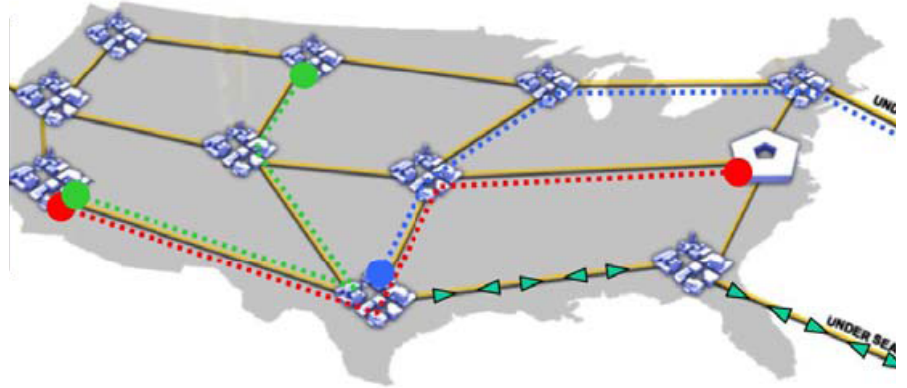
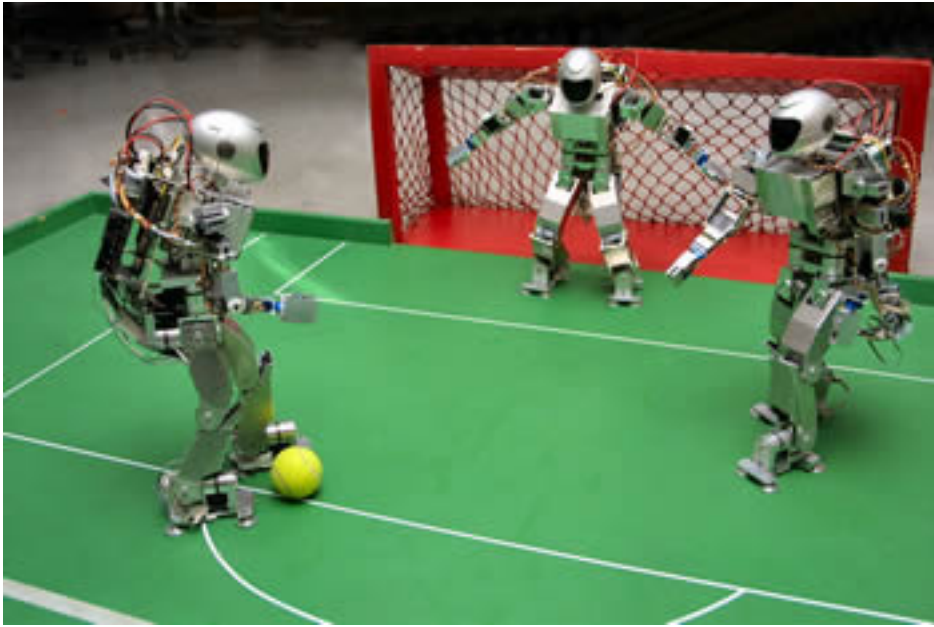


Graph Routing Problems: Approximation, Hardness, and Graph-Theoretic Insights

Julia Chuzhoy

Toyota Technological Institute at
Chicago





Graph Routing Problems

maximum s-t flow

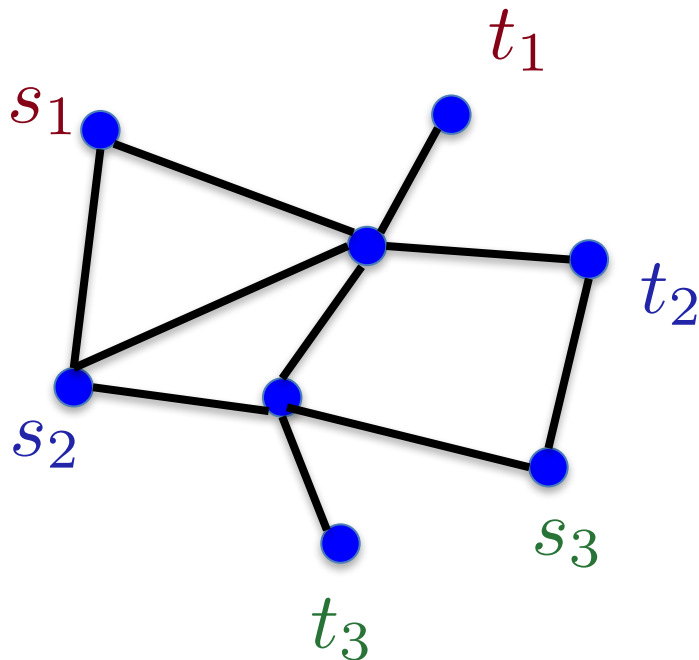
maximum
multicommodity flow

maximum
node-disjoint paths
(NDP)

Node-Disjoint Paths (NDP)

Input: Graph G , source-sink pairs $(s_1, t_1), \dots, (s_k, t_k)$.

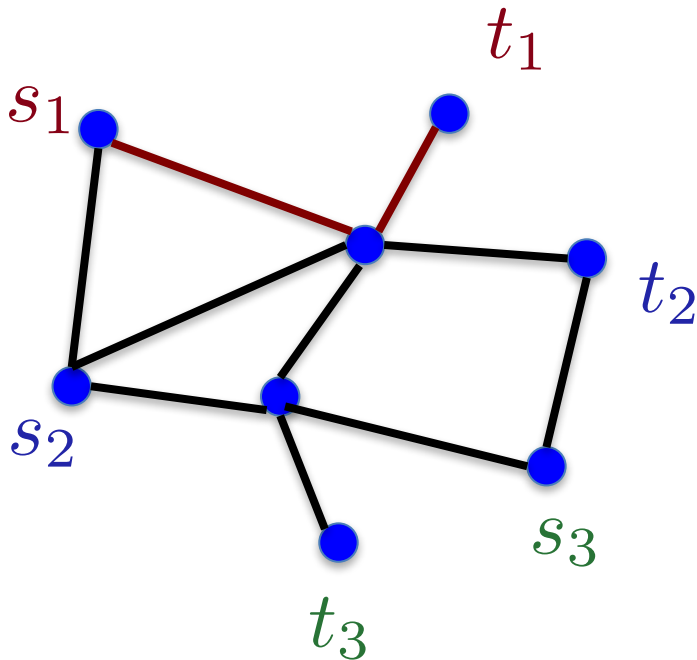
Goal: Route as many pairs as possible via node-disjoint paths



Node-Disjoint Paths (NDP)

Input: Graph G , source-sink pairs $(s_1, t_1), \dots, (s_k, t_k)$.

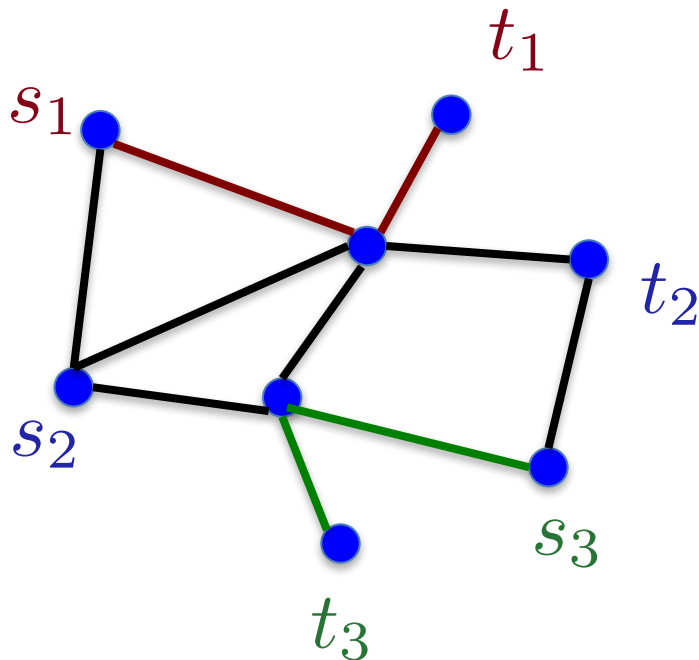
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Node-Disjoint Paths (NDP)

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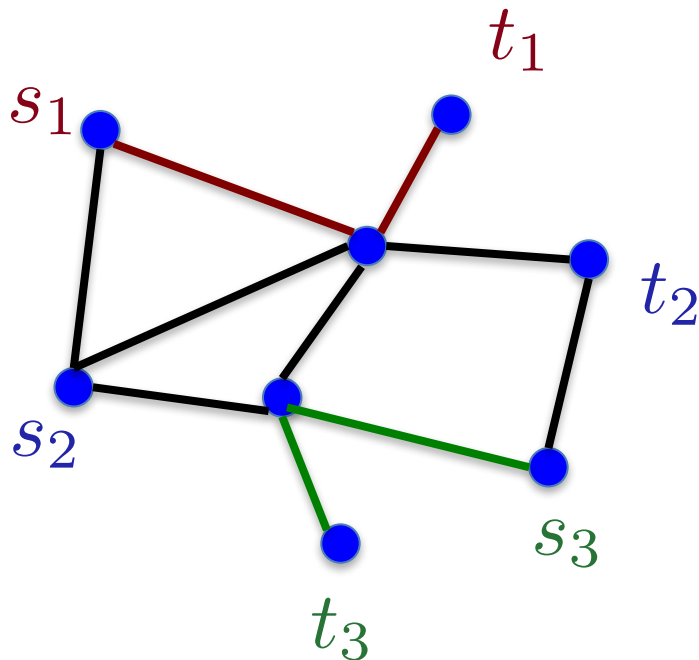
Solution value: 2

OPT: value of best possible solution

Node-Disjoint Paths (NDP)

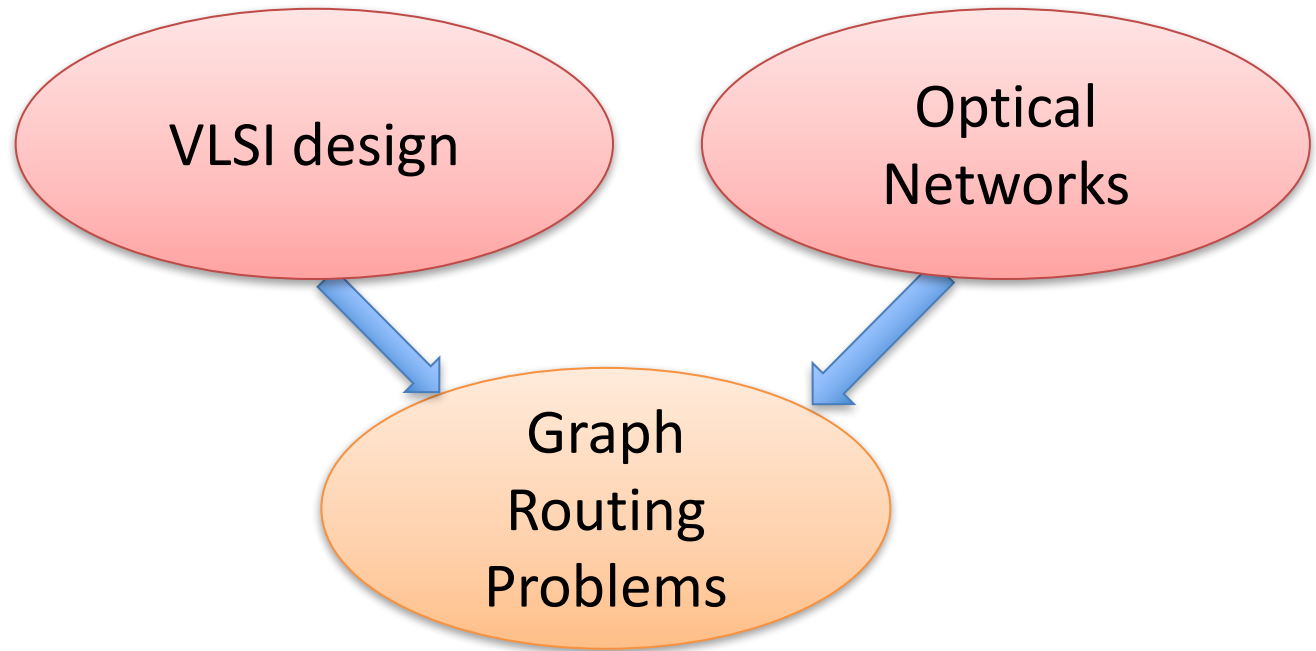
Input: Graph G , source-sink pairs $(s_1, t_1), \dots, (s_k, t_k)$.

Goal: Route as many pairs as possible via node-disjoint paths



Solution value: 2

Edge-disjoint Paths (EDP):
paths must be edge-disjoint

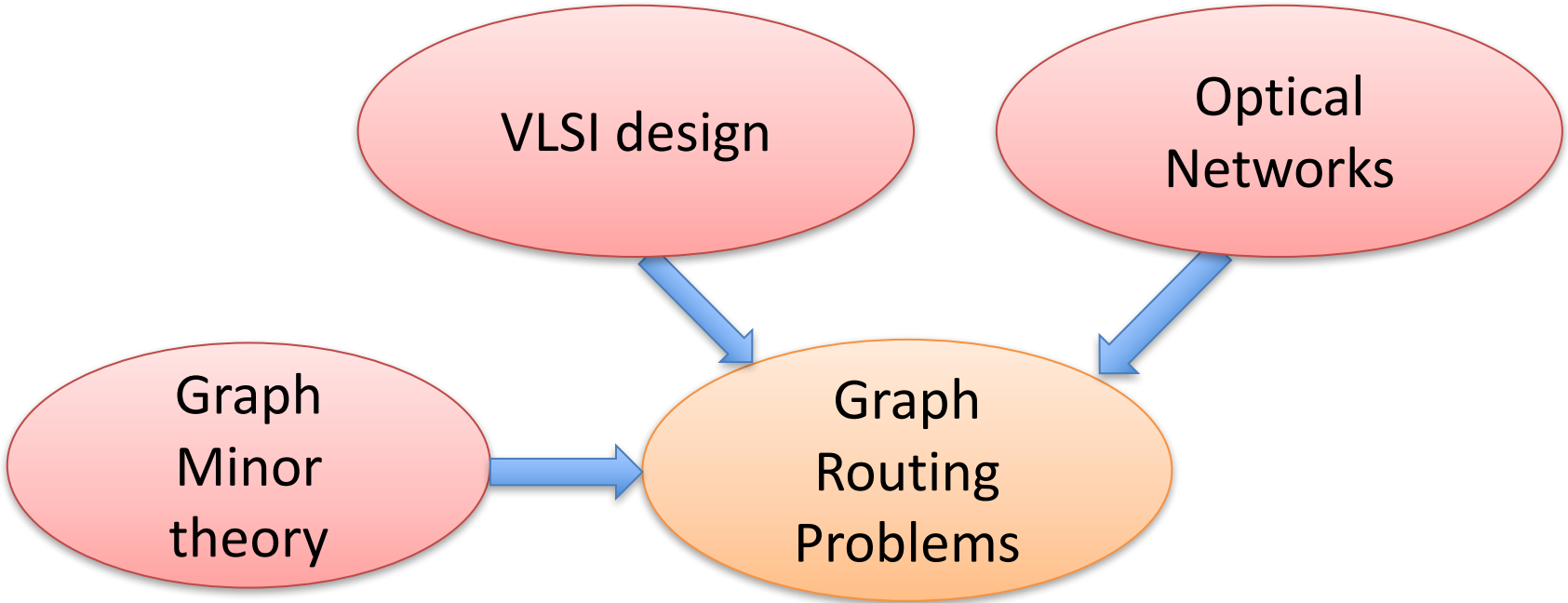


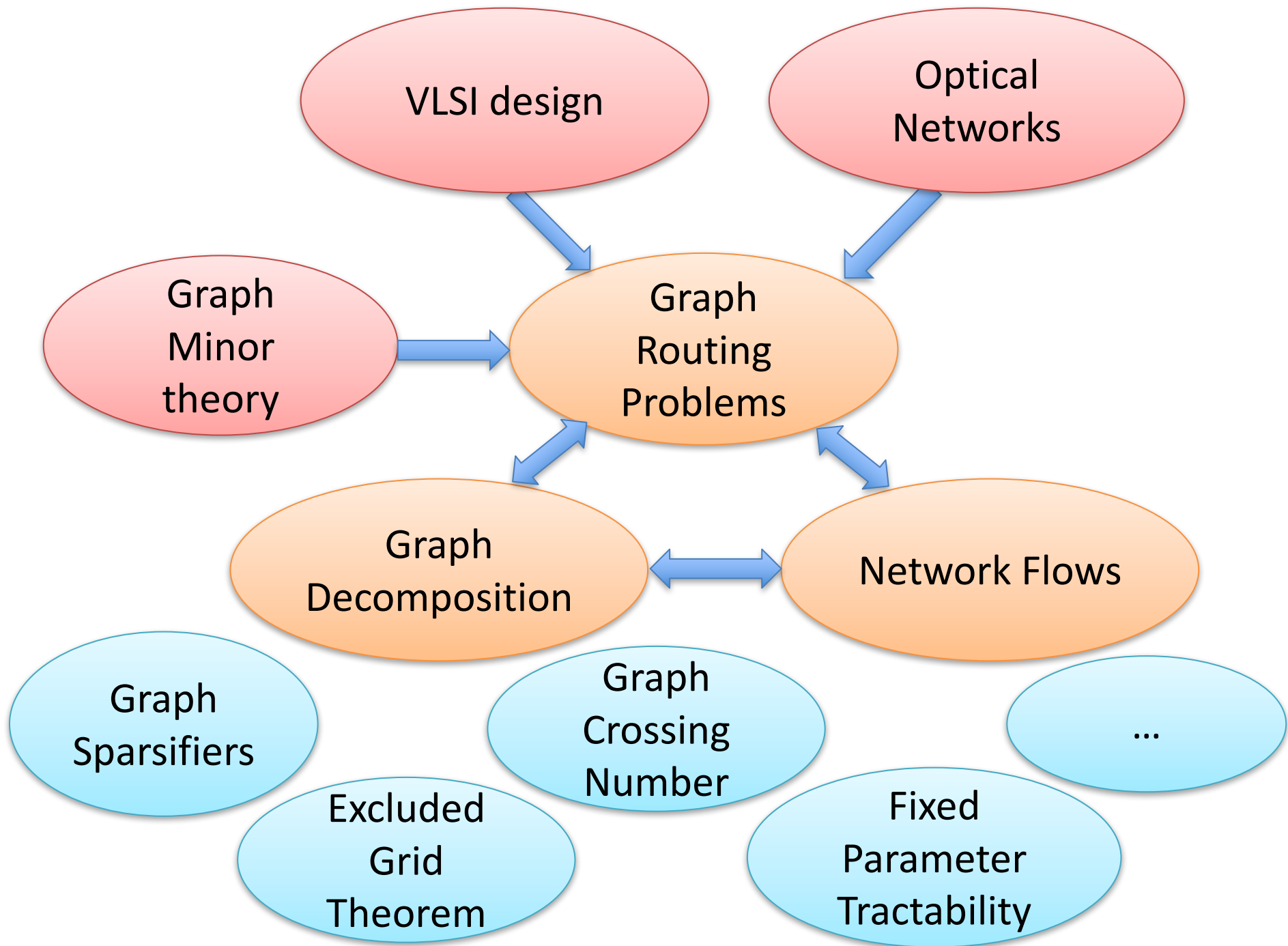
VLSI design

Optical
Networks

Graph
Minor
theory

Graph
Routing
Problems

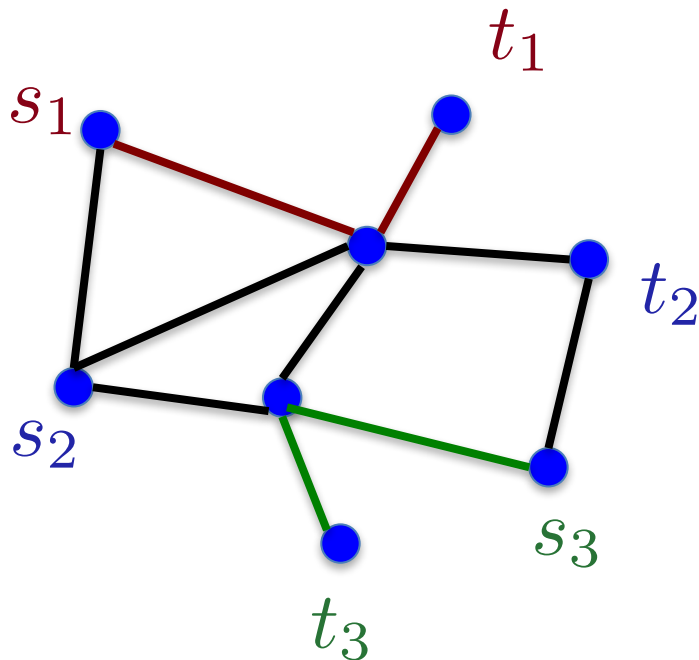




Node-Disjoint Paths (NDP)

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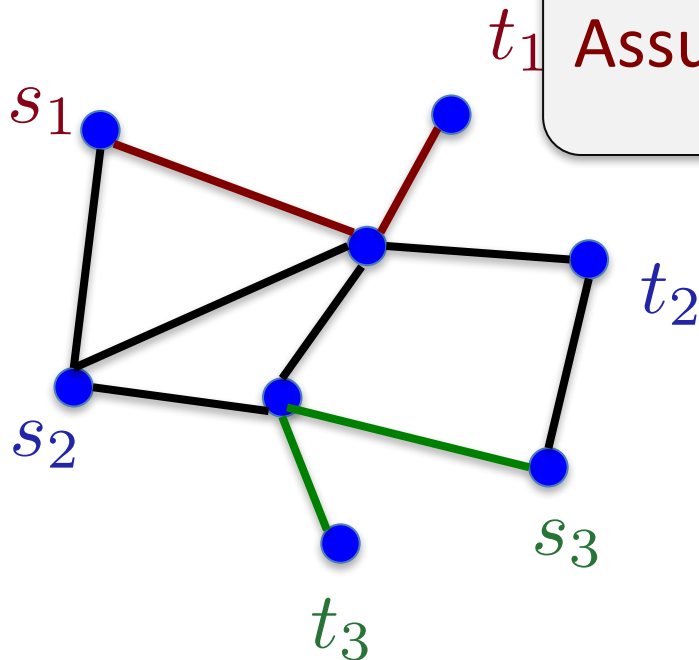


terminals

Node-Disjoint Paths (NDP)

Input: Graph G , source-sink pairs $(s_1, t_1), \dots, (s_k, t_k)$.

Goal: Route as many pairs as possible via node-disjoint paths



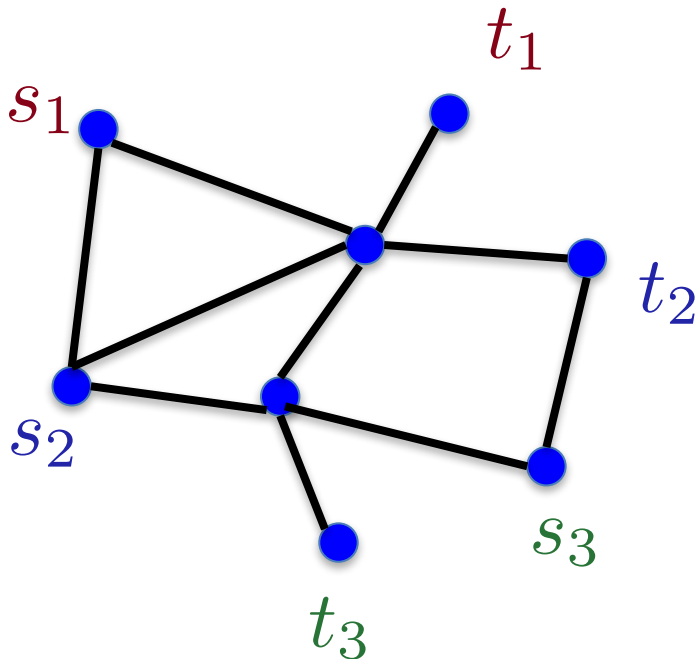
Assumption: All terminals are distinct

n – number of graph vertices
 k – number of demand pairs

Node-Disjoint Paths (NDP)

Input: Graph G , source-sink pairs $(s_1, t_1), \dots, (s_k, t_k)$.

Goal: Route as many pairs as possible via node-disjoint paths



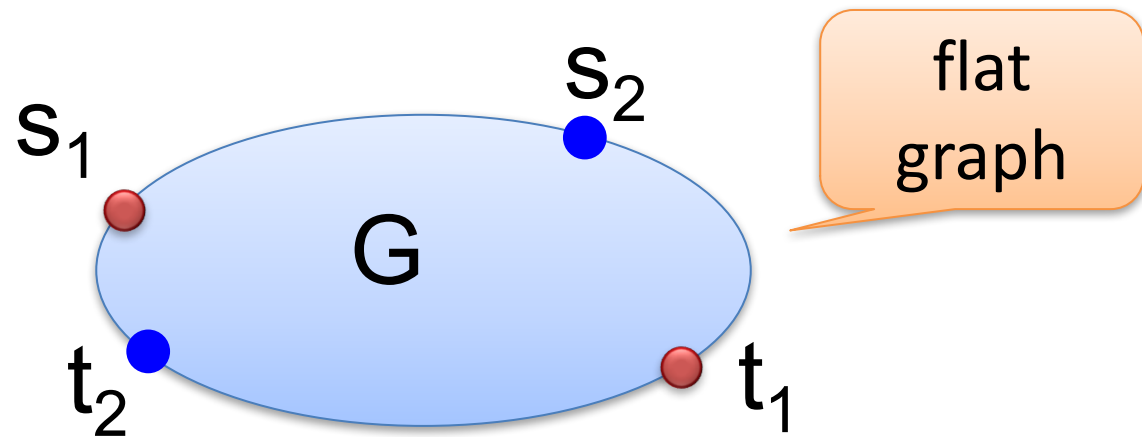
Can we solve it efficiently?

$k=1?$ ✓

$k=2?$

NDP with $k=2$

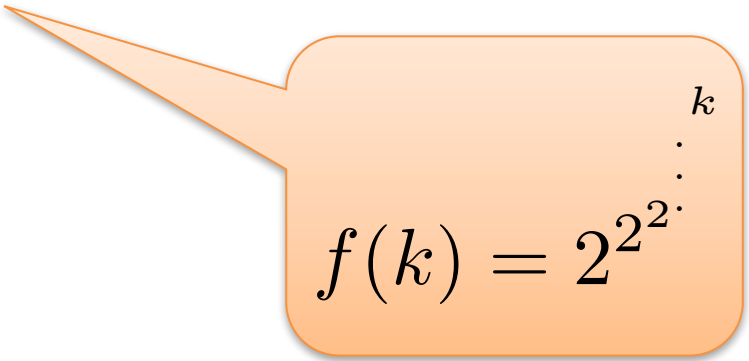
- NP-hard in directed graphs [Fortune, Hopcroft, Wyllie '80]
- Efficiently solvable in undirected graphs [Jung '70, Shiloach '80, Thomassen '80, Robertson-Seymour '90]



Larger k ?

Larger k?

- Constant k: efficiently solvable [Robertson, Seymour '90]
 - Running time: $f(k) \cdot n^2$ [Kawarabayashi, Kobayashi, Reed '12]

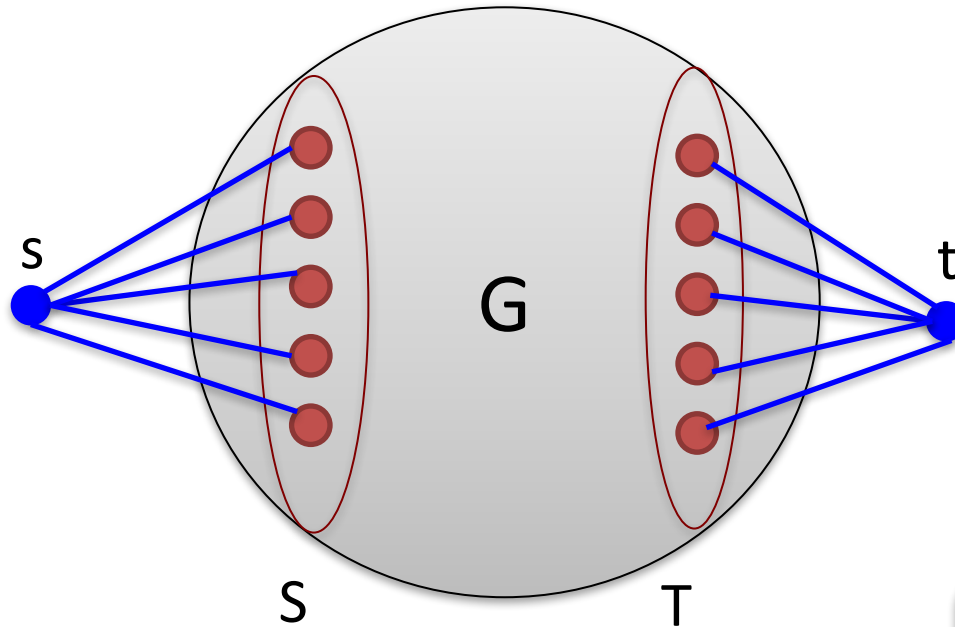


$f(k) = 2^{2^{\cdot^{\cdot^{\cdot^k}}}}$

Larger k?

- Constant k: efficiently solvable [Robertson, Seymour '90]
 - Running time: $f(k) \cdot n^2$ [Kawarabayashi, Kobayashi, Reed '12]
- NP-hard when k is part of input [Knuth, Karp '74]

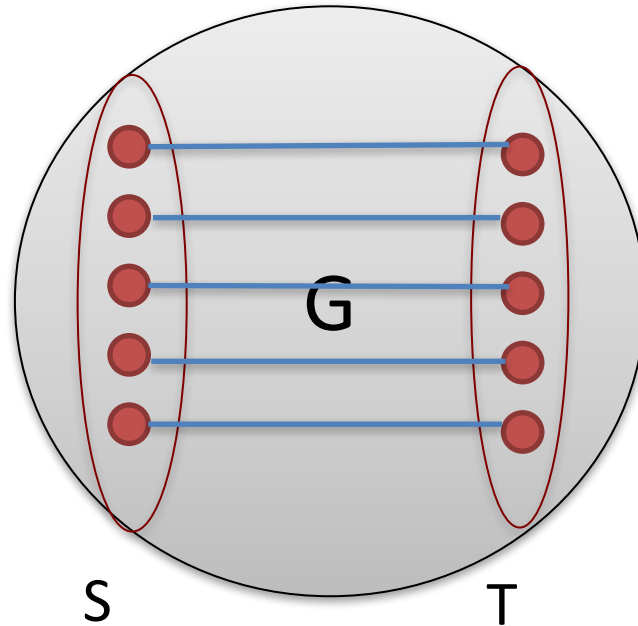
Example



Max s-t
flow

- Set of demand pairs is $S \times T$: can solve efficiently

Example



- Set of demand pairs is $S \times T$: can solve efficiently
- Demand pairs are a specific matching between S and T : NP-hard

Dealing with NP-Hardness

An α -approximation algorithm:

- efficient algorithm
- always produces solutions routing at least OPT/α demand pairs.

Dealing with NP-Hardness

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Dealing with NP-Hardness

An α -approximation algorithm:

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optimum
solution
value

On Approximation Factors

- A simple way to compare algorithms
 - $\alpha=1+\epsilon$
 - $\alpha=2$
 - $\alpha=O(\log n)$
 - $\alpha=O(\sqrt{n})$
 - ...

On Approximation Factors

- A simple way to compare algorithms
- Design algorithms with good approximation factors α
- Establish best possible approximation factor α for a given problem

Hardness of
approximation results

On Approximation Factors

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Hardness of
approximation results

On Approximation Factors

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Goal: powerful, simple algorithmic techniques with provable bounds

On Approximation Factors

- A simple way to compare algorithms
- Design algorithms with good approximation factors α
- Establish best possible approximation factor α for a given problem

Better models for real-life problems

Understanding what makes a problem difficult

On Approximation Factors

- A simple way to compare algorithms
- Design algorithms with good approximation factors α
- Establish best possible approximation factor α for a given problem

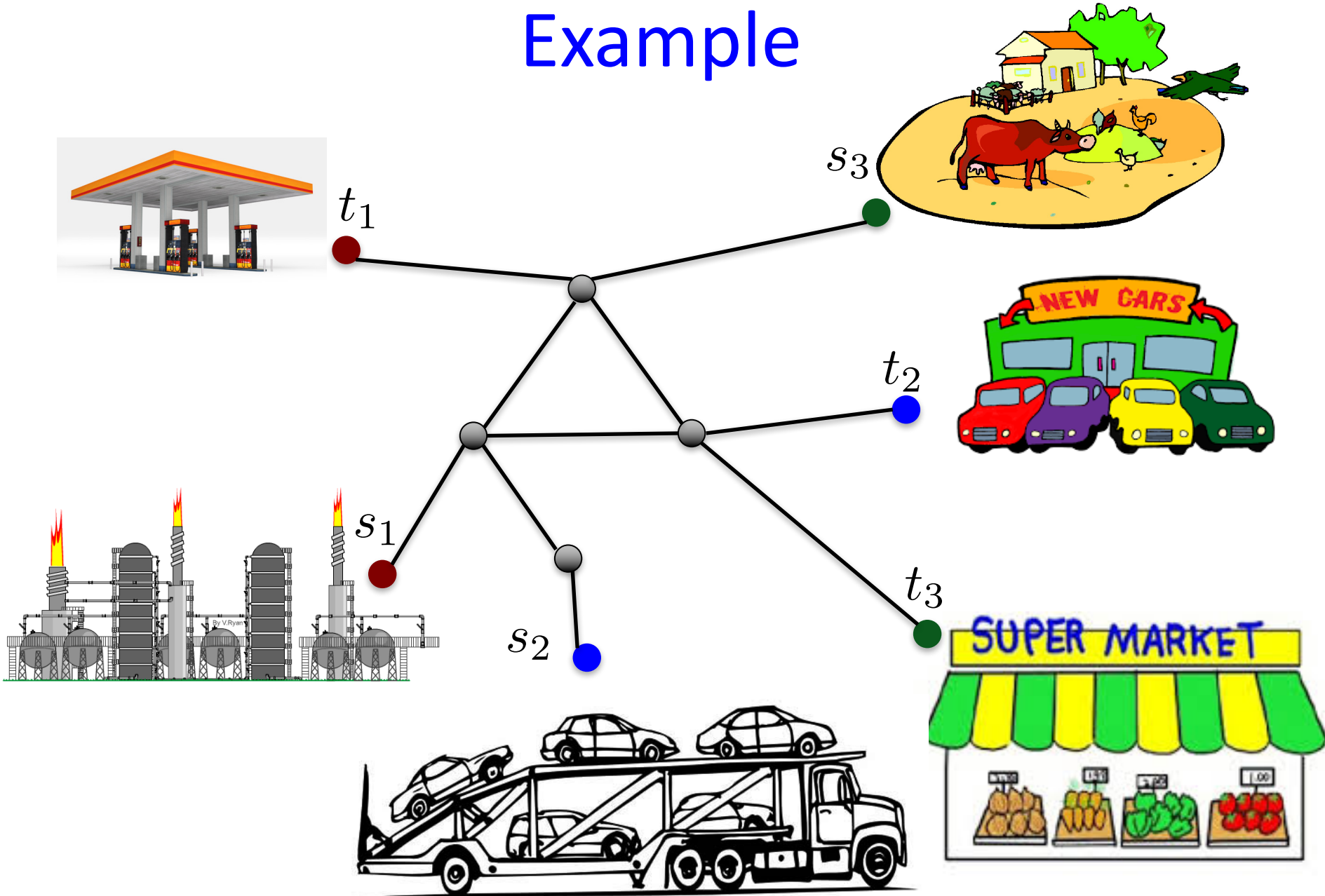
Dealing with NP-Hardness

An α -approximation algorithm:

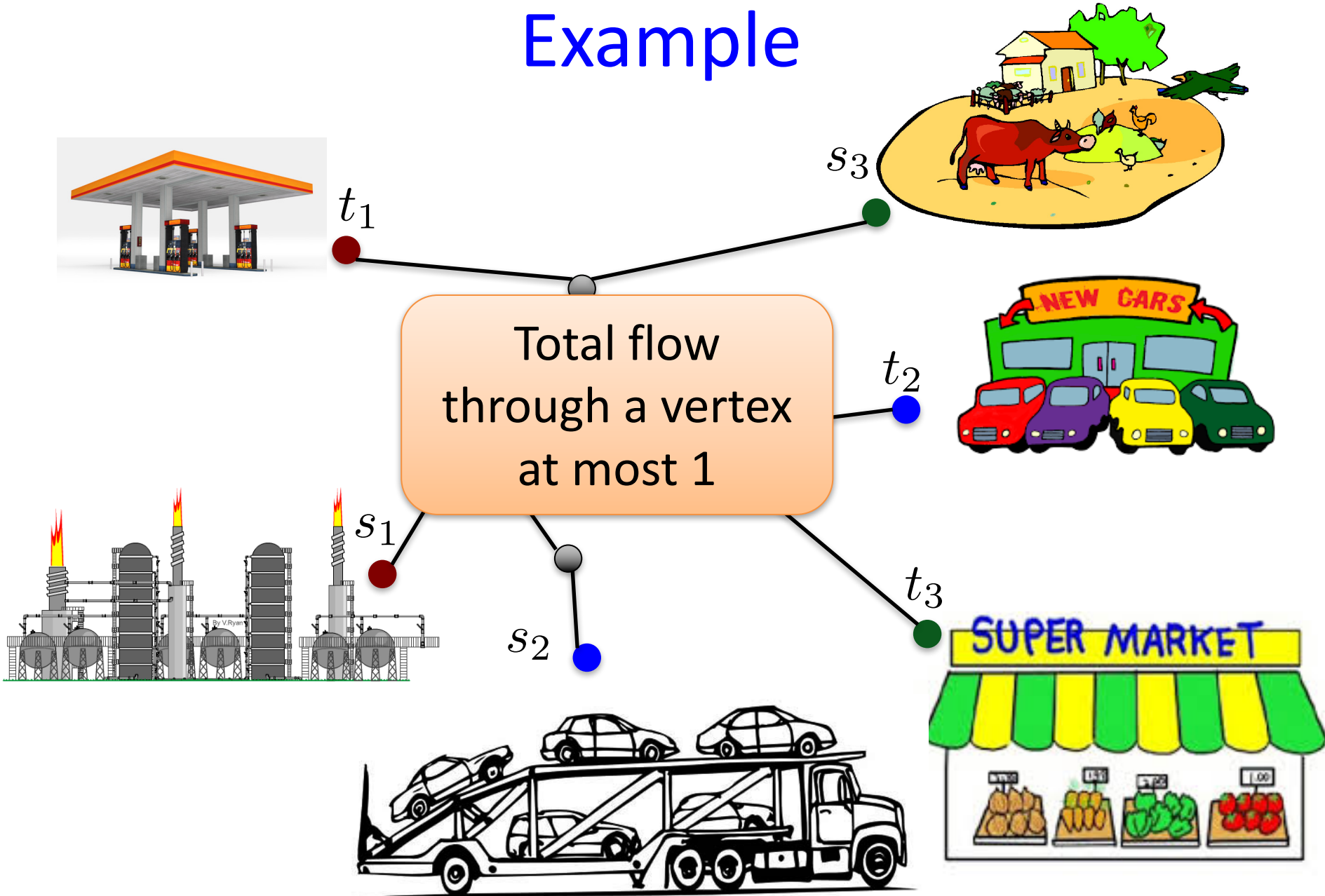
- efficient algorithm
- always produces solutions routing at least OPT/α demand pairs.

Multicommodity Flow relaxation: send as much flow as possible between the s_i - t_i pairs.

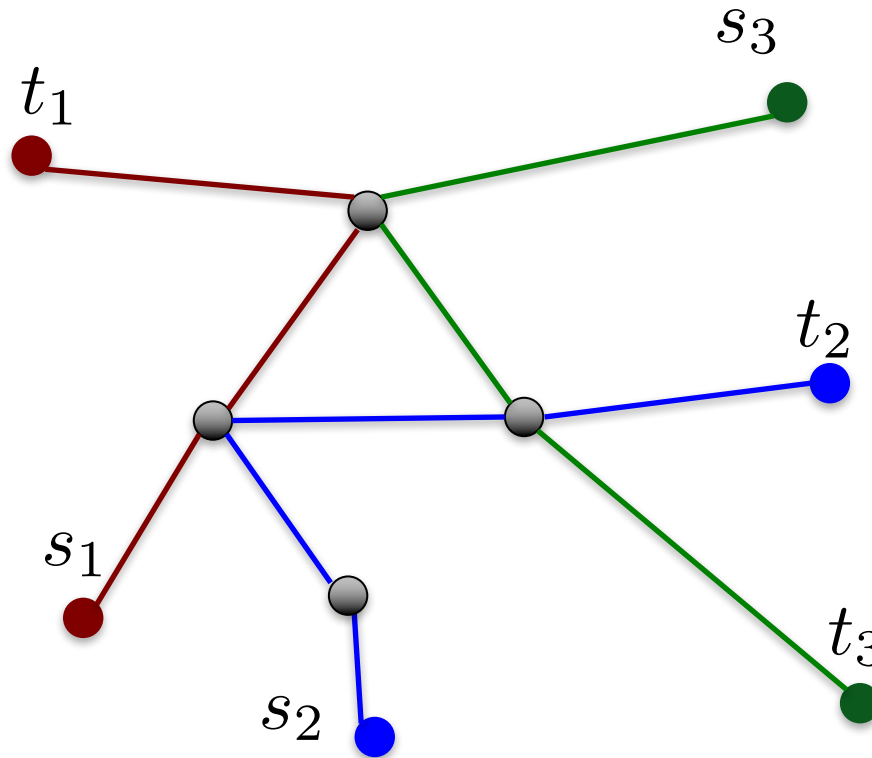
Example



Example



Example



NDP solution
value: 1

- send $\frac{1}{2}$ flow unit on each of the 3 paths
- solution value: $\frac{3}{2}$

Multicommodity Flows

- Can be computed efficiently

- $\text{OPT}_{\text{flow}} \geq \text{OPT}$

fractional
solution

integral
solution

multicommodity
flow LP-relaxation

Multicommodity Flows

- Can be computed efficiently
- $\text{OPT}_{\text{flow}} \geq \text{OPT}$
- Use the flow to find integral routing of at least $\text{OPT}_{\text{flow}}/\alpha$ demand pairs

multicommodity
flow LP-relaxation

α -approximation
algorithm

LP-rounding technique

Approximation Algorithm [Kolliopoulos, Stein '98]

While there is a path P with $f(P) > 0$:

- Add such shortest path P to the solution
- For each path P' sharing vertices with P , set $f(P')$ to 0

Approximation Algorithm [Kolliopoulos, Stein '98]

While there is a path P with $f(P) > 0$:

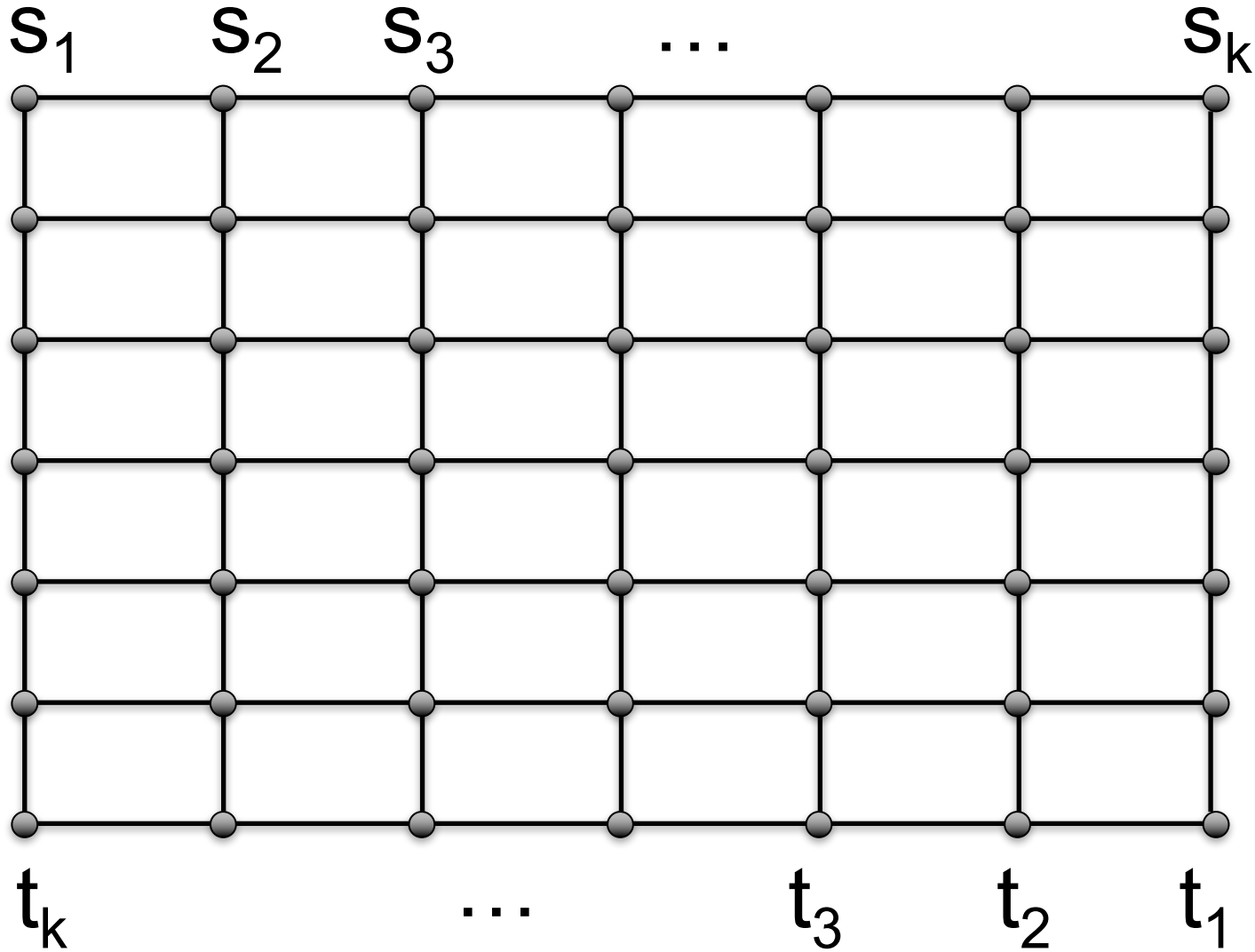
- Add such shortest path P to the solution
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$O(\sqrt{n})$ -approximation

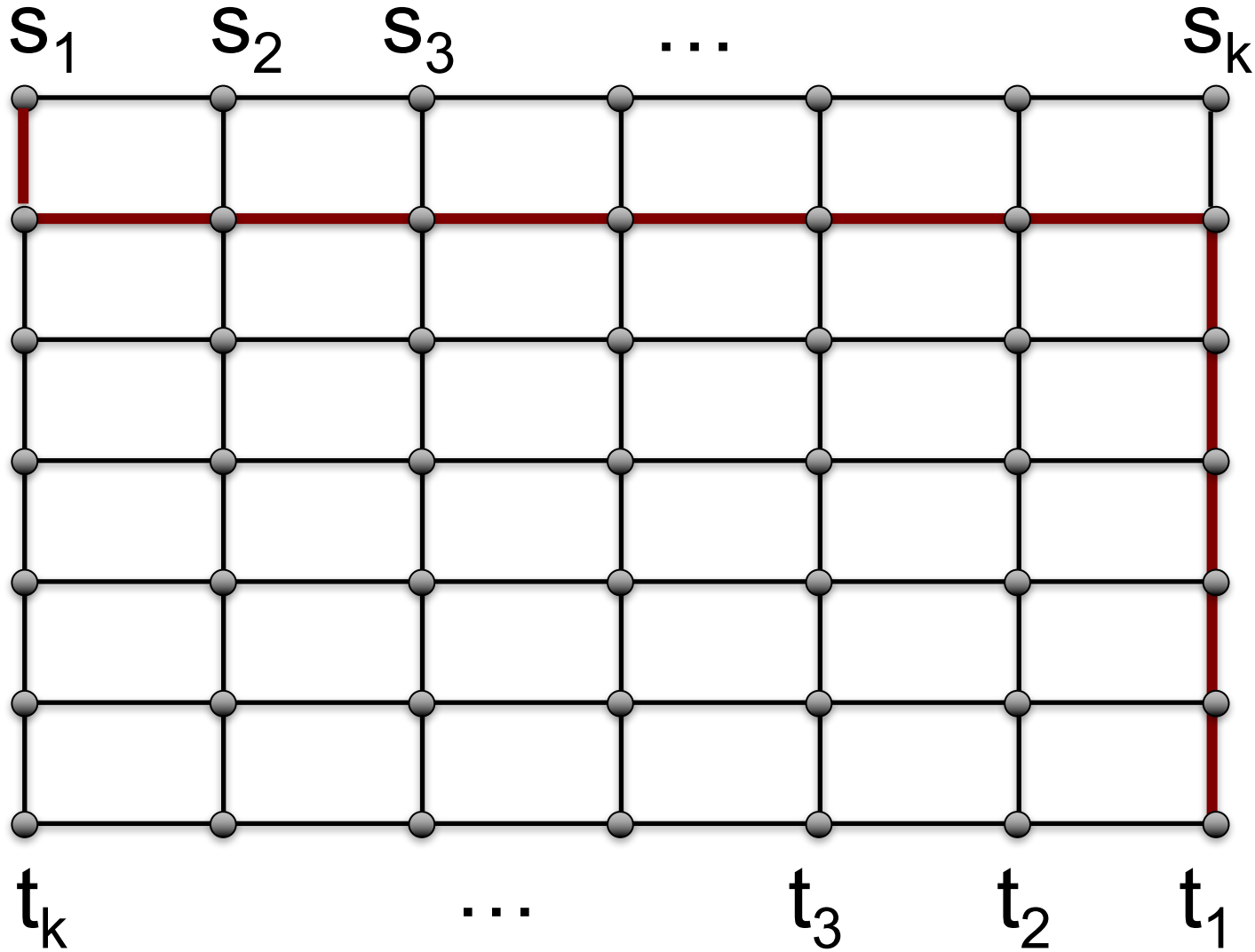
Can We Do Better?

- Not if we use the maximum multicommodity flow approach!

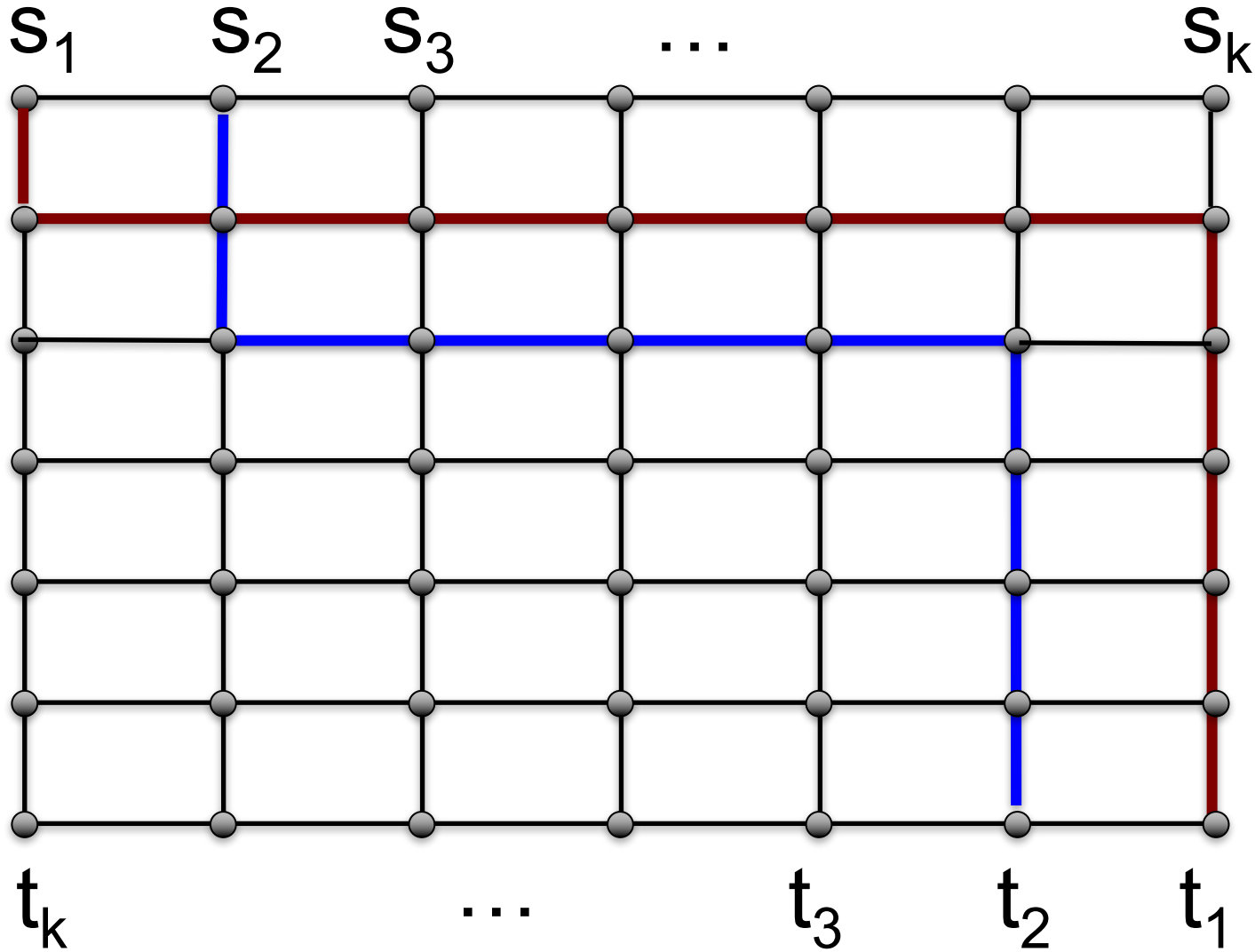
Bad Example



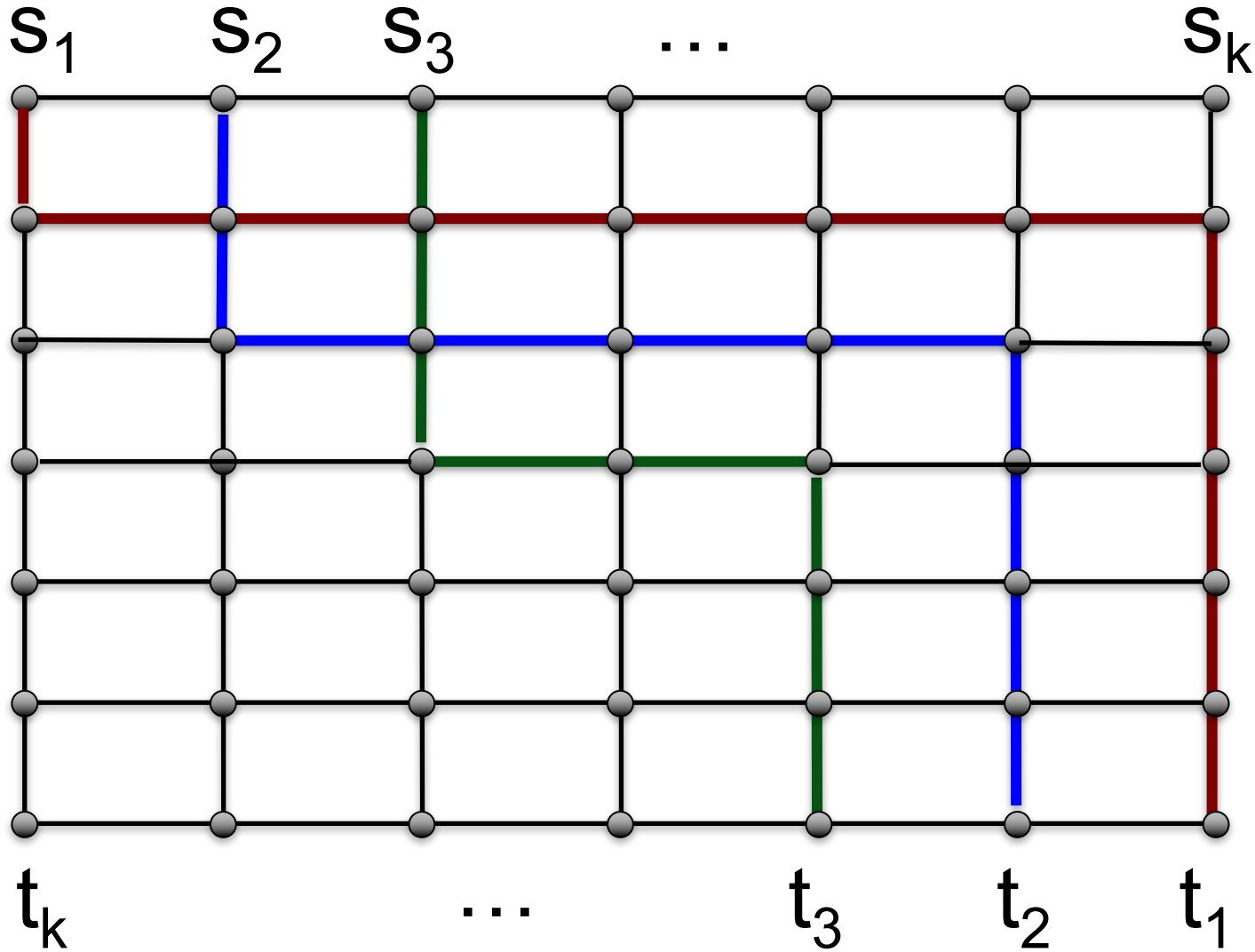
Bad Example



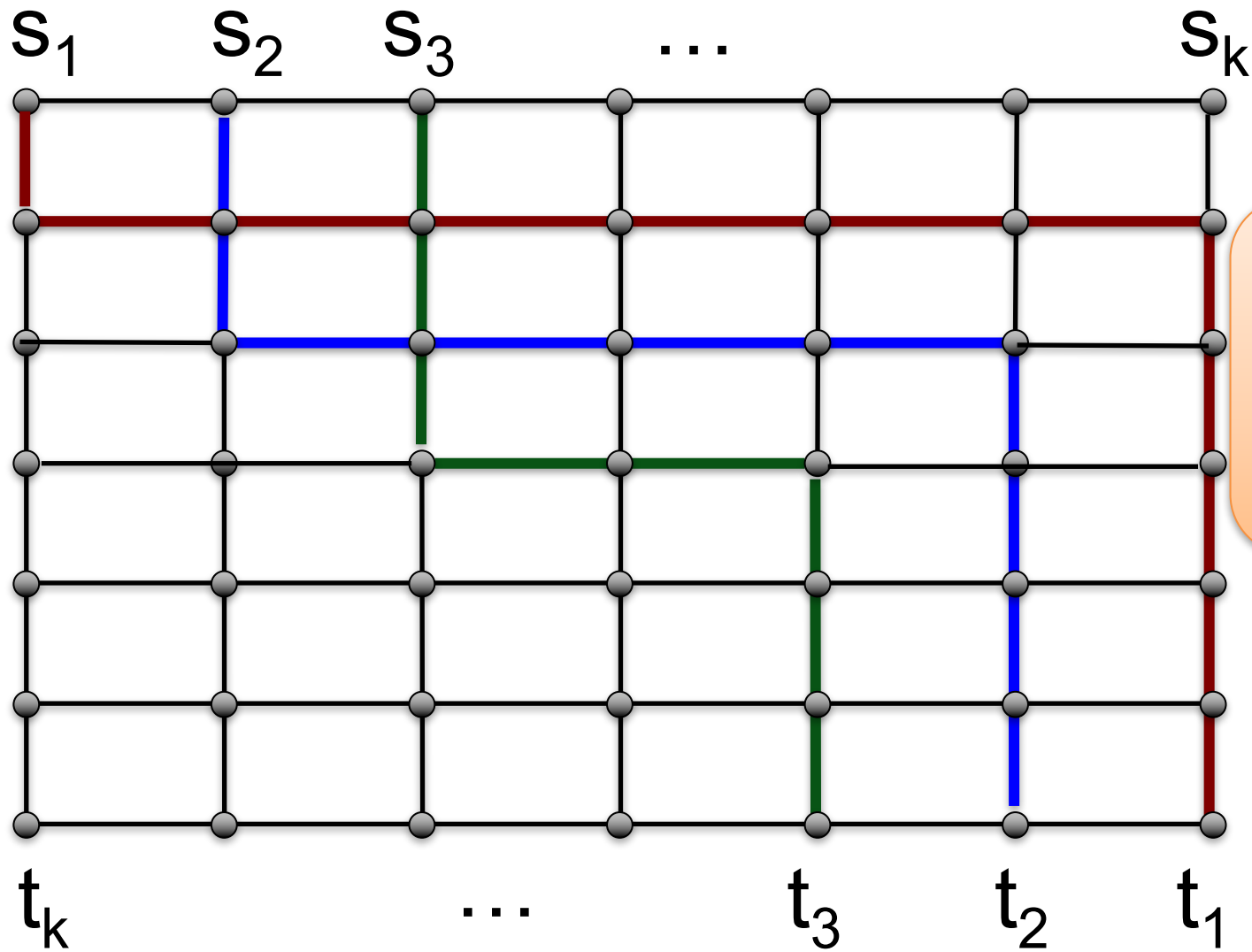
Bad Example



Bad Example

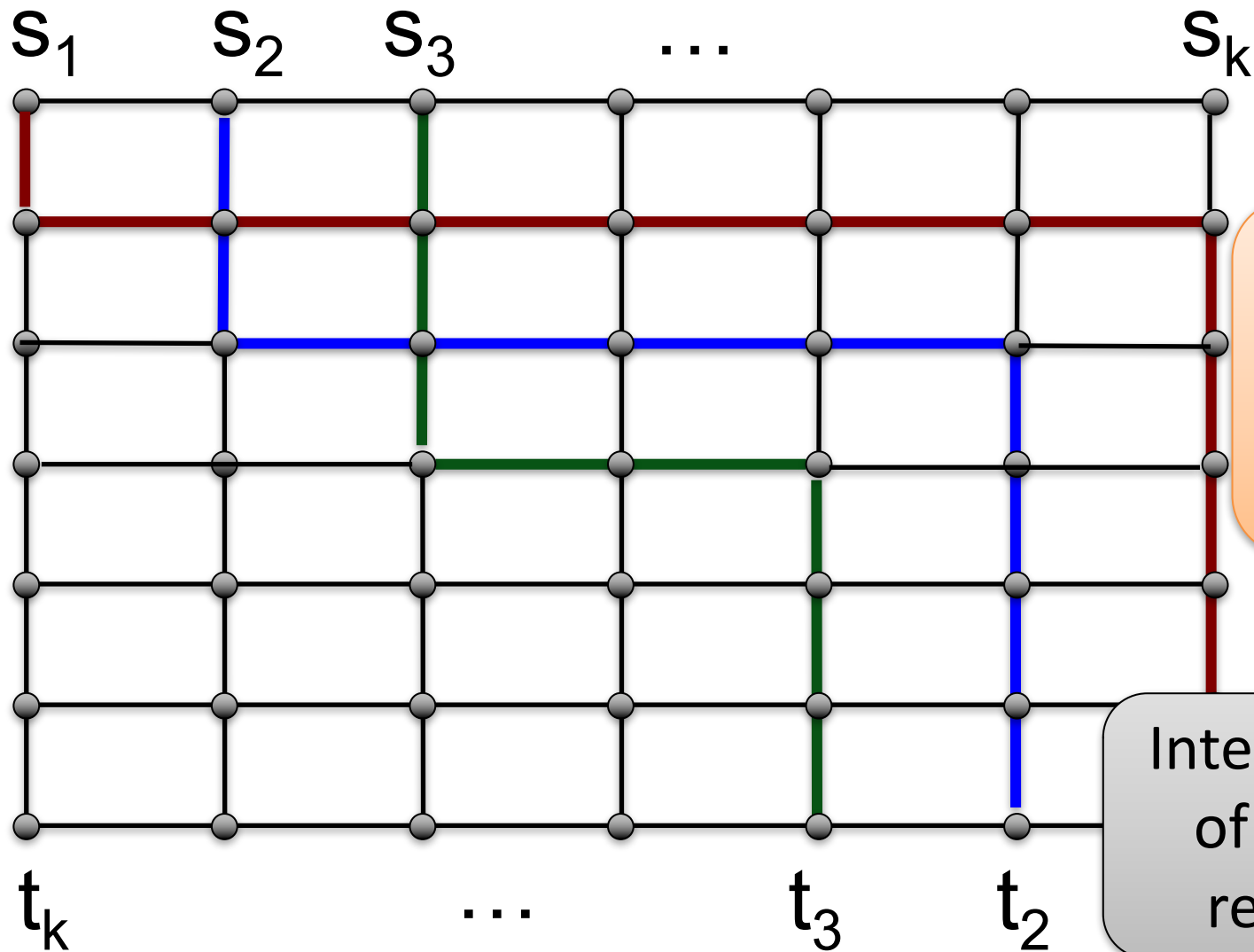


Bad Example



$OPT_{\text{flow}} = k/3$
 $OPT = 1$
gap:
 $\Omega(k) = \Omega(\sqrt{n})$

Bad Example



$$\text{OPT}_{\text{flow}} = k/3$$

$$\text{OPT} = 1$$

gap:

$$\Omega(k) = \Omega(\sqrt{n})$$

Integrality gap
of the flow
relaxation

Can We Do Better?

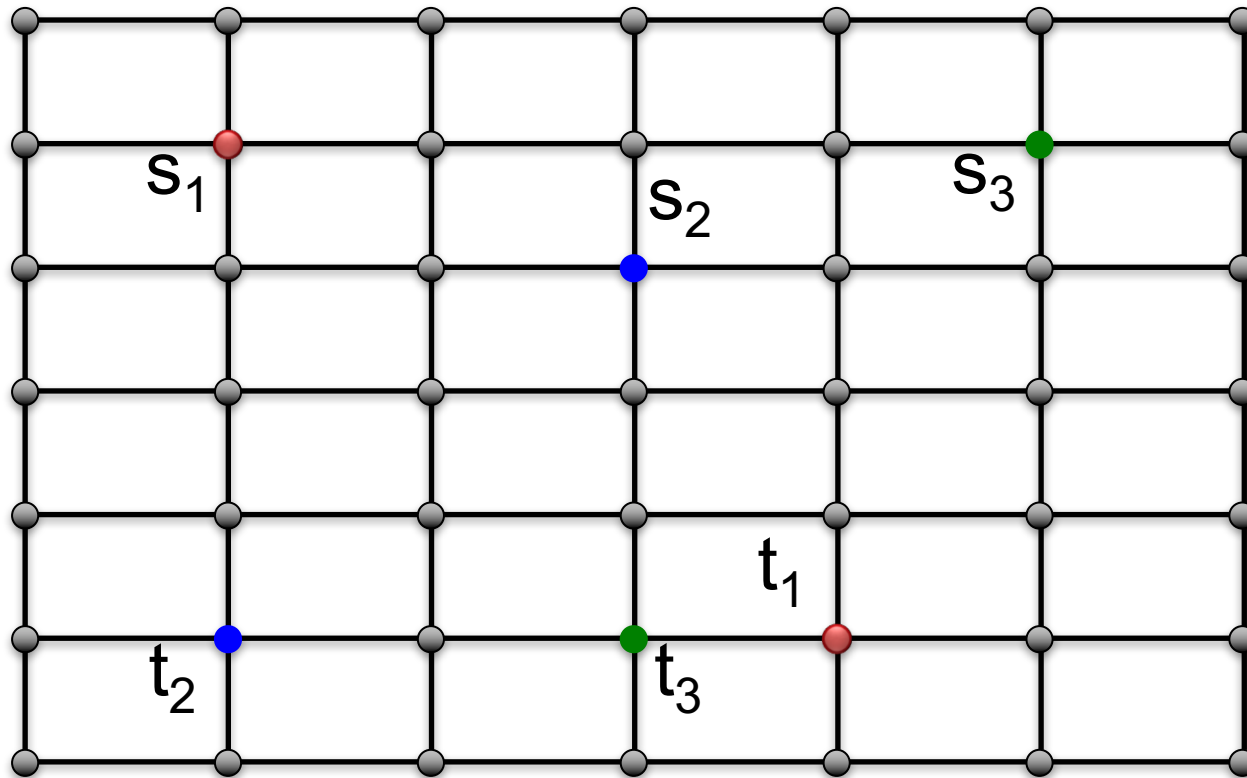
- Not if we use the maximum multicommodity flow approach!
- $\Omega(\log^{1/2-\epsilon} n)$ -hardness of approximation for any ϵ [Andrews, Zhang '05], [Andrews, C, Guruswami, Khanna, Talwar, Zhang '10]

Approximation Status of NDP

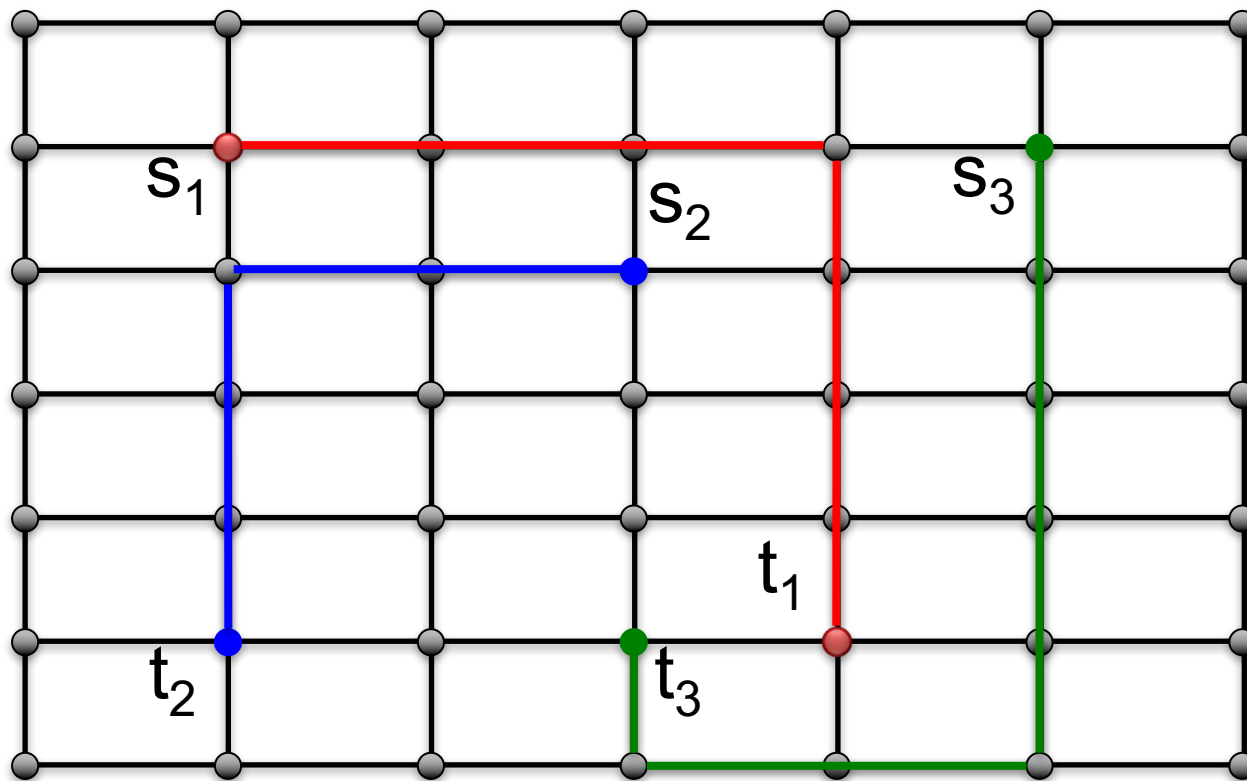
- $O(\sqrt{n})$ -approximation algorithm
 - even on planar graphs
 - even on grid graphs
- $\Omega(\log^{1/2-\epsilon} n)$ -hardness of approximation for any ϵ
[Andrews, Zhang '05], [Andrews, C, Guruswami, Khanna, Talwar, Zhang '10]

Only NP-hardness known for planar graphs and grids

NDP in Grids



NDP in Grids



Approximation Status of NDP

- $O(\sqrt{n})$ -approximation algorithm

Until recently:

- even on planar graphs
- even on grid graphs

[C, Kim '15]

- $\Omega(\log^{1/2-\epsilon} n)$ -hardness of $\tilde{O}(n^{1/4})$ -approximation

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$\tilde{O}(n^{1/4})$ -approximation

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$2^{\Omega(\sqrt{\log n})}$ -hardness of approximation for subgraphs of grids

Approximation Status of NDP

- $O(\sqrt{n})$ -approximation algorithms

Until recently:

– even

– even

- $\Omega(\log n)$ -hardness

[Andrews, Zhang '05], [Andrews, C, Guruswami, Khanna, Talwar, Zhang '10]

[C, Kim, Li '16]

Work in Progress:

Almost polynomial hardness for NDP in grid graphs [C, Kim, Nimavat '17]

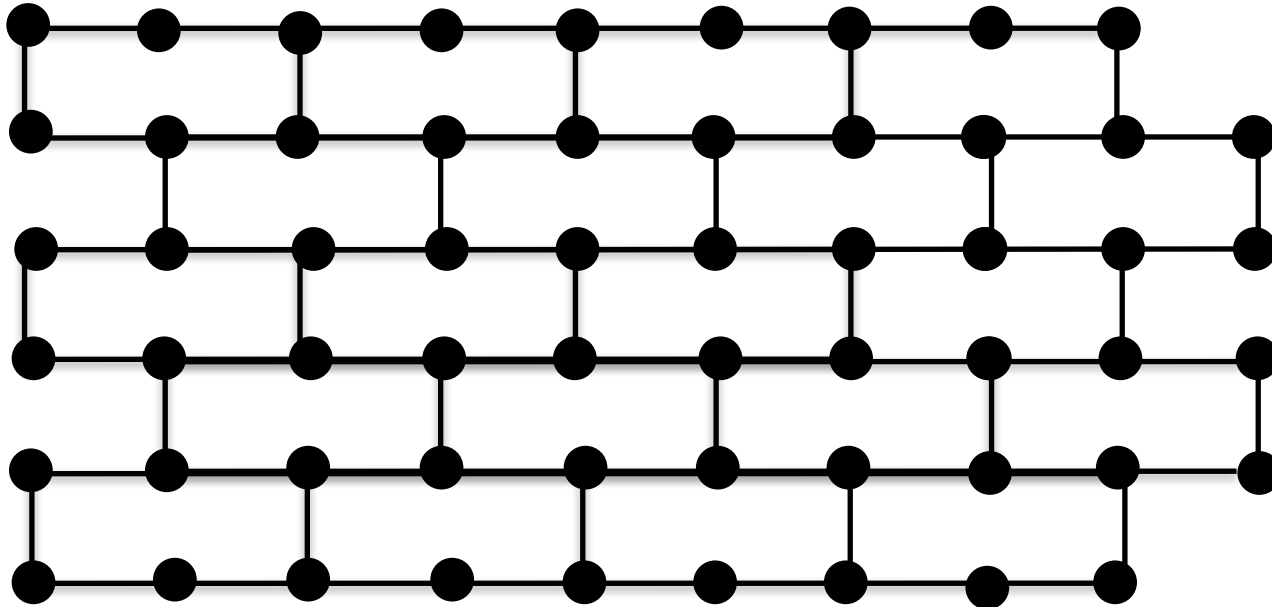
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$2^{\Omega(\sqrt{\log n})}$ -hardness of approximation for subgraphs of grids

Approximation Status of EDP

- $O(\sqrt{n})$ -approximation algorithm [Chekuri, Khanna, Shepherd '06]
- $2^{\Omega(\sqrt{\log n})}$ -hardness of approximation even for subgraphs of wall graphs [C, Kim, Nimavat '16]

A Wall



Approximation Status of EDP

- $O(\sqrt{n})$ -approximation algorithm [Chekuri, Khanna, Shepherd '06]
- $2^{\Omega(\sqrt{\log n})}$ -hardness of approximation even for subgraphs of wall graphs [C, Kim, Nimavat '16]
- Work in progress: almost polynomial hardness for EDP on wall graphs [C, Kim, Nimavat '17]

Summary so Far

EDP and NDP do not have reasonable approximation algorithms, even on planar graphs

What if we allow
some congestion?

EDP/NDP with Congestion

An α -approximation algorithm with congestion c routes OPT/α demand pairs with congestion at most c .

up to c paths can share an edge or a vertex

EDP/NDP with Congestion

An α -approximation algorithm with congestion c routes OPT/α demand pairs with congestion at most c .

optimum number of pairs
with no congestion allowed

EDP with Congestion

- Congestion $O(\log n / \log \log n)$: constant approximation [Raghavan, Thompson '87]
- Congestion c : $O(n^{1/c})$ -approximation [Azar, Regev '01], [Baveja, Srinivasan '00], [Kolliopoulos, Stein '04]
- Congestion $\text{poly}(\log \log n)$: $\text{polylog}(n)$ -approx [Andrews '10]
- Congestion 2: $O(n^{3/7})$ -approximation [Kawarabayashi, Kobayashi '11]
- Congestion 14: $\text{polylog}(k)$ -approximation [C, '11]
- Congestion 2: $\text{polylog}(k)$ -approximation [C, Li '12]
- $\text{polylog}(k)$ -approximation for NDP with congestion 2 [Chekuri, Ene '12], [Chekuri, C '16]

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- $\text{polylog}(k)$ -approx for NDP with congestion 2 [Chekuri, Ene '12], [Chekuri, C '16]

All these results are based on the multicommodity flow relaxation

“Tight” due to known hardness results

EDP with Congestion

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- Congestion 14: $\text{polylog}(k)$ -approximation [C, '11]
- new results in $\text{polylog}(k)$ -approximation [C, Li '12]
- graph theory! approximation for NDP with congestion 2 [Chekuri, Ene '12], [Chekuri, C '16]

Structural results
about graphs

graph theory!

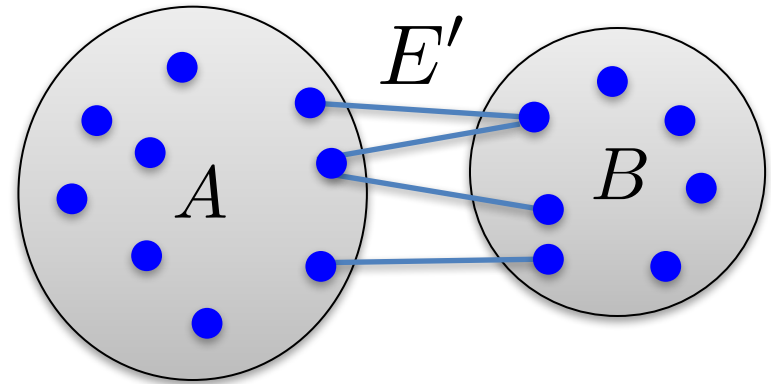
EDP with Congestion

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Edge-Disjoint Paths with Constant Congestion

EDP on Expanders

$$|E'| \geq \frac{\min\{|A|, |B|\}}{2}$$



In a strong enough expander, if the set of demand pairs is not too large, can route almost all of them on Node-Disjoint Paths!

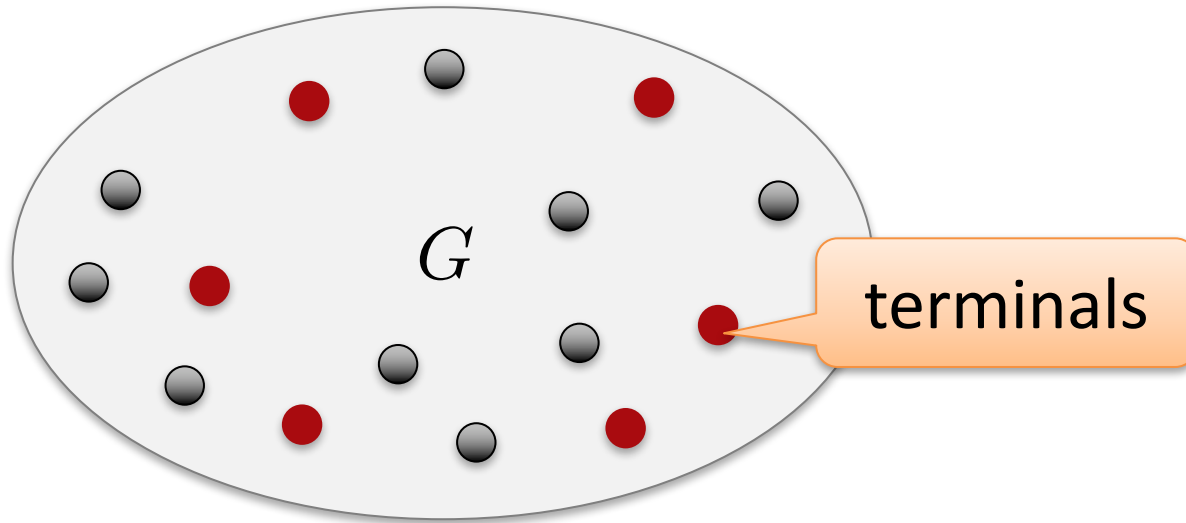
Main Idea: Exploit Algorithms for Expanders!

But our graph is nothing like an expander

Find expander-like structure in the graph and use it for routing!

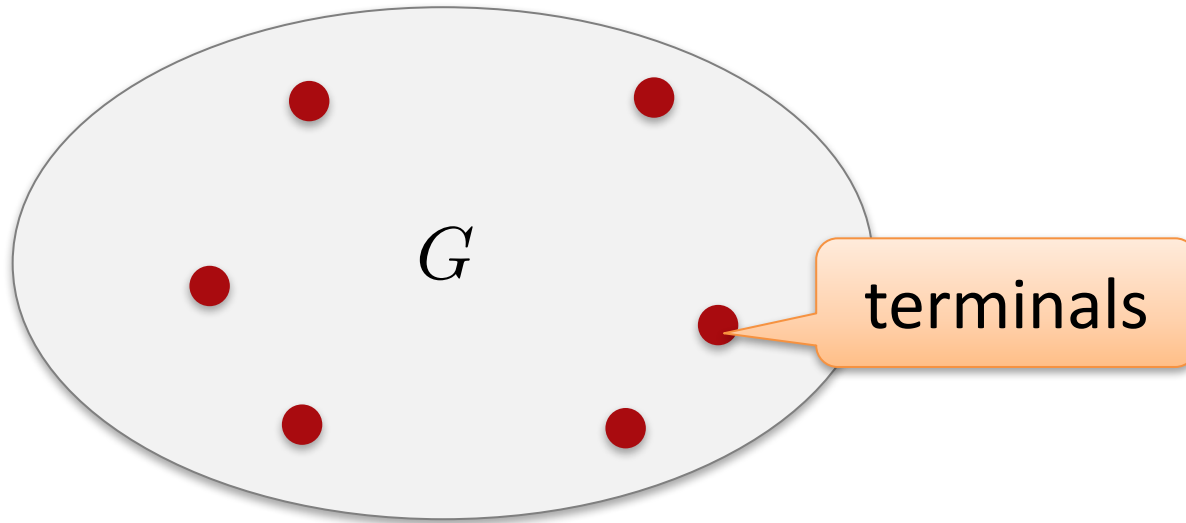
Well-Linkedness

[Robertson, Seymour], [Chekuri, Khanna, Shepherd], [Raecke]



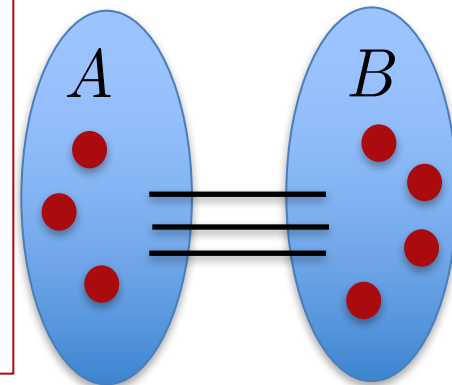
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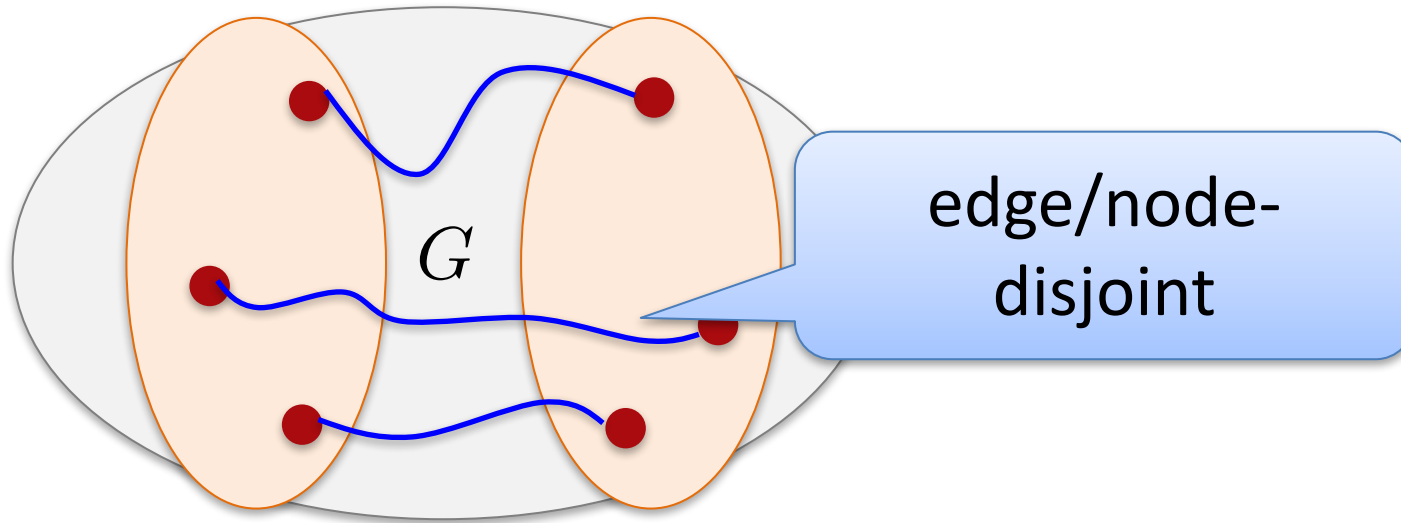
Set T of terminals is well-linked in G , iff for any partition (A, B) of $V(G)$,

$$|E(A, B)| \geq \min\{|A \cap T|, |B \cap T|\}$$



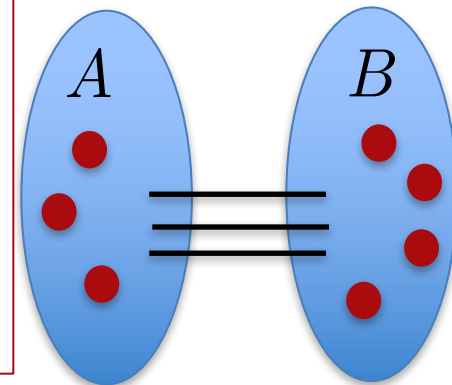
Well-Linkedness

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EDP: Well-Linked Instances

- **Terminals**: vertices participating in the demand pairs
- An instance is **well-linked** iff the set of terminals is well-linked in G .

Theorem [Chekuri, Khanna Shepherd '04]: an α -approximation algorithm on well-linked instances gives an $O(\alpha \log^2 k)$ -approximation on any instance.

EDP: Well-Linked Instances

- **Terminals**: vertices participating in the demand pairs
- An instance is **well-linked** iff the graph with terminals is well-linked in G .

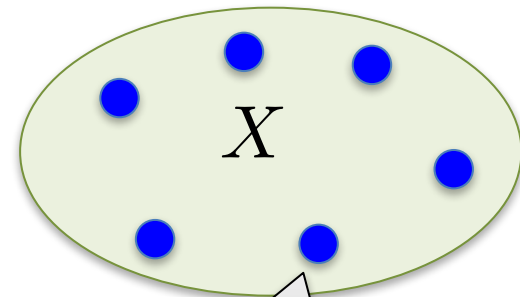
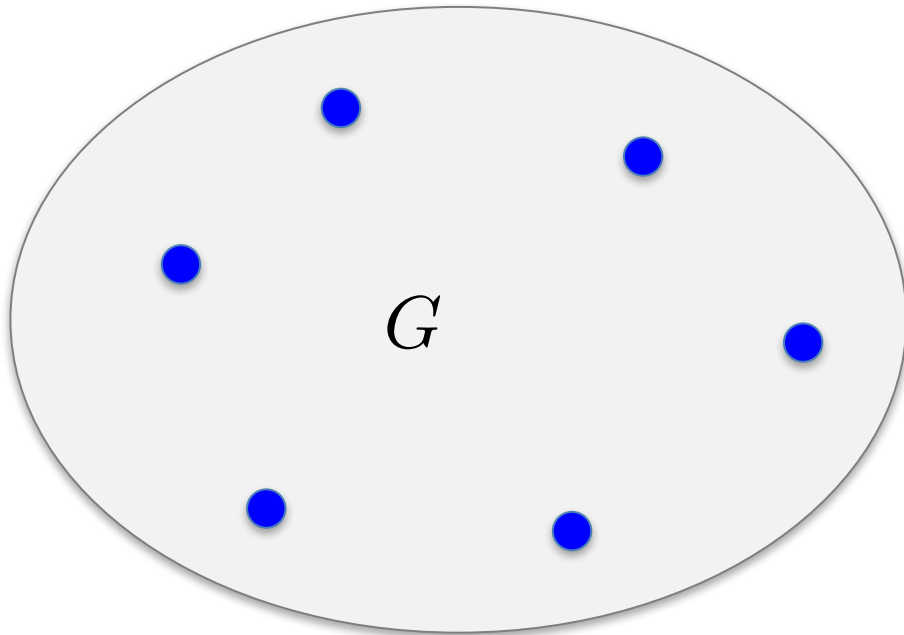
Only true if the algorithm rounds the flow relaxation

Theorem [Chekuri, Khanna Shepherd '04]: an α -approximation algorithm on well-linked instances gives an $O(\alpha \log^2 k)$ -approximation on any instance.

Main Idea

[Chekuri, Khanna, Shepherd], [Rao, Zhou]

Embed an expander over the terminals into G !

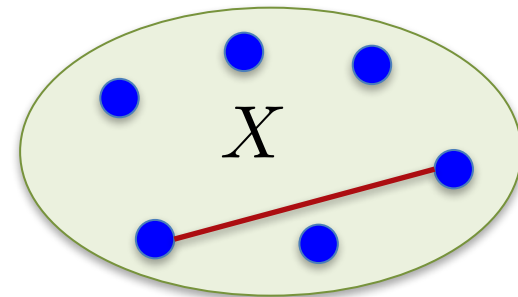
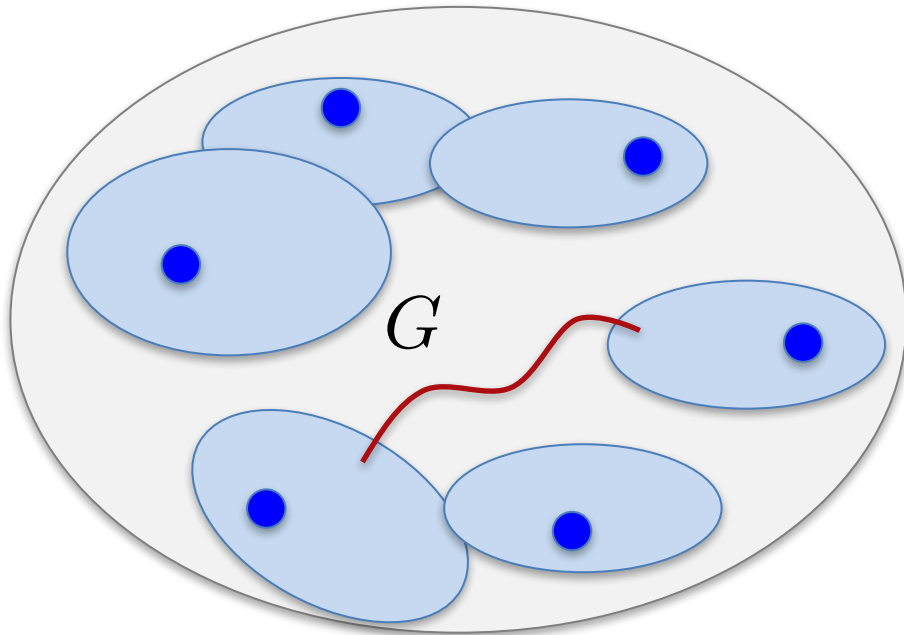


terminals of G

Main Idea

[Chekuri, Khanna, Shepherd], [Rao, Zhou]

Embed an expander over the terminals into G !



An edge of G may belong to at most 2 clusters/paths

Main Idea

[Chekuri, Khanna, Shepherd], [Rao, Zhou]

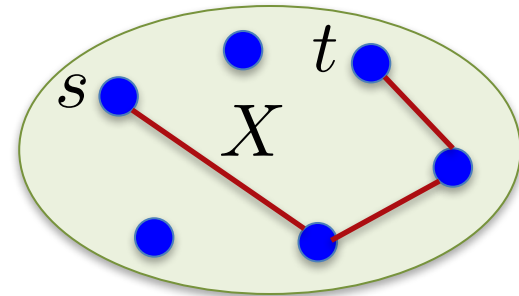
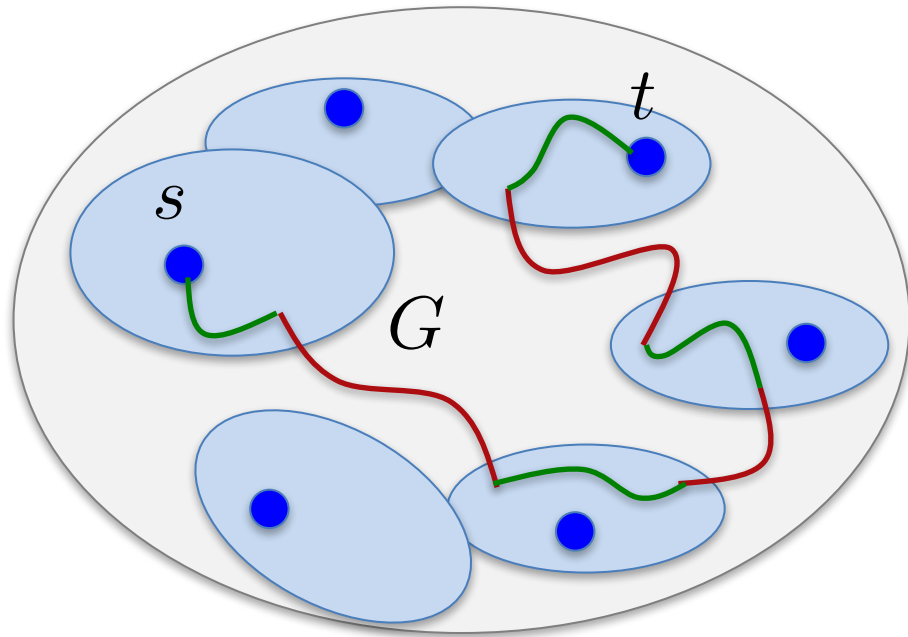
1. Embed an expander over the terminals into G

2. Find a routing on node-disjoint paths in the expander

3. Translate it into congestion-2 routing in G

An edge of G may belong to at most 2 clusters/paths

Embedding an Expander into G



Routing on **vertex-disjoint** paths in X gives a good routing in G !

Main Idea

1. Embed an expander over the terminals into G

2. Find a routing on node-disjoint paths in the expander

3. Translate it into congestion-2 routing in G

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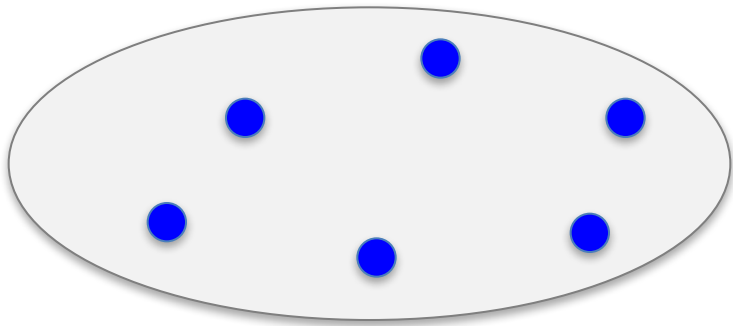
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An edge of G may belong to at most 2 clusters/paths

Cut-Matching Game [Khandekar, Rao, Vazirani '06]

Cut Player: wants to build an expander

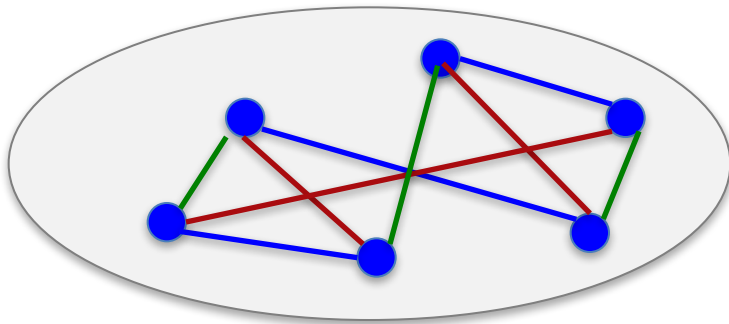
Matching Player: wants to delay its construction



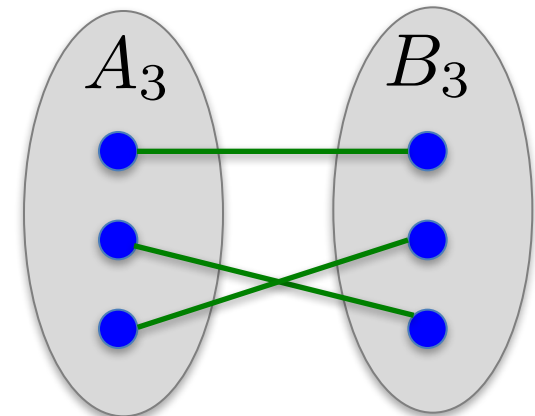
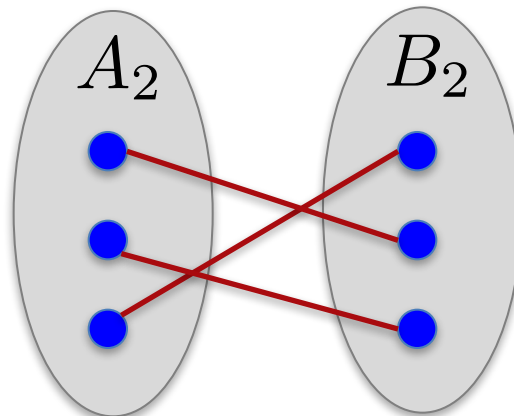
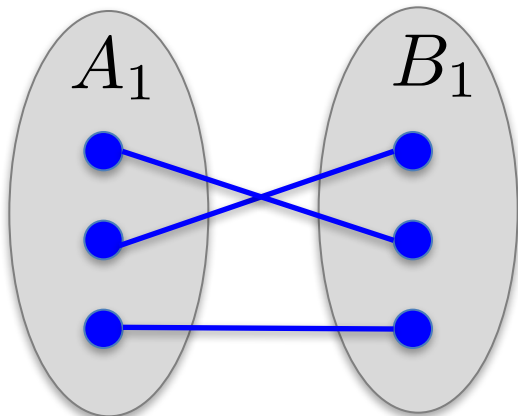
Cut-Matching Game [Khandekar, Rao, Vazirani '06]

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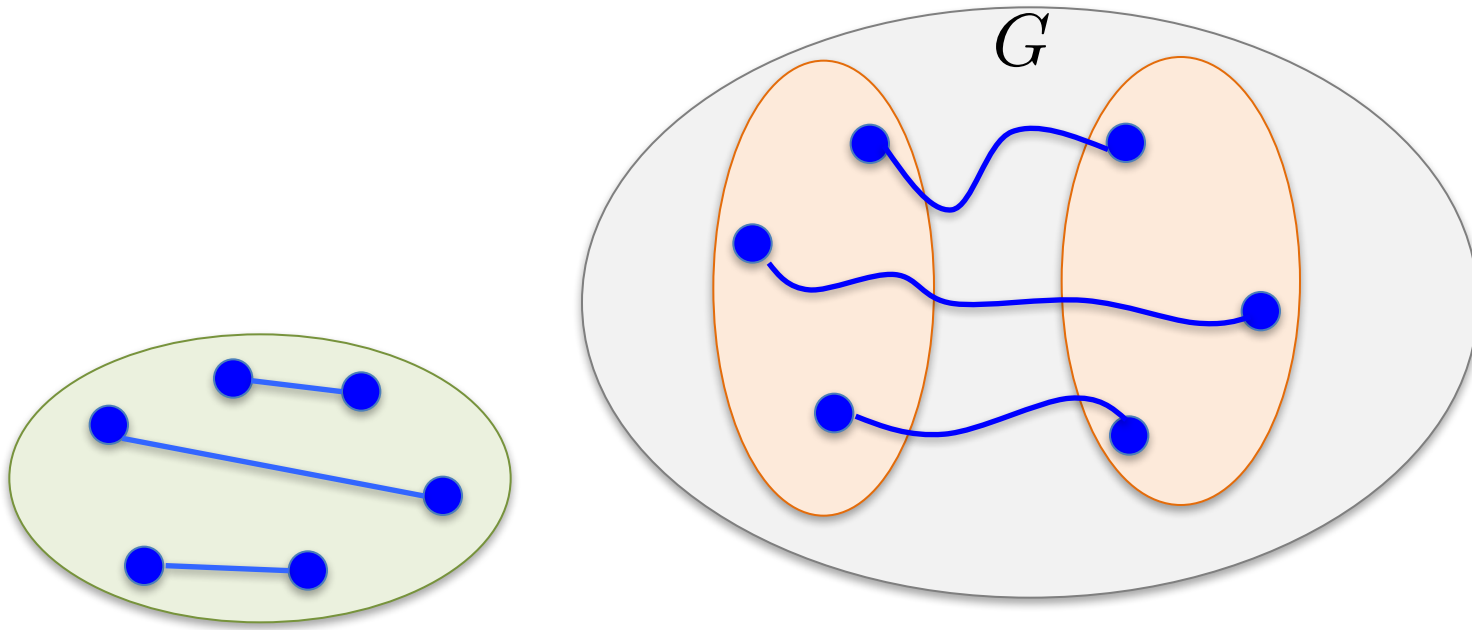
Matching Player: wants to delay its construction



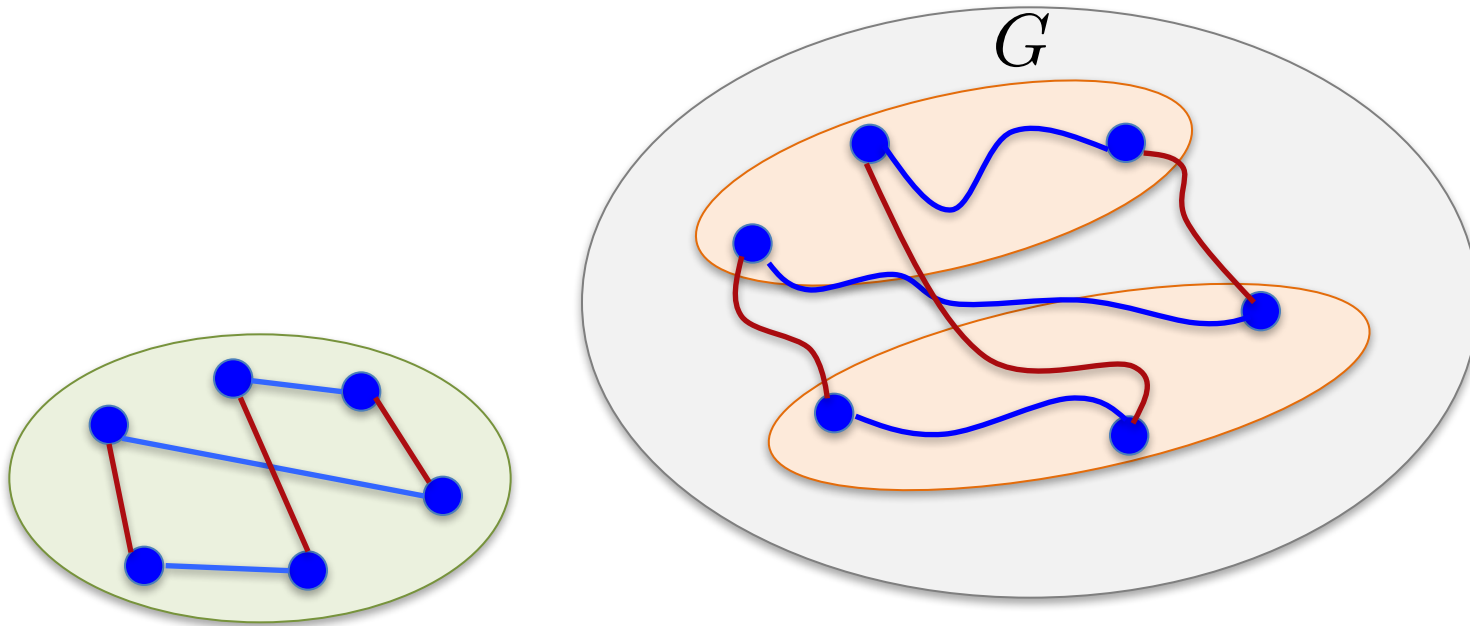
There is a strategy for cut player, s.t. after $O(\log^2 n)$ iterations, we get an expander!



Embedding Expander into Graph



Embedding Expander into Graph



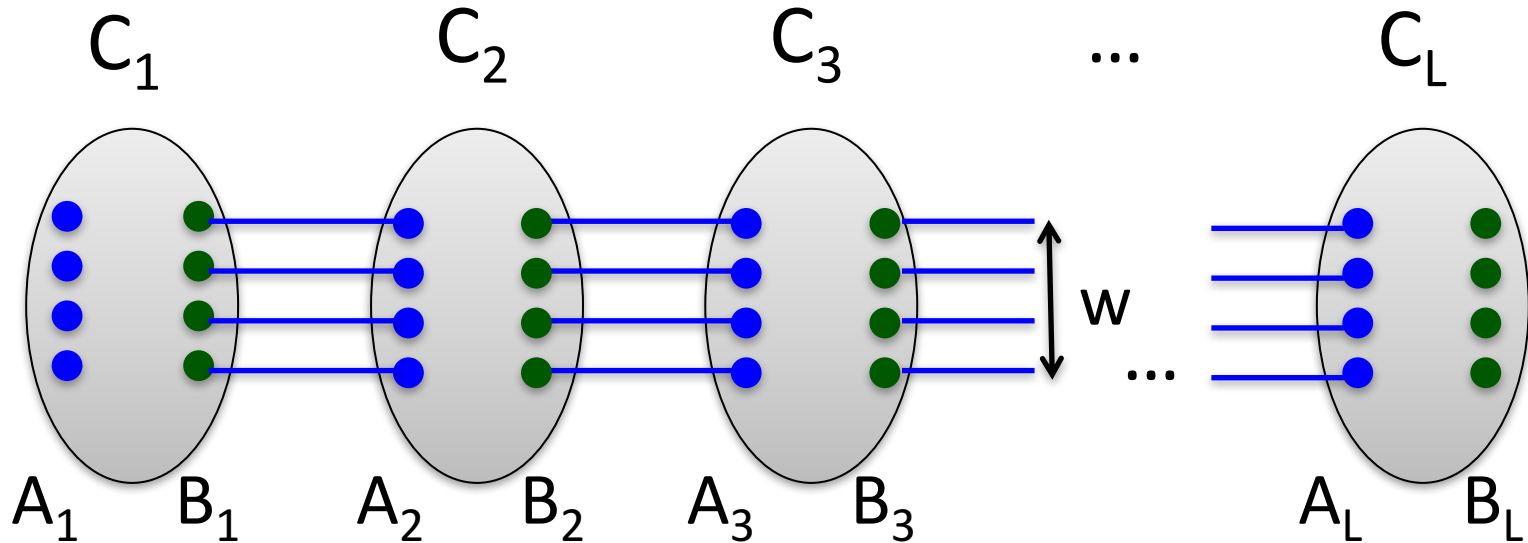
After $O(\log^2 k)$ iterations, we get an expander embedded into G .

Problem: congestion $\Omega(\log^2 k)$

Path-of-Sets System

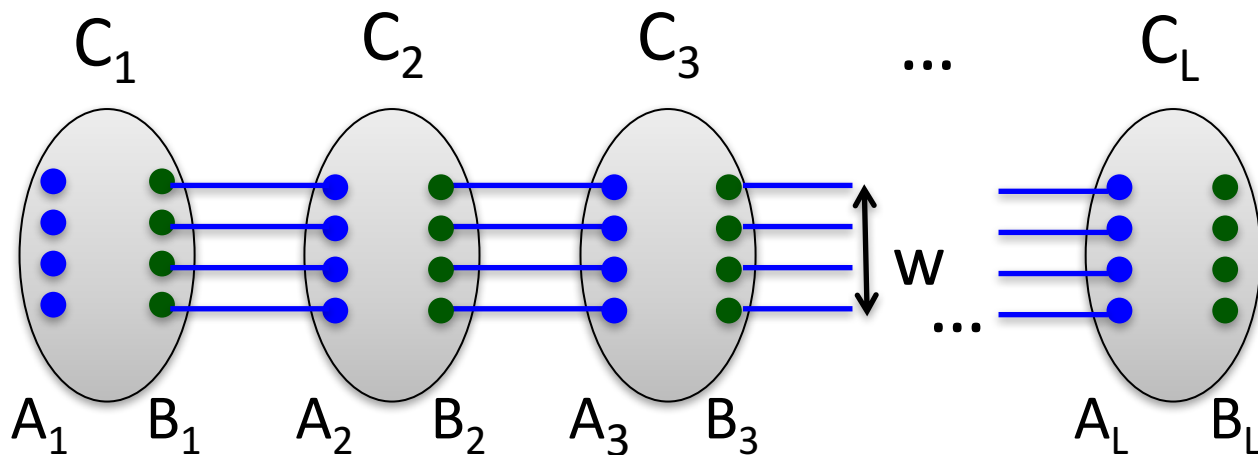
A Path-of-Sets System

width w
length L



- L disjoint connected clusters
- Two disjoint sets A_i, B_i of w vertices in each cluster C_i
- $A_i \cup B_i$ is well-linked in C_i
- For all i , set P_i of w disjoint paths connecting B_i to A_{i+1}
- All paths are disjoint from each other and internally disjoint from clusters

From Well-Linkedness to Path-of-Sets



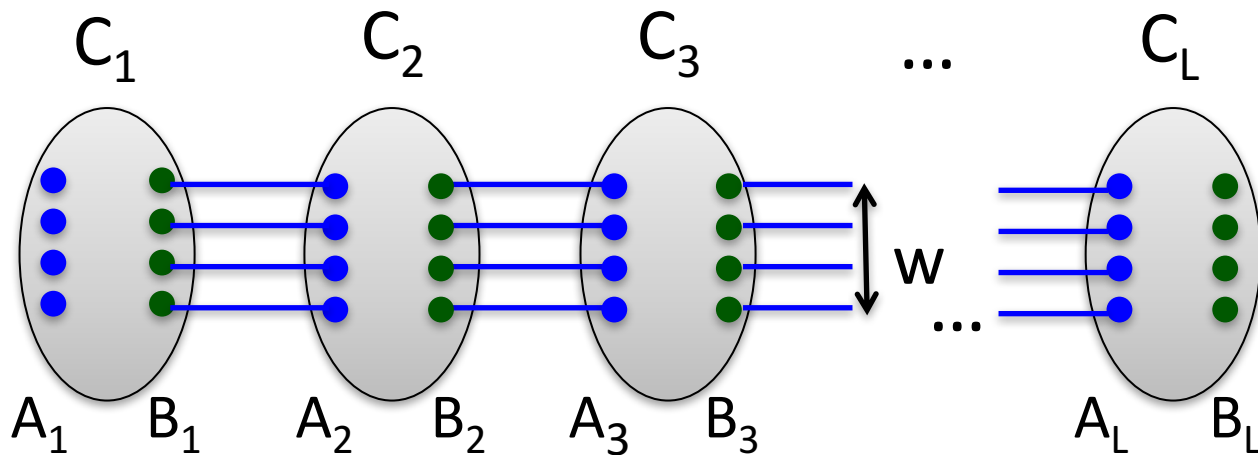
Theorem [C, '11], [C, Li '12], [Chekuri, C '13]:

Suppose G has a set of k well-linked vertices.

Then we can efficiently construct a path-of-sets system in

G with parameters L and w , if: $w \cdot L^{48} < \tilde{O}(k)$

From Well-Linkedness to Path-of-Sets



We'll use:
 $L = O(\log^2 k)$
 $w = k / \text{polylog } k$

Theorem [C, '11], [C, Li '12], [Chekuri, C '13]:

Suppose G has a set of k well-linked vertices.

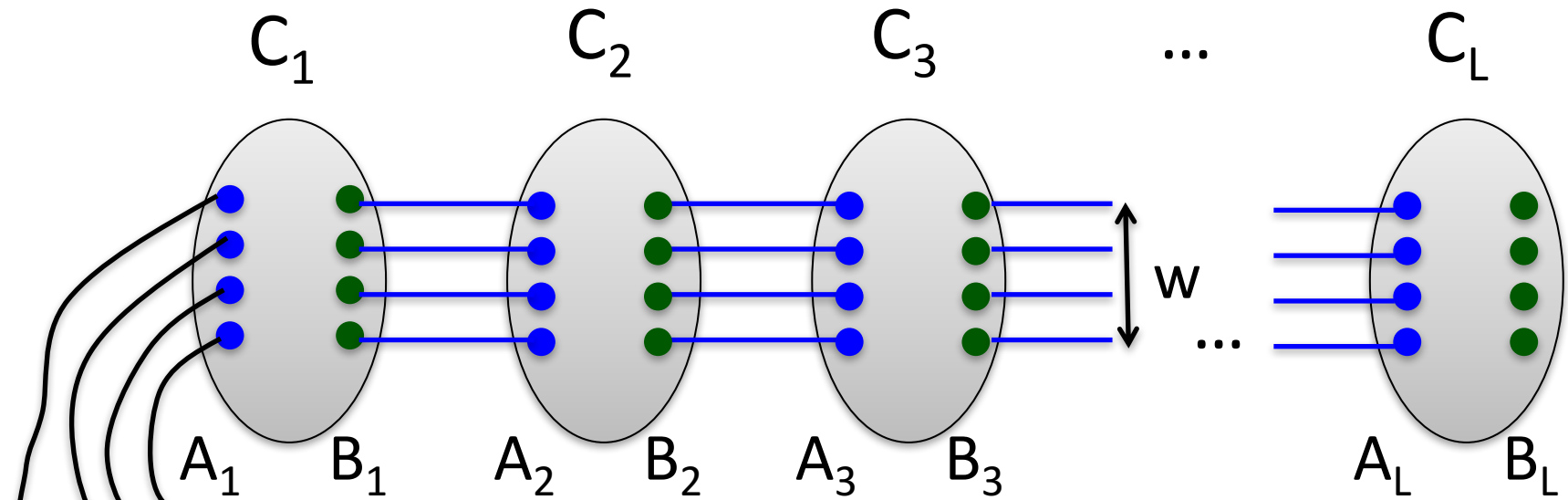
Then we can efficiently construct a path-of-sets system in

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Extras:

- Can connect w terminals to A_1 by disjoint paths
- Can make sure they form demand pairs!

From Well-Linkedness to Path-of-Sets

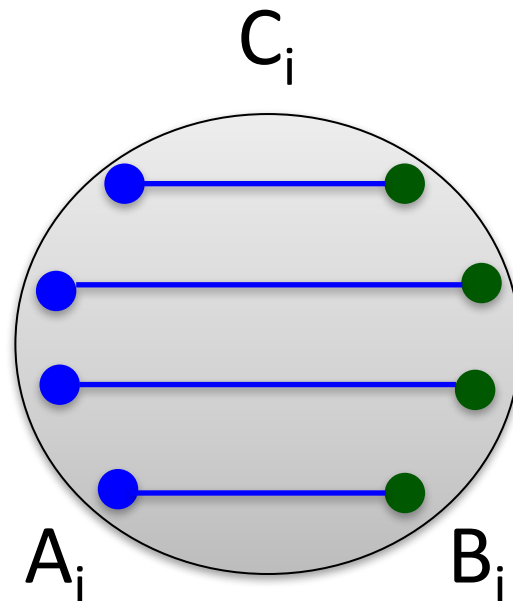
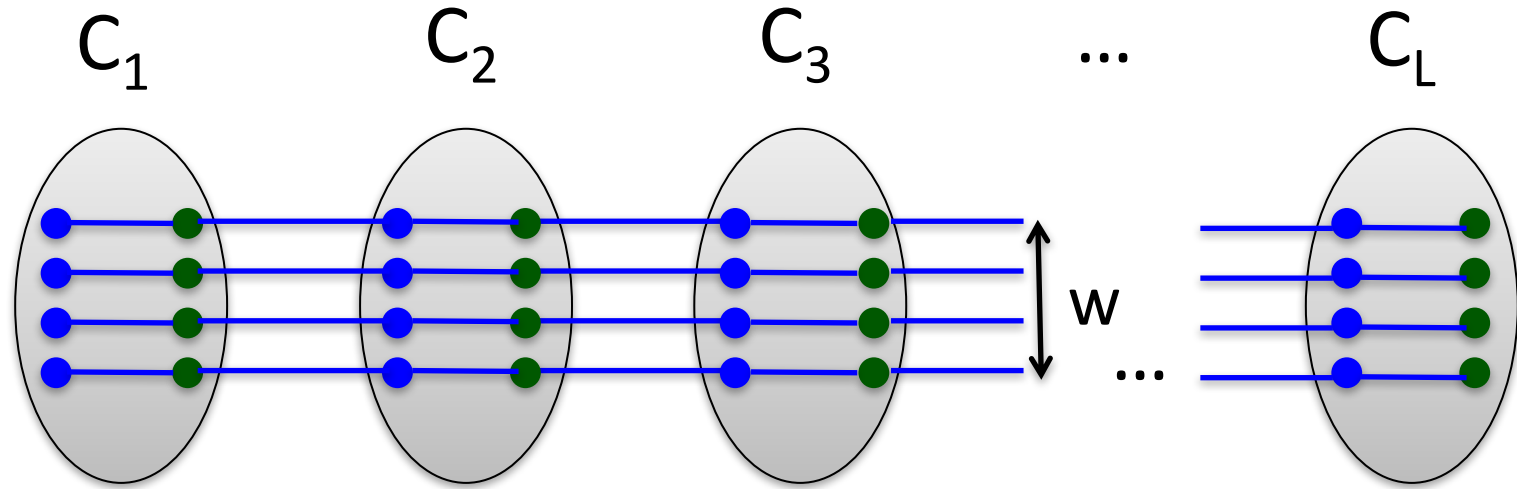


The terminals form demand pairs

The paths are disjoint from each other and the PoS system

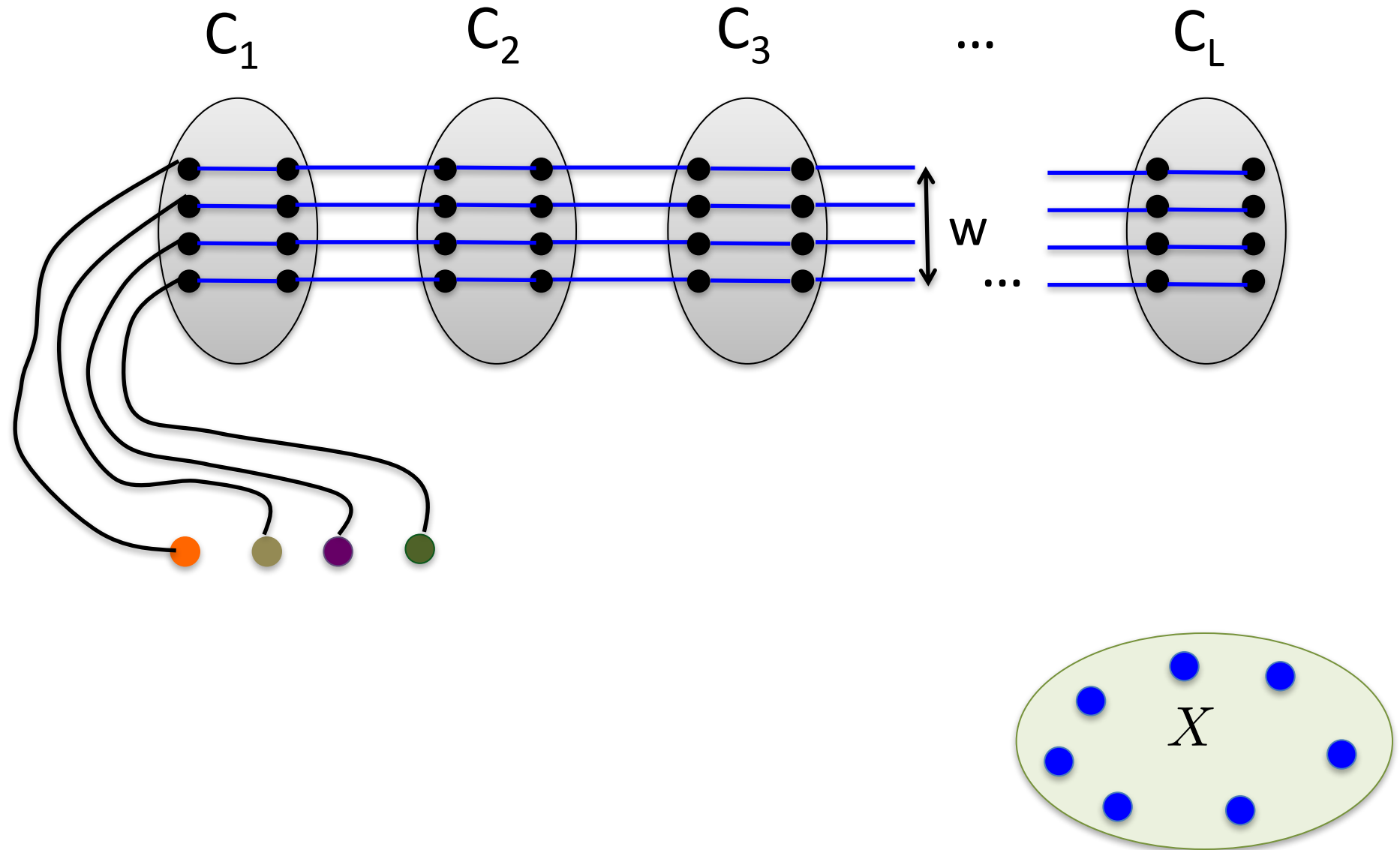
Given the PoS, can embed an expander!

Embedding the Expander

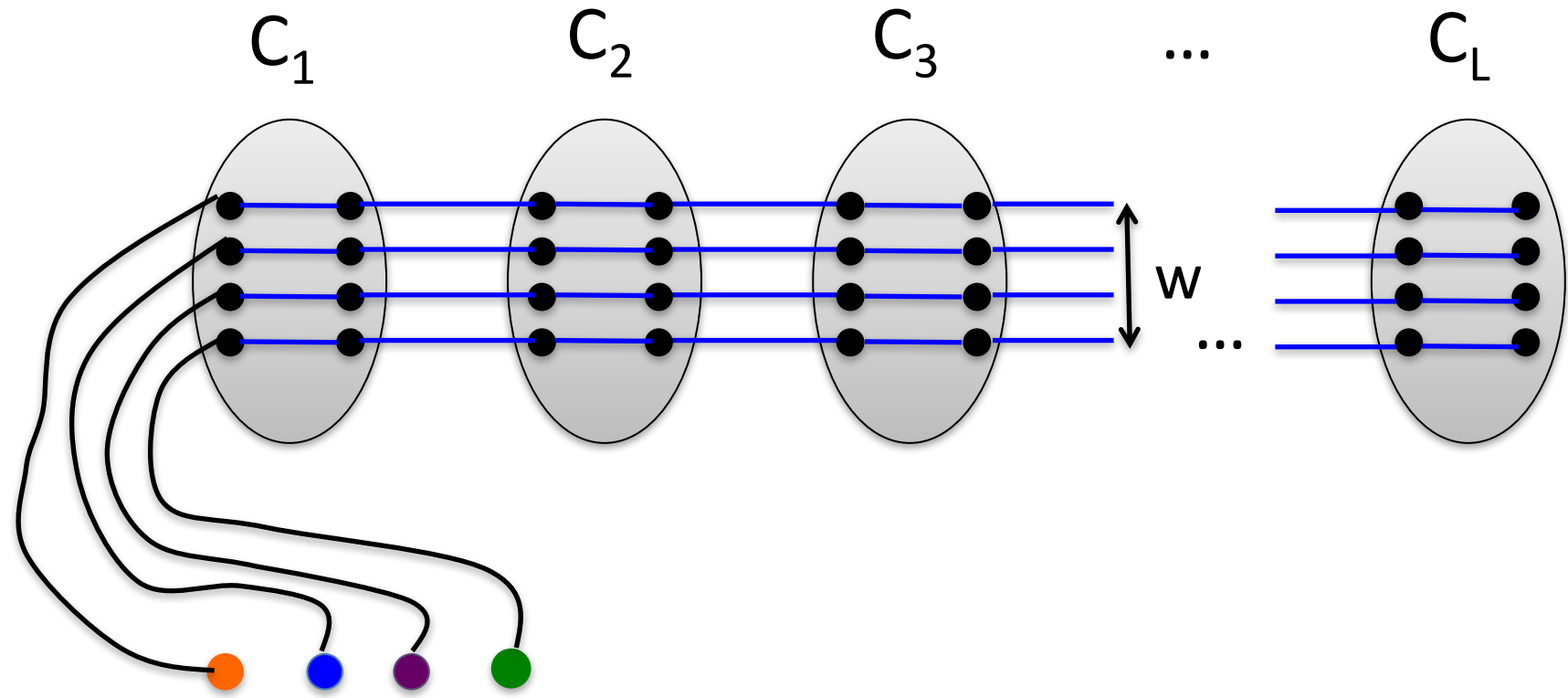


$A_i \cup B_i$ is well-linked inside C_i

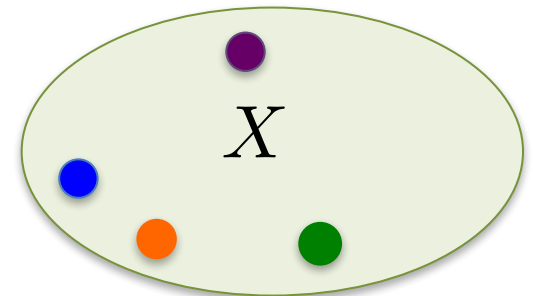
Embedding the Expander



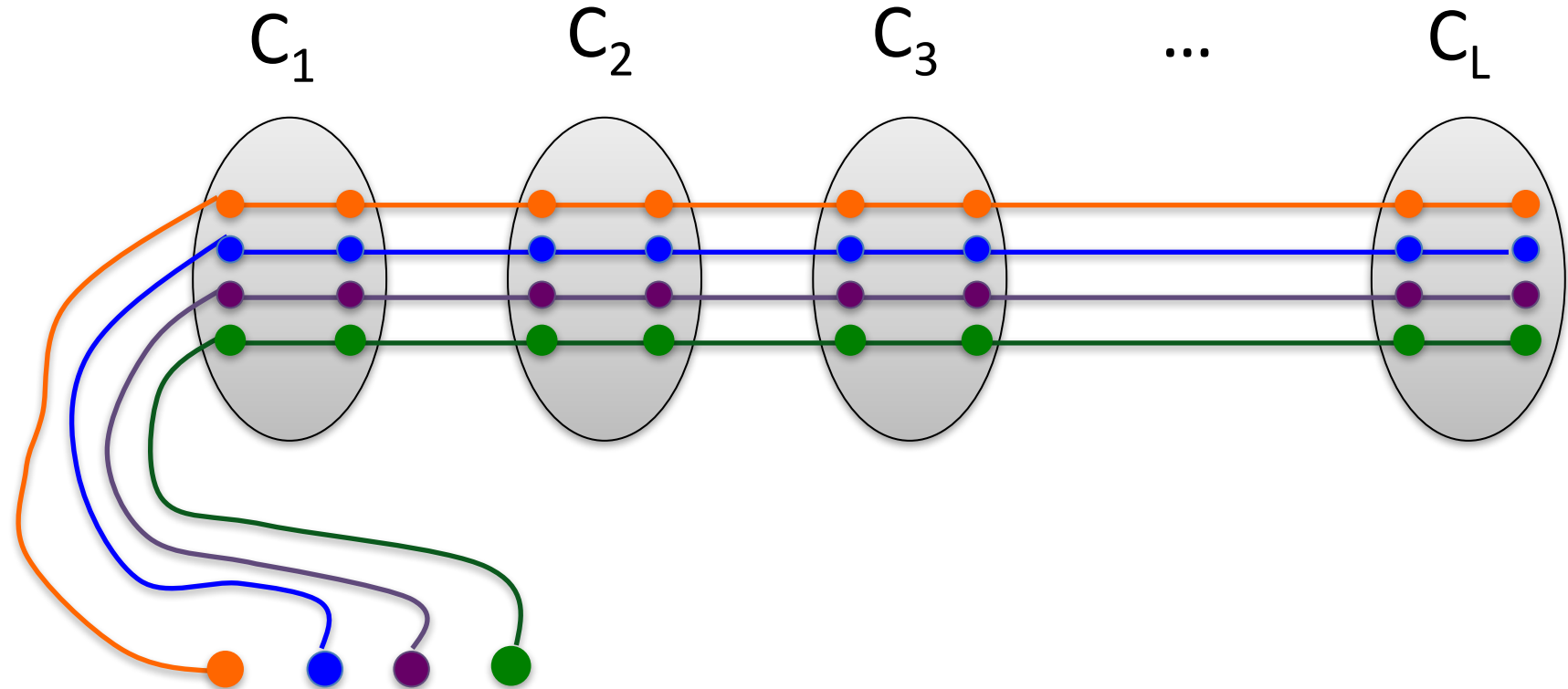
Embedding the Expander



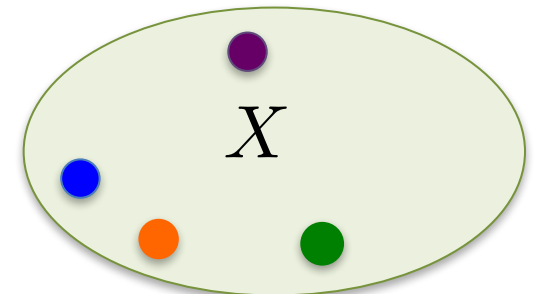
Expander vertex \longrightarrow the path containing the terminal



Embedding the Expander

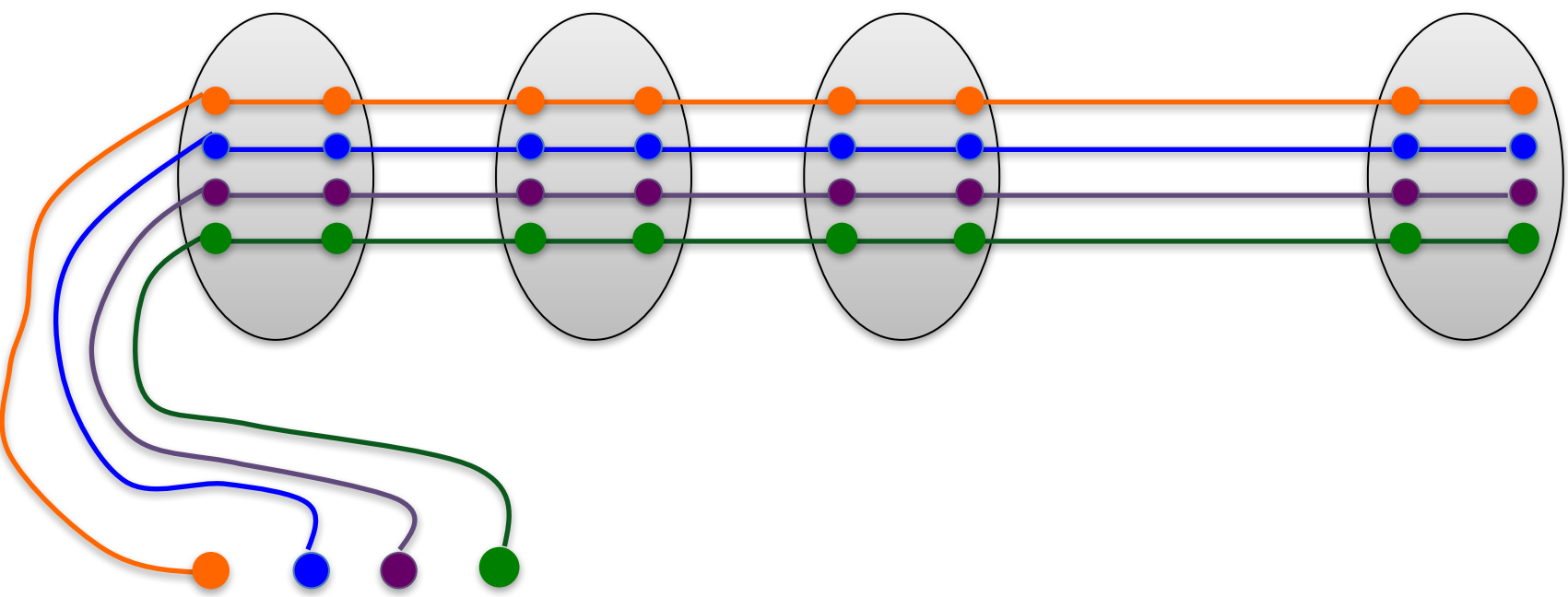


Expander vertex \longrightarrow the path
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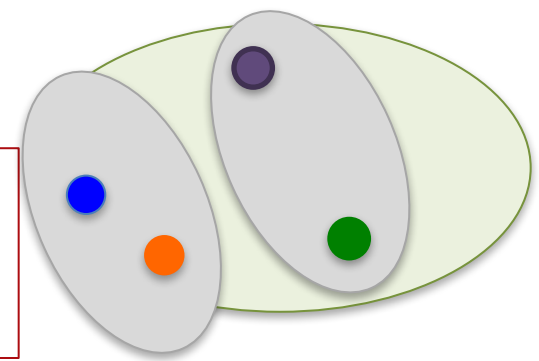


Embedding the Expander

C_1 C_2 C_3 ... C_L

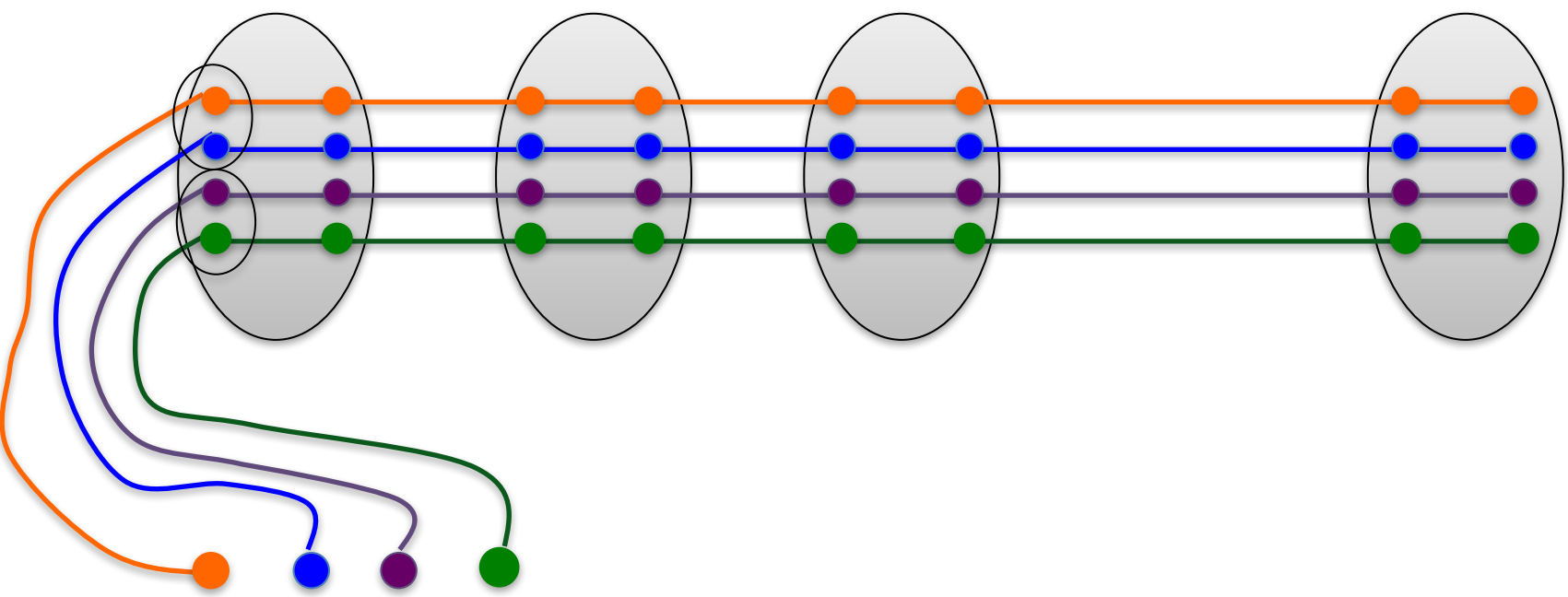


Expander edges? \longrightarrow cut-matching game!

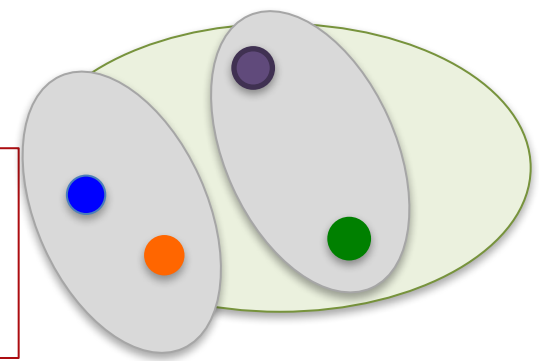


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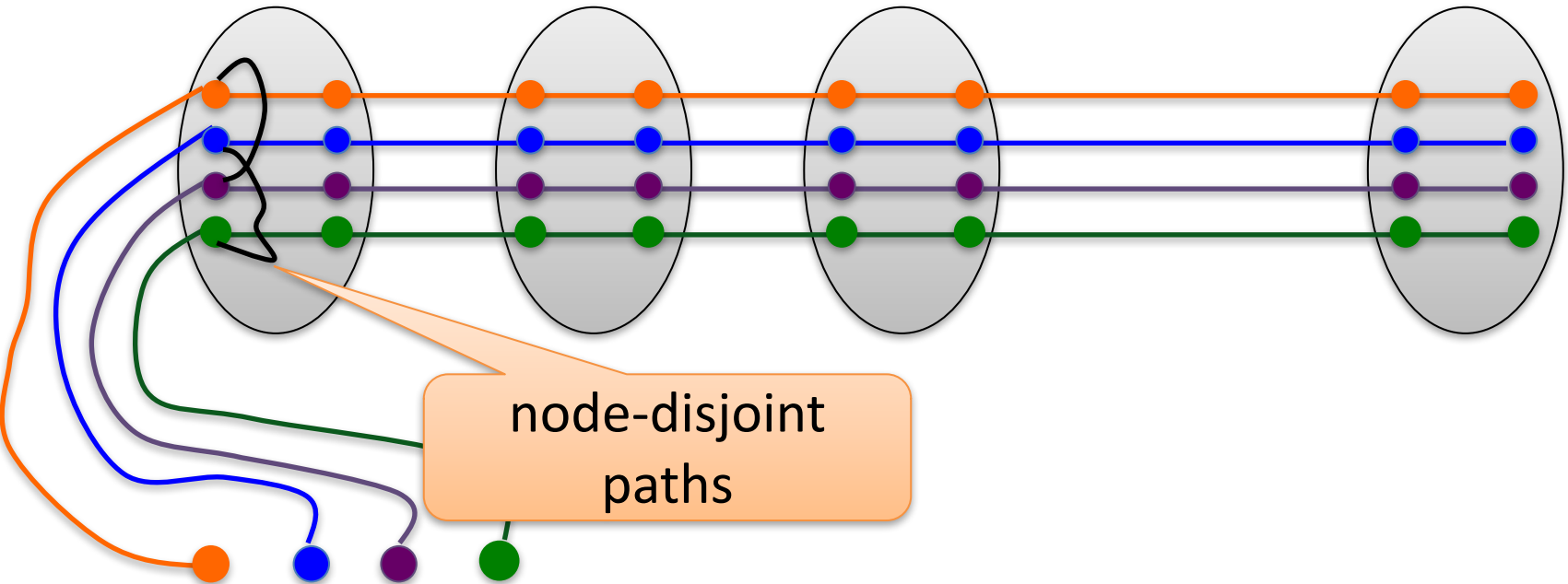


Expander edges? \longrightarrow cut-matching game!

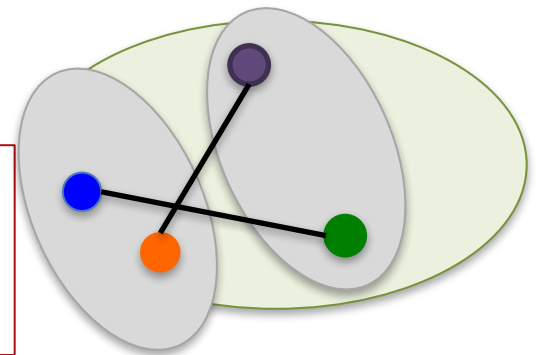


Embedding the Expander

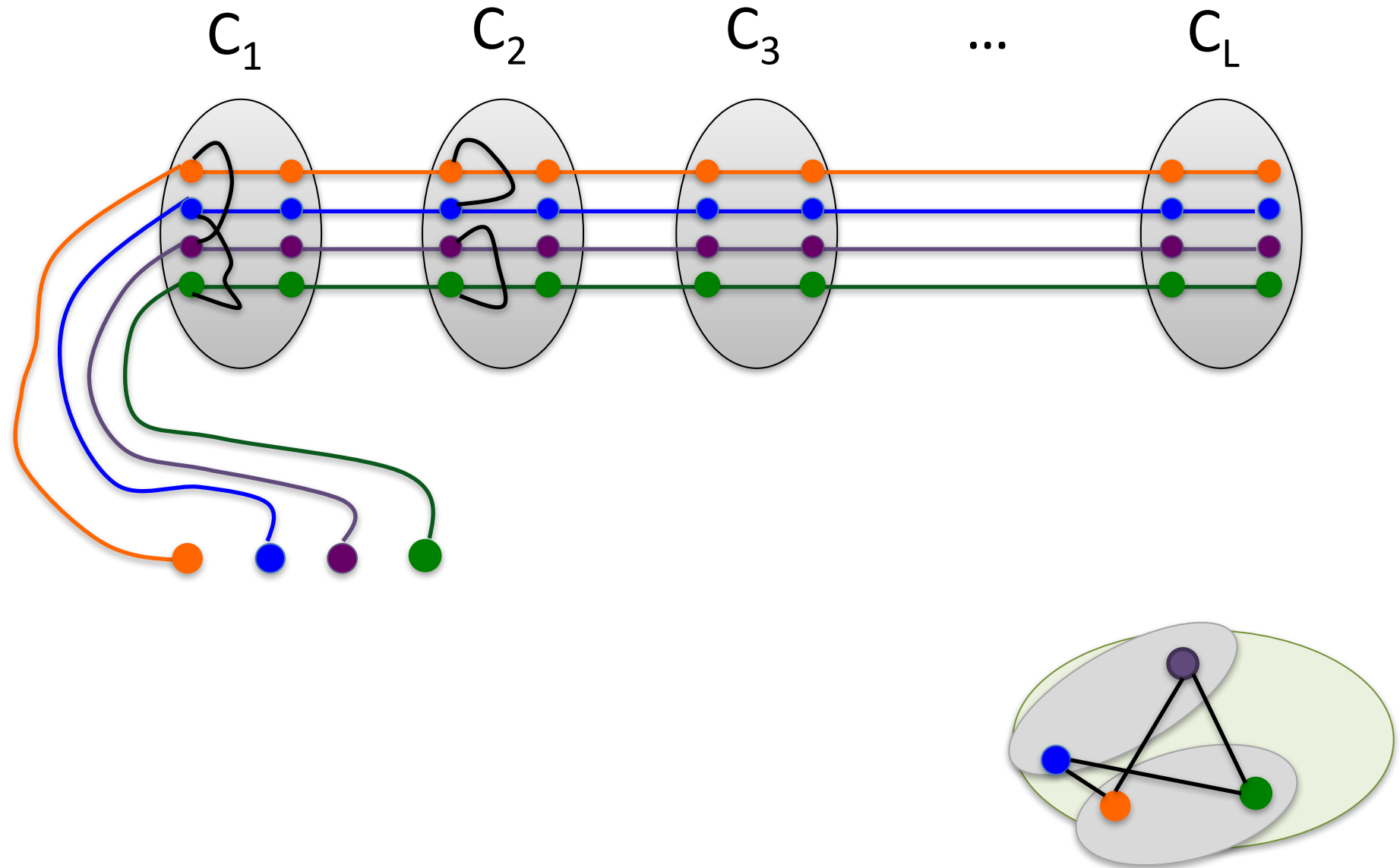
C_1 C_2 C_3 ... C_L



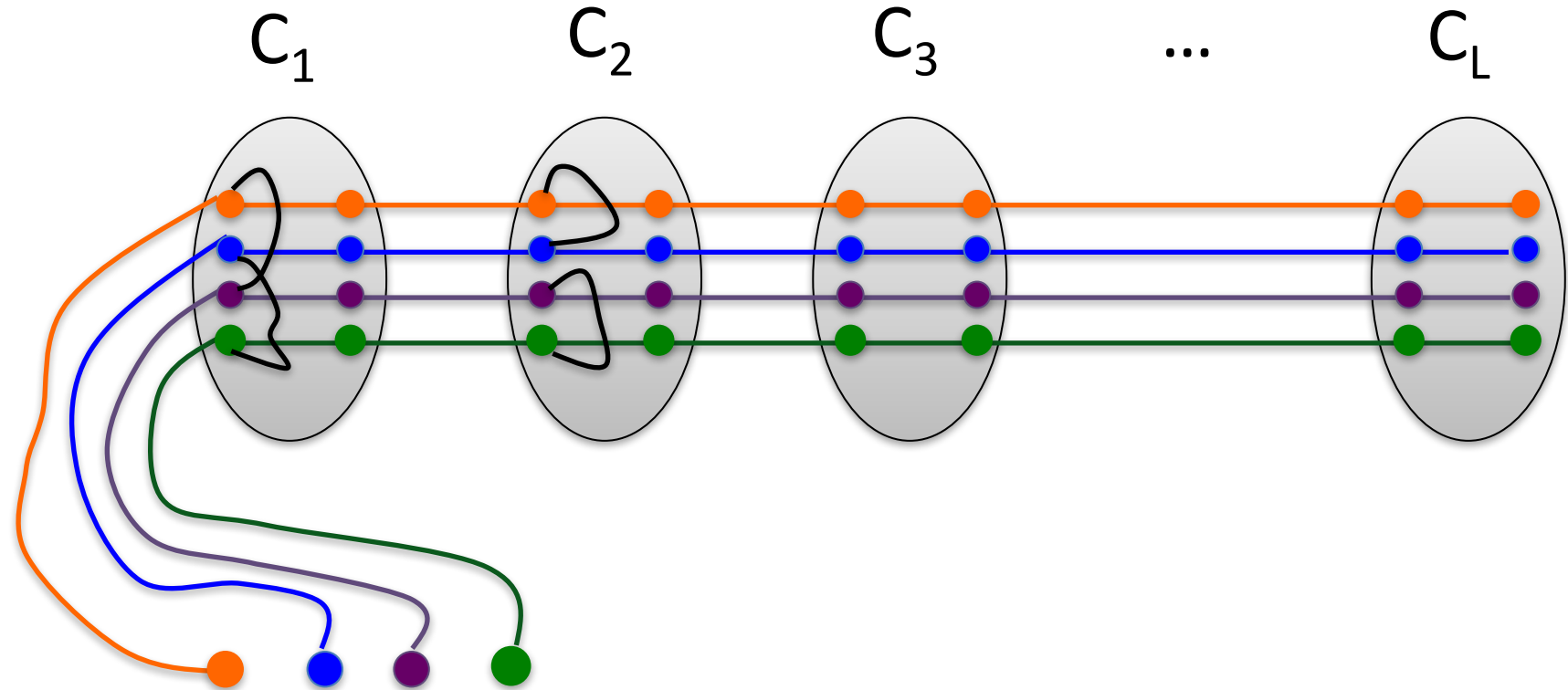
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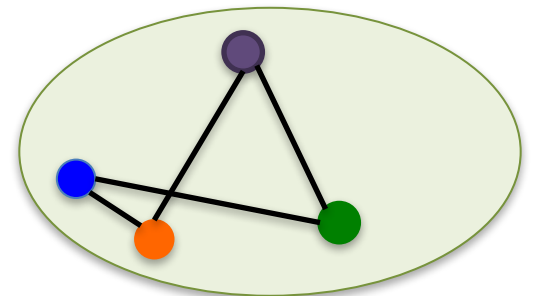
Embedding the Expander



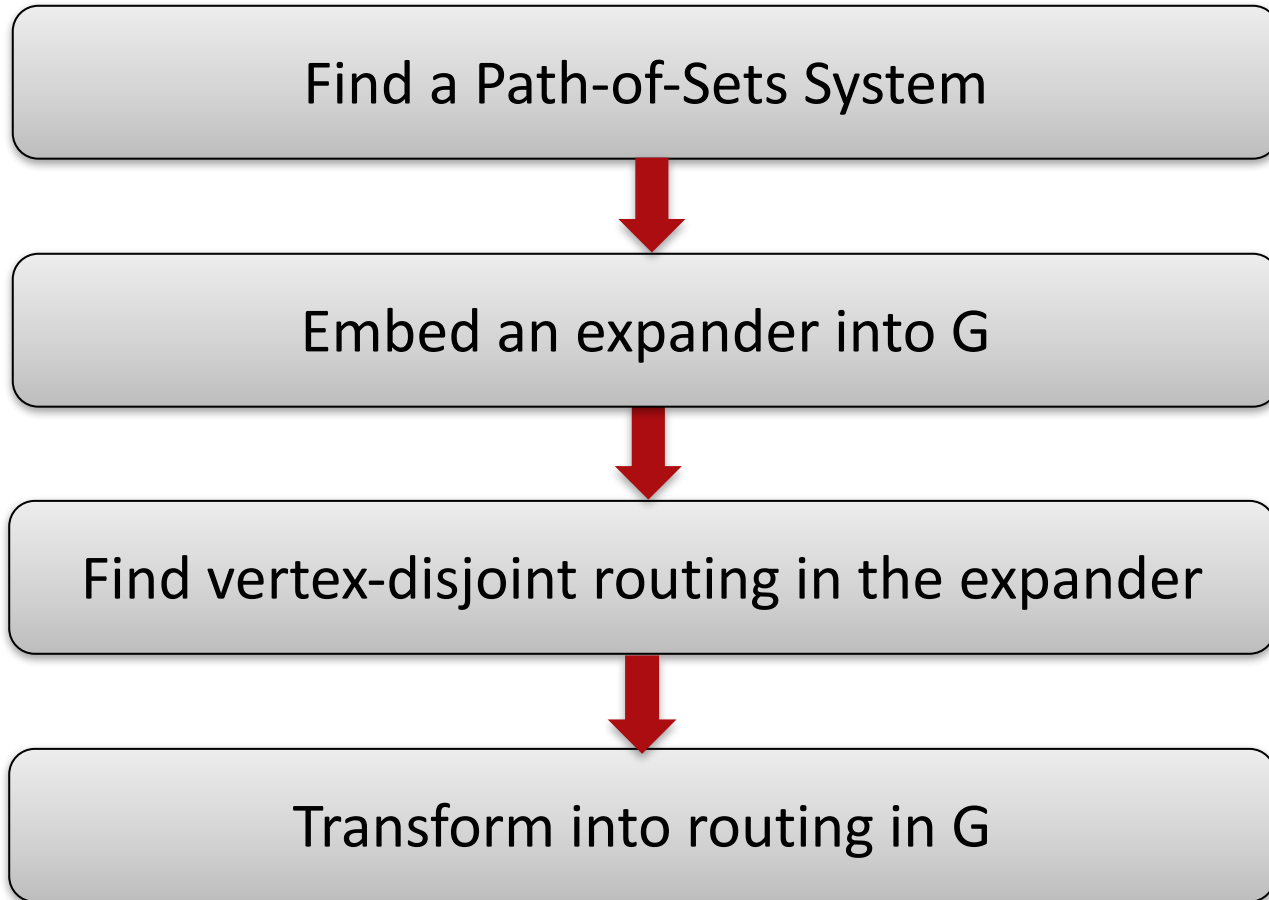
Embedding the Expander



After $O(\log^2 k)$ iterations, we obtain an expander embedded into G with congestion 2.



Algorithm for EDPwC in Well-Linked Instances



Structural Result

If G contains a large well-linked set of vertices,
then it contains a large Path-of-Sets System

Excluded grid
theorem

Treewidth
sparsifiers

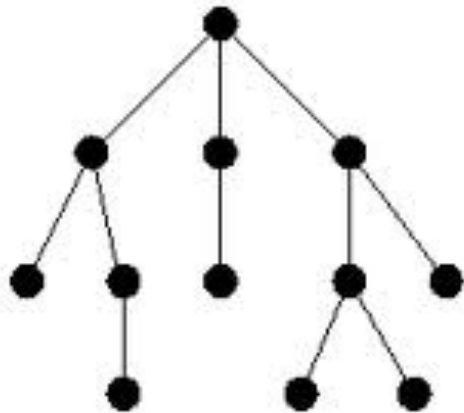
Large-treewidth
graph
decompositions

Vertex flow
sparsifiers

Excluded Grid Theorem [Robertson, Seymour]

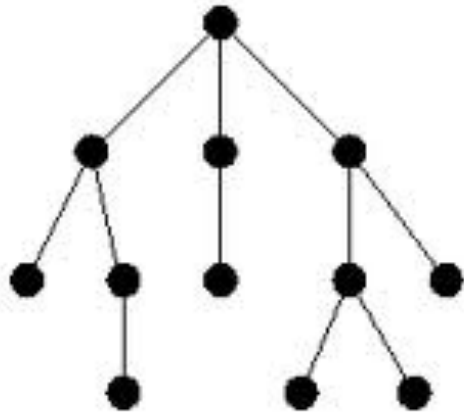
Excluded Grid Theorem [Robertson, Seymour]

Simple graphs

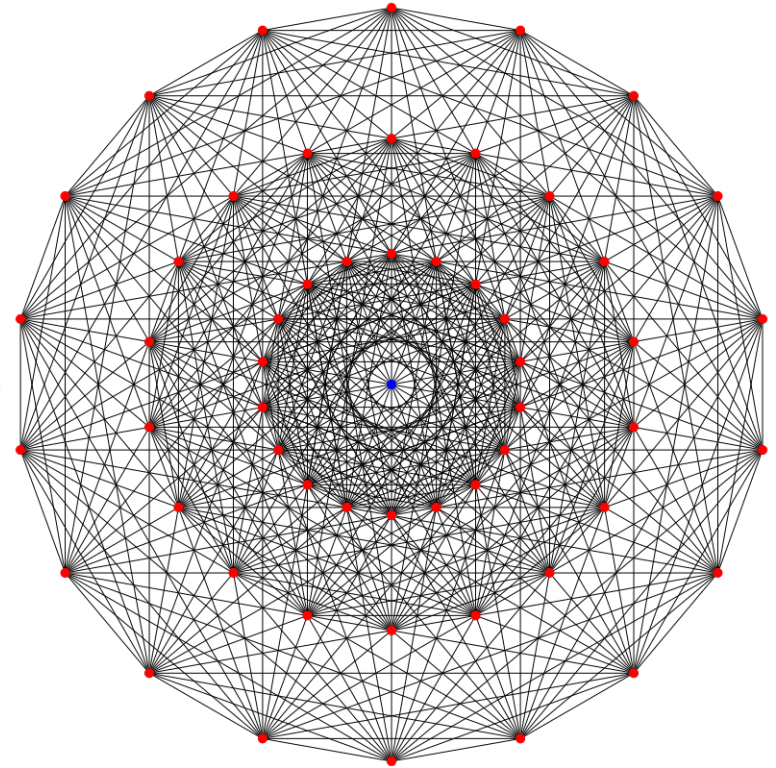


Excluded Grid Theorem [Robertson, Seymour]

Simple graphs



Complicated graphs

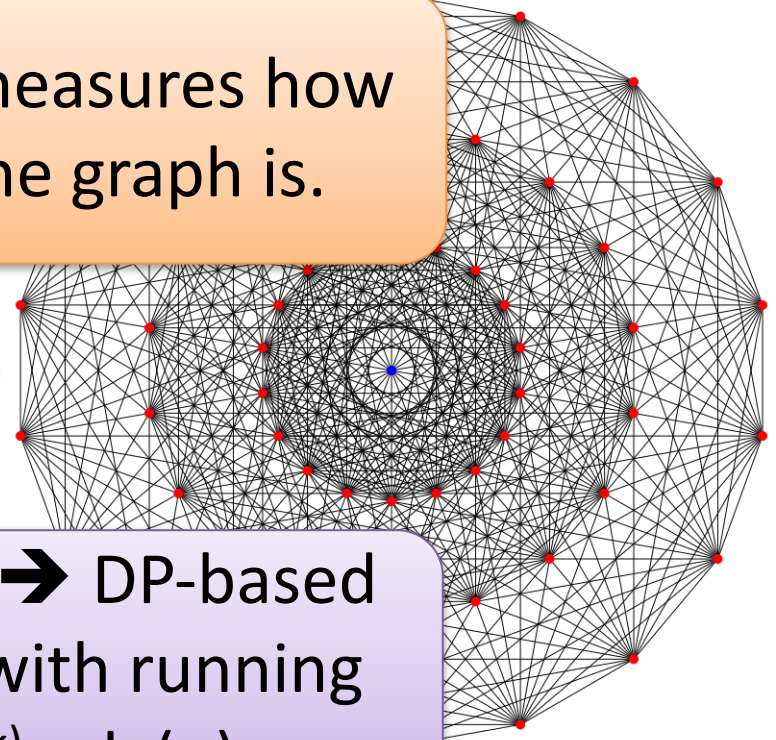
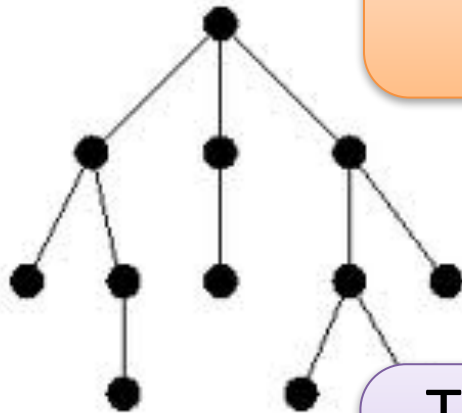


Excluded Grid Theorem [Robertson, Seymour]

Simple graphs

Complicated graphs

Treewidth: measures how complex the graph is.

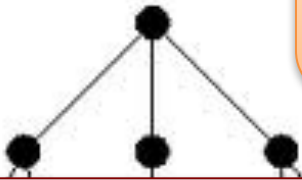


Treewidth $k \rightarrow$ DP-based algorithms with running time $2^{O(k)} \text{poly}(n)$.

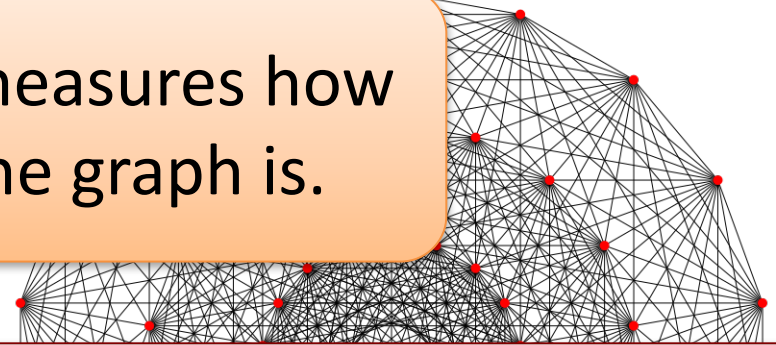


Excluded Grid Theorem [Robertson, Seymour]

Simple graphs



Complicated graphs



Treewidth: measures how complex the graph is.

Original definition:

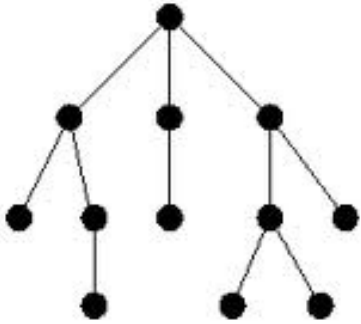
Treewidth is the smallest “width” of a tree-like structure that correctly “simulates” the graph.

(Almost) Equivalent definition:

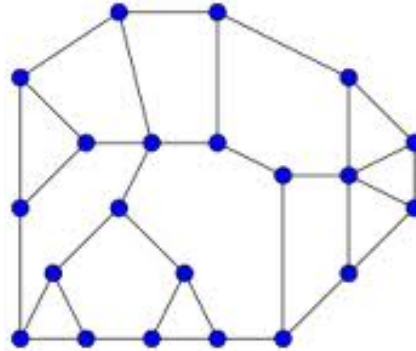
Treewidth is the cardinality of the largest well-linked set of vertices in the graph.

Treewidth

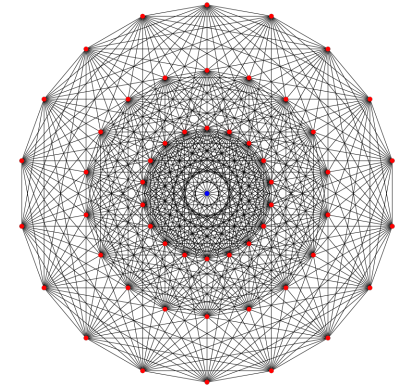
Trees



Low-Treewidth
Graphs

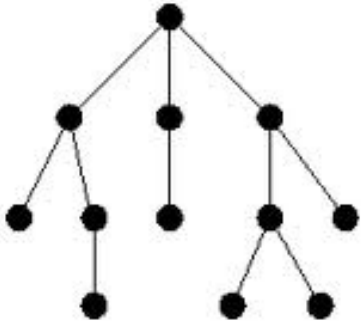


High-Treewidth
Graphs

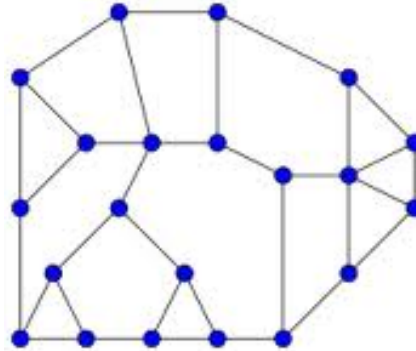


Treewidth

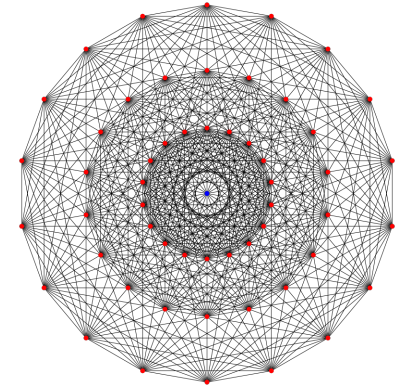
Trees



Low-Treewidth Graphs



High-Treewidth Graphs



Excluded Grid Theorem

[Robertson, Seymour '86]

If the treewidth of G is large, then G contains a large grid as a minor.

Can embed a large grid into G with no congestion

Excluded Grid Theorem

[Robertson, Seymour]

If the treewidth of G is large, then it contains a large grid minor, so:

- G contains many disjoint cycles
- G contains many disjoint cycles of length $0 \pmod m$
- G contains a convenient routing structure
- The size of the vertex cover in G is large
- ...

Applications

- Fixed parameter tractability
- Erdos-Posa type results
- Graph minor theory
 - Algorithm for NDP where k is small
- Algorithms for graph crossing number
- ...

Excluded Grid Theorem

[Robertson, Seymour '86]

If the treewidth of G is k , then G contains a grid of size $f(k) \times f(k)$ as a minor.

Excluded Grid Theorem

[Robertson, Seymour '86]

If the treewidth of G is k , then G contains a grid of size $f(k) \times f(k)$ as a minor.

How large is $f(k)$?

- [Robertson, Seymour '94]:
$$f(k) = O\left(\sqrt{k / \log k}\right)$$
- Conjecture [Robertson, Seymour '94]: This is tight.

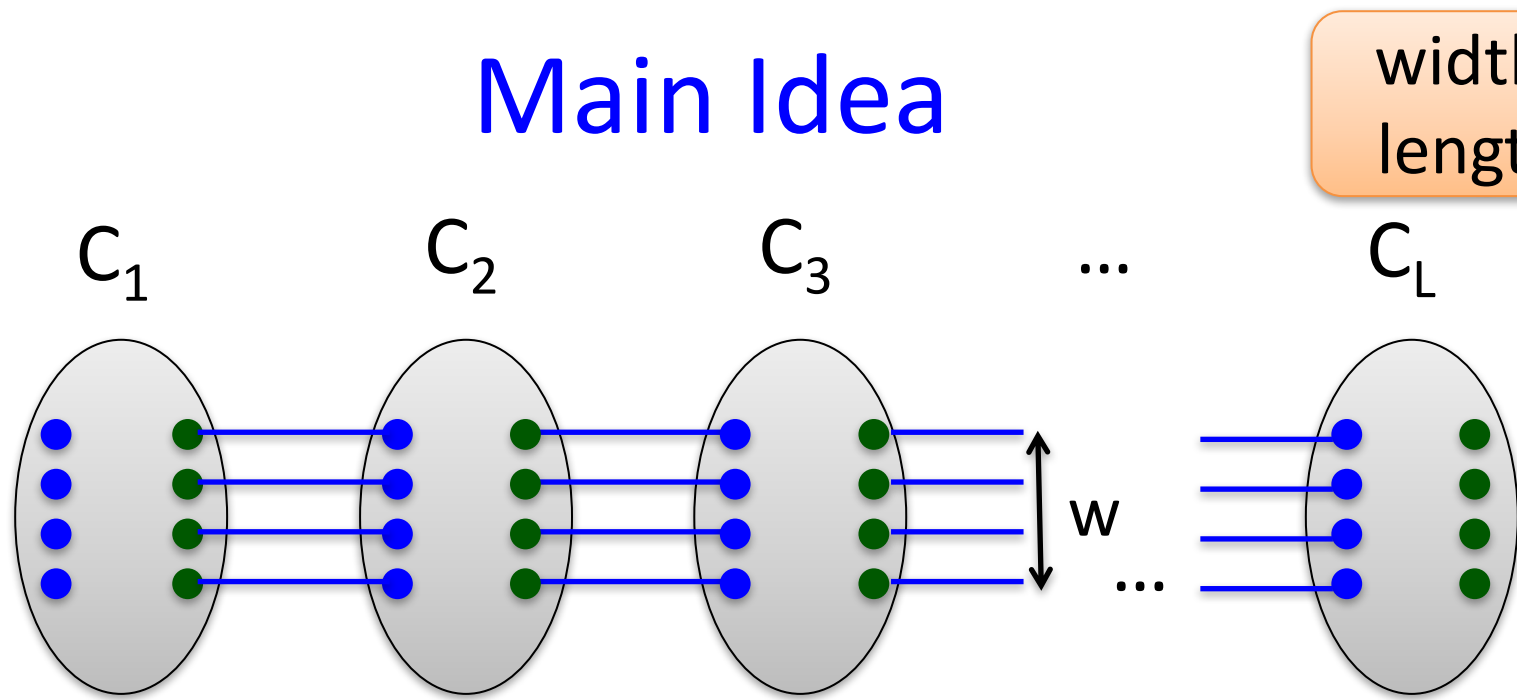
Excluded Grid Theorem

- [Robertson, Seymour, Thomas '89]: $f(k) = \Omega\left(\log^{1/5} k\right)$
- [Diestel, Gorbunov, Jensen, Thomassen '99] – simpler proof
- [Kawarabayashi, Kobayashi '12], [Leaf, Seymour '12]:

$$f(k) = \Omega\left(\sqrt{\frac{\log k}{\log \log k}}\right)$$

- [Chekuri, C '13]: $f(k) = \tilde{\Omega}\left(k^{1/98}\right)$
- [C, '16]: $f(k) = \tilde{\Omega}\left(k^{1/19}\right)$

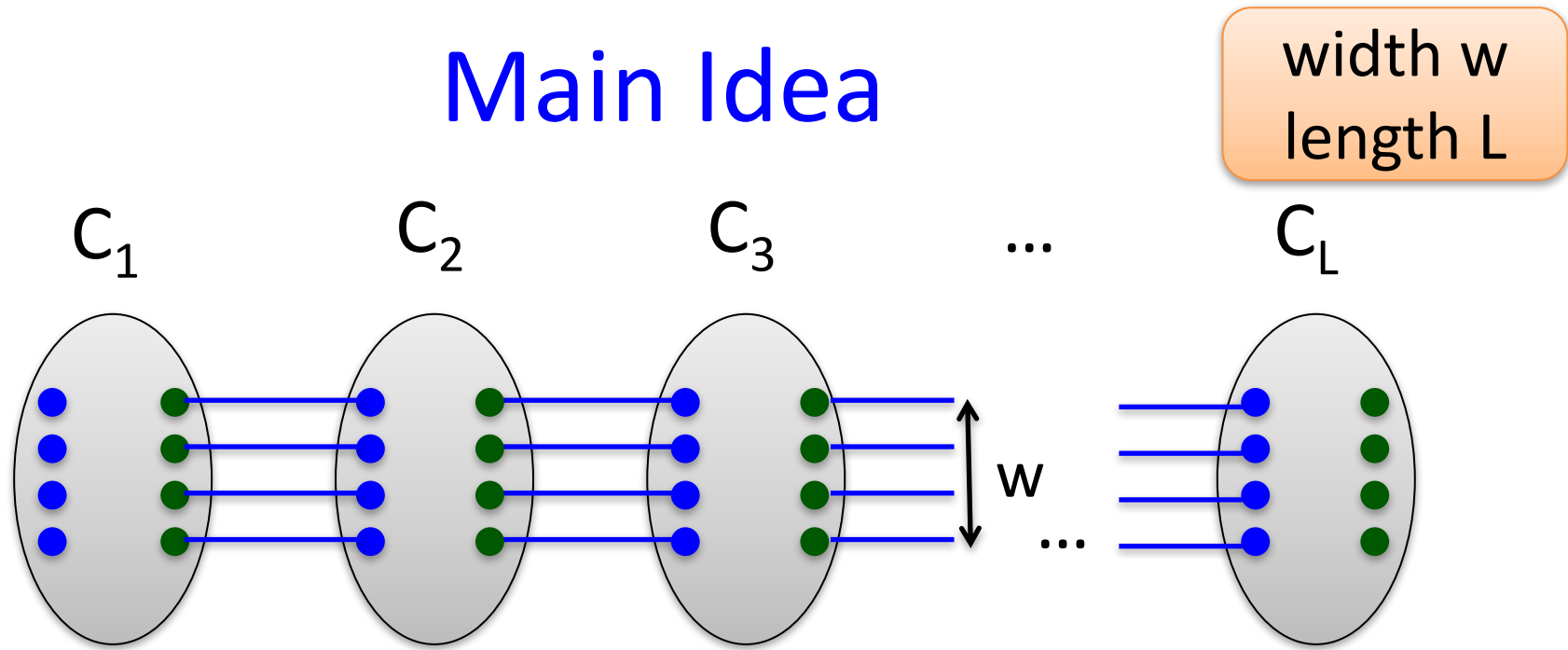
Main Idea



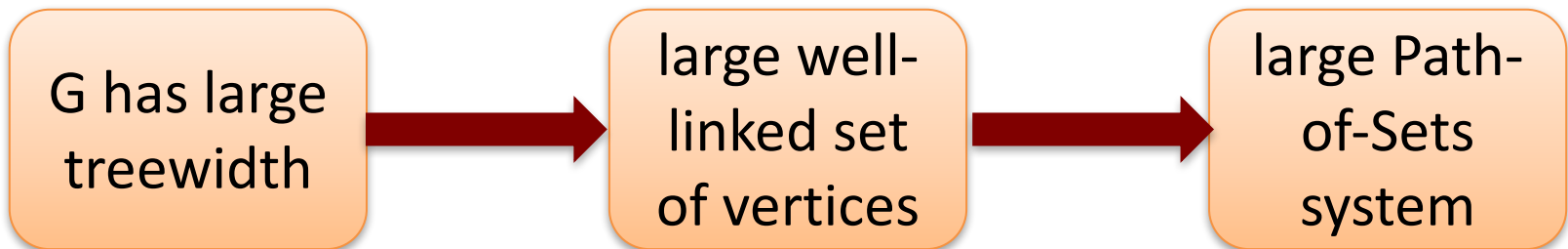
Thm: If G contains a path-of-sets system of width and length $\Theta(g^2)$, then there is a (gxg) -grid minor in G .

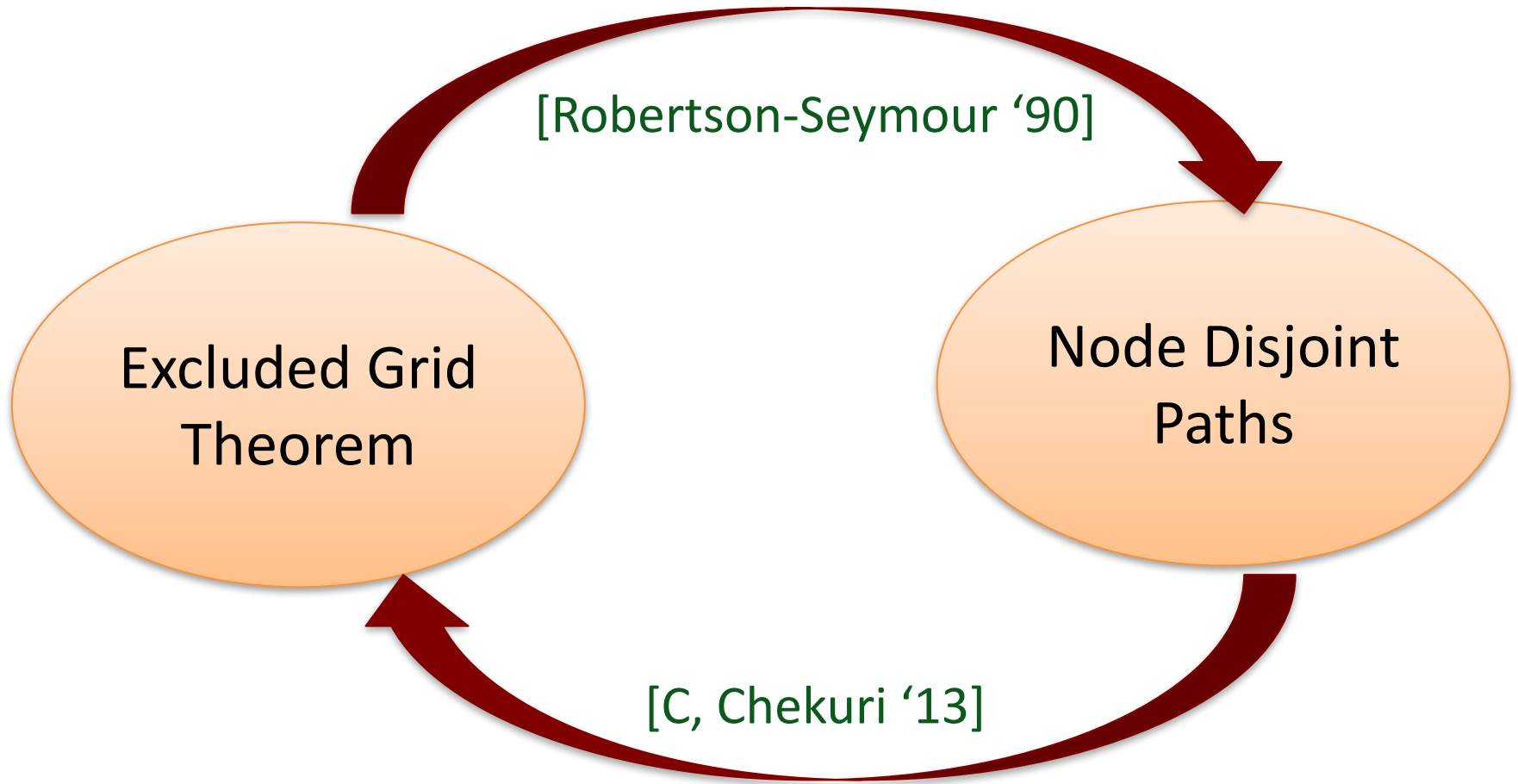
[Leaf, Seymour '12]
[Chekuri, C '13]

Main Idea



Thm: If G contains a path-of-sets system of width and length $\Theta(g^2)$, then there is a (gxg) -grid minor in G .

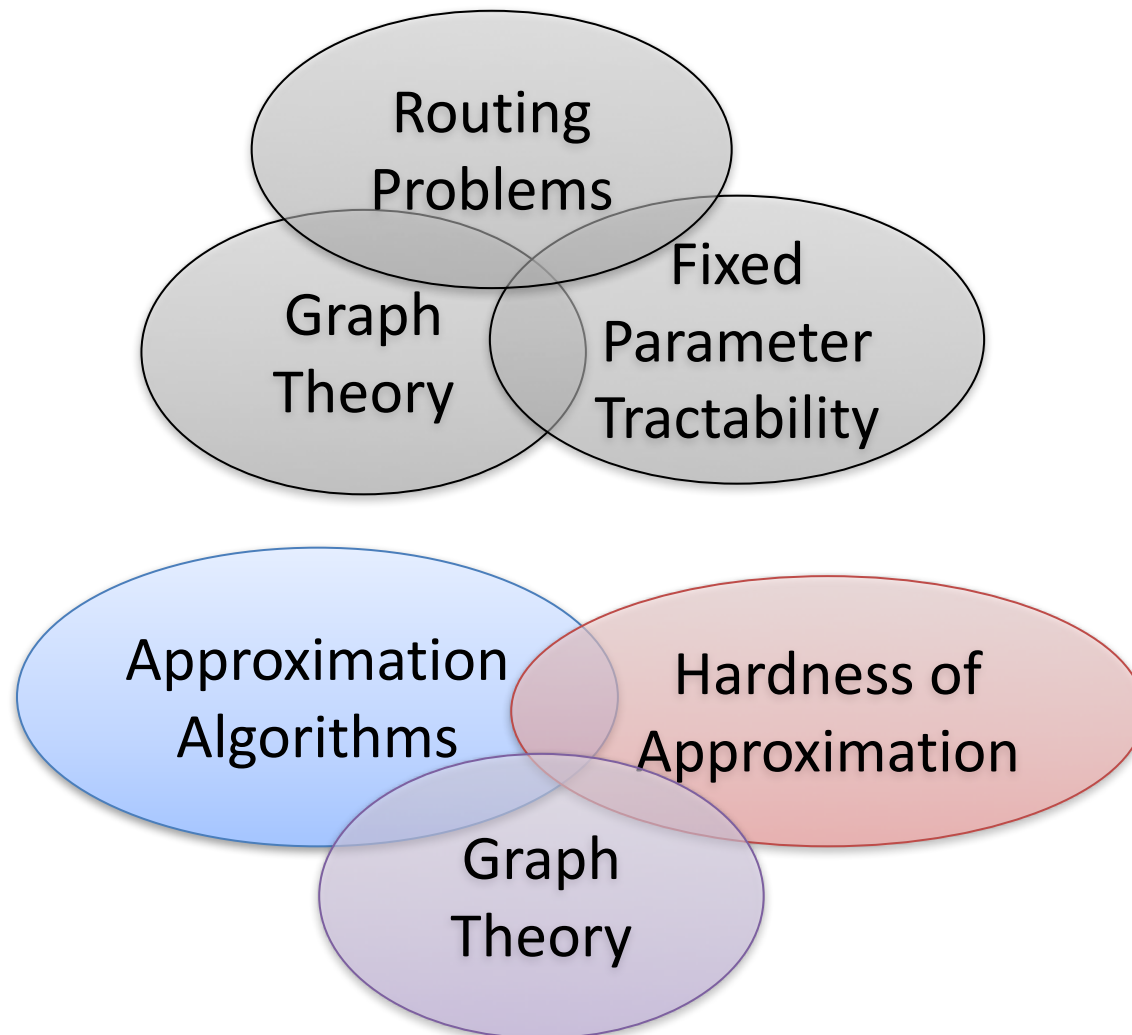




Historical Note

- Work on routing gave slightly weaker structure than Path-of-Sets System, called Tree-of-Sets System
- We later modified it to get the Path-of-Sets system for the Excluded Grid theorem.
- This in turn helped improve results for routing problems.

Exc

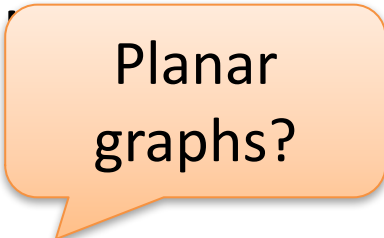


Open Problems

- Getting tight bounds for the Excluded Grid Theorem.
- Simpler algorithms for NDP with constant k
- Congestion minimization:
 - $O(\log n / \log \log n)$ -approximation algorithm
 - $\Omega(\log \log n)$ -hardness of approximation
 - Integrality gap of the multicommodity LP relaxation open

Open Problems

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Planar graphs?

Thank you!