

1. Suppose that  $Y_i$  are independent exponential random variables with  $E(Y_i) = \psi\lambda_i$ , and  $Z_i$  are independent exponential random variables with  $E(Z_i) = \psi/\lambda_i$ ,  $i = 1, \dots, n$ .
  - (a) Show that  $\psi$  is orthogonal to  $\lambda = (\lambda_1, \dots, \lambda_n)$ , with respect to expected Fisher information.
  - (b) Find the maximum likelihood estimates of  $\lambda$  and  $\psi$ .
  - (c) Show that  $\hat{\psi}$  is not consistent for  $\psi$  as  $n \rightarrow \infty$ .
  - (d) Derive the adjusted profile log-likelihood for  $\psi$ :

$$\ell_a(\psi) = \ell_p(\psi) - \frac{1}{2} \log |j_{\lambda\lambda}(\psi, \hat{\lambda}_\psi)|,$$

and find the probability limit of the adjusted maximum likelihood estimator  $\hat{\psi}_a$  obtained by maximizing  $\ell_a(\psi)$ .

2. (Knight, 2000 Ch. 5.6; Owen, 1988). Suppose  $Y_1, \dots, Y_n$  are independent and identically distributed from an unknown distribution function  $F$ . To estimate  $F$  we restrict attention to distributions putting positive probability mass only at the points  $Y_1, \dots, Y_n$ , assumed distinct. Knight defines the non-parametric log-likelihood function for  $F(\cdot)$  as

$$L(p_1, \dots, p_n) = \sum_{i=1}^n \log(p_i), \quad p_i \geq 0, \Sigma p_i = 1,$$

where  $p_i$  is the probability mass at  $Y_i$ .

- (a) Show that  $L(p)$  (or equivalently  $\ell(p) = \log L(p)$ ) is maximized at  $\hat{p}_i = 1/n$ .
- (b) Suppose that  $\mu = E(Y_i) = \int y dF(y)$  is the parameter of interest, with  $F(\cdot)$  as a nuisance parameter. The profile likelihood is obtained by maximizing

$$L(p_1, \dots, p_n), \text{ subject to } p_i \geq 0, \Sigma p_i = 1, \Sigma p_i Y_i = \mu,$$

where there is now an additional constraint on the vector  $p$ . Show that the solution to the maximization problem is given by

$$\hat{p}_i(\mu) = \frac{1}{n} \frac{1}{1 + \lambda(Y_i - \mu)}, \text{ where } \lambda \text{ solves}$$
$$0 = \frac{1}{n} \sum_{i=1}^n \frac{Y_i - \mu}{1 + \lambda(Y_i - \mu)}.$$