Part IV

Flows and Cuts
The following slides are partially based on slides by Kevin Wayne.
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
10 Introduction

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![Flow Network Diagram]
10 Introduction

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

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**Definition 2**
The **capacity** of a cut \(A\) is defined as

\[
\text{cap}(A, V \setminus A) := \sum_{e \in \text{out}(A)} c(e),
\]

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

Flows

Definition 4
An \((s, t)\)-flow is a function \(f : E \rightarrow \mathbb{R}^+\) that satisfies

1. For each edge \(e\)
   \[0 \leq f(e) \leq c(e)\]  
   (capacity constraints)

2. For each \(v \in V \setminus \{s, t\}\)
   \[\sum_{e \in \text{out}(v)} f(e) = \sum_{e \in \text{into}(v)} f(e)\]  
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Flows

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

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\text{val}(f) = \sum_{e \in \text{out}(s)} f(e).
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Maximum Flow Problem: Find an \((s, t)\)-flow with maximum value.
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Maximum Flow Problem: Find an \((s, t)\)-flow with maximum value.
The value of the flow is $\text{val}(f) = 24$. 
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.,

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

\[ \text{val}(f) = \sum_{e \in \text{out}(s)} f(e) + \sum_{v \in A \setminus \{s\}} \left( \sum_{e \in \text{out}(v)} f(e) - \sum_{e \in \text{in}(v)} f(e) \right) = \sum_{e \in \text{out}(A)} f(e) - \sum_{e \in \text{in}(A)} f(e) \]

The last equality holds since every edge with both endpoints 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 \( A \).
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\[ = 0 \]

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Example 8

10 Introduction
Corollary 9

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

$$\text{val}(f) = \text{cap}(A, V \setminus A).$$

Then $f$ is a maximum flow.
**Corollary 9**

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Then $f$ is a maximum flow.

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

$$\text{cap}(A, V \setminus A) < \text{val}(f') = \sum_{e \in \text{out}(A)} f'(e) - \sum_{e \in \text{into}(A)} f'(e) \leq \sum_{e \in \text{out}(A)} f'(e) \leq \text{cap}(A, V \setminus A).$$
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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
11 Augmenting Path Algorithms

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The Residual Graph

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):

- Suppose the original graph has edges $e_1 = (u, v)$ and $e_2 = (v, u)$ between $u$ and $v$.
- $G_f$ has edge $e'_1$ with capacity $\max\{0, c(e_1) - f(e_1) + f(e_2)\}$ and $e'_2$ with capacity $\max\{0, c(e_2) - f(e_2) + f(e_1)\}$. 

11.1 The Generic Augmenting Path Algorithm
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\[ G \]
\[ \begin{array}{c}
\text{G} \\
\text{u} \\
\text{14|16} \\
\text{10|20} \\
\text{v}
\end{array} \]

\[ G_f \]
\[ \begin{array}{c}
\text{G}_f \\
\text{u} \\
\text{12} \\
\text{24} \\
\text{v}
\end{array} \]
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**

```
Algorithm 1 FordFulkerson(G = (V, E, c))
1: Initialize $f(e) \leftarrow 0$ for all edges.
2: while $\exists$ augmenting path $p$ in $G_f$ do
3: augment as much flow along $p$ as possible.
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Augmenting Path Algorithm

$G$

$G_f$

Flow value = 0

11.1 The Generic Augmenting Path Algorithm

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Augmenting Path Algorithm

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\[ G \]

\[ G_f \]

Flow value = 8

11.1 The Generic Augmenting Path Algorithm
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$G$

$G_f$

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11.1 The Generic Augmenting Path Algorithm
Augmenting Path Algorithm

\begin{align*}
G
\end{align*}

\begin{align*}
G_f
\end{align*}

Flow value = 8
### 11.1 The Generic Augmenting Path Algorithm

Augmenting Path Algorithm

**Flow value = 10**

#### 1. Presentation of the Algorithm

- The algorithm starts with an initial flow, often zero, in all edges.
- The algorithm iteratively finds augmenting paths in the residual graph.
- An augmenting path is a path from the source to the sink where the flow is not saturated in any direction.
- The flow value is increased by the minimum capacity of the augmenting path.

#### 2. Example

Consider the graph $G = (V, E)$ and the flow network $G_f = (V, E_f)$.

- **Initial Flow**: $f_0 = 0$.
- **Augmenting Paths**:
  - From source $s$ to sink $t$ with capacity $C$.
- **Flow Update**: Increase the flow along the augmenting path by the minimum capacity.

#### 3. Properties

- **Flow Conservation**: $\sum_{v \in V} f(v) = 0$.
- **Maximum Flow**: The maximum flow value is the total capacity of the minimum cut.

#### 4. Complexity

- **Time Complexity**: $O(|V| \cdot |E| \cdot \text{OPT})$ for finding the augmenting path with $\text{OPT}$ being the maximum flow value.

---

**Diagram**

- Graph $G$ with vertices $s$, $2$, $3$, $4$, $5$, $t$.
- Edges with capacities and flows.
- Graph $G_f$ with augmented flows.
- Flow value for the network.
Augmenting Path Algorithm

\[ G \]

\[ G_f \]

Flow value = 10

11.1 The Generic Augmenting Path Algorithm
Augmenting Path Algorithm

$G$

$G_f$

Flow value = 10

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11.1 The Generic Augmenting Path Algorithm

Flow value = 16
Augmenting Path Algorithm

$G$

$G_f$

Flow value = 16

11.1 The Generic Augmenting Path Algorithm
Augmenting Path Algorithm

\[ G \]

\[ G_f \]

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$G$

$G_f$

Flow value = 18

11.1 The Generic Augmenting Path Algorithm
Augmenting Path Algorithm

\[ G \]

\[ G_f \]

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Augmenting Path Algorithm

\[ G \]

\[ G_f \]

Flow value = 19

11.1 The Generic Augmenting Path Algorithm
Augmenting Path Algorithm

$G$

$G_f$

Flow value = 19

11.1 The Generic Augmenting Path Algorithm
Augmenting Path Algorithm

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Augmenting Path Algorithm

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:
1. There exists a cut $A, B$ such that $\text{val}(f) = \text{cap}(A, B)$.
2. Flow $f$ is a maximum flow.
3. There is no augmenting path w.r.t. $f$.

11.1 The Generic Augmenting Path Algorithm
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Augmenting Path Algorithm

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Augmenting Path Algorithm

1. $\Rightarrow$ 2.
This we already showed.

2. $\Rightarrow$ 3.
If there were an augmenting path, we could improve the flow.
Contradiction.

3. $\Rightarrow$ 1.

Let $f$ be a flow with no augmenting paths.

Let $A$ be the set of vertices reachable from $s$ in the residual graph along non-zero capacity edges.

Since there is no augmenting path we have $s \in A$ and $t \not\in A$. 

11.1 The Generic Augmenting Path Algorithm

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Augmenting Path Algorithm

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Augmenting Path Algorithm

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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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Analysis

Assumption:
All capacities are integers between $1$ and $C$.

Invariant:
Every flow value $f(e)$ and every residual capacity $c_f(e)$ remains integral throughout the algorithm.
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Invariant:
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Lemma 13
The algorithm terminates in at most $\text{val}(f^*) \leq nC$ iterations, where $f^*$ denotes the maximum flow. Each iteration can be implemented in time $O(m)$. This gives a total running time of $O(nmC)$.

Theorem 14
If all capacities are integers, then there exists a maximum flow for which every flow value $f(e)$ is integral.
Lemma 13
The algorithm terminates in at most $\text{val}(f^*) \leq nC$ iterations, where $f^*$ denotes the maximum flow. Each iteration can be implemented in time $\mathcal{O}(m)$. This gives a total running time of $\mathcal{O}(nmC)$.

Theorem 14
If all capacities are integers, then there exists a maximum flow for which every flow value $f(e)$ is integral.
A Bad Input

Problem: The running time may not be polynomial.

Question: Can we tweak the algorithm so that the running time is polynomial in the input length?

11.1 The Generic Augmenting Path Algorithm
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A Pathological Input

Let \( r = \frac{1}{2}(\sqrt{5} - 1) \). Then \( r^{n+2} = r^n - r^{n+1} \).
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Running time may be infinite!!!
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How to choose augmenting paths?

▶ We need to find paths efficiently.
▶ We want to guarantee a small number of iterations.

Several possibilities:

▶ Choose path with maximum bottleneck capacity.
▶ Choose path with sufficiently large bottleneck capacity.
▶ Choose the shortest augmenting path.
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Overview: Shortest Augmenting Paths

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

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After at most $O(m)$ augmentations, the length of the shortest augmenting path strictly increases.
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These two lemmas give the following theorem:

**Theorem 17**

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

**Proof.**

- We can find the shortest augmenting paths in time $O(mn)$ via BFS.
- Each augmentation for paths of exactly $k$ new edges.
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Let $L_G$ denote the subgraph of the residual graph $G_f$ that contains only those edges $(u, v)$ with $\ell(v) = \ell(u) + 1$. 
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A path $P$ is a shortest $s-u$ path in $G_f$ if it is a an $s-u$ path in $L_G$. 

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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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First Lemma:
The length of the shortest augmenting path never decreases.
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![Graph of Shortest Augmenting Path](image)
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![Diagram of the graph with labeled edges and nodes]
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Theorem 19 (without proof)
There exist networks with $m = \Theta(n^2)$ that require $\Theta(mn)$ augmentations, when we restrict ourselves to only augment along shortest augmenting paths.

Note:
There always exists a set of $m$ augmentations that gives a maximum flow (why?).
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When sticking to shortest augmenting paths we cannot improve (asymptotically) on the number of augmentations.

However, we can improve the running time to $\Theta(mn^2)$ by improving the running time for finding an augmenting path (currently we assume $\Theta(m)$ per augmentation for this).
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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 $E_L$.

When $E_L$ does not contain an $s$-$t$ path anymore the distance between $s$ and $t$ strictly increases.

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Suppose that the initial distance between $s$ and $t$ in $G_f$ is $k$.

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Perform a DFS search to find a path from $s$ to $t$ using edges from $E_L$.

Either you find $t$ after at most $n$ steps, or you end at a node $v$ that does not have any outgoing edges.

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

Intuition:
▶ Choosing a path with the highest bottleneck increases the flow as much as possible in a single step.
▶ Don't worry about finding the exact bottleneck.
▶ Maintain scaling parameter $\Delta$.

$G_f(\Delta)$ is a sub-graph of the residual graph $G_f$ that contains only edges with capacity at least $\Delta$. 
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![Graphs](image-url)
## Capacity Scaling

**Algorithm 2** $\text{maxflow}(G, s, t, c)$

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. $G_f(\Delta) \leftarrow \Delta$-residual graph
5. **while** there is augmenting path $P$ in $G_f(\Delta)$ **do**
6. $f \leftarrow \text{augment}(f, c, P)$
7. $\text{update}(G_f(\Delta))$
8. $\Delta \leftarrow \Delta/2$
9. **return** $f$
Capacity Scaling

Assumption: All capacities are integers between 1 and C.

Invariant: All flows and capacities are/remain integral throughout the algorithm.

Correctness: The algorithm computes a maxflow:
- because of integrality we have $G_f(1) = G_f$
- therefore after the last phase there are no augmenting paths anymore
- this means we have a maximum flow.
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Lemma 20

There are $\lceil \log C \rceil$ iterations over $\Delta$.

Proof: obvious.

Lemma 21

Let $f$ be the flow at the end of a $\Delta$-phase. Then the maximum flow is smaller than $\text{val}(f) + m \Delta$.

Proof: less obvious, but simple:

▶ There must exist an $s$-$t$ cut in $G_f(\Delta)$ of zero capacity.

▶ In $G_f$ this cut can have capacity at most $m \Delta$.

▶ This gives me an upper bound on the flow that I can still add.
Capacity Scaling

**Lemma 20**

*There are \( \lceil \log C \rceil \) iterations over \( \Delta \).*

**Proof:** obvious.

**Lemma 21**

Let \( f \) be the flow at the end of a \( \Delta \)-phase. Then the maximum flow is smaller than \( \text{val}(f) + m\Delta \).

**Proof:** less obvious, but simple:

1. There must exist an \( s-t \) cut in \( G_f(\Delta) \) of zero capacity.
2. In \( G_f \) this cut can have capacity at most \( m\Delta \).
3. This gives me an upper bound on the flow that I can still add.
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There are $\lceil \log C \rceil$ iterations over $\Delta$.

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Let $f$ be the flow at the end of a $\Delta$-phase. Then the maximum flow is smaller than $\text{val}(f) + m\Delta$.

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Proof: obvious.

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- In \(G_f\) this cut can have capacity at most \(m\Delta\).
- This gives me an upper bound on the flow that I can still add.
Lemma 22
There are at most $2m$ augmentations per scaling-phase.

Proof:
Let $f$ be the flow at the end of the previous phase.
$\text{val}(f^\ast) \leq \text{val}(f) + 2m \Delta$
Each augmentation increases flow by $\Delta$.

Theorem 23
We need $O(m \log C)$ augmentations. The algorithm can be implemented in time $O(m^2 \log C)$. 
Lemma 22

*There are at most* $2m$ *augmentations per scaling-phase.*
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*There are at most* $2m$ *augmentations per scaling-phase.*

**Proof:**

- Let $f$ be the flow at the end of the previous phase.
Capacity Scaling

Lemma 22

There are at most $2m$ augmentations per scaling-phase.

Proof:

- Let $f$ be the flow at the end of the previous phase.
- $\text{val}(f^*) \leq \text{val}(f) + 2m\Delta$
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Theorem 23

We need $\Theta(m \log C)$ augmentations. The algorithm can be implemented in time $\Theta(m^2 \log C)$. 
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 $G = (L \sqcup R, E)$.
- $M \subseteq E$ 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 $G = (L \cup R, E)$.
- $M \subseteq E$ is a matching if each node appears in at most one edge in $M$.
- Maximum Matching: find a matching of maximum cardinality

![Diagram of a bipartite matching with nodes and edges labeled 1 to 5, connected in pairs]$\overline{1} \overline{2} \overline{3} \overline{4} \overline{5}$

$L \overline{3} \overline{4} \overline{5}$

$R \overline{1} \overline{2}$

12.1 Matching

Ernst Mayr, Harald Räcke
Maxflow Formulation

- Input: undirected, bipartite graph $G = (L \cup R \cup \{s, t\}, E')$.
- 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 $k$. 

![Diagram of graphs $G$ and $G'$ showing matching and flow](diagram.png)
Proof

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![Diagram of graphs $G$ and $G'$ with matching and flow paths indicated.]
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Max cardinality matching in \( G \) ≤ value of maxflow in \( G' \)

- Given a maximum matching \( M \) of cardinality \( k \).
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- \( f \) is a flow and has cardinality \( k \).
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- $f$ is a flow and has cardinality $k$. 

![Diagram showing the matching and maxflow for comparison]
Proof

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

- 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.
Proof

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

- Let $f$ be a maxflow in $G'$ of value $k$
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- $|M| = k$, as the flow must use at least $k$ middle edges.
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

<table>
<thead>
<tr>
<th>team ( i )</th>
<th>wins ( w_i )</th>
<th>losses ( l_i )</th>
<th>remaining games</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>83</td>
<td>71</td>
<td>−</td>
</tr>
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<td></td>
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<td>1</td>
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<td>1</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>80</td>
<td>79</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
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<tr>
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<td></td>
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<tr>
<td>Montreal</td>
<td>77</td>
<td>82</td>
<td>1</td>
</tr>
<tr>
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<tr>
<td></td>
<td></td>
<td></td>
<td>−</td>
</tr>
</tbody>
</table>

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

\[
\begin{align*}
  w(T) &:= \sum_{i \in T} w_i, \quad r(T) := \sum_{i,j \in T, i < j} r_{ij}
\end{align*}
\]

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 $\sum_{i,j \in S \setminus \{z\}, i < j} r_{ij}$.
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Proof ($\iff$)

- Consider the mincut $A$ in the flow network. Let $T$ be the set of team-nodes in $A$. 
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- We don’t find a flow that saturates all source edges:

$$r(S \setminus \{z\})$$
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$$r(S \setminus \{z\}) > \text{cap}(A, V \setminus A)$$
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- We don’t find a flow that saturates all source edges:

$$r(S \setminus \{z\}) > \cap(A, V \setminus A) \geq \sum_{i<j: i \notin T \lor j \notin T} r_{ij} + \sum_{i \in T} (M - w_i)$$

$$\geq r(S \setminus \{z\}) - r(T) + |T| M - w(T)$$

This gives $M < (w(T) + r(T)) / |T|$, i.e., $z$ is eliminated.
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Baseball Elimination

Proof ($\Rightarrow$)

- 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.
- Hence, team $z$ is not eliminated.
Baseball Elimination

Proof (⇒)

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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.
**Theorem 25**

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

**Proof.**

- $A$ is feasible because of capacity infinity edges.
Theorem 25

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

**Proof.**

- *A* is feasible because of capacity infinity edges.
- \( \text{cap}(A, V \setminus A) \)
Theorem 25

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

Proof.

- $A$ is feasible because of capacity infinity edges.
- $\text{cap}(A, V \setminus A) = \sum_{v \in \bar{A} : p_v > 0} p_v + \sum_{v \in A : p_v < 0} (-p_v)$
**Theorem 25**

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

**Proof.**

- \( A \) is feasible because of capacity infinity edges.
- \( \text{cap}(A, V \setminus A) = \sum_{v \in \bar{A} : p_v > 0} p_v + \sum_{v \in A : p_v < 0} (-p_v) \)
  
  \[= \sum_{v : p_v > 0} p_v - \sum_{v \in A} p_v \]

![Prerequisite Graph](image-url)
Preflows

Definition 26
An \((s, t)\)-preflow is a function \( f : E \rightarrow \mathbb{R}^+ \) that satisfies

1. For each edge \( e \),
   \[ 0 \leq f(e) \leq c(e) \]
   (capacity constraints)

2. For each node \( v \in V \setminus \{s, t\} \),
   \[ \sum_{e \in \text{out}(v)} f(e) \leq \sum_{e \in \text{into}(v)} f(e) \]

13.1 Generic Push Relabel

Ernst Mayr, Harald Räcke
**Definition 26**

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   0 \leq f(e) \leq c(e) .
   \]

   *(capacity constraints)*

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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.
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

Definition:
A labelling is a function $\ell : V \rightarrow \mathbb{N}$. It is valid for preflow $f$ if $\nabla \ell(u) \leq \ell(v) + 1$ for all edges $(u,v)$ in the residual graph $G_f$ (only non-zero capacity edges!!!) $\nabla \ell(s) = n \nabla \ell(t) = 0$

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

Definition:
A labelling is a function \( \ell : V \rightarrow \mathbb{N} \). It is valid for preflow \( f \) if
- \( \ell(u) \leq \ell(v) + 1 \) for all edges \((u, v)\) in the residual graph \( G_f \) (only non-zero capacity edges!!!)
Preflows

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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

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel

Ernst Mayr, Harald Räcke
Preflows

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflows

Lemma 28
A preflow that has a valid labelling saturates a cut.

Proof:
There are $n$ nodes but $n + 1$ different labels from 0,\ldots, $n$.
There must exist a label $d \in \{0,\ldots, n\}$ such that none of the nodes carries this label.
Let $A = \{v \in V | \ell(v) > d\}$ and $B = \{v \in V | \ell(v) < d\}$.
We have $s \in A$ and $t \in B$ and there is no edge from $A$ to $B$ in the residual graph $G_f$; this means that $(A,B)$ is a saturated cut.

Lemma 29
A flow that has a valid labelling is a maximum flow.
Lemma 28

A *preflow* that has a valid labelling saturates a cut.

Proof:

There are \( n \) nodes but \( n + 1 \) different labels from 0, ..., \( n \).

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**Lemma 28**

A *preflow* that has a valid labelling saturates a cut.

**Proof:**

- There are \(n\) nodes but \(n + 1\) different labels from \(0, \ldots, n\).
Preflows

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**Lemma 29**
A *flow* that has a valid labelling is a maximum flow.
Push Relabel Algorithms

Idea:

1. Start with some preflow and some valid labelling.
2. Successively change the preflow while maintaining a valid labelling.
3. Stop when you have a flow (i.e., no more active nodes).

Note that this is somewhat dual to an augmenting path algorithm. The former maintains the property that it has a feasible flow. It successively changes this flow until it saturates some cut in which case we conclude that the flow is maximum. A preflow push algorithm maintains the property that it has a saturated cut. The preflow is changed iteratively until it fulfills conservation constraints in which case we can conclude that we have a maximum flow.
Push Relabel Algorithms

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Push Relabel Algorithms

Idea:

- 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 \( \ell \)).

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 (!!!).

- **saturating push:** \( \min\{f(u), c_f(e)\} = c_f(e) \) the arc \( e \) is deleted from the residual graph
- **non-saturating push:** \( \min\{f(u), c_f(e)\} = f(u) \) the node \( u \) becomes inactive

Note that a push-operation may be saturating and non-saturating at the same time.
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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 \(\ell\)).

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## 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 \(\ell\)).

### 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 (!!!).

- **saturating push:** \(\min\{f(u), c_f(e)\} = c_f(e)\)
  - the arc \(e\) is deleted from the residual graph
- **non-saturating push:** \(\min\{f(u), c_f(e)\} = f(u)\)
  - the node \(u\) becomes inactive
Push Relabel Algorithms

13.1 Generic Push Relabel

Consider an active node \( u \) that does not have an outgoing admissible arc. 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: \( \ell(u) \leq \ell(w) + 1 \).
The relabel operation
Consider an active node $u$ that does not have an outgoing admissible arc.
Push Relabel Algorithms

The relabel operation
Consider an active node $u$ that does not have an outgoing admissible arc.

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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.
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 disappear 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\((G, s, t, c)\)

1: find initial preflow \(f\)
2: while there is active node \(u\) do
3: \hspace{0.5cm} if there is admiss. arc \(e\) out of \(u\) then
4: \hspace{1cm} push\((G, e, f, c)\)
5: \hspace{0.5cm} else
6: \hspace{1cm} relabel\((u)\)
7: \hspace{0.5cm} \textbf{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: \hspace{1em} if there is admiss. arc \(e\) out of \(u\) then
4: \hspace{2em} push\((G, e, f, c)\)
5: \hspace{1em} else
6: \hspace{2em} relabel\((u)\)
7: \hspace{1em} 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

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel

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Preflow Push Algorithm

**push**

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

push

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel

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Preflow Push Algorithm

**Push**

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel 6 times

\( G \)

\( G_f \)

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

non-saturated push

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel

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Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel 6 times

\[ G \]

\[ G_f \]
Preflow Push Algorithm

\[ G \]

\( s \) \hspace{1cm} 10|10 \hspace{1cm} 3 \hspace{1cm} 7 \hspace{1cm} 4|4 \hspace{1cm} 0 \hspace{1cm} 0|6 \hspace{1cm} 0|8 \hspace{1cm} t \)

\[ G_f \]

\( s \) \hspace{1cm} 14|20 \hspace{1cm} 14|20 \hspace{1cm} 2|2 \hspace{1cm} 8|8 \hspace{1cm} 4|0 \hspace{1cm} 5 \)

13.1 Generic Push Relabel
Preflow Push Algorithm

non-saturated push

\[ G \]

\[ G_f \]
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

**non-saturated push**

![Graph G](image)

**Graph G**

![Graph G_f](image)

**Graph G_f**

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel

Ernst Mayr, Harald Räcke
Preflow Push Algorithm

$G$

$G_f$
Preflow Push Algorithm

relabel

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

push

$G$

$G_f$
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel

$G$

$G_f$

13.1 Generic Push Relabel

Ernst Mayr, Harald Räcke
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel 6 times

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

non-saturated push

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

push

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

relabel 7 times

$G$

$G_f$
Preflow Push Algorithm

$G$

$G_f$

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Preflow Push Algorithm

push

$G$

$G_f$
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

13.1 Generic Push Relabel

Ernst Mayr, Harald Räcke
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

non-saturated push

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

non-saturated push

\[ G \]

\[ G_f \]
Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel

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Preflow Push Algorithm

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

non-saturated push

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

$G$

$G_f$

13.1 Generic Push Relabel
Preflow Push Algorithm

non-saturated push

\[ G \]

\[ G_f \]

13.1 Generic Push Relabel
Preflow Push Algorithm
Analysis

Lemma 30
An active node has a path to $s$ in the residual graph.
Analysis

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

Proof.

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

Lemma 30

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

Proof.

▶ Let $A$ denote the set of nodes that can reach $s$, and let $B$ denote the remaining nodes. Note that $s \in A$.
▶ In the following we show that a node $b \in B$ has excess flow $f(b) = 0$ which gives the lemma.
Analysis

Lemma 30

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

Proof.

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

Lemma 30

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Proof.

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

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

We have

\[
f(B) = \sum_{b \in B} f(b) = \sum_{b \in B} \left( \sum_{v \in V} f(v, b) - \sum_{v \in V} f(b, v) \right) = \sum_{b \in B} \left( \sum_{v \in A} f(v, b) + \sum_{v \in B} f(v, b) - \sum_{v \in A} f(b, v) - \sum_{v \in B} f(b, v) \right) \leq 0
\]

Hence, the excess flow $f(b)$ must be 0 for every node $b \in B$.
Let $f : E \rightarrow \mathbb{R}_0^+$ be a preflow. We introduce the notation

$$f(x, y) = \begin{cases} 
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We have

$$f(B)$$

Hence, the excess flow $f(b)$ must be 0 for every node $b \in B$. 

13.1 Generic Push Relabel
Let \( f : E \rightarrow \mathbb{R}_0^+ \) be a preflow. We introduce the notation

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

We have

\[
f(B) = \sum_{b \in B} f(b)
\]

Hence, the excess flow \( f(b) \) must be 0 for every node \( b \in B \).
Let $f : E \rightarrow \mathbb{R}_0^+$ be a preflow. We introduce the notation

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

We have

$$f(B) = \sum_{b \in B} f(b)$$

$$= \sum_{b \in B} \left( \sum_{v \in V} f(v, b) - \sum_{v \in V} f(b, v) \right)$$

$$\leq 0$$

Hence, the excess flow $f(b)$ must be 0 for every node $b \in B$. 

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We have
\[
f(B) = \sum_{b \in B} f(b) = \sum_{b \in B} \left( \sum_{v \in V} f(v, b) - \sum_{v \in V} f(b, v) \right) = \sum_{b \in B} \left( \sum_{v \in A} f(v, b) + \sum_{v \in B} f(v, b) - \sum_{v \in A} f(b, v) - \sum_{v \in B} f(b, v) \right) \leq 0.
\]
Hence, the excess flow $f(b)$ must be 0 for every node $b \in B$. 

13.1 Generic Push Relabel
Let \( f : E \to \mathbb{R}_0^+ \) be a preflow. We introduce the notation
\[
f(x, y) = \begin{cases} 
0 & (x, y) \notin E \\
f((x, y)) & (x, y) \in E
\end{cases}
\]

We have
\[
f(B) = \sum_{b \in B} f(b)
\]
\[
= \sum_{b \in B} \left( \sum_{v \in V} f(v, b) - \sum_{v \in V} f(b, v) \right)
\]
\[
= \sum_{b \in B} \left( \sum_{v \in A} f(v, b) + \sum_{v \in B} f(v, b) - \sum_{v \in A} f(b, v) - \sum_{v \in B} f(b, v) \right)
\]
\[
= \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 \( b \in B \).
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$$= 0$$

Hence, the excess flow $f(b)$ must be $0$ for every node $b \in B$. 

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$$\leq 0$$

Hence, the excess flow $f(b)$ must be 0 for every node $b \in B$. 

13.1 Generic Push Relabel
Lemma 31

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 $n$. 

Lemma 32

There are only $O(n^2)$ relabel operations.
Analysis

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Proof.
- Suppose that we just made a saturating push along $(u, v)$.
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The number of saturating pushes performed is at most $O(mn)$.

Proof.
- Suppose that we just made a saturating push along $(u,v)$.
- Hence, the edge $(u,v)$ is deleted from the residual graph.
Analysis

Lemma 33

The number of saturating pushes performed is at most $O(mn)$.

Proof.

- Suppose that we just made a saturating push along $(u, v)$.
- Hence, the edge $(u, v)$ is deleted from the residual graph.
- For the edge to appear again, a push from $v$ to $u$ is required.
Analysis

**Lemma 33**
The number of *saturating pushes* performed is at most $O(mn)$.

**Proof.**
- Suppose that we just made a saturating push along $(u,v)$.
- Hence, the edge $(u,v)$ is deleted from the residual graph.
- For the edge to appear again, a push from $v$ to $u$ is required.
- Currently, $\ell(u) = \ell(v) + 1$, as we only make pushes along admissible edges.
Analysis

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The number of saturating pushes performed is at most $O(mn)$.

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- Suppose that we just made a saturating push along $(u,v)$.
- Hence, the edge $(u,v)$ is deleted from the residual graph.
- For the edge to appear again, a push from $v$ to $u$ is required.
- Currently, $\ell(u) = \ell(v) + 1$, as we only make pushes along admissible edges.
- For a push from $v$ to $u$ the edge $(v,u)$ must become admissible. The label of $v$ must increase by at least 2.
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The number of saturating pushes performed is at most $O(mn)$.

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- Currently, $\ell(u) = \ell(v) + 1$, as we only make pushes along admissible edges.
- 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 $(u, v)$. 
Lemma 34

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

Proof.

Define a potential function $\Phi(f) = \sum$ active nodes $v \ell(v)$.

A saturating push increases $\Phi$ by at most $2n$ (when the target node becomes active it may contribute at most $2n$ to the sum).

A relabel increases $\Phi$ by at most $1$.

A non-saturating push decreases $\Phi$ 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, $\#\text{non-saturating pushes} \leq \#\text{relabels} + 2n \cdot \#\text{saturating pushes} \leq O(n^2 m)$. 

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

Proof.
- Define a potential function $\Phi(f) = \sum_{\text{active nodes}} \ell(v)$.
Lemma 34
The number of non-saturating pushes performed is at most $O(n^2m)$.

Proof.

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

$\therefore$ \#non-saturating pushes $\leq$ \#relabels $+ 2n \cdot$ \#saturating pushes $\leq O(n^2m)$.
Lemma 34

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

Proof.

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

$$\#\text{non-saturating\_pushes} \leq \#\text{relabels} + 2n \cdot \#\text{saturating\_pushes} \leq O(n^2 m) .$$
Theorem 35

There is an implementation of the generic push relabel algorithm with running time $O(n^2m)$.
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 \(G\)
- 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 \(\Theta(n)\):
- check for all outgoing edges if they become admissible
- check for all incoming edges if they become non-admissible
Analysis

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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 \(O(n)\)

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

Proof:

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

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

- check for all outgoing edges if they become admissible
- check for all incoming edges if they become non-admissible
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)
1: while u is active do
2: v ← u.current-neighbour
3: if v = null then
4: relabel(u)
5: u.current-neighbour ← u.neighbour-list-head
6: else
7: if (u, v) admissible then push(u, v)
8: else u.current-neighbour ← v.next-in-list
```

Note that $u.current-neighbour$ is a global variable. It is only changed within the discharge routine, but keeps its value between consecutive calls to discharge.
Lemma 36
If \( v = \text{null} \) 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 (\( v = \text{null} \)) all edges are not admissible.

This shows that \( \text{discharge}(u) \) is correct, and that we can perform a relabel in Line 4.
13.2 Relabel to Front

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

1: initialize preflow
2: initialize node list $L$ containing $V \setminus \{s, t\}$ in any order
3: **foreach** $u \in V \setminus \{s, t\} \text{ do}$
4: \hspace{1em} $u.$current-neighbour $\leftarrow$ $u.$neighbour-list-head
5: \hspace{1em} $u \leftarrow L.$head
6: **while** $u \neq \text{null} \text{ do}$
7: \hspace{1em} old-height $\leftarrow \ell(u)$
8: \hspace{1em} discharge$(u)$
9: \hspace{1em} **if** $\ell(u) > \text{old-height} \text{ then} // \text{ relabel happened}$
10: \hspace{2em} move $u$ to the front of $L$
11: \hspace{1em} $u \leftarrow u.$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 not create any new admissible edges. Therefore, if discharge() does not relabel $u$, $L$ is still topologically sorted.
  2. 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.
Lemma 38
There are at most $O(n^3)$ 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 $n(\#\text{relabels} + 1) = O(n^3)$. 
Lemma 39

The cost for all relabel-operations is only $O(n^2)$.

A relabel-operation at a node is constant time (increasing the label and resetting $u.current-neighbour$). In total we have $O(n^2)$ 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 \( \Theta(mn) \).*

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 \( u.current-neighbour \).

This pointer can traverse the neighbour-list at most \( \Theta(n) \) times (upper bound on number of relabels) and the neighbour-list has only \( \text{degree}(u) + 1 \) many entries (+1 for null-entry).
13.2 Relabel to Front

**Lemma 41**

*The cost for all non-saturating push-operations is only $O(n^3)$.*

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

**Theorem 42**

*The push-relabel algorithm with the rule relabel-to-front takes time $O(n^3)$.*
13.3 Highest Label

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

1: initialize preflow
2: **foreach** \(u \in V \setminus \{s, t\}\) **do**
3: \(u.current-neighbour \leftarrow u.neighbour-list-head\)
4: **while** \(\exists\) active node \(u\) **do**
5: select active node \(u\) with highest label
6: discharge\((u)\)
13.3 Highest Label

Lemma 43
When using highest label the number of non-saturating pushes is only $O(n^3)$.

A push from a node on level $\ell$ can only “activate” nodes on levels strictly less than $\ell$.

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 $n(#\text{relabels} + 1) = O(n^3)$.
Since a discharge-operation is terminated by a non-saturating push this gives an upper bound of $O(n^3)$ 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 $L_i, i \in \{0, \ldots, 2n\}$, 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 $L_k, L_{k-1}, \ldots, L_0$, (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

\[ \Theta(n^3) + n(\#\text{non-saturating-pushes-to-s-or-t}) \]

**Lemma 44**

*The number of non-saturating pushes to s or t is at most \( \Theta(n^2) \).*

With this lemma we get

**Theorem 45**

*The push-relabel algorithm with the rule highest-label takes time \( \Theta(n^3) \).*
13.3 Highest Label

Proof of the Lemma.

- We only show that the number of pushes to the source is at most $O(n^2)$. 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 $O(n^2)$. 
Mincost Flow

Problem Definition:

\[
\begin{align*}
\min & \quad \sum_{e} c(e)f(e) \\
\text{s.t.} & \quad \forall e \in E : \ 0 \leq f(e) \leq u(e) \\
& \quad \forall v \in V : \ f(v) = b(v)
\end{align*}
\]

\[G = (V, E)\] is a directed graph.

\[u : E \rightarrow \mathbb{R}^{+ \cup \{\infty\}}\] is the capacity function.

\[c : E \rightarrow \mathbb{R}\] is the cost function.

\[b : V \rightarrow \mathbb{R}, \quad \sum_{v \in V} b(v) = 0\] is a demand function.
Mincost Flow

Problem Definition:

\[
\begin{align*}
\text{min} & \quad \sum_e c(e)f(e) \\
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- \( G = (V,E) \) is a directed graph.
- \( u : E \to \mathbb{R}_0^+ \cup \{\infty\} \) is the capacity function.
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- \( b : V \to \mathbb{R}, \sum_{v \in V} b(v) = 0 \) is a demand function.
Mincost Flow

Problem Definition:

\[ \min \sum_e c(e) f(e) \]
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**Mincost Flow**

**Problem Definition:**

\[ \text{min} \sum_{e} c(e)f(e) \]
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- \( G = (V, E) \) is a directed graph.
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- \( b : V \to \mathbb{R}, \sum_{v \in V} b(v) = 0 \) is a demand function.
Solve Maxflow Using Mincost Flow

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.

- 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 $f_{\text{min}}$ is a mincost-flow.
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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.
Solve decision version of maxflow:

- Given a flow network for a standard maxflow problem, and a value $k$.
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Generalization

Our model:

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

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?

\[
\begin{align*}
\text{min} & \quad \sum_e c(e)f(e) \\
\text{s.t.} & \quad \forall e \in E : \ \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V : \ a(v) \leq f(v) \leq b(v)
\end{align*}
\]

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

\( c : E \to \mathbb{R}; \)
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\( c : E \to \mathbb{R}; \)
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

\[
\begin{align*}
\text{min} & \quad \sum_e c(e) f(e) \\
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& \quad \forall v \in V: \; a(v) \leq f(v) \leq b(v)
\end{align*}
\]

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

1. Add new node \( r \).
2. Add edge \((r,v)\) for all \( v \in V \).
3. Set \( \ell(e) = c(e) = 0 \) for these edges.
4. Set \( u(e) = b(v) - a(v) \) for edge \((r,v)\).
5. Set \( a(v) = b(v) \) for all \( v \in V \).
6. Set \( b(r) = -\sum_v b(v) \).

\( -\sum_v b(v) \) is negative; hence \( r \) is only sending flow.
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\begin{align*}
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Add edge $(r, v)$ for all $v \in V$.

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\(-\sum_{v} b(v)\) is negative; hence \( r \) is only sending flow.
Reduction II

\[
\begin{align*}
\min & \quad \sum_e c(e) f(e) \\
\text{s.t.} & \quad \forall e \in E : \quad \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V : \quad f(v) = b(v)
\end{align*}
\]

We can assume that either \( \ell(e) \neq -\infty \) or \( u(e) \neq \infty \):

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 \( c(e) = 0 \).
Reduction II

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\begin{align*}
\min & \quad \sum_e c(e)f(e) \\
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Reduction II

We can transform any network so that a particular edge has cost $c(e) = 0$:

Additionally we set $b(u) = 0$. 

$u(e) = \infty$  
$\ell(e) = -\infty$  
$c(e) = \delta \neq 0$
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Reduction III

\[
\begin{align*}
\text{min} & \quad \sum_e c(e) f(e) \\
\text{s.t.} & \quad \forall e \in E : \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V : f(v) = b(v)
\end{align*}
\]

We can assume that \(\ell(e) \neq -\infty\):

Replace the edge by an edge in opposite direction.
Reduction IV

\[
\begin{align*}
\min & \quad \sum_e c(e)f(e) \\
\text{s.t.} & \quad \forall e \in E : \ \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V : \ f(v) = b(v)
\end{align*}
\]

We can assume that \( \ell(e) = 0 \): 

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.
- At the end of each day she should determine how many to send to each laundry and how many to buy in order to fulfill demand.
- Minimize cost.
Applications

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- She needs to supply $r_i$ napkins on $N$ successive days.
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- At the end of each day she should determine how many to send to each laundry and how many to buy in order to fulfill demand.
- Minimize cost.
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: \( u(e_i) = \infty \);
lower bound: \( \ell(e_i) = 0 \);
cost: \( c(e) = 0 \)
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: $c(e) = 0$
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.

For a flow of $z$ from $u$ to $v$ the residual edge $(v,u)$ has capacity $z$ and a cost of $-c((u,v))$. 
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A circulation in a graph $G = (V, E)$ is a function $f : E \rightarrow \mathbb{R}^+$ that has an excess flow $f(v) = 0$ for every node $v \in V$.

A circulation is feasible if it fulfills capacity constraints, i.e., $f(e) \leq u(e)$ for every edge of $G$. 
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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.

Suppose that $g$ is a feasible circulation of negative cost in the residual graph. Then $f + g$ is a feasible flow with cost $\text{cost}(f) + \text{cost}(g) < \text{cost}(f)$. Hence, $f$ is not minimum cost.

$\Rightarrow$

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. (after sending $-f$ in the residual graph (pushing all flow back) we arrive at the original graph; for this $f^*$ is clearly feasible)
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$\Leftarrow$ 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.

Clearly $f^* - f$ is a circulation of negative cost. One can also easily see that it is feasible for the residual graph. (after sending $-f$ in the residual graph (pushing all flow back) we arrive at the original graph; for this $f^*$ is clearly feasible).
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A graph (without zero-capacity edges) has a feasible circulation of negative cost if and only if it has a negative cycle w.r.t. edge-weights $c : E \rightarrow \mathbb{R}$.

Proof.
Suppose that we have a negative cost circulation.
Find directed path only using edges that have non-zero flow.
If this path has negative cost you are done.
Otherwise send flow in opposite direction along the cycle until the bottleneck edge(s) does not carry any flow.
You still have a circulation with negative cost.
Repeat.
14 Mincost Flow

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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: $\delta \leftarrow \min\{u_f(e) | e \in Z\}$
5: augment $\delta$ 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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Lemma 48

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

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

Note that this lemma is weak since it does not allow for edges with infinite capacity.
A general mincost flow problem is of the following form:

\[
\begin{align*}
\min & \quad \sum_{e} c(e)f(e) \\
\text{s.t.} & \quad \forall e \in E : \quad \ell(e) \leq f(e) \leq u(e) \\
& \quad \forall v \in V : \quad a(v) \leq f(v) \leq b(v)
\end{align*}
\]

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

![Diagram of a directed graph](image)
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- Construct a directed graph $G' = (V, E')$ that has edges $(u, v)$ and $(v, u)$ for every edge $\{u, v\} \in E$.
- 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: $O(n^4)$)

![Graph Diagram](image-url)
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- Construct a directed graph $G' = (V, E')$ that has edges $(u, v)$ and $(v, u)$ for every edge \( \{u, v\} \in E \).
- 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: $O(n^4)$)
- 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 $|\{s, t\} \cap S| = 1$. 

![Diagram of a directed graph](image)
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.
Edge Contractions

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Edge Contractions

We can perform an edge-contraction in time $O(n)$. 
Algorithm 1 KargerMincut($G = (V, E, c)$)

1: for $i = 1 \rightarrow n - 2$ do
2: \hspace{0.5cm} choose $e \in E$ randomly with probability $c(e)/c(E)$
3: \hspace{0.5cm} $G \leftarrow G/e$
4: \hspace{0.5cm} return only cut in $G$
Randomized MinCut Algorithm

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\textbf{Algorithm 1} \quad \text{KargerMinCut}(G = (V, E, c))
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1: \textbf{for} \( i = 1 \rightarrow n - 2 \) \textbf{do}
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\[\triangleright\] Let \( G_t \) denote the graph after the \((n - t)\)-th iteration, when \( t \) nodes are left.
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- Note that the final graph \(G_2\) only contains a single edge.
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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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$n - i + 1$ is the number of nodes in graph $G_{n-i+1} = (V_{n-i+1}, E_{n-i+1})$, the graph at the start of iteration $i$.  

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Analysis

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1 - \frac{2}{n - i + 1} = \frac{n - i - 1}{n - i + 1}.
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The probability that the cut is alive after iteration \( n - t \) (after which \( t \) nodes are left) is

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

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\left(1 - \frac{1}{\binom{n}{2}}\right)^{\binom{n}{2} c \ln n} \leq \left(e^{-1/(\binom{n}{2})}\right)^{\binom{n}{2} c \ln n} \leq n^{-c},
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where we used \( 1 - x \leq e^{-x} \).

**Theorem 51**

*The randomized mincut algorithm computes an optimal cut with high probability. The total running time is \( \Theta(n^4 \log n) \).*
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The randomized mincut algorithm computes an optimal cut with high probability. The total running time is \( \Theta(n^4 \log n) \).
Analysis

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

\[
\left(1 - \frac{1}{\binom{n}{2}}\right)^{\binom{n}{2}c \ln n} \leq \left(e^{-1/\binom{n}{2}}\right)^{\binom{n}{2}c \ln n} \leq n^{-c},
\]

where we used \( 1 - x \leq e^{-x} \).

Theorem 51
The randomized mincut algorithm computes an optimal cut with high probability. The total running time is \( \Theta(n^4 \log n) \).
Analysis

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

$$\left(1 - \frac{1}{\binom{n}{2}}\right)^{\binom{n}{2} c \ln n} \leq \left(e^{-1/\binom{n}{2}}\right)^{\binom{n}{2} c \ln n} \leq n^{-c},$$

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

**Theorem 51**
The randomized mincut algorithm computes an optimal cut with high probability. The total running time is $O(n^4 \log n)$. 
Analysis

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

$$\left(1 - \frac{1}{\binom{n}{2}}\right)^{\binom{n}{2}c \ln n} \leq \left(e^{-1/\binom{n}{2}}\right)^{\binom{n}{2}c \ln n} \leq n^{-c},$$

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

**Theorem 51**

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

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

1: for \(i = 1 \rightarrow n - n/\sqrt{2}\) do
2: choose \(e \in E\) randomly with probability \(c(e)/c(E)\)
3: \(G \leftarrow G/e\)
4: if \(|V| = 2\) return cut-value;
5: \(cuta \leftarrow\) RecursiveMincut\((G)\);
6: \(cutb \leftarrow\) RecursiveMincut\((G)\);
7: return \(\min\{cuta, cutb\}\)

Running time:

\[T(n) = 2T\left(n/\sqrt{2}\right) + O(n^2)\]

This gives \(T(n) = O(n^2 \log n)\).

Note that the above implementation only works for very special values of \(n\).
Improved Algorithm

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

1: \textbf{for} \(i = 1 \rightarrow n - n/\sqrt{2}\) \textbf{do}
2: \hspace{1em} choose \(e \in E\) randomly with probability \(c(e)/c(E)\)
3: \hspace{1em} \(G \leftarrow G/e\)
4: \hspace{1em} \textbf{if} \(|V| = 2\) \textbf{return} cut-value;
5: \hspace{1em} \(cuta \leftarrow \text{RecursiveMincut}(G)\);
6: \hspace{1em} \(cutb \leftarrow \text{RecursiveMincut}(G)\);
7: \hspace{1em} \textbf{return} \(\min\{cuta, cutb\}\)

Running time:

\[ T(n) = 2T\left(\frac{n}{\sqrt{2}}\right) + \Theta(n^2) \]

This gives \(T(n) = \Theta(n^2 \log n)\).
Improved Algorithm

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

1: \textbf{for } \(i = 1 \rightarrow n - n/\sqrt{2}\) \textbf{ do}
2: \hspace{1em} \text{choose } e \in E \text{ randomly with probability } c(e)/c(E)
3: \hspace{1em} G \leftarrow G/e
4: \hspace{1em} \textbf{if } |V| = 2 \textbf{ return cut-value;}
5: \hspace{1em} cuta \leftarrow \text{RecursiveMincut}(G);
6: \hspace{1em} cutb \leftarrow \text{RecursiveMincut}(G);
7: \textbf{return} \ \min\{cuta, cutb\}

Running time:

- \(T(n) = 2T\left(\frac{n}{\sqrt{2}}\right) + \mathcal{O}(n^2)\)
- This gives \(T(n) = \mathcal{O}(n^2 \log n)\).
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 \( t = \frac{n}{\sqrt{2}} \).

We can estimate the success probability by using the following game on the recursion tree. Delete every edge with probability $\frac{1}{2}$. If in the end you have a path from the root to at least one leaf node you are successful.
Probability of Success

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

We can estimate the success probability by using the following game on the recursion tree. Delete every edge with probability \( \frac{1}{2} \). If in the end you have a path from the root to at least one leaf node you are successful.
Probability of Success

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

We can estimate the success probability by using the following game on the recursion tree. Delete every edge with probability $\frac{1}{2}$. If in the end you have a path from the root to at least one leaf node you are successful.
**Probability of Success**

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.

**Lemma 52**

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

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.

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Lemma 52

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**Lemma 52**

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

Proof.

- An edge \( e \) with \( h(e) = 1 \) is alive if and only if it is not deleted. Hence, it is alive with probability at least \( \frac{1}{2} \).
Probability of Success

Proof.

- An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.

- Let $p_d$ be the probability that an edge $e$ with $h(e) = d$ is alive. For $d > 1$ this happens for edge $e = \{c, p\}$ if it is not deleted and if one of the child-edges connecting to $c$ is alive.
Probability of Success

Proof.

- An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.

- Let $p_d$ be the probability that an edge $e$ with $h(e) = d$ is alive. For $d > 1$ this happens for edge $e = \{c, p\}$ if it is not deleted and if one of the child-edges connecting to $c$ is alive.

- This happens with probability $\frac{1}{2}$ (since $h(e) = d$ and $h(e) = d - 1$ are independent events).
Proof.

- An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.
- Let $p_d$ be the probability that an edge $e$ with $h(e) = d$ is alive. For $d > 1$ this happens for edge $e = \{c, p\}$ if it is not deleted and if one of the child-edges connecting to $c$ is alive.
- This happens with probability $p_d$
Probability of Success

Proof.

- An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.

- Let $p_d$ be the probability that an edge $e$ with $h(e) = d$ is alive. For $d > 1$ this happens for edge $e = \{c, p\}$ if it is not deleted and if one of the child-edges connecting to $c$ is alive.

- This happens with probability

$$p_d = \frac{1}{2} \left( 2p_{d-1} - p_{d-1}^2 \right)$$
Probability of Success

Proof.

▶ An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.

▶ Let $p_d$ be the probability that an edge $e$ with $h(e) = d$ is alive. For $d > 1$ this happens for edge $e = \{c, p\}$ if it is not deleted and if one of the child-edges connecting to $c$ is alive.

▶ This happens with probability

$$p_d = \frac{1}{2} \left( 2p_{d-1} - p^2_{d-1} \right)$$

$$\Pr[A \lor B] = \Pr[A] + \Pr[B] - \Pr[A \land B]$$
Probability of Success

Proof.

▶ An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.

▶ Let $p_d$ be the probability that an edge $e$ with $h(e) = d$ is alive. For $d > 1$ this happens for edge $e = \{c, p\}$ if it is not deleted and if one of the child-edges connecting to $c$ is alive.

▶ This happens with probability

$$p_d = \frac{1}{2} \left(2p_{d-1} - p_{d-1}^2\right)$$

$$= p_{d-1} - \frac{p_{d-1}^2}{2}$$

$$\Pr[A \lor B] = \Pr[A] + \Pr[B] - \Pr[A \land B]$$
Probability of Success

Proof.

- An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.

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$$p_d = \frac{1}{2} \left( 2p_{d-1} - p_{d-1}^2 \right)$$

$$= p_{d-1} - \frac{p_{d-1}^2}{2}$$

$x - x^2/2$ is monotonically increasing for $x \in [0, 1]$
Probability of Success

Proof.

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- Let $p_d$ be the probability that an edge $e$ with $h(e) = d$ is alive. For $d > 1$ this happens for edge $e = \{c, p\}$ if it is not deleted and if one of the child-edges connecting to $c$ is alive.
- This happens with probability

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$x - x^2/2$ is monotonically increasing for $x \in [0, 1]$

Pr[$A \lor B$] = Pr[$A$] + Pr[$B$] − Pr[$A \land B$]
Probability of Success

Proof.

- An edge $e$ with $h(e) = 1$ is alive if and only if it is not deleted. Hence, it is alive with probability at least $\frac{1}{2}$.

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$Pr[A \lor B] = Pr[A] + Pr[B] - Pr[A \land B]$
Probability of Success

Proof.

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- This happens with probability

$$p_d = \frac{1}{2} \left( 2p_{d-1} - p_{d-1}^2 \right)$$

$$= p_{d-1} - \frac{p_{d-1}^2}{2}$$

$x - x^2/2$ is monotonically increasing for $x \in [0, 1]$

$$\geq \frac{1}{d} - \frac{1}{2d^2} \geq \frac{1}{d} - \frac{1}{d(d + 1)} = \frac{1}{d + 1}.$$
Lemma 53

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

Doing $\Theta(\log^2 n)$ runs gives that the algorithm succeeds with high probability. The total running time is $\Theta(n^2 \log^3 n)$. 
Lemma 53

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

Doing $\Theta(\log^2 n)$ runs gives that the algorithm succeeds with high probability. The total running time is $\Theta(n^2 \log^3 n)$. 
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 $S_1, \ldots, S_t$), and a spanning tree $T$ on the vertex set $\{S_1, \ldots, S_t\}$.

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 $V$. 
Overview of the Algorithm

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

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Overview of the Algorithm

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In the end this gives a tree on the vertex set $V$. 
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 $f_H(a, b)$.
- Replace an edge $\{S_i, S_x\}$ by $\{S_i^a, S_x\}$ if $S_x \subset A$ and by $\{S_i^b, S_x\}$ if $S_x \subset B$. 

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  - Replace an edge $\{S_i, S_x\}$ by $\{S_i^a, S_x\}$ if $S_x \subseteq A$ and by $\{S_i^b, S_x\}$ if $S_x \subseteq B$. 

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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 $f_H(a, b)$.
- Replace an edge $\{S_i, S_x\}$ by $\{S_i^a, S_x\}$ if $S_x \subset A$ and by $\{S_i^b, S_x\}$ if $S_x \subset B$. 
**Details of the Split-operation**

- Select $S_i$ that contains at least two nodes $a$ and $b$.
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- 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 $f_H(a,b)$.
- Replace an edge $\{S_i, S_x\}$ by $\{S_i^a, S_x\}$ if $S_x \subset A$ and by $\{S_i^b, S_x\}$ if $S_x \subset B$. 
Example: Gomory-Hu Construction
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Analysis

Lemma 54
For nodes $s, t, x \in V$ we have $f(s, t) \geq \min\{f(s, x), f(x, t)\}$

Lemma 55
For nodes $s, t, x_1, \ldots, x_k \in V$ we have
$$f(s, t) \geq \min\{f(s, x_1), f(x_1, x_2), \ldots, f(x_{k-1}, x_k), f(x_k, t)\}$$
Lemma 54

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$f(s, t) \geq \min\{f(s, x_1), f(x_1, x_2), \ldots, f(x_{k-1}, x_k), f(x_k, t)\}$
Lemma 56

Let $S$ be some minimum $r$-$s$ cut for some nodes $r, s \in V$ ($s \in S$), and let $v, w \in S$. Then there is a minimum $v$-$w$-cut $T$ with $T \subset S$.

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

We may assume w.l.o.g. $s \in X$.

First case $r \in X$.

$\cap B (X \setminus S) + \cap B (S \setminus X) \leq \cap B (S) + \cap B (X)$

$\cap B (X) \geq \cap B (S)$ because $X \setminus S$ is an $r$-$s$ cut.

This gives $\cap B (S \setminus X) \leq \cap B (X)$.

Second case $r \notin X$.

$\cap B (X \cup (S \setminus X)) + \cap B (S \cap X) \leq \cap B (S) + \cap B (X)$

$\cap B (X \cup S) \geq \cap B (S)$ because $X \cup S$ is an $r$-$s$ cut.

This gives $\cap B (S \cap X) \leq \cap B (X)$. 
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First case $r \in X$.
- $\cap_p (X \setminus S) + \cap_p (S \setminus X) \leq \cap_p (S) + \cap_p (X)$.
- $\cap_p (X \setminus S) \geq \cap_p (S)$ because $X \setminus S$ is an $r$-$s$ cut.
  - This gives $\cap_p (S \setminus X) \leq \cap_p (X)$.

Second case $r \notin X$.
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This gives $\cap (S \setminus X) \leq \cap (X)$.

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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 $S$. We may assume w.l.o.g. $s \in X$.

First case $r \in X$.

Second case $r \notin X$. 

This gives us the desired result.
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- This gives $\text{cap}(S \setminus X) \leq \text{cap}(X)$.

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Second case $r \not\in X$.
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- This gives $\cap (S \setminus X) \leq \cap (X)$.

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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 $H$. 

16 Gomory Hu Trees

Ernst Mayr, Harald Räcke
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 \( G \).
**Analysis**

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

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- Let $s = x_0, x_1, \ldots, x_{k-1}, x_k = t$ be the unique simple path from $s$ to $t$ in the final tree $T$. From the invariant we get that $f(x_i, x_{i+1}) = w(x_i, x_{i+1})$ for all $j$.

- Then $f_T(s, t) = \min_{i \in \{0, \ldots, k-1\}} \{w(x_i, x_{i+1})\} = \min_{i \in \{0, \ldots, k-1\}} \{f(x_i, x_{i+1})\} \leq f(s, t)$.

- 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 $f(s, t) \leq f(x_j, x_{j+1}) = f_T(s, t)$. 

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

- Let $s = x_0, x_1, \ldots, x_k = t$ be the unique simple path from $s$ to $t$ in the final tree $T$. From the invariant we get that $f(x_i, x_{i+1}) = w(x_i, x_{i+1})$ for all $j$.
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Analysis

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

- Let $s = x_0, x_1, \ldots, x_{k-1}, x_k = t$ be the unique simple path from $s$ to $t$ in the final tree $T$. From the invariant we get that $f(x_i, x_{i+1}) = w(x_i, x_{i+1})$ for all $j$.
- Then

$$f_T(s, t) = \min_{i \in \{0, \ldots, k-1\}} \{ w(x_i, x_{i+1}) \}$$
Analysis

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

- Let $s = x_0, x_1, \ldots, x_{k-1}, x_k = t$ be the unique simple path from $s$ to $t$ in the final tree $T$. From the invariant we get that $f(x_i, x_{i+1}) = w(x_i, x_{i+1})$ for all $j$.
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$$f_T(s, t) = \min_{i \in \{0, \ldots, k-1\}} \{w(x_i, x_{i+1})\}$$

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Analysis

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

1. Let $s = x_0, x_1, \ldots, x_{k-1}, x_k = t$ be the unique simple path from $s$ to $t$ in the final tree $T$. From the invariant we get that $f(x_i, x_{i+1}) = w(x_i, x_{i+1})$ for all $j$.

2. Then

$$f_T(s, t) = \min_{i \in \{0, \ldots, k-1\}} \{w(x_i, x_{i+1})\}$$

$$= \min_{i \in \{0, \ldots, k-1\}} \{f(x_i, x_{i+1})\} \leq f(s, t) .$$
Analysis

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

- Let \( s = x_0, x_1, \ldots, x_{k-1}, x_k = t \) be the unique simple path from \( s \) to \( t \) in the final tree \( T \). From the invariant we get that \( f(x_i, x_{i+1}) = w(x_i, x_{i+1}) \) for all \( j \).

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- Let \( \{x_j, x_{j+1}\} \) be the edge with minimum weight on the path.
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- Since by the invariant this edge induces an $s$-$t$ cut with capacity $f(x_j, x_{j+1})$ we get $f(s, t) \leq f(x_j, x_{j+1}) = f_T(s, t)$. 
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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- 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).
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 $\{S^a_i, S^b_i\}$ with capacity $w(S^a_i, S^b_i) = f_H(a, b)$ we can simply choose $a$ and $b$ as representatives.
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.

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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 $\{S^a_i, S^b_i\}$ with capacity $w(S^a_i, S^b_i) = f_H(a, b)$ 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.

Consider an edge $\{X, S_i\}$, and suppose that before the split it used representatives $x \in X$, and $s \in S_i$. Assume that this edge is replaced by $\{X, S_i^a\}$ in the new tree (the case when it is replaced by $\{X, S_i^b\}$ is analogous).

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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Proof of Invariant

Because the invariant was true before the split we know that the edge \( \{X, S_i\} \) induces a cut in \( G \) of capacity \( f(x, s) \). Since, \( x \) and \( a \) are on opposite sides of this cut, we know that 
\[ f(x, a) \leq f(x, s). \]

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 
\[ f'(x, a) = f(x, a) \text{ as } x, a \not\in B. \]

We further have 
\[ f'(x, a) \geq \min\{f'(x, v_B), f'(v_B, a)\}. \]

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

Also, \( f'(a, v_B) \geq f(a, b) \geq f(x, s) \) 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

$S_i$
Analysis

Gomory Hu Trees
Analysis
Analysis

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Ernst Mayr, Harald Räcke
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