CSE 312 Foundations of Computing II

Lecture 12: Zoo of Discrete RVs

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Variance – Properties

Definition. The **variance** of a (discrete) RV *X* is

$$\operatorname{Var}(X) = \mathbb{E}\left[\left(X - \mathbb{E}(X)\right)^2\right] = \sum_{x} \mathbb{P}_X(x) \cdot \left(x - \mathbb{E}(X)\right)^2$$

Theorem. For any $a, b \in \mathbb{R}$, $Var(a \cdot X + b) = a^2 \cdot Var(X)$

(Proof: Exercise!)

Theorem. $Var(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2$



Important Facts about Independent Random Variables

Theorem. If *X*, *Y* independent, $\mathbb{E}(X \cdot Y) = \mathbb{E}(X) \cdot \mathbb{E}(Y)$

Theorem. If *X*, *Y* independent, Var(X + Y) = Var(X) + Var(Y)

Corollary. If $X_1, X_2, ..., X_n$ mutually independent, $Var\left(\sum_{i=1}^n X_i\right) = \sum_i^n Var(X_i)$

Motivation: "Named" Random Variables

Random Variables that show up all over the place.

 Easily solve a problem by recognizing it's a special case of one of these random variables.

Each RV introduced today will show:

- A general situation it models
- Its name and parameters
- Its PMF, Expectation, and Variance
- Example scenarios you can use it

Welcome to the Zoo! (Preview) 🖪 🕼 😨 🚱 😫 🏠 🚏

$$X \sim \text{Unif}(a, b)$$
 $X \sim \text{Ber}(p)$
 $X \sim \text{Bin}(n, p)$
 $P(X = k) = \frac{1}{b - a + 1}$
 $P(X = 1) = p, P(X = 0) = 1 - p$
 $P(X = k) = \binom{n}{k} p^k (1 - p)^k$
 $E[X] = \frac{a + b}{2}$
 $P(X = 1) = p, P(X = 0) = 1 - p$
 $P(X = k) = \binom{n}{k} p^k (1 - p)^k$
 $Var(X) = \frac{(b - a)(b - a + 2)}{12}$
 $P(X = 1) = p, P(X = 0) = 1 - p$
 $P(X = k) = \binom{n}{k} p^k (1 - p)^k$
 $Var(X) = \frac{(b - a)(b - a + 2)}{12}$
 $Var(X) = p(1 - p)$
 $Y \sim \text{NegBin}(r, p)$
 $X \sim \text{HypGeo}(N, K, n)$
 $X \sim \text{Geo}(p)$
 $X \sim \text{NegBin}(r, p)$
 $X \sim \text{HypGeo}(N, K, n)$
 $P(X = k) = \binom{k-1}{r-1} p^r (1 - p)^{k-r}$
 $P(X = k) = \binom{\binom{k}{k} \binom{N-k}{n-k}}{\binom{n}{n}}$
 $E[X] = \frac{1}{p}$
 $P(X = k) = \binom{r(1 - p)}{p^2}$
 $P(X = k) = \binom{\binom{k}{k} \binom{N-k}{n-k}$
 $E[X] = n \frac{K}{N}$
 $Var(X) = \frac{r(1 - p)}{p^2}$
 $Var(X) = n \frac{K(N - K)(N - n)}{N^2(N - 1)}$
 $P(X = k) = \binom{k}{N^2(N - 1)}$



- Discrete Uniform Random Variables <
- Bernoulli Random Variables
- Binomial Random Variables
- Geometric Random Variables
- Applications

Discrete Uniform Random Variables $\chi(\mathcal{N}) = \{a, a \neq 1, \dots, b = 1, b\}$

A discrete random variable *X* equally likely to take any (int.) value between integers *a* and *b* (inclusive), is uniform.

Notation: $X \sim Unif(a_{1}b)$ PMF: $P(X=K) = \begin{cases} 1 & \text{if } k \in X(\mathcal{A}) \\ 0 & 0.W. \end{cases}$ Expectation: $E[X] = \frac{a+b}{2}$

Variance:



Example: value shown on one

roll of a fair die $U_{ni}f(1,6)$

Discrete Uniform Random Variables

22-sided die :
$$X \sim Unif(1,22)$$

 $P_r(X=i) = \frac{1}{22}$
 $E[X] = \frac{23}{2}$, $V_{ur}(X) = \frac{21 \cdot 23}{12}$

A discrete random variable *X* equally likely to take any (int.) value between integers *a* and *b* (inclusive), is uniform.

Notation: *X* ~ Unif(*a*, *b*)

PMF:
$$Pr(X = i) = \frac{1}{b - a + 1}$$

Expectation:
$$E[X] = \frac{a+b}{2}$$

Variance:
$$Var(X) = \frac{(b-a)(b-a+2)}{12}$$

Example: value shown on one roll of a fair die is Unif(1,6):

• $\Pr(X = i) = 1/6$

•
$$E[X] = 7/2$$

•
$$Var(X) = 35/12$$



Agenda

- Discrete Uniform Random Variables
- Bernoulli Random Variables 🕳
- Binomial Random Variables
- Geometric Random Variables
- Applications

a. p

b. p 1-p

c. p p(1-p)

A random variable X that takes value 1 ("Success") with probability p, and 0 ("Failure") otherwise. X is called a Bernoulli random variable. Notation: $X \sim \text{Ber}(p)$ **PMF:** Pr(X = 1) = p, Pr(X = 0) = 1 - pExpectation: $E[X] = I \cdot P + O \cdot (I-P) = P$ Variance: $V_{ar}(X) = E[X^2] - E[X]^2 = \rho - \rho^2$ Poll: pollev.com/hunter312 =p(1-p)Mean Variance

 $E[x^{2}] = |^{2} \cdot p + O \cdot (1 - p)$

=P

Bernoulli Random Variables

A random variable X that takes value 1 ("Success") with probability p, and 0 ("Failure") otherwise. X is called a Bernoulli random variable. Notation: $X \sim Ber(p)$ PMF: Pr(X = 1) = p, Pr(X = 0) = 1 - pExpectation: E[X] = p Note: $E[X^2] = p$ Variance: $Var(X) = E[X^2] - E[X]^2 = p - p^2 = p(1 - p)$

Examples:

- Coin flip
- Randomly guessing on a MC test question
- A server in a cluster fails

Agenda

- Discrete Uniform Random Variables
- Bernoulli Random Variables
- Binomial Random Variables 🗲
- Geometric Random Variables
- Applications

Binomial Random Variables Y₁, Y₂,..., Y_n ~ Ber(p) iid iid= Independent and Identically Distributed

A discrete random variable X that is the number of successes in n independent random variables $Y_i \sim \text{Ber}(p)$. X is a Binomial random variable where $X = \sum_{i=1}^{n} Y_i$ $P(X=k) = \binom{n}{k} P^k(I-p)^{n-k}$

Examples:

- # of heads in n coin flips
- # of 1s in a randomly generated n bit string
- # of servers that fail in a cluster of n computers
- # of bit errors in file written to disk
- # of elements in a bucket of a large hash table

Poll: pollev.com/hunter312 Pr(X = k)a. $p^k(1-p)^{n-k}$ b. npc. $\binom{n}{k}p^k(1-p)^{n-k}$ d. $\binom{n}{n-k}p^k(1-p)^{n-k}$

Binomial Random Variables

 $Y_i \sim Bor(P)$ $E[Y_i] = P$ $Vor(Y_i) = P(I-P)$

A discrete random variable *X* that is the number of successes in *n* independent random variables $Y_i \sim \text{Ber}(p)$. *X* is a Binomial random variable where $X = \sum_{i=1}^{n} Y_i$

Notation: $X \sim Bin(n, p)$

PMF:
$$Pr(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

Expectation:

Variance:

 $E[X] = E[\sum_{i=1}^{n} Y_i] = \sum_{i=1}^{n} E[Y_i] = \sum_{i=1}^{n} p = np$ $Var(X) = Var(\sum_{i=1}^{n} Y_i) = \sum_{i=1}^{n} Var(Y_i) = \sum_{i=1}^{n} p(1-p) = np(1-p)$

I	Poll:		
I	pollev.com/hunter312		
	Mean	Variance	
ć	а. р	p	
	b. np	np(1-p)	
(c. np	np^2	
(d. np	n^2p	

Binomial Random Variables

A discrete random variable *X* that is the number of successes in *n* independent random variables $Y_i \sim \text{Ber}(p)$. *X* is a Binomial random variable where $X = \sum_{i=1}^{n} Y_i$

Notation: $X \sim Bin(n, p)$

PMF: $Pr(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$

Expectation: E[X] = np

Variance: Var(X) = np(1-p)

Mean, Variance of the Binomial

If $Y_1, Y_2, ..., Y_n \sim \text{Ber}(p)$ and independent (i.i.d), then $X = \sum_{i=1}^n Y_i, X \sim \text{Bin}(n, p)$

Claim
$$E[X] = np$$

$$E[X] = E\left[\sum_{i=1}^{n} Y_i\right] = \sum_{i=1}^{n} E[Y_i] = nE[Y_1] = np$$
Claim $Var(X) = np(1-p)$

$$Var(X) = Var\left(\sum_{i=1}^{n} Y_i\right) = \sum_{i=1}^{n} Var(Y_i) = nVar(Y_1) = np(1-p)$$



Binomial PMFs



Example 010((0001))

Success w/ prob 0.9999, fail w/ prob 0.001

Sending a binary message of length 1024 bits over a network with probability 0.999 of correctly sending each bit in the message without corruption (independent of other bits). Let X be the number of corrupted bits. What is E[X]?

 $X \sim Bin (1024, 0.001)$

E[X] = 1024·0.001 = 1.024 J From lust slide

Ро	Poll:		
pollev.com/hunter312			
a.	1022.99		
b.	1.024		
с.	1.02298		
d.	1		
e.	Not enough		
	information to		
	compute		

Brain Break



Agenda

- Discrete Uniform Random Variables
- Bernoulli Random Variables
- Binomial Random Variables
- Geometric and other Random Variables

Geometric Random Variables

$$Y_1 = Y_2 = ... = Y_{k-1} = 0 \land Y_k = 1$$

A discrete random variable X that models the number of independent trials $Y_i \sim \text{Ber}(p)$ before seeing the first success. X is called a Geometric random variable with parameter p.

Notation:
$$X \sim \text{Geo}(p)$$

PMF: $P(X=k) = (1-p)^{k-1}P$
Expectation: $E \Sigma X = V_P$ (proved in L9)
Variance:

Examples:

trials until first success

- # of coin flips until first head
- # of random guesses on MC questions until you get one right
- # of random guesses at a password until you hit it

Geometric Random Variables



A discrete random variable X that models the number of independent trials $Y_i \sim \text{Ber}(p)$ before seeing the first success. X is called a Geometric random variable with parameter p.

Notation: $X \sim \text{Geo}(p)$ PMF: $\Pr(X = k) = (1 - p)^{k-1}p$ Expectation: $\mathbb{E}[X] = \frac{1}{p}$ Variance: $\operatorname{Var}(X) = \frac{1-p}{p^2}$

Examples:

- # of coin flips until first head
- # of random guesses on MC questions until you get one right
- *#* of random guesses at a password until you hit it

Example: Music Lessons

Your music teacher requires you to play a 1000 note song without mistake. You have been practicing, so you have a probability of 0.999 of getting each note correct (independent of the others). If you mess up a single note in the song, you must start over and play from the beginning. Let X be the number of times you have to play the song from the start. What is E[X]?

 $X \sim Geo(p)$ $X \sim Geo(0.3677)$ $E[X] = \frac{1}{6.3677} \approx 2.72$

p is prob of playing song correctly

$$Y = \# \text{ correct notes in one play of the song}$$

 $Y \sim Bin(1000, 0.9999)$
 $P = Pr(Y = 1000) = \binom{1000}{1000} 0.9999 \cdot 0.001$

 $\simeq 0.3677$

Negative Binomial Random Variables

A discrete random variable X that models the number of independent trials $Y_i \sim Ber(p)$ before seeing the r^{th} success. Equivalently, $X = \sum_{i=1}^{r} Z_i$ where $Z_i \sim Geo(p)$. X is called a Negative Binomial random variable with parameters r, p.

Notation: $X \sim \text{NegBin}(r, p)$ PMF: $\Pr(X = k) = \binom{k-1}{r-1}p^r(1-p)^{k-r}$ Expectation: $\mathbb{E}[X] = \frac{r}{p}$ Variance: $\operatorname{Var}(X) = \frac{r(1-p)}{p^2}$

Hypergeometric Random Variables

A discrete random variable X that models the number of successes in n draws (without replacement) from N items that contain K successes in total. X is called a Hypergeometric RV with parameters N, K, n.

Notation: $X \sim \text{HypGeo}(N, K, n)$

PMF:
$$Pr(X = k) = \frac{\binom{K}{k}\binom{N-K}{n-k}}{\binom{N}{n}}$$

Expectation: $E[X] = n\frac{K}{N}$

Variance: $Var(X) = n \frac{K(N-K)(N-n)}{N^2(N-1)}$

X= # red balls drawn in 4 draws W/o replacement

 $\chi \sim Hyp \, Geo (9,3,4)$

Hope you enjoyed the zoo! 🗗 🕼 😨 🎲 🞲

$$\begin{array}{c} X \sim \text{Unif}(a,b) \\
 P(X = k) = \frac{1}{b - a + 1} \\
 E[X] = \frac{a + b}{2} \\
 Var(X) = \frac{(b - a)(b - a + 2)}{12} \\
 \end{array}$$

$$\begin{array}{c} X \sim \text{Ber}(p) \\
 P(X = 1) = p, P(X = 0) = 1 - p \\
 E[X] = p \\
 Var(X) = p(1 - p) \\
 \end{array}$$

$$\begin{array}{c} P(X = k) = (1 - p)^{k - 1} p \\
 E[X] = \frac{1}{p} \\
 Var(X) = \frac{1 - p}{p^2} \\
 \end{array}$$

$$\begin{array}{c} X \sim \text{NegBin}(r, p) \\
 \end{array}$$

$$\begin{array}{c} X \sim \text{NegBin}(r, p) \\
 P(X = k) = (\frac{k - 1}{r - 1})p^r(1 - p)^{k - r} \\
 E[X] = \frac{r}{p} \\
 Var(X) = \frac{r(1 - p)}{p^2} \\
 \end{array}$$

$$\begin{array}{c} X \sim \text{NegBin}(r, p) \\
 P(X = k) = (\frac{k - 1}{r - 1})p^r(1 - p)^{k - r} \\
 E[X] = n \\
 E[X] = n \\
 F[X] = \frac{r}{p} \\
 Var(X) = \frac{r(1 - p)}{p^2} \\
 \end{array}$$

$$\begin{array}{c} X \sim \text{NegBin}(r, p) \\
 P(X = k) = (\frac{k - 1}{r - 1})p^r(1 - p)^{k - r} \\
 E[X] = n \\
 F[X] = n \\
 F[X] = n \\
 F[X] = n \\
 Var(X) = n \\
 \hline
 \end{array}$$

Preview: Poisson

Model: # events that occur in an hour

- Expect to see 3 events per hour (but will be random)
- The expected number of events in t hours, is 3t
- Occurrence of events on disjoint time intervals is independent