# FIT1043 Introduction to Data Science

# Assignment 1

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## Introduction

This is an analysis of life expectancy, population and gross domestic product (GDP) in Southeast Asian countries. The data for life expectancy covers the years from 2000 to 2015 whereas for population and GDP, data from 2019 will be used.

All data used is sourced from the following three dataset:

- `LifeExpectancyData-v2.csv`, containing information related to life expectancy and health factors for 193 countries (source: https://www.kaggle.com/kumarajarshi/life-expectancy-who)
- `2019-GDP.csv`, containing information on the gross domestic product (GDP) for almost all countries in the world for the year 2019 (source: https://datacatalog.worldbank.org/dataset/gdp-ranking)
- `2020-Population.csv`, containing information on country and region populations from 1950 to 2020 (source: https://population.un.org/wpp/Download/Standard/CSV/)

## Importing libraries

The very first step is to import **NumPy** and **pandas**. **NumPy** is a Python library that allows us to create special objects called arrays as well as matrices, and perform mathematical operations on these objects in addition to other useful mathematical features. **pandas**, on the other hand, is an extremely useful library for Python that provides tools for data analysis. By using **pandas**, we are able to directly convert CSV files into clear and concise data structures called *DataFrames*.

For data visualisation, we import the libraries **Matplotlib** and **Seaborn**. **Matplotlib** provides useful tools to visualise data as various graphs and charts. **Seaborn** is another data visualisation library built on top of **Matplotlib**. It allows us to plot graphs and charts using simpler syntax and makes it easier to adjust styles and colours. Most conveniently, since it is based on **Matplotlib**, many **Matplotlib** functions can be used to fine-tune **Seaborn** plots.

We import **NumPy**, **pandas**, **Matplotlib** and **Seaborn** as `np`, `pd`, `plt` and `sns` respectively as they are conventional abbreviations that make it faster to access the features of these libraries (ie. type less code). Only the `pyplot` module of **Matplotlib** is imported. `pyplot` is a module of **Matplotlib** that allows graphs to be plotted using a MATLAB-like interface, albeit with Python code.

Finally, `%matplotlib inline` is executed to make our graphs and charts appear properly in our Jupyter notebook.

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

%matplotlib inline
```

# Wrangling the data

## Life expectancy

Let us use **pandas** to read `LifeExpectancyData-v2.csv` into a DataFrame called `life_exp`. The **pandas** function to read CSV files is `read_csv`. Since the CSV file is in the folder called `data`, and this notebook file is in the same directory as the folder, the path of the CSV file is `data/LifeExpectancyData-v2.csv`.

`life_exp.info()` gives us some information about the data, including the names of columns.

In [2]:
```
life_exp = pd.read_csv('data/LifeExpectancyData-v2.csv')

life_exp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2938 entries, 0 to 2937
Data columns (total 15 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   country                          2938 non-null   object 
 1   Year                             2938 non-null   int64  
 2   Status                           2938 non-null   object 
 3   Life expectancy                  2930 non-null   float64
 4   infant deaths                    2938 non-null   int64  
 5   Adult Mortality                  2928 non-null   float64
 6    BMI                             2904 non-null   float64
 7   Alcohol consumption              2744 non-null   float64
 8   Hepatitis B                      2385 non-null   float64
 9   Measles                          2938 non-null   int64  
 10  Polio                            2919 non-null   float64
 11  Diphtheria                       2919 non-null   float64
 12   HIV/AIDS                        2938 non-null   float64
 13  Income composition of resources  2771 non-null   float64
 14  Schooling                        2775 non-null   float64
dtypes: float64(10), int64(3), object(2)
memory usage: 344.4+ KB
```

Some of the column labels have leading and trailing whitespaces, so we remove them using `strip()`. The stripped labels can then be applied through every column via a for loop that executes the `rename` method with every iteration. `inplace` is `True` for the changes to be permanent. Additionally, the DataFrame is sorted using `sort_values` by `country`, then by `Year`. This gives us the same DataFrame but with the rows in ascending order of year.

Next, we copy this DataFrame into another variable called `life_exp_ori`. We will be making changes to `life_exp` as we continue to wrangle the data, so it is a good idea to keep a copy of the original DataFrame.

In [3]:
```
for col in life_exp:
    life_exp.rename(columns = {col: col.strip()}, inplace = True)

life_exp = life_exp.sort_values(['country', 'Year'])

life_exp_ori = life_exp

life_exp.head()
```

Out[3]:

| | country | Year | Status | Life expectancy | infant deaths | Adult Mortality | BMI | Alcohol consumption | Hepat |
|---|---|---|---|---|---|---|---|---|---|
| **15** | Afghanistan | 2000 | Developing | 54.8 | 88 | 321.0 | 12.2 | 0.01 | 6 |
| **14** | Afghanistan | 2001 | Developing | 55.3 | 88 | 316.0 | 12.6 | 0.01 | 6 |
| **13** | Afghanistan | 2002 | Developing | 56.2 | 88 | 3.0 | 13.0 | 0.01 | 6 |
| **12** | Afghanistan | 2003 | Developing | 56.7 | 87 | 295.0 | 13.4 | 0.01 | 6 |
| **11** | Afghanistan | 2004 | Developing | 57.0 | 87 | 293.0 | 13.8 | 0.02 | 6 |

Now we have a DataFrame that displays detailed information about life expectancies in various countries, with each country having separate entries for different years.

There is also data for various health and sociocultural factors that contribute to mortality rate. This amount of data is a little overwhelming, so some skimming is necessary.

Since `Life expectancy` is a responding variable of infant deaths and adult mortality, we can drop the two latter columns. `BMI` is influenced by health factors as well so we can keep that and drop the columns for diseases and alcohol consumption.

This should give us a subset of the original DataFrame containing the most essential data.

In [4]:
```
life_exp = life_exp.filter(['country', 'Status', 'Life expectancy', 'BMI',
                            'Income composition of resources', 'Schooling']

life_exp.head()
```

Out[4]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|---|---|
| **15** | Afghanistan | Developing | 54.8 | 12.2 | 0.338 | 5.5 |
| **14** | Afghanistan | Developing | 55.3 | 12.6 | 0.340 | 5.9 |
| **13** | Afghanistan | Developing | 56.2 | 13.0 | 0.341 | 6.2 |
| **12** | Afghanistan | Developing | 56.7 | 13.4 | 0.373 | 6.5 |
| **11** | Afghanistan | Developing | 57.0 | 13.8 | 0.381 | 6.8 |

For this assignment, we will only be analysing the data for Southeast Asian countries (including East Timor). Using the `unique` function on a Series returns all the unique country names in this dataset, formatted as a **NumPy** array.

In [5]:

```
life_exp['country'].unique()
```

Out[5]:
```
array(['Afghanistan', 'Albania', 'Algeria', 'Angola',
       'Antigua and Barbuda', 'Argentina', 'Armenia', 'Australia',
       'Austria', 'Azerbaijan', 'Bahamas', 'Bahrain', 'Bangladesh',
       'Barbados', 'Belarus', 'Belgium', 'Belize', 'Benin', 'Bhutan',
       'Bolivia (Plurinational State of)', 'Bosnia and Herzegovina',
       'Botswana', 'Brazil', 'Brunei Darussalam', 'Bulgaria',
       'Burkina Faso', 'Burundi', 'Cabo Verde', 'Cambodia', 'Cameroon',
       'Canada', 'Central African Republic', 'Chad', 'Chile', 'China',
       'Colombia', 'Comoros', 'Congo', 'Cook Islands', 'Costa Rica',
       'Croatia', 'Cuba', 'Cyprus', 'Czechia', "Côte d'Ivoire",
       "Democratic People's Republic of Korea",
       'Democratic Republic of the Congo', 'Denmark', 'Djibouti',
       'Dominica', 'Dominican Republic', 'Ecuador', 'Egypt',
       'El Salvador', 'Equatorial Guinea', 'Eritrea', 'Estonia',
       'Ethiopia', 'Fiji', 'Finland', 'France', 'Gabon', 'Gambia',
       'Georgia', 'Germany', 'Ghana', 'Greece', 'Grenada', 'Guatemala',
       'Guinea', 'Guinea-Bissau', 'Guyana', 'Haiti', 'Honduras',
       'Hungary', 'Iceland', 'India', 'Indonesia',
       'Iran (Islamic Republic of)', 'Iraq', 'Ireland', 'Israel', 'Italy',
       'Jamaica', 'Japan', 'Jordan', 'Kazakhstan', 'Kenya', 'Kiribati',
       'Kuwait', 'Kyrgyzstan', "Lao People's Democratic Republic",
       'Latvia', 'Lebanon', 'Lesotho', 'Liberia', 'Libya', 'Lithuania',
       'Luxembourg', 'Madagascar', 'Malawi', 'Malaysia', 'Maldives',
       'Mali', 'Malta', 'Marshall Islands', 'Mauritania', 'Mauritius',
       'Mexico', 'Micronesia (Federated States of)', 'Monaco', 'Mongolia',
       'Montenegro', 'Morocco', 'Mozambique', 'Myanmar', 'Namibia',
       'Nauru', 'Nepal', 'Netherlands', 'New Zealand', 'Nicaragua',
       'Niger', 'Nigeria', 'Niue', 'Norway', 'Oman', 'Pakistan', 'Palau',
       'Panama', 'Papua New Guinea', 'Paraguay', 'Peru', 'Philippines',
       'Poland', 'Portugal', 'Qatar', 'Republic of Korea',
       'Republic of Moldova', 'Romania', 'Russian Federation', 'Rwanda',
       'Saint Kitts and Nevis', 'Saint Lucia',
       'Saint Vincent and the Grenadines', 'Samoa', 'San Marino',
       'Sao Tome and Principe', 'Saudi Arabia', 'Senegal', 'Serbia',
       'Seychelles', 'Sierra Leone', 'Singapore', 'Slovakia', 'Slovenia',
       'Solomon Islands', 'Somalia', 'South Africa', 'South Sudan',
       'Spain', 'Sri Lanka', 'Sudan', 'Suriname', 'Swaziland', 'Sweden',
       'Switzerland', 'Syrian Arab Republic', 'Tajikistan', 'Thailand',
       'The former Yugoslav republic of Macedonia', 'Timor-Leste', 'Togo',
       'Tonga', 'Trinidad and Tobago', 'Tunisia', 'Turkey',
       'Turkmenistan', 'Tuvalu', 'Uganda', 'Ukraine',
       'United Arab Emirates',
       'United Kingdom of Great Britain and Northern Ireland',
       'United Republic of Tanzania', 'United States of America',
       'Uruguay', 'Uzbekistan', 'Vanuatu',
       'Venezuela (Bolivarian Republic of)', 'Viet Nam', 'Yemen',
       'Zambia', 'Zimbabwe'], dtype=object)
```

The names are already arranged neatly in alphabetical order. Referring to this table, we can easily take note of the names of Southeast Asian countries.

To make our data more viewable, some of the countries' names can be shortened to more conventional versions. We can do this by creating a dictionary mapping each name to its shortened version, then applying it into the `country` column using `replace`.

In [6]:
```
renames = {'Brunei Darussalam': 'Brunei',
           'Timor-Leste': 'East Timor',
           'Lao People\'s Democratic Republic': 'Laos',
           'Viet Nam': 'Vietnam'
          }
```

```
life_exp['country'] = life_exp['country'].replace(renames)
```

Then, we can create a list containing all Southeast Asian countries including East Timor and obtain a subset of the original DataFrame containing only those countries via the `isin` method, that accepts our list as an argument.

In [7]:
```
sea = ['Brunei', 'Cambodia', 'East Timor', 'Indonesia', 'Laos', 'Malaysia',

life_exp_sea = life_exp[life_exp['country'].isin(sea)]

life_exp_sea
```

Out[7]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|---|---|
| **383** | Brunei | Developing | 74.4 | 26.1 | 0.818 | 13.4 |
| **382** | Brunei | Developing | 74.7 | 27.0 | 0.819 | 13.4 |
| **381** | Brunei | Developing | 74.8 | 28.0 | 0.820 | 13.3 |
| **380** | Brunei | Developing | 76.0 | 29.1 | 0.823 | 13.4 |
| **379** | Brunei | Developing | 76.4 | 3.1 | 0.828 | 13.7 |
| **...** | ... | ... | ... | ... | ... | ... |
| **2878** | Vietnam | Developing | 75.4 | 14.7 | 0.655 | 12.0 |
| **2877** | Vietnam | Developing | 75.6 | 15.3 | 0.662 | 12.2 |
| **2876** | Vietnam | Developing | 75.7 | 16.0 | 0.668 | 12.3 |
| **2875** | Vietnam | Developing | 75.9 | 16.7 | 0.675 | 12.5 |
| **2874** | Vietnam | Developing | 76.0 | 17.5 | 0.678 | 12.6 |

176 rows × 6 columns

We should now audit the data for missing or erroneous values, using `info` and `describe`.

In [8]:
```
life_exp_sea.info()
life_exp_sea.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 176 entries, 383 to 2874
Data columns (total 6 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   country                          176 non-null    object 
 1   Status                           176 non-null    object 
 2   Life expectancy                  176 non-null    float64
 3   BMI                              176 non-null    float64
 4   Income composition of resources  176 non-null    float64
 5   Schooling                        176 non-null    float64
dtypes: float64(4), object(2)
memory usage: 9.6+ KB
```

Out[8]:

| | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|
| **count** | 176.000000 | 176.000000 | 176.000000 | 176.000000 |
| **mean** | 70.035227 | 19.828977 | 0.643858 | 11.454545 |
| **std** | 6.220933 | 9.502169 | 0.140019 | 2.111325 |
| **min** | 57.700000 | 1.000000 | 0.000000 | 0.000000 |
| **25%** | 65.675000 | 13.975000 | 0.540000 | 10.475000 |
| **50%** | 68.300000 | 18.300000 | 0.641000 | 11.600000 |
| **75%** | 74.600000 | 27.000000 | 0.733250 | 12.725000 |
| **max** | 87.000000 | 41.200000 | 0.924000 | 15.400000 |

The output of `info` shows 176 non-null objects, which means there are no missing values. However, we deduce from the output of `describe` that there are discrepancies in the data for `BMI`, as evident from its minimum value of 1 (which is a realistically impossible value!).

One way to approach this is to impute the erroneous data with the mean of the correct data. The strategy is to replace the erroneous values with `NaN` and then set all `NaN` values with the mean using conditional slicing. The intermediate step of replacing these values with `NaN` is to ensure that the calculation of the mean does not include those values.

The lowest `BMI` value that is not obviously erroneous can be found in Vietnam's data ('not obviously' meaning the value fits into the trend of the other values), as shown below:

In [9]:

```
life_exp_sea[life_exp_sea['country'] == 'Vietnam']
```

Out[9]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|---|---|
| **2889** | Vietnam | Developing | 73.4 | 9.2 | 0.569 | 10.4 |
| **2888** | Vietnam | Developing | 73.6 | 9.6 | 0.576 | 10.6 |
| **2887** | Vietnam | Developing | 73.8 | 1.0 | 0.584 | 10.7 |
| **2886** | Vietnam | Developing | 74.0 | 1.4 | 0.592 | 10.9 |
| **2885** | Vietnam | Developing | 74.2 | 1.9 | 0.601 | 11.0 |
| **2884** | Vietnam | Developing | 74.4 | 11.3 | 0.609 | 11.1 |
| **2883** | Vietnam | Developing | 74.6 | 11.8 | 0.618 | 11.3 |
| **2882** | Vietnam | Developing | 74.7 | 12.3 | 0.625 | 11.4 |
| **2881** | Vietnam | Developing | 74.9 | 12.9 | 0.633 | 11.6 |
| **2880** | Vietnam | Developing | 75.0 | 13.4 | 0.641 | 11.7 |
| **2879** | Vietnam | Developing | 75.2 | 14.0 | 0.647 | 11.9 |
| **2878** | Vietnam | Developing | 75.4 | 14.7 | 0.655 | 12.0 |
| **2877** | Vietnam | Developing | 75.6 | 15.3 | 0.662 | 12.2 |
| **2876** | Vietnam | Developing | 75.7 | 16.0 | 0.668 | 12.3 |
| **2875** | Vietnam | Developing | 75.9 | 16.7 | 0.675 | 12.5 |
| **2874** | Vietnam | Developing | 76.0 | 17.5 | 0.678 | 12.6 |

Thus, we can define an erroneous `BMI` value as one below 9.2.

Using `loc`, we can slice (by index) all rows where the value of `BMI` is less than 9.2 and (by column) the `BMI` column. Then, using a simple assignment operator, we can set all these values to `np.nan`, which is a **NumPy** constant.

In [10]:

```
life_exp_sea.loc[life_exp_sea['BMI'] < 9.2, 'BMI'] = np.nan

life_exp_sea
```

Out[10]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|---|---|
| **383** | Brunei | Developing | 74.4 | 26.1 | 0.818 | 13.4 |
| **382** | Brunei | Developing | 74.7 | 27.0 | 0.819 | 13.4 |
| **381** | Brunei | Developing | 74.8 | 28.0 | 0.820 | 13.3 |
| **380** | Brunei | Developing | 76.0 | 29.1 | 0.823 | 13.4 |
| **379** | Brunei | Developing | 76.4 | NaN | 0.828 | 13.7 |
| **...** | ... | ... | ... | ... | ... | ... |
| **2878** | Vietnam | Developing | 75.4 | 14.7 | 0.655 | 12.0 |
| **2877** | Vietnam | Developing | 75.6 | 15.3 | 0.662 | 12.2 |
| **2876** | Vietnam | Developing | 75.7 | 16.0 | 0.668 | 12.3 |
| **2875** | Vietnam | Developing | 75.9 | 16.7 | 0.675 | 12.5 |
| **2874** | Vietnam | Developing | 76.0 | 17.5 | 0.678 | 12.6 |

176 rows × 6 columns

`life_exp_sea['country'].unique()` returns an array of the country names. Using a for loop, we iterate through each country, calculating the mean `BMI` value for each country (**pandas**'s `mean` method has an argument called `skipna` that is `True` by default, meaning it automatically excludes `NaN` values from calculation).

Then, we replace all `NaN` values for that country with the mean using `loc` and assignment. The by-index slice is all rows with the matching country name **and** where the `BMI` value is `NaN`, which can be easily identified via the `isnull` method. The by-column slice is the `BMI` column.

In [11]:
```
for c in life_exp_sea['country'].unique():
    mean_bmi = life_exp_sea[life_exp_sea['country'] == c]['BMI'].mean()
    life_exp_sea.loc[(life_exp_sea['country'] == c) & (life_exp_sea['BMI'].i

life_exp_sea
```

Out[11]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|---|---|
| **383** | Brunei | Developing | 74.4 | 26.100000 | 0.818 | 13.4 |
| **382** | Brunei | Developing | 74.7 | 27.000000 | 0.819 | 13.4 |
| **381** | Brunei | Developing | 74.8 | 28.000000 | 0.820 | 13.3 |
| **380** | Brunei | Developing | 76.0 | 29.100000 | 0.823 | 13.4 |
| **379** | Brunei | Developing | 76.4 | 33.442857 | 0.828 | 13.7 |
| **...** | ... | ... | ... | ... | ... | ... |
| **2878** | Vietnam | Developing | 75.4 | 14.700000 | 0.655 | 12.0 |
| **2877** | Vietnam | Developing | 75.6 | 15.300000 | 0.662 | 12.2 |
| **2876** | Vietnam | Developing | 75.7 | 16.000000 | 0.668 | 12.3 |
| **2875** | Vietnam | Developing | 75.9 | 16.700000 | 0.675 | 12.5 |
| **2874** | Vietnam | Developing | 76.0 | 17.500000 | 0.678 | 12.6 |

176 rows × 6 columns

In addition, the values for `Income composition of resources` and `Schooling` for East Timor are 0 for the year 2000.

In [12]:

```
life_exp_sea[life_exp_sea['country'] == 'East Timor']
```

Out[12]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|---|---|
| **2616** | East Timor | Developing | 58.7 | 11.9 | 0.000 | 0.0 |
| **2615** | East Timor | Developing | 59.4 | 12.3 | 0.470 | 9.8 |
| **2614** | East Timor | Developing | 62.0 | 12.6 | 0.475 | 9.8 |
| **2613** | East Timor | Developing | 61.0 | 12.9 | 0.485 | 9.8 |
| **2612** | East Timor | Developing | 62.3 | 13.2 | 0.484 | 10.2 |
| **2611** | East Timor | Developing | 63.7 | 13.5 | 0.492 | 10.6 |
| **2610** | East Timor | Developing | 64.9 | 13.9 | 0.511 | 11.0 |
| **2609** | East Timor | Developing | 65.8 | 14.2 | 0.541 | 11.3 |
| **2608** | East Timor | Developing | 66.2 | 14.7 | 0.566 | 11.7 |
| **2607** | East Timor | Developing | 66.6 | 15.1 | 0.599 | 12.1 |
| **2606** | East Timor | Developing | 66.9 | 15.5 | 0.599 | 12.4 |
| **2605** | East Timor | Developing | 67.2 | 15.8 | 0.607 | 12.5 |
| **2604** | East Timor | Developing | 67.4 | 16.2 | 0.618 | 12.5 |
| **2603** | East Timor | Developing | 67.7 | 16.6 | 0.620 | 12.5 |
| **2602** | East Timor | Developing | 68.0 | 17.0 | 0.612 | 12.5 |
| **2601** | East Timor | Developing | 68.3 | 17.4 | 0.603 | 12.5 |

Since this is the first year in the dataset, it is not a good idea to simply impute these values with the mean. A simple look at the DataFrame and we can see that `Income composition of resources` grows at a consistent rate of 0.005 per year whereas `Schooling` remains at a constant value of 9.8 for the first few years. Hence, we can impute the zero values with dummy values of 0.465 and 9.8 respectively.

The `at` property allows quick access of the value in a specific cell of a DataFrame. We can then use assignment to directly replace the value.

In [13]:

```
life_exp_sea.at[2616, 'Income composition of resources'] = 0.465
life_exp_sea.at[2616, 'Schooling'] = 9.8
```

```python
life_exp_sea[life_exp_sea['country'] == 'East Timor'].head()
```

Out[13]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling |
|---|---|---|---|---|---|---|
| **2616** | East Timor | Developing | 58.7 | 11.9 | 0.465 | 9.8 |
| **2615** | East Timor | Developing | 59.4 | 12.3 | 0.470 | 9.8 |
| **2614** | East Timor | Developing | 62.0 | 12.6 | 0.475 | 9.8 |
| **2613** | East Timor | Developing | 61.0 | 12.9 | 0.485 | 9.8 |
| **2612** | East Timor | Developing | 62.3 | 13.2 | 0.484 | 10.2 |

Now we have a DataFrame that covers all the core data for Southeast Asian countries. This is useful for observing trends and growth of the data.

But what if we need a summary? Each country has many entries in the DataFrame, one for each year in the dataset. We can go one step further and obtain aggregated values for each statistic. More specifically, we reorganise the DataFrame so that it shows only the mean values for each statistic. Mean is a good measure of central tendency as its calculation involves every value in the dataset. As the responding variable, life expectancy will also get a column for its max values as well, so that they may be compared with the corresponding mean values.

Since `country` is the set of values we want to separate our data by, we will utilise the `groupby` function to group the data by `country`.

We first create a dictionary of keyword arguments to be passed into the `agg` function. For each entry in the dictionary, the string before the colon is the name of the column to be added. The tuple after the colon contains first the label of the column whose data is to be aggregated, then the function used for aggregation.

The groupby object is then assigned to a new variable called `life_exp_sea_agg`. `as_index` is set to False to prevent the country column from being used as the index of the DataFrame. `agg` is then applied to this DataFrame with the keyword arguments. The characters `**` must be included to denote that our argument is a dictionary of keyword arguments to be unpacked.

In [14]:

```python
fun = {'max_life_expectancy': ('Life expectancy', 'max'),
       'mean_life_expectancy': ('Life expectancy', 'mean'),
       'mean_BMI': ('BMI', 'mean'),
       'mean_income_composition_of_resources': ('Income composition of resou
       'mean_schooling': ('Schooling', 'mean'),
      }

life_exp_sea_agg = life_exp_sea.groupby(['country'], as_index = False).agg(

life_exp_sea_agg
```

Out[14]:

| | country | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_income_compos |
|---|---|---|---|---|---|
| **0** | Brunei | 78.3 | 76.48750 | 33.442857 | |
| **1** | Cambodia | 68.7 | 64.34375 | 15.362500 | |
| **2** | East Timor | 68.3 | 64.75625 | 14.550000 | |
| **3** | Indonesia | 69.1 | 67.55625 | 21.120000 | |
| **4** | Laos | 65.7 | 62.38125 | 16.057143 | |
| **5** | Malaysia | 75.0 | 73.75625 | 32.742857 | |
| **6** | Myanmar | 66.6 | 64.20000 | 18.100000 | |
| **7** | Philippines | 68.5 | 67.57500 | 21.592857 | |
| **8** | Singapore | 87.0 | 81.47500 | 31.069231 | |
| **9** | Thailand | 74.9 | 73.08125 | 25.946154 | |
| **10** | Vietnam | 76.0 | 74.77500 | 13.438462 | |

It is a good idea to include `Status` as it can be linked to the numerical statistics in our new DataFrame.

First, we want to see if any countries changed their status throughout the years. We slice the `life_exp_sea` DataFrame using `iloc`. `[:, 0:2]` means include all rows and include only the first two columns.

In [15]:
```
life_exp_sea.iloc[:, 0:2]
```

Out[15]:

| | country | Status |
|---|---|---|
| **383** | Brunei | Developing |
| **382** | Brunei | Developing |
| **381** | Brunei | Developing |
| **380** | Brunei | Developing |
| **379** | Brunei | Developing |
| **...** | ... | ... |
| **2878** | Vietnam | Developing |
| **2877** | Vietnam | Developing |
| **2876** | Vietnam | Developing |
| **2875** | Vietnam | Developing |
| **2874** | Vietnam | Developing |

176 rows × 2 columns

Then, we remove duplicate rows using `drop_duplicates`. If any countries changed their status, they will appear twice in the DataFrame; once with `Developing` status, and once with `Developed` status. Otherwise, there will be as many rows as there are countries.

We also use `sort_values` to reorder the DataFrame by alphabetical order of country names. This is necessary as `Timor-Leste` has been renamed to `East Timor`.

In [16]:
```
life_exp_sea_status = life_exp_sea.iloc[:, 0:2].drop_duplicates().sort_value

life_exp_sea_status
```

Out[16]:

| | country | Status |
|---|---|---|
| **383** | Brunei | Developing |
| **479** | Cambodia | Developing |
| **2616** | East Timor | Developing |
| **1217** | Indonesia | Developing |
| **1441** | Laos | Developing |
| **1601** | Malaysia | Developing |
| **1795** | Myanmar | Developing |
| **2038** | Philippines | Developing |
| **2328** | Singapore | Developed |
| **2584** | Thailand | Developing |
| **2889** | Vietnam | Developing |

So, for the years covered in this dataset, no countries experienced a change in development status. We do not need to worry about this influencing our data. We can now proceed to add the other columns from `life_exp_sea_agg` (using `merge`) to `life_sea_exp_status`, then reassign this complete DataFrame to the the `life_exp_sea_agg` variable. We do not need to pass in any arguments as the `country` column is found in both DataFrames, so **pandas** uses that as the default column to merge on.

In [17]:
```
life_exp_sea_agg = life_exp_sea_status.merge(life_exp_sea_agg)

life_exp_sea_agg
```

Out[17]:

| | country | Status | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_inc |
|---|---|---|---|---|---|---|
| 0 | Brunei | Developing | 78.3 | 76.48750 | 33.442857 | |
| 1 | Cambodia | Developing | 68.7 | 64.34375 | 15.362500 | |
| 2 | East Timor | Developing | 68.3 | 64.75625 | 14.550000 | |
| 3 | Indonesia | Developing | 69.1 | 67.55625 | 21.120000 | |
| 4 | Laos | Developing | 65.7 | 62.38125 | 16.057143 | |
| 5 | Malaysia | Developing | 75.0 | 73.75625 | 32.742857 | |
| 6 | Myanmar | Developing | 66.6 | 64.20000 | 18.100000 | |
| 7 | Philippines | Developing | 68.5 | 67.57500 | 21.592857 | |
| 8 | Singapore | Developed | 87.0 | 81.47500 | 31.069231 | |
| 9 | Thailand | Developing | 74.9 | 73.08125 | 25.946154 | |
| 10 | Vietnam | Developing | 76.0 | 74.77500 | 13.438462 | |

## Population

Now, let us integrate data from other datasets into our DataFrame. Population is a good choice as we can observe how population influences the data we currently have. We import `2020-Population.csv`, a dataset containing populations of countries from 1950 to 2020.

In [18]:

```
population = pd.read_csv('data/2020-Population.csv')

population.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 305 entries, 0 to 304
Data columns (total 78 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Unnamed: 0   299 non-null    object
 1   Unnamed: 1   290 non-null    object
 2   Unnamed: 2   290 non-null    object
 3   Unnamed: 3   83 non-null     object
 4   Unnamed: 4   290 non-null    object
 5   Unnamed: 5   290 non-null    object
 6   Unnamed: 6   290 non-null    object
 7   Unnamed: 7   291 non-null    object
 8   Unnamed: 8   290 non-null    object
 9   Unnamed: 9   290 non-null    object
 10  Unnamed: 10  290 non-null    object
 11  Unnamed: 11  290 non-null    object
 12  Unnamed: 12  290 non-null    object
 13  Unnamed: 13  290 non-null    object
 14  Unnamed: 14  290 non-null    object
 15  Unnamed: 15  290 non-null    object
 16  Unnamed: 16  290 non-null    object
 17  Unnamed: 17  290 non-null    object
 18  Unnamed: 18  290 non-null    object
 19  Unnamed: 19  290 non-null    object
 20  Unnamed: 20  290 non-null    object
 21  Unnamed: 21  290 non-null    object
 22  Unnamed: 22  290 non-null    object
 23  Unnamed: 23  290 non-null    object
 24  Unnamed: 24  290 non-null    object
 25  Unnamed: 25  290 non-null    object
 26  Unnamed: 26  290 non-null    object
 27  Unnamed: 27  290 non-null    object
 28  Unnamed: 28  290 non-null    object
 29  Unnamed: 29  290 non-null    object
 30  Unnamed: 30  290 non-null    object
 31  Unnamed: 31  290 non-null    object
 32  Unnamed: 32  290 non-null    object
 33  Unnamed: 33  290 non-null    object
 34  Unnamed: 34  290 non-null    object
 35  Unnamed: 35  290 non-null    object
 36  Unnamed: 36  290 non-null    object
 37  Unnamed: 37  290 non-null    object
 38  Unnamed: 38  290 non-null    object
 39  Unnamed: 39  290 non-null    object
 40  Unnamed: 40  290 non-null    object
 41  Unnamed: 41  290 non-null    object
 42  Unnamed: 42  290 non-null    object
 43  Unnamed: 43  290 non-null    object
 44  Unnamed: 44  290 non-null    object
 45  Unnamed: 45  290 non-null    object
 46  Unnamed: 46  290 non-null    object
 47  Unnamed: 47  290 non-null    object
 48  Unnamed: 48  290 non-null    object
 49  Unnamed: 49  290 non-null    object
 50  Unnamed: 50  290 non-null    object
 51  Unnamed: 51  290 non-null    object
 52  Unnamed: 52  290 non-null    object
 53  Unnamed: 53  290 non-null    object
 54  Unnamed: 54  290 non-null    object
 55  Unnamed: 55  290 non-null    object
 56  Unnamed: 56  290 non-null    object
 57  Unnamed: 57  290 non-null    object
 58  Unnamed: 58  290 non-null    object
```

```
 59  Unnamed: 59  290 non-null    object
 60  Unnamed: 60  290 non-null    object
 61  Unnamed: 61  290 non-null    object
 62  Unnamed: 62  290 non-null    object
 63  Unnamed: 63  290 non-null    object
 64  Unnamed: 64  290 non-null    object
 65  Unnamed: 65  290 non-null    object
 66  Unnamed: 66  290 non-null    object
 67  Unnamed: 67  290 non-null    object
 68  Unnamed: 68  290 non-null    object
 69  Unnamed: 69  290 non-null    object
 70  Unnamed: 70  290 non-null    object
 71  Unnamed: 71  290 non-null    object
 72  Unnamed: 72  290 non-null    object
 73  Unnamed: 73  290 non-null    object
 74  Unnamed: 74  290 non-null    object
 75  Unnamed: 75  290 non-null    object
 76  Unnamed: 76  290 non-null    object
 77  Unnamed: 77  290 non-null    object
dtypes: object(78)
memory usage: 186.0+ KB
```

The dataset looks to be messy. We will have to wrangle it. First, we look at its head.

In [19]:
```
population.head()
```

Out[19]:

| | Unnamed: 0 | Unnamed: 1 | Unnamed: 2 | Unnamed: 3 | Unnamed: 4 | Unnamed: 5 | Unnamed: 6 | Unname |
|---|---|---|---|---|---|---|---|---|
| **0** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | Na |
| **1** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | Na |
| **2** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | Na |
| **3** | United Nations | NaN | NaN | NaN | NaN | NaN | NaN | Na |
| **4** | Population Division | NaN | NaN | NaN | NaN | NaN | NaN | Na |

5 rows × 78 columns

The head of the DataFrame does not tell us much about the content of the dataset. Let us look at the first 20 rows instead.

In [20]:
```
population[:20]
```

Out[20]:

| | Unnamed: 0 | Unnamed: 1 | Unnamed: 2 | Unnamed: 3 | Unnamed: 4 | Unnar |
|---|---|---|---|---|---|---|
| **0** | NaN | NaN | NaN | NaN | NaN | |
| **1** | NaN | NaN | NaN | NaN | NaN | |
| **2** | NaN | NaN | NaN | NaN | NaN | |
| **3** | United Nations | NaN | NaN | NaN | NaN | |
| **4** | Population Division | NaN | NaN | NaN | NaN | |
| **5** | Department of Economic and Social Affairs | NaN | NaN | NaN | NaN | |
| **6** | NaN | NaN | NaN | NaN | NaN | |
| **7** | World Population Prospects 2019 | NaN | NaN | NaN | NaN | |
| **8** | File POP/1-1: Total population (both sexes com... | NaN | NaN | NaN | NaN | |
| **9** | Estimates, 1950 - 2020 | NaN | NaN | NaN | NaN | |
| **10** | POP/DB/WPP/Rev.2019/POP/F01-1 | NaN | NaN | NaN | NaN | |
| **11** | © August 2019 by United Nations, made availabl... | NaN | NaN | NaN | NaN | |
| **12** | Suggested citation: United Nations, Department... | NaN | NaN | NaN | NaN | |
| **13** | NaN | NaN | NaN | NaN | NaN | |
| **14** | NaN | NaN | NaN | NaN | NaN | |
| **15** | Index | Variant | Region, subregion, country or area * | Notes | Country code | |
| **16** | 1 | Estimates | WORLD | NaN | 900 | |
| **17** | 2 | Estimates | UN development groups | a | 1803 | Label/Sep |
| **18** | 3 | Estimates | More developed regions | b | 901 | Develo |
| **19** | 4 | Estimates | Less developed regions | c | 902 | Develo |

20 rows × 78 columns

Thus, we can see the data really only begins starting from row 16, with row 15 being the headers. All the rows above it just contain information about the dataset that we can safely drop.

In [21]:
```
population = population.drop(index = range(15))

population.head()
```

Out[21]:

| | Unnamed: 0 | Unnamed: 1 | Unnamed: 2 | Unnamed: 3 | Unnamed: 4 | Unnamed: 5 | Unnamed: 6 |
|---|---|---|---|---|---|---|---|
| **15** | Index | Variant | Region, subregion, country or area * | Notes | Country code | Type | Parent code |
| **16** | 1 | Estimates | WORLD | NaN | 900 | World | 0 |
| **17** | 2 | Estimates | UN development groups | a | 1803 | Label/Separator | 900 |
| **18** | 3 | Estimates | More developed regions | b | 901 | Development Group | 1803 |
| **19** | 4 | Estimates | Less developed regions | c | 902 | Development Group | 1803 |

5 rows × 78 columns

Now, we set the first row of the DataFrame as the headers of the columns. The original row can then be removed from the DataFrame. The column `Index` can also be removed as we will be working with the built-in indexes of the DataFrame.

Since we used row 15 as our column headers, the index of our DataFrame will now have a name called '15'. We remove it using `rename_axis`.

In [22]:
```
population.columns = population.iloc[0]
population = population.drop(index = 15, columns = 'Index')
population.rename_axis(None, axis = 1, inplace = True)

population.head()
```

Out[22]:

| | Variant | Region, subregion, country or area * | Notes | Country code | Type | Parent code | 1950 | 1951 | 1952 | 195 |
|---|---|---|---|---|---|---|---|---|---|---|
| **16** | Estimates | WORLD | NaN | 900 | World | 0 | 2 536 431 | 2 584 034 | 2 630 862 | 2 67 60 |
| **17** | Estimates | UN development groups | a | 1803 | Label/Separator | 900 | ... | ... | ... | .. |
| **18** | Estimates | More developed regions | b | 901 | Development Group | 1803 | 814 819 | 824 004 | 833 720 | 84 78 |
| **19** | Estimates | Less developed regions | c | 902 | Development Group | 1803 | 1 721 612 | 1 760 031 | 1 797 142 | 83 82 |
| **20** | Estimates | Least developed countries | d | 941 | Development Group | 902 | 195 428 | 199 180 | 203 015 | 20 98 |

5 rows × 77 columns

Again, we only want the data for Southeast Asian countries. We can reuse the code we used above, but let us first rename the label of the column of country/region names to something shorter for convenience. We will only work with countries in the end anyways.

In [23]:

```
population.rename(columns = {'Region, subregion, country or area *': 'count

population.head()
```

Out[23]:

| | Variant | country | Notes | Country code | Type | Parent code | 1950 | 1951 | 1952 | 195 |
|---|---|---|---|---|---|---|---|---|---|---|
| **16** | Estimates | WORLD | NaN | 900 | World | 0 | 2 536 431 | 2 584 034 | 2 630 862 | 677 609 |
| **17** | Estimates | UN development groups | a | 1803 | Label/Separator | 900 | ... | ... | ... | .. |
| **18** | Estimates | More developed regions | b | 901 | Development Group | 1803 | 814 819 | 824 004 | 833 720 | 84 78 |
| **19** | Estimates | Less developed regions | c | 902 | Development Group | 1803 | 1 721 612 | 1 760 031 | 1 797 142 | 83 82 |
| **20** | Estimates | Least developed countries | d | 941 | Development Group | 902 | 195 428 | 199 180 | 203 015 | 20 98 |

5 rows × 77 columns

We use `unique` again to list down the names of countries in an array. We are trying to note the names of Southeast Asian countries and see if they match the conventional versions we used before. Since the names are not in alphabetical order, we can use `np.sort`, which sorts a **NumPy** array and returns a copy.

In [24]:
```
np.sort(population['country'].unique())
```

Out[24]:
```
array(['AUSTRALIA/NEW ZEALAND', 'Afghanistan', 'Africa', 'Albania',
       'Algeria', 'American Samoa', 'Andorra', 'Angola', 'Anguilla',
       'Antigua and Barbuda', 'Argentina', 'Armenia', 'Aruba', 'Asia',
       'Australia', 'Austria', 'Azerbaijan', 'Bahamas', 'Bahrain',
       'Bangladesh', 'Barbados', 'Belarus', 'Belgium', 'Belize', 'Benin',
       'Bermuda', 'Bhutan', 'Bolivia (Plurinational State of)',
       'Bonaire, Sint Eustatius and Saba', 'Bosnia and Herzegovina',
       'Botswana', 'Brazil', 'British Virgin Islands',
       'Brunei Darussalam', 'Bulgaria', 'Burkina Faso', 'Burundi',
       'CENTRAL AND SOUTHERN ASIA', 'Cabo Verde', 'Cambodia', 'Cameroon',
       'Canada', 'Caribbean', 'Cayman Islands',
       'Central African Republic', 'Central America', 'Central Asia',
       'Chad', 'Channel Islands', 'Chile', 'China',
       'China, Hong Kong SAR', 'China, Macao SAR',
       'China, Taiwan Province of China', 'Colombia', 'Comoros', 'Congo',
       'Cook Islands', 'Costa Rica', 'Croatia', 'Cuba', 'Curaçao',
       'Cyprus', 'Czechia', "Côte d'Ivoire",
       "Dem. People's Republic of Korea",
       'Democratic Republic of the Congo', 'Denmark', 'Djibouti',
       'Dominica', 'Dominican Republic', 'EASTERN AND SOUTH-EASTERN ASI
A',
       'EUROPE', 'EUROPE AND NORTHERN AMERICA', 'Eastern Africa',
       'Eastern Asia', 'Eastern Europe', 'Ecuador', 'Egypt',
       'El Salvador', 'Equatorial Guinea', 'Eritrea', 'Estonia',
       'Eswatini', 'Ethiopia', 'Europe', 'Falkland Islands (Malvinas)',
       'Faroe Islands', 'Fiji', 'Finland', 'France', 'French Guiana',
       'French Polynesia', 'Gabon', 'Gambia', 'Geographic regions',
       'Georgia', 'Germany', 'Ghana', 'Gibraltar', 'Greece', 'Greenland',
       'Grenada', 'Guadeloupe', 'Guam', 'Guatemala', 'Guinea',
       'Guinea-Bissau', 'Guyana', 'Haiti', 'High-income countries',
       'Holy See', 'Honduras', 'Hungary', 'Iceland', 'India', 'Indonesi
a',
       'Iran (Islamic Republic of)', 'Iraq', 'Ireland', 'Isle of Man',
       'Israel', 'Italy', 'Jamaica', 'Japan', 'Jordan', 'Kazakhstan',
       'Kenya', 'Kiribati', 'Kuwait', 'Kyrgyzstan',
       'LATIN AMERICA AND THE CARIBBEAN',
       'Land-locked Developing Countries (LLDC)',
       "Lao People's Democratic Republic",
       'Latin America and the Caribbean', 'Latvia',
       'Least developed countries', 'Lebanon', 'Lesotho',
       'Less developed regions',
       'Less developed regions, excluding China',
       'Less developed regions, excluding least developed countries',
       'Liberia', 'Libya', 'Liechtenstein', 'Lithuania',
       'Low-income countries', 'Lower-middle-income countries',
       'Luxembourg', 'Madagascar', 'Malawi', 'Malaysia', 'Maldives',
       'Mali', 'Malta', 'Marshall Islands', 'Martinique', 'Mauritania',
       'Mauritius', 'Mayotte', 'Melanesia', 'Mexico', 'Micronesia',
       'Micronesia (Fed. States of)', 'Middle Africa',
       'Middle-income countries', 'Monaco', 'Mongolia', 'Montenegro',
       'Montserrat', 'More developed regions', 'Morocco', 'Mozambique',
       'Myanmar', 'NORTHERN AFRICA AND WESTERN ASIA', 'NORTHERN AMERICA',
       'Namibia', 'Nauru', 'Nepal', 'Netherlands', 'New Caledonia',
       'New Zealand', 'Nicaragua', 'Niger', 'Nigeria', 'Niue',
       'No income group available', 'North Macedonia', 'Northern Africa',
       'Northern America', 'Northern Europe', 'Northern Mariana Islands',
       'Norway', 'OCEANIA (EXCLUDING AUSTRALIA AND NEW ZEALAND)',
       'Oceania', 'Oman', 'Pakistan', 'Palau', 'Panama',
       'Papua New Guinea', 'Paraguay', 'Peru', 'Philippines', 'Poland',
       'Polynesia', 'Portugal', 'Puerto Rico', 'Qatar',
       'Republic of Korea', 'Republic of Moldova', 'Romania',
       'Russian Federation', 'Rwanda', 'Réunion', 'SUB-SAHARAN AFRICA',
       'Saint Barthélemy', 'Saint Helena', 'Saint Kitts and Nevis',
       'Saint Lucia', 'Saint Martin (French part)',
```

```
'Saint Pierre and Miquelon', 'Saint Vincent and the Grenadines',
'Samoa', 'San Marino', 'Sao Tome and Principe', 'Saudi Arabia',
'Senegal', 'Serbia', 'Seychelles', 'Sierra Leone', 'Singapore',
'Sint Maarten (Dutch part)', 'Slovakia', 'Slovenia',
'Small Island Developing States (SIDS)', 'Solomon Islands',
'Somalia', 'South Africa', 'South America', 'South Sudan',
'South-Eastern Asia', 'Southern Africa', 'Southern Asia',
'Southern Europe', 'Spain', 'Sri Lanka', 'State of Palestine',
'Sudan', 'Suriname', 'Sustainable Development Goal (SDG) regions',
'Sweden', 'Switzerland', 'Syrian Arab Republic', 'Tajikistan',
'Thailand', 'Timor-Leste', 'Togo', 'Tokelau', 'Tonga',
'Trinidad and Tobago', 'Tunisia', 'Turkey', 'Turkmenistan',
'Turks and Caicos Islands', 'Tuvalu', 'UN development groups',
'Uganda', 'Ukraine', 'United Arab Emirates', 'United Kingdom',
'United Republic of Tanzania', 'United States Virgin Islands',
'United States of America', 'Upper-middle-income countries',
'Uruguay', 'Uzbekistan', 'Vanuatu',
'Venezuela (Bolivarian Republic of)', 'Viet Nam', 'WORLD',
'Wallis and Futuna Islands', 'Western Africa', 'Western Asia',
'Western Europe', 'Western Sahara', 'World Bank income groups',
'Yemen', 'Zambia', 'Zimbabwe'], dtype=object)
```

Looks like the names for to this dataset have to be shortened as well. Fortunately, their 'long' versions are the same as the ones from `LifeExpectancyData-v2.csv`. We still have the `renames` dictionary as well as the list of Southeast Asian country names, `sea`, from earlier, which we can safely reuse.

```
renames = {'Brunei Darussalam': 'Brunei',
           'Timor-Leste': 'East Timor',
           'Lao People\'s Democratic Republic': 'Laos',
           'Viet Nam': 'Vietnam'
          }

sea = ['Brunei', 'Cambodia', 'East Timor', 'Indonesia',
'Laos', 'Malaysia', 'Myanmar', 'Philippines', 'Singapore',
'Thailand', 'Vietnam']
```

Just like before, the necessary country names are shortened using `replace` and `isin` is used to filter out the data for Southeast Asian countries.

For a clean appearance, we also use `reset_index` so the indexes start from 0. `drop` is set to `True` so there would not be a new column for the original indexes added to the DataFrame. The end result is assigned to a new variable called `population_sea`.

Finally, the DataFrame is sorted by `country` as `Timor-Leste` has been renamed to `East Timor`.

In [25]:
```
population['country'] = population['country'].replace(renames)
population_sea = population[population['country'].isin(sea)].reset_index(dro
population_sea = population_sea.sort_values('country')

population_sea
```

Out[25]:

| | Variant | country | Notes | Country code | Type | Parent code | 1950 | 1951 | 1952 | 1953 | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Estimates | Brunei | NaN | 96 | Country/Area | 920 | 48 | 51 | 54 | 57 | ... |
| **1** | Estimates | Cambodia | NaN | 116 | Country/Area | 920 | 4 433 | 4 538 | 4 656 | 4 783 | ... |
| **9** | Estimates | East Timor | NaN | 626 | Country/Area | 920 | 415 | 419 | 423 | 428 | ... |
| **2** | Estimates | Indonesia | NaN | 360 | Country/Area | 920 | 69 543 | 70 849 | 72 275 | 73 821 | ... |
| **3** | Estimates | Laos | NaN | 418 | Country/Area | 920 | 1 683 | 1 723 | 1 764 | 1 806 | ... |
| **4** | Estimates | Malaysia | 13 | 458 | Country/Area | 920 | 6 110 | 6 271 | 6 450 | 6 639 | ... |
| **5** | Estimates | Myanmar | NaN | 104 | Country/Area | 920 | 17 780 | 18 104 | 18 441 | 18 793 | ... |
| **6** | Estimates | Philippines | NaN | 608 | Country/Area | 920 | 18 580 | 19 247 | 19 945 | 20 670 | ... |
| **7** | Estimates | Singapore | NaN | 702 | Country/Area | 920 | 1 022 | 1 068 | 1 120 | 1 178 | ... |
| **8** | Estimates | Thailand | NaN | 764 | Country/Area | 920 | 20 710 | 21 263 | 21 838 | 22 437 | ... |
| **10** | Estimates | Vietnam | NaN | 704 | Country/Area | 920 | 24 810 | 25 365 | 25 977 | 26 646 | ... |

11 rows × 77 columns

We will be merging data for the gross domestic product (GDP) of each country later. The GDP data is from 2019. Hence, we just need the population values for 2019. Using `filter`, we extract only the country names and values for 2019 from `population_sea`.

In [26]:

```
population_sea = population_sea.filter(['country', '2019'])

population_sea
```

Out[26]:

| | country | 2019 |
|---|---|---|
| **0** | Brunei | 433 |
| **1** | Cambodia | 16 487 |
| **9** | East Timor | 1 293 |
| **2** | Indonesia | 270 626 |
| **3** | Laos | 7 169 |
| **4** | Malaysia | 31 950 |
| **5** | Myanmar | 54 045 |
| **6** | Philippines | 108 117 |
| **7** | Singapore | 5 804 |
| **8** | Thailand | 69 626 |
| **10** | Vietnam | 96 462 |

Looks good. But the following output shows otherwise:

In [27]:
```
population_sea.dtypes
```

Out[27]:
```
country     object
2019        object
dtype: object
```

The values of `2019` are strings! This will give us trouble if we attempt to visualise the data later.

Before we convert the strings to integers, we have to remove the whitespaces or Python would not be able to cast them. For this, we use the `apply` function with a lambda expression that replaces all whitespaces with empty strings. Then, the strings can be converted into integers by calling the `to_numeric` function on the `2019` series.

In addition, the values of `2019` are in thousands. This can be easily verified by searching for the exact population of a few of the countries using Google. We prefer to use exact values for our DataFrame, so we can multiply every value in `2019` by 1000.

In [28]:
```
population_sea['2019'] = population_sea['2019'].apply(lambda x: x.replace('
population_sea['2019'] = pd.to_numeric(population_sea['2019'])
population_sea['2019'] = population_sea['2019'] * 1000

population_sea
```

Out[28]:

| | country | 2019 |
|---|---|---|
| 0 | Brunei | 433000 |
| 1 | Cambodia | 16487000 |
| 9 | East Timor | 1293000 |
| 2 | Indonesia | 270626000 |
| 3 | Laos | 7169000 |
| 4 | Malaysia | 31950000 |
| 5 | Myanmar | 54045000 |
| 6 | Philippines | 108117000 |
| 7 | Singapore | 5804000 |
| 8 | Thailand | 69626000 |
| 10 | Vietnam | 96462000 |

Let us verify that the values have been casted to integers correctly.

In [29]:
```
population_sea.dtypes
```

Out[29]:
```
country    object
2019        int64
dtype: object
```

Now, we merge the DataFrame to `life_exp_sea_agg`, renaming the column `2019` to just `population`. We will reassign this newly combined DataFrame to a new variable called `life_exp_sea_pop`.

In [30]:
```
population_sea.rename(columns = {'2019': 'population'}, inplace = True)
life_exp_sea_pop = life_exp_sea_agg.merge(population_sea)

life_exp_sea_pop
```

Out[30]:

| | country | Status | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_inc |
|---|---|---|---|---|---|---|
| 0 | Brunei | Developing | 78.3 | 76.48750 | 33.442857 | |
| 1 | Cambodia | Developing | 68.7 | 64.34375 | 15.362500 | |
| 2 | East Timor | Developing | 68.3 | 64.75625 | 14.550000 | |
| 3 | Indonesia | Developing | 69.1 | 67.55625 | 21.120000 | |
| 4 | Laos | Developing | 65.7 | 62.38125 | 16.057143 | |
| 5 | Malaysia | Developing | 75.0 | 73.75625 | 32.742857 | |
| 6 | Myanmar | Developing | 66.6 | 64.20000 | 18.100000 | |
| 7 | Philippines | Developing | 68.5 | 67.57500 | 21.592857 | |
| 8 | Singapore | Developed | 87.0 | 81.47500 | 31.069231 | |
| 9 | Thailand | Developing | 74.9 | 73.08125 | 25.946154 | |
| 10 | Vietnam | Developing | 76.0 | 74.77500 | 13.438462 | |

## GDP

We can now proceed to integrate the data from `2019-GDP.csv` into our DataFrame.

In [31]:
```
gdp = pd.read_csv('data/2019-GDP.csv')

gdp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 6 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Unnamed: 0                   229 non-null    object 
 1   Gross domestic product 2019  209 non-null    object 
 2   Unnamed: 2                   0 non-null      float64
 3   Unnamed: 3                   230 non-null    object 
 4   Unnamed: 4                   231 non-null    object 
 5   Unnamed: 5                   8 non-null      object 
dtypes: float64(1), object(5)
memory usage: 11.6+ KB
```

Again, this dataset will require wrangling from the look of its column labels. We first read its head.

In [32]:
```
gdp.head()
```

Out[32]:

| | Unnamed: 0 | Gross domestic product 2019 | Unnamed: 2 | Unnamed: 3 | Unnamed: 4 | Unnamed: 5 |
|---|---|---|---|---|---|---|
| **0** | NaN | NaN | NaN | NaN | NaN | NaN |
| **1** | NaN | NaN | NaN | NaN | (millions of | NaN |
| **2** | NaN | Ranking | NaN | Economy | US dollars) | NaN |
| **3** | NaN | NaN | NaN | NaN | NaN | NaN |
| **4** | USA | 1 | NaN | United States | 21,427,700 | NaN |

Similar to the `2020-Population.csv` file, the head does not tell us much. We will need to look at more of the DataFrame and tidy it up.

In [33]:
```
gdp.iloc[:20]
```

Out[33]:

| | Unnamed: 0 | Gross domestic product 2019 | Unnamed: 2 | Unnamed: 3 | Unnamed: 4 | Unnamed: 5 |
|---|---|---|---|---|---|---|
| **0** | NaN | NaN | NaN | NaN | NaN | NaN |
| **1** | NaN | NaN | NaN | NaN | (millions of | NaN |
| **2** | NaN | Ranking | NaN | Economy | US dollars) | NaN |
| **3** | NaN | NaN | NaN | NaN | NaN | NaN |
| **4** | USA | 1 | NaN | United States | 21,427,700 | NaN |
| **5** | CHN | 2 | NaN | China | 14,342,903 | NaN |
| **6** | JPN | 3 | NaN | Japan | 5,081,770 | NaN |
| **7** | DEU | 4 | NaN | Germany | 3,845,630 | NaN |
| **8** | IND | 5 | NaN | India | 2,875,142 | NaN |
| **9** | GBR | 6 | NaN | United Kingdom | 2,827,113 | NaN |
| **10** | FRA | 7 | NaN | France | 2,715,518 | NaN |
| **11** | ITA | 8 | NaN | Italy | 2,001,244 | NaN |
| **12** | BRA | 9 | NaN | Brazil | 1,839,758 | NaN |
| **13** | CAN | 10 | NaN | Canada | 1,736,426 | NaN |
| **14** | RUS | 11 | NaN | Russian Federation | 1,699,877 | a |
| **15** | KOR | 12 | NaN | Korea, Rep. | 1,642,383 | NaN |
| **16** | ESP | 13 | NaN | Spain | 1,394,116 | NaN |
| **17** | AUS | 14 | NaN | Australia | 1,392,681 | NaN |
| **18** | MEX | 15 | NaN | Mexico | 1,258,287 | NaN |
| **19** | IDN | 16 | NaN | Indonesia | 1,119,191 | NaN |

The columns labelled `Unnamed: 2` and `Unnamed: 5` consist mostly of `NaN` values. We will remove them along with rows 0, 1 and 3, which do not provide meaningful data as well.

In [34]:
```
gdp = gdp.drop(index = [0, 1, 3], columns = ['Unnamed: 2', 'Unnamed: 5'])

gdp.head()
```

Out[34]:

| | Unnamed: 0 | Gross domestic product 2019 | Unnamed: 3 | Unnamed: 4 |
|---|---|---|---|---|
| **2** | NaN | Ranking | Economy | US dollars) |
| **4** | USA | 1 | United States | 21,427,700 |
| **5** | CHN | 2 | China | 14,342,903 |
| **6** | JPN | 3 | Japan | 5,081,770 |
| **7** | DEU | 4 | Germany | 3,845,630 |

Just like we observed in `2020-Population.csv`, the column headers of this DataFrame are in the first row. This row should be set as the column labels of this DataFrame. `rename_axis` is also used as we do not want the index to be labelled.

In [35]:
```
gdp.columns = gdp.iloc[0]
gdp = gdp.drop(index = 2)
gdp.rename_axis(None, axis = 1, inplace = True)

gdp.head()
```

Out[35]:

| | NaN | Ranking | Economy | US dollars) |
|---|---|---|---|---|
| **4** | USA | 1 | United States | 21,427,700 |
| **5** | CHN | 2 | China | 14,342,903 |
| **6** | JPN | 3 | Japan | 5,081,770 |
| **7** | DEU | 4 | Germany | 3,845,630 |
| **8** | IND | 5 | India | 2,875,142 |

Now we have column headers, but they still do not make much sense (eg. `Economy` is not a correct label). Using `rename`, we give each column a more accurate name. Based on the original CSV file, the GDP is in millions of US dollars, so we have to mention that in the label as well.

Using `np.nan`, we can directly refer to the `NaN` value and rename it to `country code`. `'NaN': 'country code'` does not work in this case as `NaN` is not a string.

In [36]:
```
gdp.rename(columns = {np.nan: 'country code',
                      'Economy': 'country',
                      'US dollars)': 'GDP (in millions USD)'},
           inplace = True)

gdp.head()
```

Out[36]:

| | country code | Ranking | country | GDP (in millions USD) |
|---|---|---|---|---|
| **4** | USA | 1 | United States | 21,427,700 |
| **5** | CHN | 2 | China | 14,342,903 |
| **6** | JPN | 3 | Japan | 5,081,770 |
| **7** | DEU | 4 | Germany | 3,845,630 |
| **8** | IND | 5 | India | 2,875,142 |

To ensure the country names for this dataset match the conventional version, we call `unique` again.

In [37]:
```
gdp['country'].unique()
```

Out[37]:
```
array(['United States', 'China', 'Japan', 'Germany', 'India',
       'United Kingdom', 'France', 'Italy', 'Brazil', 'Canada',
       'Russian Federation', 'Korea, Rep.', 'Spain', 'Australia',
       'Mexico', 'Indonesia', 'Netherlands', 'Saudi Arabia', 'Turkey',
       'Switzerland', 'Poland', 'Thailand', 'Sweden', 'Belgium',
       'Argentina', 'Nigeria', 'Austria', 'Iran, Islamic Rep.',
       'United Arab Emirates', 'Norway', 'Israel', 'Ireland',
       'Philippines', 'Singapore', 'Hong Kong SAR, China', 'Malaysia',
       'South Africa', 'Denmark', 'Colombia', 'Egypt, Arab Rep.',
       'Bangladesh', 'Chile', 'Pakistan', 'Finland', 'Vietnam', 'Romani
a',
       'Czech Republic', 'Portugal', 'Iraq', 'Peru', 'Greece',
       'New Zealand', 'Qatar', 'Kazakhstan', 'Algeria', 'Hungary',
       'Ukraine', 'Kuwait', 'Morocco', 'Ecuador', 'Slovak Republic',
       'Puerto Rico', 'Cuba', 'Ethiopia', 'Kenya', 'Angola',
       'Dominican Republic', 'Sri Lanka', 'Oman', 'Guatemala', 'Myanmar',
       'Luxembourg', 'Bulgaria', 'Ghana', 'Panama', 'Tanzania', 'Belaru
s',
       'Costa Rica', 'Croatia', "Côte d'Ivoire", 'Uzbekistan', 'Uruguay',
       'Lithuania', 'Macao SAR, China', 'Slovenia', 'Lebanon', 'Libya',
       'Serbia', 'Azerbaijan', 'Congo, Dem. Rep.', 'Jordan', 'Bolivia',
       'Turkmenistan', 'Tunisia', 'Cameroon', 'Bahrain', 'Paraguay',
       'Uganda', 'Latvia', 'Estonia', 'Nepal', 'Yemen, Rep.', 'Cambodia',
       'El Salvador', 'Honduras', 'Papua New Guinea', 'Cyprus', 'Icelan
d',
       'Trinidad and Tobago', 'Senegal', 'Zambia', 'Zimbabwe',
       'Bosnia and Herzegovina', 'Afghanistan', 'Sudan', 'Botswana',
       'Lao PDR', 'Georgia', 'Mali', 'Gabon', 'Jamaica', 'Burkina Faso',
       'Albania', 'Mozambique', 'Malta', 'West Bank and Gaza', 'Benin',
       'Mauritius', 'Madagascar', 'Mongolia', 'Armenia', 'Guinea',
       'Brunei Darussalam', 'Niger', 'Bahamas, The', 'North Macedonia',
       'Nicaragua', 'Namibia', 'Moldova', 'Chad', 'Equatorial Guinea',
       'Congo, Rep.', 'Rwanda', 'Haiti', 'Kyrgyz Republic', 'Tajikistan',
       'Kosovo', 'Malawi', 'Mauritania', 'Monaco', 'Isle of Man',
       'Liechtenstein', 'Guam', 'Maldives', 'Fiji', 'Montenegro',
       'Cayman Islands', 'Togo', 'Barbados', 'Eswatini', 'Guyana',
       'Suriname', 'Sierra Leone', 'Virgin Islands (U.S.)', 'Djibouti',
       'Andorra', 'Curaçao', 'Liberia', 'Aruba', 'Greenland', 'Burundi',
       'Faroe Islands', 'Lesotho', 'Bhutan', 'Central African Republic',
       'St. Lucia', 'Cabo Verde', 'Belize', 'Gambia, The',
       'Antigua and Barbuda', 'Seychelles', 'Timor-Leste', 'San Marino',
       'Solomon Islands', 'Guinea-Bissau', 'Northern Mariana Islands',
       'Grenada', 'Comoros', 'St. Kitts and Nevis',
       'Turks and Caicos Islands', 'Vanuatu', 'Samoa',
       'St. Vincent and the Grenadines', 'American Samoa', 'Dominica',
       'Tonga', 'São Tomé and Principe', 'Micronesia, Fed. Sts.', 'Pala
u',
       'Marshall Islands', 'Kiribati', 'Nauru', 'Tuvalu', 'Bermuda',
       'British Virgin Islands', 'Channel Islands', 'Eritrea',
       'French Polynesia', 'Gibraltar', "Korea, Dem. People's Rep.",
       'New Caledonia', 'Sint Maarten (Dutch part)', 'South Sudan',
       'St. Martin (French part)', 'Syrian Arab Republic',
       'Venezuela, RB', 'Somalia', nan, 'World', 'East Asia & Pacific',
       'Europe & Central Asia', 'Latin America & Caribbean',
       'Middle East & North Africa', 'North America', 'South Asia',
       'Sub-Saharan Africa', 'Low income', 'Lower middle income',
       'Upper middle income', 'High income'], dtype=object)
```

We cannot call `np.sort` on this array as it contains both strings and float values (`NaN` is considered a float). `NaN` values are useless in our case anyway, so we remove them from the array.

We use list comprehension to create a list of all country names that are not `NaN` values. `NaN` is a float so we will have to cast every name to a string and compare it with the string `'nan'`. Python's `sorted` function is then used to sort the list.

In [38]:
```
countries = gdp['country'].unique()
not_nan_countries = [c for c in countries if str(c) != 'nan']

sorted(not_nan_countries)
```

Out[38]:
```
['Afghanistan',
 'Albania',
 'Algeria',
 'American Samoa',
 'Andorra',
 'Angola',
 'Antigua and Barbuda',
 'Argentina',
 'Armenia',
 'Aruba',
 'Australia',
 'Austria',
 'Azerbaijan',
 'Bahamas, The',
 'Bahrain',
 'Bangladesh',
 'Barbados',
 'Belarus',
 'Belgium',
 'Belize',
 'Benin',
 'Bermuda',
 'Bhutan',
 'Bolivia',
 'Bosnia and Herzegovina',
 'Botswana',
 'Brazil',
 'British Virgin Islands',
 'Brunei Darussalam',
 'Bulgaria',
 'Burkina Faso',
 'Burundi',
 'Cabo Verde',
 'Cambodia',
 'Cameroon',
 'Canada',
 'Cayman Islands',
 'Central African Republic',
 'Chad',
 'Channel Islands',
 'Chile',
 'China',
 'Colombia',
 'Comoros',
 'Congo, Dem. Rep.',
 'Congo, Rep.',
 'Costa Rica',
 'Croatia',
 'Cuba',
 'Curaçao',
 'Cyprus',
 'Czech Republic',
 "Côte d'Ivoire",
 'Denmark',
 'Djibouti',
 'Dominica',
 'Dominican Republic',
 'East Asia & Pacific',
 'Ecuador',
 'Egypt, Arab Rep.',
 'El Salvador',
 'Equatorial Guinea',
 'Eritrea',
 'Estonia',
```

```
'Eswatini',
'Ethiopia',
'Europe & Central Asia',
'Faroe Islands',
'Fiji',
'Finland',
'France',
'French Polynesia',
'Gabon',
'Gambia, The',
'Georgia',
'Germany',
'Ghana',
'Gibraltar',
'Greece',
'Greenland',
'Grenada',
'Guam',
'Guatemala',
'Guinea',
'Guinea-Bissau',
'Guyana',
'Haiti',
'High income',
'Honduras',
'Hong Kong SAR, China',
'Hungary',
'Iceland',
'India',
'Indonesia',
'Iran, Islamic Rep.',
'Iraq',
'Ireland',
'Isle of Man',
'Israel',
'Italy',
'Jamaica',
'Japan',
'Jordan',
'Kazakhstan',
'Kenya',
'Kiribati',
"Korea, Dem. People's Rep.",
'Korea, Rep.',
'Kosovo',
'Kuwait',
'Kyrgyz Republic',
'Lao PDR',
'Latin America & Caribbean',
'Latvia',
'Lebanon',
'Lesotho',
'Liberia',
'Libya',
'Liechtenstein',
'Lithuania',
'Low income',
'Lower middle income',
'Luxembourg',
'Macao SAR, China',
'Madagascar',
'Malawi',
'Malaysia',
'Maldives',
```

```
'Mali',
'Malta',
'Marshall Islands',
'Mauritania',
'Mauritius',
'Mexico',
'Micronesia, Fed. Sts.',
'Middle East & North Africa',
'Moldova',
'Monaco',
'Mongolia',
'Montenegro',
'Morocco',
'Mozambique',
'Myanmar',
'Namibia',
'Nauru',
'Nepal',
'Netherlands',
'New Caledonia',
'New Zealand',
'Nicaragua',
'Niger',
'Nigeria',
'North America',
'North Macedonia',
'Northern Mariana Islands',
'Norway',
'Oman',
'Pakistan',
'Palau',
'Panama',
'Papua New Guinea',
'Paraguay',
'Peru',
'Philippines',
'Poland',
'Portugal',
'Puerto Rico',
'Qatar',
'Romania',
'Russian Federation',
'Rwanda',
'Samoa',
'San Marino',
'Saudi Arabia',
'Senegal',
'Serbia',
'Seychelles',
'Sierra Leone',
'Singapore',
'Sint Maarten (Dutch part)',
'Slovak Republic',
'Slovenia',
'Solomon Islands',
'Somalia',
'South Africa',
'South Asia',
'South Sudan',
'Spain',
'Sri Lanka',
'St. Kitts and Nevis',
'St. Lucia',
'St. Martin (French part)',
```

```
 'St. Vincent and the Grenadines',
 'Sub-Saharan Africa',
 'Sudan',
 'Suriname',
 'Sweden',
 'Switzerland',
 'Syrian Arab Republic',
 'São Tomé and Principe',
 'Tajikistan',
 'Tanzania',
 'Thailand',
 'Timor-Leste',
 'Togo',
 'Tonga',
 'Trinidad and Tobago',
 'Tunisia',
 'Turkey',
 'Turkmenistan',
 'Turks and Caicos Islands',
 'Tuvalu',
 'Uganda',
 'Ukraine',
 'United Arab Emirates',
 'United Kingdom',
 'United States',
 'Upper middle income',
 'Uruguay',
 'Uzbekistan',
 'Vanuatu',
 'Venezuela, RB',
 'Vietnam',
 'Virgin Islands (U.S.)',
 'West Bank and Gaza',
 'World',
 'Yemen, Rep.',
 'Zambia',
 'Zimbabwe']
```

Unlike before, we have fewer country names to shorten. Based on the list, the only country names different from the conventional versions that we are using for this assignment is `Brunei Darussalam`, `Timor-Leste` and `Lao PDR`.

We can then reuse the code from before (albeit with changes to `renames`) and obtain a DataFrame called `gdp_sea` that contains GDP data for Southeast Asian countries only.

In [39]:

```
renames_gdp = {'Brunei Darussalam': 'Brunei',
               'Timor-Leste': 'East Timor',
               'Lao PDR': 'Laos'
              }

gdp['country'] = gdp['country'].replace(renames_gdp)
gdp_sea = gdp[gdp['country'].isin(sea)].reset_index(drop = True)

gdp_sea
```

Out[39]:

| | country code | Ranking | country | GDP (in millions USD) |
|---|---|---|---|---|
| **0** | IDN | 16 | Indonesia | 1,119,191 |
| **1** | THA | 22 | Thailand | 543,650 |
| **2** | PHL | 33 | Philippines | 376,796 |
| **3** | SGP | 34 | Singapore | 372,063 |
| **4** | MYS | 36 | Malaysia | 364,702 |
| **5** | VNM | 45 | Vietnam | 261,921 |
| **6** | MMR | 71 | Myanmar | 76,086 |
| **7** | KHM | 103 | Cambodia | 27,089 |
| **8** | LAO | 117 | Laos | 18,174 |
| **9** | BRN | 133 | Brunei | 13,469 |
| **10** | TLS | 182 | East Timor | 1,674 |

The original DataFrame is sorted by GDP ranking instead of country name. Using `sort_values`, we sort the DataFrame by alphabetical order of the country names.

In [40]:

```
gdp_sea = gdp_sea.sort_values('country')
gdp_sea
```

Out[40]:

| | country code | Ranking | country | GDP (in millions USD) |
|---|---|---|---|---|
| **9** | BRN | 133 | Brunei | 13,469 |
| **7** | KHM | 103 | Cambodia | 27,089 |
| **10** | TLS | 182 | East Timor | 1,674 |
| **0** | IDN | 16 | Indonesia | 1,119,191 |
| **8** | LAO | 117 | Laos | 18,174 |
| **4** | MYS | 36 | Malaysia | 364,702 |
| **6** | MMR | 71 | Myanmar | 76,086 |
| **2** | PHL | 33 | Philippines | 376,796 |
| **3** | SGP | 34 | Singapore | 372,063 |
| **1** | THA | 22 | Thailand | 543,650 |
| **5** | VNM | 45 | Vietnam | 261,921 |

The DataFrame is now in alphabetical order. We reset the indexes so they start from 0, and use `filter` to retain only the `country` and `GDP (in millions USD)` columns, as `GDP (in millions USD)` is the new Series of data that we want to merge into our final DataFrame.

In [41]:

```
gdp_sea = gdp_sea.reset_index(drop = True).filter(['country', 'GDP (in milli
gdp_sea
```

Out[41]:

| | country | GDP (in millions USD) |
|---|---|---|
| 0 | Brunei | 13,469 |
| 1 | Cambodia | 27,089 |
| 2 | East Timor | 1,674 |
| 3 | Indonesia | 1,119,191 |
| 4 | Laos | 18,174 |
| 5 | Malaysia | 364,702 |
| 6 | Myanmar | 76,086 |
| 7 | Philippines | 376,796 |
| 8 | Singapore | 372,063 |
| 9 | Thailand | 543,650 |
| 10 | Vietnam | 261,921 |

Almost there! Let us look at the data type of `GDP (in millions USD)`.

In [42]:
```
gdp_sea.dtypes
```

Out[42]:
```
country                  object
GDP (in millions USD)    object
dtype: object
```

As expected, they are strings. We will have to convert them to integers.

Just like before, the `apply` function is used in tandem with a lambda expression. The strings now contain commas instead of whitespaces to separate every three digits, so we replace the commas with empty strings.

The strings can then be casted to integers using `to_numeric`.

In [43]:
```
gdp_sea['GDP (in millions USD)'] = gdp_sea['GDP (in millions USD)'].apply(la
gdp_sea['GDP (in millions USD)'] = pd.to_numeric(gdp_sea['GDP (in millions U

gdp_sea
```

Out[43]:

| | country | GDP (in millions USD) |
|---|---|---|
| **0** | Brunei | 13469 |
| **1** | Cambodia | 27089 |
| **2** | East Timor | 1674 |
| **3** | Indonesia | 1119191 |
| **4** | Laos | 18174 |
| **5** | Malaysia | 364702 |
| **6** | Myanmar | 76086 |
| **7** | Philippines | 376796 |
| **8** | Singapore | 372063 |
| **9** | Thailand | 543650 |
| **10** | Vietnam | 261921 |

To confirm that the casts have been performed correctly:

In [44]:
```
gdp_sea.dtypes
```

Out[44]:
```
country                    object
GDP (in millions USD)       int64
dtype: object
```

Now we can merge the data for GDP to `life_exp_sea_pop`. We will call this DataFrame `life_exp_sea_pop_gdp`.

In [45]:
```
life_exp_sea_pop_gdp = life_exp_sea_pop.merge(gdp_sea)

life_exp_sea_pop_gdp
```

Out[45]:

| | country | Status | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_inc |
|---|---|---|---|---|---|---|
| **0** | Brunei | Developing | 78.3 | 76.48750 | 33.442857 | |
| **1** | Cambodia | Developing | 68.7 | 64.34375 | 15.362500 | |
| **2** | East Timor | Developing | 68.3 | 64.75625 | 14.550000 | |
| **3** | Indonesia | Developing | 69.1 | 67.55625 | 21.120000 | |
| **4** | Laos | Developing | 65.7 | 62.38125 | 16.057143 | |
| **5** | Malaysia | Developing | 75.0 | 73.75625 | 32.742857 | |
| **6** | Myanmar | Developing | 66.6 | 64.20000 | 18.100000 | |
| **7** | Philippines | Developing | 68.5 | 67.57500 | 21.592857 | |
| **8** | Singapore | Developed | 87.0 | 81.47500 | 31.069231 | |
| **9** | Thailand | Developing | 74.9 | 73.08125 | 25.946154 | |
| **10** | Vietnam | Developing | 76.0 | 74.77500 | 13.438462 | |

Now that we have for the population of Southeast Asian countries as well as their GDP in 2019, we can now compute an additional metric: GDP per capita. The formula is simply GDP divided by population.

In [46]:
```
life_exp_sea_pop_gdp['perCapitaGDP'] = life_exp_sea_pop_gdp['GDP (in millior

life_exp_sea_pop_gdp
```

Out[46]:

| | country | Status | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_inc |
|---|---|---|---|---|---|---|
| **0** | Brunei | Developing | 78.3 | 76.48750 | 33.442857 | |
| **1** | Cambodia | Developing | 68.7 | 64.34375 | 15.362500 | |
| **2** | East Timor | Developing | 68.3 | 64.75625 | 14.550000 | |
| **3** | Indonesia | Developing | 69.1 | 67.55625 | 21.120000 | |
| **4** | Laos | Developing | 65.7 | 62.38125 | 16.057143 | |
| **5** | Malaysia | Developing | 75.0 | 73.75625 | 32.742857 | |
| **6** | Myanmar | Developing | 66.6 | 64.20000 | 18.100000 | |
| **7** | Philippines | Developing | 68.5 | 67.57500 | 21.592857 | |
| **8** | Singapore | Developed | 87.0 | 81.47500 | 31.069231 | |
| **9** | Thailand | Developing | 74.9 | 73.08125 | 25.946154 | |
| **10** | Vietnam | Developing | 76.0 | 74.77500 | 13.438462 | |

Our GDP columns was in millions of USD. Upon dividing by population, we get float values with too many leading zeroes. This makes the data hard to interpret. We can simply multiply each value by 1 million to get the exact figures. We will also rename the column for clarity.

In [47]:
```
life_exp_sea_pop_gdp['perCapitaGDP'] = life_exp_sea_pop_gdp['perCapitaGDP']
life_exp_sea_pop_gdp.rename(columns = {'perCapitaGDP': 'perCapitaGDP (in USI

life_exp_sea_pop_gdp
```

Out[47]:

| | country | Status | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_inc |
|---|---|---|---|---|---|---|
| **0** | Brunei | Developing | 78.3 | 76.48750 | 33.442857 | |
| **1** | Cambodia | Developing | 68.7 | 64.34375 | 15.362500 | |
| **2** | East Timor | Developing | 68.3 | 64.75625 | 14.550000 | |
| **3** | Indonesia | Developing | 69.1 | 67.55625 | 21.120000 | |
| **4** | Laos | Developing | 65.7 | 62.38125 | 16.057143 | |
| **5** | Malaysia | Developing | 75.0 | 73.75625 | 32.742857 | |
| **6** | Myanmar | Developing | 66.6 | 64.20000 | 18.100000 | |
| **7** | Philippines | Developing | 68.5 | 67.57500 | 21.592857 | |
| **8** | Singapore | Developed | 87.0 | 81.47500 | 31.069231 | |
| **9** | Thailand | Developing | 74.9 | 73.08125 | 25.946154 | |
| **10** | Vietnam | Developing | 76.0 | 74.77500 | 13.438462 | |

But now there are way too many decimal places! We can truncate them using `round`, a **pandas** function that rounds numbers to the desired number of decimal places. For readability, we are going with 2 decimal places and will apply it to all float values in the DataFrame.

We will iterate through every column using a for loop. If the datatype of the column is a **NumPy** float, the `round` function is applied.

After this cell, we get the final DataFrame.

In [48]:

```
for col in life_exp_sea_pop_gdp:
    if life_exp_sea_pop_gdp[col].dtype == np.float64:
        life_exp_sea_pop_gdp[col] = life_exp_sea_pop_gdp[col].round(2)

life_exp_sea_pop_gdp
```

Out[48]:

| | country | Status | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_inc |
|---|---|---|---|---|---|---|
| 0 | Brunei | Developing | 78.3 | 76.49 | 33.44 | |
| 1 | Cambodia | Developing | 68.7 | 64.34 | 15.36 | |
| 2 | East Timor | Developing | 68.3 | 64.76 | 14.55 | |
| 3 | Indonesia | Developing | 69.1 | 67.56 | 21.12 | |
| 4 | Laos | Developing | 65.7 | 62.38 | 16.06 | |
| 5 | Malaysia | Developing | 75.0 | 73.76 | 32.74 | |
| 6 | Myanmar | Developing | 66.6 | 64.20 | 18.10 | |
| 7 | Philippines | Developing | 68.5 | 67.58 | 21.59 | |
| 8 | Singapore | Developed | 87.0 | 81.47 | 31.07 | |
| 9 | Thailand | Developing | 74.9 | 73.08 | 25.95 | |
| 10 | Vietnam | Developing | 76.0 | 74.78 | 13.44 | |

## Interpreting the data

Of the 11 Southeast Asian countries in this study, Singapore is the only country with `Developed` status. Hence, it is no surprise that Singapore has the highest values of `max_life_expectancy` (87.0) and `mean_life_expectancy` (81.47). In contrast, Laos has lowest values of both `max_life_expectancy` (65.7) and `mean_life_expectancy` (62.38). Interestingly, it can be noted that countries in the centre of Southeast Asia (eg. Singapore, Brunei, Malaysia) generally have higher life expectancies than those in the north and south (eg. Laos, Indonesia, East Timor). For the north, this can probably be explained by regular instability, such as famine and war. Indonesia takes up most of the south, so its large population may contribute to the calculation of a lower life expectancy.

Based on information from the NHS, the values of `mean_BMI` calculated from this dataset are quite unrealistic. It is highly like the `BMI` values in the original dataset are inaccurate. For example, the mean BMI of the Vietnamese population is 13.44, a severely low figure.

`mean_income_composition_of_resources` seems to have strong correlation with `mean_schooling` and `perCapitaGDP`, as well as `mean_life_expectancy`. This makes sense as higher schooling increases the number of educated citizens, which in turn increases the mean income composition of resources. High income composition of resources will then lead to higher GDP per capita, giving the citizens of the country better quality of life and thus longer life expectancy.

# Question 1

This question requires us to visualise expected life expectancies in Southeast Asia based on country status (Developing or Developed). We use **Seaborn** to create a barplot for this, as **Seaborn** makes it easier for us to display the values above each bar. Furthermore, **Seaborn** automatically takes the mean of all mean life expectancies of developing countries and uses it as the value for the bar chart. Thus, no extra calculation is needed.

Since **Seaborn** is built on top of **Matplotlib**, we can use **Matplotlib**'s `figure` function to create a blank figure with a specified size, the `title` function to set the title of the graph, then call **Seaborn**'s `barplot` function to plot the bars. `ci`, or confidence intervals, is set to `None` as we do not need to display them in this scenario.

When the bar chart is plotted, the values are stored in an object created by **Matplotlib** called `containers`. We can then display the values of each bar by passing the first element of `containers` into the `bar_label` function.

Finally, `set_ylabel` is used to display a clear y-axis label with the unit in parantheses.

In [49]:

```
# this code sets the visual theme for all plots to Seaborn's default theme i
# Seaborn's theme has dark grids and softer colours which makes the plot mo
sns.set_theme()
```

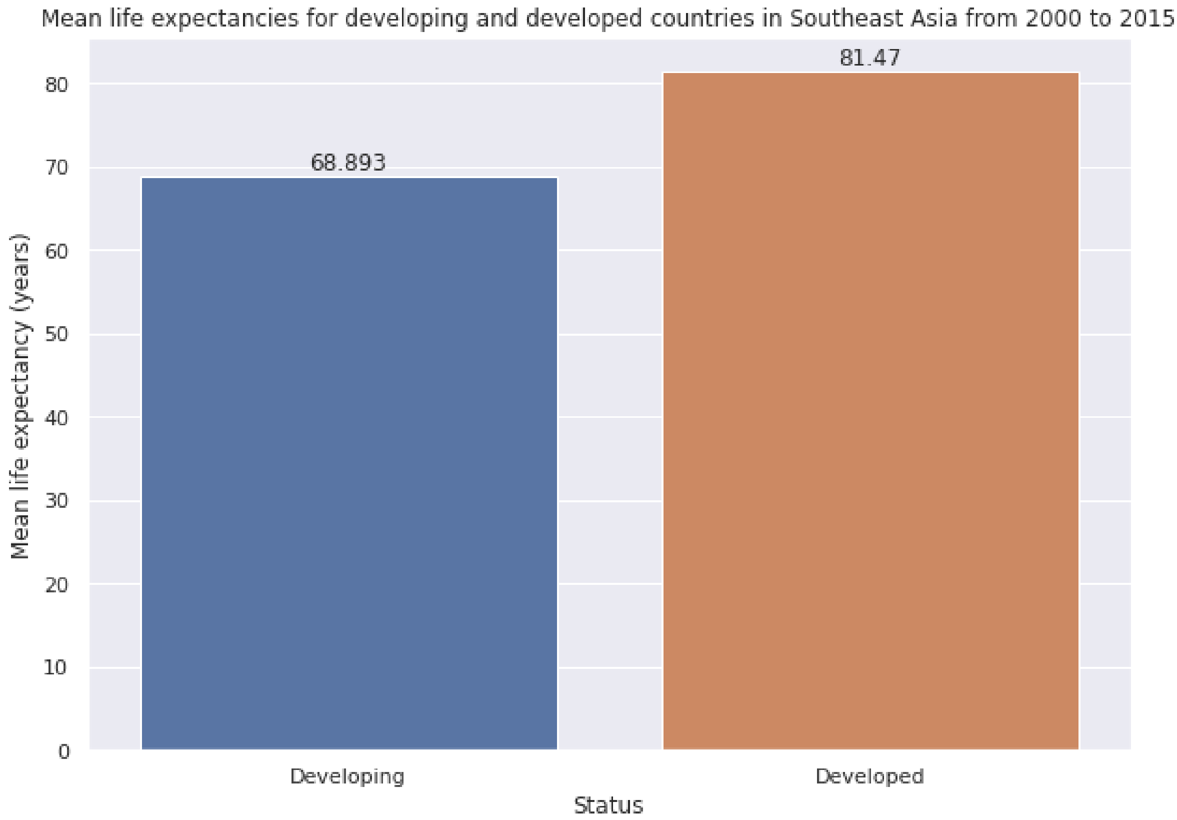
In [50]:

```
q1 = plt.figure(figsize = (10, 7))
q1 = plt.title('Mean life expectancies for developing and developed countrie
q1 = sns.barplot(x = 'Status', y = 'mean_life_expectancy', data = life_exp_s
q1.bar_label(q1.containers[0])
q1.set_ylabel('Mean life expectancy (years)')

q1
```

Out[50]:

```
<AxesSubplot:title={'center':'Mean life expectancies for developing and d
eveloped countries in Southeast Asia from 2000 to 2015'}, xlabel='Statu
s', ylabel='Mean life expectancy (years)'>
```




## Insight

A bar chart is chosen to visualise and compare the expected life expectancies for developing and developed countries in Southeast Asia, since the data involved is categorical. A bar chart can give us a straightforward comparison of the data. The mean was chosen as the aggregation to represent expected life expectancies as it is a measure of central tendency. Values are more likely to occur the closer they are to the mean, so it gives us an idea of what values to 'expect' in a sample or population.

The 'mean life expectancy for developing countries' is the mean of all mean life expectancies for developing countries as shown in the DataFrame `life_exp_sea_pop_gdp`. Since Singapore is the only developed country in Southeast Asia, the 'mean life expectancy for developed countries' is simply the mean life expectancy for Singapore. From the graph, the former value is 68.893 years whereas the latter is 81.47 years.

Thus, the insight we gain is that the difference between life expectancies for developing and developed countries in Southeast Asia is quite large (about 12.58 years). However, due to the fact that there are 10 developing countries and only one developed country, it is not a fair representation of the difference in life expectancies for developing and developed countries in general.

# Question 2

Now we need to create a bar graph with countries on the x-axis, and side-by-side bars for population, mean life expectancy and adult mortality. We have dropped the data for adult mortality earlier on, but we can restore it easily. If you remember, we have kept a copy of the original DataFrame in `life_exp_ori`. Using the `concat` function, we can slice the `country` and `Adult Mortality` columns from `life_exp_ori` and concatenate them to get a 2-column DataFrame.

The approach to handling this DataFrame is similar to what we did before. We use `replace` with the `renames` dictionary to shorten the country names, and remove all rows except those for Southeast Asian countries. We then audit the data using `info` and `describe`.

In [51]:
```
adult_mort = pd.concat([life_exp_ori['country'], life_exp_ori['Adult Mortal
adult_mort['country'] = adult_mort['country'].replace(renames)
adult_mort = adult_mort[adult_mort['country'].isin(sea)]

adult_mort.info()
adult_mort.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 176 entries, 383 to 2874
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   country          176 non-null    object
 1   Adult Mortality  176 non-null    float64
dtypes: float64(1), object(1)
memory usage: 4.1+ KB
```

Out[51]:

| | Adult Mortality |
|---|---|
| **count** | 176.000000 |
| **mean** | 148.846591 |
| **std** | 75.842350 |
| **min** | 1.000000 |
| **25%** | 84.000000 |
| **50%** | 158.000000 |
| **75%** | 213.250000 |
| **max** | 296.000000 |

There are no missing values but there is definitely some erroneous data, as evident from the minimum value of 1.

We can use the same strategy we used to remove the erroneous `BMI` values from `life_exp_sea`, but adult mortality is a metric that can be very different in each country, and it can change in large intervals. It is not easy to find the erroneous data.

A quick and dirty way is to replace all outliers with the mean of non-outlier values for each country. Outliers can be defined as any value below the lower quartile subtracted by 1.5 times the interquartile range, or above the upper quartile subtracted by 1.5 times the interquartile range*.

Since `Adult Mortality` will have to be used **Question 3**, we save a

* Source: https://www.thoughtco.com/what-is-an-outlier-3126227

In [52]:
```
for c in adult_mort['country'].unique():
    upper = adult_mort[adult_mort['country'] == c].quantile(0.75)['Adult Mo
    lower = adult_mort[adult_mort['country'] == c].quantile(0.25)['Adult Mo
    outlier = 1.5 * (upper - lower)

    adult_mort.loc[(adult_mort['country'] == c) & (adult_mort['Adult Mortal
    adult_mort.loc[(adult_mort['country'] == c) & (adult_mort['Adult Mortal

    mean_am = adult_mort[adult_mort['country'] == c]['Adult Mortality'].mear
    adult_mort.loc[(adult_mort['country'] == c) & (adult_mort['Adult Mortal

adult_mort
```

Out[52]:

| | country | Adult Mortality |
|---|---|---|
| **383** | Brunei | 85.750000 |
| **382** | Brunei | 85.750000 |
| **381** | Brunei | 95.000000 |
| **380** | Brunei | 89.000000 |
| **379** | Brunei | 89.000000 |
| **...** | ... | ... |
| **2878** | Vietnam | 131.000000 |
| **2877** | Vietnam | 134.133333 |
| **2876** | Vietnam | 129.000000 |
| **2875** | Vietnam | 128.000000 |
| **2874** | Vietnam | 127.000000 |

176 rows × 2 columns

We then create a groupby object based on `country` and aggregate the values of `Adult Mortality` to mean values. Finally, `Adult Mortality` is renamed to `mean_adult_mortality`.

In [53]:
```
adult_mort_agg = adult_mort.groupby(['country'], as_index = False).agg('mear
adult_mort_agg.rename(columns = {'Adult Mortality': 'mean_adult_mortality'}
```

Now that `life_exp_sea_pop_gdp` and `adult_mort_agg` share an identical `country` column, they can be merged easily. We assign this new DataFrame to the variable `q2_df` so the unmerged version is not overwritten.

In [54]:
```
q2_df = life_exp_sea_pop_gdp.merge(adult_mort_agg)

q2_df
```

Out[54]:

| | country | Status | max_life_expectancy | mean_life_expectancy | mean_BMI | mean_inc |
|---|---|---|---|---|---|---|
| **0** | Brunei | Developing | 78.3 | 76.49 | 33.44 | |
| **1** | Cambodia | Developing | 68.7 | 64.34 | 15.36 | |
| **2** | East Timor | Developing | 68.3 | 64.76 | 14.55 | |
| **3** | Indonesia | Developing | 69.1 | 67.56 | 21.12 | |
| **4** | Laos | Developing | 65.7 | 62.38 | 16.06 | |
| **5** | Malaysia | Developing | 75.0 | 73.76 | 32.74 | |
| **6** | Myanmar | Developing | 66.6 | 64.20 | 18.10 | |
| **7** | Philippines | Developing | 68.5 | 67.58 | 21.59 | |
| **8** | Singapore | Developed | 87.0 | 81.47 | 31.07 | |
| **9** | Thailand | Developing | 74.9 | 73.08 | 25.95 | |
| **10** | Vietnam | Developing | 76.0 | 74.78 | 13.44 | |

In order to visualise the values for `population`, `mean_life_expectancy` and `mean_adult_mortality` in a side-by-side bar chart, we will need to unpivot these columns (ie. convert them from 'wide' to 'long'). This can be done with **pandas**'s `melt` function.

Since `country` is our categorical values, it is set as the sole identifier variable, whereas the three variables we want to represent are the value variables. The 'melted' DataFrame is assigned to a new variable called `melted`.

We also rename the column labels and the names of each statistic for consistency in capitalisation and to show the units in parentheses.

In [55]:

```
melted = pd.melt(q2_df, id_vars = 'country',
                 value_vars = ['population', 'mean_life_expectancy', 'mean_a

melted.rename(columns = {'country': 'Country',
                         'variable': 'Statistic',
                         'value': 'Value'},
              inplace = True)

melted['Statistic'].replace({'population': 'Population',
                             'mean_life_expectancy': 'Mean life expectancy (
                             'mean_adult_mortality': 'Mean adult mortality (
                             inplace = True)

melted
```

Out[55]:

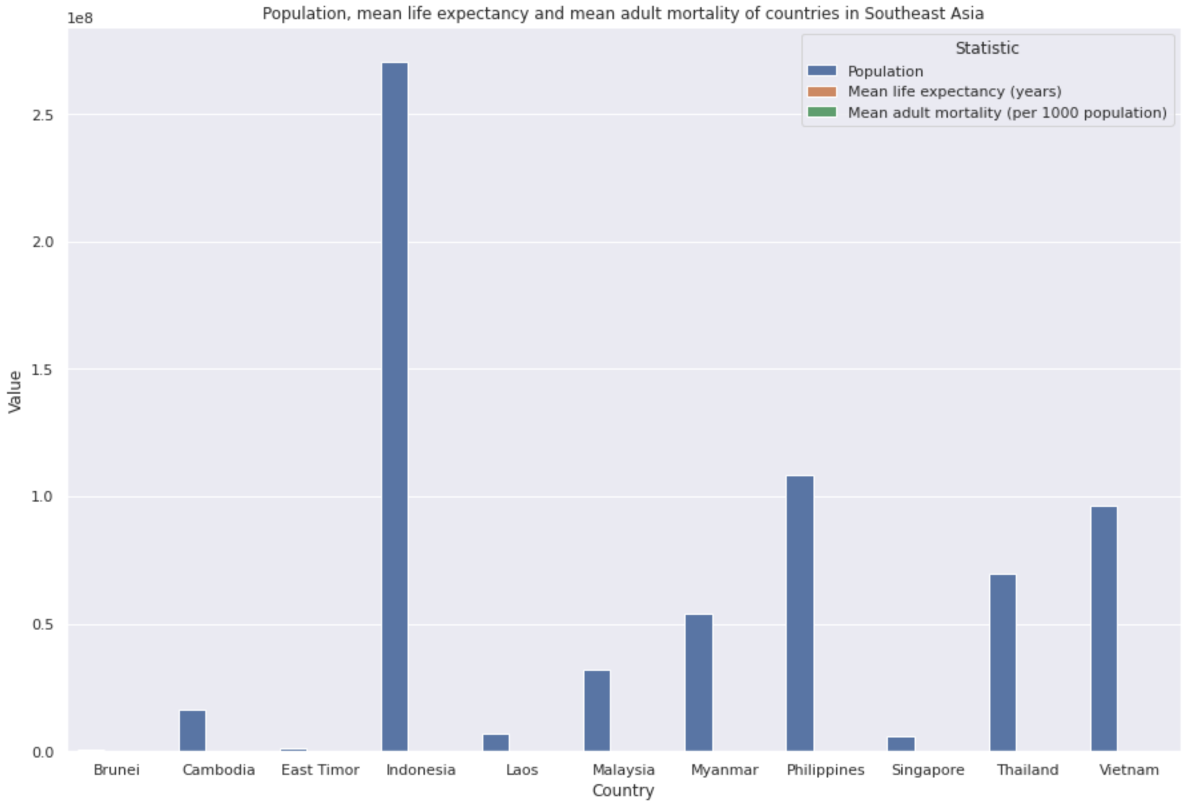
| | Country | Statistic | Value |
|---|---|---|---|
| **0** | Brunei | Population | 4.330000e+05 |
| **1** | Cambodia | Population | 1.648700e+07 |
| **2** | East Timor | Population | 1.293000e+06 |
| **3** | Indonesia | Population | 2.706260e+08 |
| **4** | Laos | Population | 7.169000e+06 |
| **5** | Malaysia | Population | 3.195000e+07 |
| **6** | Myanmar | Population | 5.404500e+07 |
| **7** | Philippines | Population | 1.081170e+08 |
| **8** | Singapore | Population | 5.804000e+06 |
| **9** | Thailand | Population | 6.962600e+07 |
| **10** | Vietnam | Population | 9.646200e+07 |
| **11** | Brunei | Mean life expectancy (years) | 7.649000e+01 |
| **12** | Cambodia | Mean life expectancy (years) | 6.434000e+01 |
| **13** | East Timor | Mean life expectancy (years) | 6.476000e+01 |
| **14** | Indonesia | Mean life expectancy (years) | 6.756000e+01 |
| **15** | Laos | Mean life expectancy (years) | 6.238000e+01 |
| **16** | Malaysia | Mean life expectancy (years) | 7.376000e+01 |
| **17** | Myanmar | Mean life expectancy (years) | 6.420000e+01 |
| **18** | Philippines | Mean life expectancy (years) | 6.758000e+01 |
| **19** | Singapore | Mean life expectancy (years) | 8.147000e+01 |
| **20** | Thailand | Mean life expectancy (years) | 7.308000e+01 |
| **21** | Vietnam | Mean life expectancy (years) | 7.478000e+01 |
| **22** | Brunei | Mean adult mortality (per 1000 population) | 8.575000e+01 |
| **23** | Cambodia | Mean adult mortality (per 1000 population) | 2.213571e+02 |
| **24** | East Timor | Mean adult mortality (per 1000 population) | 1.699091e+02 |
| **25** | Indonesia | Mean adult mortality (per 1000 population) | 1.856923e+02 |
| **26** | Laos | Mean adult mortality (per 1000 population) | 2.369231e+02 |
| **27** | Malaysia | Mean adult mortality (per 1000 population) | 1.323846e+02 |
| **28** | Myanmar | Mean adult mortality (per 1000 population) | 1.543125e+02 |
| **29** | Philippines | Mean adult mortality (per 1000 population) | 2.180714e+02 |
| **30** | Singapore | Mean adult mortality (per 1000 population) | 6.573333e+01 |
| **31** | Thailand | Mean adult mortality (per 1000 population) | 1.700000e+02 |
| **32** | Vietnam | Mean adult mortality (per 1000 population) | 1.341333e+02 |

Now we can use **Seaborn** to create a barplot of `melted`, where `country` is on the x-axis, `value` is on the y-axis, and `hue` is set to `variable` so we get side-by-side multicoloured bars, each representing a different variable for that country.

In [56]:
```
q2 = plt.figure(figsize = (15, 10))
q2 = plt.title('Population, mean life expectancy and mean adult mortality of
q2 = sns.barplot(x = 'Country', y = 'Value', hue = 'Statistic', data = melte

q2
```

Out[56]:
```
<AxesSubplot:title={'center':'Population, mean life expectancy and mean a
dult mortality of countries in Southeast Asia'}, xlabel='Country', ylabel
='Value'>
```




Notice how the orange and green bars are not visible. This is because the values for `population` are too large relative to that of the other two variables. To shorten this disparity between numbers, we can represent the values of `population` in millions instead.

A new column called `population (in millions)` is created, containing the values of `population` divided by 1 million. Then, we do the same melting process with `population (in millions)` replacing `population`.

In [57]:
```
melted.loc[melted['Statistic'] == 'Population', 'Value'] /= 1000000
melted['Statistic'].replace('Population', 'Population (in millions)', inplac

melted
```

Out[57]:

| | Country | Statistic | Value |
|---|---|---|---|
| 0 | Brunei | Population (in millions) | 0.433000 |
| 1 | Cambodia | Population (in millions) | 16.487000 |
| 2 | East Timor | Population (in millions) | 1.293000 |
| 3 | Indonesia | Population (in millions) | 270.626000 |
| 4 | Laos | Population (in millions) | 7.169000 |
| 5 | Malaysia | Population (in millions) | 31.950000 |
| 6 | Myanmar | Population (in millions) | 54.045000 |
| 7 | Philippines | Population (in millions) | 108.117000 |
| 8 | Singapore | Population (in millions) | 5.804000 |
| 9 | Thailand | Population (in millions) | 69.626000 |
| 10 | Vietnam | Population (in millions) | 96.462000 |
| 11 | Brunei | Mean life expectancy (years) | 76.490000 |
| 12 | Cambodia | Mean life expectancy (years) | 64.340000 |
| 13 | East Timor | Mean life expectancy (years) | 64.760000 |
| 14 | Indonesia | Mean life expectancy (years) | 67.560000 |
| 15 | Laos | Mean life expectancy (years) | 62.380000 |
| 16 | Malaysia | Mean life expectancy (years) | 73.760000 |
| 17 | Myanmar | Mean life expectancy (years) | 64.200000 |
| 18 | Philippines | Mean life expectancy (years) | 67.580000 |
| 19 | Singapore | Mean life expectancy (years) | 81.470000 |
| 20 | Thailand | Mean life expectancy (years) | 73.080000 |
| 21 | Vietnam | Mean life expectancy (years) | 74.780000 |
| 22 | Brunei | Mean adult mortality (per 1000 population) | 85.750000 |
| 23 | Cambodia | Mean adult mortality (per 1000 population) | 221.357143 |
| 24 | East Timor | Mean adult mortality (per 1000 population) | 169.909091 |
| 25 | Indonesia | Mean adult mortality (per 1000 population) | 185.692308 |
| 26 | Laos | Mean adult mortality (per 1000 population) | 236.923077 |
| 27 | Malaysia | Mean adult mortality (per 1000 population) | 132.384615 |
| 28 | Myanmar | Mean adult mortality (per 1000 population) | 154.312500 |
| 29 | Philippines | Mean adult mortality (per 1000 population) | 218.071429 |
| 30 | Singapore | Mean adult mortality (per 1000 population) | 65.733333 |
| 31 | Thailand | Mean adult mortality (per 1000 population) | 170.000000 |
| 32 | Vietnam | Mean adult mortality (per 1000 population) | 134.133333 |

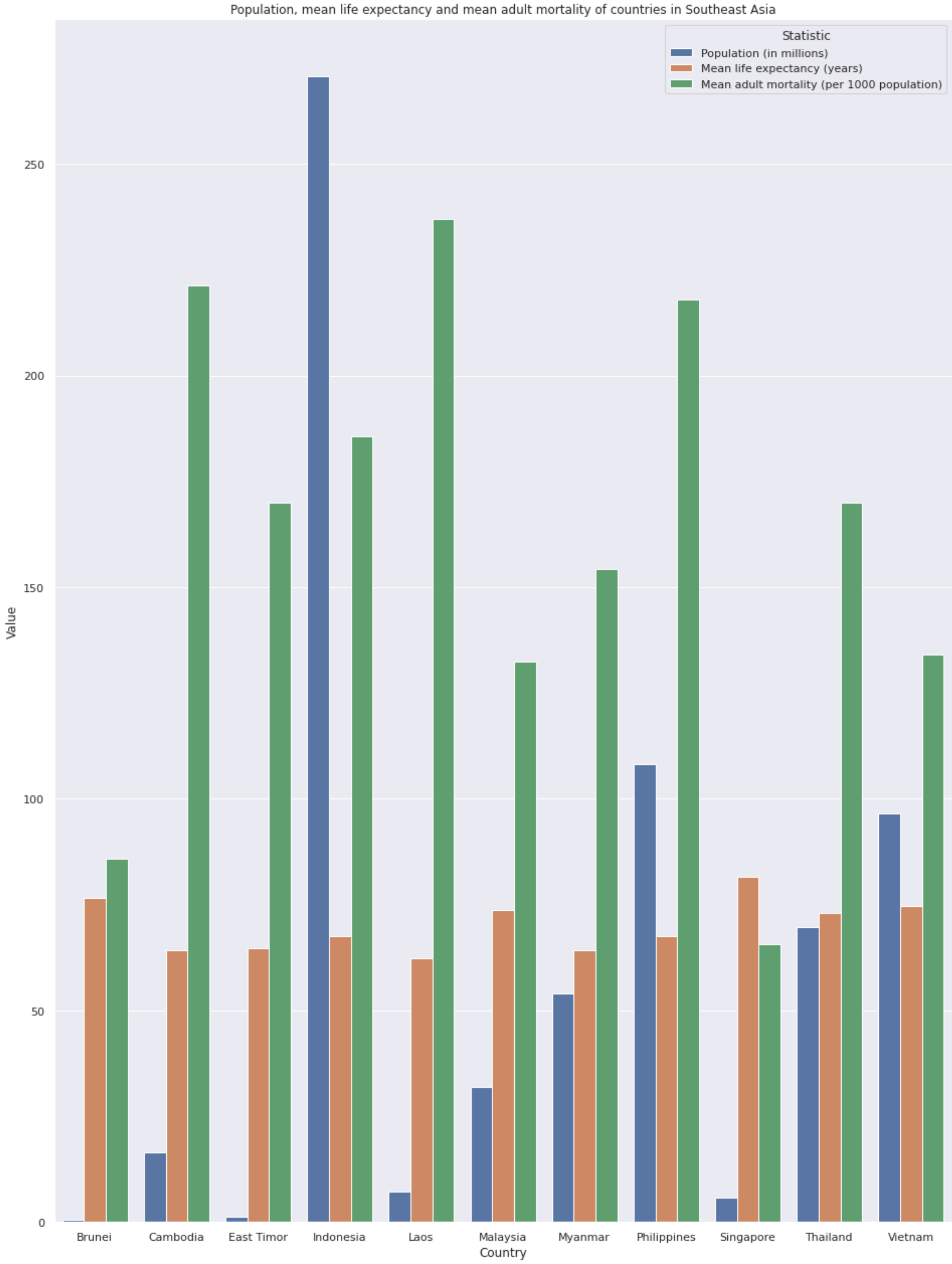
The same code is used to recreate the bar graph, albeit with the figure size increased.

This will be explained later.

```
In [58]: q2 = plt.figure(figsize = (16, 22))
         q2 = plt.title('Population, mean life expectancy and mean adult mortality of
         q2 = sns.barplot(x = 'Country', y = 'Value', hue = 'Statistic', data = melte

         q2
```

```
Out[58]: <AxesSubplot:title={'center':'Population, mean life expectancy and mean a
dult mortality of countries in Southeast Asia'}, xlabel='Country', ylabel
='Value'>
```




Now we have a much better bar graph that visualises the values of population, mean life expectancy and mean adult mortality.

## The problem

Unfortunately, the data presented in this graph is not very appropriate. It does not really give much insight at all, and could be misleading to readers.

This is due to the difference in units. Population is a discrete and unitless statistic, whereas mean life expectancy is continuous and measured in years. Mean adult mortality is also discrete and unitless. It may seem like it can be linked closely to population, but mean adult mortality in this graph is measured per 1000 population. This is why the graph can be misleading. In order to accommodate the huge range of population values, it has to be visualised in millions while mean adult mortality remains visualised in thousands. It is tough to study the relationship between population and mean adult mortality from the graph this way.

Hence, it is not a good idea to represent these three metrics in a side-by-side bar chart. The ranges of each metric vary greatly, so adjustment of units is required. Sometimes, even adjustment of units cannot enable extreme values to be shown clearly in a standard sized figure. For example, the `22` in `figsize = (16, 22)` (ie. the height of the plot in inches) is the bare minimum required to show a miniscule bar for the population of Brunei.

An appropriate side-by-side bar chart for this dataset would be one comparing the values `mean_life_expectancy` and `max_life_expectancy`, or one that cmpares the values of `GDP` and `perCapitaGDP`.

# Question 3

For this question, we require the non-aggregated data from `LifeExpectancyData-v2.csv`, as we will be visualising the changes in statistics over a duration of years specific to a single country - Singapore.

The non-aggregated data we need is readily available in the DataFrame `life_exp_sea`, but it is missing the `Year` column. We can use `merge` to combine the Singapore section of `life_exp_sea` with the `Year` column from `life_exp_ori`. The `Year` column alone does not share any columns with `life_exp_sea`, but both still share the same indexes since `life_exp_sea` was extracted from `life_exp`. Thus, we set both `left_index` and `right_index` as `True` so **pandas** knows to join them by using the indexes as the key. We assign this new DataFrame to a variable called `sg`.

We will be investigating `Adult Mortality` and `infant deaths`, so `sg` is merged with the `Adult Mortality` column from `adult_mort`, also using the indexes as the key.

The data for infant deaths is available in the `life_exp_ori` DataFrame. We can subset the Singapore part of this DataFrame and assign it to a temporary variable called `sg_ori` so the next line of code is not too long. `sg` is then merged with the `tnfant deaths` column of `sg_ori`, also on the indexes.

The rename function is then used to create some consistency with capitalisation in the column labels, and the `sg` DataFrame is complete.

In [59]:
```
sg = life_exp_sea[life_exp_sea['country'] == 'Singapore'].merge(life_exp_or:
                                                                 left_index =
                                                                 right_index

sg = sg.merge(adult_mort['Adult Mortality'], left_index = True, right_index

sg_ori = life_exp_ori[life_exp_ori['country'] == 'Singapore']
sg = sg.merge(sg_ori['infant deaths'], left_index = True, right_index = True

sg.rename(columns = {'Adult Mortality': 'Adult mortality',
                     'infant deaths': 'Infant deaths'},
          inplace = True)

sg
```

Out[59]:

| | country | Status | Life expectancy | BMI | Income composition of resources | Schooling | Year | Adult mortality |
|---|---|---|---|---|---|---|---|---|
| **2328** | Singapore | Developed | 78.3 | 28.500000 | 0.810 | 12.5 | 2000 | 78.00000C |
| **2327** | Singapore | Developed | 78.7 | 28.900000 | 0.820 | 12.7 | 2001 | 76.00000C |
| **2326** | Singapore | Developed | 79.0 | 29.200000 | 0.818 | 12.6 | 2002 | 74.00000C |
| **2325** | Singapore | Developed | 79.3 | 29.600000 | 0.819 | 12.7 | 2003 | 73.00000C |
| **2324** | Singapore | Developed | 79.7 | 29.900000 | 0.820 | 12.7 | 2004 | 71.00000C |
| **2323** | Singapore | Developed | 82.0 | 31.069231 | 0.821 | 12.6 | 2005 | 69.00000C |
| **2322** | Singapore | Developed | 87.0 | 31.069231 | 0.839 | 13.9 | 2006 | 66.00000C |
| **2321** | Singapore | Developed | 81.1 | 31.069231 | 0.873 | 14.1 | 2007 | 65.00000C |
| **2320** | Singapore | Developed | 81.4 | 31.200000 | 0.880 | 14.2 | 2008 | 64.00000C |
| **2319** | Singapore | Developed | 81.7 | 31.500000 | 0.887 | 14.4 | 2009 | 62.00000C |
| **2318** | Singapore | Developed | 82.0 | 31.800000 | 0.889 | 14.5 | 2010 | 61.00000C |
| **2317** | Singapore | Developed | 82.2 | 32.100000 | 0.911 | 15.2 | 2011 | 65.733333 |
| **2316** | Singapore | Developed | 82.5 | 32.400000 | 0.917 | 15.4 | 2012 | 59.00000C |
| **2315** | Singapore | Developed | 82.7 | 32.700000 | 0.920 | 15.4 | 2013 | 57.00000C |
| **2314** | Singapore | Developed | 82.9 | 32.900000 | 0.922 | 15.4 | 2014 | 56.00000C |
| **2313** | Singapore | Developed | 83.1 | 33.200000 | 0.924 | 15.4 | 2015 | 55.00000C |

To plot a line graph of `Life expectancy` over time, we once again use **Matplotlib** to initialise a figure with a set size and title, then use **Seaborn**'s `lineplot` function with `Year` on the x-axis and `Life expectancy` on the y-axis.

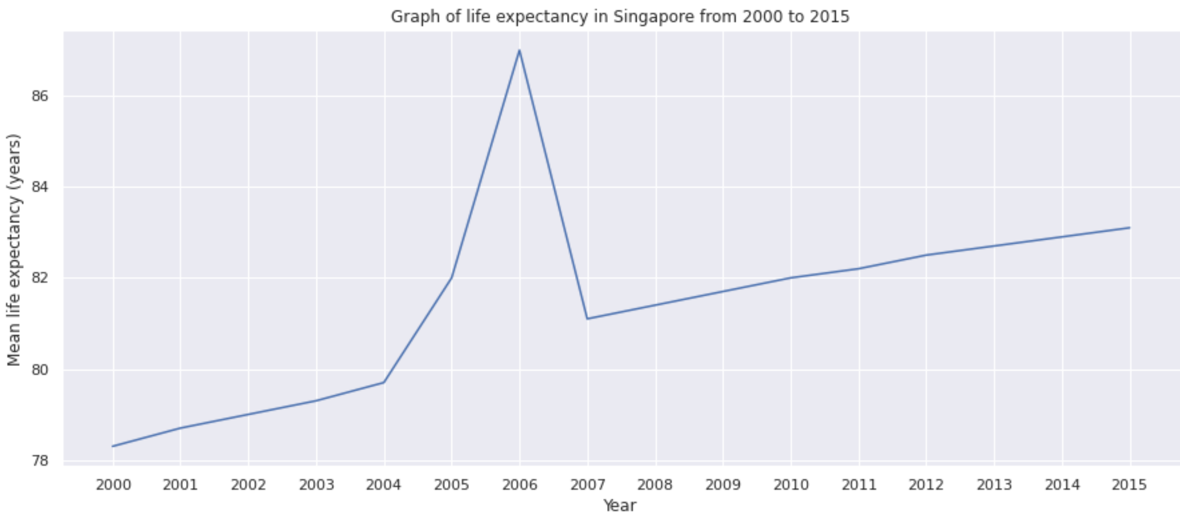
The values on the x-axis will be shown in intervals of two. To force the graph to show every year on the x-axis, we use `set_xticks`, which can take an array of appropriate x-axis values and display them explicitly. The argument we pass in is `sg['Year'].unique()`, since this returns an array of all unique values of `Year`, which is essentially every year.

Finally, the label of the y-axis is edited to included the unit in parentheses, and the graph is done.

In [60]:
```
q3_1 = plt.figure(figsize = (15, 6))
q3_1 = plt.title('Graph of life expectancy in Singapore from 2000 to 2015')
q3_1 = sns.lineplot(x = 'Year', y = 'Life expectancy', data = sg)
q3_1.set_xticks(sg['Year'].unique())
q3_1.set_ylabel('Mean life expectancy (years)')

q3_1
```

Out[60]:
```
<AxesSubplot:title={'center':'Graph of life expectancy in Singapore from 20
00 to 2015'}, xlabel='Year', ylabel='Mean life expectancy (years)'>
```




To display two lines in a single plot, we have to make use of the `melt` function again. `melt` is applied to `sg` with `Year` as the identifier variable and `Adult mortality` and `Infant deaths` as value variables. Like in **Question 2**, the column labels and variable names are renamed for consistency and clarity.

In [61]:
```
sg_melted = pd.melt(sg, id_vars = 'Year', value_vars = ['Adult mortality',

sg_melted.rename(columns = {'country': 'Country',
                            'variable': 'Statistic',
                            'value': 'Value'},
                 inplace = True)

sg_melted['Statistic'].replace({'Adult mortality': 'Adult mortality (per 100
                                'Infant deaths': 'Infant deaths (per 1000 po
                                inplace = True)

sg_melted
```

Out[61]:

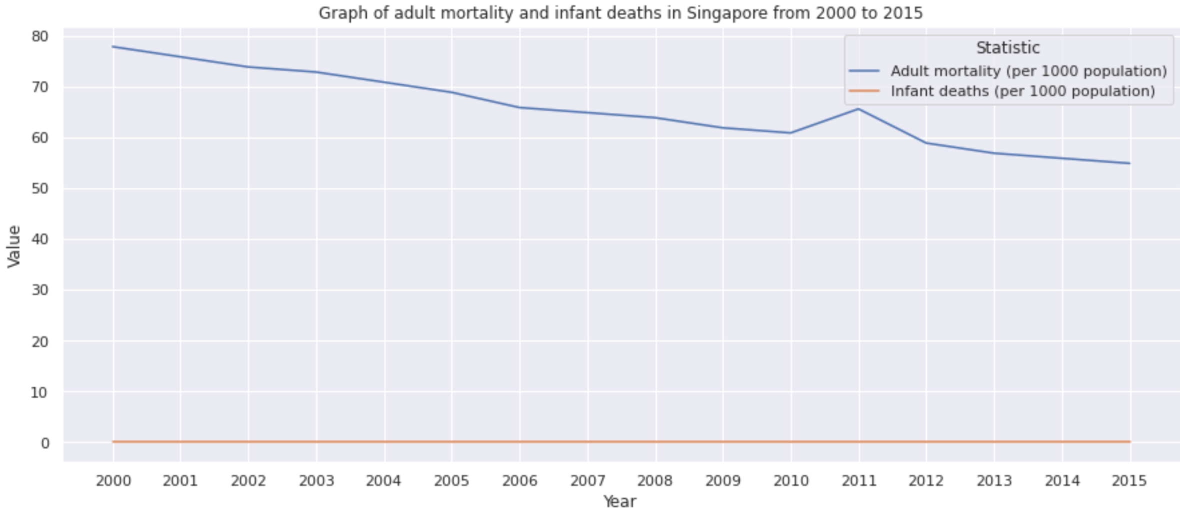
| | Year | Statistic | Value |
|---|---|---|---|
| **0** | 2000 | Adult mortality (per 1000 population) | 78.000000 |
| **1** | 2001 | Adult mortality (per 1000 population) | 76.000000 |
| **2** | 2002 | Adult mortality (per 1000 population) | 74.000000 |
| **3** | 2003 | Adult mortality (per 1000 population) | 73.000000 |
| **4** | 2004 | Adult mortality (per 1000 population) | 71.000000 |
| **5** | 2005 | Adult mortality (per 1000 population) | 69.000000 |
| **6** | 2006 | Adult mortality (per 1000 population) | 66.000000 |
| **7** | 2007 | Adult mortality (per 1000 population) | 65.000000 |
| **8** | 2008 | Adult mortality (per 1000 population) | 64.000000 |
| **9** | 2009 | Adult mortality (per 1000 population) | 62.000000 |
| **10** | 2010 | Adult mortality (per 1000 population) | 61.000000 |
| **11** | 2011 | Adult mortality (per 1000 population) | 65.733333 |
| **12** | 2012 | Adult mortality (per 1000 population) | 59.000000 |
| **13** | 2013 | Adult mortality (per 1000 population) | 57.000000 |
| **14** | 2014 | Adult mortality (per 1000 population) | 56.000000 |
| **15** | 2015 | Adult mortality (per 1000 population) | 55.000000 |
| **16** | 2000 | Infant deaths (per 1000 population) | 0.000000 |
| **17** | 2001 | Infant deaths (per 1000 population) | 0.000000 |
| **18** | 2002 | Infant deaths (per 1000 population) | 0.000000 |
| **19** | 2003 | Infant deaths (per 1000 population) | 0.000000 |
| **20** | 2004 | Infant deaths (per 1000 population) | 0.000000 |
| **21** | 2005 | Infant deaths (per 1000 population) | 0.000000 |
| **22** | 2006 | Infant deaths (per 1000 population) | 0.000000 |
| **23** | 2007 | Infant deaths (per 1000 population) | 0.000000 |
| **24** | 2008 | Infant deaths (per 1000 population) | 0.000000 |
| **25** | 2009 | Infant deaths (per 1000 population) | 0.000000 |
| **26** | 2010 | Infant deaths (per 1000 population) | 0.000000 |
| **27** | 2011 | Infant deaths (per 1000 population) | 0.000000 |
| **28** | 2012 | Infant deaths (per 1000 population) | 0.000000 |
| **29** | 2013 | Infant deaths (per 1000 population) | 0.000000 |
| **30** | 2014 | Infant deaths (per 1000 population) | 0.000000 |
| **31** | 2015 | Infant deaths (per 1000 population) | 0.000000 |

Using the melted DataFrame, can now use `lineplot` to create a a graph with two lines. Like in the previous graph, the x-tick labels are manually set to show every year.

In [62]:
```
q3_2 = plt.figure(figsize = (15, 6))
q3_2 = plt.title('Graph of adult mortality and infant deaths in Singapore fi
q3_2 = sns.lineplot(x = 'Year', y = 'Value', hue = 'Statistic', data = sg_me
q3_2.set_xticks(sg['Year'].unique())

q3_2
```

Out[62]:
```
<AxesSubplot:title={'center':'Graph of adult mortality and infant deaths in Singapore from 2000 to 2015'}, xlabel='Year', ylabel='Value'>
```




## Explanation

The line graph titled `Graph of life expectancy in Singapore from 2000 to 2015` would be useful to study the advancement of healthcare and the welfare of citizens in Singapore from the year 2000 to 2015. These are major contributing factors of life expectancy. However, this graph alone can only provide a very general visualisation, and may not even be perfectly accurate (suggested by the outlier value for the year 2006). For a more insightful visualisation, plots for other metrics should be included as well.

Based on the graph titled `Graph of adult mortality and infant deaths in Singapore from 2000 to 2015`, life expectancy in Singapore increases as the adult mortality rate decreases. Logically, the same can be said about infant deaths, but according to this dataset, Singapore registered zero infant deaths from 2000 to 2015, meaning no relationship can technically be drawn between this and life expectancy. This can either be an impressive medical feat on Singapore's part, or the data has simply been erroneously omitted from the dataset. Other than providing insight to the growth of healthcare in Singapore, this graph can be combined with the previous graph to present a strong visualisation of how the reduction in the adult mortality rate contributes to increasing life expectancy.

# Conclusion

The analysis of data from these three datasets provided us with some knowledge about the life expectancies, populations and GDP of Southeast Asian countries. As a summary, Southeast Asia is mostly still a developing region of the world, with Singapore being the sole developed country and therefore having the highest life expectancy as well as GDP per capita. Fortunately, life expectancy in all Southeast Asian countries generally increases with time. Regardless of the rate of increase, this is a good sign that all countries in this region are seeing advancement in healthcare.

In addition, this assignment was a great opportunity to practise wrangling and visualing real-world data for the first time in the course of this unit. It was a fun way to experience the powerful tools Python has to offer in the field of data science.