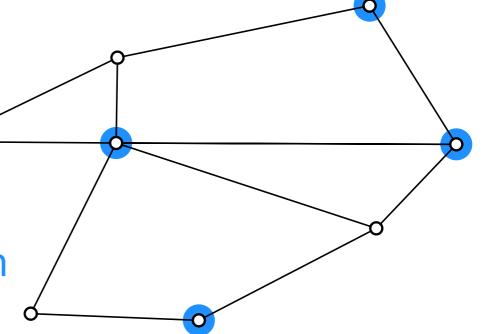
Introduction

NP-Optimization Problems and Approximation Approximation Algorithm for Vertex Cover



"All exact science is dominated by the idea of approximation."

Bertrand Russell (1872 – 1970)

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today:

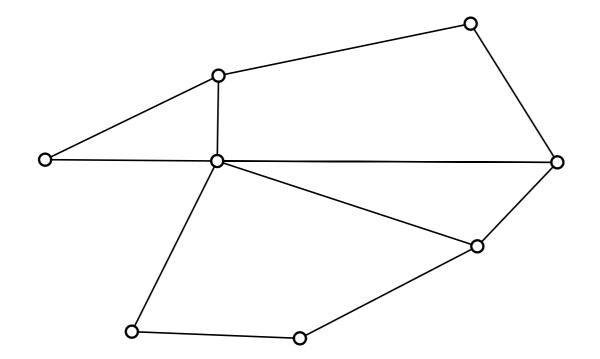
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#### today:

technique: lower bounding optimal solution (key ingredient for approximation!) optimization problem: vertex cover

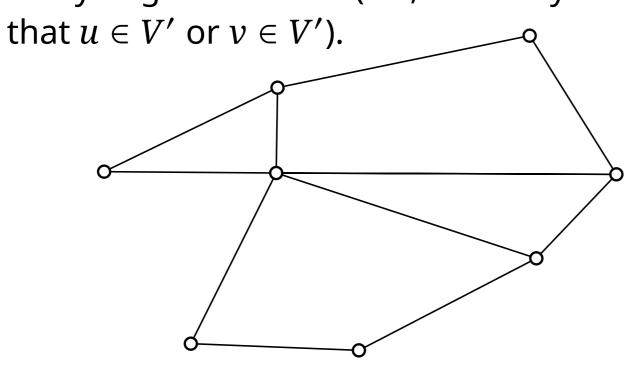
Input: Graph G = (V, E)

#### **Output:**



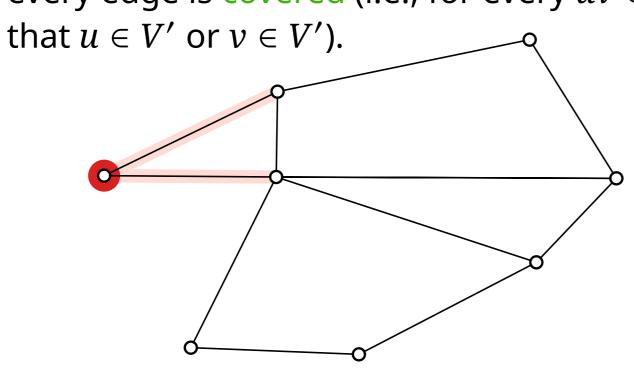
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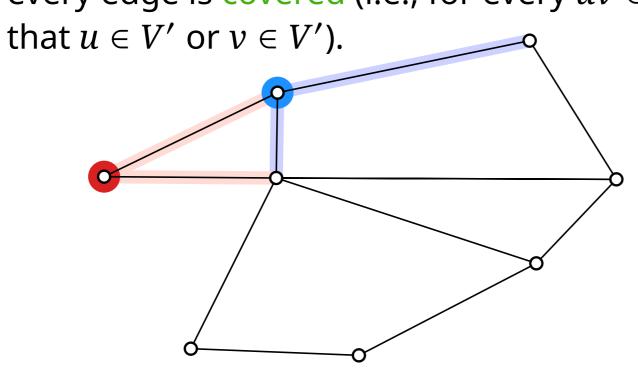
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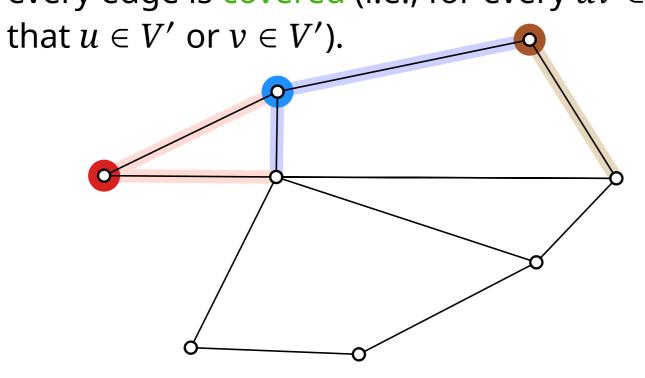
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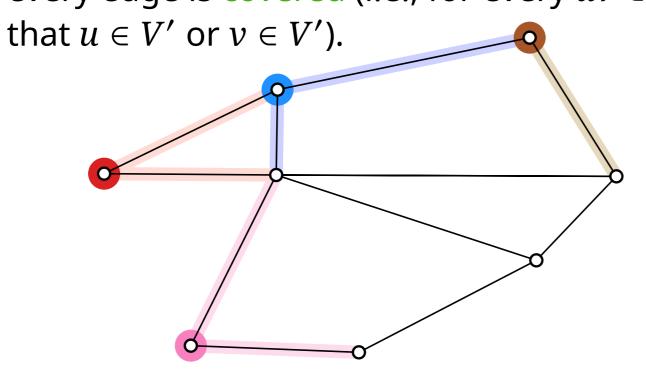
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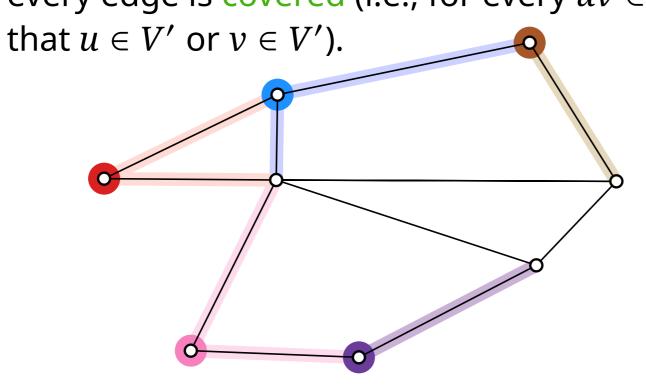
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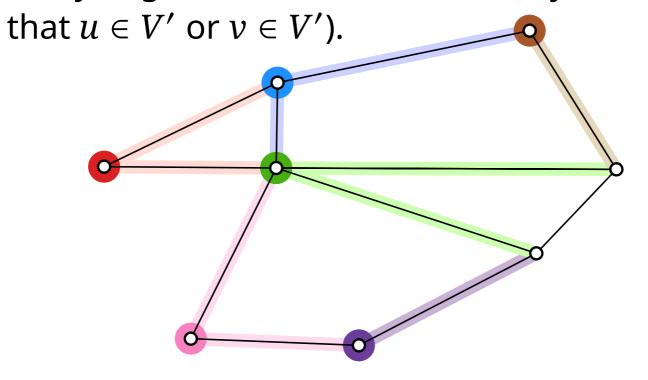
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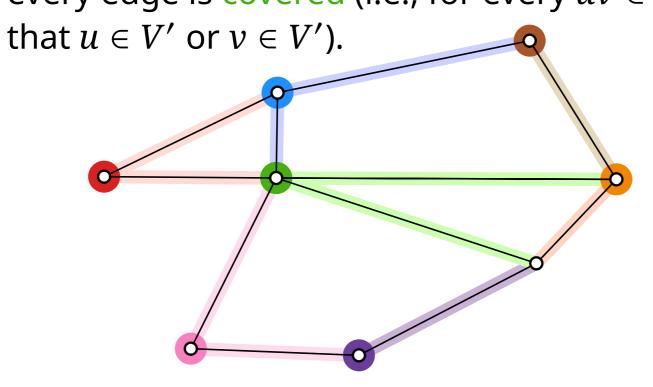
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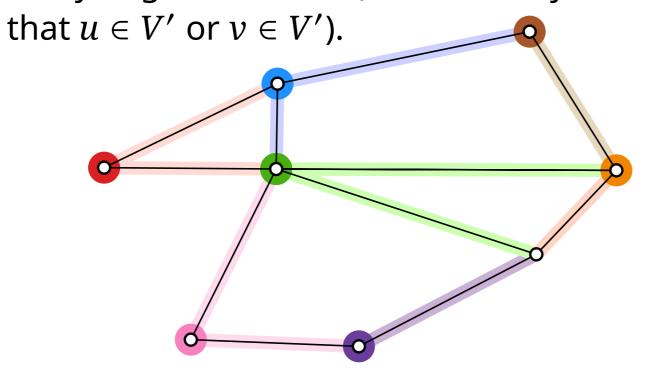
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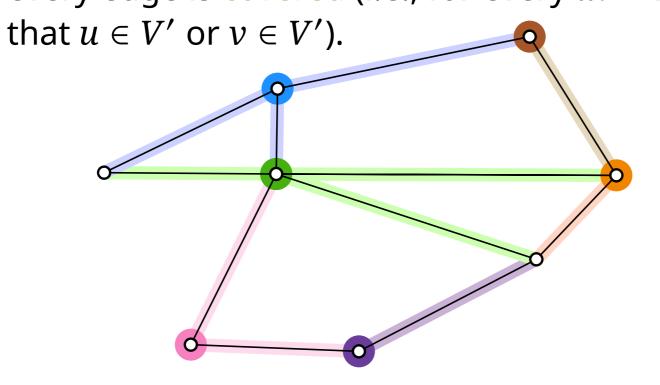
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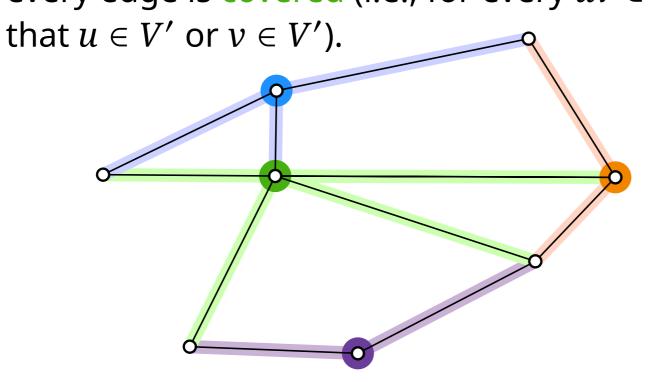
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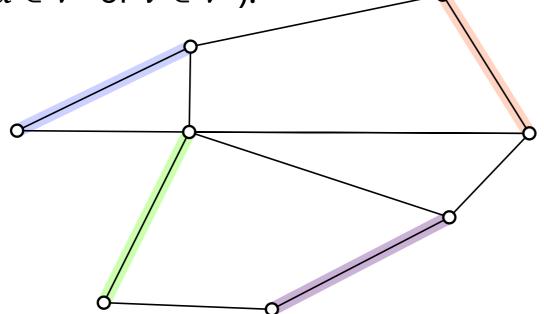
this is a vertex cover Q: can you argue that it is optimal?

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this is a vertex cover 1 vertex per colored edge needed

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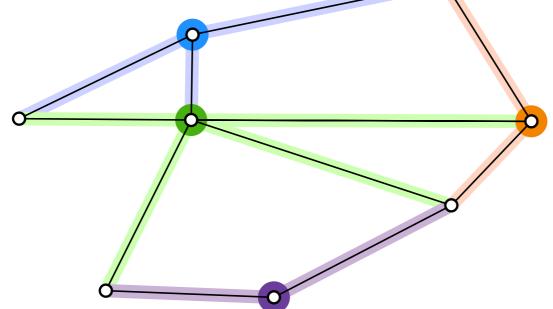
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**Exact Algorithm: ???** 



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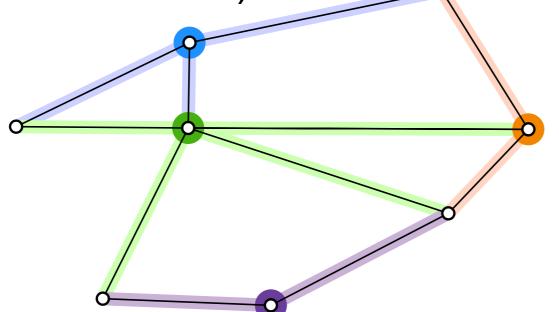
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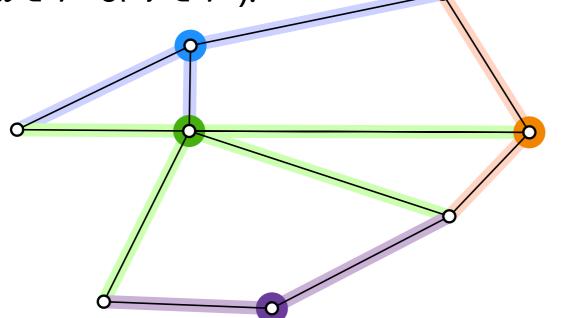
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"good" (5/4-) approximate solution

# Key Concepts: NP-Optimization Problems and Approximation Algorithms

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- $\blacksquare$  Is either a minimization or maximization problem.

Task: Fill in the gaps for the problem  $\Pi = VERTEX$  COVER.

$$D_\Pi= ???$$
 For  $I\in D_\Pi\colon ???$   $|I|= ???$   $S_\Pi(I)= ???$ 

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The optimal value  $\operatorname{obj}_{\Pi}(I, s^*)$  of the objective function is denoted by  $\operatorname{OPT}_{\Pi}(I)$  or simply by  $\operatorname{OPT}$  in context.

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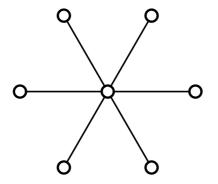
$$\frac{\mathsf{obj}_{\Pi}(I,s)}{\mathsf{OPT}_{\Pi}(I)} \stackrel{\geq}{\leq} \mathscr{A}. \quad \alpha(|I|)$$

#### Ideas?

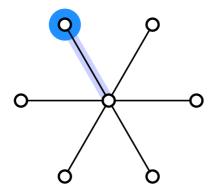
Edge-Greedy

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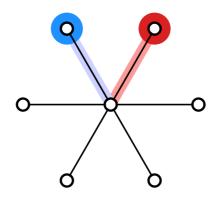
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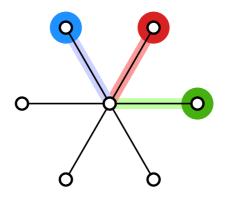
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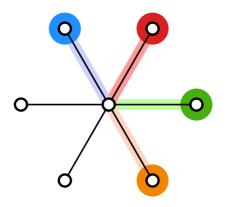
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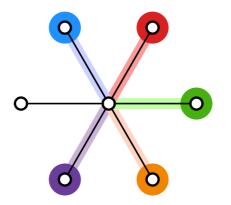
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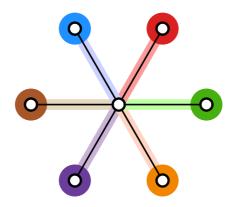
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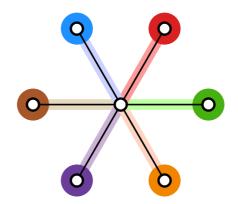
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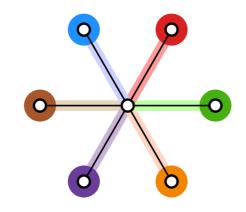
Quality?



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Problem:

How can we estimate  $obj_{\Pi}(I, s)/OPT$ ,

when it is hard to compute OPT?

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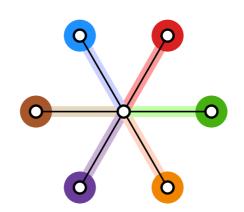
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**Idea:** Find a "good" lower bound  $L \leq OPT$  for OPT and

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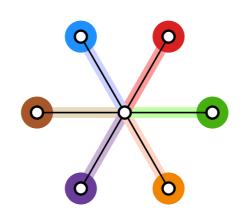
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$$\frac{\operatorname{obj}_{\Pi}(I,s)}{\operatorname{OPT}} \leq \frac{\operatorname{obj}_{\Pi}(I,s)}{L}$$

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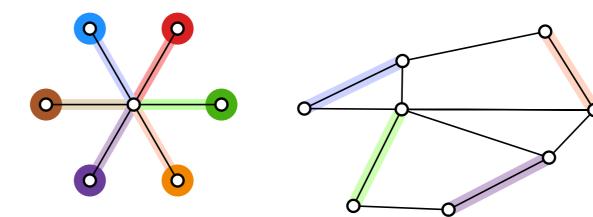
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How did we argue that OPT = 4 for this instance?

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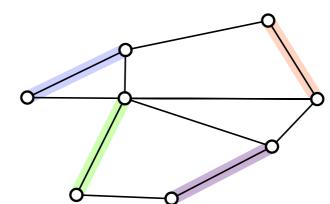
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**Problem:** How can we estimate  $obj_{\Pi}(I, s)/OPT$ ,

when it is hard to compute OPT?

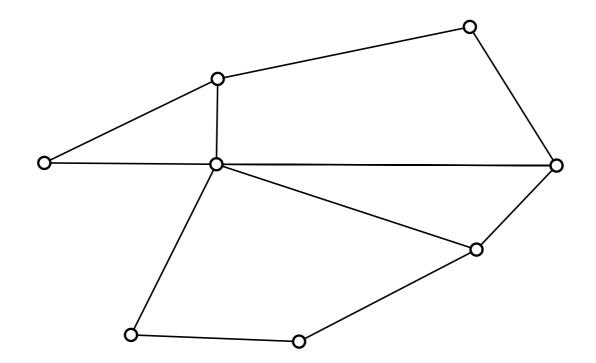
**Idea:** Find a "good" lower bound  $L \leq OPT$  for OPT and

compare it to our approximate solution.

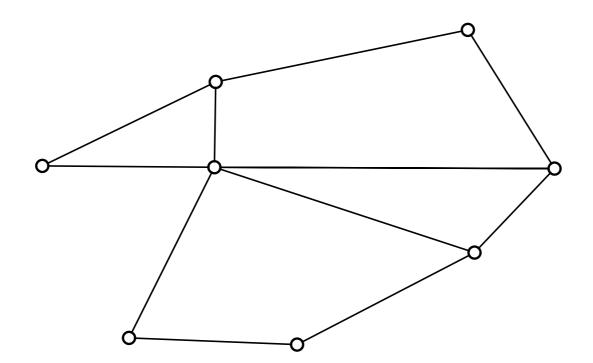
$$\frac{\operatorname{obj}_{\Pi}(I,s)}{\operatorname{OPT}} \leq \frac{\operatorname{obj}_{\Pi}(I,s)}{L}$$

#### Q: how can we lower bound the size of a vertex cover?

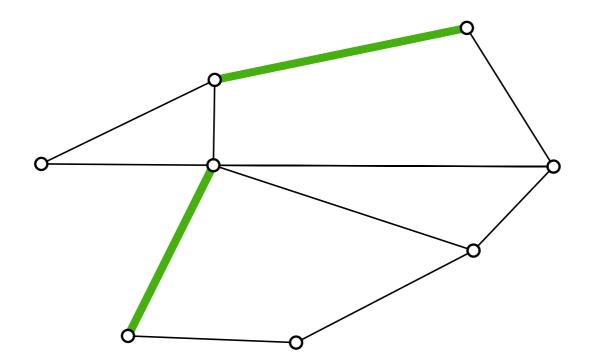
need at least one vertex for each edge in a vertex-disjoint set of edges



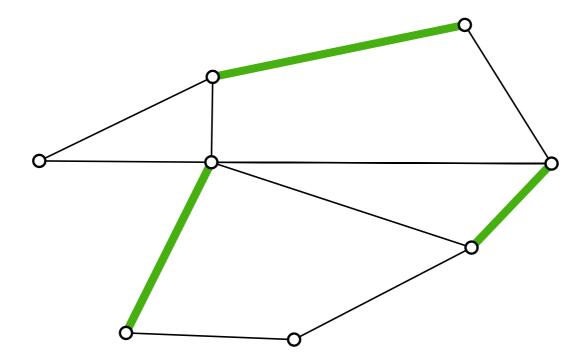
An edge set  $M \subseteq E$  of a graph G = (V, E) is a matching if no two edges of M are adjacent (i.e., share an end vertex).



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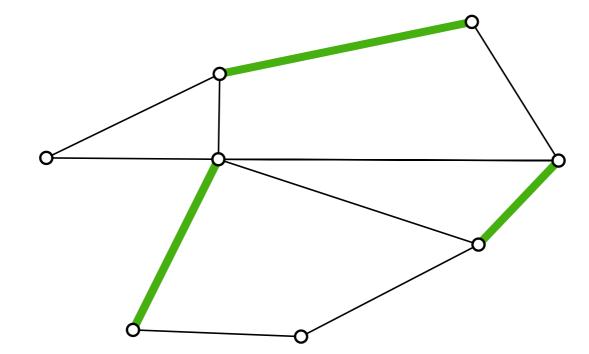


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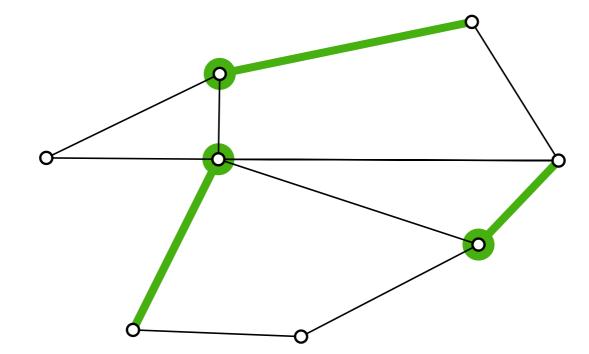
$$OPT \ge |M|$$



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M is maximal if there is no matching M' with  $M' \supseteq M$ .

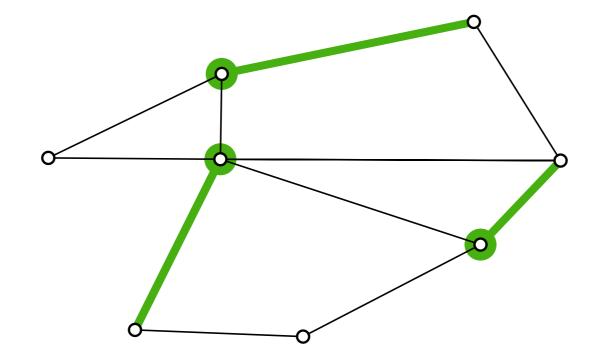
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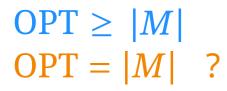
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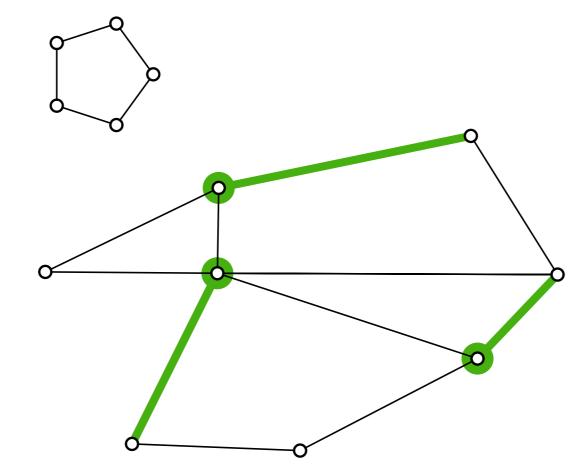
$$\begin{array}{c|c}
OPT \ge |M| \\
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\end{array}$$
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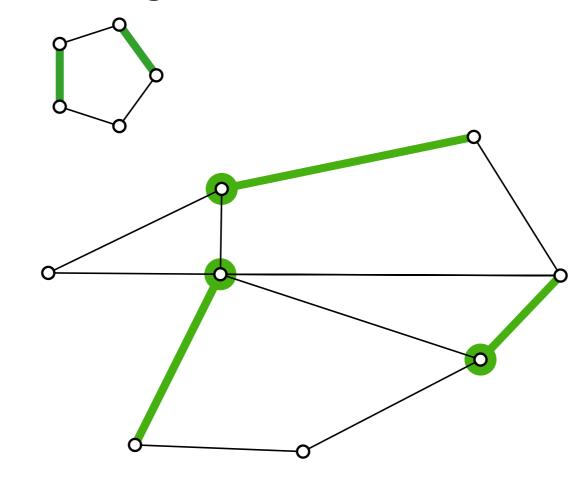




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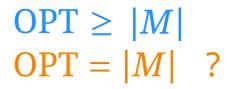
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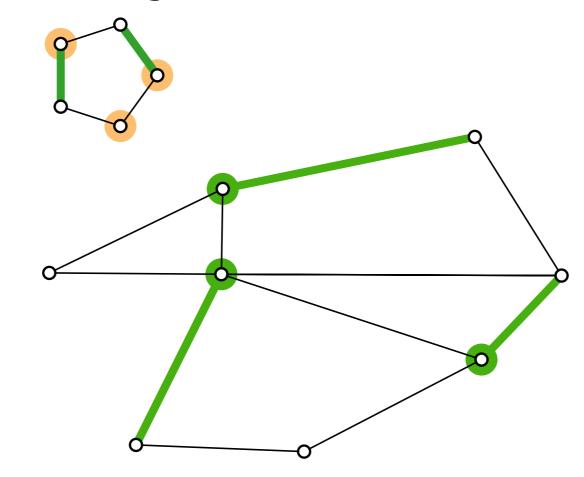
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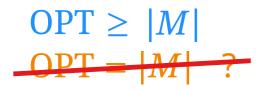
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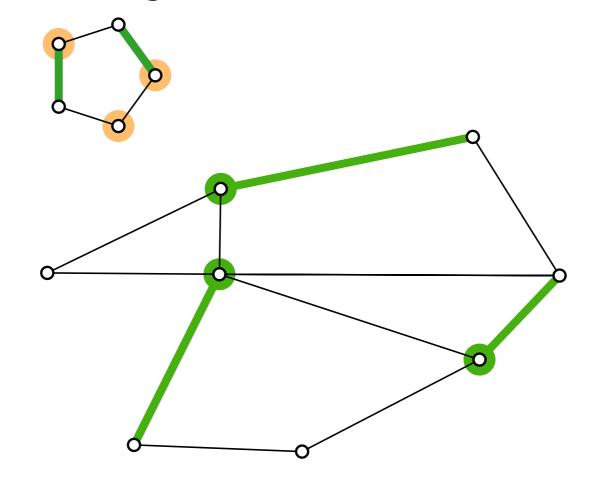




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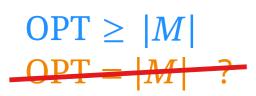
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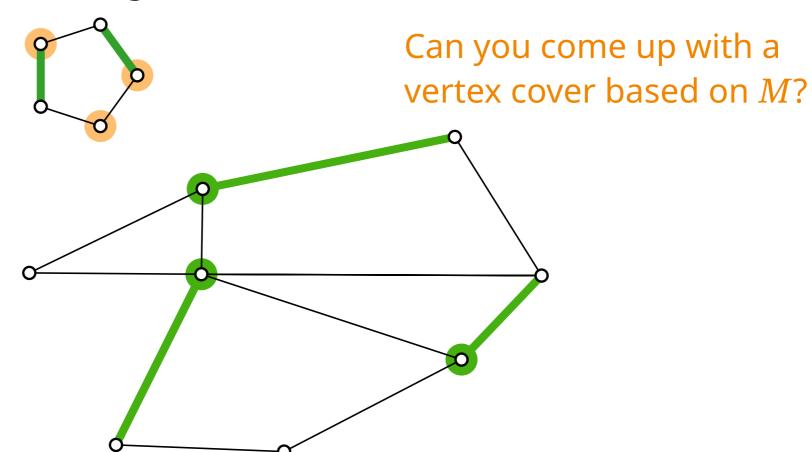




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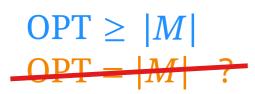
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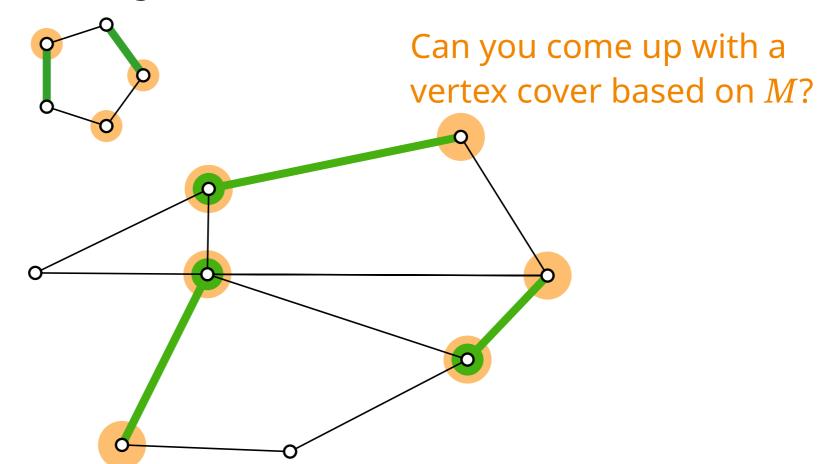


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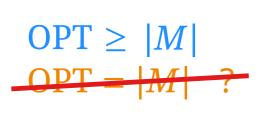


Vertex cover of *M*Vertex cover of *E* 

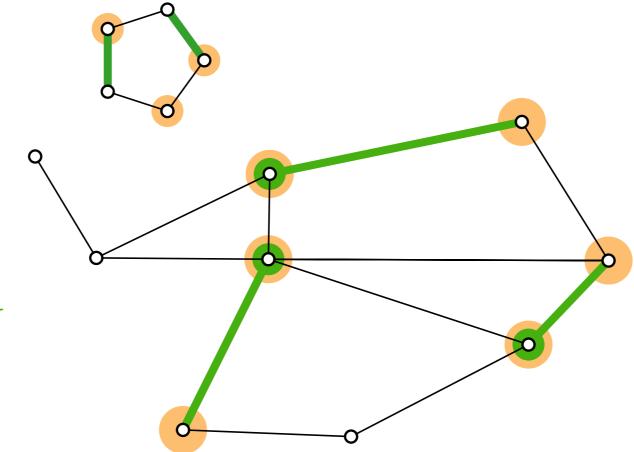


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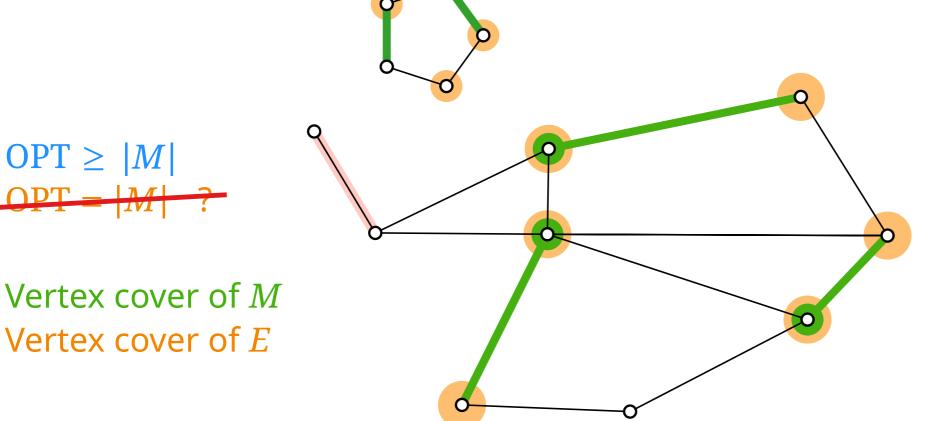
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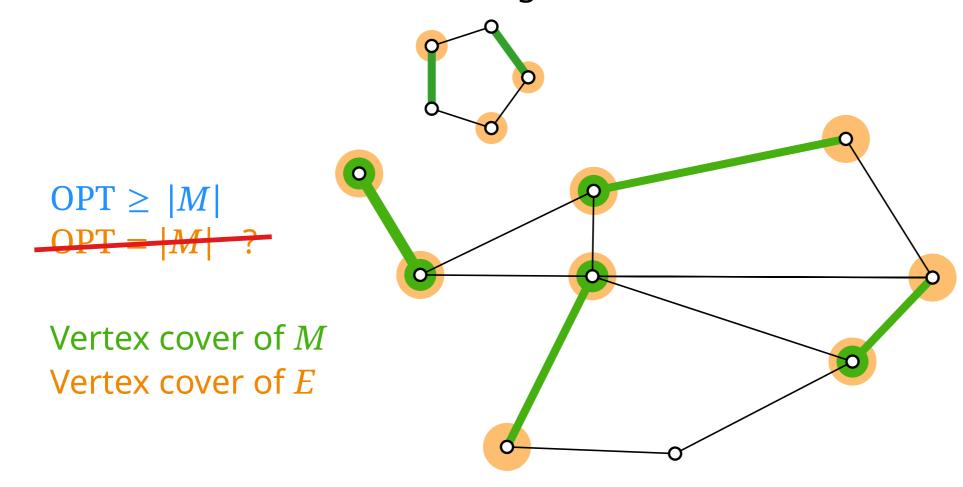
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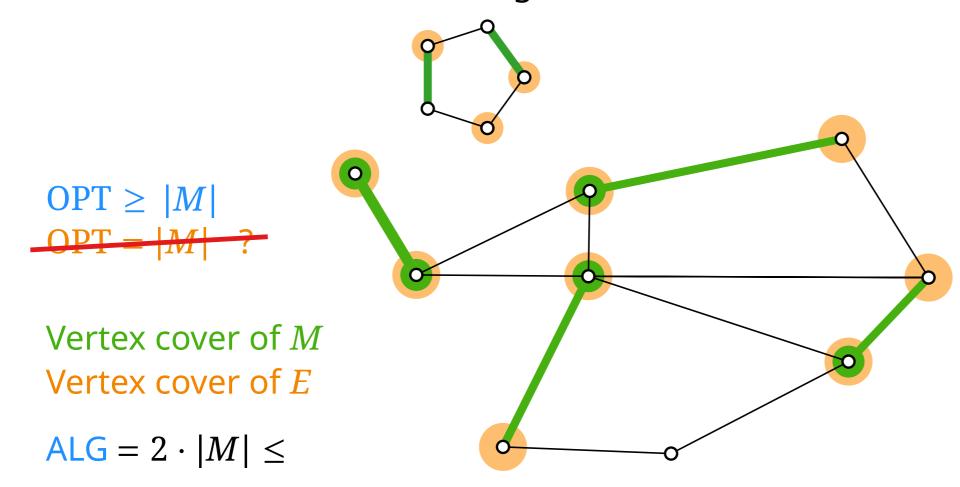
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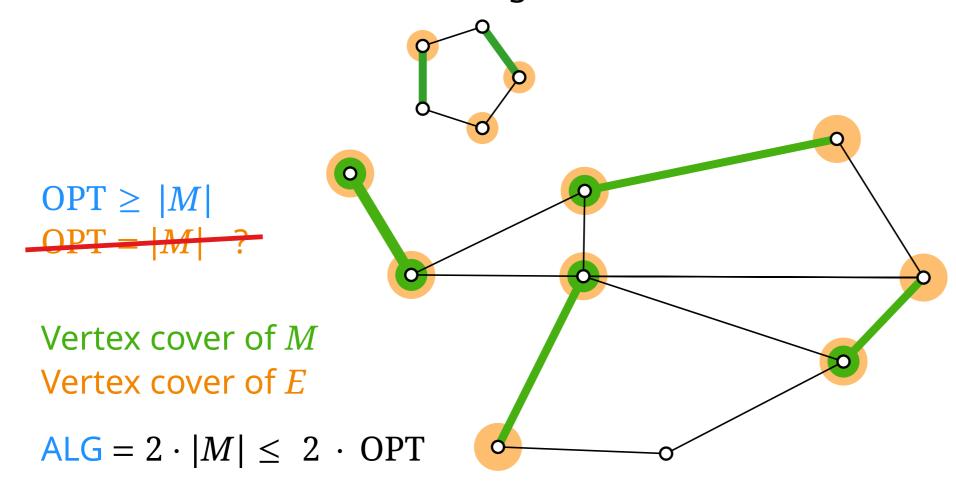
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Algorithm VertexCover(*G*)

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M \leftarrow \emptyset
foreach e \in E(G) do
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if e is not adjacent to any edge in M then
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- better algorithm based on this lower bound?
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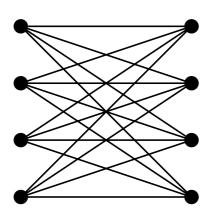
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tight example: graph with ALG = 2 OPT?

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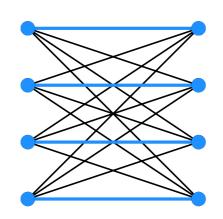
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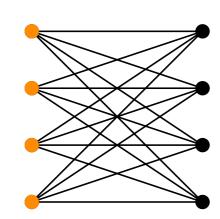
because any maximal matching has size *n* 



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but an optimal vertex cover has size *n* 



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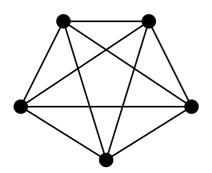
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tight example: graph with |M| = OPT/2?

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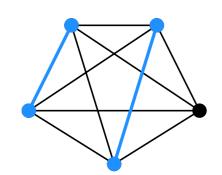
No! On the  $K_n$ , where n odd, the size . . .



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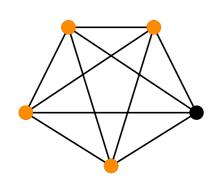


of a maximal matching is (n-1)/2

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of a maximal matching is (n-1)/2

of a minimal vertex cover is n-1

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Still open!

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The best known approximation factor for VertexCover is

$$2 - \Theta(1/\sqrt{\log n}).$$

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If P  $\neq$  NP, VertexCover cannot be approximated within a factor of 1.3606.

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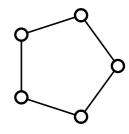
VERTEXCOVER cannot be approximated within a factor of  $2 - \Theta(1)$ 

if the Unique Games Conjecture holds.

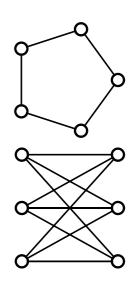
assuming that a certain problem is NP-hard to approximate

we used the lower bound  $max | matching | \leq min | vertex cover |$ 

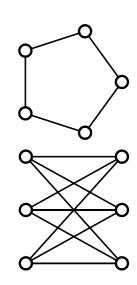
we used the lower bound  $\max |matching| \le \min |vertex|$  and we saw graphs where  $\max |matching| < \min |vertex|$ 



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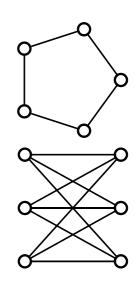


we used the lower bound  $max | matching | \le min | vertex cover |$ and we saw graphs where max | matching | < min | vertex cover |as well as graphs where max | matching | = min | vertex cover |in fact, this holds for all bipartite graphs!



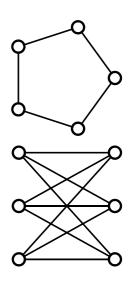
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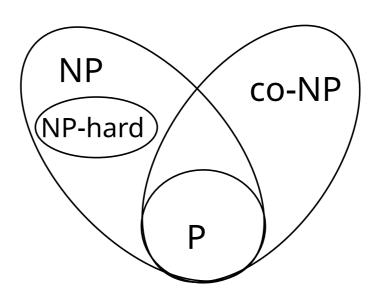
Hence, (only) for bipartite graphs, these problems are equal!

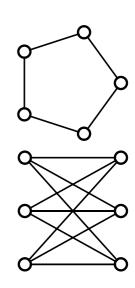
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A little complexity theory

Q: Where are vertex cover and matching in general?

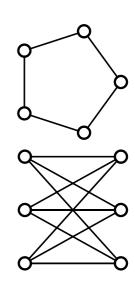




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#### Summary

Theorem.

Minimum-cardinality VertexCover can be approximated within a factor-2 by greedily computing a maximal matching M, and taking as vertex cover the endpoints of the edges in M.

- lacktriangle key ingredient: lower bound |M| on OPT
- giving tight examples provides crucial insight into the functioning and the algorithm and can provide ideas what to improve

## Acknowledgements

Slides for approximation algorithms are mostly due to colleagues in Würzburg, in particular Joachim Spoerhase and Alexander Wolff. **Thanks!**