

Derivations = $(d, \omega) T \frac{\delta}{\delta \theta}$

or Gradient Descent

we know that

~~cost function~~ \rightarrow mean squared error

$$J(\omega, b) = \frac{1}{2m} \sum_{i=1}^m (f_{\omega, b}(x_i) - y_i)^2$$

$$(i y - d + i x \omega)^2 = (d, \omega) T \frac{\delta}{\delta \theta}$$

where $f_{\omega, b}(x) = \omega x + b$

$m \rightarrow$ no. of tuples

$$\omega = \omega - \alpha \frac{\partial J(\omega, b)}{\partial \omega}$$

$$b = ((b - (\omega x)) \alpha \frac{\partial J(\omega, b)}{\partial b}) = d$$

This process will be repeated upto the point of convergence

$$\begin{aligned}
 \frac{\partial}{\partial w} J(w, b) &= \frac{\partial}{\partial w} \frac{1}{2m} \sum_{i=1}^m (w x_i + b - y_i)^2 \\
 &= \frac{1}{\partial w} \frac{1}{2m} \sum_{i=1}^m (w x_i + b - y_i)^2 \\
 &= \frac{1}{m} \sum_{i=1}^m (w x_i + b - y_i)^2 / x_i \\
 &= \frac{1}{m} \sum_{i=1}^m (w x_i + b - y_i) \cdot x_i
 \end{aligned}$$

From chain rule,

$$\boxed{\frac{\partial}{\partial w} J(w, b) = \frac{1}{m} \sum_{i=1}^m (w x_i + b - y_i) \cdot x_i}$$

$$\begin{aligned}
 \frac{\partial}{\partial b} J(w, b) &= \frac{\partial}{\partial b} \sum_{i=1}^m (w x_i + b - y_i)^2 \times \frac{1}{2m} \\
 &= \frac{\partial}{\partial b} \sum_{i=1}^m (w x_i + b - y_i)^2 \times \frac{1}{2m} \\
 &= \frac{1}{2m} \sum_{i=1}^m (w x_i + b - y_i) \times \cancel{x_i}
 \end{aligned}$$

$$\boxed{\frac{\partial}{\partial b} J(w, b) = \frac{1}{m} \sum_{i=1}^m (w x_i + b - y_i)}$$

$$\begin{aligned}
 w &= w - \alpha \left(\sum_{i=1}^m (w x_i + b - y_i) \right) \\
 b &= b - \alpha \left(\sum_{i=1}^m (w x_i + b - y_i) \right)
 \end{aligned}$$

$$\begin{aligned}
 b &= b - \alpha \left(\sum_{i=1}^m (w x_i + b - y_i) \right) / m
 \end{aligned}$$

Gradient descent
for linear regression