

## Chapter 2. Discrete Distributions

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Math 3215 Spring 2024

Georgia Institute of Technology

**Section 1.**  
**Random Variables of the Discrete**  
**Type**

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## Random variables

### Definition

Given a random experiment with a sample space  $S$ , a function  $X$  that assigns one and only one real number  $X(s) = r$  to each element in  $S$  is called a **random variable**.

The **space of  $X$**  is the set of real numbers  $\{x : X(s) = x, s \in S\}$  and denoted by  $S(X)$  = the support of  $X$

Example

$$S = \{ \text{Male}, \text{Female} \}$$

$$X : S \rightarrow \mathbb{R} = \{ \text{Real numbers} \}$$

$$\text{Male} \mapsto 1$$

$$\text{Female} \mapsto 2$$

$$S(X) = \{1, 2\}$$

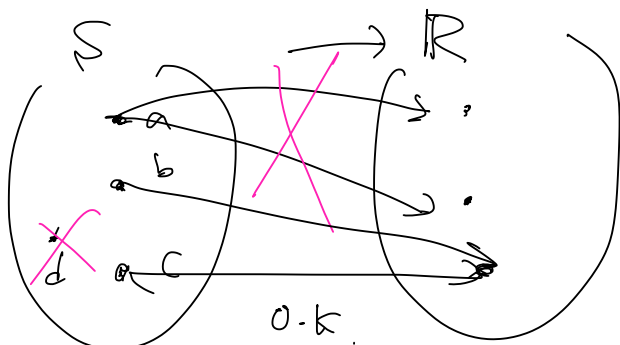
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$$Y : S \rightarrow \mathbb{R}$$

$$\text{Male} \mapsto -1$$

$$\text{Female} \mapsto 3$$

$$S(Y) = \{-1, 3\}$$



## Random variables

### Example

A rat is selected at random from a cage and its sex is determined.

The set of possible outcomes is female and male. Thus, the sample space is  $S = \{\text{female, male}\}$ .

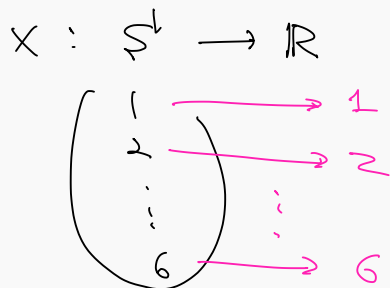
## Random variables

### Example

Consider a random experiment in which we roll a six-sided die.

The sample space associated with this experiment is  $S = \{1, 2, 3, 4, 5, 6\}$ .

Let  $X(s) = s$ . Compute  $\mathbb{P}(2 \leq X \leq 4)$ .



$$\begin{aligned} & \mathbb{P}(2 \leq X \leq 4) \\ &= \mathbb{P}(X = 2 \text{ or } 3 \text{ or } 4) \\ &= \mathbb{P}(X=2) + \mathbb{P}(X=3) + \mathbb{P}(X=4) \\ &= \frac{1}{6} + \frac{1}{6} + \frac{1}{6} = \frac{1}{2}. \end{aligned}$$

## Discrete random variables

ex  $\mathcal{S}^t = [0, 1]$  : uncountable outcomes

### Definition

Let  $X$  be a random variable defined on a sample space  $S$ .

If  $S$  consists of finite outcomes or countable outcomes, then  $X$  is called a **discrete random variable**.

The **probability mass function (pmf)** of  $X$  is  
only for discrete RV

$$f: \mathcal{S}(X) \rightarrow \mathbb{R}$$
$$f(x) = \mathbb{P}(X = x)$$

The **cumulative distribution function (cdf)** of  $X$  is

$$F(x) = \mathbb{P}(X \leq x)$$

for any RV

$$F: \mathbb{R} \rightarrow \mathbb{R}$$



## Discrete random variables

$$f(x) = \mathbb{P}(X = x)$$

### Properties of PMF

The pmf  $f(x)$  of a discrete random variable  $X$  is a function that satisfies the following properties:

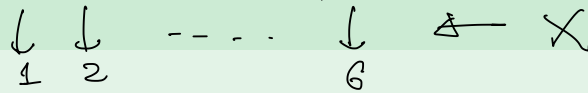
- $f(x) \geq 0$  for all  $x$ ,  $\text{---} = \mathbb{P}(\mathcal{S})$
- $\sum_{x \in \mathcal{S}(X)} f(x) = 1$ , and
- $\mathbb{P}(X \in A) = \sum_{x \in A} f(x)$ .

## Discrete random variables

$$\Omega = \{1, 2, 3, 4, 5, 6\}$$

### Example

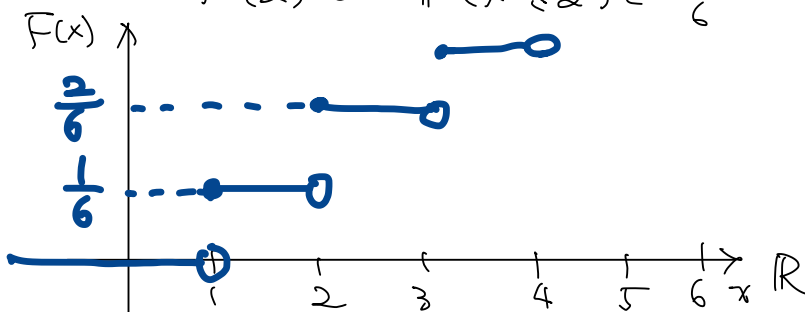
Roll a die, let  $X$  be the outcome.



Find the pmf and the cdf of  $X$ .

$$\text{PMF : } f(x) = P(X=x) = \begin{cases} \frac{1}{6} & \text{for } x=1, \dots, 6 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{CDF : } F(x) = P(X \leq x) = \begin{cases} 0 & \text{for } x < 1 \\ \frac{1}{6} & \text{for } 1 \leq x < 2 \\ \frac{2}{6} & \text{for } 2 \leq x < 3 \\ \frac{3}{6} & \text{for } 3 \leq x < 4 \\ \frac{4}{6} & \text{for } 4 \leq x < 5 \\ \frac{5}{6} & \text{for } 5 \leq x < 6 \\ \frac{6}{6} & \text{for } x \geq 6 \end{cases}$$





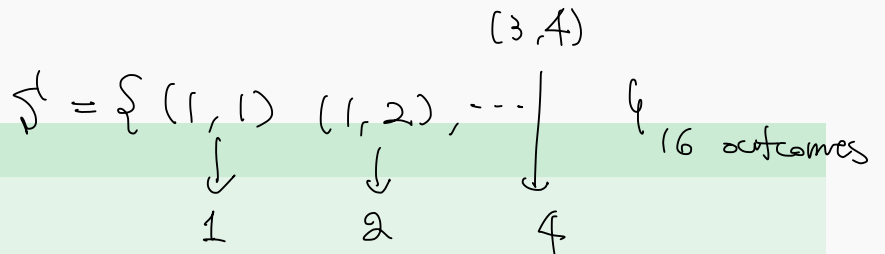
## Discrete random variables

### Example

Roll a fair four-sided die twice.

Let  $X$  equal the larger of the two outcomes if they are different and the common value if they are the same.

Find the pmf and the cdf of  $X$ .



$$\text{PMF } f(x) = P(X=x) =$$

$$\mathcal{S}(x) = \{1, 2, 3, 4\}$$

$$\left. \begin{array}{l} 1/16 \\ 3/16 \\ 5/16 \\ 7/16 \end{array} \right\} \begin{array}{l} x=1 \\ x=2 \\ x=3 \\ x=4 \end{array}$$

$f(1) = P(X=1)$   
 $P(X=3)$   
 $P((1,3), (2,3), (3,3), (3,1), (3,2))$

$$\text{CDF } F(x) = P(X \leq x)$$

$$= \begin{cases} 0 & x < 1 \\ \frac{1}{16} & 1 \leq x < 2 \\ \frac{1}{16} + \frac{3}{16} = \frac{4}{16} & 2 \leq x < 3 \\ \frac{1}{16} + \frac{3}{16} + \frac{5}{16} = \frac{9}{16} & 3 \leq x < 4 \\ 1 & x \geq 4 \end{cases}$$

RV:  $X : \mathcal{S} \rightarrow \mathbb{R}$   
 $\uparrow$   
 sample.

$X$  Discrete RV of  
 $\mathcal{S}$  finite, countable.

$$\mathcal{S}(X) = \{s : X = s\}$$

PMF  $f(x) = f_X(x) = P(X = x)$

CDF  $F(x) = F_X(x) = P(X \leq x)$

### Bar graph, Probability histogram, relative frequency histogram

$$\mathcal{S} = \{ (1,1) \quad (1,2) \quad (1,3), \dots \dots \}$$

$$\begin{matrix} \downarrow & \downarrow & \downarrow \\ 2 & 3 & 4 \end{matrix}$$

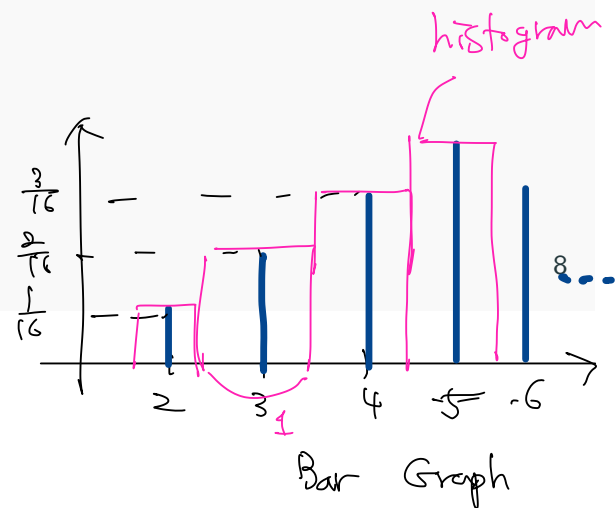
#### Example

A fair four-sided die with outcomes 1, 2, 3, and 4 is rolled twice.

Let  $X$  equal the sum of the two outcomes.

$$\mathcal{S}(X) = \{2, 3, \dots, 8\}$$

PMF $f(x) =$	$\left\{ \begin{array}{l} 1/16 \\ 2/16 \\ 3/16 \\ 4/16 \\ 3/16 \\ 2/16 \\ 1/16 \\ \circ \end{array} \right.$	$x = 2$
		$x = 3$
		$x = 4$
		$x = 5$
		$x = 6$
		$x = 7$
		$x = 8$
		otherwise



## Bar graph, Probability histogram, relative frequency histogram

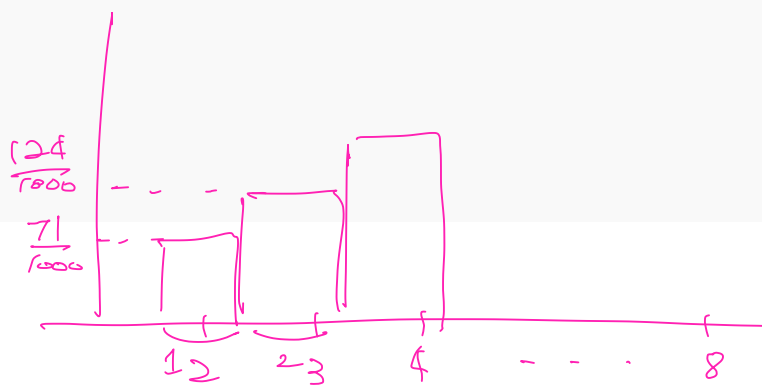
### Example

Two fair four-sided dice are rolled. Write down the sum of the two outcomes. Repeat this 1000 times.

The sum of two outcomes	2	3	4	5	6	7	8
Number of Observations	71	124	194	258	177	122	54

$$\frac{71}{1000} \quad \frac{124}{1000} \quad \dots \quad \frac{54}{1000}$$

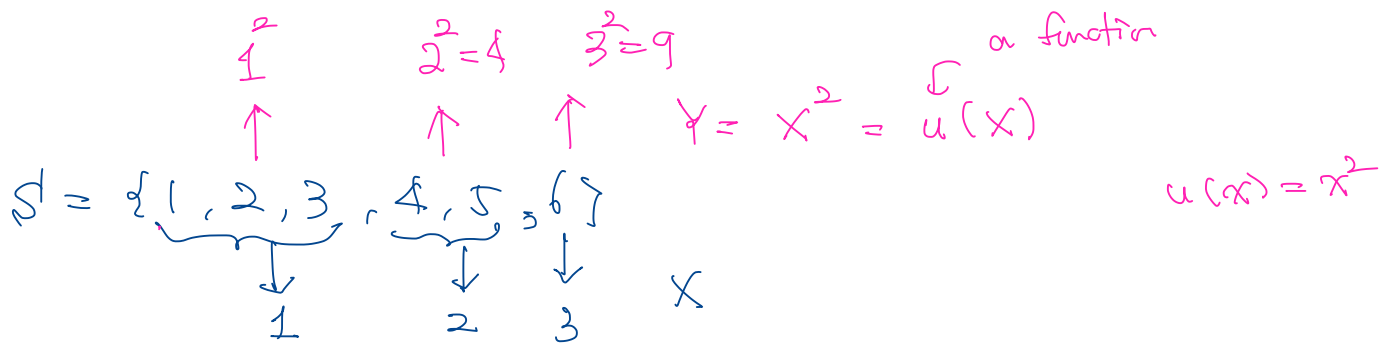
relative frequency.



## **Section 2.**

# **Mathematical Expectation**

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## Definition of Expectation

$$E[u(X)] = P(A) \cdot 1^2 + P(B) \cdot 2^2 + P(C) \cdot 3^2$$

$$= \sum u(x) P(X=x)$$

### Example

Consider the following game. A player roll a fair die.

If the event  $A = \{1, 2, 3\}$  occurs, he receives one dollar.

If  $B = \{4, 5\}$  occurs, he receives two dollars.

If  $C = \{6\}$  occurs, he receives three dollars.

If the game is repeated a large number of times, what is the average payment?

Suppose play 6000 times

- A happens about 3000 times  
 $\Rightarrow \$3000 \times 1$
- B happens about 2000 times  
 $\Rightarrow \$2000 \times 2$
- C happens about 1000 times  
 $\Rightarrow \$1000 \times 3$

Expected Profit per Game

$$= \frac{1}{6000} \cdot (3000 \cdot 1 + 2000 \cdot 2 + 1000 \cdot 3)$$

$$= P(A) \cdot 1 + P(B) \cdot 2 + P(C) \cdot 3$$

$$= P(X=1) \cdot 1 + P(X=2) \cdot 2 + P(X=3) \cdot 3$$

$$= \sum_{x \in S(X)} x \cdot \underbrace{P(X=x)}$$

$$= \sum_{x \in S(X)} x \cdot f(x) = \mathbb{E}[X]$$

Expectation of  $X$   
(expected value)

## Definition of Expectation

### Definition

If  $f(x)$  is the pmf of a discrete random variable  $X$  with the space  $S(X)$ , and if the summation

$$\sum_{x \in S(X)} u(x)f(x)$$

**exists**, then the sum is called **the mathematical expectation or the expected value of  $u(X)$** , and denoted by  $\mathbb{E}[u(X)]$ .

$$\begin{aligned} \underline{\mathbb{E}} \quad \mathbb{E}[X] &= x_1 \cdot P(X=x_1) + x_2 \cdot P(X=x_2) + \dots \\ \mathbb{E}[X^2] &= x_1^2 \cdot P(X=x_1) + x_2^2 \cdot P(X=x_2) + \dots \end{aligned}$$

$$\begin{aligned} \mathbb{E}_X \quad S(X) &= \{1, 2, 3, 4\} & f_X \\ Y &= X - (X-1) \\ S(Y) &= \{0, 2, 6, 12\} \\ f_Y(0) &= f_X(1), \quad f_Y(2) = f_X(2), \quad f_Y(6) = f_X(3) \end{aligned}$$

## Definition of Expectation

### Example

Let the random variable  $X$  have the pmf  $f(x) = \frac{1}{3}$  for  $x \in \{-1, 0, 1\} = S(X)$ .

Let  $Y = u(X) = X^2$ .

Find the pmf of  $Y$  and  $\mathbb{E}[Y] = \mathbb{E}[X^2]$ .

$$S(Y) = \{0, 1\}$$

$$f_Y(y) = P(Y = y) = \begin{cases} \frac{1}{3} & y = 0 \\ \frac{2}{3} & y = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E}[Y] = \sum_{y \in S(Y)} y \cdot f_Y(y) = 0 \cdot f_Y(0) + 1 \cdot f_Y(1) = \frac{2}{3} \quad 12$$

$$\mathbb{E}[X^2] = \sum_{x \in S(X)} x^2 \cdot f_X(x)$$

$$= (-1)^2 \cdot \underbrace{f_X(-1)}_{\frac{1}{3}} + 0^2 \cdot f_X(0) + 1^2 \cdot \underbrace{f_X(1)}_{\frac{1}{3}} = \frac{2}{3}$$

## Properties of Expectation

### Theorem

1. If  $c$  is a constant, then  $\mathbb{E}[c] = c$ .
2. If  $c$  is a constant and  $u$  is a function, then  $\mathbb{E}[cu(X)] = c\mathbb{E}[u(X)]$ .
3. If  $c_1$  and  $c_2$  are constants and  $u_1$  and  $u_2$  are functions. then

$$\mathbb{E}[c_1 u_1(X) + c_2 u_2(X)] = c_1 \mathbb{E}[u_1(X)] + c_2 \mathbb{E}[u_2(X)].$$

Ex

$$\begin{aligned} \mathbb{E}[X(X-2)] &= \sum_{x \in \mathcal{S}(X)} x(x-2) f(x) \\ &= \mathbb{E}[X^2 - 2X] = \mathbb{E}[X^2] - \mathbb{E}[2X] \\ &= \mathbb{E}[X^2] - 2 \cdot \mathbb{E}[X]. \end{aligned}$$



$$\sum x \cdot f(x) \quad \text{Same value}$$

## Properties of Expectation

$$\mathcal{S}(x) = \{1, 2, 3, 4\}$$

$$f(x) = \begin{cases} \frac{1}{10} & x=1 \\ \frac{2}{10} & x=2 \\ \frac{3}{10} & x=3 \\ \frac{4}{10} & x=4 \end{cases}$$

### Example

Let  $X$  have the pmf  $f(x) = \frac{x}{10}$  for  $x = 1, 2, 3, 4$ .

Find  $\mathbb{E}[X]$ ,  $\mathbb{E}[X^2]$  and  $\mathbb{E}[X(5-X)]$ .

$$\mathbb{E}[X] = 1 \cdot \frac{1}{10} + 2 \cdot \frac{2}{10} + 3 \cdot \frac{3}{10} + 4 \cdot \frac{4}{10}$$

$$= \frac{1}{10} \cdot (1^2 + 2^2 + 3^2 + 4^2) = 3$$

$$\mathbb{E}[X^2] = 1^2 \cdot \frac{1}{10} + 2^2 \cdot \frac{2}{10} + 3^2 \cdot \frac{3}{10} + 4^2 \cdot \frac{4}{10}$$

$$= \frac{1}{10} \cdot (1^3 + 2^3 + 3^3 + 4^3) = 10$$

$$\begin{aligned} \mathbb{E}[X(5-X)] &= \mathbb{E}[5X - X^2] = 5 \cdot \mathbb{E}[X] - \mathbb{E}[X^2] \\ &= 5 \cdot 3 - 10 = 5. \end{aligned}$$

Note

$$\mathbb{E}[X^2] \neq (\mathbb{E}[X])^2$$

$$\mathbb{E}[u(X)] \neq u(\mathbb{E}[X])$$

$$E[X] = \sum_{x \in S(X)} x \cdot f(x) = P(X=x)$$

$$E[\underbrace{u(X)}_{\text{New RV}}] = \sum_{x \in S(X)} u(x) f(x)$$

$\in$  : belongs to

$(0, 1)$  : open interval

## Properties of Expectation

$$S(X) = \{1, 2, 3, \dots\}$$

### Example

An experiment has probability of success  $p \in (0, 1)$  and probability of failure  $q = 1 - p$ .

This experiment is repeated independently until the first success occurs.

Let  $X$  be the number of trials. Find  $E[X]$ .

$$E[X] = \frac{1}{p}$$

$X=1$ : H	$f(1) = P(X=1) = p$
$X=2$ : T H	$f(2) = P(X=2) = (1-p)p$
$X=3$ : T T H	$f(3) = (1-p)^2 p$
$X=4$ : T T T H	$f(4) = (1-p)^3 \cdot p$
$\vdots$	$\vdots$

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$$\begin{aligned} \textcircled{A} = E[X] &= 1 \cdot p + 2 \cdot (1-p)p + 3 \cdot (1-p)^2 p + 4 \cdot (1-p)^3 p + \dots \\ (1-p)A &= 1 \cdot (1-p)p + 2 \cdot (1-p)^2 p + 3 \cdot (1-p)^3 p + \dots \end{aligned}$$

$$\begin{aligned} A - (1-p)A &= 1 \cdot p + 1 \cdot (1-p) \cdot p + 1 \cdot (1-p)^2 p + 1 \cdot (1-p)^3 p + \dots \\ pA &= \text{Geometric series} = \frac{\text{First}}{1 - \text{ratio}} = \frac{p}{1 - (1-p)} = 1 \end{aligned}$$

1<sup>st</sup> trial  $\begin{cases} \rightarrow H, & E[\# \text{ of trials}] = 1 \\ \rightarrow T, & \quad \quad \quad = 1 + A \end{cases}$

$$E[X] = A$$

$$\Rightarrow E[X] = A = p \cdot 1 + (1-p)(1+A)$$

Solve for A  $\Rightarrow A = p + \underbrace{(1-p)}_{=1} + (1-p) \cdot A$

$pA = 1 \quad \therefore A = \frac{1}{p}$

### Section 3.

### Special Mathematical Expectations

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## Moments

The expectation or **mean** of a random variable  $X$  is

$$\mu = \mathbb{E}[X] = \sum xf(x).$$

(m.w.)

This is also called the **first moment** about the origin.

The first moment about the mean  $\mu$  is  $\mathbb{E}[X - \mu] = \mathbb{E}[X] - \mathbb{E}[\mu] = \mathbb{E}[X] - \overset{\text{constant}}{\mu} = 0$

1<sup>st</sup> moment of  $X$  about  $b = \mathbb{E}[X - b]$

## Moments

$$\mu = \mathbb{E}[X]$$

The second moment of  $X$  about  $b$  is  $\mathbb{E}[(X - b)^2]$ .

If  $b = \mu$ , it is also called **the variance** of  $X$  and denoted by  $\text{Var}(X) = \overset{\text{sigma}}{\sigma^2}$ .

Its positive square root is **the standard deviation** of  $X$  and denoted by  $\text{Std}(X) = \sigma$ .

$$\mu = \mu_X = \mathbb{E}[X], \quad \sigma^2 = \sigma_X^2 = \mathbb{E}[(X - \mu)^2] = \text{Var}(X) \\ = \mathbb{E}[(X - \mathbb{E}(X))^2]$$

$$\text{Std}(X) = \sigma_X = \sigma = \sqrt{\mathbb{E}[(X - \mu)^2]}$$

with probability

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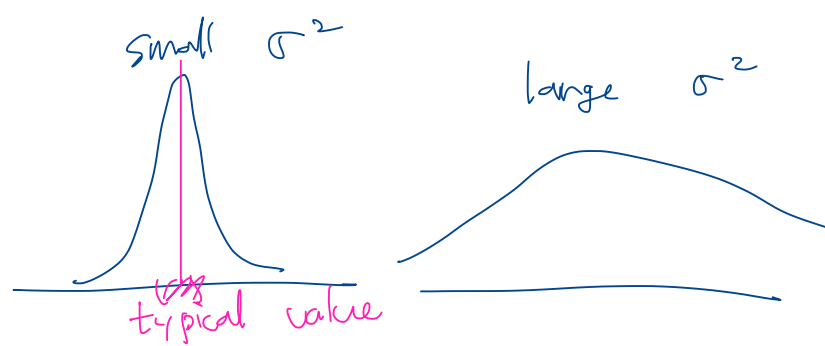
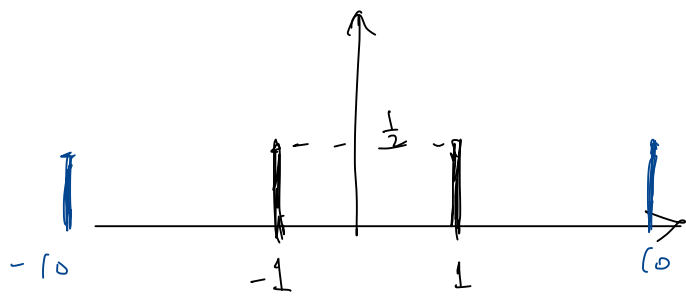
Ex

$$X = \begin{cases} 1 & \text{w.p. } \frac{1}{2} \\ -1 & \text{w.p. } \frac{1}{2} \end{cases}, \quad f_X(x) = \frac{1}{2} \quad \text{for } x = 1, -1$$

$$Y = \begin{cases} 10 & \text{w.p. } \frac{1}{2} \\ -10 & \text{w.p. } \frac{1}{2} \end{cases}, \quad f_Y(y) = \frac{1}{2}, \quad \text{for } y = 10, -10$$

$$\mathbb{E}[X] = \mu_X = 1 \cdot \frac{1}{2} + (-1) \cdot \frac{1}{2} = 0, \quad \mathbb{E}[Y] = 10 \cdot \frac{1}{2} + (-10) \cdot \frac{1}{2} = 0$$

$$\text{Var}(X) = \mathbb{E}[(X - \mu_X)^2] = \mathbb{E}[X^2] \\ = 1^2 \cdot \frac{1}{2} + (-1)^2 \cdot \frac{1}{2} = 1$$
$$\text{Var}(Y) = \mathbb{E}[(Y - \mu_Y)^2] = \mathbb{E}[Y^2] \\ = 10^2 \cdot \frac{1}{2} + (-10)^2 \cdot \frac{1}{2} = 100$$



## Moments

### Example

Roll a fair die and let  $X$  be the outcome.

Find  $\mathbb{E}[X]$  and  $\text{Var}(X)$ .

$$\begin{aligned}\mathbb{E}[X] &= 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + 3 \cdot \frac{1}{6} + 4 \cdot \frac{1}{6} + 5 \cdot \frac{1}{6} + 6 \cdot \frac{1}{6} \\ &= \frac{1}{6} \cdot (\underline{1 + 2 + \dots + 6}) = \frac{21}{6} = \frac{7}{2} = \mu\end{aligned}$$

$$\text{Var}(X) = \mathbb{E}[(X - \mu)^2] = \mathbb{E}\left[\left(X - \frac{7}{2}\right)^2\right]$$

$$\begin{aligned}&= \left(1 - \frac{7}{2}\right)^2 \cdot \frac{1}{6} + \left(2 - \frac{7}{2}\right)^2 \cdot \frac{1}{6} + \dots + \left(6 - \frac{7}{2}\right)^2 \cdot \frac{1}{6} \\ &= \frac{1}{6} \cdot \left[ \underbrace{\left(-\frac{5}{2}\right)^2 + \left(-\frac{3}{2}\right)^2 + \left(-\frac{1}{2}\right)^2}_{35} + \underbrace{\left(\frac{1}{2}\right)^2 + \left(\frac{3}{2}\right)^2 + \left(\frac{5}{2}\right)^2}_{35} \right] \\ &= \frac{1}{6} \cdot 2 \cdot \frac{1}{2} \cdot \left( \frac{1^2 + 3^2 + 5^2}{35} \right) = \left( \frac{35}{12} \right)\end{aligned}$$

# Moments

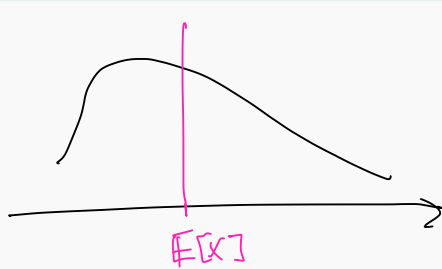
In general, the  $r$ -th moment of  $X$  about  $b$  is  $\mathbb{E}[(X - b)^r]$ .

## Definition

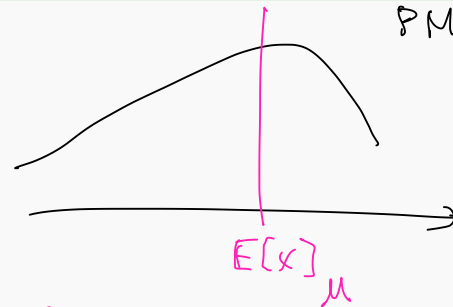
**Index of skewness** is defined by

$$\gamma = \mathbb{E}[(X - \mu)^3] / \sigma^3.$$

$\gamma > 0$  skew to right  
 $\gamma < 0$  " left



or



$\gamma > 0$ ?  
 $\gamma < 0$ ?



## Moments

$$\gamma = \frac{\mathbb{E}[(X-\mu)^3]}{\sigma^3}$$

### Example

Let  $f(x) = \frac{4-x}{6}$  for  $x = 1, 2, 3$  be the pmf of  $X$ . Compute the index of skewness.

$$\begin{aligned}\mathbb{E}[X] &= \frac{5}{3} = 1 \cdot \frac{(4-1)}{6} + 2 \cdot \frac{(4-2)}{6} + 3 \cdot \frac{(4-3)}{6} \\ &= \frac{1}{6} \cdot (1 \cdot 3 + 2 \cdot 2 + 3 \cdot 1) = \frac{10}{6} = \frac{5}{3}.\end{aligned}$$

$$\begin{aligned}\sigma^2 = \text{Var}(X) &= \mathbb{E}\left[\left(X - \frac{5}{3}\right)^2\right] \\ &= \left(1 - \frac{5}{3}\right)^2 \cdot \frac{3}{6} + \left(2 - \frac{5}{3}\right)^2 \cdot \frac{2}{6} + \left(3 - \frac{5}{3}\right)^2 \cdot \frac{1}{6} \\ &= \frac{4}{9} \cdot \frac{1}{2} + \frac{1}{9} \cdot \frac{1}{3} + \frac{16}{9} \cdot \frac{1}{6} \\ &= \frac{1}{9} \cdot \frac{1}{6} (12 + 2 + 16) = \frac{5}{9}\end{aligned}$$

$$\sigma = \frac{\sqrt{5}}{3}$$

$$\begin{aligned}\mathbb{E}[(X-\mu)^3] &= \left(1 - \frac{5}{3}\right)^3 \cdot \frac{3}{6} + \left(2 - \frac{5}{3}\right)^3 \cdot \frac{2}{6} + \left(3 - \frac{5}{3}\right)^3 \cdot \frac{1}{6} \\ &= \frac{1}{6} \cdot \left[ -\frac{8}{27} \cdot 3 + \frac{1}{27} \cdot 2 + \frac{64}{27} \cdot 1 \right]\end{aligned}$$

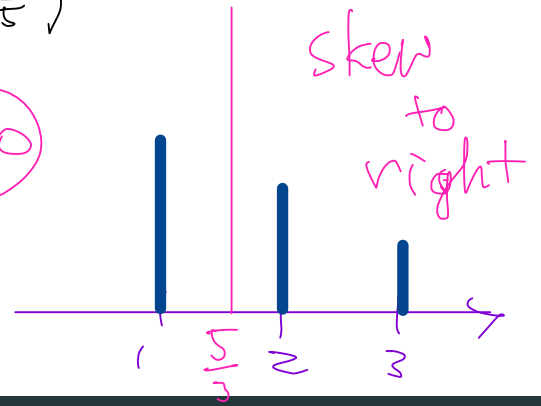


$$= \frac{1}{27 \cdot 6} [-24 + 2 + 64] = \frac{7}{27}$$

$$\gamma = \frac{\mathbb{E}[(X-\mu)^3]}{\sigma^3} = \frac{7}{27} \left(\frac{3}{\sqrt{5}}\right)^3$$

$$= \frac{7}{25\sqrt{5}}$$

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## Moments

$$\sigma^2 = \sum_i \underbrace{(x-\mu)^2}_{>0} \underbrace{f(x)}_{>0} > 0$$

### Theorem

$$0 \leq \sigma^2 = \mathbb{E}[(X-\mu)^2] = \mathbb{E}[X^2] - \mu^2 = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$$

$$= \mathbb{E}[X^2 - 2X\mu + \mu^2]$$

$$= \mathbb{E}[X^2] - 2\mu \underbrace{\mathbb{E}[X]}_{\mu} + \mu^2$$

$$= \mathbb{E}[X^2] - 2\mu^2 + \mu^2 = \mathbb{E}[X^2] - \mu^2$$

Note

$$\mathbb{E}[X^2] \geq (\mathbb{E}[X])^2$$

## Moment generating functions

$$\text{For } u(x) = e^{tx}, \quad \mathbb{E}[e^{tX}] = \mathbb{E}[u(X)]$$

### Definition

Let  $X$  be a discrete random variable and assume that there exists  $h > 0$  such that

$$\mathbb{E}[e^{tX}] = \sum e^{tx} f(x)$$

*Sum  $t$  around 0*

is finite for all  $t \in (-h, h)$ . Then,  $M(t) = \mathbb{E}[e^{tX}]$  is called **the moment generating function (mgf)**.

$$\text{---} \overbrace{\hspace{10em}}^{(t \text{ around } 0)} \text{---}$$

$-h \quad 0 \quad h$

$$r^{\text{th}} \text{ moment about } b = \mathbb{E}[(X - b)^r]$$

## Moment generating functions

$$M(t) = \mathbb{E}[e^{tX}]$$

### Properties

1.  $M(0) = 1$
2.  $M'(0) = \mathbb{E}[X]$
3.  $M''(0) = \mathbb{E}[X^2]$
4. In general,  $M^{(r)}(0) = \mathbb{E}[X^r]$ .

$$M(0) = \mathbb{E}[e^{0 \cdot X}] = \mathbb{E}[1] = 1$$

$$\begin{aligned} M'(0) &= \frac{d}{dt} \mathbb{E}[e^{tX}] \Big|_{t=0} = \mathbb{E} \left[ \frac{d}{dt} (e^{tX}) \right] \Big|_{t=0} \\ &= \mathbb{E}[X] \end{aligned}$$

$= X \cdot e^{tX}$

$$M(t) = \mathbb{E}[e^{tX}] \quad \text{for } -h < t < h, \quad h > 0$$

$$M(0) = 1$$

$$M'(0) = \frac{d}{dt} M(t) \Big|_{t=0} = \mathbb{E}[X e^{tX}] \Big|_{t=0} = \mathbb{E}[X]$$

$$M''(0) = \mathbb{E}[X^2]$$

$$M'''(0) = \mathbb{E}[X^3]$$

⋮

## Moment generating functions

$X$  : Geometric RV.

$$X = 1, 2, \dots$$

### Example

Let  $f(x) = q^{x-1}p$  where  $p \in (0, 1)$  and  $q = 1 - p$ .

Compute  $M(t)$ .

$$\mathbb{E}[X] = ?$$

$$\begin{aligned} M(t) &= \mathbb{E}[e^{tX}] = e^{t-1} \cdot \underbrace{q^0 \cdot p}_{f(1)} + e^{t-2} \cdot \underbrace{q^1 \cdot p}_{f(2)} + e^{t-3} \cdot \underbrace{q^2 \cdot p}_{f(3)} + \dots \\ &= \sum_{x=1}^{\infty} e^{tx} \cdot f(x) \\ &= \frac{e^t \cdot q^0 \cdot p}{1 - e^t \cdot q} = \boxed{\frac{p \cdot e^t}{1 - e^t(1-p)}} \end{aligned}$$

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Geometric Series

$$a + a \cdot r + a r^2 + a r^3 + \dots = \frac{a}{1 - r}$$

first term

ratio

only when  $|r| < 1$

$$M(t) = \mathbb{E}[e^{tX}] = \frac{p e^t}{1 - e^t(1-p)} \quad \text{for } t < \ln\left(\frac{1}{1-p}\right)$$

$$|r| = |e^t \cdot (1-p)| < 1 \quad \rightarrow \quad e^t < \frac{1}{1-p} \quad \rightarrow \quad t < \ln\left(\frac{1}{1-p}\right)$$

$$M(t) = \frac{p e^t \cdot e^{-t}}{(1 - e^t(1-p)) \cdot e^{-t}} = \frac{p}{\underbrace{e^{-t} - (1-p)}_{= h(t)}}$$

$$M'(t) = p \cdot \frac{d}{dt} \left( \frac{1}{h(t)} \right) = -p \cdot \frac{1}{h(t)^2} \cdot h'(t) \quad \left( \frac{1}{x} \right)' = -\frac{1}{x^2}$$

$$= -p \cdot \frac{1}{(e^{-t} - (1-p))^2} \cdot (-e^{-t})$$

$$M'(0) = (-p) \cdot \frac{1}{(1 - (1-p))^2} \cdot (-1) = \frac{1}{p} = \mathbb{E}[X].$$

## Section 4.

### The Binomial Distribution

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## Bernoulli random variables

A **Bernoulli experiment**, more commonly called a **Bernoulli trial**, is a random experiment with two outcomes.

Say  $S = \{\text{success, failure}\}$  and  $\mathbb{P}(\text{success}) = p$  for some  $p \in (0, 1)$ . Then  $\mathbb{P}(\text{failure}) = q = 1 - p$ .

A random variable  $X$  is a **Bernoulli random variable** with **success probability**  $p$  is  $X = 1$  if success and 0 otherwise.

$$X = \begin{cases} 1 & \text{with success probability } p \\ 0 & \text{otherwise} \end{cases}$$

• PMF  $f(x) = \begin{cases} p & , x=1 \\ 1-p & , x=0 \\ 0 & , \text{otherwise} \end{cases}$

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•  $\mathbb{E}[X] = 1 \cdot p + 0 \cdot (1-p) = p = \mu$

•  $\text{Var}(X) = \mathbb{E}[(X-\mu)^2] = \mathbb{E}[(X-p)^2]$   
 $= (1-p)^2 \cdot p + (0-p)^2 \cdot (1-p) = (1-p)^2 \cdot p + p^2 \cdot (1-p)$   
 $= p \cdot (1-p) \cdot ((1-p) + p) = p \cdot (1-p)$

$$\text{Var}(X) = \sigma^2 = \underline{\mathbb{E}[X^2]} - (\mathbb{E}[X])^2 = p - p^2 = p(1-p).$$

$$(\mathbb{E}[X^2] = 1^2 \cdot p + 0^2 \cdot (1-p) = p)$$

$$\bullet M(t) = \mathbb{E}[e^{tX}] = \underline{e^{t \cdot 1}} p + e^{t \cdot 0} (1-p) = pe^t + (1-p)$$

## Bernoulli random variables

### Theorem

Let  $X$  be a Bernoulli random variable with success probability  $p$ . ,  $q = 1-p$ .

$$\mathbb{E}[X] = p$$

$$\text{Var}[X] = p \cdot (1-p) = p \cdot q$$

## Binomial random variables

Consider a sequence of independent Bernoulli experiments with success probability  $p$ .

Let  $X$  be the number of success trials in the first  $n$  experiments.

This is called a **Binomial random variable** with the number of trials  $n$  and success probability  $p$ .

We use the notation  $X \sim b(n, p) = \text{Bin}(n, p)$ .

Ex       $n = 5$       ,       $p = 0.5 = \frac{1}{2}$

$X = \#$  of Heads

$X \sim b(5, \frac{1}{2}) = \text{Bin}(5, \frac{1}{2})$

*textbook*      *almost everyone use this.*

PMF       $f(x) = \begin{cases} (\frac{1}{2})^5 & x=0 \\ 5(\frac{1}{2})^5 & x=1 \\ 10(\frac{1}{2})^5 & x=2 \\ \binom{5}{3}(\frac{1}{2})^5 & x=3 \\ \binom{5}{4}(\frac{1}{2})^5 & x=4 \\ \binom{5}{5}(\frac{1}{2})^5 & x=5 \end{cases} \quad (x = 0, 1, 2, 3, 4, 5)$

$10 = 5C_2 = \binom{5}{2}$

HH TTT  
HTHTT  
⋮

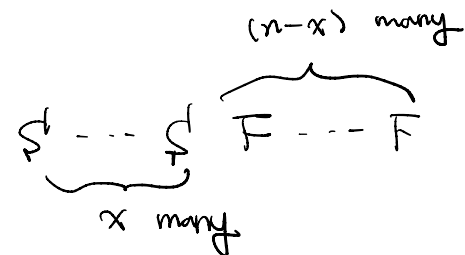
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$\binom{5}{x} (\frac{1}{2})^5$

$(1-p)^5$   
 $p(1-p)^4$   
 $p^2(1-p)^3$   
 $p^3(1-p)^2$   
 $p^4(1-p)$   
 $p^5$

In general,       $X \sim \text{Bin}(n, p)$

$f(x) = \binom{n}{x} p^x \cdot (1-p)^{n-x}$





$$\binom{5}{0} \cdot \left(\frac{1}{2}\right)^5 + \binom{5}{1} \left(\frac{1}{2}\right)^5 + \dots + \binom{5}{5} \left(\frac{1}{2}\right)^5 = 1$$

$f(0)$                        $f(1)$                        $f(5)$

Recall

$$(a+b)^n = \sum_{x=0}^n \binom{n}{x} a^x \cdot b^{n-x}$$

Binomial Thm

special case where  $n=5$   $a=\frac{1}{2}$   $b=\frac{1}{2}$

In general,  $\sum_{x=0}^n f(x) = \binom{n}{0} p^0 (1-p)^n + \binom{n}{1} p^1 (1-p)^{n-1} + \dots + \binom{n}{n} p^n (1-p)^0 = 1$   
 $= (p + (1-p))^n$

## Binomial random variables

$$\text{Var}(X) = n \cdot p \cdot (1-p) = n \cdot p \cdot q, \quad q = 1-p$$

$X \sim \text{Bin}(n, p)$

### Theorem

Let  $X$  a binomial random variable with the number of trials  $n$  and success probability  $p$ .

The pmf of  $X$  is

$$f(x) = \binom{n}{x} p^x \cdot (1-p)^{n-x}, \quad x=0, 1, \dots, n$$

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

$$\text{Var}[X] = \mathbb{E}[X^2] - (\mathbb{E}[X])^2, \quad \mathbb{E}[X(X-1)] + \mathbb{E}[X] = \mathbb{E}[X^2]$$

$$\mathbb{E}[X] = \sum_{x=0}^n x \cdot f(x) = \sum_{x=1}^n x \cdot \binom{n}{x} p^x (1-p)^{n-x}$$

$$x \cdot \binom{n}{x} = x \cdot \frac{n!}{x!(n-x)!} = n \cdot \frac{(n-1)!}{(x-1)!((n-1)-(x-1))!} = n \cdot \binom{n-1}{x-1}$$

$$= n \sum_{x=1}^n \binom{n-1}{x-1} p^x (1-p)^{n-x}$$

$$= np \sum_{x=1}^n \binom{n-1}{x-1} p^{x-1} (1-p)^{(n-1)-(x-1)}$$

$$= np$$

by Binomial Thm

$$\sum_{x=1}^n \binom{n-1}{x-1} p^{x-1} (1-p)^{(n-1)-(x-1)} = \sum_{y=0}^{n-1} \binom{n-1}{y} p^y (1-p)^{(n-1)-y} = (p + (1-p))^n = 1.$$

## Binomial random variables

### Example

Out of millions of instant lottery tickets, suppose that 20% are winners. If eight such tickets are purchased, what is the probability of purchasing two winning ticket?

$$X = \# \text{ of winning tickets} \sim \text{Bin}(8, 0.2)$$

$$P(X=2) = \binom{8}{2} (0.2)^2 (1-0.2)^6$$

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Binomial RV : Repeat Bernoulli trials  $n$  times  
indep. (2 outcomes)

$X = \#$  of success. success probability =  $p$  ( $0 < p < 1$ )

$\uparrow$  Binomial RV.  $X \sim \text{Bin}(n, p) = b(n, p)$

$$\text{PMF} : f(x) = \binom{n}{x} p^x (1-p)^{n-x}$$

$$E[X] = np$$

$$\text{Var}(X) = n \cdot p \cdot (1-p)$$

## Binomial random variables

### Example

H5N1 is a type of influenza virus that causes a severe respiratory disease in birds called avian influenza (or “bird flu”).

Although human cases are rare, they are deadly; according to the World Health Organization the mortality rate among humans is 60%.  $\Rightarrow$  survival prob = 0.4

Let  $X$  equal the number of people, among the next 25 reported cases, who survive the disease.

$$X \sim \text{Bin}(25, 0.4)$$

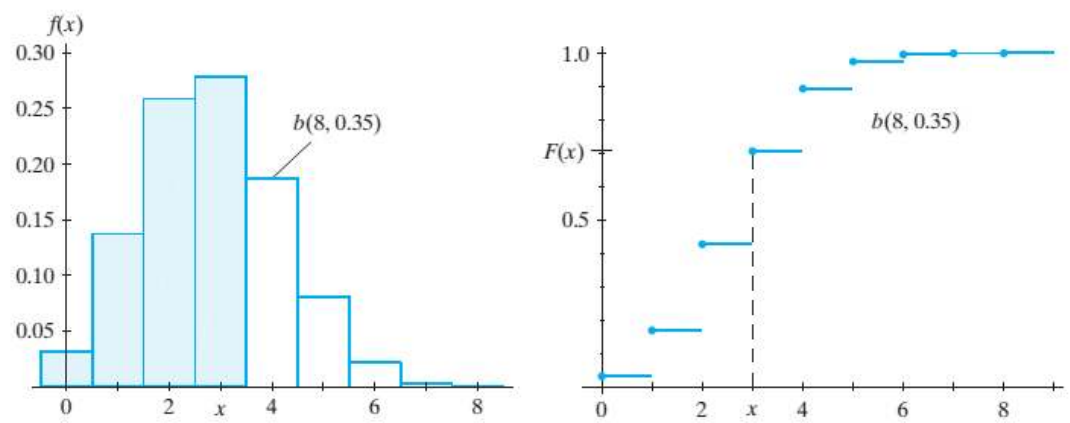
Assuming independence, the distribution of  $X$  is  $b(25, 0.4)$ . What is the probability that ten or fewer of the cases survive?

$$\begin{aligned} F(10) &= P(X \leq 10) = \sum_{x=0}^{10} P(X=x) \\ &= \sum_{x=0}^{10} \binom{25}{x} (0.4)^x (0.6)^{25-x} \end{aligned}$$

$n = 25$ ,  $p = 0.4$   
 $x = 10$

CDF

**Table II** The Binomial Distribution



$$F(x) = P(X \leq x) = \sum_{k=0}^x \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k}$$

$n$	$x$	$p$									
		0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
2	0	0.9025	0.8100	0.7225	0.6400	0.5625	0.4900	0.4225	0.3600	0.3025	0.2500
	1	0.9975	0.9900	0.9775	0.9600	0.9375	0.9100	0.8775	0.8400	0.7975	0.7500
	2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3	0	0.8574	0.7290	0.6141	0.5120	0.4219	0.3430	0.2746	0.2160	0.1664	0.1250
	1	0.9928	0.9720	0.9392	0.8960	0.8438	0.7840	0.7182	0.6480	0.5748	0.5000
	2	0.9999	0.9990	0.9966	0.9920	0.9844	0.9730	0.9571	0.9360	0.9089	0.8750
	3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
4	0	0.8145	0.6561	0.5220	0.4096	0.3164	0.2401	0.1785	0.1296	0.0915	0.0625
	1	0.9860	0.9477	0.8905	0.8192	0.7383	0.6517	0.5630	0.4752	0.3910	0.3125
	2	0.9995	0.9963	0.9880	0.9728	0.9492	0.9163	0.8735	0.8208	0.7585	0.6875
	3	1.0000	0.9999	0.9995	0.9984	0.9961	0.9919	0.9850	0.9744	0.9590	0.9375
	4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5	0	0.7738	0.5905	0.4437	0.3277	0.2373	0.1681	0.1160	0.0778	0.0503	0.0312
	1	0.9774	0.9185	0.8352	0.7373	0.6328	0.5282	0.4284	0.3370	0.2562	0.1875
	2	0.9988	0.9914	0.9734	0.9421	0.8965	0.8369	0.7648	0.6826	0.5931	0.5000
	3	1.0000	0.9995	0.9978	0.9933	0.9844	0.9692	0.9460	0.9130	0.8688	0.8125
	4	1.0000	1.0000	0.9999	0.9997	0.9990	0.9976	0.9947	0.9898	0.9815	0.9688
	5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
6	0	0.7351	0.5314	0.3771	0.2621	0.1780	0.1176	0.0754	0.0467	0.0277	0.0156
	1	0.9672	0.8857	0.7765	0.6553	0.5339	0.4202	0.3191	0.2333	0.1636	0.1094
	2	0.9978	0.9842	0.9527	0.9011	0.8306	0.7443	0.6471	0.5443	0.4415	0.3438
	3	0.9999	0.9987	0.9941	0.9830	0.9624	0.9295	0.8826	0.8208	0.7447	0.6562
	4	1.0000	0.9999	0.9996	0.9984	0.9954	0.9891	0.9777	0.9590	0.9308	0.8906
	5	1.0000	1.0000	1.0000	0.9999	0.9998	0.9993	0.9982	0.9959	0.9917	0.9844
	6	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
7	0	0.6983	0.4783	0.3206	0.2097	0.1335	0.0824	0.0490	0.0280	0.0152	0.0078
	1	0.9556	0.8503	0.7166	0.5767	0.4449	0.3294	0.2338	0.1586	0.1024	0.0625



## Binomial random variables

$$M(t) = \mathbb{E}[e^{tX}]$$

$$X \sim \text{Bin}(n, p)$$

### Theorem

The mgf of a binomial random variable  $X$  is

$$M(t) =$$

$$\begin{aligned} M(t) = \mathbb{E}[e^{tX}] &= \sum_{x=0}^n e^{tx} \cdot \binom{n}{x} p^x \cdot (1-p)^{n-x} \\ &= \sum_{x=0}^n \binom{n}{x} (e^t p)^x (1-p)^{n-x} \\ &= (e^t p + (1-p))^n \end{aligned}$$

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Binomial Thm

$$(a+b)^n = \sum_{x=0}^n \binom{n}{x} a^x b^{n-x}$$

$X$  : Bernoulli RV

$$X = \begin{cases} 1 & \text{w.p. } p \\ 0 & \text{w.p. } 1-p \end{cases}$$

$$\Rightarrow \text{MGF } M_X(t) = e^{tp} + (1-p)$$

$Y$  : Binomial RV  $Y \sim \text{Bin}(n, p)$

$$\Rightarrow \text{MGF } M_Y(t) = (e^{tp} + (1-p))^n = (M_X(t))^n$$

## Binomial random variables

### Exercise

It is believed that approximately 75% of American youth now have insurance due to the health care law.

Suppose this is true, and let  $X$  equal the number of American youth in a random sample of  $n = 15$  with private health insurance.

How is  $X$  distributed? Find the probability that  $X$  is at least 10. Find the mean, variance, and standard deviation of  $X$ .

$$X \sim \text{Bin}(15, 0.75) \quad \text{under } \left\{ \begin{array}{l} \text{indep.} \\ 2 \text{ outcomes} \\ \text{same prob.} \end{array} \right.$$

$$P(X \geq 10) = \sum_{x=10}^{15} \binom{15}{x} (0.75)^x (0.25)^{15-x}$$

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Use table

$$X + Y = 15 \quad X = \underline{15 - Y}$$

$X = \#$  of people having insurance  
 $p = 0.75$

$Y = \#$  of people not having insurance  
 $p = 0.25$

$$X \sim B_{15}(15, 0.75) \quad 15 - Y$$

$$P(X \geq 10) = P(Y \leq 5)$$

Table II continued		p									
n	x	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
15	11	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9994	0.9978	0.9935
	12	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9997	0.9991
	13	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999
	14	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	0	0.4633	0.2059	0.0874	0.0352	0.0134	0.0047	0.0016	0.0005	0.0001	0.0000
	1	0.8290	0.5490	0.3186	0.1671	0.0802	0.0353	0.0142	0.0052	0.0017	0.0005
	2	0.9638	0.8159	0.6042	0.3980	0.2361	0.1268	0.0617	0.0271	0.0107	0.0037
	3	0.9945	0.9444	0.8227	0.6482	0.4613	0.2969	0.1727	0.0905	0.0424	0.0176
	4	0.9994	0.9873	0.9383	0.8358	0.6865	0.5155	0.3519	0.2173	0.1204	0.0592
	5	0.9999	0.9978	0.9832	0.9389	0.8516	0.7216	0.5643	0.4032	0.2608	0.1509
	6	1.0000	0.9997	0.9964	0.9819	0.9434	0.8689	0.7548	0.6098	0.4522	0.3036
	7	1.0000	1.0000	0.9994	0.9958	0.9827	0.9500	0.8868	0.7869	0.6535	0.5000
	8	1.0000	1.0000	0.9999	0.9992	0.9958	0.9848	0.9578	0.9050	0.8182	0.6964
	9	1.0000	1.0000	1.0000	0.9999	0.9992	0.9963	0.9876	0.9662	0.9231	0.8491
	10	1.0000	1.0000	1.0000	1.0000	0.9999	0.9993	0.9972	0.9907	0.9745	0.9408
	11	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9995	0.9981	0.9937	0.9824
12	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9987	0.9989	0.9963	
13	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9995	
14	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
15	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
16	0	0.4401	0.1853	0.0743	0.0281	0.0100	0.0033	0.0010	0.0003	0.0001	0.0000
	1	0.8108	0.5147	0.2839	0.1407	0.0635	0.0261	0.0098	0.0033	0.0010	0.0003
	2	0.9571	0.7892	0.5614	0.3518	0.1971	0.0994	0.0451	0.0183	0.0066	0.0021
	3	0.9930	0.9316	0.7899	0.5981	0.4050	0.2459	0.1339	0.0651	0.0281	0.0106
	4	0.9991	0.9830	0.9209	0.7982	0.6302	0.4499	0.2892	0.1666	0.0853	0.0384
	5	0.9999	0.9967	0.9765	0.9183	0.8103	0.6598	0.4900	0.3288	0.1976	0.1051
	6	1.0000	0.9995	0.9944	0.9733	0.9204	0.8247	0.6881	0.5272	0.3660	0.2272
	7	1.0000	0.9999	0.9989	0.9930	0.9729	0.9256	0.8406	0.7161	0.5629	0.4018
	8	1.0000	1.0000	0.9998	0.9985	0.9925	0.9743	0.9329	0.8577	0.7441	0.5982
	9	1.0000	1.0000	1.0000	0.9998	0.9984	0.9929	0.9771	0.9417	0.8759	0.7728
	10	1.0000	1.0000	1.0000	1.0000	0.9997	0.9984	0.9938	0.9809	0.9514	0.8949
	11	1.0000	1.0000	1.0000	1.0000	1.0000	0.9997	0.9987	0.9951	0.9851	0.9616
	12	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9998	0.9991	0.9965	0.9894
	13	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9994	0.9979
	14	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9997
	15	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
16	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
20	0	0.3585	0.1216	0.0388	0.0115	0.0032	0.0008	0.0002	0.0000	0.0000	0.0000
	1	0.7358	0.3917	0.1756	0.0692	0.0243	0.0076	0.0021	0.0005	0.0001	0.0000
	2	0.9245	0.6769	0.4049	0.2061	0.0913	0.0355	0.0121	0.0036	0.0009	0.0002
	3	0.9841	0.8670	0.6477	0.4114	0.2252	0.1071	0.0444	0.0160	0.0049	0.0013
	4	0.9974	0.9568	0.8298	0.6296	0.4148	0.2375	0.1182	0.0510	0.0189	0.0059



## **Section 5.**

# **The Hypergeometric Distribution**

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Ex 6 Blue Balls 4 Red Balls  
 Choose 4 balls with replacement. → } indep. same prob.

$X = \#$  of Blue balls among 4 chosen balls.

$$X \sim \text{Bin}(4, 0.6)$$

Q: If **without replacement** B B R R

$$P(X=2) = \frac{6}{10} \cdot \frac{5}{9} \cdot \frac{4}{8} \cdot \frac{3}{7} \cdot \binom{4}{2} \stackrel{\text{Equal}}{=} \frac{\binom{6}{2} \cdot \binom{4}{2}}{\binom{10}{4}}$$

## The Hypergeometric Distribution

There is a collection of  $N_1$  red balls and  $N_2$  blue balls.

Sample  $n$  balls at random **without replacement** ( $n \leq N_1 + N_2$ ).

Let  $X$  be the number of red balls chosen.

Then,  $X$  is called a **hypergeometric random variable** with parameters  $N_1, N_2, n$ , and denoted by  $\text{HG}(N_1, N_2, n)$ .

If with replacement  $X \sim \text{Bin}\left(n, \frac{N_1}{N_1 + N_2}\right)$

## The Hypergeometric Distribution

### Example

In a small pond there are 50 fish, <sup>2 kind</sup> ten of which have been tagged.

If a fisherman's catch consists of seven fish selected at random and without replacement, and  $X$  denotes the number of tagged fish,

what is the probability that exactly two tagged fish are caught?

$$X \sim HG(N_1, N_2, n)$$
$$P(X=2) = \frac{\binom{10}{2} \binom{40}{5}}{\binom{50}{7}} = \frac{10}{50} \cdot \frac{9}{49} \cdot \frac{40}{48} \cdot \frac{39}{47} \cdots \times \binom{7}{2}$$

10 R      5 B       $\xrightarrow{\text{Choose}}$       12 balls  
 $X = \# \text{ of Red balls chosen}$   
 $X \sim HG(10, 5, 12)$        $f(k) = \dots$   
 $k=0, 1, \dots, 10$

## The Hypergeometric Distribution

$k = \begin{cases} \max\{0, n-N_2\} \\ \min\{n, N_1\} \end{cases}$

$X \sim HG(N_1, N_2, n)$   
 $n \leq N_1 + N_2$

### Theorem

$P(X = k) = f(k) =$

$\frac{\binom{N_1}{k} \binom{N_2}{n-k}}{\binom{N_1+N_2}{n}}$

$n-k \leq N_2$   
 $k \geq n - N_2$

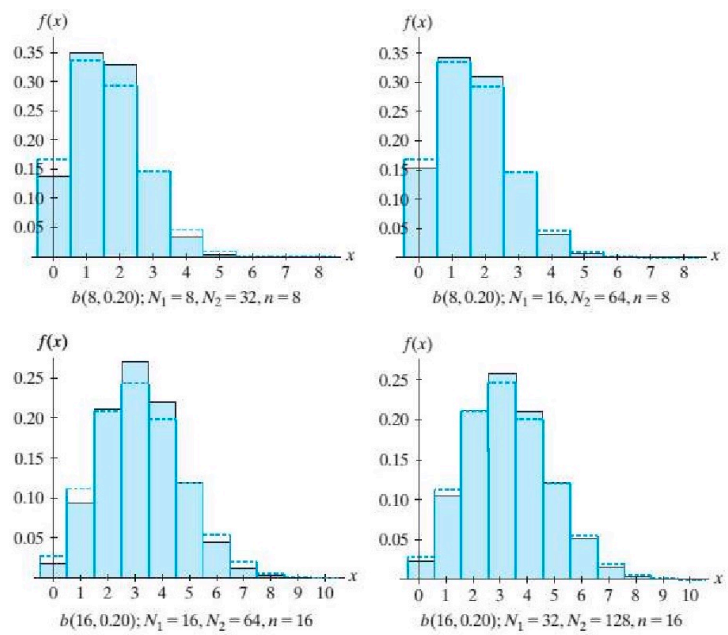
$E[X] = n \frac{N_1}{N_1+N_2}$

$Var[X] = n \frac{N_1}{N_1+N_2} \frac{N_2}{N_1+N_2} \cdot \frac{N_1+N_2-n}{N_1+N_2-1}$

With replacement

$Bin(n, \frac{N_1}{N_1+N_2}) \rightarrow Exp = n \cdot p$   
 $= n \cdot \frac{N_1}{N_1+N_2}$

$Var = n \cdot p \cdot (1-p)$   
 $= n \cdot \frac{N_1}{N_1+N_2} \cdot \frac{N_2}{N_1+N_2}$



If  $N_1, N_2$  large

$\frac{N_1}{N_1+N_2} \rightarrow p$

$HG(N_1, N_2, n) \approx Bin(n, p)$   
 $\begin{matrix} Y \\ \text{---} \\ X \end{matrix}$

$P(Y=k) \approx P(X=k)$

Figure 2.5-2 Binomial and hypergeometric (shaded) probability histograms

## The Hypergeometric Distribution

### Exercise

In a lot (collection) of 100 light bulbs, there are five bad bulbs.

An inspector inspects ten bulbs selected at random.

Find the probability of finding at least one defective bulb.

$$X = \# \text{ of defective} \sim HG(5, 95, 10)$$

$$P(X \geq 1) = 1 - P(X = 0)$$

$$= 1 - \frac{\binom{5}{0} \binom{95}{10}}{\binom{100}{10}}$$

## **Section 6.**

# **The Negative Binomial Distribution**

---

## Geometric random variables

Consider a sequence of independent Bernoulli trials with success probability  $p \in (0, 1)$ . <sup>tossing a coin</sup>

Let  $X$  be the number of trials **until the first success**.

This random variable is called a **geometric random variable**.

$$\begin{aligned} H &: X = 1 \\ TH &: X = 2 \\ TTH &: X = 3 \\ &\vdots \\ &\vdots \end{aligned}$$

$$f(x) = (1-p)^{x-1} \cdot p \quad x = 1, 2, \dots$$

↑  
# of trials

$$\underbrace{T \dots T T H}_{(x-1) \text{ times}}$$

## Geometric random variables

$$q = 1 - p.$$

### Theorem

The pmf of  $X$  is  $f_X(x) = (1-p)^{x-1} \cdot p$   $x = 1, 2, \dots$

$E[X] = \frac{1}{p}$  ← covered previously.

$\text{Var}[X] = \frac{q}{p^2}$  ← use MGF

$$M(t) = \frac{pe^t}{1-(1-p)e^t}$$

↪ for  $t < -\ln(1-p)$ .

Geom. Series :  $a + a \cdot r + a \cdot r^2 + \dots = \frac{a}{1-r}$   
when  $|r| < 1$ .



## Geometric random variables

### Example

Some biology students were checking eye color in a large number of fruit flies.

For the individual fly, suppose that the probability of white eyes is  $1/4$  and the probability of red eyes is  $3/4$ , and that we may treat these observations as independent Bernoulli trials.

What is the probability that at least four flies have to be checked for eye color to observe a white-eyed fly?

$$p = \frac{1}{4}$$

$X = \#$  of observations until the first white.

$$\sim \text{Geom}\left(\frac{1}{4}\right)$$

$$\begin{aligned} P(X > 3) &= P(X \geq 4) = \sum_{x=4}^{\infty} P(X=x) \\ &= \sum_{x=4}^{\infty} (1-p)^{x-1} \cdot p \\ &= (1-p)^3 \cdot p + (1-p)^4 \cdot p + (1-p)^5 \cdot p + \dots \\ &= \frac{(1-p)^3 \cdot p}{1 - (1-p)} = (1-p)^3 = \left(\frac{3}{4}\right)^3. \end{aligned}$$

Note:  $P(X > k) = (1-p)^k$ .

## Negative Binomial random variables

Consider a sequence of independent Bernoulli trials with success probability

Let  $X$  be the number of trials until the  $r$ -th success.

This random variable is called a **negative binomial random variable**.

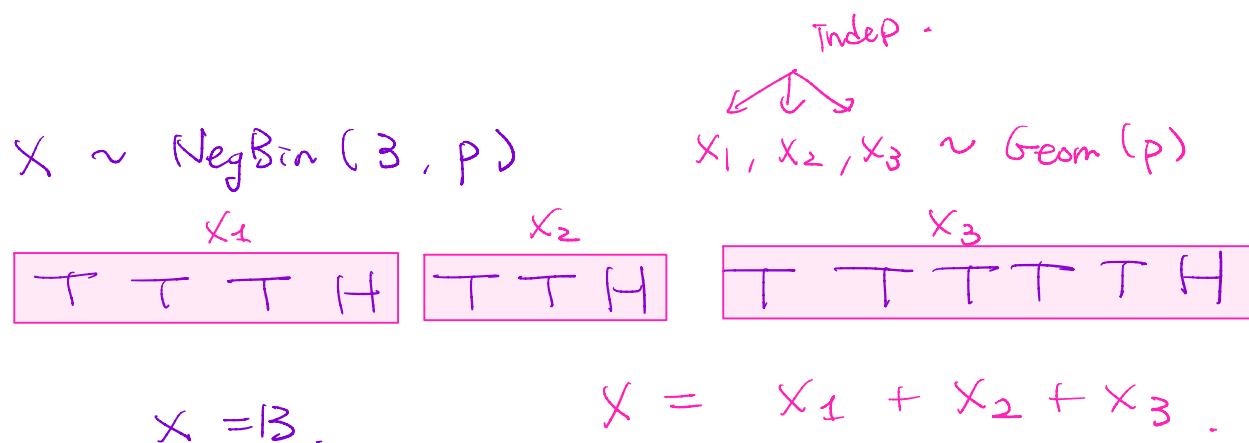
$$X \sim \text{NegBin}(r, p)$$

$$\begin{aligned} f_X(x) &= \mathbb{P}(X = x) & x = r, r+1, \dots \\ &= \binom{x-1}{r-1} p^r (1-p)^{x-r} \end{aligned}$$

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$$\left[ \begin{array}{l} H : (r-1) \text{ many} \\ T : (x-r) \text{ many} \end{array} \right] H$$

(x-1) trials



## Negative Binomial random variables

### Theorem

The pmf of  $X$  is

$$f(k) = \binom{k-1}{r-1} p^r (1-p)^{k-r}$$

for  $k = r, r+1, \dots$  and otherwise zero.

$$\mathbb{E}[X] = \frac{r}{p}$$

$$\text{Var}[X] = \frac{rq}{p^2}$$

$$M(t) = \left( \frac{pe^t}{1-(1-p)e^t} \right)^r$$

A negative binomial random variable can be written as a sum of independent geometric random variables.

$$X \sim \text{NegBin}(r, p)$$

$$X = X_1 + X_2 + \dots + X_r$$

$$X_1, \dots, X_r \sim \text{Geom}(p) \text{ indep.}$$

## Negative Binomial random variables

### Example

Suppose that during practice a basketball player can make a free throw 80% of the time.

Furthermore, assume that a sequence of free-throw shooting can be thought of as independent Bernoulli trials.

Let  $X$  equal the minimum number of free throws that this player must attempt to make a total of ten shots.

Find the mean of  $X$ .

$$X \sim \text{NegBin}(10, 0.8)$$

$$\mathbb{E}[X] = 10 \cdot \frac{5}{4} = \frac{25}{2} = \underline{12.5}.$$

$$\frac{10}{12.5} = 80\%$$

## Negative Binomial random variables

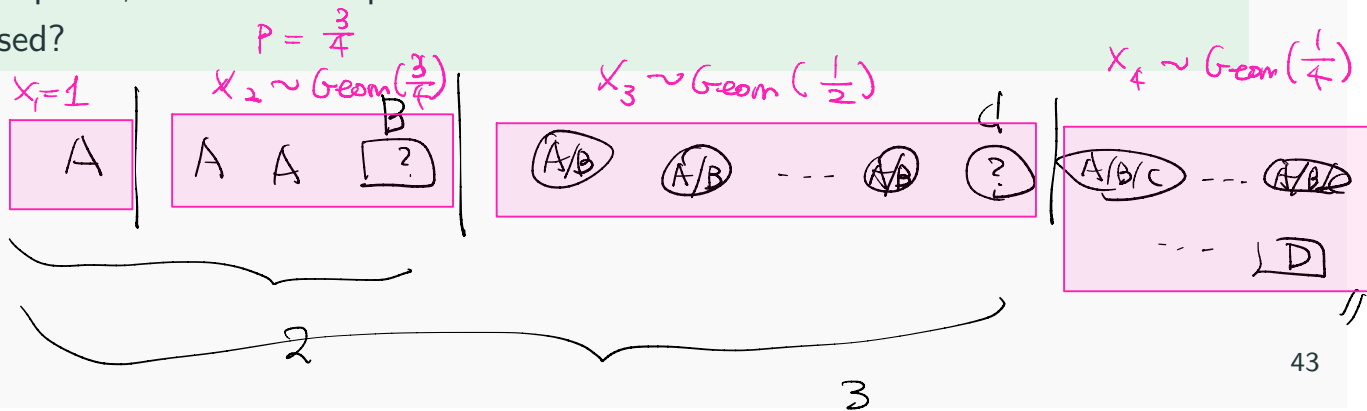
"Coupon Collecting Problem"

16.

### Exercise

One of four different prizes was randomly put into each box of a cereal.

If a family decided to buy this cereal until it obtained at least one of each of the four different prizes, what is the expected number of boxes of cereal that must be purchased?



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$E[\# \text{ of boxes purchased}]$

$$= E[X_1 + X_2 + X_3 + X_4]$$

$$= E[X_1] + E[X_2] + E[X_3] + E[X_4]$$

$$= 1 + \frac{4}{3} + 2 + 4 = 7 + \frac{4}{3} = \frac{25}{3}$$

## **Section 7.**

# **The Poisson Distribution**

---

## Definition

Some experiments result in counting the number of times particular events occur at given times or with given physical objects.

### Example

- the number of cell phone calls passing through a relay tower between 9 and 10am.
- the number of flaws in 100 feet of wire
- the number of customers that arrive at a ticket window between noon and 2pm.
- the number of defects in a 100-foot roll of aluminum screen that is 2 feet wide.

## Definition

Counting such events can be looked upon as observations of a random variable associated with an **approximate Poisson process**, provided that the conditions in the following definition are satisfied.

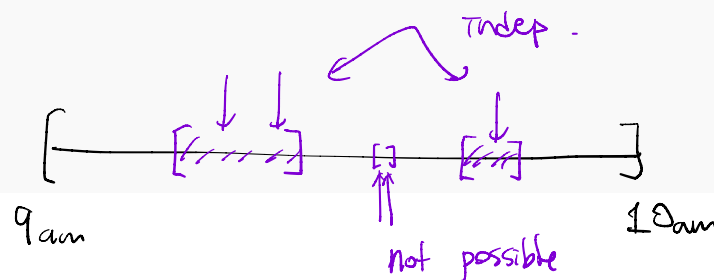


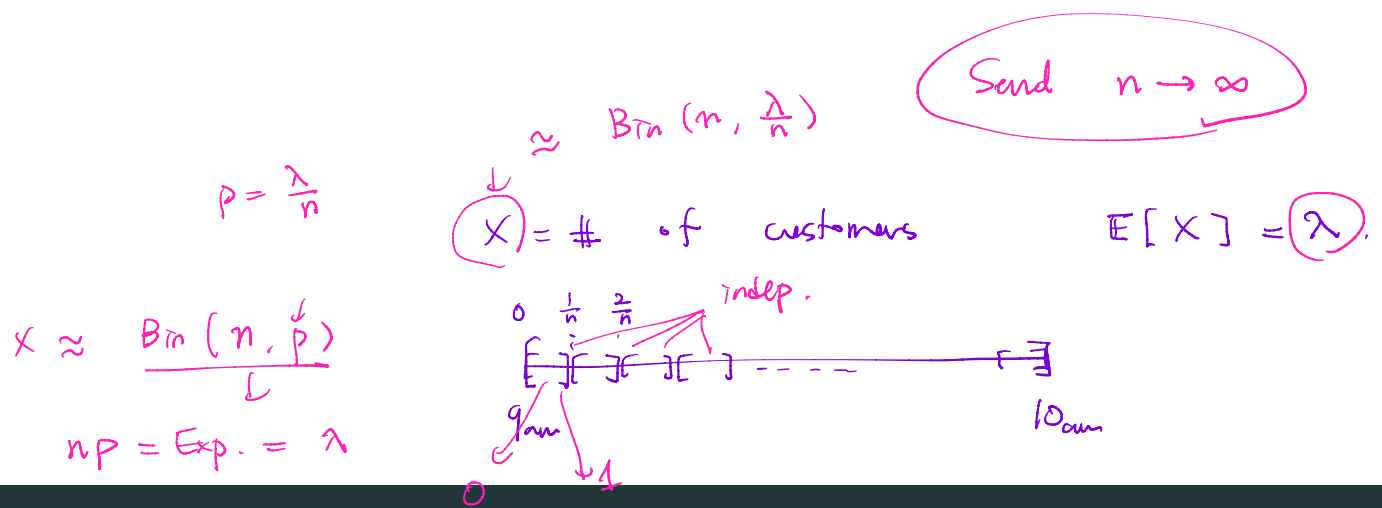
## Definition

Let the number of occurrences of some event in a given continuous interval be counted. Then we have an **approximate Poisson process** with parameter  $\lambda > 0$  if

- The numbers of occurrences in nonoverlapping subintervals are independent.
- The probability of exactly one occurrence in a sufficiently short subinterval of length  $h$  is approximately  $\lambda h$ .
- The probability of two or more occurrences in a sufficiently short subinterval is essentially zero.

Under these assumption, consider the number of occurrences in a time interval  $[0, 1]$ .





## Definition

Split  $[0, 1]$  into  $n$  subintervals  $[0, \frac{1}{n}]$ ,  $[\frac{1}{n}, \frac{2}{n}]$ ,  $\dots$ ,  $[\frac{n-1}{n}, 1]$ .

In each subinterval, at most one event occurs with probability  $\frac{\lambda}{n}$ .

Thus, the number of occurrences is a binomial random variable with  $n$  and  $\frac{\lambda}{n}$ .

As  $n \rightarrow \infty$ , the random variable gets close to some random variable  $X$ .

We say  $X$  is a **Poisson random variable with parameter  $\lambda$**  if its pmf is

$$\mathbb{P}(X = k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

for  $k = 0, 1, 2, \dots$ .

$$X \sim \text{Pois}(\lambda)$$

$$f(x) = e^{-\lambda} \frac{\lambda^k}{k!} \quad k=0, 1, 2, \dots$$

## Definition

$$e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!}$$

## Theorem

$$E[X] = \lambda$$

$$\text{Var}[X] = \lambda$$

$$M(t) = e^{\lambda(e^t - 1)}$$

$$\begin{aligned} E[X] &= \sum_{k=0}^{\infty} k \cdot f(k) = \sum_{k=1}^{\infty} k \cdot e^{-\lambda} \frac{\lambda^k}{k!} \\ &= e^{-\lambda} \left( \sum_{n=0}^{\infty} \frac{\lambda^{n+1}}{n!} \right) = \lambda \cdot e^{-\lambda} \left( \sum_{n=0}^{\infty} \frac{\lambda^n}{n!} \right) = \lambda \cdot e^{-\lambda} e^{\lambda} = \lambda \end{aligned}$$

$n = k-1$

$$\text{Var}(X) = E[X^2] - (E[X])^2$$

$$E[X^2] = E[X(X-1)] + \lambda \cdot E[X]$$

## Definition

### Example

In a large city, telephone calls to 911 come on the average of two every 3 minutes.

If one assumes an approximate Poisson distribution, what is the probability of five or more calls arriving in a 9 minute period?

$$\begin{aligned} X &= \# \text{ of calls in } 9 \text{ min} \\ X &\sim \text{Pois}(6) \\ P(X \geq 5) &= \sum_{k=5}^{\infty} e^{-6} \frac{6^k}{k!} \end{aligned}$$

$X \sim \text{Pois}(\lambda)$  : # of customer in 1 hr.

•  $f(x) = e^{-\lambda} \frac{\lambda^x}{x!}$ ,  $x = 0, 1, 2, \dots$

•  $E[X] = \lambda$ ,  $\text{Var}(X) = \lambda$ ,  $M(t) = e^{\lambda(e^t - 1)}$

•  $X \sim \text{Bin}(n, p)$  large  $n$ , small  $p$

$n \cdot p = \lambda$

$\Rightarrow X \approx \text{Pois}(\lambda)$   
 $\binom{n}{k} p^k (1-p)^{n-k} = P(X=k) \approx e^{-\lambda} \frac{\lambda^k}{k!}$

## Poisson Approximation to Binomial

$X \sim \text{Pois}(\lambda) \leftarrow \text{From } \text{Bin}(n, \frac{\lambda}{n})$

Suppose  $X$  is a binomial random variable  $b(n, p)$ ,  $n$  is large, and  $p$  is small but  $np$  converges to some constant, say  $\lambda$ .

In this case,  $X$  can be approximated by a Poisson random variable with parameter  $\lambda$ .

This approximation is quite accurate if  $n \geq 20, p \leq 0.05$  or  $n \geq 100, p \leq 0.1$ .

$\text{Bin}(n, p)$        $n$  large       $p$  small  
     $\approx$                        $n \cdot p \approx \lambda$   
 $\text{Pois}(\lambda)$

## Poisson Approximation to Binomial

### Example

A manufacturer of Christmas tree light bulbs knows that 2% of its bulbs are defective. Assuming independence, the number of defective bulbs in a box of 100 bulbs has a binomial distribution with parameters  $n = 100$  and  $p = 0.02$ .

Find the probability that a box of 100 of these bulbs contains at most three defective bulbs.

$X = \#$  of defective ones in a box

$$\sim \text{Bin}(100, 0.02)$$

↑ large      ↑ small

$$100 \cdot 0.02 = 2$$

$$\approx \text{Pois}(2) \sim Y$$

$$P(X \leq 3) \approx P(Y \leq 3)$$

$$= \sum_{k=0}^3 \boxed{e^{-2}} \frac{2^k}{k!}$$

$$= e^{-2} \left( 1 + \frac{2^1}{1!} + \frac{2^2}{2!} + \frac{2^3}{3!} \right)$$

$$= \frac{19}{3} \cdot e^{-2}$$









## Poisson Approximation to Binomial

### Exercise

Suppose that the probability of suffering a side effect from a certain flu vaccine is 0.005. If 1000 persons are vaccinated, approximate the probability that (a) At most one person suffers. (b) Four, five, or six persons suffer.

$X = \#$  of people suffering a side effect.

$$\sim \text{Bin}(1000, 0.005) \approx \text{Pois}\left(\underset{1000 \cdot 0.005}{5}\right) \sim Y.$$

$$(a) \quad P(X \leq 1) \approx P(Y \leq 1) = e^{-5} \frac{5^0}{0!} + e^{-5} \frac{5^1}{1!} \quad 52 \\ = 6 \cdot e^{-5} \approx 0.04.$$

$$(b) \quad P(X = 4, 5, 6) \approx P(Y = 4, 5, 6) \\ = e^{-5} \cdot \left( \frac{5^4}{4!} + \frac{5^5}{5!} + \frac{5^6}{6!} \right)$$

$\approx$   
 $\uparrow$   
using table.



1-5, 15, 3

/ sm 2, 5

#5

5G, 7R → Sample 9.

(a) with replacement.

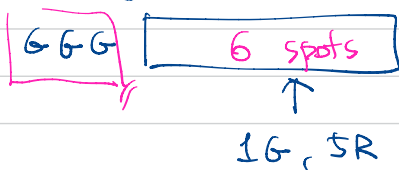
$$P(B) = P(X=4) = \binom{9}{4} \left(\frac{5}{12}\right)^4 \left(\frac{7}{12}\right)^5$$

↑  
(4G, 5R)

X = # of G in 9 samples  
 $\sim \text{Bin}(9, \frac{5}{12})$

$$P(A \cap B) = \binom{6}{4} \left(\frac{5}{12}\right)^4 \cdot \left(\frac{7}{12}\right)^5$$

↑  
4G, 5R



$$P(A) = 1 \cdot \left(\frac{5}{12}\right)^3$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{\binom{6}{4}}{\binom{9}{4}}$$

(b) without replacement.

$$P(A) = \frac{5 \cdot 4 \cdot 3}{12 \cdot 11 \cdot 10} = \frac{1}{22} = \frac{\binom{5}{3}}{\binom{12}{3}} = \frac{5 \cdot 4 \cdot 3}{12 \cdot 11 \cdot 10}$$

$$P(B) = P(Y=4) = \frac{\binom{5}{4} \cdot \binom{7}{5}}{\binom{12}{9}}$$

Y = # of G in 9 sample without replacement.  
 $\sim \text{HG}(5, 7, 9)$

$$P(B|A) = P(Z=1) = \frac{\binom{2}{1} \binom{7}{5}}{\binom{9}{6}} = \frac{2 \cdot \frac{7 \cdot 6}{2}}{\frac{9 \cdot 8 \cdot 7}{3!}} = \frac{6 \cdot 6}{9 \cdot 8} = \frac{1}{2}$$



$$Z \sim \text{HG}(2, 7, 6)$$

6 sample from 9 (2G, 7R) without replacement.

$$P(A|B) = P(B|A) \cdot \frac{P(A)}{P(B)} = \frac{1}{2!}$$

#15

#3 Exhaustive :  $A_1 \cup A_2 \cup \dots \cup A_6 = \mathcal{S}$   
 Mutually exclusive :  $A_1 \cap A_2 = A_2 \cap A_3 = \dots = \emptyset$

$$\Rightarrow P(A_1 \cup A_2 \cup \dots \cup A_6) = 1$$

$$\parallel$$

$$P(A_1) + P(A_2) + \dots + P(A_6)$$

$$P(A_1) = \frac{P(A_2)}{2} = \frac{P(A_3)}{3} = \dots = \frac{P(A_6)}{6} = a$$

$$\Rightarrow P(A_k) = k \cdot a$$

$$P(A_1) + \dots + P(A_6) = 1 \cdot a + 2 \cdot a + \dots + 6 \cdot a = 1$$

$$a(1 + \dots + 6) = 1$$

$$a = \frac{1}{1 + \dots + 6} = \frac{1}{21}$$

$$P(A_4) = 4 \cdot a = 4 \cdot \frac{1}{21}$$

(#5)  $M(t) = \underbrace{c}_{=1} \cdot (1-2t)^{-5} \quad t < \frac{1}{2}$

$$M(t) = E[e^{tX}]$$

$$M(0) = 1$$

$$M'(0) = E[X]$$

$$M''(0) = E[X^2]$$

$$(a) \quad M(0) = c \cdot (1-0)^{-5} = \underbrace{c}_{=1} = 1$$

$$(b) \quad E[X] = M'(t) \Big|_{t=0}$$

$$= (-5) \cdot \underbrace{(1-2t)^{-6}}_{=1} \cdot \underbrace{(1-2t)'}_{(-2)} \Big|_{t=0}$$

$$= (-5) \cdot \underbrace{(1-2t)^{-6}}_{=1} \cdot (-2) \Big|_{t=0} = \underbrace{10}_{=10 \cdot (1-2t)^{-6}}$$

$$(c) \quad M''(0) = 10 \cdot (-6) (1-2t)^{-7} \cdot (-2) \Big|_{t=0} = 120.$$

$$= E[X^2] \neq \text{Var}(X)$$

$$\text{Var}(X) = E[X^2] - (E[X])^2 = 120 - (10)^2 = 20.$$

#4

$$f(k) = \begin{cases} c & k=0 \\ \frac{1}{k! 3^k} & k=1, 2, 3, \dots \end{cases}$$

$$1 = \sum_{k=0}^{\infty} f(k) = c + \underbrace{\sum_{k=1}^{\infty} \frac{1}{k!} \left(\frac{1}{3}\right)^k}_{= e^{\frac{1}{3}}} - 1$$

$$c = 2 - e^{\frac{1}{3}}.$$

$$\begin{aligned} E[X] &= \sum_{k=1}^{\infty} k \cdot f(k) = \sum_{k=1}^{\infty} \frac{1}{(k-1)!} \cdot \left(\frac{1}{3}\right)^k \\ &= \sum_{k=1}^{\infty} \frac{1}{(k-1)!} \left(\frac{1}{3}\right)^{(k-1)+1} \\ &= \frac{1}{3} \sum_{k=1}^{\infty} \frac{1}{(k-1)!} \left(\frac{1}{3}\right)^{(k-1)=n} \\ &= \frac{1}{3} \sum_{n=0}^{\infty} \frac{1}{n!} \cdot \left(\frac{1}{3}\right)^n = \frac{1}{3} e^{\frac{1}{3}}. \end{aligned}$$