

# Randomized Algorithms

## Coupon Collector's Problem and Conditional Expectation

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# Review

- Expectation of discrete random variables
- Linearity of expectation.
- Bernoulli and Binomial random variable

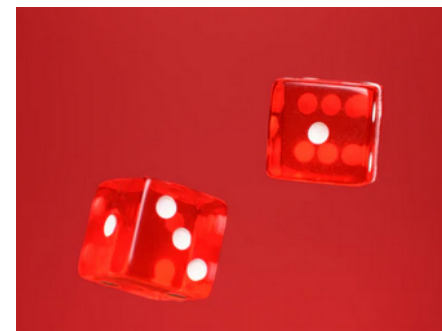
# Expectation

- The expectation of a discrete random variable  $X$ , denoted by  $\mathbf{E}[X]$ , is

$$\mathbf{E}[X] = \sum_i i \cdot \Pr[X = i]$$

- Example: Let  $X$  denote the sum of of dices:

$$\mathbf{E}[X] = \frac{1}{36} \cdot 2 + \frac{2}{36} \cdot 3 + \frac{3}{36} \cdot 4 + \cdots + \frac{1}{36} \cdot 12 = 7.$$



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# Linearity of Expectation

- For any finite collection of discrete random variables  $X_1, X_2, \dots, X_n$  with finite expectations,

$$\mathbf{E} \left[ \sum_{i=1}^n X_i \right] = \sum_{i=1}^n \mathbf{E}[X_i].$$

- For any constant  $c$  and discrete random variable  $X$ ,

$$\mathbf{E}[cX] = c \cdot \mathbf{E}[X].$$

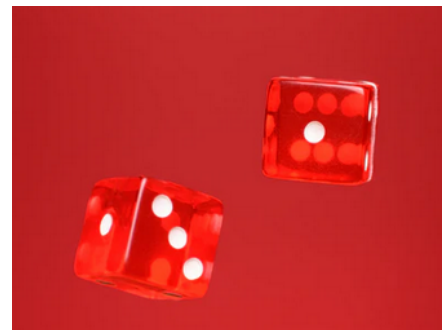
- Why is it useful?

# Example

- Consider the dice-throwing example again.
  - $X_1$  : the outcome of die 1
  - $X_2$  : the outcome of die 2

$$\mathbf{E}[X_1] = \mathbf{E}[X_2] = \frac{1}{6} \cdot \sum_{j=1}^6 j = \frac{7}{2}$$

$$\mathbf{E}[X] = \mathbf{E}[X_1 + X_2] = 7.$$



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# Bernoulli random variable

- Suppose we run an experiment that succeeds with probability  $p$  and fails with probability  $1-p$ .

$$Y = \begin{cases} 1 & \text{if the experiment succeeds,} \\ 0 & \text{otherwise.} \end{cases}$$

- $Y$ : Bernoulli random variable.
  - or *indicator random variable*.

$$\mathbf{E}[Y] = 1 \cdot \Pr[Y = 1] + 0 \cdot \Pr[Y = 0] = \Pr[Y = 1] = p.$$



# Binomial random variable

- A binomial random variable  $X$  with parameters  $n$  and  $p$ , denoted by  $B(n, p)$ , is defined as

$$\Pr[X = j] = \binom{n}{j} p^j (1 - p)^{n-j}.$$

for  $j = 0, 1, 2, \dots, n$ .

- Exercise: Show that  $\sum_{j=0}^n \Pr[X = j] = 1$ .

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$X$ : the number of successful trials in the  $n$  experiments.

- Exercise: Show that  $\sum_{j=0}^n \Pr[X = j] = 1$ .



# Binomial random variable (expectation)

- $$\begin{aligned}\mathbf{E}[X] &= \sum_{j=0}^n j \binom{n}{j} p^j (1-p)^{n-j} \\&= \sum_{j=0}^n j \frac{n!}{j!(n-j)!} p^j (1-p)^{n-j} \\&= \sum_{j=1}^n \frac{n!}{(j-1)!(n-j)!} p^j (1-p)^{n-j} \\&= np \sum_{j=1}^n \frac{(n-1)!}{(j-1)!((n-1)-(j-1))!} p^{j-1} (1-p)^{(n-1)-(j-1)} \\&= np \sum_{k=0}^{n-1} \frac{(n-1)!}{k!((n-1)-k)!} p^k (1-p)^{(n-1)-k} \\&= np \sum_{k=0}^{n-1} \binom{n-1}{k} p^k (1-p)^{(n-1)-k} \\&= np.\end{aligned}$$

# Binomial random variable (expectation)

- $\mathbf{E}[X] = \sum_{j=0}^n j \binom{n}{j} p^j (1-p)^{n-j}$

$$= \sum_{j=0}^n j \frac{n!}{j!(n-j)!} p^j (1-p)^{n-j}$$


$$= \sum_{j=1}^n \frac{n!}{(j-1)!(n-j)!} p^j (1-p)^{n-j}$$

$$= np \sum_{j=1}^n \frac{(n-1)!}{(j-1)!((n-1)-(j-1))!} p^{j-1} (1-p)^{(n-1)-(j-1)}$$

$$= np \sum_{k=0}^{n-1} \frac{(n-1)!}{k!((n-1)-k)!} p^k (1-p)^{(n-1)-k}$$

$$= np \sum_{k=0}^{n-1} \binom{n-1}{k} p^k (1-p)^{(n-1)-k}$$

$$= np.$$


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

# Let's make it simpler!

- Denote a set of  $n$  Bernoulli random variables  $X_1, X_2, \dots, X_n$ .
  - $X_i = 1$  if the  $i$ th trial is successful and 0 otherwise.
  - $X = X_1 + X_2 + \dots + X_n$

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  - Compute  $\mathbf{E}[X]$  using linearity of expectation:

$$\mathbf{E}[X] = \mathbf{E} \left[ \sum_{i=1}^n X_i \right] = \sum_{i=1}^n \mathbf{E}[X_i] = np.$$

# Geometric Distribution

- Imagine: *flip a coin until it lands on a head.*
  - What's the distribution of the number of flips?

# Geometric Distribution

- Imagine: *flip a coin until it lands on a head.*
  - What's the distribution of the number of flips?
- Definition. A geometric random variable  $X$  with parameter  $p$  is

$$\Pr[X = n] = (1 - p)^{n-1}p.$$

for  $n = 1, 2, \dots$

- Exercise. Show that  $\sum_{n \geq 1} \Pr[X = n] = 1.$

# Memoryless

- Let  $X$  be a geometric random variable  $X$  with parameter  $p > 0$ .
- For any  $n, k > 0$ ,  $\Pr[X = n + k \mid X > k] = \Pr[X = n]$ .



# Memoryless

- Let  $X$  be a geometric random variable  $X$  with parameter  $p > 0$ .
- For any  $n, k > 0$ ,  $\Pr[X = n + k \mid X > k] = \Pr[X = n]$ .

• *Proof.*

$$\begin{aligned}\Pr[X = n + k \mid X > k] &= \frac{\Pr[(X = n + k) \cap (X > k)]}{\Pr[X > k]} \\ &= \frac{\Pr[X = n + k]}{\Pr[X > k]} \\ &= \frac{(1 - p)^{n+k-1}p}{\sum_{i=k}^{\infty} (1 - p)^i p} \\ &= \frac{(1 - p)^{n+k-1}p}{(1 - p)^k} \\ &= (1 - p)^{n-1}p = \Pr[X = n].\end{aligned}$$

# The mean of a geometric r.v. $X(p)$

$$\mathbf{E}[X] = \sum_{j=1}^{\infty} j \Pr[X = j]$$

$$= \sum_{j=1}^{\infty} \sum_{i=1}^j \textcolor{blue}{1} \Pr[X = j]$$

$$= \sum_{i=1}^{\infty} \sum_{j \geq i} \Pr[X = j]$$

$$= \sum_{i=1}^{\infty} \textcolor{red}{\Pr[X \geq i]}.$$

$$\textcolor{red}{\Pr[X \geq i]} = \sum_{k=i}^{\infty} (1-p)^{k-1} p = (1-p)^{i-1}$$

$$\mathbf{E}[X] = \sum_{i=1}^{\infty} (1-p)^{i-1} = \frac{1}{1 - (1-p)} = \textcolor{red}{\frac{1}{p}}.$$

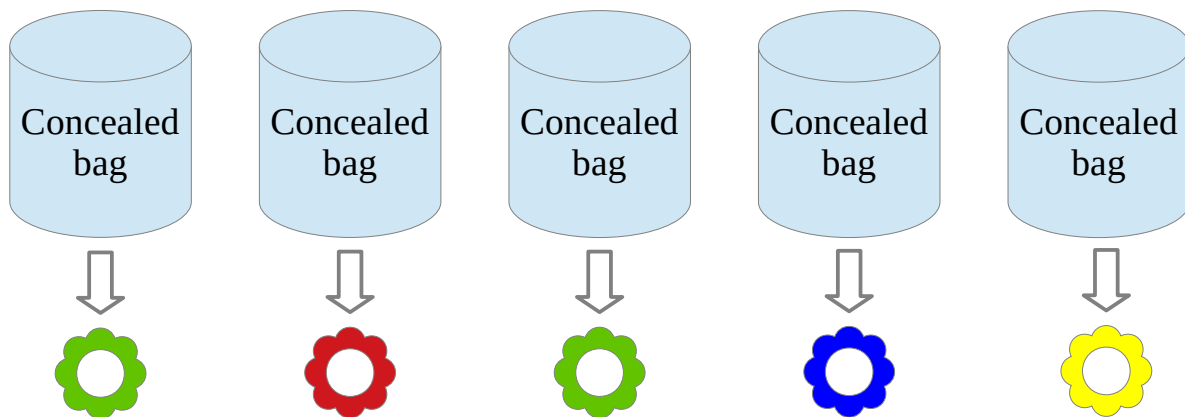
# Coupon Collector's Problem



▲一名網友在臉書社團「爆廢公社公開版」表示，多年前為了收集連鎖便利商店 7-11 的一款贈品，花了不少金額，還拿到許多重複的款式，貼文引發 3 千多名網友共鳴。（圖／翻攝自爆廢公社公開版）

# Coupon Collector's Problem

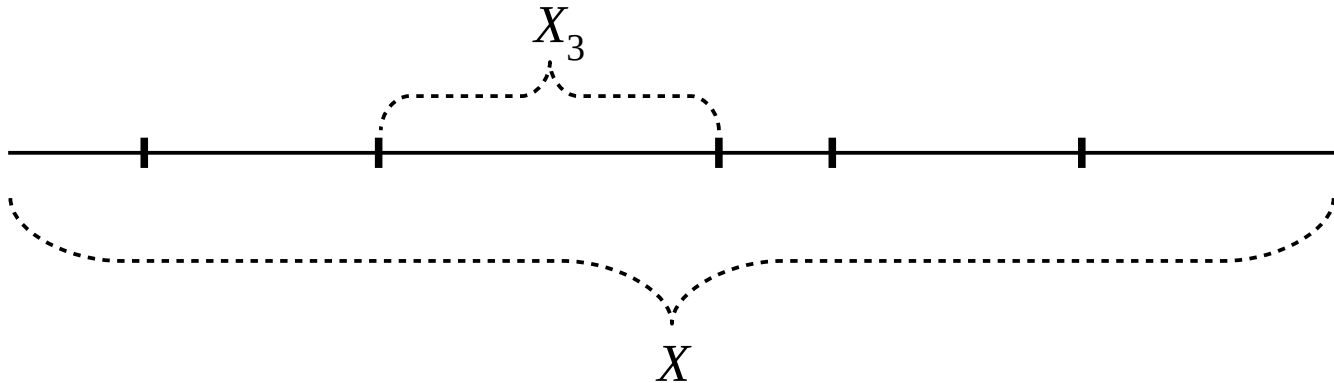
- Have you already got all of them (totally  $n$  types)?
- Have you ever thought about how much you should pay for them?



- Each bag is chosen independently and uniformly at random from the  $n$  possibilities.

# Coupon Collector's Problem

- Let  $X$  be the number of bags bought until every type of coupon is obtained.
- Let  $X_i$  be the number of bags bought while you had already got exactly  $i-1$  different coupons.



# Coupon Collector's Problem

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# Coupon Collector's Problem

- Let  $X$  be the number of bags bought until every type of coupon is obtained.
- Let  $X_i$  be the number of bags bought while you had already got exactly  $i-1$  different coupons.
  - Geometric random variables?!
  - What about  $X = \sum_{i=1}^n X_i$ ?

# Coupon Collector's Problem

- When exactly  $i-1$  coupons have been collected, the probability of obtaining a new one is

$$p_i = 1 - \frac{i-1}{n}$$

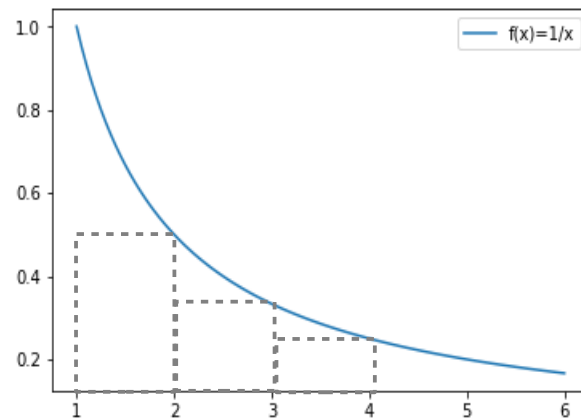
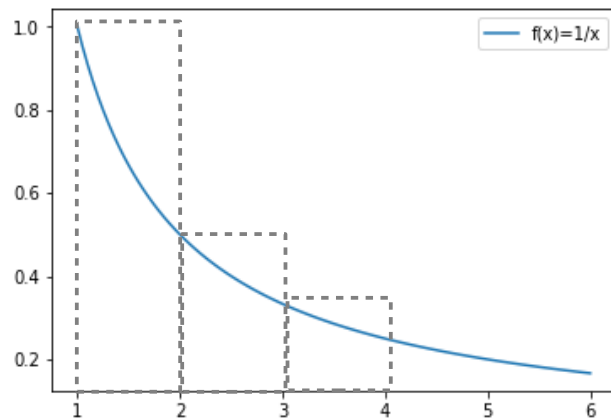
- $X_i$  is a **geometric random variable**, so

$$\mathbf{E}[X_i] = \frac{1}{p_i} = \frac{n}{n-i+1}.$$



# Coupon Collector's Problem (contd.)

$$\begin{aligned}
 \bullet \mathbf{E}[X] &= \mathbf{E}\left[\sum_{i=1}^n X_i\right] \\
 &= \sum_{i=1}^n \mathbf{E}[X_i] \\
 &= \sum_{i=1}^n \frac{n}{n-i+1} \\
 &= n \cdot \sum_{i=1}^n \frac{1}{i}.
 \end{aligned}$$



$$\sum_{k=1}^n \frac{1}{k} \geq \int_{x=1}^n \frac{1}{x} dx = \ln n$$

$$\sum_{k=2}^n \frac{1}{k} \leq \int_{x=1}^n \frac{1}{x} dx = \ln n$$

$$\rightarrow H(n) = \sum_{i=1}^n \frac{1}{i} = \ln n + \Theta(1).$$

# Coupon Collector's Problem (contd.)

- So, you are about to buy  $n \ln n + \Theta(n)$  bags for collecting all the coupons (stickers)!

# On conditional expectation

- There are terminologies which may confusing you.

# Conditional Expectation

- Definition.

$$\mathbf{E}[Y \mid Z = z] = \sum_y y \Pr[Y = y \mid Z = z].$$

- Example of two dices.
  - $X_1$ : the number showing on the first die
  - $X_2$ : the number showing on the second die
  - $X = X_1 + X_2$

$$\mathbf{E}[X \mid X_1 = 2] = \sum_{x=3}^8 x \cdot \frac{1}{6} = \frac{11}{2}.$$

# Conditional Expectation (contd.)

- Lemma. For any random variables  $X$  and  $Y$ ,

$$\mathbf{E}[X] = \sum_y \Pr[Y = y] \mathbf{E}[X \mid Y = y].$$

- *Proof*.
$$\begin{aligned} \sum_y \Pr[Y = y] \cdot \mathbf{E}[X \mid Y = y] &= \sum_y \Pr[Y = y] \cdot \sum_x x \Pr[X = x \mid Y = y] \\ &= \sum_x \sum_y x \Pr[X = x \mid Y = y] \cdot \Pr[Y = y] \\ &= \sum_x \sum_y x \Pr[X = x \cap Y = y] \\ &= \sum_x x \Pr[X = x] \\ &= \mathbf{E}[X]. \end{aligned}$$

# Conditional Expectation

- Lemma. For any finite collection of discrete random variables  $X_1, X_2, \dots, X_n$  with finite expectations and for any random variable  $Y$ ,

$$\mathbf{E} \left[ \sum_{i=1}^n X_i \mid Y = y \right] = \sum_{i=1}^n \mathbf{E}[X_i \mid Y = y].$$

# Conditional Expectation (contd.)

- A weird definition.
- $\mathbf{E}[Y \mid Z]$  : regarded as a **random variable**  $f(Z)$ .
  - It takes on the value  $\mathbf{E}[Y \mid Z = z]$  when  $Z = z$ .
- In the previous example,

$$\mathbf{E}[X \mid X_1] = \sum_x x \cdot \Pr[X = x \mid X_1] = \sum_{X_1+1}^{X_1+6} x \cdot \frac{1}{6} = X_1 + \frac{7}{2}.$$

- So it makes sense that

$$\mathbf{E}[\mathbf{E}[X \mid X_1]] = \mathbf{E}\left[X_1 + \frac{7}{2}\right] = \frac{7}{2} + \frac{7}{2} = 7.$$

# Conditional Expectation (contd.)

- Theorem.  $\mathbf{E}[Y] = \mathbf{E}[\mathbf{E}[Y \mid Z]]$ .

- *Proof.*

$$\mathbf{E}[\mathbf{E}[Y \mid Z]] = \sum_z \mathbf{E}[Y \mid Z = z] \cdot \Pr[Z = z] = \mathbf{E}[Y].$$