

Jointly Normal R.V.'s

2 r.v.'s  $X$  and  $Y$  are jointly Normal (or jointly Gaussian) if their joint density is

$$f_{X,Y}(x,y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\gamma^2}} \cdot \exp\left\{-\frac{1}{2(1-\gamma^2)}\left(\frac{(x-\mu_1)^2}{\sigma_1^2} + \frac{(y-\mu_2)^2}{\sigma_2^2} - 2\gamma\frac{(x-\mu_1)(y-\mu_2)}{\sigma_1\sigma_2}\right)\right\}$$

$$|\gamma| < 1.$$

( $\gamma \Rightarrow$  Correlation Coefficient)

Marginal densities:

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}}; \quad f_Y(y) = \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{(y-\mu_2)^2}{2\sigma_2^2}}$$

Important Facts:

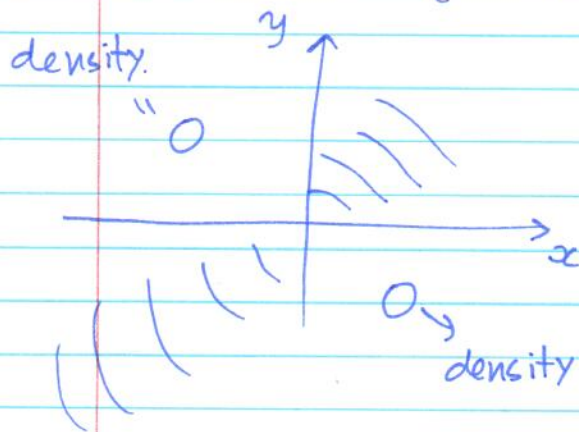
① If two random variables are jointly normal, they are also marginally normal. The reverse statement is not true in general.

② Joint normality can also be defined as follows:

$X$  and  $Y$  are jointly normal if the sum  $aX + bY$  is normal for every  $a$  and  $b$ .

Counter-Example :

$$f_{X,Y}(x,y) = \begin{cases} \frac{1}{\pi} e^{-\frac{(x^2+y^2)}{2}} & xy \geq 0 \\ 0 & xy < 0 \end{cases}$$



Check if  $Z = X + Y$  is a Normal r.v.

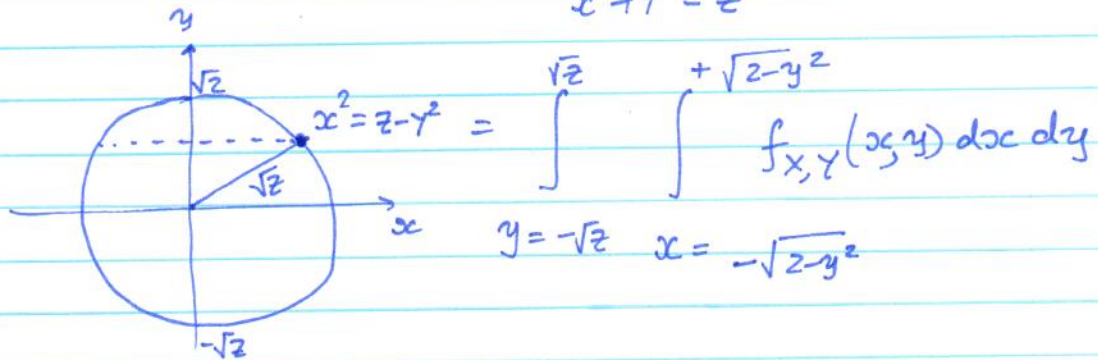
Answer  $\rightarrow$  No.

[Try this Yourself]

Eg

$$Z = X^2 + Y^2$$

$$F_Z(z) = P(X^2 + Y^2 \leq z) = \iint_{x^2 + y^2 \leq z} f_{X,Y}(x,y) dx dy$$



$$F_Z(z) = \int_{y=-\sqrt{z}}^{\sqrt{z}} \left( \int_{x=-\sqrt{z-y^2}}^{+\sqrt{z-y^2}} f_{X,Y}(x,y) dx \right) dy$$

$$f_Z(z) = \frac{d F_Z(z)}{dz} \quad \left. \vphantom{\frac{d F_Z(z)}{dz}} \right\} \text{(Leibniz Rule)}$$

$$= \left( \frac{d(\sqrt{z})}{dz} (0) - \frac{d(-\sqrt{z})}{dz} (0) \right) + \int_{-\sqrt{z}}^{\sqrt{z}} \frac{d}{dz} \left( \int_{-\sqrt{z-y^2}}^{\sqrt{z-y^2}} f_{X,Y}(x,y) dx \right) dy$$

$$= \int_{-\sqrt{z}}^{\sqrt{z}} \left[ \frac{1}{2\sqrt{z-y^2}} f_{X,Y}(\sqrt{z-y^2}, y) - \left( \frac{-1}{2\sqrt{z-y^2}} \right) \cdot f_{X,Y}(-\sqrt{z-y^2}, y) \right] dy$$

again Leibniz Rule...

$$= \int_{-\sqrt{z}}^{\sqrt{z}} \frac{1}{2\sqrt{z-y^2}} \left( f_{X,Y}(\sqrt{z-y^2}, y) + f_{X,Y}(-\sqrt{z-y^2}, y) \right) dy.$$



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Eg. continued...

Suppose  $X$  and  $Y$  are independent normal r.v.'s with 0 mean & common variance  $\sigma^2$ . Find  $f_z(z)$  when  $z = X^2 + Y^2$ .

$$\begin{aligned} f_{X,Y}(x,y) &= f_X(x) f_Y(y) \\ &= \frac{1}{2\pi\sigma^2} \cdot e^{-\frac{x^2}{2\sigma^2}} \cdot e^{-\frac{y^2}{2\sigma^2}} \end{aligned}$$

From prev. page,...

$$\begin{aligned} f_{X,Y}(\sqrt{z-y^2}, y) &= \frac{1}{2\pi\sigma^2} e^{-\frac{(z-y^2)}{2\sigma^2}} \cdot e^{-\frac{y^2}{2\sigma^2}} \\ &= \frac{e^{-z/2\sigma^2}}{2\pi\sigma^2} \end{aligned}$$

$$f_{X,Y}(-\sqrt{z-y^2}, y) = \frac{e^{-z/2\sigma^2}}{2\pi\sigma^2}$$

$$\Rightarrow f_z(z) = \int_{-\sqrt{z}}^{\sqrt{z}} \frac{1}{2\sqrt{z-y^2}} \cdot \frac{2}{2\pi\sigma^2} e^{-z/2\sigma^2} dy$$

$$\begin{aligned} &= \frac{e^{-z/2\sigma^2}}{\pi\sigma^2} \left( \int_{-\sqrt{z}}^{\sqrt{z}} \frac{dy}{2\sqrt{z-y^2}} \right) \\ &= \left( \frac{e^{-z/2\sigma^2}}{\pi\sigma^2} \right) \cdot 2 \int_0^{\sqrt{z}} \frac{dy}{2\sqrt{z-y^2}} = \frac{e^{-z/2\sigma^2}}{(\sigma^2)} \quad \text{even function } -z/2\sigma^2, z \geq 0 \end{aligned}$$

Exponential r.v.

Worth Remembering....

$X, Y$  are independent normal r.v.'s.  
with 0 mean & variance  $\sigma^2$  each

$$Z = X^2 + Y^2 \sim \text{exponential} \left( \frac{1}{2\sigma^2} \right)$$

$$Z = \sqrt{X^2 + Y^2} \sim \text{Rayleigh r.v.}$$

$$f_Z(z) = \begin{cases} \frac{z}{\sigma^2} e^{-z^2/2\sigma^2} & z \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$W = X + iY$$

$X, Y$  are real, independent normal r.v.'s  
with 0 mean, equal variance  $\sigma^2$ .

Amplitude  $\Rightarrow |W| = \sqrt{X^2 + Y^2} \rightarrow \text{Rayleigh}$

Phase  $\Rightarrow \theta = \tan^{-1}\left(\frac{Y}{X}\right) \rightarrow \text{Uniform}(-\pi, \pi)$

If  $X$  &  $Y$  do not have zero mean, say  $\mu_X$  and  $\mu_Y$   
(still independent and normal),

$$\sqrt{X^2 + Y^2} \sim \text{Rician random variable.}$$

eg  $Z = \max(X, Y) = \begin{cases} X & \text{if } X > Y \\ Y & \text{if } X \leq Y \end{cases}$

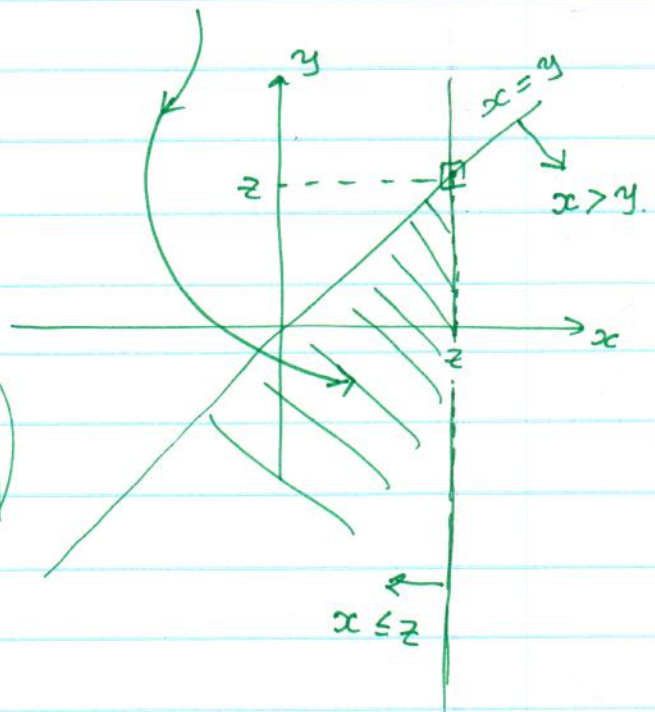
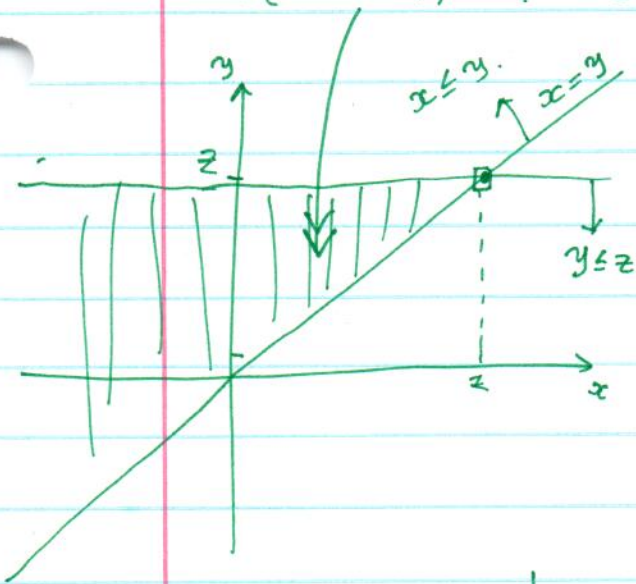
$$F_Z(z) = P(\max(X, Y) \leq z)$$

mutually exclusive

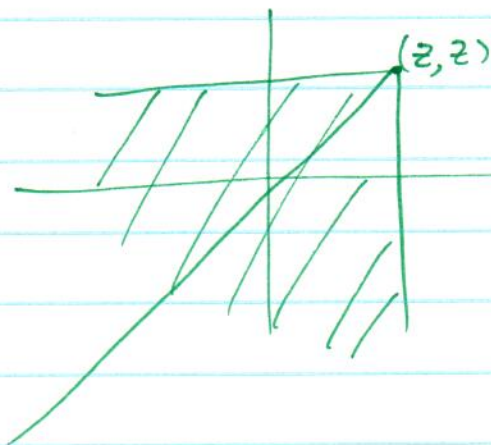
$$= P\left((\max(X, Y) \leq z) \cap \underbrace{\{(X \leq Y) \cup (X > Y)\}}_{\text{Sample space}}\right)$$

$$= P(X \leq Y, \max(X, Y) \leq z) + P(X > Y, \max(X, Y) \leq z)$$

$$= P(X \leq Y, Y \leq z) + P(X > Y, X \leq z)$$



$\Rightarrow$



$$\Rightarrow F_Z(z) = F_{X, Y}(z, z)$$



If  $X$  and  $Y$  are independent...

$$F_Z(z) = F_{X,Y}(z, z) = F_X(z) F_Y(z)$$

$$\Rightarrow \frac{d}{dz} F_Z(z) = f_X(z) F_Y(z) + F_X(z) f_Y(z)$$

$\Rightarrow$  For  $X, Y$  independent,  $Z = \max(X, Y)$

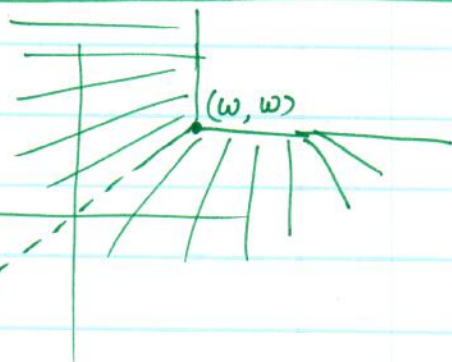
$$\rightarrow f_Z(z) = f_X(z) F_Y(z) + F_X(z) f_Y(z).$$

$$W = \min(X, Y) \rightarrow$$

$$F_W(w) = 1 - P(W > w)$$

$$= 1 - P(X > w, Y > w)$$

$$F_W(w) = F_X(w) + F_Y(w) - F_{X,Y}(w, w).$$



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## Two functions of 2 r.v.'s

Let  $Z = g(X, Y)$

$W = h(X, Y)$

If the functions  $g(x, y)$  and  $h(x, y)$  are continuous and differentiable, then we can directly obtain the joint density of  $(Z, W)$  from the joint density of  $(X, Y)$  as follows: →

Step 1: Consider the equations

$$g(x, y) = z ; \quad h(x, y) = w$$

For a given pair  $(z, w)$ , Let

$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$  denote the simultaneous solutions of the above, i.e

$$g(x_i, y_i) = z, \quad h(x_i, y_i) = w \quad \text{for } i=1, 2, \dots, n.$$

Step 2: ~~very~~ ~~easy~~

Find the Jacobian

$$J(x_i, y_i) = \begin{vmatrix} \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \\ \frac{\partial h}{\partial x} & \frac{\partial h}{\partial y} \end{vmatrix} \quad \begin{matrix} x = x_i, \\ y = y_i \end{matrix}$$



Step 3:

$$f_{z,w}(z,w) = \sum_i \frac{1}{|J(x_i, y_i)|} \cdot f_{x,y}(x_i, y_i)$$


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Eg 1:       $z = aX + bY$   
                   $w = cX + dY$

If  $ad - bc \neq 0$ , then the above system has only one  
 Solution:       $\left. \begin{array}{l} x = Az + Bw \\ y = Cz + Dw \end{array} \right\} \rightarrow (x_i, y_i)$

$$J(x, y) = \begin{vmatrix} a & b \\ c & d \end{vmatrix} = \cancel{ad} - bc$$

$$\Rightarrow f_{z,w}(z,w) = \frac{1}{|ad - bc|} f_{x,y}(Az + Bw, Cz + Dw)$$


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Eg 2:  $X, Y$  are zero mean, independent Gaussian r.v.'s with the same variance  $\sigma^2$ .

Find joint density of  $(r, \theta)$ , where

$$r = \sqrt{x^2 + y^2}$$

$$\theta = \tan^{-1}(y/x), \quad |\theta| < \pi$$

$$f_{X,Y}(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

$$\left. \begin{aligned} r &= g(x,y) = \sqrt{x^2+y^2} \\ \theta &= h(x,y) = \tan^{-1}(y/x) \end{aligned} \right\} \rightarrow \text{only 1 solution} \\ (x_1, y_1) = \begin{pmatrix} r \cos \theta \\ r \sin \theta \end{pmatrix}$$

$$J(x,y) = \begin{vmatrix} \frac{x}{\sqrt{x^2+y^2}} & \frac{y}{\sqrt{x^2+y^2}} \\ \frac{-y}{x^2+y^2} & \frac{x}{x^2+y^2} \end{vmatrix} = \frac{1}{\sqrt{x^2+y^2}} = \frac{1}{r}$$

$\Rightarrow$

$$\begin{aligned} f_{r,\theta}(r,\theta) &= \frac{1}{|J(x_1, y_1)|} \cdot f_{X,Y}(x_1, y_1) \\ &= r \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2\sigma^2} (r^2 \cos^2 \theta + r^2 \sin^2 \theta)} \end{aligned}$$

$$f_{r,\theta}(r,\theta) = \frac{r}{2\pi\sigma^2} e^{-r^2/2\sigma^2}, \quad 0 < r < \infty, \quad |\theta| < \pi$$

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$$f_{r,\theta}(r,\theta) = \frac{r}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} \quad \begin{matrix} 0 < r < \infty \\ |\theta| < \pi \end{matrix}$$

Marginal of  $r$

$$\underbrace{f_r(r)}_{\theta=-\pi} = \int_{-\pi}^{\pi} f_{r,\theta}(r,\theta) d\theta = \frac{r}{\sigma^2} e^{-\frac{r^2}{2\sigma^2}}, \quad 0 < r < \infty$$

↓  
Rayleigh r.v.

Marginal of  $\theta$

$$\underbrace{f_{\theta}(\theta)}_{r=0} = \int_0^{\infty} f_{r,\theta}(r,\theta) dr = \frac{1}{2\pi}, \quad |\theta| < \pi$$

↓  
uniform r.v.

$$\Rightarrow f_{r,\theta}(r,\theta) = f_r(r) \cdot f_{\theta}(\theta)$$

$\Rightarrow$   $r$  &  $\theta$  are independent r.v.'s  
(magnitude) (phase).



**IMPORTANT**

Eg 3 Let  $X$  and  $Y$  be independent exponential r.v.'s with <sup>(same)</sup> parameter  $\lambda$ .

$$U = X + Y$$

$$V = X - Y$$

$$f_{X,Y}(x,y) = \left( \frac{1}{\lambda} e^{-\frac{x}{\lambda}} \right) \left( \frac{1}{\lambda} e^{-\frac{y}{\lambda}} \right) \quad \begin{matrix} x > 0 \\ y > 0 \end{matrix}$$

$$= \frac{1}{\lambda^2} e^{-(x+y)/\lambda}$$

$$\left. \begin{matrix} u = x + y \\ v = x - y \end{matrix} \right\} \rightarrow \text{one solution } \left( \begin{matrix} x_1 = \left( \frac{u+v}{2} \right) \\ y_1 = \left( \frac{u-v}{2} \right) \end{matrix} \right)$$

$$J(x,y) = \begin{vmatrix} 1 & 1 \\ 1 & -1 \end{vmatrix} = -1 - 1 = -2$$

$$\Rightarrow f_{U,V}(u,v) = \frac{1}{|-2|} f_{X,Y}(x_1, y_1)$$

$$= \frac{1}{2} \frac{1}{\lambda^2} e^{-\left( \frac{u+v}{2} + \frac{u-v}{2} \right) / \lambda}$$

$$= \frac{1}{2\lambda^2} e^{-u/\lambda}, \quad 0 < |v| < u < \infty.$$

Why??  $\Rightarrow$

$$\left. \begin{matrix} x > 0, y > 0 \\ u = x + y \\ v = x - y \end{matrix} \right\} \Rightarrow |v| < u.$$

Marginal of U

$$f_U(u) = \int_{v=-u}^u f_{U,V}(u,v) dv = \frac{1}{2\lambda^2} \int_{-u}^u e^{-u/\lambda} dv$$

$$= \frac{1}{2\lambda^2} \cdot e^{-u/\lambda} \cdot 2u = \frac{u}{\lambda^2} e^{-u/\lambda},$$

$$0 < u < \infty$$

Marginal of V

$$f_V(v) = \int_{u=|v|}^{\infty} f_{U,V}(u,v) du = \int_{|v|}^{\infty} \frac{1}{2\lambda^2} e^{-u/\lambda} du$$

$$= \frac{e^{-|v|/\lambda}}{2\lambda}, \quad -\infty < v < \infty$$

$$f_{U,V}(u,v) \neq f_U(u) f_V(v)$$

$\Rightarrow$  U and V are NOT independent  
r.v.'s

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EXPECTED VALUE of a FUNCTION of 2 R.V.'s  
 $g(X, Y)$

$$E(g(X, Y)) = \int_{x=-\infty}^{\infty} \int_{y=-\infty}^{\infty} g(x, y) f_{X,Y}(x, y) dx dy$$

LINEARITY of EXPECTATION

$$\begin{aligned} E(a_1 g_1(X, Y) + a_2 g_2(X, Y) + \dots + a_n g_n(X, Y)) \\ = \sum_{i=1}^n a_i E(g_i(X, Y)) \end{aligned}$$

Recall,  $E(X+Y) = E(X) + E(Y)$

However, in general  $E(XY) \neq E(X)E(Y)$  ✓



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## COVARIANCE of 2 RANDOM VARIABLES

 $C$  or  $C_{XY}$  or  $\sigma_{XY}$ 

$$C_{XY} = E[(X - \mu_X)(Y - \mu_Y)]$$

$$= E[XY - \mu_Y X - \mu_X Y + \mu_X \mu_Y]$$

$$= E(XY) - \mu_Y \mu_X - \mu_X \mu_Y + \mu_X \mu_Y$$

$$= E(XY) - \mu_X \mu_Y$$

$$C_{XY} = E(XY) - E(X)E(Y)$$

$$\text{Var}(X+Y) = E[(X+Y - (\mu_X + \mu_Y))^2]$$

$$= E[(X - \mu_X + Y - \mu_Y)^2]$$

$$= \underbrace{E[(X - \mu_X)^2]}_{\text{Var}(X)} + \underbrace{E[(Y - \mu_Y)^2]}_{\text{Var}(Y)} + 2 \underbrace{E[(X - \mu_X)(Y - \mu_Y)]}_{\text{Cov}(X, Y)}$$

or  
 $C_{XY}$

 $\Rightarrow$ 

$$V(X+Y) = V(X) + V(Y) + 2C_{XY}$$