initial-results-and-the-code

March 30, 2024

This notebook presents the data cleaning, exploratory data analysis and feature engineering using data from Gapminder that will be used for linear, polynomial and logarithmic regression in another notebook.

1 Import packages and data

[1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

# load the datset (csv files)
data = pd.read_csv("https://raw.githubusercontent.com/BME1478H/Winter2022class/
↪master/data/world-data-gapminder.csv")
```

2 Description of data set and a summary of its attributes

This data set has been generated using data from the Gapminder website, which focuses on gathering and sharing statistics and other information about social, economic and environmental development at local, national and global levels.

This particular data set describes the values of several parameters (see the list below) between 1800 and 2018 for a total of 192 countries. The parameters included in the data set and the column name of the dataframe are as follows:

- Country (country): Describes the country name
- Year (year): Describes the year to which the data belongs
- Population(population): Describes the number of population.
- Region (region): Describes the region to which the country belongs *Sub Region (sub_region): Describes the sub-region to which the country belongs.
- Income Group (income_group): Classifies the people into income levels orclasses.
- Life expectancy (life_expectancy): Describes the life expectancy for a given country in a given year
- Income (income): Describes the Income per person in dollars for a given country in a given year
- Children per woman (children_per-woman): Describes average number of children per woman
- Child Mortality (child-mortality): Describe number of child mortality in a country.
- Population Density (pop_density): Describes the population density in a country.

- CO2 emissions per capita (co2_per_capita): Describes the CO2 emissions in tonnes per person for a given country in a given year
- Years in school for Men (years_in_school_men): Describe the number of years on average a men spent in school
- Years in school for Women (years_in_school_women): Describe the number of years on average an women spent in school

Let's have a look at the data.

Let's check the data types and the number of samples for each column:

[2]:
```
#Dataset chekup
data.sample(n=10)
```

[2]:
```
          country  year  population    region  \
17124     Jamaica  1842      400000  Americas
29762     Senegal  1997     9200000    Africa
219       Albania  1800      410000    Europe
8220   Costa Rica  1917      400000  Americas
24398       Nepal  1889     5240000      Asia
34974        Togo  1953     1450000    Africa
1961      Austria  2009     8370000    Europe
1638    Australia  1905     4020000   Oceania
14796       Haiti  1923     2230000  Americas
27204    Paraguay  1848      318000  Americas

                        sub_region income_group  life_expectancy  income  \
17124  Latin America and the Caribbean  Upper middle             34.2     977
29762               Sub-Saharan Africa           Low             58.8    1760
219                   Southern Europe  Upper middle             35.4     667
8220   Latin America and the Caribbean  Upper middle             35.6    2300
24398                   Southern Asia           Low             33.8     758
34974               Sub-Saharan Africa           Low             39.0    1080
1961                   Western Europe          High             80.3   42500
1638         Australia and New Zealand          High             52.7    7140
14796  Latin America and the Caribbean           Low             28.5    1810
27204  Latin America and the Caribbean  Upper middle             35.5    1190

       children_per_woman  child_mortality  pop_density  co2_per_capita  \
17124                5.13            390.0          NaN             NaN
29762                5.77            143.0         47.8          0.3550
219                  4.60            375.0          NaN             NaN
8220                 6.71            366.0          NaN             NaN
24398                6.15            407.0          NaN             NaN
34974                6.33            308.0         26.7          0.0202
1961                 1.39              4.5        102.0          7.4900
1638                 3.51            117.0          NaN          3.0000
14796                6.31            462.0          NaN             NaN
```

```
27204                  6.49           374.0         NaN              NaN

       years_in_school_men  years_in_school_women
17124                  NaN                    NaN
29762                 3.34                   1.82
219                    NaN                    NaN
8220                   NaN                    NaN
24398                  NaN                    NaN
34974                  NaN                    NaN
1961                 12.40                  12.40
1638                   NaN                    NaN
14796                  NaN                    NaN
27204                  NaN                    NaN
```

[3]:
```python
# Display the first few rows of the dataset to understand its structure
print(data.head())
```

```
       country  year  population region      sub_region income_group  \
0  Afghanistan  1800     3280000   Asia  Southern Asia          Low
1  Afghanistan  1801     3280000   Asia  Southern Asia          Low
2  Afghanistan  1802     3280000   Asia  Southern Asia          Low
3  Afghanistan  1803     3280000   Asia  Southern Asia          Low
4  Afghanistan  1804     3280000   Asia  Southern Asia          Low

   life_expectancy  income  children_per_woman  child_mortality  pop_density  \
0             28.2     603                 7.0            469.0          NaN
1             28.2     603                 7.0            469.0          NaN
2             28.2     603                 7.0            469.0          NaN
3             28.2     603                 7.0            469.0          NaN
4             28.2     603                 7.0            469.0          NaN

   co2_per_capita  years_in_school_men  years_in_school_women
0             NaN                  NaN                    NaN
1             NaN                  NaN                    NaN
2             NaN                  NaN                    NaN
3             NaN                  NaN                    NaN
4             NaN                  NaN                    NaN
```

[4]:
```python
# Display data types
print(data.dtypes)
```

```
country                   object
year                       int64
population                 int64
region                    object
sub_region                object
income_group              object
life_expectancy          float64
```

```
income                      int64
children_per_woman        float64
child_mortality           float64
pop_density               float64
co2_per_capita            float64
years_in_school_men       float64
years_in_school_women     float64
dtype: object
```

[5]:
```
# List of columns for reference in the analyses below
print(data.columns)
```

```
Index(['country', 'year', 'population', 'region', 'sub_region', 'income_group',
       'life_expectancy', 'income', 'children_per_woman', 'child_mortality',
       'pop_density', 'co2_per_capita', 'years_in_school_men',
       'years_in_school_women'],
      dtype='object')
```

[6]:
```
# For categorical attributes, let's look at the frequency of countries or other␣
↪categorical fields
print(data['country'].value_counts())  # Assuming 'country' is one of the␣
↪columns
```

```
United States    438
Afghanistan      219
Panama           219
New Zealand      219
Nicaragua        219
                ...
Greece           219
Grenada          219
Guatemala        219
Guinea           219
Zimbabwe         219
Name: country, Length: 178, dtype: int64
```

[7]:
```
# Basic information about the dataset
print(data.info())
#data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39201 entries, 0 to 39200
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   country                39201 non-null  object
 1   year                   39201 non-null  int64
 2   population             39201 non-null  int64
```

```
 3    region                 39201 non-null   object
 4    sub_region             39201 non-null   object
 5    income_group           39201 non-null   object
 6    life_expectancy        39201 non-null   float64
 7    income                 39201 non-null   int64
 8    children_per_woman     39201 non-null   float64
 9    child_mortality        39199 non-null   float64
 10  pop_density            12351 non-null   float64
 11  co2_per_capita         16500 non-null   float64
 12  years_in_school_men    8234 non-null    float64
 13  years_in_school_women  8234 non-null    float64
dtypes: float64(7), int64(3), object(4)
memory usage: 4.2+ MB
None
```

3 Initial plan for data exploration

The initial plan for data exploration is as follows:

*Data cleaning: The data cleaning process is split into following two main actions . . . Null values: Understand the reason why there are null values to find out the best way to deal with them.

Outliers: Similarly to the null values, the first step is to understand the presence of outliers as well as to find out if removing them is a good idea or it's actually valuable data.

*Feature extraction: Understand the relationship between the different features, perform transformation to help improve those relationships and perform Principal Component Analyisis to understand how some of the features explain the HDI index variance

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*Hypothesis testing: Formulate three hypotheses and test one of them

Next, Let's find out how many null values there are:

[8]:
```python
# To find out the number of Null values
data.isnull().sum()
```

[8]:
```
country                0
 year                  0
 population            0
 region                0
 sub_region            0
 income_group          0
 life_expectancy       0
 income                0
 children_per_woman    0
 child_mortality       2
```

```
pop_density            26850
co2_per_capita         22701
years_in_school_men    30967
years_in_school_women  30967
dtype: int64
```

4 Data cleaning

4.1 Null values

Data cleaning is always tricky and this dataset isn't an exception. In fact, it's even trickier because the number of samples, 39202, is spread accross 218 different years. This means that there are 218 different sub-datasets with around 205 elements each. Therefore, the sample size is relatively small and the impact of each value in the final metrics is greater. One needs to be careful and undrestand the reason behind the NaN values before replacing or deleting them.

Prior to the analysis, I considered the following techniques to deal with null values:

- Remove them, provided that we don't lose a lot of data
- Impute data using the one of the following options:
  - Mean value
  - Most common value
  - Interpolation provided that there is enough data to make a prediction

However, let's starts by checking which are the null values and try to understand why there are missing values.

[9]:
```
data[data.isna().any(axis=1)]
```

[9]:
```
           country  year  population  region          sub_region income_group  \
0      Afghanistan  1800     3280000    Asia       Southern Asia          Low
1      Afghanistan  1801     3280000    Asia       Southern Asia          Low
2      Afghanistan  1802     3280000    Asia       Southern Asia          Low
3      Afghanistan  1803     3280000    Asia       Southern Asia          Low
4      Afghanistan  1804     3280000    Asia       Southern Asia          Low
...            ...   ...         ...     ...                 ...          ...
39151     Zimbabwe  1969     5010000  Africa  Sub-Saharan Africa          Low
39197     Zimbabwe  2015    15800000  Africa  Sub-Saharan Africa          Low
39198     Zimbabwe  2016    16200000  Africa  Sub-Saharan Africa          Low
39199     Zimbabwe  2017    16500000  Africa  Sub-Saharan Africa          Low
39200     Zimbabwe  2018    16900000  Africa  Sub-Saharan Africa          Low

       life_expectancy  income  children_per_woman  child_mortality  \
0                 28.2     603                7.00            469.0
1                 28.2     603                7.00            469.0
2                 28.2     603                7.00            469.0
3                 28.2     603                7.00            469.0
4                 28.2     603                7.00            469.0
```

```
...                ...      ...                 ...                ...
39151              57.2     2160               7.42              115.0
39197              58.3     1890               3.84               59.9
39198              59.3     1860               3.76               56.4
39199              59.8     1910               3.68               56.8
39200              60.2     1950               3.61               55.5

       pop_density  co2_per_capita  years_in_school_men  years_in_school_women
0              NaN             NaN                  NaN                    NaN
1              NaN             NaN                  NaN                    NaN
2              NaN             NaN                  NaN                    NaN
3              NaN             NaN                  NaN                    NaN
4              NaN             NaN                  NaN                    NaN
...            ...             ...                  ...                    ...
39151         12.9            1.35                  NaN                    NaN
39197         40.8             NaN                 11.1                   10.2
39198         41.7             NaN                  NaN                    NaN
39199         42.7             NaN                  NaN                    NaN
39200         43.7             NaN                  NaN                    NaN

[31484 rows x 14 columns]
```

Let's have a look at the list of unique countries and years whose rows include null values for the pop_densityColumn:

[10]:
```
print(set(data[data["pop_density"].isna()]["country"]))
print(set(data[data["pop_density"].isna()]["year"]))
```

```
{'Gambia', 'Montenegro', 'Swaziland', 'Iraq', 'Peru', 'Tunisia', 'Congo, Dem.
Rep.', 'Zimbabwe', 'Uganda', 'Chile', 'Czech Republic', 'Oman', 'Malaysia',
'Lithuania', 'Australia', 'Mauritania', 'Estonia', 'Poland', 'Netherlands',
'Bolivia', 'Sri Lanka', 'Benin', 'Italy', 'Niger', 'Slovenia', 'Cambodia',
'Afghanistan', 'Solomon Islands', 'Spain', 'Malawi', 'Gabon', 'Ghana', 'Canada',
'Denmark', 'Latvia', 'Norway', 'France', 'Equatorial Guinea', 'Jamaica',
'Guinea-Bissau', 'Senegal', 'Moldova', 'Burundi', 'Bahamas', 'Burkina Faso',
'Argentina', 'Liberia', 'South Sudan', 'Venezuela', 'Kiribati', 'Mexico',
'Switzerland', 'El Salvador', 'New Zealand', 'Sweden', 'Kazakhstan', 'South
Africa', 'Samoa', 'Croatia', 'Djibouti', 'Trinidad and Tobago', 'Brazil',
'Thailand', 'Tonga', 'Kenya', 'Slovak Republic', 'Ireland', 'Central African
Republic', 'Bhutan', 'Lebanon', 'Panama', 'Cuba', 'Serbia', 'Uzbekistan', 'Papua
New Guinea', 'Greece', 'Bulgaria', 'Bangladesh', 'Saudi Arabia', 'Lao',
'Mongolia', 'Ecuador', 'Cyprus', 'United Arab Emirates', 'Somalia', 'Vietnam',
'Seychelles', 'Paraguay', 'Palestine', 'Romania', 'Libya', 'Botswana',
'Algeria', 'Germany', 'Zambia', 'Tajikistan', 'Azerbaijan', 'Georgia',
'Ethiopia', 'Macedonia, FYR', 'United Kingdom', 'Uruguay', 'Suriname', 'Costa
Rica', 'Egypt', 'Guinea', 'Pakistan', 'Hungary', 'Rwanda', 'Mozambique',
'Mauritius', 'Kuwait', 'Togo', 'Kyrgyz Republic', 'Syria', 'Iceland', 'Chad',
```

```
'Barbados', 'Qatar', 'Albania', 'Nepal', 'Namibia', 'Dominican Republic',
'Guatemala', "Cote d'Ivoire", 'India', 'Bahrain', 'Belize', 'Nicaragua',
'Comoros', 'Finland', 'Malta', 'United States', 'Grenada', 'Israel', 'Nigeria',
'China', 'Armenia', 'Luxembourg', 'Japan', 'Tanzania', 'Haiti', 'Morocco',
'Bosnia and Herzegovina', 'Congo, Rep.', 'Mali', 'Sierra Leone', 'South Korea',
'Singapore', 'Fiji', 'Myanmar', 'Turkey', 'Jordan', 'North Korea', 'Sudan',
'Honduras', 'Belarus', 'Austria', 'Yemen', 'Maldives', 'Eritrea', 'Angola',
'Colombia', 'Iran', 'Belgium', 'Indonesia', 'Portugal', 'Russia', 'Timor-Leste',
'Turkmenistan', 'Cameroon', 'Madagascar', 'Guyana', 'Lesotho', 'Vanuatu',
'Antigua and Barbuda', 'Philippines', 'Ukraine'}
{1800, 1801, 1802, 1803, 1804, 1805, 1806, 1807, 1808, 1809, 1810, 1811, 1812,
1813, 1814, 1815, 1816, 1817, 1818, 1819, 1820, 1821, 1822, 1823, 1824, 1825,
1826, 1827, 1828, 1829, 1830, 1831, 1832, 1833, 1834, 1835, 1836, 1837, 1838,
1839, 1840, 1841, 1842, 1843, 1844, 1845, 1846, 1847, 1848, 1849, 1850, 1851,
1852, 1853, 1854, 1855, 1856, 1857, 1858, 1859, 1860, 1861, 1862, 1863, 1864,
1865, 1866, 1867, 1868, 1869, 1870, 1871, 1872, 1873, 1874, 1875, 1876, 1877,
1878, 1879, 1880, 1881, 1882, 1883, 1884, 1885, 1886, 1887, 1888, 1889, 1890,
1891, 1892, 1893, 1894, 1895, 1896, 1897, 1898, 1899, 1900, 1901, 1902, 1903,
1904, 1905, 1906, 1907, 1908, 1909, 1910, 1911, 1912, 1913, 1914, 1915, 1916,
1917, 1918, 1919, 1920, 1921, 1922, 1923, 1924, 1925, 1926, 1927, 1928, 1929,
1930, 1931, 1932, 1933, 1934, 1935, 1936, 1937, 1938, 1939, 1940, 1941, 1942,
1943, 1944, 1945, 1946, 1947, 1948, 1949}
```

It makes sense to see some of these countries and years as some of them declared their independence recently, others underwent foreign military occupations or wars.

Next, Let's follow a similar approach for the 'co2_per_capita' column:

[11]:
```
data[data["co2_per_capita"].isna()].sample(n=10)
```

[11]:
```
        country  year  population    region                       sub_region  \
31094  Slovenia  2015     2070000    Europe                  Southern Europe
38406   Vietnam  1881    11600000      Asia               South-eastern Asia
19826   Liberia  1916      702000    Africa               Sub-Saharan Africa
19511   Lesotho  1820      282000    Africa               Sub-Saharan Africa
32916  Suriname  1866      114000  Americas  Latin America and the Caribbean
17626    Jordan  1906      342000      Asia                     Western Asia
13387    Greece  1828     2490000    Europe                  Southern Europe
38596     Yemen  1852     2750000      Asia                     Western Asia
16250      Iraq  1844     1310000      Asia                     Western Asia
15019  Honduras  1927      942000  Americas  Latin America and the Caribbean

       income_group life_expectancy  income  children_per_woman  \
31094          High            80.7   29100                1.61
38406  Lower middle            31.7     917                4.70
19826           Low            34.1    1030                6.19
19511  Lower middle            32.8     398                5.84
32916  Upper middle            32.9    2240                6.58
```

```
17626  Upper middle          32.1     1590              6.97
13387          High          36.6     1520              6.03
38596           Low          23.4     1020              6.88
16250  Upper middle          31.2     1070              7.13
15019  Lower middle          35.7     2650              6.35

       child_mortality  pop_density  co2_per_capita  years_in_school_men  \
31094              2.4        103.0             NaN                 13.4
38406            417.0          NaN             NaN                  NaN
19826            416.0          NaN             NaN                  NaN
19511            407.0          NaN             NaN                  NaN
32916            406.0          NaN             NaN                  NaN
17626            417.0          NaN             NaN                  NaN
13387            361.0          NaN             NaN                  NaN
38596            540.0          NaN             NaN                  NaN
16250            428.0          NaN             NaN                  NaN
15019            371.0          NaN             NaN                  NaN

       years_in_school_women
31094                   14.2
38406                    NaN
19826                    NaN
19511                    NaN
32916                    NaN
17626                    NaN
13387                    NaN
38596                    NaN
16250                    NaN
15019                    NaN
```

[12]:
```
print(set(data[data["co2_per_capita"].isna()]["country"]))
print(set(data[data["co2_per_capita"].isna()]["year"]))
```

```
{'Gambia', 'Montenegro', 'Swaziland', 'Iraq', 'Peru', 'Tunisia', 'Congo, Dem.
Rep.', 'Zimbabwe', 'Uganda', 'Chile', 'Czech Republic', 'Oman', 'Malaysia',
'Lithuania', 'Australia', 'Mauritania', 'Estonia', 'Poland', 'Netherlands',
'Bolivia', 'Sri Lanka', 'Benin', 'Italy', 'Niger', 'Slovenia', 'Cambodia',
'Afghanistan', 'Solomon Islands', 'Spain', 'Malawi', 'Gabon', 'Ghana', 'Canada',
'Denmark', 'Latvia', 'Norway', 'France', 'Equatorial Guinea', 'Jamaica', 'Guinea-
Bissau', 'Senegal', 'Moldova', 'Burundi', 'Bahamas', 'Burkina Faso', 'Argentina',
'Liberia', 'South Sudan', 'Venezuela', 'Kiribati', 'Mexico', 'Switzerland', 'El
Salvador', 'New Zealand', 'Sweden', 'Kazakhstan', 'South Africa', 'Samoa',
'Croatia', 'Djibouti', 'Trinidad and Tobago', 'Brazil', 'Thailand', 'Tonga',
'Kenya', 'Slovak Republic', 'Ireland', 'Central African Republic', 'Bhutan',
'Lebanon', 'Panama', 'Cuba', 'Serbia', 'Uzbekistan', 'PapuaNew Guinea',
'Greece', 'Bulgaria', 'Bangladesh', 'Saudi Arabia', 'Lao',
```

```
'Mongolia', 'Ecuador', 'Cyprus', 'United Arab Emirates', 'Somalia', 'Vietnam',
'Seychelles', 'Paraguay', 'Palestine', 'Romania', 'Libya', 'Botswana',
'Algeria', 'Germany', 'Zambia', 'Tajikistan', 'Azerbaijan', 'Georgia',
'Ethiopia', 'Macedonia, FYR', 'United Kingdom', 'Uruguay', 'Suriname', 'Costa
Rica', 'Egypt', 'Guinea', 'Pakistan', 'Hungary', 'Rwanda', 'Mozambique',
'Mauritius', 'Kuwait', 'Togo', 'Kyrgyz Republic', 'Syria', 'Iceland', 'Chad',
'Barbados', 'Qatar', 'Albania', 'Nepal', 'Namibia', 'Dominican Republic',
'Guatemala', "Cote d'Ivoire", 'India', 'Bahrain', 'Belize', 'Nicaragua',
'Comoros', 'Finland', 'Malta', 'United States', 'Grenada', 'Israel', 'Nigeria',
'China', 'Armenia', 'Luxembourg', 'Japan', 'Tanzania', 'Haiti', 'Morocco',
'Bosnia and Herzegovina', 'Congo, Rep.', 'Mali', 'Sierra Leone', 'South Korea',
'Singapore', 'Fiji', 'Myanmar', 'Turkey', 'Jordan', 'North Korea', 'Sudan',
'Honduras', 'Belarus', 'Austria', 'Yemen', 'Maldives', 'Eritrea', 'Angola',
'Colombia', 'Iran', 'Belgium', 'Indonesia', 'Portugal', 'Russia', 'Timor-Leste',
'Turkmenistan', 'Cameroon', 'Madagascar', 'Guyana', 'Lesotho', 'Vanuatu',
'Antigua and Barbuda', 'Philippines', 'Ukraine'}
{1800, 1801, 1802, 1803, 1804, 1805, 1806, 1807, 1808, 1809, 1810, 1811, 1812,
1813, 1814, 1815, 1816, 1817, 1818, 1819, 1820, 1821, 1822, 1823, 1824, 1825,
1826, 1827, 1828, 1829, 1830, 1831, 1832, 1833, 1834, 1835, 1836, 1837, 1838,
1839, 1840, 1841, 1842, 1843, 1844, 1845, 1846, 1847, 1848, 1849, 1850, 1851,
1852, 1853, 1854, 1855, 1856, 1857, 1858, 1859, 1860, 1861, 1862, 1863, 1864,
1865, 1866, 1867, 1868, 1869, 1870, 1871, 1872, 1873, 1874, 1875, 1876, 1877,
1878, 1879, 1880, 1881, 1882, 1883, 1884, 1885, 1886, 1887, 1888, 1889, 1890,
1891, 1892, 1893, 1894, 1895, 1896, 1897, 1898, 1899, 1900, 1901, 1902, 1903,
1904, 1905, 1906, 1907, 1908, 1909, 1910, 1911, 1912, 1913, 1914, 1915, 1916,
1917, 1918, 1919, 1920, 1921, 1922, 1923, 1924, 1925, 1926, 1927, 1928, 1929,
1930, 1931, 1932, 1933, 1934, 1935, 1936, 1937, 1938, 1939, 1940, 1941, 1942,
1943, 1944, 1945, 1946, 1947, 1948, 1949, 1950, 1951, 1952, 1953, 1954, 1955,
1956, 1957, 1958, 1959, 1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968,
1969, 1970, 1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981,
1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 1994,
1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007,
2008, 2009, 2010, 2011, 2015, 2016, 2017, 2018}
```

We can also see countries that have undergone difficult periods. Given the complexity of these events, it will be difficult to make predictions or find the right value to replace for all countries, i.e. the mean value might be good for some but it might lead to uncertainty in others. Furthermore, we can see that there is a period (2013-2015) in which there are no null values. Therefore, it seems like the best approach is to **remove the null values**.

[13]:
```python
data = data.dropna().reset_index(drop=True)
data.isnull().sum()
```

[13]:
```
country       0
year          0
population    0
region        0
```

```
sub_region              0
income_group            0
life_expectancy         0
income                  0
children_per_woman      0
child_mortality         0
pop_density             0
co2_per_capita          0
years_in_school_men     0
years_in_school_women   0
dtype: int64
```

4.2 Select a subset

Given the range of the data (1800-2018), drawing conclusions based on the entire data set is difficult and counter productive. We can expect similar relationship for adjacent years, such as 1995-1998,1998-2000, 2005-2007 and so on, but most likely those relationship have changed between 1800 and 2018. Therefore, working with the entire data set might lead to not seing the full picture.

This being said, we can select a subset of the data and in the data cleaning section we identified a subset that included no null values and it isn't affected by the loss of information.

[14]:
```
# select the subset belonging to the year range 2013-2015
data_period = data[
    (data["year"] == 2013) | (data["year"] == 2014) | (data["year"] == 2015)
]

data_period.head()
```

[14]:
```
         country  year  population  region       sub_region income_group  \
43   Afghanistan  2013    31700000    Asia    Southern Asia          Low
44   Afghanistan  2014    32800000    Asia    Southern Asia          Low
88       Albania  2013     2920000  Europe  Southern Europe  Upper middle
89       Albania  2014     2920000  Europe  Southern Europe  Upper middle
133      Algeria  2013    38300000  Africa  Northern Africa  Upper middle

     life_expectancy  income  children_per_woman  child_mortality  \
43              57.7    1810                5.17             79.3
44              57.8    1780                4.98             76.1
88              77.2   10500                1.70             14.9
89              77.4   10700                1.71             14.4
133             77.0   13300                2.92             25.8

     pop_density  co2_per_capita  years_in_school_men  years_in_school_women
43          48.6           0.316                 3.94                   0.92
44          50.2           0.299                 4.04                   0.95
88         107.0           1.730                11.70                  11.90
89         107.0           1.960                11.80                  12.10
```

```
133        16.1        3.510        8.24        7.42
```

[15]:
```
data_period.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 358 entries, 43 to 7716
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   country                358 non-null    object
 1   year                   358 non-null    int64
 2   population             358 non-null    int64
 3   region                 358 non-null    object
 4   sub_region             358 non-null    object
 5   income_group           358 non-null    object
 6   life_expectancy        358 non-null    float64
 7   income                 358 non-null    int64
 8   children_per_woman     358 non-null    float64
 9   child_mortality        358 non-null    float64
 10  pop_density            358 non-null    float64
 11  co2_per_capita         358 non-null    float64
 12  years_in_school_men    358 non-null    float64
 13  years_in_school_women  358 non-null    float64
dtypes: float64(7), int64(3), object(4)
memory usage: 42.0+ KB
```

[16]:
```
data_period.groupby("region").describe()
```

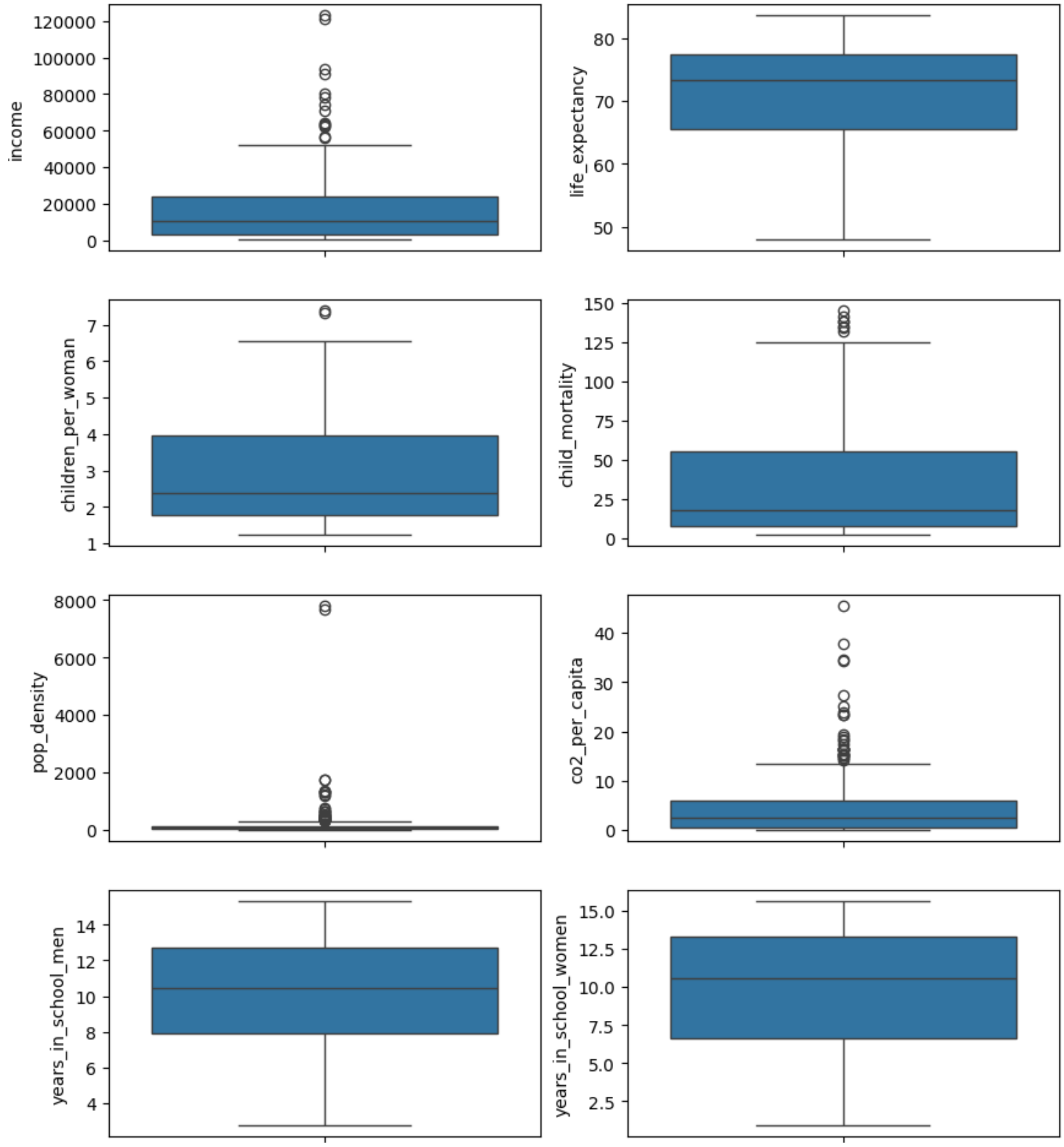
[16]:
```
          year                                                          \
         count    mean       std     min     25%     50%     75%     max
region
Africa    104.0  2013.5  0.502421  2013.0  2013.0  2013.5  2014.0  2014.0
Americas   62.0  2013.5  0.504082  2013.0  2013.0  2013.5  2014.0  2014.0
Asia       94.0  2013.5  0.502681  2013.0  2013.0  2013.5  2014.0  2014.0
Europe     78.0  2013.5  0.503236  2013.0  2013.0  2013.5  2014.0  2014.0
Oceania    20.0  2013.5  0.512989  2013.0  2013.0  2013.5  2014.0  2014.0

         population               ... years_in_school_men        \
              count         mean  ...                 75%   max
region                            ...
Africa        104.0  2.205035e+07 ...              8.9275  11.3
Americas       62.0  3.124632e+07 ...             11.8750  15.3
Asia           94.0  9.190187e+07 ...             12.4000  15.0
Europe         78.0  1.896846e+07 ...             13.9000  14.8
Oceania        20.0  3.546855e+07 ...             13.9250  14.5

         years_in_school_women                                          \
```

```
                     count       mean       std    min      25%    50%
region
Africa               104.0   5.646827  2.886351   1.12   3.5250   5.38
Americas              62.0  11.053226  2.121167   6.35   9.7200  10.85
Asia                  94.0   9.859362  3.658881   0.92   7.5700  10.60
Europe                78.0  13.733333  1.039938  11.00  13.3250  14.00
Oceania               20.0  11.268000  3.093146   5.75   8.7375  11.90

             75%   max
region
Africa     7.795  11.4
Americas  12.700  15.5
Asia      12.800  15.6
Europe    14.400  15.3
Oceania   14.325  14.9

[5 rows x 80 columns]
```

5 Outliers

The presence of outliers can easily be identified by using box plots. However, one has to be careful as a boxplot of the entire data frame will show many outliers. Let's create the box plots

[17]:
```python
# Create a list using the features that contain numerical data
column_list_plot = [
    "income",
    "life_expectancy",
    "children_per_woman",
    "child_mortality",
    "pop_density",
    "co2_per_capita",
    "years_in_school_men",
    "years_in_school_women",
]

# Create a 4x2 figure with 8 subplots, where 8 of them will be used
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(10, 12))

# Flatten the axes array to iterate over it
axes = axes.flatten()

# Use a for loop to create the subplots
for index, col_name in enumerate(column_list_plot):
    sns.boxplot(ax=axes[index], y=col_name, data=data_period)
```



As expected, the box plots for four of the features (income, child_mortality, pop_density and co2_emissions) show many outliers, but this isn't the full picture. An accurate analysis of the outliers requires to plot the data split into continents.

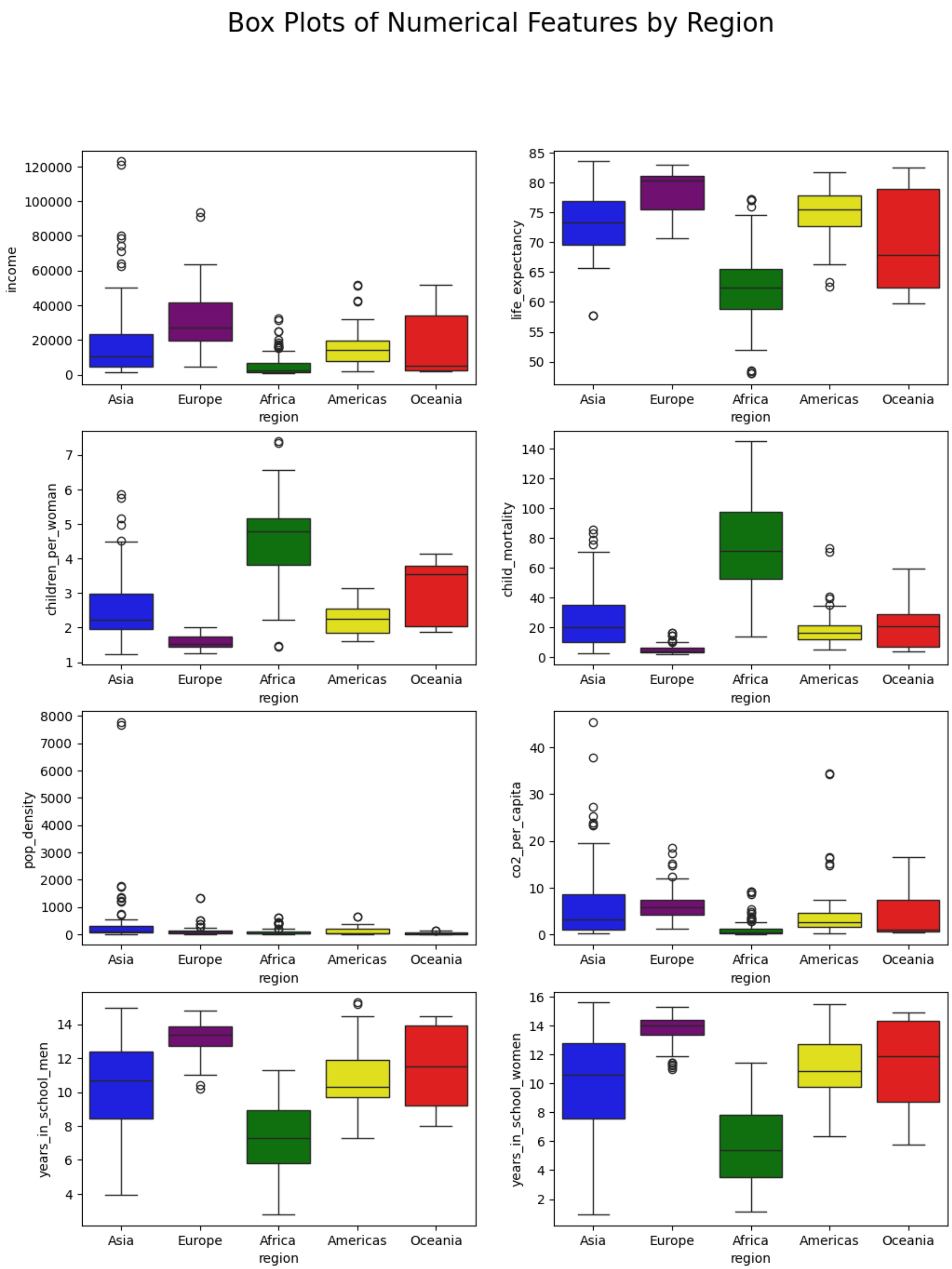
[18]:
```
# Create a list of colors for different regions
region_colors = {
    "Africa": "green",
    "Americas": "yellow",
    "Asia": "blue",
    "Europe": "purple",
    "Oceania": "red",
```

```python
}
# Create a 4x2 figure with 8 subplots, Where 8 of them will be used
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(12, 15))

# Flatten the axes array to iterate over it
axes = axes.flatten()

# Use a for loop to create the subplots
for index, col_name in enumerate(column_list_plot):
    sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,␣
↪palette=region_colors)

# Add a title to the entire figure
fig.suptitle("Box Plots of Numerical Features by Region", fontsize=20)
```

```
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
palette=region_colors)
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
palette=region_colors)
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
palette=region_colors)
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
```

```
palette=region_colors)
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
palette=region_colors)
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
palette=region_colors)
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
palette=region_colors)
<ipython-input-18-28821a18bb68>:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(ax=axes[index], x="region", y=col_name, data=data_period,
palette=region_colors)
```

[18]:
```
Text(0.5, 0.98, 'Box Plots of Numerical Features by Region')
```



Actually, these box plots show more outliers than the previous graphs. As studied in this course, the presence of outliers can be due to errors in the measurement, but it can also be right. Let's have a look at data belonging to `Oceania` to understand the reason behind the outliers:

[19]:
```
data_period[data_period["region"] == "Oceania"]
```

[19]:
```
               country  year  population   region                 sub_region  \
358          Australia  2013    23200000  Oceania  Australia and New Zealand
359          Australia  2014    23500000  Oceania  Australia and New Zealand
2336              Fiji  2013      880000  Oceania                  Melanesia
2337              Fiji  2014      886000  Oceania                  Melanesia
3686          Kiribati  2013      109000  Oceania                 Micronesia
3687          Kiribati  2014      110000  Oceania                 Micronesia
4928       New Zealand  2013     4520000  Oceania  Australia and New Zealand
4929       New Zealand  2014     4570000  Oceania  Australia and New Zealand
5358  Papua New Guinea  2013     7590000  Oceania                  Melanesia
5359  Papua New Guinea  2014     7760000  Oceania                  Melanesia
5808             Samoa  2013      191000  Oceania                  Polynesia
5809             Samoa  2014      192000  Oceania                  Polynesia
6169   Solomon Islands  2013      564000  Oceania                  Melanesia
6170   Solomon Islands  2014      576000  Oceania                  Melanesia
6905             Tonga  2013      105000  Oceania                  Polynesia
6906             Tonga  2014      106000  Oceania                  Polynesia
7354     United States  2013   316000000  Oceania                 Micronesia
7356     United States  2014   318000000  Oceania                 Micronesia
7490           Vanuatu  2013      253000  Oceania                  Melanesia
7491           Vanuatu  2014      259000  Oceania                  Melanesia

      income_group  life_expectancy  income  children_per_woman  \
358           High             82.5   42900                1.89
359           High             82.6   43400                1.87
2336  Upper middle             65.5    7980                2.59
2337  Upper middle             65.5    8350                2.57
3686  Lower middle             61.2    1830                3.77
3687  Lower middle             61.4    1840                3.73
4928          High             81.5   33800                2.05
4929          High             81.5   34500                2.03
5358  Lower middle             59.8    2470                3.81
5359  Lower middle             60.1    2620                3.76
5808  Upper middle             71.6    5490                4.15
5809  Upper middle             71.6    5510                4.09
6169  Lower middle             62.4    2030                4.03
6170  Lower middle             62.4    2020                3.97
6905  Upper middle             70.1    4950                3.77
6906  Upper middle             70.2    5030                3.72
7354          High             78.9   51000                1.96
7356          High             78.9   51800                1.95
7490  Lower middle             63.5    2890                3.38
7491  Lower middle             63.5    2890                3.35

      child_mortality  pop_density  co2_per_capita  years_in_school_men  \
```

358	4.2	3.01	16.100	13.90
359	4.0	3.06	15.400	14.00
2336	23.4	48.20	1.310	11.40
2337	23.0	48.50	1.320	11.50
3686	58.8	134.00	0.574	9.36
3687	57.4	136.00	0.564	9.48
4928	5.9	17.20	7.410	14.20
4929	5.7	17.30	7.590	14.30
5358	59.5	16.80	0.815	8.01
5359	57.9	17.10	0.815	8.15
5808	18.4	67.40	1.040	12.10
5809	18.1	67.90	1.030	12.20
6169	27.2	20.10	0.358	8.63
6170	26.8	20.60	0.350	8.78
6905	17.4	146.00	1.080	11.50
6906	17.1	147.00	1.140	11.60
7354	6.9	34.50	16.400	14.40
7356	6.8	34.70	16.500	14.50
7490	29.1	20.80	0.420	9.09
7491	28.7	21.20	0.595	9.23

	years_in_school_women
358	14.30
359	14.40
2336	11.80
2337	11.90
3686	9.70
3687	9.85
4928	14.80
4929	14.90
5358	5.75
5359	5.89
5808	12.90
5809	13.00
6169	7.50
6170	7.68
6905	11.90
6906	12.00
7354	14.80
7356	14.90
7490	8.61
7491	8.78

We can see that the outliers from the `income` column are Australia and New Zealand. These values represent actual data and removing them would cause a loss of data. The same can be said regarding the `child_mortality`, `pop_density` and `co2_per_capita` besides any other feature for any other continents. Therefore, ***The outliers would not be removed***.

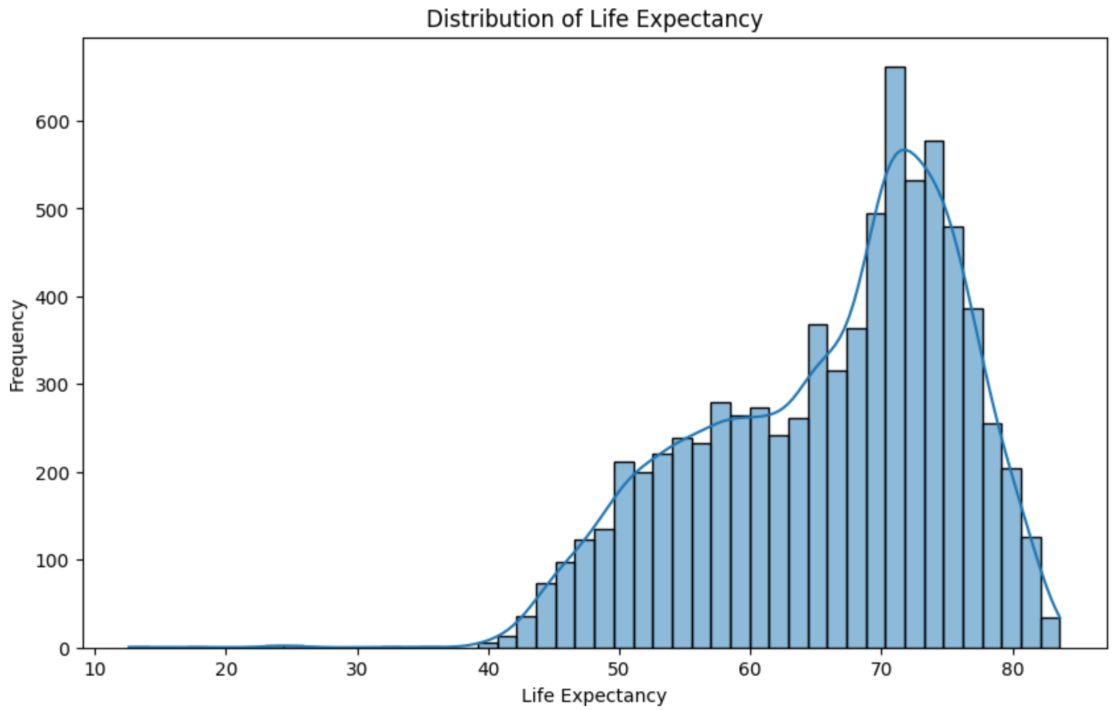
5.1 Exploratory Data Analysis

##Univariate Analysis

[20]:
```
# For numerical attributes, let's describe the dataset to get mean, median, etc.
data.describe()
```

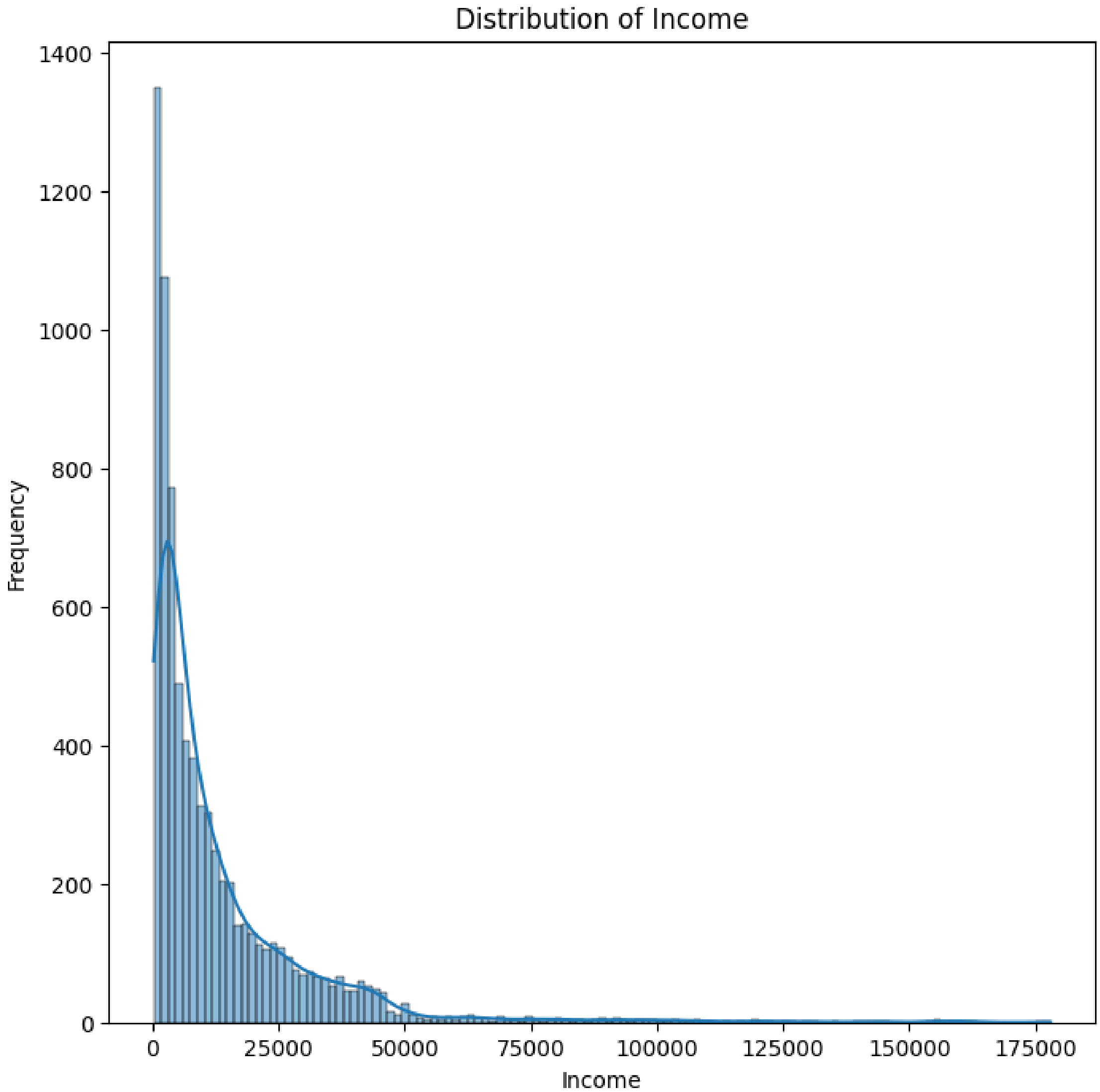
[20]:
```
              year    population  life_expectancy         income  \
count  7717.000000  7.717000e+03      7717.000000    7717.000000
mean   1992.435921  3.313877e+07        66.028768   12962.267850
std      12.979325  1.188602e+08         9.654891   17553.735789
min    1970.000000  5.120000e+04        12.600000     247.000000
25%    1981.000000  2.440000e+06        58.700000    2280.000000
50%    1993.000000  7.120000e+06        68.400000    6560.000000
75%    2004.000000  2.080000e+07        73.600000   16600.000000
max    2014.000000  1.390000e+09        83.600000  178000.000000

       children_per_woman  child_mortality  pop_density  co2_per_capita  \
count         7717.000000      7717.000000  7717.000000     7717.000000
mean             3.913842        74.726785   136.687679        4.665658
std              1.990729        73.384581   417.938633        7.215037
min              1.120000         2.300000     0.823000        0.004330
25%              2.060000        17.000000    18.000000        0.421000
50%              3.480000        46.700000    53.400000        1.870000
75%              5.710000       113.000000   122.000000        6.570000
max              8.870000       399.000000  7780.000000       87.700000

       years_in_school_men  years_in_school_women
count          7717.000000            7717.000000
mean              7.720621               6.981117
std               3.190283               3.888600
min               0.900000               0.210000
25%               5.180000               3.600000
50%               7.680000               7.030000
75%              10.200000              10.100000
max              15.300000              15.600000
```

[21]:
```
# Visualizing distributions of numerical  attributes
# Histogram for Life Expectancy

plt.figure(figsize=(10, 6))
sns.histplot(data['life_expectancy'], kde=True)
plt.title('Distribution of Life Expectancy')
plt.xlabel('Life Expectancy')
plt.ylabel('Frequency')
plt.show()
```



Here, we can see Life Expectancy is left-skewed, which means that most of the data points are concentrated towards the higher end of the scale, while a few extreme values (outliers) pull the distribution towards the lower end. In other words, the majority of countries or regions tend to have relatively high life expectancies, but there are a few places with significantly lower life expectancies that drag the overall distribution to the left. This skewness can occur due to various factors, such as differences in healthcare, socioeconomic conditions, and lifestyle choices etc.

[22]:
```
# Histogram for Income
plt.figure(figsize=(8, 8))
sns.histplot(data['income'], kde=True)  # Replace 'income' with the relevant␣
↪column name

plt.title('Distribution of Income')
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.show()
```



The right-skewed distribution of income indicates that most data points are concentrated towards the lower end of the income scale, while a few extreme values (outliers) pull the distribution towards the higher end. In other words, the majority of individuals tend to have relatively lower incomes, but there are a few high-income outliers that stretch the overall distribution to the right. Factors contributing to this skewness include income disparities, wealth concentration, and economic inequality.

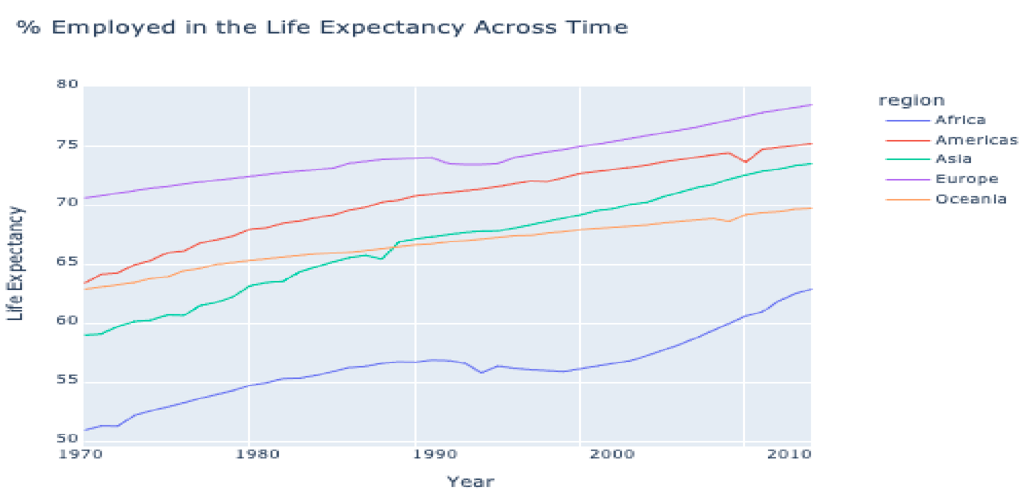
5.2 Bivariate Analysis

1. Line Charts
2. Scatter Plots
3. Correlation plots

[23]:
```
## Line Charts or Visualizing the trend
life_expectancy_regional_data = data.groupby(['region', 'year'], as_index=␣
↪False).agg({'life_expectancy': 'mean'})
print(life_expectancy_regional_data)
```

```
      region  year  life_expectancy
0     Africa  1970        51.029787
1     Africa  1971        51.374468
2     Africa  1972        51.364583
3     Africa  1973        52.268750
4     Africa  1974        52.650000
..       ...   ...              ...
220  Oceania  : 10        69.240000
221  Oceania  : 11        69.400000
222  Oceania  : 12        69.500000
223  Oceania  : 13        69.700000
224  Oceania  : 14        69.770000

[225 rows x 3 columns]
```

[24]:
```
import plotly.express as px
import plotly.graph_objects as go

#Comparing Life expectancy among regions
fig = px.line(data_frame= life_expectancy_regional_data, x='year',␣
↪y='life_expectancy', color='region', labels = {'year': 'Year',␣
↪'life_expectancy': 'Life Expectancy'}, title = '% Employed in the Life␣
↪Expectancy Across Time')
fig.show()
```



Although Europe has the highest life_expectancy index and Africa having the lowest index, Asia seems to have the highest rate of increase in Life expectancy!

[25]:
5.2.1 Let's now take a look at our Income Plots

```
income_region_data = data.groupby(['region', 'year'], as_index= False).
↪agg({'income': 'mean'})
print(income_region_data)
```

```
     region  year        income
0    Africa  1970   3866.170213
1    Africa  1971   3826.659574
2    Africa  1972   3676.395833
3    Africa  1973   3712.062500
4    Africa  1974   3791.562500
..      ...   ...           ...
220  Oceania  2010  14938.000000
221  Oceania  2011  15142.000000
222  Oceania  2012  15381.000000
223  Oceania  2013  15534.000000
224  Oceania  2014  15796.000000
```

[26]:

```
fig = px.line(data_frame=income_region_data, x='year', y='income',
 ↪color='region', labels = {'year': 'Year', 'income': 'Income'}, title = '%
 ↪Employed in Income Across Time')
#add annotations
fig.show()
```

5.2.2 Now we are able to get ideas about our initial 2 questions: How have socio-economic indicators evolved globally over the years? Can we predict future trends in key indicators?

Which region has the highest Life Expectancy? Is it the same for Income? Europe has the highest Life Expectancy and Income value across time, and Africa at the lowest for both

5.3 What about Life expectancy and Income values for countries in each continent?

Let's start by grouping and aggregating our data! We will examine Life Expectancy first

```
life_exp_ctry_region_data = data.groupby(['country','region', 'year'],␣
    ↪as_index= False).agg({'life_expectancy': 'mean'})
print(life_exp_ctry_region_data)
```

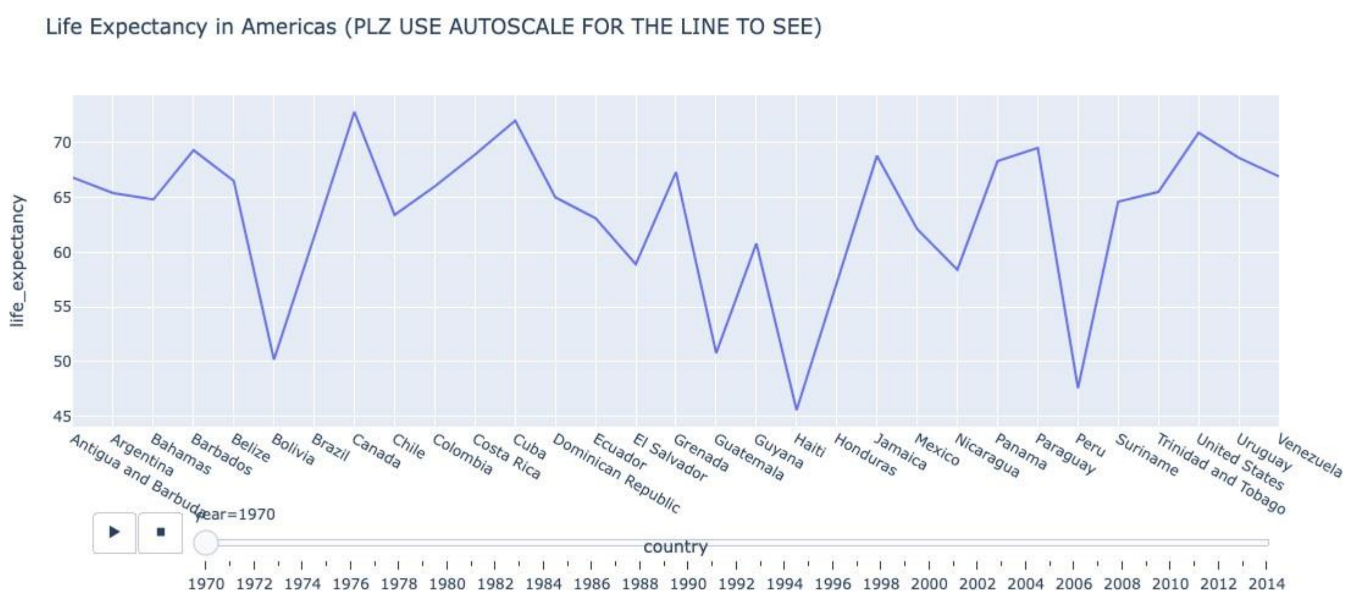
```
          country  region  year  life_expectancy
0     Afghanistan    Asia  1970             45.8
1     Afghanistan    Asia  1971             45.9
2     Afghanistan    Asia  1972             45.9
3     Afghanistan    Asia  1973             46.0
4     Afghanistan    Asia  1974             46.1
...           ...     ...   ...              ...
7712     Zimbabwe  Africa  2010             49.6
7713     Zimbabwe  Africa  2011             51.9
7714     Zimbabwe  Africa  2012             54.1
7715     Zimbabwe  Africa  2013             55.6
7716     Zimbabwe  Africa  2014             57.0

[7717 rows x 4 columns]
```

Let's examine Americas' Life Expectancy

[28]:
```
ame_lif_exp = life_exp_ctry_region_data[life_exp_ctry_region_data.
    ↪region=='Americas']
```

```python
print(ame_lif_exp)
```

```
                  country    region  year  life_expectancy
180   Antigua and Barbuda  Americas  1970             66.8
181   Antigua and Barbuda  Americas  1971             67.2
182   Antigua and Barbuda  Americas  1972             67.6
183   Antigua and Barbuda  Americas  1973             68.0
184   Antigua and Barbuda  Americas  1974             68.3
...                   ...       ...   ...              ...
7532            Venezuela  Americas  2010             75.4
7533            Venezuela  Americas  2011             75.4
7534            Venezuela  Americas  2012             75.3
7535            Venezuela  Americas  2013             75.4
7536            Venezuela  Americas  2014             75.5

[1395 rows x 4 columns]
```



Life Expectancy Index for United States and canada are the highest in Americas where Haiti has the least life expectancy

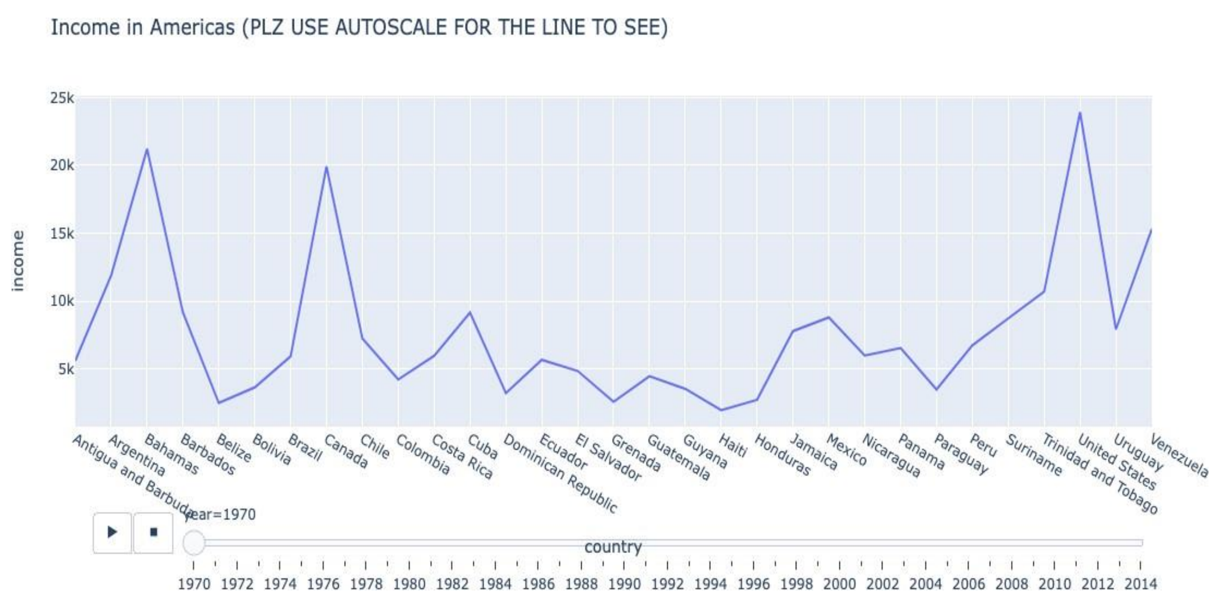
5.3.1 Examining Income data by Country

[30]:
```python
income_ctry_region_data = data.groupby(["country","region", "year"], as_index=False).agg({"income": "mean"})
income_ctry_region_data
```

	country	region	year	income
0	Afghanistan	Asia	1970	1180.0
1	Afghanistan	Asia	1971	1100.0

```
2       Afghanistan      Asia   1972  1050.0
3       Afghanistan      Asia   1973  1150.0
4       Afghanistan      Asia   1974  1180.0
...             ...       ...    ...     ...
7712      Zimbabwe    Africa   2010  1460.0
7713      Zimbabwe    Africa   2011  1660.0
7714      Zimbabwe    Africa   2012  1850.0
7715      Zimbabwe    Africa   2013  1900.0
7716      Zimbabwe    Africa   2014  1910.0

[7717 rows x 4 columns]
```

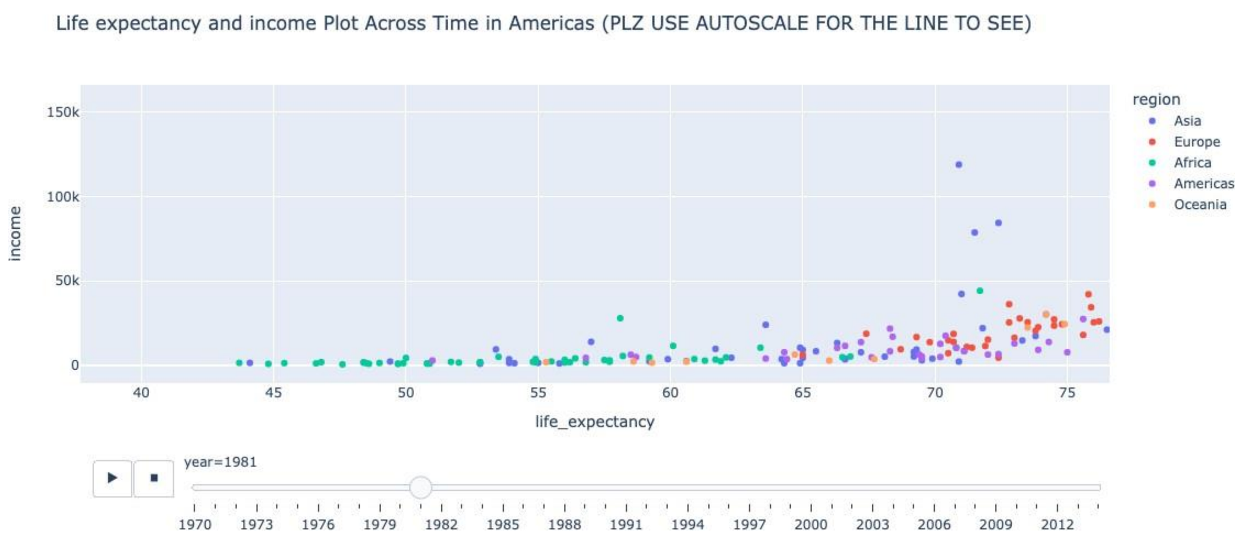
Taking a look at America Again



We see that, income seems very much aligned with life expectancy. As United states and Canada again score highest in Americans regions. On the other hand, Guatemala, Haiti & Honduras' income data had not changed likely life expectancy. Haiti's income value as well as Life Expectancy are lower than Guatemala's & Honduras

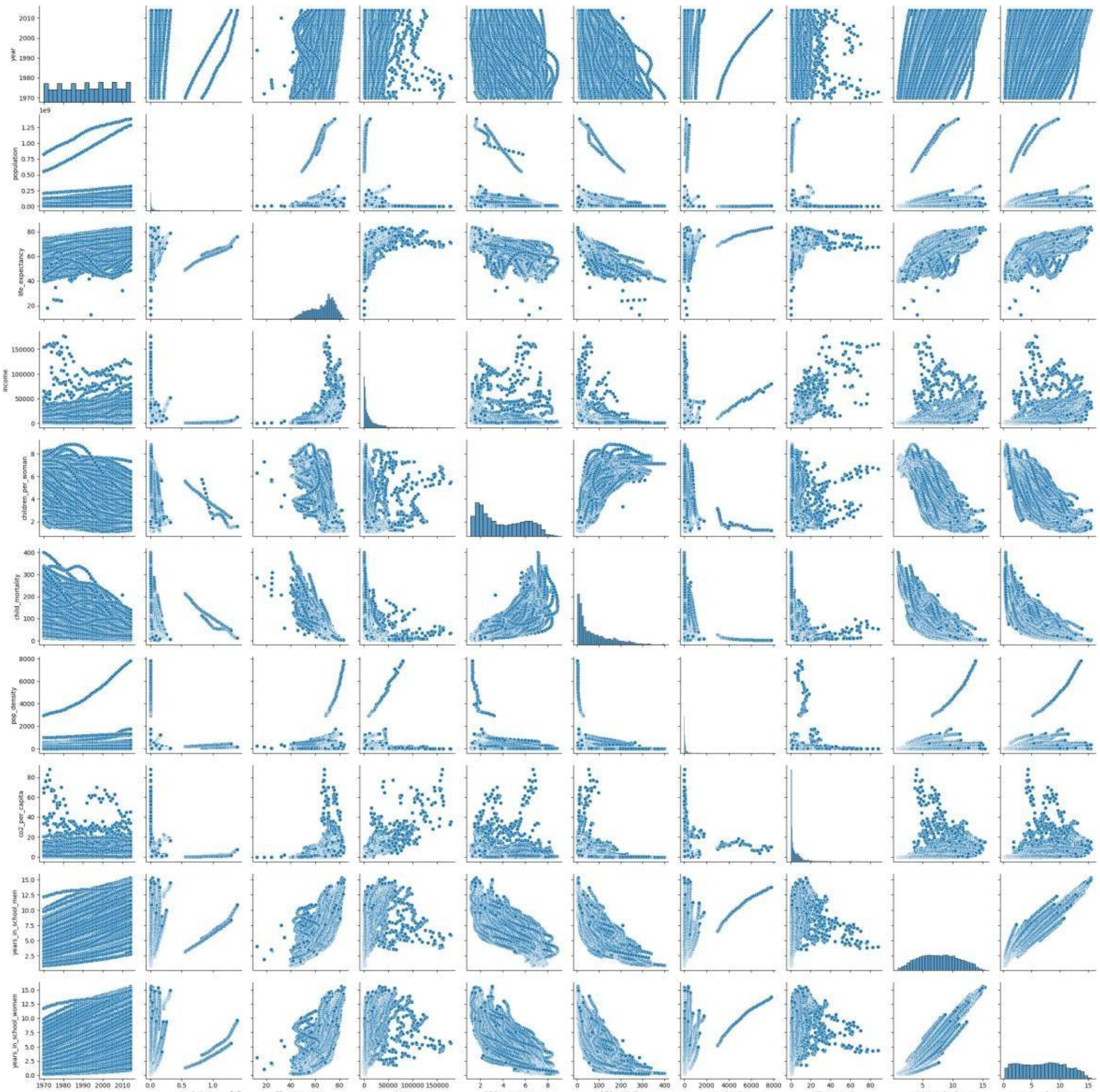
5.3.2 Let's plot Life Expectancy against Income to have a better understanding!

```
## 2 Scatter plots to see the picture

fig = px.scatter(data,x = "life_expectancy",  y = "income", title = 'Life␣
↪expectancy and income Plot Across Time in Americas (PLZ USE AUTOSCALE FOR␣
↪THE LINE TO SEE)',
                 color = "region",animation_frame="year", range_x=[0,1],␣
↪range_y= [0,100])
fig.show()
```



We can see higher income is highly correlated with Life expectancy and gradually increase upto a certain level.

[33]:
```
## Lets see the relationship among different variables

# Pairplot to visualize relationships
sns.pairplot(data)

# Adjust the plot size
plt.figure(figsize=(10, 15))

# Show the plot
plt.show()
```



<Figure size 1000x1500 with 0 Axes>

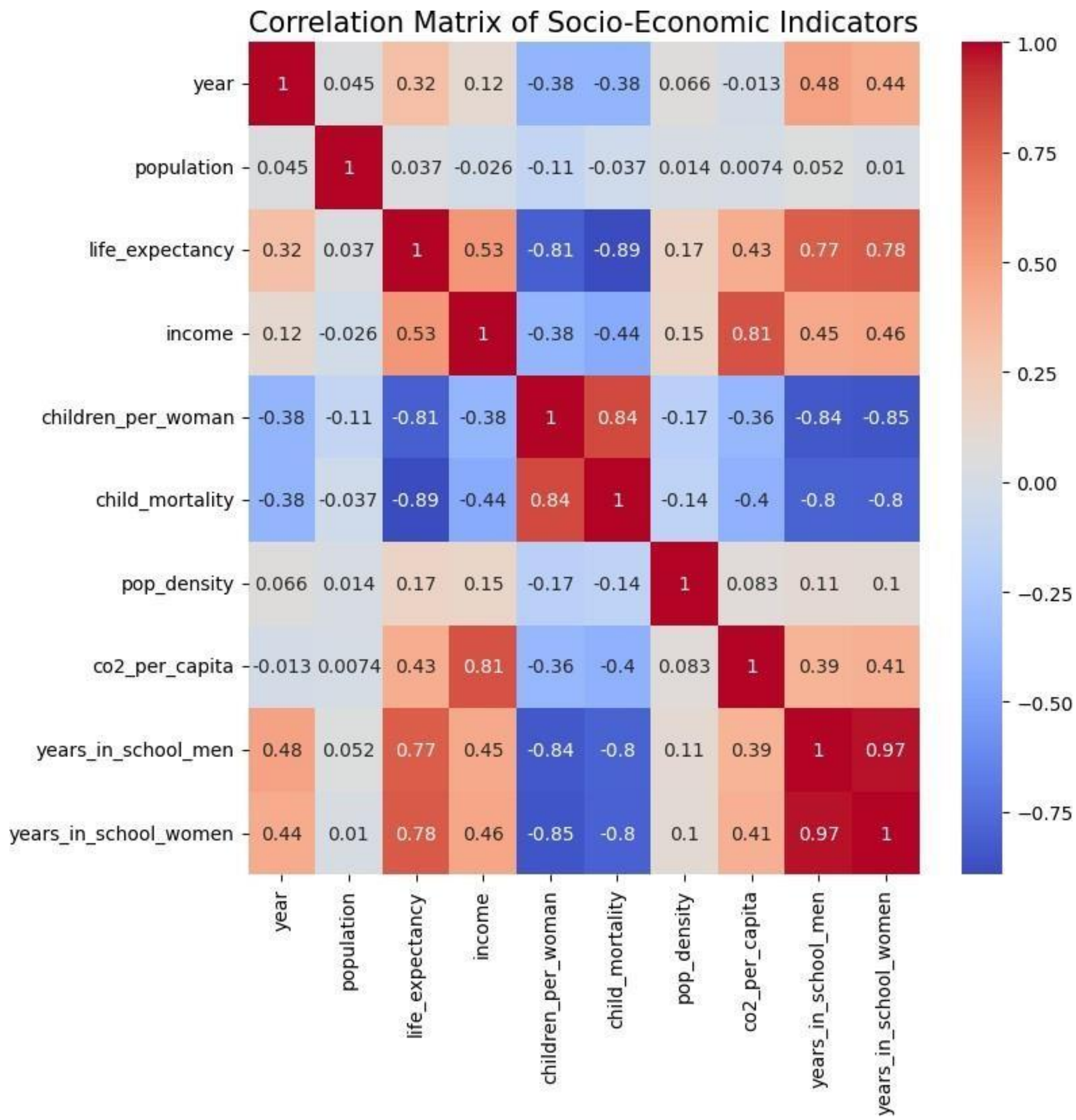
[34]:
```
4  # 3  Correlation  Analysis
## Let's calculate the correlation matrix
correlation_matrix = data.corr()
print(correlation_matrix)
```

```
                        year  population  life_expectancy    income  \
year                1.000000    0.045262         0.318198  0.118619
population          0.045262    1.000000         0.036585 -0.025842
life_expectancy     0.318198    0.036585         1.000000  0.534823
income              0.118619   -0.025842         0.534823  1.000000
children_per_woman -0.383632   -0.111739        -0.810229 -0.379525
```

```
child_mortality        -0.383741   -0.037471          -0.893179 -0.443640
pop_density             0.066457    0.014499           0.165861  0.152944
co2_per_capita         -0.013448    0.007397           0.428303  0.809062
years_in_school_men     0.481321    0.052143           0.774083  0.448381
years_in_school_women   0.436158    0.010254           0.783480  0.462974

                       children_per_woman  child_mortality  pop_density  \
year                            -0.383632        -0.383741     0.066457
population                      -0.111739        -0.037471     0.014499
life_expectancy                 -0.810229        -0.893179     0.165861
income                          -0.379525        -0.443640     0.152944
children_per_woman               1.000000         0.839869    -0.174382
child_mortality                  0.839869         1.000000    -0.144161
pop_density                     -0.174382        -0.144161     1.000000
co2_per_capita                  -0.362924        -0.401001     0.082978
years_in_school_men             -0.835096        -0.796552     0.112296
years_in_school_women           -0.854199        -0.804230     0.104472

                       co2_per_capita  years_in_school_men  \
year                        -0.013448             0.481321
population                   0.007397             0.052143
life_expectancy              0.428303             0.774083
income                       0.809062             0.448381
children_per_woman          -0.362924            -0.835096
child_mortality             -0.401001            -0.796552
pop_density                  0.082978             0.112296
co2_per_capita               1.000000             0.387477
years_in_school_men          0.387477             1.000000
years_in_school_women        0.412187             0.972736

                       years_in_school_women
year                                0.436158
population                          0.010254
life_expectancy                     0.783480
income                              0.462974
children_per_woman                 -0.854199
child_mortality                    -0.804230
pop_density                         0.104472
co2_per_capita                      0.412187
years_in_school_men                 0.972736
years_in_school_women               1.000000

<ipython-input-34-3d3b8c7d9b3a>:3:   FutureWarning:
```

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

[35]:
```python
## Visualizing the correlation matrix
plt.figure(figsize=(8, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix of Socio-Economic Indicators', fontsize=15)
plt.show()
```



6 Feature Selection

Feature selection is a crucial step in machine learning and data analysis. It involves choosing a subset of relevant features (variables) from your dataset to build a more effective model. Another step of the feature engineering process is to to create classes of the categorical data and the resulting labels are encoded as integers (0, 1, 2)

[36]:
```
from sklearn.model_selection import train_test_split, GridSearchCV,␣
↪cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from sklearn.svm import SVR, SVC
from sklearn.metrics import mean_squared_error, accuracy_score,␣
↪classification_report

# Considering features for
features = ['year', 'population', 'life_expectancy', 'children_per_woman',␣
↪'child_mortality', 'pop_density', 'co2_per_capita', 'years_in_school_men']
X = data[features]
y_regression = data['income']  # Regression target
y_classification = pd.qcut(data['life_expectancy'], q=3, labels=False)  #␣
↪Classification target, dividing life expectancy into 3 classes
```

##Data Preprocessing

[37]:
```
# Split the data into train and test sets
X_train, X_test, y_train_reg, y_test_reg = train_test_split(X, y_regression,␣
↪test_size=0.2, random_state=42)
X_train, X_test, y_train_cls, y_test_cls = train_test_split(X,␣
↪y_classification, test_size=0.2, random_state=42)

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

##Model Selection, Training, and Evaluation

Regression Models

[38]:
```
# Linear Regression
lr = LinearRegression()
lr.fit(X_train_scaled, y_train_reg)
lr_score = cross_val_score(lr, X_train_scaled, y_train_reg, cv=5,␣
↪scoring='neg_mean_squared_error')
print(f"Linear Regression RMSE: {np.sqrt(-lr_score.mean())}")

# Random Forest Regressor
rf_reg = RandomForestRegressor()
rf_reg.fit(X_train_scaled, y_train_reg)
rf_reg_score = cross_val_score(rf_reg, X_train_scaled, y_train_reg, cv=5,␣
↪scoring='neg_mean_squared_error')
```

```
print(f"Random Forest Regressor RMSE: {np.sqrt(-rf_reg_score.mean())}")

# Support Vector Regressor
svr = SVR()
svr.fit(X_train_scaled, y_train_reg)
svr_score = cross_val_score(svr, X_train_scaled, y_train_reg, cv=5,␣
↪scoring='neg_mean_squared_error')
print(f"SVR RMSE: {np.sqrt(-svr_score.mean())}")
```

```
Linear Regression RMSE: 9146.103687168454
Random Forest Regressor RMSE: 3461.2778357076218
SVR RMSE: 18803.063264451783
```

Classification Models

[ ]:
```
#from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report
#from sklearn.model_selection import cross_val_predict

# Assuming X_test_scaled and y_test_cls are your test sets

# Decision Tree Classifier
dt_cls = DecisionTreeClassifier()#
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
print(f"Decision Tree Classifier:")
print(f"Accuracy: {accuracy_score(y_test_cls, dt_cls_pred)}")
print(f"Precision: {precision_score(y_test_cls, dt_cls_pred,␣
↪average='weighted')}")
print(f"Recall: {recall_score(y_test_cls, dt_cls_pred, average='weighted')}")
print(f"F1-Score: {f1_score(y_test_cls, dt_cls_pred, average='weighted')}")
print(classification_report(y_test_cls, dt_cls_pred))

# K-Nearest Neighbors Classifier
knn_cls = KNeighborsClassifier()
```

```
knn_cls_pred = cross_val_predict(knn_cls, X_test_scaled, y_test_cls, cv=5)
print(f"K-Nearest Neighbors Classifier:")
print(f"Accuracy: {accuracy_score(y_test_cls, knn_cls_pred)}")
print(f"Precision: {precision_score(y_test_cls, knn_cls_pred,␣
↪average='weighted')}")
print(f"Recall: {recall_score(y_test_cls, knn_cls_pred, average='weighted')}")
print(f"F1-Score: {f1_score(y_test_cls, knn_cls_pred, average='weighted')}")
print(classification_report(y_test_cls, knn_cls_pred))

# Logistic Regression Evaluation

log_reg = LogisticRegression
```

```
knn_cls_pred = cross_val_predict(knn_cls, X_test_scaled, y_test_cls, cv=5)
print(f"K-Nearest Neighbors Classifier:")
print(f"Accuracy: {accuracy_score(y_test_cls, knn_cls_pred)}")
print(f"Precision: {precision_score(y_test_cls, knn_cls_pred,␣
↪average='weighted')}")
print(f"Recall: {recall_score(y_test_cls, knn_cls_pred, average='weighted')}")
print(f"F1-Score: {f1_score(y_test_cls, knn_cls_pred, average='weighted')}")
print(classification_report(y_test_cls, knn_cls_pred))

# Logistic Regression Evaluation
log_reg = LogisticRegression()#
log_reg_pred = cross_val_predict(log_reg, X_test_scaled, y_test_cls, cv=5)
print(f"Logistic Regression:")
print(f"Accuracy: {accuracy_score(y_test_cls, log_reg_pred)}")
print(f"Precision: {precision_score(y_test_cls, log_reg_pred,␣
↪average='weighted')}")
print(f"Recall: {recall_score(y_test_cls, log_reg_pred, average='weighted')}")
print(f"F1-Score: {f1_score(y_test_cls, log_reg_pred, average='weighted')}")
print(classification_report(y_test_cls, log_reg_pred))

# Random Forest Classifier Evaluation
rf_cls = RandomForestClassifier()#
rf_cls_pred = cross_val_predict(rf_cls, X_test_scaled, y_test_cls, cv=5)
print(f"Random Forest Classifier:")
print(f"Accuracy: {accuracy_score(y_test_cls, rf_cls_pred)}")
print(f"Precision: {precision_score(y_test_cls, rf_cls_pred,␣
↪average='weighted')}")
print(f"Recall: {recall_score(y_test_cls, rf_cls_pred, average='weighted')}")
print(f"F1-Score: {f1_score(y_test_cls, rf_cls_pred, average='weighted')}")
print(classification_report(y_test_cls, rf_cls_pred))

# Support Vector Classifier Evaluation
svc = SVC()#
svc_pred = cross_val_predict(svc, X_test_scaled, y_test_cls, cv=5)
print(f"Support Vector Classifier:")
print(f"Accuracy: {accuracy_score(y_test_cls, svc_pred)}")
```

```
print(f"Precision: {precision_score(y_test_cls, svc_pred, average='weighted')}")
print(f"Recall: {recall_score(y_test_cls, svc_pred, average='weighted')}")
print(f"F1-Score: {f1_score(y_test_cls, svc_pred, average='weighted')}")
print(classification_report(y_test_cls, svc_pred))
```

```
Decision Tree Classifier:
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1-Score: 1.0
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       491
           1       1.00      1.00      1.00       513
           2       1.00      1.00      1.00       540

    accuracy                           1.00      1544
   macro avg       1.00      1.00      1.00      1544
weighted avg       1.00      1.00      1.00      1544


K-Nearest Neighbors Classifier:
Accuracy: 0.9067357512953368
Precision: 0.9064837751919158
Recall: 0.9067357512953368
F1-Score: 0.9065946357646312
              precision    recall  f1-score   support

           0       0.95      0.96      0.95       491
           1       0.86      0.85      0.86       513
           2       0.91      0.91      0.91       540

    accuracy                           0.91      1544
   macro avg       0.91      0.91      0.91      1544
weighted avg       0.91      0.91      0.91      1544

Logistic Regression:
Accuracy: 0.9715025906735751
Precision: 0.9715436731234735
Recall: 0.9715025906735751
F1-Score: 0.971518945936874
              precision    recall  f1-score   support

           0       0.98      0.98      0.98       491
           1       0.96      0.96      0.96       513
           2       0.98      0.98      0.98       540

    accuracy                           0.97      1544
   macro avg       0.97      0.97      0.97      1544
weighted avg       0.97      0.97      0.97      1544
```

Accuracy: 0.9993523316062176
Precision: 0.9993535916614584
Recall: 0.9993523316062176
F1-Score: 0.9993523468023884

	precision	recall	f1-score	support
0	1.00	1.00	1.00	491
1	1.00	1.00	1.00	513

```
           2       1.00      1.00      1.00       540

    accuracy                           1.00      1544
   macro avg       1.00      1.00      1.00      1544
weighted avg       1.00      1.00      1.00      1544

Support Vector Classifier:
Accuracy: 0.9540155440414507
Precision:  0.9538671907249489
Recall:  0.9540155440414507
F1-Score: 0.9538865505825469
              precision    recall  f1-score   support

           0       0.96      0.98      0.97       491
           1       0.94      0.92      0.93       513
           2       0.96      0.97      0.96       540

    accuracy                           0.95      1544
   macro avg       0.95      0.95      0.95      1544
weighted avg       0.95      0.95      0.95      1544
```

3 To Check Effectiveness of the Models

For Classification Models we have alredy measured: "Accuracy", "Precision", "Recall" and "F1-Score".

For Regression Models, we have measured: "RMSE (Root Mean Square Error)"

4 Now, to Check Efficiency of the Models

For Classification: We are measuring Cross-Validation time (which is a mix of "Training Time" and "Prediction/Testing Time" scores.)

We are using "Training Time" and "Prediction/Testing Time" which can help us understand the computational cost of your models.

[ ]:
```
import time

## For Regression Models

# Linear Regression
start_train = time.time()
lr.fit(X_train_scaled, y_train_reg)
end_train = time.time()

start_pred = time.time()
lr_pred = lr.predict(X_test_scaled)
```

```
end_pred = time.time()

print(f"Linear Regression Training Time: {end_train - start_train} seconds")
print(f"Linear Regression Prediction Time: {end_pred - start_pred} seconds")

# Random Forest Regressor
start_train = time.time()
lr.fit(X_train_scaled, y_train_reg)
end_train = time.time()

start_pred = time.time()
lr_pred = lr.predict(X_test_scaled)
end_pred = time.time()

print(f"Random Forest Regressor Training Time: {end_train - start_train}␣
↪seconds")
print(f"Random Forest Regressor Prediction Time: {end_pred - start_pred}␣
↪seconds")

# Support Vector Regressor (SVR)
start_train = time.time()
lr.fit(X_train_scaled, y_train_reg)
end_train = time.time()

start_pred = time.time()
lr_pred = lr.predict(X_test_scaled)
end_pred = time.time()

print(f"Support Vector Regressor (SVR) Training Time: {end_train - start_train}␣
↪seconds")
print(f"Support Vector Regressor (SVR) Prediction Time: {end_pred - start_pred}␣
↪seconds")
```

```
Linear Regression Training Time: 0.010734319686889648 seconds
Linear Regression Prediction Time: 0.0053863525390625 seconds
Random Forest Regressor Training Time: 0.009481191635131836 seconds
Random Forest Regressor Prediction Time: 0.002129316329956054 seconds
Support Vector Regressor (SVR) Training Time: 0.004905223846435547 seconds
Support Vector Regressor (SVR) Prediction Time: 0.0004973411560058594 seconds
```

[ ]:
```
## For Classification Models

# Decision Tree Classifier
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()
```

```python
print(f"Decision Tree Classifier Cross-Validation Time: {end - start} seconds")

# K-Nearest Neighbors Classifier
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"K-Nearest Neighbors Classifier Cross-Validation Time: {end - start}␣
↪seconds")

# Logistic Regression
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"Logistic Regression Cross-Validation Time: {end - start} seconds")

# Random Forest Classifier
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"Random Forest Classifier Cross-Validation Time: {end - start} seconds")

# Support Vector Classifier (SVC)
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"Support Vector Classifier (SVC) Cross-Validation Time: {end - start}␣
↪seconds")
```

```
Decision Tree Classifier Cross-Validation Time: 0.04507708549499512 seconds
K-Nearest Neighbors Classifier Cross-Validation Time: 0.024494171142578125
seconds
Logistic Regression Cross-Validation Time: 0.02387261390686035 seconds
Random Forest Classifier Cross-Validation Time: 0.02438497543334961 seconds
Support Vector Classifier (SVC) Cross-Validation Time: 0.023949623107910156
seconds
```

5 To check Stability of the Models

We have already used "Cross-Validation Scores" to finalize among our models.

But Since our result shows that "Decision Tree" results the best scores in terms of "Accuracy", "Precision", "Recall" and "F1-Score" although it does not show efficiency in terms of "Cross-Validation Time" which is a mix of "Training Time" and "Prediction/Testing Time" scores.

#To ensure that our "Decision Tree" model's high performance metrics are not a result of over-fitting, we employ more robust cross-validation technique to check the stability of "Decision Tree" accuracy.

```
[ ]: from sklearn.model_selection import StratifiedKFold, GridSearchCV
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
      ↪recall_score, f1_score
     from sklearn.model_selection import train_test_split

     # Assuming X and y_classification are your features and target variable for␣
      ↪classification

     # Split the dataset into a training set and a test set to validate the model␣
      ↪performance on unseen data
     X_train, X_test, y_train, y_test = train_test_split(X, y_classification,␣
      ↪test_size=0.2, random_state=42)

     # Define a range of hyperparameters for the Decision Tree
     param_grid = {
         'criterion': ['gini', 'entropy'],
         'max_depth': [None, 10, 20, 30, 40, 50],
         'min_samples_split': [2, 5, 10],
         'min_samples_leaf': [1, 2, 4]
     }

     # Create a DecisionTreeClassifier instance
     dt = DecisionTreeClassifier(random_state=42)

     # Define the scoring function you want to optimize for, you can adjust these␣
      ↪based on your requirements
     scoring = {'Accuracy': make_scorer(accuracy_score),
                'Precision': make_scorer(precision_score, average='weighted'),
                'Recall': make_scorer(recall_score, average='weighted'),
                'F1': make_scorer(f1_score, average='weighted')}

     # Set up Stratified k-fold
     cv_strategy = StratifiedKFold(n_splits=10)

     # Set up GridSearchCV
     grid_search = GridSearchCV(dt, param_grid, scoring=scoring, refit='Accuracy',␣
      ↪cv=cv_strategy, verbose=1, n_jobs=-1, return_train_score=True)

     # Fit the model
     grid_search.fit(X_train, y_train)

     # Best model result
```

```
best_model = grid_search.best_estimator_

# Validate on the test set
predictions = best_model.predict(X_test)
print("Test Set Evaluation:")
print(f"Accuracy: {accuracy_score(y_test, predictions)}")
print(f"Precision: {precision_score(y_test, predictions, average='weighted')}")
print(f"Recall: {recall_score(y_test, predictions, average='weighted')}")
print(f"F1-Score: {f1_score(y_test, predictions, average='weighted')}")
```

```
Fitting 10 folds for each of 108 candidates, totalling 1080 fits
Test Set Evaluation:
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1-Score: 1.0
```

##Finalizing the Best Model

After running the above codes for analysing performance of models, we compare the RMSE for regression analysis models and accuracy, precision, recall as well as f1-score for classification models. Besides, accuracy score of "Decion tree" remains the same as before after checking the biaseness by overfitting, noisy or outlier-prone features of our dataset.

##The model with the lowest RMSE wih better efficiency (Random Forest Regressor) and highest accuracy, precision, recall as well as f1-score (Decision Tree Classifier), respectively, should be considered the best model for this particular dataset and research questions.

This approach provides a comprehensive answer to the posed research questions, utilizing machine learning to explore socio-economic indicators and predict future trends.

6 Key Notes and insights

The intial analysis has helped to draw the following conclusions about the data: * The null values exist for a reason and imputing them using any other value would lead to wrong conclusions about the data set. * Similarly, the presence of outliers is not due to error measurement. Removing these values would lead to wrong results and inferences about the data. * The pair plot and correlation heat map help the most identifying the relationship of the different features.

asuring Cross-Validation time (which is a mix of "Training Time"and "Prediction/Testing Time" scores.)

We are using "Training Time" and "Prediction/Testing Time" which can help us understand the computational cost of your models.

```
import time

## For Regression Models

# Linear Regression
start_train = time.time()
lr.fit(X_train_scaled, y_train_reg)
end_train = time.time()

start_pred = time.time()
```

```
end_pred = time.time()

print(f"Linear Regression Training Time: {end_train - start_train} seconds")
print(f"Linear Regression Prediction Time: {end_pred - start_pred} seconds")

# Random Forest Regressor
start_train = time.time()
lr.fit(X_train_scaled, y_train_reg)
end_train = time.time()

start_pred = time.time()
lr_pred = lr.predict(X_test_scaled)
end_pred = time.time()

print(f"Random Forest Regressor Training Time: {end_train - start_train}␣
↪seconds")
print(f"Random Forest Regressor Prediction Time: {end_pred - start_pred}␣
↪seconds")

# Support Vector Regressor (SVR)
start_train = time.time()
lr.fit(X_train_scaled, y_train_reg)
end_train = time.time()

start_pred = time.time()
lr_pred = lr.predict(X_test_scaled)
end_pred = time.time()

print(f"Support Vector Regressor (SVR) Training Time: {end_train - start_train}␣
↪seconds")
print(f"Support Vector Regressor (SVR) Prediction Time: {end_pred - start_pred}␣
↪seconds")
```

```
Linear Regression Training Time: 0.010734319686889648 seconds
Linear Regression Prediction Time: 0.0053863525390625 seconds
Random Forest Regressor Training Time: 0.009481191635131836 seconds
Random Forest Regressor Prediction Time: 0.0021293163299560547 seconds
Support Vector Regressor (SVR) Training Time: 0.004905223846435547 seconds
Support Vector Regressor (SVR) Prediction Time: 0.0004973411560058594 seconds
```

[ ]:
```
## For Classification Models

# Decision Tree Classifier
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()
```

```
print(f"Decision Tree Classifier Cross-Validation Time: {end - start} seconds")

# K-Nearest Neighbors Classifier
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"K-Nearest Neighbors Classifier Cross-Validation Time: {end - start}␣
↪seconds")

# Logistic Regression
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"Logistic Regression Cross-Validation Time: {end - start} seconds")

# Random Forest Classifier
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"Random Forest Classifier Cross-Validation Time: {end - start} seconds")

# Support Vector Classifier (SVC)
start = time.time()
dt_cls_pred = cross_val_predict(dt_cls, X_test_scaled, y_test_cls, cv=5)
end = time.time()

print(f"Support Vector Classifier (SVC) Cross-Validation Time: {end - start}␣
↪seconds")
```

```
Decision Tree Classifier Cross-Validation Time: 0.04507708549499512 seconds
K-Nearest Neighbors Classifier Cross-Validation Time: 0.024494171142578125
seconds
Logistic Regression Cross-Validation Time: 0.02387261390686035 seconds
Random Forest Classifier Cross-Validation Time: 0.02438497543334961 seconds
Support Vector Classifier (SVC) Cross-Validation Time: 0.023949623107910156
seconds
```

7 To check Stability of the Models

We have already used “Cross-Validation Scores” to finalize among our models.

But Since our result shows that “Decision Tree” results the best scores in terms of “Accuracy”, “Precision”, “Recall” and “F1-Score” although it does not show efficiency in terms of “Cross-Validation Time” which is a mix of “Training Time” and “Prediction/Testing Time” scores.

#To ensure that our "Decision Tree" model's high performance metrics are not a result of overfitting, we employ more robust cross-validation technique to check the stability of "Decision Tree" accuracy.

```
[ ]: from sklearn.model_selection import StratifiedKFold, GridSearchCV
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
      ↪recall_score, f1_score
     from sklearn.model_selection import train_test_split

     # Assuming X and y_classification are your features and target variable for␣
      ↪classification

     # Split the dataset into a training set and a test set to validate the model␣
      ↪performance on unseen data
     X_train, X_test, y_train, y_test = train_test_split(X, y_classification,␣
      ↪test_size=0.2, random_state=42)

     # Define a range of hyperparameters for the Decision Tree
     param_grid = {
         'criterion': ['gini', 'entropy'],
         'max_depth': [None, 10, 20, 30, 40, 50],
         'min_samples_split': [2, 5, 10],
         'min_samples_leaf': [1, 2, 4]
     }

     # Create a DecisionTreeClassifier instance
     dt = DecisionTreeClassifier(random_state=42)

     # Define the scoring function you want to optimize for, you can adjust these␣
      ↪based on your requirements
     scoring = {'Accuracy': make_scorer(accuracy_score),
                'Precision': make_scorer(precision_score, average='weighted'),
                'Recall': make_scorer(recall_score, average='weighted'),
                'F1': make_scorer(f1_score, average='weighted')}

     # Set up Stratified k-fold
     cv_strategy = StratifiedKFold(n_splits=10)

     # Set up GridSearchCV
     grid_search = GridSearchCV(dt, param_grid, scoring=scoring, refit='Accuracy',␣
      ↪cv=cv_strategy, verbose=1, n_jobs=-1, return_train_score=True)

     # Fit the model
     grid_search.fit(X_train, y_train)

     # Best model result
```

```
best_model = grid_search.best_estimator_

# Validate on the test set
predictions = best_model.predict(X_test)
print("Test Set Evaluation:")
print(f"Accuracy: {accuracy_score(y_test, predictions)}")
print(f"Precision: {precision_score(y_test, predictions, average='weighted')}")
print(f"Recall: {recall_score(y_test, predictions, average='weighted')}")
print(f"F1-Score: {f1_score(y_test, predictions, average='weighted')}")
```

```
Fitting 10 folds for each of 108 candidates, totalling 1080 fits
Test Set Evaluation:
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1-Score: 1.0
```

##Finalizing the Best Model

After running the above codes for analysing performance of models, we compare the RMSE for regression analysis models and accuracy, precision, recall as well as f1-score for classification models. Besides, accuracy score of "Decion tree" remains the same as before after checking the biaseness by overfitting, noisy or outlier-prone features of our dataset.

##The model with the lowest RMSE wih better efficiency (Random Forest Regressor) and highest accuracy, precision, recall as well as f1-score (Decision Tree Classifier), respectively, should be considered the best model for this particular dataset and research questions.

This approach provides a comprehensive answer to the posed research questions, utilizing machine learning to explore socio-economic indicators and predict future trends.

8 Key Notes and insights

The intial analysis has helped to draw the following conclusions about the data: * The null values exist for a reason and imputing them using any other value would lead to wrong conclusions about the data set. * Similarly, the presence of outliers is not due to error measurement. Removing these values would lead to wrong results and inferences about the data. * The pair plot and correlation heat map help the most identifying the relationship of the different features.