#### ml lab homework 9

March 7, 2024

- 1 Machine Learning Lab Homework 9
- 2 Connor O'Keefe
- $3 \quad 03/07/2024$
- 4 0.) Import and Clean data

```
[1]: import pandas as pd
     import matplotlib.pyplot as plt
     import numpy as np
     from sklearn.preprocessing import StandardScaler
     from sklearn.cluster import KMeans
     from sklearn.metrics import silhouette_score
[2]: df = pd.read_csv("Country-data.csv", sep = ",")
[3]: df
[3]:
                       country
                                 child_mort
                                             exports
                                                       health
                                                                imports
                                                                         income
                                                                   44.9
     0
                   Afghanistan
                                       90.2
                                                 10.0
                                                         7.58
                                                                            1610
     1
                       Albania
                                       16.6
                                                 28.0
                                                         6.55
                                                                   48.6
                                                                           9930
     2
                       Algeria
                                       27.3
                                                 38.4
                                                         4.17
                                                                   31.4
                                                                          12900
     3
                                      119.0
                                                 62.3
                                                         2.85
                                                                   42.9
                                                                           5900
                        Angola
     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
                                                 72.0
                                                         6.84
                                                                   80.2
     164
                       Vietnam
                                       23.3
                                                                            4490
     165
                                       56.3
                                                 30.0
                                                         5.18
                                                                   34.4
                                                                            4480
                         Yemen
     166
                                                 37.0
                                                                   30.9
                        Zambia
                                       83.1
                                                         5.89
                                                                            3280
          inflation
                     life_expec
                                   total_fer
                                                gdpp
     0
                9.44
                            56.2
                                        5.82
                                                 553
               4.49
                            76.3
                                        1.65
                                                4090
     1
     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
                                           1310
                                   1.95
165
         23.60
                       67.5
                                   4.67
                                           1310
         14.00
                                   5.40
166
                       52.0
                                           1460
```

[167 rows x 10 columns]

```
[4]: X = df.drop('country', axis=1)
scaler = StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

Question we want to answer: Can k-means identify developing economies?

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

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

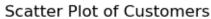
C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

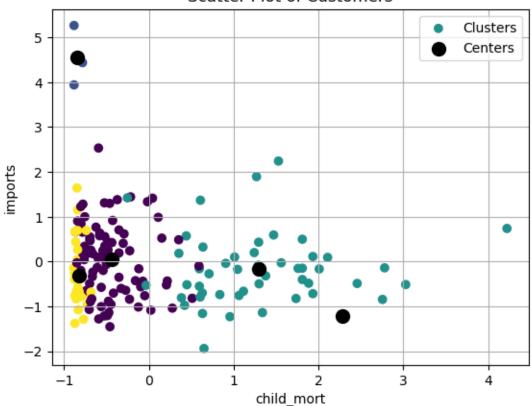
warnings.warn(

## 6 2.) Pick two features to visualize across

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

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





# 7 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_)
```

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the

environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446:

UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

```
warnings.warn(
```

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

```
warnings.warn(
```

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

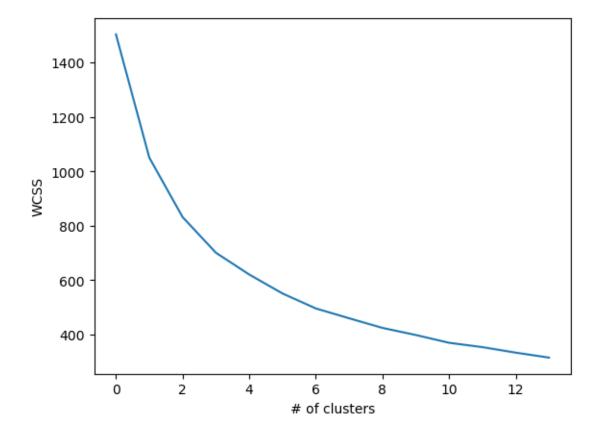
```
warnings.warn(
```

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

8 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.

```
[10]: plt.plot(WCSSs)
    plt.xlabel('# of clusters')
    plt.ylabel('WCSS')
    plt.show()
```



As can be seen above, there is no real elbow. This does not mean that the method is not working, just that the ideal number of clusters is up for interpretation and dependent on the context. Choosing two clusters for comparison seems to be an ideal number, because we could compare affluent countries to impoverished countries.

## 9 5.) Do the same for a silhoutte plot

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when

there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

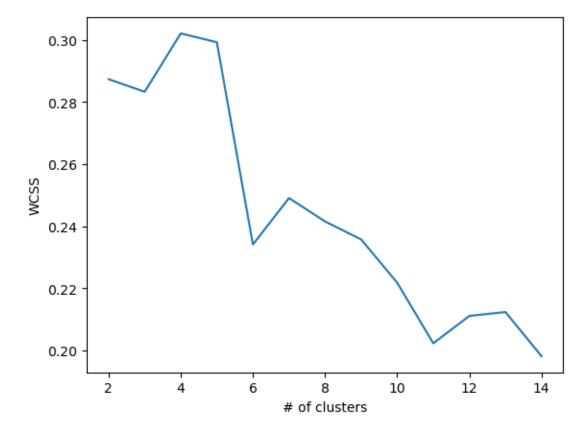
C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

warnings.warn(

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



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

```
[14]: # choosing two clusters below
kmeans = KMeans(n_clusters = 2, n_init = 30).fit(X_scaled)
```

C:\Users\12282\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP\_NUM\_THREADS=1.

```
environment variable OMP_NUM_THREADS=1.
       warnings.warn(
[15]: preds = pd.DataFrame(kmeans.labels_)
[16]: output = pd.concat([preds, df], axis = 1)
      output
[16]:
           0
                                     child_mort
                           country
                                                 exports
                                                          health
                                                                    imports
                                                                             income
      0
           0
                       Afghanistan
                                           90.2
                                                     10.0
                                                             7.58
                                                                       44.9
                                                                               1610
                                                     28.0
                                                                       48.6
      1
                           Albania
                                           16.6
                                                             6.55
                                                                               9930
      2
                                                             4.17
                                                                       31.4
           1
                           Algeria
                                           27.3
                                                     38.4
                                                                              12900
      3
           0
                            Angola
                                          119.0
                                                     62.3
                                                             2.85
                                                                       42.9
                                                                               5900
                                                             6.03
      4
           1
              Antigua and Barbuda
                                           10.3
                                                     45.5
                                                                       58.9
                                                                              19100
      162 0
                                           29.2
                                                     46.6
                                                             5.25
                                                                       52.7
                                                                               2950
                           Vanuatu
                                                             4.91
                                                                       17.6
      163 1
                         Venezuela
                                           17.1
                                                     28.5
                                                                              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
                                                             5.89
      166
                            Zambia
                                           83.1
                                                     37.0
                                                                       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
                             63.0
      162
                 2.62
                                         3.50
                                                2970
                             75.4
      163
               45.90
                                         2.47
                                               13500
      164
               12.10
                             73.1
                                         1.95
                                                1310
      165
                             67.5
               23.60
                                         4.67
                                                1310
               14.00
      166
                             52.0
                                         5.40
                                                1460
      [167 rows x 11 columns]
[17]: cluster1 = list(output.loc[output[0] == 0, 'country'])
```

print('Cluster 1: ', cluster1)

```
Cluster 1: ['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']
```

```
[18]: cluster2 = list(output.loc[output[0] == 1, 'country'])
print('Cluster 2: ', cluster2)
```

```
Cluster 2: ['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']
```

Because I am an American, my first point of interest was indentifying how the United States was classified (Cluster 2). Overall, Cluster 2 seems to classify the more developed countries and Cluster 1 seems to classify developing countries, with a fair amount from Africa and Asia. More analysis follows below.

7.) 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
                                                                         inflation
                         exports
                                     health
                                                imports
                                                                income
      0
          76.280882
      0
                                   6.090147
                                             43.642146
                       30.198515
                                                           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
          76.493939
      1
                        1.941111
                                   20507.979798
      output.drop('country', axis = 1).groupby(0).std()
[20]:
          child_mort
                         exports
                                     health
                                                imports
                                                                income
                                                                         inflation
      0
                                                                         13.682630
      0
          38.076068
                       18.201742
                                   2.645319
                                             19.323451
                                                           4890.581414
                                             26.928785
      1
            8.523122
                       30.116032
                                  2.716652
                                                         20441.749847
                                                                          6.957187
         life_expec
                       total_fer
                                           gdpp
      0
      0
            6.897418
                        1.285590
                                    2528.509189
            3.735757
      1
                        0.486744
                                   20578.727127
```

### 12 8.) Write an observation about the descriptive statistics.

As I hypothesized above, I think Cluster 1 may classify developing countries and Cluster 2 may classify developed countries. So now, turning to the above statistics, some important differences can be noticed. Every "good" and "bad" mean statistic is more optimal for Cluster 2, which supports my claim. For example, mean income of Cluster 2 is more than 6x that of Cluster 1. The standard deviation statistics are a little bit harder to interpret, and can be for a few different reasons. For example, the standard deviation of inflation of the developing countries could be higher because there is a huge variation in inflation rates, impacted by countries like Sri Lanka and Venezuela.