```python
#import library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

# load the dataset if you are using Jupyter Notebook

# identify the path of your dataset

World_Marriage_df = pd.read_csv("World Marriage Dataset.csv")

World_Marriage_df.shape
```

```
(271604, 9)
```

```python
World_Marriage_df.head()
```

```
   Sr.No.      Country AgeGroup  Sex MaritalStatus DataProcess  \
0       1  Afghanistan  [15-19]  Man      Divorced      Survey
1       2  Afghanistan  [20-24]  Man      Divorced      Survey
2       3  Afghanistan  [25-29]  Man      Divorced      Survey
3       4  Afghanistan  [30-34]  Man      Divorced      Survey
4       5  Afghanistan  [35-39]  Man      Divorced      Survey

   Data Collection (Start Year)  Data Collection (End Year)  \
0                          1972                        1974
1                          1972                        1974
2                          1972                        1974
3                          1972                        1974
4                          1972                        1974

            Data Source
0  National statistics
1  National statistics
2  National statistics
3  National statistics
4  National statistics
```

```python
World_Marriage_df.tail()
```

```
        Sr.No.   Country AgeGroup    Sex MaritalStatus DataProcess  \
271599  271600  Zimbabwe  [55-59]  Woman       Widowed      Survey
271600  271601  Zimbabwe  [60-64]  Woman       Widowed      Survey
271601  271602  Zimbabwe  [65-69]  Woman       Widowed      Survey
271602  271603  Zimbabwe  [70-74]  Woman       Widowed      Survey
271603  271604  Zimbabwe    [75+]  Woman       Widowed      Survey
```

```
        Data Collection (Start Year)  Data Collection (End Year)  \
271599                          2017                        2017   
271600                          2017                        2017   
271601                          2017                        2017   
271602                          2017                        2017   
271603                          2017                        2017   

                Data Source  
271599  National statistics  
271600  National statistics  
271601  National statistics  
271602  National statistics  
271603  National statistics  
```

```
World_Marriage_df.dtypes
```

```
Sr.No.                           int64
Country                         object
AgeGroup                        object
Sex                             object
MaritalStatus                   object
DataProcess                     object
Data Collection (Start Year)     int64
Data Collection (End Year)       int64
Data Source                     object
dtype: object
```

```
World_Marriage_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271604 entries, 0 to 271603
Data columns (total 9 columns):
 #   Column                        Non-Null Count   Dtype 
---  ------                        --------------   ----- 
 0   Sr.No.                        271604 non-null  int64 
 1   Country                       271604 non-null  object
 2   AgeGroup                      271604 non-null  object
 3   Sex                           271604 non-null  object
 4   MaritalStatus                 271604 non-null  object
 5   DataProcess                   271604 non-null  object
 6   Data Collection (Start Year)  271604 non-null  int64 
 7   Data Collection (End Year)    271604 non-null  int64 
 8   Data Source                   271604 non-null  object
dtypes: int64(3), object(6)
memory usage: 18.6+ MB
```

```
print(World_Marriage_df['MaritalStatus'].unique())
```

```
['Divorced' 'Married' 'Single' 'Widowed' 'Divorced or Separated'
 'Separated' 'Never married' 'Not in union' 'Not living together']
```

```
 'Married or Living together' 'Widowed or divorced' 'Living together'
 'Consensual union' 'Ever married' 'Currently not married'
 'Consensual union, not living together' 'Married or in consensual
union'
 'Married or married but separated' 'Registred partnership'
 'Visiting partner' 'Widowed, divorced or separated'
 'Married, in consensual unions or separated'
 'Separated from consensual union'
 'Currently not married nor in consensual union' 'Marriage contract'
 'Divorced or Separated or Widowed' 'Separated from marriage'
 'Married gaunna not performed' 'Married monogamous' 'Married
polygamous'
 'Divorced or Widowed' 'Single or in consensual unions'
 'Widowed or separated' 'Married spouse absent' 'Married spouse
present']
```

```
World_Marriage_df['MaritalStatus']
```

```
0          Divorced
1          Divorced
2          Divorced
3          Divorced
4          Divorced
            ...
271599      Widowed
271600      Widowed
271601      Widowed
271602      Widowed
271603      Widowed
Name: MaritalStatus, Length: 271604, dtype: object
```

Data Transforming

```
World_Marriage_df.columns
```

```
Index(['Sr.No.', 'Country', 'AgeGroup', 'Sex', 'MaritalStatus',
'DataProcess',
       'Data Collection (Start Year)', 'Data Collection (End Year)',
       'Data Source'],
      dtype='object')
```

```
# Remove Serial No.
World_Marriage_1_df = World_Marriage_df.drop("Sr.No.", axis = 1)

# Change the name of the columns
World_Marriage_1_df.columns = ['Country', 'Age Group','Sex','Marital
Status','Data Process','Start Year','End Year','Data Source']

World_Marriage_1_df.head()
```

```
       Country Age Group   Sex Marital Status Data Process   Start Year  \
0  Afghanistan   [15-19]   Man       Divorced       Survey         1972   

1  Afghanistan   [20-24]   Man       Divorced       Survey         1972   

2  Afghanistan   [25-29]   Man       Divorced       Survey         1972   

3  Afghanistan   [30-34]   Man       Divorced       Survey         1972   

4  Afghanistan   [35-39]   Man       Divorced       Survey         1972   


   End Year           Data Source  
0      1974  National statistics  
1      1974  National statistics  
2      1974  National statistics  
3      1974  National statistics  
4      1974  National statistics  
```

Data Pre-processing

1. Identify Problematic Data

Load the Dataset and check for missing values, duplicates, and outliers.

```python
# Identify missing values
missing_values = World_Marriage_1_df.isnull().sum()
print("Missing Values:\n", missing_values)
```

```
Missing Values:
 Country           0
Age Group         0
Sex               0
Marital Status    0
Data Process      0
Start Year        0
End Year          0
Data Source       0
dtype: int64
```

```python
# Identify duplicates
duplicates = World_Marriage_1_df.duplicated().sum()
print("Number of duplicate rows: ", duplicates)
```

```
Number of duplicate rows:  187
```

```
duplicates_dt = World_Marriage_1_df[World_Marriage_1_df.duplicated()]

duplicates_dt
```

```
        Country Age Group    Sex Marital Status Data Process  Start
Year  \
140287  Lebanon   [15-19]    Man        Married       Survey
2004
140288  Lebanon   [20-24]    Man        Married       Survey
2004
140289  Lebanon   [25-29]    Man        Married       Survey
2004
140290  Lebanon   [30-34]    Man        Married       Survey
2004
140291  Lebanon   [35-39]    Man        Married       Survey
2004
...         ...       ...    ...            ...          ...           .
..
252784   Uganda   [55-59]  Woman        Widowed       Survey
2011
252785   Uganda   [60-64]  Woman        Widowed       Survey
2011
252786   Uganda   [65-69]  Woman        Widowed       Survey
2011
252787   Uganda   [70-74]  Woman        Widowed       Survey
2011
252788   Uganda     [75+]  Woman        Widowed       Survey
2011

        End Year          Data Source
140287      2004  National statistics
140288      2004  National statistics
140289      2004  National statistics
140290      2004  National statistics
140291      2004  National statistics
...          ...                  ...
252784      2011               DHS_HH
252785      2011               DHS_HH
252786      2011               DHS_HH
252787      2011               DHS_HH
252788      2011               DHS_HH

[187 rows x 8 columns]
```

```
print(World_Marriage_1_df.describe())
```

```
          Start Year       End Year
count  271604.000000  271604.000000
mean     1996.961488    1997.059097
std        14.244590      14.284136
```

```
min       1954.000000    1955.000000
25%       1986.000000    1986.000000
50%       2000.000000    2000.000000
75%       2010.000000    2010.000000
max       2019.000000    2019.000000
```

2. Cleaning the Data

Remove duplicates, handle missing values, and standardize inconsistent data.

```
# Remove duplicate rows
World_Marriage_2_df = World_Marriage_1_df.drop_duplicates()

# Handling missing data
# Option 1: Drop rows with missing values (only if missing values are
minimal)
World_Marriage_3_df = World_Marriage_2_df.dropna()

# Example: Fill missing categorical values with mode
World_Marriage_3_df.fillna(World_Marriage_3_df.mode().iloc[0],
inplace=True)


# Standardize inconsistent data (e.g., different formats of the same
information)
World_Marriage_3_df['Age Group'] = World_Marriage_3_df['Age
Group'].str.lower().str.strip()



# Standardize categorical columns
World_Marriage_3_df['Sex'] =
World_Marriage_3_df['Sex'].str.lower().str.strip()
World_Marriage_3_df['Marital Status'] = World_Marriage_3_df['Marital
Status'].str.lower().str.strip()

World_Marriage_3_df

            Country Age Group    Sex Marital Status Data Process
Start Year  \
0       Afghanistan   [15-19]    man       divorced       Survey
1972
1       Afghanistan   [20-24]    man       divorced       Survey
1972
2       Afghanistan   [25-29]    man       divorced       Survey
1972
3       Afghanistan   [30-34]    man       divorced       Survey
1972
4       Afghanistan   [35-39]    man       divorced       Survey
```

```
1972
...                ...        ...     ...            ...           ...
...
271599      Zimbabwe   [55-59]   woman          widowed        Survey
2017
271600      Zimbabwe   [60-64]   woman          widowed        Survey
2017
271601      Zimbabwe   [65-69]   woman          widowed        Survey
2017
271602      Zimbabwe   [70-74]   woman          widowed        Survey
2017
271603      Zimbabwe     [75+]   woman          widowed        Survey
2017

        End Year          Data Source
0           1974  National statistics
1           1974  National statistics
2           1974  National statistics
3           1974  National statistics
4           1974  National statistics
...          ...                  ...
271599      2017  National statistics
271600      2017  National statistics
271601      2017  National statistics
271602      2017  National statistics
271603      2017  National statistics

[271417 rows x 8 columns]
```

1. Remove Outliers or Analyze Separately Detect and analyze outliers using Z-scores or IQR methods.

```
# Detect outliers using Z-score
from scipy import stats

z_scores =
np.abs(stats.zscore(World_Marriage_3_df.select_dtypes(include=[np.numb
er])))
World_Marriage_4_df = World_Marriage_3_df[(z_scores < 3).all(axis=1)]

# Detect outliers using Z-score
z_scores =
np.abs(stats.zscore(World_Marriage_3_df.select_dtypes(include=[np.numb
er])))
# Rows where at least one Z-score is greater than or equal to 3 are
considered outliers
z_score_outliers = World_Marriage_3_df[(z_scores >= 3).any(axis=1)]

# Alternative: Detect outliers using IQR
Q1 = World_Marriage_4_df.quantile(0.25)
```

```
Q3 = World_Marriage_4_df.quantile(0.75)
IQR = Q3 - Q1
IQR_outliers = World_Marriage_3_df[((World_Marriage_3_df < (Q1 - 1.5 * 
IQR)) |
                                    (World_Marriage_3_df > (Q3 + 1.5 * 
IQR))).any(axis=1)]
World_Marriage_5_df = World_Marriage_4_df[~((World_Marriage_4_df < (Q1 
- 1.5 * IQR)) |
                                            (World_Marriage_4_df > (Q3 
+ 1.5 * IQR))).any(axis=1)]

# Show outliers detected by Z-score method
print("Outliers detected by Z-score method:")
print(z_score_outliers)

# Show outliers detected by IQR method
print("Outliers detected by IQR method:")
print(IQR_outliers)
```

```
Outliers detected by Z-score method:
      Country Age Group    Sex    Marital Status Data Process  Start 
Year  \
98611  Guinea   [14-19]    man  consensual union       Survey        
1954   
98612  Guinea   [20-24]    man  consensual union       Survey        
1954   
98613  Guinea   [25-29]    man  consensual union       Survey        
1954   
98614  Guinea   [30-34]    man  consensual union       Survey        
1954   
98615  Guinea   [35-39]    man  consensual union       Survey        
1954   
...       ...       ...    ...               ...          ...        
...   
98708  Guinea   [50-54]  woman           widowed       Survey        
1954   
98709  Guinea   [55-59]  woman           widowed       Survey        
1954   
98710  Guinea   [60-64]  woman           widowed       Survey        
1954   
98711  Guinea   [65-69]  woman           widowed       Survey        
1954   
98712  Guinea     [70+]  woman           widowed       Survey        
1954   

       End Year Data Source  
98611      1955        INED  
98612      1955        INED  
98613      1955        INED  
98614      1955        INED  
```

```
98615      1955        INED
...         ...         ...
98708      1955        INED
98709      1955        INED
98710      1955        INED
98711      1955        INED
98712      1955        INED

[102 rows x 8 columns]
Outliers detected by IQR method:
Empty DataFrame
Columns: [Country, Age Group, Sex, Marital Status, Data Process, Start
Year, End Year, Data Source]
Index: []
```

World_Marriage_5_df

```
            Country Age Group    Sex Marital Status Data Process
Start Year  \
0       Afghanistan   [15-19]    man       divorced       Survey
1972
1       Afghanistan   [20-24]    man       divorced       Survey
1972
2       Afghanistan   [25-29]    man       divorced       Survey
1972
3       Afghanistan   [30-34]    man       divorced       Survey
1972
4       Afghanistan   [35-39]    man       divorced       Survey
1972
...             ...       ...    ...            ...          ...
...
271599     Zimbabwe   [55-59]  woman        widowed       Survey
2017
271600     Zimbabwe   [60-64]  woman        widowed       Survey
2017
271601     Zimbabwe   [65-69]  woman        widowed       Survey
2017
271602     Zimbabwe   [70-74]  woman        widowed       Survey
2017
271603     Zimbabwe     [75+]  woman        widowed       Survey
2017

        End Year          Data Source
0           1974  National statistics
1           1974  National statistics
2           1974  National statistics
3           1974  National statistics
4           1974  National statistics
...          ...                  ...
271599      2017  National statistics
```

```
271600       2017  National statistics
271601       2017  National statistics
271602       2017  National statistics
271603       2017  National statistics

[271315 rows x 8 columns]
```

4. Purge Contaminated Data and Correct Leaking Pipelines

Manually inspect and purge any contaminated data, such as wrong labels or misentered data.

```
# Example: Check for any impossible values in categorical fields
valid_marital_statuses = ['single', 'married', 'divorced', 'widowed',
'separated']
invalid_marital_status =
World_Marriage_5_df[~World_Marriage_5_df['Marital
Status'].isin(valid_marital_statuses)]
print("Invalid Marital Status:\n", invalid_marital_status)

# Drop rows with invalid entries
World_Marriage_6_df = World_Marriage_5_df[World_Marriage_5_df['Marital
Status'].isin(valid_marital_statuses)]

Invalid Marital Status:
                  Country Age Group    Sex         Marital Status Data
Process  \
184      Afghanistan   [15-24]    man  divorced or separated
Survey
185      Afghanistan   [25-39]    man  divorced or separated
Survey
186      Afghanistan   [40-64]    man  divorced or separated
Survey
187      Afghanistan     [65+]    man  divorced or separated
Survey
200      Afghanistan   [15-24]  woman  divorced or separated
Survey
...              ...       ...    ...                    ...            .
..
271562      Zimbabwe   [55-59]  woman  divorced or separated
Survey
271563      Zimbabwe   [60-64]  woman  divorced or separated
Survey
271564      Zimbabwe   [65-69]  woman  divorced or separated
Survey
271565      Zimbabwe   [70-74]  woman  divorced or separated
```

```
Survey
271566     Zimbabwe     [75+]  woman  divorced or separated
Survey

        Start Year  End Year          Data Source
184           2007      2008  National statistics
185           2007      2008  National statistics
186           2007      2008  National statistics
187           2007      2008  National statistics
200           2007      2008  National statistics
...            ...       ...                  ...
271562        2017      2017  National statistics
271563        2017      2017  National statistics
271564        2017      2017  National statistics
271565        2017      2017  National statistics
271566        2017      2017  National statistics

[43099 rows x 8 columns]

World_Marriage_6_df

            Country Age Group    Sex Marital Status Data Process
Start Year  \
0       Afghanistan   [15-19]    man       divorced       Survey
1972
1       Afghanistan   [20-24]    man       divorced       Survey
1972
2       Afghanistan   [25-29]    man       divorced       Survey
1972
3       Afghanistan   [30-34]    man       divorced       Survey
1972
4       Afghanistan   [35-39]    man       divorced       Survey
1972
...             ...       ...    ...            ...          ...
...
271599     Zimbabwe   [55-59]  woman        widowed       Survey
2017
271600     Zimbabwe   [60-64]  woman        widowed       Survey
2017
271601     Zimbabwe   [65-69]  woman        widowed       Survey
2017
271602     Zimbabwe   [70-74]  woman        widowed       Survey
2017
271603     Zimbabwe     [75+]  woman        widowed       Survey
2017

        End Year          Data Source
0           1974  National statistics
1           1974  National statistics
2           1974  National statistics
```

```
3           1974  National statistics
4           1974  National statistics
...          ...                  ...
271599      2017  National statistics
271600      2017  National statistics
271601      2017  National statistics
271602      2017  National statistics
271603      2017  National statistics

[228216 rows x 8 columns]
```

5. Standardize Inconsistent Data

Ensure all similar data is standardized.

```
# Standardizing categorical columns if needed
World_Marriage_6_df['Age Group'] = World_Marriage_6_df['Age Group'].str.capitalize()
World_Marriage_6_df['Sex'] =
World_Marriage_6_df['Sex'].str.capitalize()
World_Marriage_6_df['Marital Status'] = World_Marriage_6_df['Marital Status'].str.capitalize()

World_Marriage_6_df
```

```
            Country Age Group    Sex Marital Status Data Process
Start Year  \
0       Afghanistan   [15-19]    Man       Divorced       Survey
1972
1       Afghanistan   [20-24]    Man       Divorced       Survey
1972
2       Afghanistan   [25-29]    Man       Divorced       Survey
1972
3       Afghanistan   [30-34]    Man       Divorced       Survey
1972
4       Afghanistan   [35-39]    Man       Divorced       Survey
1972
...             ...       ...    ...            ...          ...
...
271599     Zimbabwe   [55-59]  Woman        Widowed       Survey
2017
271600     Zimbabwe   [60-64]  Woman        Widowed       Survey
2017
271601     Zimbabwe   [65-69]  Woman        Widowed       Survey
2017
271602     Zimbabwe   [70-74]  Woman        Widowed       Survey
2017
271603     Zimbabwe     [75+]  Woman        Widowed       Survey
```

```
2017

        End Year          Data Source
0           1974  National statistics
1           1974  National statistics
2           1974  National statistics
3           1974  National statistics
4           1974  National statistics
...          ...                  ...
271599      2017  National statistics
271600      2017  National statistics
271601      2017  National statistics
271602      2017  National statistics
271603      2017  National statistics

[228216 rows x 8 columns]
```

6. Check Data Validity

Ensure that the data makes logical sense.

```
# Check if the data makes sense
print(World_Marriage_6_df['Sex'].unique())
print(World_Marriage_6_df['Marital Status'].unique())

['Man' 'Woman']
['Divorced' 'Married' 'Single' 'Widowed' 'Separated']
```

7. Deduplicate Records

Ensure no duplicate records remain.

```
# Ensure no duplicates after cleaning
World_Marriage_7_df = World_Marriage_6_df.drop_duplicates()

World_Marriage_7_df

            Country Age Group    Sex Marital Status Data Process
Start Year  \
0       Afghanistan   [15-19]    Man       Divorced       Survey
1972
1       Afghanistan   [20-24]    Man       Divorced       Survey
1972
2       Afghanistan   [25-29]    Man       Divorced       Survey
1972
3       Afghanistan   [30-34]    Man       Divorced       Survey
```

```
1972
4         Afghanistan   [35-39]    Man        Divorced        Survey
1972
...               ...       ...    ...             ...           ...
...
271599       Zimbabwe   [55-59]  Woman         Widowed        Survey
2017
271600       Zimbabwe   [60-64]  Woman         Widowed        Survey
2017
271601       Zimbabwe   [65-69]  Woman         Widowed        Survey
2017
271602       Zimbabwe   [70-74]  Woman         Widowed        Survey
2017
271603       Zimbabwe     [75+]  Woman         Widowed        Survey
2017

        End Year          Data Source
0           1974  National statistics
1           1974  National statistics
2           1974  National statistics
3           1974  National statistics
4           1974  National statistics
...          ...                  ...
271599      2017  National statistics
271600      2017  National statistics
271601      2017  National statistics
271602      2017  National statistics
271603      2017  National statistics

[228216 rows x 8 columns]
```

8. Rinse and Repeat

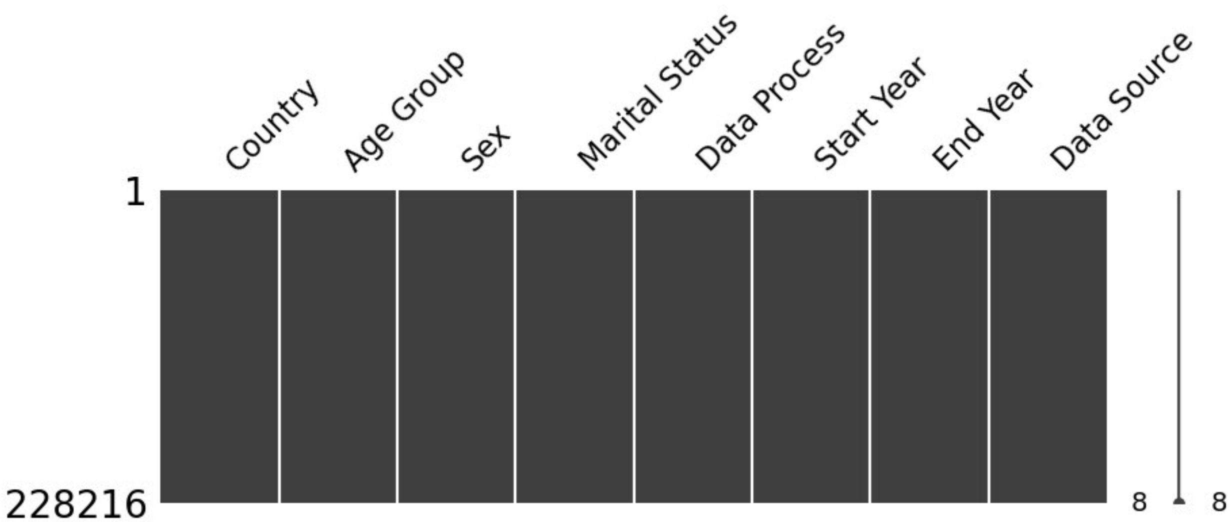
Iteratively check and clean the data as new issues might arise.

```
# After cleaning, recheck the data
print(World_Marriage_7_df.info())
print(World_Marriage_7_df.describe())

<class 'pandas.core.frame.DataFrame'>
Int64Index: 228216 entries, 0 to 271603
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Country         228216 non-null  object
 1   Age Group       228216 non-null  object
 2   Sex             228216 non-null  object
 3   Marital Status  228216 non-null  object
```

```
 4   Data Process    228216 non-null  object
 5   Start Year      228216 non-null  int64
 6   End Year        228216 non-null  int64
 7   Data Source     228216 non-null  object
dtypes: int64(2), object(6)
memory usage: 15.7+ MB
None
          Start Year       End Year
count  228216.000000  228216.000000
mean     1996.540909    1996.619619
std        14.292680      14.320451
min      1959.000000    1959.000000
25%      1985.000000    1985.000000
50%      2000.000000    2000.000000
75%      2009.000000    2010.000000
max      2019.000000    2019.000000
```

```
msno.matrix(World_Marriage_7_df, figsize = (10,  3))
```

```
<Axes: >
```




```
print(World_Marriage_7_df)
```

```
            Country Age Group    Sex Marital Status Data Process
Start Year  \
0       Afghanistan   [15-19]    Man       Divorced       Survey
1972
1       Afghanistan   [20-24]    Man       Divorced       Survey
1972
2       Afghanistan   [25-29]    Man       Divorced       Survey
1972
```

```
3         Afghanistan   [30-34]     Man        Divorced       Survey
1972
4         Afghanistan   [35-39]     Man        Divorced       Survey
1972
...               ...       ...     ...             ...          ...
...
271599       Zimbabwe   [55-59]   Woman         Widowed       Survey
2017
271600       Zimbabwe   [60-64]   Woman         Widowed       Survey
2017
271601       Zimbabwe   [65-69]   Woman         Widowed       Survey
2017
271602       Zimbabwe   [70-74]   Woman         Widowed       Survey
2017
271603       Zimbabwe     [75+]   Woman         Widowed       Survey
2017

        End Year           Data Source
0           1974  National statistics
1           1974  National statistics
2           1974  National statistics
3           1974  National statistics
4           1974  National statistics
...          ...                   ...
271599      2017  National statistics
271600      2017  National statistics
271601      2017  National statistics
271602      2017  National statistics
271603      2017  National statistics

[228216 rows x 8 columns]
```

```python
type(World_Marriage_7_df)
```

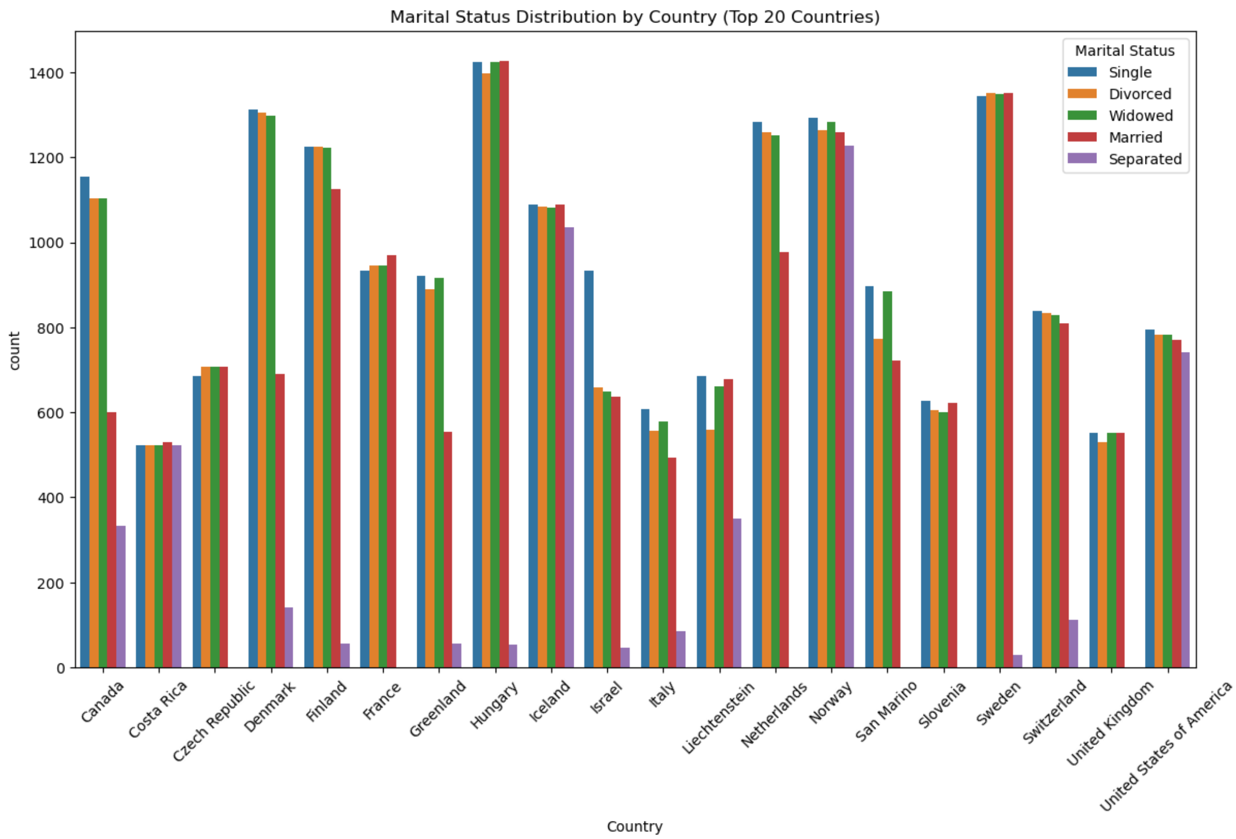
```
pandas.core.frame.DataFrame
```

```python
# saving the dataframe
World_Marriage_7_df.to_csv('World_Marriage_Cleaned_Dataset.csv',index=
False)
```

EDA

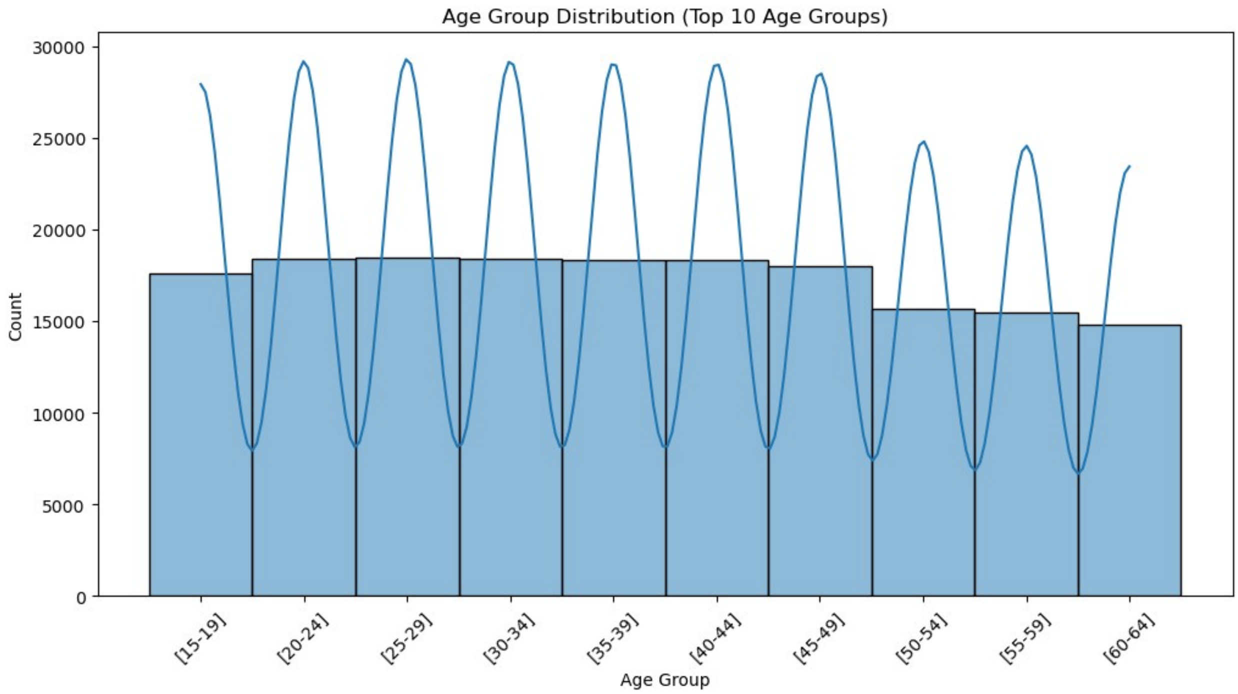
```python
# Count the number of entries per country
top_20_countries =
World_Marriage_7_df['Country'].value_counts().nlargest(20).index

# Filter the dataset for these top 10 countries
```

```
data_top_20 =
World_Marriage_7_df[World_Marriage_7_df['Country'].isin(top_20_countri
es)]

# Marital status distribution by country for the top 10 countries
plt.figure(figsize=(14, 8))
sns.countplot(data=data_top_20, x='Country', hue='Marital Status')
plt.title('Marital Status Distribution by Country (Top 20 Countries)')
plt.xticks(rotation=45)
plt.show()
```

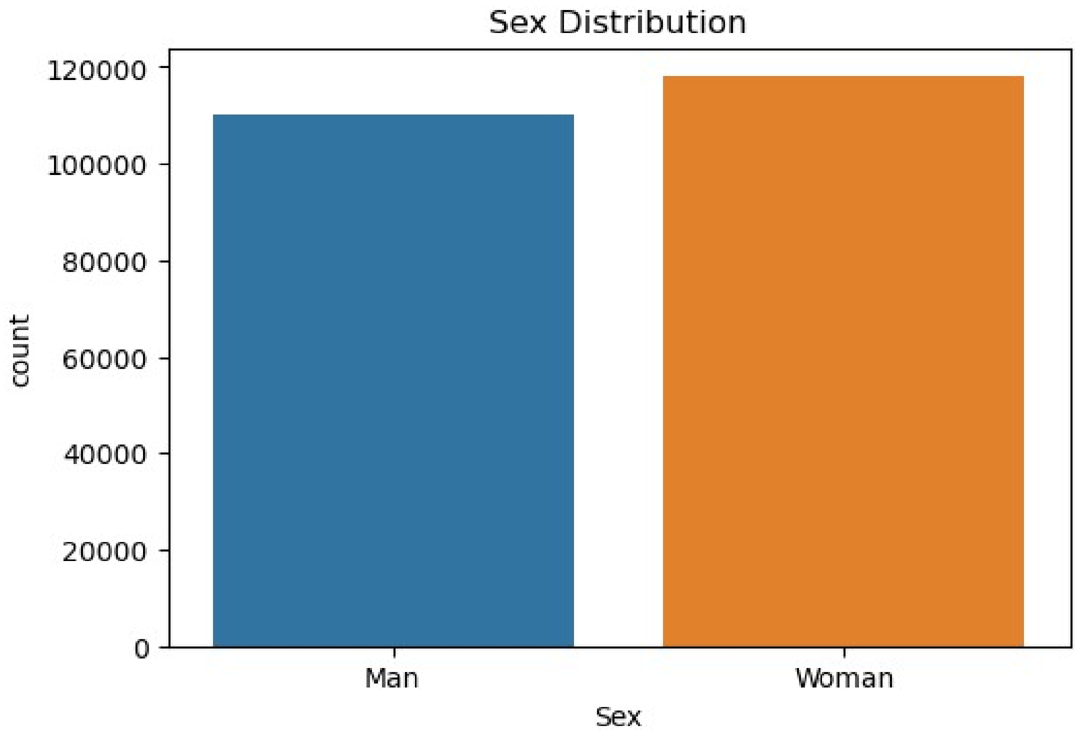



```
# Count the number of entries per age group
top_10_age_groups = World_Marriage_7_df['Age
Group'].value_counts().nlargest(10).index

# Filter the dataset for these top 15 age groups
data_top_10_age_groups = World_Marriage_7_df[World_Marriage_7_df['Age
Group'].isin(top_10_age_groups)]

# Age group distribution for the top 15 age groups
plt.figure(figsize=(12, 6))
sns.histplot(data_top_10_age_groups['Age Group'], kde=True, bins=15)
plt.title('Age Group Distribution (Top 10 Age Groups)')
```

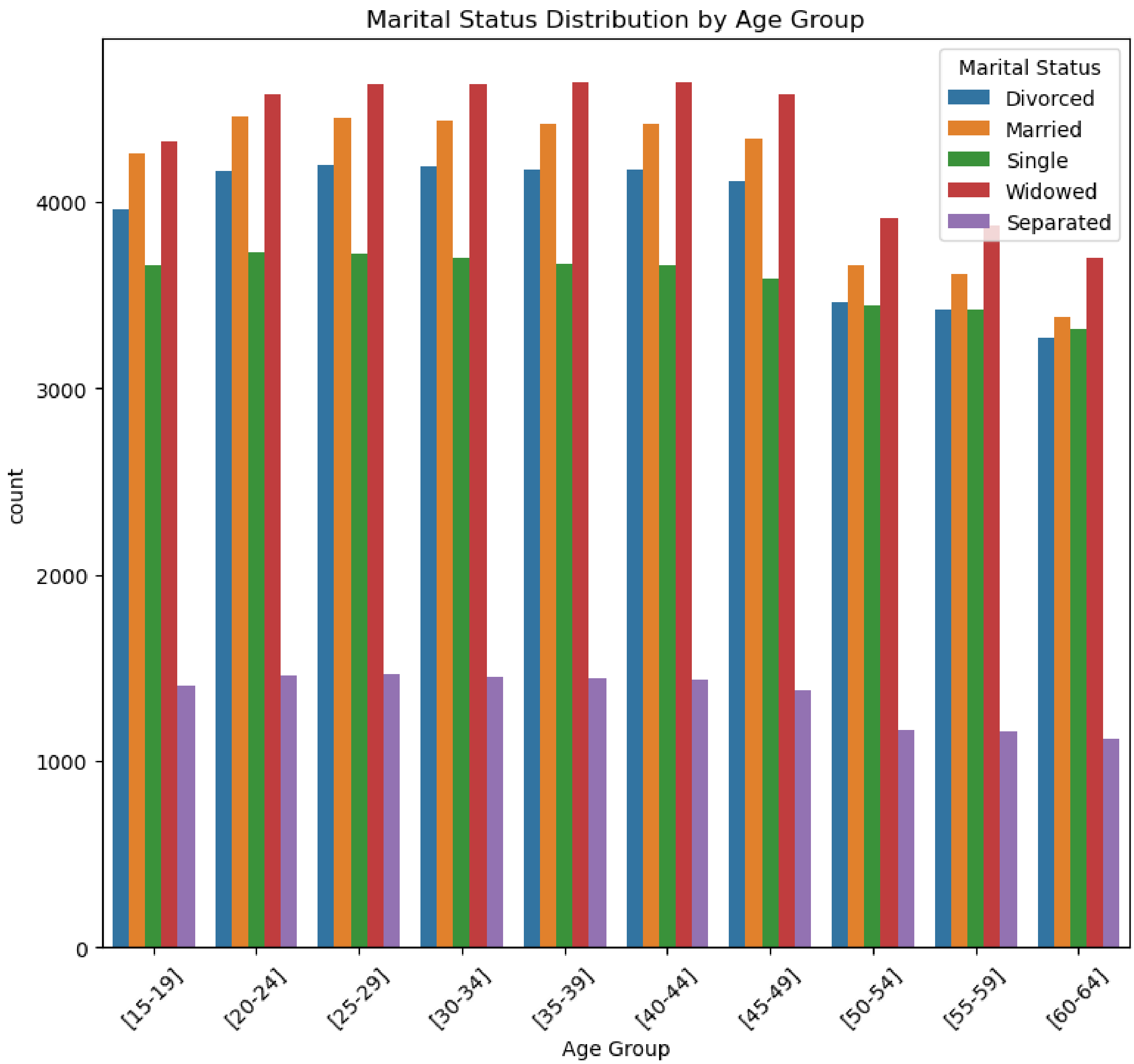
```
plt.xticks(rotation=45)
plt.show()
```



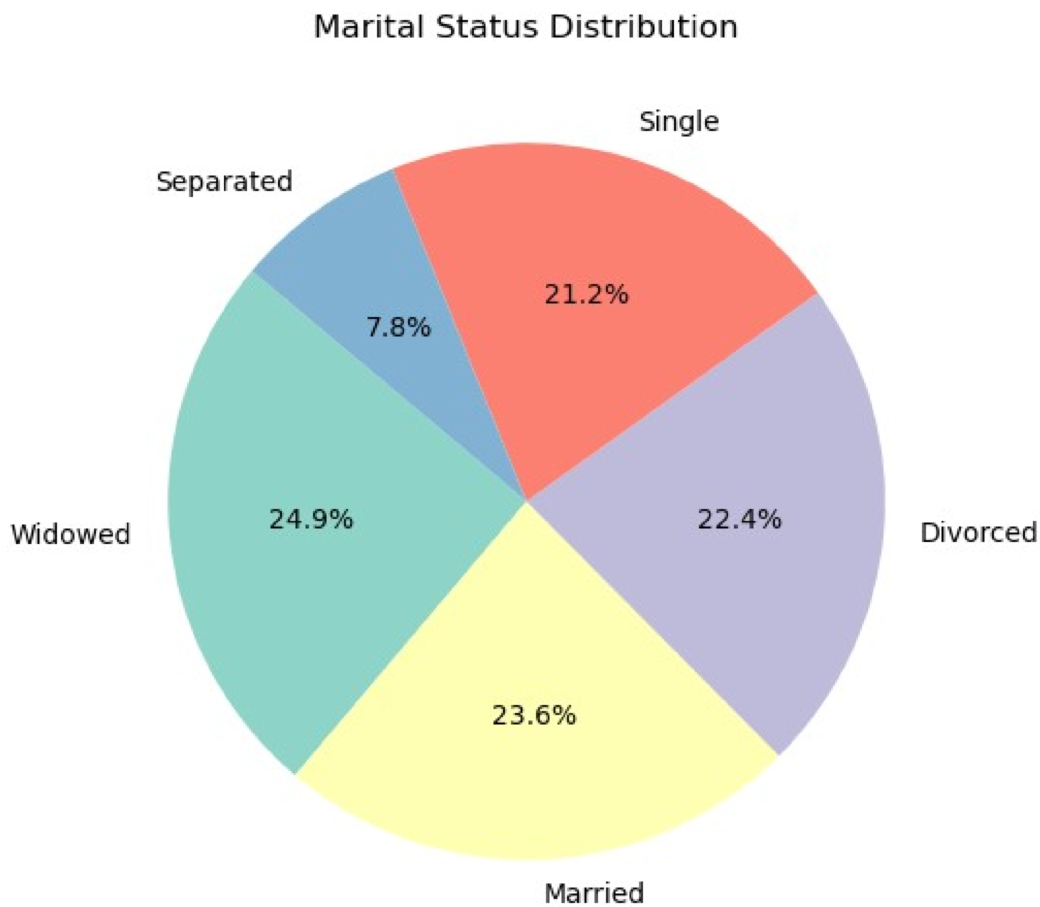

```
# Distribution of sexes in the dataset
plt.figure(figsize=(6, 4))
sns.countplot(data=World_Marriage_7_df, x='Sex')
plt.title('Sex Distribution')
plt.show()
```




```
# Marital status by age group
plt.figure(figsize=(9, 8))
sns.countplot(data=data_top_10_age_groups, x='Age Group', hue='Marital Status')
plt.title('Marital Status Distribution by Age Group')
plt.xticks(rotation=45)
plt.show()
```




```
# Calculate the distribution of marital statuses
marital_status_counts = World_Marriage_7_df['Marital
Status'].value_counts()

# Plot the pie chart
plt.figure(figsize=(10, 6))
plt.pie(marital_status_counts, labels=marital_status_counts.index,
autopct='%1.1f%%', startangle=140, colors=sns.color_palette("Set3"))
plt.title('Marital Status Distribution')
plt.show()
```




```
pip install geopandas folium

Requirement already satisfied: geopandas in c:\users\user\anaconda3\
lib\site-packages (1.0.1)
Requirement already satisfied: folium in c:\users\user\anaconda3\lib\
site-packages (0.17.0)
Requirement already satisfied: numpy>=1.22 in c:\users\user\anaconda3\
lib\site-packages (from geopandas) (1.24.3)
Requirement already satisfied: pyogrio>=0.7.2 in c:\users\user\
anaconda3\lib\site-packages (from geopandas) (0.9.0)
Requirement already satisfied: packaging in c:\users\user\anaconda3\
lib\site-packages (from geopandas) (23.0)
Requirement already satisfied: pandas>=1.4.0 in c:\users\user\
anaconda3\lib\site-packages (from geopandas) (1.5.3)
Requirement already satisfied: pyproj>=3.3.0 in c:\users\user\
anaconda3\lib\site-packages (from geopandas) (3.6.1)
Requirement already satisfied: shapely>=2.0.0 in c:\users\user\
anaconda3\lib\site-packages (from geopandas) (2.0.6)
Requirement already satisfied: branca>=0.6.0 in c:\users\user\
anaconda3\lib\site-packages (from folium) (0.7.2)
```

```
Requirement already satisfied: jinja2>=2.9 in c:\users\user\anaconda3\lib\site-packages (from folium) (3.1.2)
Requirement already satisfied: requests in c:\users\user\anaconda3\lib\site-packages (from folium) (2.29.0)
Requirement already satisfied: xyzservices in c:\users\user\anaconda3\lib\site-packages (from folium) (2022.9.0)
Requirement already satisfied: MarkupSafe>=2.0 in c:\users\user\anaconda3\lib\site-packages (from jinja2>=2.9->folium) (2.1.1)
Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\user\anaconda3\lib\site-packages (from pandas>=1.4.0->geopandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\user\anaconda3\lib\site-packages (from pandas>=1.4.0->geopandas) (2022.7)
Requirement already satisfied: certifi in c:\users\user\anaconda3\lib\site-packages (from pyogrio>=0.7.2->geopandas) (2023.5.7)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\user\anaconda3\lib\site-packages (from requests->folium) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\user\anaconda3\lib\site-packages (from requests->folium) (3.4)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\user\anaconda3\lib\site-packages (from requests->folium) (1.26.16)
Requirement already satisfied: six>=1.5 in c:\users\user\anaconda3\lib\site-packages (from python-dateutil>=2.8.1->pandas>=1.4.0->geopandas) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

```
pip install plotly
```

```
Requirement already satisfied: plotly in c:\users\user\anaconda3\lib\site-packages (5.9.0)
Requirement already satisfied: tenacity>=6.2.0 in c:\users\user\anaconda3\lib\site-packages (from plotly) (8.2.2)
Note: you may need to restart the kernel to use updated packages.
```

```python
# Example assuming each row represents an individual
World_Marriage_7_df['Count'] = 1

# Pivot the data
marital_counts = World_Marriage_7_df.pivot_table(index='Country', columns='Marital Status', values='Count', aggfunc='sum', fill_value=0).reset_index()

# Rename the columns for clarity
marital_counts.columns = ['Country', 'Divorced', 'Married', 'Single', 'Widowed','Separated']
```

```python
marital_counts.columns
```

```
Index(['Country', 'Divorced', 'Married', 'Single', 'Widowed', 'Separated'], dtype='object')
```

```
marital_counts
```

```
                Country  Divorced  Married  Single  Widowed  Separated
0           Afghanistan       100      116      14       71        116
1               Albania       141      185      61       91        191
2               Algeria       129      162      57      129        160
3        American Samoa        84       86      58       90         86
4                Angola       101       95      87       48        121
..                  ...       ...      ...     ...      ...        ...
229  Wallis and Futuna         77      152       0      156        143
230      Western Sahara        28        0      28       28         28
231               Yemen       204      205       0      102        205
232              Zambia       252      252     101       86        272
233            Zimbabwe       219      353      66      191        377

[234 rows x 6 columns]
```

```python
# Calculate the total population for each country
marital_counts['Total'] = marital_counts[['Divorced', 'Married',
'Single', 'Widowed','Separated']].sum(axis=1)

marital_counts
```

```
                Country  Divorced  Married  Single  Widowed  Separated
Total
0           Afghanistan       100      116      14       71        116
417
1               Albania       141      185      61       91        191
669
2               Algeria       129      162      57      129        160
637
3        American Samoa        84       86      58       90         86
404
4                Angola       101       95      87       48        121
452
..                  ...       ...      ...     ...      ...        ...
...
229  Wallis and Futuna         77      152       0      156        143
528
230      Western Sahara        28        0      28       28         28
112
231               Yemen       204      205       0      102        205
716
232              Zambia       252      252     101       86        272
963
233            Zimbabwe       219      353      66      191        377
1206

[234 rows x 7 columns]
```

```python
import geopandas as gpd
import matplotlib.pyplot as plt
import plotly.express as px

# Example: Aggregate the data by country without using percentage
fields
marriage_patterns = marital_counts.groupby('Country').agg({
    'Married': 'sum',
    'Single': 'sum',
    'Divorced': 'sum',
    'Widowed': 'sum',
    'Separated': 'sum',
    'Total': 'sum'
}).reset_index()

import geopandas as gpd
import matplotlib.pyplot as plt

# Load the world map from Natural Earth (this approach should work
with newer versions)
shapefile_path =
r"C:/Users/user/Desktop/ne_10m_admin_0_countries/ne_10m_admin_0_countr
ies.shp"

# Load the shapefile
world = gpd.read_file(shapefile_path)

# Check the columns
print(world.columns)

world
```

```
Index(['scalerank', 'featurecla', 'LABELRANK', 'SOVEREIGNT', 'SOV_A3',
       'ADM0_DIF', 'LEVEL', 'TYPE', 'ADMIN', 'ADM0_A3', 'GEOU_DIF',
'GEOUNIT',
       'GU_A3', 'SU_DIF', 'SUBUNIT', 'SU_A3', 'BRK_DIFF', 'NAME',
'NAME_LONG',
       'BRK_A3', 'BRK_NAME', 'BRK_GROUP', 'ABBREV', 'POSTAL',
'FORMAL_EN',
       'FORMAL_FR', 'NOTE_ADM0', 'NOTE_BRK', 'NAME_SORT', 'NAME_ALT',
       'MAPCOLOR7', 'MAPCOLOR8', 'MAPCOLOR9', 'MAPCOLOR13', 'POP_EST',
       'GDP_MD_EST', 'POP_YEAR', 'LASTCENSUS', 'GDP_YEAR', 'ECONOMY',
       'INCOME_GRP', 'WIKIPEDIA', 'FIPS_10_', 'ISO_A2', 'ISO_A3',
'ISO_N3',
       'UN_A3', 'WB_A2', 'WB_A3', 'WOE_ID', 'WOE_ID_EH', 'WOE_NOTE',
       'ADM0_A3_IS', 'ADM0_A3_US', 'ADM0_A3_UN', 'ADM0_A3_WB',
'CONTINENT',
       'REGION_UN', 'SUBREGION', 'REGION_WB', 'NAME_LEN', 'LONG_LEN',
       'ABBREV_LEN', 'TINY', 'HOMEPART', 'geometry'],
      dtype='object')
```

```
     scalerank       featurecla  LABELRANK      SOVEREIGNT SOV_A3
ADM0_DIF  \
0            3  Admin-0 country        5.0     Netherlands    NL1
1.0
1            0  Admin-0 country        3.0     Afghanistan    AFG
0.0
2            0  Admin-0 country        3.0          Angola    AGO
0.0
3            3  Admin-0 country        6.0  United Kingdom    GB1
1.0
4            0  Admin-0 country        6.0         Albania    ALB
0.0
..         ...              ...        ...             ...    ...
...
250          3  Admin-0 country        4.0           Samoa    WSM
0.0
251          0  Admin-0 country        3.0           Yemen    YEM
0.0
252          0  Admin-0 country        2.0    South Africa    ZAF
0.0
253          0  Admin-0 country        3.0          Zambia    ZMB
0.0
254          0  Admin-0 country        3.0        Zimbabwe    ZWE
0.0

     LEVEL               TYPE         ADMIN ADM0_A3  ...
CONTINENT  \
0      2.0            Country         Aruba     ABW  ...  North
America
1      2.0  Sovereign country   Afghanistan     AFG  ...
Asia
2      2.0  Sovereign country        Angola     AGO  ...
Africa
3      2.0         Dependency      Anguilla     AIA  ...  North
America
4      2.0  Sovereign country       Albania     ALB  ...
Europe
..     ...                ...           ...     ...  ...             ..
.
250    2.0  Sovereign country         Samoa     WSM  ...
Oceania
251    2.0  Sovereign country         Yemen     YEM  ...
Asia
252    2.0  Sovereign country  South Africa     ZAF  ...
Africa
253    2.0  Sovereign country        Zambia     ZMB  ...
Africa
254    2.0  Sovereign country      Zimbabwe     ZWE  ...
Africa
```

```
    REGION_UN        SUBREGION                   REGION_WB NAME_LEN
LONG_LEN  \
0    Americas        Caribbean   Latin America & Caribbean      5.0
5.0
1        Asia    Southern Asia                  South Asia     11.0
11.0
2      Africa    Middle Africa          Sub-Saharan Africa      6.0
6.0
3    Americas        Caribbean   Latin America & Caribbean      8.0
8.0
4      Europe  Southern Europe       Europe & Central Asia      7.0
7.0
..        ...              ...                         ...      ...
...
250   Oceania        Polynesia         East Asia & Pacific      5.0
5.0
251      Asia     Western Asia  Middle East & North Africa      5.0
5.0
252    Africa  Southern Africa          Sub-Saharan Africa     12.0
12.0
253    Africa   Eastern Africa          Sub-Saharan Africa      6.0
6.0
254    Africa   Eastern Africa          Sub-Saharan Africa      8.0
8.0

     ABBREV_LEN  TINY HOMEPART  \
0           5.0   4.0    -99.0
1           4.0 -99.0      1.0
2           4.0 -99.0      1.0
3           4.0 -99.0    -99.0
4           4.0 -99.0      1.0
..          ...   ...      ...
250         5.0 -99.0      1.0
251         4.0 -99.0      1.0
252         5.0 -99.0      1.0
253         6.0 -99.0      1.0
254         5.0 -99.0      1.0

                                               geometry
0    POLYGON ((-69.99694 12.57758, -69.93639 12.531...
1    POLYGON ((71.0498 38.40866, 71.05714 38.40903,...
2    MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...
3    MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...
4    POLYGON ((19.74777 42.5789, 19.74601 42.57993,...
..                                                  ...
250  MULTIPOLYGON (((-171.57002 -13.93816, -171.564...
251  MULTIPOLYGON (((53.30824 12.11839, 53.31027 12...
252  MULTIPOLYGON (((37.86378 -46.94085, 37.83644 -...
253  POLYGON ((31.11984 -8.61663, 31.14102 -8.60619...
```

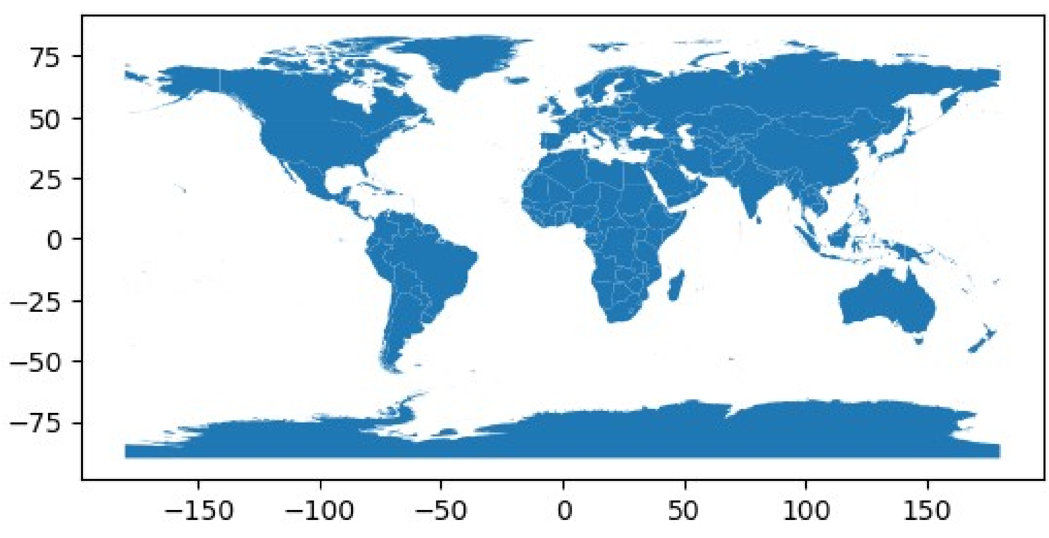
```
254  POLYGON ((30.01065 -15.64623, 30.05024 -15.640...

[255 rows x 66 columns]
```

```
print(world.columns)
```

```
Index(['scalerank', 'featurecla', 'LABELRANK', 'SOVEREIGNT', 'SOV_A3',
       'ADM0_DIF', 'LEVEL', 'TYPE', 'ADMIN', 'ADM0_A3', 'GEOU_DIF',
'GEOUNIT',
       'GU_A3', 'SU_DIF', 'SUBUNIT', 'SU_A3', 'BRK_DIFF', 'NAME',
'NAME_LONG',
       'BRK_A3', 'BRK_NAME', 'BRK_GROUP', 'ABBREV', 'POSTAL',
'FORMAL_EN',
       'FORMAL_FR', 'NOTE_ADM0', 'NOTE_BRK', 'NAME_SORT', 'NAME_ALT',
       'MAPCOLOR7', 'MAPCOLOR8', 'MAPCOLOR9', 'MAPCOLOR13', 'POP_EST',
       'GDP_MD_EST', 'POP_YEAR', 'LASTCENSUS', 'GDP_YEAR', 'ECONOMY',
       'INCOME_GRP', 'WIKIPEDIA', 'FIPS_10_', 'ISO_A2', 'ISO_A3',
'ISO_N3',
       'UN_A3', 'WB_A2', 'WB_A3', 'WOE_ID', 'WOE_ID_EH', 'WOE_NOTE',
       'ADM0_A3_IS', 'ADM0_A3_US', 'ADM0_A3_UN', 'ADM0_A3_WB',
'CONTINENT',
       'REGION_UN', 'SUBREGION', 'REGION_WB', 'NAME_LEN', 'LONG_LEN',
       'ABBREV_LEN', 'TINY', 'HOMEPART', 'geometry'],
      dtype='object')
```

```
world.plot()
```

```
<Axes: >
```




```
print(world['ADMIN'].to_string())
```

```
0                                                 Aruba
1                                           Afghanistan
```

2	Angola
3	Anguilla
4	Albania
5	Aland
6	Andorra
7	United Arab Emirates
8	Argentina
9	Armenia
10	American Samoa
11	Antarctica
12	Ashmore and Cartier Islands
13	French Southern and Antarctic Lands
14	Antigua and Barbuda
15	Australia
16	Austria
17	Azerbaijan
18	Burundi
19	Belgium
20	Benin
21	Burkina Faso
22	Bangladesh
23	Bulgaria
24	Bahrain
25	The Bahamas
26	Bosnia and Herzegovina
27	Bajo Nuevo Bank (Petrel Is.)
28	Saint Barthelemy
29	Belarus
30	Belize
31	Bermuda
32	Bolivia
33	Brazil
34	Barbados
35	Brunei
36	Bhutan
37	Botswana
38	Central African Republic
39	Canada
40	Switzerland
41	Chile
42	China
43	Ivory Coast
44	Clipperton Island
45	Cameroon
46	Cyprus No Mans Area
47	Democratic Republic of the Congo
48	Republic of Congo
49	Cook Islands
50	Colombia

51	Comoros
52	Cape Verde
53	Costa Rica
54	Coral Sea Islands
55	Cuba
56	Curaçao
57	Cayman Islands
58	Northern Cyprus
59	Cyprus
60	Czech Republic
61	Germany
62	Djibouti
63	Dominica
64	Denmark
65	Dominican Republic
66	Algeria
67	Ecuador
68	Egypt
69	Eritrea
70	Dhekelia Sovereign Base Area
71	Spain
72	Estonia
73	Ethiopia
74	Finland
75	Fiji
76	Falkland Islands
77	France
78	Faroe Islands
79	Federated States of Micronesia
80	Gabon
81	United Kingdom
82	Georgia
83	Guernsey
84	Ghana
85	Gibraltar
86	Guinea
87	Gambia
88	Guinea Bissau
89	Equatorial Guinea
90	Greece
91	Grenada
92	Greenland
93	Guatemala
94	Guam
95	Guyana
96	Hong Kong S.A.R.
97	Heard Island and McDonald Islands
98	Honduras
99	Croatia

100	Haiti
101	Hungary
102	Indonesia
103	Isle of Man
104	India
105	Indian Ocean Territories
106	British Indian Ocean Territory
107	Ireland
108	Iran
109	Iraq
110	Iceland
111	Israel
112	Italy
113	Jamaica
114	Jersey
115	Jordan
116	Japan
117	Baykonur Cosmodrome
118	Siachen Glacier
119	Kazakhstan
120	Kenya
121	Kyrgyzstan
122	Cambodia
123	Kiribati
124	Saint Kitts and Nevis
125	South Korea
126	Kosovo
127	Kuwait
128	Laos
129	Lebanon
130	Liberia
131	Libya
132	Saint Lucia
133	Liechtenstein
134	Sri Lanka
135	Lesotho
136	Lithuania
137	Luxembourg
138	Latvia
139	Macao S.A.R
140	Saint Martin
141	Morocco
142	Monaco
143	Moldova
144	Madagascar
145	Maldives
146	Mexico
147	Marshall Islands
148	Macedonia

149	Mali
150	Malta
151	Myanmar
152	Montenegro
153	Mongolia
154	Northern Mariana Islands
155	Mozambique
156	Mauritania
157	Montserrat
158	Mauritius
159	Malawi
160	Malaysia
161	Namibia
162	New Caledonia
163	Niger
164	Norfolk Island
165	Nigeria
166	Nicaragua
167	Niue
168	Netherlands
169	Norway
170	Nepal
171	Nauru
172	New Zealand
173	Oman
174	Pakistan
175	Panama
176	Pitcairn Islands
177	Peru
178	Spratly Islands
179	Philippines
180	Palau
181	Papua New Guinea
182	Poland
183	Puerto Rico
184	North Korea
185	Portugal
186	Paraguay
187	Palestine
188	French Polynesia
189	Qatar
190	Romania
191	Russia
192	Rwanda
193	Western Sahara
194	Saudi Arabia
195	Scarborough Reef
196	Sudan
197	South Sudan

198	Senegal
199	Serranilla Bank
200	Singapore
201	South Georgia and South Sandwich Islands
202	Saint Helena
203	Solomon Islands
204	Sierra Leone
205	El Salvador
206	San Marino
207	Somaliland
208	Somalia
209	Saint Pierre and Miquelon
210	Republic of Serbia
211	Sao Tome and Principe
212	Suriname
213	Slovakia
214	Slovenia
215	Sweden
216	Swaziland
217	Sint Maarten
218	Seychelles
219	Syria
220	Turks and Caicos Islands
221	Chad
222	Togo
223	Thailand
224	Tajikistan
225	Turkmenistan
226	East Timor
227	Tonga
228	Trinidad and Tobago
229	Tunisia
230	Turkey
231	Tuvalu
232	Taiwan
233	United Republic of Tanzania
234	Uganda
235	Ukraine
236	United States Minor Outlying Islands
237	Uruguay
238	United States of America
239	US Naval Base Guantanamo Bay
240	Uzbekistan
241	Vatican
242	Saint Vincent and the Grenadines
243	Venezuela
244	British Virgin Islands
245	United States Virgin Islands
246	Vietnam

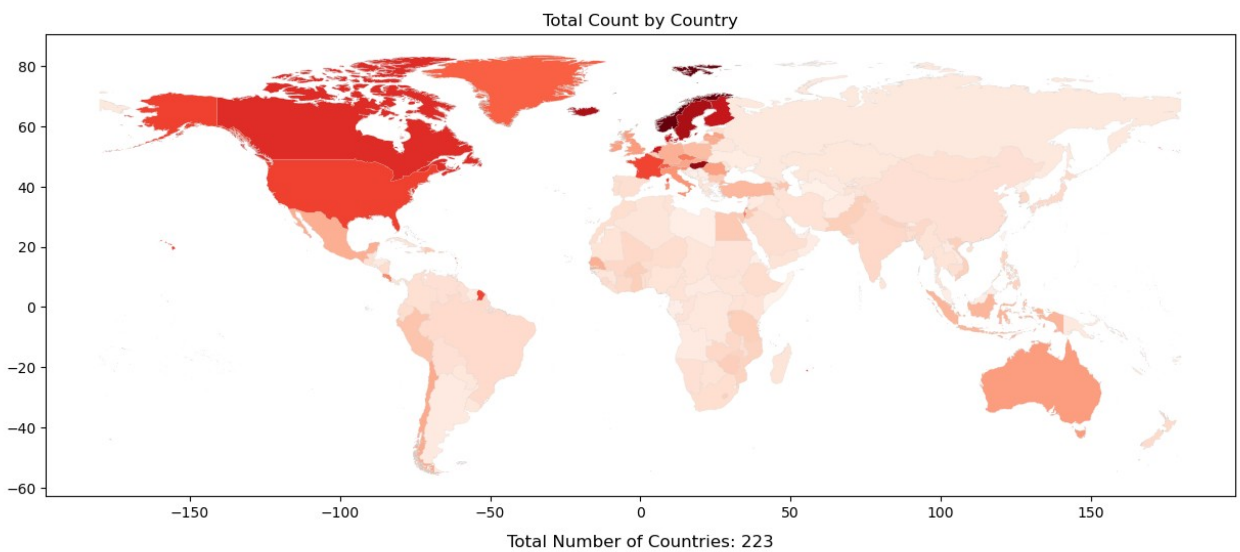
```
247                                       Vanuatu
248                             Wallis and Futuna
249                   Akrotiri Sovereign Base Area
250                                         Samoa
251                                         Yemen
252                                  South Africa
253                                        Zambia
254                                      Zimbabwe
```

```
world_MAS = world.merge(marriage_patterns, how='left',
left_on='ADMIN', right_on='Country')

# Display the first few rows to check the merge
print(world_MAS.head())
```

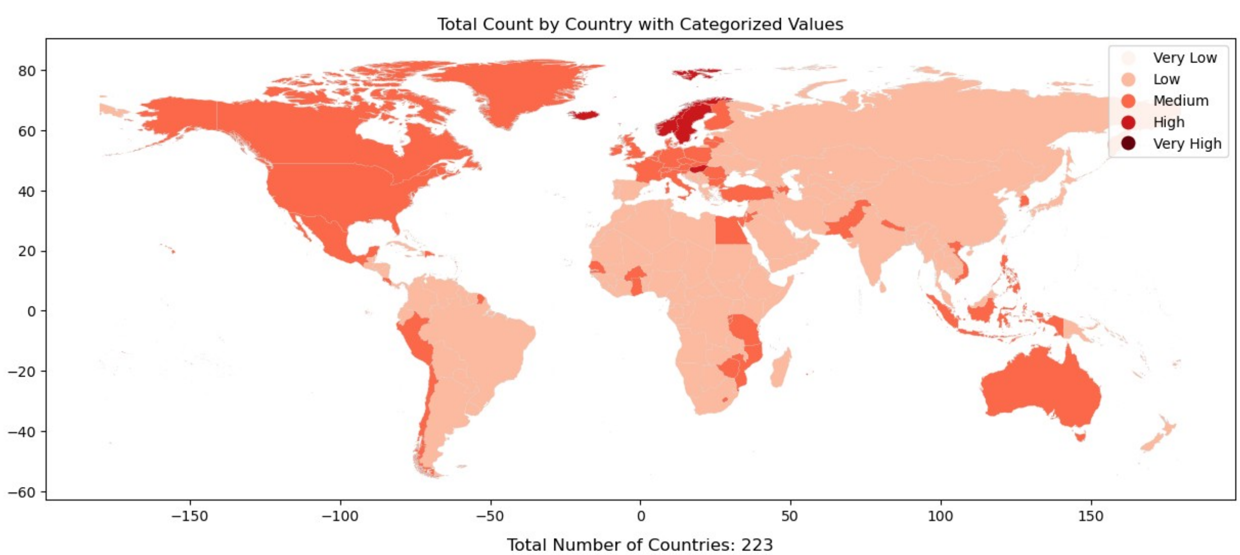
```
   scalerank       featurecla  LABELRANK      SOVEREIGNT SOV_A3
ADM0_DIF  \
0          3  Admin-0 country        5.0     Netherlands    NL1
1.0
1          0  Admin-0 country        3.0     Afghanistan    AFG
0.0
2          0  Admin-0 country        3.0          Angola    AGO
0.0
3          3  Admin-0 country        6.0  United Kingdom    GB1
1.0
4          0  Admin-0 country        6.0         Albania    ALB
0.0

   LEVEL              TYPE        ADMIN ADM0_A3  ...  TINY
HOMEPART  \
0    2.0           Country        Aruba     ABW  ...   4.0    -99.0

1    2.0  Sovereign country  Afghanistan     AFG  ... -99.0      1.0

2    2.0  Sovereign country       Angola     AGO  ... -99.0      1.0

3    2.0        Dependency     Anguilla     AIA  ... -99.0    -99.0

4    2.0  Sovereign country      Albania     ALB  ... -99.0      1.0


                                            geometry      Country
Married  \
0  POLYGON ((-69.99694 12.57758, -69.93639 12.531...        Aruba
112.0
1  POLYGON ((71.0498 38.40866, 71.05714 38.40903,...  Afghanistan
116.0
2  MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...       Angola
95.0
3  MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...     Anguilla
38.0
```

```
4  POLYGON ((19.74777 42.5789, 19.74601 42.57993,...      Albania
185.0

  Single  Divorced Widowed Separated  Total
0   28.0     112.0   112.0     112.0  476.0
1   14.0     100.0    71.0     116.0  417.0
2   87.0     101.0    48.0     121.0  452.0
3   38.0      38.0    38.0      38.0  190.0
4   61.0     141.0    91.0     191.0  669.0

[5 rows x 73 columns]
```

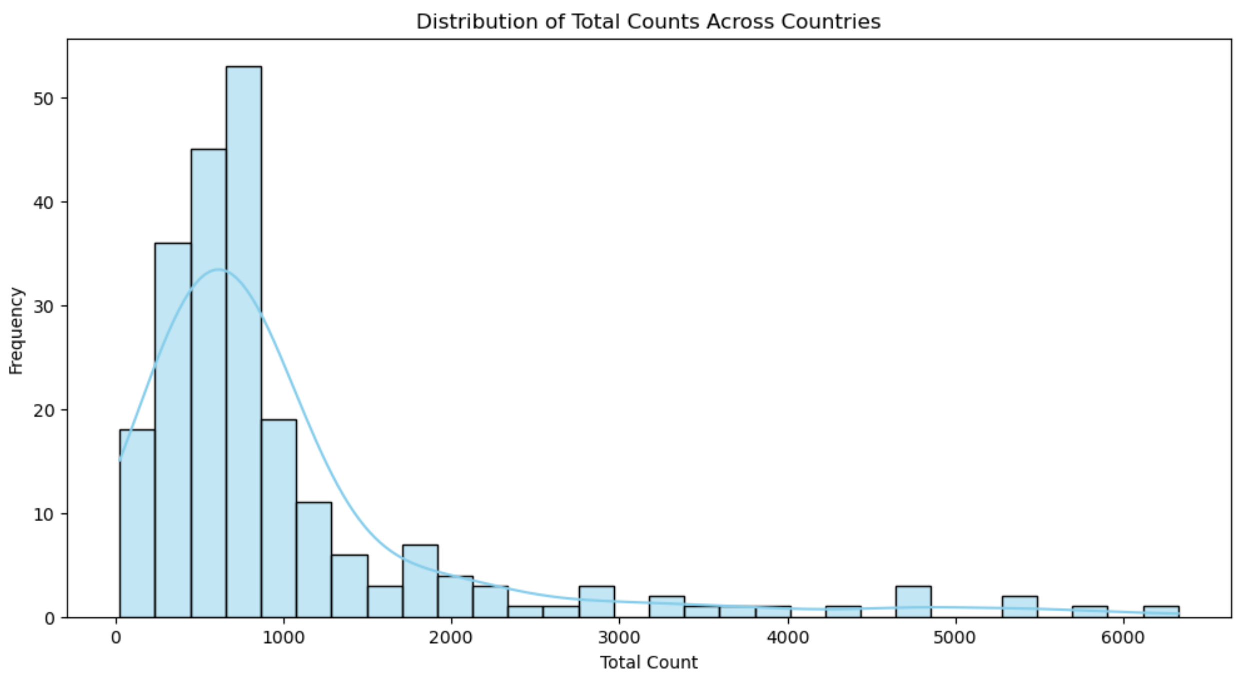
```python
import matplotlib.pyplot as plt

# Calculate the total number of unique countries
total_countries = world_MAS['Country'].nunique()

# Plot Total Count by Country on a Map
fig, ax = plt.subplots(1, 1, figsize=(15, 10))

world_MAS.plot(column='Total', cmap='Reds', linewidth=0.1, ax=ax,
edgecolor='0.8')

# Set the title
ax.set_title('Total Count by Country')

# Display the total number of countries as a text annotation on the
map
plt.text(0.5, -0.1, f'Total Number of Countries: {total_countries}',
         ha='center', va='center', transform=ax.transAxes,
fontsize=12)

plt.show()
```

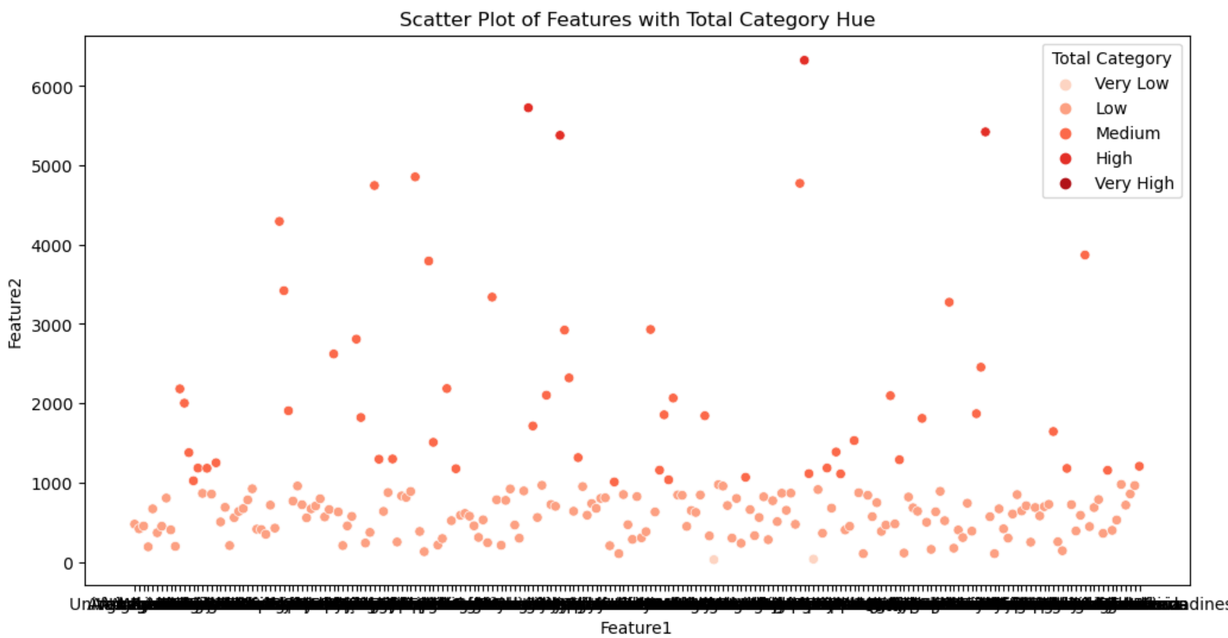


```
import matplotlib.pyplot as plt
import numpy as np

# Categorize the 'Total' values into bins (for example, low, medium,
high)
bins = [0, 100, 1000, 5000, 10000, np.inf]  # Adjust the bin edges
based on your data
labels = ['Very Low', 'Low', 'Medium', 'High', 'Very High']
world_MAS['Total_Category'] = pd.cut(world_MAS['Total'], bins=bins,
labels=labels)

# Calculate the total number of unique countries
total_countries = world_MAS['Country'].nunique()

# Plot Total Count by Country on a Map with Hue based on categories
fig, ax = plt.subplots(1, 1, figsize=(15, 10))

world_MAS.plot(column='Total_Category', cmap='Reds', linewidth=0.1,
ax=ax, edgecolor='0.8', legend=True)

# Set the title
ax.set_title('Total Count by Country with Categorized Values')

# Display the total number of countries as a text annotation on the
map
plt.text(0.5, -0.1, f'Total Number of Countries: {total_countries}',
         ha='center', va='center', transform=ax.transAxes,
fontsize=12)

plt.show()
```



```python
import matplotlib.pyplot as plt
import seaborn as sns

# Plot distribution of total counts across countries
plt.figure(figsize=(12, 6))
sns.histplot(world_MAS['Total'], bins=30, kde=True, color='skyblue')
plt.title('Distribution of Total Counts Across Countries')
plt.xlabel('Total Count')
plt.ylabel('Frequency')
plt.show()

# Scatter plot if you have multiple features
plt.figure(figsize=(12, 6))
sns.scatterplot(data=world_MAS, x='Country', y='Total',
hue='Total_Category', palette='Reds')
plt.title('Scatter Plot of Features with Total Category Hue')
plt.xlabel('Feature1')
plt.ylabel('Feature2')
plt.legend(title='Total Category')
plt.show()
```






```
# Check for missing values
print(world_MAS.isna().sum())

# Option 1: Drop rows with missing values
world_MAS = world_MAS.dropna(subset=['Total'])

# Option 2: Fill missing values (e.g., with mean, median, or a
constant value)
# Replace missing values with the mean of the column
world_MAS['Total'] =
world_MAS['Total'].fillna(world_MAS['Total'].mean())

scalerank          0
featurecla         0
LABELRANK          0
SOVEREIGNT         0
SOV_A3             0
                  ..
Divorced          32
Widowed           32
Separated         32
Total             32
Total_Category    32
Length: 74, dtype: int64
```

4. Modelling

4.1 K-Mean Clustering

```
# Step 1: Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns

cleaned_dataset = pd.read_csv("World_Marriage_Cleaned_Dataset.csv")

cleaned_dataset
```

```
            Country Age Group    Sex Marital Status Data Process
Start Year  \
0       Afghanistan   [15-19]    Man       Divorced       Survey
1972
1       Afghanistan   [20-24]    Man       Divorced       Survey
1972
2       Afghanistan   [25-29]    Man       Divorced       Survey
1972
3       Afghanistan   [30-34]    Man       Divorced       Survey
1972
4       Afghanistan   [35-39]    Man       Divorced       Survey
1972
...             ...       ...    ...            ...          ...
...
228211     Zimbabwe   [55-59]  Woman        Widowed       Survey
2017
228212     Zimbabwe   [60-64]  Woman        Widowed       Survey
2017
228213     Zimbabwe   [65-69]  Woman        Widowed       Survey
2017
228214     Zimbabwe   [70-74]  Woman        Widowed       Survey
2017
228215     Zimbabwe     [75+]  Woman        Widowed       Survey
2017

        End Year          Data Source
0           1974  National statistics
1           1974  National statistics
2           1974  National statistics
3           1974  National statistics
4           1974  National statistics
...          ...                  ...
```

```
228211      2017  National statistics
228212      2017  National statistics
228213      2017  National statistics
228214      2017  National statistics
228215      2017  National statistics

[228216 rows x 8 columns]
```

```
#App 1: Identifying country groups based on marriage patterns
# Select columns that may be relevant for clustering
New_Data = cleaned_dataset[['Country', 'Marital Status']]

New_Data
```

```
            Country Marital Status
0       Afghanistan       Divorced
1       Afghanistan       Divorced
2       Afghanistan       Divorced
3       Afghanistan       Divorced
4       Afghanistan       Divorced
...             ...            ...
228211     Zimbabwe        Widowed
228212     Zimbabwe        Widowed
228213     Zimbabwe        Widowed
228214     Zimbabwe        Widowed
228215     Zimbabwe        Widowed

[228216 rows x 2 columns]
```

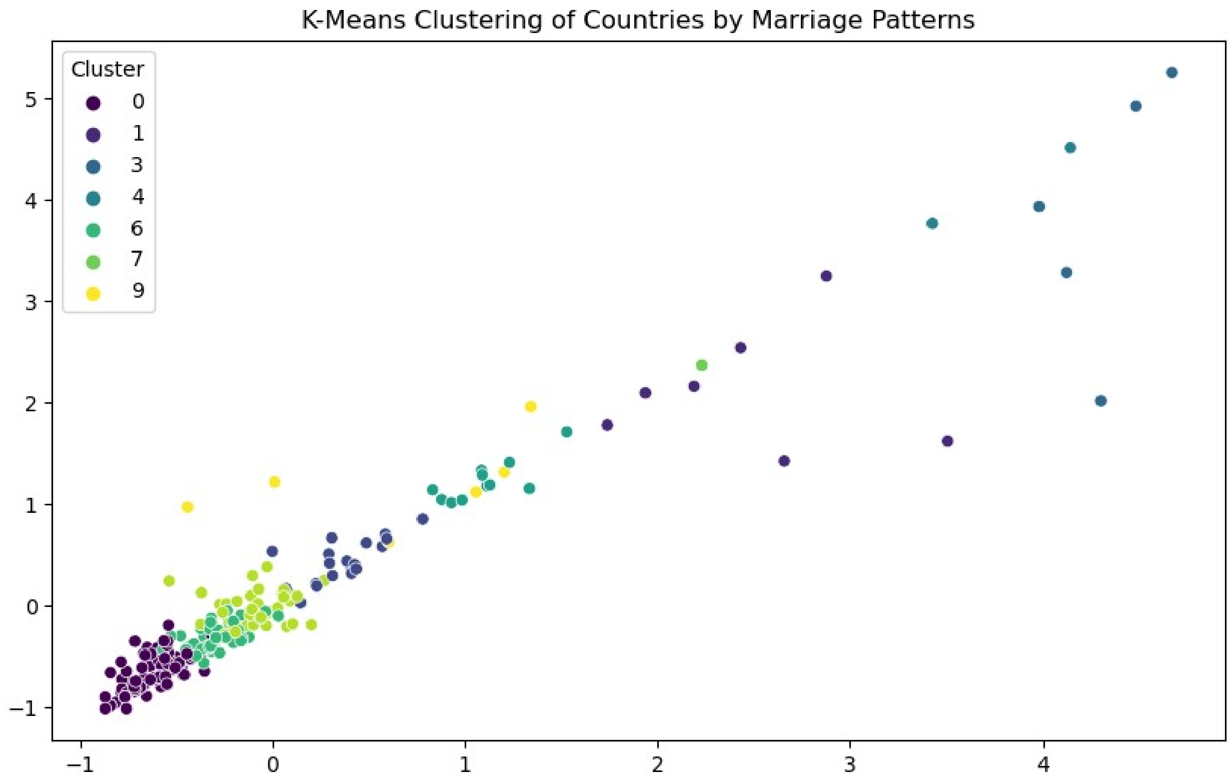
```
# Example: Aggregate the data by country without using percentage
fields
marriage_patterns = marital_counts.groupby('Country').agg({
    'Married': 'sum',
    'Single': 'sum',
    'Divorced': 'sum',
    'Widowed': 'sum',
    'Separated': 'sum',
}).reset_index()

# Example assuming each row represents an individual
cleaned_dataset['Count'] = 1

# Pivot the data
marital_counts = cleaned_dataset.pivot_table(index='Country',
columns='Marital Status', values='Count', aggfunc='sum',
fill_value=0).reset_index()

# Rename the columns for clarity
marital_counts.columns = ['Country', 'Divorced', 'Married', 'Single',
'Widowed','Separated']
```

```
marital_counts

                Country  Divorced  Married  Single  Widowed  Separated
0           Afghanistan       100      116      14       71        116
1               Albania       141      185      61       91        191
2               Algeria       129      162      57      129        160
3        American Samoa        84       86      58       90         86
4                Angola       101       95      87       48        121
..                  ...       ...      ...     ...      ...        ...
229   Wallis and Futuna        77      152       0      156        143
230      Western Sahara        28        0      28       28         28
231               Yemen       204      205       0      102        205
232              Zambia       252      252     101       86        272
233            Zimbabwe       219      353      66      191        377

[234 rows x 6 columns]

# Calculate the total population for each country
marital_counts['Total'] = marital_counts[['Divorced', 'Married',
'Single', 'Widowed','Separated']].sum(axis=1)

marital_counts

                Country  Divorced  Married  Single  Widowed  Separated
Total
0           Afghanistan       100      116      14       71        116
417
1               Albania       141      185      61       91        191
669
2               Algeria       129      162      57      129        160
637
3        American Samoa        84       86      58       90         86
404
4                Angola       101       95      87       48        121
452
..                  ...       ...      ...     ...      ...        ...
...
229   Wallis and Futuna        77      152       0      156        143
528
230      Western Sahara        28        0      28       28         28
112
231               Yemen       204      205       0      102        205
716
232              Zambia       252      252     101       86        272
963
233            Zimbabwe       219      353      66      191        377
1206

[234 rows x 7 columns]

X = marital_counts
```

```python
# Drop non-numeric columns (like 'Country')
App1 = X.drop(columns=['Country'])

# Check for any non-numeric columns that need encoding
print(App1.dtypes)

# If there are categorical columns, apply encoding before scaling
(optional)
# Example: Suppose there's a column 'Marital_Status', encode it like
this:
# X['Marital_Status'] =
X['Marital_Status'].astype('category').cat.codes

# Apply StandardScaler to the numerical data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(App1)

# Perform K-Means clustering
optimal_k = 10  # Choose based on the Elbow method
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
X['Cluster'] = kmeans.fit_predict(X_scaled)

# Print and visualize the results
print(X[['Country', 'Cluster']].head())
```

```
Divorced     int64
Married      int64
Single       int64
Widowed      int64
Separated    int64
Total        int64
dtype: object
          Country  Cluster
0     Afghanistan        0
1         Albania        6
2         Algeria        6
3  American Samoa        0
4          Angola        0
```

```python
# Visualize the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=X_scaled[:, 0], y=X_scaled[:, 1], hue=X['Cluster'],
palette='viridis')
plt.title('K-Means Clustering of Countries by Marriage Patterns')
plt.show()

# Print the clustering results
print(X[['Country', 'Cluster']].head())
```

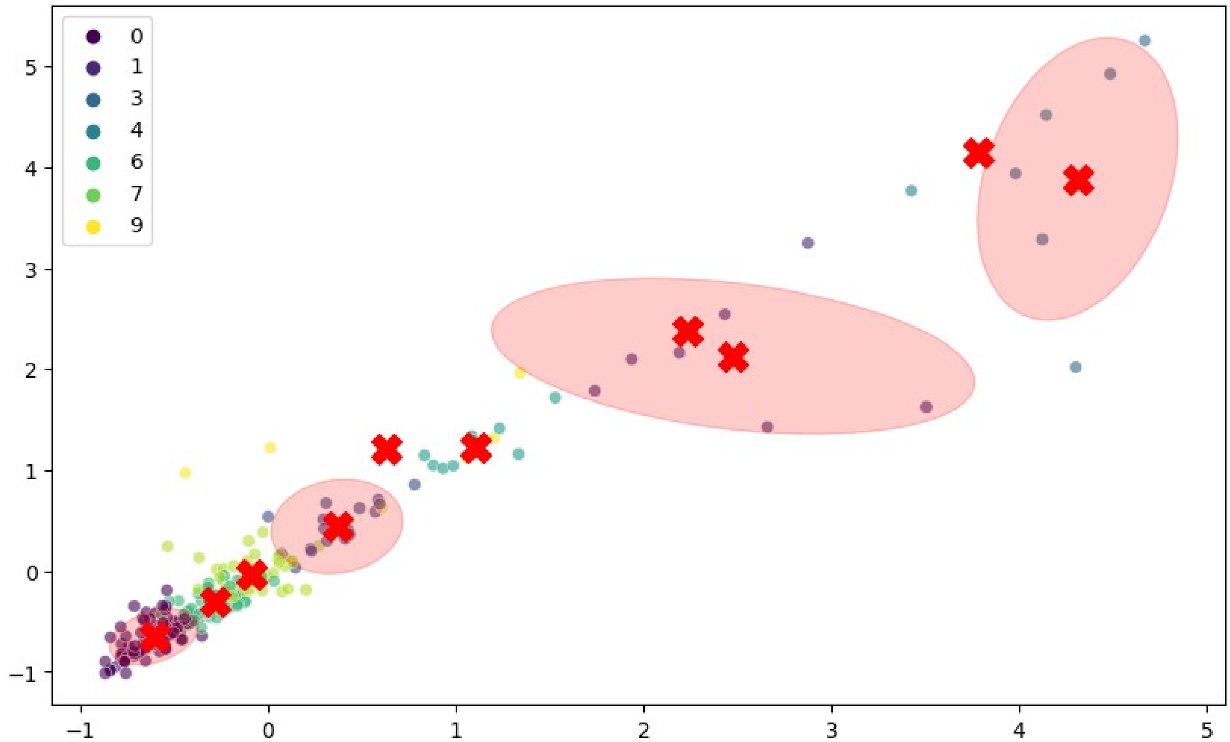



```
           Country  Cluster
0      Afghanistan        0
1          Albania        6
2          Algeria        6
3   American Samoa        0
4           Angola        0
```

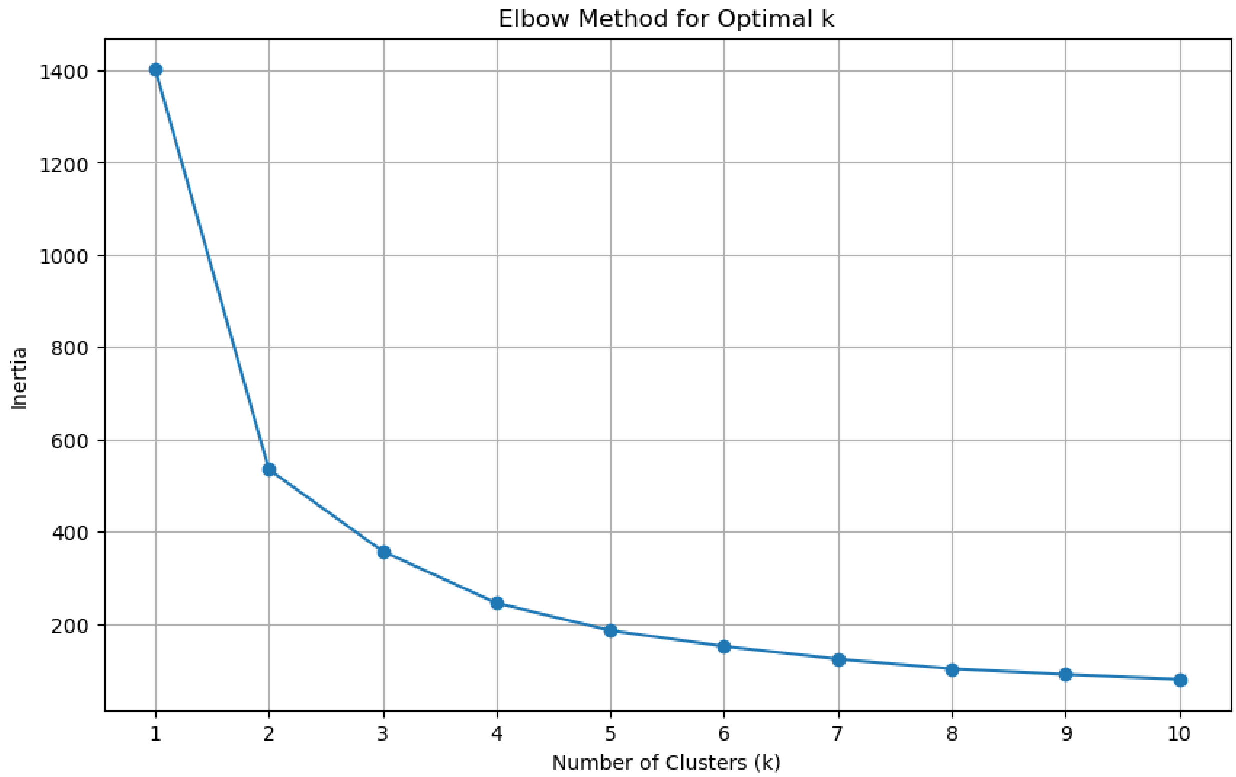
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from matplotlib.patches import Ellipse

# Assuming 'X_scaled' contains the scaled data and 'kmeans' is your
KMeans object
centroids = kmeans.cluster_centers_
labels = X['Cluster'].values

# Create a scatter plot
plt.figure(figsize=(10, 6))
scatter = sns.scatterplot(x=X_scaled[:, 0], y=X_scaled[:, 1],
hue=labels, palette='viridis', alpha=0.6)

# Plot centroids
plt.scatter(centroids[:, 0], centroids[:, 1], s=200, c='red',
label='Centroids', marker='X')
```

```
# Add ellipses for each cluster
for i in range(centroids.shape[0]):
    cluster_data = X_scaled[labels == i]
    if cluster_data.size > 0:
        # Calculate the mean and covariance
        mean = cluster_data.mean(axis=0)
        cov = np.cov(cluster_data, rowvar=False)

        # Calculate the ellipse parameters
        eigenvalues, eigenvectors = np.linalg.eig(cov)
        # Ensure the eigenvalues are sorted in descending order
        order = eigenvalues.argsort()[::-1]
        eigenvalues = eigenvalues[order]
        eigenvectors = eigenvectors[:, order]

        # Create the ellipse
        angle = np.arctan2(eigenvectors[1, 0], eigenvectors[0, 0])
        ellipse = Ellipse(xy=mean, width=2 * np.sqrt(eigenvalues[0]),
height=2 * np.sqrt(eigenvalues[1]),
                          angle=np.degrees(angle), color='red',
alpha=0.2)
        plt.gca().add_patch(ellipse)

# Add titles and labels
plt.title('K-Means Clustering of Countries by Marriage Patterns')
plt.xlabel('Feature 1')  # Replace with appropriate feature label
plt.ylabel('Feature 2')  # Replace with appropriate feature label
plt.legend()
plt.show()

# Print the clustering results in ellipses
print("\nClustering Results:")
print("─────────────────────────────")
print(X[['Country', 'Cluster']].head().to_string(index=False))
print("─────────────────────────────")

----------------------------------------------------------------------
-----
TypeError                                 Traceback (most recent call
last)
Cell In[196], line 33
     30 eigenvectors = eigenvectors[:, order]
     32 # Create the ellipse
---> 33 angle = np.arctan2(eigenvectors[1, 0], eigenvectors[0, 0])
     34 ellipse = Ellipse(xy=mean, width=2 * np.sqrt(eigenvalues[0]),
height=2 * np.sqrt(eigenvalues[1]),
     35                   angle=np.degrees(angle), color='red',
alpha=0.2)
     36 plt.gca().add_patch(ellipse)
```

```
TypeError: ufunc 'arctan2' not supported for the input types, and the
inputs could not be safely coerced to any supported types according to
the casting rule ''safe''
```

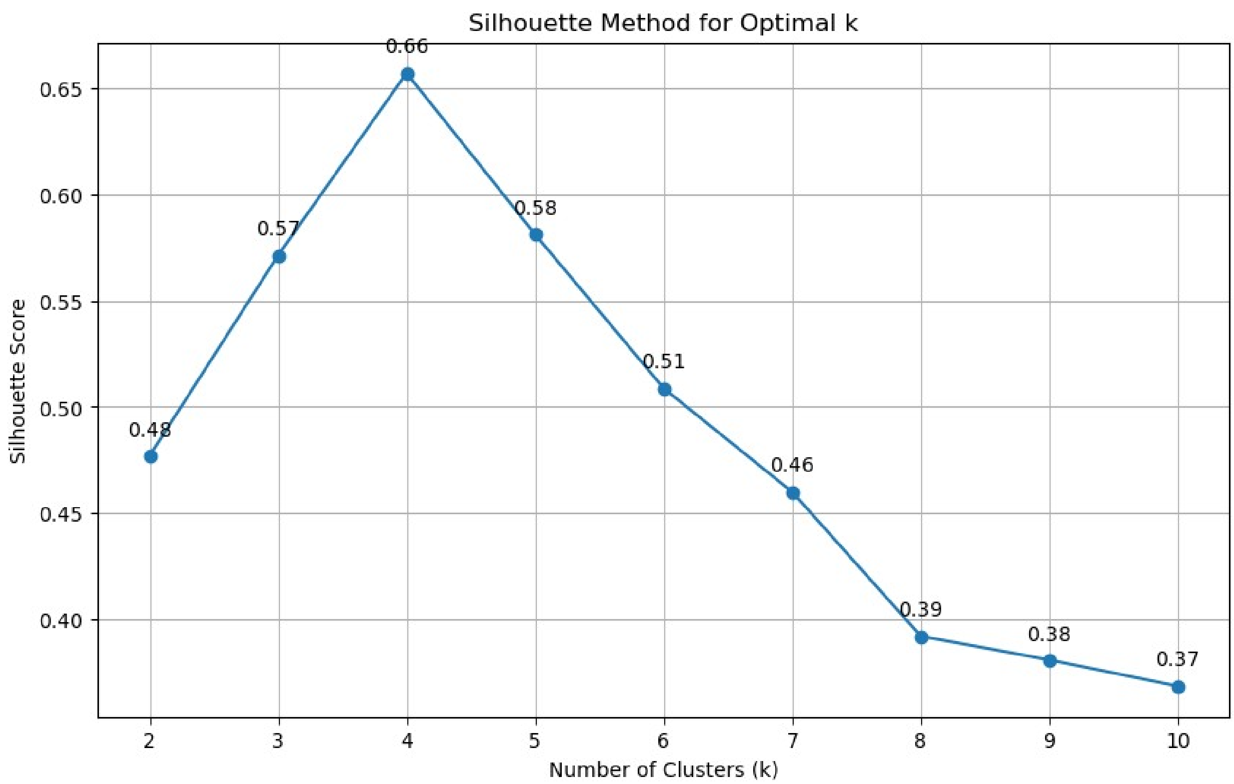



```python
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# Range of clusters to try
inertia = []
k_values = range(1, 11)

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

# Plotting the Elbow Method
plt.figure(figsize=(10, 6))
plt.plot(k_values, inertia, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.xticks(k_values)
plt.grid()
plt.show()
```




```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs
from sklearn.preprocessing import StandardScaler

# Generate sample data
X, _ = make_blobs(n_samples=300, centers=4, cluster_std=0.60,
random_state=0)
X_scaled = StandardScaler().fit_transform(X)

# Define the range of k values
k_values = range(2, 11)  # You can adjust this range as needed

silhouette_scores = []

for k in k_values:  # start from 2 clusters
    kmeans = KMeans(n_clusters=k, random_state=42)
    cluster_labels = kmeans.fit_predict(X_scaled)
    silhouette_avg = silhouette_score(X_scaled, cluster_labels)
    silhouette_scores.append(silhouette_avg)

# Plotting the Silhouette Method
plt.figure(figsize=(10, 6))
plt.plot(k_values, silhouette_scores, marker='o')
```

```python
plt.title('Silhouette Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.xticks(k_values)
plt.grid()

# Annotate each point with its silhouette score
for i, score in enumerate(silhouette_scores):
    plt.annotate(f'{score:.2f}',
                 (k_values[i], score),
                 textcoords="offset points",
                 xytext=(0,10),
                 ha='center')

plt.show()

# Print the silhouette scores
for k, score in zip(k_values, silhouette_scores):
    print(f'Number of clusters: {k}, Silhouette Score: {score:.2f}')
```



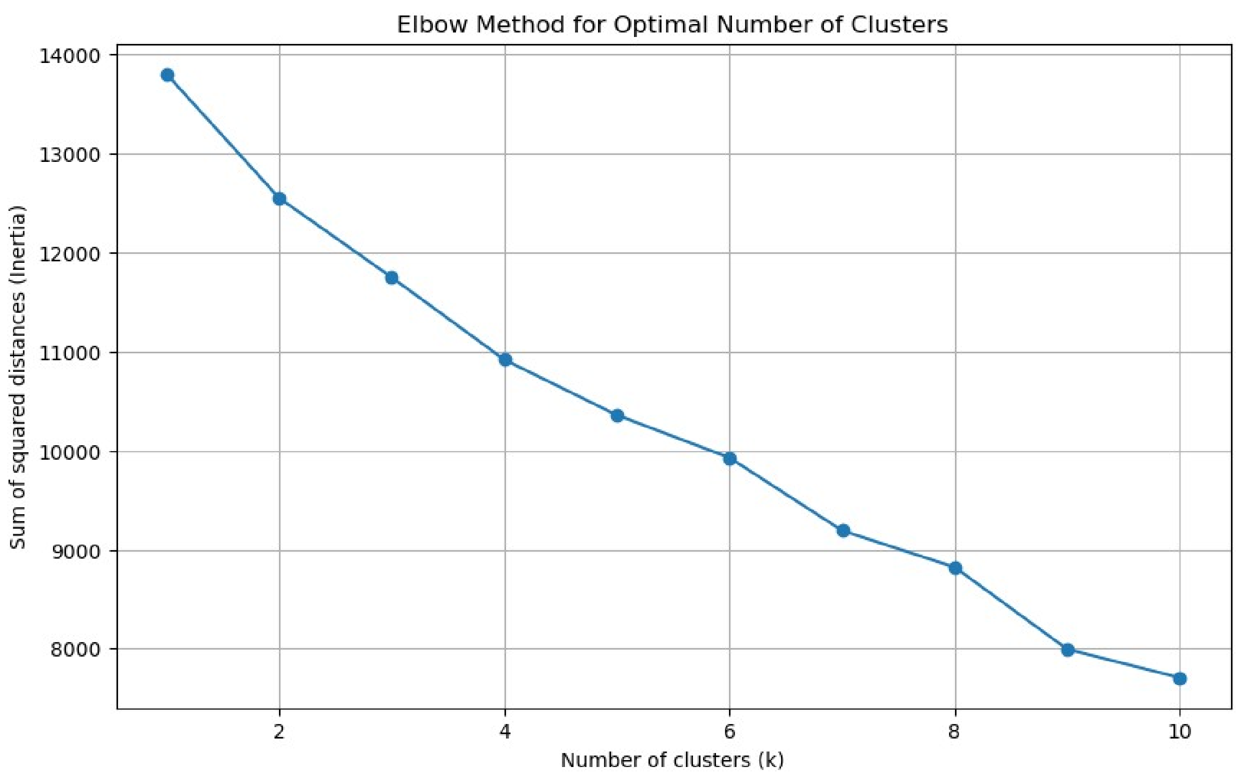

```
Number of clusters: 2, Silhouette Score: 0.48
Number of clusters: 3, Silhouette Score: 0.57
Number of clusters: 4, Silhouette Score: 0.66
Number of clusters: 5, Silhouette Score: 0.58
Number of clusters: 6, Silhouette Score: 0.51
```

```
Number of clusters: 7, Silhouette Score: 0.46
Number of clusters: 8, Silhouette Score: 0.39
Number of clusters: 9, Silhouette Score: 0.38
Number of clusters: 10, Silhouette Score: 0.37
```

```
#App 2: K-Means
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

# Load the dataset
df = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')

# Verify and correct column names if needed
df.columns = df.columns.str.strip()  # Remove any leading/trailing
whitespace

if 'Count' not in df.columns:
    df['Population_Count'] = 1

# Select relevant columns
columns = ['Country', 'Age Group', 'Marital Status',
'Population_Count']  # Ensure these columns exist
marriage_data = df[columns].dropna()

# Pivot the data to create a matrix for clustering
pivot_data = marriage_data.pivot_table(index='Country', columns='Age
Group', values='Population_Count', fill_value=0)

# Standardize the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(pivot_data)

# Check scaled data shape
print(scaled_data)
```

```
[[ 6.164414   -0.18814417 -0.06551218 ...  0.28867513 -0.09284767
   0.27989465]
 [-0.16222142 -0.18814417 -0.06551218 ...  0.28867513 -0.09284767
   0.27989465]
 [-0.16222142 -0.18814417 -0.06551218 ...  0.28867513 -0.09284767
   0.27989465]
 ...
 [-0.16222142 -0.18814417 -0.06551218 ...  0.28867513 -0.09284767
   0.27989465]
```

```
 [-0.16222142 -0.18814417 -0.06551218 ...  0.28867513 -0.09284767
   0.27989465]
 [-0.16222142 -0.18814417 -0.06551218 ...  0.28867513 -0.09284767
   0.27989465]]

# Use the Elbow method to find the optimal number of clusters
sse = []
k_range = range(1, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)
    sse.append(kmeans.inertia_)

# Plot the Elbow graph
plt.figure(figsize=(10,6))
plt.plot(k_range, sse, marker='o')
plt.title('Elbow Method for Optimal Number of Clusters')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Sum of squared distances (Inertia)')
plt.grid(True)
plt.show()
```




```
# Apply K-Means with the optimal number of clusters (e.g., k = 4)
optimal_k = 4  # Replace with the optimal k from the Elbow graph
```

```python
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans.fit(scaled_data)

# Add cluster labels to the original data
pivot_data['Cluster'] = kmeans.labels_
print(pivot_data.head())
```

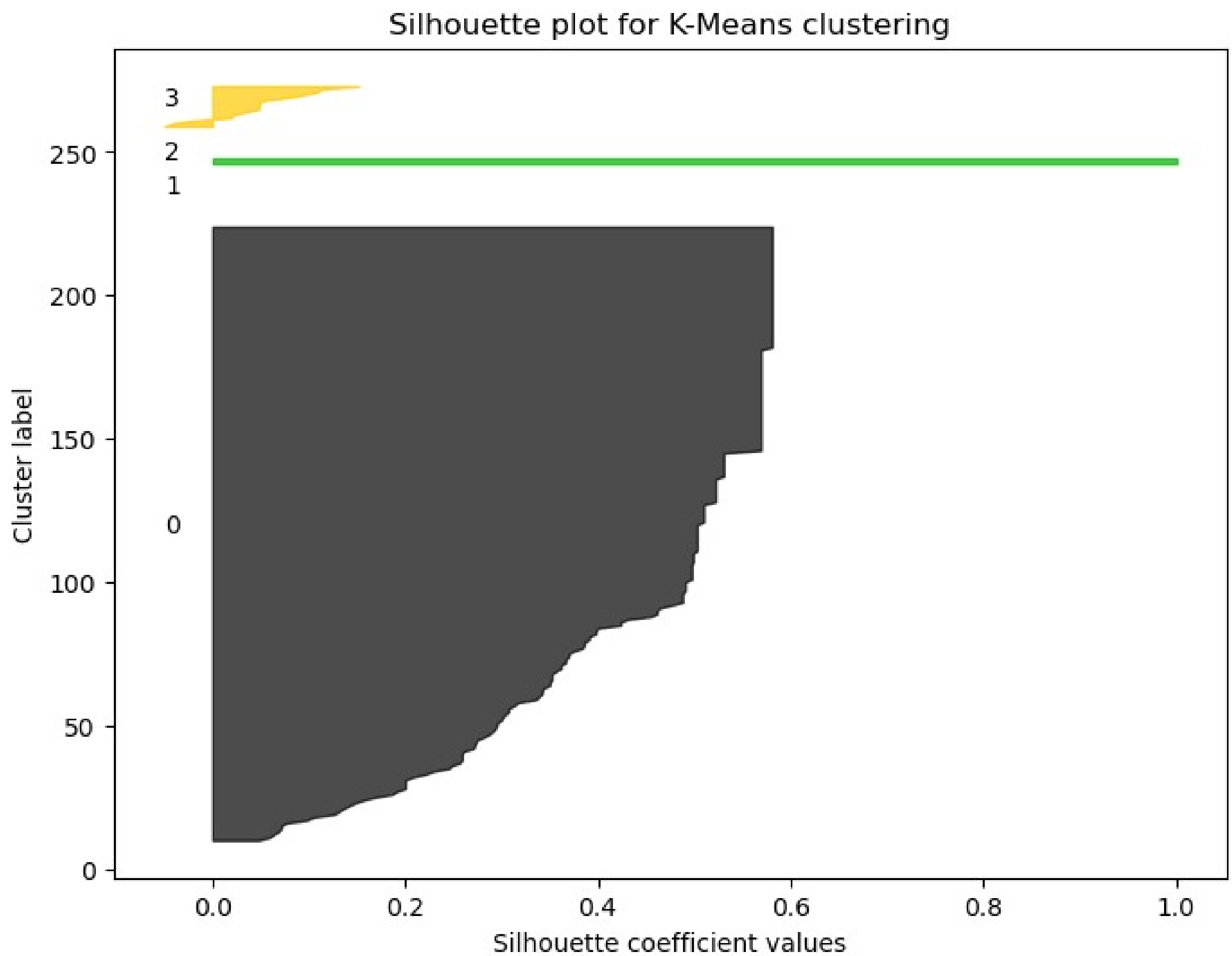
```
Age Group       [0-14]  [0-15]  [0-19]  [10-14]  [10-19]  [12-14]
[12-19]  \
Country

Afghanistan          1       0       0        1        0        0
0
Albania              0       0       0        1        0        0
0
Algeria              0       0       0        1        0        0
0
American Samoa       0       0       0        1        0        0
0
Angola               0       0       0        1        0        0
0

Age Group       [14-19]  [15-17]  [15-19]  ...  [65+]  [65-69]  [65-
74]  \
Country                                    ...

Afghanistan           0        0        1  ...      1        1
0
Albania               0        0        1  ...      1        1
0
Algeria               0        0        1  ...      1        1
0
American Samoa        0        0        1  ...      1        1
0
Angola                0        0        1  ...      0        1
0

Age Group       [65-79]  [67-69]  [70+]  [70-74]  [70-79]  [75+]
Cluster
Country

Afghanistan           0        0      0        1        0      1
0
Albania               0        0      0        1        0      1
0
Algeria               0        0      1        1        0      1
0
American Samoa        0        0      0        1        0      1
3
Angola                0        0      0        1        0      1
```

```
0

[5 rows x 64 columns]
```

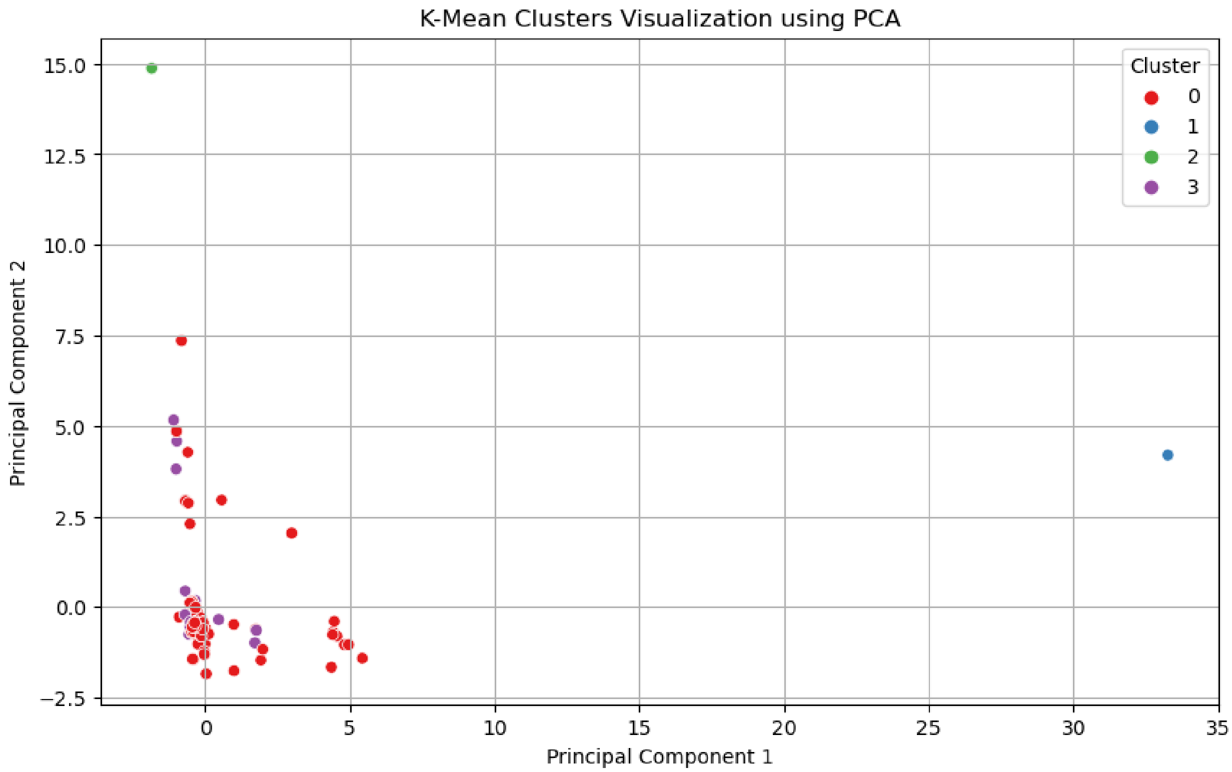
```
# Calculate the Silhouette score
silhouette_avg = silhouette_score(scaled_data, kmeans.labels_)
print(f'Silhouette Score for {optimal_k} clusters: {silhouette_avg}')
```

```
Silhouette Score for 4 clusters: 0.42536525462212244
```

```
# Optional: Visualize Silhouette Score for each sample
from sklearn.metrics import silhouette_samples
import matplotlib.cm as cm

# Compute the silhouette scores for each sample
sample_silhouette_values = silhouette_samples(scaled_data,
kmeans.labels_)

fig, ax = plt.subplots(1, 1, figsize=(8, 6))
y_lower = 10
for i in range(optimal_k):
    ith_cluster_silhouette_values =
sample_silhouette_values[kmeans.labels_ == i]
    ith_cluster_silhouette_values.sort()
    size_cluster_i = ith_cluster_silhouette_values.shape[0]
    y_upper = y_lower + size_cluster_i
    color = cm.nipy_spectral(float(i) / optimal_k)
    ax.fill_betweenx(np.arange(y_lower, y_upper), 0,
ith_cluster_silhouette_values, facecolor=color, edgecolor=color,
alpha=0.7)
    ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
    y_lower = y_upper + 10

ax.set_title("Silhouette plot for K-Means clustering")
ax.set_xlabel("Silhouette coefficient values")
ax.set_ylabel("Cluster label")
plt.show()
```




```python
# Perform PCA for 2D visualization
pca = PCA(n_components=2)
pca_data = pca.fit_transform(scaled_data)

# Create a DataFrame for the PCA data
pca_df = pd.DataFrame(data=pca_data, columns=['PC1', 'PC2'])
pca_df['Cluster'] = kmeans.labels_

# Plot the PCA result with clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PC1', y='PC2', hue='Cluster', data=pca_df,
palette='Set1')
plt.title('K-Mean Clusters Visualization using PCA')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.grid(True)
plt.show()
```

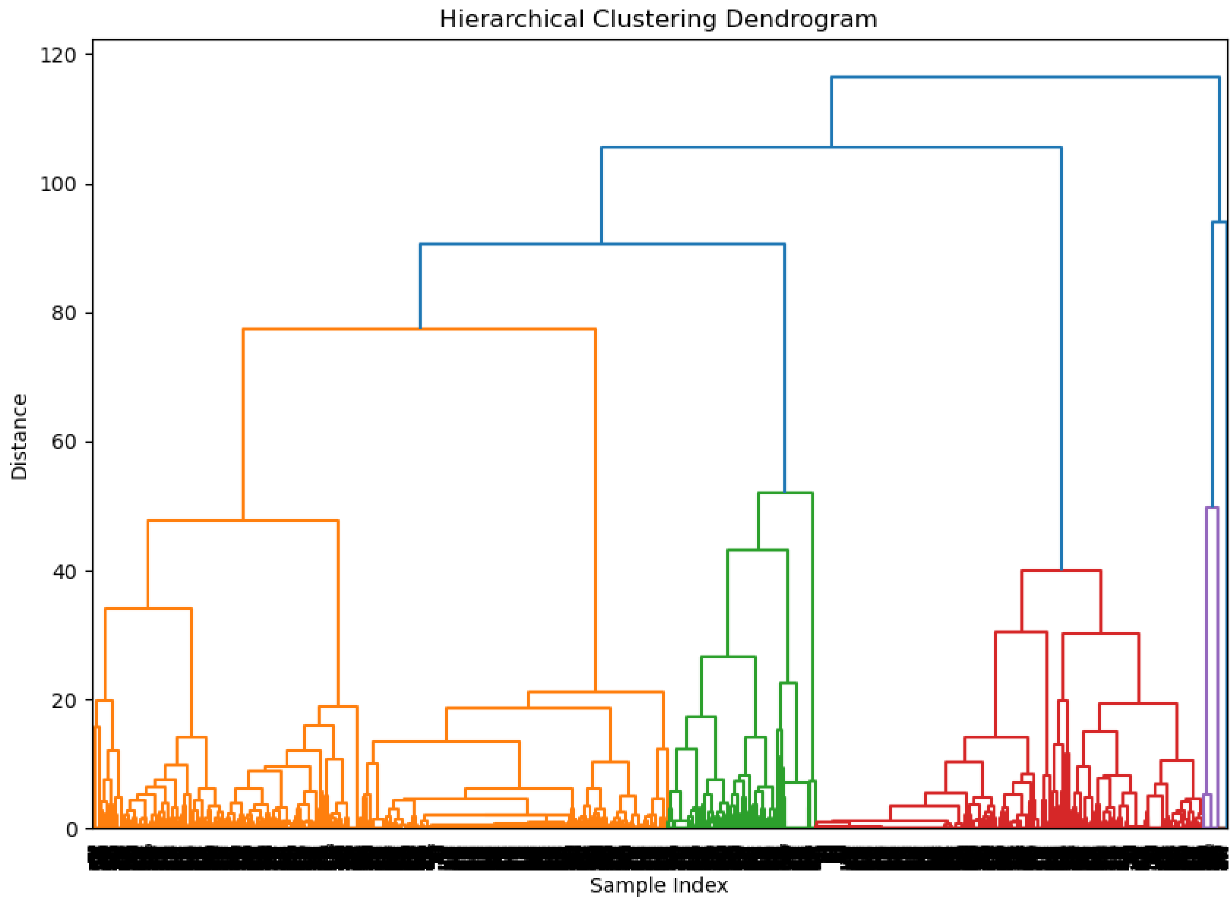


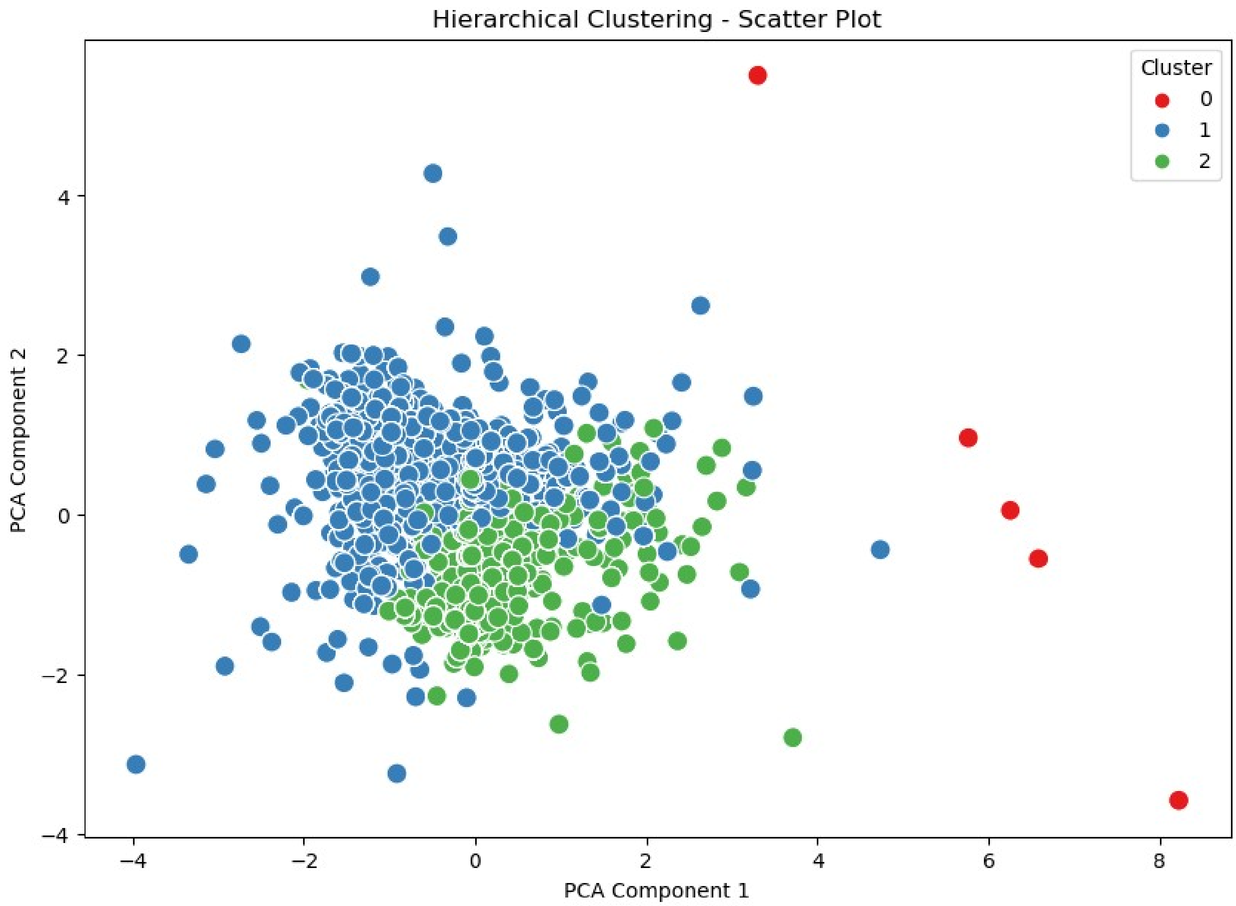
4.2 Hierarchical Clustering

```
import pandas as pd
from sklearn.preprocessing import OneHotEncoder

# Load dataset
df = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')

# Select relevant columns
df = df[['Country', 'Age Group', 'Sex', 'Marital Status']]

# One-hot encoding
encoder = OneHotEncoder(sparse=False)
encoded_features = encoder.fit_transform(df[['Country', 'Age Group',
'Sex', 'Marital Status']])

# Aggregate data
# For example, you might group by Country, Age Group, and Sex and
calculate proportions of marital status

# Example aggregation
df_aggregated = df.groupby(['Country', 'Age Group', 'Sex', 'Marital
Status']).size().unstack(fill_value=0)
df_normalized = df_aggregated.div(df_aggregated.sum(axis=1), axis=0)
```

```python
import pandas as pd
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.decomposition import PCA
from sklearn.cluster import AgglomerativeClustering
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset
df = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')

# Select relevant columns
df = df[['Country', 'Age Group', 'Sex', 'Marital Status']]

# One-hot encoding for categorical variables
encoder = OneHotEncoder(sparse_output=False)
encoded_features = encoder.fit_transform(df[['Country', 'Age Group',
'Sex', 'Marital Status']])

# Convert encoded features back to a DataFrame and ensure the correct
length
encoded_df = pd.DataFrame(encoded_features,
columns=encoder.get_feature_names_out(['Country', 'Age Group', 'Sex',
'Marital Status']))

# Concatenate the encoded features back with the original DataFrame
(optional)
# df_encoded = pd.concat([df.reset_index(drop=True), encoded_df],
axis=1)

# Aggregation step - ensure the aggregation is compatible with encoded
data
# Example: Group by 'Country', 'Age Group', and 'Sex' and calculate
counts for marital status
df_aggregated = df.groupby(['Country', 'Age Group', 'Sex', 'Marital
Status']).size().unstack(fill_value=0)

# Normalize the aggregated data
df_normalized = df_aggregated.div(df_aggregated.sum(axis=1), axis=0)

# Scale features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(df_normalized)

# Perform hierarchical clustering
linked = linkage(scaled_features, method='ward')

# Plot dendrogram
plt.figure(figsize=(10, 7))
```

```
dendrogram(linked, orientation='top', distance_sort='descending',
show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Sample Index')
plt.ylabel('Distance')
plt.show()

# Use Agglomerative Clustering to fit the data
n_clusters = 3  # You can adjust this number
hc = AgglomerativeClustering(n_clusters=n_clusters,
affinity='euclidean', linkage='ward')
df_normalized['Cluster'] = hc.fit_predict(scaled_features)

# Reduce dimensionality to 2D using PCA for scatter plot visualization
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_features)
df_normalized['PCA1'] = pca_result[:, 0]
df_normalized['PCA2'] = pca_result[:, 1]

# Plot the clusters in a scatter plot
plt.figure(figsize=(10, 7))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=df_normalized,
palette='Set1', s=100, marker='o')
plt.title('Hierarchical Clustering - Scatter Plot')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend(title='Cluster')
plt.savefig('Hierarchical Clustering')
plt.show()
```


Hierarchical Clustering Dendrogram
Distance
120
100
80
60
40
20
0
Sample Index

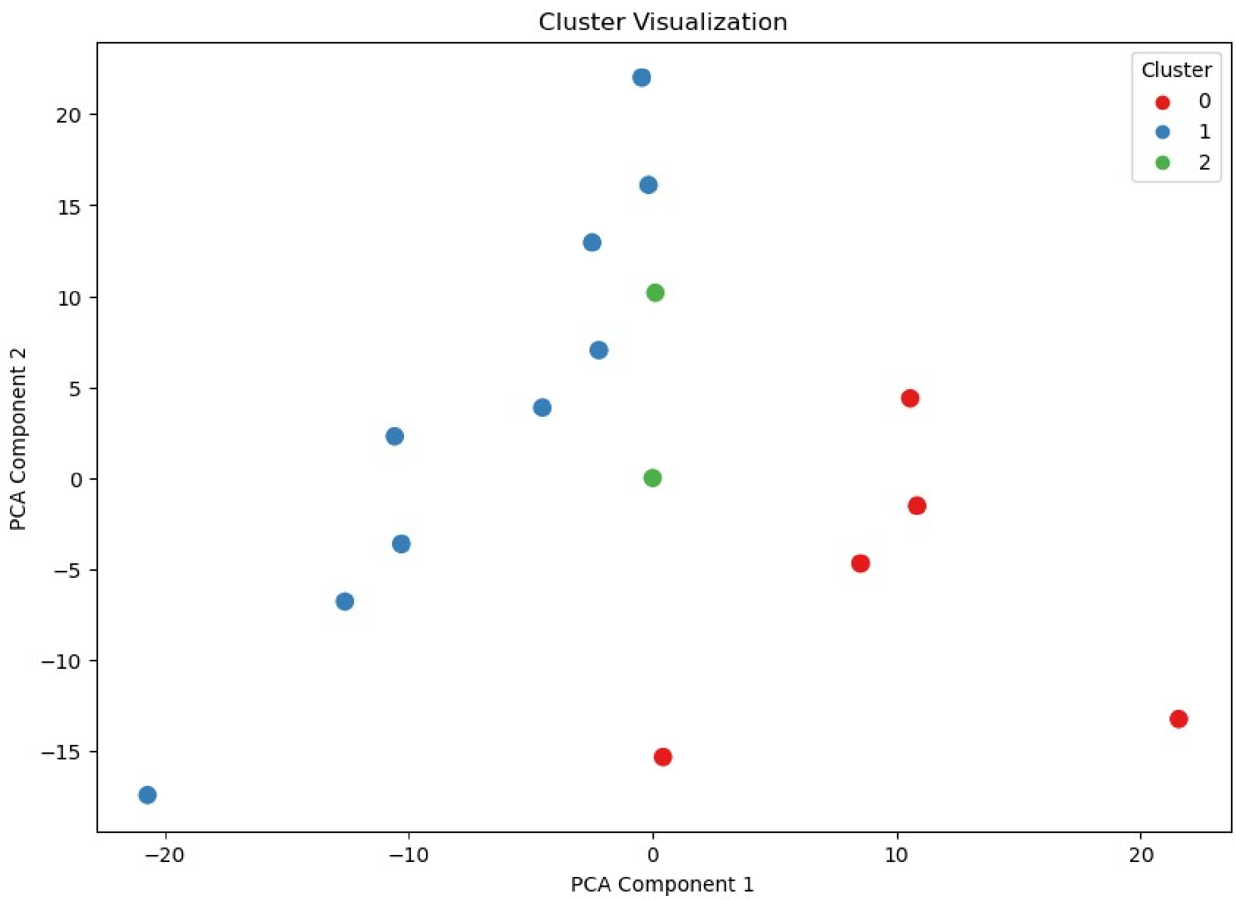


App 2: Analyze marriage patterns evolution with algorithms.

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import TruncatedSVD, PCA
from sklearn.cluster import MiniBatchKMeans
from scipy.sparse import csr_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset
df = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')

# Downsample the dataset
df_sampled = df.sample(frac=0.01, random_state=42)

# Convert data types to more memory-efficient types
df_sampled['Start Year'] = pd.to_numeric(df_sampled['Start Year'],
errors='coerce', downcast='integer')
```

```python
df_sampled['Age Group'] = df_sampled['Age Group'].astype('category')
df_sampled['Sex'] = df_sampled['Sex'].astype('category')
df_sampled['Marital Status'] = df_sampled['Marital
Status'].astype('category')

# Aggregate data
df_aggregated = df_sampled.groupby(['Country', 'Age Group', 'Start
Year', 'Marital Status']).size().unstack(fill_value=0)

# Normalize the aggregated data
df_normalized = df_aggregated.div(df_aggregated.sum(axis=1),
axis=0).fillna(0)

# Convert to sparse matrix
sparse_features = csr_matrix(df_normalized.values)

# Check number of features
num_features = sparse_features.shape[1]
print(f'Number of features: {num_features}')

# Apply dimensionality reduction
n_components = min(5, num_features)  # Adjust n_components based on
the number of features
svd = TruncatedSVD(n_components=n_components)
reduced_features = svd.fit_transform(sparse_features)

# Scale features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(reduced_features)

# Perform clustering using MiniBatchKMeans
n_clusters = 3  # Adjust this number based on your analysis
kmeans = MiniBatchKMeans(n_clusters=n_clusters, random_state=42)
df_aggregated['Cluster'] = kmeans.fit_predict(scaled_features)

# Reduce dimensionality to 2D for scatter plot
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_features)
df_aggregated['PCA1'] = pca_result[:, 0]
df_aggregated['PCA2'] = pca_result[:, 1]

# Plot the clusters in a scatter plot
plt.figure(figsize=(10, 7))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=df_aggregated,
palette='Set1', s=100, marker='o')
plt.title('Cluster Visualization')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend(title='Cluster')
plt.show()
```

```
Number of features: 5
```




```python
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import TruncatedSVD
from sklearn.cluster import MiniBatchKMeans
from scipy.sparse import csr_matrix
from sklearn.metrics import silhouette_score

# Load dataset in chunks
chunk_size = 100000  # Adjust based on memory capacity
chunks = pd.read_csv('World_Marriage_Cleaned_Dataset.csv',
chunksize=chunk_size)

# Initialize an empty DataFrame for aggregation
df_aggregated = pd.DataFrame()

for chunk in chunks:
    # Convert data types
```

```
    chunk['Start Year'] = pd.to_numeric(chunk['Start Year'],
errors='coerce', downcast='integer')
    chunk['Age Group'] = chunk['Age Group'].astype('category')
    chunk['Sex'] = chunk['Sex'].astype('category')
    chunk['Marital Status'] = chunk['Marital
Status'].astype('category')

    # Aggregate data in the chunk
    chunk_aggregated = chunk.groupby(['Country', 'Age Group', 'Start
Year', 'Marital Status']).size().unstack(fill_value=0)

    # Concatenate chunk with aggregated DataFrame
    df_aggregated = pd.concat([df_aggregated, chunk_aggregated])

# Drop duplicates and fill NaN values
df_aggregated = df_aggregated.groupby(level=0).sum()
df_normalized = df_aggregated.div(df_aggregated.sum(axis=1),
axis=0).fillna(0)

# Convert to sparse matrix
sparse_features = csr_matrix(df_normalized.values)

# Apply dimensionality reduction
n_components = min(5, sparse_features.shape[1])
svd = TruncatedSVD(n_components=n_components)
reduced_features = svd.fit_transform(sparse_features)

# Scale features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(reduced_features)

# Perform MiniBatchKMeans clustering
n_clusters = 10  # Adjust number of clusters as needed
kmeans = MiniBatchKMeans(n_clusters=n_clusters, batch_size=10000)
clusters = kmeans.fit_predict(scaled_features)

# Evaluate clustering (optional)
silhouette_avg = silhouette_score(scaled_features, clusters)
print(f'Silhouette Score: {silhouette_avg}')
```

```
Silhouette Score: 0.33236253509218044
```

4.3 DBSCAN Clustering

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

```
from sklearn.cluster import DBSCAN
from sklearn.datasets import make_blobs
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder

cleaned_dataset = pd.read_csv("World_Marriage_Cleaned_Dataset.csv")

# Verify and correct column names if needed
cleaned_dataset.columns = cleaned_dataset.columns.str.strip()  #
Remove any leading/trailing whitespace

if 'Count' not in cleaned_dataset.columns:
    cleaned_dataset['Count'] = 1

# Extract relevant columns for all age groups
relevant_data = cleaned_dataset[['Country', 'Marital Status',
'Count']]

# Pivot the data to get counts per country and age group
DBSCAN_pivot = relevant_data.pivot_table(index='Country',
columns='Marital Status', values='Count', aggfunc='sum',
fill_value=0).reset_index()

# Print columns to confirm
print(DBSCAN_pivot.columns)

# Show the first few rows to inspect
print(DBSCAN_pivot.head())

Index(['Country', 'Divorced', 'Married', 'Separated', 'Single',
'Widowed'], dtype='object', name='Marital Status')
Marital Status          Country  Divorced  Married  Separated  Single
Widowed
0                   Afghanistan       100      116         14      71
116
1                       Albania       141      185         61      91
191
2                       Algeria       129      162         57     129
160
3                American Samoa        84       86         58      90
86
4                        Angola       101       95         87      48
121

# Count the total number of people for each country
DBSCAN_pivot['Total_People'] =
DBSCAN_pivot.drop(columns='Country').sum(axis=1)

# Show the updated pivot table with total counts
print(DBSCAN_pivot.head())
```

```
Marital Status          Country  Divorced  Married  Separated  Single
Widowed  \
0                   Afghanistan       100      116         14      71
116
1                       Albania       141      185         61      91
191
2                       Algeria       129      162         57     129
160
3                American Samoa        84       86         58      90
86
4                        Angola       101       95         87      48
121

Marital Status  Total_People
0                        417
1                        669
2                        637
3                        404
4                        452
```

```python
from sklearn.preprocessing import StandardScaler

# Standardize the features
X = DBSCAN_pivot.drop(columns=['Country', 'Total_People'])  # Dropping
Country and Total_People for clustering
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)  # Adjust parameters as needed
clusters = dbscan.fit_predict(X_scaled)

# Add cluster labels to the dataset
DBSCAN_pivot['Cluster'] = clusters

print(DBSCAN_pivot.columns)
```

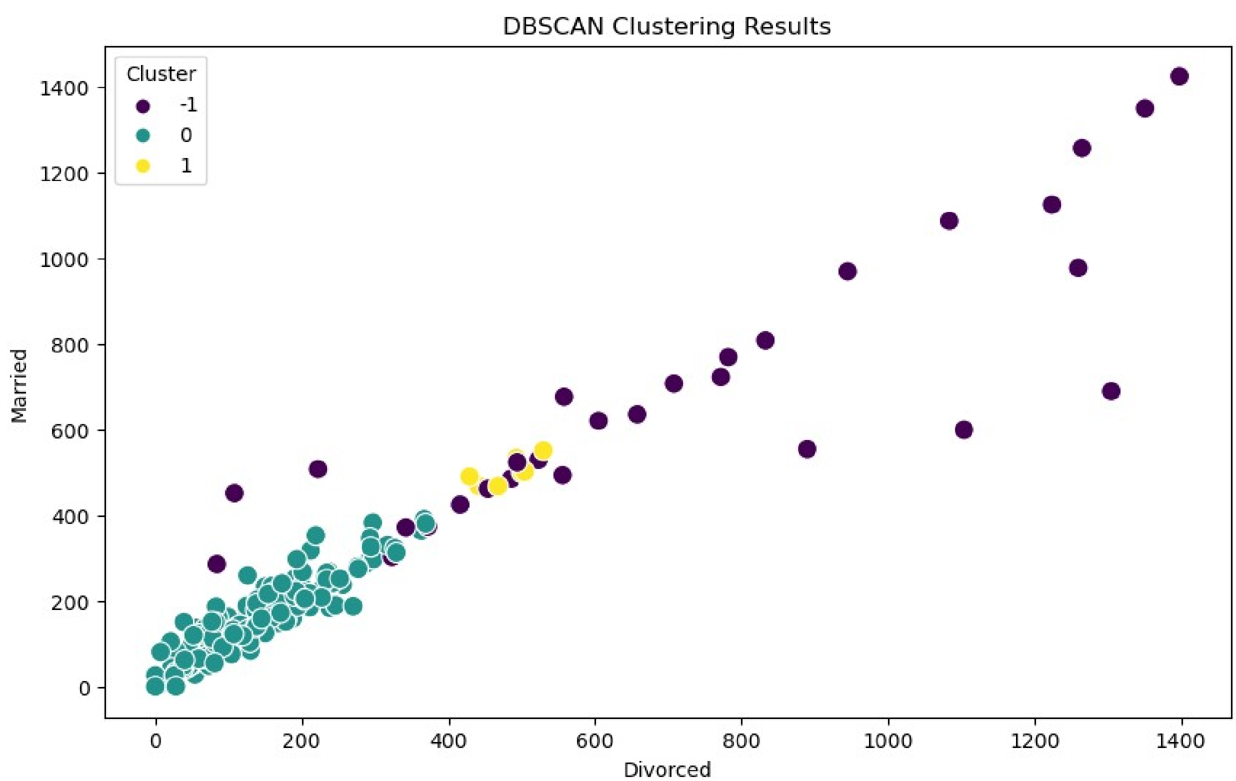
```
Index(['Country', 'Divorced', 'Married', 'Separated', 'Single',
'Widowed',
       'Total_People', 'Cluster'],
      dtype='object', name='Marital Status')
```

```python
# Evaluate clustering - Cluster labels distribution
print("Cluster labels distribution:")
print(DBSCAN_pivot['Cluster'].value_counts())
```

```
Cluster labels distribution:
 0    198
-1     29
 1      7
Name: Cluster, dtype: int64
```

```
# Add cluster labels to the dataset
DBSCAN_pivot['Cluster'] = clusters

# Evaluate clustering - Cluster labels distribution
print("Cluster labels distribution:")
print(DBSCAN_pivot['Cluster'].value_counts())

# Visualization using two marital statuses (adjust the column names accordingly)
plt.figure(figsize=(10, 6))
sns.scatterplot(x=DBSCAN_pivot[DBSCAN_pivot.columns[1]],
y=DBSCAN_pivot[DBSCAN_pivot.columns[2]], hue=DBSCAN_pivot['Cluster'],
palette='viridis', s=100)
plt.title('DBSCAN Clustering Results')
plt.xlabel(DBSCAN_pivot.columns[1])
plt.ylabel(DBSCAN_pivot.columns[2])
plt.legend(title='Cluster')
plt.show()
```

```
Cluster labels distribution:
 0    198
-1     29
 1      7
Name: Cluster, dtype: int64
```



```python
outliers = DBSCAN_pivot[DBSCAN_pivot['Cluster'] == -1]
print("Outliers:")
print(outliers)
```

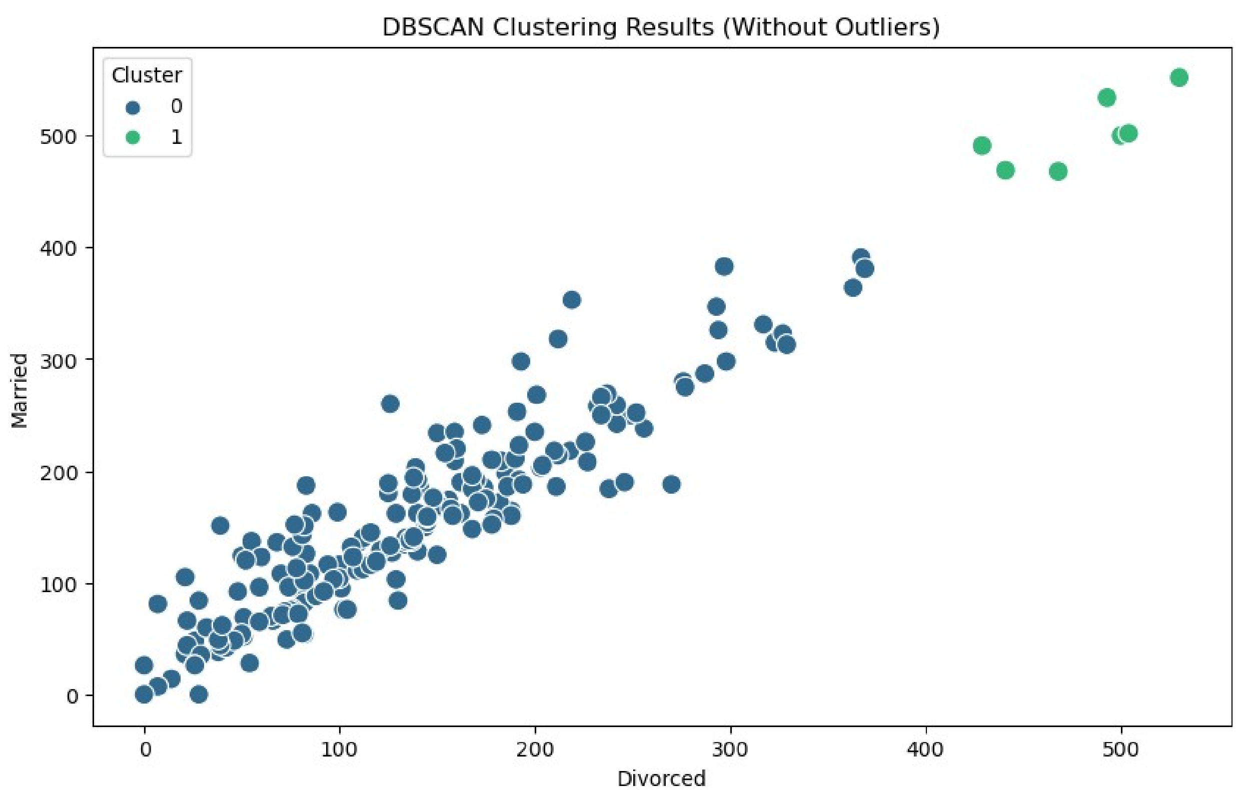
```
Outliers:
Marital Status                            Country  Divorced  Married  Separated  \
10                                      Australia       486      486        236

33                                         Canada      1104      600        332

39                                          Chile       108      452        442

41                                       Colombia        84      286         48

44                                     Costa Rica       523      530        523

49                                 Czech Republic       708      708          0

51                                        Denmark      1305      690        140

64                                  Faroe Islands       323      303        237

67                                        Finland      1224     1126         56

68                                         France       945      970          0

78                                      Greenland       890      555         56

89                                        Hungary      1398     1426         54

90                                        Iceland      1084     1088       1036

92                                      Indonesia       454      462         58

95                                        Ireland       222      508        188

97                                         Israel       658      636         46

98                                          Italy       556      494         84

116                                 Liechtenstein       558      677        350

132                                        Mexico       372      374        366

144                                   Netherlands      1260      978          0

154                                        Norway      1265     1258       1227

164                                        Poland       342      372         84

180                                    San Marino       772      723          0
```

```
183                          Senegal     494     524       87

189                         Slovenia     605     621        0

200                           Sweden    1351    1351       28

201                      Switzerland     833     809      112

213                           Turkey     416     425      125

222         United States of America     782     770      742


Marital Status  Single  Widowed  Total_People  Cluster
10                 488      486          2182       -1
33                1154     1104          4294       -1
39                 452      452          1906       -1
41                  92      286           796       -1
44                 523      523          2622       -1
49                 686      707          2809       -1
51                1312     1299          4746       -1
64                 332      313          1508       -1
67                1226     1223          4855       -1
68                 934      945          3794       -1
78                 922      916          3339       -1
89                1424     1424          5726       -1
90                1090     1081          5379       -1
92                 287      453          1714       -1
95                 592      592          2102       -1
97                 934      649          2923       -1
98                 608      578          2320       -1
116                686      660          2931       -1
132                360      371          1843       -1
144               1284     1252          4774       -1
154               1292     1283          6325       -1
164                362      370          1530       -1
180                896      884          3275       -1
183                177      528          1810       -1
189                628      601          2455       -1
200               1344     1348          5422       -1
201                838      828          3420       -1
213                256      422          1644       -1
222                794      782          3870       -1
```

```python
# Add cluster labels to the dataset
DBSCAN_pivot['Cluster'] = clusters

# Remove outliers (DBSCAN labels outliers as -1)
DBSCAN_no_outliers = DBSCAN_pivot[DBSCAN_pivot['Cluster'] != -1]
```

```python
# Evaluate clustering - Cluster labels distribution without outliers
print("Cluster labels distribution (without outliers):")
print(DBSCAN_no_outliers['Cluster'].value_counts())

# Visualization without outliers using two marital statuses (adjust
the column names accordingly)
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x=DBSCAN_no_outliers[DBSCAN_no_outliers.columns[1]],
    y=DBSCAN_no_outliers[DBSCAN_no_outliers.columns[2]],
    hue=DBSCAN_no_outliers['Cluster'],
    palette='viridis',
    s=100
)
plt.title('DBSCAN Clustering Results (Without Outliers)')
plt.xlabel(DBSCAN_no_outliers.columns[1])
plt.ylabel(DBSCAN_no_outliers.columns[2])
plt.legend(title='Cluster')
plt.show()
```

```
Cluster labels distribution (without outliers):
0    198
1      7
Name: Cluster, dtype: int64
```



```
import geopandas as gpd
import matplotlib.pyplot as plt

# Load the world map from Natural Earth (this approach should work
with newer versions)
shapefile_path =
r"C:/Users/user/Desktop/ne_10m_admin_0_countries/ne_10m_admin_0_countr
ies.shp"

# Load the shapefile
world = gpd.read_file(shapefile_path)

# Check the columns
print(world.columns)

world
```

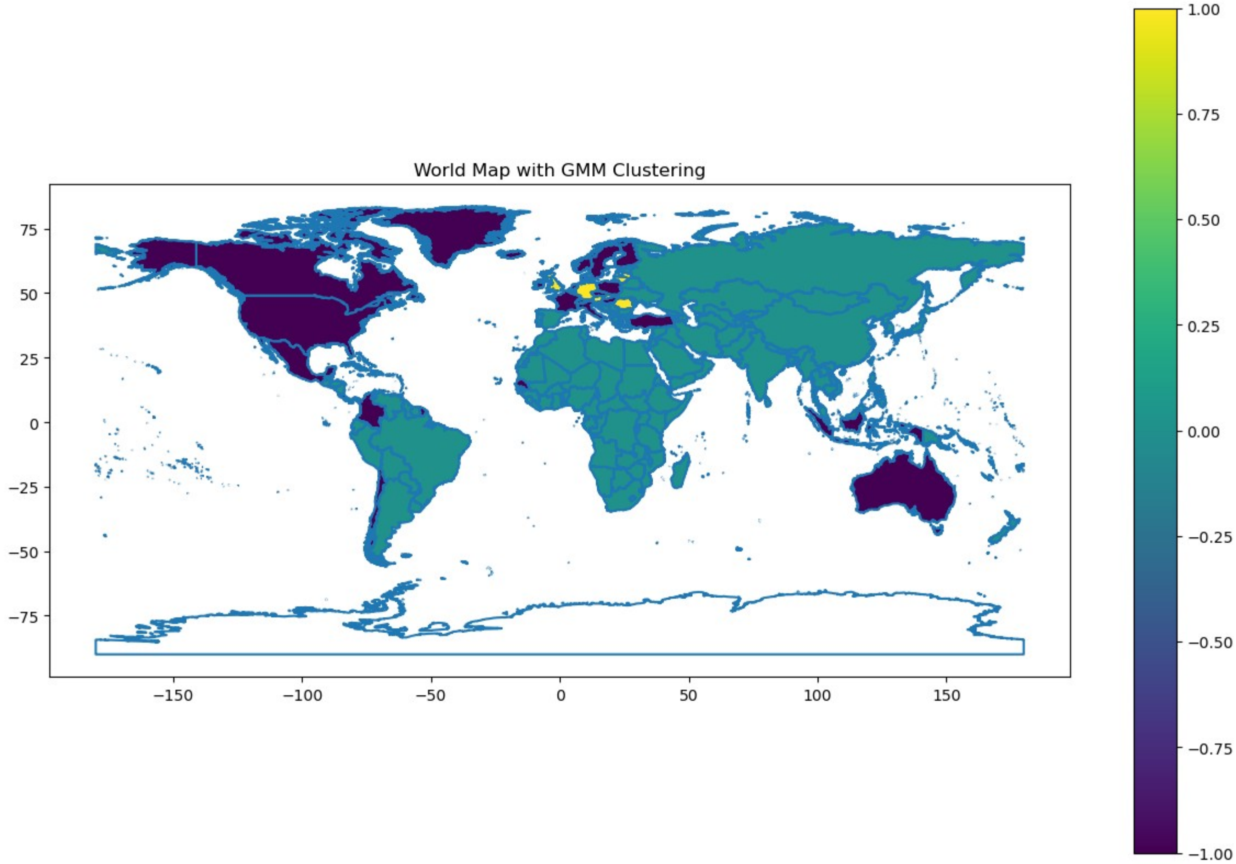
```
Index(['scalerank', 'featurecla', 'LABELRANK', 'SOVEREIGNT', 'SOV_A3',
       'ADM0_DIF', 'LEVEL', 'TYPE', 'ADMIN', 'ADM0_A3', 'GEOU_DIF',
'GEOUNIT',
       'GU_A3', 'SU_DIF', 'SUBUNIT', 'SU_A3', 'BRK_DIFF', 'NAME',
'NAME_LONG',
       'BRK_A3', 'BRK_NAME', 'BRK_GROUP', 'ABBREV', 'POSTAL',
'FORMAL_EN',
       'FORMAL_FR', 'NOTE_ADM0', 'NOTE_BRK', 'NAME_SORT', 'NAME_ALT',
       'MAPCOLOR7', 'MAPCOLOR8', 'MAPCOLOR9', 'MAPCOLOR13', 'POP_EST',
       'GDP_MD_EST', 'POP_YEAR', 'LASTCENSUS', 'GDP_YEAR', 'ECONOMY',
       'INCOME_GRP', 'WIKIPEDIA', 'FIPS_10_', 'ISO_A2', 'ISO_A3',
'ISO_N3',
       'UN_A3', 'WB_A2', 'WB_A3', 'WOE_ID', 'WOE_ID_EH', 'WOE_NOTE',
       'ADM0_A3_IS', 'ADM0_A3_US', 'ADM0_A3_UN', 'ADM0_A3_WB',
'CONTINENT',
       'REGION_UN', 'SUBREGION', 'REGION_WB', 'NAME_LEN', 'LONG_LEN',
       'ABBREV_LEN', 'TINY', 'HOMEPART', 'geometry'],
      dtype='object')
```

```
     scalerank       featurecla  LABELRANK      SOVEREIGNT SOV_A3
ADM0_DIF  \
0            3  Admin-0 country        5.0     Netherlands    NL1
1.0
1            0  Admin-0 country        3.0     Afghanistan    AFG
0.0
2            0  Admin-0 country        3.0          Angola    AGO
0.0
3            3  Admin-0 country        6.0  United Kingdom    GB1
1.0
4            0  Admin-0 country        6.0         Albania    ALB
0.0
..         ...              ...        ...             ...    ...
...
```

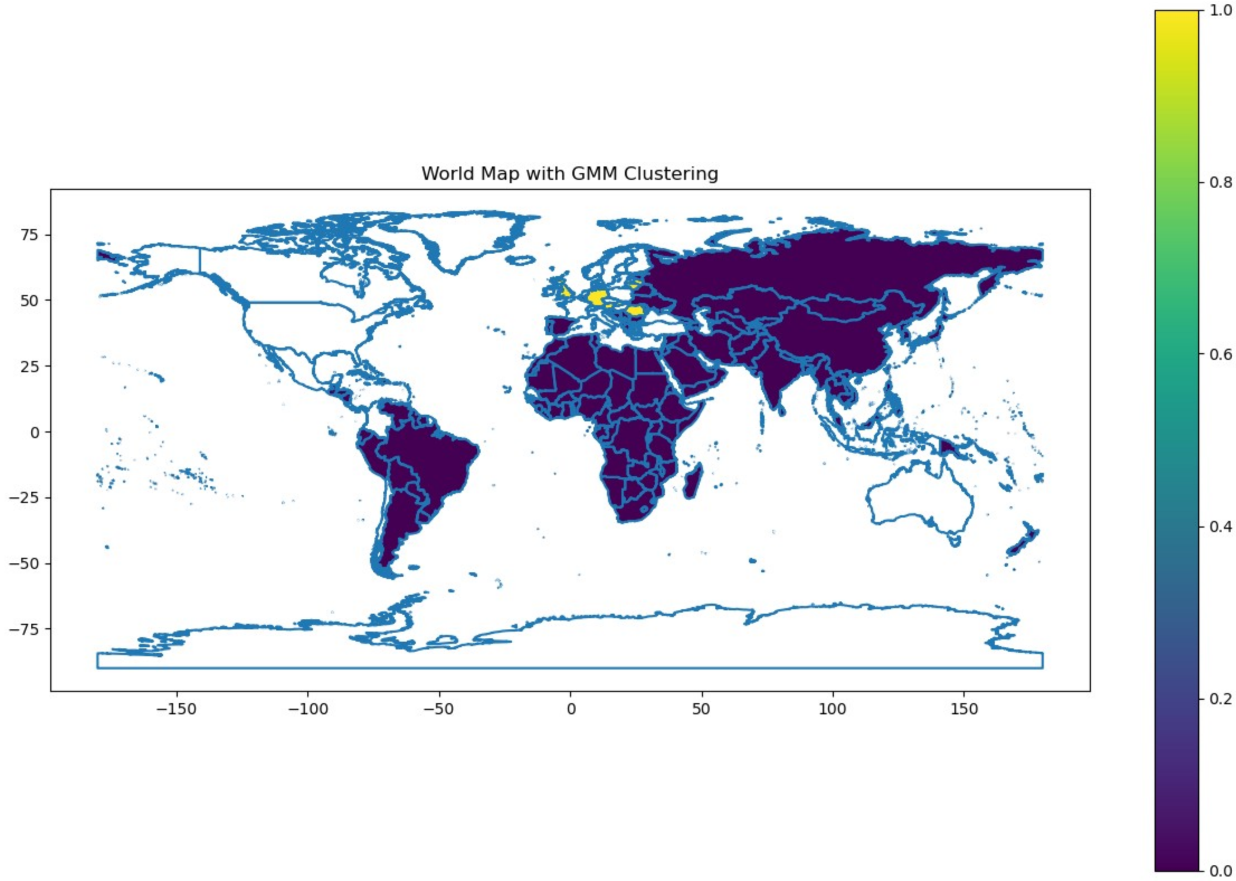
```
250           3  Admin-0 country        4.0           Samoa    WSM
0.0
251           0  Admin-0 country        3.0           Yemen    YEM
0.0
252           0  Admin-0 country        2.0    South Africa    ZAF
0.0
253           0  Admin-0 country        3.0          Zambia    ZMB
0.0
254           0  Admin-0 country        3.0        Zimbabwe    ZWE
0.0

     LEVEL               TYPE         ADMIN ADM0_A3  ...
CONTINENT  \
0      2.0            Country         Aruba     ABW  ...  North
America
1      2.0  Sovereign country   Afghanistan     AFG  ...
Asia
2      2.0  Sovereign country        Angola     AGO  ...
Africa
3      2.0         Dependency      Anguilla     AIA  ...  North
America
4      2.0  Sovereign country       Albania     ALB  ...
Europe
..     ...                ...           ...     ...  ...            ..
.
250    2.0  Sovereign country         Samoa     WSM  ...
Oceania
251    2.0  Sovereign country         Yemen     YEM  ...
Asia
252    2.0  Sovereign country  South Africa     ZAF  ...
Africa
253    2.0  Sovereign country        Zambia     ZMB  ...
Africa
254    2.0  Sovereign country      Zimbabwe     ZWE  ...
Africa

    REGION_UN        SUBREGION                   REGION_WB NAME_LEN
LONG_LEN  \
0    Americas        Caribbean   Latin America & Caribbean      5.0
5.0
1        Asia    Southern Asia                  South Asia     11.0
11.0
2      Africa    Middle Africa          Sub-Saharan Africa      6.0
6.0
3    Americas        Caribbean   Latin America & Caribbean      8.0
8.0
4      Europe  Southern Europe       Europe & Central Asia      7.0
7.0
..        ...              ...                         ...      ...
```

```
...
250   Oceania         Polynesia         East Asia & Pacific      5.0
5.0
251      Asia      Western Asia  Middle East & North Africa      5.0
5.0
252    Africa  Southern Africa          Sub-Saharan Africa     12.0
12.0
253    Africa   Eastern Africa          Sub-Saharan Africa      6.0
6.0
254    Africa   Eastern Africa          Sub-Saharan Africa      8.0
8.0

     ABBREV_LEN  TINY HOMEPART  \
0           5.0   4.0    -99.0
1           4.0 -99.0      1.0
2           4.0 -99.0      1.0
3           4.0 -99.0    -99.0
4           4.0 -99.0      1.0
..          ...   ...      ...
250         5.0 -99.0      1.0
251         4.0 -99.0      1.0
252         5.0 -99.0      1.0
253         6.0 -99.0      1.0
254         5.0 -99.0      1.0

                                              geometry
0    POLYGON ((-69.99694 12.57758, -69.93639 12.531...
1    POLYGON ((71.0498 38.40866, 71.05714 38.40903,...
2    MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...
3    MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...
4    POLYGON ((19.74777 42.5789, 19.74601 42.57993,...
..                                                 ...
250  MULTIPOLYGON (((-171.57002 -13.93816, -171.564...
251  MULTIPOLYGON (((53.30824 12.11839, 53.31027 12...
252  MULTIPOLYGON (((37.86378 -46.94085, 37.83644 -...
253  POLYGON ((31.11984 -8.61663, 31.14102 -8.60619...
254  POLYGON ((30.01065 -15.64623, 30.05024 -15.640...

[255 rows x 66 columns]

# Merge with clustering results
world_clusters = world.merge(DBSCAN_pivot[['Country', 'Cluster']],
how='left', left_on='ADMIN', right_on='Country')

# Plot the world map with clusters
fig, ax = plt.subplots(1, 1, figsize=(15, 10))
world.boundary.plot(ax=ax)
world_clusters.plot(column='Cluster', ax=ax, legend=True,
cmap='viridis', edgecolor='k', linewidth=0.5)
```

```
plt.title('World Map with GMM Clustering')
plt.show()
```




```
# Merge with clustering results
world_clusters = world.merge(DBSCAN_no_outliers[['Country',
'Cluster']], how='left', left_on='ADMIN', right_on='Country')

# Plot the world map with clusters
fig, ax = plt.subplots(1, 1, figsize=(15, 10))
world.boundary.plot(ax=ax)
world_clusters.plot(column='Cluster', ax=ax, legend=True,
cmap='viridis', edgecolor='k', linewidth=0.5)
plt.title('World Map with GMM Clustering')
plt.show()
```



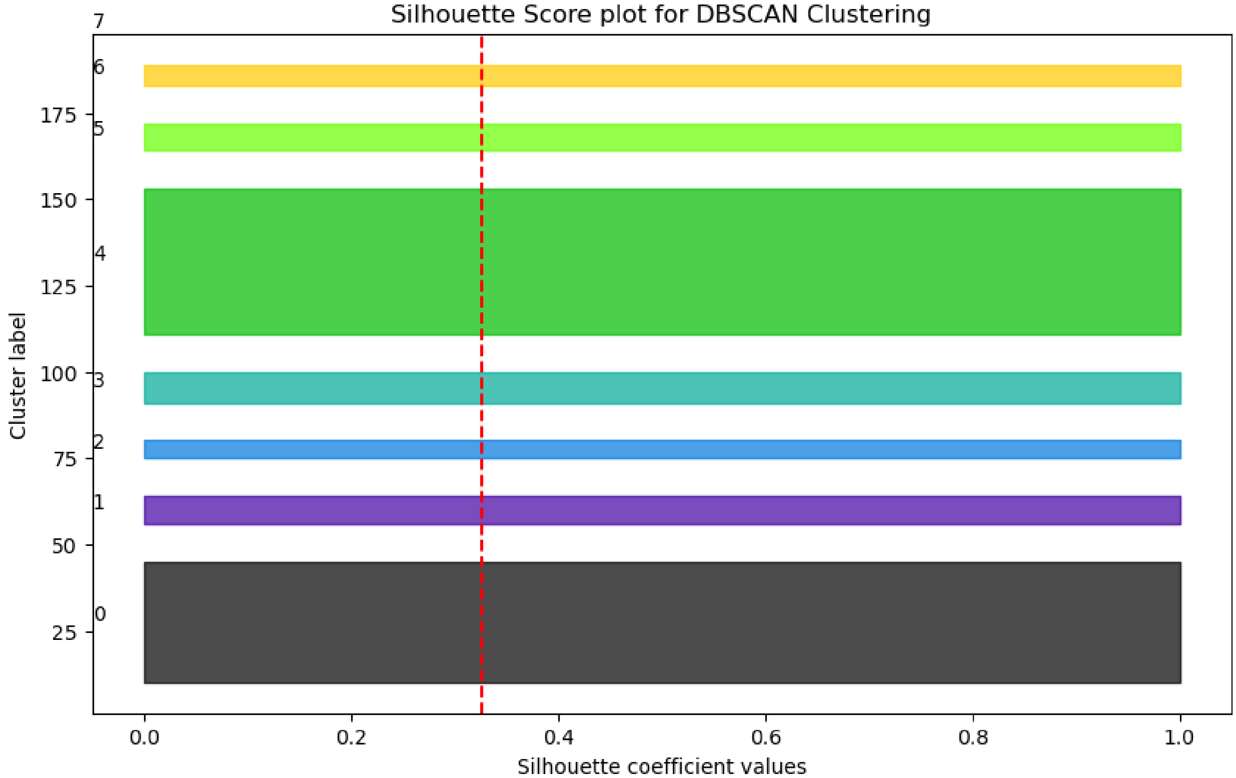
App 2

```
# Required Libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import DBSCAN
from sklearn.metrics import silhouette_score, silhouette_samples
import matplotlib.pyplot as plt
import seaborn as sns

data = pd.read_csv("World_Marriage_Cleaned_Dataset.csv")

if 'Count' not in data.columns:
    data['Count'] = 1

# Select relevant columns (Assuming you have 'Country', 'Age Group',
'Marital Status' and 'Count')
df = data[['Country', 'Age Group', 'Marital Status', 'Count']]

# Pivot data to have Age Group as columns for clustering
pivot_df = df.pivot_table(index='Country', columns='Age Group',
```

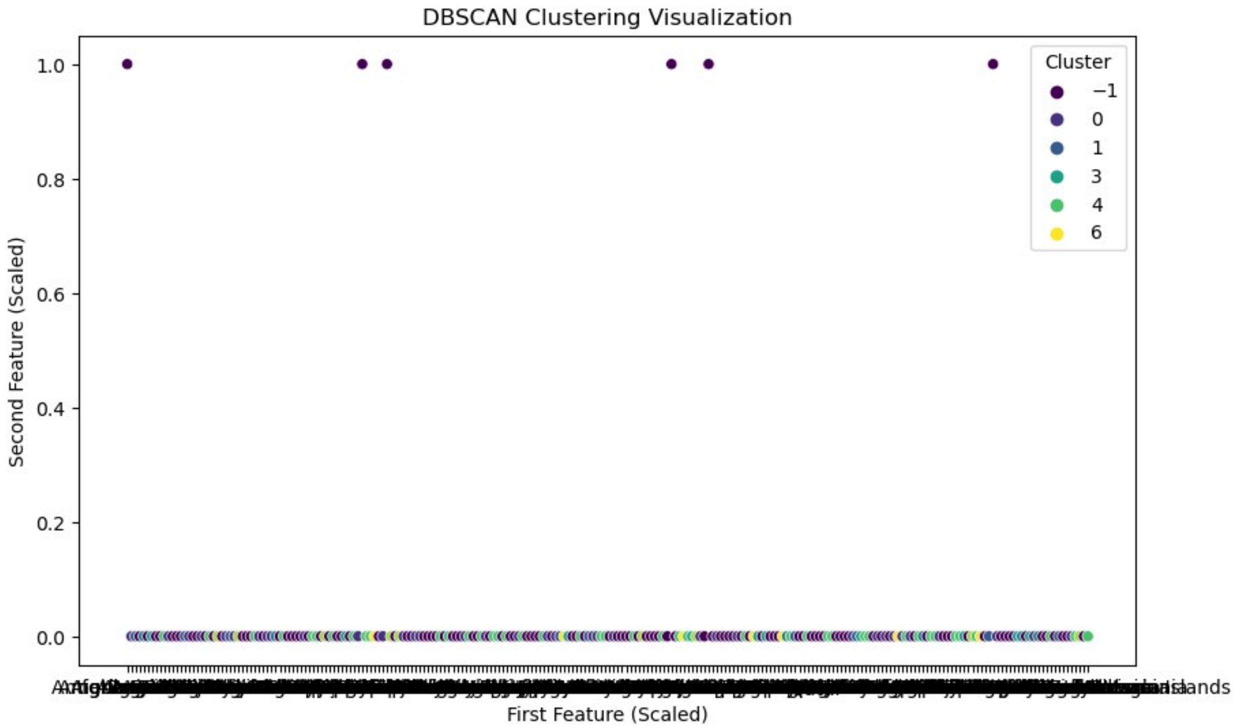
```
values='Count', fill_value=0).reset_index()

# Drop the country column for clustering
X = pivot_df.drop('Country', axis=1)

# Standardize the data for better DBSCAN performance
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)  # Adjust eps and min_samples
based on the data
dbscan_labels = dbscan.fit_predict(X_scaled)

# Add the DBSCAN cluster labels to the original dataframe
pivot_df['Cluster'] = dbscan_labels

# Step 4: Use Silhouette Score to evaluate clustering quality
if len(set(dbscan.labels_)) > 1:  # Check if we have more than 1
cluster
    silhouette_avg = silhouette_score(X_scaled, dbscan.labels_)
    print(f"Average Silhouette Score for DBSCAN: {silhouette_avg}")

    # Silhouette samples for each point
    sample_silhouette_values = silhouette_samples(X_scaled,
dbscan.labels_)

    # Plot Silhouette scores
    plt.figure(figsize=(10, 6))
    y_lower = 10
    for i in range(len(set(dbscan.labels_))):
        ith_cluster_silhouette_values =
sample_silhouette_values[dbscan.labels_ == i]
        ith_cluster_silhouette_values.sort()
        size_cluster_i = ith_cluster_silhouette_values.shape[0]
        y_upper = y_lower + size_cluster_i

        color = plt.cm.nipy_spectral(float(i) /
len(set(dbscan.labels_)))
        plt.fill_betweenx(np.arange(y_lower, y_upper),
                          0, ith_cluster_silhouette_values,
facecolor=color, edgecolor=color, alpha=0.7)
        plt.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))
        y_lower = y_upper + 10

    plt.axvline(x=silhouette_avg, color="red", linestyle="--")
    plt.title("Silhouette Score plot for DBSCAN Clustering")
    plt.xlabel("Silhouette coefficient values")
    plt.ylabel("Cluster label")
    plt.show()
```

```
else:
    print("DBSCAN resulted in 1 or fewer clusters, silhouette score is not applicable.")
```

```
Average Silhouette Score for DBSCAN: 0.32677868141256244
```




```
# Step 5: Visualize the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=pivot_df.iloc[:, 0], y=pivot_df.iloc[:, 1],
hue=pivot_df['Cluster'], palette="viridis")
plt.title("DBSCAN Clustering Visualization")
plt.xlabel('First Feature (Scaled)')
plt.ylabel('Second Feature (Scaled)')
plt.show()
```



4.4 GMM Clustering

```
# import required libraries
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
import random
from sklearn.mixture import GaussianMixture
from sklearn.datasets import make_blobs
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA


warnings.filterwarnings('ignore')

cleaned_dataset = pd.read_csv("World_Marriage_Cleaned_Dataset.csv")

# Verify and correct column names if needed
cleaned_dataset.columns = cleaned_dataset.columns.str.strip()  #
Remove any leading/trailing whitespace

if 'Count' not in cleaned_dataset.columns:
    cleaned_dataset['Count'] = 1
```

```python
# Extract relevant columns for all age groups
relevant_data = cleaned_dataset[['Country', 'Age Group', 'Marital
Status', 'Count']]

# Pivot the data to get counts per country and age group
marital_pivot = relevant_data.pivot_table(index='Country',
columns='Marital Status', values='Count', aggfunc='sum',
fill_value=0).reset_index()

# Print columns to confirm
print(marital_pivot.columns)

# Show the first few rows to inspect
print(marital_pivot.head())
```

```
Index(['Country', 'Divorced', 'Married', 'Separated', 'Single',
'Widowed'], dtype='object', name='Marital Status')
Marital Status          Country  Divorced  Married  Separated  Single
Widowed
0                   Afghanistan       100      116         14      71
116
1                       Albania       141      185         61      91
191
2                       Algeria       129      162         57     129
160
3                American Samoa        84       86         58      90
86
4                        Angola       101       95         87      48
121
```

```python
print("Features shape:", features.shape)
print("Marital pivot shape:", marital_pivot.shape)
```

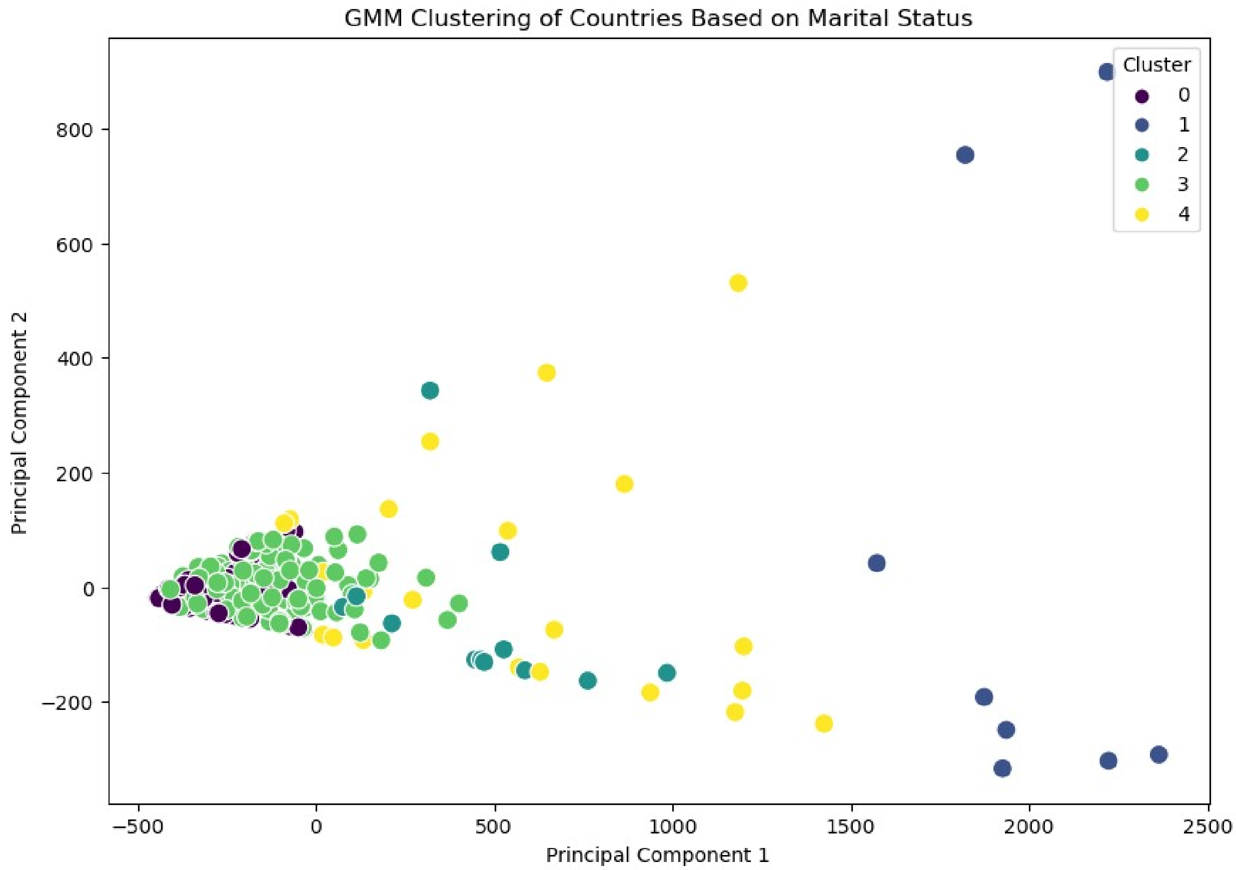
```
Features shape: (223, 1)
Marital pivot shape: (234, 6)
```

```python
# Initialize and fit GMM
gmm = GaussianMixture(n_components=5, random_state=0)  # Adjust
n_components as needed
gmm.fit(features)

# Predict clusters
clusters = gmm.predict(features)

features = marital_pivot.drop(columns=['Country'])  # Make sure
'Country' column is excluded

gmm.fit(features)
clusters = gmm.predict(features)
```

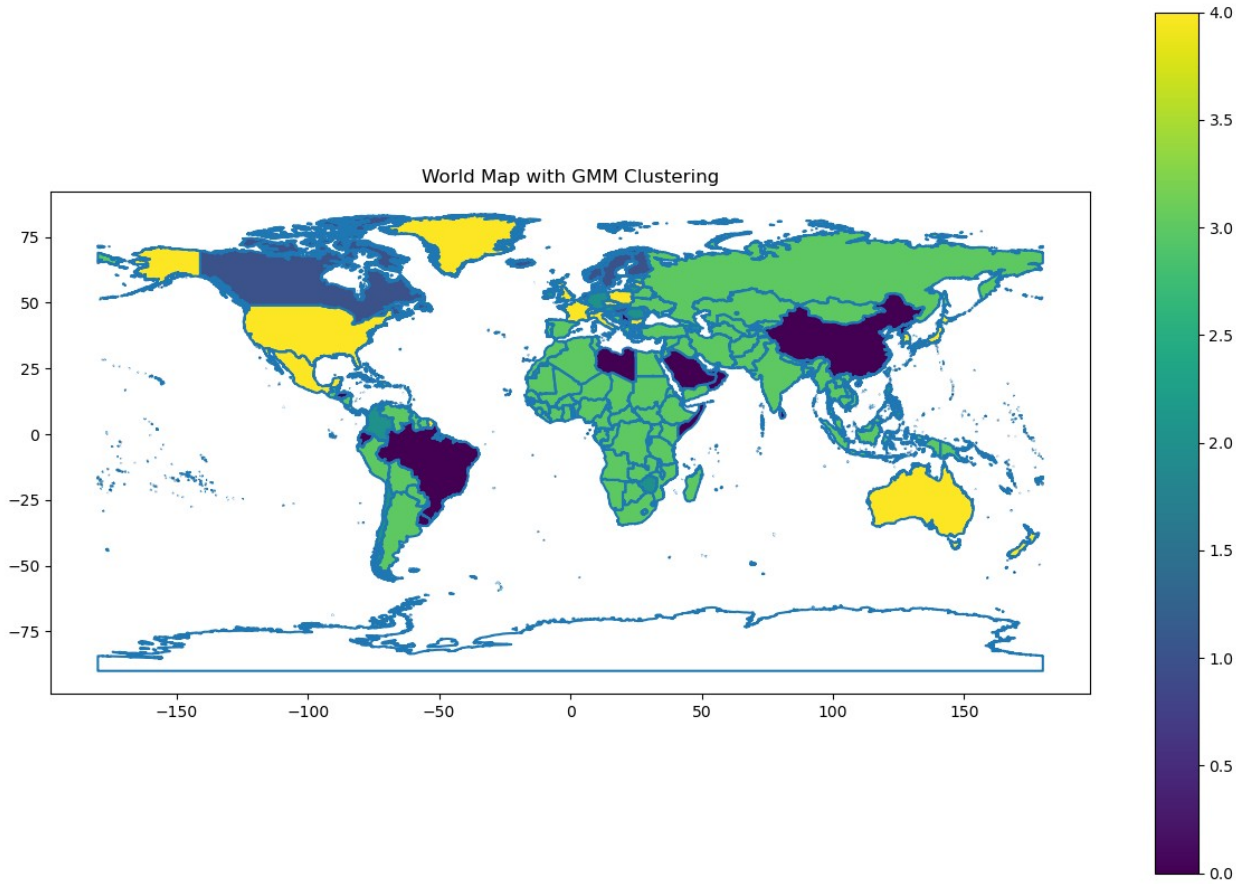
```python
print("Length of clusters:", len(clusters))
print("Number of rows in marital_pivot:", len(marital_pivot))
```

```
Length of clusters: 234
Number of rows in marital_pivot: 234
```

```python
# Add cluster labels to the original DataFrame
marital_pivot['Cluster'] = clusters

# Apply PCA to reduce dimensions to 2 for visualization
pca = PCA(n_components=2)
reduced_features = pca.fit_transform(features)

# Create a DataFrame for plotting
plot_df = pd.DataFrame(reduced_features, columns=['PC1', 'PC2'])
plot_df['Cluster'] = clusters
plot_df['Country'] = marital_pivot['Country']

# Plot the clusters
plt.figure(figsize=(10, 7))
sns.scatterplot(x='PC1', y='PC2', hue='Cluster', data=plot_df,
palette='viridis', s=100)
plt.title('GMM Clustering of Countries Based on Marital Status')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Cluster')
plt.show()
```




```python
# Merge with clustering results
world_clusters = world.merge(marital_pivot[['Country', 'Cluster']],
how='left', left_on='ADMIN', right_on='Country')

# Plot the world map with clusters
fig, ax = plt.subplots(1, 1, figsize=(15, 10))
world.boundary.plot(ax=ax)
world_clusters.plot(column='Cluster', ax=ax, legend=True,
cmap='viridis', edgecolor='k', linewidth=0.5)
plt.title('World Map with GMM Clustering')
plt.show()
```

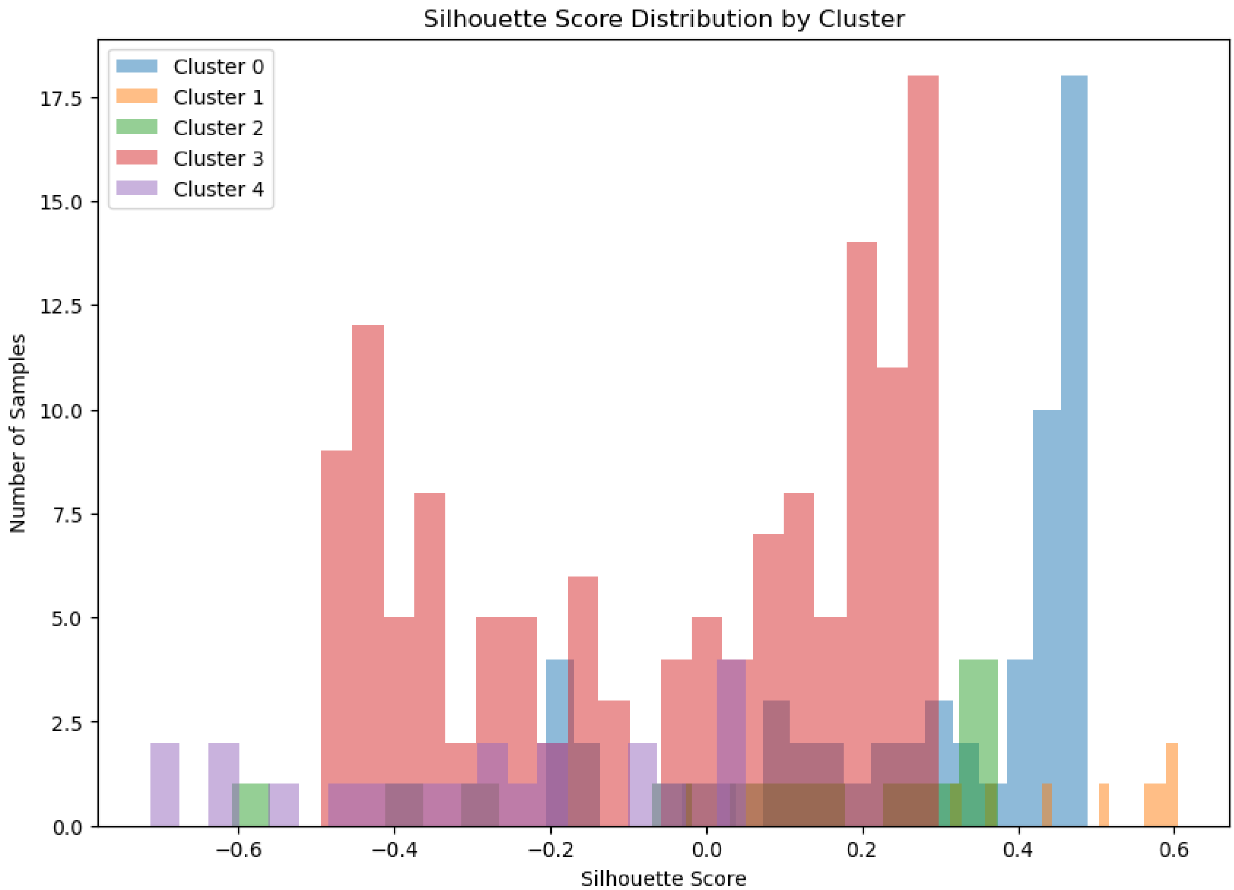



```python
from sklearn.metrics import silhouette_score

# Calculate the silhouette score
silhouette_avg = silhouette_score(features, clusters)
print(f'Silhouette Score: {silhouette_avg}')
```

```
Silhouette Score: 0.04074134517951543
```

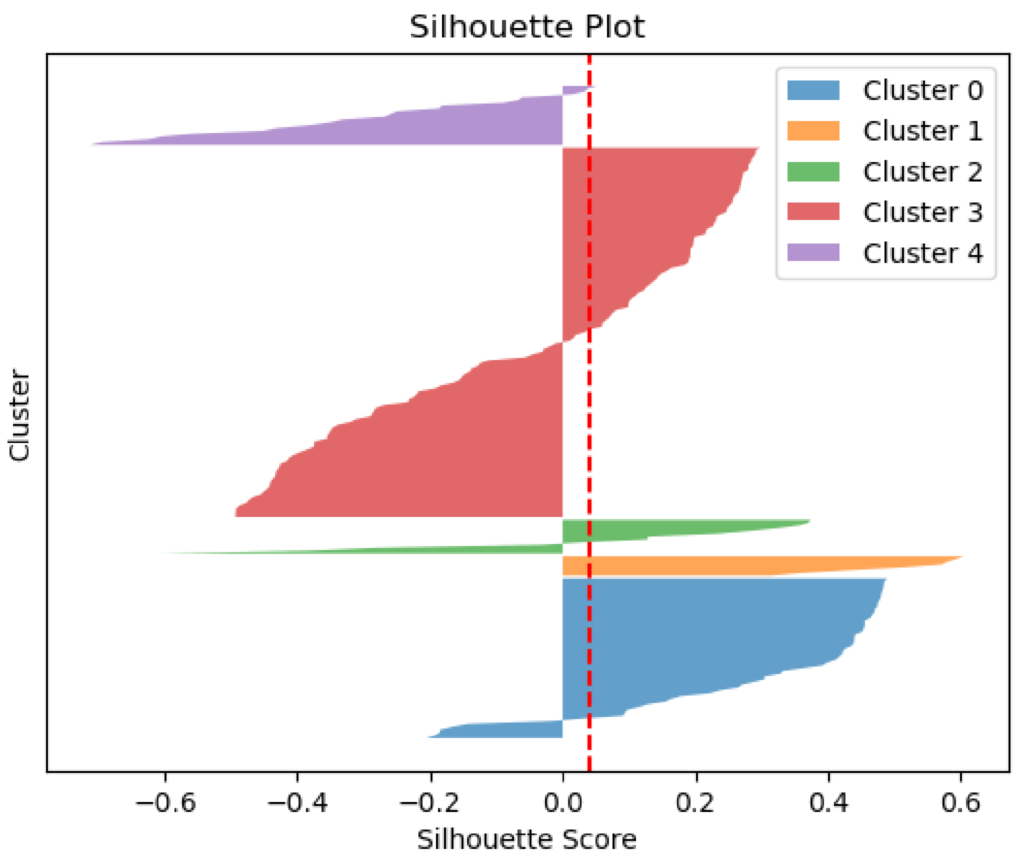
```python
import matplotlib.pyplot as plt
from sklearn.metrics import silhouette_samples
import numpy as np

# Compute the silhouette scores for each sample
silhouette_vals = silhouette_samples(features, clusters)

# Plot the silhouette scores
plt.figure(figsize=(10, 7))

# Silhouette plot for each cluster
unique_clusters = np.unique(clusters)
for cluster in unique_clusters:
    cluster_silhouette_vals = silhouette_vals[clusters == cluster]
    plt.hist(cluster_silhouette_vals, bins=20, alpha=0.5,
```

```
label=f'Cluster {cluster}')

plt.title('Silhouette Score Distribution by Cluster')
plt.xlabel('Silhouette Score')
plt.ylabel('Number of Samples')
plt.legend()
plt.show()
```



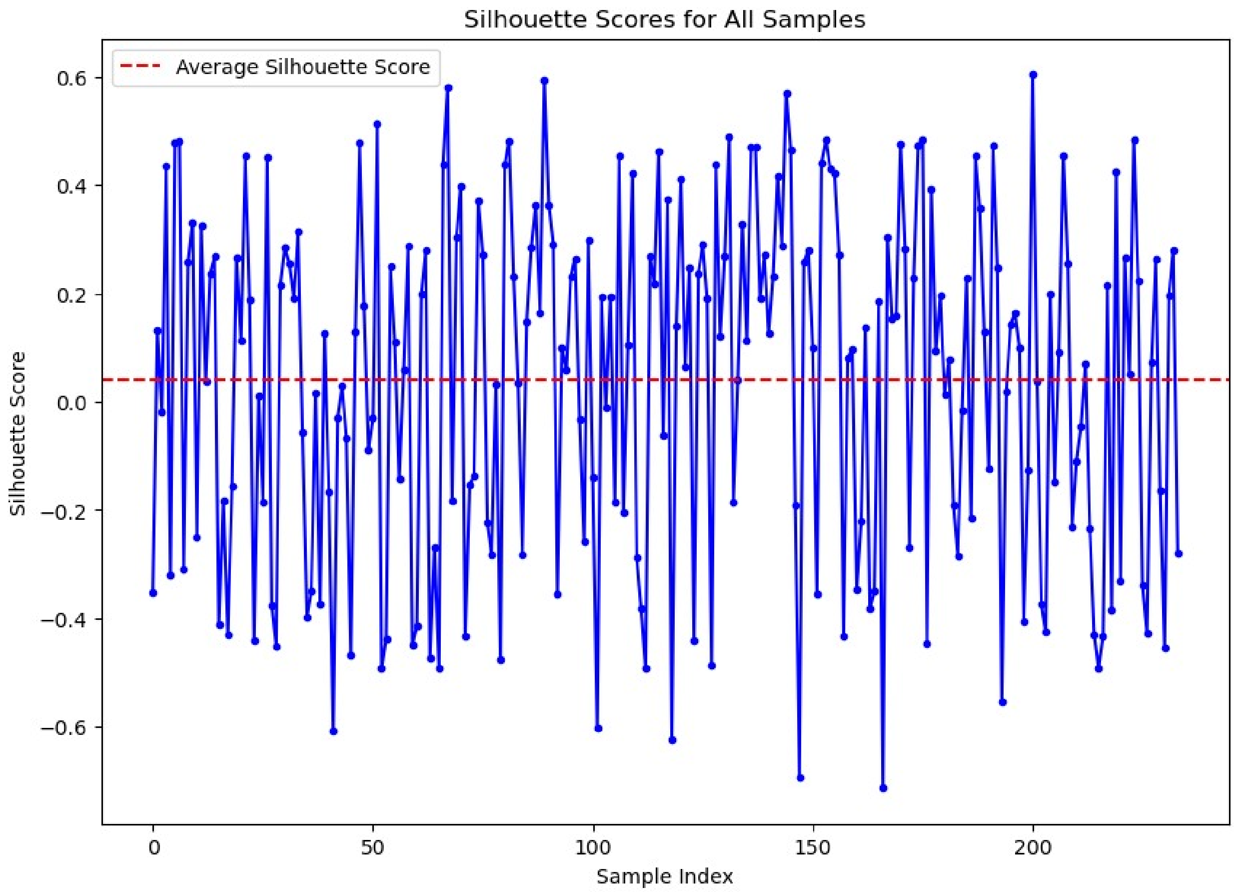

```
import matplotlib.pyplot as plt
from matplotlib.collections import PathCollection

def plot_silhouette(X, y_pred):
    # Compute silhouette scores
    silhouette_vals = silhouette_samples(X, y_pred)
    y_lower, y_upper = 0, 0
    for i in np.unique(y_pred):
        # Aggregate the silhouette scores for samples belonging to
cluster i
        cluster_silhouette_vals = silhouette_vals[y_pred == i]
        cluster_silhouette_vals.sort()
        y_upper += len(cluster_silhouette_vals)
        plt.fill_betweenx(np.arange(y_lower, y_upper), 0,
```

```
cluster_silhouette_vals, alpha=0.7, label=f'Cluster {i}')
        y_lower += len(cluster_silhouette_vals)

    plt.title('Silhouette Plot')
    plt.xlabel('Silhouette Score')
    plt.ylabel('Cluster')
    plt.yticks([])
    plt.axvline(x=silhouette_avg, color='red', linestyle='--')
    plt.legend()
    plt.show()

# Use the function to plot
plot_silhouette(features, clusters)
```



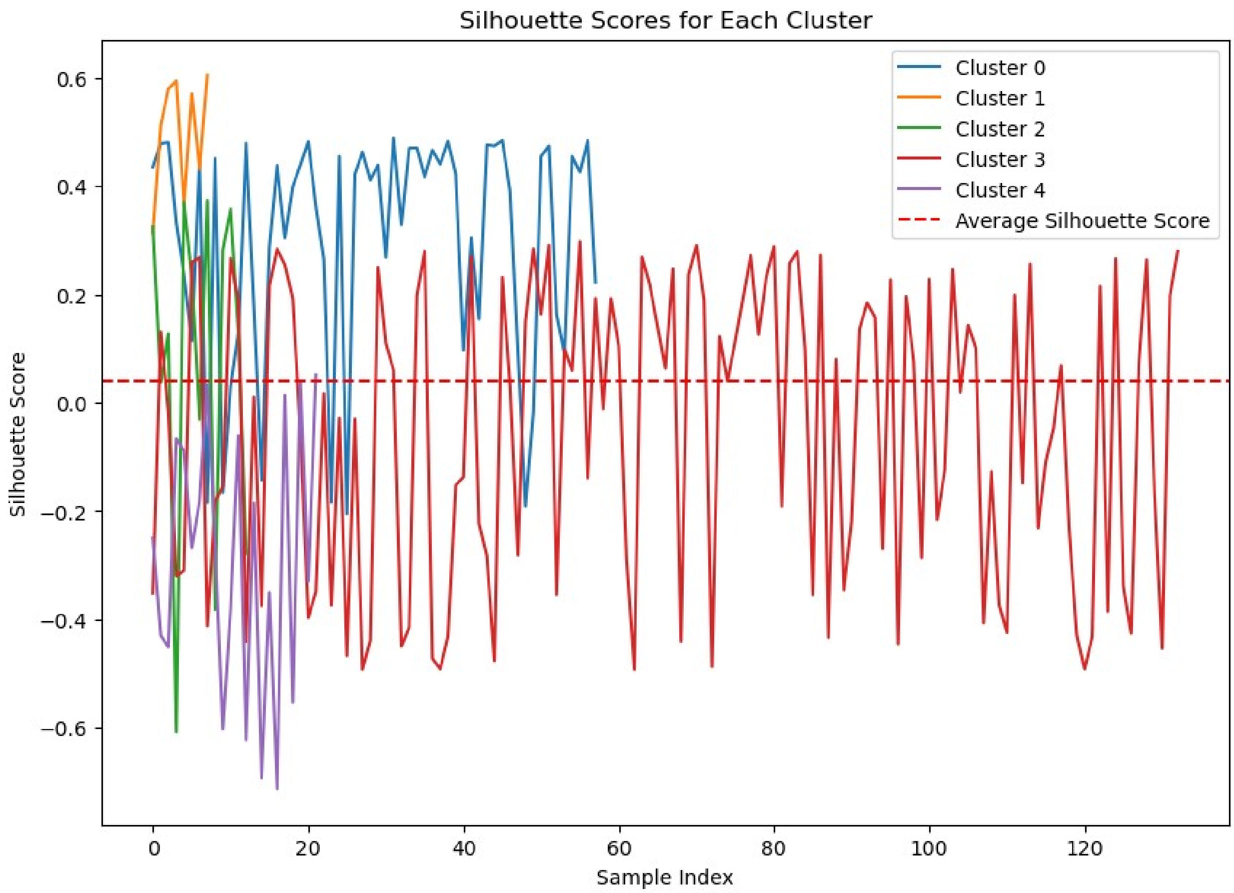

```
# Create a figure
plt.figure(figsize=(10, 7))

# Plot silhouette scores for all samples
plt.plot(np.arange(len(silhouette_vals)), silhouette_vals,
color='blue', marker='o', linestyle='-', markersize=3)

plt.title('Silhouette Scores for All Samples')
plt.xlabel('Sample Index')
```

```
plt.ylabel('Silhouette Score')
plt.axhline(y=silhouette_avg, color='red', linestyle='--',
label='Average Silhouette Score')
plt.legend()
plt.show()
```




```
import matplotlib.pyplot as plt
from sklearn.metrics import silhouette_samples
import numpy as np

# Compute silhouette scores for each sample
silhouette_vals = silhouette_samples(features, clusters)

# Create a figure
plt.figure(figsize=(10, 7))

# For each cluster, plot the silhouette scores
for cluster in np.unique(clusters):
    cluster_silhouette_vals = silhouette_vals[clusters == cluster]
    plt.plot(np.arange(len(cluster_silhouette_vals)),
cluster_silhouette_vals, label=f'Cluster {cluster}')
```

```
plt.title('Silhouette Scores for Each Cluster')
plt.xlabel('Sample Index')
plt.ylabel('Silhouette Score')
plt.axhline(y=silhouette_avg, color='red', linestyle='--',
label='Average Silhouette Score')
plt.legend()
plt.show()
```

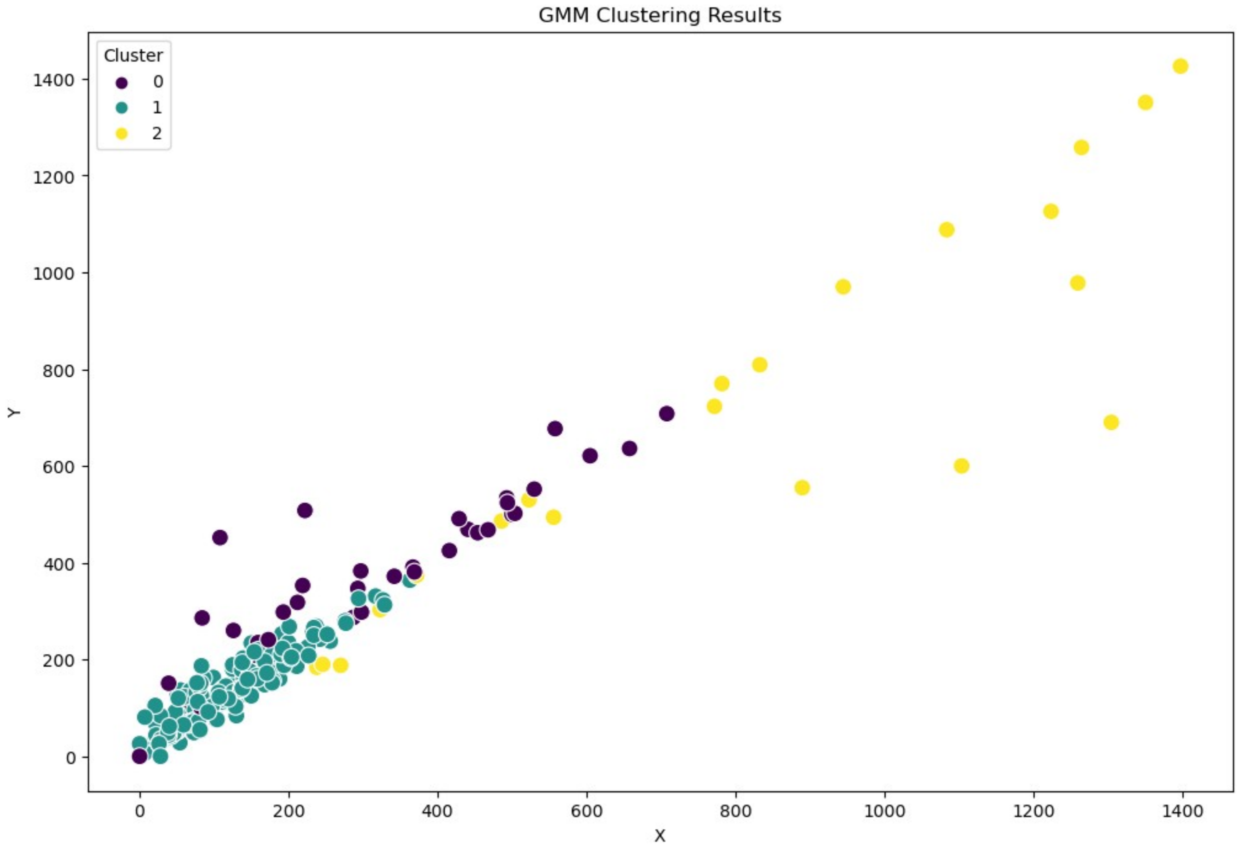



```
# Extract relevant columns for all age groups
relevant_data = cleaned_dataset[['Country', 'Age Group', 'Marital
Status', 'Count']]

# Pivot the data to get counts per country and age group
marital_pivot = relevant_data.pivot_table(index='Country',
columns='Marital Status', values='Count', aggfunc='sum',
fill_value=0).reset_index()

# Print columns to confirm
print(marital_pivot.columns)
```

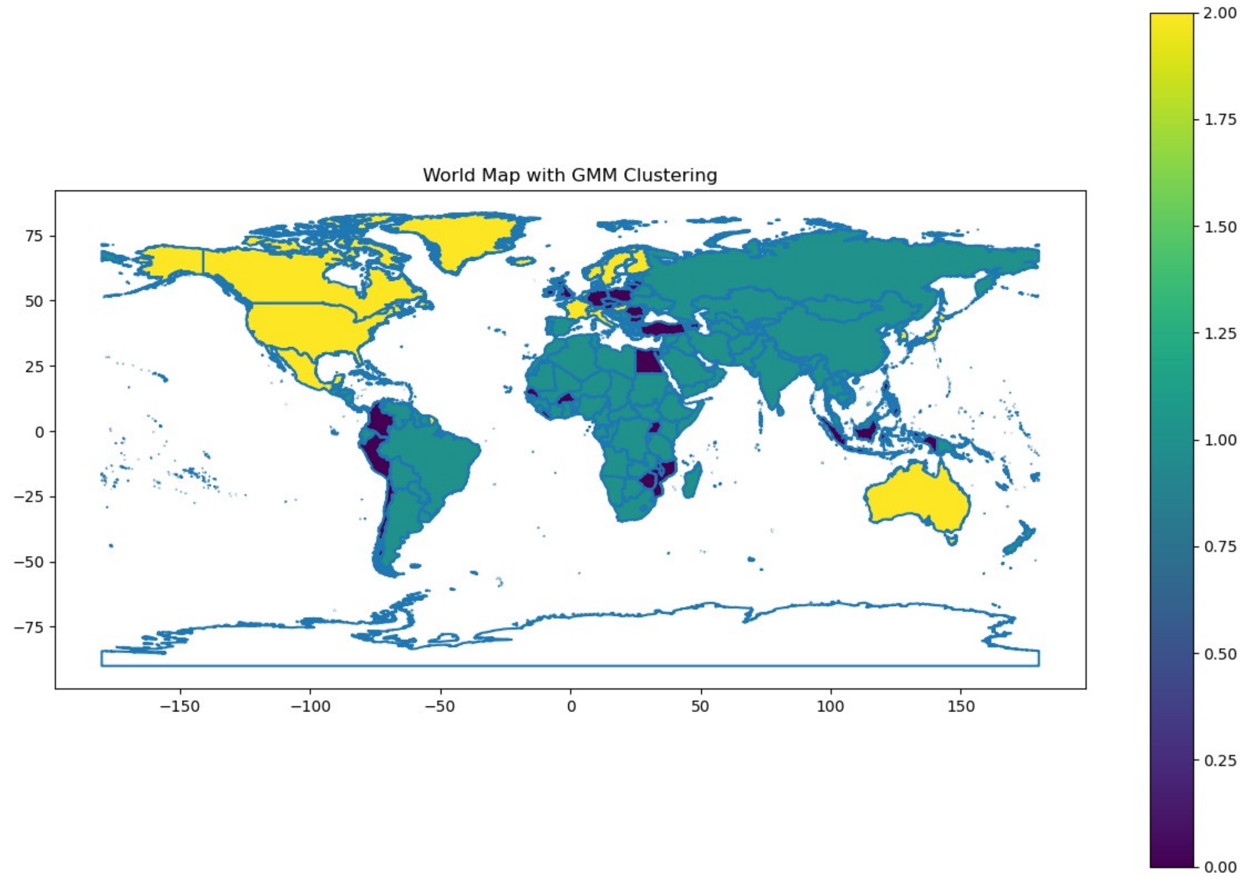
```
# Show the first few rows to inspect
print(marital_pivot.head())

Index(['Country', 'Divorced', 'Married', 'Separated', 'Single',
'Widowed'], dtype='object', name='Marital Status')
Marital Status           Country  Divorced  Married  Separated  Single
Widowed
0                    Afghanistan       100      116         14      71
116
1                        Albania       141      185         61      91
191
2                        Algeria       129      162         57     129
160
3                 American Samoa        84       86         58      90
86
4                         Angola       101       95         87      48
121

# Count the total number of people for each country
marital_pivot['Total_People'] =
marital_pivot.drop(columns='Country').sum(axis=1)

# Show the updated pivot table with total counts
print(marital_pivot.head())

Marital Status           Country  Divorced  Married  Separated  Single
Widowed  \
0                    Afghanistan       100      116         14      71
116
1                        Albania       141      185         61      91
191
2                        Algeria       129      162         57     129
160
3                 American Samoa        84       86         58      90
86
4                         Angola       101       95         87      48
121

Marital Status  Total_People
0                        417
1                        669
2                        637
3                        404
4                        452

from sklearn.mixture import GaussianMixture
from sklearn.preprocessing import StandardScaler

# Prepare data for GMM by including the total number of people
Y = marital_pivot.drop(columns='Country')
```

```python
# Standardize the features
scaler = StandardScaler()
Y_scaled = scaler.fit_transform(Y)

# Apply GMM
gmm2 = GaussianMixture(n_components=3, random_state=42)  # Adjust the
number of components as needed
clusters2 = gmm2.fit_predict(Y_scaled)

# Add cluster labels to the pivoted data
marital_pivot['Cluster'] = clusters2

import matplotlib.pyplot as plt
import seaborn as sns

# Cluster distribution
print("Cluster labels distribution:")
print(marital_pivot['Cluster'].value_counts())

# Visualize the results (for two selected age groups)
plt.figure(figsize=(12, 8))
sns.scatterplot(x=marital_pivot.iloc[:, 1], y=marital_pivot.iloc[:,
2], hue=marital_pivot['Cluster'], palette='viridis', s=100)
plt.title('GMM Clustering Results')
plt.xlabel('X')  # Adjust based on your age groups
plt.ylabel('Y')  # Adjust based on your age groups
plt.legend(title='Cluster')
plt.show()
```

```
Cluster labels distribution:
1    177
0     36
2     21
Name: Cluster, dtype: int64
```




```
# Merge with clustering results
world_clusters2 = world.merge(marital_pivot[['Country', 'Cluster']],
how='left', left_on='ADMIN', right_on='Country')

# Plot the world map with clusters
fig, ax = plt.subplots(1, 1, figsize=(15, 10))
world.boundary.plot(ax=ax)
world_clusters2.plot(column='Cluster', ax=ax, legend=True,
cmap='viridis', edgecolor='k', linewidth=0.5)
plt.title('World Map with GMM Clustering')
plt.show()
```



4.5 Spectral Clustering

App 1: Identifying marriage patterns in countries, complex relationships.

```
import pandas as pd
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.cluster import SpectralClustering
import re

# Function to calculate midpoint of age ranges
def age_group_midpoint(age_range):
    # Extract the two numbers from the age range
    numbers = list(map(int, re.findall(r'\d+', age_range)))
    return sum(numbers) / len(numbers)

# Load dataset
data = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')
```

```python
# Select relevant columns
data_subset = data[['Country', 'Age Group', 'Sex', 'Marital Status']]

# Convert Age Group to midpoints
data_subset['Age Group Midpoint'] = data_subset['Age
Group'].apply(age_group_midpoint)

# One-Hot Encoding for categorical columns
encoder = OneHotEncoder()
encoded_data = encoder.fit_transform(data_subset[['Country', 'Sex',
'Marital Status']])

# Standardizing the Age Group Midpoints
scaler = StandardScaler()
age_scaled = scaler.fit_transform(data_subset[['Age Group Midpoint']])

# Combine encoded data and scaled age group midpoints
X = pd.concat([pd.DataFrame(encoded_data.toarray()),
pd.DataFrame(age_scaled)], axis=1)

# Apply Spectral Clustering
spectral_clustering = SpectralClustering(n_clusters=5,
affinity='nearest_neighbors', random_state=42)
clusters = spectral_clustering.fit_predict(X)

# Add clusters to the original dataset
data['Cluster'] = clusters

# View the clustered dataset
print(data.head())
```

```
----------------------------------------------------------------------
-----
KeyboardInterrupt                         Traceback (most recent call
last)
Cell In[260], line 34
     32 # Apply Spectral Clustering
     33 spectral_clustering = SpectralClustering(n_clusters=5,
affinity='nearest_neighbors', random_state=42)
---> 34 clusters = spectral_clustering.fit_predict(X)
     36 # Add clusters to the original dataset
     37 data['Cluster'] = clusters

File ~\anaconda3\Lib\site-packages\sklearn\cluster\_spectral.py:785,
in SpectralClustering.fit_predict(self, X, y)
    763 def fit_predict(self, X, y=None):
    764     """Perform spectral clustering on `X` and return cluster
labels.
    765
    766     Parameters
```

```
   (...)
    783         Cluster labels.
    784     """
--> 785     return super().fit_predict(X, y)

File ~\anaconda3\Lib\site-packages\sklearn\base.py:753, in
ClusterMixin.fit_predict(self, X, y)
    735 """
    736 Perform clustering on `X` and returns cluster labels.
    737 
   (...)
    749     Cluster labels.
    750 """
    751 # non-optimized default implementation; override when a better
    752 # method is possible for a given clustering algorithm
--> 753 self.fit(X)
    754 return self.labels_

File ~\anaconda3\Lib\site-packages\sklearn\cluster\_spectral.py:750,
in SpectralClustering.fit(self, X, y)
    745     self.affinity_matrix_ = pairwise_kernels(
    746         X, metric=self.affinity, filter_params=True, **params
    747     )
    749 random_state = check_random_state(self.random_state)
--> 750 self.labels_ = spectral_clustering(
    751     self.affinity_matrix_,
    752     n_clusters=self.n_clusters,
    753     n_components=self.n_components,
    754     eigen_solver=self.eigen_solver,
    755     random_state=random_state,
    756     n_init=self.n_init,
    757     eigen_tol=self.eigen_tol,
    758     assign_labels=self.assign_labels,
    759     verbose=self.verbose,
    760 )
    761 return self

File ~\anaconda3\Lib\site-packages\sklearn\cluster\_spectral.py:371,
in spectral_clustering(affinity, n_clusters, n_components,
eigen_solver, random_state, n_init, eigen_tol, assign_labels, verbose)
    363 n_components = n_clusters if n_components is None else
n_components
    365 # We now obtain the real valued solution matrix to the
    366 # relaxed Ncut problem, solving the eigenvalue problem
    367 # L_sym x = lambda x  and recovering u = D^-1/2 x.
    368 # The first eigenvector is constant only for fully connected
graphs
    369 # and should be kept for spectral clustering (drop_first =
False)
    370 # See spectral_embedding documentation.
```

```
--> 371 maps = spectral_embedding(
    372     affinity,
    373     n_components=n_components,
    374     eigen_solver=eigen_solver,
    375     random_state=random_state,
    376     eigen_tol=eigen_tol,
    377     drop_first=False,
    378 )
    379 if verbose:
    380     print(f"Computing label assignment using {assign_labels}")

File ~\anaconda3\Lib\site-packages\sklearn\manifold\
_spectral_embedding.py:314, in spectral_embedding(adjacency,
n_components, eigen_solver, random_state, eigen_tol, norm_laplacian,
drop_first)
    312 laplacian *= -1
    313 v0 = _init_arpack_v0(laplacian.shape[0], random_state)
--> 314 _, diffusion_map = eigsh(
    315     laplacian, k=n_components, sigma=1.0, which="LM", tol=tol,
v0=v0
    316 )
    317 embedding = diffusion_map.T[n_components::-1]
    318 if norm_laplacian:
    319     # recover u = D^-1/2 x from the eigenvector output x

File ~\anaconda3\Lib\site-packages\scipy\sparse\linalg\_eigen\arpack\
arpack.py:1697, in eigsh(A, k, M, sigma, which, v0, ncv, maxiter, tol,
return_eigenvectors, Minv, OPinv, mode)
   1695 with _ARPACK_LOCK:
   1696     while not params.converged:
-> 1697         params.iterate()
   1699     return params.extract(return_eigenvectors)

File ~\anaconda3\Lib\site-packages\scipy\sparse\linalg\_eigen\arpack\
arpack.py:537, in _SymmetricArpackParams.iterate(self)
    535 def iterate(self):
    536     self.ido, self.tol, self.resid, self.v, self.iparam,
self.ipntr, self.info = \
--> 537         self._arpack_solver(self.ido, self.bmat, self.which,
self.k,
    538                             self.tol, self.resid, self.v,
self.iparam,
    539                             self.ipntr, self.workd,
self.workl, self.info)
    541     xslice = slice(self.ipntr[0] - 1, self.ipntr[0] - 1 +
self.n)
    542     yslice = slice(self.ipntr[1] - 1, self.ipntr[1] - 1 +
self.n)

KeyboardInterrupt:
```

```python
import pandas as pd
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.cluster import SpectralClustering
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import re

# Function to calculate midpoint of age ranges
def age_group_midpoint(age_range):
    numbers = list(map(int, re.findall(r'\d+', age_range)))
    return sum(numbers) / len(numbers)

# Load dataset
data = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')

# Select relevant columns
data_subset = data[['Country', 'Age Group', 'Sex', 'Marital Status']]

# Convert Age Group to midpoints
data_subset['Age Group Midpoint'] = data_subset['Age
Group'].apply(age_group_midpoint)

# One-Hot Encoding for categorical columns
encoder = OneHotEncoder()
encoded_data = encoder.fit_transform(data_subset[['Country', 'Sex',
'Marital Status']])

# Standardizing the Age Group Midpoints
scaler = StandardScaler()
age_scaled = scaler.fit_transform(data_subset[['Age Group Midpoint']])

# Combine encoded data and scaled age group midpoints
X = pd.concat([pd.DataFrame(encoded_data.toarray()),
pd.DataFrame(age_scaled)], axis=1)

# Apply Spectral Clustering
spectral_clustering = SpectralClustering(n_clusters=5,
affinity='nearest_neighbors', random_state=42)
clusters = spectral_clustering.fit_predict(X)

# Add clusters to the original dataset
data['Cluster'] = clusters

# Dimensionality Reduction with PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Plot clusters
plt.figure(figsize=(10, 6))
for cluster in sorted(data['Cluster'].unique()):
    cluster_data = X_pca[data['Cluster'] == cluster]
```

```
    plt.scatter(cluster_data[:, 0], cluster_data[:, 1],
label=f'Cluster {cluster}', alpha=0.6)

plt.title('Spectral Clustering of Marriage Patterns')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.grid(True)
plt.show()

import pandas as pd

# Example geographical coordinates data
geo_data = {
    'Country': ['Afghanistan', 'Albania', 'Algeria', 'Andorra',
'Angola'],
    'Latitude': [33.93911, 41.15303, 28.03389, 42.50779, -11.20269],
    'Longitude': [67.70995, 20.16831, 1.65962, 1.52109, 17.87389]
}

# Convert to DataFrame
geo_df = pd.DataFrame(geo_data)

# Save to CSV
geo_df.to_csv('Geographical_Coordinates.csv', index=False)

# Load the newly created geographical coordinates file
geo_data = pd.read_csv('Geographical_Coordinates.csv')

# Proceed with merging and analysis as previously described

import pandas as pd
import numpy as np
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.cluster import SpectralClustering
import re

# Function to calculate midpoint of age ranges
def age_group_midpoint(age_range):
    numbers = list(map(int, re.findall(r'\d+', age_range)))
    return sum(numbers) / len(numbers)

# Load the dataset
data = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')

# Convert Age Group to midpoints
data['Age Group Midpoint'] = data['Age
Group'].apply(age_group_midpoint)

# One-Hot Encoding for categorical columns
encoder = OneHotEncoder()
```

```
encoded_data = encoder.fit_transform(data[['Country', 'Sex', 'Marital
Status']])

# Standardizing the Age Group Midpoints
scaler = StandardScaler()
age_scaled = scaler.fit_transform(data[['Age Group Midpoint']])

# Combine encoded data and scaled age midpoints
X = pd.concat([
    pd.DataFrame(encoded_data.toarray()),
    pd.DataFrame(age_scaled)
], axis=1)

# Apply Spectral Clustering
spectral_clustering = SpectralClustering(n_clusters=5,
affinity='nearest_neighbors', random_state=42)
clusters = spectral_clustering.fit_predict(X)

# Add clusters to the original dataset
data['Cluster'] = clusters

# View the clustered dataset
print(data.head())

import pandas as pd
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.cluster import SpectralClustering
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import re

# Function to calculate midpoint of age ranges
def age_group_midpoint(age_range):
    numbers = list(map(int, re.findall(r'\d+', age_range)))
    return sum(numbers) / len(numbers)

# Load dataset
data = pd.read_csv('World_Marriage_Cleaned_Dataset.csv')

# Select relevant columns
data_subset = data[['Country', 'Age Group', 'Sex', 'Marital Status']]

# Convert Age Group to midpoints
data_subset['Age Group Midpoint'] = data_subset['Age
Group'].apply(age_group_midpoint)

# One-Hot Encoding for categorical columns
encoder = OneHotEncoder()
encoded_data = encoder.fit_transform(data_subset[['Country', 'Sex',
'Marital Status']])
```

```
# Standardizing the Age Group Midpoints
scaler = StandardScaler()
age_scaled = scaler.fit_transform(data_subset[['Age Group Midpoint']])

# Combine encoded data and scaled age group midpoints
X = pd.concat([pd.DataFrame(encoded_data.toarray()),
pd.DataFrame(age_scaled)], axis=1)

# Apply Spectral Clustering
spectral_clustering = SpectralClustering(n_clusters=5,
affinity='nearest_neighbors', random_state=42)
clusters = spectral_clustering.fit_predict(X)

# Add clusters to the original dataset
data['Cluster'] = clusters

# Dimensionality Reduction with PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Plot clusters
plt.figure(figsize=(10, 6))
for cluster in sorted(data['Cluster'].unique()):
    cluster_data = X_pca[data['Cluster'] == cluster]
    plt.scatter(cluster_data[:, 0], cluster_data[:, 1],
label=f'Cluster {cluster}', alpha=0.6)

plt.title('Spectral Clustering of Marriage Patterns')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.grid(True)
plt.show()
```