

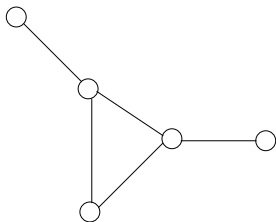
# Finding small stabilizer for unstable graphs

Adrian Bock<sup>1</sup>, Karthik Chandrasekaran<sup>2</sup>, Jochen Könemann<sup>3</sup>,  
Britta Peis<sup>4</sup>, and Laura Sanitá<sup>3</sup>

(<sup>1</sup>Lausanne, <sup>2</sup>Boston, <sup>3</sup>Waterloo, <sup>4</sup>Aachen)

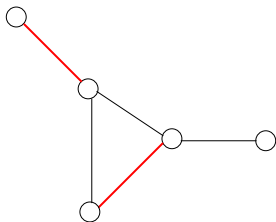
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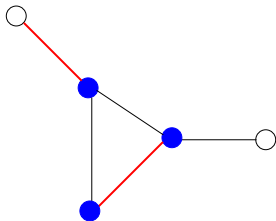
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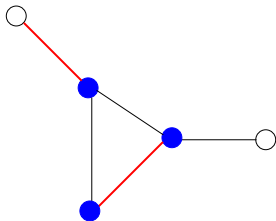
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- ▶ a **matching** is a set  $M \subseteq E$  of non-adjacent edges,
- ▶ a **vertex cover** is a set of vertices  $C \subseteq V$  such that each edge has at least one endpoint in  $C$ .
- ▶ Finding a maximum matching is "easy" whereas finding a minimum cover is "hard".

As usual, let

- ▶  $\nu(G) = \max\{|M| \mid M \text{ matching in } G\}$ , and
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- ▶  $\nu_f(G) = \max\{\sum_{e \in E} y_e \mid y(\delta(v)) \leq 1 \forall v \in V; y \in \mathbb{R}_+^E\}$ ,
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By duality theory:

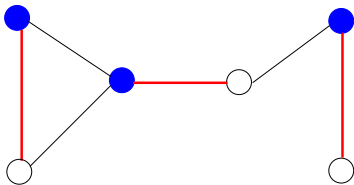
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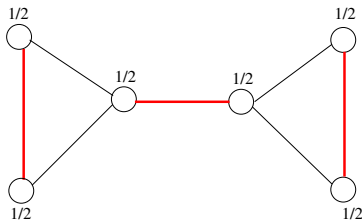
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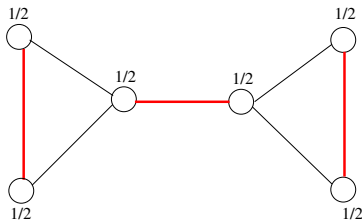
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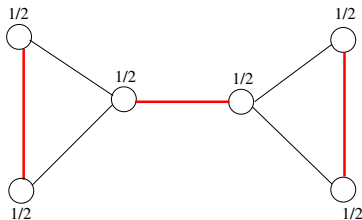


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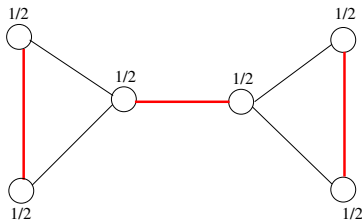


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**This talk:** Given an **unstable** graph, how can we find a small **stabilizer**, i.e., a subset  $F \subseteq E$  s.t.  $G \setminus F$  is stable.

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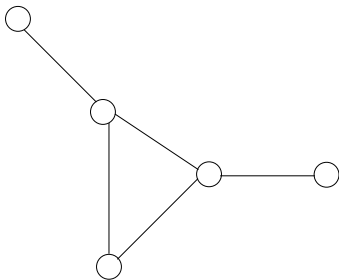
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**Note:**  $\text{Core}(G) \neq \emptyset \iff G$  is stable.

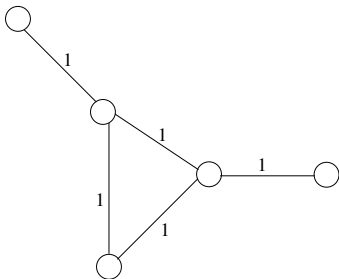
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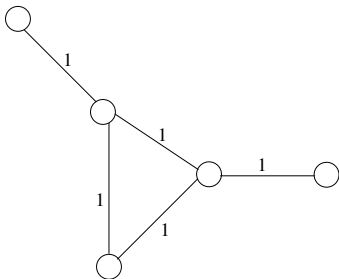
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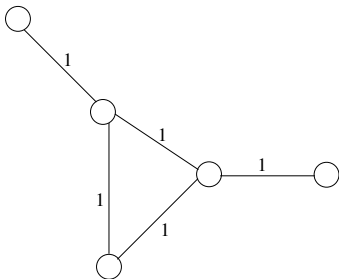
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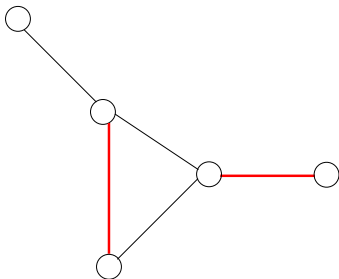


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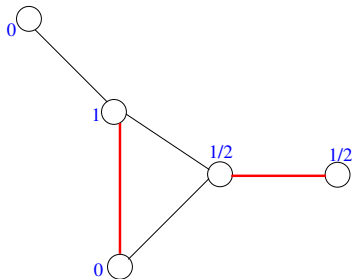
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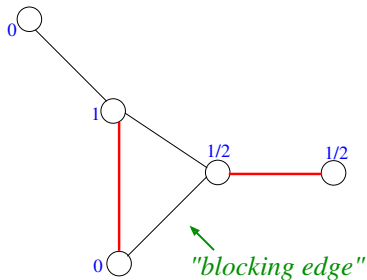
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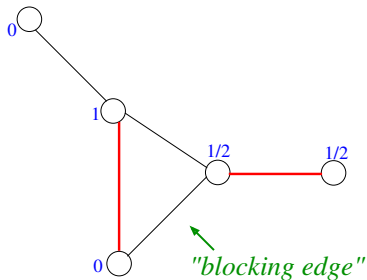
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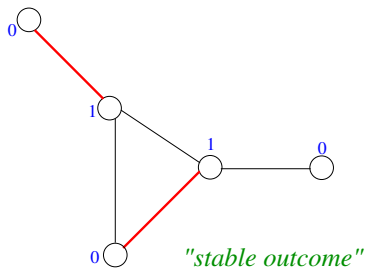
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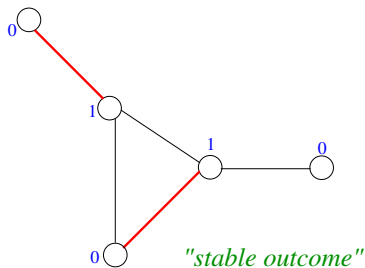
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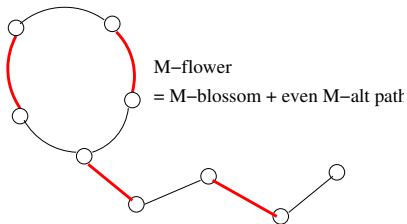
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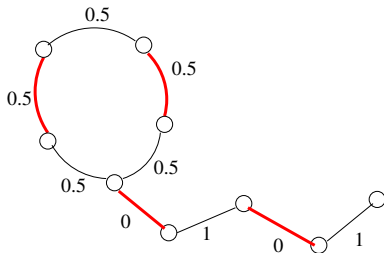
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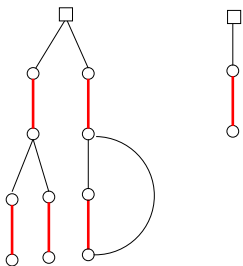


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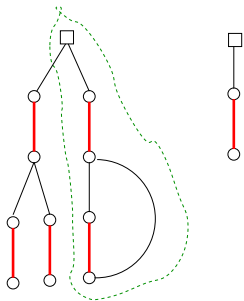


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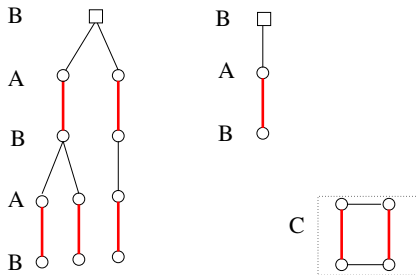
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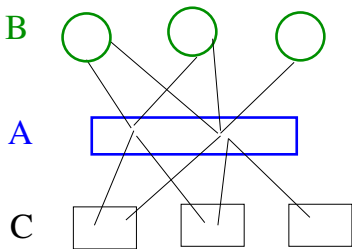
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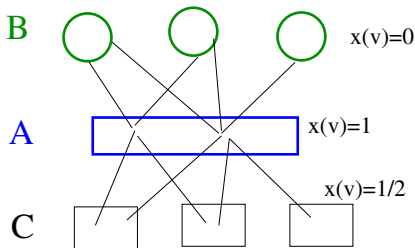
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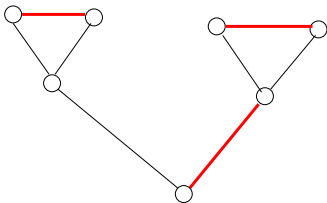
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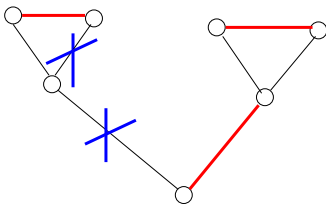
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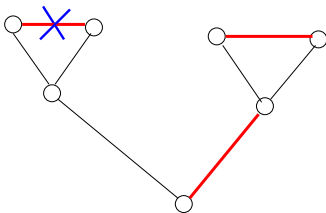


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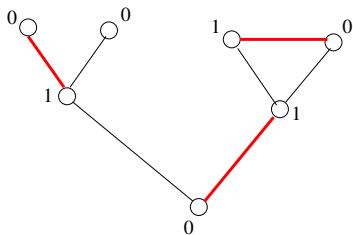


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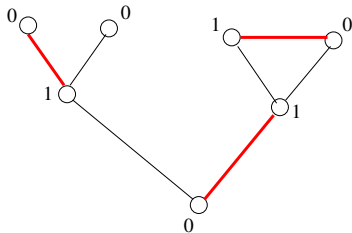


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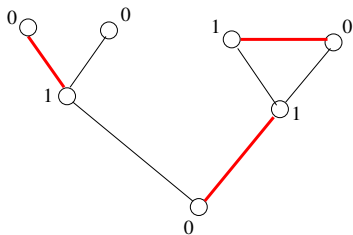


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**Theorem (Key)**

*If  $F$  is a minimum stabilizer, then  $\nu(G \setminus F) = \nu(G)$ .*

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*2-approximation for regular graphs.*

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However, as  $M$  is max matching in  $G$ , one end of the path must be adjacent to  $f \in M \cap F$ . It follows that  $\hat{M} = M \Delta (P + f)$  is max matching in  $G$  with  $|\hat{M} \cap F| < |M \cap F|$ . Contradiction!  $\square$

## Theorem

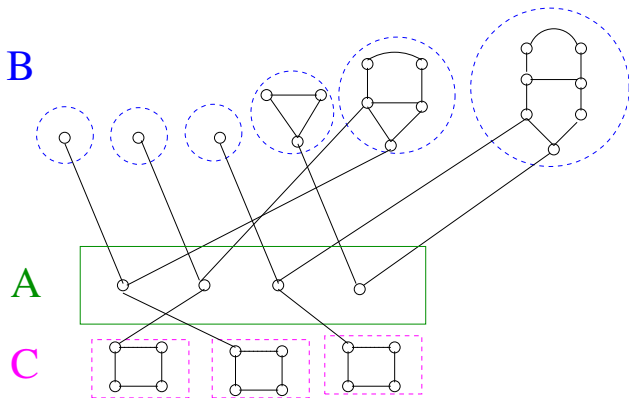
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Proof:

Consider the Gallai–Edmonds' Decomposition  $V=B+A+C$





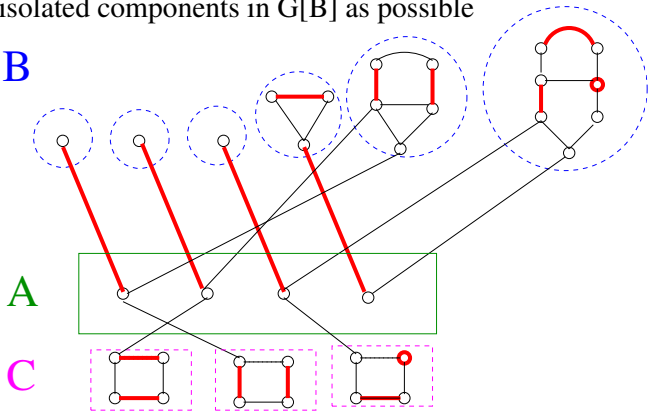
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Proof:

Choose max matching  $M$  linking as much isolated components in  $G[B]$  as possible

**B**

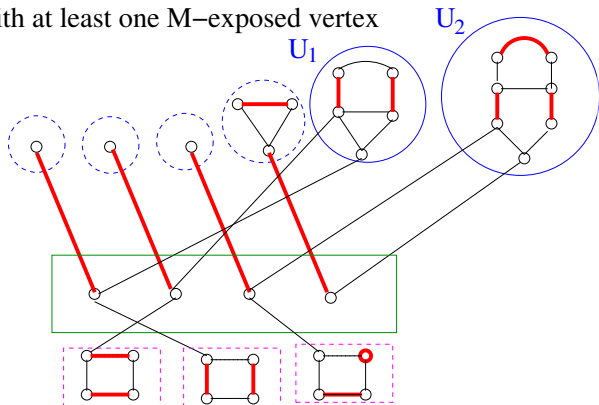


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Proof:

Let  $U_1, \dots, U_k$  denote the non-trivial components in  $G[B]$  with at least one  $M$ -exposed vertex

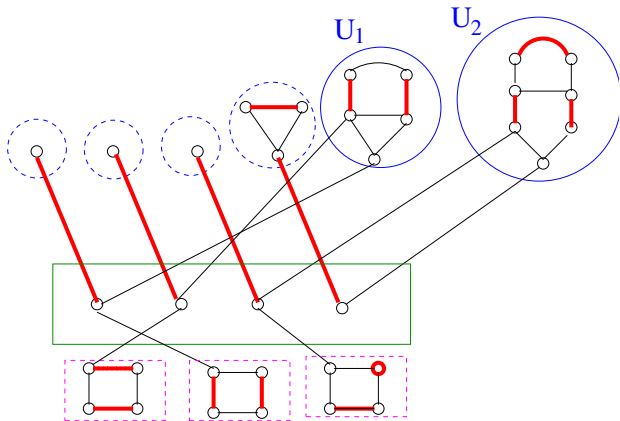


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Each  $U_i$  has at least one vertex  $v_i$  essential in  $GF$

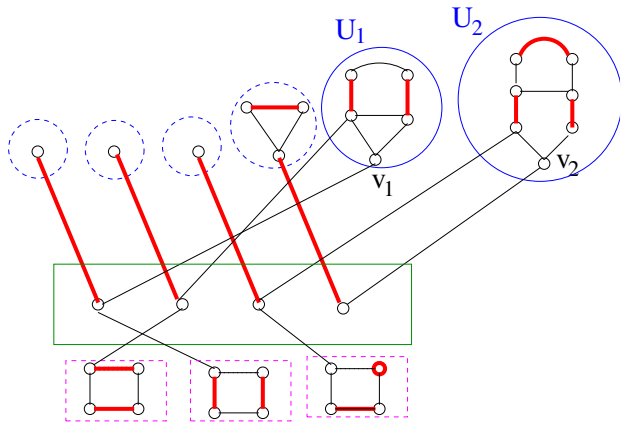


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Can assume that  $v_i$  is  $M$ -exposed

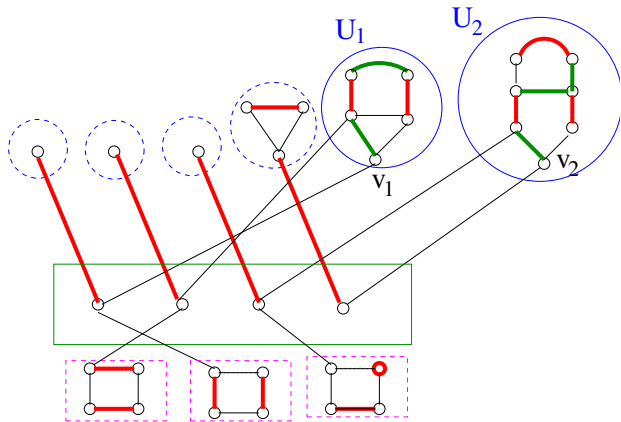


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Choose  $\max$  matching  $N$  in  $GF$

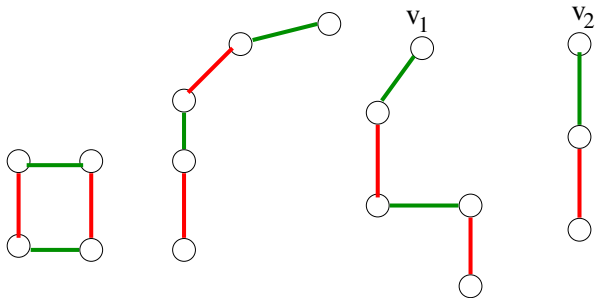


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Proof:

$N\Delta M$  is disjoint union of even cycles and even paths

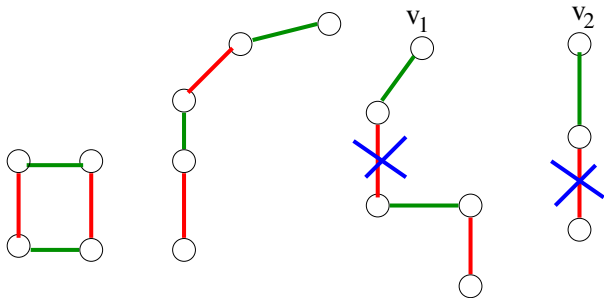


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Note: each of the  $k$  paths starting at  $v_i$  has at least one edge in  $F$ .



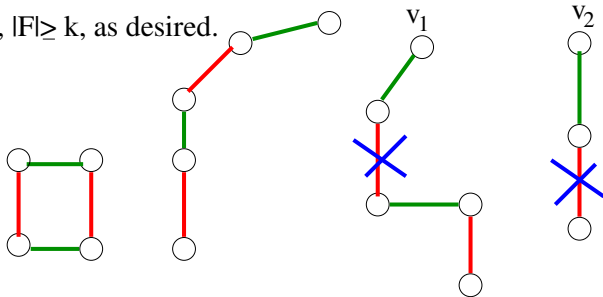
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Thus,  $|F| \geq k$ , as desired.





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If  $\nu(G) < \nu_f(G)$ , can find in poly-time a set  $L \subseteq E$  with  $|L| \leq 4\omega$ ,  $\nu(G) = \nu(G \setminus L)$ , and  $\nu_f(G \setminus L) = \nu_f(G) - \frac{1}{2}$ .

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**Note:** In each iteration, at most  $4\omega$  edges are added to  $F$ ;  
At most  $2(\nu_f(G) - \nu(G)) \leq \text{OPT}$  iterations.

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