# UNIVERSITY OF MASSACHUSETTS <br> Department of Mathematics and Statistics <br> ADVANCED EXAM - LINEAR MODELS <br> January 15, 2010 

Work all problems. 70 points are needed to pass.

1. (35 points) Suppose that we observe statistically independent observations with the same variance $\sigma^{2}, Y_{i j}$ for $i=1,2$ and $j=1,2$, where $E\left(Y_{i j}\right)$ is modeled as follows:

$$
E\left(Y_{11}\right)=\mu, \quad E\left(Y_{12}\right)=\mu+\gamma, \quad E\left(Y_{21}\right)=\mu+\alpha, \quad E\left(Y_{22}\right)=\mu+\alpha+\gamma
$$

(a) With $\boldsymbol{\beta}=(\mu, \alpha, \gamma)^{\prime}$, present this model in a linear regression form $\mathbf{y}=X \boldsymbol{\beta}+\boldsymbol{\varepsilon}$, and specify $\mathbf{y}, X$, and $\varepsilon$.
(b) What is the rank of $X$ ?, and what will be the d.f. of SSE?
(c) Are $\mu, \alpha$, and $\gamma$ estimable? Give a reason.
(d) Find a least squares (LS) estimate vector $\widehat{\boldsymbol{\beta}}=(\widehat{\mu}, \widehat{\alpha}, \widehat{\gamma})^{\prime}$ for $\boldsymbol{\beta}$, and write each of $\widehat{\mu}, \widehat{\alpha}$ and $\widehat{\gamma}$ explicitely as a linear combination of $Y_{i j}$ 's. You may use

$$
\left(\begin{array}{lll}
4 & 2 & 2 \\
2 & 2 & 1 \\
2 & 1 & 2
\end{array}\right)^{-1}=\left(\begin{array}{ccc}
3 / 4 & -1 / 2 & -1 / 2 \\
-1 / 2 & 1 & 0 \\
-1 / 2 & 0 & 1
\end{array}\right)
$$

(e) Are those LS estimators $\widehat{\mu}, \widehat{\alpha}$ and $\hat{\gamma}$ unique LS estimators for $\mu, \alpha$ and $\gamma$ respectively? Further, are they the best linear unbiased estimators (BLUE) for $\mu, \alpha$ and $\gamma$ respectively? Based on what theorem you make such conclusions?
(f) Find the BLUE for $2 \mu+\gamma$ with explanations.
(g) If $Y_{11}$ is missing (not available), show that each of $\mu, \alpha$ and $\gamma$ is still estimable.
2. (15 points)
(a) Let $\mathbf{Y}$ be a $N_{p}(\boldsymbol{\mu}, \Sigma)$ random vector, where $\Sigma$ is positive definit, and $A$ be a $p \times p$ symmetric matric with rank $k(k \leq p)$. State a complete theorem concerning a necessary and sufficient condition for $\mathbf{Y}^{\prime} A \mathbf{Y}$ to be a chi-square distribution.
(b) Let $U_{1}, \cdots, U_{n}$ be i.i.d. random vectors, where $U_{i}=\left(x_{i}, y_{i}\right)^{\prime}$ has a bivariate normal distribution with mean $\boldsymbol{\mu}=\left(\mu_{1}, \mu_{2}\right)^{\prime}, \operatorname{Var}\left(x_{i}\right)=\operatorname{var}\left(y_{i}\right)=1$, and $\operatorname{Cov}\left(x_{i}, y_{i}\right)=\rho$ with $\rho \neq-1$ or 1 , for $i=1, \ldots, n$. Define

$$
q=n\left(\bar{x}^{2}-2 \rho \overline{x y}+\bar{y}^{2}\right) /\left(1-\rho^{2}\right)
$$

wnere $\bar{x}=\mathbf{1}^{\prime} \mathbf{x} / n$ and $\bar{y}=\mathbf{1}^{\prime} \mathbf{y} / n$ with $\mathbf{x}=\left(x_{1}, \cdots, x_{n}\right)^{\prime}$ and $\mathbf{y}=\left(y_{1}, \cdots, y_{n}\right)^{\prime}$. Show that $q$ has a chi-square distribution, and specify its degrees of freedom and non-centrality parameter. [Hint: Cosider a quadratic form in

$$
\left.\mathrm{z}=\binom{\mathrm{x}}{\mathbf{y}} \cdot\right]
$$

3. (10 points) Consider the simple regression model:

$$
Y_{i}=\beta_{0}+\beta_{1} x_{i}+\varepsilon_{i}, \quad i=1, \ldots, n
$$

where $\varepsilon_{i}$ are independent with $E\left(\varepsilon_{i}\right)=0$, and $\operatorname{Var}\left(\varepsilon_{i}\right)=\sigma^{2} x_{i}^{2}$ (non-uniform variances) with $\sigma^{2}>0$. Find the BLUE for $\beta_{0}$ and $\beta_{1}$, and an unbiased estimator for $\sigma^{2}$. (Note: You may give answers in matrix form, no need to be simplified.)
4. (20 points) Suppose we want to compare two simple linear models:

$$
\begin{aligned}
\text { Model I: } Y_{1 j}=\alpha_{1}+\beta_{1} x_{1 j}+\varepsilon_{1 j}, & j=1,2,3 \\
\text { Model II: } Y_{2 j}=\alpha_{2}+\beta_{2} x_{2 j}+\varepsilon_{2 j}, & j=1,2,3,4
\end{aligned}
$$

where all $\varepsilon_{i j}$ are i.i.d. $\mathrm{N}\left(0, \sigma^{2}\right)$.
(a) As a full model, write the two models in one form $\mathbf{Y}=X \beta+\varepsilon$ and define $\mathbf{Y}, \mathrm{X}, \boldsymbol{\beta}$ and $\varepsilon$. Write down a LS $\widehat{\boldsymbol{\beta}}$ and SSE using these notations.
(b) Suppose we want to test the null hypothesis $H_{0}$ : $\alpha_{1}=\alpha_{2}$ and $\beta_{1}=\beta_{2}$ against the alternative $H_{1}: \alpha_{1} \neq \alpha_{2}$ or $\beta_{1} \neq \beta_{2}$. Explain why $H_{0}$ is a testable linear hypothesis if all matrices need to be inverted are non-singular.
(c) Write down the reduced model (under $H_{0}$ ) in the form $\mathbf{Y}=Z \boldsymbol{\beta}_{0}+\varepsilon_{0}$, and define $\mathbf{Y}$, $\mathrm{Z}, \boldsymbol{\beta}_{0}$ and $\varepsilon_{0}$. Then write down a LS $\widehat{\boldsymbol{\beta}}_{0}$ and $\mathrm{SSE}_{0}$ using these notations.
(d) Write down the test statistic $F$ and specify the criterion for rejecting $H_{0}$ at $5 \%$ level.
5. (10 points) Let $E_{1}, \cdots, E_{k}$ be $k$ events, then we have the Bonferroni inequality:

$$
\left.\operatorname{Pr}\left[\bigcap_{i=1}^{k} E_{i}\right] \geq 1-\sum_{i=1}^{k} \operatorname{Pr}\left[E_{i}^{c}\right]\right]
$$

We want to apply this inequality to construct simultaneous confidence intervals for $k$ contrasts of means. Consider independent $Y_{i j}$ for $i=1,2,3$ and $j=1,2, \ldots, n_{i}$, where $Y_{i j} \sim N\left(\mu_{i}, \sigma^{2}\right)$. Describe how to construct simultaneous confidence intervals for $\mu_{2}-\mu_{1}$ and $\frac{1}{2}\left(\mu_{2}+\mu_{3}\right)-\mu_{1}$ with confidence at least 0.95 . (Note: you need to write down expicit formulae for your notations.)
6. (10 points) Suppose we consider two competing models: $Y=X \beta+\epsilon$ (reduced model) and $Y=X \beta+Z \gamma+\eta$ (full model), where the error vectors ( $\epsilon$ and $\eta$ respectively) follow a $N\left(0, \sigma^{2} \mathbf{I}\right)$ distribution . Discuss how the estimated residuals from the reduced model can be used (through relevant plots) to assess model inadequacy. That is, what can the relevant residual plots reveal when the reduced model is correct and what can they reveal when the full model is correct. In, particular discuss what happens when the the reduced model is a simple linear regression and the full model is a quadratic regression of $Y$ on $X$.

