Ancillary Statistics

Suppose  $X \sim P_{\Theta}, \Theta \in \Theta$ . A statistic is <u>ancillary</u> if its distr. does not depend on  $\Theta$ . More precisely, A statistic S(X) is ancillary for  $\Theta$ if its distr. is the same for all  $\theta \in \Theta$ .

That is,  $P_{\Theta}(S(X) \in A)$  is constant for  $\Theta \in \Theta$  for any set A.

Example:  $X = (X_{1}, \dots, X_{n})$  iid  $N(\mu, \sigma^{2})$ . Let  $s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \overline{x})^2$ . We know (n-1)s2~~ Xn-1 or equivalently  $S^2 \sim \frac{\sigma^2}{n-1} \chi^2_{n-1}$ so that the distn. of s2 depends upon or but not on u. Thus  $s^2$  is ancillary for  $\Theta_1 = \{(\mu_3 \sigma^2): \sigma^2 = \sigma^2 z_3, \sigma^2\}$ but is not ancillary for  $H_z = \{ (\mu, \sigma^2) : \sigma^2 > 0 \}.$ 



## **Examples of Location families:**

- Uniform $(\theta, \theta + 1)$  distributions  $(\theta \in \Theta = \mathbb{R})$  with pdf  $f(x \mid \theta) = I(\theta \le x \le \theta + 1)$ .
- Cauchy location family with pdf

$$f(x \mid \theta) = \frac{1}{\pi (1 + (x - \theta)^2)}$$

•  $N(\mu, \sigma_0^2)$  distributions ( $\mu \in \mathbb{R}$  unknown,  $\sigma^2 = \sigma_0^2$  known)

## **Examples of Scale families:**

- Uniform(0, $\theta$ ) distributions ( $\theta > 0$  unknown) with pdf  $f(x \mid \theta) = \theta^{-1}I(0 \le x \le \theta)$
- Cauchy scale family with pdf

$$f(x \mid \theta) = \frac{1}{\theta \pi \left[1 + (x/\theta)^2\right]}.$$

- $N(0, \sigma^2)$  distributions with  $\sigma^2 > 0$  unknown.
- Exponential( $\beta$ ) distributions ( $\beta > 0$  unknown) with pdf  $f(x \mid \beta) = \beta^{-1} e^{-x/\beta} I(x \ge 0)$ .

## Examples of Location-Scale families:

- Uniform $(\alpha, \beta)$ ,  $-\infty < \alpha < \beta < \infty$  (all uniform distns).
- $N(\mu, \sigma^2)$ ,  $\mu \in \mathbb{R}$ ,  $\sigma^2 > 0$  (all normal distns).

Facts .

(2) If  $\chi = (\chi_1, ..., \chi_n)$  is ind from a SF and  $S(\chi)$  is a <u>scale invariant</u> function,  $\begin{bmatrix} S(c\chi) = S(\chi) \text{ for all } \chi \in \mathbb{R}^n \\ and c > 0 \end{bmatrix}$ 

then S(X) is <u>ancillary</u>.

 $\exists \text{ If } X = (X_{1}, \dots, X_{n}) \text{ is iid from a LSF} \\ \text{ and } S(X) \text{ is } \underline{\text{location-scale invariant}}, \\ \left[ S(a X + b 1) = S(X) \text{ for all} \\ \chi \in \mathbb{R}^{n}, a > 0, b \in \mathbb{R}. \right] \\ \text{ then } S(X) \text{ is } \underline{\text{ancillary}}. \end{cases}$ 

Proofs: Let  $X = (X_1, \dots, X_n)$  be iid  $\sim f(\cdot | \theta)$ and  $Z = (Z_1, \dots, Z_n)$  be iid  $\sim \Psi(\cdot)$ . () Since  $\chi \stackrel{d}{=} Z + \Theta 1$  we have  $P(S(X) \in A) = P(S(Z + \Theta 1) \in A)$ (does not)  $\rightarrow = P(S(Z) \in A)$  $(involve \Theta)$  by location invariance of S. 2) Since  $\chi \stackrel{d}{=} \Theta Z$  we have  $P(S(X) \in A) = P(S(\Theta Z) \in A)$  $= P(S(z) \in A)$ by scale invariance of S.

③ Since × d σZ+µ1 we have
P(S(X)∈A) = P(S(σZ+µ1)∈A)
= P(S(Z)∈A)
by location-scale invariance of S.

Alternate Proof for (3):  $P(S(X) \in A) = P(S(\frac{X - \mu}{2}) \in A)$ since  $S(X) = S(\frac{X-\mu}{2})$ by location-scale invariance of S  $= P(S(Z) \in A)$ since  $\frac{\chi - \mu}{\chi} \stackrel{d}{=} \frac{\chi}{\chi}$ . But this does not depend on  $\theta = (u, \sigma)$ . Since A is arbitrary, this shows that

 $\mathcal{L}(S(X))$  does not depend on  $\Theta$ .

$$\frac{\text{Location Invariant Statistics}}{S(X) = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \overline{X})^2 \text{ is location invariant:}}$$

$$S(X+c) = \frac{1}{n-1} \sum_{i=1}^{n} (X_i + c - (\overline{X}+c))^2 = S(X)$$

$$\text{since the } c^2 s \text{ cancel.}$$

$$\text{Here we are using the fact that}$$

$$\overline{X}(X+c) = \frac{1}{n} \sum_{i=1}^{n} (X_i + c)$$

$$= (\frac{1}{n} \sum_{i=1}^{n} X_i) + c = \overline{X}(X) + c$$

$$\rightarrow S(X) = \sum_{i=1}^{n} |X_i - Median(X)|$$
 is  
location invariant:

$$S(x+c) = \sum_{i=1}^{n} |x_i + c - Median(x+c)|$$
  
= Median(x)+c  
= S(x) since the c's cancel.

 $\rightarrow S(X) = \max X_{i} - \min X_{i} = X_{(n)} - X_{(1)}$ is location invariant:  $S(X+c) = \max(X_{i} + c) - \min(X_{i} + c)$  $= (\max X_{i}) + c - ((\min X_{i}) + c)$ 

= S(X) since the c's cancel  $\rightarrow$  The vector S(X) = $(X_2 - X_{1_9} X_3 - X_{1_9} \cdots X_n - X_1)$ is location invariant by a similar argument. Scale Invariant Statistics  $\rightarrow t = \frac{X-0}{SAIR}$  is scale invariant:  $t(cx) = \frac{c\overline{x}}{cS/Nn} = t(x) \text{ since the } c^{3}s \text{ cancel.}$ Here we have used:  $\overline{X}(c\chi) = \frac{1}{n} \sum_{j=1}^{n} c\chi_{j} = c(\frac{1}{n} \ge \chi_{j})$  $= c \overline{X}(x)$ ,  $S(c\chi) = \sqrt{\frac{1}{n-1}\sum(c\chi_{i}-c\overline{\chi})^{2}}$  $= c \sqrt{\frac{1}{h-1} \sum (\chi_{1} - \overline{\chi})^{2}}$  $= c S(\alpha)$ .





They are both location-scale invariant. It suffices to show : (1) S(ax) = S(x) for a > 0, and (2) S(X+b) = S(X) for all b. Part (2) follows from  $(X_{2}+b) - (\overline{X}+b) = X_{2} - \overline{X}$ . Part (1) follows from  $\sum (cx_1 - c\overline{x})^m = c^m \sum (x_1 - \overline{x})^m$ -> The standardized residuals  $Z = (Z_1, Z_2, \dots, Z_n) \text{ with } Z_2 = \frac{\chi_2 - \chi}{2}$ are location-scale invariant.