线性判别分析

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- 线性判别分析算法 (LDA) 是一个有监督学习算法。
- 假设特征都是连续数值、服从高斯分布,而且个类别特征高斯分布 的协方差矩阵一样。
- LDA是一个线性分类器。
- LDA将样本输入投影到一个具有最大分类能力的一维空间中。

- 给定一个样本输入向量 $x = [x_1 \ x_2 \ \cdots \ x_m]^T$
- 假设在标签类别给定前提下输入向量服从高斯分布,而且每个类别特征的高斯分布的协方差矩阵相同

$$p(\mathbf{x}|y=0) = \frac{1}{(2\pi)^{m/2} |\mathbf{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\mathbf{x} - \mu_0)^T \mathbf{\Sigma}^{-1} (\mathbf{x} - \mu_0)}$$

$$p(\mathbf{x}|y=1) = \frac{1}{(2\pi)^{m/2} |\mathbf{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\mathbf{x} - \mu_1)^T \mathbf{\Sigma}^{-1} (\mathbf{x} - \mu_1)}$$

根据贝叶斯准则

$$p(y=0|\mathbf{x}) = \frac{p(y=0)p(\mathbf{x}|y=0)}{p(\mathbf{x})} = \frac{p(y=0)}{p(\mathbf{x})} \frac{1}{(2\pi)^{m/2}|\mathbf{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\mathbf{x}-\mu_0)^T \mathbf{\Sigma}^{-1}(\mathbf{x}-\mu_0)}$$

$$p(y=1|\mathbf{x}) = \frac{p(y=1)p(\mathbf{x}|y=1)}{p(\mathbf{x})} = \frac{p(y=1)}{p(\mathbf{x})} \frac{1}{(2\pi)^{m/2} |\mathbf{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\mathbf{x}-\mu_1)^T \mathbf{\Sigma}^{-1} (\mathbf{x}-\mu_1)}$$

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$$p(y=1|\mathbf{x}) = \frac{p(y=1)p(\mathbf{x}|y=1)}{p(\mathbf{x})} = \frac{p(y=1)}{p(\mathbf{x})} \frac{1}{(2\pi)^{m/2} |\mathbf{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\mathbf{x}-\mu_1)^T \mathbf{\Sigma}^{-1} (\mathbf{x}-\mu_1)}$$

• 如果p(y=1|x) > p(y=0|x), 预测类别为1; 否则, 预测类别为0.

$$p(y=1|x) \le p(y=0|x) \quad \longleftrightarrow \quad \frac{p(y=1|x)}{p(y=0|x)} \le 1 \quad \longleftrightarrow \quad \log\left(\frac{p(y=1|x)}{p(y=0|x)}\right) \le 0$$

$$\frac{p(y=1|\mathbf{x})}{p(y=0|\mathbf{x})} = \frac{p(y=1)p(\mathbf{x}|y=1)/p(\mathbf{x})}{p(y=0)p(\mathbf{x}|y=0)/p(\mathbf{x})} = \frac{p(y=1)p(\mathbf{x}|y=1)}{p(y=0)p(\mathbf{x}|y=0)}$$
$$= \frac{p(y=1)}{p(y=0)}e^{-\frac{1}{2}(\mathbf{x}-\mu_1)^T\mathbf{\Sigma}^{-1}(\mathbf{x}-\mu_1) + \frac{1}{2}(\mathbf{x}-\mu_0)^T\mathbf{\Sigma}^{-1}(\mathbf{x}-\mu_0)}$$

$$\log \left(\frac{p(y=1|x)}{p(y=0|x)} \right) = \log \left(\frac{p(y=1)}{p(y=0)} \right) - \frac{1}{2} (x - \mu_1)^T \mathbf{\Sigma}^{-1} (x - \mu_1) + \frac{1}{2} (x - \mu_0)^T \mathbf{\Sigma}^{-1} (x - \mu_0)$$

$$= \log \left(\frac{p(y=1)}{p(y=0)} \right) - \frac{1}{2} \mu_1^T \mathbf{\Sigma}^{-1} \mu_1 + \frac{1}{2} \mu_0^T \mathbf{\Sigma}^{-1} \mu_0 + x^T \mathbf{\Sigma}^{-1} \mu_1 - x^T \mathbf{\Sigma}^{-1} \mu_0$$

$$\log\left(\frac{p(y=1|x)}{p(y=0|x)}\right) = \log\left(\frac{p(y=1)}{p(y=0)}\right) - \frac{1}{2}\mu_1^T \mathbf{\Sigma}^{-1} \mu_1 + \frac{1}{2}\mu_0^T \mathbf{\Sigma}^{-1} \mu_0 + x^T \mathbf{\Sigma}^{-1} \mu_1 - x^T \mathbf{\Sigma}^{-1} \mu_0$$

$$\log \left(\frac{p(y=1|x)}{p(y=0|x)} \right) \leq 0 \iff x^T \mathbf{\Sigma}^{-1} (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0) \leq \log \left(\frac{p(y=0)}{p(y=1)} \right) + \frac{1}{2} (\boldsymbol{\mu}_1^T \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_1 - \boldsymbol{\mu}_0^T \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_0)$$

$$x^{T} \mathbf{\Sigma}^{-1}(\boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}) > \log \left(\frac{p(y=0)}{p(y=1)} \right) + \frac{1}{2} (\boldsymbol{\mu}_{1}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{0}) \implies \hat{y} = 1$$

$$x^{T} \mathbf{\Sigma}^{-1}(\boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}) < \log \left(\frac{p(y=0)}{p(y=1)} \right) + \frac{1}{2} (\boldsymbol{\mu}_{1}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{0}) \implies \hat{y} = 0$$

$$\boldsymbol{x}^{T} \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}) \leq \log \left(\frac{p(y=0)}{p(y=1)} \right) + \frac{1}{2} (\boldsymbol{\mu}_{1}^{T} \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}^{T} \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_{0})$$

$$\boldsymbol{x}^{T} \boldsymbol{\omega} \leq t$$

$$x^{T} \mathbf{\Sigma}^{-1}(\boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}) > \log \left(\frac{p(y=0)}{p(y=1)}\right) + \frac{1}{2}(\boldsymbol{\mu}_{1}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{0}) \longrightarrow \hat{y} = 1$$

$$x^{T} \mathbf{\Sigma}^{-1}(\boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}) < \log \left(\frac{p(y=0)}{p(y=1)}\right) + \frac{1}{2}(\boldsymbol{\mu}_{1}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{1} - \boldsymbol{\mu}_{0}^{T} \mathbf{\Sigma}^{-1} \boldsymbol{\mu}_{0}) \longrightarrow \hat{y} = 0$$

$$x^{T} \boldsymbol{\omega} \leq t$$



