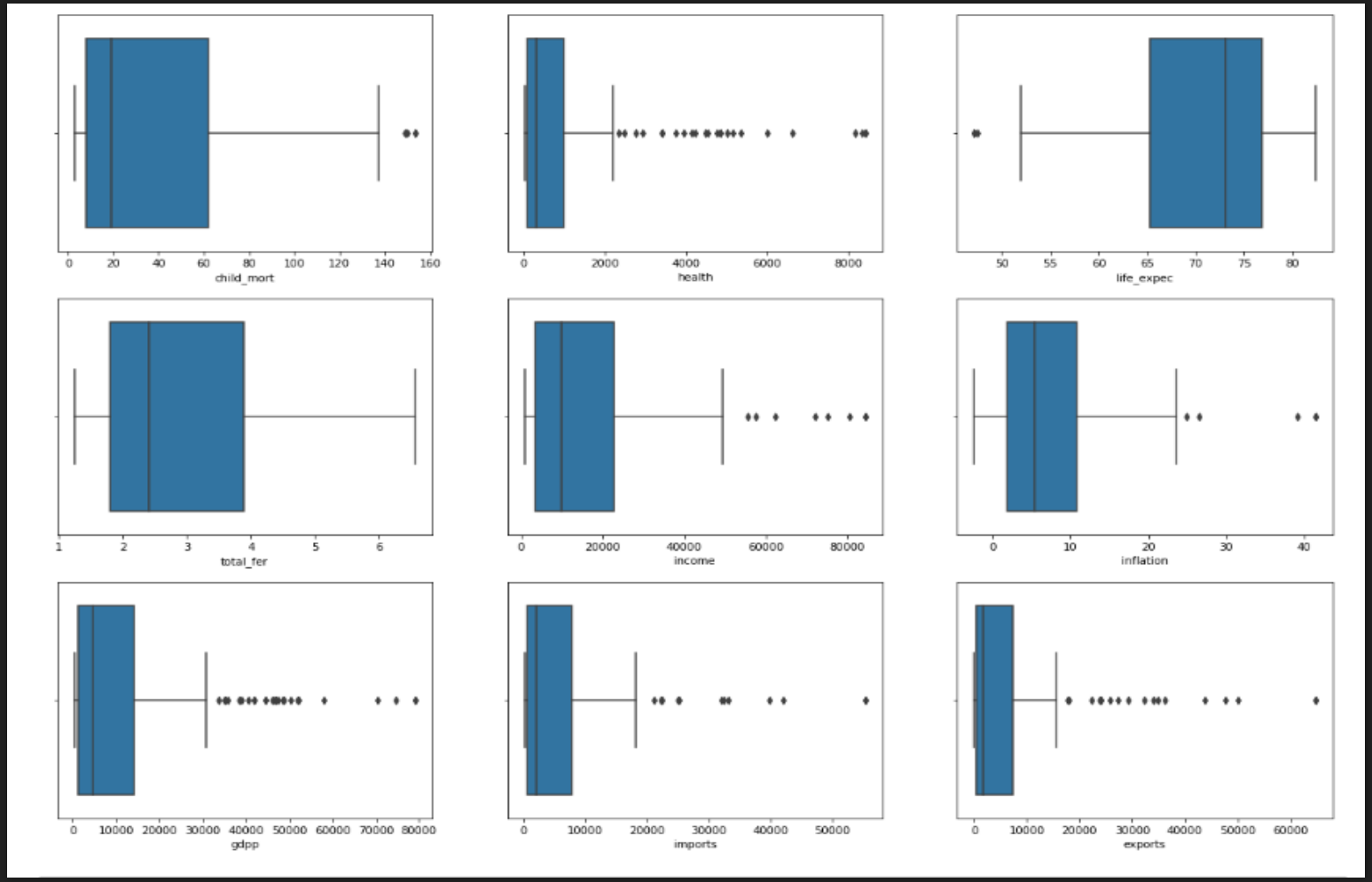


# Outlier Treatment

Keeping in mind we need to identify backward countries based on socio economic and health factors. We will cap the outliers to values accordingly for analysis.

**Choose capping technique over IQR technique**
**Assumption : below 1% data will cap in 1%**
Above 99% data will cap in 99%

**After capping done , few outliers got removed , have to work with these outliers now**



# Hopkins Check

The Hopkins statistic (introduced by Brian Hopkins and John Gordon Skellam) 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.

Inference: 0.92 is a good Hopkins score for Clustering.

# Scaling

The Euclidean distance is calculated by taking the square root of the sum of the squared differences between observations. This distance can be greatly affected by differences in scale among the variables.
So I performed scaling of the variables.

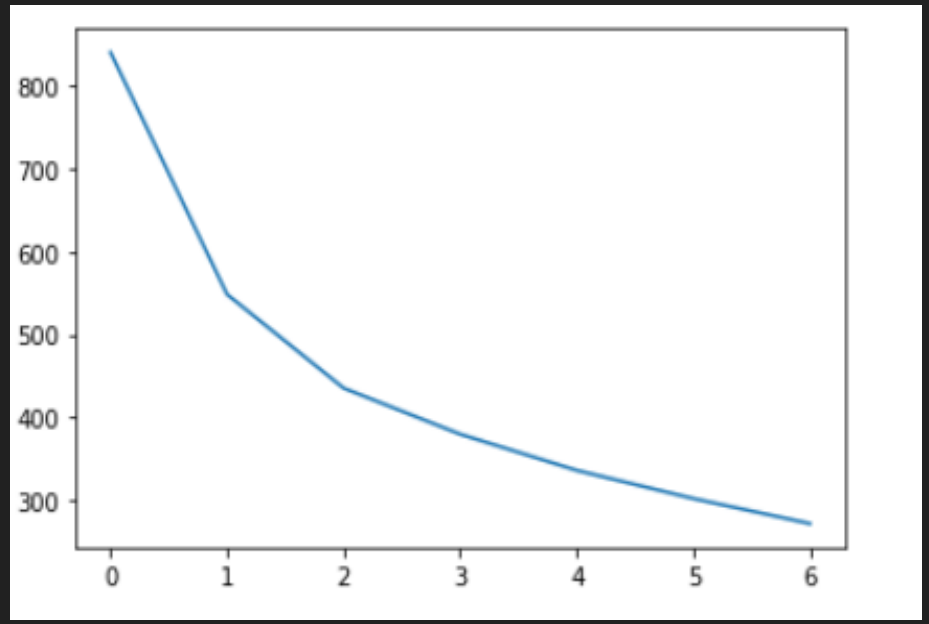
| | child_mort | exports | health | imports | income | inflation | life_expec | total_fer | gdpp |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1.344012 | -0.569638 | -0.565164 | -0.598844 | -0.851772 | 0.263649 | -1.693799 | 1.926928 | -0.702314 |
| 1 | -0.547543 | -0.473873 | -0.439335 | -0.413679 | -0.387025 | -0.375251 | 0.663053 | -0.865911 | -0.498775 |
| 2 | -0.272548 | -0.424015 | -0.484946 | -0.476198 | -0.221124 | 1.123260 | 0.686504 | -0.035427 | -0.477483 |
| 3 | 2.084186 | -0.381264 | -0.532486 | -0.464070 | -0.612136 | 1.936405 | -1.236499 | 2.154642 | -0.531000 |
| 4 | -0.709457 | -0.086754 | -0.178874 | 0.139659 | 0.125202 | -0.768917 | 0.721681 | -0.544433 | -0.032079 |

# Finding the Optimal Number of Clusters
## **Method 1:**Elbow-Curve/SSD to get the right no. of clusters

- A fundamental step for any unsupervised algorithm is to determine the optimal number of clusters into which the data may be clustered. The Elbow Method is one of the most popular methods to determine this optimal value of k.

Conclusion:

After observing this curve I selected my optimum value of cluster as 3.

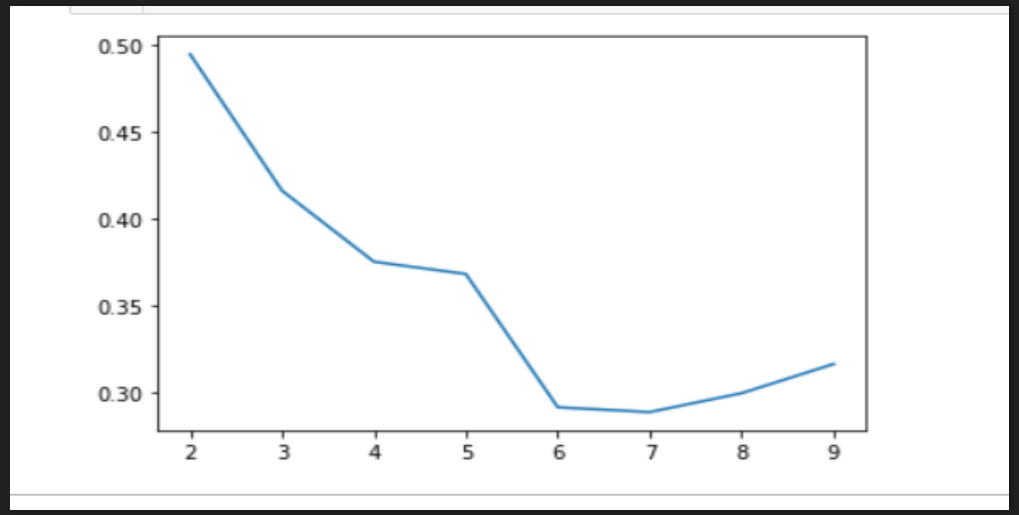


# Finding the Optimal Number of Clusters
## **Method 2:** Silhouette Analysis

**Before proceeding into clustering the data, we find out the optimal number of clusters by the following two methods**

- The value of the silhouette score range lies between -1 to 1.
- A score closer to 1 indicates that the data point is very similar to other data points in the cluster,
- A score closer to -1 indicates that the data point is not similar to the data points in its cluster.

```
For n_clusters=2, the silhouette score is 0.49455941306658363
For n_clusters=3, the silhouette score is 0.4160717022232288
For n_clusters=4, the silhouette score is 0.3751726233026849
For n_clusters=5, the silhouette score is 0.35136139823468543
For n_clusters=6, the silhouette score is 0.298155556685058
For n_clusters=7, the silhouette score is 0.3070589058368767
For n_clusters=8, the silhouette score is 0.2812050335739004
```




Conclusion:

The silhouette score reaches a peak at around 3 clusters indicating that it might be the ideal number of clusters. (k=3)

Also I observed this curve and silhouette score and then I selected my optimum value of cluster as 3.

# Cluster profiling:-

- From the business understanding we have learnt that Child_Mortality, Income, Gdpp are some important factors which decides the development of any country. Hence, we will proceed with cluster profiling by using these 3 variables.
- - gdpp: (The GDP per capita) Calculated as the Total GDP divided by the total population.
- - child_mort: Death of children under 5 years of age per 1000 live births.
- - income: Net income per person. g technique

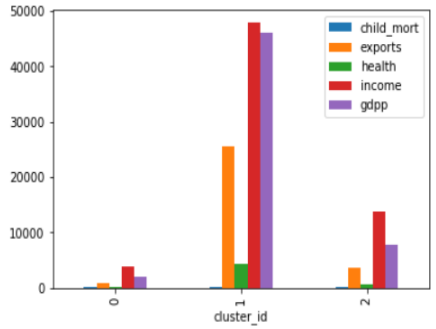
# K-Mean clustering

Clusters made using cluster_ids variable

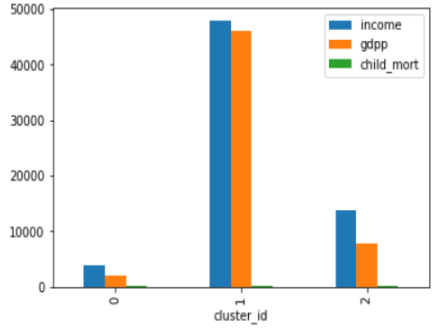
# By using K= 3, Analysis of clusters formed from k mean on basis of 3 columns i.e income, gdpp and child_mort

**Inference**:- Income and Gdpp are measures of development. Higher the per capita income and gdpp better is the country's development. Income per capita and gdpp seems lowest for countries in clusters 0 and Child Mortality is highest for Cluster 0 Hence, these countries need some help.

In [40]:
```
country1[['child_mort', 'exports','health','income', 'gdpp', 'cluster_id']].groupby('cluster_id').mean().plot(kind= 'bar')
plt.show()
```



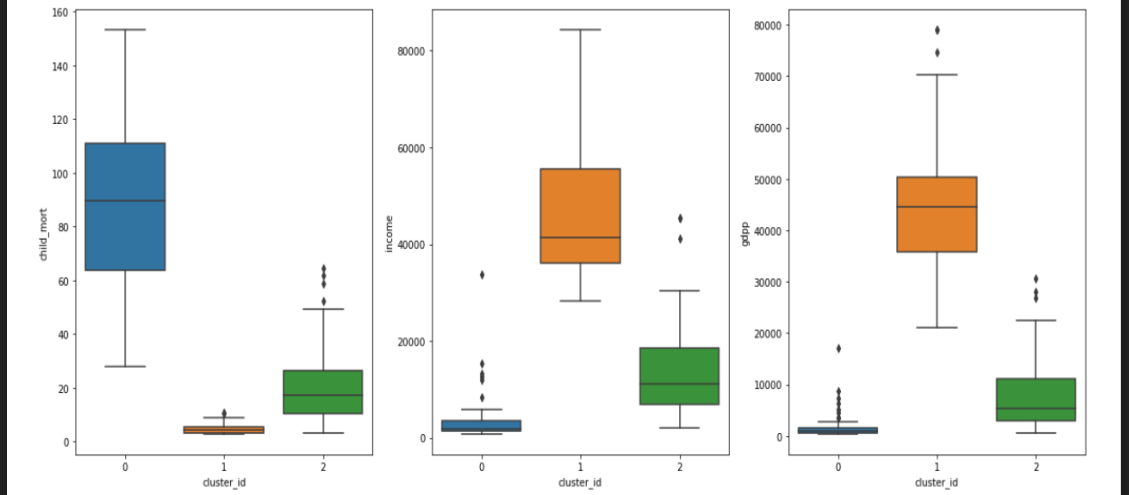

In [41]:
```
country1[['income','gdpp','child_mort', 'cluster_id']].groupby('cluster_id').mean().plot(kind= 'bar')
plt.show()
```



# By using K= 3, Analysis of clusters formed from k mean on basis of 3 columns i.e income, gdpp and child_mort

Inference:
Cluster 0 has lowest GDPP so we can say that the countries in cluster 0 must be in high Aid.
Cluster 0 has lowest income so we can say that the countries in cluster 0 must be in high Aid.
Cluster 0 has highest mortality rate so we can say that the countries in cluster 0 must be in high Aid.

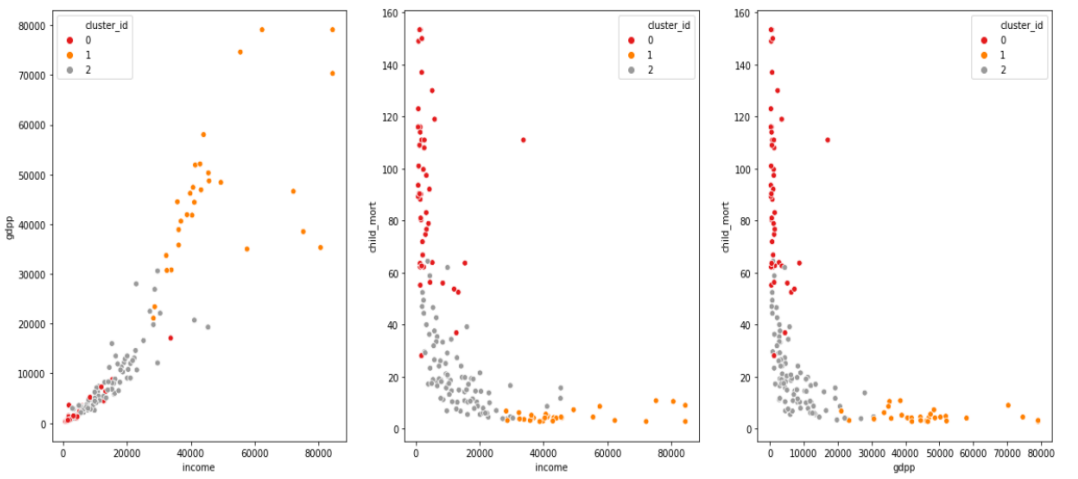
```
]:
plt.figure(figsize=(20,8))
plt.subplot(1,3,1)
sns.boxplot(x='cluster_id', y='child_mort', data=country1)
plt.subplot(1,3,2)
sns.boxplot(x='cluster_id', y='income', data=country1)
plt.subplot(1,3,3)
sns.boxplot(x='cluster_id', y='gdpp', data=country1)
plt.show()
```




**Final Inference:**
Child Mortality is highest for Cluster 0, These clusters need some aid. Income and Gdpp are measures of development. Higher the per capita income and gdpp better is the country's development. Income per capita and gdpp seems lowest for countries in

clusters 0. Hence, these countries need some help.

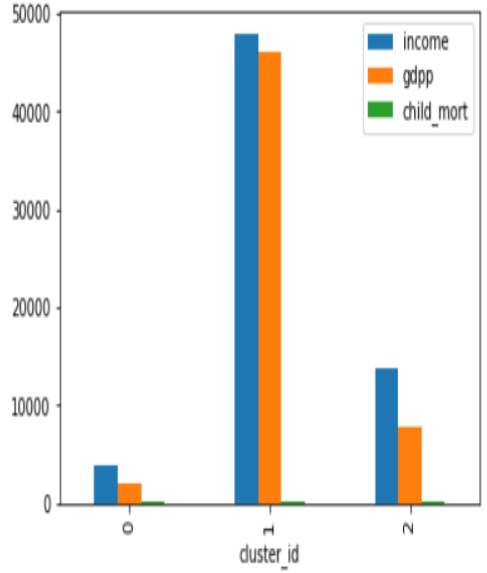
```
[35]:
# plotting the cluster ith respect to he clusters obtained
plt.figure(figsize=[20,8])
plt.subplot(1,3,1)
sns.scatterplot(x= 'income', y= 'gdpp', hue='cluster_id', legend='full', data=country1, palette= 'Set1')
plt.subplot(1,3,2)
sns.scatterplot(x= 'income', y= 'child_mort', hue='cluster_id', legend='full', data=country1, palette= 'Set1')
plt.subplot(1,3,3)
sns.scatterplot(x= 'gdpp', y= 'child_mort', hue='cluster_id', legend='full', data=country1, palette= 'Set1')
plt.show()
```



# Cluster Profiling

| cluster_id | child_mort | exports | health | imports | income | inflation | life_expec | total_fer | gdpp |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 90.335417 | 879.097657 | 115.348635 | 827.327888 | 3901.010000 | 10.608604 | 59.567083 | 4.972233 | 1911.400833 |
| 1 | 20.547778 | 3477.250726 | 528.925228 | 3589.291996 | 13804.333333 | 7.131624 | 73.393333 | 2.242591 | 7808.577778 |
| 2 | 4.989655 | 25405.359310 | 4253.879655 | 21316.695862 | 47784.413793 | 2.906731 | 80.453103 | 1.757352 | 46068.137931 |

```
1 country1[['income','gdpp','child_mort', 'cluster_id']].groupby('cluster_id').mean().plot(kind= 'bar')
2 plt.show()
```



# By Kmean clustering Top 10 countries

These countries are sorted based on ascending form of income and gdpp and descending form of child_morality

```
42]: 1 .groupby('cluster_id1').sort_values(by='child_mort', ascending= False)
     2 ister_country=country1[country1['cluster_id']==0].sort_values(by=['income','gdpp','child_mort'],ascending=[True, True,False])
     3 ister_country.head(10)
```

42]:

| | country | child_mort | exports | health | imports | income | inflation | life_expec | total_fer | gdpp | cluster_id |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 88 | Liberia | 89.3 | 62.457000 | 38.5860 | 302.80200 | 742.24 | 5.47 | 60.8 | 5.0200 | 331.62 | 0 |
| 37 | Congo, Dem. Rep. | 116.0 | 137.274000 | 26.4194 | 165.66400 | 742.24 | 20.80 | 57.5 | 6.5400 | 334.00 | 0 |
| 26 | Burundi | 93.6 | 22.243716 | 26.7960 | 104.90964 | 764.00 | 12.30 | 57.7 | 6.2600 | 331.62 | 0 |
| 112 | Niger | 123.0 | 77.256000 | 17.9568 | 170.86800 | 814.00 | 2.55 | 58.8 | 6.5636 | 348.00 | 0 |
| 31 | Central African Republic | 149.0 | 52.628000 | 17.7508 | 118.19000 | 888.00 | 2.01 | 47.5 | 5.2100 | 446.00 | 0 |
| 106 | Mozambique | 101.0 | 131.985000 | 21.8299 | 193.57800 | 918.00 | 7.64 | 54.5 | 5.5600 | 419.00 | 0 |
| 94 | Malawi | 90.5 | 104.652000 | 30.2481 | 160.19100 | 1030.00 | 12.10 | 53.1 | 5.3100 | 459.00 | 0 |
| 63 | Guinea | 109.0 | 196.344000 | 31.9464 | 279.93600 | 1190.00 | 16.10 | 58.0 | 5.3400 | 648.00 | 0 |
| 150 | Togo | 90.3 | 196.176000 | 37.3320 | 279.62400 | 1210.00 | 1.18 | 58.7 | 4.8700 | 488.00 | 0 |
| 132 | Sierra Leone | 153.4 | 67.032000 | 52.2690 | 137.65500 | 1220.00 | 17.20 | 55.0 | 5.2000 | 399.00 | 0 |

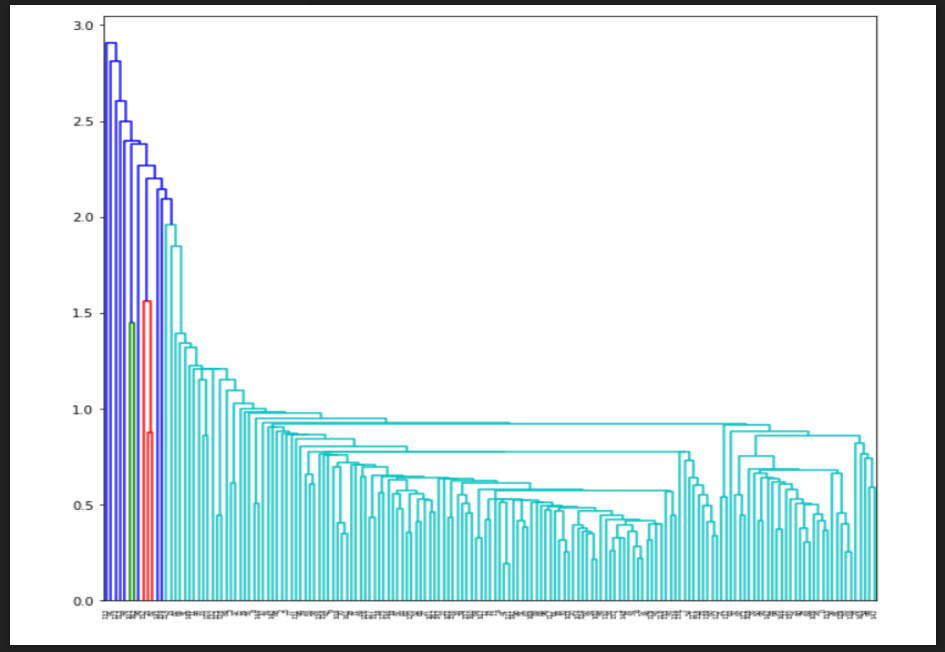
# Hierarchal clustdring

Cluster made using cluster_labels variable

# Types of hierarchal clustering

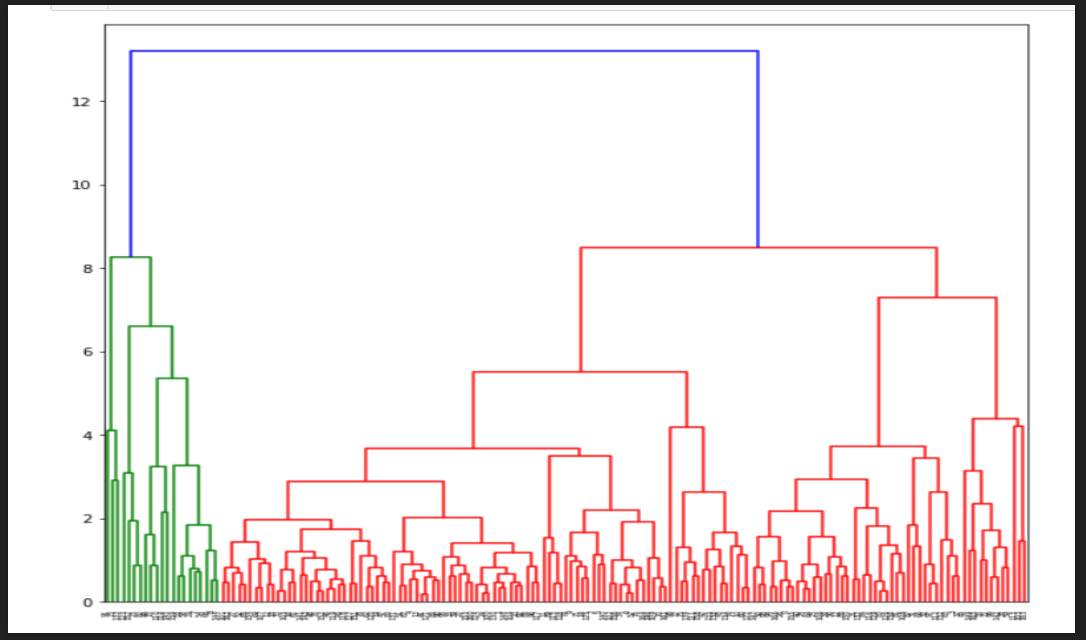
Single

- Single Linkage do not give clear cluster formation so we have to try complete linkage in the next step.




Complete

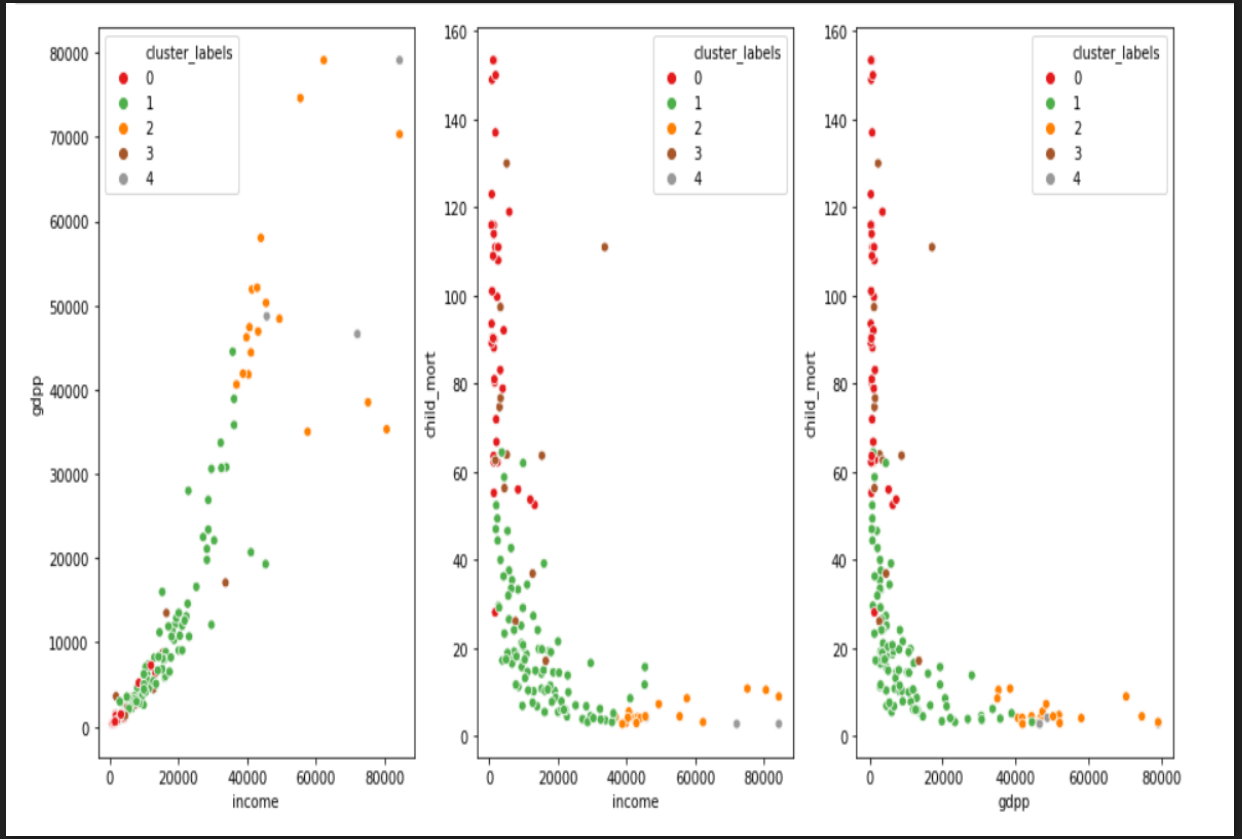
- Now we see some good amount of clusters getting formed.



**Choose cluster =4 from the dendogram which is made by complete hirarichal clustering**

# Inference:

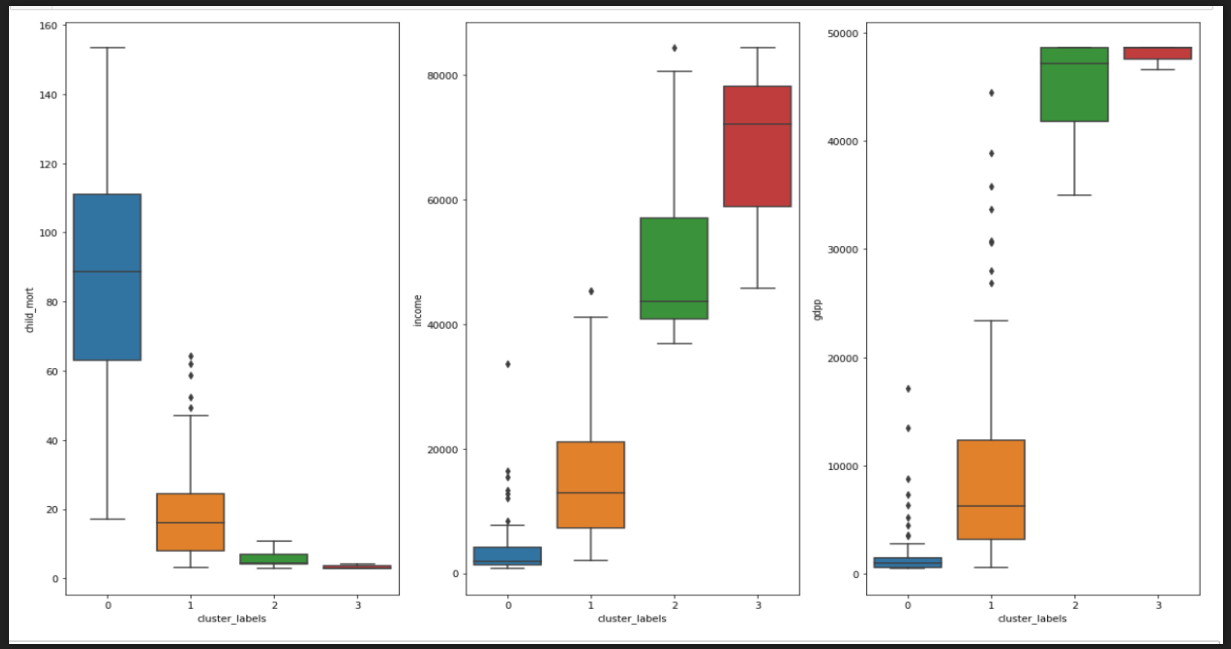
Child Mortality is highest for Cluster 0. These cluster need some aid. Income and Gdpp are measures of development. Higher the per capita income and gdpp better is the country's development. Income per capita and gdpp seems lowest for countries in clusters 0. Hence, these countries need some help.

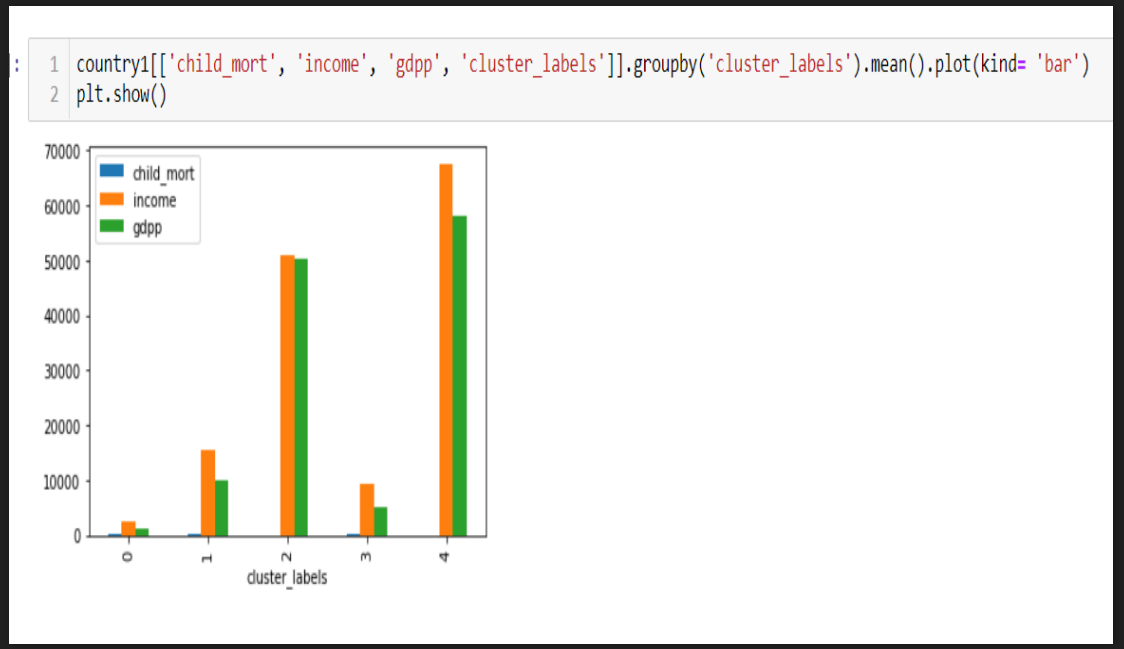


# Cluster Profiling

**Inference:**

Child Mortality is highest for Cluster 0, These clusters need some aid. Income and Gdpp are measures of development. Higher the per capita income and gdpp better is the country's development. However Income per capita and gdpp seems lowest for countries in clusters 0. Hence, countries in cluster 0 need some help.



# By Hierarchical clustering method
# Top 10 countries

These countries are sorted based on ascending form of income and  gdpp and descending form of child_morality

```
# let's filter the data with selected cluster
hirarichal_cluster_country =country1[country1['cluster_labels']==0].sort_values(by=['income','gdpp','child_mort'],ascending=
hirarichal_cluster_country
```

| | country | child_mort | exports | health | imports | income | inflation | life_expec | total_fer | gdpp | cluster_labels |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 88 | Liberia | 89.3 | 62.457000 | 38.5860 | 302.80200 | 742.24 | 5.47 | 60.8 | 5.0200 | 331.62 | 0 |
| 37 | Congo, Dem. Rep. | 116.0 | 137.274000 | 26.4194 | 165.66400 | 742.24 | 20.80 | 57.5 | 6.5400 | 334.00 | 0 |
| 26 | Burundi | 93.6 | 22.243716 | 26.7960 | 104.90964 | 764.00 | 12.30 | 57.7 | 6.2600 | 331.62 | 0 |
| 112 | Niger | 123.0 | 77.256000 | 17.9568 | 170.86800 | 814.00 | 2.55 | 58.8 | 6.5636 | 348.00 | 0 |
| 31 | Central African Republic | 149.0 | 52.628000 | 17.7508 | 118.19000 | 888.00 | 2.01 | 47.5 | 5.2100 | 446.00 | 0 |
| 106 | Mozambique | 101.0 | 131.985000 | 21.8299 | 193.57800 | 918.00 | 7.64 | 54.5 | 5.5600 | 419.00 | 0 |
| 94 | Malawi | 90.5 | 104.652000 | 30.2481 | 160.19100 | 1030.00 | 12.10 | 53.1 | 5.3100 | 459.00 | 0 |
| 63 | Guinea | 109.0 | 196.344000 | 31.9464 | 279.93600 | 1190.00 | 16.10 | 58.0 | 5.3400 | 648.00 | 0 |
| 150 | Togo | 90.3 | 196.176000 | 37.3320 | 279.62400 | 1210.00 | 1.18 | 58.7 | 4.8700 | 488.00 | 0 |
| 132 | Sierra Leone | 153.4 | 67.032000 | 52.2690 | 137.65500 | 1220.00 | 17.20 | 55.0 | 5.2000 | 399.00 | 0 |

# Top 10 countries

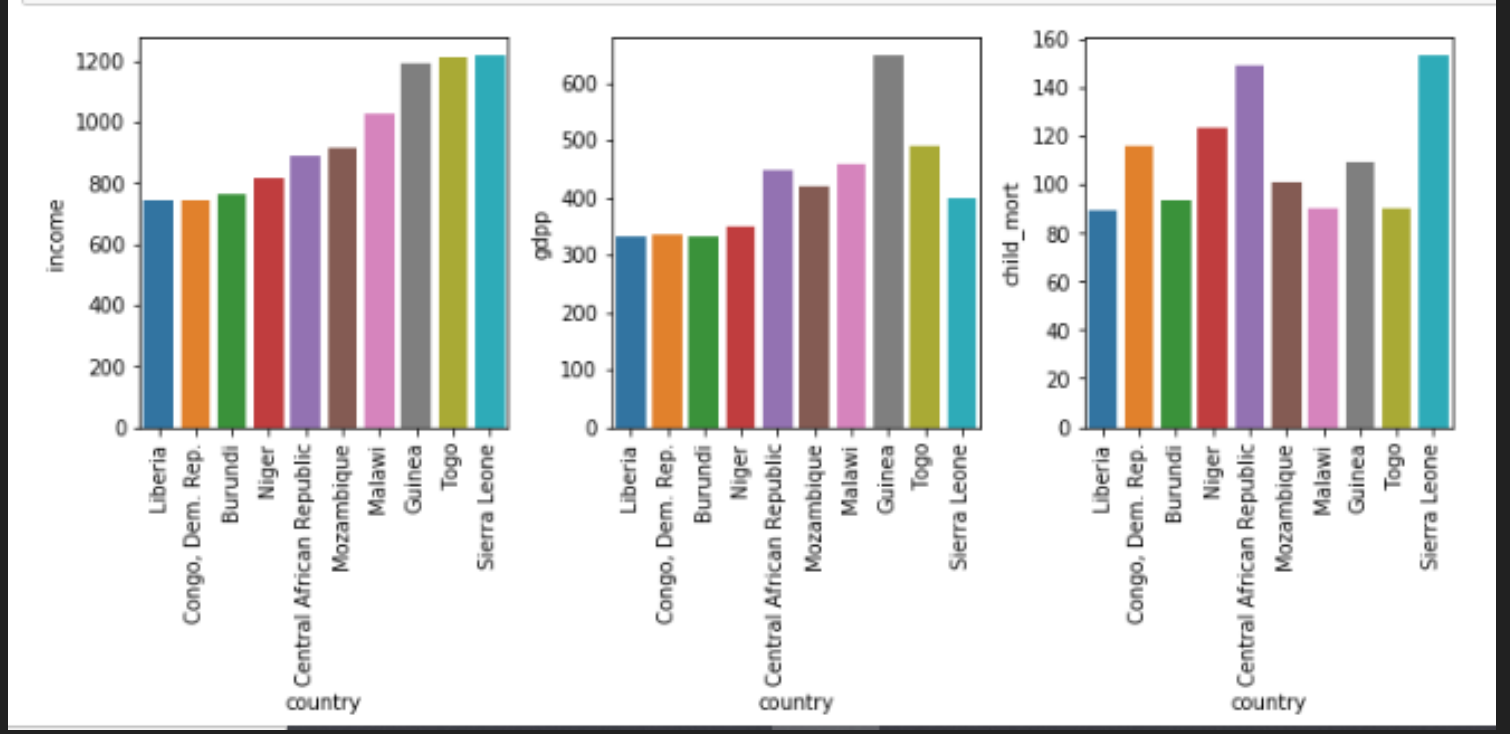
1) Liberia
2) Congo, Dem. Rep.
3) Burundi
4) Niger
5) Central African Republic
6) Mozambique
7) Malawi
8) Guinea
9) Togo
10) Sierra Leone

```
plt.subplot(1,3,1)
sns.barplot(x='country', y='income', data=select_count)
plt.xticks(rotation = 90)

plt.subplot(1,3,2)
sns.barplot(x='country', y='gdpp', data=select_count)
plt.xticks(rotation = 90)

plt.subplot(1,3,3)
sns.barplot(x='country', y='child_mort', data=select_count)
plt.xticks(rotation = 90)

fig.tight_layout()
plt.show()
```



# Final list of top 10 countries that needs Aid from CEO

| | country | child_mort | exports | health | imports | income | inflation | life_expec | total_fer | gdpp | cluster_labels1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 88 | Liberia | 89.3 | 62.457000 | 38.586000 | 302.80200 | 742.24 | 5.47 | 60.8 | 5.0200 | 331.62 | 0 |
| 37 | Congo, Dem. Rep. | 116.0 | 137.274000 | 26.419400 | 165.66400 | 742.24 | 20.80 | 57.5 | 6.5400 | 334.00 | 0 |
| 26 | Burundi | 93.6 | 22.243716 | 26.796000 | 104.90964 | 764.00 | 12.30 | 57.7 | 6.2600 | 331.62 | 0 |
| 112 | Niger | 123.0 | 77.256000 | 22.243716 | 170.86800 | 814.00 | 2.55 | 58.8 | 6.5636 | 348.00 | 0 |
| 31 | Central African Republic | 149.0 | 52.628000 | 22.243716 | 118.19000 | 888.00 | 2.01 | 47.5 | 5.2100 | 446.00 | 0 |
| 106 | Mozambique | 101.0 | 131.985000 | 22.243716 | 193.57800 | 918.00 | 7.64 | 54.5 | 5.5600 | 419.00 | 0 |
| 94 | Malawi | 90.5 | 104.652000 | 30.248100 | 160.19100 | 1030.00 | 12.10 | 53.1 | 5.3100 | 459.00 | 0 |
| 63 | Guinea | 109.0 | 196.344000 | 31.946400 | 279.93600 | 1190.00 | 16.10 | 58.0 | 5.3400 | 648.00 | 0 |
| 150 | Togo | 90.3 | 196.176000 | 37.332000 | 279.62400 | 1210.00 | 1.18 | 58.7 | 4.8700 | 488.00 | 0 |
| 132 | Sierra Leone | 153.4 | 67.032000 | 52.269000 | 137.65500 | 1220.00 | 17.20 | 55.0 | 5.2000 | 399.00 | 0 |

# Conclusion

- Based on my  analysis I followed below observations to choose the countries that are  in need of aid:
- Analysis  based on : both K-means and Hierarchical clustering
- Cluster formation: identical
- I choose : k-mean clustering method and deduce the final list of countries which are in need of aid.

# FINAL LIST OF TOP 10 COUNTRIES (USING K MEAN) TO FOCUS ON

42]:
```
.groupby('cluster_id1').sort_values(by='child_mort', ascending= False)
ıster_country=country1[country1['cluster_id']==0].sort_values(by=['income','gdpp','child_mort'],ascending=[True, True,False])
ıster_country.head(10)
```

42]:

| | country | child_mort | exports | health | imports | income | inflation | life_expec | total_fer | gdpp | cluster_id |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 88 | Liberia | 89.3 | 62.457000 | 38.5860 | 302.80200 | 742.24 | 5.47 | 60.8 | 5.0200 | 331.62 | 0 |
| 37 | Congo, Dem. Rep. | 116.0 | 137.274000 | 26.4194 | 165.66400 | 742.24 | 20.80 | 57.5 | 6.5400 | 334.00 | 0 |
| 26 | Burundi | 93.6 | 22.243716 | 26.7960 | 104.90964 | 764.00 | 12.30 | 57.7 | 6.2600 | 331.62 | 0 |
| 112 | Niger | 123.0 | 77.256000 | 17.9568 | 170.86800 | 814.00 | 2.55 | 58.8 | 6.5636 | 348.00 | 0 |
| 31 | Central African Republic | 149.0 | 52.628000 | 17.7508 | 118.19000 | 888.00 | 2.01 | 47.5 | 5.2100 | 446.00 | 0 |
| 106 | Mozambique | 101.0 | 131.985000 | 21.8299 | 193.57800 | 918.00 | 7.64 | 54.5 | 5.5600 | 419.00 | 0 |
| 94 | Malawi | 90.5 | 104.652000 | 30.2481 | 160.19100 | 1030.00 | 12.10 | 53.1 | 5.3100 | 459.00 | 0 |
| 63 | Guinea | 109.0 | 196.344000 | 31.9464 | 279.93600 | 1190.00 | 16.10 | 58.0 | 5.3400 | 648.00 | 0 |
| 150 | Togo | 90.3 | 196.176000 | 37.3320 | 279.62400 | 1210.00 | 1.18 | 58.7 | 4.8700 | 488.00 | 0 |
| 132 | Sierra Leone | 153.4 | 67.032000 | 52.2690 | 137.65500 | 1220.00 | 17.20 | 55.0 | 5.2000 | 399.00 | 0 |

# THANK YOU