# How to make quantum query algorithms 

by

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## Given: Function f: $\mathrm{x} \mapsto \mathrm{f}(\mathrm{x})$



Least queries needed to evaluate $\mathrm{f}(\mathrm{x})$

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$Q(f)=$ Least quantum queries needed to evaluate $f(x)$

## Query Algorithm



Unitary operators are free Cost of algorithm = number of queries

## Query algorithms

- Grover search unordered search in $\mathrm{O}(\sqrt{n})$ queries
- AND/OR trees
- Element distinctness
- Graph collision
- Triangle finding


## Many algorithms were given using quantum walks.

## Lower bounds on quantum query complexity

Polynomial bound [BBCMW '01]:

- Separation [A ‘03]
- Element Distinctness [AS ‘04]
- Direct products [KŠdW '07]

Adversary bound [A ‘02]:

- SDP [BSS ‘03]
- Equivalence [šs ‘06]
- Multiplicative [Š ‘08]
- $\operatorname{Adv}^{ \pm}$(f) [HLŠ ‘07]


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For any boolean function f :

$$
\mathrm{Q}(\mathrm{f})=\Theta\left(\operatorname{Adv}^{ \pm}(\mathrm{f})\right)
$$

[R ‘09]

## Vector set

## Vector set : construction

Query algorithm for $\mathrm{f}: D^{n} \longrightarrow\{0,1\}$

Construct vectors for
every element of $D^{n}$ and $[n]$

|  | x | y | $\cdots$ | Z |
| :---: | :---: | :---: | :---: | :---: |
| 1 | $u_{x, 1}$ | $u_{y, 1}$ | $\cdot$ | $u_{z, 1}$ |
| $\cdot$ |  |  |  |  |
| • | $u_{x, i}$ | $\cdot$ | $u_{w, i}$ | $\cdot$ |
| . |  |  |  |  |
| n | $u_{x, n}$ | $u_{y, n}$ | $\cdot$ | $u_{z, n}$ |

## Vector set : Example

Query algorithm for $\mathrm{f}:\{0,1\}^{n} \longrightarrow\{0,1\}$

|  | 000 | 001 | $\cdots$ | 111 |
| :--- | :--- | :--- | :---: | :---: |
| 1 | $u_{000,1}$ | $u_{001,1}$ | . | $u_{111,1}$ |
| . |  |  |  |  |
| $\cdot$ | $u_{000, i}$ | . | $u_{101, i}$ | . |
| . |  |  |  |  |
| n | $u_{000, n}$ | $u_{001, n}$ |  |  |
|  |  |  | $u_{111, n}$ |  |

Query algorithm for $\mathrm{f}: D^{n} \longrightarrow\{0,1\}$

Follow constraint for $\forall x \in f^{-1}(0), y \in f^{-1}(1)$.

$$
\begin{array}{ccc} 
& \mathrm{x} & \mathrm{y} \\
1 & u_{x, 1} & u_{y, 1} \\
\cdot & & \\
\cdot & u_{x, i} & u_{y, i} \\
\text { n } & u_{x, n} & u_{y, n}
\end{array}
$$

## Query algorithm for $\mathrm{f}: D^{n} \longrightarrow\{0,1\}$

Follow constraint for $\forall x \in f^{-1}(0), y \in f^{-1}(1)$.

$$
\begin{array}{cccc} 
& \mathrm{x} & \mathrm{y} & \text { product } \\
1 & u_{x, 1} & u_{y, 1} & <u_{x, 1}, u_{y, 1}>\cdot\left(x_{1} \neq y_{1}\right) \\
\cdot & & & + \\
\cdot & u_{x, i} & u_{y, i} & <u_{x, i}, u_{y, i}>\cdot\left(x_{i} \neq y_{i}\right) \\
\cdot & & + \\
\mathrm{n} & u_{x, n} & u_{y, n} & <u_{x, n}, u_{y, n}>\cdot\left(x_{n} \neq y_{n}\right) \\
\sum_{\left(x_{i} \neq y_{i}\right)}<u_{x, i}, u_{y, i}>=1 \quad \forall x, y .
\end{array}
$$

## The dual of adversary bound

- Vector set : solution of the dual of adversary bound
- The value of the solution :

$$
\begin{aligned}
& \max _{z \in D^{n}} \text { (length of } u_{z} \text { ) } \\
& \max _{z \in D^{n}}\left(\sum_{i}\left\|u_{z, i}\right\|^{2}\right)
\end{aligned}
$$

- The value of best construction : $\mathrm{Q}(\mathrm{f})$


## Algorithmic applications

Q. Can we develop algorithms using solution of dual?
A. Not easy, because of the great number of constraints in SDP.

1. Formula evaluation [FGG07,RŠ08]
(optimal formula evaluation algorithms
for any read-once formula)

## Algorithmic applications

Q. Can we develop algorithms using filtered factorization norm?
A. Not easy, because of the great number of constraints in SDP.
2. Learning graphs [Bel11]
(Element Distinctness and $\mathrm{n}^{1.296}$ algorithm for Triangle Finding )


## Outline

- Span programs
- Learning graphs
- Comparison
- Open problems


## Span Programs

## Span program

- For a function $f:\{0,1\}^{n} \longrightarrow\{0,1\}$
target

| $\downarrow$ |
| :---: |
| $t$ |
| 1 |
| 3 |
| . |
| . |
| . |
| 1 |

## Span program

Useful vectors for $z \in\{0,1\}^{n}$ : free vectors + vectors in column $j, z_{j}$


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$f(y)=1 \Rightarrow$
t : as linear combination of useful vectors for y

Witness: The coefficients of linear combination

Witness size : The length of witness vector

Useful vectors for $z \in\{0,1\}^{n}$ : free vectors + vectors in column $j, z_{j}$
$f(x)=0 \Rightarrow$
t : NOT a linear combination of useful vectors for x

Witness: $w:(<w, t>=1) \&(<w, v>=0$, if $v$ useful $)$.

Witness size: The length of Aw.

## Equivalence to dual solution

- Every span program can be converted to a canonical span program

Fixed vector space for columns
No free vectors

- Canonical span program is equivalent to a solution of dual adversary.
- Complexity of best span program is the query complexity of $f$.


## Features

- Easy to manipulate span programs

Complementation
Composition

- Optimal formula evaluation algorithms
- These were used to show query algorithms using adversary bound.


## Learning Graph

## Learning graph

- For a function $\mathrm{f}: D^{n} \longrightarrow\{0,1\}$
- Need to construct a graph



## Vertex: $S \subseteq[n]$

## Edge: $j \in[n]$

## Learning graph

- For a function $\mathrm{f}: D^{n} \longrightarrow\{0,1\}$
- Need to construct a graph


Edges:

$$
S \xrightarrow{j} S \cup\{j\} \quad S \subseteq[n], j \in[n]
$$

Every edge has weight $w_{e}$

## Flow for 1-input

- For every $y \in f^{-1}(1)$, there is a flow of value 1

Source: The empty vertex $\Phi$
Sink: Any "1-certificate".

Flow in edge e: $p_{e}(y)$


## Complexity of learning graph

$$
C^{0}=\max _{x} \sum_{e} w_{e}
$$

$$
C^{1}=\max _{y} \sum_{e} \frac{p_{e}(y)^{2}}{w_{e}}
$$

$$
C=\sqrt{C^{0} C^{1}}
$$



## Reduction

- Convert learning graph into vector construction

For every edge $\mathbf{S} \rightarrow \mathbf{S} \cup\{j\}:$
need $2^{|S|}$ coordinates in $u_{z, j}$
$\begin{array}{ll} & \mathrm{j}, \mathrm{e}, \alpha(\mathrm{S}) \longleftarrow \\ u_{x} & \sqrt{w_{e}} \\ u_{y} & \frac{p_{e}(y)}{\sqrt{w_{e}}}\end{array}$

## Constraint for dual adversary

Constraint:
$\sum_{\left(x_{i} \neq y_{i}\right)}<u_{x, i}, u_{y, i}>$
$=\sum_{e: c u t} \frac{p_{e}(y)}{\sqrt{w_{e}}} \sqrt{w_{e}}$
$=\sum_{e: c u t} p_{e}(y)$
$=1$ (value of the flow)
$\{2,7,9\}$

## Important results

- Element distinctness:

Showed the previous bound of $O\left(n^{\frac{2}{3}}\right)$

- Triangle finding:

Improved the upper bound to $O\left(n^{1.296}\right)$

- k-element distinctness:

Improved under certain conditions

## Limitations and improvement

- Certificate complexity barrier

Learning graph complexity $\geq 1$-certificate complexity

- Alphabet size barrier

Only depends on certificate structure

- Improved learning graph : overcomes both barriers

Gives better complexity for "OR of AND"

## Comparison

## Span Program

- Easy to manipulate
- Equivalent to dual
- ?????


## Learning graph

- Can't compose it well
- Weaker than dual
- Easy to construct


## Solution of dual adversary

## Learning graph / Span programs

- $\forall \mathrm{x}, \mathrm{y}:\left\langle\mathrm{u}_{\mathrm{x}} \mid \mathrm{v}_{\mathrm{y}}\right\rangle=\ldots$
- Symmetric
- Tight
- $\forall x:$...
- $\forall \mathrm{y}: . .$.
- Intuitive

Separation of constraints really help
Need more combinatorial constructions to make query algorithms

## Open problems

## Constructing dual solution

- Need other techniques to construct dual solution.

Easy to manipulate
Easy to construct
Tight

- Dual of "positive" adversary

$$
\sum_{\left(x_{i} \neq y_{i}\right)}<u_{x, i}, u_{y, i}>\geq 1
$$

When is positive adversary tight?

## Other query algorithms

- Graph collision Important in triangle finding.
- Triangle finding
- k-element distinctness


## Thank you

