

Machine Learning - 1

Ex-1

9. $P(\text{error} | x) = \min [P(\omega_1 | x), P(\omega_2 | x)]$

So, $P(\text{error}) = \int \min [P(\omega_1 | x), P(\omega_2 | x)] P(x) dx$

This implies :-

$$\int \min [P(\omega_1 | x), P(\omega_2 | x)] P(x) dx \leq \int \frac{2}{\frac{1}{P(\omega_1 | x)} + \frac{1}{P(\omega_2 | x)}} P(x) dx \quad (1)$$

$$\Rightarrow \min [P(\omega_1 | x), P(\omega_2 | x)] \times \left(\frac{1}{P(\omega_1 | x)} + \frac{1}{P(\omega_2 | x)} \right) \leq 2 \quad (2)$$

Now, let's Case 1. $P(\omega_1 | x) \geq P(\omega_2 | x) \Rightarrow$ Assumption

Eq 2 becomes

$$P(\omega_2 | x) \left(\frac{1}{P(\omega_1 | x)} + \frac{1}{P(\omega_2 | x)} \right) \leq 2$$

$\Rightarrow P(\omega_1 | x) \geq P(\omega_2 | x) \Rightarrow$ which validates case-1 Assumption.

Case-2 $P(\omega_2 | x) \geq P(\omega_1 | x) \Rightarrow$ Assumption.

Eq. 2 becomes $P(\omega_1 | x) \left(\frac{1}{P(\omega_1 | x)} + \frac{1}{P(\omega_2 | x)} \right) \leq 2$

$\Rightarrow P(\omega_2 | x) \geq P(\omega_1 | x) \Rightarrow$ which validates case-2 assumption.

which proves that the upper bound is the Eq. (1)

$$b. \quad P_{\text{error}} \leq \int \frac{2}{\frac{1}{P(\omega_1|x)} + \frac{1}{P(\omega_2|x)}} P(x) dx \quad (1)$$

lets solve for $\frac{1}{P(\omega_1|x)} + \frac{1}{P(\omega_2|x)}$ first $-(2)$

$$\Rightarrow P(\omega_1|x) = \frac{P(x|\omega_1) P(\omega_1)}{P(x)}, \quad P(\omega_2|x) = \frac{P(x|\omega_2) P(\omega_2)}{P(x)}$$

\Rightarrow solve $-(2)$

$$\Rightarrow P(x) \left(\frac{1}{P(x|\omega_1) P(\omega_1)} + \frac{1}{P(x|\omega_2) P(\omega_2)} \right)$$

$$\Rightarrow P(x) \left(\frac{P(\omega_2) P(x|\omega_2) + P(\omega_1) P(x|\omega_1)}{P(\omega_1) P(\omega_2) P(x|\omega_1) P(x|\omega_2)} \right)$$

$$\Rightarrow P(x) \left(\frac{\frac{P(\omega_2)}{\pi} \times \frac{1}{1+(x+\theta)^2} + \frac{P(\omega_1)}{\pi} \times \frac{1}{1+(x-\theta)^2}}{P(\omega_1) \frac{1}{\pi} \times \frac{1}{1+(x+\theta)^2} \times P(\omega_2) \times \frac{1}{\pi} \times \frac{1}{1+(x-\theta)^2}} \right)$$

$$\Rightarrow \frac{P(x) \times \pi}{P(\omega_1) P(\omega_2)} \left(P(\omega_2) (1+(x-\theta)^2) + P(\omega_1) (1+(x+\theta)^2) \right)$$

$$\Rightarrow \frac{P(x) \times \pi}{P(\omega_1) P(\omega_2)} \left(P(\omega_2) (1+x^2+\theta^2-2x\theta) + P(\omega_1) (1+x^2+\theta^2+2x\theta) \right)$$

$$\Rightarrow \frac{P(x) \times \pi}{P(\omega_1) P(\omega_2)} \left(x^2 (P(\omega_1) + P(\omega_2)) + 2\theta x (P(\omega_1) - P(\omega_2)) + (1+\theta^2) (P(\omega_1) + P(\omega_2)) \right) \quad (3)$$

→ Now, Putting (2) into (1)

$$P_{(RHS)} \leq \int \frac{2 P(x) dx}{\frac{x \times P(x)}{P(\omega_1)P(\omega_2)} + (1+\omega^2) (P(\omega_1) + P(\omega_2))}$$

RHS :-

$$\frac{2}{\pi} \int \frac{P(\omega_1) P(\omega_2)}{\left(x^2 (P(\omega_1) + P(\omega_2)) + 2\omega x (P(\omega_1) - P(\omega_2)) + (1+\omega^2) (P(\omega_1) + P(\omega_2)) \right)} dx$$

using the identity. the integration can be

$$\frac{2}{\pi} \left(\frac{2x P(\omega_1) P(\omega_2)}{\left(4x^2 (P(\omega_1) + P(\omega_2)) (P(\omega_1) + P(\omega_2)) (1+\omega^2) - 4\omega^2 (P(\omega_1) - P(\omega_2))^2 \right)^{1/2}} \right)$$

$$= \frac{2}{\pi} \left(\frac{2x P(\omega_1) P(\omega_2)}{\left(4(P(\omega_1) + P(\omega_2))^2 + 16\omega^2 P(\omega_1) P(\omega_2) \right)^{1/2}} \right)$$

$$= \frac{2}{\pi} \left(\frac{2x P(\omega_1) P(\omega_2)}{2 \sqrt{1 + 4\omega^2 P(\omega_1) P(\omega_2)}} \right) \text{ as } \boxed{P(\omega_1) + P(\omega_2) = 1}$$

$$\Rightarrow \frac{2 P(\omega_1) P(\omega_2)}{\sqrt{1 + 4\omega^2 P(\omega_1) P(\omega_2)}}$$

Now

$$P(\omega_1, \omega_2) \leq \frac{2 P(\omega_1) P(\omega_2)}{\sqrt{1 + 4 \omega_1^2 P(\omega_1) P(\omega_2)}}$$

Ex-2

9. To minimize the $P(\text{error})$ for optimal solution.

$$P(\text{error}) = \int P(\omega_1|x) P(x) dx + \int P(\omega_2|x) P(x) dx$$

\Rightarrow so, $P(\text{error}) = 0$ should be minimum which can be found by equating both error rates

$$\Rightarrow \int P(\omega_1|x) P(x) dx = \int P(\omega_2|x) P(x) dx$$

$\Rightarrow P(\omega_1|x) = P(\omega_2|x) \Rightarrow$ whose both the probabilities are equal.

$$\Rightarrow \frac{P(x|\omega_1) P(\omega_1)}{P(x)} = \frac{P(x|\omega_2) P(\omega_2)}{P(x)}$$

$$\Rightarrow \frac{1}{2\sqrt{2\pi}} e^{-\frac{(-|x-\mu_1|)^2}{6}} P(\omega_1) = \frac{1}{2\sqrt{2\pi}} e^{-\frac{(-|x-\mu_2|)^2}{6}} P(\omega_2)$$

$$\Rightarrow \frac{P(\omega_1)}{P(\omega_2)} = \frac{e^{-\frac{(-|x-\mu_1|)^2}{6}}}{e^{-\frac{(-|x-\mu_2|)^2}{6}}} = e^{-\frac{(-|x-\mu_1|)^2 + |x-\mu_2|^2}{6}}$$

\Rightarrow minimizing $\frac{P(\omega_1)}{P(\omega_2)}$ would be same as we minimize $\ln\left(\frac{P(\omega_1)}{P(\omega_2)}\right)$

so, $\ln \left(\frac{P(\omega_1)}{P(\omega_2)} \right) = \frac{-|x+\omega_1| + |x-\omega_1|}{6}$

so, decision boundary would be

0 min $\ln \left(\frac{P(\omega_1)}{P(\omega_2)} \right) = \begin{cases} -2\omega_1 & \text{for } x > \omega_1 \\ -2x & \text{for } x < \omega_1 \\ -(x+\omega_1) & \text{for } x = \omega_1 \end{cases}$