

# Advanced Machine learning Mastering Course

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**2024**

Advanced Machine Learning 2024 by  
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# Machine Learning Diploma

- 1- Statistics
- 2- Pandas

## Agenda:

<b>1</b>	<b>Introduction to Statistics</b>
<b>2</b>	<b>Statistical Measures</b>
<b>3</b>	<b>Population VS Sample</b>
<b>4</b>	<b>Statistics using Pandas</b>
<b>5</b>	<b>Random Variable</b>
<b>6</b>	<b>Expected Value</b>
<b>7</b>	<b>Data Distribution</b>
<b>8</b>	<b>Quartiles</b>
<b>9</b>	<b>Covariance &amp; Correlation</b>
<b>10</b>	<b>Sample_Space, Events, Trials, &amp; Experiments</b>
<b>11</b>	<b>Independent &amp; dependent Events</b>

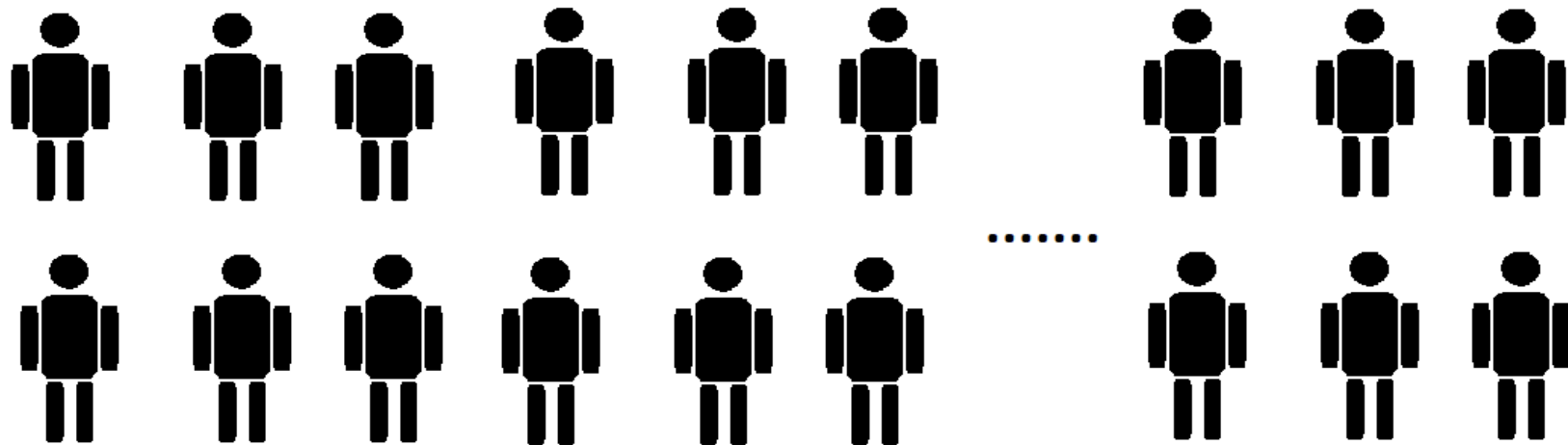
## Agenda:

<b>1</b>	<b>Pandas Basics</b>
<b>2</b>	<b>EDA Using Pandas</b>
<b>3</b>	<b>Data Manipulation</b>
<b>4</b>	<b>Indexing &amp; Slicing</b>
<b>5</b>	<b>Inserting/Dropping DataFrame Columns &amp; Rows</b>
<b>6</b>	<b>Null Values</b>

# 1. Introduction to Statistics

# What is Statistics?

- Statistics is the science of **summarizing** and describing the data.
- For example:
  - Suppose you have a dataset that contains about 100,000,000 observations about Egyptian people height.



# What is Statistics?

- If you want to describe how high Egyptian people are, you don't tell the height of each single person of the 100,000,000 people in the Egyptian **population**! But instead, you simply say "The **average height** of the Egyptian people is **170cm**".
- What you have just done is that you summarized the 100,000,000 observations into one number, **170cm**, which we call a **statistical measure**.

# 2. Statistical Measures



# Statistical

## Measures:

- A Statistical Measure is a number, that is calculated to **summarize** many records(rows) of information into **one single value**.
- Statistical measures can be used to get **statistical inference** about the population.
- Since statistical measures are related to data, let's first understand **types of the data**. Data can be:
  - **Continuous(Numerical)**.
  - Or **Discrete(Categorical)**.

## Continuous Vs Discrete:

### Continuous Data

- Is the data that has infinite number of possible values.
- Also known as **Numerical data**.
- Continuous data could be:
  - **Float dtypes**; such as, **Salary** or **Weight**.
  - **Int dtypes** that have large number of possible unique values; such as, **number-of-hours-played**.

### Discrete Data

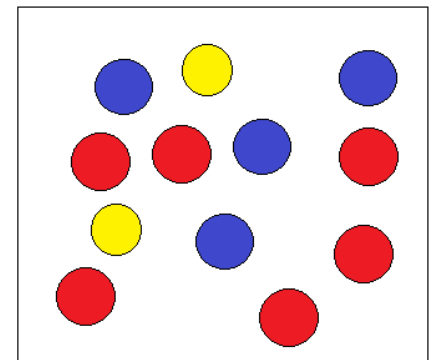
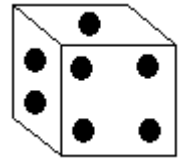
- Is the data that has finite number of possible values
- Also known as **Categorical data**.
- Continuous data could be:
  - **String dtypes**; such as, **City-name**.
  - **Int dtypes** that have small number of possible unique values; such as, **number-of-children**.

# Popular Statistical Measures:

- 1. Probability.**
- 2. Measures of Central Tendency.**
- 3. Measures of dispersion (Deviation).**

## Probability:

- Is the ratio between frequency of the unique-value & total number of samples.
- Example1, suppose you have a dice:
  - The unique possible values are; 1, 2, 3, 4, 5, 6.
  - Probability of 1 =  $1 / 6 = .167$
- Example1, suppose you have the box of balls on the right:
  - The unique possible values are; blue, red, yellow.
  - Probability of blue =  $4 / 12 = .333$



# Measures of Central Tendency:

- Are the measures used to represent the average values of the data we have.
- There are three main measures of central tendency:
  - Mean.
  - Median.
  - Mode.
- Mean & Median are used to summarize Numerical data, while Mode is used to summarize categorical data.

# Measures of Central Tendency (Mean):

- Mean is the ratio between the summation of all values and total number of observation in the data.
- For example, suppose you have the following set of observation:
  - [5, 2, 3, 10, 20].
  - $\text{Mean} = (5+2+3+10+20) / 5 = 8.$
- Mean is used with **numerical data** that doesn't contain **extreme values (outliers)**, because mean is sensitive to outliers.
- We use symbol  $\mu$  to represent the mean.

# Measures of Central tendency

## (Median):

- Median is the **middle value** in the data after being **sorted**.
- Steps:
  - First **sort** the data, then Find the number in the **middle**, and this is your **Median**. If there are two number in the middle, then the **Median** is the average between them.
- Median is used with **numerical data** that contains **outliers**.

### Example1

- Suppose you have this set of observations: [5, 2, 3, 10, 20] .
- First sort them ➔ [2, 3, 5, 10, 20].
- Median = 5.

### Example2

- Suppose you have this set of observations: [3, 5, 2, 3, 10, 20] .
- First sort them ➔ [2, 3, 3, 5, 10, 20].
- Median =  $(3+5) / 2 = 4$ .

# Measures of Central Tendency

## (Mode):

- Mode is the most frequent value in the data.
- Mode is used with categorical data.

### Example1

- Suppose you have this set of observations:  
[5, 2, 3, 3, 2, 3, 1, 5, 9, 8, 3, 1, 7, 6].
- Mode= 5.

### Example2

- Suppose you have this set of observations:  
["Cairo", "Alex", "Aswan", "Alex",  
"Alex", "Mansoura", "Alex", "Cairo"].
- Mode = "Alex".



# Measures of Dispersion:

- Are measures used to measure the spread of the data.
- Also Called **Measures of Deviation**.
- For example, suppose you have the following two sets of numbers:
  - Set1 = [5, 5, 5, 5, 5] & Set2 = [-5, 0, 5, 10, 15].
  - The two sets contains the same value of mean = 5.
  - But as you can see Set2 has more spread than set1.
  - So, we need a way to measure the amount of spread.

# Measures of Dispersion:

- There are two main measures of Dispersion:
  - Variance.
  - Standard deviation.
- Standard Deviation is the most used as a measure of dispersion, that's why we call it standard, however variance is a popular measure too and has its applications.

# Measures of Dispersion (Variance):

- Is the average of all differences between each value in the data & the mean of this data.
- $\sigma^2$  is used to represent the Variance.
- Formula:  $\sigma^2 = \frac{\sum_{i=1}^N (x_i - \mu)^2}{N}$ , where  $x_i$  represents the  $i^{\text{th}}$  value in the data, and  $N$  represents total number of values.

# Measures of Dispersion (Variance):

### Example1

- Data = [5, 5, 5, 5, 5] .
- $\mu = (5+5+5+5+5) / 5 = 5.$
- $\sigma^2 = ((5-5)^2 + (5-5)^2 + (5-5)^2 + (5-5)^2 + (5-5)^2) / 5 = 0.$
- Variance = 0

### Example2

- Data = [-5, 0, 5, 10, 15].
- $\mu = (-5+0+5+10+15) / 5 = 5.$
- $\sigma^2 = ((5--5)^2 + (5-0)^2 + (5-5)^2 + (5-10)^2 + (5-15)^2) / 5 = 50.$
- Variance = 50.

# Measures of Dispersion (Standard Deviation):

- Is the square root of the variance.
- $\sigma$  is used to represent the Standard deviation.
- Formula:  $\sigma = \sqrt{\frac{\sum_{i=1}^N (x_i - \mu)^2}{N}}$ , where  $X_i$  represents the  $i^{\text{th}}$  value in the data, and  $N$  represents total number of values.
- Standard deviation is always preferred over variance as a measure of dispersion, and the reason is that unlike variance, standard deviation is not sensitive to outliers.

# Measures of Dispersion (Standard Deviation):

### Example1

- Data = [5, 5, 5, 5, 5] .
- $\mu = (5+5+5+5+5) / 5 = 5.$
- $\sigma^2 = ((5-5)^2 + (5-5)^2 + (5-5)^2 + (5-5)^2 + (5-5)^2) / 5 = 0.$
- $\sigma = \sqrt{\sigma^2} = \sqrt{0} = 0.$
- Standard deviation = 0.

### Example2

- Data = [-5, 0, 5, 10, 15].
- $\mu = (-5+0+5+10+15) / 5 = 5.$
- $\sigma^2 = ((5--5)^2 + (5-0)^2 + (5-5)^2 + (5-10)^2 + (5-15)^2) / 5 = 50.$
- $\sigma = \sqrt{\sigma^2} = \sqrt{50} = 7.07$
- Standard deviation = 7.07

# 3. Population Vs Sample

# What is Population?

- **Population** is the whole complete set of observation.
- For example:
  - In Egypt, we have 100,000,000 people if we could collect 100,000,000 observations about their heights, then the population = heights-of-100,000,000-people.
- But could we really collect this huge number of observations? Do we have the resources(money & time) to do this?!
- The answer is No! and here comes the concept of **Sample**.



# What is Sample?

- A sample is a randomly chosen subset from the population, that represents the whole set of observations without having to actually deal with the whole population.
- For example:
  - In Egypt, we could represent the 100,000,000 people with only 1000,000 observations collected randomly.
- The larger the sample is, the more strongly it represents the population, but the harder to collect and work on.

# 4. Statistics using Pandas

# What is Pandas?

- You can apply statistics using **Numpy** or **Pandas**.
- **Pandas** is a library **built on Numpy**, which is **more suitable** for dealing with **tabular datasets**.
- In Pandas tabular data is read as **DataFrame** which is the main **datatype** in pandas that represents **matrix**.
- In pandas, **vectors** are represented by a **datatype** called **Series**.
- Each **row or column** in the **DataFrame** is a **Series**.

## Reading Tabular Data:

- Tabular datasets come in **two main file formats**:

### CSV files

```
1 import pandas as pd
2 df = pd.read_csv("file.csv")
3 df
```

	Length	Width	City	Price
0	20	10	Cairo	5000000
1	15	15	Alex	4000000
2	30	20	Aswan	1500000
3	10	50	Alex	8000000
4	5	15	Giza	800000
5	12	10	Alex	1000000
6	5	30	Luxor	500000
7	7	20	Aswan	700000
8	20	40	Alex	9000000
9	8	20	Cairo	900000

### XLSX files

```
1 import pandas as pd
2 df = pd.read_excel("file.xlsx")
3 df
```

	Length	Width	City	Price
0	20	10	Cairo	5000000
1	15	15	Alex	4000000
2	30	20	Aswan	1500000
3	10	50	Alex	8000000
4	5	15	Giza	800000
5	12	10	Alex	1000000
6	5	30	Luxor	500000
7	7	20	Aswan	700000
8	20	40	Alex	9000000
9	8	20	Cairo	900000
10	6	14	Giza	6000000

## Pandas for Statistics:

<b>Mean of Length Column</b>  <pre>1 df.Length.mean()</pre> <p>12.545454545454545</p>	<b>Median of Length Column</b>  <pre>1 df.Length.median()</pre> <p>10.0</p>	<b>Mode of City Column</b>  <pre>1 df.City.mode()</pre> <p>0 Alex</p>
<b>Variance of Length Column</b>  <pre>1 df.Length.var()</pre> <p>63.672727272727265</p>	<b>Standard-Deviation of Length column</b>  <pre>1 df.Length.std()</pre> <p>7.979519238195198</p>	

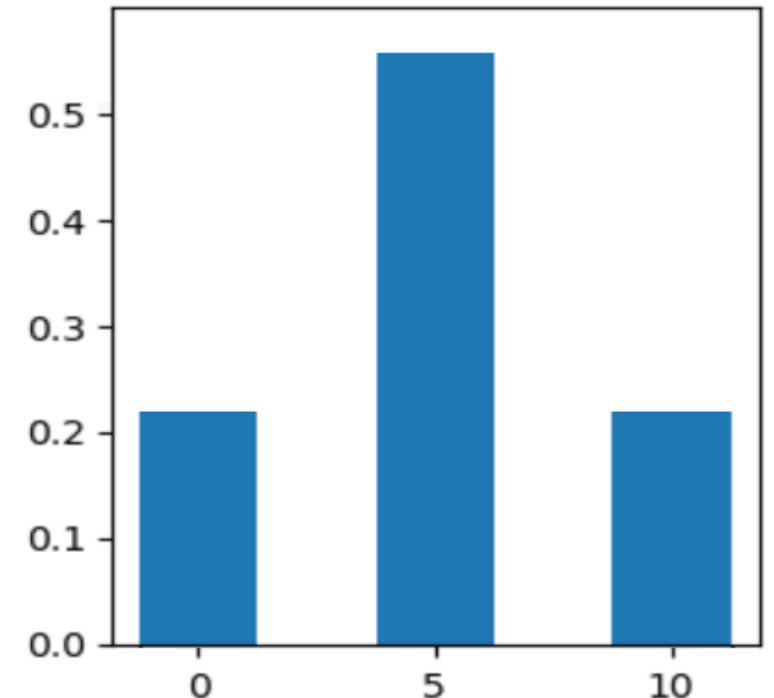
# 7. Data Distribution

# What is Data Distribution?

- Data Distribution is a way to describes how the **observations** are **distributed** or **spread** across the **unique values** of the data.
- In other words, Data Distribution represents how much each unique value occurs in the data or how frequent each unique value is.

# Data Distribution Example:

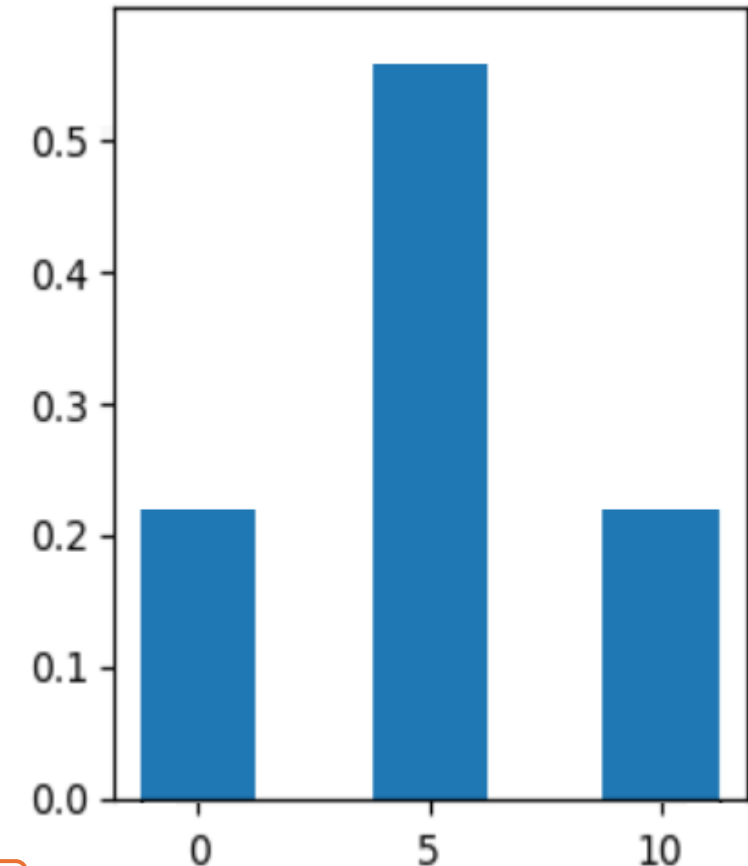
- If you have Random Variable  $X = [0, 5, 5, 5, 10, 0, 5, 10, 5]$ .
- Then the data distribution of this random variable is distributed as following:
  - 22.2% of the data belong to ( $X=0$ ).
  - 55.6% of the data belong to ( $X=5$ ).
  - 22.2% of the data belong to ( $X=10$ ).





# Data Distribution Histogram:

- It's common to represent the data distribution as a graph called **Histogram**.
- A **histogram** is a 2-dimensional graph, where:
  - X-axis represents the unique values in the Random Variable.
  - Y-axis represents the probability of each unique value.
  - Each unique value has a bar (rectangle) whose height is equal to the probability.

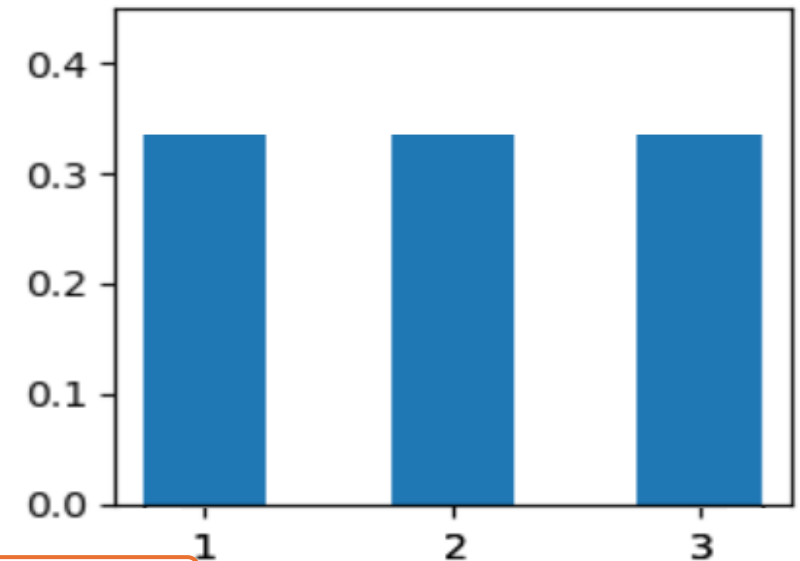


# Data Distribution Types:

- There are so many types of data distribution, however we will cover the most important & most popular ones:
  - Uniform Distribution.
  - Normal Distribution.
  - Right-Skewed Distribution.
  - Left-Skewed Distribution.

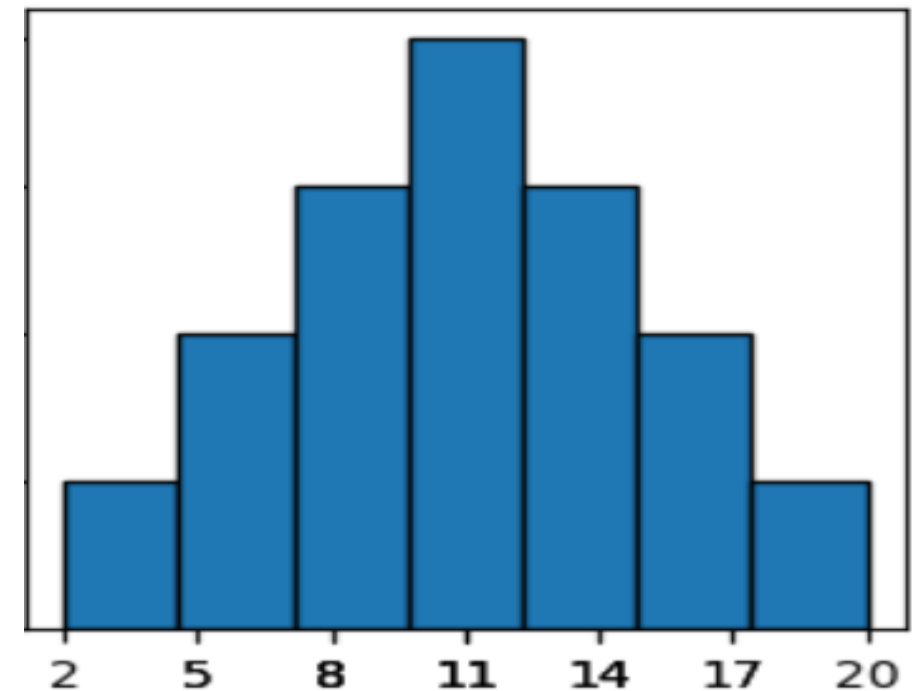
# Uniform Distribution:

- Is Data Distribution where observations are equally distributed among the unique values. In other words, all the unique values occur equally with the same frequency.
- For example, Suppose you have  $X = [1, 2, 2, 3, 1, 3]$ , then the distribution is:
  - 33.3% of the data belong to  $(X=1)$ .
  - 33.3% of the data belong to  $(X=2)$ .
  - 33.3% of the data belong to  $(X=3)$ .



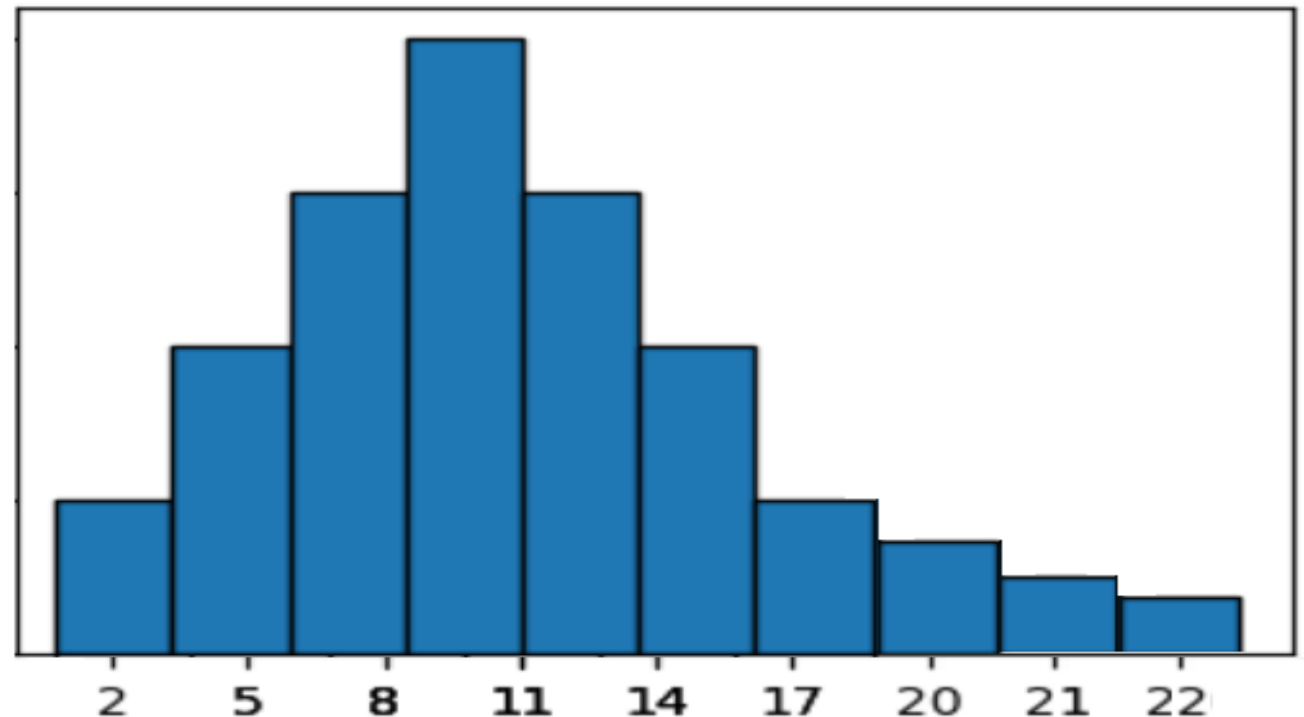
# Normal Distribution:

- Is Data Distribution where observations are distributed around the mean the most, with fewer values occurring farther away from the mean in both directions.
- The distribution histogram takes a shape of **symmetric bell**.



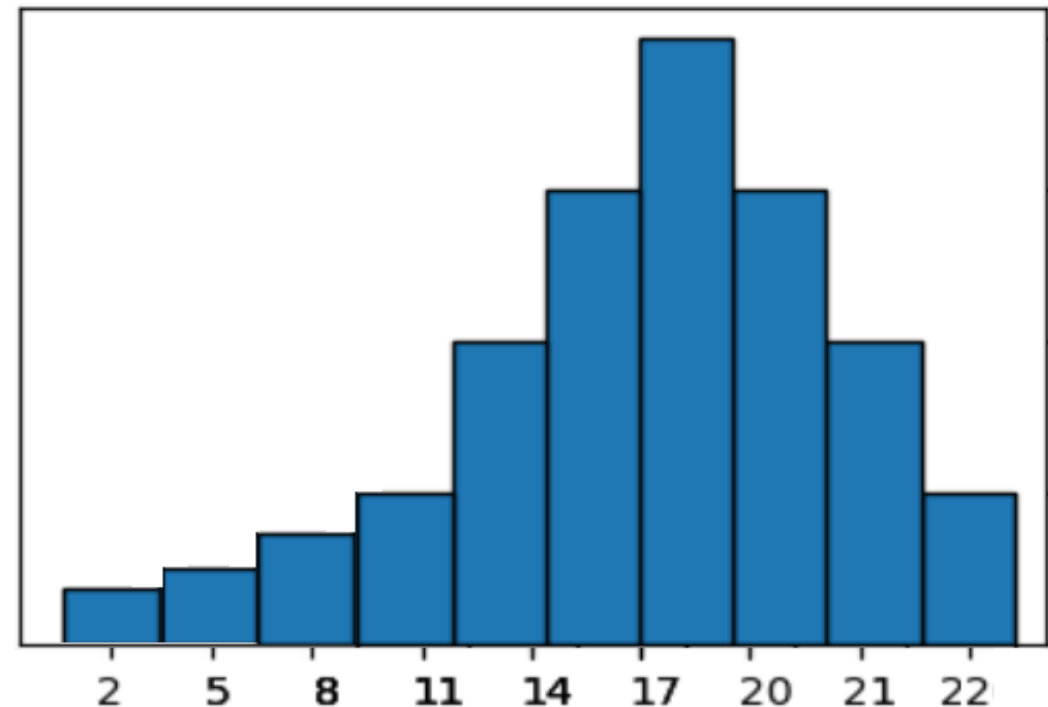
# Right-Skewed Distribution:

- Is Data Distribution where observation are mostly distributed around mean and left side to the mean, with few observations at the extreme right to the mean.



# Left-Skewed Distribution:

- Is Data Distribution where observation are mostly distributed around mean and right side to the mean, with few observations at the extreme left to the mean.



## 8. Quartiles

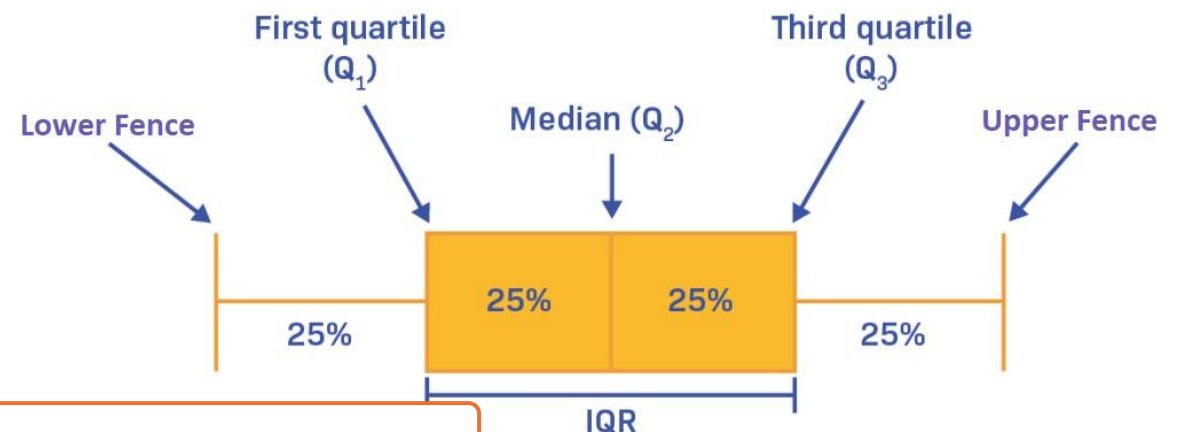
# What are Quartiles?

- Is a technique used to identify **outliers**, which are extreme values that occur in the data.
- For example:
  - Suppose you have a random variable  $X=[20, 30, 10, 50, 180]$  where  $X$  represents people ages.
  - The value 180 is an outlier because it's a strange or extreme value, since it's no common to see a 180 years-old person.



# What are Quartiles?

- Quartiles are numbers used to detect **fences** or thresholds, where if a number exceeds these **fences**, then this number is considered to be an outlier.
- There are three types of quartiles to calculate to be able to calculate the fences. These three quartiles are:
  - First Quartile (Q1).
  - Second Quartile (Q2).
  - Third Quartile (Q3).



# How to Calculate Quartiles?

Steps:

1. Sort the Random Variable data.
2. Calculate the median of the Random Variable, and this is your **Q2**.
3. Calculate the median of the subset right to Q2, and this is your **Q1**.
4. Calculate the median of the subset left to Q2, and this is your **Q3**.

## Calculate Quartiles Example:

90 33 47 -50 10 19 11 13 16 28 15 19 23 21 44 30 34 36 10 45

1- Sort: -50 10 10 11 13 15 16 19 19 21 23 28 30 33 34 36 44 45 47 90

2- Find Q2: -50 10 10 11 13 15 16 19 19 21 23 28 30 33 34 36 44 45 47 90  
Q2 = 22

3- Find Q1 & Q3: -50 10 10 11 13 15 16 19 19 21 23 28 30 33 34 36 44 45 47 90  
Q1 = 14 Q2 = 22 Q3 = 35

Q1 = 14					Q2 = 22					Q3 = 35									
-50	10	10	11	13	15	16	19	19	21	23	28	30	33	34	36	44	45	47	90

### Outlier fences:

- There are two fences we need to calculate so that if a number exceed these fences, then it is considered an outlier.
- These two fences are:
  - **Upper Fence:**
    - If a number is larger than the upper fence, then it is considered an outlier.
  - **Lower Fence:**
    - If a number is smaller than the lower fence, then it is considered an outlier.

## How to Calculate Outlier fences?

### ➤ Steps:

1. Calculate IQR, where  $IQR = Q3 - Q1$ .
2. Calculate Lower-Fence where,  $Lower-Fence = Q1 - 1.5 * IQR$ .
3. Calculate Upper-Fence where,  $Upper-Fence = Q3 + 1.5 * IQR$ .

### ➤ Example:

90 33 47 -50 10 19 11 13 16 28 15 19 23 21 44 30 34 36 10 45

Q1 = 14					Q2 = 22					Q3 = 35									
-50	10	10	11	13	15	16	19	19	21	23	28	30	33	34	36	44	45	47	90

$$IQR = Q3 - Q1 = 35 - 14 = 21$$

$$Lower-Fence = Q1 - 1.5 * IQR = 14 - 1.5 * 21 = -17.5$$

$$Upper-Fence = Q3 + 1.5 * IQR = 35 + 1.5 * 21 = 66.5$$

-50 is an outlier, because it is  $< Lower-Fence \implies (-50 < -17.5)$

90 is an outlier, because it is  $> Upper-Fence \implies (90 > 66.5)$

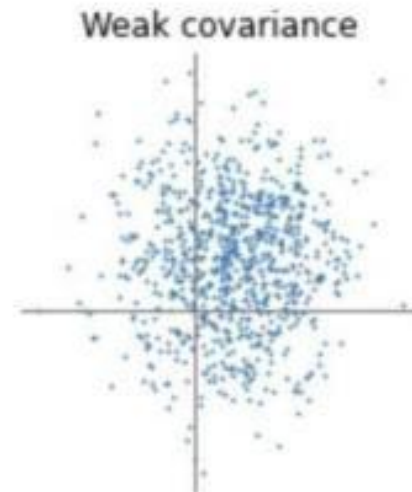
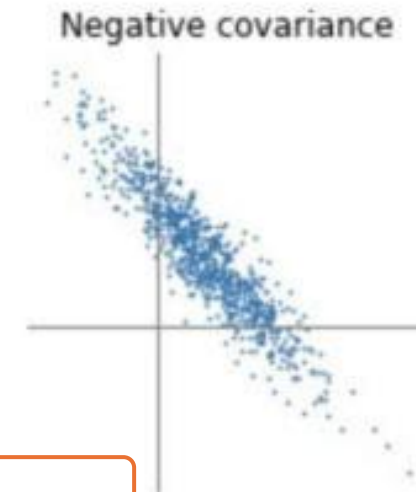
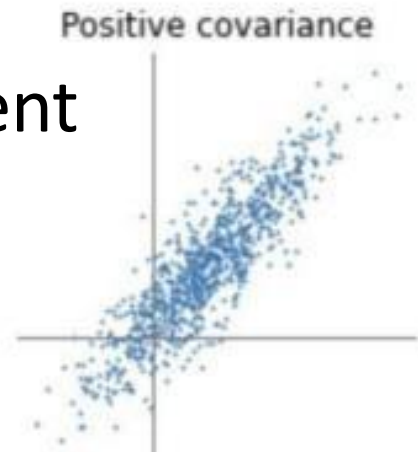
# 9. Covariance & Correlation

# What is Covariance?

- Is a **Statistical measure** used to describe how much two variables **change together**.
- For example, suppose you have two random variables X & Y:
  - If Covariance is highly **positive**, then the relation between them is **Positive**, which means **if X increases, then Y increases also**.
  - If **Covariance** is **highly negative**, then the relation between them is **Negative**, which means **if X increases, then Y decreases**.
  - If **Covariance** is near to **zero**, then the **relation is weak or there is no relation**.

# What is Covariance?

- Covariance can also be defined as “How much the deviation of one variable(X) from its mean is (related/or similar) to the deviation of another variable(Y) from its mean”.
- The deviation of a random variable from its mean represent the amount of change and the direction of this change also.
- $\text{Cov}(X, Y)$  is used to represent covariance between X & Y.





## How to Calculate Covariance?

➤ Formula:

➤ 
$$\text{Cov}(X, Y) = \sum_{i=1}^n ((X_i - \mu_x) * (Y_i - \mu_y)) / n .$$

➤  $n$  is the number of samples.

➤  $\mu_x$  is the **mean** of Random Variable  $X$ .

➤  $\mu_y$  is the **mean** of Random Variable  $Y$ .

➤ Example:

$X = [1, 2, 3, 4, 5, 6, 7, 8, 9]$

$\mu_x = 5$

$Y = [9, 8, 7, 6, 5, 4, 3, 2, 1]$

$\mu_y = 5$

$n = 9$

$$\begin{aligned} \text{Cov}(X, Y) &= ((1-5)*(9-5) + (2-5)*(8-5) + (3-5)*(7-5) + (4-5)*(6-5) + (5-5)*(5-5) \\ &\quad + (6-5)*(4-5) + (7-5)*(3-5) + (8-5)*(2-5) + (9-5)*(1-5) + )/n \\ &= -6.667 \end{aligned}$$

**Result:**  $\text{Cov}(X, Y) = -6.667 < 0$ .

**Conclusion:** The relation between  $X$  &  $Y$  is **Negative**.

# What is Correlation?

- Is a **Statistical measure** that is the same as Covariance, except that Correlation is **normalized**, which give us sense about the relation strength.
- **Normalized** means that Correlation has values in range =  **$[-1:1]$** .
- For example, suppose you have two random variables X & Y:
  - If **Correlation is near to 1**, then the relation between them is **Strong Positive**. While If **Correlation is near to -1**, then the relation between them is **Strong Negative**.
  - If **Correlation is near to 0**, then the **relation is weak**.

# Correlation Vs Covariance:

- **Correlation** has values in range  $[-1 : 1]$ . While **Covariance** had values between  $[\infty, -\infty]$ .
- Having a range between -1 & 1 is very useful since this helps us know how much strong is the relation between the two variables.
- This is useful if I want to compare two relations. While in covariance this is not possible.
- Example:

### Correlation

- Relation1 = .5
- Relation2 = .25
- Relation1 is twice strong as Relation2.

### Covariance

- Relation1 = 5
- Relation2 = 2.5
- You can't tell how much Relation1 is stronger than Relation2.

# How to Calculate Correlation?

➤ Formula:

➤  $\text{Corr}(X, Y) = \text{Cov}(X, Y) / (\sigma_x * \sigma_y).$

➤  $\sigma_x$  is the Standard-deviation of Random Variable X.

➤  $\sigma_y$  is the Standard-deviation of Random Variable Y.

➤ Example:

$X = [1, 2, 3, 4, 5, 6, 7, 8, 9]$

$Y = [9, 8, 7, 6, 5, 4, 3, 2, 1]$

$\sigma_x = 2.582$

$\sigma_y = 2.582$

$\text{Cov}(X, Y) = -6.667$

$\text{Corr}(X, Y) = \text{Cov}(X, Y) / (\sigma_x * \sigma_y) = -6.667 / (2.582 * 2.582) = -1$

Result:  $\text{Corr}(X, Y) = -1.$

Conclusion: The relation between X & Y is **Negative**.

## Covariance & Correlation using Pandas:

### Covariance Matrix

- Get the **covariance** between all the **pairs of columns** in the DataFrame.

```
1 random_variable1 = df.Length
2 random_variable2 = df.Width
3 df.cov()
```

	Length	Width	Price
Length	6.367273e+01	-7.090909e-01	6.240000e+06
Width	-7.090909e-01	1.633636e+02	2.234000e+07
Price	6.240000e+06	2.234000e+07	1.002800e+13

### Correlation Matrix

- Get the **correlation** between all the **pairs of columns** in the DataFrame.

```
1 random_variable1 = df.Length
2 random_variable2 = df.Width
3 df.corr()
```

	Length	Width	Price
Length	1.000000	-0.006953	0.246945
Width	-0.006953	1.000000	0.551948
Price	0.246945	0.551948	1.000000

# 1. Pandas Basics

## Import:

```
1 import pandas as pd
```

## Create Series:

### With default index

```
1 s = pd.Series([1, 2, 3, 4])  
2 s
```

```
0    1  
1    2  
2    3  
3    4  
dtype: int64
```

### Specify the index

```
1 # Specify the indices  
2 s = pd.Series([1, 2, 3, 4], index = ["A", "B", "C", "D"])  
3 s
```

```
A    1  
B    2  
C    3  
D    4  
dtype: int64
```

## Create DataFrame:

```
1 data = [[1, 444, 'abc'],
2         [2, 555, 'def'],
3         [3, 666, 'ghi'],
4         [4, 444, 'xyz']]
5 df = pd.DataFrame(data, columns=["col1", "col2", "col3"])
6 df
```

	col1	col2	col3
0	1	444	abc
1	2	555	def
2	3	666	ghi
3	4	444	xyz

```
1 # another way
2 data = {'col1':[1,2,3,4],
3         'col2':[444,555,666,444],
4         'col3':['abc','def','ghi','xyz']}
5
6 df = pd.DataFrame(data)
7 df
```

	col1	col2	col3
0	1	444	abc
1	2	555	def
2	3	666	ghi
3	4	444	xyz



## Rename DataFrame Columns & index:

### Rename DataFrame Columns

```

1 df = pd.DataFrame([[1, 444, 'abc'],
2                     [2, 555, 'def'],
3                     [3, 666, 'ghi'],
4                     [4, 444, 'xyz']])
5 display(df)
6 columns=["col1", "col2", "col3"]
7 df.columns = columns
8 display(df)

```

	0	1	2
0	1	444	abc
1	2	555	def
2	3	666	ghi
3	4	444	xyz

	col1	col2	col3
0	1	444	abc
1	2	555	def
2	3	666	ghi
3	4	444	xyz

### Rename DataFrame index

```

1 df = pd.DataFrame([[1, 444, 'abc'],
2                     [2, 555, 'def'],
3                     [3, 666, 'ghi'],
4                     [4, 444, 'xyz']])
5 display(df)
6 index = ["row1", "row2", "row3", "row4"]
7 df.index = index
8 display(df)

```

	0	1	2
0	1	444	abc
1	2	555	def
2	3	666	ghi
3	4	444	xyz

	0	1	2
row1	1	444	abc
row2	2	555	def
row3	3	666	ghi
row4	4	444	xyz

# Pandas Dtypes:

<b>Bool</b> <ul style="list-style-type: none"><li>➤ Represents Numerical datatypes with True &amp; False values.</li></ul>	<b>Int</b> <ul style="list-style-type: none"><li>➤ Represents Numerical datatypes with integer values.</li></ul>	<b>Float</b> <ul style="list-style-type: none"><li>➤ Represents Numerical datatypes with continuous values.</li></ul>
<b>Category</b> <ul style="list-style-type: none"><li>➤ Represents Categorical datatypes.</li></ul>	<b>Object</b> <ul style="list-style-type: none"><li>➤ Is a mix of categorical datatypes &amp; Numerical datatypes.</li><li>➤ Can carry any python object; such as, lists, tuples, strings, etc.</li></ul>	

## Pandas Dtypes:

### Get Datatypes of all columns

```
1 # Datatype of all columns  
2 df.dtypes
```

```
col1    int64  
col2    int64  
col3    object  
dtype: object
```

### Get Datatype of one column

```
1 # Datatype of one column  
2 df['col1'].dtype
```

```
dtype('int64')
```

## Change Datatype:

### Change Datatype of one column

```
1 df["col1"] = df["col1"].astype("category")
2 df.dtypes
```

```
col1    category
col2      int64
col3      object
dtype: object
```

### Change Datatypes of group of columns

```
1 cols = ["col1", "col3"]
2 df[cols] = df[cols].astype("category")
3 df.dtypes
```

```
col1    category
col2      int64
col3    category
dtype: object
```

## 2. EDA using Pandas

# EDA using Pandas:

- **EDA** is about exploring and understanding the data and getting insights about it.
- **EDA** is short for **Exploratory Data Analysis**.
- Pandas provides built-in methods and features that helps us to answer different questions about the data.

## EDA using Pandas:

### Get the first n rows of DataFrame

```
1 df.head(2)
```

	col1	col2	col3
0	1	444	abc
1	2	555	def

### Get the last n rows of DataFrame

```
1 df.tail(2)
```

	col1	col2	col3
2	3	666	ghi
3	4	444	xyz

### Get Statistical Measures about Numerical Columns

```
1 df.describe()
```

	count	mean	std	min	25%	50%	75%	max
col2	4.0	527.25	106.274409	444.0	444.0	499.5	582.75	666.0

### Get Statistical Measures about Categorical Columns

```
1 df.describe(include="category")
```

	col1
count	4
unique	4
top	1
freq	1

## EDA using Pandas:

### Get DataFrame Rows Names

```
1 df.index
```

```
RangeIndex(start=0, stop=4, step=1)
```

### Get DataFrame Columns Names

```
1 df.columns
```

```
Index(['col1', 'col2', 'col3'], dtype='object')
```

### Get Unique Values

```
1 # get the unique values
2 df['col2'].unique()
```

```
array([444, 555, 666], dtype=int64)
```

### Get Unique Values Number

```
1 # get number of unique values
2 df['col2'].nunique()
```

```
3
```



## EDA using Pandas:

### Get Max Value

```
1 df["col2"].max()
```

666

### Get Element whose value is Max

```
1 df.col2.idxmax()
```

2

### Get Min Value

```
1 df["col2"].min()
```

444

### Get Element whose value is Min

```
1 df.col2.idxmin()
```

0

## EDA using

## Pandas:

### DataFrame Basic Information

```
1 df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 3 columns):
#   Column   Non-Null Count  Dtype  
---  -
0    col1     4 non-null     category
1    col2     4 non-null     int64   
2    col3     4 non-null     object  
dtypes: category(1), int64(1), object(1)
memory usage: 400.0+ bytes
```

### Unique Values Frequency

```
1 d = df['col2'].value_counts()
2 d

444    2
555    1
666    1
Name: col2, dtype: int64
```

### Get Max Value of All Columns

```
1 df.max()

col2    666
col3    xyz
dtype: object
```

### Summation

```
1 df['col2'].sum()

2109
```

# 3. Data Manipulation

# Data Manipulation:

- Pandas provides built-in methods and attributes that allows you to apply different **operations over** Pandas **DataFrames** or **Series**.
- Below are the **most popular & Important attributes** that allows you to apply **data manipulation**.

# Data Manipulation (Pandas to Numpy):

## Convert Pandas Series into Numpy 1D-Array

```
1 df['col1'].values
```

```
[1, 2, 3, 4]  
Categories (4, int64): [1, 2, 3, 4]
```

## Convert Pandas DataFrame into Numpy 2D-Array

```
1 df.values
```

```
array([[1, 444, 'abc'],  
       [2, 555, 'def'],  
       [3, 666, 'ghi'],  
       [4, 444, 'xyz']], dtype=object)
```

## Data Manipulation (Replace Values):

### Replace a Single Value

```
1 df.replace(555, "ali")
```

	col1	col2	col3
0	1	444	abc
1	2	ali	def
2	3	666	ghi
3	4	444	xyz

### Replace Multiple Values using Dictionary

```
1 df.replace({444: "omar", "abc": 444})
```

	col1	col2	col3
0	1	omar	444
1	2	555	def
2	3	666	ghi
3	4	omar	xyz

### Replace Multiple Values by One Value

```
1 df.replace([1, 666, "abc"], "aaa")
```

	col1	col2	col3
0	aaa	444	aaa
1	2	555	def
2	3	aaa	ghi
3	4	444	xyz

# Data Manipulation (Mapping):

Before Mapping

1 df

	col1	col2	col3
0	1	444	abc
3	4	444	xyz
1	2	555	def
2	3	666	ghi

After Mapping

1 df.col2 = df.col2.map({444: "Fours", 555: "Fives", 666: "Sixs"})  
2 df

	col1	col2	col3
0	1	Fours	abc
3	4	Fours	xyz
1	2	Fives	def
2	3	Sixs	ghi

## Data Manipulation (Sorting):

### Ascending sorting

```
1 sorted_df = df.sort_values(by='col1')
2 sorted_df
```

	col1	col2	col3
0	1	Fours	abc
1	2	Fives	def
2	3	Sixs	ghi
3	4	Fours	xyz

### Descending sorting

```
1 sorted_df = df.sort_values(by='col1', ascending=False)
2 sorted_df
```

	col1	col2	col3
3	4	Fours	xyz
2	3	Sixs	ghi
1	2	Fives	def
0	1	Fours	abc



## Data Manipulation (Apply method):

- Is a methods used to apply a certain function to each sample in the DataFrame.

### Example1

```
1 def duplicate(x):
2     return x*2
3
4 df['col1'].apply(duplicate)
```

0	11
1	22
2	33
3	44

Name: col1, dtype: object

### Example2

```
1 # apply built in function
2 df['col1'].apply(len)
```

0	1
1	1
2	1
3	1

Name: col1, dtype: int64

### Example3

```
1 # or use lambda function
2 df['col1'].apply(lambda x: x*2)
```

0	11
1	22
2	33
3	44

Name: col1, dtype: object

### Example4

```
1 df2 = pd.DataFrame([[1, 'ALI' , 3],
2                     [5, 'OMAR' , 8],
3                     [4, 'AHMED', 9]])
4 df2.apply(lambda x: x*2)
```

	0	1	2
0	2	ALIALI	6
1	10	OMAROMAR	16
2	8	AHMEDAHMED	18

# 4. Indexing & Slicing

# Indexing:

- Means **accessing one element** in Series or DataFrame, using its index or name.
- There are **two ways** to apply **indexing**:
  - Either using the **element's Index**.
  - Or using the **element's Name**.

### Slicing:

- Means **accessing many elements** in Series or DataFrame, by specifying a range of Indices or name.
- There are **two ways** to apply **Slicing**:
  - Either, using a range of **elements' Indices**.
  - Or using a range of **elements' Names**.

## Indexing & Slicing using Index:

### • Series Indexing

```
1 df.col1.iloc[2]
```

3

### • Matrix Indexing

```
1 df.iloc[2, 1]
```

666

### • Series Slicing

```
1 df.col1.iloc[0:2]
```

0	1
1	2

Name: col1, dtype: category  
Categories (4, int64): [1, 2, 3, 4]

### • Matrix Slicing

```
1 df.iloc[:, 0:2]
```

	col1	col2
0	1	444
1	2	555
2	3	666
3	4	444

## Indexing & Slicing using Names:

- Series Indexing

```
1 df.col1.loc[3]
```

4

- Matrix Indexing

```
1 df.loc[2, "col1"]
```

3

- Series Slicing

```
1 df.col1.loc[2:3]
```

2 3

3 4

Name: col1, dtype: category

Categories (4, int64): [1, 2, 3, 4]

- Matrix Slicing

```
1 df.loc[:, "col1":"col2"]
```

	col1	col2
--	------	------

0	1	444
---	---	-----

1	2	555
---	---	-----

2	3	666
---	---	-----

3	4	444
---	---	-----

# 5. Inserting/Dropping DataFrame Columns & Rows

## Insert New Columns:

### The first way

```
1 new_col = df.col1 + df.col2
2 df.insert(3,"new" , new_col)
3 df
```

	col1	col2	col3	new
0	1	444	abc	445
1	2	555	def	557
2	3	666	ghi	669
3	4	444	xyz	448

### Another way

```
1 df['new'] = df.col1 + df.col2
2 df
```

	col1	col2	col3	new
0	1	444	abc	445
1	2	555	def	557
2	3	666	ghi	669
3	4	444	xyz	448



## Drop Columns:

### Drop one columns

```
1 df.drop('new',axis=1)
```

	col1	col2	col3
0	1	444	abc
1	2	555	def
2	3	666	ghi
3	4	444	xyz

### Drop many columns

```
1 df.drop(['col1', 'new'],axis=1)
```

	col2	col3
0	444	abc
1	555	def
2	666	ghi
3	444	xyz

# Insert New Rows:

```
1 new_row = {"col1": -1, "col2": 222, "col3": "OuO"}  
2 df.append(new_row, ignore_index=True)
```

	col1	col2	col3
0	1	444	abc
1	2	555	def
2	3	666	ghi
3	4	444	xyz
4	-1	222	OuO

## Drop Rows:

### Drop one row

```
1 df.drop(2, axis=0)
```

	col1	col2	col3
0	1	444	abc
1	2	555	def
3	4	444	xyz

### Drop many rows

```
1 df.drop([1, 3], axis=0)
```

	col1	col2	col3
0	1	444	abc
2	3	666	ghi

## 6. Null Values

# What are Null Values?

- **Null Values** means **missing values**, which means that an element doesn't have a value, or have a value of None or Nan.
- **Null Values** occur due to **problems during gathering data**, for example a client forgot or to enter his age.

# Check for Null Values:

```
1 null = df.isnull()  
2 pd.DataFrame(null.sum()).T
```

	col1	col2	col3
0	0	1	2

# Handle Null

## Values:

➤ There are **three options** to do to **handle missing** values:

1. **Drop rows** that contain Null Values.
2. **Drop columns** that contain Null Values.
3. **Replace Null Values** with Mean, Median, or Mode.

## Handle Null Values (Drop Rows):

### Drop all rows

```
1 df.dropna()
```

	col1	col2	col3
--	------	------	------

2	1	2.0	3.0
---	---	-----	-----

### Drop rows in specific columns

```
1 df.dropna(subset=["col2"])
```

	col1	col2	col3
--	------	------	------

0	1	2.0	3.0
---	---	-----	-----

2	1	2.0	3.0
---	---	-----	-----



## Handle Null Values (Drop Columns):

### Drop all columns

```
1 df.dropna(axis=1)
```

	col1	col3
0	1	3.0
1	5	3.0
2	1	3.0

### Drop Specific Columns

```
1 df.drop(["col3"], axis=1)
```

	col1	col2
0	1	2.0
1	5	NaN
2	1	2.0

# Handle Null Values (Replace Rows Null Values):

```
1 mean = df.col3.mean()  
2 df.col3 = df.col3.fillna(value=mean)  
3 df
```

	col1	col2	col3
0	1	2.0	3.0
1	5	NaN	3.0
2	1	2.0	3.0

## Assignment 1: The automated\_stat\_analyzer Function

A retail company needs a utility to quickly summarize sales data. Students must create a function that identifies the "Central Tendency" and "Dispersion" of any numerical column.

### Requirements:

- Accept a Pandas DataFrame and a column name.
- Calculate the **Mean**, **Median** and **Standard Deviation**.
- Identify if the data is "Skewed" by comparing the Mean and Median.
- Bonus** the user can also use **Mode** instead.

```
import pandas as pd
import numpy as np

data = {
    'Transaction_ID': range(1, 11),
    'Product_Category': ['Electronics', 'Home', 'Electronics', 'Sports', 'Home',
                        'Electronics', 'Home', 'Sports', 'Electronics', 'Electronics'],
    'Sales_Amount': [150, 200, 155, 300, 210, 180, 205, 1000, 190, 160], # 1000 is an Outlier
    'Customer_Age': [25, 34, np.nan, 45, 23, 31, 29, np.nan, 38, 40], # Contains Nulls (NaN)
    'Rating': [5, 4, 3, 5, 2, 4, 5, 2, 4, 3]
}
```

```
import pandas as pd

def automated_stat_analyzer(df, column_name):
    """
    Company Task: Provide a summary report of a specific data variable.

    Instructions:
    1. Check if the column is numerical or categorical.
    2. For numerical: Calculate Mean, Median, and Standard Deviation.
    3. For categorical: Calculate the Mode.
    4. Return a dictionary with these statistical measures.
    """
    # TODO: Implement using df[column_name].mean(), .median(), .std(), or .mode()
    pass
```

## Assignment 1 The null\_handling\_strategy Function

Incoming user data often has missing values. Students must implement a flexible strategy to handle these "Null Values" to prepare data for Machine Learning

### Requirements:

- Check for null values in the DataFrame.
- Apply a strategy based on parameters: "naidem\_llif" ro ,"naem\_llif", "swor\_pord"
- Ensure the function only fills numerical columns when using mean or median.

```
import pandas as pd
import numpy as np

data = {
    'Transaction_ID': range(1, 11),
    'Product_Category': ['Electronics', 'Home', 'Electronics', 'Sports', 'Home',
                        'Electronics', 'Home', 'Sports', 'Electronics', 'Electronics'],
    'Sales_Amount': [150, 200, 155, 300, 210, 180, 205, 1000, 190, 160], # 1000 is an Outlier
    'Customer_Age': [25, 34, np.nan, 45, 23, 31, 29, np.nan, 38, 40], # Contains Nulls (NaN)
    'Rating': [5, 4, 3, 5, 2, 4, 5, 2, 4, 3]
}

def null_handling_strategy(df, strategy="fill_mean"):
    """
    Company Task: Clean a dataset by resolving missing (NaN) values.
    """
    # TODO: Implement using .isnull(), .dropna(), or .fillna()
    pass
```

# Thank You