

Closed-Form Optimization

Given $J(\vec{\theta}) : \mathbb{R}^M \rightarrow \mathbb{R}$

① Write down the gradient $\nabla J(\vec{\theta})$

② Set gradient to all zeros $\nabla J(\vec{\theta}) = \begin{bmatrix} \partial J / \partial \theta_1 \\ \partial J / \partial \theta_2 \\ \vdots \\ \partial J / \partial \theta_M \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$

③ Solve the system of equations for $\vec{\theta}$

④ Check whether we have a min, max, or a saddle point based on the 2nd derivatives

Closed Form Solution for Linear Regression

Notation

$$\vec{y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(N)} \end{bmatrix}$$

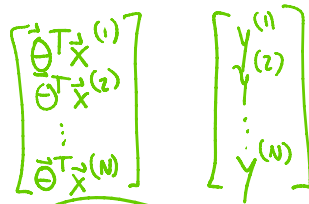
$$X = \begin{bmatrix} x_1^{(1)} & \dots & x_M^{(1)} \\ \vdots & & \vdots \\ x_1^{(N)} & \dots & x_M^{(N)} \end{bmatrix}$$

Design Matrix

① Write $J(\vec{\theta})$ in matrix/vector form

$$J(\vec{\theta}) = \frac{1}{N} \sum_{i=1}^N \frac{1}{2} (y^{(i)} - \vec{\theta}^T \vec{x}^{(i)})^2$$

$$= \frac{1}{N} \frac{1}{2} (X\vec{\theta} - \vec{y})^T (X\vec{\theta} - \vec{y})$$



② Write gradient of $J(\vec{\theta})$

$$\nabla J(\vec{\theta}) = \dots \dots \dots \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

... gradient at θ_0

$$\nabla J(\theta) = X^T X \theta - X^T y = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

③ Set to zero ("Normal Equations")



④ Solve for θ

$$X^T X \theta - X^T y = 0$$

$$\Rightarrow X^T X \theta = X^T y$$

$$\Rightarrow \theta = (X^T X)^{-1} X^T y = \underset{\theta}{\operatorname{argmin}} J(\theta)$$

$\circ H$

