

We have defined the joint cdf and joint pdf of two rvs X and Y . If X and Y are both discrete, we use: 10/18/2022

Defn. the joint probability mass function of two discrete rvs X and Y is

$$P_{XY}(x, y) = P(\{X=x\} \cap \{Y=y\}),$$
$$\forall x \in \mathcal{R}_X, y \in \mathcal{R}_Y$$

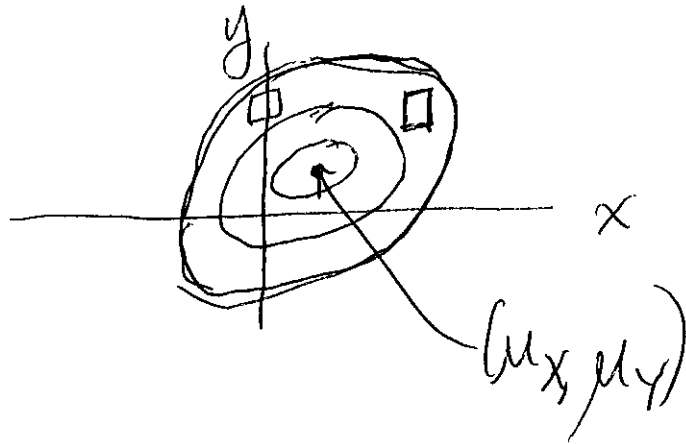
Jointly Gaussian Random Variables

Two rvs X and Y are jointly Gaussian if

$$f_{XY}(x, y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-r^2}} \exp\left[-\frac{1}{2(1-r^2)} \left[\frac{(x-\mu_x)^2}{\sigma_x^2} - \frac{2r(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y} + \frac{(y-\mu_y)^2}{\sigma_y^2} \right]\right]$$

where $\mu_x, \mu_y, \sigma_x, \sigma_y, r \in \mathbb{R}; \sigma_x > 0, \sigma_y > 0,$
 $-1 < r < 1$

Note that the contours ② of this function are ellipses



The major and minor axes (lengths and orientations) depend on σ_x, σ_y, r

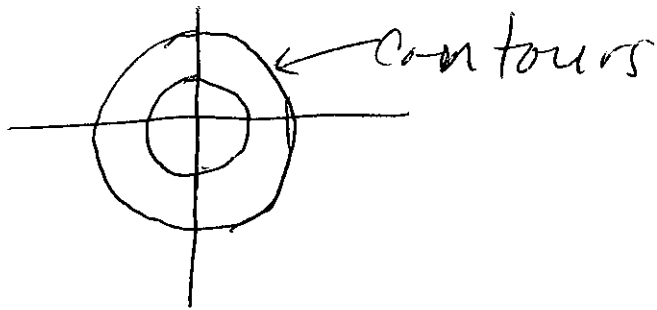
It can be shown that if X, Y are jointly Gaussian, then X and Y are each marginally Gaussian

— The converse is not necessarily true

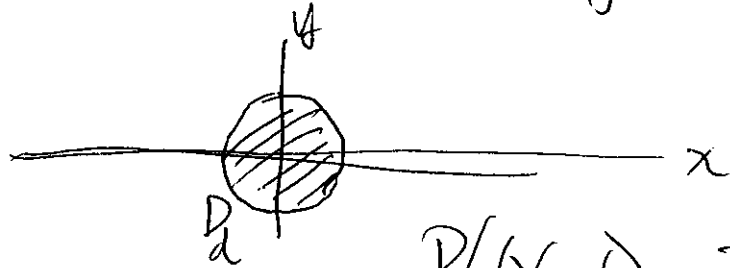
example. Consider jointly Gaussian rvs X and Y with (3)

$$\mu_x = \mu_y = r = 0, \quad \sigma_x = \sigma_y = \sigma \in \mathbb{R}$$

$$\text{Then } f_{XY}(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

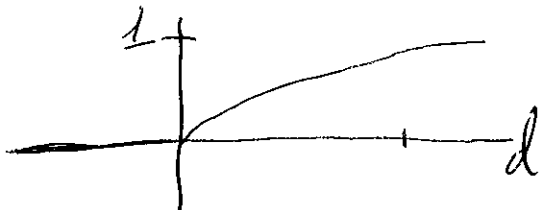


Find the probability that (X, Y) lies within a distance d of the origin



$$P((X, Y) \in D_d)?$$

$$P((X, Y) \in D_d) = \int_{D_d} \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) dx dy$$



$$= 1 - e^{-d^2/2\sigma^2}$$

Statistical Independence of (4)

Two rvs

Defn. Two rvs X and Y are statistically independent if the events $\{X \in A\}$ and $\{Y \in B\}$ are independent $\forall A, B \in \mathcal{B}(\mathbb{R})$, i.e.

$$P(\{X \in A\} \cap \{Y \in B\}) = P(X \in A)P(Y \in B)$$

Equivalent definition:

X and Y are independent if $f_{XY}(x, y) = f_X(x)f_Y(y) \forall x, y \in \mathbb{R}$

To show equivalence:

First, assume X, Y are ind. and show $f_{XY}(x, y) = f_X(x)f_Y(y)$

Let $A = (-\infty, x], B = (-\infty, y]$ for any $x, y \in \mathbb{R}$

$$\begin{aligned} \text{Then } F_{XY}(x, y) &= P(X \in A, Y \in B) \\ &= P(X \in A)P(Y \in B) \end{aligned}$$

$$\text{So } F_{XY}(x, y) = P(X \leq x)P(Y \leq y) \quad (5)$$

$$= F_X(x)F_Y(y),$$

$$\text{So } f_{XY}(x, y) = f_X(x)f_Y(y)$$

Proof of the converse is left to the student.

One Function of Two rvs

Given rvs X, Y and a function $g: \mathbb{R}^2 \rightarrow \mathbb{R}$, let $Z = g(X, Y)$.

What is $f_Z(z)$?

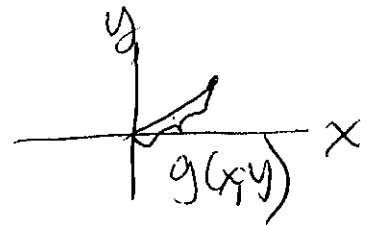
Some common examples:

- $g(x, y) = x + y$

- $g(x, y) = \frac{1}{2}(x + y)$

- $g(x, y) = \sqrt{x^2 + y^2}$

- $g(x, y) = A_{2 \times 2} \begin{bmatrix} x \\ y \end{bmatrix}$



General approach:

(5)

Find $F_Z(z)$ first, then differentiate to get f_Z

$$\begin{aligned} F_Z(z) &= P(Z \leq z) = P(g(X, Y) \leq z) \\ &= P((X, Y) \in D_z) \text{ where} \\ &\quad D_z \in \mathcal{B}(\mathbb{R}^2) \end{aligned}$$

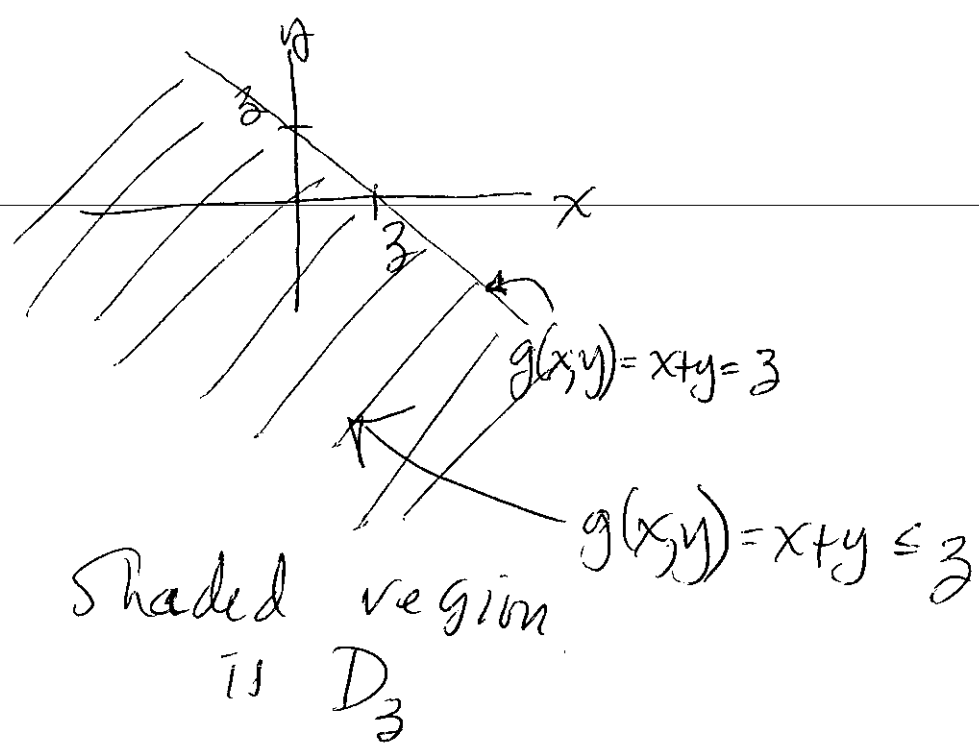
Need to find, for each $z \in \mathbb{R}$, $D_z = \{(x, y) \in \mathbb{R}^2 : g(x, y) \leq z\}$

$$\begin{aligned} \text{Then } F_Z(z) &= P((X, Y) \in D_z) \\ &= \int_{D_z} f_{X,Y}(x, y) dx dy \end{aligned}$$

Example, $Z = X + Y$

$g(x, y) = x + y$ here

$$P(Z \leq z) = P(X + Y \leq z)$$



So
$$F_z(z) = \int_{-\infty}^{\infty} \int_{-\infty}^{z-x} f_{xy}(x,y) dy dx$$

This is the result for general X, Y .

If we assume X, Y are ind., then

$$F_z(z) = \int_{-\infty}^{\infty} \int_{-\infty}^{z-x} f_x(x) f_y(y) dy dx$$

$$= \int_{-\infty}^{\infty} f_x(x) F_y(z-x) dx$$

$$f_z(z) = \int_{-\infty}^{\infty} f_x(x) f_y(z-x) dx$$

$$= (f_x * f_y)(z) \quad \forall z \in \mathbb{R}$$

Example. X and Y are ind. (7)
exponential rvs with $\mu_x = \mu_y = \mu$

Let $Z = X + Y$.

Then

$$f_z(z) = \int_{-\infty}^{\infty} \frac{1}{\mu} e^{-x/\mu} u(x) \cdot \frac{1}{\mu} e^{-\cancel{y/\mu}} e^{-(z-x)/\mu} u(z-x) dx$$

$$= \frac{z}{\mu^2} e^{-z/\mu} u(z)$$

