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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

[ ]:
```
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:

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

[ ]:
```
                   country  year  population    region  \
8065            Congo, Rep.  1981     1890000    Africa
17719                Jordan  1999     5010000      Asia
994       Antigua and Barbuda  1918       30400  Americas
344                 Albania  1925      989000    Europe
30671         Slovak Republic  1811     2140000    Europe
37625                Uruguay  1976     2840000  Americas
4522   Bosnia and Herzegovina  1942     2470000    Europe
11662                   Fiji  1855      135000   Oceania
24228                Namibia  1938      318000    Africa
10896       Equatorial Guinea  1965      277000    Africa

                        sub_region income_group  life_expectancy  income  \
8065            Sub-Saharan Africa  Lower middle             53.5    4890
17719                 Western Asia  Upper middle             73.0    7060
994    Latin America and the Caribbean         High             21.9    1600
344                Southern Europe  Upper middle             35.5    1620
30671               Eastern Europe         High             36.4    1430
37625  Latin America and the Caribbean         High             69.0    8570
4522               Southern Europe  Upper middle             27.6    1220
11662                    Melanesia  Upper middle             26.1     886
24228           Sub-Saharan Africa  Upper middle             34.8    3190
10896           Sub-Saharan Africa  Upper middle             42.4    1130

       children_per_woman  child_mortality  pop_density  co2_per_capita  \
8065                 6.13            106.0         5.55           0.250
17719                4.13             28.6        56.50           2.910
994                  4.56            182.0          NaN             NaN
344                  4.60            355.0          NaN             NaN
30671                5.94            363.0          NaN             NaN
37625                2.95             54.5        16.20           2.080
4522                 5.19            259.0          NaN             NaN
11662                6.45            499.0          NaN             NaN
24228                5.96            308.0          NaN             NaN
```

```
10896                5.73             290.0         9.89            0.106

       years_in_school_men  years_in_school_women
8065                  6.00                   3.68
17719                10.30                   9.78
994                    NaN                    NaN
344                    NaN                    NaN
30671                  NaN                    NaN
37625                 6.67                   6.83
4522                   NaN                    NaN
11662                  NaN                    NaN
24228                  NaN                    NaN
10896                  NaN                    NaN
```

[ ]:

```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
```

[ ]:

```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
```

[ ]:
```
# 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')
```

[ ]:
```
# 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
```

[ ]:
```
# 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:

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

[ ]:
```
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.

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

[ ]:
```
           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_density`Column:

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

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

```
{'Tanzania', 'Montenegro', 'India', 'Israel', 'Haiti', 'Saudi Arabia', 'North
Korea', 'Estonia', 'Nigeria', 'Mozambique', 'Azerbaijan', 'Belarus', 'Chile',
'Hungary', 'Italy', 'El Salvador', 'Liberia', 'Botswana', 'Bosnia and
Herzegovina', 'Lithuania', 'Mauritius', 'Latvia', 'South Sudan', 'Barbados',
'South Africa', 'Nicaragua', 'Iraq', 'Egypt', 'Cameroon', 'Brazil', 'Portugal',
'Canada', 'Uganda', 'Cyprus', 'Afghanistan', 'Japan', 'Georgia', 'Ecuador',
'Ukraine', 'Ethiopia', 'Solomon Islands', 'Kenya', 'Mali', 'Philippines',
'Djibouti', 'Bangladesh', 'Denmark', 'Gabon', 'Kiribati', 'Rwanda', 'Tonga',
'Luxembourg', 'Sri Lanka', 'Czech Republic', 'New Zealand', 'Norway', 'Malawi',
'Senegal', 'Burundi', 'Oman', 'Mauritania', 'Netherlands', 'Nepal', "Cote
d'Ivoire", 'Dominican Republic', 'Lesotho', 'Guinea-Bissau', 'Mongolia',
'Yemen', 'Bhutan', 'Fiji', 'Finland', 'Burkina Faso', 'Niger', 'Seychelles',
'Turkey', 'Myanmar', 'Austria', 'Jamaica', 'Bahamas', 'Gambia', 'Malaysia',
'Poland', 'Jordan', 'Australia', 'Grenada', 'Paraguay', 'Sudan', 'Albania',
'Timor-Leste', 'Angola', 'Honduras', 'Indonesia', 'Thailand', 'Croatia',
'Bolivia', 'Bulgaria', 'Panama', 'Iceland', 'Venezuela', 'Chad', 'Slovenia',
'Tunisia', 'United States', 'Equatorial Guinea', 'Belize', 'Qatar', 'Malta',
'Kuwait', 'Russia', 'Sweden', 'Namibia', 'Mexico', 'Greece', 'Samoa',
'Swaziland', 'Iran', 'Maldives', 'Costa Rica', 'Zimbabwe', 'United Kingdom',
```

```
'Benin', 'Moldova', 'Papua New Guinea', 'United Arab Emirates', 'Vanuatu',
'Somalia', 'Kazakhstan', 'Morocco', 'Vietnam', 'Pakistan', 'Belgium', 'Slovak
Republic', 'Guatemala', 'Antigua and Barbuda', 'Macedonia, FYR', 'Algeria',
'Colombia', 'Cuba', 'Uzbekistan', 'Cambodia', 'Germany', 'Congo, Rep.', 'Togo',
'Syria', 'Armenia', 'Palestine', 'Guinea', 'Peru', 'Libya', 'Ireland',
'Singapore', 'Lao', 'Eritrea', 'Turkmenistan', 'France', 'Madagascar', 'South
Korea', 'Uruguay', 'Comoros', 'Serbia', 'Suriname', 'Lebanon', 'China',
'Bahrain', 'Zambia', 'Tajikistan', 'Trinidad and Tobago', 'Sierra Leone',
'Kyrgyz Republic', 'Ghana', 'Spain', 'Central African Republic', 'Romania',
'Argentina', 'Guyana', 'Congo, Dem. Rep.', 'Switzerland'}
{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:

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

[ ]:
```
         country  year  population    region                        sub_region  \
30591  Singapore  1950     1020000      Asia                South-eastern Asia
8633     Croatia  1892     2310000    Europe                   Southern Europe
26733     Panama  1815       79900  Americas  Latin America and the Caribbean
38351    Vietnam  1826     6980000      Asia                South-eastern Asia
37498    Uruguay  1849      137000  Americas  Latin America and the Caribbean
6024    Cameroon  1911     2360000    Africa                Sub-Saharan Africa
23932    Myanmar  1861     4100000      Asia                South-eastern Asia
2888    Barbados  1841      116000  Americas  Latin America and the Caribbean
4110      Bhutan  1968      280000      Asia                     Southern Asia
29136      Samoa  1809       47200   Oceania                         Polynesia

       income_group  life_expectancy  income  children_per_woman  \
30591          High             58.8    5030                6.49
8633           High             36.0    2670                5.53
26733          High             32.9     849                5.36
38351  Lower middle             32.0     860                4.70
37498          High             32.9    3480                5.80
```

```
6024   Lower middle            30.2    974              5.54
23932  Lower middle            30.8    847              6.03
2888           High            32.1   1060              5.36
4110   Lower middle            46.8   1040              6.67
29136  Upper middle            25.4   1400              6.98

       child_mortality  pop_density  co2_per_capita  years_in_school_men  \
30591            117.0      1460.00             NaN                  NaN
8633             367.0          NaN             NaN                  NaN
26733            406.0          NaN             NaN                  NaN
38351            417.0          NaN             NaN                  NaN
37498            406.0          NaN             NaN                  NaN
6024             451.0          NaN             NaN                  NaN
23932            433.0          NaN             NaN                  NaN
2888             543.0          NaN             NaN                  NaN
4110             291.0         7.33             NaN                  NaN
29136            443.0          NaN             NaN                  NaN

       years_in_school_women
30591                    NaN
8633                     NaN
26733                    NaN
38351                    NaN
37498                    NaN
6024                     NaN
23932                    NaN
2888                     NaN
4110                     NaN
29136                    NaN
```

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

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

```
{'Tanzania', 'Montenegro', 'India', 'Israel', 'Haiti', 'Saudi Arabia', 'North
Korea', 'Estonia', 'Nigeria', 'Mozambique', 'Azerbaijan', 'Belarus', 'Chile',
'Hungary', 'Italy', 'El Salvador', 'Liberia', 'Botswana', 'Bosnia and
Herzegovina', 'Lithuania', 'Mauritius', 'Latvia', 'South Sudan', 'Barbados',
'South Africa', 'Nicaragua', 'Iraq', 'Egypt', 'Cameroon', 'Brazil', 'Portugal',
'Canada', 'Uganda', 'Cyprus', 'Afghanistan', 'Japan', 'Georgia', 'Ecuador',
'Ukraine', 'Ethiopia', 'Solomon Islands', 'Kenya', 'Mali', 'Philippines',
'Djibouti', 'Bangladesh', 'Denmark', 'Gabon', 'Kiribati', 'Rwanda', 'Tonga',
'Luxembourg', 'Sri Lanka', 'Czech Republic', 'New Zealand', 'Norway', 'Malawi',
'Senegal', 'Burundi', 'Oman', 'Mauritania', 'Netherlands', 'Nepal', "Cote
d'Ivoire", 'Dominican Republic', 'Lesotho', 'Guinea-Bissau', 'Mongolia',
'Yemen', 'Bhutan', 'Fiji', 'Finland', 'Burkina Faso', 'Niger', 'Seychelles',
'Turkey', 'Myanmar', 'Austria', 'Jamaica', 'Bahamas', 'Gambia', 'Malaysia',
```

```
'Poland', 'Jordan', 'Australia', 'Grenada', 'Paraguay', 'Sudan', 'Albania',
'Timor-Leste', 'Angola', 'Honduras', 'Indonesia', 'Thailand', 'Croatia',
'Bolivia', 'Bulgaria', 'Panama', 'Iceland', 'Venezuela', 'Chad', 'Slovenia',
'Tunisia', 'United States', 'Equatorial Guinea', 'Belize', 'Qatar', 'Malta',
'Kuwait', 'Russia', 'Sweden', 'Namibia', 'Mexico', 'Greece', 'Samoa',
'Swaziland', 'Iran', 'Maldives', 'Costa Rica', 'Zimbabwe', 'United Kingdom',
'Benin', 'Moldova', 'Papua New Guinea', 'United Arab Emirates', 'Vanuatu',
'Somalia', 'Kazakhstan', 'Morocco', 'Vietnam', 'Pakistan', 'Belgium', 'Slovak
Republic', 'Guatemala', 'Antigua and Barbuda', 'Macedonia, FYR', 'Algeria',
'Colombia', 'Cuba', 'Uzbekistan', 'Cambodia', 'Germany', 'Congo, Rep.', 'Togo',
'Syria', 'Armenia', 'Palestine', 'Guinea', 'Peru', 'Libya', 'Ireland',
'Singapore', 'Lao', 'Eritrea', 'Turkmenistan', 'France', 'Madagascar', 'South
Korea', 'Uruguay', 'Comoros', 'Serbia', 'Suriname', 'Lebanon', 'China',
'Bahrain', 'Zambia', 'Tajikistan', 'Trinidad and Tobago', 'Sierra Leone',
'Kyrgyz Republic', 'Ghana', 'Spain', 'Central African Republic', 'Romania',
'Argentina', 'Guyana', 'Congo, Dem. Rep.', 'Switzerland'}
{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**.

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

data.isnull().sum()
```

[ ]:
```
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.

[ ]:
```
# 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()
```

[ ]:
```
         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
```

[ ]:
```
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
```

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

[ ]:
```
           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

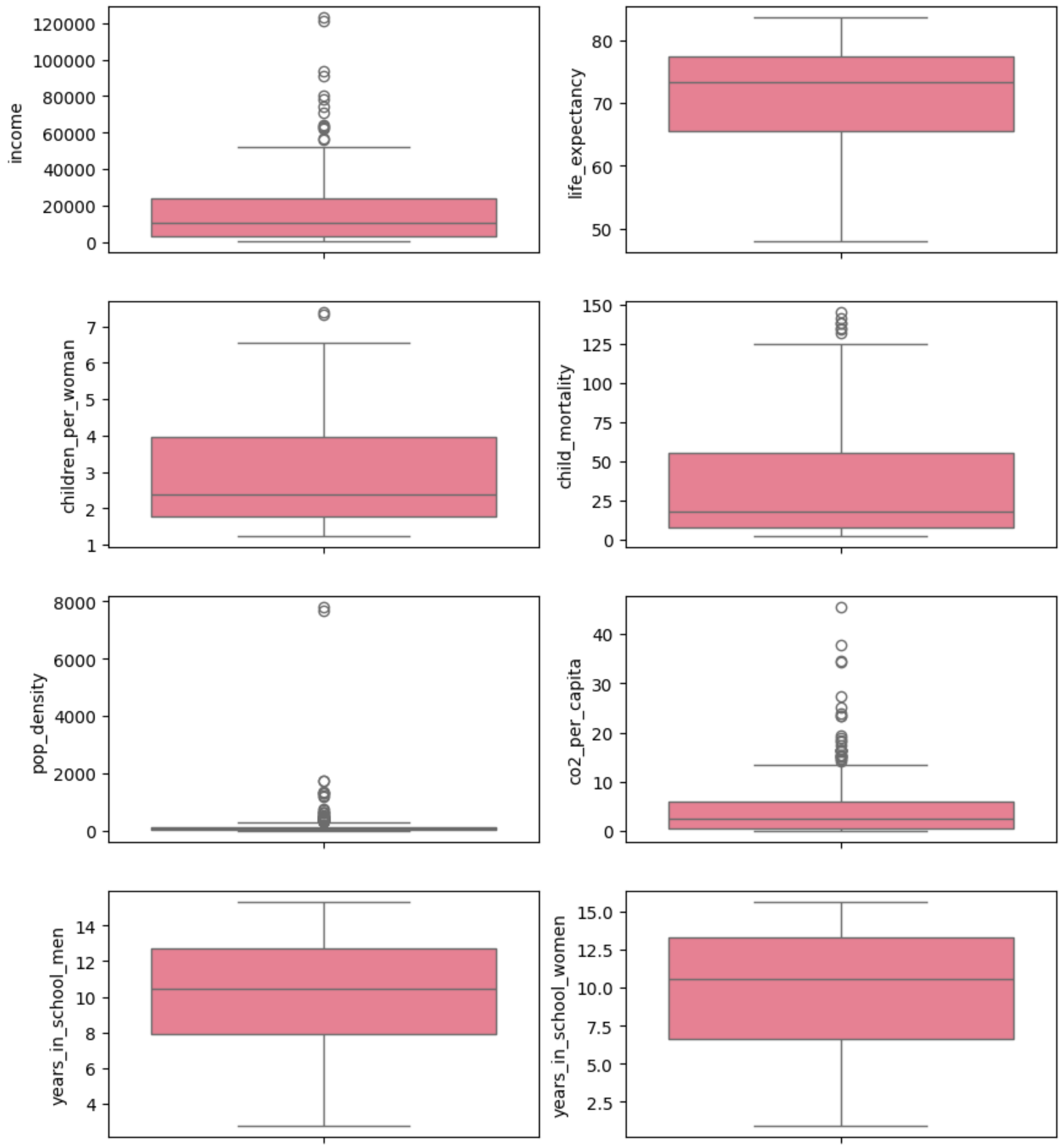
The presence of outliers can easily be identified by using box plots. However, one has to be careful as a boxplot of the entire data frame will show many outliers. Let's create the box plots

[ ]:
```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.

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

```
}

# 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-88-28821a18bb68>: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.


<ipython-input-88-28821a18bb68>: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.


<ipython-input-88-28821a18bb68>: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.


<ipython-input-88-28821a18bb68>: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.

<ipython-input-88-28821a18bb68>:18: FutureWarning:

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effect.

<ipython-input-88-28821a18bb68>:18: FutureWarning:

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effect.

<ipython-input-88-28821a18bb68>: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.

<ipython-input-88-28821a18bb68>: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.
```
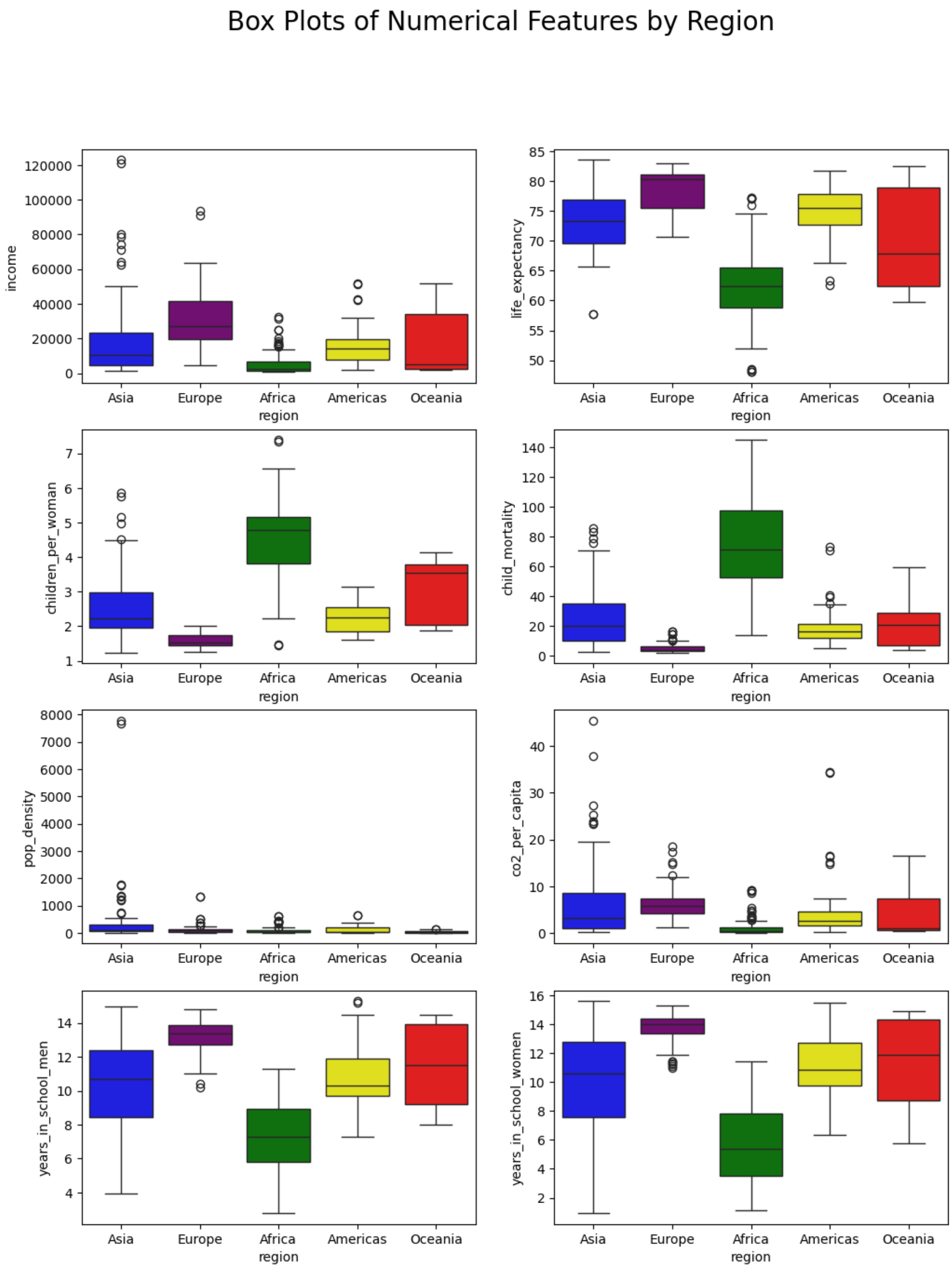

[ ]:
```
Text(0.5, 0.98, 'Box Plots of Numerical Features by Region')
```



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:

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

[ ]:
```
               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***.

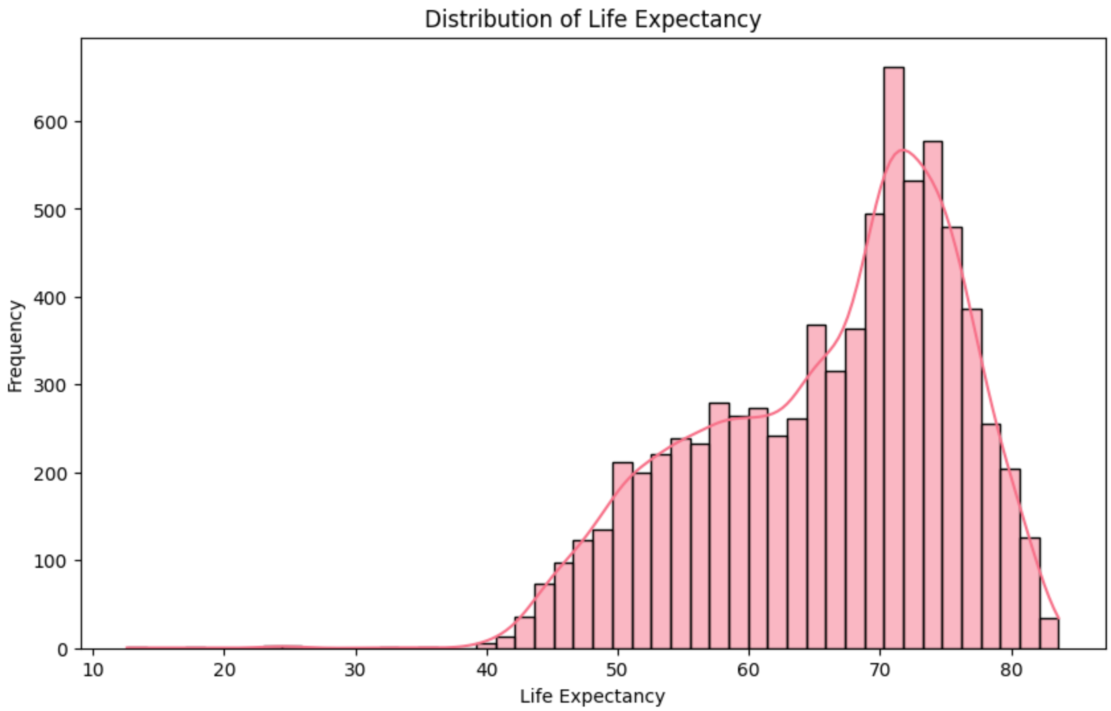
5.1 Exploratory Data Analysis

##Univariate Analysis

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

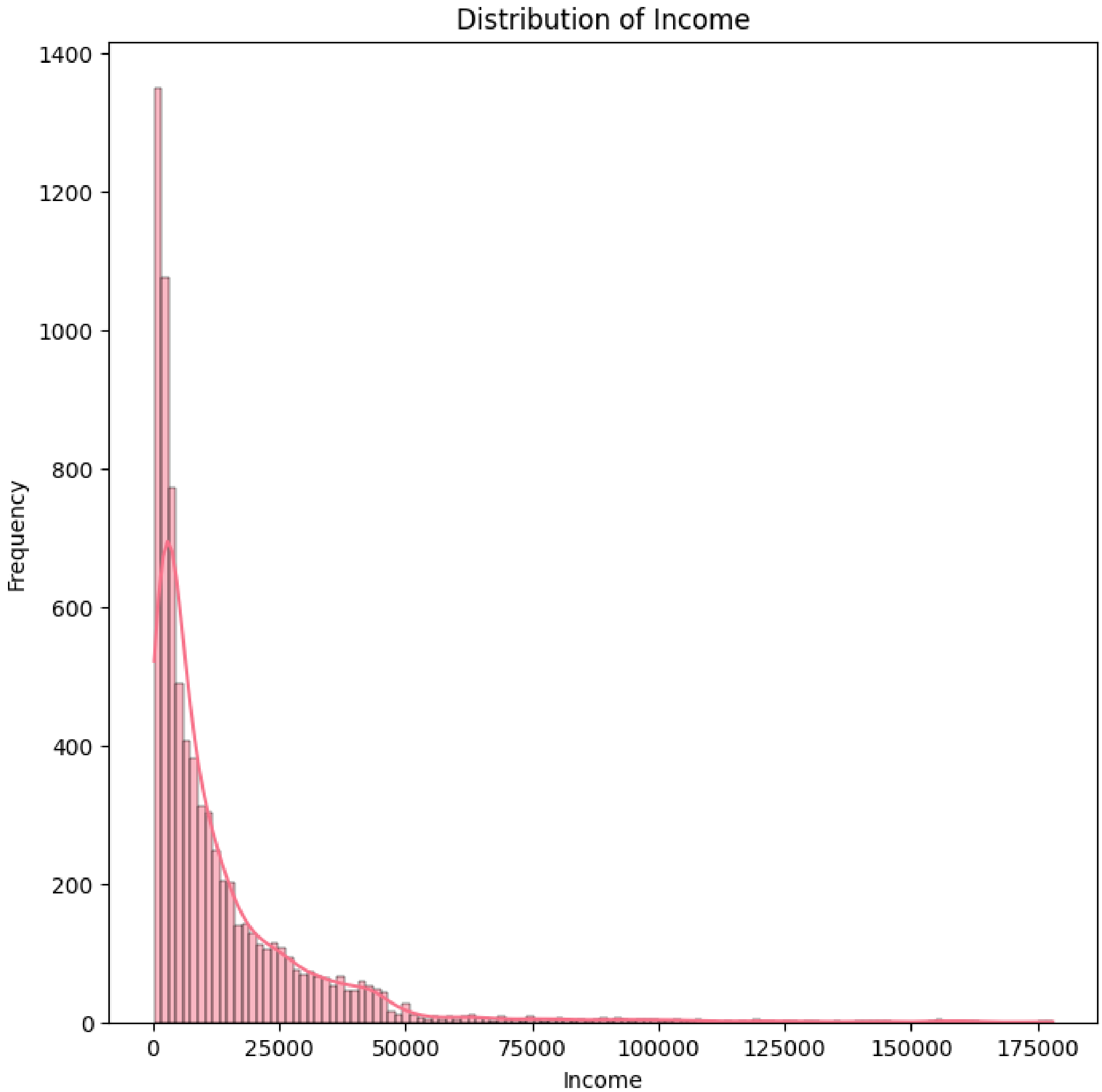
[ ]:
```
              year    population  life_expectancy         income  \
count  7717.000000  7.717000e+03      7717.000000    7717.000000
mean   1992.435921  3.313877e+07        66.028768   12962.267850
std      12.979325  1.188602e+08         9.654891   17553.735789
min    1970.000000  5.120000e+04        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
```

[ ]:
```
# 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.

[ ]:
```
# 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

[ ]:
```
## 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  2010        69.240000
221  Oceania  2011        69.400000
222  Oceania  2012        69.500000
223  Oceania  2013        69.700000
224  Oceania  2014        69.770000

[225 rows x 3 columns]
```

[ ]:
```
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!

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

[225 rows x 3 columns]
```

[ ]:
```
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()
```

Percentage employed in Income is the highest in Europe, with Africa at the lowest %.

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

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

```
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]
```

[ ]:
```
px.line(data_frame= ame_lif_exp, x='country', y='life_expectancy',␣
 ↪animation_frame='year', title='Life Expectancy in Americas (PLZ USE␣
 ↪AUTOSCALE FOR THE LINE TO SEE)', range_y=[0.4,1])
```

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

[ ]:
```
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

```
[ ]: am_income = income_ctry_region_data[income_ctry_region_data.region=='Americas']
#am_services
px.line(data_frame = am_income,x='country', y='income', animation_frame='year',␣
 ↪title='Income in Americas (PLZ USE AUTOSCALE FOR THE LINE TO␣
 ↪SEE)',range_y=[35,90])
```

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

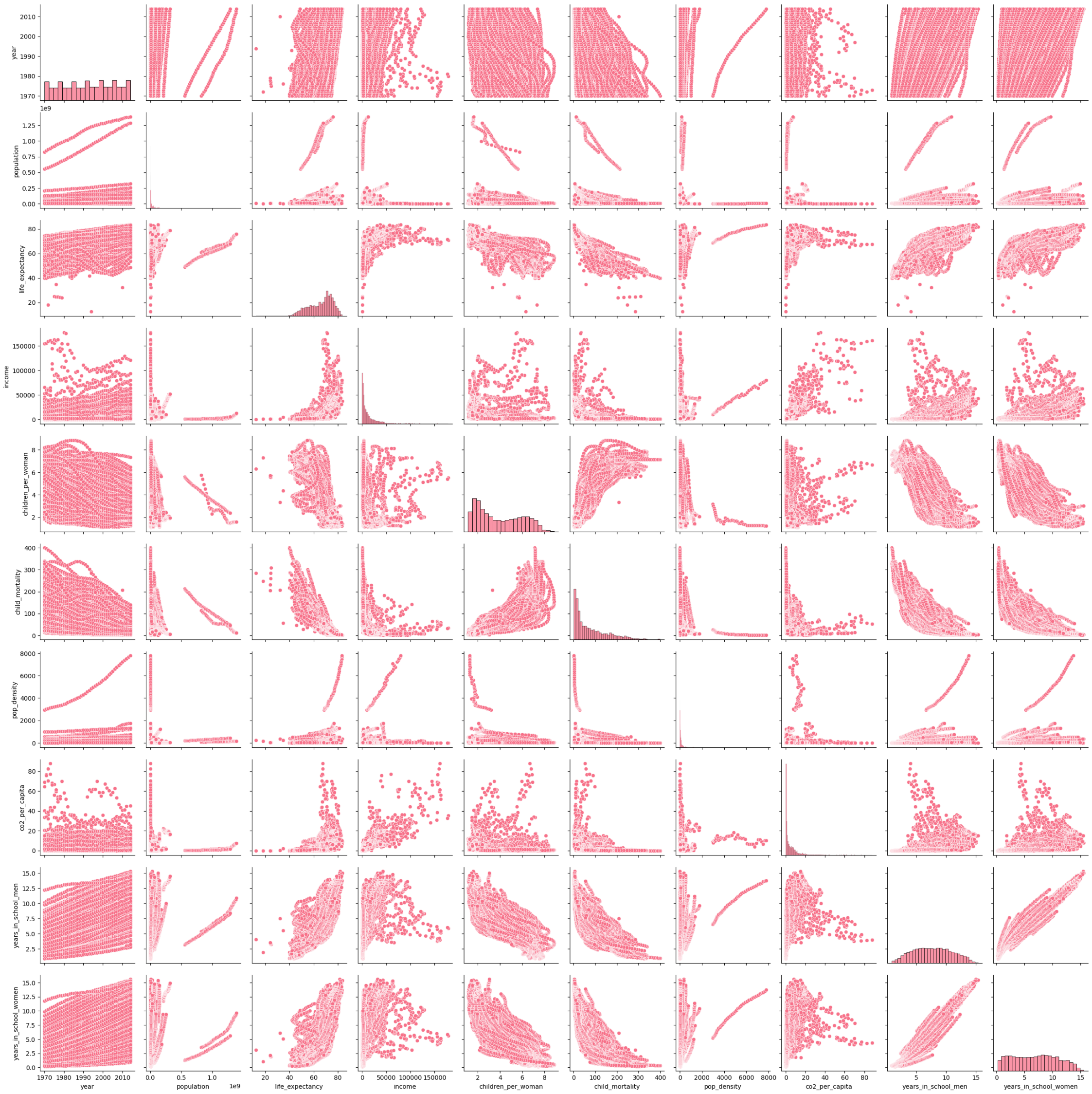
5.3.2 Let's plot Life Expectancy against Income to have a better understanding!

```
[ ]: ## 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()
```

Life Expectancy is on the increasing trend over time in Americas regions where it is not significantly influced by income level

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

```
[ ]: ## 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>

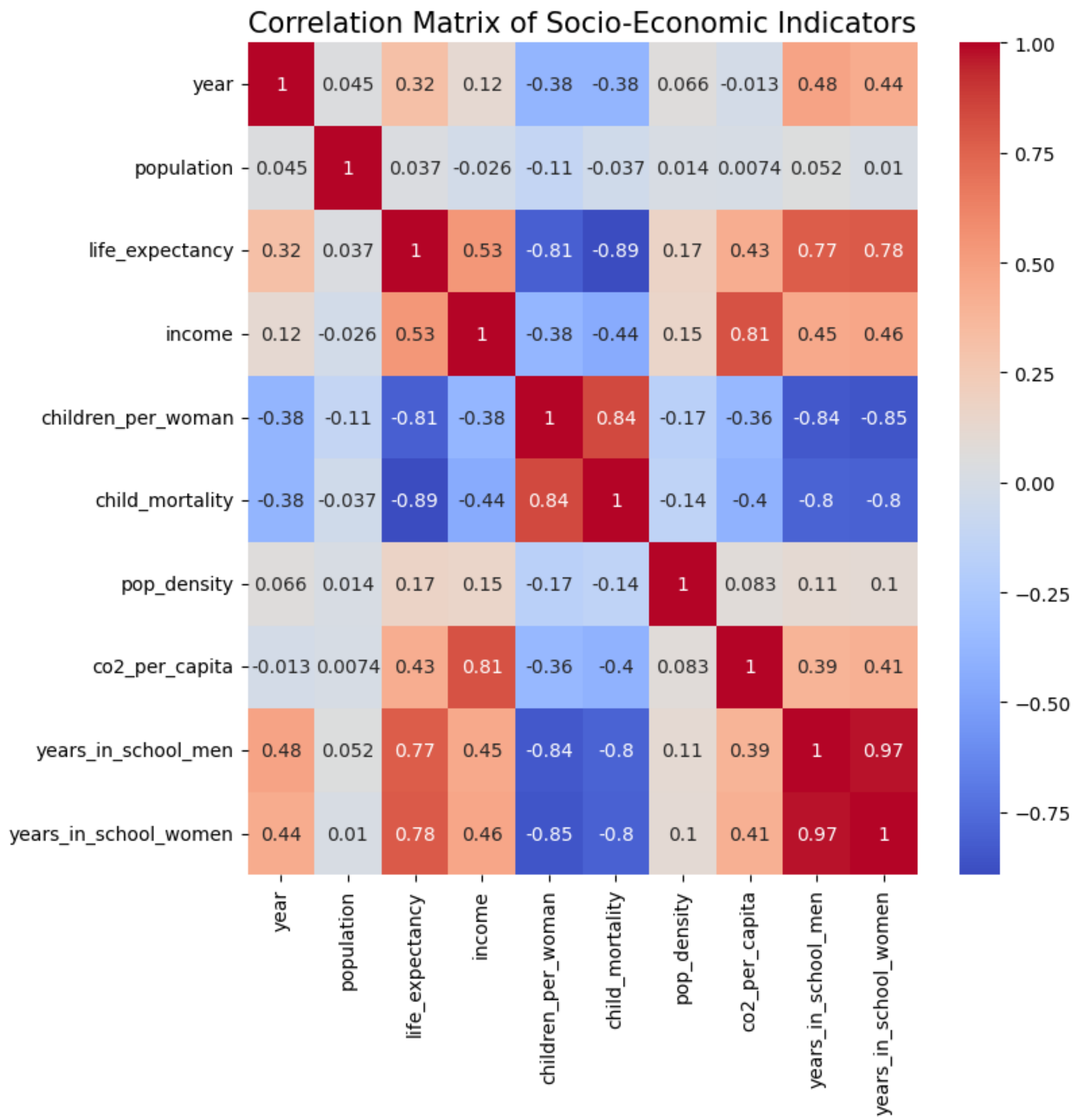
[ ]:

```
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-104-3d3b8c7d9b3a>: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.
```

```
[ ]: ## 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)

```
[ ]: 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

```
[ ]: # 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

```
[ ]: # 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: 3572.6417940143915
SVR RMSE: 18803.063264451783
```

Classification Models

[ ]:
```
# Logistic Regression
log_reg = LogisticRegression()
log_reg.fit(X_train_scaled, y_train_cls)
log_reg_score = cross_val_score(log_reg, X_train_scaled, y_train_cls, cv=5,␣
 ↪scoring='accuracy')
print(f"Logistic Regression Accuracy: {log_reg_score.mean()}")

# Random Forest Classifier
rf_cls = RandomForestClassifier()
rf_cls.fit(X_train_scaled, y_train_cls)
rf_cls_score = cross_val_score(rf_cls, X_train_scaled, y_train_cls, cv=5,␣
 ↪scoring='accuracy')
print(f"Random Forest Classifier Accuracy: {rf_cls_score.mean()}")

# Support Vector Classifier
svc = SVC()
svc.fit(X_train_scaled, y_train_cls)
svc_score = cross_val_score(svc, X_train_scaled, y_train_cls, cv=5,␣
 ↪scoring='accuracy')
print(f"SVC Accuracy: {svc_score.mean()}")
```

```
Logistic Regression Accuracy: 0.9872022782301721
Random Forest Classifier Accuracy: 1.0
SVC Accuracy: 0.975377135020571
```

##Finalizing the Most Accurate Model

After running the above code, we compare the RMSE for regression models and accuracy for classification models.

##The model with the lowest RMSE (Random Forest Regressor)or highest accuracy (Random Forest 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.

7 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 nott 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.