

Gradient descent algorithm

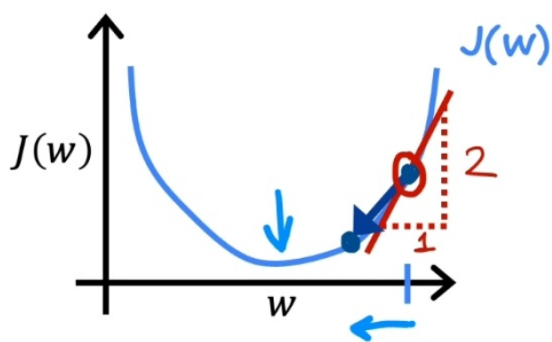
repeat until convergence {

learning rate α derivative $\frac{\partial}{\partial w} J(w, b)$

$$\begin{cases} \underline{w} = w - \alpha \frac{\partial}{\partial w} J(w, b) \\ \underline{b} = b - \alpha \frac{\partial}{\partial b} J(w, b) \end{cases}$$

$$J(w)$$
$$w = w - \alpha \frac{\partial}{\partial w} J(w)$$
$$\min_w J(w)$$

- Here is the gradient descent formulas.
- We have a partial derivative term here with multiply by α that is learning rate.
- Now, to understand we use the simplified version of those formula.
- That is $w = w - \alpha \frac{\partial}{\partial w} J(w), b = 0$



$$w = w - \alpha \frac{d}{dw} J(w)$$

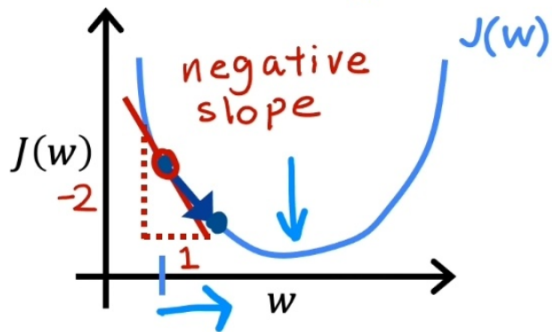
> 0

$$w = w - \alpha \cdot (\text{positive number})$$

$$\frac{d}{dw} J(w) < 0$$

$$w = w - \alpha \cdot (\text{negative number})$$

↑ ↑



→ If we pick any point from the graph, the gradient descent will gradually decrease that point towards local minima.

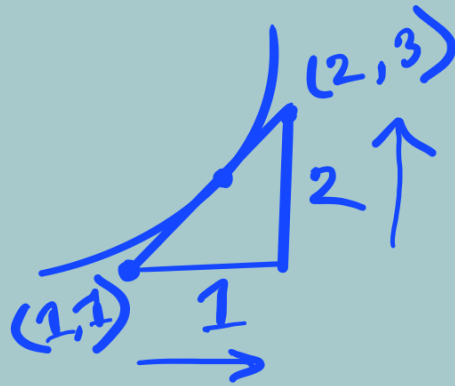
→ Here the derivative term is,

$$\frac{dJ(w)}{dw}$$

this means changes in y ones over changes in x ones.

→ And we know it is a slope of that point.

→ so, for the first point the slope is positive



→ If we consider this example we can see how the slope is positive.

$$\begin{aligned}\rightarrow \text{Here, slope} &= \frac{3-1}{2-1} \left(\frac{y_2-y_1}{x_2-x_1} \right) \\ &= 2 \text{ (positive)}\end{aligned}$$

→ If the derivative term is positive than the w will decrease as well as the point will decrease

toward local minima.

→ same will happen for the second point.

→ It is a negative slope, so the w value will increase and the point will decrease toward local minima.