Day 36 – Descriptive Statistics

In this notebook, I explored **Descriptive Statistics**, which is the branch of statistics used to **summarize and describe** data.

It helps us understand the main characteristics of a dataset through **measures of central tendency, shape of distribution, measures of variability, and data visualization.**

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1. Introduction

Descriptive statistics is the process of summarizing and describing the main features of a dataset. It provides a quick snapshot of:

- The center of the data (average, middle, most frequent value).
- The spread of the data (how much it varies).
- The shape of the data distribution (symmetry, skewness, peakness).
- The relationships between variables.

In machine learning, descriptive statistics is a necessary first step before modeling. It helps answer:

- What is the average value?
- How spread out is the data?
- Are there any outliers?
- Are variables related to each other?

Without descriptive statistics, it’s difficult to know whether the dataset is **clean, balanced, or biased**.

Example: Instead of looking at marks of 1,000 students, we can summarize with average marks, highest, lowest, and spread.

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2. Types of Data

Before applying descriptive statistics, you must identify **what type of data you’re working with**.

Type	Sub-Type	Description	Examples
Categorical	Nominal	Labels without order	Car brand: Audi, BMW, Honda
	Ordinal	Ordered categories	Customer satisfaction: Poor < Average < Excellent
Numerical	Discrete	Countable numbers	Number of children, Exam scores
	Continuous	Measurable values	Height, Weight, Temperature

Why it matters? Because the type of data decides which **statistical methods** can be applied. For example:

- Mean/median make sense for numerical data, but not for nominal categories.
- Mode is useful for categorical variables.

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3. Population vs Sample

In statistics, we differentiate between **population** (the entire dataset) and **sample** (a subset of the population).

Aspect	Population	Sample
Definition	The entire group of interest	A small portion taken from the population
Size	Usually very large	Smaller & manageable
Notation	Parameters (μ, σ^2, p)	Statistics ($\bar{x}$, s^2, $\hat{p}$)
Example	Marks of all students in India	Marks of 100 students from one school

In ML, we almost always work with **samples**, because analyzing the entire population is not feasible.

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4. Central Tendency

Central tendency refers to the **measure of the "center"** of the data distribution.

4.1 Mean (Average)

- It is the most common way to describe the “center” of the data.
- Calculated as the sum of all values divided by the number of values.
- Limitation: It is highly affected by outliers. For example, if salaries are [40k, 45k, 50k, 55k, 2M], the mean will be misleading.
- Sensitive to outliers (a single very high or low value can distort it).
- Best used for **symmetric data without extreme outliers**.

Example: Average salary in a company.

In [27]:
```
import numpy as np

data = [10, 20, 20, 30, 40, 100]
print("Mean:", np.mean(data))
```

```
Mean: 36.666666666666664
```

4.2 Median (Middle Value)

- The middle value when data is sorted in order.
- More robust than the mean because it is not influenced by extreme values.
- Not affected by outliers.
- Best for skewed data.

Example: Median house price is often reported instead of mean, because a few luxury houses can distort the average.

In [2]:
```
print("Median:", np.median(data))
```

```
Median: 25.0
```

4.3 Mode (Most Frequent Value)

- Represents the most frequently occurring value(s).
- Useful for categorical data (e.g., the most common shoe size or favorite subject).
- Data can be unimodal (1 mode), bimodal (2 modes), or multimodal (many modes).

Example: The most common shoe size sold in a store.

In [4]:
```
from scipy import stats
print("Mode:", stats.mode(data, keepdims=True).mode[0])
```

```
Mode: 20
```

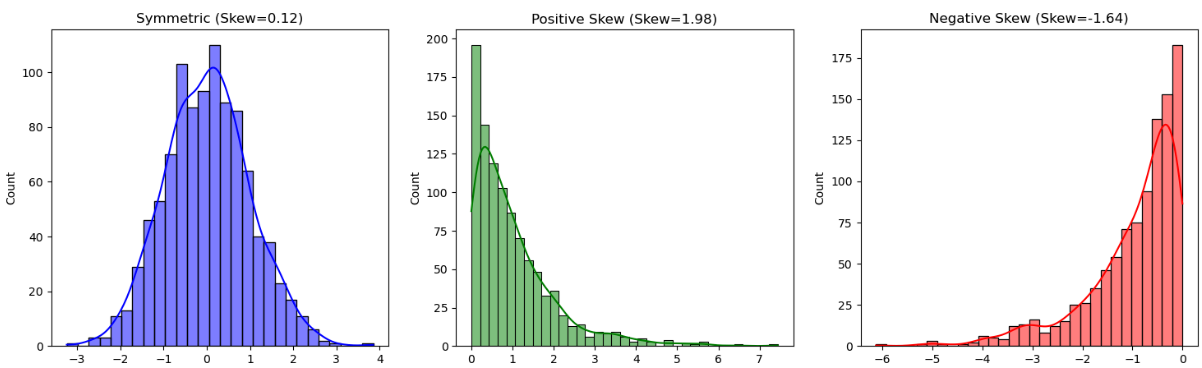
5. Shape of Distribution

5.1 Skewness

- Measures asymmetry of the distribution.
- Positive Skew (Right-Skewed) → Long tail on the right. Example: income distribution (a few very high earners).
- Negative Skew (Left-Skewed) → Long tail on the left. Example: age at retirement (most retire around 60–65, few much earlier).
- Zero Skew → Perfectly symmetric, like a normal distribution.

Type	Description	Example
Positive Skew	Tail on the right(mean > median > mode)	Income distribution
Negative Skew	Tail on the left (mean < median < mode)	Age of retirement
Zero Skew	Symmetric (mean = median = mode)	Heights of adults

In [28]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import skew

np.random.seed(42)

# Symmetric
data_symmetric = np.random.normal(loc=0, scale=1, size=1000)

# Positive Skew
data_pos_skew = np.random.exponential(scale=1, size=1000)

# Negative Skew
data_neg_skew = -np.random.exponential(scale=1, size=1000)

fig, axes = plt.subplots(1, 3, figsize=(18, 5))
sns.histplot(data_symmetric, kde=True, ax=axes[0], color="blue")
axes[0].set_title(f"Symmetric (Skew={skew(data_symmetric):.2f})")

sns.histplot(data_pos_skew, kde=True, ax=axes[1], color="green")
axes[1].set_title(f"Positive Skew (Skew={skew(data_pos_skew):.2f})")

sns.histplot(data_neg_skew, kde=True, ax=axes[2], color="red")
axes[2].set_title(f"Negative Skew (Skew={skew(data_neg_skew):.2f})")

plt.show()
```

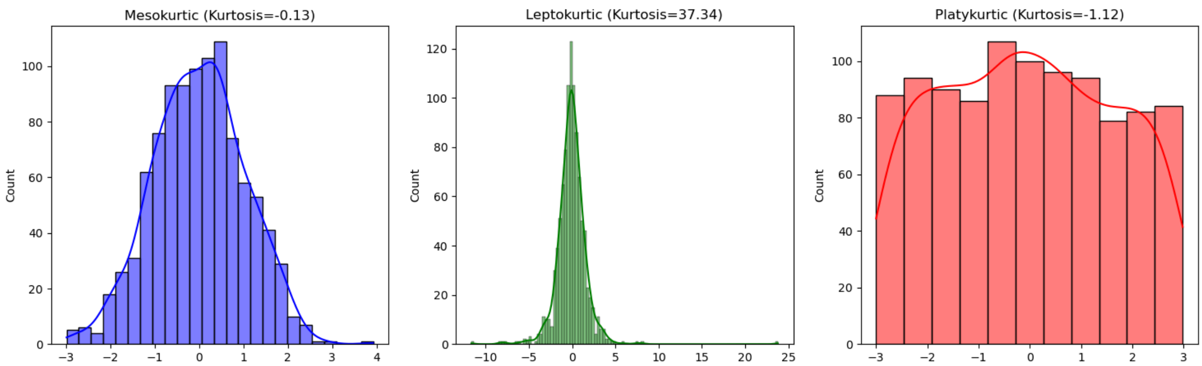


5.2 Kurtosis

- Measures the peakedness (tailedness) of the distribution.
- Mesokurtic (Normal) → Standard normal distribution, moderate tails.
- Leptokurtic (High Kurtosis) → Sharper peak, heavy tails, more outliers. Example: financial data.
- Platykurtic (Low Kurtosis) → Flatter distribution, light tails, fewer outliers.

Type	Kurtosis	Description
Leptokurtic	> 3	Tall peak, heavy tails
Platykurtic	< 3	Flat distribution
Mesokurtic	= 3	Normal bell curve

In [29]:
```
from scipy.stats import kurtosis


# Mesokurtic (Normal Distribution) -> Kurtosis ≈ 0
data_mesokurtic = np.random.normal(loc=0, scale=1, size=1000)

# Leptokurtic (t-distribution with low df -> heavy tails)
from scipy.stats import t
data_leptokurtic = t(df=3).rvs(1000)  # heavier tails

# Platykurtic (Uniform Distribution -> flat)
data_platykurtic = np.random.uniform(low=-3, high=3, size=1000)

fig, axes = plt.subplots(1, 3, figsize=(18, 5))
sns.histplot(data_mesokurtic, kde=True, ax=axes[0], color="blue")
axes[0].set_title(f"Mesokurtic (Kurtosis={kurtosis(data_mesokurtic):.2f})")

sns.histplot(data_leptokurtic, kde=True, ax=axes[1], color="green")
axes[1].set_title(f"Leptokurtic (Kurtosis={kurtosis(data_leptokurtic):.2f})")

sns.histplot(data_platykurtic, kde=True, ax=axes[2], color="red")
axes[2].set_title(f"Platykurtic (Kurtosis={kurtosis(data_platykurtic):.2f})")

plt.show()
```



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6. Measures of Spread (Variability)

These measure how spread out the data is around the center.

6.1 Range

- Difference between maximum and minimum values.

- Easy to calculate but highly sensitive to outliers.

Range = Max − Min

6.2 Variance - Average squared deviation from mean

- Tells how much the data values deviate from the mean on average.
- Squaring makes sure negative and positive differences don't cancel out.
- Formula: average of squared differences from the mean.

$\sigma^2 = \sum(xi - \mu)^2/N$

6.3 Standard Deviation (SD) - Square root of variance; shows spread in same units as data

- Square root of variance.
- More interpretable than variance since it is in the same unit as the data.
- Low Std → data is closely clustered around the mean.
- High Std → data is widely spread.

$\sigma = \sqrt{\text{Variance}}$

6.4 Coefficient of Variation (CV) - SD relative to mean (useful for comparing datasets)

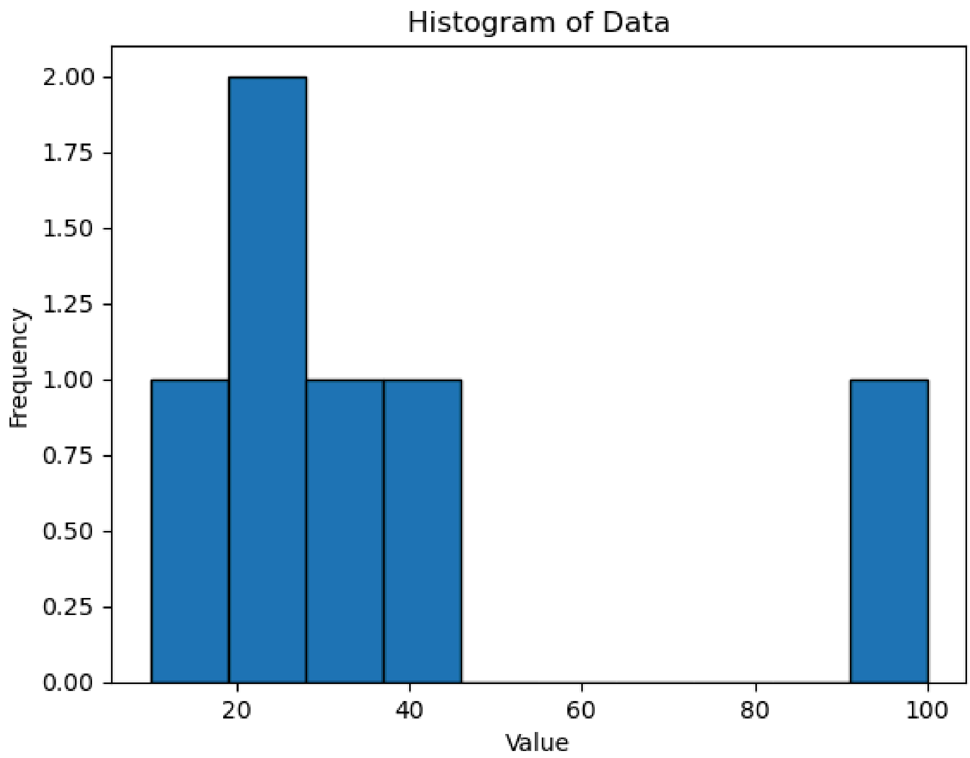
$CV = \sigma/\mu \times 100$

In [7]:
```
print("Variance:", np.var(data))
print("Standard Deviation:", np.std(data))
print("Coefficient of Variation:", (np.std(data)/np.mean(data))*100, "%")
```

```
Variance: 888.8888888888888
Standard Deviation: 29.814239699997195
Coefficient of Variation: 81.31156281817418 %
```

In [23]:
```
### Histogram (shows frequency distribution)

plt.hist(data, bins=10, edgecolor='black')
plt.title("Histogram of Data")
plt.xlabel("Value")
plt.ylabel("Frequency")
plt.show()
```



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7. Covariance & Correlation

7.1 Covariance - Shows the direction of relationship between two variables.

- Positive → both variables move in the same direction.
- Negative → one increases while the other decreases.
- Limitation: value is not standardized (depends on the scale of variables).

7.2 Correlation - Standardized covariance → between -1 and +1.

- +1 → perfect positive relationship.
- -1 → perfect negative relationship.
- 0 → no linear relationship.
- Easier to interpret than covariance because it is unit-free.
- Commonly visualized with a correlation matrix heatmap.

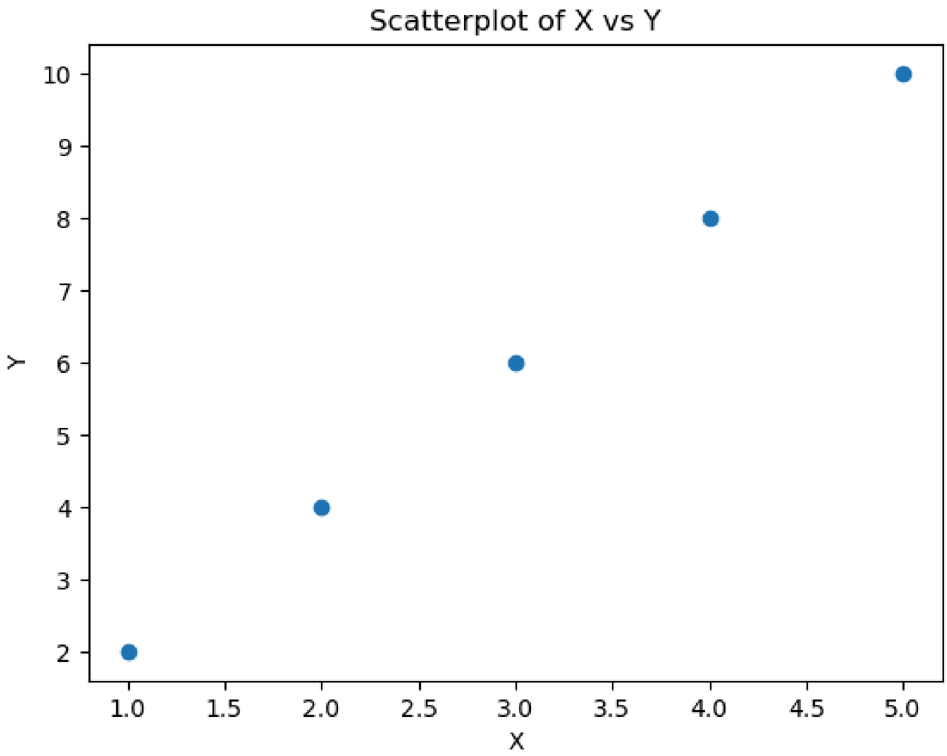
Example: Height and weight usually show positive correlation.

In [10]:

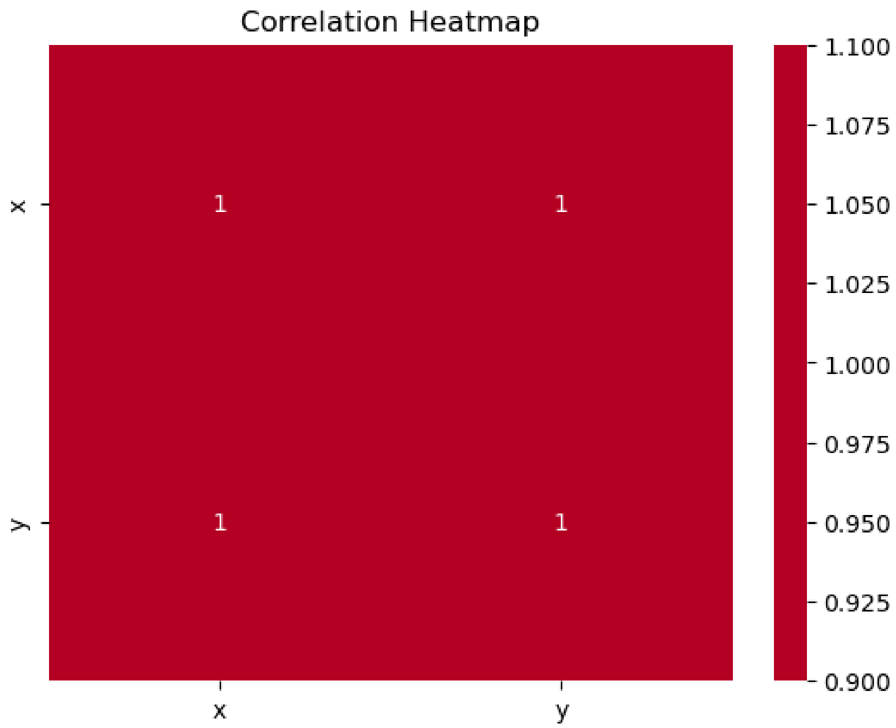
```
x = [1, 2, 3, 4, 5]
y = [2, 4, 6, 8, 10]

print("Covariance Matrix:\n", np.cov(x, y))
print("Correlation:", np.corrcoef(x, y))
```

```
Covariance Matrix:
 [[ 2.5   5. ]
 [ 5.   10. ]]
Correlation: [[1. 1.]
 [1. 1.]]
```

In [15]:
```
plt.scatter(x, y)
plt.title("Scatterplot of X vs Y")
plt.xlabel("X")
plt.ylabel("Y")
plt.show()
```



In [18]:
```
df_corr = pd.DataFrame({'x': x, 'y': y})
sns.heatmap(df_corr.corr(), annot=True, cmap='coolwarm', center=0)
plt.title("Correlation Heatmap")
plt.show()
```



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8. Summary Statistics with Pandas (.describe())

In [30]:
```python
df = pd.DataFrame({'Marks': data})
print(df.describe())
```

```
            Marks
count    6.000000
mean    36.666667
std     32.659863
min     10.000000
25%     20.000000
50%     25.000000
75%     37.500000
max    100.000000
```

Summary – Descriptive Statistics

In this notebook, I explored the fundamental concepts of **descriptive statistics**, which form the backbone of data analysis and machine learning.

Key Takeaways:

- **Measures of Central Tendency** (Mean, Median, Mode) help us understand the *center* of the data.
- **Measures of Spread** (Range, Variance, Standard Deviation) show how much the data is spread out or dispersed.
- **Shape of Distribution** is explained using **Skewness** (symmetry of data) and **Kurtosis** (peakedness and tails).
- **Covariance** indicates whether two variables move together, while **Correlation** quantifies both the *strength* and *direction* of their relationship.
- **Visualizations** such as histograms, boxplots, and heatmaps provide deeper insights into the data distribution and relationships.

Final Note:

Descriptive statistics provide the **first layer of understanding** in any dataset.
They summarize, visualize, and highlight the structure of data before applying advanced statistical models or machine learning algorithms.
Mastering these concepts ensures a strong foundation for further topics like **inferential statistics, hypothesis testing, and predictive modeling**.