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SML Assignment - 1

Q1

A) i)

for zero-one loss

$$\lambda_{ii} = \begin{cases} 0 & i=j, \\ 1 & i \neq j \end{cases}$$

$$\lambda_{11} P(\omega_1/n) + \lambda_{22} P(\omega_2/n) = \lambda_{21} P(\omega_2/n) + \lambda_{12} P(\omega_1/n)$$

$$\Rightarrow \lambda_{11} = 0 \wedge \lambda_{22} = 0$$

so

$$\Rightarrow \lambda_{12} P(\omega_2/n) = \lambda_{21} P(\omega_1/n)$$

$$\Rightarrow P(\omega_2/n) = P(\omega_1/n)$$

$$\Rightarrow P(n/\omega_2) \cdot \frac{3}{4} = P(n/\omega_1) \geq \frac{1}{4}$$

$$\Rightarrow N(S_{11}) \cdot 3 = N(2_{11})$$

$$\Rightarrow \frac{1}{\sqrt{2\pi}} e^{-\frac{(n-s)^2}{2}} \cdot 3 = \frac{1}{\sqrt{2\pi}} e^{-\frac{(n^2-2)^2}{2}}$$

$$\Rightarrow \ln 3 - \frac{1}{2} (n-s)^2 = \frac{-1}{2} (n^2-2)^2$$

$$\Rightarrow (n-s)^2 - (n^2-1)^2 = \ln(3^2)$$

$$\text{v) } (2n-1)(-3) = \lambda_n(9)$$

$$\text{v) } n^+ = \frac{21 - \lambda_n(9)}{6} = 3 \cdot 1 \quad \underline{\underline{=}}$$

Ans ii) we have

$$\lambda_{11} P(w_1/n) + \lambda_{12} P(w_2/n) = \frac{\lambda_{21} P(w_1/n)}{\lambda_{22} P(w_2/n)}$$

$$\lambda_{12} = 2, \lambda_{21} = 3, \lambda_{11} = 0, \lambda_{22} = 0$$

$$2 P(w_2/n) = 3 P(w_1/n)$$

$$2 P(n/w_1) P(w_2) = 3 \times P(n/w_1) P(w_1)$$

$$2 \times P(n/w_2) \times \frac{1}{3} = 3 \times P(n/w_1) + \frac{1}{4}$$

$$2 P(n/w_2) = P(n/w_1)$$

$$2 \times N(s_1) = N(z_1)$$

$$\Rightarrow 2 \times \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(n^+ - s)^2} = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(z_1 - s)^2}$$

$$\Rightarrow \ln(2) - \frac{1}{2}(n^+ - s)^2 = -\frac{1}{2}(z_1 - s)^2$$

$$\Rightarrow 2 \ln(2) = (n^+ - s)^2 - (z_1 - s)^2$$

$$\Rightarrow \ln(4) = -6 n^+ + 21$$

$$\text{v) } n^+ = \frac{21 - \ln(4)}{6} = 3 \cdot 3 \quad \underline{\underline{=}}$$

No, we will not prefer zero-on loss for a real test like cancer prediction on real world dataset because we can't risk a negative for a cancer patient just for a second test and real world datasets are very imperfect and unbalanced & λ_2 , λ_1 will also not be same.

Ans we have to find

$$Y = A^T X + \beta$$

we have

$$A = [2, -1, 2]^T = \begin{bmatrix} 2 \\ -1 \\ 2 \end{bmatrix}$$

$$\beta = 5$$

$$X = \{x_1, x_2, x_3\}$$

Mean vector \bar{x} is given as

$$\bar{\mu} = [5, -5, 6]$$

$$\Sigma = \begin{bmatrix} 5 & 2 & -1 \\ 2 & 5 & 0 \\ -1 & 0 & 4 \end{bmatrix}$$

$$\begin{aligned} \epsilon(y) &= \epsilon(A^T x) + \epsilon(\beta) \\ &= A^T \epsilon(x) + \text{constant } \beta \quad (\beta \text{ is constant}) \\ &= [2 \ -1 \ 2] \begin{bmatrix} 5 \\ -5 \\ 0 \end{bmatrix} + 5 \\ &= 10 + 5(-1) + 5 = \underline{\underline{32}} \end{aligned}$$

Q3

Ans A) $P(n/w_i) = \frac{1}{\pi b} \cdot \frac{1}{1 + \left(\frac{n-a_i}{b}\right)^2}, i=1,2$

for minimum zero one loss
we have:

$$P(w_1/n) = P(w_2/n)$$

$$\Rightarrow P(n/w_1) P(w_1) = P(n/w_2) P(w_2)$$

$$\Rightarrow P(n/w_1) \cancel{\neq} = P(n/w_2) \cancel{\neq}$$

$$\Rightarrow P(n/w_1) = P(n/w_2)$$

using PDF we get

$$\cancel{\frac{1}{\pi b} \left(\frac{1}{1 + \left(\frac{n-a_1}{b}\right)^2} \right)} = \frac{1}{\pi b} \left(\frac{1}{1 + \left(\frac{n-a_2}{b}\right)^2} \right)$$

$$\Rightarrow \frac{(n-a_1)^2}{b^2} = \frac{(n-a_2)^2}{b^2}$$

$\Rightarrow n-a_1 = n-a_2$ or $n-a_1 \neq n-a_2$

if we have $n-a_1 = n-a_2$
not possible.

Then we have -

$$n - a_1 = -(n - a_2)$$

$n = \frac{a_1 + a_2}{2}$

Then we have $n^* = \underbrace{\frac{a_1 + a_2}{2}}_{\text{optimal boundary}}$, $a_1 \neq a_2$.

Ans C)

Using PDF, calculating probability of error.

Hence we get -

Error Hence $e \rightarrow$ error

$$P(e) = \int_{-\infty}^e \beta(e/n) P(n) dn$$

$$\beta(e/n) = \min(\beta(\omega_1/n), \beta(\omega_2/n))$$

Considering $n < n^*$

$$\beta(e/n) = \beta(\omega_1/n)$$

for $n > n^*$

$$\beta(e/n) = \beta(\omega_2/n)$$

$$\text{v) } P(e) = \int_{-\infty}^{\infty} P(w/m) P(-) dw + \int_{\infty}^{\infty} P(w_2/m) P(w) dw$$

v) ~~the~~ as we have -

$$n^+ = \frac{a_1 + a_2}{2}$$

$$P(e) = \frac{a_1 + a_2}{2} \int_{-\infty}^{\infty} P(n_2/w_1) P(w) dw + \int_{a_1 + a_2}^{\infty} P(n/w_1) P(w_2) dw$$

$$P(e) = \frac{a_1 + a_2}{2} \int_{-\infty}^{\infty} \frac{1}{nb} \frac{1}{1/(n-a)^2} \frac{1}{2} dw$$

$$+ \int_{a_1 + a_2}^{\infty} \frac{1}{anb} \frac{1}{1/(n-a)^2} \frac{1}{2} dw$$

$$P(e) = \frac{1}{2n} \left[\left[\tan^{-1} \left(\frac{n-a_1}{b} \right) \right]_{-\infty}^{a_1 + a_2} + \left[\tan^{-1} \left(\frac{n-a_2}{b} \right) \right]_{a_1 + a_2}^{\infty} \right]$$

~~the~~ we have

$$a_1 = 3, a_2 = 5, b = 1$$

So

$$\theta(e) = \frac{1}{2n} \int \tan^{-1}(1) - \tan^{-1}(-\omega) + \tan^{-1}(\omega) - \tan^{-1}(-1)$$

$$\theta(e) = \frac{1}{2n} \left[\frac{\pi}{4} + \frac{n}{2} \cdot \frac{\pi}{1} - \frac{n}{4} \right]$$

$$= \frac{1}{2n} \times \frac{3\pi}{2} = \frac{3}{4}$$

Now 4

$$\theta(\text{error}) = \frac{3}{4} \quad \leftarrow \begin{array}{l} \text{overall error} \\ \text{rate} \end{array}$$

Q9

Ans a) we have.

$$\text{Cov}(x) = \begin{bmatrix} \theta(1-\theta) & 0 \\ 0 & \sigma^2 \end{bmatrix}$$

as $\Gamma_{11} = \Gamma_{22} = 0$

we can say that the dimensions are independent
(a, b)

Hence

$$\begin{aligned} P(x) &= P(\text{Bernoulli}(0)=a) \times P(\text{Gaussian}(\mu, \sigma^2)=b) \\ &= \underbrace{\theta^a (1-\theta)^{1-a}}_{\text{Bernoulli}} \times \frac{1}{\sqrt{2\pi\sigma^2}} \times e^{-\frac{(b-\mu)^2}{2\sigma^2}} \end{aligned}$$

b) as we have N iid

$$\text{we can say } g(x) = \prod_{i=1}^N P(x=x_i)$$

Taking log.

$$\log(g(x)) = \sum_{i=1}^N \log(P(x=x_i))$$

$$v) \log(g(x)) = \sum_{i=1}^N \log\left(\theta^{a_i} \times (1-\theta)^{1-a_i} \times \frac{1}{2\sqrt{2\pi\sigma}} \times e^{-\frac{1}{2}\left(\frac{b_i - \mu}{\sigma}\right)^2}\right)$$

$$\log(g(x)) = \sum_{i=1}^N a_i \left[\log \theta + (1-a_i) \log(1-\theta) - \log\left(\frac{\sqrt{2\pi\sigma}}{2}\right) - \frac{1}{2} \left(\frac{b_i - \mu}{\sigma}\right)^2 \right]$$

$$g) \frac{d(\log(g(x)))}{d\theta} = \sum_{i=1}^N \frac{a_i}{\theta} - \frac{(1-a_i)}{1-\theta} + 0 + 0$$

$$0 = \sum_{i=1}^N a_i(1-\theta) - \theta(1-a_i) \Rightarrow$$

$$\sum_{i=1}^N a_i - \theta = 0$$

$$\boxed{\theta = \frac{a_1 + a_2 + \dots + a_N}{N}}$$