

## Statistics 581, Problem Set 9

Wellner; 11/23/2005

**Reading:** Chapter 4, Sections 1-2;

Ferguson, ACLST, Chapter 20, pages 133-139; Chapter 22, pages 144-150;

Lehmann and Casella, Chapter 6, especially section 6.5, pages 461-468.

**Due:** Wednesday, November 30, 2005.

- (a) Lehmann and Casella, Problem 2.13, page 501.  
(b) Let  $R_n(\theta) \equiv nE_\theta(T_n - \theta)^2$  where  $T_n$  is the Hodges superefficient estimator as in Example 3.3.1 (so  $T_n = \delta_n$  of Example 2.5, Lehmann and Casella pages 440 - 443). Show that  $R_n(n^{-1/4}) \rightarrow \infty$  as  $n \rightarrow \infty$ .

- (a) Lehmann and Casella, Problem 6.6, page 142.  
(b) Consider the somewhat more general family

$$\mathcal{P} = \{(1 - \epsilon)\phi(x - \xi) + (\epsilon/\tau)\phi((x - \mu)/\tau) : \theta = (\epsilon, \xi, \mu, \tau) \in [0, 1] \times \mathbb{R} \times \mathbb{R} \times \mathbb{R}^+\}$$

where  $\phi$  is the standard normal density. Is the information matrix for  $(\epsilon, \xi, \mu, \tau)$  in this family always nonsingular? [Hint: what is the relationship of the model  $\mathcal{P}$  in (b) to the model in Lehmann and Casella's problem 5.21, page 139?]

(c) Suppose that  $(X, \Delta) \in \mathbb{R} \times \{0, 1\}$  has distribution given by  $p_\theta(x|\Delta = 0) = \phi(x)$ ,  $p_\theta(x|\Delta = 1) = \phi((x - \mu)/\tau)/\tau$ , and  $\Delta \sim \text{Bernoulli}(\epsilon)$ . Show that the marginal distributions of  $X$  are in the family  $\mathcal{P}$  of part (a). What is the relationship of the information for  $\epsilon$  based on observation of  $(X, \delta)$  to the information for  $\epsilon$  based on observation of  $X$  alone?

- (a) Exercise 2.1.6, page 10, chapter 2 notes.  
(b) Exercise 2.1.7, page 10, chapter 2 notes.
- (a) Lehmann and Casella, problem 6.3.1, page 501.  
(b) Lehmann and Casella, problem 6.3.2, page 501.  
(c) Lehmann and Casella, problem 6.3.4, page 501.
- Consider the Weibull family of example 3.2.5:  $\mathcal{P} = \{P_\theta : \theta \in \Theta\}$  with  $\Theta \subset \mathbb{R}^2$  given by the (Lebesgue) densities

$$p_\theta(x) = \frac{\beta}{\alpha} \left(\frac{x}{\alpha}\right)^{\beta-1} \exp\left(-\left(\frac{x}{\alpha}\right)^\beta\right) 1_{[0, \infty)}(x)$$

where  $\theta \equiv (\alpha, \beta) \in (0, \infty) \times (0, \infty) \subset \mathbb{R}^2$ . Suppose that  $X, X_1, \dots, X_n$  are i.i.d. with density function  $p_\theta$ .

A. If  $X \sim P_\theta \in \mathcal{P}$ , show that the distributions of  $\log X$  form a location and scale family from a Gumbel (extreme value) density on  $\mathbb{R}$ .

B. Use the result of A to construct method of moments estimators or quantile based estimators  $\bar{\theta}_n$  of  $\theta = (\alpha, \beta)$ .

C. Show that the method of moments or quantile estimators  $\bar{\theta}_n$  of  $\theta$  are asymptotically normal, and find the asymptotic distribution; i.e. show that

$$\sqrt{n}(\bar{\theta}_n - \theta) \rightarrow_d N_2(0, \Sigma) \quad \text{for some } \Sigma.$$

[We will use these estimators as “starting points” approximate (or one-step) maximum likelihood estimators in problem set 10.]

6. **Optional bonus problem:** Lehmann and Casella, TPE, problem 6.3.22, page 503, reworded as follows. (In other words, prove (vi) of theorem 1.5, page 5, chapter 4 notes). Suppose that  $X_1, \dots, X_n$  are i.i.d. with density  $p_\theta$ ,  $\theta \in \Theta \subset R^k$ , satisfying the hypotheses of theorem 4.1, page 429 (the Cramér conditions given in (A) - (D) on page 429). Show that the following Local Asymptotic Normality (LAN) result holds for the (local) log-likelihood ratios: with

$$L_n(\theta) \equiv \log\left(\prod_{i=1}^n p_\theta(X_i)\right) = \sum_{i=1}^n \log p_\theta(X_i),$$

for a fixed  $\theta_0 \in \Theta$ ,

$$\begin{aligned} L_n(\theta_0 + n^{-1/2}\underline{t}) - L_n(\theta_0) &= \frac{1}{\sqrt{n}} \sum_{i=1}^n \underline{t}^T \underline{l}_\theta(X_i) - \frac{1}{2} \underline{t}^T I(\theta_0) \underline{t} + o_p(1) \\ &\rightarrow_d N(0, \underline{t}^T I(\theta_0) \underline{t}) - \frac{1}{2} \underline{t}^T I(\theta_0) \underline{t} =_d N\left(-\frac{1}{2} \sigma^2 \sigma^2\right) \end{aligned}$$

under  $P_{\theta_0}$  where  $\sigma^2 \equiv \underline{t}^T I(\theta_0) \underline{t}$ .