Function Problems

- Decision problems are yes/no problems (SAT, TSP (D), etc.).
- **Function problems** require a solution (a satisfying truth assignment, a best TSP tour, etc.).
- Optimization problems are clearly function problems.
- What is the relation between function and decision problems?
- Which one is harder?

Function Problems Cannot Be Easier than Decision Problems

- If we know how to generate a solution, we can solve the corresponding decision problem.
  - If you can find a satisfying truth assignment efficiently, then SAT is in P.
  - If you can find the best TSP tour efficiently, then TSP (D) is in P.
- But we shall see that decision problems can be as hard as the corresponding function problems. immediately.

FSAT

- FSAT is this function problem:
  - Let $\phi(x_1, x_2, \ldots, x_n)$ be a boolean expression.
  - If ϕ is satisfiable, then return a satisfying truth assignment.
  - Otherwise, return "no."
- We next show that if SAT $\in$ P, then FSAT has a polynomial-time algorithm.
- SAT is a subroutine (black box) that returns "yes" or "no" on the satisfiability of the input.

An Algorithm for FSAT Using SAT

```
t := ϵ; {Truth assignment.}
if φ ∈ SAT then
    for i = 1, 2, ..., n do
        if φ[ x_i = true ] ∈ SAT then
            t := t ∪ { x_i = true };
            φ := φ[ x_i = true ];
        else
            t := t ∪ { x_i = false };
            φ := φ[ x_i = false ];
        end if
    end for
    return t;
else
    return "no";
end if
```

Analysis

- If SAT can be solved in polynomial time, so can FSAT.
  - There are $\leq n + 1$ calls to the algorithm for SAT.[a]
  - Boolean expressions shorter than ϕ are used in each call to the algorithm for SAT.
- Hence SAT and FSAT are equally hard (or easy).

[a] Contributed by Ms. Eva Ou (R93922132) on November 24, 2004.

Analysis (concluded)

- Note that this reduction from FSAT to SAT is not a Karp reduction.[a]
  - Will the set of NP-complete problems differ under different reductions?[b]
- Instead, it calls SAT multiple times as a subroutine, and its answers guide the search on the computation tree.

---

[a] Recall p. 275 and p. 280.

[b] Contributed by Mr. Yu-Ming Lu (R06723032, D08922008) and Mr. Han-Ting Chen (R10922073) on December 9, 2021.

TSP and TSP (D) Revisited

- We are given n cities $1, 2, \ldots, n$ and integer distances $d_{ij} = d_{ji}$ between any two cities i and j.
- TSP (D) asks if there is a tour with a total distance at most B.
- TSP asks for a tour with the shortest total distance.
  - The shortest total distance is at most $\sum_{i,j} d_{ij}$.
    - Recall that the input string contains $d_{11}, \ldots, d_{nn}$.
- Thus the shortest total distance is less than $2^{|\,x\,|}$ in magnitude, where x is the input (why?).
- We next show that if TSP (D) $\in$ P, then TSP has a polynomial-time algorithm.

An Algorithm for TSP Using TSP (D)

Perform a binary search over interval $[\,0, 2^{|\,x\,|}\,]$ by calling TSP (D) to obtain the shortest distance, C;
for $i, j = 1, 2, \ldots, n$ **do**
    Call TSP (D) with $B = C$ and $d_{ij} = C + 1$;
    if "no" **then**
        Restore d_{ij} to its old value; {Edge $[\,i, j\,]$ is critical.}
    end if
end for
return the tour with edges whose $d_{ij} \leq C$;

Analysis

- An edge which is not on *any* remaining optimal tours will be eliminated, with its d_{ij} set to $C+1$.
- So the algorithm ends with n edges which are not eliminated (why?).
- This is true even if there are multiple optimal tours![a]

[a]Thanks to a lively class discussion on November 12, 2013 and December 9, 2021.

Analysis (concluded)

- There are $O(|x| + n^2)$ calls to the algorithm for TSP (D).
- Each call has an input length of $O(|x|)$.
- So if TSP (D) can be solved in polynomial time, so can TSP.
- Hence TSP (D) and TSP are equally hard (or easy).[a]

[a]How about counting the number of optimal TSP tours? This is related to #P-completeness (p. 874). Contributed by Mr. Vincent Hwang (R10922138) on December 9, 2021.

Randomized Computation

I know that half my advertising works,
I just don't know which half.
— John Wanamaker

I know that half my advertising is
a waste of money,
I just don't know which half!
— McGraw-Hill ad.

Randomized Algorithms[a]

- Randomized algorithms flip unbiased coins.
- There are important problems for which there are no known efficient *deterministic* algorithms but for which very efficient randomized algorithms exist.
  - Extraction of square roots, for instance.
- There are problems where randomization is *necessary*.
  - Secure protocols.
- Randomized version can be more efficient.
  - Parallel algorithms for maximal independent set.[b]

---

[a] Rabin (1976); Solovay & Strassen (1977).

[b] "Maximal" (a local maximum) not "maximum" (a global maximum).

Randomized Algorithms (concluded)

- Are randomized algorithms algorithms?[a]
- Coin flips are occasionally used in politics.[b]

---

[a]Pascal, "Truth is so delicate that one has only to depart the least bit from it to fall into error."

[b]In the 2016 Iowa Democratic caucuses, e.g. (see `http://edition.cnn.com/2016/02/02/politics/hillary-clinton-coin-flip-iowa-bernie-sanders/index.html`).

"Four Most Important Randomized Algorithms"[a]

1. Primality testing.[b]

2. Graph connectivity using random walks.[c]

3. Polynomial identity testing.[d]

4. Algorithms for approximate counting.[e]

---

[a]Trevisan (2006).

[b]Rabin (1976); Solovay & Strassen (1977).

[c]Aleliunas, Karp, Lipton, Lovász, & Rackoff (1979).

[d]Schwartz (1980); Zippel (1979).

[e]Sinclair & Jerrum (1989).

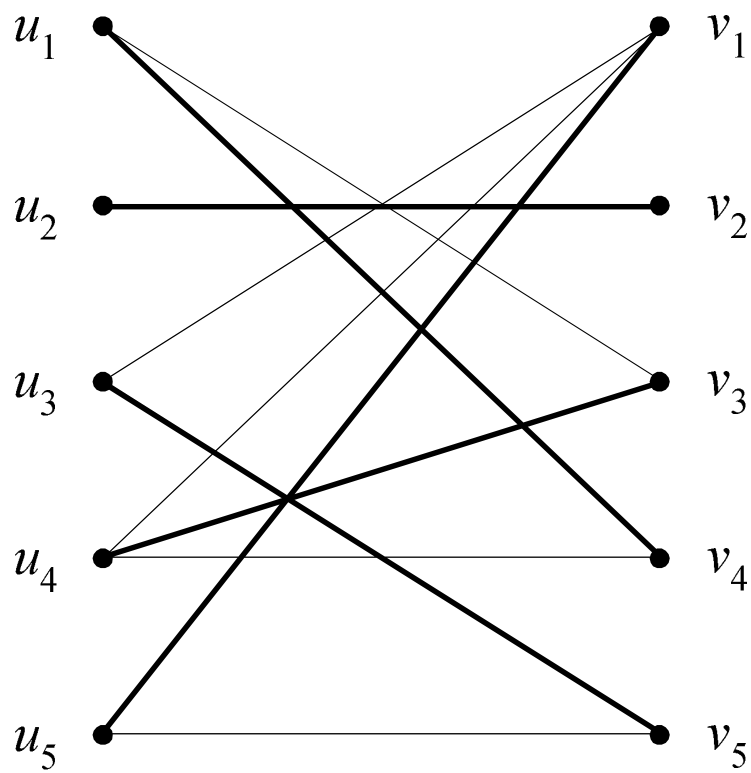
Bipartite Perfect Matching

- We are given a **bipartite graph** $G = (U, V, E)$.
  - $U = \{ u_1, u_2, \ldots, u_n \}$.
  - $V = \{ v_1, v_2, \ldots, v_n \}$.
  - $E \subseteq U \times V$.
- We are asked if there is a **perfect matching**.
  - A permutation π of $\{ 1, 2, \ldots, n \}$ such that

$$(u_i, v_{\pi(i)}) \in E$$

    for all $i \in \{ 1, 2, \ldots, n \}$.
- A perfect matching contains n edges.

A Perfect Matching in a Bipartite Graph



Symbolic Determinants

- We are given a bipartite graph G.
- Construct the $n \times n$ matrix A^G whose (i, j)th entry A^G_{ij} is a symbolic variable x_{ij} if $(u_i, v_j) \in E$ and 0 otherwise:

$$A^G_{ij} = \begin{cases} x_{ij}, & \text{if } (u_i, v_j) \in E, \\ 0, & \text{otherwise.} \end{cases}$$

Symbolic Determinants (continued)

- The matrix for the bipartite graph G on p. 533 is[a]

$$A^G = \begin{bmatrix} 0 & 0 & x_{13} & x_{14} & 0 \\ 0 & x_{22} & 0 & 0 & 0 \\ x_{31} & 0 & 0 & 0 & x_{35} \\ x_{41} & 0 & x_{43} & x_{44} & 0 \\ x_{51} & 0 & 0 & 0 & x_{55} \end{bmatrix}. \qquad (8)$$

[a]The idea is similar to the Tanner (1981) graph in coding theory.

Symbolic Determinants (concluded)

- The **determinant** of A^G is

$$\det(A^G) = \sum_{\pi} \operatorname{sgn}(\pi) \prod_{i=1}^{n} A^G_{i,\pi(i)}. \tag{9}$$

  - π ranges over all permutations of n elements.
  - $\operatorname{sgn}(\pi)$ is 1 if π is the product of an even number of transpositions and -1 otherwise.[a]

- $\det(A^G)$ contains $n!$ terms, many of which may be 0s.

---

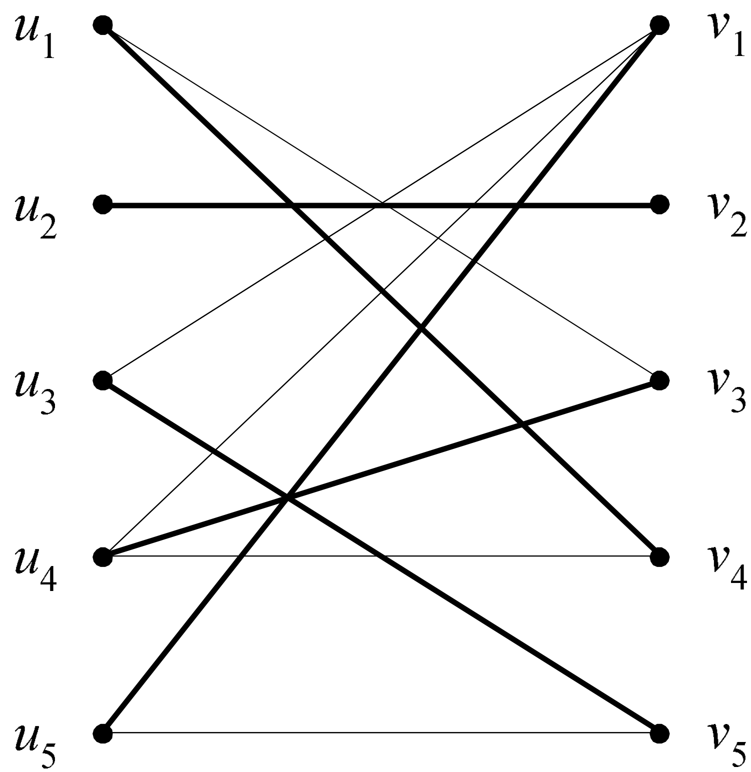
[a]Equivalently, $\operatorname{sgn}(\pi) = 1$ if the number of (i, j)s such that $i < j$ and $\pi(i) > \pi(j)$ is even. Contributed by Mr. Hwan-Jeu Yu (`D95922028`) on May 1, 2008.

Determinant and Bipartite Perfect Matching

- In $\sum_{\pi} \text{sgn}(\pi) \prod_{i=1}^{n} A^G_{i,\pi(i)}$, note the following:
  - Each summand corresponds to a possible perfect matching π.
  - Nonzero summands $\prod_{i=1}^{n} A^G_{i,\pi(i)}$ are distinct monomials and *will not cancel*.
- $\det(A^G)$ is essentially an exhaustive enumeration.

Proposition 65 (Edmonds, 1967) *G has a perfect matching if and only if* $\det(A^G)$ *is not identically zero.*

Perfect Matching and Determinant (p. 533)



Perfect Matching and Determinant (concluded)

- The matrix is (p. 535)

$$A^G = \begin{bmatrix} 0 & 0 & x_{13} & \boxed{x_{14}} & 0 \\ 0 & \boxed{x_{22}} & 0 & 0 & 0 \\ x_{31} & 0 & 0 & 0 & \boxed{x_{35}} \\ x_{41} & 0 & \boxed{x_{43}} & x_{44} & 0 \\ \boxed{x_{51}} & 0 & 0 & 0 & x_{55} \end{bmatrix}.$$

- $\det(A^G) = -x_{14}x_{22}x_{35}x_{43}x_{51} + x_{13}x_{22}x_{35}x_{44}x_{51} + x_{14}x_{22}x_{31}x_{43}x_{55} - x_{13}x_{22}x_{31}x_{44}x_{55}$.
- Each nonzero term denotes a perfect matching, and vice versa.

How To Test If a Polynomial Is Identically Zero?

- $\det(A^G)$ is a polynomial in n^2 variables.
- It has, potentially, exponentially many terms.
- Expanding the determinant polynomial is thus infeasible.
- If $\det(A^G) \equiv 0$, then it remains zero if we substitute *arbitrary* integers for the variables $x_{11}, \ldots, x_{nn}$.
- When $\det(A^G) \not\equiv 0$, what is the likelihood of obtaining a zero?

Number of Roots of a Polynomial

Lemma 66 (Schwartz, 1980) *Let* $p(x_1, x_2, \ldots, x_m) \not\equiv 0$ *be a polynomial in* m *variables each of degree at most* d*. Let* $M \in \mathbb{Z}^+$*. Then the number of* m*-tuples*

$$(x_1, x_2, \ldots, x_m) \in \{ 0, 1, \ldots, M-1 \}^m$$

such that $p(x_1, x_2, \ldots, x_m) = 0$ *is*

$$\leq mdM^{m-1}.$$

- By induction on m (consult the textbook).

Density Attack

- The density of roots in the domain is at most

$$\frac{mdM^{m-1}}{M^m} = \frac{md}{M}. \tag{10}$$

- So suppose $p(x_1, x_2, \ldots, x_m) \not\equiv 0$.
- Then a random

$$(x_1, x_2, \ldots, x_m) \in \{ 0, 1, \ldots, M-1 \}^m$$

has a probability of $\leq md/M$ of being a root of p.

- Note that M is under our control!
  - One can raise M to lower the error probability, e.g.

Density Attack (concluded)

Here is a sampling algorithm to test if $p(x_1, x_2, \ldots, x_m) \not\equiv 0$.

Choose $i_1, \ldots, i_m$ from $\{ 0, 1, \ldots, M-1 \}$ randomly;
if $p(i_1, i_2, \ldots, i_m) \neq 0$ **then**
    return "p is not identically zero";
else
    return "p is (probably) identically zero";
end if

Analysis

- If $p(x_1, x_2, \ldots, x_m) \equiv 0$, the algorithm will always be correct as $p(i_1, i_2, \ldots, i_m) = 0$.
- Suppose $p(x_1, x_2, \ldots, x_m) \not\equiv 0$.
  - The algorithm will answer incorrectly with probability at most md/M by Eq. (10) on p. 542.
- We next return to the original problem of bipartite perfect matching.

A Randomized Bipartite Perfect Matching Algorithm[a]

Choose n^2 integers $i_{11}, \ldots, i_{nn}$ from $\{ 0, 1, \ldots, 2n^2 - 1 \}$ randomly; {So $M = 2n^2$.}
Calculate $\det(A^G(i_{11}, \ldots, i_{nn}))$ by Gaussian elimination;
if $\det(A^G(i_{11}, \ldots, i_{nn})) \neq 0$ **then**
    return "G has a perfect matching";
else
    return "G has (probably) no perfect matchings";
end if

---

[a]Lovász (1979). According to Paul Erdős, Lovász wrote his first significant paper "at the ripe old age of 17."

Analysis

- If G has no perfect matchings, the algorithm will always be correct as $\det(A^G(i_{11}, \ldots, i_{nn})) = 0$.
- Suppose G has a perfect matching.
  - The algorithm will answer incorrectly with probability at most $md/M = 0.5$ with $m = n^2$, $d = 1$ and $M = 2n^2$ in Eq. (10) on p. 542.
- Run the algorithm *independently* k times.
- Output "G has no perfect matchings" if and only if *all* say "(probably) no perfect matchings."
- The error probability is now reduced to at most 2^{-k}.

Lószló Lovász (1948–)

Remarks[a]

- Note that we calculated

$$\text{prob}[\,\text{algorithm answers "no"} \,|\, G \text{ has no perfect matchings}\,],$$
$$\text{prob}[\,\text{algorithm answers "yes"} \,|\, G \text{ has a perfect matching}\,].$$

  - And they are 1 and $\geq 1/2$, respectively.

- We did *not* calculate[b]

$$\text{prob}[\,G \text{ has no perfect matchings} \,|\, \text{algorithm answers "no"}\,],$$
$$\text{prob}[\,G \text{ has a perfect matching} \,|\, \text{algorithm answers "yes"}\,].$$

[a] Thanks to a lively class discussion on May 1, 2008.

[b] *Numerical Recipes in C* (1988), "statistics is *not* a branch of mathematics!" Similar issues arise in MAP (maximum a posteriori) estimates and ML (maximum likelihood) estimates.

But How Large Can det$(A^G(i_{11}, \ldots, i_{nn}))$ Be?

- It is at most[a]

$$n! \left(2n^2\right)^n.$$

- Stirling's formula says $n! \sim \sqrt{2\pi n}\,(n/e)^n$.
- Hence

$$\log_2 \det(A^G(i_{11}, \ldots, i_{nn})) = O(n \log_2 n)$$

bits are sufficient for representing the determinant.

- We skip the details about how to make sure that all *intermediate* results are of polynomial size.

---

[a]In fact, it can be lowered to $2^{O(\log^2 n)}$ (Csanky, 1975)!

An Intriguing Question[a]

- Is there an $(i_{11}, \ldots, i_{nn})$ that will always give correct answers for the algorithm on p. 545?
- A theorem on p. 642 shows that such an $(i_{11}, \ldots, i_{nn})$ exists!
  - Whether it can be found efficiently is another matter.
- Once $(i_{11}, \ldots, i_{nn})$ is available, the algorithm can be made deterministic.
  - Is it an algorithm for bipartite perfect matching?[b]

[a]Thanks to a lively class discussion on November 24, 2004.

[b]We have one algorithm for each n — unless there is an algorithm to generate such $(i_{11}, \ldots, i_{nn})$ for all n. Contributed by Mr. Han-Ting Chen (R10922073) on December 9, 2021.

Randomization vs. Nondeterminism[a]

- What are the differences between randomized algorithms and nondeterministic algorithms?
- Think of a randomized algorithm as a nondeterministic one but with a probability associated with every guess/branch.
- So each computation path of a randomized algorithm has a probability associated with it.

---

[a] Contributed by Mr. Olivier Valery (`D01922033`) and Mr. Hasan Alhasan (`D01922034`) on November 27, 2012.

Monte Carlo Algorithms[a]

- The randomized bipartite perfect matching algorithm is called a **Monte Carlo algorithm** in the sense that
  - If the algorithm finds that a matching exists, it is always correct (no **false positives**; no **type I errors**).
  - If the algorithm answers in the negative, then it may make an error (**false negatives**; **type II errors**).
    - And the error probability must be small.

[a]Metropolis & Ulam (1949).

Monte Carlo Algorithms (continued)

- The algorithm makes a false negative with probability ≤ 0.5.[a]
- Again, this probability refers to[b]

  $$\text{prob}[\,\text{algorithm answers "no"} \,|\, G \text{ has a perfect matching}\,]$$

  not

  $$\text{prob}[\,G \text{ has a perfect matching} \,|\, \text{algorithm answers "no"}\,].$$

---

[a] Equivalently, among the coin flip sequences, at most half of them lead to the wrong answer.

[b] In general, prob[algorithm answers "no" | input is a yes instance].

Monte Carlo Algorithms (concluded)

- This probability 0.5 is *not* over the space of all graphs or determinants, but *over* the algorithm's own coin flips.
  - It holds for *any* bipartite graph.
- In contrast, to calculate

  $$\text{prob}[\, G \text{ has a perfect matching} \mid \text{algorithm answers "no"}\,],$$

  we will need the distribution of G.
- But it is an empirical statement that is very hard to verify.

The Markov Inequality[a]

Lemma 67 *Let x be a random variable taking nonnegative integer values. Then for any $k > 0$,*

$$\text{prob}[\, x \geq kE[\, x\,]\,] \leq 1/k.$$

- Let p_i denote the probability that $x = i$.

$$\begin{aligned} E[\, x\,] &= \sum_i ip_i = \sum_{i<kE[\, x\,]} ip_i + \sum_{i \geq kE[\, x\,]} ip_i \\ &\geq \sum_{i \geq kE[\, x\,]} ip_i \geq kE[\, x\,] \sum_{i \geq kE[\, x\,]} p_i \\ &\geq kE[\, x\,] \times \text{prob}[x \geq kE[\, x\,]]. \end{aligned}$$

---

[a] Andrei Andreyevich Markov (1856–1922).

Andrei Andreyevich Markov (1856–1922)

FSAT for k-SAT Formulas (p. 519)

- Let $\phi(x_1, x_2, \ldots, x_n)$ be a k-SAT formula.
- If ϕ is satisfiable, then return a satisfying truth assignment.
- Otherwise, return "no."
- We next propose a randomized algorithm for this problem.

A Random Walk Algorithm for ϕ in CNF Form

Start with an *arbitrary* truth assignment T;
for $i = 1, 2, \ldots, r$ **do**
  if $T \models \phi$ **then**
    return "ϕ is satisfiable with T";
  else
    Let c be an unsatisfied clause in ϕ under T; {All of its literals are false under T.}
    Pick any x of these literals *at random*;
    Modify T to make x true;
  end if
end for
return "ϕ is unsatisfiable";

3SAT vs. 2SAT Again

- Note that if ϕ is unsatisfiable, the algorithm will answer "unsatisfiable."
- The random walk algorithm needs expected exponential time for 3SAT.
  - In fact, it runs in expected $O((1.333\cdots+\epsilon)^n)$ time with $r = 3n$,[a] much better than $O(2^n)$.[b]
- We will show immediately that it works well for 2SAT.
- The state of the art as of 2014 is expected $O(1.30704^n)$ time for 3SAT and expected $O(1.46899^n)$ time for 4SAT.[c]

---

[a] Use this setting per run of the algorithm.

[b] Schöning (1999). Makino, Tamaki, & Yamamoto (2011) improve the bound to deterministic $O(1.3303^n)$.

[c] Hertli (2014).

Random Walk Works for 2SAT[a]

Theorem 68 *Suppose the random walk algorithm with $r = 2n^2$ is applied to any satisfiable* 2SAT *problem with n variables. Then a satisfying truth assignment will be discovered with probability at least 0.5.*

- Let $\hat{T}$ be a truth assignment such that $\hat{T} \models \phi$.
- Assume our starting T differs from $\hat{T}$ in i values.
  - Their Hamming distance is i.
- Recall T is arbitrary.

[a]Papadimitriou (1991).

The Proof

- Let $t(i)$ denote the expected number of repetitions of the flipping step[a] until a satisfying truth assignment is found.
- It can be shown that $t(i)$ is finite.
- $t(0) = 0$ because it means that $T = \hat{T}$ and hence $T \models \phi$.
- If $T \neq \hat{T}$ or any other satisfying truth assignment, then we need to flip the coin at least once.
- We flip a coin to pick among the 2 literals of a clause not satisfied by the present T.
- At least one of the 2 literals is true under $\hat{T}$ because $\hat{T}$ satisfies all clauses.

[a] That is, Statement 7.

The Proof (continued)

- So we have at least a 50% chance of moving closer to $\hat{T}$.
- Thus
$$t(i) \leq \frac{t(i-1)+t(i+1)}{2}+1$$
for $0 < i < n$.
  - Inequality is used because, for example, T may differ from $\hat{T}$ in both literals.
- It must also hold that
$$t(n) \leq t(n-1)+1$$
because at $i = n$, we can only decrease i.

The Proof (continued)

- Now, put the necessary relations together:

$$t(0) = 0, \tag{11}$$

$$t(i) \leq \frac{t(i-1)+t(i+1)}{2} + 1, \quad 0 < i < n, \tag{12}$$

$$t(n) \leq t(n-1)+1. \tag{13}$$

- Technically, this is a one-dimensional random walk with an absorbing barrier at $i = 0$ and a reflecting barrier at $i = n$ (if we replace "$\leq$" with "$=$").[a]

[a]The proof in the textbook does exactly that. But a student pointed out difficulties with this proof technique on December 8, 2004. So our proof here uses the original inequalities.

The Proof (continued)

- Add up the relations for $2t(1), 2t(2), 2t(3), \ldots, 2t(n-1), t(n)$ to obtain[a]

$$\begin{aligned} & 2t(1) + 2t(2) + \cdots + 2t(n-1) + t(n) \\ \leq \;& t(0) + t(1) + 2t(2) + \cdots + 2t(n-2) + 2t(n-1) + t(n) \\ & +2(n-1) + 1. \end{aligned}$$

- Simplify it to yield

$$t(1) \leq 2n - 1. \tag{14}$$

[a] Adding up the relations for $t(1), t(2), t(3), \ldots, t(n-1)$ will also work, thanks to Mr. Yen-Wu Ti (D91922010).

The Proof (continued)

- Add up the relations for $2t(2), 2t(3), \ldots, 2t(n-1), t(n)$ to obtain

$$\begin{aligned} & 2t(2) + \cdots + 2t(n-1) + t(n) \\ \leq \;& t(1) + t(2) + 2t(3) + \cdots + 2t(n-2) + 2t(n-1) + t(n) \\ & +2(n-2) + 1. \end{aligned}$$

- Simplify it to yield

$$t(2) \leq t(1) + 2n - 3 \leq 2n - 1 + 2n - 3 = 4n - 4$$

by Eq. (14) on p. 564.

The Proof (continued)

- Continuing the process, we shall obtain[a]

$$t(i) \leq 2in - i^2.$$

- The worst upper bound happens when $i = n$, in which case

$$t(n) \leq n^2.$$

- We conclude that

$$t(i) \leq t(n) \leq n^2$$

for $0 \leq i \leq n$.

[a]See also Feller (1968).

The Proof (concluded)

- So the expected number of steps is at most n^2.
- The algorithm picks $r = 2n^2$.
- Apply the Markov inequality (p. 555) with $k = 2$ to yield the desired probability of 0.5.
- The proof does *not* yield a polynomial bound for 3SAT.[a]

[a] Contributed by Mr. Cheng-Yu Lee (`R95922035`) on November 8, 2006.

Boosting the Performance

- We can pick $r = 2mn^2$ to have an error probability of
$$\leq \frac{1}{2m}$$
by Markov's inequality.

- Alternatively, with the same running time, we can run the "$r = 2n^2$" algorithm m times.

- The error probability is now reduced to
$$\leq 2^{-m}.$$

Primality Tests

- $\textsc{primes}$ asks if a number N is a prime.
- The classic algorithm tests if $k \mid N$ for $k = 2, 3, \ldots, \sqrt{N}$.
- But it runs in $\Omega(2^{(\log_2 N)/2})$ steps.
- $\textsc{compositeness}$ asks if a number is composite.

The Fermat Test for Primality

Fermat's "little" theorem (p. 505) suggests the following primality test for any given number N:

```
Pick a number a randomly from { 1, 2, ..., N − 1 };
if a^(N−1) ≢ 1 mod N then
    return "N is composite";
else
    return "N is (probably) a prime";
end if
```

The Fermat Test for Primality (continued)

- **Carmichael numbers** are composite numbers that will pass the Fermat test for *all* $a \in \{ 1, 2, \ldots, N-1 \}$.[a]
  - The Fermat test will return "N is a prime" for all Carmichael numbers N.
- If there are finitely many Carmichael numbers, store them for matches before running the Fermat test.
- Unfortunately, there are infinitely many such numbers.[b]
  - The number of Carmichael numbers less than N exceeds $N^{2/7}$ for N large enough.

---

[a] Carmichael (1910). Lo (1994) mentions an investment strategy based on such numbers!

[b] Alford, Granville, & Pomerance (1992).

The Fermat Test for Primality (concluded)

- The Fermat test will fail all of them.
- So the Fermat test is an *incorrect* algorithm for PRIMES.
- Even suppose N is not a Carmichael number but remains composite.
- We need many $a \in \{ 1, 2, \ldots, N-1 \}$ such that $a^{N-1} \not\equiv 1 \bmod N$.
- Otherwise, the correct answer will come only with a vanishing probability (say $1/N$).[a]

[a] Contributed by Mr. Vincent Hwang (`R10922138`) on December 9, 2021.