Cheatcode to Exploratory Data Analysis (EDA)

It is an approach to analyzing and visualizing data sets to summarize their main characteristics, often with the help of statistical graphics and other data visualization methods. The primary goal of EDA is to uncover patterns, relationships, anomalies, and trends in the data, providing insights that can guide further analysis or decision-making processes.

Types of Exploratory Data Analysis

-- There are three main types of EDA:

- Univariate
- Bivariate
- Multivariate

Step 1: Understand the Data

- Familiarize yourself with the dataset, including the number of records, columns, and data types.
- Identify the target variable (if applicable) and understand its significance.

Importing Libraries

In [1]:
```
import pandas as pd
```

In [2]:
```
data = pd.read_csv("product_data.csv")
```

1. Data Size:

Question: How big is the data?

Approach: Check the shape of the dataset.

-- `shape` returns the number of rows and columns.

In [3]:
```
data.shape
```

Out[3]:
```
(60, 10)
```

2. Data Preview:

Question: What does the data look like?

Approach: Look at the first few rows of the dataset using head() or sample().

-- `head()` displays the first few rows of the dataset.

-- `sample()` displays the randomly selected items rows of the dataset.

In [4]:
```
data.head(5)
```

Out[4]:

	ProductID	ProductName	Category	Price	CustomerRating	PromotionType	CustomerAge	Shi
0	1	Smartphone X	Electronics	500	4.2	Discount	Young	
1	2	Fashion Jacket	Clothing	80	4.5	Bundle Offer	Adult	
2	3	Kitchen Blender	Home & Kitchen	120	3.8	None	Senior	
3	4	Running Shoes	Sports	60	4.0	Discount	Young	
4	5	LED TV	Electronics	700	4.3	None	Adult	

In [5]:
```
data.sample(5)
```

Out[5]:

	ProductID	ProductName	Category	Price	CustomerRating	PromotionType	CustomerAge	Sl
0	1	Smartphone X	Electronics	500	4.2	Discount	Young	
8	9	Sneakers	Sports	40	3.9	Discount	Adult	
28	29	Desk Lamp	Home & Kitchen	25	4.0	None	Young	
11	12	Yoga Mat	Sports	20	4.2	None	Adult	
53	224	Sleeping Bag	Outdoor & Recreation	40	4.5	None	Senior	

3. Data Types:

Question: What types of information are stored in each column?

Approach: Check the data types of each column using dtypes or info().

-- `info()` provides information about the dataset, including memory usage.

-- `dtypes` returns the data types of each column.

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60 entries, 0 to 59
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   ProductID       60 non-null     int64
 1   ProductName     60 non-null     object
 2   Category        60 non-null     object
 3   Price           60 non-null     int64
 4   CustomerRating  60 non-null     float64
 5   PromotionType   60 non-null     object
 6   CustomerAge     60 non-null     object
```

```
 7   ShippingTime          60 non-null     int64
 8   CustomerSatisfaction  60 non-null     int64
 9   ShippingDate          60 non-null     object
dtypes: float64(1), int64(4), object(5)
memory usage: 4.8+ KB
```

In [7]:

```python
data.dtypes
```

Out[7]:

```
ProductID                 int64
ProductName              object
Category                 object
Price                     int64
CustomerRating          float64
PromotionType            object
CustomerAge              object
ShippingTime              int64
CustomerSatisfaction      int64
ShippingDate             object
dtype: object
```

4. Missing Values:

Question: Are there any null or missing values in the data?

Approach: Check for the presence of missing values using isnull() or isna().

-- `isnull().sum()` or `isna().sum()` gives the total number of missing values per column.

-- `isnull().mean() * 100` provides the percentage of missing values.

In [8]:

```python
data.isna().sum()
```

Out[8]:

```
ProductID               0
ProductName             0
Category                0
Price                   0
CustomerRating          0
PromotionType           0
CustomerAge             0
ShippingTime            0
CustomerSatisfaction    0
ShippingDate            0
dtype: int64
```

In [9]:

```python
data.isnull().mean() * 100
```

Out[9]:

```
ProductID               0.0
ProductName             0.0
Category                0.0
Price                   0.0
CustomerRating          0.0
PromotionType           0.0
CustomerAge             0.0
ShippingTime            0.0
CustomerSatisfaction    0.0
ShippingDate            0.0
dtype: float64
```

5. Statistical Overview:

Question: How is the data distributed statistically?

Approach: Obtain statistical measures using describe().

-- `describe()` gives statistical measures for numerical columns.

In [10]:
```
data.describe().transpose()
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
ProductID	60.0	115.500000	101.220936	1.0	15.75	115.5	215.25	230.0
Price	60.0	69.383333	110.925550	8.0	23.75	40.0	70.00	700.0
CustomerRating	60.0	4.106667	0.277926	3.5	3.90	4.1	4.30	4.6
ShippingTime	60.0	2.966667	0.822701	2.0	2.00	3.0	4.00	4.0
CustomerSatisfaction	60.0	3.600000	0.994902	2.0	3.00	4.0	4.00	5.0

-- `Central Tendency` : This term refers to values located at the data's central position or middle zone.

The three generally estimated parameters of central tendency are mean, median, and mode.

-- Mean is the average of all values in data.

-- While the mode is the value that occurs the maximum number of times.

-- The Median is the middle value with equal observations to its left and right.

In [27]:
```
data["CustomerSatisfaction"].skew()
```

Out[27]:
```
-0.28629649843102617
```

6. Duplicate Data:

Question: Are there duplicate values?

Approach: Identify and remove duplicates using duplicated().

-- `duplicated().sum()` counts the number of duplicate rows.

-- `drop_duplicates()` removes duplicate rows.

In [11]:
```
print("Total duplicate values are '", data.duplicated().sum(), "'.")
```

```
Total duplicate values are ' 0 '.
```

7. Correlation Analysis:

Question: How are different columns related to each other?

Approach: Examine the correlation matrix and visualize it if needed.

-- `corr()` calculates the correlation matrix.

-- `heatmap()` visualizes the correlation matrix.

In [12]:
```
data.corr()
```

Out[12]:

	ProductID	Price	CustomerRating	ShippingTime	CustomerSatisfaction
ProductID	1.000000	-0.288716	-0.039644	0.047830	-0.213747
Price	-0.288716	1.000000	0.235056	-0.040903	0.264957
CustomerRating	-0.039644	0.235056	1.000000	-0.065726	0.818926
ShippingTime	0.047830	-0.040903	-0.065726	1.000000	-0.223640
CustomerSatisfaction	-0.213747	0.264957	0.818926	-0.223640	1.000000

8. Exploring Diversity:

Question: How many unique values are there in a specific column? Approach: Use the nunique() method to find the number of unique values in a particular column.

-- `nunique()` method returns the number of unique values for each column.

In [13]:
```
data["ProductName"].nunique()

# Note: Understand the diversity and variety within a categorical column. Higher unique v
```

Out[13]: 60

Step 2: Univariate Graphical Analysis

- It refers to the examination and exploration of a single variable in a dataset.
- It involves generating summary statistics, visualizations (e.g., histograms, box plots), and understanding the distribution and characteristics of that specific variable.

1. Categorical Data

In [14]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

a. Countplot

-- Purpose: Count occurrences of each category in a categorical variable.

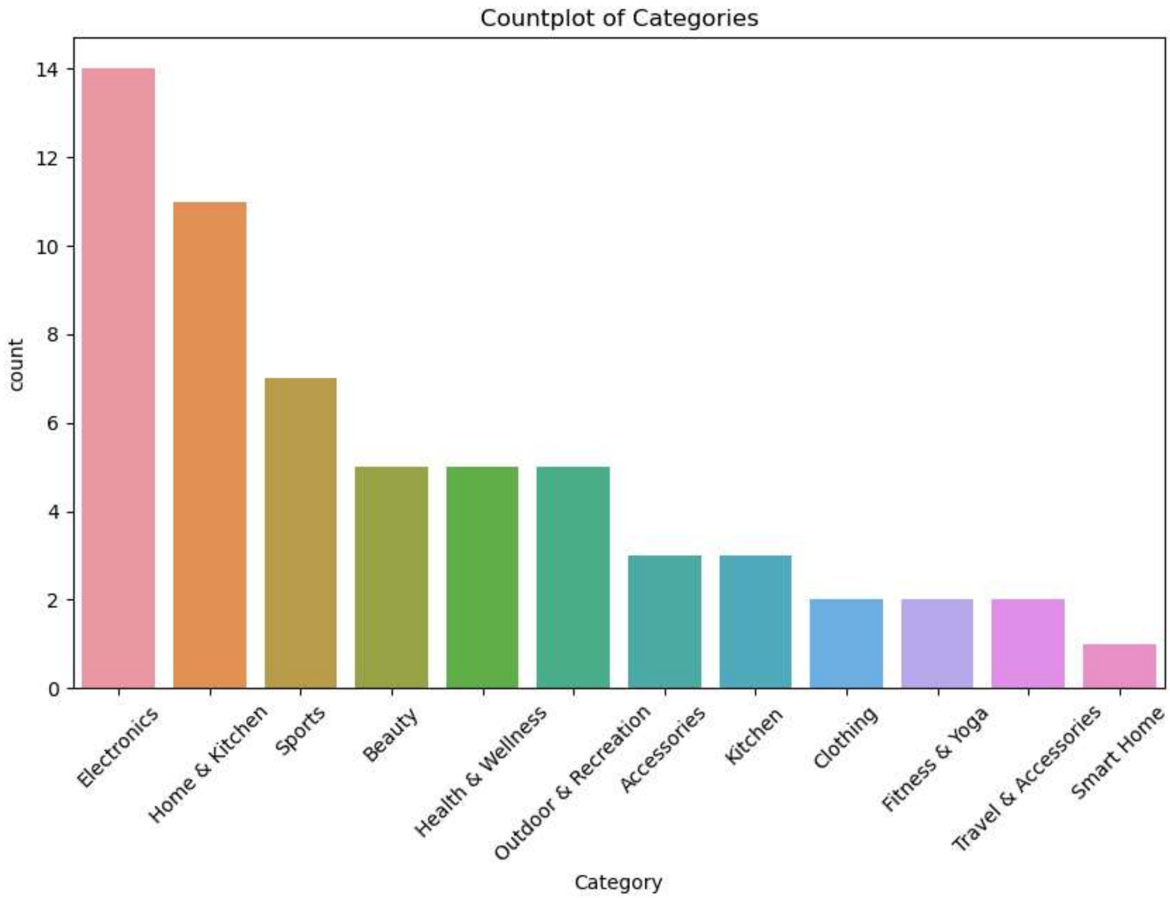
-- Usage: `sns.countplot(x='category_column', data=data)`

In [15]:
```
data["Category"].nunique()
```

Out[15]: 12

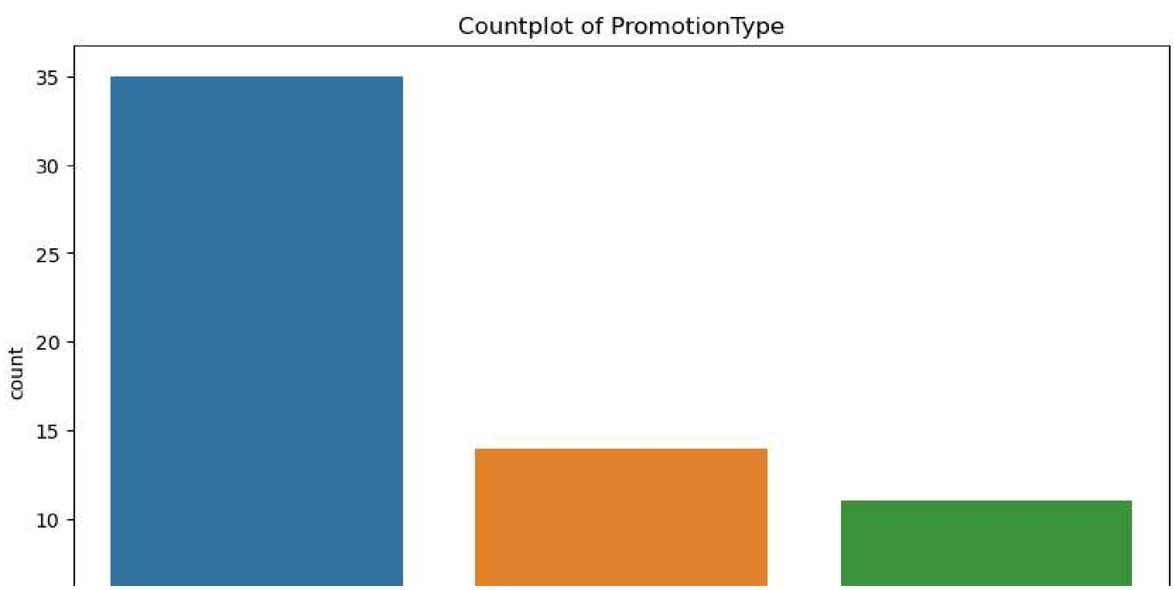
In [16]:

```
# Using a countplot to understand the "Category"
plt.figure(figsize=(10, 6))
sns.countplot(data=data, x="Category", order=data["Category"].value_counts().index)
plt.xticks(rotation=45)
plt.title("Countplot of Categories")
plt.show()
```



In [17]:

```
# Using a countplot to understand the "PromotionType"
plt.figure(figsize=(10, 6))
sns.countplot(data=data, x="PromotionType", order=data["PromotionType"].value_counts().in
plt.title("Countplot of PromotionType")
plt.show()
```



Note : It is used to show the counts of observations in each categorical bin using bars and easily compare the frequency of different categories within a single variable.

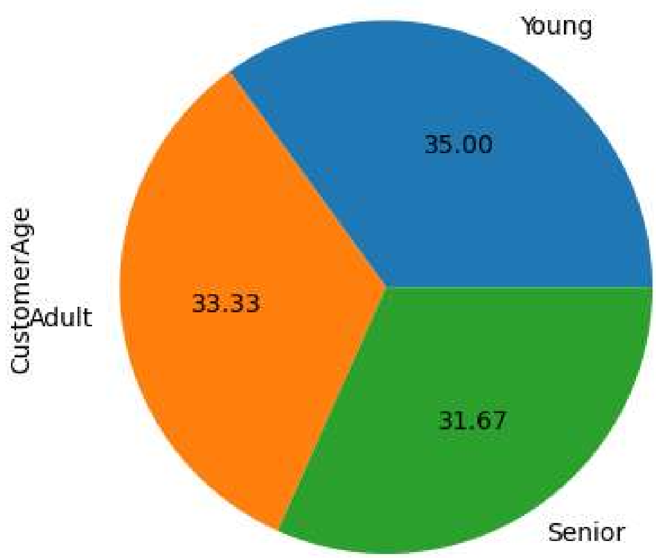
b. PieChart

-- Purpose: Display the proportion of each category in a categorical variable.

-- Usage: `plt.pie(data['category_column'].value_counts(), labels=data['category_column'].value_counts().index)`

In [20]:

```
# Using a piechart to understand the "CustomerAge"
data["CustomerAge"].value_counts().plot(kind="pie", autopct = "%.2f")
plt.show()
```



Note: A piechart provide a visual representation of how individual categories contribute to the total, to visualize the percentage of the data belonging to each category.

2. Numerical Data

a. Histogram

Histograms, a bar plot in which each bar represents the frequency (count) or proportion (count/total count) of cases for a range of values.

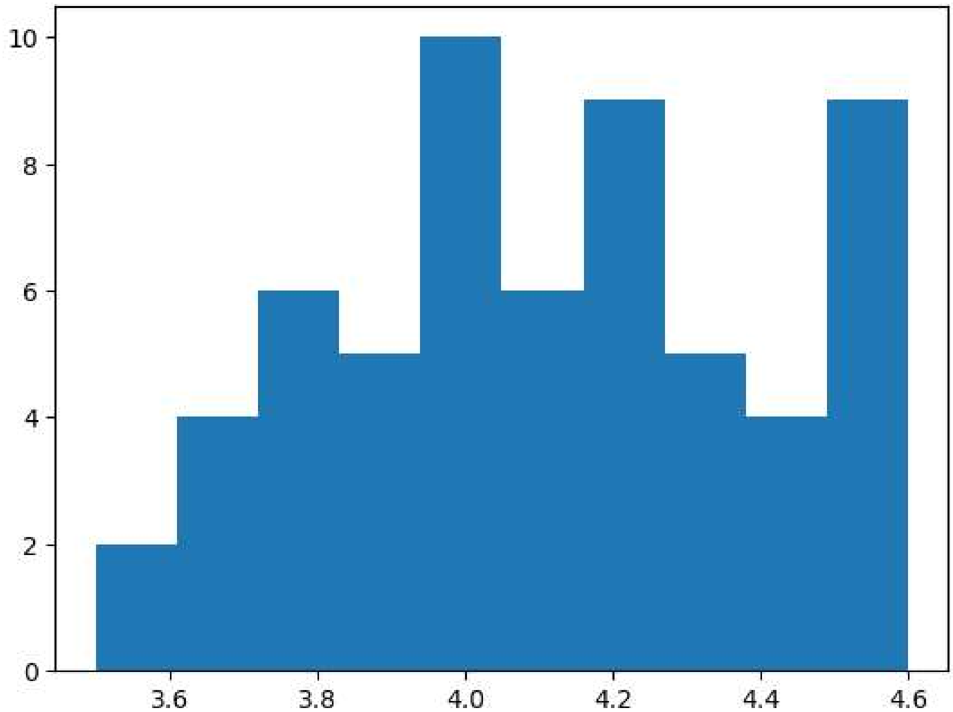
-- Purpose: Display distribution of a single numerical variable.

-- Usage: `plt.hist(data['column'])`

-- Usage: plt.hist(data['column'])

In [22]:
```
# Using a histplot to understand the "CustomerRating"
plt.hist(data["CustomerRating"])
```

Out[22]:
```
(array([ 2.,  4.,  6.,  5., 10.,  6.,  9.,  5.,  4.,  9.]),
 array([3.5 , 3.61, 3.72, 3.83, 3.94, 4.05, 4.16, 4.27, 4.38, 4.49, 4.6 ]),
 <BarContainer object of 10 artists>)
```



Note: Understand the overall shape of the data distribution, including any skewness, peaks, or gaps in the values.

b. Distplot

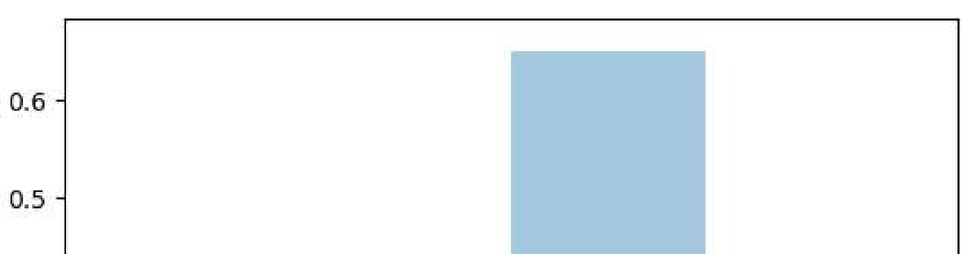
-- Purpose: Visualize distribution of a numerical column.

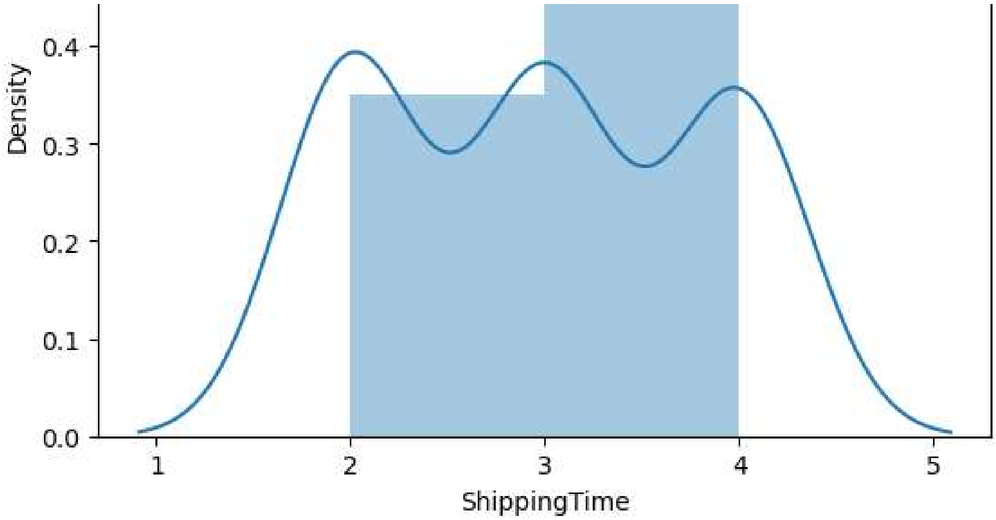
-- Usage: `sns.distplot(data['NumericalColumn'])`

In [25]:
```
# Using a distplot to understand the "ShippingTime"
sns.distplot(data["ShippingTime"])
```

```
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `
distplot` is a deprecated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar flexibility) or `hist
plot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[25]: `<AxesSubplot:xlabel='ShippingTime', ylabel='Density'>`





Note: It is beneficial for understanding the shape of the distribution/density, identifying outliers, and assessing the overall pattern of numerical data.

c. Box Plot (Box-and-Whisker Plots)

Box plots, which graphically depict the five-number summary of minimum, first quartile, median, third quartile, and maximum.

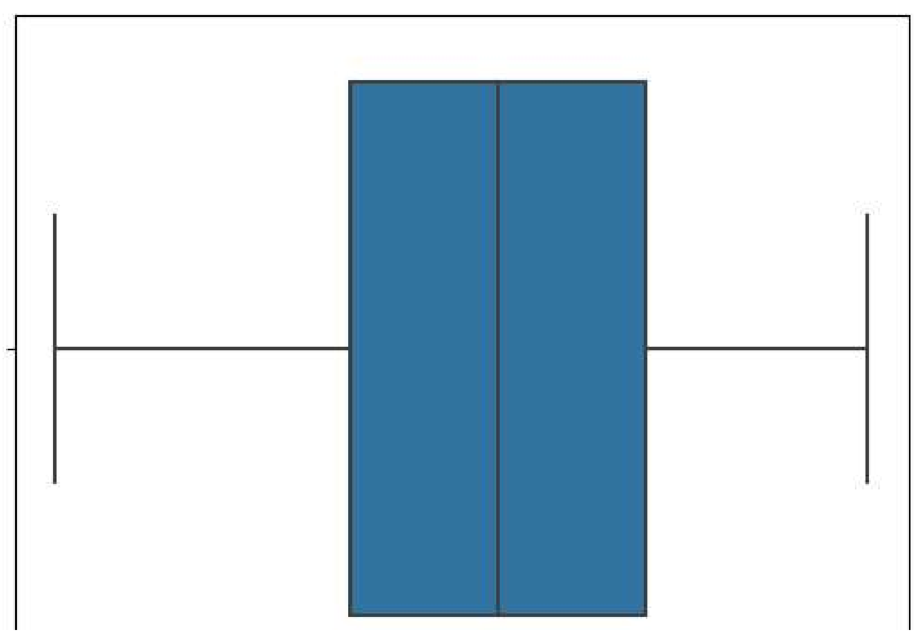
-- Purpose: Show summary statistics and identify outliers in numerical data.

-- Usage: `sns.boxplot(x='column', data=data)`

In [37]:
```
# Using a boxplot to understand the "CustomerRating"
sns.boxplot(data["CustomerRating"])
```

```
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  warnings.warn(
```

Out[37]: `<AxesSubplot:xlabel='CustomerRating'>`



Note: Visualize the distribution and central tendency of numerical data across different categories. To identify variations, outliers, and the overall spread of numerical values within distinct categorical groups.

Step 3: Bi/Multi-variate Graphical Analysis

Bivariate graphical analysis involves examining the relationship between two variables through visual representation. Multivariate Analysis is an extension of bivariate analysis which means it involves multiple variables at the same time to find correlation between them.

The main three types we will see here are:

- Numerical V/s Numerical
- Categorical v/s Numerical
- Categorical V/s Categorical data

In [33]:
```
tips_data = sns.load_dataset('tips')
```

In [63]:
```
tips_data.columns
```

Out[63]:
```
Index(['total_bill', 'tip', 'sex', 'smoker', 'day', 'time', 'size'], dtype='object')
```

In [73]:
```
tips_data
```

Out[73]:

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4
...	...	...	...	...	...	...	...
239	29.03	5.92	Male	No	Sat	Dinner	3
240	27.18	2.00	Female	Yes	Sat	Dinner	2
241	22.67	2.00	Male	Yes	Sat	Dinner	2
242	17.82	1.75	Male	No	Sat	Dinner	2
243	18.78	3.00	Female	No	Thur	Dinner	2

244 rows × 7 columns

I. Visualizing (Numerical - Numerical) Columns

I. Visualizing (Numerical - Numerical) Columns

1. Scatterplot

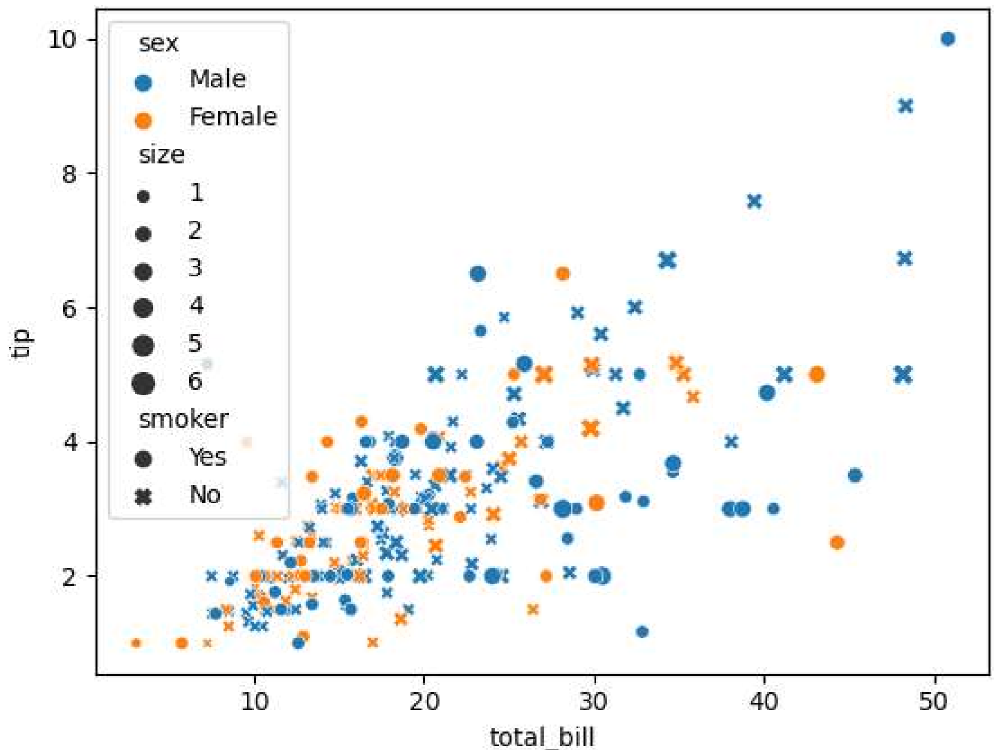
-- Purpose: Explore relationship between two numerical variables.

-- Usage: `plt.scatter(data['x_column'], data['y_column'])`

In [35]:

```
# Using a scatterplot to check the correlation between "total_bill, "tip", "sex, "smoker (
sns.scatterplot(tips_data['total_bill'],tips_data['tip'],hue=tips_data['sex'],style=tips_
xlabel='total_bill',
ylabel='tip'
```

```
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```



Note: Identify patterns, trends, or correlations between the plotted points, revealing insights into the association between the variables.

2. Lineplot

-- Purpose: Display relationship between two continuous variables.

-- Usage: `sns.lineplot(x='Variable1', y='Variable2', data=data)`

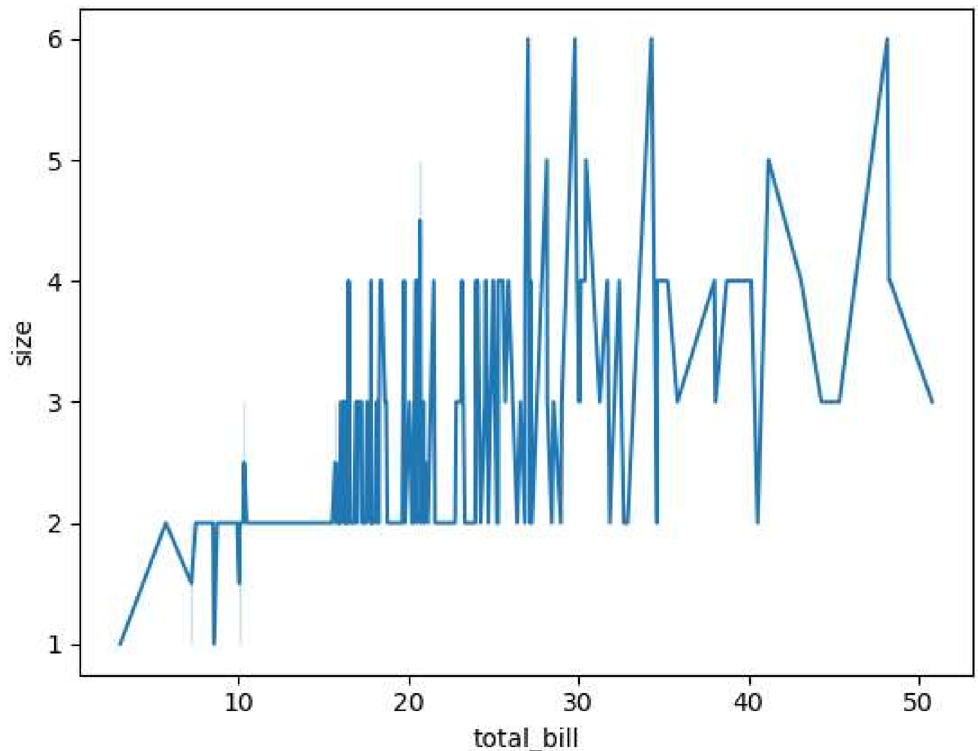
In [75]:

```
# Using a lineplot to check the relation between "total_bill" and "size"
sns.lineplot(tips_data['total_bill'],tips_data['size'])
```

```
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positional
```

```
argument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

Out[75]:
```
<AxesSubplot:xlabel='total_bill', ylabel='size'>
```



Note: It is commonly used for time-series data or any data where there is a meaningful order. It allows you to observe trends, patterns, or variations in the data.

II. Visualizing (Numerical - Categorical) Columns

1. Bar Plot

-- Purpose: Visualize the distribution of categorical variables.

-- Usage: `plt.bar(data['category_column'].value_counts().index, data['category_column'].value_counts())`

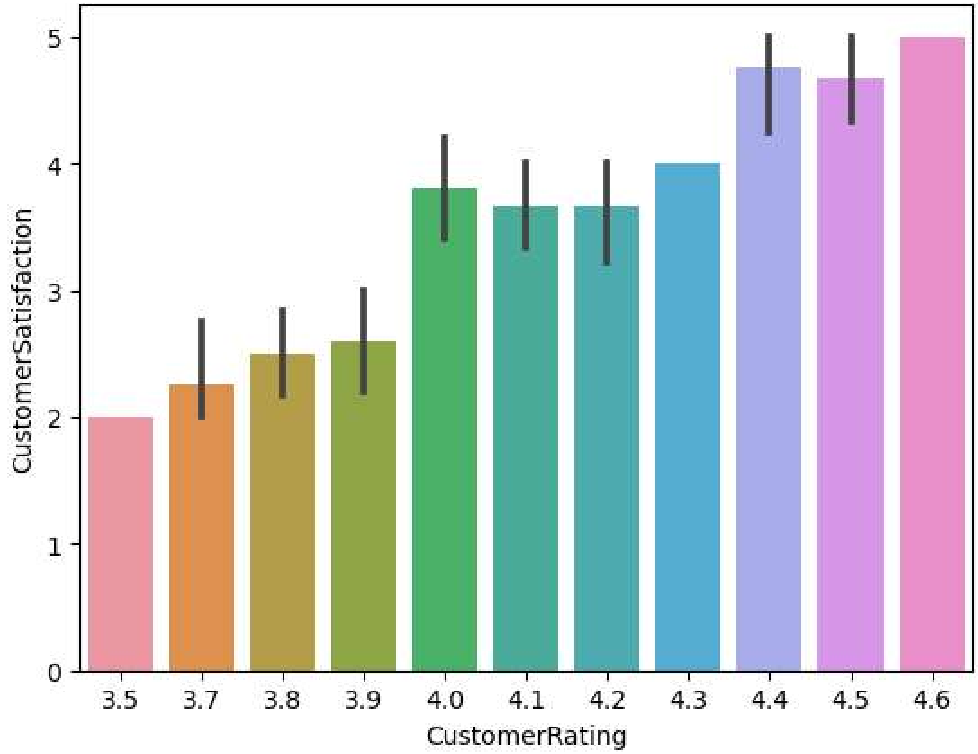
In [36]:
```
data.columns
```

Out[36]:
```
Index(['ProductID', 'ProductName', 'Category', 'Price', 'CustomerRating',
       'PromotionType', 'CustomerAge', 'ShippingTime', 'CustomerSatisfaction',
       'ShippingDate'],
      dtype='object')
```

In [40]:
```
# Using a barplot to check the correlation between "CustomerRating" and "CustomerSatisfac
sns.barplot(data["CustomerRating"], data["CustomerSatisfaction"])
```

```
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

Out[40]: <AxesSubplot:xlabel='CustomerRating', ylabel='CustomerSatisfaction'>



Note: Compare and highlight the differences in values between different categories using bars of varying lengths

2. Box Plot Grouped by Category:

-- Purpose: Compare the distribution of a numerical variable across different categories.

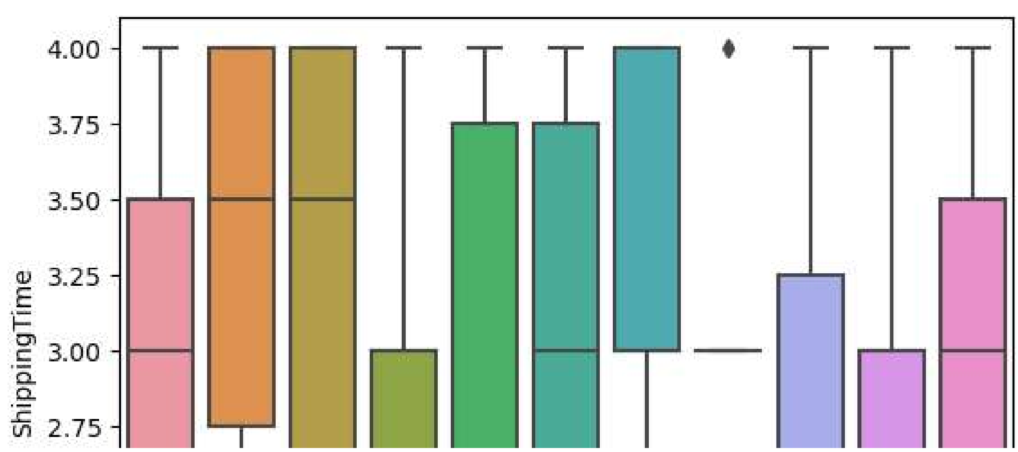
-- Usage: `sns.boxplot(x='category_column', y='numerical_column', data=data)`

In [44]:

```
# Using a boxplot to check the corelation between "CustomerRating" and "ShippingTime
sns.boxplot(data["CustomerRating"], data["ShippingTime"])
```

```
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

Out[44]: <AxesSubplot:xlabel='CustomerRating', ylabel='ShippingTime'>



Note: Identify variations, outliers, and the overall spread of numerical values within distinct categorical groups.

3. Distplot

-- Purpose: Compare distributions of numerical variables across categories.

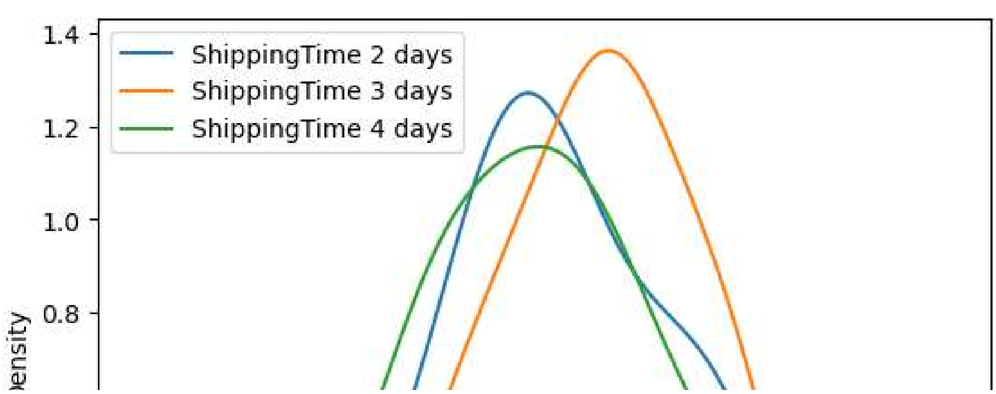
-- Usage: `sns.distplot(data['NumericalColumn'], hue=data['CategoricalColumn'], kde=False)`

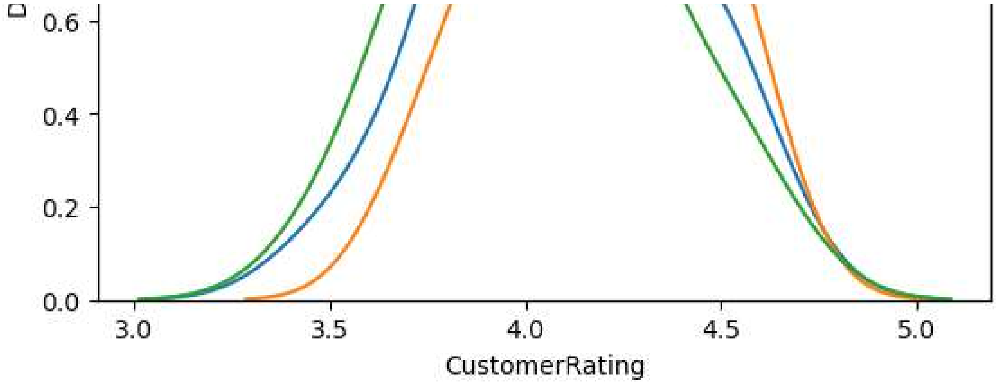
In [52]:

```python
# Using a distplot to check the compare between "ShippingTime" and "CustomerRating"

sns.distplot(data[data["ShippingTime"] == 2]["CustomerRating"],hist=False, label="Shippin
sns.distplot(data[data["ShippingTime"] == 3]["CustomerRating"],hist=False, label="Shippin
sns.distplot(data[data["ShippingTime"] == 4]["CustomerRating"],hist=False, label="Shippin
# Adding legend
plt.legend()
xlabel='CustomerRating',
ylabel='Density'
# Display the plot
plt.show()
```

```
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `
distplot` is a deprecated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar flexibility) or `kdep
lot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `
distplot` is a deprecated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar flexibility) or `kdep
lot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
c:\Users\lenovo\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `
distplot` is a deprecated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar flexibility) or `kdep
lot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```





Note: This variation helps in exploring how the distribution of numerical values varies among different groups or classes defined by a categorical variable.

III. Visualizing (Categorical - Categorical) Columns

1. HeatMap

-- Purpose: Display correlation coefficients between numerical variables.

-- Usage: `sns.heatmap(data.corr(), annot=True)`

In [64]:

```
pd.crosstab(tips_data['sex'],tips_data['smoker'])
```

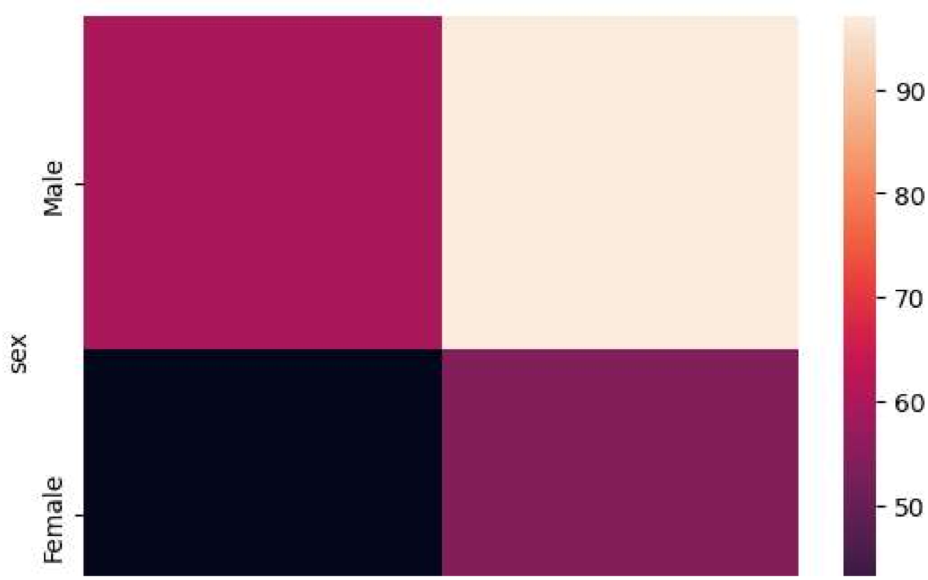
Out[64]:

smoker	Yes	No
sex		
Male	60	97
Female	33	54

In [65]:

```
# Using a heat map to check the correlation between "sex" and "smoker"
sns.heatmap(pd.crosstab(tips_data['sex'],tips_data['smoker']))
```

Out[65]: <AxesSubplot:xlabel='smoker', ylabel='sex'>



Note: It that shows the magnitude of the phenomenon as colour in two dimensions. The values of correlation can vary from -1 to 1 where -1 means strong negative and +1 means strong positive correlation.

In [67]:
```
(tips_data.groupby('sex').mean()['size']*100)
```

Out[67]:
```
sex
Male      263.057325
Female    245.977011
Name: size, dtype: float64
```

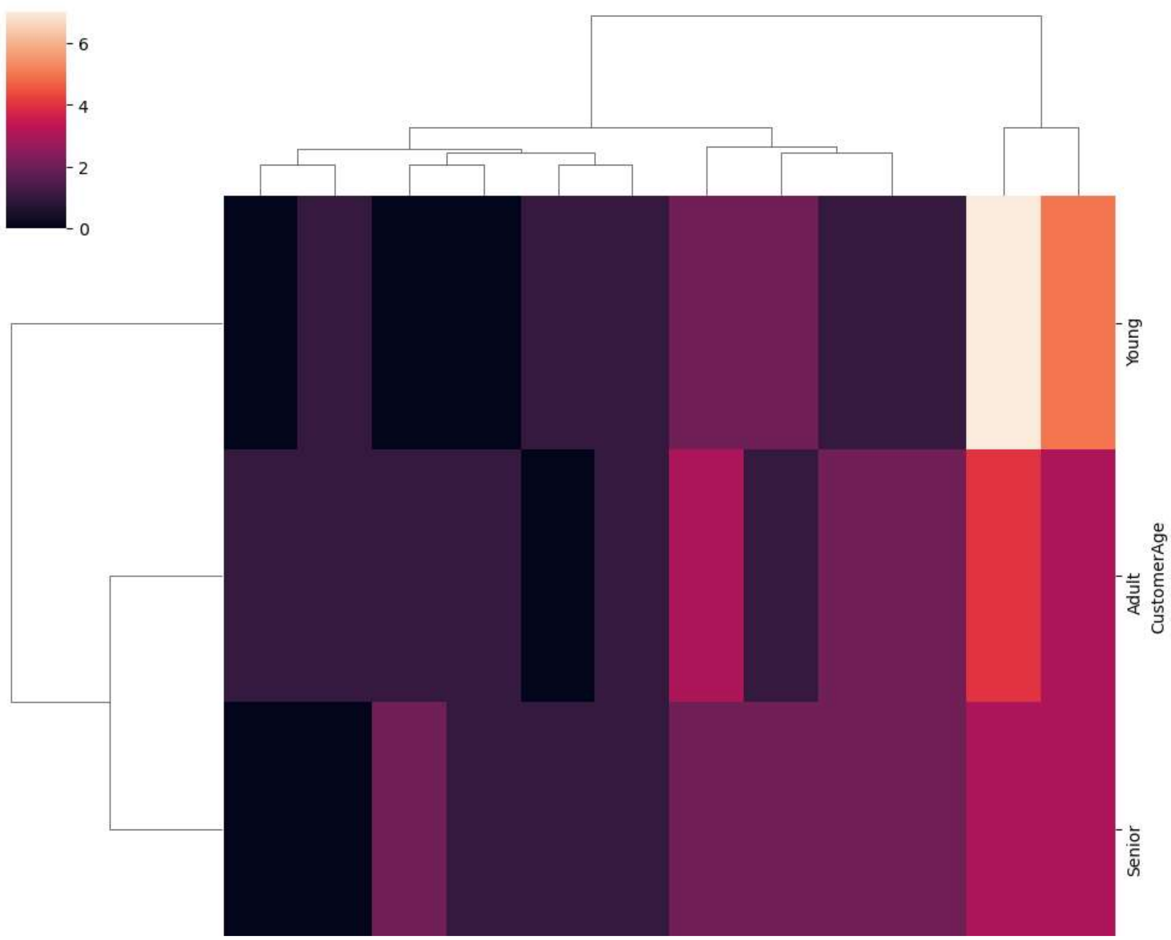
2. ClusterMap

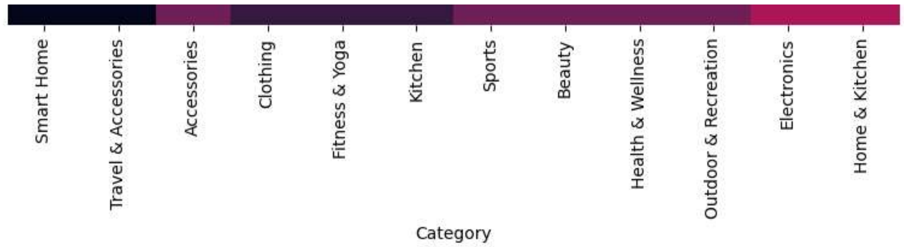
-- Purpose: Visualize clusters in dataset (especially hierarchical clustering).

-- Usage: `sns.clusterplot(data)`

In [69]:
```
# Using a cluster map to check the correlation between "CustomerAge" and "Category"
sns.clustermap(pd.crosstab(data['CustomerAge'],data['Category']))
```

Out[69]: <seaborn.matrix.ClusterGrid at 0x1d9aa4bfac0>





Note: Clusterplot is employed in clustering analysis, where data points are grouped based on their similarities. The plot assists in understanding the structure of clusters and relationships between data points.

IV. Visualizing All the Numerical Columns - Only

1. Pairplot

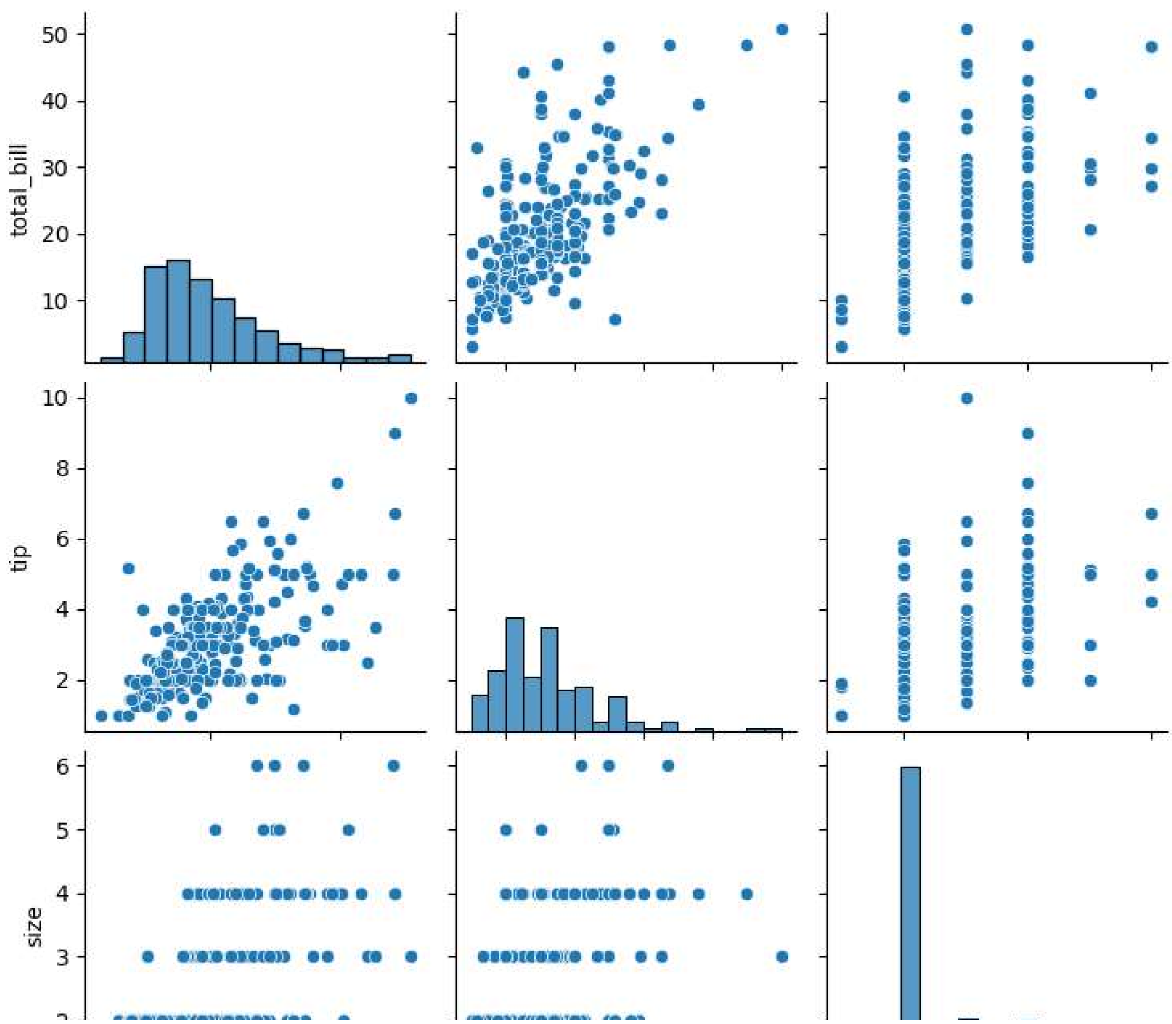
-- Purpose: Visualize pairwise relationships in a dataset.

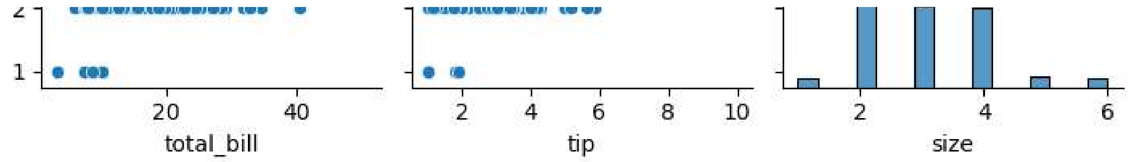
-- Usage: sns.pairplot(data)

In [71]:

```
# Using pairplot to plot the pairwise relationship btw each numerical columns present in
sns.pairplot(tips_data)
```

Out[71]: <seaborn.axisgrid.PairGrid at 0x1d9acdd29a0>





Note: The pairplot function creates a grid of Axes such that each variable in data will by shared in the y-axis across a single row and in the x-axis across a single column.

Key components of Exploratory Data Analysis include:

- `Data Summarization` : Describing the main characteristics of the data, such as central tendency, variability, and distribution.
- `Data Visualization` : Creating visual representations of the data to better understand its structure and identify patterns or trends.
- `Data Cleaning` : Identifying and handling missing or inconsistent data to ensure the accuracy of the analysis.
- `Statistical Analysis` : Using statistical methods to explore relationships between variables and test hypotheses.
- `Pattern Recognition` : Identifying outliers, clusters, or any unusual patterns in the data.
- `Hypothesis Generation` : Formulating initial hypotheses or questions about the data based on observed patterns.

Note: The dataset named as "data" utilized in this context is a synthetic toy dataset generated by ChatGPT solely for the purpose of visualization demonstration. Consequently, I refrain from providing comment on the insights derived from each graph.