In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import dendrogram, linkage
from scipy.cluster.hierarchy import fcluster
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from pandas_profiling import ProfileReport

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

In [2]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, cal
l drive.mount("/content/drive", force_remount=True).
```

In [3]:

```
data = pd.read_csv("/content/drive/MyDrive/Country-data.csv")
```

In [5]:

```
data.head()
```

Out[5]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gc
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	5
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4(
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12

EDA Using Pandas Profiling

In [89]:

```
! pip install https://github.com/pandas-profiling/pandas-profiling/archive/master.zip
```

```
Collecting https://github.com/pandas-profiling/pandas-profiling/archive/mast
er.zip (https://github.com/pandas-profiling/pandas-profiling/archive/master.
zip)
  Using cached https://github.com/pandas-profiling/pandas-profiling/archive/
master.zip (https://github.com/pandas-profiling/pandas-profiling/archive/mas
ter.zip)
Requirement already satisfied: joblib~=1.1.0 in /usr/local/lib/python3.7/dis
t-packages (from pandas-profiling==3.1.1) (1.1.0)
Requirement already satisfied: scipy>=1.4.1 in /usr/local/lib/python3.7/dist
-packages (from pandas-profiling==3.1.1) (1.7.2)
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,!=1.1.0,>=0.25.
3 in /usr/local/lib/python3.7/dist-packages (from pandas-profiling==3.1.1)
 (1.1.5)
Requirement already satisfied: matplotlib>=3.2.0 in /usr/local/lib/python3.
7/dist-packages (from pandas-profiling==3.1.1) (3.2.2)
Requirement already satisfied: pydantic>=1.8.1 in /usr/local/lib/python3.7/d
ist-packages (from pandas-profiling==3.1.1) (1.8.2)
Requirement already satisfied: PyYAML>=5.0.0 in /usr/local/lib/python3.7/dis
t-packages (from pandas-profiling==3.1.1) (6.0)
Requirement already satisfied: jinja2>=2.11.1 in /usr/local/lib/python3.7/di
st-packages (from pandas-profiling==3.1.1) (2.11.3)
Requirement already satisfied: markupsafe~=2.0.1 in /usr/local/lib/python3.
7/dist-packages (from pandas-profiling==3.1.1) (2.0.1)
Requirement already satisfied: visions[type_image_path]==0.7.4 in /usr/loca
l/lib/python3.7/dist-packages (from pandas-profiling==3.1.1) (0.7.4)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.7/dis
t-packages (from pandas-profiling==3.1.1) (1.19.5)
Requirement already satisfied: htmlmin>=0.1.12 in /usr/local/lib/python3.7/d
ist-packages (from pandas-profiling==3.1.1) (0.1.12)
Requirement already satisfied: missingno>=0.4.2 in /usr/local/lib/python3.7/
dist-packages (from pandas-profiling==3.1.1) (0.5.0)
Requirement already satisfied: phik>=0.11.1 in /usr/local/lib/python3.7/dist
-packages (from pandas-profiling==3.1.1) (0.12.0)
Requirement already satisfied: tangled-up-in-unicode==0.2.0 in /usr/local/li
b/python3.7/dist-packages (from pandas-profiling==3.1.1) (0.2.0)
Requirement already satisfied: requests>=2.24.0 in /usr/local/lib/python3.7/
dist-packages (from pandas-profiling==3.1.1) (2.26.0)
Requirement already satisfied: tqdm>=4.48.2 in /usr/local/lib/python3.7/dist
-packages (from pandas-profiling==3.1.1) (4.62.3)
Requirement already satisfied: seaborn>=0.10.1 in /usr/local/lib/python3.7/d
ist-packages (from pandas-profiling==3.1.1) (0.11.2)
Requirement already satisfied: multimethod>=1.4 in /usr/local/lib/python3.7/
dist-packages (from pandas-profiling==3.1.1) (1.6)
Requirement already satisfied: networkx>=2.4 in /usr/local/lib/python3.7/dis
t-packages (from visions[type_image_path]==0.7.4->pandas-profiling==3.1.1)
 (2.6.3)
Requirement already satisfied: attrs>=19.3.0 in /usr/local/lib/python3.7/dis
t-packages (from visions[type_image_path]==0.7.4->pandas-profiling==3.1.1)
 (21.2.0)
Requirement already satisfied: Pillow in /usr/local/lib/python3.7/dist-packa
ges (from visions[type_image_path]==0.7.4->pandas-profiling==3.1.1) (7.1.2)
Requirement already satisfied: imagehash in /usr/local/lib/python3.7/dist-pa
ckages (from visions[type_image_path]==0.7.4->pandas-profiling==3.1.1) (4.2.
1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.
7/dist-packages (from matplotlib>=3.2.0->pandas-profiling==3.1.1) (1.3.2)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python
```

```
3.7/dist-packages (from matplotlib>=3.2.0->pandas-profiling==3.1.1) (2.8.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist
-packages (from matplotlib>=3.2.0->pandas-profiling==3.1.1) (0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /
usr/local/lib/python3.7/dist-packages (from matplotlib>=3.2.0->pandas-profil
ing==3.1.1) (2.4.7)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist
-packages (from pandas!=1.0.0,!=1.0.1,!=1.0.2,!=1.1.0,>=0.25.3->pandas-profi
ling==3.1.1) (2018.9)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/
python3.7/dist-packages (from pydantic>=1.8.1->pandas-profiling==3.1.1) (3.1
0.0.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-pac
kages (from python-dateutil>=2.1->matplotlib>=3.2.0->pandas-profiling==3.1.
1) (1.15.0)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/p
ython3.7/dist-packages (from requests>=2.24.0->pandas-profiling==3.1.1) (2.
0.7)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.7/dist
-packages (from requests>=2.24.0->pandas-profiling==3.1.1) (2.10)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/pytho
n3.7/dist-packages (from requests>=2.24.0->pandas-profiling==3.1.1) (1.24.3)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.
7/dist-packages (from requests>=2.24.0->pandas-profiling==3.1.1) (2021.10.8)
Requirement already satisfied: PyWavelets in /usr/local/lib/python3.7/dist-p
ackages (from imagehash->visions[type_image_path]==0.7.4->pandas-profiling==
3.1.1) (1.2.0)
```

In [90]:

```
profile = ProfileReport(data, title='Pandas Profiling Report', explorative=True)
```

In [91]:

```
profile.to_widgets()
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render widgets:   0%|          | 0/1 [00:00<?, ?it/s]

VBox(children=(Tab(children=(Tab(children=(GridBox(children=(VBox(children=
(GridspecLayout(children=(HTML(valu…
```

EDA

In [6]:

```
data.describe(include="all")
```

Out[6]:

	country	child_mort	exports	health	imports	income	inflation	
count	167	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	1
unique	167	NaN	NaN	NaN	NaN	NaN	NaN	
top	Latvia	NaN	NaN	NaN	NaN	NaN	NaN	
freq	1	NaN	NaN	NaN	NaN	NaN	NaN	
mean	NaN	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	
std	NaN	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	
min	NaN	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	
25%	NaN	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	
50%	NaN	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	
75%	NaN	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	
max	NaN	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	

In [7]:

```
data.isnull().sum()
```

Out[7]:

```
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 [8]:

```
dups = data.duplicated()
print('Number of duplicate rows = %d' % (dups.sum()))
```

```
Number of duplicate rows = 0
```

In [9]:

```
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
```

Observation Until Now :

1. there is no missing value in column
2. And no duplicate rows found
3. Every value is a non value

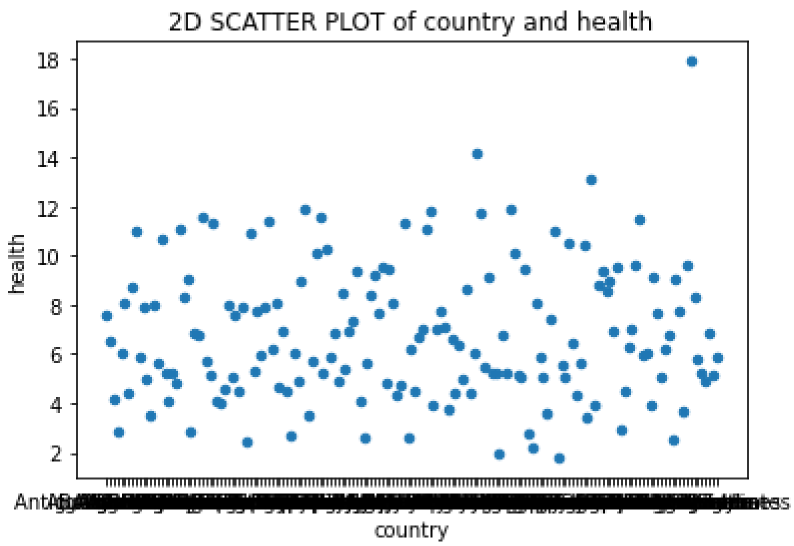
2D SCATTER PLOT

In [10]:

```
data.plot(kind="scatter",x="country",y="health",title="2D SCATTER PLOT of country and healt
```

Out[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f852ffc2c50>
```

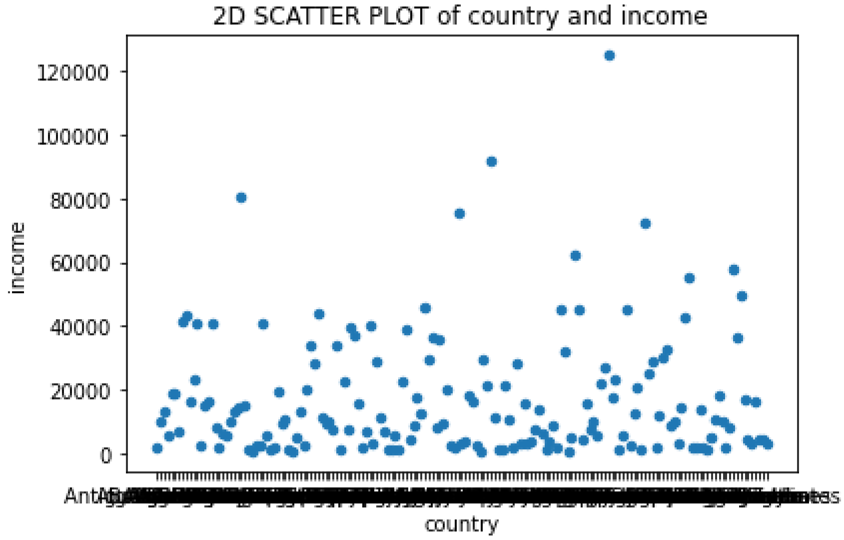


In [11]:

```
data.plot(kind="scatter",x="country",y="income",title="2D SCATTER PLOT of country and incom
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f852f86ba90>
```

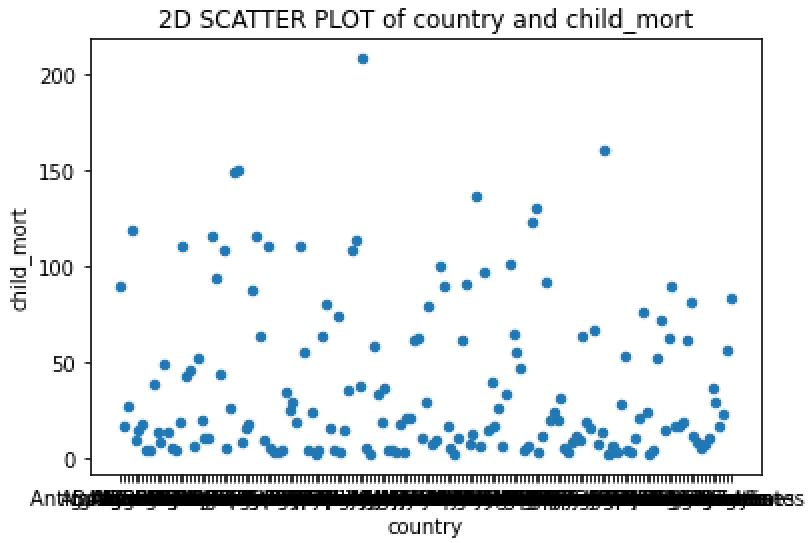


In [12]:

```
data.plot(kind="scatter",x="country",y="child_mort",title="2D SCATTER PLOT of country and c
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f852f630990>
```



Observation from 2D scatter plot

1.It make no sense from above plot since data are sCATTERED

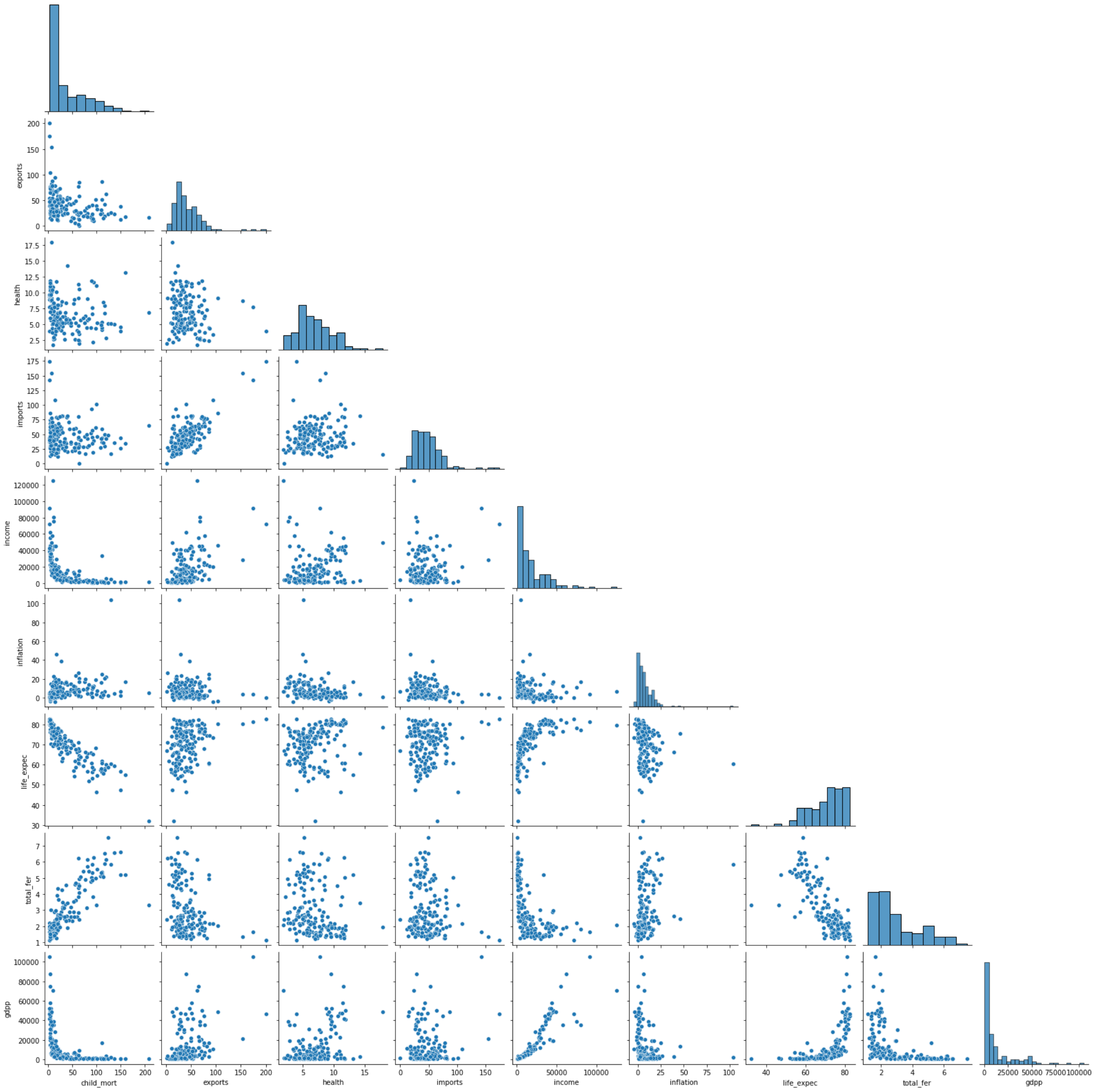
PAIR-PLOT

In [13]:

```
sns.pairplot(data,corner=True)
```

Out[13]:

```
<seaborn.axisgrid.PairGrid at 0x7f852fd8d0d0>
```



1.we are unable to classify which is the most useful feature because of too much overlapping .

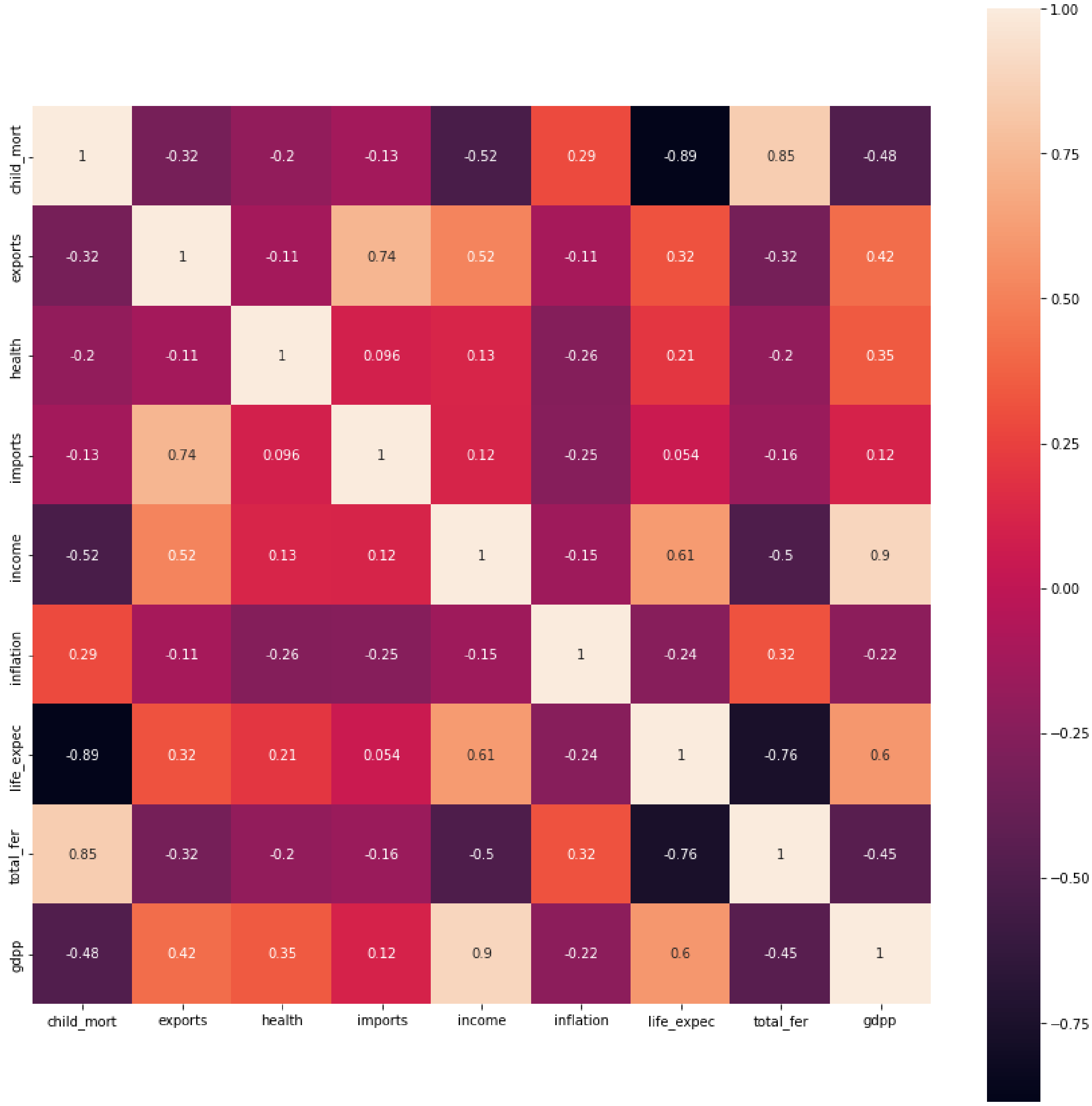
2. we will go with correlation for fetaure importance

In [14]:

```
plt.figure(figsize=(15,15))
sns.heatmap(data.corr(),annot=True,square=True)
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f852ea8e490>
```



In [15]:

```
data.corr()
```

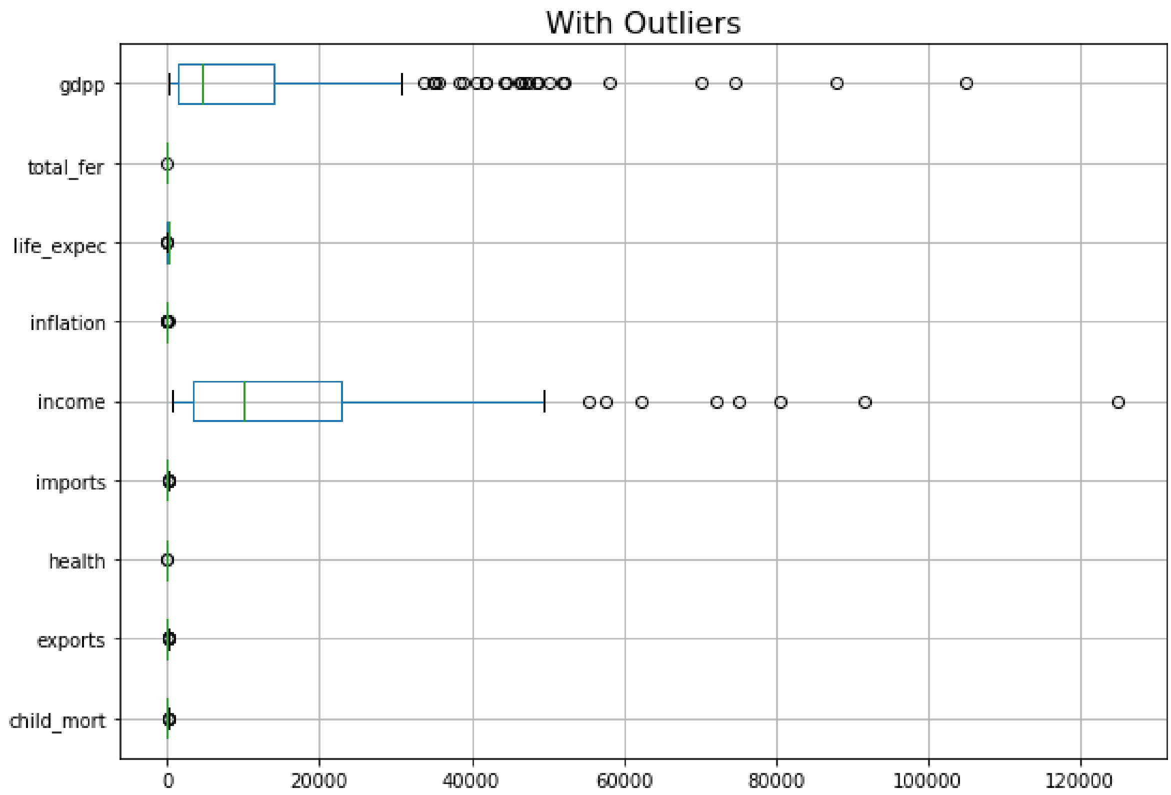
Out[15]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_
child_mort	1.000000	-0.318093	-0.200402	-0.127211	-0.524315	0.288276	-0.886676	0.8484
exports	-0.318093	1.000000	-0.114408	0.737381	0.516784	-0.107294	0.316313	-0.320
health	-0.200402	-0.114408	1.000000	0.095717	0.129579	-0.255376	0.210692	-0.196
imports	-0.127211	0.737381	0.095717	1.000000	0.122406	-0.246994	0.054391	-0.159
income	-0.524315	0.516784	0.129579	0.122406	1.000000	-0.147756	0.611962	-0.501
inflation	0.288276	-0.107294	-0.255376	-0.246994	-0.147756	1.000000	-0.239705	0.316
life_expec	-0.886676	0.316313	0.210692	0.054391	0.611962	-0.239705	1.000000	-0.760
total_fer	0.848478	-0.320011	-0.196674	-0.159048	-0.501840	0.316921	-0.760875	1.000
gdpp	-0.483032	0.418725	0.345966	0.115498	0.895571	-0.221631	0.600089	-0.454

Removing OUTLIER Points

In [16]:

```
cont=data.dtypes[(data.dtypes!='object')].index
plt.figure(figsize=(10,7))
data[cont].boxplot(vert=0)
plt.title('With Outliers',fontsize=16)
plt.show()
```



In [17]:

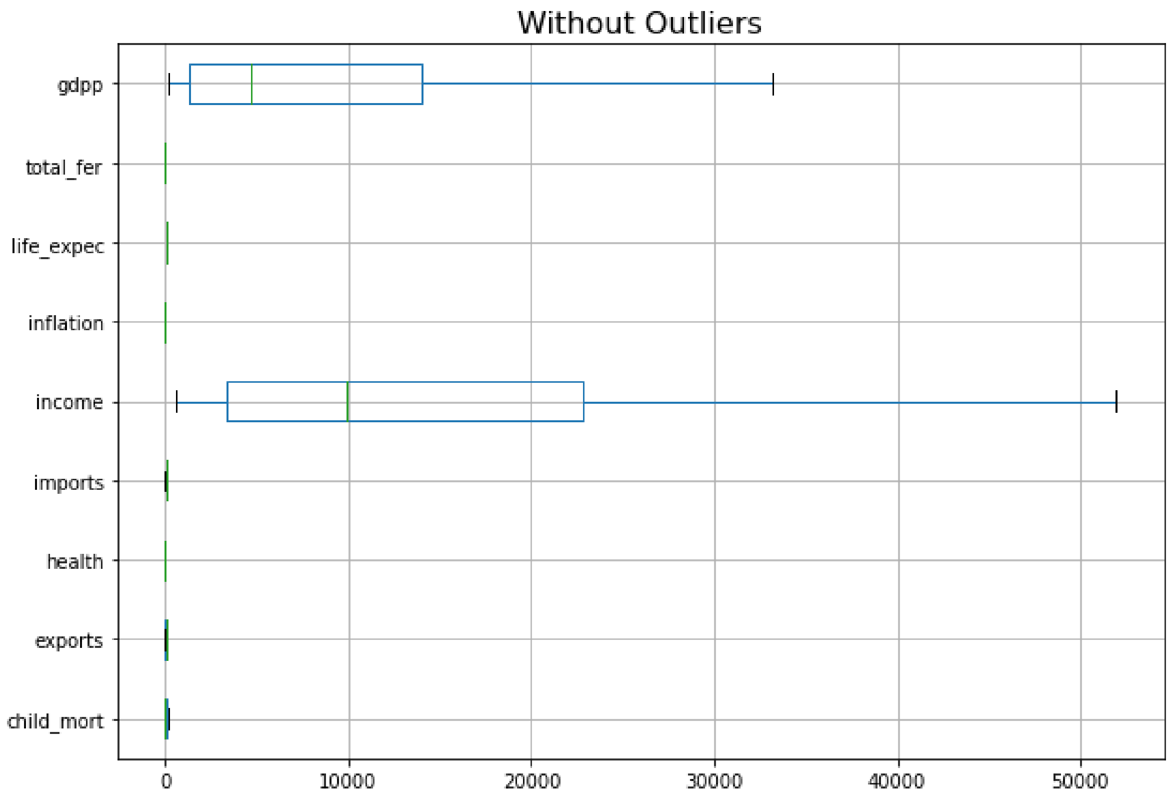
```
def remove_outlier(col):
    sorted(col)
    Q1,Q3=np.percentile(col,[25,75])
    IQR=Q3-Q1
    lower_range= Q1-(1.5 * IQR)
    upper_range= Q3+(1.5 * IQR)
    return lower_range, upper_range
```

In [18]:

```
for column in data[cont].columns:
    lr,ur=remove_outlier(data[column])
    data[column]=np.where(data[column]>ur,ur,data[column])
    data[column]=np.where(data[column]<lr,lr,data[column])
```

In [19]:

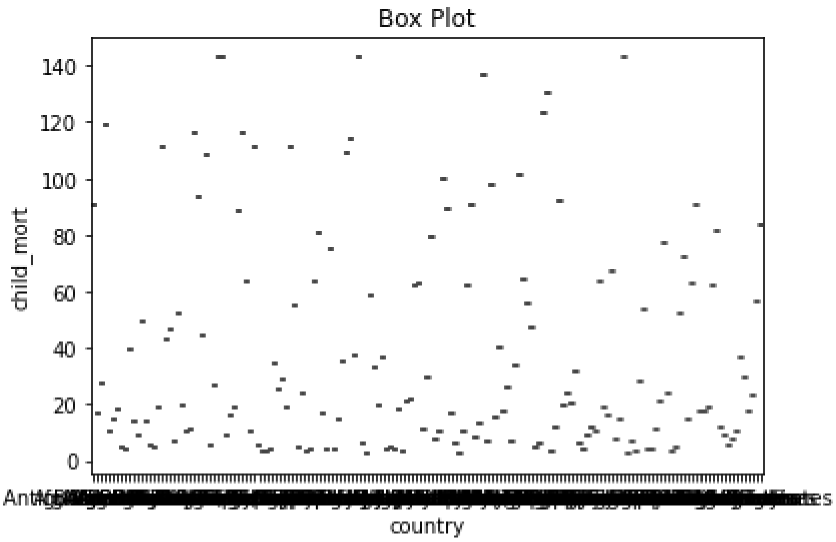
```
plt.figure(figsize=(10,7))
data[cont].boxplot(vert=0)
plt.title('Without Outliers',fontsize=16)
plt.show()
```

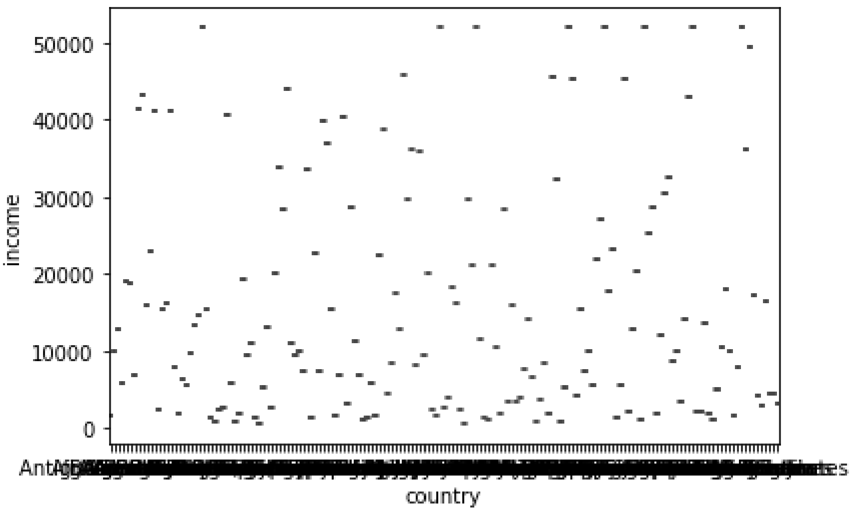


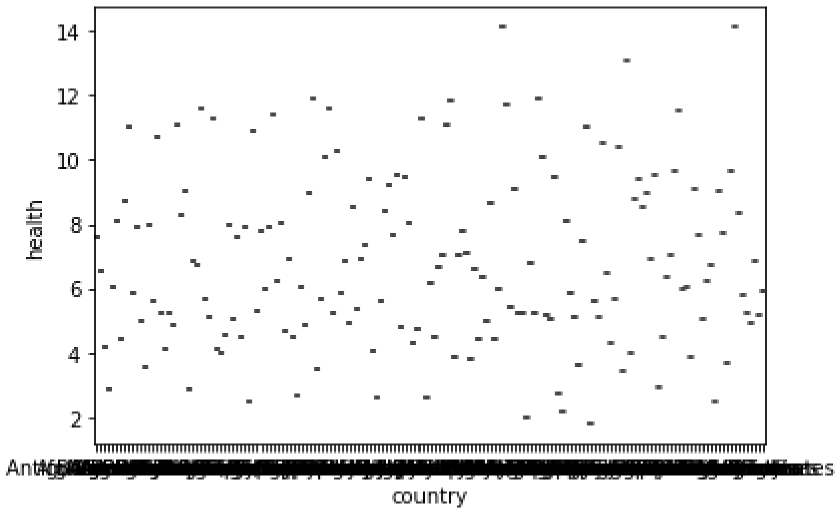
Box plot and Whiskers

In [22]:

```
plt.title("Box Plot")
sns.boxplot(x="country",y="child_mort", data=data)
plt.show()
sns.boxplot(x="country",y="income", data=data)
plt.show()
sns.boxplot(x="country",y="health", data=data)
plt.show()
```



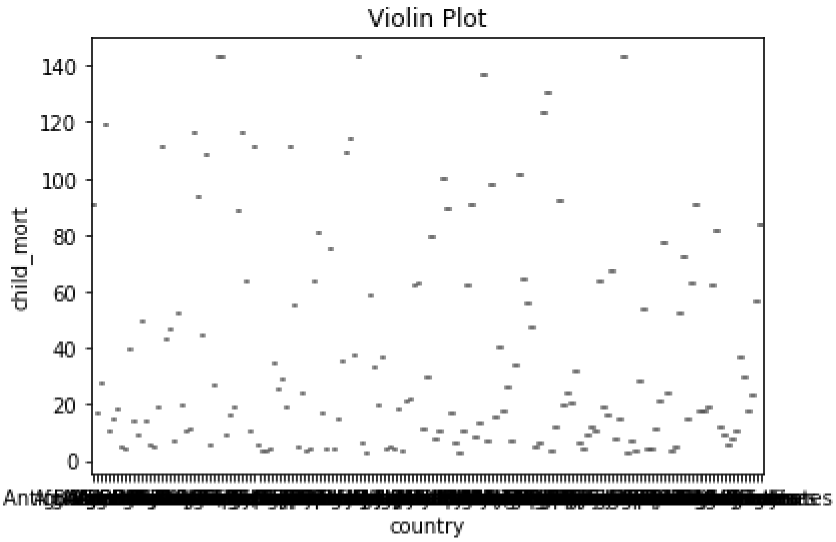


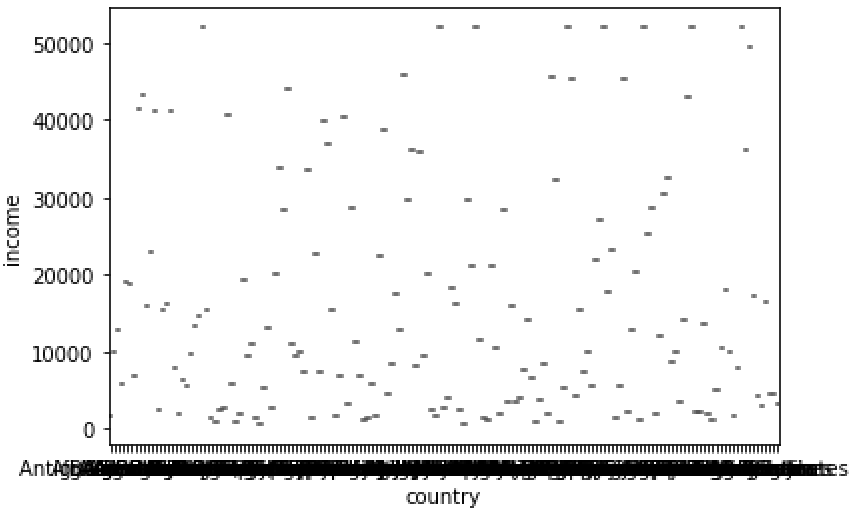


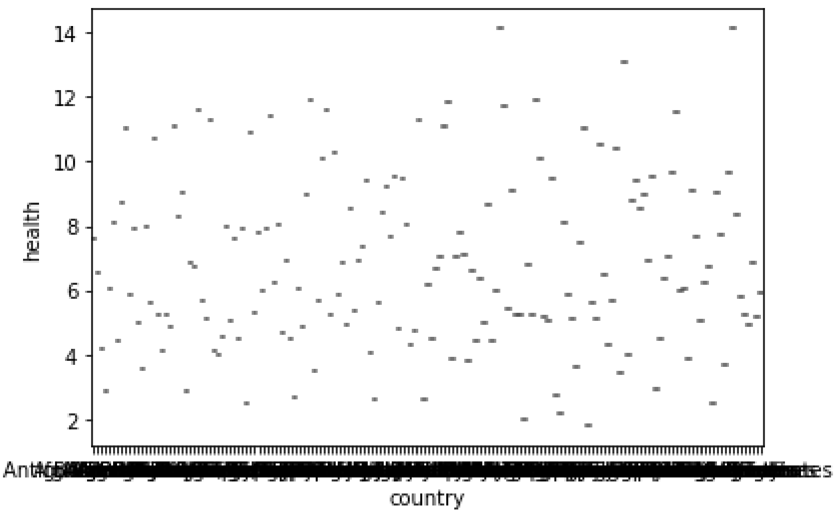
Violin plots

In [23]:

```
plt.title("Violin Plot")
sns.violinplot(x="country",y="child_mort", data=data)
plt.show()
sns.violinplot(x="country",y="income", data=data)
plt.show()
sns.violinplot(x="country",y="health", data=data)
plt.show()
```







In [25]:

```
from sklearn.preprocessing import LabelEncoder

LE = LabelEncoder()
```

In [26]:

```
datatemp=data.copy(deep=True)
```

In [27]:

```
datatemp['country'] = LE.fit_transform(datatemp['country'])
```

In [28]:

```
std = StandardScaler()
```

In [29]:

```
scaled_data = pd.DataFrame(std.fit_transform(datatemp),columns=datatemp.columns)
```

In [30]:

```
scaled_data.head()
```

Out[30]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	tota
0	-1.721710	1.369802	-1.391107	0.296013	-0.047444	-0.943936	0.355270	-1.702225	1.91
1	-1.700967	-0.550464	-0.543547	-0.091190	0.135021	-0.395181	-0.385208	0.663321	-0.86
2	-1.680223	-0.271295	-0.053846	-0.985893	-0.713196	-0.199291	1.351551	0.686859	-0.03
3	-1.659480	2.121210	1.071524	-1.482114	-0.146074	-0.660984	2.293979	-1.243238	2.14
4	-1.638736	-0.714835	0.280469	-0.286671	0.642965	0.209637	-0.841463	0.722166	-0.54

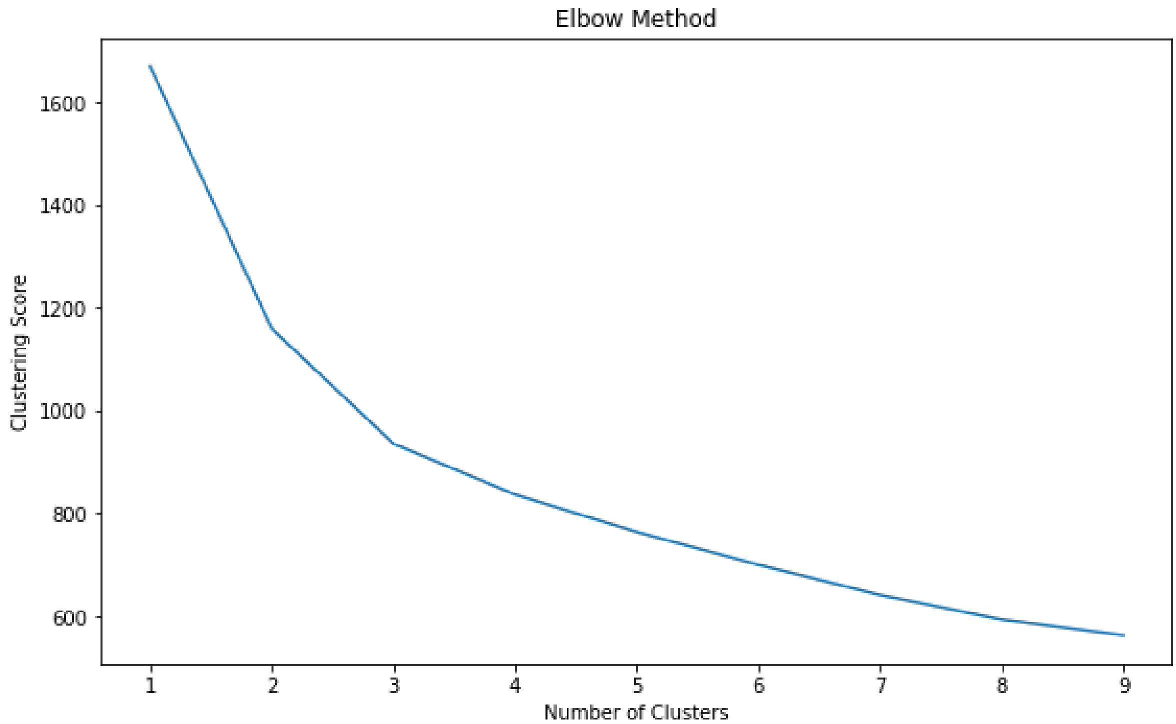
K-Means

In [31]:

```
# individual_clustering_score is inertia

individual_clustering_score = []
for i in range(1, 10):
    kmeans = KMeans(n_clusters = i, init = 'random', random_state = 42)
    kmeans.fit(scaled_data)
    individual_clustering_score.append(kmeans.inertia_)


plt.figure(figsize=(10,6))
plt.plot(range(1, 10), individual_clustering_score)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('Clustering Score')
plt.show()
```



In [32]:

```
individual_clustering_score
```

Out[32]:

```
[1670.0,
 1159.4193928326144,
 935.7159888891679,
 836.6730931012544,
 763.7685458812033,
 700.0084076389447,
 641.1483478197217,
 593.459971584319,
 562.7988340360107]
```

In [33]:

```
#Fit the model and predict
kmeans= KMeans(n_clusters = 3, random_state = 42)


kmeans.fit(scaled_data)

label =kmeans.labels_
```

In [34]:

```
label
```

Out[34]:

```
array([2, 0, 0, 2, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 2, 0, 0, 0, 0,
       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, 2, 2, 0,
       1, 1, 2, 2, 1, 1, 2, 0, 0, 0, 0, 0, 1, 1, 0, 0, 2, 0, 1, 2, 0, 0,
       2, 1, 1, 1, 0, 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], dtype=int32)
```

In [35]:

```
data_km=data.copy(deep=True)
```

In [36]:

```
data_km['clusters'] = label
```

In [37]:

```
data_km.head(10)
```

Out[37]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0	Afghanistan	90.2	10.0	7.58	44.9	1610.0	9.440	56.2	5.82
1	Albania	16.6	28.0	6.55	48.6	9930.0	4.490	76.3	1.65
2	Algeria	27.3	38.4	4.17	31.4	12900.0	16.100	76.5	2.89
3	Angola	119.0	62.3	2.85	42.9	5900.0	22.400	60.1	6.16
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100.0	1.440	76.8	2.13
5	Argentina	14.5	18.9	8.10	16.0	18700.0	20.900	75.8	2.37
6	Armenia	18.1	20.8	4.40	45.3	6700.0	7.770	73.3	1.69
7	Australia	4.8	19.8	8.73	20.9	41400.0	1.160	82.0	1.93
8	Austria	4.3	51.3	11.00	47.8	43200.0	0.873	80.5	1.44
9	Azerbaijan	39.2	54.3	5.88	20.7	16000.0	13.800	69.1	1.92

In [38]:

```
kmeans.cluster_centers_
```

Out[38]:

```
array([[-0.03380421, -0.4073848 ,  0.04041713, -0.17644622,  0.12167228,
        -0.29313626, -0.00203396,  0.22947068, -0.42744615, -0.37838209],
       [ 0.06542179, -0.83558735,  0.55828007,  0.61053738,  0.02238674,
         1.57719412, -0.56371353,  1.06738637, -0.75225834,  1.67515009],
       [ 0.00397216,  1.39544842, -0.53290874, -0.20252796, -0.22826676,
        -0.80354326,  0.47126763, -1.28117433,  1.36087688, -0.73791286]])
```

In [39]:

```
silhouette_score(scaled_data,label)
```

Out[39]:

```
0.23929271865523266
```

In [40]:

```
cluster_prof=data_km.groupby('clusters').mean()
cluster_prof['Freq']=data_km['clusters'].value_counts().sort_index()
cluster_prof
```

Out[40]:

clusters	child_mort	exports	health	imports	income	inflation	life_expec	total
0	22.083951	40.401914	6.323210	48.329321	11477.160494	7.051469	72.613580	2.303
1	5.671795	51.400000	8.416667	46.316026	39834.358974	3.296718	79.733333	1.815
2	91.182979	28.225936	6.253830	41.233317	3738.574468	10.215426	59.777660	4.987

countries which present in cluster2 is the one that needs money from HELP International NGO because the model is predicated to be less income and health report in cluster 2 and in other clusters and child_mort value seems to be higher than other 2 cluster

In [43]:

```
country_cluster=list(data_km[data_km['clusters']==2].country)
```

In [44]:

```
country_cluster
```

Out[44]:

```
['Afghanistan',
 'Angola',
 'Benin',
 'Burkina Faso',
 'Burundi',
 'Cameroon',
 'Central African Republic',
 'Chad',
 'Comoros',
 'Congo, Dem. Rep.',
 'Congo, Rep.',
 "Cote d'Ivoire",
 'Equatorial Guinea',
 'Eritrea',
 'Gabon',
 'Gambia',
 'Ghana',
 'Guinea',
 'Guinea-Bissau',
 'Haiti',
 'Iraq',
 'Kenya',
 'Kiribati',
 'Lao',
 'Lesotho',
 'Liberia',
 'Madagascar',
 'Malawi',
 'Mali',
 'Mauritania',
 'Mozambique',
 'Myanmar',
 'Namibia',
 'Niger',
 'Nigeria',
 'Pakistan',
 'Rwanda',
 'Senegal',
 'Sierra Leone',
 'South Africa',
 'Sudan',
 'Tanzania',
 'Timor-Leste',
 'Togo',
 'Uganda',
 'Yemen',
 'Zambia']
```

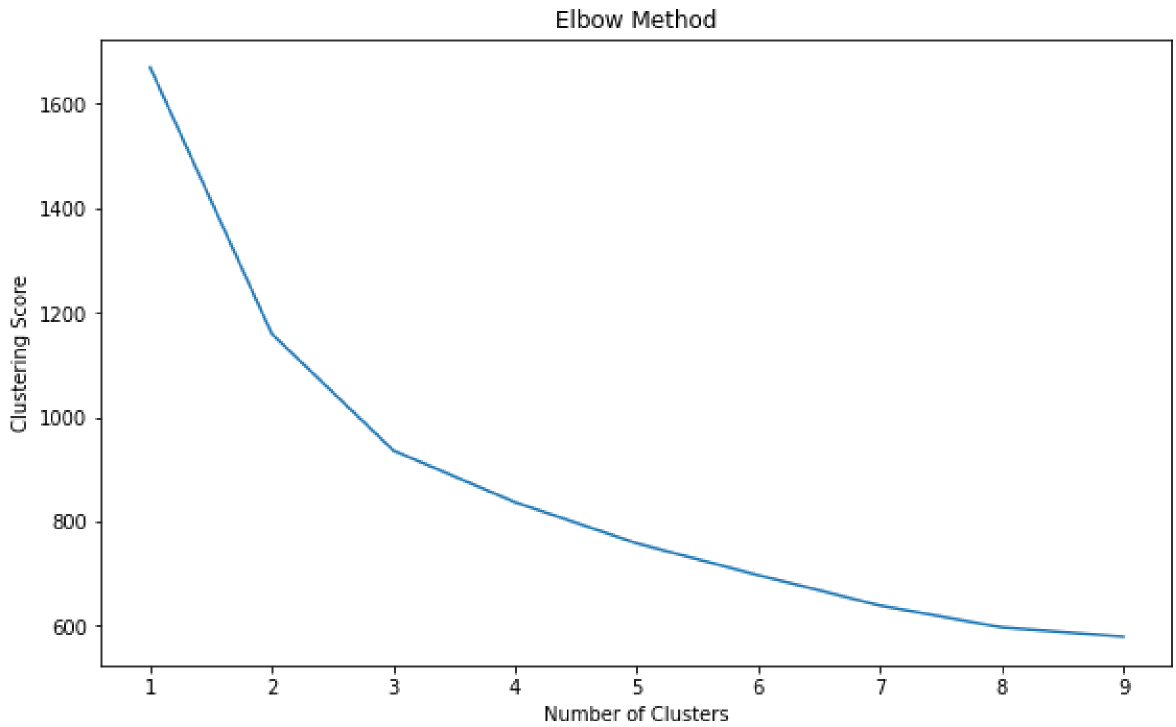
K-Means++

In [45]:

```
# individual_clustering_score is inertia

individual_clustering_score = []
for i in range(1, 10):
    kmeansplus = KMeans(n_clusters = i, init = 'k-means++' , random_state = 42)
    kmeansplus.fit(scaled_data)
    individual_clustering_score.append(kmeansplus.inertia_)


plt.figure(figsize=(10,6))
plt.plot(range(1, 10), individual_clustering_score)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('Clustering Score')
plt.show()
```



In [46]:

```
individual_clustering_score
```

Out[46]:

```
[1670.0,
 1159.4193928326144,
 935.7159888891679,
 836.6638188261788,
 757.9189638915498,
 696.7185650032675,
 638.6418109043038,
 596.739213729041,
 578.8765875619383]
```

In [47]:

```
#Fit the model and predict
kmeansplus= KMeans(n_clusters = 3, random_state = 42, init = 'k-means++')


kmeansplus.fit(scaled_data)

label1=kmeansplus.labels_
```

In [48]:

```
label1
```

Out[48]:

```
array([2, 0, 0, 2, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 2, 0, 0, 0, 0,
       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, 2, 2, 0,
       1, 1, 2, 2, 1, 1, 2, 0, 0, 0, 0, 0, 1, 1, 0, 0, 2, 0, 1, 2, 0, 0,
       2, 1, 1, 1, 0, 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], dtype=int32)
```

In [49]:

```
data_kmplus=data.copy(deep=True)
```

In [50]:

```
data_kmplus['clusters'] = label1
```

In [51]:

```
data_kmplus.head()
```

Out[51]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0	Afghanistan	90.2	10.0	7.58	44.9	1610.0	9.44	56.2	5.82
1	Albania	16.6	28.0	6.55	48.6	9930.0	4.49	76.3	1.65
2	Algeria	27.3	38.4	4.17	31.4	12900.0	16.10	76.5	2.89
3	Angola	119.0	62.3	2.85	42.9	5900.0	22.40	60.1	6.16
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100.0	1.44	76.8	2.13

In [52]:

```
kmeansplus.cluster_centers_
```

Out[52]:

```
array([[-0.03380421, -0.4073848 ,  0.04041713, -0.17644622,  0.12167228,
        -0.29313626, -0.00203396,  0.22947068, -0.42744615, -0.37838209],
       [ 0.06542179, -0.83558735,  0.55828007,  0.61053738,  0.02238674,
         1.57719412, -0.56371353,  1.06738637, -0.75225834,  1.67515009],
       [ 0.00397216,  1.39544842, -0.53290874, -0.20252796, -0.22826676,
        -0.80354326,  0.47126763, -1.28117433,  1.36087688, -0.73791286]])
```

In [53]:

```
silhouette_score(scaled_data,label1)
```

Out[53]:

```
0.23929271865523266
```

In [54]:

```
cluster_prof=data_kmplus.groupby('clusters').mean()
cluster_prof['Freq']=data_kmplus['clusters'].value_counts().sort_index()
cluster_prof
```

Out[54]:

clusters	child_mort	exports	health	imports	income	inflation	life_expec	total
0	22.083951	40.401914	6.323210	48.329321	11477.160494	7.051469	72.613580	2.303
1	5.671795	51.400000	8.416667	46.316026	39834.358974	3.296718	79.733333	1.815
2	91.182979	28.225936	6.253830	41.233317	3738.574468	10.215426	59.777660	4.987

countries which present in cluster2 is the one that needs money from HELP International NGO because the model is predicated to be less income and health report in cluster 2 and in other clusters and child_mort value seems to be higher than other 2 cluster

In [55]:

```
country_cluster=list(data_kmplus[data_kmplus['clusters']==2].country)
```

In [56]:

```
country_cluster
```

Out[56]:

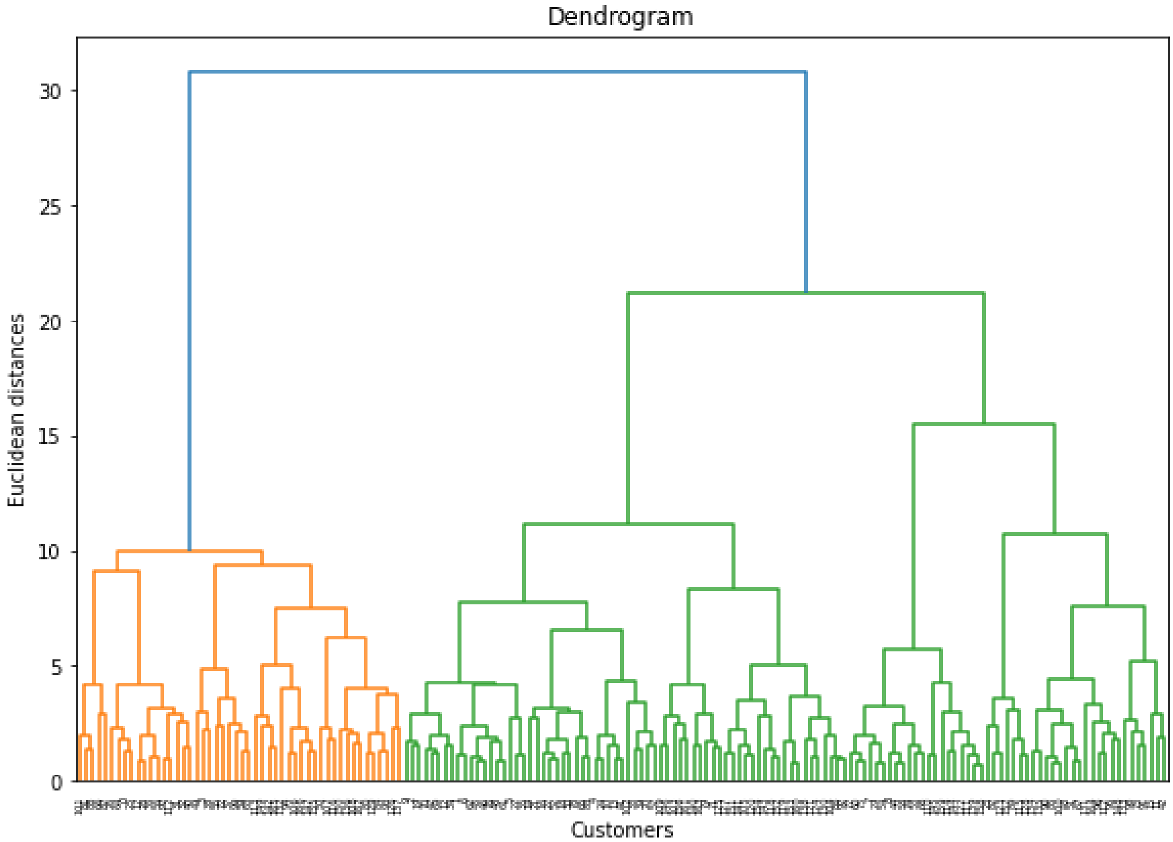
```
['Afghanistan',
 'Angola',
 'Benin',
 'Burkina Faso',
 'Burundi',
 'Cameroon',
 'Central African Republic',
 'Chad',
 'Comoros',
 'Congo, Dem. Rep.',
 'Congo, Rep.',
 "Cote d'Ivoire",
 'Equatorial Guinea',
 'Eritrea',
 'Gabon',
 'Gambia',
 'Ghana',
 'Guinea',
 'Guinea-Bissau',
 'Haiti',
 'Iraq',
 'Kenya',
 'Kiribati',
 'Lao',
 'Lesotho',
 'Liberia',
 'Madagascar',
 'Malawi',
 'Mali',
 'Mauritania',
 'Mozambique',
 'Myanmar',
 'Namibia',
 'Niger',
 'Nigeria',
 'Pakistan',
 'Rwanda',
 'Senegal',
 'Sierra Leone',
 'South Africa',
 'Sudan',
 'Tanzania',
 'Timor-Leste',
 'Togo',
 'Uganda',
 'Yemen',
 'Zambia']
```

Hierarchical Clustering

In [57]:

```
import scipy.cluster.hierarchy as sch
plt.figure(figsize=(10, 7))


dendrogram = sch.dendrogram(sch.linkage(scaled_data, method  = "ward"))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.show()
```



In [58]:

```
from sklearn.cluster import AgglomerativeClustering
cluster = AgglomerativeClustering(n_clusters=4, affinity='euclidean', linkage='ward')
cluster.fit_predict(scaled_data)
```

Out[58]:

```
array([1, 0, 0, 1, 0, 0, 0, 3, 3, 0, 0, 2, 0, 0, 0, 2, 0, 1, 0, 0, 0, 0,
       0, 2, 0, 1, 1, 0, 1, 3, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 2, 2,
       3, 0, 0, 0, 0, 1, 1, 2, 0, 3, 3, 1, 1, 0, 3, 1, 3, 0, 0, 1, 1, 0,
       1, 2, 3, 0, 0, 0, 1, 2, 3, 3, 0, 3, 0, 0, 1, 1, 2, 0, 1, 2, 0, 1,
       1, 2, 2, 2, 0, 1, 1, 2, 2, 1, 2, 1, 2, 1, 0, 0, 0, 0, 1, 1, 1, 0,
       3, 3, 1, 1, 3, 2, 1, 2, 0, 0, 0, 0, 3, 2, 0, 0, 1, 0, 2, 1, 0, 2,
       1, 2, 2, 2, 1, 1, 0, 3, 0, 0, 1, 0, 3, 3, 0, 1, 2, 1, 1, 0, 0, 0,
       0, 1, 0, 2, 3, 3, 0, 0, 1, 0, 2, 1, 1])
```

In [59]:

```
cl = cluster.labels_
```

In [60]:

```
cl
```

Out[60]:

```
array([1, 0, 0, 1, 0, 0, 0, 3, 3, 0, 0, 2, 0, 0, 0, 2, 0, 1, 0, 0, 0, 0,
       0, 2, 0, 1, 1, 0, 1, 3, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 2, 2,
       3, 0, 0, 0, 0, 1, 1, 2, 0, 3, 3, 1, 1, 0, 3, 1, 3, 0, 0, 1, 1, 0,
       1, 2, 3, 0, 0, 0, 1, 2, 3, 3, 0, 3, 0, 0, 1, 1, 2, 0, 1, 2, 0, 1,
       1, 2, 2, 2, 0, 1, 1, 2, 2, 1, 2, 1, 2, 1, 0, 0, 0, 0, 1, 1, 1, 0,
       3, 3, 1, 1, 3, 2, 1, 2, 0, 0, 0, 0, 3, 2, 0, 0, 1, 0, 2, 1, 0, 2,
       1, 2, 2, 2, 1, 1, 0, 3, 0, 0, 1, 0, 3, 3, 0, 1, 2, 1, 1, 0, 0, 0,
       0, 1, 0, 2, 3, 3, 0, 0, 1, 0, 2, 1, 1])
```

In [61]:

```
data_acw=data.copy(deep=True)
```

In [62]:

```
data_acw['clusters'] = cl
```

In [63]:

```
data_acw.head()
```

Out[63]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0	Afghanistan	90.2	10.0	7.58	44.9	1610.0	9.44	56.2	5.82
1	Albania	16.6	28.0	6.55	48.6	9930.0	4.49	76.3	1.65
2	Algeria	27.3	38.4	4.17	31.4	12900.0	16.10	76.5	2.89
3	Angola	119.0	62.3	2.85	42.9	5900.0	22.40	60.1	6.16
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100.0	1.44	76.8	2.13

In [64]:

```
silhouette_score(scaled_data,cl)
```

Out[64]:

```
0.21942224073956046
```

In [65]:

```
cluster_prof=data_acw.groupby('clusters').mean()
cluster_prof['Freq']=data_acw['clusters'].value_counts().sort_index()
cluster_prof
```

Out[65]:

	child_mort	exports	health	imports	income	inflation	life_expec	total
clusters								
0	22.941176	34.987941	6.311471	43.539706	11170.441176	7.573941	72.733824	2.293
1	87.658000	28.920380	6.437000	43.057318	3675.660000	9.867100	59.993000	4.912
2	9.378571	72.184821	5.899643	65.246429	31789.107143	4.980000	76.971429	1.873
3	4.290476	36.066667	10.387619	34.214286	39306.428571	1.525857	80.957143	1.797

countries which present in cluster1 is the one that needs money from HELP International NGO because the model is predicated to be less income and export , life_expec report in cluster 1 and in other clusters and gdpp value seems to be less than other 2 cluster

In [66]:

```
country_cluster2=list(data_acw[data_acw['clusters']==1].country)
```

In [67]:

```
country_cluster2
```

Out[67]:

```
['Afghanistan',
 'Angola',
 'Benin',
 'Burkina Faso',
 'Burundi',
 'Cameroon',
 'Central African Republic',
 'Chad',
 'Comoros',
 'Congo, Dem. Rep.',
 'Congo, Rep.',
 "Cote d'Ivoire",
 'Equatorial Guinea',
 'Eritrea',
 'Gabon',
 'Gambia',
 'Ghana',
 'Guinea',
 'Guinea-Bissau',
 'Haiti',
 'Iraq',
 'Kenya',
 'Kiribati',
 'Lao',
 'Lesotho',
 'Liberia',
 'Madagascar',
 'Malawi',
 'Mali',
 'Mauritania',
 'Micronesia, Fed. Sts.',
 'Mozambique',
 'Myanmar',
 'Namibia',
 'Niger',
 'Nigeria',
 'Pakistan',
 'Rwanda',
 'Senegal',
 'Sierra Leone',
 'Solomon Islands',
 'South Africa',
 'Sudan',
 'Tanzania',
 'Timor-Leste',
 'Togo',
 'Uganda',
 'Vanuatu',
 'Yemen',
 'Zambia']
```

In [68]:

```
from sklearn.cluster import AgglomerativeClustering
cluster = AgglomerativeClustering(n_clusters=4, affinity='euclidean', linkage='single')
cluster.fit_predict(scaled_data)
```

Out[68]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [69]:

```
cl2 = cluster.labels_
```

In [70]:

```
cl2
```

Out[70]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [71]:

```
data_acs=data.copy(deep=True)
```

In [72]:

```
data_acs['clusters'] = cl2
```

In [73]:

```
data_acs.head()
```

Out[73]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	
0	Afghanistan	90.2	10.0	7.58	44.9	1610.0	9.44	56.2	5.82	
1	Albania	16.6	28.0	6.55	48.6	9930.0	4.49	76.3	1.65	4
2	Algeria	27.3	38.4	4.17	31.4	12900.0	16.10	76.5	2.89	4
3	Angola	119.0	62.3	2.85	42.9	5900.0	22.40	60.1	6.16	3
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100.0	1.44	76.8	2.13	12

In [74]:

```
silhouette_score(scaled_data,cl2)
```

Out[74]:

0.047375471798724644

In [75]:

```
cluster_prof=data_acs.groupby('clusters').mean()
cluster_prof['Freq']=data_acs['clusters'].value_counts().sort_index()
cluster_prof
```

Out[75]:

	child_mort	exports	health	imports	income	inflation	life_expec	tota
clusters								
0	36.751982	39.076213	6.788902	45.51214	15875.506098	6.96778	70.802134	2.92
1	14.400000	92.675000	3.400000	101.57500	20400.000000	-4.21000	73.400000	2.17
2	142.875000	16.800000	13.100000	34.50000	1220.000000	17.20000	55.000000	5.20
3	111.000000	85.800000	4.480000	58.90000	33700.000000	24.16000	60.900000	5.21

By looking at silhouette score we can understand model is performing terribly wrong for this parameter and almost every country clustered in 0th cluster

In [76]:

```
from sklearn.cluster import AgglomerativeClustering
cluster = AgglomerativeClustering(n_clusters=4, affinity='euclidean', linkage='average')
cluster.fit_predict(scaled_data)
```

Out[76]:

```
array([2, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0,
       0, 0, 0, 2, 2, 0, 2, 0, 0, 2, 2, 0, 0, 0, 2, 2, 3, 0, 2, 0, 0, 0,
       0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 2, 0, 0, 2, 0, 0, 0, 2, 2, 0,
       2, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 2, 2, 0, 0, 2, 0, 0, 2,
       2, 0, 0, 1, 0, 2, 2, 0, 0, 2, 1, 3, 0, 2, 0, 0, 0, 0, 2, 0, 2, 0,
       0, 0, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 2, 0, 1,
       2, 1, 0, 0, 2, 2, 0, 0, 0, 0, 2, 0, 0, 0, 0, 2, 0, 2, 2, 0, 0, 0,
       2, 2, 0, 0, 0, 0, 0, 0, 2, 0, 0, 2, 2])
```

In [77]:

```
cl3 = cluster.labels_
```

In [78]:

```
cl3
```

Out[78]:

```
array([2, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0,
       0, 0, 0, 2, 2, 0, 2, 0, 0, 2, 2, 0, 0, 0, 2, 2, 3, 0, 2, 0, 0, 0,
       0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 2, 0, 0, 2, 0, 0, 0, 2, 2, 0,
       2, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 2, 2, 0, 0, 2, 0, 0, 2,
       2, 0, 0, 1, 0, 2, 2, 0, 0, 2, 1, 3, 0, 2, 0, 0, 0, 0, 2, 0, 2, 0,
       0, 0, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 2, 0, 1,
       2, 1, 0, 0, 2, 2, 0, 0, 0, 0, 2, 0, 0, 0, 0, 2, 0, 2, 2, 0, 0, 0,
       2, 2, 0, 0, 0, 0, 0, 0, 2, 0, 0, 2, 2])
```

In [79]:

```
data_aca=data.copy(deep=True)
```

In [80]:

```
data_aca['clusters'] = cl3
```

In [81]:

```
data_aca.head()
```

Out[81]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0	Afghanistan	90.2	10.0	7.58	44.9	1610.0	9.44	56.2	5.82
1	Albania	16.6	28.0	6.55	48.6	9930.0	4.49	76.3	1.65
2	Algeria	27.3	38.4	4.17	31.4	12900.0	16.10	76.5	2.89
3	Angola	119.0	62.3	2.85	42.9	5900.0	22.40	60.1	6.16
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100.0	1.44	76.8	2.13

In [82]:

```
silhouette_score(scaled_data,cl3)
```

Out[82]:

0.16920387063289133

cluster profiling

In [83]:

```
clusterprof=data_aca.groupby('clusters').mean()
clusterprof['Freq']=data_aca['clusters'].value_counts().sort_index()
clusterprof
```

Out[83]:

clusters	child_mort	exports	health	imports	income	inflation	life_expec	total
0	18.379310	40.806716	6.860172	43.660051	19865.215517	6.439371	74.647414	2.194
1	6.200000	92.675000	6.594000	98.560000	39667.000000	-0.005200	79.620000	1.672
2	89.078571	26.736190	6.938333	44.854762	2573.642857	8.256310	59.382143	4.943
3	97.825000	70.975000	3.550000	54.425000	12027.500000	21.540000	62.400000	5.325

In [87]:

```
country_cluster3=list(data_acw[data_acw['clusters']==2].country)
```

In [88]:

```
country_cluster3
```

Out[88]:

```
['Bahrain',
 'Belgium',
 'Brunei',
 'Cyprus',
 'Czech Republic',
 'Estonia',
 'Hungary',
 'Ireland',
 'Kuwait',
 'Latvia',
 'Libya',
 'Lithuania',
 'Luxembourg',
 'Malaysia',
 'Maldives',
 'Malta',
 'Mauritius',
 'Oman',
 'Panama',
 'Qatar',
 'Saudi Arabia',
 'Seychelles',
 'Singapore',
 'Slovak Republic',
 'Slovenia',
 'Thailand',
 'United Arab Emirates',
 'Vietnam']
```

countries which present in cluster2 is the one that needs money from HELP International NGO because the model is predicated to be less income and life_expec report in cluster 2 and in other clusters and child_mort value seems to be higher than other 2 cluster