

10.09.2024

Machine Learning

Google Classroom \rightarrow 56 = bias

Linear regression

y

$m = x$ এর কর্তৃত্ব impact

negative value remove করার জন্য square করা হয় (Loss)

cost function : loss function averaged over all training examples

$$h_0(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2$$

$$\text{price} = \theta_0 + \theta_1 \times \text{size} + \theta_2 \times \text{Bedroom}$$

$$\theta_0 = -80000$$

$$\theta_1 = 200$$

$$\theta_2 = 10000$$

$$\Rightarrow -80000 + 200 \times 1850 + 10000 \times 3$$

$$\Rightarrow 330,000$$

$$MSE = \frac{1}{5} (2^2 + (-1)^2 + (-2)^2 + 1^2 + 1^2)$$

$$= \frac{11}{5}$$

$$= 2.2$$

10.30 - 32 (multipurpose valid) - workshop

Gradient Descent

best parameters find or, optimize

A technique that iteratively finds the weights and bias that produce model with lowest loss.

একটি training example তাকে একে একে individually

batch gradient descent and stochastic

α - learning rate

θ - parameters (weight)

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Machine Learning

- main formula

First iteration

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

$$\alpha = 0.01$$

$$h_{\theta}(x) = 0.25 x_1 - 100$$

Size	Price

Data points :

$$\text{For } x_1^{(1)} = 2104 \quad y^{(1)} = 400$$

$$x_1^{(2)} = 1600 \quad y^{(2)} = 330$$

$$x_1^{(3)} = 2400 \quad y^{(3)} = 369$$

Batch GD (one iteration)

$$\Rightarrow h_{\theta}(x^{(1)}) = 0.25 \times 2104 - 100 = 426$$

$$\Rightarrow h_{\theta}(x^{(2)}) = 0.25 \times 1600 - 100 = 300$$

$$\Rightarrow h_{\theta}(x^{(3)}) = 0.25 \times 2400 - 100 = 500$$

$$\text{loss for } x_1^{(1)} = 426 - 400 = 26$$

$$\text{loss for } x_1^{(2)} = 300 - 330 = -30$$

$$\text{loss for } x_1^{(3)} = 500 - 369 = 131$$

update θ_0

Batch (Gradient Descent)

$$\theta_0 = \theta_0 - \alpha \frac{1}{3} (26 + (-30) + 131)$$

$$= -100 - 0.01 \times \frac{1}{3} \times 127 = -100.242$$

$$= -100.242$$

Batch

update rule:

$$\theta_0 = \theta_0 - \alpha (h_0(x^{(i)}) - y^{(i)})$$

$$\theta_1 = \theta_1 - \alpha (h_0(x^{(i)}) - y^{(i)}) x_1^{(i)}$$

$$\theta_1 = \theta_1 - \alpha \frac{1}{3} [(26 \times 2104) + (-30 \times 1600) + (131 \times 2400)]$$

$$= 0.25 - (0.01 \times \frac{1}{3} \times 34104)$$

$$= 0.25 - 1070.35$$

$$= -1070.10$$

overfitting and underfitting

overfitting: know everything about trained data but doesn't know anything about outside data and performs poorly

underfitting: perform poorly in every case

* models should perform ^{well} in training data and test data

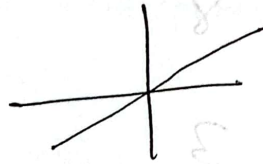
25.09.24

ML

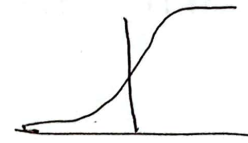
Logistic regression \rightarrow classification Algorithm.

Transform linear output using the Sigmoid function

$$z = 2x + 5$$



$$y = \frac{1}{1 + e^{-z}}$$



0 And 1

why we use Logistic regression

Logistic function also called sigmoid function

\Rightarrow Difference between Linear and Logistic regression

for classification - Logistic is used (yes or no)

Logistic regression Model

Sigmoid function — 0 থেকে 1 এর ইতিমধ্যে নিয়ে আসে

Decision Boundary

$$z = \theta_0 + \theta_1 x_1 + \theta_2 x_2$$

$$y' = \frac{1}{1 + e^{-z}}$$

Ex 1

Hours of study	Attendance (%) (x ₂)	pass/Fail (y)
5	60	
	65	
6	80	
8	70	
7	85	
9	50	
21		

$\theta_0 = -50$, $\theta_1 = 6$, $\theta_2 = 1$

Hypothesis function $h_0(x) = \frac{1}{1 + e^{-(50 + 6x_1 + x_2)}}$

$$\Rightarrow -(-50 + 6x_1 + x_2) = 0$$

$$= 50 = 6x_1 + x_2$$

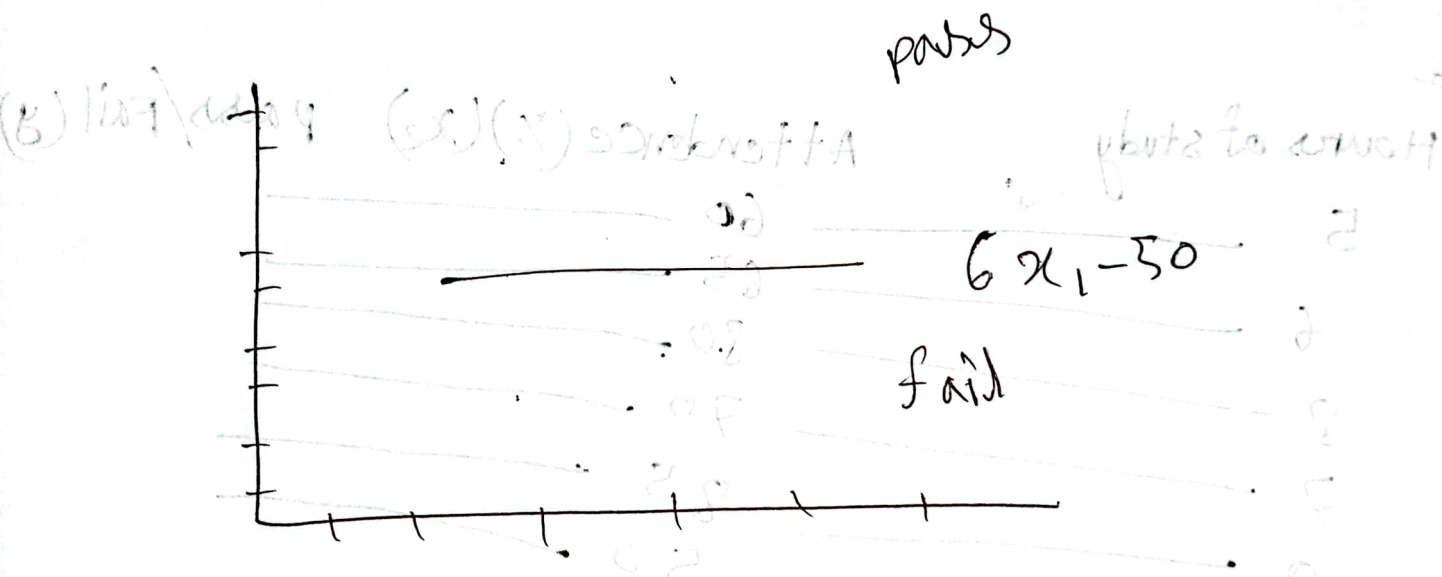
$$\Rightarrow x_2 = 6x_1 - 50$$

- Boundary line

this Line represents the decision boundary

⇒ Above the line ($x_2 > 6x_1 - 50$): the student is predicted to pass (class 1)

⇒ Below the line ($x_2 < 6x_1 - 50$): the student is predicted to fail (class 0)



⇒ what is logistic

⇒ dif betwe logis and Linear

⇒ what is decision boundary

$$0 = (w_0 + w_1x_1 + w_2x_2) - \ln(1 + e^{-(w_0 + w_1x_1 + w_2x_2)})$$