Sec_1_Homework_9

March 6, 2024

1 0.) Import and Clean data

[41]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings('ignore')
```

[42]:
```
df = pd.read_csv("Country-data.csv", sep = ",")
```

[43]:
```
names = df[["country"]].copy()
X = df.drop("country",axis =1 )
```

[44]:
```
scaler = StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

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

[45]:
```
kmeans= KMeans(n_clusters = 5).fit(X_scaled)
```

3 2.) Pick two features to visualize across

[46]:
```
X.columns
```

[46]:
```
Index(['child_mort', 'exports', 'health', 'imports', 'income', 'inflation',
       'life_expec', 'total_fer', 'gdpp'],
      dtype='object')
```

[47]:
```
import matplotlib.pyplot as plt

x1_index = 0
x2_index = 1
```

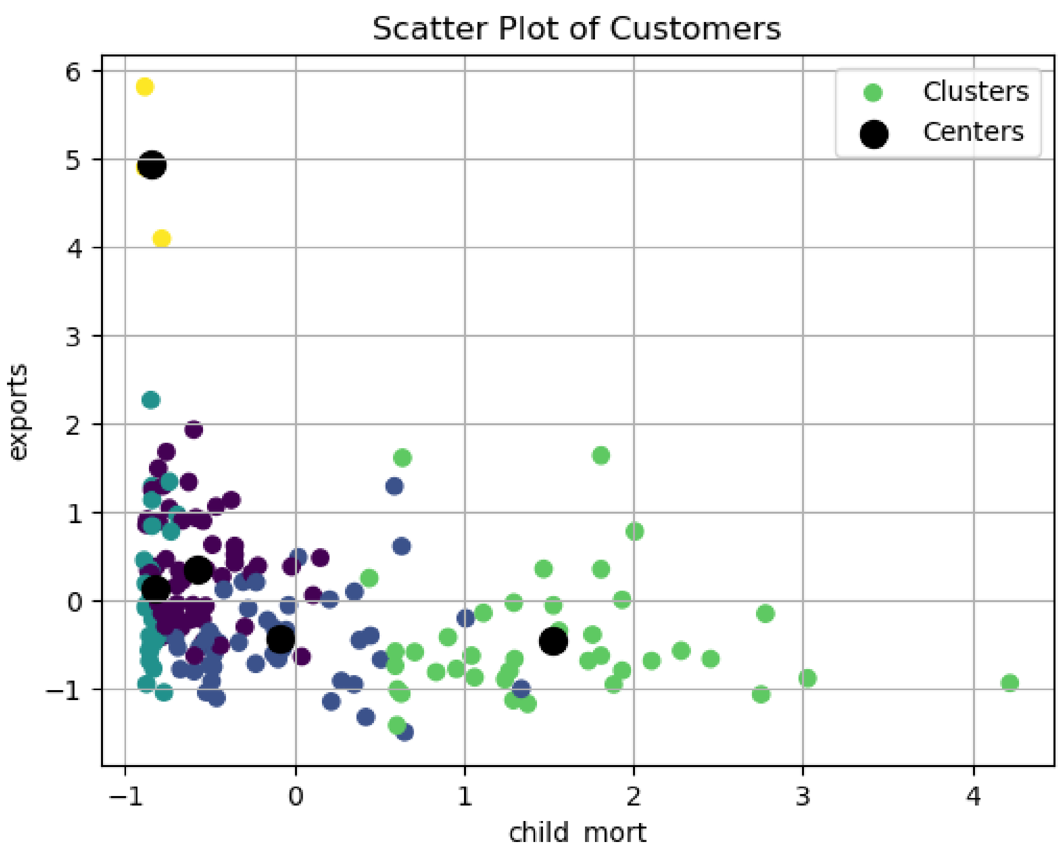
```
scatter = plt.scatter(X_scaled[:, x1_index], X_scaled[:, x2_index], c=kmeans.
 ↪labels_, cmap='viridis', label='Clusters')


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()
```



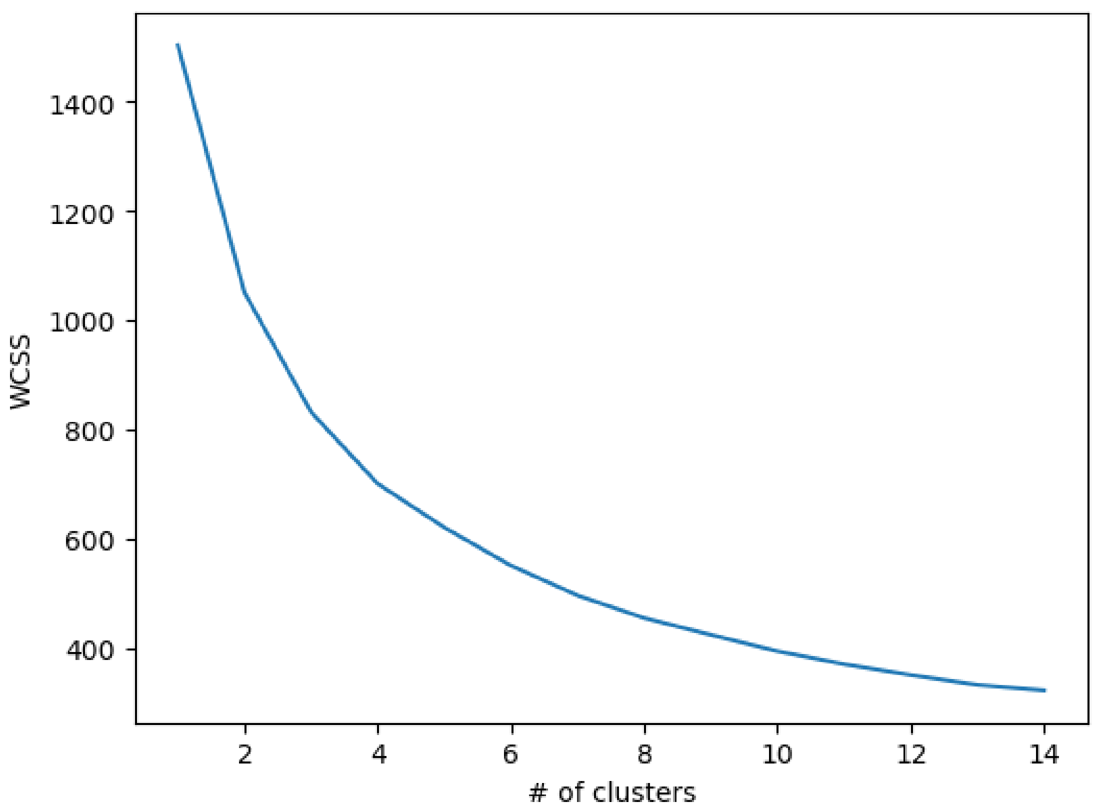
4 3.) Check a range of k-clusters and visualize to find the elbow. Test 30 different random starting places for the centroid means

[53]:
```
WCSSs = []
Ks = range(1,15)
for k in Ks:
    kmeans = KMeans(n_clusters = k, n_init = 30).fit(X_scaled)
    WCSSs.append(kmeans.inertia_)
```

[49]:
```
##OPTIONAL DO IN 1 LINE OF CODE
# 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.

[54]:
```
plt.plot(Ks,WCSSs)
plt.xlabel("# of clusters")
plt.ylabel("WCSS")
plt.show()
```

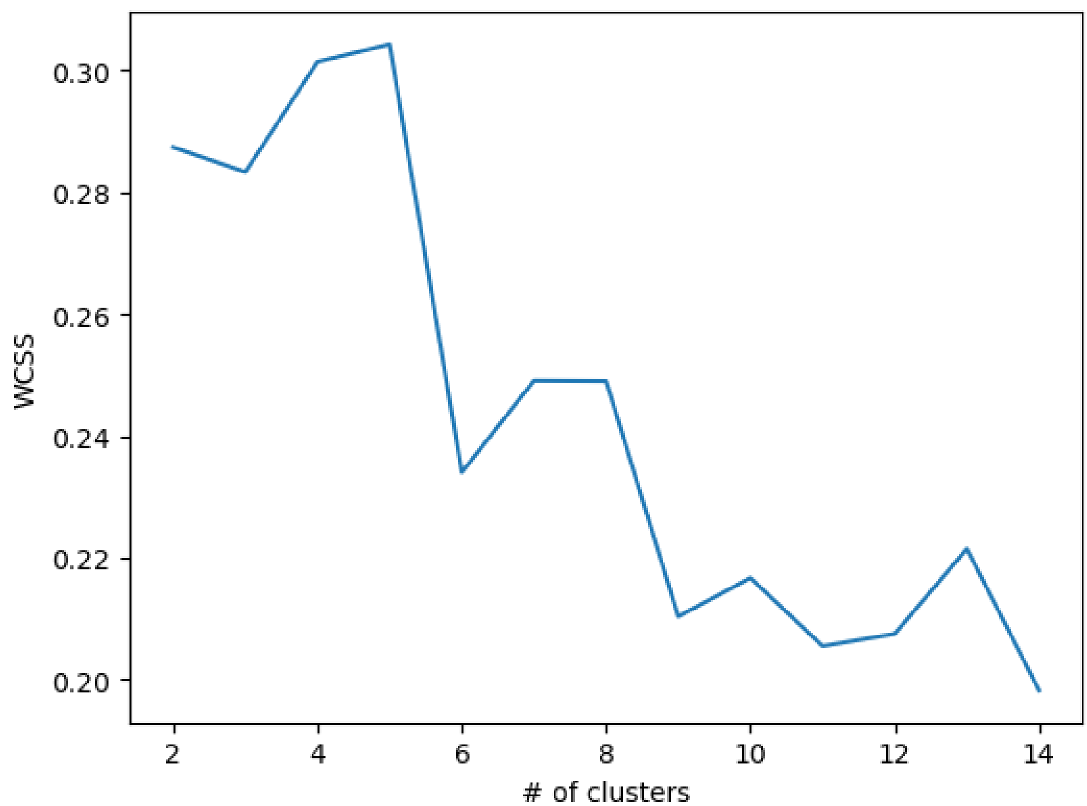


6 6.) Do the same for a silhoutte plot

[11]:
```
from sklearn.metrics import silhouette_score
```

[12]:
```
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)
```

[13]:
```
plt.plot(Ks,SSs)
plt.xlabel("# of clusters")
plt.ylabel("WCSS")
plt.show()
```



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

[14]:
```
kmeans = KMeans(n_clusters = 2, n_init = 30).fit(X_scaled)
```

[15]:
```
preds = pd.DataFrame(kmeans.labels_)
```

[16]:
```
output = pd.concat([preds,df],axis = 1)
```

[17]:
```
print("Cluster 1: ")
list(output.loc[output[0] == 0, "country"])
```

```
Cluster 1:
```

[17]:
```
['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']
```

[19]:
```
print("cluster 2: ")
list(output.loc[output[0] == 1, "country"])
```

```
cluster 2:
```

[19]:
```
['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']
```

7.0.1 Write an observation

7.0.2 Cluster 1 comprises countries with diverse economic statuses, including many developed nations such as Australia, Canada, and several European countries. Cluster 2 includes countries primarily from regions with developing economies, such as Afghanistan, Angola, Bangladesh, and several African nations. This clustering suggests a significant distinction based on socio-economic and possibly other factors related to the dataset's features like child mortality, exports, health spending, imports, income, inflation, life expectancy, total fertility, and GDP per capita.

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

[21]:
```
output.drop("country",axis = 1).groupby(0).mean()
```

[21]:
```
   child_mort    exports    health    imports        income  inflation  \
0
0   12.161616  48.603030  7.314040  49.121212  26017.171717   5.503545
1   76.280882  30.198515  6.090147  43.642146   4227.397059  11.098750

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

[22]:
```
output.drop("country",axis = 1).groupby(0).std()
```

[22]:
```
   child_mort    exports    health    imports        income  inflation  \
0
0    8.523122  30.116032  2.716652  26.928785  20441.749847   6.957187
1   38.076068  18.201742  2.645319  19.323451   4890.581414  13.682630

   life_expec  total_fer          gdpp
0
0    3.735757   0.486744  20578.727127
1    6.897418   1.285590   2528.509189
```

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

9.1 The first cluster primarily consists of developed countries characterized by lower child mortality rates, higher income levels, and greater GDP per capita, indicating better overall health outcomes and economic prosperity. In contrast, the second cluster comprises mainly developing countries, which face higher child mortality, lower incomes, and significantly lower GDP per capita. This clustering highlights the global divide in wealth, health, and access to resources, underscoring the importance of targeted interventions to address these disparities. The standard deviation values reveal the variability within each cluster, indicating the diversity of conditions among countries in the same cluster.