

Quantum speedups for graph sparsification, graph cut problems and Laplacian solving

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(arXiv:1911.07306, arXiv:2011.09823)

Graph model

Graph model

undirected, weighted graph $G = (V, E, w)$

n nodes and m edges

$$\in \mathcal{O}(n^2)$$

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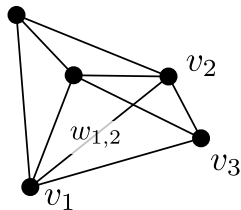
adjacency list access:

$(v_1): (v_2, w_{1,2}), (v_3, w_{1,3}), \dots$

$(v_2): (v_3, w_{2,3}), \dots$

\vdots

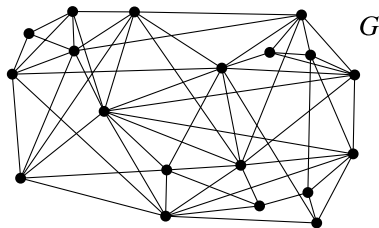
$(v_n): \dots$



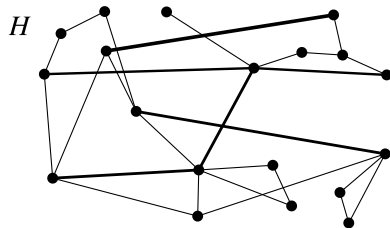
Graph Sparsification

“graph sparsification”

= reduce number of edges, while preserving interesting quantities



$$m_G \in O(n^2)$$



$$m_H < m_G$$

Graph Sparsification

“**spectral** sparsification”

Graph Sparsification

“**spectral** sparsification”

= approximately preserve all quadratic forms:

$$x^T L_H x = (1 \pm \varepsilon) x^T L_G x, \quad \forall x \in \mathbb{R}^n$$

this includes:

- cut values
- eigenvalues
- random walk properties
- ...

Graph Sparsification

how sparse can we go ?

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Theorem

Every graph has ϵ -spectral sparsifier H with a number of edges

$$\tilde{O}(n/\epsilon^2) \ll O(n^2)$$

which can be found in time $\tilde{O}(m)$.

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- crucial component of Spielman-Teng $\tilde{O}(m)$ -time algorithm for solving **Laplacian system** $Lx = b$

This work:

$$m \geq \sqrt{mn}/\epsilon \geq n/\epsilon^2, \quad \epsilon \leq \sqrt{\frac{m}{n}}$$

This work:

① **quantum algorithm** to find ϵ -spectral sparsifier H in time

$$\tilde{O}(\sqrt{mn}/\epsilon)$$

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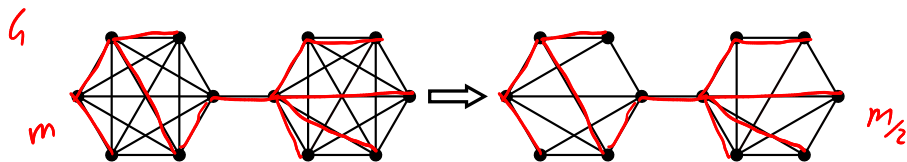
= vanilla speedup for cut approximation and Laplacian solving

- ② **quantum algorithm** for finding *exact* minimum cut

Classical Sparsification Algorithm

Iterative sparsification [Koutis-Xu '16]:

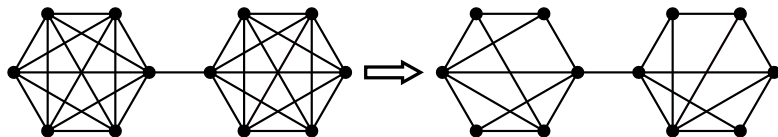
- 1 construct $\tilde{O}(1/\epsilon^2)$ “graph spanners” and keep these edges
- 2 keep any remaining edge with probability $1/2$, and double its weight



Classical Sparsification Algorithm

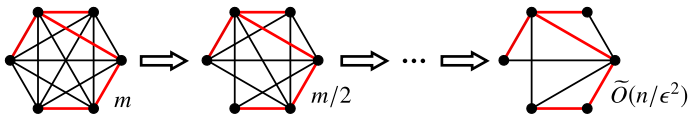
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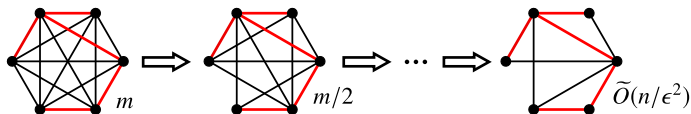


→ repeat $O(\log n)$ times: ϵ -spectral sparsifier with $\tilde{O}(n/\epsilon^2)$ edges

Quantum Sparsification Algorithm



Quantum Sparsification Algorithm



= **quantum spanner
algorithm**

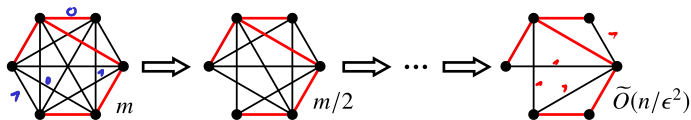
complexity $\tilde{O}(\sqrt{mn})$

builds on

Thorup-Zwick
(’01)

Dürr-Heiligman-Høyer-Mhalla
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Quantum Sparsification Algorithm



= **quantum spanner
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+ ***k*-independent
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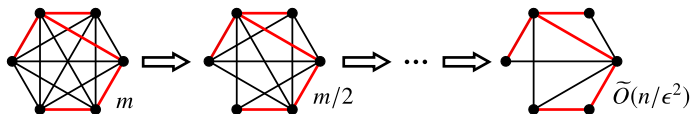
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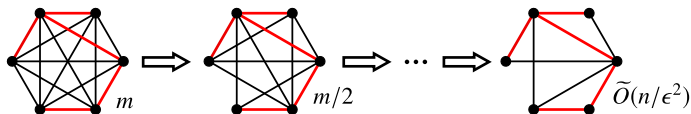
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$\tilde{O}(\sqrt{mn}/\epsilon^2)$

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= **quantum spanner algorithm**

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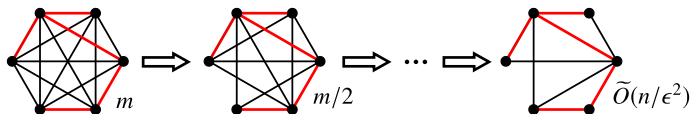
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$\tilde{O}(\sqrt{mn}/\epsilon^2)$



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Quantum Sparsification Algorithm

Theorem

There is a quantum algorithm that constructs an ϵ -spectral sparsifier with $\tilde{O}(n/\epsilon^2)$ edges in time

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This is tight (up to polylog-factors).

Matching Quantum Lower Bound

intuition:

finding k marked elements among M elements takes

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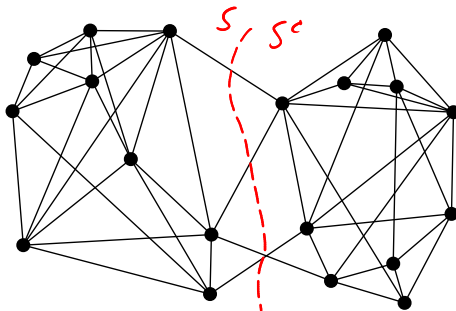
=

hiding an unsparsifiable graph [Andoni-Chen-Krauthgamer-Qin-Woodruff-Zhang '16]

+ quantum lower bound for relational problem [Belov-Lee '20]

Applications

e.g., MIN CUT:

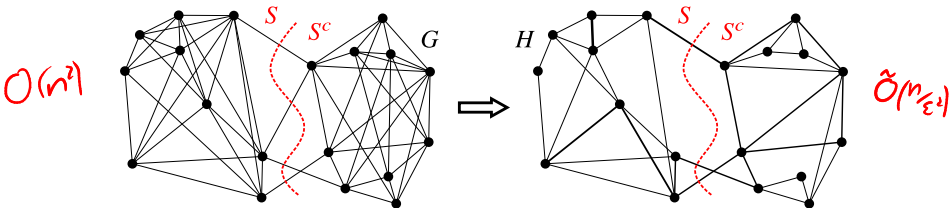


find cut (S, S^c) that minimizes cut value

$$\text{cut}_G(S) = \sum_{i \in S, j \notin S} w_{i,j} = 4$$

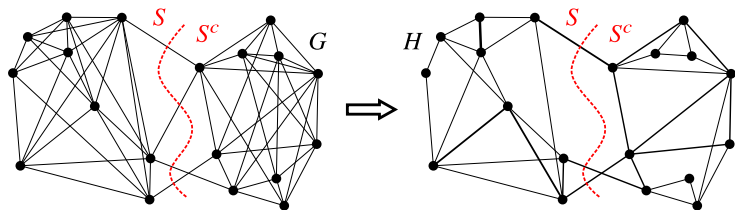
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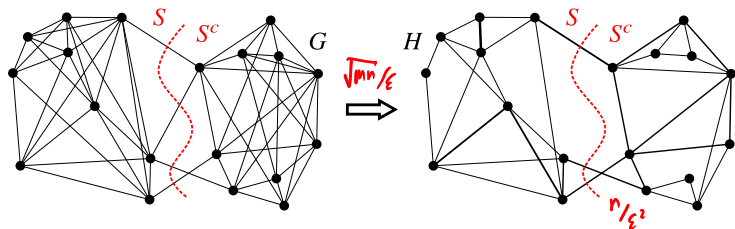
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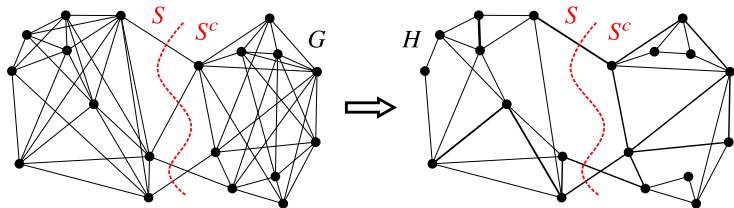
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quantum:

quantum algorithm to create sparsifier H in $\tilde{O}(\sqrt{mn}/\epsilon)$
+ **classical** MIN CUT on H in $\tilde{O}(n/\epsilon^2)$ (Karger '00)

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= $\tilde{O}(\sqrt{mn}/\epsilon)$ quantum algorithm

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→ general blueprint:

- 1 Use **quantum** algorithm to create sparsifier H in time $\tilde{O}(\sqrt{mn}/\epsilon)$
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- ▶ min cut, max cut ($\epsilon > .878$), sparsest cut ($\epsilon \in \Omega(\sqrt{\log n})$), . . .

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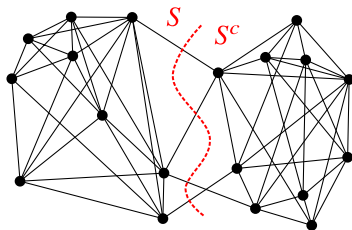
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Can we get exact quantum algorithms?

Quantum algorithm for MIN CUT

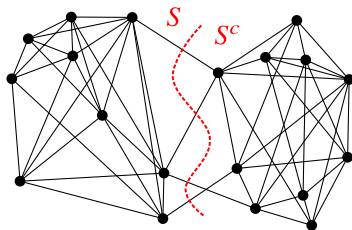
back to MIN CUT:



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Quantum algorithm for MIN CUT

back to MIN CUT:



classical: *exact* MIN CUT in time $\tilde{O}(m)$ (Karger '00)
quantum: ϵ -*approximate* MIN CUT in time $\tilde{O}(\sqrt{mn}/\epsilon)$:(

Quantum algorithm for MIN CUT

input size = m

input size = n^2

Results in adjacency *list* model and adjacency *matrix* model:

Theorem

Quantum algorithm for MIN CUT

Results in adjacency *list* model and adjacency *matrix* model:

Theorem

- There exists a family of **weighted graphs** with $\Omega(n^2)$ edges for which the quantum query complexity of exact MIN CUT is $\Omega(n^2)$ in both models. \rightarrow no quantum speedup!

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- For **unweighted graphs**, exact MIN CUT has quantum query complexity
 - ▶ $\tilde{O}(\sqrt{mn})$ in adjacency list model
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← improves $\tilde{O}(\sqrt{mn}/\epsilon)$

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tight

Lower bounds for unweighted graphs (from connectivity [DHHM'06]):

$\Omega(n)$ (list) or $\Omega(n^{3/2})$ (matrix)

Quantum algorithm for MIN CUT

Upper bounds on quantum query complexity:

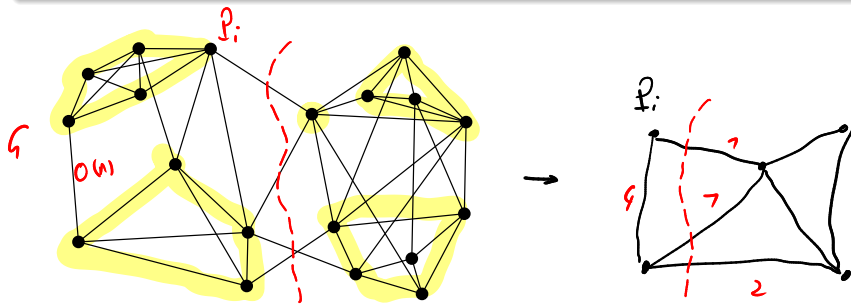
Quantum algorithm for MIN CUT

Upper bounds on quantum query complexity:

Theorem (Kawarabayashi-Thorup 2014, Rubinfeld-Schramm-Weinberg 2017)

For unweighted G , there exists partition $V = P_1 \cup \dots \cup P_k$ such that

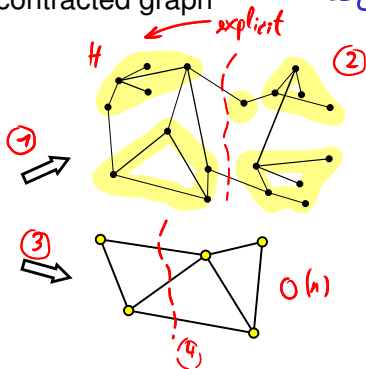
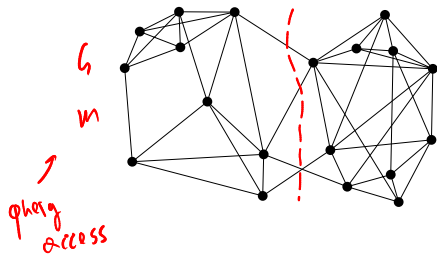
- 1 there are $O(n)$ edges between partitions,
- 2 partition “respects” all near-minimum cuts.



Quantum algorithm for MIN CUT

quantum query algorithm in list model:

- 1 construct $\epsilon = 1/10$ -sparsifier H $\rightarrow \mathcal{O}(\sqrt{mn})$
 \rightarrow min cut of G is near-minimum cut of H
- 2 learn partition $V = P_1 \cup \dots \cup P_k$ of H \rightarrow no queries
 \rightarrow respects min cut of G
- 3 Grover search over m edges to find $O(n)$ edges of G between P_i 's
- 4 classically calculate min cut of contracted graph $\rightarrow \mathcal{O}(\sqrt{mn})$
 \rightarrow no queries



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- **unweighted graphs:**
 - $\tilde{O}(n/\epsilon^2)$ for sparsification?
 - $\tilde{O}(n)$ for unweighted min cut in adjacency list model?

$$\Omega(n) \rightarrow \tilde{O}(\sqrt{mn})$$

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thank you! stay safe!

$$\tilde{O}(n^{3/2}/\epsilon) \prec \tilde{O}(n^2)$$