VISUALIZATION DOCUMENTATION: PANDAS & SEABORN

Introduction

Data visualization is the process of turning numbers and data into pictures, like charts and graphs, that are easier to understand. Instead of looking at rows of numbers, you can see trends, patterns, and insights more clearly through visual tools. Python makes this easier by offering many helpful libraries that let you create different types of visuals — from simple line graphs and bar charts to more advanced, interactive dashboards.

This guide offers a comprehensive overview of popular Python visualization libraries such as **Pandas** and **Seaborn**. It highlights their strengths, key differences, and practical applications. By the end, you'll know which library aligns best with your needs and how to start building engaging, data-driven visualizations.

PANDAS

Pandas is a versatile Python library widely used for data manipulation, analysis, and visualization. It introduces two core data structures—**Series** (1D) and **DataFrame** (2D)—that make it easy to work with structured, tabular data.

While Pandas is primarily recognized for its powerful data cleaning, transformation, and analysis capabilities, it also provides built-in visualization methods. These allow users to quickly generate plots directly from Series or DataFrames, making Pandas especially valuable for **exploratory data analysis (EDA)**.

Key Features of Pandas :

1. **Powerful Data Structures** – Provides **Series (1D)** and **DataFrame (2D)** for handling structured datasets.
2. **Flexible Data Manipulation** – Supports filtering, grouping, merging, joining, and reshaping data.
3. **Robust Handling of Missing Data** – Includes tools to detect, remove, or impute missing values.
4. **Seamless Data Import & Export** – Reads and writes multiple formats, including **CSV, Excel, JSON, and SQL databases**.
5. **Built-in Visualization** – Offers quick plotting directly from Series/DataFrames using .plot().
6. **Integration with Other Libraries** – Works efficiently with **NumPy, Matplotlib, and other data science libraries**.
7. **High Performance** – Optimized for large-scale datasets with efficient indexing and operations.

GRAPH TYPES:

1. Line Plot

Description: Plots data points connected by lines, showing trends over continuous data.
Use Case: Sales growth over months.

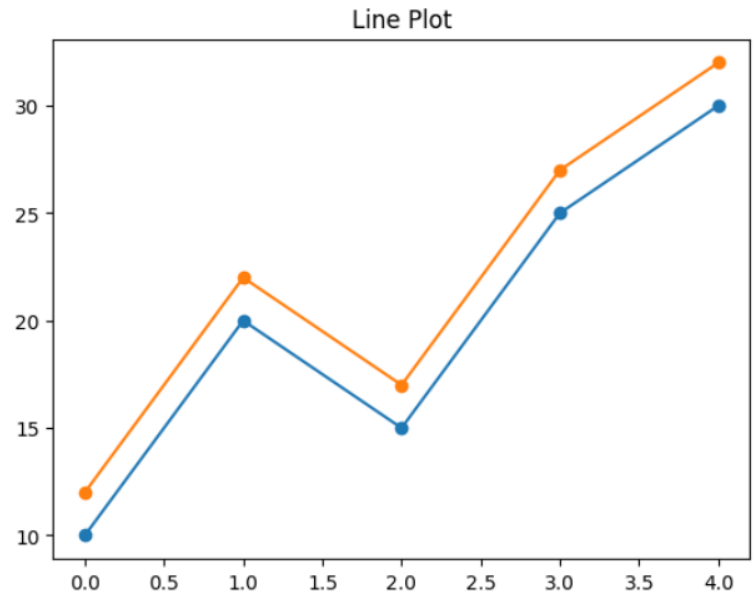
Sample Code:

```
import pandas as pd

data = pd.Series([10, 20, 15, 25, 30])
```

```
data2  = pd.Series([12,22,17,27,32])
data.plot(title="Line Plot", marker='o')
data2.plot(title="Line Plot", marker='o')
```

```
<Axes: title={'center': 'Line Plot'}>
```

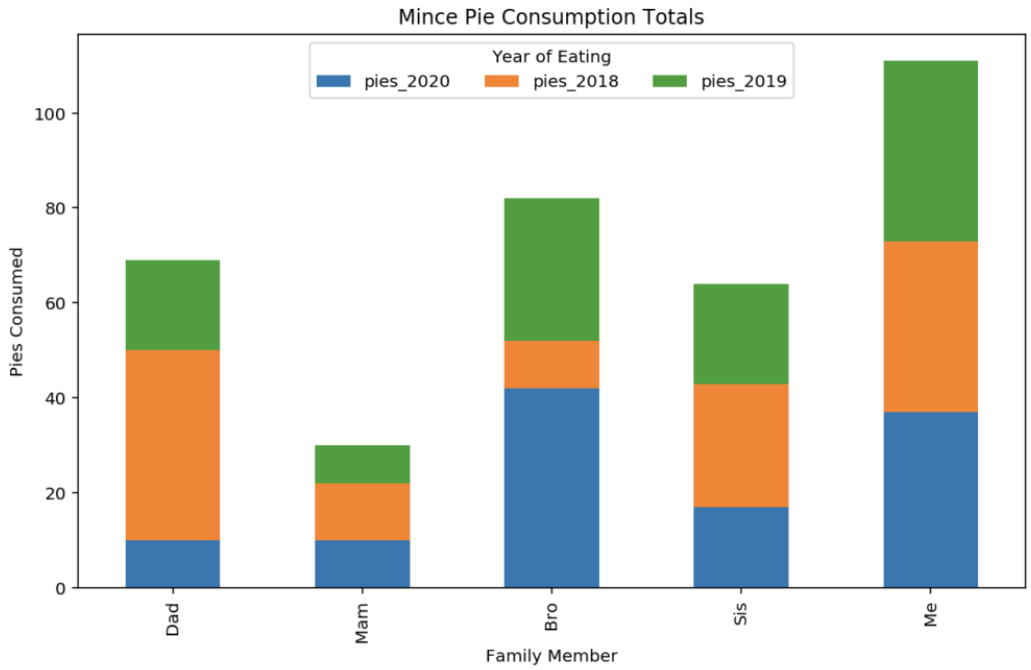


2. Bar Chart

Description: Displays data as rectangular bars for categorical comparison.
Use Case: Comparing product sales.

Sample Code:

```
df = pd.Series([5, 8, 12], index=['A', 'B', 'C'])
df.plot(kind='bar', title="Bar Chart", color='skyblue')
```

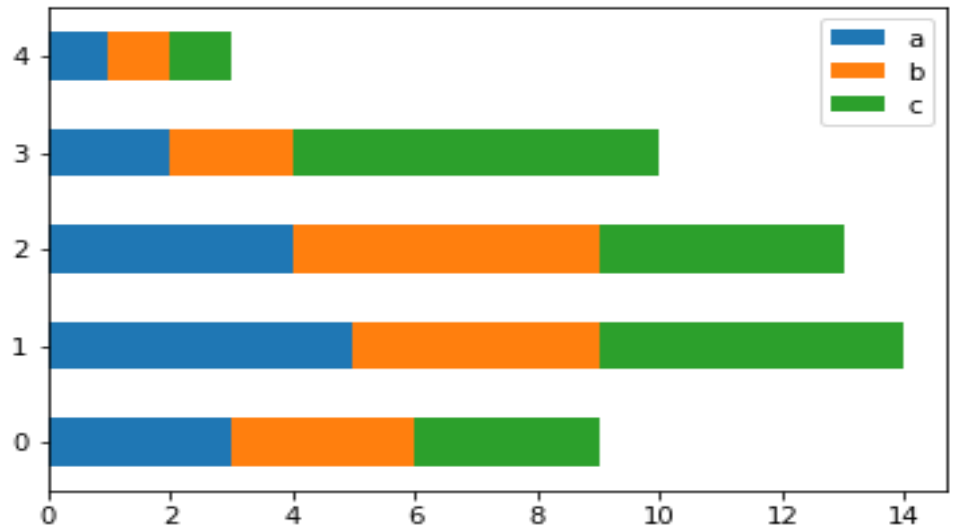


3. Horizontal Bar Chart

Description: Same as a bar chart but horizontal.
Use Case: Comparing values when category labels are long.

Sample Code:

```
df.plot(kind='barh', title="Horizontal Bar Chart",
color='lightgreen')
```



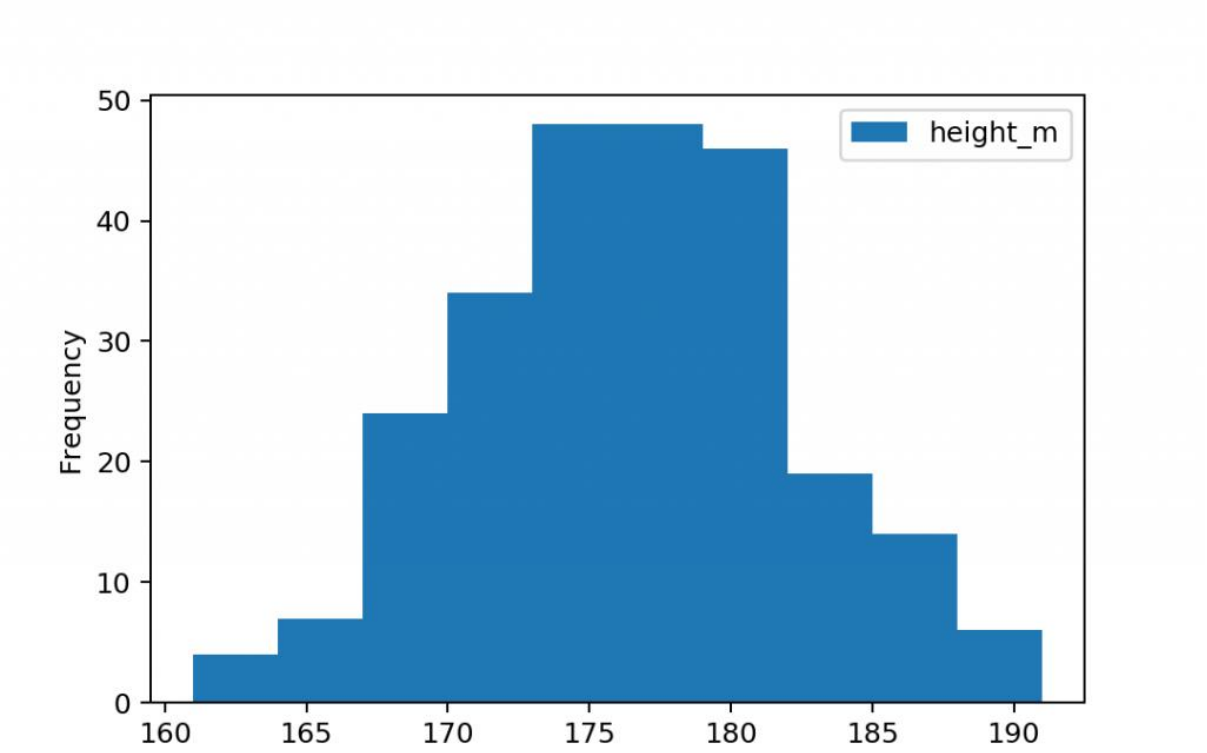
4. Histogram

Description: Groups numeric data into bins to show frequency distribution.
Use Case: Analyzing exam score distributions

Sample Code:

```
data = pd.Series([3, 5, 5, 6, 7, 8, 8, 9, 10])

data.plot(kind='hist', bins=5, title="Histogram",
color='orange', edgecolor='black')
```

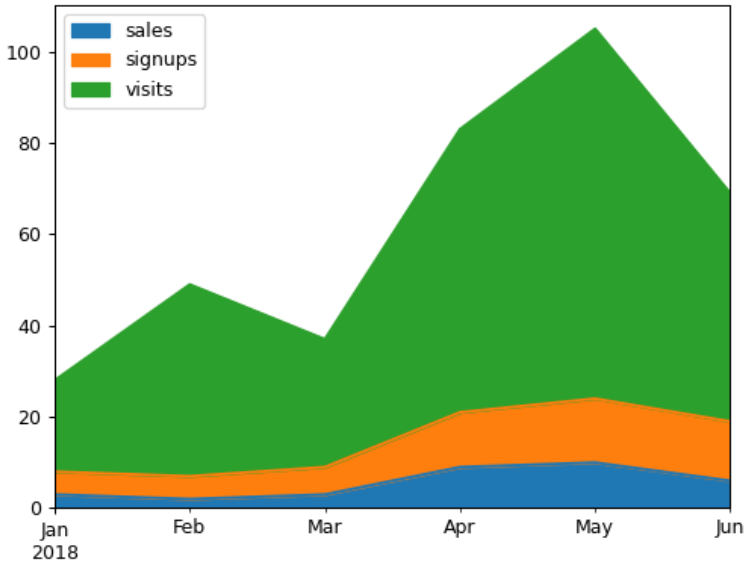


5. Area Plot

Description: Like a line plot but the area under the line is filled.
Use Case: Showing cumulative trends.

Sample Code:

```
df = pd.DataFrame({
    'A': [1, 3, 4],
    'B': [2, 4, 6]
})
df.plot(kind='area', alpha=0.5, title="Area Plot")
```



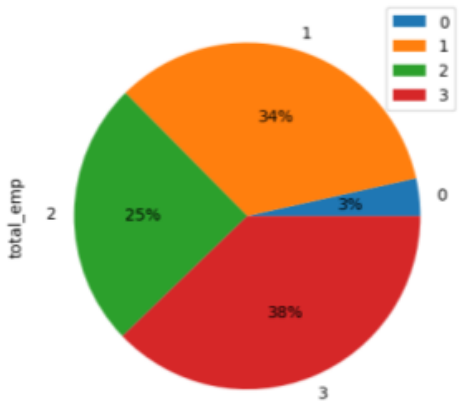
6. Pie Chart

Description: Shows proportions of a whole as slices of a circle.

Use Case: Visualizing budget distribution.

Sample Code:

```
df = pd.Series([30, 20, 50], index=['A', 'B', 'C'])
df.plot(kind='pie', autopct='%1.1f%%', title="Pie Chart")
```



SEABORN

Seaborn is a Python data visualization library built on top of Matplotlib, designed to provide a higher-level interface for creating attractive and informative graphics. Compared to Matplotlib, Seaborn offers advanced built-in features such as improved default styles, color palettes, and simplified syntax, making it easier to generate visually appealing plots with minimal code.

Seaborn supports a wide range of plot types that cater to different data visualization needs, including:

1 **Relational Plots**:

· scatterplot()

· lineplot()

· relplot()

2 **Categorical Plots**:

· barplot()

· countplot()

· boxplot()

· violinplot()

· swarmplot()

· pointplot()

· catplot()

3 **Distribution Plots**:

· histplot()

· kdeplot()

· rugplot()

· distplot()

4 **Relational Plots**:

· regplot()

· lmplot()

5 **Matrix Plots**:

· heatmap()

· clustermap()

Here are some sample codes for some of the graphs.

```
# Import required libraries
import seaborn as sns
import matplotlib.pyplot as plt

# Load sample datasets
tips = sns.load_dataset("tips")
flights = sns.load_dataset("flights")
iris = sns.load_dataset("iris")

# Set Seaborn style
sns.set(style="whitegrid")
```

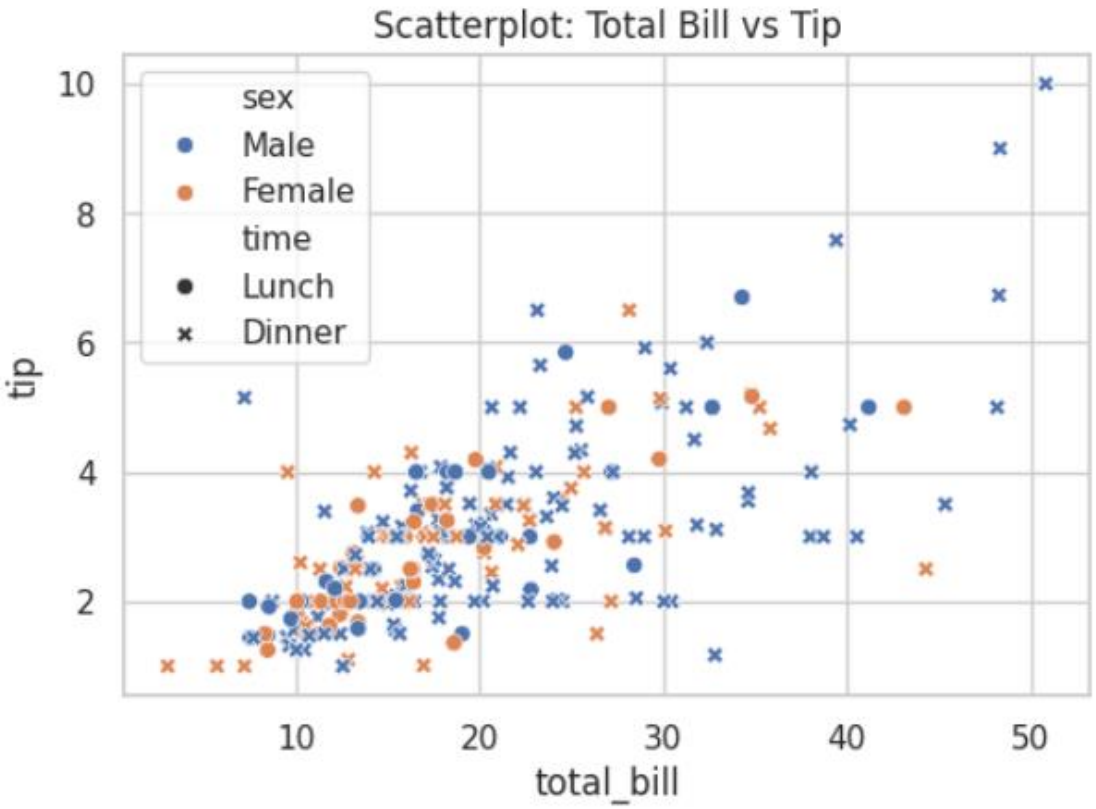
1. Scatterplot

plt.figure(figsize=(6,4))

sns.scatterplot(x="total_bill", y="tip", data=tips, hue="sex", style="time")

plt.title("Scatterplot: Total Bill vs Tip")

plt.show()



Description:

scatterplot() plots total_bill on the x-axis and tip on the y-axis.

- The hue="sex" parameter assigns different colors to Male and Female categories.

- The style="time" parameter varies marker shapes based on Lunch/Dinner.
- Each point represents one customer.
- title() adds a title, xlabel() and ylabel() label the axes.
- show() displays the scatterplot.

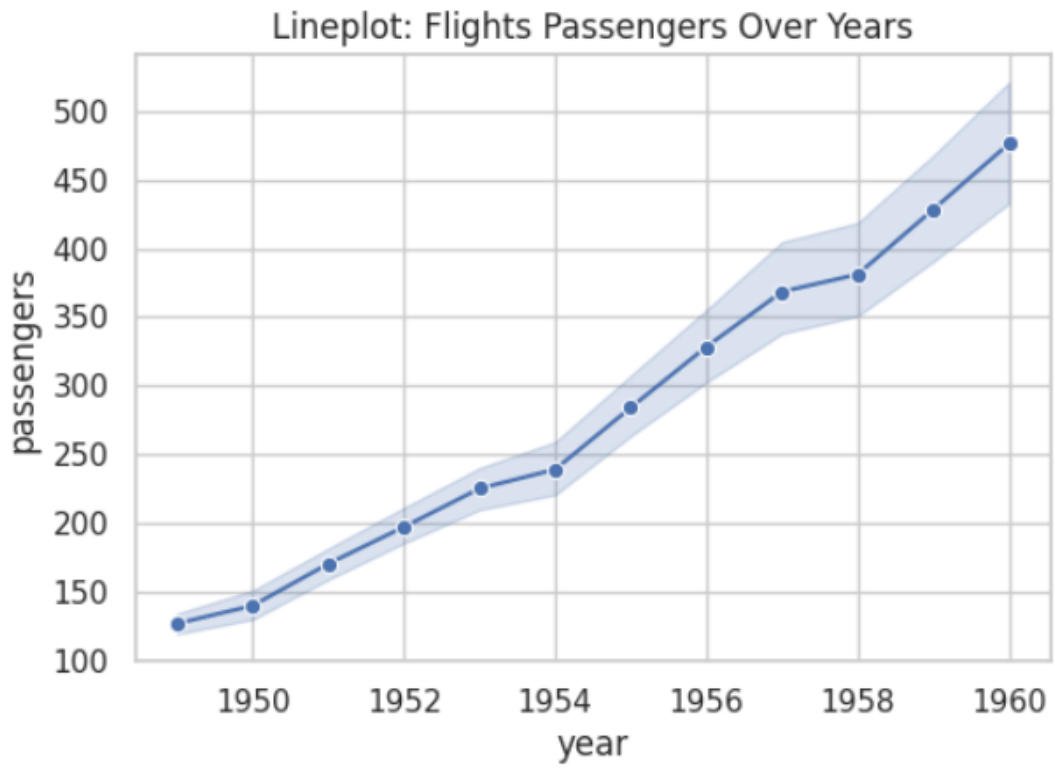
2. Lineplot

plt.figure(figsize=(6,4))

sns.lineplot(x="year", y="passengers", data=flights, marker="o")

plt.title("Lineplot: Flights Passengers Over Years")

plt.show()



Description:
lineplot() plots year on the x-axis and passengers on the y-axis.

- The line connects points to show trends over time.
- The marker="o" adds circular markers for each data point.
- Useful for visualizing how the number of passengers changes across years.

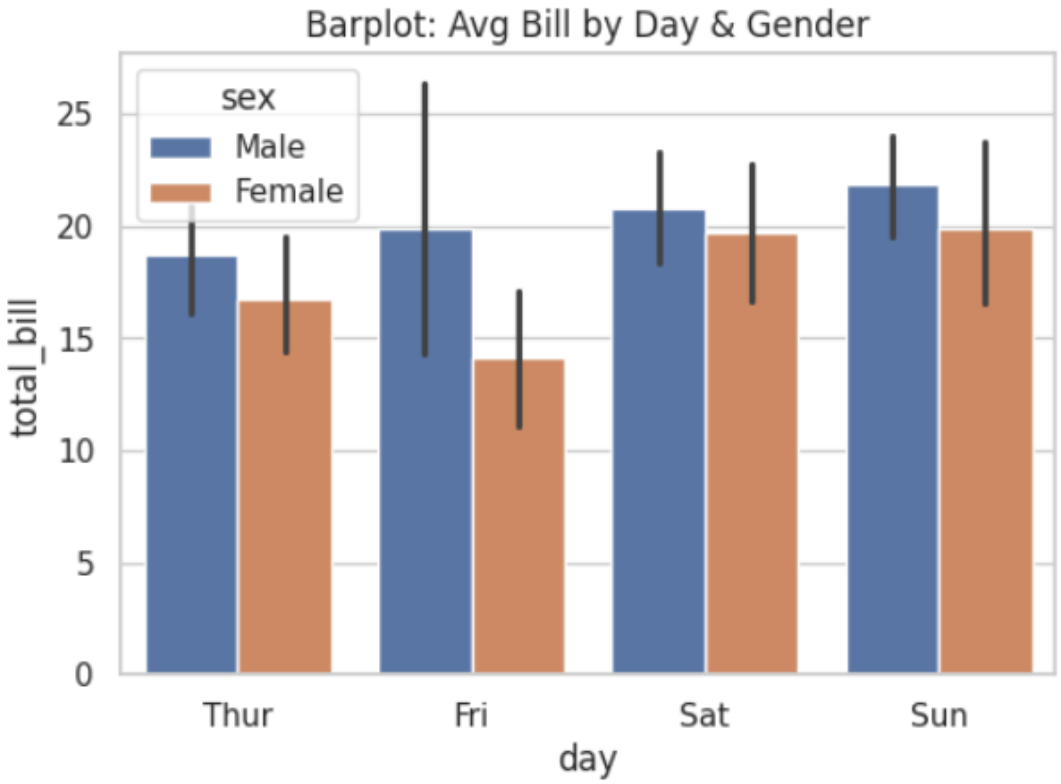
3. Barplot

plt.figure(figsize=(6,4))

sns.barplot(x="day", y="total_bill", data=tips, hue="sex")

plt.title("Barplot: Avg Bill by Day & Gender")

plt.show()



Description:
barplot() displays the average total bill for each day of the week.

- The hue="sex" parameter splits each bar by Male/Female.
- By default, it shows the mean with confidence intervals.
- Useful for comparing group averages across categories.

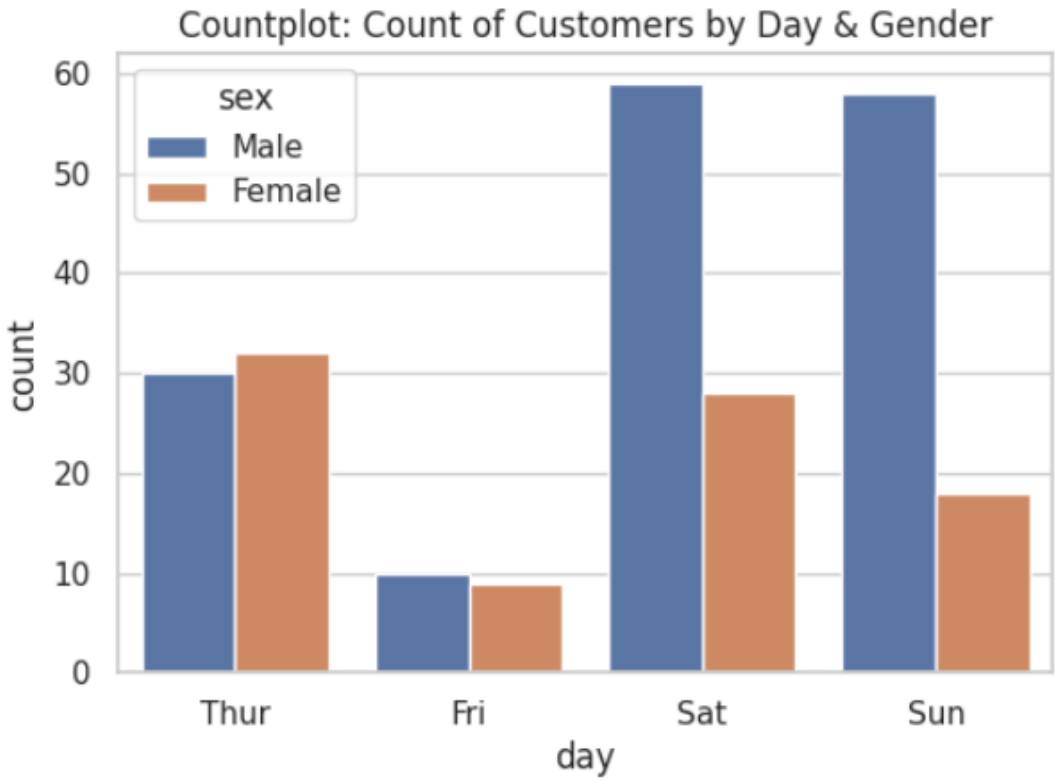
4. Countplot

plt.figure(figsize=(6,4))

sns.countplot(x="day", data=tips, hue="sex")

plt.title("Countplot: Count of Customers by Day & Gender")

plt.show()



Description:
countplot() shows the count of observations for each day of the week.

- The hue="sex" parameter splits counts into Male/Female categories.
- Bars represent frequency rather than averages.
- Helpful for seeing category distributions.

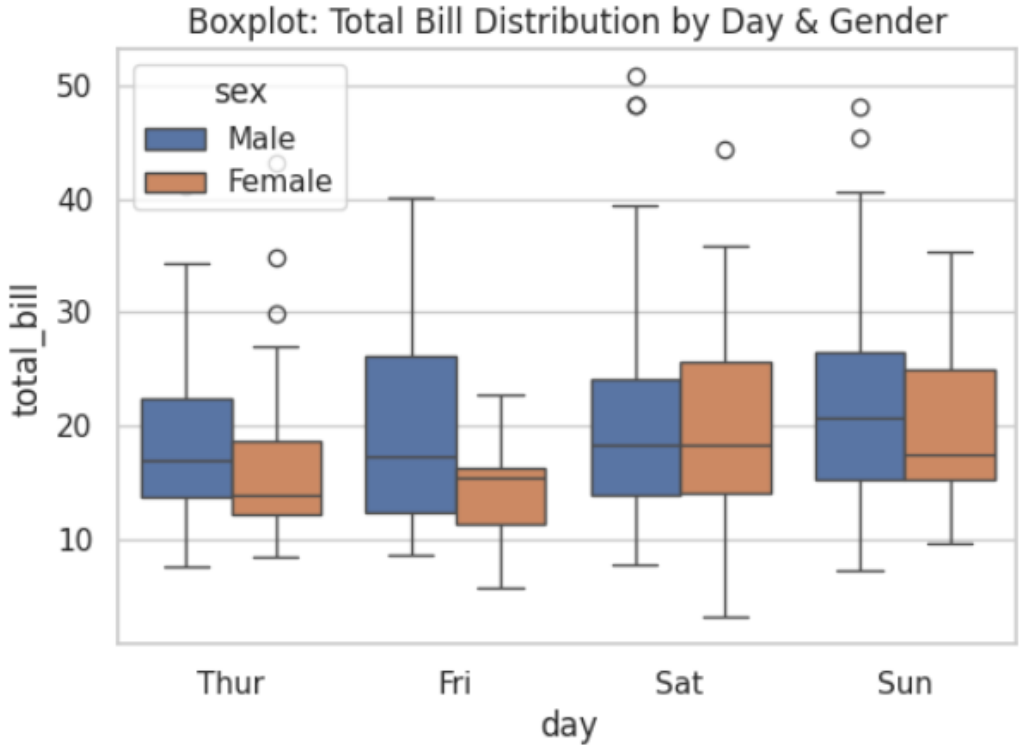
5. Boxplot

plt.figure(figsize=(6,4))

sns.boxplot(x="day", y="total_bill", data=tips, hue="sex")

plt.title("Boxplot: Total Bill Distribution by Day & Gender")

plt.show()



Description:
boxplot() displays the distribution of total bills for each day.

- The box shows the median, 25th percentile, and 75th percentile.
- Whiskers show variability outside the quartiles.
- Dots represent outliers (very high/low bills).
- The hue="sex" parameter allows Male/Female comparison.

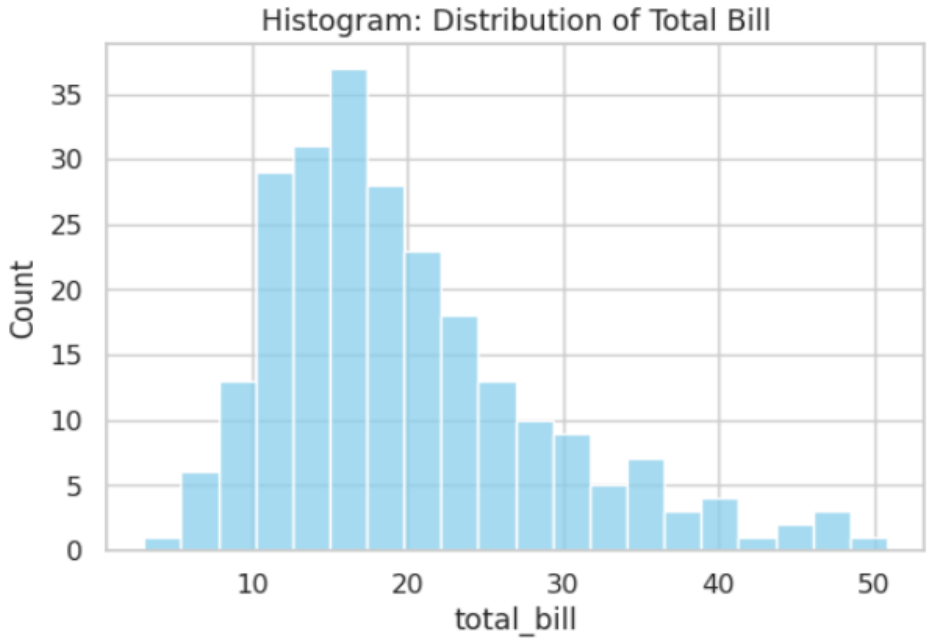
6. Histogram (Histplot)

plt.figure(figsize=(6,4))

sns.histplot(tips["total_bill"], bins=20, kde=False, color="skyblue")

plt.title("Histogram: Distribution of Total Bill")

plt.show()

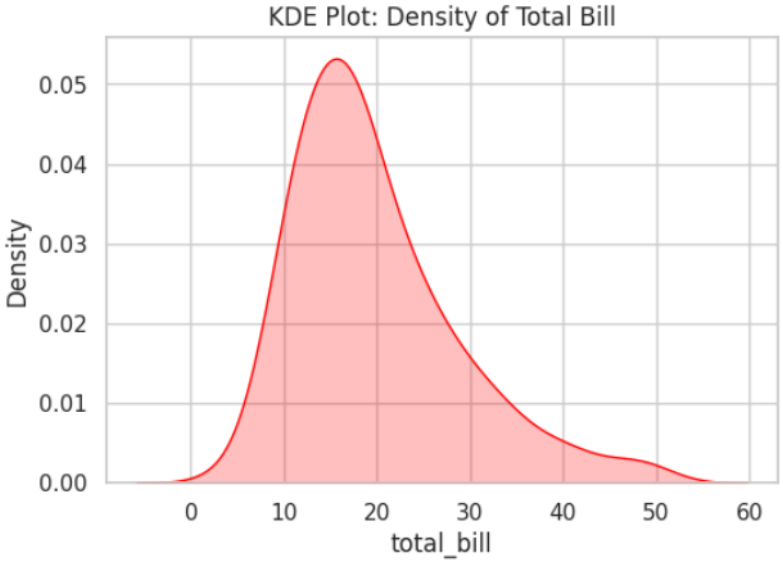


Description:
histplot() shows the frequency distribution of total bills.

- The bins=20 parameter controls the number of intervals.
- The kde=False hides the kernel density line (can be enabled if needed).
- The color parameter sets bar color.
- Useful for understanding distribution shape and spread.

7. KDE Plot

```
plt.figure(figsize=(6,4))
sns.kdeplot(tips["total_bill"], shade=True, color="red")
plt.title("KDE Plot: Density of Total Bill")
plt.show()
```



Description:
kdeplot() displays the Kernel Density Estimation for total_bill.

- The shade=True parameter fills the area under the curve.
- The curve represents a smoothed version of the histogram.
- Useful for identifying peaks and overall distribution shape.

8. Heatmap

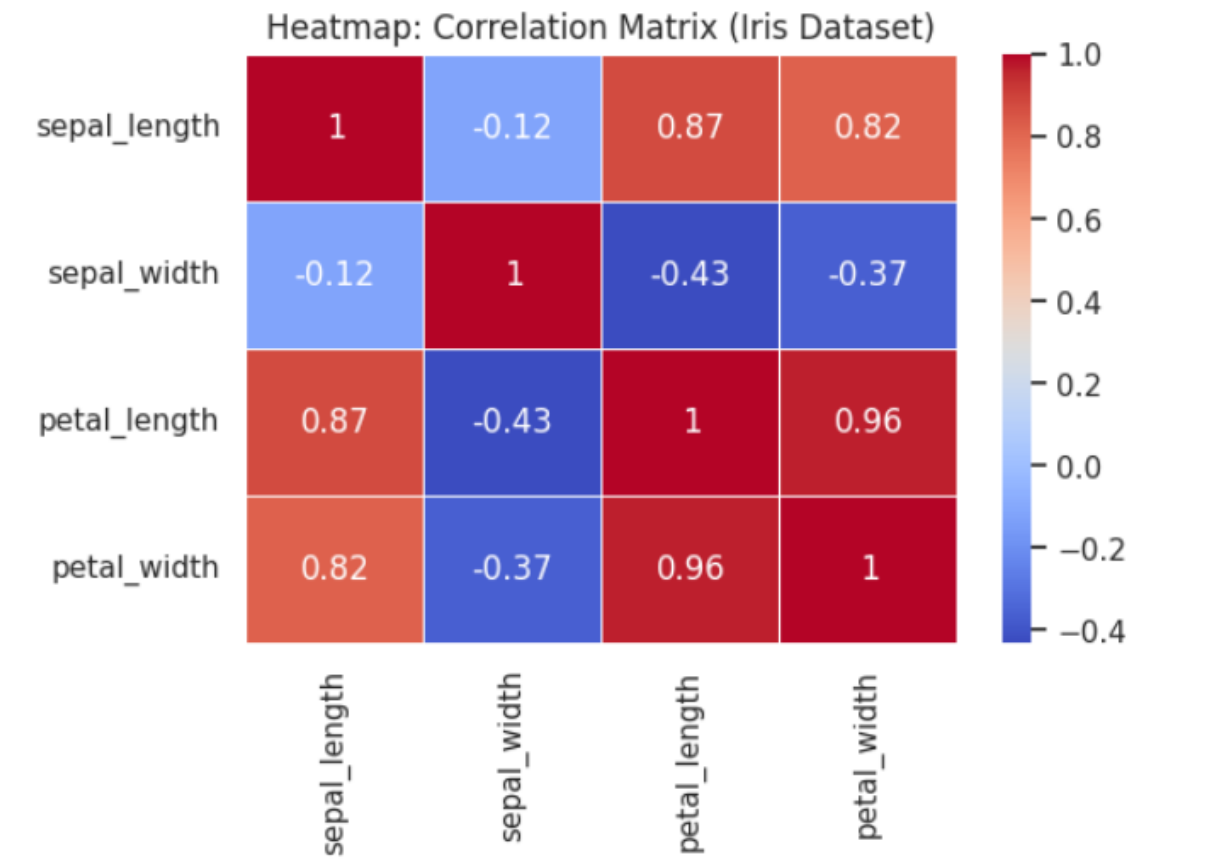
```
plt.figure(figsize=(6,4))

corr = iris.select_dtypes(include=["float64", "int64"]).corr()  # Only numeric columns

sns.heatmap(corr, annot=True, cmap="coolwarm", linewidths=0.5)

plt.title("Heatmap: Correlation Matrix (Iris Dataset)")

plt.show()
```



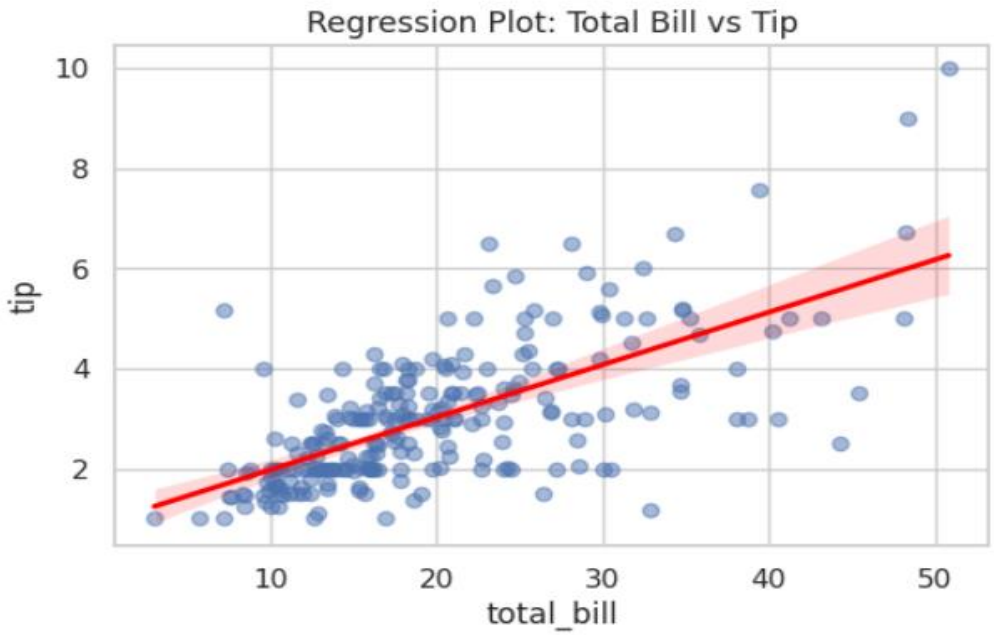
Description:

heatmap() visualizes the correlation matrix of numeric columns in the Iris dataset.

- annot=True displays correlation values inside cells.
- cmap="coolwarm" applies a blue-to-red color gradient.
- linewidths=0.5 adds spacing between cells.
- Darker colors indicate stronger positive/negative correlations.

9. Regression Plot

```
plt.figure(figsize=(6,4))
sns.regplot(x="total_bill", y="tip", data=tips,
scatter_kws={"alpha":0.5}, line_kws={"color":"red"})
plt.title("Regression Plot: Total Bill vs Tip")
plt.show()
```



Description:

regplot() shows the relationship between total bill and tip with a regression line.

- scatter_kws={"alpha":0.5} makes points semi-transparent.
- line_kws={"color":"red"} customizes the regression line color.
- Useful for analyzing linear trends and correlation strength between variables.

COMPARISON OF PANDAS AND SEABORN

□ Purpose

- **Pandas** → Mainly for data manipulation with some basic visualization.
- **Seaborn** → Mainly for data visualization with advanced statistical plots.

□ Plotting Capability

- **Pandas** → Limited to basic plots (.plot() for line, bar, histogram, scatter).
- **Seaborn** → Offers a wide variety (scatter, line, bar, box, KDE, heatmap, regression, etc.).

□ Customization

- **Pandas** → Customization needs extra work with Matplotlib**.**
- **Seaborn** → Provides beautiful defaults (colors, styles, palettes) with less effort.

□ Ease of Use

- **Pandas** → Quick plots for fast exploratory checks.
- **Seaborn** → Better for presentation-ready visuals and detailed analysis.

□ Integration

- **Pandas** → Works seamlessly with NumPy, Seaborn, Matplotlib.

- **Seaborn** → Built on Matplotlib, works smoothly with Pandas DataFrames.

CONCLUSION :

Both Pandas are essential tools in Python's data visualization ecosystem, each serving different needs. For **in-depth, highly customized visuals** → use **Seaborn**.For **fast, simple visualizations during analysis** → use **Pandas**.