

then  $\prod_{i=1}^n I(y_i \in g^*)$  could be part of  $g(T(\underline{z})|\theta)$ , 580 26

Typically  $g^*$  is an interval with endpoints  $a$  and  $b$ , not necessarily finite. For PdFs <sup>and</sup>,

$$\prod_{i=1}^n I[y_i \in [a, b]] = \underbrace{I[a < y_{(1)} \leq y_{(n)} < b]}_{\text{i) use if } a \text{ and } b \text{ are unknown}} = I[a < y_{(1)}] I[y_{(n)} < b]$$

iii) Use either i) or ii) if both  $a$  and  $b$  are known.   
 ii) use if one of  $a$  or  $b$  is unknown

$$\prod_{i=1}^n I(y_i \in [a, b]) = I(a \leq y_{(1)} \leq y_{(n)} \leq b) = I[a \leq y_{(1)}] I[y_{(n)} \leq b]$$

$$\prod_{i=1}^n I[y_i \in (-\infty, b)] = I(y_{(n)} < b)$$

$$\prod_{i=1}^n I(y_i \in [a, \infty)) = I[y_{(1)} \geq a] \quad \text{etc.}$$

ex 4.10  $y_1, \dots, y_n$  iid  $U(\theta_1, \theta_2)$ . Find a suff stat  $T$  for  $(\theta_1, \theta_2)$ .

Soh  $f(\underline{y}) = \prod_{i=1}^n f(y_i) = \prod_{i=1}^n \frac{1}{\theta_2 - \theta_1} I[\theta_1 \leq y_i \leq \theta_2]$

$$= \frac{1}{(\theta_2 - \theta_1)^n} \underbrace{I[\theta_1 \leq y_{(1)} \leq y_{(n)} \leq \theta_2]}_{g(T(\underline{y})|\theta)} \underbrace{h(\underline{y})}_{(1)}$$

So  $T(\underline{y}) = (Y_{(1)}, Y_{(n)})$  by Factorization

If  $\theta_1$  is known,  $f(\underline{y}) = \frac{1}{(\theta_2 - \theta_1)^n} I(Y_{(n)} \leq \theta_2) \underbrace{I[\theta_1 \leq y_{(1)}]}_{g(T(\underline{y})|\theta_2)} \underbrace{h(\underline{y})}_{(2)}$

and  $Y_{(n)}$  is suff for  $\theta_2$ .

If  $\theta_2$  is known,  $f(\underline{y}) = \frac{1}{(\theta_2 - \theta_1)^n} I(\theta_1 \leq y_{(1)}) \underbrace{I(Y_{(n)} \leq \theta_2)}_{g(T(\underline{y})|\theta_2)} \underbrace{h(\underline{y})}_{(3)}$

and  $Y_{(1)}$  is suff for  $\theta_1$ . by Contradiction

See ex's 4.6 - 4.10

26.5

- 16) P114 If  $\underline{T}(\underline{Y})$  is a sufficient statistic for  $\Theta$ , then any statistic  $\underline{S}(\underline{Y})$  that is a one to one function of  $\underline{T}(\underline{Y})$  (so  $\underline{S}(\underline{Y}) = k(\underline{T}(\underline{Y}))$  where  $k$  is one to one) is also a sufficient statistic for  $\Theta$ .

Know

- ex)  $Y_1, \dots, Y_n$  iid  $N(\mu, \sigma^2)$   $\underline{T}(\underline{Y}) = (\sum Y_i, \sum Y_i^2)$  is sufficient for  $(\mu, \sigma^2)$ . So  $\underline{S}(\underline{Y}) = (\bar{Y}, S^2) = \left( \frac{1}{n} \sum Y_i, \frac{1}{n-1} \left( \sum Y_i^2 - n \left( \frac{\sum Y_i}{n} \right)^2 \right) \right)$  is also suff for  $(\mu, \sigma^2)$ .

- 17) P113-4 If  $\underline{m} = \underline{T}(\underline{\Theta})$  is one to one, then the parameter has just been renamed and the distribution of  $Y_1, \dots, Y_n$  is not changed. Hence if  $\underline{T}(\underline{Y})$  is sufficient for  $\underline{\Theta}$ , then  $\underline{T}(\underline{Y})$  is sufficient for  $\underline{m}$ .
- proof  
of  
this

- ex) One to one is crucial: If  $Y_1, \dots, Y_n$  are iid  $N(\mu, \sigma^2)$ , let  $k(\sum Y_i, \sum Y_i^2) \equiv \underline{T}'(\underline{Y})$ . Then  $\underline{T}'(\underline{Y})$  is not sufficient for  $(\mu, \sigma^2)$  since  $\underline{Y} | \underline{T}'(\underline{Y}) \sim \underline{N}_n(\underline{\mu}, \sigma^2 I_n)$  which depends on  $\underline{\Theta} = (\mu, \sigma^2)$ .

(8) Know for final p111 A sufficient statistic  $\underline{T}(Y)$  for  $\underline{\theta}$  is a minimal sufficient statistic for  $\underline{\theta}$  if

$\underline{T}(Y)$  is a function of  $\underline{S}(Y)$  for any other suff stat  $\underline{S}(Y)$ . So

$$\underline{T}(Y) = k_s(\underline{S}(Y)) \text{ for some function } k_s.$$

(9) Mnemonic: if  $y_1, \dots, y_n$  have pdf or pmf  $f(y_1, \dots, y_n | \theta)$  then  
 $\underline{S}(Y) = h(\underline{z})$

$\underline{S}(Y) = Y$  is sufficient by factorization, and  $\underline{T} \equiv \underline{T}(Y)$  is a function of  $\underline{S}$ .

(10) Want to use a minimal sufficient statistic which reduces the data as far as possible without losing information about  $\underline{\theta}$ .

Note:  $\underline{T}_1(Y) = (y_1, \dots, y_n)$  and  $\underline{T}_2(Y) = (y_{(1)}, \dots, y_{(n)})$  are sufficient, but  $\underline{T}_1$  is not a function of  $\underline{T}_2$  for  $n \geq 1$ , so  $\underline{T}_1$  is not minimal suff.

(11) Know p114 Any one to one function of a minimal sufficient statistic is a minimal sufficient statistic.

22) know for final p.112 Suppose statistic 27.5

$I(Y)$  has pdf or pmf  $f(\underline{z}|\theta)$ . Then

$I(Y)$  is a complete sufficient statistic for  $\theta$  if

$$E_{\theta} [g(I(Y))] = 0 \quad \forall \theta \in \mathbb{H}$$

implies that  $P_{\theta} [g(I(Y)) = 0] = 1 \quad \forall \theta \in \mathbb{H}$ .

23) know p.114 Bahadur's theorem Suppose  $k$  does not depend on the sample size  $n$ . Then a  $k$  dimensional complete suff stat  $I(Y)$  is also minimal suff.

24) know (or final) Lehmann Scheffé LSM theorem:

Let iid sample  $\underline{Y}$  have pdf or pmf  $f(\underline{y}|\theta)$ .

Let  $c_{x,y}$  be a constant. If there exists a function  $T(\underline{y})$  such that for any two sample points  $x$  and  $y$ , the ratio  $R(\theta) = \frac{f(x|\theta)}{f(y|\theta)} = c_{x,y} \quad \forall \theta \in \mathbb{H}$

iff  $T(x) = T(y)$ , then  $I(Y)$  is

a minimal sufficient statistic for  $\theta$ .

Note: Want  $R(\theta)$  constant as a function of  $\theta$  iff  $T(x) = T(y)$ .

Actually want  $f(x|\theta) = c_{x,y} f(y|\theta) \quad \forall \theta \in \mathbb{H}$

so ignore  $\theta$  such that  $R_{x,y}(\theta) = 0$ .

But  $R_{x,y}(\theta) = 0$  or  $R_{x,y}(\theta) = \infty$  means  $I$  is not min suff.

25) <sup>11/23</sup> Know Th4.5 Let  $Y_1, \dots, Y_n$  be iid from a  $k$  parameter exp family

$$f(y|\theta) = h(y) c(\theta) \exp[w_1(\theta)t_1(y) + \dots + w_k(\theta)t_k(y)]$$

with natural parameterization

$$\ell(y|\underline{n}) = h(y) b(\underline{n}) \exp(n_1 t_1(y) + \dots + n_k t_k(y)),$$

(As usual, assume  $\mathcal{R} = \{\underline{n} \mid n_i = w_i(\theta), \theta \in \Theta\}$  except for the  $\chi^2_p$  and inverse Gaussian distributions.)

$$\text{Let } \underline{t}(y) = \left( \sum_{i=1}^n t_i(y_i), \dots, \sum_{i=1}^n t_k(y_i) \right) =$$

$\underline{t}(Y_1), \dots, \underline{t}(Y_n)$ . Then  $\underline{t}(Y)$  is minimal sufficient for  $\theta$  and  $\underline{n}$  if the  $n_i = w_i(\theta)$  do not satisfy a linearity constraint.  $\underline{t}(Y)$  is complete sufficient for  $\theta$  and  $\underline{n}$  if  $\mathcal{R}$  contains a  $k$  dimensional rectangle.

26) know (or 4.6 p174) If  $Y_1, \dots, Y_n$  are iid from a KP-REF, then  $\underline{t}(Y)$  is sufficient, minimal sufficient and complete sufficient for  $\theta$  and  $\underline{n}$ .

proof min suff and complete suff follow from Th4.5 since  $\underline{n}$  do not satisfy a linearity constraint and the  $k$ -dim open set  $\mathcal{R}$  contains a  $k$ -dim rectangle

$$\text{Proof of sufficiency } f(\underline{y}|\theta) = \prod_{j=1}^n f(y_j|\theta) =$$

$$\left[ \prod_{j=1}^n h(y_j) \right] \cdot \left[ c(\theta) \right]^n \exp \left[ w_1(\theta) \sum_{j=1}^n t_1(y_j) + \dots + w_k(\theta) \sum_{j=1}^n t_k(y_j) \right]$$

$$h_s(y) \geq 0$$

$$g(\underline{t}(y)|\theta) \geq 0$$

so true by factorization.

proof of min suff for Th 4.5 like Hwb problem

$$R_{\underline{x}, \underline{z}}^{(n)} = \frac{f(\underline{x}/\underline{z})}{f(\underline{y}/\underline{z})} = \frac{\prod_j h(x_j)}{\prod_j h(y_j)} \frac{[b(\underline{m})]^n}{[b(\underline{n})]^n} \frac{\exp\left[\sum_{i=1}^k n_i T_i(\underline{x})\right]}{\exp\left[\sum_{i=1}^k m_i T_i(\underline{y})\right]}$$
$$= \frac{\prod_j h(x_j)}{\prod_j h(y_j)} \exp\left[\sum_{i=1}^k n_i (T_i(\underline{x}) - T_i(\underline{y}))\right]$$

is equal to a constant wrt  $\underline{n}$  iff

$$\sum_{i=1}^k n_i [T_i(\underline{x}) - T_i(\underline{y})] = \sum_{i=1}^k n_i a_i = C_{\underline{x}, \underline{z}}$$

Since the  $n_i$  do not satisfy a linearity constraint,  $R_{\underline{x}, \underline{z}}^{(n)} = C_{\underline{x}, \underline{z}}$  iff all

$a_i = 0$  iff  $T_i(\underline{x}) = T_i(\underline{y})$  iff

$$T(\underline{x}) = T(\underline{y}).$$

So,  $T(\underline{Y})$  is minimal sufficient by LSM.

27] Know Tips for finding a minimal sufficient statistic.

i) Use Factorization to find a candidate suff stat  $\underline{T}$  with  $K$  as small as possible. Check that  $\underline{T}$  is min suff with LSM.

ii) Recognize or prove that the family is a KP-REF and find  $T(\underline{Y})$ .

iii) Recognize or prove that the family is

a K par exp fam (not necessarily REF) 580 29

and a) apply LSM to  $\underline{T}(\underline{Y}) = (\sum_j t_1(Y_j), \dots, \sum_j t_K(Y_j))$

or b) apply Th 4.5 by showing that  $n_1, \dots, n_K$  do not satisfy a linearity constraint.

- iv) If the support depends on unknown parameter  $\theta$ , often  $Y_{(1)}$  and/or  $Y_{(n)}$  will be a component of the min suff stat.
- v) If the family is not an exp family and after factorization  $K=N$ , try LSM on the order statistics  $(Y_{(1)}, \dots, Y_{(n)})$  (often very hard).

ex)  $Y \sim \text{Weibull}(\phi, \lambda)$ . min suff stat is  $(Y_{(1)}, \dots, Y_{(n)})$ . But if  $\phi$  is known

$$f(\underline{y} | \lambda) = \prod_{i=1}^n f(y_i) = \prod_{i=1}^n \frac{\phi}{\lambda} y_i^{\phi-1} e^{-y_i^\phi/\lambda} I(y_i > 0, \underline{y})$$
$$= \left(\frac{\phi}{\lambda}\right)^n \prod_{i=1}^n y_i^{\phi-1} e^{-\frac{1}{\lambda} \sum_{i=1}^n y_i^\phi} \prod_{i=1}^n I(y_i > 0)$$

constant w.r.t  $\lambda$  if  $\phi$  is known

$$\text{so } R_{\underline{x} \underline{y}}(\lambda) = \frac{f(\underline{x} | \lambda)}{f(\underline{y} | \lambda)} = \frac{\prod_{i=1}^n x_i^{\phi-1}}{\prod_{i=1}^n y_i^{\phi-1}} e^{-\frac{1}{\lambda} (\sum x_i^\phi - \sum y_i^\phi)}$$

set  $\underline{x} = \underline{y}$

$$\text{iff } e^{-\frac{1}{\lambda} (\sum x_i^\phi - \sum y_i^\phi)} \equiv c \cdot \lambda \quad \text{iff}$$

$$\sum x_i^\phi = \sum y_i^\phi. \therefore T(\underline{Y}) = \sum_{i=1}^n y_i^\phi \text{ is}$$

min suff by LSM. Note that  $f(y | \lambda)$

$$= \underbrace{y^{\phi-1} I(y > 0)}_{L(y | \lambda)} \underbrace{\frac{\phi}{\lambda}}_{T(y | \lambda)} \exp \left[ \frac{-y^\phi}{\lambda} + \underbrace{\ln y}_{w(y | \lambda)} \right]$$

is a IPREF if  $\phi$  is known. 29.5

So  $T(\underline{Y}) = \sum_{i=1}^n t(Y_i) = \sum_{i=1}^n Y_i^\phi$  is min suff and complete suff.

- 28) In using LSM, it is crucial to treat  $\underline{x}$  and  $\underline{y}$  as constants. The only variable in  $R_{\underline{x}, \underline{y}}(\theta)$  is  $\theta$ .

Analogy  
MLE  
 $L(\theta|\underline{x})$ )

ex)  $f(x) = \frac{\log(\theta)}{\theta-1} \theta^x \quad 0 < x < \infty, \theta > 1$

$$f(x) = \frac{\log(\theta)}{\theta-1} \underbrace{I(x>0)}_{c(\theta)>0} \underbrace{\exp(\log(\theta)x)}_{h(x)\geq 0} \underbrace{\underbrace{w(\theta)}_{\text{constant}}}_{\text{contains 1dim rectangle = interval}} \underbrace{t(x)}_{n=1}$$

$\bar{\eta} = \log(\theta), \theta > 1 \quad \text{so} \quad \mathcal{R} = (0, \infty)$

contains 1dim rectangle = interval

so  $\sum_{i=1}^n X_i$  is complete suff

by Th 4.5.

- 29) Tips for proving  $\mathcal{I}(\underline{Y})$  is complete.

i) Note that  $g$  can depend on  $n$  since  $n$  is known, but  $g$  can't depend on  $(\theta)$ .

ii) If  $\underline{Y}$  is a kP-REF with  $\dim(\mathcal{H}) = k$ , then  $\mathcal{I}(\underline{Y}) = \left( \sum_{j=1}^n t_1(Y_j), \dots, \sum_{j=1}^n t_k(Y_j) \right)$

is complete.

iii) If  $Y_1, \dots, Y_n$  are iid  $\mathcal{U}(\theta_1, \theta_2)$ ,