

BTech (Elements of AIML)

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# Overview of Machine Learning Life Cycle

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- Testing (Confusion Matrix) (1-2 Min)
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# Introduction

**Definition:** A subset of AI that enables systems to learn from data and improve over time without being explicitly programmed.

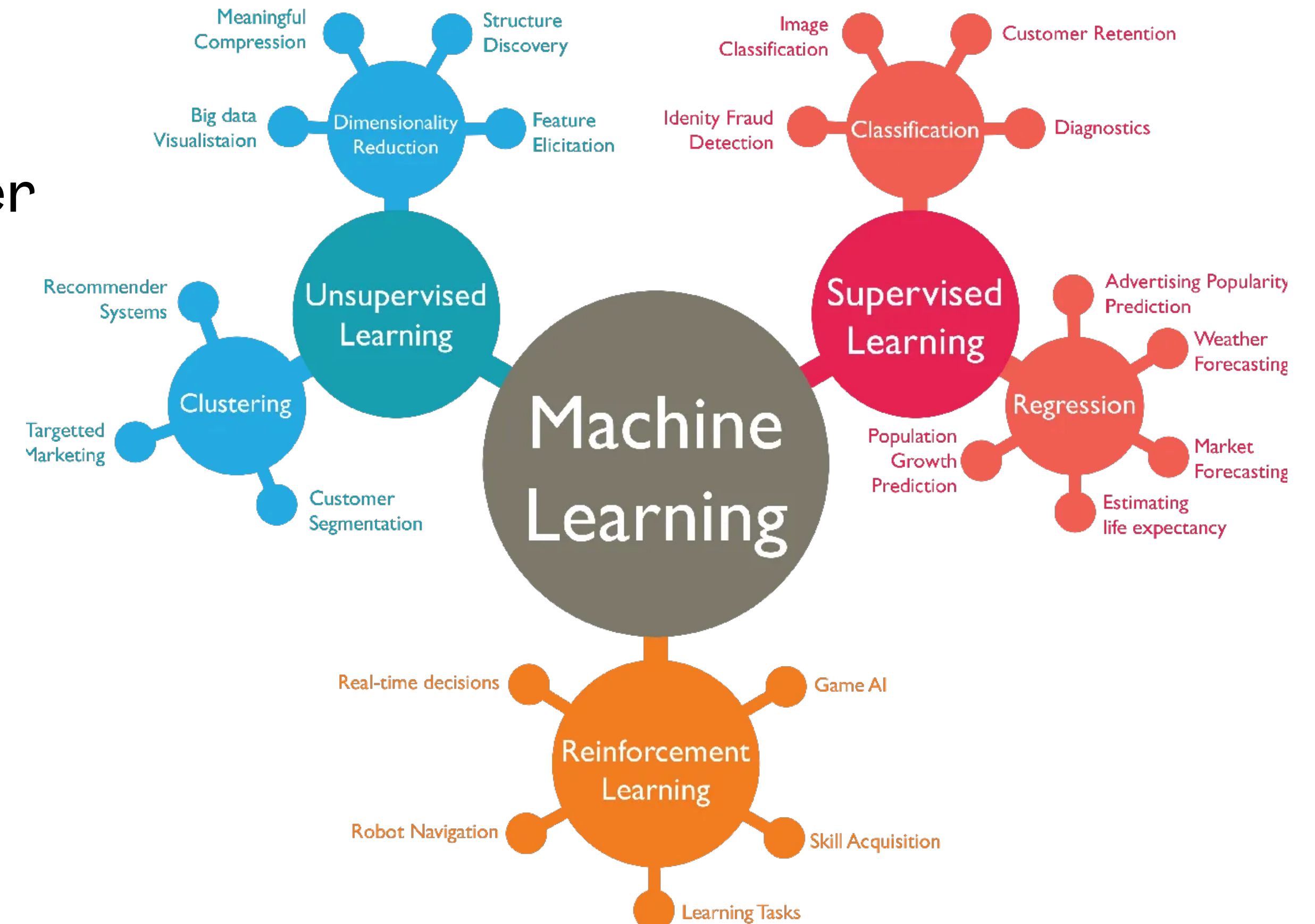
Type of Machine learning:

1. Supervised : a. Regression Model

b. Classification Model

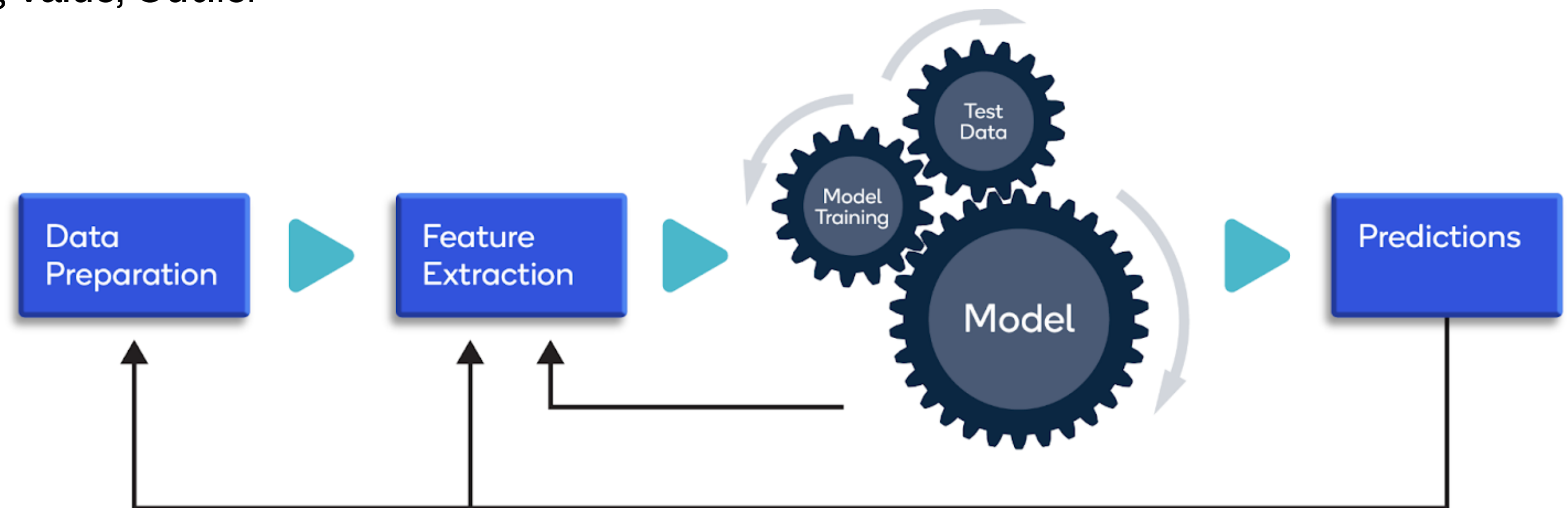
2. Unsupervised Model:

3. Reinforcement Learning



# Overview of Machine Life Cycle.

1. Collection of Data
2. Exploratory Data Analysis:
  - b. Data Visualisation
  - c. Hypothesis Testing(Statistics Analysis)
  - d. Data Cleaning: Handling Missing Value, Outlier
  - e. Feature Engineering
3. Model Building:
  - a. Trained the model
  - B. Regularisation(L1, L2)
4. Model Evaluation: Testing and Selection
5. Deploy the model: Server or Cloud.



ML Life cycle

# Data Collection

- Data: Gathering relevant data from various sources. Such: APIs, Web Scraping, Surveys, Sensor Data, Public Datasets, Databases.

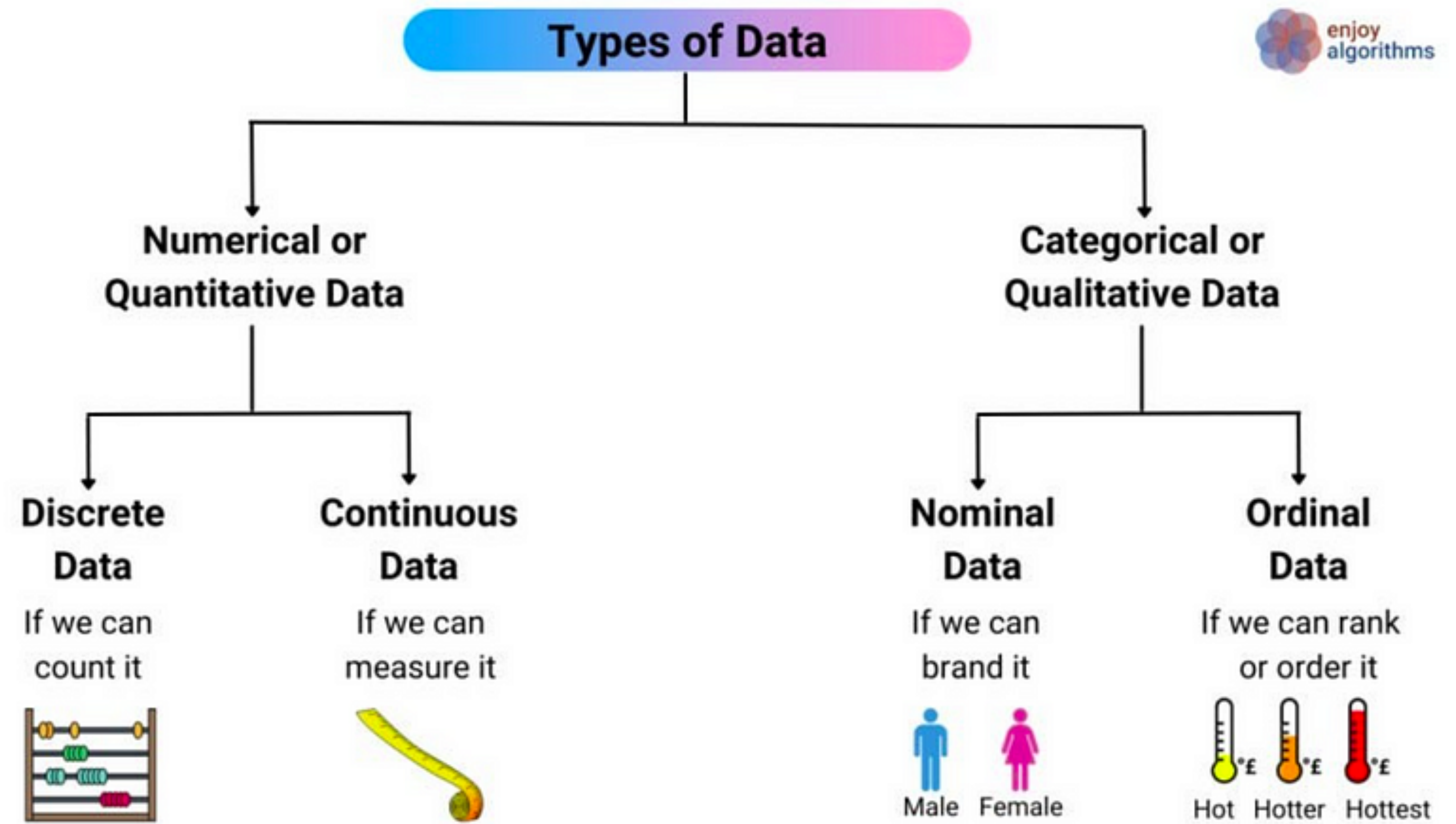
- Types of Database:

a. Structured: Relational Data base(SQL)

- Numerical, Categorical data

b. Unstructured: No SQL( Image, Audio)

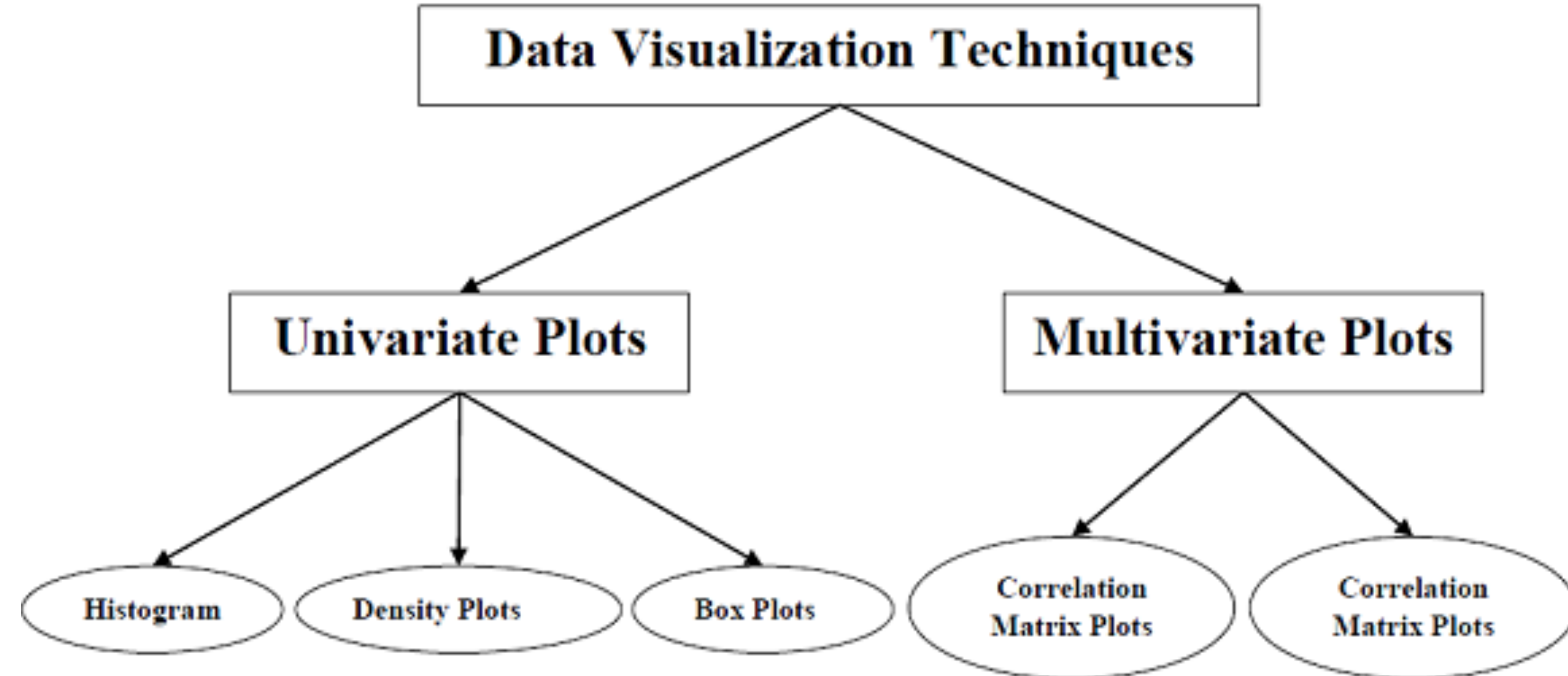
c. Semi-structured: (Xml, Json)





# Exploratory Data Analysis

- Understanding the dataset and uncovering patterns.
- Tools: Visualisation, summary statistics.

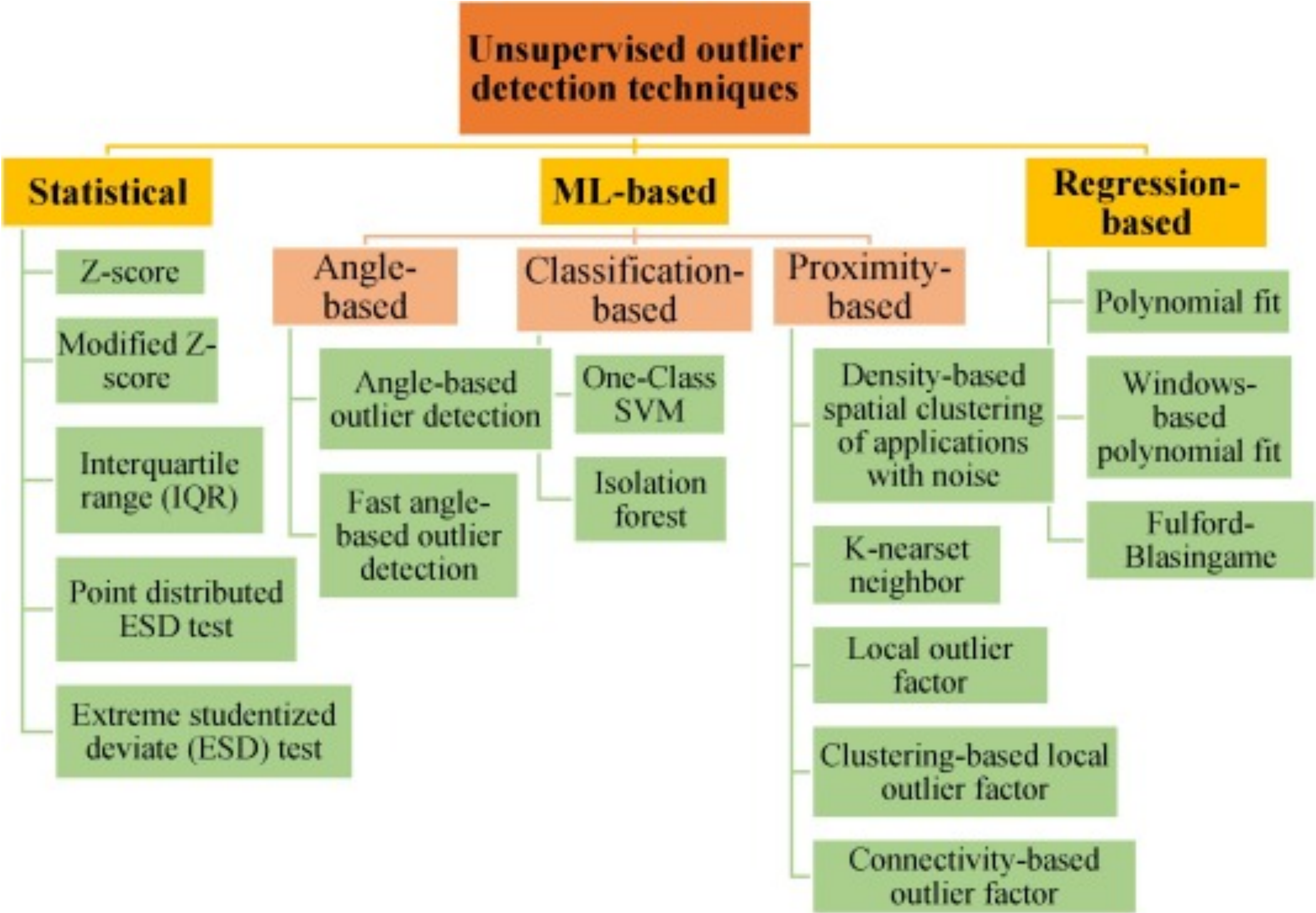


Caption

# Data Cleaning

- In Data Cleaning there are two major Parts:

- 1. Outlier Detection
- 2. Handling Missing Value

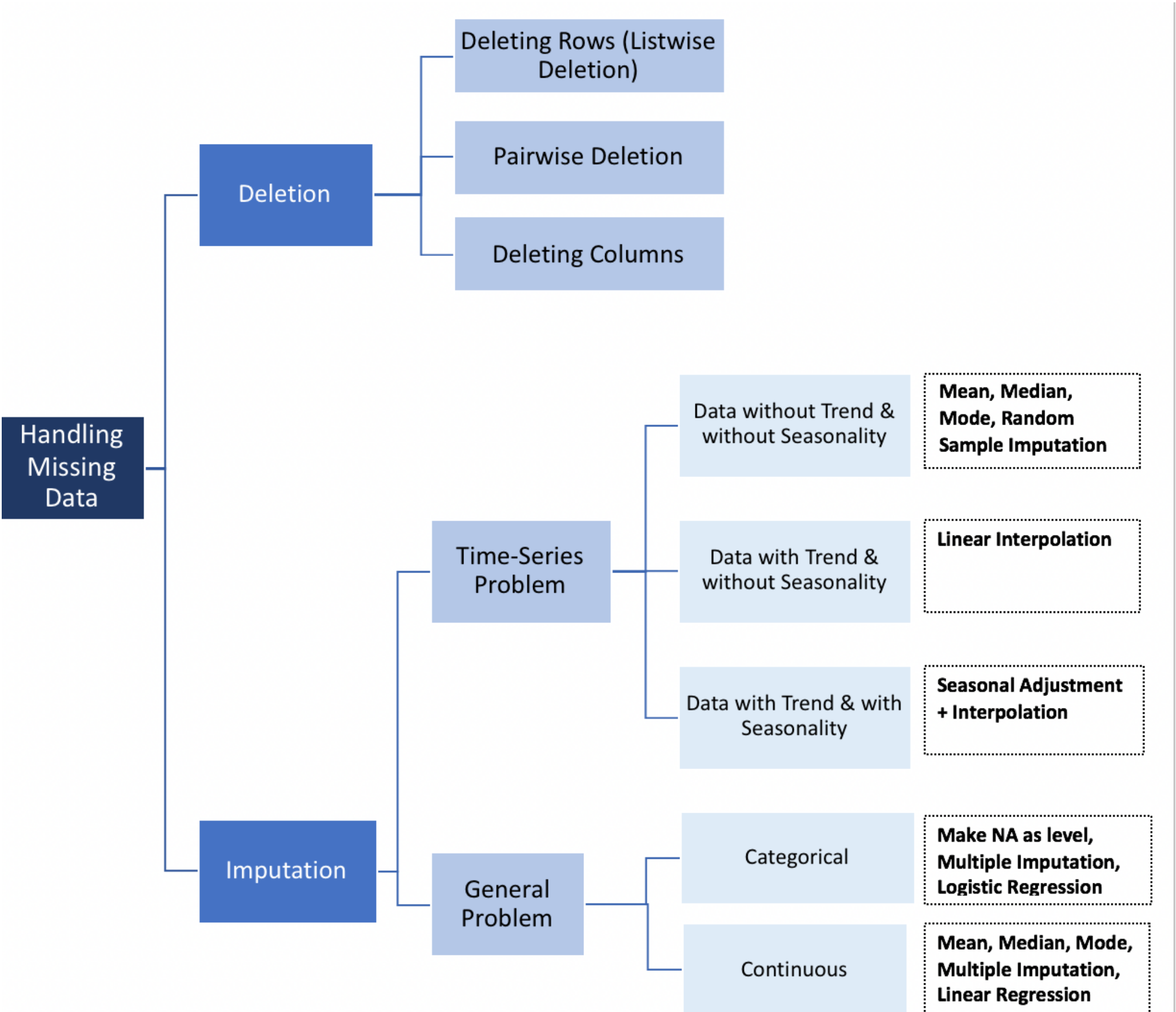


Caption



# Handling Missing Value:

Handling Missing Value:





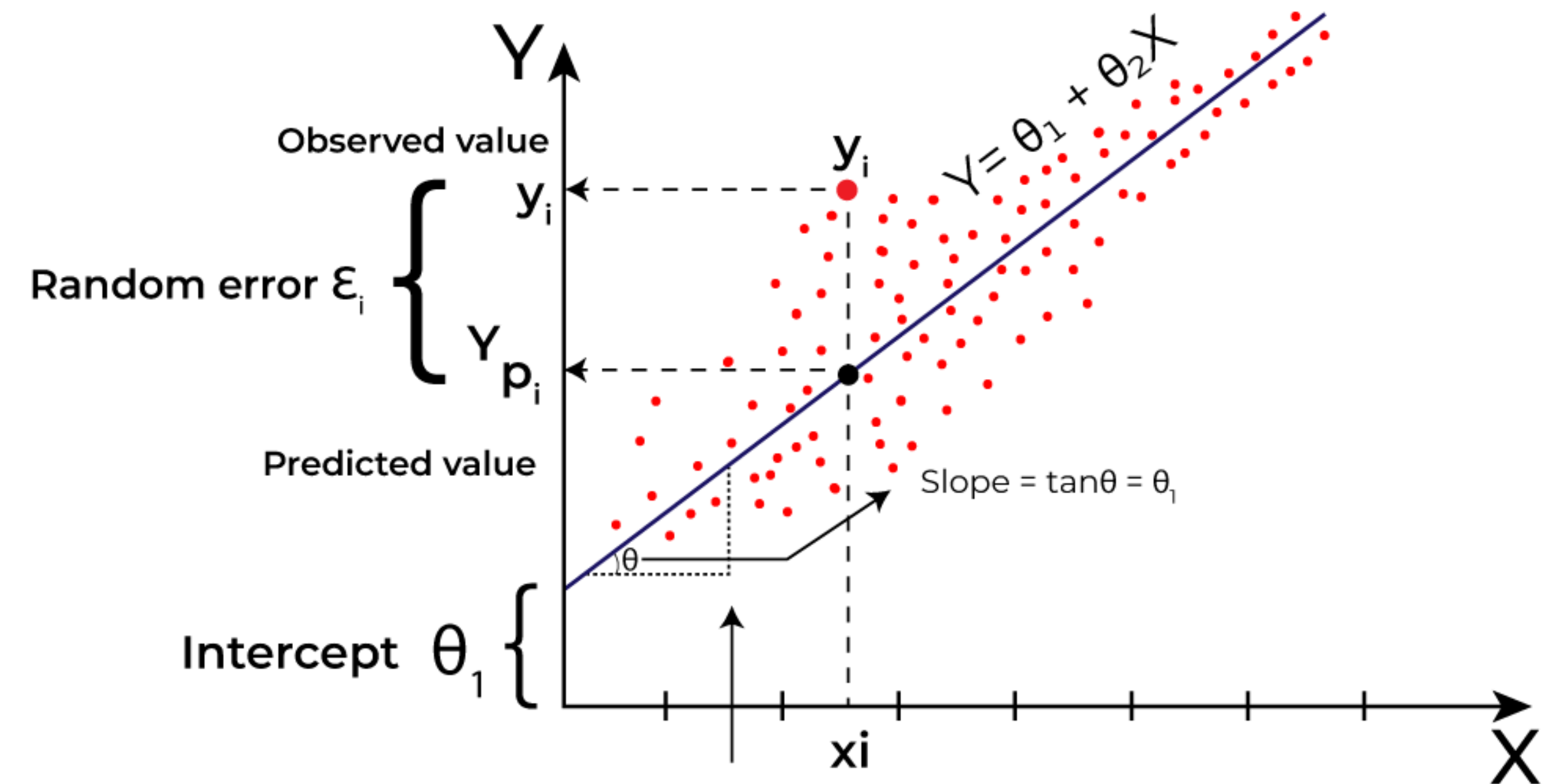
# Linear regression Model

- **Definition:** Linear approach to modelling the relationship between a dependent variable and one or more independent variables.
- Mathematical Equation:

$$Y_i = \beta_0 + \beta_1 X_i$$

Diagram illustrating the components of the linear regression equation:

- $Y_i$ : Dependent Variable
- $\beta_0$ : Constant/Intercept
- $\beta_1$ : Slope/Coefficient
- $X_i$ : Independent Variable



# Cost function( Loss or Error Function)

- The cost function measures how well the model's predictions match the actual data.  
Various way:
  1. Mean Absolute Error (MAE)
  2. Mean Square Error(MSE)
  - 3, Root Mean Square Error (RMSE)
- For linear regression, the most commonly used cost function is the Mean Squared Error
- Ratio= Sum of Square error for Own Model/ Sum of Square error for Base Model
- R squared= 1- Ratio

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}|$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y})^2$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y})^2}$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2}$$

Where,

$\hat{y}$  – predicted value of  $y$   
 $\bar{y}$  – mean value of  $y$

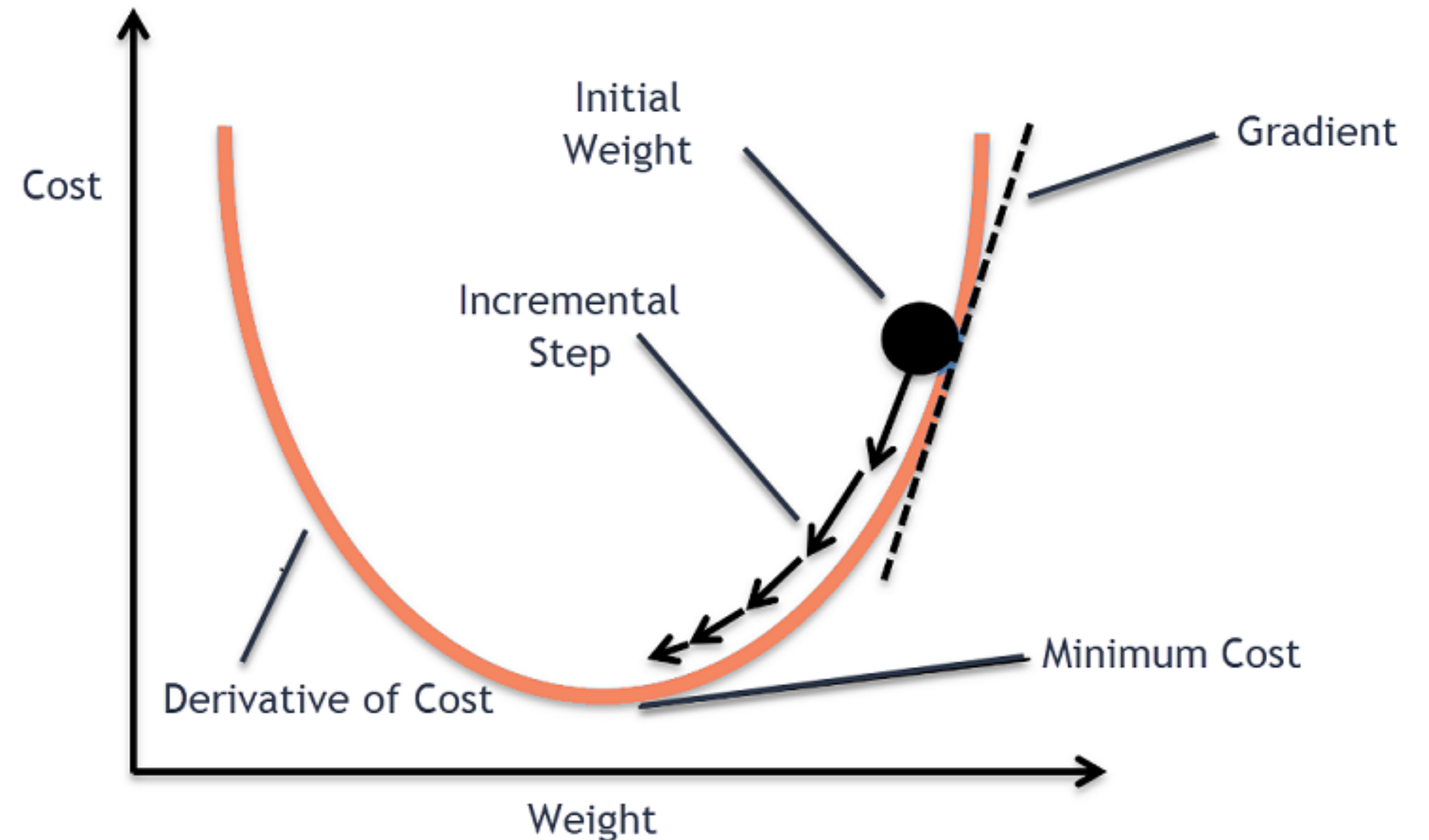
# Optimisation

- **Gradient Descent:** An iterative optimisation algorithm used to minimise the cost function.

Repeat until convergence {

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}





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# Various types of Gradient Descent

## Batch Gradient Descent

- Entire dataset for updation
- Cost function reduces smoothly
- Computation cost is very high

## Stochastic Gradient Descent (SGD)

- Single observation for updation
- Lot of variations in cost function
- Computation time is more

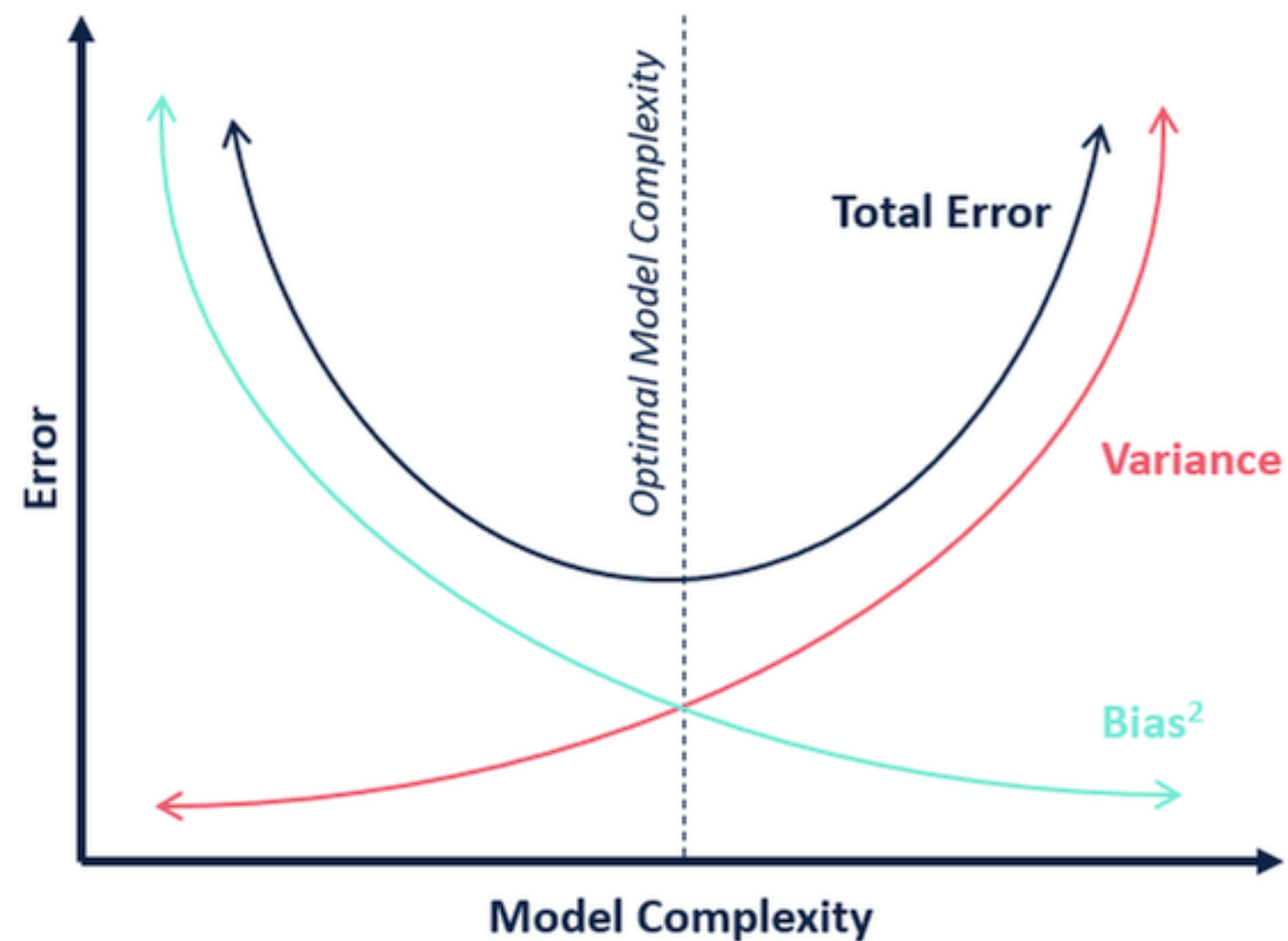
## Mini-Batch Gradient Descent

- Subset of data for updation
- Smoother cost function as compared to SGD
- Computation time is lesser than SGD
- Computation cost is lesser than Batch Gradient Descent



# Regularization

- Regularisation use for balancing the model from overfit and under fit.
- L1 Regularization (Lasso):** Adds the absolute value of magnitude of coefficient as penalty term to the loss function.
- L2 Regularization (Ridge):** Adds the squared magnitude of coefficient as penalty term to the loss function.



## L1 Regularization

$$\text{Cost} = \sum_{i=0}^N (y_i - \sum_{j=0}^M x_{ij} W_j)^2 + \lambda \sum_{j=0}^M |W_j|$$

## L2 Regularization

$$\text{Cost} = \underbrace{\sum_{i=0}^N (y_i - \sum_{j=0}^M x_{ij} W_j)^2}_{\text{Loss function}} + \lambda \underbrace{\sum_{j=0}^M W_j^2}_{\text{Regularization Term}}$$

# Testing

- R squared: Used for Regression
- **Confusion Matrix:** A table used to evaluate the performance of a classification algorithm.

- **Metrics:**

- Accuracy
- Precision
- Recall
- F1 Score

		POSITIVE	NEGATIVE
ACTUAL VALUES	POSITIVE	<b>TP</b>	<b>FN</b>
	NEGATIVE	<b>FP</b>	<b>TN</b>

$$Precision = \frac{TP}{TP + FP} \quad Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

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# Model Deployment

- Integrating the model into a production environment. Such as Cloud(AWS, Azure)
- Methods: APIs, embedded systems, cloud services.

## **Monitoring and Maintenance:**

- Continuous monitoring of the model's performance.
- Handling model drift and updating the model as necessary.

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# Conclusion

## Summary:

- Recap the stages of the machine learning life cycle.
- Emphasise the importance of each stage.
- **Challenges:**Data quality issues, model interpretability, scalability

## Final Thoughts:

- Continuous learning and adaptation are key to successful machine learning projects.
- **Best Practices:** Regular updates, thorough validation, comprehensive documentation.



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# Q&A

- Invitation for Questions:
  - Open the floor for questions and discussions.

# Thank You