Clustering the Countries by using Unsupervised Learning for "HELP International" oraganization

Description of the data set

Here we use data from kaggle

1. child_mort: Death of children under 5 years of age per 1000 live births
2. exports: Exports of goods and services per capita. Given as %age of the GDP per capita
3. health: Total health spending per capita. Given as %age of GDP per capita
4. imports: Imports of goods and services per capita. Given as %age of the GDP per capita
5. Income: Net income per person
6. Inflation: The measurement of the annual growth rate of the Total GDP
7. life_expec: The average number of years a new born child would live if the current mortality patterns are to remain the same
8. total_fer The number of children that would be born to each woman if the current age-fertility rates remain the same.
9. gdpp: The GDP per capita. Calculated as the Total GDP divided by the total population.

Objective:

To categorise the countries using socio-economic and health factors that determine the overall development of the country.

About organization:

HELP International is an international humanitarian NGO that is committed to fighting poverty and providing the people of backward countries with basic amenities and relief during the time of disasters and natural calamities.

Problem Statement:

HELPING 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, our Job is to categorise the countries using some socio-economic and health factors that determine the overall development of the country. Then to suggest the countries which the CEO needs to focus on the most.

Plan for data exploration:

1. Exploring and feature engineering
    - Examine the data types and value_counts
    - removing unimportant data if found
    - dealing with missing (NaN) values if found
    - Transforming Skewed Continuous Features
    - see the data distribution
    - feature scalling for continuous variables if needed
    - encoding for categorical variables if found as to Encode the activity label as an integer
2. Clustering
    - K_Means
    - AgglomerativeClustering
    - DBSCAN
    - MeanShift
3. Selecting the best model
4. Conclusion and Next Steps

Exploring and feature engineering

In [ ]:

```
#importing
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import LabelBinarizer, MinMaxScaler
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN, MeanShift, esti
```

In [ ]:

```
df= pd.read_csv('data/Country-data.csv',sep=',')
df.head()
```

Out[ ]:

	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 [ ]:

```
df.shape
```

Out[ ]:

```
(167, 10)
```

In [ ]:
```
df.dtypes.value_counts()
```

Out[ ]:
```
float64    7
int64      2
object     1
dtype: int64
```

The data columns are all numeric except for the 'country' label

In [ ]:
```
df_new = df.drop(columns='country')
```

In [ ]:
```
for column in df_new:
    df_new[column] =df_new[column].astype(float)

df_new.dtypes.value_counts()
```

Out[ ]:
```
float64    9
dtype: int64
```

In [ ]:
```
# checking for missing values
df_new.isnull().sum()
```

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

we will drop the country column as it's not useful for us

In [ ]:
```
# see the min and max of data excluding the target
print('min = ',df_new.iloc[:, :-1].min().value_counts())
print('max = ',df_new.iloc[:, :-1].max().value_counts())
```

```
min =    2.6000      1
 0.1090      1
 1.8100      1
 0.0659      1
 609.0000    1
-4.2100      1
 32.1000     1
 1.1500      1
dtype: int64
max =   208.00       1
200.00       1
17.90        1
174.00       1
125000.00    1
104.00       1
82.80        1
7.49         1
dtype: int64
```

Transforming Skewed Features

In [ ]:
```python
skew_limit = 0.75 # define a limit above which we will log transform
skew_vals = df_new[df_new.columns].skew()
```

In [ ]:
```python
# Showing the skewed columns
skew_cols = (skew_vals
             .sort_values(ascending=False)
             .to_frame()
             .rename(columns={0:'Skew'})
             .query('abs(Skew) > {}'.format(skew_limit)))

skew_cols
```

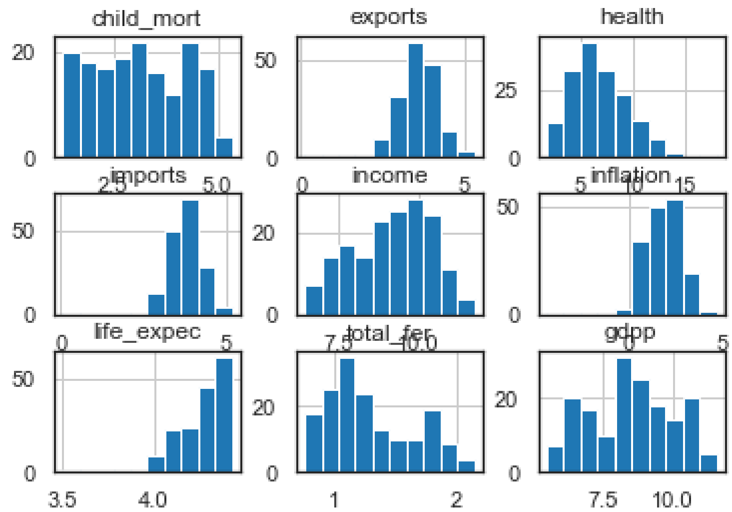
Out[ ]:

	Skew
inflation	5.154049
exports	2.445824
income	2.231480
gdpp	2.218051
imports	1.905276
child_mort	1.450774
total_fer	0.967092
life_expec	-0.970996

In [ ]:
```python
# Perform the skew transformation:
for col in skew_cols.index.values:
    df_new[col] = df_new[col].apply(np.log1p)
```

In [ ]:
```python
df_new.hist()
```

Out[ ]:
```
array([[<AxesSubplot:title={'center':'child_mort'}>,
        <AxesSubplot:title={'center':'exports'}>,
        <AxesSubplot:title={'center':'health'}>],
       [<AxesSubplot:title={'center':'imports'}>,
        <AxesSubplot:title={'center':'income'}>,
        <AxesSubplot:title={'center':'inflation'}>],
       [<AxesSubplot:title={'center':'life_expec'}>,
        <AxesSubplot:title={'center':'total_fer'}>,
        <AxesSubplot:title={'center':'gdpp'}>]], dtype=object)
```



looking at correlation

In [ ]:

```
# The correlation matrix
corr_mat = df_new.corr()
# Strip out the diagonal values for the next step
for x in range(len(df_new.columns)):
    corr_mat.iloc[x,x] = 0.0

corr_mat
```

Out[ ]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
child_mort	0.000000	-0.406777	-0.339588	-0.140941	-0.859310	0.449998	-0.848914	0.864312
exports	-0.406777	0.000000	-0.074494	0.665583	0.510340	-0.156595	0.306579	-0.355055
health	-0.339588	-0.074494	0.000000	0.126102	0.149877	-0.340010	0.178207	-0.232129
imports	-0.140941	0.665583	0.126102	0.000000	0.020655	-0.256076	0.002593	-0.096608
income	-0.859310	0.510340	0.149877	0.020655	0.000000	-0.268519	0.770702	-0.774803
inflation	0.449998	-0.156595	-0.340010	-0.256076	-0.268519	0.000000	-0.299389	0.391213
life_expec	-0.848914	0.306579	0.178207	0.002593	0.770702	-0.299389	0.000000	-0.734395
total_fer	0.864312	-0.355055	-0.232129	-0.096608	-0.774803	0.391213	-0.734395	0.000000
gdpp	-0.874668	0.465639	0.270389	0.043145	0.972024	-0.348723	0.756654	-0.738092

In [ ]:

```
corr_mat.abs().idxmax()
```

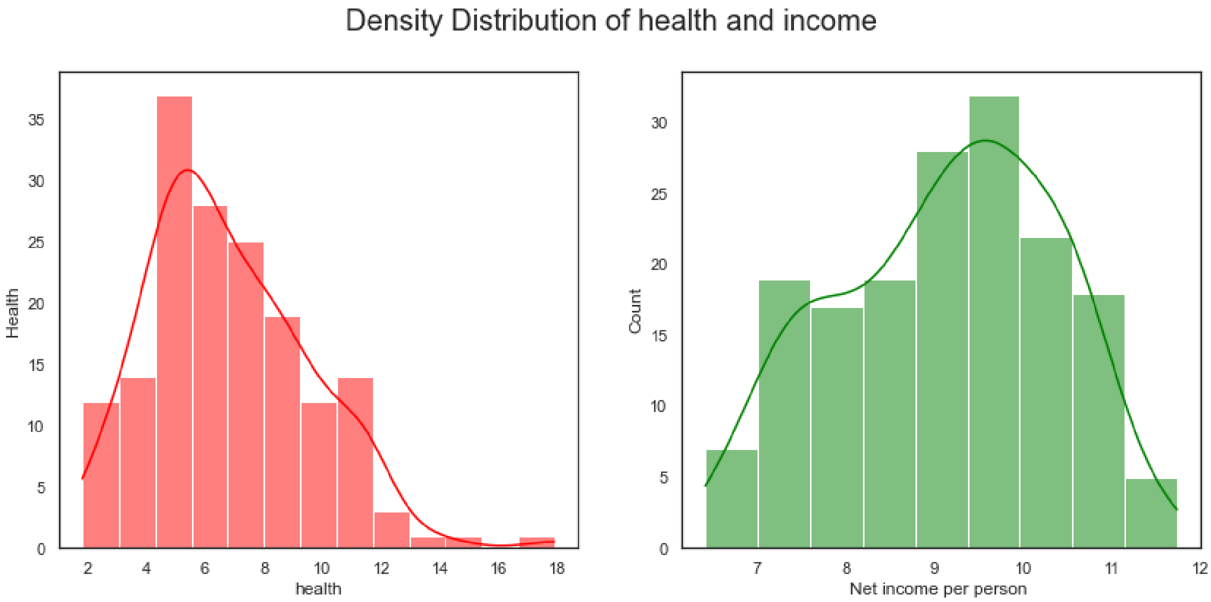
Out[ ]:

```
child_mort          gdpp
exports          imports
health         inflation
imports          exports
income              gdpp
inflation     child_mort
life_expec    child_mort
total_fer     child_mort
gdpp              income
dtype: object
```

In [ ]:

```
#  let's look at distribution of health and income
sns.set_context('notebook')
sns.set_style('white')

plt.figure(figsize=(14,6))
plt.suptitle('Density Distribution of health and income', size=20)

# create first histplot
plt.subplot(1,2,1)
sns.histplot(df_new['health'], kde=True, color='red')
plt.ylabel('Health')

# create second histplot
plt.subplot(1,2,2)
sns.histplot(df_new['income'], kde=True, color='green')
plt.xlabel('Net income per person ')
```

Out[ ]: Text(0.5, 0, 'Net income per person ')



In [ ]:

```
#scaling
mms = MinMaxScaler()

for col in df_new.columns:
    df_new[col] = mms.fit_transform(df_new[[col]]).squeeze()
```

In [ ]:

```
df_new.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
child_mort	167.0	0.454720	0.267697	0.0	0.232179	0.425884	0.705123	1.0
exports	167.0	0.663427	0.126306	0.0	0.597592	0.669262	0.741271	1.0
health	167.0	0.311106	0.170717	0.0	0.193288	0.280298	0.422001	1.0
imports	167.0	0.722024	0.105885	0.0	0.661949	0.730678	0.789330	1.0
income	167.0	0.507677	0.230849	0.0	0.320338	0.524737	0.680321	1.0
inflation	163.0	0.677629	0.116671	0.0	0.603311	0.689902	0.758904	1.0
life_expec	167.0	0.820643	0.146971	0.0	0.747827	0.867566	0.920022	1.0
total_fer	167.0	0.394844	0.257675	0.0	0.191029	0.335836	0.596801	1.0
gdpp	167.0	0.499336	0.245200	0.0	0.285665	0.490638	0.670965	1.0

In [ ]:

```
df_new.isnull().sum()
```

Out[ ]:

```
child_mort    0
exports       0
health        0
imports       0
income        0
inflation     4
life_expec    0
total_fer     0
gdpp          0
dtype: int64
```

In [ ]:
```
df_new[df_new['inflation'].isnull()]
```

Out[ ]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
43	0.049409	0.788722	0.377253	0.802495	0.720922	NaN	0.929665	0.112722	0.727189
73	0.090541	0.873282	0.458670	0.864115	0.810957	NaN	0.968718	0.254601	0.874363
77	0.037955	0.513309	0.477315	0.513080	0.765088	NaN	1.000000	0.077052	0.859614
131	0.357865	0.855470	0.098819	0.907187	0.659427	NaN	0.871916	0.282698	0.628073

In [ ]:
```
df_new.fillna(0,inplace=True)
```

Clustering

cluster analysis of health and income

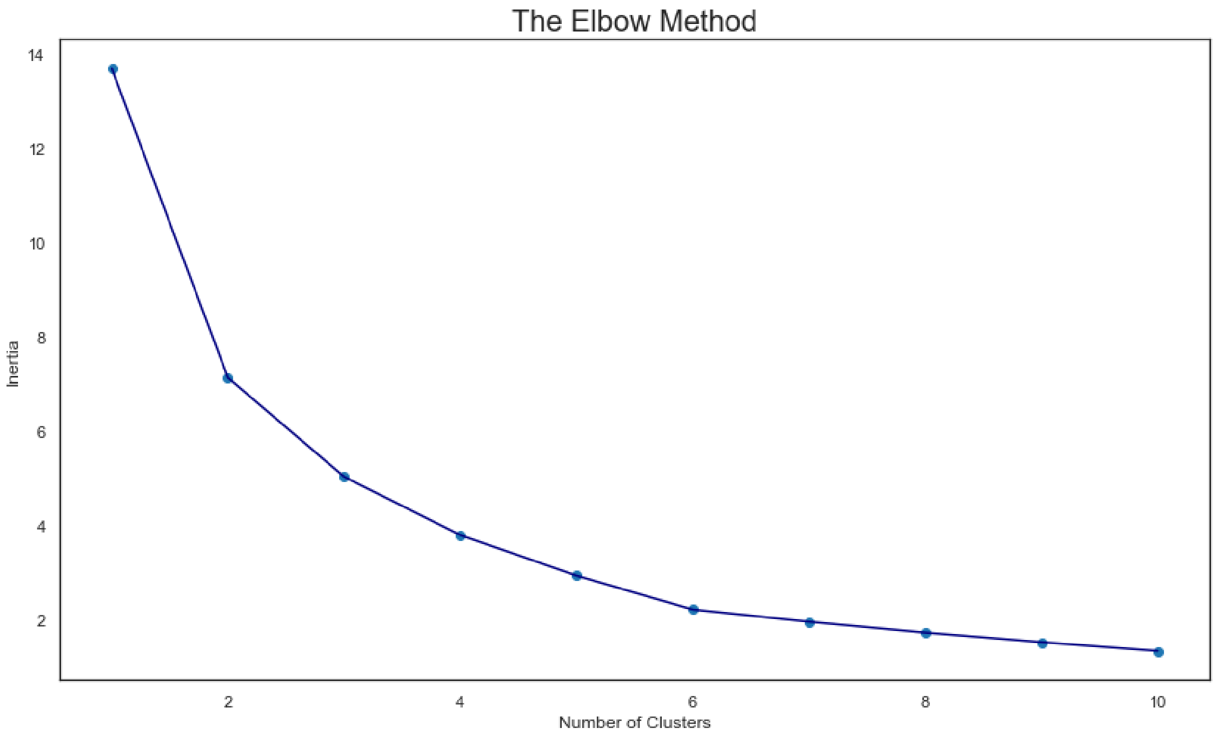
In [ ]:
```
X = df_new[['health','income']]
```

1.K-Means

In [ ]:
```
inertia = []
list_num_clusters = list(range(1,11))
for num_clusters in list_num_clusters:
    km = KMeans(n_clusters=num_clusters)
    km.fit(X)
    inertia.append(km.inertia_)
```

In [ ]:
```
# elbow method

fig, ax = plt.subplots(figsize=(14, 8))
plt.plot(list_num_clusters,inertia, color='navy')
plt.scatter(list_num_clusters,inertia)
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('The Elbow Method', fontsize=20)

# Annotate arrow
# ax.annotate('Possible Elbow Point', xy=(5, 4), xytext=(5, 6), xycoords='data',
#               arrowprops=dict(arrowstyle='->', connectionstyle='arc3', color='red',
```

Out[ ]:
```
Text(0.5, 1.0, 'The Elbow Method')
```



In [ ]:

```
X = df_new[['health','income']]
```

In [ ]:

```
# silhouette index
from sklearn.metrics import silhouette_score

range_n_clusters = list (range(2,10))
for n_clusters in range_n_clusters:
    clusterer = KMeans(n_clusters=n_clusters).fit(X)
    preds = clusterer.predict(X)
    centers = clusterer.cluster_centers_

    score = silhouette_score (X, preds, metric='euclidean')
    print ("For n_clusters = {}, silhouette score is {}".format(n_clusters, score))
```

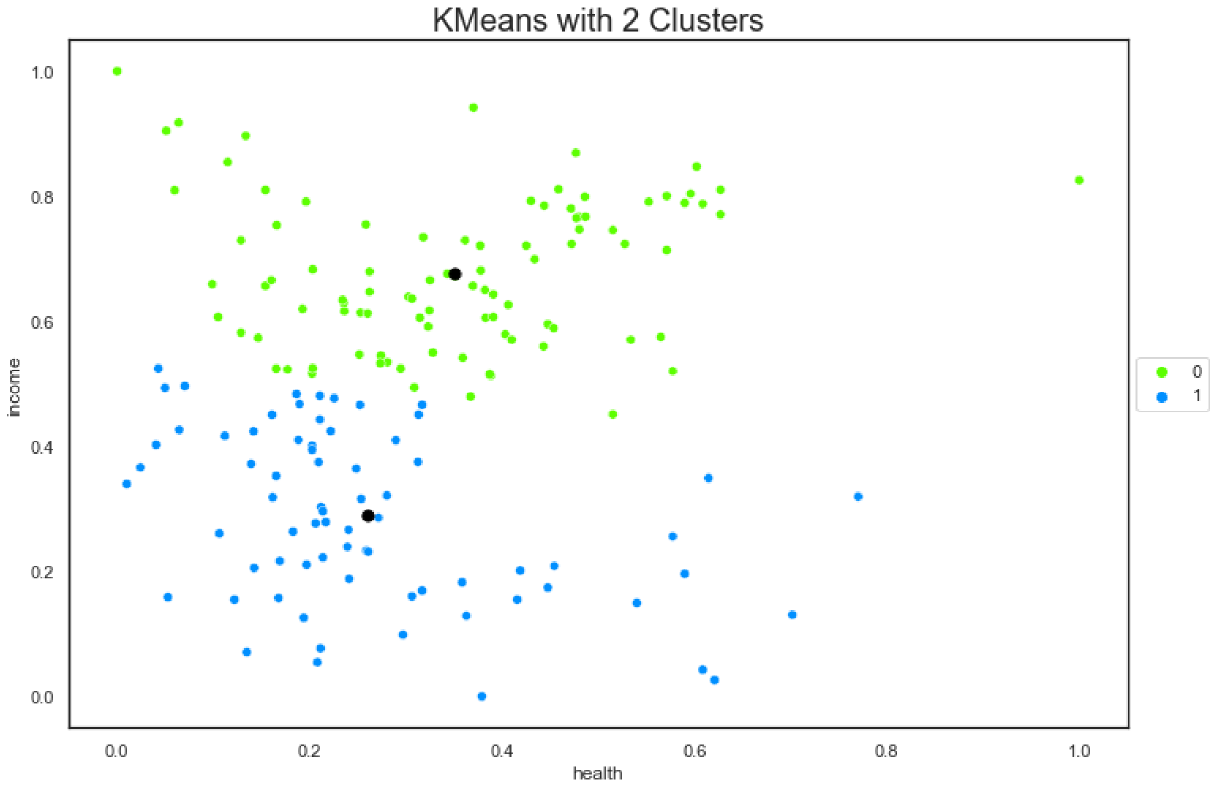
```
For n_clusters = 2, silhouette score is 0.4282963858414001
For n_clusters = 3, silhouette score is 0.38198234473396303
For n_clusters = 4, silhouette score is 0.37634872022819954
For n_clusters = 5, silhouette score is 0.39925070095785703
For n_clusters = 6, silhouette score is 0.40793792926510875
For n_clusters = 7, silhouette score is 0.3722502052540241
For n_clusters = 8, silhouette score is 0.3775488025764062
For n_clusters = 9, silhouette score is 0.370221347389093
```

In [ ]:

```
# 2 cluster
km6 = KMeans(n_clusters=2).fit(X)

X['Labels'] = km6.labels_
plt.figure(figsize=(12, 8))
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette=sns.color_palette('gist_rainbow', 2))
plt.scatter(km6.cluster_centers_[:, 0], km6.cluster_centers_[:, 1], s = 50, c = 'bla
plt.xlabel('health')
plt.ylabel('income')
plt.title('KMeans with 2 Clusters', fontsize=20)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x1d10b1248b0>
```



In [ ]:

```
df['Labels'] = km6.labels_
df[['country','Labels']].sample(5)
```

Out[ ]:

	country	Labels
39	Costa Rica	0
12	Bangladesh	1
37	Congo, Dem. Rep.	1
7	Australia	0
65	Guyana	1

Based on those two graphs above I can concluded that KMeans with 2 clusters gave better insights about clustering income and health

2.Hierarchical Clustering

In [ ]:

```
# silhouette index
from sklearn.metrics import silhouette_score

range_n_clusters = list (range(2,10))
for n_clusters in range_n_clusters:
    ward = AgglomerativeClustering(n_clusters=n_clusters)
    ward = ward.fit(X)
    preds = ward.fit_predict(X)

    score = silhouette_score (X, preds, metric='euclidean')
    print ("For n_clusters = {}, silhouette score is {}".format(n_clusters, score))
```

```
For n_clusters = 2, silhouette score is 0.7736815850029132
For n_clusters = 3, silhouette score is 0.5679359799172009
For n_clusters = 4, silhouette score is 0.45427874560263365
For n_clusters = 5, silhouette score is 0.4690255415652699
```

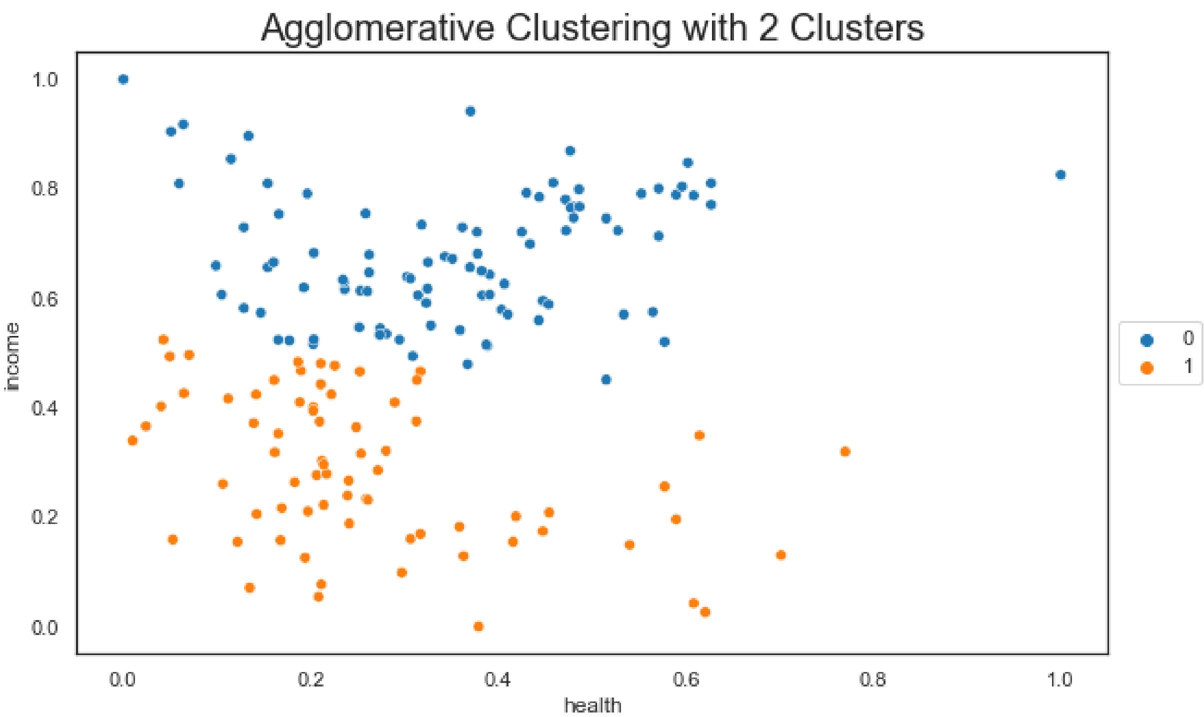
```
For n_clusters = 6, silhouette score is 0.43514539970139976
For n_clusters = 7, silhouette score is 0.4028804062034183
For n_clusters = 8, silhouette score is 0.40761724511998054
For n_clusters = 9, silhouette score is 0.3904331844243769
```

In [ ]:

```
agglom = AgglomerativeClustering(n_clusters=2).fit(X)

X['Labels'] = agglom.labels_
plt.figure(figsize=(10, 6))
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette=sns.color_palette('tab10', 2))
plt.xlabel('health')
plt.ylabel('income')
plt.title('Agglomerative Clustering with 2 Clusters', fontsize=20)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x1d10b268100>
```



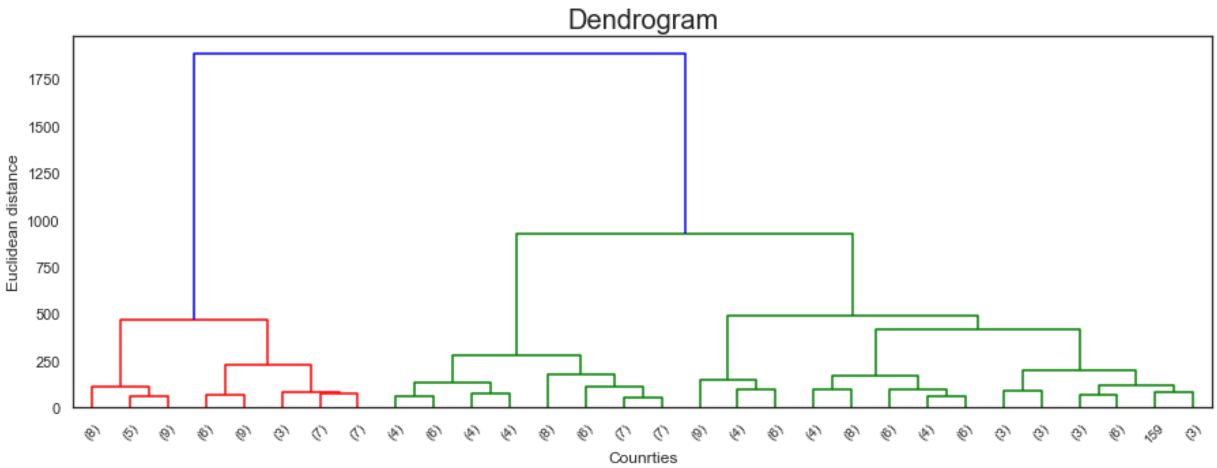
Both clustering algorithms: KMeans and Hierarchical Clustering did good job in labeling our countries into 2 different groups and both results are similar.

In [ ]:

```
from scipy.cluster import hierarchy
HL = hierarchy.linkage(agglom.children_, method='ward')

fig, ax = plt.subplots(figsize=(15,5))

hierarchy.set_link_color_palette(['red', 'green'])

den = hierarchy.dendrogram(HL, orientation='top',
                           p=30, truncate_mode='lastp',
                            show_leaf_counts=True, ax=ax,
                           above_threshold_color='blue')
plt.xlabel('Counrties')
plt.ylabel('Euclidean distance')
plt.title('Dendrogram', fontsize=20)
```

Out[ ]:

```
Text(0.5, 1.0, 'Dendrogram')
```



3.DBSCAN

In [ ]:

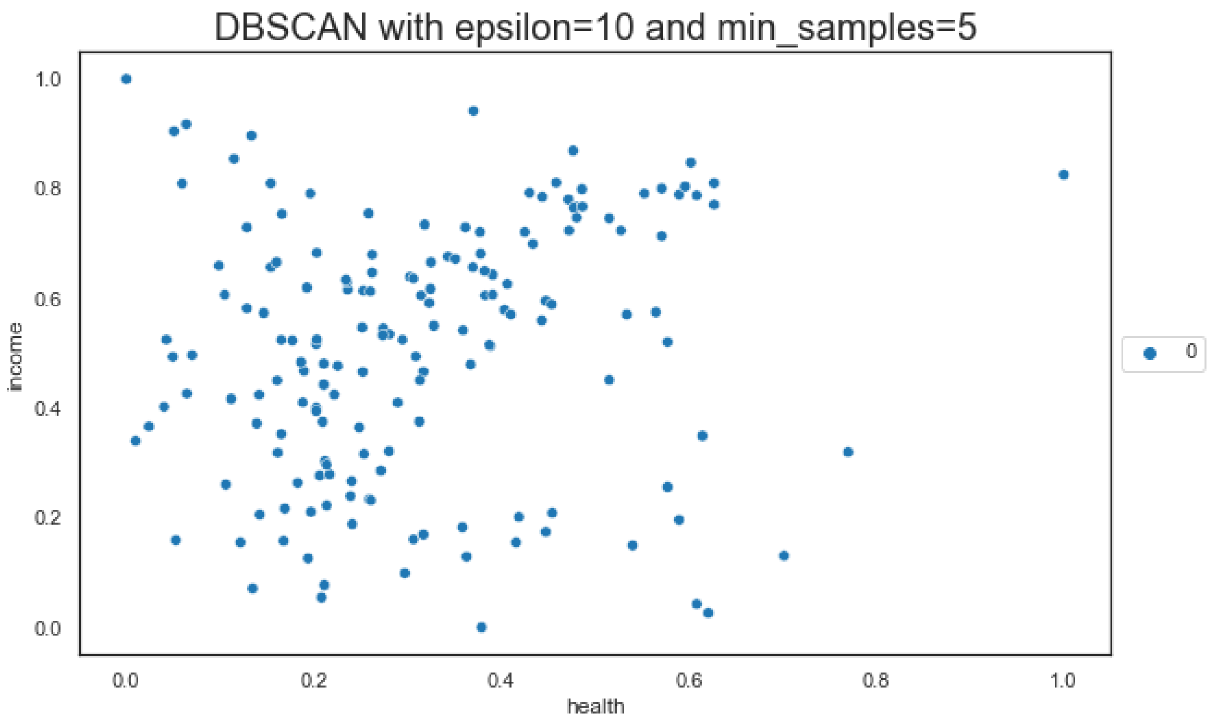
```
# determine epsilon and min_samples values
epsilon = 10
min_samples = 5
```

In [ ]:

```
# DBSCAN
db = DBSCAN(eps=epsilon, min_samples=min_samples).fit(X)

X['Labels'] = db.labels_
plt.figure(figsize=(10, 6))
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette='tab10')
plt.xlabel('health')
plt.ylabel('income')
plt.title('DBSCAN with epsilon=10 and min_samples=5', fontsize=20)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x1d10bbe3460>
```



No matter what value of epsilon or min_samples I took, the algorithm performed in similar way - all data was classified as one group. The reason why DBSCAN doesn't perform very well is a fact that density in our data isn't so strong. Probably, if the dataset will be bigger DBSCAN will donne better job.

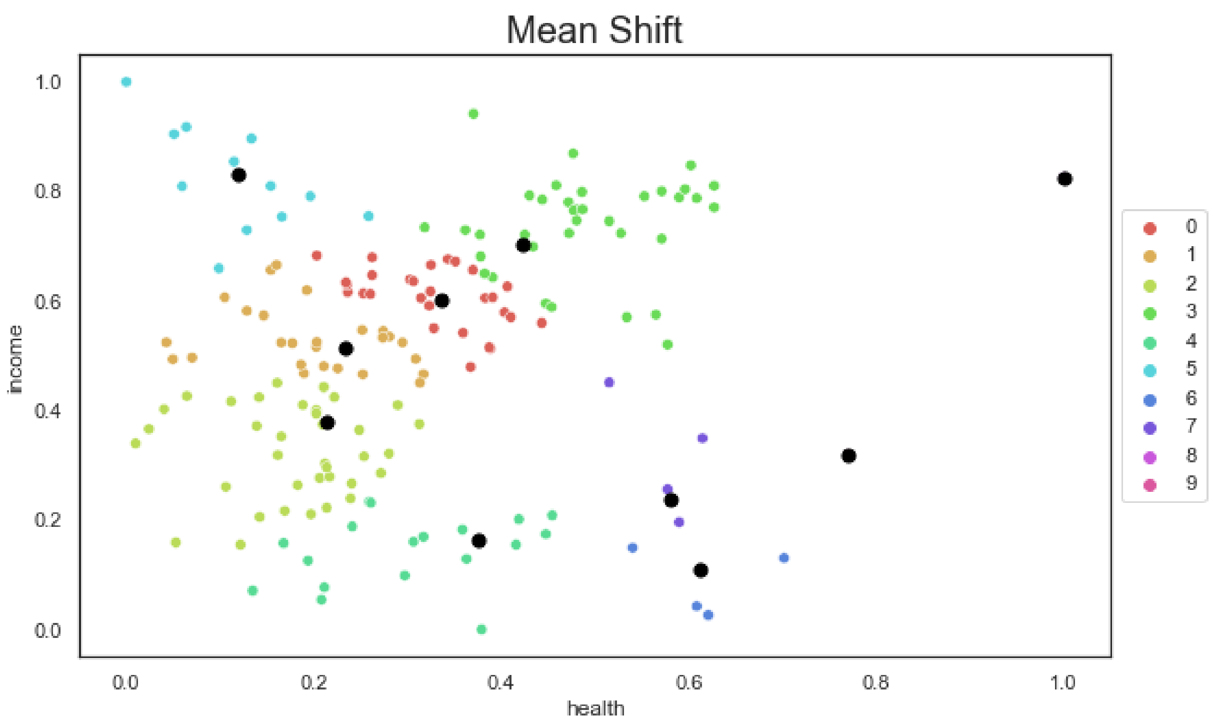
4.Mean Shift

In [ ]:

```
# the following bandwidth can be automatically detected using
bandwidth = estimate_bandwidth(X, quantile=0.1)

# MeanShift
ms = MeanShift(bandwidth=bandwidth).fit(X)

X['Labels'] = ms.labels_
plt.figure(figsize=(10, 6))
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette=sns.color_palette('hls', np.unique(ms.labels_).shape[0]))
plt.scatter(ms.cluster_centers_[:, 0], ms.cluster_centers_[:, 1], s = 50, c = 'black
plt.xlabel('health')
plt.ylabel('income')
plt.title('Mean Shift', fontsize=20)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x1d10bc8c640>
```



All in one place and selecting the best model

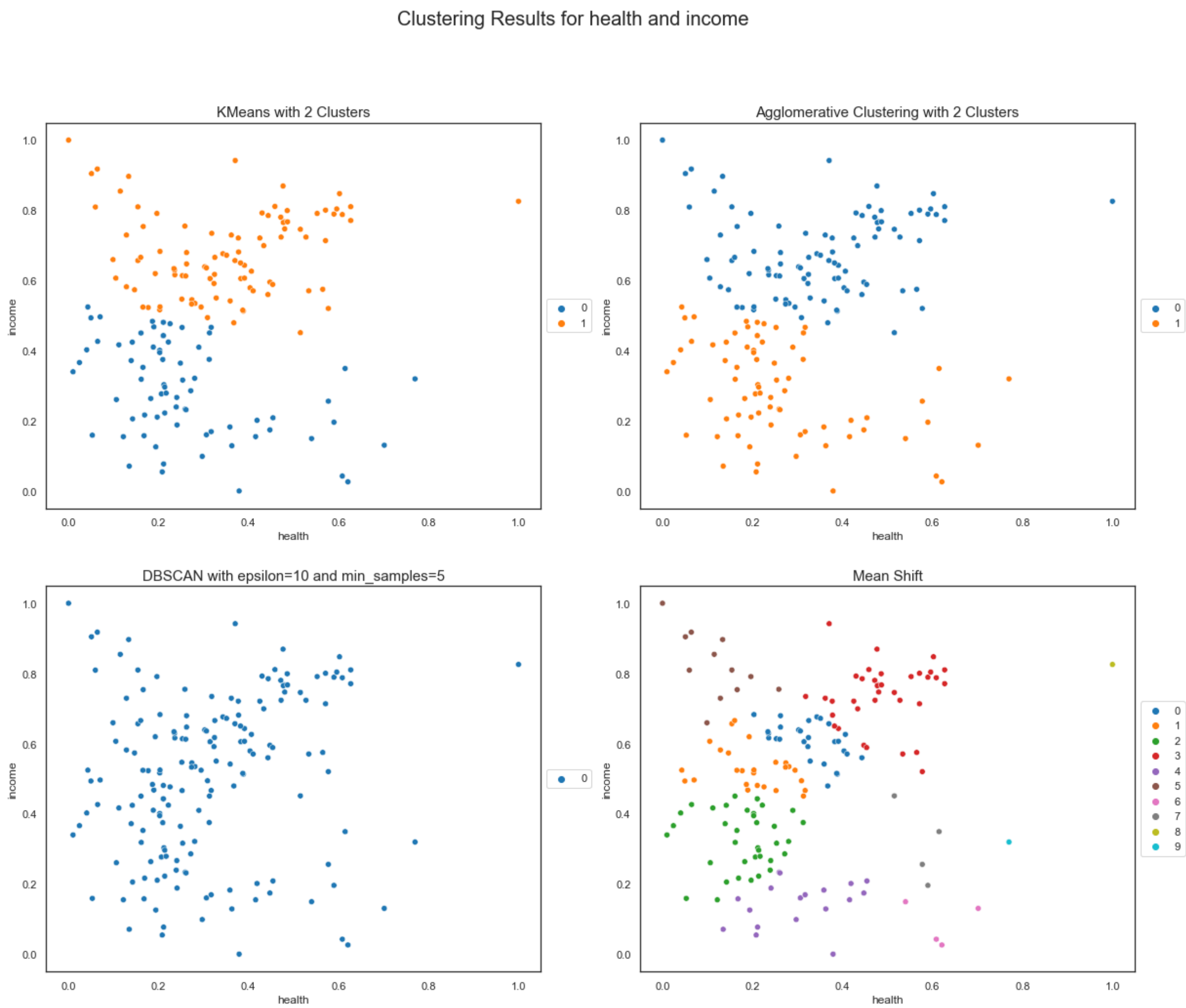
In [ ]:

```
X = df_new[['health','income']]

plt.figure(figsize=(20,16))
plt.suptitle('Clustering Results for health and income', fontsize=20)

plt.subplot(221)
km5 = KMeans(n_clusters=2).fit(X)
X['Labels'] = km5.labels_
```

```python
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette=sns.color_palette('tab10', 2))
plt.xlabel('health')
plt.ylabel('income')
plt.title('KMeans with 2 Clusters', fontsize=15)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)


plt.subplot(222)
agglom = AgglomerativeClustering(n_clusters=2).fit(X)
X['Labels'] = agglom.labels_
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette=sns.color_palette('tab10', 2))
plt.xlabel('health')
plt.ylabel('income')
plt.title('Agglomerative Clustering with 2 Clusters', fontsize=15)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)


plt.subplot(223)
db = DBSCAN(eps=10, min_samples=5).fit(X)
X['Labels'] = db.labels_
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette='tab10')
plt.xlabel('health')
plt.ylabel('income')
plt.title('DBSCAN with epsilon=10 and min_samples=5', fontsize=15)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)


plt.subplot(224)
bandwidth = estimate_bandwidth(X, quantile=0.1)
ms = MeanShift(bandwidth=bandwidth).fit(X)
X['Labels'] = ms.labels_
sns.scatterplot(X['health'], X['income'], hue=X['Labels'],
                palette=sns.color_palette('tab10', np.unique(ms.labels_).shape[0]))
plt.xlabel('health')
plt.ylabel('income')
plt.title('Mean Shift', fontsize=15)
plt.legend(loc=6, bbox_to_anchor=(1, 0.5), ncol=1)
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x1d10b2a0400>
```



we will select AgglomerativeClustering

In [ ]:

```
gglom = AgglomerativeClustering(n_clusters=2).fit(X)
df['Clusterts'] = agglom.labels_
```

In [ ]:

```
Results = df[['Clusterts','country']].groupby(['Clusterts','country']).mean()
Results
```

Out[ ]:

Clusterts	country
0	Albania
	Algeria
	Antigua and Barbuda
	Argentina
	Australia
...	...
1	Uzbekistan
	Vanuatu
	Vietnam
	Yemen
	Zambia

167 rows × 0 columns

* Label 1: low income and low/mid health --> target

* Label 0: high income and mid health --> avoid

Conclusion

K-means and Agglomerative Clustering with 2 Clusters performed best according to the silhouette_score

possible flaws:

this dataset from Kaggle was really small one. Because of it DBSCAN couldn't perform well.

Next steps:

As a further suggestion, a DBSCAN could be implemented, following a Principal Component Analysis.