

Plots for data with a single variable

```
# Importing pandas for data & seaborn, pyplot for visualizations
import pandas as pd
import seaborn as sns
import plotly.express as plx
import matplotlib.pyplot as plt
```

Importing the Dataset

Socio-Economic Country Profiles

This dataset contains about 95 statistical indicators of the 66 countries. It covers a broad spectrum of areas including General Information; Broader Economic Indicators ; Social Indicators ; Environmental & Infrastructure Indicators Military Spending ; Healthcare Indicators ; Trade Related Indicators e.t.c.

```
df = pd.read_csv('/content/soci_econ_country_profiles.csv')
df.head(10)
```

Unnamed: 0	country	Region	Surface area (km2)	Population in thousands (2017)	Population density (per km2, 2017)	Sex ratio (m per 100 f, 2017)	GDP: Gross domestic product (million current US\$)	GDP growth rate (annual %, const. 2005 prices)	GDP per capita (current US\$)	...	Inflation, consumer prices (annual %)	expect at bi fe (ye	
0	0	Argentina	SouthAmerica	2780400	44271	16.2	95.9	632343	2.4	14564.5	...	NaN	7
1	1	Australia	Oceania	7692060	24451	3.2	99.3	1230859	2.4	51352.2	...	1.948647	8
2	2	Austria	WesternEurope	83871	8736	106.0	96.2	376967	1.0	44117.7	...	2.081269	8
3	3	Belarus	EasternEurope	207600	9468	46.7	87.0	54609	-3.9	5750.8	...	6.031837	7
4	4	Belgium	WesternEurope	30528	11429	377.5	97.3	455107	1.5	40277.8	...	2.125971	8
5	5	Bosnia and Herzegovina	SouthernEurope	51209	3507	68.8	96.4	16251	3.1	4265.0	...	0.810133	7
6	6	Brazil	SouthAmerica	8515767	209288	25.0	96.6	1772591	-3.8	8528.3	...	3.446373	7
7	7	Bulgaria	EasternEurope	111002	7085	65.3	94.6	48953	3.0	6846.8	...	2.064355	7
8	8	Canada	NorthernAmerica	9984670	36624	4.0	98.5	1552808	0.9	43205.6	...	1.596884	8
9	9	Chile	SouthAmerica	756102	18055	24.3	98.2	240796	2.3	13416.2	...	2.182718	8

10 rows x 96 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 66 entries, 0 to 65
Data columns (total 96 columns):
#   Column
---  ---
0   Unnamed: 0
1   country
2   Region
3   Surface area (km2)
4   Population in thousands (2017)
5   Population density (per km2, 2017)
6   Sex ratio (m per 100 f, 2017)
7   GDP: Gross domestic product (million current US$)
8   GDP growth rate (annual %, const. 2005 prices)
9   GDP per capita (current US$)
10  Economy: Agriculture (% of GVA)
11  Economy: Industry (% of GVA)
12  Economy: Services and other activity (% of GVA)
13  Employment: Agriculture (% of employed)
14  Employment: Industry (% of employed)
15  Employment: Services (% of employed)
16  Unemployment (% of labour force)
17  Labour force participation (female/male pop. %)
18  Agricultural production index (2004-2006=100)
19  Food production index (2004-2006=100)
20  International trade: Exports (million US$)
21  International trade: Imports (million US$)
22  International trade: Balance (million US$)
```

Non-Null Count	Dtype
66 non-null	int64
66 non-null	object
66 non-null	object
66 non-null	int64
66 non-null	int64
66 non-null	float64
66 non-null	float64
66 non-null	int64
66 non-null	float64
66 non-null	float64
66 non-null	object
66 non-null	float64
66 non-null	float64
66 non-null	float64
66 non-null	float64
66 non-null	float64
66 non-null	object
66 non-null	int64
66 non-null	int64
66 non-null	int64
66 non-null	int64
66 non-null	int64

23	Balance of payments, current account (million US\$)	66 non-null	int64
24	Population growth rate (average annual %)	66 non-null	object
25	Urban population (% of total population)_x	66 non-null	float64
26	Urban population growth rate (average annual %)	66 non-null	object
27	Fertility rate, total (live births per woman)	66 non-null	float64
28	Population age distribution (0-14 / 60+ years, %)	66 non-null	object
29	International migrant stock (000/% of total pop.)	66 non-null	object
30	Refugees and others of concern to UNHCR (in thousands)	66 non-null	object
31	Infant mortality rate (per 1000 live births	66 non-null	float64
32	Health: Total expenditure (% of GDP)	66 non-null	float64
33	Health: Physicians (per 1000 pop.)	66 non-null	object
34	Education: Government expenditure (% of GDP)	66 non-null	object
35	Education: Primary gross enrol. ratio (f/m per 100 pop.)	66 non-null	object
36	Education: Secondary gross enrol. ratio (f/m per 100 pop.)	66 non-null	object
37	Education: Tertiary gross enrol. ratio (f/m per 100 pop.)	66 non-null	object
38	Seats held by women in national parliaments %	66 non-null	float64
39	Mobile-cellular subscriptions (per 100 inhabitants)	66 non-null	float64
40	Mobile-cellular subscriptions (per 100 inhabitants).1	66 non-null	float64
41	Individuals using the Internet (per 100 inhabitants)	66 non-null	int64
42	Threatened species (number)	66 non-null	float64
43	Forested area (% of land area)	66 non-null	object
44	CO2 emission estimates (million tons/tons per capita)	66 non-null	int64
45	Energy production, primary (Petajoules)	66 non-null	int64
46	Energy supply per capita (Gigajoules)	66 non-null	object
47	Pop. using improved drinking water (urban/rural, %)	66 non-null	object
48	Pop. using improved sanitation facilities (urban/rural, %)	66 non-null	object
49	Net Official Development Assist. received (% of GNI)	66 non-null	int64
50	Quality Of Life Index	66 non-null	float64
51	Purchasing Power Index	66 non-null	float64
52	Safety Index	66 non-null	float64

```
df['Education: Primary gross enrol. ratio (f/m per 100 pop.)']
```



Education: Primary gross enrol. ratio (f/m per 100 pop.)

0	109.8/110.2
1	102.1/102.3
2	102.2/103.7
3	101.3/101.4
4	104.2/104.2
...	...
61	116.0/116.7
62	108.1/108.4
63	100.0/100.3
64	98.6/101.3
65	108.4/109.3

66 rows × 1 columns

dtype: object

▼ Data Cleaning and pre-processing

```
df.isnull().sum()
```

	0
Unnamed: 0	0
country	0
Region	0
Surface area (km2)	0
Population in thousands (2017)	0
...	...
Population, female	0
Population, male	0
Tax revenue (% of GDP)	8
Taxes on income, profits and capital gains (% of revenue)	9
Urban population (% of total population)_y	0

96 rows × 1 columns

dtype: int64

```
#Drop row with null values
df.dropna(inplace = True)
```

```
# Select only numeric columns and keep 'Region' and 'country'
df = pd.concat([df[['Region', 'country']], df.select_dtypes(include=[float, int])], axis=1)
```

```
# Check the updated DataFrame types
df.info()
```

	19	International trade: Imports (million US\$)	66 non-null	int64
	20	International trade: Balance (million US\$)	66 non-null	int64
	21	Balance of payments, current account (million US\$)	66 non-null	int64
	22	Urban population (% of total population)_x	66 non-null	float64
	23	Fertility rate, total (live births per woman)	66 non-null	float64
	24	Infant mortality rate (per 1000 live births	66 non-null	float64
	25	Health: Total expenditure (% of GDP)	66 non-null	float64
	26	Seats held by women in national parliaments %	66 non-null	float64
	27	Mobile-cellular subscriptions (per 100 inhabitants)	66 non-null	float64
	28	Mobile-cellular subscriptions (per 100 inhabitants).1	66 non-null	float64
	29	Individuals using the Internet (per 100 inhabitants)	66 non-null	int64
	30	Threatened species (number)	66 non-null	float64
	31	CO2 emission estimates (million tons/tons per capita)	66 non-null	int64
	32	Energy production, primary (Petajoules)	66 non-null	int64
	33	Net Official Development Assist. received (% of GNI)	66 non-null	int64
	34	Quality Of Life Index	66 non-null	float64
	35	Purchasing Power Index	66 non-null	float64
	36	Safety Index	66 non-null	float64
	37	Health Care Index	66 non-null	float64
	38	Cost of Living	66 non-null	float64
	39	Property price to income ratio	66 non-null	float64
	40	Traffic commute time index	66 non-null	float64
	41	Pollution index	66 non-null	float64
	42	Climate index	66 non-null	float64
	43	Gross Rental Yield City Center	66 non-null	float64
	44	Gross Rental Yield Outside Center	66 non-null	float64
	45	Property Price to Rent Ratio City Center	66 non-null	float64

70	Inflation, consumer prices (annual %)	64 non-null	float64
71	Life expectancy at birth, female (years)	66 non-null	float64
72	Life expectancy at birth, male (years)	66 non-null	float64
73	Life expectancy at birth, total (years)	66 non-null	float64
74	Military expenditure (% of GDP)	63 non-null	float64
75	Population, female	66 non-null	float64
76	Population, male	66 non-null	float64
77	Tax revenue (% of GDP)	58 non-null	float64

▼ Data Visualisations

```
!pip install pillow
!pip install wordcloud
```

```
Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages (9.4.0)
Requirement already satisfied: wordcloud in /usr/local/lib/python3.10/dist-packages (1.9.3)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.10/dist-packages (from wordcloud) (1.26.4)
Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages (from wordcloud) (9.4.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from wordcloud) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (4.53.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (1.4.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (24.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (3.1.4)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil->matplotlib->wordcloud)
```

▼ Word Cloud

```
from PIL import Image
from wordcloud import WordCloud
Regions = " ".join(df['Region'].astype(str))

wordcloud = WordCloud(width=800, height=400, background_color='white').generate(Regions)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off') # No axis to show
plt.show()
```

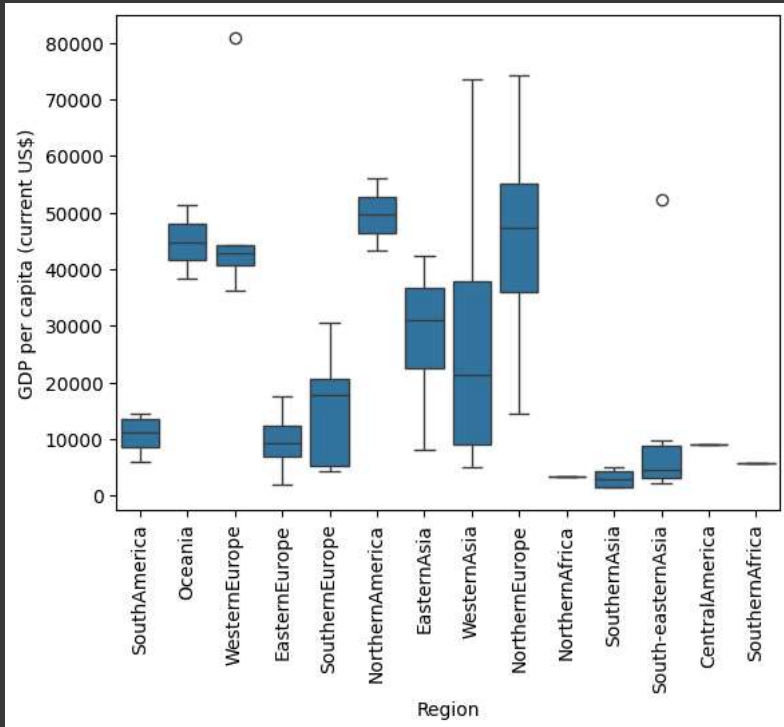


Question answered : Which regions in the world are featured most in this dataset?

The word cloud has the most frequent values in large size and the less frequent ones with tiny font

▼ Box and Whisker Plot

```
sns.boxplot(x='Region', y='GDP per capita (current US$)', data=df)
plt.xticks(rotation=90)
plt.show()
```



Question answered : How does the GDP epr capita vary across different regions?

A box and whisker plot shows us the spread of values for a numeric data. The box showcases the middle 50% of the data. The whiskers showcase the

Area Chart

```
import pandas as pd
import plotly.express as px

df['Population (2017)'] = df['Population in thousands (2017)'] * 1000

# Aggregate total population by region
region_population = df.groupby('Region')['Population (2017)'].sum().reset_index()

# Merge with the original DataFrame to get region-wise data
df = df.merge(region_population, on='Region', suffixes=('', '_total'))

# Calculate weighted averages for employment data
df['Weighted_Agriculture'] = df['Employment: Agriculture (% of employed)'] * df['Population (2017)'] / df['Population (2017)_total']
df['Weighted_Industry'] = df['Employment: Industry (% of employed)'] * df['Population (2017)'] / df['Population (2017)_total']
df['Weighted_Services'] = df['Employment: Services (% of employed)'] * df['Population (2017)'] / df['Population (2017)_total']

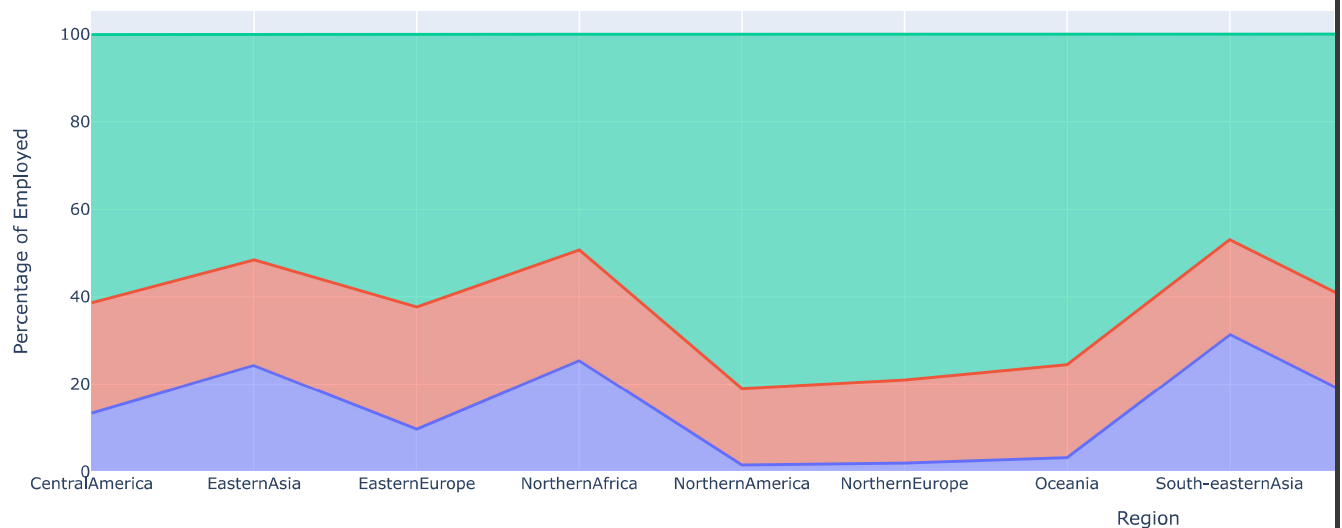
# Aggregate the weighted data by region
region_weighted_employment = df.groupby('Region')[['Weighted_Agriculture', 'Weighted_Industry', 'Weighted_Services']].sum().reset_index()

# Step 2: Plot the aggregated data
fig = px.area(region_weighted_employment, x='Region',
              y=['Weighted_Agriculture', 'Weighted_Industry', 'Weighted_Services'],
              labels={'value': 'Percentage of Employed', 'variable': 'Sector'},
              title='Weighted Sectoral Employment Distribution by Region')

# Show the chart
fig.show()
```



Weighted Sectoral Employment Distribution by Region



Question answered : Is there a regional variation in the percentage employees by the three sectors ?

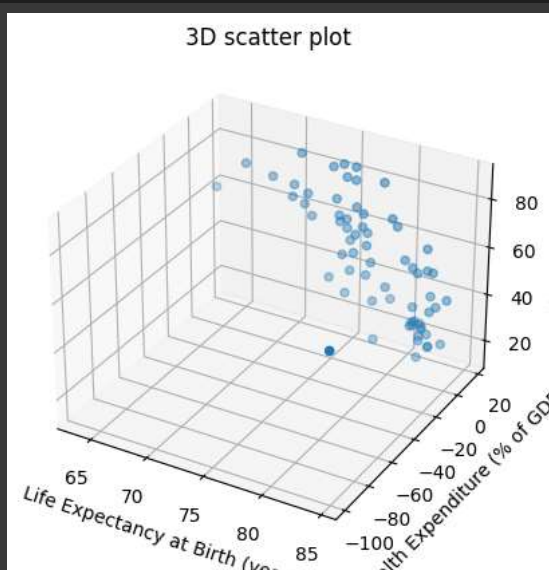
3D Chart

```
ax = plt.axes(projection="3d")

ax.scatter(df['Life expectancy at birth, total (years)'],
           df['Health: Total expenditure (% of GDP)'],
           df['Pollution index'])

plt.title("3D scatter plot")

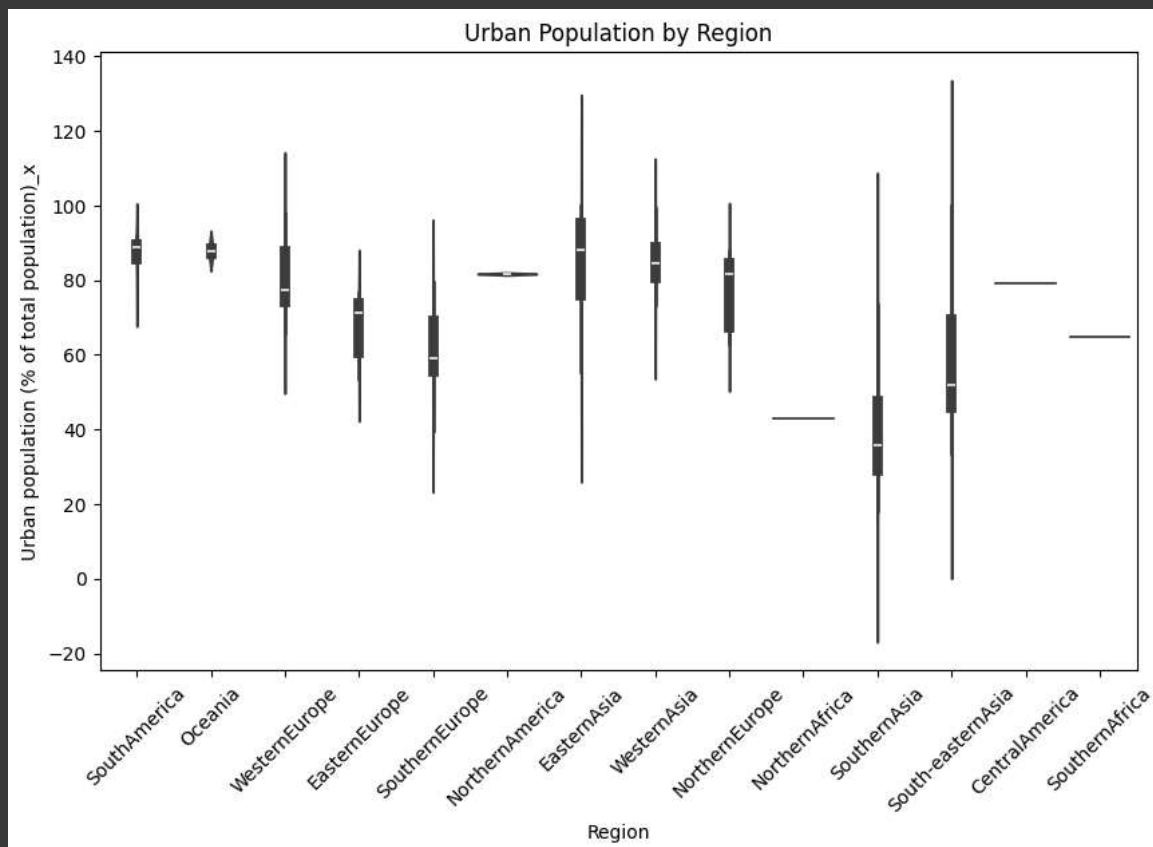
ax.set_xlabel('Life Expectancy at Birth (years)')
ax.set_ylabel('Health Expenditure (% of GDP)')
ax.set_zlabel('Pollution Index')
# show plot
plt.show()
```



Violin Plot

```
plt.figure(figsize=(10, 6))
sns.violinplot(x='Region', y='Urban population (% of total population)_x', data=df)
plt.xticks(rotation=45)
```

```
plt.title('Urban Population by Region')
plt.show()
```



Double-click (or enter) to edit

Donut Chart

```
import plotly.express as px

country_data = df[df['country'] == 'Japan']

# Aggregate the total exports and imports
total_exports = country_data['International trade: Exports (million US$)'].sum()
total_imports = country_data['International trade: Imports (million US$)'].sum()

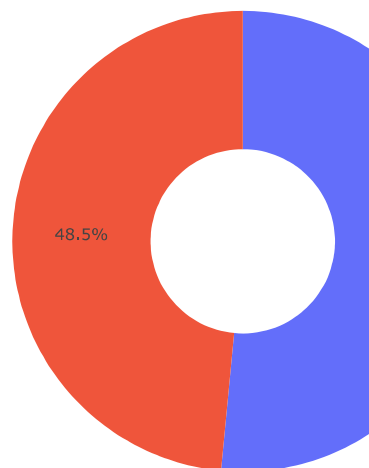
# Prepare data for the pie chart
values = [total_exports, total_imports]
labels = ['Exports', 'Imports']

# Create the pie chart
fig = px.pie(values=values, names=labels, title="Export vs Import Share for Japan", hole=0.4)

# Show the chart
fig.show()
```



Export vs Import Share for Japan



Question Answered : How does the trade baalnce for (any particular country) look?

▼ TreeMap

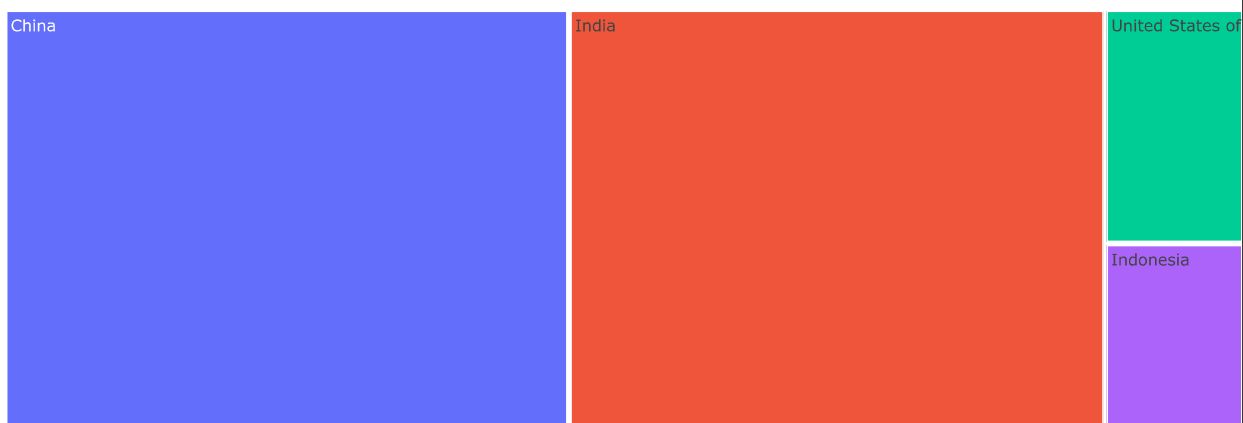
```
import plotly.express as px

# Create a treemap of population by country
fig = px.treemap(df,
                 path=['country'],
                 values='Population in thousands (2017)',
                 title="Population Distribution by Country")

# Show the chart
fig.show()
```



Population Distribution by Country



How do the populations of various countries compare with each other?

▼ Line Chart


```
df['GDP growth rate (annual %, const. 2005 prices)'] = pd.to_numeric(df['GDP growth rate (annual %, const. 2005 prices)'], errors='coerce')

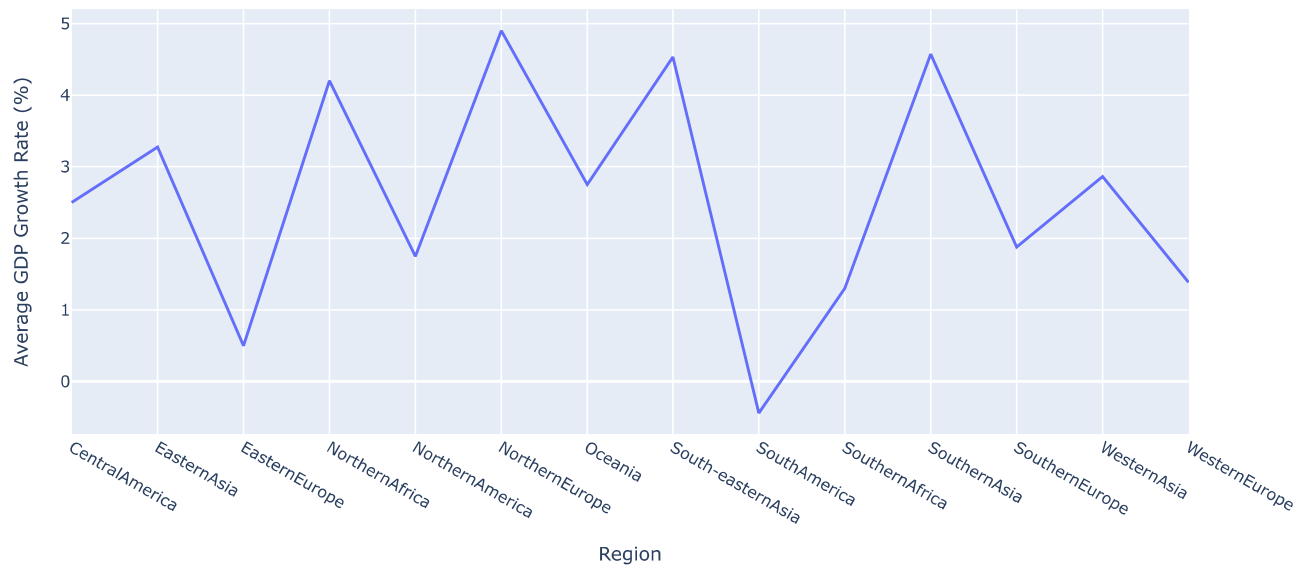
df_grouped = df.groupby('Region', as_index=False)['GDP growth rate (annual %, const. 2005 prices)'].mean()

fig = px.line(df_grouped,
              x='Region',
              y='GDP growth rate (annual %, const. 2005 prices)',
              title="Average GDP Growth Rate by Region",
              labels={'GDP growth rate (annual %, const. 2005 prices)': 'Average GDP Growth Rate (%)',
                     'Region': 'Region'})

fig.show()
```



Average GDP Growth Rate by Region



Questions answered :

Which regions show the highest GDP growth rate?

Which regions show the least GDP growth rate?

Funnel Chart

```
import plotly.graph_objects as go
country_data = df[df['country'] == 'Belgium']

population_in_thousands = country_data['Population in thousands (2017)'].iloc[0]
total_pop = int(population_in_thousands) * 1000

urban_population = country_data['Urban population (% of total population)_y'].iloc[0]
urban_population_number = int(total_pop * (urban_population / 100))

rural_population_number = total_pop - urban_population_number

# Create a funnel chart using Plotly
fig = go.Figure()

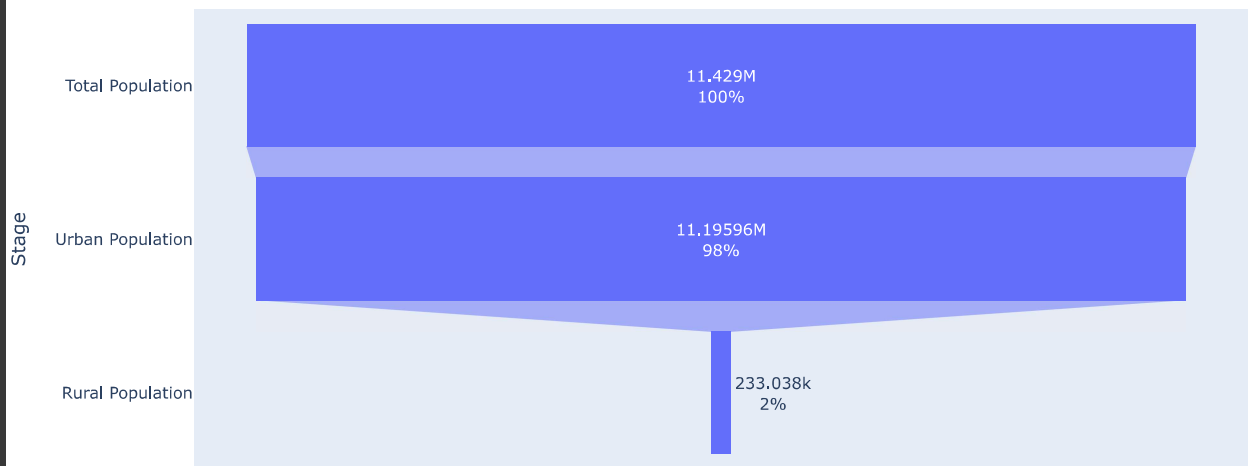
fig.add_trace(go.Funnel(
    y=["Total Population", "Urban Population", "Rural Population"],
    x=[total_pop, urban_population_number, rural_population_number],
    textinfo="value+percent initial",
)))

fig.update_layout(
    title="Funnel Chart of Population Distribution in Belgium",
    xaxis_title="Population",
    yaxis_title="Stage"
)

fig.show()
```



Funnel Chart of Population Distribution in Belgium



How urbanised is a particular country?

▼ Jitter Plot

```
plt.figure(figsize=(12, 6))
sns.stripplot(x='Region',
              y='Pollution index',
              data=df,
              jitter=True,
              palette='viridis')

plt.xlabel('Region')
plt.ylabel('Pollution Index')
plt.title('Jitter Plot of Pollution Index by Region')
plt.xticks(rotation=45)

plt.show()
```



<ipython-input-17-dde03821a72f>:2: FutureWarning: