



Cajamar, 23 de outubro de 2018

Modelo

$$y = \theta_0 x^0 + \theta_1 x^1 + \theta_2 x^2 + \theta_3 x^3$$

$$\hat{y} = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3$$

$$\theta^T X = Y$$

$$J_{\theta_j} = \frac{1}{2m} \sum_{i=1}^m \left[\sum_{j=0}^3 (\theta_j x_j^{(i)}) - \hat{y}_i \right]^2$$

$$\frac{\partial J}{\partial \theta_j} = \frac{1}{m} \sum_{i=0}^m \left[\sum_{k=0}^3 \theta_k x_k^{(i)} - \hat{y}_i \right] x_j^{(i)}$$

$$\theta_j := \theta_j - \alpha \frac{\partial J}{\partial \theta_j}$$

Gradient Descent x Normal Equation

Small steps till convergence to θ_{\min}

solve analytically the equation for θ



$$X^T \cdot X = A$$

$(n+1) \times m \quad m \times (m+1) \quad (m) \times (n+1)$

$$(m \times (n+1)) \times ((n+1) \times m)$$

$m \times m$

$$X^T \cdot \theta = Y$$

$$(X^T)^{-1} \cdot X^T \theta = (X^T)^{-1} \cdot Y \quad \{ \text{para, se vale}$$

$$\theta = (X^T)^{-1} \cdot Y \quad \text{se } X \text{ já for quadrado}$$

Então:

$$X \cdot \theta = Y$$

$$X^T X \theta = X^T Y$$

$$(X^T X)^{-1} X^T X \theta = (X^T X)^{-1} X^T Y$$

$$\theta = (X^T X)^{-1} X^T Y$$

Nesse caso, não é preciso usar feature scaling $0 \leq x_i \leq 1$