

We know that,

$$\begin{aligned} P_K(a) &= E(Y=K | X=a) \\ &= \frac{\pi_K f_K(a)}{\sum_{l=1}^K \pi_l f_l(a)} \end{aligned}$$

Here our distribution is normal

$$f_K(a) = \frac{1}{\sqrt{2\pi} \sigma_K} \exp\left(-\frac{1}{2\sigma_K^2} (a - \mu_K)^2\right)$$

we get,

$$P_K(a) = \frac{\pi_K \frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{1}{2\sigma^2} (a - \mu_K)^2\right)}{\sum_{l=1}^K \pi_l \frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{1}{2\sigma^2} (a - \mu_l)^2\right)}$$

$$P_k(x) = \frac{\pi_k \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2}(x-\mu_k)^2\right)}{\sum_{l=1}^k \pi_l \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2}(x-\mu_l)^2\right)}$$

Because σ is dependent on k , here σ would be σ_k .

$$P_k(x) = \frac{\pi_k \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left(-\frac{1}{2\sigma_k^2}(x-\mu_k)^2\right)}{\sum_{l=1}^k \pi_l \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left(-\frac{1}{2\sigma_k^2}(x-\mu_l)^2\right)}$$

$$\text{Let } a = \frac{1}{\sqrt{2\pi}}$$

$$\frac{\sum_{l=1}^k \pi_l \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2\sigma_k^2}(x-\mu_l)^2\right)}{\sum_{l=1}^k \pi_l \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2\sigma_k^2}(x-\mu_l)^2\right)}$$

because a is independent of k i.e. it does not vary with k

Taking log on both sides

$$\log(P_k(x)) = \log(a) + \log(\pi_k) - \log(\sigma_k) + \left(-\frac{1}{2\sigma_k^2}(x-\mu_k)^2\right)$$

$$\log(P_k(k)) = \left(-\frac{1}{2\sigma_k^2}(x^2 + \mu_k^2 - 2x\mu_k)\right) + \log(\pi_k) - \log(\sigma_k) + \log(a)$$