Part IV

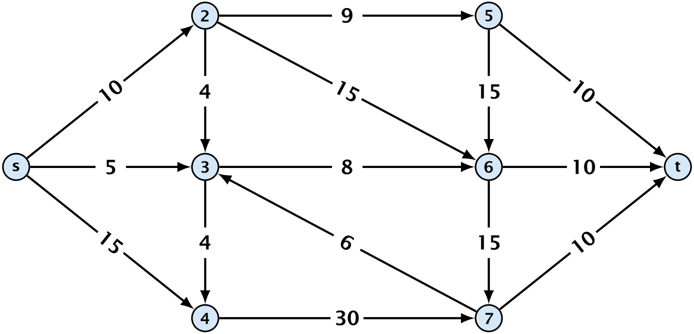
Flows and Cuts

The following slides are partially based on slides by Kevin Wayne.

10 Introduction

Flow Network

- directed graph $G = (V, E)$; edge capacities $c(e)$
- two special nodes: source s; target t;
- no edges entering s or leaving t;
- at least for now: no parallel edges;



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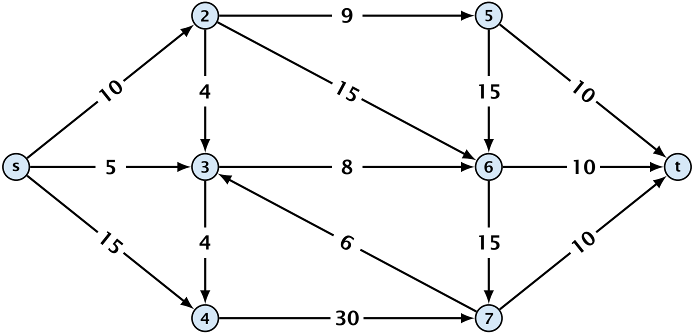

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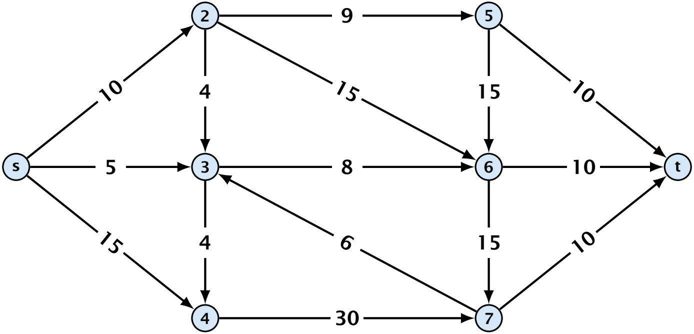

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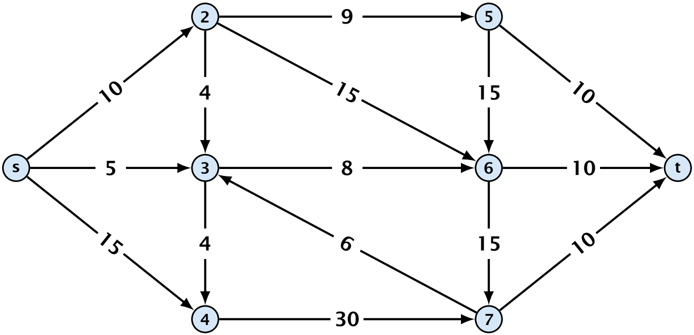

Cuts

Definition 1

An (s,t)-cut in the graph G is given by a set $A \subset V$ with $s \in A$ and $t \in V \setminus A$.

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Definition 2

The capacity of a cut A is defined as

$$\operatorname{cap}(A, V \setminus A) := \sum_{e \in \operatorname{out}(A)} c(e) \ ,$$

where $\operatorname{out}(A)$ denotes the set of edges of the form $A \times V \setminus A$ (i.e. edges leaving A).

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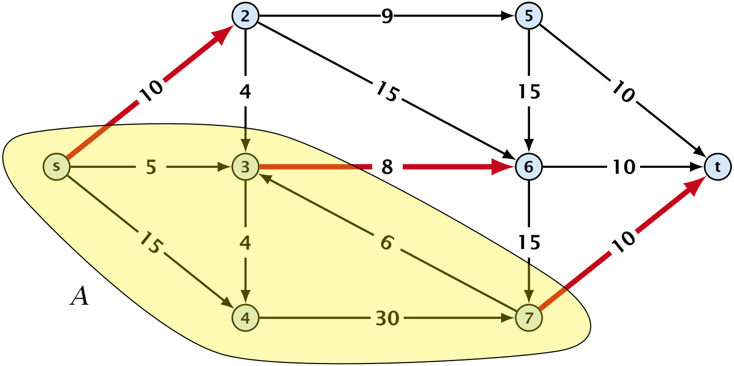
Minimum Cut Problem: Find an (s, t)-cut with minimum capacity.

Cuts

Example 3



The capacity of the cut is $\text{cap}(A, V \setminus A) = 28$.

Flows

Definition 4

An (s,t)-flow is a function $f : E \mapsto \mathbb{R}^+$ that satisfies

1. For each edge e

$$0 \le f(e) \le c(e) \enspace .$$

(capacity constraints)

2. For each $v \in V \setminus \{s,t\}$

$$\sum_{e \in \text{out}(v)} f(e) = \sum_{e \in \text{into}(v)} f(e) \enspace .$$

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Flows

Definition 5
The value of an (s,t)-flow f is defined as

$$\text{val}(f) = \sum_{e \in \text{out}(s)} f(e) \ .$$

Maximum Flow Problem: Find an (s,t)-flow with maximum value.

Flows

Definition 5
The value of an (s,t)-flow f is defined as

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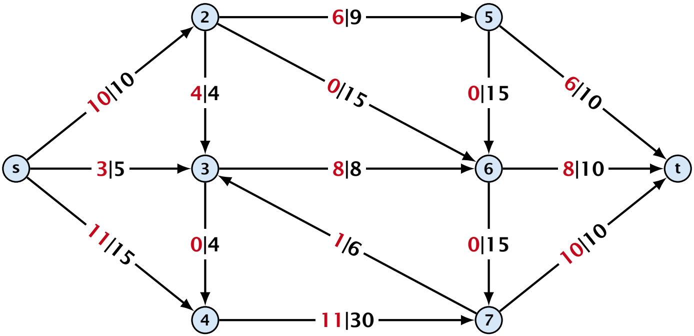
Flows

Example 6



The value of the flow is $\text{val}(f) = 24$.

Flows

Lemma 7 (Flow value lemma)

Let f be a flow, and let $A \subseteq V$ be an (s,t)-cut. Then the net-flow across the cut is equal to the amount of flow leaving s, i.e.,

$$\mathrm{val}(f) = \sum_{e \in \mathrm{out}(A)} f(e) - \sum_{e \in \mathrm{into}(A)} f(e) \enspace .$$

Proof.

$\mathrm{val}(f)$

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$$\mathrm{val}(f) = \sum_{e \in \mathrm{out}(s)} f(e)$$

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$$\begin{aligned}\mathrm{val}(f) &= \sum_{e\in\mathrm{out}(s)} f(e)\\ &= \sum_{e\in\mathrm{out}(s)} f(e) + \sum_{v\in A\setminus\{s\}}\Bigg(\sum_{e\in\mathrm{out}(v)} f(e) - \sum_{e\in\mathrm{in}(v)} f(e)\Bigg)\end{aligned}$$

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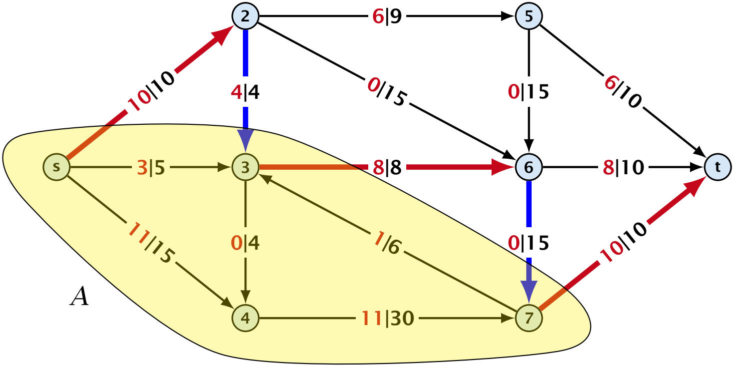
The last equality holds since every edge with both end-points in A contributes negatively as well as positively to the sum in Line 2. The only edges whose contribution doesn't cancel out are edges leaving or entering A. □

Example 8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11|15
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10|10
A
11|30

Corollary 9

Let f be an (s,t)-flow and let A be an (s,t)-cut, such that

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Then f is a maximum flow.

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$$\mathrm{cap}(A, V \setminus A) < \mathrm{val}(f')$$

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Suppose that there is a flow f' with larger value. Then

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&\le \sum_{e \in \mathrm{out}(A)} f'(e) \\
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\end{aligned}$$

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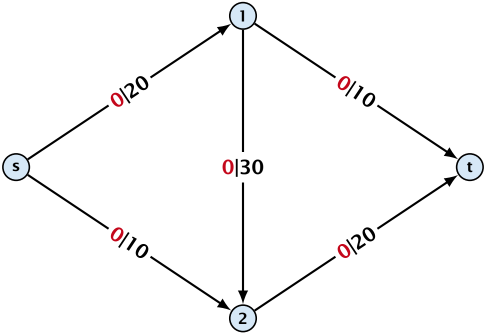
11 Augmenting Path Algorithms

Greedy-algorithm:

- start with $f(e) = 0$ everywhere
- find an s-t path with $f(e) < c(e)$ on every edge
- augment flow along the path
- repeat as long as possible



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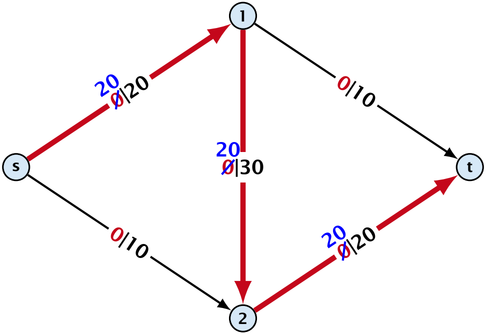

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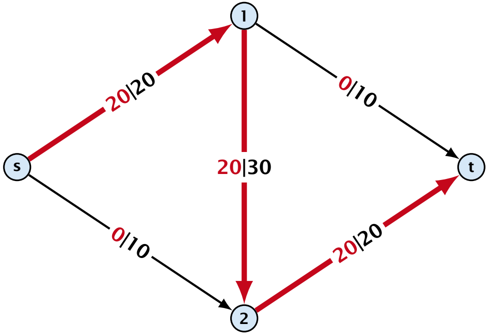

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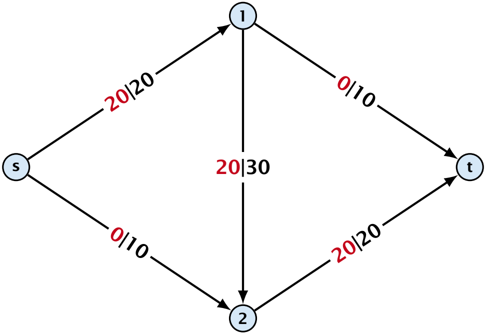

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From the graph $G = (V, E, c)$ and the current flow f we construct an auxiliary graph $G_f = (V, E_f, c_f)$ (the residual graph):

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- G_f has edge e_1' with capacity $\max\{0, c(e_1) - f(e_1) + f(e_2)\}$ and e_2' with with capacity $\max\{0, c(e_2) - f(e_2) + f(e_1)\}$.

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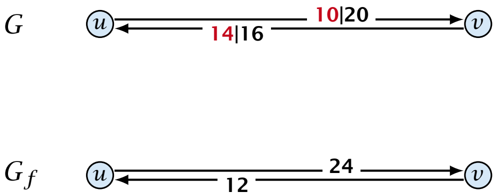

Augmenting Path Algorithm

Definition 10
An augmenting path with respect to flow f, is a path from s to t in the auxiliary graph G_f that contains only edges with non-zero capacity.

Algorithm 1 FordFulkerson($G = (V, E, c)$)

```
Initialize f(e) ← 0 for all edges.
while ∃ augmenting path p in G_f do
    augment as much flow along p as possible.
```

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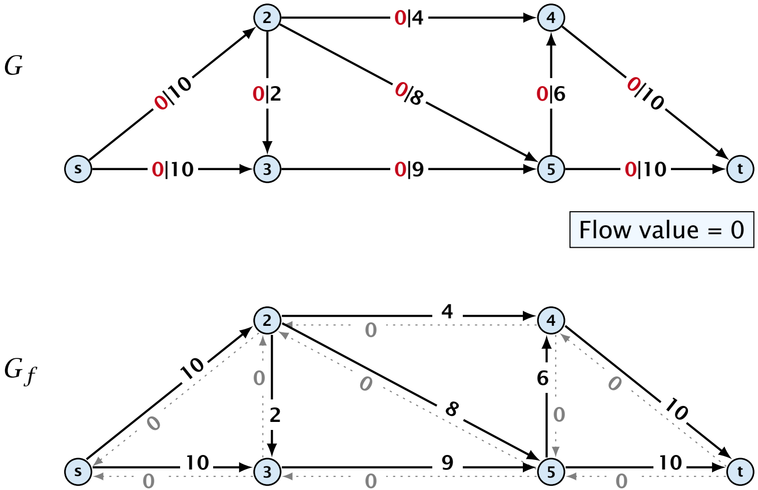
3: augment as much flow along p as possible.

Augmenting Path Algorithm



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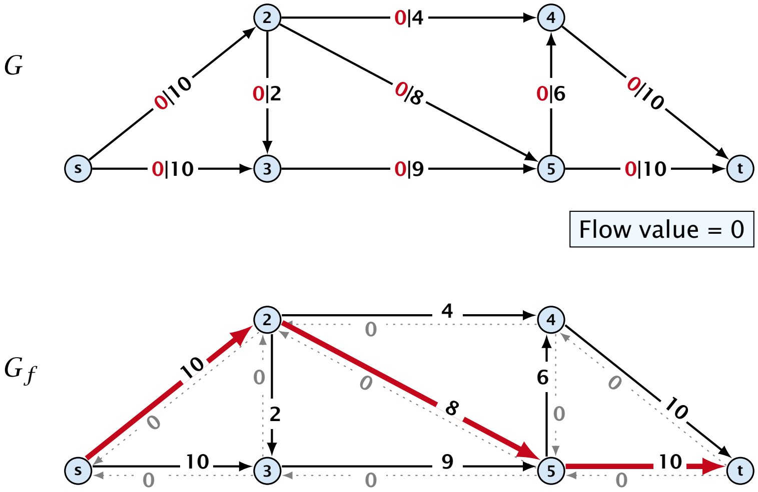

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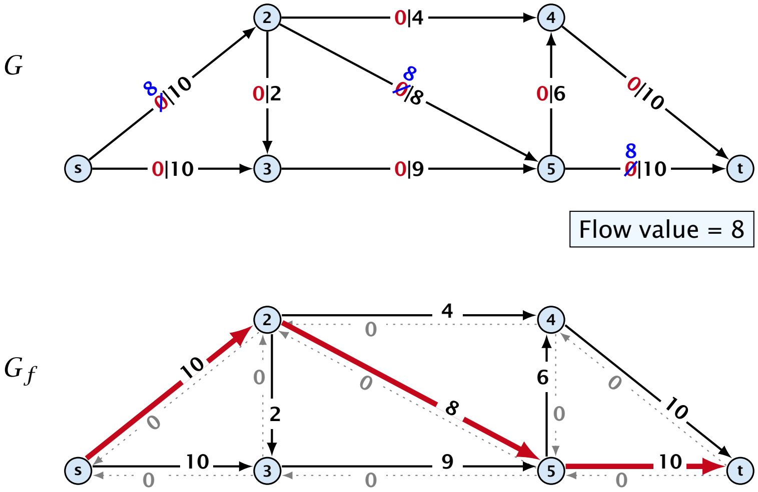

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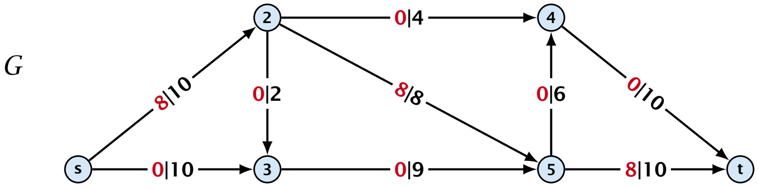
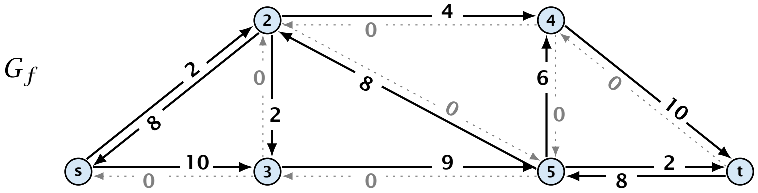


Flow value = 8



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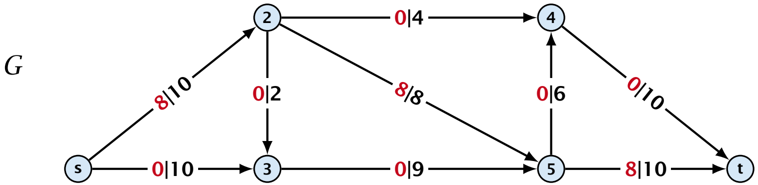

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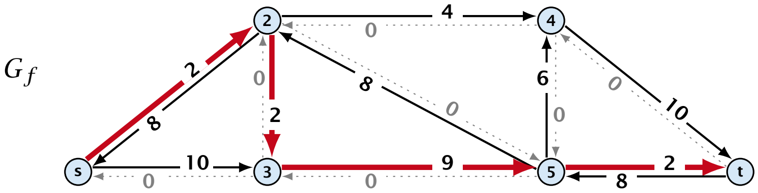

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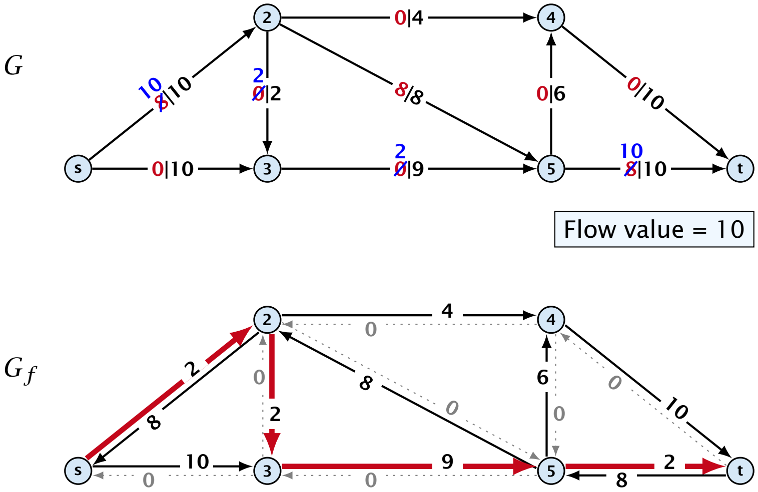

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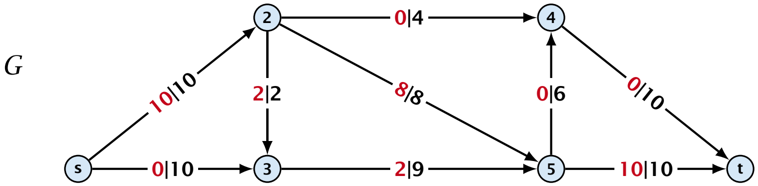

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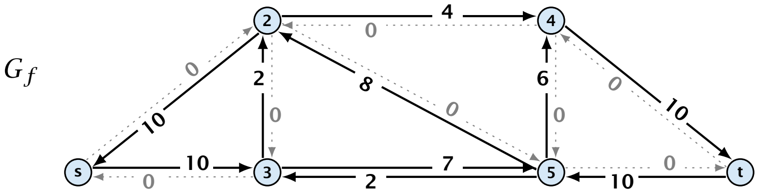
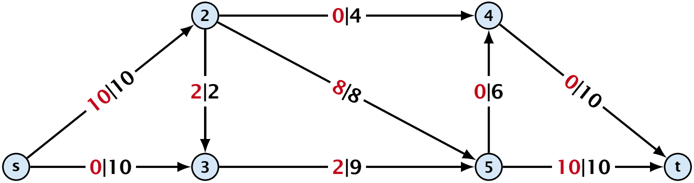


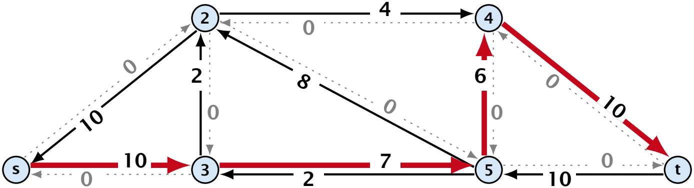
Augmenting Path Algorithm

G



Flow value = 10

G_f



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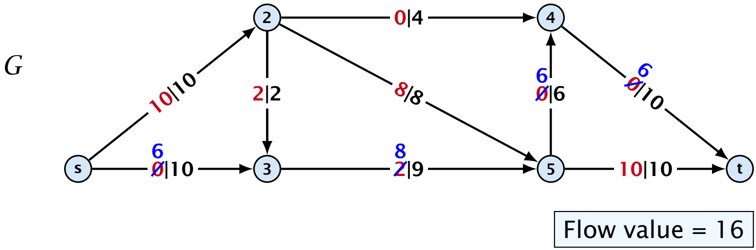

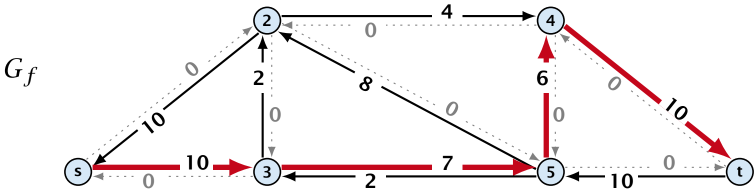

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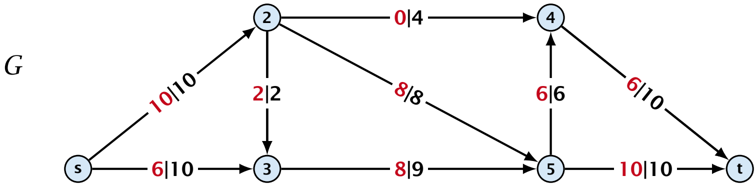
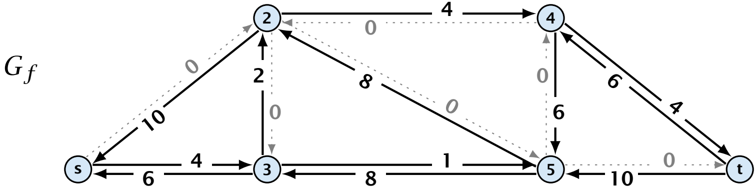
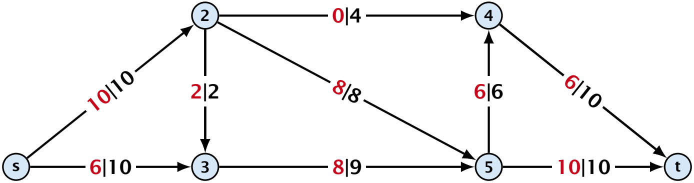


Flow value = 16



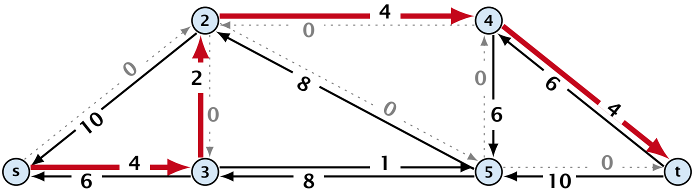
Augmenting Path Algorithm

G

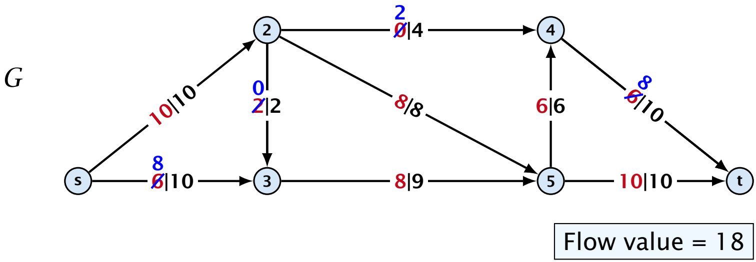


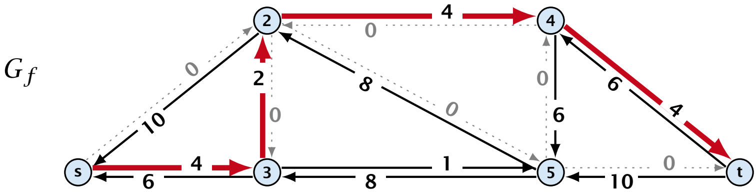
Flow value = 16

G_f



Augmenting Path Algorithm





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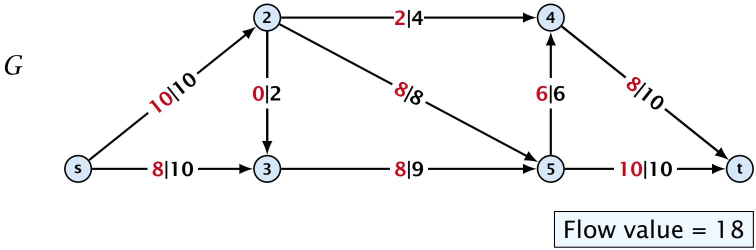
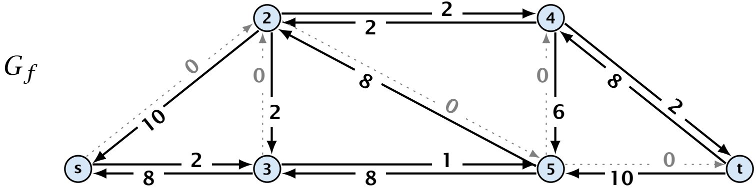
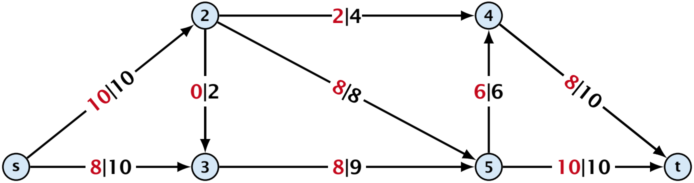




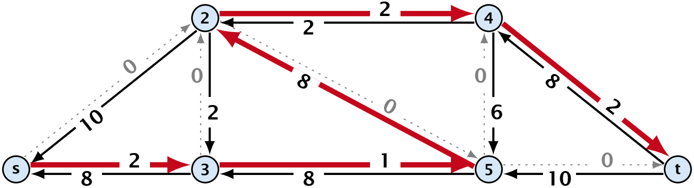
Augmenting Path Algorithm

G

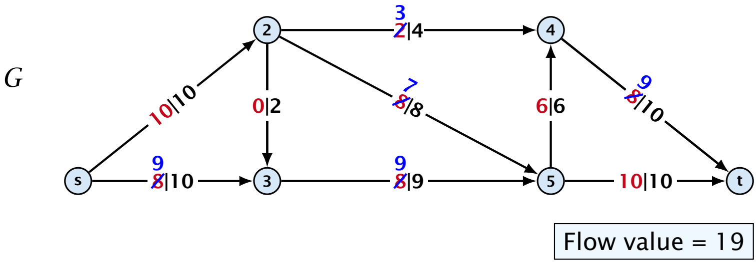


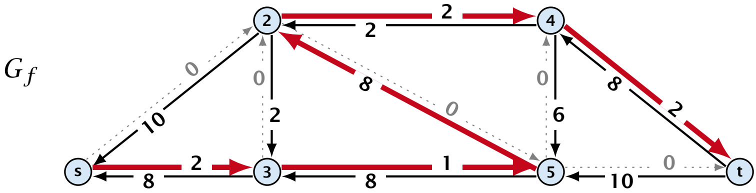
Flow value = 18

G_f



Augmenting Path Algorithm





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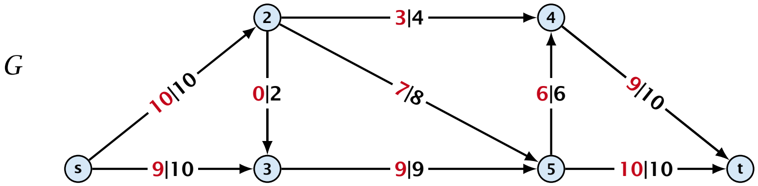
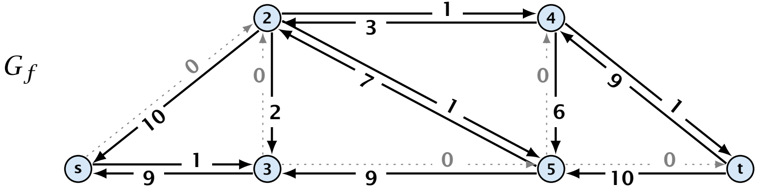
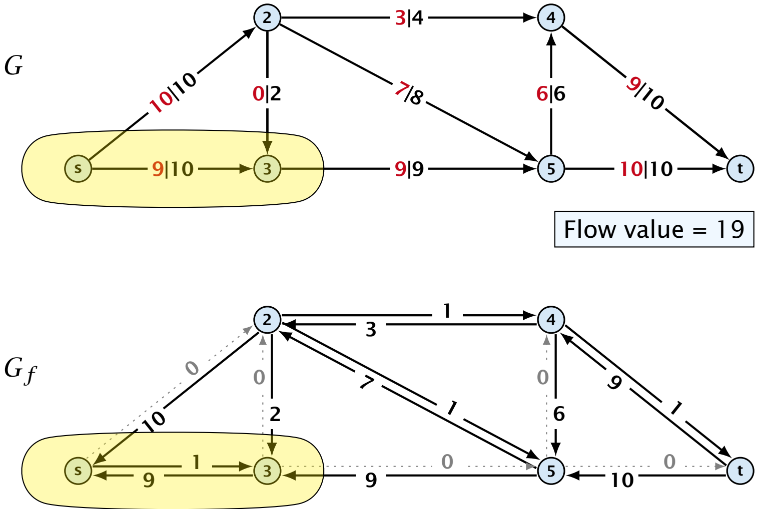


Flow value = 19



Augmenting Path Algorithm



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Theorem 11
*A flow f is a maximum flow **iff** there are no augmenting paths.*

Theorem 12
The value of a maximum flow is equal to the value of a minimum cut.

Proof.
Let f be a flow. The following are equivalent:

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This we already showed.

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This finishes the proof.

Here the first equality uses the flow value lemma, and the second exploits the fact that the flow along incoming edges must be 0 as the residual graph does not have edges leaving A.

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Assumption:
All capacities are integers between 1 and C.

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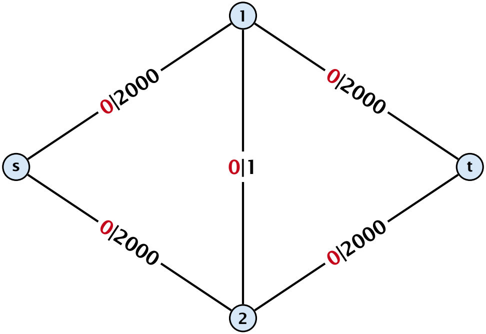

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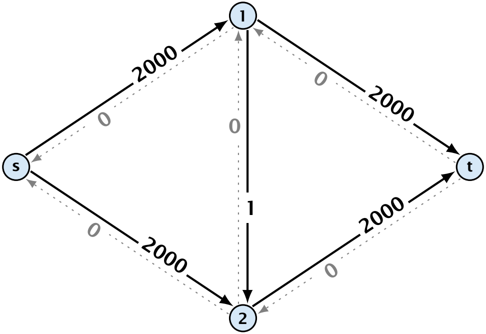

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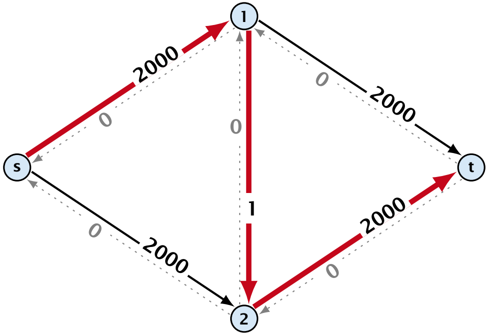

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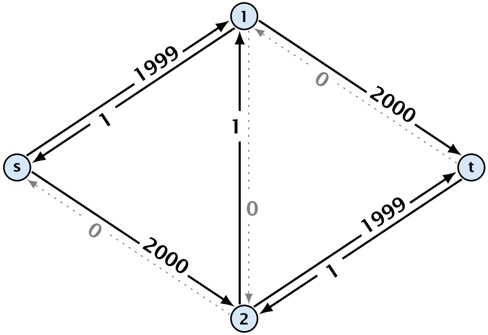

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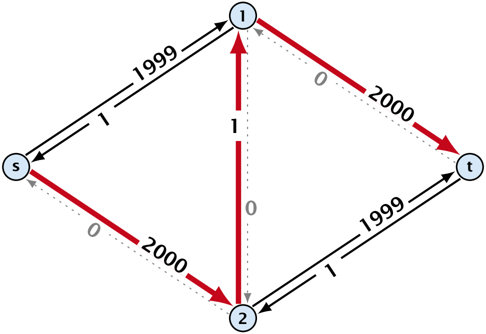

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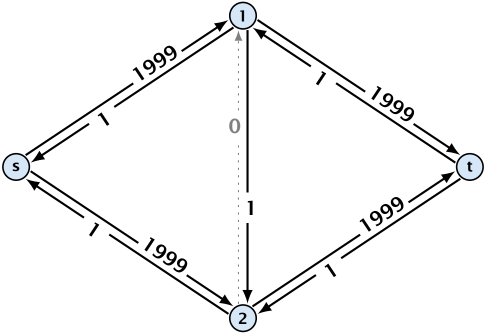

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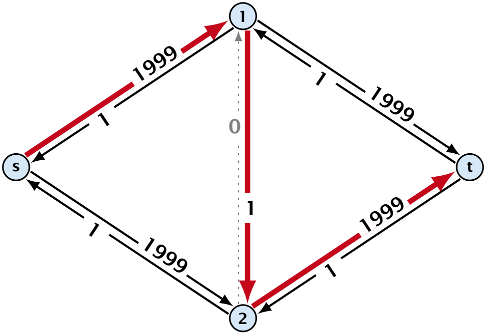

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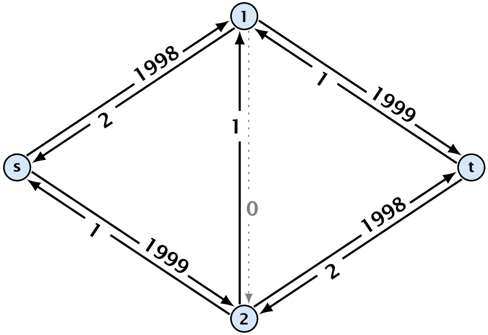

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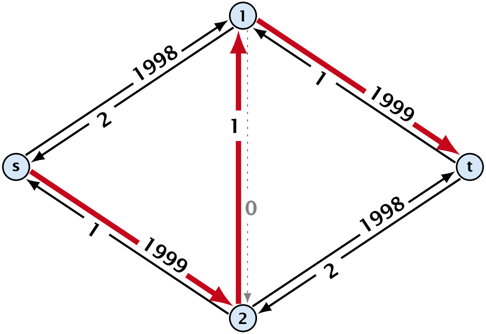

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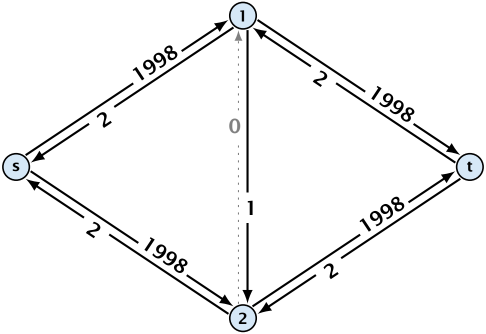

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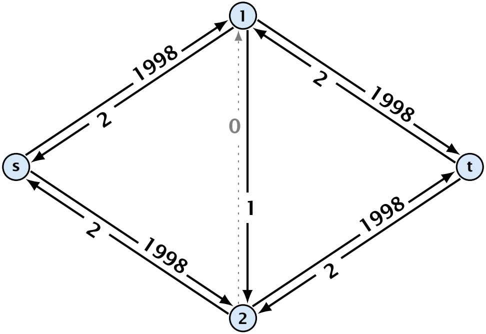

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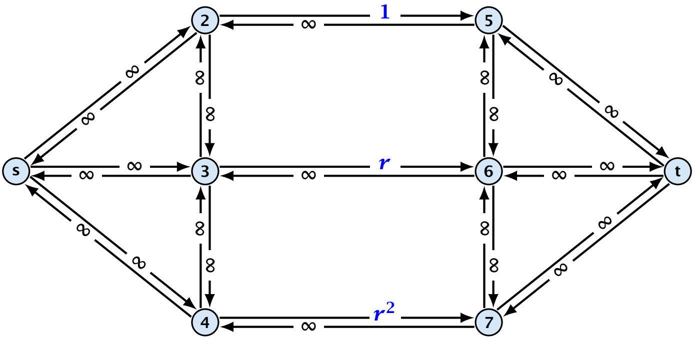

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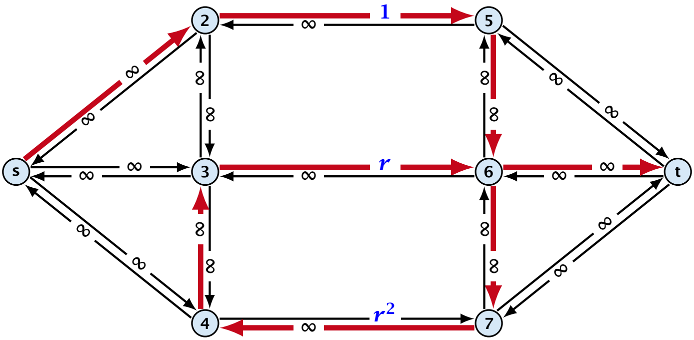

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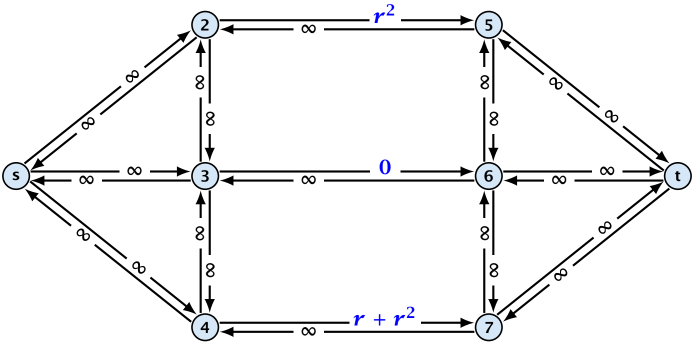

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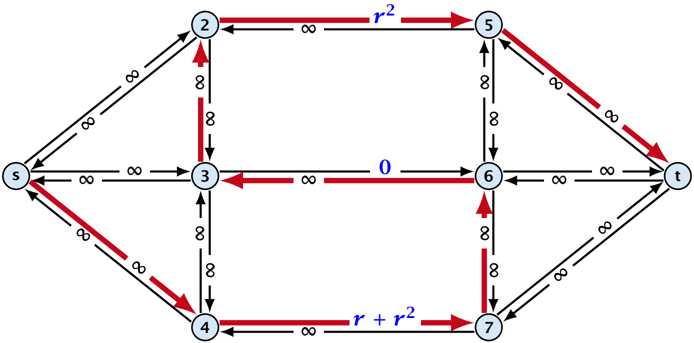

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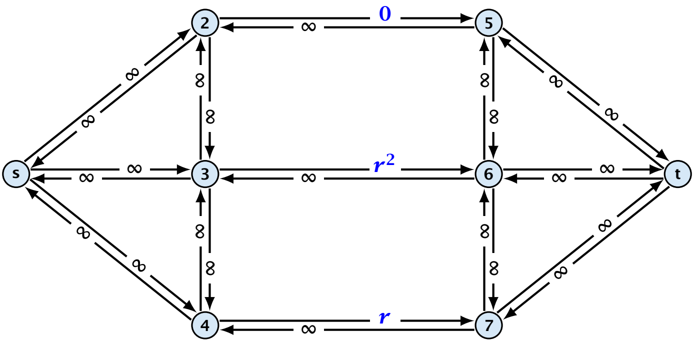

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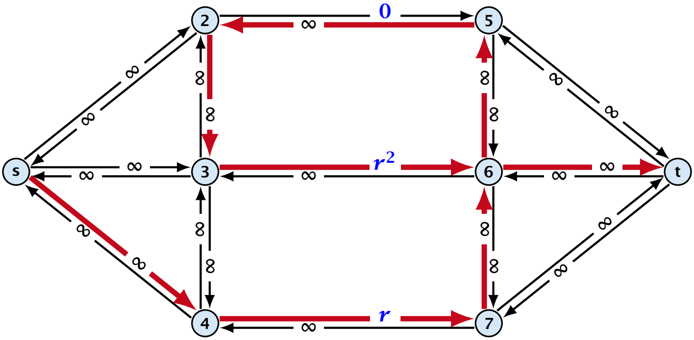

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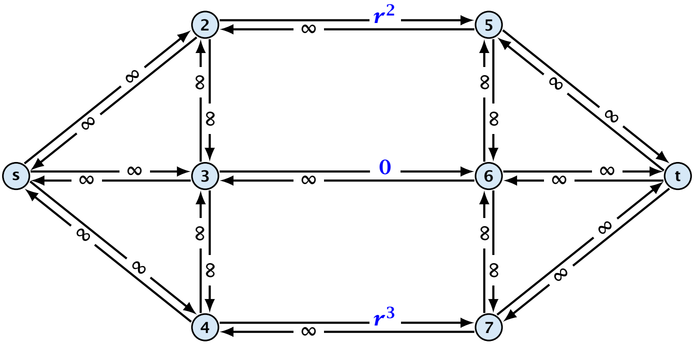

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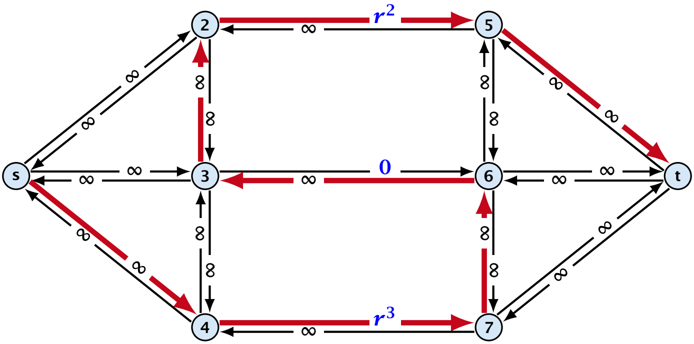

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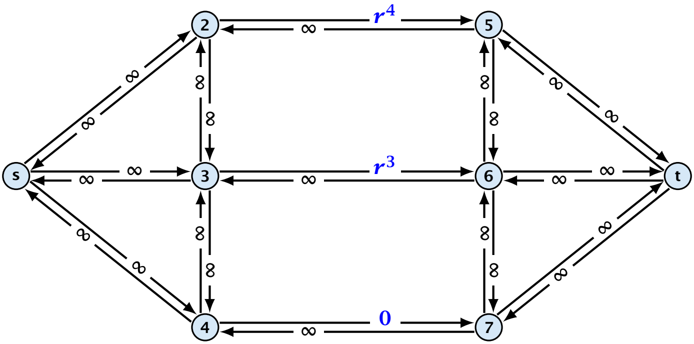

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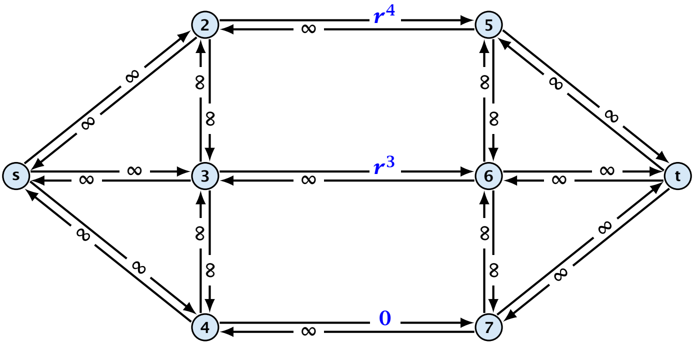

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Overview: Shortest Augmenting Paths

Lemma 15
The length of the shortest augmenting path never decreases.

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These two lemmas give the following theorem:

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The shortest augmenting path algorithm performs at most $\mathcal{O}(mn)$ augmentations. This gives a running time of $\mathcal{O}(m^2 n)$.

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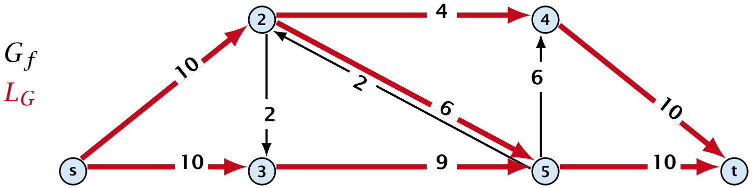

In the following we assume that the residual graph G_f does not contain zero capacity edges.

This means, we construct it in the usual sense and then delete edges of zero capacity.

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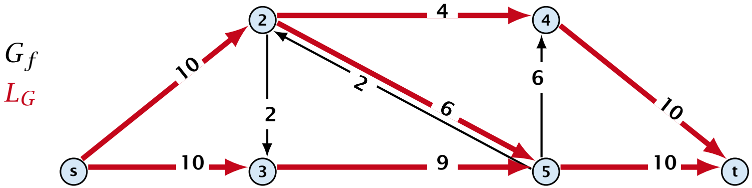

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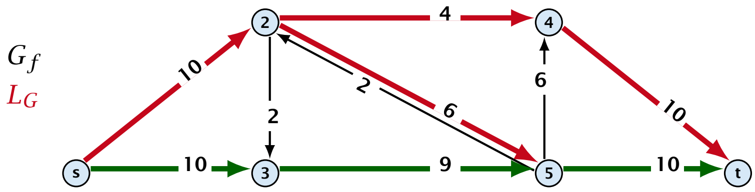

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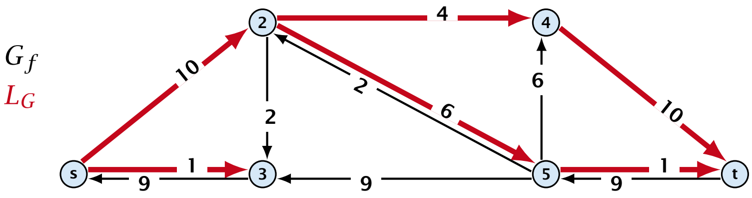

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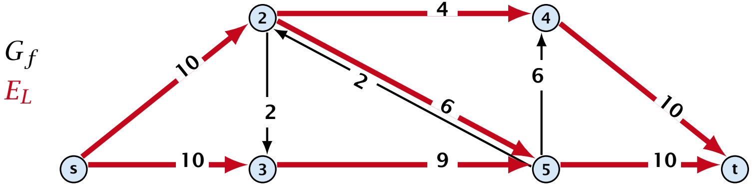

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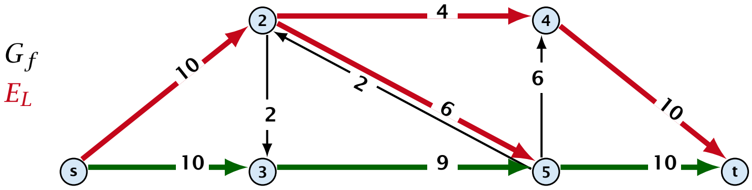

Shortest Augmenting Path

Second Lemma: After at most m augmentations the length of the shortest augmenting path strictly increases.

Let E_L denote the set of edges in graph L_G at the beginning of a round when the distance between s and t is k.

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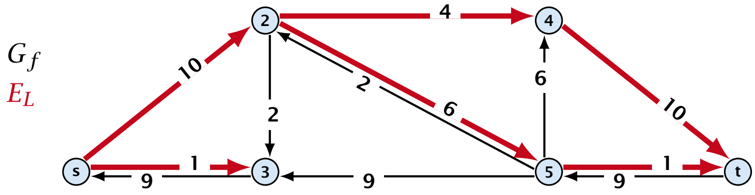

Shortest Augmenting Paths

Theorem 18
The shortest augmenting path algorithm performs at most $\mathcal{O}(mn)$ augmentations. Each augmentation can be performed in time $\mathcal{O}(m)$.

Theorem 19 (without proof)
There exist networks with $m = \Theta(n^2)$ that require $\mathcal{O}(mn)$ augmentations, when we restrict ourselves to only augment along shortest augmenting paths.

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Shortest Augmenting Paths

We maintain a subset E_L of the edges of G_f with the guarantee that a shortest s-t path using only edges from E_L is a shortest augmenting path.

With each augmentation some edges are deleted from E_L.

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There are at most n phases. Hence, total cost is $\mathcal{O}(mn^2)$.

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Several possibilities:

- Choose path with maximum bottleneck capacity.
- Choose path with sufficiently large bottleneck capacity.
- Choose the shortest augmenting path.

Capacity Scaling

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- Choosing a path with the highest bottleneck increases the flow as much as possible in a single step.

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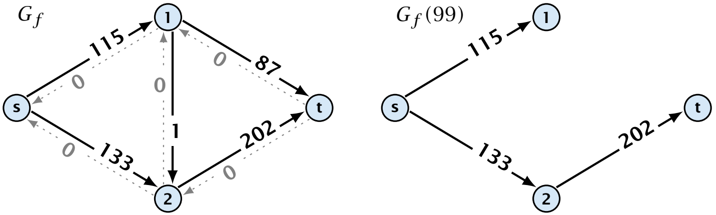

Capacity Scaling

Algorithm 2 maxflow(G, s, t, c)

1: **foreach** $e \in E$ **do** $f_e \leftarrow 0$;
2: $\Delta \leftarrow 2^{\lceil \log_2 C \rceil}$
3: **while** $\Delta \geq 1$ **do**
4: $\quad G_f(\Delta) \leftarrow \Delta$-residual graph
5: $\quad$ **while** there is augmenting path P in $G_f(\Delta)$ **do**
6: $\quad\quad f \leftarrow$ augment(f, c, P)
7: $\quad\quad$ update$(G_f(\Delta))$
8: $\quad \Delta \leftarrow \Delta/2$
9: **return** f

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- This gives me an upper bound on the flow that I can still add.

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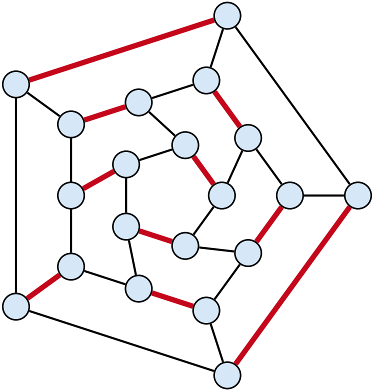
Theorem 23

We need $\mathcal{O}(m \log C)$ augmentations. The algorithm can be implemented in time $\mathcal{O}(m^2 \log C)$.

Matching

- Input: undirected graph $G = (V, E)$.
- $M \subseteq E$ is a matching if each node appears in at most one edge in M.
- Maximum Matching: find a matching of maximum cardinality



Bipartite Matching

- Input: undirected, bipartite graph $G = (L \uplus R, E)$.
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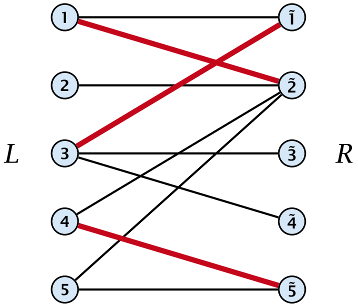

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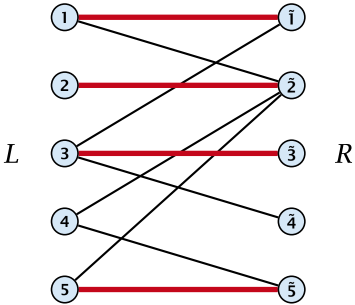
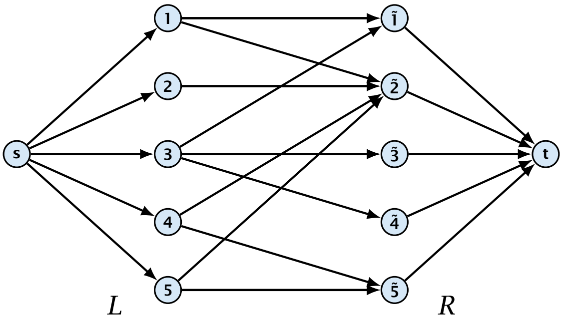


Maxflow Formulation

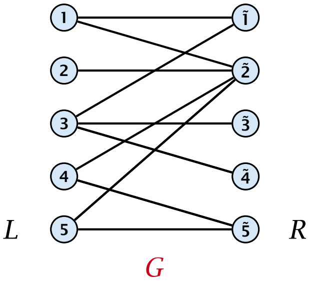
- Input: undirected, bipartite graph $G = (L \uplus R \uplus \{s,t\}, E')$.
- Direct all edges from L to R.
- Add source s and connect it to all nodes on the left.
- Add t and connect all nodes on the right to t.
- All edges have unit capacity.



Proof

Max cardinality matching in $G \leq$ value of maxflow in G'

- Given a maximum matching M of cardinality k.
- Consider flow f that sends one unit along each of k paths.
- f is a flow and has cardinality k.



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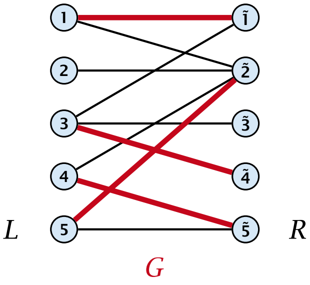

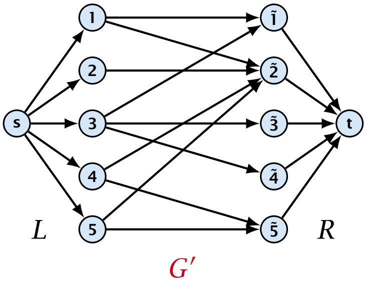

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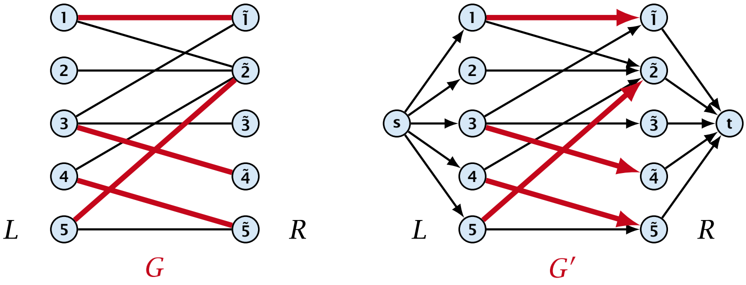

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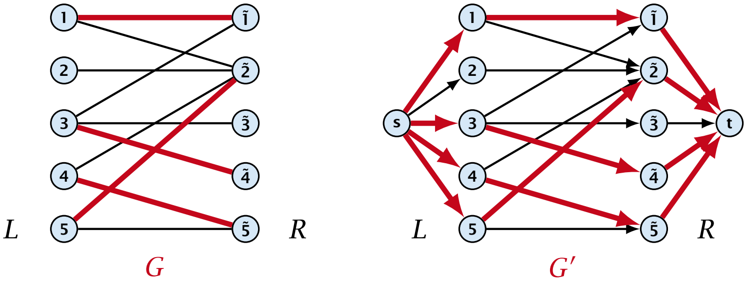

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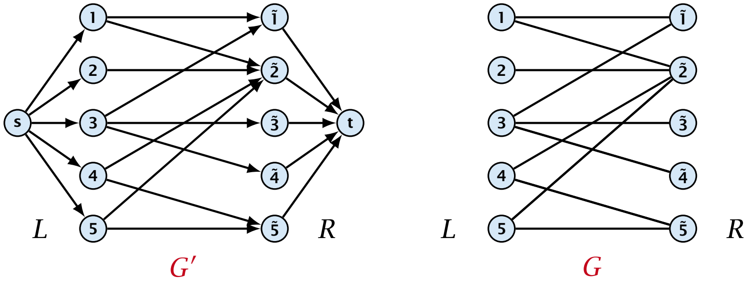
- Let f be a maxflow in G' of value k
- Integrality theorem $\Rightarrow$ k integral; we can assume f is 0/1.
- Consider M= set of edges from L to R with $f(e) = 1$.
- Each node in L and R participates in at most one edge in M.
- $|M| = k$, as the flow must use at least k middle edges.



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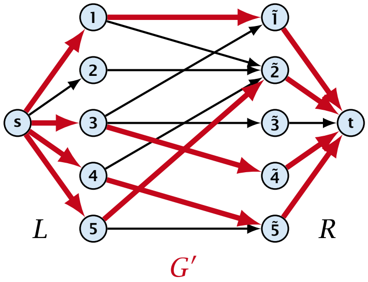

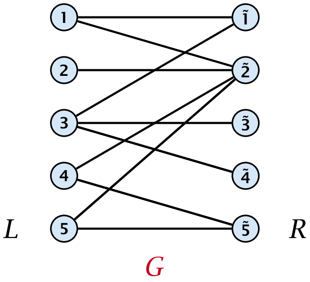

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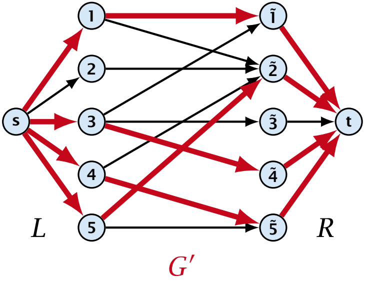
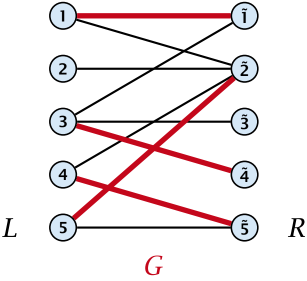




12.1 Matching

Which flow algorithm to use?

- Generic augmenting path: $\mathcal{O}(m\,\text{val}(f^*)) = \mathcal{O}(mn)$.
- Capacity scaling: $\mathcal{O}(m^2 \log C) = \mathcal{O}(m^2)$.
- Shortest augmenting path: $\mathcal{O}(mn^2)$.

For unit capacity simple graphs shortest augmenting path can be implemented in time $\mathcal{O}(m\sqrt{n})$.

Baseball Elimination

team i	wins w_i	losses ℓ_i	remaining games Atl	Phi	NY	Mon
Atlanta	83	71	–	1	6	1
Philadelphia	80	79	1	–	0	2
New York	78	78	6	0	–	0
Montreal	77	82	1	2	0	–

Which team can end the season with most wins?

- Montreal is eliminated, since even after winning all remaining games there are only 80 wins.
- But also Philadelphia is eliminated. Why?

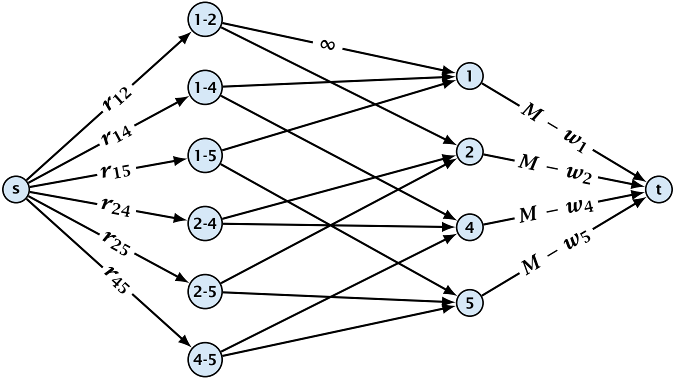
Baseball Elimination

Formal definition of the problem:

- Given a set S of teams, and one specific team $z \in S$.
- Team x has already won w_x games.
- Team x still has to play team y, r_{xy} times.
- Does team z still have a chance to finish with the most number of wins.

Baseball Elimination

Flow network for $z = 3$. M is number of wins Team 3 can still obtain.



Idea. Distribute the results of remaining games in such a way that no team gets too many wins.

Certificate of Elimination

Let $T \subseteq S$ be a subset of teams. Define

$$w(T) := \sum_{i \in T} w_i, \qquad r(T) := \sum_{i,j \in T, i<j} r_{ij}$$

wins of teams in T — remaining games among teams in T

If $\frac{w(T)+r(T)}{|T|} > M$ then one of the teams in T will have more than M wins in the end. A team that can win at most M games is therefore eliminated.

Theorem 24

A team z is eliminated if and only if the flow network for z does not allow a flow of value $\sum_{ij\in S\setminus\{z\},i<j} r_{ij}$.

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Proof (⇐)

- Consider the mincut A in the flow network. Let T be the set of team-nodes in A.

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A team z is eliminated if and only if the flow network for z does not allow a flow of value $\sum_{ij\in S\setminus\{z\},i<j} r_{ij}$.

Proof (⇐)

- Consider the mincut A in the flow network. Let T be the set of team-nodes in A.
- If for node x-y not both team-nodes x and y are in T, then x-$y \notin A$ as otw. the cut would cut an infinite capacity edge.

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\begin{aligned}
r(S\setminus\{z\}) &> \operatorname{cap}(A, V\setminus A)\\
&\geq \sum_{i<j:\, i\notin T \vee j\notin T} r_{ij} + \sum_{i\in T}(M - w_i)
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- This gives $M < (w(T) + r(T))/|T|$, i.e., z is eliminated.

Baseball Elimination

Proof (⇒)

- Suppose we have a flow that saturates all source edges.
- We can assume that this flow is integral.
- For every pairing x-y it defines how many games team x and team y should win.
- The flow leaving the team-node x can be interpreted as the additional number of wins that team x will obtain.
- This is less than $M - w_x$ because of capacity constraints.
- Hence, we found a set of results for the remaining games, such that no team obtains more than M wins in total.
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Project Selection

Project selection problem:

- Set P of possible projects. Project v has an associated profit p_v (can be positive or negative).
- Some projects have requirements (taking course EA2 requires course EA1).
- Dependencies are modelled in a graph. Edge (u, v) means "can't do project u without also doing project v."
- A subset A of projects is feasible if the prerequisites of every project in A also belong to A.

Goal: Find a feasible set of projects that maximizes the profit.

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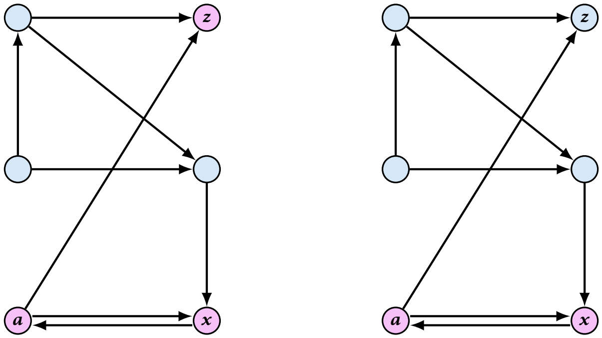
Project Selection

The prerequisite graph:

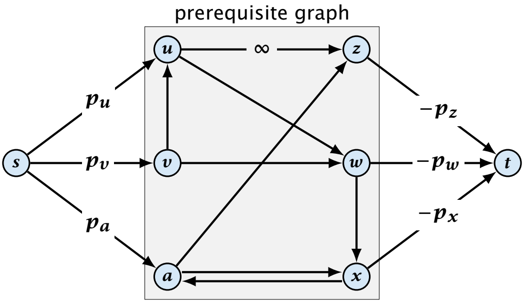
- $\{x, a, z\}$ is a feasible subset.
- $\{x, a\}$ is infeasible.



Project Selection

Mincut formulation:

- Edges in the prerequisite graph get infinite capacity.
- Add edge (s, v) with capacity p_v for nodes v with positive profit.
- Create edge (v, t) with capacity $-p_v$ for nodes v with negative profit.



Theorem 25

A is a mincut if $A \setminus \{s\}$ is the optimal set of projects.

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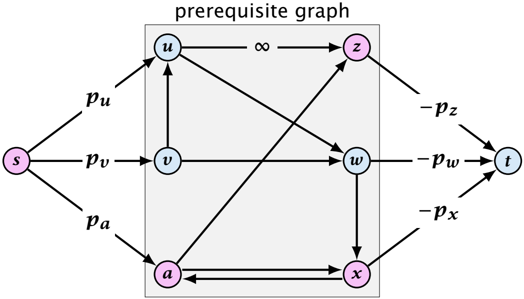
Proof.

- A is feasible because of capacity infinity edges.



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- A is feasible because of capacity infinity edges.
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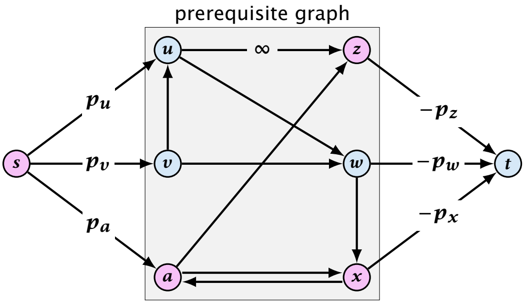

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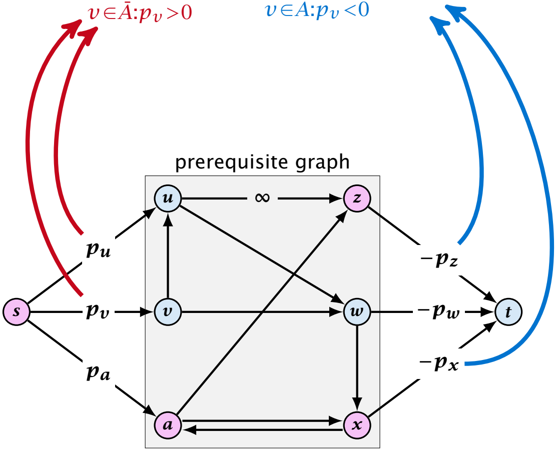
- $\text{cap}(A, V \setminus A) = \sum_{v \in \bar{A}: p_v > 0} p_v + \sum_{v \in A: p_v < 0} (-p_v)$



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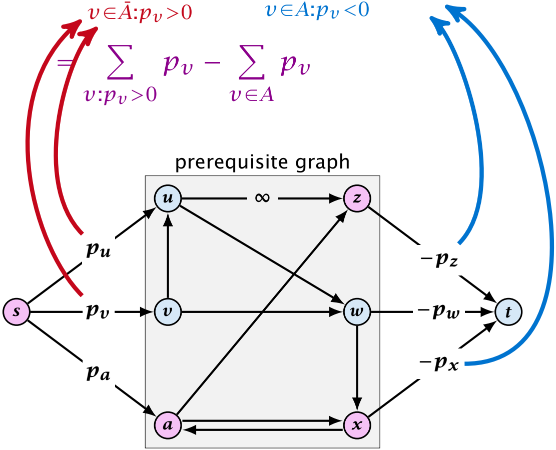
$$= \sum_{v: p_v > 0} p_v - \sum_{v \in A} p_v$$



Preflows

Definition 26

An (s,t)-preflow is a function $f : E \mapsto \mathbb{R}^+$ that satisfies

1. For each edge e
$$0 \le f(e) \le c(e) \ .$$
(capacity constraints)
2. For each $v \in V \setminus \{s,t\}$
$$\sum_{e \in \text{out}(v)} f(e) \le \sum_{e \in \text{into}(v)} f(e) \ .$$

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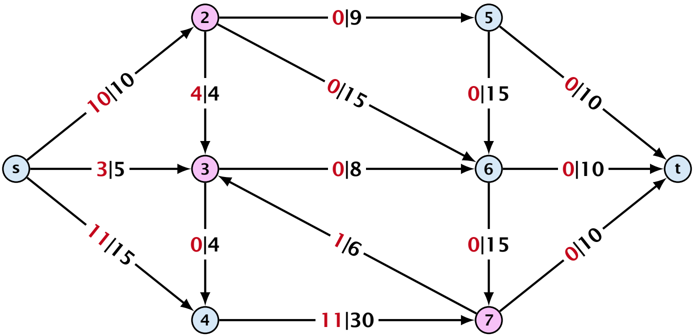
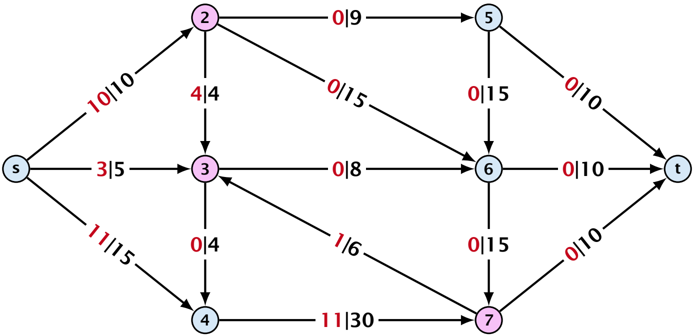
Preflows

Example 27



Preflows

Example 27



A node that has $\sum_{e\in\text{out}(v)} f(e) < \sum_{e\in\text{into}(v)} f(e)$ is called an active node.

Preflows

Preflows

Definition:

A labelling is a function $\ell : V \to \mathbb{N}$. It is valid for preflow f if

- $\ell(u) \le \ell(v) + 1$ for all edges (u, v) in the residual graph G_f (only non-zero capacity edges!!!)

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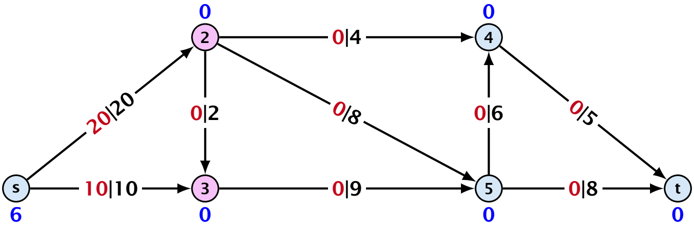
Intuition:

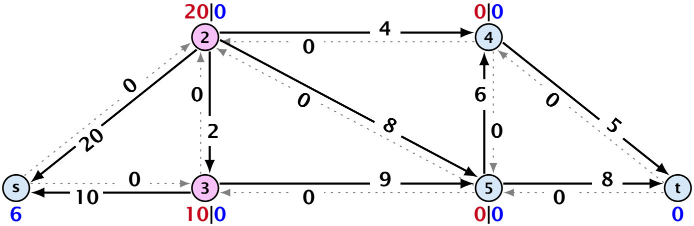
The labelling can be viewed as a height function. Whenever the height from node u to node v decreases by more than 1 (i.e., it goes very steep downhill from u to v), the corresponding edge must be saturated.

Preflows

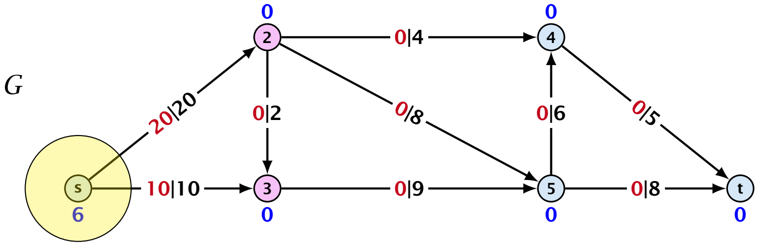
G



G_f



Preflows



G
0
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0|4
4
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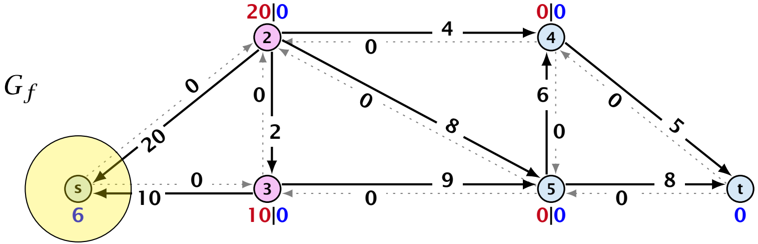
t
6
0
0
0



20|0
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0

Preflows

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Lemma 29

A flow that has a valid labelling is a maximum flow.

Push Relabel Algorithms

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Idea:

- start with some preflow and some valid labelling

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- start with some preflow and some valid labelling
- successively change the preflow while maintaining a valid labelling

Push Relabel Algorithms

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- start with some preflow and some valid labelling
- successively change the preflow while maintaining a valid labelling
- stop when you have a flow (i.e., no more active nodes)

Changing a Preflow

An arc (u,v) with $c_f(u,v) > 0$ in the residual graph is admissible if $\ell(u) = \ell(v) + 1$ (i.e., it goes downwards w.r.t. labelling ℓ).

The push operation

Consider an active node u with excess flow $f(u) = \sum_{e\in\text{into}(u)} f(e) - \sum_{e\in\text{out}(u)} f(e)$ and suppose $e = (u,v)$ is an admissible arc with residual capacity $c_f(e)$.

We can send flow $\min\{c_f(e), f(u)\}$ along e and obtain a new preflow. The old labelling is still valid (!!!).

- $\min\{f(u), c_f(e)\} = c_f(e)$
  the arc e is deleted from the residual graph
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Push Relabel Algorithms

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Increasing the label of u by 1 results in a valid labelling.

- Edges (w, u) incoming to u still fulfill their constraint $\ell(w) \leq \ell(u) + 1$.
- An outgoing edge (u, w) had $\ell(u) < \ell(w) + 1$ before since it was not admissible. Now: $\ell(u) \leq \ell(w) + 1$.

Push Relabel Algorithms

Intuition:

We want to send flow downwards, since the source has a height/label of n and the target a height/label of 0. If we see an active node u with an admissible arc we push the flow at u towards the other end-point that has a lower height/label. If we do not have an admissible arc but excess flow into u it should roughly mean that the level/height/label of u should rise. (If we consider the flow to be water then this would be natural.)

Note that the above intuition is very incorrect as the labels are integral, i.e., they cannot really be seen as the height of a node.

Reminder

- In a preflow nodes may not fulfill conservation constraints; a node may have more incoming flow than outgoing flow.
- Such a node is called active.
- A labelling is valid if for every edge (u, v) in the residual graph $\ell(u) \leq \ell(v) + 1$.
- An arc (u, v) in residual graph is admissible if $\ell(u) = \ell(v) + 1$.
- A saturating push along e pushes an amount of $c(e)$ flow along the edge, thereby saturating the edge (and making it dissappear from the residual graph).
- A non-saturating push along $e = (u, v)$ pushes a flow of $f(u)$, where $f(u)$ is the excess flow of u. This makes u inactive.

Push Relabel Algorithms

Algorithm 3 maxflow(G, s, t, c)

```
find initial preflow f
while there is active node u do
    if there is admiss. arc e out of u then
        push(G, e, f, c)
    else
        relabel(u)
return f
```

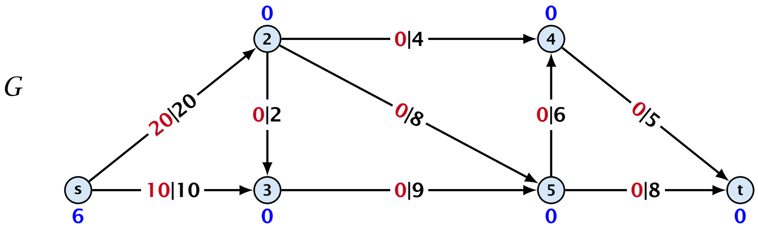
Push Relabel Algorithms

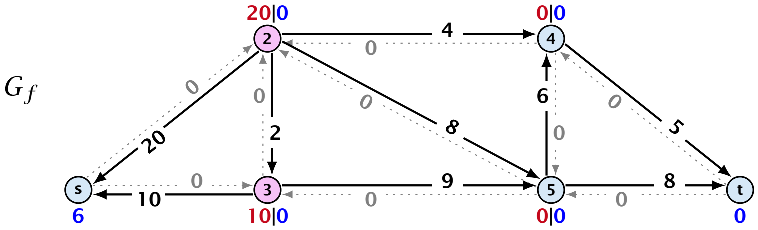
Algorithm 3 maxflow(G, s, t, c)

1: find initial preflow f
2: **while** there is active node u **do**
3:     **if** there is admiss. arc e out of u **then**
4:         push(G, e, f, c)
5:     **else**
6:         relabel(u)
7: **return** f

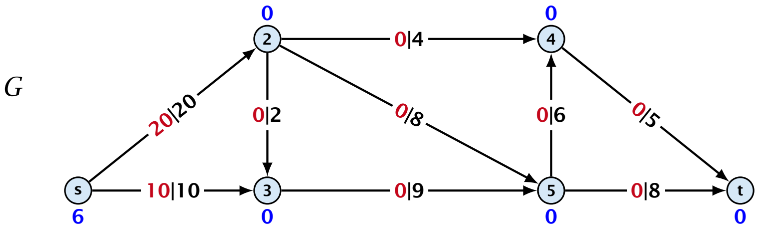
In the following example we always stick to the same active node u until it becomes inactive but this is not required.

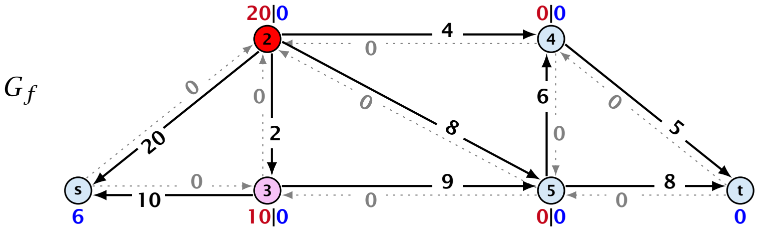
Preflow Push Algorithm





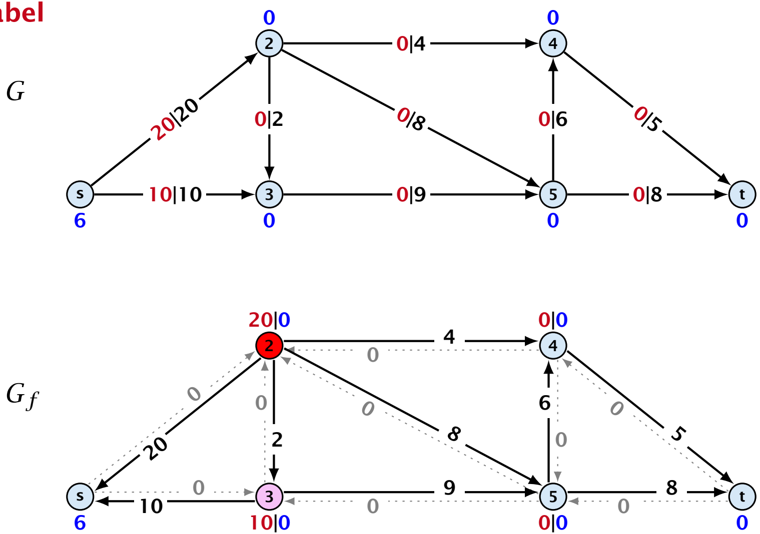
Preflow Push Algorithm



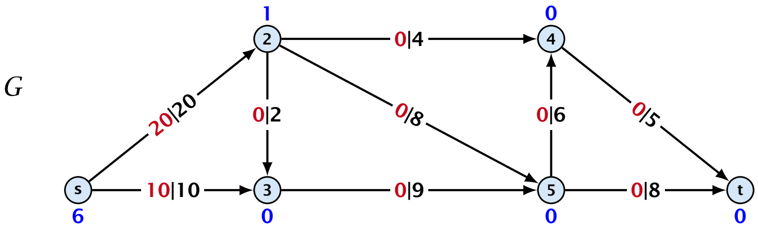


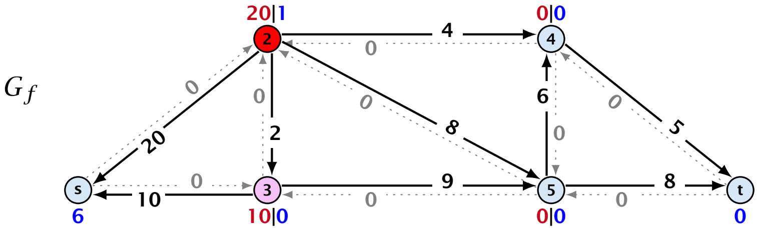
Preflow Push Algorithm

relabel



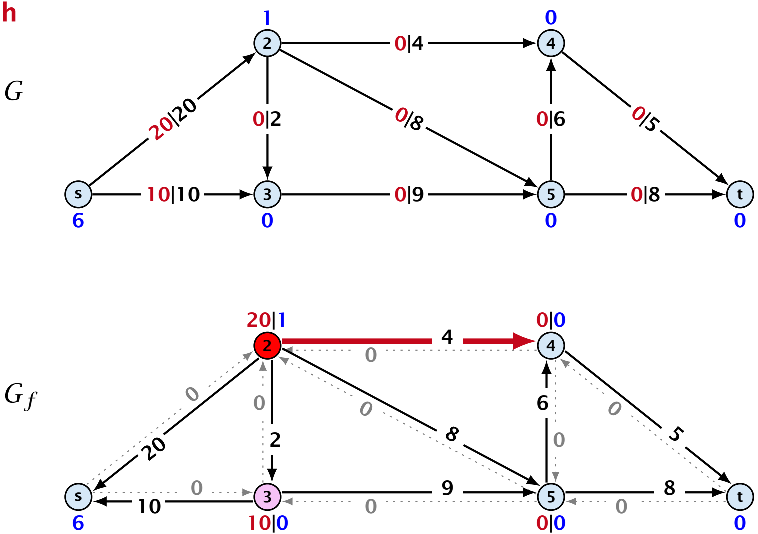
Preflow Push Algorithm





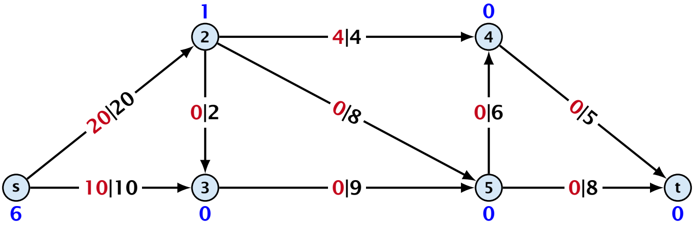
Preflow Push Algorithm

push

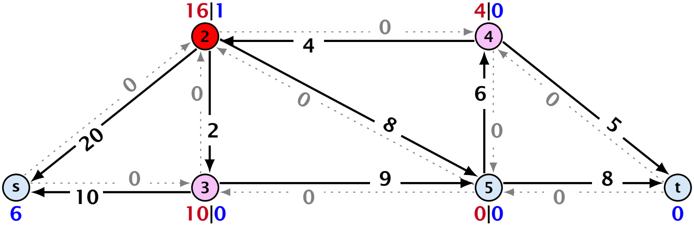


Preflow Push Algorithm

G

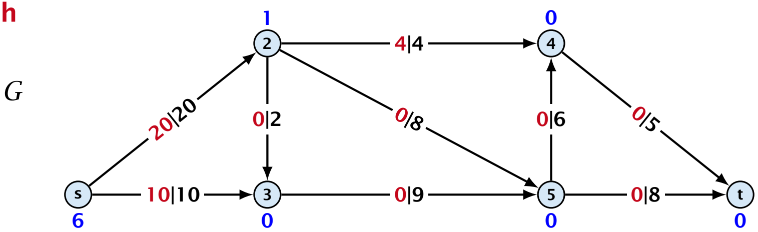


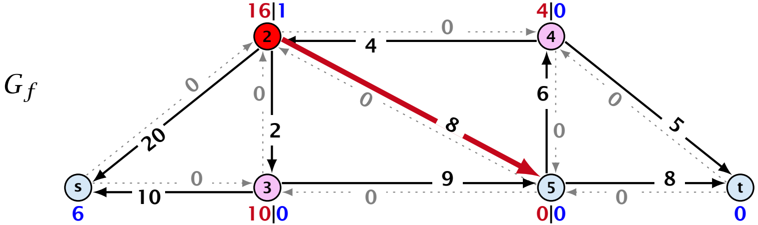
G_f



Preflow Push Algorithm

push





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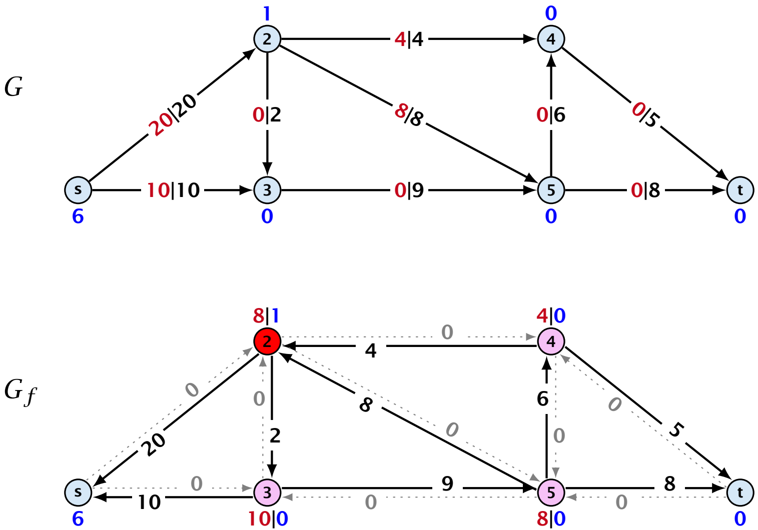

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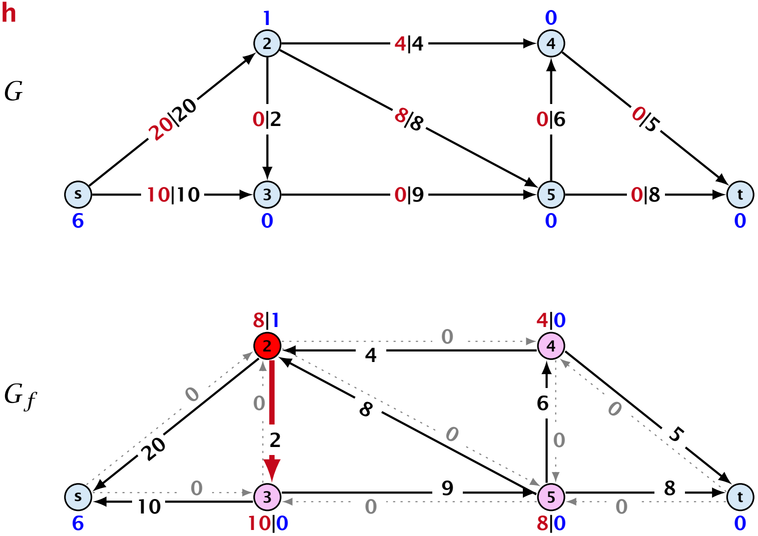
push



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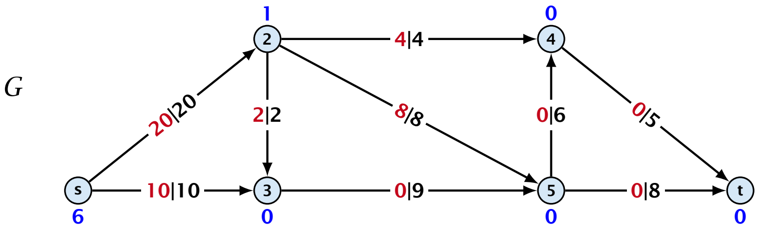
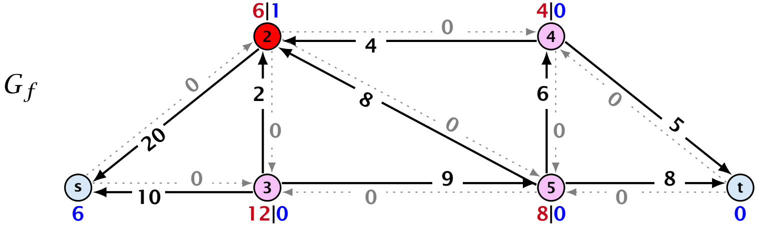
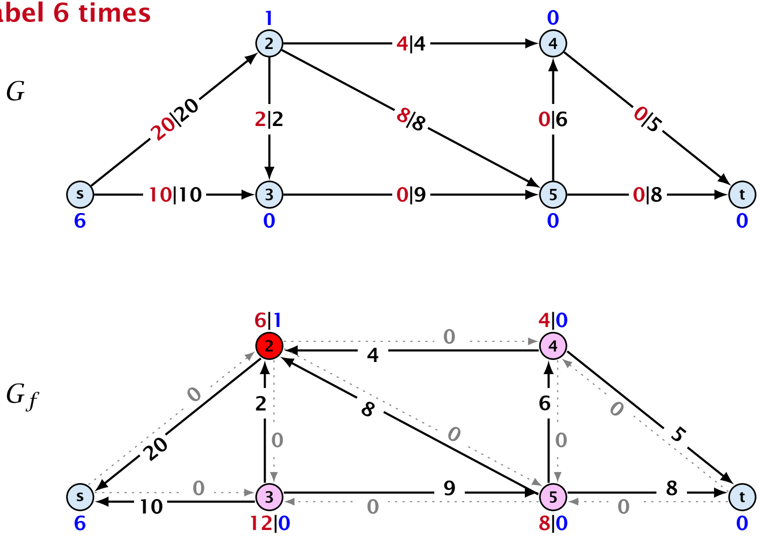




Preflow Push Algorithm

relabel 6 times



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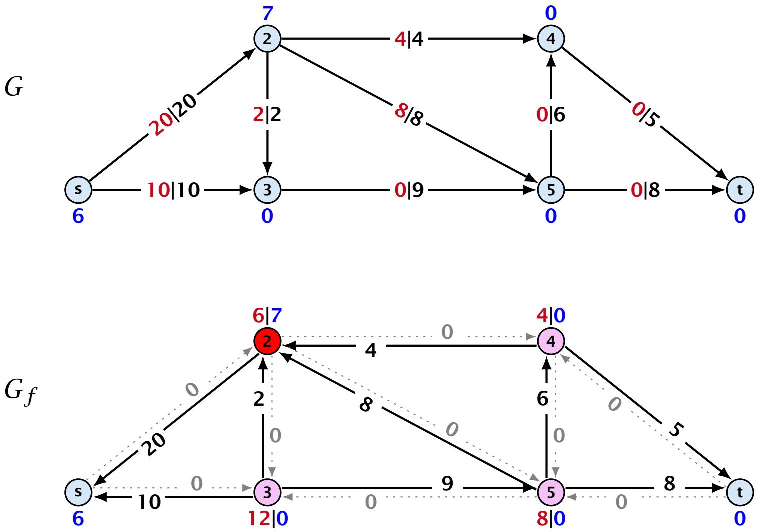
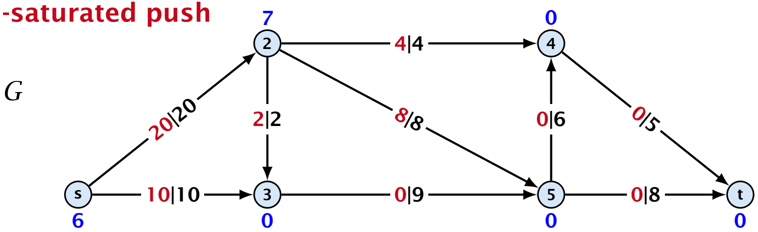
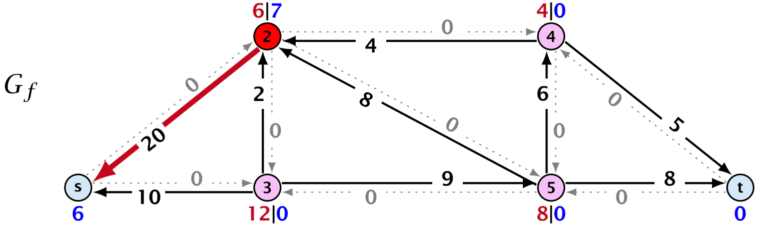


Preflow Push Algorithm

non-saturated push





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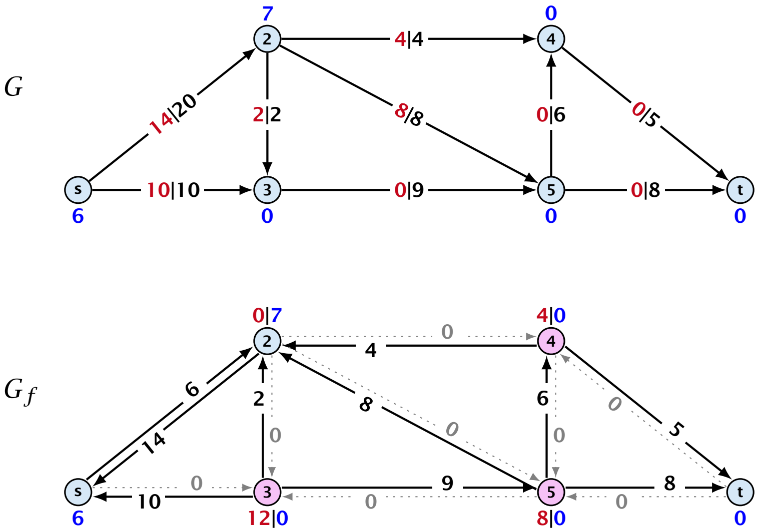

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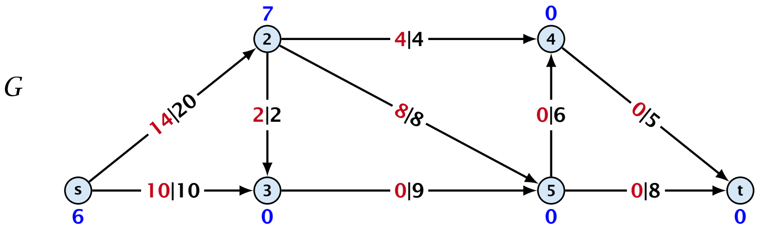
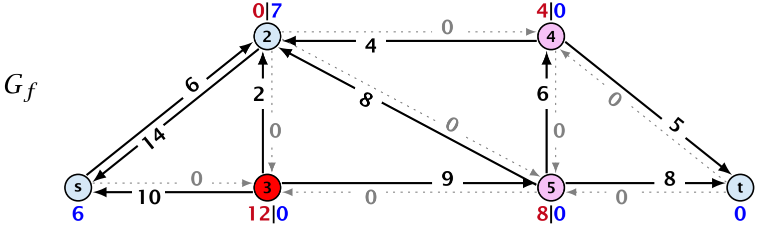
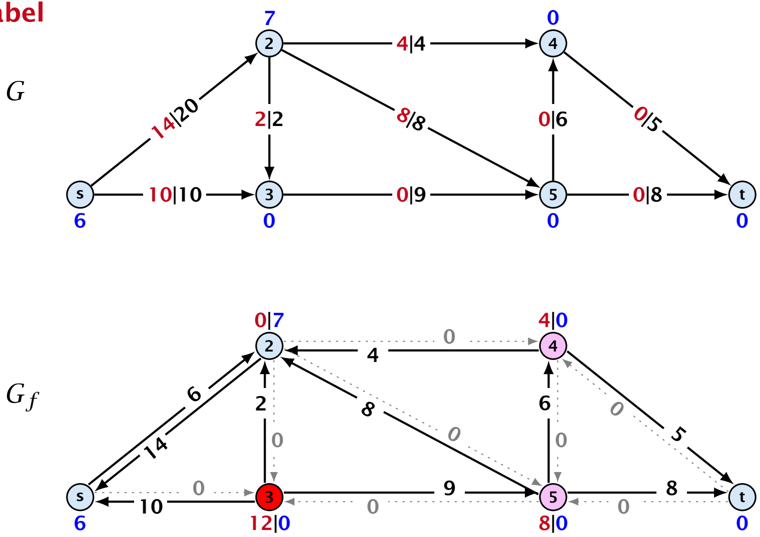




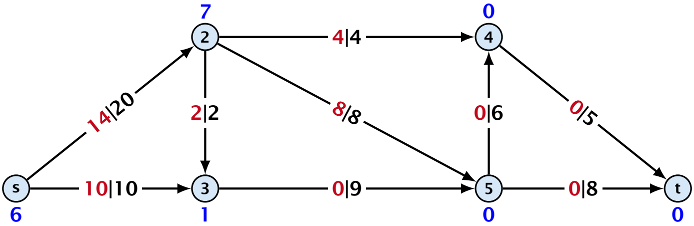
Preflow Push Algorithm

relabel

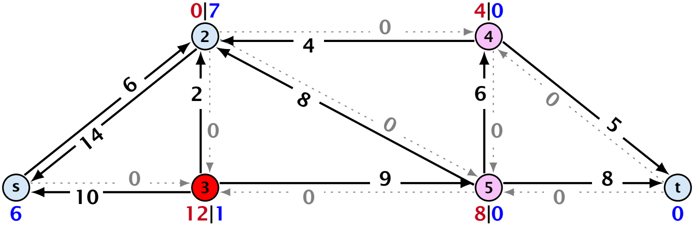


Preflow Push Algorithm

G

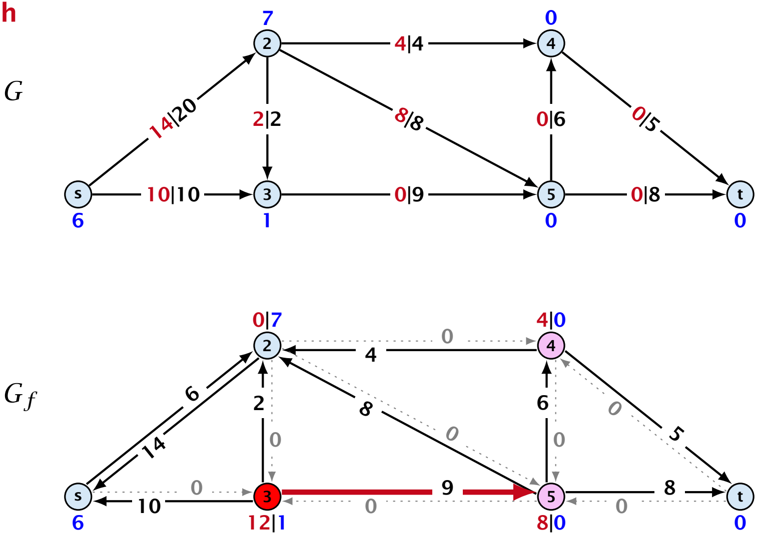


G_f



Preflow Push Algorithm

push



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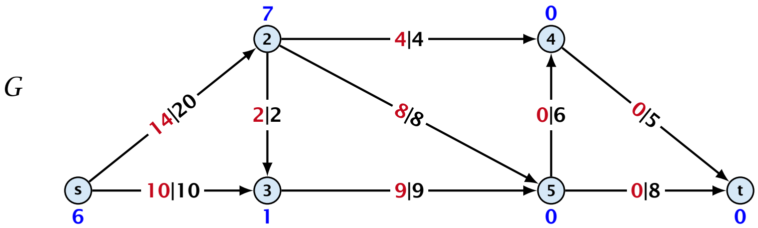
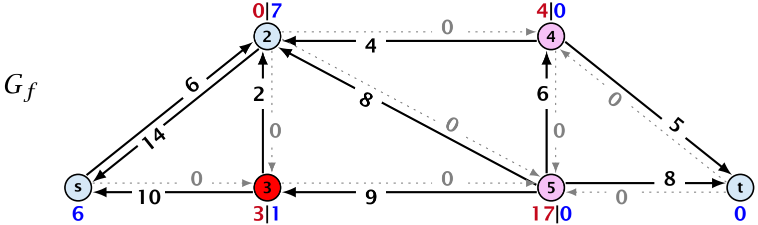
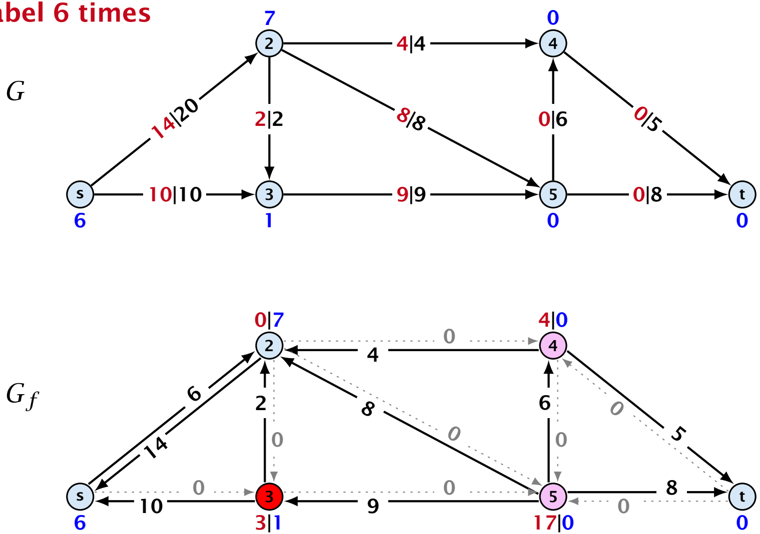




Preflow Push Algorithm

relabel 6 times



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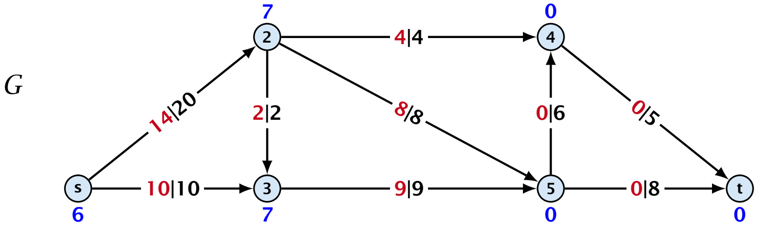
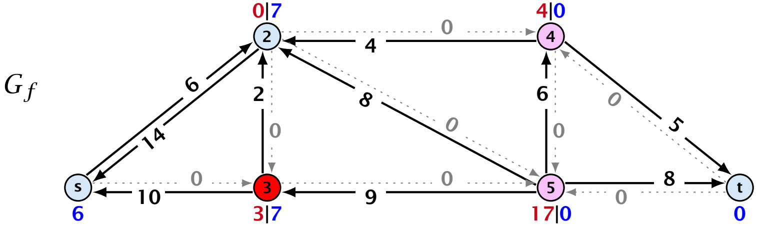
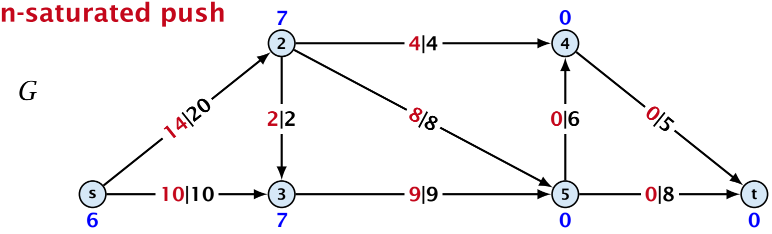
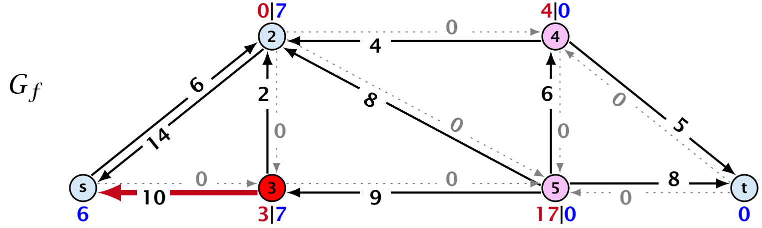




Preflow Push Algorithm

non-saturated push





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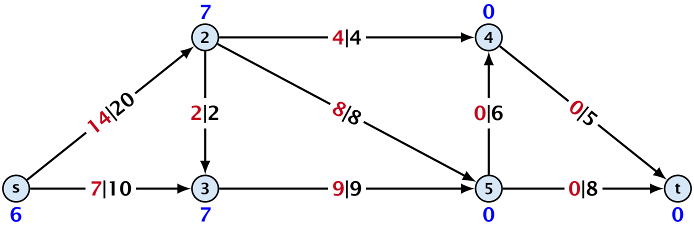

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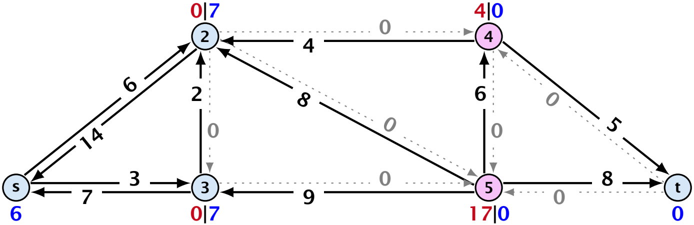

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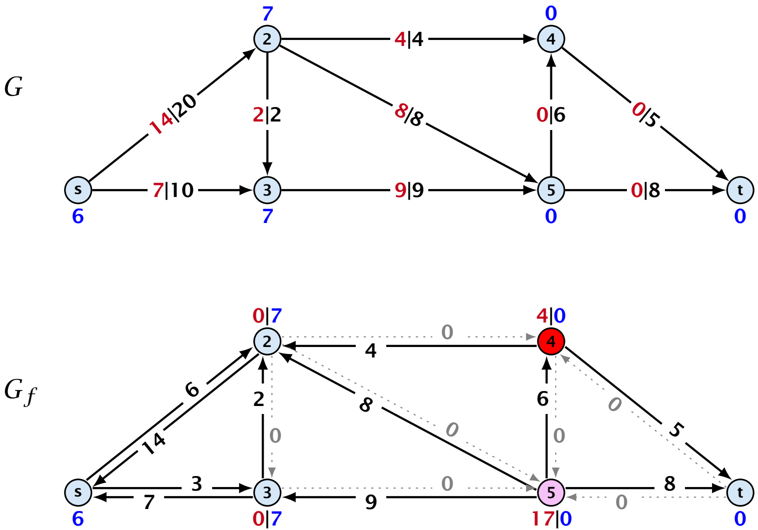
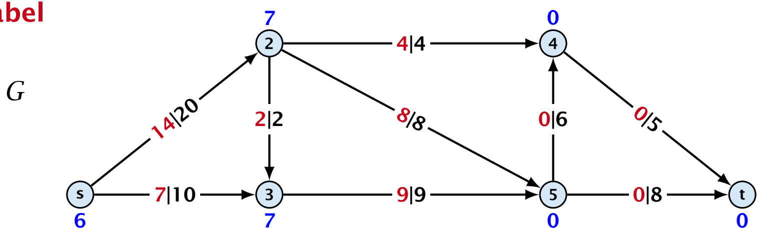
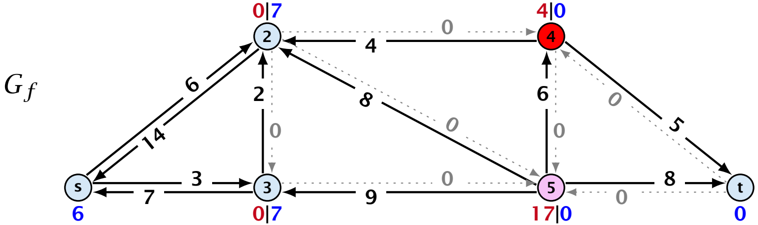


Preflow Push Algorithm

relabel





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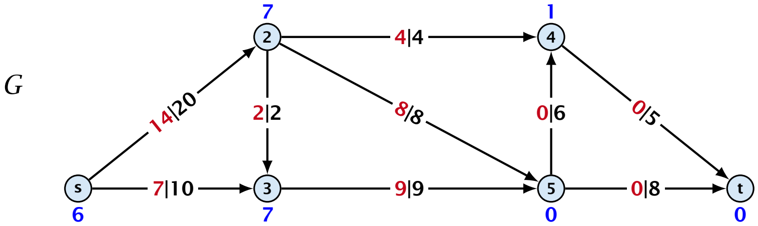
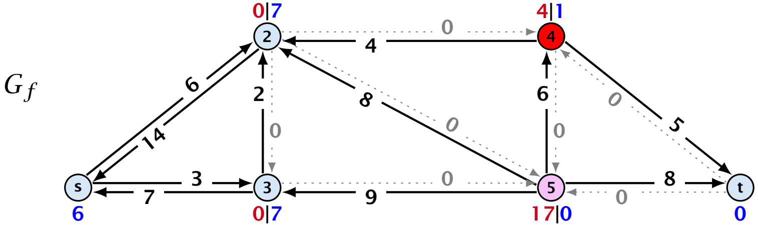
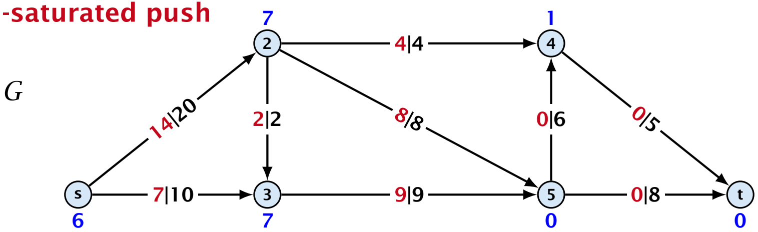
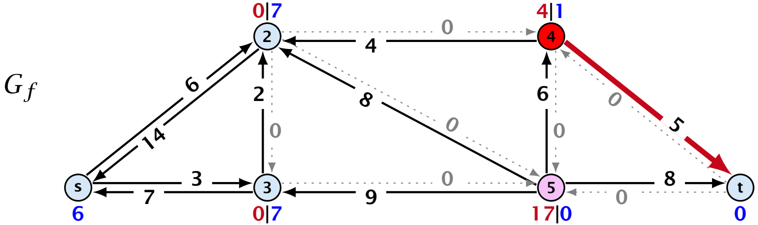




Preflow Push Algorithm

non-saturated push





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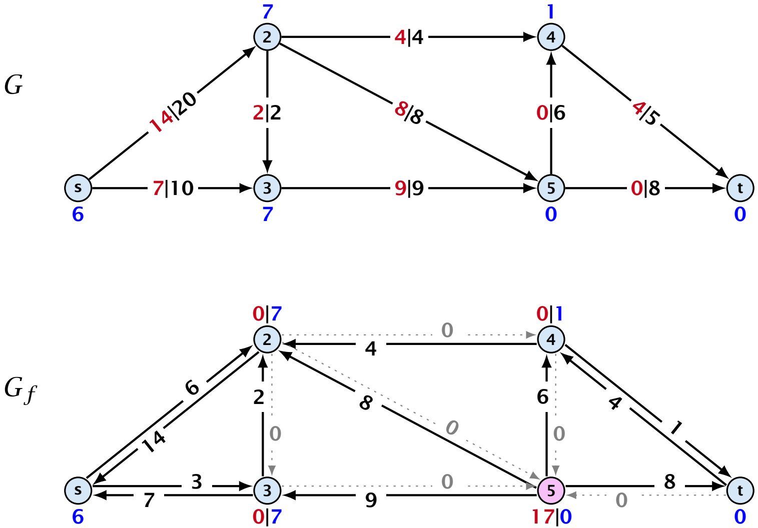

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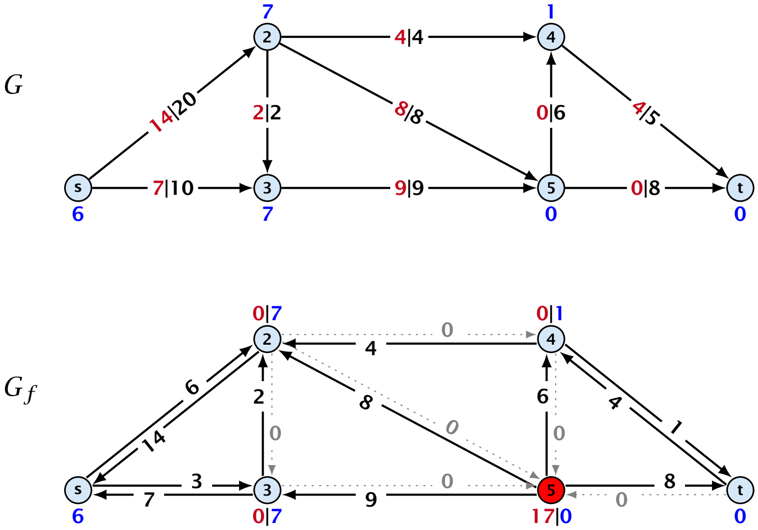
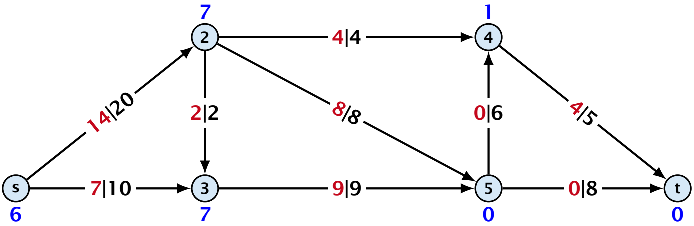


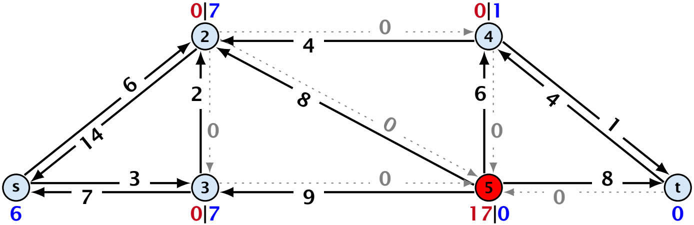
Preflow Push Algorithm

relabel

G



G_f



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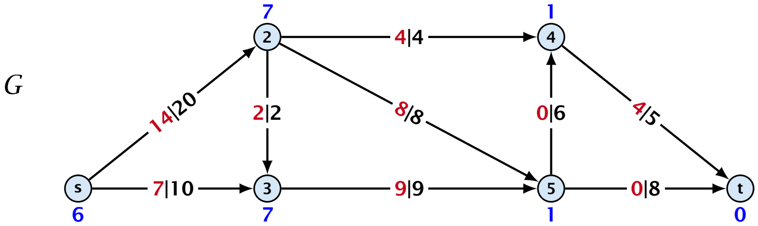
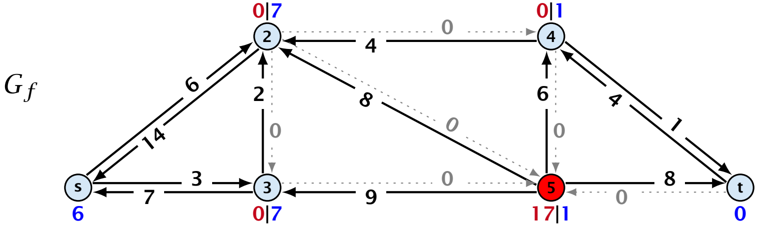
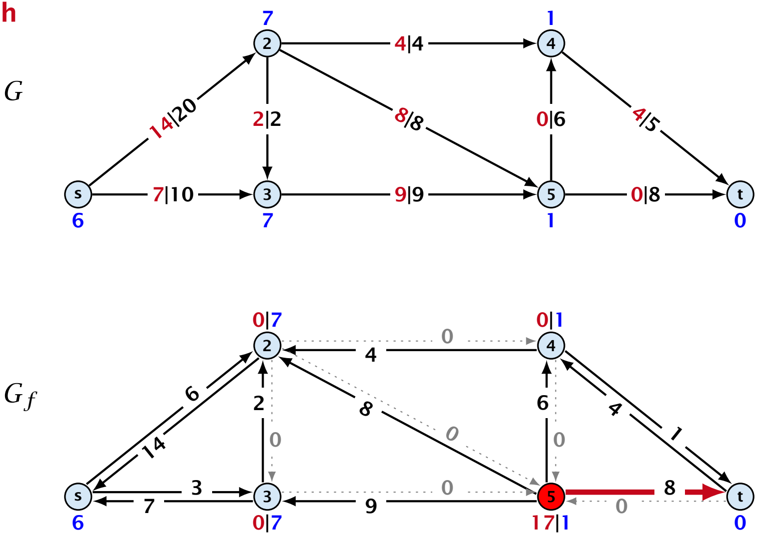




Preflow Push Algorithm

push



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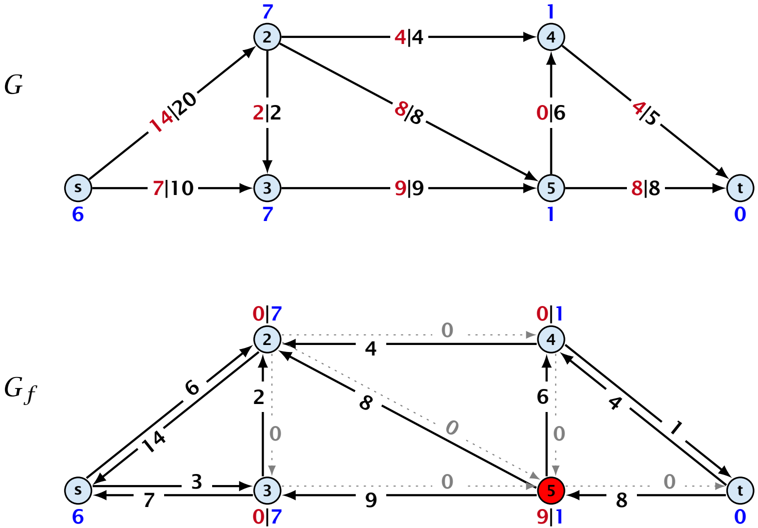
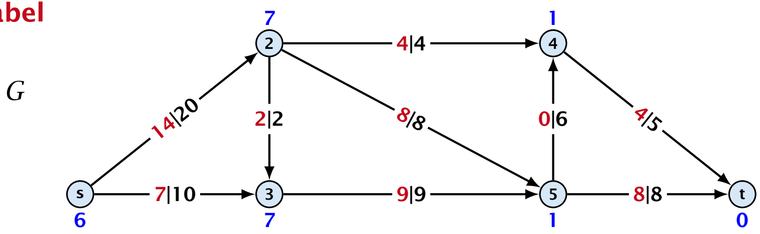
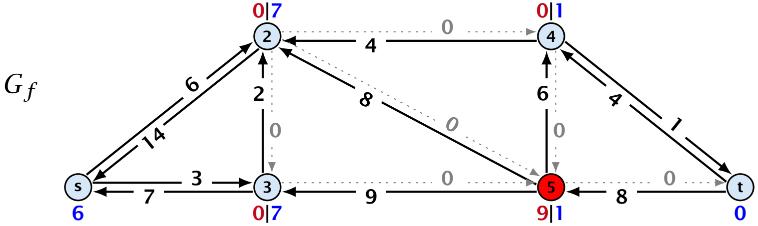


Preflow Push Algorithm

relabel





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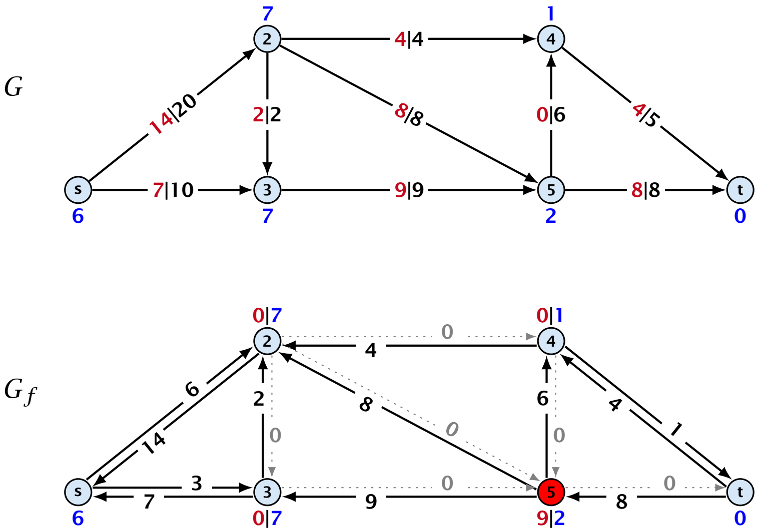
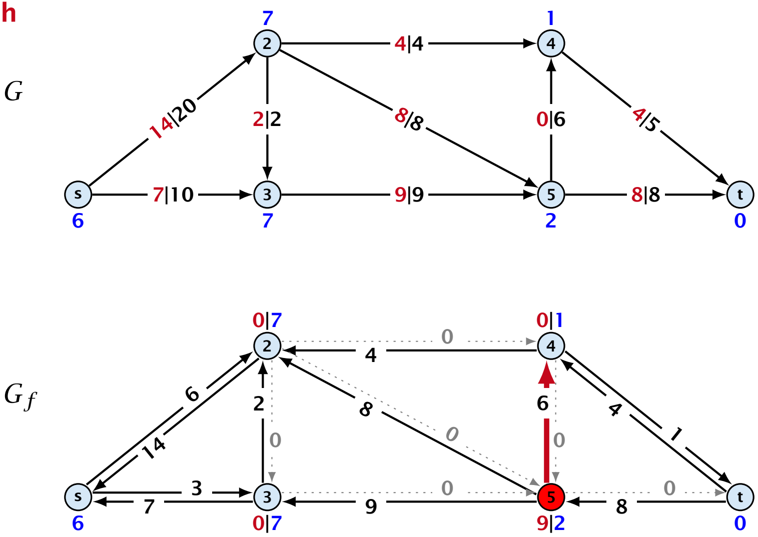


Preflow Push Algorithm

push



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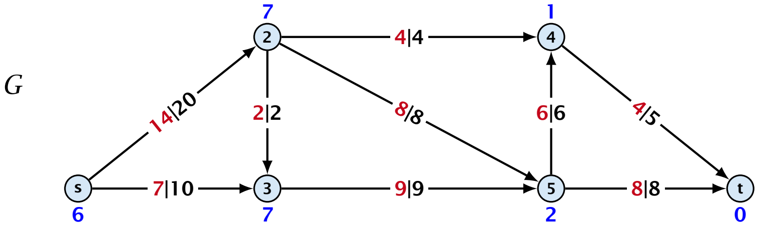
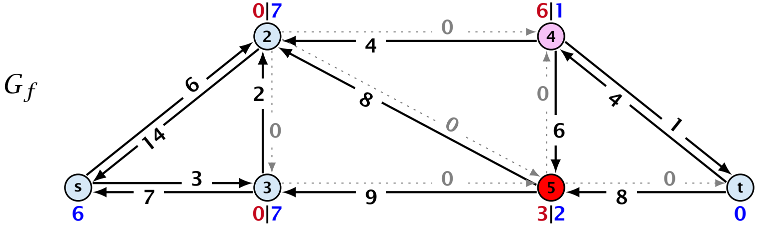
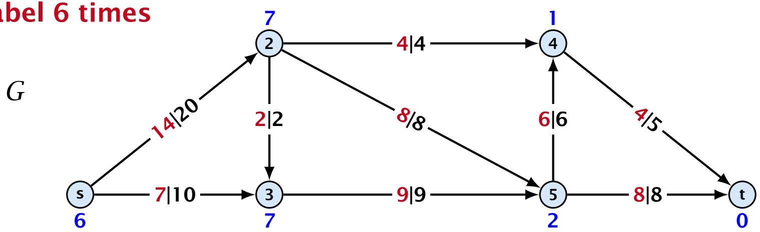
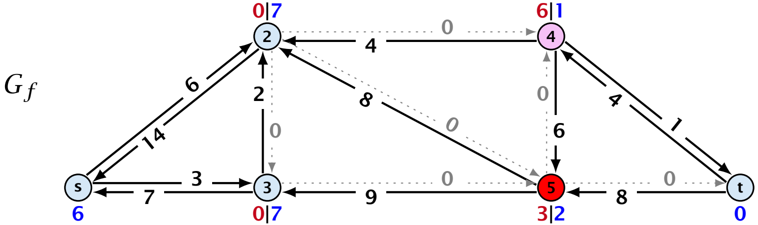




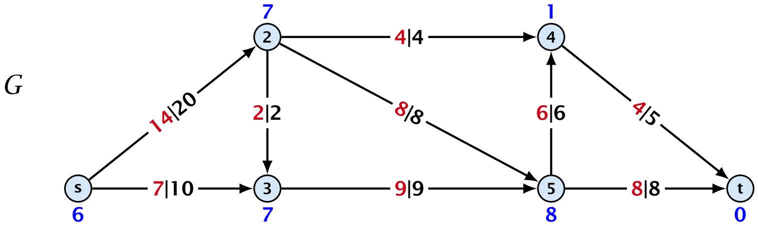
Preflow Push Algorithm

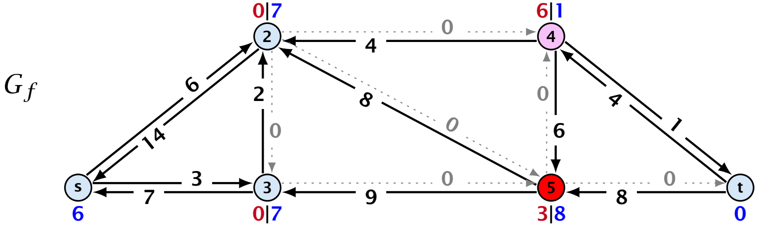
relabel 6 times





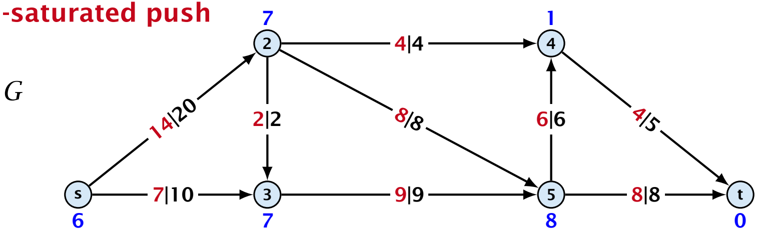
Preflow Push Algorithm

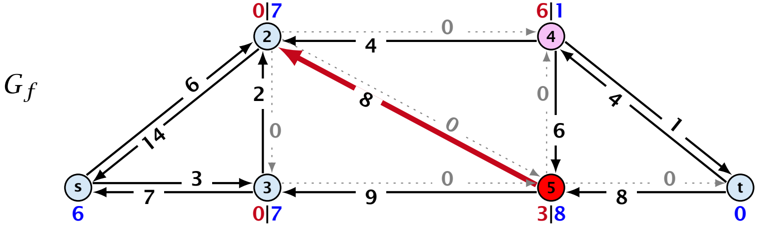




Preflow Push Algorithm

non-saturated push





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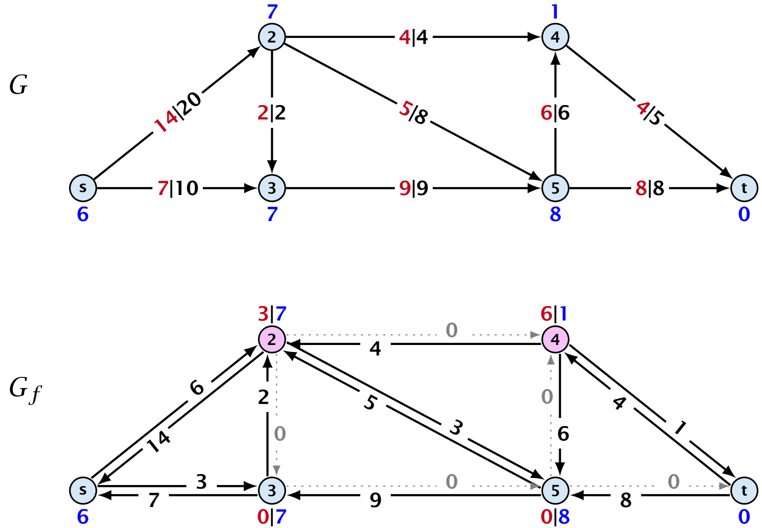

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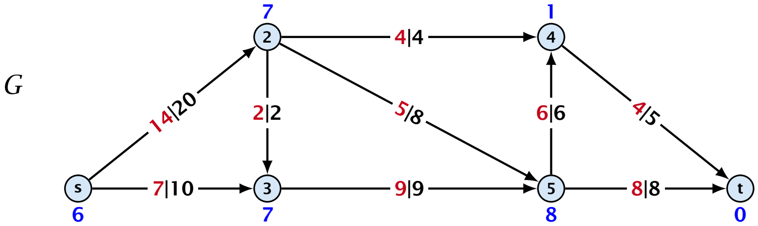
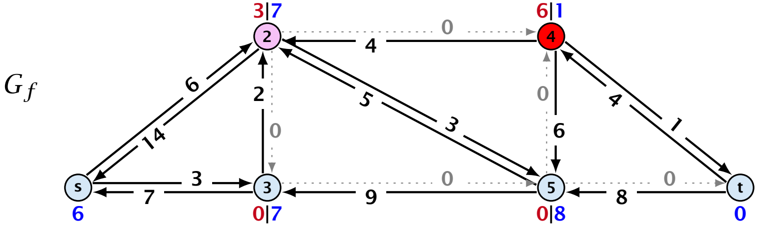
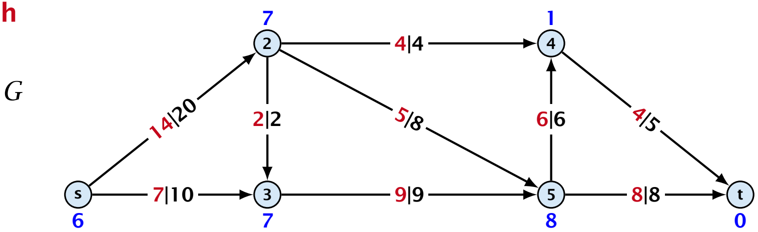
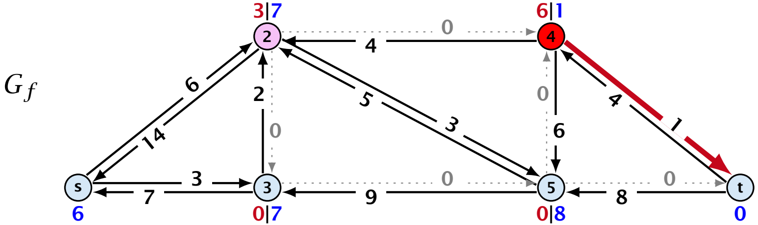




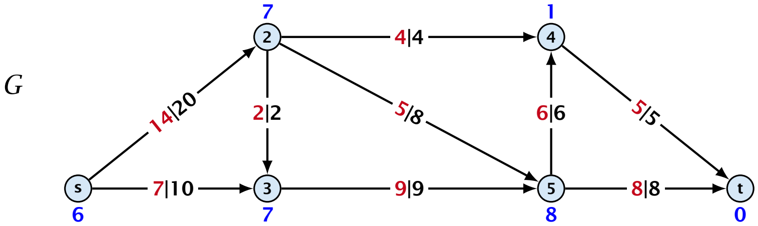
Preflow Push Algorithm

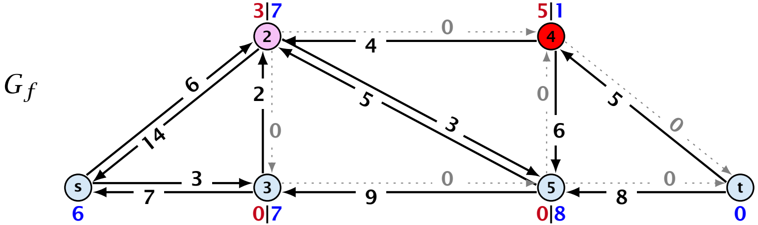
push





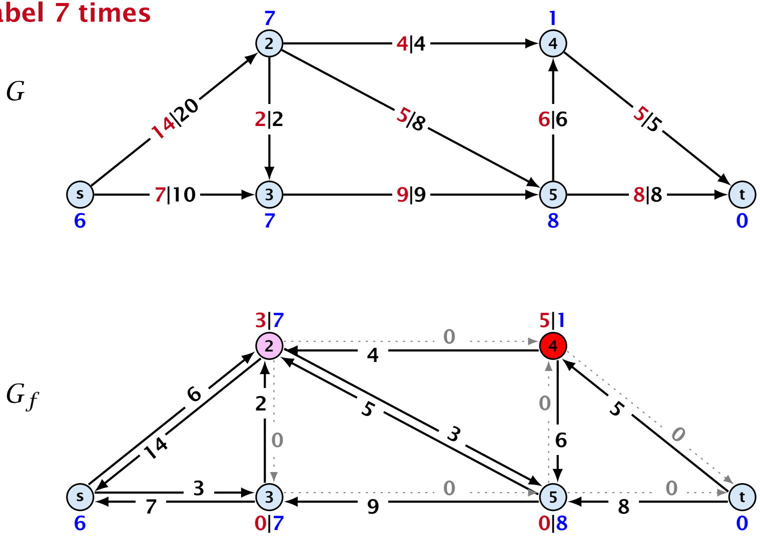
Preflow Push Algorithm





Preflow Push Algorithm

relabel 7 times



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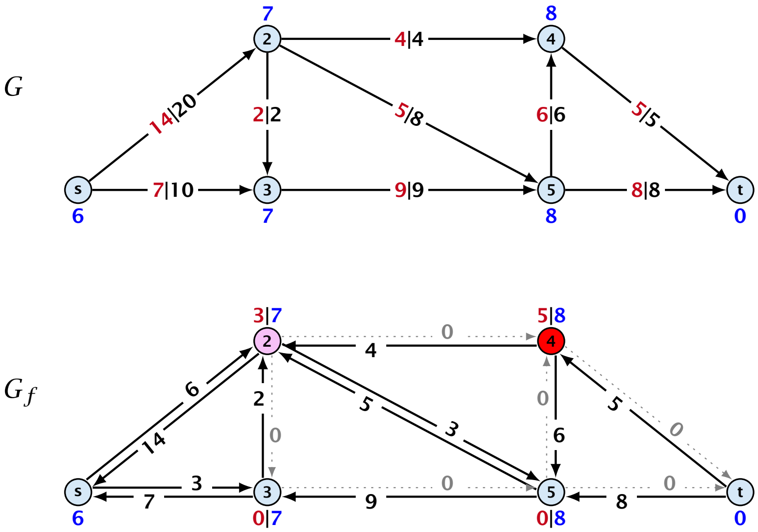
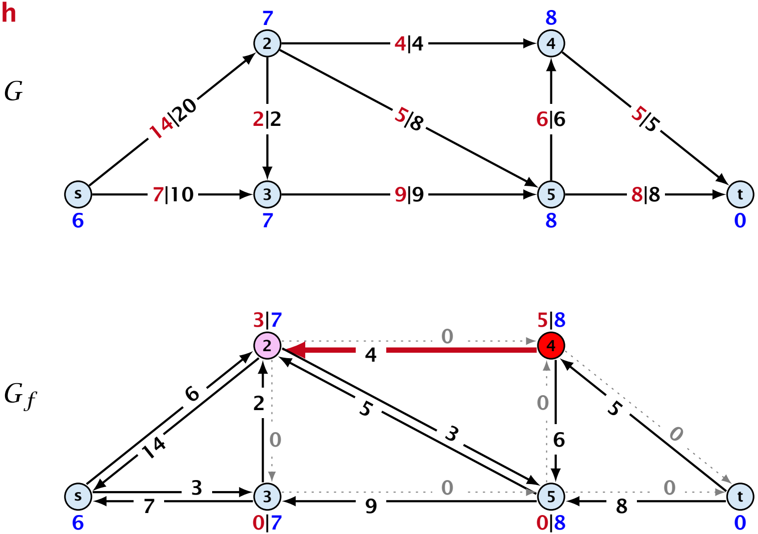
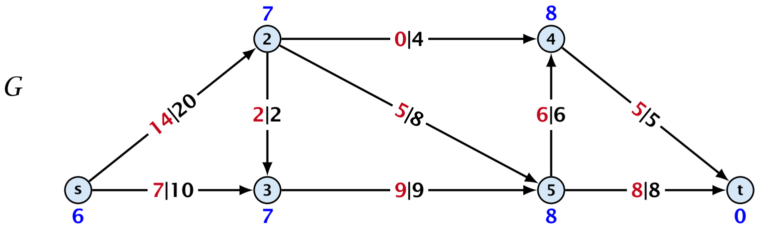


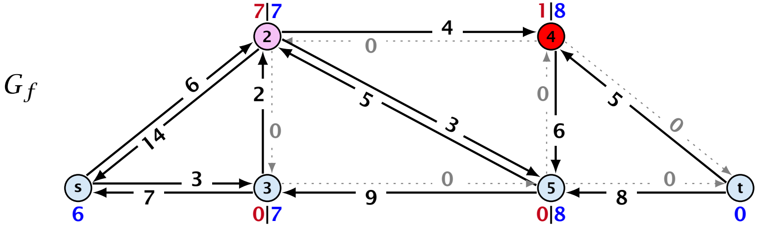
Preflow Push Algorithm

push



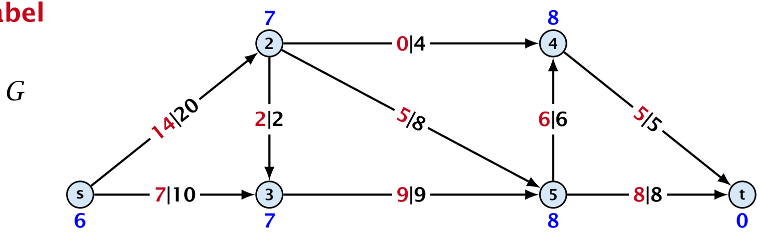
Preflow Push Algorithm

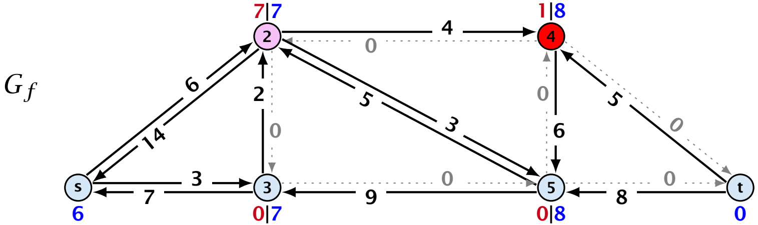




Preflow Push Algorithm

relabel





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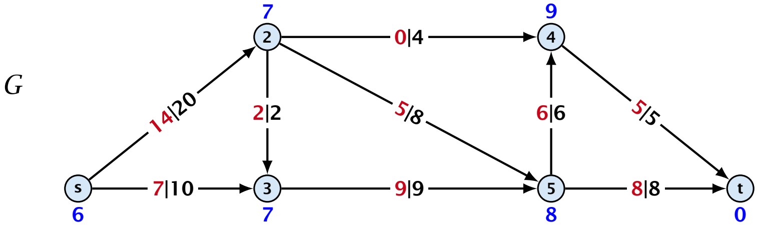
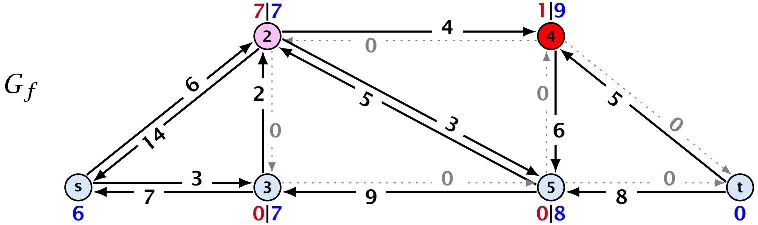
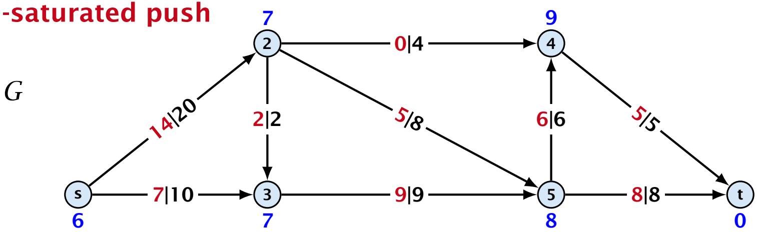
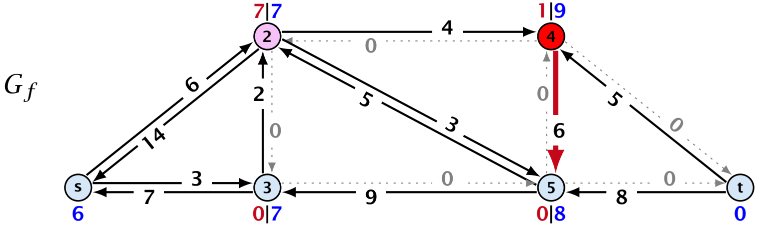




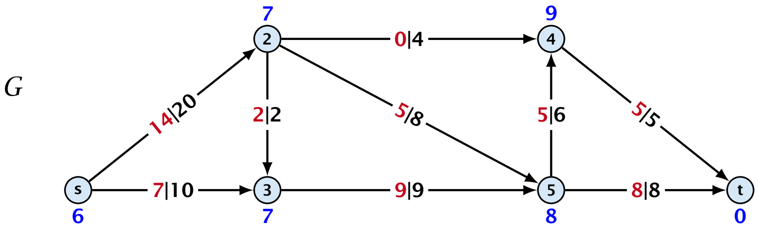
Preflow Push Algorithm

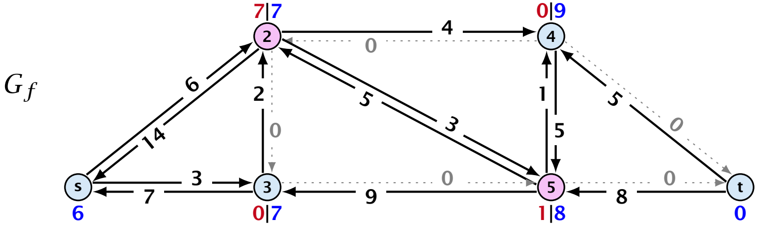
non-saturated push





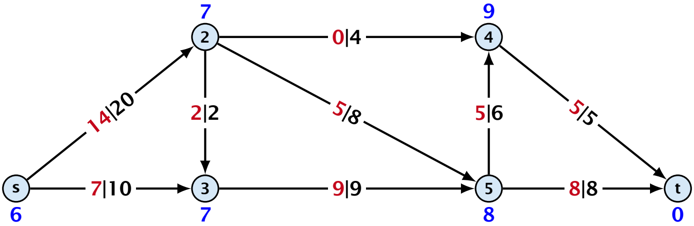
Preflow Push Algorithm



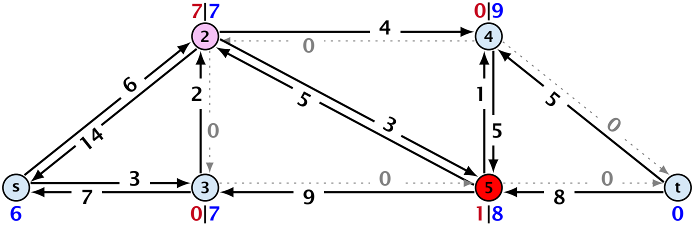


Preflow Push Algorithm

G



G_f



Preflow Push Algorithm

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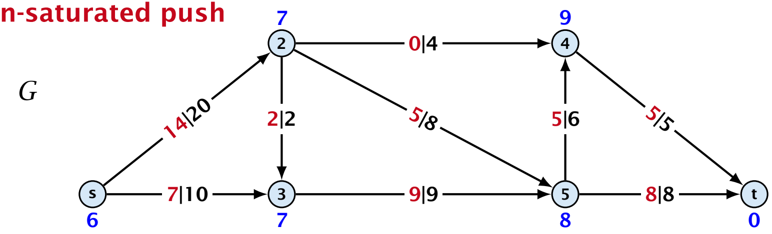

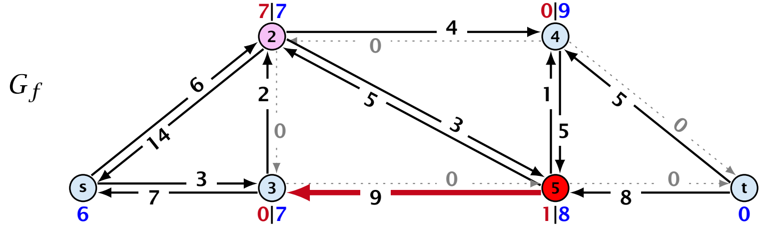

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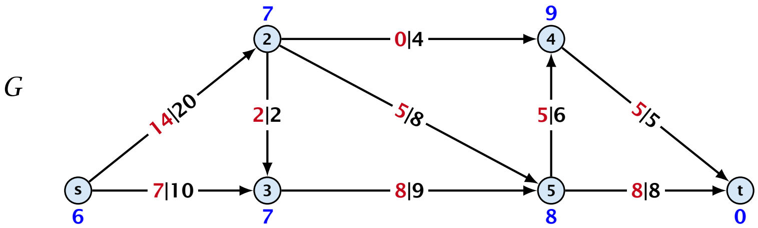

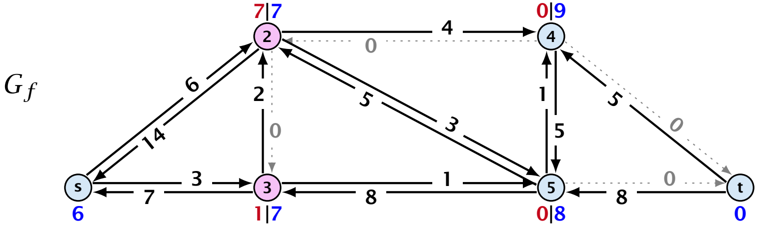

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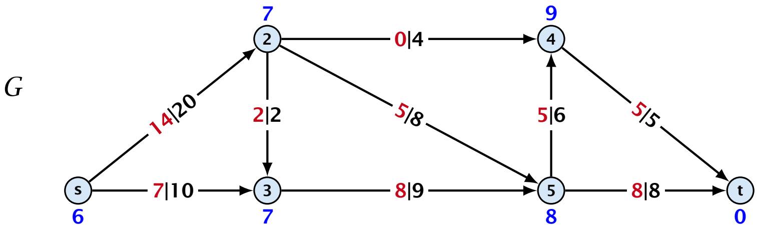
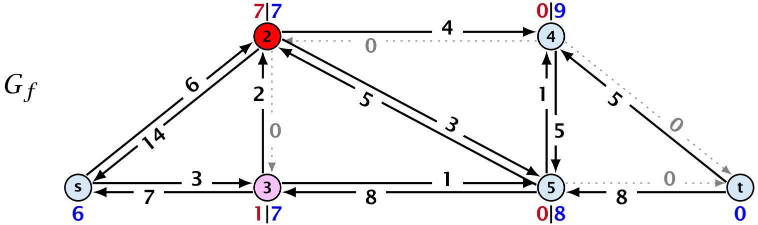
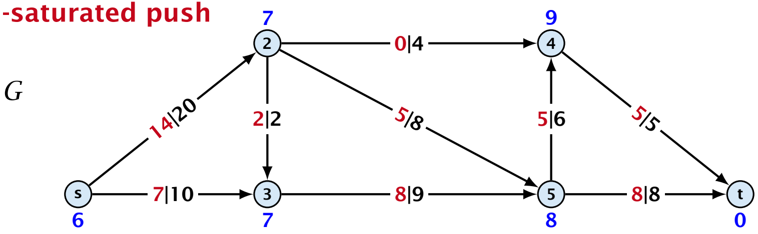
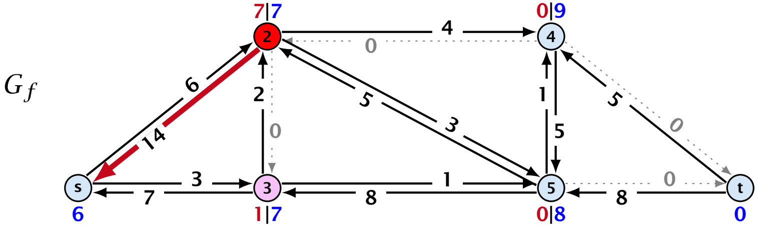




Preflow Push Algorithm

non-saturated push





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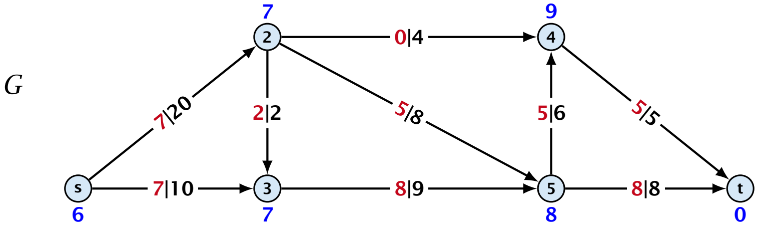
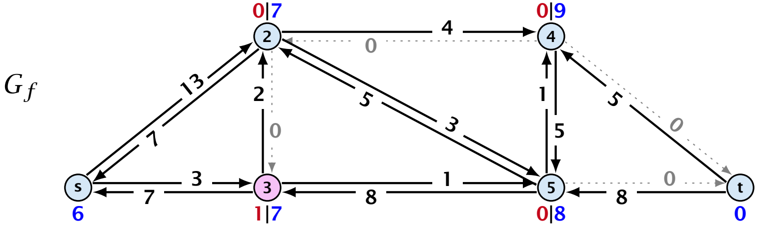
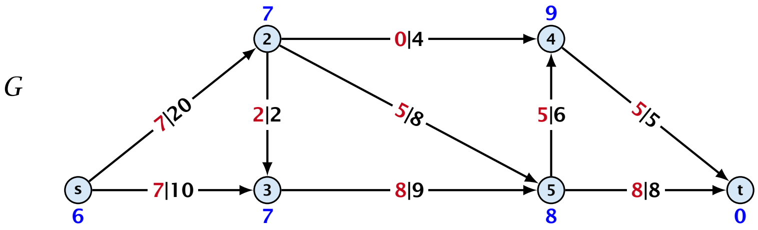
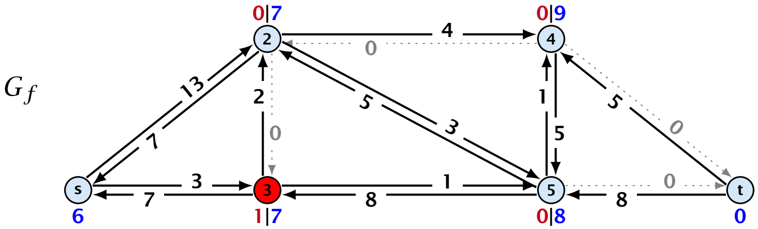




Preflow Push Algorithm





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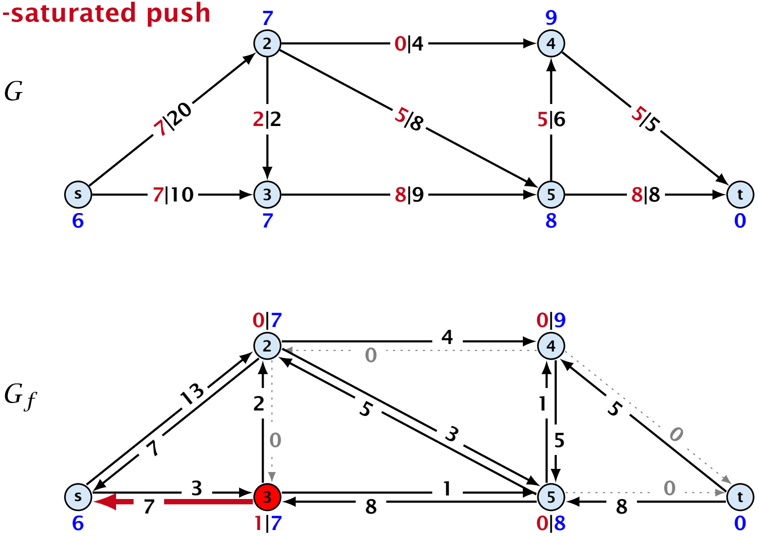

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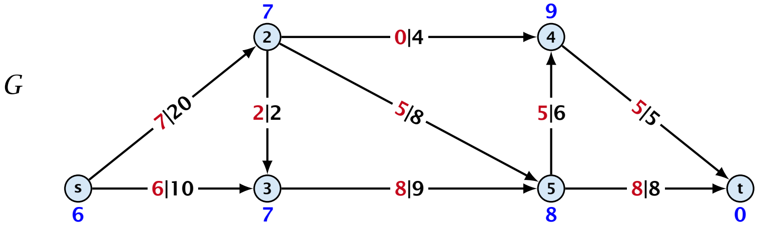

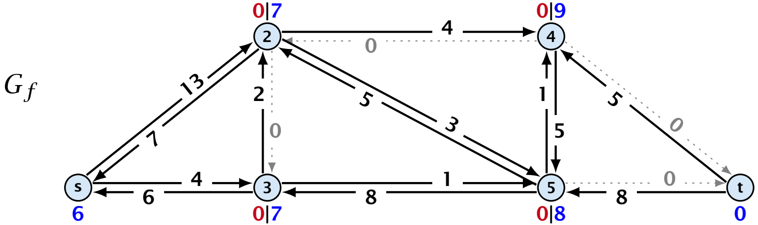

Analysis

Lemma 30

An active node has a path to s in the residual graph.

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- Let A denote the set of nodes that can reach s, and let B denote the remaining nodes. Note that $s \in A$.

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- In the following we show that a node $b \in B$ has excess flow $f(b) = 0$ which gives the lemma.
- In the residual graph there are no edges into A, and, hence, no edges leaving A/entering B can carry any flow.
- Let $f(B) = \sum_{v \in B} f(v)$ be the excess flow of all nodes in B.

Let $f : E \to \mathbb{R}_0^+$ be a preflow. We introduce the notation

$$f(x,y) = \begin{cases} 0 & (x,y) \notin E \\ f((x,y)) & (x,y) \in E \end{cases}$$

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&= \sum_{b\in B} \sum_{v\in A} f(v,b) - \sum_{b\in B} \sum_{v\in A} f(b,v) + \sum_{b\in B} \sum_{v\in B} f(v,b) - \sum_{b\in B} \sum_{v\in B} f(b,v)
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Hence, the excess flow $f(b)$ must be 0 for every node $b \in B$.

Analysis

Lemma 31
The label of a node cannot become larger than $2n - 1$.

Analysis

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The label of a node cannot become larger than $2n - 1$*.*

Proof.

- When increasing the label at a node u there exists a path from u to s of length at most $n - 1$. Along each edge of the path the height/label can at most drop by 1, and the label of the source is n.

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Lemma 32

There are only $\mathcal{O}(n^2)$ relabel operations.

Analysis

Lemma 33

The number of saturating pushes performed is at most $\mathcal{O}(mn)$.

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- Suppose that we just made a saturating push along (u, v).

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- Suppose that we just made a saturating push along (u, v).
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- For a push from v to u the edge (v, u) must become admissible. The label of v must increase by at least 2.
- Since the label of v is at most $2n - 1$, there are at most n pushes along (u, v).

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- Define a potential function $\Phi(f) = \sum_{\text{active nodes} v} \ell(v)$
- A saturating push increases Φ by $\leq 2n$ (when the target node becomes active it may contribute at most $2n$ to the sum).

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- Define a potential function $\Phi(f) = \sum_{\text{active nodes}v} \ell(v)$
- A saturating push increases Φ by $\leq 2n$ (when the target node becomes active it may contribute at most $2n$ to the sum).
- A relabel increases Φ by at most 1.

Lemma 34

The number of non-saturating pushes performed is at most $\mathcal{O}(n^2 m)$.

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- A relabel increases Φ by at most 1.
- A non-saturating push decreases Φ by at least 1 as the node that is pushed from becomes inactive and has a label that is strictly larger than the target.
- Hence,

$$\begin{aligned}\text{\#non-saturating\_pushes} &\leq \text{\#relabels} + 2n \cdot \text{\#saturating\_pushes} \\ &\leq \mathcal{O}(n^2m) \ .\end{aligned}$$

Analysis

Theorem 35
There is an implementation of the generic push relabel algorithm with running time $\mathcal{O}(n^2 m)$.

Analysis

Proof:

For every node maintain a list of admissible edges starting at that node. Further maintain a list of active nodes.

A push along an edge (u,v) can be performed in constant time

- check whether edge (v,u) needs to be added to G_f
- check whether (u,v) needs to be deleted (saturating push)
- check whether u becomes inactive and has to be deleted from the set of active nodes

A relabel at a node u can be performed in time $\mathcal{O}(n)$

- check for all outgoing edges if they become admissible
- check for all incoming edges if they become non-admissible

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Analysis

For special variants of push relabel algorithms we organize the neighbours of a node into a linked list (possible neighbours in the residual graph G_f). Then we use the discharge-operation:

Algorithm 4 discharge(u)

while u is active **do**
    $v \leftarrow u.\textit{current-neighbour}$
    if $v = \text{null}$ **then**
        relabel(u)
        $u.\textit{current-neighbour} \leftarrow u.\textit{neighbour-list-head}$
    else
        if (u, v) admissible **then** push(u, v)
        else $u.\textit{current-neighbour} \leftarrow v.\textit{next-in-list}$

Note that $u.\textit{current-neighbour}$ is a global variable. It is only changed within the discharge routine, but keeps its value between consecutive calls to discharge.

Lemma 36

If $v = \mathrm{null}$ in Line 3, then there is no outgoing admissible edge from u.

Proof.

- While pushing from u the current-neighbour pointer is only advanced if the current edge is not admissible.
- The only thing that could make the edge admissible again would be a relabel at u.
- If we reach the end of the list ($v = \mathrm{null}$) all edges are not admissible. □

This shows that discharge(u) is correct, and that we can perform a relabel in Line 4.

Algorithm 21 relabel-to-front(G, s, t)

```
initialize preflow
initialize node list L containing V \ {s, t} in any order
foreach u ∈ V \ {s, t} do
    u.current-neighbour ← u.neighbour-list-head
u ← L.head
while u ≠ null do
    old-height ← ℓ(u)
    discharge(u)
    if ℓ(u) > old-height then // relabel happened
        move u to the front of L
    u ← u.next
```

13.2 Relabel to Front

Lemma 37 (Invariant)

In Line 6 of the relabel-to-front algorithm the following invariant holds.

1. *The sequence L is topologically sorted w.r.t. the set of admissible edges; this means for an admissible edge (x, y) the node x appears before y in sequence L.*
2. *No node before u in the list L is active.*

Proof:

- Initialization:
  1. In the beginning s has label $n \geq 2$, and all other nodes have label 0. Hence, no edge is admissible, which means that any ordering L is permitted.
  2. We start with u being the head of the list; hence no node before u can be active
- Maintenance:
  1.
     - Pushes do no create any new admissible edges. Therefore, if discharge$()$ does not relabel u, L is still topologically sorted.
     - After relabeling, u cannot have admissible incoming edges as such an edge (x,u) would have had a difference $\ell(x) - \ell(u) \geq 2$ before the re-labeling (such edges do not exist in the residual graph).
       Hence, moving u to the front does not violate the sorting property for any edge; however it fixes this property for all admissible edges leaving u that were generated by the relabeling.

13.2 Relabel to Front

Proof:

- Maintenance:

  2. If we do a relabel there is nothing to prove because the only node before u' (u in the next iteration) will be the current u; the discharge(u) operation only terminates when u is not active anymore.

     For the case that we do not relabel, observe that the only way a predecessor could be active is that we push flow to it via an admissible arc. However, all admissible arc point to successors of u.

Note that the invariant means that for $u = \text{null}$ we have a preflow with a valid labelling that does not have active nodes. This means we have a maximum flow.

13.2 Relabel to Front

Lemma 38
There are at most $\mathcal{O}(n^3)$ calls to discharge(u).

Every discharge operation without a relabel advances u (the current node within list L). Hence, if we have n discharge operations without a relabel we have $u = \text{null}$ and the algorithm terminates.

Therefore, the number of calls to discharge is at most $n(\#\textit{relabels} + 1) = \mathcal{O}(n^3)$.

13.2 Relabel to Front

Lemma 39
The cost for all relabel-operations is only $\mathcal{O}(n^2)$.

A relabel-operation at a node is constant time (increasing the label and resetting $u.current\text{-}neighbour$). In total we have $\mathcal{O}(n^2)$ relabel-operations.

13.2 Relabel to Front

Note that by definition a saturating push operation ($\min\{c_f(e), f(u)\} = c_f(e)$) can at the same time be a non-saturating push operation ($\min\{c_f(e), f(u)\} = f(u)$).

Lemma 40

The cost for all saturating push-operations that are ***not*** *also non-saturating push-operations is only $\mathcal{O}(mn)$.*

Note that such a push-operation leaves the node u active but makes the edge e disappear from the residual graph. Therefore the push-operation is immediately followed by an increase of the pointer $u.\mathit{current\text{-}neighbour}$.

This pointer can traverse the neighbour-list at most $\mathcal{O}(n)$ times (upper bound on number of relabels) and the neighbour-list has only $\mathit{degree}(u) + 1$ many entries ($+1$ for null-entry).

13.2 Relabel to Front

Lemma 41

The cost for all non-saturating push-operations is only $\mathcal{O}(n^3)$.

A non-saturating push-operation takes constant time and ends the current call to discharge(). Hence, there are only $\mathcal{O}(n^3)$ such operations.

Theorem 42

The push-relabel algorithm with the rule relabel-to-front takes time $\mathcal{O}(n^3)$.

13.3 Highest Label

Algorithm 6 highest-label(G, s, t)

```
initialize preflow
foreach u ∈ V \ {s, t} do
    u.current-neighbour ← u.neighbour-list-head
while ∃ active node u do
    select active node u with highest label
    discharge(u)
```

13.3 Highest Label

Lemma 43

When using highest label the number of non-saturating pushes is only $\mathcal{O}(n^3)$.

A push from a node on level ℓ can only "activate" nodes on levels strictly less than ℓ.

This means, after a non-saturating push from u a relabel is required to make u active again.

Hence, after n non-saturating pushes without an intermediate relabel there are no active nodes left.

Therefore, the number of non-saturating pushes is at most $n(\#relabels + 1) = \mathcal{O}(n^3)$.

13.3 Highest Label

Since a discharge-operation is terminated by a non-saturating push this gives an upper bound of $\mathcal{O}(n^3)$ on the number of discharge-operations.

The cost for relabels and saturating pushes can be estimated in exactly the same way as in the case of the generic push-relabel algorithm.

Question:
How do we find the next node for a discharge operation?

13.3 Highest Label

Maintain lists L_i, $i \in \{0, \dots, 2n\}$, where list L_i contains active nodes with label i (maintaining these lists induces only constant additional cost for every push-operation and for every relabel-operation).

After a discharge operation terminated for a node u with label k, traverse the lists $L_k, L_{k-1}, \dots, L_0$, (in that order) until you find a non-empty list.

Unless the last (non-saturating) push was to s or t the list $k-1$ must be non-empty (i.e., the search takes constant time).

13.3 Highest Label

Hence, the total time required for searching for active nodes is at most

$$\mathcal{O}(n^3) + n(\#non\text{-}saturating\text{-}pushes\text{-}to\text{-}s\text{-}or\text{-}t)$$

Lemma 44

The number of non-saturating pushes to s or t is at most $\mathcal{O}(n^2)$.

With this lemma we get

Theorem 45

The push-relabel algorithm with the rule highest-label takes time $\mathcal{O}(n^3)$.

13.3 Highest Label

Proof of the Lemma.

- We only show that the number of pushes to the source is at most $\mathcal{O}(n^2)$. A similar argument holds for the target.
- After a node v (which must have $\ell(v) = n + 1$) made a non-saturating push to the source there needs to be another node whose label is increased from $\leq n + 1$ to $n + 2$ before v can become active again.
- This happens for every push that v makes to the source. Since, every node can pass the threshold $n + 2$ at most once, v can make at most n pushes to the source.
- As this holds for every node the total number of pushes to the source is at most $\mathcal{O}(n^2)$.

Mincost Flow

Problem Definition:

$$\begin{array}{ll} \text{min} & \sum_e c(e)f(e) \\ \text{s.t.} & \forall e \in E: \quad 0 \leq f(e) \leq u(e) \\ & \forall v \in V: \quad f(v) = b(v) \end{array}$$

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\end{array}
$$

- $G = (V, E)$ is a directed graph.
- $u : E \to \mathbb{R}_0^+ \cup \{\infty\}$ is the capacity function.
- $c : E \to \mathbb{R}$ is the cost function (note that $c(e)$ may be negative).
- $b : V \to \mathbb{R}$, $\sum_{v \in V} b(v) = 0$ is a demand function.

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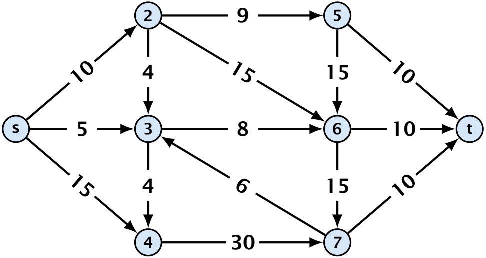
Solve Maxflow Using Mincost Flow



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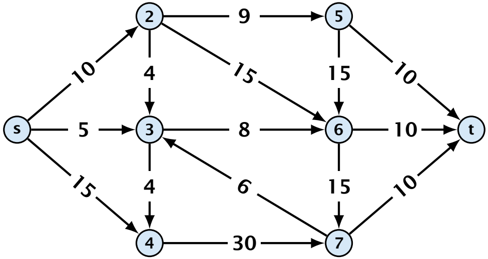

- Given a flow network for a standard maxflow problem.

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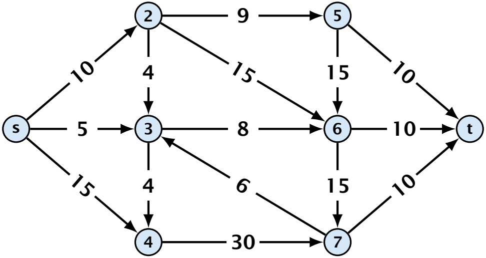

- Given a flow network for a standard maxflow problem.
- Set $b(v) = 0$ for every node. Keep the capacity function u for all edges. Set the cost $c(e)$ for every edge to 0.

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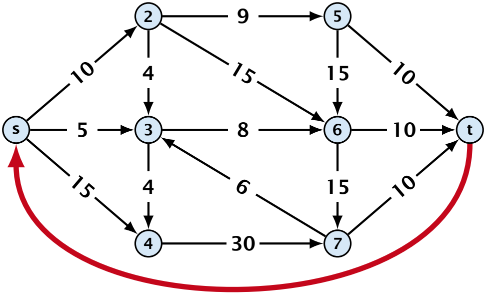

- Given a flow network for a standard maxflow problem.
- Set $b(v) = 0$ for every node. Keep the capacity function u for all edges. Set the cost $c(e)$ for every edge to 0.
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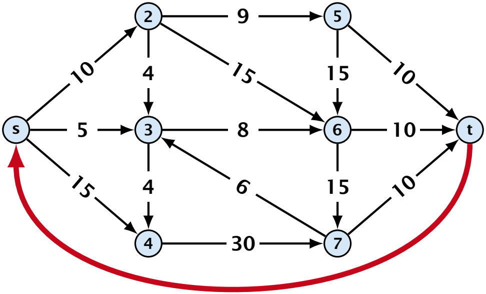

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- Set $b(v) = 0$ for every node. Keep the capacity function u for all edges. Set the cost $c(e)$ for every edge to 0.
- Add an edge from t to s with infinite capacity and cost -1.
- Then, $\text{val}(f^*) = -\text{cost}(f_{\text{min}})$, where f^* is a maxflow, and f_{min} is a mincost-flow.

Solve Maxflow Using Mincost Flow

Solve decision version of maxflow:

- Given a flow network for a standard maxflow problem, and a value k.
- Set $b(v) = 0$ for every node apart from s or t. Set $b(s) = -k$ and $b(t) = k$.
- Set edge-costs to zero, and keep the capacities.
- There exists a maxflow of value at least k if and only if the mincost-flow problem is feasible.

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Generalization

Our model:

$$\begin{array}{lll} \text{min} & \sum_e c(e) f(e) & \\ \text{s.t.} & \forall e \in E: & 0 \le f(e) \le u(e) \\ & \forall v \in V: & f(v) = b(v) \end{array}$$

where $b : V \to \mathbb{R}$, $\sum_v b(v) = 0$; $u : E \to \mathbb{R}_0^+ \cup \{\infty\}$; $c : E \to \mathbb{R}$;

A more general model?

$$\begin{array}{lll} \text{min} & \sum_e c(e) f(e) & \\ \text{s.t.} & \forall e \in E: & \ell(e) \le f(e) \le u(e) \\ & \forall v \in V: & a(v) \le f(v) \le b(v) \end{array}$$

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Generalization

Differences

- Flow along an edge e may have non-zero lower bound $\ell(e)$.
- Flow along e may have negative upper bound $u(e)$.
- The demand at a node v may have lower bound $a(v)$ and upper bound $b(v)$ instead of just lower bound = upper bound = $b(v)$.

Reduction I

$$\begin{array}{ll} \text{min} & \sum_e c(e)f(e) \\ \text{s.t.} & \forall e \in E:\ \ \ell(e) \le f(e) \le u(e) \\ & \forall v \in V:\ \ a(v) \le f(v) \le b(v) \end{array}$$

We can assume that $a(v) = b(v)$:

Add new node r.

Add edge (r, v) for all $v \in V$.

Set $\ell(e) = c(e) = 0$ for these edges.

Set $u(e) = b(v) - a(v)$ for edge (r, v).

Set $a(v) = b(v)$ for all $v \in V$.

Set $b(r) = -\sum_{v \in V} b(v)$.

$-\sum_v b(v)$ is negative; hence r is only sending flow.

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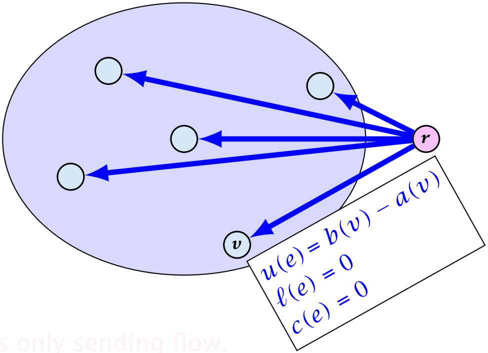

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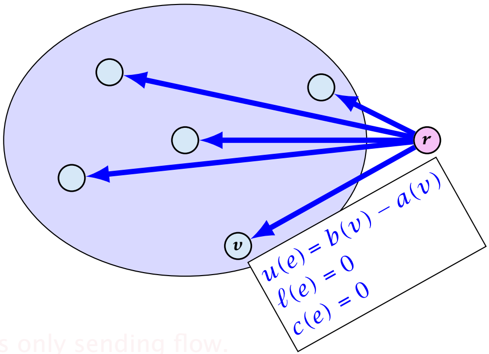

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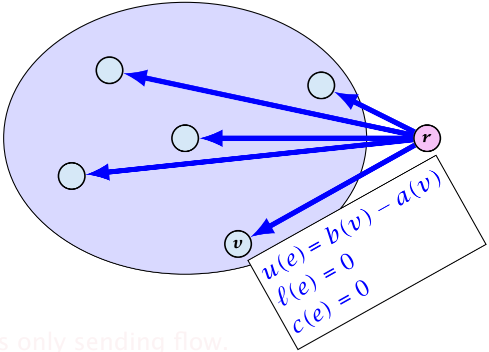

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$-\sum_v b(v)$ is negative; hence r is only sending flow.

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$$\begin{aligned} \min \quad & \textstyle\sum_e c(e) f(e) \\ \text{s.t.} \quad & \forall e \in E: \; \ell(e) \le f(e) \le u(e) \\ & \forall v \in V: \; a(v) \le f(v) \le b(v) \end{aligned}$$

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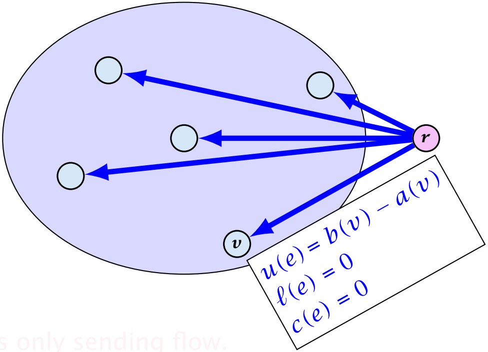

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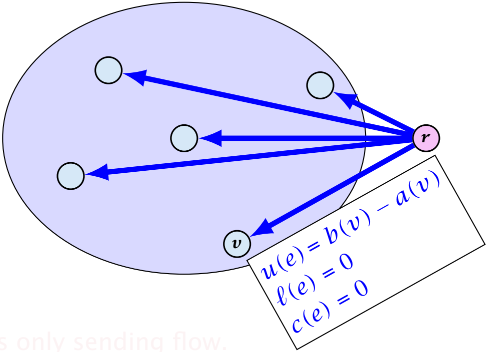

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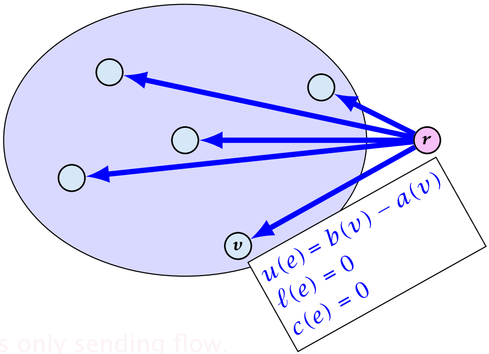

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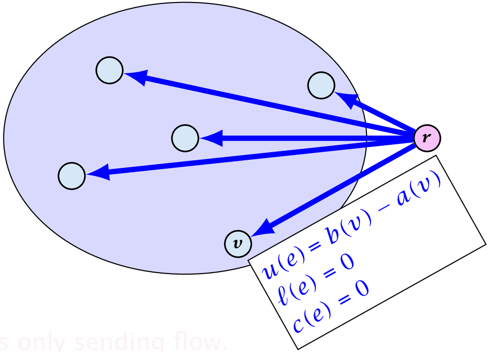

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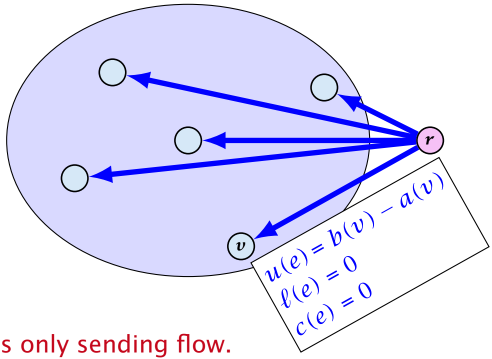

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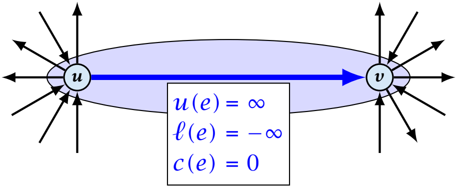

If $c(e) = 0$ we can contract the edge/identify nodes u and v.

If $c(e) \neq 0$ we can transform the graph so that $c(e) = 0$.

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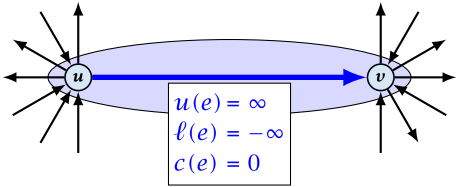

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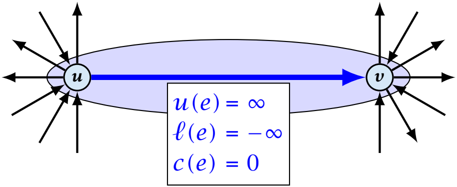

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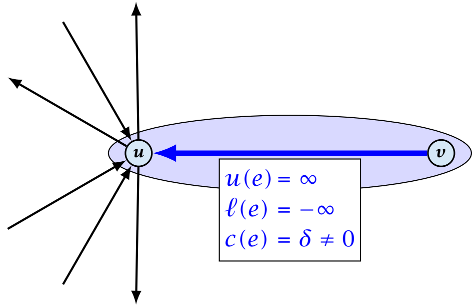

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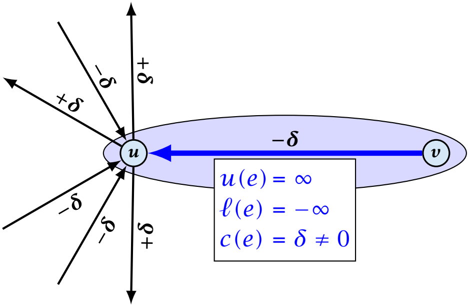

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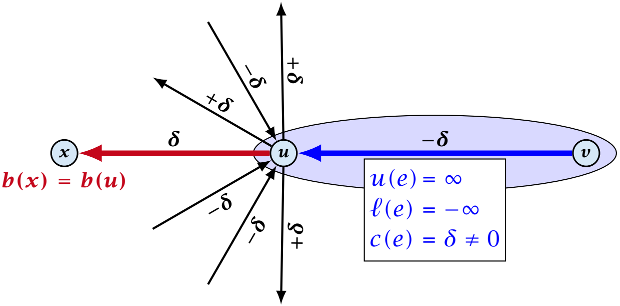

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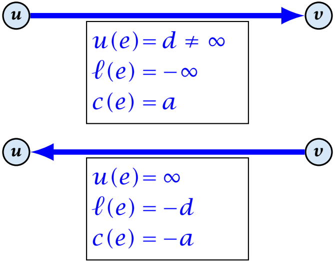

Replace the edge by an edge in opposite direction.

Reduction IV

$$\begin{array}{lll} \min & \sum_e c(e)f(e) & \\ \text{s.t.} & \forall e \in E: & \ell(e) \le f(e) \le u(e) \\ & \forall v \in V: & f(v) = b(v) \end{array}$$

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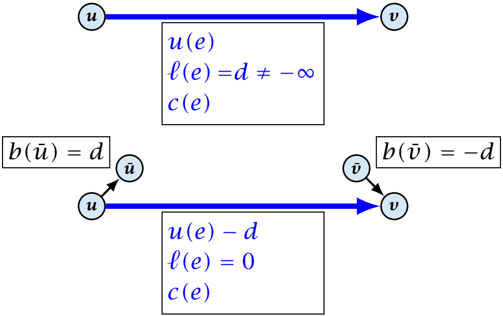

The added edges have infinite capacity and cost $c(e)/2$.

Applications

Caterer Problem

- She needs to supply r_i napkins on N successive days.
- She can buy new napkins at p cents each.
- She can launder them at a fast laundry that takes m days and cost f cents a napkin.
- She can use a slow laundry that takes $k > m$ days and costs s cents each.
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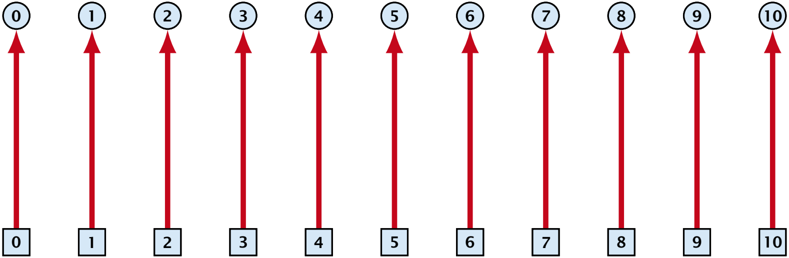
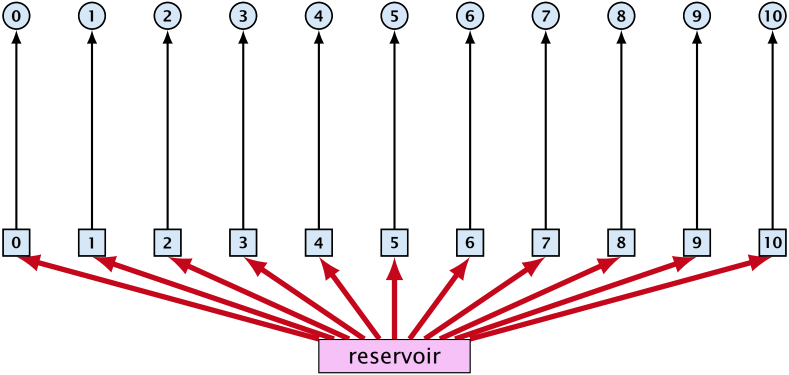


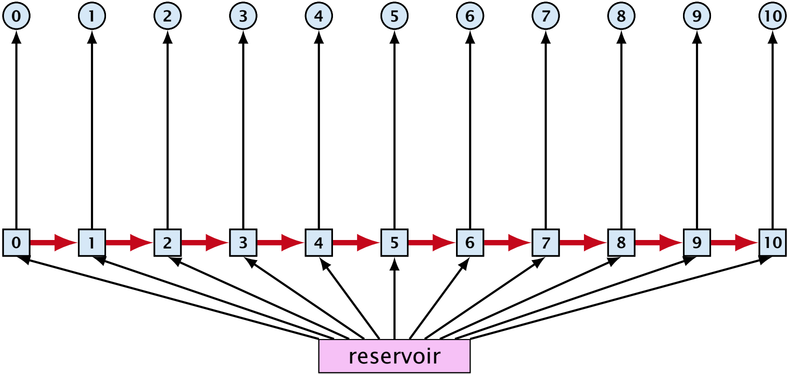
day edges:

upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = r_i$;
cost: $c(e) = 0$



buy edges:

upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = p$



forward edges:

upper bound: $u(e_i) = \infty$;
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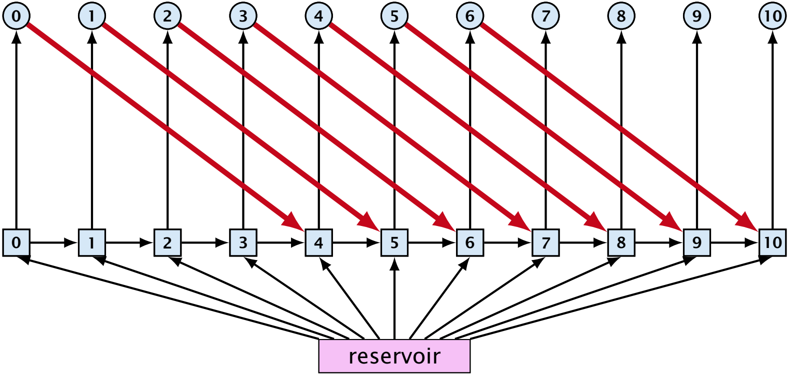
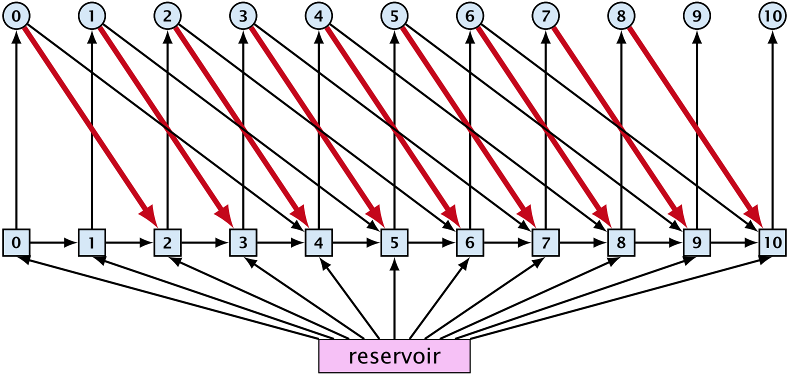


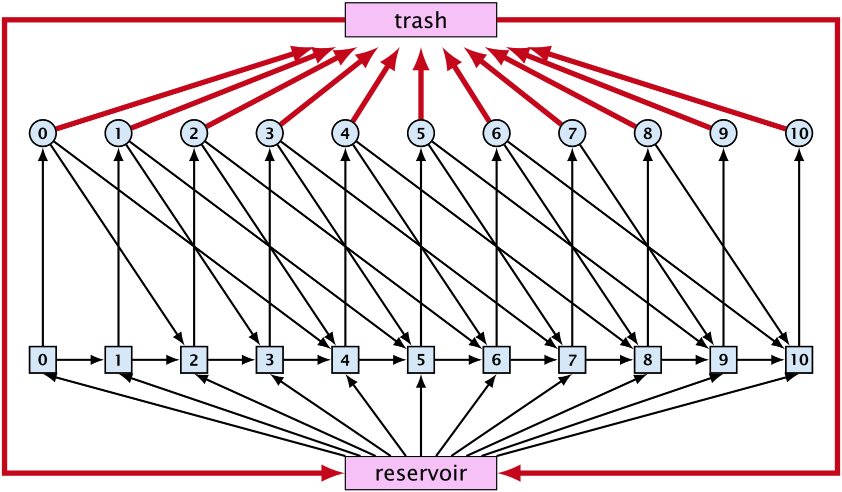
slow edges:

upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = s$



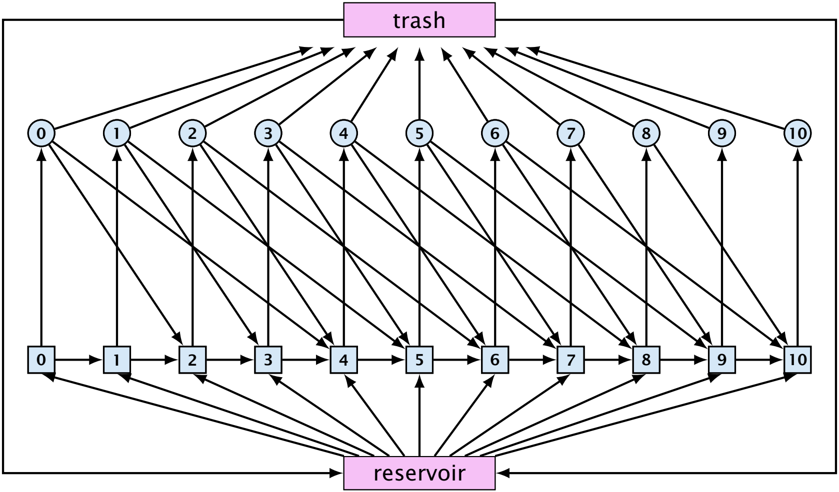
fast edges:

upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = f$



trash edges:

upper bound: $u(e_i) = \infty$;
lower bound: $\ell(e_i) = 0$;
cost: $c(e) = 0$



trash
0
1
2
3
4
5
6
7
8
9
10
0
1
2
3
4
5
6
7
8
9
10
reservoir

Residual Graph

Version A:

The residual graph G' for a mincost flow is just a copy of the graph G.

If we send $f(e)$ along an edge, the corresponding edge e' in the residual graph has its lower and upper bound changed to $\ell(e') = \ell(e) - f(e)$ and $u(e') = u(e) - f(e)$.

Version B:

The residual graph for a mincost flow is exactly defined as the residual graph for standard flows, with the only exception that one needs to define a cost for the residual edge.

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14 Mincost Flow

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Lemma 46

A given flow is a mincost-flow if and only if the corresponding residual graph G_f does not have a feasible circulation of negative cost.

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- ⇐ Let f be a non-mincost flow, and let f^* be a min-cost flow. We need to show that the residual graph has a feasible circulation with negative cost.

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- Suppose that we have a negative cost circulation.
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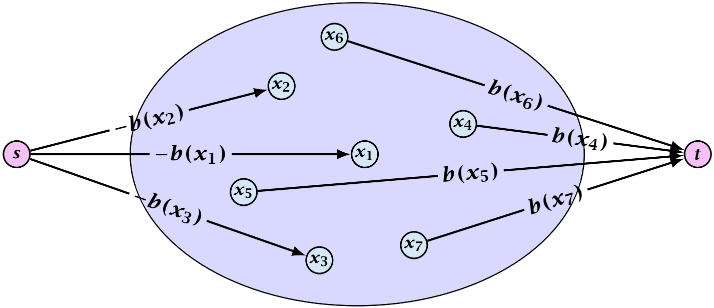
14 Mincost Flow

Algorithm 22 CycleCanceling$(G = (V, E), c, u, b)$

1: establish a feasible flow f in G
2: **while** G_f contains negative cycle **do**
3: use Bellman-Ford to find a negative circuit Z
4: $\delta \leftarrow \min\{u_f(e) \mid e \in Z\}$
5: augment δ units along Z and update G_f

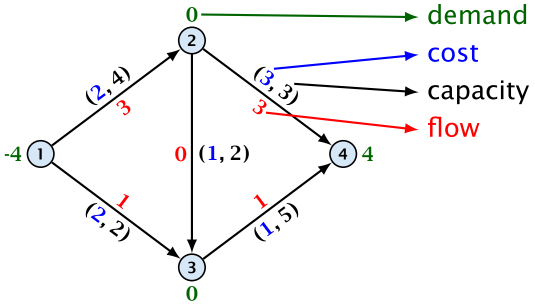
How do we find the initial feasible flow?



- Connect new node s to all nodes with negative $b(v)$-value.
- Connect nodes with positive $b(v)$-value to a new node t.
- There exist a feasible flow in the original graph iff in the resulting graph there exists an s-t flow of value

$$\sum_{v:b(v)<0} (-b(v)) = \sum_{v:b(v)>0} b(v) \ .$$

14 Mincost Flow



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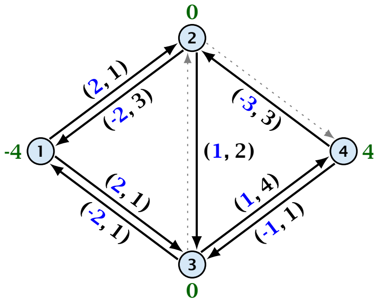

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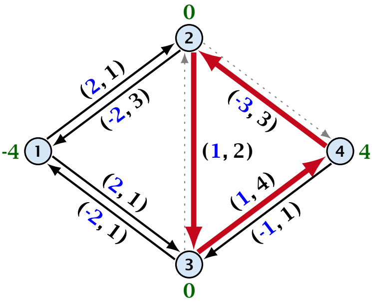

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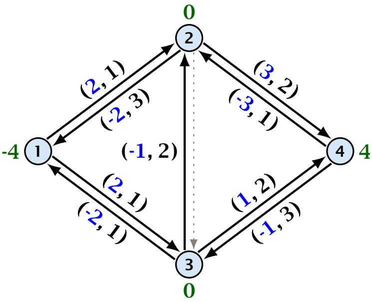

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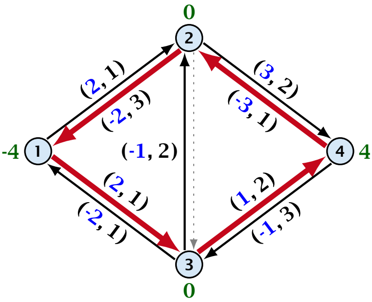

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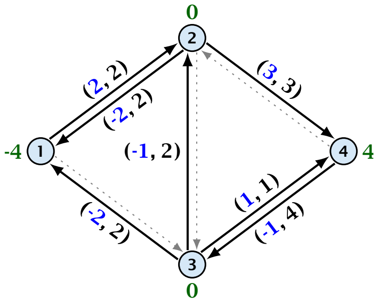


14 Mincost Flow

Lemma 48

The improving cycle algorithm runs in time $\mathcal{O}(nm^2CU)$, for integer capacities and costs, when for all edges e, $|c(e)| \le C$ and $|u(e)| \le U$.

- Running time of Bellman-Ford is $\mathcal{O}(mn)$.
- Pushing flow along the cycle can be done in time $\mathcal{O}(n)$.
- Each iteration decreases the total cost by at least 1.
- The true optimum cost must lie in the interval $[-mCU, \dots, +mCU]$.

Note that this lemma is weak since it does not allow for edges with infinite capacity.

14 Mincost Flow

A general mincost flow problem is of the following form:

$$\begin{array}{ll} \text{min} & \sum_e c(e)f(e) \\ \text{s.t.} & \forall e \in E: \quad \ell(e) \le f(e) \le u(e) \\ & \forall v \in V: \quad a(v) \le f(v) \le b(v) \end{array}$$

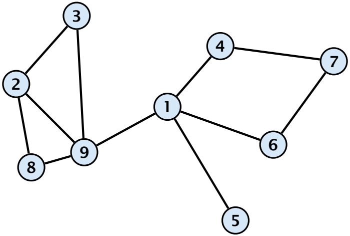
where $a : V \to \mathbb{R}$, $b : V \to \mathbb{R}$; $\ell : E \to \mathbb{R} \cup \{-\infty\}$, $u : E \to \mathbb{R} \cup \{\infty\}$ $c : E \to \mathbb{R}$;

Lemma 49 (without proof)

A general mincost flow problem can be solved in polynomial time.

15 Global Mincut

Given an undirected, capacitated graph $G = (V, E, c)$ find a partition of V into two non-empty sets $S, V \setminus S$ s.t. the capacity of edges between both sets is minimized.



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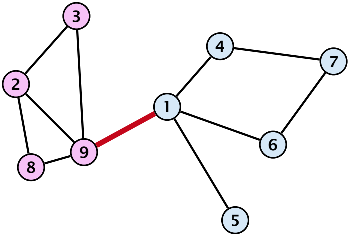

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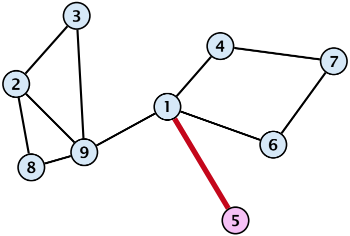

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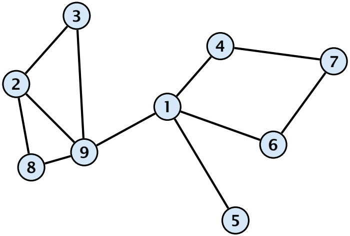

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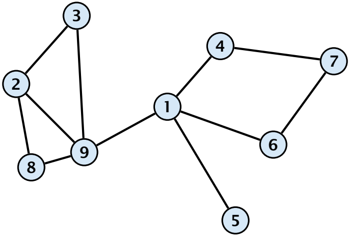
We can solve this problem using standard maxflow/mincut.



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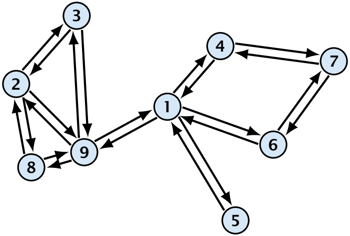
- Construct a directed graph $G' = (V, E')$ that has edges (u, v) and (v, u) for every edge $\{u, v\} \in E$.



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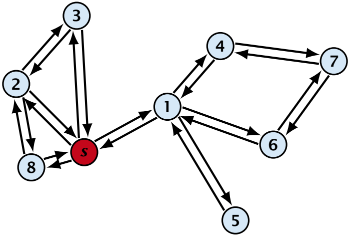

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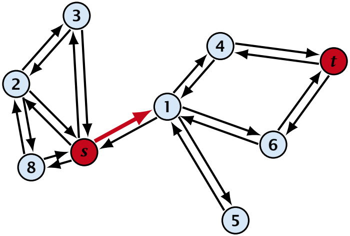
- Fix an arbitrary node $s \in V$ as source. Compute a minimum s-t cut for all possible choices $t \in V, t \neq s$. (Time: $\mathcal{O}(n^4)$)
- Let $(S, V \setminus S)$ be a minimum global mincut. The above algorithm will output a cut of capacity $\text{cap}(S, V \setminus S)$ whenever $|\{s, t\} \cap S| = 1$.



Edge Contractions

- Given a graph $G = (V, E)$ and an edge $e = \{u, v\}$.
- The graph G/e is obtained by "identifying" u and v to form a new node.
- Resulting parallel edges are replaced by a single edge, whose capacity equals the sum of capacities of the parallel edges.

Example 50

- Edge-contractions do no decrease the size of the mincut.

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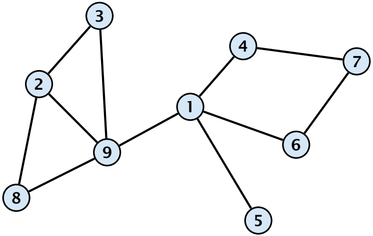

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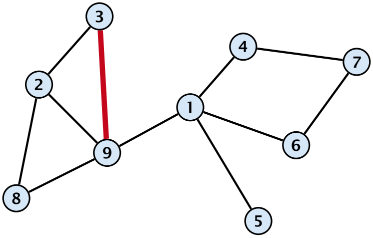

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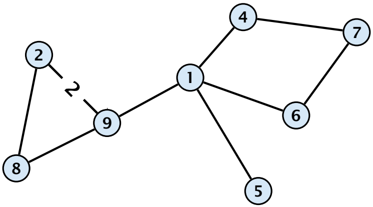

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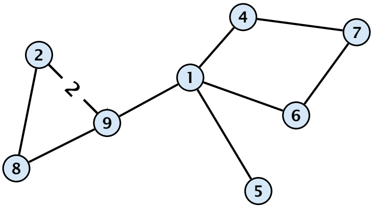

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Edge Contractions

We can perform an edge-contraction in time $\mathcal{O}(n)$.

Randomized Mincut Algorithm

Algorithm 1 KargerMincut$(G = (V, E, c))$

```
for i = 1 → n − 2 do
    choose e ∈ E randomly with probability c(e)/c(E)
    G ← G/e
return only cut in G
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- Let G_t denote the graph after the $(n - t)$-th iteration, when t nodes are left.

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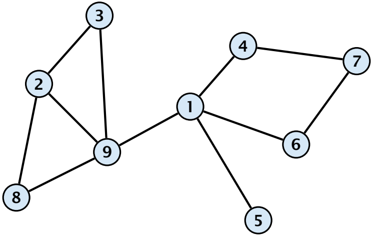
- What is the probability that this algorithm returns a mincut?

Example: Randomized Mincut Algorithm



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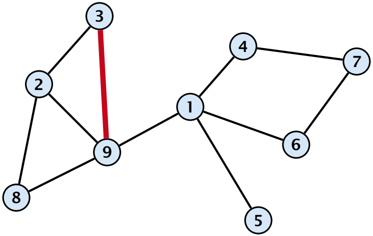

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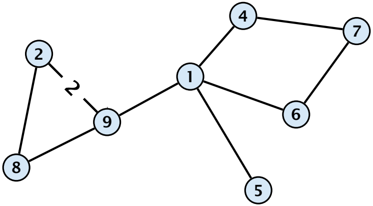

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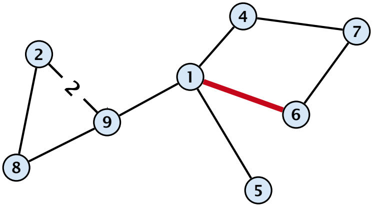

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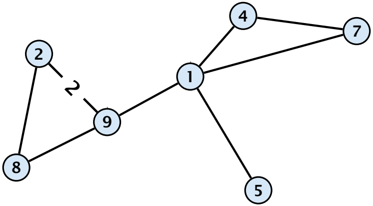

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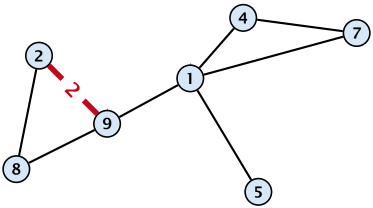

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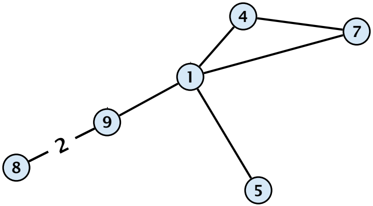

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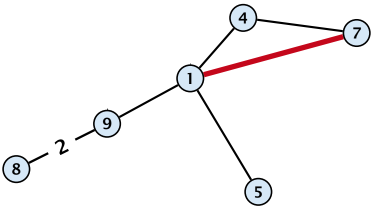

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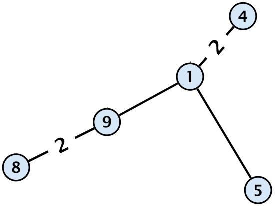

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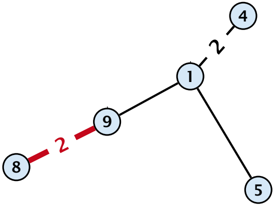

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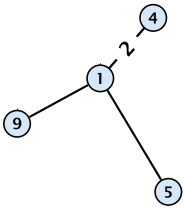

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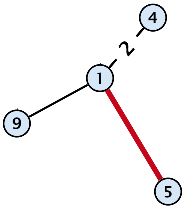

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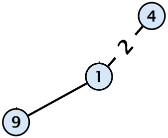

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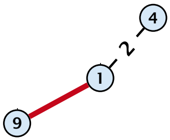

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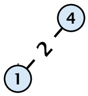

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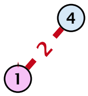

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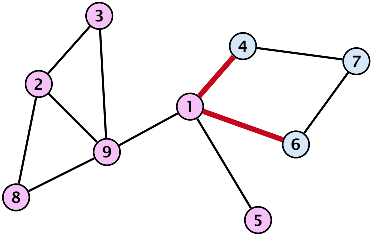

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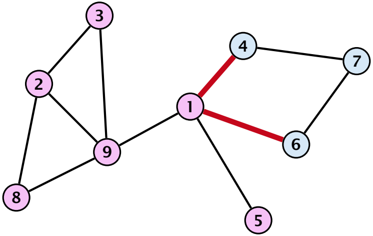

What is the probability that this algorithm returns a mincut?

Analysis

What is the probability that a given mincut A is still possible after round i?

- It is still possible to obtain cut A in the end if so far no edge in $(A, V \setminus A)$ has been contracted.

Analysis

What is the probability that we select an edge from A in iteration i?

- Let $\min = \text{cap}(A, V \setminus A)$ denote the capacity of a mincut.
- Let $\text{cap}(v)$ be capacity of edges incident to vertex $v \in V_{n-i+1}$.
- Clearly, $\text{cap}(v) \geq \min$.
- Summing $\text{cap}(v)$ over all edges gives

$$2c(E) = 2\sum_{e \in E} c(e) = \sum_{v \in V} \text{cap}(v) \geq (n-i+1) \cdot \min$$

- Hence, the probability of choosing an edge from the cut is at most $\min / c(E) \leq 2/(n-i+1)$.

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The probability that we do not choose an edge from the cut in iteration i is

$$1 - \frac{2}{n-i+1} = \frac{n-i-1}{n-i+1} \ .$$

The probability that the cut is alive after iteration $n-t$ (after which t nodes are left) is

$$\prod_{i=1}^{n-t} \frac{n-i-1}{n-i+1} = \frac{t(t-1)}{n(n-1)} \ .$$

Choosing $t = 2$ gives that with probability $1/\binom{n}{2}$ the algorithm computes a mincut.

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Choosing $t=2$ gives that with probability $1/\binom{n}{2}$ the algorithm computes a mincut.

Analysis

The probability that we do not choose an edge from the cut in iteration i is

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Repeating the algorithm $c\ln n\binom{n}{2}$ times gives that the probability that we are never successful is

$$\Bigg(1-\frac{1}{\binom{n}{2}}\Bigg)^{\binom{n}{2}c\ln n}\le\Big(e^{-1/\binom{n}{2}}\Big)^{\binom{n}{2}c\ln n}\le n^{-c}\enspace,$$

where we used $1-x\le e^{-x}$.

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The randomized mincut algorithm computes an optimal cut with high probability. The total running time is $\mathcal{O}(n^4\log n)$.

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Improved Algorithm

Algorithm 2 RecursiveMincut$(G = (V, E, c))$

for $i = 1 \to n - n/\sqrt{2}$ **do**
  choose $e \in E$ randomly with probability $c(e)/c(E)$
  $G \leftarrow G/e$
if $|V| = 2$ **return** cut-value;
$cuta \leftarrow$ RecursiveMincut(G);
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- $T(n) = 2T\left(\frac{n}{\sqrt{2}}\right) + \mathcal{O}(n^2)$
- This gives $T(n) = \mathcal{O}(n^2 \log n)$.

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Probability of Success

The probability of contracting an edge from the mincut during one iteration through the for-loop is only

$$\frac{t(t-1)}{n(n-1)} \leq \frac{t^2}{n^2} = \frac{1}{2} \ ,$$

as $t = \frac{n}{\sqrt{2}}$.

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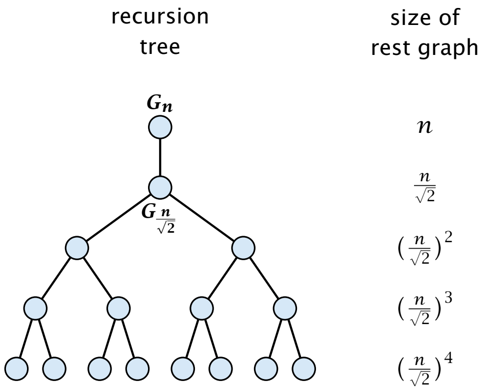

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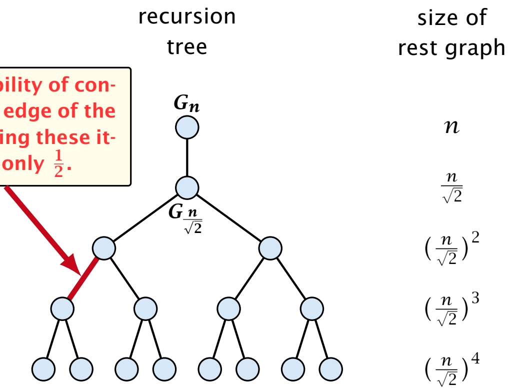
The probability of contracting an edge of the mincut during these iterations is only $\frac{1}{2}$.



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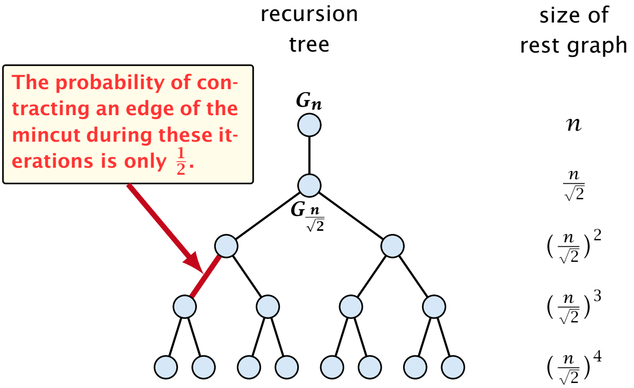

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Let for an edge e in the recursion tree, $h(e)$ denote the height (distance to leaf level) of the parent-node of e (end-point that is higher up in the tree). Let h denote the height of the root node.

Call an edge e alive if there exists a path from the parent-node of e to a descendant leaf, after we randomly deleted edges. Note that an edge can only be alive if it hasn't been deleted.

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The probability that an edge e is alive is at least $\frac{1}{h(e)+1}$.

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15 Global Mincut

Lemma 53

One run of the algorithm can be performed in time $\mathcal{O}(n^2 \log n)$ and has a success probability of $\Omega(\frac{1}{\log n})$.

Doing $\Theta(\log^2 n)$ runs gives that the algorithm succeeds with high probability. The total running time is $\mathcal{O}(n^2 \log^3 n)$.

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16 Gomory Hu Trees

Given an undirected, weighted graph $G = (V, E, c)$ a cut-tree $T = (V, F, w)$ is a tree with edge-set F and capacities w that fulfills the following properties.

1. **Equivalent Flow Tree:** For any pair of vertices $s, t \in V$, $f(s,t)$ in G is equal to $f_T(s,t)$.
2. **Cut Property:** A minimum s-t cut in T is also a minimum cut in G.

Here, $f(s,t)$ is the value of a maximum s-t flow in G, and $f_T(s,t)$ is the corresponding value in T.

Overview of the Algorithm

The algorithm maintains a partition of V, (sets $S_1, \dots, S_t$), and a spanning tree T on the vertex set $\{S_1, \dots, S_t\}$.

Initially, there exists only the set $S_1 = V$.

Then the algorithm performs $n-1$ split-operations:

- In each such split-operation it chooses a set S_i with $|S_i| \geq 2$ and splits this set into two non-empty parts X and Y.
- S_i is then removed from T and replaced by X and Y.
- X and Y are connected by an edge, and the edges that before the split were incident to S_i are attached to either X or Y.

In the end this gives a tree on the vertex set V.

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Details of the Split-operation

- Select S_i that contains at least two nodes a and b.
- Compute the connected components of the forest obtained from the current tree T after deleting S_i. Each of these components corresponds to a set of vertices from V.
- Consider the graph H obtained from G by contracting these connected components into single nodes.
- Compute a minimum a-b cut in H. Let A, and B denote the two sides of this cut.
- Split S_i in T into two sets/nodes $S_i^a := S_i \cap A$ and $S_i^b := S_i \cap B$ and add edge $\{S_i^a, S_i^b\}$ with capacity $f_H(a,b)$.
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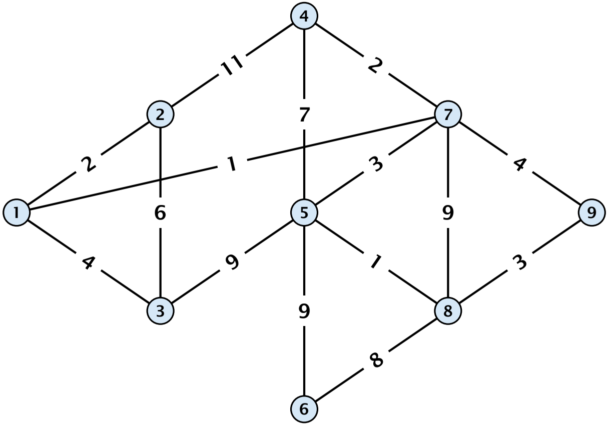

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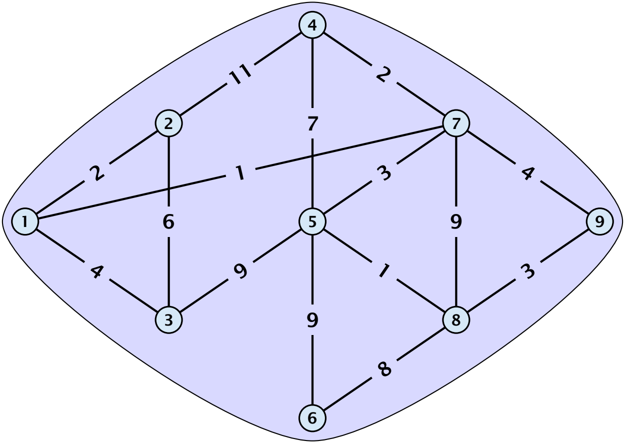

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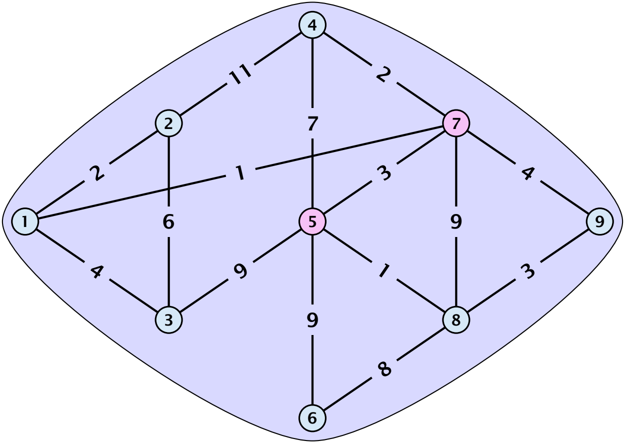

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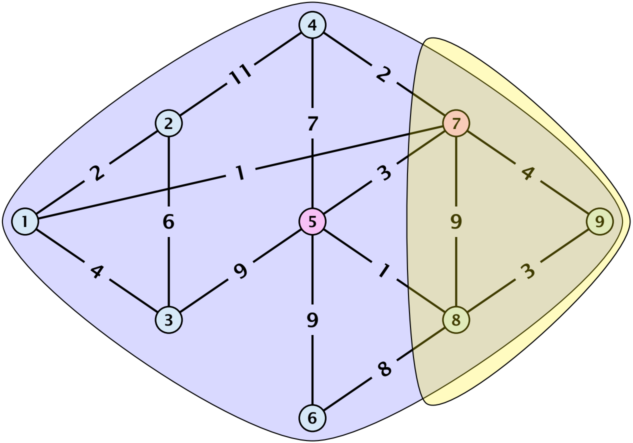

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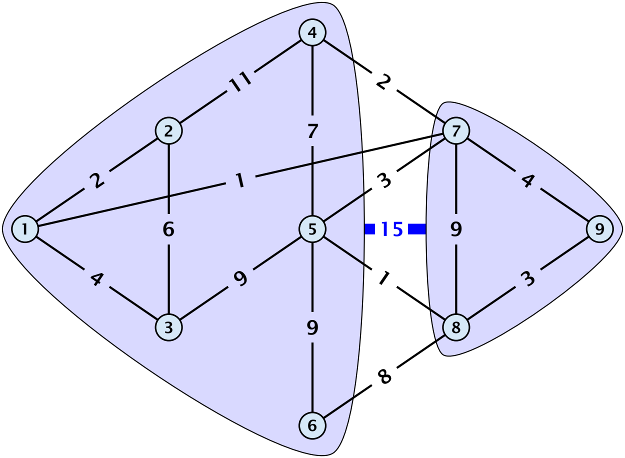

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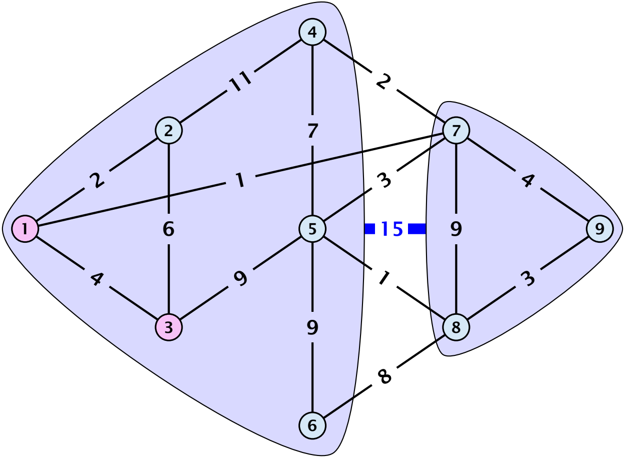

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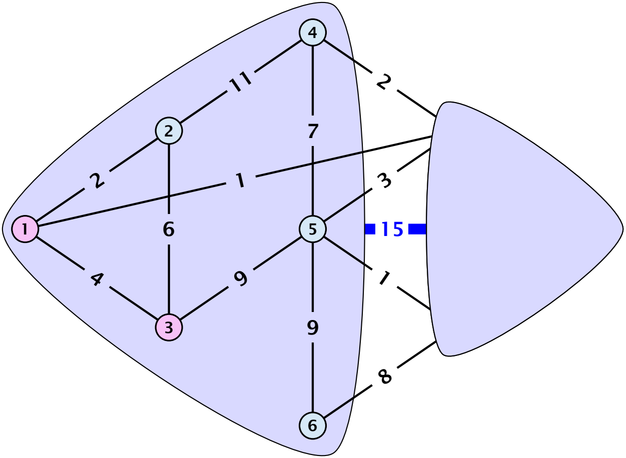

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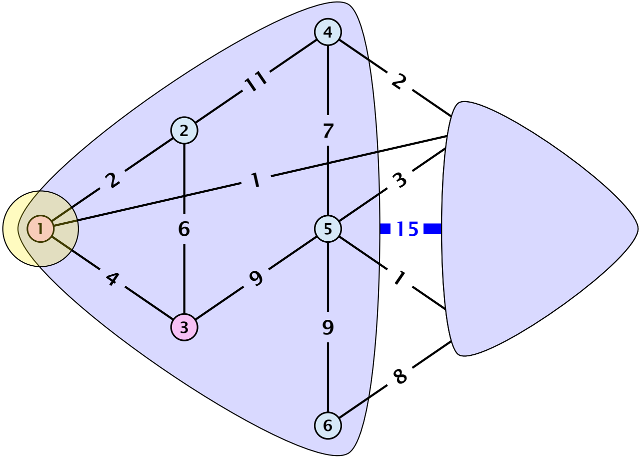

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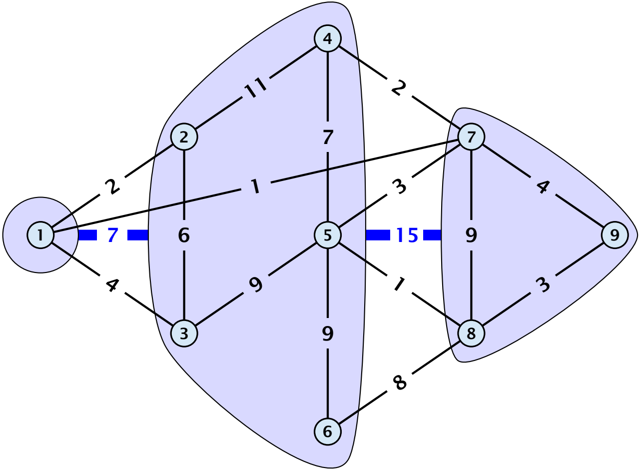

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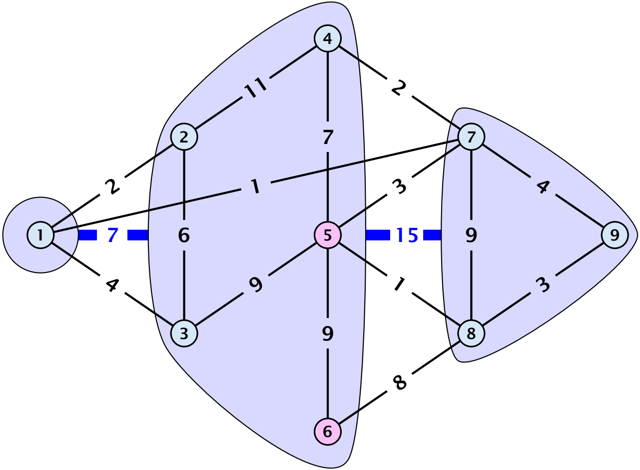

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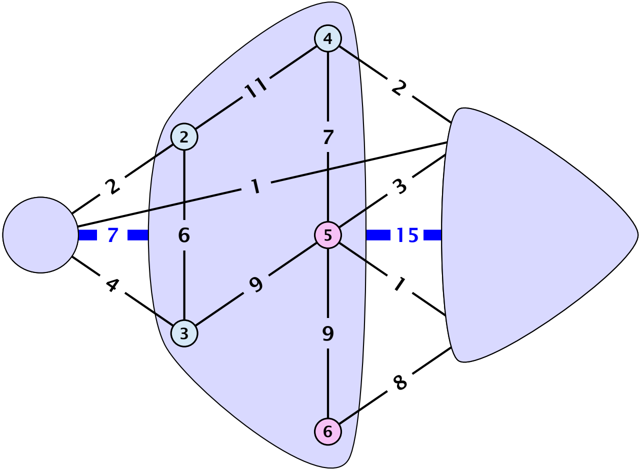

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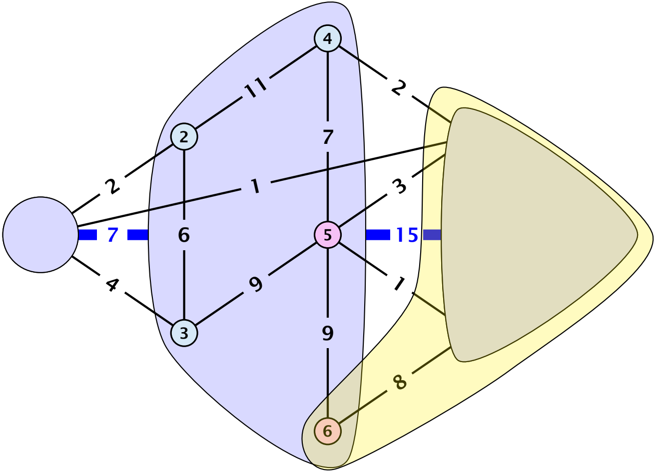

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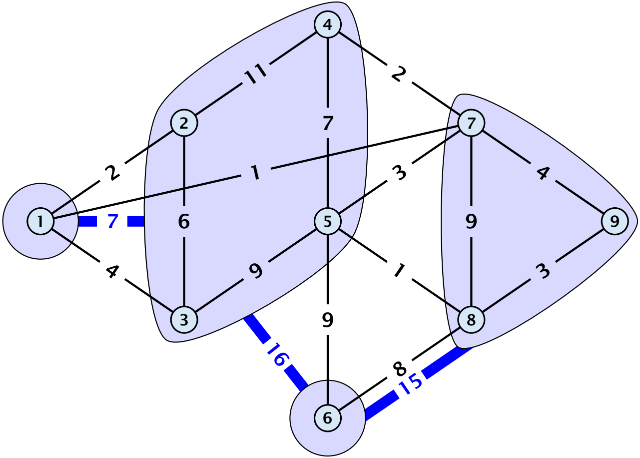

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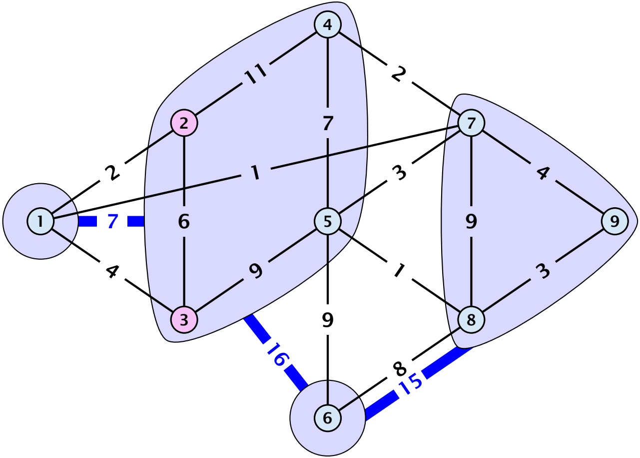

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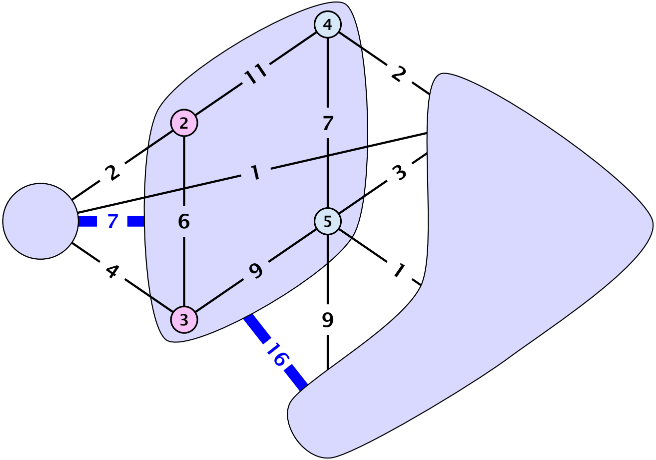

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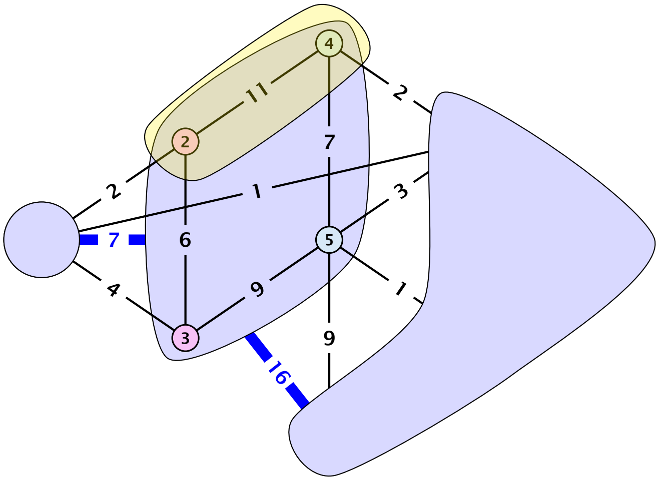

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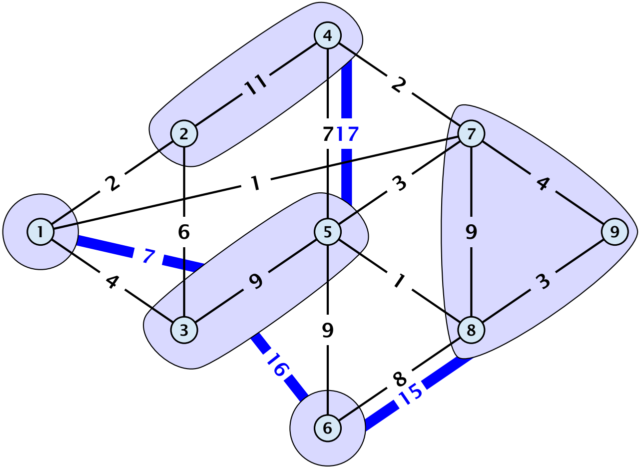

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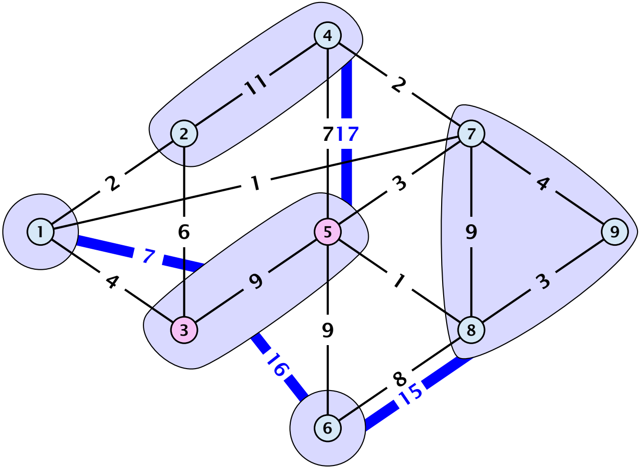

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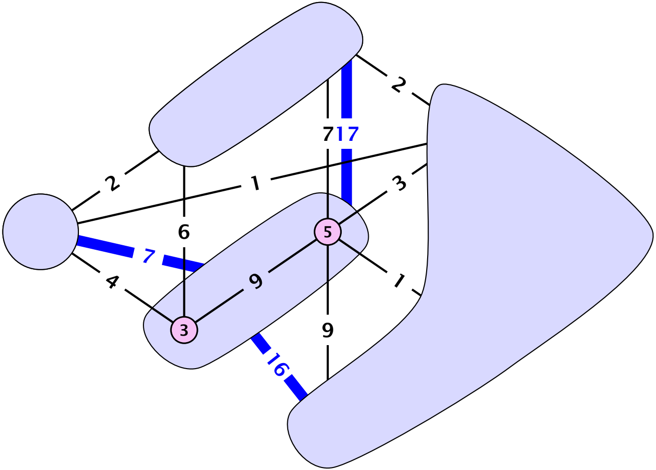

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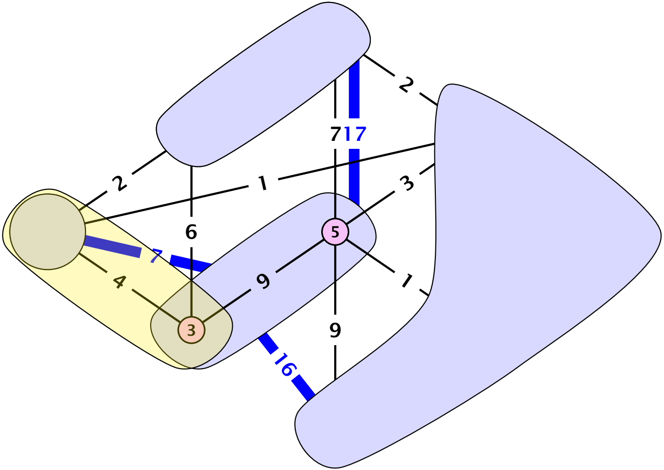

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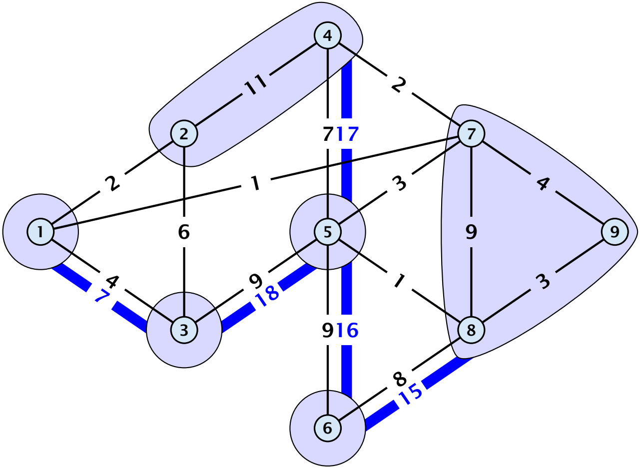

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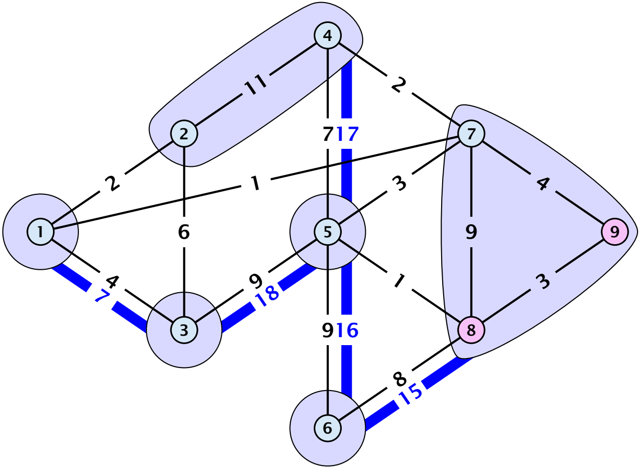

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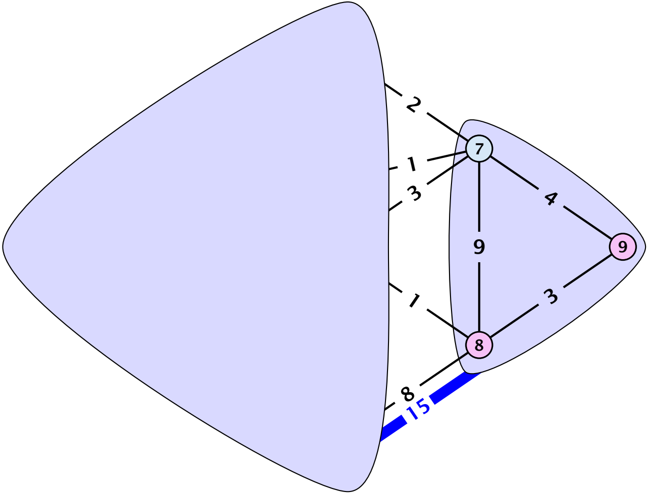

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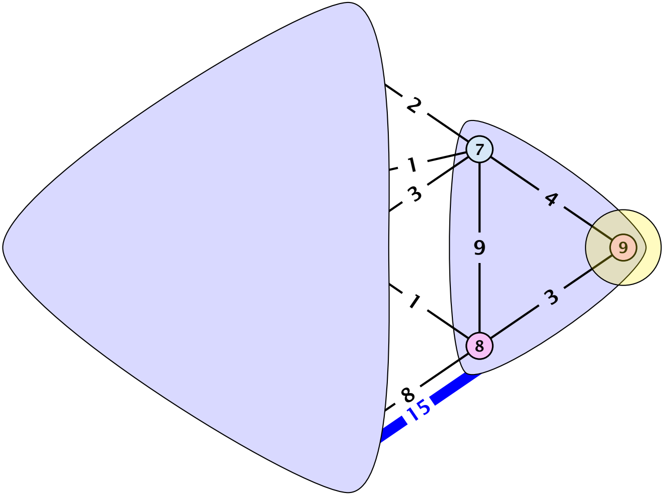

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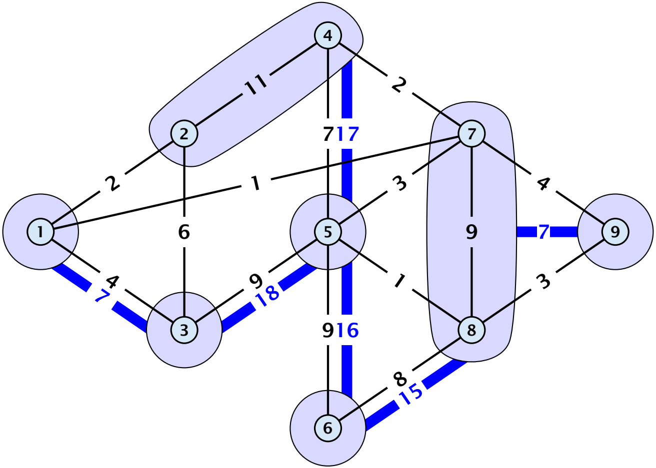

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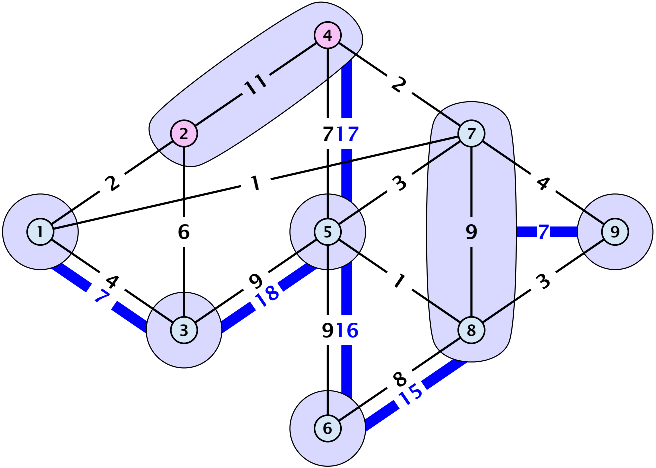

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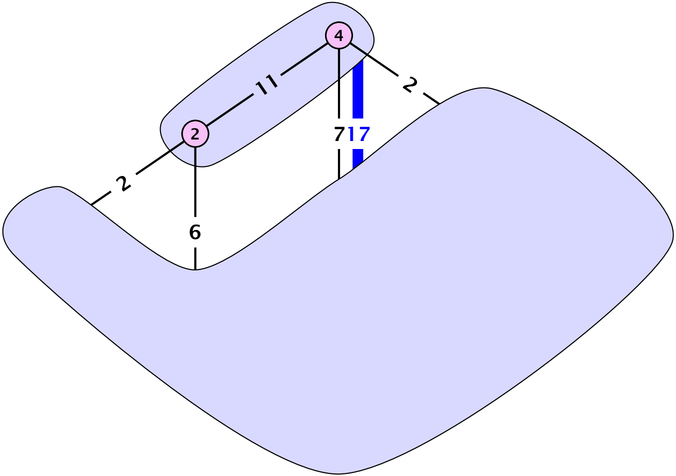

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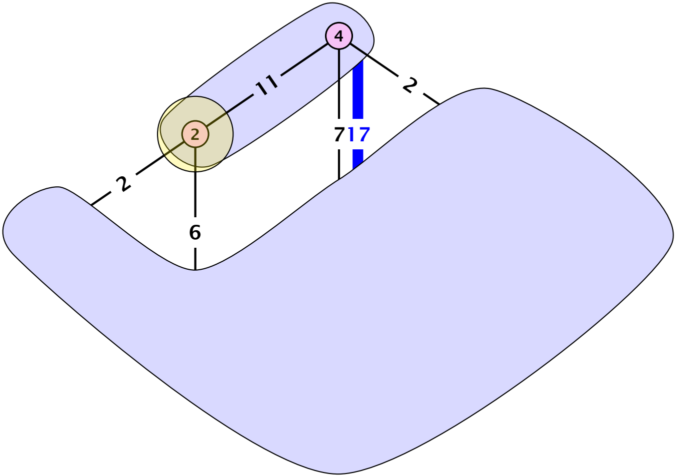

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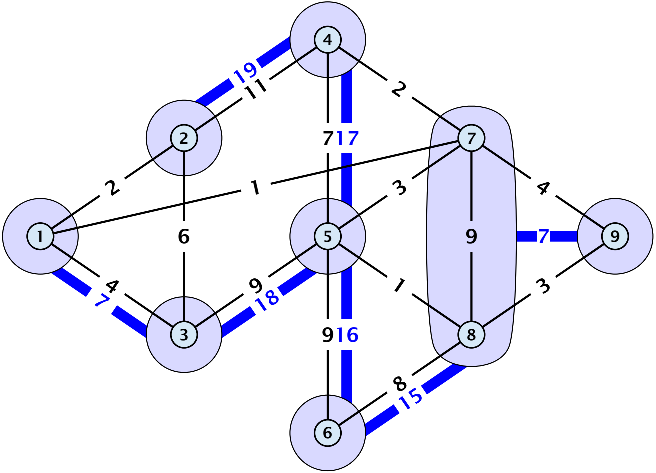

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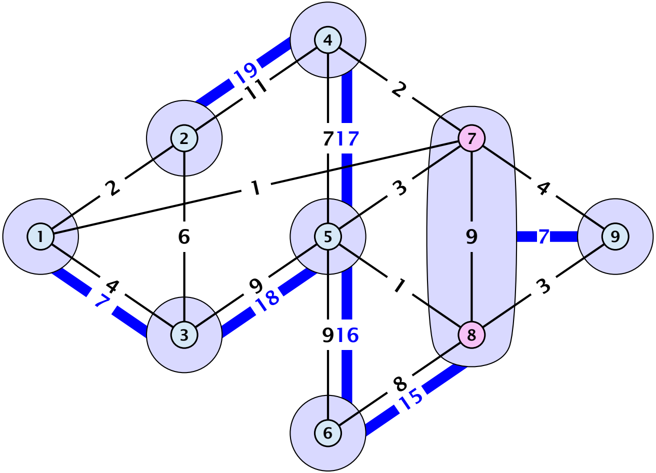

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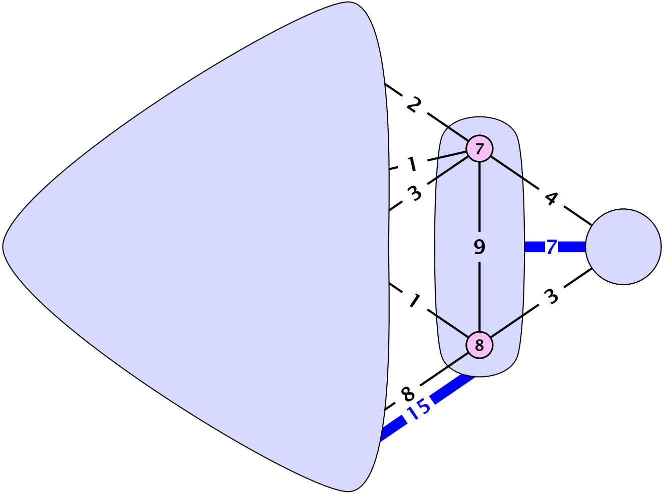

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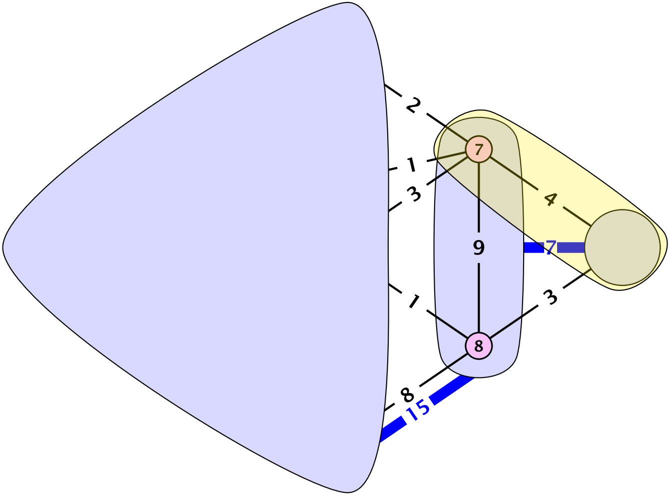

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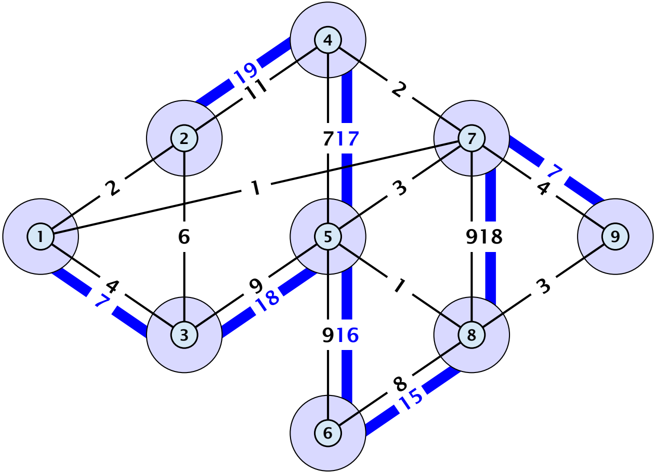

Analysis

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For nodes $s, t, x \in V$ *we have* $f(s,t) \geq \min\{f(s,x), f(x,t)\}$

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Proof: Let X be a minimum v-w cut with $X \cap S \neq \emptyset$ and $X \cap (V \setminus S) \neq \emptyset$. Note that $S \setminus X$ and $S \cap X$ are v-w cuts inside S.

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- $\text{cap}(X \cup S) + \text{cap}(S \cap X) \leq \text{cap}(S) + \text{cap}(X)$.
- $\text{cap}(X \cup S) \geq \text{cap}(S)$ because $X \cup S$ is an r-s cut.
- This gives $\text{cap}(S \cap X) \leq \text{cap}(X)$.

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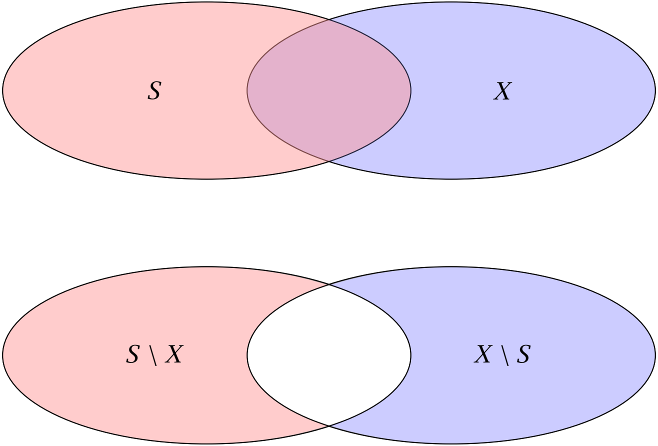

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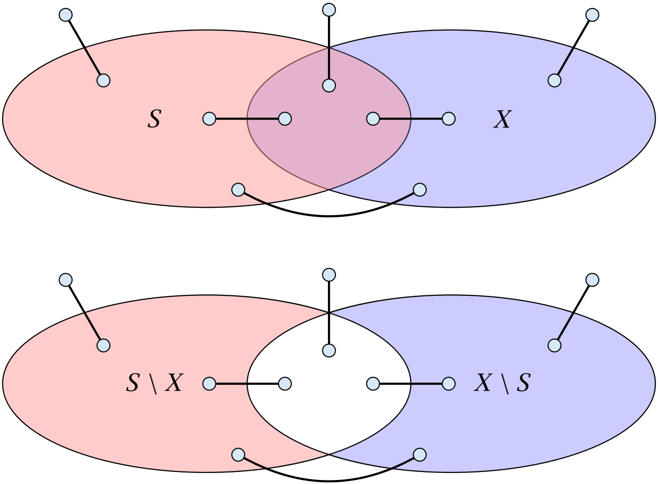

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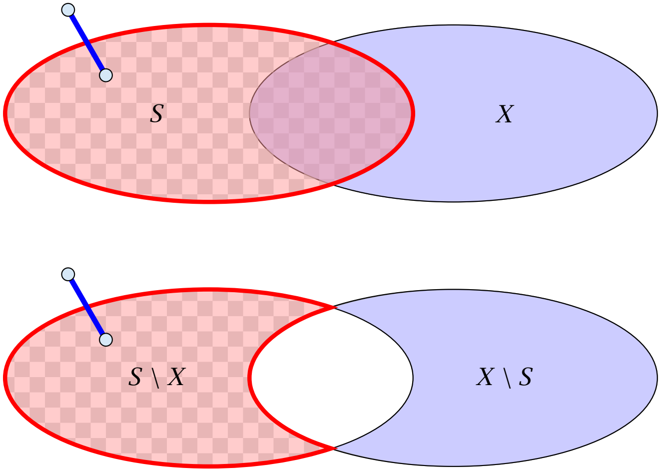

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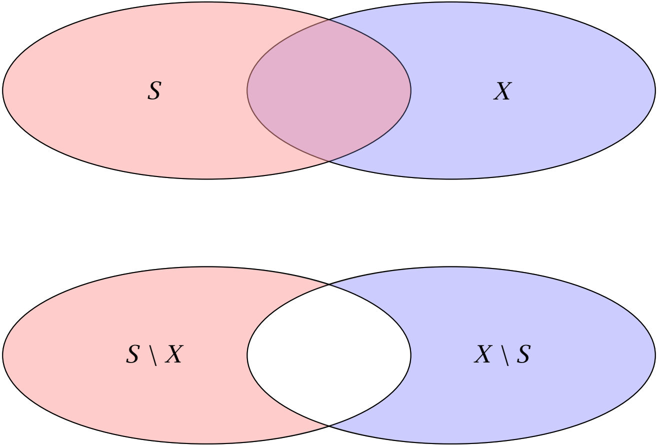

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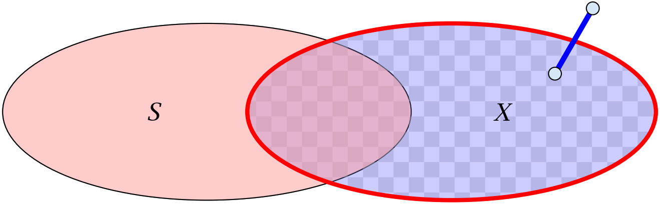

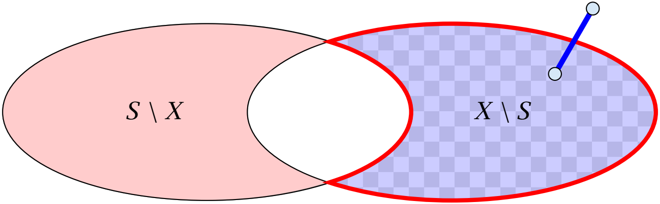

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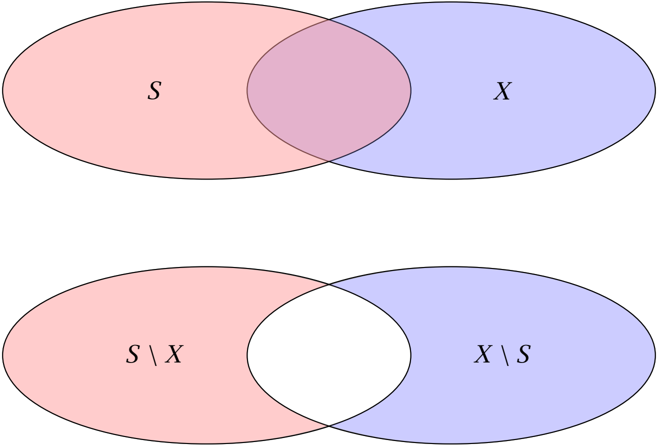

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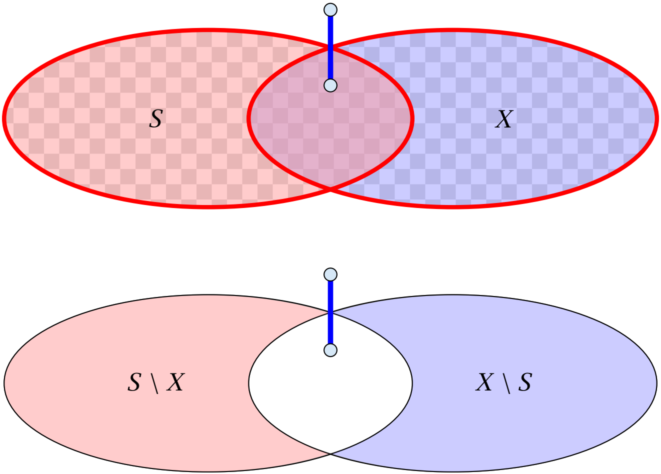

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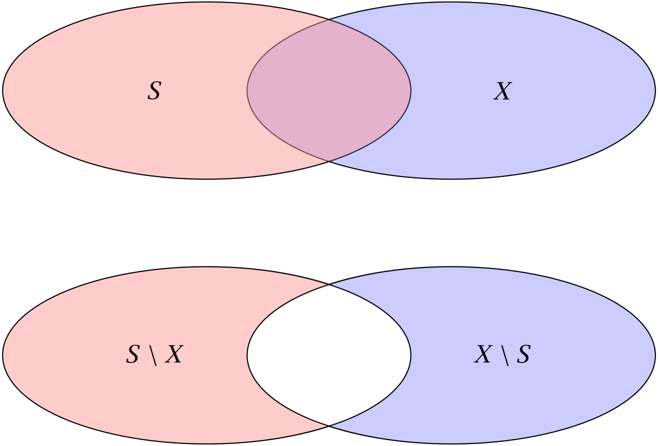

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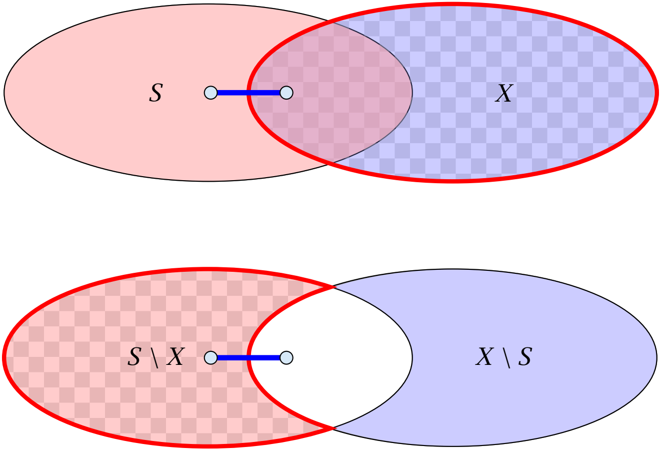

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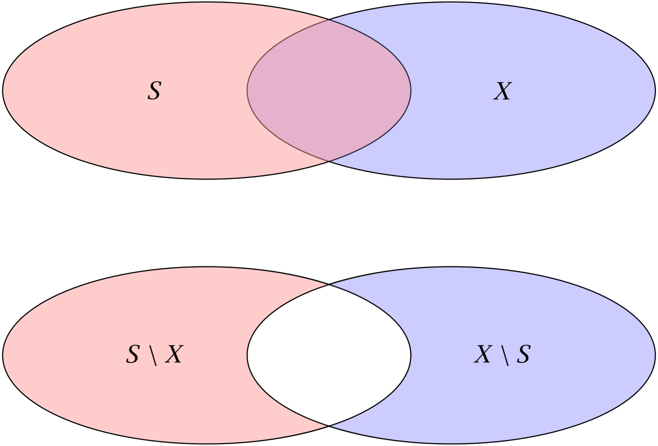

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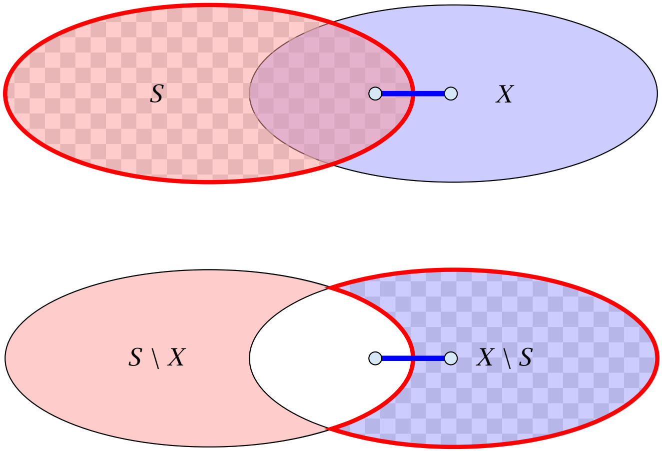

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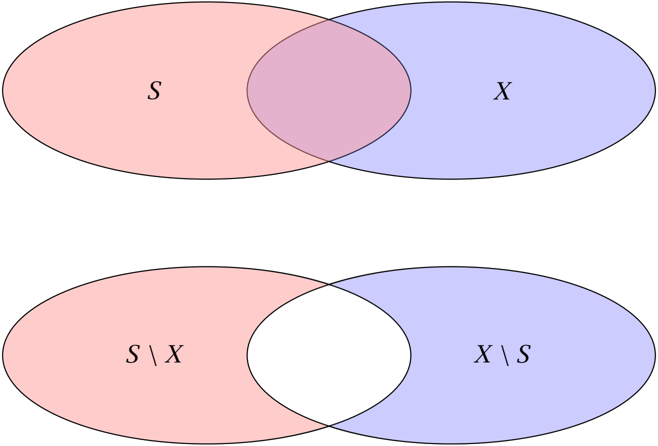

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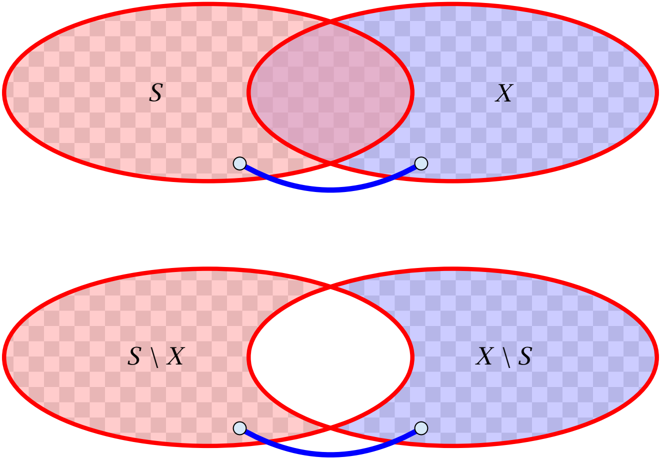

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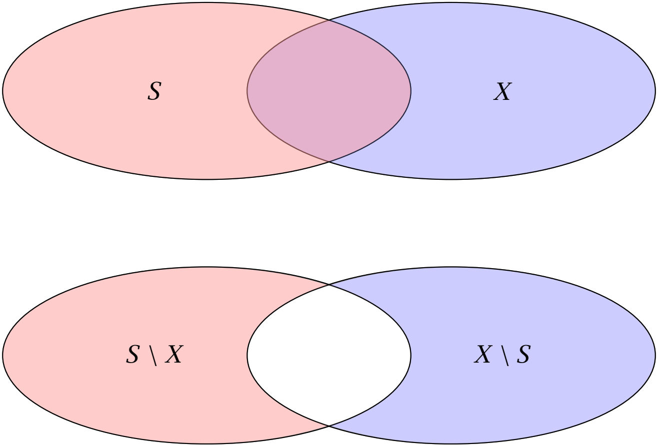

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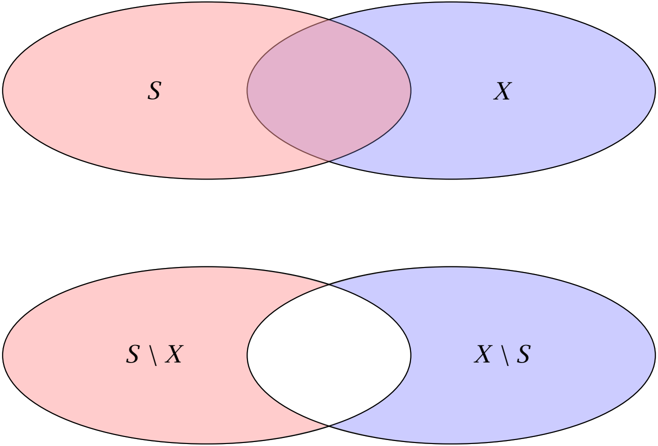

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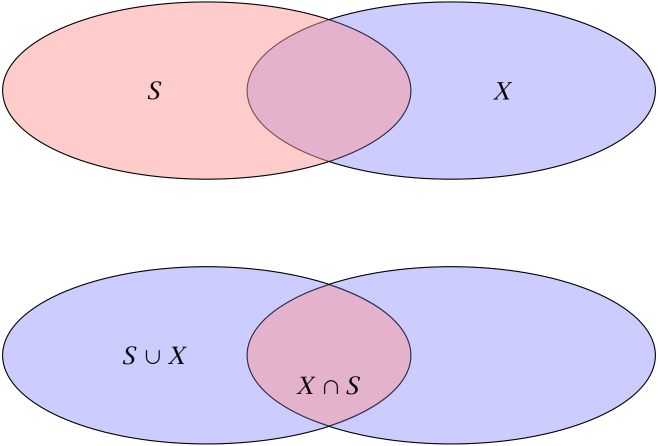

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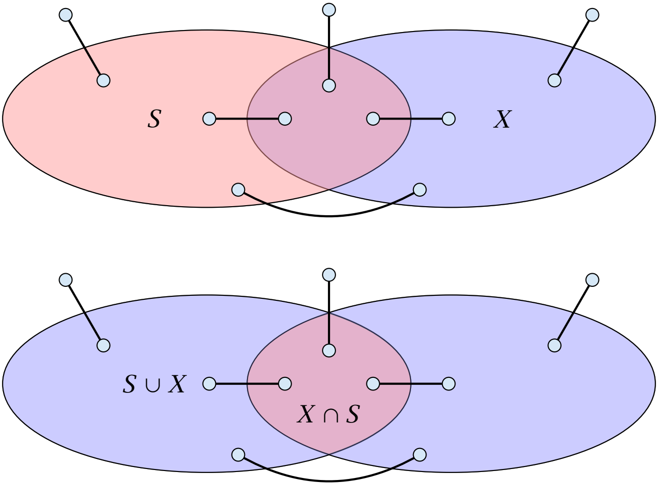

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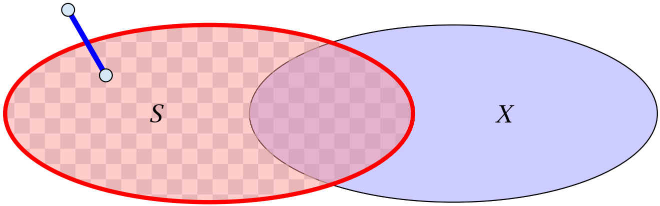

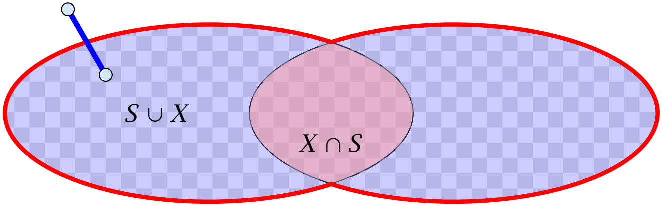

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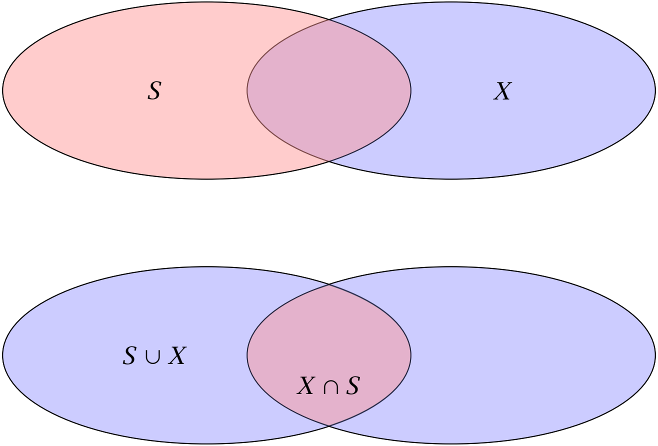

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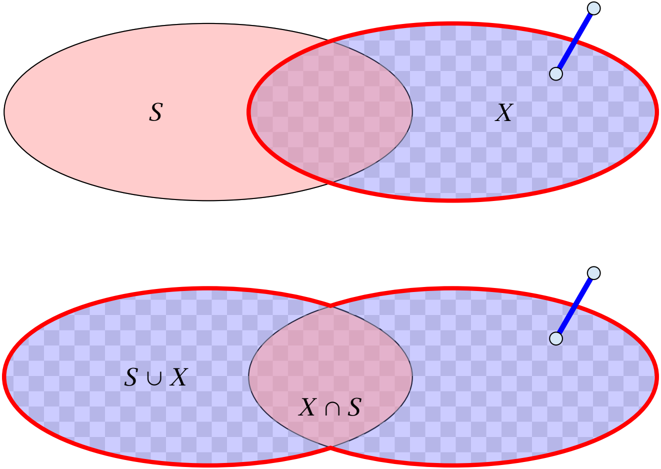

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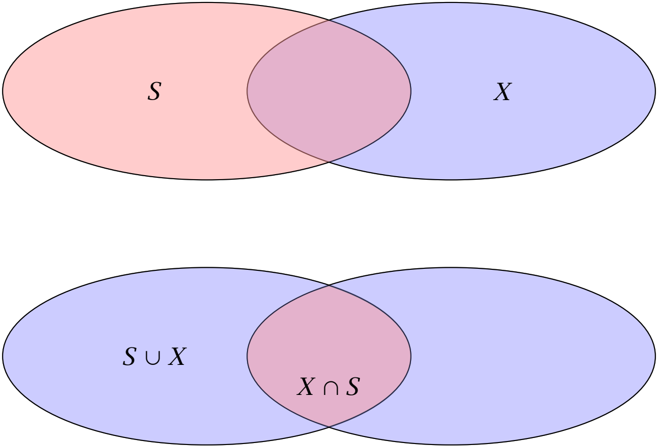

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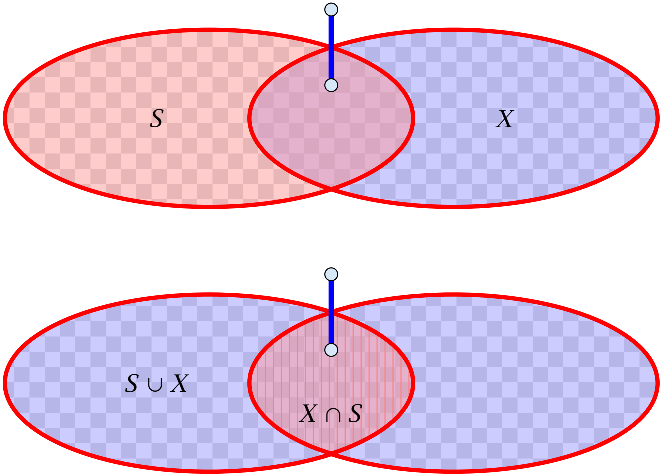

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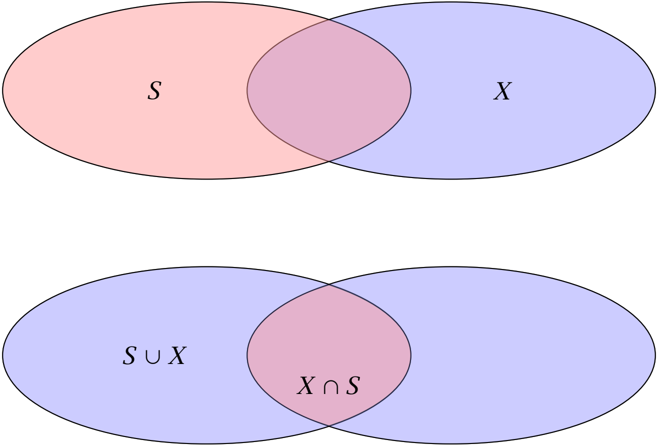

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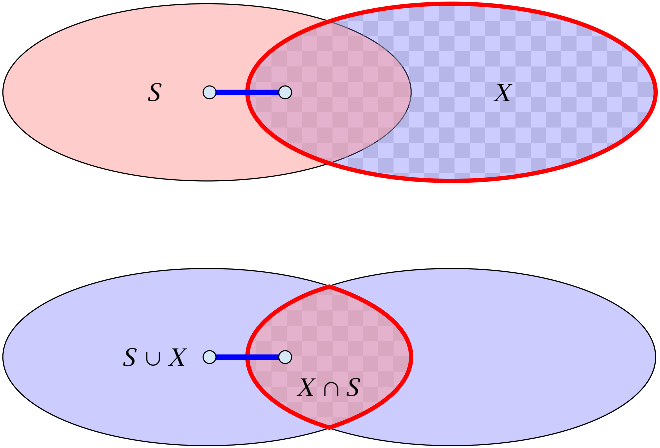

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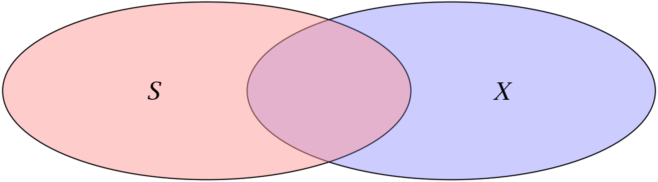

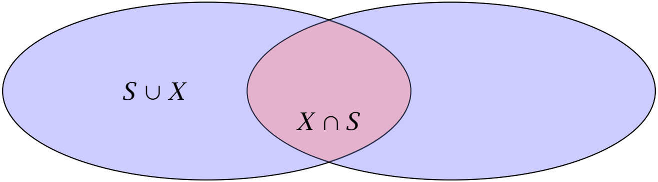

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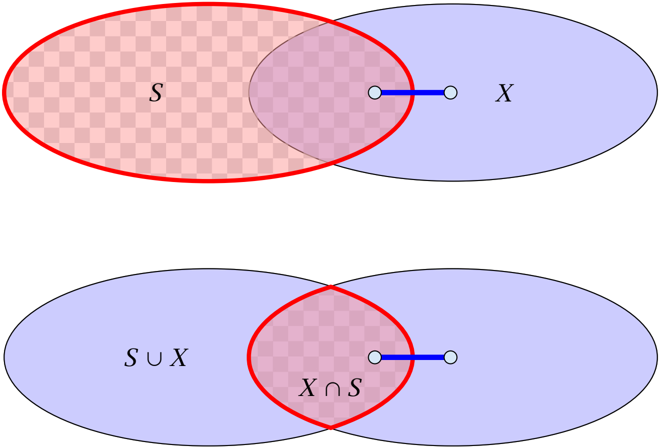

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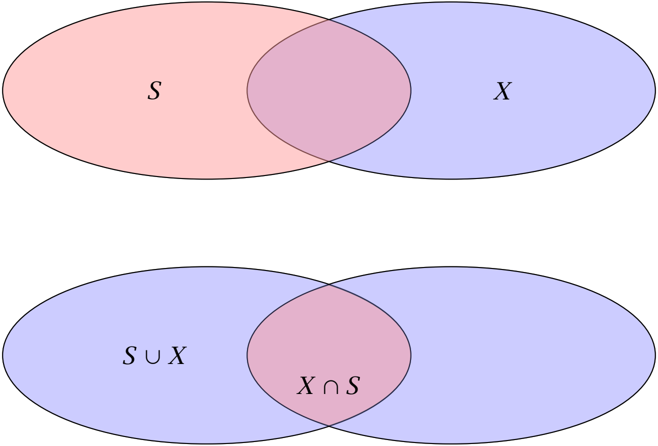

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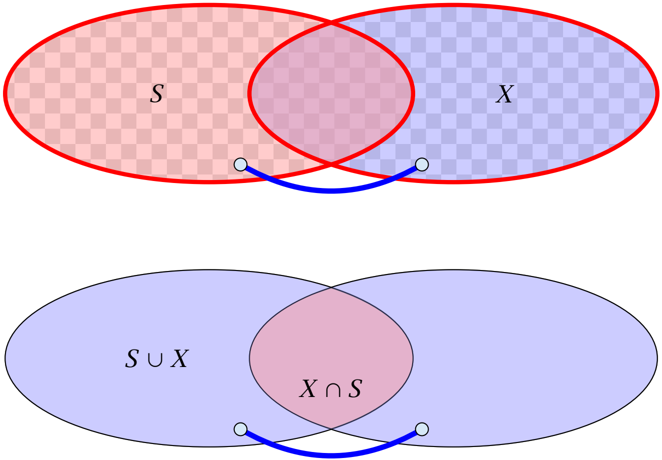

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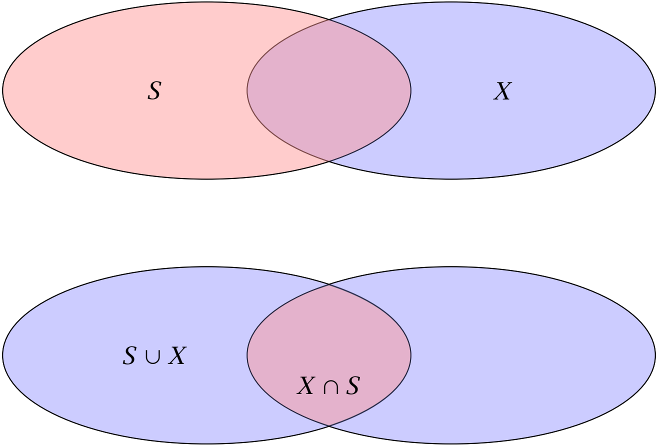

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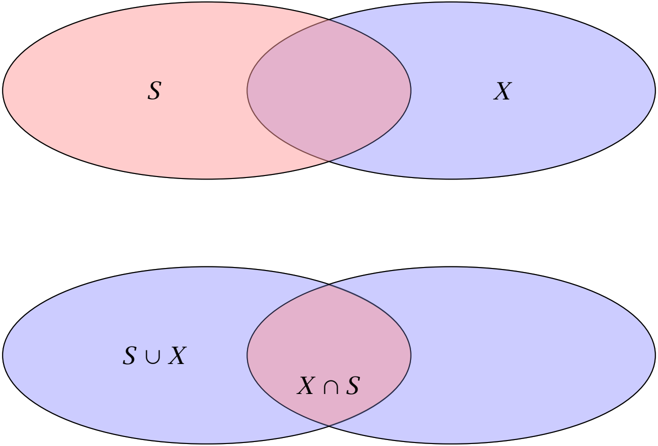

Analysis

Lemma 56 tells us that if we have a graph $G = (V, E)$ and we contract a subset $X \subset V$ that corresponds to some mincut, then the value of $f(s,t)$ does not change for two nodes $s, t \notin X$.

We will show (later) that the connected components that we contract during a split-operation each correspond to some mincut and, hence, $f_H(s,t) = f(s,t)$, where $f_H(s,t)$ is the value of a minimum s-t mincut in graph H.

Analysis

Invariant [existence of representatives]:
For any edge $\{S_i, S_j\}$ in T, there are vertices $a \in S_i$ and $b \in S_j$ such that $w(S_i, S_j) = f(a, b)$ and the cut defined by edge $\{S_i, S_j\}$ is a minimum a-b cut in G.

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We first show that the invariant implies that at the end of the algorithm T is indeed a cut-tree.

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- Let $\{x_j, x_{j+1}\}$ be the edge with minimum weight on the path.
- Since by the invariant this edge induces an s-t cut with capacity $f(x_j, x_{j+1})$ we get $f(s,t) \le f(x_j, x_{j+1}) = f_T(s,t)$.

Analysis

- Hence, $f_T(s,t) = f(s,t)$ (flow equivalence).
- The edge $\{x_j, x_{j+1}\}$ is a mincut between s and t in T.
- By invariant, it forms a cut with capacity $f(x_j, x_{j+1})$ in G (which separates s and t).
- Since, we can send a flow of value $f(x_j, x_{j+1})$ btw. s and t, this is an s-t mincut (cut property).

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Proof of Invariant

The invariant obviously holds at the beginning of the algorithm.

Now, we show that it holds after a split-operation provided that it was true before the operation.

Let S_i denote our selected cluster with nodes a and b. Because of the invariant all edges leaving $\{S_i\}$ in T correspond to some mincuts.

Therefore, contracting the connected components does not change the mincut btw. a and b due to Lemma 56.

After the split we have to choose representatives for all edges. For the new edge $\{S_i^a, S_i^b\}$ with capacity $w(S_i^a, S_i^b) = f_H(a, b)$ we can simply choose a and b as representatives.

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For edges that are not incident to S_i we do not need to change representatives as the neighbouring sets do not change.

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If $s \in S_i^a$ we can keep x and s as representatives.

Otherwise, we choose x and a as representatives. We need to show that $f(x, a) = f(x, s)$.

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Otherwise, we choose x and a as representatives. We need to show that $f(x, a) = f(x, s)$.

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For edges that are not incident to S_i we do not need to change representatives as the neighbouring sets do not change.

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The set B forms a mincut separating a from b. Contracting all nodes in this set gives a new graph G' where the set B is represented by node v_B. Because of Lemma 56 we know that $f'(x,a) = f(x,a)$ as $x, a \notin B$.

We further have $f'(x,a) \ge \min\{f'(x,v_B), f'(v_B,a)\}$.

Since $s \in B$ we have $f'(v_B,x) \ge f(s,x)$.

Also, $f'(a,v_B) \ge f(a,b) \ge f(x,s)$ since the a-b cut that splits S_i into S_i^a and S_i^b also separates s and x.

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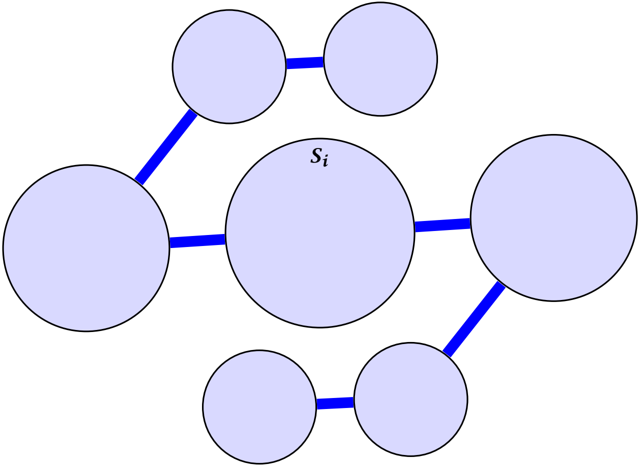
Analysis



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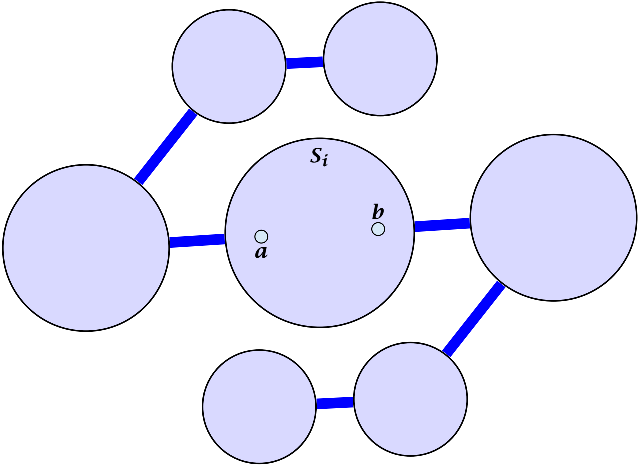

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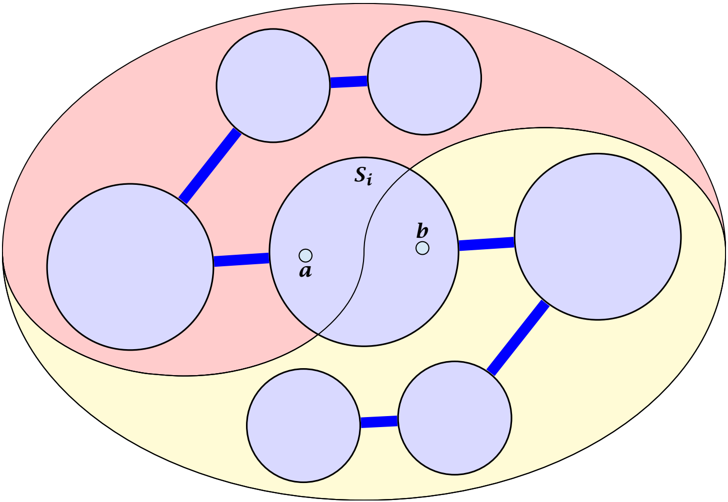

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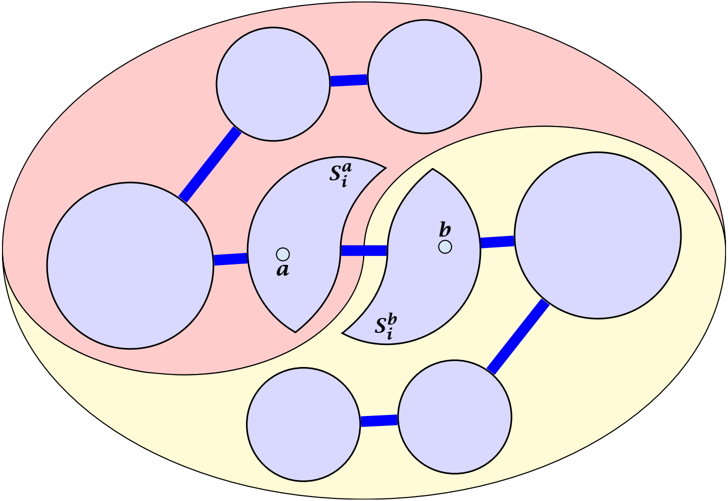

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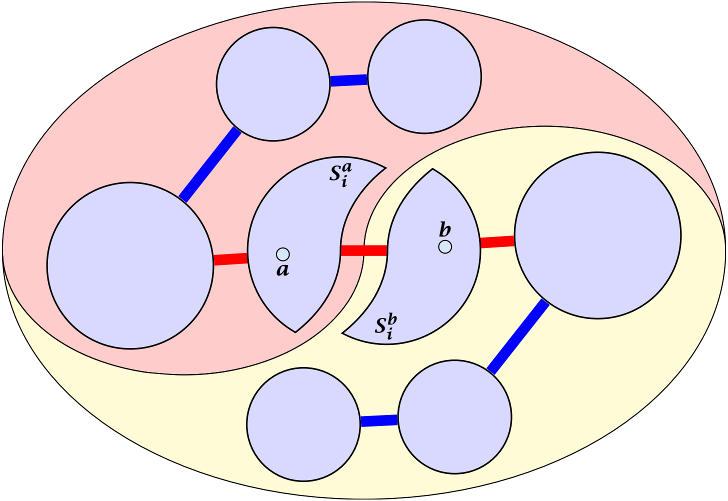

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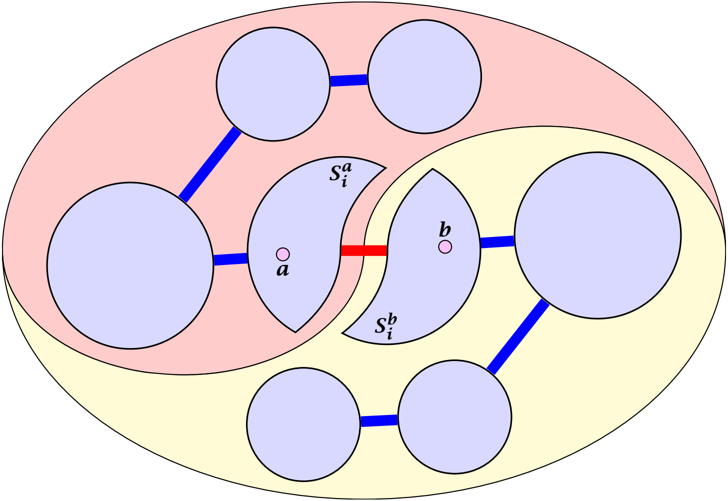

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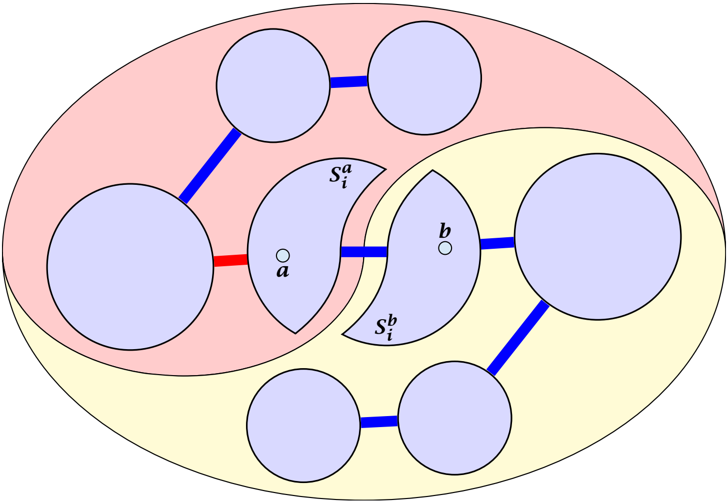

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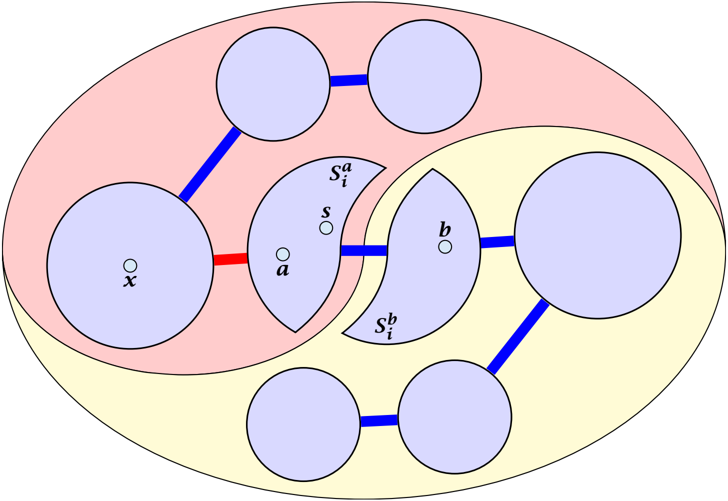

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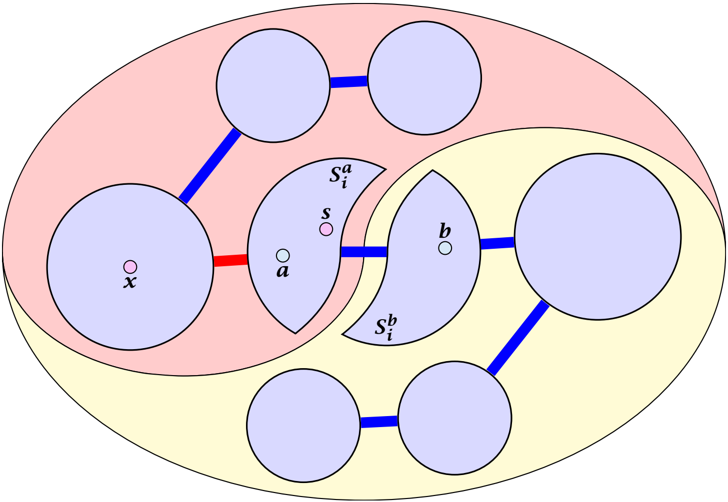

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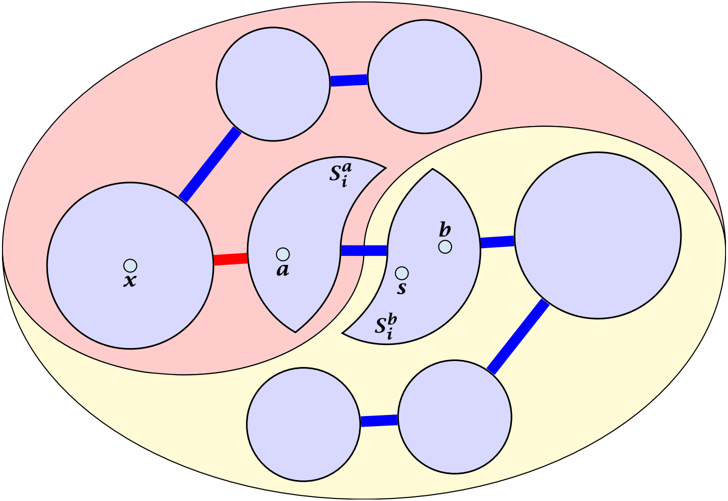

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