On Two-Pass Streaming Algorithms for Maximum Bipartite Matching

Kheeran K. Naidu

University of Bristol kn16063@bristol.ac.uk

Joint work with Dr Christian Konrad

Overview

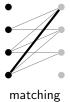
- Background
- Our Work
 - Lower Bound
 - Algorithmic
- 3 Discussion

Definition

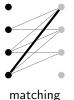
Definition



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maximal matching

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matching



maximal matching



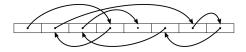
maximum matching

Definition

A **(bipartite)** matching is a subset of edges of a graph where every vertex has degree at most 1.

Finding a maximum matching:

- exact algorithms exists, i.e. Hopcroft-Karp [SWAT71];
- require random access to the graph's edges (infeasible requirement for massive graphs).



Semi-Streaming Model

Feigenbaum et al. [ICALP04]

A graph with n vertices is presented to an algorithm as a stream of edges where the storage space of the algorithm is bounded by O(n polylog n).

- Only allows sequential access to the graph.
- Algorithms with space $O(n \text{ polylog } n) = O(n (\log n)^{O(1)})$.
- Ideally with few passes of the stream.



Maximum Bipartite Matching Literature I

	Algorithmic	Lower Bound
one-pass		$\frac{1}{2} + 0.167$ [SODA12]
	$\frac{1}{2}$ [folklore]	$\frac{1}{2} + 0.132$ [SODA13]
		$\frac{1}{2} + 0.091$ [SODA21]
	$\frac{1}{2} + 0.019 \text{ [APPROX12]}$	
	$\frac{1}{2} + 0.083$ [ICDMW16]	
two-pass	$\frac{1}{2} + 0.063$ [APPROX17]	
	$\frac{1}{2} + 0.085$ [MFCS18]	

Two-Pass MBM Background Kheeran K. Naidu (UoB) 5 / 25

Main Results

Two-Pass Maximum Bipartite Matching

Class of algorithms:

- finds a maximal matching M (first-pass);
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Other strategies and techniques are required!

Maximum Bipartite Matching Literature II

	Algorithmic	Lower Bound
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two-pass	$\begin{array}{c} \frac{1}{2} + 0.019 \; [APPROX12] \\ \frac{1}{2} + 0.083 \; [ICDMW16] \\ \frac{1}{2} + 0.063 \; [APPROX17] \\ \frac{1}{2} + 0.085 \; [MFCS18] \\ \frac{1}{2} + 0.085 \end{array}$	$\frac{1}{2} + 0.167^{1}$

Two-Pass MBM Background Kheeran K. Naidu (UoB)

 $^{^{1}}$ where the first pass finds a maximal matching, i.e., at least a $\frac{1}{2}$ -approximation.

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Lower Bound Result

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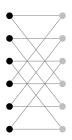
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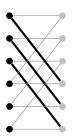
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- Uses a dense family of Rusza Szemeredi (RS) graphs which contains (many) near-perfect matchings. This result may be of independent interest.

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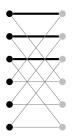
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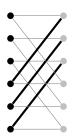
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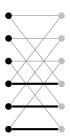
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Rusza Szemeredi (RS) graphs are a family of bipartite graphs whose edge set is made up of a union of induced matchings of the same size.

Proposition ([SODA12])

There exists a bipartite RS graph with $N^{\Omega(\frac{1}{\log\log N})}$ induced matchings of size $\frac{N}{2} - \epsilon N$ where N = |A| = |B| and $\epsilon > 0$.

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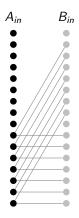
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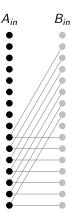
Note: This is a dense RS graph with $N^{1+\Omega(\frac{1}{\log\log N})} \supset O(N \text{ polylog } N)$ edges.

Two-Party Communication Setup

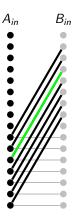
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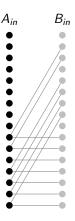
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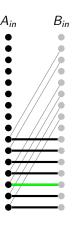
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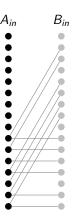
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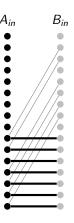
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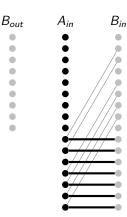


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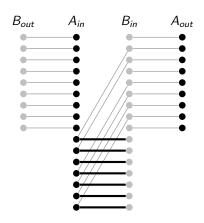
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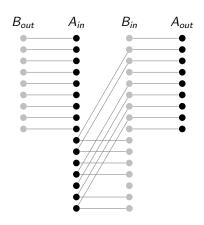


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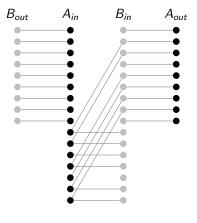
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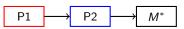


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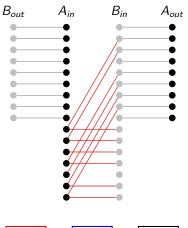


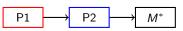
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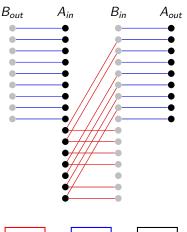


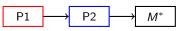
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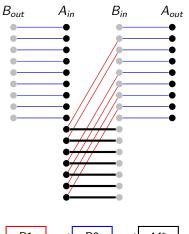


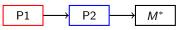
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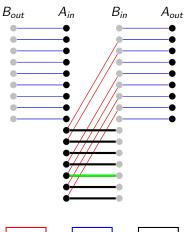


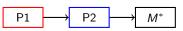
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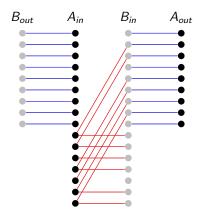


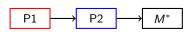
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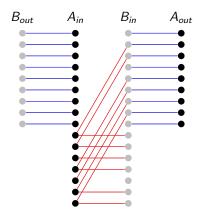


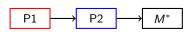
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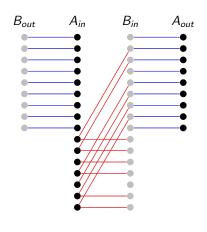


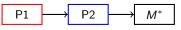
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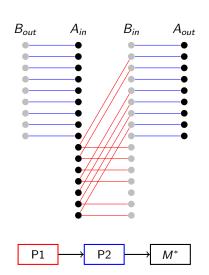


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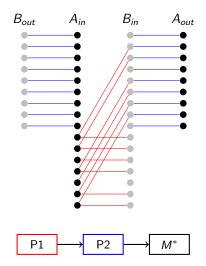
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Outline:

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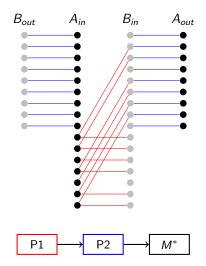
Goal: Give both players knowledge of a maximal matching without affecting the B_{out} A_{in} B_{in} dif **Proposition** There exists a bipartite RS graph with $N^{\Omega(\frac{1}{\log\log N})}$ induced matchings of size $\frac{N}{2} - \epsilon N$ where N = |A| = |B| and $\epsilon > 0$ such that there are $N^{\Omega(\frac{1}{\log \log N})}$ disjoint near-perfect matchings, each of size $N-2\epsilon N$.

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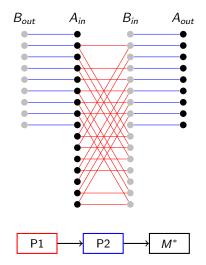
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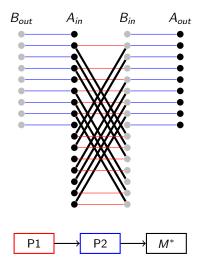


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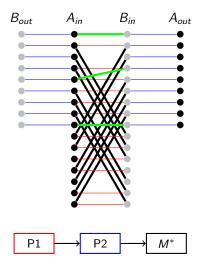
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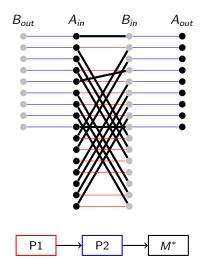
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Two-Pass Maximum Bipartite Matching

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• Even a combination of the two dominant techniques in the area cannot beat the current state-of-the-art $2-\sqrt{2}\approx \frac{1}{2}+0.085$ -approximation.

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- A novel meta algorithm that exactly achieves the current state-of-the-art.
- A family of hard-instance graphs shows the analysis is tight.

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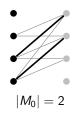
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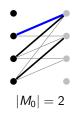
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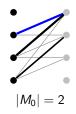
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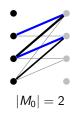
Definition



Class of algorithms:

- finds a maximal matching M (first-pass);
- ② increases the size of the matching M (second-pass).

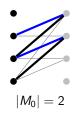
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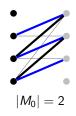
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Definition



Two-Pass Algorithm Summary

Using the two dominant techniques, parameterised by *p* and *d*:

- subsampling with probabilityp [APPROX12] [MFCS18]
- e run GREEDY_d [ICDMW16] [APPROX17]



semi-incomplete matching

Two-Pass Algorithm Summary

Using the two dominant techniques, parameterised by *p* and *d*:

- subsampling with probabilityp [APPROX12] [MFCS18]
- vun Greedy_d [ICDMW16] [APPROX17]



semi-incomplete matching

Let G = (A, B, E) be any bipartite graph.

Let $\pi = e_1, e_2, ...$ be any stream of its edges.

First pass:

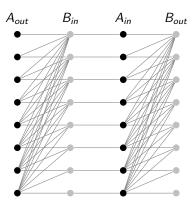
• $M \leftarrow \text{Greedy}(\pi)$

Second pass:

- subsample $M' \subseteq M$ with prob. p
- $H_L \leftarrow E \cap A_{out} \times B(M')$
- $H_R \leftarrow E \cap A(M') \times B_{out}$
- $M'_I \leftarrow \text{GREEDY}_d(\pi_{H_I})$
- $M'_R \leftarrow \text{GREEDY}_d(\pi_{H_R})$

Let G = (A, B, E) be a hard-instance (worst-case) graph.

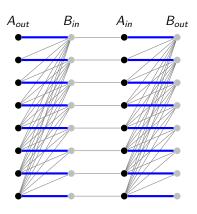
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The goal of the algorithm is to find the maximum matching M^* .



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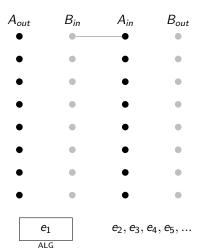
First pass:

A _{out} ●	B _{in}	A_{in}	B _{out}
•	•	•	•
•	•	•	•
•	•	•	•
•	•	•	•
•	•	•	•
•	•	•	•
•	•	•	•
		e_1, e_2, ϵ	$e_3, e_4,$

Let G = (A, B, E) be a hard-instance (worst-case) graph.

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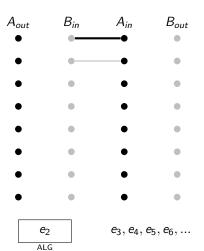
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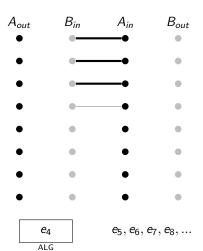
First pass:

A_{out}	B_{in}	A_{in}	B_{out}
•	•	—•	•
•	•	—•	•
•	•	—●	•
•	•	•	•
•	•	•	•
•	•	•	•
•	•	•	•
•	•	•	•
e ₃		e_4, e_5, ϵ	$e_6, e_7,$

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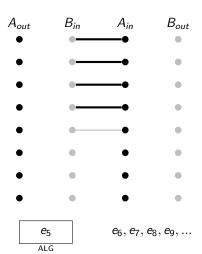
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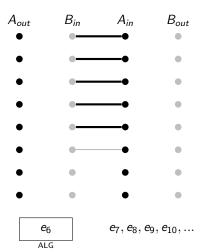
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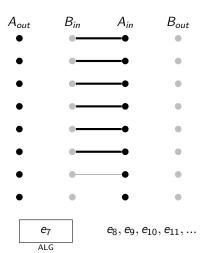
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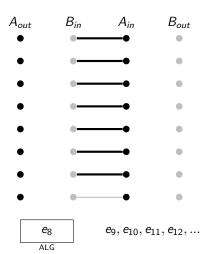
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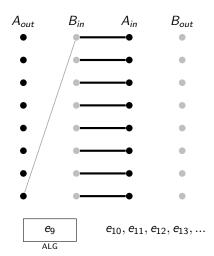
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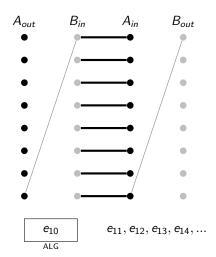
First pass:



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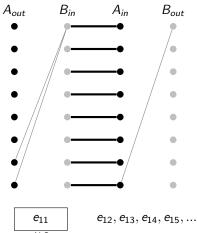
First pass:



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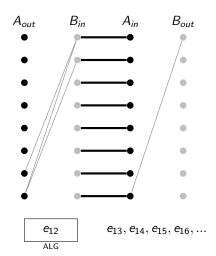
$$e_{11}$$
 $e_{12}, e_{13}, e_{14}, e_{15}, ...$

Let G = (A, B, E) be a hard-instance (worst-case) graph.

Let $\pi = e_1, e_2, ...$ be a stream of its edges in adversarial (worst-case) order.

First pass:

• $M \leftarrow \text{Greedy}(\pi)$

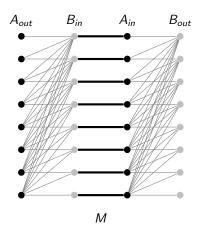


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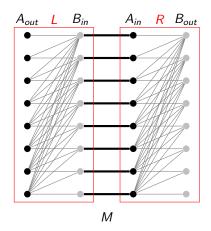


Kheeran K. Naidu (UoB)

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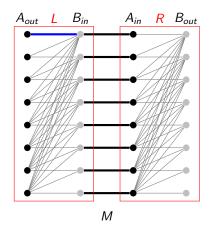


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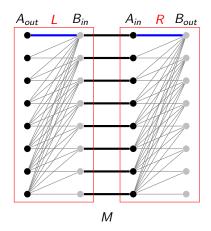
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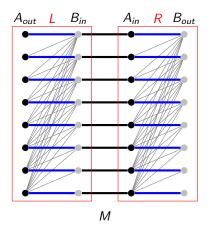


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First pass:

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Let G = (A, B, E) be a hard-instance R B_{out} A_{out} L B_{in} A_{in} (worst-case) graph. Let $\pi = e_1, e_2, ...$ be a stream of its edges in adversarial (worst-case) order. First pass: How can we find • $M \leftarrow \text{Greedy}(\pi)$ these?

Two-Pass MBM

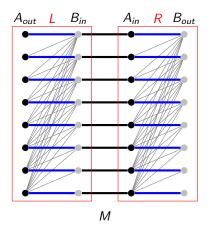
Μ

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First pass:

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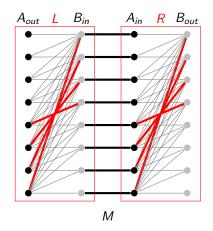


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edge orde

Using the two dominant techniques:

First

• subsample the inner vertices [APPROX12] [MFCS18]

 A_{out} L

 B_{in}

② run Greedy_d [ICDMW16] [APPROX17]



Μ

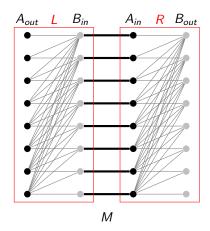
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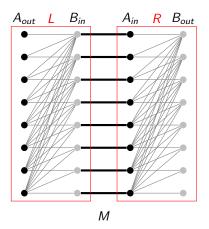
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Second pass:



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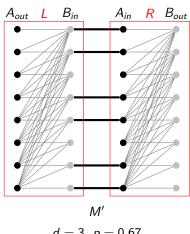
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First pass:

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Second pass:

• subsample $M' \subseteq M$ with prob. p



$$d = 3, p = 0.67$$

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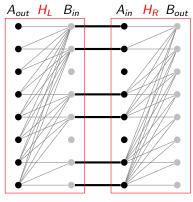
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Second pass:

- subsample $M' \subseteq M$ with prob. p
- $H_L \leftarrow E \cap A_{out} \times B(M')$
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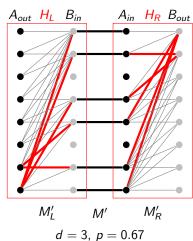
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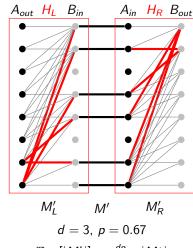
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- $M'_I \leftarrow \text{GREEDY}_d(\pi_{H_L})$
- $M'_{R} \leftarrow \text{GREEDY}_{d}(\pi_{H_{R}})$



$$\mathbb{E}_{M'}[|M'_L|] = \frac{dp}{d+p} \cdot |M_L^*|$$

Let G = (A, B, E) be a hard-instance (worst-case) graph.

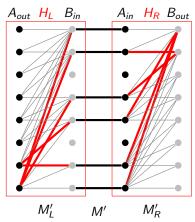
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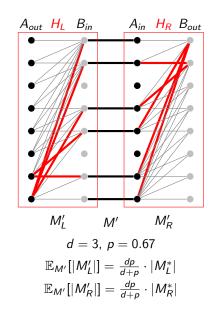


$$d = 3, p = 0.67$$

$$\mathbb{E}_{M'}[|M'_L|] = \frac{dp}{d+p} \cdot |M^*_L|$$

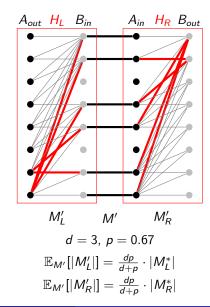
$$\mathbb{E}_{M'}[|M'_R|] = \frac{dp}{d+p} \cdot |M^*_R|$$

Analysis



Analysis

$$|\mathcal{Q}| = \left(\frac{p}{d+p} - \frac{p}{2d}\right) \cdot |M^*|.$$

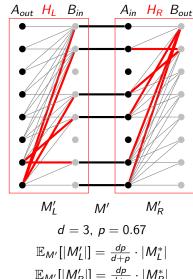


Analysis

$$|\mathcal{Q}| = \left(\frac{p}{d+p} - \frac{p}{2d}\right) \cdot |M^*|.$$

Therefore, the final matching is of size

$$(\frac{1}{2} + \frac{p}{d+p} - \frac{p}{2d}) \cdot |M^*|.$$



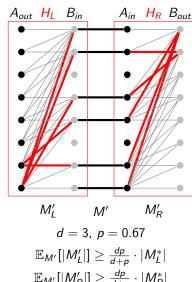
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Analysis

$$|\mathcal{Q}| \ge \left(\frac{p}{d+p} - \frac{p}{2d}\right) \cdot |M^*|.$$

Therefore, the final matching is of size at least

$$(\frac{1}{2}+\frac{p}{d+p}-\frac{p}{2d})\cdot |M^*|.$$



$$d = 3, p = 0.67$$

$$\mathbb{E}_{M'}[|M'_L|] \ge \frac{dp}{d+p} \cdot |M_L^*|$$

$$\mathbb{E}_{M'}[|M'_R|] \ge \frac{dp}{d+p} \cdot |M_R^*|$$

Main Proof Outline

A_{out}	B_i
•	•
•	•
•	•
•	•
•	•
•	•
•	•

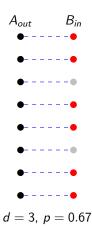
Setup:

• any bipartite graph G = (A, B, E) with a maximum matching M^* and any stream of edges π ;



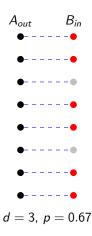
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- any bipartite graph G = (A, B, E) with a maximum matching M^* and any stream of edges π ;
- subsample $B' \subseteq B$ with prob. p to get $H = G[A \cup B']$;



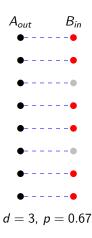
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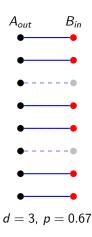


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Proof:

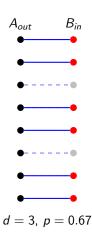
• $M_{B'}^* \leftarrow \{ab \in M^* : b \in B'\};$



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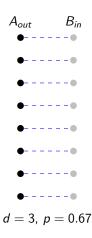
- $M_{B'}^* \leftarrow \{ab \in M^* : b \in B'\};$
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- For every edge that is added by GREEDY_d, how many edges in $M_{R'}^*$ are blocked?

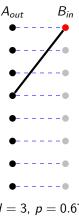


$$d = 3$$
, $p = 0.67$

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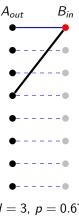


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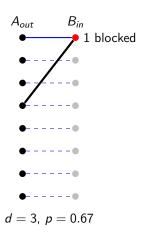
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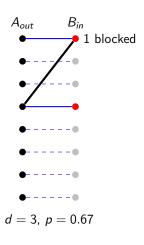


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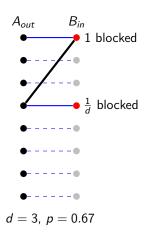
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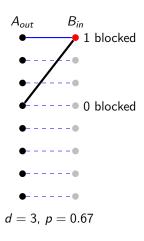


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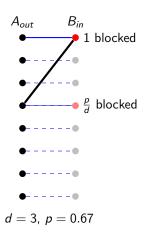


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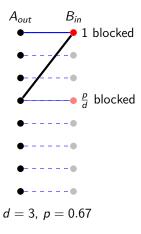
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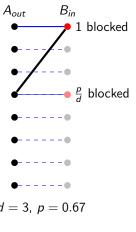


$$\mathbb{E}[|M_{B'}^*|] \le (1 + \frac{p}{d})\mathbb{E}[|M|]$$

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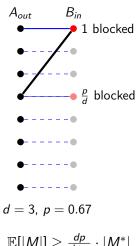
$$d = 3$$
, $p = 0.67$

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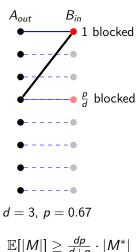


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- Formalised using Wald's Equation.



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The final matching returned is always at least of size

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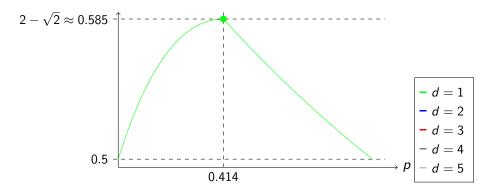
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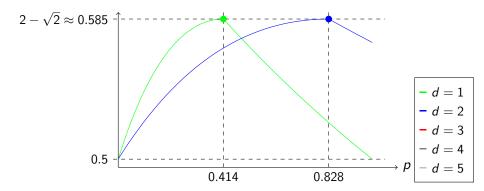
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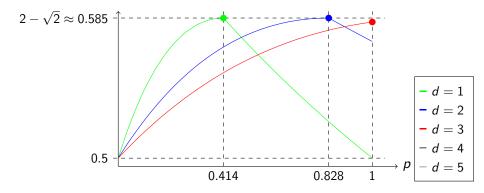
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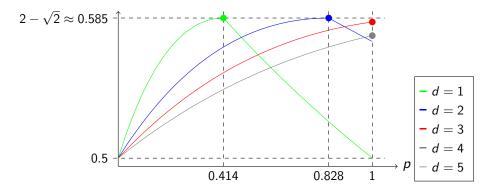
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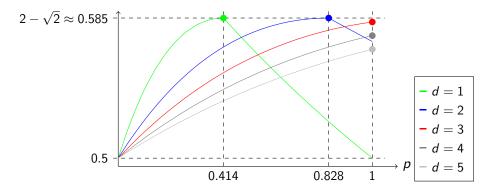
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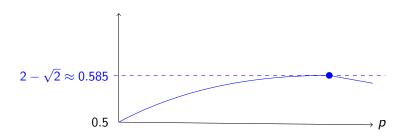
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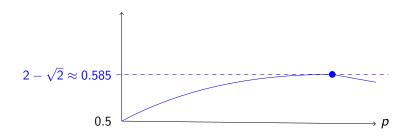
Overview

- Background
- Our Work
 - Lower Bound
 - Algorithmic
- 3 Discussion

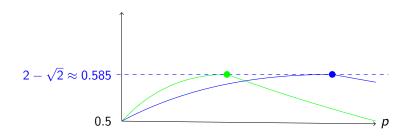
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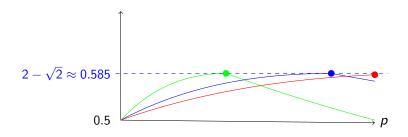
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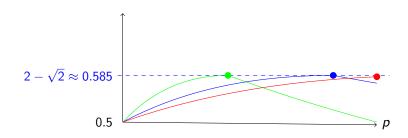
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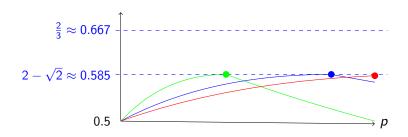
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- We reduced the gap of possibility with this class of algorithms to [0.585, 0.667].



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Open Questions

- Can we extend other one-pass lower bounds to improve the two-pass result? I.e. Kapralov's [SODA21].
- Is there a way to do better by finding more than just a maximal matching in the first-pass?
- Can we beat a $\frac{1}{2}$ -approximation in just one-pass?

Thank You