CSE 312 Foundations of Computing II

Lecture 11: Zoo of Discrete RVs

Review Variance – Properties

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

 $\operatorname{Var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \sum_x p_X(x) \cdot (x - \mathbb{E}[X])^2$

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

(Proof: Exercise!)

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

Review 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 for "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) 🏊 🖓 🏫 🏷

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



- Discrete Uniform Random Variables <
- Bernoulli Random Variables
- Binomial Random Variables
- Geometric and Other Random Variables

Discrete Uniform Random Variables

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

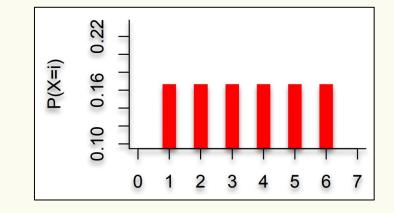
Notation:

PMF:

Expectation:

Variance:

Example: value shown on one roll of a fair die



Discrete Uniform Random Variables

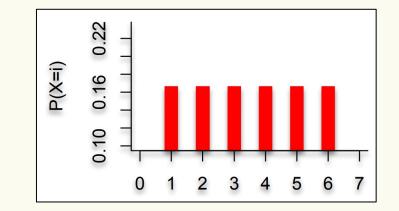
A discrete random variable X equally likely to take any (integer) value between integers a and b (inclusive), is uniform.

Notation: $X \sim \text{Unif}(a, b)$ PMF: $P(X = i) = \frac{1}{b - a + 1}$ Expectation: $\mathbb{E}[X] = \frac{a + b}{2}$ Variance: $\text{Var}(X) = \frac{(b - a)(b - a + 2)}{12}$ Example: value shown on one roll of a fair die is Unif(1,6):

• P(X = i) = 1/6

•
$$\mathbb{E}[X] = 7/2$$

•
$$Var(X) = 35/12$$



Agenda

- Discrete Uniform Random Variables
- Bernoulli Random Variables 🕳
- Binomial Random Variables
- Geometric and Other Random Variables

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: P(X = 1) = p, P(X = 0) = 1 - pExpectation: Variance:

Poll:				
pollev.com/stefanotessaro617				
	Mean	Variance		
Α.	p	p		
Β.	p	1 - p		
С.	p	p(1-p)		
D.	p	p^2		

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:** P(X = 1) = p, P(X = 0) = 1 - p**Expectation:** $\mathbb{E}[X] = p$ Note: $\mathbb{E}[X^2] = p$ Variance: $Var(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = p - p^2 = p(1-p)$ **Examples:**

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

Agenda

- Discrete Uniform Random Variables
- Bernoulli Random Variables
- Binomial Random Variables 🗨
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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 $X = \sum_{i=1}^{n} Y_i$

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/stefanotessaro617 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

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: $P(X = k) = \binom{n}{k}p^k(1-p)^{n-k}$ Expectation: Variance:

Poll:				
pollev.com/stefanotessaro617				
	Mean	Variance		
	p	p		
Β.	np	np(1-p)		
С.	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: $P(X = k) = \binom{n}{k}p^k(1-p)^{n-k}$ Expectation: $\mathbb{E}[X] = np$ Variance: Var(X) = np(1-p)

Mean, Variance of the Binomial

"i.i.d." is a commonly used phrase. It means "independent & identically distributed"

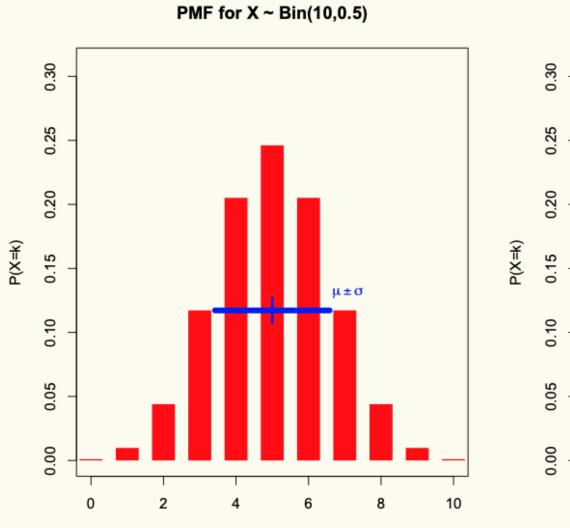
If $Y_1, Y_2, ..., Y_n \sim \text{Ber}(p)$ and independent (i.i.d.), then $X = \sum_{i=1}^n Y_i, X \sim \text{Bin}(n, p)$

Claim
$$\mathbb{E}[X] = np$$

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

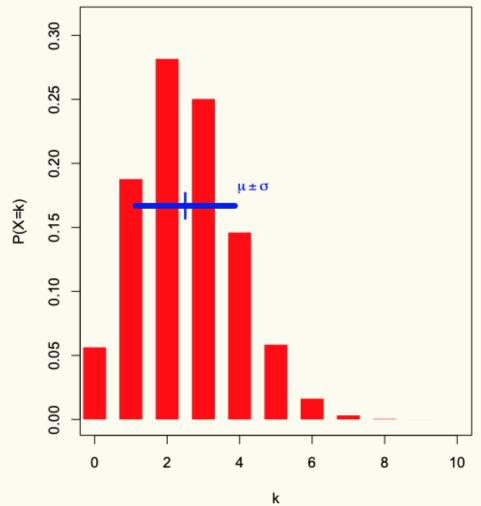
$$\operatorname{Var}(X) = \operatorname{Var}\left(\sum_{i=1}^{n} Y_{i}\right) = \sum_{i=1}^{n} \operatorname{Var}(Y_{i}) = n\operatorname{Var}(Y_{1}) = np(1-p)$$

Binomial PMFs



k

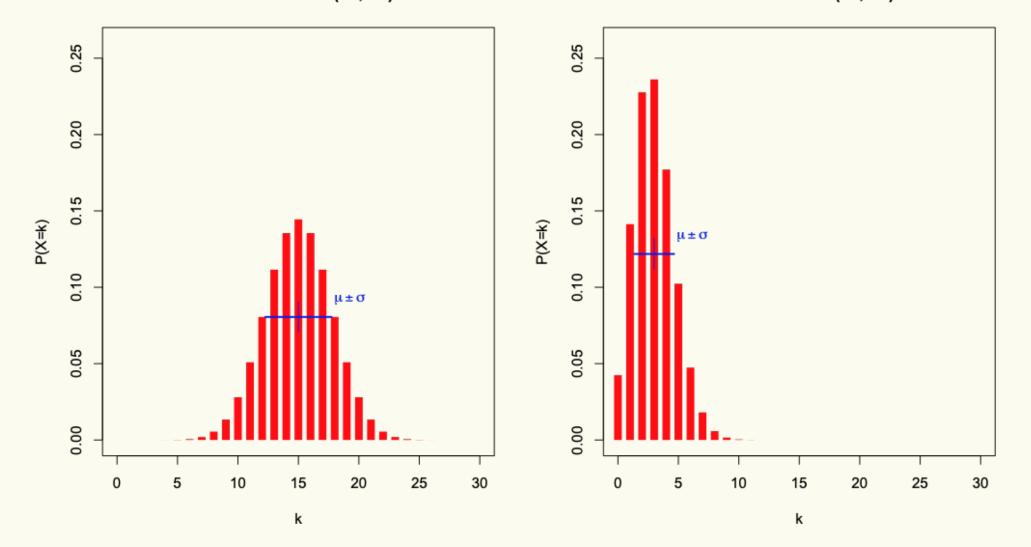
PMF for X ~ Bin(10,0.25)



Binomial PMFs

PMF for X ~ Bin(30,0.5)

PMF for X ~ Bin(30,0.1)



Example

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 $\mathbb{E}[X]$?

Poll:		
por	llev.com/stefanotessaro617	
а.	1022.99	
b.	1.024	
с.	1.02298	
d.	1	
e.	Not enough information	
	to compute	

Brain Break



Agenda

- Discrete Uniform Random Variables
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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 ~ Geo(p)
PMF:
Expectation:
Variance:
```

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

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: $P(X = k) = (1 - p)^{k-1}p$ Expectation: $\mathbb{E}[X] = \frac{1}{p}$ Variance: $\text{Var}(X) = \frac{1-p}{p^2}$ 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 $\mathbb{E}[X]$?

Negative Binomial Random Variables

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

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

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.

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

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

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

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

Hope you enjoyed the zoo! 🏊 🖓 🏫 🏷

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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