→ **Logistic Regression**

- **What is logistic regression**
Statistical classification method used to predict the probability of a categorical outcome, most commonly binary outcomes (0 or 1, Yes or No). It is used for classification, not regression.

- **Why it is used**
  - Predicts probabilities
  - Performs binary and multiclass classification
  - Simple, fast and interpretable
  - Works well when the relationship between features and log-odds is linear
  - Provides clear decision boundaries.

- **How it works**
  - Takes input features x
  - Computes a linear combination of inputs
  - Applies the sigmoid (logistic) function
  - Converts output into a probability (0 to 1)
  - Uses a threshold (e.g., 0.5) to assign class labels.

- **Where it is used**
  - Machine learning
  - Data Science
  - Healthcare analytics
  - Finance & banking
  - Marketing analytics
  - Social science research

- Formula
  - Linear Combination: $z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n$
  - Sigmoid function: $\sigma(z) = \frac{1}{1+e^{-z}}$
  - Logistic Regression model: $P(y=1|x) = \frac{1}{1+e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n)}}$

- Technical Details
  - Types: Binary, Multinomial, Ordinal
  - Cost Function (Log Loss / Binary Cross-Entropy):
    $$J(\theta) = -\frac{1}{n}\sum_{i=1}^{n}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$
  - Optimization: Gradient Descent
    Maximum Likelihood Estimation (MLE)
  - Evaluation metrics: Accuracy
    Precision, Recall
    F1-Score
    ROC-AUC
    Confusion Matrix

- Pros
  - Outputs probabilities, not just classes
  - Easy to interpret coefficients
  - Computationally efficient
  - Works well with linearly seperable data
  - Less prone to overfitting than complex models.

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- **Cons**
  - Assumes linear decision boundary
  - Cannot capture complex non-linear relationships
  - Sensitive to outliers
  - Requires feature scaling for faster convergence
  - Performance drops with highly imbalanced data

- Real World Application (Where)
  - Healthcare: Disease Diagnosis (Yes/No)
    Patient risk prediction
  - Finance: Credit default prediction
    Fraud detection
  - Marketing: Customer churn prediction
    Ad click prediction
  - HR Analytics: Employee attrition prediction
  - Cybersecurity: Spam detection
    Intrusion detection

- **Assumptions**
  - Binary dependent variables
  - Independent observations
  - Little or no multicollinearity
  - Linear relationship between predictors and log-odds
  - Large sample size preferred.

- **Purpose**
  - Predict the probability of an event occuring
  - Classify data into discrete categories, especially binary classes
  - Model the relationship between features and log-odds of an outcome.
  - Support decision-making using probability thresholds
  - Provide interpretable classification results.