ISyE 6739 – Group Activity 7 solutions

Notations: $\bar{X}^k = \frac{1}{n} \sum_{i=1}^n X_i^k$.

1. Let X be distributed with the pdf $f(x) = \lambda e^{-\lambda(x-\gamma)}$, $0 \le \gamma \le x$, $0 < \lambda$.

$$E[X] = \int_{-\infty}^{+\infty} x \cdot f(x) dx = \int_{\gamma}^{+\infty} x \cdot \lambda e^{-\lambda(x-\gamma)} dx = -x \cdot e^{-\lambda(x-\gamma)} \Big|_{\gamma}^{+\infty} + \int_{\gamma}^{+\infty} e^{-\lambda(x-\gamma)} dx =$$

$$= \gamma - \frac{e^{-\lambda(x-\gamma)}}{\lambda} \Big|_{\gamma}^{+\infty} = \gamma + \frac{1}{\lambda},$$

$$E[X^2] = \int_{-\infty}^{+\infty} x^2 \cdot f(x) dx = \int_{-\infty}^{+\infty} x \cdot \lambda e^{-\lambda(x-\gamma)} dx = -x^2 \cdot e^{-\lambda(x-\gamma)} \Big|_{\gamma}^{+\infty} + 2 \int_{-\infty}^{+\infty} x \cdot e^{-\lambda(x-\gamma)} dx = \gamma^2 + 2 \int_{-\infty}^{+\infty} x \cdot e^{-\lambda(x-\gamma)} dx = -x^2 \cdot e^{-\lambda(x-\gamma)} dx = -x$$

 $\mathrm{E}[X^2] = \int_{-\infty}^{+\infty} x^2 \cdot f(x) dx = \int_{-\infty}^{+\infty} x \cdot \lambda e^{-\lambda(x-\gamma)} dx = -x^2 \cdot e^{-\lambda(x-\gamma)} \Big|_{-\infty}^{+\infty} + 2 \int_{-\infty}^{+\infty} x \cdot e^{-\lambda(x-\gamma)} dx = \gamma^2 + \frac{2}{\lambda^2}.$

By MOM:

$$\begin{split} \bar{X} &= \gamma + \frac{1}{\lambda}, \quad \bar{X}^2 = \gamma^2 + \frac{2}{\lambda^2}, \\ \Rightarrow \hat{\lambda}_{MOM} &= \frac{1}{\sqrt{\bar{X}^2 - (\bar{X})^2}}, \hat{\gamma}_{MOM} = \bar{X} + \sqrt{\bar{X}^2 - (\bar{X})^2}. \end{split}$$

2. By MOM:

$$\begin{split} \bar{X} &= \frac{r}{\lambda}, \quad \bar{X}^2 = \frac{r}{\lambda^2} + \frac{r^2}{\lambda^2}, \\ \Rightarrow \hat{r}_{MOM} &= \frac{(\bar{X})^2}{\bar{X}^2 - (\bar{X})^2}, \quad \hat{\lambda}_{MOM} = \frac{\bar{X}}{\bar{X}^2 - (\bar{X})^2}. \end{split}$$

3.

$$L(\theta) = \prod_{i=1}^{n} (\theta + 1) X_i = (\theta + 1)^n \left(\prod_{i=1}^{n} X_i \right)^{\theta},$$

$$l(\theta) = \ln L(\theta) = n \ln(\theta + 1) + \theta \sum_{i=1}^{n} \ln X_i,$$

$$\frac{\partial l(\theta)}{\partial \theta} = \frac{n}{\theta + 1} + \sum_{i=1}^{n} \ln X_i = 0$$

$$\Rightarrow \hat{\theta}_{MOM} = -1 - \frac{n}{\sum_{i=1}^{n} X_i} = -1 - (\bar{X})^{-1}.$$

4.

$$\begin{split} L(\theta) &= \prod_{i=1}^n \frac{1}{\theta^2} X_i e^{-\frac{X_i}{\theta}} = \frac{1}{\theta^{2n}} \prod_{i=1}^n X_i e^{-\frac{\sum_{i=1}^n X_i}{\theta}}, \\ l(\theta) &= \ln L(\theta) = -2n \ln \theta + \sum_{i=1}^n \ln X_i - \frac{\sum_{i=1}^n X_i}{\theta}, \\ \frac{\partial l(\theta)}{\partial \theta} &= \frac{-2n}{\theta} + \frac{\sum_{i=1}^n X_i}{\theta^2} = 0 \\ &\Rightarrow \hat{\theta}_{MOM} = \frac{\sum_{i=1}^n X_i}{2n} = \frac{\bar{X}}{2}. \end{split}$$

5.

$$f(x) = \frac{1}{a} \mathbb{I}\{0 \le x \le a\},\$$

where $\mathbb{I}(A)$ is an indicator function, i.e.

$$\mathbb{I}(A) = \begin{cases} 1 & x \in A, \\ 0 & \text{otherwise.} \end{cases}$$

Then

$$L(a) = \prod_{i=1}^{n} f(x_i) = \prod_{i=1}^{n} \frac{1}{a} \mathbb{I}\{0 \le x \le a\} = \frac{1}{a^n} \mathbb{I}\{\min_i x_i \ge 0, \max_i x_i \le a\}$$

 $\Rightarrow L(a)$ achieves its maximum when $a = \max_{i} x_{i}$.

$$\Rightarrow \hat{a}_{MLE} = \max_{i} X_{i}.$$

6.

$$f(x) = \lambda e^{-\lambda(x-\theta)} \mathbb{I}\{x \ge \theta\},$$

$$L(\lambda, \theta) = \prod_{i=1}^{n} \lambda e^{-\lambda(X_i - \theta)} \mathbb{I}\{X_i \ge \theta\} = \lambda^n e^{-\lambda \sum_{i=1}^{n} X_i} e^{n\lambda \theta} \mathbb{I}\{\min_i X_i \ge \theta\}.$$

To maximize $L(\theta)$ θ should be as large as possible

$$\Rightarrow \hat{\theta}_{MLE} = \min_{i} X_{i}.$$

Fix θ and suppose $\theta \leq X_i \ \forall i$ (otherwise $L(\lambda, \theta) = 0$)

$$\begin{split} l(\lambda,\theta) &= \ln L(\lambda,\theta) = n \ln \lambda - \lambda \sum_{i=1}^{n} X_i + n\theta \lambda, \\ &\frac{\partial l(\lambda,\theta)}{\partial \lambda} = \frac{n}{\lambda} - \sum_{i=1}^{n} X_i + n\theta = 0 \\ &\Rightarrow \hat{\lambda}_{MLE} = \frac{1}{\bar{X} - \hat{\theta}_{MLE}} = \frac{1}{\bar{X} - \min_i X_i}. \end{split}$$

7. (a) By the definition of a probability density function:

$$1 = \int_{-\infty}^{+\infty} f(x)dx = \int_{-1}^{1} c(1+\theta x)dx = c\frac{(1+\theta x)^{2}}{2\theta} \Big|_{-1}^{1} = c\frac{4\theta}{2\theta} = 2c$$

 $\Rightarrow c = \frac{1}{2}.$

(b)
$$M_1 = \mathrm{E}[X] = \int_{-\infty}^{+\infty} x f(x) dx = \int_{-1}^1 \frac{x}{2} (1 + \theta x) dx = \frac{\theta x^3}{6} \Big|_{-1}^1 = \frac{\theta}{3}.$$
 By MOM $\bar{X} = M_1$
$$\Rightarrow \hat{\theta}_{MOM} = 3\bar{X}.$$

(c)
$$\mathrm{E}[\hat{\theta}] = \mathrm{E}\left[\frac{3}{n}\sum_{i=1}^{n}X_{i}\right] = \frac{3}{n}\cdot n\cdot 3\theta = \theta$$

 $\Rightarrow \hat{\theta}$ is an unbiased estimator for θ .

(d)
$$L(\theta) = \prod_{i=1}^{n} \frac{1}{2} (1 + \theta X_i) = \frac{1}{2^n} \prod_{i=1}^{n} (1 + \theta X_i),$$

$$l(\theta) = \ln L(\theta) = -n \ln 2 + \sum_{i=1}^{n} \ln(1 + \theta X_i),$$

The MLE can be derived from the following equation

$$\frac{\partial l(\theta)}{\partial \theta} = \sum_{i=1}^{n} \frac{X_i}{1 + \theta X_i} = 0.$$

8. (a) Consider
$$\hat{\theta} = \frac{\bar{X}^2}{2}$$

$$E[\hat{\theta}] = E\left[\frac{1}{2n}\sum_{i=1}^n X_i^2\right] = \frac{1}{2n} \cdot n \cdot 2\theta = \theta$$

 $\Rightarrow \hat{\theta}$ is an unbiased estimator for θ .

(b)
$$L(\theta) = \prod_{i=1}^n f(X_i) = \prod_{i=1}^n \frac{X_i}{\theta} e^{-X_i^2/2\theta} = \frac{\prod_{i=1}^n X_i}{\theta^n} e^{-\sum_{i=1}^n X_i^2/2\theta},$$

$$l(\theta) = \ln L(\theta) = -n \ln \theta + \sum_{i=1}^n \ln X_i - \frac{1}{2\theta} \sum_{i=1}^n X_i^2,$$

$$\frac{\partial l(\theta)}{\partial \theta} = -\frac{n}{\theta} + \frac{1}{2\theta^2} \sum_{i=1}^n X_i^2 = 0.$$

$$\hat{\theta}_{MLE} = \frac{\bar{X}^2}{2}$$

which is equal to the estimator in the part (a).

(c) Find the median m of the distribution. By definition

$$P\{X < m\} = \frac{1}{2}.$$

$$\frac{1}{2} = \int_0^m \frac{x}{\theta} e^{-\frac{x^2}{2\theta}} dx = \int_0^m e^{-\frac{x^2}{2\theta}} d\left(\frac{x^2}{2\theta}\right) = -e^{-\frac{x^2}{2\theta}} \Big|_0^m = 1 - e^{-\frac{m^2}{2\theta}}.$$

$$\Rightarrow m = \sqrt{-2\theta \ln \frac{1}{2}}.$$

By the invariance property of the MLE:

$$\hat{m}_{MLE} = \sqrt{-2\hat{\theta}_{MLE} \ln{\frac{1}{2}}} = \sqrt{-\bar{X}^2 \ln{\frac{1}{2}}}.$$

9. (a)
$$\beta = 2$$
 then
$$f(x) = \frac{2}{\delta^2} x e^{-\frac{x^2}{\delta^2}}, \quad x > 0.$$

$$L(\delta) = \prod_{i=1}^n \frac{2}{\delta^2} X_i e^{-\frac{X_i^2}{\delta^2}} = \frac{2^n}{\delta^{2n}} \prod_{i=1}^n X_i e^{-\frac{\sum_{i=1}^n X_i^2}{\delta^2}},$$

$$l(\delta) = \ln L(\delta) = -2n \ln \frac{\delta}{\sqrt{2}} + \sum_{i=1}^n \ln X_i - \frac{\sum_{i=1}^n X_i^2}{\delta^2},$$

$$\frac{\partial l(\delta)}{\partial \delta} = -\frac{2n}{\delta} + \frac{2\sum_{i=1}^n X_i^2}{\delta^3} = 0.$$

$$\Rightarrow \hat{\delta}_{MLE} = \sqrt{\bar{X}^2}.$$

(b) By MOM:

$$\begin{split} \bar{X} &= \delta \Gamma(3/2) \\ \Rightarrow \hat{\delta}_{MOM} &= \frac{\bar{X}}{\Gamma(3/2)}. \\ \mathbf{E}[\hat{\delta}_{MOM}] &= \mathbf{E}\left[\frac{1}{\Gamma(3/2)n} \sum_{i=1}^n X_i\right] = \frac{1}{\Gamma(3/2)n} \cdot n \cdot \delta \Gamma(3/2) = \delta. \end{split}$$

 $\Rightarrow \hat{\delta}_{MOM}$ is an unbiased estimator for δ .