

# Math 164 HW 5

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## Problem 1

Let  $X_1, \dots, X_n$  be a random sample from a distribution with probability mass function

$$f(a; \theta) = \theta(1 - \theta)^a \mathbb{1}_{\{0, 1, \dots\}}(a),$$

where  $0 < \theta < 1$ .

- (a) Find the maximum likelihood estimator of  $\theta$ .  
For  $X_i$  in  $\{0, 1, \dots\}$

$$\begin{aligned} \frac{d}{d\theta} \log[f(X_1, \dots, X_n; \theta)] &= \frac{d}{d\theta} \log\left[\prod_{i=1}^n \theta(1 - \theta)^{X_i}\right] = \frac{d}{d\theta} \sum_{i=1}^n [\log(\theta) + X_i \log(1 - \theta)] \\ &= \sum_{i=1}^n \left[\frac{1}{\theta} - \frac{X_i}{1 - \theta}\right] = \left[\frac{n}{\theta} - \frac{\sum_{i=1}^n X_i}{1 - \theta}\right] \end{aligned}$$

Set equal to 0

$$\frac{n}{\hat{\theta}} - \frac{\sum_{i=1}^n X_i}{1 - \hat{\theta}} = 0 \Rightarrow \frac{n}{\hat{\theta}} = \frac{\sum_{i=1}^n X_i}{1 - \hat{\theta}} \Rightarrow (1 - \hat{\theta})n = \hat{\theta} \sum_{i=1}^n X_i \Rightarrow 1 - \hat{\theta} = \frac{1}{n} \hat{\theta} \sum_{i=1}^n X_i \Rightarrow$$

$$\begin{aligned} \frac{1}{\hat{\theta}} - 1 &= \frac{1}{n} \sum_{i=1}^n X_i \Rightarrow \frac{1}{\hat{\theta}} = \frac{1}{n} \sum_{i=1}^n X_i + 1 \\ \Rightarrow \hat{\theta} &= \frac{1}{\frac{1}{n} \sum_{i=1}^n X_i + 1} \end{aligned}$$

- (b) Find the maximum likelihood estimator of

$$\tau(\theta) = E(X_1) = \frac{1 - \theta}{\theta}$$

From Proposition 1 we know that

$$\begin{aligned} \widehat{\tau(\theta)} &= \tau(\hat{\theta}) = \frac{1 - \frac{1}{\frac{1}{n} \sum_{i=1}^n X_i + 1}}{\frac{1}{\frac{1}{n} \sum_{i=1}^n X_i + 1}} = \frac{\frac{\frac{1}{n} \sum_{i=1}^n X_i}{\frac{1}{n} \sum_{i=1}^n X_i + 1}}{\frac{1}{\frac{1}{n} \sum_{i=1}^n X_i + 1}} \\ &= \frac{1}{n} \sum_{i=1}^n X_i \end{aligned}$$

- (c) Find the Cramr-Rao lower bound for variances of unbiased estimators of  $\tau(\theta)$ .  
Show  $f(a; \theta)$  is one parameter exponential family

$$\theta(1 - \theta)^a \mathbb{1}_{\{0, 1, \dots\}}(a) = \mathbb{1}_{\{0, 1, \dots\}}(a) \theta e^{a \log(1 - \theta)} = h(a) c(\theta) e^{t(a) q(\theta)}$$

and that  $\frac{d}{d\theta} q(\theta)$  is continuous for  $0 < \theta < 1$

$$\frac{d}{d\theta} q(\theta) = \frac{d}{d\theta} \log(1 - \theta) = \frac{-1}{1 - \theta}$$

Since this is continuous and  $f(a; \theta)$  is one parameter exponential family R1-R4 hold Therefore

$$I_n(\theta) = -E\left[\frac{d^2}{d\theta^2} \log[f(X_1, \dots, X_n; \theta)]\right] = -E\left[\frac{d}{d\theta} \left(\frac{n}{\theta} - \frac{\sum_{i=1}^n X_i}{1 - \theta}\right)\right] = -E\left[\frac{-n}{\theta^2} - \frac{\sum_{i=1}^n X_i}{(1 - \theta)^2}\right]$$

$$\begin{aligned}
&= \frac{n}{\theta^2} + \frac{E(\sum_{i=1}^n X_i)}{(1-\theta)^2} = \frac{n}{\theta^2} + \frac{\sum_{i=1}^n E(X_i)}{(1-\theta)^2} = \frac{n}{\theta^2} + \frac{\sum_{i=1}^n \frac{1-\theta}{(1-\theta)^2}}{(1-\theta)^2} = \frac{n}{\theta^2} + \frac{n}{\theta(1-\theta)} \\
&= \frac{n}{\theta^2} + \frac{\theta}{(1-\theta)} = \frac{n}{\theta^2} \frac{(1-\theta)}{(1-\theta)} + \frac{\theta}{(1-\theta)} = \frac{n(1-\theta) + \theta}{\theta^2(1-\theta)} \\
I_n(\theta) &= \frac{n}{\theta^2(1-\theta)}
\end{aligned}$$

Therefore the Cramer-Rao lower bound is

$$\begin{aligned}
var(T) &\geq \frac{[\frac{d}{d\theta} \frac{1-\theta}{\theta}]^2}{I_n(\theta)} = \frac{[\frac{-1}{\theta} - \frac{1-\theta}{\theta^2}]^2}{I_n(\theta)} = \frac{[\frac{1}{\theta^2} + 2\frac{1-\theta}{\theta^2} + \frac{(1-\theta)^2}{\theta^4}]^2}{I_n(\theta)} = \frac{[\frac{1}{\theta^2}][1 + 2\frac{1-\theta}{\theta} + \frac{(1-\theta)^2}{\theta^2}]}{\frac{n}{\theta^2(1-\theta)}} \\
&= \frac{\left(1 + \frac{1-\theta}{\theta}\right)^2}{\frac{n}{1-\theta}} = \frac{\left(\frac{1}{\theta}\right)^2}{\frac{n}{1-\theta}} = \frac{\frac{1}{\theta^2}}{\frac{n}{1-\theta}} \frac{\theta^2(1-\theta)}{\theta^2(1-\theta)} = \frac{1-\theta}{n\theta^2} \\
var(T) &\geq \frac{1-\theta}{n\theta^2}
\end{aligned}$$

- (d) Is the maximum likelihood estimator of  $\tau(\theta)$  a uniformly minimum variance unbiased estimator? Justify your answer.

First check if T is unbiased

$$E(T) = E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{1}{n} \sum_{i=1}^n E[X_i] = \frac{1}{n} \sum_{i=1}^n \left[\frac{1-\theta}{\theta}\right] = \frac{1-\theta}{\theta}$$

Therefore our MLE of  $\tau(\theta)$  is unbiased. In part a we found that

$$\frac{d}{d\theta} \log[f(X_1, \dots, X_n; \theta)] = \frac{n}{\theta} - \frac{\sum_{i=1}^n X_i}{1-\theta} = \frac{-n}{1-\theta} \left[-\frac{1-\theta}{\theta} + \frac{1}{n} \sum_{i=1}^n X_i\right] = a(\theta)[T - \tau(\theta)]$$

Therefore, T is and UMVUE that obtains the Cramer-Rao Lower Bound.

## Problem 2

Let  $X_1, \dots, X_n$  be a random sample from a distribution with probability mass function

$$f(a; \mu) = \frac{1}{\sqrt{18\pi}} \exp\left\{-\frac{(a-\mu)^2}{18}\right\},$$

where  $-\infty < \mu < \infty$ .

- (a) Find the Cramer-Rao lower bound for variances of unbiased estimators of  $\mu$ . First prove this is exponential family

$$\frac{1}{\sqrt{18\pi}} \exp\left\{-\frac{(a-\mu)^2}{18}\right\} = \frac{1}{\sqrt{18\pi}} \exp\left\{-\frac{(a^2 - 2a\mu + \mu^2)}{18}\right\} = \frac{1}{\sqrt{18\pi}} e^{-\frac{a^2}{18}} e^{-\frac{\mu^2}{18}} e^{\frac{2}{18}a\mu} = h(a)c(\mu)e^{t(a)q(\mu)}$$

Therefore it is exponential Check if  $q'(\mu)$  is continuous for  $-\infty < \mu < \infty$

$$\frac{d}{d\mu} q(\mu) = \frac{d}{d\mu} \mu = 1$$

which is ok. Thus R1-R4 hold.

Therefore,

$$\begin{aligned}
I_n(\mu) &= nI(\mu) = -nE\left[\frac{d^2}{d\mu^2} \log[f(X_1; \mu)]\right] = -nE\left[\frac{d^2}{d\mu^2} \log\left[\frac{1}{\sqrt{18\pi}} e^{-\frac{1}{18}a^2} e^{-\frac{1}{18}\mu^2} e^{\frac{2}{18}X_1\mu}\right]\right] = -nE\left[\frac{d^2}{d\mu^2} \left(\log\left[\frac{1}{\sqrt{18\pi}}\right] - a^2\right)\right] \\
&= -nE\left[\frac{d}{d\mu} \left(-\frac{2}{18}\mu + \frac{2}{18}\right)\right] = -nE\left[-\frac{2}{18}\right] = \frac{n}{9}
\end{aligned}$$

Therefore by theorem 1

$$var(T) \geq \frac{[\frac{d}{d\mu} \tau(\mu)]^2}{I_n(\theta)} = \frac{[\frac{d}{d\mu} \mu]^2}{\frac{n}{9}} = \frac{9}{n}$$

- (b) Is the maximum likelihood estimator of  $\mu$  a uniformly minimum variance unbiased estimator? Justify your answer. Find the MLE of  $\mu$

$$\begin{aligned}\frac{d}{d\mu} \log[f(X_1, \dots, X_n; \mu)] &= \frac{d}{d\mu} \log\left[\prod_{i=1}^n \frac{1}{\sqrt{18\pi}} \exp\left\{-\frac{(X_i - \mu)^2}{18}\right\}\right] = \frac{d}{d\mu} \sum_{i=1}^n \log\left(\frac{1}{\sqrt{18\pi}}\right) - \sum_{i=1}^n \frac{(X_i - \mu)^2}{18} \\ &= 0 - \sum_{i=1}^n \frac{-2(X_i - \mu)}{18} = \sum_{i=1}^n \frac{X_i}{9} - \sum_{i=1}^n \frac{\mu}{9} = \sum_{i=1}^n \frac{X_i}{9} - \frac{n\mu}{9}\end{aligned}$$

Set equal to 0

$$\sum_{i=1}^n \frac{X_i}{9} - \frac{n\hat{\mu}}{9} = 0 \Rightarrow \sum_{i=1}^n \frac{X_i}{9} = \frac{n\hat{\mu}}{9} \Rightarrow \sum_{i=1}^n X_i = n\hat{\mu} \Rightarrow \hat{\mu} = \frac{1}{n} \sum_{i=1}^n X_i$$

Check the second derivative

$$\frac{d}{d\mu} \sum_{i=1}^n \frac{X_i}{9} - \frac{n\mu}{9} = -\frac{n}{9} < 0$$

Since this is strictly less than zero  $\hat{\mu}$  must be a maximum  
Professor Lee asked us to check if the MLE is unbiased so

$$E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{1}{n} \sum_{i=1}^n E[X_i] = \frac{n}{n} E[X_i] = \mu$$

Let's try to rearrange the score function in the form  $a(\mu)\left[\frac{1}{n} \sum_{i=1}^n X_i - \mu\right]$

$$\frac{d}{d\mu} \log[f(X_1, \dots, X_n; \mu)] = \sum_{i=1}^n \frac{X_i}{9} - \frac{n\mu}{9} = \frac{n}{9} \left[\frac{1}{n} \sum_{i=1}^n X_i - \mu\right] = a(\mu) \left[\frac{1}{n} \sum_{i=1}^n X_i - \mu\right]$$

Therefore,  $\frac{1}{n} \sum_{i=1}^n X_i$  is a UMVUE of  $\mu$  which obtains the Cramer-Rao Lower Bound.

- (c) Is the MLE of the 95<sup>th</sup> percentile of  $f$  a UMVUE?

$$\int_{-\infty}^{\tau(\mu)} f(a; \mu) da = 0.95$$

Instead of solving this let's use the fact that  $f(a; \mu) \sim N(\mu, 9)$

$$\tau(\mu) = \mu + 4.9344$$

By prop 1

$$T = \tau(\hat{\mu}) = \frac{1}{n} \sum_{i=1}^n X_i + 4.9344$$

Check if T is unbiased

$$E(T) = E\left[\frac{1}{n} \sum_{i=1}^n X_i + 4.9344\right] = \frac{1}{n} \sum_{i=1}^n E[X_i] + 4.9344 = \mu + 4.9344 = \tau$$

Let's try to put the score function in the form  $a(\mu)\left[\left(\frac{1}{n} \sum_{i=1}^n X_i + 4.9344\right) - (\mu + 4.9344)\right]$   
Recall

$$\begin{aligned}\frac{d}{d\mu} \log[f(X_1, \dots, X_n; \mu)] &= \sum_{i=1}^n \frac{X_i}{9} - \frac{n\mu}{9} = \frac{n}{9} \left[\frac{1}{n} \sum_{i=1}^n X_i - \mu\right] = \frac{n}{9} \left[\frac{1}{n} \sum_{i=1}^n X_i + 4.9344 - \mu - 4.9344\right] \\ &= a(\mu) \left[\left(\frac{1}{n} \sum_{i=1}^n X_i + 4.9344\right) - (\mu + 4.9344)\right]\end{aligned}$$

Therefore T is a UMVUE.

### Problem 3

Let  $X_1, \dots, X_n$  be a random sample from a distribution with probability density function  $f(a; \theta) = \theta a^{\theta-1} \mathbb{1}_{(0,1)}(a)$ , where  $\theta > 0$ . Find a function of  $\theta$ , denoted  $\tau(\theta)$ , for which there exists an unbiased estimator whose variance attains the Cramer-Rao lower bound, and determine the uniformly minimum variance unbiased estimator of  $\tau(\theta)$ . First let's show that  $f(a; \theta)$  belongs to the exponential family.

$$\theta a^{\theta-1} \mathbb{1}_{(0,1)}(a) = \mathbb{1}_{(0,1)}(a) \theta \exp\{(\theta - 1) \log(a)\} = h(a) c(\theta) \exp\{t(a) q(\theta)\}$$

Therefore  $f(a; \theta)$  belongs to the exponential family and R1-R3 hold.

Next find the score function.

For  $X_1, \dots, X_n$  in  $(0,1)$

$$\begin{aligned} \frac{d}{d\theta} \log(f(X_1, \dots, X_n; \theta)) &= \frac{d}{d\theta} \log\left(\prod_{i=1}^n \theta X_i^{\theta-1}\right) = \frac{d}{d\theta} \sum_{i=1}^n \log(\theta) + (\theta - 1) \sum_{i=1}^n \log(X_i) \\ &= \frac{d}{d\theta} n \log(\theta) + (\theta \sum_{i=1}^n \log(X_i) - \sum_{i=1}^n \log(X_i)) = \frac{n}{\theta} + \sum_{i=1}^n \log(X_i) \\ &= -n \left[ -\frac{1}{n} \sum_{i=1}^n \log(X_i) - \frac{1}{\theta} \right] = a(\theta) [T - \tau(\theta)] \end{aligned}$$

Where  $T = -\frac{1}{n} \sum_{i=1}^n \log(X_i)$  and  $\tau(\theta) = \frac{1}{\theta}$

By theorem 2  $T$  is an UMVUE of  $\tau(\theta)$  if  $T$  is unbiased

Let's check if  $T$  is unbiased

$$E(T) = E\left[-\frac{1}{n} \sum_{i=1}^n \log(X_i)\right] = -\frac{1}{n} \sum_{i=1}^n E[\log(X_i)]$$

Find  $E[\log(X_i)]$

$$E[\log(X_i)] = \int_0^1 \log(a) \theta a^{\theta-1} da = \theta \int_0^1 \log(a) a^{\theta-1} da$$

Let  $u = \log(a) du = a^{-1} da dv = a^{\theta-1} v = \theta^{-1} a^{\theta}$  Then

$$\theta \int_0^1 \log(a) a^{\theta-1} da = \theta \left[ \log(a) \theta^{-1} a^{\theta} \right]_0^1 - \int_0^1 \theta^{-1} a^{\theta} a^{-1} da = 0 - \theta \theta^{-1} \int_0^1 a^{\theta-1} da = -\frac{1}{\theta} a^{\theta} \Big|_0^1 = \frac{-1}{\theta}$$

Thus

$$E(T) = -\frac{1}{n} \sum_{i=1}^n E[\log(X_i)] = -\frac{1}{n} \sum_{i=1}^n \left(-\frac{1}{\theta}\right) = \frac{1}{\theta}$$

Therefore,  $T$  is an unbiased UMVUE for  $\frac{1}{\theta}$