



# Distribution of a function of a random variable

MATH/STAT 394: Probability I  
Summer 2021 A Term

Introduction to Probability  
D. Anderson, T. Seppäläinen, B. Valkó

§ 5.2

---

Aaron Osgood-Zimmerman

Department of Statistics

## Practice solution

### Practice

Let  $X$  be a discrete r.v. s.t.

$$\mathbb{P}(X = k) = \frac{\lambda^k}{k!} e^{-\lambda} \quad \text{for } k \in \{0, 1, \dots\}$$

1. Check that  $\sum_{k=0}^{+\infty} \mathbb{P}(X = k) = 1$
2. Compute  $\mathbb{E}[X]$ ,  $\text{Var}[X]$  for  $\lambda = 1$

*Reminder:* The Taylor series expansion of  $\exp$  is  $e^x = \sum_{n=0}^{+\infty} \frac{x^n}{n!}$  for any  $x \in \mathbb{R}$ .

### Solution

- First question is clear from the reminder
- Now

$$\mathbb{E}[X] = \sum_{k=0}^{+\infty} k \frac{\lambda^k}{k!} e^{-\lambda} = \sum_{k=1}^{+\infty} k \frac{\lambda^k}{k!} e^{-\lambda} = \lambda \sum_{k=1}^{+\infty} \frac{\lambda^{k-1}}{(k-1)!} e^{-\lambda} = \lambda \sum_{j=0}^{+\infty} \frac{\lambda^j}{j!} e^{-\lambda} = \lambda$$

- Similarly  $\mathbb{E}[X(X-1)] = \lambda^2 \sum_{k=2}^{+\infty} \frac{\lambda^{k-2}}{(k-2)!} e^{-\lambda} = \lambda^2$
- Hence  $\mathbb{E}[X^2] = \mathbb{E}[X(X-1)] + \mathbb{E}[X] = \lambda^2 + \lambda$  and  $\text{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \lambda$
- So for  $\lambda = 1$  we get  $\mathbb{E}[X] = \text{Var}[X] = 1$ .

# Recap

## Variance

- Variance

$$\text{Var}(X) = \mathbb{E}((X - \mathbb{E}[X])^2) = \mathbb{E}[X^2] - \mathbb{E}[X]^2$$

- Standard deviation:  $\sqrt{\text{Var}(X)}$
- for  $X \sim \text{Ber}(p)$ ,  $\text{Var}(X) = p(1 - p)$
- Property for  $a, b \in \mathbb{R}$

$$\text{Var}(aX + b) = a^2 \text{Var}(X)$$

- $\text{Var}(X) = 0 \iff \mathbb{P}(X = a) = 1$  for some  $a \in \mathbb{R}$

## Moments

- **nth moment** of a r.v.  $X$  is  $\mathbb{E}[X^n]$
- **nth centered moment** of a r.v.  $X$  is  $\mathbb{E}[(X - \mu)^n]$
- Expectation is the first moment
- Variance is the second centered moment

# Outline

Function of a discrete r.v.

Discrete function of a continuous r.v.

Continuous function of a continuous r.v.

Proofs

## Function of a discrete r.v.

### Exercise

Consider a game where you win with equal prob.  $-1, 0, 1$  or  $2\$$ .

What is the p.m.f. of the square of your gain?

### Solution

- Let  $X \sim \text{Unif}(\{-1, 0, 1, 2\})$  be your gain (uniform dist. on the discrete set  $\{-1, 0, 1, 2\}$ )
- Let  $Y = X^2$  the square of your gain, note that  $Y \in \{0, 1, 4\}$
- We can compute

$$\mathbb{P}(Y = 0) = \mathbb{P}(X^2 = 0) = \mathbb{P}(X = 0) = 1/4$$

$$\mathbb{P}(Y = 1) = \mathbb{P}(X^2 = 1) = \mathbb{P}(X = 1 \text{ or } X = -1))$$

$$= \mathbb{P}(X = 1) + \mathbb{P}(X = -1) = 1/2$$

$$\mathbb{P}(Y = 4) = \mathbb{P}(X^2 = 4) = \mathbb{P}(X = 2 \text{ or } X = -2)$$

$$= \mathbb{P}(X = 2) + \mathbb{P}(X = -2) = 1/4 + 0 = 1/4$$

## Images and pre-images

### Motivation

- Clearly getting the distribution of a function of a discrete r.v. is easy
- Let us introduce a few more definitions to clarify what happens

### Definition (Images and pre-images)

Let  $E, F$  be two sets and  $g : E \rightarrow F$ . The **image** of  $A \subseteq E$  by  $g$  is defined as

$$g(A) = \{g(x) : x \in A\} \subseteq F$$

The **pre-image** of  $B \subseteq F$  is

$$g^{-1}(B) = \{x \in E : g(x) \in B\} \subseteq E$$

### Note:

- Here  $g$  may not be invertible
- The above definition **applies on sets not on variables**.
- So the pre-image of a set always exists even if the inverse does not exist
- If there is no element that maps onto  $B$ , then  $g^{-1}(B) = \emptyset$

## Function of a discrete r.v.

### Lemma

Let  $X$  be a discrete r.v. and  $g : \mathbb{R} \rightarrow \mathbb{R}$ , denote  $Y = g(X)$ .

The p.m.f. of  $Y$  is given as

$$p_Y(\ell) = \mathbb{P}(g(X) = \ell) = \mathbb{P}(X \in g^{-1}(\{\ell\})) = \sum_{k: g(k)=\ell} p_X(k)$$

**Proof** Follows from the definition of the pre-image, namely

$$g^{-1}(\{\ell\}) = \{k : g(k) = \ell\}$$

and  $g(X) = \ell \iff X \in g^{-1}(\{\ell\})$ .

## Outline

Function of a discrete r.v.

Discrete function of a continuous r.v.

Continuous function of a continuous r.v.

Proofs



## Distribution of a discrete function of a continuous r.v.

### Exercise

Consider the score of a student to be uniformly distributed<sup>1</sup> on  $X \sim \text{Unif}[0, 100]$ .

A teacher rounds the scores of the students to the nearest integer (rounded up in case of two numbers equally distant).

What is the p.m.f. of the resulting scores?

### Solution

- For  $x \in \mathbb{R}$ , let  $g(x)$  be the nearest integer of  $x$
- The variable of interest is  $Y$  that takes values in  $g([0, 100]) = \{0, \dots, 100\}$
- We have for  $k \in \{1, \dots, 99\}$

$$\mathbb{P}(Y = k) = \mathbb{P}(X \in [k-1/2, k+1/2)) = \int_{k-1/2}^{k+1/2} \frac{1}{100} dx = \frac{k+1/2}{100} - \frac{k-1/2}{100} = \frac{1}{100}$$

- And for  $k = 0$  or  $k = 100$ ,

$$\mathbb{P}(Y = 0) = \mathbb{P}(X \in [0, 1/2]) = \int_0^{1/2} \frac{1}{100} dx = \frac{1/2}{100}$$

$$\mathbb{P}(Y = 100) = \mathbb{P}(X \in [99 + 1/2, 100]) = \int_{99+1/2}^{100} \frac{1}{100} dx = \frac{1/2}{100}$$

## Distribution of a discrete function of a continuous r.v.

More generally we have the following result

### Lemma

Let  $X$  be a continuous r.v. and  $g : \mathbb{R} \rightarrow \mathcal{Y}$  be a function that maps  $\mathbb{R}$  onto a discrete set  $\mathcal{Y}$ .

Then the r.v.  $Y$  is discrete and for any  $k \in \mathcal{Y}$ ,

$$\mathbb{P}(Y = k) = \mathbb{P}(X \in g^{-1}(\{k\}))$$

### Note:

- We just retrieve the same property as before

# Outline

Function of a discrete r.v.

Discrete function of a continuous r.v.

Continuous function of a continuous r.v.

Proofs

# c.d.f. method

## Method

- For continuous r.v., the p.d.f. has no interpretation as a prob. dist.
- It is easier to compute the c.d.f. of  $Y = g(X)$  and then differentiate the c.d.f. to get the p.d.f.
- We will first illustrate the idea and then detail the method if
  - $g$  is invertible
  - $g$  is not invertible on  $\mathbb{R}$  but invertible on some intervals of  $\mathbb{R}$  that form a partition of  $\mathbb{R}$

## c.d.f. method

## Exercise

Let  $X$  be a continuous r.v. with p.d.f.  $f_X$

1. What is the p.d.f. of  $Y = aX + b$  with  $a > 0$ ?
2. Same but with  $a < 0$ ?

## Solution

1. • Compute the c.d.f. from the definition of the function,

$$F_Y(t) = \mathbb{P}(Y \leq t) = \mathbb{P}(aX + b \leq t) = \mathbb{P}\left(X \leq \frac{t-b}{a}\right) = F_X\left(\frac{t-b}{a}\right)$$

- Differentiate the c.d.f. to get the p.d.f.

$$f_Y(y) = F'_Y(y) = \frac{1}{a} f_X\left(\frac{t-b}{a}\right)$$

2. • Similarly, for  $a < 0$ ,

$$F_Y(t) = \mathbb{P}(Y \leq t) = \mathbb{P}(aX + b \leq t) = \mathbb{P}\left(X \geq \frac{t-b}{a}\right) = 1 - F_X\left(\frac{t-b}{a}\right)$$

- Therefore

$$f_Y(y) = F'_Y(y) = -\frac{1}{a} f_X\left(\frac{t-b}{a}\right)$$

3. In any case we get  $f_Y(y) = \frac{1}{|a|} f_X\left(\frac{t-b}{a}\right)$

## c.d.f. method

Method for  $g$  invertible and **strictly increasing**

1. Compute

$$F_Y(t) = \mathbb{P}(Y \leq t) = \mathbb{P}(X \leq g^{-1}(t)) = F_X(g^{-1}(t))$$

2. Deduce

$$\begin{aligned} f_Y(t) &= \frac{d}{dt} F_X(g^{-1}(t)) \\ &= (g^{-1}(t))' F'(g^{-1}(t)) \\ &= \frac{1}{g'(g^{-1}(t))} f_X(g^{-1}(t)) \end{aligned}$$

where we used that

- $(g^{-1}(t))' = 1/g'(g^{-1}(t))$   
(to remember that differentiate the equation  $g(g^{-1}(x))) = x$  on both sides)
- and that  $F'_X(z) = f_X(z)$

## c.d.f. method

Method for  $g$  invertible and strictly decreasing

1. Compute

$$F_Y(t) = \mathbb{P}(Y \leq t) = \mathbb{P}(X \geq g^{-1}(t)) = 1 - F_X(g^{-1}(t))$$

2. Deduce

$$f_Y(t) = -\frac{d}{dt} F_X(g^{-1}(t)) = -\frac{1}{g'(g^{-1}(t))} f_X(g^{-1}(t))$$

## Distribution of a continuous function of a continuous r.v.

Previous considerations can be summarized by the following lemma

### Lemma

Let  $X$  be a continuous r.v. with p.d.f.  $f_X$

Let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be differentiable and strictly monotonic

with inverse denoted  $\gamma = g^{-1}$ , then the p.d.f of  $Y = g(X)$  exists<sup>2</sup> and it reads

$$f_Y(y) = \begin{cases} |\gamma'(y)| f_X(\gamma(y)) & \text{if } y \in g(\mathbb{R}) \\ 0 & \text{otherwise} \end{cases}$$

where  $\gamma'(y) = \frac{1}{g'(g^{-1}(y))}$

### Note:

- It is preferable to remember the method rather than the lemma because the method is more flexible (see next slides)

---

<sup>2</sup>We admit that fact



## c.d.f. method

### Details

- What if  $g$  is not defined on  $\mathbb{R}$ ?
- The only thing you need is that  $g$  is defined on a subset  $B \subseteq \mathbb{R}$  s.t.

$$\mathbb{P}(X \in B) = 1$$

- For  $y \notin g(B)$ , define  $f_Y(y) = 0$

## c.d.f. method

## Exercise

Let  $X \sim \text{Unif}([0, 1])$  and  $g : x \rightarrow -\frac{1}{\lambda} \log(1 - x)$ , where  $\lambda > 0$ .

What is the distribution of  $Y = g(X)$ ?

## Solution

- We simply need to look at the interval  $(0, 1)$  because  $\mathbb{P}(X \in (0, 1)) = \int_0^1 f_X(x) dx = 1$
- For  $x \in (0, 1)$ ,  $g(x) = -\frac{1}{\lambda} \log(1 - x) > 0$
- Therefore  $Y$  only takes positive values, so for  $t \leq 0$   $\mathbb{P}(Y \leq t) = 0$
- Now for  $t > 0$ ,

$$\begin{aligned}\mathbb{P}(Y \leq t) &= \mathbb{P}\left(-\frac{1}{\lambda} \log(1 - X) \leq t\right) \\ &= \mathbb{P}(\log(1 - X) \geq -\lambda t) = \mathbb{P}(1 - X \geq e^{-\lambda t}) = \mathbb{P}(X \leq 1 - e^{-\lambda t}) = 1 - e^{-\lambda t}\end{aligned}$$

because for  $a \in [0, 1]$ ,  $\mathbb{P}(X \leq a) = \int_0^1 a dx = a$ .

- So

$$f_Y(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

## Practice next lecture

### Practice

Let  $X \sim \text{Exp}(\lambda)$ , what is the p.d.f. of  $Y = \sqrt{X}$ ?

## Outline

Function of a discrete r.v.

Discrete function of a continuous r.v.

Continuous function of a continuous r.v.

Proofs

# Distribution of a continuous function of a continuous r.v.

## Lemma

Let  $X$  be a continuous r.v. with p.d.f.  $f_X$

Let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be differentiable and strictly monotonic

with inverse denoted  $\gamma = g^{-1}$ , then the p.d.f of  $Y = g(X)$  exists<sup>3</sup> and it reads

$$f_Y(y) = \begin{cases} |\gamma'(y)| f_X(\gamma(y)) & \text{if } y \in g(\mathbb{R}) \\ 0 & \text{otherwise} \end{cases}$$

where  $\gamma'(y) = \frac{1}{g'(g^{-1}(y))}$

**Proof** Denote  $a = \inf_x g(x)$ ,  $b = \sup_x g(x)$ , (potentially  $a = -\infty$ ,  $b = +\infty$ )

1. If  $t < a$ ,  $F_Y(t) = \mathbb{P}(g(X) \leq t) = 0$  so  $f_Y(t) = 0$
2. If  $t > b$ ,  $F_Y(t) = \mathbb{P}(g(X) \leq t) = 1$  so  $f_Y(t) = 0$
3. Since the probability on a point does not matter we can define  $f_Y(b) = f_Y(a) = 0$  if  $a, b$  are finite
4. if  $g$  is strictly increasing, for  $t \in (a, b)$  s.t.  $\gamma(t) := g^{-1}(t)$  is defined,

$$F_Y(t) = \mathbb{P}(Y \leq t) = \mathbb{P}(g(X) \leq t) = \mathbb{P}(X \leq g^{-1}(t)) = F_X(\gamma(t))$$

$$\text{so } f_Y(t) = \gamma'(t) f_X(\gamma(t))$$

5. if  $g$  is strictly decreasing, for  $t \in (a, b)$  s.t.  $g^{-1}(t)$  is defined,

$$F_Y(t) = \mathbb{P}(Y \leq t) = \mathbb{P}(g(X) \leq t) = \mathbb{P}(X \geq g^{-1}(t)) = 1 - F_X(\gamma(t))$$

$$\text{so } f_Y(t) = -\gamma'(t) f_X(\gamma(t))$$

## Additional details

### Pre-image

- Note that  $\{g(X) \in A\} = \{X \in g^{-1}(A)\}$  and  $g^{-1}(g(B)) \supseteq B$

### Function of a r.v.

- Rigorously,  $Y$  is defined as a function  $Y : \Omega \rightarrow \mathbb{R}$  that measures subsets in  $\mathbb{R}$  as

$$\mu_Y : A \rightarrow \mathbb{P}(X \in g^{-1}(A)) \quad \text{for } A \text{ a Borel set in } \mathbb{R}$$

- This function  $\mu_Y$  satisfies  $0 \leq \mu_Y(A) \leq 1$
- Moreover for any two sets  $A, B$ ,  $g^{-1}(A \cup B) = g^{-1}(A) \cup g^{-1}(B)$  and  $g^{-1}(A \cap B) = g^{-1}(A) \cap g^{-1}(B)$
- So  $\mu_Y$  satisfies the additive property of a prob. measure
- For  $\mu_Y$  to define a proper probability distribution we then need

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

which is the case if  $g^{-1}(\mathbb{R}) \supseteq B$  where  $B \subseteq \mathbb{R}$  is s.t.  $\mathbb{P}(X \in B) = 1$ , i.e.,  $g$  is defined on  $B$