

CS473 Algorithms: Lecture 7

- logistics - part 2 due w/10
- last time - dynamic programming, optimized
 - edit distance
 - longest increasing subsequence
- today - probability review
 - randomized algo
 - quicksort

intro

Q: what is the "more realistic" model of computation? - can run on actual computers
 - captures abilities of actual computers
 ↳ rand()?

randomized algo - rand(k) - O(1) op
 ↳ returns $0 \leq i < k$ w/p $\frac{1}{k}$ [uniform distribution]

Q: who will win the next US election? ["computational" problem]
 A: ask everyone ~ 28 million people
 ~ 235 million eligible voters } [sum-legis numbers]
 ~ 138 million actual voters } [expensive! do better!]

fact: a poll of 738 uniformly random voters will estimate actual vote to 55% with probability $\geq 95\%$ [Chernoff]
 ↳ faster! [error]
 ↳ hard to get uniform voters who respond [real life is more complicated]

Q: why rand algo?

A: - can be simpler, but analysis can be more complicated
 - "faster", but may fail with some probability
 ↳ sometimes only known efficient algo is randomized, eg primality testing [before AKS]

Q: what is randomness?

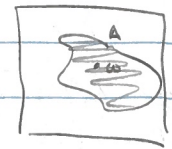
def. Ω finite/countably-infinite set, $Pr: \Omega \rightarrow [0,1]$. Then (Ω, Pr) is a discrete probability space if $\sum_{\omega \in \Omega} Pr[\omega] = 1$.

Remark - can define general probability space, eg $\Omega = \mathbb{R}$, but not tricky
 - discrete spaces suffice here

eg: - $\Omega = \{HH, HT, TH, TT\}$, $Pr[\omega] = 1/4$ ← two fair dice
 - $\Omega = \{0, 1, 2, \dots\}$, $Pr[i] =$ probability algo takes i steps [infinite]

def. (Ω, Pr) probability space. An event A is subset $A \subseteq \Omega$. $Pr[A] := \sum_{\omega \in A} Pr[\omega]$

ex: $A = \{HH, HT\}$ ← first coin is heads
 $Pr[A] = 1/2$



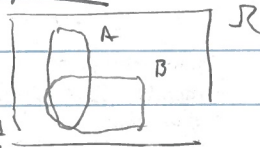
Remark - events are sets, so can use set operations
 - $\bar{A} = \Omega \setminus A$
 - $A \cap B, A \cup B$

def. (Ω, \mathcal{P}) prob. space. A, B events. A and B are independent
 $\iff P[A \cap B] = P[A]P[B]$, otherwise dependent.

ex. $\Omega = \{HH, HT, TH, TT\}$ $P[\omega] = 1/4$

$A = \{HT, TH\}$, $B = \{TT, HT\}$

$P[A] = P[B] = 1/2$, $P[A \cap B] = P[HT] = 1/4 = \frac{1}{2} \cdot \frac{1}{2}$



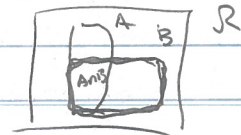
def. (Ω, \mathcal{P}) prob. space. $A \in \mathcal{P}$ event. Define the conditional probability of $\omega \in \Omega$
 to be $P[\omega | A] := \frac{P[\omega \cap A]}{P[A]} = \begin{cases} P[\omega] / P[A] & \omega \in A \\ 0 & \text{else} \end{cases}$

lem. (Ω, \mathcal{P}) prob. space. A, B events, $P[B] \neq 0$. Then

- $(B, \mathcal{P}[\cdot | B])$ is a probability space

- $P[A \cap B] = P[A | B] \cdot P[B]$

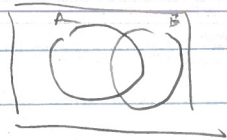
- A, B independent iff $P[A | B] = P[A]$



Pr. exercise

lem. $P[A \cup B] = P[A] + P[B] - P[A \cap B] \leq P[A] + P[B]$

Pr.



\hookrightarrow union bound

Very simple, but powerful!

def. (Ω, \mathcal{P}) . A random variable is $X: \Omega \rightarrow \mathbb{R}$

$X: \Omega \rightarrow \mathbb{R}$, $Y: \Omega \rightarrow \mathbb{R}$ are independent if all $\alpha, \beta \in \mathbb{R}$ the events $\mathbb{1}\{X = \alpha\}$ and $\mathbb{1}\{Y = \beta\}$ are independent

equiv. $P[X = \alpha \wedge Y = \beta] = P[X = \alpha] \cdot P[Y = \beta]$

ex. $\Omega = \{HH, HT, TH, TT\}$ $P[\omega] = 1/4$

$X = \begin{matrix} 1 & 1 & 0 & 0 \end{matrix}$ } $X = \text{first coin}$
 $Y = \begin{matrix} 0 & 1 & 0 & 1 \end{matrix}$ } $Y = \text{second coin}$ } \Rightarrow independent

$A \in \mathcal{P}$ event, $P[A] \neq 0$

def. (Ω, \mathcal{P}) , X rand. var. The expectation of X is $E[X] := \sum_{\omega \in \Omega} X(\omega) \cdot P[\omega]$

The conditional expectation of X conditioned on A is

$E[X | A] := \sum_{\omega \in \Omega} X(\omega) \cdot P[\omega | A] = \sum_{\omega \in A} \frac{X(\omega) \cdot P[\omega]}{P[A]}$

lem. X, Y independent $\Rightarrow E[XY] = E[X] \cdot E[Y]$ // exercise II

lem. X, Y arbitrary $E[X+Y] = E[X] + E[Y]$ // exercise II

def. if X rand. var. is $X: \Omega \rightarrow \{0, 1\}$ it is a binary random variable

if $A \in \mathcal{P}$ and $X(\omega) = \mathbb{1}\{\omega \in A\}$ then X is an indicator random variable

lem. $X = \mathbb{1}_{A_i}$. Then $E[X] = P[A] = \sum_{\omega \in A} P[\omega]$

part 0 = to compute $E[X]$ should write $X = \sum X_i \Rightarrow E[X] = \sum P[A_i]$
 $= \mathbb{1}_{A_i}$

$\text{rand}(k) \rightarrow [0, 1, \dots, k-1]$ uniform dist

Q: how to model randomized algo?

models: deterministic: deterministic algo f
 worst case input x
 $x \mapsto f(x)$
 complexity: $T(n) = \max_{|x|=n} T(x)$

probabilistic: deterministic f
 $x \leftarrow \mathcal{D}_n$ input \mathbb{I} distribution \mathbb{I}
 $x \mapsto f(x)$
 complexity: $T(n) = \mathbb{E}_{x \leftarrow \mathcal{D}_n} T(x)$
 remark: - \mathcal{D} often unknown in real life

randomized algo: randomized algo f ← algo creates randomness via $\text{rand}(\cdot)$
 worst case input: x [not random]
 $x \mapsto f(x)$ ← random var
 complexity $T(n) = \max_{|x|=n} \mathbb{E}[T(x)]$
 remark: "right" worst case notion

def: f randomized algo, The error probability of L
 - wrt x : $E(x) := \Pr_{\text{randomness of } f} [f(x) \text{ is in error}]$
 - worst case: $E(n) := \max_{|x|=n} E(x)$

def: A Las Vegas algo - $E(n) = 0$ \mathbb{I} no error
 $T(n) \leq n^{O(1)}$ fast expected runtime

def: A Monte Carlo algo - $\forall x, T(x) \leq |x|^{O(1)}$ w/p 1 \mathbb{I} always fast
 $E(n)$ is "small" $\leq 1/3$ \mathbb{I} okay
 $\leq 1/n$ \mathbb{I} pretty good
 $\leq 1/2^n$ \mathbb{I} essentially always right but often overkill

Remark: - Las Vegas is "almost" deterministic
 - real power comes from $E(n) > 0$
 - $E(n) \leq 1/2^{100}$ is "deterministic" in practice.

fact: any efficient randomized algo is wlog Monte Carlo \mathbb{I} it's all about the error

Q: example?

Quicksort $(a_1, \dots, a_n) = \bar{a}$ \mathbb{I} sort \bar{a}
 pick pivot a_{i_0} \mathbb{I} somehow
 partition $\bar{a} = (\bar{b}, a_{i_0}, \bar{c})$ w/ $b_j < a_{i_0} < c_k$
 return $(\text{quicksort}(\bar{b}), a_{i_0}, \text{quicksort}(\bar{c}))$

correctness: clear

complexity = $j = \text{rank}(a_{i_0}) \Rightarrow |\bar{b}| = j-1 \quad |\bar{c}| = n-j$
 $T(n) \leq O(n) + T(j-1) + T(n-j)$
 $\leq \dots \leq O(n^2)$

and: if $j \neq 1$ always $T(n) \geq \Omega(n^2)$

main issue: choose ^{pivot} a_{i_0} so $\text{rank}(a_{i_0}) \leq n/2$ \parallel live a balanced life \parallel

lem: pick a_{i_0} via $i_0 = \text{rand}(n) + 1 \in \{1, \dots, n\}$ \parallel will not be so favored \parallel

$\Rightarrow \text{rank}(a_{i_0}) \in [n/6, 5n/6]$ w/p $2/3$ \parallel w/ $\text{rand}(\cdot)$ in future \parallel

" \Rightarrow " $T(n) \leq T(n/6) + T(5n/6) + O(n)$ "with probability $2/3$ "

$\leq \dots \leq O(n \lg n)$ \leftarrow not a formal proof

fact: can select a_{i_0} w/ $\text{rank}(a_{i_0}) = \lfloor n/2 \rfloor$ in $O(n)$ time \leftarrow median

RMK: $\Rightarrow O(n \lg n)$ deterministic quicksort

- but is not as efficient / simple as randomized case

thm: randomized quicksort w/ $i_0 = \text{rand}(n) + 1$

- error probability 0 \parallel concentrates \parallel

- for all \bar{a} , $\mathbb{E}[T(\bar{a}_1, \dots, \bar{a}_n)] \leq O(n \lg n)$

\parallel complexity \parallel

\parallel worst case \parallel

\parallel may run in n^2 time in worst case \parallel

pf: $T(\bar{a}) = \#$ comparisions \parallel main bulk of work \parallel

$\Omega =$ all calls to $\text{rand}(\cdot)$ \parallel complicated \parallel \parallel how to decompose? \parallel

$\bar{a} \mapsto (\bar{b}, a_{i_0}, \bar{c})$

\leftarrow rand var

\parallel linearity \parallel

$\mathbb{E}[T(\bar{a})] \leq O(n) + \mathbb{E}[T(\bar{b})] + \mathbb{E}[T(\bar{c})]$

$= O(n) + \sum_{i=1}^n \mathbb{E}[T(\bar{b}) \mid \text{rank}(a_{i_0})=i] \cdot \Pr[\text{rank}=i] + \sum_{i=1}^n \mathbb{E}[T(\bar{c}) \mid \text{rank}=i] \cdot \Pr[\text{rank}=i]$
 $= \mathbb{E}[T(\bar{b}) \mid \text{rank}(a_{i_0})=i] \cdot \Pr[\text{rank}=i] \leq T(i-1) = 1/n$
 $\leq T(i-1) = 1/n$

$= O(n) + \frac{1}{n} \sum_{i=1}^n (T(i-1) + T(n-i))$ \leftarrow any \bar{a}

$\Rightarrow T(n) \leq O(n) + \frac{1}{n}$
 $\leq \dots \leftarrow$ post-0
 $\leq O(n \lg n)$

- today:
- probability
 - rand algo
 - quicksort

- next time:
- more quicksort
 - concentration bounds