

An Unconditional Lower Bound for Two-Pass Streaming Algorithms for Maximum Matching Approximation

Christian Konrad & **Kheeran K. Naidu**

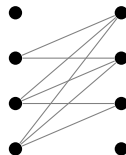
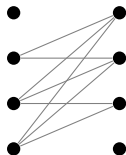
University of Bristol, UK

{christian.konrad,kheeran.naidu}@bristol.ac.uk

Maximum Bipartite Matching (MBM)

Definition

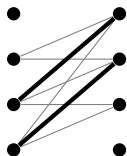
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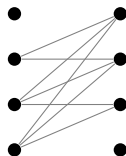
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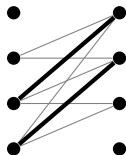
M
matching



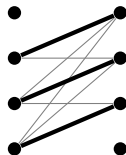
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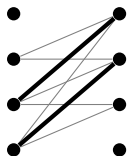


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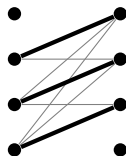
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Approximations

- M is a $(\frac{|M|}{|M^*|})$ -approximate matching (e.g. $\frac{2}{3}$).

Insertion-Only Graph Streaming Model

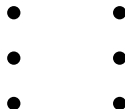
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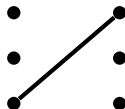
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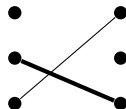
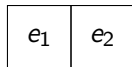
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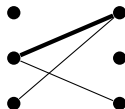
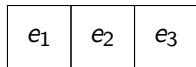
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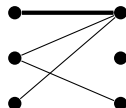
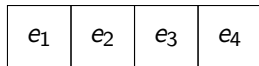
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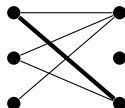
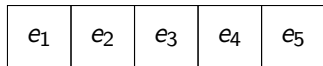
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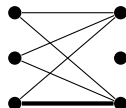
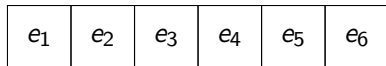
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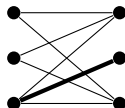
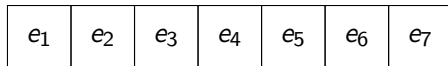
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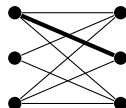
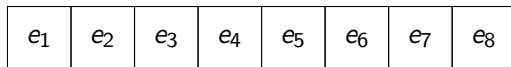
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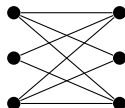
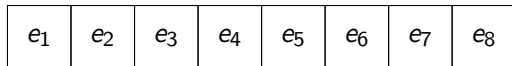
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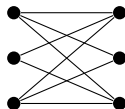
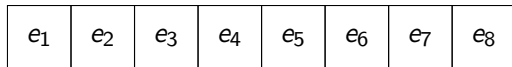
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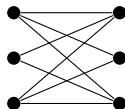
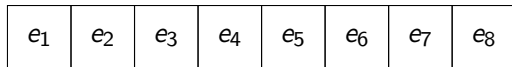
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- Store all edges with $O(n^2)$ space.

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Interesting Algorithms

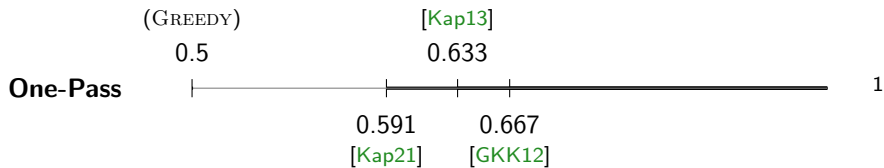
- Use $O(n \text{ polylog } n)$ space (semi-streaming).
 - Many graph problems require $\Omega(n)$ space in one pass [FKM⁺04].
- Use **one or more passes** of the stream.

Approximate MBM in the Semi-Streaming Model

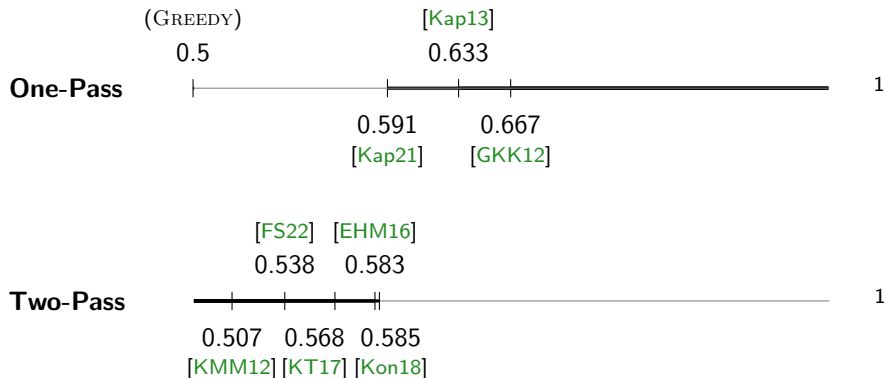
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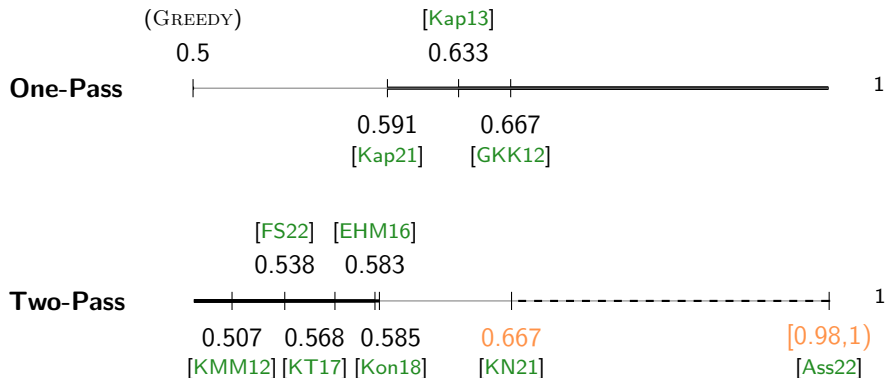
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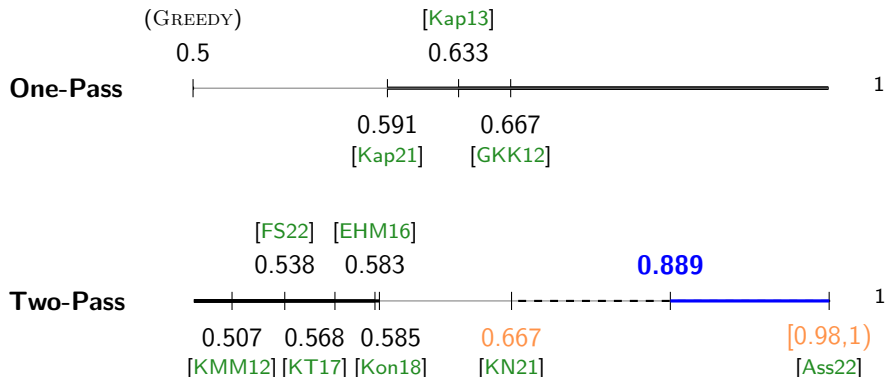
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Our Result

For $\varepsilon > 0$, any constant-error two-pass $(\frac{8}{9} + \varepsilon)$ -approximation streaming algorithm for MBM requires $n^{1+\Omega(1/(\log \log n)^2)}$ space.

Space Streaming Lower Bounds

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Goal: Construct a stream of edges that is hard for any algorithm.

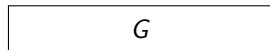
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- Construct a **hard** graph G .
- **Adversarially** order its edges.
- Prove hardness via **one-way communication complexity**.

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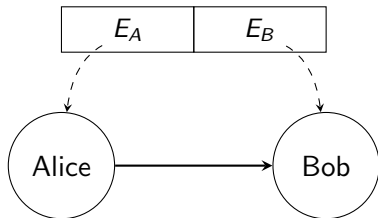
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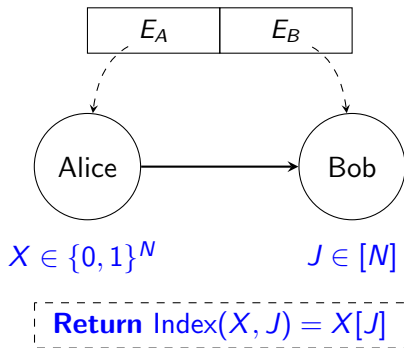
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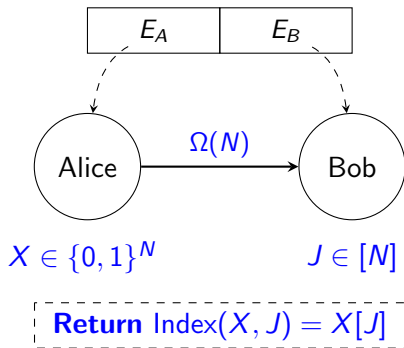
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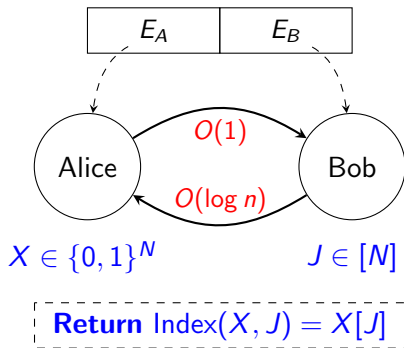
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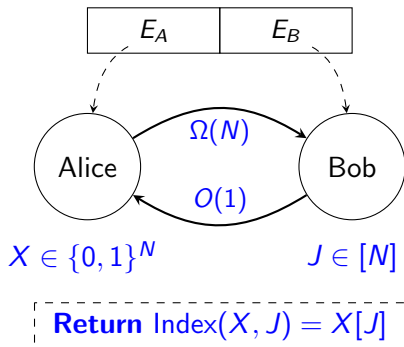
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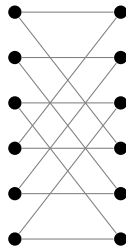
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Info Cost Tradeoff [JRS09]

- 1 If $\text{ICost}_{\mathcal{D}}^B(\pi) = O(1)$, then
- 2 $\text{ICost}_{\mathcal{D}}^A(\pi) = \Omega(N)$

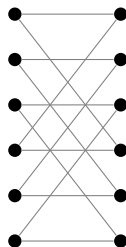
Ruzsa-Szemerédi (RS) Graphs



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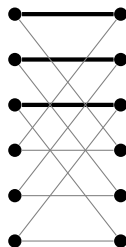
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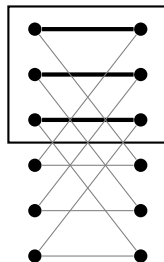
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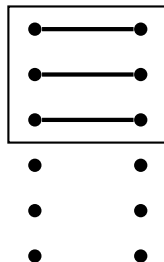
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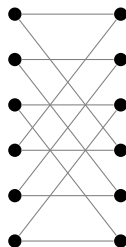
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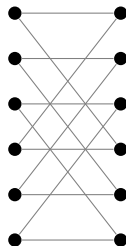
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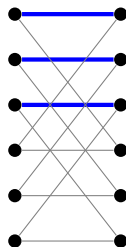
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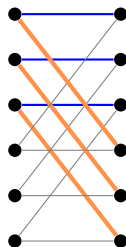
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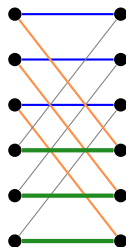
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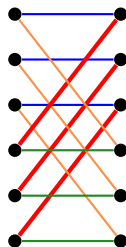
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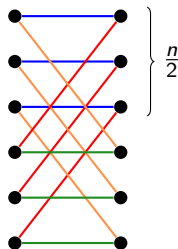
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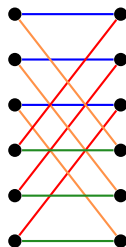
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For constant $\delta > 0$, there exists a (bipartite) (r, t) -RS graph on $2n$ vertices where $r = (\frac{1}{2} - \delta) \cdot n$ and $t = n^{\Omega(1/\log \log n)}$.



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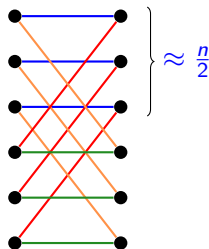
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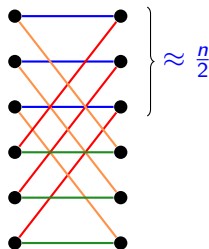
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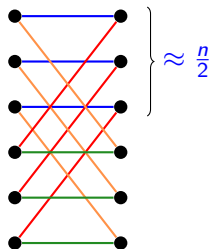
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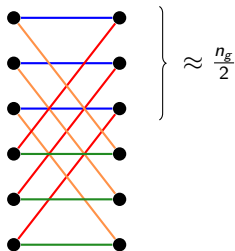


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Two-Pass Hard Graph and Adversarial Stream

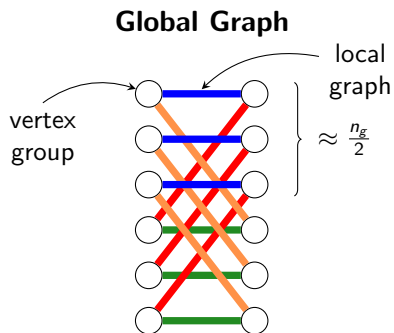
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Global Graph



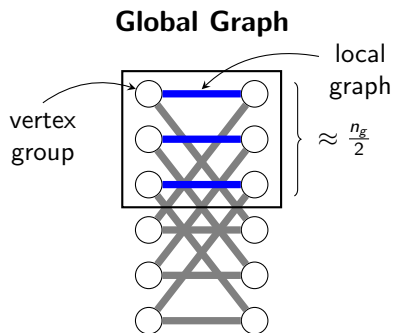
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Two-Pass Hard Graph and Adversarial Stream



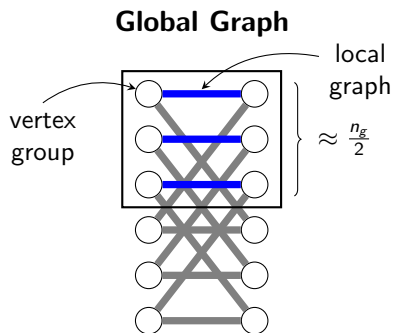
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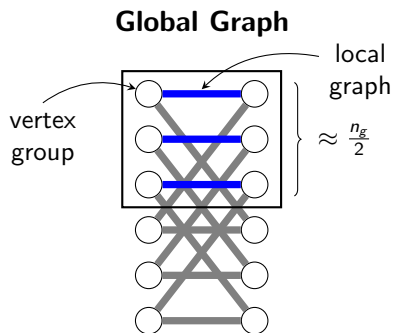
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Two-Pass Hard Graph and Adversarial Stream



- $(2n_g)$ -vertex (r_g, t_g) -RS graph.
- $\Theta(n_g)$ small hard instances

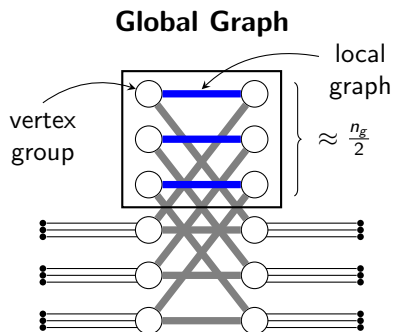
Two-Pass Hard Graph and Adversarial Stream



Q: What is the selector for MBM?

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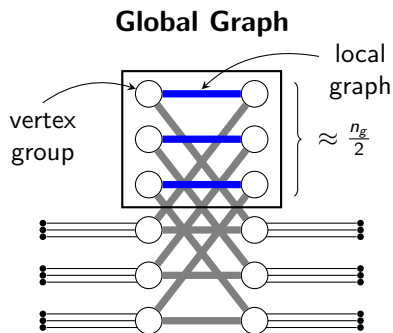
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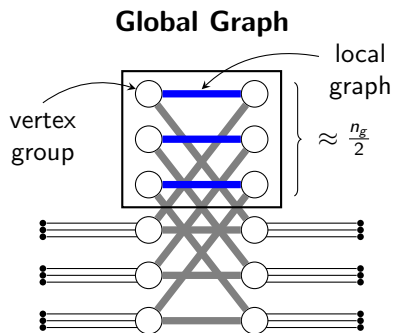
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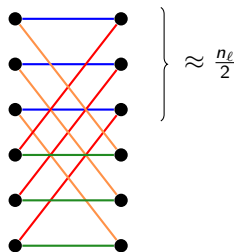
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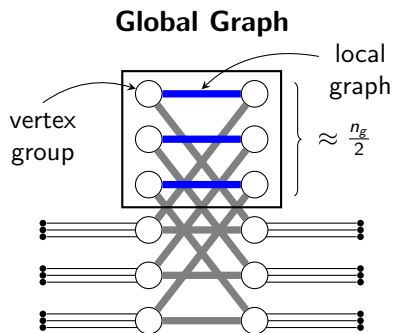
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Local Graphs



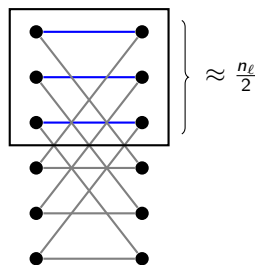
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Two-Pass Hard Graph and Adversarial Stream



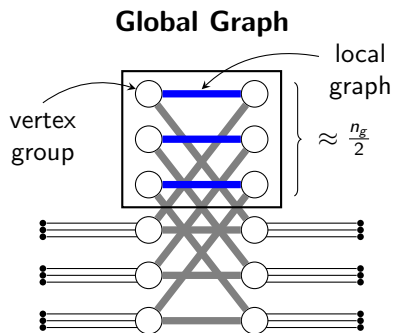
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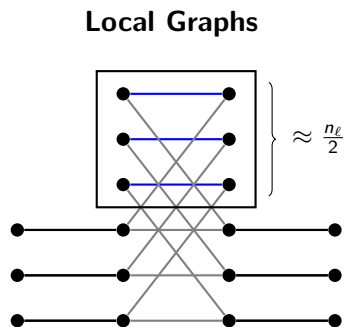


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Two-Pass Hard Graph and Adversarial Stream

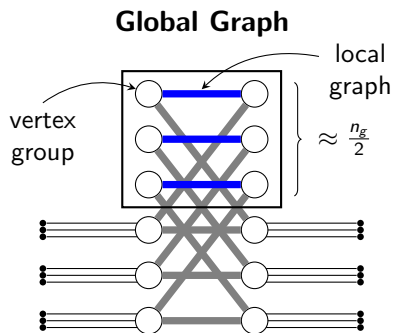


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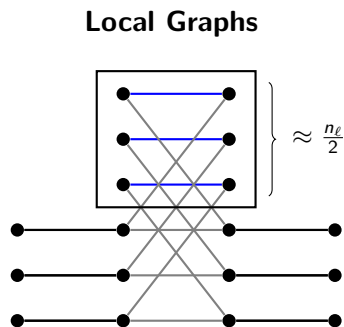


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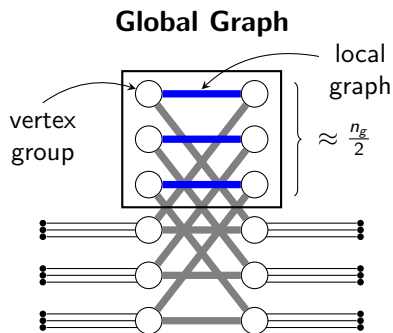


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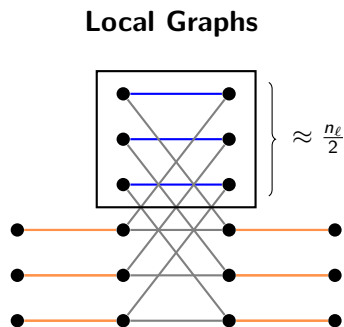


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Two-Pass Hard Graph and Adversarial Stream

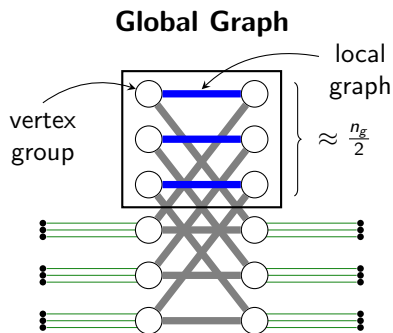


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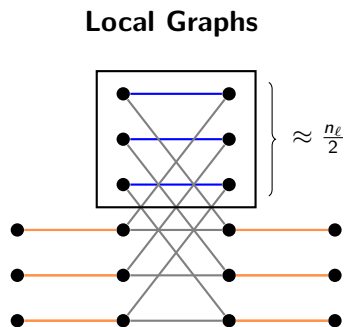


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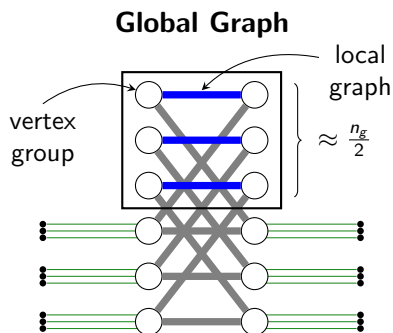


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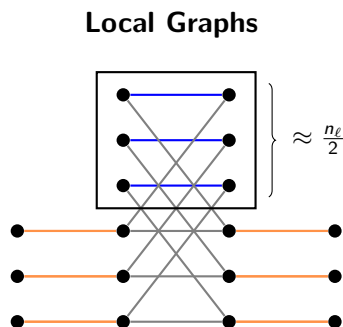


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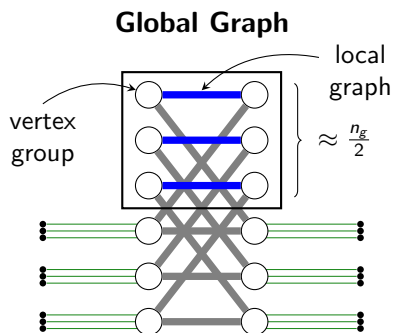
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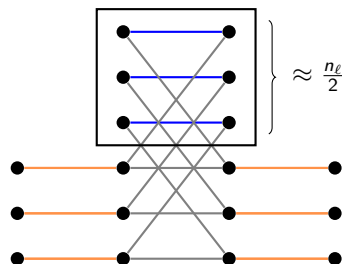
local RS-graphs	local selectors	global selector
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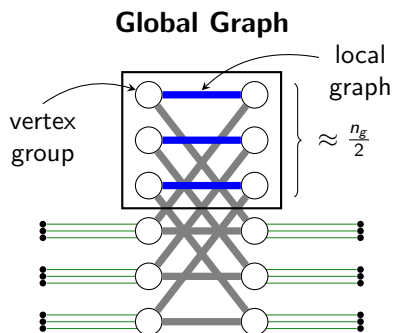


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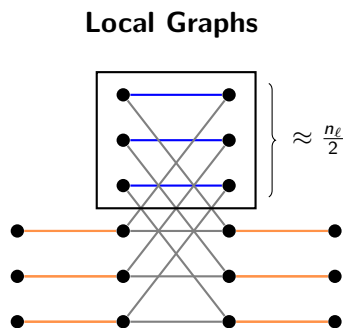
local RS-graphs	local selectors	global selector
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\mathcal{A}

Two-Pass Hard Graph and Adversarial Stream



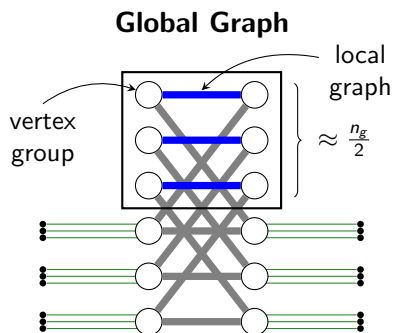
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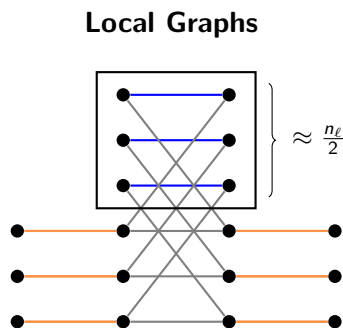
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	local RS-graphs	local selectors	global selector
A	$\ggg n \text{ polylog } n$	$\gg n \text{ polylog } n$	$O(n)$

Two-Pass Hard Graph and Adversarial Stream



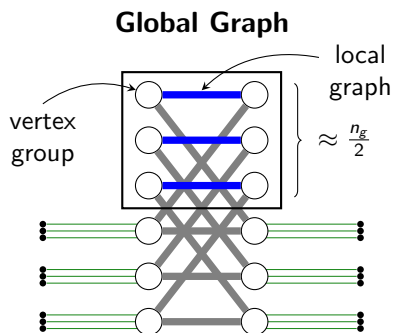
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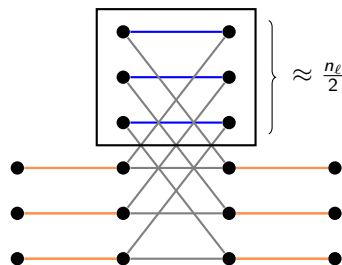
local RS-graphs	local selectors	global selector
$\underbrace{\hspace{10em}}_{o(1) \text{ per local graph (Index instance)}}$		$\mathcal{A} \quad O(n)$

Two-Pass Hard Graph and Adversarial Stream



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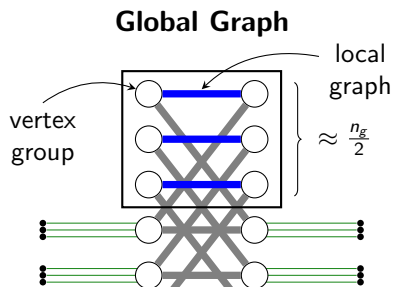
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local RS-graphs	local selectors	global selector ✓
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$o(1)$ per local graph (Index instance)

\mathcal{A}

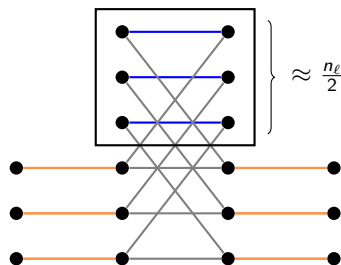
Two-Pass Hard Graph and Adversarial Stream



Info Cost Tradeoff [JRS09]

- 1 If $\text{ICost}_D^B(\pi) = O(1)$, then
- 2 $\text{ICost}_D^A(\pi) = \Omega(N)$

Local Graphs



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local RS-graphs

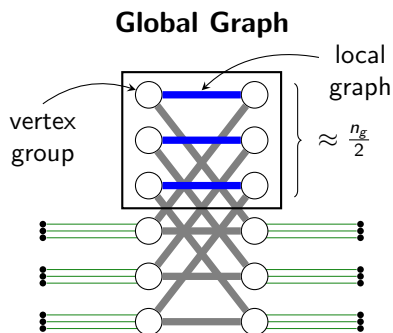
local selectors

global selector ✓

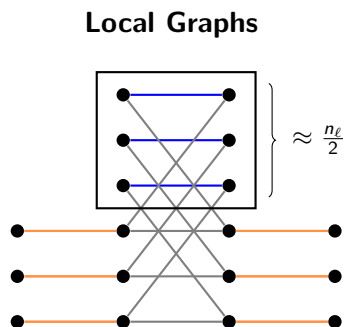
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Two-Pass Hard Graph and Adversarial Stream



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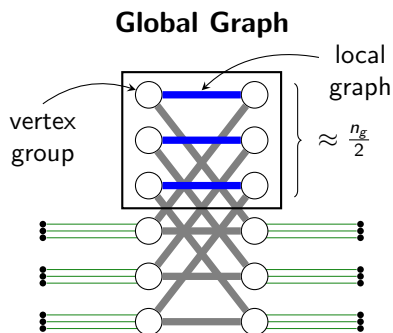
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local RS-graphs	local selectors	global selector ✓
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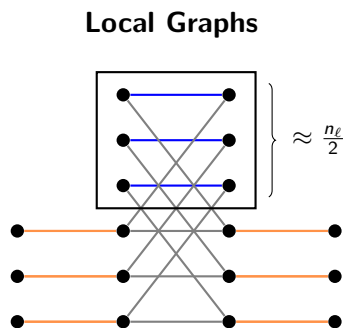
$o(1)$ per local graph (Index instance)

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Two-Pass Hard Graph and Adversarial Stream



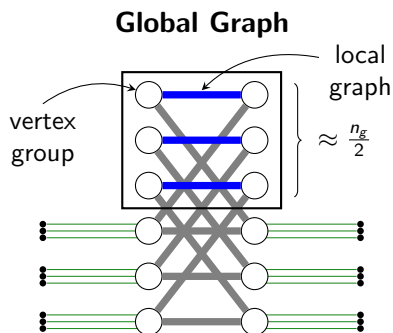
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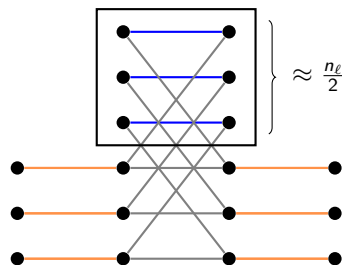
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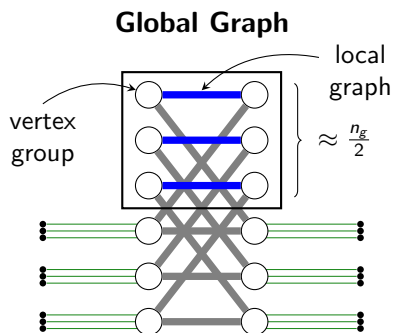


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local RS-graphs	local selectors	global selector ✓
$o(1)$ fraction of edges	$O(n)$	

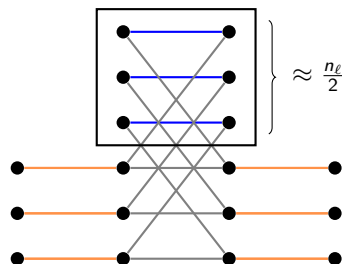
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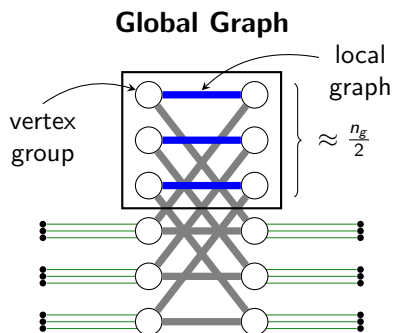
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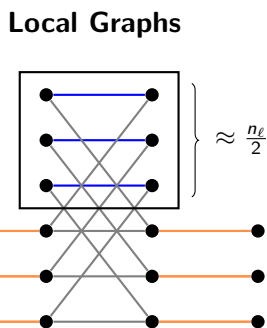
$o(1)$ fraction of edges

\mathcal{A}

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local RS-graphs	local ✓ selectors	global ✓ selector
$o(1)$ fraction of edges		$8/9$ -approximation

Next Steps

Our Result

For $\varepsilon > 0$, any constant-error two-pass $(\frac{8}{9} + \varepsilon)$ -approximation streaming algorithm for MBM requires $n^{1+\Omega(1/(\log \log n)^2)}$ space.

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- [AS23] recently showed that $(1 - \varepsilon)$ -approximations require $\Omega(\log 1/\varepsilon)$ passes (conditional)
- Algorithms require either $O(1/\varepsilon^2)$ or $O((1/\varepsilon) \cdot \log n)$ passes.

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Thank you!

References I



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