

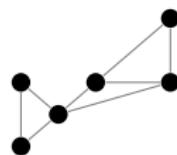
Tight Bounds for Vertex Connectivity in Dynamic Streams

Sepehr Assadi & Vihan Shah

Rutgers University

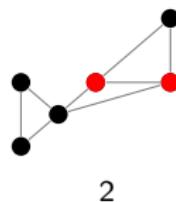
Vertex Connectivity

- Undirected Graph $G = (V, E)$
- Vertex Connectivity: Minimum number of vertices that need to be deleted to disconnect G



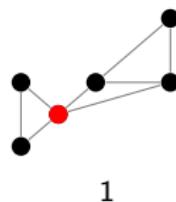
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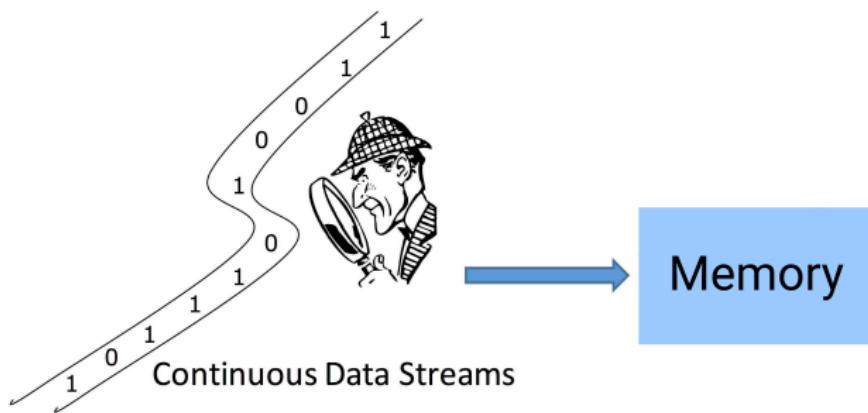
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Graph Streaming

- $G = (V, E)$
- Edges of G appear in a stream
- Trivial Solution: Store all edges ($\Omega(n^2)$ space)
- Goal: Minimize Memory ($o(n^2)$ space)

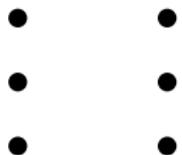


Streaming Models

Insertion-Only

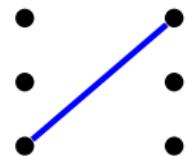
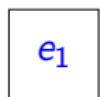
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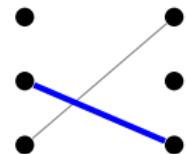
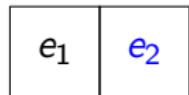
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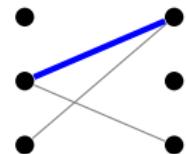
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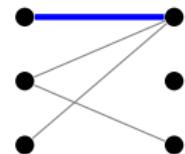
e_1	e_2	e_3
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Streaming Models

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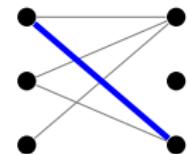
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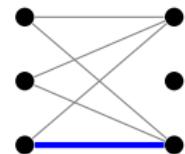
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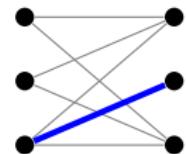
e_1	e_2	e_3	e_4	e_5	e_6
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Streaming Models

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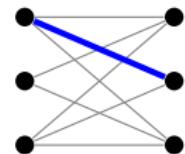
e_1	e_2	e_3	e_4	e_5	e_6	e_7
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Streaming Models

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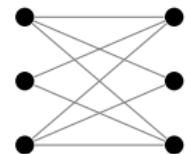
e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
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Streaming Models

Insertion-Only (finite stream)

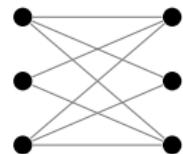
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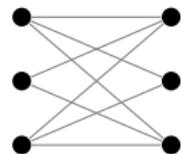


Dynamic

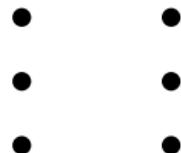
Streaming Models

Insertion-Only (finite stream)

e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
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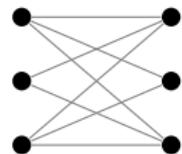
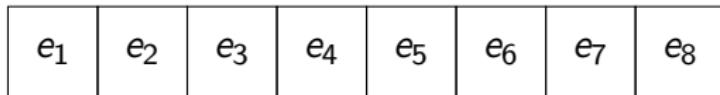


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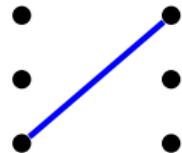


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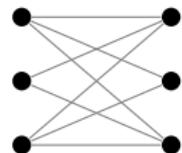
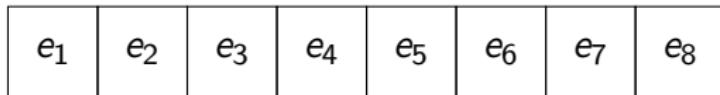


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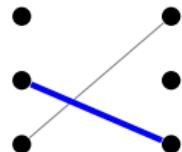
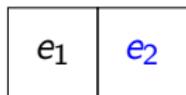


Streaming Models

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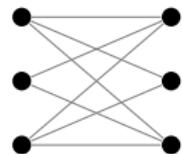
Dynamic



Streaming Models

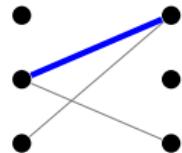
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e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
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Dynamic

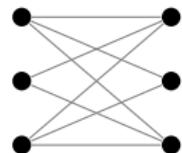
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Streaming Models

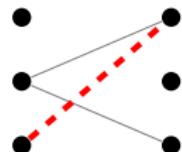
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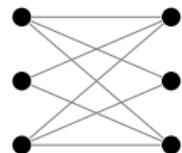
e_1	e_2	e_3	\bar{e}_1
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Streaming Models

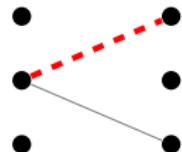
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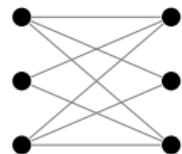
e_1	e_2	e_3	\bar{e}_1	\bar{e}_3
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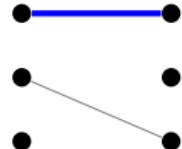
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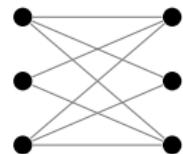
e_1	e_2	e_3	\bar{e}_1	\bar{e}_3	e_4
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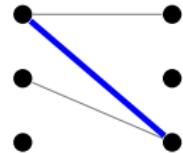
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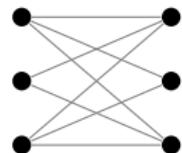
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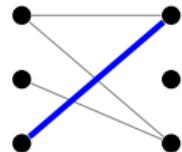
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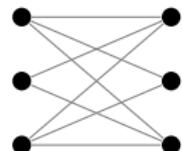
e_1	e_2	e_3	\bar{e}_1	\bar{e}_3	e_4	e_5	e_1
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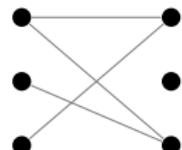
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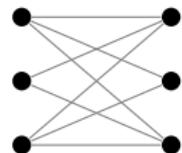
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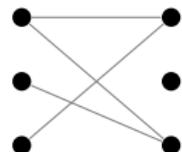
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We want to solve the problem after a **single pass** of the stream

Our Problem

- Finding exact vertex connectivity needs $\Omega(n^2)$ space in the worst case [SW15]

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- We want to solve the *k*-vertex connectivity problem in streaming (is the vertex connectivity of the input graph $G < k$ or $\geq k$)
- We also want to output a certificate of connectivity
(If G is *k*-vertex connected, output a subgraph H (certificate) that is also *k*-vertex connected)

Previous Work

Insertion-Only

- ① Upper bound: $\tilde{O}(kn)$ [FKM⁺05]
- ② Lower bound: $\Omega(kn)$ [SW15]

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Dynamic

- ① Upper bound: $\tilde{O}(k^2 n)$ [GMT15]
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There is a gap of **factor k** between the best known upper and lower bound in dynamic streams

Our Results

We bridge the gap between the upper and lower bound in dynamic streams

Theorem

There exists a randomized dynamic graph streaming algorithm for k -vertex connectivity that succeeds with high probability and uses $\tilde{O}(kn)$ space.

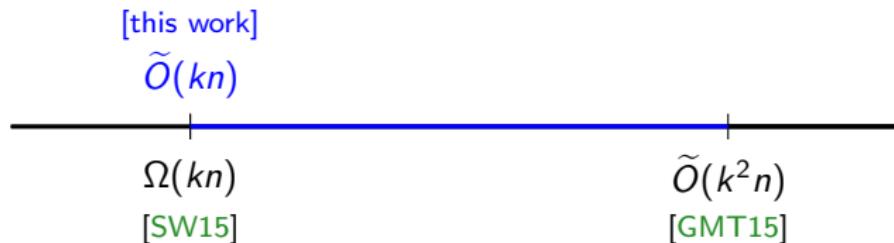


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Note: We also output a certificate of k -vertex connectivity

Our Results

We also extend the lower bound of [SW15] to **multiple pass** streams:

Theorem

Any randomized p -pass insertion-only streaming algorithm that solves the k -vertex connectivity problem with probability at least $2/3$ needs $\Omega(kn/p)$ bits of space.

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Note: This lower bound is for **multi-graphs** (also the case for [SW15])

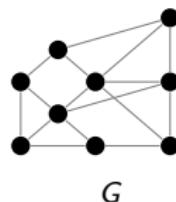
The upper bound also works for **multi-graphs**

Algorithm of [GMT15]

For $i = 1$ to $r = O(k^2 \log n)$:

- ① Sample every vertex in V_i independently with probability $1/k$
- ② Store a spanning forest H_i on $G[V_i]$

Output $H = \cup_i H_i$ as the certificate



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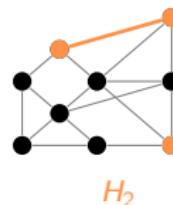
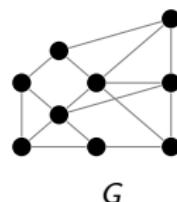


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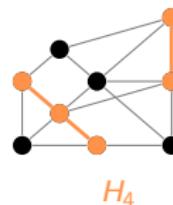
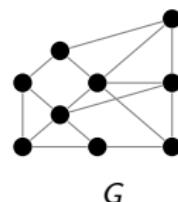


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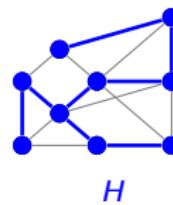
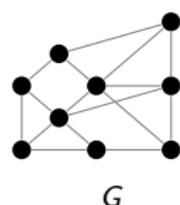


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Open Problems

- We have settled the space of the k -vertex connectivity problem only up to **polylog** factors. So the question of **optimal space bounds** (up to constant factors) is still open.
- Our lower bound and those of Sun and Woodruff [SW15] use **duplicate edges**. Obtaining lower bounds for **simple graphs** is an open problem.

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You can visit my poster!

Thank you!

References I

-  Joan Feigenbaum, Sampath Kannan, Andrew McGregor, Siddharth Suri, and Jian Zhang, *On graph problems in a semi-streaming model*, Theor. Comput. Sci. **348** (2005), no. 2-3, 207–216.
-  Sudipto Guha, Andrew McGregor, and David Tench, *Vertex and hyperedge connectivity in dynamic graph streams*, Proceedings of the 34th ACM Symposium on Principles of Database Systems, PODS 2015, Melbourne, Victoria, Australia, May 31 - June 4, 2015, 2015, pp. 241–247.
-  Xiaoming Sun and David P Woodruff, *Tight bounds for graph problems in insertion streams*, Approximation, Randomization, and Combinatorial Optimization. Algorithms and Techniques (APPROX/RANDOM 2015), Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2015.