



## Expectation, Median, Quantiles

MATH/STAT 394: Probability I  
Summer 2021 A Term

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

§ 3.3

---

Aaron Osgood-Zimmerman

Department of Statistics

## Practice solution

### Practice

The time (in min.) to wait for my bus can be modeled as an exponential r.v.

I know that the average time I need to wait for the bus is 10 min.

What is the prob. that I would wait more than 15min?

*Hint:*

1. Compute  $\mathbb{E}[X]$  for  $X \sim \text{Exp}(\lambda)$ .
2. Deduce how you could know  $\lambda$  if you only knew the expected time.

### Solution

•

$$\begin{aligned}\mathbb{E}[X] &= \int_{-\infty}^{+\infty} xf(x)dx = \int_0^{+\infty} x\lambda e^{-\lambda x}dx \\ &= \left[-xe^{-\lambda x}\right]_0^{+\infty} - \int_0^{+\infty} -e^{-\lambda x}dx = 0 + \left[-\frac{1}{\lambda}e^{-\lambda x}\right]_0^{+\infty} = \frac{1}{\lambda}\end{aligned}$$

**Take-away:** If you know that a r.v. is exponential and you don't know the parameter  $\lambda$ , you can get it from the value of the mean (a.k.a. the expectation) 2 / 15

## Practice solution

### Practice

The time (in min.) to wait for my bus can be modeled as an exponential r.v.

I know that the average time I need to wait for the bus is 10 min.

What is the prob. that I would wait more than 15min?

*Hint:*

1. Compute  $\mathbb{E}[X]$  for  $X \sim \text{Exp}(\lambda)$ .
2. Deduce how you could know  $\lambda$  if you only knew the expected time.

### Solution (continued)

- We know that  $X \sim \text{Exp}(\lambda)$  with  $\lambda$  a priori unknown and  $\mathbb{E}[X] = 10$
- Since  $\mathbb{E}[X] = \frac{1}{\lambda}$  so we deduce that  $\lambda = 1/10$
- Therefore we can compute

$$\mathbb{P}(X \geq 15) = e^{-\lambda \cdot 15} = e^{-15/10} \approx 0.22$$

# Outline

Infinite and undefined expectations

Expectation of a function of a r.v

Properties of the expectation

Linearity of the expectation

Proofs

# Infinite expectations

## Exercise

Consider the following gamble. You flip a fair coin.

- If it is heads, you get 2 dollars and the game ends,
- If it is tails, the prize is doubled and you flip the coin again

Continue like that: every tails double the prize and at the first heads you get the prize.

What is your expected gain?

## Solution

- Denote  $Y \sim \text{Geom}(1/2)$  the number of flips before getting a heads and  $X$  your gain
- Then

$$\mathbb{E}[X] = \sum_{k=1}^{+\infty} 2^k \mathbb{P}(Y = k) = \sum_{k=1}^{+\infty} 1 = +\infty$$

- So even if the game surely ends (because  $\mathbb{P}(Y \leq +\infty) = 1$ ), your expected gain is infinite.
- Called the St Petersburg Paradox first considered by N. Bernoulli

# Undefined expectation

## Exercise

John and Lucy flip a fair coin until seeing a tail.

If the number  $k$  of flips is odd, Lucy pays  $2^k$  dollars to John, if  $k$  is even, John pays  $2^k$  dollars to Lucy.

Denote by  $X$  the gain of John. What is  $\mathbb{E}[X]$ ?

## Solution

- Let  $Y \sim \text{Geom}(1/2)$ , s.t.  $\mathbb{P}(Y = k) = 2^{-k}$
- We have that  $\mathbb{P}(X = 2^k) = \mathbb{P}(Y = k) = 2^{-k}$  for  $k$  odd,  
 $\mathbb{P}(X = -2^k) = \mathbb{P}(Y = k) = 2^{-k}$  for  $k$  even
- Therefore if we want to sum up the average of the first  $n$  gains we get

$$\sum_{k=1}^n (-1)^k 2^k \mathbb{P}(Y = k) = \sum_{k=1}^n (-1)^k = \begin{cases} 0 & \text{if } n \text{ is even} \\ 1 & \text{if } n \text{ is odd} \end{cases}$$

- Therefore  $\mathbb{E}[X] = \lim_{n \rightarrow +\infty} \sum_{k=1}^n (-1)^k 2^k \mathbb{P}(Y = k)$  is not defined.

# Recap

## Discrete r.v.

- $\mathbb{E}[X] = \sum_{k \in \mathcal{X}} kp(k)$
- If  $X \sim \text{Ber}(p)$ ,  $\mathbb{E}[X] = p$
- If  $X \sim \text{Geom}(p)$ ,  $\mathbb{E}[X] = \frac{1}{p}$
- If  $X \sim \text{Bin}(n, p)$ ,  $\mathbb{E}[X] = np$

## Continuous r.v.

- $\mathbb{E}[X] = \int_{-\infty}^{+\infty} xf(x)dx$
- If  $X \sim \text{Unif}([a, b])$ ,  $\mathbb{E}[X] = \frac{a+b}{2}$
- If  $X \sim \text{Exp}(\lambda)$ ,  $\mathbb{E}[X] = \frac{1}{\lambda}$

## Finite, infinite, undefined expectations

- An expectation can be finite, infinite (positive or negative) or undefined

# Outline

Infinite and undefined expectations

Expectation of a function of a r.v

Properties of the expectation

Linearity of the expectation

Proofs



# Expectation of a function of a r.v.

## Motivation

- Given a r.v.  $X$ , we can always define a new r.v. as  $Y = g(X)$  through a given function  $g$
- We may then want to know:
  - The p.d.f./p.m.f. of  $Y$  (this will be seen later)
  - The expectation of  $Y$

## Expectation of a function of a r.v.

### Example

Roll a fair die and define the gain of a player as

$$W = \begin{cases} -1 & \text{if the roll is 1, 2 or 3} \\ 1 & \text{if the roll is 4} \\ 3 & \text{if the roll is 5 or 6} \end{cases}$$

What is  $\mathbb{E}[W]$ ?

### Solution

- Define  $X$  the face of the die and

$$g : \begin{cases} \{1, \dots, 6\} & \rightarrow \mathbb{R} \\ k & \rightarrow \begin{cases} -1 & \text{if } k \in \{1, 2, 3\} \\ 1 & \text{if } k = 4 \\ 3 & \text{if } k \in \{5, 6\} \end{cases} \end{cases}$$

- Then  $W = g(X)$  and

$$\begin{aligned} \mathbb{E}[W] &= -1 \cdot (\mathbb{P}(X=1) + \mathbb{P}(X=2) + \mathbb{P}(X=3)) + 1 \cdot \mathbb{P}(X=4) + 3 \cdot (\mathbb{P}(X=5) + \mathbb{P}(X=6)) \\ &= g(1)\mathbb{P}(X=1) + g(2)\mathbb{P}(X=2) + g(3)\mathbb{P}(X=3) + g(4)\mathbb{P}(X=4) + g(5)\mathbb{P}(X=5) + g(6)\mathbb{P}(X=6) \\ &= -1 \cdot \frac{1}{2} + 1 \cdot \frac{1}{6} + 3 \cdot \frac{1}{3} = \frac{2}{3} \end{aligned}$$

## Expectation of a function of a r.v.

### Theorem

Let  $X$  be a r.v. that takes values in  $\mathcal{X}$  and  $g : \mathcal{X} \rightarrow \mathbb{R}$  be some function.

$$\mathbb{E}[g(X)] = \sum_{k \in \mathcal{X}} g(k)p(k) \quad \text{if } X \text{ is discrete with p.m.f. } p$$

$$\mathbb{E}[g(X)] = \int_{-\infty}^{+\infty} g(x)f(x)dx \quad \text{if } X \text{ is continuous with p.d.f. } f$$

**Proof** For the discrete case,

$$\begin{aligned} \mathbb{E}[g(X)] &= \sum_y y \mathbb{P}(g(X) = y) = \sum_y y \sum_{k: g(k)=y} \mathbb{P}(X = k) \\ &= \sum_y \sum_{k: g(k)=y} y \mathbb{P}(X = k) \\ &= \sum_y \sum_{k: g(k)=y} g(k) \mathbb{P}(X = k) \\ &= \sum_k g(k) \mathbb{P}(X = k) \end{aligned}$$

For the continuous case, we take this result as granted

## Expectation of a function of a r.v.

### Example

A stick of length 1 is broken at a random location. Let  $X$  be the length of the longer piece.

What is  $\mathbb{E}(X)$ ?

### Solution

- Let  $U$  denote the random location where the stick is broken. Then  $U \sim \text{Unif}[0, 1]$ .
- Since  $X$  is the bigger broken piece, we have  $X = g(U)$ , where

$$g(u) = \max(u, 1 - u) = \begin{cases} 1 - u, & \text{if } u < 1/2 \\ u, & \text{if } u \geq 1/2. \end{cases}$$

- Thus

$$\mathbb{E}[X] = \mathbb{E}[g(U)] = \int_0^{1/2} (1 - u) du + \int_{1/2}^1 u du = \frac{3}{4}.$$

# Outline

Infinite and undefined expectations

Expectation of a function of a r.v

Properties of the expectation

Linearity of the expectation

Proofs

# Properties of the expectation

## Motivation

- The expectation is a useful characterization to compute
- Yet it may be cumbersome to do the computations each time (e.g. binomial)
- Can we use some properties to simplify the computations?

# Outline

Infinite and undefined expectations

Expectation of a function of a r.v

Properties of the expectation

Linearity of the expectation

Proofs

# Linearity of the Expectation

As an application of the expectation of a function of a r.v. we have the following result

## Theorem

Let  $X$  be a r.v. and  $a, b \in \mathbb{R}$ , then

$$\mathbb{E}[aX + b] = a\mathbb{E}[X] + b$$

**Proof** (For the continuous case, the discrete case can be treated similarly)

$$\mathbb{E}[aX + b] = \int_{-\infty}^{+\infty} (ax + b)f(x)dx = a \int_{-\infty}^{+\infty} xf(x)dx + b \int_{-\infty}^{+\infty} f(x)dx = a\mathbb{E}[X] + b$$



# Linearity of the expectation

More generally we have this very useful result

## Theorem

*Let  $X, Y$  be r.v. on the same sample space, then*

$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

**Proof** Proof is detailed in STAT395, you can have a look in the supp. slides for the discrete case

## Corollary

*Let  $X_1, \dots, X_n$  be  $n$  r.v. defined on the prob. sample space and  $g_1, \dots, g_n$  be  $n$  functions, we have that*

$$\mathbb{E}[g_1(X_1) + \dots + g_n(X_n)] = \mathbb{E}[g_1(X_1)] + \dots + \mathbb{E}[g_n(X_n)]$$

# Linearity of the expectation

## Exercise

Using the previous theorem, compute the expectation of  $X \sim \text{Bin}(n, p)$

## Solution

- $X \sim \text{Bin}(n, p)$  can be described as the sum of  $n$   $Y_i \stackrel{i.i.d.}{\sim} \text{Ber}(p)$  i.e.  
 $X = Y_1 + \dots + Y_n$ .
- Therefore using that  $\mathbb{E}[Y_i] = p$  for any  $i$ ,

$$\mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[Y_i] = np$$

## Practice next lecture

### Practice

The annual maximum one-day rainfall can be modeled by a r.v.  $X$  with p.d.f.

$$f(x) = \begin{cases} \frac{2}{\pi} \frac{1}{x^2+1} & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

What is the expectation of  $X$ ?

# Outline

Infinite and undefined expectations

Expectation of a function of a r.v

Properties of the expectation

Linearity of the expectation

Proofs

# Linearity of the expectation\*

## Theorem

Let  $X, Y$  be r.v. on the same prob. space, then

$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

**Proof** For the discrete case, summing over all the possible values of  $X$  and  $Y$  denoted resp.  $k, \ell$ ,

$$\begin{aligned}\mathbb{E}[X + Y] &= \sum_{k, \ell} (k + \ell) \mathbb{P}(X = k, Y = \ell) \\ &= \sum_k k \sum_{\ell} \mathbb{P}(X = k, Y = \ell) + \sum_{\ell} \ell \sum_k \mathbb{P}(X = k, Y = \ell)\end{aligned}$$

Now by def. the events  $A_{\ell} = \{Y = \ell\}$  form a partition of the sample space  $\Omega$ . Therefore

$$\sum_{\ell} \mathbb{P}(X = k, Y = \ell) = \sum_{\ell} \mathbb{P}(\{X = k\} \cap A_{\ell}) = \mathbb{P}(X = k) \quad (\text{by the law of total prob.})$$

So we get that

$$\mathbb{E}[X + Y] = \sum_k k \mathbb{P}(X = k) + \sum_{\ell} \ell \mathbb{P}(Y = \ell) = \mathbb{E}[X] + \mathbb{E}[Y]$$