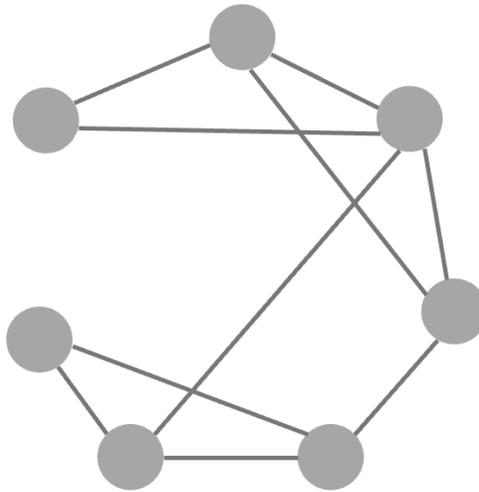
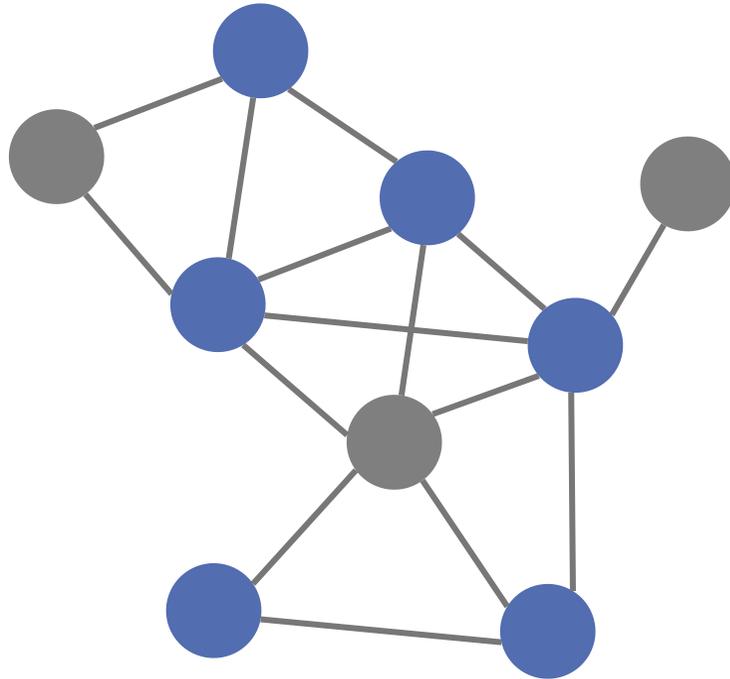


# **Greedly Growing a Maximal Independent Set to Approximate Vertex Cover**



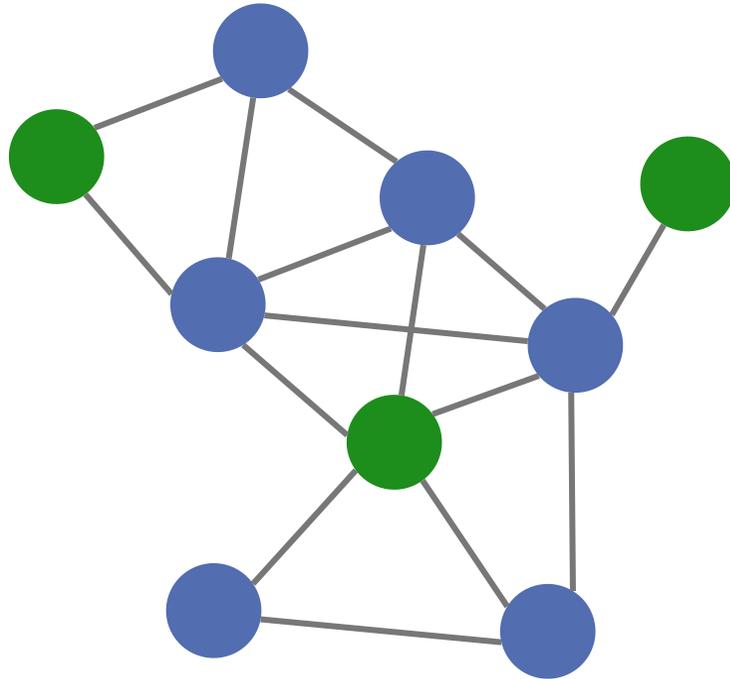
**Nate Veldt**  
**Texas A&M University**

# Finding a minimum vertex cover (Min-VC) is one of the most well-studied NP-hard problems.



A **vertex cover** is a set of nodes that “covers” all edges.

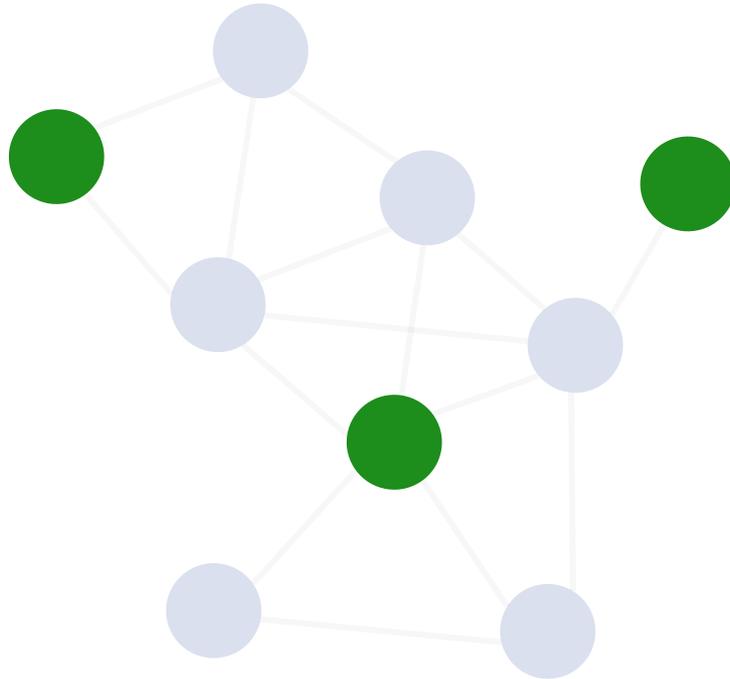
# Finding a minimum vertex cover (Min-VC) is one of the most well-studied NP-hard problems.



A **vertex cover** is a set of nodes that “covers” all edges.

The complement set is an **independent set**

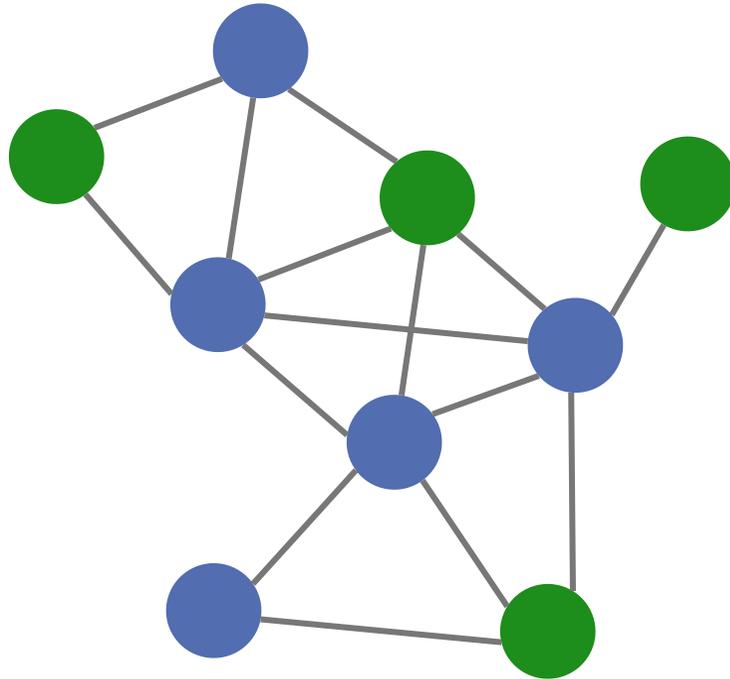
# Finding a minimum vertex cover (Min-VC) is one of the most well-studied NP-hard problems.



A **vertex cover** is a set of nodes that “covers” all edges.

The complement set is an **independent set**

# Finding a minimum vertex cover (**Min-VC**) is one of the most well-studied NP-hard problems.



Simple linear-time 2-approximation algorithms for **Min-VC** have existed since the 1970s and 1980s.

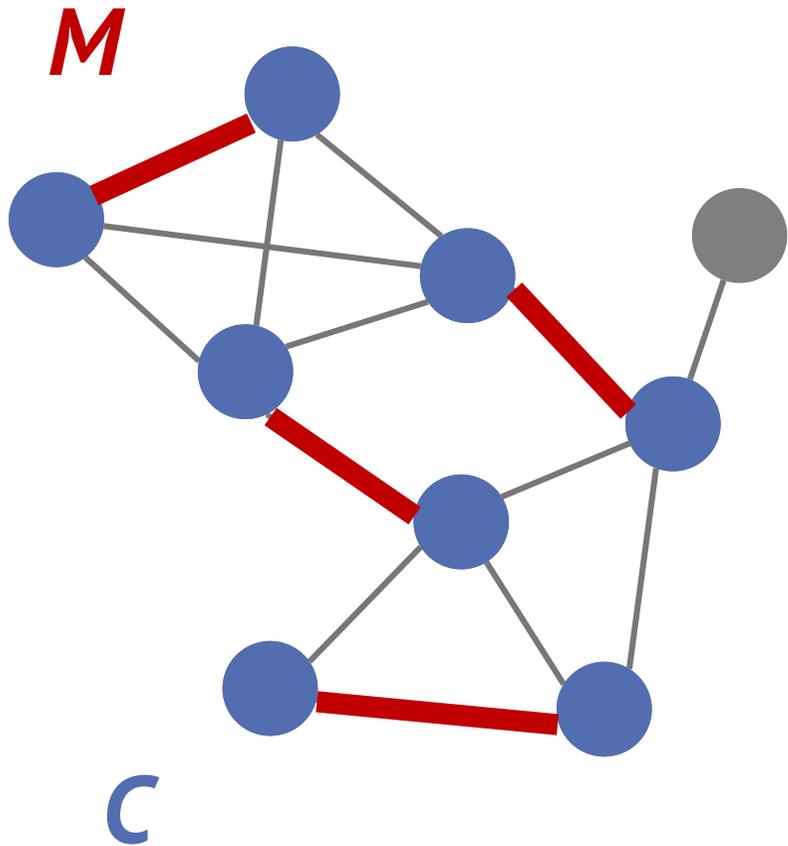
For every fixed  $\epsilon > 0$ , it is UGC-hard to obtain a  $2-\epsilon$  approximation. (KR '08)

This talk will cover a simple new 2-approximation algorithm for minimum vertex cover.

# Simple, linear-time Min-VC algorithms have been known for decades. So what is new, and what's this talk about?

1. New and unifying connections
  - Equivalence with an existing greedy independent set algorithm
  - New connections to *correlation clustering* algorithms
  - This has implications for a parallel MIS algorithm that simultaneously solves multiple problems
2. Simple and fast algorithms for problems that can be reduced to **Min-VC**
3. Open questions

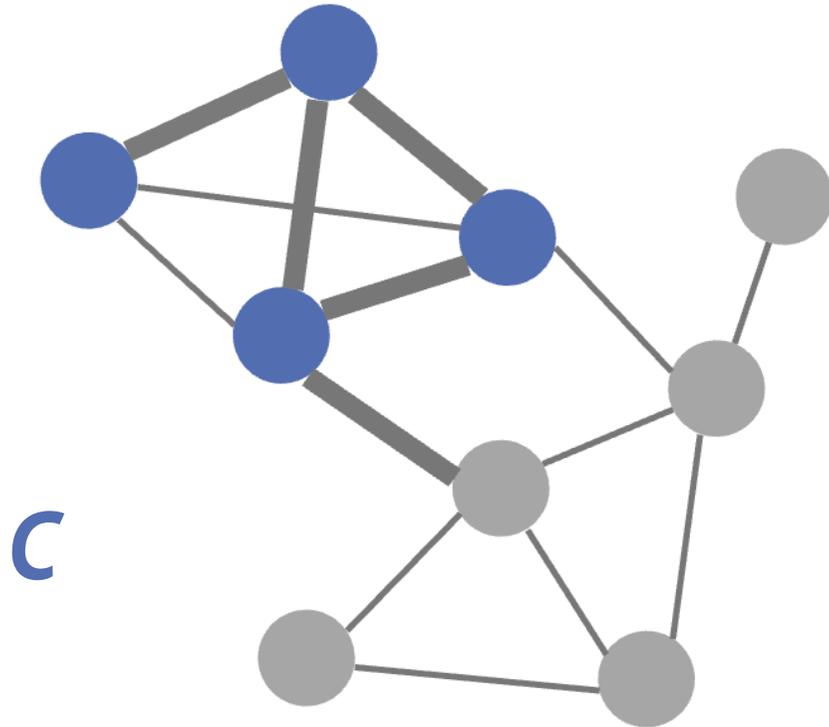
# A standard 2-approximation is to include all nodes from a maximal matching



**Theorem.**  
For every **maximal matching**,  
the **endpoints** are 2-approx for **Min-VC**.

# This can be implemented by iterating through edges

$O(E)$  runtime



for each  $(u, v) \in E$

if  $(u, v)$  is not covered

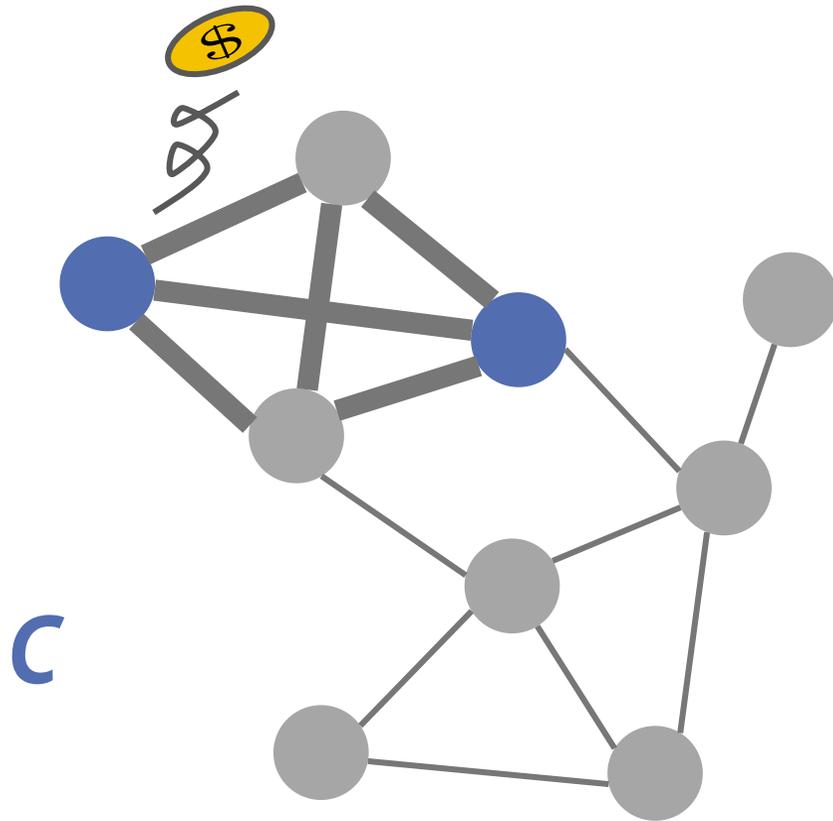
$C \leftarrow C \cup \{u, v\}$

end

end

*This has also been generalized to node-weighted Min-VC. (B-Y, E '85)*

# Pitt's algorithm is a randomized 2-approximation



$O(E)$  runtime

for each  $(u, v) \in E$

if  $(u, v)$  is not covered

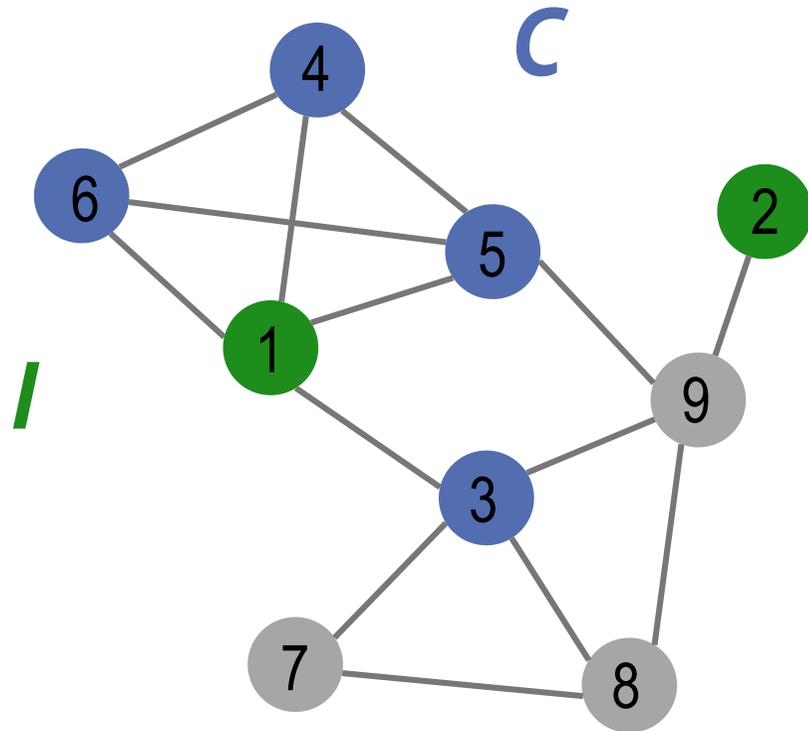
choose  $u$  or  $v$  at random

end

end

*This has also been generalized to node-weighted Min-VC*

# The new\* algorithm generates a random node permutation and greedily grows a maximal independent set



$O(E)$  runtime (unweighted case)

generate random permutation  $\sigma$

for  $i = 1$  to  $|V|$

visit node  $\sigma(i)$

add to  $I$  if possible

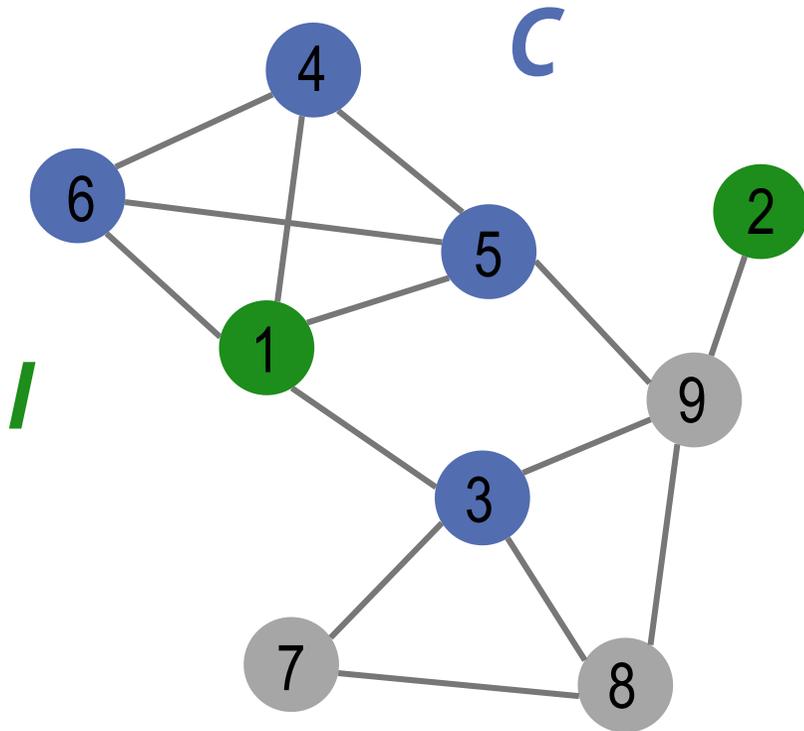
else add to  $C$

end

*Permutation  
depends on  
node weight*

*Can be easily generalized to weighted Min-VC!  
The runtime becomes  $O(V \log V + E)$*

# The unweighted version has been used for decades as a **Greedy Maximal Independent Set** algorithm



A sample of references on **GreedyMIS**

Coppersmith, Raghavan & Tompa, FOCS 1987

Gamarnik & Goldberg, Prob. & Computing 2010

Blelloch, Fineman & Shun, SPAA 2012

Bennet & Bohman, RSA 2016

Fischer & Noever, TALG 2019, SODA 2018

**J. Shi**, Wang, Shang, (survey) 2018

These focus on MIS, no mention of Min-VC

**Theorem (Veldt, 2022).** GreedyMIS is a randomized 2-approximation algorithm for Min-VC (and can be generalized to node-weighted graphs).

<https://arxiv.org/abs/2209.04673>

# A corollary regarding Parallel GreedyMIS

A simple parallel version of GreedyMIS selects multiple IS nodes in each round.

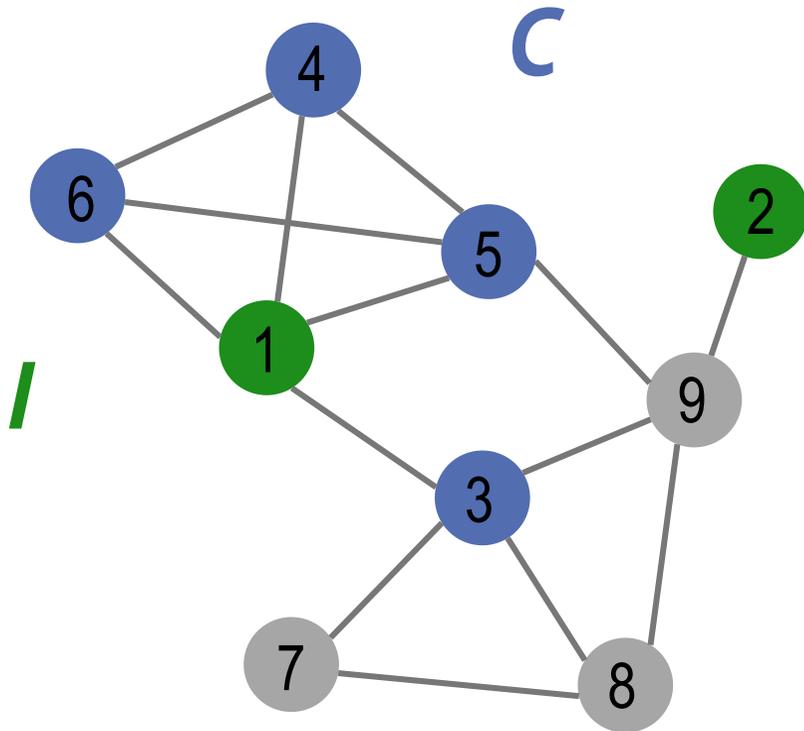
Returns same output as the sequential version!

WHP, it terminates in  $O(\log n)$  rounds (FN '18).

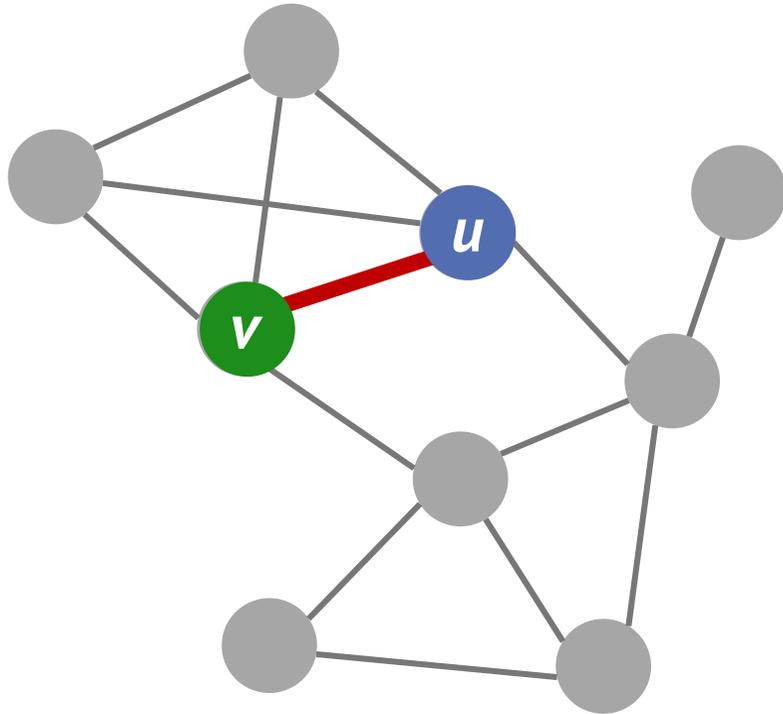
**Corollary.** Parallel GreedyMIS returns:

- A maximal independent set
- 2-approximate vertex cover
- 3-approximation for correlation clustering
- 3-approximation for STC+

*(related to Lutz's talk)*



# Proof sketch



We need to “pay” for nodes added to **C**.

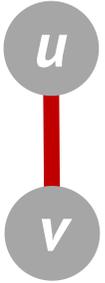
Say  $u$  is added to **C**.

It must have had a neighbor  $v$  that was added to **I**.

Charge edge  $(u,v)$  for adding  $u$  to **C**.

# Proof sketch

$p_{uv}$  = probability  $(u, v)$  is charged



**Step 1:** algorithm's expected cost is:

$$\mathbb{E}[cost] = \sum_{(u,v) \in E} p_{uv}$$

## Dual LP (fractional matching)

$$\begin{aligned} & \max \sum_{(u,v) \in E} y_{uv} \\ \text{s.t. } & \forall u \in V: \sum_{i:(u,i) \in E} y_{ui} \leq 1 \\ & y_{uv} \geq 0 \text{ for } (u,v) \in E. \end{aligned}$$

**Step 2:** Prove (implicitly) that

$y_{uv} = \frac{1}{2}p_{uv}$  is feasible for dual.

$$\text{Min-VC} \geq \text{OPT Dual LP} \geq \sum_{(u,v) \in E} \frac{p_{uv}}{2} = \frac{\mathbb{E}[cost]}{2}$$

↑  
LP duality

**Proof**  
 Inspired by the proof that  
 Pivot is a 3-approximation  
 for correlation clustering!

$p_{uv}$  = probability  $(u, v)$  is charged



Algorithm's expected cost is:

$$\mathbb{E}[cost] = \sum_{(u,v) \in E} p_{uv}$$

**Dual LP (fractional matching)**

$$\begin{aligned} & \max \sum_{(u,v) \in E} y_{uv} \\ \text{s.t. } & \forall u \in V: \sum_{i:(u,i) \in E} y_{ui} \leq 1 \\ & y_{uv} \geq 0 \text{ for } (u,v) \in E. \end{aligned}$$

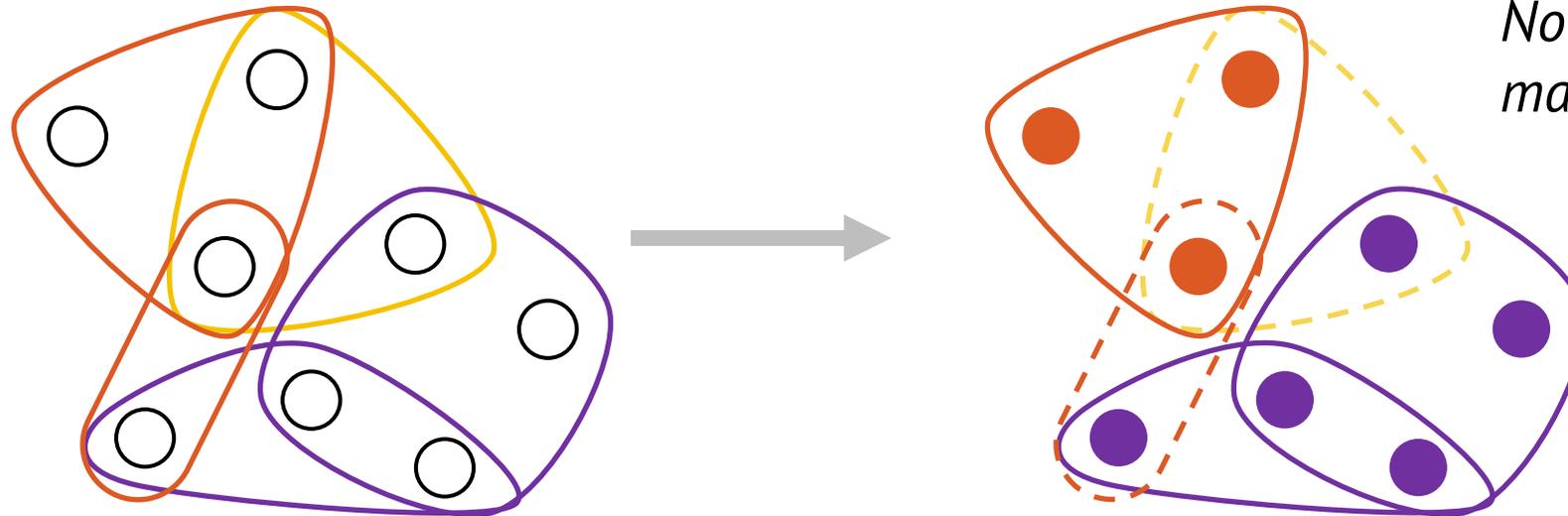
**Step 2:** Prove (implicitly) that

$y_{uv} = \frac{1}{2}p_{uv}$  is feasible for dual.

$$\text{Min-VC} \geq \text{OPT Dual LP} \geq \sum_{(u,v) \in E} \frac{p_{uv}}{2} = \frac{\mathbb{E}[cost]}{2}$$

↑  
**LP duality**

# Colored Hypergraph Clustering can be reduced to Min-VC in an approximation preserving way

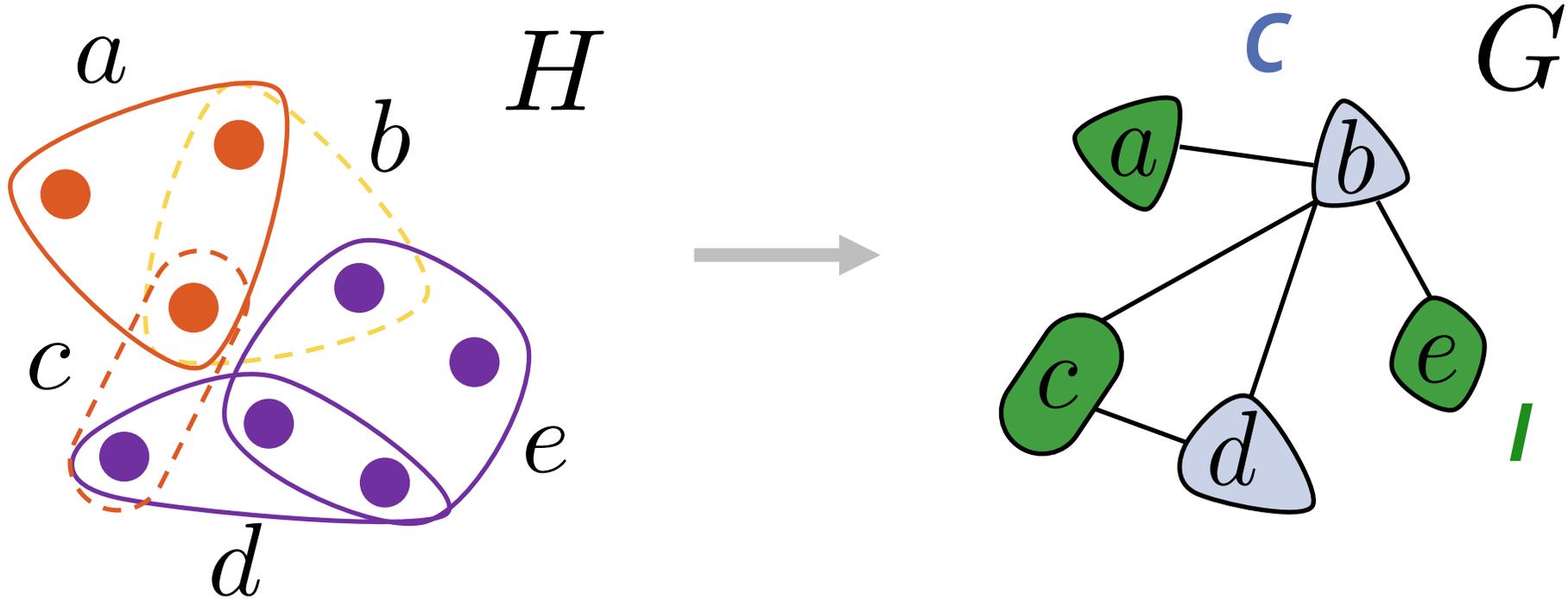


*Two unsatisfied edges:  
Node colors don't  
match edge color*

**Edge-Colored Hypergraph Clustering.** Given an edge-colored hypergraph, color nodes in a way that leaves the fewest number of edges *unsatisfied*.

**Equivalently:** delete (or cover) min # number of edges to destroy pairs of edges that overlap and are a different color.

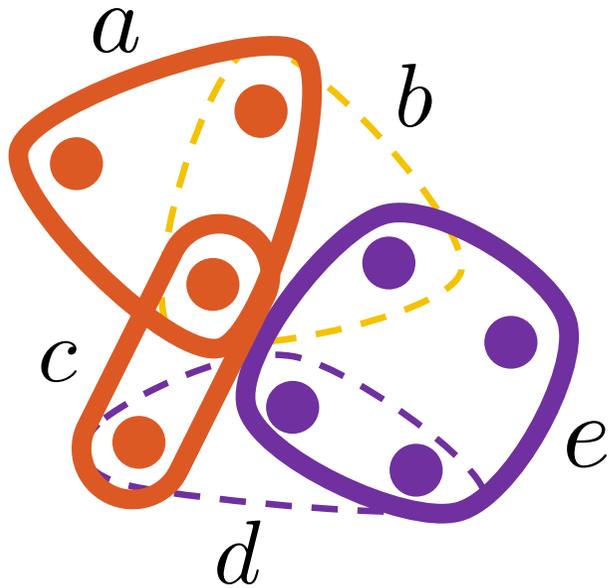
# Colored Hypergraph Clustering can be reduced to Min-VC in an approximation preserving way



**Naive 2-approximation.** Explicitly form  $G$  and run an existing 2-approximation algorithm that iterates through all edges in  $G$ .

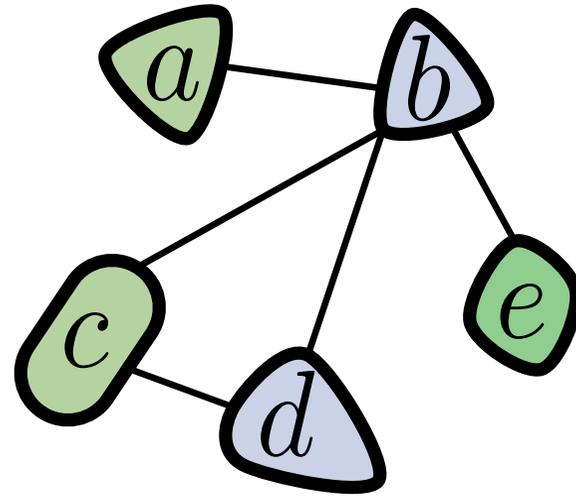
**Runtime.**  $O(\sum_{v \in V} d_v^2 + |E|^2)$ ,  $|E| = \# \text{ hyperedges}$

# We can implicitly implement GreedyMIS in linear-time!



When we visit an edge  $e$ , we just check each node in  $e$ , which takes  $O(|e|)$  time

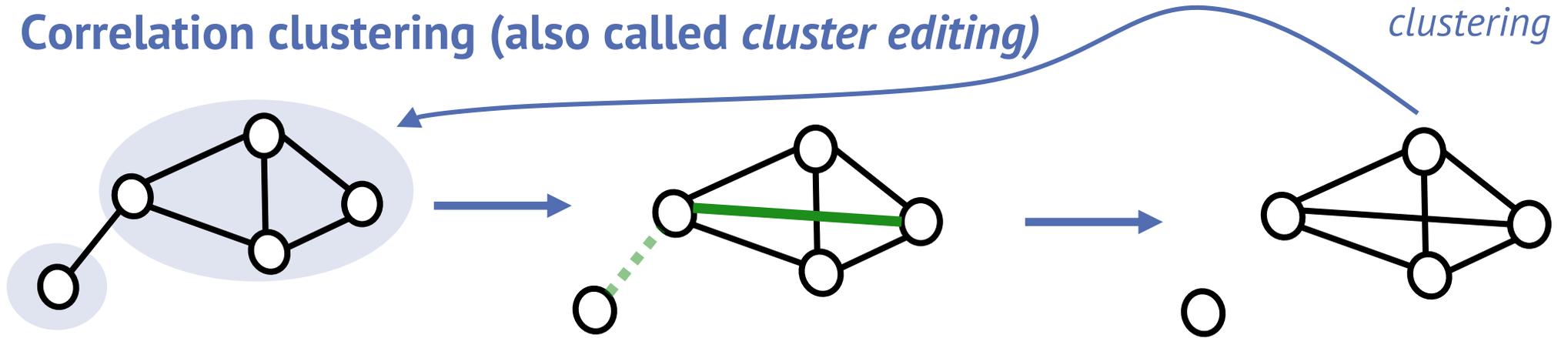
Applying this procedure to  $H$  takes  $O\left(\sum_{e \in E} |e|\right)$  time.



We never actually form this graph or consider all its edges.

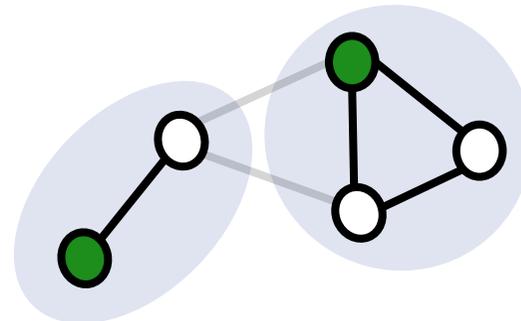
# The proof is inspired by a 3-approximation algorithm for correlation clustering called *Pivot*

Correlation clustering (also called *cluster editing*)

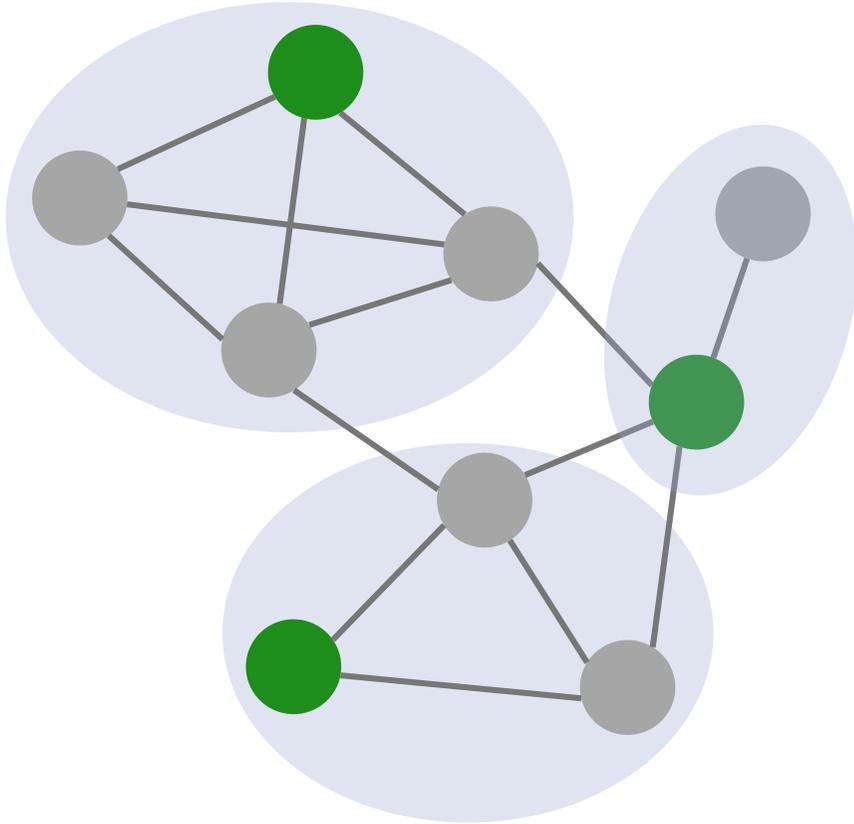


**Goal:** add/delete a minimum # of edges to change into disjoint clique graph

**Pivot algorithm:** cluster random **pivot** nodes with their unclustered neighbors



# Pivot is (basically) equivalent to GreedyMIS!



The random **pivot nodes** are a greedy maximal independent set.

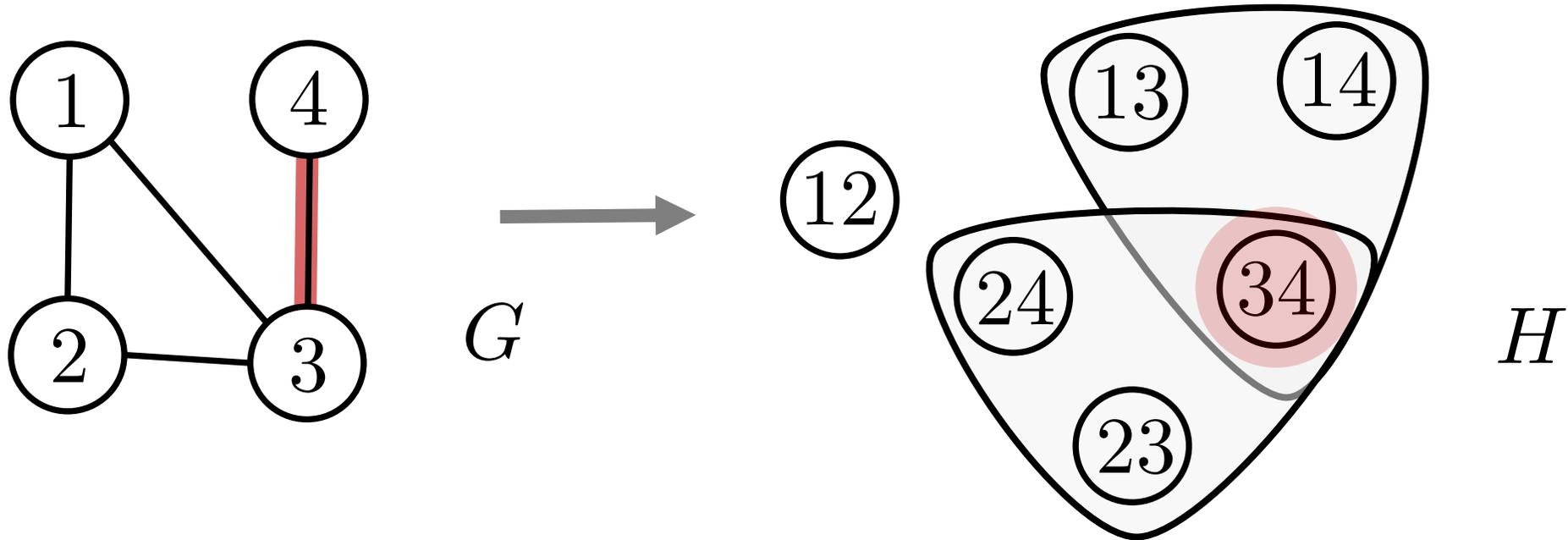
This has been observed in previous work on parallel MIS algorithms.

Fischer & Noever, TALG 2019

*However, this is not the inspiration for the new Min-VC algorithm!*

*That is related to a more subtle relationship.*

# Pivot can be implicitly viewed as a 3-approximation for a 3-uniform hypergraph Vertex Cover algorithm



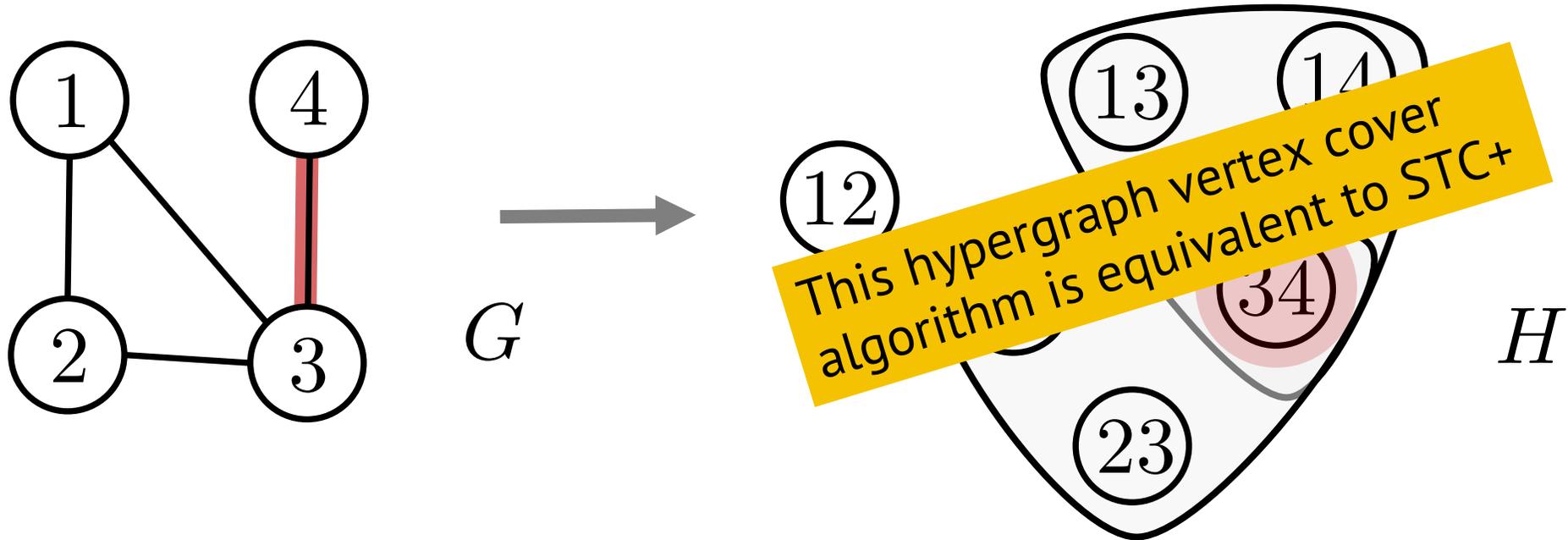
Correlation clustering in  $G$ ...

...can be lower-bounded by a Min-VC problem in a 3-uniform hypergraph  $H$

Adding/deleting an edge in  $G$ ...

....means covering a node in  $H$

# Pivot can be implicitly viewed as a 3-approximation for a 3-uniform hypergraph Vertex Cover algorithm



Correlation clustering in  $G$ ...

...can be lower-bounded by a Min-VC problem in a 3-uniform hypergraph  $H$

Adding/deleting an edge in  $G$ ...

....means covering a node in  $H$

# Open questions

Can we further simplify/unify existing parallel algorithms for finding maximal independent sets, approximating Min-VC, and approximating correlation clustering?

Can this maximal independent set approach for Min-VC be extended to hypergraph vertex cover?

Can we exploit this relationship between Min-VC and correlation clustering to develop new combinatorial and parallel algorithms for weighted correlation clustering?

---

**Growing a Random Maximal Independent Set Produces a 2-approximate Vertex Cover**

Nate Veldt, <https://arxiv.org/abs/2209.04673>

Thanks!