# CS5314 Randomized Algorithms

Lecture 5: Discrete Random Variables and Expectation (Conditional Expectation, Geometric RV)

# Objectives

- Introduce Geometric RV
- We then introduce
  - Conditional Expectation
  - Application:
    - Alternative proof of expectation of a geometric RV
    - Solving the branching process problem

### Geometric Random Variable

Definition: A geometric random variable X with parameter p, denoted by Geo(p), is defined by the following probability distribution on r = 1,2,...:

 $Pr(X = r) = p(1-p)^{r-1}$ 

The event "X = r" represents it takes exactly r independent trials to get the first success, where each trial succeeds with probability p

# Memory-less property of Geometric Random Variable

Suppose we have already failed k times. What is the probability that we still need exactly n more trials to get the first success?

Ans: p(1-p)<sup>n-1</sup>

Note that this probability is independent of how many times we have failed !!!

# Memory-less Property

Lemma: For a geometric random variable X with parameter p Pr(X = n+k | X>k) = Pr(X = n)

How to prove?

# Memory-less Property (proof)

Pr(X = n+k | X > k)

- =  $Pr((X = n+k) \cap (X > k)) / Pr(X > k)$
- = Pr(X = n+k) / Pr(X>k)
- =  $p(1-p)^{n+k-1} / \sum_{j>k+1} p(1-p)^{j-1}$
- $= p(1-p)^{n+k-1} / (1-p)^{k}$
- $= p(1-p)^{n-1}$
- = Pr(X = n)

# A Useful Formula

Lemma: Let X be a discrete random variable that takes on non-negative integral values. Then,  $E[X] = \sum_{i=1,2} Pr(X \ge i)$ 

 $\begin{array}{l} \mbox{Proof:} \\ \Sigma_{i=1,2,\ldots} \mbox{Pr}(X \geq i) &= \Sigma_{i=1,2,\ldots} \Sigma_{j=i,i+1,\ldots} \mbox{Pr}(X = j) \\ &= \Sigma_{j=1,2,\ldots} \Sigma_{i=1,2,\ldots,j} \mbox{Pr}(X = j) \\ &= \Sigma_{j=1,2,\ldots} \mbox{j} \mbox{Pr}(X = j) = \mbox{E}[X] \end{array}$ 



# Expectation of Geo(p)

Lemma: Let X be a geometric random variable with parameter p. Then, E[X] = 1/p

Proof: For the random variable Geo(p),  $Pr(X \ge i) = \sum_{n=i,i+1,...} p(1-p)^{n-1} = (1-p)^{i-1}$ 

Thus,  $E[X] = \sum_{i=1,2,...} Pr(X \ge i)$ =  $\sum_{i=1,2,...} (1-p)^{i-1} = 1/(1-(1-p)) = 1/p$ 

# **Conditional Expectation**

Definition: The conditional expectation of a random variable X given that event F occurs is defined as:

 $E[X|F] = \sum_{i} i Pr(X=i | F)$ 

Suppose X and Y are two random variables. Then,  $E[X|Y=j] = \sum_{i} i Pr(X=i | Y=j)$ 

# Example

# Let X = sum of two fair dice, and X<sub>1</sub> = result of the first die

- Without any information, E[X] = 7
- Suppose we know the outcome of first die,  $X_1$ , is 2.
  - Do we still `expect' the sum of two dice to be 7? Should the sum be larger now? or smaller?
- That is, what is  $E[X|X_1=2]$ ?

# Example (cont)

- $E[X|X_1=2]$
- =  $\Sigma_i i Pr(X=i | X_1=2)$
- =  $\sum_{i=3,4,...,8} i \Pr(X=i | X_1=2)$
- $= \sum_{i=3,4,...,8} i (1/6)$
- = 33/6
- = 5.5

## An Identity

Lemma: For any random variables X and Y  $E[X] = \sum_{j} Pr(Y=j) E[X|Y=j]$ 

How to prove?

- = E[X]
- =  $\Sigma_i$  i Pr(X=i)
- =  $\Sigma_i i \Sigma_j \Pr(X=i \cap Y=j)$
- =  $\Sigma_i \Sigma_j i \Pr(Y=j) \Pr(X=i | Y=j)$
- =  $\Sigma_j \Pr(Y=j) \Sigma_i i \Pr(X=i | Y=j)$
- $\Sigma_{j} \Pr(Y=j) E[X|Y=j]$

Proof

#### Another Lemma

Lemma:  $E[X|Y=j] = \sum_{\omega} X(\omega) Pr(\omega|Y=j)$ 

How to prove? ... similar to proving  $E[X] = \sum_{\omega} X(\omega) Pr(\omega)$ 

# Expectation of Geo(p) (revisited) Another way to find E[X] for X = Geo(p) is by using the memory-less property: Let Y be a random variable such that Y=1 if the first trial succeeds, and Y=0 if the first trial fails

E[X] = Pr(Y=1) E[X|Y=1] + Pr(Y=0) E[X|Y=0]= p E[X|Y=1] + (1-p) E[X|Y=0] = p + (1-p) (1+E[X]) [why??] = (1-p) E[X] + 1  $\rightarrow$  E[X] = 1/p

# Linearity of Conditional Expectation

Lemma: For any finite collection of random variables X<sub>1</sub>, X<sub>2</sub>, ..., X<sub>k</sub>, each with finite expectation, and for any random variable Y

$$E[\Sigma_i X_i | Y=j] = \Sigma_i E[X_i | Y=j]$$

How to prove? ... similar to proving  $E[\Sigma_i X_i] = \Sigma_i E[X_i]$ 

# A new notation: E[X|Y]

Definition: Let X and Y be two random variables. The expression E[X|Y] is a random variable that takes on the value E[X|Y=j] when Y = j

Is each the following a constant? E[X], E[X| Y=j ], E[X|Y], E[ E[X|Y] ]

Note: E[X|Y] is not a constant... its value depends on Y so that it is a function of Y

# E[X| Y] is a function of Y Ex: Let X = sum of two fair dice, and Y = outcome of the first dice $E[X|Y] = \sum_{i} i Pr(X=i|Y)$ = $\sum_{i=y+1,y+2,...,y+6} i \Pr(X=i | Y)$ $= \sum_{i=y+1,y+2,...,y+6} i (1/6)$ = Y + 3.5

# What is E[E[X|Y]]?

Theorem: Let X and Y be two random variables. Then, E[X] = E[E[X|Y]]

Proof: E[E[X|Y]]  $= \sum_{j} E[X|Y=j] Pr(Y=j)$  = E[X]

Imagine we have a strange program P which, before it finishes running, will create a random number of new copies of itself

Now, consider running the first copy of P.

- Before this P finishes its execution, it may create some new copies of P
- Similarly, before each such P finishes its execution, it may create some new copies of P, and so on ...



Suppose we now know that:

the number of new copies each P creates is a binomial random variable Bin(n,p)

Question: What is the expected number of copies of P created?

Let us introduce the idea of generations. The initial copy of P is in generation 0. For other copy, it is in generation i if it is created by a copy of P in generation i-1. Let Y<sub>i</sub> = number of copies in generation i Thus,

$$Y_0 = 1$$
 and  $E[Y_1] = np$ 

# Our target is to find $E[Y_0 + Y_1 + Y_2 + Y_3 + ...]$ $= E[Y_0] + E[Y_1] + E[Y_2] + ...$

The first two terms are known.

For the remaining terms, such as  $E[Y_2]$ , it may be easy to compute IF we know the exact number of copies in the previous generation ... Unluckily, we don't know that

Anyway, let us see what if we "know" that the number of copies in generation i-1 is j

[ It cannot hurt to try ]

Question: Can we find  $E[Y_i | Y_{i-1} = j]$ ? Here, we have j copies in generation i-1 Let  $Z_k = \#$  new copies created by k<sup>th</sup> P in generation i-1

- $E[Y_i | Y_{i-1} = j]$
- $= \mathsf{E}[\Sigma_{k=1,2,\ldots,j} Z_k \mid Y_{i-1} = j]$
- $= \sum_{k=1,2,\dots,j} \mathbb{E}[\mathbb{Z}_k \mid \mathbb{Y}_{i-1} = j]$
- =  $\sum_{k=1,2,\dots,j} \sum_{r} r \Pr(Z_k = r | Y_{i-1} = j)$
- =  $\sum_{k=1,2,\dots,j} \sum_{r} r \Pr(Z_k = r)$
- $= \sum_{k=1,2,\dots,j} E[Z_k] = j np$

# Then, we have: $E[Y_i] = E[E[Y_i|Y_{i-1}]]$ $= \sum_j E[Y_i|Y_{i-1}=j] Pr(Y_{i-1}=j)$ $= \sum_j j np Pr(Y_{i-1}=j)$ $= np \sum_j j Pr(Y_{i-1}=j)$ $= np E[Y_{i-1}]$

Though we still don't know what exactly E[Y<sub>i</sub>] is, we get a very useful relationship

In other words,

```
E[Y_0] = Y_0 = 1 = (np)^0

E[Y_1] = np

E[Y_2] = np E[Y_1] = (np)^2

E[Y_3] = np E[Y_2] = (np)^3

\vdots

E[Y_i] = (np)^i
```

Total copies =  $\sum_{i \ge 0} Y_i$ Thus, expected total copies =  $E[\sum_{i \ge 0} Y_i] = \sum_{i \ge 0} E[Y_i] = \sum_{i \ge 0} (np)^i$ If  $np \ge 1$ , the above term is unbounded. If np < 1, the above term is 1/(1-np)