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# Mastering data visualization with Python: practical tips for researchers

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Big data have revolutionized the way data are processed and used across all fields. In the past, research was primarily conducted with a focus on hypothesis confirmation using sample data. However, in the era of big data, this has shifted to gaining insights from the collected data. Visualizing vast amounts of data to derive insights is crucial. For instance, leveraging big data for visualization can help identify and predict characteristics and patterns related to various infectious diseases. When data are presented in a visual format, patterns within the data become clear, making it easier to comprehend and provide deeper insights. This study aimed to comprehensively discuss data visualization and the various techniques used in the process. It also sought to enable researchers to directly use Python programs for data visualization. By providing practical visualization exercises on GitHub, this study aimed to facilitate their application in research endeavors.

Keywords: Big data, Data visualization, Matplotlib, Seaborn, Python

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# **INTRODUCTION**

This article will cover the following topics: (1) why data visualization is important; (2) data visualization libraries in Python; and (3) method of drawing graphs using data visualization libraries.

# WHY IS DATA VISUALIZATION IMPORTANT?

#### What is data visualization?

Data visualization refers to the graphical representation of 'raw' data and simple summary information. It is also useful for data cleaning, exploration of data structures, outlier detection, clus-

tering and pattern discovery, evaluation of modeling results, and presenting findings [1]. Owing to these benefits, effective visualization aids researchers in understanding their data and conveying insights [2]. Additionally, graphics stimulate researchers to propose questions and ideas. However, interpreting graphics requires experience, and to prevent overinterpretation, statistical knowledge is necessary [1].

#### **Data exploration**

Through data visualization, complex datasets can be understood more easily. Valuable insights that are difficult to grasp from raw data alone can be obtained. Visual representation facilitates the identification of patterns and correlations more effortlessly.

#### Identifying trends and anomalies

Data visualization aids in grasping trends, outliers, extreme values, and more. It is useful in identifying sudden increases or decreases in the data, possible performance improvements, and factors influencing specific outcomes.

#### **Effective communication**

Visualization is a powerful tool for conveying data to others. It allows complex concepts and results to be presented in a visual and intuitive manner, enabling smooth communication. Data visualization promotes communication and collaboration among experts from various fields, facilitating informed decision-making based on information.

In summary, data visualization is an essential tool for obtaining meaningful insights from data, ultimately leading to better outcomes.

# DATA VISUALIZATION LIBRARIES IN PYTHON

Data visualization tools and techniques are essential for analyzing vast amounts of information and making data-driven decisions. Although there are several programming languages available for this purpose, the present study focuses only on data visualization libraries commonly used in Python. This programming language provides rich libraries for data visualization, and we describe the Matplotlib and Seaborn libraries in this study. Using these libraries, we can generate various charts such as bar charts, histograms, and scatter plots.

#### Matplotlib

Matplotlib [3] is a graphic library for data visualization that has been well-established, undergoing almost 20 years of continuous development. It is the most popular data visualization library in Python and is used by scientists and researchers worldwide [4]. Matplotlib is a comprehensive package with all the modules and libraries included, and it offers great flexibility to precisely control the arrangement and visual appearance of objects within plots.

#### Seaborn

Seaborn is a Python data visualization library based on Matplotlib and closely integrated with numpy and pandas data structures [5]. It is a specialized interface for creating statistical graphics. Seaborn provides simpler syntax and more appealing designs than Matplotlib. It automatically maps data values to visual attributes like color, size, and style, and internally computes statistical transformations [6].

# METHOD OF DRAWING GRAPHS USING DATA VISUALIZATION LIBRARIES

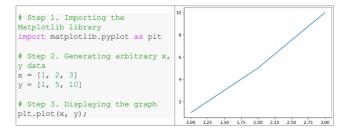
In this study, we aimed to explain how to implement data visualization using Python's Matplotlib and Seaborn libraries. Practical code and data can be downloaded from GitHub for learning purposes (https://github.com/soyul5458/Python\_data\_visualization). The practical exercises were conducted using Google Colab, which is free and can be accessed anytime, anywhere with a Gmail account, without the need to download any separate program.

#### **Matplotlib**

#### Basic visualization

Using Matplotlib, various types of graphs can be easily drawn. The "pyplot" module is a sub-module of Matplotlib that provides a simple and user-friendly interface for generating different types of graphs, such as line plots, bar plots, histograms, and scatter plots. To use it conveniently, we import it with the alias "plt."

Generally, the visualization process in Fig. 1 consists of three steps: (1) step 1: import the visualization library; (2) step 2: decide which data to display on the x and y axes; and (3) step 3: enter the graph output function.





#### Specifying options for creating figures

When creating graphs for data visualization, there are several options that can be used to effectively present the figures. For example, adding graph titles, x- and y-axis names, legends, and other options can help the reader to better understand the figures.



#### 1) Title (Fig. 2)

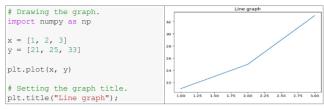


Fig. 2. Setting the graph title.

#### 2) Axis labels (Fig. 3)

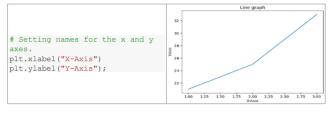


Fig. 3. Setting names for the x and y axes.

## 3) Legend (Fig. 4)

The plt.legend() function is used to add a legend, and the label of the added legend is displayed with the name set in the label argument of the plot() function. The position of the legend can be set using the loc argument.

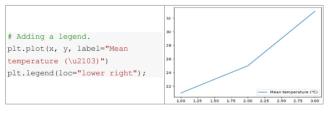


Fig. 4. Adding a legend.

## 4) Line width (Fig. 5)

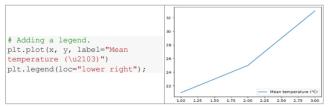


Fig. 5. Setting the line width.

## 5) Line style (Fig. 6)

Four different styles listed in Table 1 can be used. Using the linestyle argument, different line styles can be displayed as shown in Fig. 6.

 Table 1. Line styles in Matplotlib

Character	Description	
-	solid	
	dashed	
	dash-dot	
:	dotted	

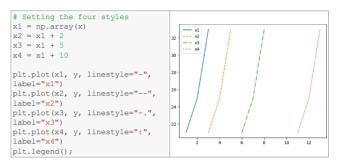


Fig. 6. The line graph displays four different line styles.

## 6) Marker (Fig. 7)

If you want to represent points, add the marker argument. The shape of the marker can be changed in various ways, and the types can be found in matplotlib.markers (https://matplotlib. org/stable/api/markers\_api.html). The size of the marker can also be set as desired.

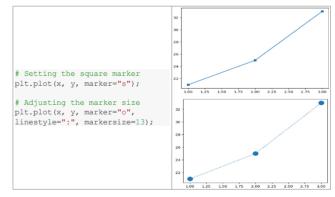


Fig. 7. Setting the marker.

## 7) Color (Fig. 8)

Graph color is added to the plot function using the color argument. It is possible to change to default colors using color abbreviations, and various colors can be selected from the Matplotlib gallery. Not only the line color but also the color of the marker and its edge can be changed.

In addition to the above, practical codes for resizing the graph, setting dpi, background color, axis ranges, axis ticks, grid, and saving the graph can be found in the matplotlib.ipynb



#### file on GitHub.

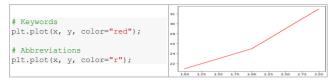


Fig. 8. Setting color.

#### Basic plotting with Matplotlib

1) Line plot (Fig. 9)

Line graphs are frequently used to represent trends over time.

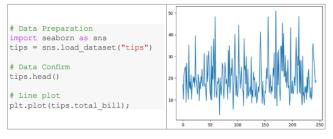


Fig. 9. Line graph representation with Matplotlib.

#### 2) Bar plot

Bar graphs are used to represent group differences. Each bar's length corresponds to the respective value. Both vertical and horizontal bar graphs can be created. Additionally, patterns can be added to the bars and adjust their widths.

#### (1) Vertical bar graph (Fig. 10)

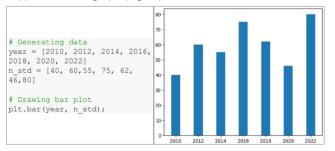


Fig. 10. Vertical bar graph representation with Matplotlib.

#### (2) Horizontal bar graph (Fig. 11)



Fig. 11. Horizontal bar graph representation with Matplotlib.

(3) Displaying different bar colors (Fig. 12)

Bars can be displayed in different colors based on categorical variables, as demonstrated in the following example, where we will perform a practical code exercise to show colors corresponding to major categories.

		Ye	ar	Sti	uden	ts	Maj	or
# Step 1. Creating Data for		20	10			40		Α
<pre>Practice df1 = pd.DataFrame({'Year': year, 'Students' :n std, 'Major' : ['A','B','C','C','B','A','A']})</pre>	1	20	12			60		в
	2	20	14			55		С
# Step 2. Extracting Data by Major	3	20	16			75		С
<pre>sub1 = df1.loc[df1["Major"]=='A'] sub2 = df1.loc[df1["Major"]=='B'] sub3 = df1.loc[df1["Major"]=='C']</pre>	4	20	18			62		В
	5	20	20			46		Α
<pre># Step 3. Displaying Different Bar Colors Based on the Major plt.bar(sub1.Year, sub1.Students,</pre>		20	22			80		А
<pre>color = 'r', label="A") plt.bar(sub2.Year, sub2.Students, color = 'b', label="B") plt.bar(sub3.Year, sub3.Students, color = 'y', label="C") plt.legend(ncol=3, loc="upper center");</pre>	80 - 70 - 50 - 30 - 20 - 10 - 0	2010	2012	A A	2016	C C	2020	
		2010	2012	2014	2016	2018	2020	2022

Fig. 12. Displaying different bar colors based on categorical variables.

#### 3) Box plot

Box plots are exploratory graphs that represent data distributions. They quickly show the range, median, and outliers of the dataset.

#### (1) Drawing a single box plot (Fig. 13)



Fig. 13. Visualization of a single box plot with Matplotlib.

#### (2) Drawing multiple box plots (Fig. 14)



Fig. 14. Visualization of multiplt box plot with Matplotlib.

#### 4) Histogram

Histograms graphically represent frequency distribution



tables. The horizontal axis represents intervals, and the vertical axis represents frequencies. The hist() function can be used to create histograms that divide data values into equal intervals called bins, and the size of bins affects the frequency and shape of the histogram.

#### (1) Basic histogram (Fig. 15)

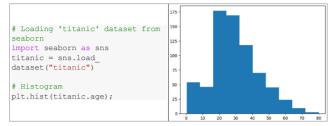


Fig. 15. Visualization of histogram with Matplotlib.



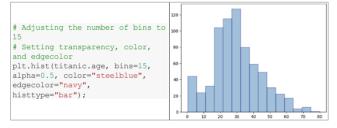


Fig. 16. Adjusting the histogram using various options.

#### 5) Scatter plot (Fig. 17)

Scatter plots graphically represent the correlation between two variables on a coordinate plane using dots. Scatter plots can easily be drawn using the scatter() function. The markers can be changed to different shapes using the marker argument described above.

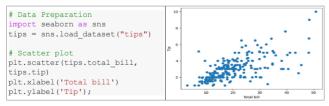


Fig. 17. Visualization of scatter plot with Matplotlib.

#### 6) Pie chart

Pie charts are used to visually display the overall proportions of categorical data. They provide a convenient way to see the size and relative proportions of each section. The autopct argument in the pie() function specifies the format of the numbers displayed inside the sectors. The value %.2f displays numbers up to two decimal places. The percentage symbol can be included by inputting %.2f%% consecutively. A legend can also be added using the legend() function.

(1) Data preparation (Fig. 18)

<pre>import seaborn as sns titanic = sns.load_ dataset("titanic") titanic.head() total = titanic["sex"].value_ counts() total</pre>	male 577 female 314 Name: sex, dtype: int64
---	---

Fig. 18. Verification of data quantity.

(2) Drawing pie chart (Fig. 19)

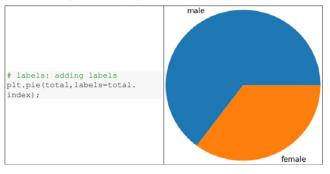


Fig. 19. Visualization of pie chart with Matplotlib.

#### (3) Displaying percentage (Fig. 20)

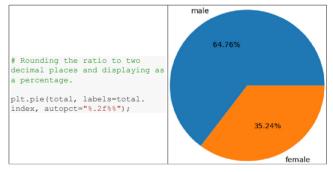


Fig. 20. Displaying percentages in a pie chart.

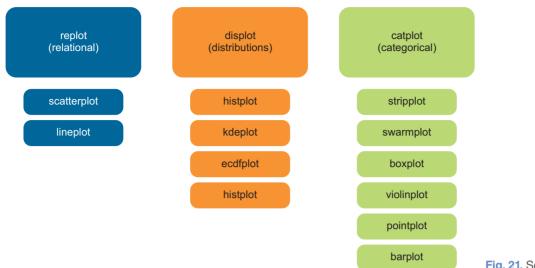
#### Seaborn

#### Figure-level vs. axes-level function

Seaborn functions can be broadly categorized into 'figurelevel' and 'axes-level' functions. The three large boxes at the top in Fig. 21 (replot, displot, catplot) are figure-level functions, and the smaller boxes below are axes-level functions. Figurelevel functions create a Seaborn figure separately from Matplotlib and perform plotting on that figure. Therefore, the layout can be changed using facetgrid (Seaborn's figure). Axes-level functions, on the other hand, specify where to plot using the ax

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#### Table 2. Types of Seaborn graphs

No	Туре	Name	Figure-level function	Axes-level function	
1	Relational plot	Scatter plot	sns.relplot(kind="scatter")	sns.scatterplot()	
2		Line plot	sns.relplot(kind="line")	sns.lineplot()	
3	Distribution plot	Histogram plot	sns.displot(kind="hist")	sns.histplot()	
4		Kernel density plot	sns.displot(kind="kde")	sns.kdeplot()	
5		Cumulative distribution plot	sns.displot(kind="ecdf")	sns.ecdfplot()	
6		Rug plot	-	sns.rugplot()	
7		Distribution plot	sns.distplot()	-	
8	Categorical scatter plot	Strip plot	sns.catplot(kind="strip")	sns.stripplot()	
9		Swarm plot	sns.catplot(kind="swarm")	sns.swarmplot()	
10	Categorical distributiona plot	Box plot	sns.catplot(kind="box")	sns.boxplot()	
11		Violin plot	sns.catplot(kind="violin")	sns.violinplot()	
12		Letter value plot	sns.catplot(kind="boxen")	sns.boxenplot()	
13	Categorical estimate plots	Point plot	sns.catplot(kind="point")	sns.pointplot()	
14		Bar plot	sns.catplot(kind="bar")	sns.barplot()	
15		Count plot	sns.catplot(kind="count")	sns.countplot()	
16	Regression plot	Regression line and scatter plot	-	sns.regplot()	
17		Multiple regression plot	sns.Implot()	-	
18		Residual plot	-	sns.residplot()	
19	Matrix plot	Heatmap	-	sns.heatmap()	
20		Dendrogram and Heatmap	-	sns.clustermap()	
21	Multi-plot grids	Grid settings	sns.FacetGrid()	-	
22		Multivariable plot	sns.pairplot()	-	
23		Multivariate grid settings	sns.PairGrid()	-	
24		Bivariate plot	sns.jointplot()	-	
25		Bivariate grid settings	sns.JointGrid()	-	



#### Table 3. Visualization by variable type

Variable		Analysis	<b>Recommended Visualization</b>
Single Variable	Categorical	Frequency analysis, Cross-tabulation	Countplot
	Continuous	Descriptive statistics	Histogram
Two Variables	Continuous/Continuous	Correlation analysis	Scatter plot
	Categorical/Categorical	Chi-square test	Heatmap
	Categorical/Continuous	Multivariate analysis	Violin plot
			Strip plot
			Swarm plot

parameter, and thus the layout can be changed using methods such as plt.figure(). Table 2 summarizes the various graphs available in the Seaborn library.

#### Data type determines visualization

Table 3 summarizes the statistical analysis and visualization methods based on variable types. Understanding variable types is crucial during the visualization process because different graphic methods are used depending on the type. Visualization guides based on variables are well-documented on the Python gallery page, so please refer to it (https://www.data-to-viz.com/).

#### Basic plotting with Seaborn

1) Relational plot: scatter plot (Table 2, No. 1)

Scatter plots represent graphs using points on the x and y axes. In other words, they show the relationship between two different continuous variables using dots. Both codes below are for outputting scatter plots.

- · sns.relplot(x, y, data, kind="scatter", hue, style, size, sizes)
- sns.scatterplot(x, y, data, hue, style, size, sizes)

relplot is a higher-level function for scatter plots and line plots (Fig. 21). Therefore, both scatter plots and line graphs can be drawn using the replot() function. Note that the kind argument of replot() defaults to "scatter." The functions' features are summarized below, and the functionality of each argument can be verified through practice code. When specifying hue, style, and size together, the complexity may increase, making it difficult to understand the relationships between variables. Please be cautious when using them.

- hue: Specifies the column to distinguish features (distinguishes by color).
- style: Specifies the column to distinguish features (distinguishes by marker shape).
- size: Specifies the variable that sets the size of markers, applicable to both continuous and categorical variables.

 sizes: Specifies the minimum and maximum size of the markers.

#### (1) hue (Fig. 22)

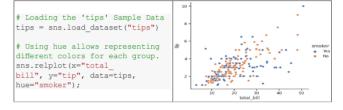


Fig. 22. Utilization of the hue option with Seaborn.

#### (2) style (Fig. 23)

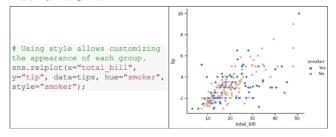


Fig. 23. Utilization of the style option with Seaborn.

#### (3) size (Fig. 24)

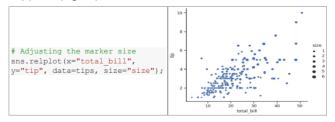


Fig. 24. Utilization of the size option with Seaborn.



#### (4) sizes (Fig. 25)



Fig. 25. Utilization of the sizes option with Seaborn.

#### 2) Distribution plot: kernel density plot (Table 2, No. 4)

Seaborn provides additional features compared to simple histograms in Matplotlib, such as kernel density, rug display, and multidimensional composite distribution. Among them, the kernel density plot displays a smoother distribution curve than a histogram by overlapping kernels. Both codes below are for outputting kernel density plots.

- sns.displot(kind="kde")
- $\cdot$  sns.kdeplot(x, y, data, bw\_adjust, cumulative)
- bw\_adjust: Adjusts the data interval for density estimation (default = 1).
- cumulative: If True, estimates the cumulative distribution function.

For kernel density plots, by assigning variable values to the y axis instead of the x axis, the graph can also be drawn horizontally or overlapped. Additionally, multiple variables can be overlaid on one graph. Please refer to the GitHub practice code for details.

#### (1) Kernel density plot (Fig. 26)

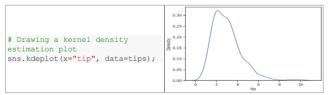


Fig. 26. Visualization of kernel density plot with Seaborn.

#### (2) Horizontal density plot (Fig. 27)

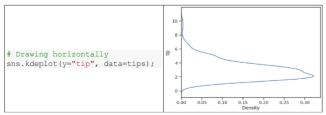
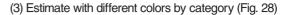


Fig. 27. Visualization of horizontal density plot with Seaborn.



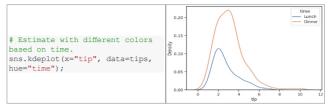


Fig. 28. Displaying estimations in different colors by categorical variables.

#### 3) Distribution plot: rug plot (Table 2, No. 6; Fig. 29)

A rug plot is used to describe the distribution of data by showing data positions as small vertical lines (rugs) on the xaxis.

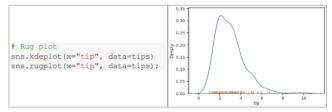


Fig. 29. Visualization of rug plot with Seaborn.

4) Categorical scatter plot: strip plot (Table 2, No. 8; Fig. 30)

A strip plot is a graph that represents all data points as dots, similar to a scatter plot.

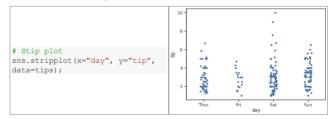


Fig. 30. Visualization of strip plot with Seaborn.

5) Categorical scatter plot: swam plot (Table 2, No. 9; Fig. 31) A swarm plot is similar to a strip plot but arranges the dots horizontally to avoid overlap of data points.

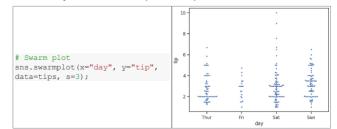


Fig. 31. Visualization of swarm plot with Seaborn.



6) Categorical distribution plot: box plot (Fig. 32)

The Seaborn library's box plot can be used with a strip plot overlaid.

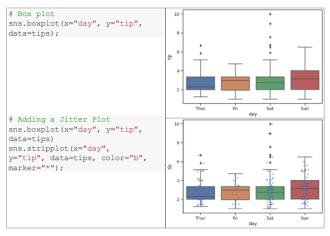


Fig. 32. Visualization of box plot with Seaborn.

7) Categorical distribution plot: violin plot (Fig. 33)

A violin plot is a visualization of data distribution, resembling a box plot combined with a kernel density plot.

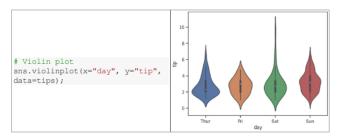


Fig. 33. Visualization of violin plot with Seaborn.

# **CONCLUSIONS**

In conclusion, data visualization is essential. It presents complex concepts in an easy-to-understand manner, allowing for the identification of patterns and trends, gaining insights, and making better decisions more quickly. In the field of clinical research, large amounts of data are being collected, and Python visualization tools are effective for visual representation. Using appropriate data visualization tools according to data types can significantly improve the quality and impact of research, enabling readers to understand complex concepts easily.

# Notes

# Authors' contributions

Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization: SYH Project administration: IYK Writing–original draft: SYH Writing–review & editing: SYH, IYK

# **Conflict of interest**

All authors have no conflicts of interest to declare.

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None.

# Data availability

The data presented in this study are available at: https://github. com/soyul5458/Python\_data\_visualization.

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