# **CLUSTERING COUNTRY PROBLEM**

```
In [41]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.preprocessing import StandardScaler
         from sklearn.cluster import KMeans
         from sklearn.decomposition import PCA
         from sklearn.metrics import silhouette score
         from sklearn.model selection import train test split
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.inspection import permutation importance
         from sklearn.cluster import AgglomerativeClustering
         from sklearn.mixture import GaussianMixture
         plt.style.use("seaborn-darkgrid")
In [2]:
         C:\Users\gadoc\AppData\Local\Temp\ipykernel 32172\1120890811.py:1: MatplotlibDeprecationWarning: The seaborn styles shipped by M
         atplotlib are deprecated since 3.6, as they no longer correspond to the styles shipped by seaborn. However, they will remain ava
         ilable as 'seaborn-v0 8-<style>'. Alternatively, directly use the seaborn API instead.
           plt.style.use("seaborn-darkgrid")
In [3]: file path = 'country data.csv'
         data = pd.read csv(file path)
         print("First few rows of the dataset:")
         display(data.head())
         First few rows of the dataset:
```

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

In [5]: print("\nDataset statistics:")
 display(data.describe())

#### Dataset statistics:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000
mean	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689	2.947964	12964.155689
std	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172	1.513848	18328.704809
min	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000	1.150000	231.000000
25%	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000	1.795000	1330.000000
50%	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000	2.410000	4660.000000
75%	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000	3.880000	14050.000000
max	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000	7.490000	105000.000000

In [6]: print("\nMissing values in each column:")
 print(data.isnull().sum())

```
Missing values in each column:
country
              0
child mort
              0
exports
              0
health
              0
imports
              0
income
              0
inflation
              0
life expec
              0
total fer
              0
gdpp
              0
dtype: int64
```

NaN

NaN

NaN

NaN

min

25%

**50%** 

**75%** 

max

2.600000

8.250000

19.300000

62.100000

208.000000

0.109000

23.800000

35.000000

51.350000

200.000000

```
In [7]: data_description = data.describe(include='all')
    data_description
```

health gdpp Out[7]: country child mort exports imports income inflation life expec total fer 167.000000 167.000000 167.000000 167.000000 167.000000 167.000000 167.000000 167.000000 167.000000 count 167 unique 167 NaN NaN NaN NaN NaN NaN NaN NaN NaN top Afghanistan NaN NaN NaN NaN NaN NaN NaN NaN NaN freq 1 NaN 38.270060 41.108976 6.815689 46.890215 17144.688623 7.781832 70.555689 2.947964 12964.155689 mean 40.328931 27.412010 2.746837 24.209589 10.570704 8.893172 18328.704809 std NaN 19278.067698 1.513848

0.065900

30.200000

43.300000

58.750000

## Check for outliers by identifying values that are far from mean values in specific columns

17.900000 174.000000

1.810000

4.920000

6.320000

8.600000

```
In [8]: outliers_info = data[(data['inflation'] > 50) | (data['gdpp'] > 100000) | (data['income'] > 100000)]
```

609.000000

3355.000000

9960.000000

22800.000000

125000.000000

-4.210000

1.810000

5.390000

10.750000

104.000000

32.100000

65.300000

73.100000

76.800000

82.800000

1.150000

1.795000

2.410000

3.880000

7.490000

231.000000

1330.000000

4660.000000

14050.000000

105000.000000

```
scaler = StandardScaler()
 In [9]:
           data[['income', 'gdpp', 'inflation']] = scaler.fit transform(data[['income', 'gdpp', 'inflation']])
           normalized summary = data.describe()
In [10]:
           outliers info
Out[10]:
                    country child mort exports health imports income inflation life expec total fer
                                                                                                         gdpp
                                    2.8
                                           175.0
                                                   7.77
                                                           142.0
                                                                   91700
                                                                               3.62
                                                                                                        105000
            91 Luxembourg
                                                                                         81.3
                                                                                                   1.63
           113
                     Nigeria
                                  130.0
                                                   5.07
                                                            17.4
                                                                    5150
                                                                             104.00
                                                                                                   5.84
                                                                                                          2330
                                            25.3
                                                                                         60.5
           123
                      Qatar
                                    9.0
                                            62.3
                                                   1.81
                                                            23.8
                                                                  125000
                                                                              6.98
                                                                                         79.5
                                                                                                   2.07
                                                                                                         70300
           normalized summary
In [11]:
                  child_mort
                                             health
                                                                                    inflation
                                                                                                           total fer
Out[11]:
                                 exports
                                                        imports
                                                                      income
                                                                                              life expec
                                                                                                                             gdpp
           count 167.000000
                             167.000000 167.000000
                                                     167.000000
                                                                 1.670000e+02
                                                                                1.670000e+02 167.000000
                                                                                                                     1.670000e+02
                                                                                                         167.000000
                   38.270060
                               41.108976
                                            6.815689
                                                      46.890215
                                                                -7.977650e-17
                                                                               -1.063687e-17
                                                                                               70.555689
                                                                                                           2.947964
                                                                                                                      5.850277e-17
           mean
                   40.328931
             std
                               27.412010
                                           2.746837
                                                      24.209589
                                                                 1.003008e+00
                                                                                1.003008e+00
                                                                                                8.893172
                                                                                                           1.513848
                                                                                                                     1.003008e+00
                    2.600000
                                0.109000
                                           1.810000
                                                                -8.603259e-01 -1.137852e+00
                                                                                               32.100000
                                                                                                           1.150000 -6.968005e-01
             min
                                                       0.065900
            25%
                    8.250000
                               23.800000
                                           4.920000
                                                      30.200000
                                                                 -7.174558e-01
                                                                               -5.666409e-01
                                                                                               65.300000
                                                                                                           1.795000
                                                                                                                     -6.366596e-01
            50%
                   19.300000
                               35.000000
                                           6.320000
                                                      43.300000
                                                                -3.738080e-01
                                                                               -2.269504e-01
                                                                                              73.100000
                                                                                                           2.410000 -4.544309e-01
                   62.100000
                               51.350000
                                           8.600000
                                                      58.750000
                                                                 2.942370e-01
                                                                                               76.800000
                                                                                                                     5.942100e-02
            75%
                                                                                2.816364e-01
                                                                                                           3.880000
            max 208.000000 200.000000
                                          17.900000
                                                    174.000000
                                                                 5.611542e+00
                                                                                9.129718e+00
                                                                                               82.800000
                                                                                                           7.490000 5.036507e+00
           features = data.select dtypes(include=[np.number])
In [12]:
           scaler = StandardScaler()
In [13]:
           scaled features = scaler.fit transform(features)
           scaled features
In [14]:
```

### Determine Optimal Number of Clusters Using the Elbow Method

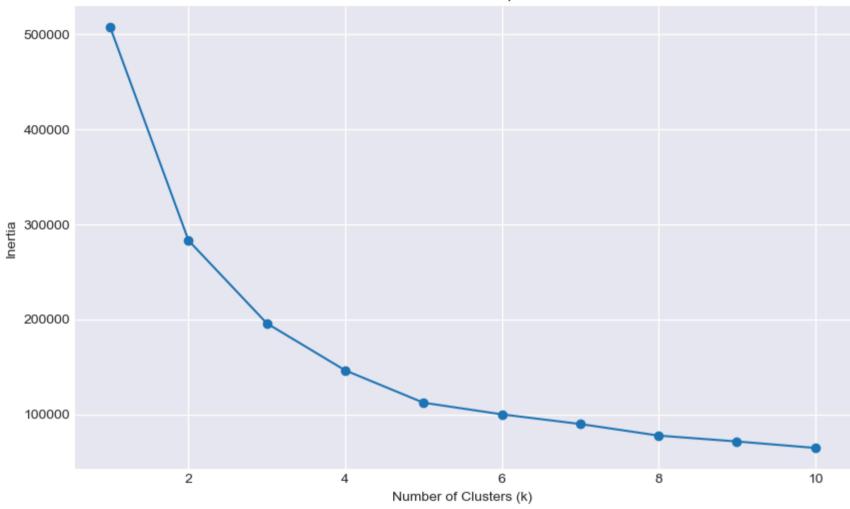
```
In [15]: k_values = range(1, 11)
    inertia_values = []

In [17]: for k in k_values:
        kmeans = KMeans(n_clusters=k, random_state=42)
        kmeans.fit(data[['income', 'gdpp', 'inflation', 'child_mort', 'exports', 'health', 'imports', 'life_expec', 'total_fer']])
        inertia_values.append(kmeans.inertia_)
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
  super(). check params vs input(X, default n init=10)
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
n 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:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
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  warnings.warn(
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  warnings.warn(
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
  super(). check params vs input(X, default n init=10)
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
n 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:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
ange from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super(). check params vs input(X, default n init=10)
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
n 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:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
```

```
ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
           super(). check params vs input(X, default n init=10)
         C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
         n 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:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
         ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
           super(). check params vs input(X, default n init=10)
         C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
         n 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:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
         ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
           super(). check params vs input(X, default n init=10)
         C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
         n 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:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
         ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
           super(). check params vs input(X, default n init=10)
         C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
         n 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(
         plt.figure(figsize=(10, 6))
In [18]:
         plt.plot(k values, inertia values, marker='o')
         plt.title("Elbow Method for Optimal k")
         plt.xlabel("Number of Clusters (k)")
         plt.vlabel("Inertia")
         plt.grid(True)
         plt.show()
```

### Elbow Method for Optimal k



# **Apply K-Means Clustering**

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will ch
ange from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
    super()._check_params_vs_input(X, default_n_init=10)
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
n 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(
```

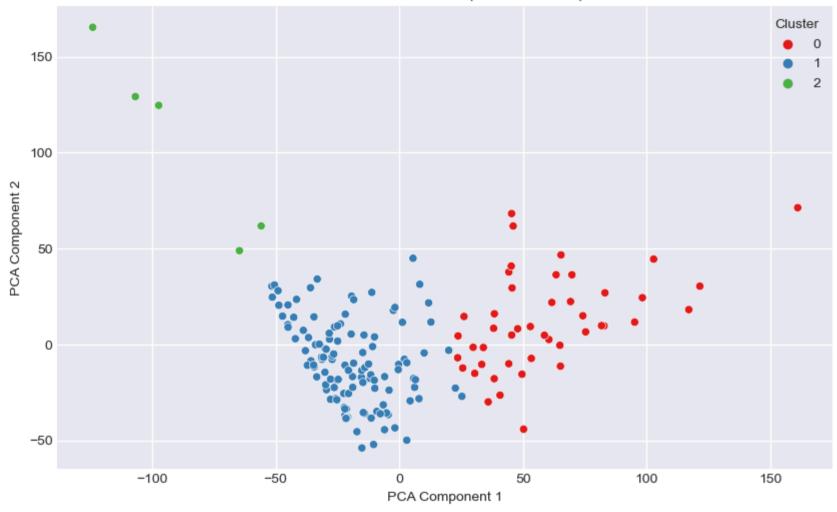
```
In [106... data['Cluster'] = clusters
```

## Visualize clusters using PCA for 2D plotting

```
In [21]:    pca = PCA(n_components=2)
    pca_features = pca.fit_transform(data[['income', 'gdpp', 'inflation', 'child_mort', 'exports', 'health', 'imports', 'life_expec',

In [22]:    plt.figure(figsize=(10, 6))
    sns.scatterplot(x=pca_features[:, 0], y=pca_features[:, 1], hue=data['Cluster'], palette='Set1')
    plt.xlabel('PCA Component 1')
    plt.ylabel('PCA Component 2')
    plt.title('Clusters of Countries (PCA Reduced)')
    plt.legend(title='Cluster')
    plt.show()
```

### Clusters of Countries (PCA Reduced)



In [107...
silhouette\_avg = silhouette\_score(data[['income', 'gdpp', 'inflation', 'child\_mort', 'exports', 'health', 'imports', 'life\_expec'
print(f'Silhouette Score for {optimal\_k} clusters: {silhouette\_avg:.2f}')

Silhouette Score for 3 clusters: 0.50

# Feature importance analysis for clustering

In [24]: cont\_data = data

```
cont data = cont data.select dtypes(include=[float, int])
In [25]:
          cont data.head()
In [26]:
Out[26]:
             child mort exports health imports
                                                           inflation life expec total fer
                                                  income
                                                                                           qdpp Cluster
          0
                   90.2
                           10.0
                                  7.58
                                           44.9
                                                -0.808245
                                                           0.157336
                                                                         56.2
                                                                                  5.82 -0.679180
                                                                                                      0
          1
                           28.0
                                   6.55
                                           48.6 -0.375369 -0.312347
                                                                                       -0.485623
                   16.6
                                                                         76.3
                                                                                  1.65
                                                                                                      1
          2
                                           31.4 -0.220844
                                                           0.789274
                   27.3
                           38.4
                                   4.17
                                                                         76.5
                                                                                       -0.465376
                                                                                                      1
          3
                  119.0
                           62.3
                                   2.85
                                           42.9 -0.585043
                                                           1.387054
                                                                         60.1
                                                                                  6.16
                                                                                       -0.516268
                                                                                                      0
          4
                   10.3
                           45.5
                                   6.03
                                           58.9
                                                 0.101732 -0.601749
                                                                         76.8
                                                                                  2.13 -0.041817
                                                                                                      1
          cluster summary = cont data.groupby('Cluster').mean()
In [48]:
          print("\nAverage values for each cluster:")
          display(cluster summary)
          Average values for each cluster:
                  child mort
                                exports
                                          health
                                                              income
                                                                       inflation life expec total fer
                                                    imports
                                                                                                       gdpp
          Cluster
                   95.180000
                              26.153756 6.229556
                                                  40.345909
                                                            -0.714221
               0
                                                                       0.381614 59.366667 4.986667
                                                                                                   -0.619562
                   17.752137
                              42.422906 7.050598
                                                  45.731624
                                                             0.198002
                                                                      -0.115199 74.471795 2.218376
                                                                                                    0.160006
               2
                    6.200000 144.960000 6.594000 132.900000
                                                             1.794737 -0.738877 79.620000 1.672000
                                                                                                    1.831909
In [49]: for cluster in range(optimal k):
               print(f"\nCluster {cluster}:")
              print("Interpret characteristics and implications based on feature averages.")
          Cluster 0:
          Interpret characteristics and implications based on feature averages.
          Cluster 1:
          Interpret characteristics and implications based on feature averages.
          Cluster 2:
          Interpret characteristics and implications based on feature averages.
```

```
scaler = StandardScaler()
In [27]:
         data scaled = scaler.fit transform(cont data)
         kmeans = KMeans(n clusters=3, random state=42) # Using 3 clusters as chosen earlier
In [28]:
         data['Cluster'] = kmeans.fit predict(data scaled)
         C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
         ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
           super(). check params vs input(X, default n init=10)
         C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
         n 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(
In [29]: X = cont data.drop('Cluster', axis=1)
          v = cont data['Cluster']
In [30]: X train, X test, y train, y test = train test split(X, y, test size=0.3, random state=42)
In [31]: clf = RandomForestClassifier(random state=42)
          clf.fit(X train, y train)
Out[31]:
                   RandomForestClassifier
         RandomForestClassifier(random state=42)
         perm importance = permutation importance(clf, X test, y test, random state=42)
In [32]:
In [33]: feature importance df = pd.DataFrame({
              'Feature': X.columns,
              'Importance': perm importance.importances mean
         }).sort values(by='Importance', ascending=False)
         print("Feature Importance in Determining Clusters:")
In [34]:
          print(feature importance df)
```

```
Feature Importance in Determining Clusters:
     Feature Importance
  child mort
                 0.156863
3
     imports
                 0.019608
     exports
                 0.015686
  life expec
                 0.003922
2
      health
                0.000000
4
      income
                0.000000
   inflation
                0.000000
8
         gdpp
                0.000000
   total fer
               -0.015686
```

#### REVISED FITTING OF MODEL BASED ON FEATURE IMPORTANCE RESULTS

```
important features = ['child mort', 'imports', 'exports', 'life expec']
In [101...
          data selected = data[important features]
          scaler = StandardScaler()
In [102...
          data scaled = scaler.fit transform(data selected)
In [103...
          kmeans = KMeans(n clusters=3, random state=0)
          data['Cluster'] = kmeans.fit predict(data scaled)
          C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1412: FutureWarning: The default value of `n init` will ch
          ange from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning
            super(). check params vs input(X, default n init=10)
          C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarning: KMeans is known to have a memory leak o
          n 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(
          silhouette avg = silhouette score(data scaled, data['Cluster'])
In [108...
          print(f"Silhouette Score with selected features: {silhouette avg:.2f}")
          Silhouette Score with selected features: 0.44
 In [
 In [ ]:
 In [ ]:
```