

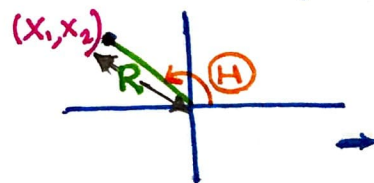
In the previous example and the ~~exercises~~ exercises (based on the change of joint density formula), the choice of I (and ~~hence~~ hence J) was obvious — just take $I = \text{Range}(X_1, X_2)$, the most natural joint range of X_1 and X_2 . Now we shall go through an example for which I has to be ~~a~~ chosen carefully.

Example: Suppose $X_1, X_2 \stackrel{iid}{\sim} N(0, 1)$.

Define $Y_1 \doteq R = +\sqrt{X_1^2 + X_2^2}$ and

$Y_2 = \textcircled{H} = \text{Angle}_{\text{in radian}} \text{ made by } (X_1, X_2) \text{ with}$
 (in the ~~anticlock~~ anticlockwise direction) ~~with~~ the positive side of X_1 -axis.
 (horizontal axis)

In other words, $(Y_1, Y_2) = (R, \textcircled{H})$ is the polar coordinate transform of (X_1, X_2) . Find the ^{joint} dist^n of (R, \textcircled{H}) .



Solution: Since $X_1, X_2 \stackrel{iid}{\sim} N(0, 1)$, the most natural choice for I is \mathbb{R}^2 . However, there are some issues with this ~~choice~~ choice (see below).

Issue #1: \textcircled{H} is not well-defined for the

point $(0,0)$.

One may think that removing origin from \mathbb{R}^2 will ~~not~~ resolve the problem but that will still leave us with the following issue.

Issue # 2: The function \textcircled{H} won't even be continuous at ~~all~~ ^{any} points on the positive side of the X_1 -axis, i.e., the horizontal axis.

In order to resolve the above issues, we need to take/choose

$$I = \mathbb{R}^2 \setminus \{(x_1, 0) : x_1 \geq 0\}.$$

Exc: Check that I is open (either use the defⁿ or the thm stated in Pg $\textcircled{126}$) and and path-connected (verify visually).

We also need to ~~take~~ use the following joint pdf of (X_1, X_2) :

$$f_{X_1, X_2}(x_1, x_2) = \begin{cases} \frac{1}{2\pi} \exp\{-\frac{1}{2}(x_1^2 + x_2^2)\} & \text{if } (x_1, x_2) \in I, \\ 0 & \text{if } (x_1, x_2) \notin I. \end{cases}$$

With these choices of I and f_{x_1, x_2} , we define $g: I \rightarrow \mathbb{R}^2$ by

$$g(x_1, x_2) = (r, \theta), \quad (x_1, x_2) \in I,$$

where

$$r = +\sqrt{x_1^2 + x_2^2} \in (0, \infty), \quad \text{and}$$

$\theta = \text{angle}_{\text{in radian}} \text{ made by } (x_1, x_2) \text{ with the positive side of the } x_1\text{-axis (i.e., the horizontal axis) in the anticlockwise direction}$

$\in (0, 2\pi)$. We want to find the joint distⁿ of $(R, \Theta) = g(x_1, x_2)$.

It is clear that $g(I) \subseteq (0, \infty) \times (0, 2\pi)$.

Exc: Show that $g(I) = (0, \infty) \times (0, 2\pi) =: J$

and $g: I \rightarrow J$ is a bijection.

Exc: Show that the inverse map of g is given by $g^{-1}: J \rightarrow I$

$$g^{-1}(r, \theta) = (r \cos \theta, r \sin \theta), \quad (r, \theta) \in J.$$

In particular, in the notation of P_g (130)-(131), the maps $h_1: J \rightarrow \mathbb{R}$ and $h_2: J \rightarrow \mathbb{R}$ are given by

$$h_1(r, \theta) = r \cos \theta, \quad (r, \theta) \in J$$

$$h_2(r, \theta) = r \sin \theta, \quad (r, \theta) \in J$$

so that

$$g^{-1}(r, \theta) = (h_1(r, \theta), h_2(r, \theta)), \quad (r, \theta) \in J.$$

Hence the Jacobian matrix of g^{-1} is given by

$$J_{g^{-1}}(r, \theta) = \begin{pmatrix} \frac{\partial h_1}{\partial r} & \frac{\partial h_1}{\partial \theta} \\ \frac{\partial h_2}{\partial r} & \frac{\partial h_2}{\partial \theta} \end{pmatrix}, \quad (r, \theta) \in J$$

$$= \begin{pmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{pmatrix}, \quad (r, \theta) \in J$$

$$\begin{aligned} \Rightarrow \det(J_{g^{-1}}(r, \theta)) &= r \cos^2 \theta - (-r \sin^2 \theta) \\ &= r (\cos^2 \theta + \sin^2 \theta) = r, \quad (r, \theta) \in J. \end{aligned}$$

In particular, this means that g is indeed "smooth" in the sense of Pg (133), i.e., the partial derivatives $\frac{\partial h_1}{\partial r}$, $\frac{\partial h_1}{\partial \theta}$, $\frac{\partial h_2}{\partial r}$, $\frac{\partial h_2}{\partial \theta}$ exist and are cont on J , and

$$\frac{dg^{-1}(r, \theta)}{d(r, \theta)} = \det(J_{g^{-1}}(r, \theta)) = r \neq 0 \text{ on } J. \\ (\text{in fact } r > 0 \text{ on } J.)$$

We have verified that all the assumptions of the bivariate change of joint density formula are satisfied. Therefore, it follows that $(R, \Theta) = g(X_1, X_2)$ is also a cont random vector with a joint pdf

$$\begin{aligned} f_{R, \Theta}(r, \theta) &= f_{X_1, X_2}(g^{-1}(r, \theta)) \left| \frac{dg^{-1}(r, \theta)}{d(r, \theta)} \right|, \quad (r, \theta) \in J \\ &= f_{X_1, X_2}(r \cos \theta, r \sin \theta) \cdot r, \quad (r, \theta) \in J \\ &= \frac{1}{2\pi} r e^{-\frac{1}{2}r^2} \quad \text{if } r > 0, \theta \in (0, 2\pi). \end{aligned}$$

Note that the above joint pdf of R and Θ

splits into a product of a function of r (say, $\frac{1}{2\pi} r e^{-r^2/2}$, $r \in (0, \infty)$ and a function of θ (namely, the constant function 1 for $\theta \in (0, 2\pi)$)

and the ranges of r and θ do not depend on each other. Therefore it follows that $R \perp\!\!\!\perp \textcircled{H}$.

Exc: Show that R follows Rayleigh distribution with a pdf

$$f_R(r) = \begin{cases} r e^{-\frac{1}{2}r^2} & \text{if } r > 0, \\ 0 & \text{if } r \leq 0, \end{cases}$$

$\textcircled{H} \sim \text{Unif}(0, 2\pi)$ with a pdf

$$f_{\textcircled{H}}(\theta) = \begin{cases} \frac{1}{2\pi} & \text{if } \theta \in (0, 2\pi), \\ 0 & \text{if } \theta \notin (0, 2\pi), \end{cases}$$

and $R \perp\!\!\!\perp \textcircled{H}$.

Remarks: ① Note that $R^2 = X_1^2 + X_2^2 \sim \chi_2^2$

$$\Rightarrow R^2 \sim \chi_2^2 \equiv \text{Gamma}(1, \frac{1}{2}) \equiv \text{Exp}(\frac{1}{2})$$

\Rightarrow If $T \sim \text{Exp}(\frac{1}{2})$, then \sqrt{T} follows Rayleigh distⁿ. (Exc: Check this directly.)

② Heuristically speaking, the independence of R and Θ , and $\Theta \sim \text{Unif}(0, 2\pi)$ are manifestations of the "rotational symmetry" of (X_1, X_2) ~~when X_1, X_2~~ (when $X_1, X_2 \stackrel{\text{iid}}{\sim} N(0, 1)$): ~~More precisely,~~

Exc: Suppose $X_1, X_2 \stackrel{\text{iid}}{\sim} N(0, 1)$. Define

~~Y_1, Y_2~~ Fix $\phi \in (0, 2\pi)$ and define

$$Y_1 = X_1 \cos \phi - X_2 \sin \phi \quad \text{and}$$

$$Y_2 = X_1 \sin \phi + X_2 \cos \phi.$$

In other words, (Y_1, Y_2) is the random

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vector obtained by rotating (X_1, X_2) by an angle ϕ (in radian) anticlockwise. Show

that $Y_1, Y_2 \stackrel{iid}{\sim} N(0,1)$. (Therefore, the ^{joint} distⁿ of (X_1, X_2) remains unchanged when we apply a rotation.)

③ It can be shown that the converse of the above example (given in Pg (140)) also holds.

That is, if we take

$$\begin{array}{l} \text{ind} \left\{ \begin{array}{l} R \sim \text{Rayleigh dist}^n \\ \textcircled{H} \sim \text{Unif}(0, 2\pi) \end{array} \right. \end{array},$$

then

$$X_1 := R \cos \textcircled{H}, \quad X_2 := R \sin \textcircled{H} \stackrel{iid}{\sim} N(0,1).$$

Thanks to

④ ~~Using~~ ^{Thanks to} ③, one can simulate a pair of

iid standard normal random variables using the following method (known as the Box-Muller method):

Step 1: Generate $U_1, U_2 \stackrel{\text{iid}}{\sim} \text{Unif}(0,1)$.

Step 2: Define $Z_1 := \sqrt{-2 \log_e U_1} \cos(2\pi U_2)$,
 $Z_2 := \sqrt{-2 \log_e U_1} \sin(2\pi U_2)$.

Then $Z_1, Z_2 \stackrel{\text{iid}}{\sim} N(0,1)$.

Exc: Assuming ③, show that the Box-Muller method actually works.

Exc: Write a program and simulate a random sample (i.e., iid sample) of size 10000 from the standard normal distⁿ λ using Box-Muller method. Draw the histogram of ~~these~~ ~~point~~ this sample and check how close it is ~~looks~~ to the bell-shaped ^{normal} curve.

Linearity and Monotonicity of Expectation

Recall that for a (discrete or continuous) r.v. X and a function $h: \text{Range}(X) \rightarrow \mathbb{R}$, the r.v. $h(X)$ has finite mean provided

$$\sum_{x \in \text{Range}(X)} |h(x)| p_x(x) < \infty \quad \text{when } X \text{ is discrete (with pmf } p_x), \text{ and}$$

$$\int_{-\infty}^{\infty} |h(x)| f_x(x) dx < \infty \quad \text{when } X \text{ is cont (with a pdf } f_x).$$

In the above situation,

$$E[h(X)] = \begin{cases} \sum_{x \in \text{Range}(X)} h(x) p_x(x) & \text{when } X \text{ is discrete,} \\ \int_{-\infty}^{\infty} h(x) f_x(x) dx & \text{when } X \text{ is cont.} \end{cases}$$

This univariate fact has a multivariate generalization, which we shall state without proof.

Now suppose that $\underline{X} = (X_1, X_2, \dots, X_k)$ is a ~~r.v.~~ (discrete or continuous) random vector and $h: \text{Range}(\underline{X}) \rightarrow \mathbb{R}$ is a function. Then the r.v. $h(\underline{X}) = h(X_1, X_2, \dots, X_k)$ has finite mean provided

$\sum_{\underline{z} \in \text{Range}(\underline{X})} |h(\underline{z})| p_{\underline{X}}(\underline{z}) < \infty$ when \underline{X} is a discrete random vector with joint pmf $p_{\underline{X}}$,
and

~~$$\int_{\mathbb{R}} \dots \int_{\mathbb{R}} |h(\underline{z})| dz_1 \dots dz_k < \infty \text{ when } \underline{X}$$~~

$\int_{\mathbb{R}^k} |h(\underline{z})| f_{\underline{X}}(\underline{z}) d\underline{z} < \infty$ when \underline{X} is a cont random vector with a joint pdf $f_{\underline{X}}$.

In the above situation,

$$E[h(\underline{X})] = \begin{cases} \sum_{\underline{z} \in \text{Range}(\underline{X})} h(\underline{z}) p_{\underline{X}}(\underline{z}) & \text{when } \underline{X} \text{ is discrete,} \\ \int_{\mathbb{R}^k} h(\underline{z}) f_{\underline{X}}(\underline{z}) d\underline{z} & \text{when } \underline{X} \text{ is cont.} \end{cases}$$

(e)