

Problem Sheet 7

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$$1a) \quad x \sim \frac{x}{\theta^2} e^{-x/\theta} \quad \begin{array}{l} x \geq 0 \\ \theta > 0 \end{array}$$

[3]

$$E[x] = 2\theta, \quad V[x] = 2\theta^2$$

i.i.d. sample x_1, \dots, x_n

$$L(\theta) = \prod_{i=1}^n \frac{x_i}{\theta} e^{-x_i/\theta}$$

$$\Rightarrow \ln L(\theta) = -2n \ln \theta - \sum_{i=1}^n \frac{x_i}{\theta} + C$$

$$\frac{\partial \ln L}{\partial \theta} = -\frac{2n}{\theta} + \frac{\sum_{i=1}^n x_i}{\theta^2} \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \hat{\theta} = \frac{1}{2n} \sum_{i=1}^n x_i$$

$$1b) \quad \text{Use } E[x] = 2\theta, \quad V[x] = 2\theta^2$$

$$[4] \quad \Rightarrow E[\hat{\theta}] = E\left[\frac{1}{2n} \sum_{i=1}^n x_i\right] = \frac{1}{2n} \sum_{i=1}^n E[x_i]$$

$$= \frac{n}{2n} \cdot 2\theta = \theta \quad \Rightarrow b = 0$$

$$V[\hat{\theta}] = V\left[\frac{1}{2n} \sum_{i=1}^n x_i\right] = \frac{1}{4n^2} \sum_{i=1}^n V[x_i]$$

$$= \frac{1}{4n^2} \cdot n \cdot 2\theta^2 = \frac{\theta^2}{2n}$$

(b) cont.

$$MVB = - \frac{\left(1 + \frac{\partial b}{\partial \theta}\right)^2}{E\left[\frac{\partial^2 \ln L}{\partial \theta^2}\right]}$$

$$\frac{\partial^2 \ln L}{\partial \theta^2} = \frac{2n}{\theta^2} - \frac{2}{\theta^3} \sum_{i=1}^n x_i$$

$$E\left[\frac{\partial^2 \ln L}{\partial \theta^2}\right] = \frac{2n}{\theta^2} - \frac{2}{\theta^3} \sum_{i=1}^n \underbrace{E[x_i]}_{2\theta}$$

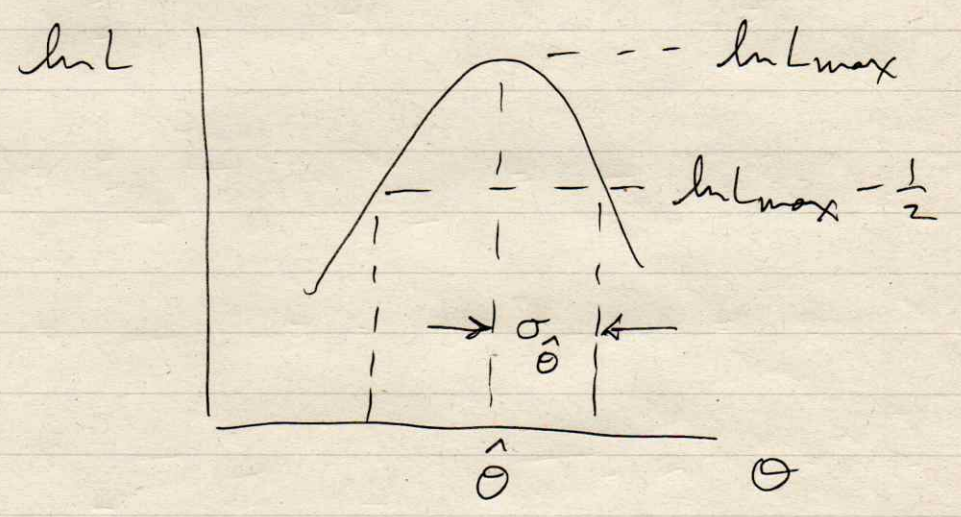
$n = 2\theta$

$$= - \frac{2n}{\theta^2}$$

$$\Rightarrow MVB = \frac{\theta^2}{2n} \quad \left(= V[\hat{\theta}] \right)$$

(c)

[2]



$$1d) \quad f(x; \theta) = \frac{x}{\theta^2} e^{-x/\theta}, \quad E[X] = 2\theta, \quad V[X] = 2\theta^2$$

$$[4] \quad P(n; \theta) = \frac{(\alpha \theta^2)^n}{n!} e^{-\alpha \theta^2} \quad \text{Poisson,}$$

$$E[n] = \lambda$$

$$= \alpha \theta^2$$

↑ known

$$P(n, \vec{x} | \theta) = f(\vec{x} | n, \theta) \cdot P(n | \theta) = L(\theta)$$

$$= \frac{(\alpha \theta^2)^n}{n!} e^{-\alpha \theta^2} \prod_{i=1}^n \frac{x_i}{\theta^2} e^{-x_i/\theta}$$

$$\ln L(\theta) = \cancel{2n \ln \theta} - \alpha \theta^2 - \cancel{2n \ln \theta} + \sum_{i=1}^n (\ln x_i - \frac{x_i}{\theta}) + C$$

$$= -\alpha \theta^2 - \frac{1}{\theta} \sum_{i=1}^n x_i + C'$$

$$\frac{\partial \ln L}{\partial \theta} = -2\alpha \theta + \frac{1}{\theta^2} \sum_{i=1}^n x_i \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \hat{\theta} = \left(\frac{1}{2\alpha} \sum_{i=1}^n x_i \right)^{1/3}$$

$$[3] \quad e) \quad E[a(n, \vec{x})] = \sum_{n=0}^{\infty} \int a(\vec{x}, n) \underbrace{P(n, \vec{x})}_{f(\vec{x} | n) P(n)} d\vec{x}$$

$$= \sum_{n=0}^{\infty} P(n) \cdot \int a(\vec{x}, n) f(\vec{x} | n) d\vec{x}$$

" $E_{\vec{x}}[a(\vec{x}, n) | n]$ "

$$= E_n \left[E_{\vec{x}}[a(\vec{x}, n) | n] \right]$$

IF) $\frac{\partial^2 \ln L}{\partial \theta^2} = -2\alpha - \frac{2}{\theta^3} \sum_{i=1}^n x_i$ depends on n & \bar{x}

$\Rightarrow -E\left[\frac{\partial^2 \ln L}{\partial \theta^2}\right] = 2\alpha + \frac{2}{\theta^3} E\left[\sum_{i=1}^n x_i\right]$

Use $E\left[\sum_{i=1}^n x_i\right] = E_n\left[\underbrace{E_x\left[\sum_{i=1}^n x_i \mid n\right]}_{n \cdot 2\theta}\right]$

$= E_n[2n\theta] = 2 \cdot \underbrace{\alpha\theta^2}_v \cdot \theta = 2\alpha\theta^3$

$\Rightarrow -E\left[\frac{\partial^2 \ln L}{\partial \theta^2}\right] = 2\alpha + \frac{2}{\theta^3} \cdot 2\alpha\theta^3 = 6\alpha$

$\Rightarrow V[\hat{\theta}] = \frac{1}{6\alpha}$ (assumes $b=0$ & info ineq. \rightarrow equality)

$E[n] \equiv v = \alpha\theta^2$

$\Rightarrow V[\hat{\theta}] = \frac{\theta^2}{6v}$ compare to case

where n fixed, $V[\hat{\theta}] = \frac{\theta^2}{2n}$

Now $V[\hat{\theta}]$ smaller because n provides additional info about θ .

$$f(x | \theta_1, \theta_2) = \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x - \theta_1 - \theta_2)^2}{2\sigma^2}}$$

$$g(y | \theta_2) = \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(y - \theta_2)^2}{2\sigma^2}}$$

a) $L(\theta_1, \theta_2) = P(x, y | \theta_1, \theta_2) = f(x | \theta_1, \theta_2) g(y | \theta_2)$

$$= \frac{1}{2\pi\sigma^2} \exp\left[-\frac{(x - \theta_1 - \theta_2)^2 + (y - \theta_2)^2}{2\sigma^2}\right]$$

$$\ln L(\theta_1, \theta_2) = -\frac{1}{2} \left[\frac{(x - \theta_1 - \theta_2)^2 + (y - \theta_2)^2}{\sigma^2} \right]$$

b) $\frac{\partial \ln L}{\partial \theta_1} = \frac{x - \theta_1 - \theta_2}{\sigma^2} \stackrel{\text{set}}{=} 0$

$$\frac{\partial \ln L}{\partial \theta_2} = \underbrace{\frac{x - \theta_1 - \theta_2}{\sigma^2}}_{\text{cancel}} + \frac{y - \theta_2}{\sigma^2} \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \begin{cases} \theta_2 = y \\ \theta_1 = x - y \end{cases}$$

c) $E[\hat{\theta}_1] = E[x] - E[y] = \theta_1 + \theta_2 - \theta_2 = \theta_1 \quad \checkmark$

$$E[\hat{\theta}_2] = E[y] = \theta_2$$

$$V[\hat{\theta}_1] = V[x] + V[y] = 2\sigma^2$$

$$V[\hat{\theta}_2] = V[y] = \sigma^2$$

c) cont.)

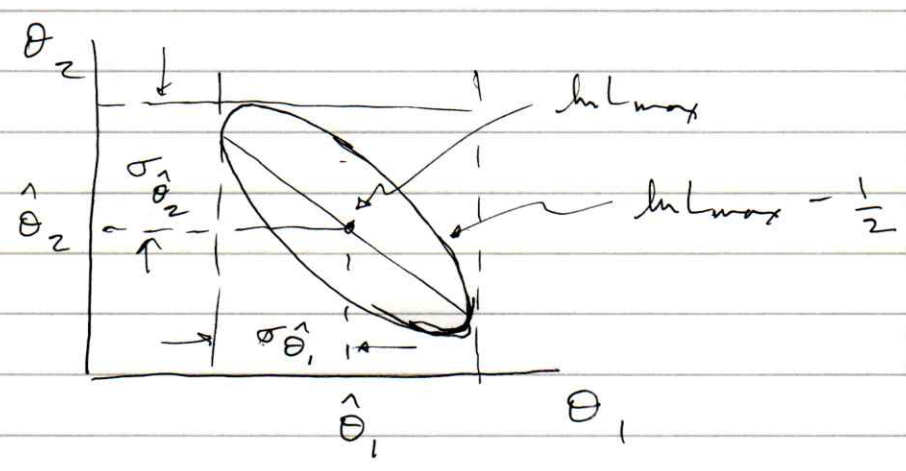
$$\text{cov}[\hat{\theta}_1, \hat{\theta}_2] = \text{cov}[x-y, y]$$

$$= \cancel{\text{cov}[x, y]} - \text{cov}[y, y] \quad (\text{show})$$

$$= -\sigma^2$$

$$\Rightarrow \rho_{12} = \frac{-\sigma^2}{\sqrt{2}\sigma \cdot \sigma} = -\frac{1}{\sqrt{2}}$$

d)



e) $\hat{\theta}_2(\theta_1)$ from soln to $\frac{\partial \ln L}{\partial \theta_2} = 0$

$$\frac{x - \theta_1 - \theta_2}{\sigma^2} + \frac{y - \theta_2}{\sigma^2} = 0$$

$$\hat{\theta}_2(\theta_1) = \frac{1}{2}(x + y - \theta_1)$$

$$\Rightarrow \ln L_p(\theta_1) = -\frac{1}{2} \left[\frac{(x - \theta_1 - \frac{1}{2}(x + y - \theta_1))^2 + (y - \frac{1}{2}(x + y - \theta_1))^2}{\sigma^2} \right]$$

$$= -\frac{1}{2\sigma^2} \left((x - \theta_1)^2 - (x - \theta_1)(x + y - \theta_1) + \frac{1}{4}(x + y - \theta_1)^2 + y^2 - 2y\theta_1 + \theta_1^2 \right)$$

$$\ln L_p(\theta_1) = -\frac{1}{2\sigma^2} \left[\left(\frac{x}{2} - \frac{y}{2} - \frac{\theta_1}{2} \right)^2 + \left(\frac{y}{2} - \frac{x}{2} + \frac{\theta_1}{2} \right)^2 \right]$$

$$= -\frac{1}{4} \frac{(x-y-\theta_1)^2}{\sigma^2}$$

$$\frac{\partial^2 \ln L_p}{\partial \theta_1^2} = -\frac{1}{2\sigma^2}$$

$$\Rightarrow -E \left[\frac{\partial^2 \ln L}{\partial \theta_1^2} \right] = \frac{1}{2\sigma^2}$$

$$\rightarrow V[\hat{\theta}_1] \approx I^{-1}(\theta) = 2\sigma^2 \quad (\leftarrow \text{same as before})$$