

# **Linearity of Expectation**

CSE 312 24Su

Lecture 9

# Outline

Last time, we introduced random variables (RVs)

*function that assign a quantitative value to an outcome of a random experiment*

- Describe RVs with things like the support, PMF, CDF
- Expected value of a RV is like the “average” value it takes on

Today...

> **Independence** of random variables

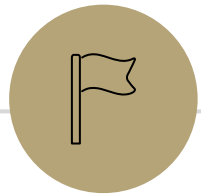
> **Expectation of a function** of a random variable (e.g.,  $E[X^2]$ )

> **Linearity of expectation**

Statement

Proof

A whole bunch of examples



# Independence of Random Variables

# Independence of events

Recall the definition of independence of **events**:

## Independence

Two events  $A, B$  are independent if

$$\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$$

*“knowing whether one event occurred doesn’t tell us anything about whether the other event occurred”*

# Independence of Random Variables

That's for events...what about random variables?

## Independence (of random variables)

$X$  and  $Y$  are independent if for all  $k, \ell$

$$\mathbb{P}(X = k, Y = \ell) = \mathbb{P}(X = k)\mathbb{P}(Y = \ell)$$

We'll often use commas instead of  $\cap$  symbol to save space.

*"knowing the value of one random variable doesn't tell us anything about what the value of the other might be"*

# Independence of Random Variables

The “for all values” is important.

We say that the event “the sum is 7” is independent of “the red die is 5”  
What about  $S$  = “the sum of two dice” and  $R$  = “the value of the red die”

# Independence of Random Variables

The “for all values” is important.

We say that the event “the sum is 7” is independent of “the red die is 5”  
What about  $S$  = “the sum of two dice” and  $R$  = “the value of the red die”

NOT independent.

$\mathbb{P}(S = 2, R = 5) \neq \mathbb{P}(S = 2)\mathbb{P}(R = 5)$  (for example)

# Independence of Random Variables

Flip a coin independently  $2n$  times.

Let  $X$  be "the number of heads in the first  $n$  flips."

Let  $Y$  be "the number of heads in the last  $n$  flips."

$X$  and  $Y$  are independent.



# Mutual Independence for RVs

A little simpler to write down than for events

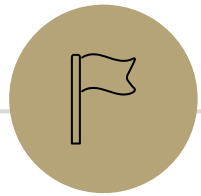
## Mutual Independence (of random variables)

$X_1, X_2, \dots, X_n$  are mutually independent if for all  $x_1, x_2, \dots, x_n$

$$\mathbb{P}(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = \mathbb{P}(X_1 = x_1)\mathbb{P}(X_2 = x_2) \cdots \mathbb{P}(X_n = x_n)$$

DON'T need to check all subsets for random variables...

But you do need to check all values (all possible  $x_i$ ) still.



# Expectation of a *Function* of a Random Variable

# Expectation

## Expectation

The “expectation” (or “expected value”) of a random variable  $X$  is:

$$\mathbb{E}[X] = \sum_{k \in \Omega_X} k \cdot \mathbb{P}(X = k)$$

$$\mathbb{E}[X] = \sum_{\omega \in \Omega} X(\omega) \cdot \mathbb{P}(\omega)$$

Intuition: The weighted average of values  $X$  could take on.  
Weighted by the probability you actually see them.

# What about $\mathbb{E}[g(X)]$ ? (e.g., $\mathbb{E}[X^2]$ , $\mathbb{E}[2^X]$ )

Applying **functions** on a random variable(s).

$$g(X) = 2X + 3$$

$$g(X) = X^2$$

$$g(X) = 2^X$$

$$g(X, Y) = X + Y$$

Still gives us a random variable!

*Given an outcome, these functions give you a number.*

They're functions from  $\Omega \rightarrow \mathbb{R}$ . That's the definition of a random variable!

# What about $\mathbb{E}[g(X)]$ ? (e.g., $\mathbb{E}[X^2]$ , $\mathbb{E}[2^X]$ )

What if we want to find the expected value of some function of  $X$ ?

Let's say we want to find  $\mathbb{E}[X^2]$ . Is  $\mathbb{E}[X^2] = (\mathbb{E}[X])^2$  ?

**Not necessarily!** For example,

If we have a random variable  $X$  that following the PMF:

$$p_X(k) = \begin{cases} 0.5 & k = 1 \\ 0.5 & k = -1 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E}[X] = 0.5 \cdot 1 + 0.5 \cdot -1 = 0 \rightarrow (\mathbb{E}[X])^2 = 0$$

$$\mathbb{E}[X^2] = 1$$

# What about $\mathbb{E}[g(X)]$ ? (e.g., $\mathbb{E}[X^2]$ )

What if we want to find the expected value of some function of  $X$ ?

Let's say we want to find  $\mathbb{E}[X^2]$ . Is  $\mathbb{E}[X^2] = (\mathbb{E}[X])^2$  ?

**Not necessarily!** For example,

If we have a random variable  $X$  that follows the PMF:

$$p_X(k) = \begin{cases} 0.5 & k = 1 \\ 0.5 & k = -1 \\ 0 & \text{otherwise} \end{cases} \quad p_{X^2}(k) = \mathbb{P}(X^2 = k) = \begin{cases} 0.5 & k = 1^2 \\ 0.5 & k = (-1)^2 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E}[X] = 0.5 \cdot 1 + 0.5 \cdot (-1) = 0$$

$$\mathbb{E}[X^2] = 0.5 \cdot 1^2 + 0.5 \cdot (-1)^2 = 1$$

# What about $\mathbb{E}[g(X)]$ ? (e.g., $\mathbb{E}[X^2]$ )

What if we want to find the expected value of some function of  $X$ ?

Let's say we want to find  $\mathbb{E}[X^2]$ . Is  $\mathbb{E}[X^2] = (\mathbb{E}[X])^2$  ?

**Not necessarily!** For example,

If we have a random variable  $X$  that follows the PMF:

$$p_X(k) = \begin{cases} 0.5 & k = 1 \\ 0.5 & k = -1 \\ 0 & \text{otherwise} \end{cases} \quad p_{X^2}(k) = \mathbb{P}(X^2 = k) = \begin{cases} 1 & k = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E}[X] = 0.5 \cdot 1 + 0.5 \cdot (-1) = 0$$

$$\mathbb{E}[X^2] = 0.5 \cdot 1^2 + 0.5 \cdot (-1)^2 = 1$$

# Expectation of $g(X)$

## “Law of the unconscious statistician” (LOTUS)

The “expectation” (or “expected value”) of  $g(X)$  is:

$$\mathbb{E}[g(X)] = \sum_{k \in \Omega_X} g(k) \cdot \mathbb{P}(X = k)$$

Exact same as formula for  $E[X]$ , but we **apply the function on each of the values in the support of  $X$**  (the corresponding probabilities are the same)



# Expectation of $g(X)$

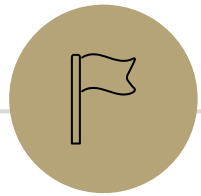
## “Law of the unconscious statistician” (LOTUS)

The “expectation” (or “expected value”) of  $g(X)$  is:

$$\mathbb{E}[g(X)] = \sum_{k \in \Omega_X} g(k) \cdot \mathbb{P}(X = k)$$

Exact same as formula for  $E[X]$ , but we **apply the function on each of the values in the support of  $X$**  (the corresponding probabilities are the same)

What if  $g(X)$  is a linear function? E.g.,  $g(X, Y) = X + Y$



# Linearity of Expectation

---

# Linearity of Expectation

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

# Linearity of Expectation

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

Extending this to  $n$  random variables,  $X_1, X_2, \dots, X_n$

$$\mathbb{E}[X_1 + X_2 + \dots + X_n] = \mathbb{E}[X_1] + \mathbb{E}[X_2] + \dots + \mathbb{E}[X_n]$$

This can be proven by induction.

# Linearity of Expectation - Proof

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

Proof:

$$\mathbb{E}[X + Y] = \sum_{\omega \in \Omega} \mathbb{P}(\omega) (X(\omega) + Y(\omega))$$

Definition of expectation:

$$\mathbb{E}[X] = \sum_{\omega \in \Omega} X(\omega) \cdot \mathbb{P}(\omega)$$

# Linearity of Expectation - Proof

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

Proof:

$$\begin{aligned}\mathbb{E}[X + Y] &= \sum_{\omega \in \Omega} \mathbb{P}(\omega) (X(\omega) + Y(\omega)) \\ &= \sum_{\omega \in \Omega} (\mathbb{P}(\omega)X(\omega) + \mathbb{P}(\omega)Y(\omega))\end{aligned}$$

Definition of expectation:

$$\mathbb{E}[X] = \sum_{\omega \in \Omega} X(\omega) \cdot \mathbb{P}(\omega)$$

# Linearity of Expectation - Proof

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

Proof:

$$\begin{aligned}\mathbb{E}[X + Y] &= \sum_{\omega \in \Omega} \mathbb{P}(\omega) (X(\omega) + Y(\omega)) \\ &= \sum_{\omega \in \Omega} (\mathbb{P}(\omega)X(\omega) + \mathbb{P}(\omega)Y(\omega)) \\ &= \sum_{\omega \in \Omega} \mathbb{P}(\omega)X(\omega) + \sum_{\omega \in \Omega} \mathbb{P}(\omega)Y(\omega)\end{aligned}$$

Definition of expectation:

$$\mathbb{E}[X] = \sum_{\omega \in \Omega} X(\omega) \cdot \mathbb{P}(\omega)$$

# Linearity of Expectation - Proof

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

Proof:

$$\begin{aligned}\mathbb{E}[X + Y] &= \sum_{\omega \in \Omega} \mathbb{P}(\omega) (X(\omega) + Y(\omega)) \\ &= \sum_{\omega \in \Omega} (\mathbb{P}(\omega)X(\omega) + \mathbb{P}(\omega)Y(\omega)) \\ &= \sum_{\omega \in \Omega} \mathbb{P}(\omega)X(\omega) + \sum_{\omega \in \Omega} \mathbb{P}(\omega)Y(\omega) \\ &= \mathbb{E}[X] + \mathbb{E}[Y]\end{aligned}$$

Definition of expectation:

$$\mathbb{E}[X] = \sum_{\omega \in \Omega} X(\omega) \cdot \mathbb{P}(\omega)$$



# Linearity of Expectation

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

Constants are also fine:

For real numbers  $a, b, c$

$$\begin{aligned}\mathbb{E}[aX + bY + c] &= \mathbb{E}[aX] + \mathbb{E}[bY + c] \\ &= a\mathbb{E}[X] + b\mathbb{E}[Y] + c\end{aligned}$$

# Fishy Business

Say you and your friend go fishing everyday.

- You catch  $X$  fish, with  $\mathbb{E}[X] = 3$
- Your friend catches  $Y$  fish, with  $\mathbb{E}[Y] = 7$
  
- How many fish do both of you bring on an average day?

# Fishy Business

Say you and your friend go fishing everyday.

- You catch  $X$  fish, with  $\mathbb{E}[X] = 3$
- Your friend catches  $Y$  fish, with  $\mathbb{E}[Y] = 7$
  
- How many fish do both of you bring on an average day?

Let  $Z$  be the r.v. representing the total number of fish you both catch

# Fishy Business

Say you and your friend go fishing everyday.

- You catch  $X$  fish, with  $\mathbb{E}[X] = 3$
- Your friend catches  $Y$  fish, with  $\mathbb{E}[Y] = 7$
- How many fish do both of you bring on an average day?

Let  $Z$  be the r.v. representing the total number of fish you both catch

$$\mathbb{E}[Z] = \mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y] = 3 + 7 = 10$$

# Fishy Business

Say you and your friend go fishing everyday.

- You catch  $X$  fish, with  $\mathbb{E}[X] = 3$
- Your friend catches  $Y$  fish, with  $\mathbb{E}[Y] = 7$

- How many fish do both of you bring on an average day?

Let  $Z$  be the r.v. representing the total number of fish you both catch

$$\mathbb{E}[Z] = \mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y] = 3 + 7 = 10$$

- You can sell each for \$10 per fish, but you need \$15 (total) for expenses. What is your average profit?

# Fishy Business

Say you and your friend go fishing everyday.

- You catch  $X$  fish, with  $\mathbb{E}[X] = 3$
- Your friend catches  $Y$  fish, with  $\mathbb{E}[Y] = 7$

- How many fish do both of you bring on an average day?

Let  $Z$  be the r.v. representing the total number of fish you both catch

$$\mathbb{E}[Z] = \mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y] = 3 + 7 = 10$$

- You can sell each for \$10 per fish, but you need \$15 (total) for expenses. What is your average profit?

$$\mathbb{E}[10Z - 15] = 10\mathbb{E}[Z] - 15 = 100 - 15 = 85$$

# Coin Tosses

If we flip a coin twice, what is the expected number of heads that come up?

# Coin Tosses

If we flip a coin twice, what is the expected number of heads that come up?

Let  $Y$  be the r.v. representing the total number of heads

$$p_Y(y) = \begin{cases} \frac{1}{4} & \text{if } y = 0 \\ \frac{1}{2} & \text{if } y = 1 \\ \frac{1}{4} & \text{if } y = 2 \\ 0 & \textit{otherwise} \end{cases}$$



# Coin Tosses

If we flip a coin twice, what is the expected number of heads that come up?

Let  $Y$  be the r.v. representing the total number of heads

$$p_Y(y) = \begin{cases} \frac{1}{4} & \text{if } y = 0 \\ \frac{1}{2} & \text{if } y = 1 \\ \frac{1}{4} & \text{if } y = 2 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E}[Y] = \sum_{k \in \Omega_Y} p_Y(k) \cdot k = \frac{1}{4} \cdot 0 + \frac{1}{2} \cdot 1 + \frac{1}{4} \cdot 2 = 1$$

# Repeated Coin Tosses

Now what if the probability of flipping a head was  $p$  and that we wanted to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the r.v. representing the total number of heads.

# Repeated Coin Tosses

Now what if the probability of flipping a head was  $p$  and that we wanted to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the r.v. representing the total number of heads.

Make a prediction --- what should  $\mathbb{E}[X]$  be?

- a)  $n + p$
- b)  $p^n$
- c)  $np$
- d)  $n/p$

Fill out the poll everywhere:  
[pollev.com/cse312](https://pollev.com/cse312)

# Repeated Coin Tosses

Now what if the probability of flipping a head was  $p$  and that we wanted to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the r.v. representing the total number of heads.

$$\mathbb{E}[X] = \sum_{k=0}^n k \cdot \mathbb{P}(X = k) = \sum_{k=0}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k}$$

Ok, but what actually is it?  
I don't have intuition for this  
formula.

# Repeated Coin Tosses

Now what if the probability of flipping a head was  $p$  and that we wanted to find the total number of heads flipped when we flip the coin  $n$  times?

$$\begin{aligned}\mathbb{E}[X] &= \sum_{k=0}^n k \cdot \mathbb{P}(Y = k) = \sum_{k=0}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k} \\ &= \sum_{k=1}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k} \\ &= \sum_{k=1}^n n \cdot \binom{n-1}{k-1} p^k (1-p)^{n-k} \\ &= np \sum_{i=0}^{n-1} \binom{n-1}{i} p^i (1-p)^{n-1-i} \\ &= np(p + (1-p))^{n-1} = np\end{aligned}$$

$$k \binom{n}{k} = n \binom{n-1}{k-1}$$

Binomial Theorem!

We did it! And all it took was a clever application of the binomial theorem, setup by a very non-obvious application of an obscure combinatorial identity. Ezipz.

# Repeated Coin Tosses

Now what if the probability of flipping a head was  $p$  and that we wanted to find the total number of heads flipped when we flip the coin  $n$  times?

$$\mathbb{E}[X] = \sum_{k=0}^n k \cdot \mathbb{P}(Y = k) = \sum_{k=0}^n k \binom{n}{k} p^k (1-p)^{n-k}$$

$$= \sum_{k=1}^n k \binom{n}{k} p^k (1-p)^{n-k}$$

$$= \sum_{k=1}^n k \binom{n-1}{k-1} p^k (1-p)^{n-k}$$

$$= np \sum_{i=0}^{n-1} \binom{n-1}{i} p^i (1-p)^{n-1-i}$$

$$= np(p + (1-p))^{n-1} = np$$

$$k \binom{n}{k} = n \binom{n-1}{k-1}$$

Binomial Theorem!

We did it! And all it took was a clever application of the binomial theorem, setup by a very non-obvious application of an obscure combinatorial identity. Ezipz.

**No one wants to do proofs like this every time!**

# Linearity of Expectation

## Linearity of Expectation

For any two random variables  $X$  and  $Y$ :

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

Note:  $X$  and  $Y$  do not have to be independent

Extending this to  $n$  random variables,  $X_1, X_2, \dots, X_n$

$$\mathbb{E}[X_1 + X_2 + \dots + X_n] = \mathbb{E}[X_1] + \mathbb{E}[X_2] + \dots + \mathbb{E}[X_n]$$

This can be proven by induction.

# Indicator Random Variables

For any event  $A$ , we can define the indicator random variable  $\mathbf{1}[A]$  for  $A$

$$\mathbf{1}[A] = X = \begin{cases} 1 & \text{if event } A \text{ occurs} \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \mathbb{P}(X = 1) &= \mathbb{P}(A) \\ \mathbb{P}(X = 0) &= 1 - \mathbb{P}(A) \end{aligned}$$

You'll also see notation like:

$$\underline{\mathbf{1}}[A], \mathbf{1}_A, \underline{\mathbf{1}}[\text{some boolean}]$$

$$p_X(k) = \begin{cases} \mathbb{P}(A) & \text{if } k = 1 \\ 1 - \mathbb{P}(A) & \text{if } k = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \mathbb{E}[X] &= 1 \cdot p_X(1) + 0 \cdot p_X(0) \\ &= p_X(1) = \mathbb{P}(A) \end{aligned}$$



# Repeated Coin Tosses (Again)

The probability of flipping a head is  $p$  and we want to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the total number of heads

What indicators can we define? What 'Booleans' have enough information to combine (add) and solve the problem?

# Repeated Coin Tosses (Again)

The probability of flipping a head is  $p$  and we want to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the total number of heads

Define  $X_i$  as follows:

$$X_i = \begin{cases} 1 & \text{if the } i\text{th coin flip is heads} \\ 0 & \text{otherwise} \end{cases}$$

# Repeated Coin Tosses (Again)

The probability of flipping a head is  $p$  and we want to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the total number of heads

Define  $X_i$  as follows:

$$X_i = \begin{cases} 1 & \text{if the } i\text{th coin flip is heads} \\ 0 & \text{otherwise} \end{cases} \longrightarrow X = \sum_{i=1}^n X_i$$

# Repeated Coin Tosses (Again)

The probability of flipping a head is  $p$  and we want to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the total number of heads

$$\begin{aligned}\mathbb{P}(X_i = 1) &= p \\ \mathbb{P}(X_i = 0) &= 1 - p\end{aligned}$$

Define  $X_i$  as follows:

$$X_i = \begin{cases} 1 & \text{if the } i\text{th coin flip is heads} \\ 0 & \text{otherwise} \end{cases} \longrightarrow X = \sum_{i=1}^n X_i$$

# Repeated Coin Tosses (Again)

The probability of flipping a head is  $p$  and we want to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the total number of heads

$$\begin{aligned}\mathbb{P}(X_i = 1) &= p \\ \mathbb{P}(X_i = 0) &= 1 - p\end{aligned}$$

Define  $X_i$  as follows:

$$X_i = \begin{cases} 1 & \text{if the } i\text{th coin flip is heads} \\ 0 & \text{otherwise} \end{cases} \longrightarrow X = \sum_{i=1}^n X_i$$

$$\mathbb{E}[X_i] = 1 \cdot p + 0 \cdot (1 - p) = p$$

# Repeated Coin Tosses (Again)

The probability of flipping a head is  $p$  and we want to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the total number of heads

Define  $X_i$  as follows:

$$X_i = \begin{cases} 1 & \text{if the } i\text{th coin flip is heads} \\ 0 & \text{otherwise} \end{cases} \longrightarrow X = \sum_{i=1}^n X_i$$

$$\begin{aligned} \mathbb{P}(X_i = 1) &= p \\ \mathbb{P}(X_i = 0) &= 1 - p \end{aligned}$$

$$\mathbb{E}[X_i] = 1 \cdot p + 0 \cdot (1 - p) = p$$

By Linearity of Expectation,

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{E}[X_i]$$

# Repeated Coin Tosses (Again)

The probability of flipping a head is  $p$  and we want to find the total number of heads flipped when we flip the coin  $n$  times?

Let  $X$  be the total number of heads

Define  $X_i$  as follows:

$$X_i = \begin{cases} 1 & \text{if the } i\text{th coin flip is heads} \\ 0 & \text{otherwise} \end{cases} \longrightarrow X = \sum_{i=1}^n X_i$$

$$\begin{aligned} \mathbb{P}(X_i = 1) &= p \\ \mathbb{P}(X_i = 0) &= 1 - p \end{aligned}$$

$$\mathbb{E}[X_i] = 1 \cdot p + 0 \cdot (1 - p) = p$$

By Linearity of Expectation,

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{E}[X_i] = \sum_{i=1}^n p = np$$

# Computing complicated expectations

We often use these three steps to solve complicated expectations

1. Decompose: Finding the right way to decompose the random variable into sum of simple random variables

$$X = X_1 + X_2 + \cdots + X_n$$

2. LOE: Apply Linearity of Expectation

$$\mathbb{E}[X] = \mathbb{E}[X_1] + \mathbb{E}[X_2] + \cdots + \mathbb{E}[X_n]$$

3. Conquer: Compute the expectation of each  $X_i$

Often  $X_i$  are indicator random variables



# Pairs with the same birthday

In a class of  $m$  students, on average how many pairs of people have the same birthday?

Decompose: Let  $X$  be the number of pairs with the same birthday

LOE:

Conquer:

# Pairs with the same birthday

In a class of  $m$  students, on average how many pairs of people have the same birthday?

Decompose: Let  $X$  be the number of pairs with the same birthday

Define  $X_{ij}$  as follows:

$$X_{ij} = \begin{cases} 1 & \text{if person } i, j \text{ have the same birthday} \\ 0 & \text{otherwise} \end{cases} \quad X = \sum_{i,j} X_{ij}$$

LOE:

Conquer:

# Pairs with the same birthday

In a class of  $m$  students, on average how many pairs of people have the same birthday?

Decompose: Let  $X$  be the number of pairs with the same birthday

Define  $X_{ij}$  as follows:

$$X_{ij} = \begin{cases} 1 & \text{if person } i, j \text{ have the same birthday} \\ 0 & \text{otherwise} \end{cases} \quad X = \sum_{i,j} X_{ij}$$

LOE:

$$\mathbb{E}[X] = \mathbb{E}[\sum_{i,j} X_{ij}] = \sum_{i,j} \mathbb{E}[X_{ij}]$$

Conquer:

# Pairs with the same birthday

In a class of  $m$  students, on average how many pairs of people have the same birthday?

Decompose: Let  $X$  be the number of pairs with the same birthday

Define  $X_{ij}$  as follows:

$$X_{ij} = \begin{cases} 1 & \text{if person } i, j \text{ have the same birthday} \\ 0 & \text{otherwise} \end{cases} \quad X = \sum_{i,j} X_{ij}$$

LOE:

$$\mathbb{E}[X] = \mathbb{E}[\sum_{i,j} X_{ij}] = \sum_{i,j} \mathbb{E}[X_{ij}]$$

Conquer:

$$\mathbb{E}[X_{ij}] = \mathbb{P}(X_{ij} = 1) = \frac{365}{365 \cdot 365} = \frac{1}{365}$$
$$\mathbb{E}[X] = \binom{m}{2} \cdot \mathbb{E}[X_{ij}] = \binom{m}{2} \cdot \frac{1}{365}$$

# Rotating the table

$n$  people are sitting around a circular table. There is a name tag in each place. Nobody is sitting in front of their own name tag.

Rotate the table by a random number  $k$  of positions between 1 and  $n-1$  (equally likely)

Let  $X$  be the number of people that end up in front of their own name tag. Find  $\mathbb{E}[X]$ .

Decompose:

What  $X_i$  can we define that have the needed information?

LOE:

Conquer:

# Rotating the table

$n$  people are sitting around a circular table. There is a name tag in each place. Nobody is sitting in front of their own name tag.

Rotate the table by a random number  $k$  of positions between 1 and  $n-1$  (equally likely)

$X$  is the number of people that end up in front of their own name tag. Find  $\mathbb{E}[X]$ .

Decompose: Define  $X_i$  as follows:

$$X_i = \begin{cases} 1 & \text{if person } i \text{ sits in front of their own name tag} \\ 0 & \text{otherwise} \end{cases}$$

Note:  $X = \sum_{i=1}^n X_i$

LOE:

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

Conquer:

These  $X_i$  are not independent!  
That's ok!!

# Rotating the table

$n$  people are sitting around a circular table. There is a name tag in each place. Nobody is sitting in front of their own name tag.

Rotate the table by a random number  $k$  of positions between 1 and  $n-1$  (equally likely)

$X$  is the number of people that end up in front of their own name tag. Find  $\mathbb{E}[X]$ .

Decompose: Define  $X_i$  as follows:

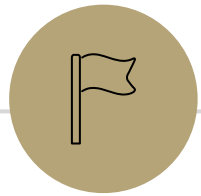
$$X_i = \begin{cases} 1 & \text{if person } i \text{ sits in front of their own name tag} \\ 0 & \text{otherwise} \end{cases} \quad X = \sum_{i=1}^n X_i$$

LOE:

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

Conquer:

$$\mathbb{E}[X_i] = P(X_i = 1) = \frac{1}{n-1} \quad \mathbb{E}[X] = n \cdot \mathbb{E}[X_i] = \frac{n}{n-1}$$



## Extra Practice





# Frogger



A frog starts on a 1-dimensional number line at 0.

Each second, independently, the frog takes a unit step right with probability  $p_1$ , to the left with probability  $p_2$ , and doesn't move with probability  $p_3$ , where  $p_1 + p_2 + p_3 = 1$ .

After 2 seconds, let  $X$  be the location of the frog. **Find  $\mathbb{E}[X]$ .**

# Frogger – Brute Force



A frog starts on a 1-dimensional number line at 0. At each second, independently, the frog takes a unit step right with probability  $p_R$ , to the left with probability  $p_L$ , and doesn't move with probability  $p_S$ , where  $p_L + p_R + p_S = 1$ . After 2 seconds, let  $X$  be the location of the frog. Find  $\mathbb{E}[X]$ .

We could find the PMF by computing the probability for each value in the range of  $X$ , and then applying definition of expectation:

$$p_X(x) = \begin{cases} p_L^2 & x = -2 \\ 2p_L p_S & x = -1 \\ 2p_L p_R + p_S^2 & x = 0 \\ 2p_R p_S & x = 1 \\ p_R^2 & x = 2 \\ 0 & \text{otherwise} \end{cases}$$

*We think about the outcomes that correspond to each value of  $X$  and compute the probability of that. For example,  $X=0$  happens when the frog doesn't move – this means it either moved left and then right, or right and then left, or did not move both seconds.*

$$\mathbb{E}[X] = \sum_{\omega} P(\omega)X(\omega) = (-2)p_L^2 + (-1)2p_L p_S + 0 \cdot (2p_L p_R + p_S^2) + (1)2p_R p_S + (2)p_R^2 = 2(p_R - p_L)$$

# Frogger – LOE



Or we can apply LoE!

A frog starts on a 1-dimensional number line at 0. At each second, independently, the frog takes a unit step right with probability  $p_R$ , to the left with probability  $p_L$ , and doesn't move with probability  $p_S$ , where  $p_L + p_R + p_S = 1$ . After 2 seconds, let  $X$  be the location of the frog. Find  $\mathbb{E}[X]$ .

Define  $X_i$  as follows:

$$X_i = \begin{cases} -1 & \text{if the frog moved left on the } i\text{th step} \\ 0 & \text{otherwise} \\ 1 & \text{if the frog moved right on the } i\text{th step} \end{cases}$$

$$\mathbb{E}[X_i] = -1 \cdot p_L + 1 \cdot p_R + 0 \cdot p_S = (p_R - p_L)$$

By Linearity of Expectation,

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^2 X_i\right] = \sum_{i=1}^2 \mathbb{E}[X_i] = 2(p_R - p_L)$$

# Frogger – LOE



If we interested in a whole minute (60 sec), the first approach would be awful because we would need to compute many probabilities or deal with a gnarly summation! Instead, we can use LoE!

A frog starts on a 1-dimensional number line at 0. At each second, independently, the frog takes a unit step right with probability  $p_R$ , to the left with probability  $p_L$ , and doesn't move with probability  $p_S$ , where  $p_L + p_R + p_S = 1$ . After **60** seconds, let  $X$  be the location of the frog. Find  $\mathbb{E}[X]$ .

Define  $X_i$  as follows:

$$X_i = \begin{cases} -1 & \text{if the frog moved left on the } i\text{th step} \\ 0 & \text{otherwise} \\ 1 & \text{if the frog moved right on the } i\text{th step} \end{cases}$$

$$\mathbb{E}[X_i] = -1 \cdot p_L + 1 \cdot p_R + 0 \cdot p_S = (p_R - p_L)$$

By Linearity of Expectation,

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^{60} X_i\right] = \sum_{i=1}^{60} \mathbb{E}[X_i] = \mathbf{60}(p_R - p_L)$$