

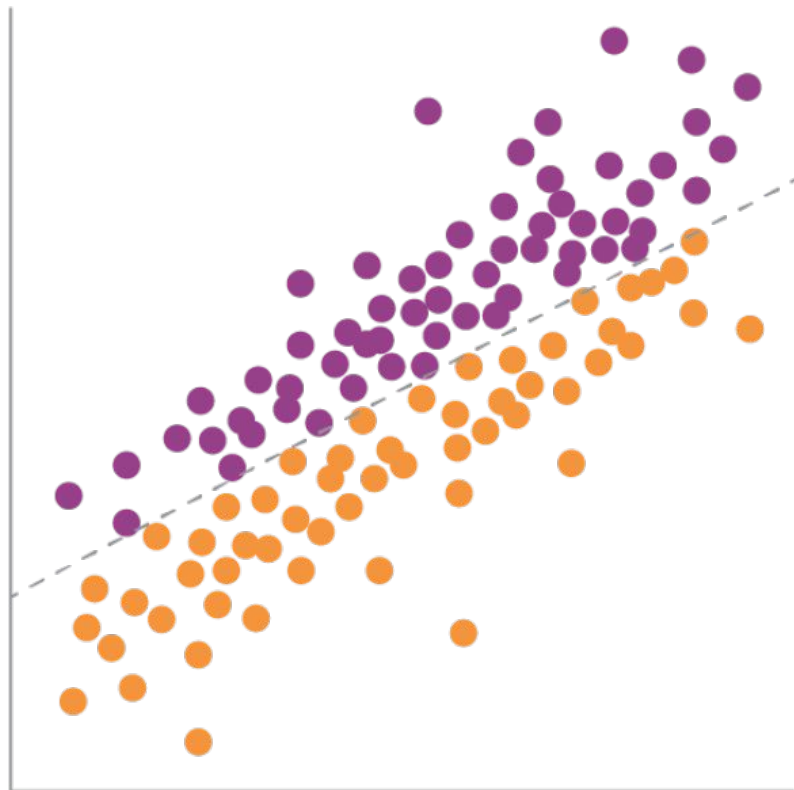
# ENGR 3321: Introduction to Deep Learning for Robotics

Binary Classification

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# Binary Classification



# Binary Labels

A dataset with  $M$  samples:

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

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

# Feature (Input) Matrix

$$\mathbf{x}_n = \begin{bmatrix} {}^{(1)}x_n \\ {}^{(2)}x_n \\ \cdot \\ \cdot \\ \cdot \\ {}^{(M)}x_n \end{bmatrix}_{(M,1)}$$

$$\mathbf{X} = [\mathbf{x}_1 \quad \mathbf{x}_2 \quad \dots \quad \mathbf{x}_N]_{(M,N)}$$

# Model Parameters

$$\mathbf{w} = [w_1 \quad w_2 \quad \dots \quad w_N]_{(1,N)}$$

$$\mathbf{b} = \begin{bmatrix} b \\ b \\ \cdot \\ \cdot \\ \cdot \\ b \end{bmatrix}_{(M,1)}$$

# Target (Output) Vector

$$\mathbf{y} = \begin{bmatrix} {}^{(1)}y \\ {}^{(2)}y \\ \cdot \\ \cdot \\ \cdot \\ {}^{(M)}y \end{bmatrix}_{(M,1)}$$

# Model in Matrix Form

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

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

Matrix Multiplication



# Binary Cross Entropy Loss

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



# Gradient of Loss

$$\nabla \mathcal{L} = \left[ \frac{\partial \mathcal{L}}{\partial w_1} \quad \frac{\partial \mathcal{L}}{\partial w_2} \quad \cdots \quad \frac{\partial \mathcal{L}}{\partial w_N} \quad \frac{\partial \mathcal{L}}{\partial b} \right]$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{\partial w_1} = \frac{1}{M} \sum_{i=1}^M ((^{(i)}\hat{y} - ^{(i)}y)^{(i)}x_1)$$

$$\frac{\partial \mathcal{L}}{\partial w_2} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{\partial w_2} = \frac{1}{M} \sum_{i=1}^M ((^{(i)}\hat{y} - ^{(i)}y)^{(i)}x_2)$$

...

$$\frac{\partial \mathcal{L}}{\partial w_N} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{\partial w_N} = \frac{1}{M} \sum_{i=1}^M ((^{(i)}\hat{y} - ^{(i)}y)^{(i)}x_N)$$

$$\frac{\partial \mathcal{L}}{\partial b} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b} = \frac{1}{M} \sum_{i=1}^M ((^{(i)}\hat{y} - ^{(i)}y))$$



# 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