

# ENGR 3321: Introduction to Deep Learning for Robotics

Neural Network 201:

Two-Input One-Output Linear Function

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# Outline

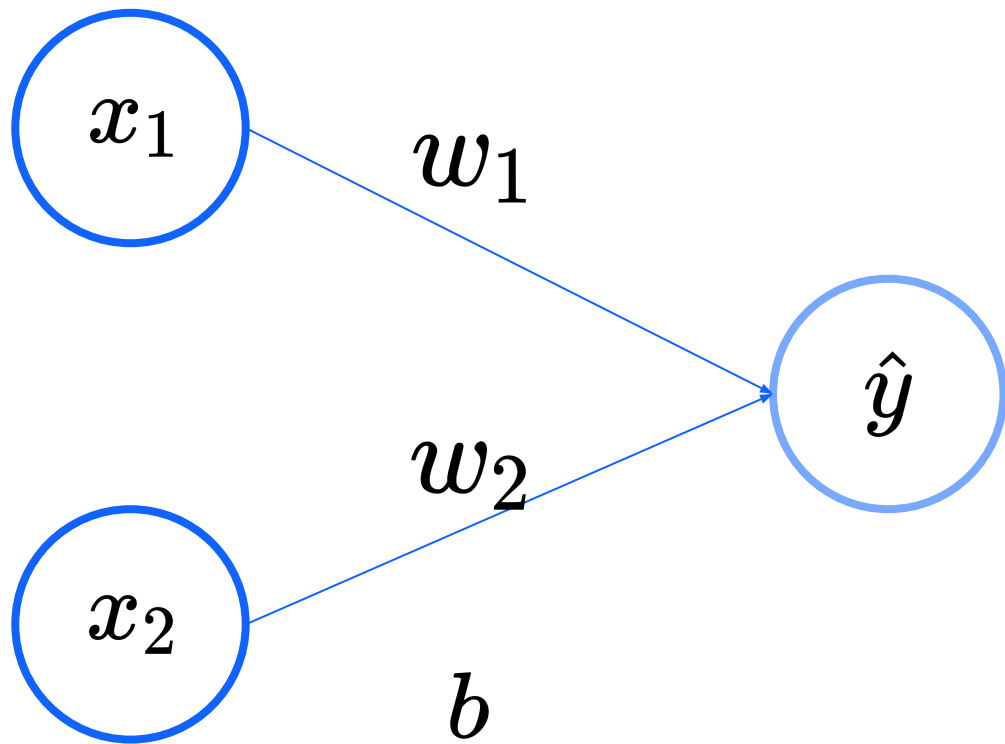
- Matrix Format
- Review: Model Training

# Two-Input One-Output Linear Function

A Linear model predicts a sample's property using two of its features.

$$f(x_1, x_2) = \hat{y} = w_1x_1 + w_2x_2 + b$$

# Neural Network Form



# Input (Feature) Matrix

$$\mathbf{x}_1 = \begin{bmatrix} {}^{(1)}x_1 \\ {}^{(2)}x_1 \\ \vdots \\ {}^{(M)}x_1 \end{bmatrix}_{(M,1)}$$

$$\mathbf{x}_2 = \begin{bmatrix} {}^{(1)}x_2 \\ {}^{(2)}x_2 \\ \vdots \\ {}^{(M)}x_2 \end{bmatrix}_{(M,1)}$$

$$\mathbf{X} = [\mathbf{x}_1 \quad \mathbf{x}_2]_{(M,2)}$$

# Model Parameters

$$\mathbf{w} = [w_1 \quad w_2]_{(1,2)}$$

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

# 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. MSE).
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 2 features:  $x_1$  and  $x_2$
- Each sample is labeled:  $y$

$$\begin{aligned}\mathcal{D} &= \{({}^{(1)}x_1, {}^{(1)}x_2, {}^{(1)}y), ({}^{(2)}x_1, {}^{(2)}x_2, {}^{(2)}y), \dots, ({}^{(M)}x_1, {}^{(M)}x_2, {}^{(M)}y)\} \\ &= \{({}^{(1)}\mathbf{x}, {}^{(1)}y), ({}^{(2)}\mathbf{x}, {}^{(2)}y), \dots, ({}^{(M)}\mathbf{x}, {}^{(M)}y)\}\end{aligned}$$



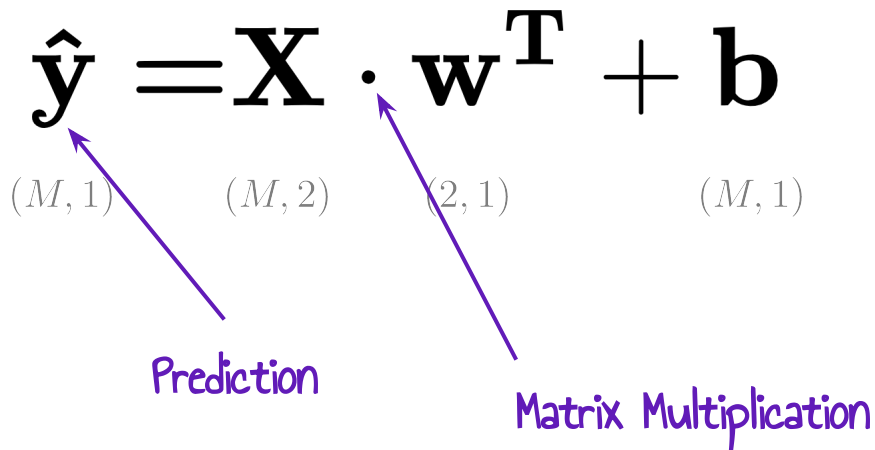
# Initialize Model

$$\hat{\mathbf{y}} = \mathbf{X} \cdot \mathbf{w}^T + \mathbf{b}$$

$(M, 1)$        $(M, 2)$        $(2, 1)$        $(M, 1)$

Prediction

Matrix Multiplication



The diagram shows the equation  $\hat{\mathbf{y}} = \mathbf{X} \cdot \mathbf{w}^T + \mathbf{b}$ . Below the terms, their dimensions are given:  $\hat{\mathbf{y}}$  is  $(M, 1)$ ,  $\mathbf{X}$  is  $(M, 2)$ ,  $\mathbf{w}^T$  is  $(2, 1)$ , and  $\mathbf{b}$  is  $(M, 1)$ . A purple arrow points from the word 'Prediction' to  $\hat{\mathbf{y}}$ . Another purple arrow points from the word 'Matrix Multiplication' to the dot operator between  $\mathbf{X}$  and  $\mathbf{w}^T$ .

$$^{(1)}\hat{y} = ^{(1)}x_1w_1 + ^{(1)}x_2w_2 + b$$

$$^{(2)}\hat{y} = ^{(2)}x_1w_1 + ^{(2)}x_2w_2 + b$$


$\vdots$

$$^{(M)}\hat{y} = ^{(M)}x_1w_1 + ^{(M)}x_2w_2 + b$$

# Evaluate Model (MSE)

$$\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{M} \sum_{i=1}^M ({}^{(i)}\hat{y} - {}^{(i)}y)^2 = \overline{(\hat{\mathbf{y}} - \mathbf{y})^2}$$

Loss



# Gradient of Loss

$$\nabla \mathcal{L} = \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial w_1} & \frac{\partial \mathcal{L}}{\partial w_2} & \frac{\partial \mathcal{L}}{\partial b} \end{bmatrix}$$

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

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

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

# Vectorized Gradient

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \left[ \frac{\partial \mathcal{L}}{\partial w_1} \quad \frac{\partial \mathcal{L}}{\partial w_2} \right] = \frac{1}{M} (\hat{\mathbf{y}} - \mathbf{y})^T \cdot \mathbf{X}$$

$(1, M)$                        $(M, 2)$

Matrix Multiplication

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

# Vectorized 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