Mini Project - CT2

Group Number: CT2 Project Group - 5

Team Members

1. Vinod A
2. Ramarajan V
3. Francis Alexandre Akshay Rajan

Apply **DBSCAN Clustering** for the **Country Status DataSet**. It contains the following data fields: country, child_mort, exports, health, imports, income, inflation, life_expec, total_fer, gdpp

Define the Required Libraries for this problem. **(2 marks)**

In [1]:
```
import pandas as pd
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
from matplotlib import colors as clr
import warnings
warnings.filterwarnings('ignore')

from sklearn.cluster import KMeans
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.neighbors import NearestNeighbors
from sklearn.decomposition import PCA
```

Open the CSV file and display the statistical information about the dataset **(1 mark)**

In [2]:
```
df = pd.read_csv("Country-data.csv")
df.describe(include='all')
```

Out[2]:

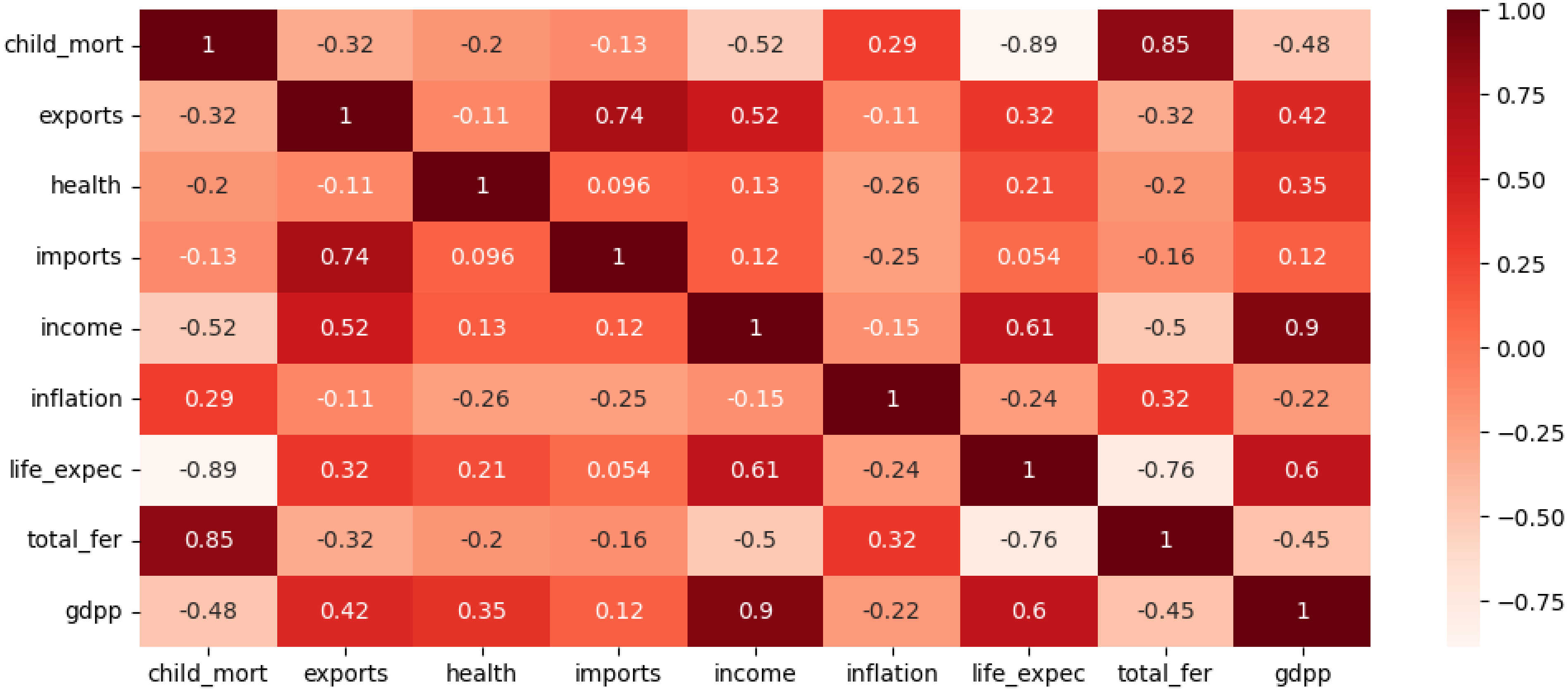
	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
count	167	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000
unique	167	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	Afghanistan	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689	2.947964	12964.155689
std	NaN	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172	1.513848	18328.704809
min	NaN	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000	1.150000	231.000000
25%	NaN	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000	1.795000	1330.000000
50%	NaN	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000	2.410000	4660.000000
75%	NaN	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000	3.880000	14050.000000
max	NaN	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000	7.490000	105000.000000

In [3]:
```
df.drop(columns='country', inplace=True)
```

INFERENCE: As per statistical infromation of the dataframe explains that most of them are normally distributed to each other and defines the SD is good enough for clustering it. But "Country" attribute will not requied as there is no repetation in occurance and not considered as categorical value.
Therefore we are removing "Country" attribute, as its not useful for clustering.

Print the correlation map and find the most related features. **(1 mark)**

In [4]:
```
plt.figure(figsize=(12,5))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
child_mort	1	-0.32	-0.2	-0.13	-0.52	0.29	-0.89	0.85	-0.48
exports	-0.32	1	-0.11	0.74	0.52	-0.11	0.32	-0.32	0.42
health	-0.2	-0.11	1	0.096	0.13	-0.26	0.21	-0.2	0.35
imports	-0.13	0.74	0.096	1	0.12	-0.25	0.054	-0.16	0.12
income	-0.52	0.52	0.13	0.12	1	-0.15	0.61	-0.5	0.9
inflation	0.29	-0.11	-0.26	-0.25	-0.15	1	-0.24	0.32	-0.22
life_expec	-0.89	0.32	0.21	0.054	0.61	-0.24	1	-0.76	0.6
total_fer	0.85	-0.32	-0.2	-0.16	-0.5	0.32	-0.76	1	-0.45
gdpp	-0.48	0.42	0.35	0.12	0.9	-0.22	0.6	-0.45	1

In [5]:
```
arr = cor.to_numpy()
np.fill_diagonal(arr, 0)
corrFeature = pd.DataFrame(cor[abs(cor) > .8].stack())
corrFeatureIndex = [tuple(set(i)) for i in corrFeature.index]
corrFeature = list(set(corrFeatureIndex))
print("The Top correlated combination of the dataset:")
pd.DataFrame(corrFeature)
```

```
The Top correlated combination of the dataset:
```

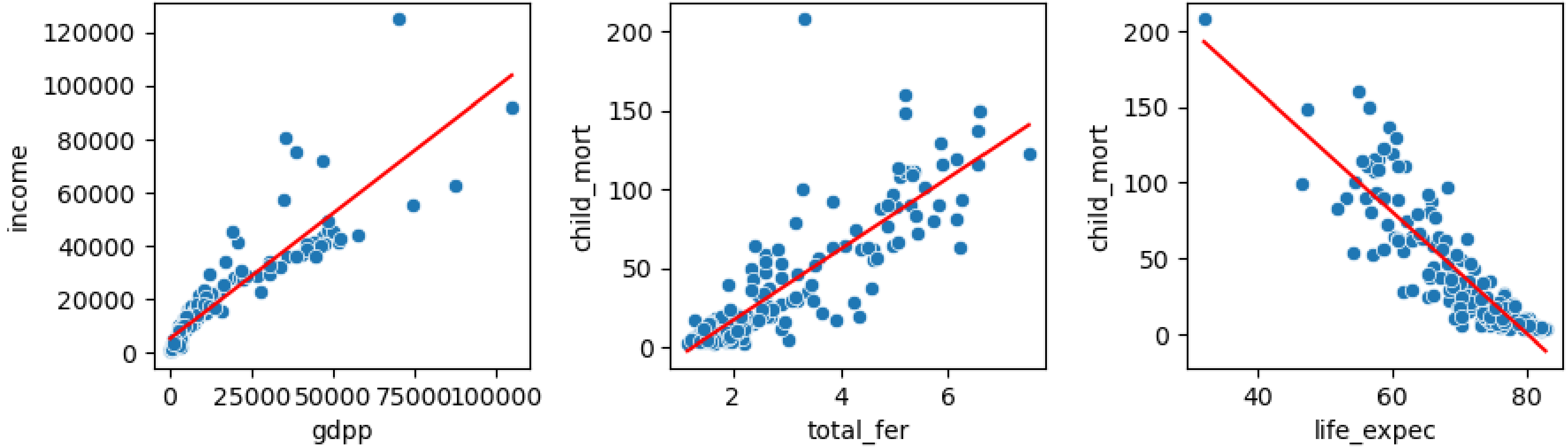
Out[5]:

	0	1
0	gdpp	income
1	total_fer	child_mort
2	life_expec	child_mort

INFERENCE: **As per Coorelation matrix we can find that the above mentioned 3 combinations were having more than 80%**

Plot a graph with the correlated features. **(1 mark)**

In [6]:
```
plt.figure(figsize=(12,5))
for i, fe in enumerate(corrFeature):
    x, y = df[fe[0]], df[fe[1]]
    plt.subplot(round(len(corrFeature)/4)+1, 4, i+1)
    sns.scatterplot(x, y)
    plt.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))
        (np.unique(x)), color='red')
plt.tight_layout()
plt.show()
```



INFERENCE: **The Scatter plots were used to represent the corelation and how its been corelated with respect to each other**

Apply Elbow Method to find optimal clusters. **(1 marks)**

In [7]:
```
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df)
df_scaled = pd.DataFrame(df_scaled, columns=df.columns)
df_scaled.head()
```

Out[7]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	1.291532	-1.138280	0.279088	-0.082455	-0.808245	0.157336	-1.619092	1.902882	-0.679180
1	-0.538949	-0.479658	-0.097016	0.070837	-0.375369	-0.312347	0.647866	-0.859973	-0.485623
2	-0.272833	-0.099122	-0.966073	-0.641762	-0.220844	0.789274	0.670423	-0.038404	-0.465376
3	2.007808	0.775381	-1.448071	-0.165315	-0.585043	1.387054	-1.179234	2.128151	-0.516268
4	-0.695634	0.160668	-0.286894	0.497568	0.101732	-0.601749	0.704258	-0.541946	-0.041817

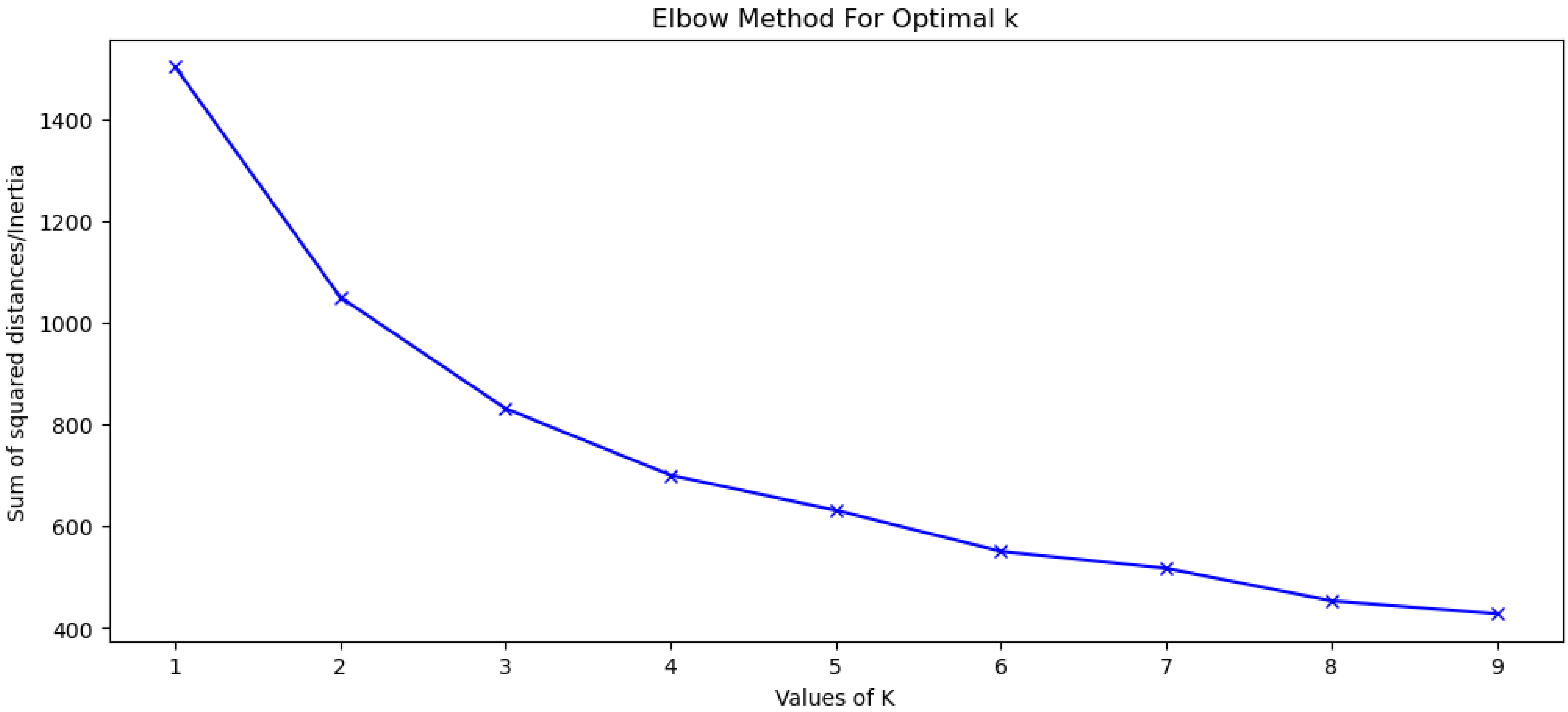
INFERENCE: Before taking a Elbow method or moving into the concept of clustering , we are making the dataset to be scaled with StandardScaler. As this scaling technique scales the values with respect to standard deviation.

In [8]:
```
Sum_of_squared_distances = []
K = range(1,10)
for num_clusters in K :
    kmeans = KMeans(n_clusters=num_clusters)
    kmeans.fit(df_scaled)
    Sum_of_squared_distances.append(kmeans.inertia_)
print("Value of k", Sum_of_squared_distances)
```

```
Value of k [1502.9999999999998, 1050.2145582853304, 831.4244352086873, 700.3229986404374, 631.387785996057, 550.712602
4726136, 517.3769743137748, 453.51612965537197, 428.2024400953263]
```

Plot Elbow curve **(1 mark)**

In [9]:
```
plt.figure(figsize=(12,5))
plt.plot(K,Sum_of_squared_distances,'bx-')
plt.xlabel('Values of K')
plt.ylabel('Sum of squared distances/Inertia')
plt.title('Elbow Method For Optimal k')
plt.show()
```



INFERENCE: **Upon using K-means for calculation the number of clusters in elbow method , it provides the value to K = 3**

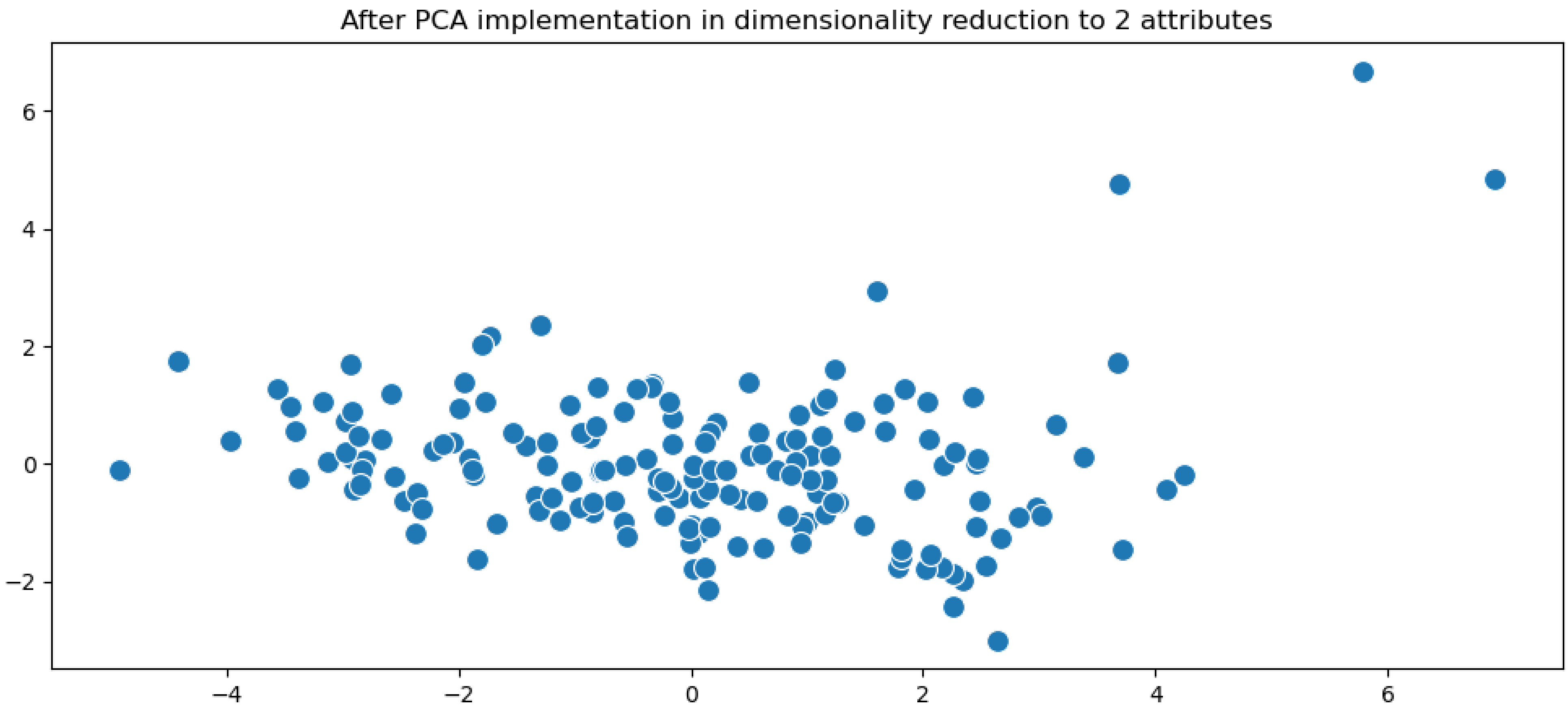
Apply DBSCAN to find optimal eps and minpts. **(2 marks)**

In [10]:
```
pca = PCA(n_components = 2)
dim_red_data = pca.fit_transform(df_scaled)
```

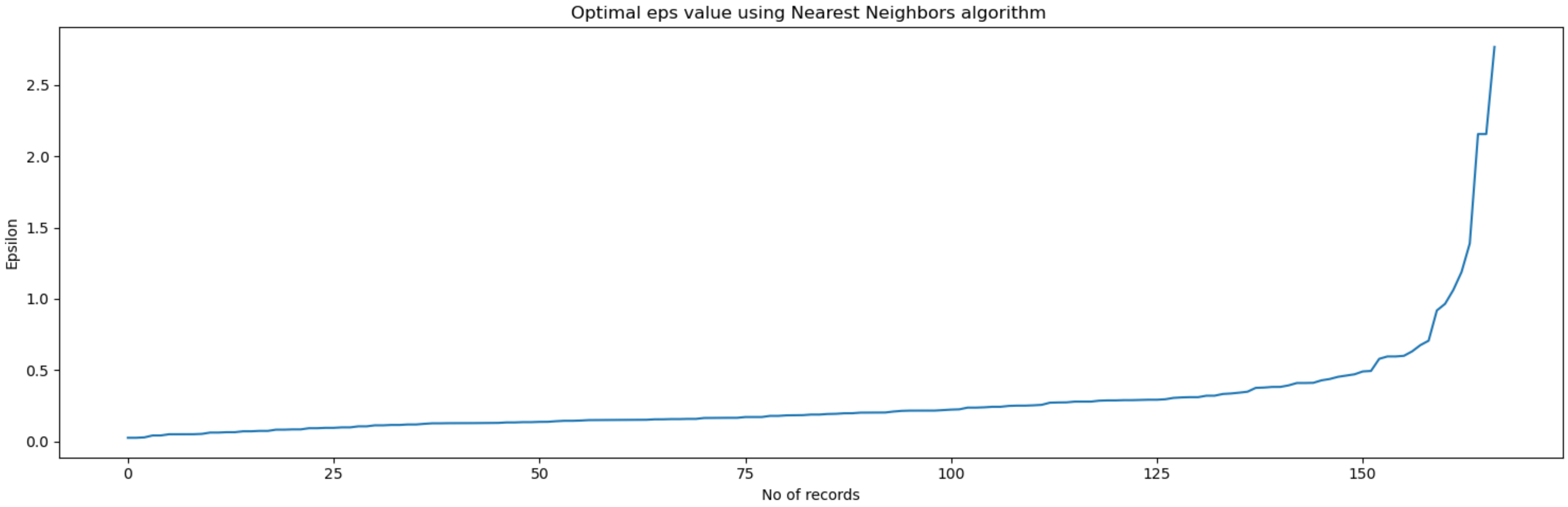
INFERENCE: **Before Forming cluster with DBSCAN, We are using PCA to reduce the dimension to 2 attributes.**

In [11]:
```

plt.figure(figsize=(12,5))
sns.scatterplot(dim_red_data[:,0], dim_red_data[:,1], s=100)
plt.title("After PCA implementation in dimensionality reduction to 2 attributes")
plt.show()
```



In [12]:
```
neighbors = NearestNeighbors(n_neighbors=5)
neighbors_fit = neighbors.fit(dim_red_data)
distances, indices = neighbors_fit.kneighbors(dim_red_data)
distances = np.sort(distances, axis=0,)
distances = distances[:,1]
plt.figure(figsize=(15, 5))
plt.plot(distances)
plt.title("Optimal eps value using Nearest Neighbors algorithm ")
plt.ylabel("Epsilon")
plt.xlabel("No of records")
plt.tight_layout()
plt.show()
```

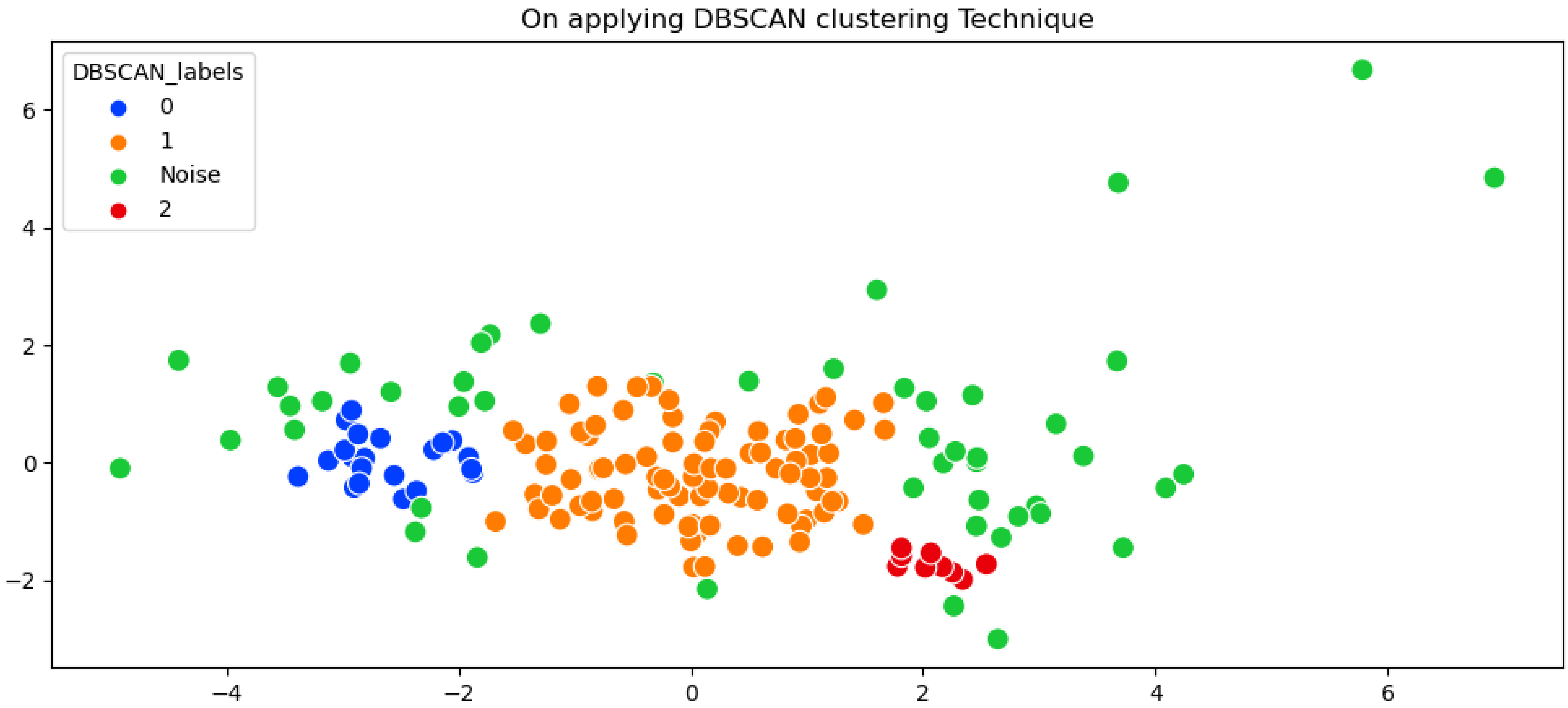


In [13]:
```
dbscan=DBSCAN(eps=.5, min_samples=7)
dbscan.fit(dim_red_data)
df_scaled['DBSCAN_labels']=dbscan.labels_
df_scaled['DBSCAN_labels'].value_counts()
df_scaled[df_scaled['DBSCAN_labels'] == -1] ='Noise'
```

INFERENCE: **To find optimal eps and minpts we are using Nearest Neighbors algorithm. As per graph, we can find the eps value is .35 and taking min_samples as 5 to get 3 clusters**

Plot the DBSCAN clustered datapoints using scatter plot. **(1 mark)**

In [14]:
```
plt.figure(figsize=(12,5))
sns.scatterplot(x=dim_red_data[:,0], y=dim_red_data[:,1],hue=df_scaled.iloc[:,-1], palette='bright', s=100)
plt.title("On applying DBSCAN clustering Technique")
plt.show()
```



INFERENCE: **As per DBSCAN results the scatter plots are plotted to exhibit the clustering**

Apply **Fuzzy C Means Clustering** for the Country Status DataSet. It contains the following data fields: country, child_mort, exports, health, imports, income, inflation, life_expec, total_fer, gdpp

Define the Required Libraries for this problem. **(2 marks)**

In [15]:
```
import pandas as pd
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import LabelEncoder
from fcmeans import FCM
```

Open the CSV file and display the statistical information about the dataset **(1 mark)**

In [16]:
```
df = pd.read_csv("Country-data.csv")
df.describe(include='all')
```

Out[16]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
count	167	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000
unique	167	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	Afghanistan	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689	2.947964	12964.155689
std	NaN	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172	1.513848	18328.704809
min	NaN	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000	1.150000	231.000000
25%	NaN	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000	1.795000	1330.000000
50%	NaN	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000	2.410000	4660.000000
75%	NaN	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000	3.880000	14050.000000
max	NaN	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000	7.490000	105000.000000

INFERENCE: As per statistical infromation of the dataframe explains that most of them are normally distributed to each other and defines the SD is good enough for clustering it.

Label encode the country field from the dataset. **(1 mark)**

In [17]:
```python
le = LabelEncoder()
df['country'] = le.fit_transform(df['country'])
df.head()
```

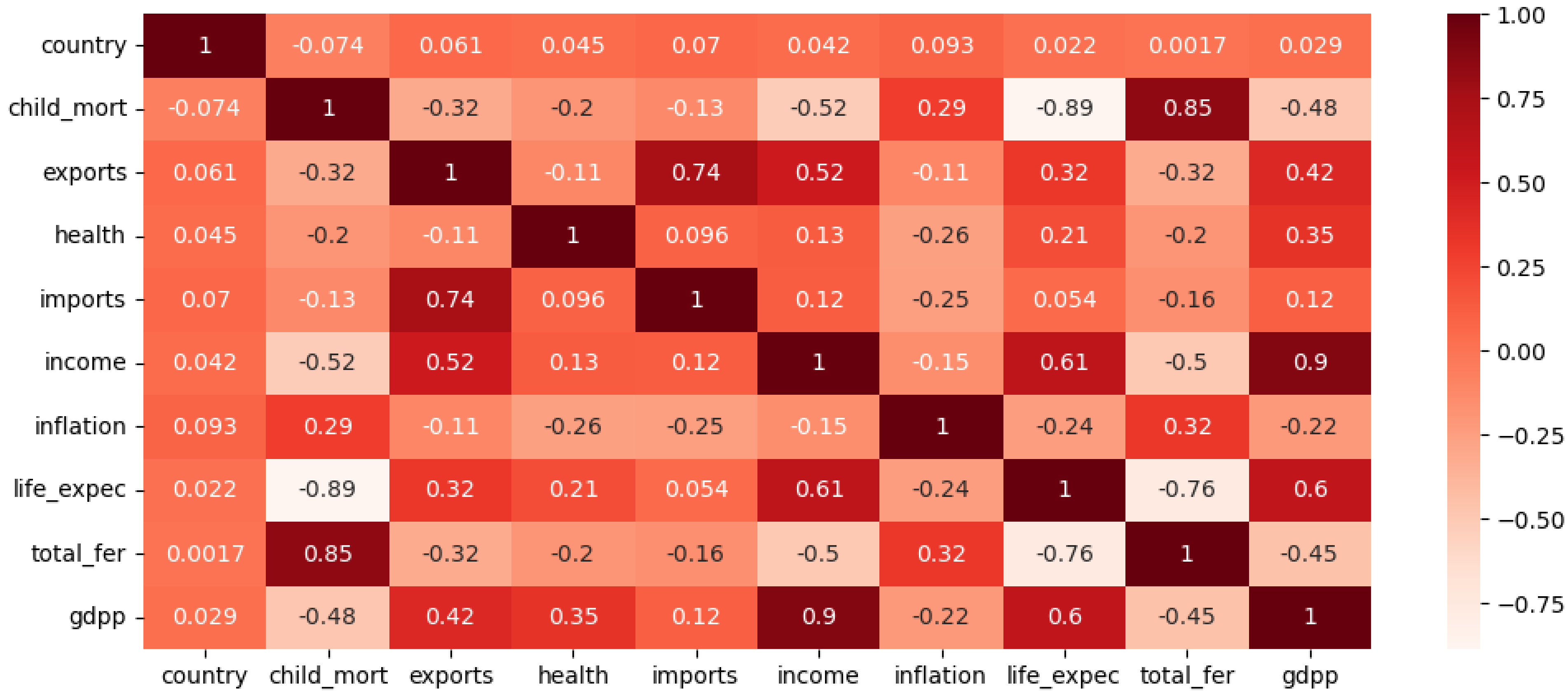
Out[17]:

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

INFERENCE: **Label encoding is done for Country attribute and convertied them to numerical values**

Print the correlation map and find the most related features. **(1 mark)**

In [18]:
```
plt.figure(figsize=(12,5))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



In [19]:
```
arr = cor.to_numpy()
np.fill_diagonal(arr, 0)
temp = cor[cor.isin([arr.max()])].stack()
print(temp.index[0][0],' vs ',temp.index[0][1],' : ', temp.values[0])
```

```
income  vs  gdpp  :  0.895571433087531
```

INFERENCE: **As per corelation matrix , we can find "income vs gdpp" has the max corelation**

Scaling the dataset. **(1 mark)**

In [20]:
```
scaler = StandardScaler()
```

In [21]:
```
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df)
df_scaled = pd.DataFrame(df_scaled, columns=df.columns)
```

INFERENCE: **Before taking a Elbow method or moving into the concept of clustering , we are making the dataset to be scaled with StandardScaler. As this scaling technique scales the values with respect to standard deviation.**

Apply Fuzzy C-Means Algorithm. **(2 marks)**

In [22]:
```
# pip install fuzzy-c-means
```

In [23]:
```
pca = PCA(n_components = 2)
dim_red_data = pca.fit_transform(df_scaled)
X = dim_red_data
```

INFERENCE: **Before Forming cluster with Fuzzy C means, We are using PCA to reduce the dimension to 2 attributes.**

In [24]:
```
from fcmeans import FCM
```

In [25]:
```
fcm = FCM(n_clusters=3)
fcm.fit(X)
```

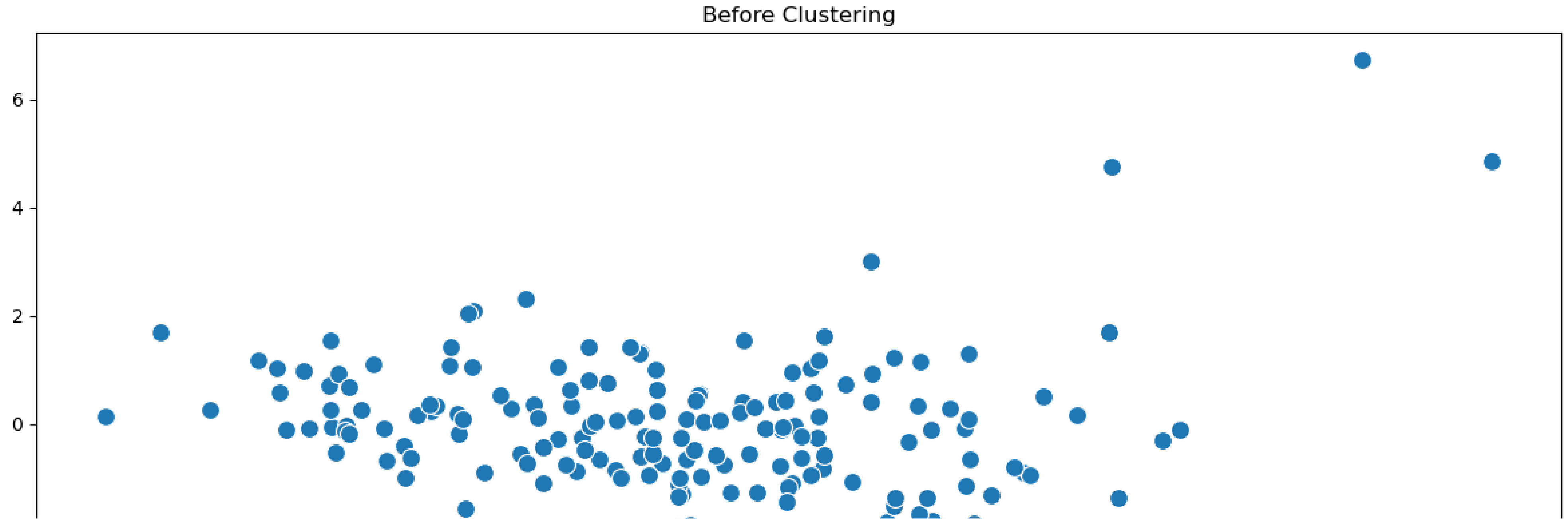
Merge the predicted label with the dataframe. **(2 marks)**

In [26]:
```
df['fcm_labels'] = fcm.predict(X)
np.unique(df['fcm_labels'])
```

Out[26]:
```
array([0, 1, 2])
```

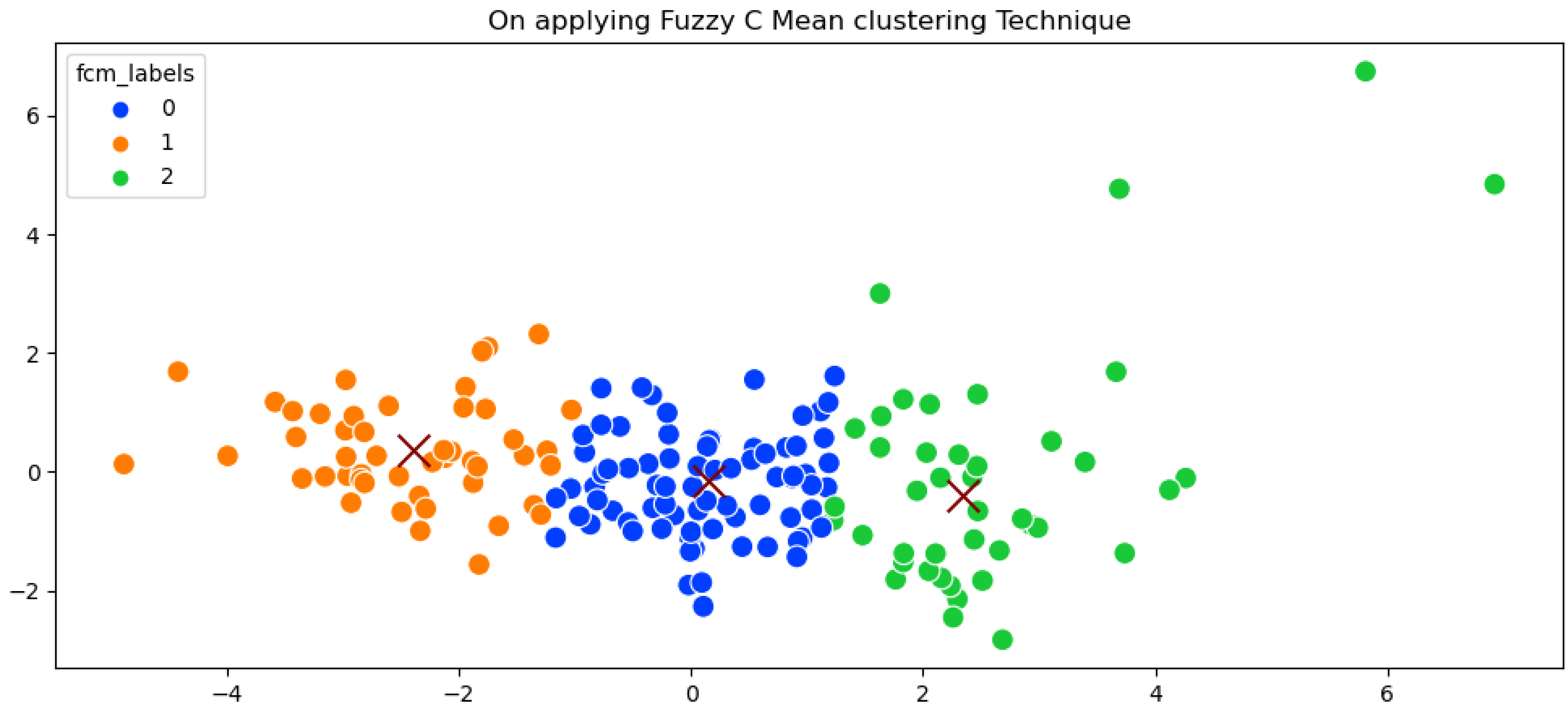
Plot the Fuzzy C Means clustered datapoints using scatter plot. **(1 mark)**

In [27]:
```
f, axes = plt.subplots(figsize=(12,5))
sns.scatterplot(X[:,0], X[:,1], s=100)
plt.title("Before Clustering")
plt.tight_layout()
plt.show()
```



In [28]:
```
fcm_centers = fcm.centers
f, axes = plt.subplots(figsize=(12,5))
plt.title("On applying Fuzzy C Mean clustering Technique")
sns.scatterplot(X[:,0], X[:,1], hue=df['fcm_labels'], s=100, palette='bright')
plt.scatter(fcm_centers[:,0], fcm_centers[:,1], marker="x", s=200, c='maroon')
```

Out[28]:
```
<matplotlib.collections.PathCollection at 0x7feb188e2850>
```



INFERENCE: **As per Fuzzy C means results the scatter plots are plotted to exhibit the clustering**