Finding a Maximum Matching in a Sparse Random Graph in O(n) Expected Time

Prasad Chebolu

Joint work with Alan Frieze and Páll Melsted

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• Preliminaries and previous work

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Overview

Preliminaries and previous work

• The Karp-Sipser algorithm

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- Preliminaries and previous work
- The Karp-Sipser algorithm
- Our algorithm

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Overview

Preliminaries and previous work

- The Karp-Sipser algorithm
- Our algorithm
- Analysis

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Introduction

Given a graph G = (V, E) a *matching* is a set of vertex-disjoint edges $M \subseteq E$.

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Maximum cardinality matching is a fundamental problem in combinatorial optimization.

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Matchings in bipartite graphs can be found using flows. We are interested in general graphs.

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Algorithms timeline

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Random Graphs

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 $G_{n,p}$ is a graph on *n* vertices where each edge appears independently with probability *p*.

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- Bast et al. [2005] $O(n \log n)$ for sparse graphs, i.e. $p = \frac{c}{n}$

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Our Work

Theorem

The maximum cardinality matching can be found in O(n) expected time in $G_{n,m}$ where $m = c_1 n$.

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Augmenting Paths

An augmenting path is a path between two unmatched vertices in a graph s.t. every other edge on the path is a matching edge.

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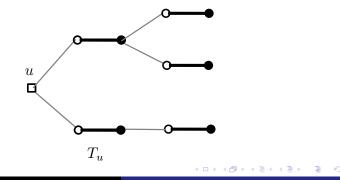
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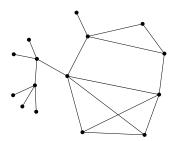


Augmenting Trees

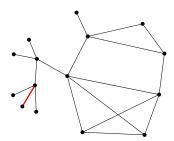
Augmenting trees are rooted at an unmatched vertex, all leaves are connected with a matching edge and all paths from leaves to the root alternate between matching and nonmatching edges.



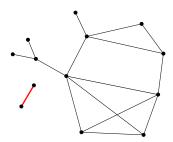
- If there are vertices of degree 1, pick one at random and include it in the matching
- Otherwise pick an edge at random, include it in the matching



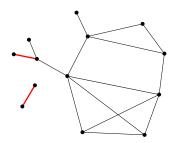
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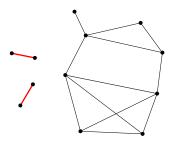
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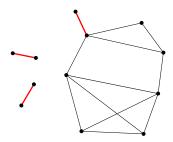
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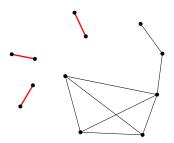
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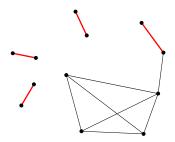
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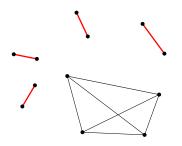
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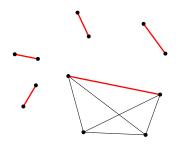
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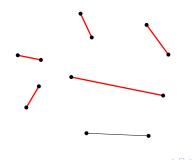
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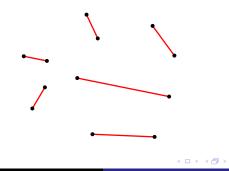
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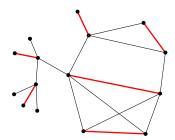
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Karp-Sipser

Simple heuristic. Given a graph G

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Karp-Sipser

We split the execution of Karp-Sipser into two phases.

We start in phase 1 and go into phase 2 when there are no vertices of degree 1 for the first time.

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Karp-Sipser

We split the execution of Karp-Sipser into two phases.

We start in phase 1 and go into phase 2 when there are no vertices of degree 1 for the first time.

The Karp-Sipser algorithm makes no mistakes in phase 1.

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Karp and Sipser (1981): KS on $G_{n,cn/2}$:

- If c ≤ e then whp at the end of Phase 1, G has only o(n) vertices
- If *c* > *e* then **whp** Phase 2 leaves *o*(*n*) vertices unmatched

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- If c < e then whp at the end of Phase 1, G consists of disjoint cycles
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Frieze and Pittel (2004):

If c > e then **whp** the graph at the end of Phase 2 has a perfect matching modulo isolated odd cycles.

- Run KS to find initial matching. Let *G* be the graph at the end of Phase 2
- For every two unmatched vertices in G, find an augmenting path by growing augmenting trees from both vertices.

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Why should this work?

• KS finds a matching in G with $\tilde{O}(n^2)$ unmatched vertices

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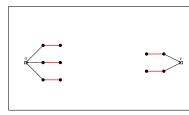
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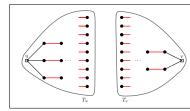
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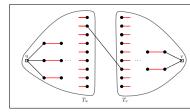


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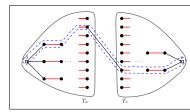
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Finding a Maximum Matching in a Sparse Random Graph in (

Prasad Chebolu Finding a Maximum Matching in a Sparse Random Graph in C

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Prasad Chebolu Finding a Maximum Matching in a Sparse Random Graph in C

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Analysis - KS conditioning

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When vertices are removed from the graph they either have degree \geq 2, 1 or 0. We refer to them as regular, pendant and isolated.

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Witness edges

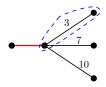
Prasad Chebolu Finding a Maximum Matching in a Sparse Random Graph in 0

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Witness edges

If KS removes a regular vertex, the first edge incident to it becomes its regular witness edge.

It ensures this vertex had degree at least 2

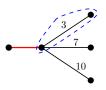


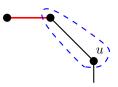
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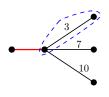
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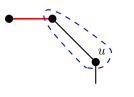
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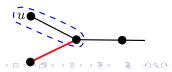
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If KS removes an edge such that one of its endpoints becomes isolated, this edge is an isolated witness edge. It ensures this vertex was not isolated before that time

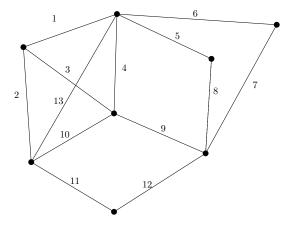








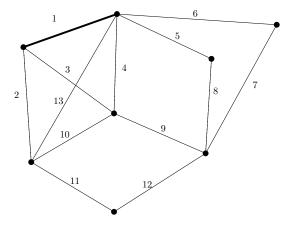
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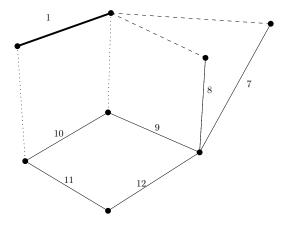
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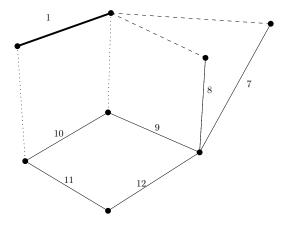


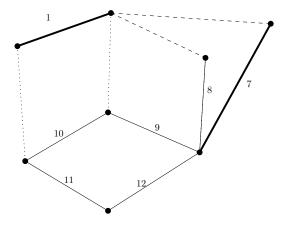
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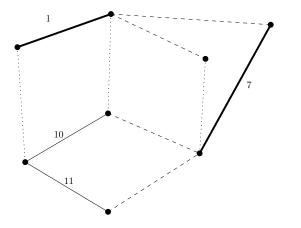
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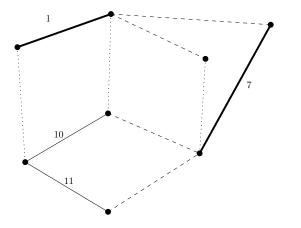
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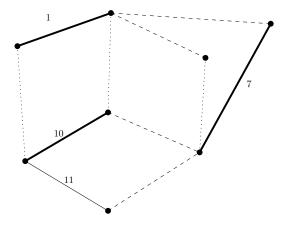


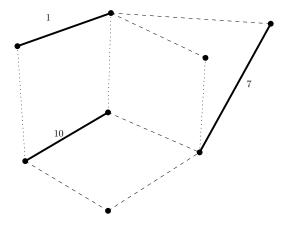






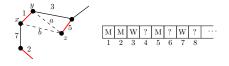






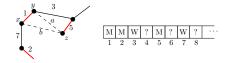
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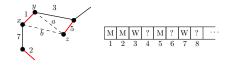
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a can go into boxes 4,6 and 8

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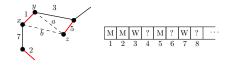


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• Image: A image:



been revealed.

a can go into boxes 4,6 and 8 *b* cannot go into boxes 4 or 6, since edge 7 would not be a witness edge for *x*, but *b* can go into box 8

• Image: A image:

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• the edge is placed in a box after the witness edge of x

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- the edge is placed in a box after the witness edge of x
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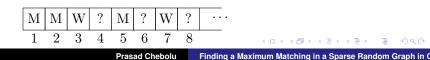
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Whether an edge can go into a box or not depends only on the matching and witness edges.

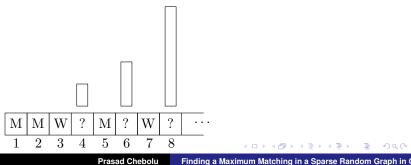
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This allows us to sample the random graph, conditioned on the output of $\ensuremath{\mathsf{KS}}$



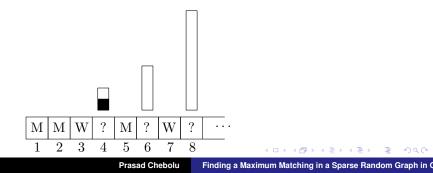
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For each open box, create a list of potential edges



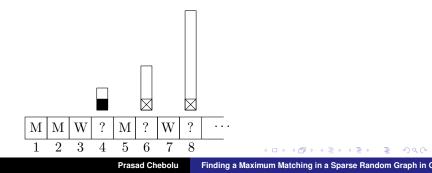
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This allows us to sample the random graph, conditioned on the output of $\ensuremath{\mathsf{KS}}$

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- Remove the edge chosen from all the remaining lists



Prasad Chebolu Finding a Maximum Matching in a Sparse Random Graph in C

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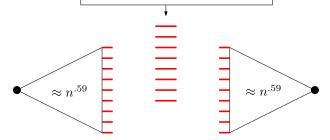


Start with large augmenting trees

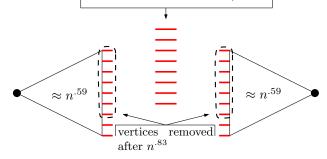
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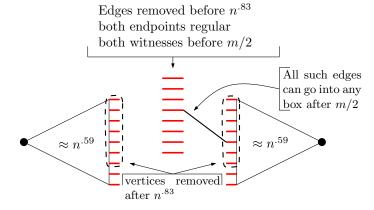
Edges removed before $n^{.83}$ both endpoints regular both witnesses before m/2



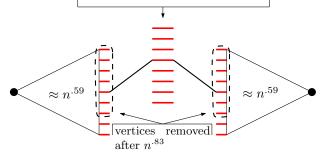
Start with large augmenting trees Good edges can help us connect across Edges removed before $n^{.83}$ both endpoints regular both witnesses before m/2



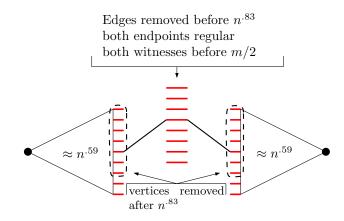
Start with large augmenting trees Good edges can help us connect across



Start with large augmenting trees Good edges can help us connect across Such pairs of edges ensure the algorithm finds an augmenting path after two rounds Edges removed before $n^{.83}$ both endpoints regular both witnesses before m/2



Start with large augmenting trees Good edges can help us connect across Such pairs of edges ensure the algorithm finds an augmenting path after two rounds



We have skipped a few technical details here.

Since the trees are at most $O(n^{.79})$ in size

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when we repeat this $\tilde{O}(n^2)$ times. Consecutive iterations are not independent.

Still, this can be shown to take no more than o(n) time.

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Thank you

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