

Jilin Zheng // U49258796

EK381 Homework #7

Problem 7.1

$X = U + V$ ,  $Y = U - 2V$ ,  $U$  and  $V$  are independent, standard Gaussians ( $\text{Gaussian}(0, 1)$ )

(a) Yes,  $X$  and  $Y$  are linear functions of independent, standard Gaussian random variables, so they are jointly Gaussian

(b)  $\mathbb{E}[X] = \mathbb{E}[U + V] = \mathbb{E}[U] + \mathbb{E}[V] = 0$

$\mathbb{E}[Y] = \mathbb{E}[U - 2V] = 0 - 2(0) = 0$

(c)  $\text{Cov}[X, Y] = \text{Cov}[U + V, U - 2V] = 1 \cdot \text{Var}[U] + (-2) \text{Var}[V] + (-2 + 1) \text{Cov}[U, V]$   
 $= 1 + (-2) + (-1)(0) = -1$

(d)  $\text{Var}[X] = \text{Var}[U + V] = \text{Var}[U] + \text{Var}[V] + 2 \text{Cov}[U, V] = 1 + 1 + 2(0) = 2$

$\text{Var}[Y] = \text{Var}[U - 2V] = \text{Var}[U] + (-2)^2 \text{Var}[V] + 2(1)(-2) \text{Cov}[U, V] = 1 + 4 = 5$

$\rho_{X,Y} = \frac{\text{Cov}[X,Y]}{\sqrt{\text{Var}[X] \text{Var}[Y]}} = \frac{-1}{\sqrt{2 \cdot 5}} = \frac{-1}{\sqrt{10}}$

(e)  $\mathbb{E}[X|Y=y] = \mu_X + \frac{\text{Cov}[X,Y]}{\text{Var}[Y]} (y - \mu_Y) = 0 + \frac{-1}{5} (y - 0) = \frac{-y}{5}$

(f)  $\text{Var}[X|Y] = (1 - \rho_{X,Y}^2) \sigma_X^2 = (1 - (\frac{-1}{\sqrt{10}})^2) 2 = (1 - \frac{1}{10}) 2 = \frac{9}{10} = \frac{9}{5}$

# Problem 7.2

$$(a) \underline{\mu}_Y = \begin{bmatrix} E[Y_1] \\ E[Y_2] \end{bmatrix} = \begin{bmatrix} E[2X_1 + 1] \\ E[X_1 - X_2] \end{bmatrix} = \begin{bmatrix} 2(\emptyset) + 1 \\ \emptyset - \emptyset \end{bmatrix} = \begin{bmatrix} 1 \\ \emptyset \end{bmatrix}$$

$$(b) \underline{\Sigma}_Y = \begin{bmatrix} \text{Cov}[Y_1, Y_1] & \text{Cov}[Y_1, Y_2] \\ \text{Cov}[Y_2, Y_1] & \text{Cov}[Y_2, Y_2] \end{bmatrix} = \begin{bmatrix} 4 & 4/3 \\ 4/3 & 4/3 \end{bmatrix}$$

$$\text{Var}[Y_1] = \text{Var}[2X_1 + 1] = 4\text{Var}[X_1] = 4$$

$$\text{Var}[Y_2] = \text{Var}[X_1 - X_2] = \text{Var}[X_1] + \text{Var}[X_2] + 2(1)(-1)\text{Cov}[X_1, X_2] = 1 + 1 + (-2)(1/3) = 2 - 2/3 = 6/3 - 2/3 = 4/3$$

$$\begin{aligned} \text{Cov}[Y_1, Y_2] &= \text{Cov}[2X_1 + 1, X_1 - X_2] = 2\text{Var}[X_1] + \emptyset + (2(-1) + \emptyset)\text{Cov}[X_1, X_2] = 2 + (-2)(1/3) = 6/3 + (-2/3) = 4/3 \\ &= \text{Cov}[Y_2, Y_1] \end{aligned}$$

(c)  $Y_1$  and  $Y_2$  are linear functions of jointly Gaussian  $X_1$  and  $X_2$ , so  $Y_1$  and  $Y_2$  are also jointly Gaussian

$$\rho_{Y_1, Y_2} = \frac{\text{Cov}[Y_1, Y_2]}{\sqrt{\text{Var}[Y_1]\text{Var}[Y_2]}} = \frac{4/3}{\sqrt{4 \cdot 4/3}} = \frac{4/3}{\sqrt{16/3}} = \frac{4/3}{4/\sqrt{3}} = \frac{4}{3} \cdot \frac{\sqrt{3}}{4} = \frac{\sqrt{3}}{3}$$

since  $Y_1$  and  $Y_2$  are NOT uncorrelated ( $\rho_{Y_1, Y_2} \neq \emptyset$ ), they are NOT independent

$$\begin{aligned} (d) E[Y_1 | Y_2 = y_2] &= \mu_{Y_1} + \frac{\text{Cov}[Y_1, Y_2]}{\text{Var}[Y_2]}(y_2 - \mu_{Y_2}) \\ &= 1 + \frac{4/3}{4/3}(y_2 - \emptyset) \\ &= 1 + y_2 \end{aligned}$$

### Problem 7.3

$$(a) E[X] = \underline{\mu}_X = \begin{bmatrix} E[X_1] \\ \vdots \\ E[X_n] \end{bmatrix} = \begin{bmatrix} \mu \\ \vdots \\ \mu \end{bmatrix}$$

$$\Sigma_X = \begin{bmatrix} \text{Cov}[X_1, X_1] & \dots & \text{Cov}[X_1, X_n] \\ \vdots & & \vdots \\ \text{Cov}[X_n, X_1] & \dots & \text{Cov}[X_n, X_n] \end{bmatrix} = \begin{bmatrix} \sigma^2 & 0 & \dots & 0 \\ 0 & \sigma^2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \dots & 0 & \sigma^2 \end{bmatrix}$$

$$(b) Y = \frac{1}{n} \left( \sum_{i=1}^n X_i \right) = AX = \begin{bmatrix} \frac{1}{n} & \dots & \frac{1}{n} \end{bmatrix} \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix}$$

$$(c) E[Y] = E[AX] = A E[X] = \begin{bmatrix} \frac{1}{n} & \dots & \frac{1}{n} \end{bmatrix} \begin{bmatrix} \mu \\ \vdots \\ \mu \end{bmatrix} = \sum_{i=1}^n \frac{1}{n} \mu = \frac{\mu}{n} (n) = \mu$$

$$(d) \Sigma_Y = A \Sigma_X A^T = \begin{bmatrix} \frac{1}{n} & \dots & \frac{1}{n} \end{bmatrix} \begin{bmatrix} \sigma^2 & 0 & \dots & 0 \\ \vdots & \ddots & & \vdots \\ 0 & \dots & 0 & \sigma^2 \end{bmatrix} \begin{bmatrix} \frac{1}{n} \\ \vdots \\ \frac{1}{n} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\sigma^2}{n} & \dots & \frac{\sigma^2}{n} \end{bmatrix} \begin{bmatrix} \frac{1}{n} \\ \vdots \\ \frac{1}{n} \end{bmatrix} = \frac{\sigma^2}{n} \left( \frac{1}{n} \right) n = \frac{\sigma^2}{n}$$

$$\text{Var}[Y] = \frac{\sigma^2}{n}$$

$$(e) P[|Y - E[Y]| > \delta] = 1 - P[|Y - E[Y]| < \delta]$$

$$= 1 - P[-\delta < Y - E[Y] < \delta]$$

$$= 1 - P[-\delta + \mu < Y < \delta + \mu]$$

$$= 1 - \left[ \Phi\left(\frac{\delta + \mu - \mu}{\sigma/\sqrt{n}}\right) - \Phi\left(\frac{-\delta + \mu - \mu}{\sigma/\sqrt{n}}\right) \right]$$

$$= 1 - \left[ \Phi\left(\frac{\delta\sqrt{n}}{\sigma}\right) - \Phi\left(\frac{-\delta\sqrt{n}}{\sigma}\right) \right]$$

$$= Q\left(\frac{\delta\sqrt{n}}{\sigma}\right) + \Phi\left(\frac{-\delta\sqrt{n}}{\sigma}\right) = Q\left(\frac{\delta}{\frac{\sigma}{\sqrt{n}}}\right) + \Phi\left(\frac{-\delta}{\frac{\sigma}{\sqrt{n}}}\right) = 2Q\left(\frac{\delta}{\frac{\sigma}{\sqrt{n}}}\right)$$

$$(f) \delta = \frac{1}{10}$$

$$\frac{1}{1000} = 2Q\left(\frac{\frac{1}{10}}{\frac{\sigma}{\sqrt{n}}}\right) = 2Q\left(\frac{\sqrt{n}}{10\sigma}\right)$$

$$Q\left(\frac{\sqrt{n}}{10\sigma}\right) = \frac{1}{2000}$$

$$\frac{\sqrt{n}}{10\sigma} = 3.29$$

$$\sqrt{n} = 32.9\sigma$$

$$n = 1082.41 \sigma^2$$