

## STAT 610: Discussion 1

### 1 Summary

- Minimal sufficient statistics

- Definition: A statistic  $T(\mathbf{X})$  is minimal sufficient if for any other sufficient statistics  $T'(\mathbf{X})$ ,  $T(\mathbf{x})$  is a function of  $T'(\mathbf{x})$ .
- Theorem 6.2.13.  $T(\mathbf{X})$  is minimal sufficient for  $\boldsymbol{\theta}$  if  $T$  has the property that

$$T(\mathbf{x}) = T(\mathbf{y}) \Leftrightarrow \frac{f(\mathbf{x}|\boldsymbol{\theta})}{f(\mathbf{y}|\boldsymbol{\theta})} \text{ does not depend on } \boldsymbol{\theta}.$$

- Theorem 6.6.5. See lecture 3.

- In the case of exponential families

Let  $X_1, \dots, X_n$  be i.i.d. from an exponential family with pdf

$$f_{\boldsymbol{\theta}}(x) = h(x)c(\boldsymbol{\theta}) \exp\{\boldsymbol{\eta}(\boldsymbol{\theta})^T \mathbf{T}(x)\},$$

where  $\boldsymbol{\eta}(\boldsymbol{\theta})^T = (w_1(\boldsymbol{\theta}), \dots, w_k(\boldsymbol{\theta}))$ , and  $\mathbf{T}(x)^T = (t_1(x), \dots, t_k(x))$ . Then,

- $T(\mathbf{X}) = (\sum_{i=1}^n t_1(X_i), \dots, \sum_{i=1}^n t_k(X_i))$  is a sufficient statistic for  $\boldsymbol{\theta}$ .
- $T(\mathbf{X}) = (\sum_{i=1}^n t_1(X_i), \dots, \sum_{i=1}^n t_k(X_i))$  is also minimal sufficient if the parameter space contains an open set in  $\mathbb{R}^k$ .

- Ancillary statistics

- Definition:  $U(\mathbf{X})$  is ancillary of  $\theta$  if the distribution of  $U$  does not depend on  $\theta$ .

- Complete statistics

- Definition:  $T(\mathbf{X})$  is complete if  $T$  has the property that

$$\mathbb{E}_{\theta}g(T) = 0 \text{ for any measurable } g \text{ and } \theta \Rightarrow g(T) = 0 \text{ a.s.}$$

- Basu's Theorem: Complete sufficient statistics and ancillary statistics for parameter  $\theta$  are independent for all  $\theta$ .

## 2 Questions

1. Let  $(X_1, \dots, X_n)$  be a random sample from density  $\theta^{-1}e^{-(x-\theta)/\theta}I_{(\theta, \infty)}(x)$ , where  $\theta > 0$  is an unknown parameter.

- (a) Find a statistic that is minimal sufficient for  $\theta$ .
- (b) Show whether the minimal sufficient statistic in (a) is complete.

2. Let  $X$  be a discrete random variable with

$$\mathbb{P}_\theta(X = x) = \frac{\binom{\theta}{x} \binom{N-\theta}{n-x}}{\binom{N}{n}}, \quad x = 0, 1, 2, \dots, \min\{\theta, n\}, n - x \leq N - \theta$$

where  $n$  and  $N$  are known positive integers,  $N \geq n$ , and  $\theta = 0, 1, \dots, N$ . Show that  $X$  is complete.

3. (a) If  $\frac{X}{Y}$  and  $Y$  are independent random variables, show that

$$\mathbb{E}\left(\frac{X}{Y}\right)^k = \frac{\mathbb{E}(X^k)}{\mathbb{E}(Y^k)}.$$

- (b) Use Basu's theorem to show that if  $X_1, \dots, X_n$  are iid  $\text{gamma}(\alpha, \beta)$ , where  $\alpha$  is known, then for  $T = \sum_{j=1}^n X_j$

$$\mathbb{E}(X_{(i)}|T) = \mathbb{E}\left(\frac{X_{(i)}}{T}T|T\right) = T \frac{\mathbb{E}(X_{(i)})}{\mathbb{E}T}$$

4. Let  $(X_1, \dots, X_n)$ ,  $n \geq 2$ , be a random sample from a distribution having density  $f_{\theta,j}$ , where  $\theta > 0$ ,  $j = 1, 2$ ,  $f_{\theta,1}$  is the density of  $\mathcal{N}(0, \theta^2)$ , and  $f_{\theta,2}(x) = (2\theta)^{-1}e^{-|x|/\theta}$ . Show that  $T = (T_1, T_2)$  is minimal sufficient for  $(\theta, j)$ , where  $T_1 = \sum_{i=1}^n X_i^2$  and  $T_2 = \sum_{i=1}^n |X_i|$ .

Q1

$$(a) X_1, \dots, X_n \sim \text{Exp}(\theta, \theta)$$

$$f(X|\theta) = \prod_{i=1}^n \frac{1}{\theta} \exp\left\{-\frac{X_i - \theta}{\theta}\right\} \mathbb{1}_{\{X_i > \theta\}}$$

$$= \theta^{-n} \exp\left\{-\frac{\sum X_i - n\theta}{\theta} + n\right\} \prod \mathbb{1}_{\{X_i > \theta\}}$$

$$= \theta^{-n} \exp\left\{-\frac{\sum X_i}{\theta} + n\right\} \mathbb{1}_{\{X_{(1)} > \theta\}}$$

By F-T  $\Rightarrow \{\sum X_i, X_{(1)}\}$  is sufficient.

(Thm. 6.2.13)

Given  $X \neq Y$ .

$$\frac{f(X|\theta)}{f(Y|\theta)} = \exp\left\{-\frac{(\sum X_i - \sum Y_i)}{\theta}\right\} \frac{\mathbb{1}_{\{X_{(1)} > \theta\}}}{\mathbb{1}_{\{Y_{(1)} > \theta\}}}$$

• If  $\sum X_i = \sum Y_i$  &  $X_{(1)} = Y_{(1)}$ ,  $\frac{f(X|\theta)}{f(Y|\theta)}$  is indep of  $\theta$ .

• If  $\frac{f(X|\theta)}{f(Y|\theta)}$  is indep of  $\theta$ ,

we can see  $\sum X_i = \sum Y_i$  &  $X_{(1)} = Y_{(1)}$

(b) Complete or not first order.

Find an not trivial ancillary statistics.

$$E \sum_{i=1}^n (X_i - \theta) = n\theta \quad (\because X_i - \theta \sim \text{Exp}(\theta))$$

$$\Rightarrow E(\sum X_i) = n\theta$$

$$\underline{X_{(1)} - \theta \sim \text{Exp}(\theta, \frac{\theta}{n})}$$

$$\text{So } E(X_{(1)} - \theta) = \frac{\theta}{n} \Rightarrow E(\underline{X_{(1)}}) = \left(1 + \frac{1}{n}\right)\theta$$

$$E \left[ \underbrace{\frac{\sum_{i=1}^n X_i - \frac{2n}{(1+\frac{1}{n})} X_{(1)}}{11}}_{\parallel} \right] = 0 \quad \text{for all } \theta.$$

$$g(\sum X_i, X_{(1)})$$

But  $g$  is not zero.

So,  $(\sum X_i, X_{(1)})$  is not complete statistics for  $\theta$ .

$$X_1, \dots, X_n \sim \text{Exp}(\theta)$$

$$P(X_{(1)} > t) = P(X_i > t)^n$$

Q<sub>2</sub>:

Let  $h(\theta) = \sum_{x=0}^{\min(\theta, n)} g(x) \frac{\binom{\theta}{x} \binom{N-x}{n-x}}{\binom{n}{x}}$

Show that  $h(\theta) = 0 \quad \forall \theta$

$$\Rightarrow g(x) = 0 \quad \forall x = 0, 1, \dots, n \}$$

(which can imply  $x$  is complete)

Pf) plug in different  $\theta$ .

Let  $\theta = 0$

$$h(0) = g(0) \frac{\binom{0}{0} \binom{N}{n}}{\binom{N}{n}} = 0 \Rightarrow g(0) = 0$$

Let  $\theta = 1$

$$h(1) = g(0) \cancel{\frac{\binom{1}{0} \binom{N}{n}}{\binom{N}{n}}} + g(1) \frac{\binom{1}{1} \binom{N-1}{n-1}}{\binom{N}{n}} = 0$$
$$\Rightarrow g(1) = 0$$

Continues the procedure

We can get  $g(k) = 0 \quad \forall k = 0, 1, \dots, n \#$

Q3:

a)

$$\frac{X}{Y} \perp\!\!\!\perp Y$$

$$E X^n = E \left( \frac{X}{Y} Y \right)^n = E \left( \frac{X}{Y} \right)^n E Y^n$$

b)  $E[X_{(i)} | T] = T E\left[\frac{X_{(i)}}{T} | T\right]$

If

$$\frac{X_{(i)}}{T} \perp\!\!\!\perp T \quad \Rightarrow \quad T E\left[\frac{X_{(i)}}{T}\right] = T \frac{E[X_{(i)}]}{E T}$$

Claim:  $\frac{X_{(i)}}{T} \perp\!\!\!\perp T$

Pf) It is sufficient to claim

•  $T$  is complete for  $\beta$

$\Rightarrow$

•  $\frac{X_{(i)}}{T}$  is ancillary statistics for  $\beta$ .

\*  $T$  is complete

$$T = \sum_{j=1}^n X_j \sim \text{Gamma}(\alpha, \theta)$$

$$f_T(t) = \frac{1}{P(\alpha) \theta^\alpha} t^{\alpha-1} \exp\{-t/\theta\}$$

which is a exponential family  
full rank  $\Rightarrow T$  is complete.

Then

$$\frac{X_{(i)}/\beta}{T/\beta} = \frac{Y_{(i)}}{\sum_{j=1}^n Y_j}, \text{ where } Y_1, \dots, Y_n \sim \text{Gamma}(\alpha, 1)$$

so  $\frac{X_{(i)}}{T}$  is an ancillary statistics  $\#$

Q4:

$$f(\mathbf{x} | \mathbf{j}, \theta) = \left( \frac{1}{\sqrt{2\pi\theta^2}} \right)^n \exp \left\{ -\frac{\sum x_i^2}{2\theta^2} \right\} \mathbb{1}_{\{j=1\}}$$

$$+ \left( \frac{1}{2\theta} \right)^n \exp \left\{ -\frac{\sum |x_i|}{\theta} \right\} \mathbb{1}_{\{j=2\}}$$

which is a function of  $(\sum x_i^2, \sum |x_i|)$

$\stackrel{FT}{\Rightarrow}$   $(\sum x_i^2, \sum |x_i|)$  is sufficient for  $\theta$  and  $j$

\* Use thm 6.2.13

$$\frac{f(\mathbf{x} | \mathbf{j}, \theta)}{f(\mathbf{y} | \mathbf{j}, \theta)} = \frac{\left( \frac{1}{\sqrt{2\pi\theta^2}} \right)^n \exp \left\{ -\frac{\sum x_i^2}{2\theta^2} \right\} \mathbb{1}_{\{j=1\}} + \left( \frac{1}{2\theta} \right)^n \exp \left\{ -\frac{\sum |x_i|}{\theta} \right\} \mathbb{1}_{\{j=2\}}}{\left( \frac{1}{\sqrt{2\pi\theta^2}} \right)^n \exp \left\{ -\frac{\sum y_i^2}{2\theta^2} \right\} \mathbb{1}_{\{j=1\}} + \left( \frac{1}{2\theta} \right)^n \exp \left\{ -\frac{\sum |y_i|}{\theta} \right\} \mathbb{1}_{\{j=2\}}}$$

which is indep of  $(\theta, j)$

$$\Leftrightarrow (\sum x_i^2, \sum |x_i|) = (\sum y_i^2, \sum |y_i|)$$

So  $(\sum x_i^2, \sum |x_i|)$  is a minimal statistic