Sublinear Algorithms

LECTURE 4

Last time



- Estimating the number of connected components.
- Estimating the weight of a MST

Today

- Limitations of sublinear-time algorithms
- Yao's Minimax Principle

HW2 is out tonight, due next Thursday at 11am



Query Complexity

- Query complexity of an algorithm is the maximum number of queries the algorithm makes.
 - Usually expressed as a function of input length (and other parameters)
 - Example: the test for sortedness (from Lecture 2) had query complexity $O(\log n)$ for constant ε , more precisely $O\left(\frac{\log n}{\varepsilon}\right)$
 - running time ≥ query complexity
- Query complexity of a problem P, denoted q(P), is the query complexity of the best algorithm for the problem.
 - What is q(testing sortedness)? How do we know that there is no better algorithm?

Today: Techniques for proving lower bounds on q(P).

Yao's Principle

A Method for Proving Lower Bounds

Yao's Minimax Principle

Consider a computational problem on a finite domain.

The following statements are equivalent.

Statement 1

For every **probabilistic** algorithm \mathcal{A} of complexity q there exists an input x s.t. $\Pr_{coin\ tosses\ of\ \mathcal{A}}[\mathcal{A}(x)\ \text{is}\ \text{wrong}] > 1/3.$

Statement 2

There is a distribution **D** on the inputs,

s.t. for every **deterministic** algorithm \mathcal{A} of complexity q, $\Pr_{x \leftarrow D}[\mathcal{A}(x) \text{ is wrong}] > 1/3.$

The direction needed for lower bounds:

Yao's Minimax Principle (easy direction): Statement 2 \Rightarrow Statement 1.

Proof of Easy Direction of Yao's Principle

- Consider a finite set of inputs X (e.g., all inputs of length n).
- Consider a randomized algorithm that takes an input $x \in X$, makes $\leq q$ queries to x and outputs accept or reject.
- Every randomized algorithm can be viewed as a distribution μ on deterministic algorithms (which are decision trees).

 Let Y be the set of all q-query deterministic algorithms that run on inputs in X.

Proof of Easy Direction of Yao's Principle

- Consider a matrix M with
 - rows indexed by inputs x from X,
 - columns indexed by algorithms y from Y,
 - entry $M(x,y) = \begin{cases} 1 & \text{if algorithm } y \text{ is correct on input } x \\ 0 & \text{if algorithm } y \text{ is wrong on input } x \end{cases}$

	y_1	y_2	•••	
x_1	1	0		
x_2	1	1		
•••			•.	

• Then an algorithm \mathcal{A} is a distribution μ over columns Y with probabilities satisfying $\sum_{v \in Y} \mu(y) = 1$.

Rephrasing Statements 1 and 2 in Terms of M

Statement 1

For every **probabilistic** algorithm \mathcal{A} of complexity q there exists an input x s.t. $\Pr_{coin\ tosses\ of\ \mathcal{A}}[\mathcal{A}(x)\ \text{is}\ \text{wrong}] > 1/3.$

• For all distributions μ over columns Y, there exists a row x s.t. $\Pr_{v \leftarrow \mu}[M(x,y) = 0] > 1/3.$

Statement 2

There is a distribution **D** on the inputs,

s.t. for every **deterministic** algorithm \mathcal{A} of complexity q, $\Pr_{x \leftarrow D}[\mathcal{A}(x) \text{ is wrong}] > 1/3.$

• There is a distribution D over rows X, s.t. for all columns y, $\Pr_{x \leftarrow D}[M(x, y) = 0] > 1/3.$

Statement $2 \Rightarrow Statement 1$

- Suppose there is a distribution D over X, s.t. for all columns y, $\Pr_{x \leftarrow D}[M(x,y) = 0] > 1/3.$
- Then for all distributions μ over Y,

$$\Pr_{\substack{x \leftarrow D \\ \mathbf{y} \leftarrow \boldsymbol{\mu}}} [M(x, y) = 0] > 1/3.$$

• Then for all distributions μ over Y, there exists a row x, $\Pr_{\mathbf{v} \leftarrow \mu}[M(x,y) = 0] > 1/3$.

	y_1	y_2	•••	
x_1	1	0		
x_2	1	1		
•••			•.	

Yao's Principle (Easy Direction)

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NOTE: Also applies to restricted algorithms

- 1-sided error tests
- nonadaptive tests

Yao's Minimax Principle as a game

Players: Evil algorithms designer Al and poor lower bound prover Lola.

Game1

Move 1. Al selects a q-query randomized algorithm \mathcal{A} for the problem.

Move 2. Lola selects an input on which \mathcal{A} errs with largest probability.

Game2

Move 1. Lola selects a distribution on inputs.

Move 2. Al selects a q-query deterministic algorithm with as large probability of success on Lola's distribution as possible.

Toy Example: a Lower Bound for Testing 0*

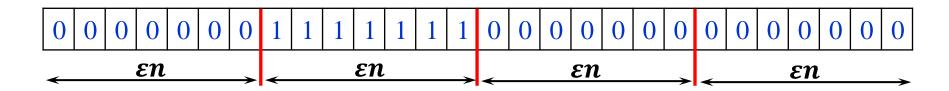
Input: string of n bits

Question: Does the string contain only 0's or is it ε -far form the all-0 string?

Claim. Any algorithm needs $\Omega(1/\varepsilon)$ queries to answer this question w.p. $\geq 2/3$. Proof: By Yao's Minimax Principle, enough to prove Statement 2.

Distribution D on n-bit strings

- Divide the input string into $1/\epsilon$ blocks of size ϵn .
- Let y_i be the string where the *i*th block is 1s and remaining bits are 0.
- Distribution D gives the all-0 string w.p. 1/2 and y_i with w.p. 1/2, where i is chosen uniformly at random from $1, ..., 1/\epsilon$.

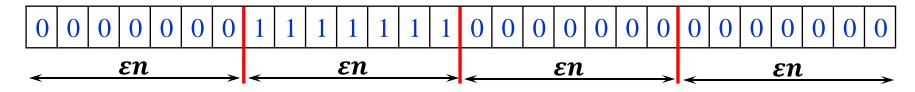


A Lower Bound for Testing 0*

Claim. Any ε -test for 0* needs $\Omega(1/\varepsilon)$ queries.

Proof (continued): Now fix a deterministic tester \mathcal{A} making $q < \frac{1}{3\varepsilon}$ queries.

- 1. \mathcal{A} must accept if all answers are 0. Otherwise, it would be wrong on all-0 string, that is, with probability 1/2 with respect to D.
- 2. Let i_1, \ldots, i_q be the positions \mathcal{A} queries when it sees only 0s. The test can choose its queries based on previous answers. However, since all these answers are 0 and since \mathcal{A} is deterministic, the query positions are fixed.
- At least $\frac{1}{\varepsilon} q > \frac{2}{3\varepsilon}$ of the blocks do not hold any queried indices.
- Therefore, \mathcal{A} accepts > 2/3 of the inputs y_i . Thus, it is wrong with probability > $\frac{2}{3\varepsilon} \cdot \frac{\varepsilon}{2} = \frac{1}{3}$



Context: [Alon Krivelevich Newman Szegedy 99]

A Lower Bound for Testing Sortedness

Input: a list of *n* numbers $x_1, x_2, ..., x_n$

Question: Is the list sorted or ε -far from sorted?

Already saw: an $O((\log n)/\varepsilon)$ time tester.

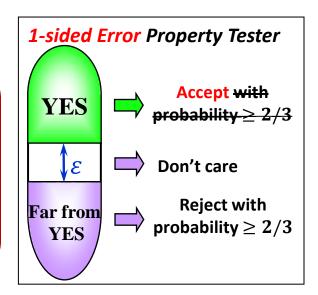
Known [Ergün Kannan Kumar Rubinfeld Viswanathan 98, Fischer 01]:

 $\Omega(\log n)$ queries are required for all constant $\varepsilon \leq 1/2$

Today: $\Omega(\log n)$ queries are required for all constant $\varepsilon \leq 1/2$

for every 1-sided error nonadaptive test.

- A test has 1-sided error if it always accepts all YES instances.
- A test is nonadaptive if its queries do not depend on answers to previous queries.



1-Sided Error Tests Must Catch "Mistakes"

• A pair (i, j) is **violated** if i < j but $x_i > x_j$

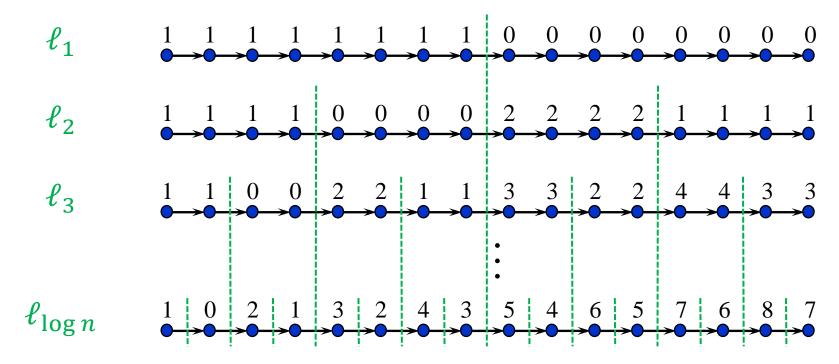
Claim. A 1-sided error test can reject only if it finds a violated pair.

Proof: Every sorted partial list can be extended to a sorted list.



Yao's Principle Game [Jha]

Lola's distribution is uniform over the following $\log n$ lists:

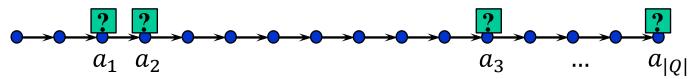


Claim 1. All lists above are 1/2-far from sorted.

Claim 2. Every pair (i, j) is violated in exactly one list above.

Yao's Principle Game: Al's Move

Al picks a set $Q = \{a_1, a_2, ..., a_{|Q|}\}$ of positions to query.



- His test must be correct, i.e., must find a violated pair with probability ≥
 2/3 when input is picked according to Lola's distribution.
- Q contains a violated pair $\Leftrightarrow (a_i, a_{i+1})$ is violated for some i

 $\Pr_{\ell \leftarrow \text{Lola's distribution}} \left[(a_i, a_{i+1}) \text{ for some } i \text{ is vilolated in list } \ell \right] \leq \frac{|Q| - 1}{\log n}$

• If $|Q| \le \frac{2}{3} \log n$ then this probability is $< \frac{2}{3}$

By the Union Bound

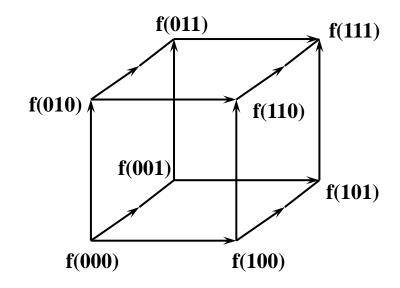
- So, $|Q| = \Omega(\log n)$
- By Yao's Minimax Principle, every randomized 1-sided error nonadaptive test for sortedness must make $\Omega(\log n)$ queries.

Testing Monotonicity of functions on Hypercube

Non-adaptive 1-sided error Lower Bound

Boolean Functions $f: \{0,1\}^n \rightarrow \{0,1\}$

Graph representation: n-dimensional hypercube

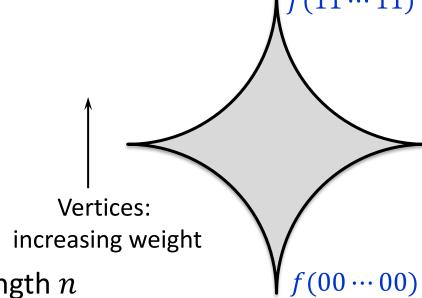


- vertices: bit strings of length n
- edges: (x, y) is an edge if y can be obtained from x by increasing one bit from 0 to 1 $\begin{pmatrix} x & 001001 \\ y & 011001 \end{pmatrix}$
- each vertex x is labeled with f(x)

Boolean Functions $f: \{0, 1\}^n \rightarrow \{0, 1\}$

Graph representation:

n-dimensional hypercube



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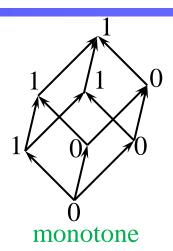
- 2ⁿ vertices: bit strings of length n
- $2^{n-1}n$ edges: (x, y) is an edge if y can be obtained from x by increasing one bit from 0 to 1 001001 011001

each vertex x is labeled with f(x)

Monotonicity of Functions

[Goldreich Goldwasser Lehman Ron Samorodnitsky,
Dodis Goldreich Lehman Raskhodnikova Ron Samorodnitsky
Fischer Lehman Newman Raskhodnikova Rubinfeld Samorodnitsky]

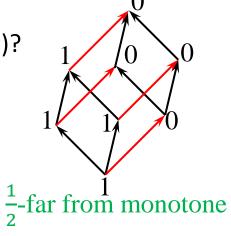
• A function $f: \{0,1\}^n \to \{0,1\}$ is monotone if increasing a bit of x does not decrease f(x).



- Is f monotone or ε -far from monotone (f has to change on many points to become monontone)?
 - Edge $x \rightarrow y$ is violated by f if f(x) > f(y).

Time:

- $O(n/\varepsilon)$, logarithmic in the size of the input, 2^n
- $\Omega(\sqrt{n}/\varepsilon)$ for 1-sided error, nonadaptive tests
- Advanced techniques: $\Theta(\sqrt{n}/\varepsilon^2)$ for nonadaptive tests, $\Omega(\sqrt[3]{n})$ [Khot Minzer Safra 15, Chen De Servidio Tang 15, Chen Waingarten Xie 17]



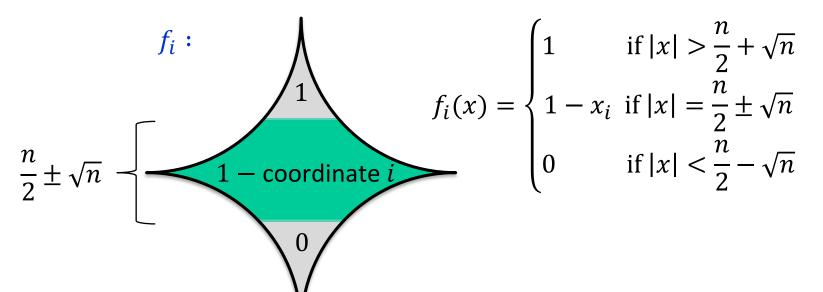
Lemma [Fischer Lehman Newman Raskhodnikova Rubinfeld Samorodnitsky]

Every 1-sided error nonadaptive test for monotonicity of functions $f:\{0,1\}^n \to \{0,1\}$ requires $\Omega(\sqrt{n})$ queries.

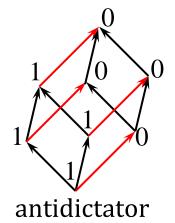
• 1-sided error test must accept if no violated pair is uncovered.

A distribution on far from monotone functions suffices.

• Hard distribution: pick coordinate i at random and output f_i .



A ``truncation'' of an antidicator



The Fraction of Nodes in Middle Layers

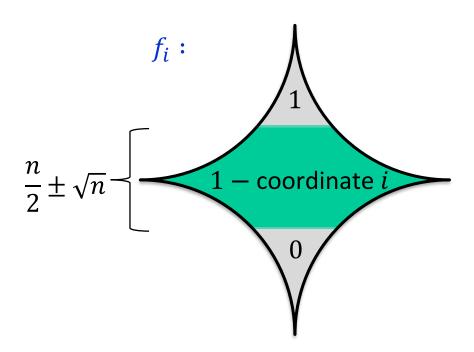
Hoeffding Bound

Let $Y_1, ..., Y_s$ be independently distributed random variables in [0,1].

Let $Y = \frac{1}{s} \cdot \sum_{i=1}^{s} Y_i$ (called *sample mean*). Then $\Pr[|Y - \mathbb{E}[Y]| \ge \varepsilon] \le 2e^{-2s\varepsilon^2}$.

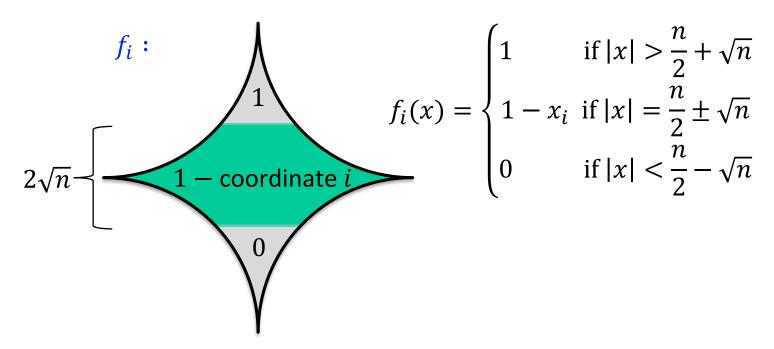
 $\mathbb{E}[Y]=$

 $\varepsilon =$



Hard Functions are Far

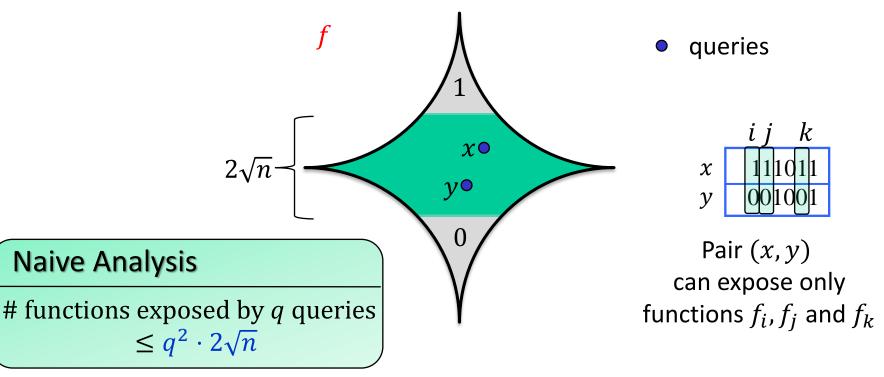
• Hard distribution: pick coordinate i at random and output f_i .



Analysis

- The middle contains a constant fraction of vertices.
- Edges from $(x_1, ..., x_{i-1}, 0, x_{i+1}, ..., x_n)$ to $(x_1, ..., x_{i-1}, 1, x_{i+1}, ..., x_n)$ are violated if both endpoints are in the middle.
- All n functions are ε -far from monotone for some constant ε .

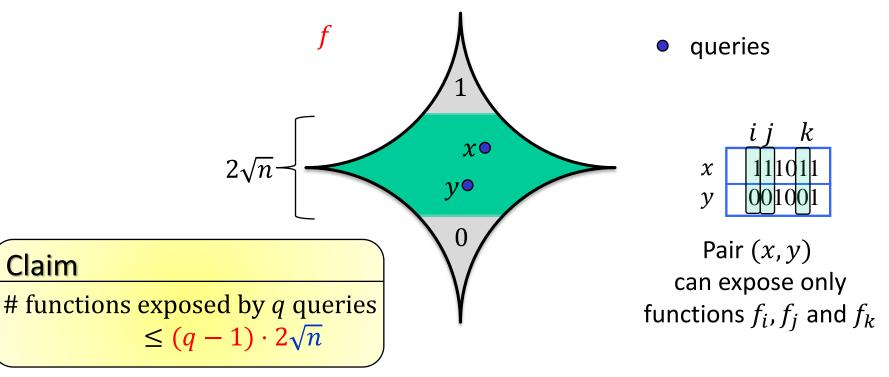
How many functions does a set of q queries expose?



functions that a query pair (x, y) exposes \leq # coordinates on which x and y differ $\leq 2\sqrt{n}$

Only pairs of queries in the Green Band can be violated \Rightarrow disagreements $\leq 2\sqrt{n}$

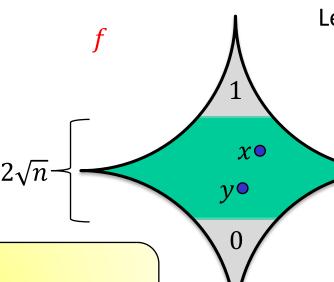
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How many functions does a set of q queries expose?



Let Q be the set of queries made.

The tester catches a violation

 \bigcirc

Q contains comparable x, y that differ in coordinate i

Draw an undirected graph (Q, E) by connected comparable queries

Consider its spanning forest.

x, y exist

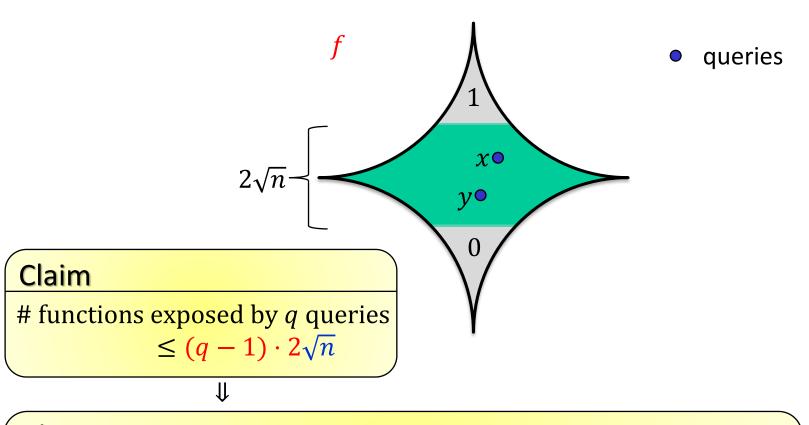
there are adjacent vertices on the path from x to y that differ in coordinate i

Claim

functions exposed by q queries $\leq (q-1) \cdot 2\sqrt{n}$

sufficient to consider adjacent vertices in a minimum spanning forest on the query set

How many functions does a set of q queries expose?



Claim

Every deterministic test that makes a set Q of q queries (in the middle) succeeds with probability $O\left(\frac{q}{\sqrt{n}}\right)$ on our distribution.



Lemma [Fischer Lehman Newman Raskhodnikova Rubinfeld Samorodnitsky]

Every 1-sided error nonadaptive test for monotonicity of functions $f:\{0,1\}^n \to \{0,1\}$ requires $\Omega(\sqrt{n})$ queries.