0.) Import and Clean data

```
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
```

```
drive.mount('/content/gdrive/', force_remount = True)
```

```
Mounted at /content/gdrive/
```

```
df = pd.read_csv("/content/gdrive/MyDrive/Econ441B/Country-data.csv", sep = ",")
```

```
df.head()
```

	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	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13

```
df.columns
```

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

```
names = df[["country"]]
X = df.drop(["country"], axis = 1)
# we want all of the features to be our x variables that we will cluster on and the coutry names we will want to keep on the side for future
```

```
scaler = StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

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

```
kmeans = KMeans(n_clusters= 5
                , random_state=42).fit(X_scaled)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
  warnings.warn(
```

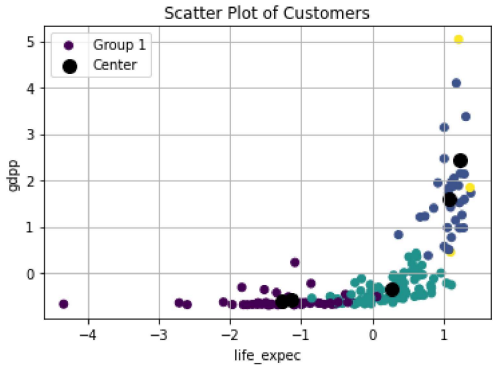
2.) Pick two features to visualize across

```
X.columns
```

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

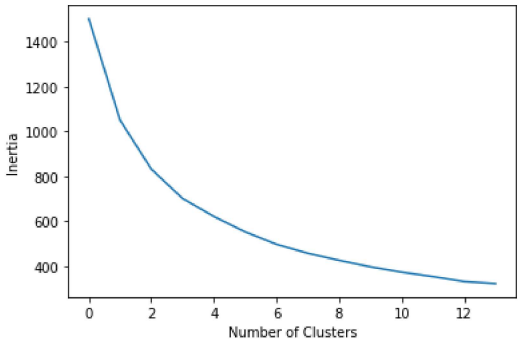
```
# comparing based on the column index 0-n
# CHANGE THESE BASED ON WHICH IS INTERESTING TO YOU
```

```
x1_index = 6
x2_index = 8


plt.scatter(X_scaled[:, x1_index], X_scaled[:, x2_index], c=kmeans.labels_, cmap='viridis')
plt.scatter(kmeans.cluster_centers_[:, x1_index], kmeans.cluster_centers_[:, x2_index], marker='o', color='black', s=100)

plt.xlabel(X.columns[x1_index])
plt.ylabel(X.columns[x2_index])
plt.title('Scatter Plot of Customers')
plt.legend(["Group 1", "Center", "Group 2"])
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

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


plt.plot(WCSSs)
plt.xlabel("Number of Clusters")
plt.ylabel('Inertia')
plt.show()
```



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.

I chose 3 clusters. The reason behind this is based on the graph above and the economic interpretation of it. Looking at the above graph, you can see that after 3, the line begins to decrease at a slower rate than before that point. Additionally, from an economic interpretation, I would think there would be 3 distinct groups of countries: countries with low gdp and low life expectancy, countries with medium gdp and higher life expectancy, and countries with the highest gdp and the highest life expectancy.

```
k = 3
# want to see if clustering identifies developing countries
# will be dif for ours


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

```
/usr/local/lib/python3.9/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
  warnings.warn(
```

5.) Create a list of the countries that are in each cluster. Write interesting things you notice. Hint : Use .predict(method)

```
# i am not 100% sure that this code for 5 is all that we need, some might be for 6
preds = pd.DataFrame(kmeans.predict(X_scaled))


preds
```

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

167 rows × 1 columns

```
output = pd.concat([preds,names], axis = 1)


output
```

	0	country
0	1	Afghanistan
1	0	Albania
2	0	Algeria
3	1	Angola
4	0	Antigua and Barbuda
...	...	...
162	0	Vanuatu
163	0	Venezuela
164	0	Vietnam
165	1	Yemen
166	1	Zambia

167 rows × 2 columns

```
print('Cluster 1')
[output[output[0]==0]['country']]
```

```
Cluster 1
[1                  Albania
 2                  Algeria
 4      Antigua and Barbuda
 5                Argentina
 6                  Armenia
                 ...
 160              Uruguay
 161            Uzbekistan
 162              Vanuatu
 163            Venezuela
 164              Vietnam
 Name: country, Length: 84, dtype: object]
```

```
print('Cluster 2')
[output[output[0]==1]['country']]
```

```
Cluster 2
[0                   Afghanistan
 3                        Angola
 17                        Benin
 21                     Botswana
 25                 Burkina Faso
 26                      Burundi
 28                     Cameroon
 31     Central African Republic
 32                         Chad
 36                      Comoros
 37             Congo, Dem. Rep.
 38                  Congo, Rep.
 40                Cote d'Ivoire
 49            Equatorial Guinea
 50                      Eritrea
 55                        Gabon
 56                       Gambia
 59                        Ghana
 63                       Guinea
 64                Guinea-Bissau
 66                        Haiti
 72                         Iraq
 80                        Kenya
 81                     Kiribati
 84                          Lao
 87                      Lesotho
 88                      Liberia
 93                   Madagascar
 94                       Malawi
 97                         Mali
 99                   Mauritania
 106                  Mozambique
 108                     Namibia
 112                       Niger
 113                     Nigeria
 116                    Pakistan
 126                      Rwanda
 129                     Senegal
 132                Sierra Leone
 137                South Africa
 142                       Sudan
 147                    Tanzania
 149                 Timor-Leste
 150                        Togo
 155                      Uganda
 165                       Yemen
 166                      Zambia
 Name: country, dtype: object]
```

```
print('Cluster 3')
[output[output[0]==2]['country']]
```

```
Cluster 3
[7                  Australia
 8                    Austria
 11                   Bahrain
 15                   Belgium
 23                    Brunei
 29                    Canada
 42                    Cyprus
 43            Czech Republic
 44                   Denmark
 53                   Finland
 54                    France
```

```
58                  Germany
60                   Greece
68                  Iceland
73                  Ireland
74                   Israel
75                    Italy
77                    Japan
82                   Kuwait
91               Luxembourg
98                    Malta
110            Netherlands
111            New Zealand
114                 Norway
122               Portugal
123                  Qatar
133              Singapore
134        Slovak Republic
135               Slovenia
138            South Korea
139                  Spain
144                 Sweden
145            Switzerland
157    United Arab Emirates
158          United Kingdom
159           United States
Name: country, dtype: object]
```

We can see 3 distinct groups of countries from the above clusters. In cluster 3, we notice the richest countries with the greatest life expectancy: countries like the U.S., UK, and Switzerland. In cluster 2, we notice some of the poorest countries in the world: many countries from Africa, which we would expect to have lower life expectancies. In cluster 1, we notice middling countries in terms of wealth and life expectancy: Vietnam, Argentina, and Venezuela.

6.) 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

```
q6df = pd.concat([preds,X], axis = 1)
```

```
q6df
```

	0	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	1	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	55
1	0	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	409
2	0	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	446
3	1	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	353
4	0	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	1220
...	...	...	...	...	...	...	...	...	...	..
162	0	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	297
163	0	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	1350
164	0	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	131
165	1	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	131
166	1	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	146

167 rows × 10 columns

```
q6df.groupby(0).mean()
```

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0								

```
q6df.groupby(0).std()
```

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer
0								
0	13.757919	19.029182	2.167233	20.103873	8180.073696	7.849516	3.960745	0.696957
1	33.375229	18.160597	2.662015	17.732741	5641.790360	15.509958	6.443521	1.041382
2	2.188933	41.930782	3.178015	36.843998	20852.017526	4.077719	1.815742	0.373054

Q7.) Write an observation about the descriptive statistics.

Looking at the tables above, we can see the 3 distinct groups of countries: rich countries with the greatest life expectancy (index 2), countries that are in the middle in terms of life expectancy and gdp (index 0), and the countries that are the poorest with the worst life expectancy (index 1). As we can see above, the richest countries have the smallest standard deviation for life expectancy, while the poorest have the largest standard deviation for life expectancy.