

UNIVERSITY OF MASSACHUSETTS  
Department of Mathematics and Statistics  
ADVANCED EXAM - "Mathematical Statistics" and Probability  
Monday, August 25, 2008

Work all problems. 70 points are required to pass with at least 25 from each part ("Linear models/Multivariate = questions 1 and 2; Probability = questions 3-5).

1. (30 PTS) Suppose that  $\mathbf{X}$  ( $p \times 1$ ) has a multivariate normal distribution with mean  $\boldsymbol{\mu}$  and covariance matrix  $\boldsymbol{\Sigma}$ , (written  $\mathbf{X} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ ) where  $\boldsymbol{\Sigma}$  is assumed to be non-singular.

- (a) Write down the density of  $\mathbf{X}$  and then prove that the moment generating function of  $\mathbf{X}$  is

$$M(\mathbf{t}) = e^{\mathbf{t}'\boldsymbol{\mu} + (\mathbf{t}'\boldsymbol{\Sigma}\mathbf{t}/2)}.$$

- (b) Prove using moment generating functions that  $\mathbf{a} + \mathbf{B}\mathbf{X}$  is distributed as a  $q$  dimensional multivariate normal distribution with mean  $\mathbf{a} + \mathbf{B}\boldsymbol{\mu}$  and covariance matrix  $\mathbf{B}\boldsymbol{\Sigma}\mathbf{B}'$ , where  $\mathbf{a}$  is a  $q \times 1$  vector of constants and  $\mathbf{B}$  a  $q \times p$  matrix of constants.
- (c) Show how you can linearly transform  $\mathbf{X}$  to  $\mathbf{Z}$  such that  $\mathbf{Z} \sim N(\mathbf{0}, \mathbf{I})$ , where  $\mathbf{Z}$  is  $p \times 1$ ,  $\mathbf{0}$  is a  $p \times 1$  vector of 0's and  $\mathbf{I}$  is the  $p \times p$  identity matrix.
- (d) Let  $\mathbf{A}$  be a  $p \times p$  matrix and define  $Q = \mathbf{X}'\mathbf{A}\mathbf{X}$ . Find  $E(Q)$ , expressing your answer in the simplest way you can as a function of  $\boldsymbol{\mu}$ ,  $\boldsymbol{\Sigma}$  and  $\mathbf{A}$ . Note: Do NOT use the normality of  $\mathbf{X}$  here, but just the fact that  $E(\mathbf{X}) = \boldsymbol{\mu}$  and  $Cov(\mathbf{X}) = \boldsymbol{\Sigma}$ .
- (e) State the definition of a non-central chi-square distribution with  $d$  degrees of freedom and non-centrality parameter  $\lambda$ . Do this not by giving a density function but by explaining how the distribution arises as the distribution of a random variable  $C$ , formed as a function of a suitably defined normal random vector.
- (f) Now return to the assumption that  $\mathbf{X} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$  and state a necessary and sufficient condition on the matrix  $\mathbf{A}$  such that  $\mathbf{X}'\mathbf{A}\mathbf{X}$  is distributed as a non-central chi-square.
- Give the degrees of freedom and non-centrality parameter involved.
  - Prove the sufficiency.

2. (20 PTS) Consider random vectors  $\mathbf{Y}$ ,  $\mathbf{X}$  and  $\mathbf{W}$ . For convenience assume that all are continuous with density functions (so you can use integrals for expectations).

(a) Prove that

i)  $E(\mathbf{Y}) = E_{\mathbf{X}}[E(\mathbf{Y}|\mathbf{X})]$

ii)  $Cov(\mathbf{Y}, \mathbf{W}) = Cov_{\mathbf{X}}[E(\mathbf{Y}|\mathbf{X}), E(\mathbf{W}|\mathbf{X})] + E_{\mathbf{X}}[Cov(\mathbf{Y}, \mathbf{W}|\mathbf{X})]$ .

Two notes. First, The outside expectation is written  $E_{\mathbf{X}}$  to remind you that it is with respect to random  $\mathbf{X}$ . Second, there is nothing that says that  $\mathbf{Y}$  can't be  $\mathbf{W}$  so a special case of ii) is  $Cov(\mathbf{Y}) = Cov_{\mathbf{X}}[E(\mathbf{Y}|\mathbf{X})] + E_{\mathbf{X}}[Cov(\mathbf{Y}|\mathbf{X})]$ .

(b) Now suppose that  $Y$  is a random variable with (unconditional) mean  $\mu_Y$  and variance  $\sigma_Y^2$ ,  $\mathbf{X}$  is  $p \times 1$  with  $E(\mathbf{X}) = \boldsymbol{\mu}_X$ ,  $Cov(\mathbf{X}) = \boldsymbol{\Sigma}_X$  (assumed non-singular) and  $Cov(\mathbf{X}, Y) = \boldsymbol{\sigma}_{XY}$  ( $p \times 1$ ). It is assumed that

$$E(Y|\mathbf{X} = \mathbf{x}) = \beta_0 + \beta_1' \mathbf{x}$$

and  $V(Y|\mathbf{X} = \mathbf{x}) = \sigma^2$ ; this is our usual linear regression model. Use the previous part to PROVE that this assumption implies the following relationships:

i)  $\beta_1 = \boldsymbol{\Sigma}_X^{-1} \boldsymbol{\sigma}_{XY}$

ii)  $\beta_0 = \mu_Y - \beta_1' \boldsymbol{\mu}_X$

iii)  $\sigma^2 = \sigma_Y^2 - \beta_1' \boldsymbol{\Sigma}_X \beta_1$ .

Note: There is no normality assumption here, just assumptions on the moments.

3. (15 PTS) Let  $\{X_n\}$  be a sequence of random variables, and suppose for each  $n$  that  $m_n$  is a median of  $X_n$ , i.e., that

$$P(X_n \geq m_n) \geq \frac{1}{2} \leq P(X_n \leq m_n).$$

Show that if  $X_n \rightarrow 0$  in probability (in measure), then  $m_n \rightarrow 0$ , though  $E(X_n)$  need not converge to zero. Show the latter with a counterexample.

4. (20 PTS) Let  $F(x)$  be a distribution function.

(a) Show that

$$\int_{-\infty}^{\infty} [F(x+c) - F(x)] dx = c,$$

for every real  $c$ .

(b) Show that if  $X$  is a positive random variable then

$$E(X) = \int_{x=0}^{\infty} (1 - F(x)) dx.$$

5. (15 PTS) Show that if  $\phi$  is a real-valued characteristic function, then for all real  $t$ ,

$$2\phi(t)^2 \leq 1 + \phi(2t).$$

**Hint:** Recall that  $2 \cos^2 \theta - 1 = \cos 2\theta$ .