

Assignment 2A

~~Let~~

1, let $P(A)$ be probability that Alice collects the tickets
and $P(B)$ be probability that Bob collects tickets

Given: $\frac{P(A)}{P(B)} = \frac{1}{10}$

$$P(m_1, m_2, m_3, m_4, m_5 | A) = \prod_{i=1}^5 P(m_i | A)$$

$$= \frac{10^{12+10+11+4+11} e^{-5(10)}}{12! 10! 11! 4! 11!}$$

(Likelihood that tickets were collected by Alice over 5 samples)

$\left[\begin{array}{l} \cancel{P(X|A)} \sim \text{Poisson}(\lambda) \\ P(X|A=\lambda) \end{array} \right]$ where X is number of tickets collected and $\lambda = 10$ in case of Alice

Similarly

$$L(B) = \prod_{i=1}^5 P(m_i | B)$$

$$= \frac{15^{12+10+11+4+11} e^{-5(15)}}{12! 10! 11! 4! 11!}$$

Since $P(A | m_1, m_2, m_3, m_4, m_5) = \frac{\overset{\text{(Likelihood)}}{P(m_1, m_2, m_3, m_4, m_5 | A)} \overset{\text{(Prior)}}{P(A)}}{P(m_1, m_2, m_3, m_4, m_5)}$

(Posterior)

$$\therefore \frac{P(A | m_1, \dots, m_5)}{P(B | m_1, \dots, m_5)} = \frac{L(A) P(A)}{L(B) P(B)}$$

Posterior odds

$$= \left(\frac{10^{48} e^{-50}}{15^{48} e^{-75}} \right) \left(\frac{1}{10} \right) \approx \underline{\underline{25.4}}$$

2) Given $x = \theta + \varepsilon \rightarrow \text{noise}$

$$\varepsilon \sim N(0, 4)$$

$$\theta \sim N(5, 9) \text{ (Prior)}$$

$$x|\theta \sim N(\theta, 4) \text{ (Since } x \text{ depends upon } \theta)$$

As we know

$$f(\theta|x) = \frac{f(x|\theta) f(\theta)}{f(x)}$$

(Posterior)

given $n=6$

$$f(x|\theta) = \frac{1}{\sqrt{2\pi(4)}} e^{-\frac{(n-\theta)^2}{2(4)}}$$

$$= \frac{1}{2\sqrt{\pi}} e^{-\frac{(n-\theta)^2}{8}}$$

$$f(6|\theta) = \frac{1}{2\sqrt{2\pi}} e^{-\frac{(6-\theta)^2}{8}}$$

$$f_{\theta}(\theta) = \frac{1}{3\sqrt{2\pi}} e^{-\frac{(\theta-5)^2}{18}}$$

$$= \frac{(13n^2 - 148n + 424)}{72}$$

$$\therefore f(6|\theta) f_{\theta}(\theta) = \frac{1}{12\pi} e^{-\frac{(6-\theta)^2}{8} - \frac{(\theta-5)^2}{18}}$$

$$\propto f_{x,\theta}(n,\theta) = f(x|\theta) f_{\theta}(\theta)$$

$$\therefore \text{and } f_x(n) = \int_{-\infty}^{\infty} f_{x,\theta}(n,\theta) d\theta$$

$$\therefore f_x(\theta) = \int_{-\infty}^{\infty} f(m|\theta) f(\theta) d\theta$$

$$f_x(\theta) = \int_{-\infty}^{\infty} f(\theta|m) f(\theta) d\theta$$

$$f(G|\theta) f(\theta) = \frac{1}{12\pi} e^{-\frac{(13\theta^2 - 148\theta + 424)}{72}}$$

$$= \frac{1}{12\pi} e^{-\frac{13(\theta^2 - 2(\frac{74}{13})\theta + (\frac{74}{13})^2) + \frac{36}{13}}{72}}$$

$$= \frac{1}{12\pi} e^{-\frac{13}{72}((\theta - \frac{74}{13})^2) - \frac{36}{13 \times 72}}$$

$$= \frac{1}{12\pi} e^{-\frac{13}{72}(\theta - \frac{74}{13})^2} e^{-\frac{1}{26}}$$

$$= \frac{1}{12\pi} e^{-\frac{13}{72}(\theta - \frac{74}{13})^2} e^{-\frac{1}{26}}$$

$$= \frac{e^{-\frac{13}{72}(\theta - \frac{74}{13})^2} e^{-\frac{1}{26}}}{12\pi}$$

$$f_x(\theta) = \int_{-\infty}^{\infty} \frac{e^{-\frac{13}{72}(\theta - \frac{74}{13})^2} e^{-\frac{1}{26}}}{12\pi} d\theta$$

$$\text{put } \frac{13}{72}(\theta - \frac{74}{13})^2 = t^2$$

$$\text{or } \sqrt{\frac{13}{72}}(\theta - \frac{74}{13}) = t$$

$$\sqrt{\frac{13}{72}} d\theta = dt$$

$$= \frac{e^{-\frac{1}{26}}}{12\pi} \int_{-\infty}^{\infty} e^{-t^2} \sqrt{\frac{72}{13}} dt$$

$$= \sqrt{\frac{72}{13}} \frac{e^{-\frac{1}{26}}}{12\pi} \int_{-\infty}^{\infty} e^{-t^2} dt$$

$$= \sqrt{\frac{72}{13}} \frac{e^{-1/26}}{12\pi} (\sqrt{\pi})$$

$$= \sqrt{\frac{72}{13}} \frac{e^{-1/26}}{12\sqrt{\pi}}$$

$$\therefore f(\theta|6) = \frac{e^{-\frac{13}{72} \left(\theta - \frac{74}{13}\right)^2} e^{-1/26}}{\left(\sqrt{\frac{72}{13}} \frac{e^{-1/26}}{12\sqrt{\pi}}\right) \left(\frac{12\pi}{12\sqrt{\pi}}\right)}$$

$$= \frac{e^{-\frac{13}{72} \left(\theta - \frac{74}{13}\right)^2}}{\sqrt{\frac{72}{13}} \sqrt{\pi}} \cdot \frac{1}{\sqrt{2\pi \left(\frac{36}{13}\right)}}$$

The above equation is similar to pdf of $N(\mu, \sigma^2)$ which is
$$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$
 where $\mu = \frac{74}{13}$ and $\sigma^2 = \frac{36}{13}$

we can say $\theta|6 \sim N\left(\frac{74}{13}, \frac{36}{13}\right)$

b) Given $n = 4$
 $\bar{m} = 6$

$$a = \frac{1}{\sigma^2_{prior}} = \frac{1}{9}$$

$$b = \frac{n}{\sigma^2} = \frac{4}{4} = 1$$

$$\mu_{post} = \frac{a\mu_{prior} + b\bar{m}}{a+b} = \frac{(\frac{1}{9})(5) + (1)(6)}{\frac{1}{9}+1} = \frac{59}{10} = 5.9$$

$$\sigma^2_{post} = \frac{1}{\frac{1}{9}+1} = \frac{9}{10} = 0.9$$

thus posterior on $\theta \sim N(5.9, 0.9)$

c) As ~~per~~ more data is received, variance of posterior decreases since $\sigma^2_{post} \propto \frac{1}{n}$ thus we get more precise values.

We can say μ_{post} is weighted average of μ_{prior} and sample mean. As we increase the value of n the sample mean will tend towards μ_{prior} as noise added has zero mean. Thus overall overall μ_{post} will tend towards μ_{prior} .

d) i) Using above formulae
 expected value of his true IQ = $\frac{\frac{100}{152} + \frac{80}{100}}{\frac{1}{152} + \frac{1}{100}} \approx \underline{\underline{87.93}}$

ii) Expected value of her true IQ = $\frac{\frac{100}{152} + \frac{150}{100}}{\frac{1}{152} + \frac{1}{100}} \approx \underline{\underline{130.15}}$