Advanced Algorithms (II)

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The expectation $\mathbf{E}[X] = \sum_{a \in \Omega: \Pr[X=a] > 0} a \cdot \Pr[X=a]$

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

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$$\mathbf{E}[X_1 + X_2] = \sum_{a,b} (a+b) \cdot \Pr[X_1 = a, X_2 = b]$$

= $\sum_{a,b} a \cdot \Pr[X_1 = a, X_2 = b] + \sum_{a,b} b \cdot \Pr[X_1 = a, X_2 = b]$
= $\sum_{a} a \cdot \Pr[X_1 = a] + \sum_{b} b \cdot \Pr[X_2 = b] = \mathbf{E}[X_1] + \mathbf{E}[X_2]$

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How many times one needs to draw to collect all coupons?

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For any *i*, X_i follows *geometric distribution* with probability $\frac{n-i}{n}$

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It is not hard to see that $\mathbf{E}[X] = \frac{1}{p}$

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$$\mathbf{E}[X] = \mathbf{E}\left[\sum_{i=0}^{n-1} X_i\right] = \sum_{i=0}^{n-1} \mathbf{E}[X_i]$$

= $\sum_{i=0}^{n-1} \frac{n}{n-i} = \frac{n}{n} + \frac{n}{n-1} + \frac{n}{n-2} + \dots + \frac{n}{1}$
= $n \cdot H(n) \to n \log n + \gamma n$

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The constant $\gamma = 0.577...$ is called Euler constant

• $n = \infty$

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St. Petersburg paradox

Each stage of the game a fair coin is tossed and a gambler guesses the result. He wins the amount he bet if his guess is correct and lose the money if he is wrong. He bets \$1 at the first stage. If he loses, he doubles the money and bets again. The game ends when the gambler wins.

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- On the other hand, he eventually wins \$1,

- so
$$\mathbf{E}\left[\sum_{i=1}^{\infty} X_i\right] = 1 \neq \sum_{i=1}^{\infty} \mathbf{E}[X_i]!$$

• n = N is random

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Suppose we draw a number *N* and toss *N* dices X_1, \ldots, X_N , what is $\mathbf{E}\left[\sum_{i=1}^N X_N\right]$?

Each X_i is uniform in $\{1, \dots, 6\}$, one might expect $\mathbf{E}\left[\sum_{i=1}^N X_i\right] = \mathbf{E}[N] \cdot \mathbf{E}[X_1] = 3.5 \times 3.5 = 12.25$

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Then **E** $\left[\sum_{i=1}^{N} X_{i} \right] = \mathbf{E}[N \cdot N] = 15.166..$

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More generally if N is a stopping time

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Find(A, k)

Randomly choose a pivot $x \in A$

- 1. Partition $A \{x\}$ into A_1, A_2 such that $\forall y \in A_1, y < x, \forall z \in A_2, z > x$
- 2. If $|A_1| = k 1$, return *x*
- 3. If $|A_1| \ge k$, return **Find** (A_1, k)
- 4. return **Find**($A_2, k |A_1| 1$)

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 X_i - size of A at i-th round

$$X_1 = n \text{ and } \mathbf{E}[X_{i+1} \mid X_i] \le \frac{3}{4}X_i$$

The time cost is

$$\sum_{i=1}^{\infty} X_i$$

$$\mathbf{E}[X_{i+1} \mid X_i] \le \frac{3}{4}X_i$$

$$\implies \mathbf{E}[X_{i+1}] = \mathbf{E}[\mathbf{E}[X_{i+1} \mid X_i]] \le \frac{3}{4}\mathbf{E}[X_i] \le \left(\frac{3}{4}\right)^i n$$

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$$\mathbf{E}\left[\sum_{i=1}^{\infty} X_i\right] = \mathbf{E}\left[\sum_{i=1}^{n} X_i\right]$$
$$= \sum_{i=1}^{n} \mathbf{E}[X_i] \le \sum_{i=1}^{n} \left(\frac{3}{4}\right)^{i-1} n$$
$$= 4n.$$

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Theorem. (Karp-Upfal-Wigderson Inequality)

Assume for every $n, 0 \le X_n \le n - a$ is an integer for some a such that T(a) = 0. If $\mathbf{E}[X_n] \ge \mu(n)$ for all n > a, where $\mu(n)$ is positive and increasing , then

$$\mathbf{E}[T(n)] \le \int_{a}^{n} \frac{1}{\mu(t)} \,\mathrm{d}t$$

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Choosing
$$\mu(n) = p$$
 gives $\mathbf{E}[T(1)] \le \int_0^1 \frac{1}{p} dt = \frac{1}{p}$

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 (Why?)
KUW implies $\mathbf{E}[T(n)] \le \int_{1}^{n} \frac{4}{t} dt = 4 \log n$

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 where $X_m \sim \text{Ber}(m/n)$

So we can choose
$$\mu(m) = \frac{|m|}{n}$$

KUW implies $\mathbf{E}[T(n)] \le \int_0^n \frac{n}{\lceil t \rceil} dt = n \cdot H_n$

Proof of KUW inequality