

# MTH211A: Theory of Statistics

## Problem set 3

### Part I: Completeness and Ancillarity

- Show that the following families are not complete:
  - Poisson distribution with parameter  $\theta$ , where  $\theta \in \{0, 1\}$ .
  - The family of distribution of  $(\bar{X}, S_n^2)$ , when  $\{X_1, \dots, X_n\}$  is a random sample from normal distribution with mean  $\theta$  and  $\theta^2$ .
  - Uniform distribution supported on  $(-\theta, \theta)$  where  $\theta > 0$ .

[Hint: To show a distribution is not complete, you need to find a function  $g$  such that  $E_\theta(g(T)) = 0$ , but  $P(g(T) = 0) < 1$ .]
- Find a complete-sufficient statistic for  $\theta$  (or  $\boldsymbol{\theta} = (\theta_1, \theta_2)^\top$ ) when  $X_1, \dots, X_n$  are random samples from each of the following distributions:
  - $X$  has the pdf  $f_X(x) = 2x\theta^{-1}$ , with  $0 < x < \theta$  and  $\theta > 0$ .
  - $X$  has the pdf  $f_X(x) = e^{(x-\theta)} \exp[-\exp\{-(x-\theta)\}]$ , with  $x \in \mathbb{R}$  and  $\theta \in \mathbb{R}$ .
  - The distribution of  $X_{(1)}$  when  $X$  is distributed as location exponential family (see PS2) with parameter  $\theta$ .
  - Inverse Gaussian distribution with parameters  $(\theta_1, \theta_2)$  (see PS2).
- For a  $\text{Normal}(\mu, \sigma^2)$  population with  $\sigma^2$  known, show that  $\bar{X}$  and  $S_n^2$  are independent, where  $S_n^2$  is the sample variance.
- The random variable  $X$  takes 3 values 0, 1, 2 according to one of the following distributions:

	$P(X = 0)$	$P(X = 1)$	$P(X = 2)$	Range of $p$
Distribution 1	$p$	$3p$	$(1 - 4p)$	$(0, 0.25)$
Distribution 2	$p$	$p^2$	$(1 - p - p^2)$	$(0, 0.50)$

In each case determine if the family of distributions is complete.

- Let  $X_1, \dots, X_n$  be  $n$  random samples from some distribution with mean  $\mu$  and finite variance  $\sigma^2$ .
  - Show that both  $T_1 = (X_1 - X_2)^2/2$  and  $T_2 = S_n^{*2}$  are unbiased for  $\sigma^2$ .
  - Show that both  $X_1$  and  $\bar{X}_n$  are unbiased estimators of  $\mu$ . Is the statistic  $T(\mathbf{X}) = E(X_1 \mid \bar{X}_n = \bar{x})$  unbiased for  $\mu$ ?
- Let  $Y_1$  and  $Y_2$  be two independent unbiased estimators of  $\theta$ . Assume that variance of  $Y_1$  is twice the variance of  $Y_2$ . Find the constants  $k_1$  and  $k_2$  so that  $k_1 Y_1 + k_2 Y_2$  is an unbiased estimator of  $\theta$  with smallest possible variance for such a linear combinations.

7. Consider a random sample  $X_1, \dots, X_n$  which belongs to a location-scale family of the form

$$X_i = \theta_1 + \theta_2 W_i, \quad i = 1, \dots, n,$$

where  $W_i$ s are iid with the common pdf (or pmf)  $f_W$ , free of  $(\theta_1, \theta_2)$ .

- (a) What property should a statistic  $S(\cdot)$  would satisfy so that it becomes ancillary for both  $\theta_1$  and  $\theta_2$ ?
- (b) Using part (a), show that for a random sample of size  $n$  from  $\text{Normal}(\mu, \sigma^2)$ , the distribution of  $S_i(\mathbf{X}) = (X_i - \bar{X})/S_n$  is independent of  $\bar{X}_n$ .
8. Let  $X_1, \dots, X_n$  be a random sample from  $\text{Exponential}(\theta)$  distribution. Show that the statistics

$$T_1(\mathbf{X}) = \frac{X_1 + X_2}{\sum_{i=1}^n X_i} \quad \text{and} \quad T_2(\mathbf{X}) = \sum_{i=1}^n X_i$$

are independent.

9. Show that  $Y = |X|$  is a complete sufficient statistic for  $\theta > 0$ , where  $X$  is a random sample ( $n = 1$ ) from a  $\text{Uniform}(-\theta, \theta)$  distribution,  $\theta > 0$ . Further, show that  $Y$  is independent of  $Z = \text{sign}(X)$ .

## Part II: UMVUE

10. Let  $X$  follows some distribution with p.m.f. as follows:

$$f_X(-1; \theta) = \theta, \quad f_X(x; \theta) = \theta^x(1 - \theta)^2, \quad x = 0, 1, \dots, \quad \text{and} \quad f_X(x; \theta) = 0 \quad \text{otherwise, } 0 < \theta < 1.$$

Show that  $T$  is an unbiased estimator of 0 (based on a sample  $X$ ) iff  $T(x) = -xT(-1)$  for each  $x = 0, 1, \dots$

11. Show that if  $T_j$  is the UMVUE of  $g_j(\theta)$  for  $j = 1, \dots, k$ , then  $\sum_{j=1}^k c_j T_j$  is the UMVUE of  $\sum_{j=1}^k c_j g_j(\theta)$  for real constants  $c_1, \dots, c_k$ .
12. Let  $X_1, \dots, X_n$  be i.i.d. samples from the following distributions. In each case, find the UMVUE of  $\theta$ .
- (a) **Bernoulli**( $p$ ), where (i)  $\theta = p(1 - p)$ , (ii)  $\theta = P(X_1 + \dots + X_5 = k)$ , and  $k$  is a positive integer less than or equal to 5, (iii)  $\theta = p + (1 - p)e^2$ .
- (b) **Uniform**( $0, \alpha$ ) and  $\theta = \alpha^k$  where  $k$  is an integer bigger than  $-n$ .
- (c) **Location – scale Exponential**( $\mu, \sigma$ ) with p.d.f.

$$f_{\mathbf{X}}(x; \mu, \sigma) = \begin{cases} \sigma^{-1} \exp\{-\sigma^{-1}(x - \mu)\} & x > \mu, \\ 0 & \text{otherwise,} \end{cases}$$

and (i)  $\theta = \mu$  when  $\sigma$  is known, (ii)  $\theta = \sigma$  when  $\mu$  is known, (iii)  $\theta = \mu$  when  $\sigma$  is unknown, (iv)  $\theta = \sigma$  when  $\mu$  is unknown.

[Hint: For the part (iii) and (iv), use the fact that  $\mathbf{T}(\mathbf{X}) = (X_{(1)}, \sum_{i=1}^n X_i)$  is complete-sufficient for  $(\mu, \sigma)$ ]

- (d) **Normal**( $\mu, \sigma^2$ ), (i)  $\theta = \exp\{2\mu\}$  when  $\sigma^2$  is known, (ii)  $\theta = \mu^2$ , (iii)  $\theta = \sigma^p$ , where  $p > 0$ .
- (e) **Negative Binomial**( $r, p$ ) distribution with p.m.f.

$$f_X(x) = \begin{cases} \binom{x+r-1}{r-1} p^r (1-p)^x, & x = 0, 1, \dots, \\ 0 & \text{otherwise,} \end{cases}$$

and  $\theta = p^{-2}$  when  $r$  is known.

13. Let  $X_1, \dots, X_n$  be a random sample from  $\text{Normal}(\theta, \theta^2)$  distribution. Show that  $\bar{X}_n$  can not be the UMVUE of  $\theta$ .
14. Let  $X_1, \dots, X_n$  be independent samples from a Gaussian polynomial regression model such that  $X_i \sim N(\alpha t_i + \beta t_i^2, 1)$  where  $t_i, i = 1, \dots, n$  are known constants. Find UMVUE of  $\alpha$  and  $\beta$ .
15. Let  $Y_i, i = 1, \dots, n$  be the order statistics of a random sample of size  $n = 2m + 1$  from  $\text{Uniform}(0, \theta)$  distribution. Show that,  $T = 2Y_m$  is an unbiased estimator of  $\theta$ . Find the UMVUE of  $\theta$  by Rao-Blackwellizing  $T$ .
16. Let  $W_1, \dots, W_k$  be unbiased estimators of a parameter  $\theta$  with known variances  $\text{var}(W_i) = \sigma_i^2, i = 1, \dots, k$ . Find the best unbiased estimator of  $\theta$  of the form  $\sum_{i=1}^k a_i W_i$ .
17. Suppose that when the radius of a circle is measured, a random error is made, which is modeled as  $N(0, \sigma^2)$ . If  $n$  repeated independent measurements are made, then find an unbiased estimator of area of the circle. Is it the UMVUE?
18. For a random sample of size  $n$  from the  $\text{Poisson}(\lambda)$  distribution, find  $E(S_n^{*2} | \bar{X}_n)$ .
19. Consider a random sample of size  $n$  from the  $\text{Binomial}(m, p)$  distribution, where  $m$  is known. Find the UMVUE of  $p(1-p)^{m-1}$ .
20. Consider the  $\text{Normal}(\mu, \sigma^2)$  distribution.
  - (a) Among the estimators  $S_n^2$  and  $S_n^{*2}$  of  $\sigma^2$ , which one has a lower MSE?
  - (b) Among the estimators  $S_n^2$  and  $S_n^{*2}$  of  $\sigma^2$ , which is the UMVUE? Why?
  - (c) Find the value of  $c > 0$  for which the class of estimators  $S_c(\mathbf{X}) = c \sum_{i=1}^n (X_i - \bar{X})^2$  has the lowest MSE.

### Part III: CRLB

21. Let  $X_1, \dots, X_n$  are i.i.d. samples from the following distribution. Find the Cramér Rao lower bound of variance of the estimators  $T(\mathbf{X})$ :
  - (a)  $\text{Gamma}(\alpha, \beta)$  and  $T(\mathbf{X}) = \bar{X}_n$ , when  $\alpha$  is known.
  - (b)  $\text{Normal}(\mu, \sigma^2)$  and (i)  $T(\mathbf{X}) = n^{-1} \sum_{i=1}^n |X_i - \bar{X}_n|$  when  $\mu$  is known, (ii)  $T(\mathbf{X}) = \bar{X}_n^2 - \sigma^2/n$  when  $\sigma$  is known.
22. Show that for a scale family with scale parameter  $\theta$  the Fisher information is of the form  $c/\theta^2$ . Further, show that the Fisher information of  $\xi = \log(\theta)$  is free of  $\theta$ .
23. Let  $X_1, \dots, X_n$  be an i.i.d. sample from the following distributions. In each case, find the Fisher information matrix,  $\mathbf{I}_n(\boldsymbol{\theta})$ , for the parameter  $\boldsymbol{\theta}$ :
  - (a)  $\text{Gamma}(\alpha, \beta)$  and  $\boldsymbol{\theta} = (\alpha, \beta)$ .
  - (b)  $\text{Normal}(\mu, \sigma^2)$  and  $\boldsymbol{\theta} = (\alpha, \beta)$ .

[Note: The Fisher information matrix for a vector valued parameter  $\boldsymbol{\theta}$  is defined as

$$\mathbf{I}_n(\boldsymbol{\theta}) = E \left[ \left( \frac{\partial}{\partial \boldsymbol{\theta}} \log f_{\mathbf{X}}(\mathbf{X}; \boldsymbol{\theta}) \right) \left( \frac{\partial}{\partial \boldsymbol{\theta}} \log f_{\mathbf{X}}(\mathbf{X}; \boldsymbol{\theta}) \right)^{\top} \right] = -E \left[ \left( \frac{\partial^2}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}^{\top}} \log f_{\mathbf{X}}(\mathbf{X}; \boldsymbol{\theta}) \right) \right]$$

- (c) From the above definition of  $\mathbf{I}_n(\boldsymbol{\theta})$  show that, when  $X_1, \dots, X_n$  are i.i.d., then  $\mathbf{I}_n(\boldsymbol{\theta}) = n\mathbf{I}_1(\boldsymbol{\theta})$ , where  $\mathbf{I}_1(\boldsymbol{\theta})$  is the Fisher information matrix for one sample.

24. Let  $X_1, \dots, X_n$  be a random sample from **Gamma** $(\alpha, \beta)$  distribution with  $\alpha$  known, and  $T = \sum_{i=1}^n X_i$ . Show that

$$E(X_{(1)} | T) = T \frac{E(X_{(1)})}{E(T)}.$$

25. Let  $X_1, \dots, X_n$  be a random sample from **Normal** $(0, \theta)$  distribution.

(a) Find UMVUE of  $\sqrt{\theta}$ .

(b) Is the UMVUE an efficient estimator of  $\sqrt{\theta}$ ?

26. Let  $X \sim \text{Beta}(\alpha, 2)$  distribution, show that

$$E(\log X) = \frac{\Gamma'(\alpha + 2)}{\Gamma(\alpha + 2)} - \frac{\Gamma'(\alpha)}{\Gamma(\alpha)}, \quad \text{where } \Gamma'(u) = \frac{\partial}{\partial u} \Gamma(u).$$