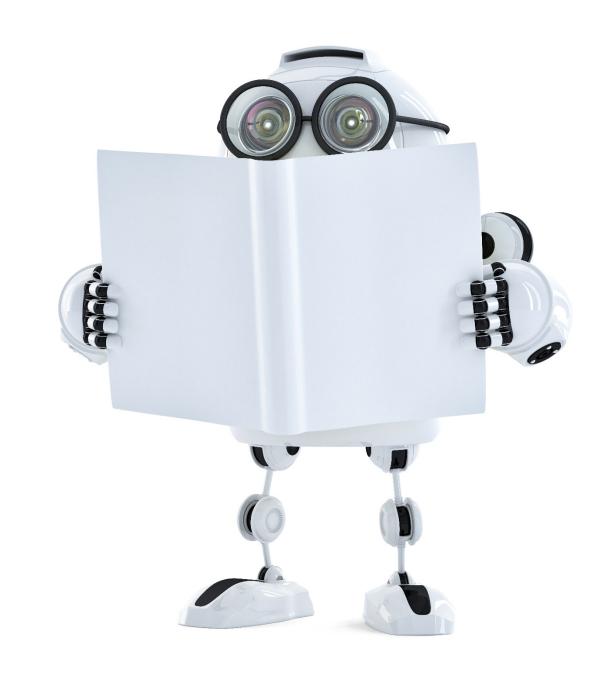
L2 – Regularization / Ridge

Linear Regression

Director of TEAMLAB Sungchul Choi



L2 regularization

- 기존 Cost function L2(norm) penalty term을 추가

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_{\theta}(x^{(i)}) - y^{(i)} \right)^{2} + \frac{\lambda}{2} \sum_{j=1}^{m} \theta_{j}^{2}$$

- norm 벡터의 길이 혹은 크기를 측정하는 방법
 - $\|(\theta)\|_2^2$ L2는 Euclidean distance 원점에서 벡터 좌표까지의 거리

L2 regularization

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_{\theta}(x^{(i)}) - y^{(i)} \right)^{2} + \frac{\lambda}{2} \sum_{j=1}^{m} \theta_{j}^{2}$$

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_0^{(i)}$$

$$\theta_j := \theta_j - \alpha \left[\left(\frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)} \right) + \frac{\lambda}{m} \theta_j \right] j \in \{1, 2...n\}$$

L2 regularization

$$\theta_j := \theta_j - \alpha \left[\left(\frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)} \right) + \frac{\lambda}{m} \theta_j \right]$$

$$\theta_j := \theta_j (1 - \alpha \frac{\lambda}{m}) - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

Normal equation approach

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_{\theta}(x^{(i)}) - y^{(i)} \right)^{2} + \frac{\lambda}{2} \sum_{j=1}^{m} \theta_{j}^{2}$$

$$J(\theta) = (y - X\theta)^{T} (y - X\theta) + \lambda \theta^{T} \theta$$

$$= y^{T} y - \theta^{T} X^{T} y - y^{T} X \theta + \theta^{T} X^{T} X \theta + \lambda \theta^{T} \theta$$

$$= y^{T} y - \theta^{T} X^{T} y - \theta^{T} X^{T} y + \theta^{T} X^{T} X \theta + \theta^{T} \lambda I \theta$$

$$= y^{T} y - 2\theta^{T} X^{T} y + \theta^{T} (X^{T} X + \lambda I) \theta$$

Normal equation approach

$$J(\theta) = y^T y - 2\theta^T X^T y + \theta^T (X^T X + \lambda I)\theta$$

$$\frac{\partial J(\theta)}{\partial \theta} = -2X^T y + 2(X^T X + \lambda I)\theta$$

$$(X^T X + \lambda I)\theta = X^T y \to \hat{\theta} = (X^T X + \lambda I)^{-1} X^T y$$

L1 regularization

- 기존 Cost function L1(norm) penalty term을 추가

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_{\theta}(x^{(i)}) - y^{(i)} \right)^{2} + \frac{\lambda}{2} \sum_{j=1}^{m} |\theta_{j}|$$

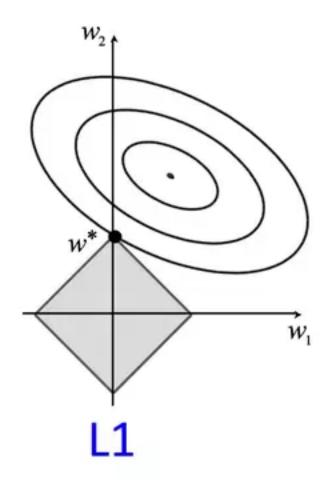
- norm - 벡터의 길이 혹은 크기를 측정하는 방법

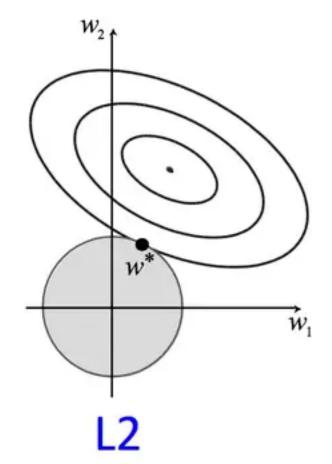
$$\|x\|_1:=\sum_{i=1}^n|x_i|$$
 L1는 manhattan distance 원점에서 벡터 좌표까지의 거리

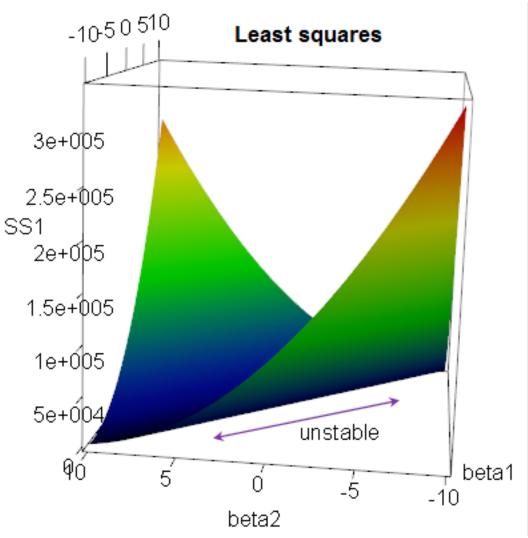
L1 vs L2

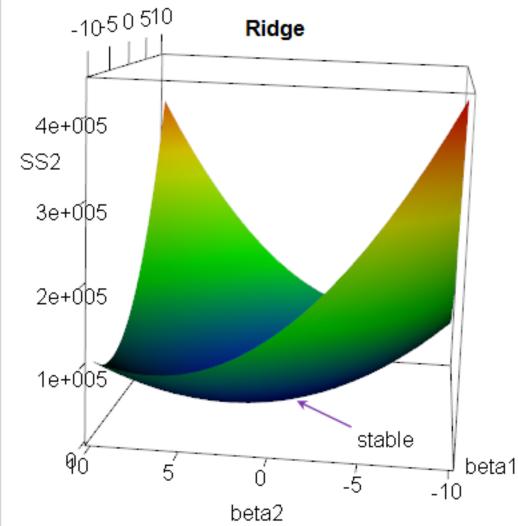
$$\sum_{j=1}^{2} |w_i| \le s$$

$$\sum_{j=1}^{2} |w_i| \le s \qquad \qquad \sum_{j=1}^{2} (w_i)^2 \le s$$









https://stats.stackexchange.com/questions/151304/why-is-ridge-regression-called-ridge-why-is-it-needed-and-what-happens-when

L1 L2

Unstable solution Stable solution

Always on solution Only one solution

Sparse solution Non-sparse solution

Feature selection



Human knowledge belongs to the world.