

# **Artificial Intelligence Club**

## **Week 6 Slides**

**November 5th, 2025**



# Supervised Learning Basics

**Goal:** learn a mapping from features (inputs) to labels (outputs) using labeled examples

**Training data:** pairs of (features, target) used to fit a model

**Choose a model and a loss function; minimize average loss on the training set**

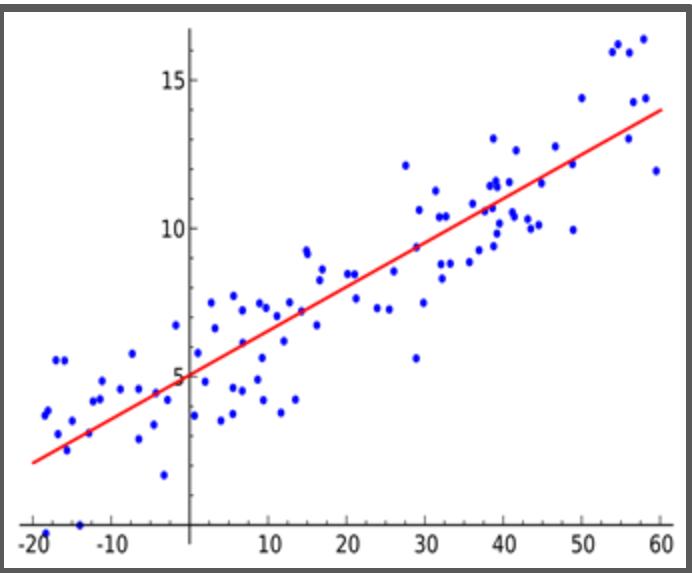
**Tasks:** regression (numbers) and classification (categories)

**Metrics:** Root mean squared error for regression or log loss for classification





# Linear Regression



**Model:** prediction = weighted sum of features + bias

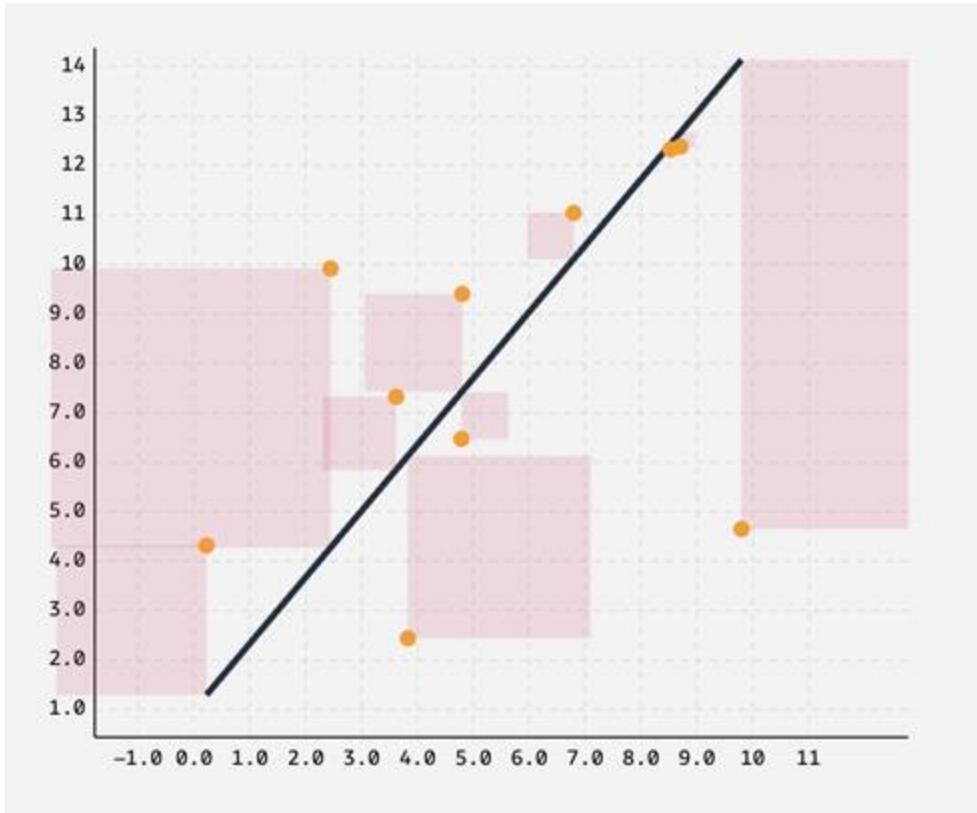
**MLE/Ordinary Least Squares:** choose coefficients that minimize the sum of squared errors

**Assumptions:** linear relationship and independent errors

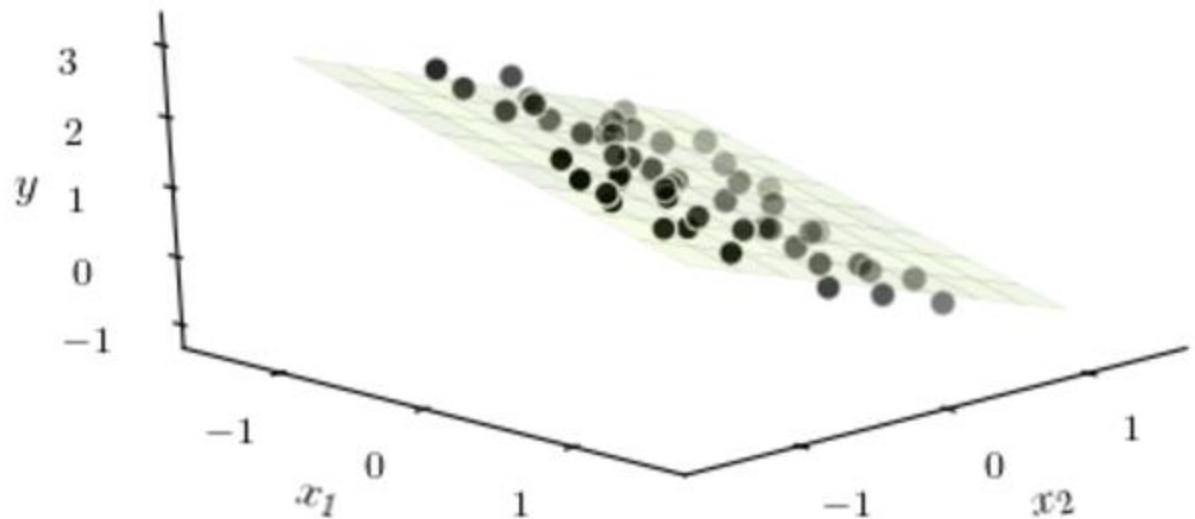
**Evaluation:** root mean squared error

- We minimize MSE (our loss function)
  - We report RMSE (to put it in the same units as "y")
- 

# Linear Regression



# Linear Regression





# Linear Regression Practice

<https://www.mladdict.com/linear-regression-simulator>

<https://mlu-explain.github.io/linear-regression/>

[https://kenndanielso.github.io/mlrefined/blog\\_posts/8\\_Linear\\_regression/8\\_1\\_Least\\_squares\\_regression.html](https://kenndanielso.github.io/mlrefined/blog_posts/8_Linear_regression/8_1_Least_squares_regression.html)





$$\mathbf{x}^{(1)} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \quad \mathbf{x}^{(2)} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \quad \mathbf{x}^{(3)} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}, \quad y^{(1)} = 5, \quad y^{(2)} = 6, \quad y^{(3)} = 7$$

$$\hat{y}^{(i)} = \mathbf{w}^T \mathbf{x}^{(i)} + b, \quad \mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}, \quad b \in R$$

$$\mathbf{w} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad b = 0$$

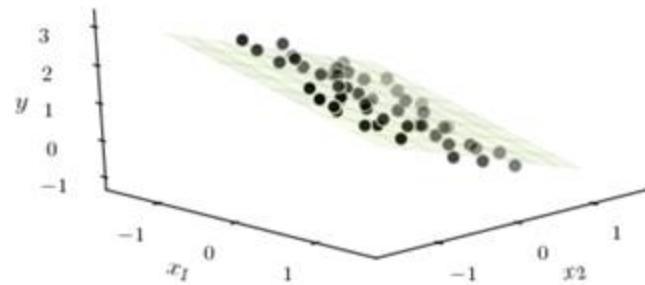
$$\hat{y}^{(1)} = 0, \quad \hat{y}^{(2)} = 0, \quad \hat{y}^{(3)} = 0$$

$$\text{MSE} = \frac{1}{3} \sum_{i=1}^3 (y^{(i)} - \hat{y}^{(i)})^2$$

$$\text{MSE} = \frac{1}{3} ((5-0)^2 + (6-0)^2 + (7-0)^2) = \frac{110}{3} \approx 36.67$$

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{110}{3}} \approx 6.06$$

# Linear Regression





$$\frac{\partial \text{MSE}}{\partial \mathbf{w}} = -\frac{2}{3} \sum_{i=1}^3 (y^{(i)} - \hat{y}^{(i)}) \mathbf{x}^{(i)}, \quad \frac{\partial \text{MSE}}{\partial b} = -\frac{2}{3} \sum_{i=1}^3 (y^{(i)} - \hat{y}^{(i)})$$

$$\mathbf{w}_{\text{new}} = \mathbf{w}_{\text{old}} - \eta \frac{\partial \text{MSE}}{\partial \mathbf{w}}, \quad b_{\text{new}} = b_{\text{old}} - \eta \frac{\partial \text{MSE}}{\partial b}$$

$$\frac{\partial \text{MSE}}{\partial w_1} = -\frac{2}{3} ((5-0)(1) + (6-0)(2) + (7-0)(3)) = -25.33$$

$$\frac{\partial \text{MSE}}{\partial w_2} = -\frac{2}{3} ((5-0)(2) + (6-0)(0) + (7-0)(1)) = -11.33$$

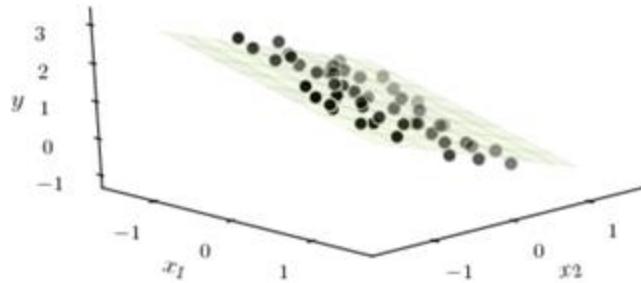
$$\frac{\partial \text{MSE}}{\partial b} = -\frac{2}{3} ((5-0) + (6-0) + (7-0)) = -12$$

$$w_1^{\text{new}} = w_1^{\text{old}} - \eta \frac{\partial \text{MSE}}{\partial w_1} = 0 - 0.01 * (-25.33) = 0.2533$$

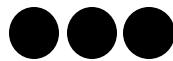
$$w_2^{\text{new}} = w_2^{\text{old}} - \eta \frac{\partial \text{MSE}}{\partial w_2} = 0 - 0.01 * (-11.33) = 0.1133$$

$$b^{\text{new}} = b^{\text{old}} - \eta \frac{\partial \text{MSE}}{\partial b} = 0 - 0.01 * (-12) = 0.12$$

# Linear Regression

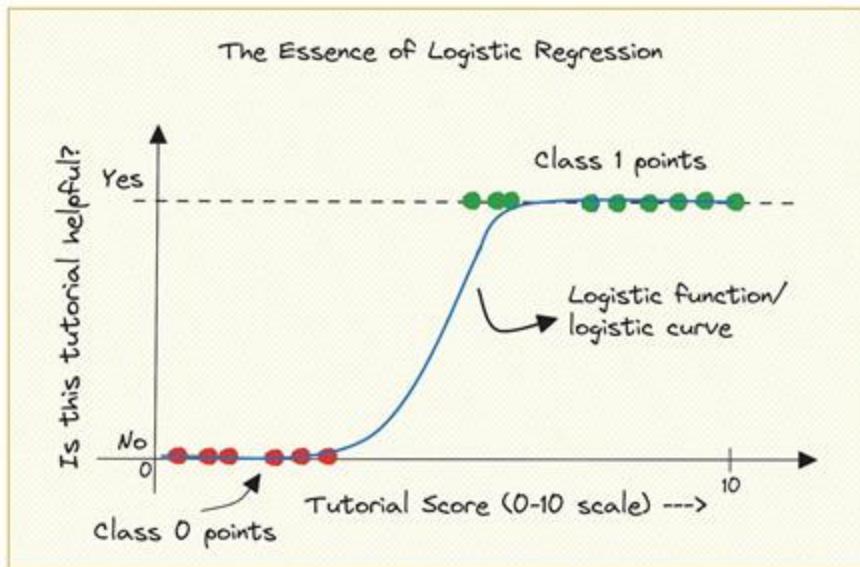


# Logistic Regression



**Model:** probability of the positive class = sigmoid(weighted sum of features)

**Fitting:** maximize the log-likelihood (or minimize log loss) using gradient-based optimization



**Outputs:** 0-1 predicted probabilities; choose a threshold (often halfway) to produce class labels

**Evaluation:** accuracy and log loss



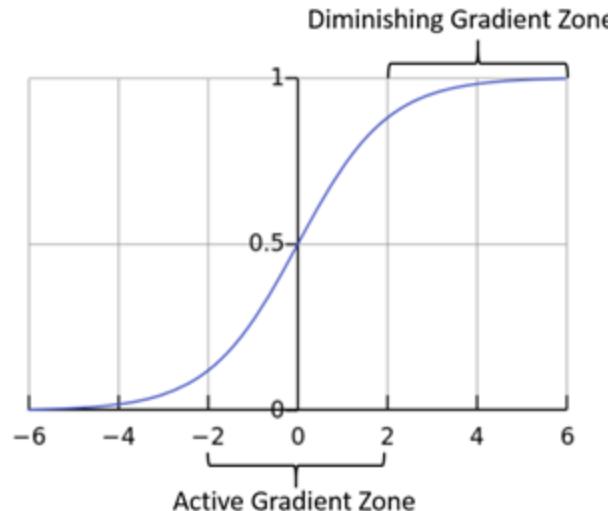


# Logistic Regression Practice

<https://mlu-explain.github.io/logistic-regression/>

[https://kenndanielso.github.io/mlrefined/blog\\_posts/9\\_Linear\\_twoclass\\_classification/9\\_1\\_Logistic\\_regression.html](https://kenndanielso.github.io/mlrefined/blog_posts/9_Linear_twoclass_classification/9_1_Logistic_regression.html)

$$A = \frac{1}{1+e^{-x}}$$



**Note:**  
After we are done (our loss looks low enough), we convert our percentage to **Class 0 or Class 1.**





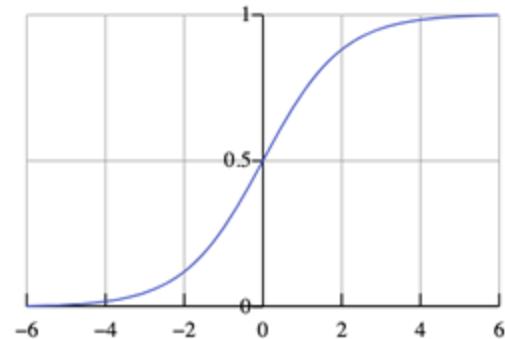
# Logistic Regression

$$\mathbf{x}^{(1)} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \quad \mathbf{x}^{(2)} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \quad \mathbf{x}^{(3)} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}, \quad y^{(1)} = 0, \quad y^{(2)} = 1, \quad y^{(3)} = 1$$

$$\hat{y}^{(i)} = \sigma(\mathbf{w}^T \mathbf{x}^{(i)} + b), \quad \sigma(z) = \frac{1}{1 + e^{-z}}, \quad \mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}, \quad b \in R$$

$$\mathbf{w} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad b = 0$$

$$\hat{y}^{(1)} = \hat{y}^{(2)} = \hat{y}^{(3)} = \sigma(0) = 0.5$$



$$\text{Binary Cross-Entropy Loss: BCE} = -\frac{1}{3} \sum_{i=1}^3 \left[ y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log (1 - \hat{y}^{(i)}) \right]$$

$$\text{BCE} = -\frac{1}{3} \left[ ((0) \log 0.5 + (1-0) \log 0.5) + ((1) \log 0.5 + (1-1) \log 0.5) + ((1) \log 0.5 + (1-1) \log 0.5) \right] = 0.693$$





# Logistic Regression

$$\frac{\partial \text{BCE}}{\partial \mathbf{w}} = \frac{1}{3} \sum_{i=1}^3 (\hat{y}^{(i)} - y^{(i)}) \mathbf{x}^{(i)}, \quad \frac{\partial \text{BCE}}{\partial b} = \frac{1}{3} \sum_{i=1}^3 (\hat{y}^{(i)} - y^{(i)})$$

$$\frac{\partial \text{BCE}}{\partial w_1} = \frac{1}{3} ((0.5 - 0) * 1 + (0.5 - 1) * 2 + (0.5 - 1) * 3) = \frac{1}{3} (0.5 - 1 - 1.5) = -0.667$$

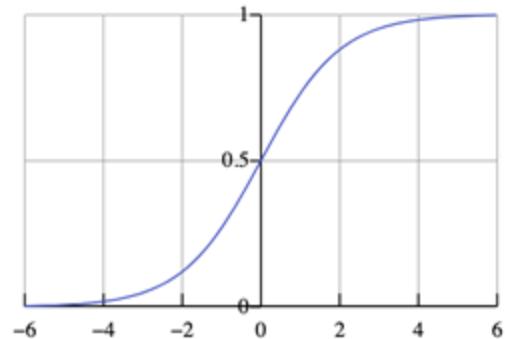
$$\frac{\partial \text{BCE}}{\partial w_2} = \frac{1}{3} ((0.5 - 0) * 2 + (0.5 - 1) * 0 + (0.5 - 1) * 1) = \frac{1}{3} (1 + 0 - 0.5) = 0.167$$

$$\frac{\partial \text{BCE}}{\partial b} = \frac{1}{3} ((0.5 - 0) + (0.5 - 1) + (0.5 - 1)) = \frac{1}{3} (0.5 - 0.5 - 0.5) = -0.167$$

$$w_1^{\text{new}} = w_1^{\text{old}} - \eta \frac{\partial \text{BCE}}{\partial w_1} = 0 - 0.01 * (-0.667) = 0.00667$$

$$w_2^{\text{new}} = w_2^{\text{old}} - \eta \frac{\partial \text{BCE}}{\partial w_2} = 0 - 0.01 * (0.167) = -0.00167$$

$$b^{\text{new}} = b^{\text{old}} - \eta \frac{\partial \text{BCE}}{\partial b} = 0 - 0.01 * (-0.167) = 0.00167$$





Feedback

**Connections + Pizza + Talk to Officers**