

# *Randomness in Computing*

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## **LECTURE 5**

### **Last time**

- Random variables
- Linearity of expectation
- Jensen's inequality

### **Today**

- Bernoulli and binomial RVs
- Conditional expectation
- Branching process
- Geometric RVs

# Bernoulli random variables

- A **Bernoulli random variable** with parameter  $p$ :
$$\begin{cases} 1 & \text{with probability } p; \\ 0 & \text{otherwise.} \end{cases}$$
- The expectation of a Bernoulli R.V.  $X$  is
$$\mathbb{E}[X] = p \cdot 1 + (1 - p) \cdot 0 = p.$$

The distribution of a Bernoulli random variable is called the **Bernoulli distribution**.

# Binomial random variables

The **binomial distribution** with parameters  $n$  and  $p$ , denoted  $\text{Bin}(n, p)$ , is the distribution of the number of HEADS in  $n$  tosses of a coin with bias  $p$ .

A random variable  $X \sim \text{Bin}(n, p)$  is a **binomial R.V.**

Notation  $\sim$  : “has probability distribution” or “is distributed according to”

- **Lemma.** The probability distribution of  $X \sim \text{Bin}(n, p)$  is

$$\Pr[X = j] = \binom{n}{j} p^j (1 - p)^{n-j} \quad \text{for all } j = 0, 1, \dots, n.$$

- **Lemma.** The expectation of  $X \sim \text{Bin}(n, p)$  is  
 $\mathbb{E}[X] = np.$

# Review Question

Throw  $m$  balls into  $n$  bins uniformly and independently at random.

Let  $X$  be the number of balls that land into bin 1.

(Recall that  $\text{Bin}(n, p)$  is the binomial distribution, i.e., the distribution of the number of HEADS in  $n$  tosses of a coin with bias  $p$ .)

Then the distribution of  $X$  is

- A.  $\text{Bin}(n, m)$
- B.  $\text{Bin}(m, 1/n)$
- C.  $\text{Bin}\left(m, \frac{n-1}{n}\right)$
- D. a binomial distribution, but none of the above.
- E. not a binomial distribution.

# Review Question

Throw  $m$  balls into  $n$  bins. Let  $Y$  be the number of empty bins.

Compute  $\mathbb{E}[Y]$ .

A. 1

B.  $n/2$

C.  $\left(1 - \frac{1}{n}\right)^m$

D.  $n \left(1 - \frac{1}{n}\right)^m$

E. None of the above.

# Review question

For arbitrary random variables  $X$  and  $Y$ , by linearity of expectation:

- A.  $\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$
- B.  $\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y]$  for all  $a, b \in \mathbb{R}$ .
- C.  $\mathbb{E}[XY] = \mathbb{E}[X] \mathbb{E}[Y]$
- D. Both A and B are correct.
- E. A, B and C are correct.

# Product of independent RVs

- **Theorem.** For any two **independent** random variables  $X$  and  $Y$  on the same probability space,

$$\mathbb{E}[X \cdot Y] = \mathbb{E}[X] \cdot \mathbb{E}[Y].$$

- **Note.** The equality does not hold, in general, for dependent random variables.

**Example.** We toss two coins.

Let  $X$ = number of HEADS,  $Y$ = number of TAILS.

Calculate  $\mathbb{E}[X]$ ,  $\mathbb{E}[Y]$  and  $\mathbb{E}[XY]$ .

# Conditional expectation: definition

- For any random variable  $X$  and event  $E$ , the **conditional expectation** of  $X$  given  $E$  is

$$\mathbb{E}[X|E] = \sum_i i \cdot \Pr[X = i|E],$$

where the sum is over all possible values  $i$  taken by  $X$ .



You roll two dice. Let  $X_1$  be the value on the first die,  $X_2$  be the value on the second die, and  $X = X_1 + X_2$ .

Calculate  $\mathbb{E}[X_1 | X = 5]$

# Linearity of conditional expectation

- **Theorem.** For all random variables  $X$  and  $Y$  and all events  $A$ ,

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

Also, for all  $c \in \mathbb{R}$ ,

$$\mathbb{E}[cX \mid A] = c \cdot \mathbb{E}[X \mid A].$$

You roll two dice. Let  $A$  be the event that you got no sixes.

Let  $X_1$  be the value on the first die,  $X_2$  be the value on the second die, and  $X = X_1 + X_2$ .

Calculate  $\mathbb{E}[X \mid A]$

# Recall: Law of total probability

Let  $A$  be an event and let  $E_1, \dots, E_n$  be mutually disjoint events whose union is  $\Omega$ .

- Law of total probability.

$$\Pr[A] = \sum_{i \in [n]} \Pr[A \cap E_i] = \sum_{i \in [n]} \Pr[A \mid E_i] \cdot \Pr[E_i].$$

# Law of total expectation

Let  $X$  be a random variable over sample space  $\Omega$  and let  $E_1, \dots, E_n$  be mutually disjoint events whose union is  $\Omega$ .

- Law of total expectation:

$$\mathbb{E}[X] = \sum_{i \in [n]} \mathbb{E}[X \mid E_i] \cdot \Pr[E_i].$$

- Notable special case of law of total expectation.

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

$$\mathbb{E}[X] = \sum_{y \in \text{Range}(Y)} \mathbb{E}[X \mid Y = y] \Pr[Y = y].$$

# Conditional expectation: definition

- For random variables  $X$  and  $Y$ ,  
the **conditional expectation** of  $X$  given  $Y$ ,  
denoted  $\mathbb{E}[X|Y]$ ,  
is a random variable that depends on  $Y$ .  
Its value, when  $Y = y$ , is  $\mathbb{E}[X | Y = y]$ .
- Example:** Let  $N$  be the number you get when you roll a die. You roll a fair coin  $N$  times and get  $H$  heads.

Find  $\mathbb{E}[H|N]$ .

$$\mathbb{E}[H|N = n] = n/2.$$

$$\mathbb{E}[H|N] = N/2.$$

# Law of total expectation: compact form

- **Recall:** For any two random variables  $X$  and  $Y$ ,

$$\mathbb{E}[X] = \sum_{y \in \text{Range}(Y)} \mathbb{E}[X \mid Y = y] \Pr[Y = y].$$

- In other words,

$$\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X|Y]].$$

- **Example:** Let  $N$  be the number you get when you roll a die. You roll a fair coin  $N$  times and get  $H$  heads.

Find  $\mathbb{E}[H]$ .

$$\mathbb{E}[H] = \mathbb{E}[\mathbb{E}[H|N]] = \mathbb{E}\left[\frac{N}{2}\right] = \frac{3.5}{2} = 1.75.$$

# Law of total expectation: application

**Branching Process:** A program  $P$  tosses  $n$  coins with bias  $p$  and calls itself recursively for every HEADS.

If we call  $P$  once, what is total expected number of calls to  $P$  that will be generated?



# Branching process

**Idea:** Consider ``generations'' of calls

- Original call is *generation 0*.
- A recursive call is *generation  $i$*  if it was called by a call of *generation  $i - 1$* .

**Random variables:**  $Y_i = \#$  of recursive calls of generation  $i$ , for  $i = 1, 2, \dots$

**Need to find:**  $\mathbb{E}[Y]$ , where  $Y = \sum_{i=0}^{\infty} Y_i$ .

$$Y_0 = 1$$

$$Y_1 \sim \text{Bin}(n, p), \text{ so } \mathbb{E}[Y_1] =$$

By compact form of law of total expectation,  $\mathbb{E}[Y_2] = \mathbb{E}[\mathbb{E}[Y_2|Y_1]]$

$$\mathbb{E}[Y_2|Y_1 = y_1] = \mathbb{E}[\text{Bin}(\quad, \quad)] =$$

$$\mathbb{E}[Y_2|Y_1] =$$

$$\mathbb{E}[Y_2] =$$

$$\text{Similarly, } \mathbb{E}[Y_i] = \mathbb{E}[\mathbb{E}[Y_i|Y_{i-1}]] =$$

$$\text{By linearity of expectation, } \mathbb{E}[Y] = \sum_{i=0}^{\infty} \mathbb{E}[Y_i] = \sum_{i=0}^{\infty} (np)^i = \begin{cases} \frac{1}{1 - np} & \text{if } np < 1 \\ \text{unbounded o. w.} \end{cases}$$

# Geometric random variables

The **geometric distribution** with parameter  $p$ , denoted  $\text{Geom}(p)$ , is the distribution of the number of tosses of a coin with bias  $p$  until it shows HEADS.

- **Lemma.** The probability distribution of  $X \sim \text{Geom}(p)$  is

$$\Pr[X = n] = (1 - p)^{n-1}p$$

for all  $n = 1, 2, \dots$

- **Lemma.** The expectation of  $X \sim \text{Geom}(p)$  is  $\mathbb{E}[X] = 1/p$ .