

References

1. Pattern Classification

Duda, Hart, Stork

2. Probabilistic Theory of Pattern Recognition

Devroye, Györfi, Lugosi

3. Pattern recognition and Machine Learning

Chris Bishop

$X \rightarrow$ Instance space

$Y \rightarrow$ Label space

Binary Classification
 $Y = \{-1, 1\}$

Classifier
 $h: X \rightarrow \{-1, 1\}$ $X \subseteq \mathbb{R}^d$

Prior

$P_1 = P(Y=1)$, $P_2 = P(Y=-1)$

Class conditional Distribution

$P(X=x|Y=1)$, $P(X=x|Y=-1)$

[Densities / p.m.f]

$$\eta(x) = P(Y=1 | X=x)$$

$$1 - \eta(x) = P(Y=-1 | X=x)$$

$$P(Y=1 | X=x) = \frac{P(Y=1) P(X=x | Y=1)}{P(X=x)}$$

Bayes Classifier

$$h(x) = \begin{cases} 1 & P(Y=1 | X=x) > P(Y=-1 | X=x) \\ -1 & P(Y=-1 | X=x) \geq P(Y=1 | X=x) \end{cases}$$

$$h(x) = \begin{cases} 1 & \eta(x) > 1 - \eta(x) \\ -1 & 1 - \eta(x) \geq \eta(x) \end{cases}$$

$$h(x) = \text{sign}(2\eta(x) - 1) \rightarrow BC$$

$$\text{sign}(z) = \begin{cases} 1 & z > 0 \\ -1 & z \leq 0 \end{cases}$$

Specific case

$$N(x|\mu, C)$$

$$x \in \mathbb{R}^d, \mu \in \mathbb{R}^d$$

$C \in \mathbb{R}^{d \times d}$, Symmetric
positive semi-definite

$$= \frac{1}{(\sqrt{2\pi})^d |C|^{1/2}} e^{-\frac{1}{2}(x-\mu)^T C^{-1}(x-\mu)}$$

$$|C| \equiv \det(C)$$

$$P(X=x|Y=1) = N(x|\mu_1, C_1)$$

$$P(X=x|Y=0) = N(x|\mu_2, C_2)$$

$$C_1 = C_2 = C$$

$$\eta(x) = \frac{p_1 N(x | \mu_1, C_1)}{P(X=x)}$$

$$h^*(x) = \begin{cases} 1 & \log \frac{\eta(x)}{1-\eta(x)} > 0 \\ -1 & \text{otherwise} \end{cases}$$

$$h^*(x) = \text{Sign} \left(\log \frac{\eta(x)}{1-\eta(x)} \right)$$

$$\log \frac{\eta(x)}{1-\eta(x)} = \log \frac{P_1 N(x|\mu_1, C)}{P_2 N(x|\mu_2, C)}$$

$$= \log \frac{P_1}{P_2} + \log \frac{N(x|\mu_1, C)}{N(x|\mu_2, C)}$$

$$\log \frac{N(x|\mu_1, C)}{N(x|\mu_2, C)}$$

$$= -\frac{1}{2} (x - \mu_1)^T C^{-1} (x - \mu_1) \\ + \frac{1}{2} (x - \mu_2)^T C^{-1} (x - \mu_2)$$

$$= (\mu_1 - \mu_2)^T C^{-1} x$$

$$- \frac{1}{2} (\mu_1^T C^{-1} \mu_1 - \mu_2^T C^{-1} \mu_2)$$

$$\log \frac{\eta(x)}{1-\eta(x)}$$

$$= (\mu_1 - \mu_2)^T C^{-1} x$$

$$- \frac{1}{2} (\mu_1^T C^{-1} \mu_1 - \mu_2^T C^{-1} \mu_2) + \log \frac{P_1}{P_2}$$

$$= w^T x + b$$

$$w = C^{-1} (\mu_1 - \mu_2)$$

$$b = \log \frac{P_1}{P_2} - \frac{1}{2} (\mu_1^T C^{-1} \mu_1 - \mu_2^T C^{-1} \mu_2)$$

$$h(x), \text{ sign}(w^T x - b)$$

Bayes Classifier is a linear function

Examine the case

$$C_1 \neq C_2, \quad C_1 = \sigma_1^2 I$$

$$C_2 = \sigma_2^2 I$$

$$w^T x = b$$

hyperplane

$$w^T x > b$$

half space

$$w^T x < b$$

half space

How good is the
Bayes Classifier (BC)

$$E(1_A) = P(A)$$

$$P(h(x) \neq y)$$

$$= E_{x,y} 1_{\{h(x) \neq y\}}$$

$$= E_x E_{y|x} 1_{\{h(x) \neq y\}}$$

$$E_{y|x} 1_{\{h(x) \neq y\}}$$

$$= \eta(x) 1_{\{h(x) \neq 1\}} + (1 - \eta(x)) 1_{\{h(x) \neq -1\}}$$

$$P(h(X) \neq Y) =$$

$$E_x \left(\eta(X) \mathbb{1}_{\{h(X) \neq 1\}} + (1-\eta(X)) \mathbb{1}_{\{h(X) \neq -1\}} \right)$$

$$P(h(X) \neq Y) - P(h^*(X) \neq Y)$$

$$= E_x \left(E_{Y|X} \left(\mathbb{1}_{\{h(X) \neq Y\}} - \mathbb{1}_{\{h^*(X) \neq Y\}} \right) \right)$$

$$h(X) \neq h^*(X)$$

$$\Rightarrow h(X) \neq Y \Rightarrow h^*(X) = Y$$

$$E_{Y|X} \left(\mathbb{1}_{\{h(X) \neq Y\}} - \mathbb{1}_{\{h^*(X) \neq Y\}} \right)$$

$$= E_{Y|X} \left(\mathbb{1}_{\{h^*(X) = Y\}} - \mathbb{1}_{\{h^*(X) \neq Y\}} \right)$$

$$= E_{Y|X} \left(2\mathbb{1}_{\{h^*(X) = Y\}} - 1 \right)$$

$$= \eta(x) \left(2\mathbb{1}_{\{h^*(x) = 1\}} - 1 \right)$$

$$+ (1 - \eta(x)) \left(2\mathbb{1}_{\{h^*(x) = -1\}} - 1 \right)$$

$$= \eta(x) (2 \mathbb{1}_{\{h^*(x)=1\}} - 1) \\ + (1 - \eta(x)) (2(1 - \mathbb{1}_{\{h^*(x)=1\}}))$$

$$= (2\eta(x) - 1) (2 \mathbb{1}_{\{h^*(x)=1\}} - 1)$$

$\eta(x)$	$(2\eta(x) - 1)$	$2 \mathbb{1}_{\{h^*(x)=1\}} - 1$
$> \frac{1}{2}$	> 0	> 0
$\leq \frac{1}{2}$	≤ 0	< 0

$$\begin{aligned}
 & E_{Y|X} \left(\mathbb{1}_{\{h(X) \neq Y\}} - \mathbb{1}_{\{h^*(X) \neq Y\}} \right) \\
 &= (2\eta(X) - 1) (2\mathbb{1}_{\{h^*(X) = Y\}} - 1) \\
 &= |2\eta(X) - 1|
 \end{aligned}$$

$$P(h(X) \neq Y) - P(h^*(X) \neq Y)$$

$$= E_X |2\eta(X) - 1| \geq 0$$

[Thm 2.1 DGL]