STA 313F2004 Assignment 3

Do this assignment in preparation for the quiz on Friday, Oct. 22. The hand-written parts are practice for the quiz, and are not to be handed in. The computer part (last question) may be handed in, so bring a printout to the quiz.

- 1. Let **X** and **Y** be random matrices of the same dimensions. Show $E(\mathbf{X} + \mathbf{Y}) = E(\mathbf{X}) + E(\mathbf{Y})$.
- 2. Let X be a random matrix, and B be a matrix of constants. Show E(XB) = E(X)B.
- 3. If the $p \times 1$ random vector **X** has variance-covariance matrix Σ and **A** is an $m \times p$ matrix of constants, prove that the variance-covariance matrix of **AX** is **A** Σ **A**'. Start with the definition of a variance-covariance matrix.
- 4. If the $p \times 1$ random vector **X** has mean $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$, show $\boldsymbol{\Sigma} = E(\mathbf{X}\mathbf{X}') \boldsymbol{\mu}\boldsymbol{\mu}'$.
- 5. Let **X** and **Y** be random matrices such that the product **XY** can be formed, and let all elements of **X** be independent of the elements of **Y**. Prove $E(\mathbf{XY}) = E(\mathbf{X})E(\mathbf{Y})$.
- 6. Let **X** be a $p \times 1$ random vector with mean $\boldsymbol{\mu}_x$ and variance-covariance matrix $\boldsymbol{\Sigma}_x$, and let **Y** be an $r \times 1$ random vector with mean $\boldsymbol{\mu}_y$ and variance-covariance matrix $\boldsymbol{\Sigma}_y$. Define $C(\mathbf{X}, \mathbf{Y})$ by the $p \times r$ matrix $C(\mathbf{X}, \mathbf{Y}) = E\left((\mathbf{X} \boldsymbol{\mu}_x)(\mathbf{Y} \boldsymbol{\mu}_y)'\right)$.
 - (a) What is the (i, j) element of $C(\mathbf{X}, \mathbf{Y})$?
 - (b) Find an expression for $V(\mathbf{X} + \mathbf{Y})$ in terms of Σ_x , Σ_y and $C(\mathbf{X}, \mathbf{Y})$. Show your work.
- 7. Let X_1 be Normal (μ_1, σ_1^2) , and X_2 be Normal (μ_2, σ_2^2) , independent of X_1 . What is the joint distribution of $Y_1 = X_1 + X_2$ and $Y_2 = X_1 X_2$? What is required for Y_1 and Y_2 to be independent?
- 8. Let $\mathbf{X} = (X_1, X_2, X_3)'$ be multivariate normal with

$$\boldsymbol{\mu} = \begin{bmatrix} 1\\0\\6 \end{bmatrix} \text{ and } \boldsymbol{\Sigma} = \begin{bmatrix} 1 & 0 & 0\\0 & 2 & 0\\0 & 0 & 1 \end{bmatrix}.$$

Let $Y_1 = X_1 + X_2$ and $Y_2 = X_2 + X_3$. Find the joint distribution of Y_1 and Y_2 .

9. Let $\mathbf{X}_1, \ldots, \mathbf{X}_n$ be independent $MVN(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ random vectors, and let $\boldsymbol{\Sigma}$ be fixed and *known*. Derive the maximum likelihood estimate of $\boldsymbol{\mu}$. "Derive" means show all the work. Where do you use the fact that $\boldsymbol{\Sigma}^{-1}$ is positive definite? Indicate this clearly.

- 10. Let $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$, where \mathbf{X} is an $n \times p$ matrix of known constants, $\boldsymbol{\beta}$ is a $p \times 1$ vector of unknown constants, and $\boldsymbol{\epsilon}$ is multivariate normal with mean zero and covariance matrix $\sigma^2 \mathbf{I}_n$, with $\sigma^2 > 0$ an unknown constant.
 - (a) What is the distribution of \mathbf{Y} ?
 - (b) It will be assumed that the rank of **X** is p < n, so the maximum likelihood estimate (MLE) of $\boldsymbol{\beta}$ is $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'Y$. You may use this without proof. Given the MLE of $\boldsymbol{\beta}$, find the MLE of σ^2 . Show your work.
 - (c) What is the distribution of $\hat{\boldsymbol{\beta}}$? Show the calculations.
 - (d) Let $\widehat{\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}}$. What is the distribution of $\widehat{\mathbf{Y}}$? Show the calculations.
 - (e) Let the vector of residuals $\mathbf{e} = (\mathbf{Y} \widehat{\mathbf{Y}})$. What is the distribution of \mathbf{e} ? Show the calculations. Simplify!
- 11. Let $\mathbf{X}_1, \ldots, \mathbf{X}_n$ be a random sample from a multivariate normal population with mean $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$. Using the MLEs

$$\widehat{\boldsymbol{\mu}} = \overline{\mathbf{X}} \text{ and } \widehat{\boldsymbol{\Sigma}} = \frac{1}{n} \sum_{i=1}^{n} (\mathbf{X}_i - \overline{\mathbf{X}}) (\mathbf{X}_i - \overline{\mathbf{X}})',$$

derive the large-sample likelihood ratio test G for testing whether the components of the random vectors \mathbf{X}_i are independent. That is, we want to test whether $\boldsymbol{\Sigma}$ is diagonal. If your simplification of -2 log likelihood does not use the trace of a matrix (see lecture notes) you are leaving something out. What are the degrees of freedom for this test?

12. Write an S function to compute the test you derived in the preceding question. The function should return 3 values: G, the degrees of freedom, and the p-value. Run your function on the sample in fourvars.dat; see link to the data on the course web page. Bring a printout showing the definition of your function and illustrating the run on fourvars.dat.