## BASIC PHD WRITTEN EXAMINATION IN BIOSTATISTICS

## THEORY, SECTION 1

(9:00 AM- 1:00 PM Tuesday, August 7, 2012)

## **INSTRUCTIONS:**

- a) This is a CLOSED-BOOK examination.
- b) The time limit for this Examination is four hours.
- c) Answer any TWO (2) (BUT ONLY TWO) of the THREE (3) questions that follow.
- d) Put the answers to different questions on separate sets of paper.
- e) Put your exam code, **NOT YOUR NAME**, on each page. The same code will be used for Section 1 and Section 2 of the PhD Theory Exam. Please keep the code confidential and do not share this information with any students or faculty. Sharing your code with either students or faculty is viewed as a violation of the UNC honor code.
- f) Return the examination with a signed statement of the UNC honor pledge, separately from your answers. The pledge statement is given on the last page of the exam handout.
- g) In the questions to follow, you are required to answer only what is asked, and not to tell all you know about the topics involved.

1. Let N be a Poisson random variable with parameter  $\mu$ , and let  $X_1, X_2, \ldots$ , be a sequence of i.i.d. Poisson random variables with parameter  $\lambda$ , where  $0 < \mu, \lambda < \infty$ . Define

$$U = 1(N > 0) \sum_{i=1}^{N} X_i,$$

where 1(A) is the indicator of the event A. Do the following:

- (a) Show that  $E(U) = \mu \lambda$  and  $var(U) = \mu \lambda (1 + \lambda)$ .
- (b) In this part, we add a subscript k to the Poisson parameters  $\mu$  and  $\lambda$  defined above to denote dependence on an integer  $k \geq 1$ . Specifically let  $\mu = \mu_k = k$  and  $\lambda = \lambda_k = h/k$ , where  $0 < h < \infty$  is a fixed scalar. We want to study what happens to U as  $k \to \infty$ . Let  $D_i = 1(X_i = 1)$ , for all  $i \geq 1$ , and define

$$T = 1(N > 0) \sum_{i=1}^{N} D_i.$$

Do the following:

- (i) Derive the limits of E(U) and var(U) as  $k \to \infty$ .
- (ii) Show that  $\operatorname{pr}(X_i \neq D_i) = \lambda_k^2 \{1 + o(\lambda_k)\}$  as  $k \to \infty$ .
- (iii) Show that

$$1(U \neq T) \le 1(N > 0) \sum_{i=1}^{N} 1(X_i \neq D_i);$$

and thus  $U - T \to 0$ , in probability, as  $k \to \infty$ .

- (iv) Show that  $T \sum_{i=1}^k D_i \to 0$ , in probability, as  $k \to \infty$ .
- (v) Show that U converges in distribution to a Poisson random variable with parameter h, as  $k \to \infty$ .
- (c) We now modify the setting in (b) so that  $\mu = \mu_k = h/k$  and  $\lambda = \lambda_k = k$ . Do the following:
  - (i) Derive the limits of E(U) and var(U) as  $k \to \infty$ .
  - (ii) Show that  $U \to 0$  in distribution as  $k \to \infty$ .

- 2. Let  $Y_1, ..., Y_n$  be i.i.d random variables from a distribution with mean  $\mu$  and finite variance. Due to non-response, we may not be able to observe all the  $Y_i$ 's for these n subjects. Let  $R_1, ..., R_n$  denote indicator of response, i.e.,  $R_i = 1$  means that  $Y_i$  observed and  $R_i = 0$  otherwise. Suppose that we also collect additional information  $X_1, ..., X_n$ , which are i.i.d random variables, from these n subjects. Assume that  $R_i$  and  $Y_i$  are independent given  $X_i$  and that the random vectors  $(Y_i, R_i, X_i)$  are i.i.d. for i = 1, ..., n. Define  $\pi(x) = P(R_i = 1 | X_i = x)$  and assume  $\pi(x)$  is known and bounded by a positive constant from below for any x in the support of  $X_i$ .
  - (a) A simple estimator for  $\mu$  is the average of the observed  $Y_i$ 's:

$$\hat{\mu}_1 = \sum_{i=1}^n R_i Y_i / \sum_{i=1}^n R_i.$$

Derive the asymptotic limit of  $\hat{\mu}_1$ , denoted by  $\mu^*$ , and give the asymptotic distribution of  $\sqrt{n}(\hat{\mu}_1 - \mu^*)$ . Leave expressions in the result.

(b) A Horwitz-Thompson estimator for  $\mu$  is given as

$$\hat{\mu}_2 = n^{-1} \sum_{i=1}^n R_i Y_i / \pi(X_i).$$

Show that  $\hat{\mu}_2$  is a consistent estimator for  $\mu$  and derive the asymptotic distribution of  $\sqrt{n}(\hat{\mu}_2 - \mu)$ . Leave expressions in the result.

(c) For any measurable function  $g(X_i)$  with finite second moment, we define

$$\hat{\mu}_g = n^{-1} \left\{ \sum_{i=1}^n R_i Y_i / \pi(X_i) + \sum_{i=1}^n (1 - R_i / \pi_i(X_i)) g(X_i) \right\}.$$

Show that  $\hat{\mu}_g$  is a consistent estimator for  $\mu$  and derive the asymptotic distribution of  $\sqrt{n}(\hat{\mu}_g - \mu)$ . Leave expressions in the result.

- (d) Determine a function g which minimizes the asymptotic variance of  $\hat{\mu}_g$ . Denote this function by  $g^*(x)$ .
- (e) Suppose that  $X_i$  is a discrete random variable with K categories. Suggest a consistent estimator for  $g^*(x)$ , denoted by  $\hat{g}$ . Justify your answer.
- (f) Following (e), derive the asymptotic distribution of  $\sqrt{n}(\hat{\mu}_{\hat{g}} \mu)$ .
- (g) How would you estimate  $g^*$  if  $X_i$  is a continuous variable?

- 3. (a) In this part, let  $T_0$  be an unbiased estimator of an unknown parameter  $\theta$  and consider the properties of  $T_0$  under squared error loss.
  - (i) Show that  $T_0 + c$  is not a minimax estimator under squared error loss, where  $c \neq 0$  is a known constant.
  - (ii) Show that the estimator  $cT_0$  is not minimax under squared error loss unless  $\sup_{\theta} R_T(\theta) = \infty$  for any estimator T of  $\theta$ , where  $c \in (0,1)$  is a known constant and  $R_T(\theta)$  is the frequentist risk function for T.
  - (b) In this part, let X=1 or 0 with probabilities p and q respectively, and consider the estimation of p with loss function L(p,a) equal to 1 when  $|a-p| \ge 0.25$  and equal to 0 otherwise. The most general randomized estimator is  $T_0 = U$  when X = 0 and  $T_0 = V$  when X = 1, where U and V are two random variables with known distributions.
    - (i) Evaluate the risk function and the maximum risk of  $T_0$  when U and V are uniform on (0,0.5) and (0.5,1), respectively.
    - (ii) Is  $T_0$  is minimax? Justify your answer rigorously.
  - (c) In this part, one has a sample of n iid normal random variables with mean  $\theta$  and variance  $\sigma^2, X_1, \ldots, X_n$ .
    - (i) Assume  $0 < \sigma^2 < K$  is known, where K is a finite positive constant. Is the sample mean  $\overline{X}$  minimax with respect to the loss function  $L(\theta, a) = \{\theta a\}^2/\sigma^2$ ? Justify your answer rigorously.
    - (ii) Redo part (i) without assuming  $\sigma^2$  is known.

## 2012 PhD Theory Exam, Section 1

	of the honor code, $I$ certify that $I$ have $d$ that $I$ will report all Honor Code viola	Ü
(Signed)	NAME	
(Printed)	NAME	

Statement of the UNC honor pledge: