

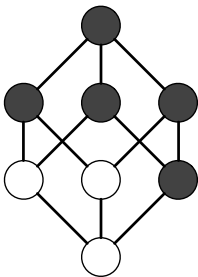
# New algorithms for testing monotonicity

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# Monotone functions

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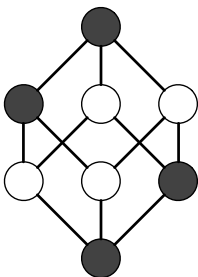


Definition (Monotone functions;  $\mathcal{M}$ )

$f : \{0, 1\}^n \rightarrow \{0, 1\}$  is *monotone* if for every  $x \preceq y \in \{0, 1\}^n$ , it satisfies  $f(x) \leq f(y)$ .

## Functions that are far from monotone

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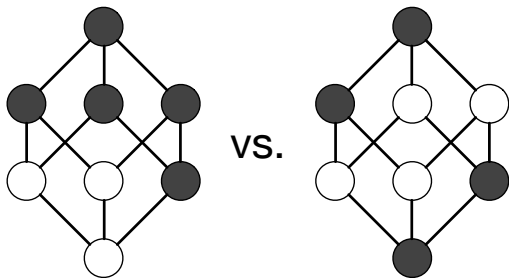


Definition (Functions far from monotone;  $\overline{\mathcal{M}}_\epsilon$ )

$f : \{0, 1\}^n \rightarrow \{0, 1\}$  is  $\epsilon$ -far from monotone if for every monotone function  $g$ , we have  $|\{x : f(x) \neq g(x)\}| \geq \epsilon 2^n$ .

## Testing monotonicity

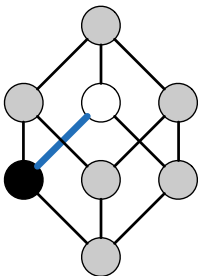
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How many queries does a bounded-error randomized algorithm need to distinguish monotone functions from functions that are  $\epsilon$ -far from monotone?

## Edge tester

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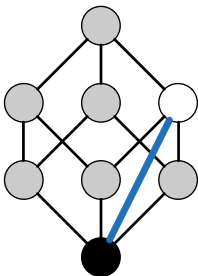


Definition (Goldreich, Goldwasser, Lehman, Ron '98)

The *edge tester* selects edges  $(x, y)$  of the hypercube uniformly at random and checks that  $f(x) \leq f(y)$ .

## Pair testers

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Definition (Dodis, Goldreich, Lehman, Raskhodnikova, Ron, Samorodnitsky '99)

A *pair tester* selects comparable pairs  $x \preceq y \in \{0, 1\}^n$  from some distribution and checks that  $f(x) \leq f(y)$ .

## Another view of pair testers

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The query complexity of pair testers can also be viewed as the solution to the following optimization problem.

$$\begin{array}{ll} \text{minimize} & \sum_{x \preceq y} \phi_{x,y} \\ \text{subject to} & \sum_{x \preceq y: f(x) > f(y)} \phi_{x,y} \geq 1 \quad \forall f \in \overline{\mathcal{M}}_\epsilon \\ & \phi_{x,y} \geq 0 \quad \forall x \preceq y \in \{0, 1\}^n \end{array}$$

## A different optimization problem

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$$\begin{aligned} &\text{minimize} && \max_{f \in \mathcal{M} \cup \overline{\mathcal{M}}_\epsilon} \sum_x \left( \sum_{y \succeq x} \phi_{x,y}(f) \right)^2 \\ &\text{subject to} && \sum_{x: f(x) \neq g(x)} \left( \sum_{y \succeq x} \phi_{x,y}(f) \cdot \phi_{x,y}(g) \right) = 1 \quad \forall f \in \mathcal{M}, g \in \overline{\mathcal{M}}_\epsilon. \end{aligned}$$



## A different optimization problem

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$$\begin{aligned} &\text{minimize} && \max_{f \in \mathcal{M} \cup \overline{\mathcal{M}}_\epsilon} \sum_x \left( \sum_{y \succeq x} \phi_{x,y}(f) \right)^2 \\ &\text{subject to} && \sum_{x: f(x) \neq g(x)} \left( \sum_{y \succeq x} \phi_{x,y}(f) \cdot \phi_{x,y}(g) \right) = 1 \quad \forall f \in \mathcal{M}, g \in \overline{\mathcal{M}}_\epsilon. \end{aligned}$$

Corollary (to the Dual adversary bound Theorem)

*Every feasible solution to this problem gives an upper bound on the quantum query complexity for testing monotonicity.*

# The dual adversary bound

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## Theorem (Dual adversary bound)

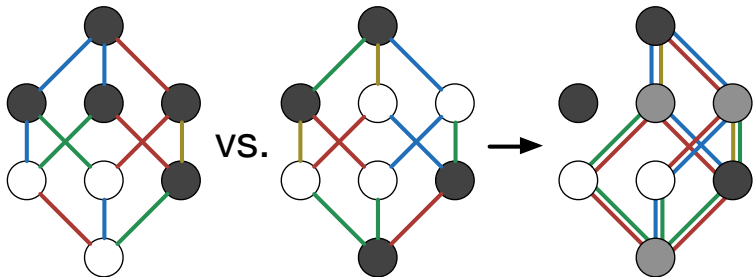
*The quantum query complexity for distinguishing  $\mathcal{X}$  and  $\mathcal{Y}$  is the solution to the optimization problem*

$$\begin{aligned} \text{minimize} \quad & \max_{f \in \mathcal{X} \cup \mathcal{Y}} \sum_x X_x[f, f] \\ \text{subject to} \quad & \sum_{x: f(x) \neq g(x)} X_x[f, g] = 1 \quad \forall f \in \mathcal{X}, g \in \mathcal{Y} \\ & X_x \succeq 0 \quad \forall x \in \{0, 1\}^n \end{aligned}$$

# Simplifying the optimization problem

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$$\begin{aligned} & \text{minimize} && \max_{f \in \mathcal{M} \cup \overline{\mathcal{M}}_\epsilon} \sum_x \left( \sum_{j \in [n]} \phi_{x,j}(f) \right)^2 \\ & \text{s.t.} && \sum_{x: f(x) \neq g(x)} \sum_{j \in [n]} \phi_{x,j}(f) \cdot \phi_{x,j}(g) = 1 \quad \forall f \in \mathcal{M}, g \in \overline{\mathcal{M}}_\epsilon. \end{aligned}$$



## First quantum monotonicity tester

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For  $f \in \mathcal{M}$ , define

$$\phi_{x,j}(f) = \begin{cases} 1/L & \text{if } x_j = 0 \text{ and } f(x) = 0 \\ & \text{or } x_j = 1 \text{ and } f(x) = f(x^{\oplus j}) = 1 \\ 0 & \text{otherwise.} \end{cases}$$

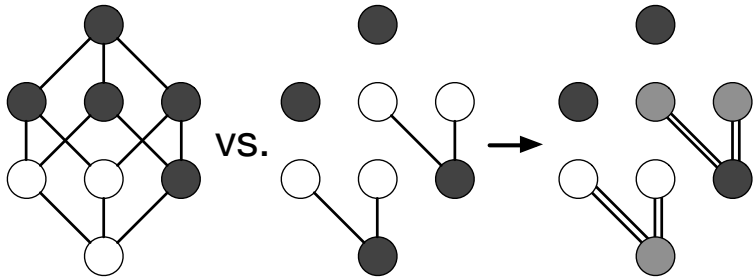
For  $g \in \overline{\mathcal{M}}_\epsilon$ , define

$$\phi_{x,j}(g) = \begin{cases} L/|E_g| & \text{if } (x, x^{\oplus j}) \in E_g \\ 0 & \text{otherwise} \end{cases}$$

where  $E_g$  is the set of edges of the hypercube on which  $g$  is anti-monotone and  $L$  is a constant to be fixed later.

# First quantum tester: Correctness

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$$\sum_{x:f(x)\neq g(x)} \sum_{j\in[n]} \phi_{x,j}(f) \cdot \phi_{x,j}(g) = |E_g| \cdot \left(\frac{1}{L} \cdot \frac{L}{|E_g|}\right) = 1.$$

## First quantum tester: Complexity I

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For  $f \in \mathcal{M}$ , the objective value of the optimization is

$$\sum_x \left( \sum_{j \in [n]} \phi_{x,j}(f) \right)^2 = \frac{n2^n}{L^2}$$

And for  $g \in \overline{\mathcal{M}}_\epsilon$ , it is

$$\sum_x \left( \sum_{j \in [n]} \phi_{x,j}(g) \right)^2 = 2|E_g| \frac{L}{|E_g|^2} = \frac{2L}{|E_g|}.$$

## First quantum tester: Complexity II

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When  $L = \sqrt{n\epsilon} \cdot 2^{n-1}$ , the objective value of the optimization problem is

$$\max \left\{ \sqrt{n/\epsilon}, \max_{g \in \overline{\mathcal{M}}_\epsilon} \frac{2^n \sqrt{n\epsilon}}{|E_g|} \right\}.$$

## First quantum tester: Complexity II

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Lemma (Goldreich, Goldwasser, Lehman, Ron, Samorodnitsky '00)

*For every  $g \in \overline{\mathcal{M}}_\epsilon$ ,  $|E_g| \geq \epsilon 2^n$ .*

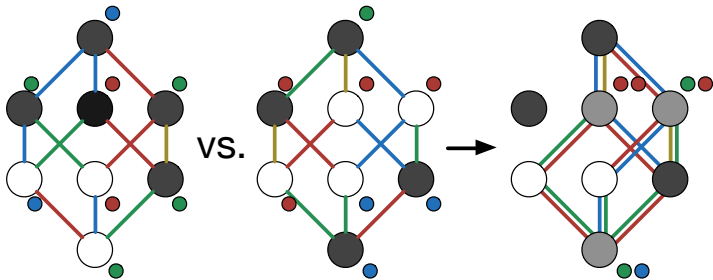
So the quantum query complexity of the first tester is  $\sqrt{n/\epsilon}$ .



# A more flexible optimization problem

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$$\begin{aligned} \text{min.} \quad & \max_{f \in \mathcal{M} \cup \overline{\mathcal{M}}_\epsilon} \sum_x \left( \psi_x(f) + \sum_{j \in [n]} \phi_{x,j}(f) \right)^2 \\ \text{s.t.} \quad & \sum_{x: f(x) \neq g(x)} \left( \psi_x(f) \cdot \psi_x(g) + \sum_{j \in [n]} \phi_{x,j}(f) \cdot \phi_{x,j}(g) \right) = 1 \quad \forall \dots \end{aligned}$$



## Second quantum monotonicity tester

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Theorem (Belovs, B. '15)

*There is a feasible solution to this optimization problem with objective value*

$$\frac{2^n \sqrt{\epsilon}}{\log n |E_g|} \left( \frac{\Delta(G_g)}{n^{1/4}} + n^{1/4} \right)$$

*where  $G_g$  is any subgraph of the  $(1,0)$ -graph of  $g$ ,  $\Delta(G_g)$  is its maximum degree, and  $E_g$  is the set of non-monotone edges in  $G_g$ .*

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Theorem (Khot, Minzer, Safra '15)

*For every  $g \in \overline{\mathcal{M}}_\epsilon$ , there exists a such a subgraph  $G_g$  that satisfies*

$$|E_g| = \Omega \left( \frac{\epsilon 2^n \sqrt{\Delta(G_g)}}{\log^2 n} \right).$$

# Conclusions

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- ▶ We can test monotonicity with  $\tilde{O}(n^{1/4}/\sqrt{\epsilon})$  quantum queries.
- ▶ The design of quantum testers can be done by considering natural optimization problems.
- ▶ The analysis of quantum monotonicity testers uncovers the key inequalities that are also required to analyze classical monotonicity testers.
- ▶ Are there other property testing problems where considering quantum testers may yield insights on promising directions?

Thank you!

*For all the details, see*

A. Belovs and E.B. Quantum Algorithm for Monotonicity Testing on the Hypercube. *Theory of Computing* 11(16), 2015.