Foundations Of Neural Networks and Deep Learning

Day-5

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recap:

1. What is the main objective of Gradient Descent?

A. To increase the loss function
B. To minimize the loss function by adjusting parameters
C. To maximize accuracy directly
D. To randomly update weights and bias

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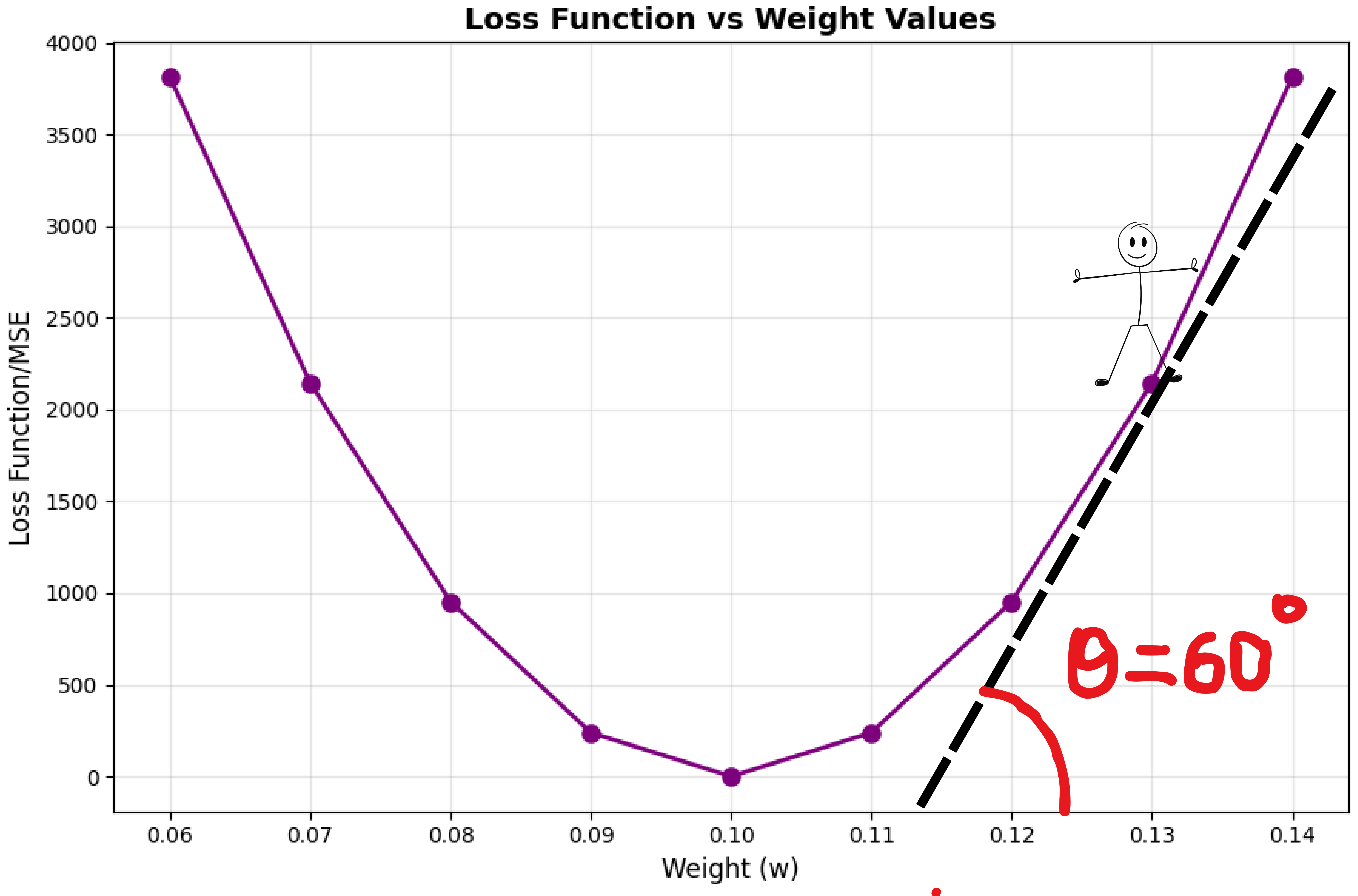
Loss Function vs Weight Values
Loss Function/MSE
Weight (w)
0
500
1000
1500
2000
2500
3000
3500
4000
0.06
0.07
0.08
0.09
0.10
0.11
0.12
0.13
0.14
θ=60°

What does a negative gradient indicate in the context of loss vs. weight graph?

A. Loss increases when weight increases
B. Loss decreases when weight increases
C. No relation between weight and loss
D. Model is unstable

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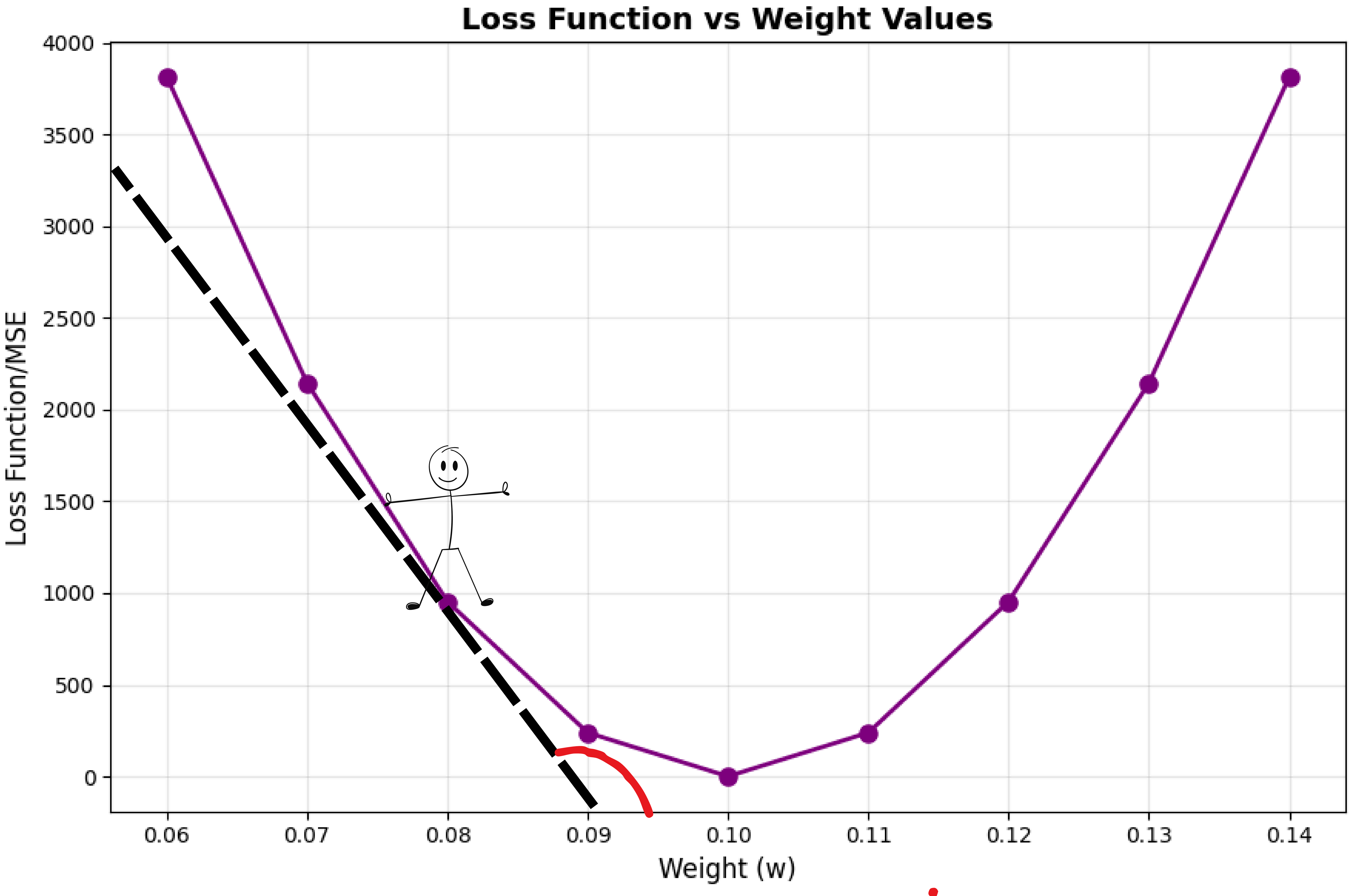

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B. Bias factor
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Which of the following best represents the weight update rule in Gradient Descent?

A. $w = w + \alpha \times \partial L/\partial w$
B. $w = w - \alpha \times \partial L/\partial w$
C. $w = \alpha \times \partial L/\partial w$
D. $w = w \times \alpha \times L$

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B. w = w - α × ∂L/∂w

C. w = α × ∂L/∂w

D. w = w × α × L

$$w := w - \alpha \frac{dL}{dw}$$

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A. The rate of change of weights
B. The rate at which loss changes with respect to weights
C. The curvature of the data
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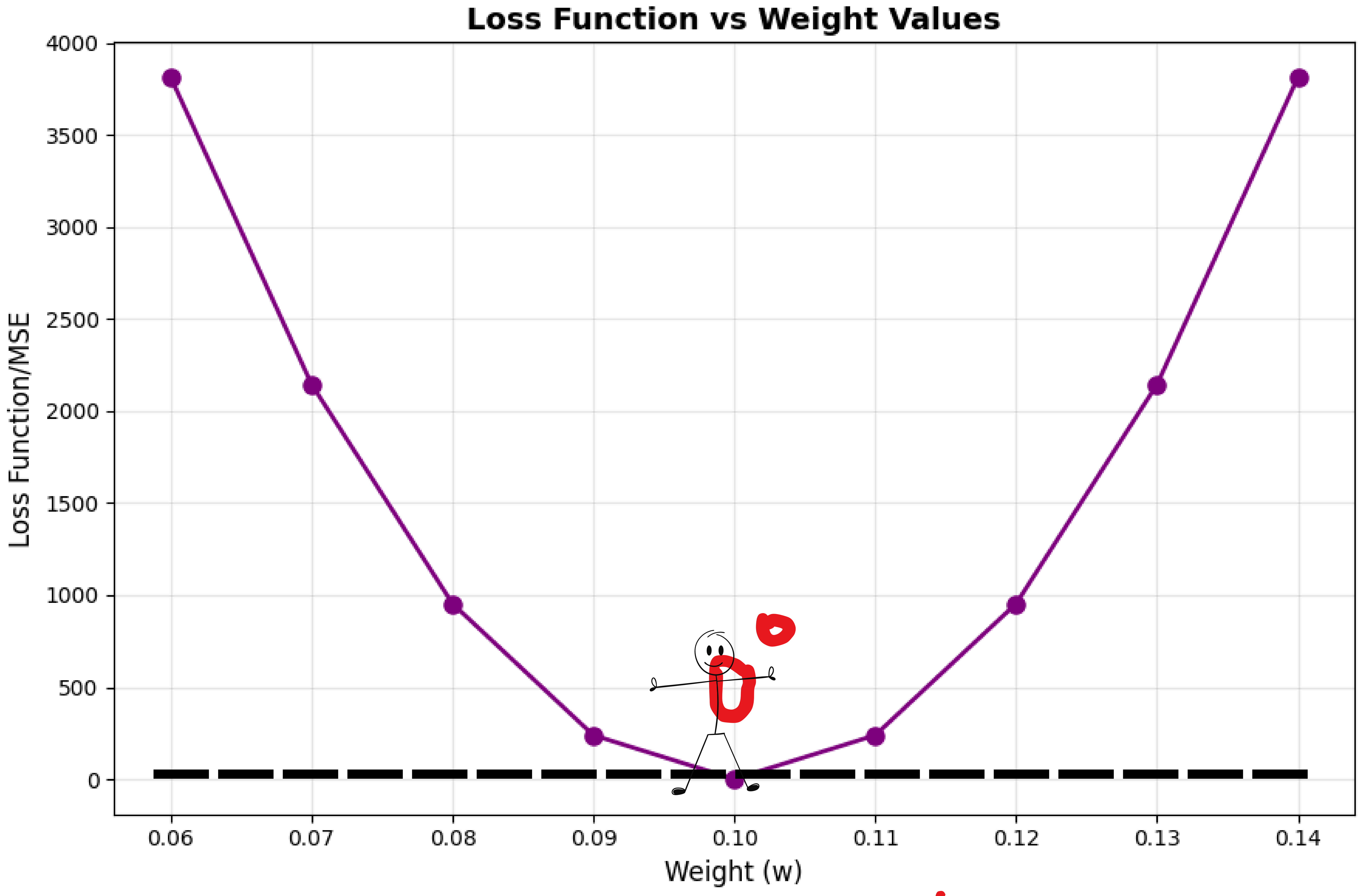

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Weight (w)

what we learnt last class

$$L(w,b) = \frac{1}{n}\sum_{i=1}^{n}(y_i - (wx_i + b))^2$$

what we learnt last class

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

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

$$\frac{\partial L}{\partial w} = \frac{-2}{n} \sum_{i=1}^{n} x_i(y_i - (wx_i + b))$$

$$\frac{\partial L}{\partial b} = \frac{-2}{n} \sum_{i=1}^{n} (y_i - (wx_i + b))$$

what we learnt last class

```
for epoch in range(epochs):
    y_pred = w * X + b
    dw = (-2/n) * np.sum(X * (y - y_pred))
    db = (-2/n) * np.sum(y - y_pred)
    w = w - alpha * dw
    b = b - alpha * db
```

day 5 - training a linear regression model on california housing dataset

hands on session