

CSE 312

# Foundations of Computing II

## Lecture 9: Linearity of Expectation



**Anna R. Karlin**

Slide Credit: Based on Stefano Tessaro's slides for 312 19au incorporating ideas from Alex Tsun, Rachel Lin, Hunter Schafer & myself 😊

## Last Class:

- Random Variables
- Probability Mass Function (PMF)
- Cumulative Distribution Fn (CDF)
- Expectation

## Today:

- Recap
- Linearity of Expectation
- Indicator Random Variables

**Kandinsky**

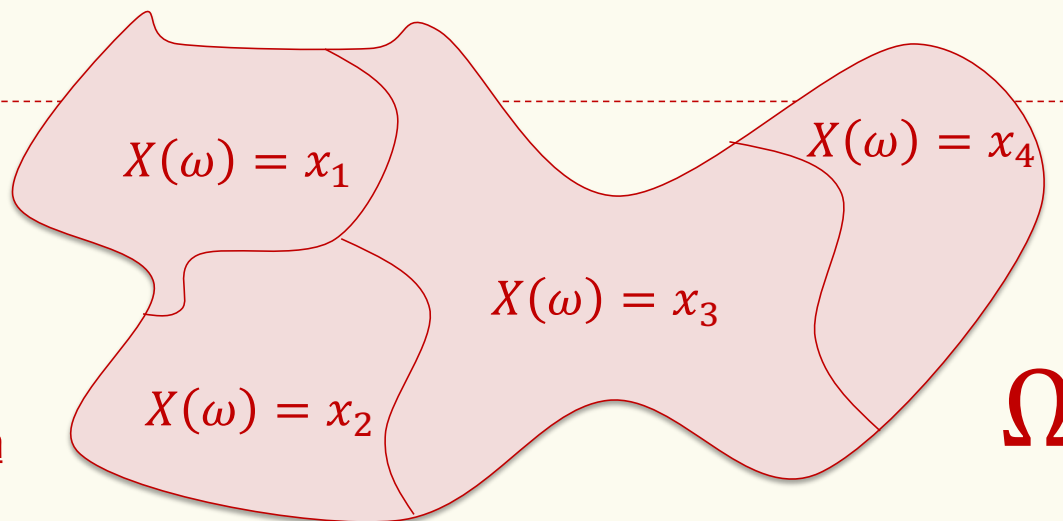
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## Reminder: Random Variables

**Definition.** A **random variable (RV)** defined on a probability space  $(\Omega, \mathbb{P})$  is a function  $X: \Omega \rightarrow \mathbb{R}$ .

The set of values that  $X$  can take on is called its range/support  $\Omega_X$



$$\{X = x_i\} \stackrel{\text{def}}{=} \{\omega \in \Omega \mid X(\omega) = x_i\}$$

Random variables partition  
the sample space.

## Coin flipping again

Suppose we flip a coin independently  $n$  times with probability  $p$  of coming up Heads each time. Let the r.v.  $Z$  be the number of Heads in the  $n$  coin flips.

# Probability Mass Function (pmf) and Cumulative Distribution Function (CDF)

## Definitions.

For a RV  $X: \Omega \rightarrow \mathbb{R}$ , the **probability mass function (pmf)** of  $X$  specifies for any real number  $x$ , the probability that  $X = x$ .

$$p_X(x) = \Pr(X = x) = \mathbb{P}(\{\omega \in \Omega \mid X(\omega) = x\})$$

$$\sum_{x \in \Omega_X} \mathbb{P}(X = x) = 1$$

For a RV  $X: \Omega \rightarrow \mathbb{R}$ , the **cumulative distribution function** of  $X$  specifies for any real number  $x$ , the probability that  $X \leq x$ .

$$F_X(x) = \Pr(X \leq x)$$

## Coin flipping again

Suppose we flip a coin independently  $n$  times with probability  $p$  of coming up Heads each time. Let the r.v.  $Z$  be the number of Heads in the  $n$  coin flips. What is the p.m.f. of  $Z$  ?

## Expectation of Random Variable

**Definition.** Given a discrete RV  $X: \Omega \rightarrow \mathbb{R}$ , the **expectation or expected value** of  $X$  is

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

or equivalently

$$E[X] = \sum_{x \in \Omega_X} x \cdot \Pr(X = x)$$

Intuition: “Weighted average” of the possible outcomes (weighted by probability)

## Coin flipping again

Suppose we flip a coin independently  $n$  times with probability  $p$  of coming up Heads each time. Let the r.v.  $Z$  be the number of Heads in the  $n$  coin flips. What is the  $\mathbb{E}(Z)$  ?



## The brute force method

we flip  $n$  coins, each one heads with probability  $p$ ,

$Z$  is the number of heads, what is  $\mathbb{E}(Z)$ ?

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



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## Linearity of Expectation (Idea)



Let's say you and your friend sell fish for a living.

- Every day you catch  $X$  fish, with  $E[X] = 3$ .
- Every day your friend catches  $Y$  fish, with  $E[Y] = 7$ .

How many fish do the two of you bring in ( $Z = X + Y$ ) on an average day?

$$E[Z] = E[X + Y] = E[X] + E[Y] = 3 + 7 = 10$$

## Linearity of Expectation (Idea)



Let's say you and your friend sell fish for a living.

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$$E[Z] = E[X + Y] = E[X] + E[Y] = 3 + 7 = 10$$

You can sell each fish for \$5 at a store, but you need to pay \$20 in rent. How much profit do you expect to make?

$$E[5Z - 20] = 5E[Z] - 20 = 5 \times 10 - 20 = 30$$

## Linearity of Expectation – Proof

**Theorem.** For **any** two random variables  $X$  and  $Y$

$$\mathbb{E}(X + Y) = \mathbb{E}(X) + \mathbb{E}(Y).$$

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

## Linearity of Expectation

**Theorem.** For **any** two random variables  $X$  and  $Y$

$$\mathbb{E}(X + Y) = \mathbb{E}(X) + \mathbb{E}(Y).$$

Or, more generally: For any random variables  $X_1, \dots, X_n$ ,

$$\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n).$$

**Because:**  $\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}((X_1 + \dots + X_{n-1}) + X_n)$   
 $= \mathbb{E}(X_1 + \dots + X_{n-1}) + \mathbb{E}(X_n) = \dots$

## Coin flipping again

Suppose we flip a coin independently  $n$  times with probability  $p$  of coming up Heads each time. Let the r.v.  $Z$  be the number of Heads in the  $n$  coin flips. What is the  $\mathbb{E}(Z)$  ?

## Example – Coin Tosses

we flip  $n$  coins, each one heads with probability  $p$

$Z$  is the number of heads, what is  $\mathbb{E}(Z)$  ?

$$- X_i = \begin{cases} 1, & i\text{-th coin-flip is heads} \\ 0, & i\text{-th coin-flip is tails.} \end{cases}$$

$$\text{Fact. } Z = X_1 + \cdots + X_n$$

### Linearity of Expectation:

$$\mathbb{E}(Z) = \mathbb{E}(X_1 + \cdots + X_n) = \mathbb{E}(X_1) + \cdots + \mathbb{E}(X_n) = n \cdot p$$

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

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

## Computing complicated expectations

Often boils down to the following three steps

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

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

- LOE: Observe linearity of expectation.

$$\mathbb{E}(X) = \mathbb{E}(X_1) + \cdots + \mathbb{E}(X_n).$$

- Conquer: Compute the expectation of each  $X_i$

Often,  $X_i$  are **indicator** (0/1) random variables.

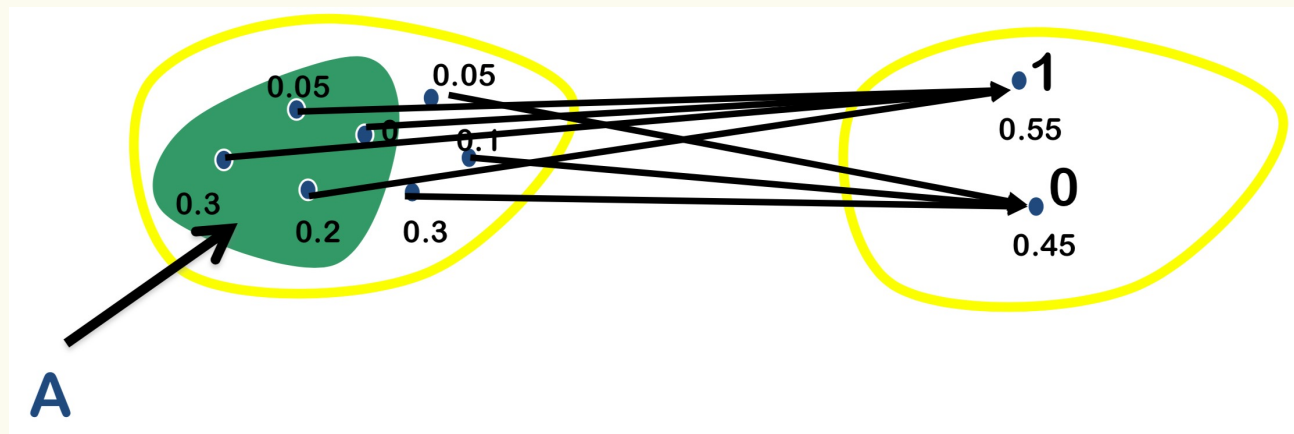


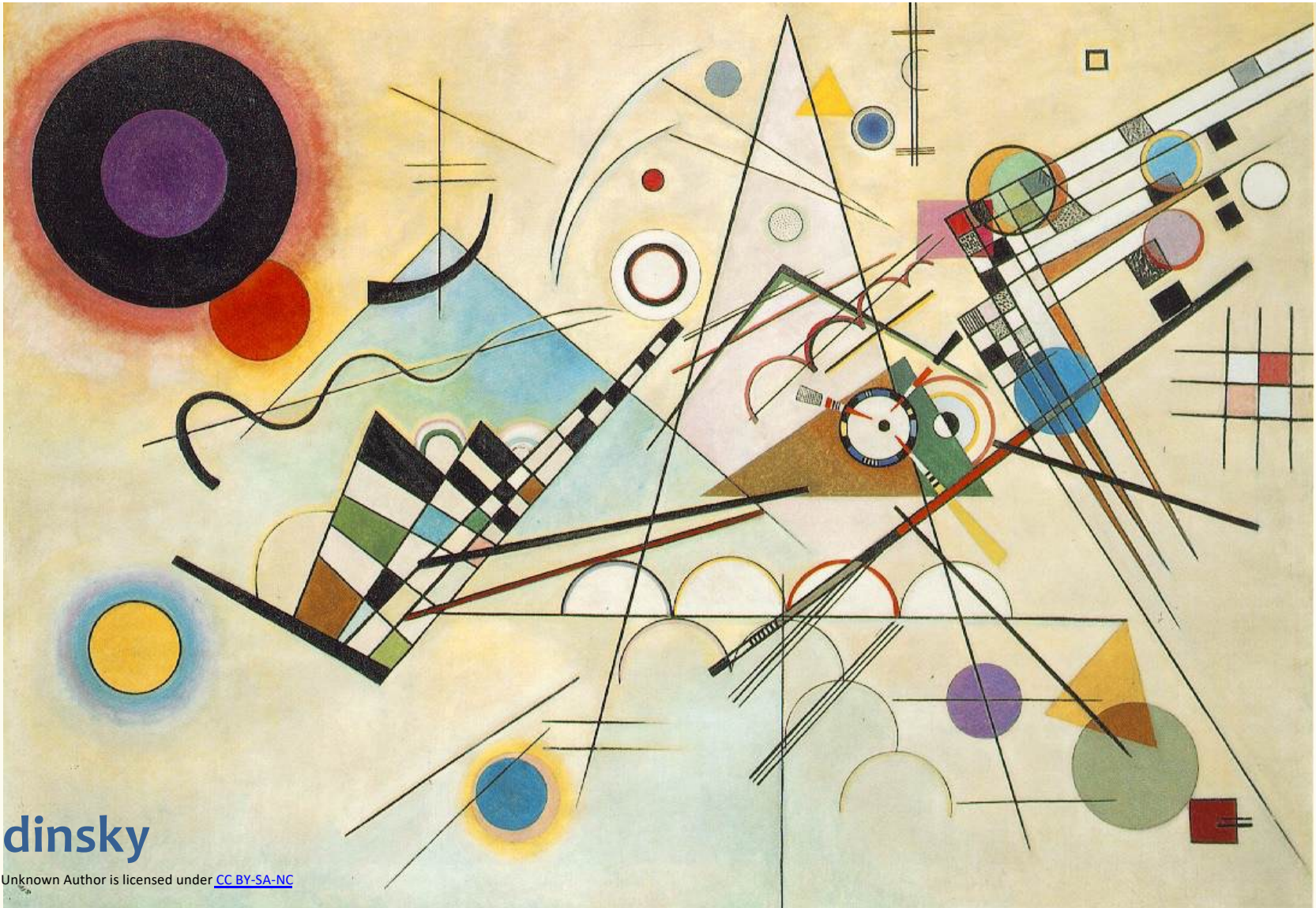
## Indicator random variable

For any event  $A$ , can define the indicator random variable  $X$  for  $A$

$$X = \begin{cases} 1 & \text{if event } A \text{ occurs} \\ 0 & \text{if event } A \text{ does not occur} \end{cases}$$

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





# Kandinsky

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## Example: Returning Homeworks

- Class with  $n$  students, randomly hand back homeworks. All permutations equally likely.
- Let  $X$  be the number of students who get their own HW
- what is  $\mathbb{E}(X)$ ?

$\Pr(\omega)$	$\omega$	$X(\omega)$
1/6	1, 2, 3	3
1/6	1, 3, 2	1
1/6	2, 1, 3	1
1/6	2, 3, 1	0
1/6	3, 1, 2	0
1/6	3, 2, 1	1

## Example: Returning Homeworks

- Class with  $n$  students, randomly hand back homeworks. All permutations equally likely.
- Let  $X$  be the number of students who get their own HW
- what is  $\mathbb{E}(X)$ ?
- Use Linearity of Expectation

Decompose: What is  $X_i$ ?

$\Pr(\omega)$	$\omega$	$X(\omega)$
1/6	1, 2, 3	3
1/6	1, 3, 2	1
1/6	2, 1, 3	1
1/6	2, 3, 1	0
1/6	3, 1, 2	0
1/6	3, 2, 1	1

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1/6	1, 2, 3	3
1/6	1, 3, 2	1
1/6	2, 1, 3	1
1/6	2, 3, 1	0
1/6	3, 1, 2	0
1/6	3, 2, 1	1

Decompose:  $X_i$  indicates if student  $i$  got their own HW back

LOE:

Conquer: What is  $\mathbb{E}(X_i)$ ?

A.  $\frac{1}{n}$  B.  $\frac{1}{n-1}$  C.  $\frac{1}{2}$

## Pairs with same birthday

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

Decompose:

LOE:

Conquer:

## Linearity of Expectation – Even stronger

**Theorem.** For any random variables  $X_1, \dots, X_n$ , and real numbers  $a_1, \dots, a_n \in \mathbb{R}$ ,

$$\mathbb{E}(a_1X_1 + \dots + a_nX_n) = a_1\mathbb{E}(X_1) + \dots + a_n\mathbb{E}(X_n).$$

Very important: In general, we do not have  $\mathbb{E}(X \cdot Y) = \mathbb{E}(X) \cdot \mathbb{E}(Y)$

## Linearity is special!

In general  $\mathbb{E}(g(X)) \neq g(\mathbb{E}(X))$

E.g.,  $X = \begin{cases} 1 & \text{with prob } 1/2 \\ -1 & \text{with prob } 1/2 \end{cases}$

- $\mathbb{E}(XY) \neq \mathbb{E}(X)\mathbb{E}(Y)$
- $\mathbb{E}(X/Y) \neq \mathbb{E}(X)/\mathbb{E}(Y)$
- $\mathbb{E}(X^2) \neq \mathbb{E}(X)^2$

How DO we compute  $\mathbb{E}(g(X))$ ?



## Expectation of $g(X)$

**Definition.** Given a discrete RV  $X: \Omega \rightarrow \mathbb{R}$ , the **expectation or expected value** of  $X$  is

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

or equivalently

$$E[X] = \sum_{x \in X(\Omega)} g(x) \cdot \Pr(X = x)$$

## Example: Returning Homeworks

- Class with  $n$  students, randomly hand back homeworks. All permutations equally likely.
- Let  $X$  be the number of students who get their own HW
- Let  $Y = (X^2 + 4) \bmod 8$ .
- what is  $\mathbb{E}(Y)$ ?

$\Pr(\omega)$	$\omega$	$X(\omega)$
1/6	1, 2, 3	3
1/6	1, 3, 2	1
1/6	2, 1, 3	1
1/6	2, 3, 1	0
1/6	3, 1, 2	0
1/6	3, 2, 1	1

# Kandinsky

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