HW 9

March 8, 2024

1 0.) Import and Clean data

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

[2]:
```python
data = pd.read_csv("Country-data.csv", sep = ",")
data
```

[2]:
```
                 country  child_mort  exports  health  imports  income  \
0            Afghanistan        90.2     10.0    7.58     44.9    1610
1                Albania        16.6     28.0    6.55     48.6    9930
2                Algeria        27.3     38.4    4.17     31.4   12900
3                 Angola       119.0     62.3    2.85     42.9    5900
4    Antigua and Barbuda        10.3     45.5    6.03     58.9   19100
..                   …           …      …      …       …      …
162              Vanuatu        29.2     46.6    5.25     52.7    2950
163            Venezuela        17.1     28.5    4.91     17.6   16500
164              Vietnam        23.3     72.0    6.84     80.2    4490
165                Yemen        56.3     30.0    5.18     34.4    4480
166               Zambia        83.1     37.0    5.89     30.9    3280

     inflation  life_expec  total_fer   gdpp
0         9.44        56.2       5.82    553
1         4.49        76.3       1.65   4090
2        16.10        76.5       2.89   4460
3        22.40        60.1       6.16   3530
4         1.44        76.8       2.13  12200
..         …          …         …      …
162       2.62        63.0       3.50   2970
163      45.90        75.4       2.47  13500
164      12.10        73.1       1.95   1310
165      23.60        67.5       4.67   1310
166      14.00        52.0       5.40   1460
```

```
[167 rows x 10 columns]
```

[3]:
```
names = data[["country"]].copy()
X = data.drop("country", axis =1)
```

[4]:
```
scaler = StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

2 1.) Fit a kmeans Model with any Number of Clusters

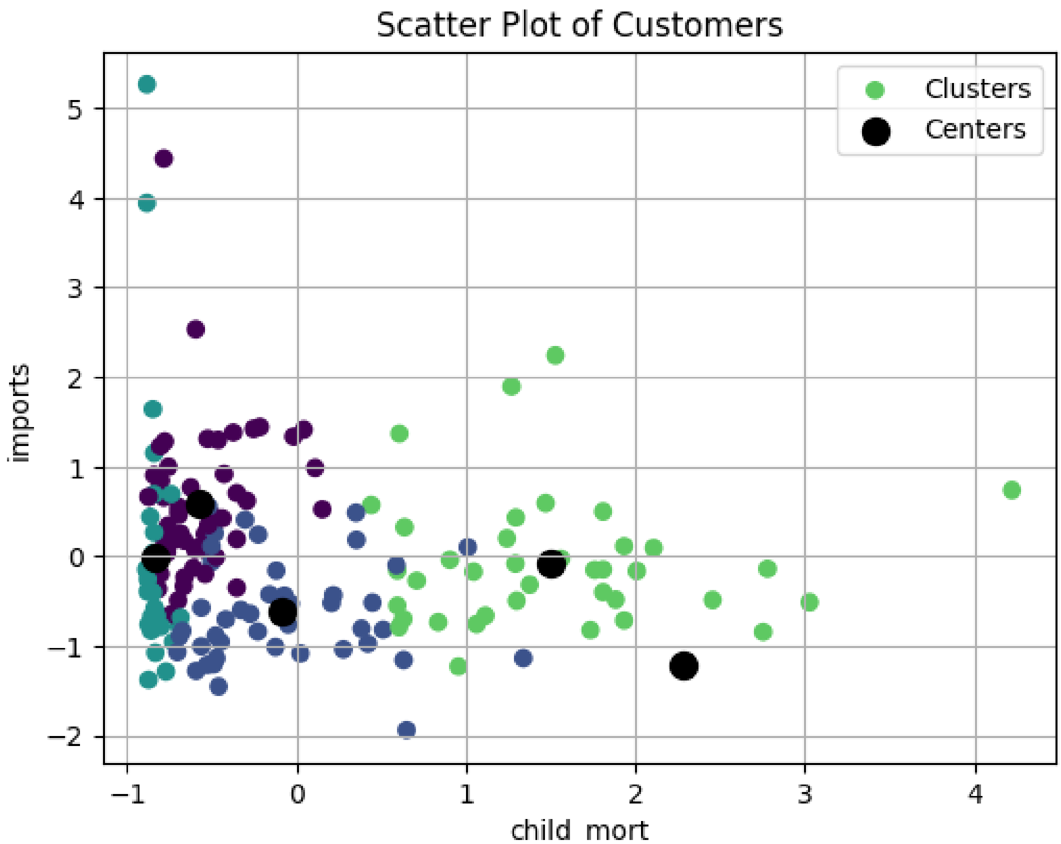
[5]:
```
kmeans = KMeans(n_clusters = 5).fit(X_scaled)
```

3 2.) Pick two features to visualize across

[6]:
```
X.columns
```

[6]:
```
Index(['child_mort', 'exports', 'health', 'imports', 'income', 'inflation',
       'life_expec', 'total_fer', 'gdpp'],
      dtype='object')
```

[7]:
```
import matplotlib.pyplot as plt

x1_index = 0
x2_index = 3


scatter = plt.scatter(X_scaled[:, x1_index], X_scaled[:, x2_index], c=kmeans.
 ↪labels_, cmap='viridis', label='Clusters')


centers = plt.scatter(kmeans.cluster_centers_[:, x1_index], kmeans.
 ↪cluster_centers_[:, x2_index], marker='o', color='black', s=100,␣
 ↪label='Centers')

plt.xlabel(X.columns[x1_index])
plt.ylabel(X.columns[x2_index])
plt.title('Scatter Plot of Customers')

# Generate legend
plt.legend()

plt.grid()
plt.show()
```

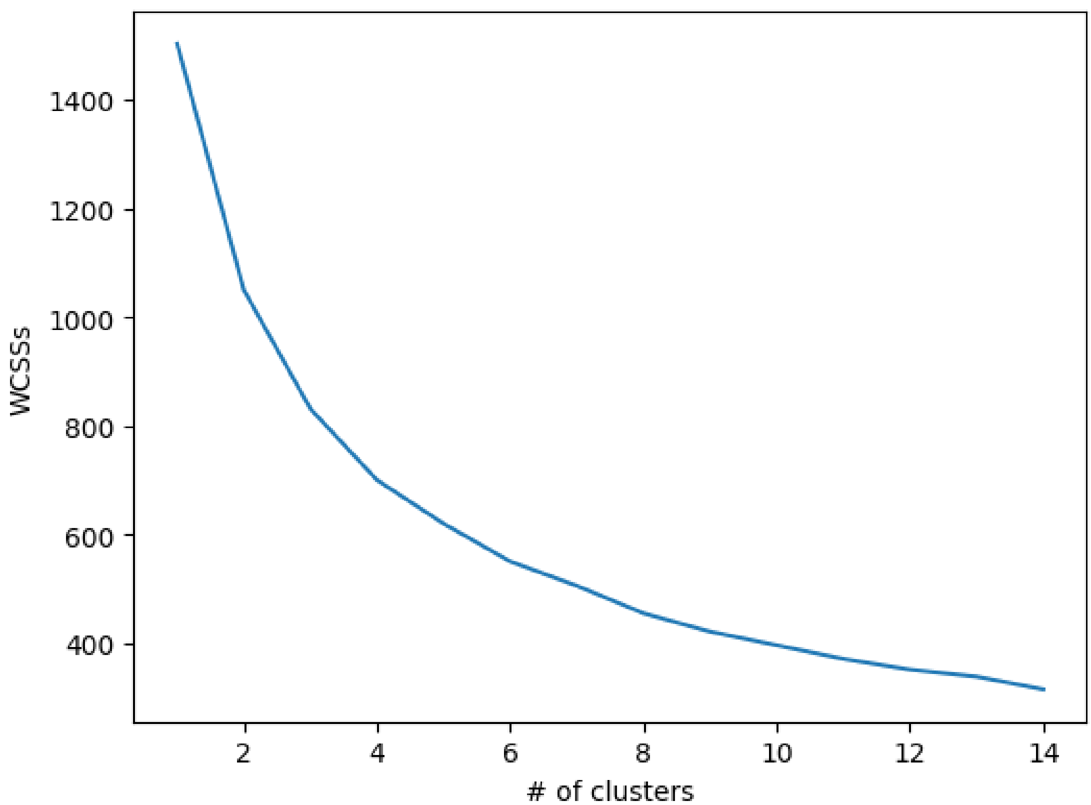


4 3.) Check a range of k-clusters and visualize to find the elbow. Test 30 different random starting places for the centroid means

[8]:
```
WCSSs = []
Ks = range(1,15)
for k in Ks:
    kmeans = KMeans(n_clusters = k,n_init = 30).fit(X_scaled)
    WCSSs.append(kmeans.inertia_)

# WCSSs = [KMeans(n_clusters = 5,n_init = 30).fit(X_scaled).inertia_ for k in␣
 ↪range(1,15)]
```

5 4.) Use the above work and economic critical thinking to choose a number of clusters. Explain why you chose the number of clusters and fit a model accordingly.

[9]:
```
plt.plot(Ks,WCSSs)
plt.xlabel("# of clusters")
plt.ylabel("WCSSs")
plt.show()
```



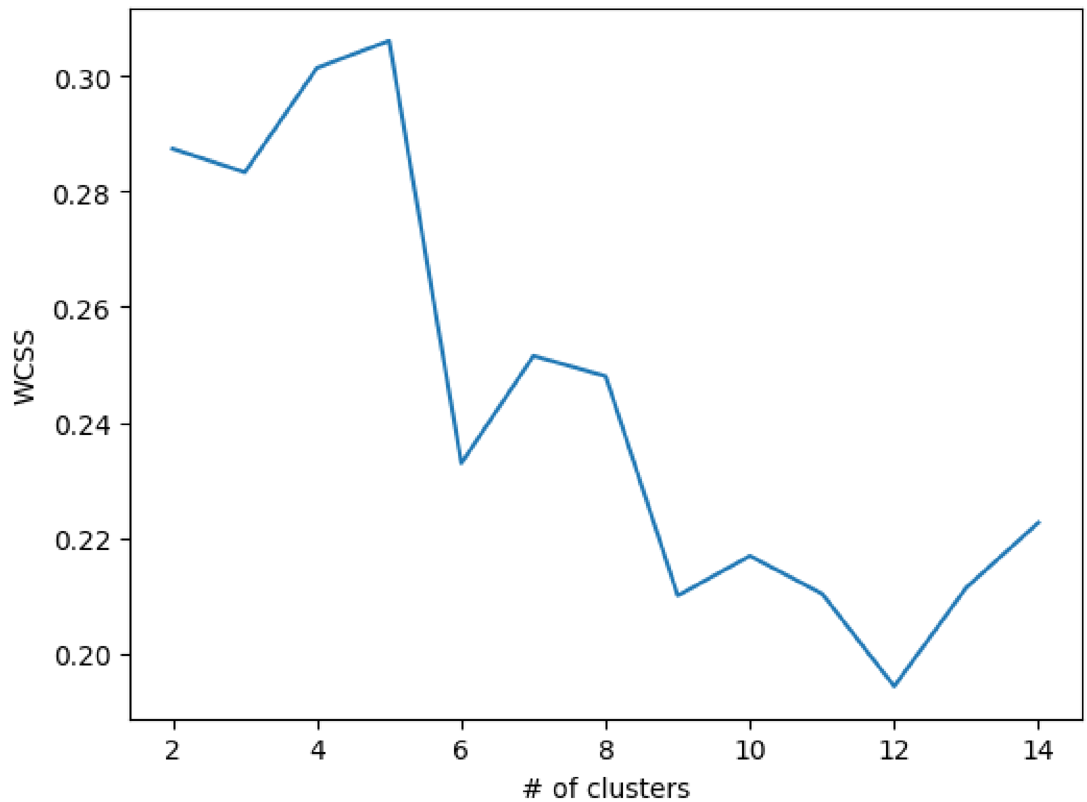
We chose 6 clusters based on the “elbow point” observed in the plot of within-cluster sum of squares (WCSS) versus the number of clusters. The elbow point signifies the point at which the rate of decrease in WCSS slows down significantly. 6 clusters is the optimal number to balance model complexity and explanatory power, aiming to capture meaningful patterns in the data without overfitting. Beyond 8 clusters, the reduction in WCSS didn’t justify the addition of more clusters in explaining the variance in the data.

6 6.) Do the same for a silhoutte plot

[10]:
```
from sklearn.metrics import silhouette_score
```

[11]:
```
SSs = []
Ks = range(2,15)
for k in Ks:
    kmeans = KMeans(n_clusters = k,n_init = 30).fit(X_scaled)
    sil = silhouette_score(X_scaled,kmeans.labels_)
    SSs.append(sil)
```

[12]:
```
plt.plot(Ks,SSs)
plt.xlabel("# of clusters")
plt.ylabel("WCSS")
plt.show()
```



We choose 5 clusters based on the silhouette score analysis, as this number corresponds to the configuration where the data points are most appropriately grouped into clusters. The highest silhouette score around 5 clusters indicates better-defined clusters and greater separation between them. By selecting 5 clusters, we ensure that each cluster captures a meaningful and distinct subset of the data. Moreover, having fewer clusters simplifies the model and enhances interpretability, which is beneficial in various applications.

7 7.) Create a list of the countries that are in each cluster. Write interesting things you notice.

[13]:
```
# Fit KMeans model with the chosen number of clusters

kmeans_final = KMeans(n_clusters=5, n_init=30).fit(X_scaled)
```

[14]:
```
preds = pd.DataFrame(kmeans.labels_)
```

[15]:
```
output = pd.concat([preds,data],axis=1)
```

[17]:
```
from collections import defaultdict

# Create a dictionary to store countries in each cluster
clusters_countries = defaultdict(list)

# Iterate through each country and its corresponding cluster label
for country, label in zip(data["country"], kmeans_final.labels_):
    clusters_countries[label].append(country)

# Print the countries in each cluster
for cluster, countries_list in clusters_countries.items():
    print(f"Cluster {cluster + 1}: {countries_list}")
```

```
Cluster 2: ['Afghanistan', 'Angola', 'Benin', 'Botswana', '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', 'Namibia', 'Niger', 'Pakistan', 'Rwanda', 'Senegal',
'Sierra Leone', 'South Africa', 'Sudan', 'Tanzania', 'Timor-Leste', 'Togo',
'Uganda', 'Yemen', 'Zambia']
Cluster 4: ['Albania', 'Algeria', 'Antigua and Barbuda', 'Argentina', 'Armenia',
'Azerbaijan', 'Bahamas', 'Bahrain', 'Bangladesh', 'Barbados', 'Belarus',
'Belize', 'Bhutan', 'Bolivia', 'Bosnia and Herzegovina', 'Brazil', 'Bulgaria',
'Cambodia', 'Cape Verde', 'Chile', 'China', 'Colombia', 'Costa Rica', 'Croatia',
'Czech Republic', 'Dominican Republic', 'Ecuador', 'Egypt', 'El Salvador',
'Estonia', 'Fiji', 'Georgia', 'Grenada', 'Guatemala', 'Guyana', 'Hungary',
'India', 'Indonesia', 'Iran', 'Jamaica', 'Jordan', 'Kazakhstan', 'Kyrgyz
Republic', 'Latvia', 'Lebanon', 'Libya', 'Lithuania', 'Macedonia, FYR',
'Malaysia', 'Maldives', 'Mauritius', 'Micronesia, Fed. Sts.', 'Moldova',
'Mongolia', 'Montenegro', 'Morocco', 'Myanmar', 'Nepal', 'Oman', 'Panama',
'Paraguay', 'Peru', 'Philippines', 'Poland', 'Romania', 'Russia', 'Samoa',
'Saudi Arabia', 'Serbia', 'Seychelles', 'Slovak Republic', 'Solomon Islands',
'Sri Lanka', 'St. Vincent and the Grenadines', 'Suriname', 'Tajikistan',
```

```
'Thailand', 'Tonga', 'Tunisia', 'Turkey', 'Turkmenistan', 'Ukraine', 'Uruguay',
'Uzbekistan', 'Vanuatu', 'Venezuela', 'Vietnam']
Cluster 1: ['Australia', 'Austria', 'Belgium', 'Brunei', 'Canada', 'Cyprus',
'Denmark', 'Finland', 'France', 'Germany', 'Greece', 'Iceland', 'Ireland',
'Israel', 'Italy', 'Japan', 'Kuwait', 'Netherlands', 'New Zealand', 'Norway',
'Portugal', 'Qatar', 'Slovenia', 'South Korea', 'Spain', 'Sweden',
'Switzerland', 'United Arab Emirates', 'United Kingdom', 'United States']
Cluster 3: ['Luxembourg', 'Malta', 'Singapore']
Cluster 5: ['Nigeria']
```

Cluster 1: This cluster consists of a diverse range of countries from various regions, including both developed and developing nations. Notable countries include Brazil, China, India, and Russia, indicating a mix of emerging and established economies with varying levels of development.

Cluster 2: This cluster contains a large number of African countries, including conflict-affected nations like Democratic Republic of the Congo, as well as resource-rich countries like Gabon and Angola. These countries likely face common socio-economic challenges such as poverty, political instability, and limited access to healthcare and education.

Cluster 3: This cluster comprises only three countries: Luxembourg, Malta, and Singapore. These countries are known for their high levels of prosperity, economic stability, and favorable business environments. They often serve as global financial hubs and have high per capita incomes.

Cluster 4: Countries in this cluster are predominantly high-income nations with advanced economies and high standards of living. Notable examples include the United States, Germany, Japan, and the United Kingdom. These countries typically have strong healthcare systems, stable political environments, and diverse economies.

Cluster 5: Nigeria stands alone in this cluster, indicating unique socio-economic challenges compared to the other countries in the dataset. As one of the most populous countries in Africa, Nigeria faces issues such as political instability, economic inequality, and infrastructure deficits. This separation from other countries may suggest that Nigeria requires specific attention and tailored interventions to address its unique challenges.

8 8.) Create a table of Descriptive Statistics. Rows being the Cluster number and columns being all the features. Values being the mean of the centroid. Use the nonscaled X values for interpolotation

[18]:
```
output
```

[18]:
```
    0              country  child_mort  exports  health  imports  income  \
0   8          Afghanistan        90.2     10.0    7.58     44.9    1610
1  11              Albania        16.6     28.0    6.55     48.6    9930
2  13              Algeria        27.3     38.4    4.17     31.4   12900
3   1               Angola       119.0     62.3    2.85     42.9    5900
4   4  Antigua and Barbuda        10.3     45.5    6.03     58.9   19100
..  ..                  …           …        …       …        …       …
```

```
162   2              Vanuatu        29.2      46.6     5.25      52.7     2950
163  13            Venezuela        17.1      28.5     4.91      17.6    16500
164   4              Vietnam        23.3      72.0     6.84      80.2     4490
165   3                Yemen        56.3      30.0     5.18      34.4     4480
166   8               Zambia        83.1      37.0     5.89      30.9     3280

     inflation  life_expec  total_fer   gdpp
0         9.44        56.2       5.82    553
1         4.49        76.3       1.65   4090
2        16.10        76.5       2.89   4460
3        22.40        60.1       6.16   3530
4         1.44        76.8       2.13  12200
..         …           …        …     …
162       2.62        63.0       3.50   2970
163      45.90        75.4       2.47  13500
164      12.10        73.1       1.95   1310
165      23.60        67.5       4.67   1310
166      14.00        52.0       5.40   1460

[167 rows x 11 columns]
```

[19]:

```
# Get centroids from the KMeans model
centroids = kmeans_final.cluster_centers_

# Create a DataFrame to store descriptive statistics
cluster_stats = pd.DataFrame(centroids, columns=X.columns)

# Add a column for cluster number
cluster_stats['Cluster'] = range(1, len(centroids) + 1)

# Set the cluster number as the index
cluster_stats.set_index('Cluster', inplace=True)

# Display the table
cluster_stats
```

[19]:

```
         child_mort   exports    health   imports    income  inflation  \
Cluster
1         -0.828609  0.172621  0.859190 -0.296373  1.462275  -0.478189
2          1.340192 -0.434470 -0.145518 -0.166756 -0.688260   0.212380
3         -0.849003  4.935673 -0.008163  4.548058  2.439542  -0.504206
4         -0.419827  0.006648 -0.211724  0.047581 -0.217274  -0.034953
5          2.281385 -0.578452 -0.637438 -1.221785 -0.624065   9.129718

         life_expec  total_fer      gdpp
Cluster
1          1.107649  -0.763681  1.661902
```

```
2          -1.285398   1.352961 -0.604727
3           1.226824  -1.038863  2.440797
4           0.268420  -0.438222 -0.330805
5          -1.134121   1.916133 -0.581936
```

9 9.) Write an observation about the descriptive statistics.

Cluster 1: This cluster has relatively low values for child mortality, income, inflation, and GDP per capita, but higher values for life expectancy compared to other clusters. These countries might represent economically stable regions with moderate development levels.

Cluster 2: This cluster exhibits high values for child mortality and inflation, indicating regions facing socio-economic challenges such as poverty and inadequate healthcare. Additionally, the low values for income, life expectancy, and GDP per capita suggest underdeveloped economies.

Cluster 3: This cluster stands out for its exceptionally high values in exports, imports, and GDP per capita. These countries likely have strong trade economies with high levels of economic activity and development.

Cluster 4: Countries in this cluster demonstrate moderate to high values for health, income, life expectancy, and GDP per capita, indicating relatively developed and prosperous regions with adequate healthcare and economic stability.

Cluster 5: This cluster is characterized by extremely high values for child mortality and inflation, suggesting significant socio-economic challenges. Despite the high inflation rates, the GDP per capita is relatively low, indicating economic struggles and potential instability in these countries.