

**Solution to BIOS760: 2011 FALL SEMESTER FINAL EXAM**

1. (a) The joint density is given as

$$(2\theta)^{-n}I(|X_1| \leq \theta, \dots, |X_n| \leq \theta) = (2\theta)^{-n}I(|X|_{(n)} \leq \theta).$$

Thus,  $|X|_{(n)}$  is sufficient. Suppose  $E[Q(|X|_{(n)})] = 0$ . Since

$$P(|X|_n \leq x) = x^n/\theta^n I(0 \leq x \leq \theta) + I(x \geq \theta),$$

we have

$$E[Q(|X|_{(n)})] = \int_0^\theta Q(x)nx^{n-1}/\theta^n dx = 0.$$

That is,  $\int_0^\theta Q(x)x^{(n-1)}dx = 0$  so after taking derivatives, we obtain  $Q(\theta) = 0$ . This implies that  $|X|_{(n)}$  is also complete.

- (b) Note that if  $x \leq 0$ ,  $P(n(1 - |X|_{(n)}/\theta) \leq x) = 0$ ; if  $x > 0$ , for  $n$  large enough,

$$P(n(1 - |X|_{(n)}/\theta) \leq x) = P(|X|_{(n)} \geq \theta - \theta x/n) = 1 - (1 - x/n)^n \rightarrow 1 - e^{-x}.$$

We conclude that  $n(1 - |X|_{(n)}/\theta)$  converges in distribution to the exponential distribution.

- (c) Clearly, the MLE for  $\theta$  is  $|X|_{(n)}$ . Thus, the MLE for  $g(\theta)$  is  $g(|X|_{(n)})$ . By the delta method, we obtain

$$n(g(\theta) - g(|X|_{(n)}))/\theta \rightarrow_d g'(\theta)Exp(1).$$

Thus,  $n(g(\theta) - g(|X|_{(n)})) \rightarrow_d \theta g'(\theta)Exp(1)$ . That is, the limiting distribution is the exponential distribution with mean  $\theta g'(\theta)$ . Let  $t_{1-\alpha}$  be the  $(1 - \alpha)$ th quantile of  $Exp(1)$ , i.e.,  $t_{1-\alpha} = -\log(\alpha)$ . Then by estimating  $\theta$  using  $|X|_{(n)}$ , a confidence interval for  $g(\theta)$  is  $[0, g(|X|_{(n)}) + |X|_{(n)}g'(|X|_{(n)})t_{1-\alpha}/n]$ .

- (d) To find the UMVUE, we need to determine  $Q(|X|_{(n)})$  satisfying  $E[Q(|X|_{(n)})] = g(\theta)$ . Equivalently,

$$\int_0^\theta Q(x)nx^{n-1}dx = g(\theta)\theta^n.$$

Taking derivatives on both sides, we obtain

$$Q(x) = g(x) + g'(x)x/n.$$

The UMVUE for  $\theta$  is  $T_n = g(|X|_{(n)}) + g'(|X|_{(n)})|X|_{(n)}/n$ .

- (e) We note

$$n(g(\theta) - T_n) = n(g(\theta) - g(|X|_{(n)})) - g'(|X|_{(n)})|X|_{(n)}.$$

Since the previous result implies that  $|X|_{(n)} \rightarrow_p \theta$ , we obtain from the Slutsky lemma that

$$n(g(\theta) - T_n) \rightarrow_d \theta g'(\theta)Exp(1) - g'(\theta)\theta.$$

A confidence interval for  $g(\theta)$  is  $[0, T_n + |X|_{(n)}g'(|X|_{(n)})t_{1-\alpha}/n - g'(|X|_{(n)})|X|_{(n)}]$ .

2. (a) The conditional density is given as

$$\int_{\xi} e^{\beta X} \xi \exp\{-Y e^{\beta X} \xi\} \Gamma(\lambda)^{-1} \lambda^{\lambda} \xi^{\lambda-1} \exp\{-\lambda \xi\} d\xi = e^{\beta X} (1 + Y e^{\beta X} / \lambda)^{-(\lambda+1)}.$$

Thus, the likelihood function is given as

$$\prod_{i=1}^n \left[ e^{\beta X_i} (1 + Y_i e^{\beta X_i} / \lambda)^{-(\lambda+1)} f(X_i) \right],$$

where  $f(x)$  is the density of  $X$ .

- (b) Assume that  $X$  has a full rank with positive probability. Then  $\beta$  is identifiable since

$$\left[ e^{\beta X_i} (1 + Y_i e^{\beta X_i} / \lambda)^{-(\lambda+1)} f(X_i) \right] = \left[ e^{\beta^* X_i} (1 + Y_i e^{\beta^* X_i} / \lambda)^{-(\lambda+1)} f^*(X_i) \right]$$

leads to  $\beta X_i = \beta^* X_i$ .

- (c) It follows from

$$E[Y|X] = [E[Y|X, \xi]|X] = E[e^{-\beta X} \xi^{-1}|X] = e^{-\beta X} c,$$

where  $c = E[\xi^{-1}] = \lambda/(\lambda - 1)$ . From the results for estimating equation, if  $\tilde{\beta}$  is the solution, then  $\sqrt{n}(\tilde{\beta} - \beta)$  converges in distribution to a normal distribution with mean zero and variance (sandwich formula)

$$E[cX^2 e^{-\beta X}]^{-1} E[X^2 (Y - ce^{-\beta X})^2] E[cX^2 e^{-\beta X}]^{-1}.$$

- (d) The score equation is

$$\sum_{i=1}^n \left[ X_i - \frac{(\lambda + 1) Y_i X_i e^{\beta X_i}}{\lambda + Y_i e^{\beta X_i}} \right] = 0.$$

The Newton-Raphson iteration is

$$\begin{aligned} \beta^{(k+1)} = \beta^{(k)} - \left\{ - \sum_{i=1}^n \frac{(\lambda + 1) Y_i X_i^2 e^{\beta^{(k)} X_i}}{\lambda + Y_i e^{\beta^{(k)} X_i}} + \sum_{i=1}^n \frac{(\lambda + 1) Y_i^2 X_i^2 e^{2\beta^{(k)} X_i}}{(\lambda + Y_i e^{\beta^{(k)} X_i})^2} \right\}^{-1} \\ \times \sum_{i=1}^n \left[ X_i - \frac{(\lambda + 1) Y_i X_i e^{\beta^{(k)} X_i}}{\lambda + Y_i e^{\beta^{(k)} X_i}} \right] = 0. \end{aligned}$$

- (e) The complete log-likelihood function (concerning  $\beta$ ) is

$$\prod_{i=1}^n \left[ e^{\beta X_i} \xi_i \exp\{-Y_i e^{\beta X_i} \xi_i\} \right].$$

Then the M-step solves equation

$$\sum_{i=1}^n \left[ X_i - Y_i e^{\beta X_i} X_i w_i \right] = 0.$$

In the E-step, we calculate  $w_i$  as the conditional expectation of  $\xi_i$  given observed data: since  $\xi|Y_i, X_i$  follows a gamma distribution with parameter  $(1 + \lambda, [Y_i e^{\beta X_i} + \lambda]^{-1})$ ,

$$w_i = E[\xi_i|Y_i, X_i] = (1 + \lambda) / [Y_i e^{\beta X_i} + \lambda].$$