Chapter 6
Graph Algorithms

Algorithm Theory
WS 2018/19

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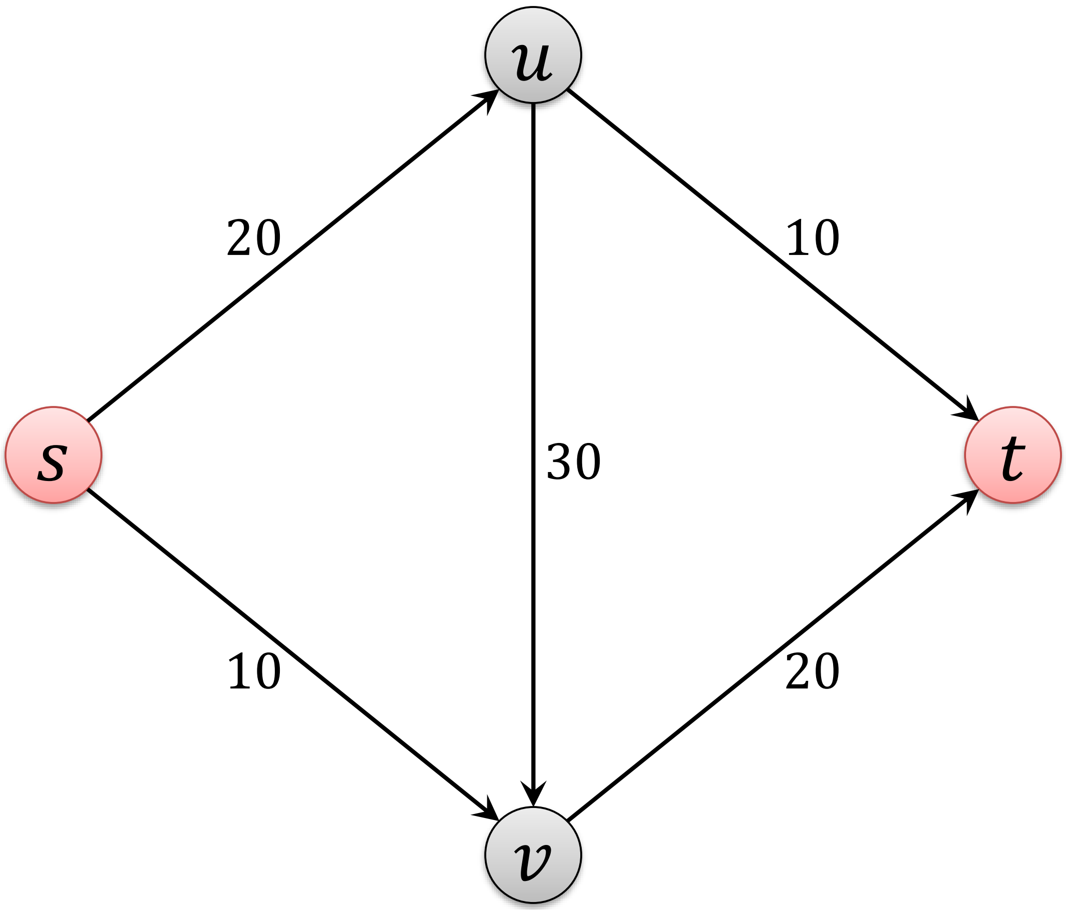
Example: Flow Network



Network Flow: Definition

Flow: function $\boldsymbol{f}: \boldsymbol{E} \to \mathbb{R}_{\geq 0}$

- $f(e)$ is the amount of flow carried by edge e

Capacity Constraints:

- For each edge $e \in E$, $f(e) \leq c_e$

Flow Conservation:

- For each node $v \in V \setminus \{s, t\}$,

$$\sum_{e \text{ into } v} f(e) = \sum_{e \text{ out of } v} f(e)$$

Flow Value:

$$|f| := \sum_{e \text{ out of } s} f\big((s,u)\big) = \sum_{e \text{ into } t} f\big((v,t)\big)$$

The Maximum-Flow Problem

Maximum Flow:

Given a flow network, find a flow of maximum possible value

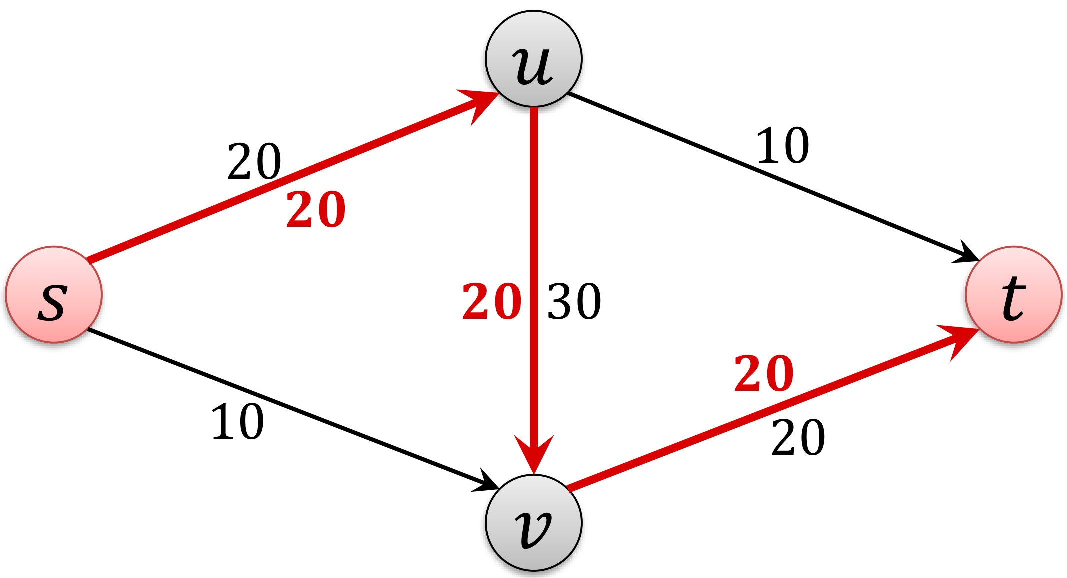
- Classical graph optimization problem
- Many applications (also beyond the obvious ones)
- Requires new algorithmic techniques

Residual Graph

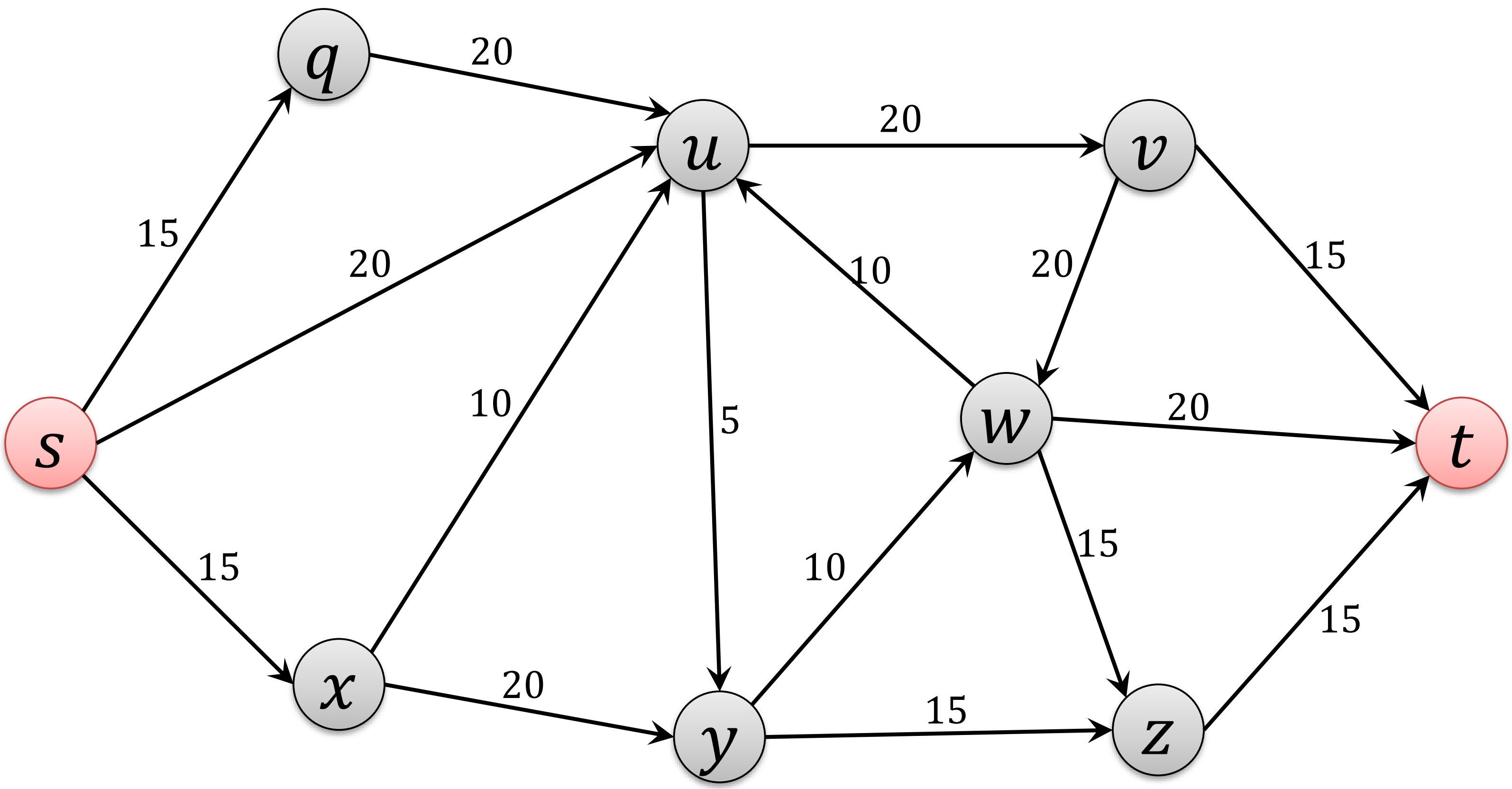
Given a flow network $G = (V, E)$ with capacities c_e (for $e \in E$)

For a flow f on G, define directed graph $G_f = (V_f, E_f)$ as follows:

- Node set $V_f = V$
- For each edge $e = (u, v)$ in E, there are two edges in E_f:
  - forward edge $e = (u, v)$ with residual capacity $c_e - f(e)$
  - backward edge $e' = (v, u)$ with residual capacity $f(e)$

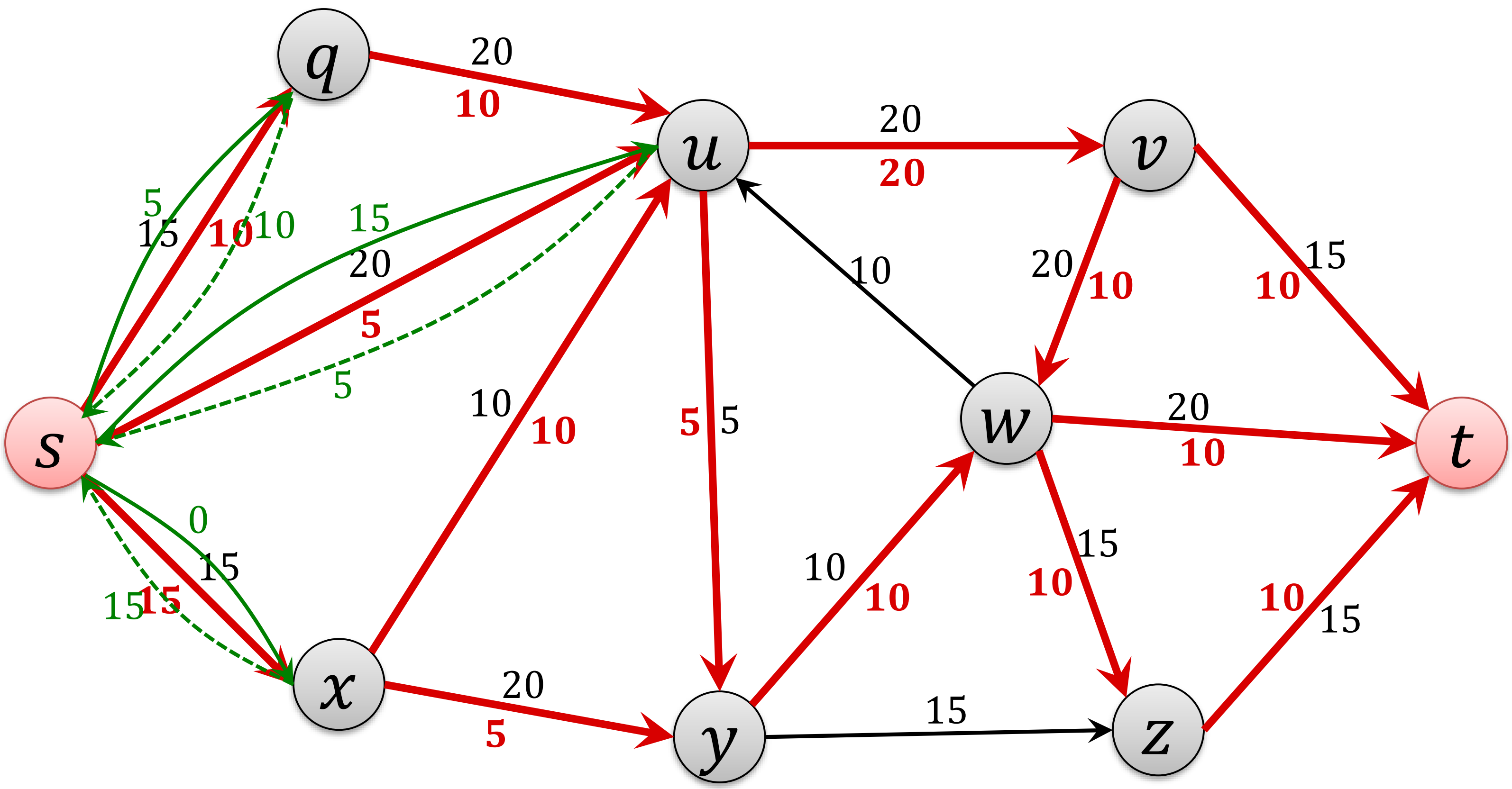


Residual Graph: Example



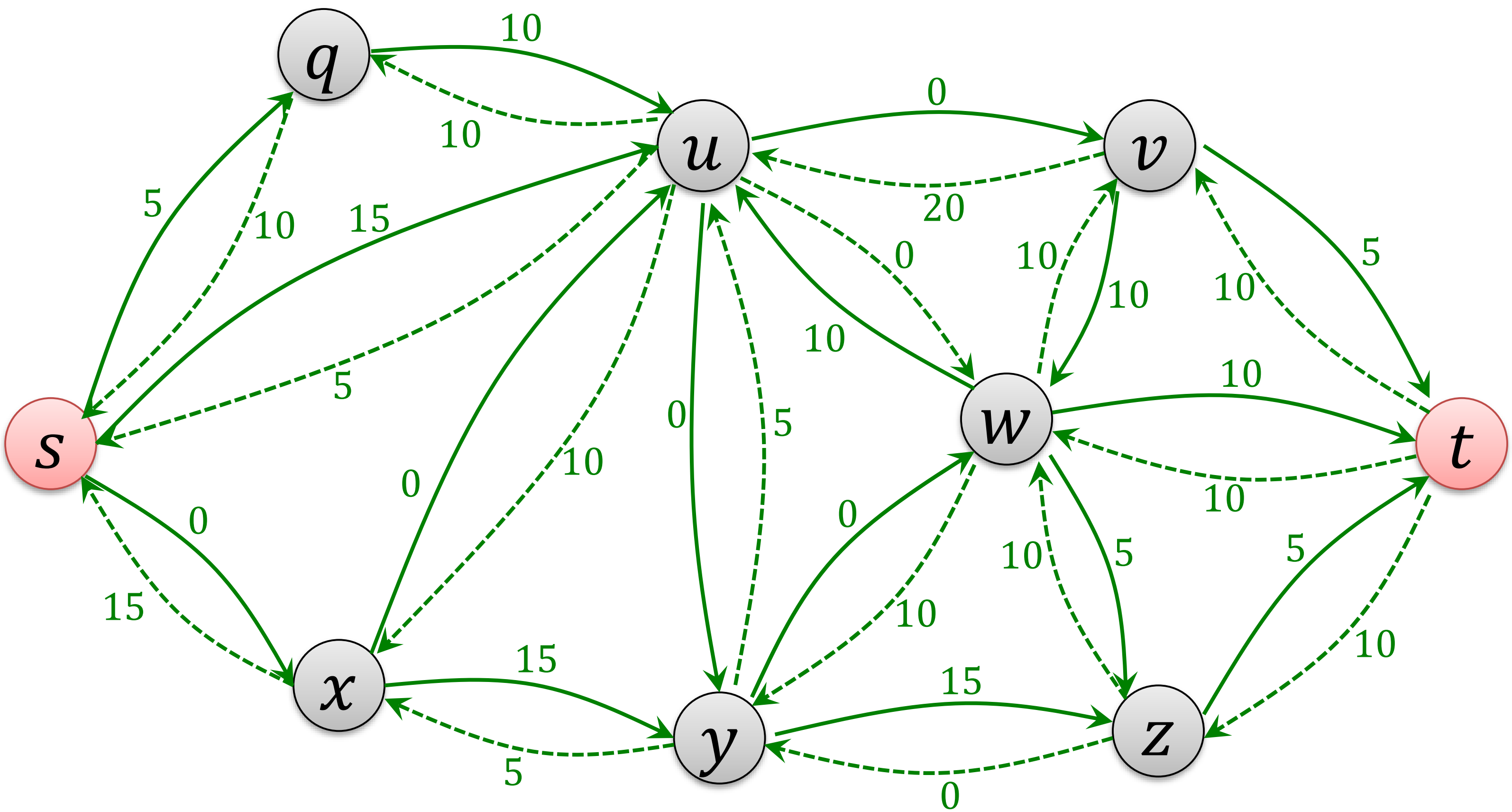
Residual Graph: Example

Flow f



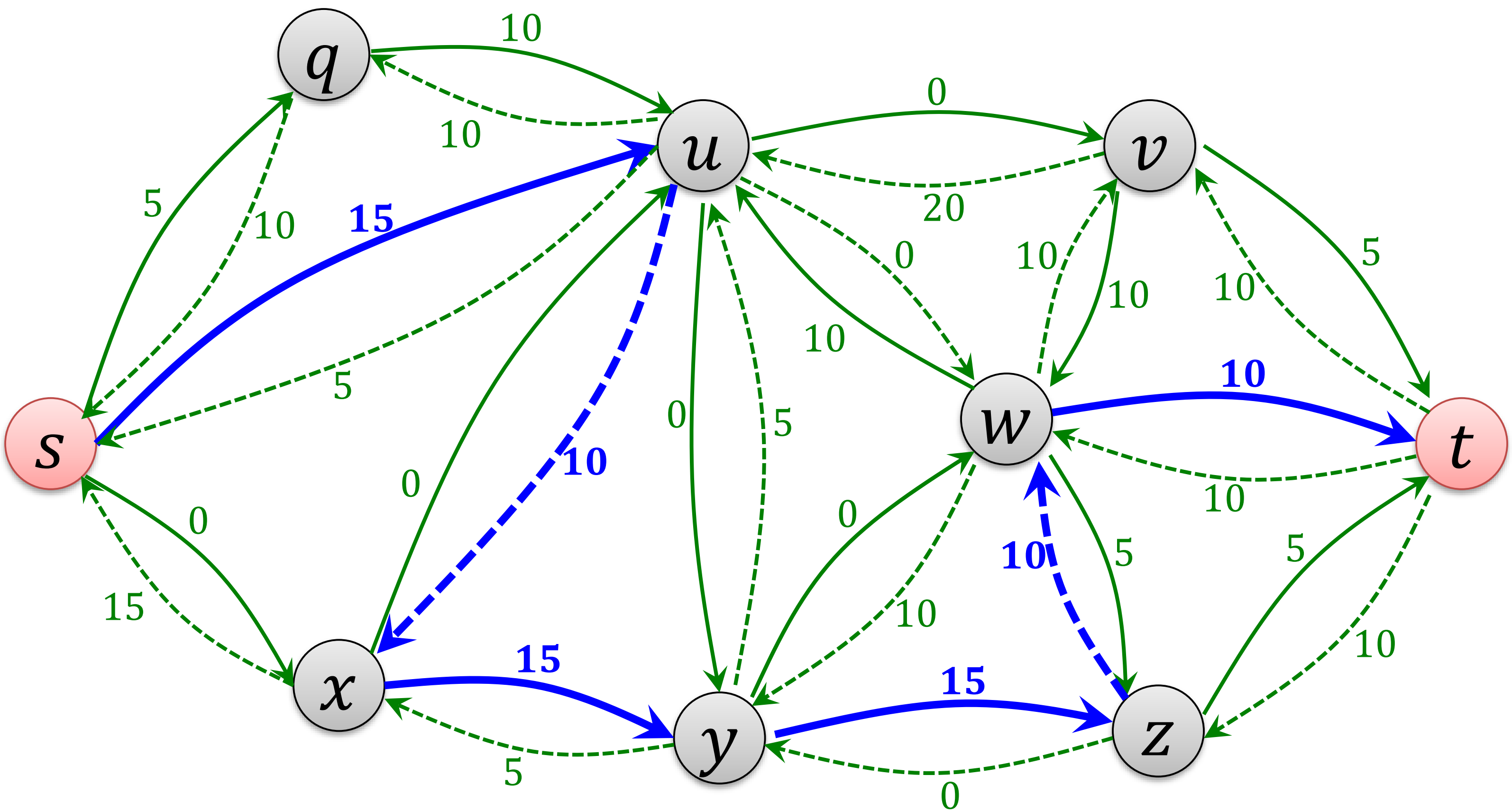
Residual Graph: Example

Residual Graph G_f

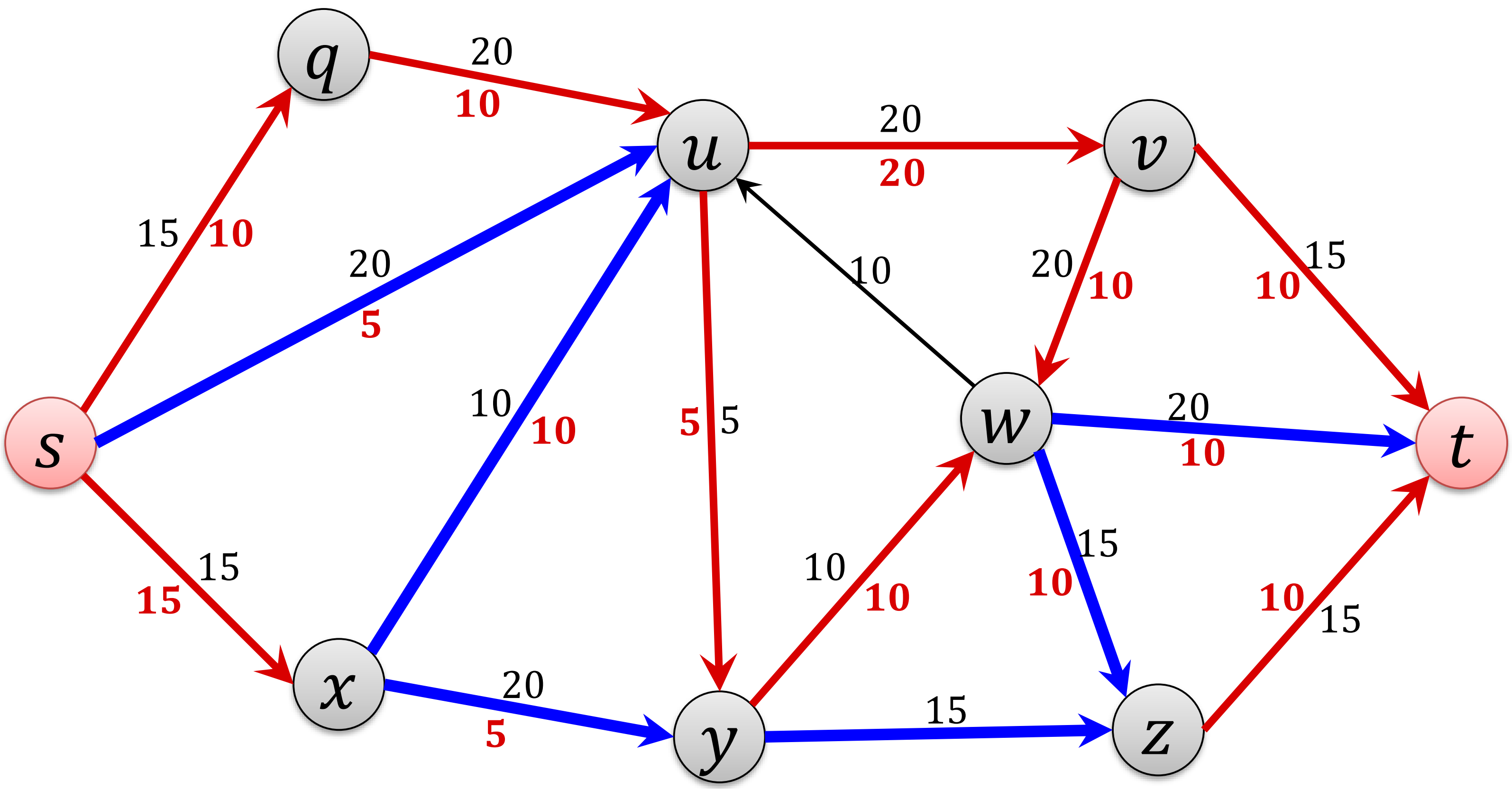


Augmenting Path

Residual Graph G_f

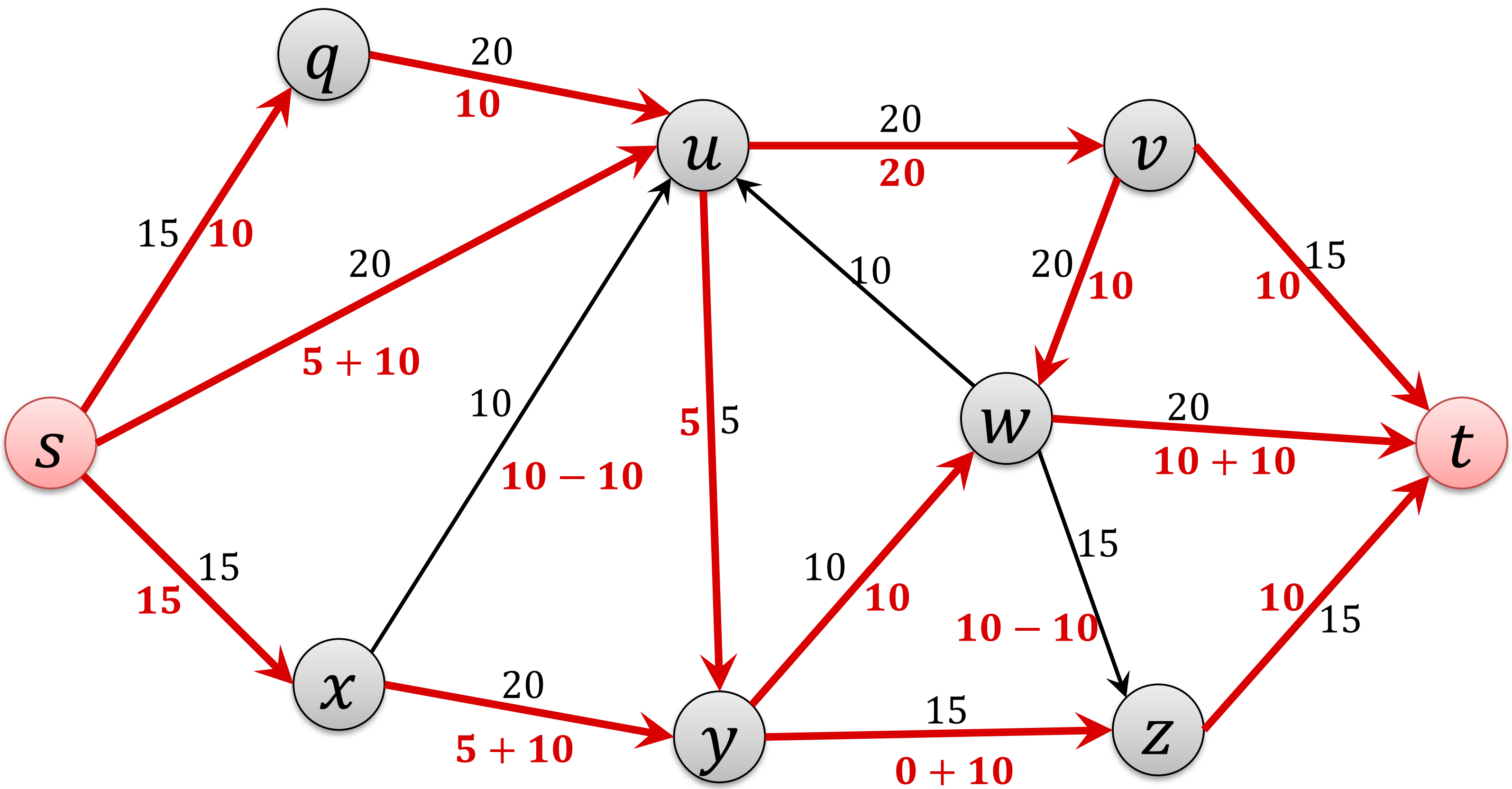


Augmenting Path



Augmenting Path

New Flow



Augmenting Path

Definition:
An augmenting path P is a (simple) s-t-path on the residual graph G_f on which each edge has residual capacity > 0.

$\text{bottleneck}(P, f)$: minimum residual capacity on any edge of the augmenting path P

Augment flow $\boldsymbol{f}$ to get flow $\boldsymbol{f'}$:

- For every forward edge (u, v) on P:

$$\boldsymbol{f'\big((u,v)\big) := f\big((u,v)\big) + \textbf{bottleneck}(P,f)}$$

- For every backward edge (u, v) on P:

$$\boldsymbol{f'\big((v,u)\big) := f\big((v,u)\big) - \textbf{bottleneck}(P,f)}$$

Augmented Flow

Lemma: Given a flow f and an augmenting path P, the resulting augmented flow f' is legal and its value is

$$|\boldsymbol{f}'| = |\boldsymbol{f}| + \mathbf{bottleneck}(\boldsymbol{P}, \boldsymbol{f}).$$

Proof:

Augmented Flow

Lemma: Given a flow f and an augmenting path P, the resulting augmented flow f' is legal and its value is

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Proof:

Ford-Fulkerson Algorithm

- Improve flow using an augmenting path as long as possible:

1. Initially, $f(e) = 0$ for all edges $e \in E$, $G_f = G$
2. **while** there is an augmenting s-t-path P in G_f **do**
3. Let P be an augmenting s-t-path in G_f;
4. $f' \coloneqq \text{augment}(f, P)$;
5. update f to be f';
6. update the residual graph G_f
7. **end**;

Ford-Fulkerson Running Time

Theorem: If all edge capacities are integers, the Ford-Fulkerson algorithm terminates after at most C iterations, where

$$C = \text{"max flow value"} \leq \sum_{e \text{ out of } s} c_e \,.$$

Proof:

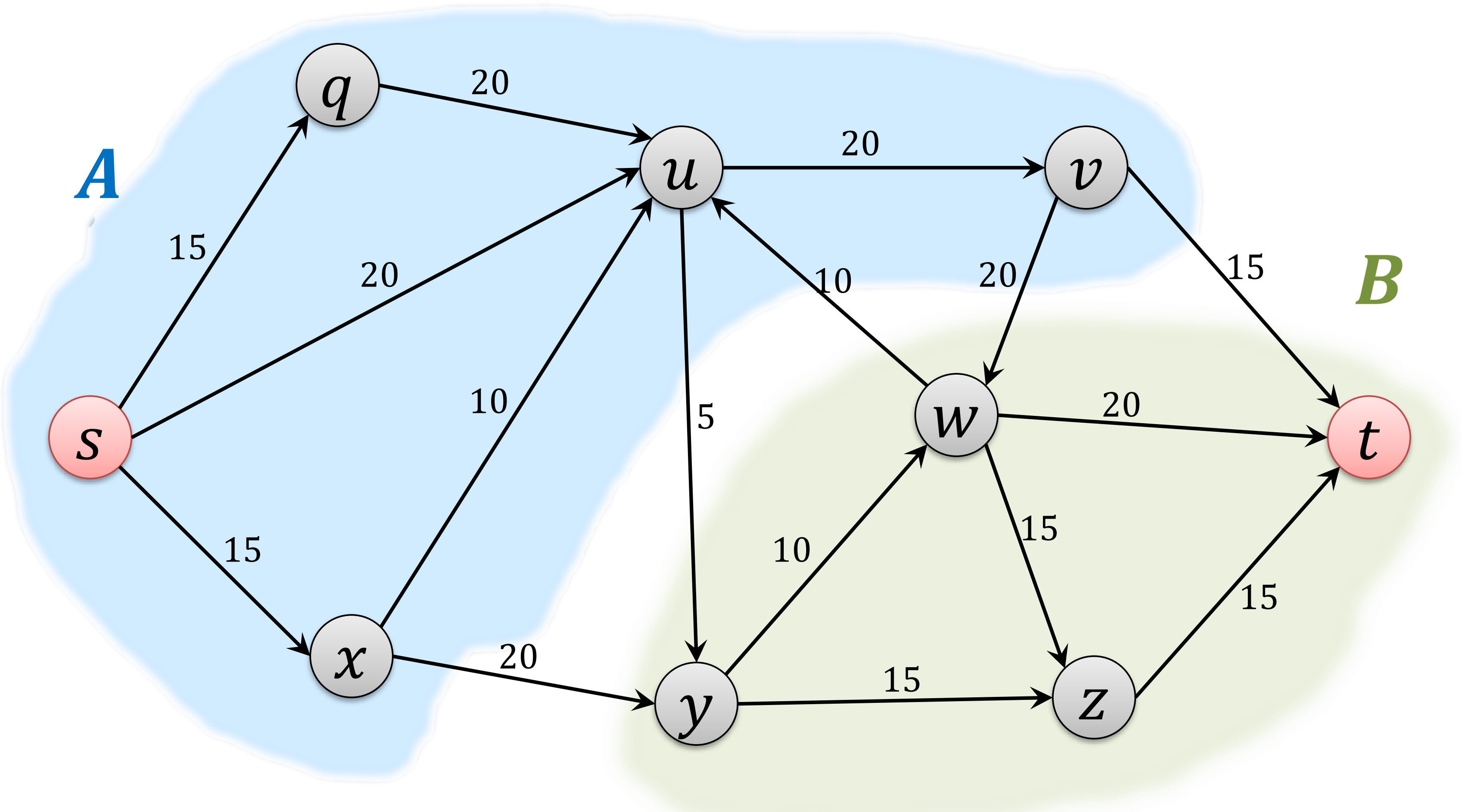
Ford-Fulkerson Running Time

Theorem: If all edge capacities are integers, the Ford-Fulkerson algorithm can be implemented to run in $O(mC)$ time.

Proof:

s-t Cuts

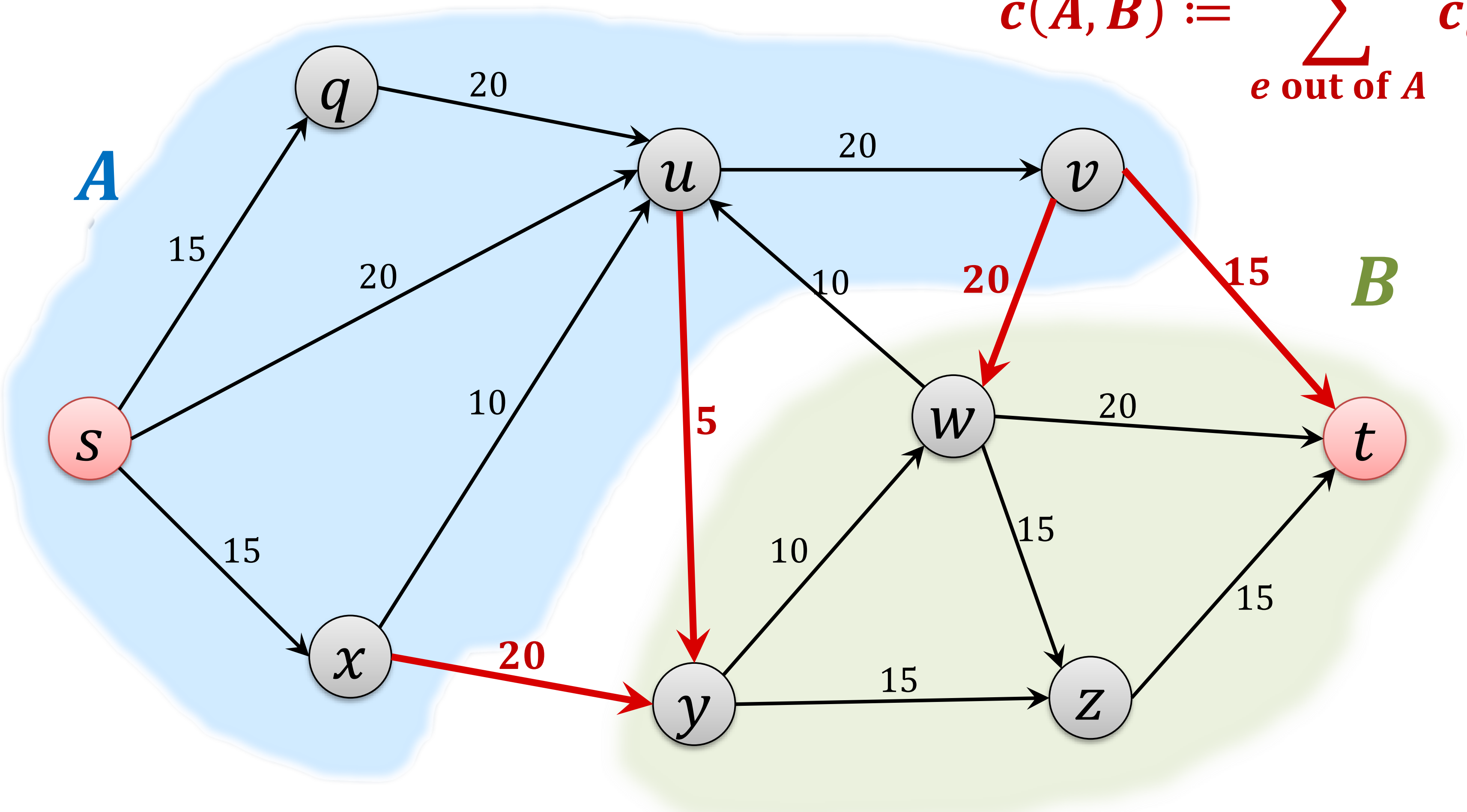
Definition:
An s-t cut is a partition (A, B) of the vertex set such that $s \in A$ and $t \in B$



Cut Capacity

Definition:
The capacity $c(A, B)$ of an s-t-cut (A, B) is defined as

$$c(A, B) := \sum_{e \text{ out of } A} c_e .$$



Cuts and Flow Value

Lemma: Let f be any s-t flow, and (A, B) any s-t cut. Then,

$$|\boldsymbol{f}| = \boldsymbol{f}^{\mathbf{out}}(\boldsymbol{A}) - \boldsymbol{f}^{\mathbf{in}}(\boldsymbol{A}).$$

Proof:

Cuts and Flow Value

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Proof:

Upper Bound on Flow Value

Lemma:

Let f be any s-t flow and (A, B) any s-t cut. Then $|\boldsymbol{f}| \leq \boldsymbol{c}(\boldsymbol{A}, \boldsymbol{B})$.

Proof:

Ford-Fulkerson Gives Optimal Solution

Lemma: If f is an s-t flow such that there is no augmenting path in G_f, then there is an s-t cut (A^*, B^*) in G for which

$$|\boldsymbol{f}| = \boldsymbol{c}(\boldsymbol{A}^*, \boldsymbol{B}^*).$$

Proof:

- Define $\boldsymbol{A}^*$: set of nodes that can be reached from s on a path with positive residual capacities in G_f:

- For $B^* = V \setminus A^*$, (A^*, B^*) is an s-t cut
  - By definition $s \in A^*$ and $t \notin A^*$

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Proof:

Ford-Fulkerson Gives Optimal Solution

Theorem: The flow returned by the Ford-Fulkerson algorithm is a maximum flow.

Proof:

Min-Cut Algorithm

Ford-Fulkerson also gives a min-cut algorithm:

Theorem: Given a flow f of maximum value, we can compute an s-t cut of minimum capacity in $O(m)$ time.

Proof:

Max-Flow Min-Cut Theorem

Theorem: **(Max-Flow Min-Cut Theorem)**

In every flow network, the maximum value of an s-t flow is equal to the minimum capacity of an s-t cut.

Proof:

Integer Capacities

Theorem: **(Integer-Valued Flows)**

If all capacities in the flow network are integers, then there is a maximum flow f for which the flow $f(e)$ of every edge e is an integer.

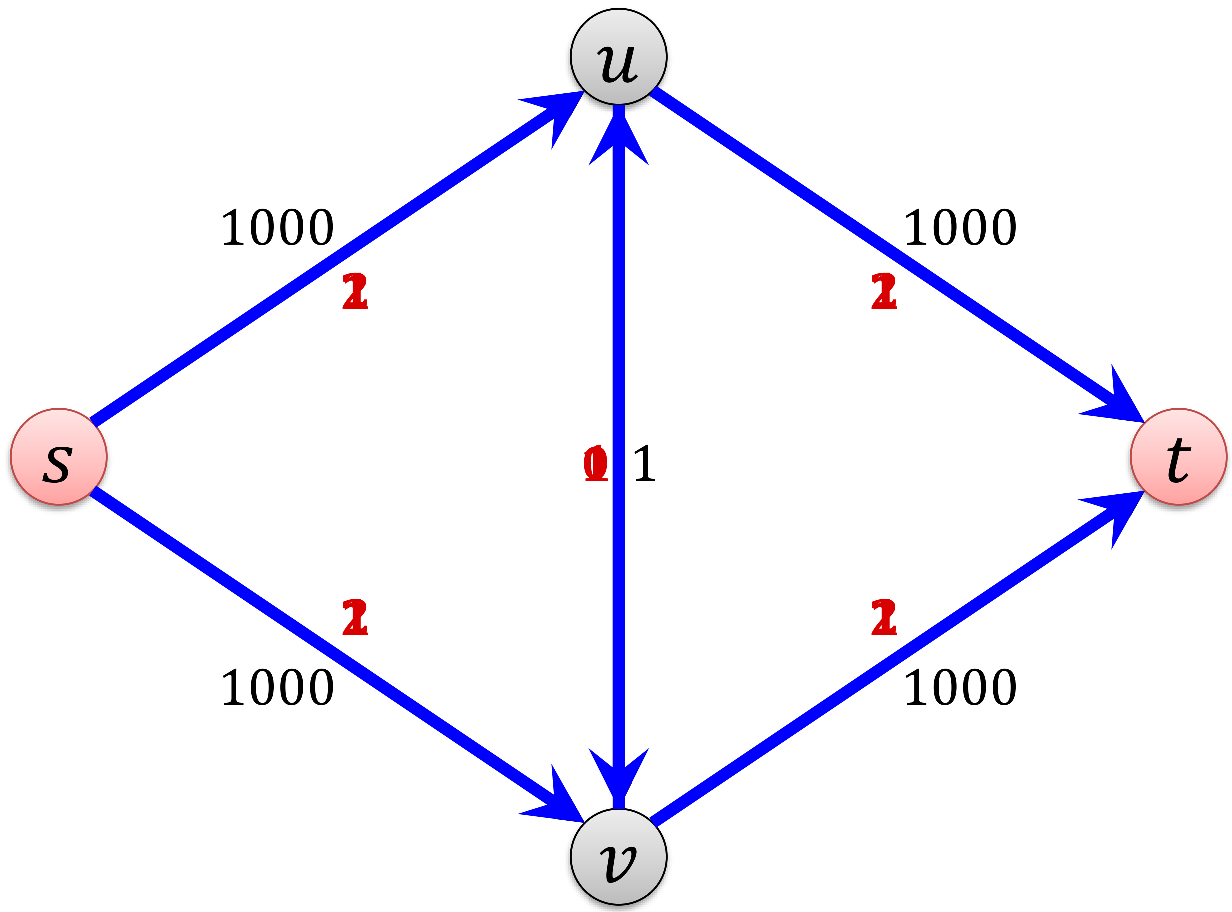
Proof:

Non-Integer Capacities

What if capacities are not integers?

- rational capacities:
  - can be turned into integers by multiplying them with large enough integer
  - algorithm still works correctly
- real (non-rational) capacities:
  - not clear whether the algorithm always terminates
- even for integer capacities, time can linearly depend on the value of the maximum flow

Slow Execution



- Number of iterations: 2000 (value of max. flow)

Improved Algorithm

Idea: Find the best augmenting path in each step

- best: path P with maximum $\text{bottleneck}(P, f)$

- Best path might be rather expensive to find
  → find almost best path

- **Scaling parameter Δ:**
  (initially, $\Delta =$ "$\max c_e$ rounded down to next power of 2")

- As long as there is an augmenting path that improves the flow by at least Δ, augment using such a path

- If there is no such path: $\Delta := {}^{\Delta}/_{2}$

Scaling Parameter Analysis

Lemma: If all capacities are integers, number of different scaling parameters used is $\leq 1 + \lfloor \log_2 C \rfloor$.

- **Δ-scaling phase:** Time during which scaling parameter is Δ

Length of a Scaling Phase

Lemma: If f is the flow at the end of the Δ-scaling phase, the maximum flow in the network has value at most $|f| + m\Delta$.

Length of a Scaling Phase

Lemma: The number of augmentation in each scaling phase is at most $2m$.

Running Time: Scaling Max Flow Alg.

Theorem: The number of augmentations of the algorithm with scaling parameter and integer capacities is at most $O(m \log C)$. The algorithm can be implemented in time $O(m^2 \log C)$.

Strongly Polynomial Algorithm

- Time of regular Ford-Fulkerson algorithm with integer capacities:

$$O(mC)$$

- Time of algorithm with scaling parameter:

$$O(m^2 \log C)$$

- $O(\log C)$ is polynomial in the size of the input, but not in n

- Can we get an algorithm that runs in time polynomial in n?

- Always picking a shortest augmenting path leads to running time

$$O(m^2 n)$$

  – also works for arbitrary real-valued weights

Other Algorithms

- There are many other algorithms to solve the maximum flow problem, for example:

- **Preflow-push algorithm:**
  - Maintains a preflow (∀ nodes: inflow ≥ outflow)
  - Alg. guarantees: As soon as we have a flow, it is optimal
  - Detailed discussion in 2012/13 lecture
  - Running time of basic algorithm: $O(m \cdot n^2)$
  - Doing steps in the “right” order: $O(n^3)$

- **Current best known complexity: $\boldsymbol{O(m \cdot n)}$**
  - For graphs with $m \geq n^{1+\epsilon}$ [King,Rao,Tarjan 1992/1994]
    (for every constant $\epsilon > 0$)
  - For sparse graphs with $m \leq n^{16/15-\delta}$ [Orlin, 2013]