

STATS 531 / ECON 677 WINTER 09  
HOMEWORK 7

**PROBLEM 1**

(i) Let  $I$  be the identity matrix of appropriate dimensions,  $\mathbf{0}$  be a matrix of zeros of appropriate dimensions and  $A'$  be the transpose of  $A$ . Then,

$$\begin{aligned} \text{cov}(\mathbf{z}, \mathbf{y}) &= \text{cov}(\mathbf{x} - \Sigma_{xy}\Sigma_y^{-1}\mathbf{y}, \mathbf{y}) \\ &= \text{cov}(\mathbf{x}, \mathbf{y}) - \text{cov}(\Sigma_{xy}\Sigma_y^{-1}\mathbf{y}, \mathbf{y}) \\ &= \Sigma_{xy} - \Sigma_{xy}\Sigma_y^{-1}\text{cov}(\mathbf{y}, \mathbf{y})I' = \Sigma_{xy} - \Sigma_{xy}\Sigma_y^{-1}\Sigma_y \\ &= \Sigma_{xy} - \Sigma_{xy} = \mathbf{0}. \end{aligned}$$

Hence  $\mathbf{z}$  and  $\mathbf{y}$  are uncorrelated in the sense that the correlation coefficient  $\rho_{ij} = \frac{\text{cov}(z_i, y_j)}{\sigma_{z_i}\sigma_{y_j}}$  for  $\forall i, j$  will be zero. Since 2 uncorrelated Gaussian random variables are also independent, one may argue that  $\mathbf{z}$  and  $\mathbf{y}$  are independent as well. Formally, letting  $\mathbf{w} = (\mathbf{z}, \mathbf{y})'$ , this follows because

$$\begin{aligned} \frac{1}{\sqrt{(2\pi)^n |\Sigma_z|}} e^{-\frac{1}{2}(\mathbf{z}-\mu_z)'\Sigma_z^{-1}(\mathbf{z}-\mu_z)} &= f_z(\mathbf{z}) \\ &= f_{z|y}(\mathbf{z}|\mathbf{y}), \end{aligned}$$

which may be shown using  $\text{cov}(\mathbf{z}, \mathbf{y}) = \mathbf{0}$  and the properties of the block matrices to show that  $|\Sigma_w| = |\Sigma_z\Sigma_y - \mathbf{0}| = |\Sigma_z||\Sigma_y|$  and  $\Sigma_w^{-1} = \begin{pmatrix} \Sigma_z^{-1} & \mathbf{0} \\ \mathbf{0} & \Sigma_y^{-1} \end{pmatrix}$ .

**(ii)**

$$\begin{aligned} E[\mathbf{x}|\mathbf{y}] &= E[\mathbf{z} + \Sigma_{xy}\Sigma_y^{-1}\mathbf{y}|\mathbf{y}] \\ &= E[\mathbf{z}|\mathbf{y}] + \Sigma_{xy}\Sigma_y^{-1}\mathbf{y} \\ &= E[\mathbf{z}] + \Sigma_{xy}\Sigma_y^{-1}\mathbf{y} \\ &= \mu_x - \Sigma_{xy}\Sigma_y^{-1}\mu_y + \Sigma_{xy}\Sigma_y^{-1}\mathbf{y} = \mu_x + \Sigma_{xy}\Sigma_y^{-1}(\mathbf{y} - \mu_y) \end{aligned}$$

where the first equality follows by the definition of  $\mathbf{z}$  and the third one by independence of  $\mathbf{z}$  and  $\mathbf{y}$ .

(iii)

$$\begin{aligned}V[\mathbf{x}|\mathbf{y}] &= V[\mathbf{z} + \Sigma_{xy}\Sigma_y^{-1}\mathbf{y}|\mathbf{y}] \\&= V[\mathbf{z}|\mathbf{y}] \\&= V[\mathbf{z}] \\&= V[\mathbf{x} - \Sigma_{xy}\Sigma_y^{-1}\mathbf{y}] \\&= V[\mathbf{x}] - \text{cov}[\Sigma_{xy}\Sigma_y^{-1}\mathbf{y}, \mathbf{x}] - \text{cov}[\mathbf{x}, \Sigma_{xy}\Sigma_y^{-1}\mathbf{y}] + V[\Sigma_{xy}\Sigma_y^{-1}\mathbf{y}] \\&= \Sigma_x - \Sigma_{xy}\Sigma_y^{-1}\Sigma_{xy}I' - I\Sigma_{xy}(\Sigma_{xy}\Sigma_y^{-1})' + \Sigma_{xy}\Sigma_y^{-1}\Sigma_y(\Sigma_{xy}\Sigma_y^{-1})' \\&= \Sigma_x - \Sigma_{xy}\Sigma_y^{-1}\Sigma_{xy}\end{aligned}$$

**PROBLEM 2**  $z_1$  and  $z_2$  are linear combinations of the complex normal variables  $x$  and  $y$ . Hence,  $\mathbf{z}$  is bivariate complex normal with mean  $\mu_z$  and covariance matrix  $\Sigma_z$ . Since  $A = [a_{ij}]$ ,

$$\mathbf{z} = A \begin{pmatrix} x \\ y \end{pmatrix}$$

and  $E[\mathbf{z}] = \mathbf{0}$  because  $x$  and  $y$  have mean zero. By definition, the complex normal random variables  $x$  and  $y$  may be written as

$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} u \\ s \end{pmatrix} + i \begin{pmatrix} v \\ t \end{pmatrix}$$

where  $u, v, s$  and  $t$  are independent  $N(0, \sigma^2/2)$ . Letting  $A = B + iC$  (as in the hint),

$$\begin{aligned}\mathbf{z} &= (B + iC) \left[ \begin{pmatrix} u \\ s \end{pmatrix} + i \begin{pmatrix} v \\ t \end{pmatrix} \right] \\&= B \begin{pmatrix} u \\ s \end{pmatrix} - C \begin{pmatrix} v \\ t \end{pmatrix} + i \left[ C \begin{pmatrix} u \\ s \end{pmatrix} + B \begin{pmatrix} v \\ t \end{pmatrix} \right] = \mathbf{d} + i\mathbf{e}.\end{aligned}$$

From class, if  $V \left[ \begin{pmatrix} \mathbf{d} \\ \mathbf{e} \end{pmatrix} \right] = \frac{1}{2} \begin{pmatrix} R & -S \\ S & R \end{pmatrix}$ , and  $S' = -S$ , then  $V[\mathbf{z}] = R + iS$ . Note that

$$\begin{aligned} V[\mathbf{d}] &= V \left[ B \begin{pmatrix} u \\ s \end{pmatrix} - C \begin{pmatrix} v \\ t \end{pmatrix} \right] \\ &= V \left[ B \begin{pmatrix} u \\ s \end{pmatrix} \right] + V \left[ C \begin{pmatrix} v \\ t \end{pmatrix} \right] - B \text{cov} \left[ \begin{pmatrix} u \\ s \end{pmatrix}, \begin{pmatrix} v \\ t \end{pmatrix} \right] C' - C \text{cov} \left[ \begin{pmatrix} v \\ t \end{pmatrix}, \begin{pmatrix} u \\ s \end{pmatrix} \right] B' \\ &= \frac{\sigma^2}{2} B I B' + \frac{\sigma^2}{2} C I C' = \frac{\sigma^2}{2} (B B' + C C') = V[\mathbf{e}]. \end{aligned}$$

where the last equality follows by independence of  $u, v, s$  and  $t$ . Also note that

$$\begin{aligned} \text{cov}[\mathbf{d}, \mathbf{e}] &= \text{cov} \left[ B \begin{pmatrix} u \\ s \end{pmatrix} - C \begin{pmatrix} v \\ t \end{pmatrix}, C \begin{pmatrix} u \\ s \end{pmatrix} + B \begin{pmatrix} v \\ t \end{pmatrix} \right] \\ &= E \left[ \left( B(u, s)' - C(v, t)' \right) \left( (u, s)C' + (v, t)B' \right) \right] \\ &= E \left[ B(u, s)'(u, s)C' + B(u, s)'(v, t)B' - C(v, t)'(u, s)C' - C(v, t)'(v, t)B' \right] \\ &= E \left[ B \begin{pmatrix} u^2 & us \\ us & s^2 \end{pmatrix} C' + B \begin{pmatrix} uv & ut \\ sv & st \end{pmatrix} B' - C \begin{pmatrix} vu & vs \\ tu & ts \end{pmatrix} C' - C \begin{pmatrix} v^2 & vt \\ vt & t^2 \end{pmatrix} B' \right] \\ &= \frac{\sigma^2}{2} B I C' - \frac{\sigma^2}{2} C I B' = \frac{\sigma^2}{2} (B C' - C B') = -\text{cov}[\mathbf{e}, \mathbf{d}]. \end{aligned}$$

Finally, letting  $R = 2V[\mathbf{d}]$  and  $S = 2\text{cov}[\mathbf{e}, \mathbf{d}]$ , it follows that

$$\begin{aligned} \Sigma_z &= R + iS \\ &= \sigma^2(BB' + CC') + i\sigma^2(CB' - BC'), \\ &= \sigma^2(BB' + CC' - i(BC' - CB')) \end{aligned}$$

and, by definition,

$$\begin{aligned} A\bar{A}' &= (B + iC)(\overline{B + iC})' = (B + iC)(B - iC)' \\ &= BB' - iBC' + iCB' - (-1)CC' \\ &= BB' + CC' - i(BC' - CB'), \end{aligned}$$

so that  $\mathbf{z} \sim N^c(\mathbf{0}, \sigma^2 A\bar{A}')$