

3. Linear discrimination. \rightarrow Fisher Classification

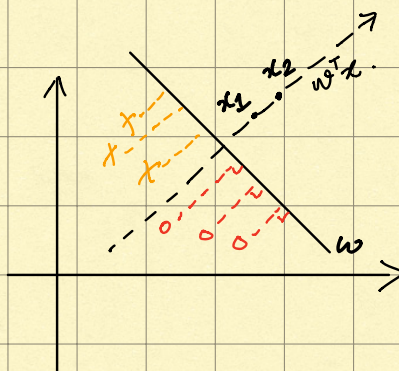
Assumption

- ① $X = (x_1, x_2, x_3, \dots, x_{N_1})^T$
- ② $Y = (y_1, y_2, y_3, \dots, y_{N_2})^T$
- ③ $y_i \in \{+1, -1\}$ ($+1 \rightarrow$ class C_1 ; $-1 \rightarrow$ class C_2)
- ④ $|x_{C_1}| + |x_{C_2}| = N_1 + N_2 = N$

Motivation

a. 类内紧凑

b. 类间分散



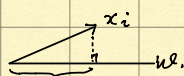
$\|w\| = 1$

Fig. 1.

相关系数推导

(1) for fig. 1: x_1, x_2 位于 w^\perp : $w^T x_1 - w^T x_2 = 0 \rightarrow w^T (x_1 - x_2) = 0$

for x_i : x_i 在 w 上的投影: $w^T x_i$



$\Delta = |x_i| \cdot \cos \theta$ — ①

$x_i w^T = |x_i| |w| \cos \theta$ — ②

$\|w\| = 1$ — ③

①, ②, ③: $\Delta = x_i w^T$ (向量内积)

(2). 均值 \bar{z}

$z_i = w^T x_i \rightarrow \bar{z} = \frac{1}{N} \sum_{i=1}^N z_i \rightarrow \bar{z} = \frac{1}{N} \sum_{i=1}^N w^T x_i$

$\text{Var}[z_i] = \frac{1}{N} \sum_{i=1}^N (z_i - \bar{z})(z_i - \bar{z})^T$

$= \frac{1}{N} \sum_{i=1}^N (w^T x_i - \bar{z})(w^T x_i - \bar{z})^T \rightarrow \text{Var}[z_i] = S_z$

$\therefore C_1: \bar{z}_1 = \frac{1}{N} \sum_{i=1}^N w^T x_i; S_1 = \frac{1}{N} \sum_{i=1}^N (w^T x_i - \bar{z}_1)(w^T x_i - \bar{z}_1)^T$

$C_2: \bar{z}_2 = \frac{1}{N} \sum_{i=1}^N w^T x_i; S_2 = \frac{1}{N} \sum_{i=1}^N (w^T x_i - \bar{z}_2)(w^T x_i - \bar{z}_2)^T$

(3). 类内类间的表示

①. 2个样本投影到 z 轴, 用样本点均值作差的平方 \rightarrow 类间差

②. 类内: 各自 C_1 与 C_2 的方差之和, 表示它们的 \rightarrow 类内

$\Rightarrow \frac{(\bar{z}_1 - \bar{z}_2)^2}{S_1 + S_2}$

目标函数

$$J(w) = \frac{(\bar{z}_1 - \bar{z}_2)^2}{S_1 + S_2} \quad (*)$$

⑧: 分子: $(\bar{z}_1 - \bar{z}_2)^2 = \left(\frac{1}{N_1} \sum_{i=1}^{M_1} w^T x_i - \frac{1}{N_2} \sum_{i=1}^{M_2} w^T x_i \right)^2 = \left(w^T \left(\frac{1}{N_1} \sum_{i=1}^{M_1} x_i - \frac{1}{N_2} \sum_{i=1}^{M_2} x_i \right) \right)^2 = w^T (\bar{x}_{c_1} - \bar{x}_{c_2}) (\bar{x}_{c_1} - \bar{x}_{c_2})^T w$

分母: $S_1 + S_2 = \frac{1}{N_1} \sum_{i=1}^{M_1} (w^T x_i - \bar{z}_1) (w^T x_i - \bar{z}_1)^T + \frac{1}{N_2} \sum_{i=1}^{M_2} (w^T x_i - \bar{z}_2) (w^T x_i - \bar{z}_2)^T$

$$= \frac{1}{N_1} \sum_{i=1}^{M_1} w^T (x_i - \frac{1}{N_1} \sum_{j=1}^{M_1} x_j) (x_i - \frac{1}{N_1} \sum_{j=1}^{M_1} x_j)^T w + \dots$$

$$= w^T \left[\frac{1}{N_1} \sum_{i=1}^{M_1} (x_i - \bar{x}_{c_1}) (x_i - \bar{x}_{c_1})^T \right] w + \dots \Rightarrow S_1 + S_2 = w^T S_{c_1} w + w^T S_{c_2} w = w^T (S_{c_1} + S_{c_2}) w$$

$$(1) J(w) = \frac{(\bar{z}_1 - \bar{z}_2)^2}{S_{z_1} + S_{z_2}} = \frac{w^T (\bar{x}_{c_1} - \bar{x}_{c_2}) (\bar{x}_{c_1} - \bar{x}_{c_2})^T w}{w^T (S_{c_1} + S_{c_2}) w}$$

(S_B : between-class 类间方差; S_W : within-class 类内方差)

$$= \frac{w^T S_B w}{w^T S_W w}$$

(2) 最优解

$$\frac{\partial J(w)}{\partial w} = \frac{2 S_B w}{w^T S_W w} \cdot w^T S_B w \cdot (-1) (w^T S_W w)^{-2} \cdot 2 S_W w = 0 \quad (1)$$

$$\frac{(1)}{2} = \frac{S_B w}{w^T S_W w} \cdot w^T S_B w \cdot (-1) (w^T S_W w)^{-2} \cdot S_W w = 0$$

$$\Rightarrow S_B w \cdot (w^T S_W w)^{-1} \cdot (w^T S_B w) \cdot (-1) (w^T S_W w)^{-2} \cdot S_W w = 0$$

$$\Rightarrow S_B w \cdot (w^T S_W w) - (w^T S_B w) \cdot S_W w$$

$$\Rightarrow (w^T S_W w) S_B w = (w^T S_B w) \cdot S_W w \quad (2)$$

②: w^T : $1 \times p$ 维; w : $p \times 1$ 维; S_B : $p \times p$ 维. $\Rightarrow w^T S_B w \in \mathbb{R}^+(1 \text{ 维})$.
同理, $(w^T S_W w)$ - 1 维. ($\in \mathbb{R}^+$). (对方向无影响)

$$\Rightarrow S_w w = \frac{w^T S_w w}{w^T S_B w} \cdot S_B \cdot w.$$

$$\Rightarrow S_w \cdot w = R^+ : S_B \cdot w$$

$$\Rightarrow w = R^+ \cdot S_B w S_w^{-1} \quad (w \propto S_B w S_w^{-1}) \quad \text{--- ③}$$

$$\text{for ③: } S_B w = \underbrace{(\bar{x}_{c1} - \bar{x}_{c2})}_{1 \times p} \underbrace{(\bar{x}_{c1} - \bar{x}_{c2})^T}_{p \times 1} \cdot w$$

1维的实数 R^+ , 对方向无影响.

$$\Rightarrow w \propto S_w^{-1} (\bar{x}_{c1} - \bar{x}_{c2})$$

↖ 我们所关注的 w 的方向