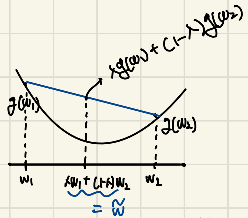

LAD 정의

- $g(w) = \sum_{i=1}^{N} |\underbrace{y_i}_{\text{target}} - \underbrace{w}_{\text{parameter}}^T \underbrace{x_i}_{\text{Input}}|$

$\tilde{w} = \lambda w_1 + (1-\lambda) w_2$

↳ LAD에 넣기.

$$g(\tilde{w}) = \sum_{i=1}^{N} |y_i - \tilde{w}^T x_i|$$

$$= \sum |y_i - \{\lambda w_1 + (1-\lambda) w_2\}^T x_i|$$

$$= \underline{\sum |y_i - \lambda w_1^T x_i + (1-\lambda) w_2^T x_i|}$$

↳ 여기서 삼각부등식 쓸 수 있음. λ와 (1-λ)가 [0,1] 사이에 있으므로,,

$\|\vec{x} + \vec{y}\| \leq \|\vec{x}\| + \|\vec{y}\|$

$\vec{x} = y_i - \lambda w_1^T x_i + (1-\lambda) w_2^T x_i$

$\vec{y} = \lambda(y_i - w_1^T x_i) + (1-\lambda)(y_i - w_2^T x_i)$

↳ $\cancel{\lambda y_i} - \lambda w_1^T x_i + y_i - w_2^T x_i - \cancel{\lambda y_i} + \lambda w_2^T x_i$

$$= \sum \lambda (y_i - w_1^T x_i) + (1-\lambda)(y_i - w_2^T x_i)$$

$$= \lambda \underbrace{\sum_{i=1}^{N} (y_i - w_1^T x_i)}_{g(w_1)} + (1-\lambda) \underbrace{\sum_{i=1}^{N} (y_i - w_2^T x_i)}_{g(w_2)}$$

$\rightarrow \therefore g(\tilde{w}) = \lambda g(w_1) + (1-\lambda) g(w_2)$

↳ λ가 [0,1]의 값을 가지므로

$g(\lambda w_1 + (1-\lambda) w_2) \leq \lambda g(w_1) + (1-\lambda) g(w_2)$ 가 되므로

Convex 함수를 증명할 수 있다.