

problem 1

assume IID sample and this density function

$$f(x|\theta) = \begin{cases} \frac{2(\theta-x)}{\theta^2} & 0 < x < \theta \\ 0 & \text{otherwise} \end{cases}$$

likelihood function is

$$X = (X_1, \dots, X_n)$$

$$L(\theta; X) = \prod_{k=1}^n \frac{2(\theta - X_k)}{\theta^2} = \frac{2^n}{\theta^{2n}} \prod_{k=1}^n (\theta - X_k)$$

log likelihood function is

$$\ln L(\theta; X) = n \ln 2 - 2n \ln \theta + \sum_{k=1}^n \ln(\theta - X_k)$$

FOC

$$\frac{\partial \ln L(\cdot)}{\partial \theta} = -\frac{2n}{\theta} + \sum_{k=1}^n \frac{1}{\theta - X_k} = 0$$

$$\frac{2n}{\theta} = \sum_{k=1}^n \frac{1}{\theta - X_k}$$

- seems to have no analytical solution
- should be solved numerically
- SOC and other conditions should be checked afterwards $\frac{\partial^2 \ln L(\cdot)}{\partial \theta^2} < 0$

problem 2

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assume IID sample and this density function

$$f(x; \theta) = \begin{cases} (\theta+1)x^\theta & \text{for } 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

likelihood function is (where $X = (X_1, \dots, X_n)$)

$$L(\theta; X) = \prod_{k=1}^n (\theta+1) X_k^\theta = (\theta+1)^n \prod_{k=1}^n X_k^\theta$$

obtain log likelihood function

$$\ln L(\theta; X) = n \ln(\theta+1) + \theta \sum_{k=1}^n \ln X_k$$

FOC

$$\frac{\partial \ln L(\theta; X)}{\partial \theta} = \frac{n}{\theta+1} + \sum_{k=1}^n \ln X_k = 0$$

$$\frac{n}{\theta+1} = - \sum_{k=1}^n \ln X_k$$

$$\frac{\theta+1}{n} = - \frac{1}{\sum_{k=1}^n \ln X_k}$$

$$\hat{\theta} = \frac{-n}{\sum_{k=1}^n \ln X_k} - 1$$

before claiming that $\hat{\theta}$ is ML estimator
Second order condition should be checked

SoC $\frac{\partial^2 \ln L(\theta; X)}{\partial \theta^2} < 0$ for maximum

$$\frac{\partial^2 \ln L(\theta; X)}{\partial \theta^2} = n(-1)(\theta+1)^{-2} = \frac{-n}{(\theta+1)^2} < 0$$

thus $\hat{\theta} = \hat{\theta}_{ML}$

problem 3

$$\begin{aligned} \textcircled{a} f(x|y) &= f(y|x) \cdot f(x) = \frac{e^{-\beta x} (\beta x)^y}{y!} \cdot \theta e^{-\theta x} = \frac{e^{-\beta x - \theta x} (\beta x)^y}{y!} \\ &= \frac{e^{-(\beta+\theta)x} (\beta x)^y \cdot \theta}{y!} \end{aligned}$$

$$\textcircled{b} f(y) = \int_0^{\infty} f(x|y) dx = \int_0^{\infty} \frac{e^{-(\beta+\theta)x} (\beta x)^y}{y!} (\beta x)^{\theta} dx = \infty$$

now check out section 5.4.2b. in Green's text book (p. 178)

the Gamma function: $\Gamma(p) = \int_0^{\infty} t^{p-1} e^{-t} dt$ (*)

$p > 0$ and $\Gamma(p) = (p-1)!$ if p is integer (**)

lets make use of the above formulas

$$\text{set } c = \beta + \theta \Rightarrow \frac{\theta \beta^y}{y! c^y} \int_0^{\infty} x^y e^{-cx} dx$$

$$\Rightarrow \frac{\theta \beta^y}{y! c^y} \int_0^{\infty} x^y c^y e^{-cx} dx = \frac{\theta \beta^y}{y! c^y} \int_0^{\infty} (cx)^y e^{-cx} dx = \infty$$

now set $Cx = t$ and thus $\frac{dt}{c} = dx$ page 4

$\infty = \frac{\theta \beta^y}{\gamma! c^\gamma} \int_0^\infty t^\gamma \cdot e^{-t} dt$ now notice resemblance
marked (*) and $P-1 = \gamma \Rightarrow P = (\gamma+1)$

$\infty = \frac{\theta \beta^y}{\gamma! c^{\gamma+1}} \cdot \Gamma(\gamma+1) = \infty$ apply the equation

marked (**)

$$\infty = \frac{\theta \beta^y}{\gamma! c^{\gamma+1}} \cdot \gamma! = \frac{\theta \beta^y}{c^{\gamma+1}} = \frac{\theta \beta^y}{(\theta + \beta)^\gamma \cdot (\theta + \beta)}$$

$$= \left[\frac{\theta}{\theta + \beta} \right] \left[\frac{\beta}{\beta + \theta} \right]^\gamma$$

take a rest now - you deserve it...

(c) $E(x) = \int_0^{\infty} x f(x) dx$

$E(x) = \int_0^{\infty} x \theta e^{-\theta x} dx$ this integral (I think) can be solved by parts:

define $u = \theta x$ and $v = e^{-\theta x} / \theta$
 $\frac{du}{dx} = \theta$ and $dv = e^{-\theta x} dx$
 $du = \theta dx$ and

$$-x e^{-\theta x} - \int_0^{\infty} -e^{-\theta x} dx = uv - \int v du$$

$$= -x e^{-\theta x} \Big|_0^{\infty} - \frac{1}{\theta} \int_0^{\infty} e^{-\theta x} \theta dx =$$

$$= -x e^{-\theta x} \Big|_0^{\infty} - \frac{1}{\theta} e^{-\theta x} \Big|_0^{\infty} = (0-0) -$$

$$-(0 - \frac{1}{\theta}) = \frac{1}{\theta} = E(x)$$

$Var(x) = E(x^2) - (E(x))^2 = E(x^2) - (\frac{1}{\theta})^2$

$E(x^2) = \int_0^{\infty} x^2 \theta e^{-\theta x} dx$

integration by parts: $u = x^2 \theta$ $dv = e^{-\theta x}$
 $du = 2\theta x dx$ $v = \frac{-e^{-\theta x}}{\theta}$

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$$\begin{aligned}
 &= -x^2 e^{-\theta x} - \int -2x e^{-\theta x} dx + \frac{2}{\theta} \int x e^{-\theta x} dx = \\
 &= \frac{2}{\theta} E(X) - x^2 e^{-\theta x} \Big|_0^\infty = \\
 &= \frac{2}{\theta} \cdot \frac{1}{\theta} - 0 = \frac{2}{\theta^2} \\
 \text{Var}(X) &= \frac{2}{\theta^2} - \frac{1}{\theta^2} = \frac{1}{\theta^2}
 \end{aligned}$$

(d)

$$E(Y) = E_x[E(Y|X)] = \infty$$

$$E(Y|X) = \beta X \quad (\text{see 3c})$$

$$\infty = E_x(\beta X) = \beta E_x(X) = \beta \cdot \frac{1}{\theta} = \frac{\beta}{\theta}$$

$$\text{Var}(Y) = E_x[\text{Var}(Y|X)] + \text{Var}_x[E(Y|X)] = \infty$$

$$\text{Var}(Y|X) = E(Y|X) = \beta X \quad (\text{see 3c})$$

$$\infty = E_x(\beta X) + \underbrace{\text{Var}_x(\beta X)} = \beta E_x(X) + \beta^2 \text{Var}_x(X)$$

$$= \frac{\beta}{\theta} + \beta^2 \frac{1}{\theta^2} = \frac{\beta}{\theta} \left(1 + \frac{\beta}{\theta}\right) = \infty$$

$$\gamma = \beta/\theta$$

$$\infty = \gamma(1 + \gamma)$$

$$\text{Cov}(X|Y) = \text{Cov}(X; E(Y|X)) = \infty$$

$$E(Y|X) = \beta$$

$$\begin{aligned} \infty &= \text{Cov}(X; \beta X) = E(XY) - E(X) \cdot E(Y) = \\ &= E(\beta X^2) - E(X) \cdot E(\beta X) = \beta E(X^2) - \frac{\beta}{\theta^2} = \\ &= \frac{2\beta}{\theta^2} - \frac{\beta}{\theta^2} = \frac{\beta}{\theta^2} = \infty \end{aligned}$$

$$\gamma = \beta/\theta$$

$$\infty = \frac{\gamma}{\theta}$$

$$(3e) \quad f(x|y) = \frac{f(y|x) \cdot f(x)}{f(x|y)} = \frac{e^{-\beta x} (\beta x)^y \theta e^{-\theta x}}{y! \left(\frac{\theta}{\theta+\beta}\right) \left(\frac{\beta}{\theta+\beta}\right)^y} =$$

$$= \frac{\theta e^{-x(\theta+\beta)} (x\beta)^y}{y! \left(\frac{\theta}{\theta+\beta}\right) \left(\frac{\beta}{\theta+\beta}\right)^y} = \infty$$

$$\text{set } c = \theta + \beta$$

$$\infty = \frac{\theta e^{-xc} (\beta x)^y}{y! \left(\frac{\theta}{c}\right) \left(\frac{\beta}{c}\right)^y} = \left(\frac{e^{-xc} (x)^y}{y! \left(\frac{1}{c}\right) \left(\frac{1}{c}\right)^y} \right) =$$

$$= \frac{e^{-xc} x^{\gamma} e^{\gamma+1}}{\gamma!}$$

$$E(X|Y) = \int_0^{\infty} x \cdot f(x|Y) dx = \infty$$

set $t = xc \Rightarrow \frac{dt}{dx} = c \Rightarrow dx = \frac{1}{c} dt$

$$\infty = \int_0^{\infty} \frac{xc \cdot t^{\gamma} \cdot e^{-t}}{\gamma!} dx = \int_0^{\infty} \frac{t^{\gamma+1} \cdot e^{-t}}{\gamma!} dx =$$

$$= \frac{1}{c \cdot \gamma!} \int_0^{\infty} t^{\gamma+1} \cdot e^{-t} dt = \infty$$

go back to page 178 in Greene or 3b
the integral became a Gamma function

$$\infty = \frac{1}{c \cdot \gamma!} \cdot \Gamma(\gamma+2) = \frac{1}{c \cdot \gamma!} \cdot (\gamma+1)! =$$

because of $\gamma+1 = p-1$

$$= \frac{1}{c \cdot \gamma!} \cdot \gamma! (\gamma+1) = \frac{\gamma+1}{c} = \frac{\gamma+1}{\theta+\beta}$$

$$= \frac{\gamma}{\theta+\beta} + \frac{1}{\theta+\beta} = \infty$$

set $\mu = \frac{1}{\theta+\beta}$

$$\infty = \gamma \mu + \mu$$

problem 4

(a)

X is a discrete random variable

$$\begin{aligned}
 E(X) &= \sum_{k=1}^n x_k f_x(x) = \sum_{k=1}^n x_k \frac{e^{-\lambda} \lambda^{x_k}}{x_k!} = \\
 &= \sum_{k=1}^n \frac{x_k e^{-\lambda} \lambda^{x_k}}{x_k (x_k - 1)!} = \sum_{k=1}^n \frac{e^{-\lambda} \lambda^{x_k} \lambda}{(x_k - 1)!} = \\
 &= \lambda \sum_{k=1}^n \frac{e^{-\lambda} \lambda^{(x_k - 1)}}{(x_k - 1)!} = \lambda \cdot 1 = \lambda
 \end{aligned}$$

$$\text{Var}(X) = E(X^2) - E(X)^2$$

lets deal with $E(X^2)$ first

$$\begin{aligned}
 E(X^2) &= \sum_{k=1}^n x_k^2 \frac{e^{-\lambda} \lambda^{x_k}}{x_k!} = \sum_{k=1}^n x_k \frac{e^{-\lambda} \lambda^{x_k - 1}}{(x_k - 1)!} \\
 &= \lambda \sum_{k=1}^n \frac{(x_k - 1 + 1) e^{-\lambda} \lambda^{x_k - 1}}{(x_k - 1)!} = \lambda \left(1 + \sum_{k=1}^n \frac{e^{-\lambda} \lambda^{x_k - 2}}{(x_k - 2)!} \right)
 \end{aligned}$$

$$= \lambda [1 + \lambda] = \lambda + \lambda^2$$

$$\text{Var}(X) = \lambda^2 + \lambda - (\lambda)^2 = \lambda$$

(4b)

$f(x; \lambda) = \frac{e^{-\lambda} \lambda^x}{x!}$ given density
assume random sample $X = (X_1, \dots, X_n)$

likelihood is $L(\lambda; X) = \prod_{k=1}^n \frac{e^{-\lambda} \lambda^{x_k}}{x_k!} =$
 $= \frac{e^{-n\lambda} \cdot \prod_{k=1}^n \lambda^{x_k}}{\prod_{k=1}^n x_k!}$

log of likelihood function is

$\ln L(\lambda; X) = -n\lambda + \sum_{k=1}^n x_k \ln \lambda - \sum_{k=1}^n \ln(x_k!)$

FOC $\frac{\partial \ln L(\cdot)}{\partial \lambda} = 0$ gives

$-n + \sum_{k=1}^n x_k = 0$

$\hat{\lambda} = \frac{1}{n} \left(\sum_{k=1}^n x_k \right) = \bar{X}$

SOC $\frac{\partial^2 \ln L(\cdot)}{\partial \lambda^2} = \frac{(-1) \left(\sum_{k=1}^n x_k \right)}{\lambda^2} < 0$

thus $\hat{\lambda} = \hat{\lambda}_{ML} = \bar{X}$

(4c)

$E(X) = \lambda$ apply moment matching principle $\Rightarrow \frac{1}{n} \sum_{k=1}^n x_k = \hat{\lambda}_{MM}$

(4d)
$$E(\hat{\lambda}) = E\left(\frac{1}{n} \sum_{k=1}^n X_k\right) = \frac{1}{n} \sum_{k=1}^n E(X_k) = \frac{1}{n} \sum_{k=1}^n \lambda = \frac{1}{n} \cdot n \cdot \lambda = \lambda$$

thus unbiased

(4e)
$$CRLB = [I(\lambda)]^{-1} = \left[-E\left(\frac{\partial^2 \ln L(\lambda)}{\partial \lambda^2}\right)\right]^{-1}$$

from SE in 4b:

$$CRLB = \left[-E\left(-\frac{\sum_{k=1}^n X_k}{\lambda^2}\right)\right]^{-1} = \left[\frac{n \cdot \lambda}{\lambda^2}\right]^{-1} = \frac{\lambda}{n}$$

and
$$\text{Var}(\hat{\lambda}) = \text{Var}(\bar{X}) = \frac{1}{n^2} \cdot n \lambda = \frac{\lambda}{n}$$

thus $\text{Var}(\hat{\lambda}) = CRLB$: (efficient)

problem 5

(a)
$$E(x) = \int_0^{\infty} x \cdot f(x) dx = \int_0^{\infty} x \cdot \frac{1}{\theta} \cdot e^{-x/\theta} dx = \infty$$

integration by parts:

$$\begin{aligned} u &= x/\theta & du &= \frac{1}{\theta} dx \\ dv &= e^{-x/\theta} dx & v &= -\theta e^{-x/\theta} \end{aligned}$$

$$\begin{aligned}
 \infty &= -xe^{-x/\theta} - \int_0^{\infty} e^{-x/\theta} dx = -xe^{-x/\theta} - \int_0^{\infty} \theta e^{-u} du = \\
 &= -xe^{-x/\theta} - \theta \int_0^{\infty} e^{-u} du = -xe^{-x/\theta} - \theta e^{-x/\theta} \Big|_0^{\infty} = \theta
 \end{aligned}$$

$$\text{Var}(x) = E(x^2) - [E(x)]^2$$

lets concentrate on $E(x^2)$

$$E(x^2) = \int_0^{\infty} x^2 f(x) dx = \infty$$

again integration by parts

$$\begin{aligned}
 u &= x^2/\theta & du &= e^{-x/\theta} dx \\
 du &= \frac{2x}{\theta} dx & v &= -\theta e^{-x/\theta}
 \end{aligned}$$

$$\begin{aligned}
 \infty &= -x^2 e^{-x/\theta} + 2\theta \int_0^{\infty} \frac{x e^{-x/\theta}}{\theta} dx = \\
 &= -x^2 e^{-x/\theta} + 2\theta \left(\frac{x e^{-x/\theta}}{\theta} \Big|_0^{\infty} \right) = \\
 &= -x^2 e^{-x/\theta} + x e^{-x/\theta} + 2\theta^2 = 2\theta^2
 \end{aligned}$$

$$\text{Var}(x) = 2\theta^2 - (\theta)^2 = \theta^2$$

(5b)

likelihood function assuming a random sample is:

$$L(\theta; X) = \prod_{k=1}^n \frac{1}{\theta} e^{-x_k/\theta} = \left(\frac{1}{\theta}\right)^n e^{-\frac{1}{\theta} \sum_{k=1}^n x_k}$$

$$\ln L(\theta; X) = -n \ln(\theta) - \frac{1}{\theta} \sum_{k=1}^n x_k$$

$$\text{FOE gives: } -\frac{n}{\theta} + \frac{1}{\theta^2} \sum_{k=1}^n x_k = 0$$

$$\Rightarrow \hat{\theta} = \frac{\sum_{k=1}^n x_k}{n} = \bar{x}$$

$$\begin{aligned} \text{Soe gives: } \frac{\partial^2 \ln L(\cdot)}{\partial \theta^2} &= \frac{n}{\theta^2} - \frac{2 \sum_{k=1}^n x_k}{\theta^3} \\ &= \frac{1}{\theta^2} \left(n - \frac{2 \sum_{k=1}^n x_k}{\theta} \right) < 0 \end{aligned}$$

$$\text{Thus } \hat{\theta} = \hat{\theta}_{ML} = \bar{x}$$

(5c)

$$E(\hat{\theta}) = E\left(\frac{1}{n} \sum_{k=1}^n x_k\right) = \frac{1}{n} \sum_{k=1}^n E(x_k) = \frac{1}{n} \cdot n \cdot \theta = \theta$$

unbiased

(5d) CRLB = $[\mathcal{I}(\theta)]^{-1} = \left[-E \left(\frac{\partial^2 \ln L(\theta; X)}{\partial \theta^2} \right) \right]^{-1}$ page 14
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∞∞ from SOE of 5b

$$\begin{aligned} \infty\infty &= \left[-E \left(\frac{n}{\theta^2} - \frac{2}{\theta^3} \sum_{k=1}^n X_k \right) \right]^{-1} = \left[\frac{n}{\theta^2} + \frac{2}{\theta^3} \cdot n\theta \right]^{-1} \\ &= \left[\frac{n}{\theta^2} \right]^{-1} = \frac{\theta^2}{n} \end{aligned}$$

$$\text{Var} \left(\frac{1}{\hat{\theta}} \right) = \text{Var}(\bar{X}) = \frac{\theta^2}{n}$$

$\text{Var}(\hat{\theta}) = \text{CRLB}$: thus $\hat{\theta}$ is minimum variance estimator.