K-MEANS CLUSTERING

- Unsupervised learning ml algorithm
- here we will be working with unlabelled data

In [26]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans


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

In [3]:
```
c_data = pd.read_csv(r"C:\Users\Bhupendra\Desktop\DataCenter\Clustering\Coun
c_data.head()
```

Out[3]:

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

In [4]:
```
c_data.shape
```

Out[4]: (167, 10)

In [5]:

```python
c_data.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 [6]:

```python
c_data.describe()
```

Out[6]:

	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

In [8]:

```python
c_data.duplicated().sum()
```

Out[8]: 0

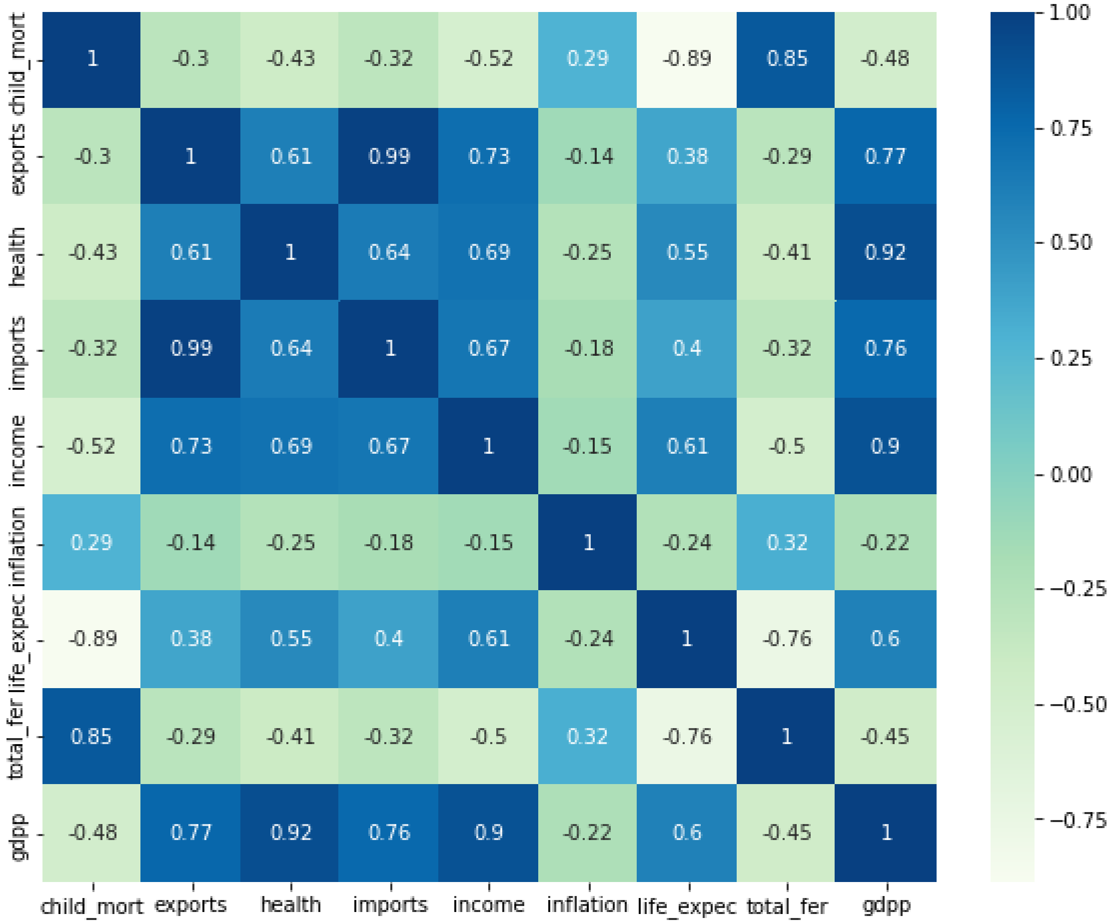
In [14]:

```python
# converting the percentage values into their absolute values

c_data['imports'] = (c_data['gdpp'] * c_data['imports'])/100
c_data['exports'] = (c_data['gdpp'] * c_data['exports'])/100
c_data['health'] = (c_data['gdpp'] * c_data['health'])/100
```

In [15]:
```python
# correlation

plt.figure(figsize = (10,8))
sns.heatmap(c_data.corr(), annot = True, cmap = 'GnBu')
plt.show()
```



Scaling

In [22]:
```python
mmscaler = MinMaxScaler()
X_new = mmscaler.fit_transform(c_data.drop('country', axis = 1))
```

In [24]:
```python
X_new[:1]
```

Out[24]:
```
array([[4.26484907e-01, 2.95093321e-04, 3.36341972e-03, 1.66094560e-03,
        8.04720599e-03, 1.26143610e-01, 4.75345168e-01, 7.36593060e-01,
        3.07342821e-03]])
```

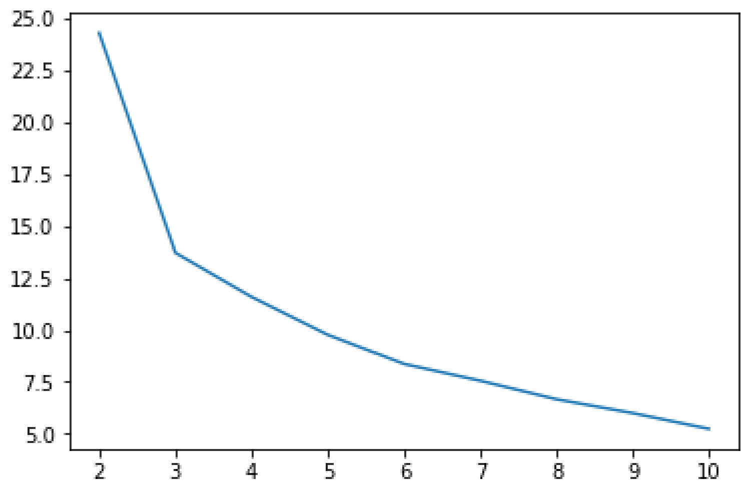
Elbow Curve

- finding the optimal value of K

In [27]:
```
# Elbow Curve for initialising the value of K

wcss = []
for k in range(2, 11):
    kmean = KMeans(n_clusters = k).fit(X_new)
    wcss.append([k, kmean.inertia_])

df_ec = pd.DataFrame(wcss)
plt.plot(df_ec[0], df_ec[1])
plt.show()
```



In [28]:
```
wcss
```

Out[28]:
```
[[2, 24.291592668614573],
 [3, 13.728241930514683],
 [4, 11.601847847563672],
 [5, 9.77643391749045],
 [6, 8.368497447598385],
 [7, 7.559151166085805],
 [8, 6.6679662690017185],
 [9, 6.0018565667804555],
 [10, 5.241773582243932]]
```

K = 3

In [29]:
```
kmean = KMeans(n_clusters = 3).fit(X_new)
```

In [34]:
```
labels = kmean.predict(X_new)
labels
```

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

In [41]:
```
new_df = pd.concat([c_data, pd.DataFrame(labels, columns = ["class"])], axis
```

In [42]:
```
new_df.head()
```

Out[42]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gd
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	5
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	40
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	44
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	35
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	122

In [43]:
```
new_df['class'].value_counts()
```

Out[43]:
```
1    92
0    46
2    29
Name: class, dtype: int64
```

In [45]:
```
class_0 = new_df[new_df['class']==0]
class_1 = new_df[new_df['class']==1]
class_2 = new_df[new_df['class']==2]
```

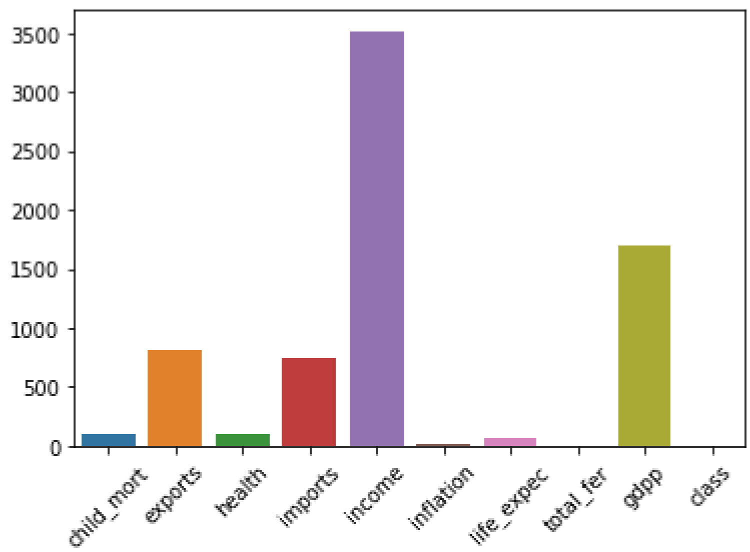
EDA on the above classes

Class_0

In [46]:
```
class_0.mean()
```

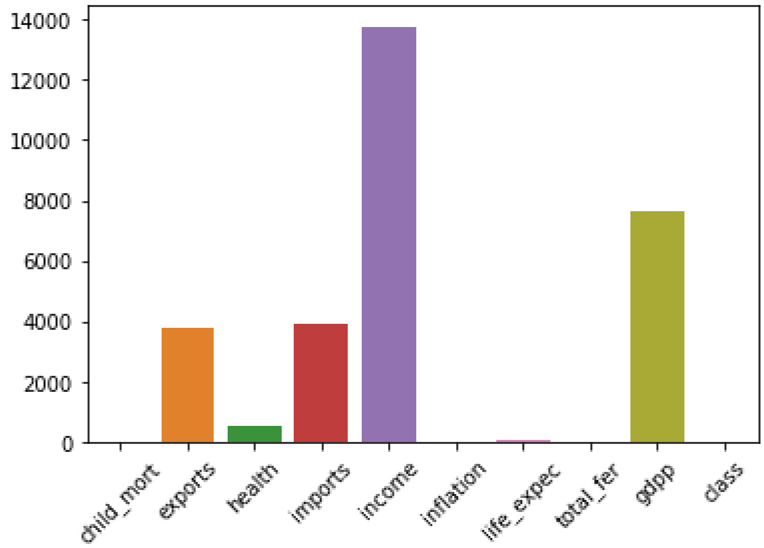
Out[46]:
```
child_mort      93.284783
exports        811.834109
health          94.207885
imports        748.806761
income        3516.804348
inflation       12.097065
life_expec      59.393478
total_fer        5.090217
gdpp          1695.913043
class            0.000000
dtype: float64
```

In [50]:
```
sns.barplot(class_0.mean().index,class_0.mean().values)
plt.xticks(rotation = 45)
plt.show()
```



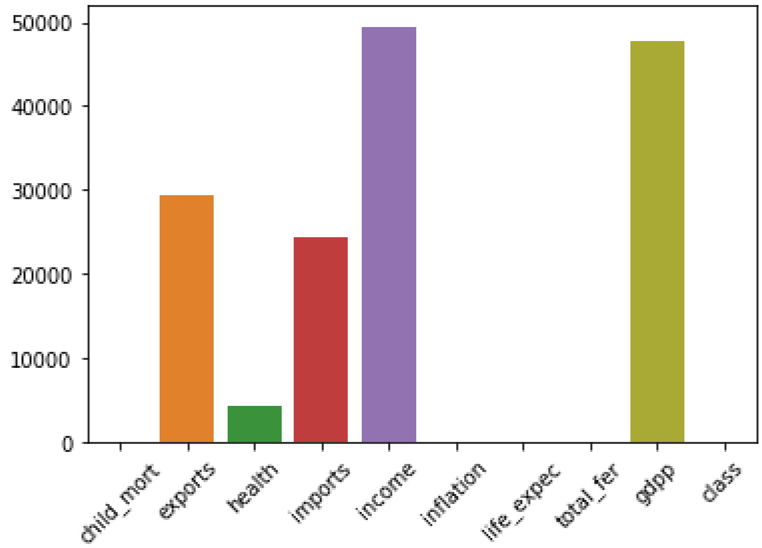
Class_1

In [51]:
```
sns.barplot(class_1.mean().index,class_1.mean().values)
plt.xticks(rotation = 45)
plt.show()
```



Class_2

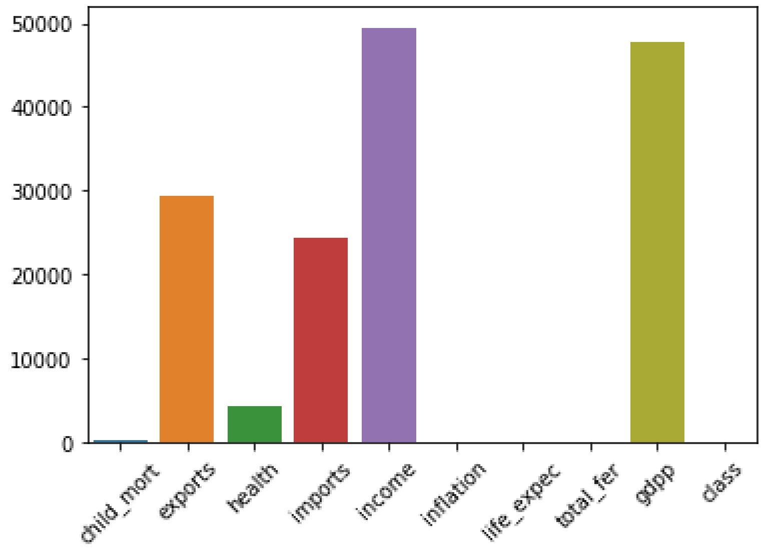
In [52]:
```
sns.barplot(class_2.mean().index,class_2.mean().values)
plt.xticks(rotation = 45)
plt.show()
```



In [57]:

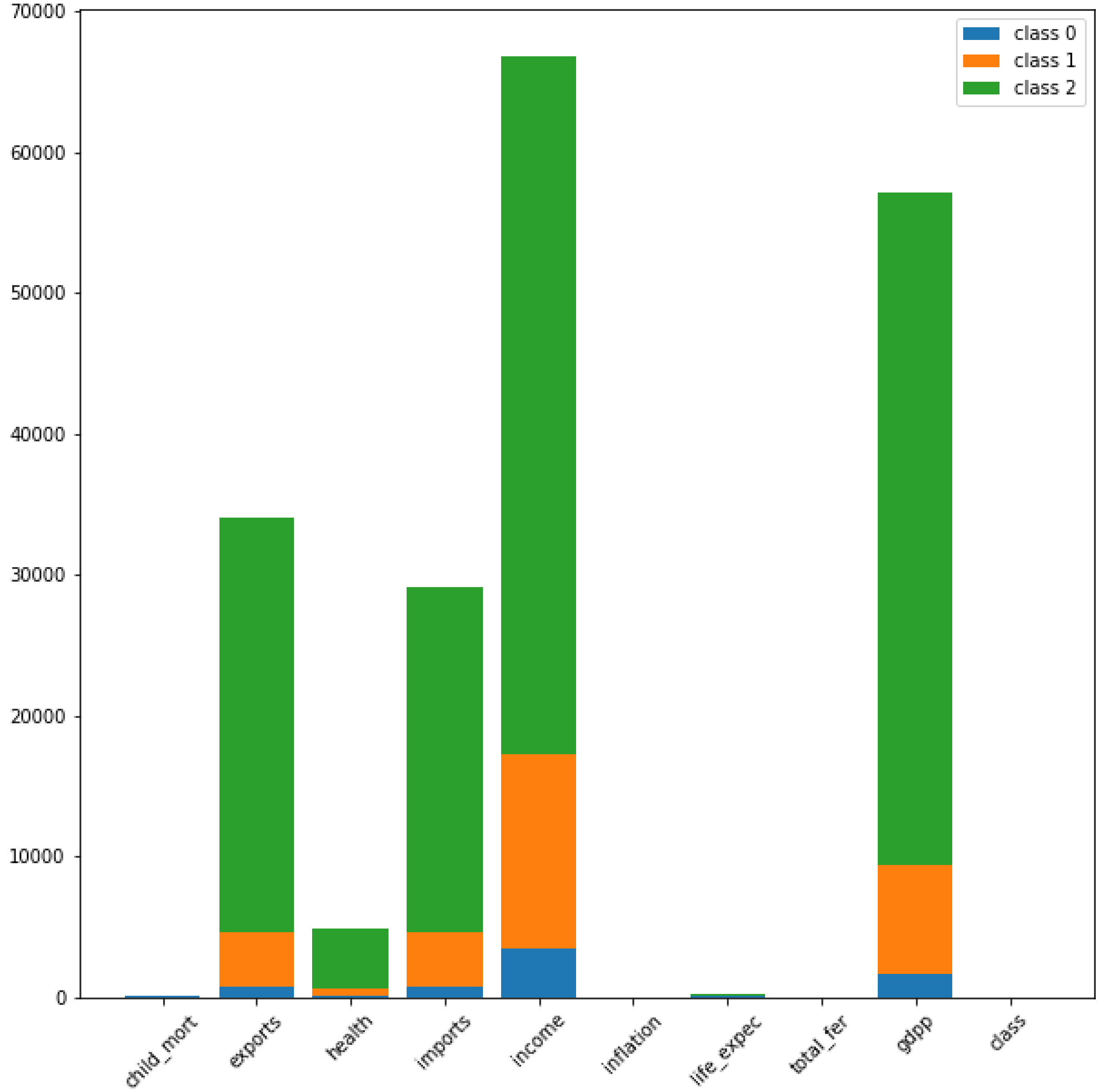
```
sns.barplot(class_0.mean().index,class_0.mean().values)
sns.barplot(class_1.mean().index,class_1.mean().values)
sns.barplot(class_2.mean().index,class_2.mean().values)

plt.xticks(rotation = 45)
plt.show()
```



In [65]:

```
plt.figure(figsize = (10,10))
plt.bar(class_0.mean().index,class_0.mean().values, label = 'class 0')
plt.bar(class_1.mean().index,class_1.mean().values, bottom = class_0.mean().
plt.bar(class_2.mean().index,class_2.mean().values, bottom = np.array(class_
plt.legend()
plt.xticks(rotation = 45)
plt.show()
```



Here countries belonging to class_0 are the poor countries in comparison to class_1 & class_2

Finding the top 5 countries who are in direst need of funding

In [70]:
```
class_0.sort_values(by = ['gdpp','income','exports','imports']).head()
```

Out[70]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
26	Burundi	93.6	20.6052	26.7960	90.552	764	12.30	57.7	6.26	231
88	Liberia	89.3	62.4570	38.5860	302.802	700	5.47	60.8	5.02	327
37	Congo, Dem. Rep.	116.0	137.2740	26.4194	165.664	609	20.80	57.5	6.54	334
112	Niger	123.0	77.2560	17.9568	170.868	814	2.55	58.8	7.49	348
132	Sierra Leone	160.0	67.0320	52.2690	137.655	1220	17.20	55.0	5.20	399

Burundi, Liberia, Congo, Niger and Sierra Leone are the most poor conuntries who are in direst need of funding.

In [ ]:
```

```