Title:

Clustering the Countries by performing K-means and Hierarchical Clustering Algorithms

Problem Statement

HELP International 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. So, CEO has to make decision to choose the countries that are in the direst need of aid. Hence, your Job as a Data scientist is to categorise the countries using some socio-economic and health factors that determine the overall development of the country. Then you need to suggest the countries which the CEO needs to focus on the most.

Import libraries into the dataset

In [1]:
```
# for supressing warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#load the libaries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [3]:
```
# To display data dictionary fully
pd.set_option('display.max_columns', None)
pd.set_option('display.expand_frame_repr', False)
pd.set_option('max_colwidth', 1000)
```

In [4]:
```
# For Hopkins Statistics
from sklearn.neighbors import NearestNeighbors
from random import sample
from numpy.random import uniform
from math import isnan
```

In [5]:
```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
```

In [6]:
```
# For K Means
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

In [7]:
```
# For Hierarchical Clustering
from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram
from scipy.cluster.hierarchy import cut_tree
```

Read the csv file/dataset

In [8]:
```
country_df = pd.read_csv('country-data.csv')
country_df.head() # Checking the top 5 rows of the dataframe
```

Out[8]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	55
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	409
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	446
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	353
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	1220

In [9]:
```
# checking botton 5 rows of the dataframe
country_df.tail()
```

Out[9]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gd
162	Vanuatu	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	29
163	Venezuela	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	135
164	Vietnam	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	13
165	Yemen	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	13
166	Zambia	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	14

In [10]:
```
# Checking the shape of the dataframe
country_df.shape
```

Out[10]: (167, 10)

In [11]:
```
# How many types of each data type column exists and total memory usage
country_df.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
```

In [12]:
```
# To check the duplicates in the dataset
country_df.duplicated().sum()
```

Out[12]:
```
0
```

In [13]:
```
# To check unique in the each categorical column
country_df.nunique().sort_values()
```

Out[13]:
```
life_expec    127
total_fer     138
child_mort    139
exports       147
health        147
imports       151
income        156
inflation     156
gdpp          157
country       167
dtype: int64
```

In [14]:
```
# Checking the numerical columns data distribution
country_df.describe()
```

Out[14]:

	child_mort	exports	health	imports	income	inflation	life_expec
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000
mean	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689
std	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172
min	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000
25%	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000
50%	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000
75%	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000
max	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000

Exploratory Data Analysis (EDA) & Data Cleaning

In [15]:
```
# To check the null value in each column
print(country_df.isnull().sum())
```

```
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
```

In [16]:
```
country_df.head()
```

Out[16]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	55
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	409
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	446
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	353
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	1220

comment

- Here health, exports, imports are in percentage of gdp. Hence, we have to convert these percentage values to actual values.

In [17]:
```
country_df['exports'] = country_df['exports'] * country_df['gdpp']/100
country_df['imports'] = country_df['imports'] * country_df['gdpp']/100
country_df['health'] = country_df['health'] * country_df['gdpp']/100
```

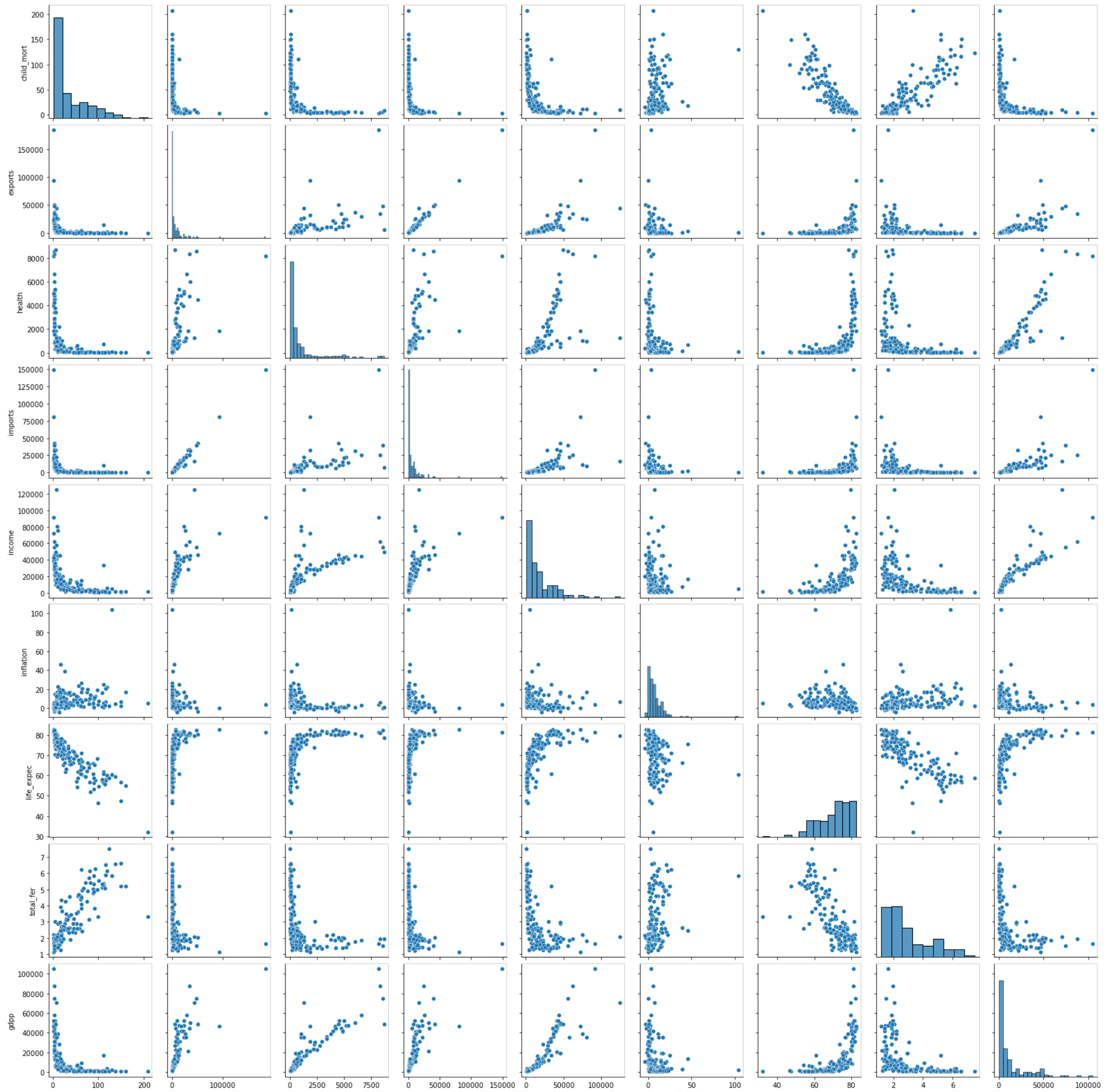
In [18]:
```
country_df.head() # Lets check data after conversion
```

Out[18]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	g
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	1

Bivariate Analysis

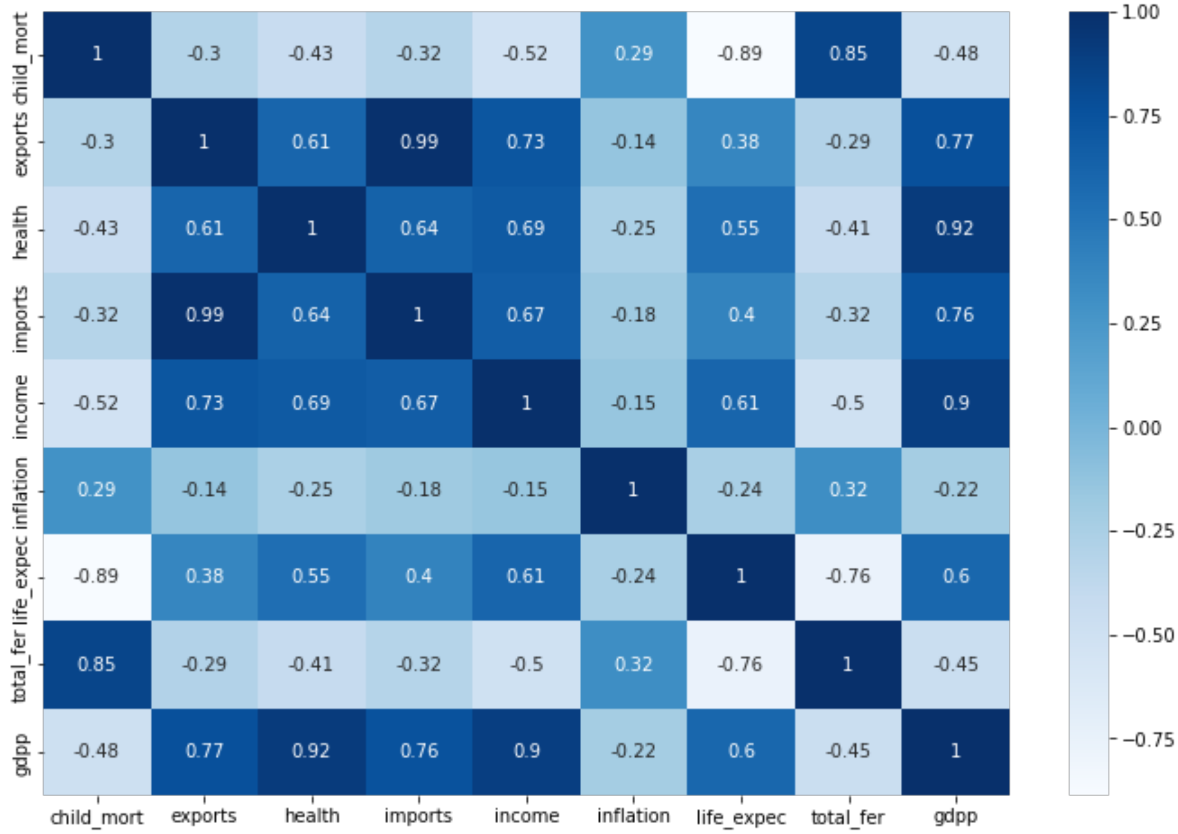
In [19]:
```
sns.pairplot(country_df)
plt.show( )
```



Comment

- gdpp is linearly related with exports, health, imports, income. (positively correlated)
- child_mort is negatively correlated with life_expec (greater the child mortality, lesser the life expectancy)and positively correlated with total_fer

In [20]:
```
plt.figure(figsize=(12,8))
sns.heatmap(country_df.corr( ),cmap='Blues',annot=True)
plt.show( )
```



Comment:

Following feature pairs are highly correlated (positively or negatively)

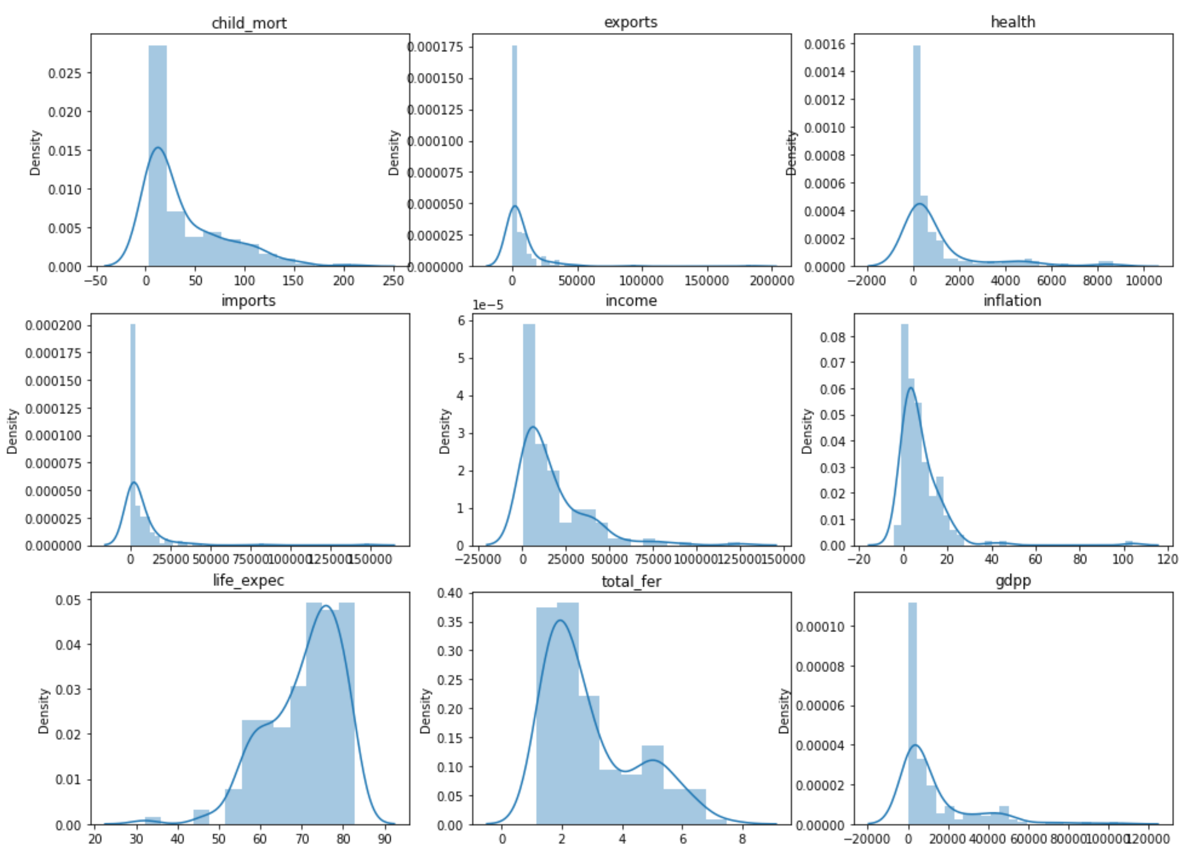
- imports and exports (correlation factor = 0.99)
- health and gdpp (correlation factor = 0.92)
- income and gdpp (correlation factor = 0.9)
- life_expce and child_mort (correlation factor = -0.89)
- total_fer and child_mort (correlation factor = 0.85)

univariate Analysis

In [21]:
```
numerical_cols = list(country_df.columns) # Get all column names
numerical_cols.remove('country') # Remove country as its not numerical
numerical_cols
```

Out[21]:
```
['child_mort',
 'exports',
 'health',
 'imports',
 'income',
 'inflation',
 'life_expec',
 'total_fer',
 'gdpp']
```

In [22]:
```
# Distplot
plt.figure(figsize=[16,12])
i=1 # to track the ith plot in the subplot
for col in numerical_cols:
    plt.subplot(3,3,i)
    sns.distplot(country_df[col])
    plt.title(col)
    plt.xlabel('')
    i+=1
```



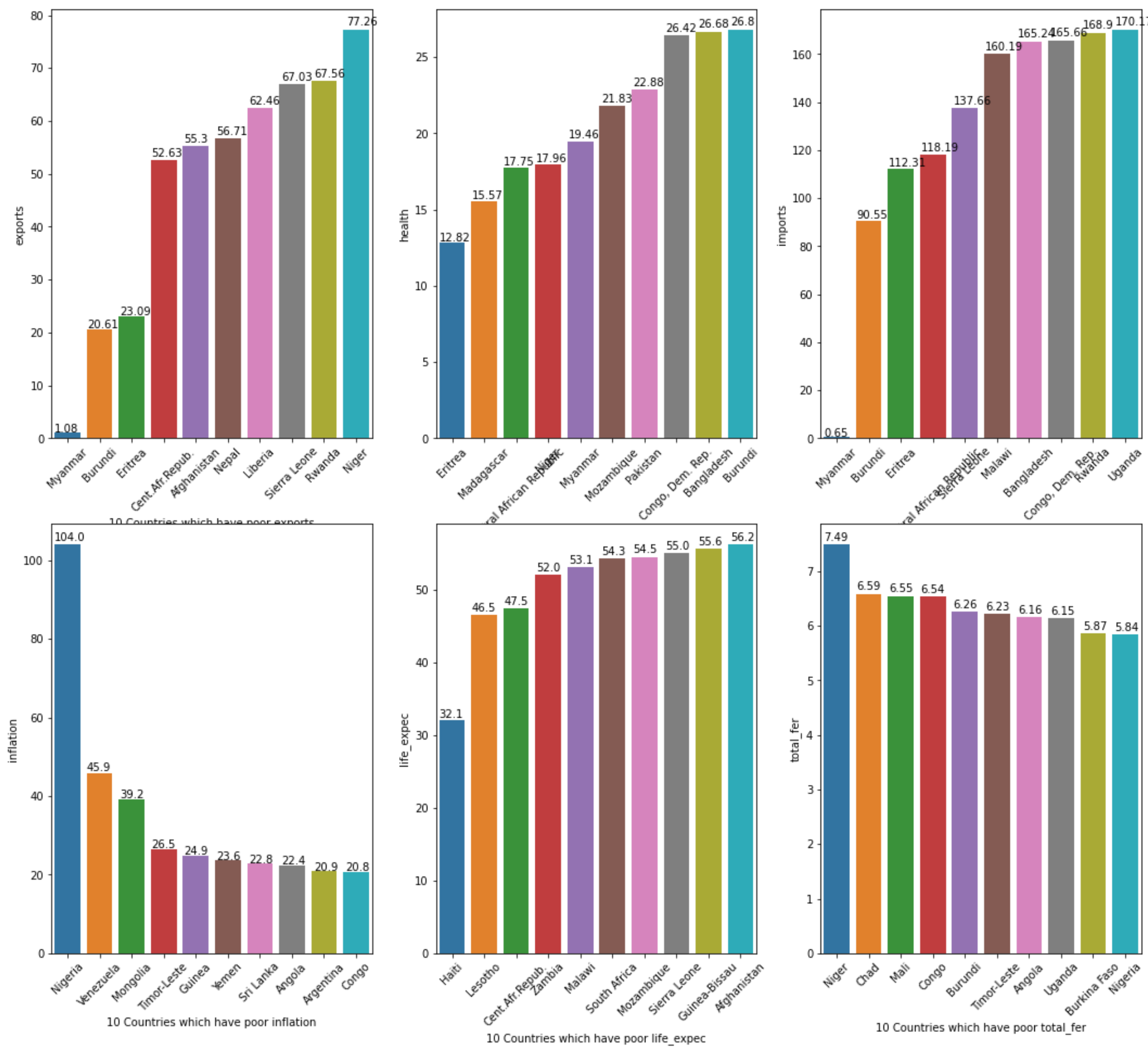
comment

- Expect life expecteancy(life_expec) all the features are right-skewwd.

In [23]:
```
# Visualize bottom 10 countries w.r.t exports, imports, health, inflation, lif

def plot_bottom10_countries(y_column, sort_order=True, truncate_string=False):
    sorted_df = country_df[['country',y_column]].sort_values(y_column, ascendi
    sorted_df[y_column] = sorted_df[y_column].round(2) # roundoff to 2 decimal
    if truncate_string: # truncate only for subplots proper visualization purp
        sorted_df.loc[sorted_df['country'].str.contains('Central African Repub
        sorted_df.loc[sorted_df['country'].str.contains('Congo'),'country'] =
        sorted_df.loc[sorted_df['country'].str.contains('Equatorial Guinea'),'

    ax = sns.barplot(x='country', y=y_column, data= sorted_df)
    for each_bar in ax.patches:
        ax.annotate(str(each_bar.get_height()), (each_bar.get_x() * 1.01 , eac
    plt.ylabel(y_column)
    plt.xlabel('10 Countries which have poor %s' %y_column)
    ax.set_xticklabels(sorted_df['country'], rotation=45, ha='center')
```

In [24]:

```
plt.figure(figsize = (18,16))
plt.subplot(2,3,1)
plot_bottom10_countries("exports", sort_order=True, truncate_string=True)
plt.subplot(2,3,2)
plot_bottom10_countries("health")
plt.subplot(2,3,3)
plot_bottom10_countries("imports")
plt.subplot(2,3,4)
plot_bottom10_countries("inflation", sort_order=False, truncate_string=True)
plt.subplot(2,3,5)
plot_bottom10_countries("life_expec", sort_order=True, truncate_string=True)
plt.subplot(2,3,6)
plot_bottom10_countries("total_fer", sort_order=False, truncate_string=True)
plt.show()
```



comment:

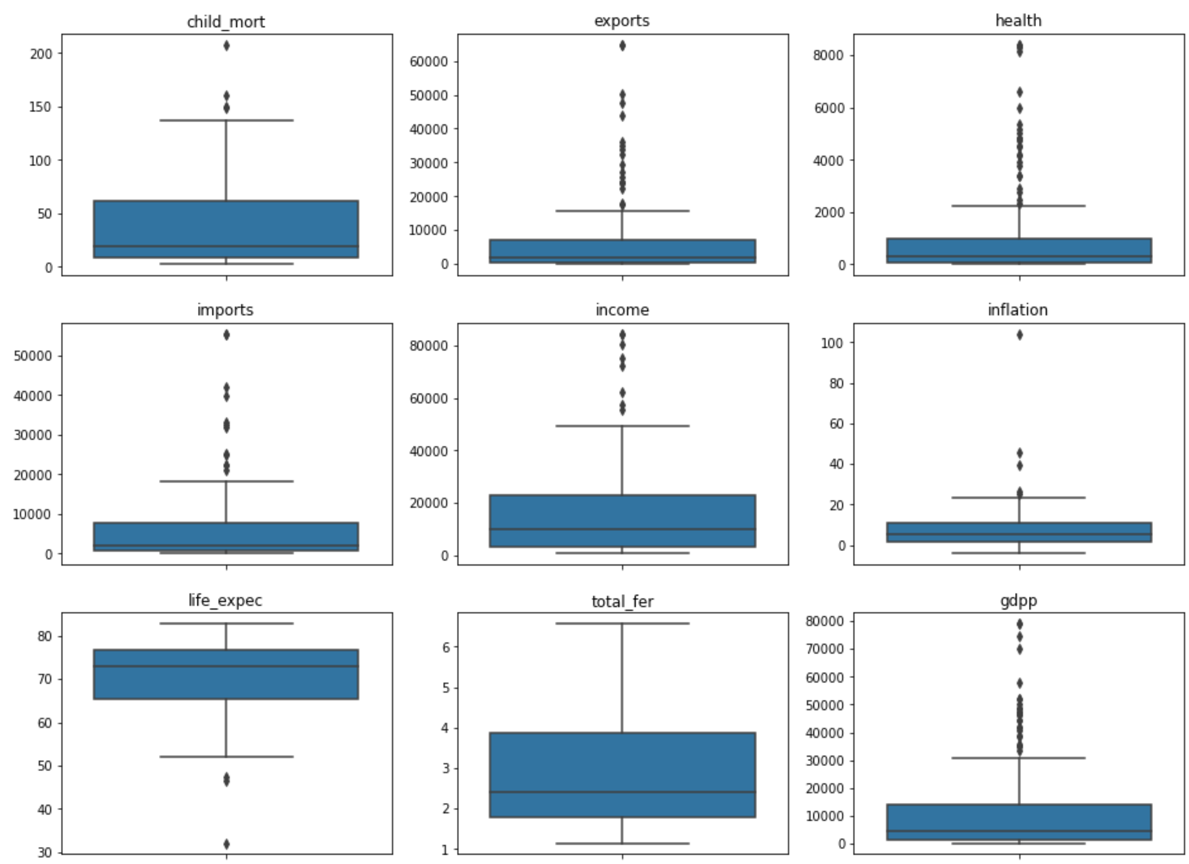
- exports, health follow GDPP and income plots pattern and the countries which had low GDPP seem to have low exports.
- imports show a different trend indicating that these countries manufacture a lot of goods

sufficiently.
- inflation shows countries that are not stable and not self-sufficient and suffering from other political and social issues.

Handiling Outliers

In [101]:
```
def boxplot_for_outlier_analysis():
    plt.figure(figsize=[16,12])
    i=1 # to track the ith plot in the subplot
    for col in numerical_cols:
        plt.subplot(3,3,i)
        sns.boxplot(y=country_df[col])
        plt.title(col)
        plt.ylabel('')
        i+=1
```

In [102]:
```
boxplot_for_outlier_analysis()
```



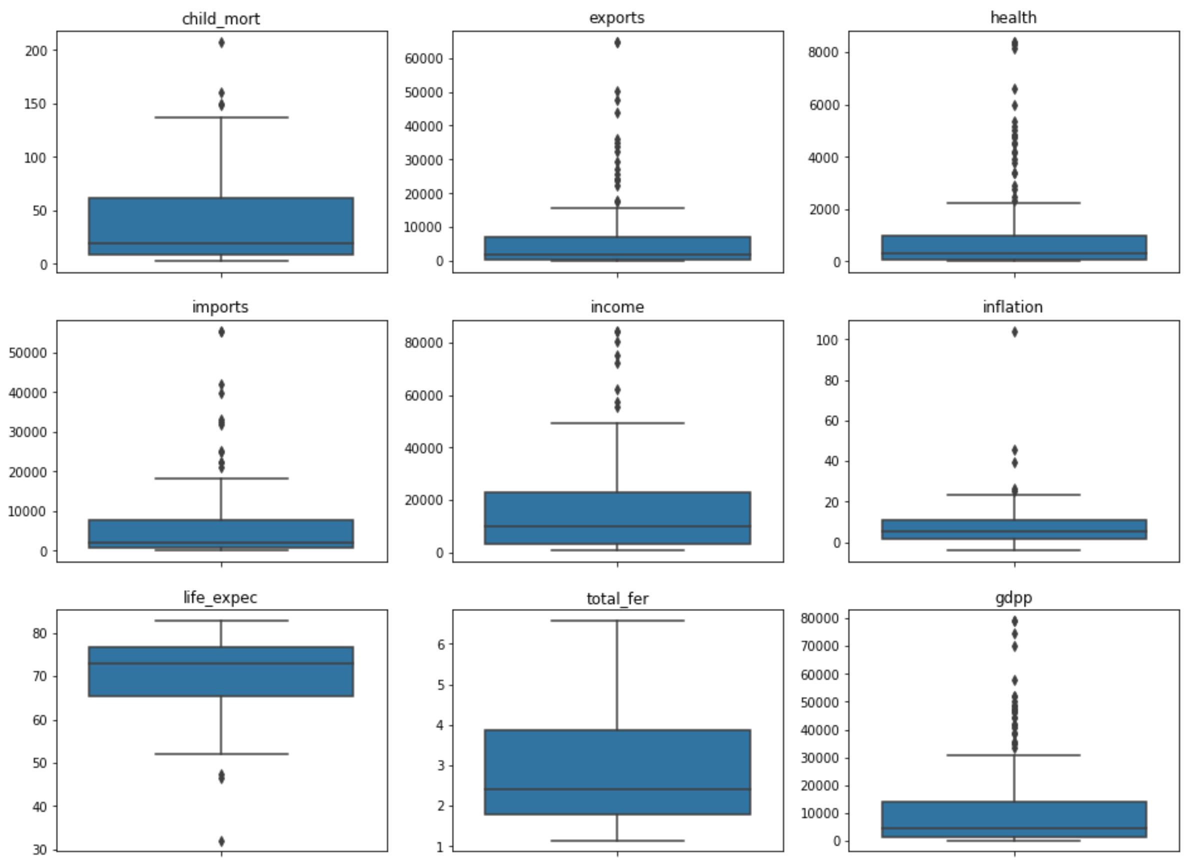
There are different ranges in capping the outliers:

- Soft range: 1th and 99th percentile.
- Mid range: 5th and 95th percentile.
- 25th and 75th percentile.

We will be doing **Soft capping** as the data points are few and the capping should not influence the clusters much.

In [27]:
```
higher_outlier_cols = ['exports','imports','health','income','total_fer','gdpp

for col in higher_outlier_cols:
    Q4 = country_df[col].quantile(0.99) # Get 99th quantile
    country_df.loc[country_df[col] >= Q4, col] = Q4 # outlier capping
```

In [28]:
```
boxplot_for_outlier_analysis()
```



In [29]:
```
country_df.describe(percentiles=[.1,.5,.25,.75,.90,.95,.99])
```

Out[29]:

	child_mort	exports	health	imports	income	inflation	life_exp
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.0000
mean	38.270060	6538.214776	1054.206622	5873.135222	16857.550898	7.781832	70.5556
std	40.328931	11415.308590	1790.845342	9422.700869	17957.012855	10.570704	8.8931
min	2.600000	1.076920	12.821200	0.651092	609.000000	-4.210000	32.1000
10%	4.200000	110.224800	36.502560	211.005600	1524.000000	0.587800	57.8200
25%	8.250000	447.140000	78.535500	640.215000	3355.000000	1.810000	65.3000
50%	19.300000	1777.440000	321.886000	2045.580000	9960.000000	5.390000	73.1000
75%	62.100000	7278.000000	976.940000	7719.600000	22800.000000	10.750000	76.8000
90%	100.220000	17760.600000	3825.416000	15034.280000	41220.000000	16.640000	80.4000
95%	116.000000	31385.100000	4966.701000	24241.560000	48290.000000	20.870000	81.4000
99%	153.400000	55136.308400	8352.982736	46629.102600	81883.160000	41.478000	82.3700
max	208.000000	64794.260000	8410.330400	55371.390000	84374.000000	104.000000	82.8000

Hopkins test

In [30]:
```
#Calculating the Hopkins statistic

def hopkins(X):
    d = X.shape[1]
    #d = len(vars) # columns
    n = len(X) # rows
    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
        ujd.append(u_dist[0][1])
        w_dist, _ = nbrs.kneighbors(X.iloc[rand_X[j]].values.reshape(1, -1), 2
        wjd.append(w_dist[0][1])

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

    return H
```

In [105]:
```
hopkins(country_df[numerical_cols])
```

Out[105]:
```
0.9308205363599092
```

comment

- Hopkins Statistic over .70 is a good score that indicated that the data is good for cluster analysis.
- A 'Hopkins Statistic' 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.

In [32]:
```
# Scaling on numerical features

scaler = StandardScaler() # instantiate scaler

country_df_scaled = scaler.fit_transform(country_df[numerical_cols]) # fit par
country_df_scaled = pd.DataFrame(country_df_scaled, columns = numerical_cols)
country_df_scaled
```

Out[32]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	
0	1.291532	-0.569622	-0.566958	-0.598741	-0.851668	0.157336	-1.619092	1.926396	-0.7
1	-0.538949	-0.473858	-0.440393	-0.413584	-0.386946	-0.312347	0.647866	-0.865054	-0.4
2	-0.272833	-0.424000	-0.486271	-0.476100	-0.221053	0.789274	0.670423	-0.034983	-0.4
3	2.007808	-0.381249	-0.534088	-0.463973	-0.612045	1.387054	-1.179234	2.153997	-0.5
4	-0.695634	-0.086742	-0.178410	0.139728	0.125254	-0.601749	0.704258	-0.543736	-0.0
...	...	...	...	...	...	...	...	...	
162	-0.225578	-0.452874	-0.503105	-0.458563	-0.776821	-0.489784	-0.852161	0.373359	-0.5
163	-0.526514	-0.236420	-0.219189	-0.372256	-0.019971	3.616865	0.546361	-0.316136	0.0
164	-0.372315	-0.491607	-0.540250	-0.513337	-0.690802	0.409732	0.286958	-0.664231	-0.6
165	0.448417	-0.539950	-0.552429	-0.577202	-0.691361	1.500916	-0.344633	1.156572	-0.6
166	1.114951	-0.527016	-0.542272	-0.577149	-0.758388	0.590015	-2.092785	1.645243	-0.6

167 rows × 9 columns

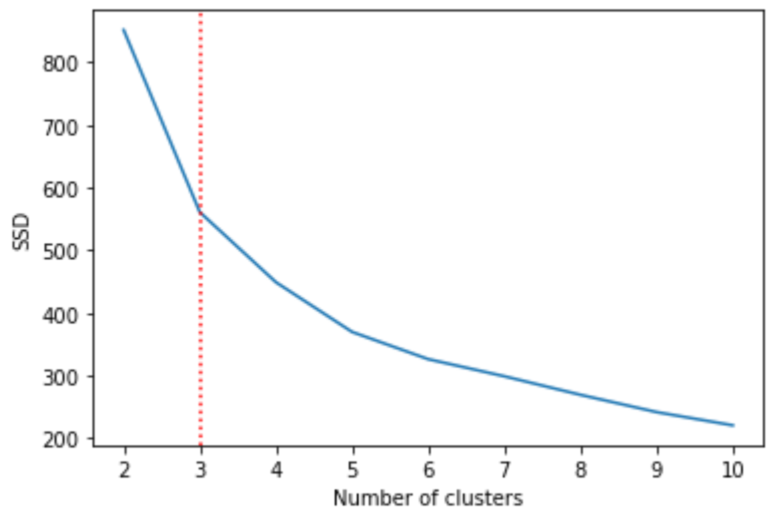
K-means algorithm

Metrics to choose the value of K

- There are two common approaches that help to find k:

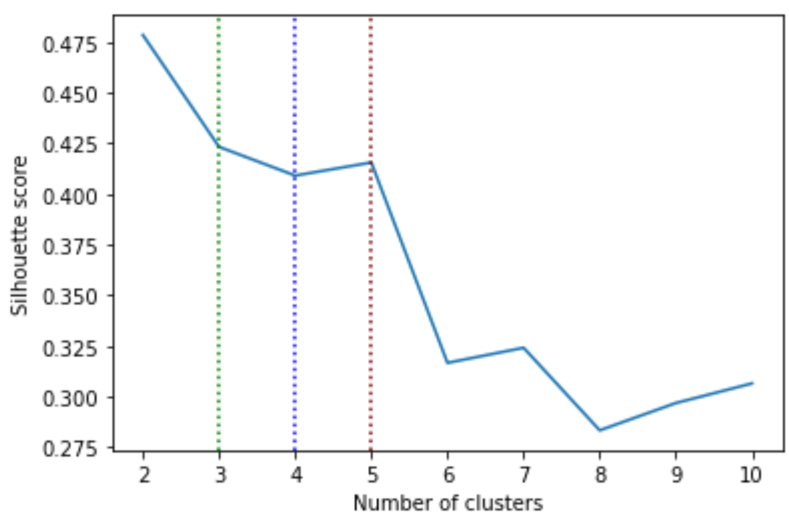
1. Elbow method
2. Silhouette Analysis

In [33]:
```
# Elbow method
ssd = []
for k in range(2, 11):
    kmean = KMeans(n_clusters = k).fit(country_df_scaled)
    ssd.append([k, kmean.inertia_])

temp = pd.DataFrame(ssd)
ax = plt.axes()
ax.plot(temp[0], temp[1]) # plot the SSDs for each n_clusters
ax.axvline(3, ls='dotted',color='red') # elbow formed as 3
plt.xlabel('Number of clusters')
plt.ylabel('SSD')
plt.show()
```



In [34]:
```
# Silhouette score

from sklearn.metrics import silhouette_score
silhouette_scores_list = []
for k in range(2, 11):
    kmean = KMeans(n_clusters = k).fit(country_df_scaled) # intialise kmeans
    silhouette_avg = silhouette_score(country_df_scaled, kmean.labels_) # silh
    silhouette_scores_list.append([k, silhouette_avg])
    print("For k_clusters={0}, the silhouette score is {1:2f}".format(k, silho

temp = pd.DataFrame(silhouette_scores_list)
ax = plt.axes()
ax.plot(temp[0], temp[1])
ax.axvline(3, ls='dotted',color='green') # elbow formed as 3
ax.axvline(4, ls='dotted',color='blue') # elbow formed as 3
ax.axvline(5, ls='dotted',color='maroon') # elbow formed as 3
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette score')
plt.show()
```

```
For k_clusters=2, the silhouette score is 0.478554
For k_clusters=3, the silhouette score is 0.423307
For k_clusters=4, the silhouette score is 0.409140
For k_clusters=5, the silhouette score is 0.415582
For k_clusters=6, the silhouette score is 0.316661
For k_clusters=7, the silhouette score is 0.324122
For k_clusters=8, the silhouette score is 0.283355
For k_clusters=9, the silhouette score is 0.296828
For k_clusters=10, the silhouette score is 0.306515
```



comment:

- The silhouette score is maximum when k is 2 which is 0.47
- 2 is very less number of clusters and countries within the 2 clusters might be very different.

So lets look at the next optimal silhouette score.

- 3,4,5 seem to have good silhouette scores. As k increases, silhouette score decreases and hence these will have definitely lesser sihouette score than that of k=2.

- Though elbow curve indicate 3 is optimal number and silhouette score of 3 seem to be the best, lets use K-means algorithm for k=3,4,5 and see which value of k gives us better cluster profiling.

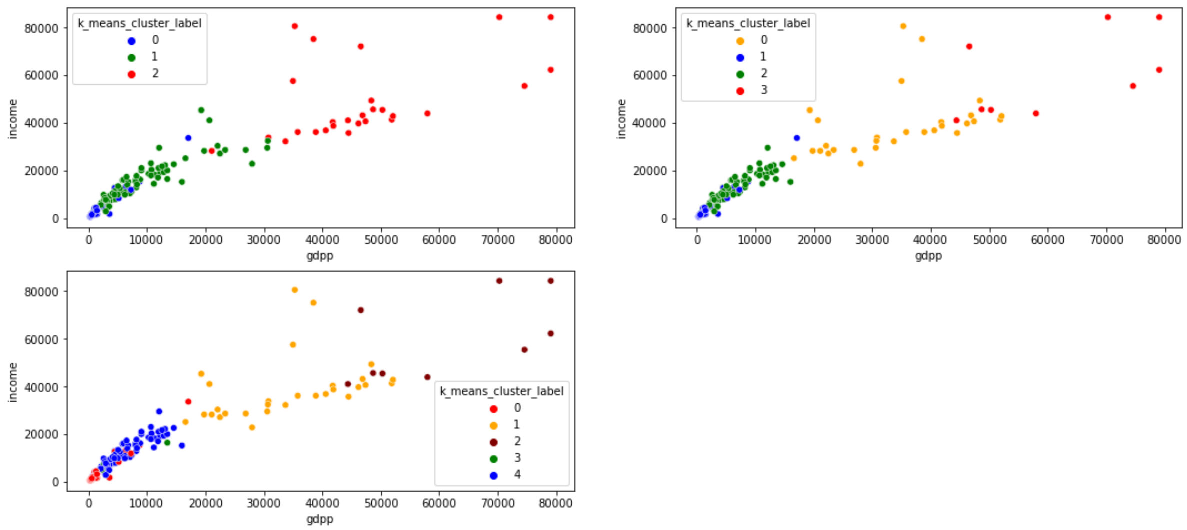
In [35]:
```
# Function for all steps of Kmean Clustering; Call with K=3,4,5
def K_means_model(k):
    kmean = KMeans(n_clusters = k, random_state = 50+k)
    kmean.fit(country_df_scaled)
    country_df_kmean = country_df.copy() # copy the actual data into a new dat
    label  = pd.DataFrame(kmean.labels_, columns= ['k_means_cluster_label'])
    country_df_kmean = pd.concat([country_df_kmean, label], axis =1) # assign
    print("Number of countries in each cluster(k=%s):" %k)
    print(country_df_kmean.k_means_cluster_label.value_counts())# shows how ma
    return(country_df_kmean) # returns clustered labelled dataset for further
```

In [36]:
```
# Created Models are available globally to access inside cluster profiling fun
k_3_model = K_means_model(3) # K means model with 3 clusters
k_4_model = K_means_model(4) # K means model with 4 clusters
k_5_model = K_means_model(5) # K means model with 5 clusters
```

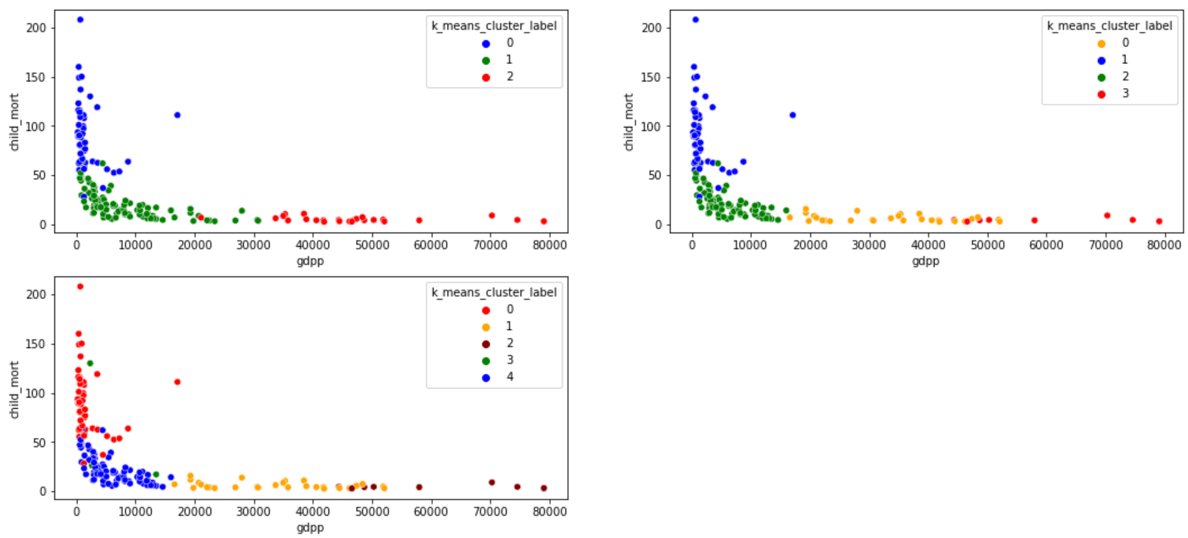
```
Number of countries in each cluster(k=3):
1    92
0    48
2    27
Name: k_means_cluster_label, dtype: int64
Number of countries in each cluster(k=4):
2    80
1    48
0    30
3     9
Name: k_means_cluster_label, dtype: int64
Number of countries in each cluster(k=5):
4    78
0    47
1    30
2     9
3     3
Name: k_means_cluster_label, dtype: int64
```

In [37]:
```
# Function for Profiling Clusters to plot scatter plots
def clusters_scatter_plots(col1, col2):
    plt.figure(figsize=(18,8))
    plt.subplot(2,2,1)
    sns.scatterplot(x = col1, y = col2, hue = 'k_means_cluster_label', data =
    plt.subplot(2,2,2)
    sns.scatterplot(x = col1, y = col2, hue = 'k_means_cluster_label', data =
    plt.subplot(2,2,3)
    sns.scatterplot(x = col1, y = col2, hue = 'k_means_cluster_label', data =
```

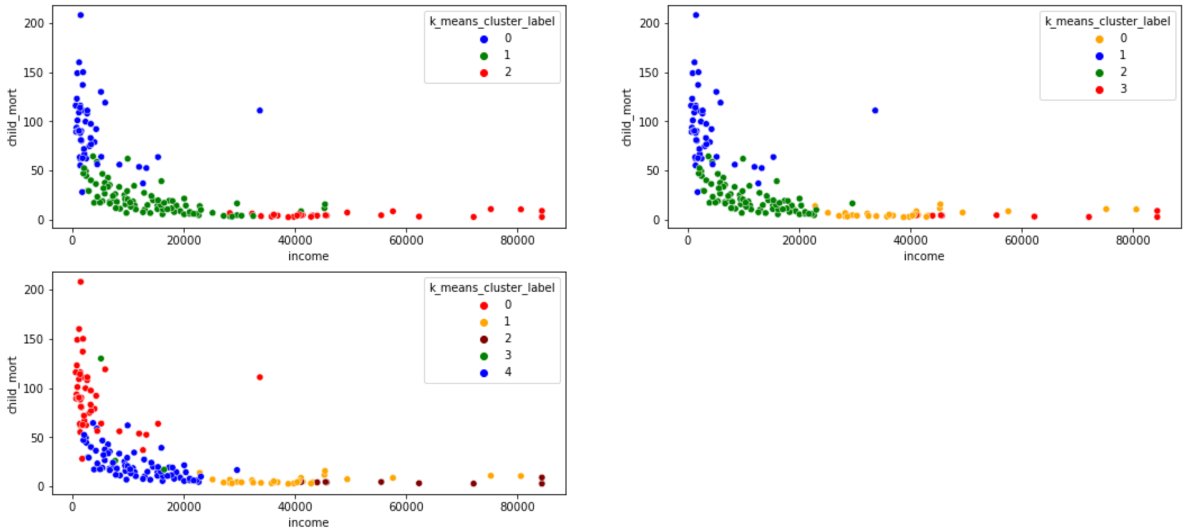
In [38]:
```
clusters_scatter_plots('gdpp','income')
```



In [39]:
```
clusters_scatter_plots('gdpp','child_mort')
```

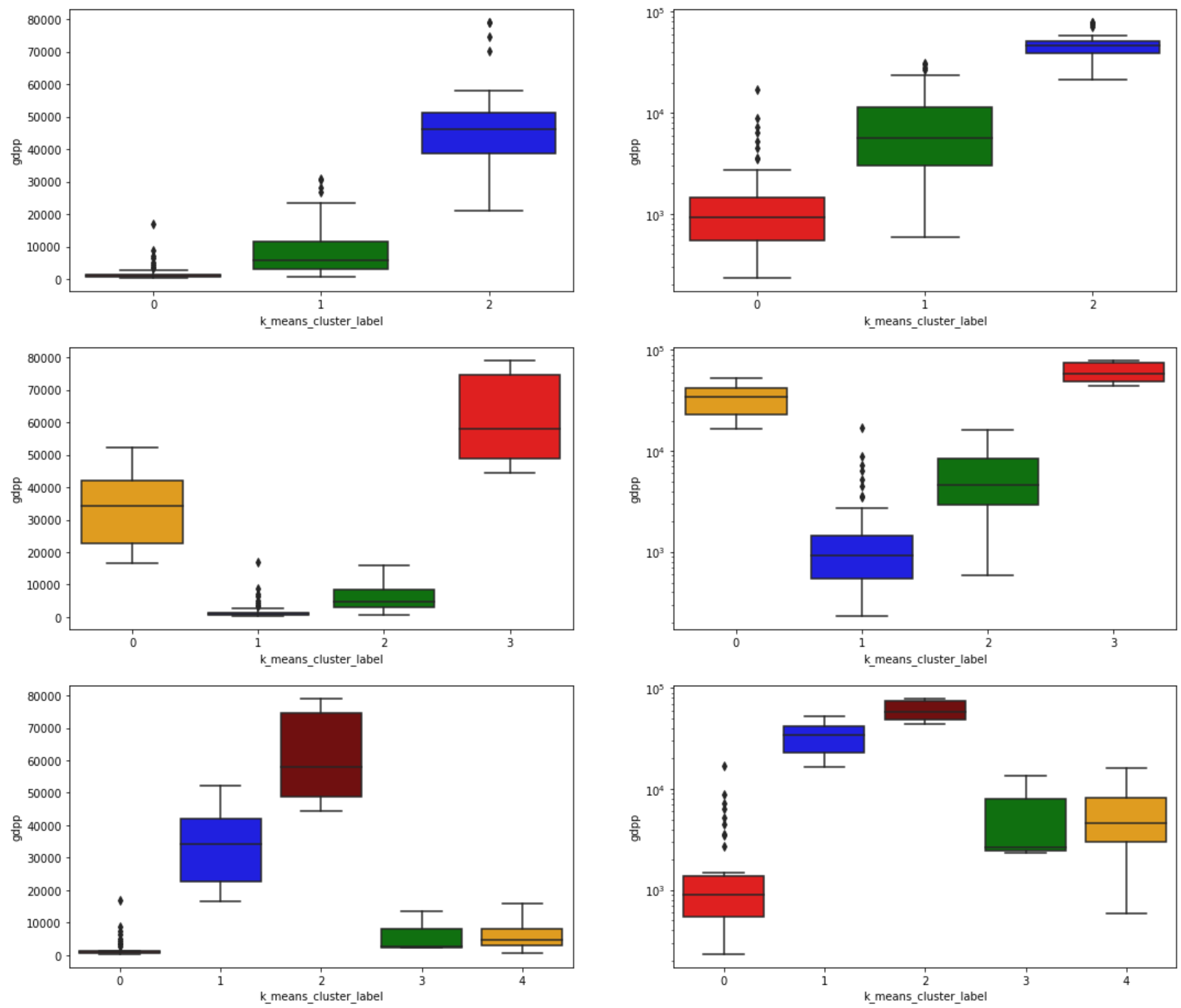


In [40]:
```
clusters_scatter_plots('income','child_mort')
```



In [41]:
```
# Function for Profiling Clusters to plot box plots
def clusters_box_plots(column_name, logy=False):
    #plt.figure(figsize=(18,8))

    if logy:
        i=1
    else:
        i=0

    plt.subplot(2+i,2,1)
    sns.boxplot(x = 'k_means_cluster_label', y = column_name, data = k_3_model
    if logy:
        plt.subplot(3,2,2)
        sns.boxplot(x = 'k_means_cluster_label', y = column_name, data = k_3_m
        plt.yscale('log')

    plt.subplot(2+i,2,2+i)
    sns.boxplot(x = 'k_means_cluster_label', y = column_name, data = k_4_model
    if logy:
        plt.subplot(3,2,4)
        sns.boxplot(x = 'k_means_cluster_label', y = column_name, data = k_4_m
        plt.yscale('log')

    plt.subplot(2+i,2,3+i+i)
    sns.boxplot(x = 'k_means_cluster_label', y = column_name, data = k_5_model
    if logy:
        plt.subplot(3,2,6)
        sns.boxplot(x = 'k_means_cluster_label', y = column_name, data = k_5_m
        plt.yscale('log')
```

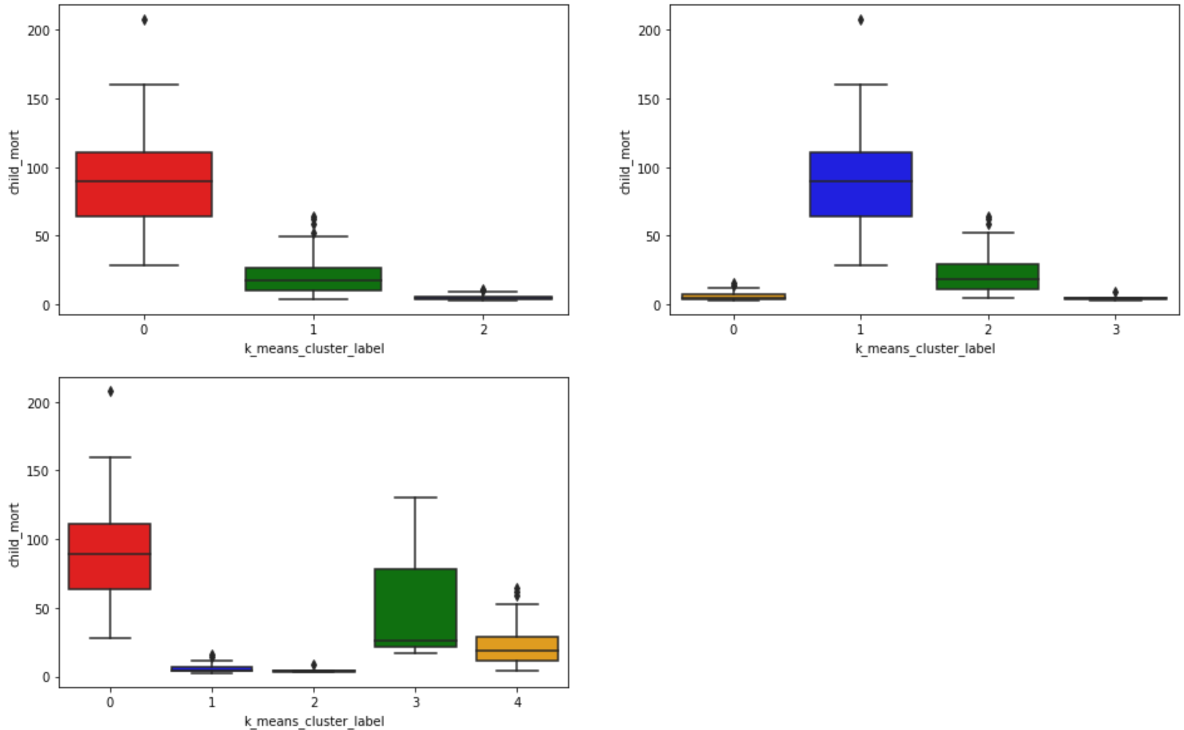
In [42]:
```
plt.figure(figsize = (18,16))
clusters_box_plots('gdpp',True) # log scaled
plt.show()
```



comment

- First set of 3 plots at the left show the distribution without log scale and the next 3 plots show the distribution with GDPP log scaled
- GDPP of the developed countries are so high that we are unable to see the GDPP of the poor countries properly in this boxplot.
- From the right side 3 plots, it can be seen that GDPP of cluster 0 is in the range of 10000(10^4) and cluster 1 is in 100000(10^5) whereas cluster 2 is in range of 10^3 indicating help
- There is a slight overlap in the clusters when k=5 and k=4

In [43]:
```
plt.figure(figsize = (16,10))
clusters_box_plots('child_mort')
plt.show()
```

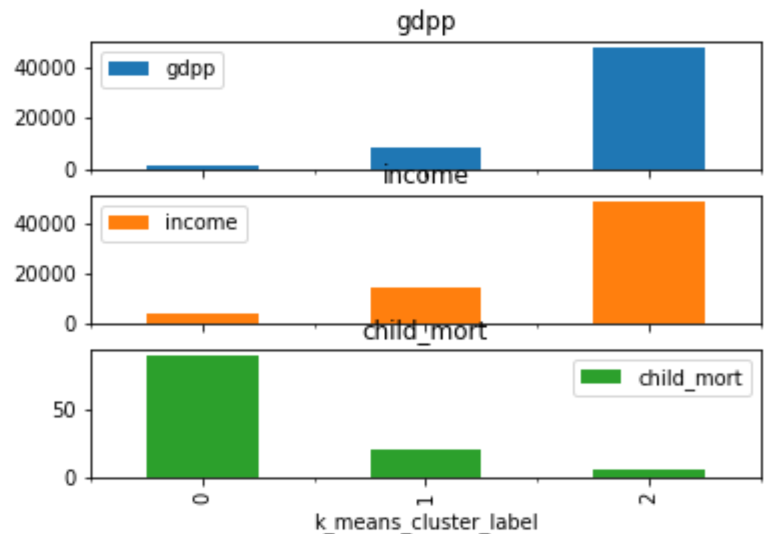


comment

- Child mortality follows the opposite pattern of GDPP and income.
- Clusters which were high on GDPP and income have less child mortality, indicating that these countries have ample amount of money to take care of child mortaliy and health issues.
- We can see that k=3 gives good clusters as the cohesion within the cluster is good and clusters are well separated.

In [44]:
```
#Visualization of Mean of GDPP, income and Child mortality when k=3,4,5
plt.figure(figsize=(18,8))
grouped_df_k3 = k_3_model[['gdpp', 'income', 'child_mort','k_means_cluster_lab
axes = grouped_df_k3.plot.bar(subplots=True)
plt.show()
```

```
<Figure size 1296x576 with 0 Axes>
```

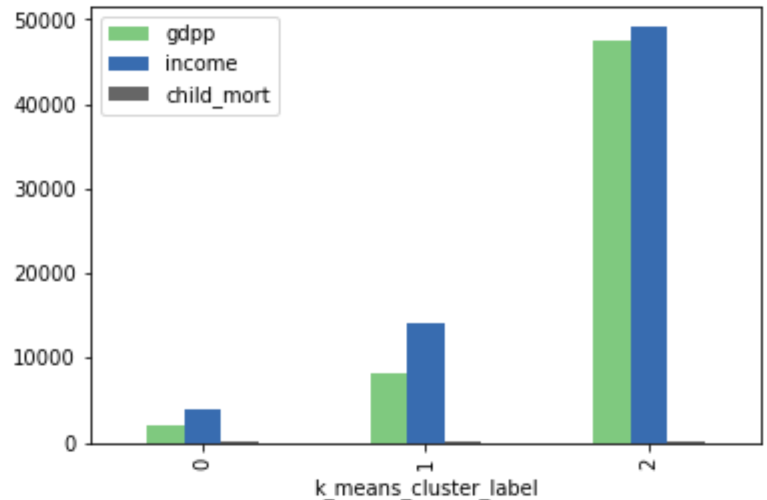


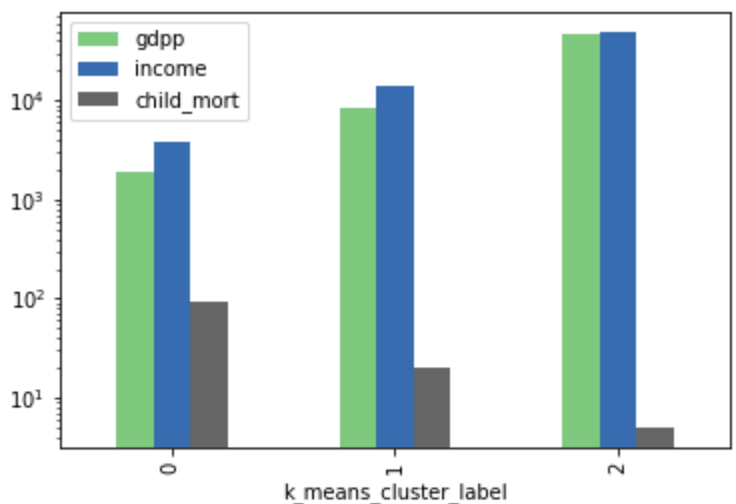
comment:

When K=3, the clusters can be profiled as

- 1 : Medium GDPP, medium Income and mild child mortality rate.
- 2 : High GDPP, High income and very low child mortality rate.
- 0 : Low GDPP, Low income and very high mortality rate.

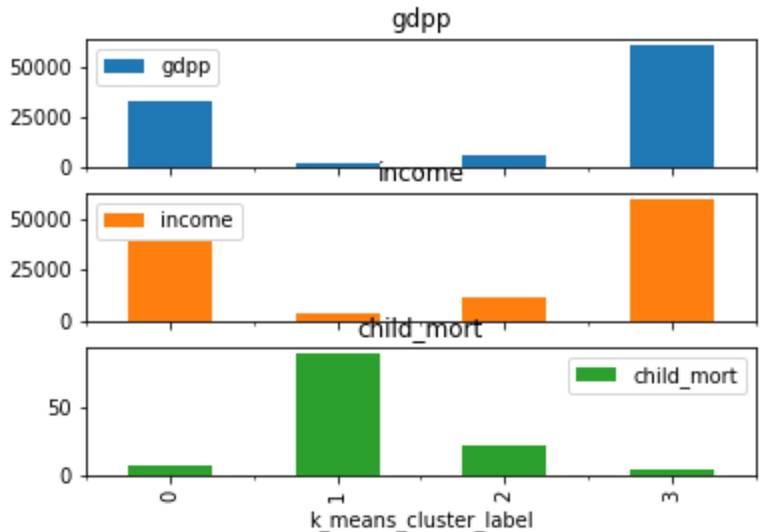
In [45]:
```
# Profiling GDP, INCOME AND CHID_MORT together

grouped_df_k3.plot(kind='bar', colormap='Accent')
grouped_df_k3.plot(kind='bar',logy=True, colormap='Accent')
plt.show()
```



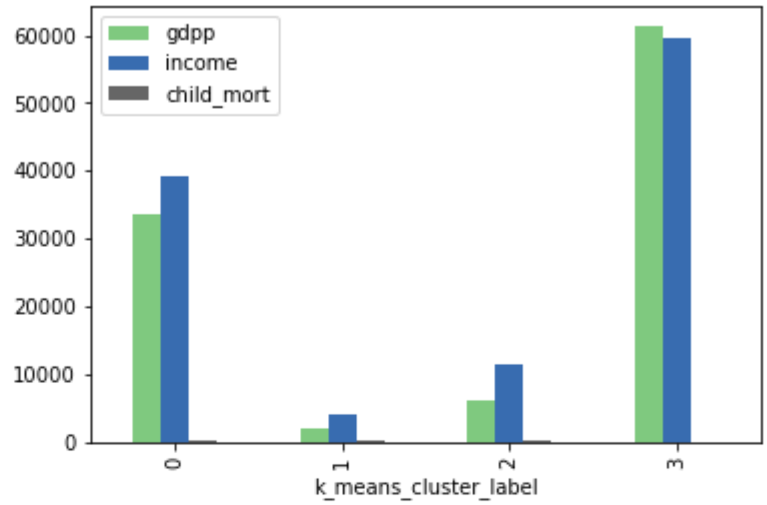


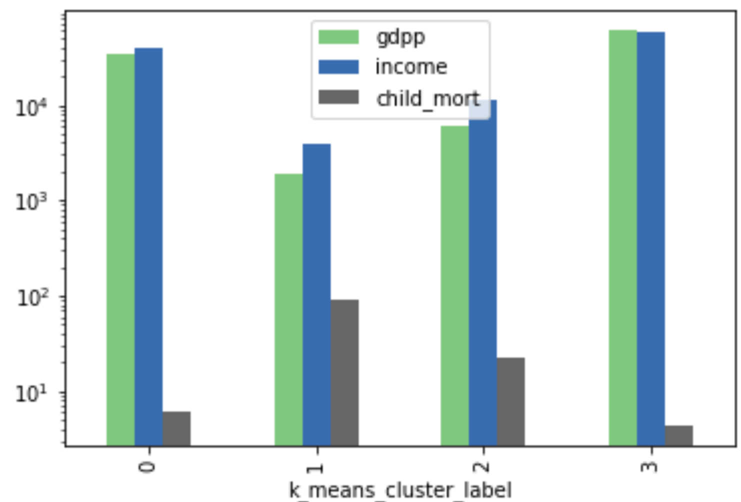
In [46]:
```
plt.figure(figsize=(18,8))
grouped_df_k4 = k_4_model[['gdpp', 'income', 'child_mort','k_means_cluster_lab
axes = grouped_df_k4.plot.bar(subplots=True)
plt.show()
```

```
<Figure size 1296x576 with 0 Axes>
```



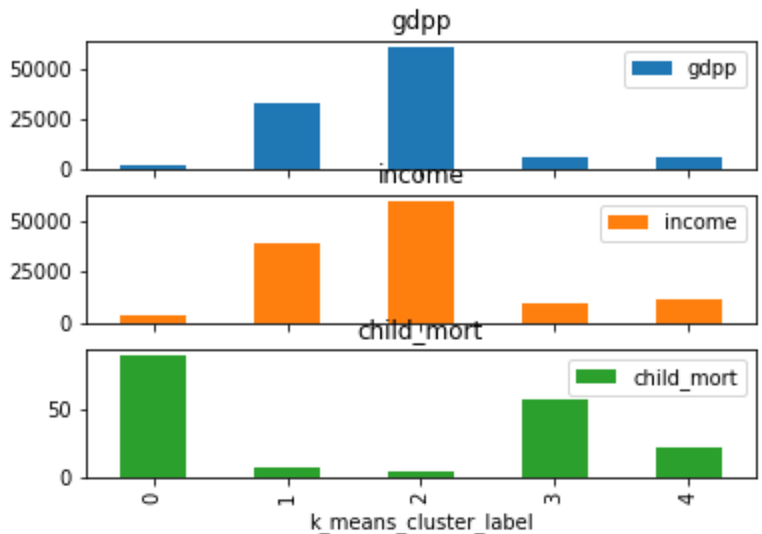
In [47]:
```
# Profiling GDP, INCOME AND CHID_MORT together
grouped_df_k4.plot(kind='bar', colormap='Accent')
grouped_df_k4.plot(kind='bar',logy=True, colormap='Accent')
plt.show()
```





In [48]:
```
plt.figure(figsize=(18,8))
grouped_df_k5 = k_5_model[['gdpp', 'income', 'child_mort','k_means_cluster_lab
axes = grouped_df_k5.plot.bar(subplots=True)
plt.show()
```

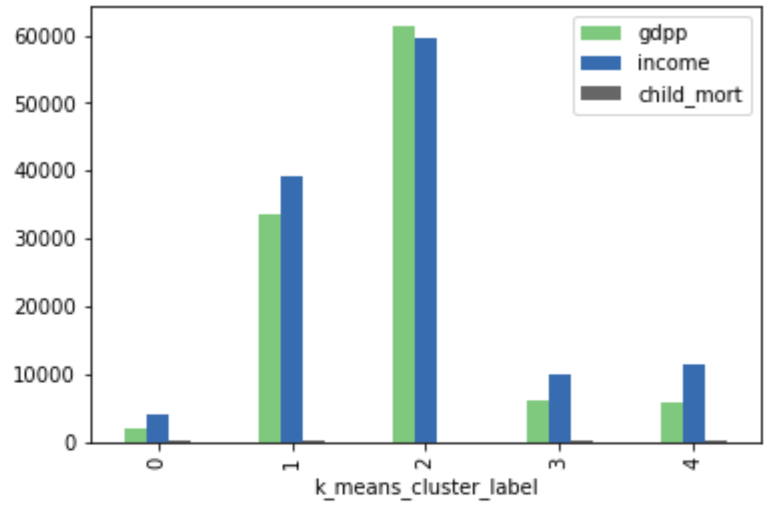
```
<Figure size 1296x576 with 0 Axes>
```

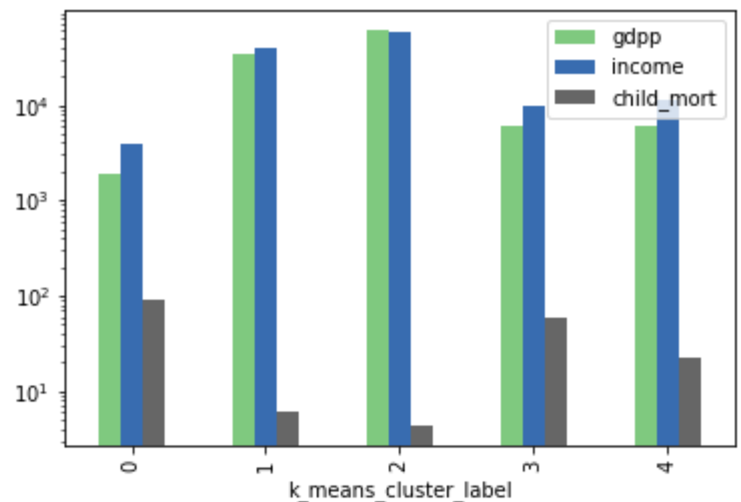


comment:

- The clusters 1 and 3 are a bit similar and it seems to be in same cluster when k=3
- Cluster 4 is not effective as its just one country and we cannot compare it with other clusters.So k=5 is not effective for identifying the countries that are in need of aid.

In [49]:
```
# Profiling GDP, INCOME AND CHID_MORT together
grouped_df_k5.plot(kind='bar', colormap='Accent')
grouped_df_k5.plot(kind='bar',logy=True, colormap='Accent')
plt.show()
```





In [50]:
```
k_5_model[k_5_model['k_means_cluster_label']==4]
```

Out[50]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
1	Albania	16.6	1145.20	267.895	1987.74	9930.0	4.49	76.3	1.65
2	Algeria	27.3	1712.64	185.982	1400.44	12900.0	16.10	76.5	2.89
4	Antigua and Barbuda	10.3	5551.00	735.660	7185.80	19100.0	1.44	76.8	2.13
5	Argentina	14.5	1946.70	834.300	1648.00	18700.0	20.90	75.8	2.37
6	Armenia	18.1	669.76	141.680	1458.66	6700.0	7.77	73.3	1.69
...	...	...	...	...	...	...	...	...	...
156	Ukraine	11.7	1398.87	229.284	1517.67	7820.0	13.40	70.4	1.44
160	Uruguay	10.6	3129.70	993.650	3022.60	17100.0	4.91	76.4	2.08
161	Uzbekistan	36.3	437.46	80.178	393.30	4240.0	16.50	68.8	2.34
162	Vanuatu	29.2	1384.02	155.925	1565.19	2950.0	2.62	63.0	3.50
164	Vietnam	23.3	943.20	89.604	1050.62	4490.0	12.10	73.1	1.95

78 rows × 11 columns

Final Model: K-means clustering with K =3

In [51]:
```
kmean = KMeans(n_clusters = 3, random_state = 50)
kmean.fit(country_df_scaled)
```

Out[51]: KMeans(n_clusters=3, random_state=50)

In [52]:
```
country_df_kmean = country_df.copy() # copy df into new df, as the same df wil
label  = pd.DataFrame(kmean.labels_, columns= ['k_means_cluster_label'])
label.head()
```

Out[52]:

	k_means_cluster_label
0	1
1	0
2	0
3	1
4	0

In [53]:
```
country_df_kmean = pd.concat([country_df_kmean, label], axis =1)
country_df_kmean.head()
```

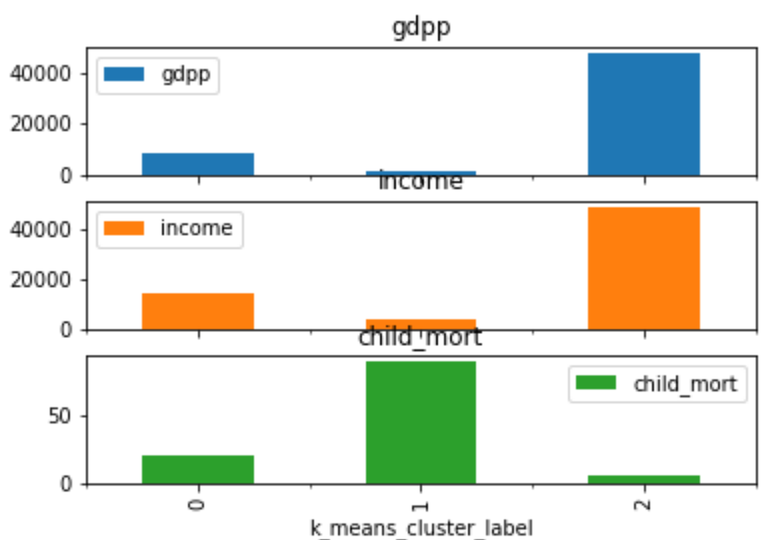
Out[53]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0	Afghanistan	90.2	55.30	41.9174	248.297	1610.0	9.44	56.2	5.82
1	Albania	16.6	1145.20	267.8950	1987.740	9930.0	4.49	76.3	1.65
2	Algeria	27.3	1712.64	185.9820	1400.440	12900.0	16.10	76.5	2.89
3	Angola	119.0	2199.19	100.6050	1514.370	5900.0	22.40	60.1	6.16
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100.0	1.44	76.8	2.13 1

In [54]:
```
country_df_kmean.k_means_cluster_label.value_counts()
```

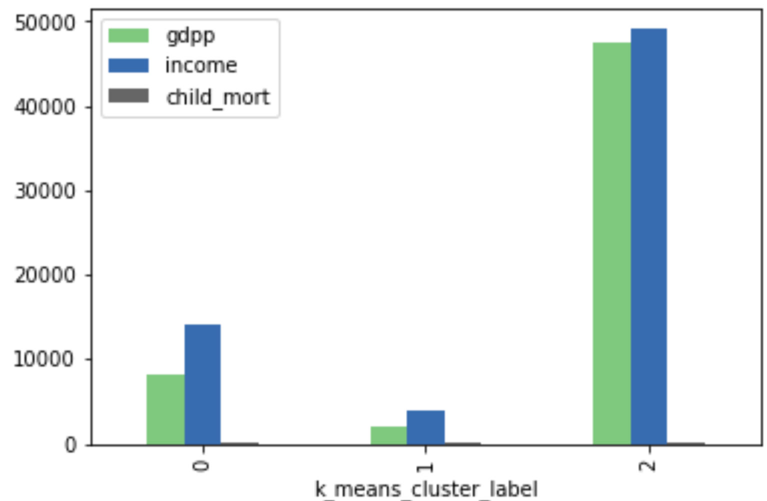
Out[54]:
```
0    92
1    48
2    27
Name: k_means_cluster_label, dtype: int64
```

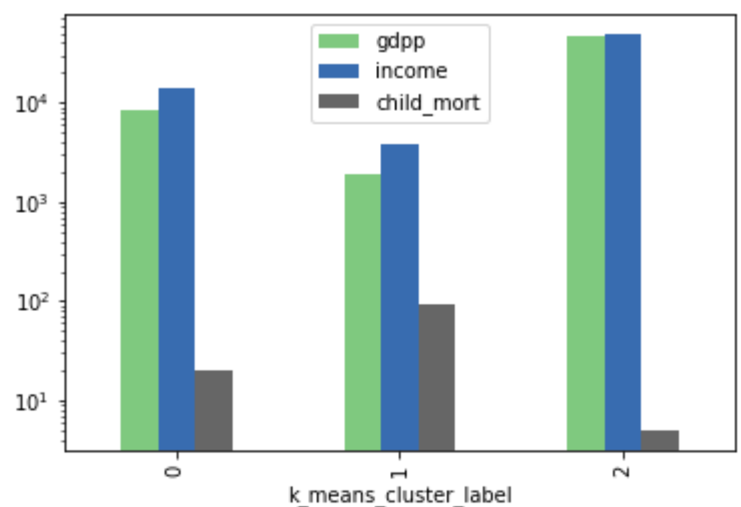
In [55]:
```
# Profiling GDP, INCOME AND CHID_MORT in separate plots

grouped_df = country_df_kmean[['gdpp', 'income', 'child_mort','k_means_cluster
axes = grouped_df.plot.bar(subplots=True)
plt.show()
```



In [56]:
```
# Profiling GDP, INCOME AND CHID_MORT together
grouped_df.plot(kind='bar', colormap='Accent')
grouped_df.plot(kind='bar',logy=True, colormap='Accent')
```

Out[56]: <AxesSubplot:xlabel='k_means_cluster_label'>





In [57]:
```
country_df_kmean.loc[country_df_kmean['k_means_cluster_label'] == 0,'k_means_c
country_df_kmean[country_df_kmean['k_means_cluster_label'] == 'Developing Coun
```

Out[57]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
1	Albania	16.6	1145.20	267.895	1987.74	9930.0	4.49	76.3	1.65
2	Algeria	27.3	1712.64	185.982	1400.44	12900.0	16.10	76.5	2.89
4	Antigua and Barbuda	10.3	5551.00	735.660	7185.80	19100.0	1.44	76.8	2.13
5	Argentina	14.5	1946.70	834.300	1648.00	18700.0	20.90	75.8	2.37
6	Armenia	18.1	669.76	141.680	1458.66	6700.0	7.77	73.3	1.69
...	...	...	...	...	...	...	...	...	...
160	Uruguay	10.6	3129.70	993.650	3022.60	17100.0	4.91	76.4	2.08
161	Uzbekistan	36.3	437.46	80.178	393.30	4240.0	16.50	68.8	2.34
162	Vanuatu	29.2	1384.02	155.925	1565.19	2950.0	2.62	63.0	3.50
163	Venezuela	17.1	3847.50	662.850	2376.00	16500.0	45.90	75.4	2.47
164	Vietnam	23.3	943.20	89.604	1050.62	4490.0	12.10	73.1	1.95

92 rows × 11 columns

In [58]:
```
country_df_kmean[country_df_kmean['k_means_cluster_label'] == 'Developing Coun
```

Out[58]:

	child_mort	exports	health	imports	income	inflation	life_expec
count	92.000000	92.000000	92.000000	92.000000	92.000000	92.000000	92.000000
mean	20.177174	3650.066288	573.165330	3759.545881	14169.456522	6.995435	73.552174
std	14.095983	3758.035772	623.537749	3463.217447	9474.287745	7.768033	4.097908
min	3.200000	1.076920	19.463600	0.651092	1990.000000	-4.210000	63.000000
25%	10.275000	1003.987500	179.336250	1375.405000	7150.000000	1.735000	70.400000
50%	17.150000	1876.810000	366.440000	2370.465000	11300.000000	5.025000	74.100000
75%	26.200000	5184.400000	740.455000	5183.775000	19175.000000	9.187500	76.400000
max	64.400000	15046.200000	2928.780000	14718.600000	45400.000000	45.900000	81.900000

In [59]:
```
# Developed Countries: High income, High GDP and Low Child_mort
# Filter the data for that clsuter
country_df_kmean.loc[country_df_kmean['k_means_cluster_label'] == 1,'k_means_c
country_df_kmean[country_df_kmean['k_means_cluster_label'] == 'Developed Count
```

Out[59]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	tota
0	Afghanistan	90.2	55.3000	41.9174	248.297	1610.0	9.440	56.2	5
3	Angola	119.0	2199.1900	100.6050	1514.370	5900.0	22.400	60.1	6
17	Benin	111.0	180.4040	31.0780	281.976	1820.0	0.885	61.8	5
21	Botswana	52.5	2768.6000	527.0500	3257.550	13300.0	8.920	57.1	2
25	Burkina Faso	116.0	110.4000	38.7550	170.200	1430.0	6.810	57.9	5
26	Burundi	93.6	20.6052	26.7960	90.552	764.0	12.300	57.7	6
28	Cameroon	108.0	290.8200	67.2030	353.700	2660.0	1.910	57.3	5
31	Central African Republic	149.0	52.6280	17.7508	118.190	888.0	2.010	47.5	5
32	Chad	150.0	330.0960	40.6341	390.195	1930.0	6.390	56.5	6
36	Comoros	88.2	126.8850	34.6819	397.573	1410.0	3.870	65.9	4
37	Congo, Dem. Rep.	116.0	137.2740	26.4194	165.664	609.0	20.800	57.5	6
38	Congo, Rep.	63.9	2331.7400	67.4040	1498.780	5190.0	20.700	60.4	4
40	Cote d'Ivoire	111.0	617.3200	64.6600	528.260	2690.0	5.390	56.3	5
49	Equatorial Guinea	111.0	14671.8000	766.0800	10071.900	33700.0	24.900	60.9	5
50	Eritrea	55.2	23.0878	12.8212	112.306	1420.0	11.600	61.7	4
55	Gabon	63.7	5048.7500	306.2500	1653.750	15400.0	16.600	62.9	4
56	Gambia	80.3	133.7560	31.9778	239.974	1660.0	4.300	65.5	5
59	Ghana	74.7	386.4500	68.3820	601.290	3060.0	16.600	62.2	4
63	Guinea	109.0	196.3440	31.9464	279.936	1190.0	16.100	58.0	5
64	Guinea-Bissau	114.0	81.5030	46.4950	192.544	1390.0	2.970	55.6	5
66	Haiti	208.0	101.2860	45.7442	428.314	1500.0	5.450	32.1	3
72	Iraq	36.9	1773.0000	378.4500	1534.500	12700.0	16.600	67.2	4
80	Kenya	62.2	200.1690	45.9325	324.912	2480.0	2.090	62.8	4
81	Kiribati	62.7	198.1700	168.3700	1190.510	1730.0	1.520	60.7	3
84	Lao	78.9	403.5600	50.9580	562.020	3980.0	9.200	63.8	3
87	Lesotho	99.7	460.9800	129.8700	1181.700	2380.0	4.150	46.5	3
88	Liberia	89.3	62.4570	38.5860	302.802	700.0	5.470	60.8	5
93	Madagascar	62.2	103.2500	15.5701	177.590	1390.0	8.790	60.8	4

	country	child_mort	exports	health	imports	income	inflation	life_expec	tota
94	Malawi	90.5	104.6520	30.2481	160.191	1030.0	12.100	53.1	5
97	Mali	137.0	161.4240	35.2584	248.508	1870.0	4.370	59.5	6
99	Mauritania	97.4	608.4000	52.9200	734.400	3320.0	18.900	68.2	4
106	Mozambique	101.0	131.9850	21.8299	193.578	918.0	7.640	54.5	5
108	Namibia	56.0	2480.8200	351.8820	3150.330	8460.0	3.560	58.6	3
112	Niger	123.0	77.2560	17.9568	170.868	814.0	2.550	58.8	6
113	Nigeria	130.0	589.4900	118.1310	405.420	5150.0	104.000	60.5	5
116	Pakistan	92.1	140.4000	22.8800	201.760	4280.0	10.900	65.3	3
126	Rwanda	63.6	67.5600	59.1150	168.900	1350.0	2.610	64.6	4
129	Senegal	66.8	249.0000	56.6000	403.000	2180.0	1.850	64.0	5
132	Sierra Leone	160.0	67.0320	52.2690	137.655	1220.0	17.200	55.0	5
136	Solomon Islands	28.1	635.9700	110.2950	1047.480	1780.0	6.810	61.7	4
137	South Africa	53.7	2082.0800	650.8320	1994.720	12000.0	6.350	54.3	2
142	Sudan	76.7	291.5600	93.5360	254.560	3370.0	19.600	66.3	4
147	Tanzania	71.9	131.2740	42.1902	204.282	2090.0	9.250	59.3	5
149	Timor-Leste	62.6	79.2000	328.3200	1000.800	1850.0	26.500	71.1	6
150	Togo	90.3	196.1760	37.3320	279.624	1210.0	1.180	58.7	4
155	Uganda	81.0	101.7450	53.6095	170.170	1540.0	10.600	56.8	6
165	Yemen	56.3	393.0000	67.8580	450.640	4480.0	23.600	67.5	4

In [60]:
```
country_df_kmean[country_df_kmean['k_means_cluster_label'] == 'Developed Count
```

Out[60]:

	child_mort	exports	health	imports	income	inflation	life_expec
count	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000
mean	91.610417	879.063521	114.821765	827.028771	3897.354167	11.911146	59.239583
std	34.319855	2252.474004	165.518331	1540.981910	5590.168621	15.362485	6.384914
min	28.100000	20.605200	12.821200	90.552000	609.000000	0.885000	32.100000
25%	63.675000	102.873750	34.005875	193.319500	1390.000000	4.080000	56.725000
50%	89.750000	196.260000	51.613500	339.306000	1860.000000	8.855000	59.800000
75%	111.000000	552.522500	95.303250	801.000000	3522.500000	16.600000	62.825000
max	208.000000	14671.800000	766.080000	10071.900000	33700.000000	104.000000	71.100000

In [61]:
```
# Under-Developed Countries:Low income, Low GDP and High Child_mort
# Filter the data for that clsuter

country_df_kmean.loc[country_df_kmean['k_means_cluster_label'] == 2,'k_means_c
country_df_kmean[country_df_kmean['k_means_cluster_label'] == 'Under-Developed
```

Out[61]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_1
7	Australia	4.8	10276.20	4530.8700	10847.10	41400.0	1.160	82.0	1.
8	Austria	4.3	24059.70	5159.0000	22418.20	43200.0	0.873	80.5	1.
15	Belgium	4.5	33921.60	4750.8000	33166.80	41100.0	1.880	80.0	1.
23	Brunei	10.5	23792.20	1002.5200	9884.00	80600.0	16.700	77.1	1.
29	Canada	5.6	13793.40	5356.2000	14694.00	40700.0	2.870	81.3	1.
42	Cyprus	3.6	15461.60	1838.7600	17710.00	33900.0	2.010	79.9	1.
44	Denmark	4.1	29290.00	6612.0000	25288.00	44000.0	3.220	79.5	1.
53	Finland	3.0	17879.40	4134.9000	17278.80	39800.0	0.351	80.0	1.
54	France	4.2	10880.80	4831.4000	11408.60	36900.0	1.050	81.4	2.
58	Germany	4.2	17681.40	4848.8000	15507.80	40400.0	0.758	80.1	1.
68	Iceland	2.6	22374.60	3938.6000	18142.70	38800.0	5.470	82.0	2.
73	Ireland	4.2	50161.00	4475.5300	42125.50	45700.0	-3.220	80.4	2.
75	Italy	4.0	9021.60	3411.7400	9737.60	36200.0	0.319	81.7	1.
77	Japan	3.2	6675.00	4223.0500	6052.00	35800.0	-1.900	82.8	1.
82	Kuwait	10.8	25679.50	1012.5500	11704.00	75200.0	11.200	78.2	2.
91	Luxembourg	2.8	64794.26	8158.5000	55371.39	84374.0	3.620	81.3	1.
98	Malta	6.8	32283.00	1825.1500	32494.00	28300.0	3.830	80.3	1.
110	Netherlands	4.5	36216.00	5985.7000	31990.80	45500.0	0.848	80.7	1.
111	New Zealand	6.2	10211.10	3403.7000	9436.00	32300.0	3.730	80.9	2.
114	Norway	3.2	34856.60	8323.4400	25023.00	62300.0	5.950	81.0	1.

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_f
123	Qatar	9.0	43796.90	1272.4300	16731.40	84374.0	6.980	79.5	2.
133	Singapore	2.8	64794.26	1845.3600	55371.39	72100.0	-0.046	82.7	1.
144	Sweden	3.0	24070.20	5017.2300	21204.70	42900.0	0.991	81.5	1.
145	Switzerland	4.5	47744.00	8410.3304	39761.80	55500.0	0.317	82.2	1.
157	United Arab Emirates	8.6	27195.00	1281.0000	22260.00	57600.0	12.500	76.5	1.
158	United Kingdom	5.2	10969.80	3749.9600	11981.20	36200.0	1.570	80.3	1.

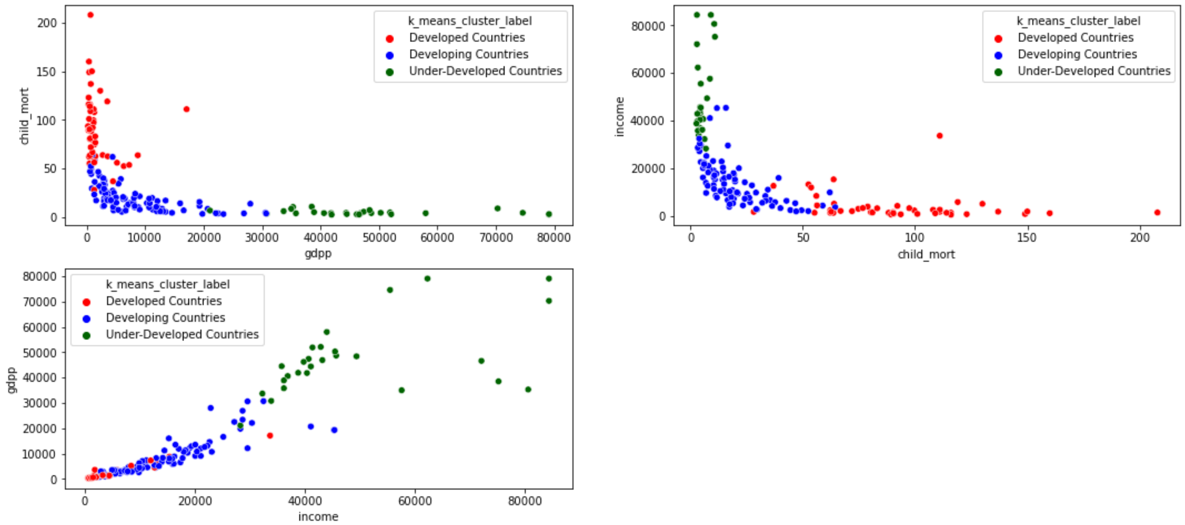
In [62]:
```
country_df_kmean[country_df_kmean['k_means_cluster_label'] == 'Under-Developed
```

Out[62]:

	child_mort	exports	health	imports	income	inflation	life_expec
count	27.000000	27.000000	27.000000	27.000000	27.000000	27.000000	27.000000
mean	5.092593	26440.026667	4363.327807	22045.851111	49057.333333	3.120407	80.462963
std	2.319470	16535.307518	2290.539971	13644.366817	16604.947131	4.399902	1.540017
min	2.600000	6001.600000	1002.520000	6052.000000	28300.000000	-3.220000	76.500000
25%	3.400000	12381.600000	2624.530000	11556.300000	37850.000000	0.803000	79.950000
50%	4.300000	24059.700000	4475.530000	17710.000000	42900.000000	1.570000	80.500000
75%	5.900000	34389.100000	5257.600000	28639.400000	56550.000000	3.780000	81.450000
max	10.800000	64794.260000	8410.330400	55371.390000	84374.000000	16.700000	82.800000

In [63]:
```
profiling_cols = ['gdpp','child_mort','income'] # create a list to store profi
```

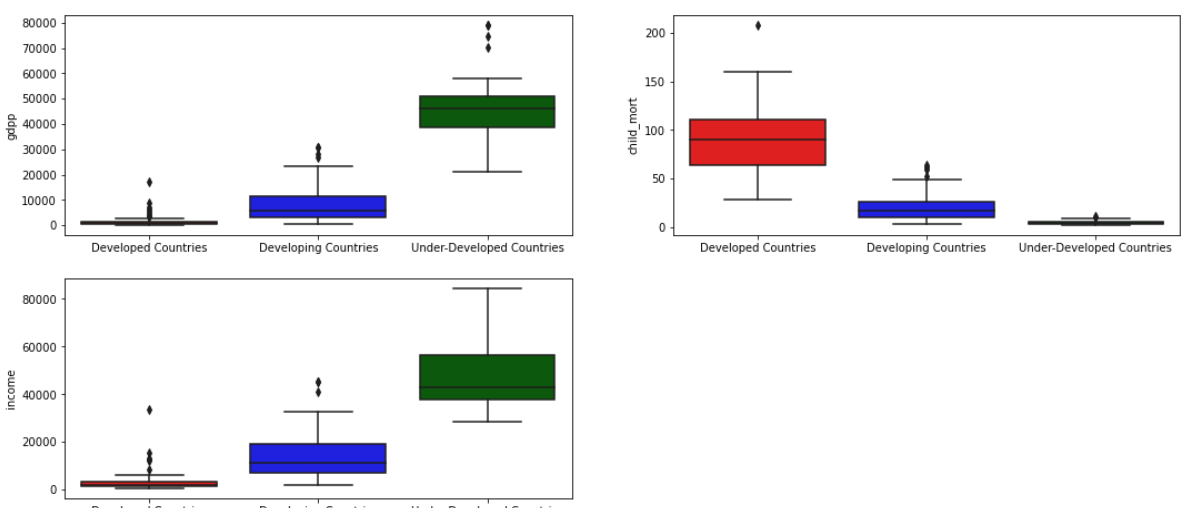
In [64]:
```
plt.figure(figsize=(18,8))
i=0
for i in range(len(profiling_cols)):
    plt.subplot(2,2,i+1)
    sns.scatterplot(x = profiling_cols[i], y = profiling_cols[(i+1)%len(profil
```



comments:

- Developing countries have Medium GDPP, medium Income and mild child mortality rate.
- Developed countries have High GDPP, High income and very low child mortality rate.
- Under-Developed countries have Low GDPP, Low income and very high mortality rate and should be our primary focus.

In [65]:
```
plt.figure(figsize=(18,8))
i=0
for i in range(len(profiling_cols)):
    plt.subplot(2,2,i+1)
    sns.boxplot(x = 'k_means_cluster_label', y = profiling_cols[i], data = cou
    plt.xlabel('')
```

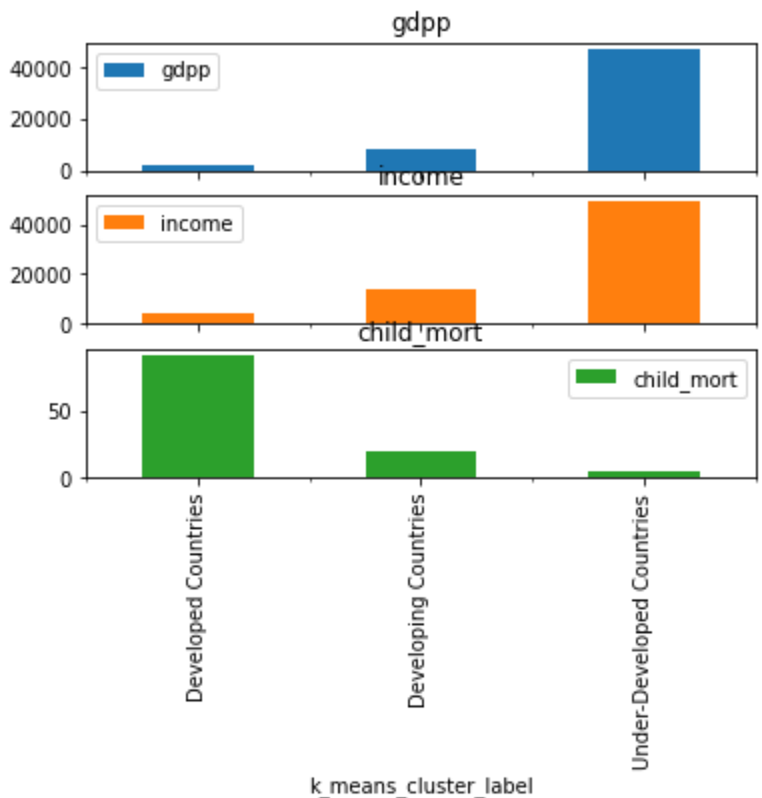


comment

- Developing countries have Medium GDPP, medium Income and mild child mortality rate.
- Developed countries have High GDPP, High income and very low child mortality rate.
- Under-Developed countries have Low GDPP, Low income and very high mortality rate and should be our primary focus.

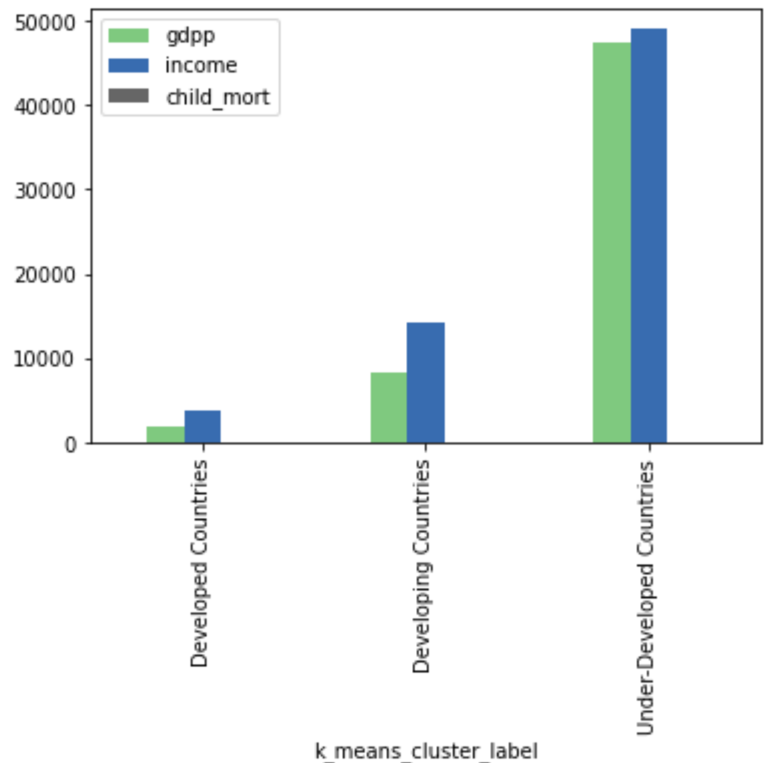
In [66]:
```
# Profiling GDP, INCOME AND CHID_MORT in sub-plots
plt.figure(figsize=(18,8))
grouped_df = country_df_kmean[['gdpp', 'income', 'child_mort','k_means_cluster
axes = grouped_df.plot.bar(subplots=True)
plt.show()
```

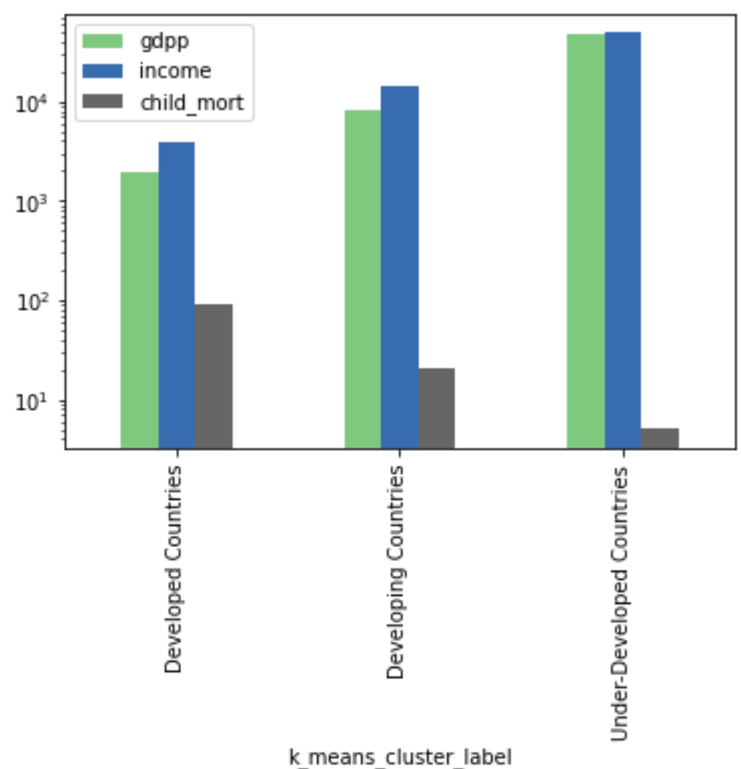
```
<Figure size 1296x576 with 0 Axes>
```



In [67]:
```
# Profiling GDP, INCOME AND CHID_MORT together from the above grouped_df
grouped_df.plot(kind='bar', colormap='Accent')
grouped_df.plot(kind='bar',logy=True, colormap='Accent')
```

Out[67]:
```
<AxesSubplot:xlabel='k_means_cluster_label'>
```





Identification of Top 10 countries that require aid on priority using

K-means algorithm:

In [68]:
```
K_top10 = country_df_kmean[country_df_kmean['k_means_cluster_label'] =='Under-
K_top10
```

Out[68]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	g
98	Malta	6.8	32283.0	1825.15	32494.0	28300.0	3.830	80.3	1.36	211
42	Cyprus	3.6	15461.6	1838.76	17710.0	33900.0	2.010	79.9	1.42	308
111	New Zealand	6.2	10211.1	3403.70	9436.0	32300.0	3.730	80.9	2.17	337
157	United Arab Emirates	8.6	27195.0	1281.00	22260.0	57600.0	12.500	76.5	1.87	350
23	Brunei	10.5	23792.2	1002.52	9884.0	80600.0	16.700	77.1	1.84	353
75	Italy	4.0	9021.6	3411.74	9737.6	36200.0	0.319	81.7	1.46	358
82	Kuwait	10.8	25679.5	1012.55	11704.0	75200.0	11.200	78.2	2.21	385
158	United Kingdom	5.2	10969.8	3749.96	11981.2	36200.0	1.570	80.3	1.92	389
54	France	4.2	10880.8	4831.40	11408.6	36900.0	1.050	81.4	2.03	406
58	Germany	4.2	17681.4	4848.80	15507.8	40400.0	0.758	80.1	1.39	418

In [69]:
```
K_top10.country
```

Out[69]:
```
98                    Malta
42                   Cyprus
111             New Zealand
157    United Arab Emirates
23                   Brunei
75                    Italy
82                   Kuwait
158          United Kingdom
54                   France
58                  Germany
Name: country, dtype: object
```

Hierarchical Clustering Algorithm

Linkage Criteria

- The two most similar parts of a cluster in a **single-linkage**
- The two least similar bits of a cluster in a **complete-linkage**

- The center of the clusters in a mean or average-linkage

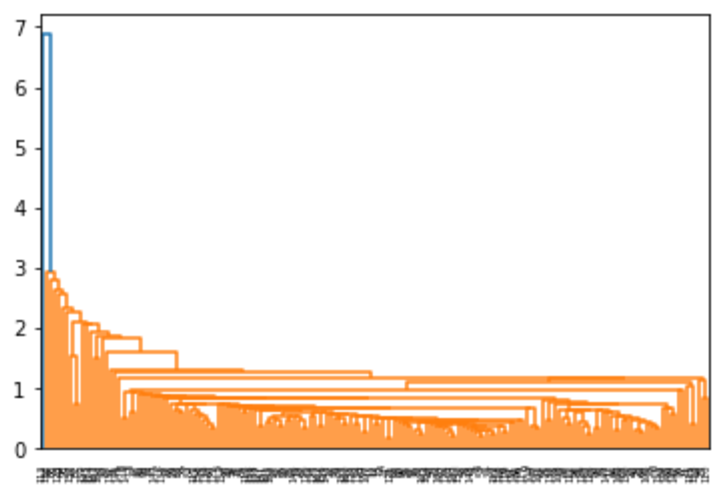
In [70]:
```
#Single Linkage
country_df_scaled
```

Out[70]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	
0	1.291532	-0.569622	-0.566958	-0.598741	-0.851668	0.157336	-1.619092	1.926396	-0.7(
1	-0.538949	-0.473858	-0.440393	-0.413584	-0.386946	-0.312347	0.647866	-0.865054	-0.4!
2	-0.272833	-0.424000	-0.486271	-0.476100	-0.221053	0.789274	0.670423	-0.034983	-0.4:
3	2.007808	-0.381249	-0.534088	-0.463973	-0.612045	1.387054	-1.179234	2.153997	-0.5:
4	-0.695634	-0.086742	-0.178410	0.139728	0.125254	-0.601749	0.704258	-0.543736	-0.0:
...	...	...	...	...	...	...	...	...	
162	-0.225578	-0.452874	-0.503105	-0.458563	-0.776821	-0.489784	-0.852161	0.373359	-0.5(
163	-0.526514	-0.236420	-0.219189	-0.372256	-0.019971	3.616865	0.546361	-0.316136	0.0
164	-0.372315	-0.491607	-0.540250	-0.513337	-0.690802	0.409732	0.286958	-0.664231	-0.6!
165	0.448417	-0.539950	-0.552429	-0.577202	-0.691361	1.500916	-0.344633	1.156572	-0.6!
166	1.114951	-0.527016	-0.542272	-0.577149	-0.758388	0.590015	-2.092785	1.645243	-0.6!

167 rows × 9 columns

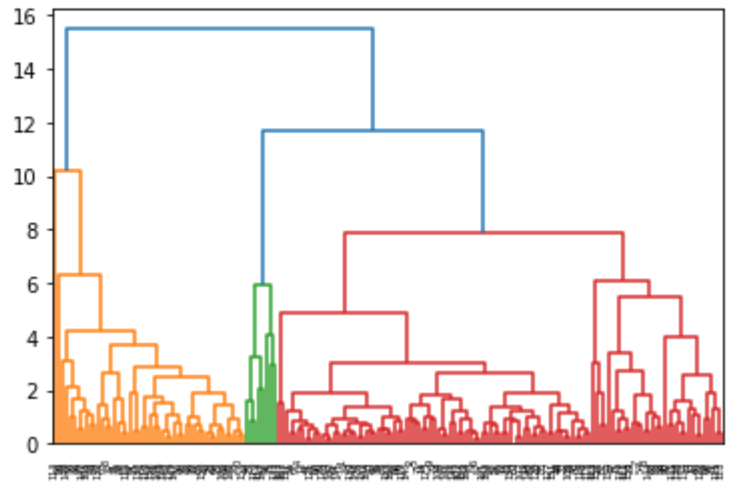
In [71]:
```
mergings = linkage(country_df_scaled, method="single", metric='euclidean')
dendrogram(mergings)
plt.show()
```



- Single linkage's dendogram is not readable or interpretable. Hence we cannot use this for our problem.

In [72]:
```
#Complete Linkage
```

In [73]:
```
mergings = linkage(country_df_scaled, method="complete", metric='euclidean')
dendrogram(mergings)
plt.show()
```



###comment:

- Complete linkage's dendogram is readable and better to interpret when compared to single linkage's dendogram.
- If we cut the dendogram tree at SCORE 5 or 6, we have 4 clusters. But we can see the dissimilarity between 4 clusters and 3 clusters is not much as at score 8 itself, we see 3 clusters forming. Only at higher score of 12, 2 sets of clusters available.
- This indicates 3 clusters is a good choice as there will be good dissimilarity between clusters and good similarity within clusters.

In [74]:
```
# 3 clusters
cluster_labels = cut_tree(mergings, n_clusters=3).reshape(-1, )
cluster_labels
```

Out[74]:
```
array([0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 0, 1, 1, 1, 0,
       1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1,
       2, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1,
       0, 1, 1, 1, 1, 1, 0, 2, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0,
       0, 1, 1, 2, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1,
       2, 1, 0, 0, 2, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1,
       0, 2, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 2, 1, 0, 1, 0, 0, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0])
```

In [75]:
```
# assign cluster labels
country_df['cluster_labels'] = cluster_labels
country_df.head()
```

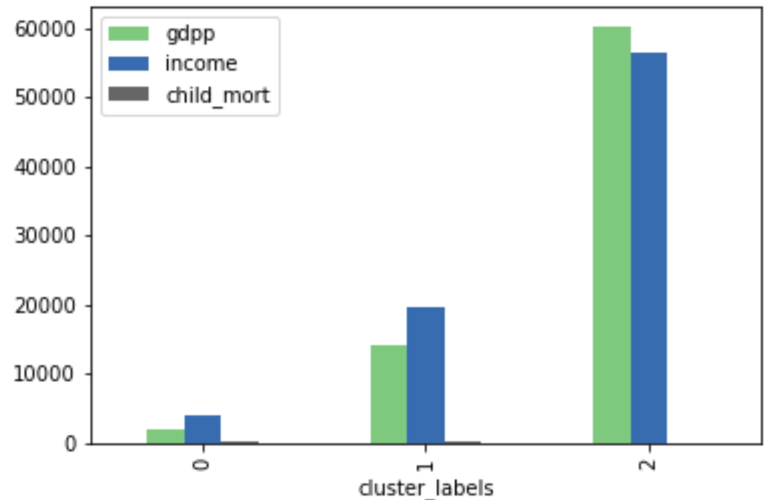
Out[75]:

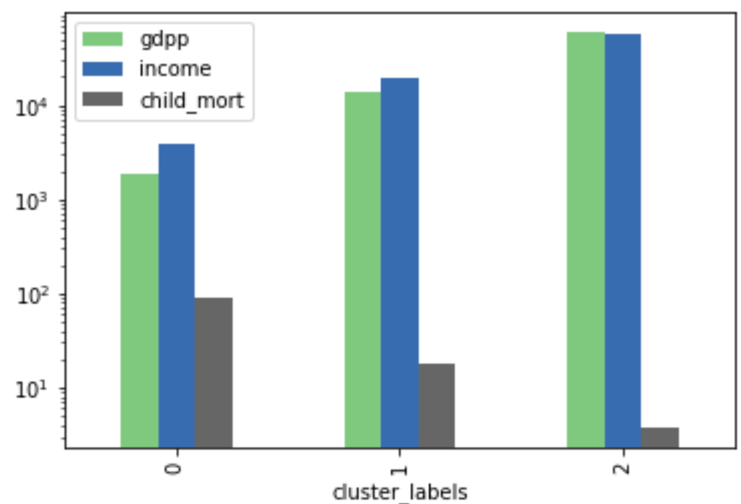
	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0	Afghanistan	90.2	55.30	41.9174	248.297	1610.0	9.44	56.2	5.82
1	Albania	16.6	1145.20	267.8950	1987.740	9930.0	4.49	76.3	1.65
2	Algeria	27.3	1712.64	185.9820	1400.440	12900.0	16.10	76.5	2.89
3	Angola	119.0	2199.19	100.6050	1514.370	5900.0	22.40	60.1	6.16
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100.0	1.44	76.8	2.13 1

In [76]:
```
country_df.cluster_labels.value_counts()
```

Out[76]:
```
1    111
0     48
2      8
Name: cluster_labels, dtype: int64
```

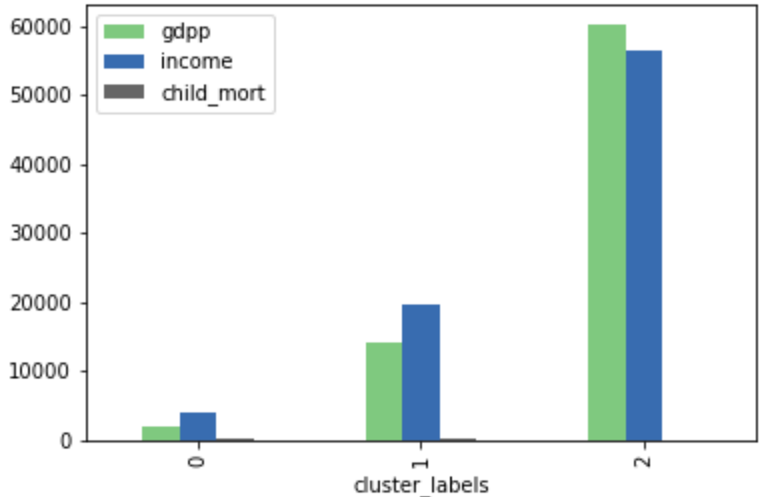
In [77]:
```
# Profiling GDP, INCOME AND CHID_MORT in separete plots
grouped_df = country_df[['gdpp', 'income', 'child_mort','cluster_labels']].gro
grouped_df.plot(kind='bar', colormap='Accent')
grouped_df.plot(kind='bar',logy=True, colormap='Accent')
plt.show()
```

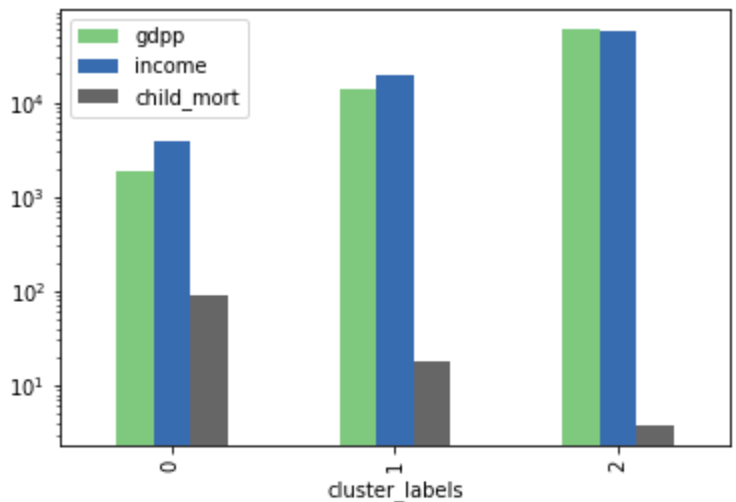




In [78]:
```
# Profiling GDP, INCOME AND CHID_MORT together
grouped_df.plot(kind='bar', colormap='Accent')
grouped_df.plot(kind='bar',logy=True, colormap='Accent')
```

Out[78]: <AxesSubplot:xlabel='cluster_labels'>





From the above plots, its evident that the cluster labels

- 0 : Under-developed countries having low GDPP, low income and high child mortality rate.
- 1 : Developing countries having medium GDPP, medium income and mild child mortality rate.
- 2 : Developed countries having high GDPP, high income and very low child mortality rate.

Countries Segmentation

Lets rename the cluster labels as

- 0 : Under-developed Countries
- 1 : Developing Countries

- 2 : Developed Countries

In [79]:
```
# Low income, Low GDP and High Child_mort
# Filter the data for that clsuter

country_df.loc[country_df['cluster_labels'] == 0,'cluster_labels'] ='Under-Dev
country_df[country_df['cluster_labels'] == 'Under-Developed Countries']
```

Out[79]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	tota
0	Afghanistan	90.2	55.3000	41.9174	248.297	1610.0	9.440	56.2	5
3	Angola	119.0	2199.1900	100.6050	1514.370	5900.0	22.400	60.1	6
17	Benin	111.0	180.4040	31.0780	281.976	1820.0	0.885	61.8	5
21	Botswana	52.5	2768.6000	527.0500	3257.550	13300.0	8.920	57.1	2
25	Burkina Faso	116.0	110.4000	38.7550	170.200	1430.0	6.810	57.9	5
26	Burundi	93.6	20.6052	26.7960	90.552	764.0	12.300	57.7	6
28	Cameroon	108.0	290.8200	67.2030	353.700	2660.0	1.910	57.3	5
31	Central African Republic	149.0	52.6280	17.7508	118.190	888.0	2.010	47.5	5
32	Chad	150.0	330.0960	40.6341	390.195	1930.0	6.390	56.5	6
36	Comoros	88.2	126.8850	34.6819	397.573	1410.0	3.870	65.9	4
37	Congo, Dem. Rep.	116.0	137.2740	26.4194	165.664	609.0	20.800	57.5	6
38	Congo, Rep.	63.9	2331.7400	67.4040	1498.780	5190.0	20.700	60.4	4
40	Cote d'Ivoire	111.0	617.3200	64.6600	528.260	2690.0	5.390	56.3	5
49	Equatorial Guinea	111.0	14671.8000	766.0800	10071.900	33700.0	24.900	60.9	5
50	Eritrea	55.2	23.0878	12.8212	112.306	1420.0	11.600	61.7	4

	country	child_mort	exports	health	imports	income	inflation	life_expec	tota
55	Gabon	63.7	5048.7500	306.2500	1653.750	15400.0	16.600	62.9	4
56	Gambia	80.3	133.7560	31.9778	239.974	1660.0	4.300	65.5	5
59	Ghana	74.7	386.4500	68.3820	601.290	3060.0	16.600	62.2	4
63	Guinea	109.0	196.3440	31.9464	279.936	1190.0	16.100	58.0	5
64	Guinea-Bissau	114.0	81.5030	46.4950	192.544	1390.0	2.970	55.6	5
66	Haiti	208.0	101.2860	45.7442	428.314	1500.0	5.450	32.1	3
72	Iraq	36.9	1773.0000	378.4500	1534.500	12700.0	16.600	67.2	4
80	Kenya	62.2	200.1690	45.9325	324.912	2480.0	2.090	62.8	4
81	Kiribati	62.7	198.1700	168.3700	1190.510	1730.0	1.520	60.7	3
84	Lao	78.9	403.5600	50.9580	562.020	3980.0	9.200	63.8	3
87	Lesotho	99.7	460.9800	129.8700	1181.700	2380.0	4.150	46.5	3
88	Liberia	89.3	62.4570	38.5860	302.802	700.0	5.470	60.8	5
93	Madagascar	62.2	103.2500	15.5701	177.590	1390.0	8.790	60.8	4
94	Malawi	90.5	104.6520	30.2481	160.191	1030.0	12.100	53.1	5
97	Mali	137.0	161.4240	35.2584	248.508	1870.0	4.370	59.5	6
99	Mauritania	97.4	608.4000	52.9200	734.400	3320.0	18.900	68.2	4
106	Mozambique	101.0	131.9850	21.8299	193.578	918.0	7.640	54.5	5

	country	child_mort	exports	health	imports	income	inflation	life_expec	tota
108	Namibia	56.0	2480.8200	351.8820	3150.330	8460.0	3.560	58.6	3
112	Niger	123.0	77.2560	17.9568	170.868	814.0	2.550	58.8	6
113	Nigeria	130.0	589.4900	118.1310	405.420	5150.0	104.000	60.5	5
116	Pakistan	92.1	140.4000	22.8800	201.760	4280.0	10.900	65.3	3
126	Rwanda	63.6	67.5600	59.1150	168.900	1350.0	2.610	64.6	4
129	Senegal	66.8	249.0000	56.6000	403.000	2180.0	1.850	64.0	5
132	Sierra Leone	160.0	67.0320	52.2690	137.655	1220.0	17.200	55.0	5
136	Solomon Islands	28.1	635.9700	110.2950	1047.480	1780.0	6.810	61.7	4
137	South Africa	53.7	2082.0800	650.8320	1994.720	12000.0	6.350	54.3	2
142	Sudan	76.7	291.5600	93.5360	254.560	3370.0	19.600	66.3	4
147	Tanzania	71.9	131.2740	42.1902	204.282	2090.0	9.250	59.3	5
149	Timor-Leste	62.6	79.2000	328.3200	1000.800	1850.0	26.500	71.1	6
150	Togo	90.3	196.1760	37.3320	279.624	1210.0	1.180	58.7	4
155	Uganda	81.0	101.7450	53.6095	170.170	1540.0	10.600	56.8	6
165	Yemen	56.3	393.0000	67.8580	450.640	4480.0	23.600	67.5	4

In [80]:
```
country_df[country_df['cluster_labels'] == 'Under-Developed Countries'].descri
```

Out[80]:

	child_mort	exports	health	imports	income	inflation	life_expec
count	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000	48.000000
mean	91.610417	879.063521	114.821765	827.028771	3897.354167	11.911146	59.239583
std	34.319855	2252.474004	165.518331	1540.981910	5590.168621	15.362485	6.384914
min	28.100000	20.605200	12.821200	90.552000	609.000000	0.885000	32.100000
25%	63.675000	102.873750	34.005875	193.319500	1390.000000	4.080000	56.725000
50%	89.750000	196.260000	51.613500	339.306000	1860.000000	8.855000	59.800000
75%	111.000000	552.522500	95.303250	801.000000	3522.500000	16.600000	62.825000
max	208.000000	14671.800000	766.080000	10071.900000	33700.000000	104.000000	71.100000

In [81]:
```
# Medium income, Medium GDP and Mild Child_mort
# Filter the data for that clsuter

country_df.loc[country_df['cluster_labels'] == 1,'cluster_labels'] ='Developin
country_df[country_df['cluster_labels'] == 'Developing Countries']
```

Out[81]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	
1	Albania	16.6	1145.20	267.895	1987.74	9930.0	4.49	76.3	1.65	
2	Algeria	27.3	1712.64	185.982	1400.44	12900.0	16.10	76.5	2.89	
4	Antigua and Barbuda	10.3	5551.00	735.660	7185.80	19100.0	1.44	76.8	2.13	1
5	Argentina	14.5	1946.70	834.300	1648.00	18700.0	20.90	75.8	2.37	1
6	Armenia	18.1	669.76	141.680	1458.66	6700.0	7.77	73.3	1.69	
...	...	...	...	...	...	...	...	...	...	
160	Uruguay	10.6	3129.70	993.650	3022.60	17100.0	4.91	76.4	2.08	1
161	Uzbekistan	36.3	437.46	80.178	393.30	4240.0	16.50	68.8	2.34	
162	Vanuatu	29.2	1384.02	155.925	1565.19	2950.0	2.62	63.0	3.50	
163	Venezuela	17.1	3847.50	662.850	2376.00	16500.0	45.90	75.4	2.47	1
164	Vietnam	23.3	943.20	89.604	1050.62	4490.0	12.10	73.1	1.95	

111 rows × 11 columns

In [82]:
```
country_df[country_df['cluster_labels'] == 'Developing Countries'].describe()
```

Out[82]:

	child_mort	exports	health	imports	income	inflation	life_expe
count	111.000000	111.000000	111.000000	111.000000	111.000000	111.000000	111.00000
mean	17.686486	6197.379266	1098.913521	5702.860550	19617.693694	6.443802	74.69819
std	13.991286	7689.510140	1507.213347	5929.947700	16238.417922	7.432669	4.55733
min	2.600000	1.076920	19.463600	0.651092	1990.000000	-4.210000	63.00000
25%	6.850000	1198.840000	195.479500	1513.755000	7850.000000	1.420000	71.45000
50%	14.500000	3124.400000	469.908000	3022.600000	15300.000000	4.220000	74.70000
75%	23.700000	9297.200000	1038.195000	8336.650000	28300.000000	8.870000	77.90000
max	64.400000	43796.900000	8410.330400	32494.000000	84374.000000	45.900000	82.80000

In [83]:
```
# High income, High GDP and Low Child_mort
# Filter the data for that clsuter

country_df.loc[country_df['cluster_labels'] == 2,'cluster_labels'] ='Developed
country_df[country_df['cluster_labels'] == 'Developed Countries']
```

Out[83]:

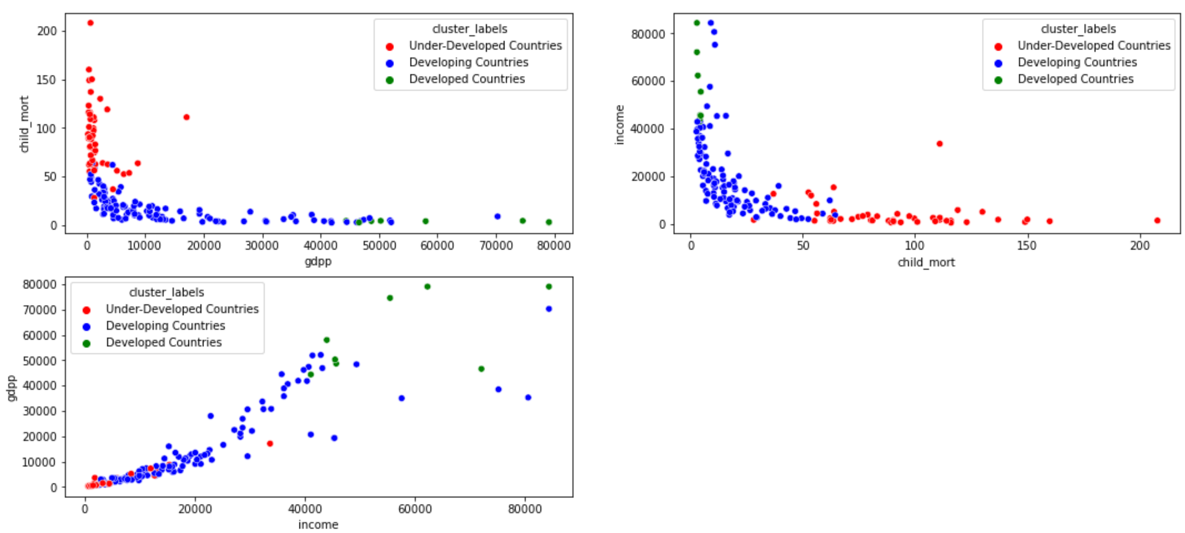
	country	child_mort	exports	health	imports	income	inflation	life_expec	total_f
15	Belgium	4.5	33921.60	4750.8000	33166.80	41100.0	1.880	80.0	1.
44	Denmark	4.1	29290.00	6612.0000	25288.00	44000.0	3.220	79.5	1.
73	Ireland	4.2	50161.00	4475.5300	42125.50	45700.0	-3.220	80.4	2.
91	Luxembourg	2.8	64794.26	8158.5000	55371.39	84374.0	3.620	81.3	1.
110	Netherlands	4.5	36216.00	5985.7000	31990.80	45500.0	0.848	80.7	1.
114	Norway	3.2	34856.60	8323.4400	25023.00	62300.0	5.950	81.0	1.
133	Singapore	2.8	64794.26	1845.3600	55371.39	72100.0	-0.046	82.7	1.
145	Switzerland	4.5	47744.00	8410.3304	39761.80	55500.0	0.317	82.2	1.

In [84]:
```
country_df[country_df['cluster_labels'] == 'Developed Countries'].describe()
```

Out[84]:

	child_mort	exports	health	imports	income	inflation	life_expec
count	8.000000	8.000000	8.000000	8.000000	8.000000	8.000000	8.000000
mean	3.825000	45222.215000	6070.207550	38512.335000	56321.750000	1.571125	80.975000
std	0.762983	13974.354802	2309.856117	12017.974355	15518.448429	2.773660	1.076701
min	2.800000	29290.000000	1845.360000	25023.000000	41100.000000	-3.220000	79.500000
25%	3.100000	34622.850000	4681.982500	30315.100000	45125.000000	0.226250	80.300000
50%	4.150000	41980.000000	6298.850000	36464.300000	50600.000000	1.364000	80.850000
75%	4.500000	53819.315000	8199.735000	45436.972500	64750.000000	3.320000	81.525000
max	4.500000	64794.260000	8410.330400	55371.390000	84374.000000	5.950000	82.700000

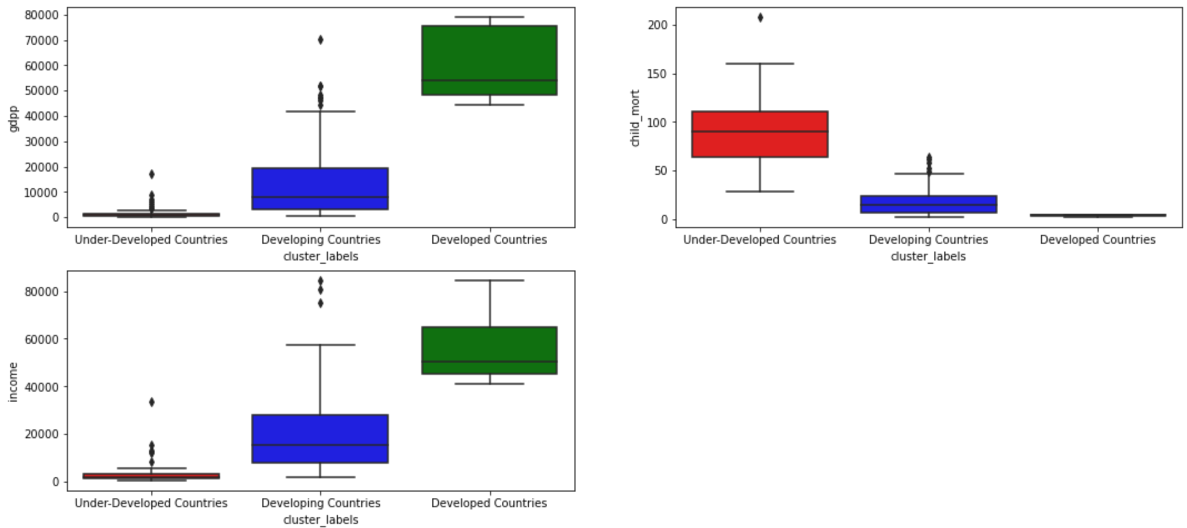
In [85]:
```
plt.figure(figsize=(18,8))
i=0
for i in range(len(profiling_cols)):
    plt.subplot(2,2,i+1)
    sns.scatterplot(x = profiling_cols[i], y = profiling_cols[(i+1)%len(profil
```



comment:

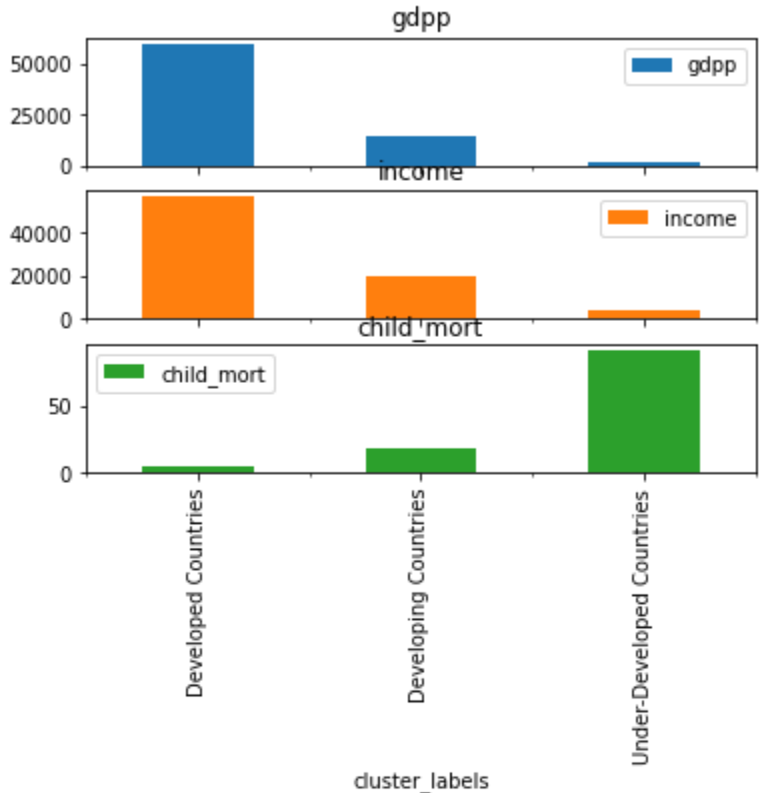
- Developing countries have Medium GDPP, medium Income and mild child mortality rate.
- Developed countries have High GDPP, High income and very low child mortality rate.
- Under-Developed countries have Low GDPP, Low income and very high mortality rate and should be our primary focus.

In [86]:
```
plt.figure(figsize=(18,8))
i=0
for i in range(len(profiling_cols)):
    plt.subplot(2,2,i+1)
    sns.boxplot(x = 'cluster_labels', y = profiling_cols[i], data = country_df
```



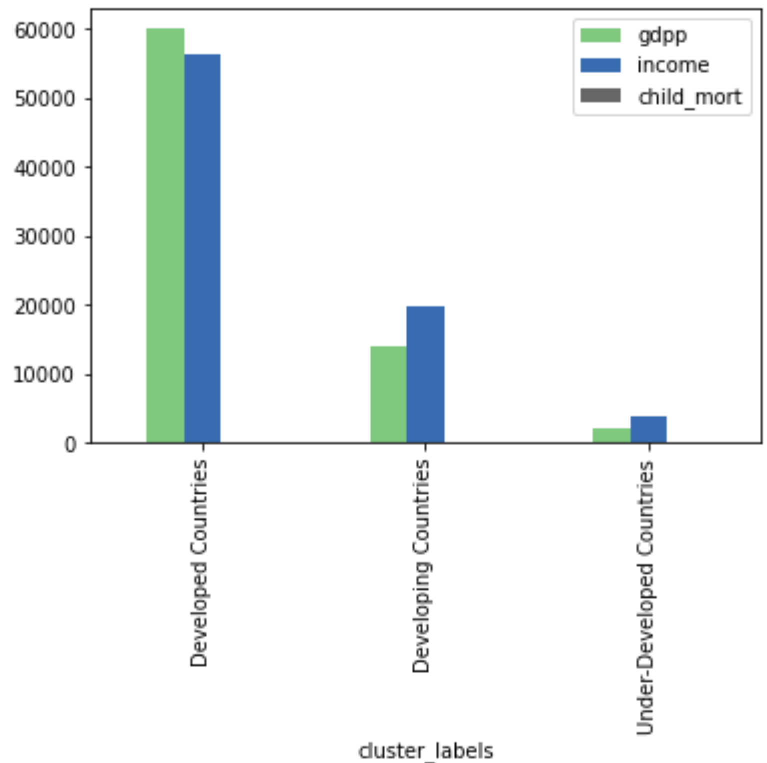
- Developing countries have Medium GDPP, medium Income and mild child mortality rate.
- Developed countries have High GDPP, High income and very low child mortality rate.
- Under-Developed countries have Low GDPP, Low income and very high mortality rate and should be our primary focus.

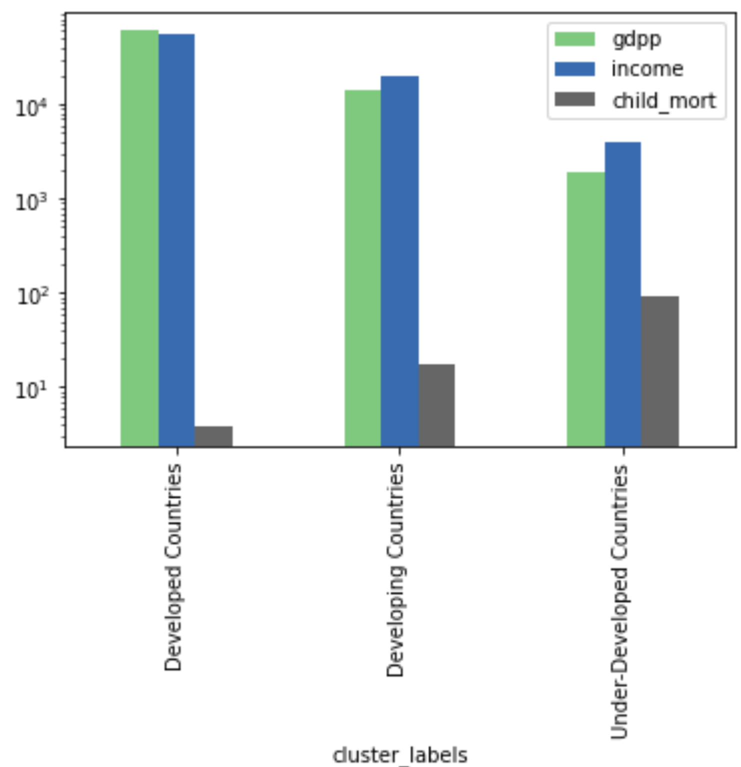
In [87]:
```
# Profiling GDP, INCOME AND CHID_MORT in sub-plots
grouped_df = country_df[['gdpp', 'income', 'child_mort','cluster_labels']].gro
grouped_df.plot(kind='bar', subplots=True)
plt.show()
```



In [88]:
```
# Profiling GDP, INCOME AND CHID_MORT together
grouped_df.plot(kind='bar', colormap='Accent')
grouped_df.plot(kind='bar',logy=True, colormap='Accent')
```

Out[88]: <AxesSubplot:xlabel='cluster_labels'>





Identification of Top 10 countries that require aid on priority using

Hierarchical clustering:

In [89]:
```
H_top10 = country_df[country_df['cluster_labels'] =='Under-Developed Countries
H_top10
```

Out[89]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
26	Burundi	93.6	20.6052	26.7960	90.552	764.0	12.30	57.7	6.2600
88	Liberia	89.3	62.4570	38.5860	302.802	700.0	5.47	60.8	5.0200
37	Congo, Dem. Rep.	116.0	137.2740	26.4194	165.664	609.0	20.80	57.5	6.5400
112	Niger	123.0	77.2560	17.9568	170.868	814.0	2.55	58.8	6.5636
132	Sierra Leone	160.0	67.0320	52.2690	137.655	1220.0	17.20	55.0	5.2000
93	Madagascar	62.2	103.2500	15.5701	177.590	1390.0	8.79	60.8	4.6000
106	Mozambique	101.0	131.9850	21.8299	193.578	918.0	7.64	54.5	5.5600
31	Central African Republic	149.0	52.6280	17.7508	118.190	888.0	2.01	47.5	5.2100
94	Malawi	90.5	104.6520	30.2481	160.191	1030.0	12.10	53.1	5.3100
50	Eritrea	55.2	23.0878	12.8212	112.306	1420.0	11.60	61.7	4.6100

In [90]:
```
H_top10.country
```

Out[90]:
```
26                      Burundi
88                      Liberia
37             Congo, Dem. Rep.
112                       Niger
132                Sierra Leone
93                   Madagascar
106                  Mozambique
31     Central African Republic
94                       Malawi
50                      Eritrea
Name: country, dtype: object
```

In [91]:
```
list(K_top10.country)==list(H_top10.country)
```

Out[91]: False

- This indicates both K-means and Hierarchical Clustering returned same list of 10 countries which are in need of aid.

In [92]:
```
Priority_1_countries = K_top10.head(5)
Priority_1_countries['Aid Priority'] = "Aid Requirement Priority 1"
Priority_1_countries
```

Out[92]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	g
98	Malta	6.8	32283.0	1825.15	32494.0	28300.0	3.83	80.3	1.36	211
42	Cyprus	3.6	15461.6	1838.76	17710.0	33900.0	2.01	79.9	1.42	308
111	New Zealand	6.2	10211.1	3403.70	9436.0	32300.0	3.73	80.9	2.17	337
157	United Arab Emirates	8.6	27195.0	1281.00	22260.0	57600.0	12.50	76.5	1.87	350
23	Brunei	10.5	23792.2	1002.52	9884.0	80600.0	16.70	77.1	1.84	353

In [93]:
```
Priority_2_countries = K_top10.tail(5)
Priority_2_countries['Aid Priority'] = "Aid Requirement Priority 2"
Priority_2_countries
```

Out[93]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	g
75	Italy	4.0	9021.6	3411.74	9737.6	36200.0	0.319	81.7	1.46	358
82	Kuwait	10.8	25679.5	1012.55	11704.0	75200.0	11.200	78.2	2.21	385
158	United Kingdom	5.2	10969.8	3749.96	11981.2	36200.0	1.570	80.3	1.92	389
54	France	4.2	10880.8	4831.40	11408.6	36900.0	1.050	81.4	2.03	406
58	Germany	4.2	17681.4	4848.80	15507.8	40400.0	0.758	80.1	1.39	418

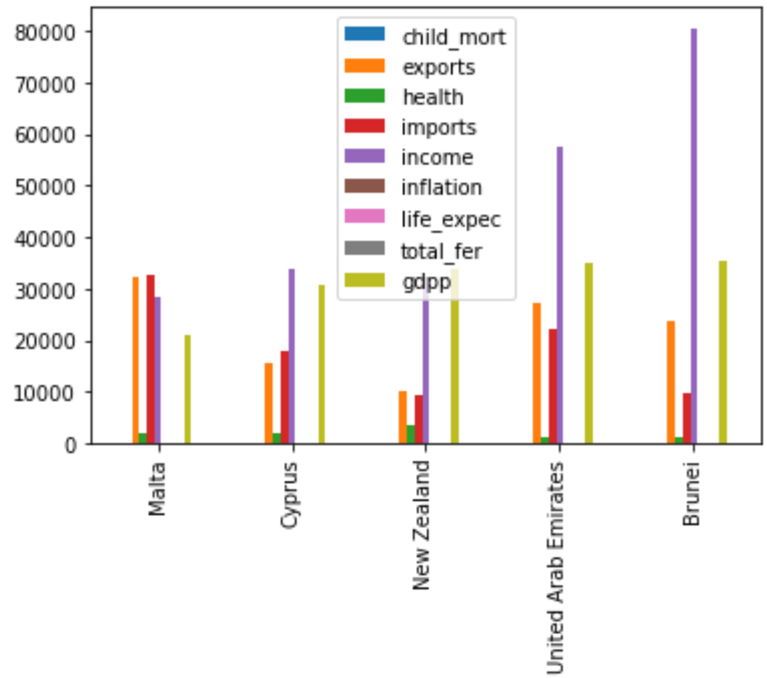
In [94]:
```
def results_plots(df_name):
    plt.figure(figsize=[18,6])
    for i,column_name in enumerate(profiling_cols):
        plt.subplot(2,2,i+1)
        ax = sns.barplot(x='country', y=column_name, data= df_name)
        for each_bar in ax.patches:
            ax.annotate(str(each_bar.get_height()), (each_bar.get_x() * 1.01 ,
        plt.ylabel(column_name)
        plt.xlabel('Countries which have poor %s' %column_name)
```

In [95]:
```
Priority_1_countries
```

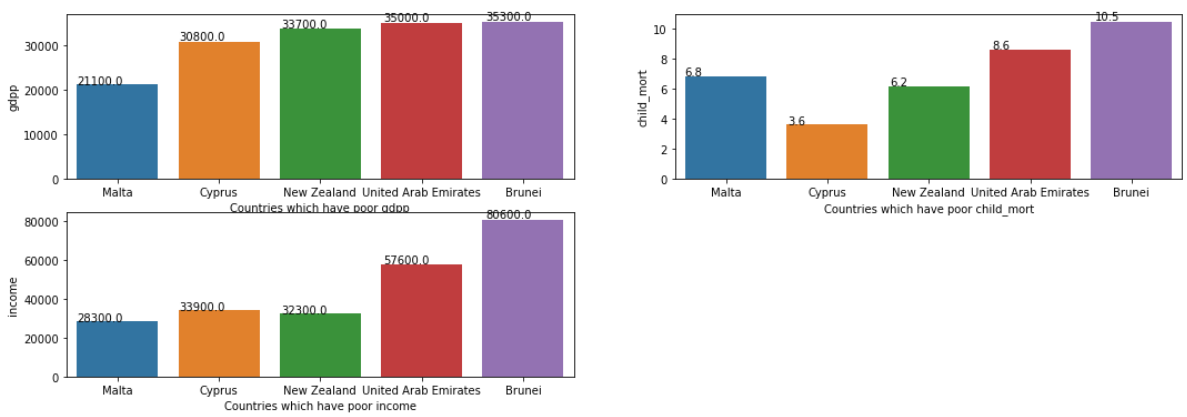
Out[95]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	g
98	Malta	6.8	32283.0	1825.15	32494.0	28300.0	3.83	80.3	1.36	211
42	Cyprus	3.6	15461.6	1838.76	17710.0	33900.0	2.01	79.9	1.42	308
111	New Zealand	6.2	10211.1	3403.70	9436.0	32300.0	3.73	80.9	2.17	337
157	United Arab Emirates	8.6	27195.0	1281.00	22260.0	57600.0	12.50	76.5	1.87	350
23	Brunei	10.5	23792.2	1002.52	9884.0	80600.0	16.70	77.1	1.84	353

In [96]:
```
Priority_1_countries.set_index('country').plot(kind='bar')
plt.xlabel('')
plt.show()
```



In [97]:
```
results_plots(Priority_1_countries)
```

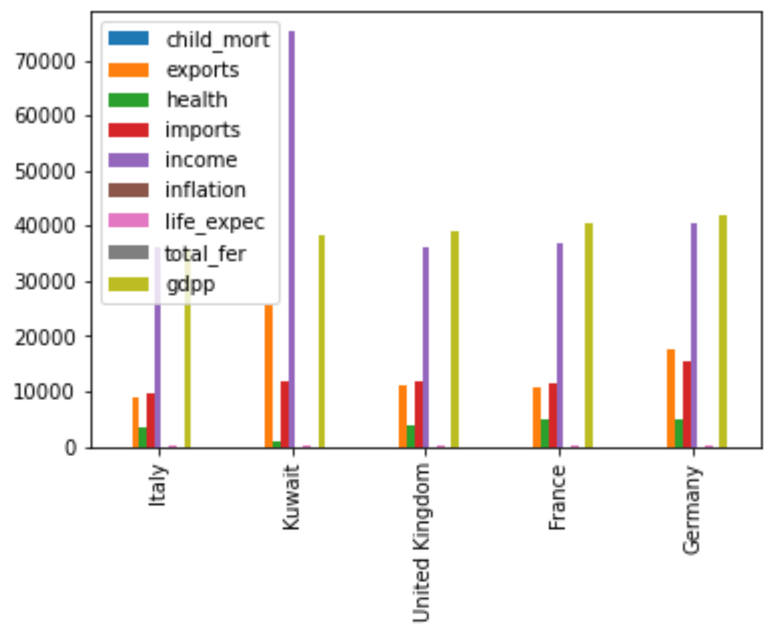


In [98]:
```
Priority_2_countries
```

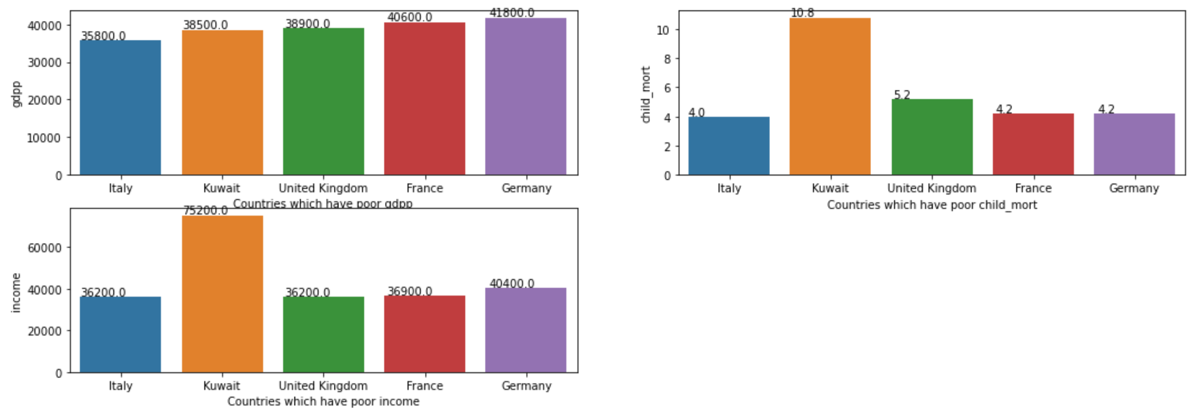
Out[98]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	g
75	Italy	4.0	9021.6	3411.74	9737.6	36200.0	0.319	81.7	1.46	358
82	Kuwait	10.8	25679.5	1012.55	11704.0	75200.0	11.200	78.2	2.21	385
158	United Kingdom	5.2	10969.8	3749.96	11981.2	36200.0	1.570	80.3	1.92	389
54	France	4.2	10880.8	4831.40	11408.6	36900.0	1.050	81.4	2.03	406
58	Germany	4.2	17681.4	4848.80	15507.8	40400.0	0.758	80.1	1.39	418

In [99]:
```
Priority_2_countries.set_index('country').plot(kind='bar')
plt.xlabel('')
plt.show()
```



In [100]:
```
results_plots(Priority_2_countries)
```



Suggestion for CEO of NGO

The following 5 are the countries which have to be provided aid first:

1. Burundi
2. Liberia
3. Congo, Dem. Rep.
4. Niger
5. Sierra Leone

Once the above countries are provided with Aid, the following are the next set of countries which would require aid in order to reduce the child mortality rate and improve their GDPP and income per person:

6. Madagascar
7. Mozambique
8. Central African Republic
9. Malawi
10. Eritrea