

# MA582 Homework UC

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## 1 Problem 1

Suppose a parameter family has parameter  $\theta = E(X^3)$ , where  $\theta$  is real. Devise an estimator of  $\theta$  and show it is UC for  $\theta$ .

*Solution.* Let  $Y_n = X_n^3$  and consider

$$\hat{\theta}_n = \frac{Y_1 + \cdots + Y_n}{n} = \frac{X_1^3 + \cdots + X_n^3}{n}.$$

This estimator is unbiased for  $\theta$  because

$$E(\hat{\theta}_n) = \frac{1}{n} \sum_{i=1}^n E(Y_i) = \frac{1}{n} \sum_{i=1}^n \theta = \theta.$$

This estimator is consistent for  $\theta$  because the weak law of large numbers gives

$$\hat{\theta}_n = \frac{Y_1 + \cdots + Y_n}{n} \xrightarrow{p} \theta.$$

□

## 2 Problem 2

We say the rv  $X$  has the Weiner distribution with parameter  $\theta > 0$  if  $X$  has pdf  $f(x) = 2x/\theta^2$  for  $0 < x < \theta$  and  $f(x) = 0$  elsewhere.

Consider the parameterized Weiner family  $\{W(\theta) : \theta > 0\}$ .

- (a) Let  $Y_n$  be the maximum of the random sample of size  $n$  from  $W(\theta)$ . Show that  $Y_n$  is a consistent estimator of  $\theta$ .
- (b) Find the pdf of  $Y_n$ .
- (c) Show that  $Y_n$  is NOT an unbiased estimator of  $\theta$ .

- (d) Show how to “correct”  $Y_n$  here to make a new unbiased estimator  $T_n$ . Show  $T_n$  is also consistent, hence UC.
- (e) Obtain the asymptotic distribution of  $n(\theta - Y_n)$ . [Originally:  $n(Y_n - \theta)$ ]
- (f) Obtain the asymptotic distribution of  $n(\theta - T_n)$ . [Originally:  $n(T_n - \theta)$ ]

*Solution.* If  $X \sim W(\theta)$ , then the cdf of  $X$  satisfies  $F_X(x) = 0$  for  $x < 0$  and  $F_X(x) = 1$  for  $x \geq \theta$ . In between, we calculate

$$F_X(x) = \int_0^x \frac{2t}{\theta^2} dt = \frac{x^2}{\theta^2}.$$

Then, as discussed in class, when  $Y_n = \max(X_1, \dots, X_n)$  we have

$$F_{Y_n}(y) = (F_X(y))^n = \begin{cases} 0 & y < 0, \\ (y/\theta)^{2n} & 0 \leq y < \theta, \\ 1 & y \geq \theta. \end{cases}$$

- (a) Since  $Y_n \leq \theta$ , for any small  $\epsilon > 0$ ,

$$P(|Y_n - \theta| \geq \epsilon) = P(Y_n \leq \theta - \epsilon) = \left(\frac{\theta - \epsilon}{\theta}\right)^{2n} = \left(1 - \frac{\epsilon}{\theta}\right)^{2n}.$$

As  $n \rightarrow \infty$ , the right hand side tends to 0. As  $\epsilon > 0$  was arbitrary,  $Y_n \xrightarrow{p} \theta$ .

- (b) The pdf of  $Y_n$  is

$$f_{Y_n}(y) = F'_{Y_n}(y) = \frac{2n}{\theta^{2n}} \cdot y^{2n-1}$$

when  $0 < y < \theta$ , with  $f_{Y_n}(y) = 0$  for all other  $y$ .

- (c) The expected value of  $Y_n$  is

$$\begin{aligned} E(Y_n) &= \int_0^\theta y \cdot f_{Y_n}(y) dy = \int_0^\theta \frac{2n}{\theta^{2n}} y^{2n} dy \\ &= \frac{2n}{(2n+1)\theta^{2n}} \cdot \theta^{2n+1} = \frac{2n}{2n+1} \cdot \theta. \end{aligned}$$

In particular, this is not  $\theta$  itself, so  $Y_n$  is not an unbiased estimator for  $\theta$ .

- (d) If we define  $T_n = \frac{2n+1}{2n} Y_n$ , then

$$E(T_n) = \frac{2n+1}{2n} E(Y_n) = \theta,$$

so  $T_n$  is an unbiased estimator for  $\theta$ . Also, since  $\frac{2n+1}{2n} \rightarrow 1$  and  $Y_n \xrightarrow{p} \theta$  as  $n \rightarrow \infty$ , another “preservation of convergence in probability” result gives us

$$T_n = \frac{2n+1}{2n} Y_n \xrightarrow{p} 1 \cdot \theta = \theta.$$

Thus  $T_n$  is consistent for  $\theta$  and hence UC for  $\theta$ .

(e) When  $t < 0$ , we have  $P(n(\theta - Y_n) \leq t) = 0$ . Otherwise, for all  $n$  sufficiently large ( $n\theta > t$ ),

$$\begin{aligned} P(n(\theta - Y_n) \leq t) &= P\left(Y_n \geq \theta - \frac{t}{n}\right) = 1 - P\left(Y_n \leq \theta - \frac{t}{n}\right) \\ &= 1 - \left(\frac{\theta - t/n}{\theta}\right)^{2n} = 1 - \left(1 - \frac{t/\theta}{n}\right)^{2n}. \end{aligned}$$

As  $n \rightarrow \infty$ , this tends to  $1 - e^{-2t/\theta}$ , so the asymptotic distribution of  $n(\theta - Y_n)$  has CDF

$$t \mapsto \begin{cases} 0 & t < 0, \\ 1 - e^{-2t/\theta} & t \geq 0. \end{cases}$$

This is the  $\text{Exp}(2/\theta)$  distribution.

(f) We start by writing

$$n(\theta - T_n) = n(\theta - Y_n) + n(Y_n - T_n) = n(\theta - Y_n) - \frac{1}{2}Y_n.$$

Since  $n(\theta - Y_n) \xrightarrow{\mathcal{D}} \text{Exp}(2/\theta)$  and  $Y_n \xrightarrow{P} \theta$ , Slutsky's lemma tells us that

$$n(\theta - T_n) \xrightarrow{\mathcal{D}} \text{Exp}\left(\frac{2}{\theta}\right) - \frac{\theta}{2},$$

the  $\text{Exp}(2/\theta)$  distribution shifted a constant amount  $\theta/2$  to the left.

□