# Great Ideas in Theoretical CS

Lecture 22: Probability II

Anil Ada Ariel Procaccia (this time)

#### DEEP QUESTIONS



#### GREAT EXPECTATIONS



#### 15251 Fall 2017: Lecture 22

#### RANDOM VARIABLE

- Let S be a sample space
- A random variable is a function  $X\colon S\to \mathbb{R}$
- Examples:
  - X = value of red die when red and blue are rolled:

 $X(3,4) = 3, \qquad X(1,5) = 1$ 

• X = value of the sum of two dice when red and blue are rolled:

$$X(3,4) = 7, \qquad X(1,5) = 6$$

#### TWO COINS TOSSED

•  $X\colon\{TT,HT,TH,HH\}\to\{0,1,2\}$  counts the number of heads



#### FROM RVS TO EVENTS

• For RV X and  $a \in \mathbb{R}$  we can define the event E that X = a:

 $\Pr[E] = \Pr[X = a] = \Pr[\{t \in S | X(t) = a\}]$ 



 $\Pr[X = 1] = \Pr[\{HT, TH\}] = 1/2$ 



# FROM EVENTS TO RVS

• For any event *E*, define the indicator random variable for *E*:

$$\mathbb{I}_E(t) = \begin{cases} 1 & t \in E \\ 0 & t \notin E \end{cases}$$



# INDEPENDENT RVS

• Two random variables are independent if for every a, b, the events X = a and Y = bare independent



#### EXPECTATION

• The expectation of a random variable X is:

$$\mathbb{E}[X] = \sum_{t \in S} \Pr[t] \times X(t) = \sum_{k} \Pr[X = k] \times k$$

- Poll 1: X is the #heads in 3 coin tosses.  $\mathbb{E}[X] = ?$ 
  - 1
    4/3
    3/2
    2

Don't always expect the expected!  $\Pr[X = \mathbb{E}[X]]$ could be 0

15251 Fall 2017: Lecture 22

#### EXPECTATION

- If  $\mathbb{I}_E$  is the indicator RV for the event E,  $\mathbb{E}[\mathbb{I}_E] = \Pr[\mathbb{I}_E = 1] \times 1 = \Pr[E]$
- If X and Y are two RVs (on the same sample space S) then Z = X + Y is also an RV, defined by Z(t) = X(t) + Y(t)
- Example: X is one die roll, Y is another, and Z is their sum

#### LINEARITY OF EXPECTATION



Even if X and Y are not independent!

15251 Fall 2017: Lecture 22

#### LINEARITY OF EXPECTATION

$$E[Z] = \sum_{t \in S} \Pr[t]Z(t)$$
  
=  $\sum_{t \in S} \Pr[t](X(t) + Y(t))$   
=  $\sum_{t \in S} \Pr[t]X(t) + \sum_{t \in S} \Pr[t]Y(t)$   
=  $\mathbb{E}[X] + \mathbb{E}[Y]$ 

15251 Fall 2017: Lecture 22

General approach: View thing you care about as expected value of some RV; write this RV as sum of simpler RVs (typically indicator RVs); Solve for their expectations and add them up!

15251 Fall 2017: Lecture 22

• If I randomly put 100 letters into 100 addressed envelopes, what is the expected number of letters that will end up in their correct envelopes?



- Let  $A_i$  be the event that the *i*th letter is in the correct envelope
- Let  $\mathbb{I}_{A_i}$  be the indicator variable for  $A_i$  $\circ$  Not independent!
- $\mathbb{E}[\mathbb{I}_{A_i}] = \Pr[A_i = 1] = 1/100$
- We are interested in  $Z = \sum_{i=1}^{100} \mathbb{I}_{A_i}$

• 
$$\mathbb{E}[Z] = 100 \times \frac{1}{100} = 1$$

15251 Fall 2017: Lecture  $\overline{22}$ 

- Poll 2: We flip *n* coins of bias *p*; what is the expected number of heads?
  - *1.* 1
  - 2. p
  - 3. N
  - 4. np



### BALLS AND BINS

- n jobs are assigned to n servers uniformly at random
- What is the expected number of jobs per server?



15251 Fall 2017: Lecture 22

# BALLS AND BINS

- Let  $X_i$  be the number of jobs on server i
- $n = \mathbb{E}[X_1 + \cdots + X_n] = \mathbb{E}[X_1] + \cdots + \mathbb{E}[X_n]$
- By symmetry,  $\mathbb{E}[X_i] = 1$  for all i
- Fact: The expected number of jobs assigned to the busiest server is roughly  $\log n / \log \log n$

## BALLS AND BINS

- *n* jobs are assigned to *n* servers, but for every job we choose two servers uniformly at random, and use the less busy server
- Poll 3: Expected number of jobs per server?
  - 1. 1/n
  - 2. 1/4
  - *3.* 1/2
  - *4.* 1



• Fact: Busiest server has  $\sim \log \log n$  jobs

15251 Fall 2017: Lecture 22

### CONDITIONAL EXPECTATION

- $\mathbb{E}[X \mid E] = \sum_{k} \Pr[X = k \mid E] \times k$
- Similarly to conditional probability:  $\mathbb{E}[X] = \mathbb{E}[X \mid E] \times \Pr[E] + \mathbb{E}[X \mid \overline{E}] \times \Pr[\overline{E}]$



### GEOMETRIC RVS

- Flip a coin with probability p of heads
- X = #flips until first heads
- $\mathbb{E}[X] = \mathbb{E}[X \mid H] \Pr[H] + \mathbb{E}[X \mid T] \Pr[T]$ =  $1 \cdot p + (\mathbb{E}[X] + 1)(1 - p)$ =  $1 + \mathbb{E}[X](1 - p)$
- It follows that  $\mathbb{E}[X] = 1/p$

### 251 Land



- All 15251 students fly off to space and colonize Mars
- Faced with the problem that there are 57% men, the authorities impose a new rule: When having kids, stop after you have a girl
- Poll 4 yes/no: Will the number of new boys be larger than the number of new girls?
- Poll 5 yes/no: What if the rule is: stop after having two girls?

#### CAPSTONE PROJECT \*

computational social choice + approximation algs + linearity of expectation (+ randomized algs)

Just for fun

- A k-selection system receives a directed graph as input and outputs  $V' \subseteq V$  such that |V'| = k
- Edges are interpreted as approval votes, trust, or support
- Think of graph as directed social network
- A k-selection system f is impartial if  $i \in f(G)$  does not depend on the votes of i

- Optimization target: sum of indegrees of selected vertices
- Optimal solution: not impartial
- k = n: no problem
- k = 1: no positive impartial approximation
- k = n 1: no positive impartial approximation, even if each vertex has at most one outgoing edge!





- Each tribe member votes for at most one member
- One member must be eliminated
- Impartial rule cannot have property: if unique member received votes he is not eliminated



- The random partition algorithm:

  - For each subset, select  $\sim \frac{\kappa}{2}$ vertices with highest indegrees based on edges from the other subset
- This mechanism is clearly impartial





\* Just for fun

# SELECTING A SUBSET \*

- Theorem [Alon et al. 2011]: Random Partition is a  $\frac{1}{4}$ -approximation algorithm
- Proof:
  - Assume for ease of exposition: k is even
  - Let K be the optimal set
  - A partition  $\pi = (\pi_1, \pi_2)$  divides K into two subsets  $K_1^{\pi} = K \cap \pi_1$  and  $K_2^{\pi} = K \cap \pi_2$
  - $\circ \quad d_1^{\pi} = \{(u,v) \in E \mid u \in \pi_2, v \in K_1^{\pi}\}, d_2^{\pi} \text{ defined analogously}$
  - $\mathbb{E}[d_1^{\pi} + d_2^{\pi}] = \frac{OPT}{2}$  by linearity of expectation

• We get at least 
$$\frac{d_1^{\pi} + d_2^{\pi}}{2}$$



#### \* Just for fun

# SUMMARY

- Terminology:
  - Random variables
  - $\circ$  Expectation
  - Conditional expectation
  - $\circ$  Geometric RVs
- Principles:
  - Using the linearity of expectation by writing RVs as sums of simple RVs



#### 15251 Fall 2017: Lecture 22