

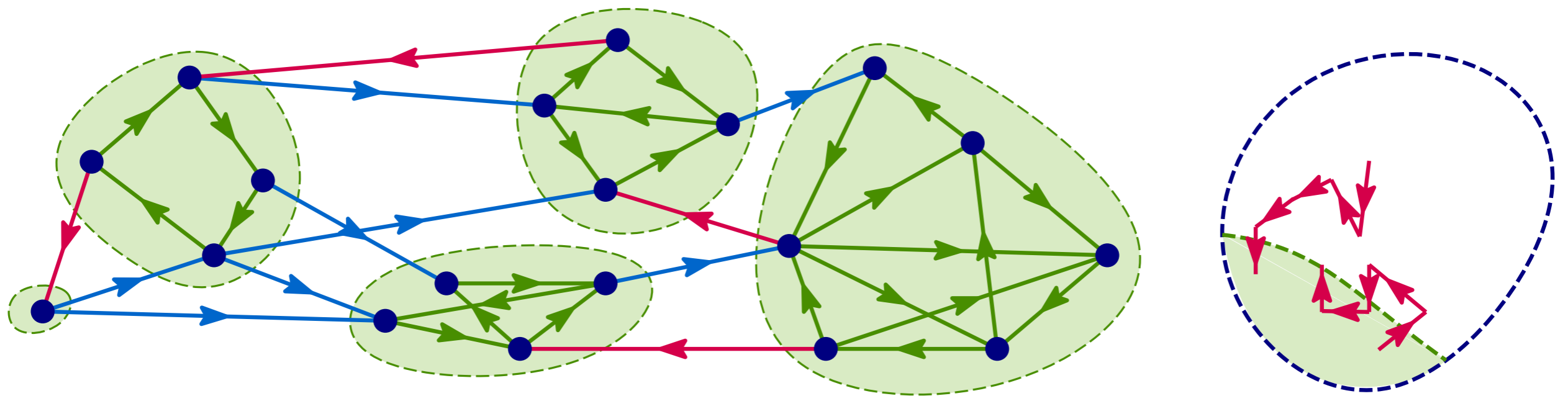
Combinatorial Maxflow in $n^{2+o(1)}$ Time

Aaron Bernstein

Joakim Blikstad[†]

Thatchaphol Saranurak

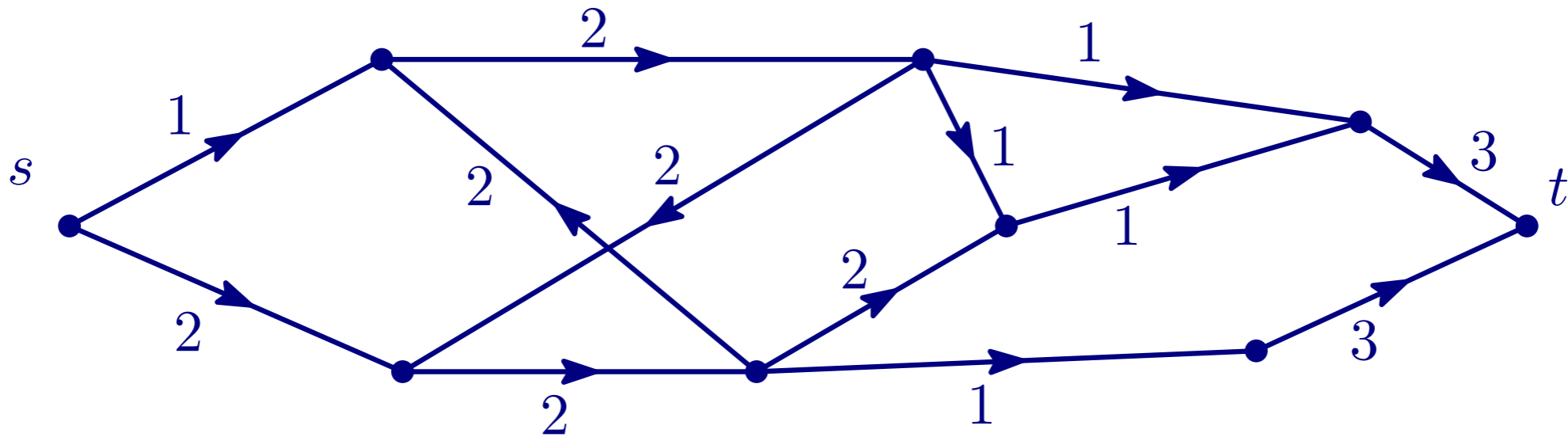
Ta-Wei Tu



Maximum Flow

Given: Directed graph $G = (V, E)$, edge capacities $c : E \rightarrow \mathbb{Z}_{\geq 1}$, source s , and sink t .

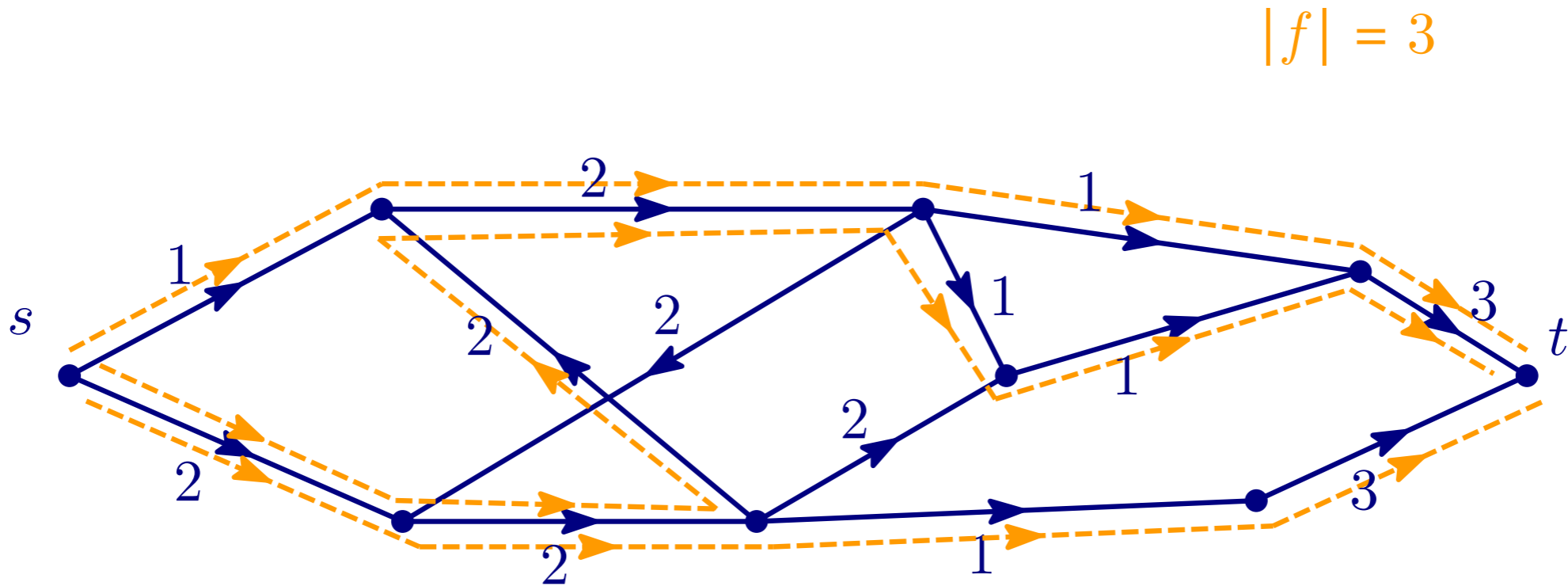
Goal: Compute s, t -flow f of largest size.



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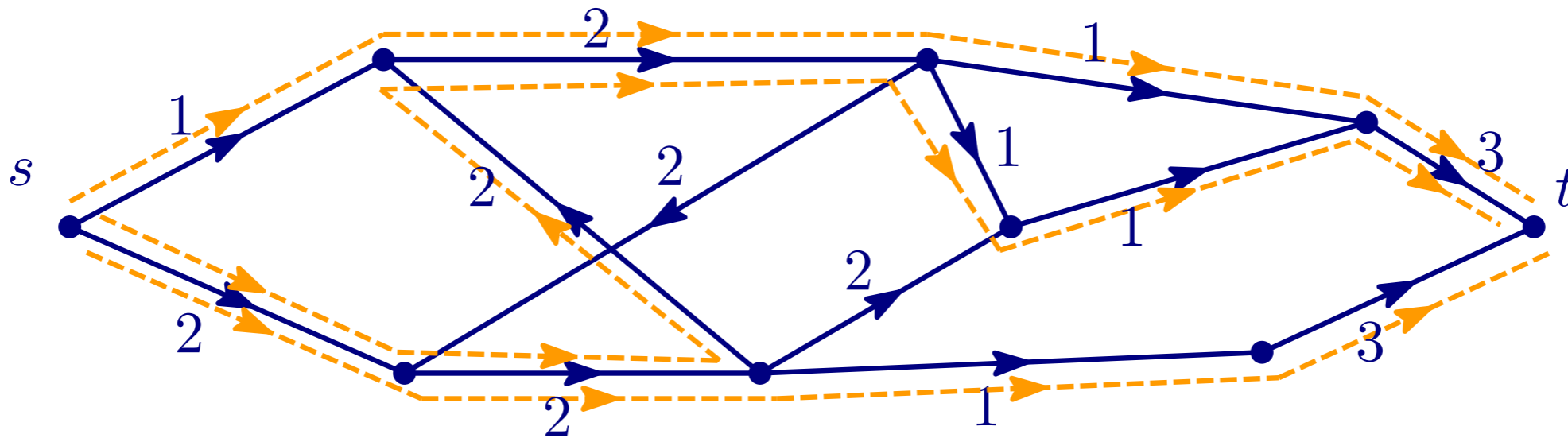
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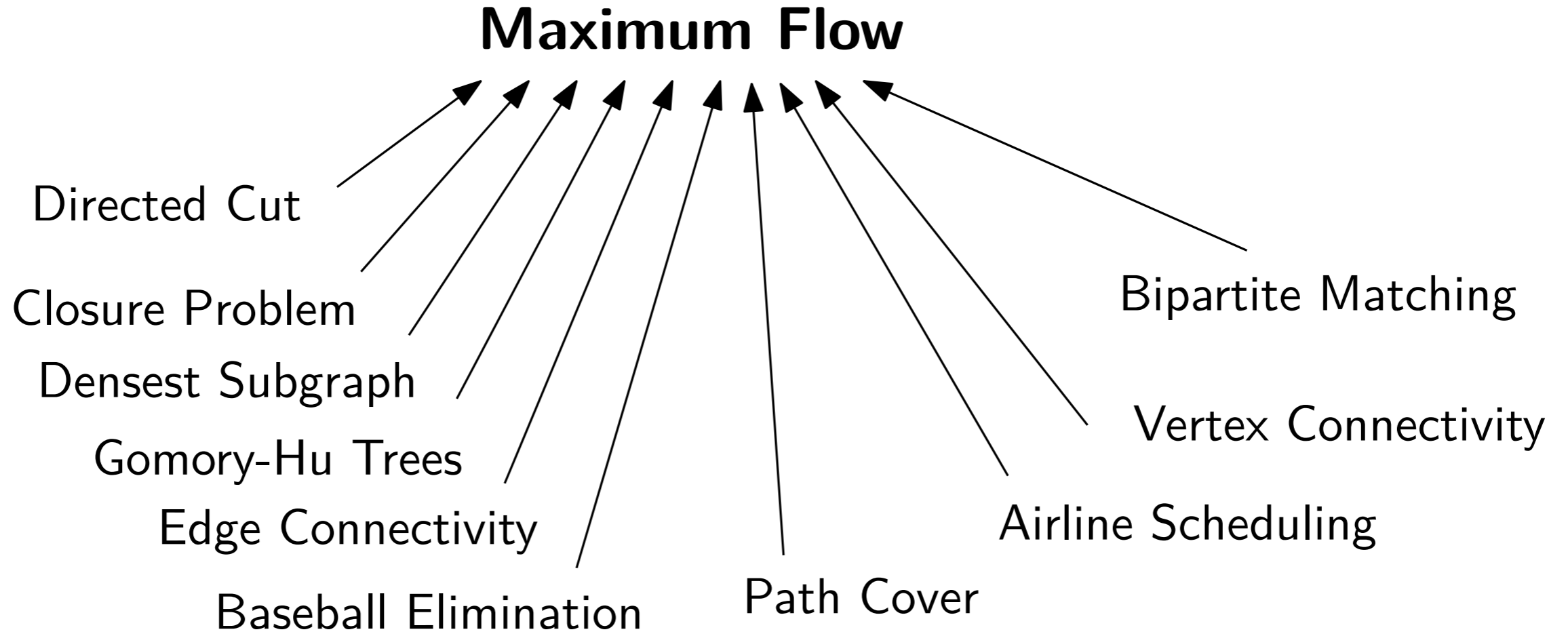
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Flow satisfies:

- (1) Capacity constraints $f(e) \leq c(e)$
- (2) Conservation of flow “incoming = outgoing”

$$|f| = 3$$





Maximum Flow — A Brief History

1955	Ford-Fulkerson	$O(E \cdot \ \text{answer}\)$	\tilde{O} : hides polylog
1970	Edmonds-Karp	$O(VE^2)$	\hat{O} : hides $n^{o(1)}$
1970	Dinic “Blocking Flow”	$O(V^2E)$	
1978	Malhotra-Kumar-Maheshwari	$O(V^3)$	
1983	Dinics Dynamic Trees	$\tilde{O}(VE)$	
1986	Goldberg-Tarjan “Push-Relabel”	$\tilde{O}(V^3)$	
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2020	Kathuria-Liu-Sidford	$\hat{O}(E^{4/3})$ (unit-capacity)	
2020	BLNPSSSW / BLLSSSW	$\tilde{O}(E + V\sqrt{V})$	
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2020	Kathuria	Continuous Optimization, Interior Point Methods	(capacity)
2020	BLNPSS	"Precision issues", "I don't understand them"	
2022	Chen-Kyng, Liu-Teng, Goldberg-Jacobs	$O(E)$	

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New Era? — Comeback of Combinatorial Algorithms

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Independent Work:
 $n^{2+o(1)}$ combinatorial
bipartite matching
[Chuzhoy-Khanna'24]

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Augmenting Paths (new version of Push-Relabel)

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My Hope: (in a few years)

“Simple”, “Combinatorial” $\tilde{O}(E)$ Maximum Flow?

Non-bipartite Maximum Matching in $\tilde{O}(V^2)$ or $\tilde{O}(E)$ time?

Independent Work:

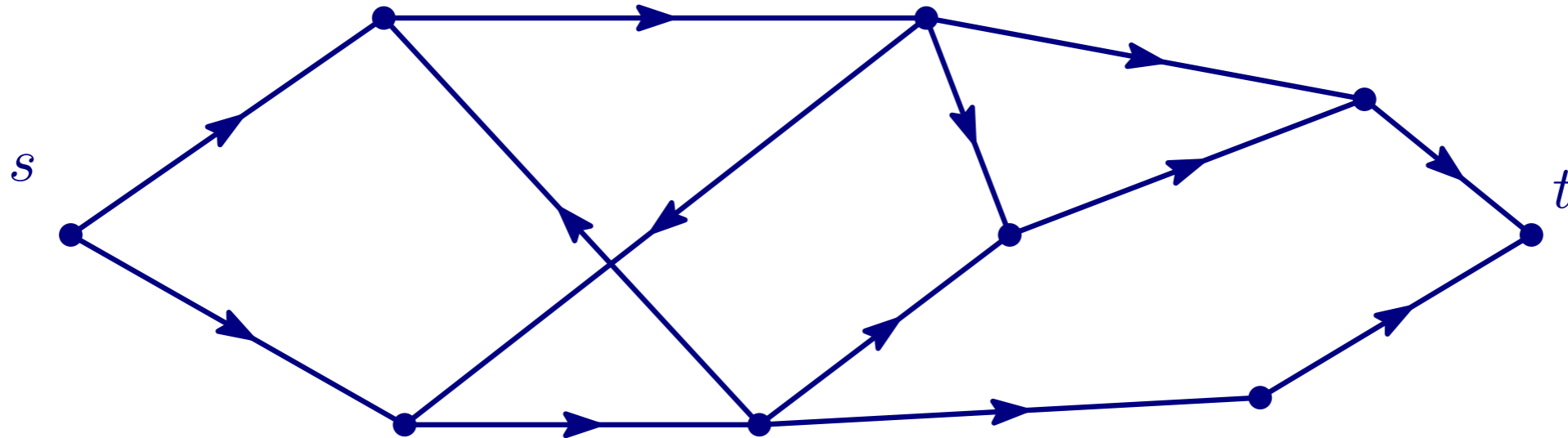
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Augmenting Paths

[Ford-Fulkerson 1955]
[Jacobi 1836]

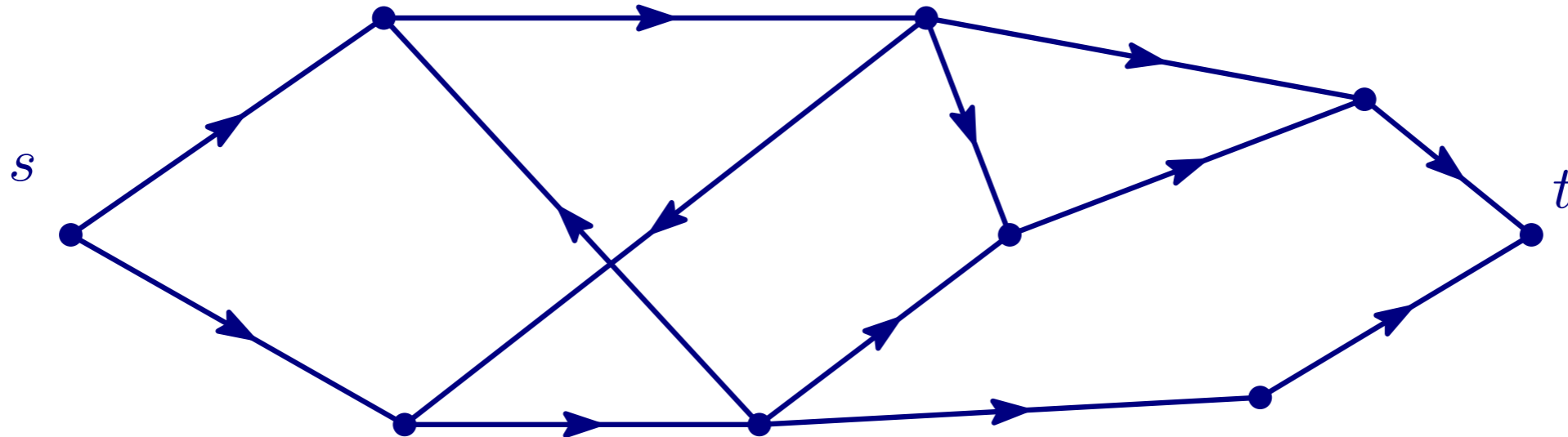


Augmenting Paths

[Ford-Fulkerson 1955]

Remainder of this talk: unit-capacities $c(e) = 1$

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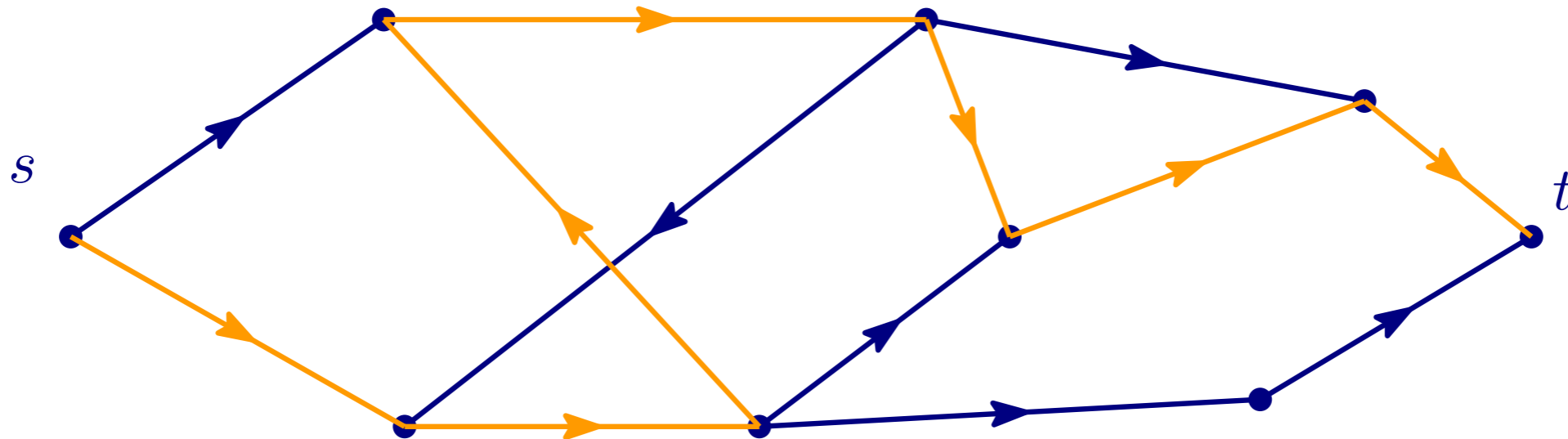
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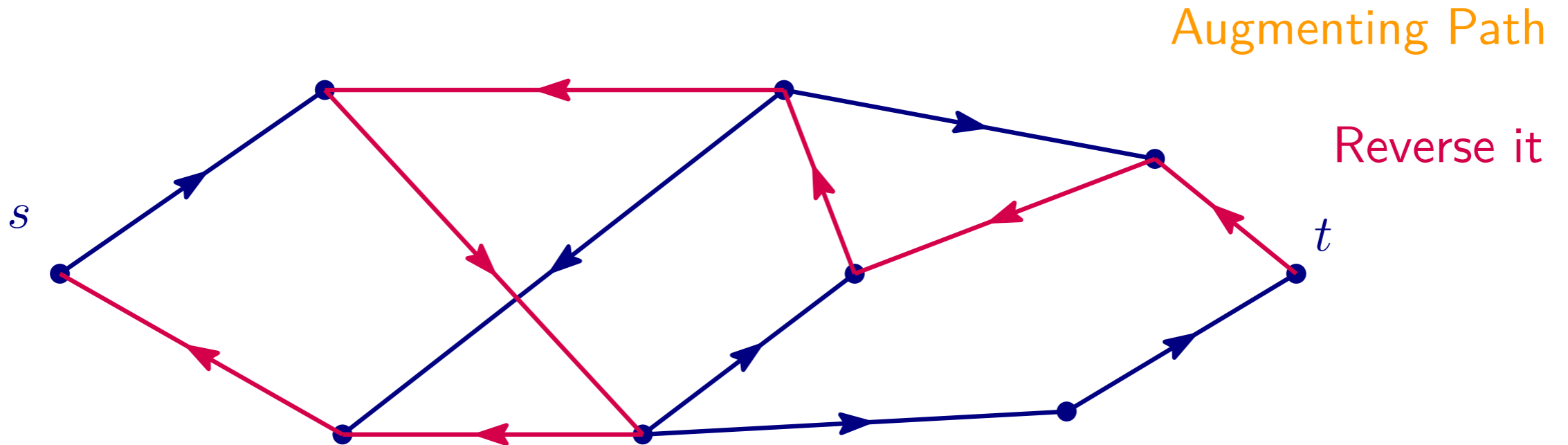


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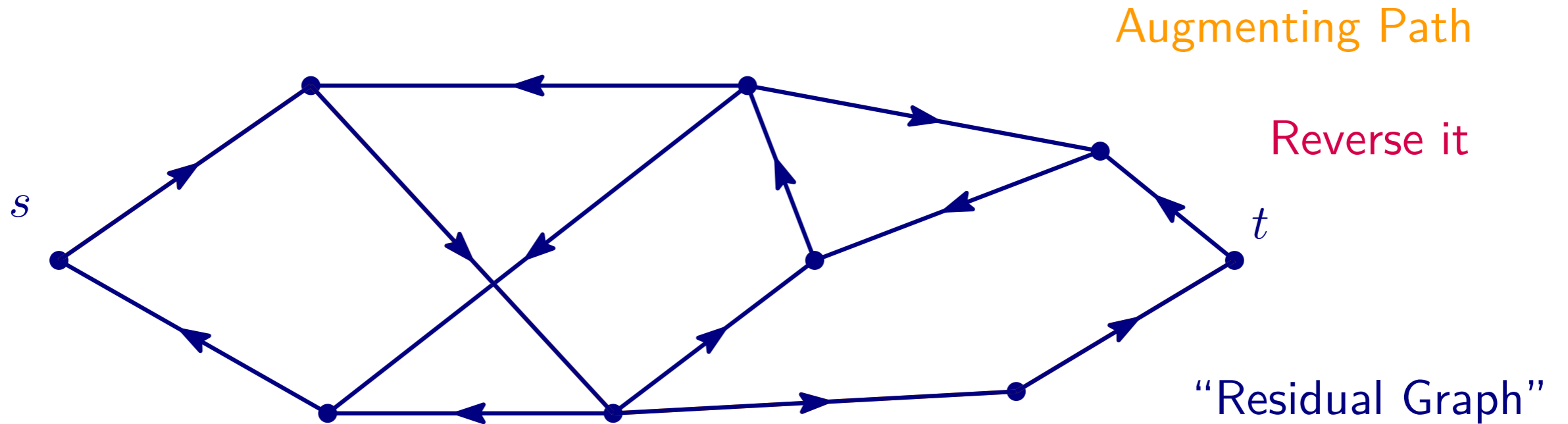


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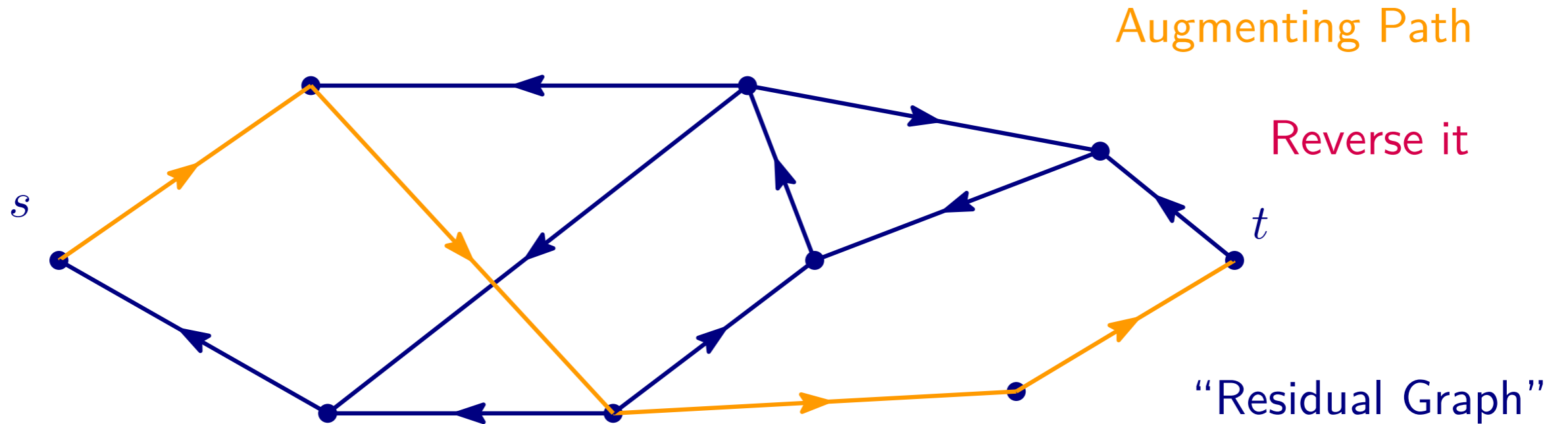


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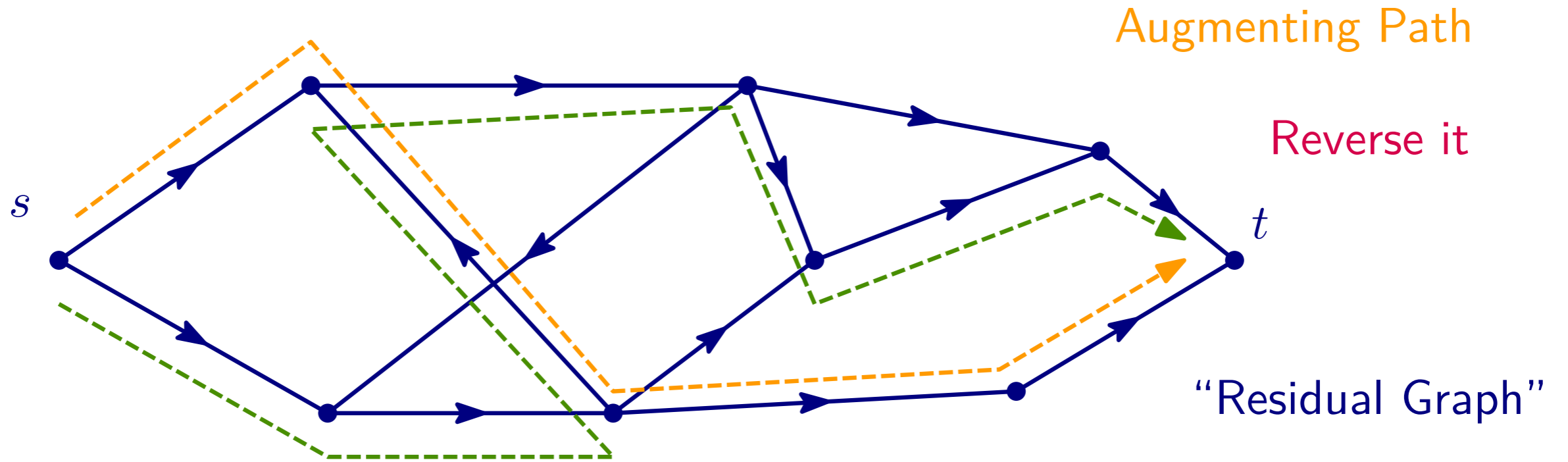


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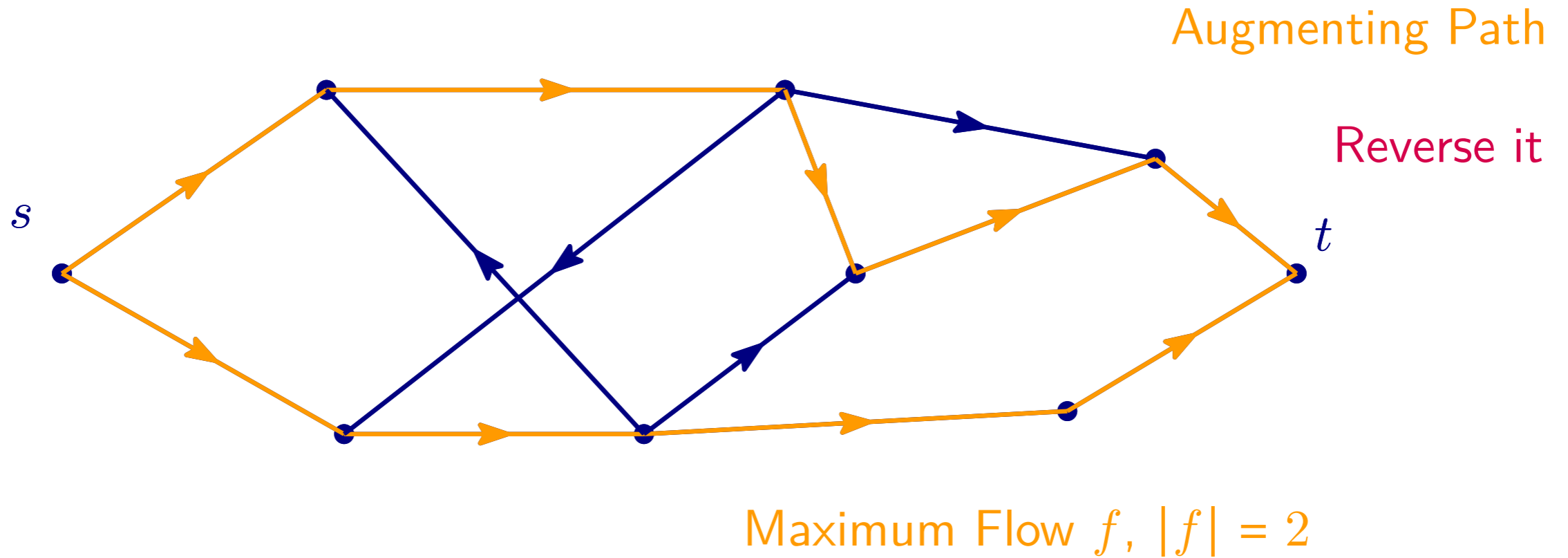


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Approximate Flow \implies Exact Flow

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Proof. Recurse on residual graph.

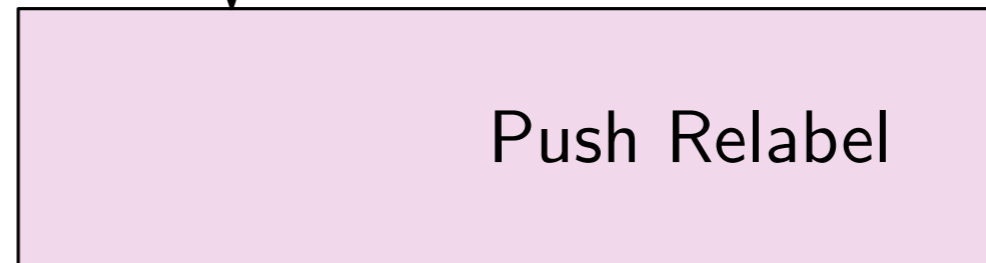
Goal in rest of talk: constant- or $\frac{1}{n^{o(1)}}$ -approx flow.

(does not work in undirected graphs)

Outline

1. Recap: Push-Relabel

Graph G



Max Flow

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2. Weighted PR

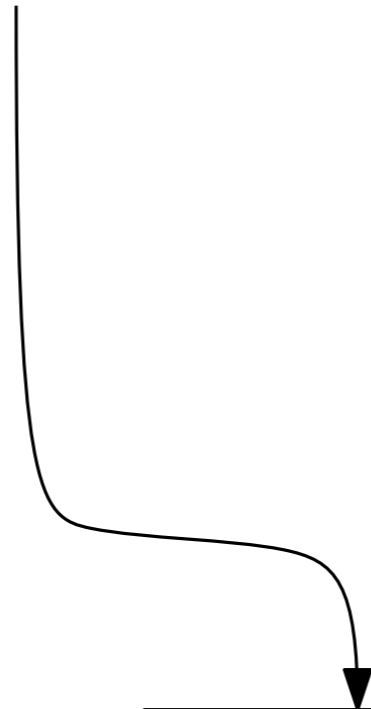
Graph G

“Good” edge lengths

“hint”

Weighted Push Relabel

Approximate Max Flow



Outline

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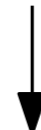
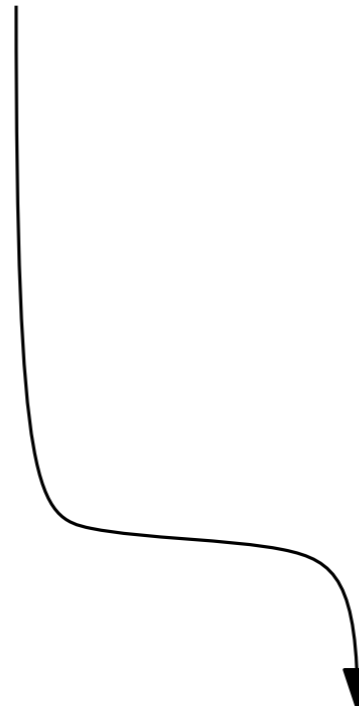
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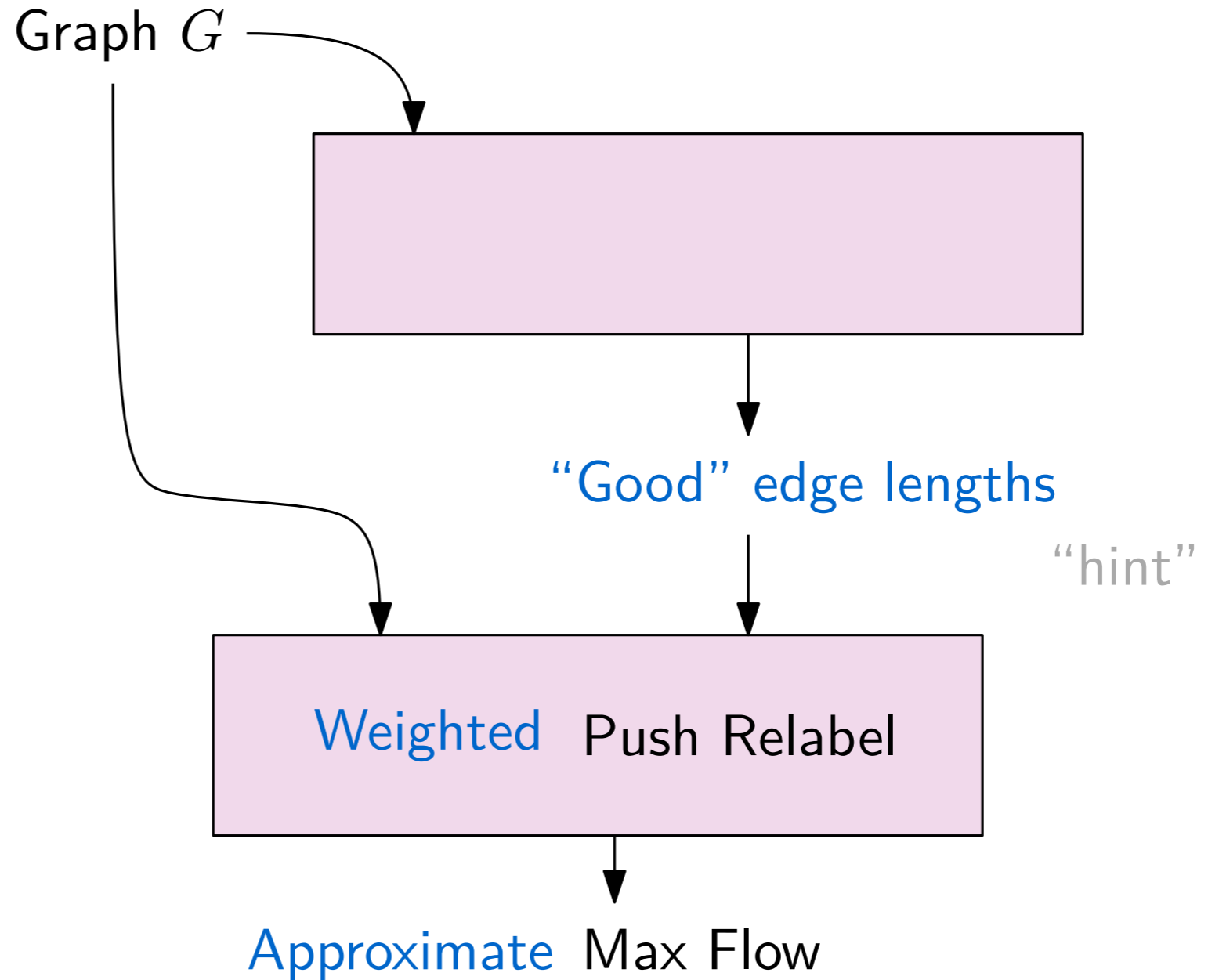
Weighted Push Relabel

Approximate Max Flow



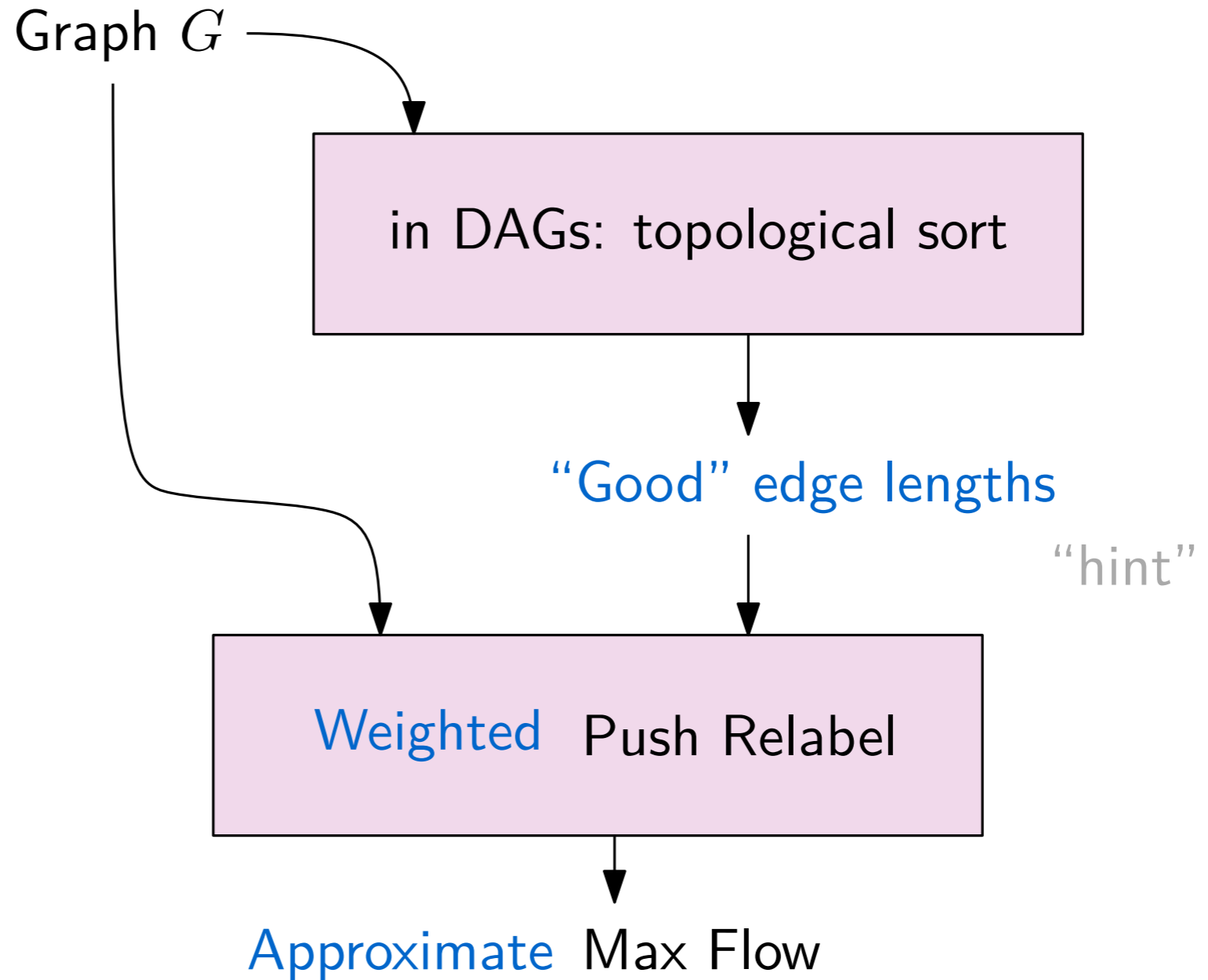
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4. Edge Lengths in DAGs

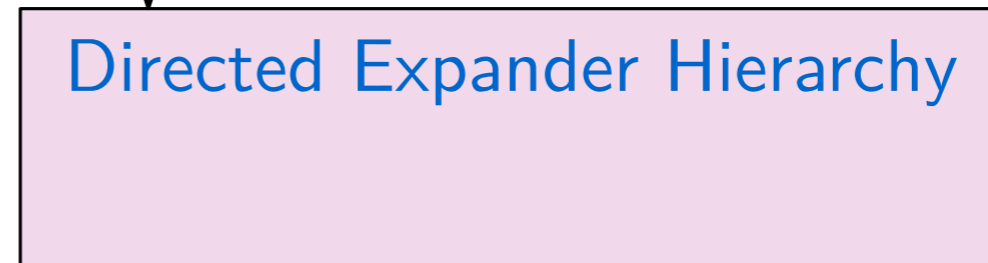


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5. General Graphs:

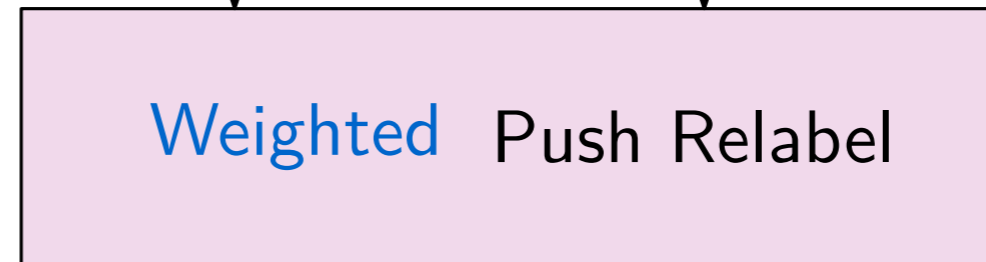
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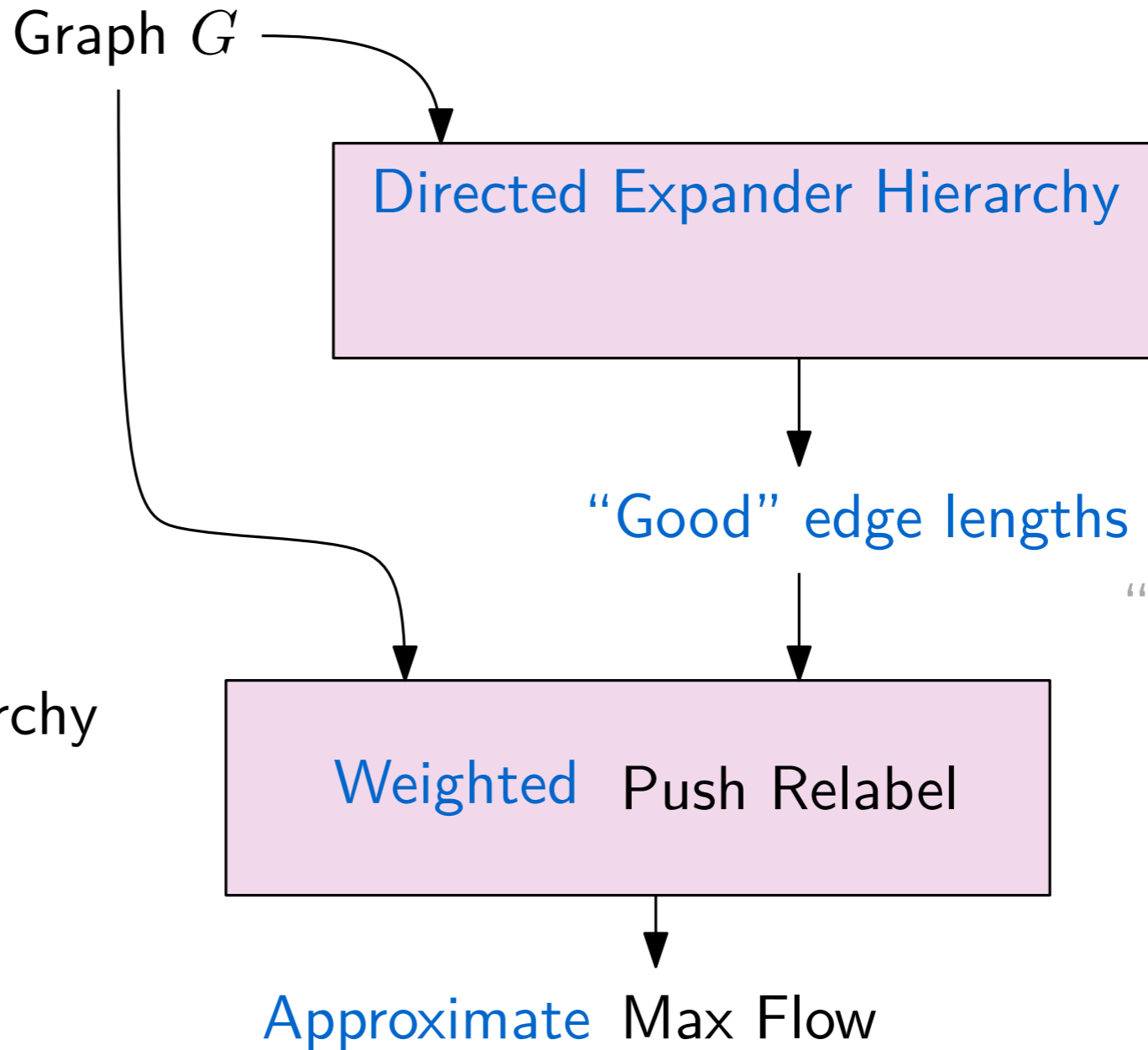


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Approximate Max Flow

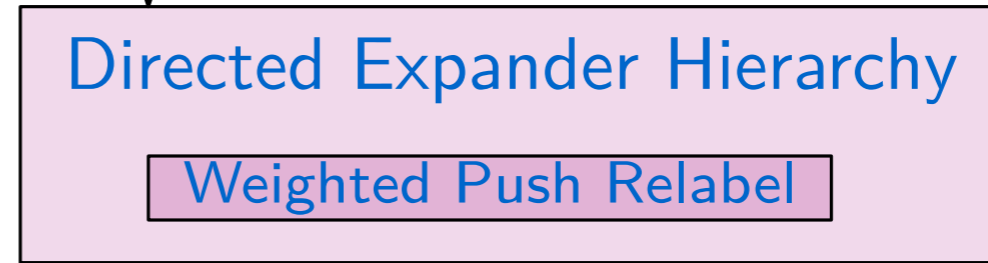


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Weighted Push Relabel

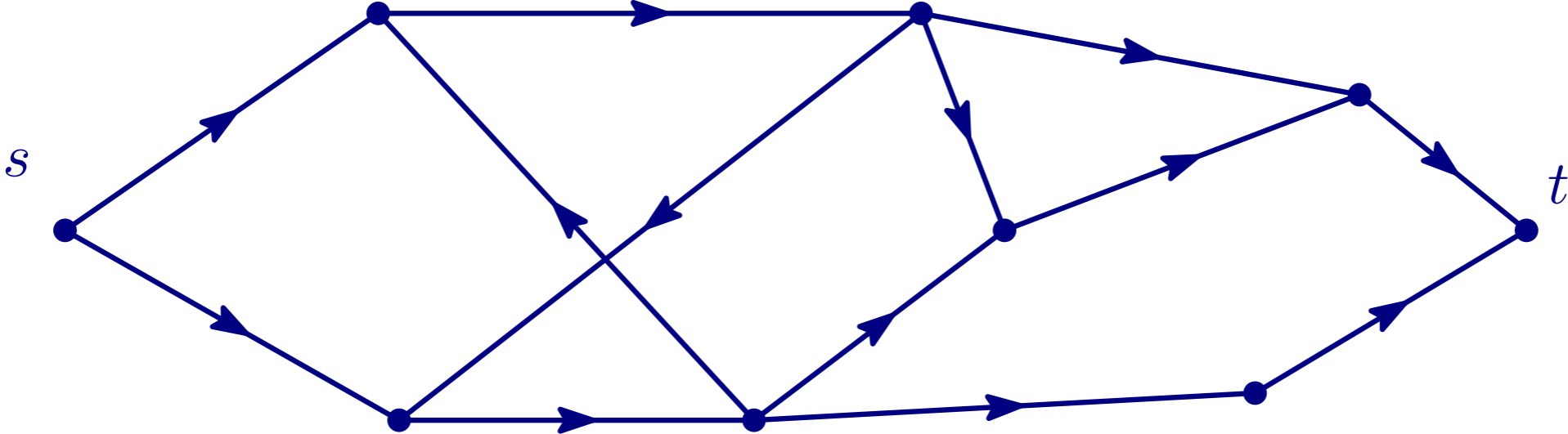
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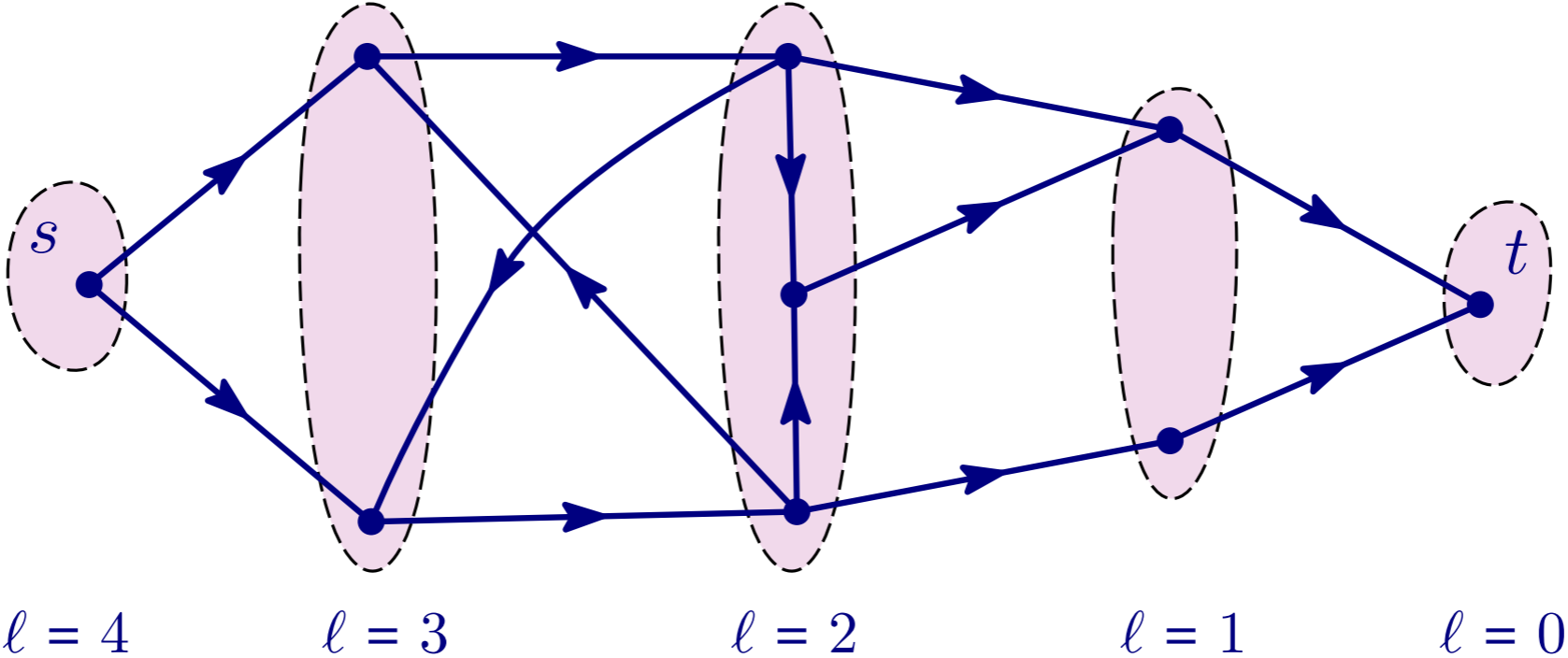
Approximate Max Flow

Push-Relabel / Augment-Relabel [Goldberg-Tarjan'88]



Push-Relabel / Augment-Relabel [Goldberg-Tarjan'88]

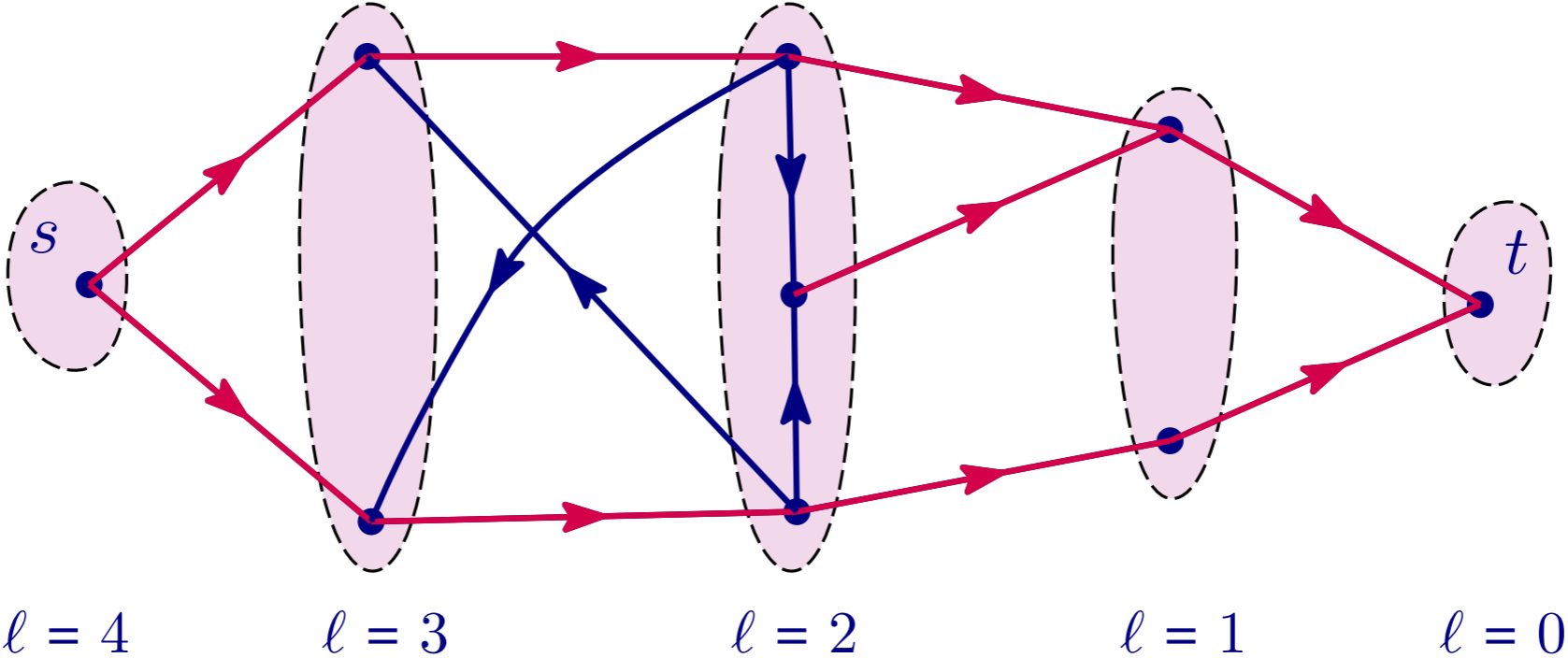
$$l(v) = \text{dist}(v, t)$$



Push-Relabel / Augment-Relabel [Goldberg-Tarjan'88]

edge $e = (u, v)$ admissible iff $l(u) = l(v) + 1$

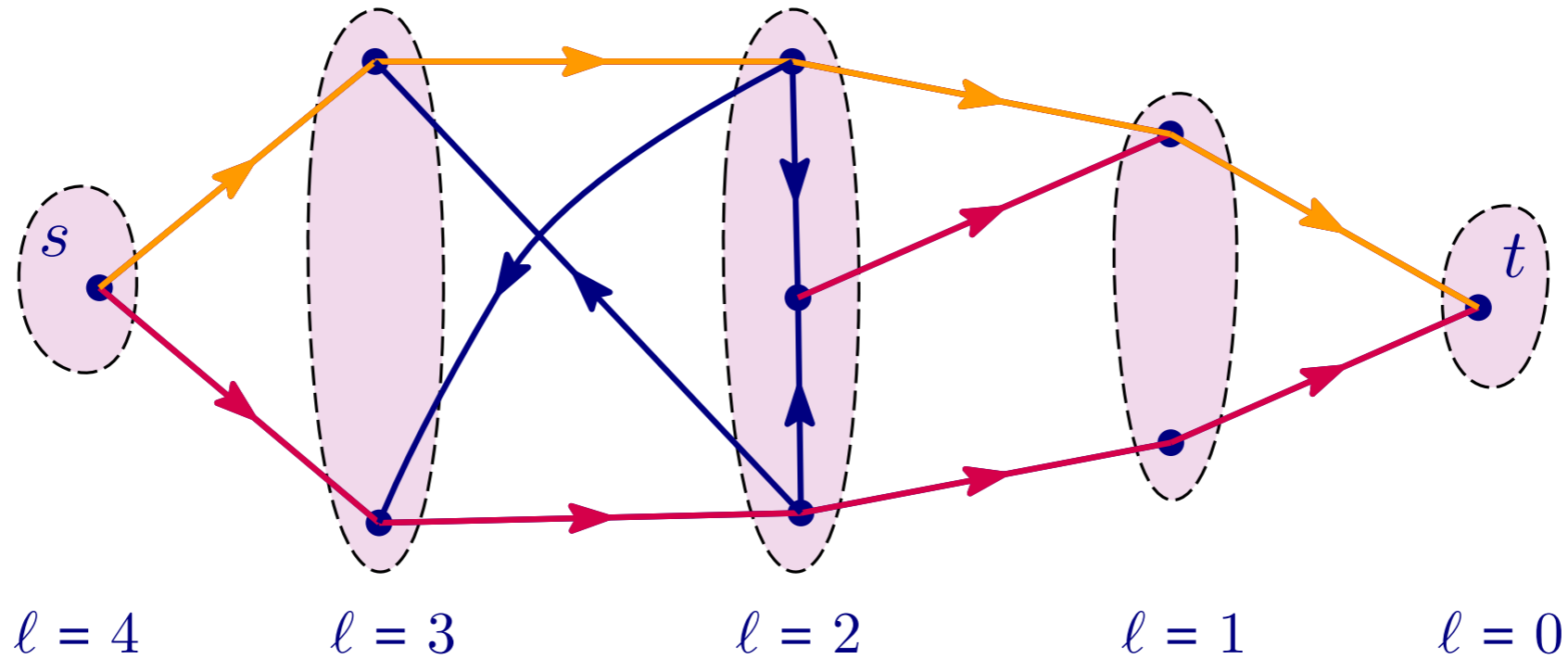
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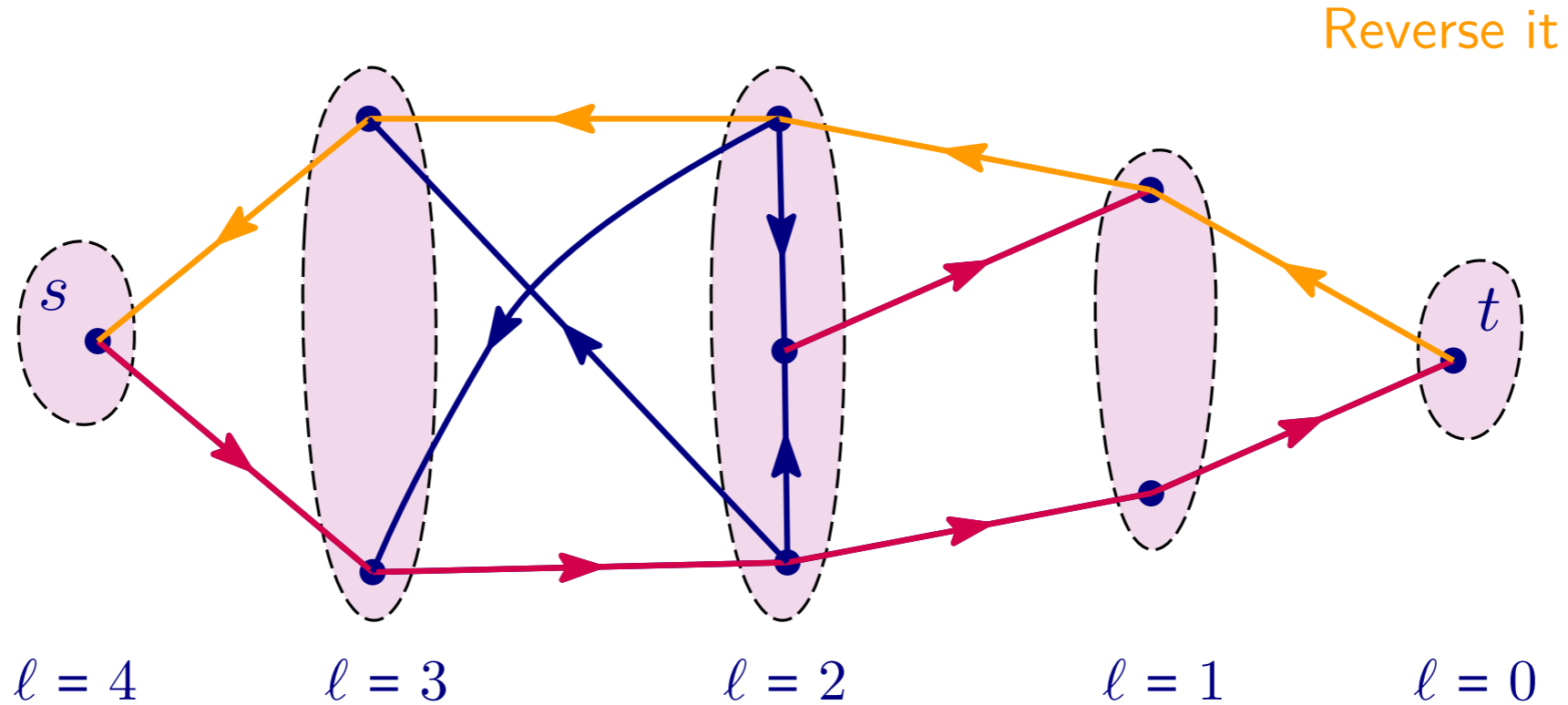


Shortest Augmenting Path: follow admissible edges from s

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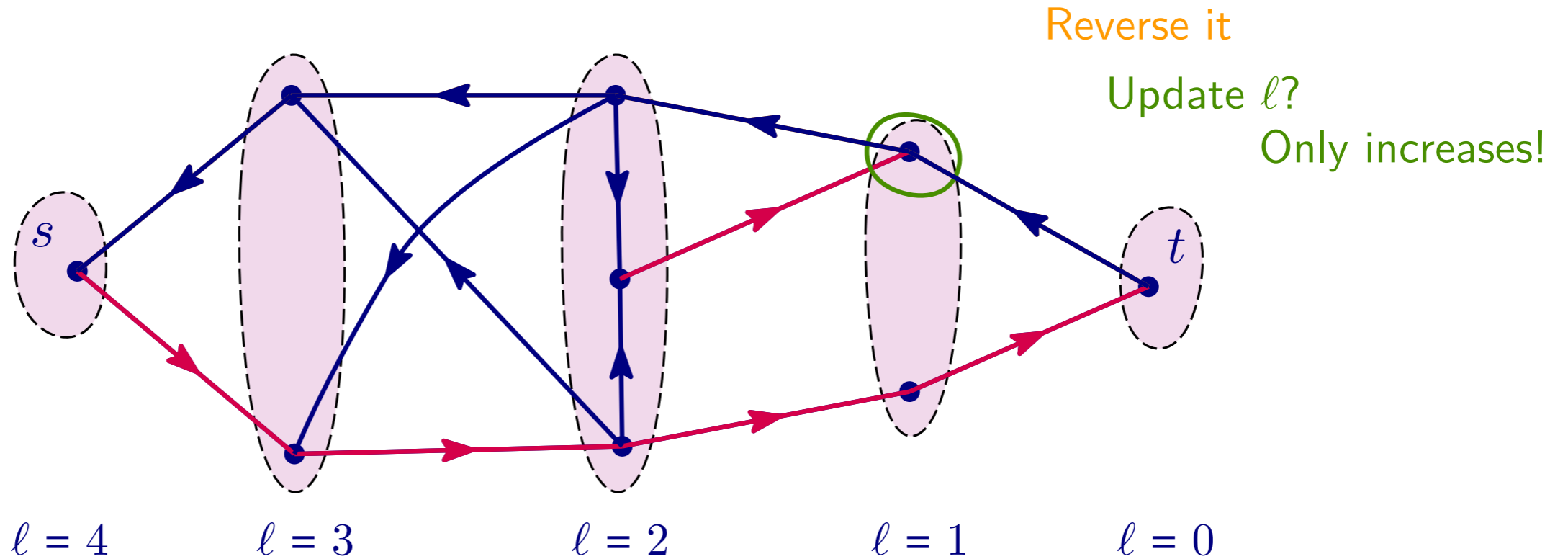


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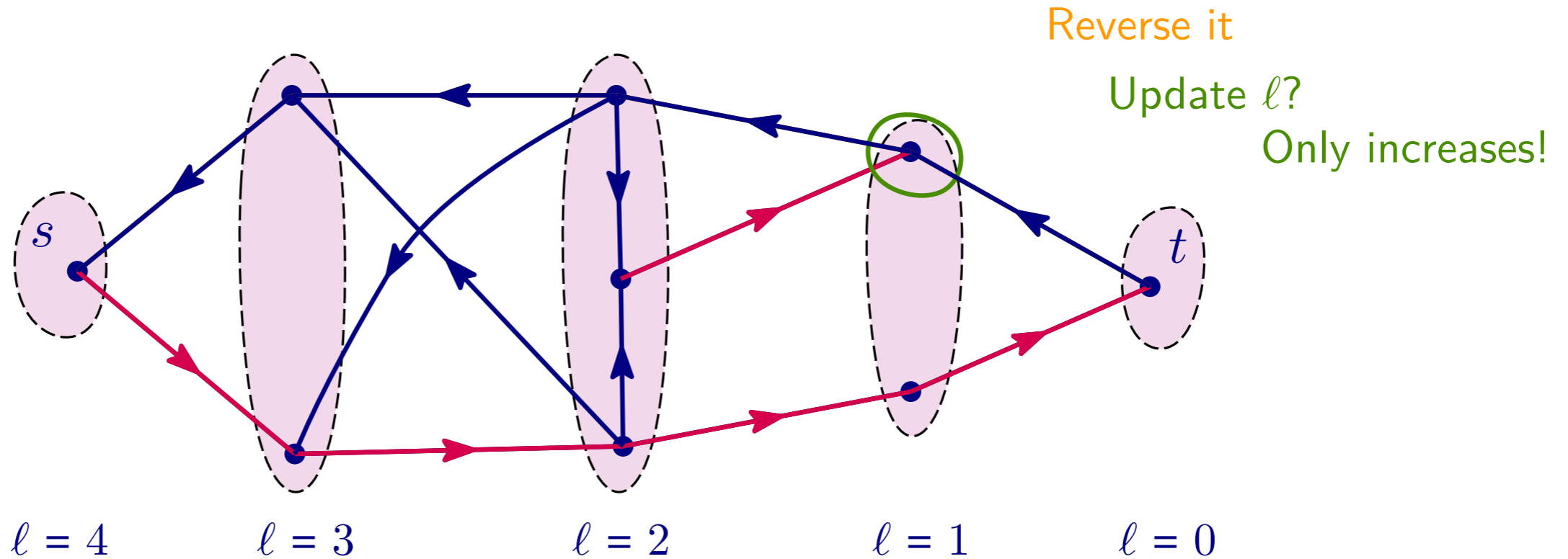


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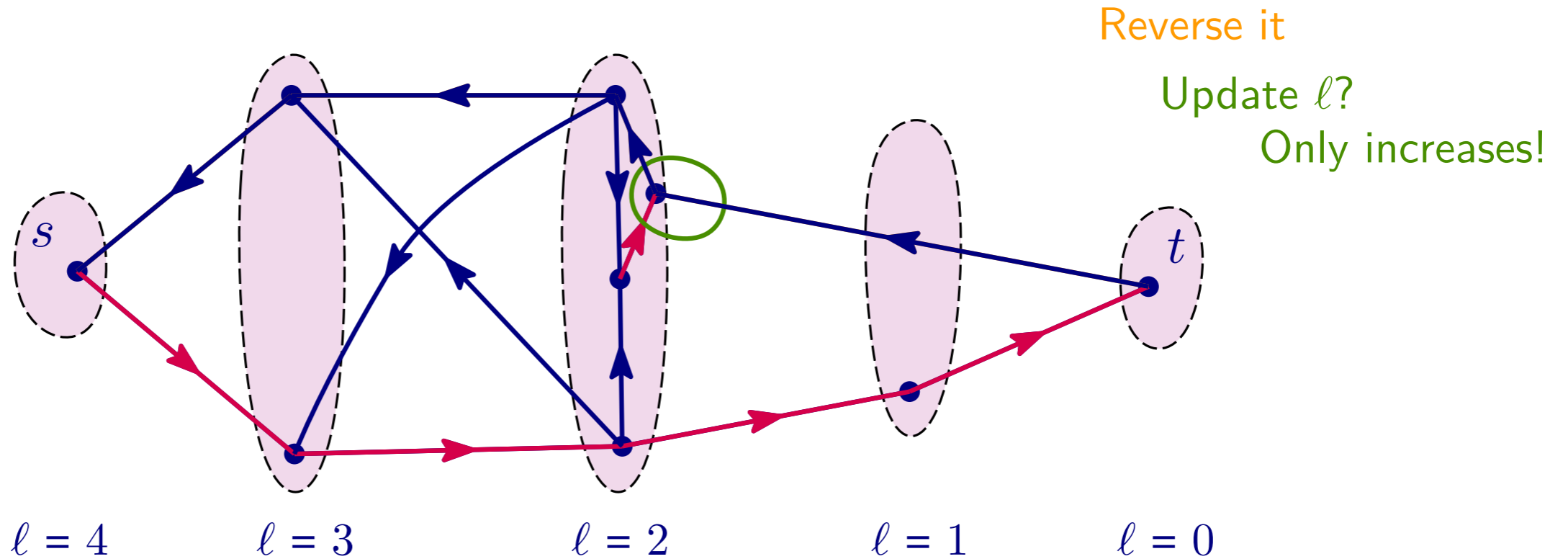
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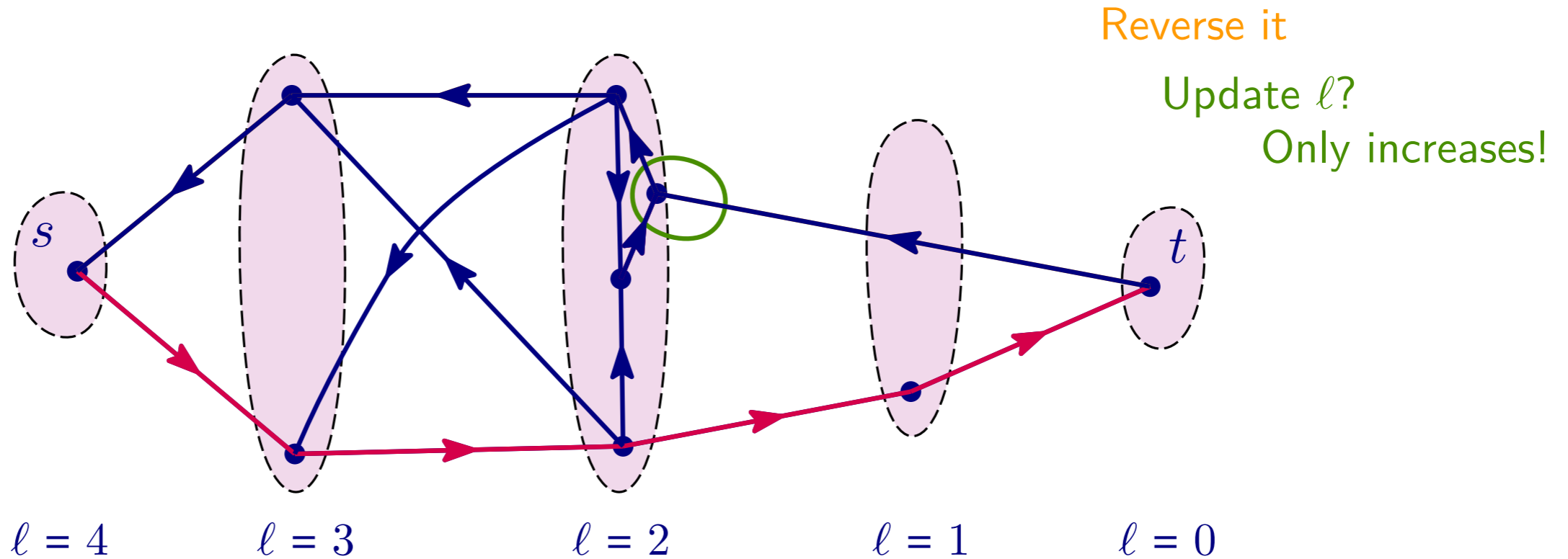
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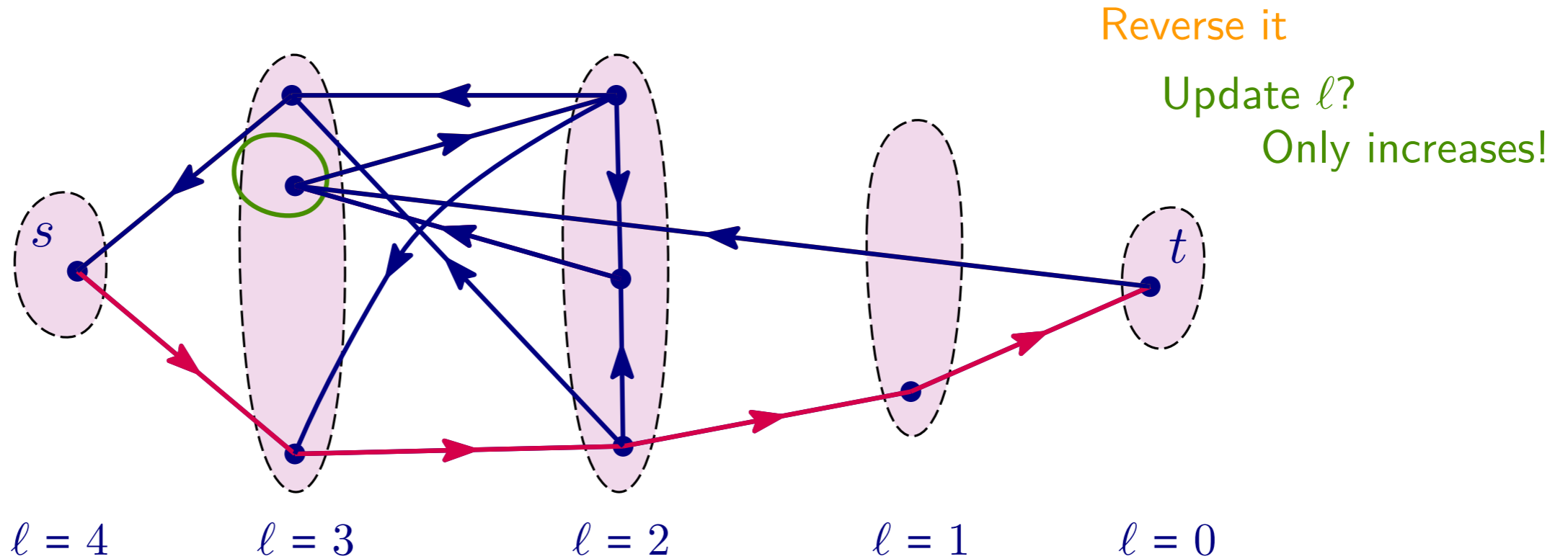
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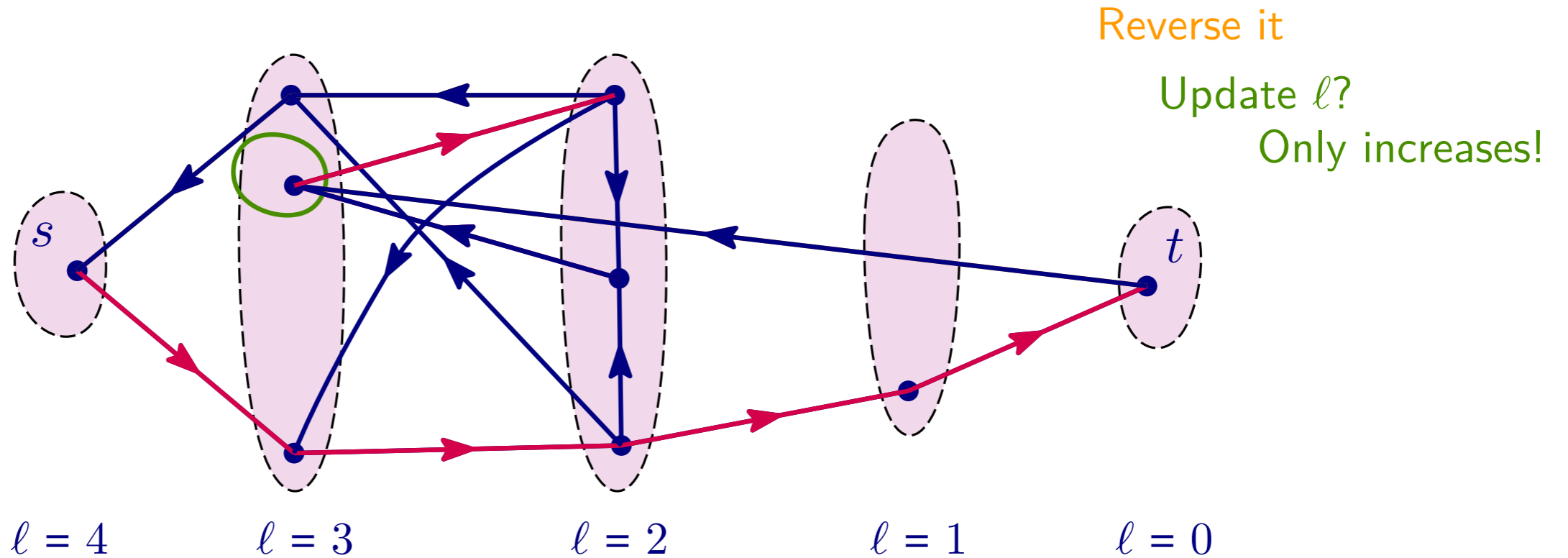
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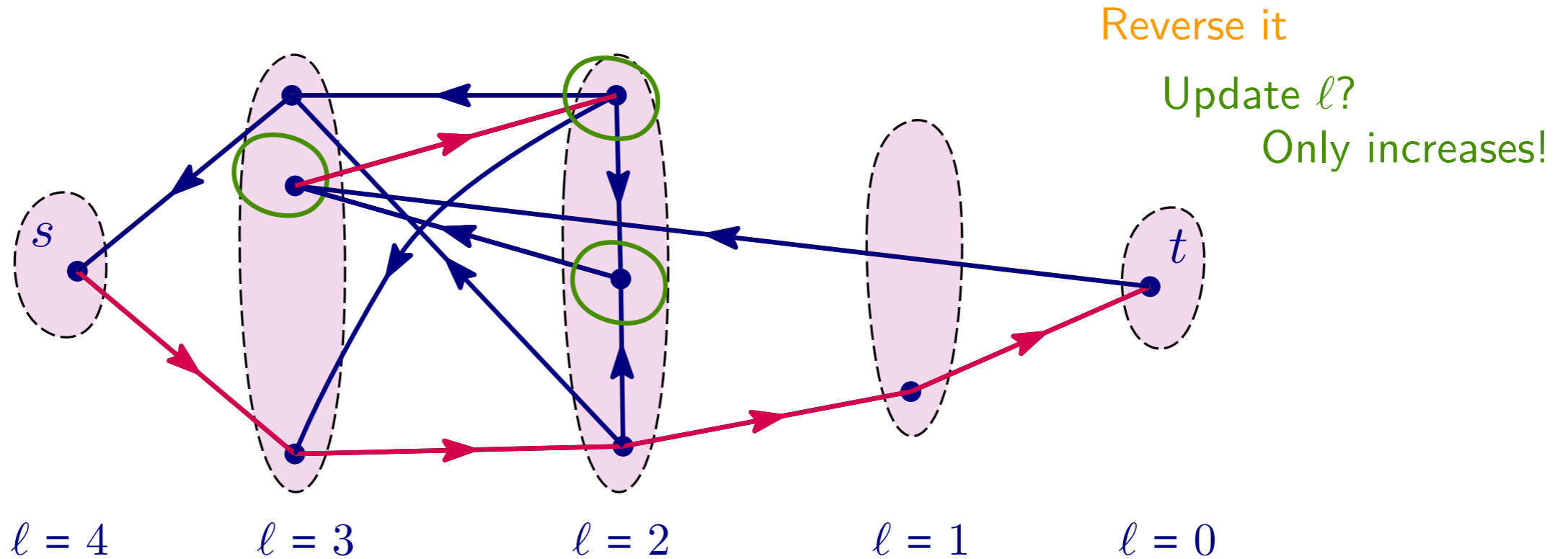
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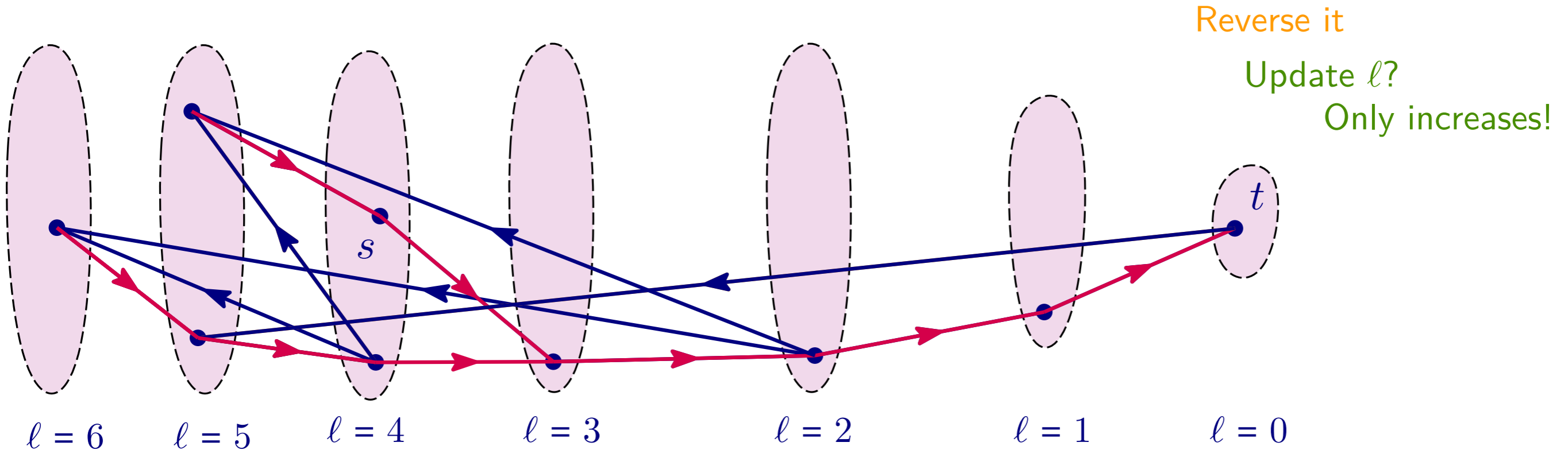
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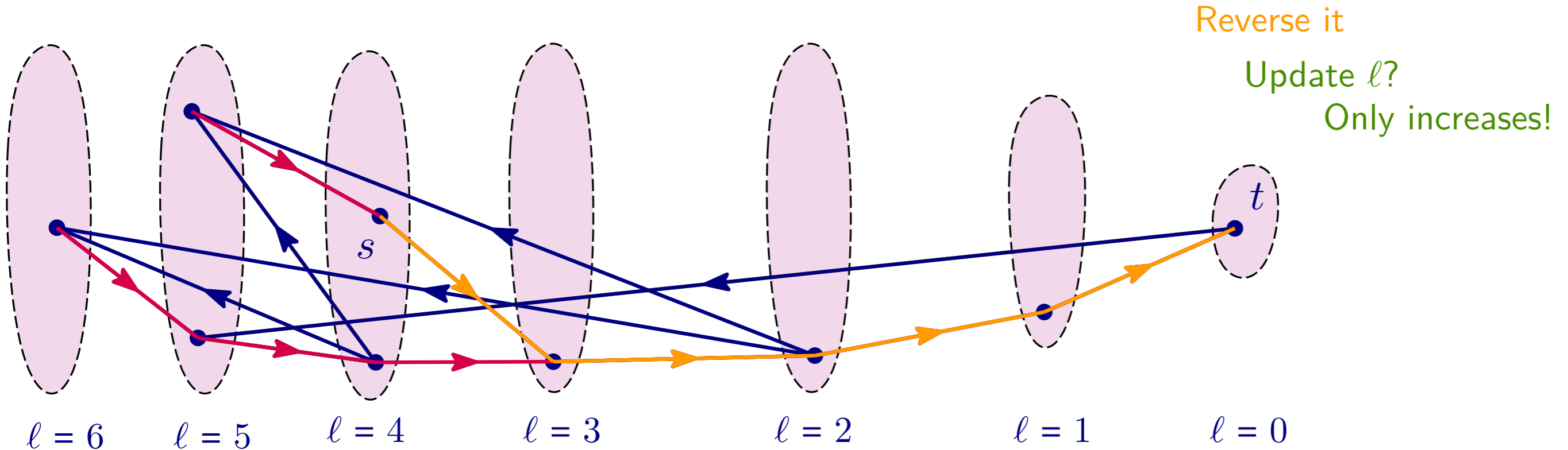
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Push-Relabel / Augment-Relabel [Goldberg-Tarjan'88] —Analysis

RELABEL

$O(n^2)$ (n vertices, n layers)

Push-Relabel / Augment-Relabel [Goldberg-Tarjan'88] —Analysis

RELABEL $O(n^2)$ (n vertices, n layers)

Keeping track of admissible edges: $O(nm)$ (after relabel: recheck incident edges)

Push-Relabel / Augment-Relabel [Goldberg-Tarjan'88] —Analysis

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Augmentations	$O(nm)$	(n per edge)



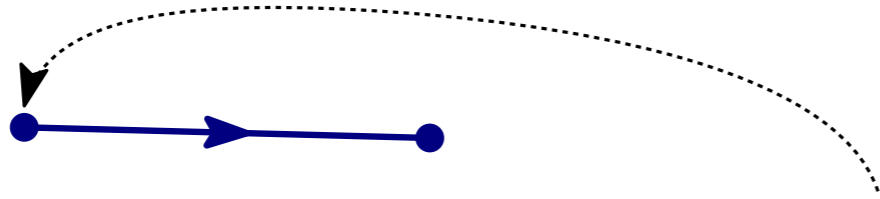
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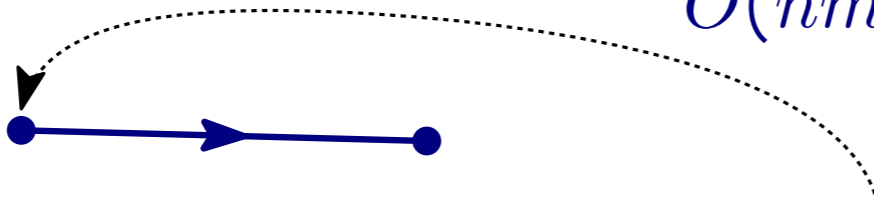
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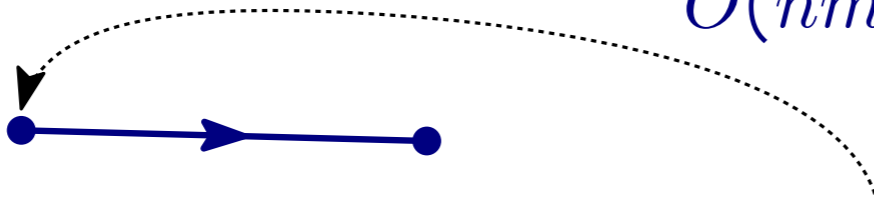
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Keeping track of admissible edges:	$O(nm)$	(after relabel: recheck incident edges)
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Total: $\tilde{O}(nm)$

How to speed it up?

New Idea: Edge Lengths



$$w(e) = 2$$



$$w(e) = 10$$

New Idea: Edge Lengths

“short” = “frequent”



$$w(e) = 2$$

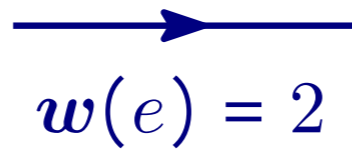
“long” = “infrequent”



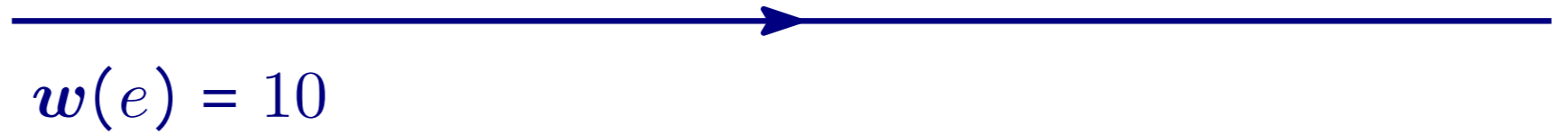
$$w(e) = 10$$

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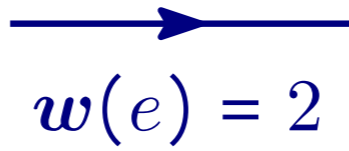
Guarantee: Path P in maxflow f^*



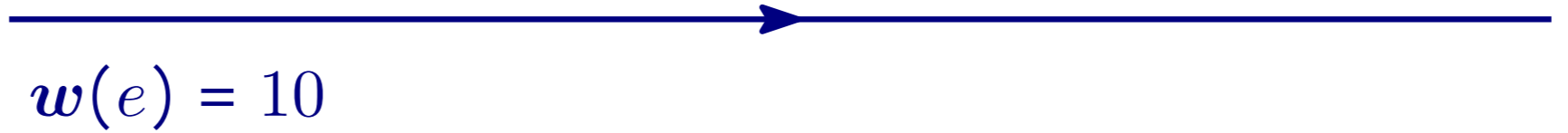
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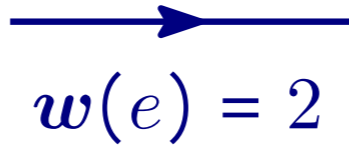
$$w(P) \leq n^{1+o(1)}$$



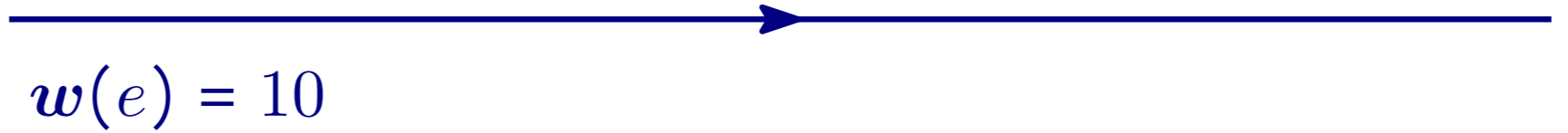
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Potential Faster Algo:

look for short paths

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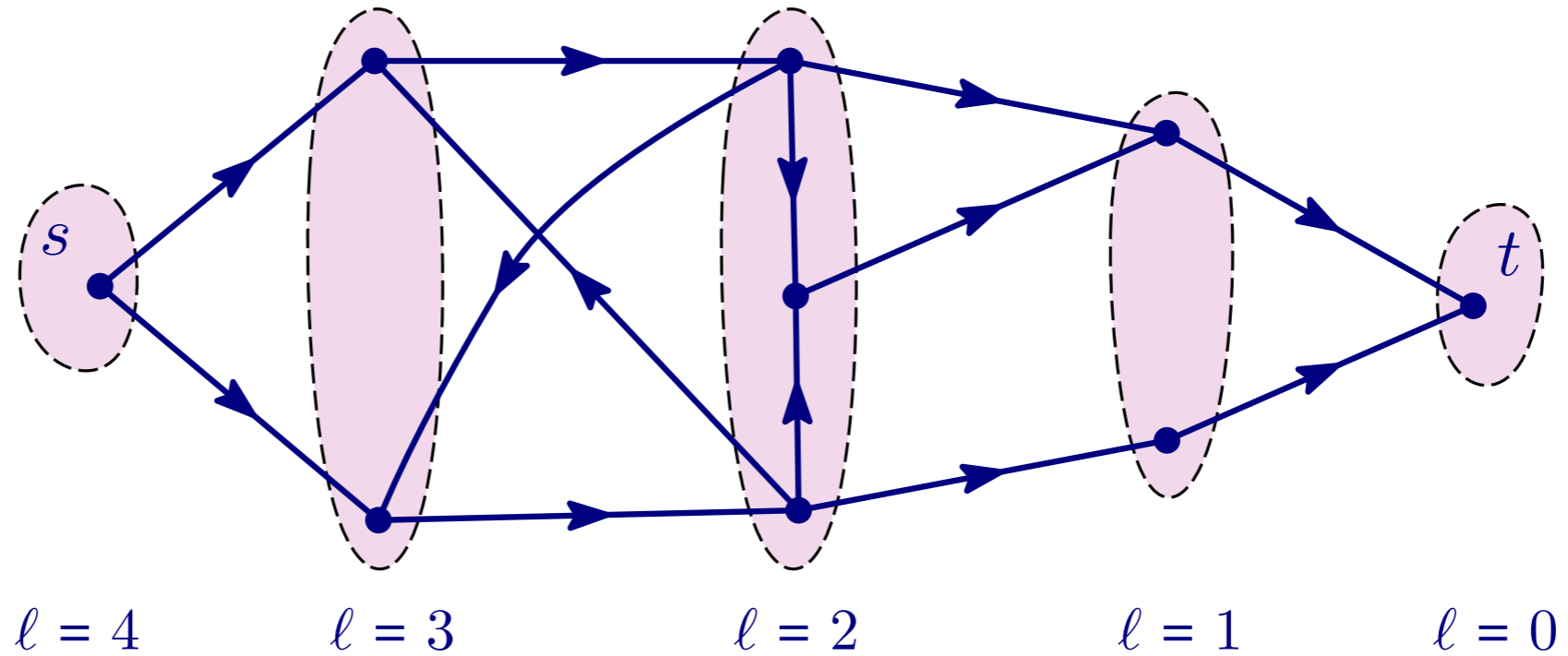
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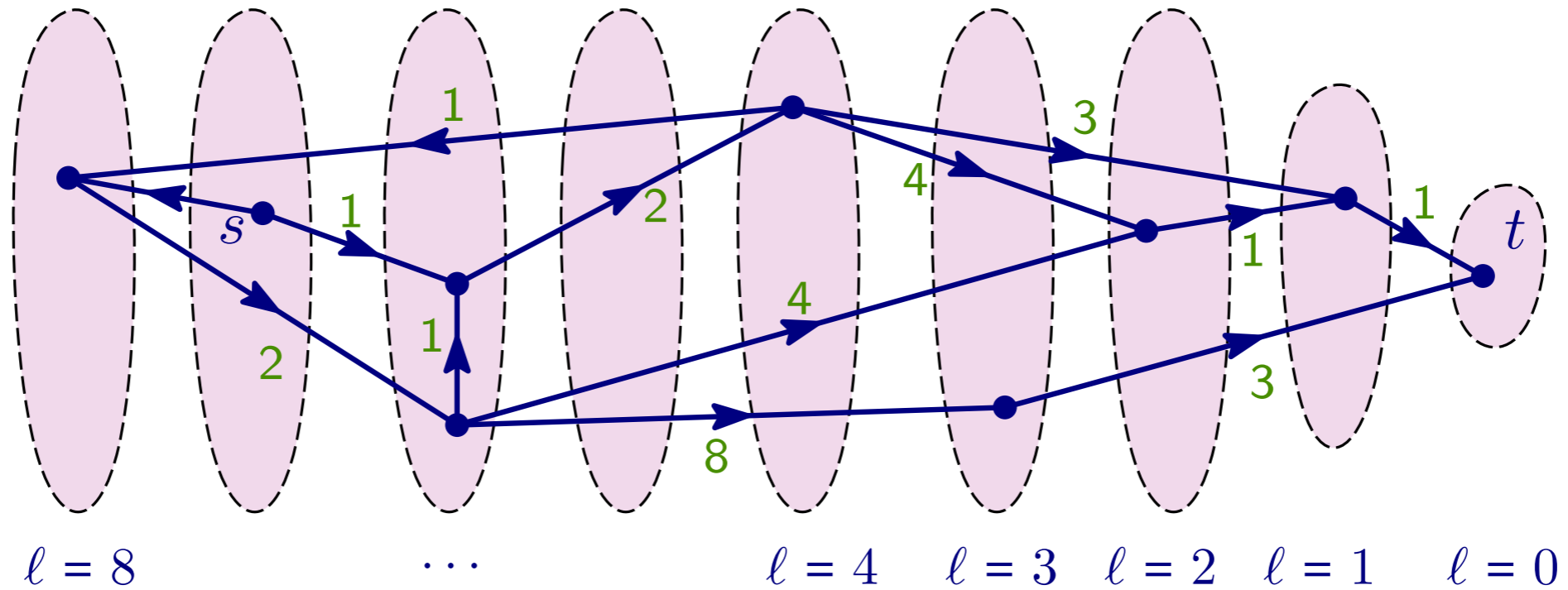
Weighted Push-Relabel

$$l(v) = \text{dist}(v, t)$$



Weighted Push-Relabel

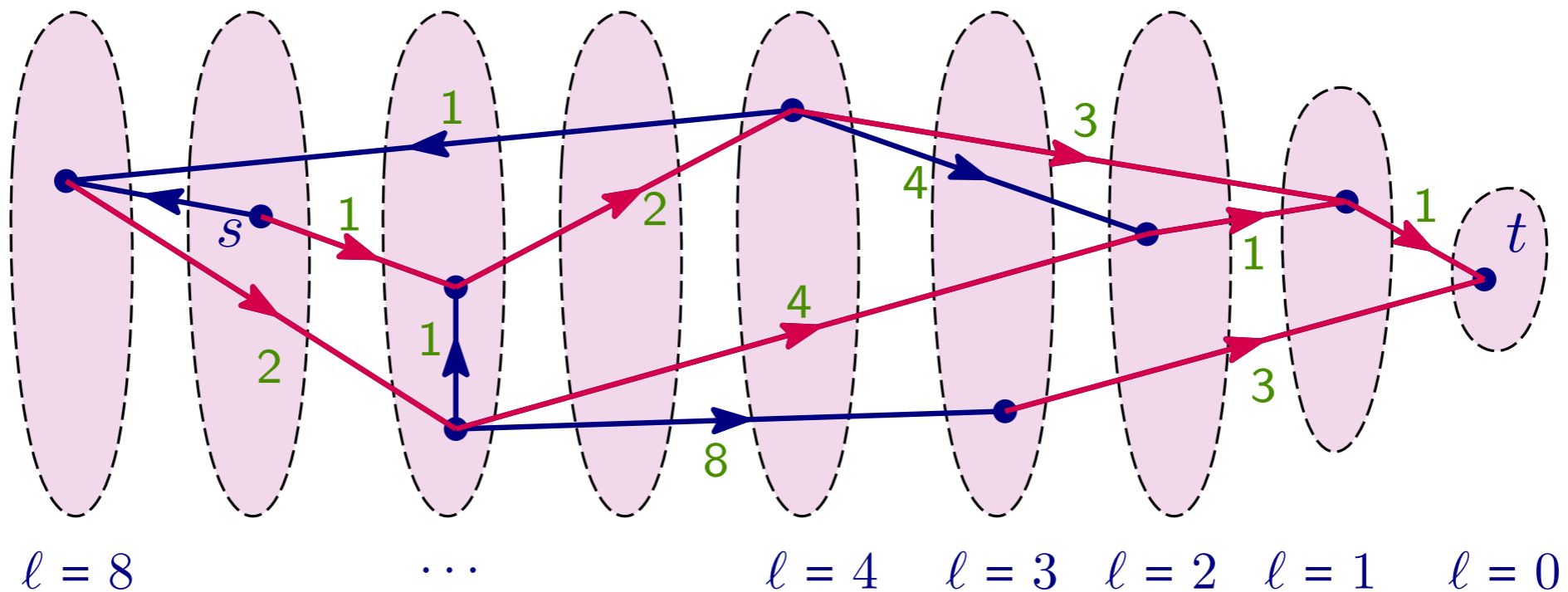
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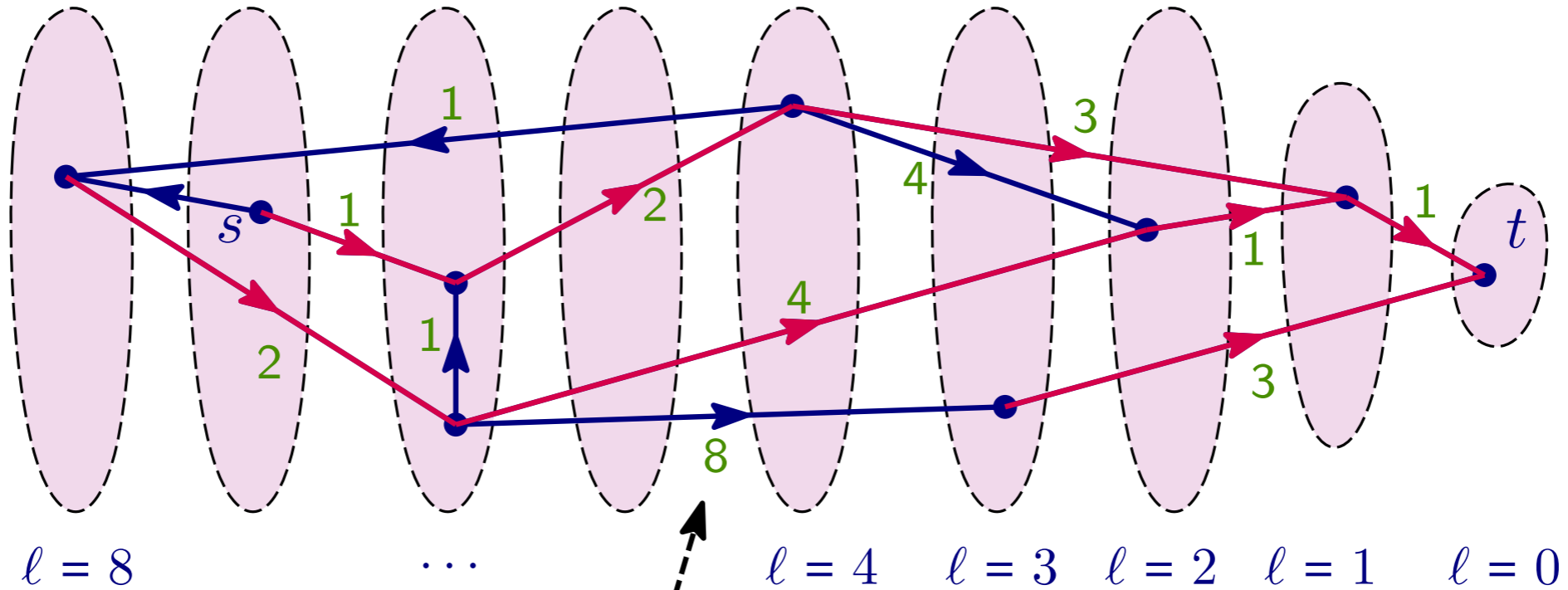
edge $e = (u, v)$ *admissible* iff $l(u) = l(v) + w(e)$



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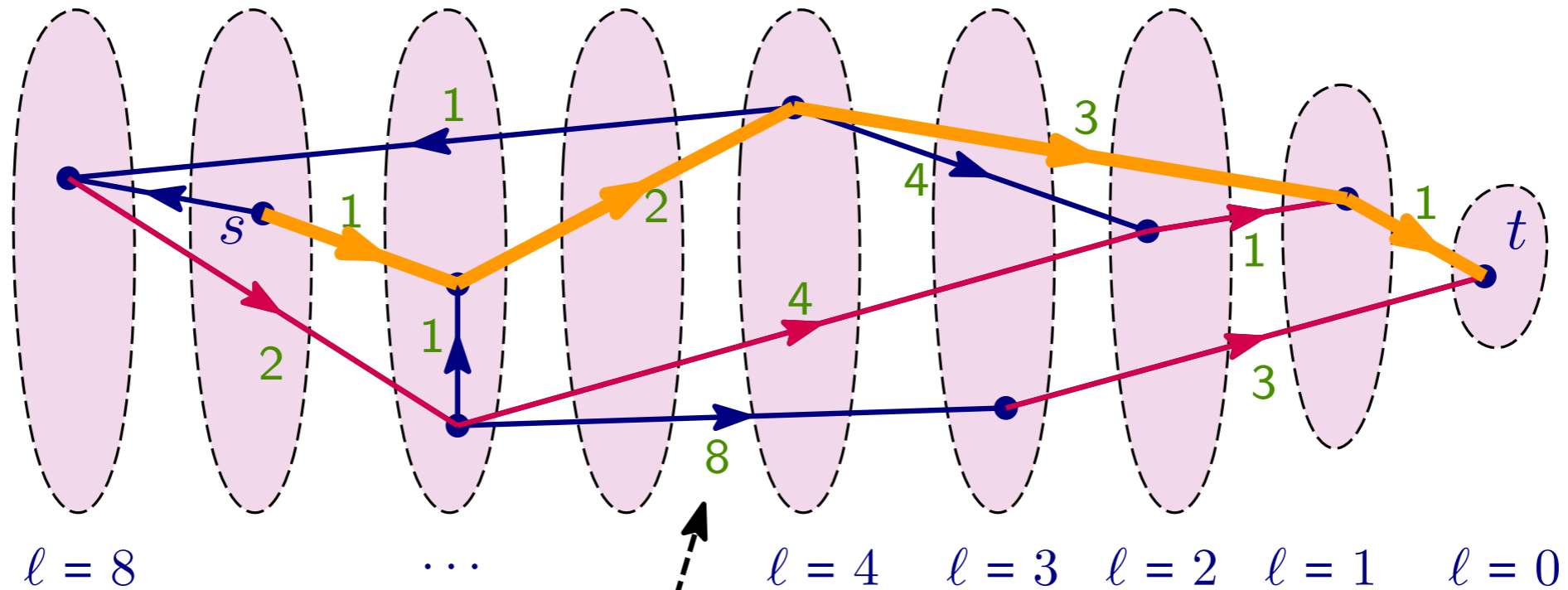


Not all forward edges are admissible!

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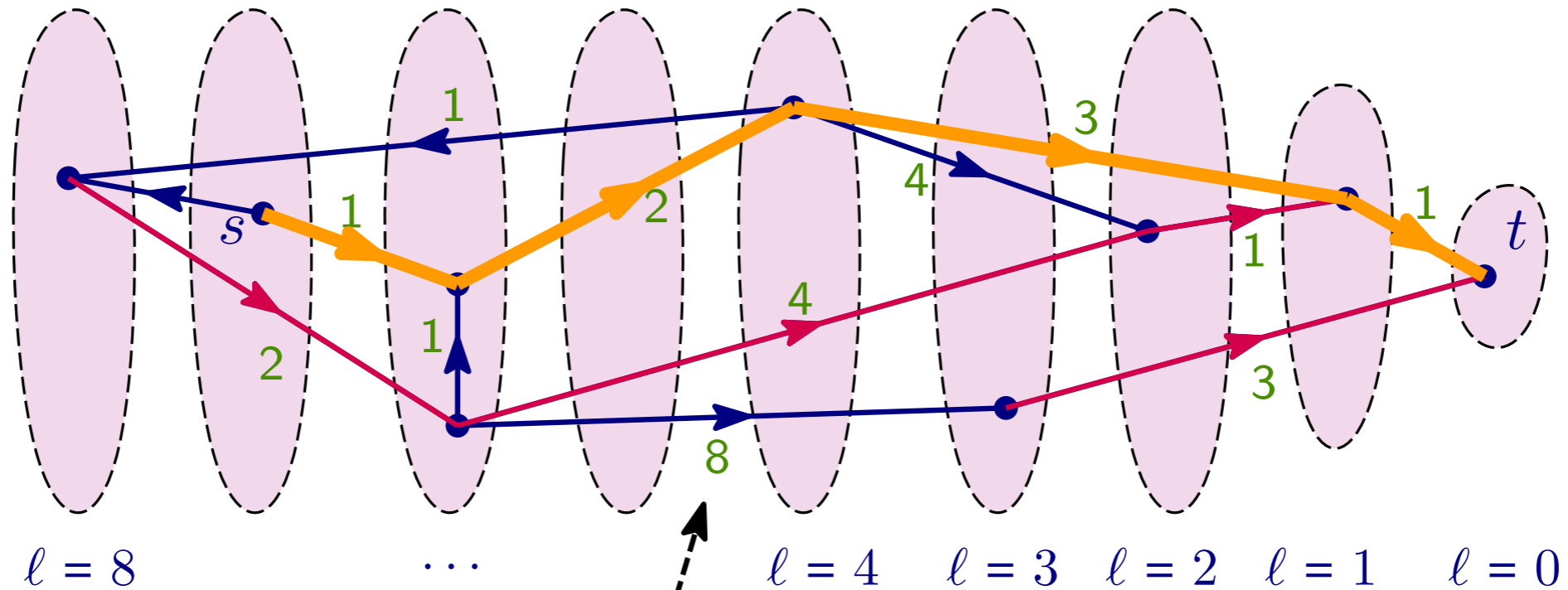
Not all forward edges are admissible!

w -Shortest Augmenting Path: follow admissible edges from s

Weighted Push-Relabel

$$l(v) \approx \text{dist}_w(v, t)$$

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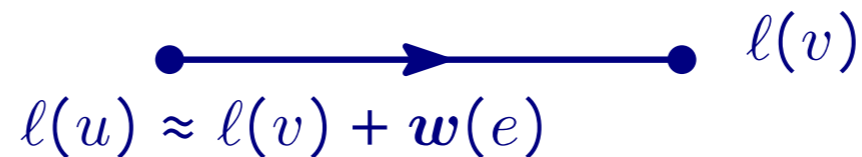
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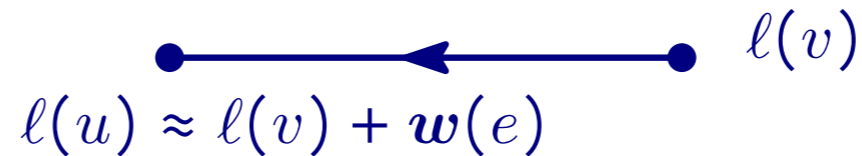
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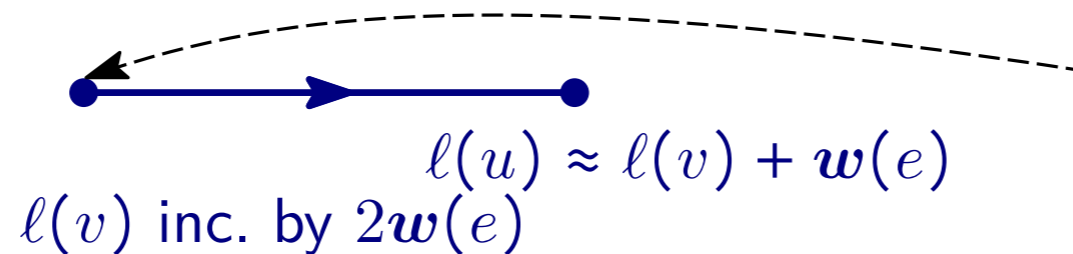
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Augmentations



Pseudo-Code

Algorithm 1: PUSHRELABEL($G, c, \Delta, \nabla, w, h$)

```
1 Initialize  $f$  as the empty flow.
2 Let  $\ell(v) = 0$  for all  $v \in V$ . // levels
3 Mark each edge  $e \in \vec{E} \cup \overleftarrow{E}$  as inadmissible and all vertices as alive.
4 function RELABEL( $v$ )
5   Set  $\ell(v) \leftarrow \ell(v) + 1$ .
6   if  $\ell(v) > 9h$  then
7     mark  $v$  as dead and return.
8   for each edge  $e \ni v$  where  $w(e)$  divides  $\ell(v)$  do
9     Let  $(x, y) = e$ .
10    if  $\ell(x) - \ell(y) \geq 2w(e)$  and  $c_f(e) > 0$  then mark  $e$  as admissible.
11    else mark  $e$  as inadmissible.

12 main loop
13 while there is an alive vertex  $v$  with  $\nabla_f(v) = 0$  and without an admissible out-edge do
14   RELABEL( $v$ )
15 if there is some alive vertex  $s$  with  $\Delta_f(s) > 0$  then
16   //  $P$  is an "augmenting path"
17   Trace a path  $P$  from  $s$  to some sink  $t$ , by arbitrarily following admissible out-edges.
18   Let  $c^{\text{augment}} \leftarrow \min\{\Delta_f(s), \nabla_f(t), \min_{e \in P} c_f(e)\}$ .
19   for  $e \in P$  do // Augment  $f$  along  $P$ 
20     if  $e$  is a forward edge then  $f(e) \leftarrow f(e) + c^{\text{augment}}$ .
21     else  $f(e') \leftarrow f(e') - c^{\text{augment}}$ , where  $e'$  is the corresponding forward edge to  $e$ .
22     Adjust residual capacities  $c_f$  of  $e$  and the corresponding reverse edge.
23     if  $c_f(e) = 0$  then mark  $e$  as inadmissible.
24   //  $\Delta_f(s)$  and  $\nabla_f(t)$  goes down by  $c^{\text{augment}}$ 
25 else return  $f$ 
```

Similar to normal
Augment-Relabel / Push-Relabel

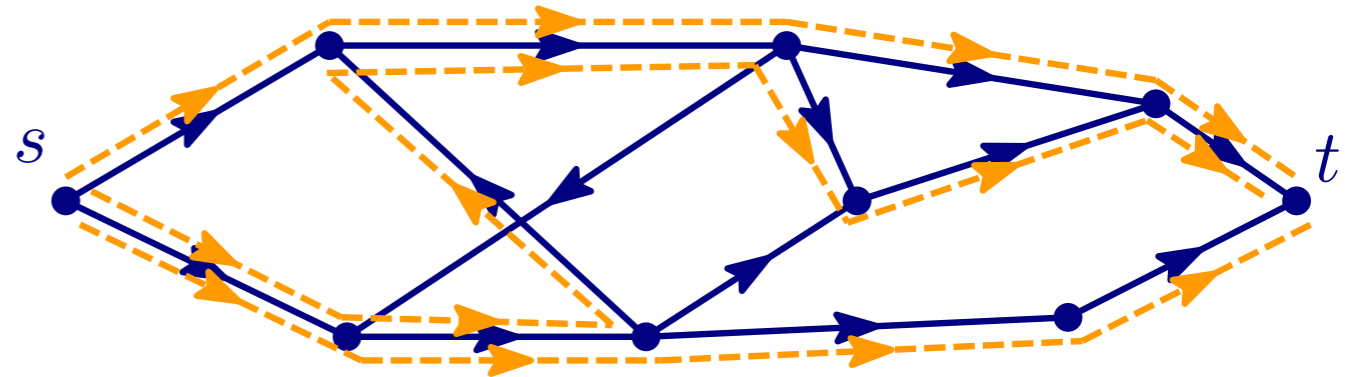
Good Edge Lengths

- *Good w :*

- $\sum_{e \in E} \frac{n}{w(e)}$ is small

($\approx n^{2+o(1)}$, running-time)

- “Optimal” flow f^* which is short w.r.t. w (flow paths of length $\approx n^{1+o(1)}$)



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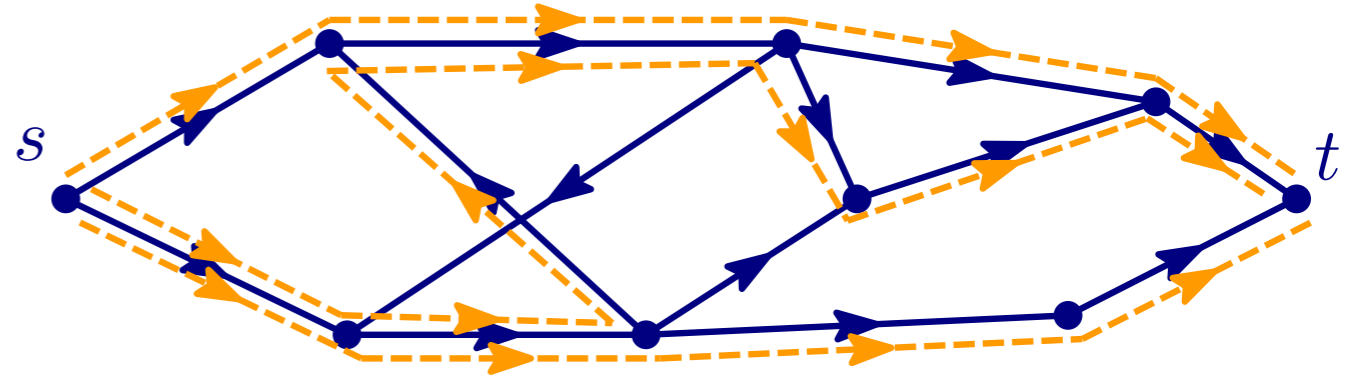
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Lemma.

Weighted Push-Relabel finds f

with $|f| \geq \frac{1}{10} |f^*|$



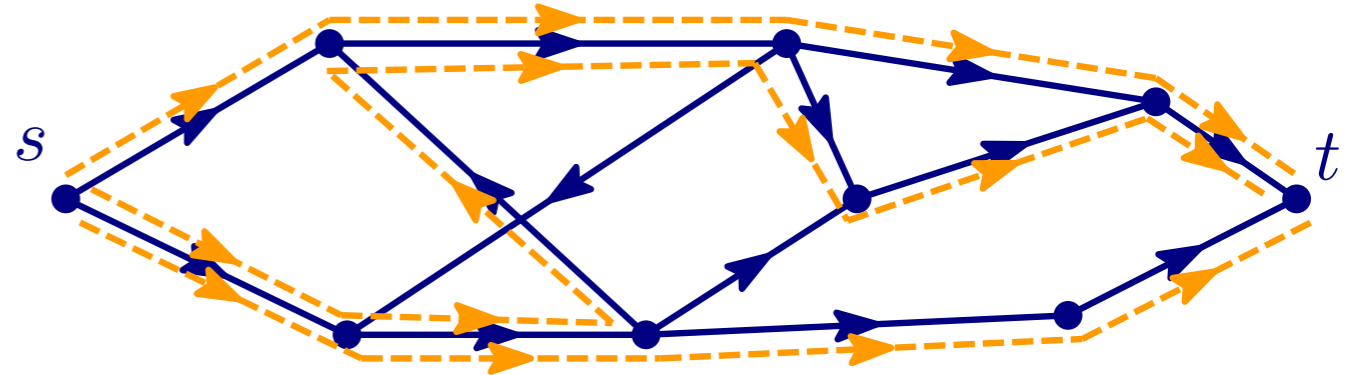
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Lemma.

Weighted Push-Relabel finds f
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Proof Sketch.

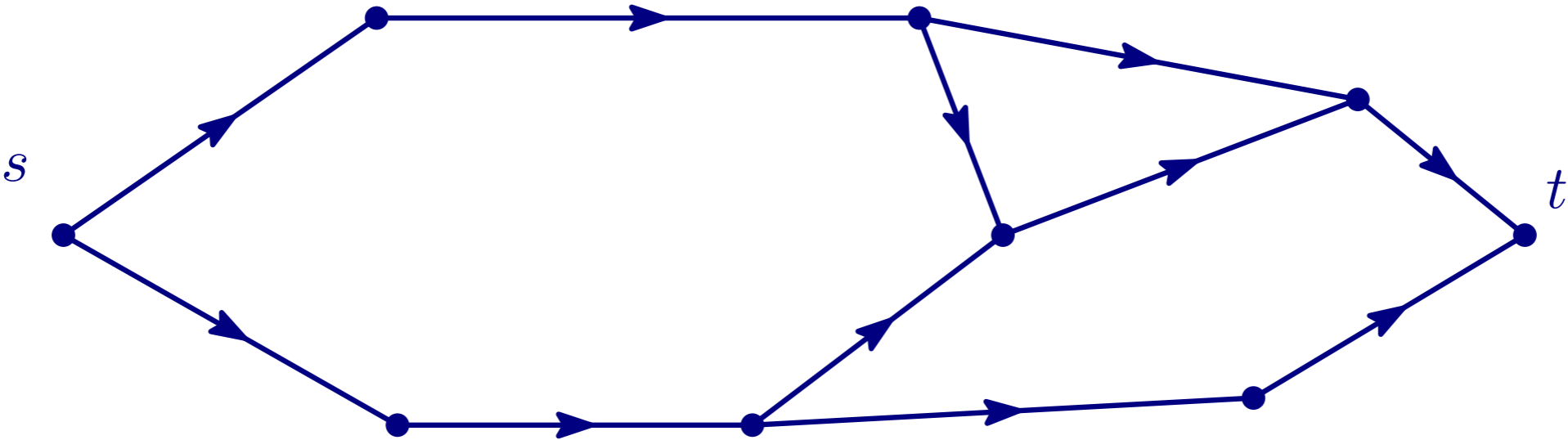
If not: $|f| < \frac{1}{10} |f^*|$

\implies some flow path is still short in residual graph G_f

How to find good edge lengths?

Directed Acyclic Graphs (DAG)

Def: no directed cycles

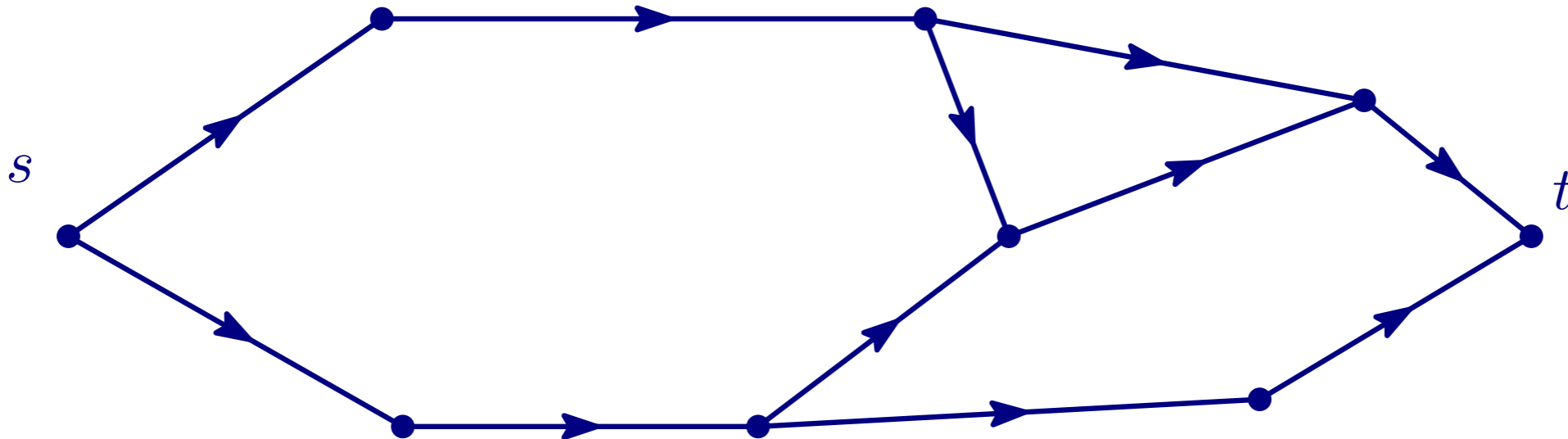


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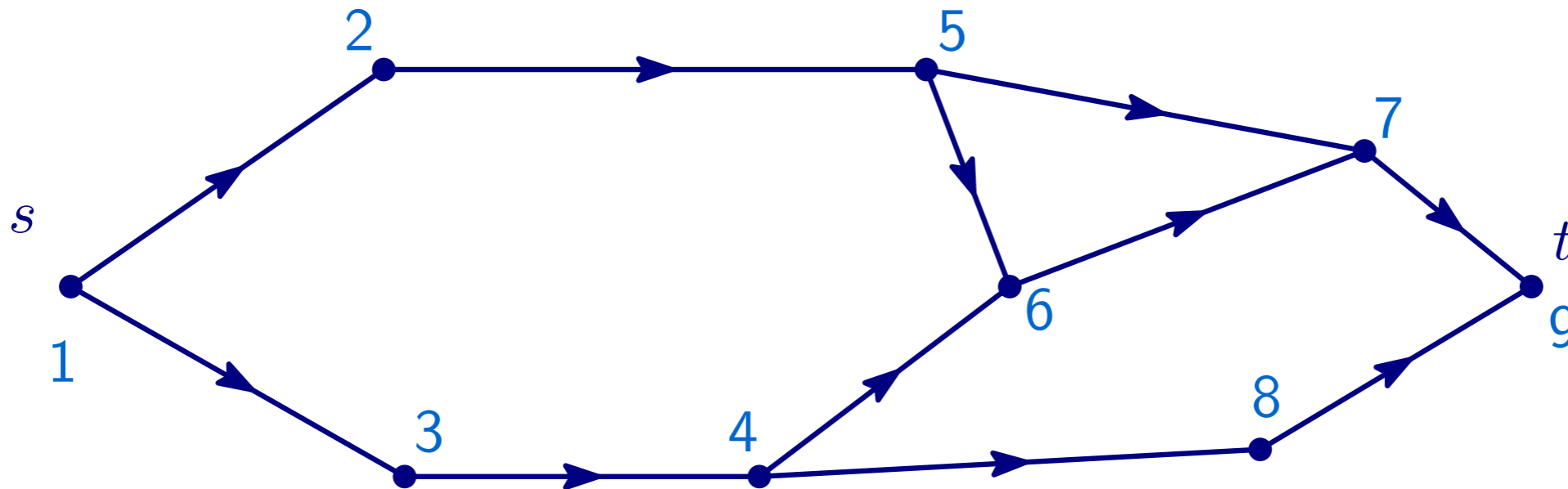
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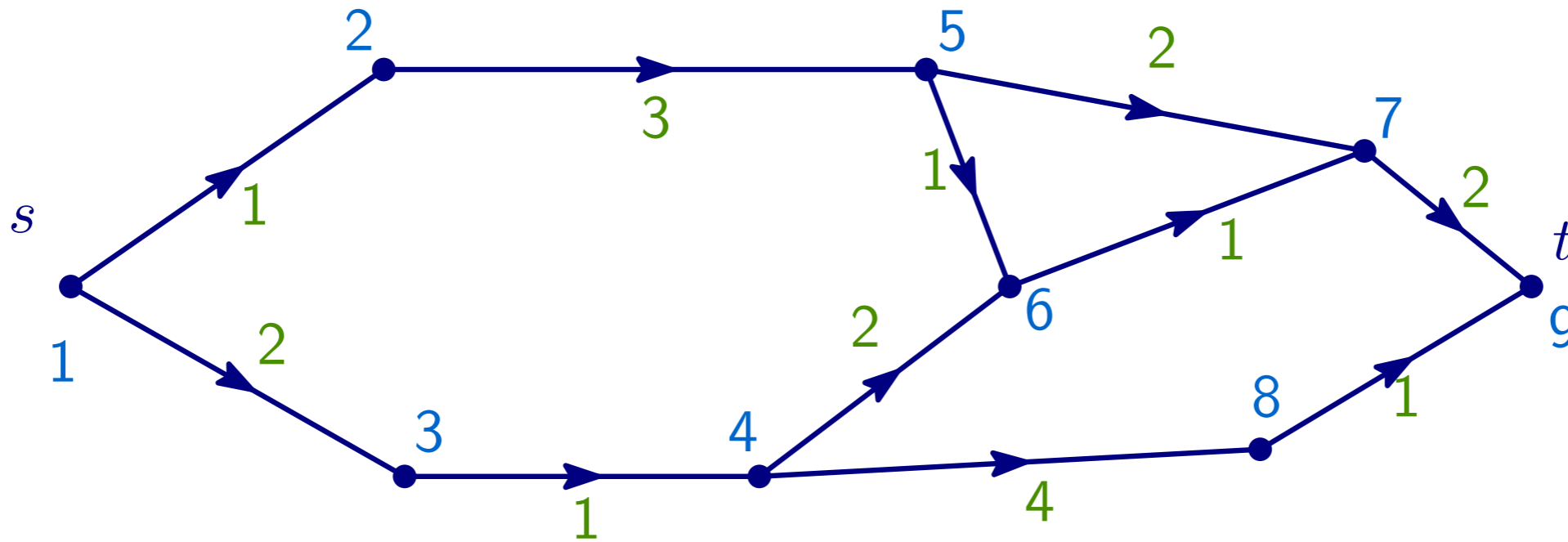
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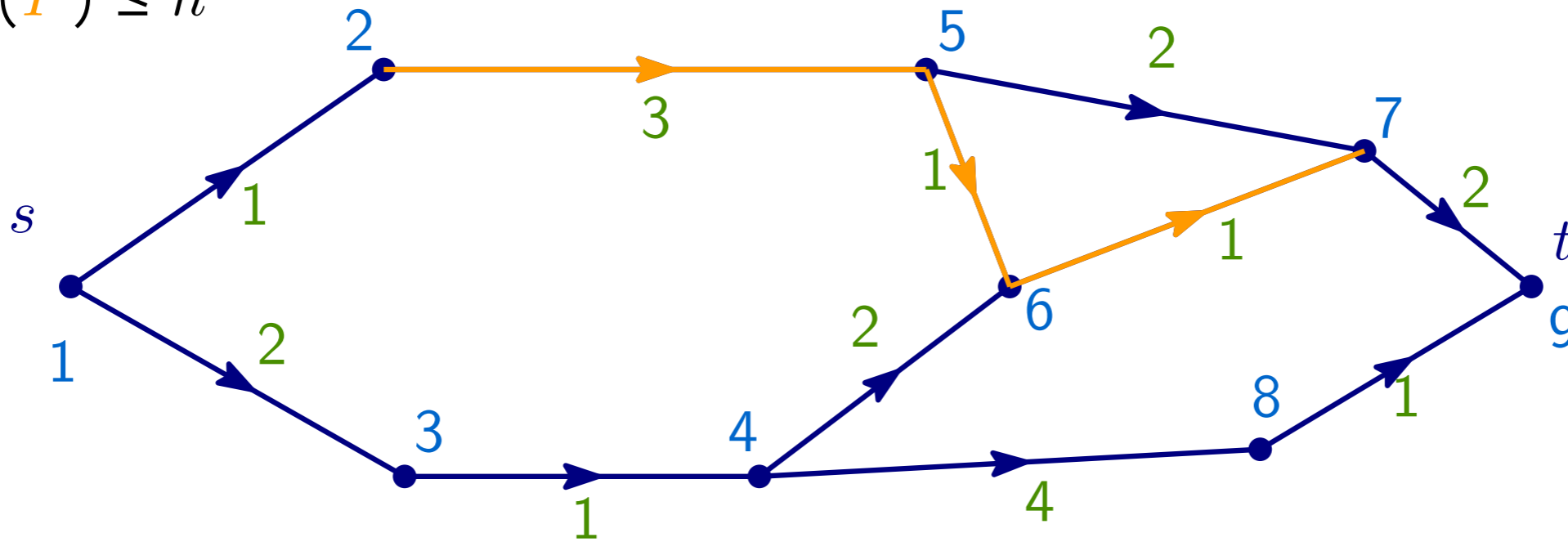
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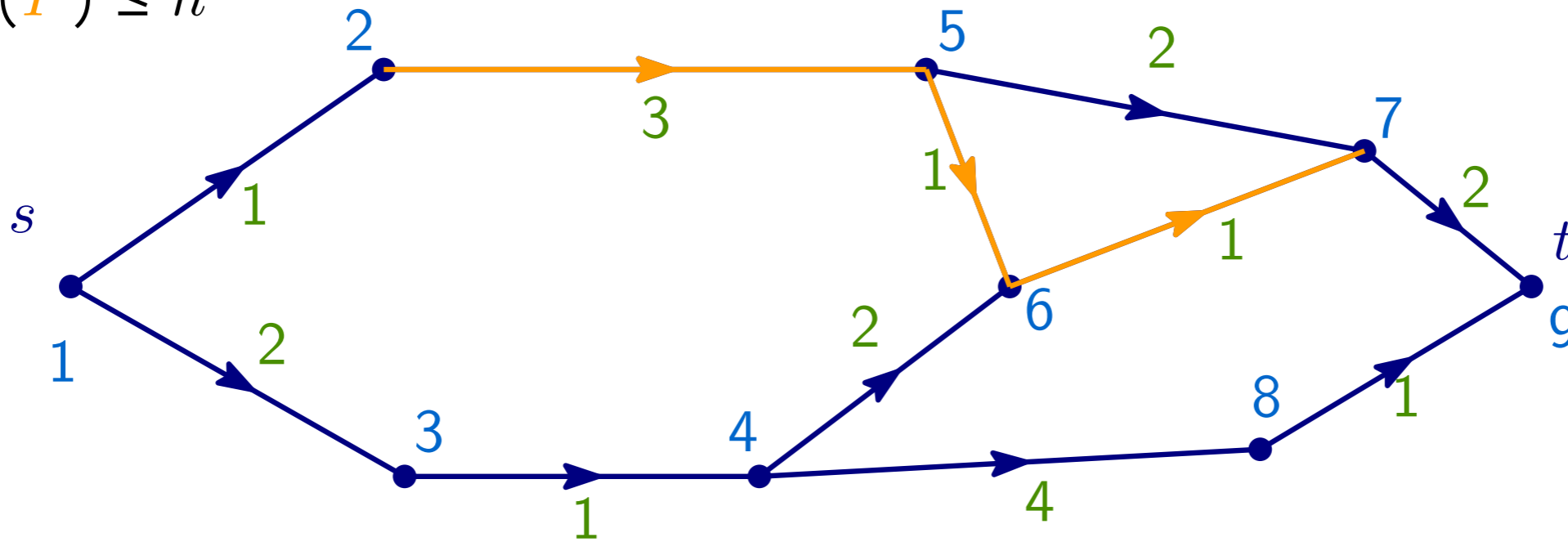
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$$\sum_{(u,v)} \frac{n}{|\tau(u) - \tau(v)|} \leq n \sum_{v \in V} \sum_{k=1}^{n-1} \frac{1}{k} \leq n^2 \log n$$

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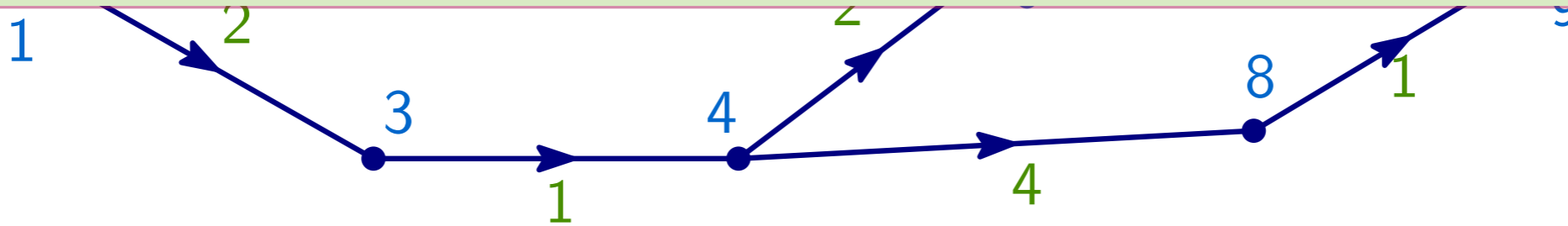
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Theorem: “Simple” $\frac{1}{6}$ -approx flow on n -vertex DAGs in $O(n^2 \log^2 n)$ time.



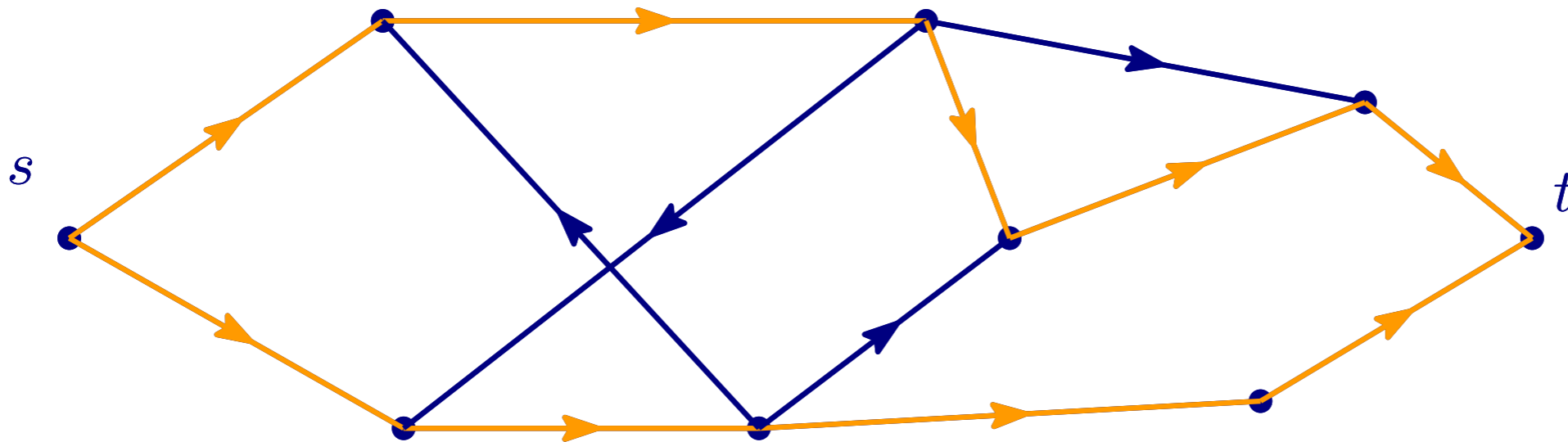
$$\sum_{(u,v)} \frac{n}{|\tau(u) - \tau(v)|} \leq n \sum_{v \in V} \sum_{k=1}^{n-1} \frac{1}{k} \leq n^2 \log n$$

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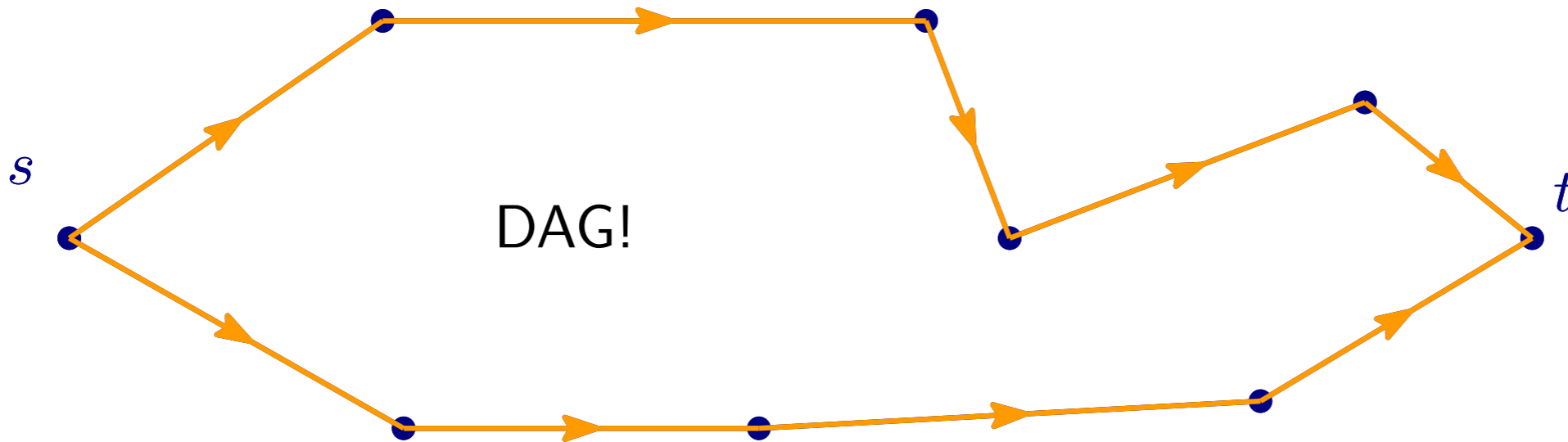


General Graphs — Attempt One

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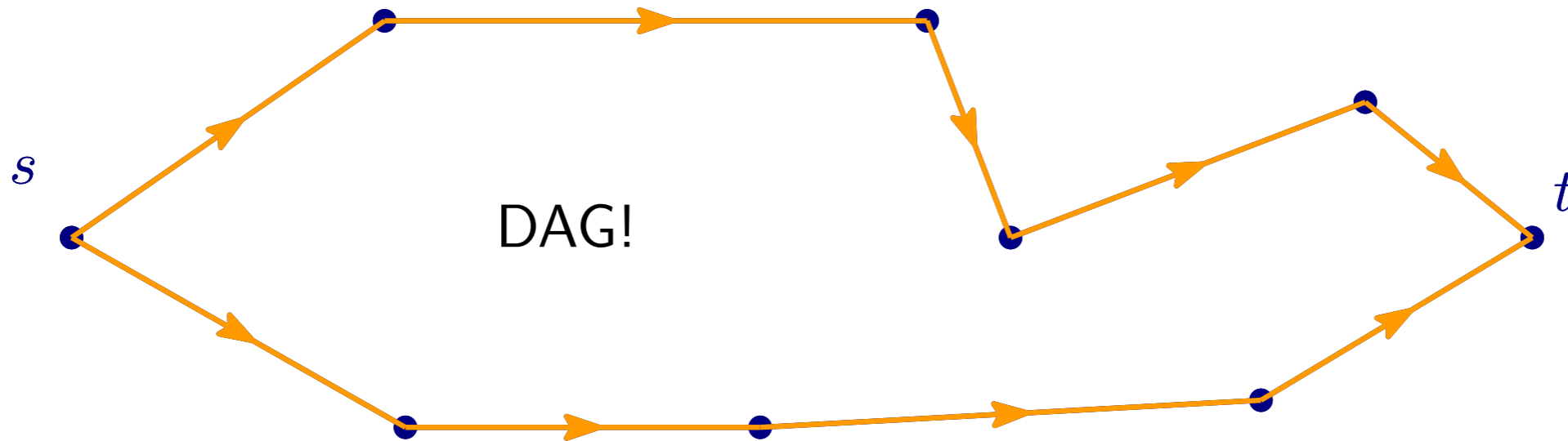


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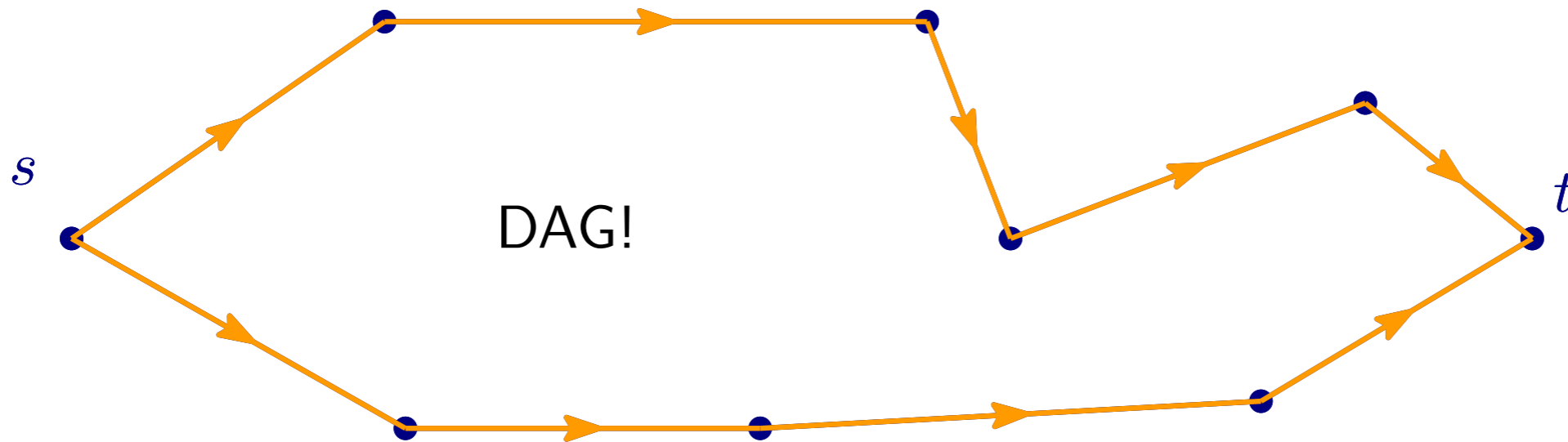


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4. Use weighted push-relabel to solve approx maxflow :)

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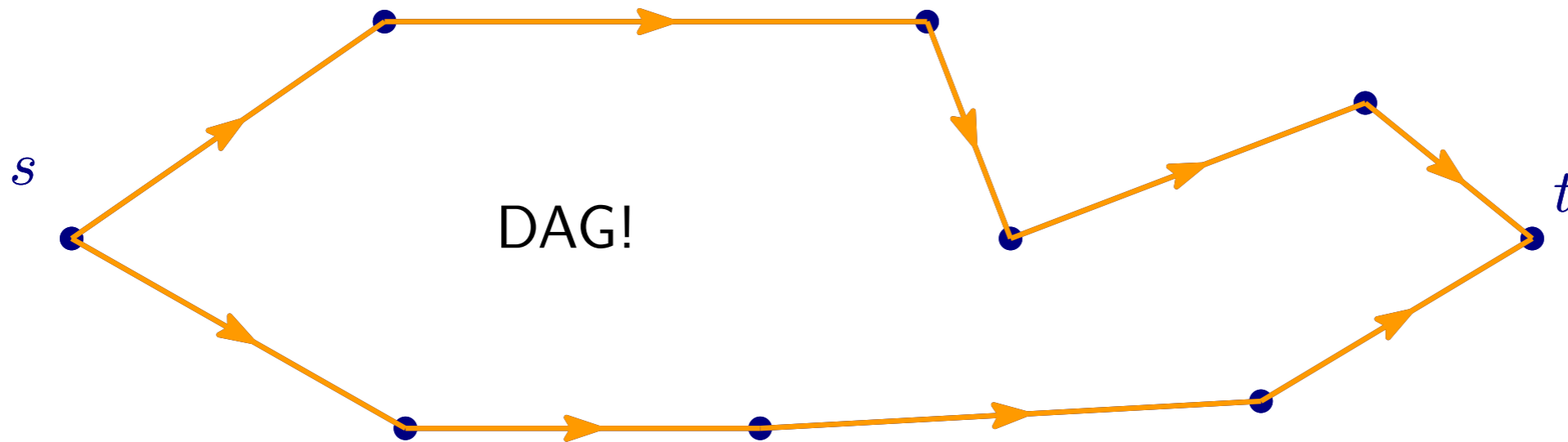


General Graphs — Attempt One

1. Compute maxflow f^* ← **Cheating!**
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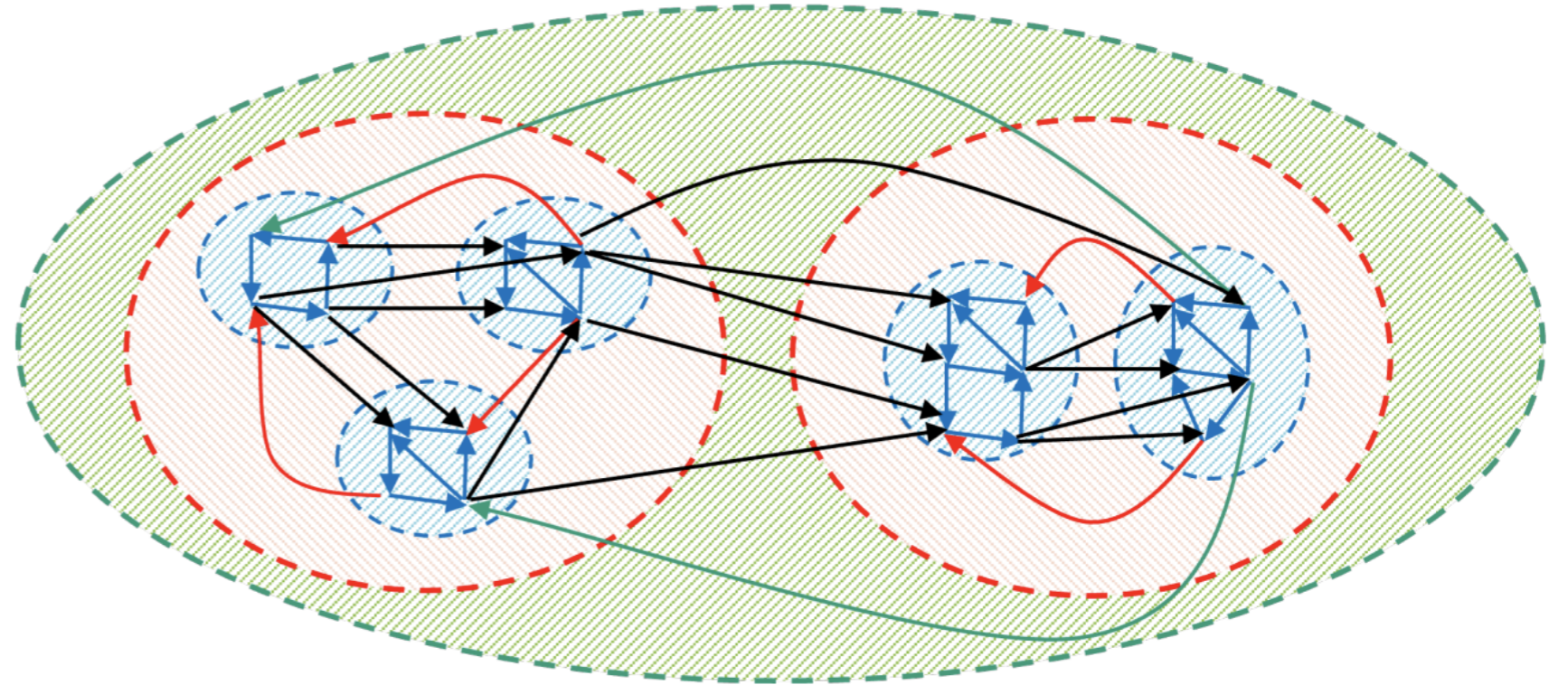
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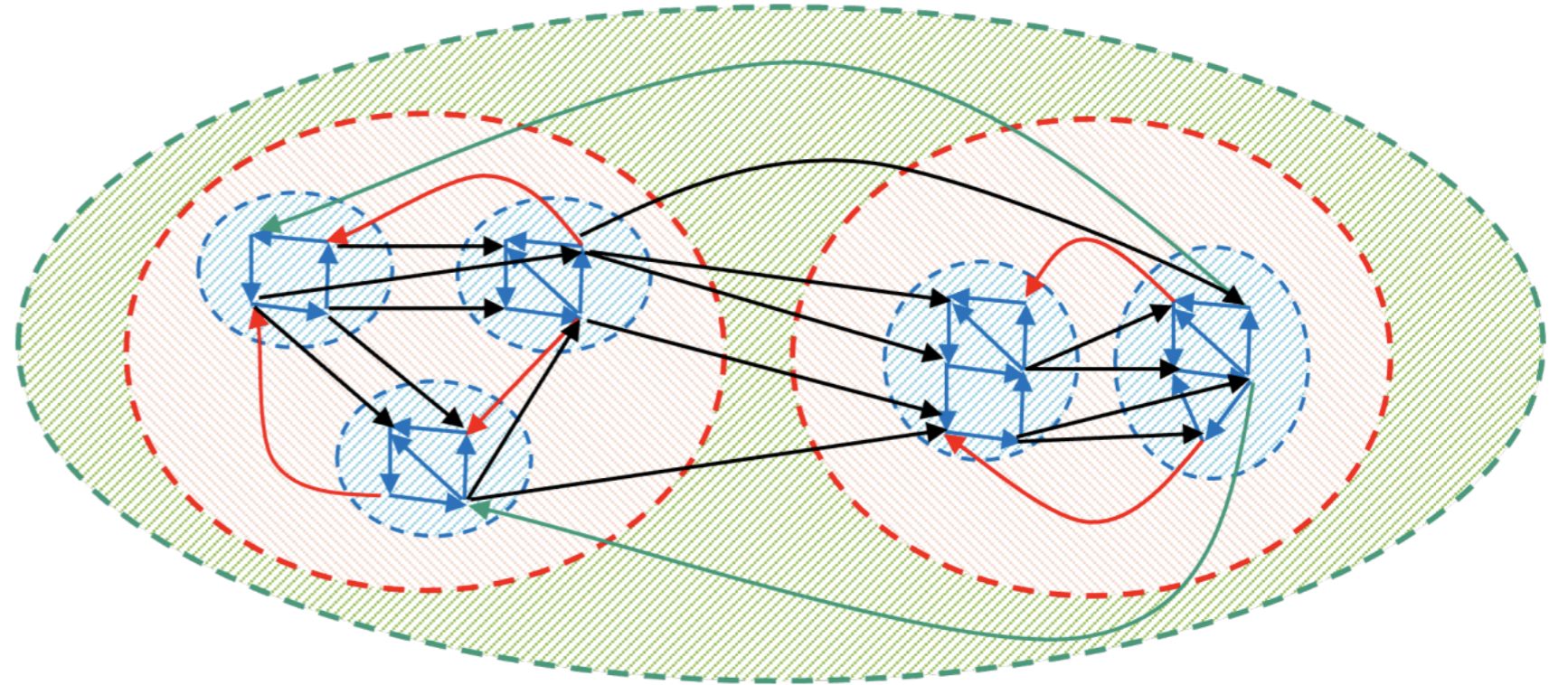
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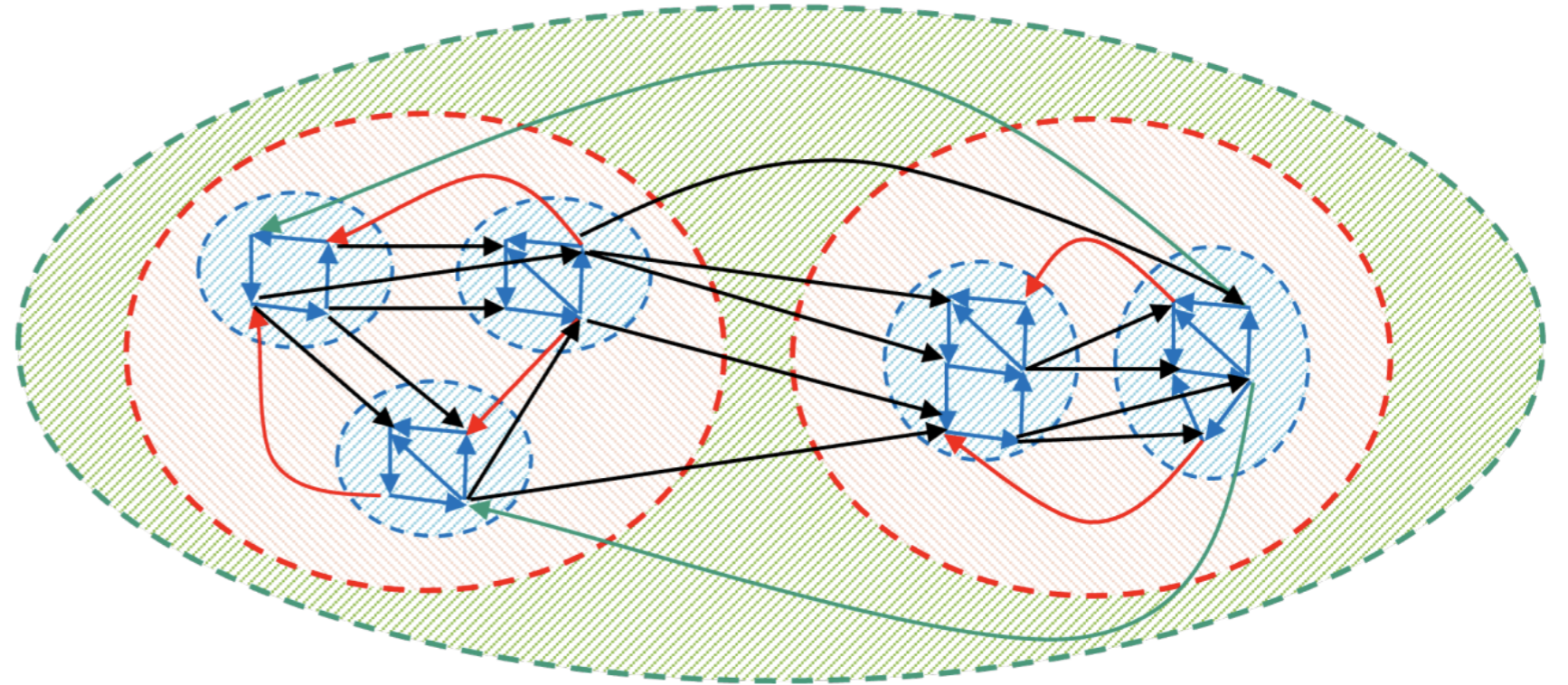
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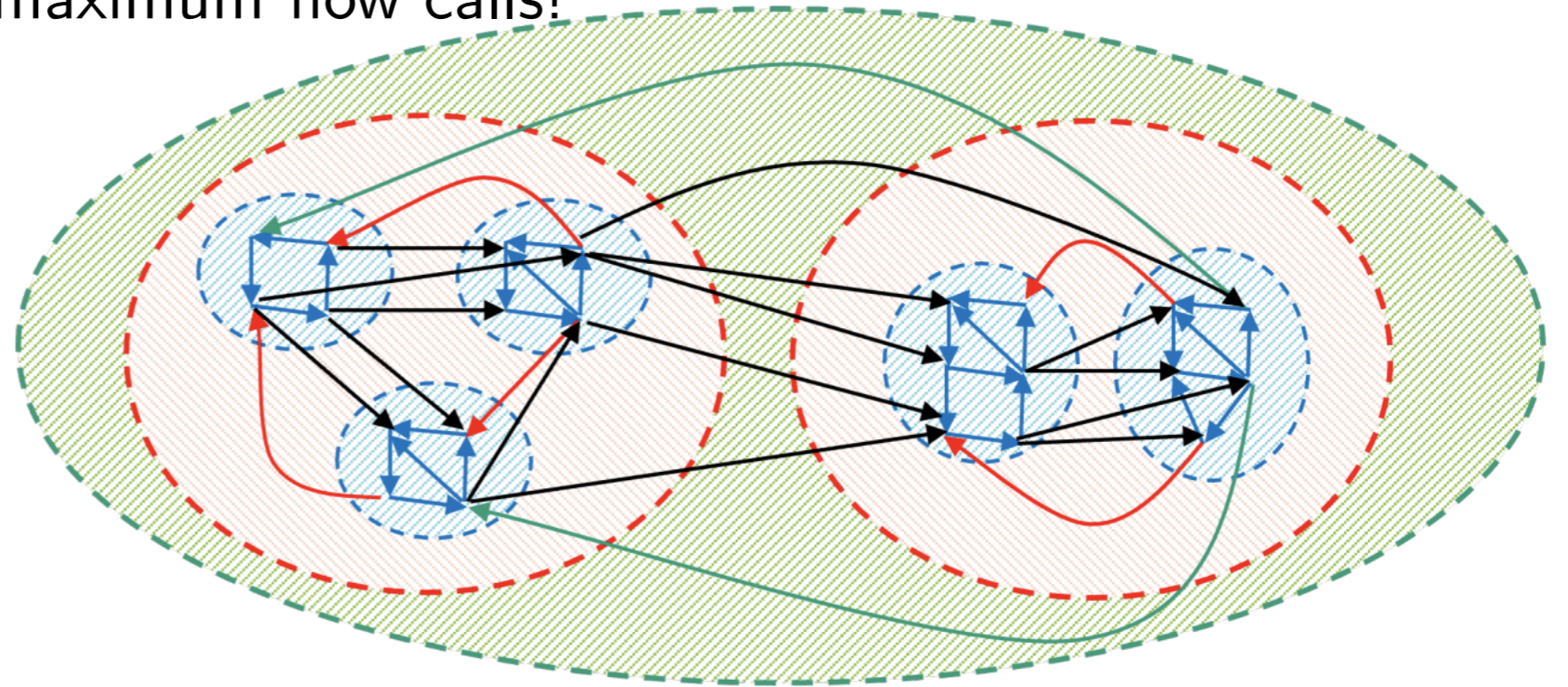
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Can build using $n^{o(1)}$ many maximum flow calls!

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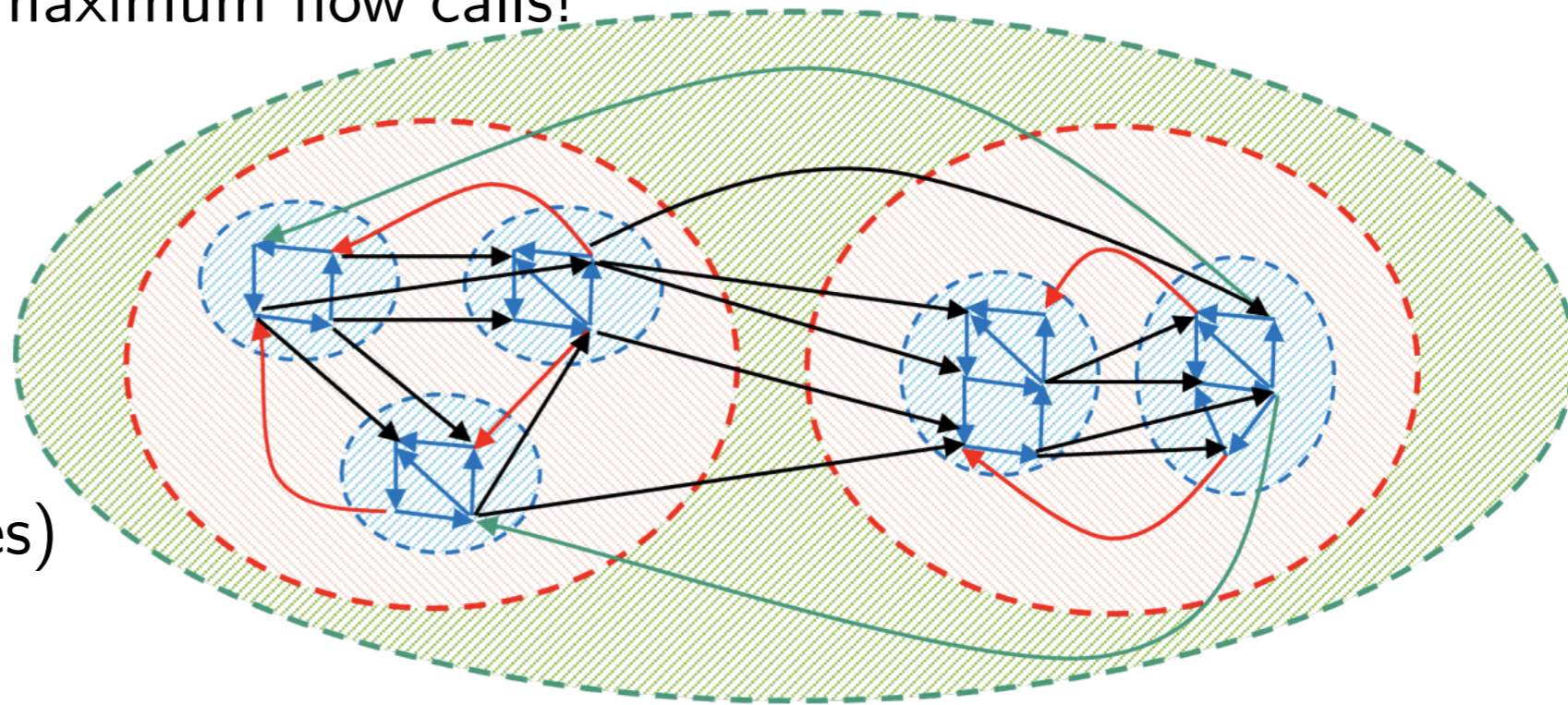
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Instead:

Build Bottom Up
Bootstrap Weighted P.R.
(solve “easier” flow instances)

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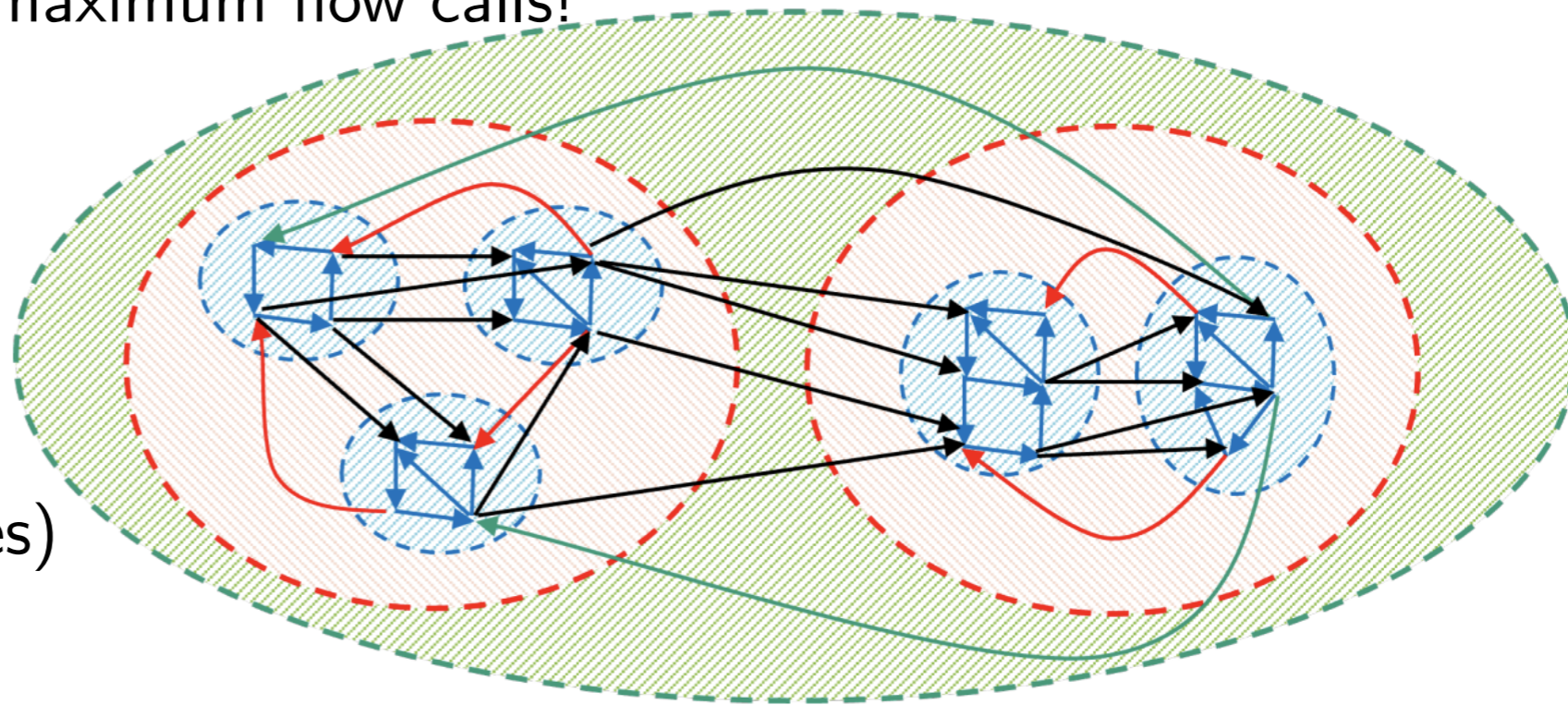
Technically Complicated :(
(bad guy: nestedness)

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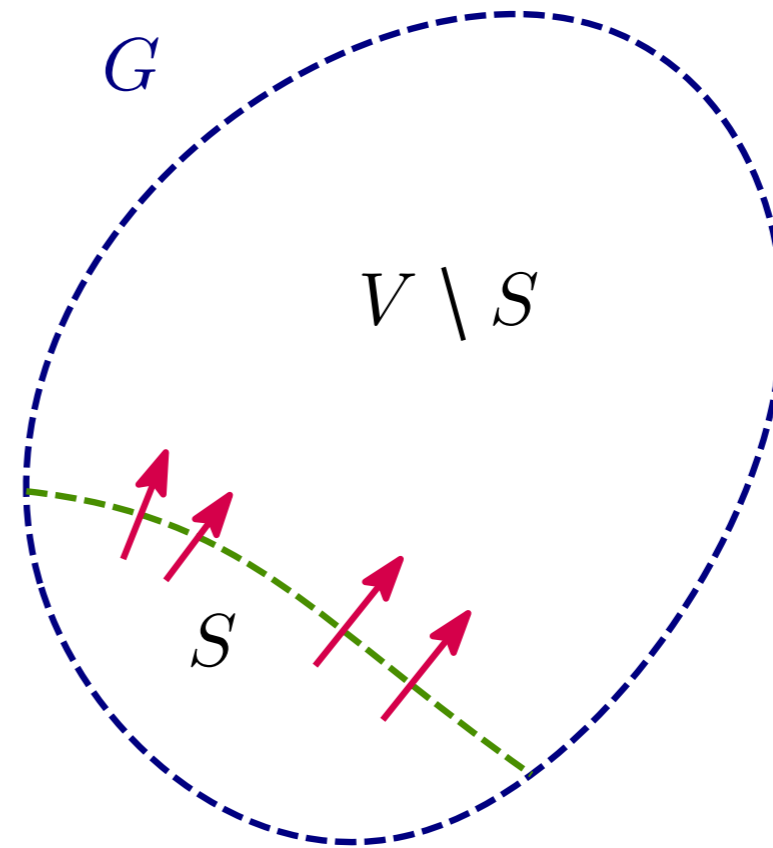


(half of our 99 page paper)

(Directed) Expanders

Def: G is ϕ -expander if $E(S, V \setminus S) \geq \phi \cdot \min\{\text{vol}(S), \text{vol}(V \setminus S)\} \quad \forall S$

($\text{vol}(S) = \sum_{v \in S} \deg(v)$, $\phi \approx 1/n^{o(1)}$)



(Directed) Expanders

Def: G is ϕ -expander if $E(S, V \setminus S) \geq \phi \cdot \min\{\text{vol}(S), \text{vol}(V \setminus S)\} \quad \forall S$

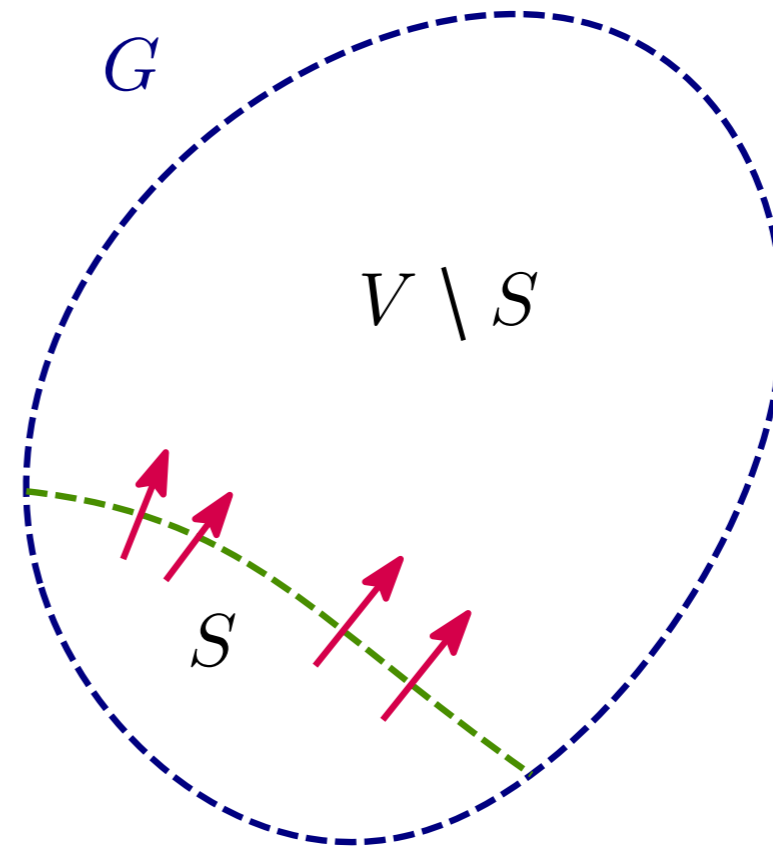
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Examples:

Cliques

Bidirected Stars

Random



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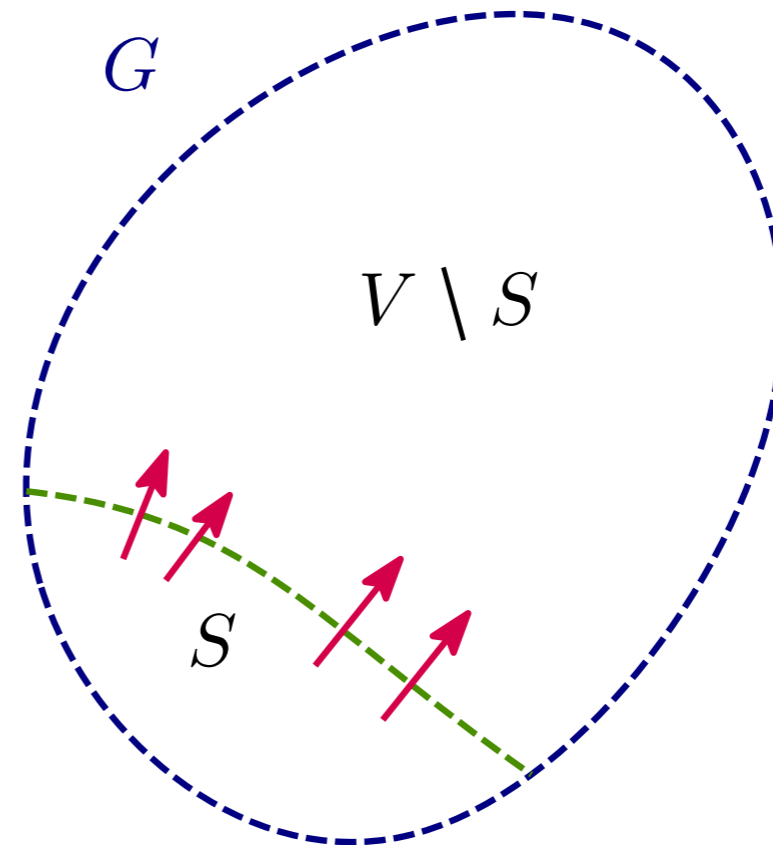
Why?

Well-connected

Low diameter $\frac{\log(n)}{\phi}$

Easy to route (short) flow in

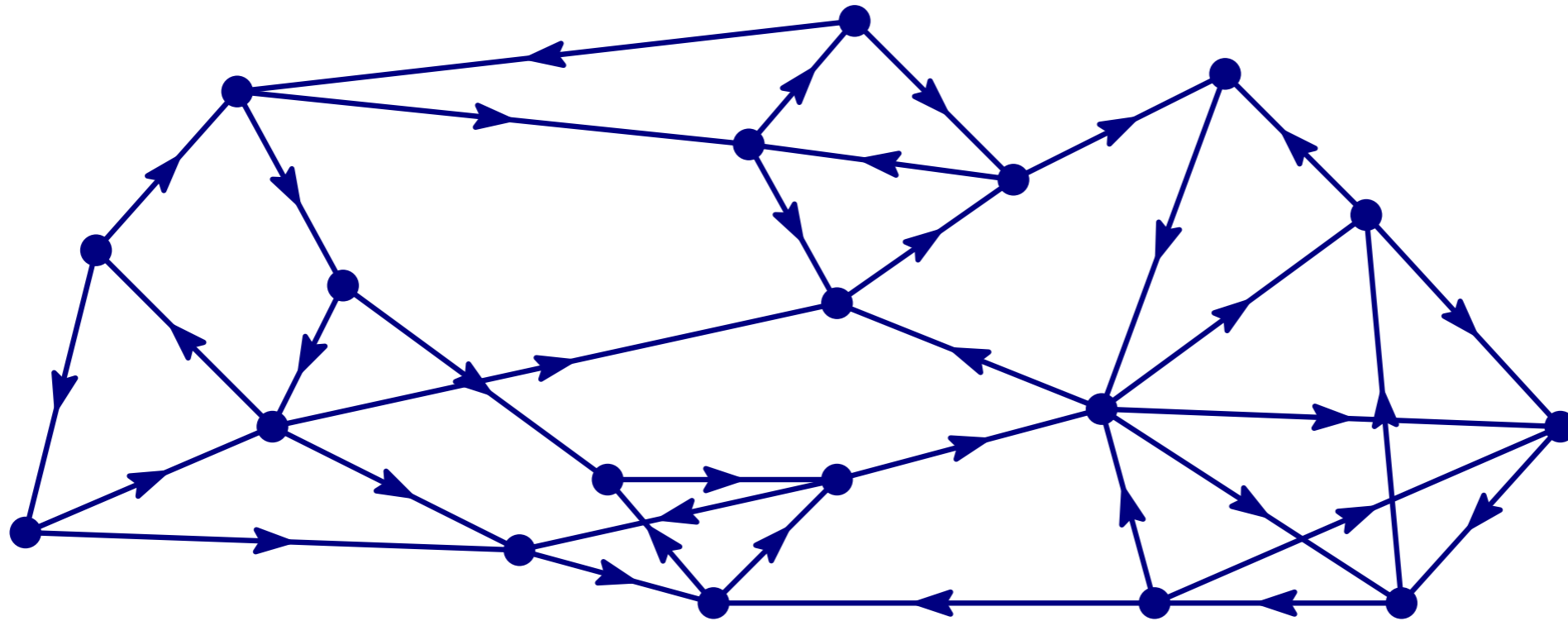
Robust to small changes



(Directed) Expander Decomposition

Every graph can be decomposed into:

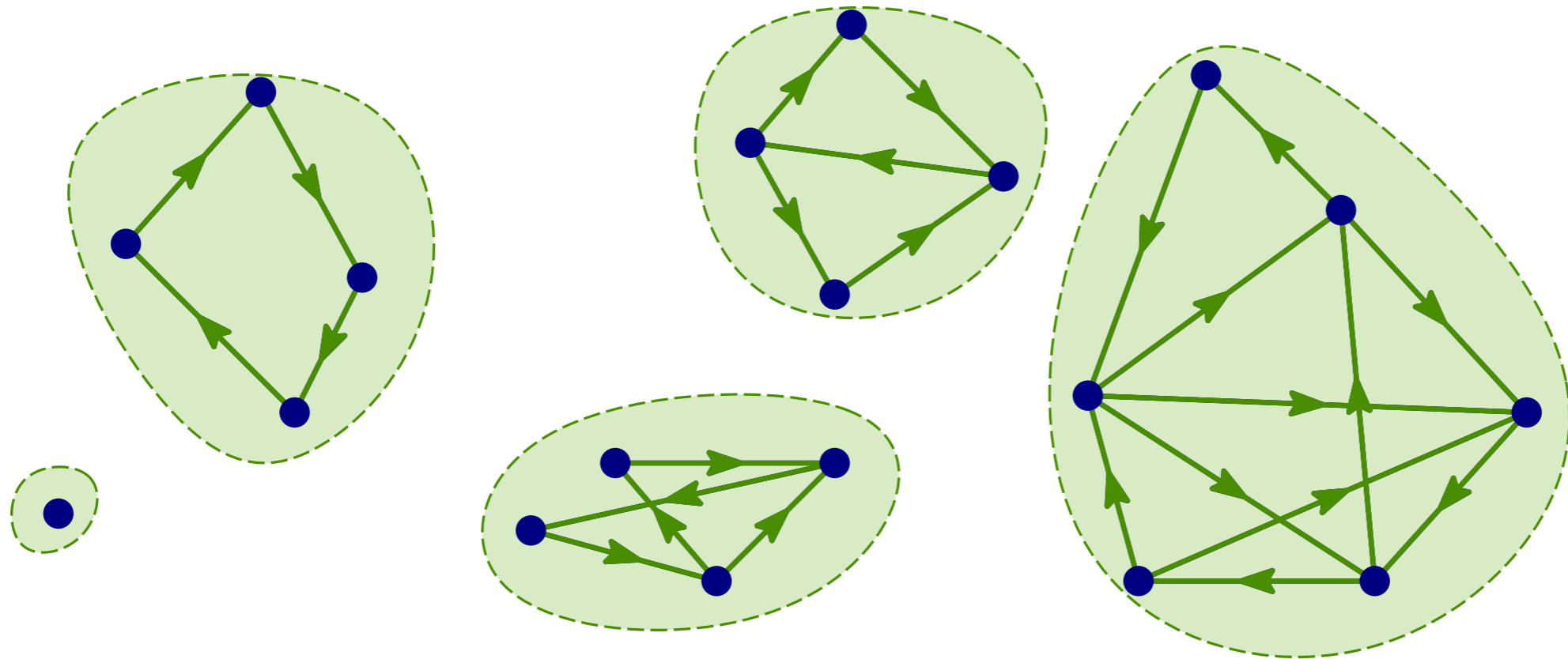
- 1.
- 2.
- 3.



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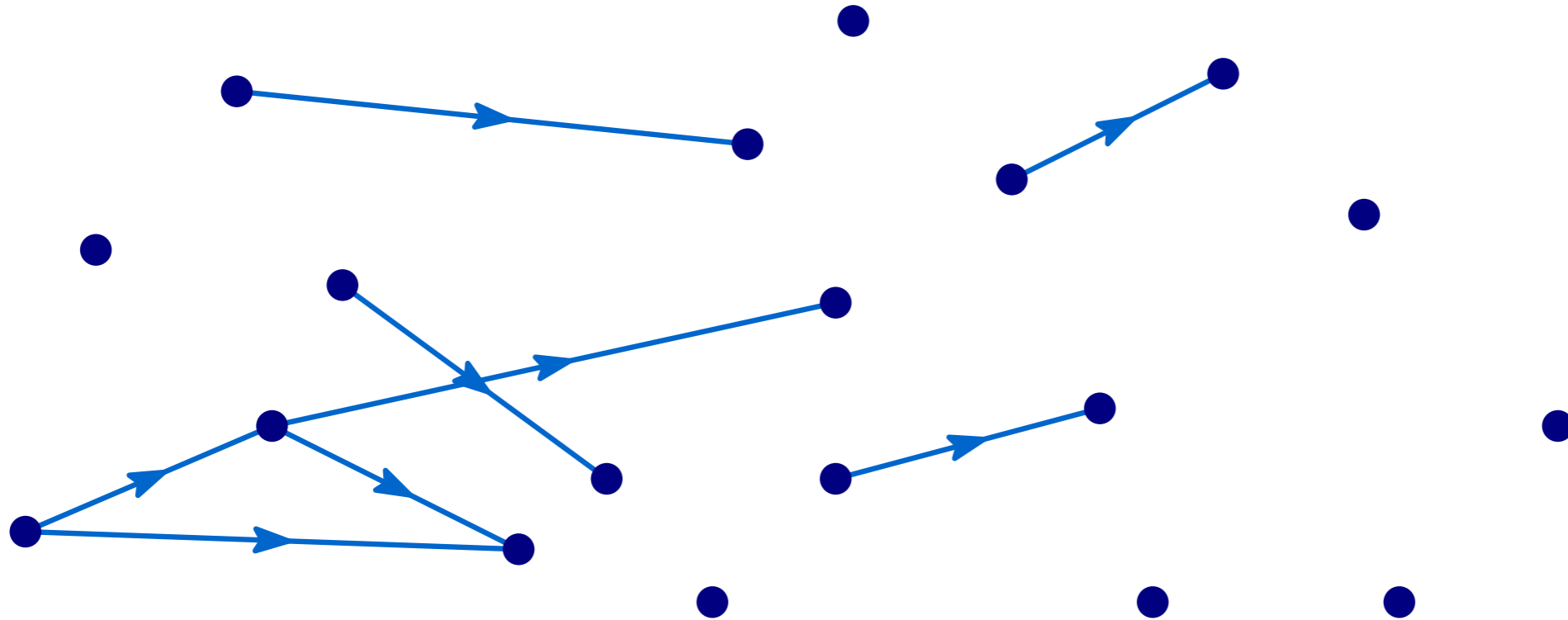
1. Expanders X_1, \dots, X_k
- 2.
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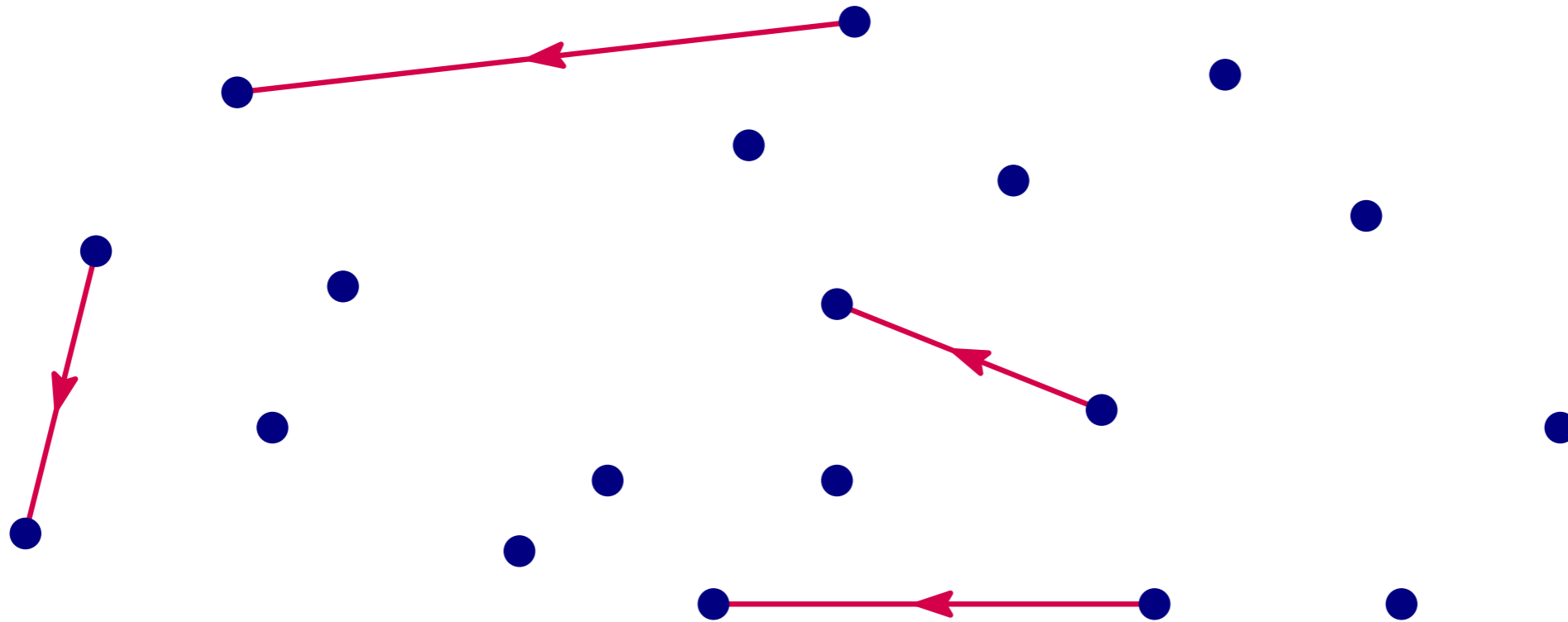
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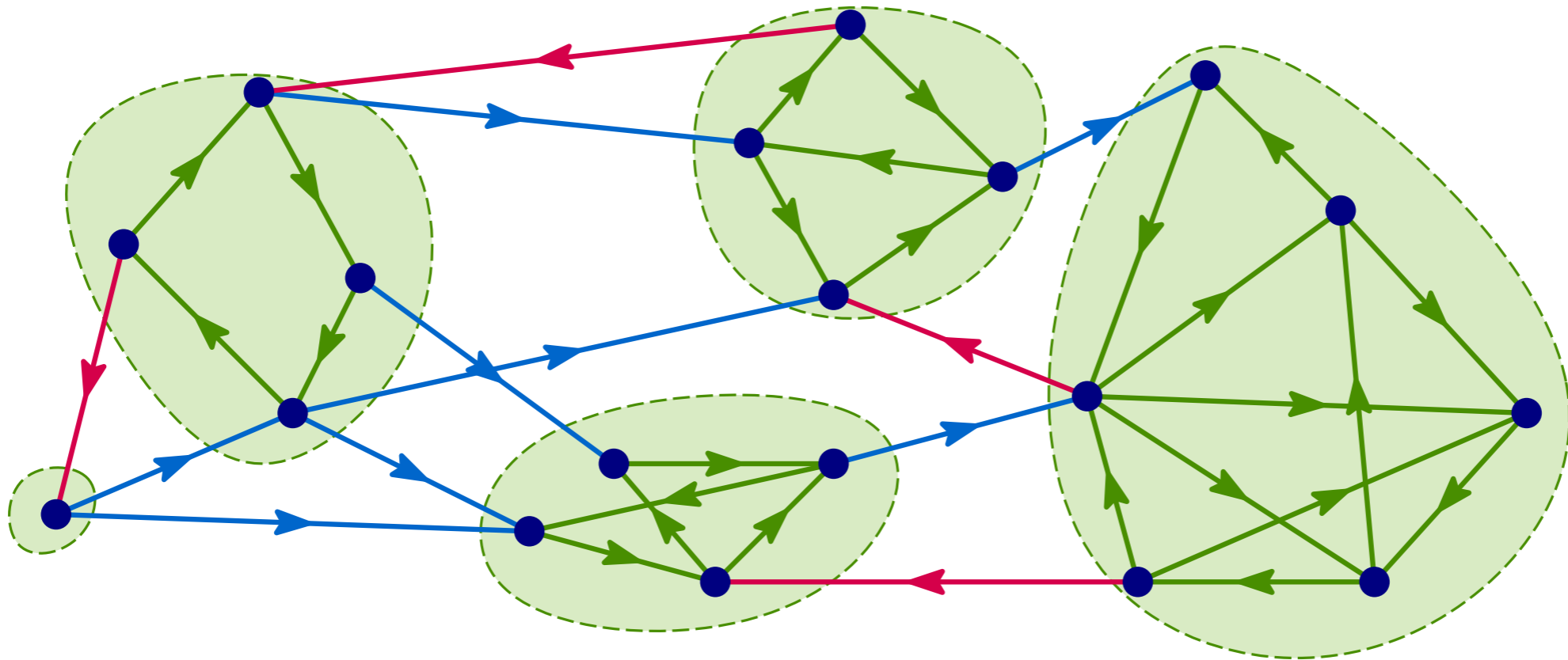
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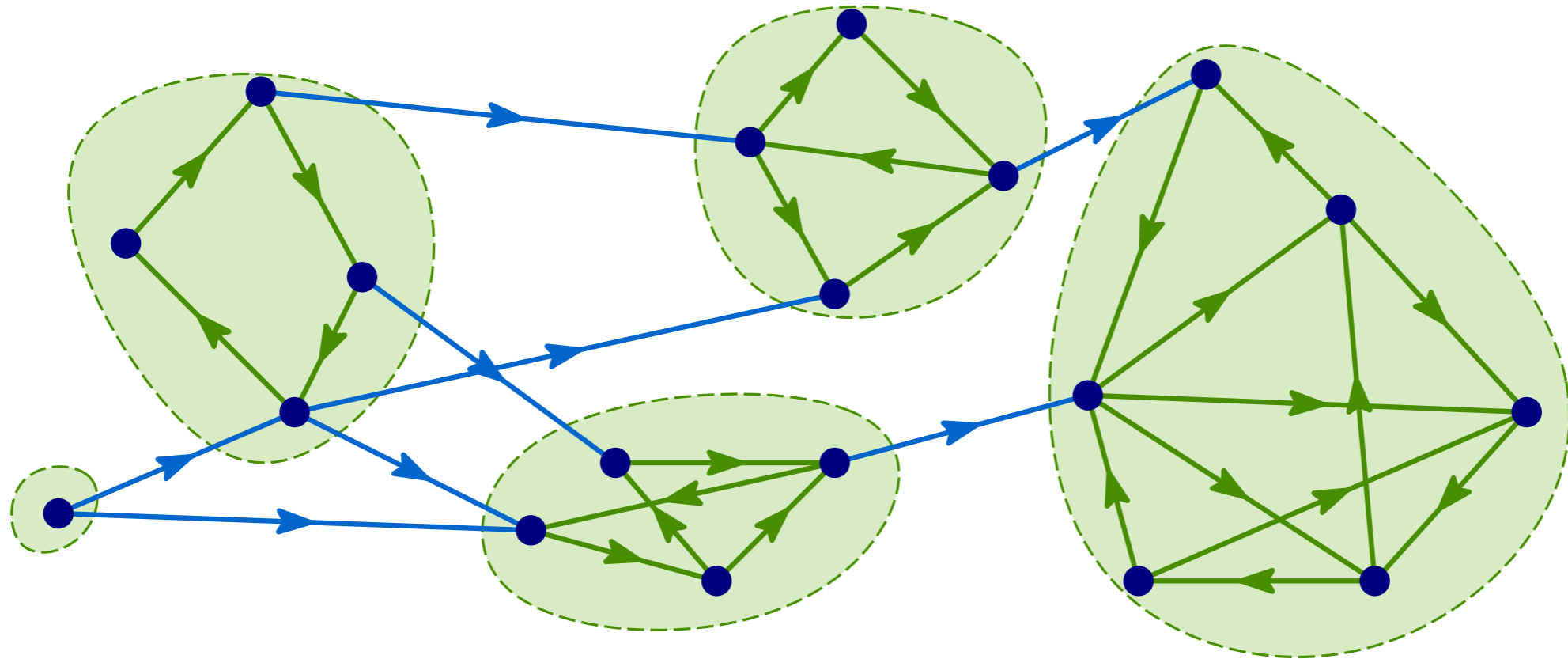
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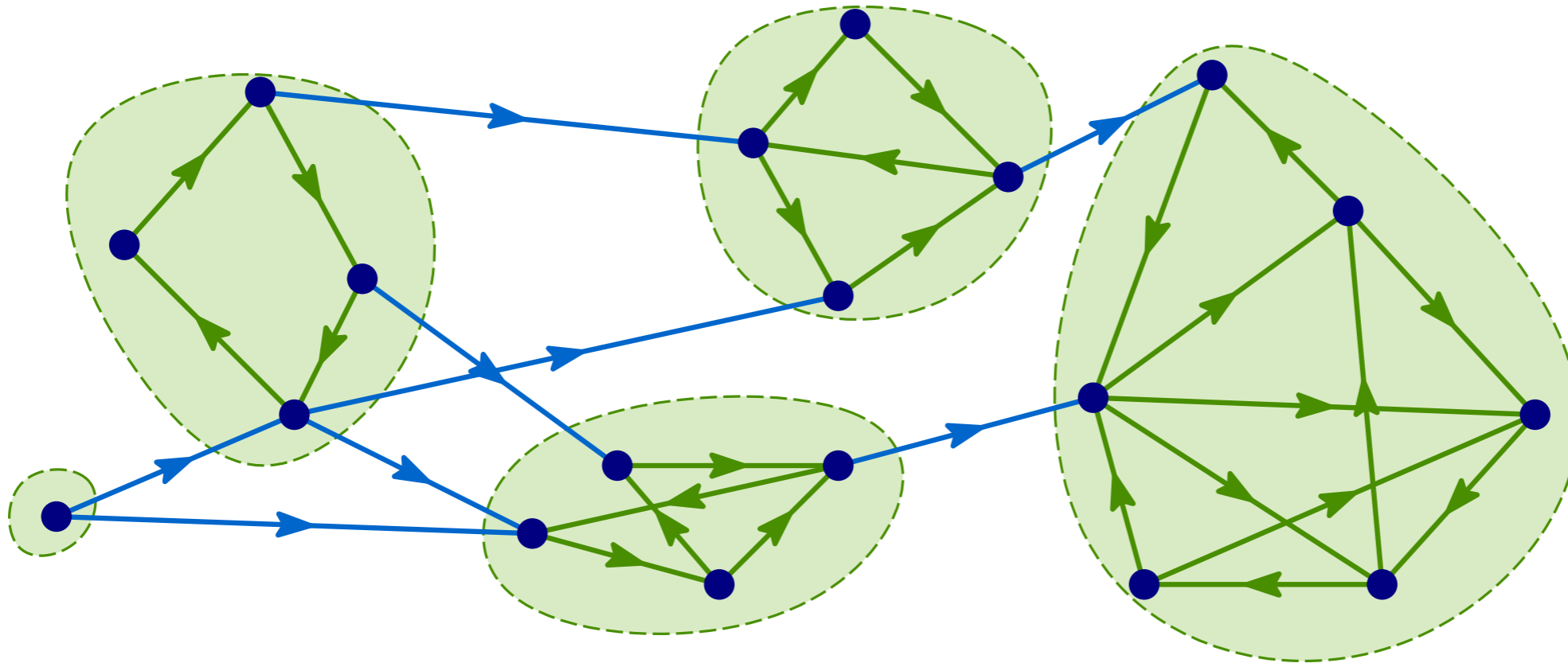
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Good edge lengths in $G \setminus B$:

$$w(u, v) = |\tau(u) - \tau(v)|$$

τ respects DAG

τ contiguous in expanders



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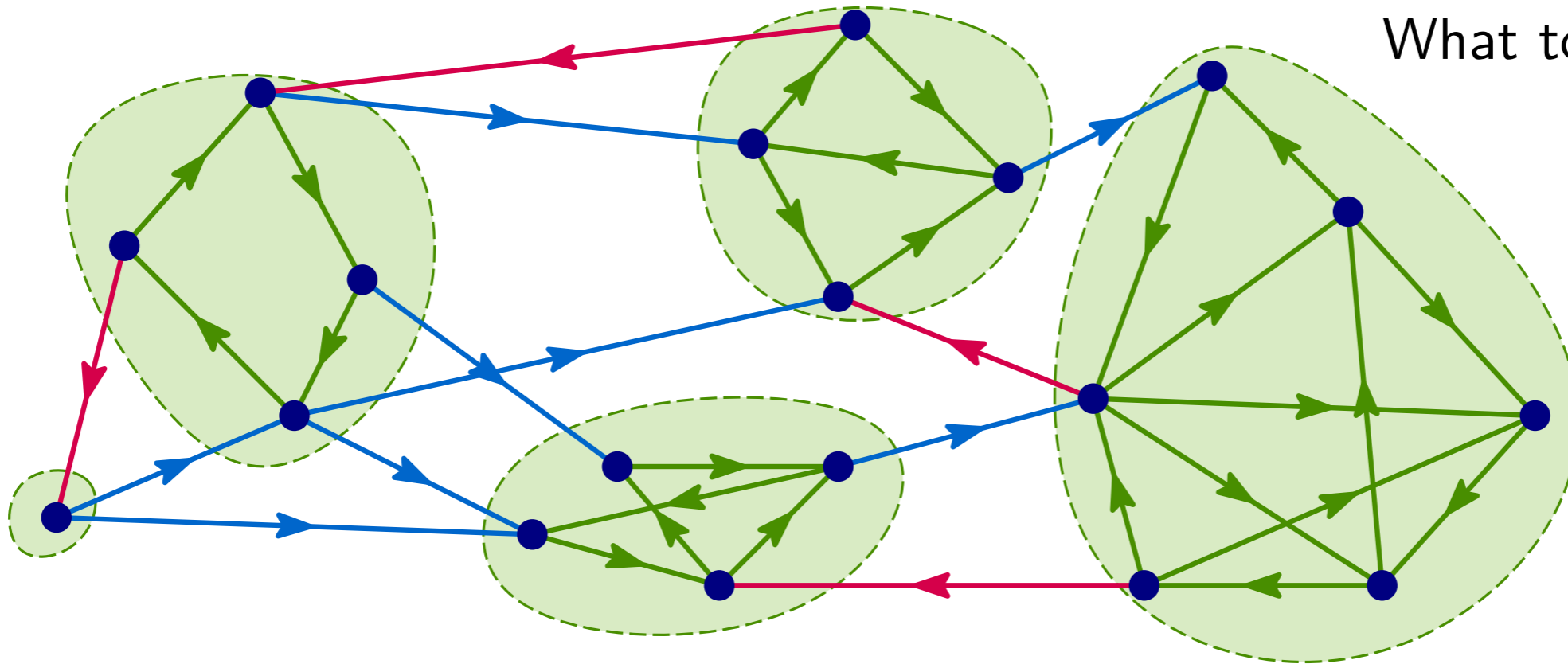
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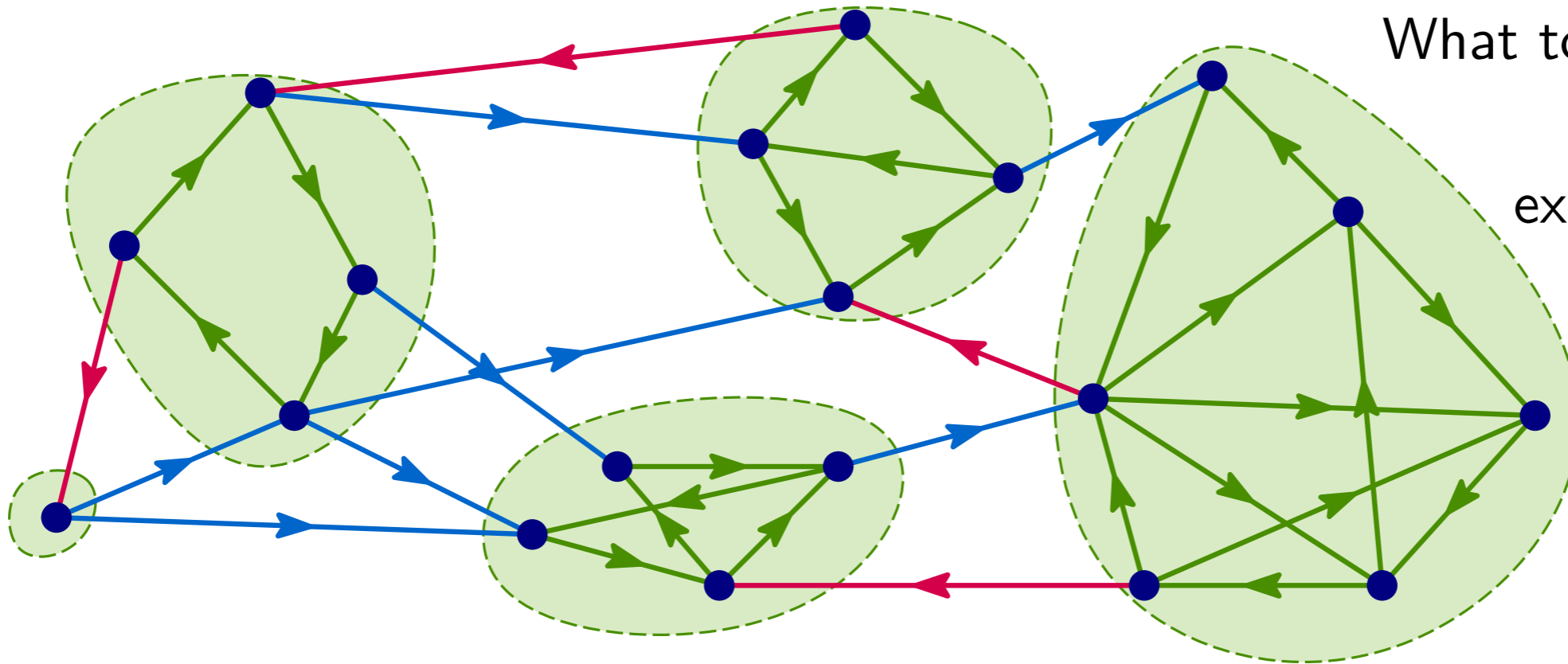
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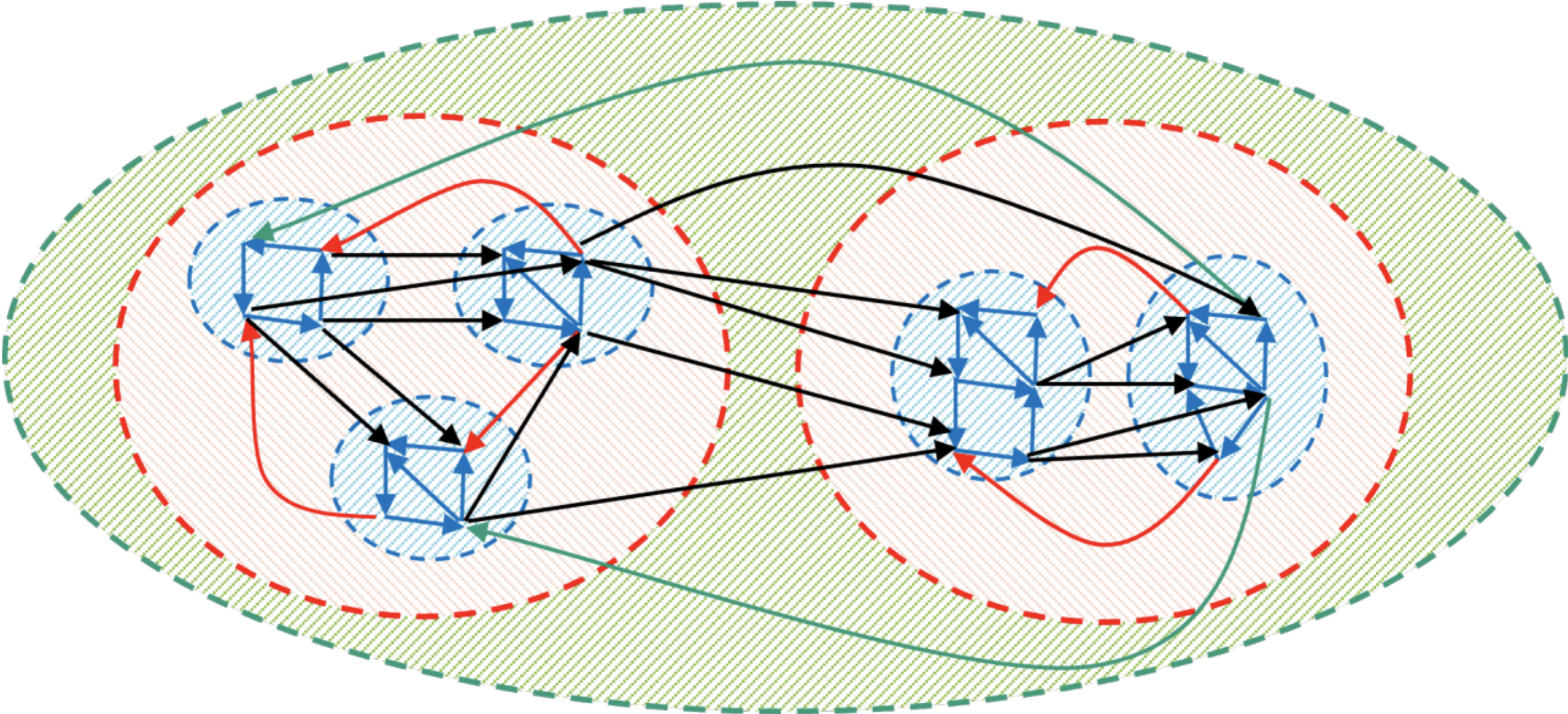
What to do about B ?

recurse!

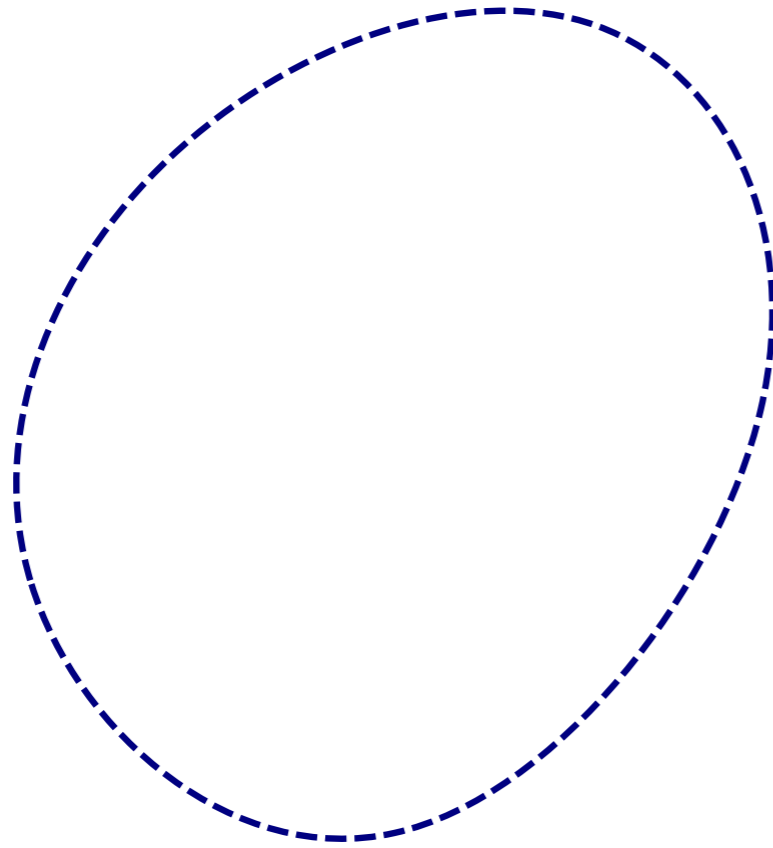
expander decomp.

w.r.t B

(Directed) Expander Decomposition

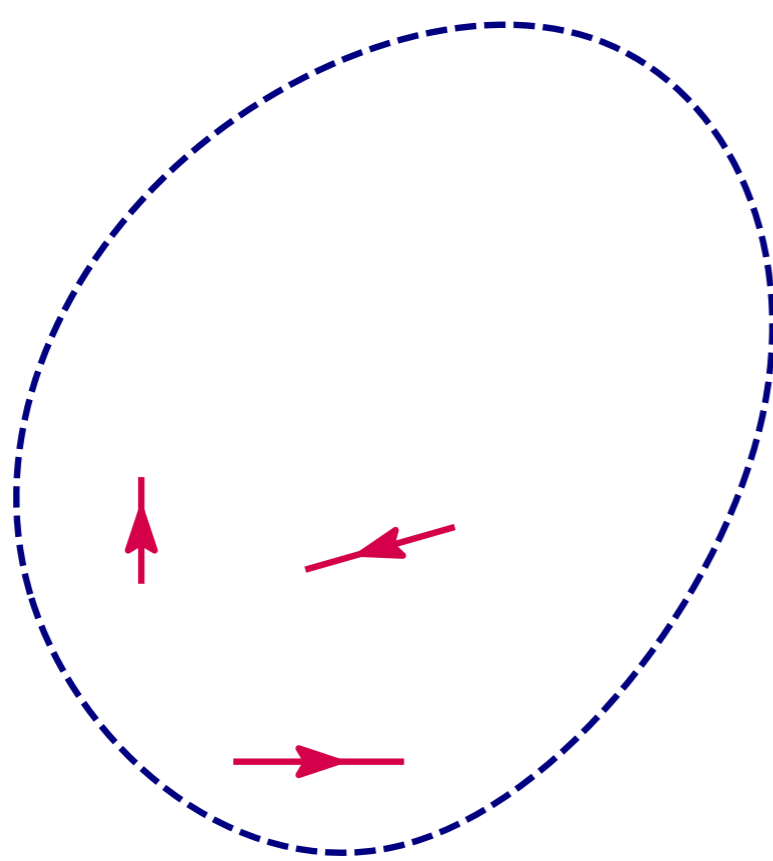


Technique Highlight: Path-Reversal Expander Pruning



Expander X

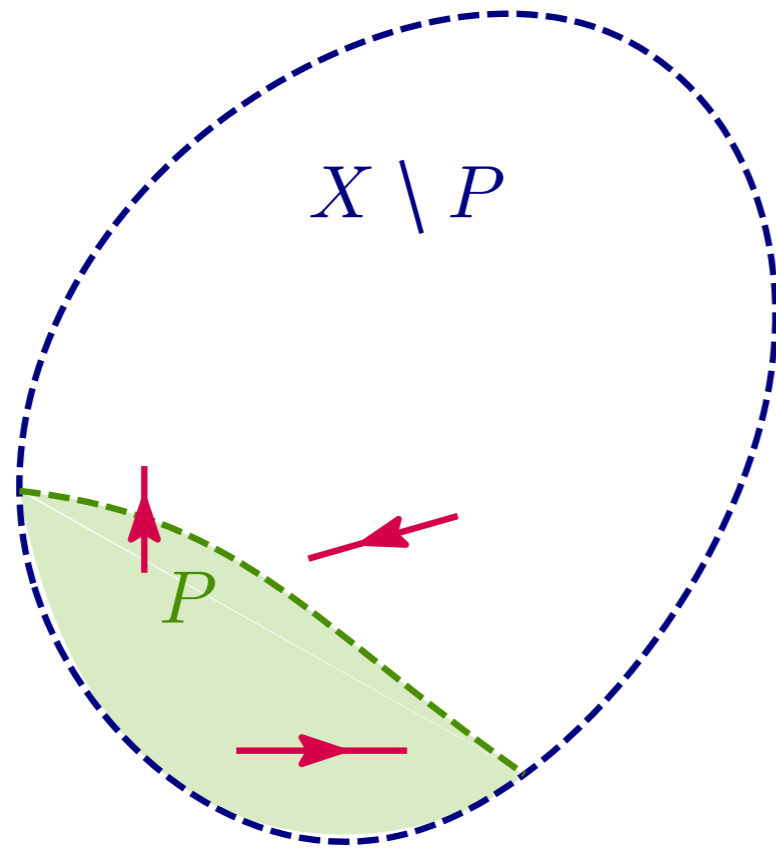
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Expander X

Delete D edges

Technique Highlight: Path-Reversal Expander Pruning



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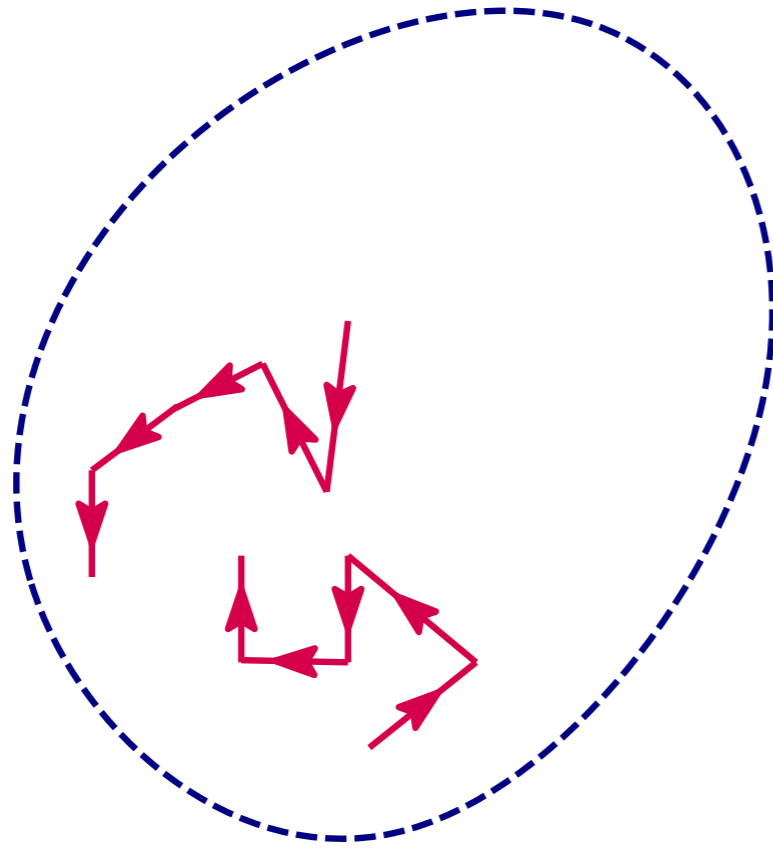
Delete D edges

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$X \setminus P$ is still expander

Known: “Expander Pruning”

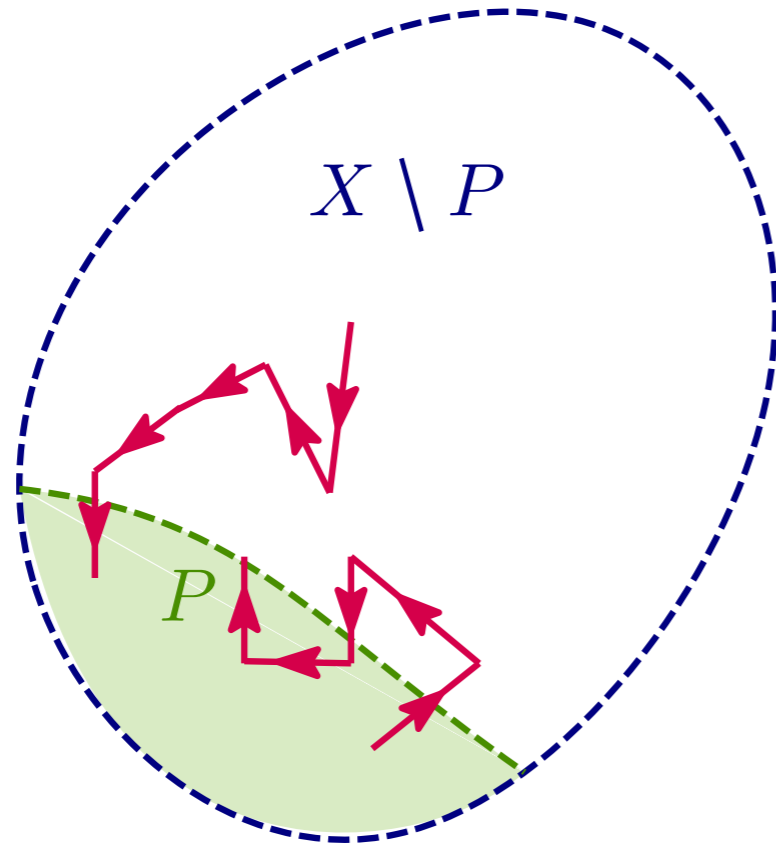
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Expander X

reverse D paths

Technique Highlight: Path-Reversal Expander Pruning



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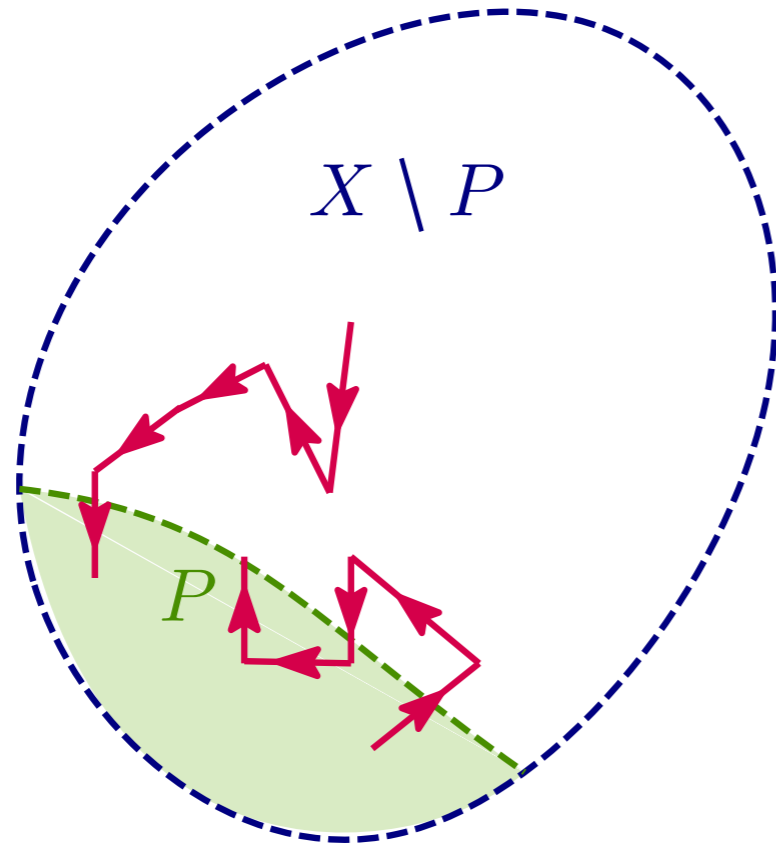
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Directed Expander Hierarchy is robust under flow augmentation

Bottleneck towards $\tilde{O}(m)$:
Approximate Max Flow in DAGs

Summary & Open Problems

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Main Result: Maximum flow in on n -vertex graphs in $n^{2+o(1)}$ time.

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Augmenting Paths (new version of Push-Relabel)

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Directed Expander Hierarchy

Mostly Self-Contained

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“Simple”, “Combinatorial”, “Implementable”: $E^{1+o(1)}$ or $\tilde{O}(E)$ Maximum Flow?
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Thanks!

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Ours

[Chen-Kyng-Liu-Peng-Gutenberg-Sachdeva'22]

Comparision

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Combinatorial
Augmenting Paths

Implementable?

[Chen-Kyng-Liu-Peng-Gutenberg-Sachdeva'22]

Minimum Cost Maximum Flow

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Continuous Optimization
Dynamic Data Structures

Tricky to implement