## B Math III, Second Semester, March 09, 2007, Midterm

Answer any six questions. All questions carry equal weight.

1. (a). Suppose that  $X_n \xrightarrow{p} X$  and  $Y_n \xrightarrow{p} Y$ . Show that if f(x, y) is a continuous function, then

$$f(X_n, Y_n) \xrightarrow{p} f(X, Y)$$
.

(b). If in addition P(Y = 0) = 0, then show that

$$\frac{X_n}{Y_n} \xrightarrow{p} \frac{X}{Y}.$$

2. Suppose that  $\xi_1, \xi_2, \dots$  are independent and identically distributed random variables such that  $E[\xi_1] = \mu$  and  $E[\xi_1^2] < \infty$ . Define random variables recursively

$$X_k = \rho X_{k-1} + \xi_k, \ k \ge 1, \ \text{and} \ X_0 = 0$$

where

$$|\rho| < 1.$$

Let

$$\overline{X}_n = \frac{1}{n} \sum_{k=1}^n X_k.$$

(a). Show that

$$E\left[\overline{X}_n\right] \to \frac{\mu}{1-\rho}$$

and for any  $l \geq 0$ ,

Cov 
$$(X_{k+l}, X_k) = \rho^l (1 + \rho^2 + \dots + \rho^{2k-2}).$$

(b). Show that

$$\overline{X}_n = \frac{1}{n} \sum_{k=1}^n X_k \xrightarrow{p} \frac{\mu}{1-\rho}.$$

3 Let  $(X_1, ..., X_n)$  be a random sample with a common mean  $\mu$  and a common variance  $\sigma^2$ . Suppose that g(y) is differentiable such that

$$g'(\mu) \neq 0,$$

where  $g'(\mu)$  is the first derivative of g(y) at  $y = \mu$ . Recall that this means, if we let  $R(\mu, h)$  to be such that  $g(\mu + h) - g(\mu) - hg'(\mu) = hR(\mu, h)$ , then

$$\sup_{0 < |h| \le \varepsilon} |R(\mu, h)| \to 0 \text{ as } \varepsilon \to 0.$$

(a). Show that  $R\left(\mu, \left(\overline{X}_n - \mu\right)\right) \xrightarrow{p} 0$  and  $\sqrt{n}\left(\overline{X}_n - \mu\right) R\left(\mu, \left(\overline{X}_n - \mu\right)\right) \xrightarrow{p} 0$ .

(b). Using (a), show that  $\sqrt{n} \left( g\left(\overline{X}_n\right) - g\left(\mu\right) \right)$  converges in distribution to a normal distribution with mean 0 and variance  $\sigma^2 \left( g'\left(\mu\right) \right)^2$ .

(If you are applying CLT in (a) and/or (b), explain.)

(c). Let  $S_n$  be binomially distributed with parameters n and  $p, 0 . Deduce from part (b) that <math>\sqrt{n}\left(\left(\frac{S_n}{n}\right)^2 - p^2\right)$  converges in distribution to a normal distribution. Give the explicit expression for the variance of the limiting normal distribution.

4. (a). Show that if the random vector  $\mathbf{V} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_k - \boldsymbol{\phi} \boldsymbol{\phi}')$  where  $\mathbf{I}_k$  is a unit matrix of order k and  $\boldsymbol{\phi}' = (\sqrt{\pi_1}, ..., \sqrt{\pi_k})$  with  $\pi_j > 0, j = 1, ..., k$ , and  $\pi_1 + ... + \pi_k = 1$ , then the quadratic  $\mathbf{V'V}$  has a  $\chi^2(k-1)$  distribution with k-1 degrees of freedom.

(b). Consider a multinomial population with k (mutually exclusive) outcomes, with the corresponding probabilities  $\pi_1, ..., \pi_k$ . We have a random sample of size n from this population. Let  $N_j$  = the number of times the *j*th outcome occurs in the sample, j = 1, ..., k. Define

$$\chi_n^2 = \sum_{j=1}^k \frac{\left(N_j - n\pi_j\right)^2}{n\pi_j}.$$

Show that, when  $\pi_1, ..., \pi_k$  are the true population probabilities,  $\chi_n^2$  converges in distribution to a  $\chi^2 (k-1)$  distribution with k-1 degrees of freedom.

5. The population is as in question 4 (b). For testing the simple null hypothesis

$$\pi_1 = \pi_{10}, \quad , \pi_{k-1} = \pi_{k-1,0},$$

consider the likelihood ratio statistic

$$\lambda_n = \frac{l_n\left(\boldsymbol{\pi}_0\right)}{\sup_{\boldsymbol{\pi}} l_n\left(\boldsymbol{\pi}\right)},$$

where  $\boldsymbol{\pi} = (\pi_1, ..., \pi_k)'$  and

$$l_n\left(\boldsymbol{\pi}\right) = \pi_1^{N_1} \dots \pi_k^{N_k}$$

with  $N_j$  as defined in question 4 (b) based on a random sample of size n.

- (a). Show that  $\sup_{\boldsymbol{\pi}} l_n(\boldsymbol{\pi}) = l_n(\widehat{\boldsymbol{\pi}}_n)$  where  $\widehat{\boldsymbol{\pi}}_n = \left(\frac{N_1}{n}, \dots, \frac{N_k}{n}\right)'$ .
- (b). Show that, under the null hypothesis

$$-2\log\lambda_n - \sum_{j=1}^k \frac{\left(N_j - n\pi_{j0}\right)^2}{n\pi_{j0}} \xrightarrow{p} 0$$

6. Consider two discrete populations with respective cell probabilities  $\pi_1 = (\pi_{11}, ..., \pi_{1k})$  and  $\pi_2 = (\pi_{21}, ..., \pi_{2k})$ . Define the column vectors

$$\phi_1 = (\sqrt{\pi_{11}}, ..., \sqrt{\pi_{1k}})', \qquad \phi_2 = (\sqrt{\pi_{21}}, ..., \sqrt{\pi_{2k}})'$$

Let the vector  $\mathbf{V}_1$  be k-variate normal with mean vector  $\mathbf{0}$  and variance-covariance matrix  $\mathbf{I}_k - \phi_1 \phi'_1$ . Similarly let  $\mathbf{V}_2$  be k-variate normal with mean vector  $\mathbf{0}$  and variance-covariance matrix  $\mathbf{I}_k - \phi_2 \phi'_2$ . Assume that  $\mathbf{V}_1$  and  $\mathbf{V}_2$  are independent.

Let

$$\mathbf{V} = \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \end{bmatrix} = (\mathbf{V}_1', \mathbf{V}_2')',$$

and

$$oldsymbol{\phi} = \left[ egin{array}{cc} oldsymbol{\phi}_1 & oldsymbol{0} \ oldsymbol{0} & oldsymbol{\phi}_2 \end{array} 
ight]_{2k imes 2}.$$

Then

(a). Show that **V** is 2*k*-variate normal with mean vector **0** and variancecovariance matrix  $\mathbf{I}_{2k} - \phi \phi'$ .

(b). Show that if the quadratic  $\mathbf{V}'\mathbf{CV}$  is such that

 $\mathbf{C}^2 = \mathbf{C}$  and  $\mathbf{C}\boldsymbol{\phi} = \boldsymbol{\phi}$ ,

then  $\mathbf{V'CV}$  has a  $\chi^{2}(l)$  distribution with the degrees of freedom l given by

$$l = \operatorname{Rank}\left(\mathbf{C}\right) - 2$$

(c). Generalize the preceding two population situation to the case of m populations.

7 Consider two multinomial populations, each with the same number of outcomes or cells, with respective cell probabilities  $\pi_1 = (\pi_{11}, ..., \pi_{1k})$  and  $\pi_2 = (\pi_{21}, ..., \pi_{2k})$ . We want to test the null hypothesis

$$(\pi_{11},...,\pi_{1k}) = (\pi_{21},...,\pi_{2k}) = (\pi_1,...,\pi_k)$$
, say.

Suppose that we have a sample of size  $n_1$  from the first population, and denote the corresponding sample frequencies by  $N_{11}, ..., N_{1k}$ . Similarly, let  $N_{21}, ..., N_{21k}$ be the sample frequencies corresponding to the sample of size  $n_2$  from the second population.

An appropriate Chi-squared statistic is

$$\chi_n^2 = \sum_{j=1}^k \frac{(N_{1j} - n_1 \widehat{\pi}_j)^2}{n_1 \widehat{\pi}_j} + \sum_{j=1}^k \frac{(N_{2j} - n_2 \widehat{\pi}_j)^2}{n_2 \widehat{\pi}_j}$$

where

$$\widehat{\pi}_j = \frac{N_{1j} + N_{2j}}{n_1 + n_2}$$

(a). Assuming for simplicity that  $n_1 = n_2 = n$ , show that  $\chi_n^2$  has asymptotically a  $\chi^2 (k-1)$  with k-1+k-1-k=k-1 degrees of freedom.

(b). Generalize the preceding parts (a) to the situation of m populations, and show that the resulting  $\chi_n^2$  statistic will have asymptotically a  $\chi^2(l)$  with l = (m-1)(k-1) degrees of freedom.