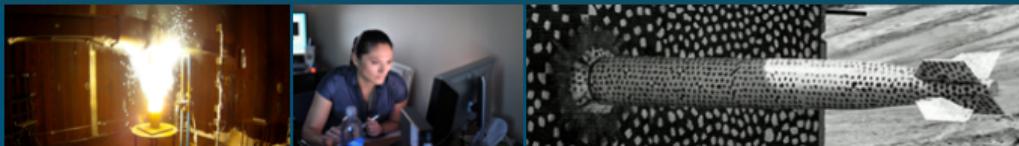




National
Laboratories

A Quantum Advantage for a Natural Streaming Problem



Presented by:

John Kallaugher¹



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2 | Streaming Algorithms



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Primary quantity of interest is *space complexity*.



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- [Le Gall '06] Can require exponentially less space than classical algorithms (but for a contrived problem).
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In this talk: a quantum advantage for a natural one-pass streaming problem.

Quantum-Classical Separations



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- A classical lower bound that does not generalize to the quantum setting.
- A quantum algorithm that beats it.

5 Triangle Counting



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- [K., Price '17] Tight classical bounds (in some parameter regimes) from the *Boolean Hidden Matching* problem.
- [Gavinsky, Kempe, Kerenidis, Raz, Wolf '07] BHM *exponentially* separates quantum and classical one-way communication complexity.

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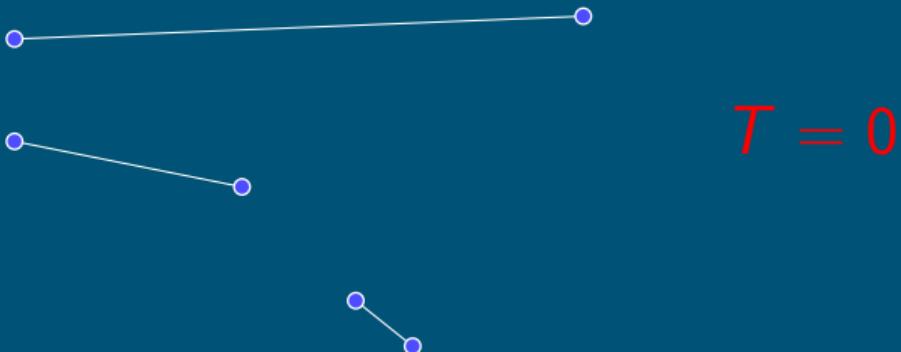
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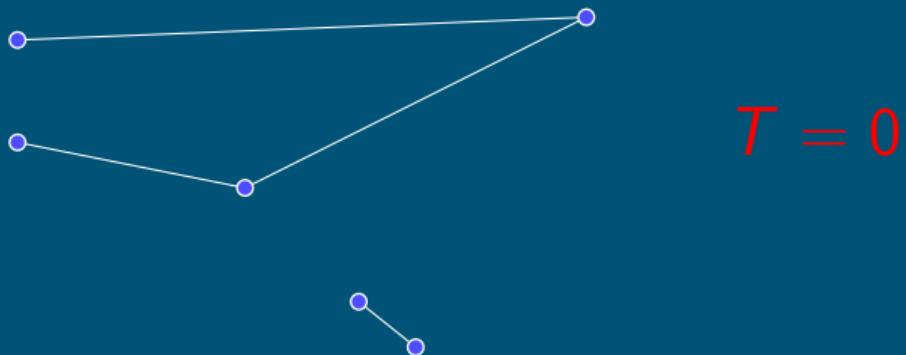
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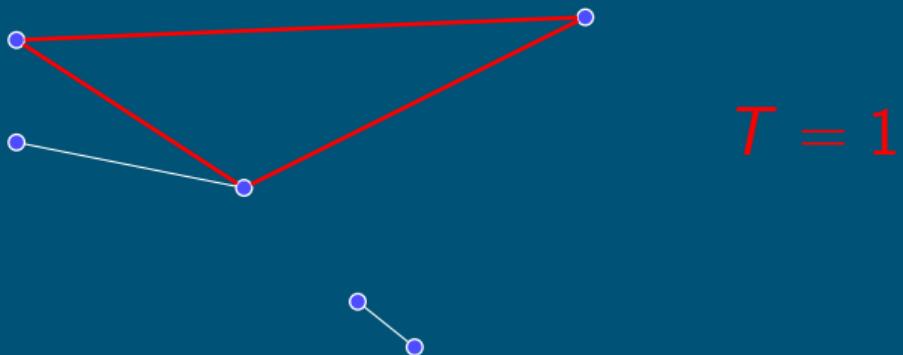
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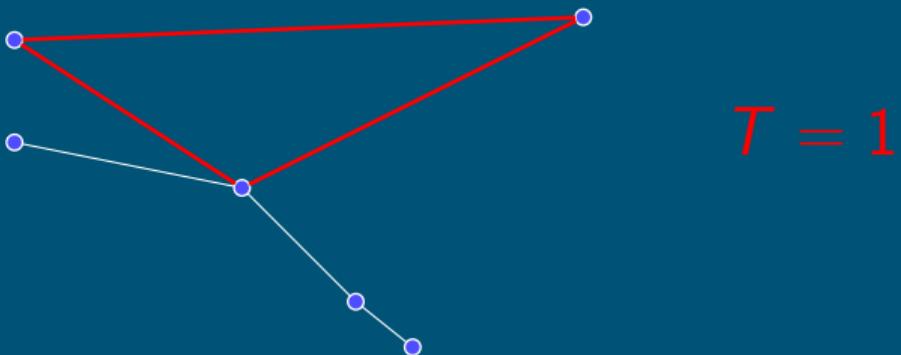
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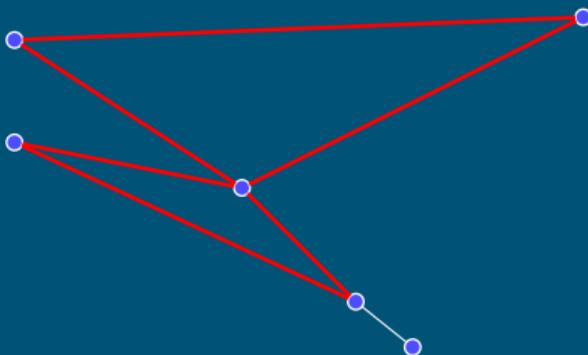
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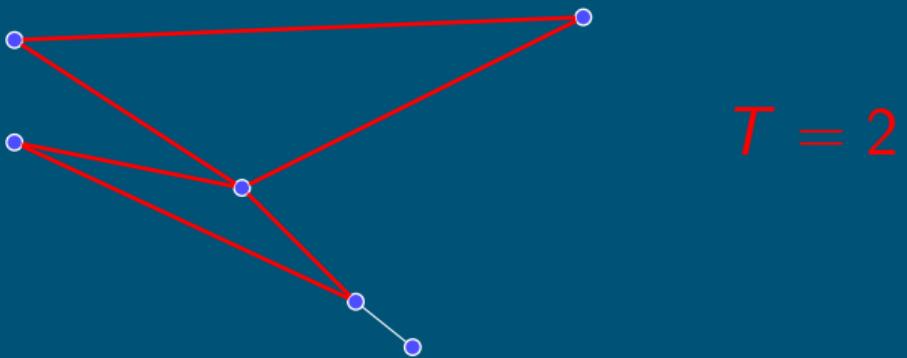


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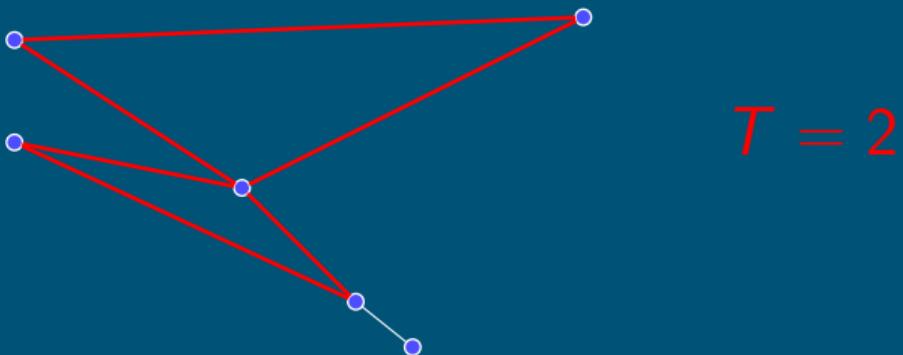


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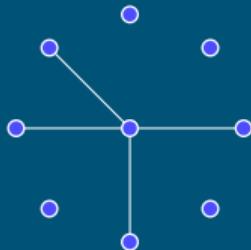


- [Braverman, Ostrovsky, Vilenchik '13] Non-trivial results require parametrization even if $T = \Omega(m)$.
- For this talk assume m edges, $T = \Theta(m)$ edge-disjoint triangles.

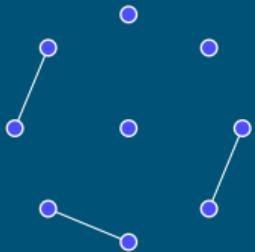
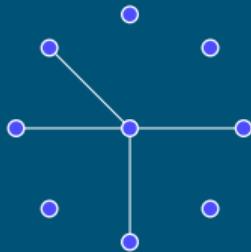


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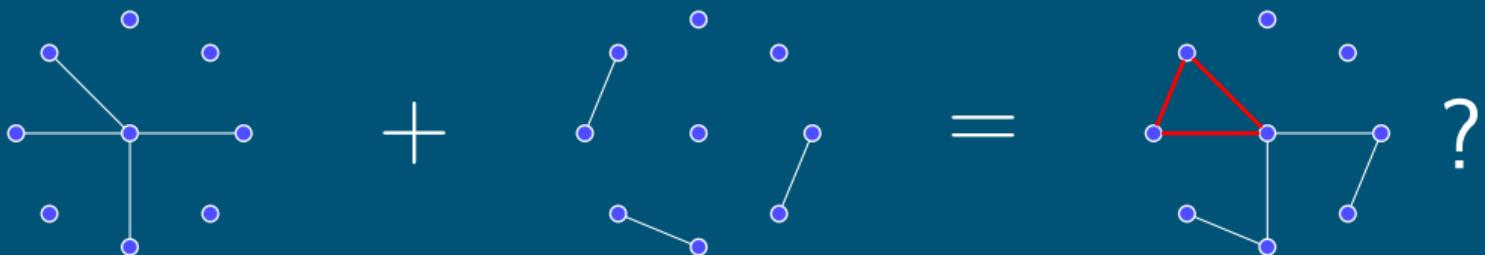


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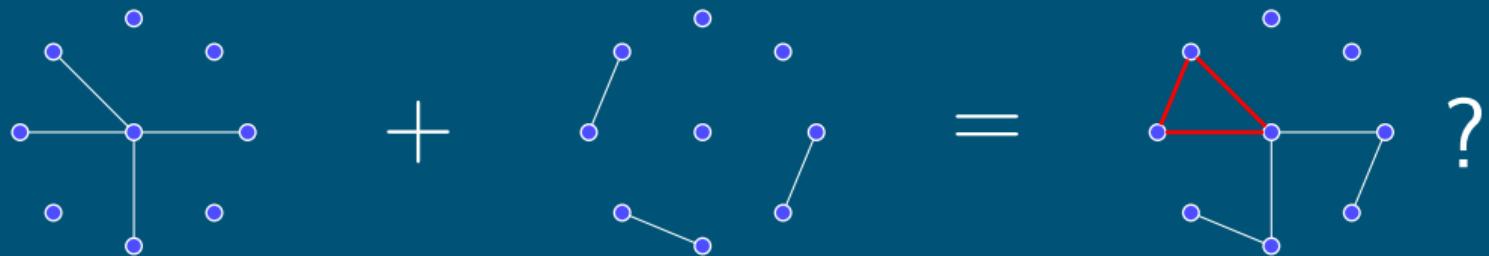


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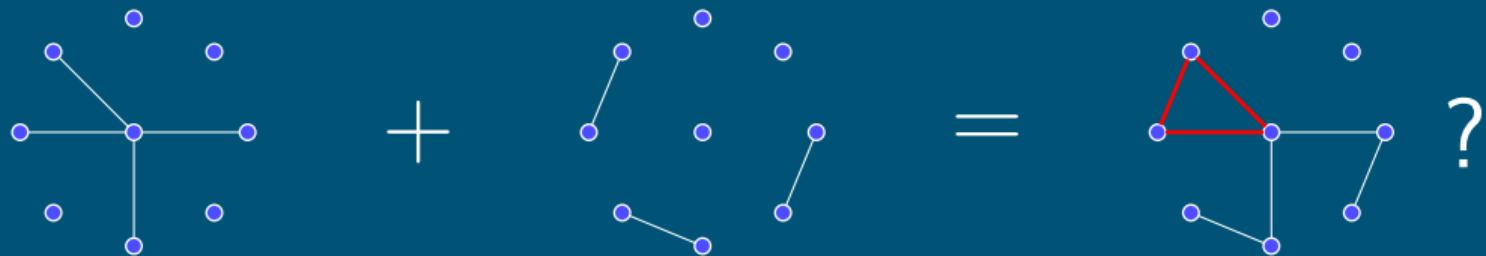
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- Intuitively: if we keep k star edges, we have a $\sim T \times \left(\frac{k}{m}\right)^2 = \frac{k^2}{m}$ chance of getting both edges of at least one of $T = \Theta(m)$ triangles, so we need \sqrt{m} samples.



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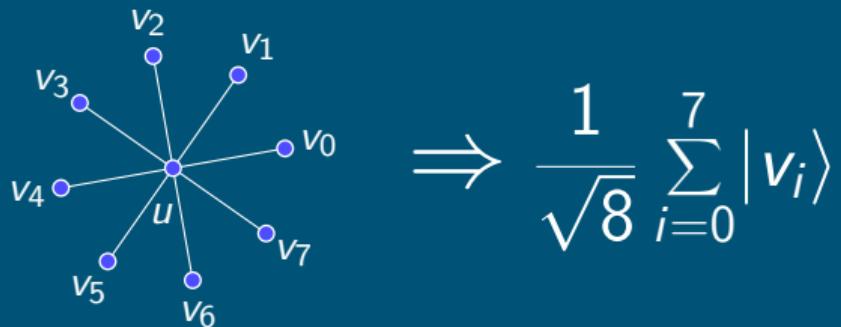
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- Reduction extends this to general (classical) algorithms.



Consider the two-player version of the problem: Alice has the star, Bob the matching.



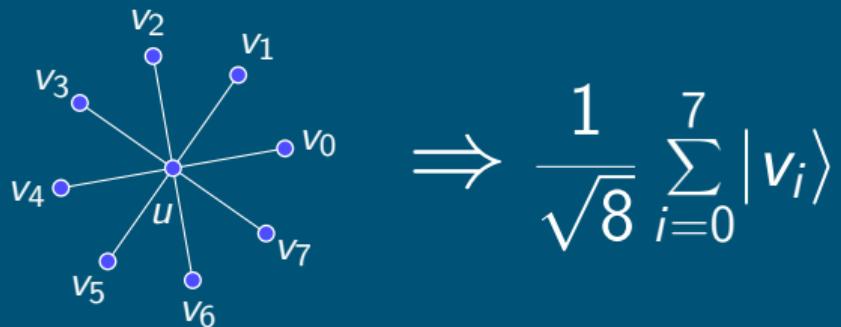
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$$v \bullet \xrightarrow{\hspace{1cm}} w \Rightarrow \frac{|v\rangle + |w\rangle}{\sqrt{2}}, \frac{|v\rangle - |w\rangle}{\sqrt{2}}$$

Bob measures with $(|v\rangle + |w\rangle)/\sqrt{2}$ and $(|v\rangle - |w\rangle)/\sqrt{2}$ for each vw in matching.



Measuring $\frac{1}{\sqrt{d_v}} \sum_{w \in N(u)} |v\rangle$ in the basis $\left\{ \frac{|v\rangle + |w\rangle}{\sqrt{2}}, \frac{|v\rangle - |w\rangle}{\sqrt{2}} : vw \in M \right\}$.



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- Gives a $O(\log m)$ qubit protocol.

Towards an Algorithm



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- Generalize to Alice and Bob holding arbitrary graphs.



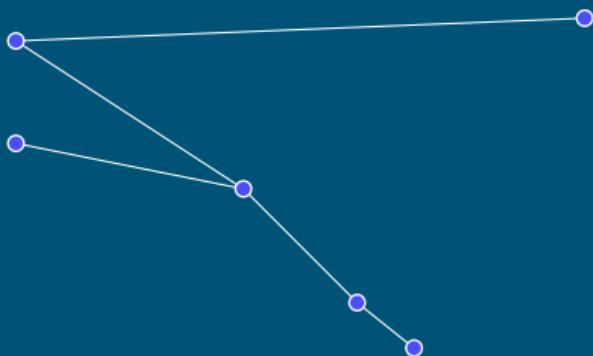
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- Generalize to Alice and Bob holding arbitrary graphs.
- Go from two player protocol to full streaming.

Generalizing the Graph: Alice



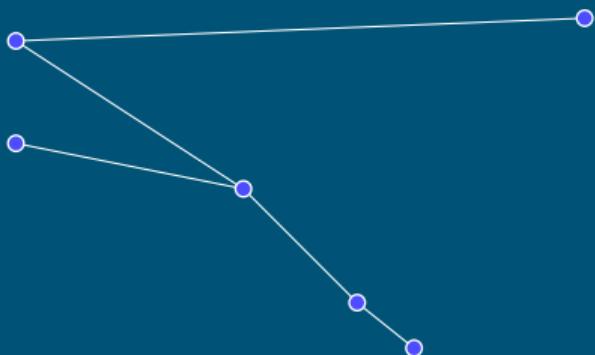
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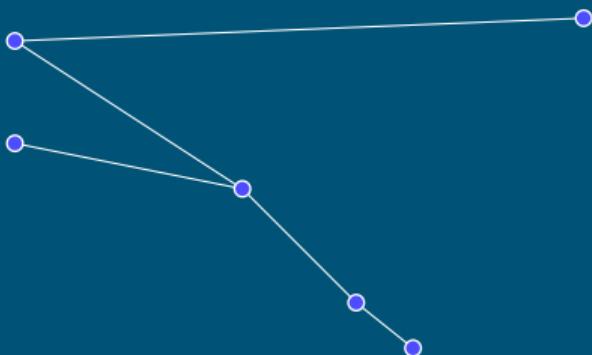
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- For each of Bob's edges vw we now measure with the basis vectors $\frac{|uv\rangle + |uw\rangle}{\sqrt{2}}, \frac{|uv\rangle - |uw\rangle}{\sqrt{2}}$ for every $u \in V$.

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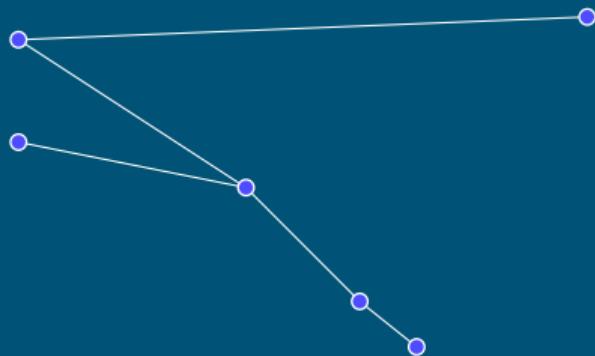


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$$\begin{array}{ccc} u \bullet & \diagdown & \bullet w \\ & v \bullet & \diagup \\ & \diagdown & \end{array} \Rightarrow \frac{|u\rangle + |v\rangle}{\sqrt{2}} \neq \frac{|v\rangle + |w\rangle}{\sqrt{2}}$$

Now the basis vectors generated are no longer orthogonal.

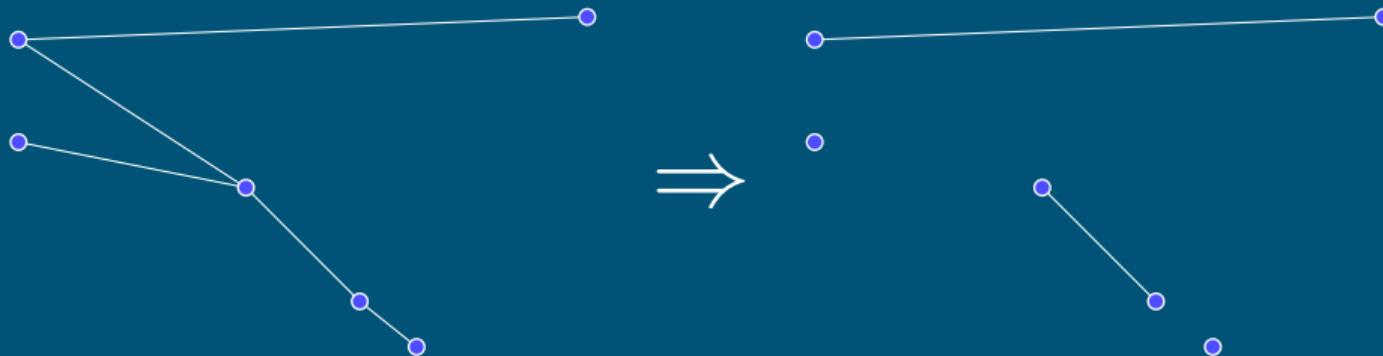
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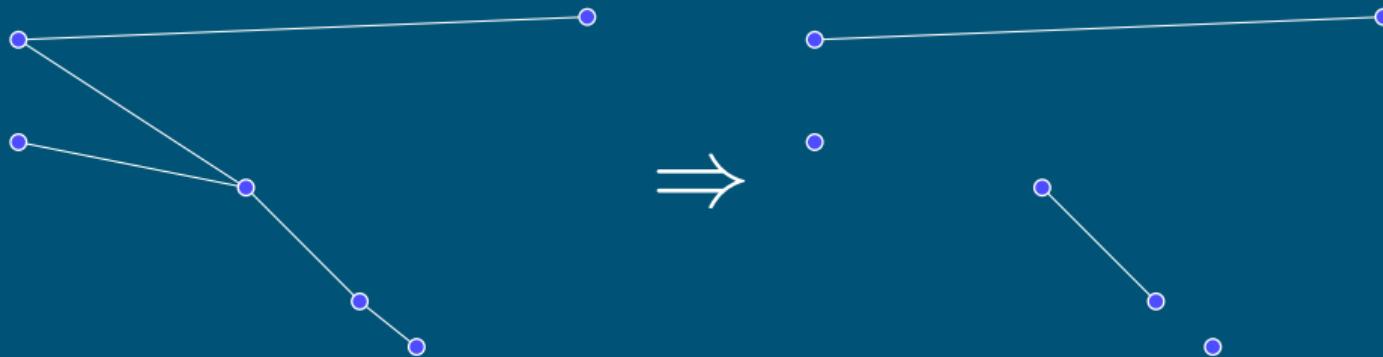
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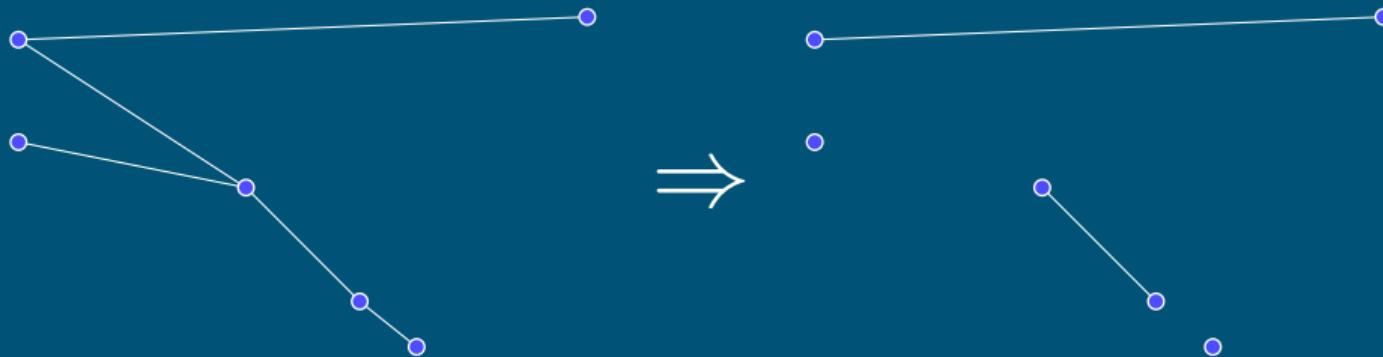
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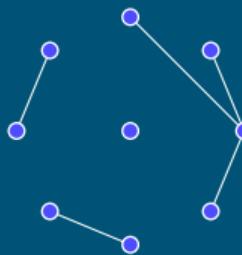
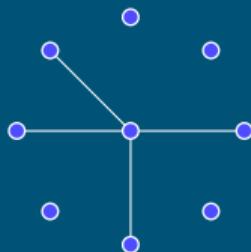


- The expectation of our estimator is now $2T/md$, so we need d^2 as many repeats.
- Not very helpful if d is unbounded.

How Much do High-Degree Vertices Matter?



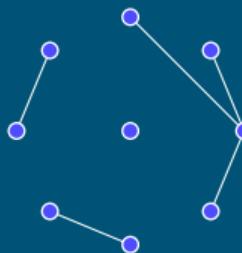
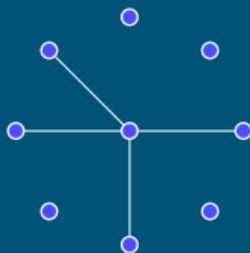
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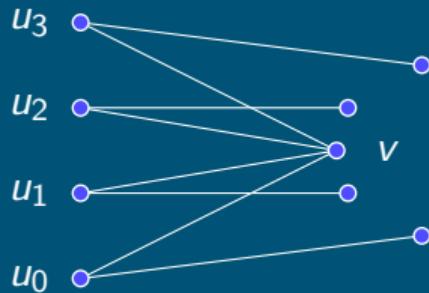


If all of the potential triangles are in one star Alice holds, at most a few of them are incident to Bob's high degree vertices.

Interpolating



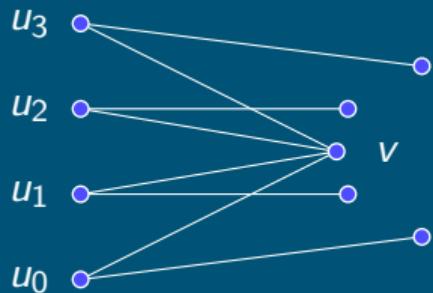
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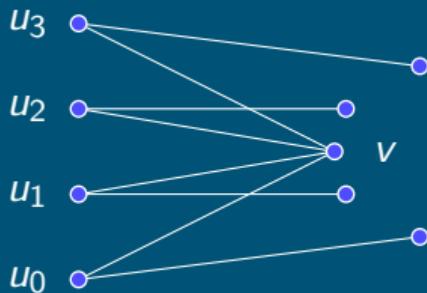


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- But this makes counting them *classically* easier!
- Interpolating gives us an $m^{2/5}$ (instead of \sqrt{m}) space algorithm.

Making a Streaming Algorithm



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- Perform the “Bob” measurement one edge at a time by measuring with three projectors, onto $\text{span}(\{|uv\rangle + |uw\rangle\}_{u \in V})$, $\text{span}(\{|uv\rangle - |uw\rangle\}_{u \in V})$ and the remaining space, whenever an edge vw arrives.



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- Now for each triangle the third edge to arrive will act as a “Bob edge” and the first two as “Alice edges”.



Theorem (Informal)

There is a quantum streaming algorithm that uses

$$O\left(\frac{m^{8/5}}{T^{6/5}} \Delta_E^{4/5} \log n \cdot \frac{1}{\varepsilon^2} \log \frac{1}{\delta}\right)$$

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- Best lower bound for quantum is $\Omega\left(\frac{m\Delta_E}{T}\right)$. Is exponential separation possible?