

PCR

$$V^T = \begin{bmatrix} \underline{v_1^T} \\ \underline{v_2^T} \\ \underline{v_3^T} \end{bmatrix}$$

$$\cancel{X} v_1 = d_1 u_1 \text{ (fact)}$$

$$\textcircled{1} \cancel{X} = U D V^T$$

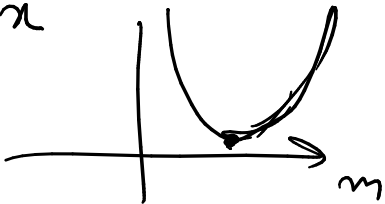
$N \times P \quad N \times P \quad P \times P \quad P \times P$

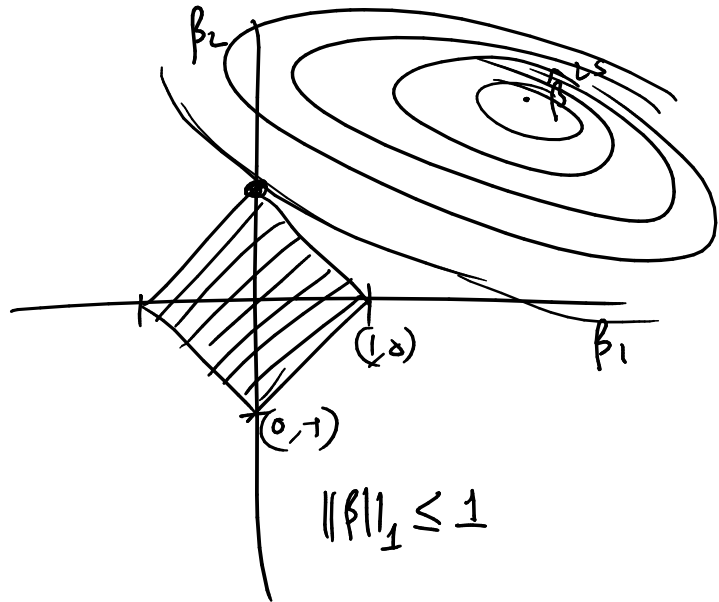
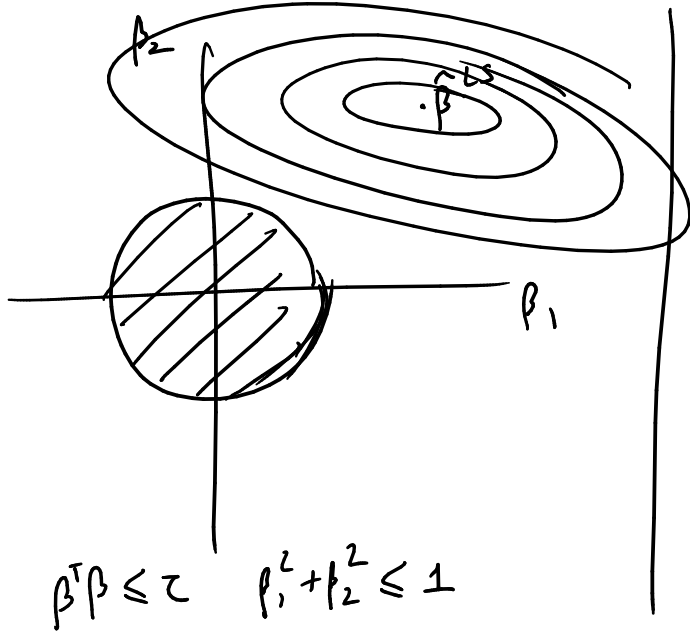
$$\textcircled{2} \left[\underbrace{\underbrace{(d_1 u_1)}_{\text{3 components}} \quad \underbrace{(d_2 u_2)}_{\text{3 components}} \quad \dots}_{N \times P} \right]$$

LASSO

$$(\mathbf{y} - \mathbf{X}\beta)^T (\mathbf{y} - \mathbf{X}\beta) + \lambda \underbrace{\|\beta\|_1}_{= \sum_{j=1}^p |\beta_j|} \quad \ell_1 \text{ norm}$$

eg: $y = mx$
 $\sum_{i=1}^n (y_i - mx_i)^2$





$$1. \quad X, G \begin{cases} 1 \\ 2 \\ \vdots \\ k \end{cases}$$

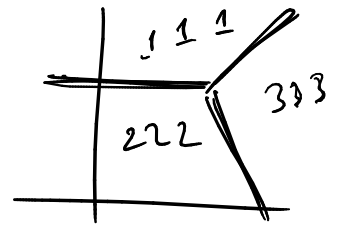
$$\hat{\beta}_k^T X$$

$$\hat{\beta}_k^T X = \hat{\beta}_l^T X$$

hyperplane

$$\begin{bmatrix} Y_1 & \dots & Y_k \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & \dots \\ 1 & 0 & 0 & 0 & \dots \\ 0 & 0 & 1 & 0 & \dots \end{bmatrix}$$

$$\begin{matrix} G_{data} \\ \begin{bmatrix} 1 \\ 2 \\ 1 \\ 3 \\ 2 \\ \vdots \end{bmatrix} \\ N \times 1 \end{matrix}$$



discriminant functions.

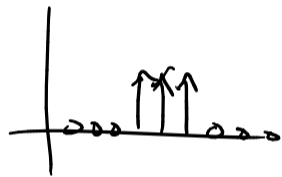
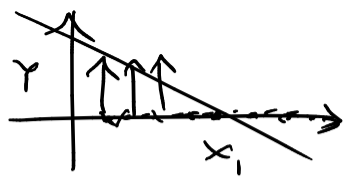
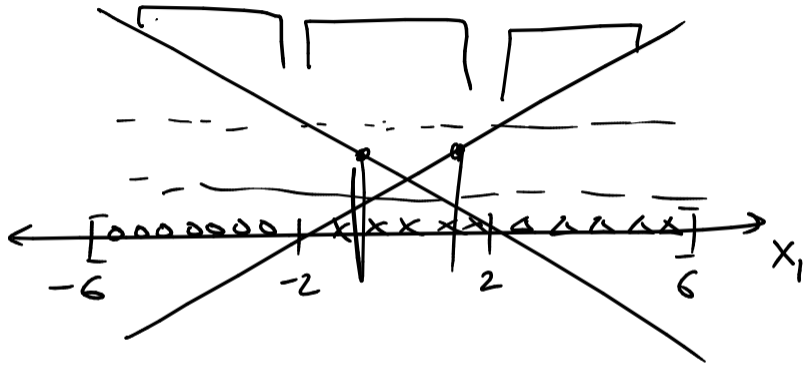
$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

$\begin{matrix} P \times K & & & & N \times K \end{matrix}$

issue 1: $\hat{\beta}_k^T X \in [0, 1]$

issue 2: class marking

$$\begin{aligned} & \rightarrow \underline{E[Y|X=x]} = \underline{\beta^T x} \\ & P(G=k|X=x) \\ & \rightarrow \underline{\underline{P(Y_k=1|X=x)}} \end{aligned}$$



$$\arg \max_{K=1, \dots, K} \hat{\beta}_K^T X$$

$$\underbrace{P_{X,G}}_{\left[P(G=k | X=x) \right]} = \frac{\underbrace{\prod_{j=1}^p P(X_j = x_j | G=k)}_{P(X=x | G=k)} \underbrace{P(G=k)}_{\pi_k \text{ ①}}}{P(X=x)}$$

$$P(X=x | G=k) = \mathcal{N}(x, \mu_k, \Sigma) \text{ ②}$$

$$\pi_1, \pi_2, \pi_3, \mu_1, \mu_2, \mu_3, \Sigma$$

$1 \times 1 \quad 1 \times 1 \quad 1 \times 1 \quad p \times p$

$$\log \left(\frac{P(G=1|X=x)}{P(G=2|X=x)} \right) = 0$$

$$\frac{1}{\sqrt{2\pi \det(\Sigma)}} \exp \left(-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu) \right)$$

$$g(x) = c^T x$$

$$QDA: \pi_1, \pi_2, \pi_3, \mu_1, \mu_2, \mu_3, \underbrace{\Sigma_1, \Sigma_2, \Sigma_3}_{p=2}$$

$$p=2$$

$$LDA: X_{2 \times 1}^{\text{original}} \rightarrow \begin{bmatrix} X_1 \cdot \\ X_2 \cdot \\ X_1, X_2 \cdot \end{bmatrix} \quad \begin{array}{l} \pi_1', \pi_2', \pi_3' \\ \underline{\mu_1', \mu_2', \mu_3'} \in \mathbb{R}^3 \\ \underline{\Sigma'}_{3 \times 3} \end{array}$$

Computation: "easy" due to MLE

Logistic Regression

3 classes

$$\log \left(\frac{P(G=1|X=x)}{P(G=3|X=x)} \right) = \beta_1^T x.$$

$$\log \left(\frac{P(G=2|X=x)}{P(G=3|X=x)} \right) = \beta_2^T x$$

$$\Rightarrow \underline{\underline{P(G=k|X=x)}} = \frac{e^{\beta_k^T x}}{1 + e^{\beta_1^T x} + e^{\beta_2^T x}}$$

loss: $\sum_{i=1}^N \log P(G=g_i | X=x_i)$ $\{x_i, g_i\}_{i=1}^N$

Some function of β_1, β_2 for each observation i .

in example $\log P(g_i | x_i) = \sum_{j=1}^p y_{ij} \log P(y_{ij} | x_i)$

$\sum_{j=1}^p q_j \log q_j$ 3 classes $g_{i=1}$ $y_i^T = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$

\uparrow y_{i1} \uparrow y_{i2} \uparrow y_{i3}

negative of entropy

AIC, BIC



$\frac{1}{N}$ Training error

$\underbrace{\hspace{10em}}_{\text{err}}$

$$+ \frac{2}{N} \left(g\left(\frac{1}{\lambda}\right) \right)$$

$$\frac{2 \log N}{N} \left(g\left(\frac{1}{\lambda}\right) \right)$$



$$\log_e a = \frac{\log_2 a}{\log_2 e} = \log_2 2.73 = 1.6$$