Sec_1_Homework_9

March 8, 2024

1 0.) Import and Clean data

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

[3]:
```
#drive.mount('/content/gdrive/', force_remount = True)
df = pd.read_csv("Country-data.csv", sep = ",")
```

[4]:
```
df.head()
```

[4]:
```
               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

   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
```

[5]:
```
names = df[['country']].copy()
X = df.drop('country', axis = 1)
```

[6]:
```
scaler = StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

[2]:

[2]:

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[ ]:

```

```

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

[7]:

```
kmeans = KMeans(n_clusters = 5).fit(X_scaled)
```

[2]:

```

```

3 2.) Pick two features to visualize across

[8]:

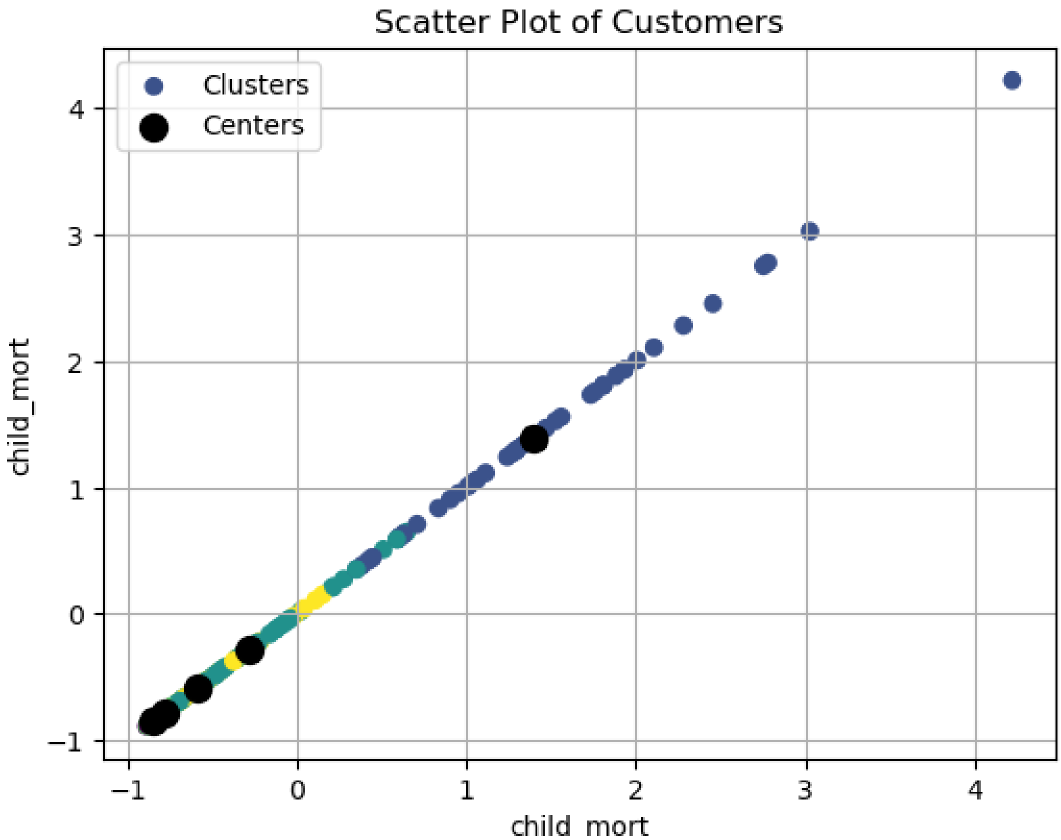
```
X.columns
```

[8]:

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

[9]:

```
import matplotlib.pyplot as plt

x1_index = 0
x2_index = 0


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()
```




```
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```

```
[ ]:
```

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

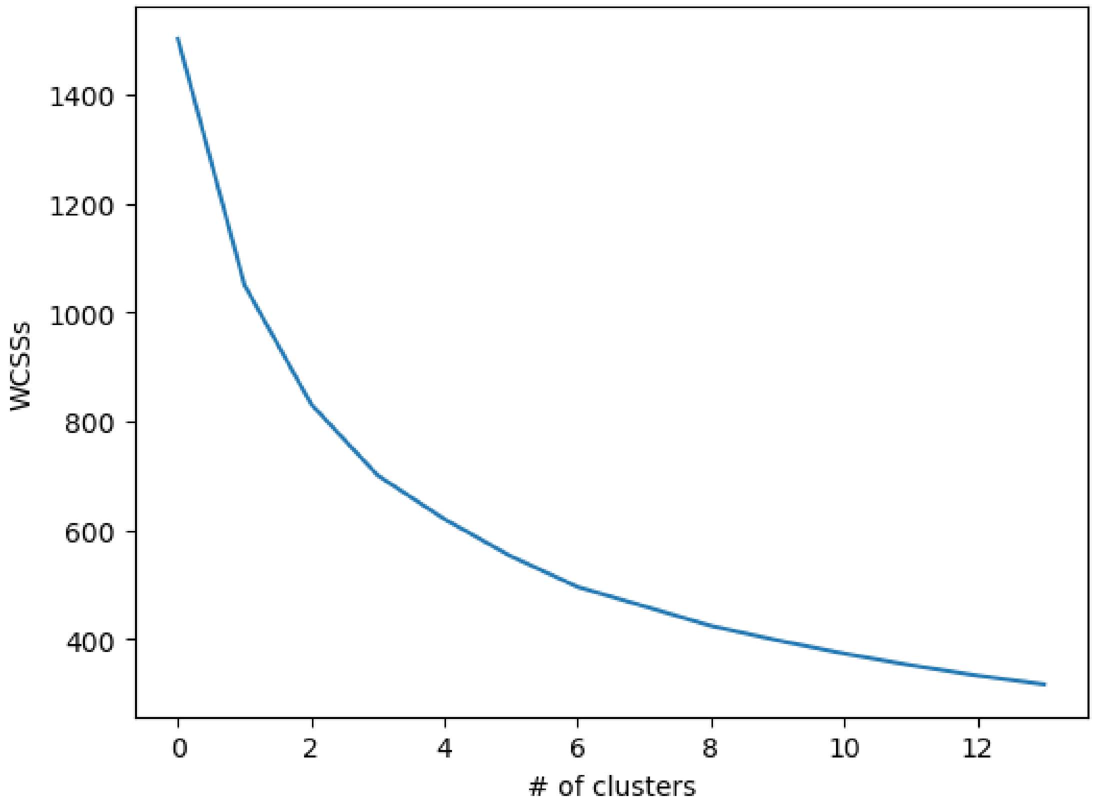
```
[16]: WCSSs = []
Ks = range(1,5)
for k in Ks:
        kmeans = KMeans(n_clusters = k, n_init = 30).fit(X_scaled)
        WCSSs.append(kmeans.inertia_)
```

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

```
[2]:
```

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.

[18]:
```
plt.plot(WCSSs)
plt.xlabel("# of clusters")
plt.ylabel("WCSSs")
plt.show()
```



[2]:
```
```

[2]:
```
```

[ ]:
```
```

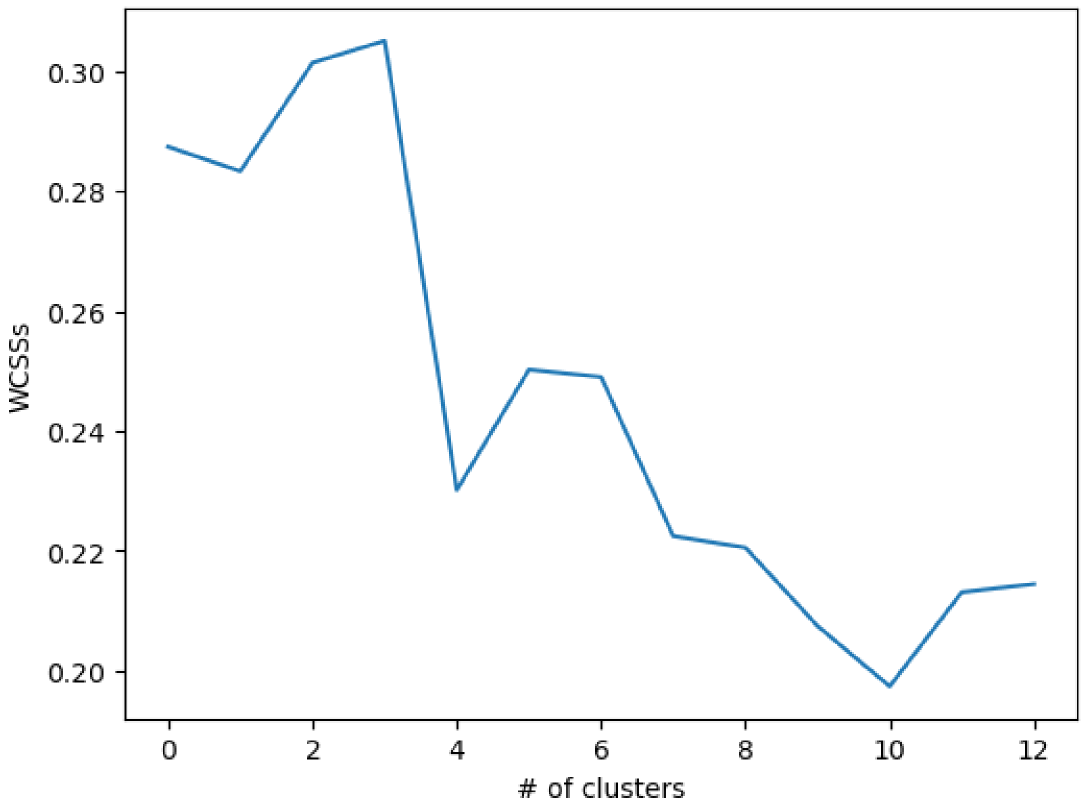
[ ]:
```
```

6 6.) Do the same for a silhoutte plot

[19]:
```
from sklearn.metrics import silhouette_score
```

[24]:
```
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)
```

[26]:
```
plt.plot(SSs)
plt.xlabel("# of clusters")
plt.ylabel("WCSSs")
plt.show()
```



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

[27]:
```
kmeans = KMeans(n_clusters = 2, n_init = 30).fit(X_scaled)
```

[29]:
```
kmeans.labels_
```

[29]:
```
array([0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0,
       1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1,
       1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0,
       0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1,
       0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1,
       0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0], dtype=int32)
```

[30]:
```
preds = pd.DataFrame(kmeans.labels_)
```

[31]:
```
output = pd.concat([preds,df], axis = 1)
```

[32]:
```
output
```

[32]:
```
     0              country  child_mort  exports  health  imports  income  \
0    0          Afghanistan        90.2     10.0    7.58     44.9    1610
1    1              Albania        16.6     28.0    6.55     48.6    9930
2    1              Algeria        27.3     38.4    4.17     31.4   12900
3    0               Angola       119.0     62.3    2.85     42.9    5900
4    1  Antigua and Barbuda        10.3     45.5    6.03     58.9   19100
..  ..                  …           …        …      …        …       …
162  0              Vanuatu        29.2     46.6    5.25     52.7    2950
163  1            Venezuela        17.1     28.5    4.91     17.6   16500
164  1              Vietnam        23.3     72.0    6.84     80.2    4490
165  0                Yemen        56.3     30.0    5.18     34.4    4480
166  0               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]
```

[33]:
```python
print("Cluster 1: ")
list(output.loc[output[0] == 0, "country"])
```

```
Cluster 1:
```

[33]:
```
['Afghanistan',
 'Angola',
 'Bangladesh',
 'Benin',
 'Bolivia',
 'Botswana',
 'Burkina Faso',
 'Burundi',
 'Cambodia',
 'Cameroon',
 'Central African Republic',
 'Chad',
 'Comoros',
 'Congo, Dem. Rep.',
 'Congo, Rep.',
 "Cote d'Ivoire",
 'Egypt',
 'Equatorial Guinea',
 'Eritrea',
 'Gabon',
 'Gambia',
 'Ghana',
 'Guatemala',
 'Guinea',
 'Guinea-Bissau',
 'Guyana',
 'Haiti',
 'India',
 'Indonesia',
 'Iraq',
 'Kenya',
 'Kiribati',
 'Kyrgyz Republic',
 'Lao',
 'Lesotho',
 'Liberia',
 'Madagascar',
 'Malawi',
 'Mali',
 'Mauritania',
```

```
 'Micronesia, Fed. Sts.',
 'Mongolia',
 'Mozambique',
 'Myanmar',
 'Namibia',
 'Nepal',
 'Niger',
 'Nigeria',
 'Pakistan',
 'Philippines',
 'Rwanda',
 'Samoa',
 'Senegal',
 'Sierra Leone',
 'Solomon Islands',
 'South Africa',
 'Sudan',
 'Tajikistan',
 'Tanzania',
 'Timor-Leste',
 'Togo',
 'Tonga',
 'Turkmenistan',
 'Uganda',
 'Uzbekistan',
 'Vanuatu',
 'Yemen',
 'Zambia']
```

[35]:
```
print("Cluster 2: ")
list(output.loc[output[0] == 1, "country"])
```

```
Cluster 2:
```

[35]:
```
['Albania',
 'Algeria',
 'Antigua and Barbuda',
 'Argentina',
 'Armenia',
 'Australia',
 'Austria',
 'Azerbaijan',
 'Bahamas',
 'Bahrain',
 'Barbados',
 'Belarus',
 'Belgium',
 'Belize',
```

```
'Bhutan',
'Bosnia and Herzegovina',
'Brazil',
'Brunei',
'Bulgaria',
'Canada',
'Cape Verde',
'Chile',
'China',
'Colombia',
'Costa Rica',
'Croatia',
'Cyprus',
'Czech Republic',
'Denmark',
'Dominican Republic',
'Ecuador',
'El Salvador',
'Estonia',
'Fiji',
'Finland',
'France',
'Georgia',
'Germany',
'Greece',
'Grenada',
'Hungary',
'Iceland',
'Iran',
'Ireland',
'Israel',
'Italy',
'Jamaica',
'Japan',
'Jordan',
'Kazakhstan',
'Kuwait',
'Latvia',
'Lebanon',
'Libya',
'Lithuania',
'Luxembourg',
'Macedonia, FYR',
'Malaysia',
'Maldives',
'Malta',
'Mauritius',
```

```
'Moldova',
'Montenegro',
'Morocco',
'Netherlands',
'New Zealand',
'Norway',
'Oman',
'Panama',
'Paraguay',
'Peru',
'Poland',
'Portugal',
'Qatar',
'Romania',
'Russia',
'Saudi Arabia',
'Serbia',
'Seychelles',
'Singapore',
'Slovak Republic',
'Slovenia',
'South Korea',
'Spain',
'Sri Lanka',
'St. Vincent and the Grenadines',
'Suriname',
'Sweden',
'Switzerland',
'Thailand',
'Tunisia',
'Turkey',
'Ukraine',
'United Arab Emirates',
'United Kingdom',
'United States',
'Uruguay',
'Venezuela',
'Vietnam']
```

[ ]:
```
#### Write an observation
```

7.0.1 Cluster 1:

This cluster mainly includes countries that are potentially less economically developed, as suggested by the presence of countries like Afghanistan, Angola, Bangladesh, and others in the list. These countries might be characterized by higher child mortality rates, lower income levels, and possibly higher inflation rates, indicative of developing or underdeveloped economies.

7.0.2 Cluster 2:

This cluster likely represents more economically developed or developing countries with better health outcomes, higher income levels, and lower child mortality rates. This cluster includes countries like Albania, Algeria, Antigua and Barbuda, Argentina, and others, suggesting a more stable economic condition compared to countries in Cluster 1.

7.0.3 Interesting Observations:

- **Economic Development**: The clustering seems to reflect varying levels of economic development and possibly other socio-economic indicators like health, education, and infrastructure.
- **Geographical Diversity**: Both clusters include countries from various parts of the world, indicating that the clustering is based more on economic and social indicators rather than geographical location.
- **Potential for Targeted Policies**: The clustering can provide a basis for targeted economic policies, development aid, and other forms of international support, focusing on the specific needs and characteristics of countries in each cluster.

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 interprotation

[39]:
```
Q8DF = pd.concat([preds, X], axis = 1)
```

[40]:
```
Q8DF.groupby(0).mean()
```

[40]:
```
   child_mort    exports    health    imports        income  inflation  \
0
0   76.280882  30.198515  6.090147  43.642146   4227.397059  11.098750
1   12.161616  48.603030  7.314040  49.121212  26017.171717   5.503545

   life_expec  total_fer          gdpp
0
0   61.910294   4.413824   1981.235294
1   76.493939   1.941111  20507.979798
```

[41]:
```
Q8DF.groupby(0).std()
```

[41]:
```
   child_mort    exports    health    imports        income  inflation  \
0
0   38.076068  18.201742  2.645319  19.323451   4890.581414  13.682630
1    8.523122  30.116032  2.716652  26.928785  20441.749847   6.957187

   life_expec  total_fer          gdpp
0
0    6.897418   1.285590   2528.509189
```

```
1    3.735757   0.486744  20578.727127
```

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

1. **Child Mortality (child_mort):**
   - Cluster 0 has a significantly higher mean child mortality rate (76.28) compared to Cluster 1 (12.16). This suggests that countries in Cluster 0 are likely to have less access to healthcare services, nutrition, and living conditions conducive to child survival compared to those in Cluster 1.
2. **Exports, Imports, and GDP per capita (exports, imports, gdpp):**
   - The mean values for exports (30.20 for Cluster 0 and 48.60 for Cluster 1) and imports (43.64 for Cluster 0 and 49.12 for Cluster 1) indicate that countries in Cluster 1 are more integrated into the global economy, engaging more in international trade.
   - The GDP per capita (gdpp) significantly differs between the clusters, with Cluster 1 countries having a much higher mean GDP per capita compared to Cluster 0, reflecting higher economic prosperity and development levels in Cluster 1 countries.
3. **Health Expenditure (health):**
   - The average health expenditure as a percentage of GDP is higher in Cluster 1 (7.31) than in Cluster 0 (6.09), hinting at potentially better healthcare infrastructure and access in Cluster 1 countries.
4. **Income and Inflation (income, inflation):**
   - There is a stark difference in mean income levels, with Cluster 1 countries having an average income, significantly higher than Cluster 0. This aligns with the higher GDP per capita observed in Cluster 1 and points to a higher standard of living.
   - Inflation rates are higher on average in Cluster 0 (11.10%) compared to Cluster 1 (5.50%), which could indicate economic instability or challenges in managing the cost of living in Cluster 0 countries.
5. **Life Expectancy and Total Fertility Rate (life_expec, total_fer):**
   - Life expectancy is higher in Cluster 1 (76.49 years) than in Cluster 0 (61.91 years), suggesting better health outcomes and living conditions in Cluster 1.
   - The total fertility rate is lower in Cluster 1 (1.94) compared to Cluster 0 (4.41), which often correlates with higher education levels, access to family planning, and economic development.
6. **Variability within Clusters:**
   - The standard deviations (std) for most variables are generally higher in Cluster 0 than in Cluster 1, indicating greater variability within Cluster 0 countries. This suggests that while countries in Cluster 0 share some common characteristics, there's a broader range of values for these indicators within the cluster.

These observations reflect the socio-economic and health disparities between the clusters, with Cluster 1 likely representing more developed countries with better health outcomes, higher income levels, and lower child mortality rates, while Cluster 0 includes countries with more significant challenges in these areas.