Lasso & Ridge Regression

Mathematical Proof

Ridge (L2) → Used for overfitting

θ would never go to 0

$$\text{Cost } J(\theta) = \frac{1}{2m} \sum (h(\theta) - y_i)^2 + \lambda (\theta/\text{slope}/\text{coff})^2$$

finding minima

$$\frac{dJ}{d\theta} = 0$$

$$\frac{d}{d\theta}\left[\frac{1}{2}(\theta - z)^2 + \lambda(\theta)^2\right]$$

if $z \neq 0$

$\theta_{ridge} \neq 0$ for finite λ

$$(\theta - z) + 2\lambda\theta = 0$$

$$\theta(1 + 2\lambda) = z$$

$$\theta_{ridge} = \frac{z}{(2\lambda + 1)}$$

Lasso (L1) → Used for feature Selection

θ could go to zero

$$\text{Cost } J(\theta) = \frac{1}{2m} \sum (h(\theta) - y_i)^2 + \lambda |\theta/\text{slop}/\text{coffe}|$$

Case a ($\theta > 0$)

$$\frac{1}{2}\frac{d}{d\theta}(\theta - z)^2 + \lambda\theta = 0$$

$$(\theta - z) + \lambda = 0$$

$$\theta = z - \lambda$$

as $\theta \to +ve$

$$z - \lambda > 0$$

$$z > \lambda$$

Case B ($\theta < 0$)

$$\frac{1}{2}\frac{d}{d\theta}(\theta - z)^2 - \lambda\theta = 0$$

$$(\theta - z) - \lambda = 0$$

$$\theta = \lambda + z$$

as $\theta < 0$

$$z < -\lambda$$

θ → tell relation of particular independent variable to target variable