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Final Project

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.

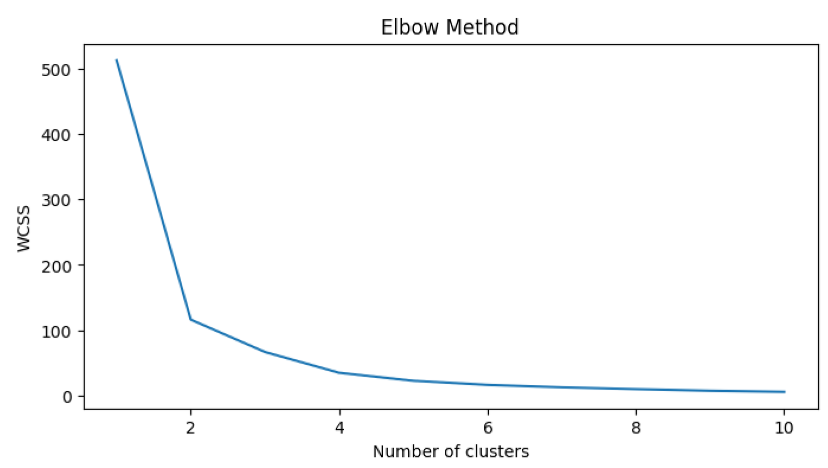
```
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import drive
drive.mount('/content/drive')
```

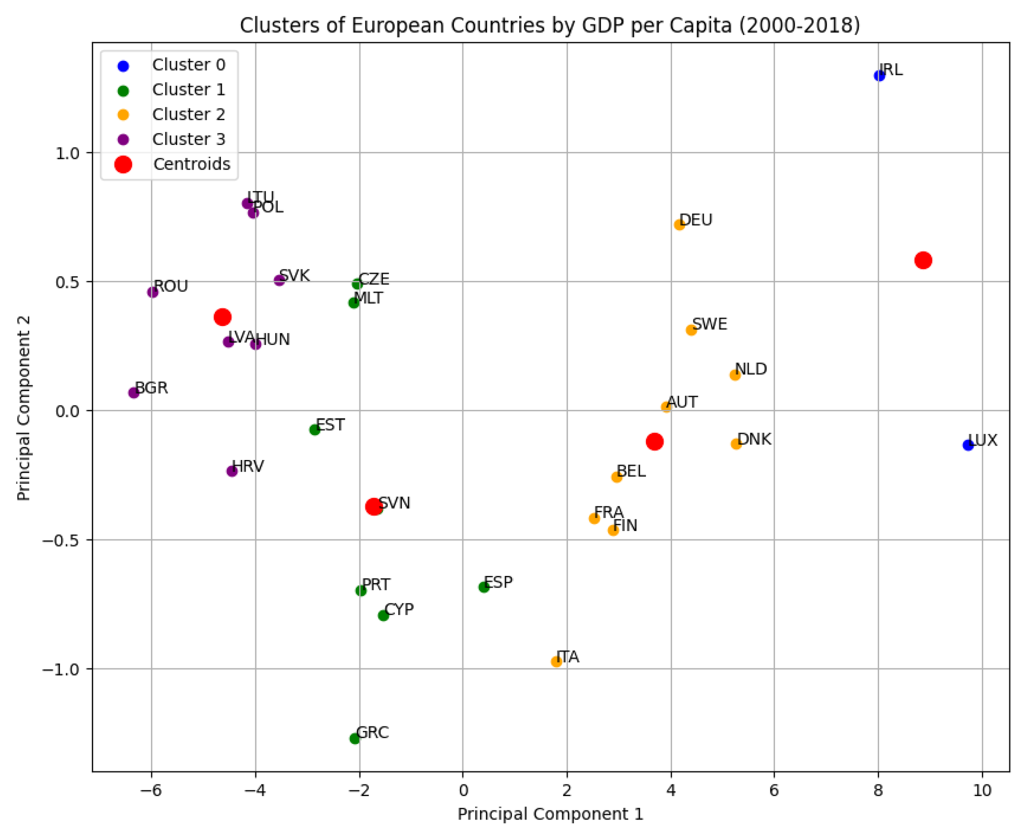
```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
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
```

```python
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()
```






```python
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)
```

```
   Code   2000   2001   2002   2003   2004   2005   2006   2007   2008   2009  \
0   IRL  44.84  44.89  45.09  56.13  51.99  52.41  61.75  54.03  55.25  49.47
1   LUX  21.87  21.89  21.81  39.50  48.19  47.93  46.88  52.58  44.47  41.56
2   EST    NaN    NaN    NaN    NaN  21.26  23.29  26.85  27.85  53.72  39.42
4   DEU  21.78  22.95  25.13  25.09  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
```

```
27  19.03  17.85  17.62  18.25  18.56  18.99  19.34  20.47  19.97
28  13.89  13.84  14.86  14.53  16.92  18.12  17.70  18.40  20.10
29  19.92  18.71  16.74  16.55  16.93  16.99  17.32  17.50  18.83
31    NaN    NaN  11.31  11.46  11.59  12.35  13.12  14.67  15.73
<ipython-input-75-d8d5ec59d987>:27: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
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
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/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
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/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
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/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(
```
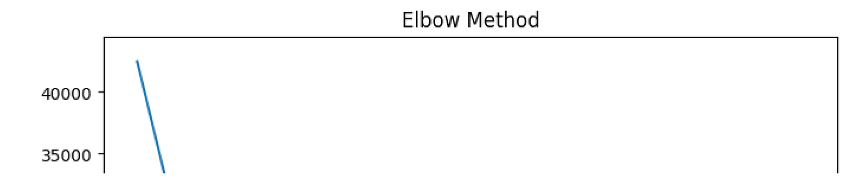




```
# Reset index to make sure 'Code' is a column in eu_data
eu_data.reset_index(drop=True, inplace=True)

# 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)
```

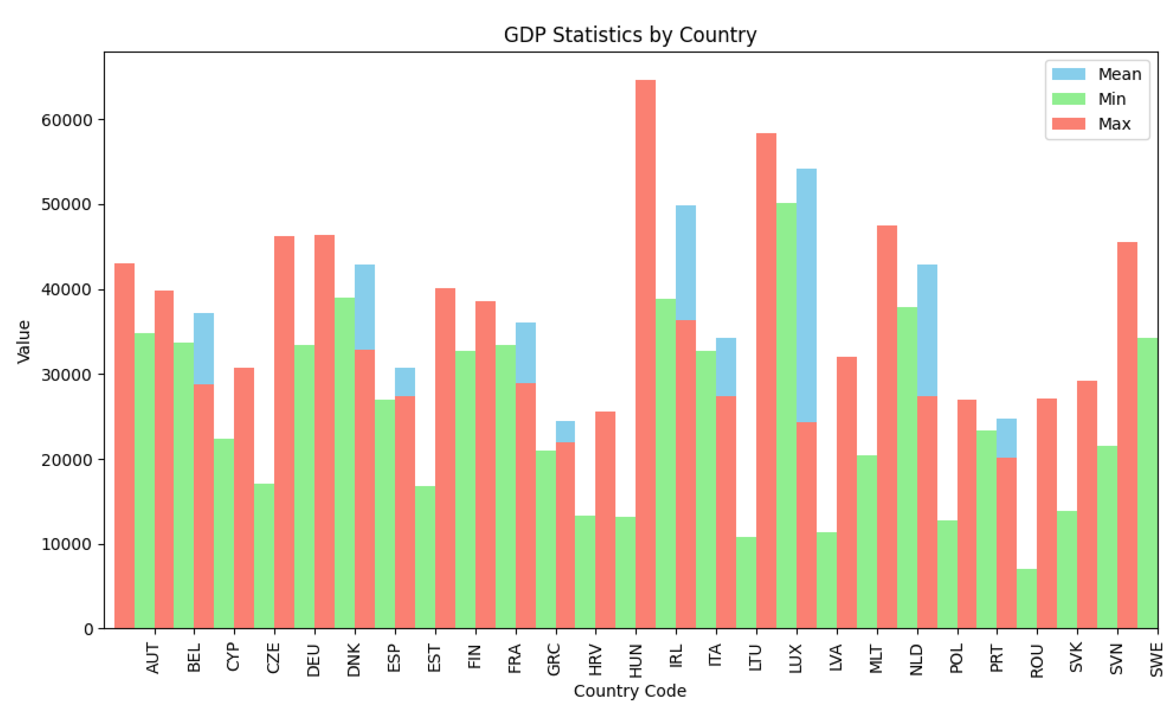
	Code	GDP_2000	GDP_2001	GDP_2002	GDP_2003	GDP_2004	GDP_2005	\
0	IRL	38806.5000	40966.3320	43012.816	44372.758	47028.863	49223.383	
1	LUX	50063.8240	50527.6640	51709.734	51717.030	52624.164	53262.094	
2	NLD	37899.9500	38636.2230	38653.125	38803.957	39682.375	40679.490	
3	DNK	39021.1760	39425.8630	39709.370	39983.145	41178.562	42264.630	
4	DEU	33367.2850	34260.2900	34590.930	34716.440	35528.715	36205.574	
5	SWE	34202.6050	34666.6640	35569.773	36435.754	38016.062	39258.992	
6	AUT	34796.2580	35272.2230	35823.586	36063.120	36957.113	37642.760	
7	BEL	33719.7700	33923.3440	34419.695	34588.477	35740.350	36338.383	
8	FIN	32689.7700	33481.6800	33986.555	34607.220	35888.613	36787.258	
9	FRA	33409.6800	33920.0980	34152.773	34292.030	35093.824	35495.465	
10	ITA	32716.9800	33511.4340	33780.055	33917.800	34472.130	34872.125	
11	MLT	20434.5490	20413.0500	20873.984	21273.135	21233.002	21905.215	
12	ESP	26994.8600	28153.5530	28753.322	29371.865	30088.092	30885.602	
13	CZE	17056.1600	17868.5680	18431.027	19344.090	20555.035	22128.580	
14	SVN	21501.3360	22006.9530	22725.312	23257.422	24150.584	24966.940	
15	POL	12732.1670	13017.5840	13415.571	14035.637	14906.094	15580.937	
16	EST	16806.9750	17696.6100	18589.150	19771.742	20803.758	22518.541	
17	LTU	10806.8740	11606.7290	12490.621	13917.508	14995.767	16417.950	
18	CYP	22326.7990	23095.7360	23828.072	24347.076	25355.240	26164.209	
19	SVK	13904.9850	14361.9010	14984.731	15773.095	16570.861	17649.520	
20	PRT	23372.0410	23751.3710	23896.459	23677.520	24142.766	24377.950	
21	HUN	13129.2730	13933.5620	14899.307	15829.899	16999.006	18140.617	
22	LVA	11309.7400	12103.8280	13015.475	14142.124	15371.182	17069.656	
23	GRC	20965.3320	21913.7970	22893.959	24380.066	25780.385	26091.523	
24	HRV	13244.5410	13817.6810	14683.838	15740.499	16628.574	17581.360	
25	ROU	7089.9463	7860.4434	8673.619	9369.233	10531.172	11313.822	

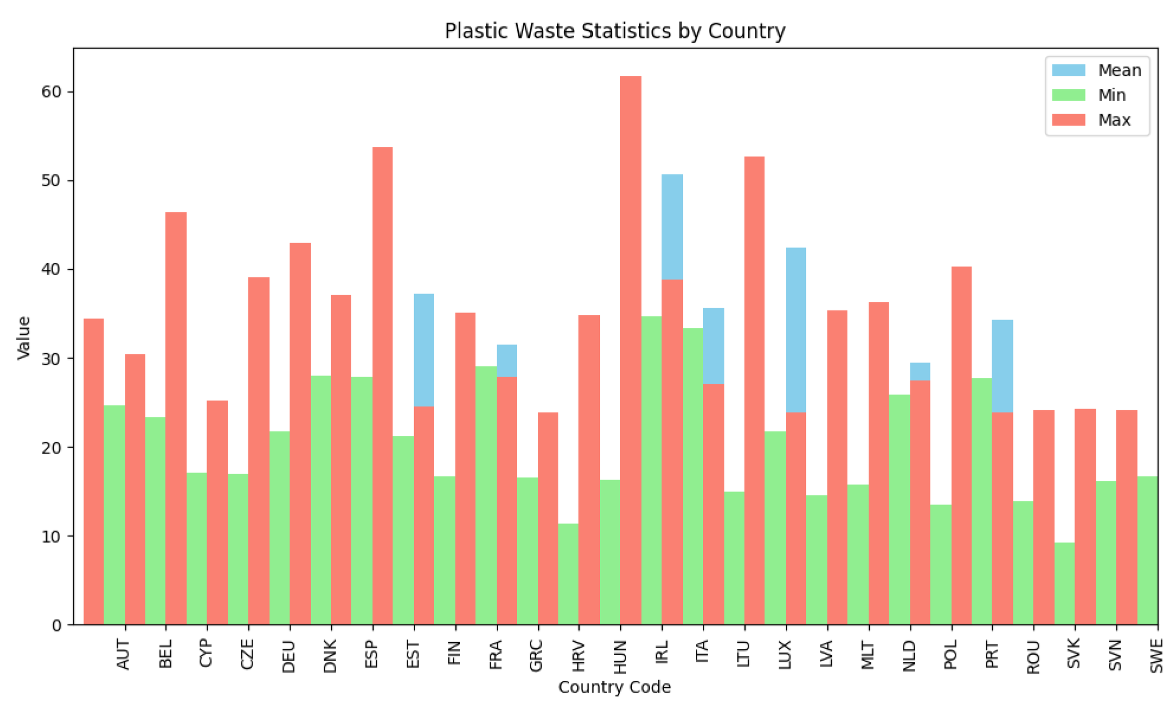
	GDP_2006	GDP_2007	GDP_2008	GDP_2009	GDP_2010	GDP_2011	GDP_2012	\
0	51296.195	52322.230	49583.140	47375.734	48623.810	48980.0	48333.0	
1	54920.810	58369.703	56383.190	52731.390	54086.336	54031.0	52562.0	
2	42286.510	44008.750	44840.710	43178.508	43812.348	44591.0	43957.0	
3	44025.484	44481.470	44246.400	42090.170	42932.400	43575.0	43510.0	
4	38014.137	39752.207	40715.434	38962.938	41109.582	43189.0	43320.0	
5	40992.300	42399.844	42189.965	40116.312	42634.754	42079.0	41650.0	
6	38866.848	40305.273	40964.793	39463.656	40288.348	41446.0	41565.0	
7	37051.902	38082.875	38117.348	36998.650	37739.330	38130.0	37906.0	
8	38160.703	39998.527	40129.652	36662.613	37615.113	38432.0	37704.0	
9	36166.160	36845.684	36761.793	35534.926	36086.727	36691.0	36571.0	
10	35713.805	36310.734	35942.938	34055.227	34765.938	35151.0	34068.0	
11	22233.717	23048.264	23674.594	22927.654	23632.625	23871.0	24301.0	
12	31907.424	32735.434	32844.324	31669.691	31786.404	31600.0	30699.0	
13	23888.164	25382.807	26186.045	25093.863	25922.395	26725.0	26474.0	
14	26182.780	27832.764	28473.596	25905.514	26000.920	26004.0	25252.0	
15	16711.447	18067.428	19011.547	19718.465	20608.693	21837.0	22188.0	
16	24578.816	26177.871	24429.021	20538.049	20713.426	21997.0	23026.0	
17	17916.059	20138.473	20879.803	17983.350	18663.762	20243.0	21303.0	
18	27142.018	28109.996	28736.975	27735.033	27630.104	27272.0	26011.0	
19	19099.428	21109.940	22231.988	20953.037	21941.213	22483.0	22816.0	
20	24809.040	25477.205	25590.880	24902.457	25463.164	25133.0	24218.0	
21	19253.062	19763.791	20380.630	19461.070	20036.334	20886.0	20631.0	
22	19128.690	21042.367	20342.200	17582.111	17140.227	18428.0	19405.0	
23	27731.111	28822.916	28907.926	27839.898	26517.465	24349.0	22693.0	
24	18707.490	19984.037	20717.316	19501.588	19511.350	19813.0	19441.0	
25	12823.231	14418.830	16347.344	15866.127	16377.328	17174.0	17174.0	

	GDP_2013	GDP_2014	GDP_2015	GDP_2016	GDP_2017	GDP_2018	\
0	48743.0	52651.0	54278.0	56597.0	60544.277	64684.300	

```
# 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'])
```

```
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")
```



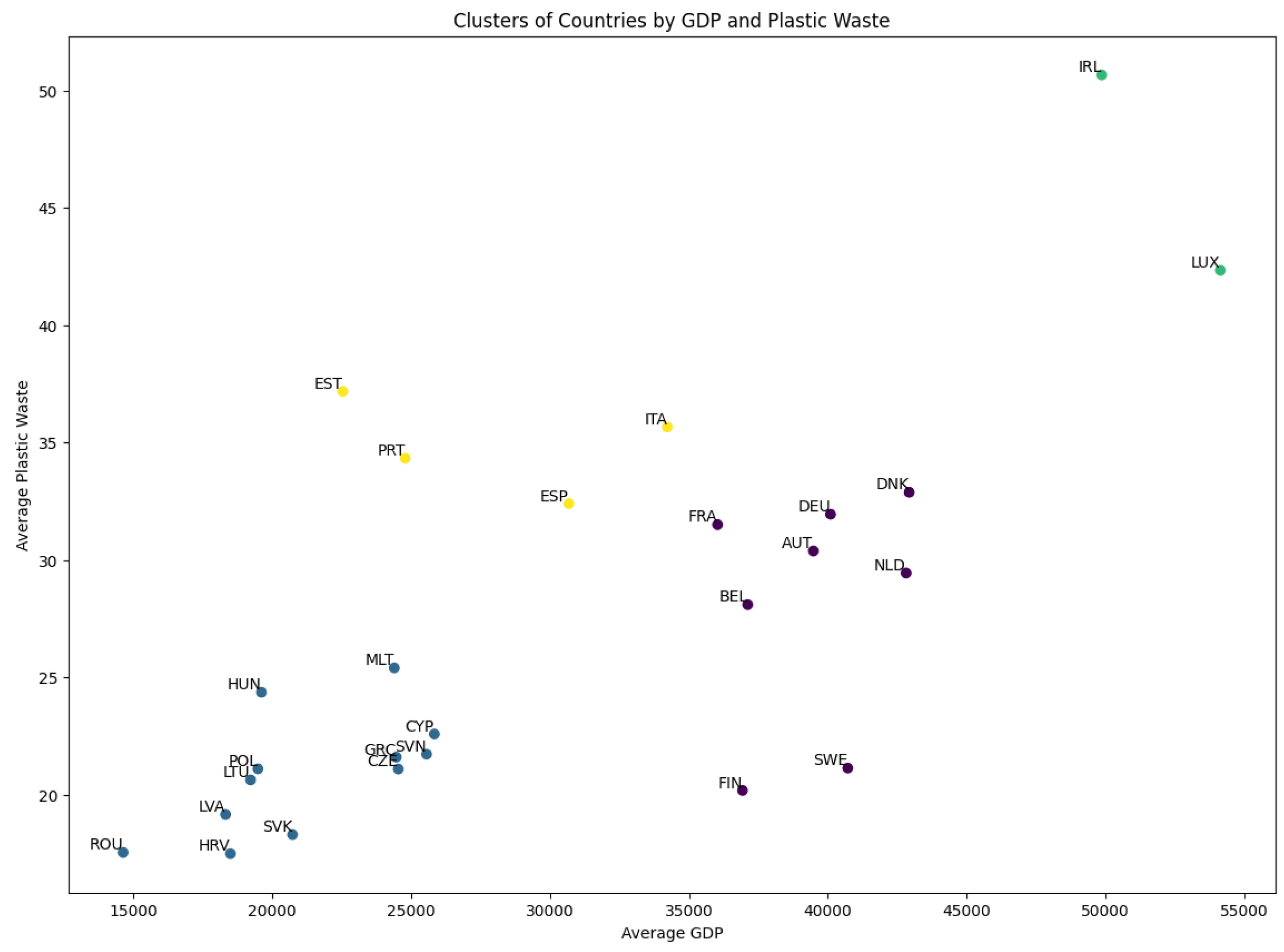


```python
import pandas as pd

# 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

```python
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(
```




```python
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)
```

```python
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

```python
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
```

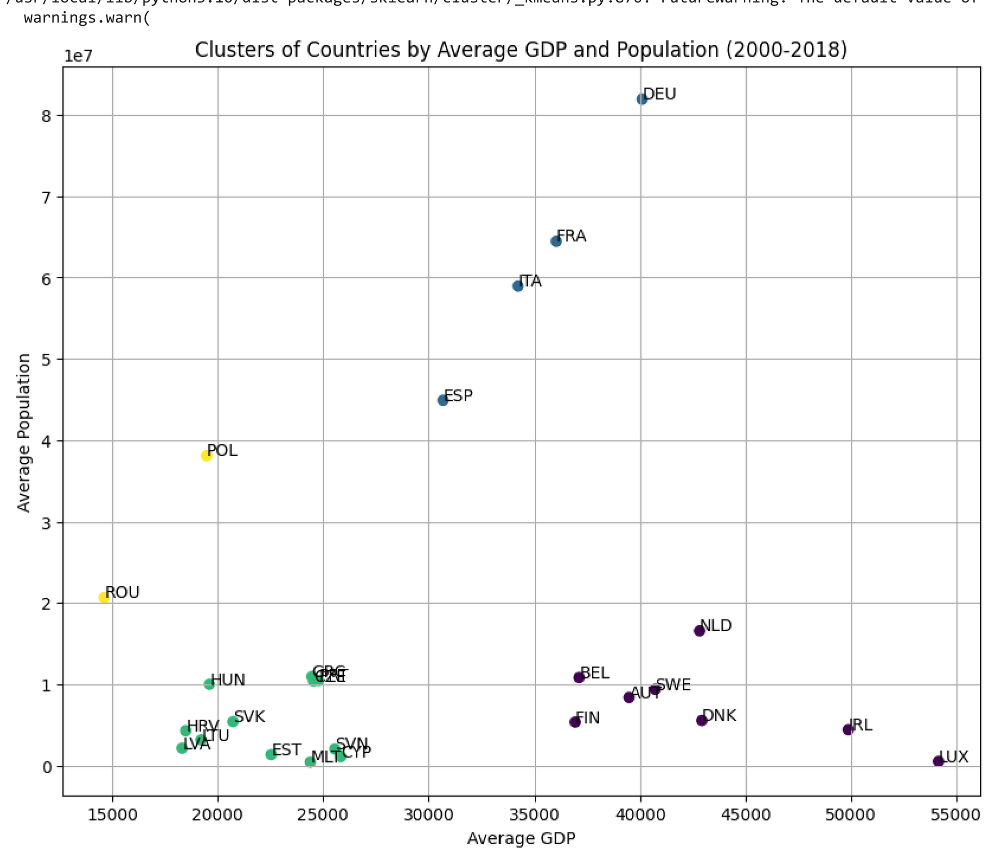
```
import pandas as pd

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))
```

```
    15           57.7           59.8           69.5           61.8
    16           66.0           70.0           70.3           69.7
    17           48.4           50.1           49.7           49.7
    18           41.1           37.1           39.7           35.6
    19           70.5           71.7           72.6           78.1

        recy_rate_2018  recy_rate_2019  recy_rate_2020  recy_rate_2021
    0              NaN             NaN             NaN             NaN
    1             85.3            83.5            79.7            80.4
    2             60.4            61.2             NaN             NaN
    3             69.6            71.2            67.9            69.1
    4             70.1            70.4            64.0             NaN
    5             68.5            64.0            68.1            67.9
    6             60.4            66.2            71.4            70.4
    7             63.9            62.5            62.4            58.1
    8             63.6            60.1             NaN             NaN
    9             68.8            69.6            68.3            70.1
    10            63.5            65.6            60.3            61.8
    11            58.4            48.9            54.2            50.8
    12            68.3            69.6            72.8            72.9
    13            70.2            66.8            59.9            63.5
    14            55.8            62.4            61.4            61.0
    15            60.7            61.9            61.8             NaN
    16            70.9            71.5            71.9            73.7
    17            46.1            47.0            52.4             NaN
    18            35.7            33.7            40.0            38.4
    19            79.4            80.7            76.5            76.8
        Year recy_rate_2010  recy_rate_2011  recy_rate_2012  recy_rate_2013  \
    0   Code            NaN             NaN             NaN             NaN
    1    BEL           79.8            80.2            80.3            78.7
    2    BGR           61.6            65.1            66.5            65.7
    3    CZE             70            69.7            69.9            69.9
    4    DNK             84            54.3            61.6            69.8
    5    DEU           72.7            71.8            71.3            71.8
    6    EST           56.1            62.9            61.3            58.4
    7    IRL           66.2            70.9            74.0            70.2
    8    GRC           58.7            62.1            58.6            52.4
    9    ESP           61.9            63.9            65.5            66.6
    10   FRA           61.1            61.3            64.9            66.4
    11   HRV            NaN             NaN            59.7            58.8
    12   ITA           64.4            64.5            66.6            66.7
    13   CYP             50            52.0            55.3            56.6
    14   LVA           48.9            50.9            51.1            51.0
    15   LTU           60.4            62.2            62.2            53.5
    16   LUX             66            66.0            62.5            62.8
    17   HUN           58.7            59.3            48.5            49.2
    18   MLT           28.5            42.3            46.6            38.1
    19   NLD           73.9            71.9            69.3            70.4

        recy_rate_2014  recy_rate_2015  recy_rate_2016  recy_rate_2017  \
    0              NaN             NaN             NaN             NaN
    1             81.3            81.5            81.9            83.8
    2             62.0            64.1            63.8            65.6
    3             73.0            74.3            75.3            72.3
    4             69.8            73.9            79.0            71.5
    5             71.4            69.3            70.7            69.9
    6             60.3            59.0            56.0            53.5
    7             68.3            67.5            67.0            65.6
    8             53.8            60.3            66.1            68.6
```

```
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))
```

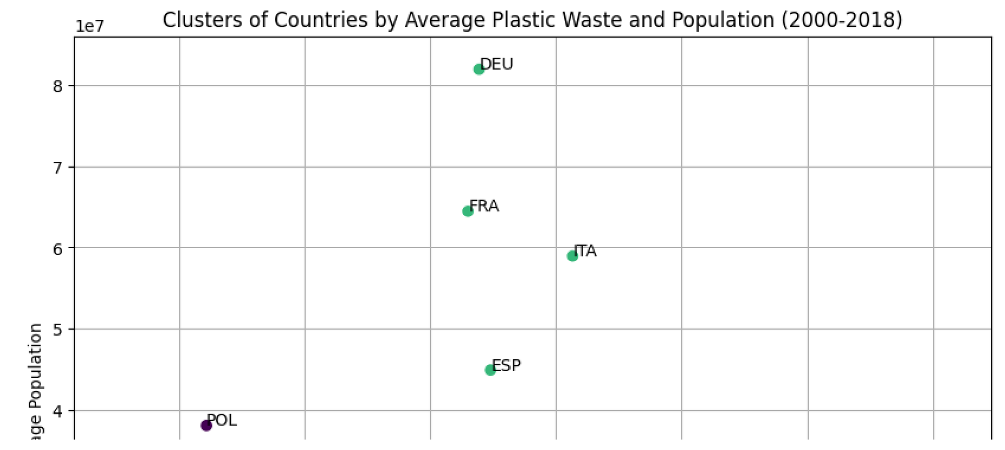
```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import numpy as np

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.")
```

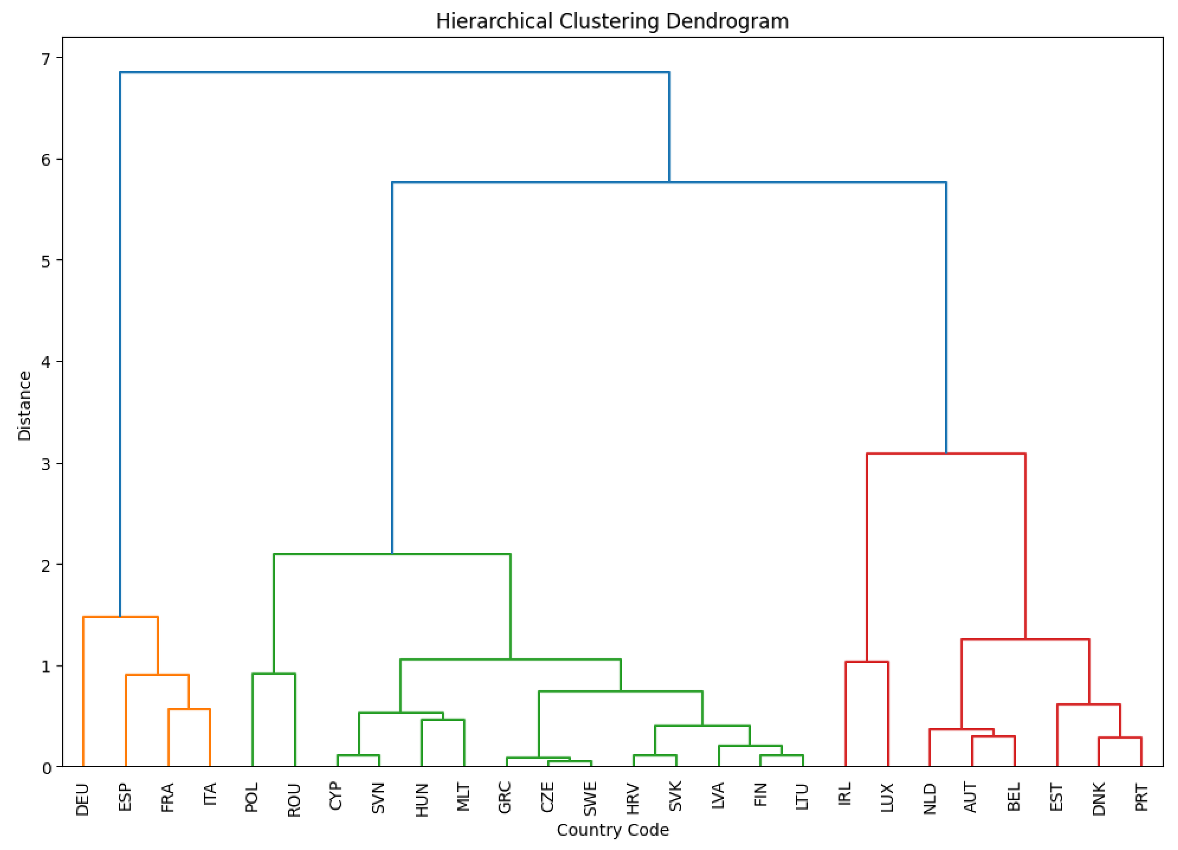
```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```



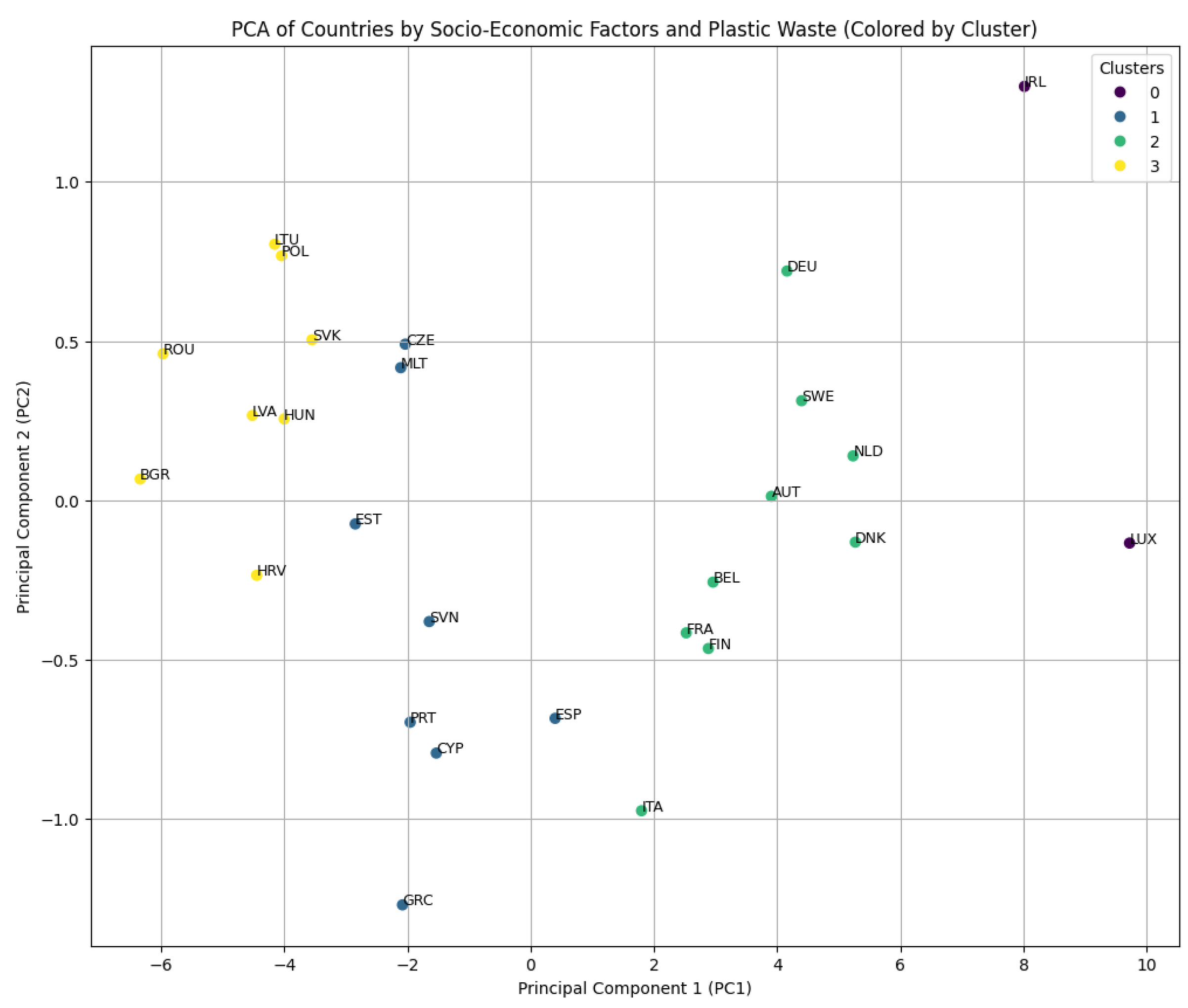

```
# Calculate average GDP, population, and plastic waste for each country
gdp_columns = [f'GDP_{year}' for year in range(2000, 2019)]
pop_columns = [f'Population_{year}' for year in range(2000, 2019)]
plastic_waste_columns = [f'Plastic_Waste_{year}' for year in range(2000, 2019)]

# 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()
```




```
from sklearn.decomposition import PCA

# Re-apply K-Means clustering to PCA results for color coding
kmeans = KMeans(n_clusters=4, random_state=0, n_init=10)
pca_clusters = kmeans.fit_predict(principal_components)
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']):
    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
```




```
array([0.82893139, 0.09388619])
```