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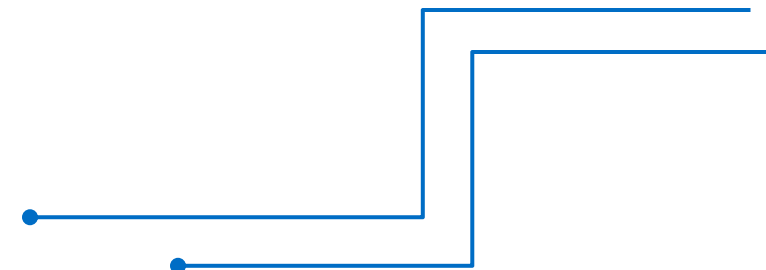
Our outcomes are  
over 5000 trainees.

# Artificial Intelligence Engineering (Level-1)

## Module 2

# Content

- Module 1: Introduction to AI and Machine Learning
- Module 2: Linear Algebra, Statistics and Probability for AI
- Module 3: Neural Network Architecture
- Module 4: Building Machine Learning Models
- Module 5: Deep Learning Concepts
- Module 6: Python Data Structure
- Module 7: Data Handling with Pandas and NumPy
- Module 8: Python for AI
- Module 9: Classification AI Project
- Module 10: Prediction AI Project

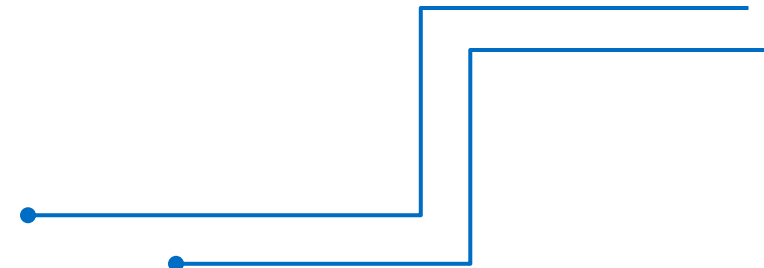


# Artificial Intelligence Engineering (Level-1)

## **Module 2: Linear Algebra, Statistics and Probability for AI**

# Content

- Introduction to Linear Algebra
- Vector, Matrices, Dot Product and Matrix Multiplication
- Calculatus Basics for Optimization (Derivatives, Gradient Descent)
- Introduction to Statistics
- Types of Statistics
- Measures of Central Tendency (Mean, Median, Mode)
- Measures of Dispersion (Range, Variance, Standard Deviation)
- Data Distributions
- Probability for AI



# Learning Outcomes

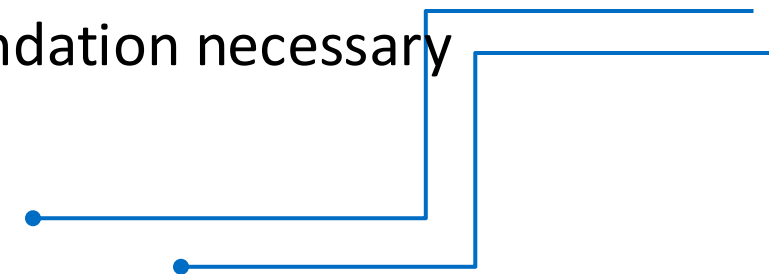


- Understand Linear Algebra Basics: Grasp the concepts of vectors, matrices, dot products, and matrix multiplication as fundamental tools in AI and machine learning.
- Apply Calculus to Optimization: Learn the basics of derivatives and gradient descent for optimizing functions in AI models.
- Introduction to Statistics: Develop a foundational understanding of statistics to analyze and interpret data effectively.
- Differentiate Types of Statistics: Distinguish between descriptive and inferential statistics and their applications in data analysis.
- Analyze Central Tendencies: Calculate and interpret mean, median, and mode to summarize datasets.

# Learning Outcomes



- Understand Measures of Dispersion: Compute range, variance, and standard deviation to evaluate data spread and variability.
- Explore Data Distributions: Identify and understand common data distributions such as normal and skewed distributions.
- Understand Probability Basics: Learn foundational probability concepts to assess uncertainty in AI.
- Develop Problem-Solving Skills: Apply linear algebra, statistics, and calculus to solve real-world AI-related problems.
- Prepare for Advanced AI Concepts: Build the mathematical foundation necessary for deeper exploration into machine learning and AI.



# Introduction to Linear Algebra

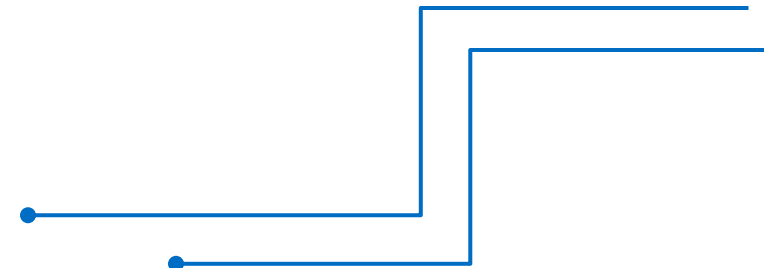
## What is Linear Algebra?

- ❑ Linear algebra is the branch of mathematics that deals with vectors, matrices, and linear transformations.
- ❑ Essential for data representation and manipulation in AI and machine learning.



## Why is it important in AI?

- ❑ Used for data analysis, neural networks, optimization, and dimensionality reduction.





# Introduction to Linear Algebra



## Application of Linear Algebra in AI

### ❑ Neural Networks:

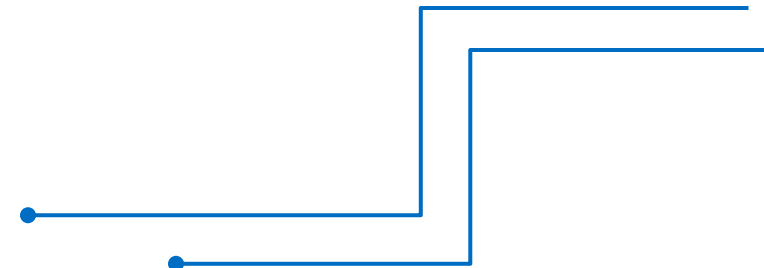
- Represent weights as matrices, use matrix multiplication for layer outputs.

### ❑ Computer Vision:

- Image data is represented as matrices; transformations like rotation, scaling and translation are matrix operations.

### ❑ Data Dimensionality Reduction:

- Techniques like Principal Component Analysis (PCA) use eigenvectors and eigenvalues.



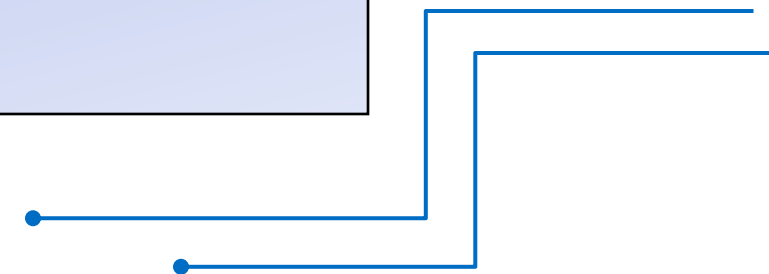
# Understanding Vectors

## What is a Vector?

- ❑ A vector is a one-dimensional array of numbers (e.g., [3, 5, 7]).
- ❑ Represents quantities with both magnitude and direction.

## Common Uses in AI

- ❑ Data points, features in datasets, model weights.



# Understanding Vectors

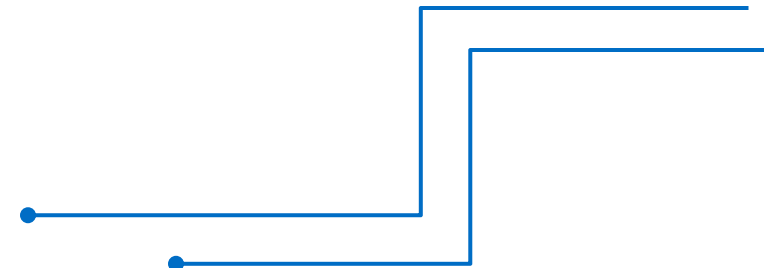
## Basic Vector Operations:

- ❑ **Addition:** Adds corresponding elements.

**Example:**  $[1, 2] + [3, 4] = [4, 6]$

- ❑ **Scalar Multiplication:** Multiplies each element by a scalar.

**Example:**  $3 \times [2, 4] = [6, 12]$



# Understanding Vectors

## Notation

- A vector is often written in bold lowercase letters (e.g.,  $\mathbf{v}$ ).

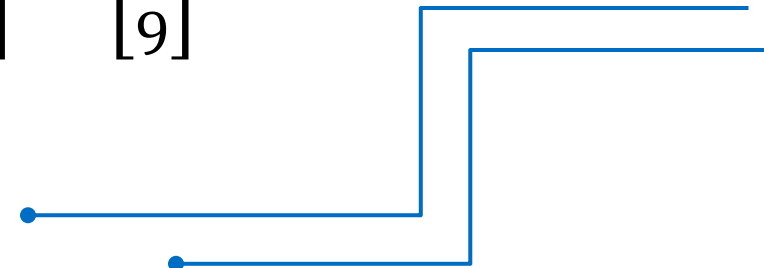
Example:  $\mathbf{v} = \begin{bmatrix} 3 \\ 4 \\ 5 \end{bmatrix}$

- Addition:

$$\mathbf{a} + \mathbf{b} = \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 3 \\ 4 \end{bmatrix} = \begin{bmatrix} 4 \\ 6 \end{bmatrix}$$

- Scalar Multiplication:

$$3 \times \mathbf{v} = 3 \times \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 3 \\ 6 \\ 9 \end{bmatrix}$$



# Matrices



## What is Matrix?

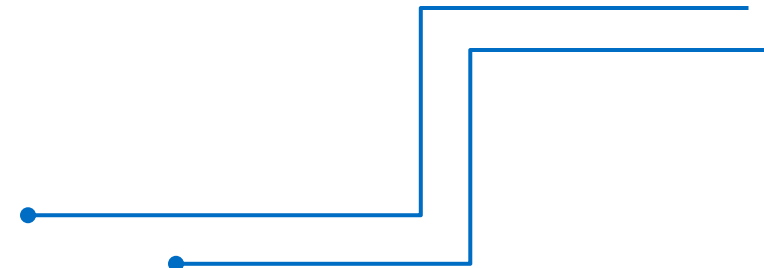
### □ Definition:

- A matrix is a two-dimensional array of numbers, arranged in rows and columns.

**Example:**  $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$

### □ Use Cases in Ai:

- Represent datasets, image pixels, weights in neural networks, and transformations.



# Matrices



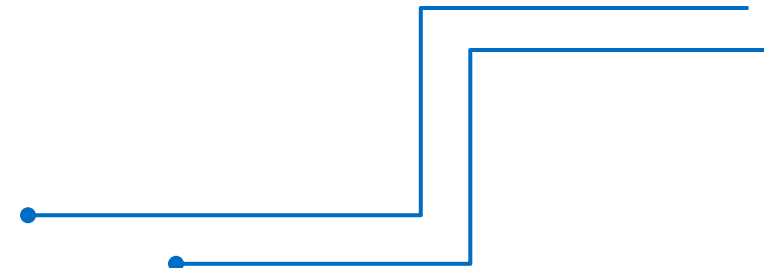
## □ Basic Matrix Operations:

- **Matrix Addition:** Adds corresponding elements.

$$\mathbf{A} + \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} + \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} = \begin{bmatrix} 6 & 8 \\ 10 & 12 \end{bmatrix}$$

- **Scalar Multiplication:** Multiplies each element by a scalar.

$$\mathbf{A} \times \mathbf{B} = \begin{bmatrix} (1 \times 5 + 2 \times 7) & (1 \times 6 + 2 \times 8) \\ (3 \times 5 + 4 \times 7) & (3 \times 6 + 4 \times 8) \end{bmatrix} = \begin{bmatrix} 19 & 22 \\ 43 & 50 \end{bmatrix}$$



# Matrices

## Matrix Multiplication

### ❑ What is Matrix Multiplication?

- Used to transform data, compute weighted sums in neural networks.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \times \begin{bmatrix} i & j \\ k & l \end{bmatrix} = \begin{bmatrix} a.i + b.k & a.j + b.l \\ c.i + d.k & c.j + d.l \end{bmatrix}$$

# Linear Equations and System

We are solving the system of equations:  $2x + 3y = 8$   
 $4x + y = 10$

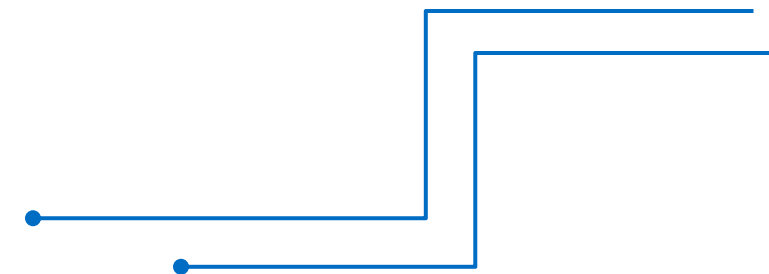
## Step 1: Matrix Form

The system can be written in matrix form as:  $\begin{bmatrix} 2 & 3 \\ 4 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 8 \\ 10 \end{bmatrix}$

## Step 2: Solving Using Substitution or Elimination

Using Substitution:

From the second equation, solve for  $y$  in terms of  $x$ :  $4x + y = 10 \Rightarrow y = 10 - 4x$





# Linear Equations and System

Substitute  $y = 10 - 4x$  into the first equation:  $2x + 3(10 - 4x) = 8$

$$2x + 30 - 12x = 8$$

$$-10x + 30 = 8$$

$$-10x = -22$$

$$x = \frac{22}{10} = 2.2$$

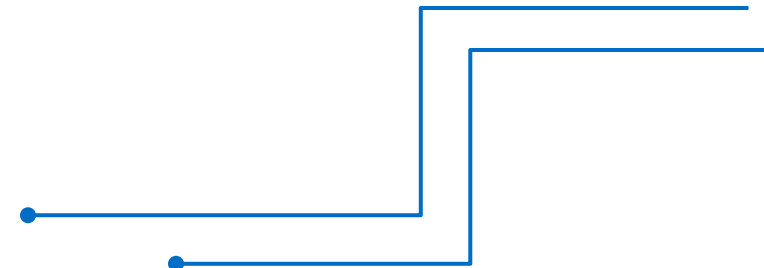
Substitute  $x = 2.2$  back into  $y = 10 - 4x$ :  $y = 10 - 4(2.2)$

$$y = 10 - 8.8$$

$$y = 1.2$$

**Step 3: Final Solution**

$$x = 2.2, y = 1.2$$



# Linear Equations and System

## Verification

Substitute  $x = 2.2, y = 1.2$  into both equation:

1.  $2x + 3y = 8$ :

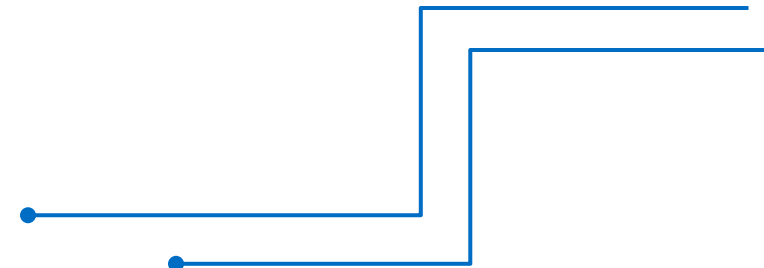
$$2(2.2) + 3(1.2) = 4.4 + 3.6 = 8 \text{ (Correct!)}$$

2.  $4x + y = 10$ :

$$4(2.2) + 1.2 = 8.8 + 1.2 = 10 \text{ (Correct!)}$$

Thus, the solution is:

$$x = 2.2, y = 1.2$$



# Matrices



## □ How to Multiply Matrices:

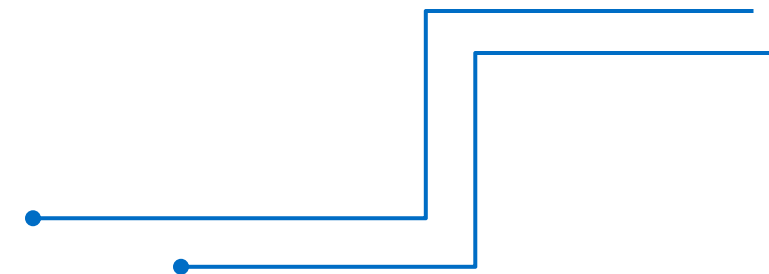
➤ For matrices **A** (size  $m \times n$ ) and **B** (size  $n \times p$ ), the result is a matrix of size  $m \times p$ .

➤ **Formula:**  $\mathbf{C} = \mathbf{A} \times \mathbf{B}$  where  $c_{ij} = \sum_{k=1}^n a_{ik} \times b_{kj}$

➤ **Example:**

$$\mathbf{A} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$$

$$\mathbf{A} \times \mathbf{B} = \begin{bmatrix} (1 \times 5 + 2 \times 7) & (1 \times 6 + 2 \times 8) \\ (3 \times 5 + 4 \times 7) & (3 \times 6 + 4 \times 8) \end{bmatrix} = \begin{bmatrix} 19 & 22 \\ 43 & 50 \end{bmatrix}$$



# Dot Product and Matrix Multiplication

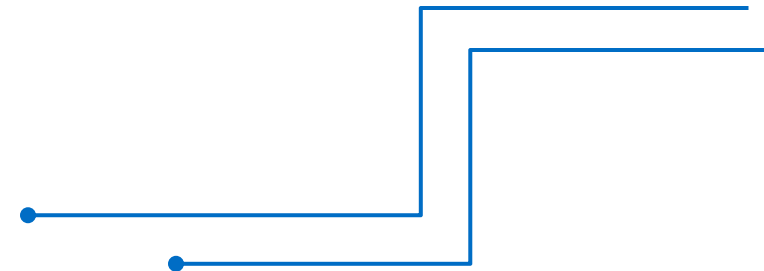
## Dot Product

- ❑ The dot product of two vectors **a** and **b** is the sum of the products of their corresponding elements.

$$a \cdot b = a_1b_1 + a_2b_2 + \dots + a_nb_n$$

- ❑ Used in AI to compute weights in neural networks:

$$output = w \cdot x + b$$



# Determinants



For  $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ , the determinant is:

$$\det(A) = 1 \cdot 4 - 2 \cdot 3 = 4 - 6 = -2$$

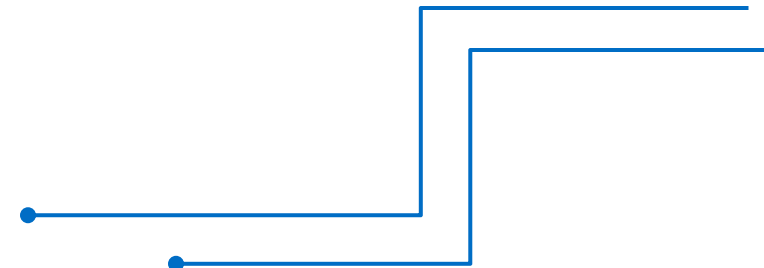
For a  $3 \times 3$  matrix:

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 4 & 5 \\ 1 & 0 & 6 \end{bmatrix}$$

$$\det(A) = 1 \cdot \begin{vmatrix} 4 & 5 \\ 0 & 6 \end{vmatrix} - 2 \cdot \begin{vmatrix} 0 & 5 \\ 1 & 6 \end{vmatrix} + 3 \cdot \begin{vmatrix} 0 & 4 \\ 1 & 0 \end{vmatrix}$$

$$= 1 \cdot (4 \cdot 6 - 0 \cdot 5) - 2 \cdot (0 \cdot 6 - 1 \cdot 5) + 3 \cdot (0 \cdot 0 - 1 \cdot 4)$$

$$= 24 + 10 - 12 = 22$$



# Eigenvalues & Eigenvectors

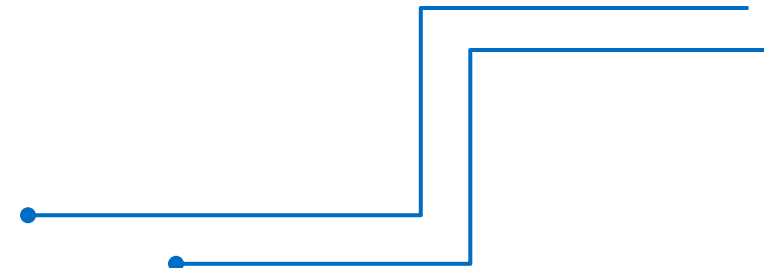
For  $A = \begin{bmatrix} 4 & 1 \\ 2 & 3 \end{bmatrix}$ :

Find eigenvalues ( $\lambda$ ) using:

$$\det(A - \lambda I) = 0$$

$$\det \begin{bmatrix} 4 - \lambda & 1 \\ 2 & 3 - \lambda \end{bmatrix} = (4 - \lambda)(3 - \lambda) - 2 \cdot 1 = \lambda^2 - 7\lambda + 10 = 0$$

Solve  $\lambda^2 - 7\lambda + 10 = 0$  to find  $\lambda = 5, 2$ .



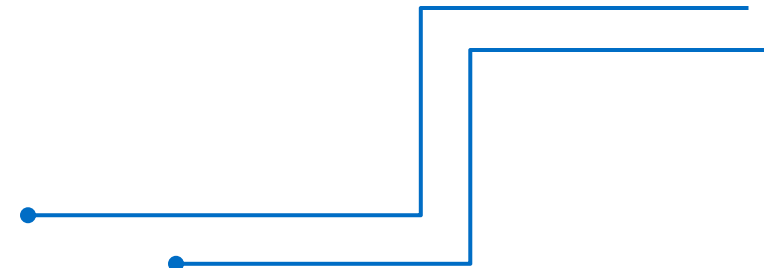
# Linear Transformations

Given transformation  $\mathbf{T}(\mathbf{x}) = \mathbf{A}\mathbf{x}$ , where:

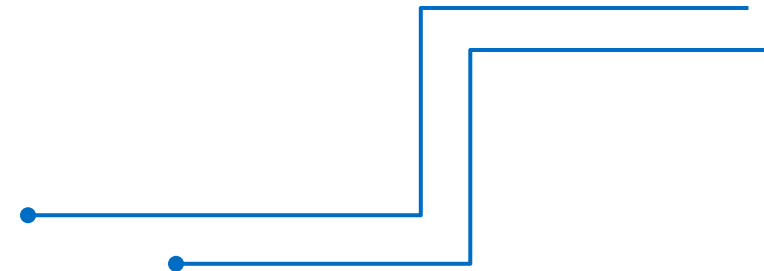
$$\mathbf{A} = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\mathbf{T}(\mathbf{x}) = \begin{bmatrix} 2x_1 \\ 3x_2 \end{bmatrix}$$

Determine how  $\mathbf{T}$  stretches/compresses vectors.

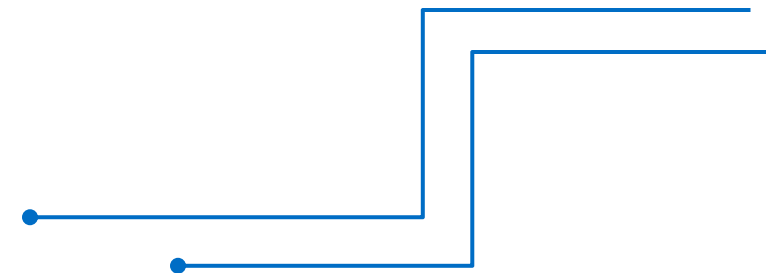


# Assignment 1





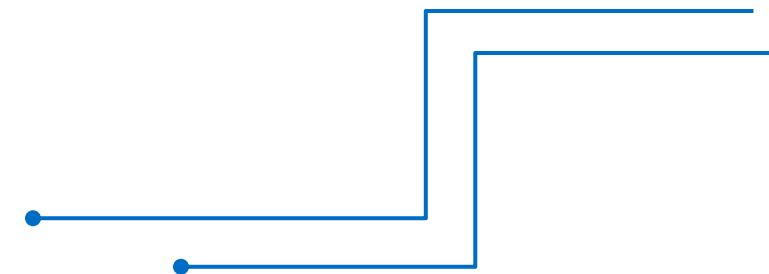
# Assignment 2



# Calculus Basics for Optimization

## Objectives:

- ❑ Understand how calculus is used in AI, particularly for optimization.
- ❑ Learn about derivatives, gradients, and their role in training models.



# Calculus Basics for Optimization

## Derivatives

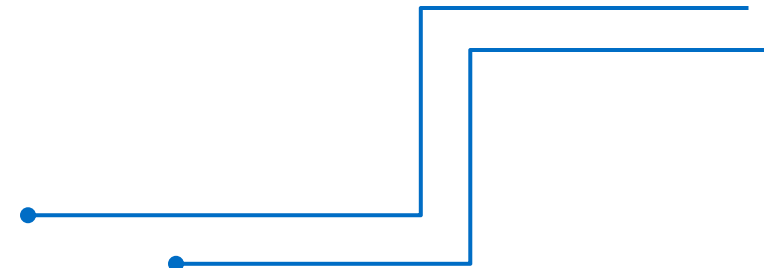
- ❑ Concept of rate of change and how derivatives are used to optimize functions.
- ❑ **Partial Derivatives:** Useful for understanding gradients in multivariable functions.

**Example:** If  $f(x) = x^2$ , at  $x = 3$ , the slope of the tangent (rate of change) is  $f'(3) = 2 \cdot 3 = 6$ .

The derivative of a function  $f(x)$  measures how  $f(x)$  changes with respect to  $x$ . For instance:

$$f(x) = x^2$$

The derivative  $f'(x) = 2x$  tells us the rate of change of  $f(x)$  at any point  $x$ .



# Derivative



- **Definition:** The derivative measures the rate of change of a function with respect to one variable in a single-variable function.
- **Context:** It applies to functions of one variable, such as  $f(x)$ .
- **Notation:** Represented as  $\frac{df}{dx}$ ,  $f'(x)$ , or  $\dot{f}(x)$ .
- **Example:** For  $f(x) = x^2 + 3x$ :

$$\frac{df}{dx} = 2x + 3$$

# Partial Derivative



- **Definition:** The partial derivative measures the rate of change of a multivariable function with respect to one variable, keeping all other variables constant.
- **Context:** It applies to functions of multiple variables, such as  $f(x, y, z)$ .
- **Notation:** Represented as  $\frac{\partial f}{\partial x}$ ,  $\partial_x f$  or  $f_x$ .
- **Example:** For  $f(x, y) = x^2y + y^3$ :

- Partial derivative with respect to  $x$ :

$$\frac{\partial f}{\partial x} = 2xy$$

- Partial derivative with respect to  $y$ :

$$\frac{\partial f}{\partial y} = x^2 + 3y^2$$

# Difference between Derivative & Partial Derivative



## Key Differences

| Aspect                  | Derivative                             | Partial Derivative                                     |
|-------------------------|--|--|
| Applicability           | Single-variable functions<br>$(f(x))$  | Multivariable functions<br>$(f(x, y, z))$              |
| Number of Variables     | One variable                           | More than one variable                                 |
| Notation                | $\frac{d}{dx}, f'(x)$                  | $\frac{\partial}{\partial x}, \partial_x f$            |
| Variables Kept Constant | Not applicable (only one variable)     | All other variables are kept constant                  |
| Use Cases               | Rates of change,<br>Tangents to curves | Multivariable calculus,<br>gradients, and optimization |

# When to use Derivative & Partial Derivative



## When to Use Each

- **Derivative:** When studying functions of a single variable (e.g.,  $y = f(x)$ ).
- **Partial Derivative:** When working with functions of multiple variables (e.g.,  $z = f(x, y)$ ), especially in physics, engineering, and machine learning.

# Basics Derivatives Rules



## Basic Derivatives Rules

### 1. Power Rule:

$$\frac{d}{dx} [x^n] = nx^{n-1}$$

### 2. Sum/Difference Rule:

$$\frac{d}{dx} [f(x) + g(x)] = f'(x) + g'(x)$$

### 3. Product Rule:

$$\frac{d}{dx} [f(x)g(x)] = f'(x)g(x) + f(x)g'(x)$$

### 4. Quotient Rule:

$$\frac{d}{dx} \left[ \frac{f(x)}{g(x)} \right] = \frac{f'(x)g(x) - f(x)g'(x)}{[g(x)]^2}$$

### 5. Chain Rule:

$$\frac{d}{dx} f(g(x)) = f'(g(x)) \cdot g'(x)$$

### 6. Exponential and Logarithmic Rules:

$$\frac{d}{dx} e^x = e^x, \quad \frac{d}{dx} \ln(x) = \frac{1}{x}$$



# Using the Power Rule

## Example 1: Using the Power Rule

Find  $\frac{d}{dx} [3x^4 - 5x^2 + 7x - 10]$ :

$$\frac{d}{dx} [3x^4] = 12x^3, \quad \frac{d}{dx} [-5x^2] = -10x, \quad \frac{d}{dx} [7x] = 7, \quad \frac{d}{dx} [-10] = 0$$

$$\frac{d}{dx} [3x^4 - 5x^2 + 7x - 10] = 12x^3 - 10x + 7$$

# Product Rule

## Example 2: Product Rule

Find  $\frac{d}{dx} [x^2 \sin(x)]$ :

$$f(x) = x^2, \quad g(x) = \sin(x)$$

$$\frac{d}{dx} [x^2 \sin(x)] = \frac{d}{dx} [x^2] \cdot \sin(x) + x^2 \cdot \frac{d}{dx} [\sin(x)]$$

$$= 2x \sin(x) + x^2 \cos(x)$$

# Quotient Rule



## Example 3: Quotient Rule

Find  $\frac{d}{dx} \left[ \frac{x^2}{\cos(x)} \right]$ :

$$f(x) = x^2, \quad g(x) = \cos(x)$$

$$\frac{d}{dx} \left[ \frac{x^2}{\cos(x)} \right] = \frac{\frac{d}{dx} [x^2] \cdot \cos(x) - x^2 \cdot \frac{d}{dx} [\cos(x)]}{[\cos(x)]^2}$$

$$= \frac{2x \cos(x) + x^2 \sin(x)}{\cos^2(x)}$$

# Chain Rule



## Example 4: Chain Rule

Find  $\frac{d}{dx} [(3x^2 + 2)^5]$ :

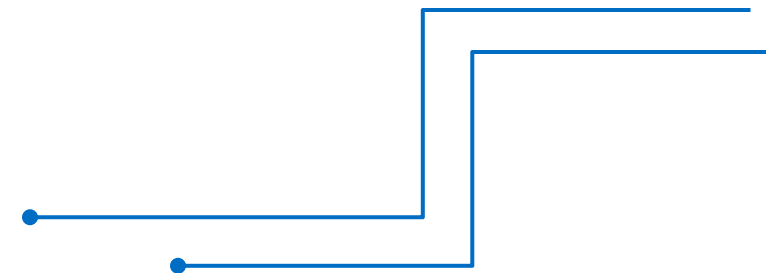
$$f(g(x)) = g(x)^5, \quad g(x) = 3x^2 + 2$$

$$\frac{d}{dx} [(3x^2 + 2)^5] = 5(3x^2 + 2)^4 \cdot \frac{d}{dx} [3x^2 + 2]$$

$$= 5(3x^2 + 2)^4 \cdot 6x$$

$$= 30x(3x^2 + 2)^4$$

# Assignment 3



# Calculus Basics for Optimization

## Gradient Descent

- ❑ An optimization algorithm used to minimize loss functions.
- ❑ Understanding how gradients help update weights in machine learning models.

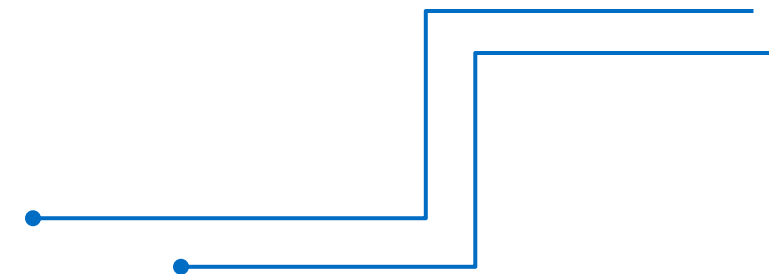
Gradient descent is an optimization algorithm used to minimize a function, typically a cost function  $J(\theta)$ .

- Example:**
- Start with an initial guess for the parameters  $\theta$ .
  - Update  $\theta$  iteratively using:

$$\theta = \theta - \alpha \cdot \frac{\partial J(\theta)}{\partial \theta}$$

where:

- $\alpha$ : Learning rate.
- $\frac{\partial J(\theta)}{\partial \theta}$ : Gradient of  $J$  with respect to  $\theta$ .



# Gradient Descent for Minimization

## Problem:

Minimize  $f(x) = x^2 - 4x + 4$ .

### 1. Objective Function:

$$f(x) = x^2 - 4x + 4$$

### 2. Gradient:

$$\frac{df}{dx} = 2x - 4$$

### 3. Update Rule:

$$x_{t+1} = x_t - \eta \cdot (2x_t - 4)$$

# Gradient Descent for Minimization

**4. Iterations:** Start with  $x_0 = 0$  and learning rate  $\eta = 0.1$ :

- Iteration 1:

$$x_1 = 0 - 0.1(2(0) - 4) = 0 - 0.1(-4) = 0.4$$

- Iteration 2:

$$x_2 = 0.4 - 0.1(2(0.4) - 4) = 0.4 - 0.1(-3.2) = 0.72$$

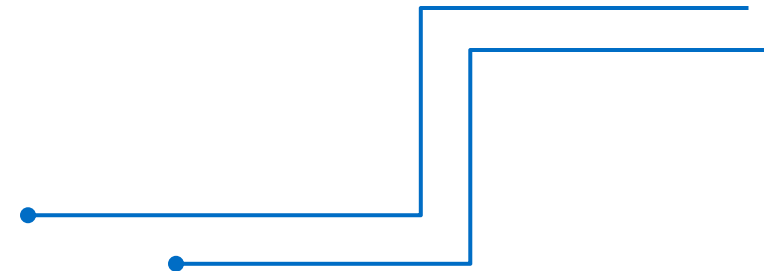
- Iteration 3:

$$x_3 = 0.72 - 0.1(2(0.72) - 4) = 0.72 - 0.1(-2.56) = 0.976$$

The algorithm converges towards  $x = 2$ , where  $f(x)$  has its minimum value.



# Assignment 4



# Introduction to Statistics

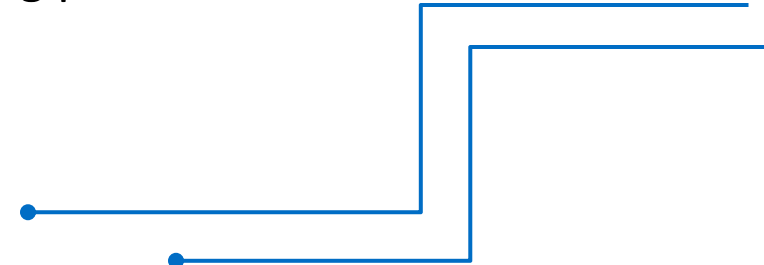


## What is Statistics?

- ❑ Statistics is the science of collecting, analyzing, and interpreting data.
- ❑ Used to draw conclusions and make informed decisions based on data.

## Why is Statistics important in AI?

- ❑ Helps understand data distributions, relationships, and trends.
- ❑ Essential for evaluating model performance, detecting biases, and making predictions.



# Types of Statistics

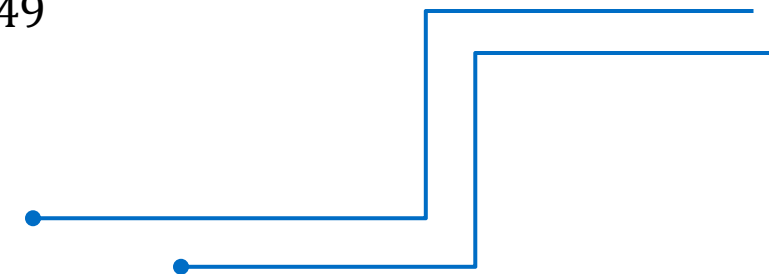


## Descriptive Statistics

- ❑ Summarizes and describes data.
- ❑ Examples: mean, median, mode, range, variance, and standard deviation.

**Example:** Given a dataset: [10, 20, 20, 40, 50]

- **Mean:** Average value =  $\frac{10+20+20+40+50}{5} = 28$
- **Median:** Middle value (sorted) = 20
- **Mode:** Most frequent value = 20
- **Range:** Difference between max and min =  $50 - 10 = 40$
- **Variance:** Measure of data spread =  $\frac{(10-28)^2 + \dots + (50-28)^2}{5} = 240$
- **Standard Deviation:**  $\sqrt{240} \approx 15.49$



# Types of Statistics

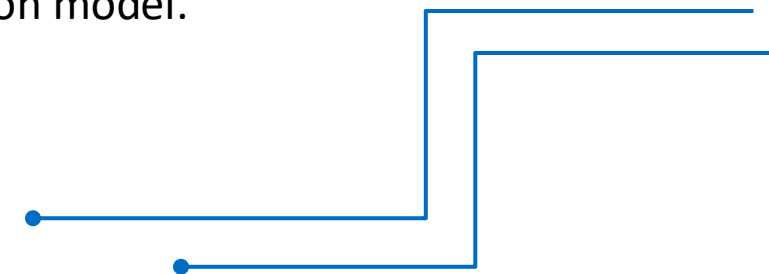


## Inferential Statistics

- ❑ Makes predictions or inferences about a population based on a sample.
- ❑ Examples: hypothesis testing, confidence intervals, and regression analysis.

### Example:

- A sample of 100 students shows an average height of 5.5 ft.
  - **Confidence Interval:** "We are 95% confident the true mean height of the population is between 5.4 and 5.6 ft."
  - **Hypothesis Testing:** Test if the mean height of the population is different from 5.5 ft.
  - **Regression Analysis:** Predict a student's weight based on height using a linear regression model.



# Measures of Central Tendency

## □ Central Tendency and Summarize datasets

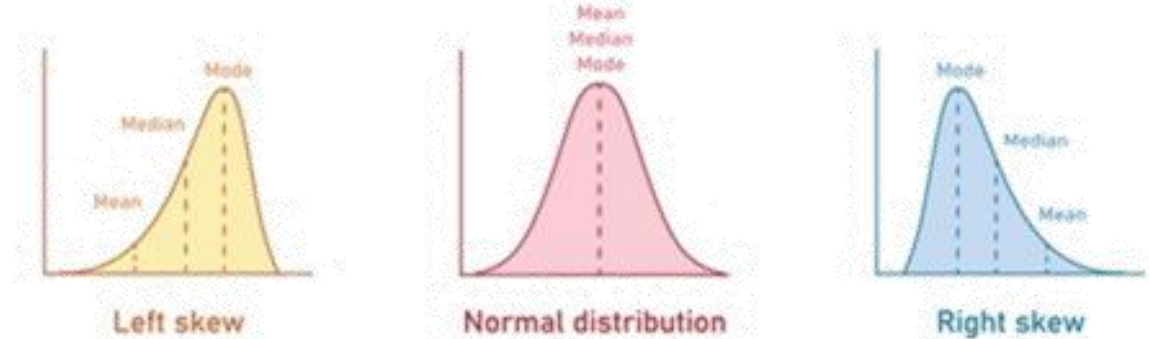
- Mean
- Median
- Mode

### Examples:

Dataset: [3, 7, 5, 5, 10]

Mean = 6, Median = 5, Mode = 5

### Mean, Median and Mode



# Mean (Average)



□ The sum of all values divided by the number of values.

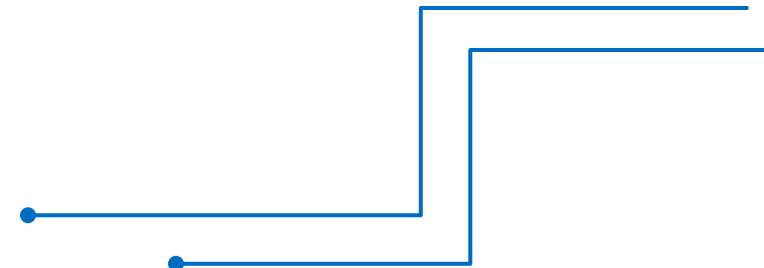
$$Mean = \frac{\sum x_i}{n}$$

**For example:**

$$2 + 2 + 5 + 6 + 7 + 8 = 30$$

$$30 \div 6 = 5$$

*The mean number is 5.*



# Median

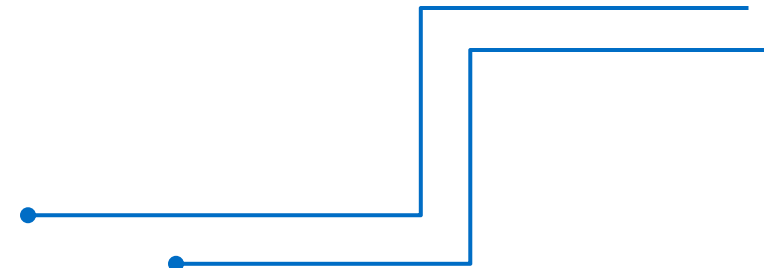


- ❑ The middle value when data is sorted.
- ❑ Useful when data has outliers.

**For example:**

$$2 + 2 + 5 + 6 + 7 + 8 + 9$$

*The median number is 6.*



# Mode

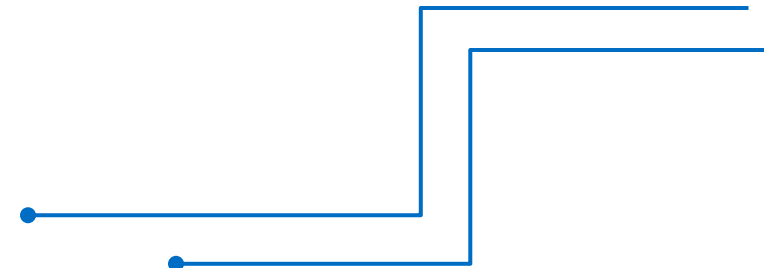


- The most frequently occurring value in the dataset.

**For example:**

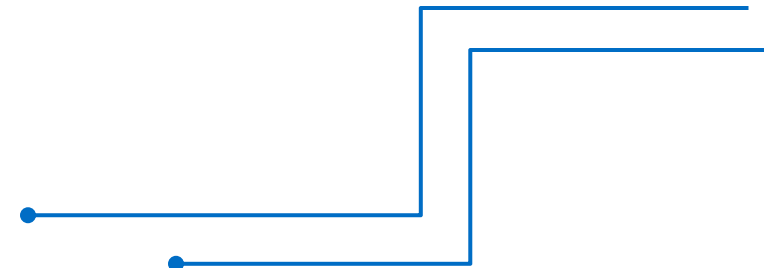
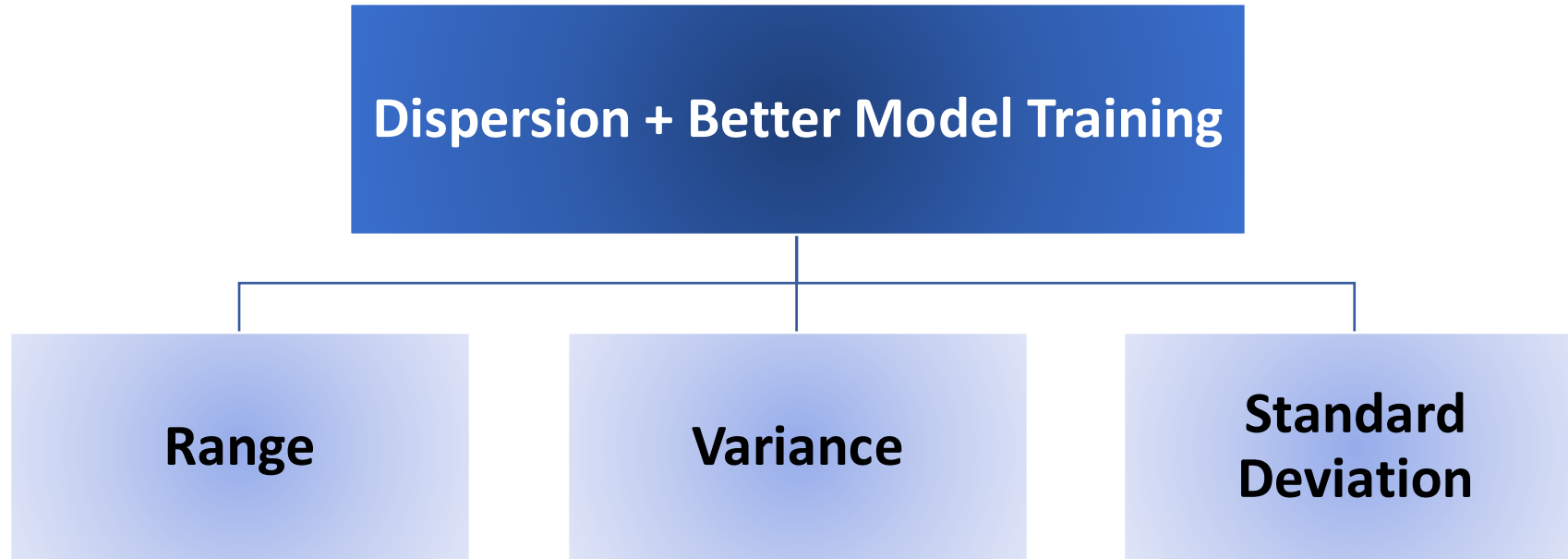
$$2 + 2 + 5 + 6 + 7 + 8$$

*The mode number is **2**.*





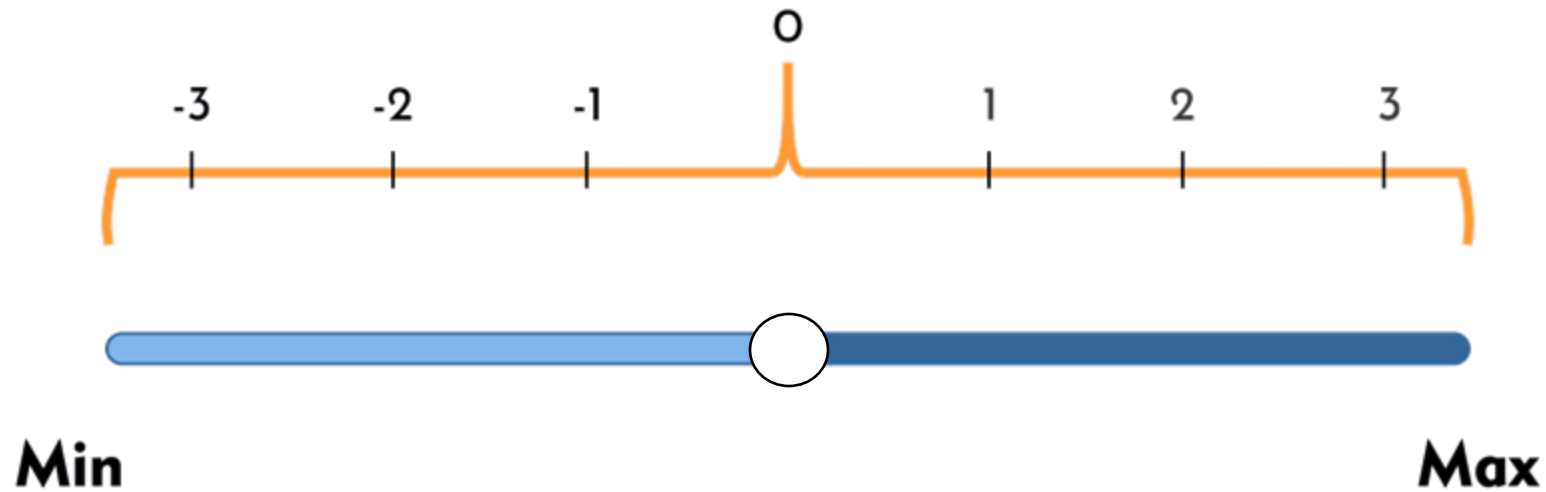
# Measures of Dispersion



# Range

- The difference between the maximum and minimum values.

$$\text{Range} = \text{Max} - \text{Min}$$

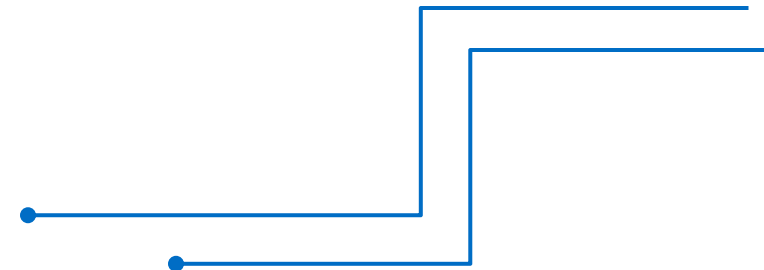


# Variance



- Measures how far data points are from the mean.

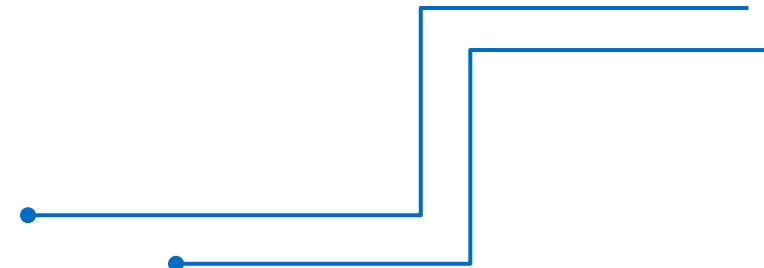
$$Variance = \frac{\sum (x_i - mean)^2}{n}$$



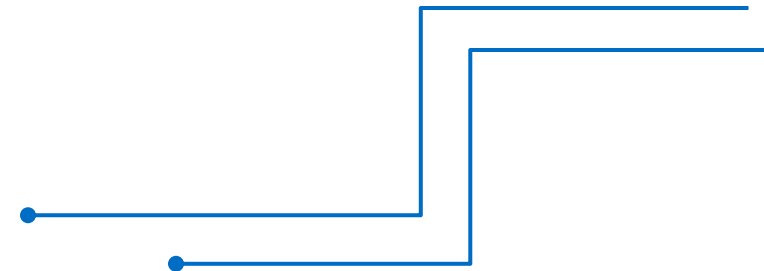
# Standard Deviation (SD)

- The square root of variance, showing the average deviation from the mean.

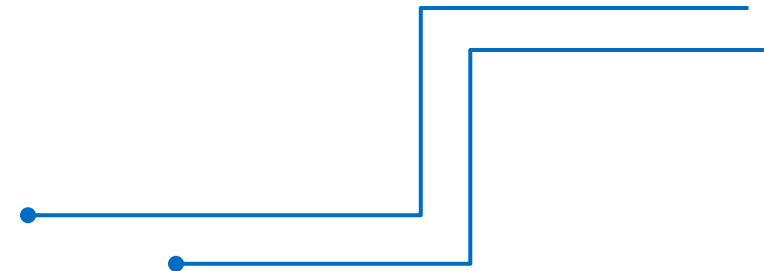
$$SD = \sqrt{Variance}$$



# Assignment 5



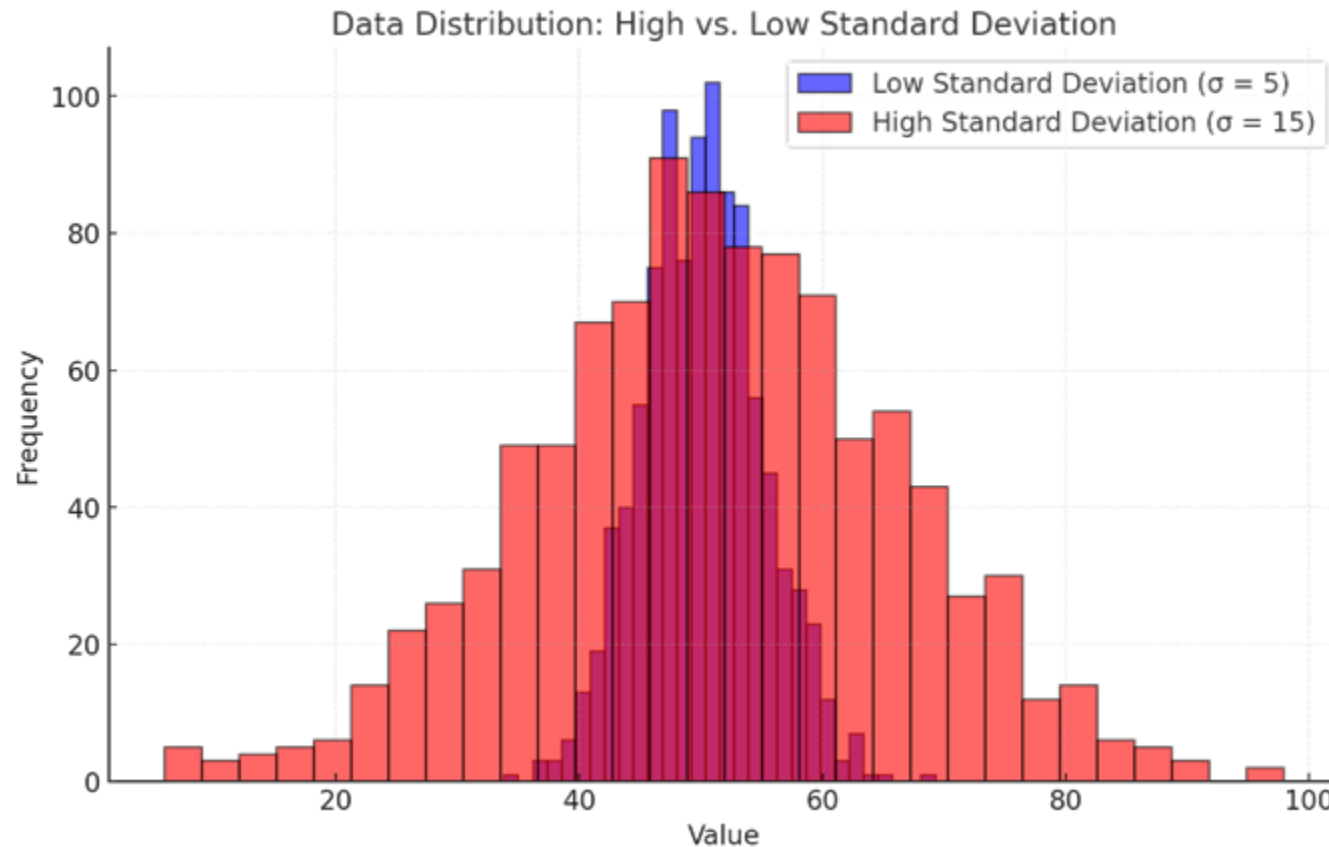
# Assignment 6



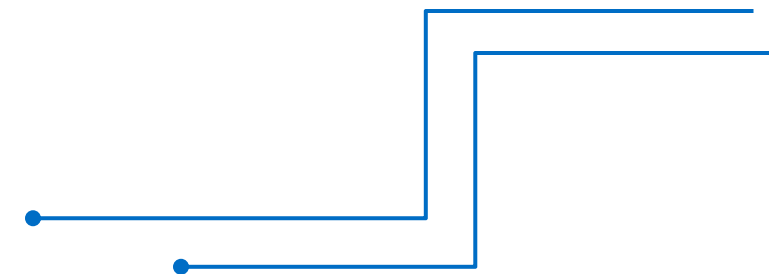
# Measures of Dispersion

## Why it matters in AI?

- Understanding data variability helps in model selection and evaluation.



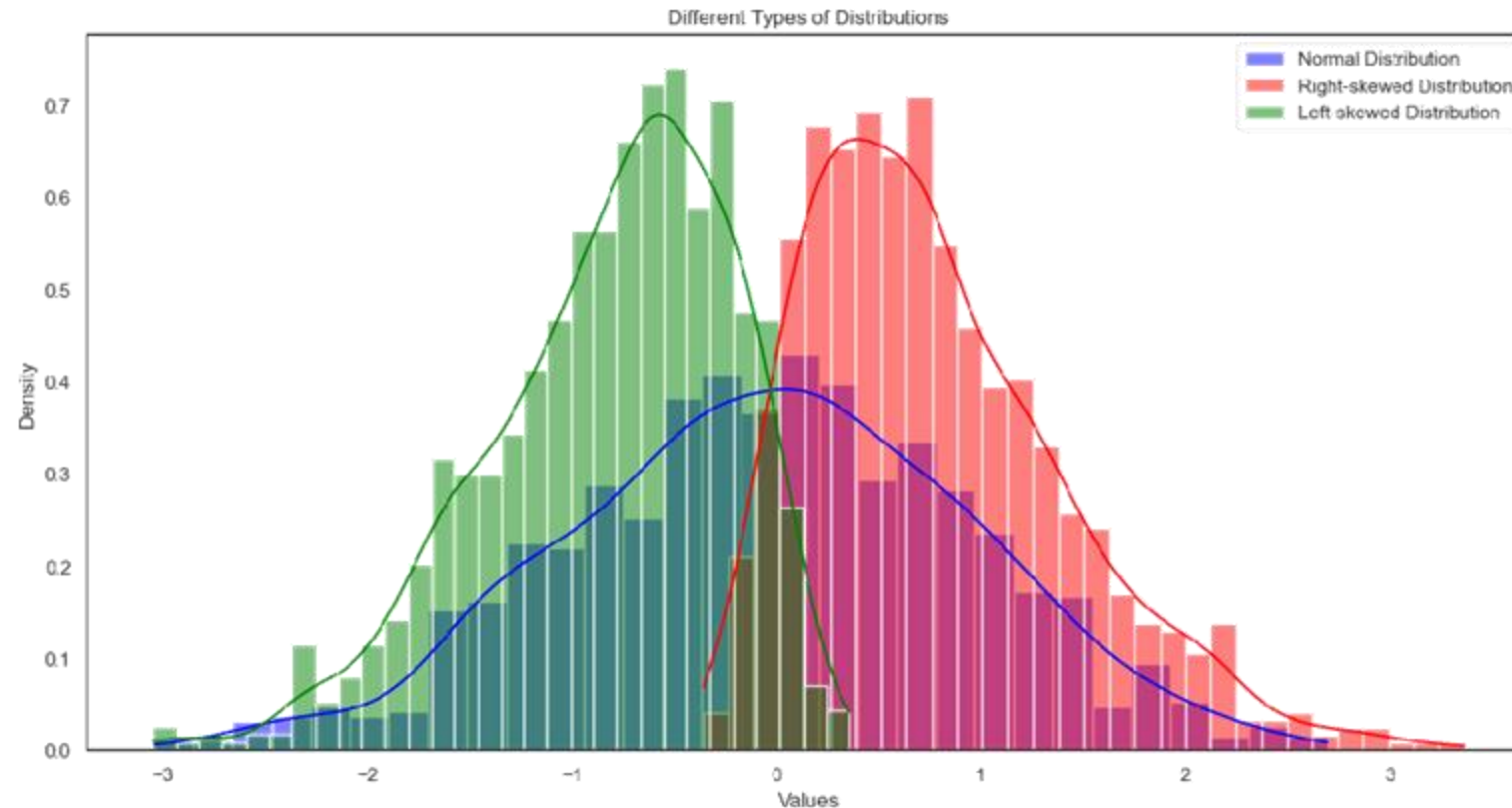
- Graph showing data distribution with a high and low standard deviation.



# Data Distributions

## What is Data Distributions?

- ❑ A distribution shows how often each value in a dataset occurs.

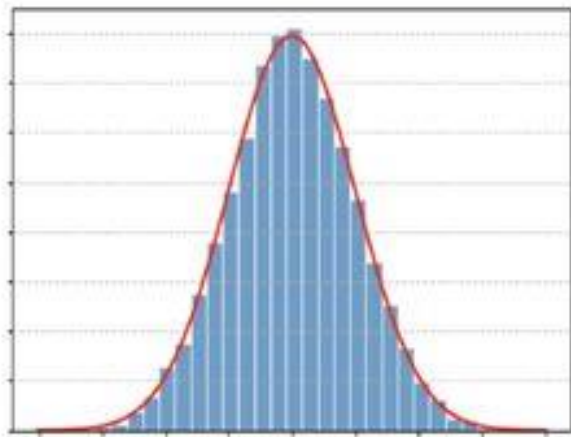




# Types of Distributions

## Normal Distribution

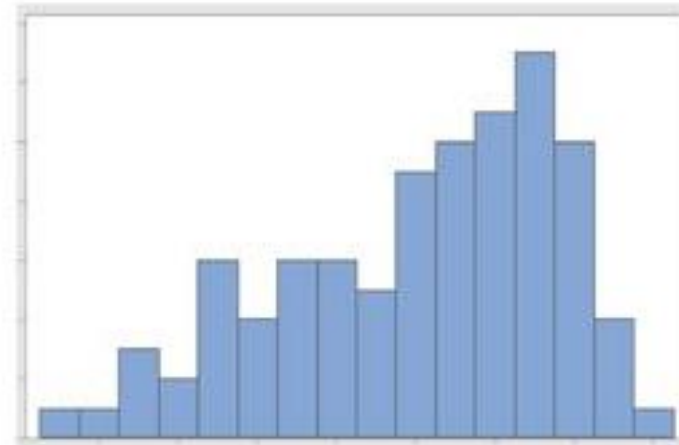
- ☐ Symmetrical, bell-shaped curve centered around the mean.
- ☐ Properties: 68% of data falls within 1 SD, 95% within 2 SDs



Normal Distribution

## Skewed Distribution

- ☐ **Left-Skewed:** Tail on the left, mean < median.
- ☐ **Right-Skewed:** Tail on the right, mean > median.



Skewed Distribution

# Probability for AI

## What is Probability?

- ❑ The likelihood of an event occurring, ranging from 0 (impossible) to 1 (certain).

## Why Probability is important in AI?

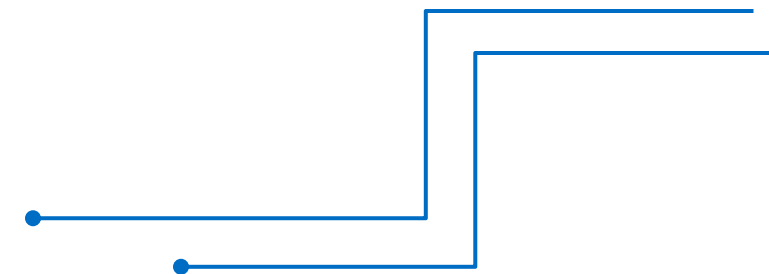
- ❑ Used in algorithms for classification, regression, and prediction.

## Descriptive Statistics

- ❑ Measures of central tendency (mean, median, mode).
- ❑ Measures of dispersion (variance, standard deviation).

## Inferential Statistics

- ❑ Hypothesis testing, p-values, confidence intervals.
- ❑ Correlation and causation.



# Basic Probability Rules

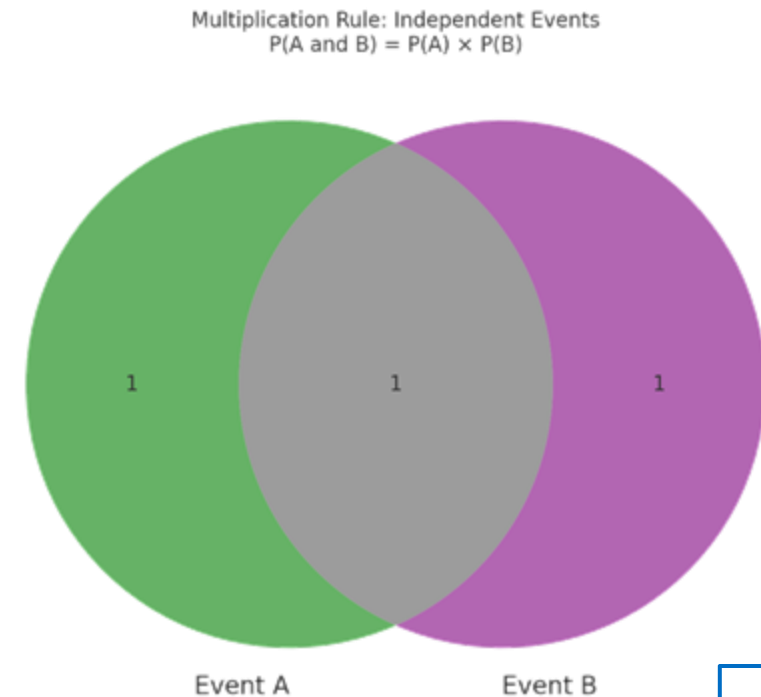
□ **Addition Rule:** For mutually exclusive events:

$$P(A \text{ or } B) = P(A) + P(B)$$



□ **Multiplication Rule:** For independent events:

$$P(A \text{ and } B) = P(A) \times P(B)$$

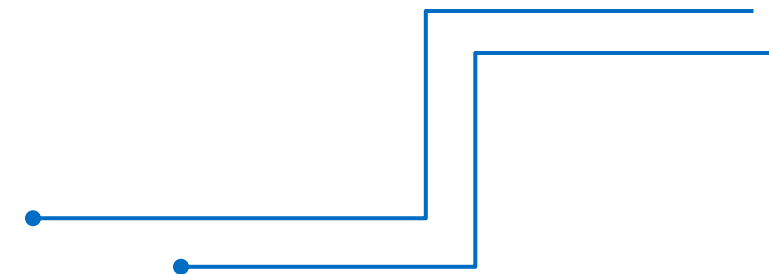
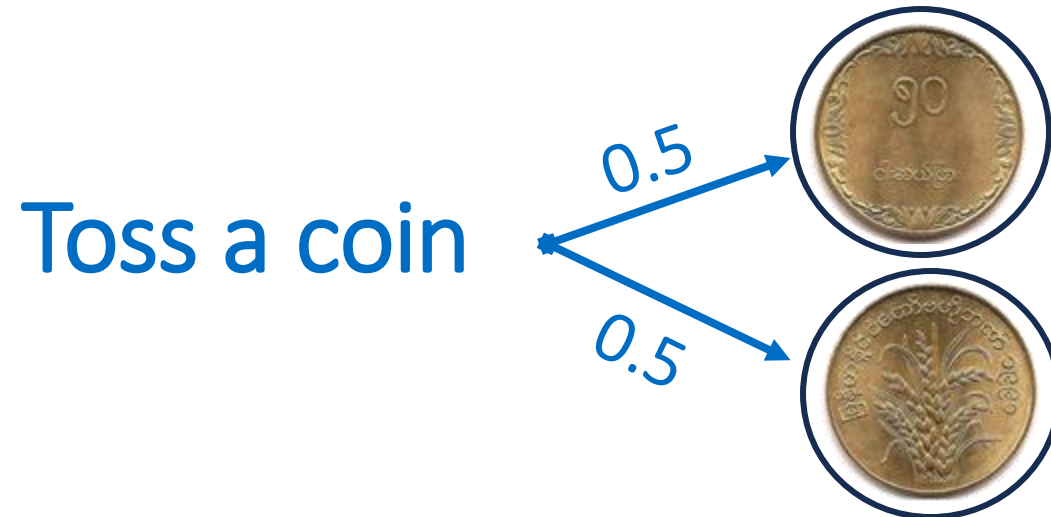


Venn diagrams illustrating addition and multiplication rules.

# Basic Probability Rules

**Example:** What is the probability of getting heads when flipping a coin?

- When flipping a coin, the probability of getting heads is 0.5 since there are two equally likely outcomes (heads or tails).



# Prior Probability

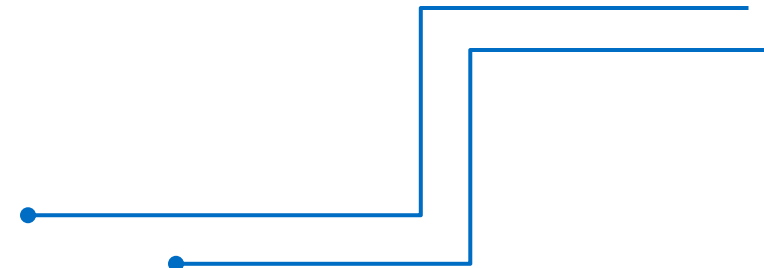
- $P(\text{Spam})$ : The Proportion of emails labeled as spam.
- $P(\text{Not Spam})$ : The Proportion of emails not labeled as spam.

**Example:** Suppose you have an email dataset where:

- 40% of the emails are labeled as **Spam**.
- 60% of the emails are labeled as **Not Spam**.

## Prior Probability:

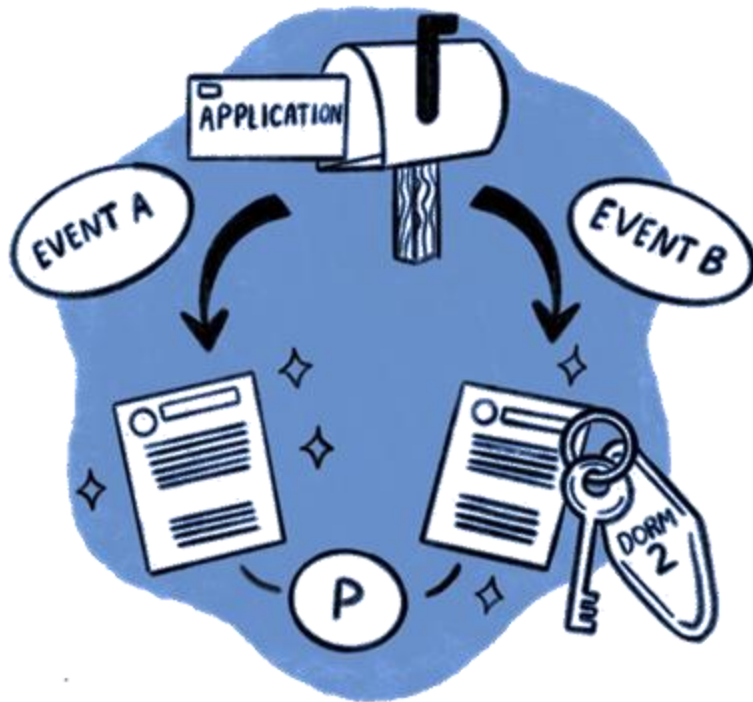
- $P(\text{Spam}) = 0.4$  (Proportion of emails labeled as spam)
- $P(\text{Not Spam}) = 0.6$  (Proportion of emails not labeled as spam)



# Conditional Probability

- Calculate the likelihood of certain words appearing in spam vs. non-spam emails.

$$P(\text{Word}|\text{Spam})$$



# Conditional Probability

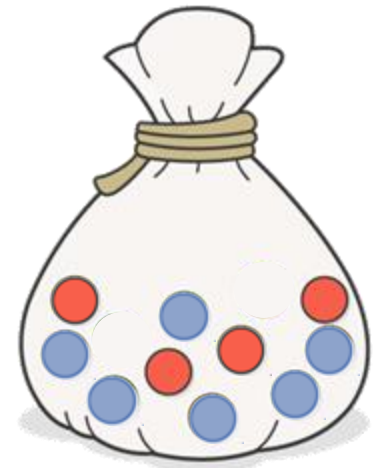
**Scenario:** You have a bag of 10 marbles:

- 4 are **red**.
- 6 are **blue**.

Now, suppose you randomly pick a marble, and you are told it's **blue**. What's the probability that this blue marble came from the bag?

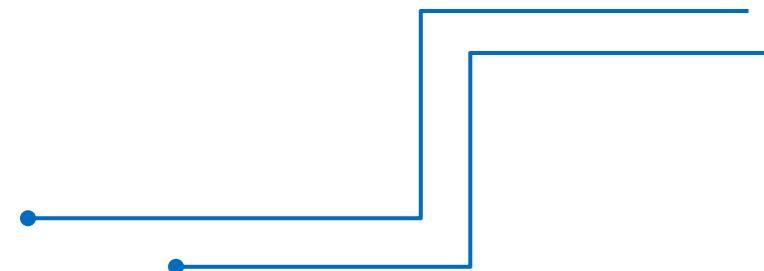
**Conditional Probability:** The probability of picking a **blue marble** is:

$$P(\text{Blue}) = \frac{\text{Number of blue marbles}}{\text{Total marbles}} = \frac{6}{10} = 0.6$$

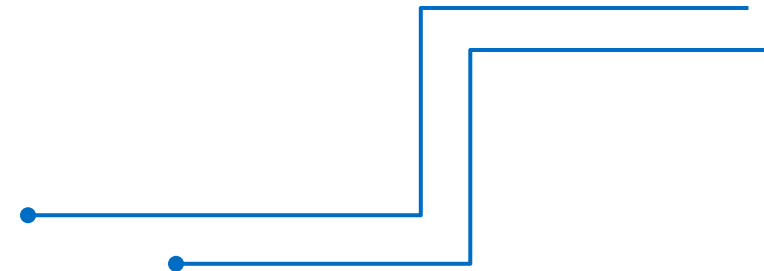


If we are given the condition that the marble is **blue**, the probability stays the same, since we're directly working with the blue marbles. This illustrates:

$$P(\text{Blue} | \text{Condition: Bag}) = 0.6$$



# Assignment 7





# Bayesian Approach



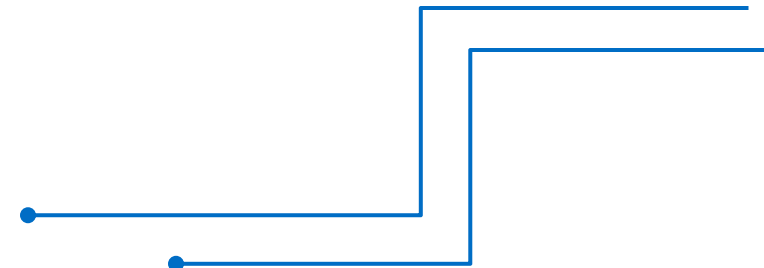
- Use Bayes' Theorem to classify a new email:

$$P(\text{Spam}|\text{Words}) = \frac{P(\text{Words}|\text{Spam}) \times P(\text{Spam})}{P(\text{Words})}$$

**Scenario:** You have two bowls of candies

- **Bowl A:** 30% chocolate candies, 70% fruit candies.
- **Bowl B:** 80% chocolate candies, 20% fruit candies.

You randomly pick a bowl, and from that bowl, you pick a **chocolate candy**. What's the probability it came from **Bowl B**?



# Bayesian Approach

- Given:
- $P(\text{Bowl } B) = 0.5$
  - $P(\text{Chocolate} \mid \text{Bowl } B) = 0.8$
  - $P(\text{Chocolate} \mid \text{Bowl } A) = 0.3$

Formula to use:

$$P(\text{Bowl } B \mid \text{Chocolate}) = \frac{P(\text{Chocolate} \mid \text{Bowl } B) \cdot P(\text{Bowl } B)}{P(\text{Chocolate})}$$

1. Calculate  $P(\text{Chocolate})$ :

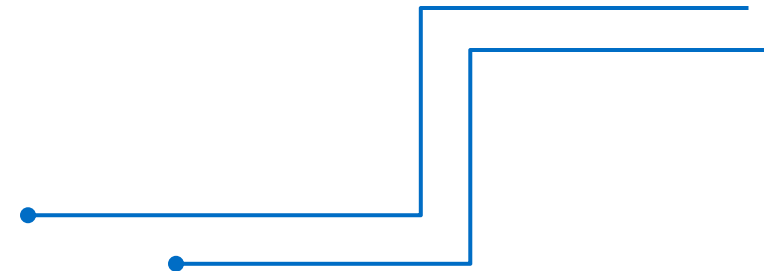
$$\begin{aligned} P(\text{Chocolate}) &= P(\text{Chocolate} \mid \text{Bowl } A) \cdot P(\text{Bowl } A) + P(\text{Chocolate} \mid \text{Bowl } B) \cdot P(\text{Bowl } B) \\ P(\text{Chocolate}) &= (0.3 \cdot 0.5) + (0.8 \cdot 0.5) = 0.15 + 0.4 = \mathbf{0.55} \end{aligned}$$

2. Calculate  $P(\text{Bowl } B \mid \text{Chocolate})$ :

$$P(\text{Bowl } B \mid \text{Chocolate}) = \frac{0.8 \cdot 0.5}{0.55} = \frac{0.4}{0.55} \approx \mathbf{0.727}$$



# Assignment 8 (Python Assignment)



# Assignment: Predicting Loan

## ❑ Problem Statement:

- Build a model to predict whether a customer will default on a loan based on past data.

## Applying Probability:

### ➤ Prior Probability:

The historical rate of loan defaults:  $P(\text{Default})$

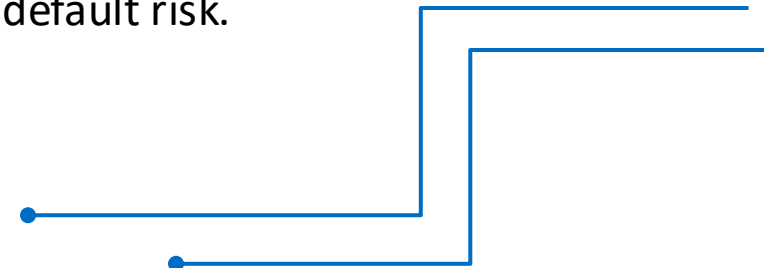
### ➤ Conditional Probability:

Probability of default given income level:  $P(\text{Default} \mid \text{Income Level})$

Probability of default given credit score:  $P(\text{Default} \mid \text{Credit Score})$

### ➤ Using Bayesian Networks:

Model relationships between variables like income, credit score, and loan default risk.

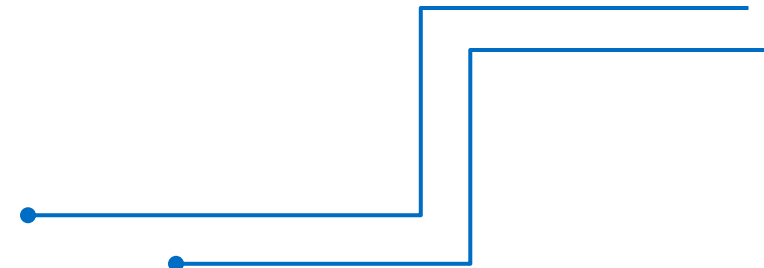


# Assignment: Predicting Loan



```
import pandas as pd
from sklearn.model_selection
import train_test_split

from sklearn.naive_bayes
import GaussianNB from sklearn.metrics
import confusion_matrix, accuracy_score
# Load dataset (simulated example)
data = pd.DataFrame({ "income": [50, 100, 150, 30, 120], "credit_score": [700, 850, 650, 600,
720], "default": [0, 0, 1, 1, 0] })
# Feature matrix and target variable
X = data[['income', 'credit_score']] y = data['default']
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
# Train a Gaussian Naive Bayes classifier
model = GaussianNB() model.fit(X_train, y_train)
# Make predictions
predictions = model.predict(X_test)
accuracy = accuracy_score(y_test, predictions)
print("Accuracy:", accuracy)
```





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