





$$P =$$

$$\begin{pmatrix} \mu \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \alpha_1 \\ \alpha_2 \\ \beta_6 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \\ \alpha_8 \\ \alpha_9 \\ \beta_8 \end{pmatrix}$$

$$LH = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$L = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

Ridge } penalized version of
Lasso } the linear regression.

optimization p^b in classical linear regression is:

$$\min_{\beta \in \mathbb{R}^{p+1}} \left\| y - \left(\mu_0 + \sum_{i=1}^p \beta_i X^i \right) \right\|_2^2$$

now: $P > n$

$$\text{rk}(X) < n < P$$

$$X = \begin{pmatrix} 1 & x^1 & x^2 & x^3 & \dots & x^P \end{pmatrix}$$

\Rightarrow $X^T X$
not invertible

We have $p \gg n$

↳ the information inside the p variables is repeated.

⇒ my model: $y = f(x^1, \dots, x^p) + \varepsilon$

In fact: $y = g(\{x^i, i \in I \text{ with } |I| \leq p\}) + \varepsilon$
↑ linear $p \ll n$

↳ notion of sparsity.

Ridge:

optimization problem:

$$\min_{\beta \in \mathbb{R}^{p+1}} \left\| y - \left(\mu + \sum_{i=1}^p \beta_i X^i \right) \right\|^2$$

$$\mu + \sum_{i=1}^p \beta_i^2 \leq s.$$

with $s \geq 0$!

$$\Leftrightarrow \min_{\beta \in \mathbb{R}^{p+1}} \left(\left\| y - \left(\mu + \sum_{i=1}^p \beta_i x^i \right) \right\|^2 + \lambda \sum_{i=0}^p \beta_i^2 \right)$$

RR: $\lambda \rightarrow 0$
 we find Ordinary
 least Square

$\lambda \rightarrow +\infty$
 all β_i closed to 0!

with $\beta_0 = \mu$

to solve the p^b :

$$-2^t X (y - X\beta) + 2X\beta = 0$$

$$X = \left(1 \mid X' \mid \dots \mid X^p \right) \quad \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}$$

$$\hat{\beta}_{\lambda}^{\text{ridge}} = \left(\sum X X^T + \lambda I_p \right)^{-1} \sum X Y$$

P^b : How to choose λ ?

↳ by cross-validation

$$E \left[\hat{\beta}_{\lambda}^{\text{ridge}} \right] = \left(I_p + \lambda R^{-1} \right) \beta$$

with $R = \sum X X^T$

$$\hat{\beta}_{\lambda}^{\text{ridge}} = \left(I_p + \lambda R^{-1} \right)^{-1} \hat{\beta}^{\text{LS}}$$

Lasso:

min

$\beta \in \mathbb{R}^p$

$$\left(\|y - X\beta\|^2 + \lambda \sum_{i=0}^p |\beta_i| \right)$$

↳ no analytic expression of
the solution!