

$$\theta^T = [\theta_0 \theta_1 \dots \theta_n]_{1 \times (n+1)}$$

row matrix vector

$$\theta^T x = [\theta_0 \theta_1 \dots \theta_n] \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$$

$$= \theta_0 x_0 + \theta_1 x_1 + \dots + \theta_n x_n$$

→ a.k.a multivariate linear regression.

$$\therefore, h_0(x) = \sum_{i=0}^n \theta_i x_i = \theta^T x$$

where,  $x_0 = 1$

$$\begin{aligned} J(\theta_0, \theta_1, \dots, \theta_n) &= J(\theta) = \frac{1}{2m} \sum_{i=1}^n (h_0(x^{(i)}) - y^{(i)})^2 \\ &\quad \text{[cost func]} \\ &= \frac{1}{2m} \sum_{i=1}^n \left( \sum_{j=0}^n \theta_j x_j^{(i)} - y^{(i)} \right)^2 \\ &\quad \text{where, } x_0 = 1 \\ &= \frac{1}{2m} \sum_{i=1}^n \left( \theta^T x^{(i)} - y^{(i)} \right)^2 \end{aligned}$$

Gradient descent:

Repeat until convergence  $\epsilon$

$$\left\{ \begin{aligned} \theta_j^{(0)} &= \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \quad (\text{for every } j = 0, 1, \dots, n) \\ &\quad \text{[simultaneous update]} \end{aligned} \right.$$