

# Transformations

## Examples of transformations

- Linear transformations of random variables and vectors  $Y = aX + b$
- Non-linear invertible transformations of random variables  $Y = g(X)$
- Sums  $Y = X_1 + X_2$

## Transformations previously

We have a technique for computing the expectation of transformed random variable. What is its name?

LOTUS:

$$\mathbb{E}[g(X)] = \sum_x g(x) \mathbb{P}(X = x)$$

It works with continuous r.v.s:

$$\mathbb{E}[g(X)] = \int g(x) f_X(x) dx$$

And it works in multiple dimensions:

$$\mathbb{E}[g(X, Y)] = \sum_x \sum_y g(x, y) \mathbb{P}(X = x, Y = y)$$

## Transformations now

Now we want not just the expected value, but the whole distribution (CDF, PMF, PDF). The approach depends on whether the distribution is discrete or continuous.

## Discrete case

The formula:

$$\mathbb{P}(g(X) = y) = \sum_{x \text{ such that } g(x)=y} \mathbb{P}(X = x)$$

If  $g(\cdot)$  is one-to-one, it simplifies to:

$$\mathbb{P}(g(X) = y) = \mathbb{P}(X = g^{-1}(y))$$

## Example 1

Let  $X \sim Bin(n, p)$ . Find the PDF of  $Y = \exp(X)$ .

## Solution 1

So  $g(x) = \exp(x)$ , it's one-to-one and the inverse is  $g^{-1}(x) = \log x$ .

$$\mathbb{P}(Y = y) = \mathbb{P}(X = g^{-1}(y)) = \mathbb{P}(X = \log y)$$

## Continuous case

In the continuous case, when additionally  $g(\cdot)$  is one-to-one, continuous and strictly increasing, we have the following relation for CDF:

$$F_{g(X)}(y) = \mathbb{P}(g(X) \leq y) = \mathbb{P}(X \leq g^{-1}(y)) = F_X(g^{-1}(y))$$

To get the PDF, we need to differentiate this relation at every point with the chain rule:

$$f_{g(X)}(g(x))d(g(x)) = f_X(x)dx$$

To account for the case when  $g(\cdot)$  is strictly decreasing, we add the modulus

$$f_{g(X)}(g(x)) = f_X(x) \left| \frac{dg(x)}{dx} \right|^{-1}$$

This is called 1D change of variables formula. Similarly to discrete case, we can extend it to non one-to-one  $g(\cdot)$  using the sum over  $x$  such that  $g(x) = y$ .

## Example 2

Let  $X \sim Exp(1)$ . Find the PDF of  $Y = \exp(-X)$ .

## Solution 2

So  $g(x) = \exp(-x)$ , it is one-to-one, and  $g^{-1}(y) = -\log y$ . Let's find

$$\frac{dg(x)}{dx} = -\exp(-x)$$

So,

$$\begin{aligned} f_Y(y) &= f_X(x) \left| \frac{dg(x)}{dx} \right|^{-1} = f_X(-\log y) \exp(x) = \\ &= f_X(-\log y) \exp(-\log y) = \frac{1}{y} f_X(-\log y) \end{aligned}$$

## Example 3

Let  $X \sim \mathcal{N}(0, 1)$ . Find the PDF of  $Y = X^2$ . This distribution is called chi-square distribution.

## Solution 3

So,  $g(x) = x^2$ . It is not one-to-one, so we need the sum:

$$\begin{aligned}
f_Y(y) &= \sum_{x=\{-\sqrt{y}, \sqrt{y}\}} f_X(x) \left| \frac{dg(x)}{dx} \right|^{-1} = \sum_{x=\{-\sqrt{y}, \sqrt{y}\}} f_X(x) 2x = \\
&= f_X(\sqrt{y}) \frac{1}{2\sqrt{y}} + f_X(-\sqrt{y}) \frac{1}{2\sqrt{y}} = \\
&= 2f_X(\sqrt{y}) \frac{1}{2\sqrt{y}}
\end{aligned}$$

## Example 4

Let  $X$  be a random variable with PDF  $f_X$ . Find PDF of  $Y = aX + b$ .

## Solution 4

So,  $g(x) = ax + b$ , it is one-to-one, and the inverse is  $g^{-1}(y) = \frac{1}{a}(y - b)$ . We need to calculate

$$\begin{aligned}
\frac{dg(x)}{dx} &= \frac{d(ax + b)}{dx} = a \\
f_Y(y) &= f_X(x) \left| \frac{dg(x)}{dx} \right|^{-1} = f_X\left(\frac{y - b}{a}\right) \frac{1}{|a|}
\end{aligned}$$

## Multivariate transformations

Consider  $n$ -dimensional random vector  $X \in \mathbb{R}^n$  with continuous distribution with PDF  $f_X$ . Let  $g : A_0 \rightarrow B_0$  be invertive one-to-one function from open subset  $A_0$  containing support of  $X$  to an open subset  $B_0$  containing the range of  $g(\cdot)$ . Denote  $Y = g(X)$  and  $y = g(x)$ . Suppose that all partial derivatives  $\frac{\partial y_i}{\partial x_j}$  exist and are continuous. Then, we can form the Jacobian matrix:

$$\frac{\partial y}{\partial x} = \begin{pmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \cdots & \frac{\partial y_1}{\partial x_n} \\ \vdots & \ddots & & \vdots \\ \frac{\partial y_n}{\partial x_1} & \frac{\partial y_n}{\partial x_2} & \cdots & \frac{\partial y_n}{\partial x_n} \end{pmatrix}$$

Assume that this matrix is non-degenerate. Then, the PDF of  $Y$  is:

$$f_Y(y) = f_X(g^{-1}(y)) \left| \det \frac{\partial y}{\partial x} \right|^{-1}$$

If the function is not one-to-one, we add sum.

## Example 5

Consider  $n$ -dimensional random vector  $X \in \mathbb{R}^n$  with continuous distribution, a non-degenerate matrix  $A \in \mathbb{R}^{m \times n}$  and a vector  $b \in \mathbb{R}^m$ , then define random vector  $Y = AX + b$ . What is the expected value, the covariance matrix and the PDF of  $Y$ ?

## Solution 5

Its expected value will be  $\mathbb{E}[Y] = A\mathbb{E}[X] + b$  and its covariance matrix will be:

$$\Sigma_Y = \mathbb{E}[(AX - A\mathbb{E}[X])(AX - A\mathbb{E}[X])^\top] = A\mathbb{E}[(X - \mathbb{E}[X])(X - \mathbb{E}[X])^\top]A^\top = A\Sigma_X A^\top$$

So,

- $g(x) = Ax + b$
- $\frac{\partial y}{\partial x} = A$
- $g^{-1}(y) = A^{-1}(y - b)$

Therefore,

$$f_Y(y) = f_X(g^{-1}(y)) \left| \det \frac{\partial y}{\partial x} \right|^{-1} = f_X(A^{-1}(y - b)) \frac{1}{|\det A|}$$

## Example 6

Consider  $n$  independent standard normal r.v.s  $X_1, \dots, X_n \sim \mathcal{N}(0, 1)$  and vector  $X = (X_1, \dots, X_n)^\top$ . We know that

- $\mathbb{E}[X] = 0$
- $\Sigma_X = I$
- $f_X(x) = (2\pi)^{-n/2} \exp(-\frac{1}{2}x^\top x)$

Consider a non-degenerate matrix  $A \in \mathbb{R}^{n \times n}$  and  $Y = AX + m$ . Find its expectation, covariance matrix and distribution.

## Solution 6

From the previous example,  $\mathbb{E}[Y] = m$  and  $\Sigma_Y = AA^\top$

$$\begin{aligned} f_X(x) &= f_X(A^{-1}(y - m)) \frac{1}{|\det A|} = \\ &= \frac{1}{(2\pi)^{n/2} |\det A|} \exp\left(-\frac{(y - m)^\top A^{-\top} A^{-1}(y - m)}{2}\right) = \\ &= \frac{1}{(2\pi)^{n/2} \sqrt{\det \Sigma_Y}} \exp\left(-\frac{(y - m)^\top \Sigma_Y^{-1}(y - m)}{2}\right) \end{aligned}$$

What we just did, is we obtained a new random normal vector with controllable parameters from a standard normal random vector. This is a very useful property of a random normal vectors, but also demonstrates the power of linear transforms.

## Example 7

Let random vector  $(X, Y)$  have PDF  $f_{X,Y}(x, y)$ . Find the density of  $Z = X + Y$ .

## Solution 7

In order to find this density, consider transform

$$\begin{pmatrix} Z \\ Y \end{pmatrix} = A \begin{pmatrix} X \\ Y \end{pmatrix}$$

So, matrix  $A$  is...?

$$A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$$

Then,

$$f_{Z,Y}(z,y) = f_{X,Y}(A^{-1}(x,y)^\top, y) |\det A|^{-1} = f_{X,Y}(z-y, y)$$

Finally,

$$f_Z(z) = \int f_{Z,Y}(z,y) dy = \int f_{X,Y}(z-y, y) dy$$

If  $X \perp Y$ ,

$$f_Z(z) = \int f_X(z-y) f_Y(y) dy$$

This is the convolution rule that we studied on Seminar 4.

## Convolution rule

Consider independent r.v.s  $X$  and  $Y$ . Then, their sum  $Z = X + Y$  is distributed:

- If they are discrete,

$$\mathbb{P}(Z = n) = \sum_{k=-\infty}^{\infty} \mathbb{P}(X = k) \mathbb{P}(Y = n - k)$$

- If they are continuous,

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(z-y) f_Y(y) dy$$

## Example 8

Let  $X \sim Bi(n, p)$  and  $Y \sim Bi(m, p)$  be independent. What is the distribution of  $Z = X + Y$ ?

## Solution 8

$$\begin{aligned} \mathbb{P}(X + Y = k) &= \sum_j \binom{n}{j} p^j (1-p)^{n-j} \binom{m}{k-j} p^{k-j} (1-p)^{m-k+j} = \\ &= p^k (1-p)^{n+m-k} \sum_j \binom{n}{j} \binom{m}{k-j} = \\ &= \binom{n+m}{k} p^k (1-p)^{n+m-k} \end{aligned}$$

$$Z \sim Bi(n+m, p)$$

## Example 9

Let  $X, Y \sim Exp(1)$  be independent. Find the PDF of  $Z = \frac{X}{X+Y}$ .

## Solution 9

This one will be a non-linear transform. Consider transform  $(X, Y) \rightarrow (Z, U)$ , where  $U = X + Y$ . The inverse transform is  $X = UZ, Y = U - UZ$ . Jacobian of the inverse transform is

$$\frac{\partial(x, y)}{\partial(z, u)} = \begin{pmatrix} u & z \\ -u & 1-z \end{pmatrix}$$

The joint density is

$$f_{Z,U}(z, u) = f_{X,Y}(g^{-1}(z, u)) \left| \det \frac{\partial(x, y)}{\partial(z, u)} \right| = f_{X,Y}(uz, u - uz)u = ue^u, u > 0, 0 < z \leq 1$$

The joint density does not depend on  $z$ , it means that marginal density of  $Z$  is Uniform with support  $[0, 1]$ .

## Homework problems

1. Compute the moment-generating function of  $Geom(p)$ . Use it to find expectation and variance.
2. Let  $X$  and  $Y$  be i.i.d.  $Geom(p)$ , and  $N = X + Y$ . Find the joint PMF of  $X, Y, N$ . Find the joint PMF of  $X$  and  $N$ . Find the conditional PMF of  $X$  given  $N = n$
3. Let  $U \sim U[0, \frac{\pi}{2}]$ . Find the PDF of  $\sin(U)$ .
4. Let  $X$  and  $Y$  be i.i.d.  $Exp(\lambda)$ , and  $T = \log(X/Y)$ . Find the CDF and PDF of  $T$ .