

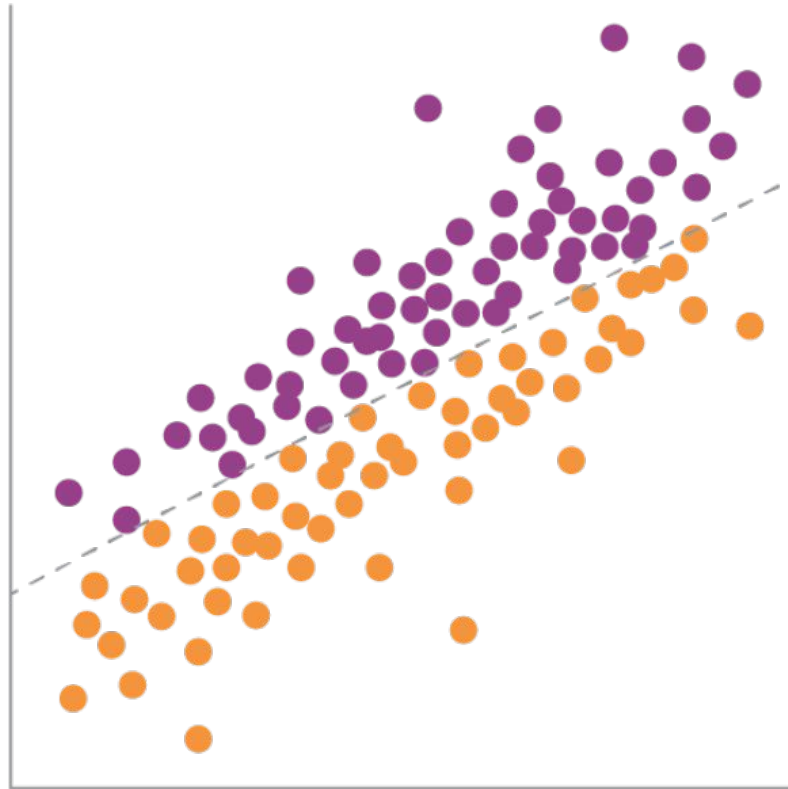
# ENGR 3321: Introduction to Deep Learning for Robotics

Binary Classification

09/22/2025



# Binary Classification



# Review: Model Training

1. Load dataset:  $X$  (features),  $y$  (labels)
2. (Randomly) Initialize model parameters:  $w$ ,  $b$ .
3. Evaluate the model with a metric (e.g. BCE).
4. Calculate gradient of loss.
5. Update parameters a small step on the directions descending the gradient of loss.
6. Repeat 3 to 5 until converge.

# Load Dataset

A dataset with  $M$  samples:

- Each sample has  $N$  features:  $x_1, x_2, \dots, x_N$
- Each sample is labeled:  $y$

$$\mathcal{D} = \{({}^{(1)}x_1, {}^{(1)}x_2, \dots, {}^{(1)}x_N, {}^{(1)}y), ({}^{(2)}x_1, {}^{(2)}x_2, \dots, {}^{(2)}x_N, {}^{(2)}y), \dots, ({}^{(M)}x_1, {}^{(M)}x_2, \dots, {}^{(M)}x_N, {}^{(M)}y)\}$$

$$= \{({}^{(1)}\mathbf{x}, {}^{(1)}y), ({}^{(2)}\mathbf{x}, {}^{(2)}y), \dots, ({}^{(M)}\mathbf{x}, {}^{(M)}y)\}$$

$${}^{(i)}y \in \{0, 1\}$$

# Initialize Model

$$\hat{\mathbf{y}} = \sigma(\mathbf{X} \cdot \mathbf{w}^T + \mathbf{b}) = \sigma(\mathbf{z})$$

$(M, 1)$

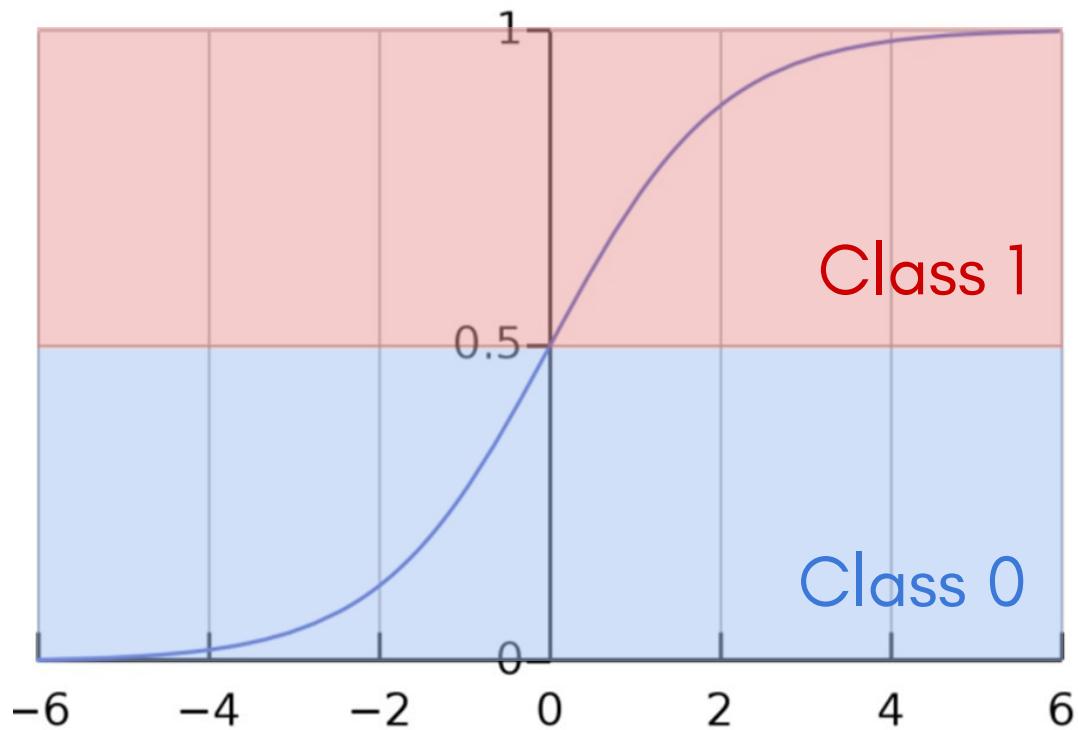
$(M, N)$

$(N, 1)$

$(M, 1)$

$(M, 1)$

# Sigmoid Classification



# Binary Cross Entropy Loss

$$\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{M} \sum_{i=1}^M -^{(i)}y \ln ^{(i)}\hat{y} - (1 - ^{(i)}y) \ln(1 - ^{(i)}\hat{y}) = \overline{-\mathbf{y} \ln \hat{\mathbf{y}} - (1 - \mathbf{y}) \ln(1 - \hat{\mathbf{y}})}$$

# Binary Classification Metrics

		ACTUAL	
		Positive	Negative
PREDICTED	Positive	True Positive (TP) 5	False Positive (FP) 10
	Negative	False Negative (FN) 15	True Negative (TN) 70

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = 0.75$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} = 0.25$$

E.g. airport security

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} = 0.33$$

E.g. investor

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} = 0.28$$

E.g. medical provider

**The higher the better!**



# Gradient of Loss (BCE)

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial w_1} & \frac{\partial \mathcal{L}}{\partial w_2} & \cdots & \frac{\partial \mathcal{L}}{\partial w_N} \end{bmatrix} = \frac{1}{M} (\hat{\mathbf{y}} - \mathbf{y})^T \cdot \mathbf{X}$$

$(1, N)$   $(1, M)$   $(M, N)$

$$\frac{\partial \mathcal{L}}{\partial b} = \overline{\hat{\mathbf{y}} - \mathbf{y}}$$

Matrix Multiplication



# Gradient of Loss (MSE)

Not Recommend

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial w_1} & \frac{\partial \mathcal{L}}{\partial w_2} & \cdots & \frac{\partial \mathcal{L}}{\partial w_N} \end{bmatrix} = \frac{1}{M} [(\hat{\mathbf{y}} - \mathbf{y}) * \hat{\mathbf{y}} * (1 - \hat{\mathbf{y}})]^T \cdot \mathbf{X}$$

$$\frac{\partial \mathcal{L}}{\partial b} = \overline{(\hat{\mathbf{y}} - \mathbf{y}) * \hat{\mathbf{y}} * (1 - \hat{\mathbf{y}})}$$

# Gradient Descent

Given dataset:  $\left\{ \left( {}^{(1)}\mathbf{x}, {}^{(1)}y \right), \left( {}^{(2)}\mathbf{x}, {}^{(2)}y \right), \dots, \left( {}^{(M)}\mathbf{x}, {}^{(M)}y \right) \right\}$

Initialize  $\mathbf{w}$  and  $b$

Repeat until converge {

$$\mathbf{w} := \mathbf{w} - \alpha \frac{\partial \mathcal{L}}{\partial \mathbf{w}}$$

$$b := b - \alpha \frac{\partial \mathcal{L}}{\partial b}$$

}

where  $\alpha$  is learning rate