

HW-3

↳ Hardik Pragapati (2678294168)

$\therefore x_j | \omega_i \sim \text{Gamma}(\beta_i, \lambda_j)$

$$f_{x_j | \omega_i}(x_j | \omega_i) = \frac{1}{\Gamma(\beta_i)} \lambda_j^{\beta_i} x_j^{\beta_i - 1} e^{-\lambda_j x_j}, \quad \beta_i, \lambda_j > 0$$

# of classes = c.

# of features = k  $\rightarrow \{x_1, x_2, \dots, x_k\}$

a) Bayes optimal classifier decision Rule:-

Decide  $\omega_i$  if  $P(\omega_i | x) > P(\omega_r | x) \quad \forall r \neq i$

$$\Rightarrow \frac{f_{x_j | \omega_i}(x_j | \omega_i) P(\omega_i)}{f_{x_j}(x_j)} > \frac{f_{x_j | \omega_r}(x_j | \omega_r) P(\omega_r)}{f_{x_j}(x_j)}$$

$$\Rightarrow \frac{\frac{1}{\Gamma(\beta_i)} \lambda_j^{\beta_i} x_j^{\beta_i - 1} e^{-\lambda_j x_j}}{\frac{1}{\Gamma(\beta_r)} \lambda_j^{\beta_r} x_j^{\beta_r - 1} e^{-\lambda_j x_j}} > \frac{P(\omega_r)}{P(\omega_i)}$$

$$\Rightarrow \frac{\Gamma(\beta_r)}{\Gamma(\beta_i)} \lambda_j^{(\beta_i - \beta_r)} x_j^{(\beta_i - \beta_r)} > \frac{P(\omega_r)}{P(\omega_i)}$$

$\rightarrow \beta_i, \beta_r, \lambda_j, P(\omega_r), P(\omega_i)$  are known quantities  
& hence  $x_j^*$  can be calculated.

Q1 b) Decision boundaries are linear functions of  $x_1, x_2, \dots, x_k$

↳ When Features in each class are independent & have the same variance, Decision boundary is a hyperplane of  $(k-1)$  dimensions

Hence, The decision boundary are linear function of  $x_1, x_2, \dots, x_k$ .

Q1 c)  $\rho_1 = 4, \rho_2 = 2, C = 2, k = 4, \lambda_1 = \lambda_3 = 1; \lambda_2 = \lambda_4 = 2$ .

$$P(\omega_1) = P(\omega_2) = \frac{1}{2}$$

$$\vec{x} = (0.1, 0.2, 0.3, 4)$$

$\Rightarrow$  Decide  $\omega_1$  if  $P(\omega_1 | \vec{x}) > P(\omega_2 | \vec{x})$

$$\Rightarrow f_{x_1|\omega_1}(\vec{x}|\omega_1) P(\omega_1) > f_{x_1|\omega_2}(\vec{x}|\omega_2) P(\omega_2)$$

$$\Rightarrow \frac{f_{x_1|\omega_1}(\vec{x}_1|\omega_1) \cdot f_{x_2|\omega_1}(\vec{x}_2|\omega_1) \cdot f_{x_3|\omega_1}(\vec{x}_3|\omega_1) \cdot f_{x_4|\omega_1}(\vec{x}_4|\omega_1)}{f_{x_1|\omega_2}(\vec{x}_1|\omega_2) \cdot f_{x_2|\omega_2}(\vec{x}_2|\omega_2) \cdot f_{x_3|\omega_2}(\vec{x}_3|\omega_2) \cdot f_{x_4|\omega_2}(\vec{x}_4|\omega_2)}$$

$>$

$$\frac{P(\omega_2)}{P(\omega_1)}$$

$$\Rightarrow \left( \frac{1}{r(4)} (1)(0.1)^{4-1} e^{-(1)(0.1)} \right) \left( \frac{1}{r(4)} (2)(0.2)^{4-1} e^{-(2)(0.2)} \right)$$

$$\times \left( \frac{1}{r(4)} (1)(0.3)^{4-1} e^{-(1)(0.3)} \right) \left( \frac{1}{r(4)} (2)(0.4)^{4-1} e^{-(2)(0.4)} \right) > \frac{1}{2}$$

$$\frac{\left( \frac{1}{r(2)} (1)^2 (0.1)^{2-1} e^{-(1)(0.1)} \right) \left( \frac{1}{r(2)} (2)^2 (0.2)^{2-1} e^{-(2)(0.2)} \right)}{\left( \frac{1}{r(2)} (1)^2 (0.3)^{2-1} e^{-(1)(0.3)} \right) \left( \frac{1}{r(2)} (2)^2 (0.4)^{2-1} e^{-(2)(0.4)} \right)}$$

$$\Rightarrow \frac{\{r(2)\}^4 (0.1)^2 (1)^2 (0.2)^2 (0.3)^2 (2)^2 (0.4)^2}{\{r(4)\}^4} > 1$$

$$\Rightarrow 0.000256 > 1$$

$$\Rightarrow \text{for } \vec{x} = (0.1, 0.2, 0.3, 4), \gamma = \omega_2$$

Q1(b)  $P_1 = 3.2, P_2 = 8, C = 2, k = 1, \lambda = 1$

$$P(\omega_1) = P(\omega_2) = \frac{1}{2}$$

Decide  $\omega_1$  if  $P(\omega_1 | x) > P(\omega_2 | x)$

$$\Rightarrow f_{x|\omega_1}(x | \omega_1) P(\omega_1) > f_{x|\omega_2}(x | \omega_2) P(\omega_2)$$

$$\Rightarrow \frac{\frac{1}{\Gamma(3.2)} (1)^{3.2} (x)^{3.2-1} e^{-1}(x)}{\frac{1}{\Gamma(8)} (1)^8 (x)^{8-1} e^{-1}(x)} > \frac{y_1}{y_2}$$

$$\Rightarrow x^{2.2-7} > \frac{2.42}{5040}$$

$$\Rightarrow 0 < x < 4.91336$$

$\Rightarrow$  Decide  $\begin{cases} \omega_1 & \text{if } 0 < x < 4.91336 \\ \omega_2 & \text{otherwise.} \end{cases}$

Type I error:- Decide  $\omega_1$  for its true label is  $\omega_1$ ,

$$\Rightarrow P(\text{error} | x) = \begin{cases} P(\omega_1 | x) & \text{if we decide } \omega_2 \\ P(\omega_2 | x) & \text{if we decide } \omega_1 \end{cases}$$

$$P(x) = \sum_{j=1}^2 P(x | \omega_j) P(\omega_j)$$

$$\begin{aligned}\Rightarrow p(x) &= p(x|\omega_1)p(\omega_1) + p(x|\omega_2)p(\omega_2) \\ &= \frac{1}{\Gamma(3.2)} (1)(x)^{2.2} e^{-x} \left(\frac{1}{2}\right) + \frac{1}{\Gamma(8)} (1)(x)^7 e^{-x} \left(\frac{1}{2}\right) \\ &= \frac{e^{-x}}{2} \left\{ \frac{x^{2.2}}{\Gamma(3.2)} + \frac{x^7}{\Gamma(8)} \right\}\end{aligned}$$

$$\begin{aligned}\Rightarrow P(\text{error}) &= \int_{-\infty}^{\infty} P(\text{error}|x) p(x) dx \\ &= \int_{-\infty}^0 P(\omega_1|x) p(x) dx + \int_0^{4.9} P(\omega_2|x) p(x) dx \\ &\quad + \int_{4.9}^{\infty} P(\omega_1|x) p(x) dx\end{aligned}$$

$$\begin{aligned}&= \int_{-\infty}^0 \frac{p(x|\omega_1)p(\omega_1)}{p(x)} p(x) dx + \int_0^{4.9} \frac{p(x|\omega_2)p(\omega_2)}{p(x)} p(x) dx \\ &\quad + \int_{4.9}^{\infty} \frac{p(x|\omega_1)p(\omega_1)}{p(x)} p(x) dx\end{aligned}$$

$$\begin{aligned}&= \int_{-\infty}^0 \frac{1}{\Gamma(3.2)} (1)(x)^{2.2} e^{-x} \left(\frac{1}{2}\right) dx + \int_0^{4.9} \frac{1}{\Gamma(8)} (1)(x)^7 e^{-x} \left(\frac{1}{2}\right) dx \\ &\quad + \int_{4.9}^{\infty} \frac{1}{\Gamma(3.2)} (1)(x)^{2.2} e^{-x} \left(\frac{1}{2}\right) dx\end{aligned}$$

$$\text{Q1. e. } p_1 = p_2 = 4, c = 2, k = 2, \lambda_1 = 8, \lambda_2 = 0.3$$

$$P(\omega_1) = \frac{1}{4}, P(\omega_2) = \frac{3}{4}$$

Decide  $\omega_1$ , if  $P(\omega_1 | z) > P(\omega_2 | z)$

$$\Rightarrow \frac{f_{x|\omega_1}(z|\omega_1) P(\omega_1)}{f_x(z)} > \frac{f_{x|\omega_2}(z|\omega_2) P(\omega_2)}{f_x(z)}$$

$$\Rightarrow \frac{\left( \frac{1}{\Gamma(4)} (8)^4 (x_1)^{4-1} e^{-8x_1} \right) \left( \frac{1}{\Gamma(4)} (0.3)^4 (x_1)^{4-1} e^{-0.3x_1} \right)}{\left( \frac{1}{\Gamma(5)} (8)^5 (x_1)^{5-1} e^{-8x_1} \right) \left( \frac{1}{\Gamma(5)} (0.3)^5 (x_1)^{5-1} e^{-0.3x_1} \right)}$$

$$>$$

$$\frac{\left( \frac{3}{4} \right)}{\left( \frac{1}{5} \right)}$$

$$\Rightarrow 1 > 3$$

$\Rightarrow$  g will always decide  $\omega_2$  irrespective of feature values  $(x_1, x_2)$ .

$$Q2. \quad x_i | w_j \sim \text{Lap}(m_{ij}, \lambda_i)$$

$$P_{x_i | w_j}(x_i | w_j) = \frac{\lambda_i}{2} e^{-\lambda_i |x_i - m_{ij}|}, \quad \lambda_i > 0$$

$$P(w_j) = \frac{1}{c}$$

$$\begin{matrix} i \in \{1, 2, \dots, k\} \\ j \in \{1, \dots, c\} \end{matrix}$$

Minimum Error rate classifier..

$$\text{Decide } w_i \text{ if } P(w_i | \underline{x}) > P(w_j | \underline{x}) \quad \forall i \neq j$$

$$\Rightarrow P_{x_1 | w_i}(x_1 | w_i) \cdot P_{x_2 | w_i}(x_2 | w_i) \cdots P_{x_k | w_i}(x_k | w_i) \cdot P(w_i)^{\frac{1}{c}}$$

$$>^{\omega_i} \quad \forall j \neq i$$

$$P_{x_1 | w_j}(x_1 | w_j) \cdot P_{x_2 | w_j}(x_2 | w_j) \cdots P_{x_k | w_j}(x_k | w_j) \cdot P(w_j)^{\frac{1}{c}}$$

$$\Rightarrow \frac{\lambda_1}{2} e^{-\lambda_1 |x_1 - m_{1i}|} \cdot \frac{\lambda_2}{2} e^{-\lambda_2 |x_2 - m_{2i}|} \cdots \frac{\lambda_k}{2} e^{-\lambda_k |x_k - m_{ki}|}$$

$$>^{\omega_i} \quad \forall j \neq i$$

$$\frac{\lambda_1}{2} e^{-\lambda_1 |x_1 - m_{1j}|} \cdot \frac{\lambda_2}{2} e^{-\lambda_2 |x_2 - m_{2j}|} \cdots \frac{\lambda_k}{2} e^{-\lambda_k |x_k - m_{kj}|}$$

$$\Rightarrow e^{\sum_{b=1}^k \lambda_b |x_b - m_{bi}|} > e^{\sum_{b=1}^k \lambda_b |x_b - m_{bj}|} \quad \forall j \neq i$$

Taking natural log on both sides

$$\Rightarrow \sum_{b=1}^k \lambda_b |x_b - m_{bi}| > \sum_{b=1}^k \lambda_b |x_b - m_{bj}| \quad \forall j \neq i$$

$$\Rightarrow \sum_{b=1}^k \lambda_b |x_b - m_{bi}| < \sum_{b=1}^k \lambda_b |x_b - m_{bj}| \quad \forall j \neq i$$

$\Rightarrow$  Hence, it can be seen that Minimum Error Rate classifier is also a minimum weighted Manhattan distance (or weighted  $L_1$ -distance) classifier.

$$\text{if } \lambda_b = 1 \quad \forall b \in \{1, \dots, k\}$$

$$\text{Then, } \sum_{b=1}^k |x_b - m_{bi}| < \sum_{b=1}^k |x_b - m_{bj}| \quad \forall j \neq i$$

becomes - the minimum Manhattan distance classifier.

Q3:

$x$	$p(x \omega_1)$	$p(x \omega_2)$	$p(x \omega_3)$	$p(x \omega_4)$
1	$\frac{1}{3}$	$\frac{1}{2}$	$\frac{1}{6}$	$\frac{2}{5}$
2	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{3}$	$\frac{2}{5}$
3	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{1}{2}$	$\frac{1}{5}$

	$\omega_1$	$\omega_2$	$\omega_3$	$\omega_4$
$\alpha_1$	0	2	3	4
$\alpha_2$	1	0	1	8
$\alpha_3$	3	2	0	2
$\alpha_4$	5	3	1	0

$\alpha_i \rightarrow$  Decide Pattern  $\omega_i$  (class)

$$P(\omega_1) = \frac{1}{10}, \quad P(\omega_2) = \frac{1}{5}, \quad P(\omega_3) = \frac{1}{2}, \quad P(\omega_4) = \frac{1}{5}$$

a)  $R(\alpha_i | x) = \sum_{j=1}^4 \lambda(\alpha_i | \omega_j) p(\omega_j | x) = \sum_{j=1}^4 \lambda(\alpha_i | \omega_j) \frac{p(x | \omega_j) p(\omega_j)}{p(x)}$

$$\Rightarrow p(x | \omega_j) = p(x | \omega_1) p(\omega_1) + p(x | \omega_2) p(\omega_2) + p(x | \omega_3) p(\omega_3) + p(x | \omega_4) p(\omega_4)$$

$$\rightarrow R(\alpha_1 | x=1) = \frac{(0)(\frac{1}{3})(\frac{1}{10}) + (2)(\frac{1}{2})(\frac{1}{5}) + (3)(\frac{1}{3})(\frac{1}{2}) + (4)(\frac{2}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{2})(\frac{1}{5}) + (\frac{1}{3})(\frac{1}{2}) + (\frac{2}{5})(\frac{1}{5})}$$

$$= \frac{231}{89}$$

$$= 2.59$$

=

$$\rightarrow R(\alpha_1 | x=2) = \frac{(0)(\frac{1}{3})(\frac{1}{10}) + (1)(\frac{1}{5})(\frac{1}{5}) + (3)(\frac{1}{3})(\frac{1}{2}) + (4)(\frac{2}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{5})(\frac{1}{5}) + (\frac{1}{3})(\frac{1}{2}) + (\frac{2}{5})(\frac{1}{5})}$$

$$= \frac{92}{33}$$

$$= 2.78$$

$$\rightarrow R(\alpha_1 | x=3) = \frac{(0)(\frac{1}{3})(\frac{1}{10}) + (1)(\frac{1}{5})(\frac{1}{5}) + (3)(\frac{1}{3})(\frac{1}{2}) + (4)(\frac{2}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{5})(\frac{1}{5}) + (\frac{1}{3})(\frac{1}{2}) + (\frac{2}{5})(\frac{1}{5})}$$

$$= \frac{303}{112}$$

$$= 2.705$$

$$\rightarrow R(\alpha_1 | x=1) = \frac{(1)(\frac{1}{3})(\frac{1}{10}) + (0)(\frac{1}{5})(\frac{1}{5}) + (1)(\frac{1}{6})(\frac{1}{2}) + (8)(\frac{2}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{5})(\frac{1}{5}) + (\frac{1}{6})(\frac{1}{2}) + (\frac{2}{5})(\frac{1}{5})}$$

$$= \frac{227}{889}$$

$$= 2.55$$

$$\rightarrow R(\alpha_1 | x=2) = \frac{(1)(\frac{1}{3})(\frac{1}{10}) + (0)(\frac{1}{5})(\frac{1}{5}) + (1)(\frac{1}{3})(\frac{1}{2}) + (8)(\frac{2}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{5})(\frac{1}{5}) + (\frac{1}{3})(\frac{1}{2}) + (\frac{2}{5})(\frac{1}{5})}$$

$$= \frac{28}{11}$$

$$= 2.55$$

$$\rightarrow R(\alpha_2 | x=3) = \frac{(1)(\frac{1}{3})(\frac{1}{10}) + (0)(\frac{1}{2})(\frac{1}{3}) + (1)(\frac{1}{2})(\frac{1}{2}) + (8)(\frac{1}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{2})(\frac{1}{3}) + (\frac{1}{2})(\frac{1}{2}) + (\frac{1}{5})(\frac{1}{5})}$$

$$= \frac{181}{112}$$

$$= 1.616$$

//

$$\rightarrow R(\alpha_3 | x=1) = \frac{(3)(\frac{1}{3})(\frac{1}{10}) + (2)(\frac{1}{2})(\frac{1}{3}) + (0)(\frac{1}{5})(\frac{1}{2}) + (2)(\frac{2}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{2})(\frac{1}{3}) + (\frac{1}{5})(\frac{1}{2}) + (\frac{2}{5})(\frac{1}{5})}$$

$$= \frac{138}{89}$$

$$= 1.55$$

//

$$\rightarrow R(\alpha_3 | x=2) = \frac{12}{11}$$

$$= 1.09$$

//

$$\rightarrow R(\alpha_3 | x=3) = \frac{3}{4}$$

$$= 0.75$$

//

$$\rightarrow R(\alpha_4 | x=1) = \frac{(5)(\frac{1}{3})(\frac{1}{10}) + (3)(\frac{1}{2})(\frac{1}{3}) + (1)(\frac{1}{5})(\frac{1}{2}) + (0)(\frac{2}{5})(\frac{1}{5})}{(\frac{1}{3})(\frac{1}{10}) + (\frac{1}{2})(\frac{1}{3}) + (\frac{1}{5})(\frac{1}{2}) + (\frac{2}{5})(\frac{1}{5})}$$

$$= \frac{165}{89}$$

$$= 1.85$$

//

$$\rightarrow R(\alpha_4 | x=2) = \frac{145}{99}$$
$$= 1.46$$
$$=$$

$$\rightarrow R(\alpha_5 | x=3) = \frac{265}{224}$$
$$= 1.18$$
$$=$$

Q3. b)  $R = \sum_{i=1}^3 R(\alpha(x_i) | x_i) p(x_i)$

$$= R(\alpha_1(x_1) | x_1) p(x_1) + R(\alpha_2(x_2) | x_2) p(x_2)$$
$$+ R(\alpha_3(x_3) | x_3) p(x_3)$$
$$= (1.55)\left(\frac{89}{300}\right) + (1.09)\left(\frac{33}{100}\right) + (0.75)\left(\frac{28}{75}\right)$$
$$= 1.099$$
$$=$$

Q4.

Tax ID	Refund	Marital Status	Taxable income	Evasion
1	Yes	Single	122K	No
2	No	Married	77K	No
3	No	Married	106K	No
4	No	Single	88 K	Yes
5	Yes	Divorced	210 K	No
6	No	Single	72 K	No
7	Yes	Married	117 K	No
8	No	Married	60 K	No
9	No	Divorced	90 K	Yes
10	No	Single	85 K	Yes

a)  $\omega_1 = \text{Yes}$ ,  $\omega_2 = \text{No}$

$$P(\omega_1) = \frac{3}{10} \quad P(\omega_2) = \frac{7}{10}$$

← Prior class probabilities

b)  $X$  - Taxable Income (Continuous R.V.)

Assuming Conditional Gaussianity

For  $\omega_1 = \text{Yes}$ ,

$$\bar{x}_1 = \frac{88 + 90 + 85}{3} \\ = 87.67$$

$$\sigma^2_1 = \frac{(88 - 87.67)^2 + (90 - 87.67)^2 + (85 - 87.67)^2}{3-1} \\ = 6.33$$

$$\Rightarrow p(x | \omega_1) \rightarrow N(87.67, 6.33)$$

For  $\omega_2 = \text{No}$ ,

$$\bar{x}_2 = \frac{122 + 77 + 106 + 210 + 72 + 117 + 60}{7}$$

$$= 109.14$$

=

$$s_2^2 = \frac{\sum_{i=1}^7 (x_i - \bar{x}_2)^2}{n-1}, n=7$$

$$= 2539.48$$

=

$$\Rightarrow p(\underline{x} | \omega_2) \rightarrow N(109.14, 2539.48)$$

==

Q4 c)  $X_j \rightarrow \text{Refund}$  (Discrete R.V.)

For  $\omega_i = \text{Yes}$ ,

$$P_{X|W_i} (x_j = \text{Yes} | \omega_i = \text{Yes}) = \frac{0}{3} = 0 //$$

$$P_{X|W_i} (x_j = \text{No} | \omega_i = \text{Yes}) = \frac{3}{3} = 1 //$$

For  $\omega_i = \text{No}$ ,

$$P_{X|W_i} (x_j = \text{Yes} | \omega_i = \text{No}) = \frac{3}{7} //$$

$$P_{X|W_i} (x_j = \text{No} | \omega_i = \text{No}) = \frac{4}{7} //$$

$x_3 \rightarrow$  Marital Status (Discrete R.V.)

For  $w_i = \text{Yes}$ ,

$$P_{x|w_i}(x_j = \text{Single} | w_i = \text{Yes}) = \frac{2}{3}$$

$$P_{x|w_i}(x_j = \text{Married} | w_i = \text{Yes}) = \frac{0}{3}$$

$$P_{x|w_i}(x_j = \text{Divorced} | w_i = \text{Yes}) = \frac{1}{3}$$

For  $w_i = \text{No}$ ,

$$P_{x|w_i}(x_j = \text{Single} | w_i = \text{No}) = \frac{2}{7}$$

$$P_{x|w_i}(x_j = \text{Married} | w_i = \text{No}) = \frac{5}{7}$$

$$P_{x|w_i}(x_j = \text{Divorced} | w_i = \text{No}) = \frac{0}{7}$$

→ This is not entirely a valid estimate of PMF because it gives us a probability 0 for certain labels which actually exist. Instead there should be a small non-zero probability assigned to such labels.

Q5 d. For  $w_i = \text{Yes}$ ,  $x_2 \rightarrow \text{Refund}$

$$P_{x_2|w_i}(x_j = \text{Yes} | w_i = \text{Yes}) = \frac{1}{3+2} = \frac{1}{5}$$

$$P_{x_2|w_i}(x_j = \text{No} | w_i = \text{Yes}) = \frac{3+1}{3+2} = \frac{4}{5}$$

For  $w_i = \text{No}$ ,

$$P_{x_2|w_i}(x_j = \text{Yes} | w_i = \text{No}) = \frac{3+1}{7+2} = \frac{4}{9}$$

$$P_{x_2|w_i}(x_j = \text{No} | w_i = \text{No}) = \frac{4+1}{7+2} = \frac{5}{9}$$

$x_3 \rightarrow \text{Marital Status}$

For  $w_i = \text{Yes}$ ,

$$P_{x_3|w_i}(x_j = \text{Single} | w_i = \text{Yes}) = \frac{2+1}{3+3} = \frac{3}{6}$$

$$P_{x_3|w_i}(x_j = \text{Married} | w_i = \text{Yes}) = \frac{0+1}{3+3} = \frac{1}{6}$$

$$P_{x_3|w_i}(x_j = \text{Divorced} | w_i = \text{Yes}) = \frac{1+1}{3+3} = \frac{2}{6}$$

For  $w_i = \text{No}$ ,

$$P_{x_3|w_i}(x_j = \text{Single} | w_i = \text{No}) = \frac{2+1}{7+3} = \frac{3}{10}$$

$$P_{x_3|w_i}(x_j = \text{Married} | w_i = \text{No}) = \frac{4+1}{7+3} = \frac{5}{10}$$

$$P_{x_3|w_i}(x_j = \text{Divorced} | w_i = \text{No}) = \frac{1+1}{7+3} = \frac{2}{10}$$

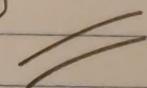
→ This is relatively more valid Estimate of PMF.  
→

e.g. Let  $\vec{x} = \{x_1 = 100K, x_2 = Yes, x_3 = Single\}$

$$\text{Then, } P(Y = Yes | \vec{x}) = \frac{P(\vec{x} | Yes) \cdot P(Yes)}{P(\vec{x})}$$

$$\text{Checking the Numerator} \Rightarrow \left\{ \frac{1}{\sqrt{2\pi}(\sqrt{6.33})} e^{-\frac{(100-87.67)^2}{(2)(6.33)}} \right\} \{0\} \left\{ \frac{2}{3} \right\}$$
$$= 0.$$

⇒ This creates a problem which gets solved by Laplace smoothing.



Q4. e) Decide  $\omega_i$  if  $P(\omega_i | \vec{x}) > P(\omega_j | \vec{x})$

$$\Rightarrow \frac{P(\vec{x} | \omega_i) P(\omega_i)}{P(\vec{x})} > \frac{P(\vec{x} | \omega_j) P(\omega_j)}{P(\vec{x})}$$

$$\Rightarrow \frac{f_{x_1 | \omega_1}(x_1 | \omega_1) \cdot f_{x_2 | \omega_1}(x_2 | \omega_1) \cdot f_{x_3 | \omega_1}(x_3 | \omega_1)}{f_{x_1 | \omega_2}(x_1 | \omega_2) \cdot f_{x_2 | \omega_2}(x_2 | \omega_2) \cdot f_{x_3 | \omega_2}(x_3 | \omega_2)} > \frac{P(\omega_1)}{P(\omega_2)}$$

$$\Rightarrow \frac{\left\{ \frac{1}{\sqrt{2\pi} \cdot \sqrt{6.33}} e^{-\frac{(x_1 - 87.67)^2}{(2)(6.33)}} \right\} P_{x_2 | \omega_1}(x_2 | \omega_1) P_{x_3 | \omega_1}(x_3 | \omega_1)}{\left\{ \frac{1}{\sqrt{2\pi} \cdot \sqrt{25.39.68}} e^{-\frac{(x_1 - 109.14)^2}{(2)(25.39.68)}} \right\} P_{x_2 | \omega_2}(x_2 | \omega_2) P_{x_3 | \omega_2}(x_3 | \omega_2)} > \frac{\frac{1}{10}}{\frac{3}{10}}$$

$$\left\{ \frac{1}{\sqrt{2\pi} \cdot \sqrt{25.39.68}} e^{-\frac{(x_1 - 109.14)^2}{(2)(25.39.68)}} \right\} P_{x_2 | \omega_2}(x_2 | \omega_2) P_{x_3 | \omega_2}(x_3 | \omega_2)$$