clustering_algos

February 11, 2022

1 Objective

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. It runs a lot of operational projects from time to time along with advocacy drives to raise awareness as well as for funding purposes.

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. Then I've to suggest the countries which the CEO needs to focus on the most. The datasets containing those socio-economic factors.

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import sklearn
from sklearn.cluster import KMeans
```

2 Data Read and Inspection

[2]:
```python
## let's read our data file and check head of the dataset
help_ngo = pd.read_csv('Country-data.csv')
help_ngo.head()
```

[2]:
```
               country  child_mort  exports  health  imports  income  \
0          Afghanistan        90.2     10.0    7.58     44.9    1610
1              Albania        16.6     28.0    6.55     48.6    9930
2              Algeria        27.3     38.4    4.17     31.4   12900
3               Angola       119.0     62.3    2.85     42.9    5900
4  Antigua and Barbuda        10.3     45.5    6.03     58.9   19100
```

```
   inflation  life_expec  total_fer   gdpp
0       9.44        56.2       5.82    553
1       4.49        76.3       1.65   4090
2      16.10        76.5       2.89   4460
3      22.40        60.1       6.16   3530
4       1.44        76.8       2.13  12200
```

[3]:
```python
## check shape of the datafreame
help_ngo.shape
```

[3]:
```
(167, 10)
```

[4]:
```python
## check info about dataframe
help_ngo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 167 entries, 0 to 166
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   country     167 non-null    object
 1   child_mort  167 non-null    float64
 2   exports     167 non-null    float64
 3   health      167 non-null    float64
 4   imports     167 non-null    float64
 5   income      167 non-null    int64
 6   inflation   167 non-null    float64
 7   life_expec  167 non-null    float64
 8   total_fer   167 non-null    float64
 9   gdpp        167 non-null    int64
dtypes: float64(7), int64(2), object(1)
memory usage: 13.2+ KB
```

[5]:
```python
## check for null values
help_ngo.isnull().sum()
```

[5]:
```
country       0
child_mort    0
exports       0
health        0
imports       0
income        0
inflation     0
life_expec    0
total_fer     0
gdpp          0
dtype: int64
```

There is no null values in any column of the data frame

[6]:
```
## lets remove duplicate if have any and check shape again
help_ngo.drop_duplicates(subset=['country'],keep='first',inplace =True)
```

[7]:
```
help_ngo.shape ## cheking shape
```

[7]: (167, 10)

There is no duplicate value as per country

[8]:
```
## checking statistical description of the data set
help_ngo.describe()
```

[8]:
```
       child_mort     exports      health     imports         income  \
count  167.000000  167.000000  167.000000  167.000000     167.000000
mean    38.270060   41.108976    6.815689   46.890215   17144.688623
std     40.328931   27.412010    2.746837   24.209589   19278.067698
min      2.600000    0.109000    1.810000    0.065900     609.000000
25%      8.250000   23.800000    4.920000   30.200000    3355.000000
50%     19.300000   35.000000    6.320000   43.300000    9960.000000
75%     62.100000   51.350000    8.600000   58.750000   22800.000000
max    208.000000  200.000000   17.900000  174.000000  125000.000000

        inflation  life_expec   total_fer           gdpp
count  167.000000  167.000000  167.000000     167.000000
mean     7.781832   70.555689    2.947964   12964.155689
std     10.570704    8.893172    1.513848   18328.704809
min     -4.210000   32.100000    1.150000     231.000000
25%      1.810000   65.300000    1.795000    1330.000000
50%      5.390000   73.100000    2.410000    4660.000000
75%     10.750000   76.800000    3.880000   14050.000000
max    104.000000   82.800000    7.490000  105000.000000
```

As per data dictinary 1. exports: Exports of goods and services per capita. Given as %age of the GDP per capita 2. health: Total health spending per capita. Given as %age of GDP per capita 3. imports: Imports of goods and services per capita. Given as %age of the GDP per capita

hence converting them to their absolute values

[9]:
```
help_ngo['exports'] = help_ngo['exports']*help_ngo['gdpp']/100
help_ngo['health'] = help_ngo['health']*help_ngo['gdpp']/100
help_ngo['imports'] = help_ngo['imports']*help_ngo['gdpp']/100
```

[10]:
```
## check head after convertion
help_ngo.head()
```

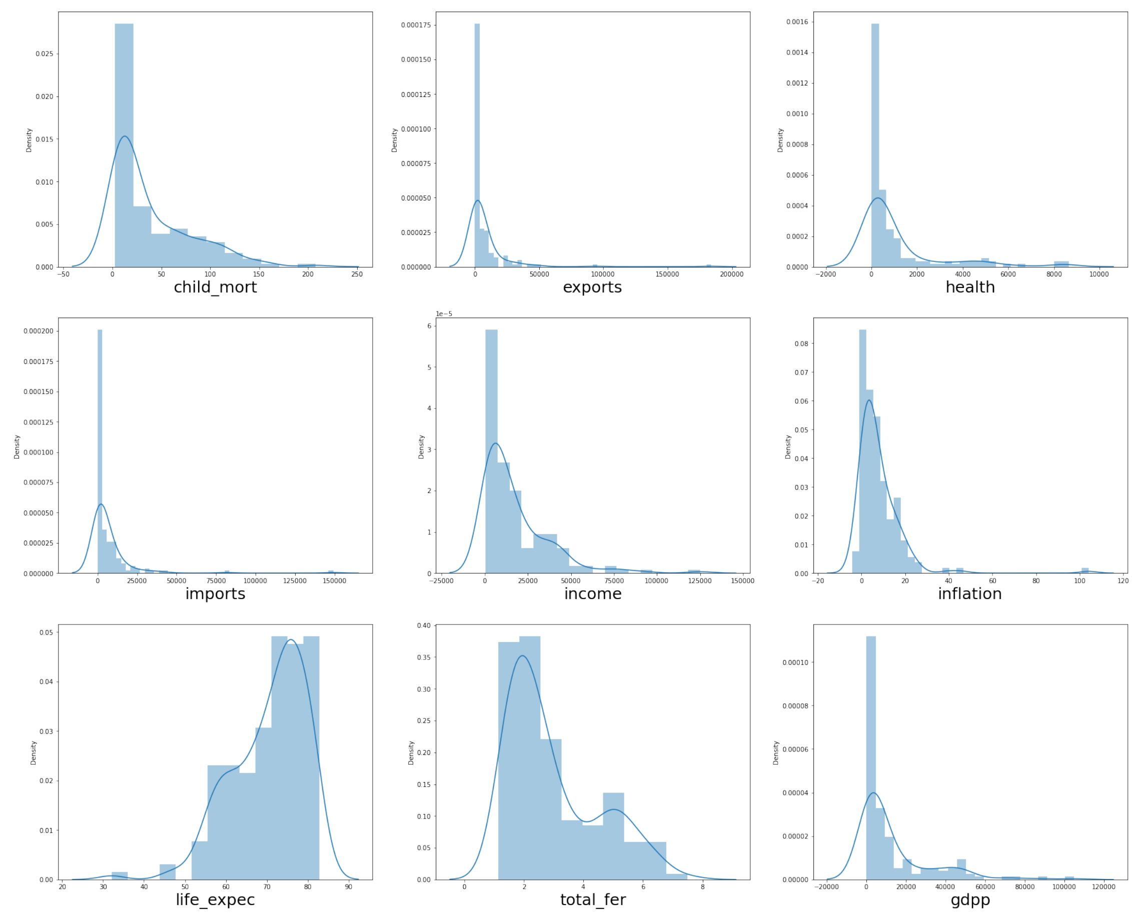
[10]:
```
               country  child_mort  exports    health   imports  income  \
0          Afghanistan        90.2    55.30   41.9174   248.297    1610
1              Albania        16.6  1145.20  267.8950  1987.740    9930
2              Algeria        27.3  1712.64  185.9820  1400.440   12900
```

```
3                Angola       119.0   2199.19   100.6050   1514.370     5900
4   Antigua and Barbuda        10.3   5551.00   735.6600   7185.800    19100

   inflation  life_expec  total_fer   gdpp
0       9.44        56.2       5.82    553
1       4.49        76.3       1.65   4090
2      16.10        76.5       2.89   4460
3      22.40        60.1       6.16   3530
4       1.44        76.8       2.13  12200
```

3 EDA

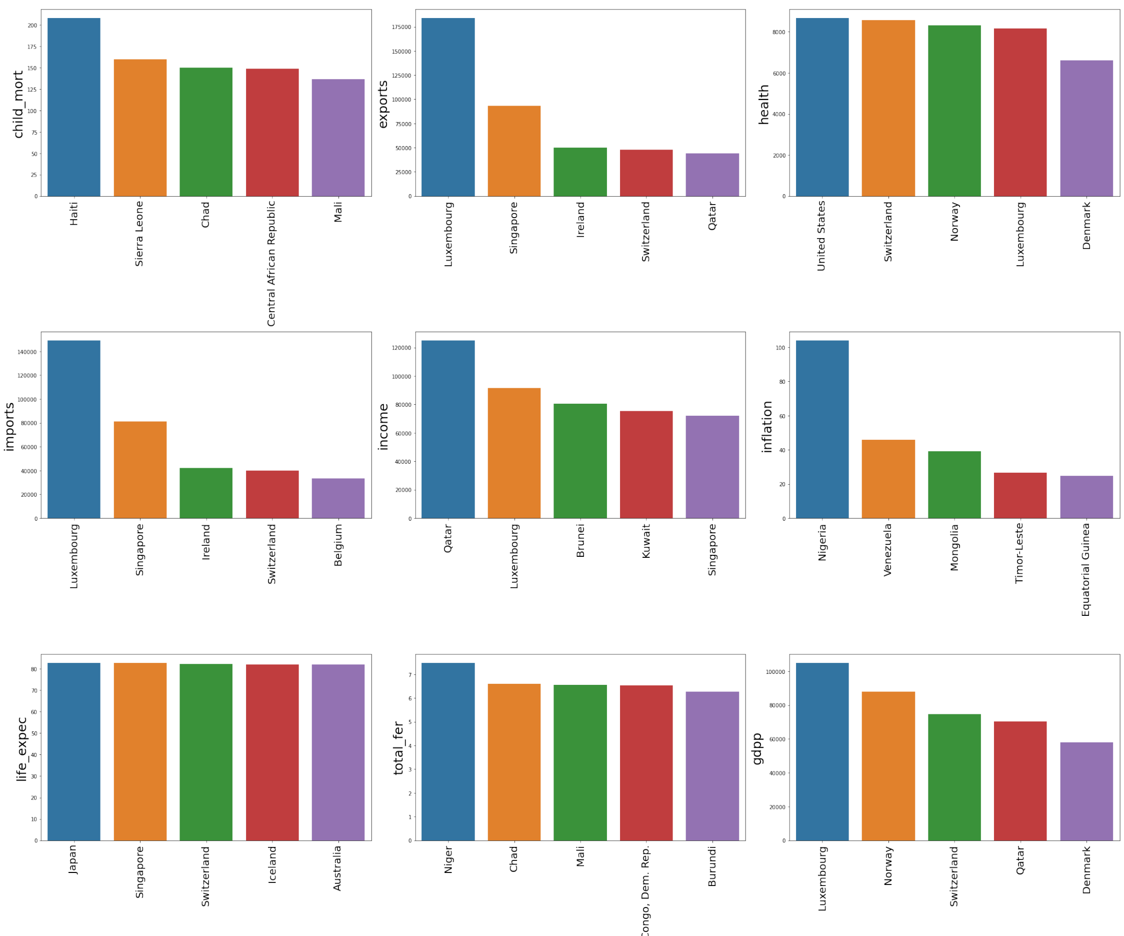
[11]:
```python
plt.figure(figsize=(30,25))
features = help_ngo.columns[1:help_ngo.shape[1]]
for i in enumerate(features):
    #print(i)
    plt.subplot(3,3,i[0]+1)
    ax = sns.distplot(help_ngo[i[1]])
    ax.set_xlabel(i[1],fontsize=25)
#plt.tight_layout()
```



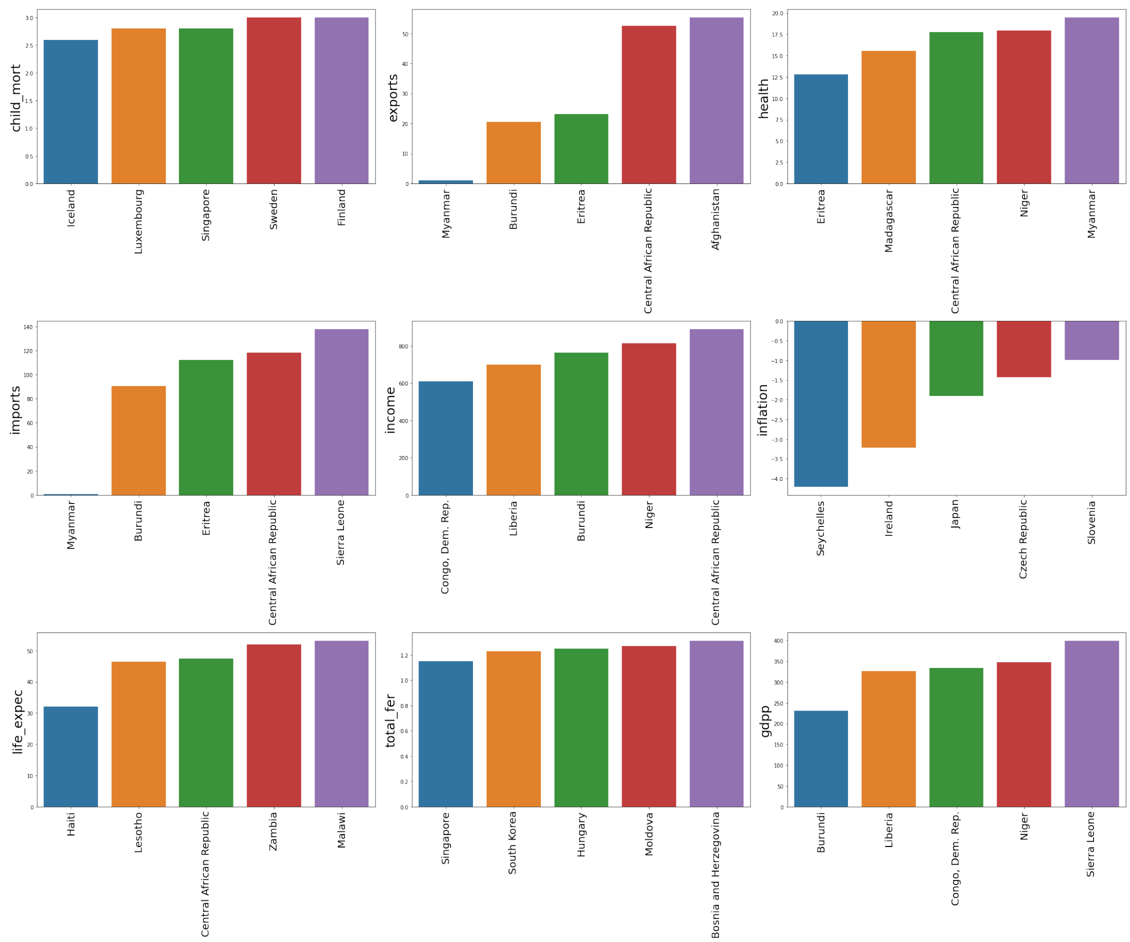
All variables are mainly left skewed except life_expectency .clearly there are two peaks on total_fer so this variable can be used for clusters profiling after created different clusters from the data .As variables are left skewed that means variables are also have outliers

[12]:
```
## let's check those countries which are high is respect of all the variables

fig = plt.figure(figsize=(30,25))
for i in enumerate(features):
    top = help_ngo[['country',i[1]]].sort_values(by=i[1],ascending=False).
 ↪head(5)
    plt.subplot(3,3,i[0]+1)
    ax = sns.barplot(x="country",y=i[1],data=top)
    ax.set_xticklabels(ax.get_xticklabels(), rotation=90 , fontsize=20)
    ax.set_xlabel("")
    ax.set_ylabel(i[1],fontsize=25)
fig.tight_layout()
plt.show()
```



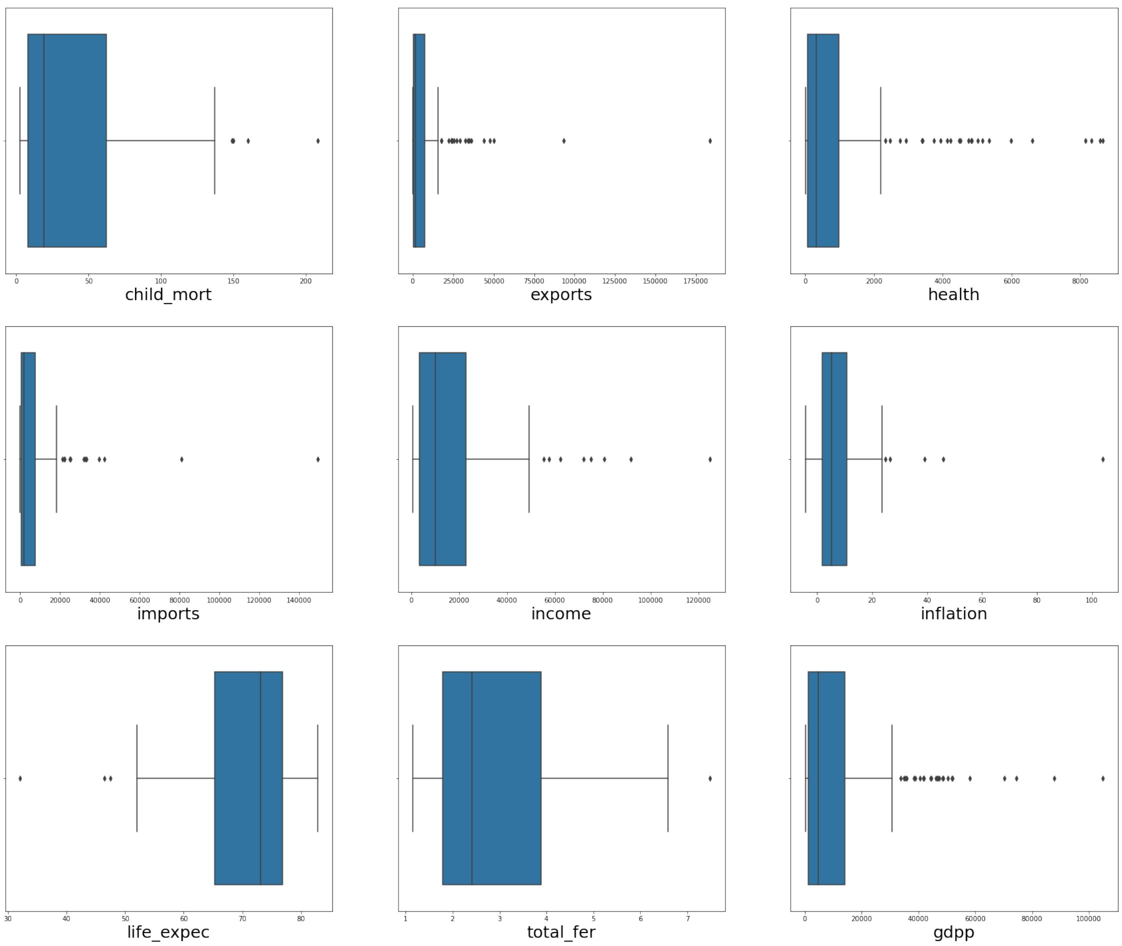
```
[13]: ## let's check which countries are low in respect of all the variabels
fig = plt.figure(figsize=(30,25))
for i in enumerate(features):
    bottom = help_ngo[['country',i[1]]].sort_values(by=i[1],ascending=False).
 ↪tail(5)
    plt.subplot(3,3,i[0]+1)
    ax = sns.barplot(x="country",y=i[1],data=bottom[::-1])
    ax.set_xticklabels(ax.get_xticklabels(), rotation=90 , fontsize=20)
    ax.set_xlabel("")
    ax.set_ylabel(i[1],fontsize=25)
fig.tight_layout()
plt.show()
```



As we can see some facts from the above figures summeriesd below 1. Mainly African countries has high child mortality rate and very low income , gdpp is also low 2. 'Haaiti' have maximum child mortality and minimum life expectancy 3. There is very low import and export in 'Mayanmar' 4. There is some countries which has a negative inflation rate (i.e seychelles,japan,ireland,check republic etc) 5. 'Qatar' has maximum income and high export rate 6. 'Luxemberg' is maximum in import,export and gdpp and also have a high income rate

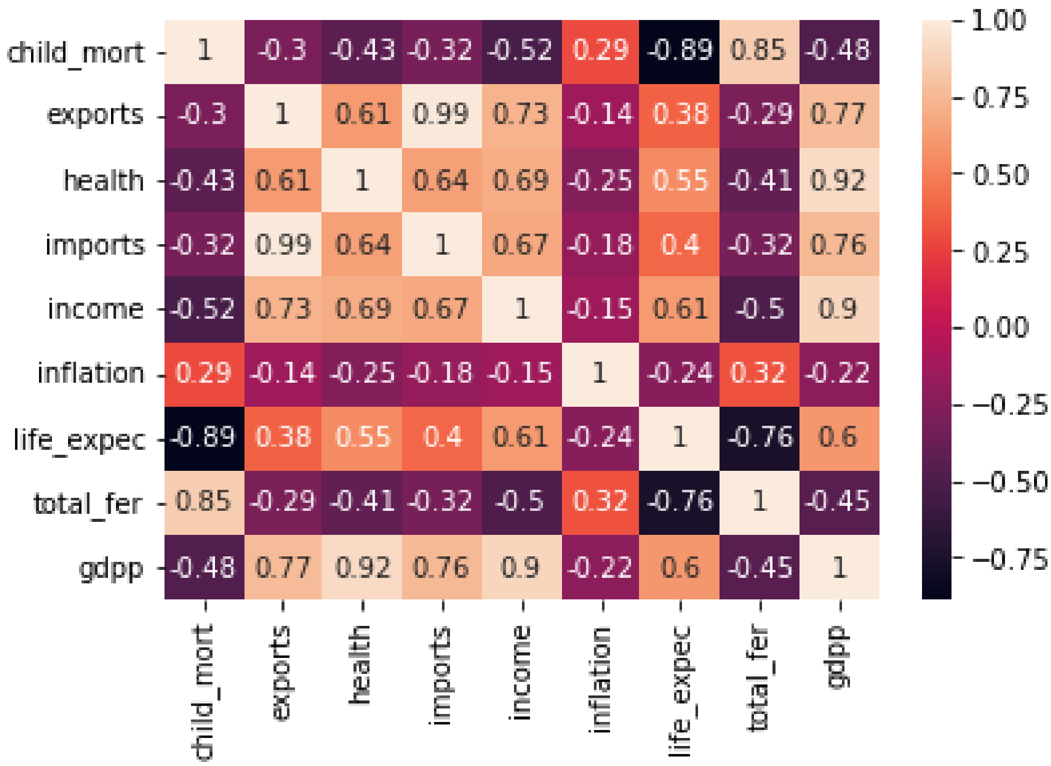
[14]:
```
## lets check for outliers in variables

plt.figure(figsize=(30,25))
features = help_ngo.columns[1:help_ngo.shape[1]]
for i in enumerate(features):
    #print(i)
    plt.subplot(3,3,i[0]+1)
    ax = sns.boxplot(help_ngo[i[1]])
    ax.set_xlabel(i[1],fontsize=25)
```



As I can see their are some good amount of outliers in the data. Hence if we remove those outliers some important information will loose on the other hand if we don't treat the outliers it can effect our clusters formation . In that case we will go for the PCA or principle component analyis. It will reduce dimentionality of the data and also preserve the important information of the data set.

```
[15]: # Let's check the correlation coefficients to see which variables are highly␣
      ↪correlated
      corr_matrix = help_ngo[features]
      sns.heatmap(corr_matrix.corr(),annot=True)
      plt.show()
```



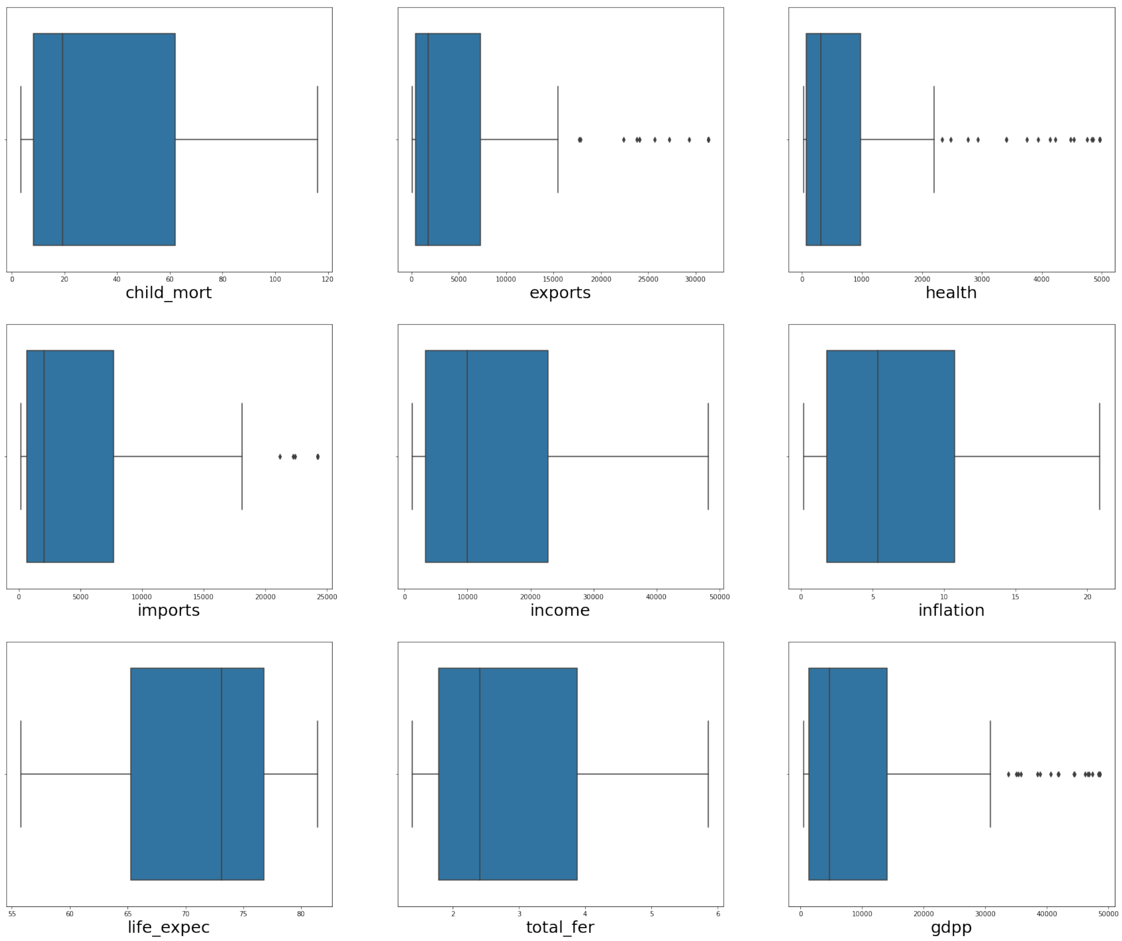
There are some features which are very positively co related like (child mortality and total fertility,import and export,income and export , gdp and export , gdp and health , gdp and income , gdp and import etc) There are some features which are very negatively co related like (life expectency and child mortality , life expectency and total fertility)

```
[16]: for i in enumerate(features):

          q1 = help_ngo[i[1]].quantile(0.05)
          q4 = help_ngo[i[1]].quantile(0.95)
          help_ngo[i[1]][help_ngo[i[1]]<=q1] = q1
          help_ngo[i[1]][help_ngo[i[1]]>=q4] = q4
```

I use Winsorization technique at 5th and 95th percentile which implies values that are less than the value at 1st percentile are replaced by the value at 5th percentile, and values that are greater than the value at 95th percentile are replaced by the value at 95th percentile.

[17]:
```
plt.figure(figsize=(30,25))
features = help_ngo.columns[1:help_ngo.shape[1]]
for i in enumerate(features):
    #print(i)
    plt.subplot(3,3,i[0]+1)
    ax = sns.boxplot(help_ngo[i[1]])
    ax.set_xlabel(i[1],fontsize=25)
```



4 Data Preparation

[18]:
```
## lets standardize our data
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
model_data_ngo = sc.fit_transform(help_ngo[features])
```

[19]:
```
## let's check transformed data
model_data_ngo = pd.DataFrame(model_data_ngo)
```

```
model_data_ngo.columns = [features]
model_data_ngo.head()
```

[19]:

```
   child_mort   exports    health   imports    income inflation life_expec  \
0    1.479588 -0.668039 -0.629778 -0.733291 -0.960575  0.387667  -1.825310
1   -0.560024 -0.542389 -0.473807 -0.472674 -0.395590 -0.404004   0.682454
2   -0.263504 -0.476048 -0.530344 -0.560668 -0.193907  1.452825   0.707406
3    2.194560 -0.419165 -0.589272 -0.543598 -0.669255  2.215708  -1.338729
4   -0.734610 -0.027297 -0.150953  0.306143  0.227115 -0.891802   0.744836

   total_fer      gdpp
0   2.020718 -0.757874
1  -0.887331 -0.523775
2  -0.022587 -0.499286
3   2.049310 -0.560839
4  -0.552591  0.012991
```

After soft range outliers capping There is no outliers in our dataset hence it is ready for run our clustering model.

5 Hopkins Test

The Hopkins statistic (introduced by Brian Hopkins and John Gordon Skellam) is a way of measuring the cluster tendency of a data set.It acts as a statistical hypothesis test where the null hypothesis is that the data is generated by a Poisson point process and are thus uniformly randomly distributed. A value close to 1 tends to indicate the data is highly clustered, random data will tend to result in values around 0.5, and uniformly distributed data will tend to result in values close to 0.

[20]:

```
## hopkins function
from sklearn.neighbors import NearestNeighbors
from random import sample
from numpy.random import uniform
from math import isnan

def hopkins(X):
    d = X.shape[1]
    n = len(X)
    m = int(0.1 * n)
    nbrs = NearestNeighbors(n_neighbors=1).fit(X.values)

    rand_X = sample(range(0, n, 1), m)

    ujd = []
    wjd = []
    for j in range(0, m):
```

```
        u_dist, _ = nbrs.kneighbors(uniform(np.amin(X,axis=0),np.
↪amax(X,axis=0),d).reshape(1, -1), 2, return_distance=True)
        ujd.append(u_dist[0][1])
        w_dist, _ = nbrs.kneighbors(X.iloc[rand_X[j]].values.reshape(1, -1), 2,␣
↪return_distance=True)
        wjd.append(w_dist[0][1])

    HS = sum(ujd) / (sum(ujd) + sum(wjd))
    if isnan(HS):
        print(ujd, wjd)
        HS = 0

    return HS
```

[21]:
```
## let's check hopkin's score

Hopkins_score = hopkins(model_data_ngo)
Hopkins_score
```

[21]:
```
0.8728614925133372
```

approx 0.80% Hopkins score is a pretty good Hopkins score Hence dataset is appropriate for clustering.

Generally two metrices are used to find the optimal number of clusters for our algorithm. 1. silhouette score 2. elbow curve

6 Silhoutte Score

Silhouette analysis can be used to study the separation distance between the resulting clusters. The silhouette plot displays a measure of how close each point in one cluster is to points in the neighboring clusters and thus provides a way to assess parameters like number of clusters visually. This measure has a range of [-1, 1].

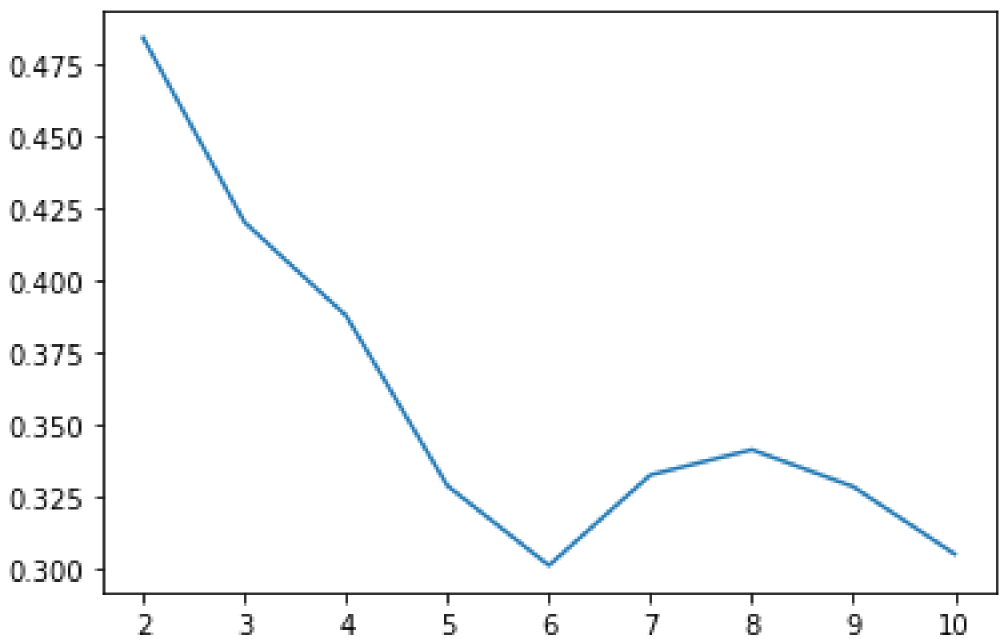
[22]:
```
model_data_ngo.head()
```

[22]:
```
   child_mort   exports    health   imports    income inflation life_expec  \
0    1.479588 -0.668039 -0.629778 -0.733291 -0.960575  0.387667  -1.825310
1   -0.560024 -0.542389 -0.473807 -0.472674 -0.395590 -0.404004   0.682454
2   -0.263504 -0.476048 -0.530344 -0.560668 -0.193907  1.452825   0.707406
3    2.194560 -0.419165 -0.589272 -0.543598 -0.669255  2.215708  -1.338729
4   -0.734610 -0.027297 -0.150953  0.306143  0.227115 -0.891802   0.744836

  total_fer      gdpp
0  2.020718 -0.757874
1 -0.887331 -0.523775
2 -0.022587 -0.499286
3  2.049310 -0.560839
```

```
4 -0.552591  0.012991
```

[23]:
```python
from sklearn.metrics  import silhouette_score
from sklearn.cluster  import KMeans
sil_score = []
for i in range(2,11):
    kmeans = KMeans(n_clusters=i).fit(model_data_ngo)
    sil_score.append([i,silhouette_score(model_data_ngo,kmeans.labels_)])
plt.plot(pd.DataFrame(sil_score)[0],pd.DataFrame(sil_score)[1])
plt.show()
```

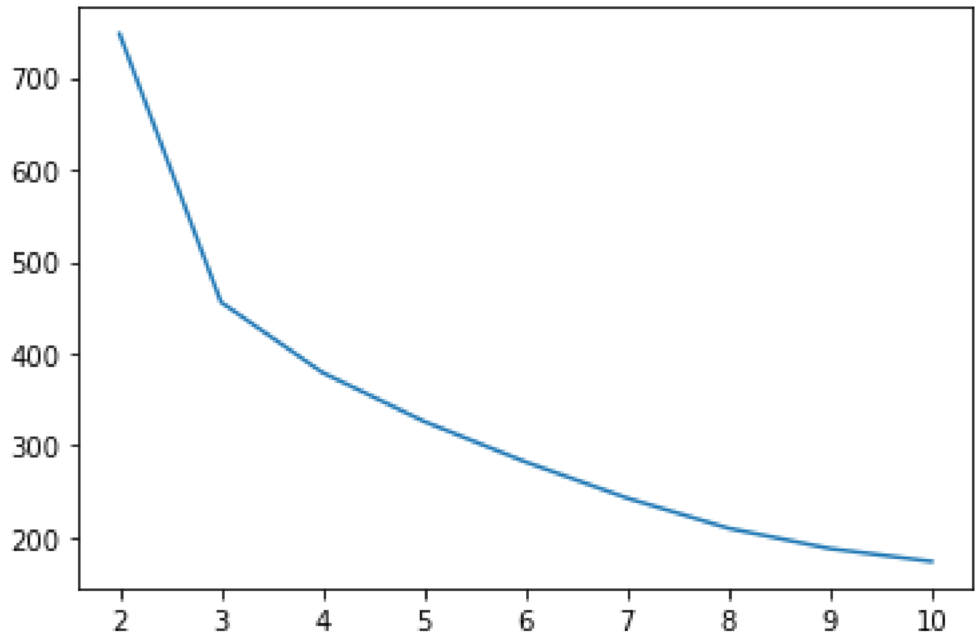


As per Silhoutte score dataset is suitable to divide it into 3 clusters

7 Elbow Curve

Another approch to find the appropriate number of clusters is elbow curve. The idea is to run k means algorithm for a number of k values and check sse for each value to find appropriate number of k.

[24]:
```python
## let's make the elbow curve for our dataset
elbow_plot = []
for i in range(2,11):
    kmeans = KMeans(n_clusters=i).fit(model_data_ngo)
    elbow_plot.append([i,kmeans.inertia_])
plt.plot(pd.DataFrame(elbow_plot)[0],pd.DataFrame(elbow_plot)[1])
plt.show()
```



If we draw a straight line from the top point of the elbow curve to the last point of the elbow curve it is clear that sse or sum of squared error is minimum for k = 3 Hence we will chose k is equal to 3 for our k means algorithm.

8 Model Building

[25]:
```
## let's run our k means algorithm for k = 3
kmeans = KMeans(n_clusters=3,random_state=10).fit(model_data_ngo)
kmeans.labels_
## check labels
```

[25]:
```
array([2, 0, 0, 2, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 2, 0, 0, 0, 2,
       0, 1, 0, 2, 2, 0, 2, 1, 0, 2, 2, 0, 0, 0, 2, 2, 2, 0, 2, 0, 1, 1,
       1, 0, 0, 0, 0, 2, 2, 0, 0, 1, 1, 2, 2, 0, 1, 2, 1, 0, 0, 2, 2, 0,
       2, 0, 1, 0, 0, 0, 2, 1, 1, 1, 0, 1, 0, 0, 2, 2, 1, 0, 2, 0, 0, 2,
       2, 0, 0, 1, 0, 2, 2, 0, 0, 2, 1, 2, 0, 0, 0, 0, 0, 0, 2, 0, 2, 0,
       1, 1, 2, 2, 1, 0, 2, 0, 0, 0, 0, 0, 1, 1, 0, 0, 2, 0, 0, 2, 0, 0,
       2, 1, 1, 1, 2, 2, 1, 1, 0, 0, 2, 0, 1, 1, 0, 2, 0, 2, 2, 0, 0, 0,
       0, 2, 0, 1, 1, 1, 0, 0, 0, 0, 0, 2, 2])
```

[26]:
```
help_ngo.head()
```

[26]:
```
       country  child_mort    exports    health   imports   income  \
0  Afghanistan        90.2    70.4688   41.9174   248.297   1610.0
1      Albania        16.6  1145.2000  267.8950  1987.740   9930.0
```

```
2             Algeria        27.3   1712.6400   185.9820   1400.440   12900.0
3              Angola       116.0   2199.1900   100.6050   1514.370    5900.0
4   Antigua and Barbuda      10.3   5551.0000   735.6600   7185.800   19100.0

   inflation  life_expec  total_fer     gdpp
0       9.44        56.2      5.820    553.0
1       4.49        76.3      1.650   4090.0
2      16.10        76.5      2.890   4460.0
3      20.87        60.1      5.861   3530.0
4       1.44        76.8      2.130  12200.0
```

[27]:
```
## add label column in help_ngo
help_ngo['cluster_id'] = kmeans.labels_
```

[28]:
```
## check head of the data frame once
help_ngo.head()
```

[28]:
```
              country  child_mort    exports     health    imports    income  \
0         Afghanistan        90.2    70.4688    41.9174    248.297    1610.0
1             Albania        16.6  1145.2000   267.8950   1987.740    9930.0
2             Algeria        27.3  1712.6400   185.9820   1400.440   12900.0
3              Angola       116.0  2199.1900   100.6050   1514.370    5900.0
4   Antigua and Barbuda      10.3  5551.0000   735.6600   7185.800   19100.0

   inflation  life_expec  total_fer     gdpp  cluster_id
0       9.44        56.2      5.820    553.0           2
1       4.49        76.3      1.650   4090.0           0
2      16.10        76.5      2.890   4460.0           0
3      20.87        60.1      5.861   3530.0           2
4       1.44        76.8      2.130  12200.0           0
```

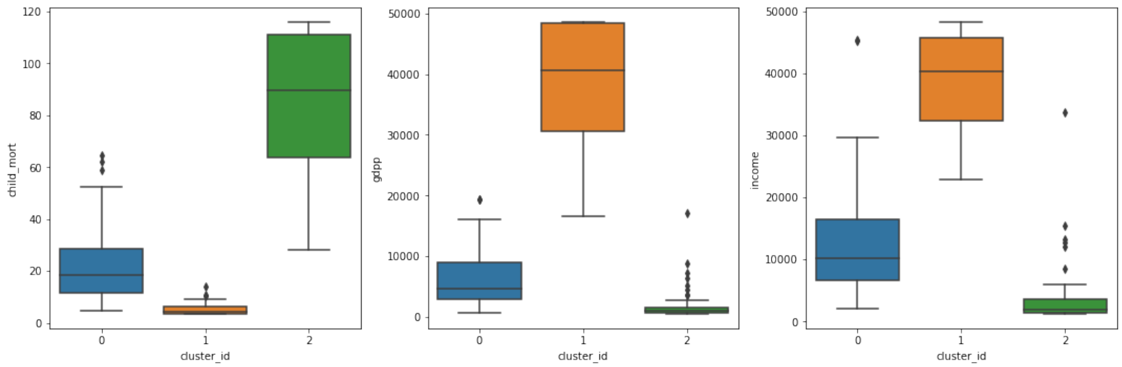
9 Cluster visualization

[29]:
```
plt.figure(figsize=(15,5))



plt.subplot(1,3,1)
sns.boxplot(x='cluster_id',y='child_mort',data=help_ngo)
plt.subplot(1,3,2)
sns.boxplot(x='cluster_id',y='gdpp',data=help_ngo)
plt.subplot(1,3,3)
sns.boxplot(x='cluster_id',y='income',data=help_ngo)

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



From the above graph it is clear that countries of cluster id 2 needed aid more than other countries as their child mortality rate is more than other countries and also their income and gdpp is very low compared to other countries.

[30]:
```
recomend = help_ngo[help_ngo.cluster_id==2]
recomend.sort_values(by='child_mort',ascending=False).head(10)
```

[30]:
```
                      country  child_mort    exports     health   imports  \
32                       Chad       116.0   330.0960   40.63410   390.195
31   Central African Republic       116.0    70.4688   26.71592   169.281
113                   Nigeria       116.0   589.4900  118.13100   405.420
132              Sierra Leone       116.0    70.4688   52.26900   169.281
37           Congo, Dem. Rep.       116.0   137.2740   26.71592   169.281
66                      Haiti       116.0   101.2860   45.74420   428.314
112                     Niger       116.0    77.2560   26.71592   170.868
97                       Mali       116.0   161.4240   35.25840   248.508
25               Burkina Faso       116.0   110.4000   38.75500   170.200
3                      Angola       116.0  2199.1900  100.60500  1514.370

     income  inflation  life_expec  total_fer    gdpp  cluster_id
32   1930.0       6.39       56.50      5.861   897.0           2
31   1213.0       2.01       55.78      5.210   465.9           2
113  5150.0      20.87       60.50      5.840  2330.0           2
132  1220.0      17.20       55.78      5.200   465.9           2
37   1213.0      20.80       57.50      5.861   465.9           2
66   1500.0       5.45       55.78      3.330   662.0           2
112  1213.0       2.55       58.80      5.861   465.9           2
97   1870.0       4.37       59.50      5.861   708.0           2
25   1430.0       6.81       57.90      5.861   575.0           2
3    5900.0      20.87       60.10      5.861  3530.0           2
```

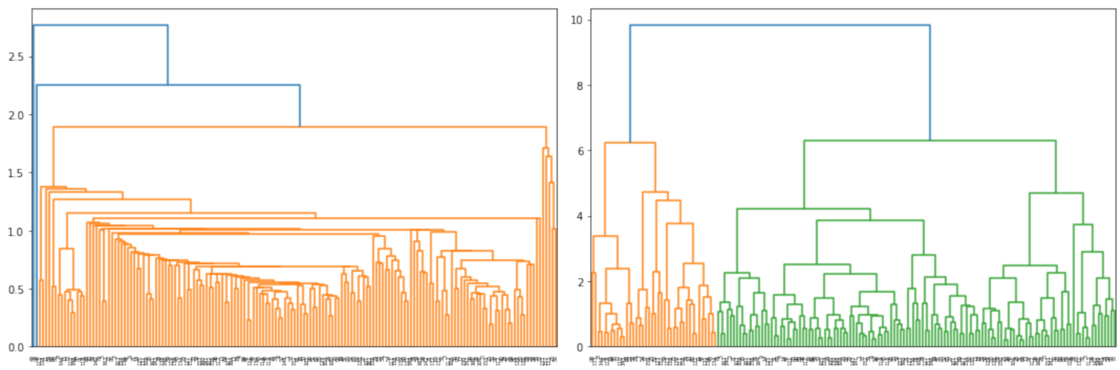
Recommendation based on clutering.

10 Hierarchical Clustering

[31]:
```python
import scipy
from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram
from scipy.cluster.hierarchy import cut_tree
```

[32]:
```python
## drop country column
```

[33]:
```python
## single linkage
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
single_linkage = linkage(model_data_ngo,method='single',metric='euclidean')
dendrogram(single_linkage)
## complete linkage
plt.subplot(1,2,2)
complete_linkage = linkage(model_data_ngo,method='complete',metric='euclidean')
dendrogram(complete_linkage)
plt.tight_layout()
plt.show()
```



From above two graphs it is shown that if i cut the tree at level 2.0 it will give three distinct clusters.

[34]:
```python
cluster_id2 = cut_tree(complete_linkage,n_clusters=3).reshape(-1,)
cluster_id2
```

[34]:
```
array([0, 1, 1, 0, 1, 1, 1, 2, 2, 1, 2, 2, 1, 1, 1, 2, 1, 0, 1, 1, 1, 1,
       1, 2, 1, 0, 0, 1, 0, 2, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 2, 2,
       2, 1, 1, 1, 1, 0, 0, 1, 1, 2, 2, 0, 0, 1, 2, 0, 2, 1, 1, 0, 0, 1,
       0, 1, 2, 1, 1, 1, 0, 2, 2, 2, 1, 2, 1, 1, 0, 1, 2, 1, 0, 1, 1, 0,
       0, 2, 1, 2, 1, 0, 0, 1, 1, 0, 2, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       2, 2, 0, 0, 2, 2, 0, 1, 1, 1, 1, 1, 2, 2, 1, 1, 0, 1, 2, 0, 1, 1,
       0, 2, 2, 2, 1, 1, 2, 2, 1, 1, 0, 1, 2, 2, 1, 0, 1, 0, 0, 1, 1, 1,
```

```
        1, 0, 1, 2, 2, 2, 1, 1, 1, 1, 1, 0, 0])
```

[35]:
```
help_ngo['cluster_id2'] = cluster_id2
help_ngo.head()
```

[35]:

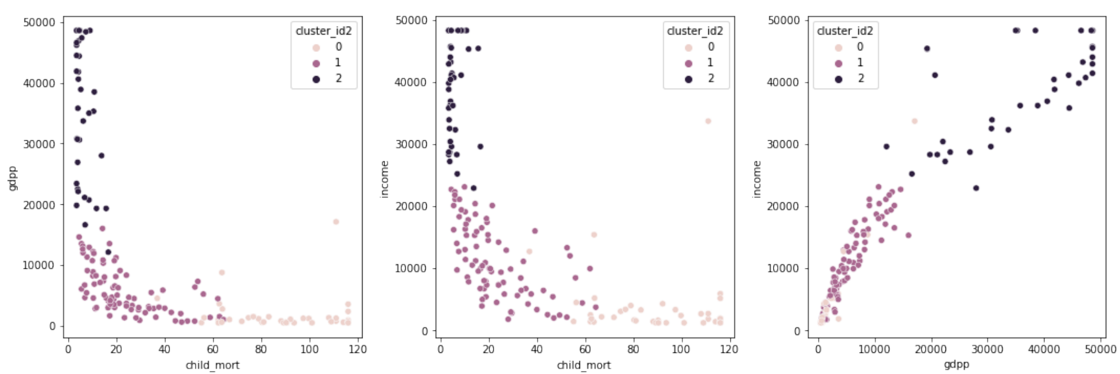
	country	child_mort	exports	health	imports	income
0	Afghanistan	90.2	70.4688	41.9174	248.297	1610.0
1	Albania	16.6	1145.2000	267.8950	1987.740	9930.0
2	Algeria	27.3	1712.6400	185.9820	1400.440	12900.0
3	Angola	116.0	2199.1900	100.6050	1514.370	5900.0
4	Antigua and Barbuda	10.3	5551.0000	735.6600	7185.800	19100.0

	inflation	life_expec	total_fer	gdpp	cluster_id	cluster_id2
0	9.44	56.2	5.820	553.0	2	0
1	4.49	76.3	1.650	4090.0	0	1
2	16.10	76.5	2.890	4460.0	0	1
3	20.87	60.1	5.861	3530.0	2	0
4	1.44	76.8	2.130	12200.0	0	1

[36]:
```
## lets visualize clusters
plt.figure(figsize=(15,5))
plt.subplot(1,3,1)
sns.scatterplot(x='child_mort',y='gdpp',data=help_ngo,hue='cluster_id2')

plt.subplot(1,3,2)
sns.scatterplot(x='child_mort',y='income',data=help_ngo,hue='cluster_id2')

plt.subplot(1,3,3)
sns.scatterplot(x='gdpp',y='income',data=help_ngo,hue='cluster_id2')
plt.tight_layout()
plt.show()
```



It is clear from the graph that countries belongs to cluster id 0 is high in child mortality and low in respect of income and gdpp.

[37]:
```python
## recommendation based on hierarchical clustering
recomend2 = help_ngo[help_ngo['cluster_id2']==0]
recomend2.sort_values('child_mort',ascending=False).head()
```

[37]:
```
          country  child_mort    exports     health   imports  income  \
132  Sierra Leone       116.0    70.4688   52.26900   169.281  1220.0
32           Chad       116.0   330.0960   40.63410   390.195  1930.0
3          Angola       116.0  2199.1900  100.60500  1514.370  5900.0
66          Haiti       116.0   101.2860   45.74420   428.314  1500.0
112         Niger       116.0    77.2560   26.71592   170.868  1213.0

     inflation  life_expec  total_fer    gdpp  cluster_id  cluster_id2
132      17.20       55.78      5.200   465.9           2            0
32        6.39       56.50      5.861   897.0           2            0
3        20.87       60.10      5.861  3530.0           2            0
66        5.45       55.78      3.330   662.0           2            0
112       2.55       58.80      5.861   465.9           2            0
```

[38]:
```python
## lets store the value of average of income and gdpp of cluster 0
avg_income = recomend2['income'].mean()
avg_gdpp = recomend2['gdpp'].mean()
avg_child_mort = recomend2['child_mort'].mean()
```

[39]:
```python
top_recom = recomend2[(recomend2.income<=avg_income) & (recomend2.
 ↪gdpp<=avg_gdpp) & (recomend2.child_mort>=avg_child_mort)]
## final ist of top recommendation
```

Sorting countries of cluster 0 showing only those countries whose child mortality rate is higher than average of cluster 0 and income and gdpp is less than average of cluster 0.

[40]:
```python
top_recom.sort_values(by='child_mort',ascending=False)
```

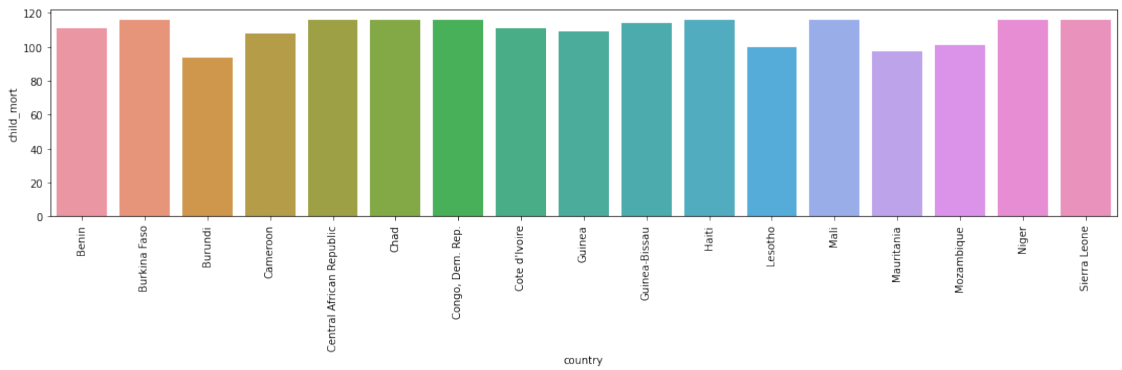
[40]:
```
                      country  child_mort   exports     health   imports  \
132              Sierra Leone       116.0   70.4688   52.26900   169.281
112                     Niger       116.0   77.2560   26.71592   170.868
97                       Mali       116.0  161.4240   35.25840   248.508
31   Central African Republic       116.0   70.4688   26.71592   169.281
32                       Chad       116.0  330.0960   40.63410   390.195
37           Congo, Dem. Rep.       116.0  137.2740   26.71592   169.281
66                      Haiti       116.0  101.2860   45.74420   428.314
25               Burkina Faso       116.0  110.4000   38.75500   170.200
64              Guinea-Bissau       114.0   81.5030   46.49500   192.544
17                      Benin       111.0  180.4040   31.07800   281.976
40              Cote d'Ivoire       111.0  617.3200   64.66000   528.260
63                     Guinea       109.0  196.3440   31.94640   279.936
28                   Cameroon       108.0  290.8200   67.20300   353.700
106                Mozambique       101.0  131.9850   26.71592   193.578
87                    Lesotho        99.7  460.9800  129.87000  1181.700
```

99	Mauritania	97.4	608.4000	52.92000	734.400
26	Burundi	93.6	70.4688	26.79600	169.281

	income	inflation	life_expec	total_fer	gdpp	cluster_id	cluster_id2
132	1220.0	17.200	55.78	5.200	465.9	2	0
112	1213.0	2.550	58.80	5.861	465.9	2	0
97	1870.0	4.370	59.50	5.861	708.0	2	0
31	1213.0	2.010	55.78	5.210	465.9	2	0
32	1930.0	6.390	56.50	5.861	897.0	2	0
37	1213.0	20.800	57.50	5.861	465.9	2	0
66	1500.0	5.450	55.78	3.330	662.0	2	0
25	1430.0	6.810	57.90	5.861	575.0	2	0
64	1390.0	2.970	55.78	5.050	547.0	2	0
17	1820.0	0.885	61.80	5.360	758.0	2	0
40	2690.0	5.390	56.30	5.270	1220.0	2	0
63	1213.0	16.100	58.00	5.340	648.0	2	0
28	2660.0	1.910	57.30	5.110	1310.0	2	0
106	1213.0	7.640	55.78	5.560	465.9	2	0
87	2380.0	4.150	55.78	3.300	1170.0	2	0
99	3320.0	18.900	68.20	4.980	1200.0	2	0
26	1213.0	12.300	57.70	5.861	465.9	2	0

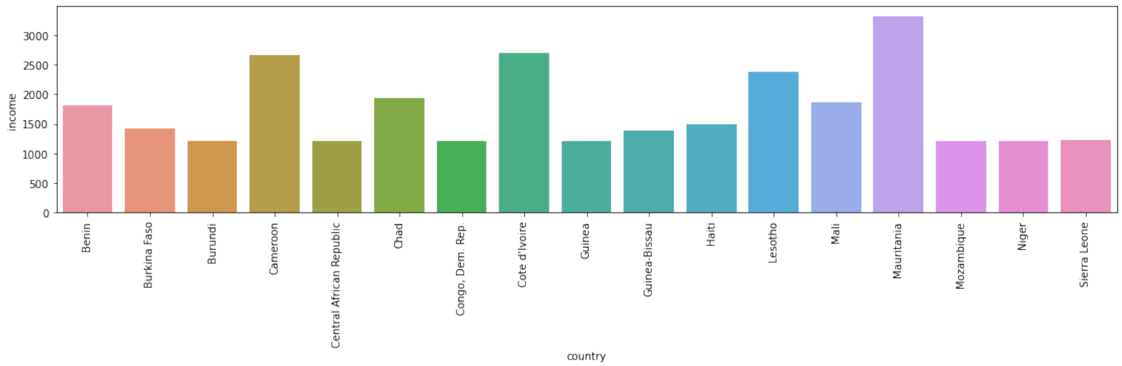
Above countries are high in child mortality and also low in income and gdpp

[41]:
```
## lets visualise final recommendation
plt.figure(figsize=(15,5))
plt.subplot(1,1,1)
ax = sns.barplot(x='country',y='child_mort',data=top_recom)
ax.set_xticklabels(ax.get_xticklabels(), rotation=90 , fontsize=10)
plt.tight_layout()
plt.show()
```

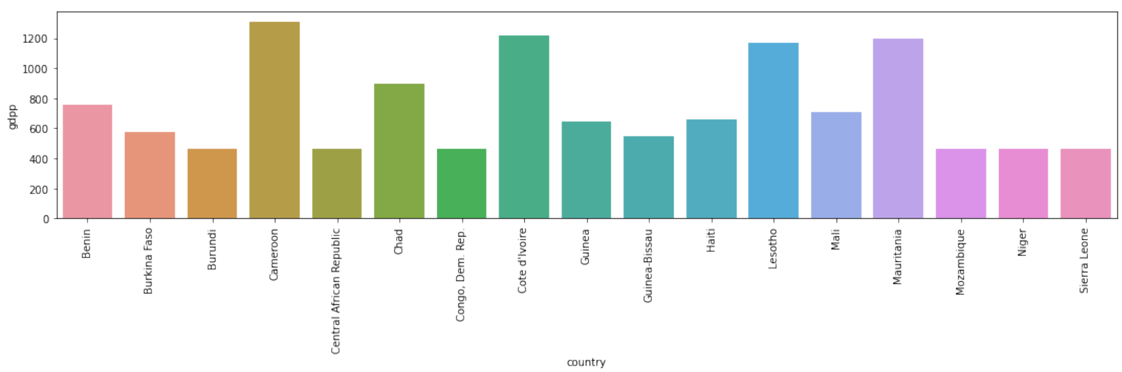


[42]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,1,1)
```

```
ax = sns.barplot(x='country',y='income',data=top_recom)
ax.set_xticklabels(ax.get_xticklabels(), rotation=90 , fontsize=10)
plt.tight_layout()
plt.show()
```



[43]:
```
plt.figure(figsize=(15,5))
plt.subplot(1,1,1)
ax = sns.barplot(x='country',y='gdpp',data=top_recom)
ax.set_xticklabels(ax.get_xticklabels(), rotation=90 , fontsize=10)
plt.tight_layout()
plt.show()
```



11 Conclusion

According to the above graphs and my full analysis i want to recommend the following 5 countries based on some socio economic factor like high child mortality , low income and low gdpp. 1. Sierra Leone 2. Niger 3. Mali 4. Central African Republic 5. Chad