

Closed form solution of Ridge Regression.

$$\min_{\beta} \frac{1}{2} \|y - X\beta\|_2^2 + \frac{\lambda}{2} \|\beta\|_2^2$$

$$f(\beta) = \frac{1}{2} \|y - X\beta\|_2^2 + \frac{\lambda}{2} \|\beta\|_2^2$$

$$f(\beta) = \frac{1}{2} (y - \beta^T X)^T (y - \beta^T X) + \frac{\lambda}{2} \beta^T \beta$$

$$\frac{\partial f(\beta)}{\partial \beta} = -X^T (y - \beta X) + \lambda \beta$$

$$\frac{\partial f(\beta)}{\partial \beta} = 0 \Leftrightarrow -X^T (y - \beta X) + \lambda \beta = 0$$

$$\Leftrightarrow \beta (X^T X + \lambda I_p) = X^T y$$

$\Leftrightarrow$

$$\boxed{\beta = (X^T X + \lambda I_p)^{-1} X^T y}$$

$$f(\beta) = \frac{1}{2n} \sum_{i=1}^n (y_i - x_i \beta)^2 + \lambda |\beta|$$

$$\begin{aligned} a) \quad f(\beta) &= \frac{1}{2n} \sum_{i=1}^n (y_i^2 - 2x_i y_i \beta + x_i^2 \beta^2) + \lambda |\beta| \\ f(\beta) &= \left( \frac{1}{2n} \sum_{i=1}^n y_i^2 \right) - \left( \sum_{i=1}^n \frac{x_i y_i}{n} \beta \right) + \sum_{i=1}^n \frac{x_i^2 \beta^2}{2n} + \lambda |\beta| \end{aligned}$$

We have:

$$\sum_{i=1}^n \frac{x_i^2}{n} = 1$$

And  $\frac{1}{2n} \sum_{i=1}^n y_i^2 \sim \text{constant}$

therefore

$$\min_{\beta \in \mathbb{R}} f(\beta) = \min_{\beta \in \mathbb{R}} \left( \frac{1}{2} \frac{\beta^2}{n} - \frac{1}{n} \beta \sum_{i=1}^n y_i x_i + \lambda |\beta| \right)$$

$$\frac{1}{n} \sum_{i=1}^n y_i x_i > 0.$$

assume:

$$\beta < 0.$$

$$\begin{aligned} \min_{\beta \in \mathbb{R}} \quad & \frac{1}{2} \beta^2 - \frac{1}{n} \beta \sum_{i=1}^n y_i x_i + \lambda |\beta| \\ = \min_{\beta \in \mathbb{R}} \quad & \frac{1}{2} \beta^2 - \frac{1}{n} \beta \sum_{i=1}^n y_i x_i - \lambda \beta \end{aligned}$$

$$\frac{\partial}{\partial \beta} = 0 \Leftrightarrow \beta - \frac{\sum_{i=1}^n y_i x_i}{n} - \lambda = 0$$

$$\Leftrightarrow \beta = \frac{\sum_{i=1}^n y_i x_i}{n} + \lambda > 0 \quad \forall.$$

(Invalid!!!)

$$\beta > 0 \text{ while } \sum_{i=1}^n y_i x_i > 0$$

Therefore:  $\beta > 0$

Case 1a:

$$\frac{1}{n} \sum_{i=1}^n y_i x_i \leq \lambda \quad ; \quad \beta > 0$$

$$\min_{\beta \in \mathbb{R}} \quad \frac{1}{2} \beta^2 - \frac{1}{n} \beta \sum_{i=1}^n y_i x_i + \lambda \beta$$

$$\geq \min_{\beta \in \mathbb{R}} \quad \frac{1}{2} \beta^2 - \frac{1}{n} \beta \lambda + \lambda \beta \geq 0$$

therefore optimum  $\beta = 0$

~~$$\frac{\partial}{\partial \beta} = 0 \Leftrightarrow$$~~

~~$$\beta - \frac{\lambda}{n} + \lambda = 0 \Leftrightarrow \beta = \lambda - \frac{\lambda}{n}$$~~

$$\frac{1}{n} \sum_{i=1}^n y_i x_i \geq \lambda$$

$$\min \left( \frac{1}{2} \beta^2 - \frac{1}{n} \beta \sum_{i=1}^n y_i x_i + \lambda \beta \right)$$

$$= \left( \frac{1}{2} \beta^2 - \frac{1}{n} \beta \lambda + \lambda \beta \right)$$

$$\frac{\partial}{\partial \beta} = \beta - \frac{\sum_{i=1}^n y_i x_i}{n} + \lambda = 0 \Rightarrow \boxed{\beta = \frac{\sum_{i=1}^n y_i x_i}{n} - \lambda}$$

Case 2:  $\frac{1}{n} \sum_{i=1}^n y_i x_i = 0$

$$\frac{1}{2} \beta^2 - \frac{1}{n} \beta \sum_{i=1}^n y_i x_i + \lambda |\beta|$$

$$= \frac{1}{2} \beta^2 + \lambda |\beta|$$

⊕ If  $\beta = 0 \Rightarrow f(\beta) = 0$  (true)

⊕ If  $\beta < 0$ :

$$\frac{\partial f}{\partial \beta} = \frac{\partial \left( \frac{1}{2} \beta^2 - \lambda \beta \right)}{\partial \beta} =$$

Therefore  $\beta = 0$  when  $\sum_{i=1}^n y_i x_i = 0$   
 $\beta - \lambda = 0$

$\Leftrightarrow \beta = \lambda$  (Invalid)  
 since  $\lambda \geq 0$

⊕ If  $\beta > 0$

$$\frac{\partial f}{\partial \beta} = \frac{\partial \left( \frac{1}{2} \beta^2 + \lambda \beta \right)}{\partial \beta} =$$

$\beta + \lambda = 0$   
 $\Leftrightarrow \beta = -\lambda$  (Invalid)  
 since  $\lambda \geq 0$

$$\frac{1}{n} \sum_{i=1}^n y_i x_i < 0.$$

3.  ~~$\beta > 0$~~ :

$$f(\beta) = \frac{1}{2} \beta^2 - \frac{\beta}{n} \sum_{i=1}^n y_i x_i + \lambda \beta$$

$$\frac{\partial f}{\partial \beta} = \beta - \frac{\sum_{i=1}^n y_i x_i}{n} + \lambda = 0.$$

$$\Leftrightarrow \frac{\partial f}{\partial \beta} = 0 \Leftrightarrow \beta = \lambda - \frac{\sum_{i=1}^n y_i x_i}{n} \quad (\text{hold true})$$

(Invalid)!!

If  $\beta < 0$ :

$$f(\beta) = \frac{1}{2} \beta^2 - \frac{\beta}{n} \sum_{i=1}^n y_i x_i - \lambda \beta$$

$$\frac{\partial f}{\partial \beta} = \beta - \frac{\sum_{i=1}^n y_i x_i}{n} - \lambda = 0$$

$$\Leftrightarrow \beta = \frac{\sum_{i=1}^n y_i x_i}{n} + \lambda \quad (\text{hold true})$$

therefore

$$\boxed{\beta \leq 0 \text{ while } \frac{\sum_{i=1}^n y_i x_i}{n} < 0.}$$

(3a)  $\frac{1}{n} \sum_{i=1}^n y_i x_i \geq -\lambda; \quad \beta \leq 0$

$$f(\beta) = \frac{1}{2} \beta^2 - \frac{1}{n} \beta \sum_{i=1}^n y_i x_i - \lambda \beta \geq 0 \quad \forall \beta \leq 0$$

$$\Rightarrow \min_{\beta \leq 0} f(\beta) = 0 \text{ when } \beta = 0$$

$$\frac{1}{n} \sum_{i=1}^n y_i x_i \leq -\lambda; \beta \leq 0$$

$$f(\beta) = \frac{1}{2} \beta^2 - \frac{\beta}{n} \sum_{i=1}^n y_i x_i - \lambda \beta$$

$$\frac{\partial f(\beta)}{\partial \beta} = \beta - \frac{\sum y_i x_i}{n} - \lambda = 0$$

$$\Rightarrow \boxed{\beta = \frac{\sum y_i x_i}{n} + \lambda}$$

1) optimal solution:

$\hat{\beta}_{\text{optimal}}$

$$= \text{sign}(\hat{\beta}) (|\hat{\beta}| - \lambda)_+$$

where  $\hat{\beta}$  is the least square estimator

$$\hat{\beta} = \arg \min_{\beta} \sum_{i=1}^n (y_i - x_i \beta)^2$$