

problem set 4 (solutions)

①: Independency  $\Rightarrow$  uncorrelation

$$K_{U_1, U_2, U_3} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} = I, f_{U_1, U_2, U_3}(u_1, u_2, u_3) = f_{U_1}(u_1) f_{U_2}(u_2) f_{U_3}(u_3)$$

$$\Rightarrow f_{U_1, U_2, U_3}(u_1, u_2, u_3) = \frac{1}{(2\pi)^{\frac{3}{2}}} e^{-\frac{u_1^2 + u_2^2 + u_3^2}{2}}$$

$$\textcircled{2}: \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix}}_A \begin{pmatrix} U_1 \\ U_2 \\ U_3 \end{pmatrix} \Rightarrow K_{X,Y,Z} = A K_{U_1, U_2, U_3} A^T = A I A^T = A A^T$$

$$= \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 2 & 2 \\ 1 & 2 & 3 \end{pmatrix}$$

$$\textcircled{3}: \begin{cases} U_1 = X \\ U_2 = Y - X \\ U_3 = Z - Y \end{cases} \Rightarrow f_{X,Y,Z}(x, y, z) = \frac{f_{U_1, U_2, U_3}(x, y-x, z-y)}{| \det(A) |}$$

$$= \frac{1}{(2\pi)^{\frac{3}{2}}} e^{-\frac{x^2 - (y-x)^2 - (z-y)^2}{2}}$$

$$\textcircled{c}: f_{y,z/x}(\gamma, z/x) = \frac{f_{x,y,z}(x, y, z)}{f_x(x)}$$

$$= \frac{\frac{1}{(2\pi)^{3/2}} e^{-\frac{x^2}{2}}}{\frac{1}{\sqrt{2\pi}} e^{-\frac{(y-x)^2}{2}}} = \frac{1}{2\pi} e^{-\frac{-(y-x)^2}{2}}$$

$$\textcircled{d}: f_{z/x,y}(z/x, y) = \frac{f_{x,y,z}(x, y, z)}{f_{x,y}(x, y)}$$

$$f_{x,y}(x, y) = \int_{-\infty}^{+\infty} f_{x,y,z}(x, y, z) dz = \int_{-\infty}^{+\infty} \frac{1}{(2\pi)^{3/2}} e^{-\frac{z^2}{2}} dz =$$

$$\frac{1}{2\pi} e^{-\frac{x^2-(y-x)^2}{2}} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(z-y)^2}{2}} dz = \frac{1}{2\pi} e^{-\frac{-x^2+(y-x)^2}{2}}$$

$$\Rightarrow f_{z/x,y}(z/x, y) = \frac{\frac{1}{(2\pi)^{3/2}} e^{-\frac{-(y-x)^2}{2}}}{\frac{1}{2\pi} e^{-\frac{-x^2+(y-x)^2}{2}}}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\frac{-(z-y)^2}{2}}$$

$$\begin{aligned}
 (2) \quad & f_T(t) = \alpha e^{-\alpha t}; t \geq 0 \\
 & \Pr\{N_i^o = k / T=t\} = \frac{e^{-\lambda_i^o t} (\lambda_i^o t)^k}{k!} \quad \left\{ \begin{array}{l} i=1, 2, 3 \\ k=0, 1, 2, \dots \end{array} \right. \\
 \Rightarrow & \Pr\{N_i^o = k\} = \int_0^{+\infty} \Pr\{N_i^o = k / T=t\} \times f_T(t) dt \\
 & = \int_0^{+\infty} \frac{e^{-\lambda_i^o t} (\lambda_i^o t)^k}{k!} \times \alpha e^{-\alpha t} dt = \frac{\lambda_i^o k}{k!} \cdot \alpha \int_0^{+\infty} t^k e^{-(\alpha + \lambda_i^o)t} dt = \\
 & \frac{\lambda_i^o \alpha}{k!} \times \frac{k!}{(\alpha + \lambda_i^o)^{k+1}} = \frac{\alpha}{\alpha + \lambda_i^o} \left( \frac{\lambda_i^o}{\alpha + \lambda_i^o} \right)^k \xrightarrow{\text{geometric random variable}} 1-p
 \end{aligned}$$

$$\Rightarrow \text{Var}\{N_i^o\} = \frac{1-p}{p^2} = \frac{1 - \frac{\alpha}{\alpha + \lambda_i^o}}{\left(\frac{\alpha}{\alpha + \lambda_i^o}\right)^2} = \frac{\lambda_i^o(\alpha + \lambda_i^o)}{\alpha^2}$$

since  $N_i^o$ 's are independent, we have  $\text{Cov}(N_i^o, N_j^o) = 0$  for  $i \neq j$

$$\Rightarrow \text{Covariance matrix} X = \begin{pmatrix} \frac{\lambda_1(\alpha + \lambda_1)}{\alpha^2} & 0 & 0 \\ 0 & \frac{\lambda_2(\alpha + \lambda_2)}{\alpha^2} & 0 \\ 0 & 0 & \frac{\lambda_3(\alpha + \lambda_3)}{\alpha^2} \end{pmatrix}$$

③:  $X \perp\!\!\!\perp Y$   $f_x(x) = \lambda_1 e^{-\lambda_1 x}; x \geq 0$   $f_y(y) = \lambda_2 e^{-\lambda_2 y}; y \geq 0$

find the PDF of  $Z = \frac{X}{Y}$

first method: (Jacobian matrix)

We define the new random variable  $W = X$

$$f_{x,y}(x,y) = f_x(x)f_y(y) = \lambda_1 \lambda_2 e^{-\lambda_1 x} e^{-\lambda_2 y}; x, y \geq 0$$

$$J = \begin{pmatrix} \frac{\partial z}{\partial x} & \frac{\partial z}{\partial y} \\ \frac{\partial w}{\partial x} & \frac{\partial w}{\partial y} \end{pmatrix} = \begin{pmatrix} 1 & -\frac{x}{y^2} \\ 1 & 0 \end{pmatrix} \Rightarrow \det(J) = \frac{x}{y^2}$$

$$\begin{cases} z = \frac{x}{y} \\ w = x \end{cases} \Rightarrow \begin{cases} x = w \\ y = \frac{w}{z} \end{cases} \Rightarrow f_{z,w}(z,w) = \frac{f_{x,y}(w, \frac{w}{z})}{|\det J|} \Big| \begin{cases} x=w \\ y=\frac{w}{z} \end{cases}$$

$$= \frac{\lambda_1 \lambda_2 e^{-\lambda_1 w} e^{-\lambda_2 \frac{w}{z}}}{\frac{w}{z^2}} = \lambda_1 \lambda_2 \frac{w}{z^2} e^{-\lambda_1 w} e^{-\lambda_2 \frac{w}{z}}$$

$$f_z(z) = \int_0^{+\infty} f_{z,w}(z,w) dw = \frac{\lambda_1 \lambda_2}{z^2} \int_0^{+\infty} w e^{-(\lambda_1 + \frac{\lambda_2}{z})w} dw =$$

$$\frac{\lambda_1 \lambda_2}{z^2} \times \frac{1}{(\lambda_1 + \frac{\lambda_2}{z})^2} = \frac{\lambda_1 \lambda_2}{(\lambda_2 + \lambda_1 z)^2}$$

Second method (CDF function)

$$F_z(z) = \Pr\{Z \leq z\} = \Pr\left\{\frac{X}{Y} \leq z\right\} = \int_{-\infty}^{+\infty} \Pr\left\{\frac{X}{Y} \leq z\right\} f_Y(y) dy$$

$$= \int_0^{+\infty} \Pr\{X \leq yz\} \lambda_2 e^{-\lambda_2 y} dy = \int_0^{+\infty} F_X(yz) \lambda_2 e^{-\lambda_2 y} dy =$$

$$F_X(x) = \Pr\{X \leq x\} = \int_0^x \lambda_1 e^{-\lambda_1 t} dt = -e^{-\lambda_1 t} \Big|_0^x = 1 - e^{-\lambda_1 x}$$

$$\Rightarrow F_z(z) = \int_0^{+\infty} (1 - e^{-\lambda_1 yz}) \lambda_2 e^{-\lambda_2 y} dy$$
~~$$= 1 - \int_0^{+\infty} -(\lambda_1 z + \lambda_2) y e^{-(\lambda_1 z + \lambda_2) y} dy = \cancel{\lambda_1 z} \cancel{\int_0^{+\infty} y e^{-y} dy} = \frac{\lambda_1 z}{\lambda_1 z + \lambda_2}$$~~

$$\Rightarrow f_z(z) = \frac{d}{dz} F_z(z) = \frac{\lambda_1 (\lambda_1 z + \lambda_2) - \lambda_1^2 z}{(\lambda_1 z + \lambda_2)^2} = \frac{\lambda_1 \lambda_2}{(\lambda_1 z + \lambda_2)^2}$$

⑦ :  $X = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix}$  is a jointly Gaussian random vector.

$M_X = 0 \quad K_X = I_{3 \times 3} \implies X_i$ 's are uncorrelated

Since  $X$  is jointly Gaussian, we conclude that they are independent.

$$Y \triangleq \max\{X_1, X_2, X_3\}$$

$$\begin{aligned} F_Y(y) &= \Pr\{Y \leq y\} = \Pr\{\max\{X_1, X_2, X_3\} \leq y\} = \Pr\{X_1 \leq y, X_2 \leq y, X_3 \leq y\} \\ &= \Pr\{X_1 \leq y\} \times \Pr\{X_2 \leq y\} \times \Pr\{X_3 \leq y\} = F_{X_1}(y)F_{X_2}(y)F_{X_3}(y) = F_{X_1}(y) \end{aligned}$$

$$\Rightarrow f_Y(y) = \frac{d}{dy} F_Y(y) = 3 \times f_{X_1}(y) \times F_{X_1}^2(y)$$

$$\Rightarrow f_Y(y) = 3 \times \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \times \left( \int_{-\infty}^y \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \right)^2$$

⑤  $X = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix}$  is a jointly Gaussian random vector.

$$K_X = \begin{pmatrix} 1 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & 1 & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & 1 \end{pmatrix}, Y = AX$$

$Y$  is a linear transformation of  $X$ . Therefore,  $y_i$ 's are independent if and only if  $y_i$ 's are uncorrelated.

$\det(K_X) = 0 \Rightarrow K_X$  is a singular matrix.

Since  $K_X$  is singular, there is not any square matrix  $A_{3 \times 3}$  to make  $y_i$ 's uncorrelated.

Now, we want to find a non-square matrix  $A_{2 \times 3}$  to generate a new vector with uncorrelated elements.

To this end, we first write  $X$  in terms of  $Y$  as:

$$X = BY$$

let us assume that  $k_y = I$

$$\Rightarrow C_X = B k_y B^T = B I B^T = B B^T$$

To simplify the task of finding  $B$ , let us assume that  $B$  is a lower triangular matrix. Then we need to solve the following matrix equation

$$\underbrace{\begin{pmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & -\frac{1}{2} & 1 \end{pmatrix}}_{k_X} = \underbrace{\begin{pmatrix} a & 0 & 0 \\ b & c & 0 \\ d & e & f \end{pmatrix}}_B \underbrace{\begin{pmatrix} a & b & d \\ 0 & c & e \\ 0 & 0 & f \end{pmatrix}}_{B^T}$$

(this decomposition  
is called cholesky  
decomposition in  
linear algebra.)

$$\Rightarrow | = a^2 \Rightarrow a = 1$$

$$ad = \frac{-1}{2} \Rightarrow d = \frac{-1}{2}$$

$$ab = \frac{-1}{2} \Rightarrow b = \frac{-1}{2}$$

$$b^2 + c^2 = 1 \Rightarrow \frac{1}{4} + c^2 = 1 \Rightarrow c = \frac{\sqrt{3}}{2}$$

$$bd + ce = \frac{-1}{2} \Rightarrow \frac{1}{4} + \frac{\sqrt{3}}{2}e = \frac{-1}{2} \Rightarrow e = -\frac{\sqrt{3}}{2}$$

$$d^2 + e^2 + f^2 = 1 \Rightarrow \frac{1}{4} + \frac{3}{4} + f^2 = 1 \Rightarrow f = 0$$

$$\Rightarrow B = \begin{pmatrix} 1 & 0 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} & 0 \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} & 0 \end{pmatrix}$$

since last column of  $B$  is zero, we can remove it  
and write the following transformation:

$$X = BY \Rightarrow \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} \end{pmatrix} \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix}$$

$$\Rightarrow \begin{cases} X_1 = Y_1 \\ X_2 = -\frac{1}{2}Y_1 + \frac{\sqrt{3}}{2}Y_2 \\ X_3 = -\frac{1}{2}Y_1 - \frac{\sqrt{3}}{2}Y_2 \end{cases} \quad (\star)$$

Let  $\tilde{X}_i = X_i - EX_i$  and  $\tilde{Y}_i = Y_i - EY_i$ . Therefore, we have:

$$\begin{cases} \tilde{X}_1 = \tilde{Y}_1 \\ \tilde{X}_2 = -\frac{1}{2}\tilde{Y}_1 + \frac{\sqrt{3}}{2}\tilde{Y}_2 \\ \tilde{X}_3 = -\frac{1}{2}\tilde{Y}_1 - \frac{\sqrt{3}}{2}\tilde{Y}_2 \end{cases}$$

$$\Rightarrow \tilde{X}_1 + \tilde{X}_2 + \tilde{X}_3 = 0 \Rightarrow \boxed{X_1 + X_2 + X_3 = EX_1 + EX_2 + EX_3}$$

As it can be seen,  $x_i$ 's are linearly dependent.  
 That is why  $k_x$  was a singular matrix.  
 Now, let us find matrix  $A_{2 \times 3}$ . Noting  $(\star)$ ,  
 We can find  $y_i$ 's in terms of  $x_i$ 's:

$$\begin{cases} y_1 = x_1 \\ y_2 = \frac{1}{\sqrt{3}}x_2 - \frac{1}{\sqrt{3}}x_3 \end{cases} \rightsquigarrow \text{This is } \underline{\text{not}} \text{ unique.}$$

$$\Rightarrow \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}_{2 \times 1} = \underbrace{\begin{pmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{3}} & \frac{-1}{\sqrt{3}} \end{pmatrix}}_{A_{2 \times 3}} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3 \times 1}$$

It is not hard to see that:

$$k_y = A k_x A^T = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{3}} & \frac{-1}{\sqrt{3}} \end{pmatrix} \begin{pmatrix} 1 & \frac{1}{2} & \frac{1}{2} \\ \frac{-1}{2} & 1 & \frac{-1}{2} \\ \frac{-1}{2} & \frac{1}{2} & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & \frac{1}{\sqrt{3}} \\ 0 & \frac{-1}{\sqrt{3}} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$\Rightarrow y_1$  and  $y_2$  are uncorrelated.

$$\textcircled{6}: \text{PDF of Cauchy random variable: } f(x) = \frac{\gamma}{\pi(\gamma^2 + x^2)}$$

$$\phi_X(w) = E\left\{e^{jwX}\right\} = e^{-\gamma|w|} \quad Y = \sum_{i=1}^n X_i$$

$X_i$ 's are independent Cauchy random variables.

with parameter  $\gamma_i$ .

$$\phi_Y(w) = E\left\{e^{jwY}\right\} = E\left\{e^{jw(X_1 + X_2 + \dots + X_n)}\right\} = E\left\{e^{jwX_1} e^{jwX_2} \dots e^{jwX_n}\right\}$$

$$= E\left\{e^{jwX_1}\right\} E\left\{e^{jwX_2}\right\} \dots E\left\{e^{jwX_n}\right\} = e^{-\gamma_1|w| - \gamma_2|w| - \dots - \gamma_n|w|}$$

$X_i$ 's are independent

$$= e^{-(\gamma_1 + \gamma_2 + \dots + \gamma_n)|w|} \quad \rightsquigarrow \phi_Y(w) \text{ is the characteristic function}$$

of a Cauchy random variable with parameter  $\sum_{i=1}^n \gamma_i$

$$f_Y(y) = F\left\{\phi_Y(w)\right\} = \frac{\sum_{i=1}^n \gamma_i}{\pi \left( \left( \sum_{i=1}^n \gamma_i \right)^2 + y^2 \right)}$$

⑦	$X_i   0 \quad 1$	$P   0.9 \quad 0.1$	$(i=1, 2, \dots, n)$
---	-------------------	---------------------	----------------------

feedback of each person is a Bernoulli random variable.

$Y = \frac{1}{n} \sum_{i=1}^n X_i \Rightarrow 1-Y$  shows the portion of participants that are unsatisfied

$$\Pr\{0.89 \leq 1-Y \leq 0.91\} > 0.99 \Rightarrow \Pr\{0.09 \leq Y \leq 0.11\} > 0.99 \\ \Rightarrow \Pr\{|Y - 0.1| \leq 0.01\} > 0.99 \Rightarrow \Pr\{\left|Y - \frac{0.1}{n}\right| \geq \frac{0.01}{n}\} \leq 0.01$$

$$6y^2 = \frac{1}{n^2} \times \sum_{i=1}^n 6x_i^2 = \frac{1}{n^2} \times n \times (0.1 - 0.01) = \frac{0.09}{n}$$

~~Chebychev inequality:~~

using chebychev inequality we have:

$$\Pr\{|Y - 0.1| \geq 0.01\} \leq \frac{6y^2}{a^2} = \frac{0.09}{n(0.01)^2}$$

To be sure that  $\Pr\{|Y - 0.1| \geq 0.01\} \leq 0.01$ , the following condition should be satisfied:

$$\frac{0.09}{n(0.01)^2} \leq 0.01 \Rightarrow \boxed{n \geq 90000}$$

$$\textcircled{8}: n=1000 \quad \Pr\left(y > \frac{1}{2}\right) \leq \min_{s>0} e^{-\frac{1}{2}s} E\left\{e^{\frac{s}{n}y}\right\}$$

$$E\left\{e^{\frac{s}{n}y}\right\} = E\left\{e^{\frac{1}{n}s\sum_{i=1}^n x_i}\right\} = \left(E\left\{e^{\frac{1}{n}sx_1}\right\}\right)^n$$

$x_i$ 's are independent

$$E\left\{e^{\frac{1}{n}sx_1}\right\} = 0.9 + 0.1 \times e^{\frac{s}{n}}$$

$$\Rightarrow \text{upper bound} = \min_{s>0} e^{-\frac{s}{2}} \times \left(0.9 + 0.1 e^{\frac{s}{1000}}\right)^{1000}$$

$$f(s) \stackrel{\Delta}{=} e^{-\frac{s}{2}} \left(0.9 + 0.1 e^{\frac{s}{1000}}\right)^{1000}$$

$$\Rightarrow f'(s) = -\frac{1}{2} e^{-\frac{s}{2}} \left(0.9 + 0.1 e^{\frac{s}{1000}}\right)^{1000} + e^{-\frac{s}{2}} \times \frac{1000}{10000} \times e^{\frac{s}{1000}} \left(0.9 + 0.1 e^{\frac{s}{1000}}\right)^{999} = 0$$

$$\Rightarrow -\frac{1}{2} \left(0.9 + 0.1 e^{\frac{s}{1000}}\right) + \frac{1}{10} e^{\frac{s}{1000}} = 0 \Rightarrow \boxed{s^* = 1000 \ln(9)}$$

$$\Rightarrow \text{upper bound} = \frac{1}{9^{500}} \times \left(0.9 + 0.1 \times 9\right)^{1000} = \frac{1.8}{9^{500}}$$