

P=NP?

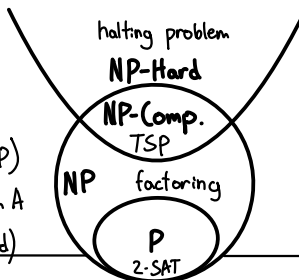
P: solvable in polynomial time

NP: solutions can be verified in polynomial time ('yes solutions')

NP-Hard: at least as hard as the hardest problem in NP (may be outside NP)

• if Problem A is in NP-Hard, every problem in NP can be reduced to Problem A

NP-Complete: problem in NP that all problems can reduce to (NP & NP-Hard)



Reductions

Using a problem that we know how to solve as a subroutine for a different problem

$A \rightarrow B$ implies...

- B is at least as hard as A
- if there is an efficient solver for B, there is an efficient solver for A
- if there is NO efficient solver for A, there is NO efficient solver for B
- a solution to an instance of A exists iff a solution to the corresponding instance of B exists

To prove NP-Complete:

1. Show that the problem is in NP (straight forward)
2. Reduce from the most similar NP-C problem: (1) $\Phi \text{ YES} \Rightarrow \Phi' \text{ YES}$, (2) $\Phi' \text{ YES} \Rightarrow \Phi \text{ YES}$

To prove NP-Hard:

1. Reduce from an NP-Hard problem

Instance I
Problem B

↓ Reduction

Instance I'
Problem A

↓ Algorithm for A

Solution to I'

↓ Reduction

Solution for I

Coping with NP Completeness

Approximate Algorithms: for an instance I of a minimization problem, approximation ratio $\alpha_A = \max_I \frac{A(I)}{\text{OPT}(I)}$

Vertex Cover: Find a maximal matching (disjoint edges) M. return all endpoints in M. $\text{OPT} \geq \# \text{ of edges in M} \Rightarrow \alpha_A = 2$

Metric TSP: Find an MST T, run DFS on T, skip all repeated vertices in traversal. $\text{OPT} \geq \text{MST} \Rightarrow 2 \text{OPT} \geq A \Rightarrow \alpha_A = 2$

Randomized Algorithms

Behavior of algorithm changes based on a random string r

Las Vegas:

• Correctness is guaranteed

• Runtime is random

• Goal: Analyze expected worst-case runtime: $T(n) = \max_x [E_r(x, n)]$; show that runtime is low with high probability

Monte Carlo:

• Correctness is random

• Runtime is always bounded

• Goal: Output a number that is close to true value with high probability

$$** (1-p)^{\binom{10}{p}} \leq e^{(-10)} \leq 0.001$$

* expected # of events
= sum of probabilities
of each event

Linearity of Indicators and Indicators: (1) $E[X + Y] = E[X] + E[Y]$, (2) $E[cX] = cE[X]$, (3) $E[\sum x_i] = \sum E[x_i]$

QuickSelect (Las Vegas): Unsorted List \rightarrow Median, pick random pivot, $T(n) \leq cn + \frac{1}{2} T(3n/4) + \frac{1}{2} T(n/4) \rightarrow E[T(n)] = O(n)$

One-Sided Error: YES \Rightarrow YES, NO \Rightarrow NO with probability p, to get $\Pr(\text{Success}) \geq 0.999$, for i in range $(10/p)$ {if ALG == NO, ret NO; ret YES} **

Two-Sided Error: ALG outputs correct with probability $\frac{1}{2} + \epsilon$, $0.999 \rightarrow$ for i in range $(1/\epsilon^2)$ {record ALG output} ret majority

- Amplification: $\Pr(S) = p$, $\Pr(F) = 1-p = q$, $\Pr(\text{all } F) = q^k$
we want $q^k \leq \delta \rightarrow k \ln q \leq \ln \delta \rightarrow k \geq \frac{\ln(1/\delta)}{\ln(1/q)}$
use $1-x \leq e^{-x} \rightarrow k \geq \frac{1}{p} \ln \frac{1}{\delta}$, $\delta = 0.001 \rightarrow k \geq 6.9/p$
- Union Bound: $\Pr\left[\bigcup_{i=1}^n A_i\right] \leq \sum_{i=1}^n \Pr[A_i]$
- $\sum_{k=0}^{\infty} ar^k = \frac{a(1-r^n)}{1-r}$

Primality Testing (Monte Carlo): Pick a random x from $1, \dots, N-1$, check if $x^{N-1} \equiv 1 \pmod{N}$, if so ret PRIME, c.t. $\rightarrow p \geq 1/2$

Karger's Algorithm (Monte Carlo): Pick a random edge, contract, until 2 vertices left; e left $\geq [(n-i+1) + |C|]/2$, $\Pr(C) = 2/(n-i+1)$

• $\Pr(\text{Success}) \geq \prod_{i=1}^{n-2} (1 - \frac{2}{n-i+1}) = 1/\binom{n}{2}$

Online Algorithms

Regret: Alg's # of mistakes - OPT (# of mistakes by best expert); $\sum_{t=1}^T 1(\text{guess}^{(t)} \neq \text{real}^{(t)}) \lesssim \min \sum_{t=1}^T 1(o_t^{(t)} \neq \text{real}^{(t)})$

Halving Algorithm: for at least one perfect expert, $T = O(\log n)$, regret = $O(\log n)$

Weighted Majority: penalize incorrect experts $w_i^{(t+1)} \leftarrow w_i^{(t)}(1 - \epsilon)$, else $w_i^{(t)}$, $\epsilon = 0.5 \rightarrow E[r] \leq 1.4 \text{OPT} + 2.4 \log(n)$

Random Weighted Majority: no regret for the right eps, samples expert at random using weighted distribution rather than choosing the expert with the largest weight, experts' behavior is NOT randomized

MW Guarantee: $E[C_{\text{ALG}}(T)] \leq \min_i C_i(T) + O(\sqrt{T \log N})$ or $E[\text{Regret}(T)] = E[C_{\text{ALG}}(T) - \text{OPT}] \leq O(\sqrt{T \log N})$

asymptotics

$$\left. \begin{aligned} \cdot f(n) &= O(g(n)) \\ \cdot f(n) &= \Theta(g(n)) \\ \cdot f(n) &= \Omega(g(n)) \end{aligned} \right\} \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \begin{cases} < \infty \\ = c \\ > 0 \end{cases}$$

exponential > polynomial > logarithm
 $3^n > 2^n > n^5 > n^4 > n^3 > (\log n)^3 > (\log n)^2 > \log \log n$
 • try substitution! or L'Hopital's!

maths

$$\begin{aligned} \cdot \log_b(M^k) &= k \cdot \log_b M \\ \cdot \log_b(b^k) &= k \\ \cdot a^{\log_b n} &= n^{\log_b a} \\ \cdot \log_b n &= \frac{\ln n}{\ln b} \end{aligned}$$

$$\begin{aligned} \cdot \log_b(M \cdot N) &= \log_b M + \log_b N \\ \cdot \log_b(M/N) &= \log_b M - \log_b N \\ \cdot \frac{1}{\log_a b} &= \log_b a \\ \cdot \sum_{j=1}^K \frac{1}{j} &= \log K \end{aligned}$$

$$\begin{aligned} \cdot \ln n &\rightarrow \frac{1}{n} \\ \cdot a^n &\rightarrow a^n \ln n \\ \cdot (\ln n)^k &\rightarrow k(\ln n)^{k-1}/n \\ \cdot n \log n &\rightarrow \log n \end{aligned}$$

$$\begin{aligned} \cdot 1 + 2 + \dots + n &= O(n^2) \\ \cdot 1 + \frac{1}{2} + \dots + \frac{1}{n} &= O(\log n) \\ \cdot a + ar + \dots + ar^n &= \frac{a(1-r^{n+1})}{1-r} \\ \cdot 1 + p + p^2 + \dots + p^k &= \frac{p^{k+1} - 1}{p - 1} \\ \cdot \text{inf geometric} &\rightarrow \frac{a}{1-r} \end{aligned}$$

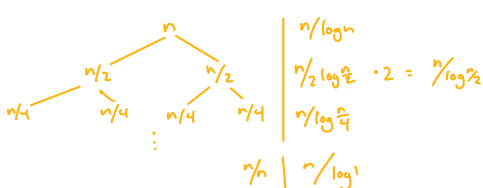
master's theorem

$$T(n) = aT(n/b) + O(n^d)$$

$$\begin{aligned} &> O(n^d) \\ d = \log_b a & O(n^d \log n) \\ < & O(n^{\log_b a}) \end{aligned}$$

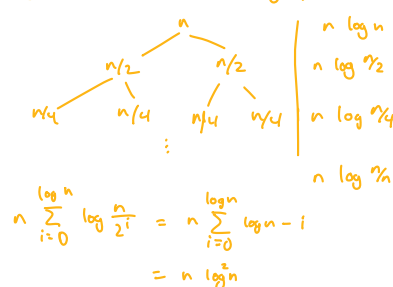
rec method

$$T(n) = 2T(n/2) + O(n) \quad w/ T(1)=1$$



$$\begin{aligned} n \sum_{j=0}^{\log n} \frac{1}{2^j} &= n \sum_{j=0}^{\log n} \frac{1}{\log n - j} \\ &= n \sum_{j=0}^{\log n} \frac{1}{\log n - j} \\ &= n \left(\sum_{i=1}^{\log n} \frac{1}{i} \right) \\ &= n \log \log n \end{aligned}$$

$$T(n) = 2T(n/2) + O(n \log n)$$



$$\begin{aligned} n \sum_{i=0}^{\log n} \log \frac{n}{2^i} &= n \sum_{i=0}^{\log n} \log n - i \\ &= n \log^2 n \end{aligned}$$

squeeze + guess & check

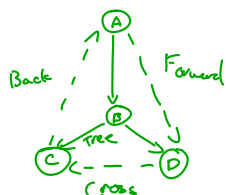
$$\begin{aligned} \cdot \text{guess U/L bounds} \\ T(n) &= T(3n/5) + T(4n/5) \\ \text{guess } a \cdot n^b, a=1 \text{ since } T(1)=1 \\ T(n) &= n^b: \left(\frac{3n}{5}\right)^b + \left(\frac{4n}{5}\right)^b \\ \Rightarrow b &= 2 \end{aligned}$$

change of variables

$$T(n) = 2T(\sqrt{n}) + O(\log n)$$

$$\begin{aligned} m &= \log n \\ T(2^m) &= 2T(2^{m/2}) + O(m) \\ S(m) &= T(2^m) \\ S(m) &= 2S(m/2) + O(m) \\ \Rightarrow S(m) &= m \log m \\ T(2^m) &= m \log m \\ T(2^{\log n}) &= T(n) = \log n \log \log n \end{aligned}$$

$$\begin{aligned} T(n) &= T(\sqrt{n}) + 1 \\ m &= \log n \\ T(2^m) &= T(2^{m/2}) + 1 \\ S(m) &= T(2^m) \\ S(m) &= S(m/2) + 1 \\ \Rightarrow S(m) &= \log m \\ T(2^m) &= \log m \\ T(2^{\log n}) &= T(n) = \log \log n \end{aligned}$$



Tree/Forward if $\begin{bmatrix} \cdot & \cdot \\ u & v \end{bmatrix}$
 $pre(u) < pre(v) < post(v) < post(u)$
 Back if $\begin{bmatrix} \cdot & \cdot \\ v & u \end{bmatrix}$
 $pre(v) < pre(u) < post(u) < post(v)$
 cross if: $\begin{bmatrix} \cdot & \cdot \\ v & u \end{bmatrix}$
 $pre(v) < post(v) < pre(u) < post(u)$

BFS/DFS: $O(|V| + |E|)$

Kosarajus: $O(|V| + |E|)$

- run DFS
- run DFS on G^R w/ decreasing post-order

Dijkstra's: $O((|E| + |V|) \log |V|)$

- init dist = ∞ , par = None
- dist(s) = 0, add to minH
- update all neighbors of first

Bellman-Ford: $O(|V||E|)$

- works w/ neg edges!
- repeat $|V| - 1$ times:
- for each e in E :
- update dist(v)