

Quiz#2, Mathematical Statistics I, 2013 Fall

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1. Let X be a random variable. Prove that
 1) If $E[X] = 0$ and $X \geq 0$, then $X = 0$.

2) $\text{Cov}(X, X) = \text{Var}(X)$.

3) $E[X] = \sum_i x_i f(x_i) = x_1 f(x_1) + x_2 f(x_2) + \dots + x_n f(x_n) = 0.$
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 consider discrete type
 $f(x_1) + f(x_2) + \dots + f(x_n) = 1$ with $x \geq 0$.
 $\Rightarrow X = 0$ *

$\Rightarrow \text{Cov}(X, X) = E(X - \mu_X)(X - \mu_X) = E(X - \mu_X)^2 = \text{Var}(X)$ *

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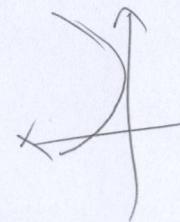
Let (X, Y) be a bivariate random vector. Prove

3) If $X \perp Y$, then $\rho_{XY} = 0$.

4) $-1 \leq \rho_{XY} \leq 1$.

3) $\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{EXY - EX\bar{Y}}{\sigma_X \sigma_Y} = \frac{EX\bar{Y} - EX\bar{Y}}{\sigma_X \sigma_Y} = 0$
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 by $X \perp Y$.

4) Let $h(t) = E[(X - \mu_X)t + (Y - \mu_Y)]^2$
 $= E[(X - \mu_X)t^2 + 2t(X - \mu_X)(Y - \mu_Y) + (Y - \mu_Y)^2]$
 $= t^2 \sigma_X^2 + 2t \text{Cov}(X, Y) + \sigma_Y^2 \geq 0$ by the definition
 of second expectation of square.
 $\Rightarrow b^2 - 4ac = (2\text{Cov}(X, Y))^2 - 4\sigma_X^2 \sigma_Y^2 \leq 0$.
 $\Rightarrow \text{Cov}(X, Y) \leq \sigma_X \sigma_Y$
 $\Rightarrow -\sigma_X \sigma_Y \leq \text{Cov}(X, Y) \leq \sigma_X \sigma_Y$
 $\Rightarrow -1 \leq \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} \leq 1$



2. A bivariate random vector (X, Y) has $\underline{EX = \mu_X}$, $\underline{EY = \mu_Y}$, $\underline{Var(X) = \sigma_X^2}$,

$\underline{Var(Y) = \sigma_Y^2}$ and the correlation $\rho_{XY} = -1$.

1) Derive the linear relationship between X and Y .

2) Simplify the above formula for the case of $\mu_X = \mu_Y$ and $(\sigma_X^2 = \sigma_Y^2)$.

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$$1) \quad \frac{\text{Cov}(X, Y)}{\sqrt{\sigma_X^2} \sqrt{\sigma_Y^2}} = \rho_{XY} = -1 \Rightarrow \text{Cov}(X, Y) = -\sqrt{\sigma_X^2} \sqrt{\sigma_Y^2} \leq 0.$$

$$\text{Consider } h(t) = E[(X - \mu_X)t + (Y - \mu_Y)]^2 = t^2 \sigma_X^2 + 2t \text{Cov}(X, Y) + \sigma_Y^2 \geq 0.$$

$$\Rightarrow \exists t \text{ s.t. } h(t) = 0.$$

$$\Rightarrow h'(t) = 2\sqrt{\sigma_X^2}t + 2\text{Cov}(X, Y) = 0.$$

$$\therefore \text{when } t = -\frac{\text{Cov}(X, Y)}{\sigma_X^2}, \quad h(t) = 0.$$

$$h(t) = 0 \Rightarrow (X - \mu_X)t + (Y - \mu_Y) = 0.$$

$$\Rightarrow Y = -tX + \mu_X t + \mu_Y$$

where $t = -\frac{\text{Cov}(X, Y)}{\sigma_X^2}$

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$$Y = aX + b.$$

$$\text{where } a = -t = \frac{\text{Cov}(X, Y)}{\sigma_X^2} \leq 0$$

2)

$$(i) \quad \text{Cov}(X, Y) = -\sigma_X^2 = -\sigma_Y^2$$

$$\Rightarrow a = -1$$

$$(ii) \quad b = \mu_X t + \mu_Y = \mu_X (1 + -\frac{\text{Cov}(X, Y)}{\sigma_X^2}) = \mu_X (1 + 1) = 2\mu_X$$

$$\Rightarrow Y = -X + 2\mu_X$$

$$E(X) = \mu_X$$

$$\text{Var}(U) = E(U - \mu_U)^2$$

$$\frac{1}{2\pi \sigma_x \sigma_y \sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)} (\gamma_1 \sum_i^t (\gamma_i^x))\right)$$

$$\Sigma = \begin{pmatrix} \sigma_x^2 & \rho \sigma_x \sigma_y \\ \rho \sigma_x \sigma_y & \sigma_y^2 \end{pmatrix}$$

3. Let $(\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2, \rho)$ be the parameters of the bivariate normal random variable (X, Y) . Let $\begin{bmatrix} U \\ V \end{bmatrix} = \begin{bmatrix} a & b \\ b & c \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix}$, where a, b, c are constant.

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$$\text{variable } (X, Y). \text{ Let } \begin{bmatrix} U \\ V \end{bmatrix} = \begin{bmatrix} a & b \\ b & c \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix}, \text{ where } a, b, c \text{ are constant.}$$

1) Derive $\text{Var}(U)$ and $\text{Var}(V)$.

2) Derive $\text{Cov}(U, V)$.

$$\begin{aligned} \Rightarrow \begin{bmatrix} U \\ V \end{bmatrix} = \begin{bmatrix} aX+bY \\ bX+cY \end{bmatrix} &\Rightarrow \begin{cases} \text{Var}(U) = \text{Var}(aX+bY) = a^2 \text{Var}(X) + b^2 \text{Var}(Y) + 2ab \text{Cov}(X, Y) \\ \text{Var}(V) = \text{Var}(bX+cY) = b^2 \text{Var}(X) + c^2 \text{Var}(Y) + 2bc \text{Cov}(X, Y) \end{cases} \\ \Rightarrow \begin{cases} \text{Var}(U) = a^2 \sigma_X^2 + b^2 \sigma_Y^2 + 2ab \rho \sigma_X \sigma_Y \\ \text{Var}(V) = b^2 \sigma_X^2 + c^2 \sigma_Y^2 + 2bc \rho \sigma_X \sigma_Y \end{cases} &\quad \checkmark \end{aligned}$$

$$\Rightarrow \text{Cov}(U, V) = \text{Cov}(aX+bY, bX+cY) = ab \text{Var}(X) + ac \text{Cov}(X, Y) + b^2 \text{Cov}(X, Y) + bc \text{Var}(Y)$$

$$\Rightarrow \text{Cov}(U, V) = ab \text{Var}(X) + (ac+bc)\rho \sigma_X \sigma_Y + bc \sigma_Y^2 \quad \checkmark$$

$$\int f(x) = \frac{1}{\beta} e^{-\frac{x}{\beta}}$$

$$4. 1) \text{ Calculate } P(X_1 > 2, \dots, X_n > 2) \quad \text{when} \quad X_1, \dots, X_n \stackrel{iid}{\sim} \text{exponential}(\beta), \quad \text{Dots} \\ \text{where } \boxed{\beta} = \boxed{EX_1}.$$

$$2) \text{ Calculate } P(0 \leq X_1 \leq 2, \dots, 0 \leq X_n \leq 2) \quad \text{when} \quad X_1, \dots, X_n \stackrel{iid}{\sim} \text{N}(\mu, \sigma^2). \quad \text{Use}$$

$$\Phi(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right) du \text{ to write the answer.}$$

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$$1) P(X_1 > 2, \dots, X_n > 2) = P(X_1 > 2) P(X_2 > 2) \dots P(X_n > 2) = [1 - F_{X_1}(2)] [1 - F_{X_2}(2)] \dots [1 - F_{X_n}(2)] \\ \stackrel{iid}{=} [1 - F_{X_1}(2)]^n \quad \text{where} \quad F_{X_1}(x) = 1 - e^{-\frac{x}{\beta}}, \quad 0 < x < \infty \\ \Rightarrow [1 - F_{X_1}(2)] = e^{-\frac{2}{\beta}} \quad \checkmark$$

$$2) P(0 \leq X_1 \leq 2) = P(X_1 \leq 2) - P(X_1 \leq 0) = P\left(\frac{X_1 - \mu}{\sigma} \leq \frac{2 - \mu}{\sigma}\right) - P\left(\frac{X_1 - \mu}{\sigma} \leq \frac{-\mu}{\sigma}\right) \\ = P\left(\frac{2 - \mu}{\sigma} \leq Z\right) - P\left(\frac{-\mu}{\sigma} \leq Z\right) \\ \Rightarrow P(0 \leq X_1 \leq 2, \dots, 0 \leq X_n \leq 2) = \left[P\left(\frac{2 - \mu}{\sigma} \leq Z\right) - P\left(\frac{-\mu}{\sigma} \leq Z\right) \right]^n \quad \checkmark$$

5. A bivariate random vector (X, Y) has a bivariate normal distribution with parameters $(\mu_x, \mu_y, \sigma_x^2, \sigma_y^2, \rho)$. Calculate EX^2Y .

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$$E[X^2Y] = E \left[\frac{\partial^3}{\partial s^2 \partial t} [e^{sx+ty}] \right] = \frac{\partial^3}{\partial s^2 \partial t} E(e^{sx+ty})$$

$$\checkmark = \frac{\partial^3}{\partial s^2 \partial t} M_{sx+ty}(1) \Big|_{s=t=0} = \frac{\partial^3}{\partial s^2 \partial t} \exp(s\mu_x + t\mu_y + \frac{1}{2}(s^2\sigma_x^2 + 2st\rho\sigma_x\sigma_y + t^2\sigma_y^2)) \Big|_{s=t=0}$$

$$\textcircled{+1} = \frac{\partial^2}{\partial s^2} (\mu_y + s\rho\sigma_x\sigma_y + t\sigma_y^2) M_{sx+ty}(1) \Big|_{s=t=0}$$

$$= \frac{\partial}{\partial s} \left(\rho\sigma_x\sigma_y M_{sx+ty}(1) \Big|_{s=t=0} + (\mu_y + s\rho\sigma_x\sigma_y + t\sigma_y^2)(\mu_x + s\sigma_x^2 + t\rho\sigma_x\sigma_y) \right) \Big|_{s=t=0}$$

$$= \rho\sigma_x\sigma_y \left(\mu_x + s\sigma_x^2 + t\rho\sigma_x\sigma_y \right) + (\rho\sigma_x\sigma_y)(\mu_x + s\sigma_x^2 + t\rho\sigma_x\sigma_y) + \\ + (\mu_y + s\rho\sigma_x\sigma_y + t\sigma_y^2) \sigma_x^2 \Big|_{s=t=0}$$

$$= \rho\sigma_x\sigma_y \mu_x + \rho\sigma_x\sigma_y \mu_x + \mu_y \sigma_x^2 \quad \text{X} \\ = 2\rho\sigma_x\sigma_y \mu_x + \mu_y \sigma_x^2 \quad \text{X}$$

should be.

$$\mu_x(\sigma_x^2 + \mu_x^2) + 2\sigma_x\sigma_y\rho\mu_x.$$