Data Visualizition For Everyone - Introduction to Matplotlib and Seaborn

December 13, 2019

1 Introduction

Welcome to the first example of **Data Science for Everyone**. The following example will be about introduction to data visualization with **Python** and plotting line charts.

In the introductory examples, we'll use Google's CoLab which provides all the libraries and the environment we'll need. You can always modify the given code snippets by clicking the play button on the left side of each code cell after modifying them.

2 Reading data

First, import pandas library, data structure and processing library for Python. By using **as** keyword, we can use pandas with **pd** alias.

[ ]:
```
import pandas as pd
```

We'll use a subset of World bank's UK data which includes:

- Urban population,
- Rural population

- GDP per capita (constant LCU)
- GDP (constant LCU)

- CO2 emissions (metric tons per capita)

- Electric power consumption (kWh per capita)

Download the data formatted as CSV using pandas' **read_csv** function and assign it to variable **data**.

data variable is a **DataFrame** which is a tabular data format of pandas. We can quickly overview the first 5 rows of data frames using **head** function.

[ ]:
```
# Read the data over a network.
data = pd.read_csv('https://gist.githubusercontent.com/furkantektas/
↪b0de8567442daf6f26624d801e6e7b20/raw/
↪bfa1f1cdd2f4d53481466a13c574142e79bad86d/uk-world-bank-data.csv')

# Display the first 5 rows of the data
data.head()
```

[ ]:

	Year	Urban population	Rural population	GDP per capita (constant LCU)	\
0	1960	41104656	11295344	8948.839808	
1	1961	41381472	11418528	9109.605488	
2	1962	41661202	11588798	9152.575522	
3	1963	41900114	11749886	9443.734631	
4	1964	42098400	11901600	9855.243363	

	GDP (constant LCU)	CO2 emissions (metric tons per capita)	\
0	4.689190e+11	11.150759	
1	4.809870e+11	11.154139	
2	4.873750e+11	11.142928	
3	5.066560e+11	11.254853	
4	5.321830e+11	11.265839	

	Electric power consumption (kWh per capita)
0	2412.137405
1	2553.693182
2	2780.657277
3	3002.087605
4	3127.462963

To have a quick analysis over the columns, we can use pandas' **`describe()`** function which gives the basic statistics including min, max, average, standard deviation and quartiles for each column.

[ ]:
```
data.describe()
```

[ ]:

	Year	Urban population	Rural population	\
count	58.000000	5.800000e+01	5.800000e+01	
mean	1988.500000	4.585411e+07	1.218020e+07	
std	16.886879	3.538235e+06	4.422552e+05	
min	1960.000000	4.110466e+07	1.112955e+07	
25%	1974.250000	4.361200e+07	1.191889e+07	
50%	1988.500000	4.458450e+07	1.227413e+07	
75%	2002.750000	4.722549e+07	1.255638e+07	
max	2017.000000	5.489374e+07	1.283936e+07	

	GDP per capita (constant LCU)	GDP (constant LCU)	\
count	58.000000	5.800000e+01	
mean	18046.455670	1.065813e+12	

```
std                          6093.622777        4.157194e+11
min                          8948.839808        4.689190e+11
25%                         12929.046842        7.269408e+11
50%                         18191.241670        1.040145e+12
75%                         24508.062405        1.460185e+12
max                         27629.745670        1.824210e+12

       CO2 emissions (metric tons per capita)  \
count                                55.000000
mean                                  9.841130
std                                   1.308239
min                                   6.497440
25%                                   9.050457
50%                                   9.870809
75%                                  10.988541
max                                  11.823036

       Electric power consumption (kWh per capita)
count                                     55.000000
mean                                    4908.429642
std                                     1019.614068
min                                     2412.137405
25%                                     4486.378521
50%                                     5082.439806
75%                                     5671.992229
max                                     6270.984059
```

2.0.1 Access rows and columns of the data

We can access data frames' columns like **`data['Urban population']`**. It will gives us the entire column of the data.

To access data row by row, we can use **`data.iloc[0]`**, where 0 is the row number. Notice that row indexes starts from 0.

[ ]:
```
# Print the first row
data.iloc[0]
```

[ ]:
```
Year                                          1.960000e+03
Urban population                              4.110466e+07
Rural population                              1.129534e+07
GDP per capita (constant LCU)                 8.948840e+03
GDP (constant LCU)                            4.689190e+11
CO2 emissions (metric tons per capita)        1.115076e+01
Electric power consumption (kWh per capita)   2.412137e+03
Name: 0, dtype: float64
```

3 Visualizing

Now that we have data, we need to visualize it to have deeper understanding. So, let's begin visualization!

We'll use **Matplotlib** library for data visualization. Like **pd**, we create **plt** alias for matplotlib library. Then, to have nice looking figures, we import **seaborn** library (as **sns**) and set our chart styles using **sns.set()**.

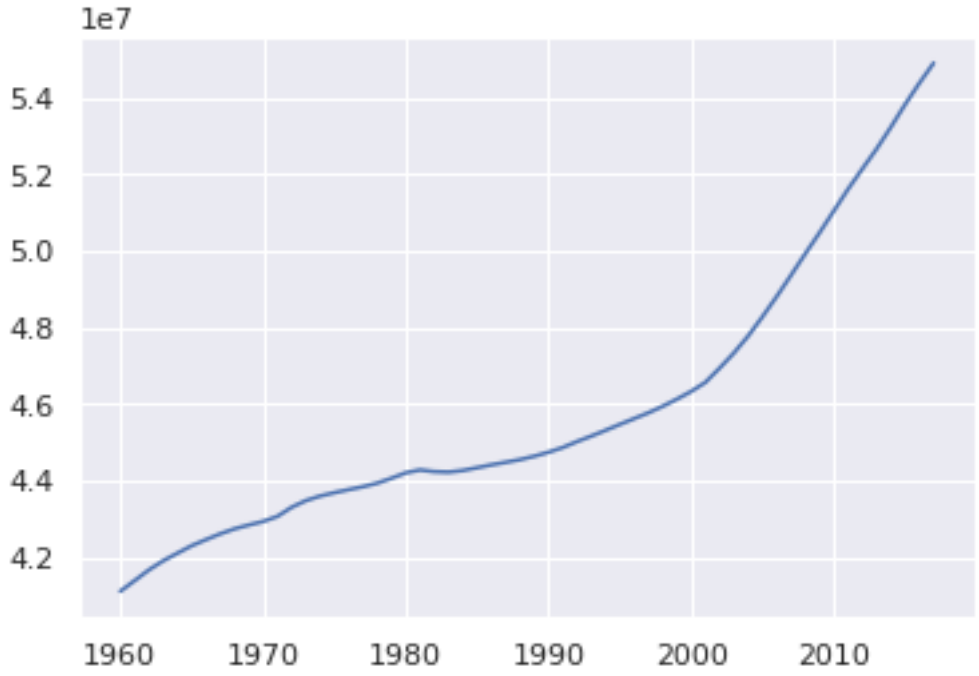
Since everything's imported for the plotting, we can begin the real work :) Using matplotlib's **plot(x,y)** function, we plot urban population over years. To do that, we select Year column as **data['Years']** and Urban Population as **data['Urban population']**. We can show the plot using **show()** function.

[ ]:
```
# import matplotlib library to use as plt
import matplotlib.pyplot as plt

# Imprt and set seaborn styles for nice chart styles
import seaborn as sns
sns.set()

# Plot the data: plt.plot(x-axis, y-axis)
plt.plot(data['Year'], data['Urban population'])

# Show the previously plotted data
plt.show()
```



Visual data is quicker to understand and easy to remember, thanks to Picture Superiority Effect. By observing the chart above for a few seconds, we can easily say urban population of UK has been a increasing with a constant rate after 2000. We wouldn't have this insight just by looking the numbers.

But, a chart without axis labels and title isn't useful. Let's add this chart a title and labels for both axis so that our plot become much more meaningful, even for complete outsiders.

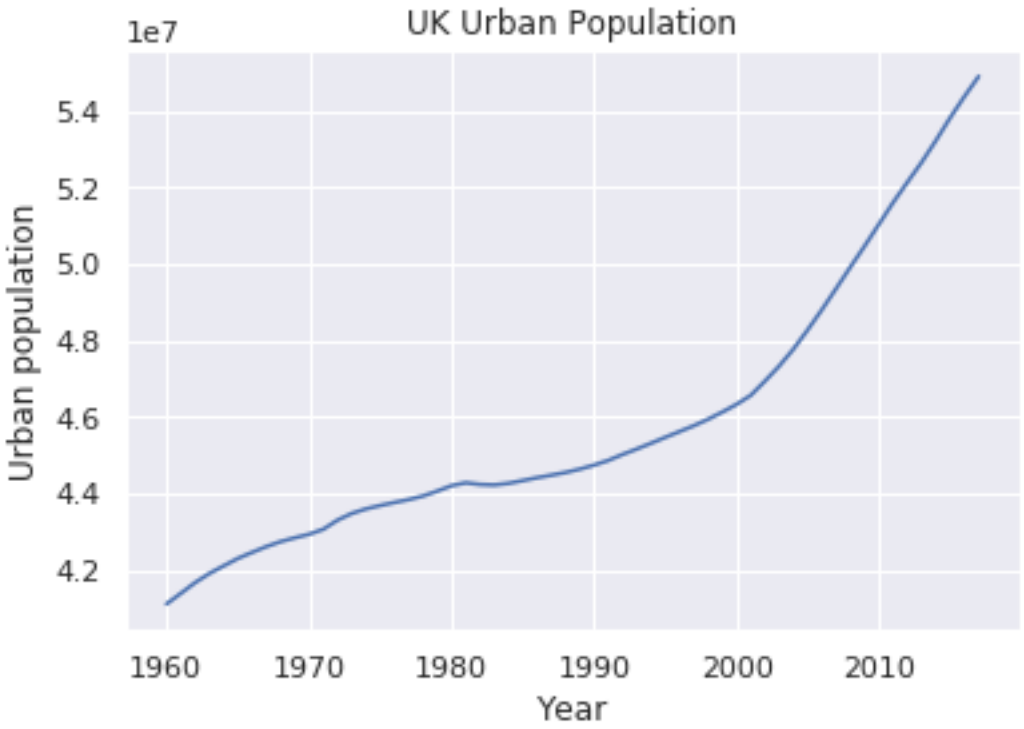
Let's plot all other metrics in the same way.

[ ]:
```
plt.plot(data['Year'],data['Urban population'])

# setting x & y axises labels
plt.xlabel('Year')
plt.ylabel('Urban population')

# setting plot title
plt.title('UK Urban Population')

# showing final plot
plt.show()
```



3.0.1 Changing line colour

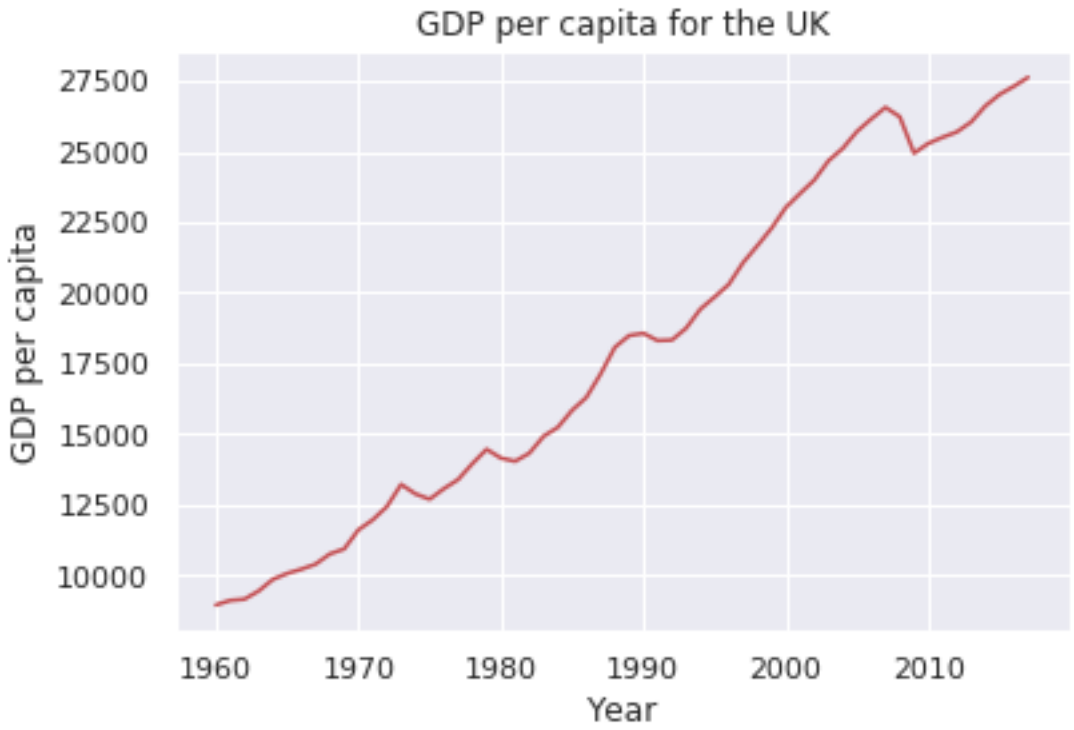
We can change the line color by parameter `c`. You can use different colors like

- b: blue
- g: green
- r: red
- c: cyan
- m: magenta
- y: yellow
- k: black
- w: white

[ ]:
```
# Plot the GDP per capita with red color using c='r'
plt.plot(data['Year'],data['GDP per capita (constant LCU)'],c='r')

# setting axis labels and plot title
plt.xlabel('Year')
plt.ylabel('GDP per capita')
plt.title('GDP per capita for the UK')

# showing plot
plt.show()
```



3.1 Plotting multiple data into one chart

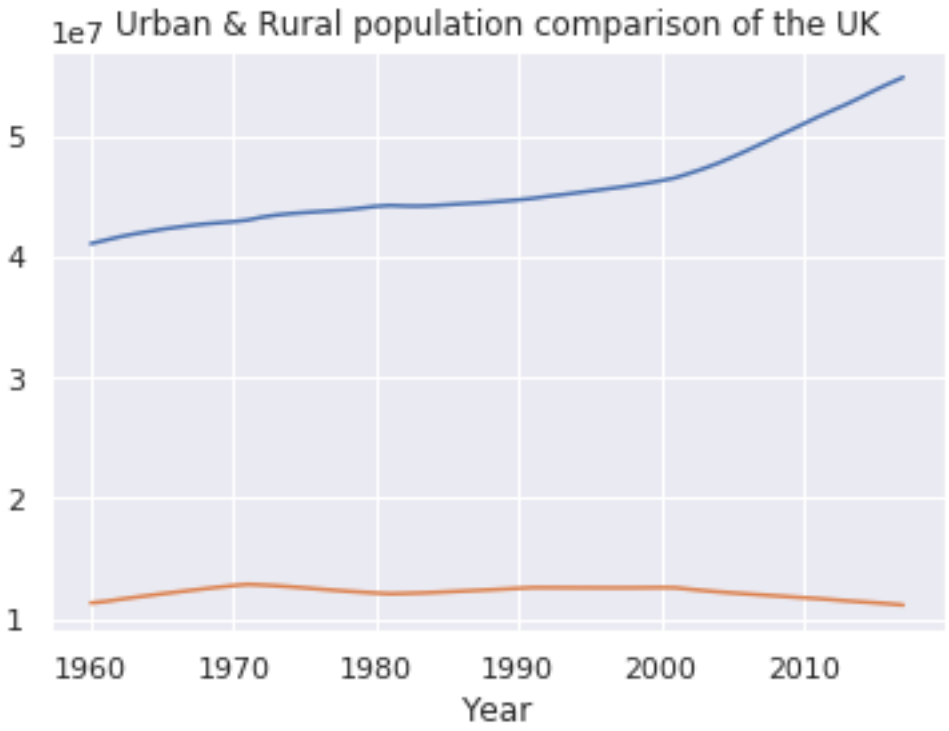
How about plotting two relative data into one plot? We can do so by calling the plot function, twice

As you can see below, matplotlib automatically chooses different colors for each plot function.

[ ]:
```
# First plot Urban population
plt.plot(data['Year'],data['Urban population'])
# Then plot Rural population on the same figure
plt.plot(data['Year'],data['Rural population'])

# Set x axis label and title
plt.xlabel('Year')
plt.title('Urban & Rural population comparison of the UK')

# Show the final results
plt.show()
```



Without prioir knowledge, we can't say which line represents urban population or rural population. So we need to add **legend** to our chart. To do so, we can call **`plt.legend()`** and it places a nice legend inside our chart.

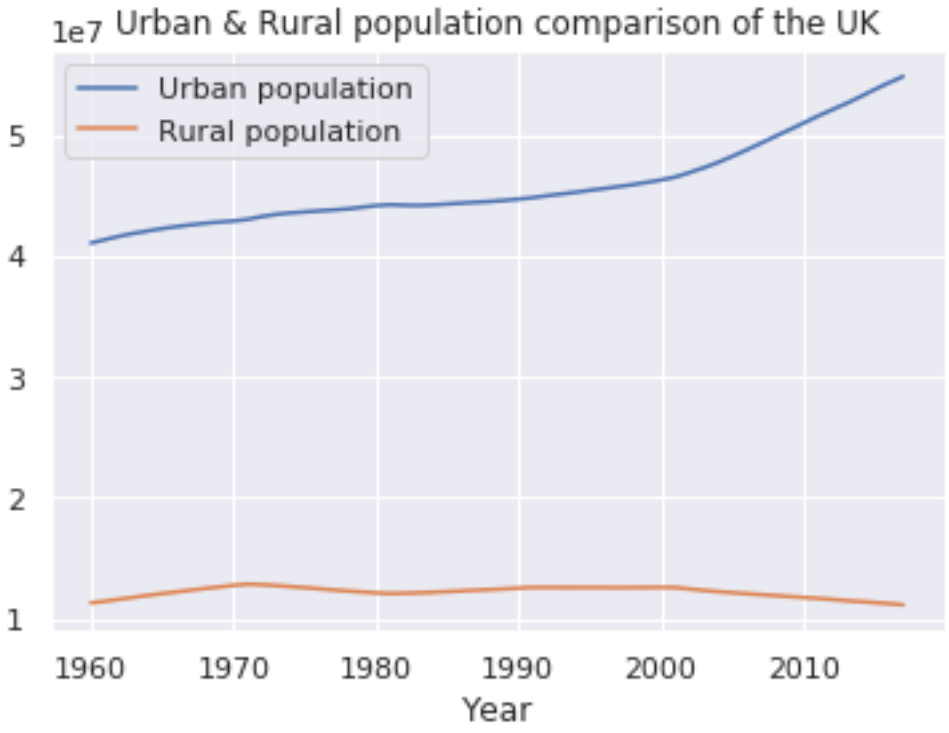
[ ]:
```
# First plot Urban population
plt.plot(data['Year'],data['Urban population'])
# Then plot Rural population on the same figure
plt.plot(data['Year'],data['Rural population'])

# Set x axis label and title
```

```
plt.xlabel('Year')
plt.title('Urban & Rural population comparison of the UK')

# Adding legend to current plot
plt.legend()

# Show the final results
plt.show()
```



3.2 Filtering data

To be able to focus on the data after 2002, we may need to filter our data. To be able to do so, we need to select only the rows with **`Year`** column is greater or equal to 2000. We can create a mask to define which rows we are interested in and which we are not.

To select rows which Year column is greater or equal to 2002, we can use **`data['Year'] >= 2002`**. This will give us a mask indicating which rows before 2002 and which rows after 2002. Let's create a variable **`mask`** and mask the whole data. Then, we can plot the same chart using the code snippet above.

Note that legend is positioned according to chart's content.

[ ]:
```
# Creating a mask for year >= 2002
mask = data['Year'] >= 2002
```

```
# Applying mask to the data and assign filtered data to a new variable
masked_data = data[mask]

# Plot the previous figure with the masked data
plt.plot(masked_data['Year'],masked_data['Urban population'], label="Urban␣
 ↪Population")
plt.plot(masked_data['Year'],masked_data['Rural population'], label="Rural␣
 ↪Population")
plt.legend()
plt.xlabel('Year')
plt.title('Urban vs Rural population of the UK after 2002')
plt.show()
```