

Q1)

1) Probability of students in CS

$\Rightarrow P(S1) \text{ of CS students} + P(S2) \text{ of CS students} + P(S3) \text{ of CS students.}$

$$\Rightarrow \left(\frac{0.2}{10} \times \frac{6}{20} \right) + \left(\frac{0.2}{10} \times \frac{10}{20} \right) + \left(\frac{0.6}{10} \times \frac{6}{20} \right)$$

$$\Rightarrow \underline{\underline{0.34}}$$

2) Probabit

Probability of students in Session 3 from stats

$$\begin{aligned} \text{Probability of Stats} &= \frac{8}{20} \times 0.2 + \frac{10}{20} \times 0.2 + \frac{6}{20} \times 0.6 \\ &= 0.36 \end{aligned}$$

Probability of students of S3 from stats

$$\Rightarrow P(S3 | STAT) = \frac{\frac{6}{20} \times 0.6}{0.36}$$

$$= \underline{\underline{\frac{1}{2}}}$$

Q2

$$1) L(\mu, \sigma | x_1, x_2, \dots, x_n) = \prod_{n=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_n - \mu)^2}$$

2) log likelihood function :-

$$\ln L(\mu, \sigma | x_1, x_2, \dots, x_n)$$

$$\Rightarrow \ln \left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_1 - \mu)^2} + \dots + \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_n - \mu)^2} \right)$$

$$\Rightarrow n \ln \left((2\pi\sigma^2)^{-\frac{1}{2}} \right) - \frac{1}{2\sigma^2} (x_1 - \mu)^2 - \dots - \frac{1}{2\sigma^2} (x_n - \mu)^2$$

$$\Rightarrow -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} [(x_1 - \mu)^2 + \dots + (x_n - \mu)^2]$$

$$\Rightarrow -\frac{n}{2} \ln(2\pi) - n \ln \sigma - \frac{1}{2\sigma^2} [(x_1 - \mu)^2 + \dots + (x_n - \mu)^2]$$

Derivative w.r.t μ :-

$$\frac{\partial \ln L(\mu, \sigma | x_1, x_2, \dots, x_n)}{\partial \mu}$$

$$= -\frac{n}{2\sigma^2} [-2(x_1 - \mu) - 2(x_2 - \mu) - \dots - 2(x_n - \mu)]$$

$$= \frac{n}{\sigma^2} [x_1 + \dots + x_n - \mu n]$$

Q1) $P(\text{Students in CS})$

equating to zero we get :-

$$\frac{n}{\sigma^2} [(x_1 + \dots + x_n) - \mu n] = 0$$

$$\Rightarrow \mu = \frac{x_1 + \dots + x_n}{n}$$

Derivative w.r. to σ :-

$$\begin{aligned} \frac{\partial \ln L(\mu, \sigma | x_1, \dots, x_n)}{\partial \sigma} &= \\ &= \frac{-n}{\sigma} + \frac{2}{\sigma^3} \times \frac{1}{2} [(x_1 - \mu)^2 + \dots + (x_n - \mu)^2] \\ &= \frac{-n}{\sigma} + \frac{1}{\sigma^3} [(x_1 - \mu)^2 + \dots + (x_n - \mu)^2] \end{aligned}$$

equating to zero, we get

$$\frac{n}{\sigma} = \frac{1}{\sigma^3} [(x_1 - \mu)^2 + \dots + (x_n - \mu)^2]$$

$$\Rightarrow \sigma = \sqrt{\frac{(x_1 - \mu)^2 + \dots + (x_n - \mu)^2}{n}}$$

Hence,

$$\mu = \frac{1409}{10} = 140.9$$

$$\sigma = \sqrt{\frac{3466.9}{10}} = 18.619$$

Q3

$$P(X=1) = \frac{2q}{3}, P(X=2) = \frac{q}{3}, P(X=3) = \frac{2(1-q)}{3}$$

$$P(X=4) = \frac{1-q}{3}$$

$$L(q | x_j) = \left(\frac{2q}{3}\right)^{n_1} \left(\frac{q}{3}\right)^{n_2} \left(\frac{2(1-q)}{3}\right)^{n_3} \left(\frac{1-q}{3}\right)^{n_4}$$

where, n_j = freq. of x_j in the distribution

$$\Rightarrow L(q | x_j) = \left(\frac{2q}{3}\right)^2 \left(\frac{q}{3}\right)^3 \left(\frac{2(1-q)}{3}\right)^3 \left(\frac{1-q}{3}\right)^2$$

$$\Rightarrow \ln L(q | x_j) = 2 \ln\left(\frac{2q}{3}\right) + 3 \ln\left(\frac{q}{3}\right) + 3 \ln\left(\frac{2(1-q)}{3}\right) + 2 \ln\left(\frac{1-q}{3}\right)$$

$$\Rightarrow \ln L(q | x_j) = 2 \ln \frac{2}{3} + 2 \ln q + 3 \ln \frac{1}{3} + 3 \ln \frac{1}{3} + 3 \ln q + 3 \ln \frac{2}{3} + 3 \ln(1-q) + 2 \ln\left(\frac{1}{3}\right) + 2 \ln(1-q)$$

$$\Rightarrow \ln(q | x_j) = 5 \ln q + 5 \ln(1-q) + c$$

Differentiation w.r.t (q) & equating to 0

$$\Rightarrow 0 = \frac{5}{q} - \frac{5}{1-q}$$

$$\Rightarrow 1-q = q$$

$$q = \underline{\underline{\frac{1}{2}}}$$

Q4)
$$P(a/b) = \frac{P(b/a) P(a)}{P(b)}$$

From Bayes theorem

$$P(w|x, y, \alpha, \beta) = \frac{P(y|w, \beta) P(w|\alpha)}{P(y)}$$

$$\therefore P(w|\alpha) = \left(\frac{\alpha}{2\pi}\right)^{(M+1)/2} e^{-\frac{\alpha}{2} w^T w}$$

$$\therefore P(w|x, y, \alpha, \beta)$$

$$\Rightarrow \left(\sqrt{\frac{\beta}{2\pi}}\right)^n e^{-\frac{\sum (y_i - f(x, w))^2}{2}} \beta \times \left(\frac{\alpha}{2\pi}\right)^{\frac{M+1}{2}} e^{-\frac{\alpha}{2} w^T w}$$

$$\Rightarrow \frac{\partial \log P(w|x, y, \alpha, \beta)}{\partial w}$$

$$\Rightarrow -\frac{\beta}{2} \frac{\partial \sum (y_i - f(x, w))^2}{\partial w} + \alpha w \quad \text{--- (i)}$$

Regularized sum of square error fun is,

$$\frac{\beta}{2} \sum (y_i - f(x, w))^2 + \frac{\alpha}{2} w^T w$$

$$\Rightarrow -\frac{\beta}{2} \frac{d}{dw} \sum (y_i - f(x, w))^2 + \alpha w$$

\therefore We can say that derivative of regularized sum is equal eqⁿ (i)