

# DCP 1206: Probability

## Lecture 8 — Expectation, Variance, and Higher Moments

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# Announcement

- ▶ HW2 is posted on E3 (Due: 10/23 in class)

# Powerball Lottery and Fortune Cookies

- ▶ One day, in 2005, 110 lucky people in the US won the same Powerball lottery.  
$$C_5^{69} \times C_1^{26}$$
- ▶ Powerball: Pick 5 numbers from 1~69 + 1 number from 1~26
  - ▶ What is the probability of winning the lottery?



<https://www.nytimes.com/2005/05/11/nyregion/who-needs-giacomo-bet-on-the-fortune-cookie.html>

# Quick Review

- ▶ Geometric ( $X \sim \text{Geometric}(p)$ )
- ▶ Negative Binomial ( $X \sim \text{NB}(p, r)$ )
- ▶ Discrete Uniform ( $X \sim \text{Unif}(a, b)$ )
- ▶ Hypergeometric ( $X \sim \text{HG}(N, D, n)$ )

# This Lecture

1. Expected Value

2. Variance and Moments

3. Special Discrete R.V.: Expected Value and Variance

- Reading material: Chapter 4.4-4.5 and 5.1-5.3

# 7. Hypergeometric Random Variables (Formally)

**Hypergeometric Random Variables:** A random variable  $X$  is hypergeometric with parameters  $(N, D, n)$  ( $N, D, n \in \mathbb{N}$  with  $D < N$  and  $n \leq \min(D, N - D)$ ), if its PMF is given by

$$P(X = k) = \frac{C_k^D C_{n-k}^{N-D}}{C_n^N}, \quad k = 0, 1, 2, \dots, n$$

Do we have  $\sum_{k=0}^n P(X = k) = 1$ ?

$$\sum_{k=0}^n \frac{C_k^D C_{n-k}^{N-D}}{C_n^N} = 1$$

$$(1+x)^N = (1+x)^D \cdot (1+x)^{N-D}$$

# Why Is It Called “Hypergeometric”?

more

$$P(X = k) = \frac{C_k^D C_{n-k}^{N-D}}{C_n^N}, \quad k = 0, 1, 2, \dots, n$$

$1, \frac{1}{2}, \left(\frac{1}{2}\right)^2, \left(\frac{1}{2}\right)^3, \dots$

$\downarrow \quad \downarrow \quad \downarrow \quad \downarrow$

$a_1, a_2, a_3, a_4$

Can we find  $\frac{P(X = k+1)}{P(X = k)}$ ?

$$\frac{\frac{C_{k+1}^D C_{n-(k+1)}^{N-D}}{C_{k+1}^D C_{n-(k+1)}^{N-D}}}{\frac{C_k^D C_{n-k}^{N-D}}{C_k^D C_{n-k}^{N-D}}} = \frac{\frac{D(D+1)\cdots(D+k)}{(k+1)\cdots(k+1)} \cdot \frac{(N-D)\cdots(n-(k+1))}{(n-(k+1))!}}{\frac{D(D+1)\cdots(D+k-1)}{K!} \cdot \frac{(N-D)\cdots(n-k)}{(n-k)!}}$$

$$= \frac{\frac{D+k}{(K+1)} \cdot \frac{(n-k)}{N-D-(n+k)+1}}{f(k) g(k)}$$

$\hat{a}_K = \left(\frac{1}{2}\right)^{K-1}$

$n-(k+1)$  terms

$a_{k+1} = \frac{1}{2}$

$(n+k)$  terms

# Hypergeometric: A Limiting Case

$$P(X = k) = \frac{C_k^D C_{n-k}^{N-D}}{C_n^N}, \quad k = 0, 1, 2, \dots, n$$

- What if  $D/N = p$  and  $D, N \gg n?$   $\Rightarrow$  Binomial  
及清小尾

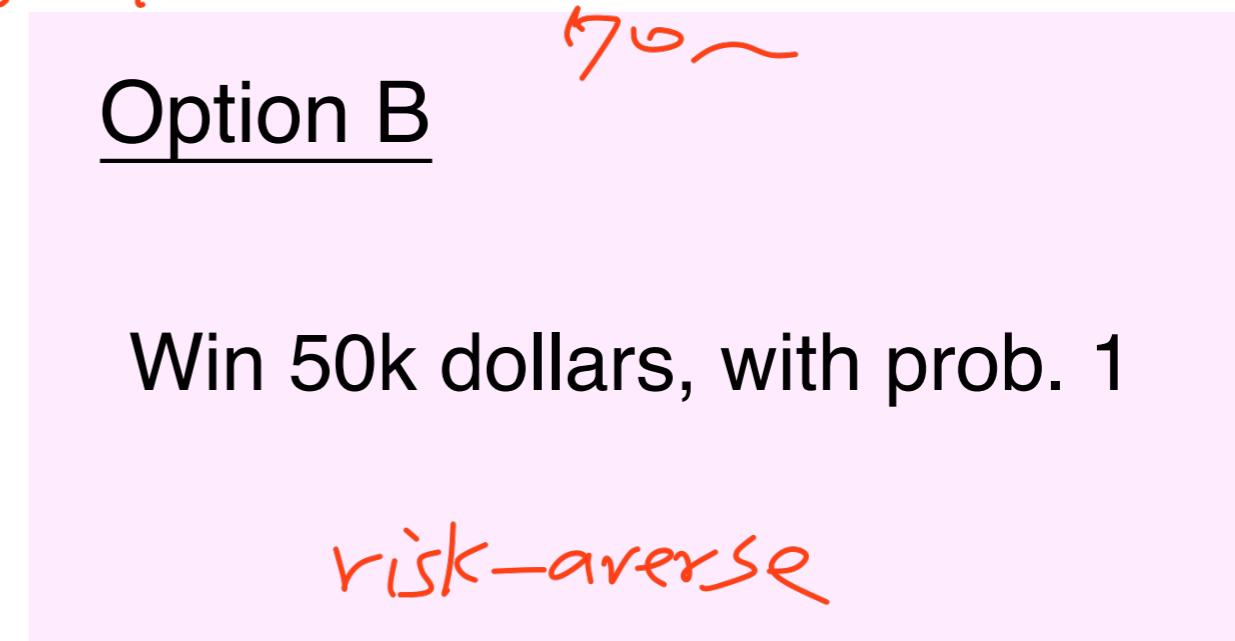
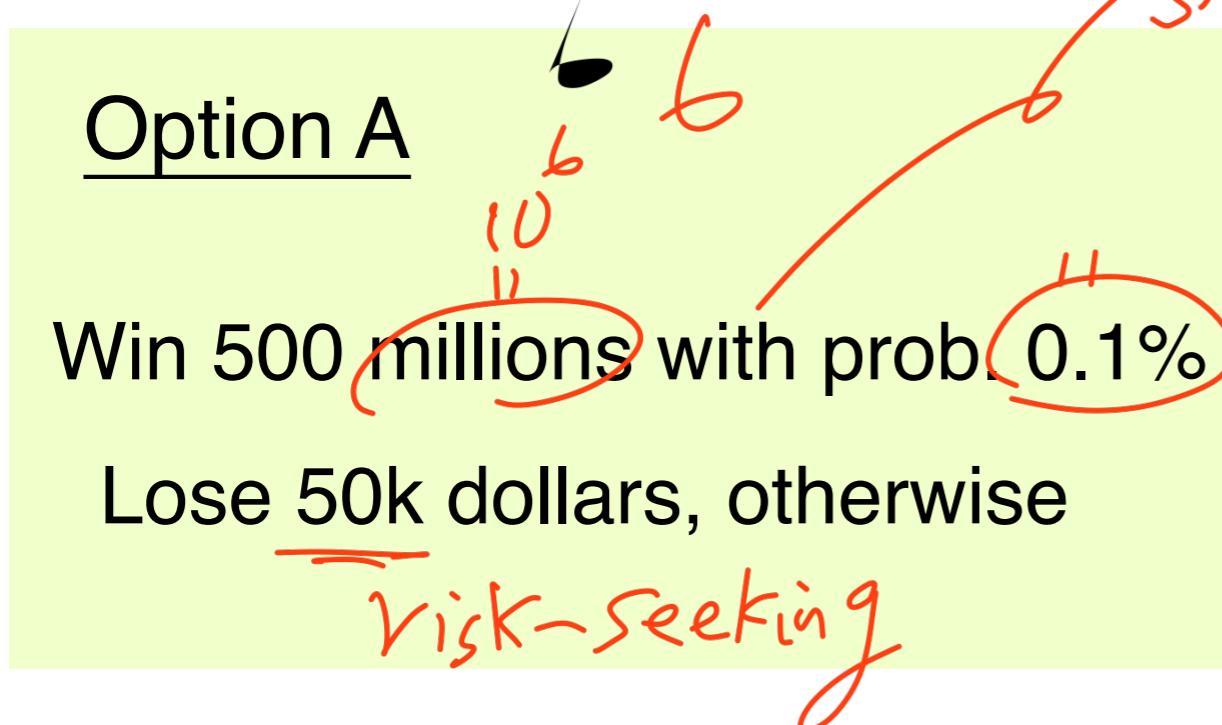
with probability  $P \rightarrow$  type A

$1-p \rightarrow$  type B

# 1. Expected Value

# Motivation: Guidelines for Decision Making?

- Suppose we are given 2 options:



- Which option will you choose?

100K

- Could you come up with a creative way to get a reward higher than B but with a lower risk than A?

# Why Expected Value?

- ▶ **Example:** Imagine you are an investor of Shinemood
  - ▶  $X = \#$  of waffles sold by Shinemood today
  - ▶ Suppose  $X \sim \text{Poisson}(\lambda = 150, T = 1 \text{ day})$
- ▶ **Question 1:** How many waffles are expected to be sold today?  
*expected value*
- ▶ **Question 2:** In the coming year, how many waffles will be sold per day on average?  
$$\frac{x_1 + x_2 + \dots + x_{365}}{365}$$
*empirical average*
- ▶ Q1 and Q2 are closely related: Law of Large Numbers

# Example: Expected Value and Poisson

- ▶ Example:  $X = \#$  of waffles sold by Shinemood today
  - ▶ Suppose  $X \sim \text{Poisson}(\lambda = 150, T = 1 \text{ day})$
  - ▶ PMF of  $X$ ? How to define the expected value of  $X$ ?

PMF of  $X$ :

$$P(X=n) = \frac{(e^{-\lambda T} \cdot (\lambda T)^n)}{n!}$$

Expected value:

$$\begin{aligned} & 1 \cdot P(X=1) \\ & + \\ & 2 \cdot P(X=2) \\ & + \\ & \vdots \\ & \infty \\ & = \sum_{n=1}^{\infty} n \cdot P(X=n). \end{aligned}$$

# Expected Value of a Discrete R.V. (Formally)

## Expected Value (or Mean / Expectation):

Let  $X$  be a discrete random variable with

- the set of possible values  $S = \{1, 2, 3, 4, 5, \dots\}$
- PMF of  $X$  is  $p_X(x)$

The expected value of  $X$  is defined as

$$E[X] := \sum_{x \in S} x \cdot p_X(x) \quad \leftarrow (\text{high school def.})$$

- Sometimes we use the notation:  $\mu_X \equiv E[X]$

# Example: Expected Value

- ▶ Example: Suppose  $X$  has a PMF:  $p_X(n) = \frac{1}{n(n+1)}$ ,  $n \geq 1$
- ▶ What is  $E[X]$ ?

$$E[X] = \sum_{n=1}^{\infty} n \cdot p_X(n)$$

$$= \sum_{n=1}^{\infty} n \cdot \frac{1}{n(n+1)}$$

$$X \in \{a_1, a_2, a_3, \dots, a_{100}\}$$

$$a_1 < a_2 < a_3 < \dots < a_{100}$$

$$E[X] \leq a_{100}$$

$$p(X=n) \quad \text{with } n \in \mathbb{N}$$

$$1. \int x \frac{1}{x(x+1)} dx$$

$$=\log x$$

$E[X]$  is not well-defined

$$= \sum_{n=1}^{\infty} \frac{1}{n+1}$$

$$\geq \frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \frac{1}{5} + \frac{1}{6} + \frac{1}{7} + \frac{1}{8} + \dots$$
$$\geq \frac{1}{2} + \left( \frac{1}{4} + \frac{1}{4} \right) + \left( \frac{1}{8} + \frac{1}{8} \right) + \left( \frac{1}{16} + \frac{1}{16} \right) + \dots$$

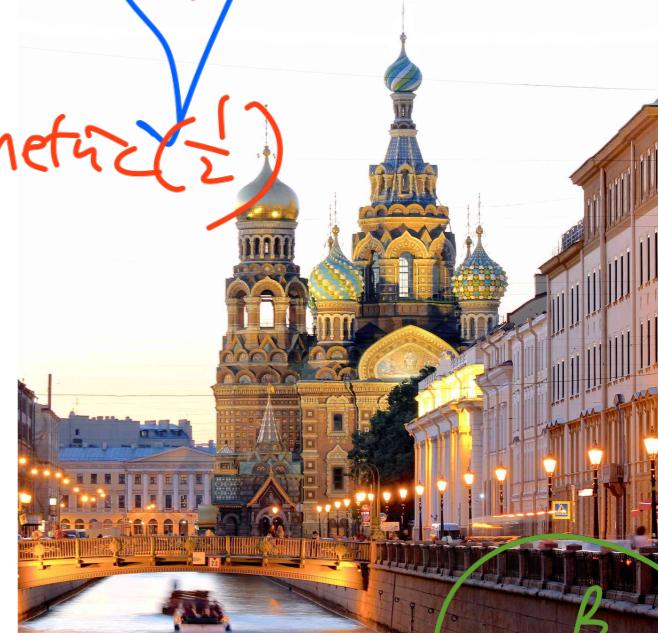
# Example: St. Petersburg Paradox

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- Example: We are asked to pay 10000 dollars to play a game.
  - We can keep flipping a fair coin until a head is observed.
  - If the 1st head occurs at  $n$ -th toss, then we get a prize of  $2^n$  dollars and the game is over.
  - Shall we play this game?

$X = \text{1st head occurs at } n\text{-th toss}$

$X \sim \text{Geometric}(\frac{1}{2})$



$Y = \text{prize we get}$

$$P(Y=k) = \begin{cases} \frac{1}{2} & k=1 \\ \left(\frac{1}{2}\right)^2 & k=2 \\ \left(\frac{1}{2}\right)^3 & k=3 \\ \vdots & \vdots \\ \left(\frac{1}{2}\right)^k & k \geq 1 \end{cases} \quad E[Y] = \sum_{y=1}^{\infty} y \cdot P(Y=y) = \sum_{k=1}^{\infty} (\frac{1}{2})^k \cdot \beta^k = \sum_{k=1}^{\infty} \left(\frac{\beta}{2}\right)^k \geq 10000$$

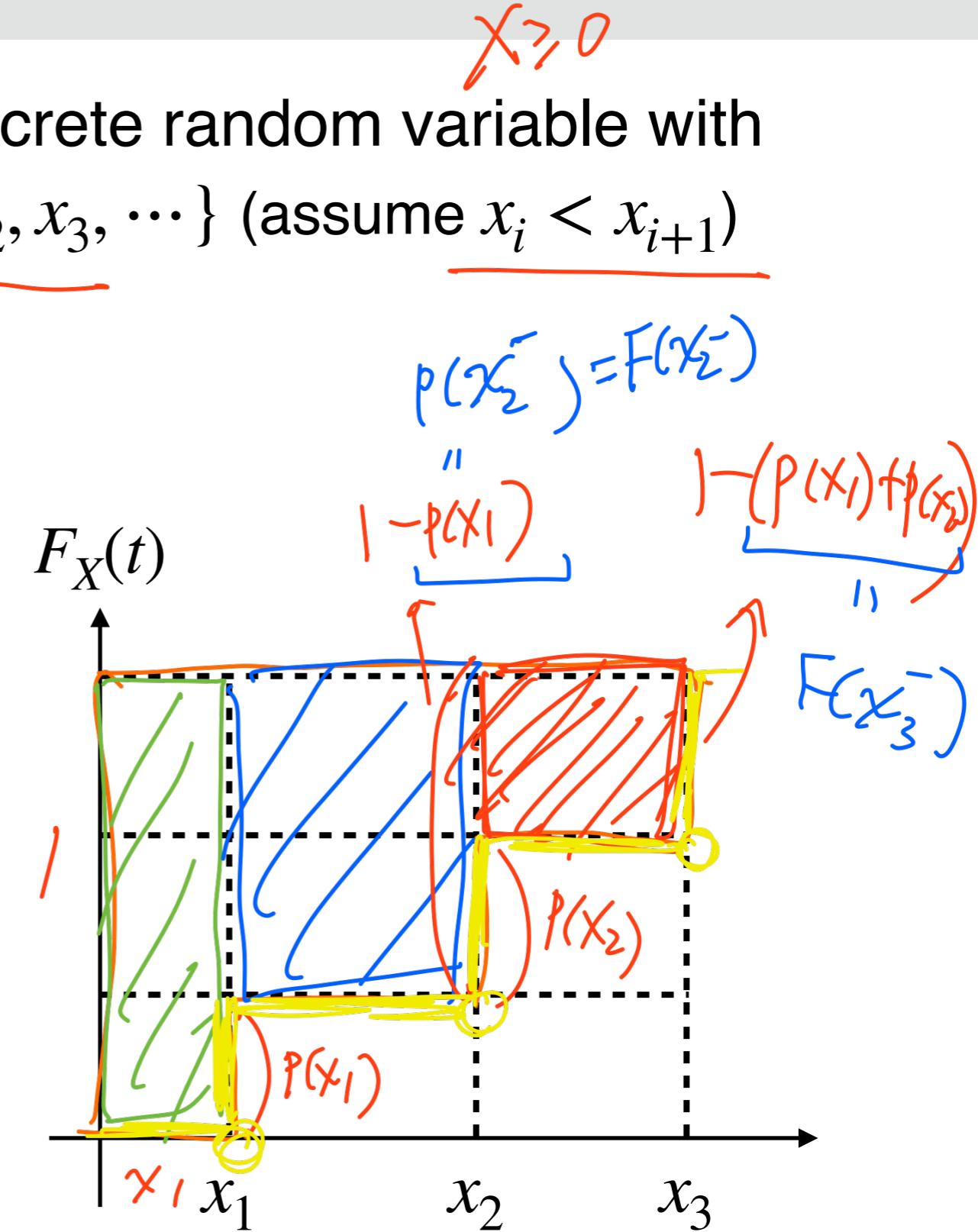
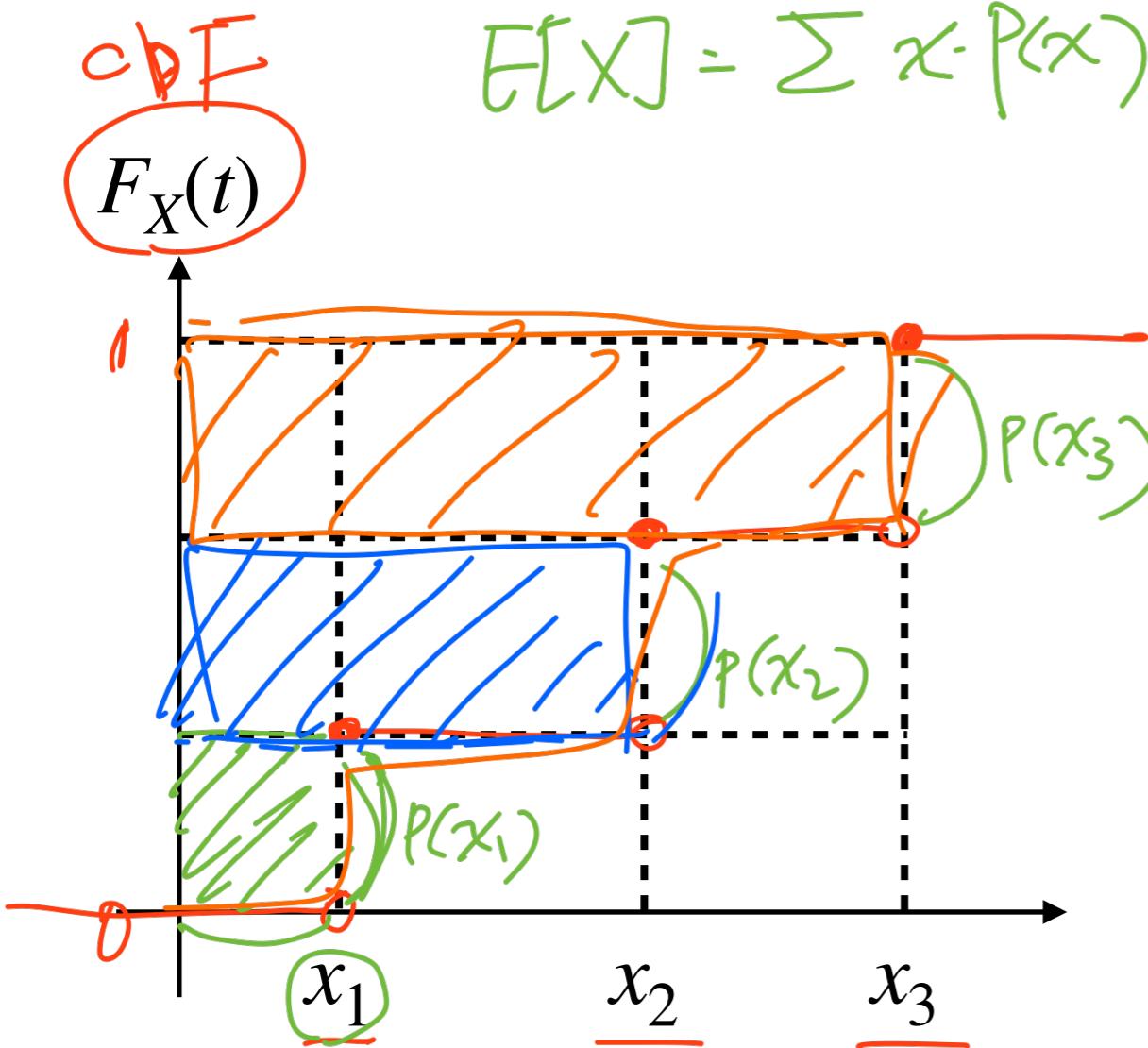
# Example: St. Petersburg Paradox

- ▶ **Example:** We are asked to pay 10000 dollars to play a game.
  - ▶ We can keep flipping a fair coin until a head is observed.
  - ▶ If the 1st head occurs at  $n$ -th toss, then we get a prize of  $\beta^n$  dollars and the game is over.
  - ▶ Under what  $\beta$  shall we play this game?



# Visualize the Expected Value Using CDF

- Suppose  $X$  is a non-negative discrete random variable with
  - The set of possible values  $\{x_1, x_2, x_3, \dots\}$  (assume  $x_i < x_{i+1}$ )
  - Denote  $x_0 = 0$



# Expected Value of a Discrete Random Variable: An Alternative Expression

## Expected Value (or Mean / Expectation):

Let  $X$  be a non-negative discrete random variable with

- the set of possible values  $S = \{x_1, x_2, x_3 \dots\}$
- CDF of  $X$  is  $F_X(t)$

Denote  $x_0 = 0$ . The expected value of  $X$  is

$$E[X] = \sum_{i=1}^{\infty} (x_i - x_{i-1}) \cdot (1 - F_X(x_i^-))$$

- What if  $S = \{1, 2, 3 \dots\}$ ?

$$E[X] = \sum_{i=1}^{\infty} i \cdot P(X > i) \quad (\text{next week})$$

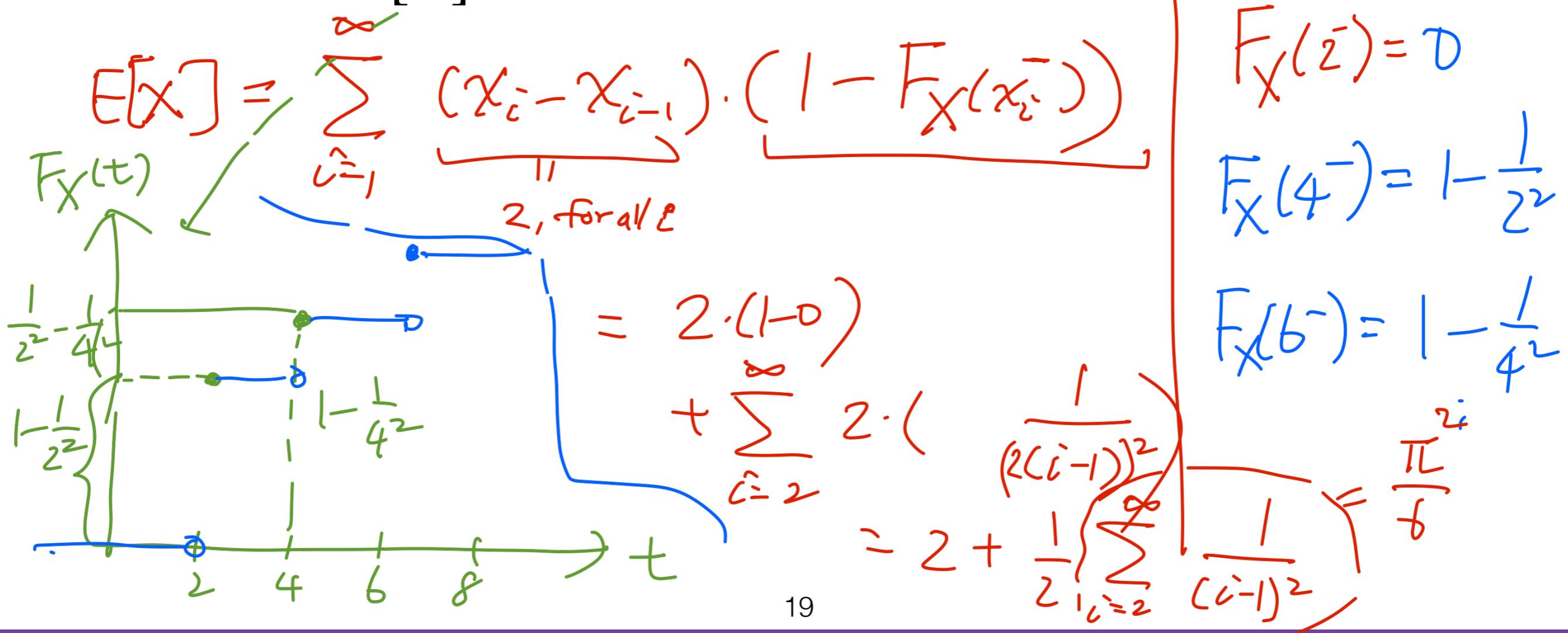
- How about continuous cases?

$$E[X] = \int_0^{\infty} P(X > t) dt$$

# Example: Using the Alternative Expression

- Example: Suppose  $X$  is a discrete random variable
  - For  $X$ , the set of possible values  $A = \{2, 4, 6, 8, \dots\}$
  - The CDF of  $X$  is  $F_X(t) = 1 - \frac{1}{t^2}$ ,  $t \in A$
  - What is  $E[X]$ ?

$$\frac{1}{1^2} + \frac{1}{2^2} + \frac{1}{3^2} + \dots$$



# A Property of Expected Value

## Theorem (Expectation of a Function of r.v.):

1. Let  $X$  be a discrete random variable with
  - the set of possible values  $S$
  - PMF of  $X$  is  $p_X(x)$
2. Let  $g(\cdot)$  be a real-valued function

$$Y = g(X)$$

$$E[Y] = \sum_y y \cdot P_Y(y)$$

The expectation of  $g(X)$  is

$$E[g(X)] = \underbrace{\sum_{x \in S} g(x) \cdot p_X(x)}_{\text{PMF}}$$

- ▶ Is this intuitive? Do we need a proof?
- ▶ Also called Law of the unconscious statistician (LOTUS)

# Proof of Law of the Unconscious Statistician

$$E[g(X)] := \sum_{x \in S} g(x) \cdot p_X(x)$$

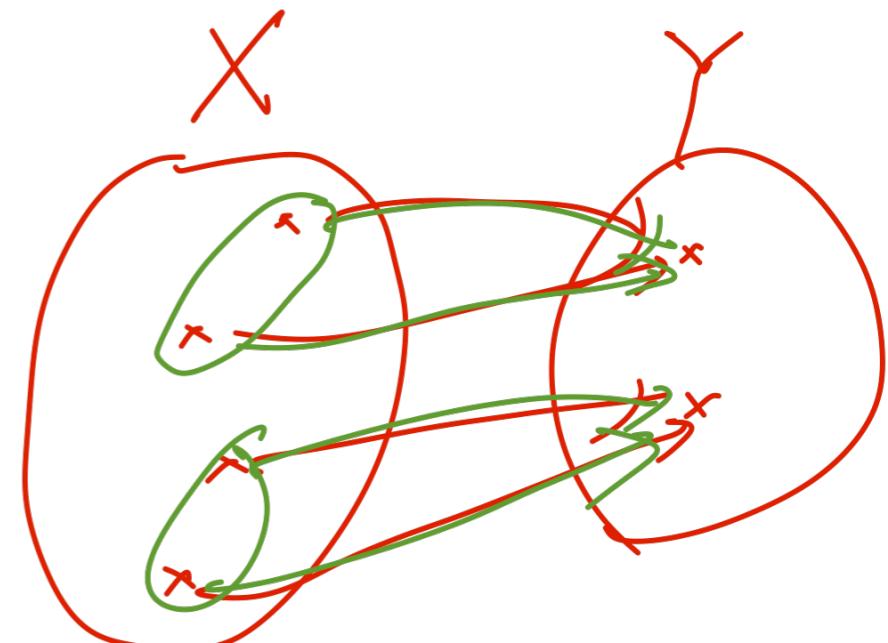
Define  $Y = g(X)$

$$E[g(X)] = E[Y]$$

$$= \sum_y y \cdot P_Y(y)$$

" "

$$\left( \sum_{x: g(x)=y} \right) P_X(x)$$



$$= \sum_x g(x) \cdot P_X(x)$$

# Linearity of Expected Values (I)

## Linearity Property (I):

Let  $\underbrace{X}$  be a discrete random variable and  $\alpha, \beta$  be real numbers. Then, we have

$$E[\alpha X + \beta] = \underbrace{\alpha}_{\text{[green bracket]}} \cdot \underbrace{E[X]}_{\text{[green bracket]}} + \underbrace{\beta}_{\text{[green bracket]}}$$

► How to show this?

LOTUS:  $E[\alpha X + \beta] = E[g(X)] = \sum_x g(x) \cdot P_X(x)$

$$\begin{aligned} &= \sum_x (\underbrace{\alpha x + \beta}_{\text{[red bracket]}}) P_X(x) \\ &= \alpha \cdot E[X] + \beta \end{aligned}$$

# Linearity of Expected Values (II)

## Linearity Property (II):

Let  $X$  be a discrete random variable and  $g(\cdot), h(\cdot)$  be real numbers. Then, we have

$$E[g(X) + h(X)] = E[g(X)] + E[h(X)]$$

||

- ▶ How to show this?

$$\begin{aligned} & \sum_x (g(x) + h(x)) \cdot P_X(x) \\ &= \sum_x g(x) \cdot \underbrace{\phantom{g(x)}_{\text{---}}}_{\text{---}} + \sum_x h(x) \cdot \underbrace{\phantom{h(x)}_{\text{---}}}_{\text{---}} \\ &= E[g(X)] + E[h(X)] \end{aligned}$$

# Conditional Expectation

- Example: Roll a fair 6-sided die once
  - Define  $X =$  the number that we observe
  - Given that  $X \geq 4$ , what is the expected value of  $X$ ?

## Conditional Expectation:

Let  $X$  be a discrete random variable with the set of possible values  $S = \{x_1, x_2, x_3 \dots\}$ . Let  $A$  be an event.

The expected value of  $X$  conditioned on  $A$

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

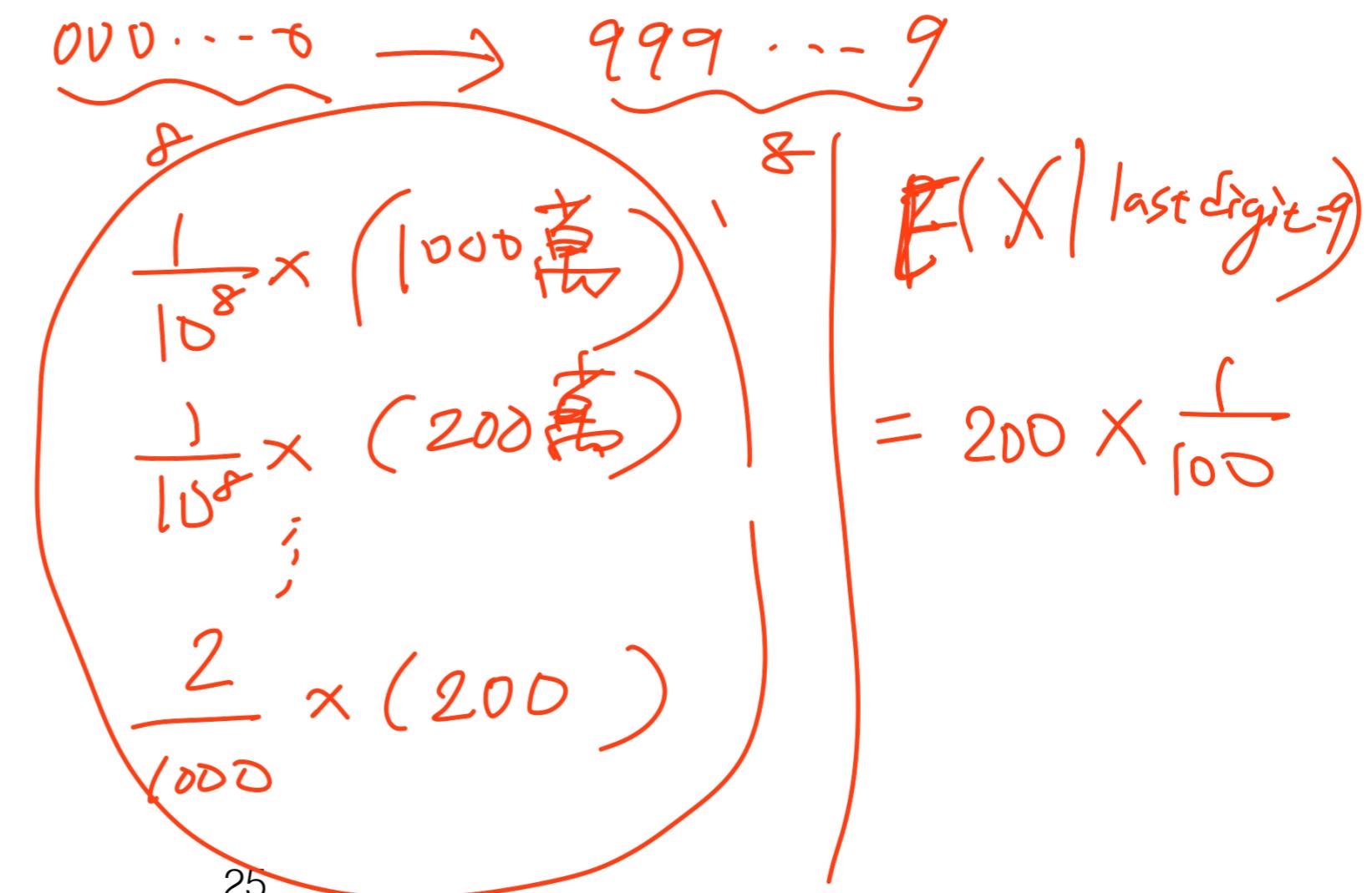
# Example: Taiwan Receipt Lottery

INVOICE

- ▶ Example: Suppose we have a receipt at hand
  - ▶ Define  $X = \text{the prize we get}$
  - ▶ What is  $E[X]$ ?
  - ▶ Given that the last digit is 9, what is the expected value of  $X$ ?

108年7-8月統一發票開獎		
特別獎	45698621	與左欄號碼相同者獎金1,000萬元
特獎	19614436	與左欄號碼相同者獎金200萬元
頭獎	96182420 47464012 62781818	頭獎 與頭獎號碼完全相同者獎金20萬元 二獎 與頭獎末7碼相同者各得獎金4萬元 三獎 與頭獎末6碼相同者各得獎金1萬元 四獎 與頭獎末5碼相同者各得獎金4千元 五獎 與頭獎末4碼相同者各得獎金1千元 六獎 與頭獎末3碼相同者各得獎金2百元
增開六獎	928 899	末3碼與增開六獎號碼相同者各得獎金2百元

00~99



## 2. Variance and Moments

# Moments and Others

$$E[g(X)] := \sum_{x \in S} g(x) \cdot p(x)$$

$\overbrace{\phantom{g(x) \cdot p(x)}}$

$\cancel{X^2}$

- ▶ Example:  $g(X) = X^2 \rightarrow$  2nd moment of  $\cancel{X}$
- ▶ Example:  $g(X) = X^n \rightarrow$  n-th moment //
- ▶ Example:  $g(X) = \underbrace{(X - \mu_X)^2}_{\rightarrow \text{Variance (2nd "central" moment)}}$
- ▶ Example:  $g(X) = (X - \mu_X)^n \rightarrow$  n-th "central" moment
- ▶ Example:  $g(X) = e^{tX} \rightarrow$  Moment Generating function (MGF)

# Variance

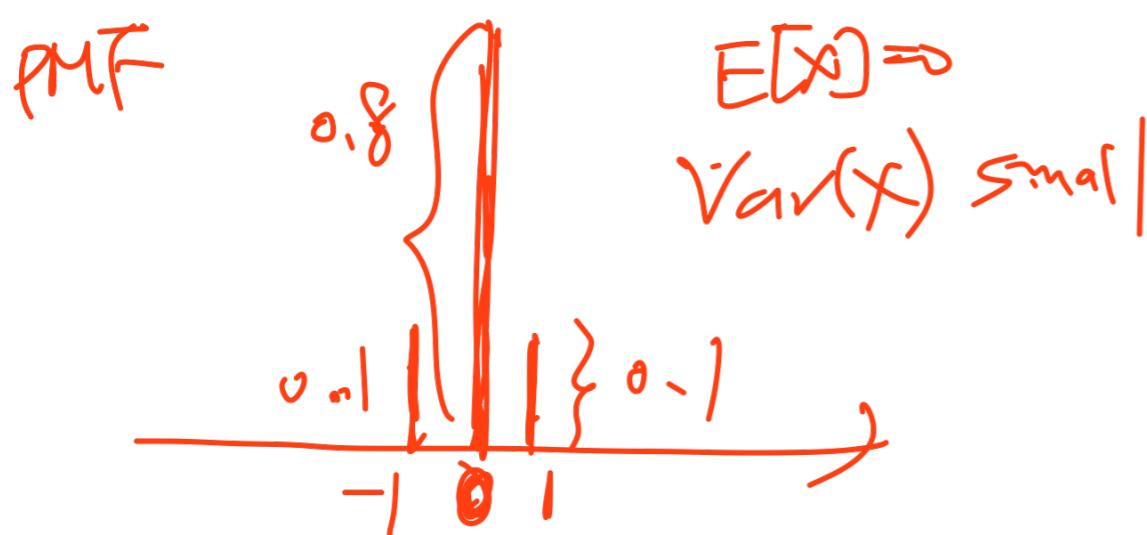
## Variance (2nd central moment):

Let  $X$  be a discrete random variable with the set of possible values  $S$  and PMF  $p_X(x)$ . The variance of  $X$  is

$$\text{Var}[X] := E[(X - \mu_X)^2] = \sum_{x \in S} (x - \mu_X)^2 \cdot p_X(x)$$

*standard deviation*

- Sometimes we use the notation:  $\sigma_X^2 \equiv \text{Var}[X]$
- Variance captures the variability of a random variable



# Variance: An Alternative Explanation

- ▶ **Example:** Suppose we are given a random variable  $X$ 
  - ▶ We need to output a prediction of  $X$  (denoted by  $z$ )
  - ▶ Penalty of prediction is  $(X - z)^2$
  - ▶ What is the minimum expected penalty?

# Another Way for Calculating Variance

## Theorem:

Let  $X$  be a random variable. Then, we have

$$\text{Var}[X] := \underbrace{E[X^2]}_{\text{平方的平均}} - \underbrace{(E[X])^2}_{\text{平均的平方}} \geq 0$$

- ▶ How to show this?

$$\begin{aligned}\text{Var}[X] &= E[(X - M_X)^2] \\ &= E[X^2 - 2 \cdot M_X \cdot X + M_X^2] \\ &= E[X^2] - E[2 \cdot M_X \cdot X] + E[M_X^2] \\ &= E[X^2] - M_X^2\end{aligned}$$

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$M_X^2$

$M_X^2$

$M_X^2$

$M_X^2$

$M_X^2$

# Properties of Variance and Moments (I)

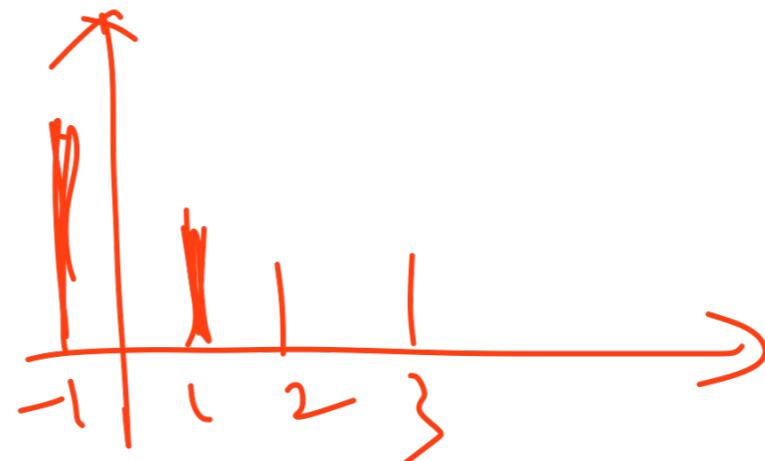
✓ 1.  $\text{Var}(X + c) = \text{Var}(X)?$

$$E[(X - \mu_X)^2]$$

2.  $\text{Var}(aX) = a^2 \cdot \text{Var}(X)?$

counter-example

3.  $\text{Var}(|X|) = \text{Var}(X)?$



✓ 4.  $E(X^2) \geq (E(X))^2?$

✓ 5. Can  $\text{Var}(X)$  be infinite? ↙ St. Petersburg.

# When are Higher Moments Useful?

## Berry-Esseen Theorem:

Let  $X_1, X_2, \dots, X_n$  be i.i.d. random variables with

$E[X_1] = 0, E[X_1^2] = \sigma^2$  and  $\underline{E[|X_1|^3] < \infty}$ . Define

$Y = (X_1 + X_2 + \dots + X_n)/n$ . Then, we have

$$|F_Y(t) - \Phi(t)| \leq \frac{C\rho}{\sigma^3\sqrt{n}}$$

- Usually higher moments are used as technical conditions
  - Hence, we usually care about  $E(X^n) < \infty$

# Properties of Variance and Moments (II)

$X$  is non-negative  
6. If  $E(X^{n+1}) < \infty$ , then  $E(X^n) < \infty$ ?  
 $n=1, 2, 3, \dots$

$$1000^3 > 1000^2$$

$|X| < 1$ : Both  $X^{n+1}$  and  $X^n$  are small

$$|X| > 1 : |X|^{n+1} \geq |X|^n$$

$$|X|^{n+1} \leq |X|^n$$

$$E[X^n] \leq E[|X|^n] \leq E[|X|^{n+1}] < \infty$$

## 3. Expected Value and Variance of Special Discrete Random Variables

# 1. Bernoulli Random Variables

- ▶ **Example:**  $X \sim \text{Bernoulli}(p)$ 
  - ▶ What is  $E[X]$ ?
  - ▶ What is  $\text{Var}[X]$ ?

## 2. Binomial Random Variables

- ▶ **Example:**  $X \sim \text{Binomial}(n, p)$ 
  - ▶ What is  $E[X]$ ?
  - ▶ What is  $\text{Var}[X]$ ?

# 3. Poisson Random Variables

- ▶ **Example:**  $X \sim \text{Poisson}(\lambda, T)$ 
  - ▶ What is  $E[X]$ ?
  - ▶ What is  $\text{Var}[X]$ ?

# 4. Geometric Random Variables

- ▶ **Example:**  $X \sim \text{Geometric}(p)$ 
  - ▶ What is  $E[X]$ ?
  - ▶ What is  $\text{Var}[X]$ ?

# Next Lecture

1. Continuous random variables
2. Probability density function (PDF)

# 1-Minute Summary

## 1. Expected Value

- Definition / alternative expression / linearity / conditional expectation
- Law of the unconscious statistician (LOTUS)

## 2. Variance and Moments

- Definition / alternative explanation using penalty / properties

## 3. Special Discrete R.V.: Expected Value and Variance

- Bernoulli / Binomial / Poisson / Geometric