

0.) Import and Clean data

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

In []:

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

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

```
Out[4]:
```

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

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

```
In [11]: scale = StandardScaler().fit(X)
X_scaled = scale.transform(X)
```

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

```
In [38]: kmeans = KMeans(n_clusters = 5)
kmeans.fit(X_scaled)
```

```
e:\..Kacie\AnacondaKC\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The
default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` ex
plicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
e:\..Kacie\AnacondaKC\Lib\site-packages\sklearn\cluster\_kmeans.py:1436: UserWarning: KMeans
is known to have a memory leak on Windows with MKL, when there are less chunks than availabl
e threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

```
Out[38]:
```

▼ KMeans

KMeans(n_clusters=5)

2.) Pick two features to visualize across

```
In [40]: X.columns
```

```
Out[40]: Index(['child_mort', 'exports', 'health', 'imports', 'income', 'inflation',  
              'life_expect', 'total_fer', 'gdpp'],  
              dtype='object')
```

```
In [42]: import matplotlib.pyplot as plt
```

```
x1_index = 0  
x2_index = 3
```

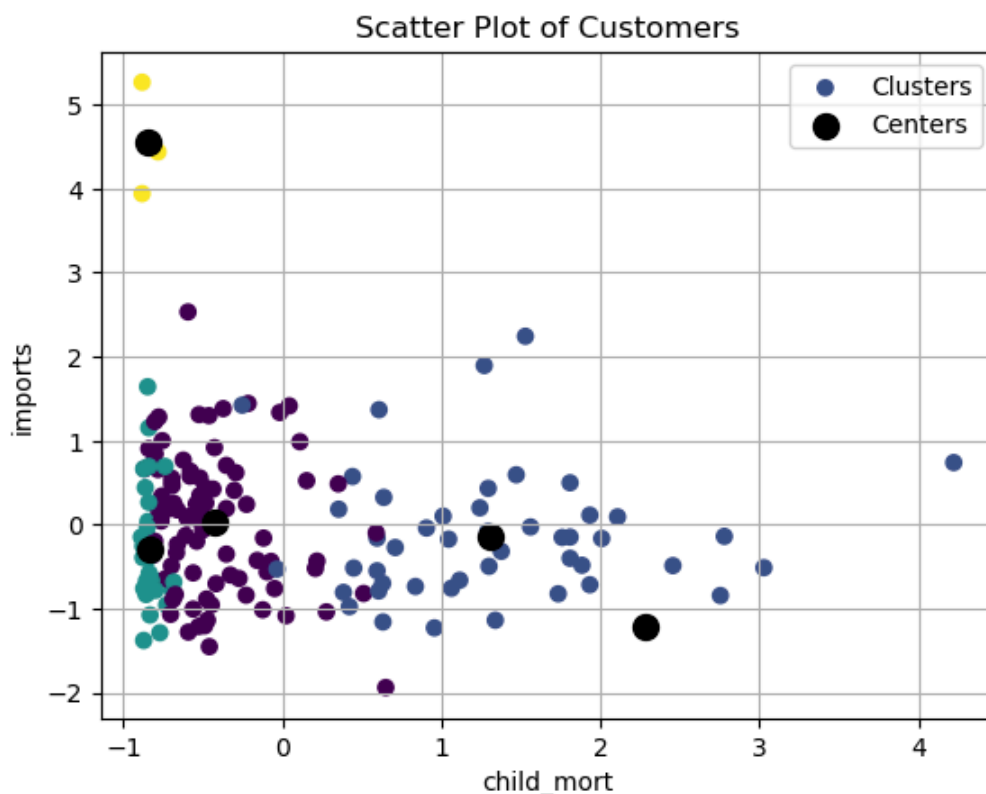
```
scatter = plt.scatter(X_scaled[:, x1_index], X_scaled[:, x2_index], c=kmeans.labels_, cmap=
```

```
centers = plt.scatter(kmeans.cluster_centers_[:, x1_index], kmeans.cluster_centers_[:, x2_i
```

```
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()
```

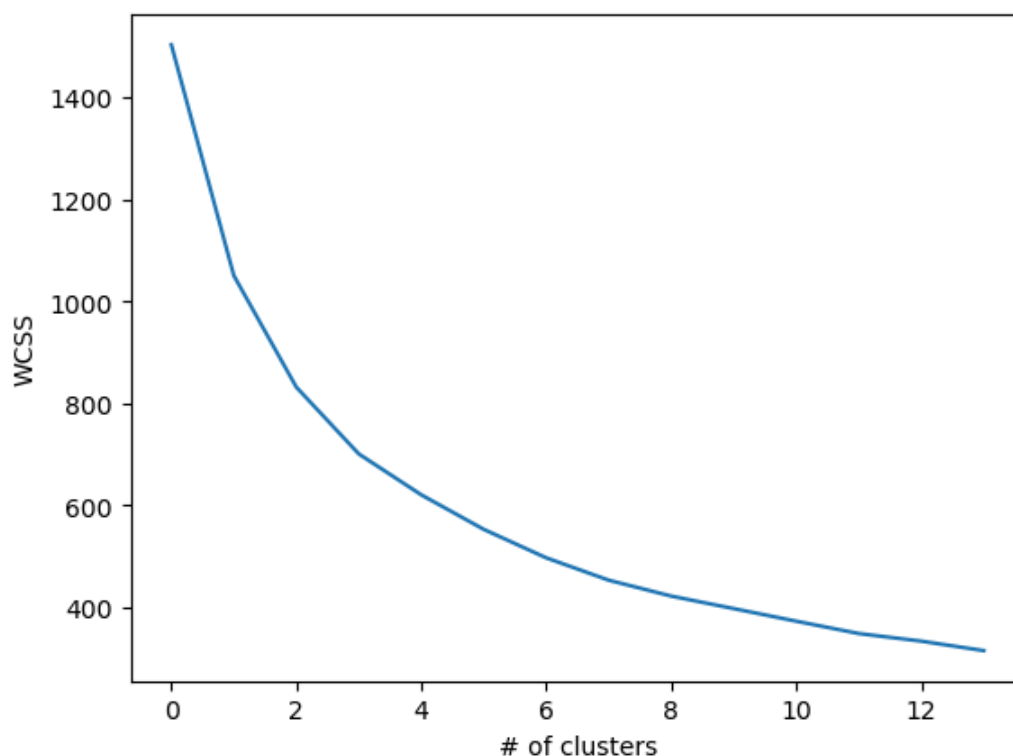


3.) Check a range of k-clusters and visualize to find the elbow. Test 30 different random starting places for the centroid means


```
Out[44]: [1503.0000000000002,  
1050.2145582853304,  
831.4244352086874,  
700.3917199643636,  
620.1633712888424,  
552.4199712763656,  
496.56905493459954,  
452.73591996440825,  
421.57499614895437,  
397.04844589950665,  
372.34142796540937,  
348.1352784320046,  
333.223760789451,  
314.6254683416746]
```

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.

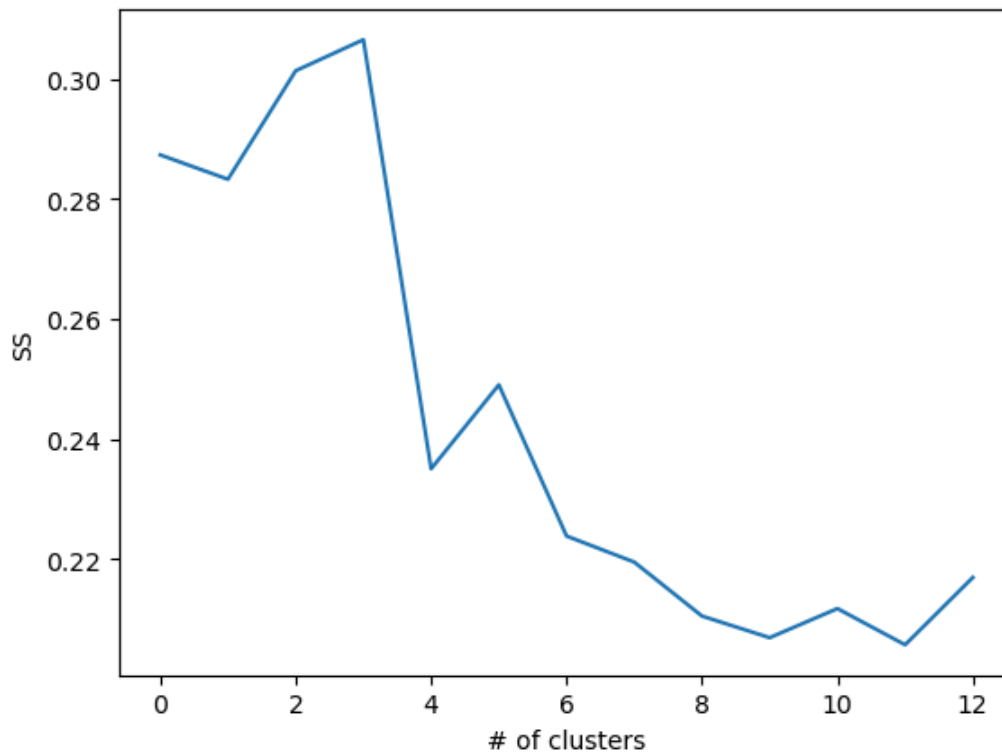
```
In [45]: plt.plot(WCSSs)  
plt.xlabel('# of clusters')  
plt.ylabel('WCSS')  
plt.show()
```



6.) Do the same for a silhouette plot

```
In [33]: from sklearn.metrics import silhouette_score
```

```
In [47]: SSs = []  
Ks = range(2,15)  
for k in Ks:  
    kmeans = KMeans(n_clusters = k, n_init=30).fit(X_scaled)
```

```
In [ ]: # our choice may be 3
```

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

```
In [53]: kmeans = KMeans(n_clusters = 2, n_init=30).fit(X_scaled)
```

```
e:\..Kacie\AnacondaKC\Lib\site-packages\sklearn\cluster\_kmeans.py:1436: UserWarning: KMeans
is known to have a memory leak on Windows with MKL, when there are less chunks than availabl
e threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
warnings.warn(
```

```
In [57]: preds = pd.DataFrame(kmeans.labels_)
preds
```

```
Out[57]:
```

	0
0	0
1	1
2	1
3	0
4	1
...	...
162	0
163	1
164	1
165	0
166	0

167 rows × 1 columns

```
In [60]: output = pd.concat([preds, df],axis = 1)
output
```

```
Out[60]:
```

	0	country	child_mort	exports	health	imports	income	inflation	life_expec	total
0	0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	
1	1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	
2	1	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	
3	0	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	
4	1	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	
...	
162	0	Vanuatu	29.2	46.6	5.25	52.7	2950	2.62	63.0	
163	1	Venezuela	17.1	28.5	4.91	17.6	16500	45.90	75.4	
164	1	Vietnam	23.3	72.0	6.84	80.2	4490	12.10	73.1	
165	0	Yemen	56.3	30.0	5.18	34.4	4480	23.60	67.5	
166	0	Zambia	83.1	37.0	5.89	30.9	3280	14.00	52.0	

167 rows × 11 columns



```
In [66]: print('Cluster1:' )
list(output.loc[output[0] == 0,'country'])
```

Cluster1:


```
Out[66]: ['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']
```

```
In [67]: print('Cluster2:' )  
list(output.loc[output[0] == 1, 'country'])
```

Cluster2:

```
Out[67]: ['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']

```

In []: *#### Write an observation*

It seems that the countries are divided by developing/developed countries. In Cluster 1, we see countries like Afghanistan, Bangladesh, Congo, Benin, and Burundi. These countries generally have lower levels of economic development. While in Cluster 2, we see countries like Australia, Canada, Germany, Japan, and the United States, which are typically with higher GDPs.

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 interpretation

In [79]: `output.drop('country',axis = 1)`

```
Out[79]:
```

	0	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	1	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	0	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	1	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200
...
162	0	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	2970
163	1	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	13500
164	1	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	1310
165	0	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	1310
166	0	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	1460

167 rows × 10 columns

```
In [80]: Q8DF = pd.concat([preds,X], axis = 1)
```

```
In [83]: group = Q8DF.groupby(0)
group.mean()
```

```
Out[83]:
```

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0								
0	76.280882	30.198515	6.090147	43.642146	4227.397059	11.098750	61.910294	4.413824
1	12.161616	48.603030	7.314040	49.121212	26017.171717	5.503545	76.493939	1.941111

```
In [84]: group.std()
```

```
Out[84]:
```

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0								
0	38.076068	18.201742	2.645319	19.323451	4890.581414	13.682630	6.897418	1.285590
1	8.523122	30.116032	2.716652	26.928785	20441.749847	6.957187	3.735757	0.486744

9.) Write an observation about the descriptive statistics.

There are some observations about my descriptive results:

We've already found that the group might be divided by developing countries (with index = 0) and developed countries (with index = 1). And from the means we can see that child mortality rate, total fertility rate in developing countries are all higher than those in developed countries, while index like economic indicators, health expenditure or life expectancy are much higher in developed countries. And looking at the variance, we see that std of econ indicators in developed countries are relatively small, indicating that they are

experiencing relatively stable econ development. As the same token, the variance of health expenditure and life expectancy are lower in developed countries because of their social and economic stability.