



National
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The Quantum and Classical Streaming Complexity of Quantum and Classical Max-Cut



Presented by:

John Kallaughher¹ Ojas Parekh¹



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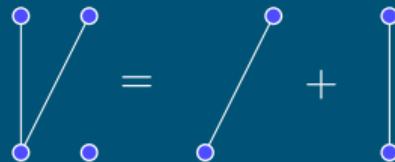


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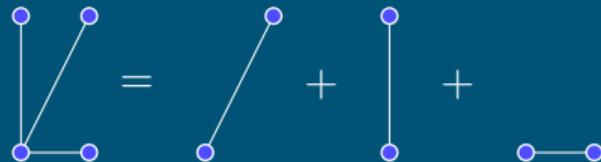


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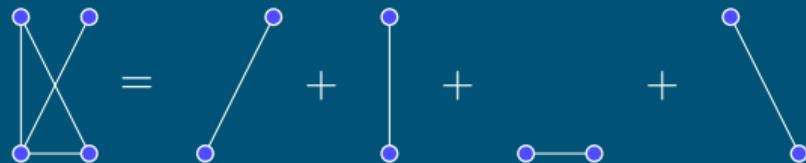


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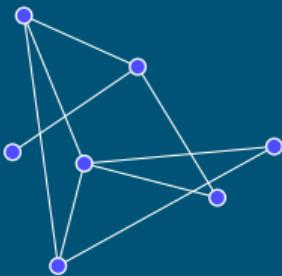
Theoretical study is mostly concerned with *space complexity*.



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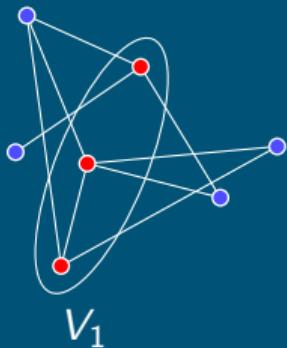


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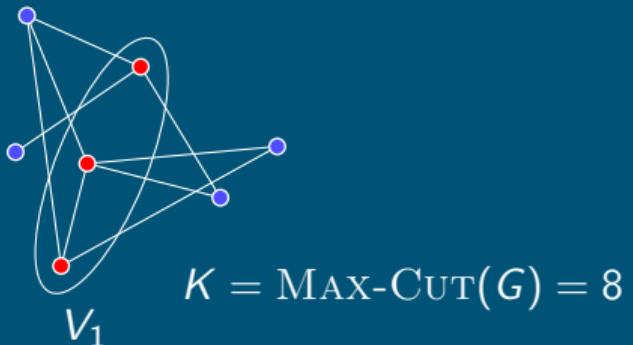


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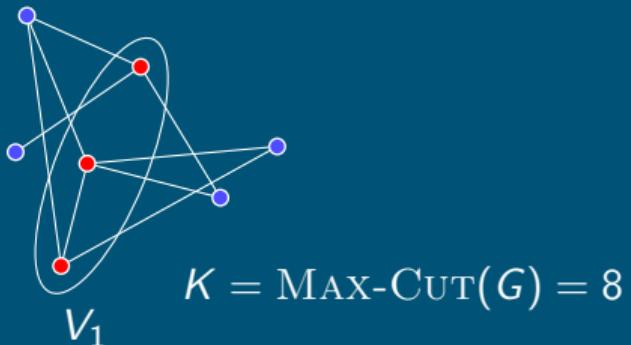


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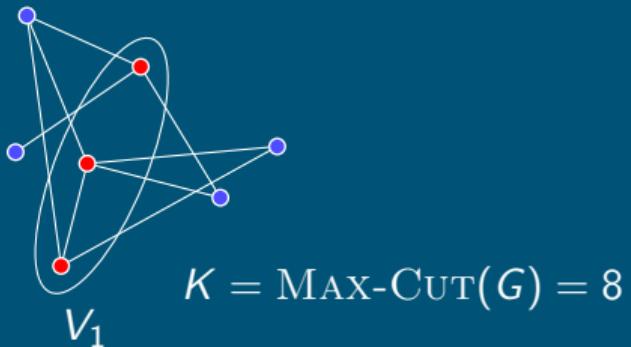
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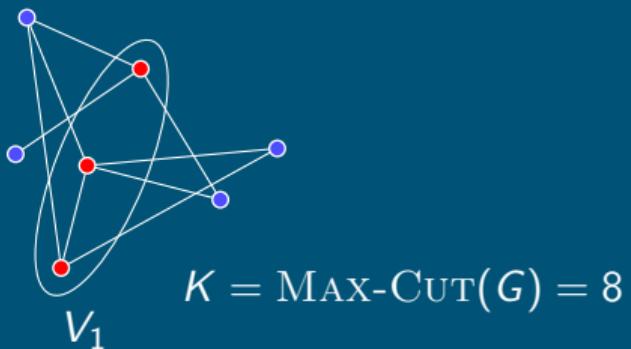


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- How much space does a streaming algorithm need to return $K' \in (K/\gamma, K)$?



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- Resolved in [Kapralov, Krachun '19]. $(2 - \varepsilon)$ -approximation requires $\Omega(n)$ space.

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We generalize these results in two directions.

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 - Matching upper bound for $(2 + \varepsilon)$ -approximation.



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- [Montanaro '16], [Hamoudi, Magniez '19], [K. '22] Polynomial advantages known for “natural” problems.

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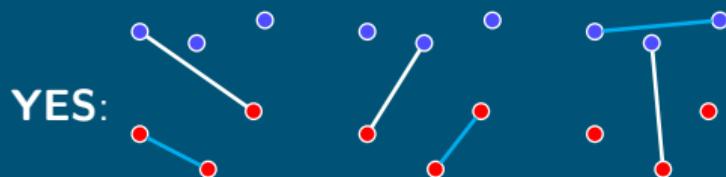
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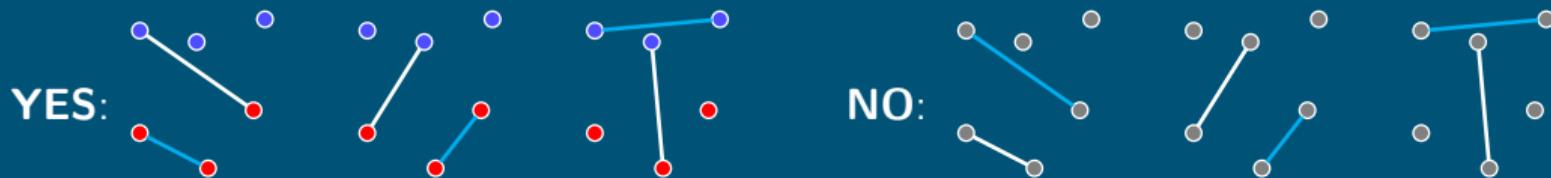


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- **NO** case: Player t gets $y \in \{0, 1\}^{M_t}$ at random.

Reduction from MAX-CUT



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- DIHP reduces to $(2 - \Theta(1/\sqrt{T}))$ approximating MAX-CUT.



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- Intuition: in a **YES** case, each edge label given to player t is “consistent” with the corresponding vertex labels.
- The “knowledge” player t has about these parities can be quantified in terms of *Fourier coefficients*.



Given a protocol, we can write down a function $f_t : \{0, 1\}^n \rightarrow \mathbb{C}^{\beta \times \beta}$ that gives the density matrix $f_t(x)$ of player t 's message if the problem is in a **YES** state with vertex labels x .



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For each set S of vertices we consider the *Fourier coefficient* $\widehat{f}_t(S) = \mathbb{E}_x [(-1)^{S \cdot x} f_t(x)]$.



Suppose player t ignored everything from player $t - 1$. Then we would have

$$\sum_{|S|=k} \|\hat{f}_t(S)\|_1^2 \leq \binom{\beta}{k}$$

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- But we need to control how player t incorporates a message from player t .



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In the quantum setting the possibility of e.g. measurements means that we have to consider player t applying an arbitrary *quantum channel*.



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Our idea is to apply Fourier analysis to the family of channels each player might apply.



Let $(\mathcal{N}_y)_{y \in \{0,1\}^n}$ be a family of channels. We extend the Boolean Fourier transform by defining:

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A convolution theorem (analogous to one for products of scalar-valued functions) applies:

$$\widehat{\mathcal{N}f}(S) = \sum_{U \in \{0,1\}^n} \widehat{\mathcal{N}_U f}(U \oplus S)$$



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So each Fourier coefficient $\hat{f}_{t-1}(S)$ can be seen as generating one Fourier coefficient $\hat{f}_t(S \oplus M_t^{\text{tr}} y)$ for each subset y of M_t .



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- DIHP requires $n/2^{1/T}$ (qu)bits of quantum *or* classical communication.
- So $(2 - \varepsilon)$ -approximation of MAX-CUT requires $n/2^{O(\varepsilon)}$ space.



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- A sum of “local” terms operating on a small number of qubits each.
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- Many important problems in physics take this form.



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- Searching for the minimum energy of this creates a Hamiltonian maximization problem that returns half the cut value of any *classical* string viewed as a partition.
- Also referred to as QUANTUM MAX-CUT.

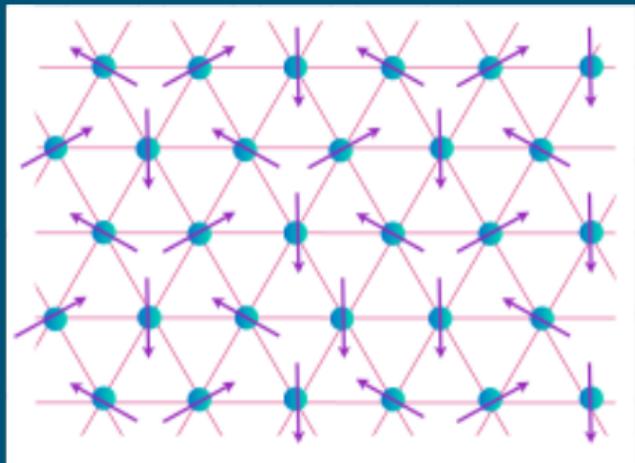


Figure: Anti-ferromagnetic Heisenberg model: roughly neighboring quantum particles aim to align in opposite directions.

[Image: Sachdev, arXiv:1203.4565]

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- If MAX-CUT value is $m/2 + O(\varepsilon)$, SDP is $O(\varepsilon)$.

So **NO** instances have QUANTUM MAX-CUT value at most $m(1/2 + \Theta(1/\sqrt{T}))$ too!

Conclusion



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- Can we sparsify (some) 2-local Hamiltonians?
- If we can, can we solve them in $O(n)$ space?