

# **Prob & Stats Review**

**STSCI/INFO/ILRST 3900: Causal Inference**

**August 30, 2023**

# Reminders and Announcements

- HW 1 due tomorrow (August 31) by 5pm
  - Submit a PDF from RMarkdown via Canvas
- Office Hours throughout the week (see Syllabus or website)
  - Mayleen: Fridays 9-10am in Rhodes 657 (Room 2) or Zoom
  - Daniel: Thursdays 1-2pm in Uris 302
  - See Ed Discussion for Zoom links/info

# Agenda for Today

- Reminders and Announcements
- Quick Icebreaker
- Probability and Statistics Review
- Homework Check-in and Questions

# Icebreaker

## Rock-Paper-Scissors Stats Review

- Introduce yourself to the person next to you and play rock-paper-scissors with them, best 2 out of 3
- The person who wins explains to the other person picks one of the topics listed below and explains what they understand about it.
  - Expectation, Variance, Conditional Expectation, Independence, Bernoulli
- The person who lost needs to come up with one follow-up question, and both of you can work together to determine the answer.

# Probability and Statistics Review

- Expectation
- Variance
- Conditional Expectation
- Independence
- Bernoulli random variables

# Expectation

(Expected Value, Population Mean, Average)

- Notation:  $E(X)$ ,  $\mu$
- The **expected value** of a *finite* random variable

$$\mu = E(X) := \sum_{i=1}^N x_i \cdot P(x_i) \text{ where } P(x_i) := \text{Prob}(X = x_i)$$

- Can also think of it as a population average;  $X = \{x_1, \dots, x_n\}$

$$E(X) = \frac{1}{N} \sum_{i=1}^N x_i$$

# Expectation

## (Expected Value, Population Mean, Average)

- The **expected value** of a *countable* random variable, i.e. the (long run) average

$$E(X) = \sum_{i=1}^{\infty} x_i \cdot P(x_i)$$

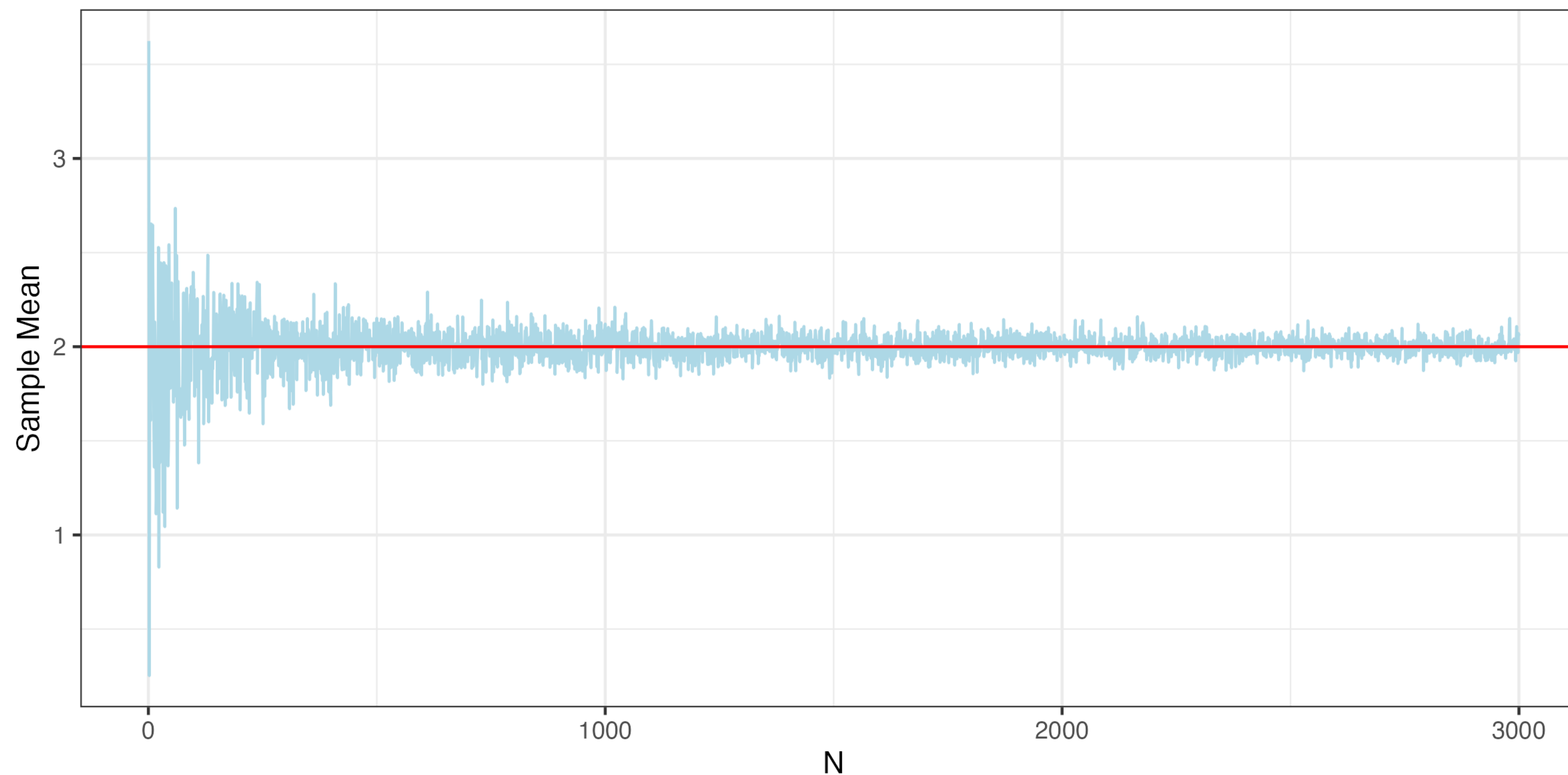
- For  $n$  independent and identically distributed (**i.i.d.**) random variables  $X_1, \dots, X_N$

the **sample mean** is  $\bar{X} = \frac{1}{N} \sum_{i=1}^N X_i$

- **Law of Large Numbers (LLN)**: the sample mean converges to the expected value (population mean) as  $N \rightarrow \infty$
- Example: R (compute the sample mean for larger and larger N)

# Expectation

- $X_i$  are random draws from  $\sim \mathcal{N}(2, 5)$  (a Normal r.v. with mean 2, variance 5)
- How quickly does the sample mean converge to the population mean?





# Variance

Describes the spread of the data

- Notation:  $V(X)$ ,  $Var(X)$ ,  $\sigma^2$
- Variance is the average of the squared differences from the mean
- For a random variable  $X$  with expected value  $\mu := E(X)$ , the variance is

$$\sigma^2 = Var(X) := E[(X - \mu)^2] = E[X^2] - \mu^2$$

More explicitly,  $Var(X) = \sum_{i=1}^n P(x_i) \cdot (x_i - \mu)^2$  where  $P(x_i) := \text{Prob}(X = x_i)$

# Sample (Empirical) Variance

For a finite dataset or finite sample

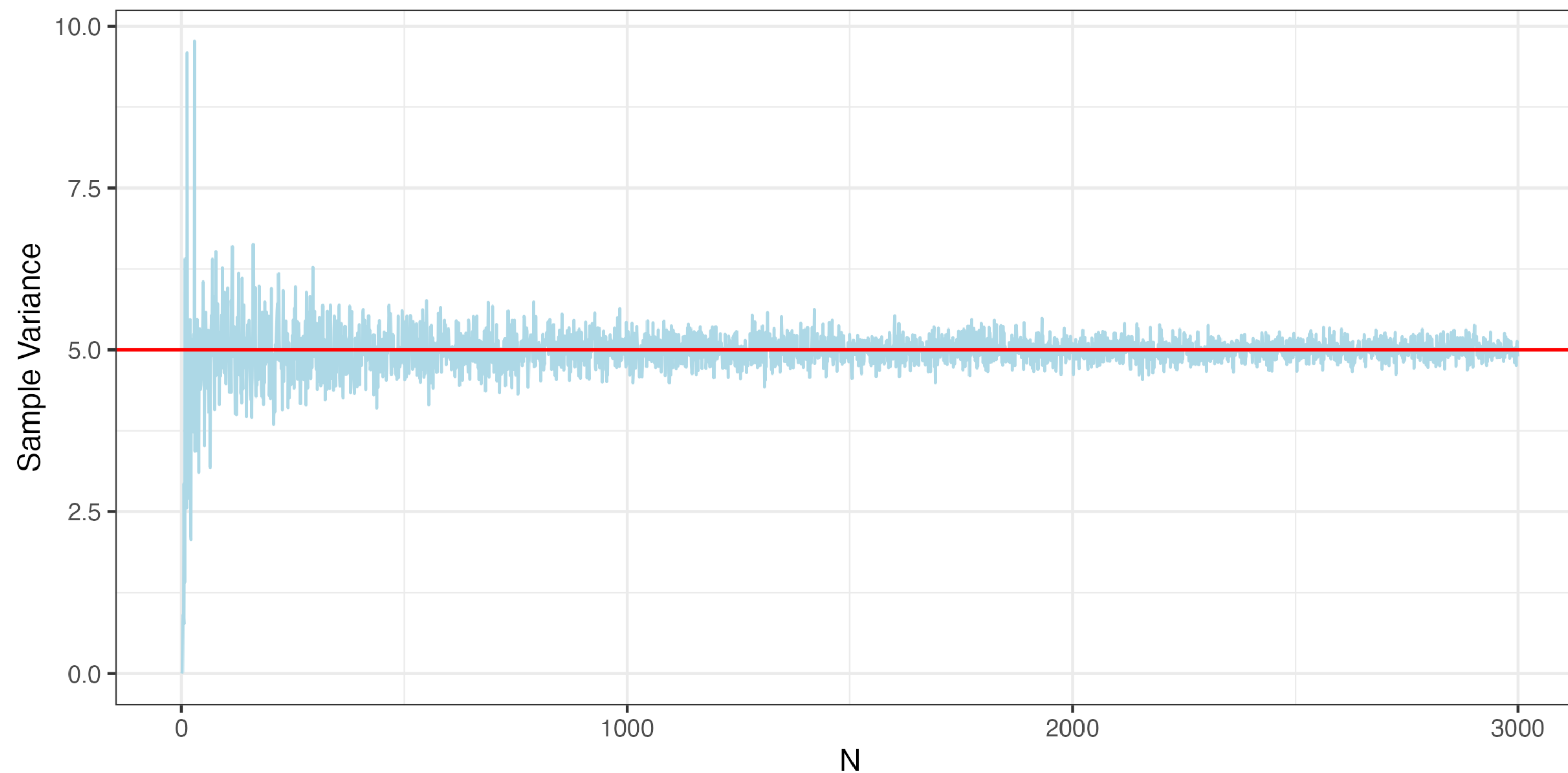
- In practice, you can compute the variance of a finite dataset as

$$\sigma^2 = \left( \frac{1}{N} \sum_{i=1}^N x_i^2 \right) - \bar{X}^2 \quad \text{where} \quad \bar{X} := \frac{1}{N} \sum_{i=1}^N x_i$$

- You don't need to have the formula memorized, just be aware of it
- Likely you'll never have to explicitly compute it this way, just use an R function

# Sample Variance

- $X_i$  are random draws from  $\sim \mathcal{N}(2, 5)$  (a Normal r.v. with mean 2, variance 5)
- How quickly does the sample variance converge to the population variance?



# Conditional Expectation

- Notation:  $E(X | Y)$
- The expected value given a set of “conditions”
- Read as “the expectation of  $X$  given (or conditioned on)  $Y$ ”

$$E(X | Y) = \sum_{i=1}^n x_i \cdot P(X = x_i | Y)$$

$$\text{where } P(X = x_i | Y) = \frac{P(X = x_i \text{ and } Y)}{P(Y)}$$

# Conditional Expectation

## Example: Roll a fair die

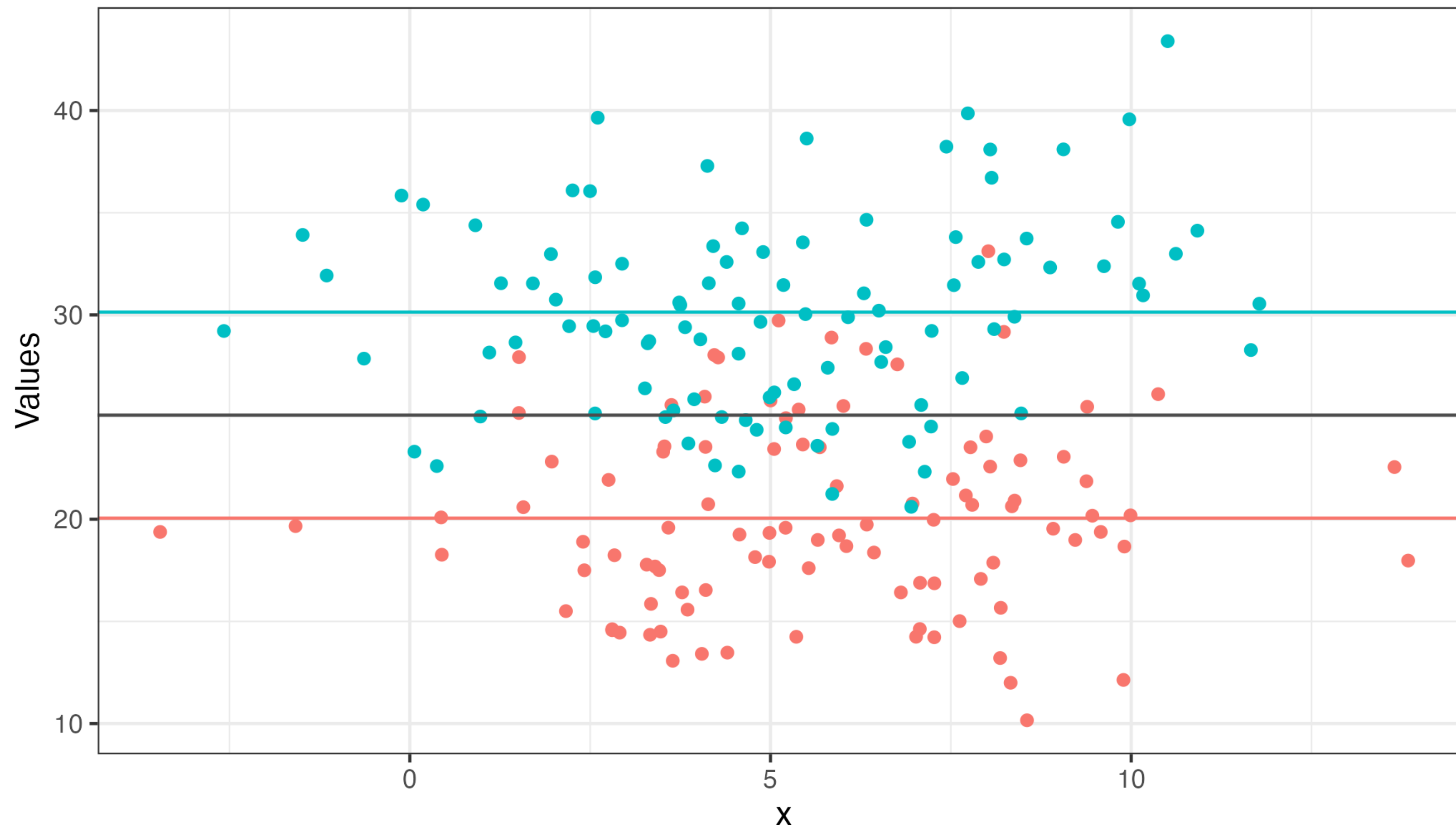
- Let  $A = 1$  if you roll an even number, 0 otherwise.
- Let  $B = 1$  if you roll a prime number, 0 otherwise. Then,

$$E[A] = \sum_{i=1}^6 a_i \cdot P(a_i) = \frac{0 + 1 + 0 + 1 + 0 + 1}{6} = \frac{1}{2}$$

and the conditional expectation of  $A$  given  $B = 1$  (i.e. we rolled 2, 3, or 5)

$$E[A | B = 1] = \sum_{i=1}^3 a_i \cdot P(a_i | B = 1) = \frac{1 + 0 + 0}{3} = \frac{1}{3}$$

# Conditional Expectation - Visualized



$$E[X] = 25$$

$$E[X | \text{group 1}] = 20$$

$$E[X | \text{group 2}] = 30$$

Group

● Group 1

● Group 2

# Independence

- Notation:  $\perp$  ,  $X \perp Y$
- Two random variables are **independent** if the outcome of one does not give any information about the outcome of the other
- Events  $A$  and  $B$  are independent if  $P(A \cap B) = P(A)P(B)$
- Recall:  $P(A \cap B) = P(A | B)P(B)$
- If  $A \perp B$ , then  $P(A | B) = P(A)$  and  $P(B | A) = P(B)$

# Independence

## Example: Dice

- Suppose you roll two fair dice. Let  $A$  be the value of the first die and let  $B$  be the value of the second die.
- If I say that  $A = 3$ , does that give you any info about what the value of  $B$  is?

- We can show that the **events**  $\{A = 3\}$  and  $\{B = 3\}$  are independent:

$$\begin{aligned}P(\{A = 3\} \cap \{B = 3\}) &= P(\{A = 3\} \mid \{B = 3\}) \cdot P(\{B = 3\}) \\ &= \frac{1}{6} \cdot \frac{1}{6} \\ &= P(\{A = 3\}) \cdot P(\{B = 3\})\end{aligned}$$

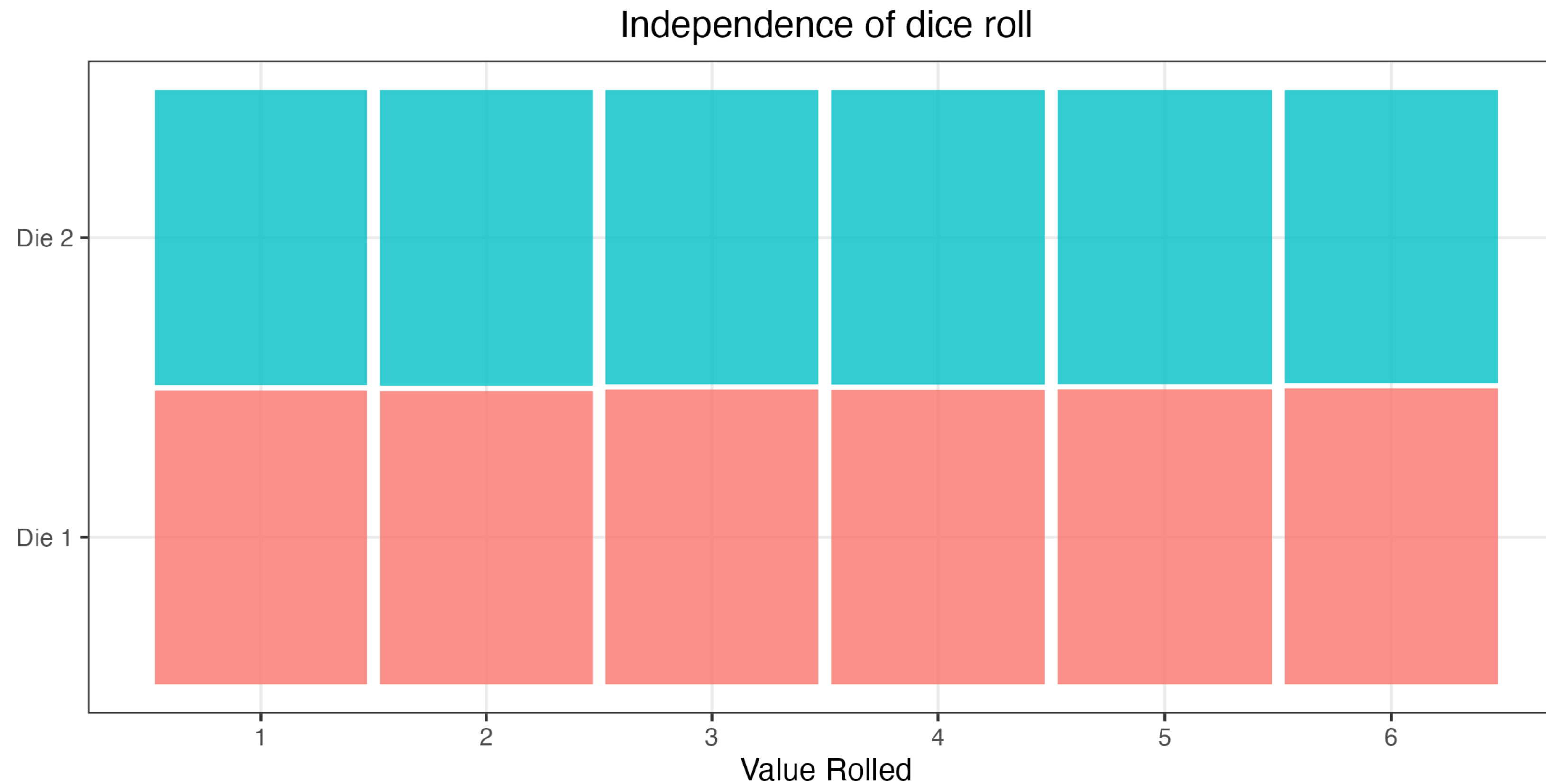
- To show  $A \perp B$ , you would show this holds for all values of  $A$  and  $B$



# Independence

## Example: Dice

- If we simulate 100k dice rolls, we see that the joint probability of each combination is equal to the individual probabilities multiplied.



# Bernoulli Random Variables

## A binary/dichotomous random variable

- Notation:  $B(p)$ , Bernoulli( $p$ ),  $\mathcal{B}(p)$
- Takes the value 1 with probability (w.p.)  $p$ , and the value 0 w.p.  $q := 1 - p$
- Let  $X \sim B(p)$ 
  - “Let  $X$  be a Bernoulli random variable with mean  $p$ ”
  - $E(X) = p$  and  $Var(X) = p(1 - p) = pq$
- Cool fact:  $E(X) = P(X = 1) = p$

# Law of Total Expectation

(i.e. law of iterated expectations, tower rule)

- Useful property (or “trick”) that will be used in class

$$E(X) = E(E(X | Y))$$

- Don't worry too much about the technical details, just add to your toolbox :)