

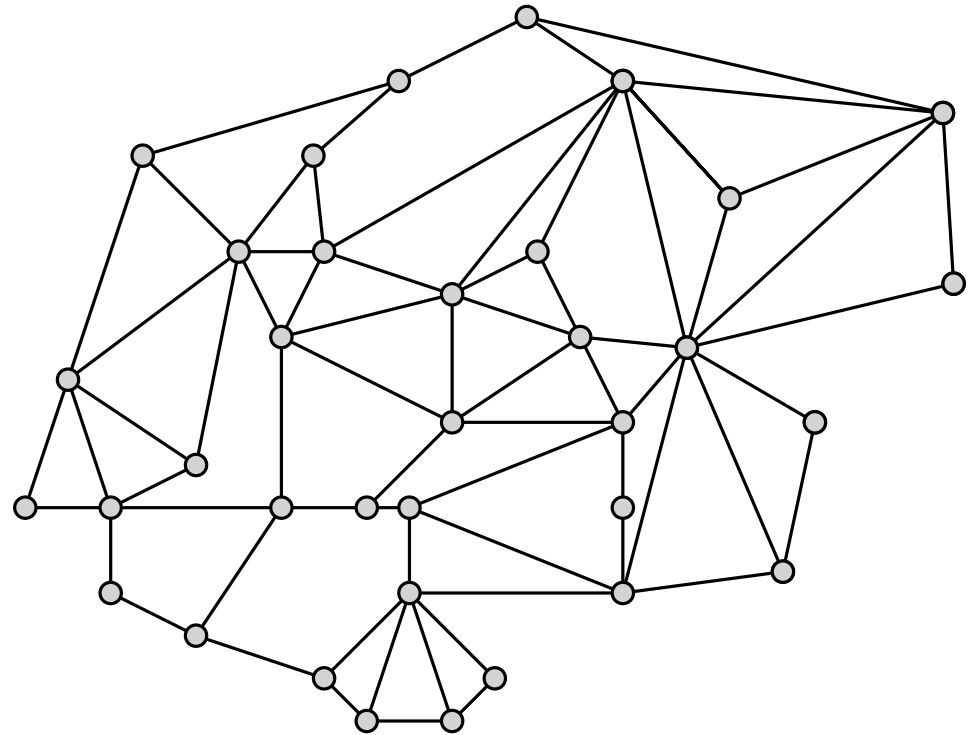
# Deterministic Distributed Matching via Rounding

Manuela Fischer

joint work with Mohsen Ghaffari

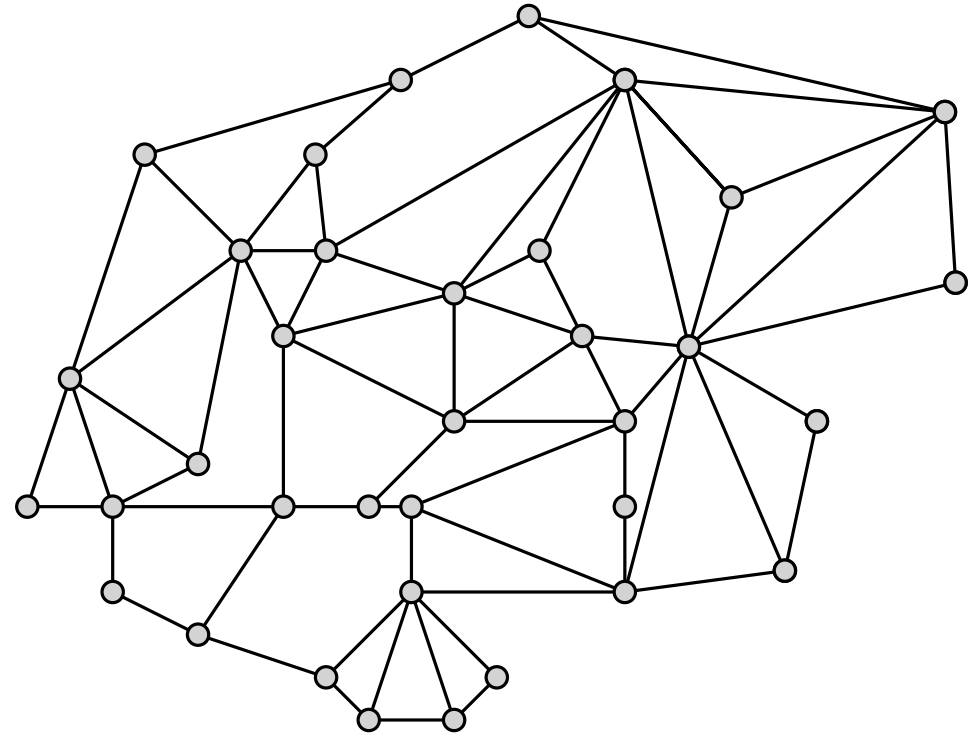
16.05.2017

# Distributed LOCAL Model



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$n$  nodes, maximum degree  $\Delta$   
unique IDs

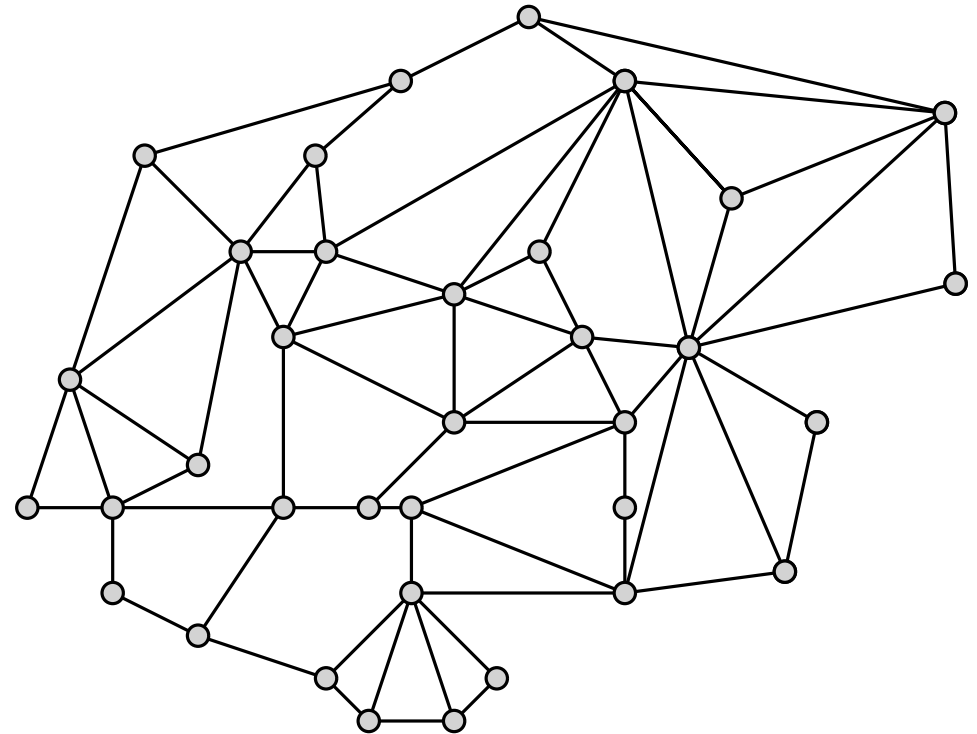


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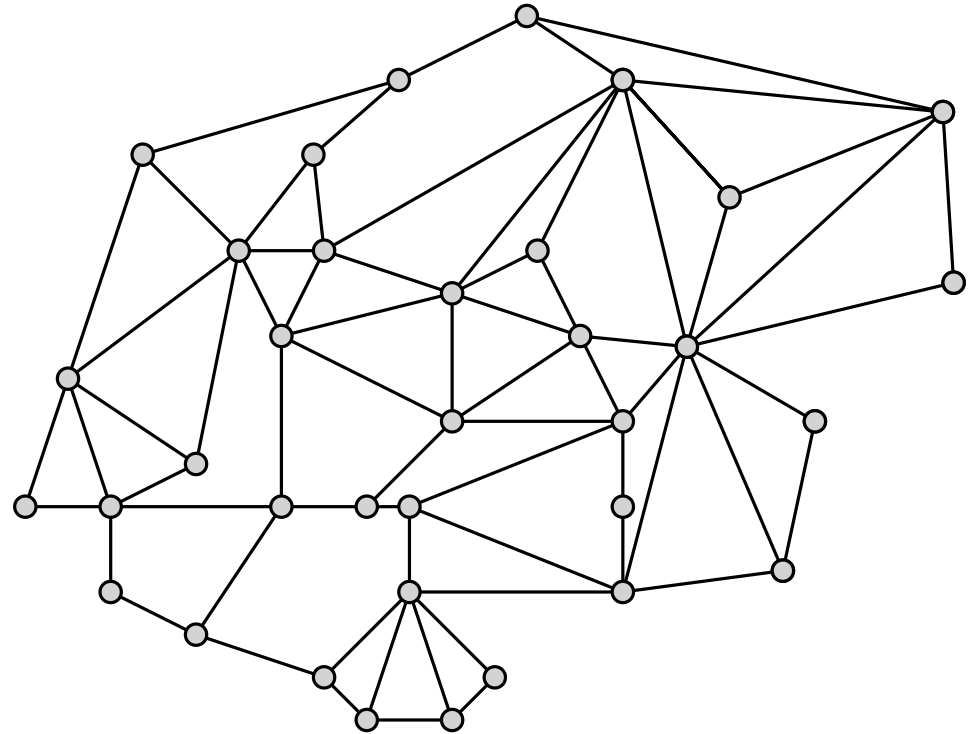
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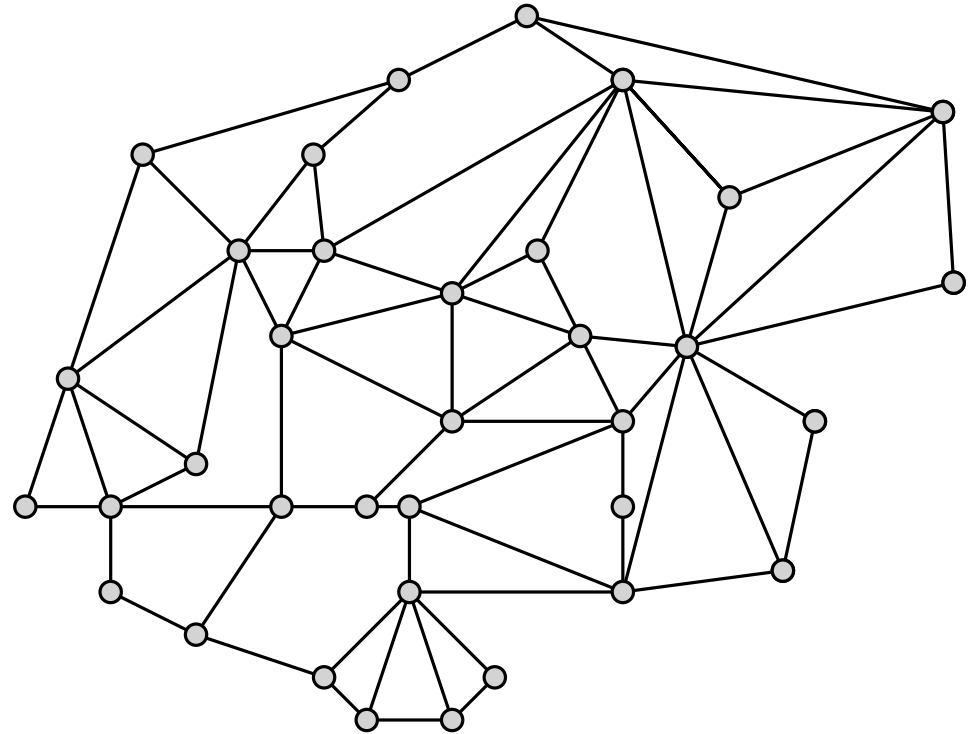
synchronous rounds  
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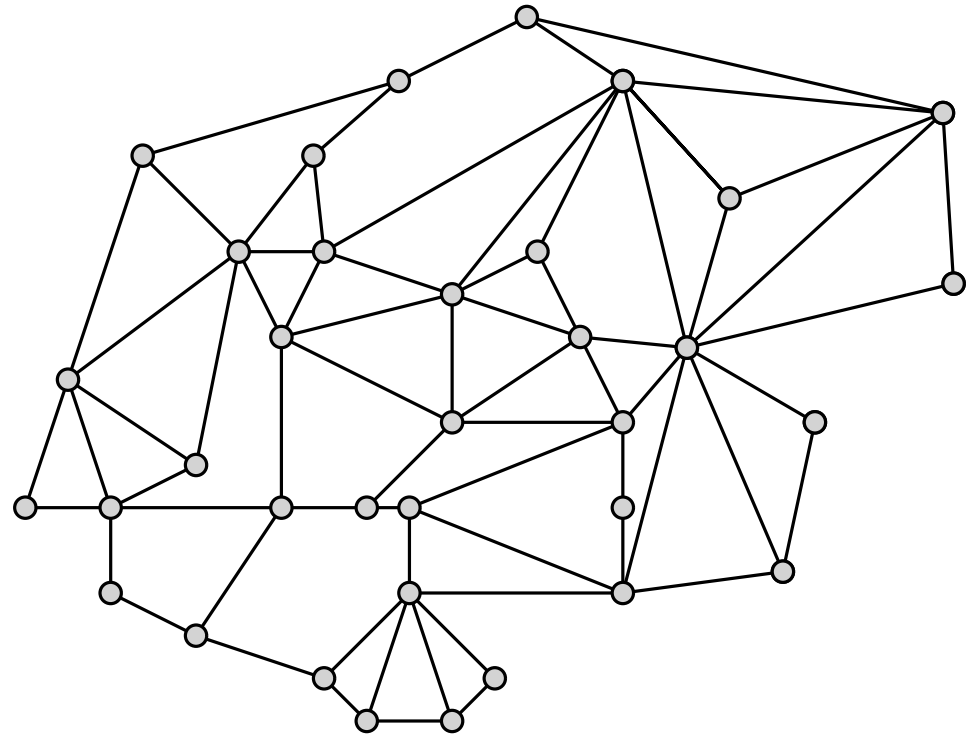
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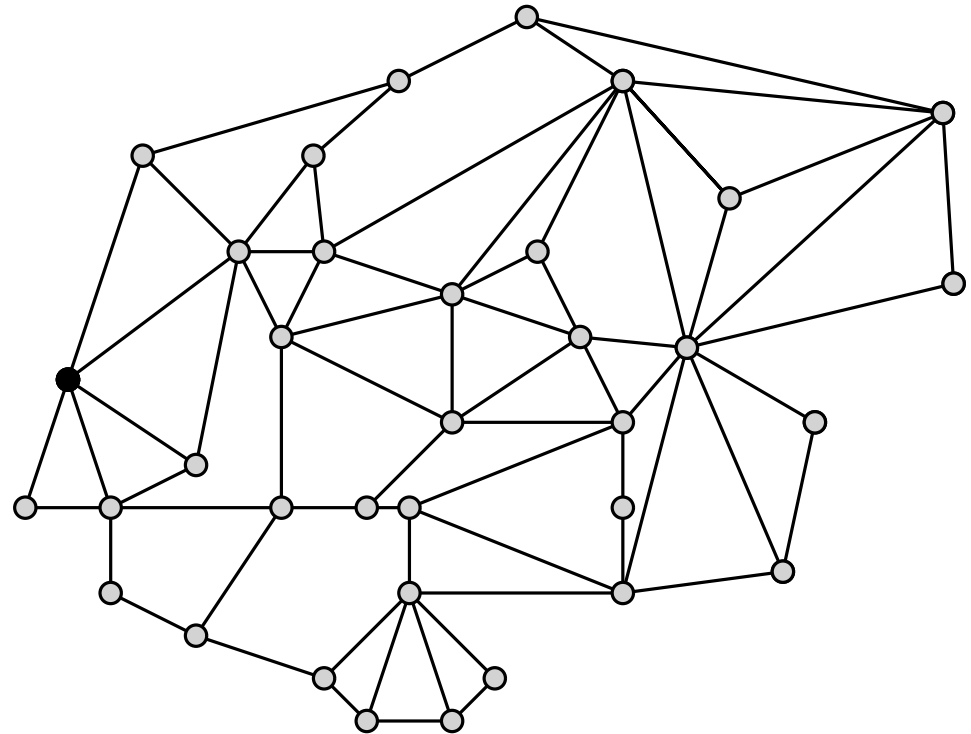


complexity = number of rounds = dependency radius

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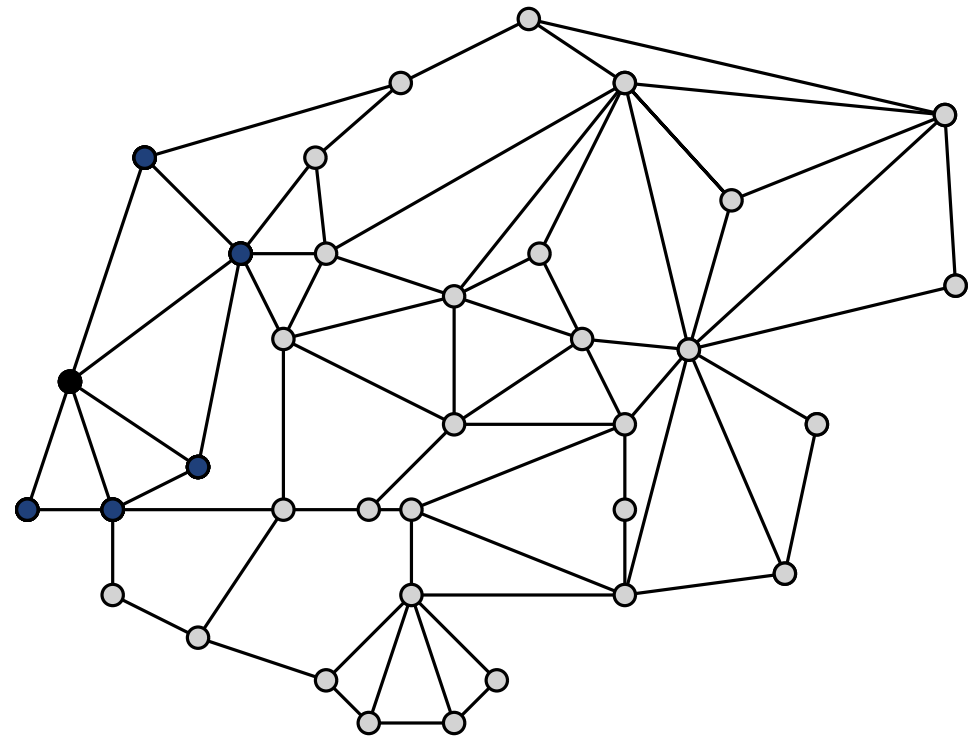
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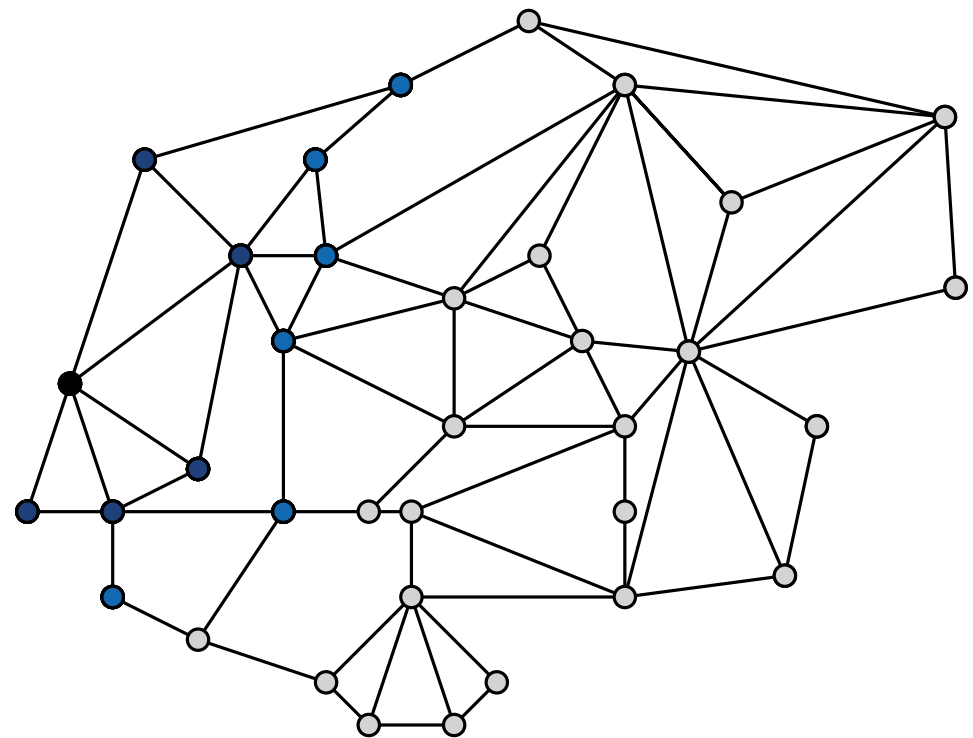


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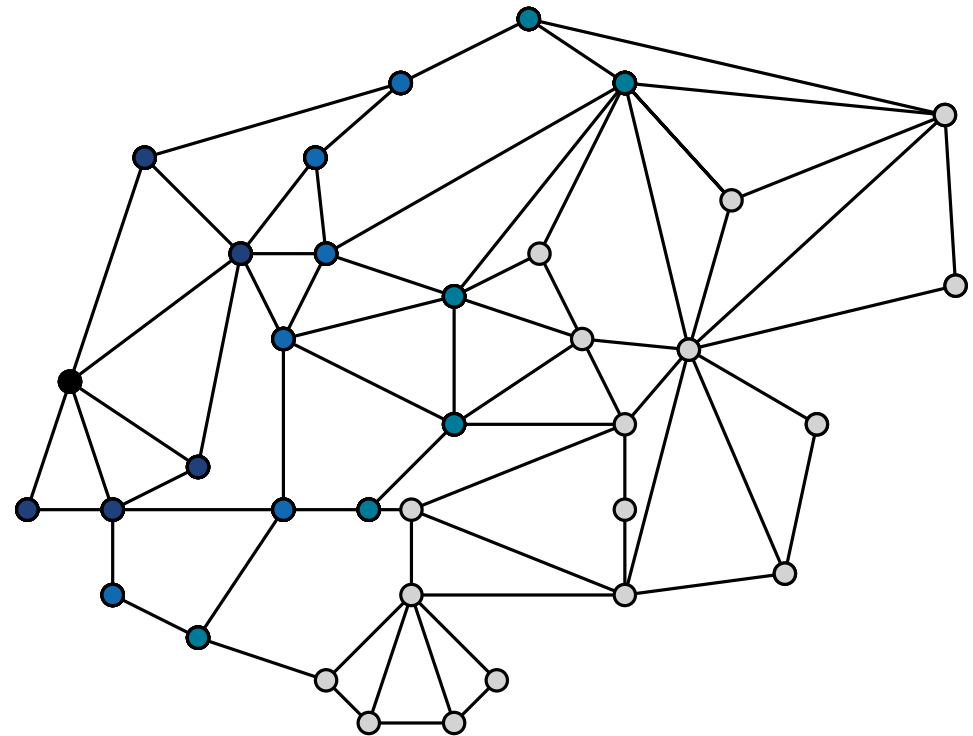


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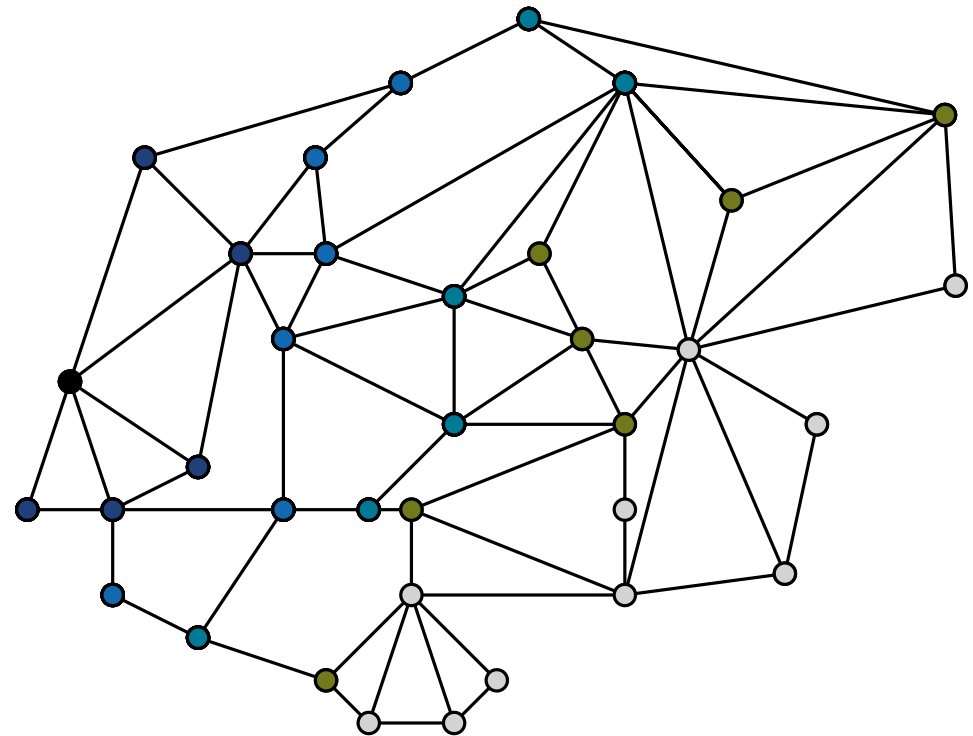


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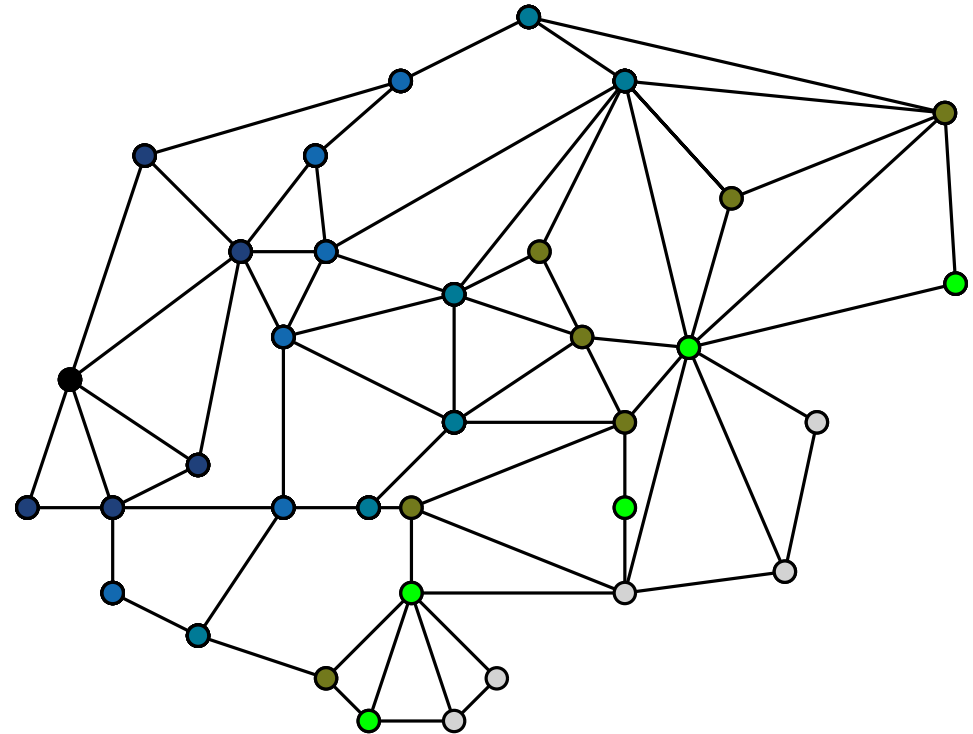


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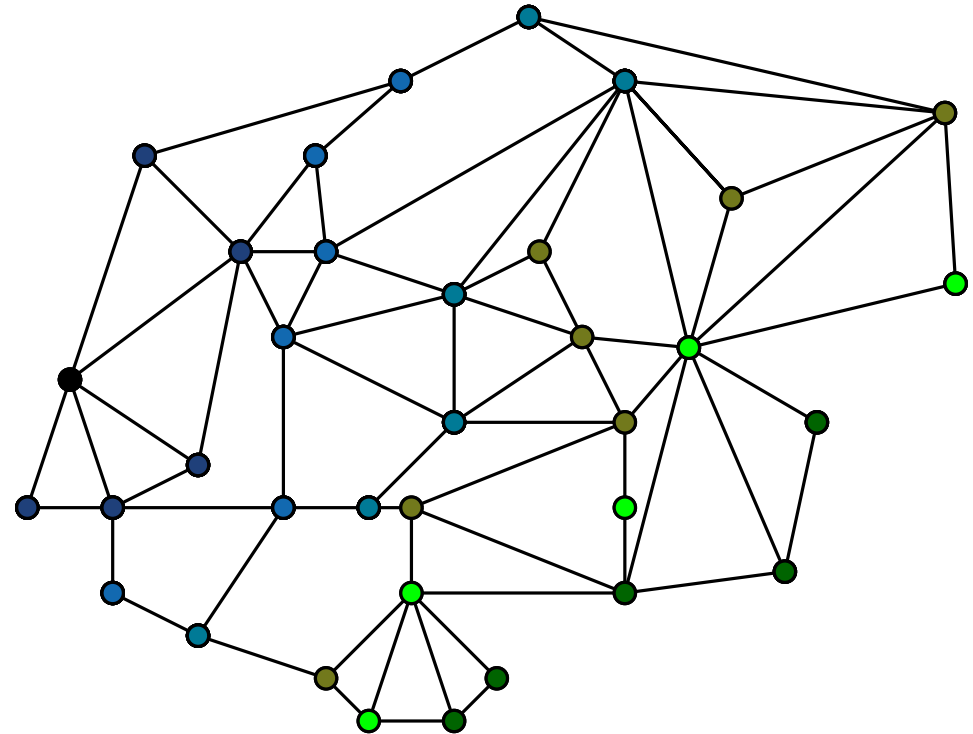


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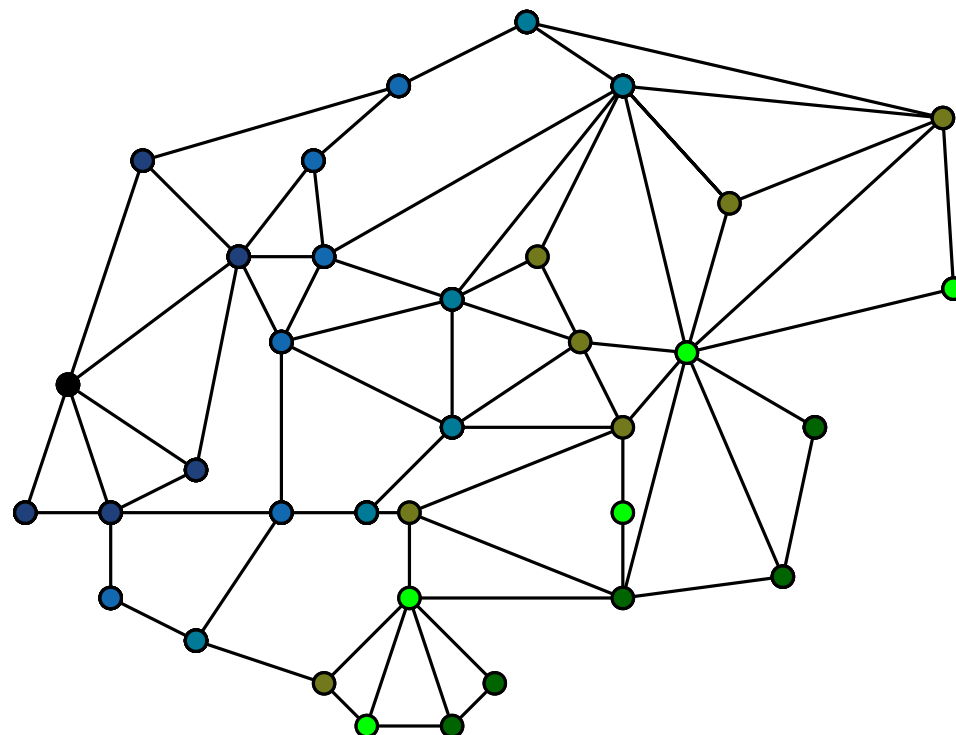
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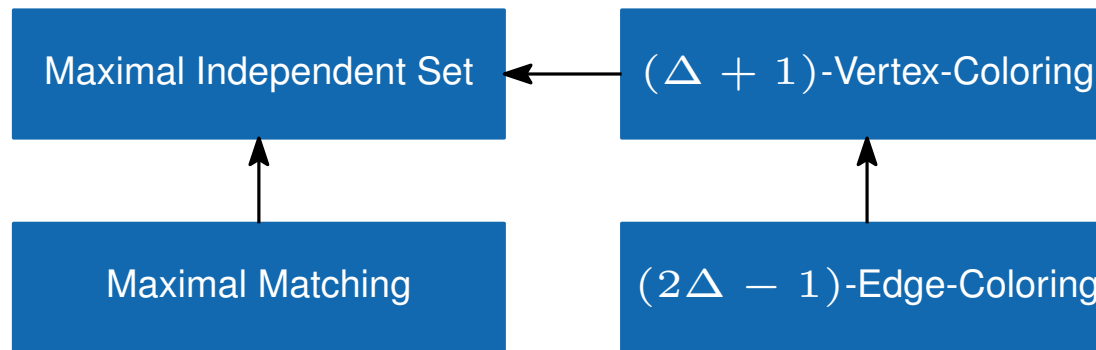
local problems:  $o(D)$  complexity

# Distributed LOCAL Model: Bigger Picture



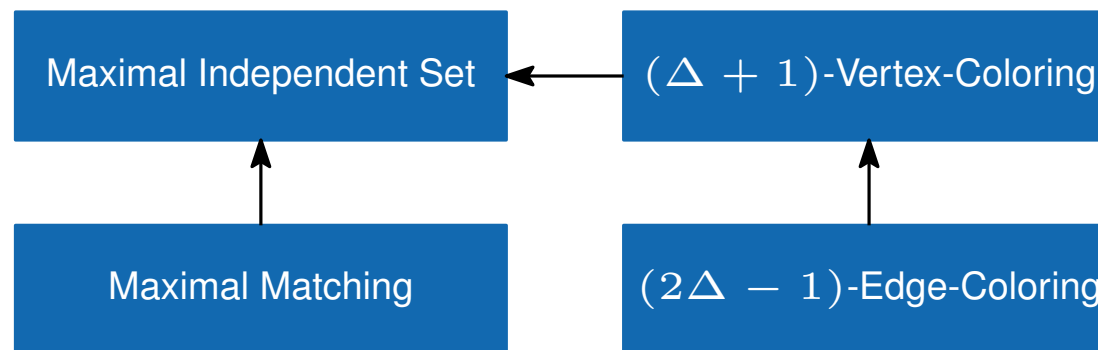
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Four Classic LOCAL Problems (studied since 1980s)



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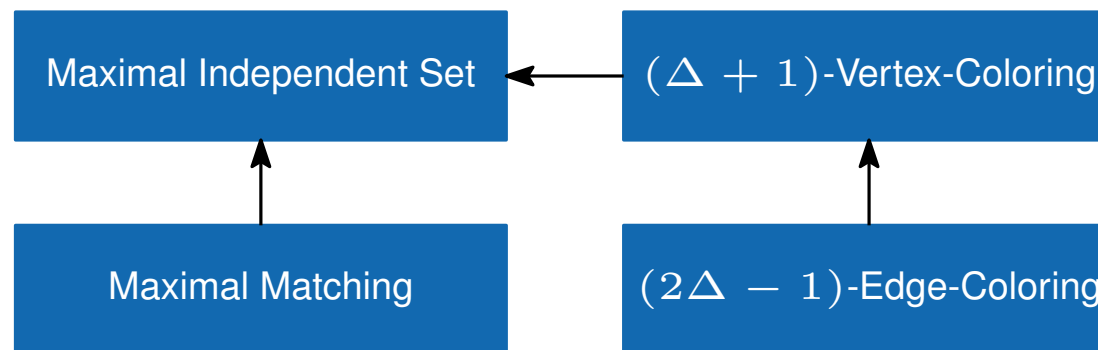
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Four Classic LOCAL Problems (studied since 1980s)



goal: efficient deterministic algorithms for these problems

completeness of rounding (by Ghaffari, Kuhn, Maus [STOC'17]):

only obstacle for finding efficient deterministic distributed algorithms is

efficient deterministic distributed rounding method

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$$O(\log^2 \Delta \cdot \log n)$$

for maximal matching (2-approximation)

# Further Extensions & Corollaries of Our Result

$$O(\log^2 \Delta \cdot \log \frac{1}{\varepsilon})$$

for  $(2 + \varepsilon)$ -approximate weighted matching

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for an  $\varepsilon$ -almost maximal matching

$$O(\log^2 \Delta \cdot \log \frac{\Delta}{\varepsilon})$$

for  $(2 + \varepsilon)$ -approximate minimum edge dominating set

# Intuitive Idea

(1) What is simple case?

(2) How to reduce to it?

# (1) Simple Case:

## Bipartite Bounded-Degree Graphs

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Lemma:

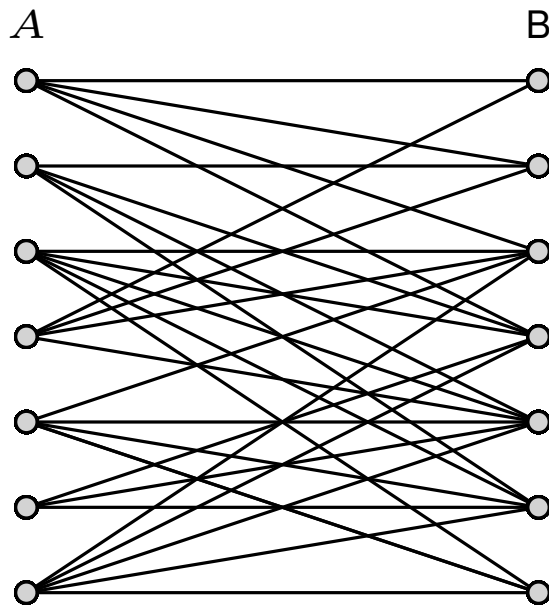
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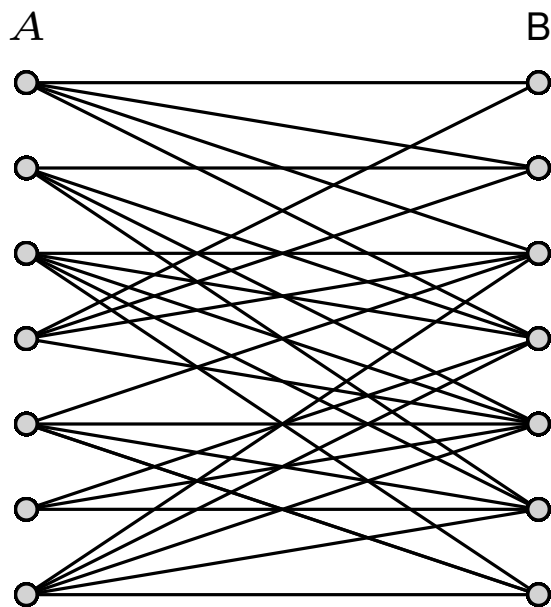


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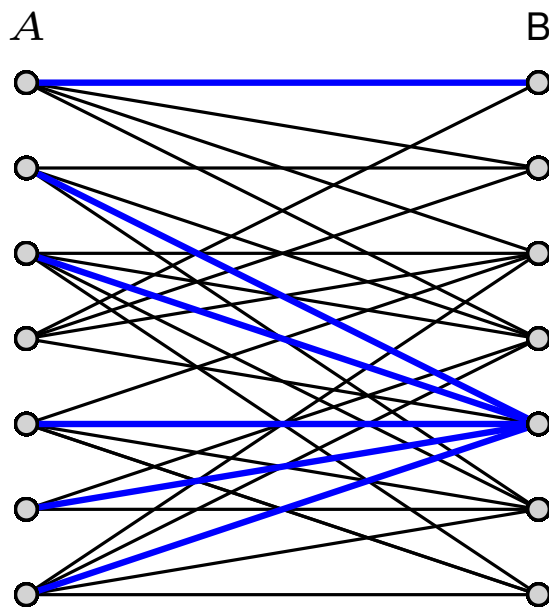
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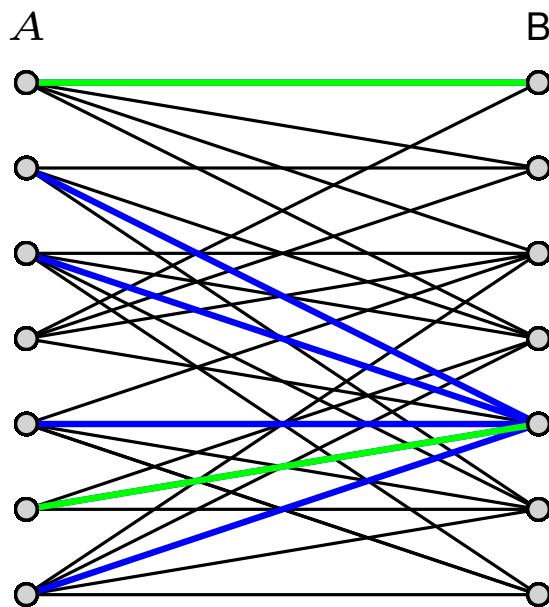
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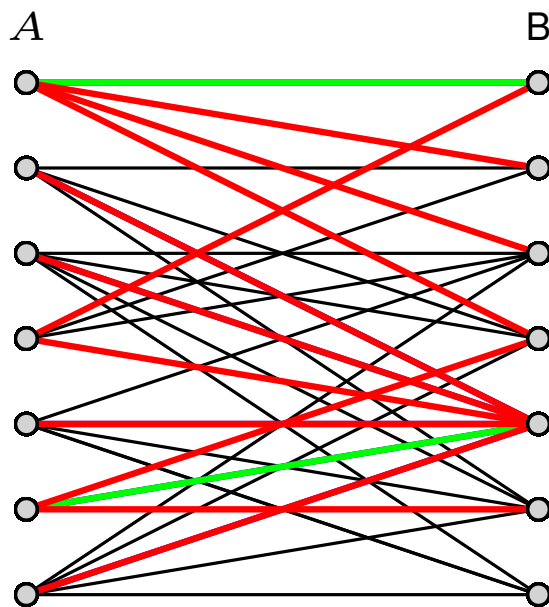
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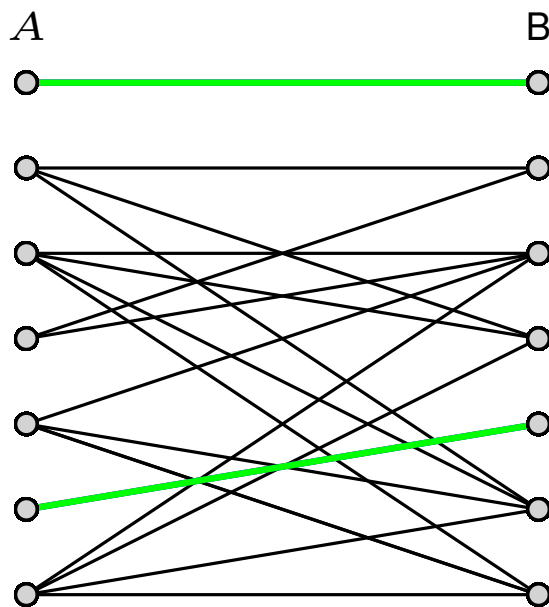
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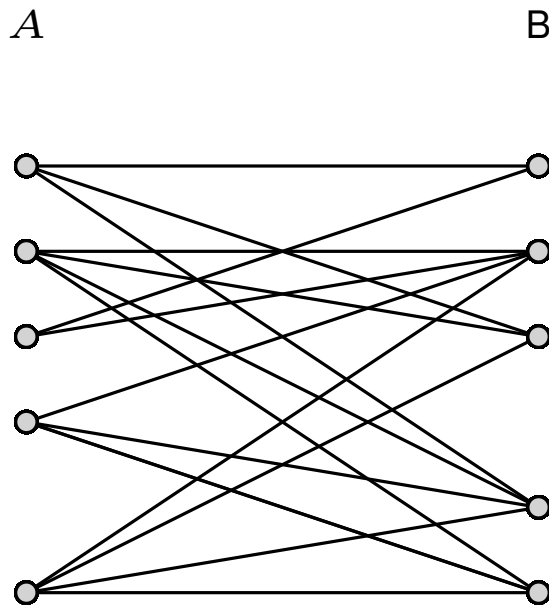
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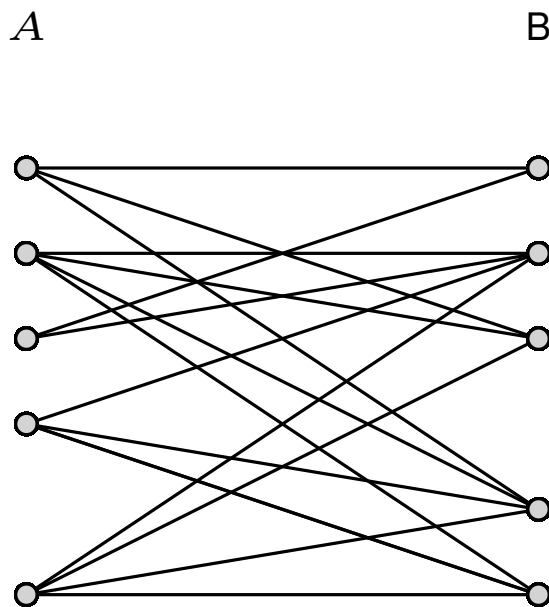
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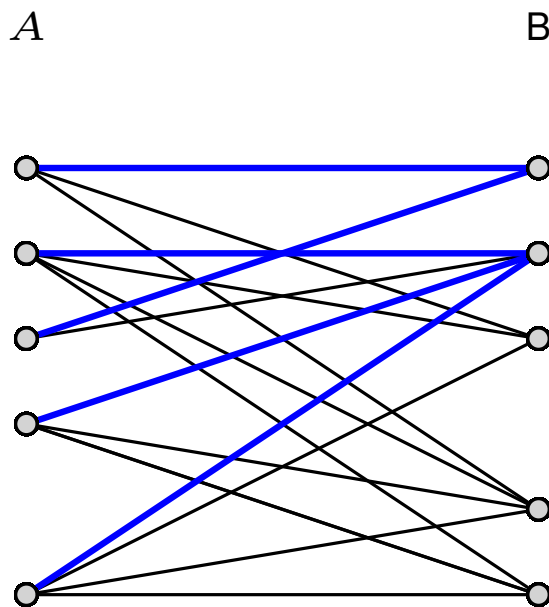
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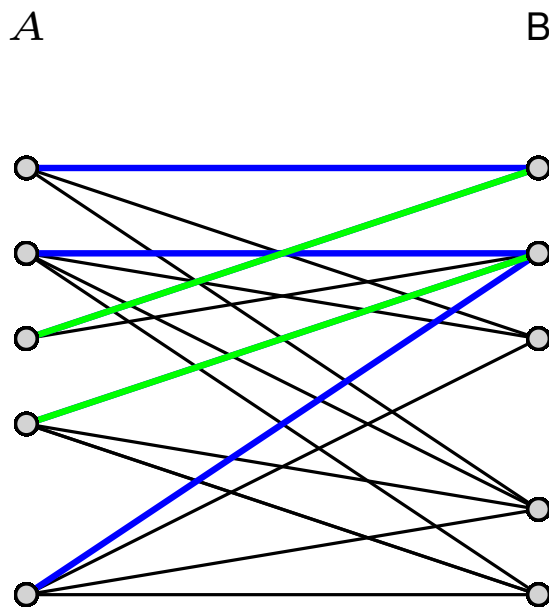
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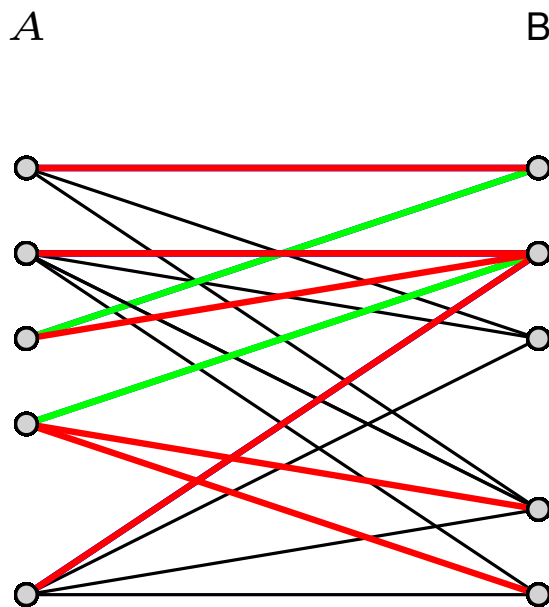
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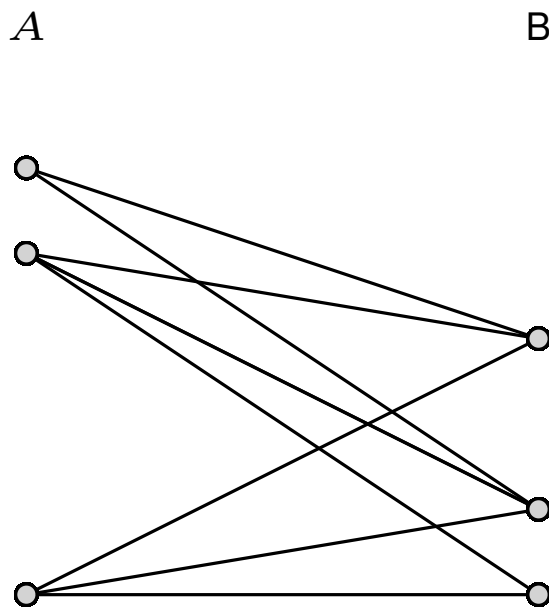
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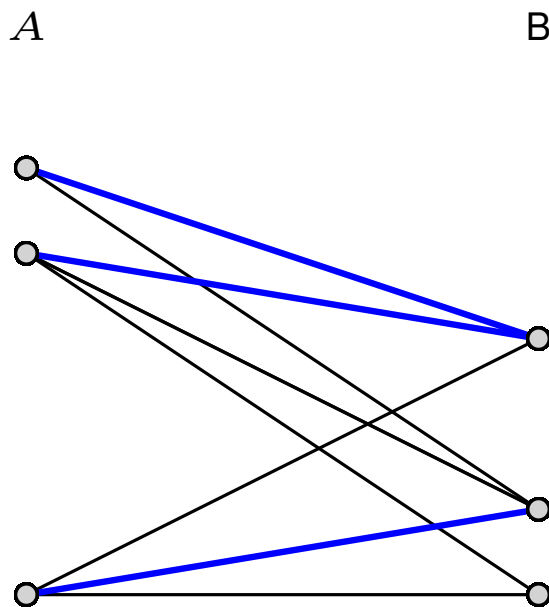
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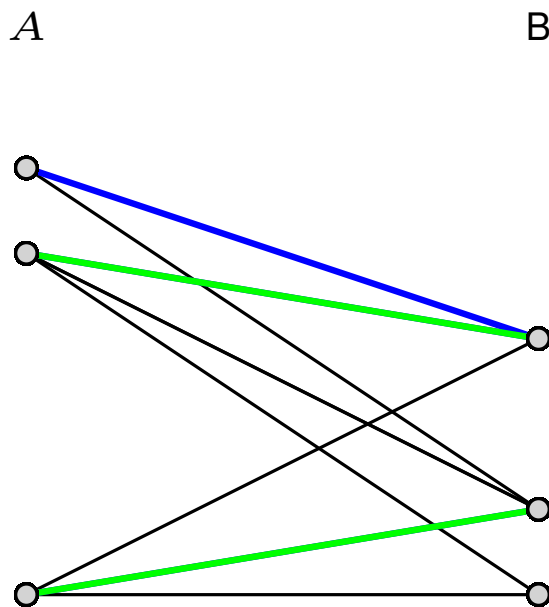
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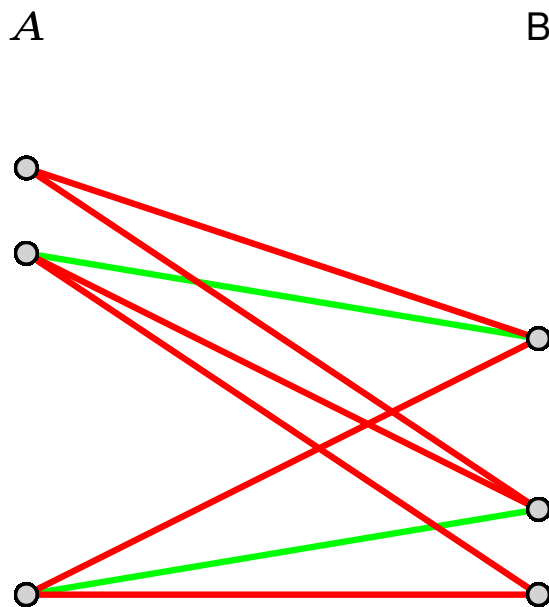
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$O(\log \Delta)$ -round  $O(\prod_i r_i)$ -approximation

Our Method:

# Matching Approximation via Rounding LPs



# Fractional Matching

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(Integral) Matching as Integer Program

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$$x_e \in \{0, 1\} \text{ for all } e \in E$$

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(Integral) Matching as Integer Program

$$\sum_{e \in E(v)} x_e \leq 1 \text{ for all } v \in V$$

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# Fractional Matching

(Integral) Matching as Integer Program

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Fractional Matching as Linear Program

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### why useful?

instead of just setting half of edges to 0 and half to 1,

pursue a more gradual approach with fractional matchings



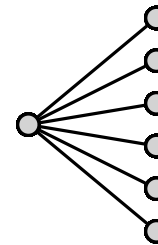
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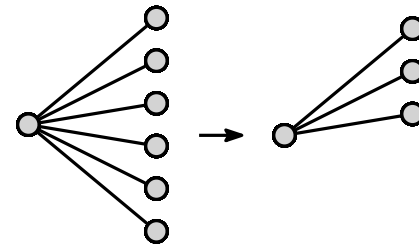
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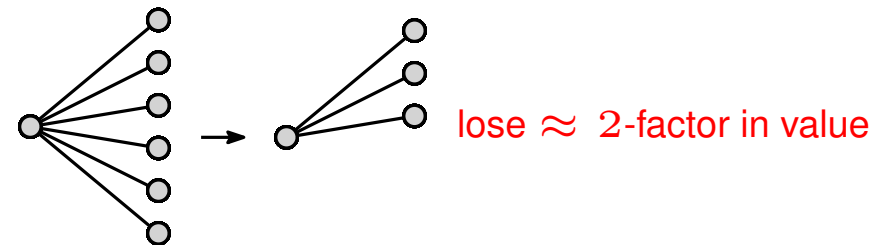
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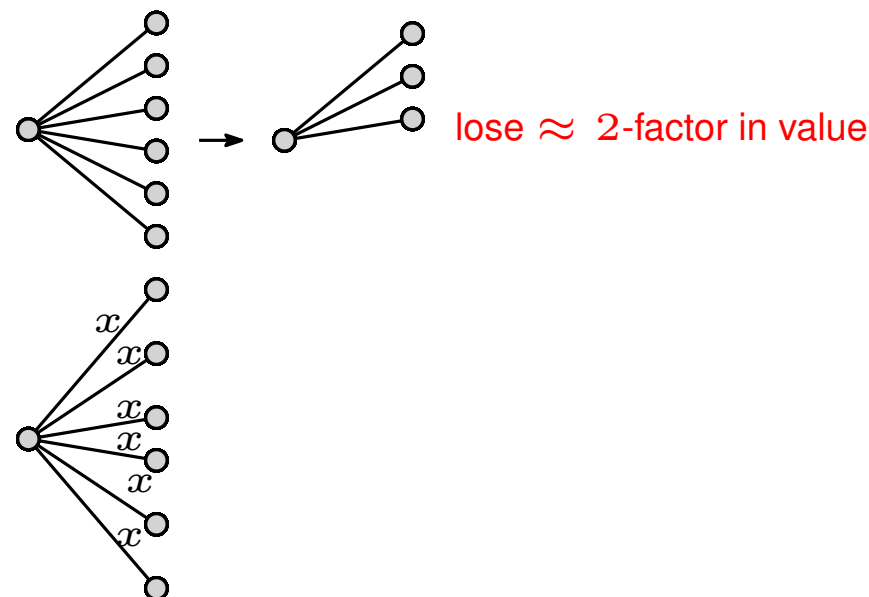
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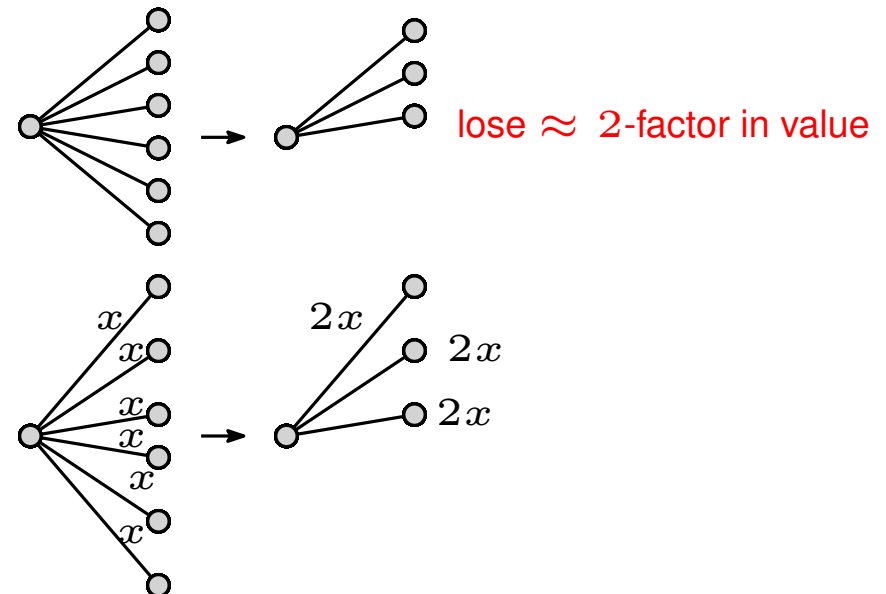
$$\max \sum_{e \in E} x_e$$

$$\text{s.t. } \sum_{e \in E(v)} x_e \leq 1 \text{ for all } v \in V$$

$$x_e \in [0, 1] \text{ for all } e \in E$$

## why useful?

instead of just setting half of edges to 0 and half to 1,  
pursue a more gradual approach with fractional matchings



# Fractional Matching

## Fractional Matching as Linear Program

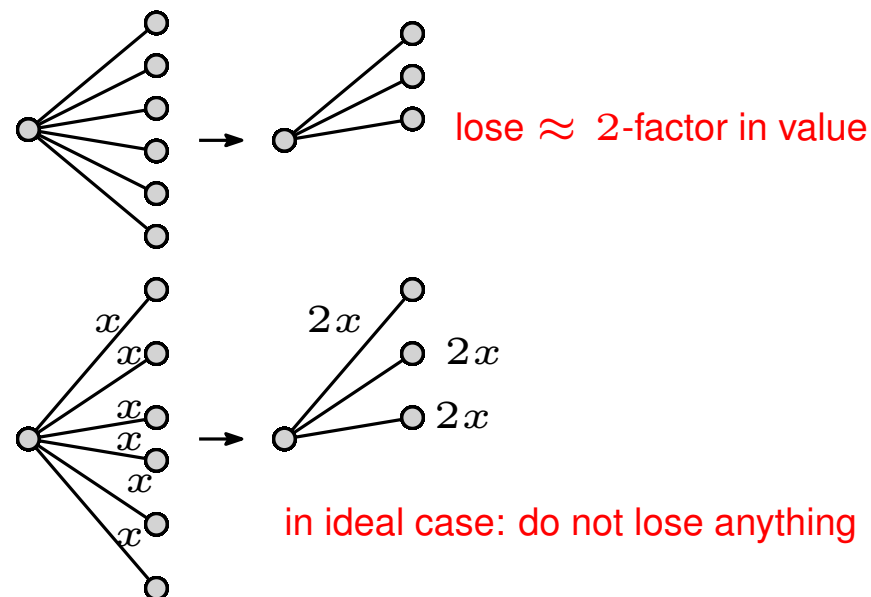
$$\max \sum_{e \in E} x_e$$

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# Our Matching Approximation Algorithm: Outline

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(1) Fractional matching



# Our Matching Approximation Algorithm: Outline

(1) Fractional matching

(2) Iterative rounding

# Our Matching Approximation Algorithm: Outline

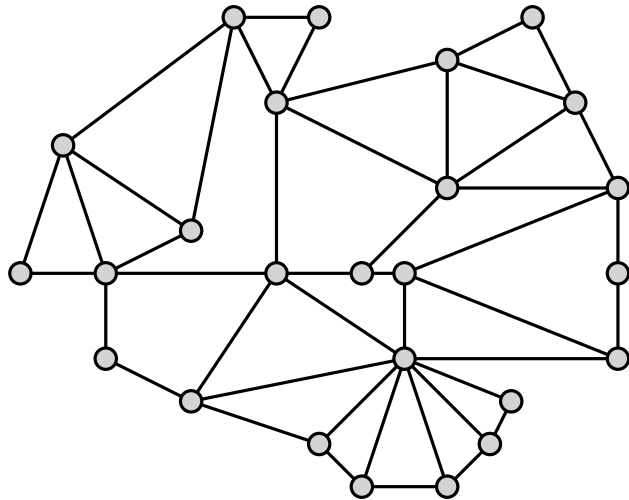
(1) Fractional matching

(2) Iterative rounding

(3) Final Rounding

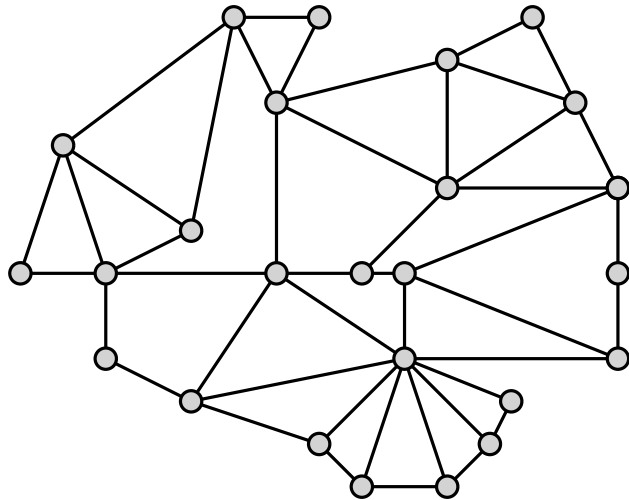
# (1) Find Fractional Matching

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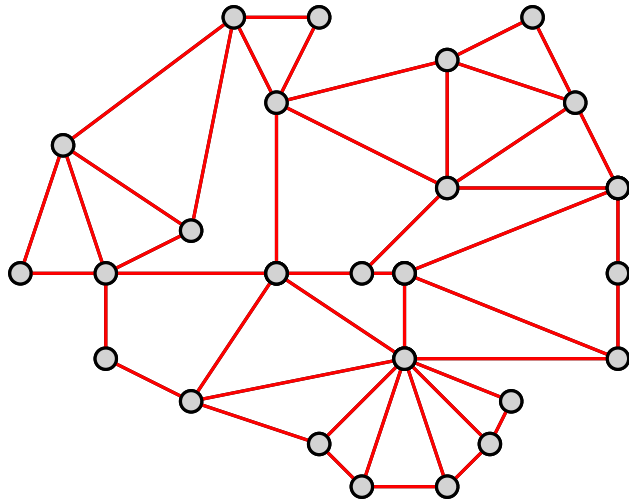
# (1) Find Fractional Matching

start with  $x_e = 2^{-\lceil \log \Delta \rceil}$

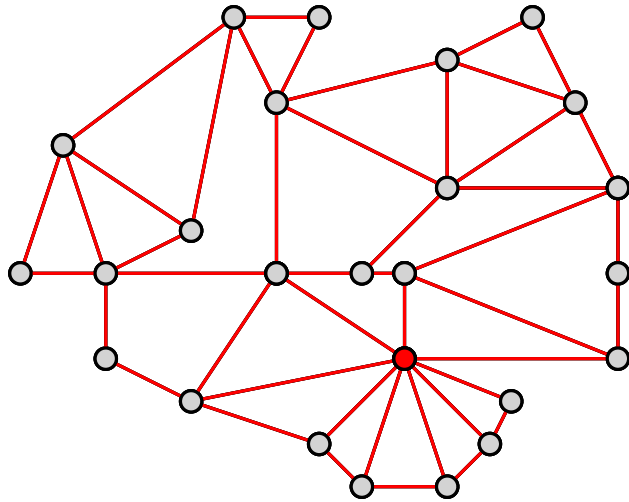


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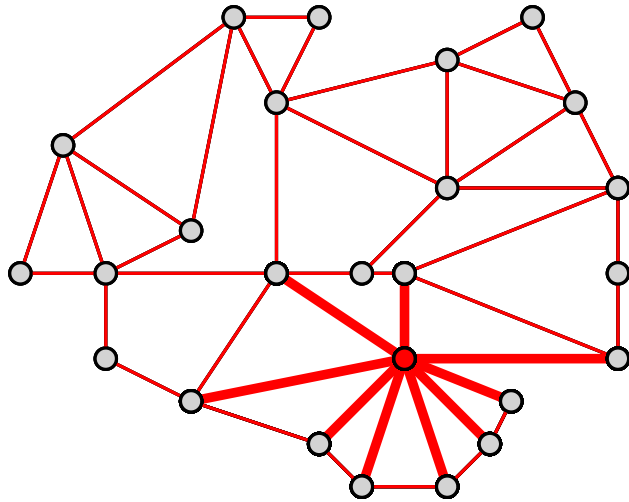
# (1) Find Fractional Matching



start with  $x_e = 2^{-\lceil \log \Delta \rceil}$

mark  $\frac{1}{2}$ -tight nodes

# (1) Find Fractional Matching



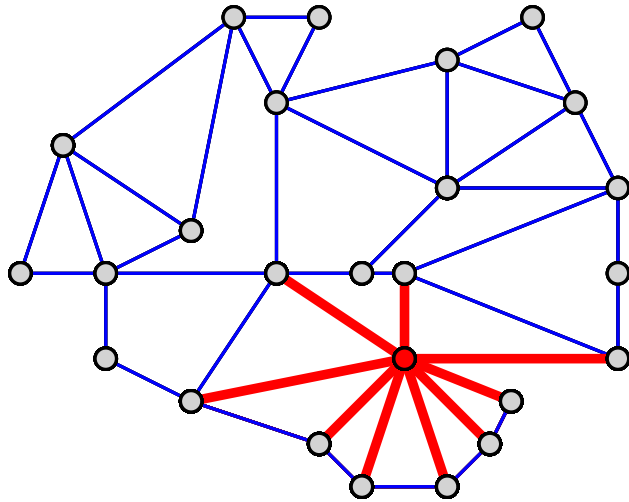
start with  $x_e = 2^{-\lceil \log \Delta \rceil}$

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block its edges



# (1) Find Fractional Matching



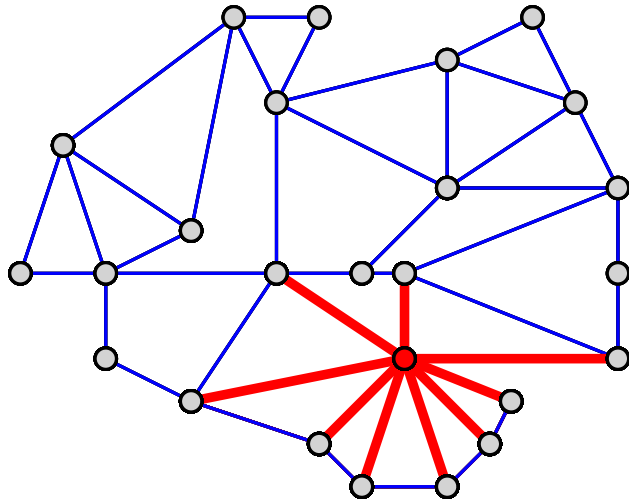
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double value of all other edges

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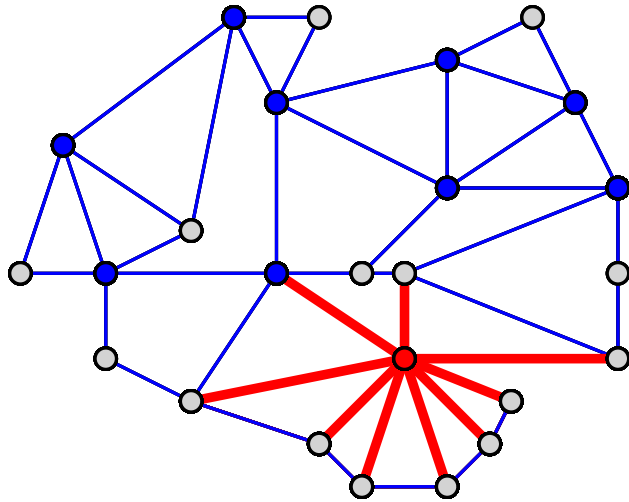
repeat

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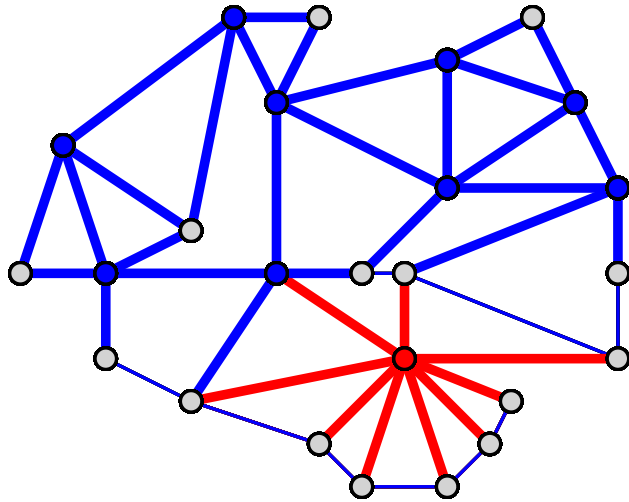
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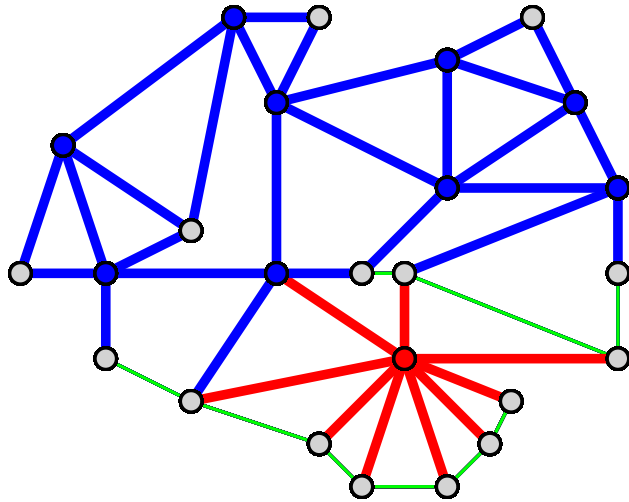
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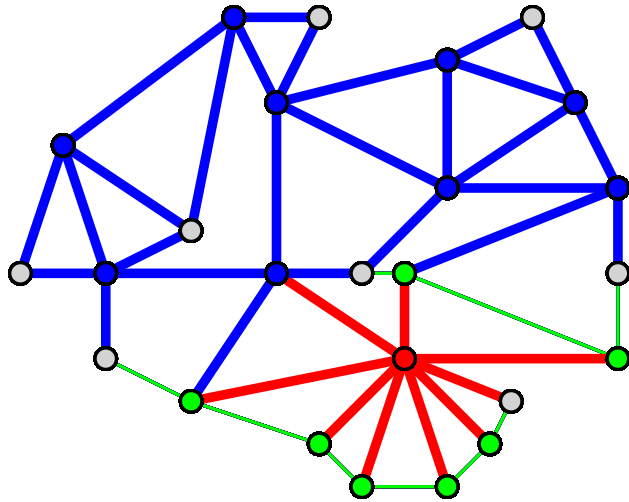
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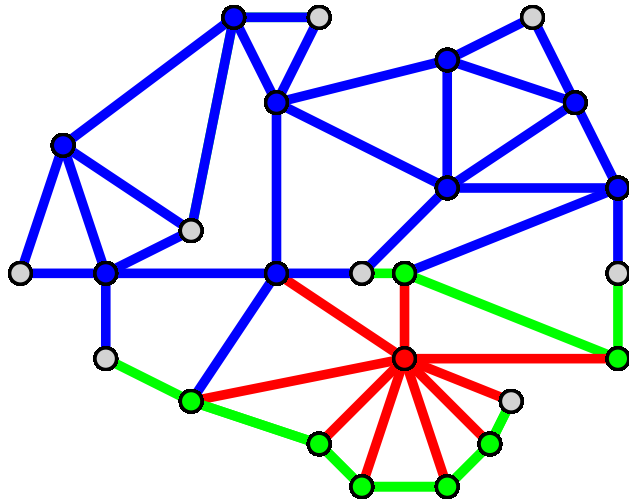
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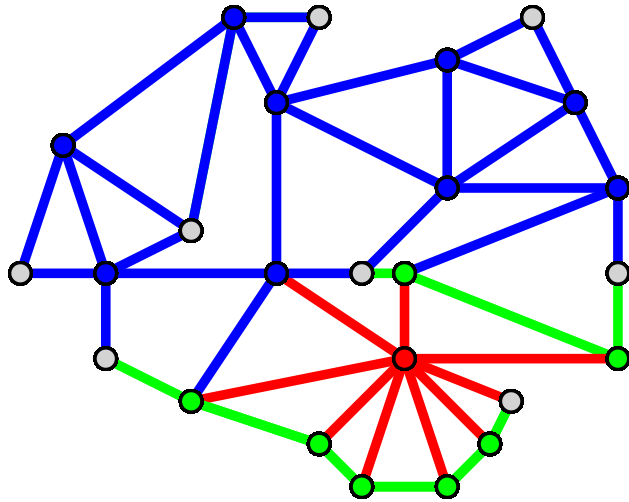
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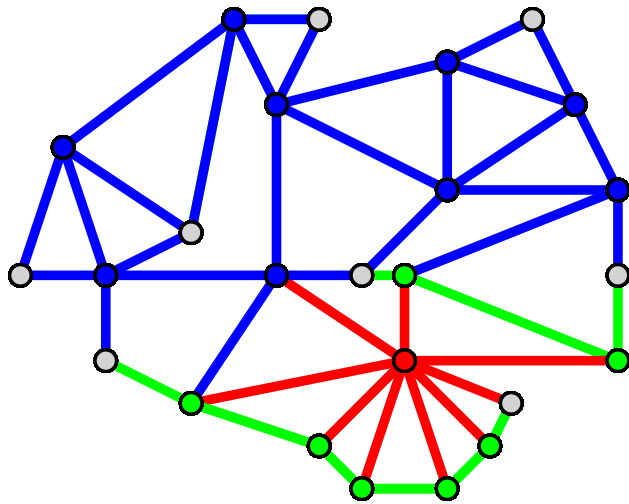
block its edges

double value of all other edges

until all edges are blocked



# (1) Find Fractional Matching



4-approximation

start with  $x_e = 2^{-\lceil \log \Delta \rceil}$

repeat

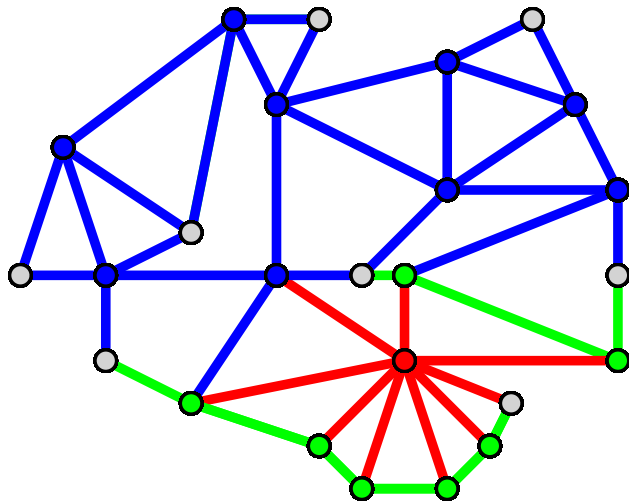
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# (1) Find Fractional Matching



4-approximation



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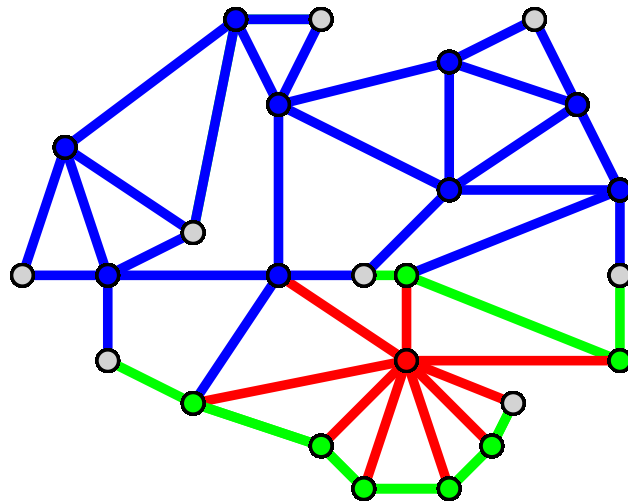
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start with  $x_e = 2^{-\lceil \log \Delta \rceil}$

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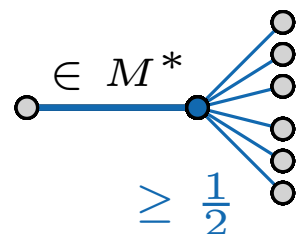
mark  $\frac{1}{2}$ -tight nodes

block its edges

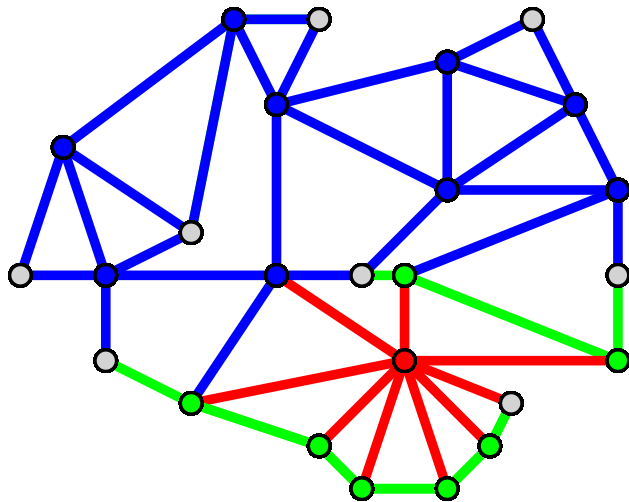
double value of all other edges

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4-approximation



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start with  $x_e = 2^{-\lceil \log \Delta \rceil}$

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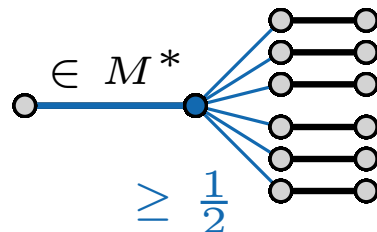
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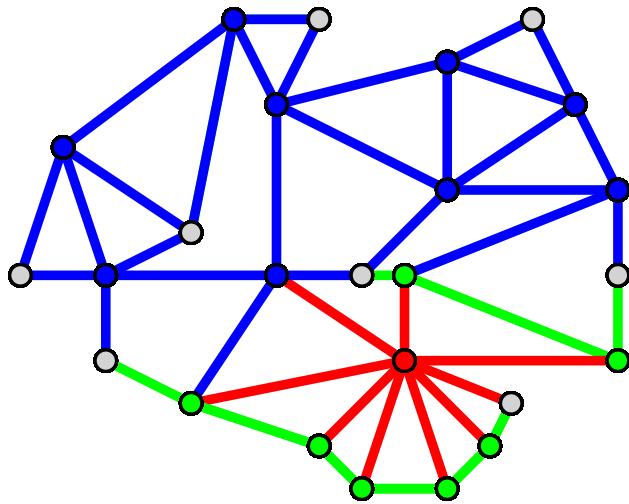
double value of all other edges

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4-approximation



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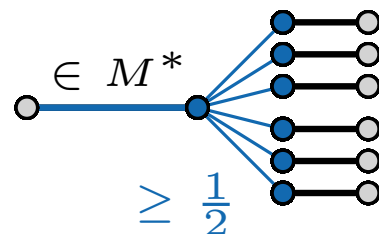
mark  $\frac{1}{2}$ -tight nodes

block its edges

double value of all other edges

until all edges are blocked

4-approximation



possible overcounting by 2-factor

# (1) Find Fractional Matching

4-approximation in  $O(\log \Delta)$  rounds

start with  $x_e = 2^{-\lceil \log \Delta \rceil}$

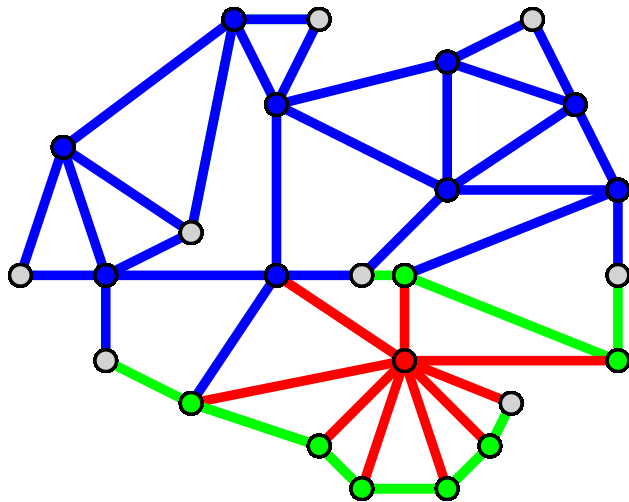
repeat

mark  $\frac{1}{2}$ -tight nodes

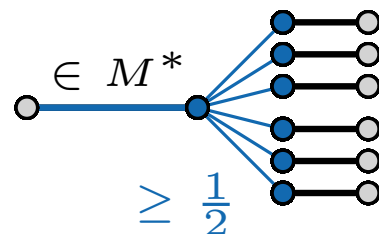
block its edges

double value of all other edges

until all edges are blocked



4-approximation



possible overcounting by 2-factor

## (2) Iterative Rounding

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for  $\lceil \log \Delta \rceil \geq i \geq 5$



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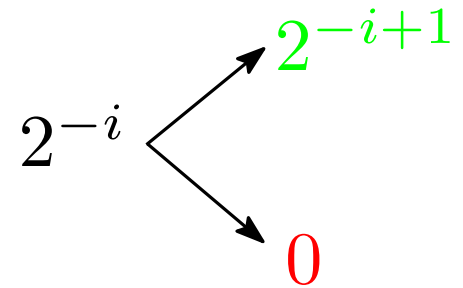
for  $\lceil \log \Delta \rceil \geq i \geq 5$

round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$

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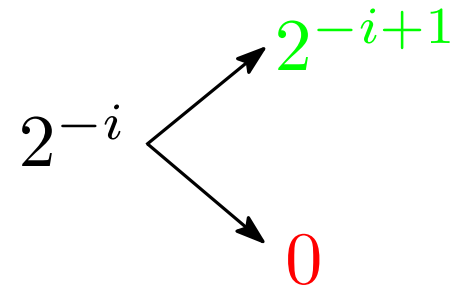
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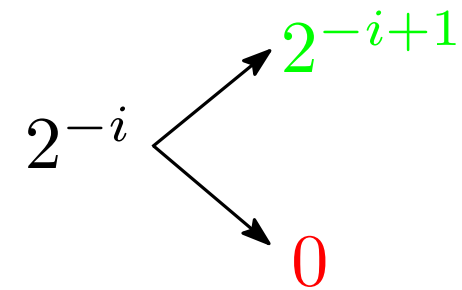


graph induced by  $x_e = 2^{-i}$

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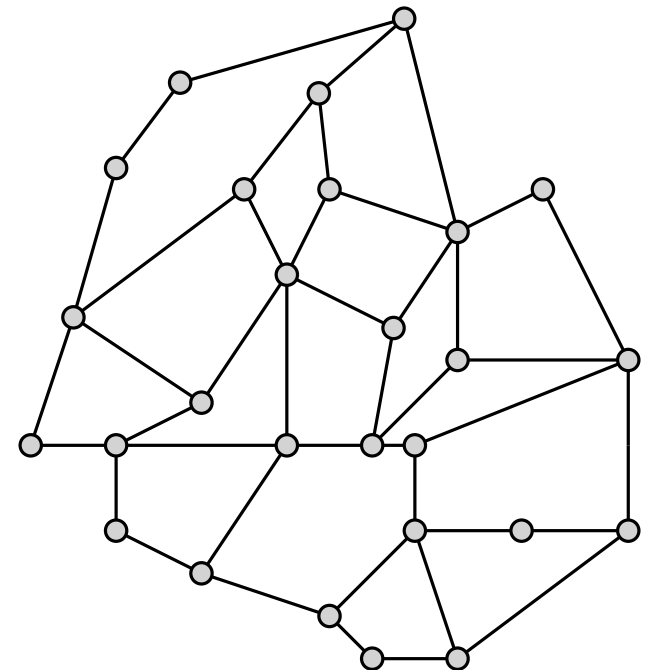
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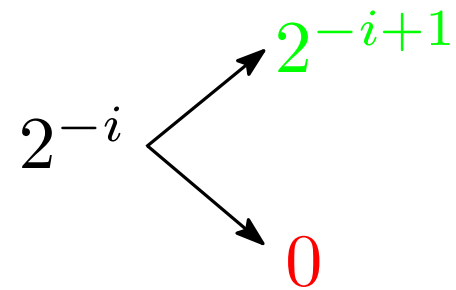
decompose into paths/cycles



## (2) Iterative Rounding

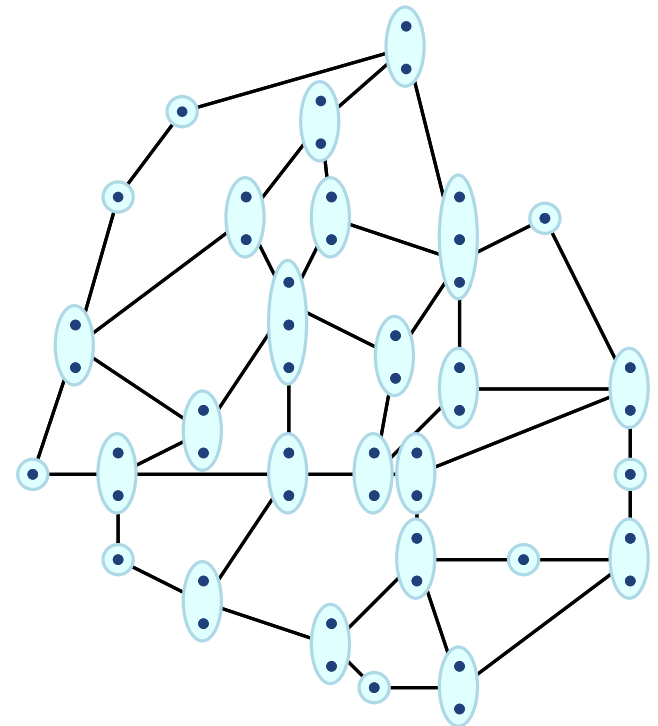
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round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



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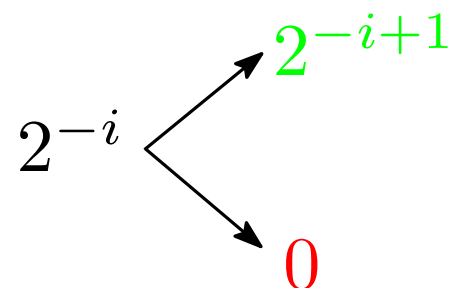
decompose into paths/cycles



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for  $\lceil \log \Delta \rceil \geq i \geq 5$

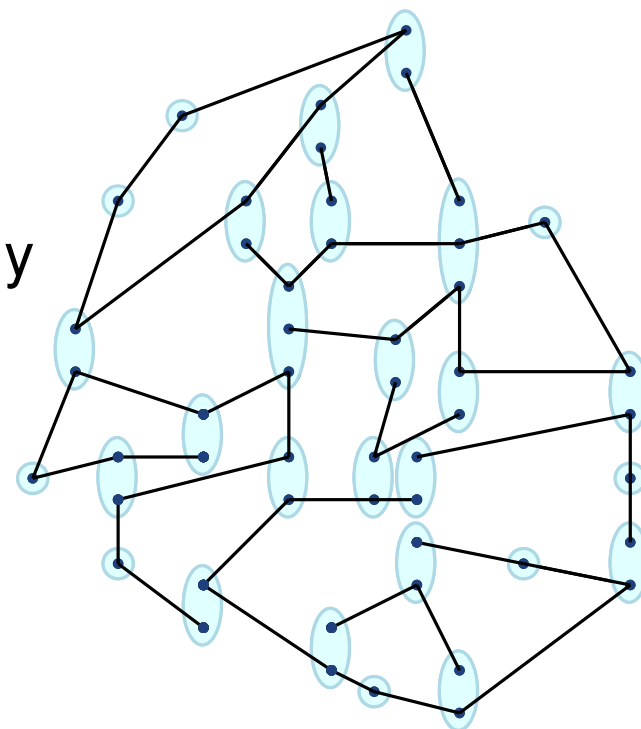
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



graph induced by  $x_e = 2^{-i}$

decompose into paths/cycles

deal with each path/cycle separately

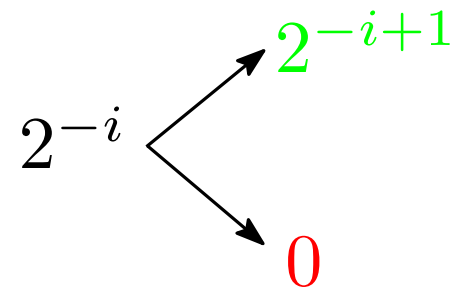


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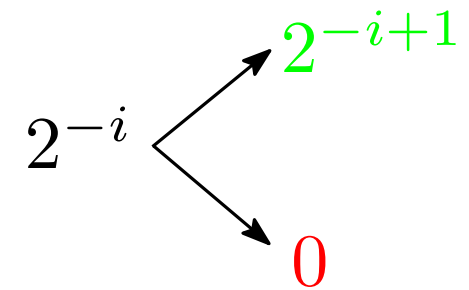
Short Cycles



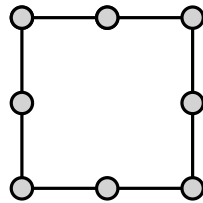
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Short Cycles

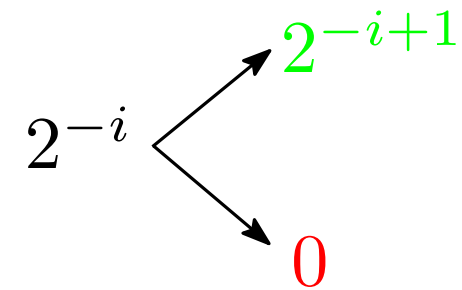




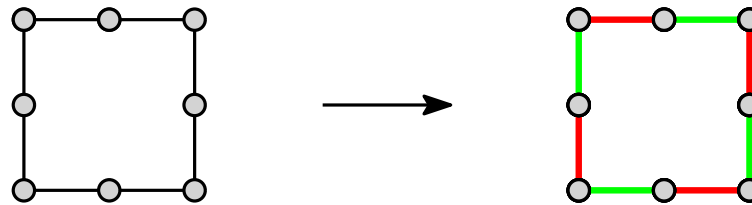
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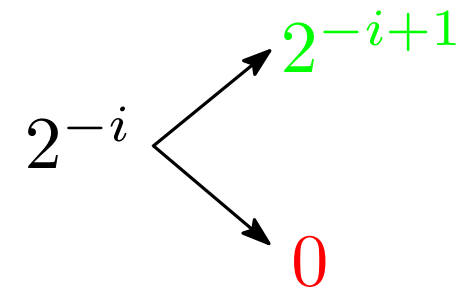
Short Cycles



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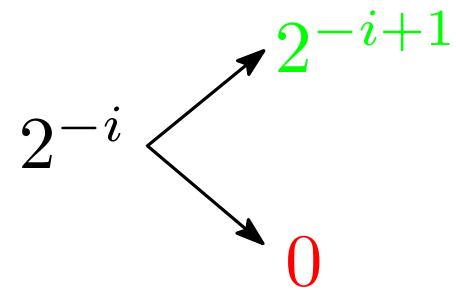
Short Cycles



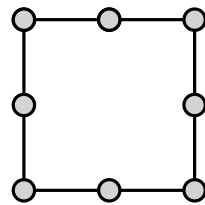
## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

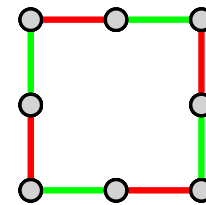
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Cycles



0 loss

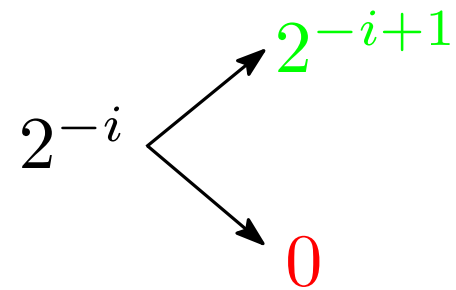


bipartite only!

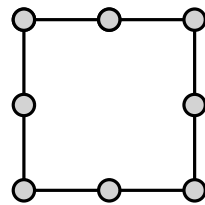
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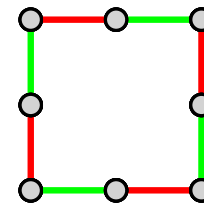
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Short Cycles



0 loss

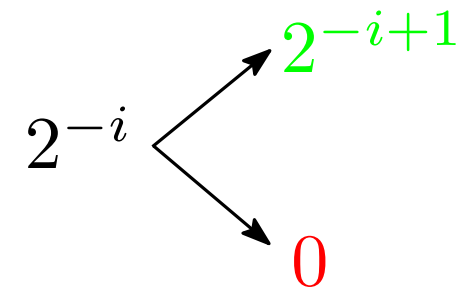


**bipartite only!**  
otherwise can lose  $O(1)$

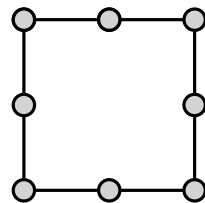
## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

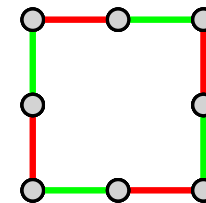
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Cycles



0 loss



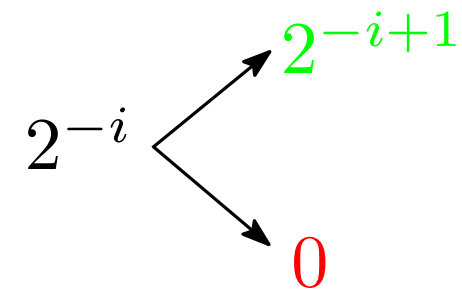
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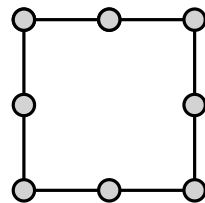
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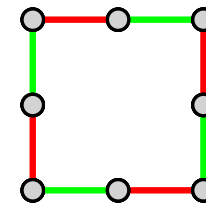
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Short Cycles



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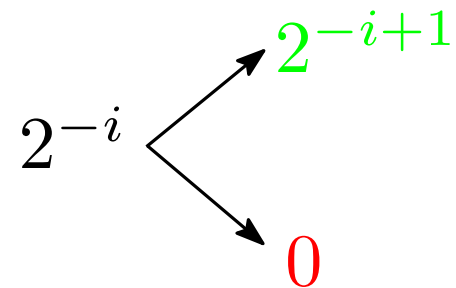
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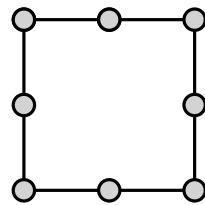
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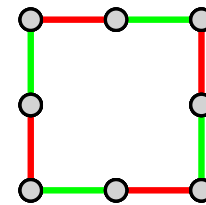
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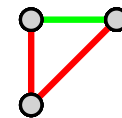
Short Cycles



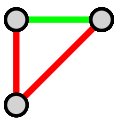
0 loss



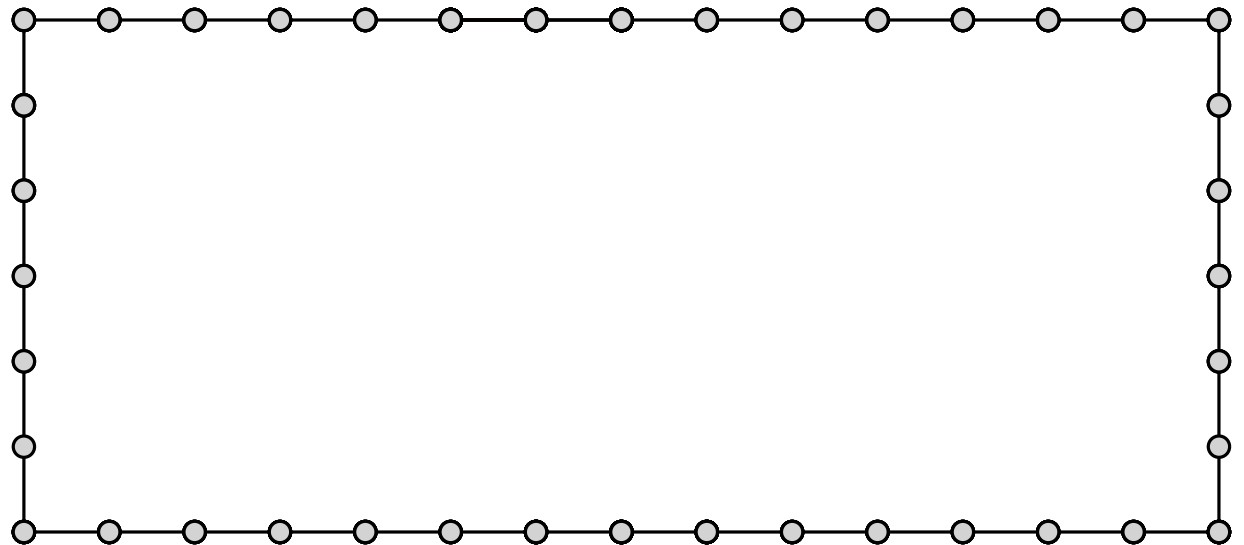
**bipartite only!**  
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...



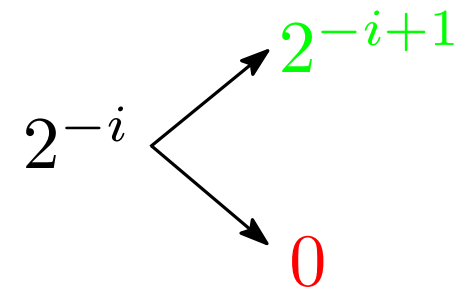
Long Cycles  
& Long Paths



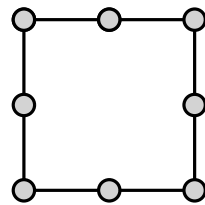
## (2) Iterative Rounding

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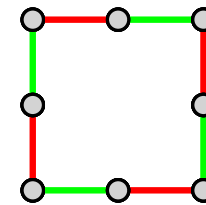
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Short Cycles



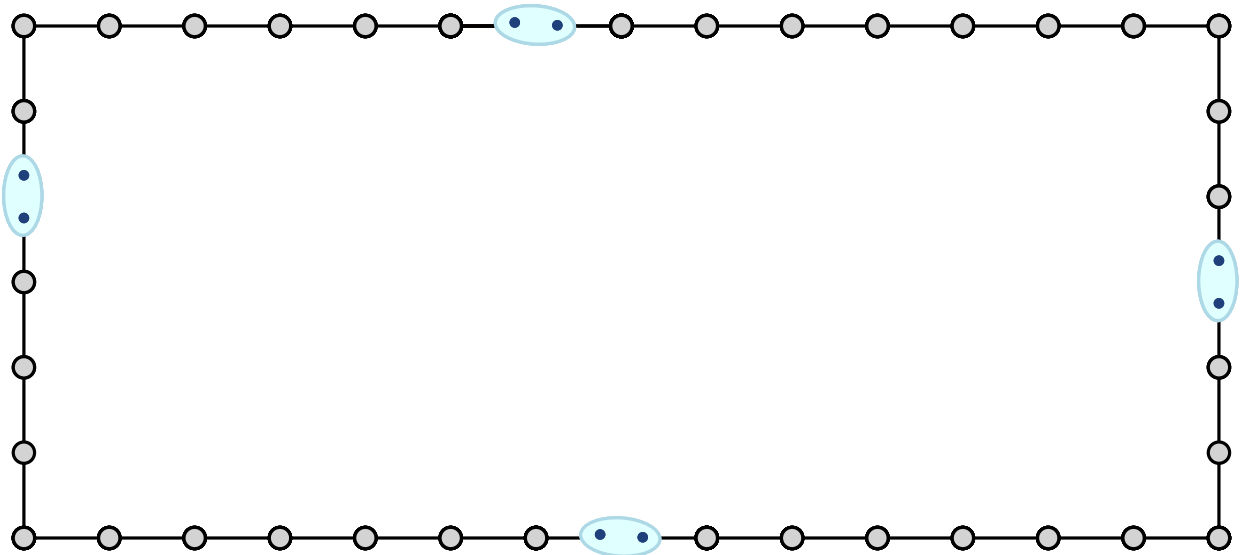
0 loss



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Long Cycles  
& Long Paths

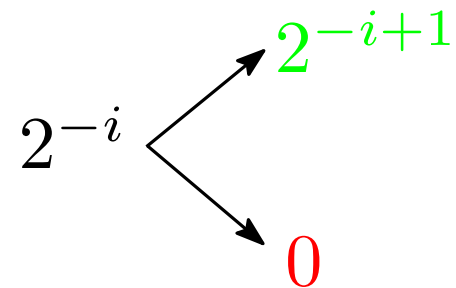




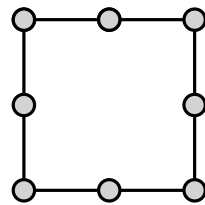
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for  $\lceil \log \Delta \rceil \geq i \geq 5$

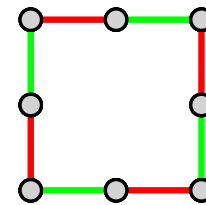
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Short Cycles



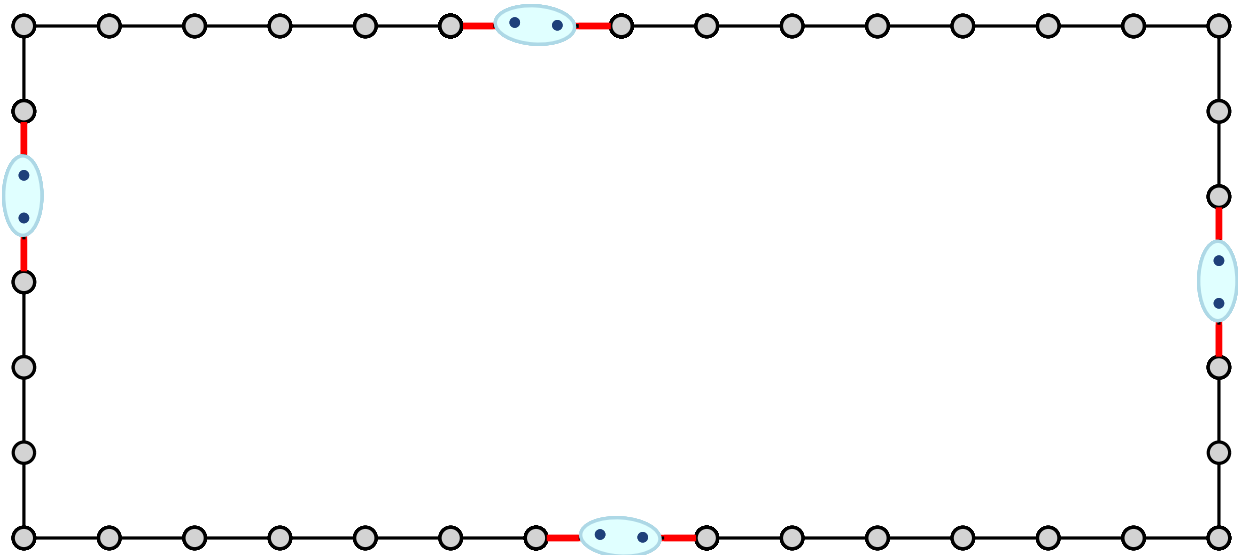
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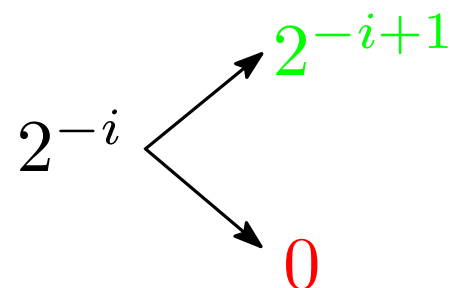
Long Cycles  
& Long Paths



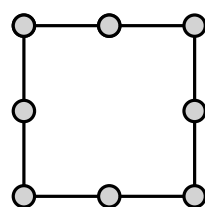
## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

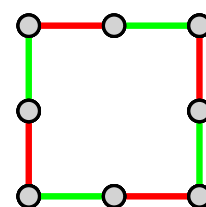
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



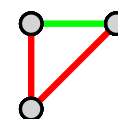
Short Cycles



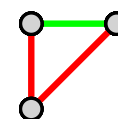
0 loss



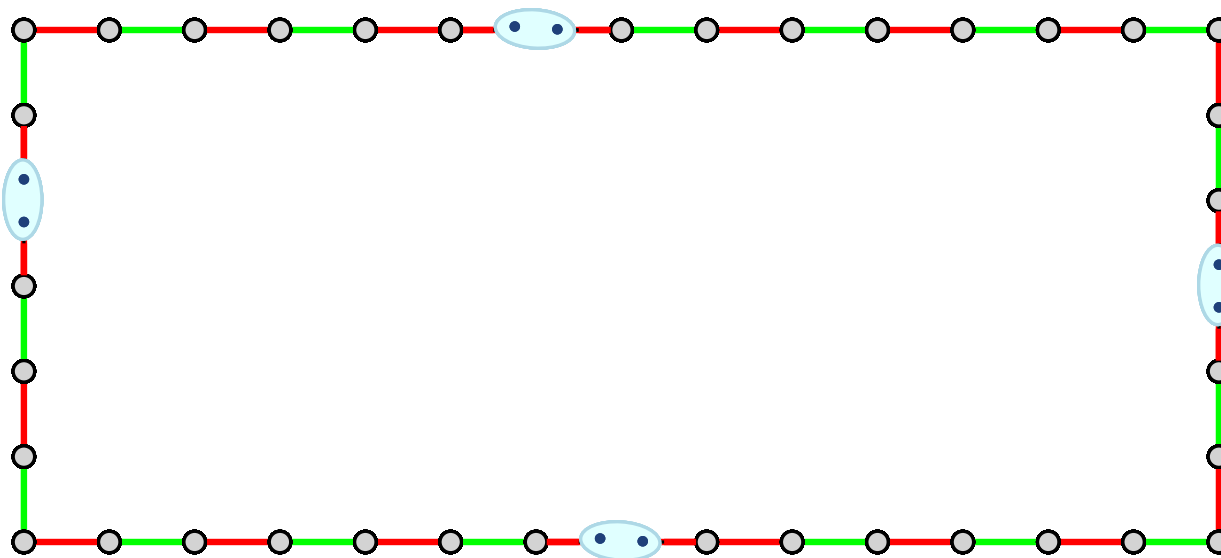
**bipartite only!**  
otherwise can lose  $O(1)$



...



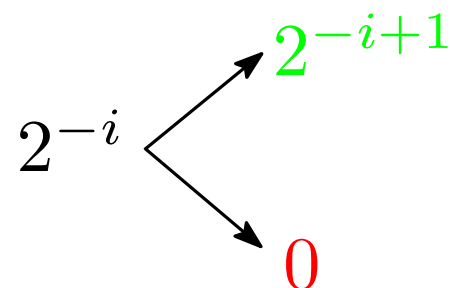
Long Cycles  
& Long Paths



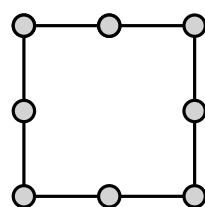
## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

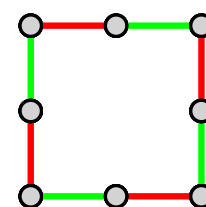
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Cycles



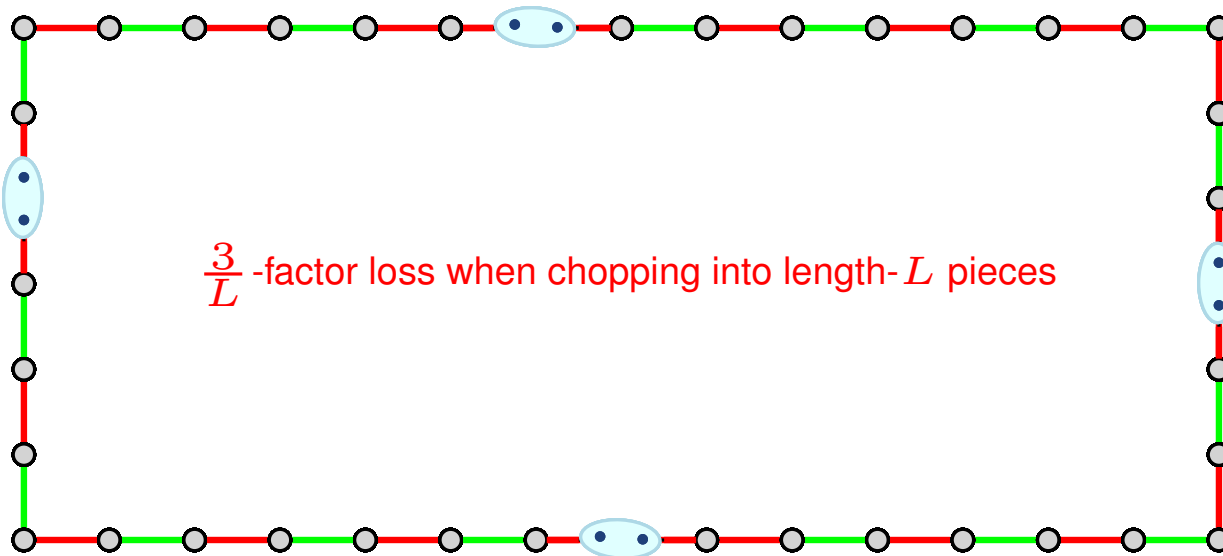
0 loss



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otherwise can lose  $O(1)$



Long Cycles  
& Long Paths

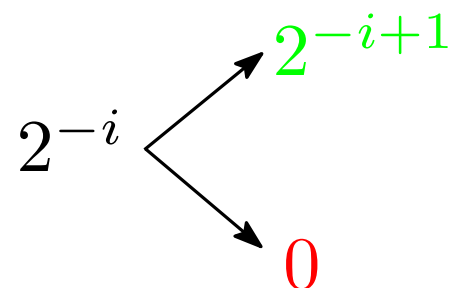


$\frac{3}{L}$ -factor loss when chopping into length- $L$  pieces

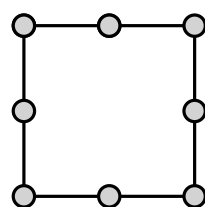
## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

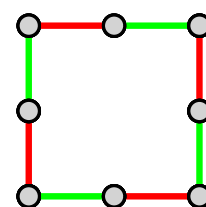
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



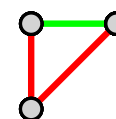
### Short Cycles



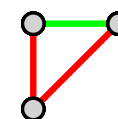
0 loss



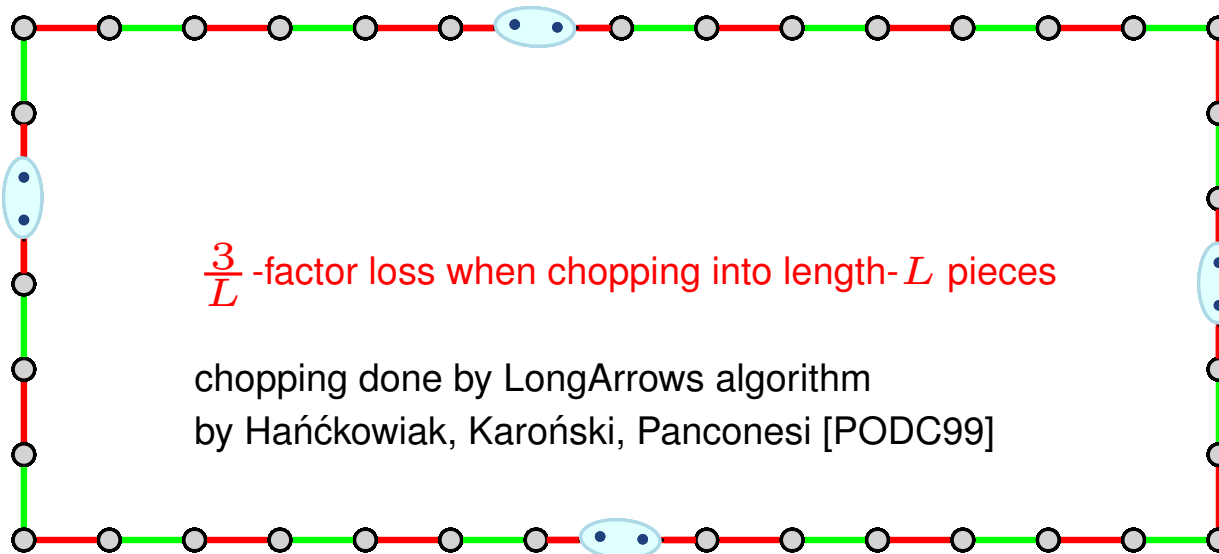
**bipartite only!**  
otherwise can lose  $O(1)$



...



### Long Cycles & Long Paths



$\frac{3}{L}$ -factor loss when chopping into length- $L$  pieces

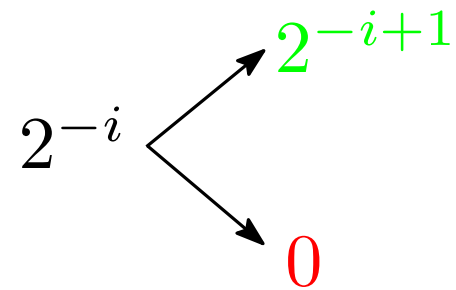
chopping done by LongArrows algorithm  
by Hańćkowiak, Karoński, Panconesi [PODC99]

## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$

Short Paths

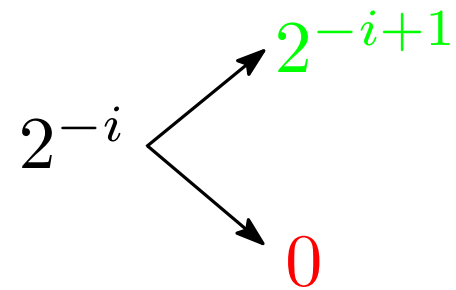
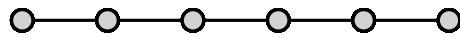


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for  $\lceil \log \Delta \rceil \geq i \geq 5$

round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$

Short Paths

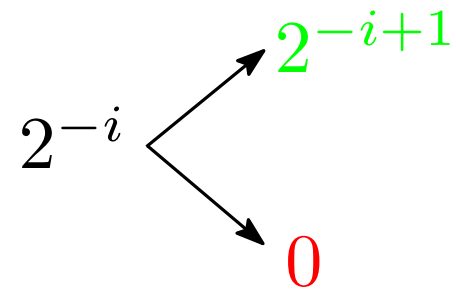
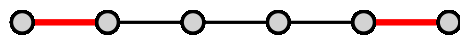


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for  $\lceil \log \Delta \rceil \geq i \geq 5$

round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$

Short Paths

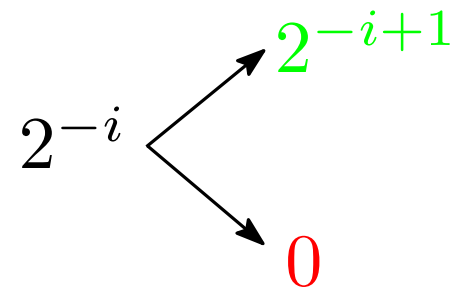


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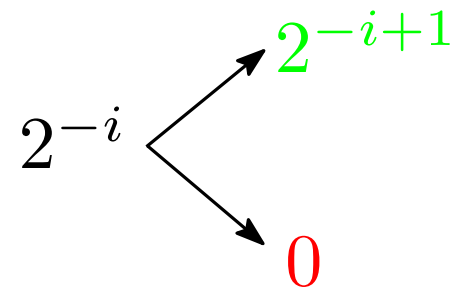


## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$

Short Paths



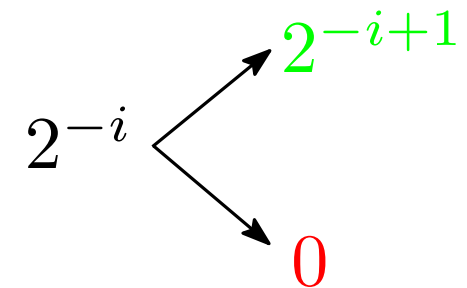
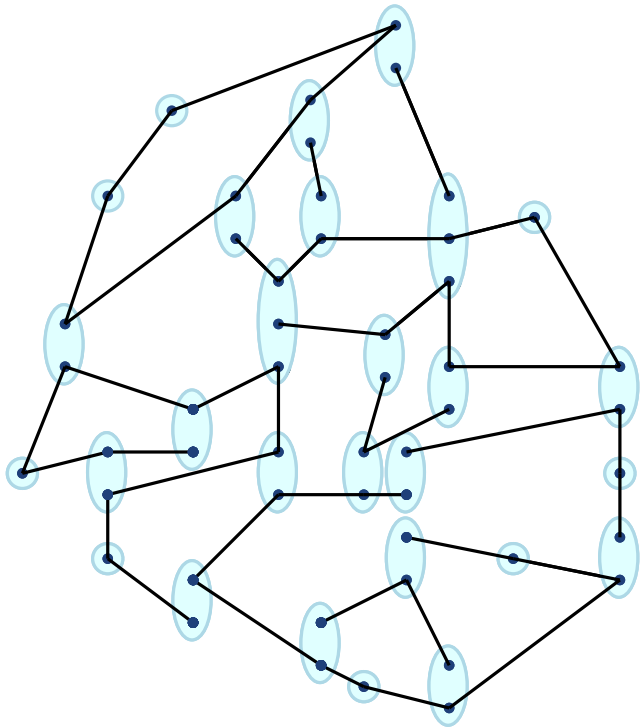
lose constant factor!

## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$

Short Paths

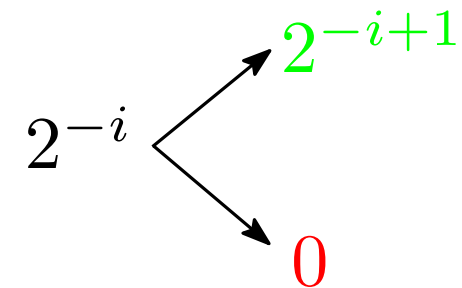


lose constant factor!

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for  $\lceil \log \Delta \rceil \geq i \geq 5$

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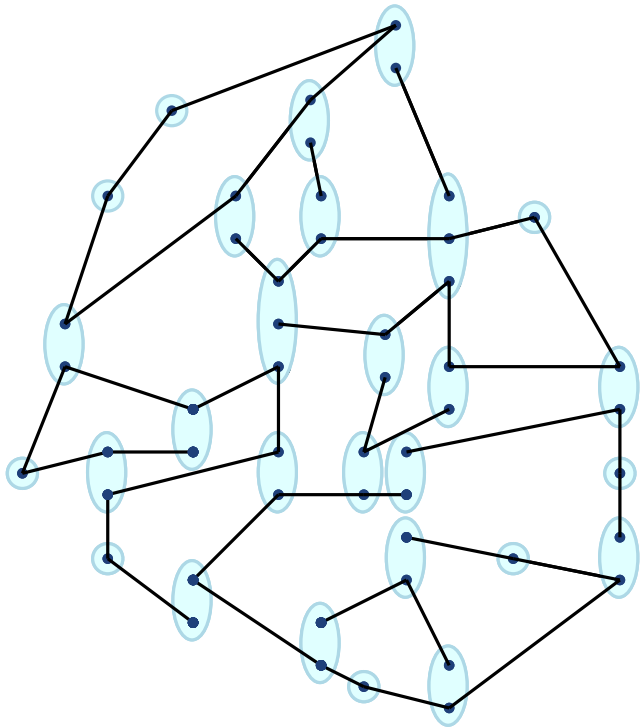
Short Paths



lose constant factor!



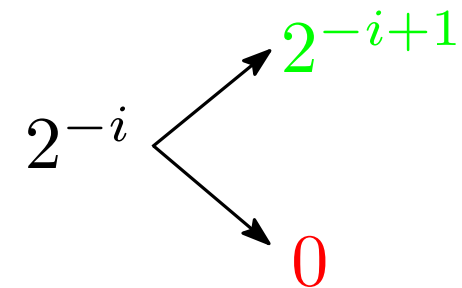
for  $\frac{1}{2}$ -loose nodes  
& even-length paths



## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

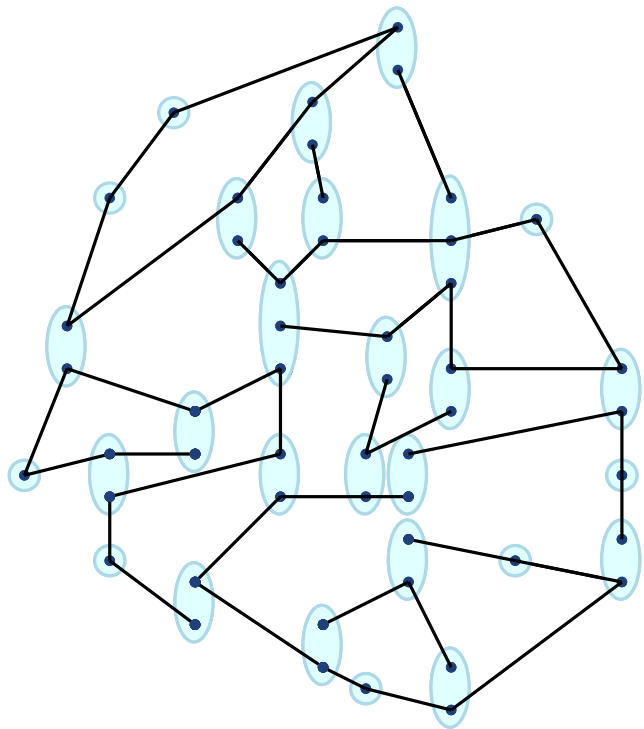
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Paths



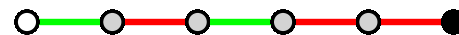
lose constant factor!



for  $\frac{1}{2}$ -loose nodes  
& even-length paths



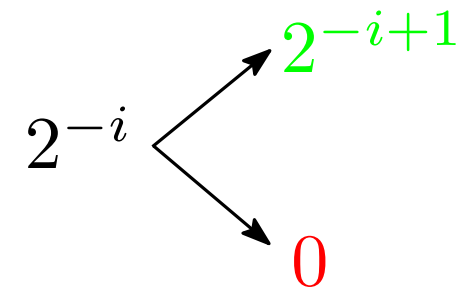
for  $\frac{1}{2}$ -loose nodes  
& odd-length paths



## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

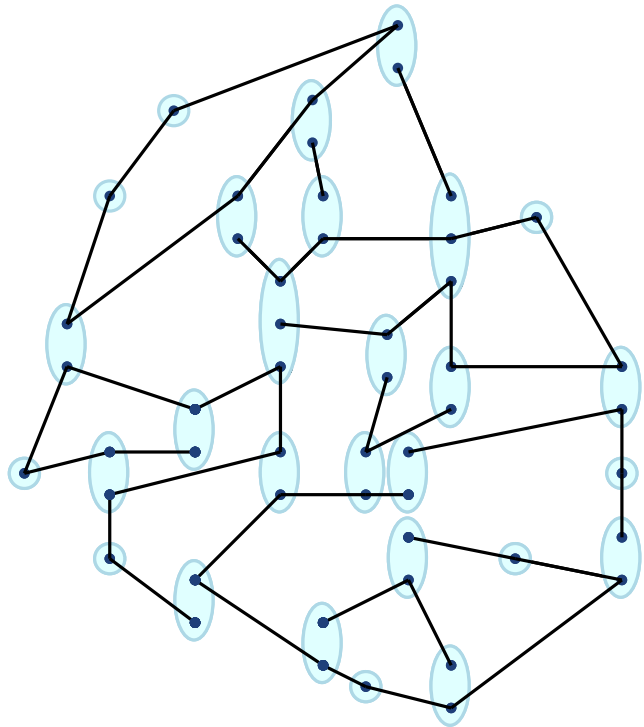
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Paths



lose constant factor!



for  $\frac{1}{2}$ -loose nodes  
& even-length paths



for  $\frac{1}{2}$ -loose nodes  
& odd-length paths



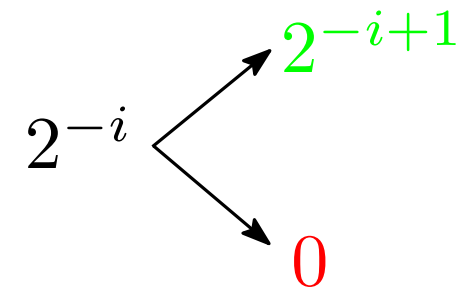
for  $\frac{1}{2}$ -loose nodes  
& even-length paths



## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

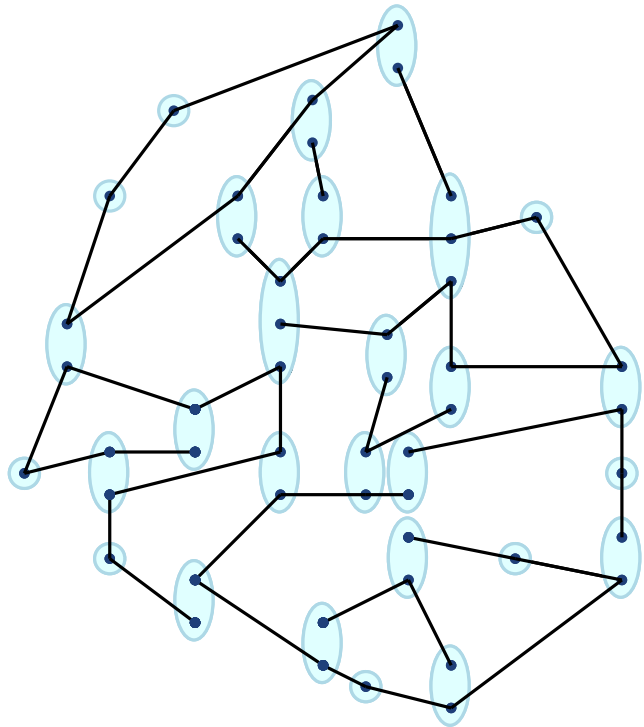
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Short Paths



lose constant factor!



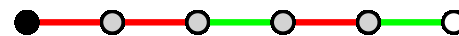
for  $\frac{1}{2}$ -loose nodes  
& even-length paths



for  $\frac{1}{2}$ -loose nodes  
& odd-length paths



for  $\frac{1}{2}$ -loose nodes  
& even-length paths



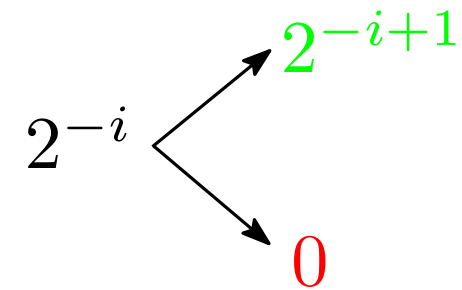
for  $\frac{1}{2}$ -tight nodes  
& odd-length paths



## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

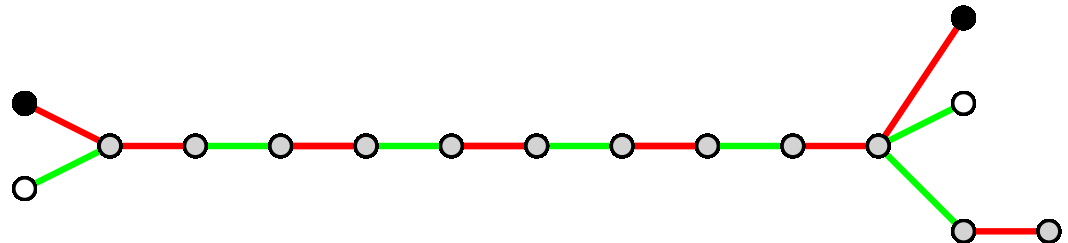
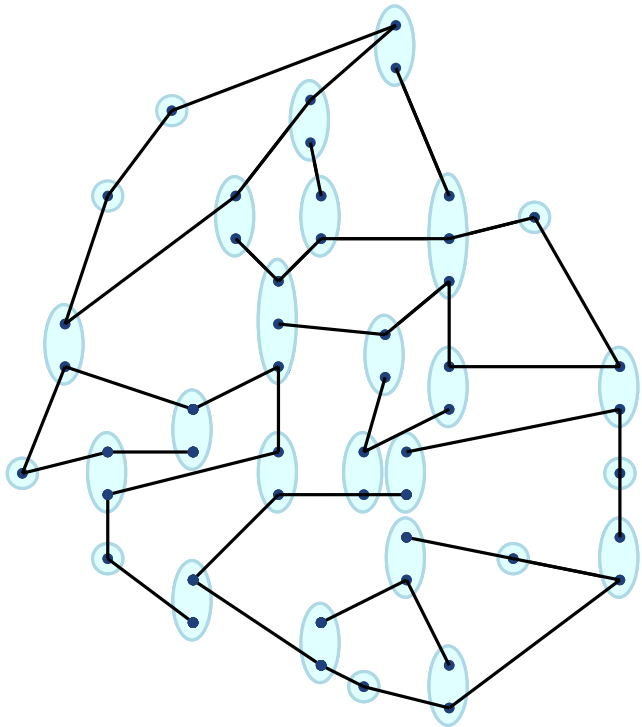
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



# Short Paths



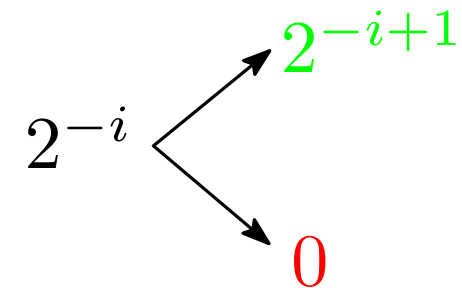
lose constant factor!



## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

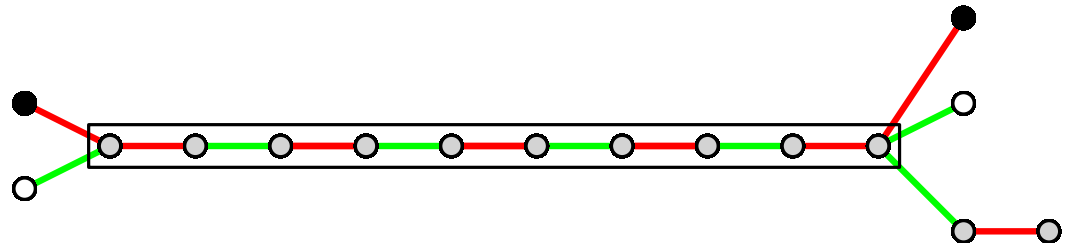
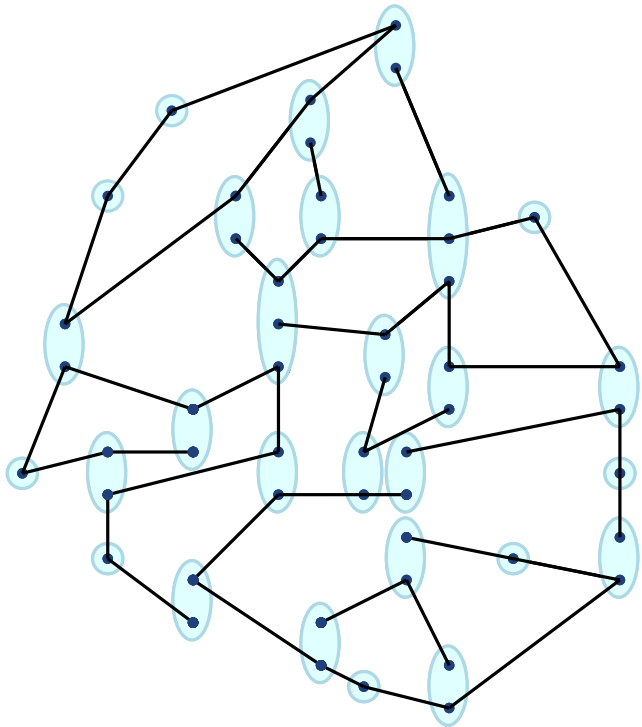
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Paths



lose constant factor!

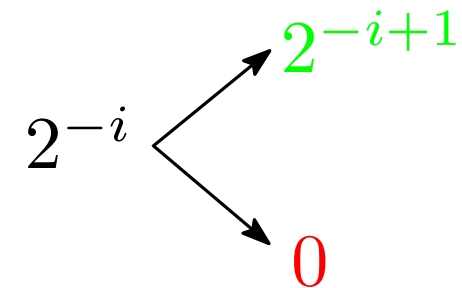




## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

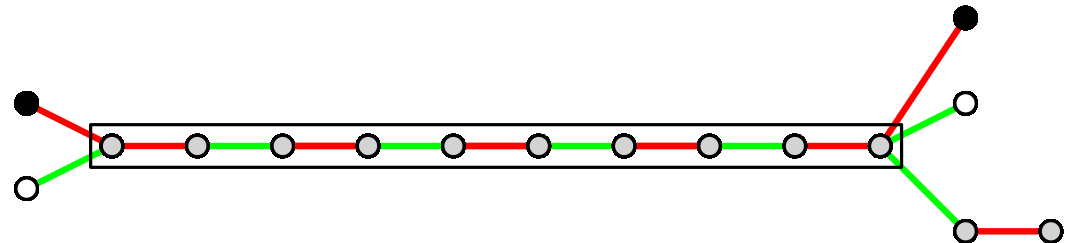
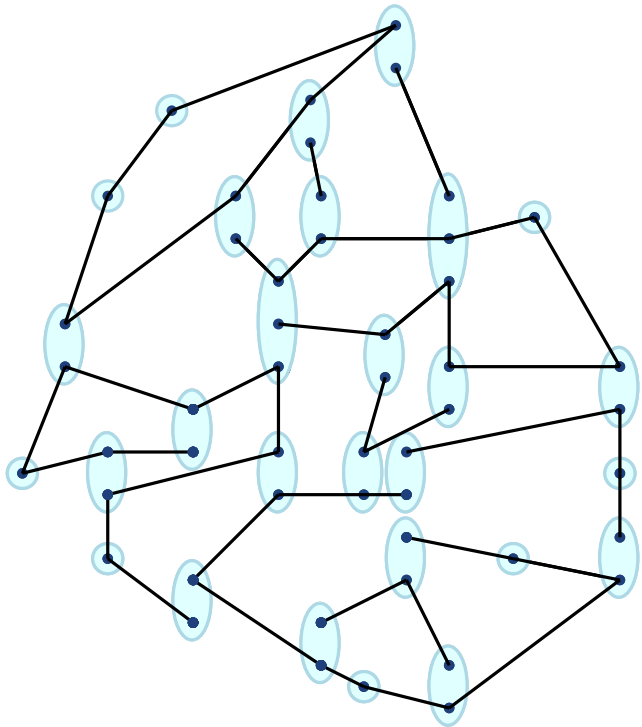
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Paths



lose constant factor!

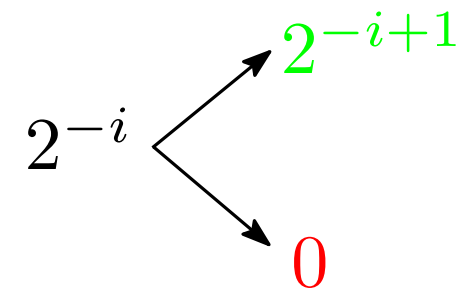


lose at most  $2^{-i+1}$  per  $\frac{1}{2}$ -tight vertex

## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

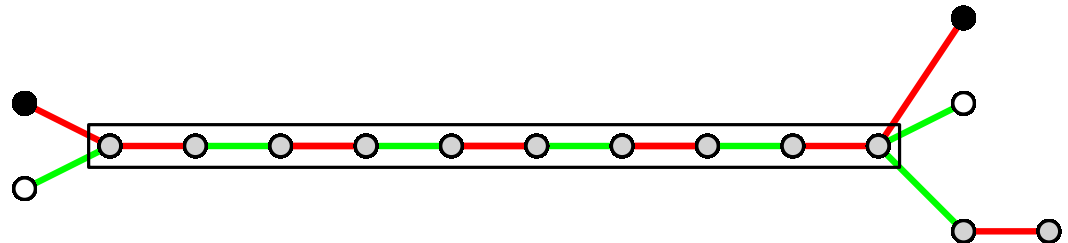
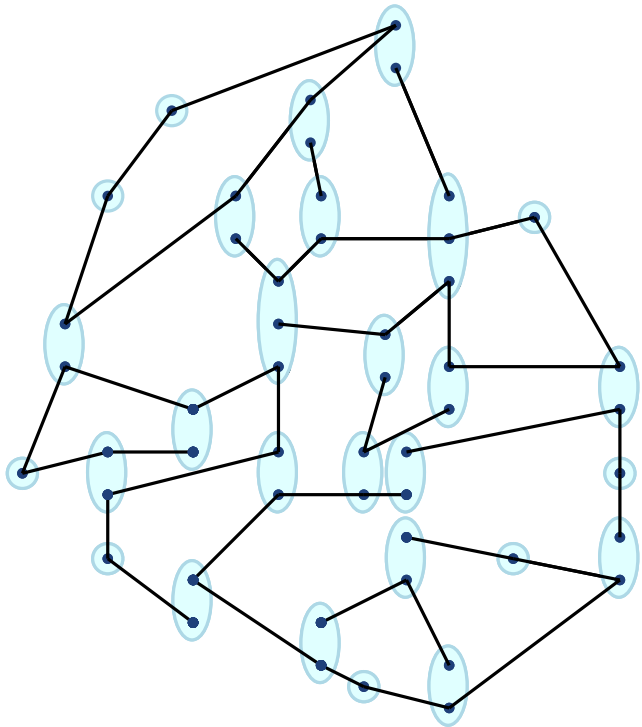
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Short Paths



lose constant factor!



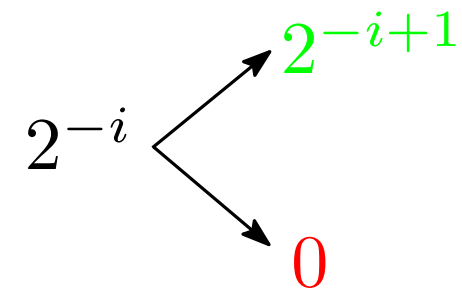
lose at most  $2^{-i+1}$  per  $\frac{1}{2}$ -tight vertex

thus at most  $2^{-i+2}$ -factor of its value

## (2) Iterative Rounding

for  $\lceil \log \Delta \rceil \geq i \geq 5$

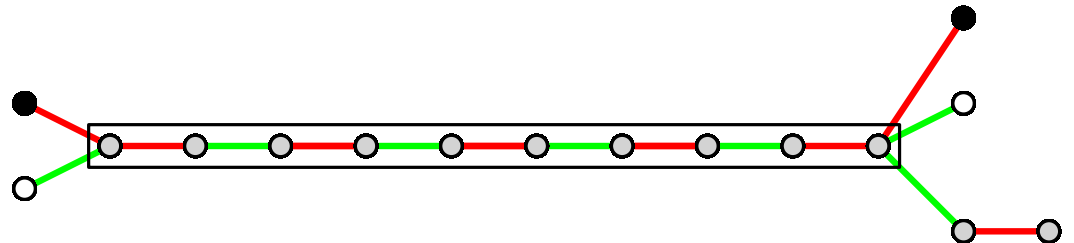
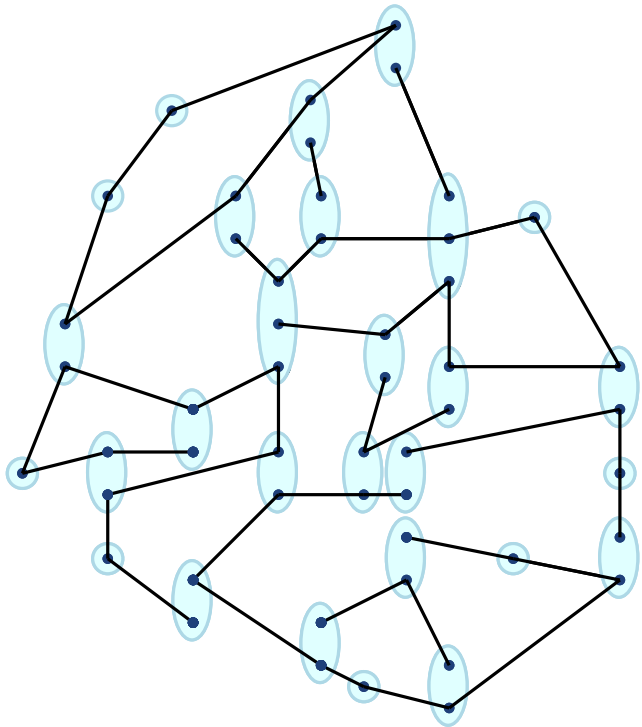
round values  $x_e = 2^{-i}$  to 0 or to  $2^{-i+1}$



Short Paths



lose constant factor!



lose at most  $2^{-i+1}$  per  $\frac{1}{2}$ -tight vertex

thus at most  $2^{-i+2}$ -factor of its value

overall, lose at most  $2^{-i+3}$ -factor

## (2) Iterative Rounding

Short Cycles

no loss at all

Long Cycles  
& Long Paths

$\frac{3}{L}$ -factor loss when chopping into length- $L$  pieces

Short Paths

$2^{-i+3}$ -factor loss

## (2) Iterative Rounding

Short Cycles

no loss at all

Long Cycles  
& Long Paths

$\frac{3}{L}$ -factor loss when chopping into length- $L$  pieces

Short Paths

$2^{-i+3}$ -factor loss

reduce value to  $(1 - \frac{3}{L} - 2^{-i+3})$ -factor of previous value

## (2) Iterative Rounding

Short Cycles

no loss at all

Long Cycles  
& Long Paths

$\frac{3}{L}$ -factor loss when chopping into length- $L$  pieces

$$L = \lceil \log \Delta \rceil$$

Short Paths

$2^{-i+3}$ -factor loss

reduce value to  $(1 - \frac{3}{L} - 2^{-i+3})$ -factor of previous value

$$\sum_{e \in E} x'_e \geq \prod_{i=5}^{\lceil \log \Delta \rceil} (1 - \frac{3}{L} - 2^{-i+3}) \sum_{e \in E} x_e \geq \frac{1}{5} \sum_{e \in E} x_e$$

## (2) Iterative Rounding

5-approximation in  $O(\log^2 \Delta)$  rounds

Short Cycles

no loss at all

Long Cycles  
& Long Paths

$\frac{3}{L}$ -factor loss when chopping into length- $L$  pieces

$$L = \lceil \log \Delta \rceil$$

Short Paths

$2^{-i+3}$ -factor loss

reduce value to  $(1 - \frac{3}{L} - 2^{-i+3})$ -factor of previous value

$$\sum_{e \in E} x'_e \geq \prod_{i=5}^{\lceil \log \Delta \rceil} (1 - \frac{3}{L} - 2^{-i+3}) \sum_{e \in E} x_e \geq \frac{1}{5} \sum_{e \in E} x_e$$

# (3) Final Rounding

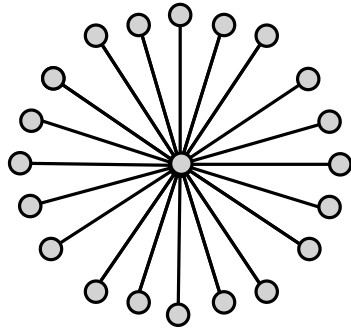


### (3) Final Rounding

values in  $\{2^{-i} \mid 4 \geq i \geq 1\} \cup \{0\}$

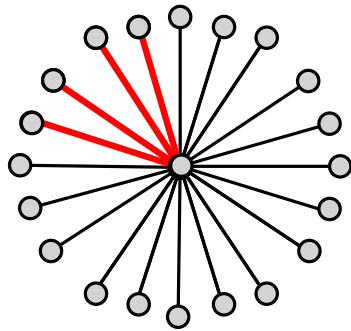
### (3) Final Rounding

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### (3) Final Rounding

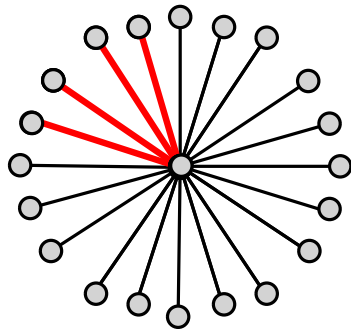
values in  $\{2^{-i} \mid 4 \geq i \geq 1\} \cup \{0\}$



maximum degree in induced graph  $\leq 16$

### (3) Final Rounding

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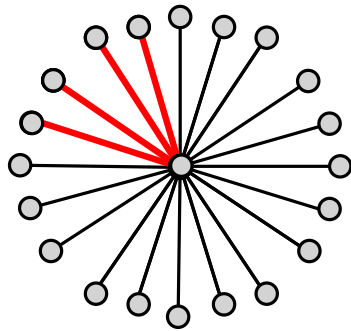


maximum degree in induced graph  $\leq 16$

find maximal matching in  $O(1)$  by Proposing Algorithm

### (3) Final Rounding

values in  $\{2^{-i} \mid 4 \geq i \geq 1\} \cup \{0\}$



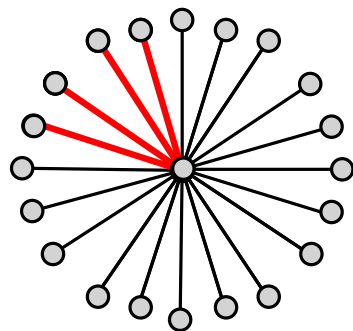
maximum degree in induced graph  $\leq 16$

find maximal matching in  $O(1)$  by Proposing Algorithm

matches constant fraction of the remaining edges

### (3) Final Rounding

values in  $\{2^{-i} \mid 4 \geq i \geq 1\} \cup \{0\}$



maximum degree in induced graph  $\leq 16$

find maximal matching in  $O(1)$  by Proposing Algorithm

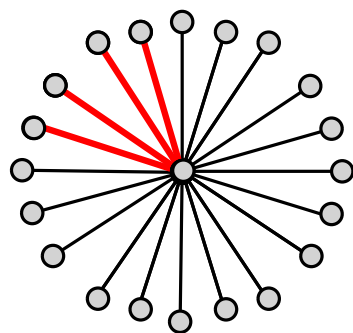
matches constant fraction of the remaining edges

(any maximal matching has size  $\geq \frac{1}{2\Delta-1} |E|$ )

### (3) Final Rounding

$O(1)$ -approximation in  $O(1)$  rounds

values in  $\{2^{-i} \mid 4 \geq i \geq 1\} \cup \{0\}$



maximum degree in induced graph  $\leq 16$

find maximal matching in  $O(1)$  by Proposing Algorithm

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# Our Matching Approximation Algorithm: Recap



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(1) Fractional matching

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## (1) Fractional matching

values in  $\{2^{-i} \mid \lceil \log \Delta \rceil \geq i \geq 1\}$

4-approximation

$O(\log \Delta)$  rounds

# Our Matching Approximation Algorithm: Recap

## (1) Fractional matching

values in  $\{2^{-i} \mid \lceil \log \Delta \rceil \geq i \geq 1\}$

4-approximation

$O(\log \Delta)$  rounds

## (2) Iterative rounding

# Our Matching Approximation Algorithm: Recap

## (1) Fractional matching

values in  $\{2^{-i} \mid \lceil \log \Delta \rceil \geq i \geq 1\}$

4-approximation

$O(\log \Delta)$  rounds

## (2) Iterative rounding

values in  $\left\{ \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, \frac{1}{2}, 1, 0 \right\}$

5-approximation of fractional matching of (1)

$O(\log \Delta)$  iterations  $O(\log \Delta)$  rounds:  $O(\log^2 \Delta)$  rounds

# Our Matching Approximation Algorithm: Recap

## (1) Fractional matching

values in  $\{2^{-i} \mid \lceil \log \Delta \rceil \geq i \geq 1\}$

4-approximation

$O(\log \Delta)$  rounds

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values in  $\left\{ \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, \frac{1}{2}, 1, 0 \right\}$

5-approximation of fractional matching of (1)

$O(\log \Delta)$  iterations  $O(\log \Delta)$  rounds:  $O(\log^2 \Delta)$  rounds

## (3) Final Rounding

# Our Matching Approximation Algorithm: Recap

## (1) Fractional matching

values in  $\{2^{-i} \mid \lceil \log \Delta \rceil \geq i \geq 1\}$

4-approximation

$O(\log \Delta)$  rounds

## (2) Iterative rounding

values in  $\left\{ \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, \frac{1}{2}, 1, 0 \right\}$

5-approximation of fractional matching of (1)

$O(\log \Delta)$  iterations  $O(\log \Delta)$  rounds:  $O(\log^2 \Delta)$  rounds

## (3) Final Rounding

values in  $\{1, 0\}$ : integral matching

$O(1)$ -approximation of fractional matching of (2)

$O(1)$  rounds

# Our Matching Approximation Algorithm:

## Recap

$O(1)$ -approximation in  $O(\log^2 \Delta)$  rounds

### (1) Fractional matching

values in  $\{2^{-i} \mid \lceil \log \Delta \rceil \geq i \geq 1\}$

4-approximation

$O(\log \Delta)$  rounds

### (2) Iterative rounding

values in  $\left\{ \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, \frac{1}{2}, 1, 0 \right\}$

5-approximation of fractional matching of (1)

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### (3) Final Rounding

values in  $\{1, 0\}$ : integral matching

$O(1)$ -approximation of fractional matching of (2)

$O(1)$  rounds

# Our Matching Approximation Algorithm:

## Recap

$O(1)$ -approximation in  $O(\log^2 \Delta)$  rounds  
in bipartite graphs

### (1) Fractional matching

values in  $\{2^{-i} \mid \lceil \log \Delta \rceil \geq i \geq 1\}$

4-approximation

$O(\log \Delta)$  rounds

### (2) Iterative rounding

values in  $\left\{ \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, \frac{1}{2}, 1, 0 \right\}$

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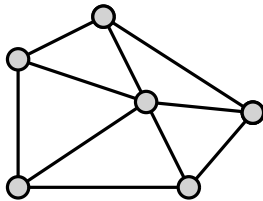
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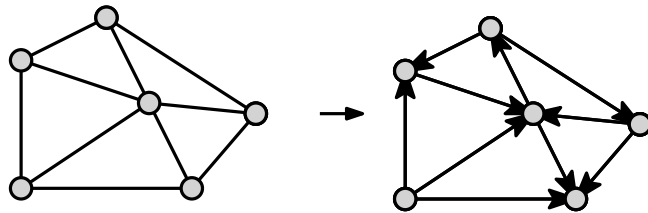
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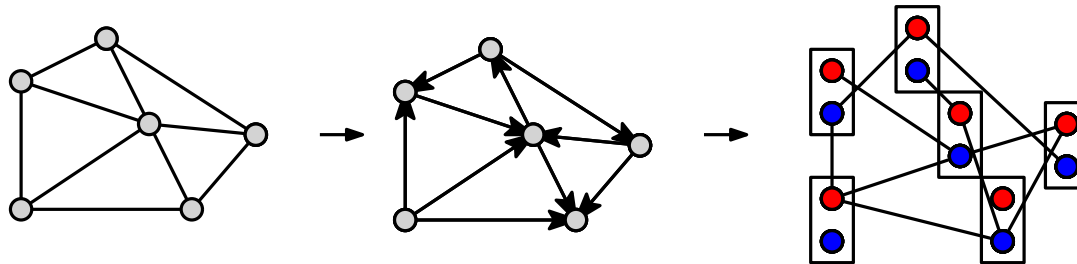
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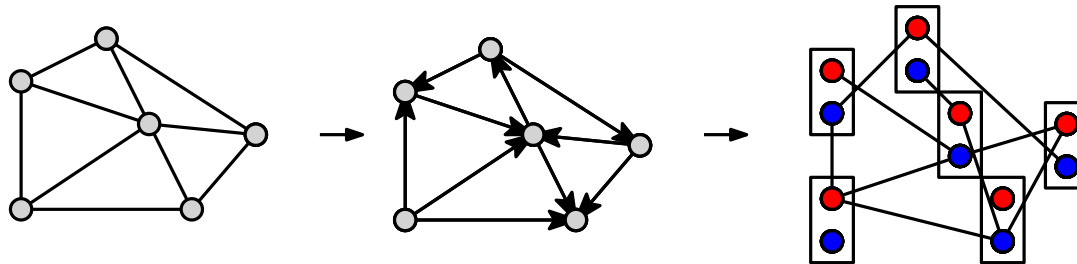
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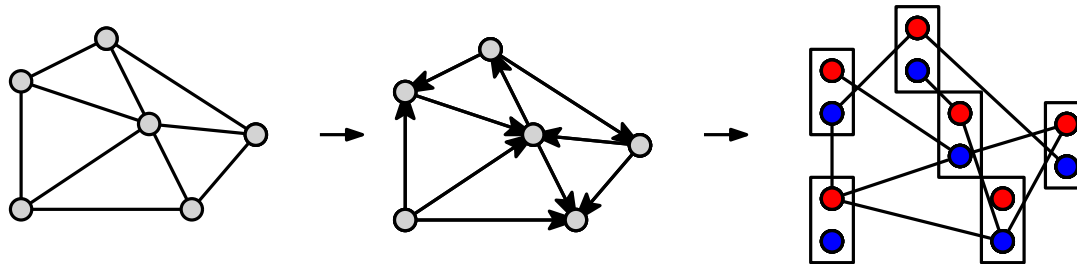
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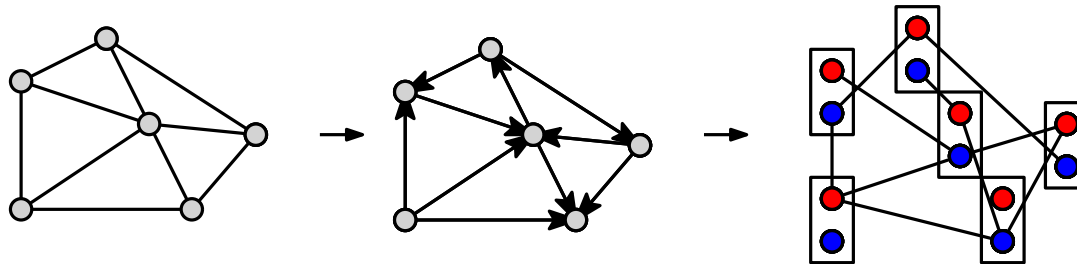


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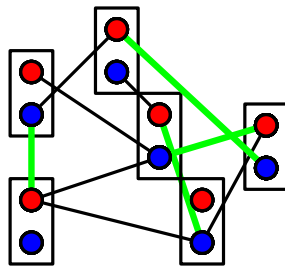
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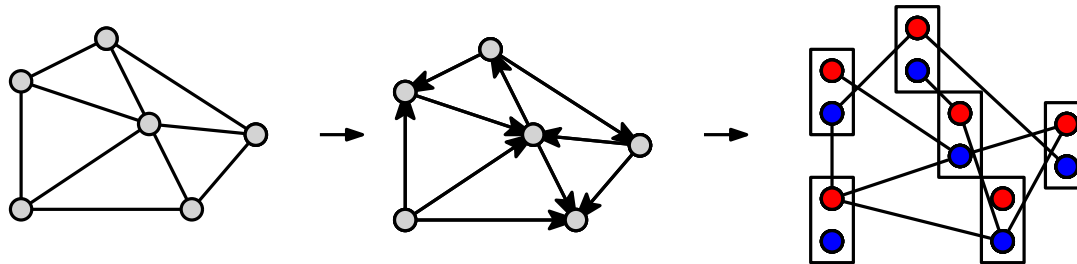
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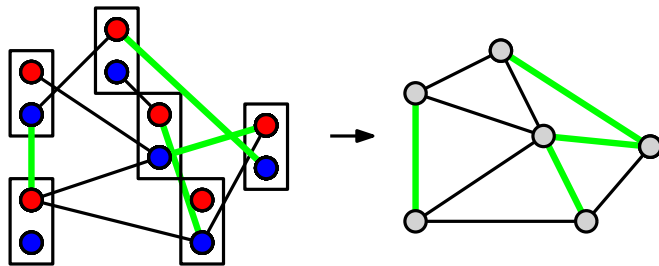
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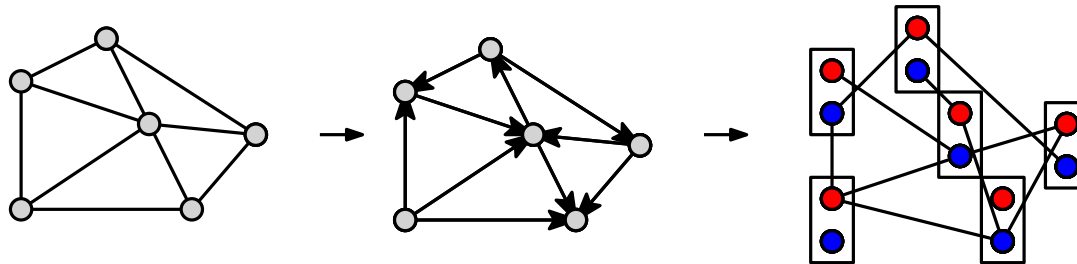
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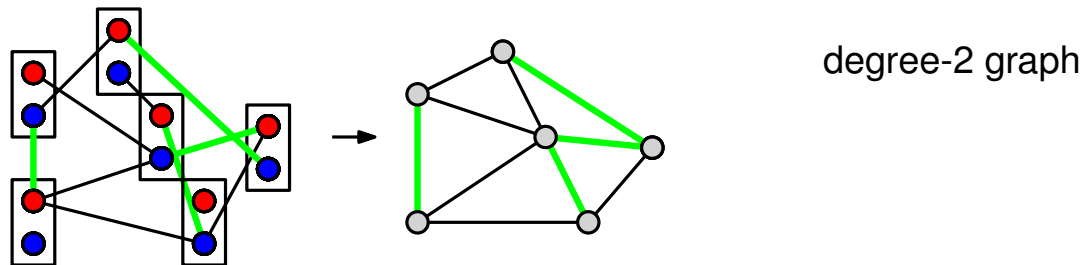
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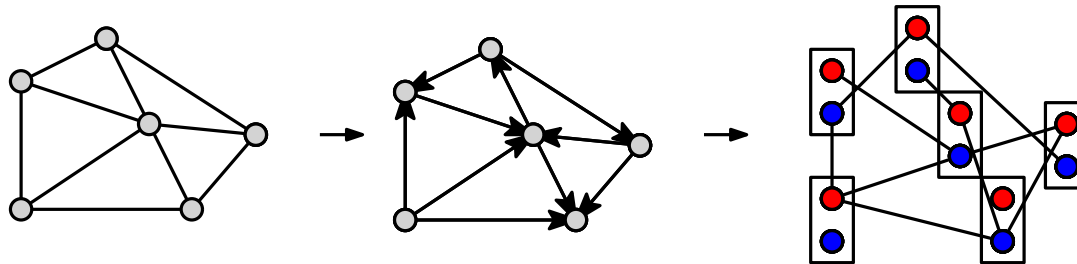
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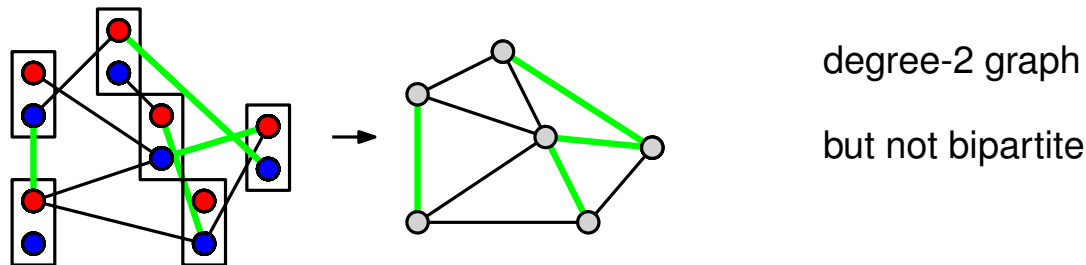
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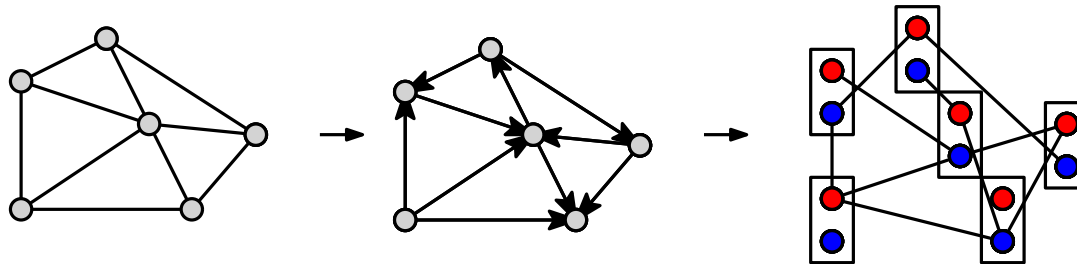
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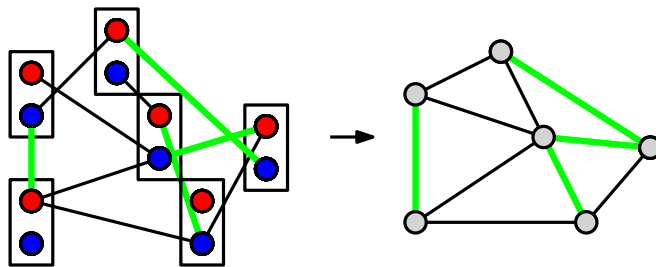
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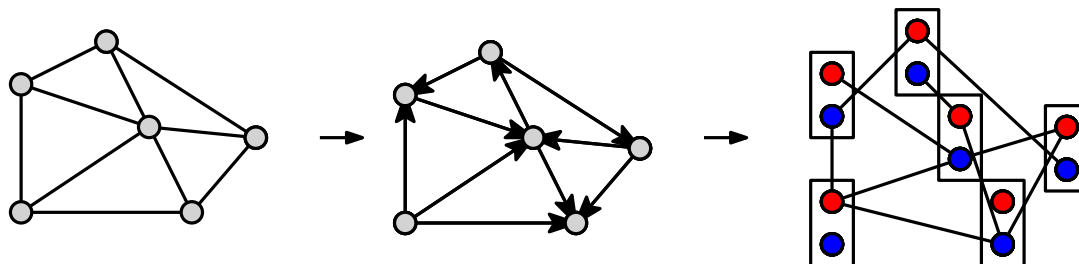
degree-2 graph

but not bipartite

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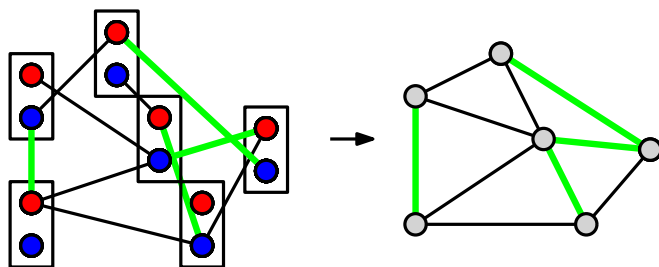
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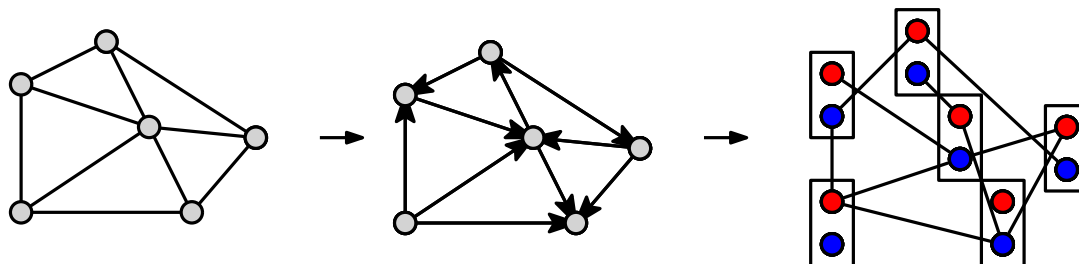
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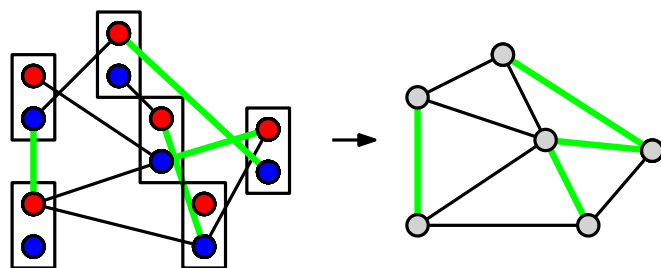
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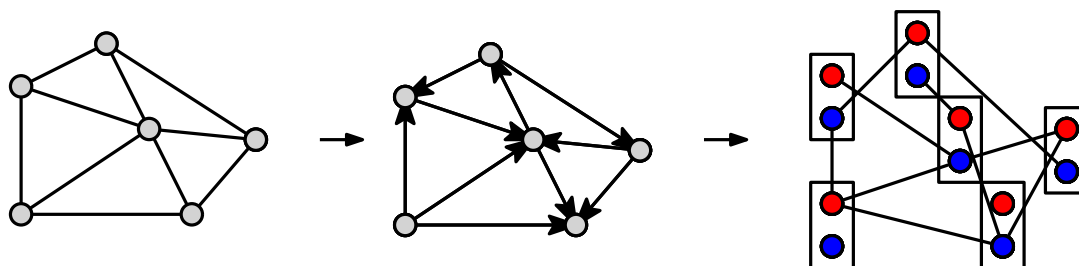
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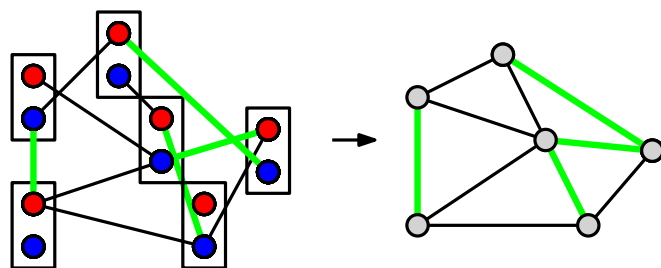
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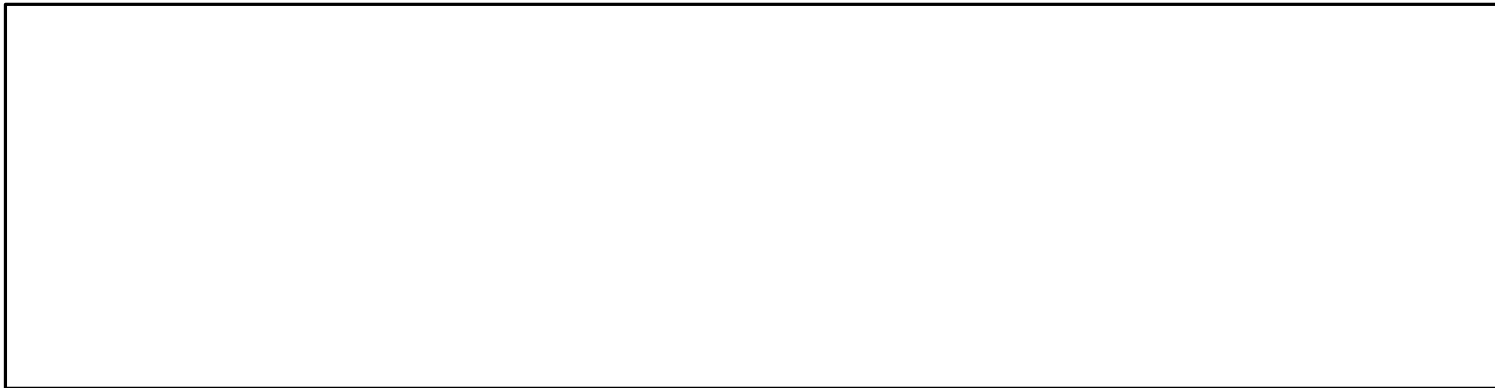


# Improving Approximation Ratio

Observation: matching size in remainder graph reduces by  $O(1)$ -factor

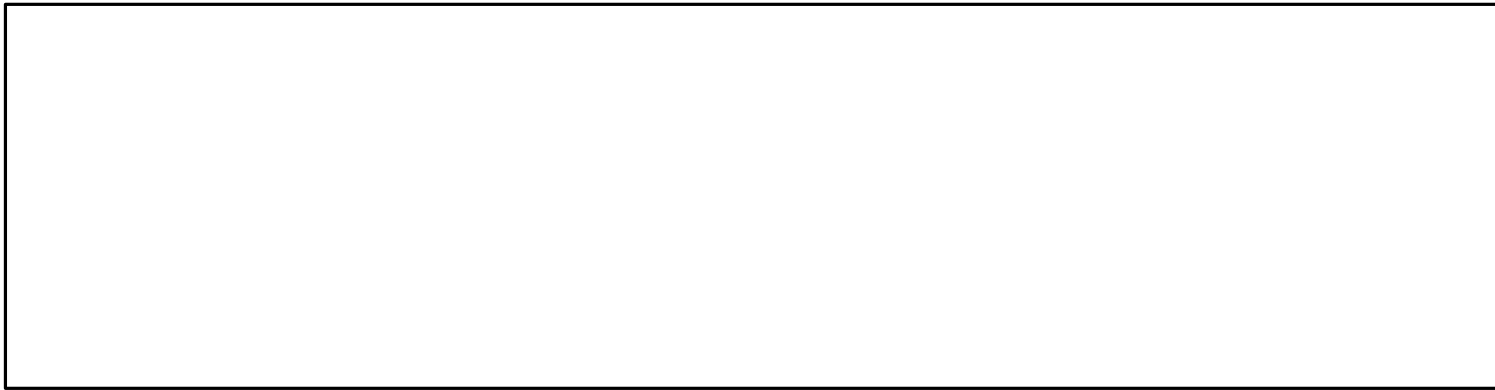
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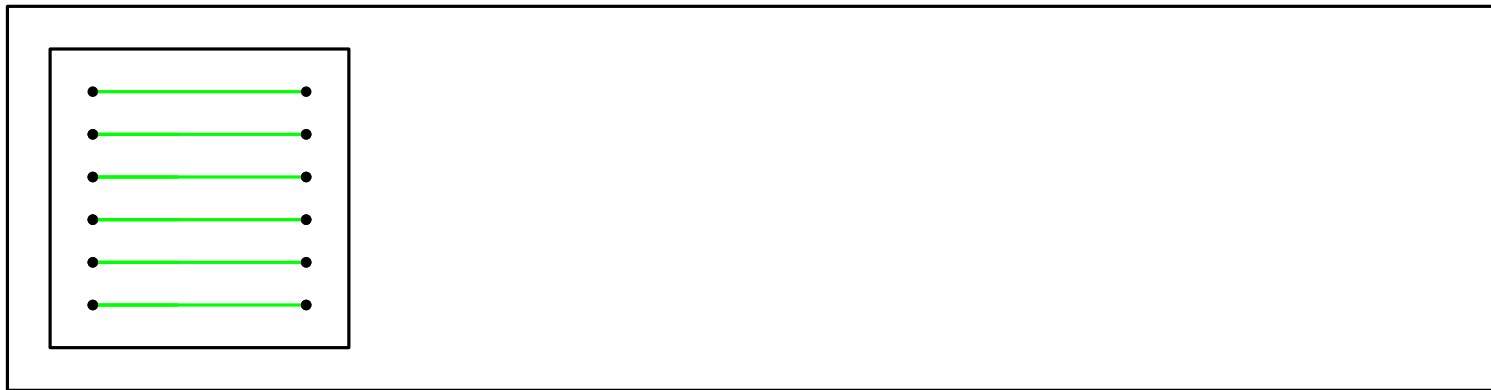


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$M^*$

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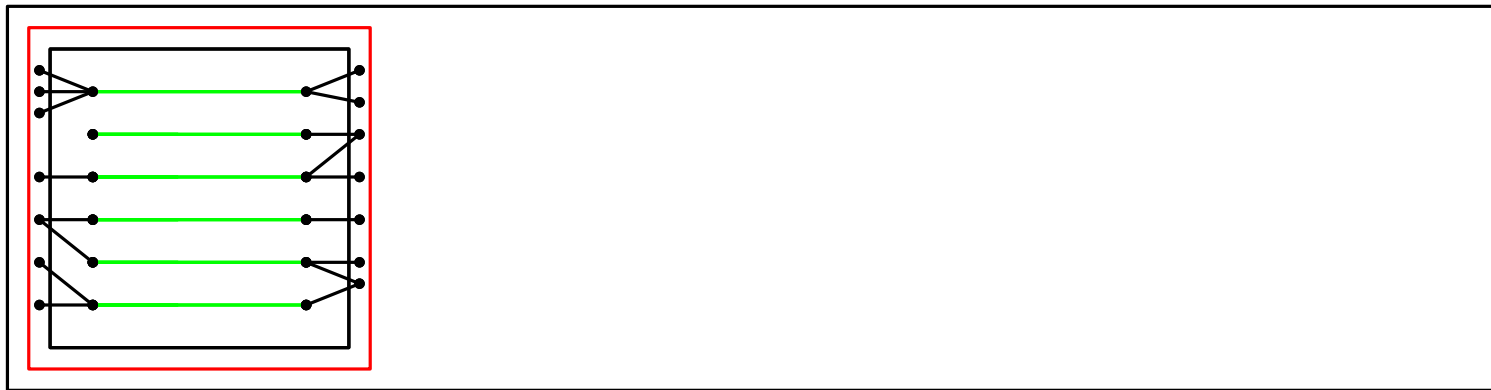
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$$|M| \geq \frac{1}{c} |M^*|$$

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$G$

$G_1$

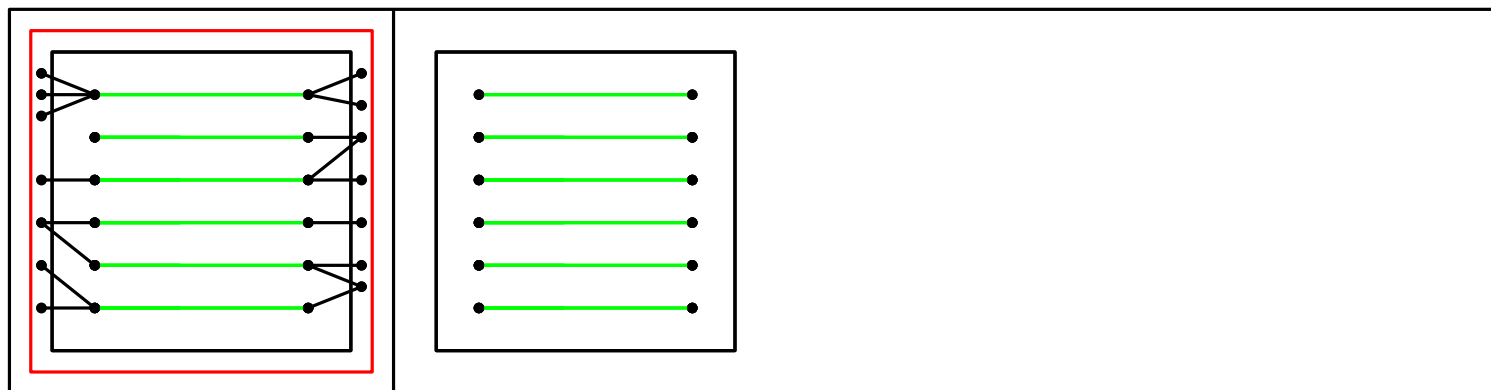
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$$|M_1^*| \leq \left(1 - \frac{1}{c}\right) |M^*|$$

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$G$

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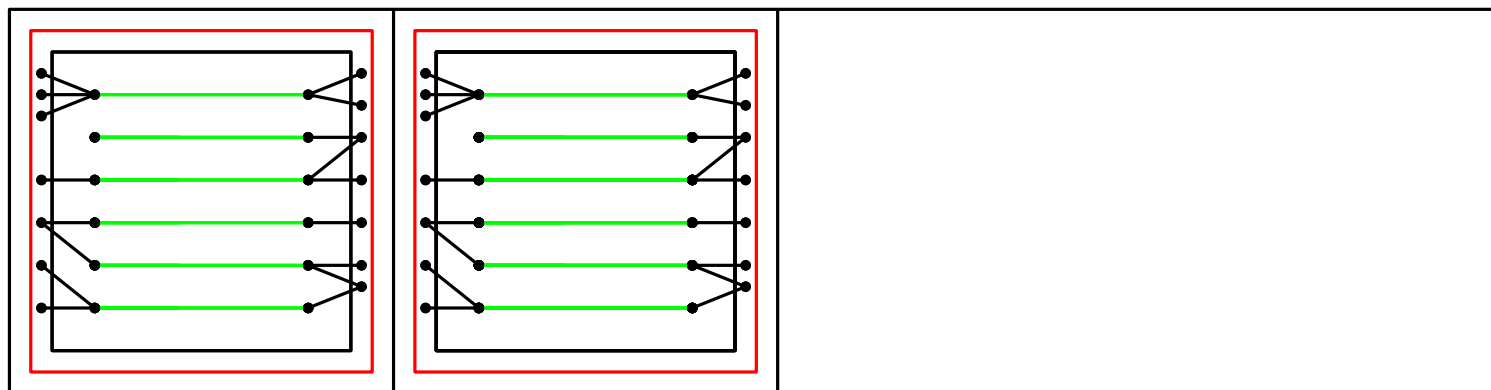
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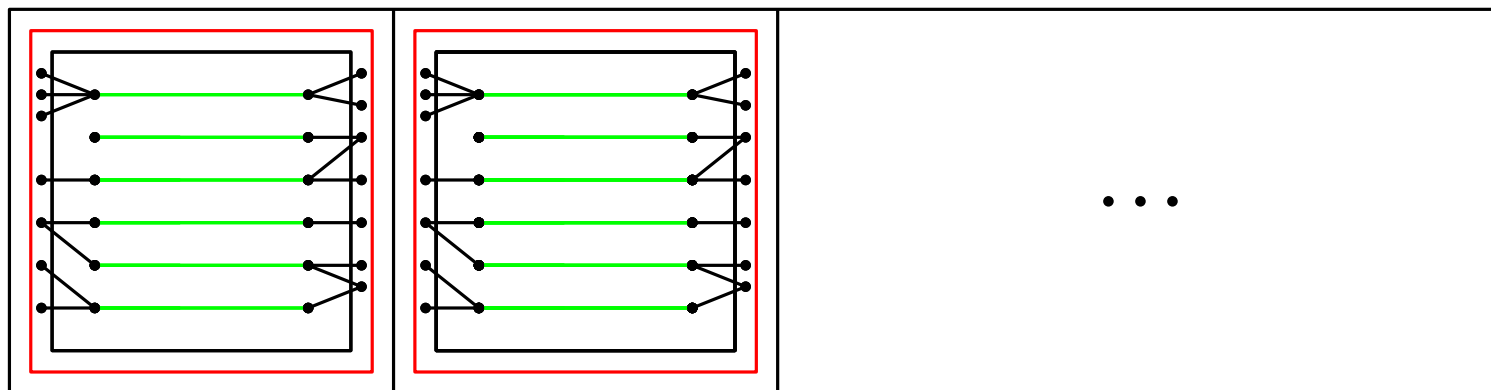
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inductively:  $|M_i^*| \leq \left(1 - \frac{1}{c}\right)^i |M^*|$

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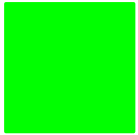
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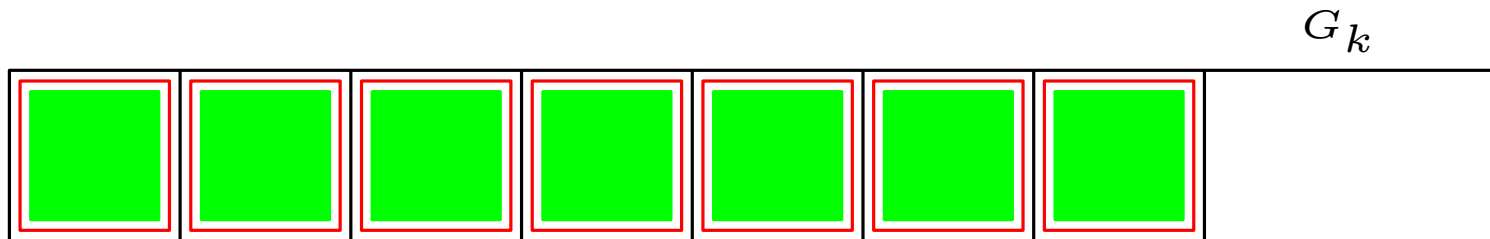
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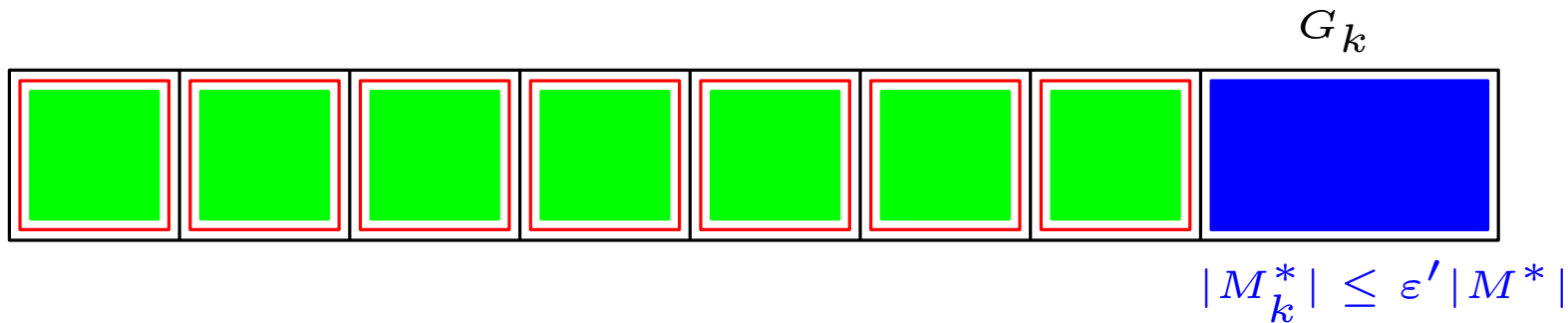
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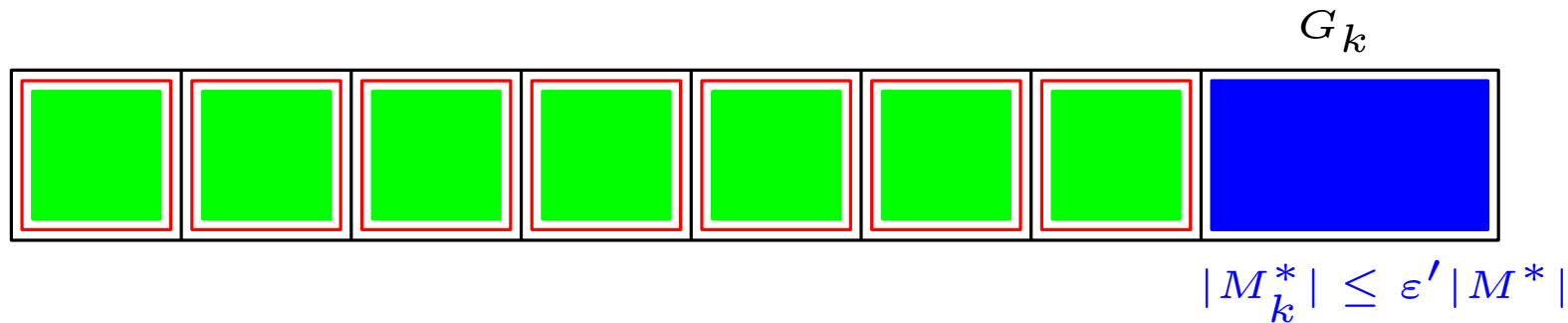
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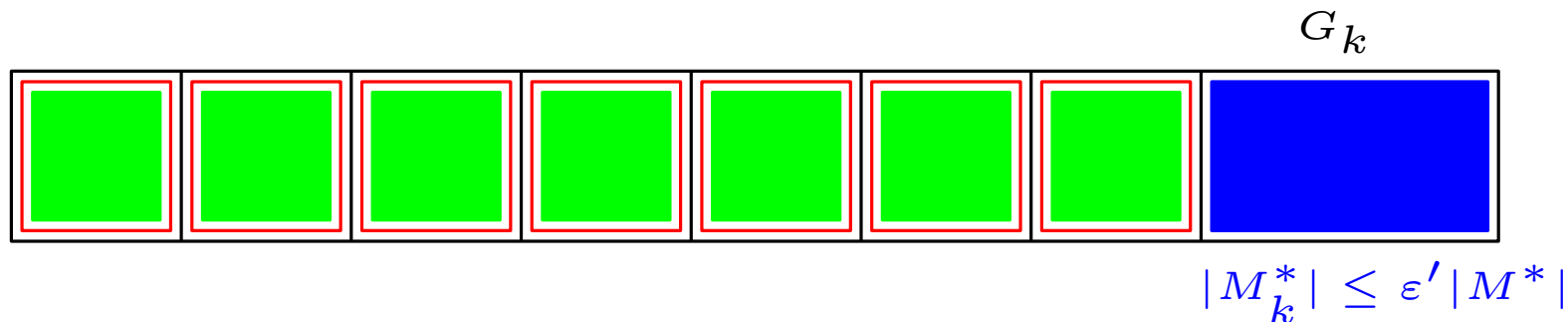
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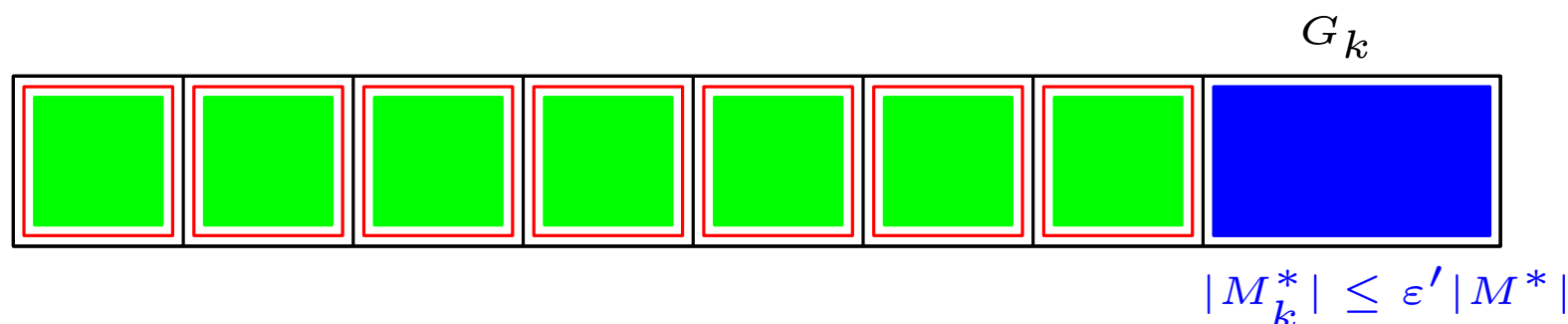


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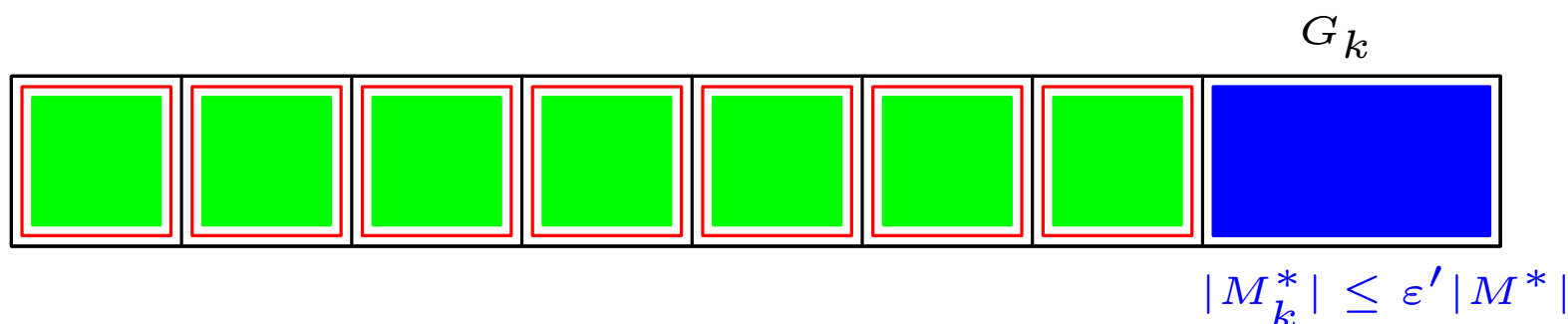
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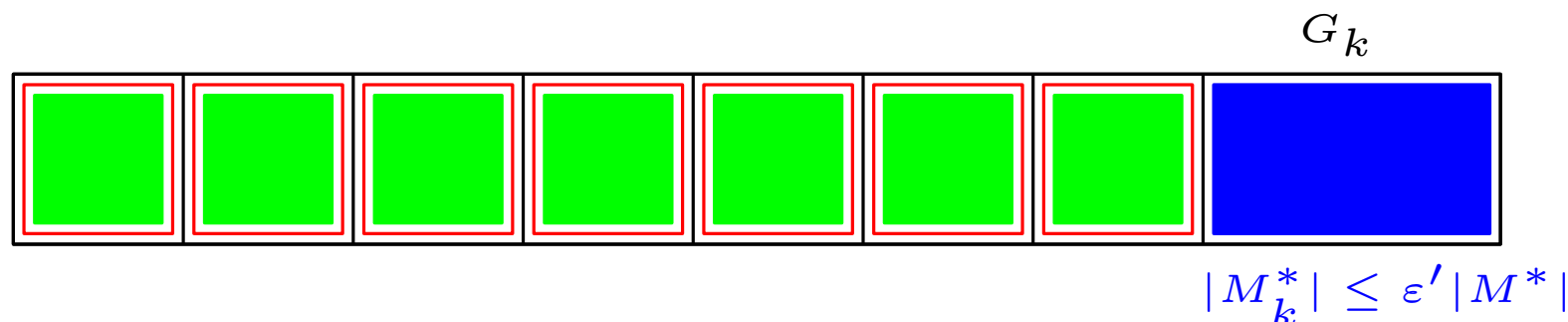
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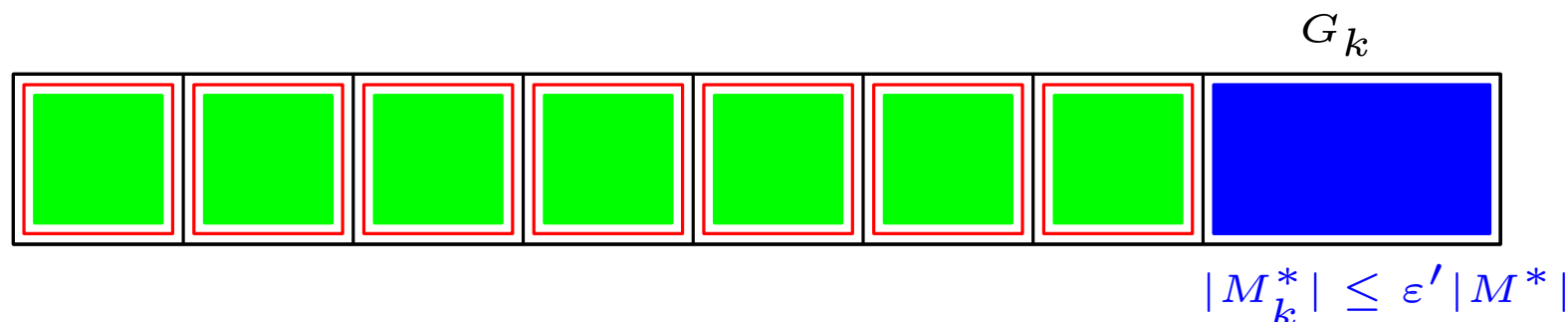
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- $O(\log^2 \Delta \cdot \log n)$  rounds for maximal matching  
 after  $k = O(\log n)$  iterations:  $|M_k^*| \leq \frac{1}{2n} |M^*| < 1$



# Recap: Our Results

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## Our Result [F., Ghaffari 2017]

$O(\log^2 \Delta + \log^* n)$  for constant approximation

$O(\log^2 \Delta \cdot \log \frac{1}{\varepsilon} + \log^* n)$  for  $(2 + \varepsilon)$ -approximation

$O(\log^2 \Delta \cdot \log n)$  for maximal matching (2-approximation)

using an  $O(\log^2 \Delta)$ -round  $O(1)$ -approximation algorithm for bipartite graphs

$O(\log^4 n)$  Hańćkowiak, Karoński, Panconesi [PODC'99]

$O(\Delta + \log^* n)$  Panconesi, Rizzi [DIST'01]

$\Omega\left(\frac{\log \Delta}{\log \log \Delta} + \log^* n\right)$  Kuhn, Moscibroda, Wattenhofer [PODC'04], Linial [FOCS'87]

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matching admits efficient deterministic rounding
- deterministic poly  $\log n$ -round algorithm for  $(2\Delta - 1)$ -edge-coloring (F., Ghaffari, Kuhn (2017))  
using deterministic rounding (for hypergraph matching)

# Open Questions & Conclusion

- **Deterministic Complexity of Matching**

- lower bound  $\Omega \left( \frac{\log \Delta}{\log \log \Delta} + \log^* n \right)$  for any  $O(1)$ -approximation
- conjecture: no  $o(\Delta) + O(\log^* n)$  for maximal matching (Göös, Hirvonen, Suomela [PODC'14])  
 $O(\log^2 \Delta \cdot \log n)$
- prove (or disprove) a lower bound  $\Omega(\log n)$  for deterministic maximal matching (for  $\Delta = \Omega(\log n)$ )

- **Rounding Method**

- completeness of rounding (Ghaffari, Kuhn, Maus [STOC'17])  
    matching admits an efficient deterministic algorithm because  
    matching admits efficient deterministic rounding
- deterministic poly  $\log n$ -round algorithm for  $(2\Delta - 1)$ -edge-coloring (F., Ghaffari, Kuhn (2017))  
    using deterministic rounding (for hypergraph matching)
- more general deterministic rounding method?