```
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#CS539-F23-F02
#Dr. Sethi
#Milestone 4: Revise and Evaluate Machine Learning Model
```


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Abstract:

This document presents a comprehensive analysis conducted to explore the research question: "Is there a statistically significant correlation between the production of plastic waste and key socio-economic factors such as GDP and population density across various countries?" Utilizing datasets from credible sources, we applied standard machine learning techniques such as correlation analysis, principal component analysis (PCA), and hierarchical clustering. The findings reveal a moderate correlation between GDP and plastic waste production, and clusters of countries with similar socio-economic profiles were identified. The results of PCA suggest that GDP is a more significant predictor of plastic waste production than population size. This analysis provides insights that could inform policy-making and strategic planning for waste management and economic development on a global scale.

Overview and Motivation:

This project investigates the link between plastic waste production and socio-economic indicators like GDP and population density, motivated by the urgent need to address global plastic pollution. By identifying the drivers of plastic waste, the study aims to inform sustainable waste management strategies. The focus on these particular factors arises from the hypothesis that a country's economic activities and population patterns significantly influence its environmental impact, specifically in terms of plastic waste generation. Through this research, I aim to provide realistic insights that could help mitigate one of the most challenging environmental issues of this century.

Related Work:

My research was inspired by the 2021 paper "Forecasting plastic waste generation and interventions for environmental hazard mitigation." This recent work provides valuable insights into the urgent global issue of plastic waste management, with a focus on European Union countries. It employs advanced machine learning techniques such as Artificial Neural Networks, Cross Validation, SHAP Analysis, and Scenario Analysis to predict and mitigate environmental hazards associated with plastic waste. However, both this paper and my research employ Clustering Analysis. My project diverges since it includes population, but the paper includes energy recovery and landfill.

Initial Questions:

My research began with the question: "Do socio-economic factors like GDP and population density significantly correlate with plastic waste production across countries?" This focus expanded to examine the role of recycling methods in mitigating plastic waste. As the project evolved, I also explored how different waste management strategies and economic development levels impact plastic waste generation, leading to a broader and more nuanced understanding of these complex relationships.

Data:

The four datasets that I've used are listed below:

- Generation of plastic packaging waste per capita https://ec.europa.eu/eurostat/web/products-datasets/-/cei_pc050
- GDP per capita https://ourworldindata.org/grapher/gdp-per-capita-maddison
- Population, total - European Union https://data.worldbank.org/indicator/SP.POP.TOTL?end=2022&locations=EU&start=2000&view=chart
- Recycling rates for packaging waste https://ec.europa.eu/eurostat/web/products-datasets/-/ten00063

In this study, I utilized datasets from Eurostat and the World Bank, focusing on metrics like plastic packaging waste per capita, GDP per capita, total population, and packaging waste recycling rates within the European Union. The years were standardized across datasets (e.g., GDP_2000, Plastic_Waste_2000, etc.). Challenges included handling missing values for countries that joined the EU in different years, which I addressed using the KNN method for data imputation. This approach helped maintain data consistency and accuracy for the analysis. I also learned that CSV were easier to work with compared to XLS files since they had less atributes to filter.

Exploratory Data Analysis:

Some of the EDA techniques used are bar charts, PCA and hierarchical clustering.The bar charts were employed to provide a clear visual comparison of GDP and plastic waste statistics across various countries, highlighting the mean, minimum, and maximum values to establish a baseline understanding of the data spread.

Then, PCA was used to reduce the dimensionality of the socio-economic factors and plastic waste data, resulting in a scatter plot that identifies natural groupings within the data while retaining the most variance.

This analysis was complemented by hierarchical clustering, which revealed the relative proximity of countries based on their socio-economic and environmental profiles, presented in a dendrogram that illustrates the hierarchical nature of these groupings.

Together, these visualizations synthesize complex multi-dimensional data into interpretable formats, allowing for the identification of patterns and relationships that can inform subsequent analysis and decision-making.

Model Revision:

I reduced the project's scope to focus on the EU due to better data organization compared to other regions (i.e. Asia, America, Africa, etc). I also encountered incomplete data within the EU, especially regarding recycling rates, so I adapted my approach to ensure a manageable analysis. The final model, based on clustering analysis, provided initial insights into the relationship between plastic waste production and socio-economic factors, confirming the value of concentrating on European data.

Full Analysis:

The data revealed a moderate positive correlation between GDP and plastic waste production, indicating that wealthier countries tend to generate more plastic waste. Population showed a weaker positive correlation with both GDP and plastic waste, suggesting that while larger countries have higher GDP and waste production, the relationship isn't as strong. These findings were initially validated by the correlation matrix.

Cluster analysis further enriched the understanding by grouping countries with similar socio-economic and plastic waste profiles. The PCA scatter plot, colored by cluster, showed natural groupings and outliers, suggesting that while some countries follow general trends, others deviate based on unique national characteristics.

The hierarchical clustering dendrogram complemented these findings by illustrating the multi-level similarity between countries, providing a visual hierarchy of the relationships within the data.

The initial metrics validated the hypotheses and provided a foundation for further exploration. Future work might include applying other machine learning algorithms, such as regression analysis, to quantify the impact of these factors on plastic waste production and explore causality.

I recently included a dataset which includes data related to the recycling rates of these countries, however, I haven't used it in the research yet since the years span over 2011 to 2021. So I need to alter some of the code for consistency.

Perhaps this additional data can explain the outliers and the weak correlation in the early analysis. Further machine learning techniques like regression could also be applied to investigate causality and impact.

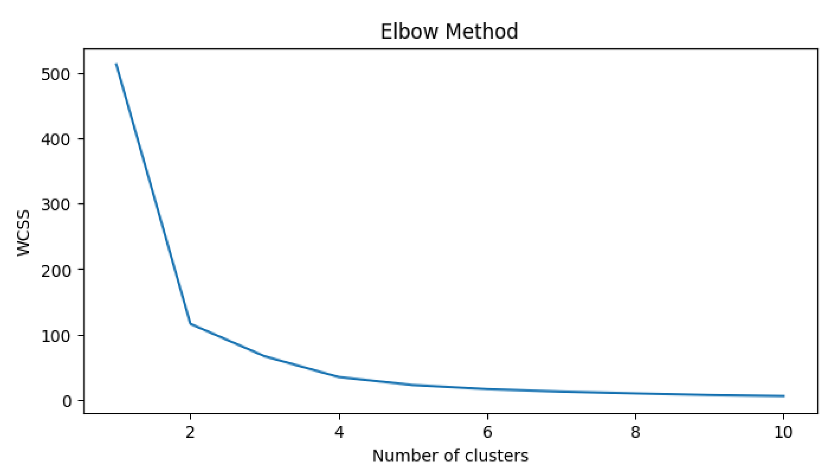
```
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import drive
drive.mount('/content/drive')
```

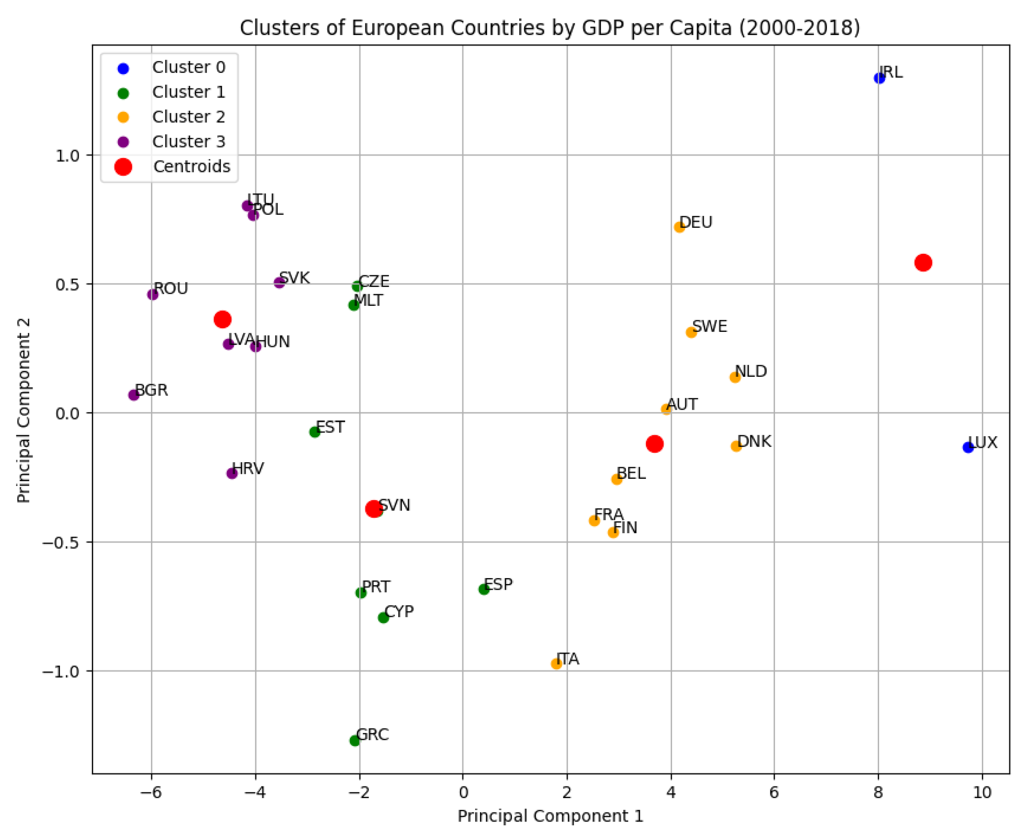
```
    Mounted at /content/drive
```

```
import pandas as pd

df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/gdp-per-capita-maddison.csv')

# Define list of EU member states by their ISO country codes
eu_countries = [
    'BEL', 'BGR', 'CZE', 'DNK', 'DEU', 'EST', 'IRL', 'GRC', 'ESP', 'FRA',
    'HRV', 'ITA', 'CYP', 'LVA', 'LTU', 'LUX', 'HUN', 'MLT', 'NLD', 'AUT',
    'POL', 'PRT', 'ROU', 'SVN', 'SVK', 'FIN', 'SWE'
]

# Filter dataset for years 2000 to 2018
df_2000_2018 = df[(df['Year'] >= 2000) & (df['Year'] <= 2018) & (df['Code'].isin(eu_countries))]

# Pivot table to have countries as rows and years as columns
pivot_table = df_2000_2018.pivot(index='Code', columns='Year', values='GDP per capita')

# Sort table by last year to see progression
pivot_table_sorted = pivot_table.sort_values(by=2018, ascending=False)

print(pivot_table_sorted)
```

```
    Year        2000        2001       2002       2003       2004       2005  \
    Code
    IRL   38806.5000  40966.3320  43012.816  44372.758  47028.863  49223.383
    LUX   50063.8240  50527.6640  51709.734  51717.030  52624.164  53262.094
    NLD   37899.9500  38636.2230  38653.125  38803.957  39682.375  40679.490
    DNK   39021.1760  39425.8630  39709.370  39983.145  41178.562  42264.630
    DEU   33367.2850  34260.2900  34590.930  34716.440  35528.715  36205.574
    SWE   34202.6050  34666.6640  35569.773  36435.754  38016.062  39258.992
    AUT   34796.2580  35272.2230  35823.586  36063.120  36957.113  37642.760
    BEL   33719.7700  33923.3440  34419.695  34588.477  35740.350  36338.383
    FIN   32689.7700  33481.6800  33986.555  34607.220  35888.613  36787.258
    FRA   33409.6800  33920.0980  34152.773  34292.030  35093.824  35495.465
    ITA   32716.9800  33511.4340  33780.055  33917.800  34472.130  34872.125
    MLT   20434.5490  20413.0500  20873.984  21273.135  21233.002  21905.215
    ESP   26994.8600  28153.5530  28753.322  29371.865  30088.092  30885.602
    CZE   17056.1600  17868.5680  18431.027  19344.090  20555.035  22128.580
    SVN   21501.3360  22006.9530  22725.312  23257.422  24150.584  24966.940
    POL   12732.1670  13017.5840  13415.571  14035.637  14906.094  15580.937
    EST   16806.9750  17696.6100  18589.150  19771.742  20803.758  22518.541
    LTU   10806.8740  11606.7290  12490.621  13917.508  14995.767  16417.950
    CYP   22326.7990  23095.7360  23828.072  24347.076  25355.240  26164.209
    SVK   13904.9850  14361.9010  14984.731  15773.095  16570.861  17649.520
    PRT   23372.0410  23751.3710  23896.459  23677.520  24142.766  24377.950
    HUN   13129.2730  13933.5620  14899.307  15829.899  16999.006  18140.617
    LVA   11309.7400  12103.8280  13015.475  14142.124  15371.182  17069.656
    GRC   20965.3320  21913.7970  22893.959  24380.066  25780.385  26091.523
    HRV   13244.5410  13817.6810  14683.838  15740.499  16628.574  17581.360
    ROU    7089.9463   7860.4434   8673.619   9369.233  10531.172  11313.822
    BGR    8410.7950   8832.2910   9471.766  10080.783  10853.785  11758.084

    Year       2006       2007       2008       2009       2010     2011     2012  \
    Code
    IRL   51296.195  52322.230  49583.140  47375.734  48623.810  48980.0  48333.0
    LUX   54920.810  58369.703  56383.190  52731.390  54086.336  54031.0  52562.0
    NLD   42286.510  44008.750  44840.710  43178.508  43812.348  44591.0  43957.0
    DNK   44025.484  44481.470  44246.400  42090.170  42932.400  43575.0  43510.0
    DEU   38014.137  39752.207  40715.434  38962.938  41109.582  43189.0  43320.0
    SWE   40992.300  42399.844  42189.965  40116.312  42634.754  42079.0  41650.0
    AUT   38866.848  40305.273  40964.793  39463.656  40288.348  41446.0  41565.0
    BEL   37051.902  38082.875  38117.348  36998.650  37739.330  38130.0  37906.0
    FIN   38160.703  39998.527  40129.652  36662.613  37615.113  38432.0  37704.0
    FRA   36166.160  36845.684  36761.793  35534.926  36086.727  36691.0  36571.0
    ITA   35713.805  36310.734  35942.938  34055.227  34765.938  35151.0  34068.0
    MLT   22233.717  23048.264  23674.594  22927.654  23632.625  23871.0  24301.0
    ESP   31907.424  32735.434  32844.324  31669.691  31786.404  31600.0  30699.0
    CZE   23888.164  25382.807  26186.045  25093.863  25922.395  26725.0  26474.0
    SVN   26182.780  27832.764  28473.596  25905.514  26000.920  26004.0  25252.0
    POL   16711.447  18067.428  19011.547  19718.465  20608.693  21837.0  22188.0
    EST   24578.816  26177.871  24429.021  20538.049  20713.426  21997.0  23026.0
    LTU   17916.059  20138.473  20879.803  17983.350  18663.762  20243.0  21303.0
    CYP   27142.018  28109.996  28736.975  27735.033  27630.104  27272.0  26011.0
    SVK   19099.428  21109.940  22231.988  20953.037  21941.213  22483.0  22816.0
    PRT   24809.040  25477.205  25590.880  24902.457  25463.164  25133.0  24218.0
    HUN   19253.062  19763.791  20380.630  19461.070  20036.334  20886.0  20631.0
    LVA   19128.690  21042.367  20342.200  17582.111  17140.227  18428.0  19405.0
    GRC   27731.111  28822.916  28907.926  27839.898  26517.465  24349.0  22693.0
    HRV   18707.490  19984.037  20717.316  19501.588  19511.350  19813.0  19441.0
    ROU   12823.231  14418.830  16347.344  15866.127  16377.328  17174.0  17174.0
```

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/gdp-per-capita-maddison.csv')

# Define list of EU member states by their ISO country codes
eu_countries = [
    'BEL', 'BGR', 'CZE', 'DNK', 'DEU', 'EST', 'IRL', 'GRC', 'ESP', 'FRA',
    'HRV', 'ITA', 'CYP', 'LVA', 'LTU', 'LUX', 'HUN', 'MLT', 'NLD', 'AUT',
    'POL', 'PRT', 'ROU', 'SVN', 'SVK', 'FIN', 'SWE'
]

# Filter dataset for years 2000 to 2018
df_2000_2018 = df[(df['Year'] >= 2000) & (df['Year'] <= 2018) & (df['Code'].isin(eu_countries))]

# Pivot table to have countries as rows and years as columns
pivot_table = df_2000_2018.pivot(index='Code', columns='Year', values='GDP per capita')

# Sort table by last year to see the progression
pivot_table_sorted = pivot_table.sort_values(by=2018, ascending=False)

# Drop any missing values if present (countries with missing data)
pivot_table_cleaned = pivot_table_sorted.dropna()

# Standardize data (important for k-means)
scaler = StandardScaler()
data_scaled = scaler.fit_transform(pivot_table_cleaned)

# Elbow Method to determine k
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
    kmeans.fit(data_scaled)
    wcss.append(kmeans.inertia_)

# Plot Elbow graph
plt.figure(figsize=(8, 4))
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')  # WCSS stands for Within-Cluster Sum of Square
plt.show()

# Based on Elbow graph, choose number of clusters (k)
k = 4
kmeans = KMeans(n_clusters=k, init='k-means++', max_iter=300, n_init=10, random_state=0)

# Fit KMeans using standardized data
clusters = kmeans.fit_predict(data_scaled)

# Perform PCA to reduce dimensions to 2 for visualization
pca = PCA(n_components=2)
principal_components = pca.fit_transform(data_scaled)

# Create a new DataFrame for PCA results
pca_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])

# Add cluster labels to PCA DataFrame
pca_df['Cluster'] = clusters

# Add country codes to PCA DataFrame for labeling
pca_df['Country'] = pivot_table_cleaned.index

# Get centroids
centroids = kmeans.cluster_centers_

# Transform centroids using PCA model
centroids_pca = pca.transform(centroids)

# Plot clusters
plt.figure(figsize=(10, 8))
colors = ['blue', 'green', 'orange', 'purple']
for i in range(k):
    plt.scatter(pca_df[pca_df['Cluster'] == i]['PC1'], pca_df[pca_df['Cluster'] == i]['PC2'], label=f'Cluster {i}', c=colors[i])

# Plotting centroids
plt.scatter(centroids_pca[:, 0], centroids_pca[:, 1], s=100, c='red', label='Centroids')

plt.title('Clusters of European Countries by GDP per Capita (2000-2018)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.grid(True)

# Annotate country codes
for i, txt in enumerate(pca_df['Country']):
    plt.annotate(txt, (pca_df['PC1'][i], pca_df['PC2'][i]))
plt.show()
```





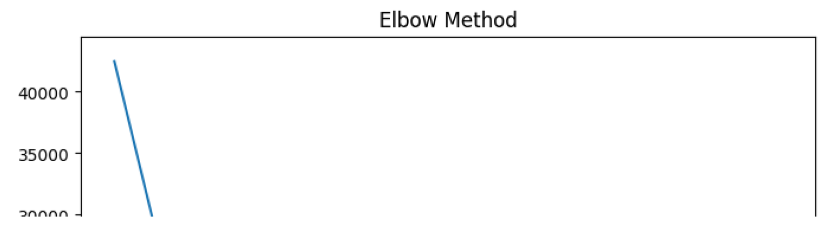

```
import pandas as pd
import numpy as np
from sklearn.impute import KNNImputer

df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Gener of plastic packaging waste per capita.csv', skiprows=8)

# only need first 20 columns, ignore rest
df = df.iloc[:, :20]  # discard empty columns

# Rename columns assuming first column is 'GEO (Labels)' and rest are years from 2000 to 2018
df.columns = ['Code'] + list(range(2000, 2019))

# Convert all entries in 'GEO (Labels)' to uppercase to match country codes in eu_countries list
df['Code'] = df['Code'].str.upper()

eu_countries = [
    'BEL', 'BGR', 'CZE', 'DNK', 'DEU', 'EST', 'IRL', 'GRC', 'ESP', 'FRA',
    'HRV', 'ITA', 'CYP', 'LVA', 'LTU', 'LUX', 'HUN', 'MLT', 'NLD', 'AUT',
    'POL', 'PRT', 'ROU', 'SVN', 'SVK', 'FIN', 'SWE'
]

# Filter dataframe to include only rows where 'GEO (Labels)' is in eu_countries list
eu_data = df[df['Code'].isin(eu_countries)]

# Replace non-numeric values with NaN and convert all columns to numeric, coercing errors to NaN
for column in eu_data.columns[1:]:  # Skipping 'GEO (Labels)' column
    eu_data.loc[:, column] = pd.to_numeric(eu_data[column], errors='coerce')


#limit data to years 2000 to 2018
eu_data = eu_data[['Code'] + list(range(2000, 2019))]

#display cleaned EU data for years 2000-2018
print(eu_data)
```

```
4   DEU  21.78  22.95  23.13  23.09  27.33  28.71  31.46  32.14  33.28  32.00
5   PRT  27.79  29.28  31.19  31.55  32.86  33.86  35.86  35.89  36.74  35.77
7   ITA  33.37  34.23  34.19  34.90  35.61  36.21  37.87  38.84  37.48  35.40
9   DNK  29.44  28.02  29.25  28.71  32.25  33.73  35.09  35.12  30.01  29.96
10  AUT  26.21  25.43  24.75  26.69  27.55  27.35  28.80  29.49  30.23  30.66
11  FRA  29.29  29.21  30.29  31.43  31.66  31.86  32.53  33.12  31.89  29.10
12  ESP  29.41  32.24  31.84  33.36  34.09  35.86  36.38  37.12  34.49  31.12
14  HUN    NaN    NaN    NaN    NaN  16.33  18.62  19.71  21.73  21.44  22.89
15  BEL  23.78  23.32  24.97  26.80  27.01  27.70  28.66  29.06  28.16  28.11
16  NLD  28.76  30.29  32.82  33.22  33.72  36.27  27.22  28.45  26.88  25.86
17  MLT    NaN    NaN    NaN    NaN  15.72  16.03  16.41  21.63  35.30  32.24
18  POL    NaN    NaN    NaN    NaN  17.37  16.59  18.09  13.53  17.57  17.47
19  SWE  16.73  17.93  18.74  18.41  19.03  19.45  20.46  20.91  20.95  20.61
20  CZE    NaN    NaN    NaN  16.94  17.37  20.25  19.93  21.08  20.82  19.99
21  LTU    NaN    NaN    NaN    NaN  14.97  15.44  17.30  19.96  19.95  17.12
22  SVN    NaN    NaN    NaN    NaN  16.20  16.97  23.59  22.66  23.69  22.85
23  FIN  16.88  16.85  16.75  17.15  17.20  19.08  18.40  18.63  21.71  21.04
25  LVA    NaN    NaN    NaN    NaN  15.96  16.22  18.24  17.95  17.66  14.59
26  SVK    NaN    NaN    NaN  12.50   9.31  16.79  11.16  13.96  15.14  16.97
27  CYP    NaN    NaN    NaN    NaN  44.83  46.36  17.05  19.18  21.11  19.48
28  ROU    NaN    NaN    NaN    NaN    NaN  15.56  16.75  17.97  16.19  14.42
29  GRC  24.06  24.86  26.14  27.45  27.84  23.85  27.22  26.70  21.66  21.34
31  HRV    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN

     2010   2011   2012   2013   2014   2015   2016   2017   2018
0   41.14  34.65  36.65  44.40  59.32  60.01  57.94  58.38  54.24
1   43.96  45.92  45.73  50.10  50.02  46.88  46.14  46.39  42.61
2   38.22  39.18  35.98  49.06  50.17  46.47  49.10  49.95  41.90
4   32.90  34.58  35.27  35.63  36.37  37.36  37.62  38.53  39.03
5   34.14  33.79  33.31  34.16  34.59  35.70  36.66  38.86  40.31
7   34.94  34.94  34.46  33.91  34.25  35.05  36.53  37.52  37.93
9   29.82  33.80  32.85  33.85  33.22  34.67  37.46  34.81  42.88
10  31.63  31.48  32.24  34.05  34.16  34.12  34.09  34.36  34.16
11  30.88  31.20  30.53  30.09  31.10  32.06  32.65  34.80  35.09
12  30.01  28.99  27.89  28.00  30.52  31.75  32.84  34.53  35.37
14  21.09  20.93  25.90  27.85  26.21  30.46  31.48  32.24  34.84
15  28.96  28.62  28.85  29.51  29.36  30.13  30.28  30.36  30.40
16  27.32  26.60  27.39  27.85  28.11  29.04  29.54  29.89  30.35
17  29.34  27.39  25.82  26.95  25.72  28.03  31.94  28.41  31.80
18  19.27  20.61  21.86  23.53  23.60  24.63  26.53  27.42  25.94
19  21.16  22.43  22.44  23.18  23.55  23.57  24.03  23.93  24.17
20  20.01  19.95  20.14  20.46  20.79  23.45  22.42  23.59  25.16
21  18.25  19.93  19.98  21.37  22.87  22.55  22.88  25.42  27.08
22  22.10  21.79  21.80  20.41  21.44  21.85  22.45  24.28  23.81
23  21.67  21.74  21.65  21.65  21.38  21.27  22.36  23.66  24.52
25  16.78  17.57  18.18  20.14  19.41  20.92  20.55  20.31  22.63
26  19.62  19.75  19.33  18.06  18.03  19.62  21.99  22.83  24.22
```

```
    A value is trying to be set on a copy of a slice from a DataFrame.
    Try using .loc[row_indexer,col_indexer] = value instead

    See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
      eu_data.loc[:, column] = pd.to_numeric(eu_data[column], errors='coerce')
    <ipython-input-4-ac213def497e>:28: DeprecationWarning: In a future version, `df.iloc[:, i] = newvals` will attempt to set the values inplace instead of always setting a new array. To retain the old behavior, use either `df[df.columns[i]] = newvals` or, if columns are non-unique, `df.isetitem(i, newvals)`
```

```python
from sklearn.impute import KNNImputer
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import pandas as pd

# Convert year columns to integers if they are not already
year_columns = list(range(2000, 2019))

#apply KNN imputer to these columns
imputer = KNNImputer(n_neighbors=5)
eu_data[year_columns] = imputer.fit_transform(eu_data[year_columns])

# Use Elbow Method to find optimal number of clusters
wcss = []
for i in range(1, 11):  # Test 1 to 10 clusters or adjust range as needed
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(eu_data[year_columns])
    wcss.append(kmeans.inertia_)

# Plot Elbow graph
plt.figure(figsize=(8, 6))
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

# select optimal number of clusters based on plot
optimal_clusters = 4

# Fit KMeans model with optimal number of clusters
kmeans = KMeans(n_clusters=optimal_clusters, random_state=0)
eu_data['cluster'] = kmeans.fit_predict(eu_data[year_columns])

# Perform PCA to reduce data to 2 dimensions for visualization
pca = PCA(n_components=2)
reduced_data = pca.fit_transform(eu_data[year_columns])

# Get cluster assignments and country codes
clusters = eu_data['cluster'].values
country_codes = eu_data['Code'].values  # Assuming 'GEO (Labels)' is column with country codes

# Scatter plot of reduced data with cluster assignments
plt.figure(figsize=(12, 10))
scatter = plt.scatter(reduced_data[:, 0], reduced_data[:, 1], c=clusters, cmap='viridis', alpha=0.6)

# Annotate each data point with country code
for i, txt in enumerate(country_codes):
    plt.annotate(txt, (reduced_data[i, 0], reduced_data[i, 1]), fontsize=9)

# Plotting centroids (transformed with PCA)
centroids = pca.transform(kmeans.cluster_centers_)
plt.scatter(centroids[:, 0], centroids[:, 1], marker='X', s=200, c='red', label='Centroids')

# Adding labels and title
plt.xlabel('PCA Feature 1')
plt.ylabel('PCA Feature 2')
plt.title('2D PCA of EU Countries Clustering')

# Adding legend for clusters
plt.legend(*scatter.legend_elements(), title="Clusters")

plt.grid(True)
plt.tight_layout()

plt.show()

# Print DataFrame with imputed values and cluster assignments
print(eu_data[['Code'] + year_columns + ['cluster']])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```




```
# Reset index to make sure 'Code' is a column in eu_data
eu_data.reset_index(drop=True, inplace=True)

# merge pivot_table_sorted and eu_data on 'Code' column
merged_data = pd.merge(pivot_table_sorted, eu_data, on='Code')
# Remove 'cluster' column from dataframe
merged_data.drop('cluster', axis=1, inplace=True)

#rename columns for clarity
column_mapping = {
    '2000_x': 'GDP_2000', '2001_x': 'GDP_2001', '2002_x': 'GDP_2002', '2003_x': 'GDP_2003',
    '2004_x': 'GDP_2004', '2005_x': 'GDP_2005', '2006_x': 'GDP_2006', '2007_x': 'GDP_2007',
    '2008_x': 'GDP_2008', '2009_x': 'GDP_2009', '2010_x': 'GDP_2010', '2011_x': 'GDP_2011',
    '2012_x': 'GDP_2012', '2013_x': 'GDP_2013', '2014_x': 'GDP_2014', '2015_x': 'GDP_2015',
    '2016_x': 'GDP_2016', '2017_x': 'GDP_2017', '2018_x': 'GDP_2018',
    '2000_y': 'Plastic_Waste_2000', '2001_y': 'Plastic_Waste_2001', '2002_y': 'Plastic_Waste_2002',
    '2003_y': 'Plastic_Waste_2003', '2004_y': 'Plastic_Waste_2004', '2005_y': 'Plastic_Waste_2005',
    '2006_y': 'Plastic_Waste_2006', '2007_y': 'Plastic_Waste_2007', '2008_y': 'Plastic_Waste_2008',
    '2009_y': 'Plastic_Waste_2009', '2010_y': 'Plastic_Waste_2010', '2011_y': 'Plastic_Waste_2011',
    '2012_y': 'Plastic_Waste_2012', '2013_y': 'Plastic_Waste_2013', '2014_y': 'Plastic_Waste_2014',
    '2015_y': 'Plastic_Waste_2015', '2016_y': 'Plastic_Waste_2016', '2017_y': 'Plastic_Waste_2017',
    '2018_y': 'Plastic_Waste_2018'
}

merged_data.rename(columns=column_mapping, inplace=True)
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
print(merged_data)
merged_data.to_csv('/content/drive/MyDrive/Colab Notebooks/merged_data.csv', index=False)
```

```
2            27.39              27.85              28.11
3            32.85              33.85              33.22
4            35.27              35.63              36.37
5            22.44              23.18              23.55
6            32.24              34.05              34.16
7            28.85              29.51              29.36
8            21.65              21.65              21.38
9            30.53              30.09              31.10
10           34.46              33.91              34.25
11           25.82              26.95              25.72
12           27.89              28.00              30.52
13           20.14              20.46              20.79
14           21.80              20.41              21.44
15           21.86              23.53              23.60
16           35.98              49.06              50.17
17           19.98              21.37              22.87
18           17.62              18.25              18.56
19           19.33              18.06              18.03
20           33.31              34.16              34.59
21           25.90              27.85              26.21
22           18.18              20.14              19.41
23           16.74              16.55              16.93
24           11.31              11.46              11.59
25           14.86              14.53              16.92

    Plastic_Waste_2015  Plastic_Waste_2016  Plastic_Waste_2017  \
0                60.01               57.94               58.38
1                46.88               46.14               46.39
2                29.04               29.54               29.89
3                34.67               37.46               34.81
4                37.36               37.62               38.53
5                23.57               24.03               23.93
6                34.12               34.09               34.36
7                30.13               30.28               30.36
8                21.27               22.36               23.66
9                32.06               32.65               34.80
10               35.05               36.53               37.52
11               28.03               31.94               28.41
12               31.75               32.84               34.53
13               23.45               22.42               23.59
14               21.85               22.45               24.28
15               24.63               26.53               27.42
16               46.47               49.10               49.95
17               22.55               22.88               25.42
18               18.99               19.34               20.47
19               19.62               21.99               22.83
20               35.70               36.66               38.86
21               30.46               31.48               32.24
22               20.92               20.55               20.31
23               16.99               17.32               17.50
24               12.35               13.12               14.67
25               18.12               17.70               18.40

    Plastic_Waste_2018
0                54.24
1                42.61
2                30.35
3                42.88
17  MLT  22.472  22.764  23.606  21.198  15.720  16.030  16.410  21.630
```

```
# Filter DataFrame to get two separate DataFrames for GDP and Plastic Waste
gdp_columns = [col for col in merged_data.columns if 'GDP' in col]
plastic_waste_columns = [col for col in merged_data.columns if 'Plastic_Waste' in col]

# Get DataFrame for GDP and Plastic Waste
gdp_data = merged_data[['Code'] + gdp_columns]
plastic_waste_data = merged_data[['Code'] + plastic_waste_columns]

#calculate summary statistics for GDP for each country
gdp_stats = gdp_data.set_index('Code').stack().groupby('Code').agg(['mean', 'min', 'max'])

#calculate summary statistics for Plastic Waste for each country
plastic_waste_stats = plastic_waste_data.set_index('Code').stack().groupby('Code').agg(['mean', 'min', 'max'])
```

```
2   53.720  ...  38.220  39.180  35.98  49.06  50.17  46.47  49.10  49.95
```

```
import matplotlib.pyplot as plt

# Filter DataFrame to get two separate DataFrames for GDP and Plastic Waste
gdp_columns = [col for col in merged_data.columns if 'GDP' in col]
plastic_waste_columns = [col for col in merged_data.columns if 'Plastic_Waste' in col]

# Get the DataFrame for GDP and Plastic Waste
gdp_data = merged_data[['Code'] + gdp_columns]
plastic_waste_data = merged_data[['Code'] + plastic_waste_columns]

#calculate summary statistics for GDP for each country
gdp_stats = gdp_data.set_index('Code').stack().groupby('Code').agg(['mean', 'min', 'max'])

#calculate summary statistics for Plastic Waste for each country
plastic_waste_stats = plastic_waste_data.set_index('Code').stack().groupby('Code').agg(['mean', 'min', 'max'])

# Function to create a bar chart for statistics
def plot_stats(df, title):
    # Create a figure and a set of subplots
    fig, ax = plt.subplots(figsize=(10, 6))

    # Plot mean, min, and max
    df['mean'].plot(kind='bar', ax=ax, color='skyblue', position=0, label='Mean')
    df['min'].plot(kind='bar', ax=ax, color='lightgreen', position=1, label='Min')
    df['max'].plot(kind='bar', ax=ax, color='salmon', position=2, label='Max')

    # Set title and labels
    ax.set_title(title)
    ax.set_ylabel('Value')
    ax.set_xlabel('Country Code')
    ax.legend()

    # Show plot
    plt.xticks(rotation=90)  # Rotate x-axis labels to show them better
    plt.tight_layout()
    plt.show()

# Plot GDP stats
plot_stats(gdp_stats, "GDP Statistics by Country")

# Plot Plastic Waste stats
plot_stats(plastic_waste_stats, "Plastic Waste Statistics by Country")
```

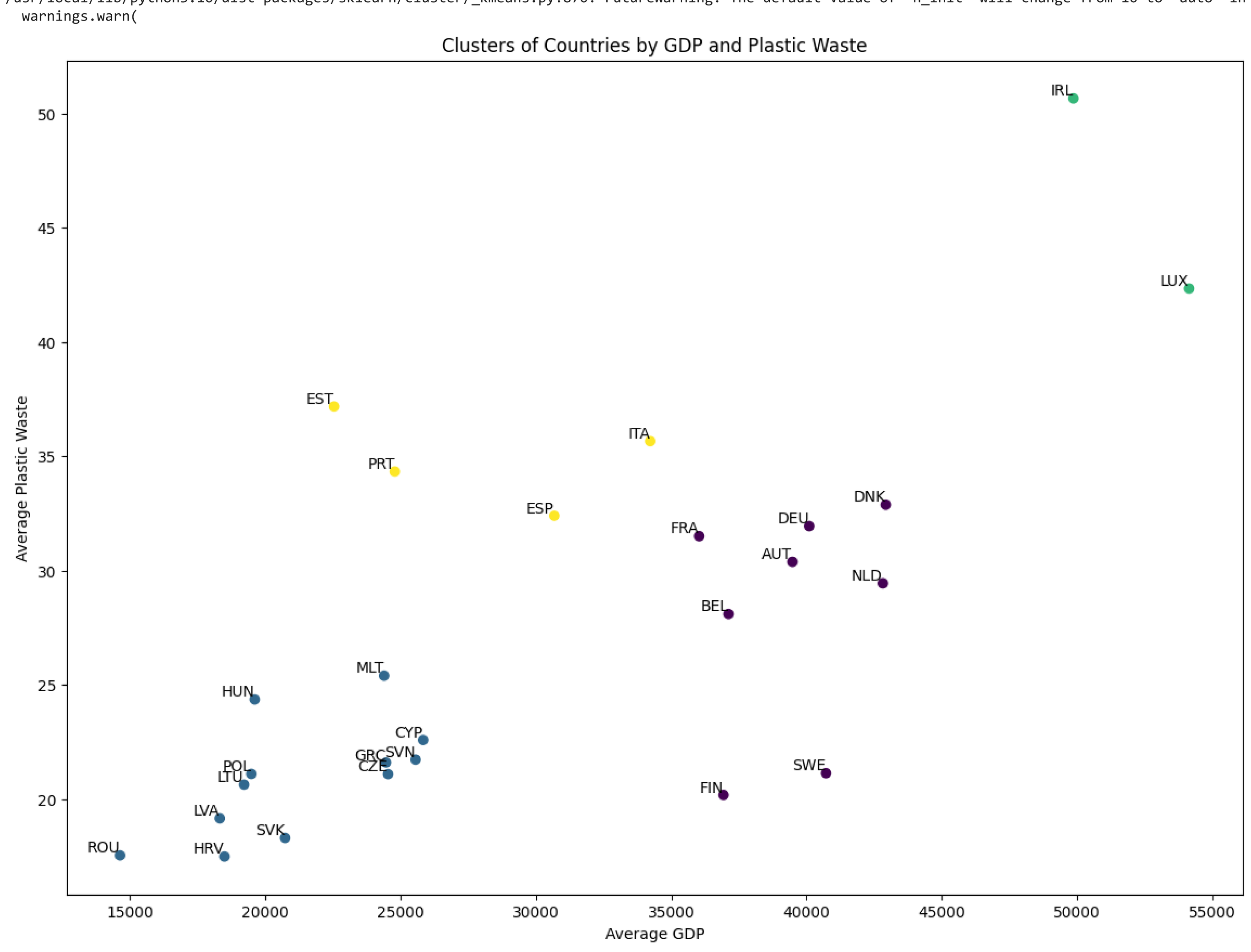
GDP Statistics by Country

```
import pandas as pd

# Calculate average of GDP and Plastic Waste over years for each country
merged_data['avg_GDP'] = merged_data[gdp_columns].mean(axis=1)
merged_data['avg_Plastic_Waste'] = merged_data[plastic_waste_columns].mean(axis=1)

#use .corr() method to find Pearson correlation coefficient
correlation_matrix = merged_data[['avg_GDP', 'avg_Plastic_Waste']].corr()

# Show correlation matrix
print(correlation_matrix)
```

```
                    avg_GDP  avg_Plastic_Waste
avg_GDP            1.000000           0.700062
avg_Plastic_Waste  0.700062           1.000000
```

```
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Filter DataFrame to only include GDP and Plastic Waste columns
features = merged_data[['avg_GDP', 'avg_Plastic_Waste']]

# Standardize features
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)

# Choose number of clusters (k) and fit KMeans model
k = 4
kmeans = KMeans(n_clusters=k, random_state=42)
kmeans.fit(features_scaled)

# Add cluster information back to original DataFrame
merged_data['cluster'] = kmeans.labels_

plt.figure(figsize=(14, 10))
plt.scatter(merged_data['avg_GDP'], merged_data['avg_Plastic_Waste'], c=merged_data['cluster'], cmap='viridis')

# Annotate each point in the scatter plot with country code
for i, row in merged_data.iterrows():
    plt.text(row['avg_GDP'], row['avg_Plastic_Waste'], row['Code'], color='black', ha='right', va='bottom')

plt.title('Clusters of Countries by GDP and Plastic Waste')
plt.xlabel('Average GDP')
plt.ylabel('Average Plastic Waste')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```




```
import pandas as pd

file_path = '/content/drive/MyDrive/Colab Notebooks/globalpop.xls'

global_df = pd.read_excel(file_path, header=3)
eu_df = global_df[global_df['Country Code'].isin(eu_countries)]
years = [str(year) for year in range(2000, 2019)]  # Years from 2000 to 2018
columns_to_keep = ['Country Name', 'Country Code', 'Indicator Name', 'Indicator Code'] + years
eu_df_years = eu_df[columns_to_keep]

years = range(2000, 2019)
for year in years:
    eu_df_years.rename(columns={str(year): f'Population_{year}'}, inplace=True)
```

```
import pandas as pd

file_path = '/content/drive/MyDrive/Colab Notebooks/merged_data.csv'
merged_data = pd.read_csv(file_path)

combined_df = pd.merge(eu_df_years, merged_data, how='inner', left_on='Country Code', right_on='Code')
output_file_path = '/content/drive/MyDrive/Colab Notebooks/combined_data.csv'
combined_df.to_csv(output_file_path, index=False)
print(combined_df.head(20))
```

```
   Country Name Country Code     Indicator Name Indicator Code  \
0       Austria          AUT  Population, total    SP.POP.TOTL
1       Belgium          BEL  Population, total    SP.POP.TOTL
2        Cyprus          CYP  Population, total    SP.POP.TOTL
3       Czechia          CZE  Population, total    SP.POP.TOTL
4       Germany          DEU  Population, total    SP.POP.TOTL
5       Denmark          DNK  Population, total    SP.POP.TOTL
6         Spain          ESP  Population, total    SP.POP.TOTL
7       Estonia          EST  Population, total    SP.POP.TOTL
8       Finland          FIN  Population, total    SP.POP.TOTL
9        France          FRA  Population, total    SP.POP.TOTL
10       Greece          GRC  Population, total    SP.POP.TOTL
11      Croatia          HRV  Population, total    SP.POP.TOTL
12      Hungary          HUN  Population, total    SP.POP.TOTL
13      Ireland          IRL  Population, total    SP.POP.TOTL
14        Italy          ITA  Population, total    SP.POP.TOTL
15    Lithuania          LTU  Population, total    SP.POP.TOTL
16   Luxembourg          LUX  Population, total    SP.POP.TOTL
17       Latvia          LVA  Population, total    SP.POP.TOTL
18        Malta          MLT  Population, total    SP.POP.TOTL
19  Netherlands          NLD  Population, total    SP.POP.TOTL

    Population_2000  Population_2001  Population_2002  Population_2003  \
0         8011566.0        8042293.0        8081957.0        8121423.0
1        10251250.0       10286570.0       10332785.0       10376133.0
2          948237.0         964830.0         982194.0        1000350.0
3        10255063.0       10216605.0       10196916.0       10193998.0
4        82211508.0       82349925.0       82488495.0       82534176.0
5         5339616.0        5358783.0        5375931.0        5390574.0
6        40567864.0       40850412.0       41431558.0       42187645.0
7         1396985.0        1388115.0        1379350.0        1370720.0
8         5176209.0        5188008.0        5200598.0        5213014.0
9        60921384.0       61367388.0       61816234.0       62256970.0
10       10805808.0       10862132.0       10902022.0       10928070.0
11        4468302.0        4299642.0        4302174.0        4303399.0
12       10210971.0       10187576.0       10158608.0       10129552.0
13        3805174.0        3866243.0        3931947.0        3996521.0
14       56942108.0       56974100.0       57059007.0       57313203.0
15        3499536.0        3470818.0        3443067.0        3415213.0
16         436300.0         441525.0         446175.0         451630.0
17        2367550.0        2337170.0        2310173.0        2287955.0
18         390087.0         393028.0         395969.0         398582.0
19       15925513.0       16046180.0       16148929.0       16225302.0

    Population_2004  Population_2005  Population_2006  Population_2007  \
0         8171966.0        8227829.0        8268641.0        8295487.0
1        10421137.0       10478617.0       10547958.0       10625700.0
2         1018684.0        1037062.0        1055438.0        1073873.0
3        10197101.0       10211216.0       10238905.0       10298828.0
4        82516260.0       82469422.0       82376451.0       82266372.0
5         5404523.0        5419432.0        5437272.0        5461438.0
6        42921895.0       43653155.0       44397319.0       45226803.0
7         1362550.0        1354775.0        1346810.0        1340680.0
8         5228172.0        5246096.0        5266268.0        5288720.0
9        62716306.0       63188395.0       63628261.0       64021737.0
10       10955141.0       10987314.0       11020362.0       11048473.0
11        4304600.0        4310145.0        4311159.0        4310217.0
12       10107146.0       10087065.0       10071370.0       10055780.0
```

```
import pandas as pd

file_path = '/content/drive/MyDrive/Colab Notebooks/recy_rates-.csv'
recycling_data = pd.read_csv(file_path, header=7)

# Replace ':' (which likely indicates missing data) with NaN
recycling_data.replace(':', pd.NA, inplace=True)

# Mapping dictionary for country names to codes
country_code_mapping = {
    'Belgium': 'BEL',
    'Bulgaria': 'BGR',
    'Czechia': 'CZE',
    'Denmark': 'DNK',
    'Germany': 'DEU',
    'Estonia': 'EST',
    'Ireland': 'IRL',
    'Greece': 'GRC',
    'Spain': 'ESP',
    'France': 'FRA',
    'Croatia': 'HRV',
    'Italy': 'ITA',
    'Cyprus': 'CYP',
    'Latvia': 'LVA',
    'Lithuania': 'LTU',
    'Luxembourg': 'LUX',
    'Hungary': 'HUN',
    'Malta': 'MLT',
    'Netherlands': 'NLD',
    'Austria': 'AUT',
    'Poland': 'POL',
    'Portugal': 'PRT',
    'Romania': 'ROU',
    'Slovenia': 'SVN',
    'Slovakia': 'SVK',
    'Finland': 'FIN',
    'Sweden': 'SWE',
    # Add other countries here as needed
}

# Replace country names with codes
recycling_data['TIME'] = recycling_data['TIME'].map(country_code_mapping)

recycling_data = recycling_data.rename(columns={str(year): f'recy_rate_{year}' for year in range(2010, 2022)})

# Save cleaned recycling dataset to a CSV file
cleaned_file_path = '/content/drive/MyDrive/Colab Notebooks/cleaned_recycling_data.csv'
recycling_data.to_csv(cleaned_file_path, index=False)

# Print a message to confirm the file has been saved
print(f"Cleaned recycling data has been saved to: {cleaned_file_path}")
```

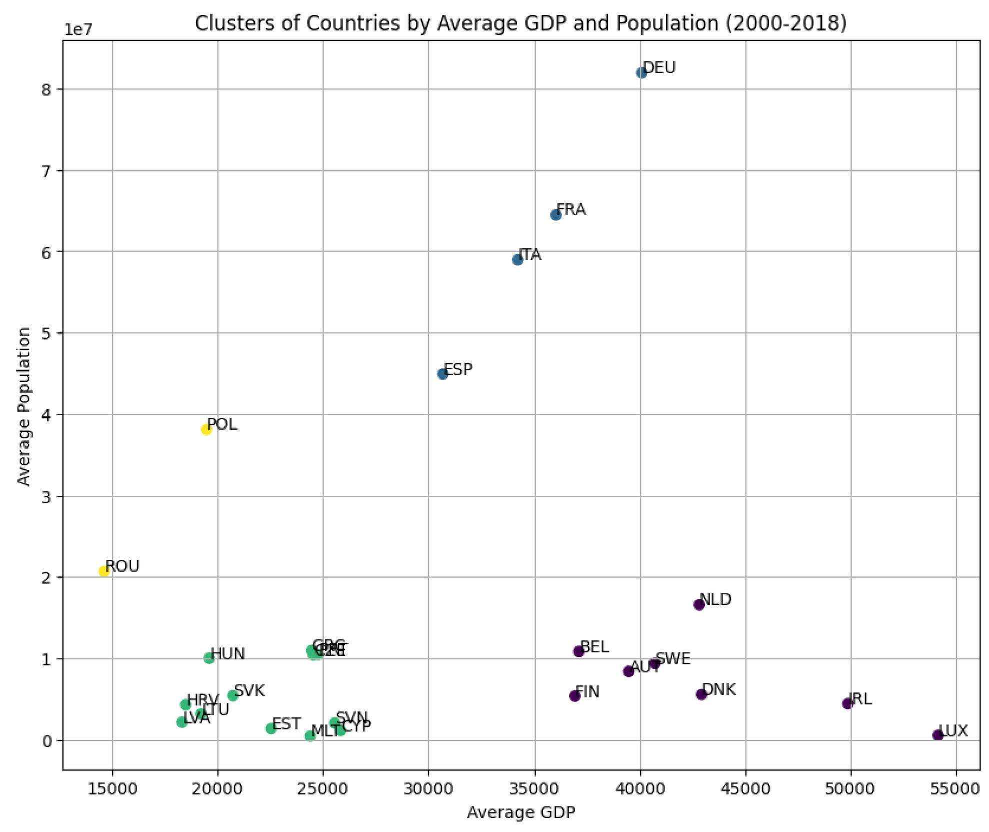
```
Cleaned recycling data has been saved to: /content/drive/MyDrive/Colab Notebooks/cleaned_recycling_data.csv
```

```
import pandas as pd

pop_file_path = '/content/drive/MyDrive/Colab Notebooks/cleaned_recy_data.csv'
cleaned_recycling_data = pd.read_csv(pop_file_path)


print(cleaned_recycling_data.head(20))
# Select columns for years 2010 to 2018
selected_columns = ['Year'] + [f'recy_rate_{year}' for year in range(2010, 2019)]
filtered_data = cleaned_recycling_data[selected_columns]

# Print filtered DataFrame to verify
print(filtered_data.head(20))



import pandas as pd

pop_file_path = '/content/drive/MyDrive/Colab Notebooks/cleaned_recy_data.csv'
cleaned_recycling_data = pd.read_csv(pop_file_path)

# Reset index to move country codes to a regular column
cleaned_recycling_data.reset_index(inplace=True)

# Rename 'Year' column to 'Country Code'
cleaned_recycling_data.rename(columns={'Year': 'Country Code'}, inplace=True)

# Select columns for years 2010 to 2018
selected_columns = ['Country Code'] + [f'recy_rate_{year}' for year in range(2010, 2019)]
filtered_data = cleaned_recycling_data[selected_columns]

# Define file path for previously combined dataset
file_path = '/content/drive/MyDrive/Colab Notebooks/combined_data.csv'

# Merge filtered data with combined data using 'Country Code' as common column
merged_data = pd.merge(combined_data, filtered_data, how='inner', on='Country Code')

# Specify the output file path to save merged dataset
#output_file_path = '/content/drive/MyDrive/Colab Notebooks/merged_combined_data.csv'

# Save merged dataset to a CSV file
merged_data.to_csv(output_file_path, index=False)
print(merged_data.head(5))
```

```
  Country Name Country Code     Indicator Name Indicator Code  \
0      Austria          AUT  Population, total    SP.POP.TOTL
1      Belgium          BEL  Population, total    SP.POP.TOTL
2       Cyprus          CYP  Population, total    SP.POP.TOTL
3      Czechia          CZE  Population, total    SP.POP.TOTL
4      Germany          DEU  Population, total    SP.POP.TOTL

   Population_2000  Population_2001  Population_2002  Population_2003  \
0        8011566.0        8042293.0        8081957.0        8121423.0
1       10251250.0       10286570.0       10332785.0       10376133.0
2         948237.0         964830.0         982194.0        1000350.0
3       10255063.0       10216605.0       10196916.0       10193998.0
4       82211508.0       82349925.0       82488495.0       82534176.0

   Population_2004  Population_2005  Population_2006  Population_2007  \
0        8171966.0        8227829.0        8268641.0        8295487.0
1       10421137.0       10478617.0       10547958.0       10625700.0
2        1018684.0        1037062.0        1055438.0        1073873.0
3       10197101.0       10211216.0       10238905.0       10298828.0
4       82516260.0       82469422.0       82376451.0       82266372.0

   Population_2008  Population_2009  Population_2010  Population_2011  \
0        8321496.0        8343323.0        8363404.0        8391643.0
1       10709973.0       10796493.0       10895586.0       11038264.0
2        1092390.0        1110974.0        1129686.0        1145086.0
3       10384603.0       10443936.0       10474410.0       10496088.0
4       82110097.0       81902307.0       81776930.0       80274983.0

   Population_2012  Population_2013  Population_2014  Population_2015  \
0        8429991.0        8479823.0        8546356.0        8642699.0
1       11106932.0       11159407.0       11209057.0       11274196.0
2        1156556.0        1166968.0        1176995.0        1187280.0
3       10510785.0       10514272.0       10525347.0       10546059.0
4       80425823.0       80645605.0       80982500.0       81686611.0

   Population_2016  Population_2017  Population_2018 Code   GDP_2000  \
0        8736668.0        8797566.0        8840521.0  AUT  34796.258
1       11331422.0       11375158.0       11427054.0  BEL  33719.770
2        1197881.0        1208523.0        1218831.0  CYP  22326.799
3       10566332.0       10594438.0       10629928.0  CZE  17056.160
4       82348669.0       82657002.0       82905782.0  DEU  33367.285

    GDP_2001   GDP_2002   GDP_2003   GDP_2004   GDP_2005   GDP_2006  \
0  35272.223  35823.586  36063.120  36957.113  37642.760  38866.848
1  33923.344  34419.695  34588.477  35740.350  36338.383  37051.902
2  23095.736  23828.072  24347.076  25355.240  26164.209  27142.018
3  17868.568  18431.027  19344.090  20555.035  22128.580  23888.164
4  34260.290  34590.930  34716.440  35528.715  36205.574  38014.137

    GDP_2007   GDP_2008   GDP_2009   GDP_2010  GDP_2011  GDP_2012  GDP_2013  \
0  40305.273  40964.793  39463.656  40288.348   41446.0   41565.0   41375.0
1  38082.875  38117.348  36998.650  37739.330   38130.0   37906.0   37737.0
2  28109.996  28736.975  27735.033  27630.104   27272.0   26011.0   24519.0
3  25382.807  26186.045  25093.863  25922.395   26725.0   26474.0   26338.0
4  39752.207  40715.434  38962.938  41109.582   43189.0   43320.0   43413.0

   GDP_2014  GDP_2015  GDP_2016   GDP_2017   GDP_2018  Plastic_Waste_2000  \
0   41338.0   41294.0   41445.0  42177.370  42988.070              26.210
```

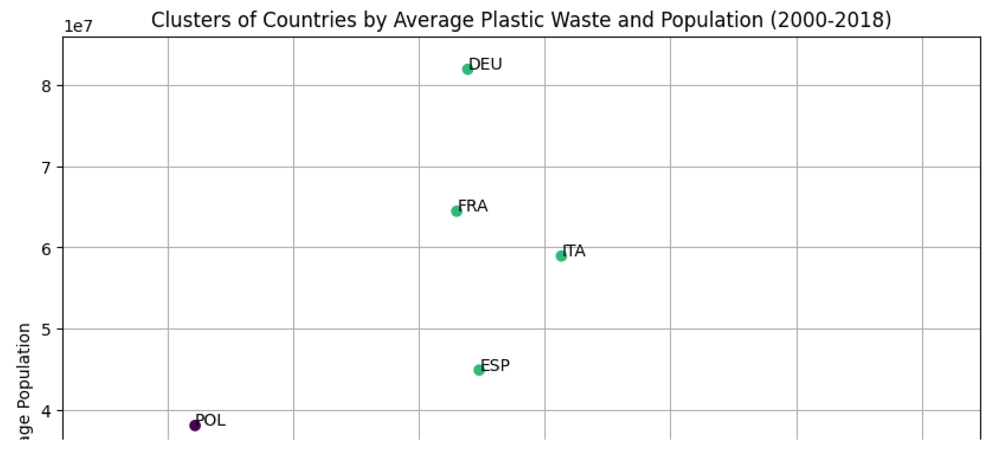
```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import numpy as np

merged_data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/merged_combined_data.csv')


# Calculate average GDP and population for each country over the years 2000 to 2018
gdp_columns = [f'GDP_{year}' for year in range(2000, 2019)]
pop_columns = [f'Population_{year}' for year in range(2000, 2019)]

merged_data['Average_GDP'] = merged_data[gdp_columns].mean(axis=1)
merged_data['Average_Population'] = merged_data[pop_columns].mean(axis=1)

# Use averages for clustering
data_to_cluster = merged_data[['Average_GDP', 'Average_Population']]

# Standardize data
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data_to_cluster)

# Apply K-Means clustering
kmeans = KMeans(n_clusters=4, random_state=0)
clusters = kmeans.fit_predict(data_scaled)

# Create a scatter plot
plt.figure(figsize=(10, 8))
plt.scatter(data_to_cluster['Average_GDP'], data_to_cluster['Average_Population'], c=clusters, cmap='viridis')

# Annotate country codes
for i, txt in enumerate(merged_data['Country Code']):
    plt.annotate(txt, (data_to_cluster['Average_GDP'][i], data_to_cluster['Average_Population'][i]))

plt.title('Clusters of Countries by Average GDP and Population (2000-2018)')
plt.xlabel('Average GDP')
plt.ylabel('Average Population')
plt.grid(True)
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```




```
plastic_waste_columns = [f'Plastic_Waste_{year}' for year in range(2000, 2019)]

# Check if all columns are present
if all(column in merged_data.columns for column in plastic_waste_columns):
    # Calculate the average plastic waste and population for each country over the years 2000 to 2018
    merged_data['Average_Plastic_Waste'] = merged_data[plastic_waste_columns].mean(axis=1)

    # Select average data for clustering
    data_to_cluster = merged_data[['Average_Plastic_Waste', 'Average_Population']].copy()

    # Standardize data
    scaler = StandardScaler()
    data_scaled = scaler.fit_transform(data_to_cluster)

    # Apply K-Means clustering
    kmeans = KMeans(n_clusters=4, random_state=0)
    clusters = kmeans.fit_predict(data_scaled)

    # Create a scatter plot
    plt.figure(figsize=(10, 8))
    plt.scatter(data_to_cluster['Average_Plastic_Waste'], data_to_cluster['Average_Population'], c=clusters, cmap='viridis')

    # Annotate the country codes
    for i, txt in enumerate(merged_data['Country Code']):
        plt.annotate(txt, (data_to_cluster['Average_Plastic_Waste'][i], data_to_cluster['Average_Population'][i]))

    plt.title('Clusters of Countries by Average Plastic Waste and Population (2000-2018)')
    plt.xlabel('Average Plastic Waste')
    plt.ylabel('Average Population')
    plt.grid(True)
    plt.show()
else:
    print("One or more columns for plastic waste are missing from the DataFrame.")
```

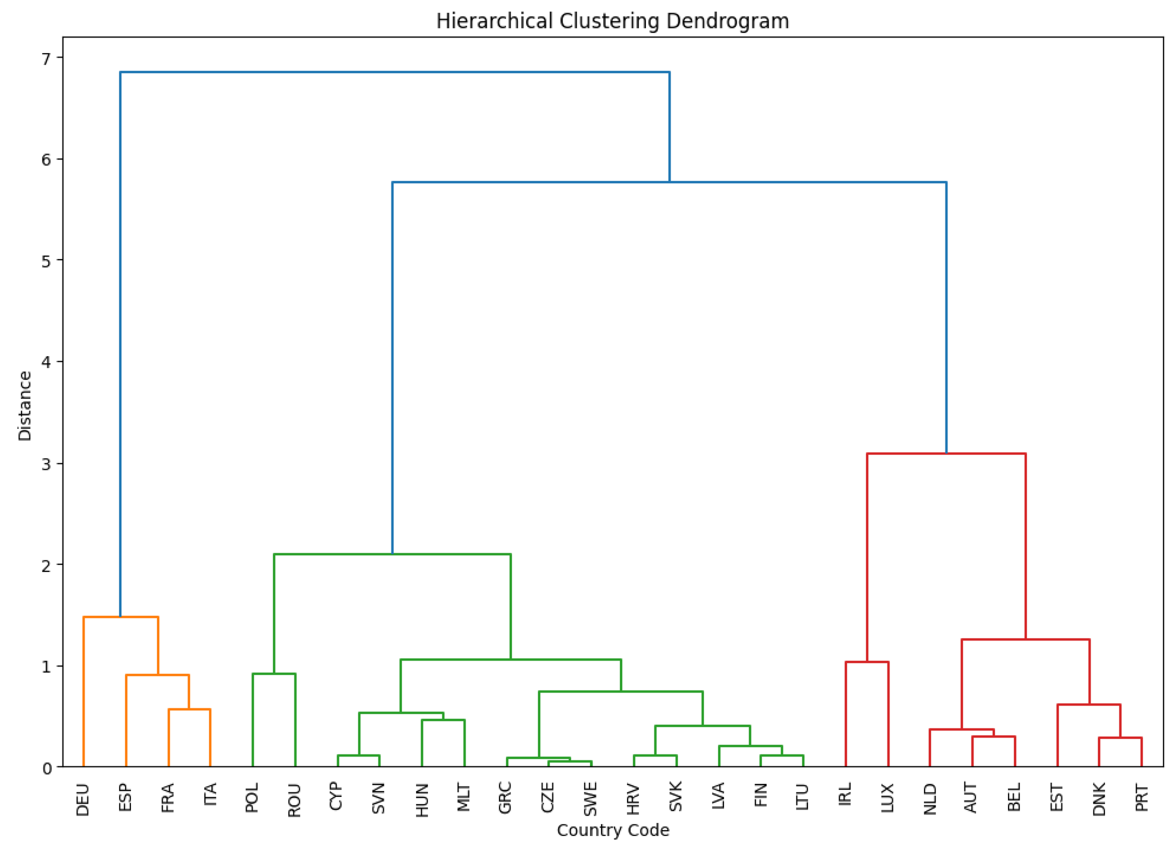
```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```




```
# Calculate average GDP, population, and plastic waste for each country
gdp_columns = [f'GDP_{year}' for year in range(2000, 2019)]
pop_columns = [f'Population_{year}' for year in range(2000, 2019)]
plastic_waste_columns = [f'Plastic_Waste_{year}' for year in range(2000, 2019)]

# Check if all columns are present
if all(column in merged_data.columns for column in gdp_columns + pop_columns + plastic_waste_columns):
    merged_data['Average_GDP'] = merged_data[gdp_columns].mean(axis=1)
    merged_data['Average_Population'] = merged_data[pop_columns].mean(axis=1)
    merged_data['Average_Plastic_Waste'] = merged_data[plastic_waste_columns].mean(axis=1)

    # Select average data for correlation
    data_for_correlation = merged_data[['Average_GDP', 'Average_Population', 'Average_Plastic_Waste']]

    # Calculate Pearson correlation matrix
    correlation_matrix = data_for_correlation.corr()
    print(correlation_matrix)

else:
    raise KeyError("One or more columns for GDP, population, or plastic waste are missing from the DataFrame.")
```

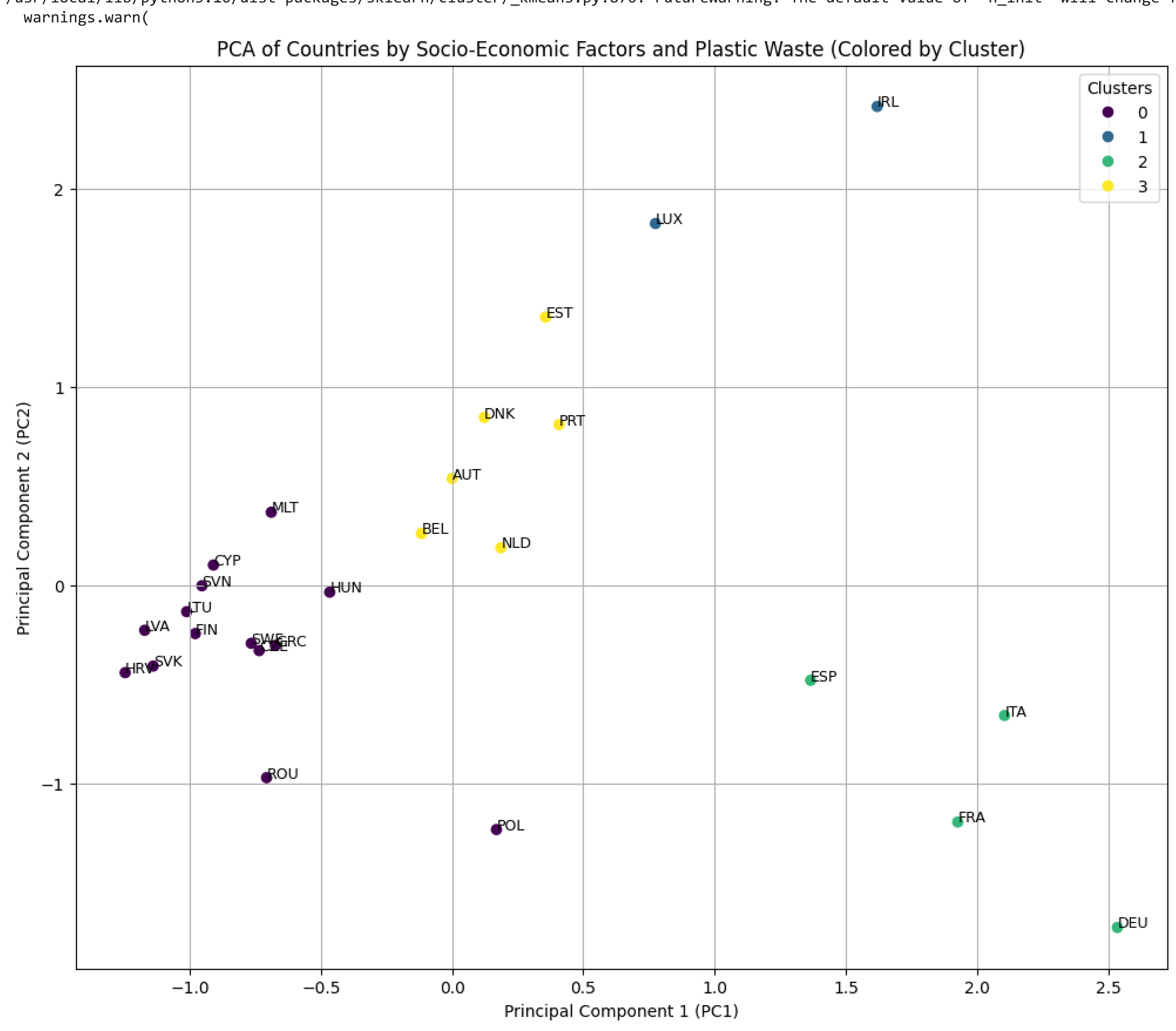
	Average_GDP	Average_Population	Average_Plastic_Waste
Average_GDP	1.000000	0.145851	0.700062
Average_Population	0.145851	1.000000	0.183462
Average_Plastic_Waste	0.700062	0.183462	1.000000

```
from scipy.cluster.hierarchy import dendrogram, linkage

# We already have scaled data in 'data_scaled' from previous standardization step.
# Generate linkage matrix for hierarchical clustering
Z = linkage(data_scaled, method='ward')

# Set up matplotlib figure
plt.figure(figsize=(12, 8))

# Generate and plot dendrogram
dendrogram(Z, labels=merged_data['Country Code'].values, leaf_rotation=90, leaf_font_size=10)

plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Country Code')
plt.ylabel('Distance')
plt.show()
```




```
# Re-apply K-Means clustering to PCA results for color coding
kmeans = KMeans(n_clusters=4, random_state=0)
pca_clusters = kmeans.fit_predict(pca_result)
pca_df['Cluster'] = pca_clusters  # Add cluster assignment to PCA results DataFrame

#plot PCA results with color coding by cluster
plt.figure(figsize=(12, 10))
scatter = plt.scatter(pca_df['PC1'], pca_df['PC2'], c=pca_df['Cluster'], cmap='viridis')

# Add annotations for each point
for i, txt in enumerate(pca_df['Country Code']):
    plt.annotate(txt, (pca_df['PC1'][i], pca_df['PC2'][i]), fontsize=9)

# Add legend for clusters
plt.legend(*scatter.legend_elements(), title="Clusters")

# Set title and axis labels
plt.title('PCA of Countries by Socio-Economic Factors and Plastic Waste (Colored by Cluster)')
plt.xlabel('Principal Component 1 (PC1)')
plt.ylabel('Principal Component 2 (PC2)')
plt.grid(True)

plt.show()

# Print explained variance
explained_variance = pca.explained_variance_ratio_
explained_variance
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```




```
array([0.59173111, 0.40826889])
```