

Answer 2 :

Homework 6

$$p(x) = \left(\frac{1}{2\pi} \right)^p |V|^{-1/2} \exp(-Q(x)/2) \quad - (1)$$

a) $p(BG) = p(FG) \quad \& \quad \sigma_1 = \sigma_2$
 $p(x_1) = p(x_2) \quad \& \quad V_1 = V_2 \quad - (2) \quad - (3)$
optimal θ , i.e., x .
Using eq. (1) & conditions (2), (3).

$$\exp(-Q(x_1)/2) = \exp(-Q(x_2)/2)$$

$$\text{Here, } Q(x) = (x-m)' V^{-1} (x-m)$$

$$\Rightarrow (x_1 - \mu_1)' V^{-1} (x_1 - \mu_1) = (x_2 - \mu_2)' V^{-1} (x_2 - \mu_2)$$

$$\text{Hence, } x_1 - \mu_1 = x_2 - \mu_2$$

$$\text{OR} \\ x_1 - \mu_1 = -(x_2 - \mu_2)$$

$$\text{At point of optimality } x_1 = x_2$$

$$\text{So, } \mu_1 = \mu_2$$

$$\text{OR} \\ x = \frac{\mu_1 + \mu_2}{2} = \theta$$

b) Since, we are taking one pixel at a time it is univariate.

$$\theta = \frac{\mu_1 + \mu_2}{2}$$

case I.

For given condition at θ

$$P(BG_2) = P(FG_2)$$

$$|\Sigma_1|^{-1/2} e^{-\frac{(\theta - \mu_1)^2}{2|\Sigma_1|}}$$

$$|\Sigma_1|^{-1/2} e^{-\frac{(\theta - \mu_1)^2}{2|\Sigma_1|}} = |\Sigma_2|^{-1/2} e^{-\frac{(\theta - \mu_2)^2}{2|\Sigma_2|}}$$

$$-\frac{1}{2} \log \left| \frac{\Sigma_1}{\Sigma_2} \right| = \frac{(\theta - \mu_1)^2}{2|\Sigma_1|} - \frac{(\theta - \mu_2)^2}{2|\Sigma_2|}$$

$$\log \left| \frac{\Sigma_2}{\Sigma_1} \right| = \frac{(\mu_2 - \mu_1)^2}{4|\Sigma_1|} - \frac{(\mu_1 - \mu_2)^2}{4|\Sigma_2|} \quad \text{--- (b)}$$

case II

In addition to assumptions in case I,

$$P(BG_1) = P(FG_1)$$

$$\mu_1 = \mu_2$$

substituting in eq. (b),

$$\log \left| \frac{\Sigma_2}{\Sigma_1} \right| = 0$$

$$\Rightarrow |\Sigma_1| = |\Sigma_2|$$

$$\text{Here, } |\Sigma_1| = |\sigma_1|$$

$$|\Sigma_2| = |\sigma_2|$$

since it is univariate.

Case III

If nothing is assumed.

$$g_1(x_{ij}) = P\left(\frac{BG_1}{x_{ij}}\right) = P(x_{ij}/BG_1) P(BG_1) / P(x_{ij})$$

$$g_2(x_{ij}) = P\left(\frac{FG_1}{x_{ij}}\right) = P(x_{ij}/FG_1) P(FG_1) / P(x_{ij})$$

At the decision boundary $g_1(x_{ij}) = g_2(x_{ij})$.

Using pdf for each function.

$$\frac{P(BG_1)}{\sqrt{2\pi}\sigma_1} e^{\left[-\frac{1}{2}\left(\frac{x-\mu_1}{\sigma_1}\right)^2\right]} = \frac{P(FG_1)}{\sqrt{2\pi}\sigma_2} e^{\left[-\frac{1}{2}\left(\frac{x-\mu_2}{\sigma_2}\right)^2\right]} \quad (b3)$$

c) If $P(BG_1) = 4 * P(FG_1)$

$\mu_1 = 100$; $\mu_2 = 200$

$\sigma_1 = \sigma_2$

Substituting in (b3),

$$4 * e^{\left[-\frac{1}{2}\left(\frac{x-100}{\sigma}\right)^2\right]} = e^{\left[-\frac{1}{2}\left(\frac{x-200}{\sigma}\right)^2\right]}$$

Taking log on both sides,

$$\log 4 + \left[-\frac{1}{2}\frac{(x-100)^2}{\sigma^2}\right] = \left[-\frac{1}{2}\frac{(x-200)^2}{\sigma^2}\right]$$

$$\frac{(x-100)^2}{2\sigma^2} - \frac{(x-200)^2}{2\sigma^2} = \log 4$$

For optimal boundary we can differentiate wrt σ ,