

Fisher 线性判别习题解答

1, 已知两类样本的数据如下:

$$\omega_1: \{(5,37), (7,30), (10,35), (11.5,40), (14,38), (12,31)\}$$

$$\omega_2: \{(35,21.5), (39,21.7), (34,16), (37,17)\}$$

试用 Fisher 判别函数法, 求出最佳投影方向 W , 及分类阈值 y_0

解: 由题意知:

$$\mu_1 = \frac{1}{6} \sum_{n=1}^6 X_n^{(1)} = (9.92 \ 35.17)^T$$

$$\mu_{-1} = \frac{1}{4} \sum_{n=1}^4 X_n^{(0)} = (36.25 \ 19.05)^T$$

则可计算出类内离差阵:

$$\Sigma_1 = \sum_{n=1}^6 (X_n^{(1)} - \mu_1) \cdot (X_n^{(1)} - \mu_1)^T = \begin{pmatrix} 56.21 & 16.58 \\ 16.58 & 78.83 \end{pmatrix}$$

$$\Sigma_{-1} = \sum_{n=1}^4 (X_n^{(0)} - \mu_{-1}) \cdot (X_n^{(0)} - \mu_{-1})^T = \begin{pmatrix} 14.75 & 9.55 \\ 9.55 & 26.53 \end{pmatrix}$$

$$S_w = \Sigma_1 + \Sigma_{-1} = \begin{pmatrix} 70.96 & 26.13 \\ 26.13 & 105.36 \end{pmatrix}$$

$$S_w^{-1} = \begin{pmatrix} 0.0155 & -0.0038 \\ -0.0038 & 0.0104 \end{pmatrix}$$

从而可计算出最佳投影方向:

$$W^* = S_w^{-1}(\mu_1 - \mu_{-1}) = (-0.4704, 0.2696)^T$$

$$y_0 = W^{*T} \frac{(\mu_1 + \mu_{-1})}{2} = -3.55$$

2, 在 Fisher 判别中, 用向量梯度的计算法则证明: $\mathbf{S}_B \mathbf{w} = \lambda \mathbf{S}_w \mathbf{w}$

证明: $L(\mathbf{w}, \lambda) = \mathbf{w}^T \mathbf{S}_B \mathbf{w} + \lambda(K - \mathbf{w}^T \mathbf{S}_w \mathbf{w}) = \mathbf{w}^T (\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{w} + \lambda K$

$$\nabla L_w(\mathbf{w}, \lambda) = \frac{\partial L(\mathbf{w}, \lambda)}{\partial \mathbf{w}} = \mathbf{0}^T$$

$$\frac{\partial L(\mathbf{w}, \lambda)}{\partial \mathbf{w}} = \frac{\partial (\mathbf{w}^T (\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{w})}{\partial \mathbf{w}} + 0$$

根据 $\frac{\partial \mathbf{u}^T \mathbf{v}}{\partial \mathbf{x}} = \mathbf{u}^T \frac{\partial \mathbf{v}}{\partial \mathbf{x}} + \mathbf{v}^T \frac{\partial \mathbf{u}}{\partial \mathbf{x}}$, $\frac{\partial A \mathbf{x}}{\partial \mathbf{x}} = \mathbf{A}$, 以及 $\frac{\partial \mathbf{x}}{\partial \mathbf{x}} = \mathbf{I}$, 上式:

$$\begin{aligned} \frac{\partial (\mathbf{w}^T (\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{w})}{\partial \mathbf{w}} &= \mathbf{w}^T (\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{I} + ((\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{w})^T \mathbf{I} \\ &= \mathbf{w}^T (\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{I} + \mathbf{w}^T (\mathbf{S}_B - \lambda \mathbf{S}_w)^T \mathbf{I} \end{aligned}$$

因为: \mathbf{S}_B 和 \mathbf{S}_w 均为对称矩阵,

所以: $(\mathbf{S}_B - \lambda \mathbf{S}_w)^T = (\mathbf{S}_B - \lambda \mathbf{S}_w)$,

又: $(\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{I} = (\mathbf{S}_B - \lambda \mathbf{S}_w)$

所以: $\frac{\partial L(\mathbf{w}, \lambda)}{\partial \mathbf{w}} = 2 \mathbf{w}^T (\mathbf{S}_B - \lambda \mathbf{S}_w) = \mathbf{0}^T$

$$2(\mathbf{S}_B - \lambda \mathbf{S}_w) \mathbf{w} = \mathbf{0}$$

$$\mathbf{S}_B \mathbf{w} = \lambda \mathbf{S}_w \mathbf{w}$$

3, 在 Fisher 判别中, 将目标函数 $J(\mathbf{w}) = \frac{\mathbf{w}^T \mathbf{S}_B \mathbf{w}}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}}$ 作为分式求梯度, 推导出 $\mathbf{w}^* = \mathbf{S}_w^{-1}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)$
解:

将 $J(\mathbf{w}) = \frac{\mathbf{w}^T \mathbf{S}_B \mathbf{w}}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}}$ 作为分式求梯度:

$$\begin{aligned}\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}} &= \frac{(\mathbf{w}^T \mathbf{S}_w \mathbf{w}) 2 \mathbf{w}^T \mathbf{S}_B - (\mathbf{w}^T \mathbf{S}_B \mathbf{w}) 2 \mathbf{w}^T \mathbf{S}_w}{(\mathbf{w}^T \mathbf{S}_w \mathbf{w})^2} = \mathbf{0}^T \\ &= \frac{(\mathbf{w}^T \mathbf{S}_w \mathbf{w}) 2 \mathbf{w}^T (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2) (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T - (\mathbf{w}^T (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2) (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T \mathbf{w}) 2 \mathbf{w}^T \mathbf{S}_w}{(\mathbf{w}^T \mathbf{S}_w \mathbf{w})^2} \\ &= \frac{2 \mathbf{w}^T (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}} ((\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T - \frac{(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T \mathbf{w} \mathbf{w}^T \mathbf{S}_w}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}}) \\ &= \frac{2 \mathbf{w}^T (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}} ((\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T - \frac{\mathbf{w}^T (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}} \mathbf{w}^T \mathbf{S}_w) = \mathbf{0}^T\end{aligned}$$

由于 $\frac{\mathbf{w}^T (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)}{\mathbf{w}^T \mathbf{S}_w \mathbf{w}}$ 为标量, 令其为 a ,

$$2a((\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T - a \mathbf{w}^T \mathbf{S}_w) = \mathbf{0}^T$$

$$(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T - a \mathbf{w}^T \mathbf{S}_w = \mathbf{0}^T$$

$$a \mathbf{w}^T \mathbf{S}_w = (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T$$

$$a \mathbf{S}_w^T \mathbf{w} = \boldsymbol{\mu}_1 - \boldsymbol{\mu}_2$$

\mathbf{S}_w 为对称矩阵, 则 $\mathbf{S}_w^T = \mathbf{S}_w$

如果 \mathbf{S}_w^{-1} 存在, 则: $\mathbf{w} = \frac{1}{a} \mathbf{S}_w^{-1}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)$

即: $\mathbf{w}^* = \mathbf{S}_w^{-1}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)$