

## LEAST SQUARES

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \|\underline{X}\Theta - y\|$$

X :  $M \times N$       data de input  
                                  $M, N \neq$

① :  $N \times 1$  parâmetros

$y$  :  $N \times 1$  output

$$\begin{aligned} J(\theta) &= \frac{1}{2} (X\theta - y)^T (X\theta - y) \\ &= \frac{1}{2} (\theta^T X^T - y^T) (X\theta - y) \\ &= \frac{1}{2} (\theta^T X^T X \theta - \theta^T X^T y - y^T X \theta + y^T y) \end{aligned}$$

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$$\frac{\partial J}{\partial \theta} (\theta^T s \theta) = 2s\theta \quad \frac{\partial}{\partial \theta} (\theta^T a) = a \quad \frac{\partial}{\partial \theta} (a^T \theta) = a^T$$

$$\frac{\partial J}{\partial \theta} = \frac{1}{2} (2x^T x \theta - x^T y - (y^T x)^T) = x^T x \theta - x^T y \stackrel{!}{=} 0$$

$$\hat{\theta} = [X^T X]^{-1} X^T y$$

\* si  $M=N \rightarrow \hat{\theta} = X^{-1}y$  si  $M < N$  no hay solución.

## ESTIMACIÓN NO-LINEAL

$$\hat{y} = f(\theta)$$

$$J(\theta) = \frac{1}{2} \|f(\theta) - y\|^2 \rightarrow \min$$

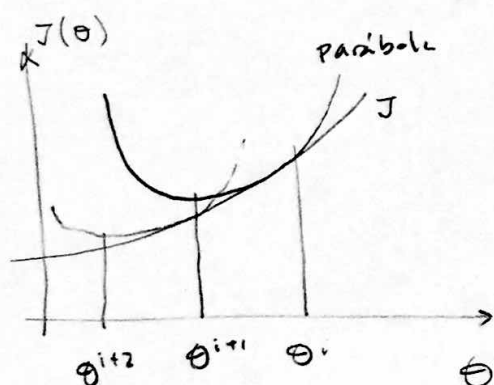
Métodos iterativos:  $\theta_0$ : valor inicial,  $\theta^{i+1} = \theta^i + \Delta\theta^i$

$$J(\theta^{i+1}) = J(\theta^i + \Delta\theta^i)$$

Serie de Taylor:

• si  $\theta \in \mathbb{R}$  (una dimensión)  $J(\theta^i + \Delta\theta^i) = \sum_{n=0}^{\infty} \frac{J^n(\theta^i)}{n!} (\Delta\theta^i)^n$

$$J(\theta^i + \Delta\theta^i) \approx J(\theta^i) + J'(\theta^i) \Delta\theta^i + \frac{J''(\theta^i)}{2} [\Delta\theta^i]^2$$



Parábola que es buena aproximación de  $J$  en  $\theta^i$

Es fácil buscar el mínimo de la parábola  $P$

$$\frac{\partial P}{\partial \Delta\theta^i} = 0 \rightarrow \Delta\theta^i = -\frac{J'(\theta^i)}{J''(\theta^i)}$$

Método de Newton-Raphson

$$\theta^{i+1} = \theta^i - \frac{J'(\theta^i)}{J''(\theta^i)} \text{ para } \theta \in \mathbb{R}$$

• si  $\theta \in \mathbb{R}^d$   $d > 1$

$$J(\theta^i + \Delta\theta^i) \approx J(\theta^i) + [\Delta\theta^i]^T J_\theta(\theta^i) + \frac{1}{2} [\Delta\theta^i]^T J_{\theta\theta}(\theta^i) \Delta\theta^i$$

$$J_\theta = \left[ \frac{\partial J}{\partial \theta_1} \cdots \frac{\partial J}{\partial \theta_n} \right] \quad J_{\theta\theta} = \begin{bmatrix} \frac{\partial^2 J}{\partial \theta_1^2} & \frac{\partial^2 J}{\partial \theta_1 \partial \theta_2} & \cdots & \frac{\partial^2 J}{\partial \theta_1 \partial \theta_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 J}{\partial \theta_n \partial \theta_1} & \frac{\partial^2 J}{\partial \theta_n \partial \theta_2} & \cdots & \frac{\partial^2 J}{\partial \theta_n^2} \end{bmatrix}$$

$$\frac{\partial J(\theta^{i+1})}{\partial \Delta\theta} = 0 + J_\theta(\theta^i) + J_{\theta\theta}(\theta^i) \Delta\theta^i = 0 \rightarrow \theta^{i+1} = \theta^i - [J_{\theta\theta}(\theta^i)]^{-1} J_\theta(\theta^i)$$

para  $\theta \in \mathbb{R}^d$