

2. Closed-form solution.

$$\theta = (x^T x)^{-1} x^T y$$

$$x = \underbrace{\begin{bmatrix} -x^1- \\ -x^i- \\ -x^i- \end{bmatrix}}_{\text{columns}} \left. \vphantom{\begin{bmatrix} -x^1- \\ -x^i- \\ -x^i- \end{bmatrix}} \right\} \text{now } y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1} \quad \theta = \begin{bmatrix} \theta^0 \\ \vdots \\ \theta^n \end{bmatrix} \left. \vphantom{\begin{bmatrix} \theta^0 \\ \vdots \\ \theta^n \end{bmatrix}} \right\} \text{unknown}$$

Structure....

$$X = \begin{bmatrix} 1 & -x^1- & z^1 \\ \vdots & -x^i- & \vdots \\ 1 & -x^i- & y_i \end{bmatrix} \quad \begin{array}{l} \text{Where} \\ z_0 = \text{constants} \\ x^i = \text{features} \\ y_i = \text{output} \end{array}$$

$$\begin{bmatrix} -x^1- \\ -x^i- \\ -x^i- \end{bmatrix} \times \begin{bmatrix} \theta^1 \\ \vdots \\ \theta^n \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \left. \vphantom{\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}} \right\} \hat{y}$$

$$\text{Cost} = (h_{\theta^i} - y)^2 \quad \left(\begin{bmatrix} \hat{y}_1 \\ \vdots \\ \hat{y}_1 \end{bmatrix} - \begin{bmatrix} y_1 \\ \vdots \\ y_i \end{bmatrix} \right)^2$$

$$\text{Cost} = (X\theta - y)^T \cdot (X\theta - y)$$

$$\text{Cost} = Z^T \cdot Z$$



$$\text{Cost} = (\hat{y} - y)^T \cdot (\hat{y} - y)$$

$$(AB)^T = B^T A^T$$

Calculation

$$(x\theta - y)^T \cdot (x\theta - y)$$

$$(x^T \theta^T - y^T) \cdot (x\theta - y)$$

$$J(\theta) = x^T \theta^T \cdot x\theta - x^T \theta^T \cdot y - y^T \cdot x\theta + y^T \cdot y$$

Compute first derivative $\nabla_{\theta} J(\theta)$

$$\nabla_{\theta} J(\theta) = \nabla_{\theta} (x^T \theta^T \cdot x\theta - x^T \theta^T \cdot y - y^T \cdot x\theta + y^T \cdot y)$$

$$2x^T x \theta - \nabla_{\theta} (\theta^T x^T y + \theta^T x^T y)$$

$$2x^T x \theta - \nabla_{\theta} (2\theta^T x^T y)$$

$$2x^T x \theta - 2x^T y = 0$$

$$x^T x \theta = x^T y$$

$$(x^T x)^{-1} (x^T x) \theta = (x^T x)^{-1} x^T y$$

$$1 \theta = (x^T x)^{-1} x^T y \Rightarrow \text{Closed-form solution...}$$

Some derivative rules for matrix.

$$1. \nabla_{\theta} a^T \theta = a \text{ is matrix}$$

$$2. \nabla_{\theta} \theta^T a = a \text{ is matrix}$$

$$3. \nabla_{\theta} \theta^T A \theta = 2A\theta$$

where A is symmetric matrix

Gradient descent

Closed-form sol.

→ Iterative approach

→ $\alpha = ?$ (step size)
unknown

→ for larger dataset

→ Quick calculation

→ for smaller dataset.

→ expensive for large dataset.

→ No need of learning rate