

**Midterm exam, Statistical Inference I: Date 11/6 (2015 Fall): [+30points]**

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**Q1 [+4].** Let  $X_1, \dots, X_n \stackrel{iid}{\sim} U(0, \theta)$

1) [+1] Find a sufficient statistic for  $\theta$  [with proof].

**Ans:**

$$\begin{aligned} f(x_1, \dots, x_n) &= \prod_{i=1}^n f_i(x_i) = \prod_{i=1}^n \frac{1}{\theta} I(0 < x_i < \theta) \\ &= \frac{1}{\theta^n} I(0 < x_1, \dots, x_n < \theta) \\ &= \frac{1}{\theta^n} I(0 < x_{(1)}) I(x_{(n)} < \theta) \\ &= g_\theta(T) h(x), \end{aligned}$$

where  $g_\theta(x) = \frac{1}{\theta^n} I(x < \theta)$ ,  $h(x) = I(0 < x_{(1)})$  and  $T = x_{(n)}$ .

By the factorization criterion,  $T = X_{(n)}$  is sufficient statistics for  $\theta$ .

2) [+3] Prove that the statistic is complete and minimal for  $\theta$ .

**Ans:**

By 1),  $T = X_{(n)}$  is sufficient statistics for  $\theta$ .

Since

$$\begin{aligned} F_T(t) &= \Pr(T \leq t) = \Pr(X_{(n)} \leq t) \\ &= \Pr(X_1, \dots, X_n \leq t) = \Pr(X_1 \leq t)^n \\ &= \left(\frac{t}{\theta}\right)^n, \quad 0 < t < \theta. \end{aligned}$$

Then

$$f_T(t) = \frac{d}{dt} F_T(t) = \frac{nt^{n-1}}{\theta^n}, \quad 0 < t < \theta.$$

Therefore, if  $E_\theta[f(T)] = 0$ , for all  $\theta$ , we have

$$\begin{aligned} \int_0^\theta f(t) \frac{nt^{n-1}}{\theta^n} dt &= 0 \Rightarrow \int_0^\theta f(t) t^{n-1} dt = 0 \\ &\Rightarrow \int_0^\theta \{f^+(t) - f^-(t)\} t^{n-1} dt = 0 \\ &\Rightarrow \int_0^\theta f^+(t) t^{n-1} dt = \int_0^\theta f^-(t) t^{n-1} dt \end{aligned}$$

$$\begin{aligned}
&\Rightarrow \frac{d}{d\theta} \int_0^\theta f^+(t) t^{n-1} dt = \frac{d}{d\theta} \int_0^\theta f^-(t) t^{n-1} dt \\
&\Rightarrow f^+(\theta) \theta^{n-1} = f^-(\theta) \theta^{n-1} \\
&\Rightarrow f^+(\theta) = f^-(\theta) \\
&\Rightarrow f(\theta) = 0, \text{ for all } \theta \\
&\Rightarrow f(t) = 0, \text{ for all } t.
\end{aligned}$$

Hence we obtain if  $E_\theta[f(T)] = 0$ , for all  $\theta \Rightarrow f(t) = 0$ , for all  $t$ .

Therefore,  $T = X_{(n)}$  is complete and minimal for  $\theta$ .

**Q2 [+4].** Let  $X_1, \dots, X_n \stackrel{iid}{\sim} p_\theta(x)$ , where the density (w.r.t. the counting measure) is

$$p_\theta(x) = \binom{n}{x} \theta^x (1-\theta)^{n-x}, \quad x = 0, 1, \dots, n \quad 1 > \theta > 0.$$

1) Express the density as the canonical form (specify all the components).

**Ans:**

$$\begin{aligned} f(x_1, \dots, x_n) &= \prod_{i=1}^n f_i(x_i) = \prod_{i=1}^n \binom{n}{x_i} \theta^{x_i} (1-\theta)^{n-x_i} \\ &= \prod_{i=1}^n \binom{n}{x_i} \theta^{\sum_{i=1}^n x_i} (1-\theta)^{n^2 - \sum_{i=1}^n x_i} \\ &= \left( \frac{\theta}{1-\theta} \right)^{\sum_{i=1}^n x_i} (1-\theta)^{n^2} \prod_{i=1}^n \binom{n}{x_i} \\ &= \exp \left\{ \sum_{i=1}^n x_i \log \left( \frac{\theta}{1-\theta} \right) + n^2 \log(1-\theta) \right\} \prod_{i=1}^n \binom{n}{x_i} \\ &= \exp \{ \eta_1(\theta) T_1(x) - A(\eta) \} h(x) \end{aligned}$$

is the canonical form, where

$$\begin{aligned} \eta_1(\theta) &= \log \left( \frac{\theta}{1-\theta} \right), \quad T_1(x) = \sum_{i=1}^n x_i, \quad A(\eta) = -n^2 \log(1 + e^\eta), \quad h(x) = \prod_{i=1}^n \binom{n}{x_i} \\ \mathcal{X} &= \{0, 1, \dots, n\} \times \dots \times \{0, 1, \dots, n\} \quad \text{and} \quad \Theta = \{ \eta_1 \mid \eta_1 > 0 \}. \end{aligned}$$

2) Find a complete and sufficient statistics (with proof).

**Ans:**

By 1),

$$f(x_1, \dots, x_n) = \exp \{ \eta_1(\theta) T_1(x) - A(\eta) \} h(x).$$

Since the natural parameter space  $\Theta = \{ \eta_1 \mid \eta_1 > 0 \}$  contains an one-dimensional open rectangle (e.g.,  $(1, 2) \in \Theta$ ). Hence it is full rank.

Since it is full rank,  $T_1(x) = \sum_{i=1}^n x_i$  is a complete and sufficient statistics.

**Q3 [+12]** Let  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\xi, \sigma^2)$ , where  $\theta = (\xi, \sigma^2)$ .

1) [+3] Let  $\delta = \frac{n-1}{n} S^2$ , where  $S^2$  is the sample variance, be an estimator of  $\sigma^2$ . Derive the risk  $R(\theta, \delta)$  under the squared error loss.

**Ans:**

Since

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{df=1}^2.$$

Therefore, we have

$$E(S^2) = \sigma^2 \quad \text{and} \quad \text{var}(S^2) = \frac{2\sigma^4}{n-1}.$$

Thus, the risk  $R(\theta, \delta)$  under the squared error loss is

$$\begin{aligned} R(\theta, \delta) &= E\left\{\left(\frac{n-1}{n}S^2 - \sigma^2\right)^2\right\} = E\left\{\left(\frac{n-1}{n}S^2 - \left(\frac{n-1}{n}\right)\sigma^2 + \left(\frac{n-1}{n}\right)\sigma^2 - \sigma^2\right)^2\right\} \\ &= E\left\{\left(\frac{n-1}{n}(S^2 - \sigma^2) - \frac{\sigma^2}{n}\right)^2\right\} = \left(\frac{n-1}{n}\right)^2 E(S^2 - \sigma^2)^2 + \frac{\sigma^4}{n^2} \\ &= \left(\frac{n-1}{n}\right)^2 \text{var}(S^2) + \frac{\sigma^4}{n^2} = \left(\frac{n-1}{n}\right)^2 \frac{2\sigma^4}{n-1} + \frac{\sigma^4}{n^2} \\ &= \frac{2\sigma^4(n-1) + \sigma^4}{n^2} = \frac{2n\sigma^4 - \sigma^4}{n^2}. \end{aligned}$$

2) [+3] Verify that the above risk is smaller or larger than the risk of  $\delta' = S^2$ .

**Ans:**

The risk  $R(\theta, \delta')$  under the squared error loss is

$$R(\theta, \delta') = E(S^2 - \sigma^2)^2 = \text{var}(S^2) = \frac{2\sigma^4}{n-1}.$$

Compare  $R(\theta, \delta)$  and  $R(\theta, \delta')$

$$\begin{aligned} R(\theta, \delta') - R(\theta, \delta) &= \frac{2\sigma^4}{n-1} - \frac{2n\sigma^4 - \sigma^4}{n^2} \\ &= \frac{2n^2\sigma^4 - 2n^2\sigma^4 + 2n\sigma^4 + n\sigma^4 - \sigma^4}{(n-1)n^2} \\ &= \frac{3n\sigma^4 - \sigma^4}{(n-1)n^2} > 0. \end{aligned}$$

Hence

$$R(\theta, \delta') > R(\theta, \delta).$$

3) [+6] Let  $\bar{X} = \sum_{i=1}^n X_i / n$  and  $\delta = (\bar{X})^2$  be an estimator of  $\xi^2$ . Derive the risk  $R(\theta, \delta)$  under the squared error loss.

**Ans:**

Since

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \Rightarrow \bar{X} \sim N(\xi, \sigma^2).$$

Therefore,

$$\begin{aligned} \frac{\bar{X} - \xi}{\sigma / \sqrt{n}} &\sim N(0, 1) \\ \Rightarrow \left( \frac{\bar{X} - \xi}{\sigma / \sqrt{n}} \right)^2 &\sim \chi_{df=1}^2 \\ \Rightarrow \frac{n}{\sigma^2} (\bar{X} - \xi)^2 &\sim \chi_{df=1}^2 \\ \Rightarrow \frac{n}{\sigma^2} (\bar{X}^2 + \xi^2 - 2\xi\bar{X}) &\sim \chi_{df=1}^2. \end{aligned}$$

Hence

$$\begin{aligned} E \left\{ \frac{n}{\sigma^2} (\bar{X}^2 + \xi^2 - 2\xi\bar{X}) \right\} &= 1 \\ \Rightarrow E(\bar{X}^2) + \xi^2 - 2\xi^2 &= \frac{\sigma^2}{n} \\ \Rightarrow E(\bar{X}^2) &= \xi^2 + \frac{\sigma^2}{n} \end{aligned}$$

and

$$\begin{aligned} \text{var} \left\{ \frac{n}{\sigma^2} (\bar{X}^2 + \xi^2 - 2\xi\bar{X}) \right\} &= 2 \\ \Rightarrow \text{var}(\bar{X}^2 - 2\xi\bar{X}) &= \frac{2\sigma^4}{n^2} \\ \Rightarrow \text{var}(\bar{X}^2) + 4\xi^2 \text{var}(\bar{X}) &= \frac{2\sigma^4}{n^2} \\ \Rightarrow \text{var}(\bar{X}^2) + \frac{4\xi^2\sigma^2}{n} &= \frac{2\sigma^4}{n^2} \\ \Rightarrow \text{var}(\bar{X}^2) &= \frac{2\sigma^4}{n^2} - \frac{4\xi^2\sigma^2}{n}. \end{aligned}$$

Thus,

$$\begin{aligned}R(\theta, \delta) &= E\left\{\bar{X}^2 - \left(\xi^2 + \frac{\sigma^2}{n}\right) + \frac{\sigma^2}{n}\right\}^2 \\&= E\left\{\bar{X}^2 - \left(\xi^2 + \frac{\sigma^2}{n}\right)\right\}^2 + \frac{\sigma^4}{n^2} \\&= \text{var}(\bar{X}^2) + \frac{\sigma^4}{n^2} \\&= \frac{3\sigma^4}{n^2} - \frac{4\xi^2\sigma^2}{n}.\end{aligned}$$

**Q4 [+10]**

[+7] State and prove Basu's Theorem

**Ans:**

Basu's Theorem

If  $T$  is a complete sufficient statistics for  $\theta$  and  $V$  is ancillary for  $\theta$ .

Then  $T \perp V$ .

**Proof:**

Let

$$P_A = \Pr_{\theta}(V \in A)$$

Since  $V$  is ancillary for  $\theta$ , we have

$$P_A = \Pr(V \in A).$$

Let

$$\eta_A(t) = \Pr(V \in A | T = t), \quad t \in \{\text{support of } T\}.$$

Then,

$$P_A = \Pr(V \in A) = E_{\theta}[P(V \in A | T)] = E_{\theta}[\eta_A(T)].$$

Hence

$$E_{\theta}[\eta_A(T) - P_A] = 0, \quad \text{for all } \theta.$$

By the definition of completeness,

$$\eta_A(t) - P_A = 0, \quad \text{for all } t \in \{\text{support of } T\}$$

$$\Rightarrow \eta_A(t) = P_A$$

$$\Rightarrow \Pr(V \in A | T = t) = \Pr(V \in A)$$

$$\Rightarrow T \perp V.$$

[+3] State how the sufficiency is used in the proof.

**Ans:**

Since

$$X \perp Y$$

$$\Leftrightarrow \Pr(X \in A, Y \in B) = \Pr(X \in A)\Pr(Y \in B), \quad \text{for all } A, B$$

$$\Leftrightarrow \frac{\Pr(X \in A, Y \in B)}{\Pr(Y \in B)} = \Pr(X \in A), \quad \text{for all } A, B$$

$$\Leftrightarrow \Pr(X \in A | Y \in B) = \Pr(X \in A), \quad \text{for all } A, B.$$

Hence

$$X \perp Y \Leftrightarrow \Pr(X \in A | Y \in B) = \Pr(X \in A), \quad \text{for all } A, B.$$