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Graduate School of Business
 Business 41912, Spring Quarter 2004, Mr. Ruey S. Tsay

Solutions to Midterm

1. This question can be answered following the lecture note or textbook.

- (a) Using the square-root matrix $\Sigma^{1/2}$ such that $\Sigma = \Sigma^{1/2}\Sigma^{1/2}$, we can take the transformation

$$\Sigma^{-1/2}\mathbf{Y} = \Sigma^{-1/2}\mathbf{Z}\boldsymbol{\beta} + \Sigma^{-1/2}\boldsymbol{\epsilon}.$$

Rewrite the above equation as

$$\mathbf{Y}_* = \mathbf{Z}_*\boldsymbol{\beta} + \boldsymbol{\epsilon}_*,$$

where $\boldsymbol{\epsilon}_* = \Sigma^{-1/2}\boldsymbol{\epsilon}$ such that $\text{Cov}(\boldsymbol{\epsilon}_*) = \mathbf{I}$, the identity matrix. Then, the estimate of $\boldsymbol{\beta}$ is

$$\hat{\boldsymbol{\beta}} = (\mathbf{Z}'_*\mathbf{Z}_*)^{-1}\mathbf{Z}'_*\mathbf{Y}_* = (\mathbf{Z}'\Sigma^{-1}\mathbf{Z})^{-1}(\mathbf{Z}'\Sigma^{-1}\mathbf{Y}).$$

The residuals in this case is

$$\hat{\boldsymbol{\epsilon}} = \mathbf{Y} - \hat{\mathbf{Y}} = \mathbf{Y} - \mathbf{Z}\hat{\boldsymbol{\beta}} = (\mathbf{I} - \mathbf{H}_*)\mathbf{Y},$$

where $\mathbf{H}_* = \mathbf{Z}'(\mathbf{Z}'\Sigma^{-1}\mathbf{Z})^{-1}\mathbf{Z}\Sigma^{-1}$. It is easy to show that $E(\boldsymbol{\epsilon}) = \mathbf{0}$ and $\text{Cov}(\boldsymbol{\epsilon}) = \Sigma - \mathbf{Z}(\mathbf{Z}'\Sigma^{-1}\mathbf{Z})^{-1}\mathbf{Z}'$. Hence, ϵ_i is normally distributed with mean zero and variance γ_{ii} , where γ_{ii} is the i th diagonal element of $\text{Cov}(\boldsymbol{\epsilon})$.

- (b) No, they are typically correlated with $\text{Cov}(\hat{\epsilon}_i, \hat{\epsilon}_j) = -h_{ij}\sigma^2$, where h_{ij} is the (i, j) th element of \mathbf{H} .
- (c) $\hat{\mathbf{Y}}'\hat{\boldsymbol{\epsilon}} = \hat{\boldsymbol{\beta}}'\mathbf{Z}'\hat{\boldsymbol{\epsilon}} = 0$, because $\mathbf{Z}'\hat{\boldsymbol{\epsilon}} = \mathbf{0}$.

2. Note that $\mathbf{X} = \mathbf{C}\mathbf{Z}$, where

$$\mathbf{C} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix}.$$

- (a) $\mathbf{X} \sim N_2(\mathbf{C}\boldsymbol{\mu}, \mathbf{C}\mathbf{I}\mathbf{C}')$, that is, $\mathbf{X} \sim N_2(\boldsymbol{\mu}_x, \boldsymbol{\Sigma}_x)$, where

$$\boldsymbol{\mu}_x = \begin{bmatrix} 3 \\ 5 \end{bmatrix}, \quad \boldsymbol{\Sigma}_x = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}.$$

- (b) $\mathbf{X} \sim N_2(\boldsymbol{\mu}_x, \boldsymbol{\Sigma}_x)$ because Z_3 and \mathbf{X} are independent.
- (c) $X_1 \sim N(3, 2)$.
- (d) Using $Y = (1, 1, -1)\mathbf{W}$, where $\mathbf{W} = (\mathbf{X}', Z_3)$ which is multivariate normal with mean $(3, 5, 3)$ and covariance matrix $\text{diag}(\boldsymbol{\Sigma}_x, 1)$, we obtain $Y \sim N(5, 7)$.

3. \mathbf{X}_t is an MA(1) process. It is easy to obtain that $\text{Cov}(\mathbf{X}_t) = \boldsymbol{\Sigma} + \boldsymbol{\theta}\boldsymbol{\Sigma}\boldsymbol{\theta}'$, $\boldsymbol{\Gamma}_1 = -\boldsymbol{\theta}\boldsymbol{\Sigma}$, $\boldsymbol{\Gamma}_{-1} = -\boldsymbol{\Sigma}\boldsymbol{\theta}'$, and $\boldsymbol{\Gamma}_k = \mathbf{0}$ for $|k| > 1$.

(a) $E(\bar{\mathbf{X}}_n) = \frac{1}{n}E(\sum_{i=1}^n \mathbf{X}_i) = \frac{1}{n} \sum_{i=1}^n E(\mathbf{X}_i) = \mathbf{c}$.

(b) $\text{Cov}(\sqrt{n}\bar{\mathbf{X}}_n) = \frac{1}{n}\text{Cov}(\sum_{i=1}^n \mathbf{X}_i) = \frac{1}{n}[n\boldsymbol{\Gamma}_0 + (n-1)\boldsymbol{\Gamma}_1 + (n-1)\boldsymbol{\Gamma}_{-1}]$.

(c) Taking the limit of part (b), we have $\boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1 + \boldsymbol{\Gamma}_{-1} = \boldsymbol{\Sigma} - \boldsymbol{\theta}\boldsymbol{\Sigma}\boldsymbol{\theta}' - \boldsymbol{\theta}\boldsymbol{\Sigma} - \boldsymbol{\Sigma}\boldsymbol{\theta}'$.

4. Use the attached output.

(a) (96.46, 42.91, 35.37, 14.51, 25.63, 9.57, 9.71)' and (99.34, 43.74, 39.31, 14.66, 30.00, 9.66, 9.37)'

(b) Based on the S-Plus output, the two means are significantly different at the 5% level.

(c) Based on the maximization lemma, the linear combination is given by the vector \mathbf{a} in Matlab output. That is, (.006, .151, -.854, .268, -.383, -2.187, 2.971)'

(d) You may use the t-dist as in Section 6.5 to construct the simultaneous C.I. as

$$d_i \pm t_{63}(.05/(7 \times 2 \times 1)) \sqrt{\frac{2 \times s_{ii}}{35}},$$

where d_i is the i th element of the mean difference and s_{ii} is the (i, i) th element of the pooled covariance estimate given in the Matlab output. The

(e) Normality, independent samples, and equal covariance matrices.