



南方科技大学
SOUTHERN UNIVERSITY OF SCIENCE AND TECHNOLOGY

07 Network Flow

CS216 Algorithm Design and Analysis (H)

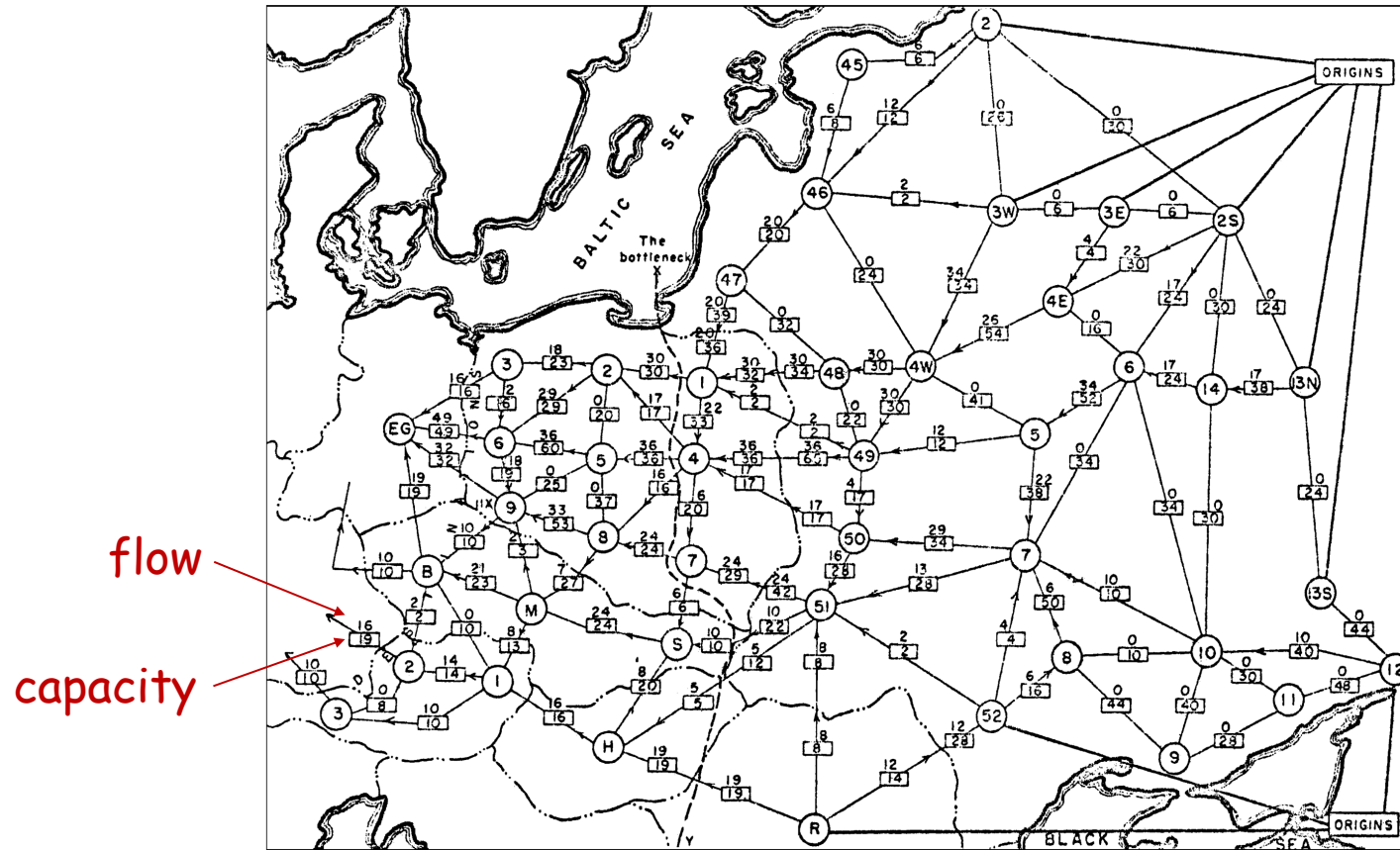
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Maximum Flow Application (Tolstoï 1930s)

- **Soviet Union goal.** Maximize flow of supplies to Eastern Europe.

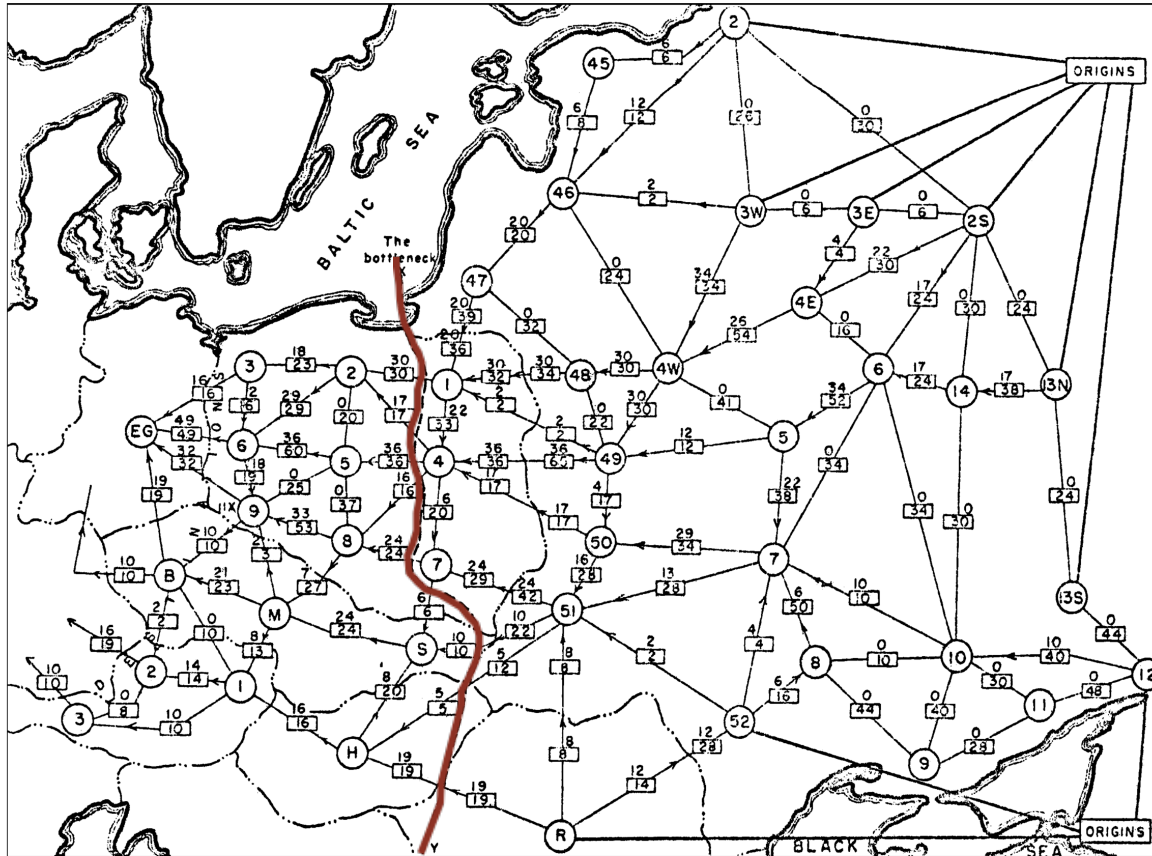


rail network connecting Soviet Union with Eastern European countries
(map declassified by Pentagon in 1999)



Minimum Cut Application (RAND 1950s)

- “Free world” goal. **Cut** supplies (if Cold War turns into real war).



rail network connecting Soviet Union with Eastern European countries
(map declassified by Pentagon in 1999)



Maximum Flow and Minimum Cut

- **Max-flow and min-cut problems.**

- Beautiful mathematical **duality**.
- Cornerstone problems in **combinatorial optimization**.

- **They are widely applicable models.**

- Data mining, open-pit mining, bipartite matching, network reliability, baseball elimination, image segmentation, network connectivity, Markov random fields, distributed computing, security of statistical data, egalitarian stable matching, network intrusion detection, multi-camera scene reconstruction, sensor placement for homeland security, etc.

↑
we will learn some of the applications later

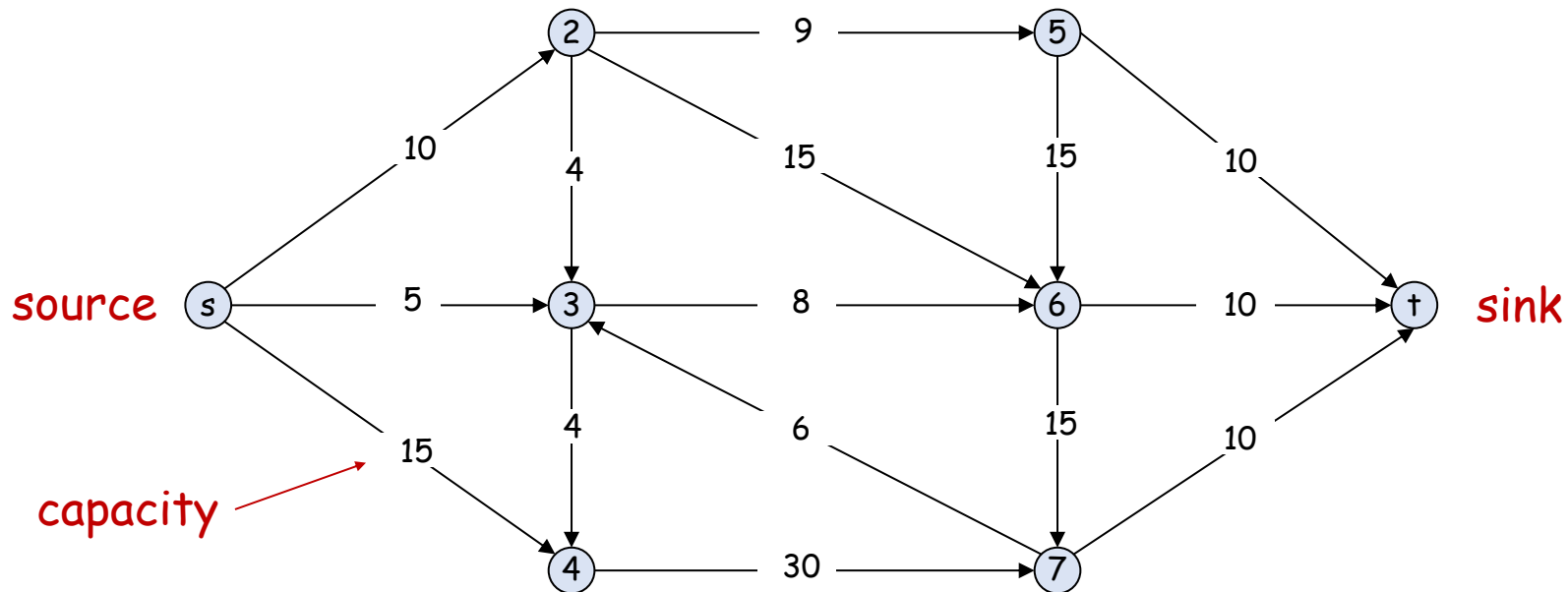


1. Max Flow and Min Cut



Flow Network

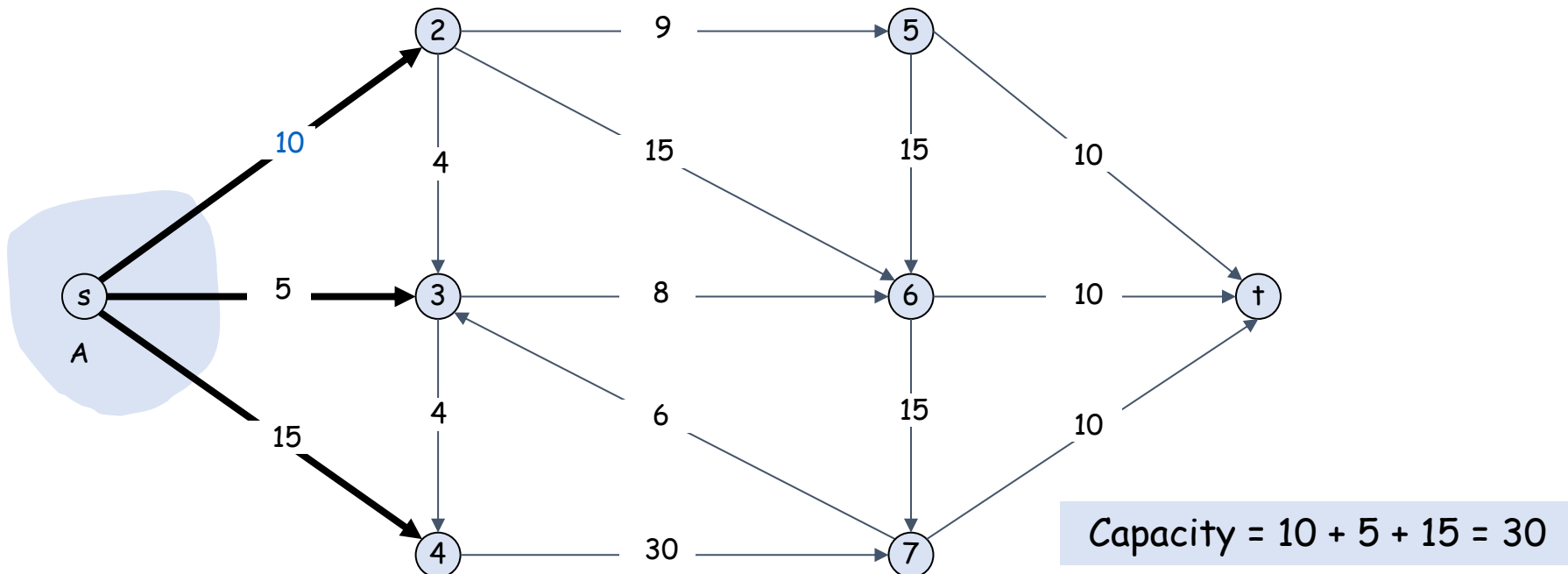
- **Def.** A flow network is a tuple $G = (V, E, s, t, c)$.
 - Directed graph $G = (V, E)$ with source s and sink t , and **no parallel edges**.
 - Capacity $c(e) \geq 0$ for each edge e . ← assume all nodes are reachable from s
- **Intuition.** Material **flowing** through a transportation network, originating from **source** and being sent to **sink**.





Minimum-Cut Problem

- **Def.** An *st*-cut (or cut) is a partition (A, B) of V with $s \in A$ and $t \in B$.
- **Def.** The *capacity* of a cut (A, B) is $c(A, B) = \sum_{e \text{ out of } A} c_e$
- **Example 1:**

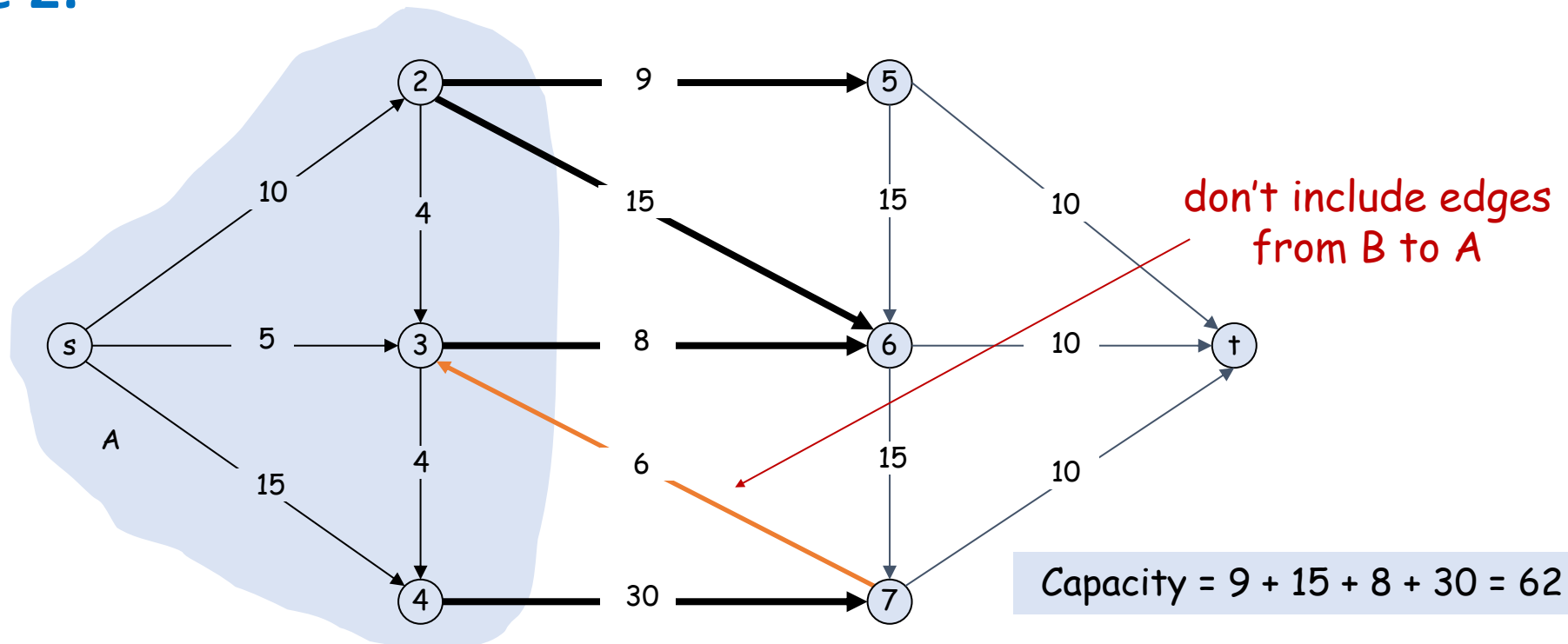




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- **Example 2:**

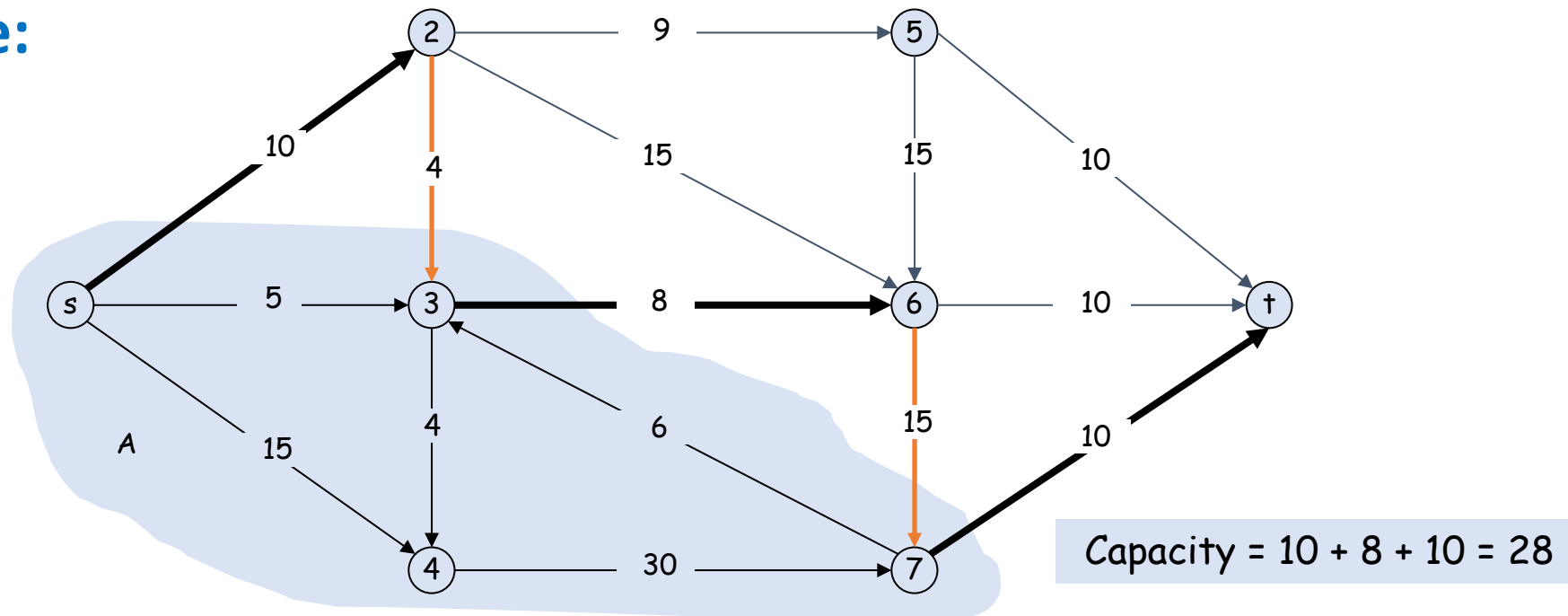




Minimum-Cut Problem

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- **Def.** The *capacity* of a cut (A, B) is $c(A, B) = \sum_{e \text{ out of } A} c_e$
- **Min-cut problem.** Find a cut of *minimum capacity*.

- **Example:**



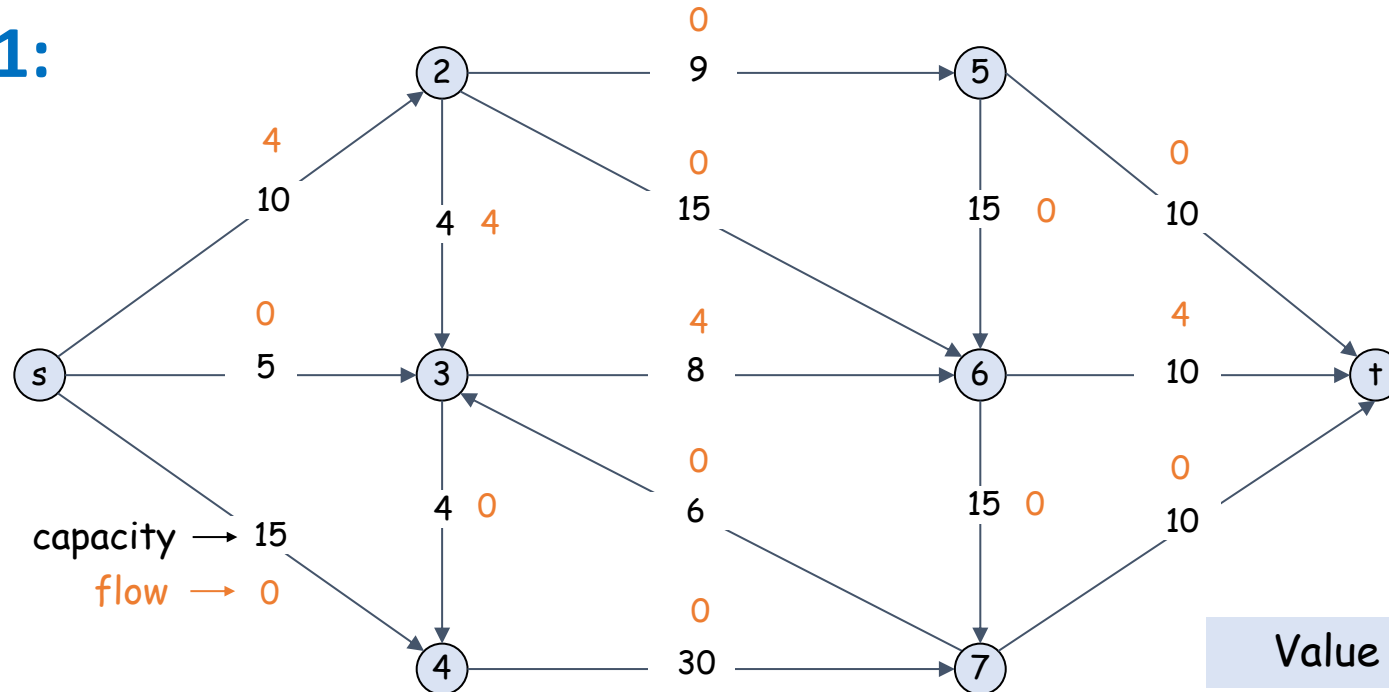


Maximum-Flow Problem

- **Def.** An *st-flow* (or flow) f is a function that satisfies
 - [Capacity] For each $e \in E: 0 \leq f(e) \leq c_e$
 - [Flow conservation] For each $v \in V - \{s, t\}: \sum_{e \text{ into } v} f(e) = \sum_{e \text{ out of } v} f(e)$
- **Def.** The **value** of a flow f is $v(f) = \sum_{e \text{ out of } s} f(e) = f^{\text{out}}(s)$.

simple notation:
 $f^{\text{in}}(v) = f^{\text{out}}(v)$

- **Example 1:**



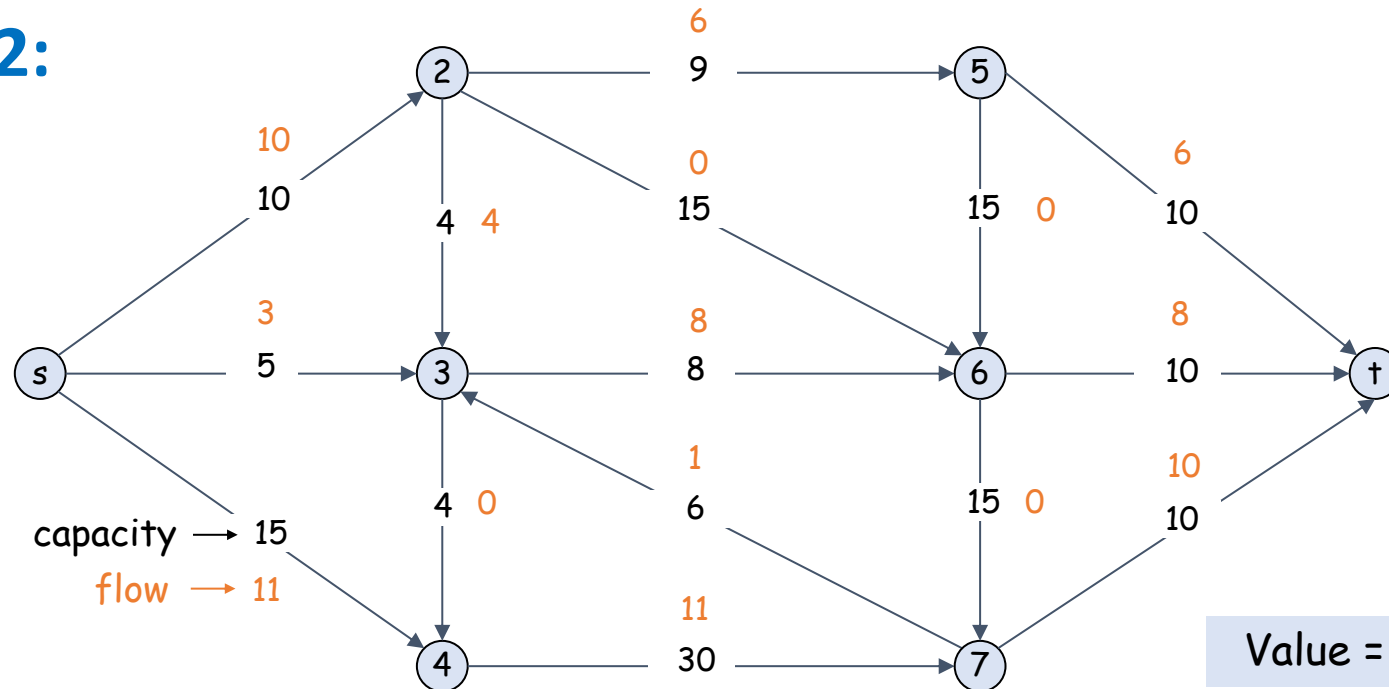


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- **Example 2:**



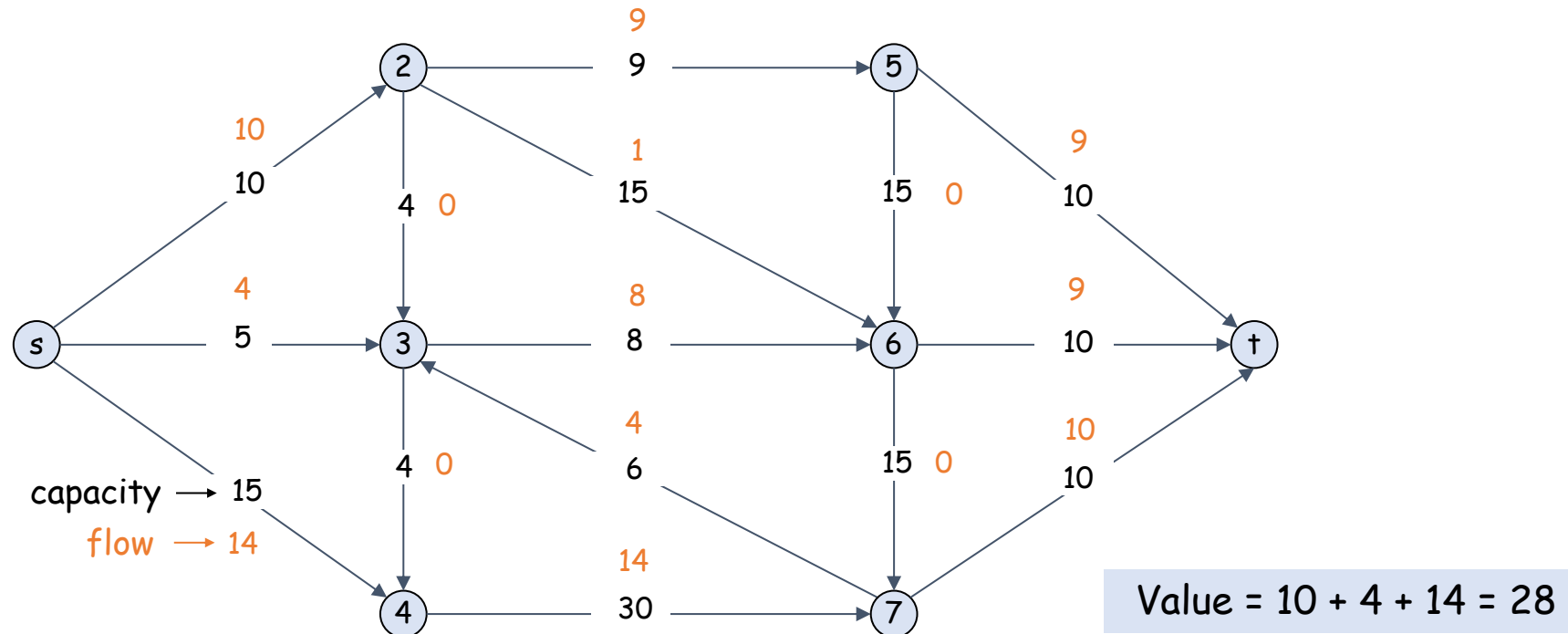
$$\text{Value} = 10 + 3 + 11 = 24$$



Maximum-Flow Problem

- **Def.** An *st-flow* (or flow) f is a function that satisfies
- **Def.** The *value* of a flow f is $v(f) = \sum_{e \text{ out of } s} f(e)$
- **Max-flow problem.** Find a flow of *maximum value*.

- **Example:**





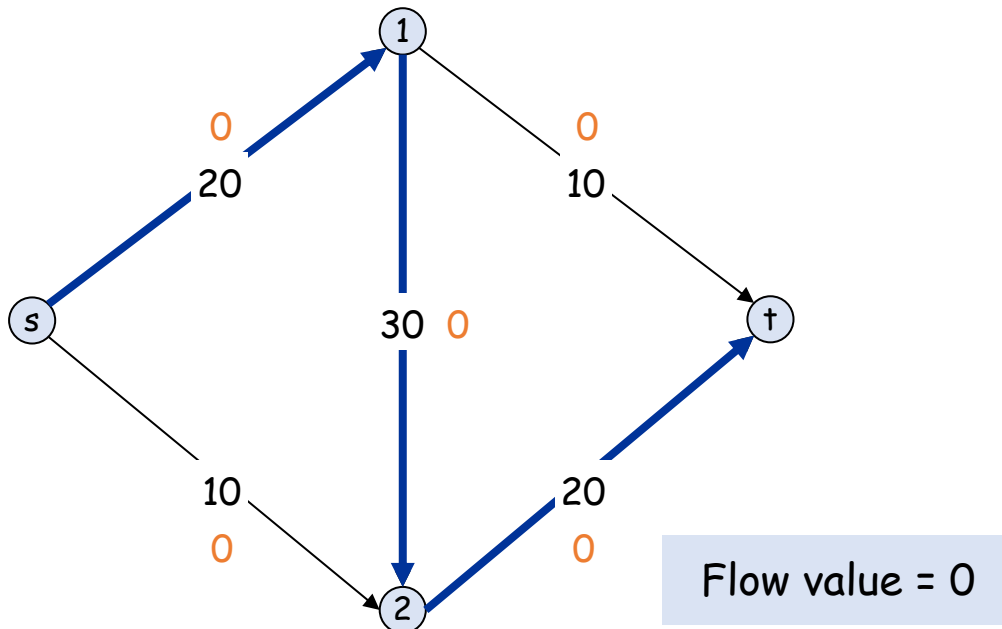
2. Ford-Fulkerson Algorithm



Toward a Max-Flow Algorithm

- **Greedy algorithm:**

- Start with $f(e) = 0$ for all edges $e \in E$.
- Find an s - t path P where each edge has $f(e) < c(e)$.
- Augment flow along path P .
- Repeat until you get stuck.

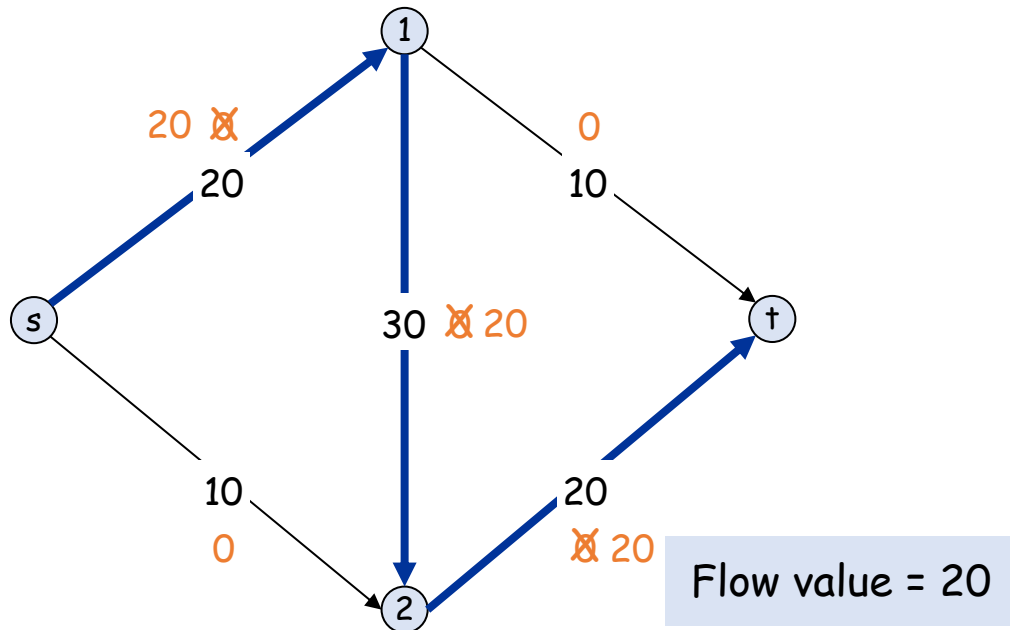




Toward a Max-Flow Algorithm

- **Greedy algorithm:**

- Start with $f(e) = 0$ for all edges $e \in E$.
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- **Augment flow along path P .**
- Repeat until you get stuck.

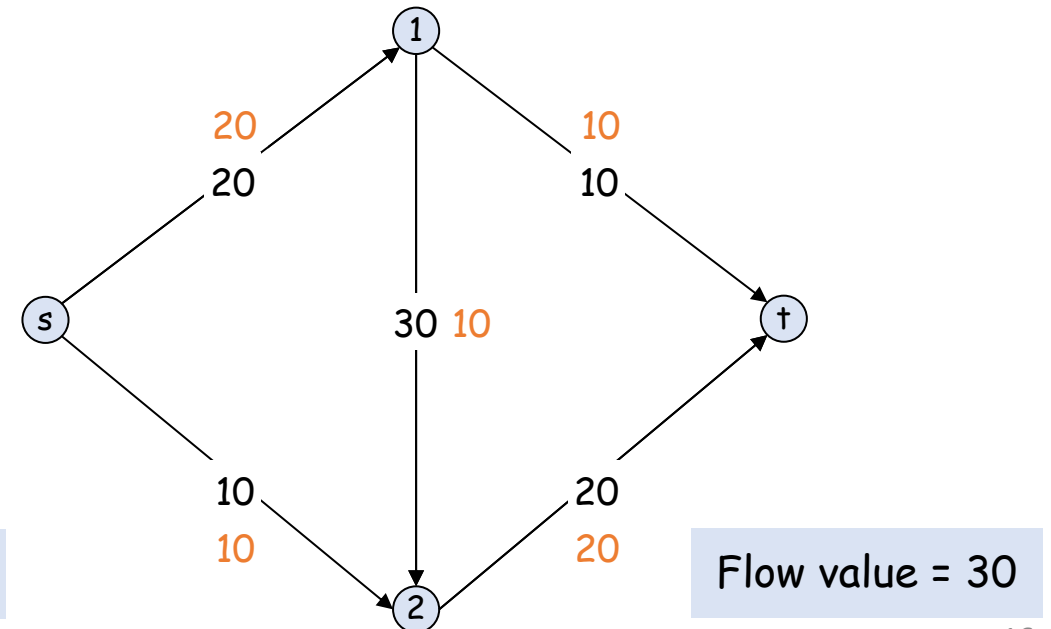
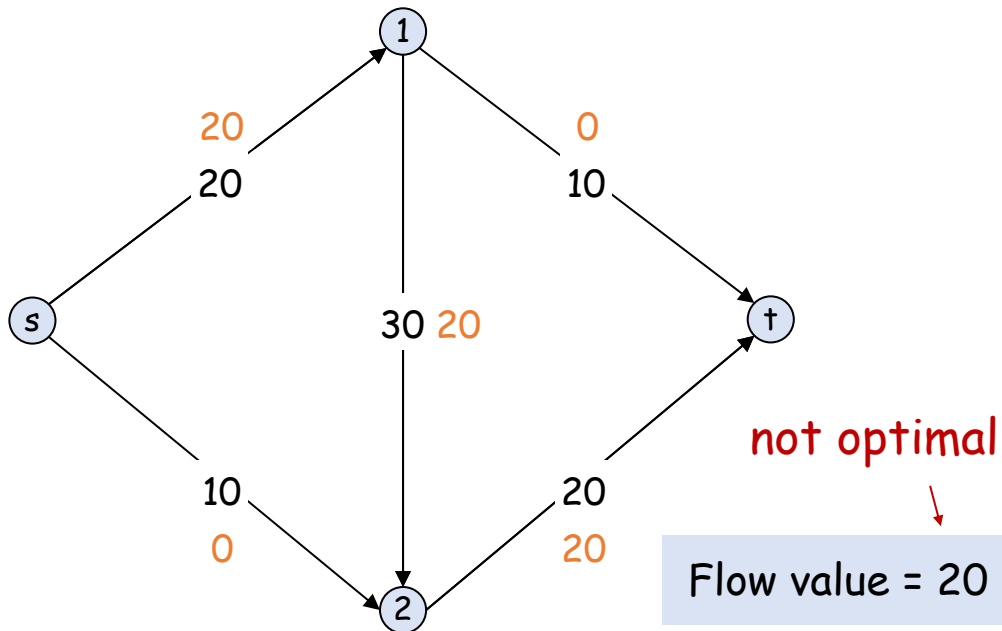




Toward a Max-Flow Algorithm

- **Greedy algorithm:**

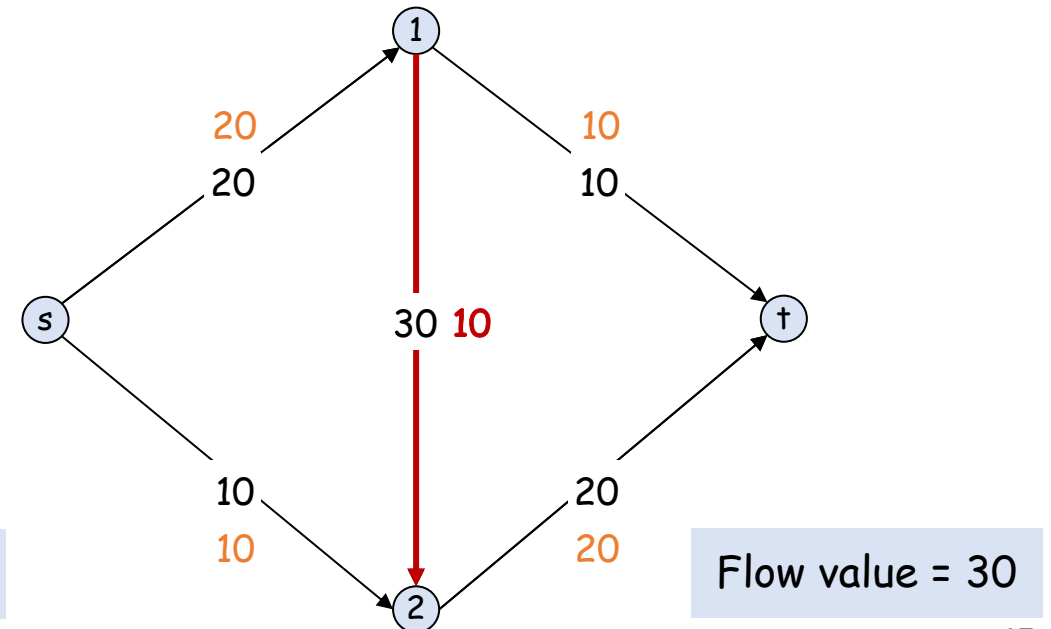
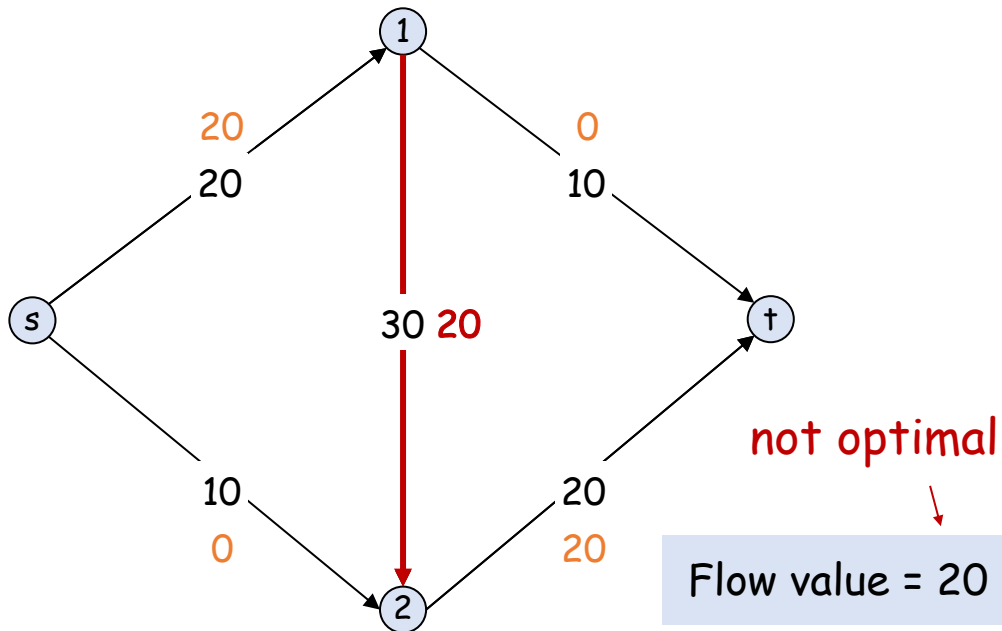
- Start with $f(e) = 0$ for all edges $e \in E$.
- Find an s - t path P where each edge has $f(e) < c(e)$.
- Augment flow along path P .
- Repeat until you get stuck.





Toward a Max-Flow Algorithm

- **Q.** Why does the greedy algorithm fail?
- **A.** Once flow on an edge is increased, it **never decreases**.
- **Bottom line.** Need some mechanism to “undo” a bad decision.





Residual Network

- **Original edge:** $e = (u, v) \in E$

- flow $f(e)$, capacity $c(e)$

- **Reverse edge:** $e^R = (v, u)$

- used to “undo” flow

- **Residual capacity:** c_f

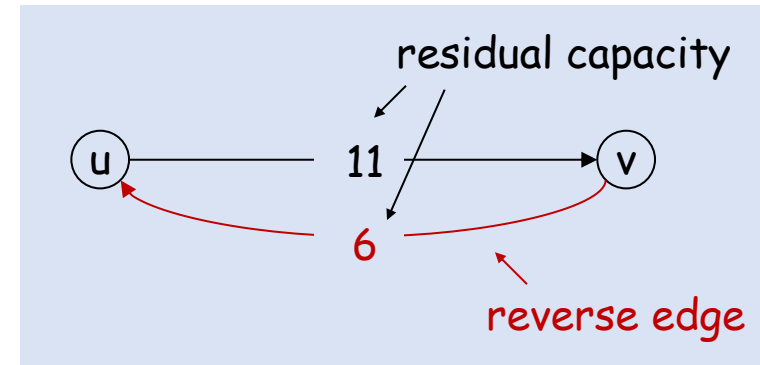
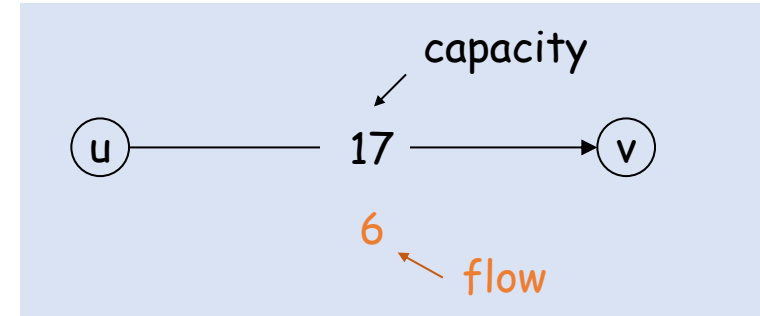
- original edge: $c_f(e) = c(e) - f(e)$

- reverse edge: $c_f(e^R) = f(e)$

- **Residual network:** $G_f = (V, E_f, s, t, c_f)$

- $E_f = \{e: f(e) < c(e)\} \cup \{e^R: f(e) > 0\}$: edges with positive residual capacity

- **Key property.** f' is a flow in G_f if and only if $f + f'$ is a flow in G .



flow on a reverse edge negates flow on corresponding original forward edge



Augmenting Path

- **Def.** An **augmenting path** P is a **simple s - t path** in the residual network G_f .
- **Def.** The **bottleneck capacity** of an augmenting path P in G_f , denoted by $\text{bottleneck}(G_f, P)$, is the **minimum residual capacity** of any edge in P .
- **Key property.** Consider a flow network $G = (V, E, s, t, c)$ with flow f and augmenting path P in G_f . After calling the following $\text{Augment}(f, c, P)$, the returned f' is a flow in G and $v(f') = v(f) + \text{bottleneck}(G_f, P)$.

```
Augment(f, c, P) {  
     $\delta = \text{bottleneck}(G_f, P)$   
    foreach  $e \in P$  {  
        if ( $e \in E$ )  $f(e) = f(e) + \delta$   
        else  $f(e^R) = f(e^R) - \delta$   
    }  
    return  $f$   
}
```

e is a reverse edge
so e^R is a forward edge



Ford-Fulkerson Algorithm

- **Ford-Fulkerson (FF) algorithm.**



- Start with $f(e) = 0$ for each edge $e \in E$.
- Find an s - t path P in the residual network G_f .
- Augment flow along path P .
- Repeat until you get stuck.

```
Ford-Fulkerson( $G, s, t, c$ ) {  
    foreach  $e \in E$ :  $f(e) = 0$   
     $G_f$  = residual network of  $G$  with respect to flow  $f$   
  
    while (there exists an augmenting path  $P$ ) {  
         $f$  = Augment( $f, c, P$ )  
        update  $G_f$   
    }  
    return  $f$   
}
```



3. Max-Flow Min-Cut Theorem

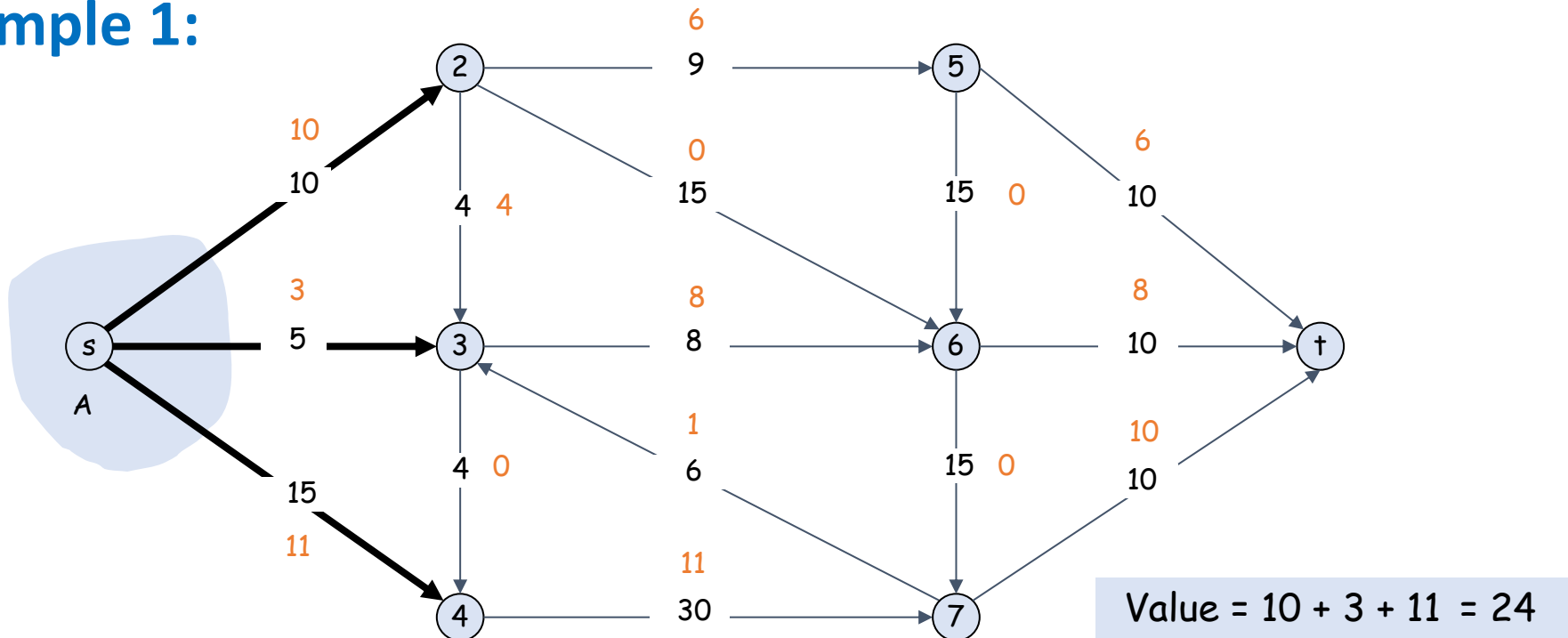


Relationship between Flows and Cuts

- **Flow value lemma.** Let f be any flow, and let (A, B) be any cut. Then, the value of the flow f equals the **net flow** across the cut (A, B) .

$$v(f) = f^{out}(A) - f^{in}(A)$$

- **Example 1:**



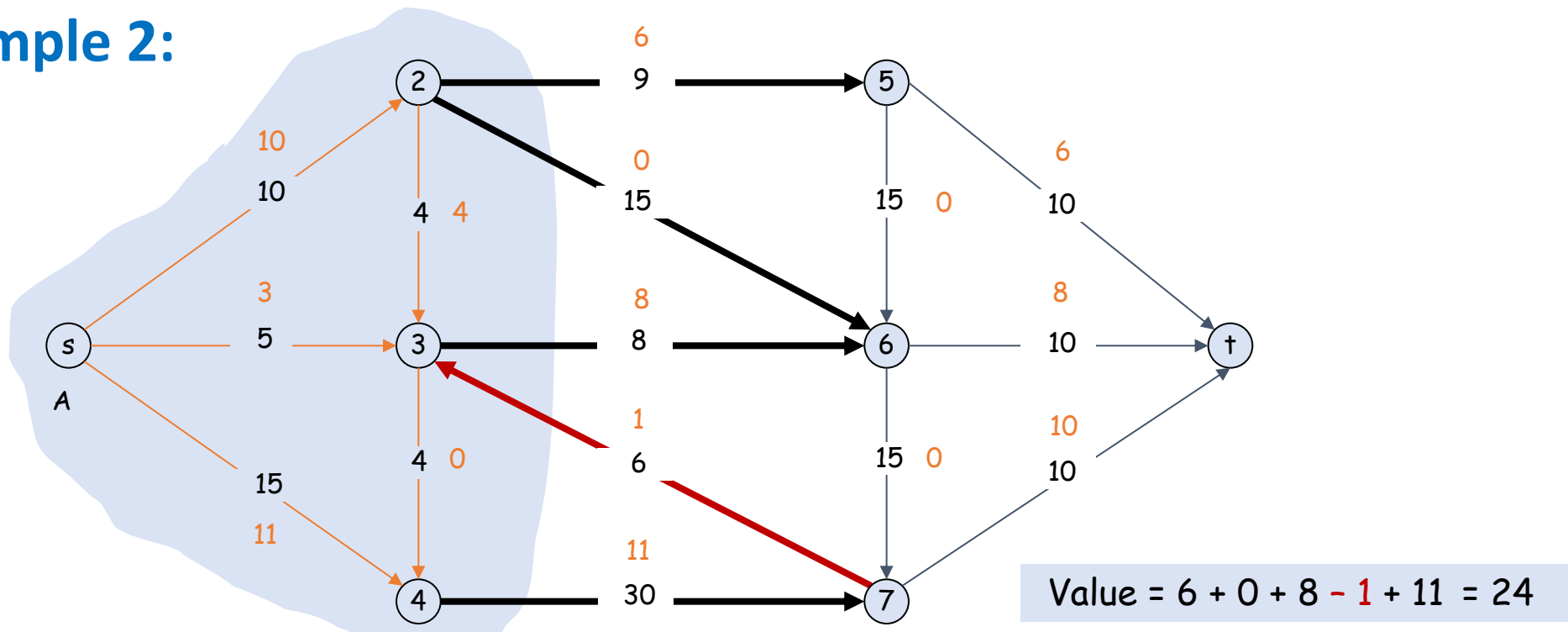


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- **Example 2:**



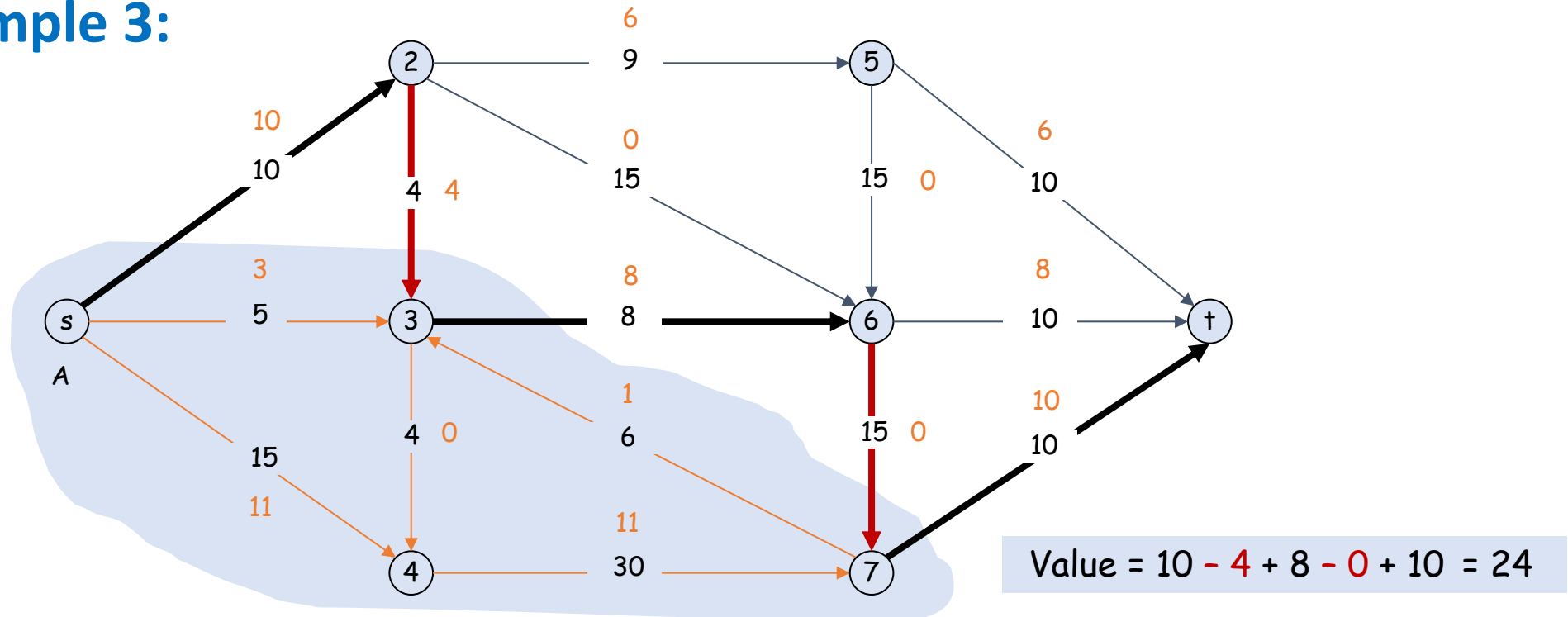


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- **Example 3:**





Relationship between Flows and Cuts

- **Flow value lemma.** Let f be any flow, and let (A, B) be any cut. Then, the value of the flow f equals the **net flow** across the cut (A, B) .

$$v(f) = f^{out}(A) - f^{in}(A) \quad v(f) = f^{in}(B) - f^{out}(B)$$

- **Pf.**

$$v(f) = \sum_{e \text{ out of } s} f(e) = f^{out}(s) = f^{out}(s) - f^{in}(s) \leftarrow f^{in}(s) = 0$$

$$= \sum_{v \in A} (f^{out}(v) - f^{in}(v)) \leftarrow \begin{array}{l} \text{by flow conservation, } f^{out}(v) - f^{in}(v) = 0 \\ \text{for all } v \text{ in } A \text{ except for } v = s \end{array}$$

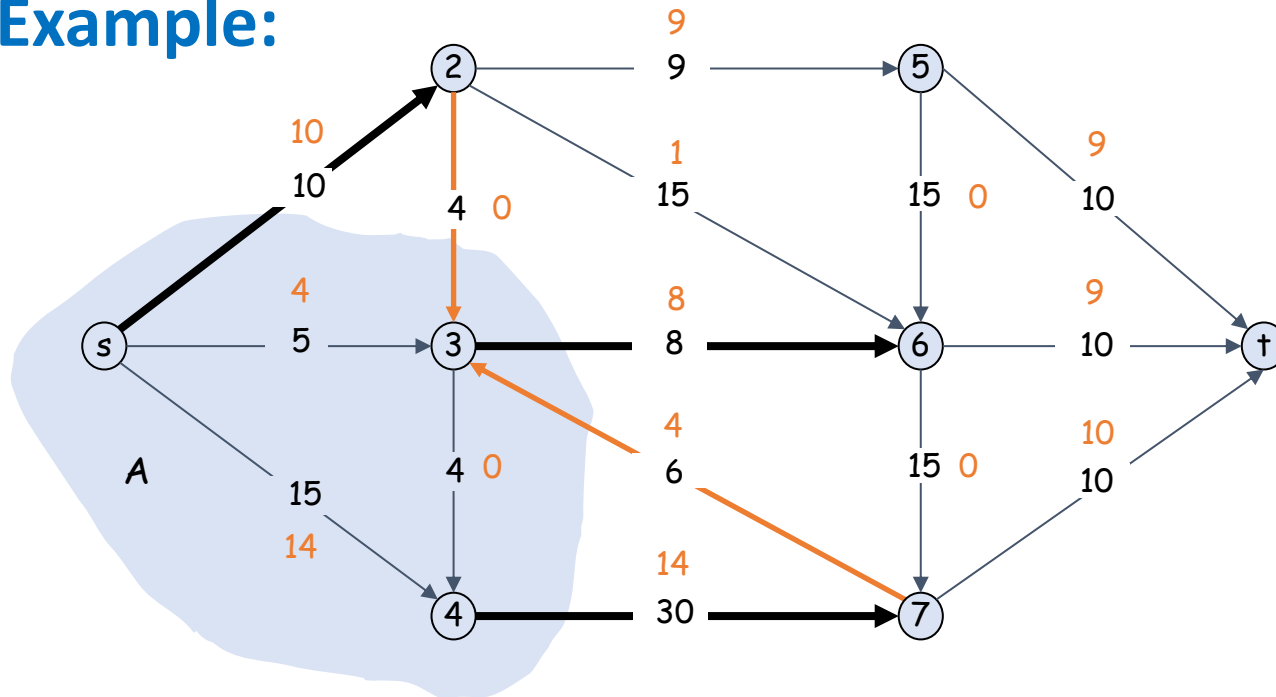
$$= \sum_{e \text{ out of } A} f(e) - \sum_{e \text{ into } A} f(e) = f^{out}(A) - f^{in}(A)$$



Relationship between Flows and Cuts

- **Weak duality.** Let f be any flow, and let (A, B) be any cut. Then the value of the flow f is at most the **capacity** of the cut: $v(f) \leq c(A, B)$.
 - Recall that $c(A, B) = \sum_{e \text{ out of } A} c_e$.

- **Example:**



Flow value = 28
Cut capacity = 48 \Rightarrow Flow value \leq 48



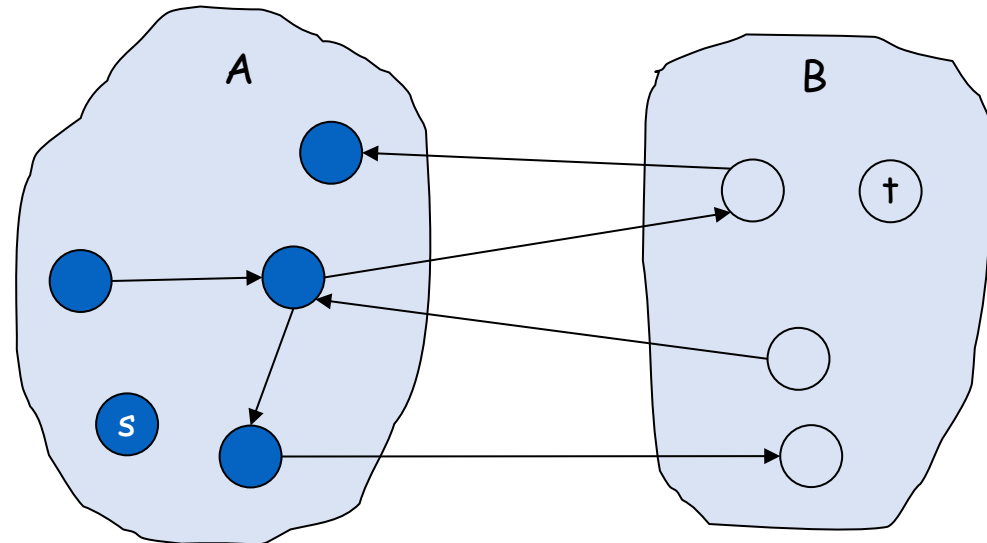
Relationship between Flows and Cuts

- **Weak duality.** Let f be any flow, and let (A, B) be any cut. Then the value of the flow f is at most the **capacity** of the cut: $v(f) \leq c(A, B)$.
 - Recall that $c(A, B) = \sum_{e \text{ out of } A} c_e$.

- **Pf.** $v(f) = f^{\text{out}}(A) - f^{\text{in}}(A)$

flow value lemma

$$\begin{aligned} &\leq f^{\text{out}}(A) \\ &= \sum_{e \text{ out of } A} f(e) \\ &\leq \sum_{e \text{ out of } A} c(e) \\ &= c(A, B) \end{aligned}$$

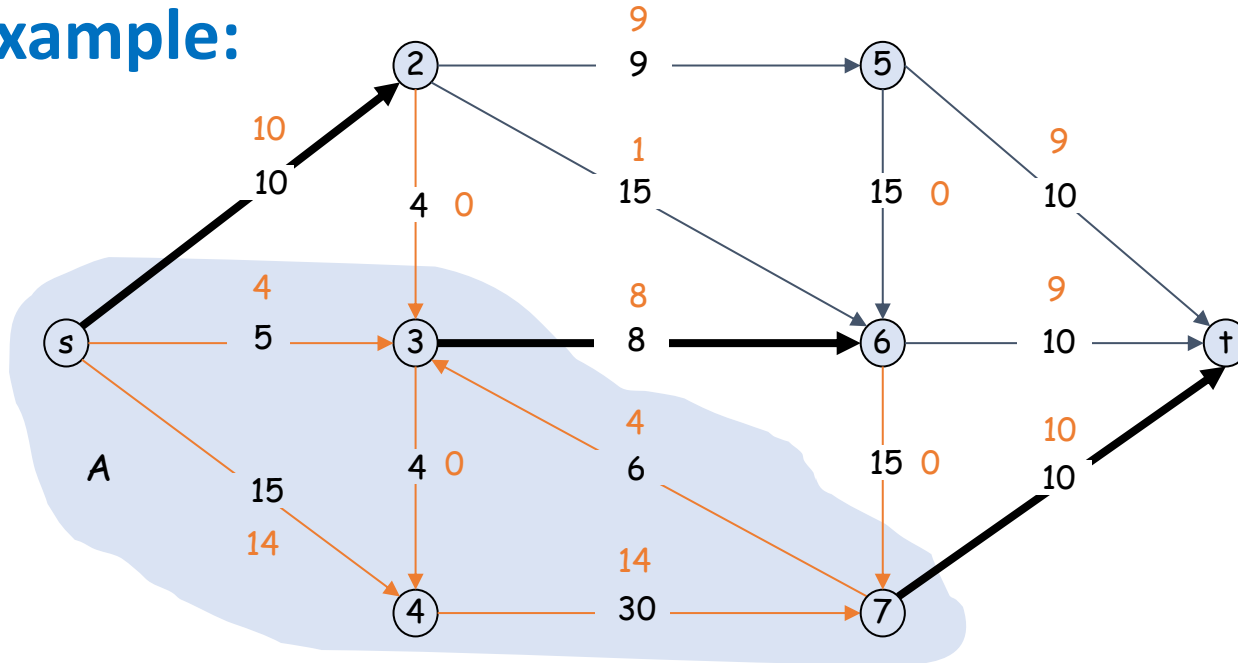




Certificate of Optimality

- **Corollary.** Let f be any flow, and let (A, B) be any cut. If $v(f) = c(A, B)$, then f is a **max flow** and (A, B) is a **min cut**.
- **Pf.** Every flow value is **upper bounded** by every cut capacity!

- **Example:**



Flow value = 28
Cut capacity = 28 \Rightarrow Flow value \leq 28



Max-Flow Min-Cut Theorem

- **Max-flow min-cut theorem.** [Ford-Fulkerson 1956] Value of a max flow is **equal** to capacity of a min cut.
- **Augmenting path theorem.** Flow f is a **max flow** iff **no augmenting paths**.
- **Pf.** We prove both by showing the following are equivalent:
 - (i) There exists a cut (A, B) such that $v(f) = c(A, B)$.
 - (ii) f is a max flow.
 - (iii) There is no augmenting path with respect to f .
- (i) \Rightarrow (ii): This was the previous **Corollary**.
- (ii) \Rightarrow (iii): We prove the **contrapositive**.
 - Let f be a flow. If there exists an augmenting path, then we can improve flow f by sending flow along this path. Then, f is not a max flow.



Max-Flow Min-Cut Theorem

- **Pf continued.**

(i) There exists a cut (A, B) such that $v(f) = c(A, B)$.

(iii) There is no augmenting path with respect to f .

(iii) \Rightarrow (i):

➤ Let f be a flow with no augmenting paths.

given a max flow f (so no augmenting path)
can find a min cut (A, B) in $O(m)$ time

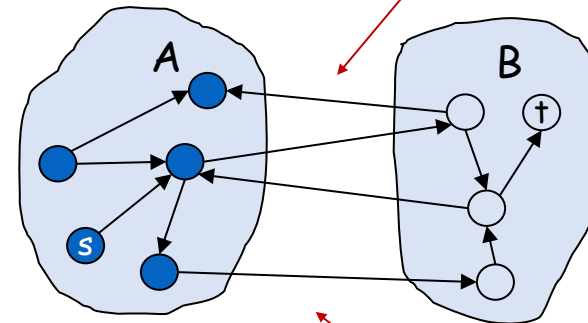
➤ Let A be the set of nodes **reachable** from s in residual network G_f .

➤ By definition of $A \Rightarrow s \in A$. No augmenting path for $f \Rightarrow t \notin A$.

flow value lemma

$$\begin{aligned} v(f) &= f^{\text{out}}(A) - f^{\text{in}}(A) \\ &= \sum_{e \text{ out of } A} c(e) - 0 \\ &= c(A, B) \end{aligned}$$

original flow network G $f(e) = 0$ from B to A



$f(e) = c_e$ from A to B



4. Capacity-Scaling Algorithm



Ford-Fulkerson Algorithm: Analysis

- **Assumption.** Every edge capacity c_e is an **integer** between **1** and **C** .
- **Integrality invariant.** Throughout **FF**, every edge flow $f(e)$ and residual capacity $c_f(e)$ are integers.
- **Theorem.** **FF** terminates after at most $v(f^*) \leq nC$ augmenting paths, where f^* is a **max flow**. (Assume flow network has no parallel edges.)
- **Pf.** Consider cut where $A = \{s\}$ and note that each augmentation increases the value of the flow by at least **1**. ▀
- **Corollary.** The running time of **Ford-Fulkerson** is $O(mnC)$.
- **Pf.** Can use either **BFS** or **DFS** to find an augmenting path in $O(m)$ time. ▀



Ford-Fulkerson Algorithm: Analysis

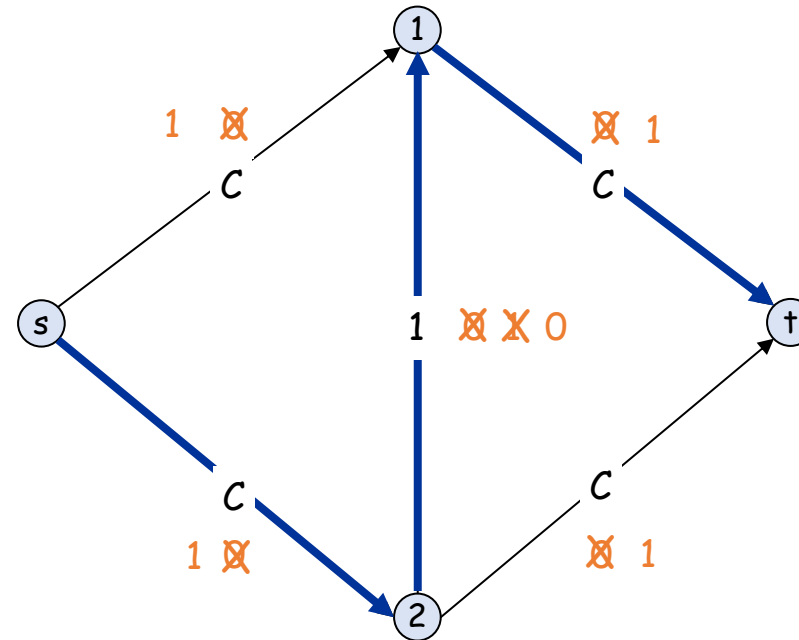
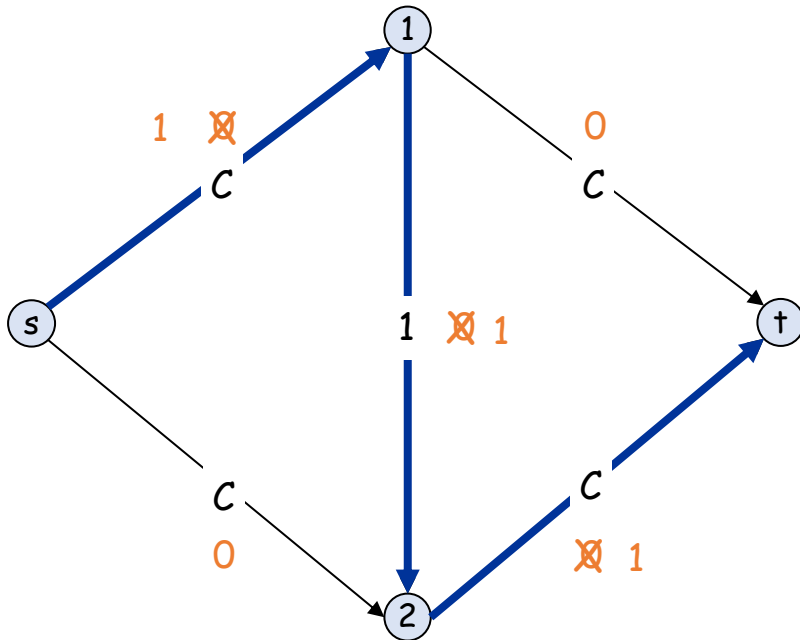
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- **Corollary.** The running time of **Ford-Fulkerson** is $O(mnC)$.
- **Integrality theorem.** There exists an **integral max flow** f^* .
- **Pf.** Since **FF** always terminates if capacities are integral, theorem follows from **integrality invariant** (and **augmenting path theorem**). ▀



Ford-Fulkerson: Exponential Example

- **Q.** Is **Ford-Fulkerson** algorithm **polynomial** in **input size**? $\leftarrow m, n, \log_2 C$
- **A.** No. If max capacity is C , then algorithm can take $2C$ iterations.

$$C = 2^{\lceil \log_2 C \rceil}$$





Choosing Good Augmenting Paths

- **Caveat.** If capacities can be **irrational**, FF may **not terminate** or converge!
- **Use care when selecting augmenting paths:**
 - Some choices lead to **exponential** algorithms.
 - Clever choices lead to **polynomial** algorithms.
- **Goal.** Choose augmenting paths so that:
 - Can find augmenting paths efficiently.
 - Few iterations.
- **Choose augmenting paths with:**
 - **Max** bottleneck capacity (“fattest”). ← difficult, how to find?
 - **Sufficiently large** bottleneck capacity. ← coming next
 - **Fewest** edges. [Edmonds-Karp 1972, Dinitz 1970] ← later sections

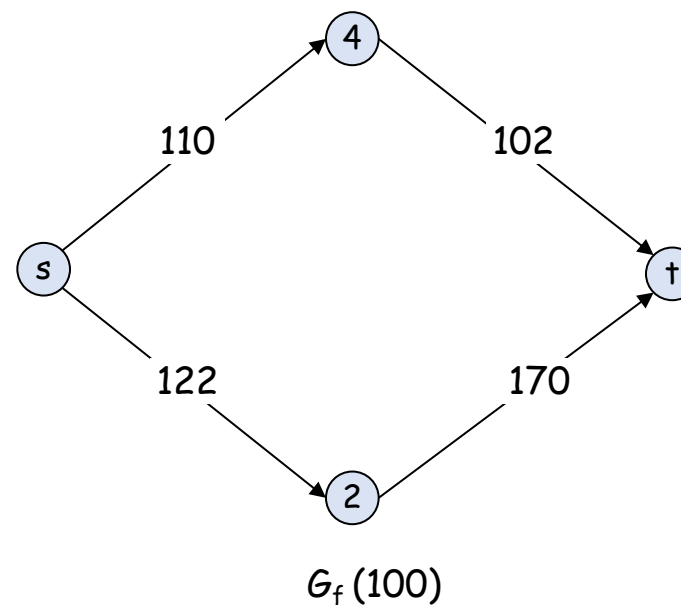
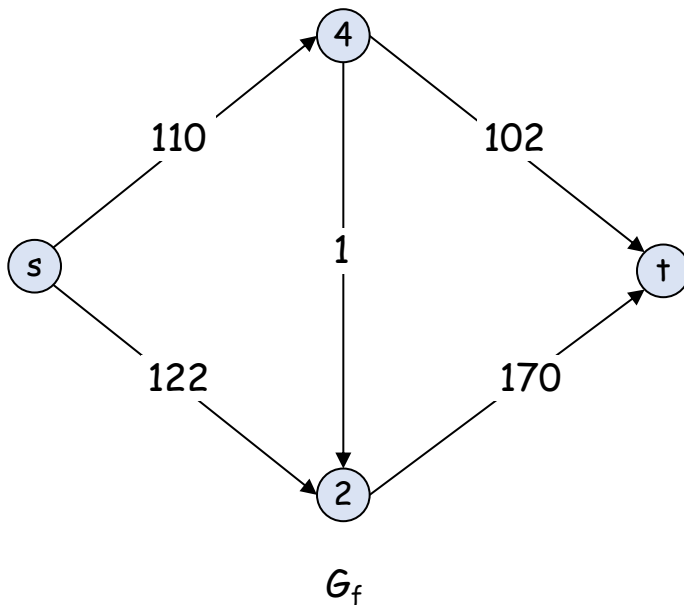
capacities are rational in practice
but FF could run in exponential time



Capacity-Scaling Algorithm

- **Overview.** Choosing augmenting paths with “large” bottleneck capacity.
 - Maintain scaling parameter Δ .
 - Let $G_f(\Delta)$ be the **subnetwork** of the residual network containing only those edges with capacity $\geq \Delta$.
 - Any augmenting path in $G_f(\Delta)$ has bottleneck capacity $\geq \Delta$.

← not necessarily largest





Capacity-Scaling Algorithm

- **Greedy algorithm.** Halve Δ when no augmenting path can be found.

```
Capacity-Scaling( $G, s, t, c$ ) {  
    foreach  $e \in E$ :  $f(e) = 0$   
     $\Delta =$  largest power of 2 that is  $\leq c$   
     $G_f =$  residual network with respect to flow  $f$   
  
    while ( $\Delta \geq 1$ ) {  
         $G_f(\Delta) = \Delta$ -residual network of  $G$  with respect to flow  $f$   
        while (there exists an augmenting path  $P$  in  $G_f(\Delta)$ ) {  
             $f = \text{Augment}(f, c, P)$   
            update  $G_f(\Delta)$   
        }  
         $\Delta = \Delta / 2$   
    }  
    return  $f$   
}
```



Capacity-Scaling Algorithm: Correctness

- **Assumption.** Every edge capacity c_e is an **integer** between **1** and **C** .
- **Integrality invariant.** Throughout **capacity-scaling** algorithm, every edge flow $f(e)$ and residual capacity $c_f(e)$ are integers.
- **Theorem.** If **capacity-scaling** algorithm terminates, then f is a max flow.
- **Pf.** (direct proof)
 - **Integrality invariant** $\Rightarrow G_f(1) = G_f$.
 - Upon termination of the $\Delta = 1$ phase, there are no augmenting paths.
 - **Augmenting path theorem** \Rightarrow the resulting flow f is a max flow. ■



Capacity-Scaling Algorithm: Running Time

- **Lemma 1.** The outer while loop repeats $1 + \lfloor \log_2 C \rfloor$ times.
- **Pf.** Initially $C/2 < \Delta \leq C$; Δ decreases by a factor of 2 each iteration. ■
- **Lemma 2.** Let f be the flow at the end of a Δ -scaling phase. Then the value of a maximum flow $\leq v(f) + m\Delta$. (Proof shown later.)
- **Pf idea.** Adding edges with capacity $< \Delta$ can only increase flow by $\leq m\Delta$.
- **Lemma 3.** There are $\leq 2m$ augmentations per scaling phase.
- **Pf.** Let f be the flow at the end of the previous scaling phase $\Delta' = 2\Delta$.
 - **Lemma 2** \Rightarrow maximum flow value $\leq v(f) + m\Delta' = v(f) + m(2\Delta)$.
 - Each augmentation in a Δ -phase increases $v(f)$ by at least Δ . ■



Capacity-Scaling Algorithm: Running Time

- **Lemma 1.** The outer while loop repeats $1 + \lfloor \log_2 C \rfloor$ times.
- **Lemma 3.** There are $\leq 2m$ augmentations per scaling phase.
- **Theorem.** The **capacity-scaling** algorithm takes $O(m^2 \log C)$ time.
- **Pf. Lemma 1 + Lemma 3** $\Rightarrow O(m \log C)$ augmentations. Finding an augmenting path takes $O(m)$ time. ■

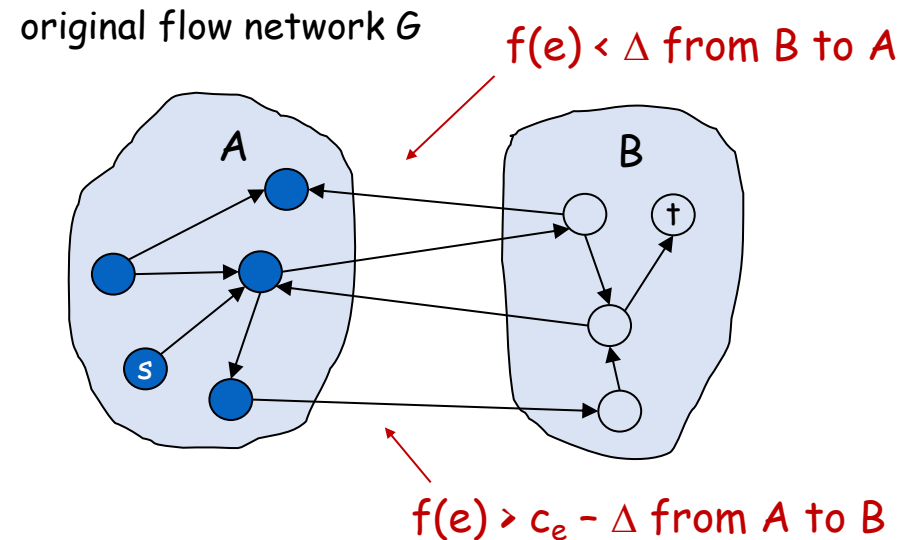


Capacity-Scaling Algorithm: Running Time

- **Lemma 2.** Let f be the flow at the end of a Δ -scaling phase. Then the value of a maximum flow $\leq v(f) + m\Delta$.
- **Pf.** (similar to the proof of max-flow min-cut theorem)
 - We show that there exists a cut (A, B) such that $c(A, B) \leq v(f) + m\Delta$.
 - Choose A to be the set of nodes **reachable** from s in $G_f(\Delta)$.
 - By definition of $A \Rightarrow s \in A$. No augmenting path for $f \Rightarrow t \notin A$.

$$\begin{aligned} v(f) &= f^{out}(A) - f^{in}(A) \\ &\geq \sum_{e \text{ out of } A} (c(e) - \Delta) - \sum_{e \text{ in to } A} \Delta \\ &\geq \sum_{e \text{ out of } A} c(e) - \sum_{e \text{ out of } A} \Delta - \sum_{e \text{ in to } A} \Delta \\ &\geq c(A, B) - m\Delta \end{aligned}$$

flow value lemma





5. Edmonds-Karp Algorithm



Shortest Augmenting Path (Edmonds-Karp)

- **Q.** How to choose next augmenting path in **Ford-Fulkerson**?
- **A.** Pick a path that uses the **fewest edges**. ← can find via BFS
- **Edmonds-Karp (EK) algorithm:**

```
Edmonds-Karp( $G, s, t, c$ ) {  
    foreach  $e \in E$ :  $f(e) = 0$   
     $G_f$  = residual network of  $G$  with respect to flow  $f$   
  
    while (there exists an augmenting path  $P$  in  $G_f$ ) {  
         $P = \text{Breath-First-Search}(G_f)$   
         $f = \text{Augment}(f, c, P)$  ← core procedure  
        update  $G_f$   
    }  
    return  $f$   
}
```



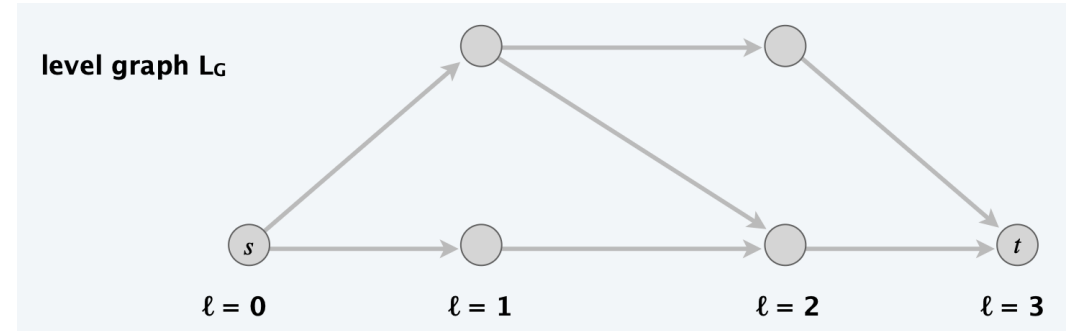
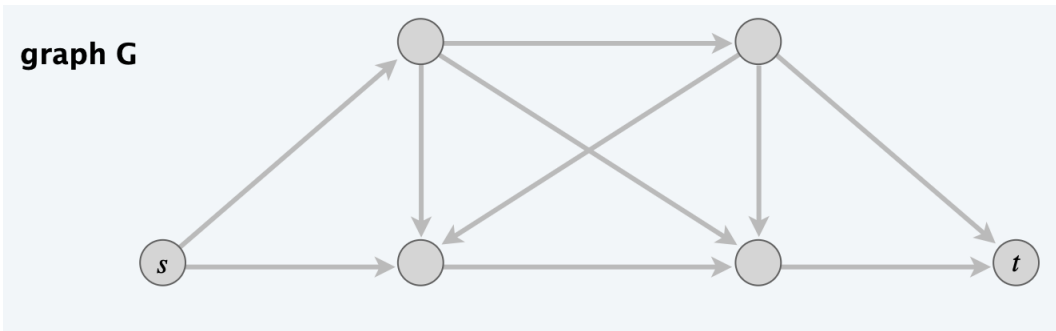
Edmonds-Karp Algorithm: Analysis Overview

- **Lemma 1.** The length of a shortest augmenting path **never decreases**. (Proof shown later.)
- **Lemma 2.** After at most m shortest-path augmentations, the length of a shortest augmenting path **strictly increases**. (Proof shown later.)
- **Theorem.** Edmonds-Karp algorithm takes $O(m^2n)$ time.
- **Pf.** (direct proof)
 - $O(m)$ time to find a shortest augmenting path via **BFS**.
 - There are $\leq mn$ augmentations.
 - ✓ Augmenting paths are **simple** \Rightarrow at most $n - 1$ different lengths
 - ✓ **Lemma 1 + Lemma 2** \Rightarrow at most m augmenting paths for each length ■



Edmonds-Karp Algorithm: Analysis

- **Def.** Given a directed graph $G = (V, E)$ with source s , its **level graph** is defined by:
 - $\ell(v)$ = number of edges in **shortest s - v** path.
 - $L_G = (V, E_G)$ is the subgraph of G that contains only those edges $(v, w) \in E$ such that $\ell(w) = \ell(v) + 1$.



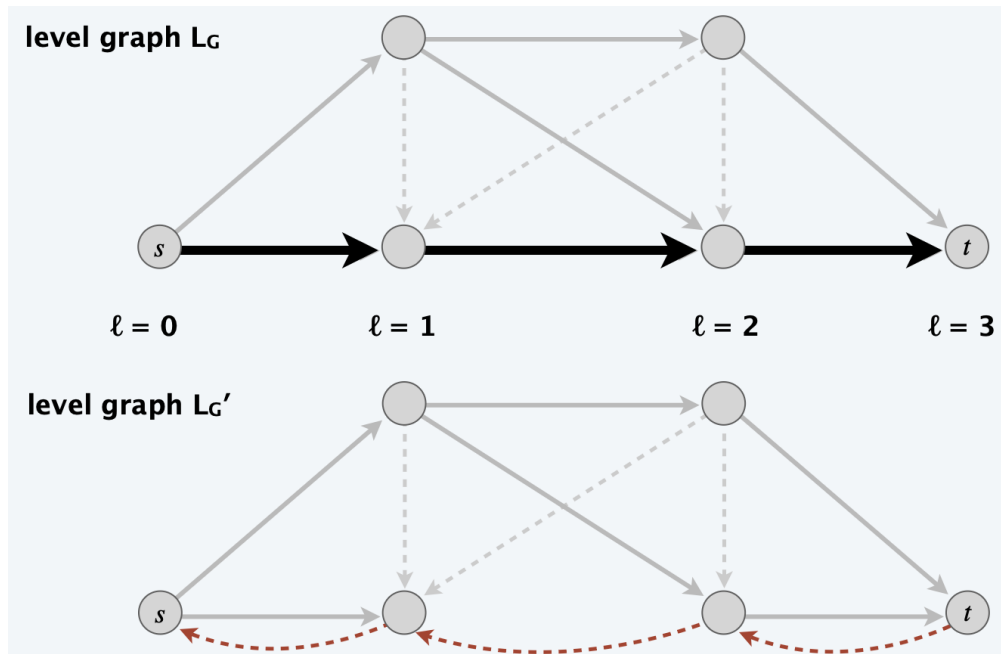
- **Key property.** P is a **shortest s - v** path in G iff P is an s - v path in L_G .

all possible shortest s - v paths are captured in L_G



Edmonds-Karp Algorithm: Analysis

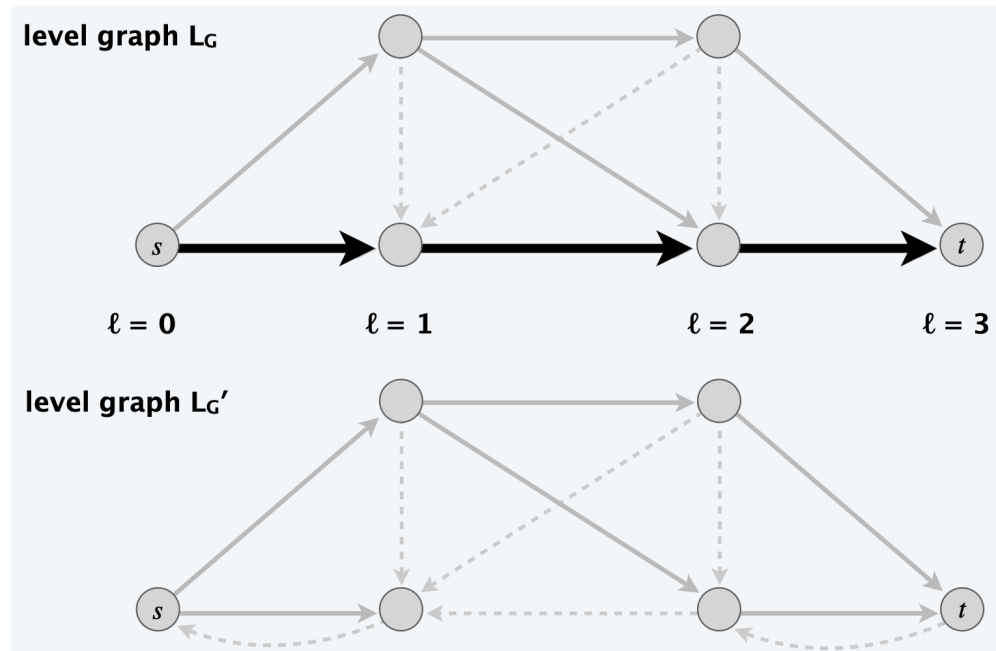
- **Pf of Lemma 1:** (Length of a shortest augmenting path never decreases.)
 - Let f and f' be flows **before** and **after** a **shortest-path** augmentation.
 - Let L_G and $L_{G'}$ be level graphs of G_f and $G_{f'}$. Only **reverse** edges added to $G_{f'}$.
 - Any s - t path that uses a reverse edge is **longer** than previous length. ▀





Edmonds-Karp Algorithm: Analysis

- **Pf of Lemma 2:** (After at most m shortest-path augmentations, the length of a shortest augmenting path strictly increases.)
 - At least one (bottleneck) edge is **deleted** from L_G per augmentation.
 - No new edge added to L_G until it does not have any s - t path, then shortest path length in the new level graph **strictly increases**. ▀





Edmonds-Karp Algorithm: Summary

- **Lemma 1.** The length of a shortest augmenting path **never decreases**.
- **Lemma 2.** After at most **m** shortest-path augmentations, the length of a shortest augmenting path **strictly increases**.
- **Theorem.** Edmonds-Karp algorithm takes **$O(m^2n)$** time.
- **Fact.** **$\Theta(mn)$** augmentations are **necessary** for some flow networks.
- **Solution.** Try to **decrease time per augmentation** instead.
 - Simple idea $\Rightarrow O(mn^2)$ [Dinitz 1970] \leftarrow next section **invented by Dinitz in response to a class exercise by Adel'son-Vel'skiĭ**
 - Dynamic trees $\Rightarrow O(mn \log n)$ [Sleator-Tarjan 1982]



6. Dinitz's Algorithm



Dinitz's Algorithm

- **Two types of augmentations:**

- Normal: length of shortest path does not change.
- Special: length of shortest path strictly increases.

- **Phase of normal augmentations:**

- Construct level graph L_G .
- Start at s , advance along an edge in L_G until reach t or get stuck.
- If reach t , augment flow; update L_G ; and restart from s .
- If get stuck, delete node from L_G and retreat to previous node.



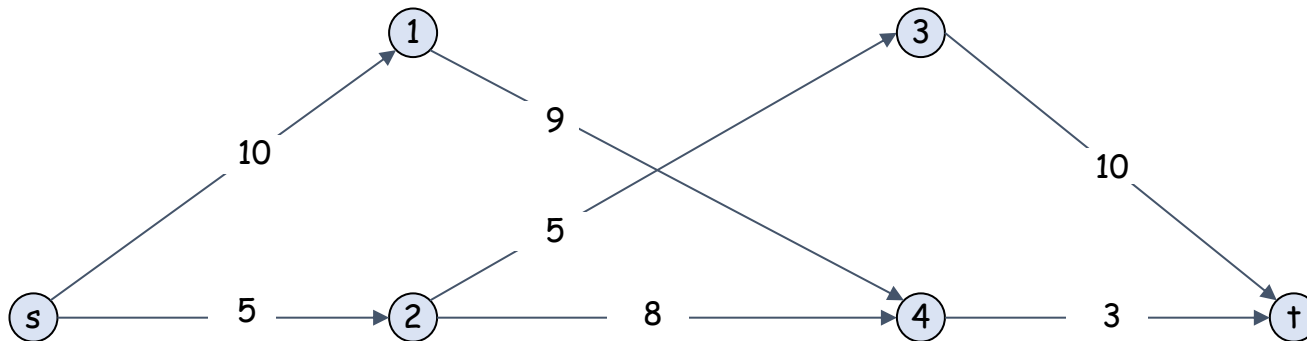
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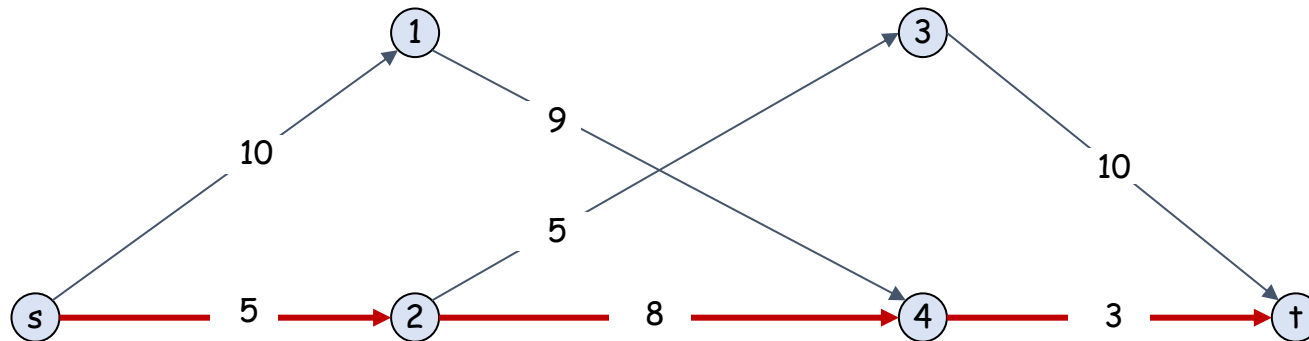
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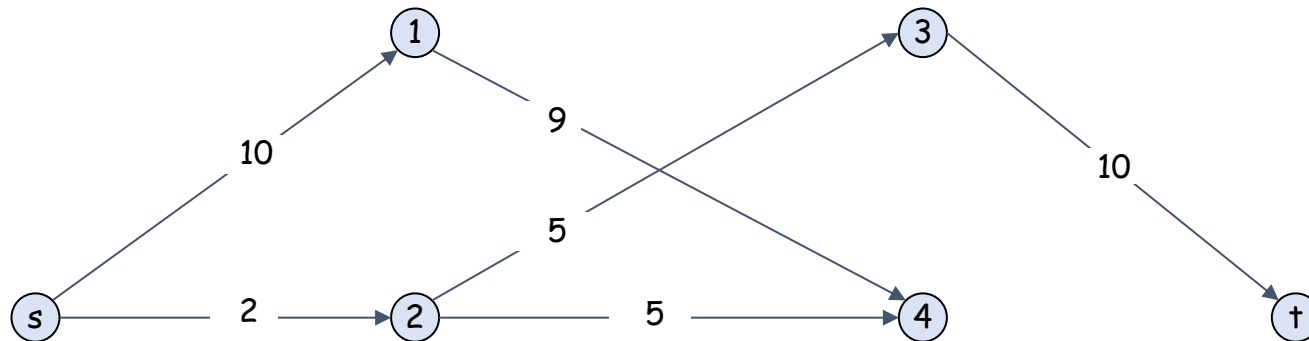
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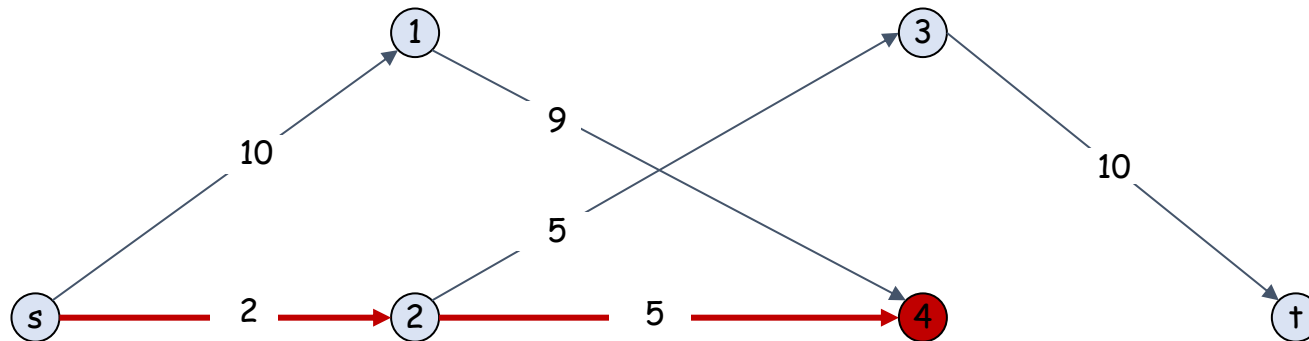
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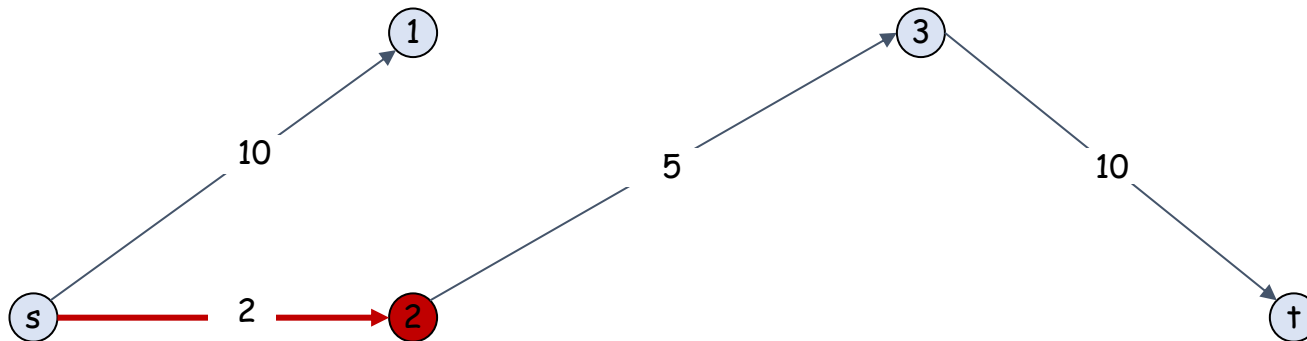
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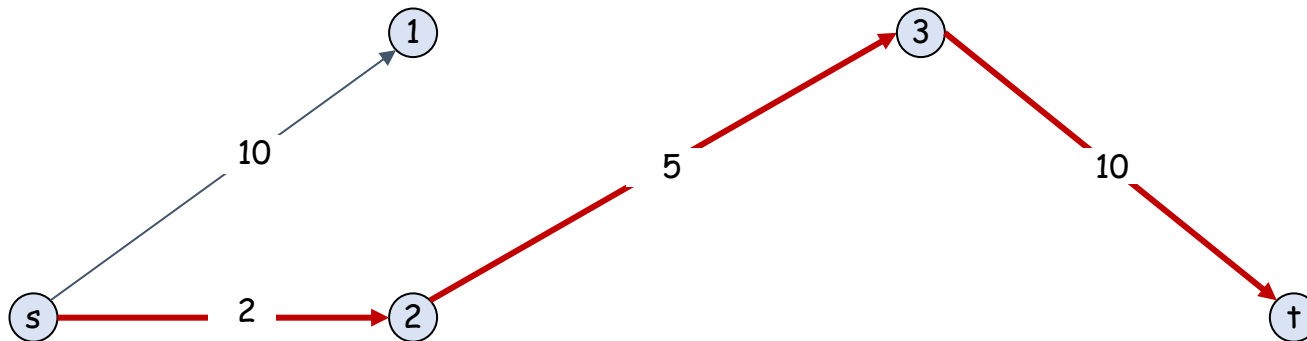
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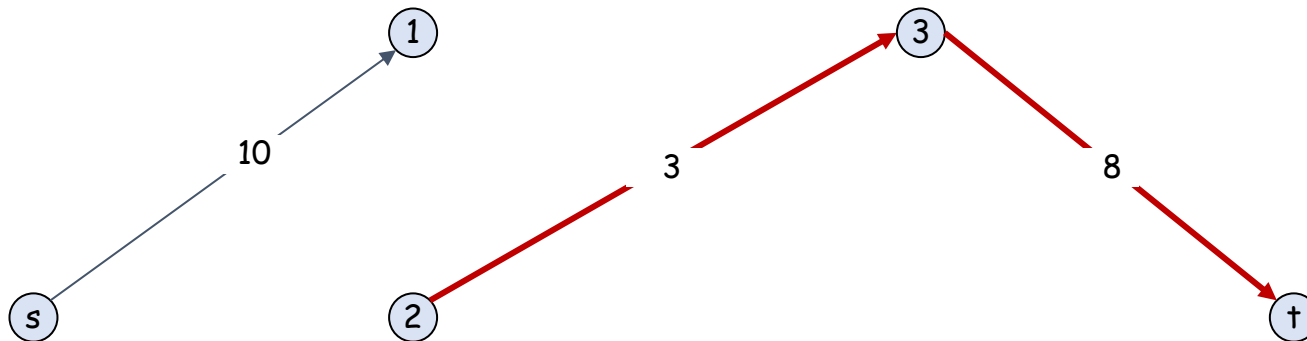
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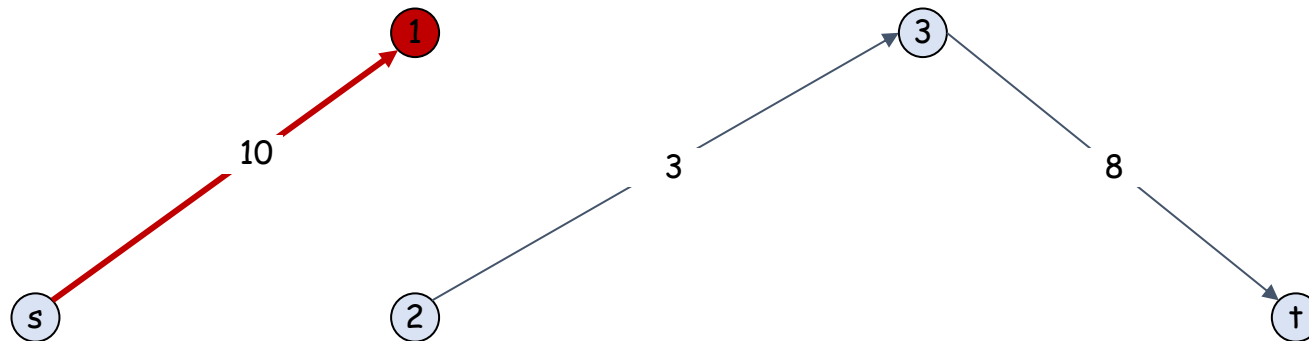
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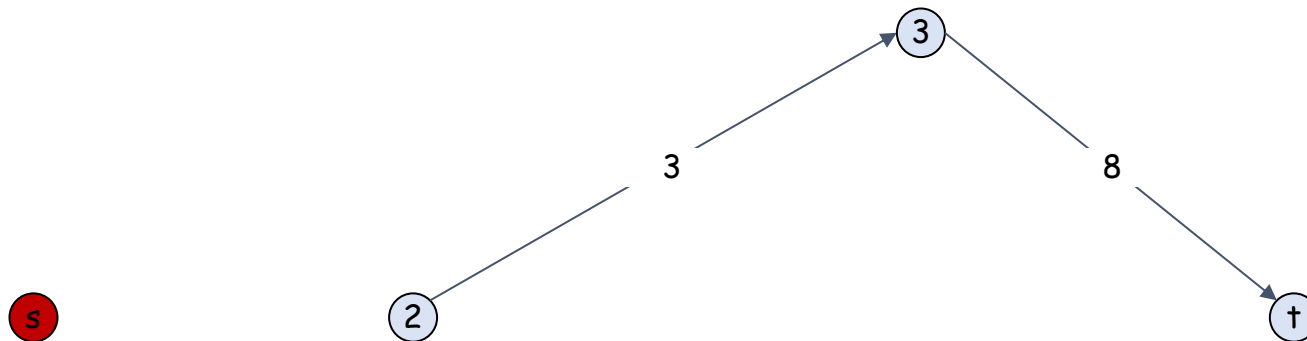
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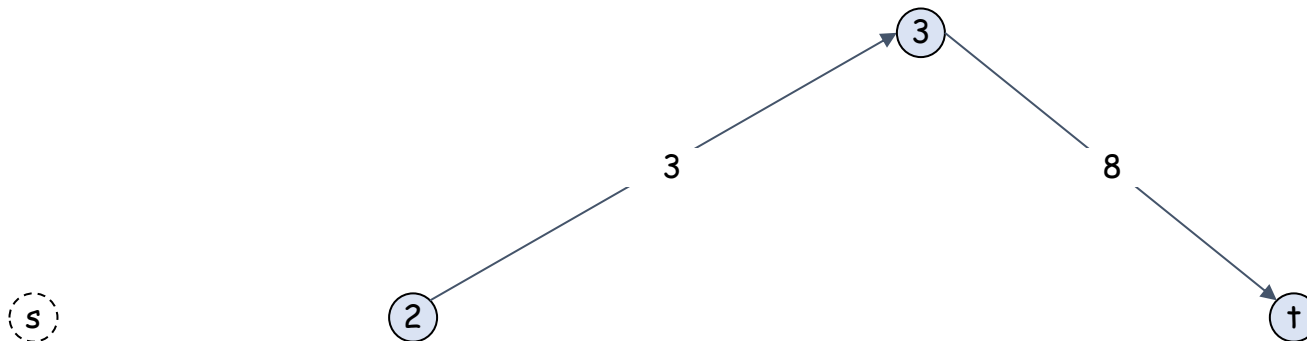
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- Start at s , advance along an edge in L_G until reach t or get stuck.
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- If get stuck, delete node from L_G and retreat to previous node.





Dinitz's Algorithm

- Two types of augmentations:

- Normal: length of shortest path does not change.
- Special: length of shortest path strictly increases.

- Dinitz's algorithm per normal phase: (as refined by Even and Itai)

```
Dinitz-Normal-Phase( $G_f$ ,  $s$ ,  $t$ ) {  
     $L_G$  = level graph of  $G_f$   
     $P$  = empty path  
    Advance( $s$ )  
}  
  
Retreat( $v$ ) {  
    if ( $v = s$ ) return  
    else  
        delete  $v$  and incident edges from  $L_G$   
        remove last edge ( $u, v$ ) from  $P$   
        Advance( $u$ )  
}  
  
Advance( $v$ ) {  
    if ( $v = t$ )  
         $f$  = Augment( $f$ ,  $c$ ,  $P$ )  
        remove bottleneck edges from  $L_G$   
         $P$  = empty path  
        Advance( $s$ )  
    if (there exists ( $v, w$ )  $\in L_G$ )  
        add edge ( $v, w$ ) to  $P$   
        Advance( $w$ )  
    Retreat( $v$ )  
}
```

optimization: can instead advance
from the nearest advancable node →



Dinitz's Algorithm

- **Two types of augmentations:**

- Normal: length of shortest path does not change.
- Special: length of shortest path strictly increases.

- **Dinitz's algorithm:**

```
Dinitz(G, s, t, c) {  
    foreach e ∈ E: f(e) = 0  
    Gf = residual network of G with respect to flow f  
  
    while (there exists an augmenting path P in Gf) {  
        Dinitz-Normal-Phase(Gf, s, t)  
    }  
    return f  
}
```



Dinitz's Algorithm: Analysis

- **Lemma.** A phase can be implemented to run in $O(mn)$ time.
- **Pf. (direct proof)**
 - Level graph initialization happens once per phase. $\leftarrow O(m)$ per phase using BFS
 - At most m augmentations per phase. $\leftarrow O(mn)$ per phase
(because an augmentation deletes at least one edge from L_G)
 - At most n retreats per phase. $\leftarrow O(m + n)$ per phase
(because a retreat deletes one node and all incident edges from L_G)
 - At most mn advances per phase. $\leftarrow O(mn)$ per phase
(because at most n advances before **retreat** or **augmentation**) ■
- **Theorem.** [Dinitz 1970] Dinitz's algorithm runs in $O(mn^2)$ time.
- **Pf.** There are at most $n - 1$ phases and each phase runs in $O(mn)$ time. ■



Augmenting-Path Algorithms: Summary

year	method	# augmentations	running time	
1955	augmenting path	$n C$	$O(m n C)$	fat paths
1972	fattest path	$m \log (m C)$	$O(m^2 \log n \log (m C))$	
1972	capacity scaling	$m \log C$	$O(m^2 \log C)$	
1985	improved capacity scaling	$m \log C$	$O(m n \log C)$	
1970	shortest augmenting path	$m n$	$O(m^2 n)$	shortest paths
1970	level graph	$m n$	$O(m n^2)$	
1983	dynamic trees	$m n$	$O(m n \log n)$	
augmenting-path algorithms with m edges, n nodes, and integer capacities between 1 and C				



Max-Flow Algorithms: Theory Highlights

year	method	worst case	discovered by
1951	simplex	$O(m n^2 C)$	Dantzig
1955	augmenting paths	$O(m n C)$	Ford–Fulkerson
1970	shortest augmenting paths	$O(m n^2)$	Edmonds–Karp, Dinitz
1974	blocking flows	$O(n^3)$	Karzanov
1983	dynamic trees	$O(m n \log n)$	Sleator–Tarjan
1985	improved capacity scaling	$O(m n \log C)$	Gabow
1988	push-relabel	$O(m n \log (n^2 / m))$	Goldberg–Tarjan
1998	binary blocking flows	$O(m^{3/2} \log (n^2 / m) \log C)$	Goldberg–Rao
2013	compact networks	$O(m n)$	Orlin
2014	interior–point methods	$\tilde{O}(m n^{1/2} \log C)$	Lee–Sidford
2016	electrical flows	$\tilde{O}(m^{10/7} C^{1/7})$	Mądry
20xx		???	

← best in practice

max-flow algorithms with m edges, n nodes, and integer capacities between 1 and C



Max-Flow Algorithms: Practice

- **Caveat.** **Worst-case** running time is generally **not useful** for predicting or comparing max-flow algorithm performance **in practice**.
- **Best in practice.** **Push-relabel** algorithm [Goldberg-Tarjan 1988] with gap relabeling: $O(m^{3/2})$ in practice. [section 7.4 of textbook]
 - Increases flow **one edge at a time** instead of one augmenting path at a time.
- **Computer vision.** Different algorithms work better for some dense problems that arise in applications to computer vision.
- **Implementation.** **MATLAB**, Google **OR-Tools**, etc.



Announcement

- **The Bonus Assignment has been released and the deadline is June 7.**
 - This bonus assignment is **optional** and the captured material is **out of the scope** of this course.
 - The grade of this assignment can be used to **replace the lowest grade** of your other 6 mandatory assignments.

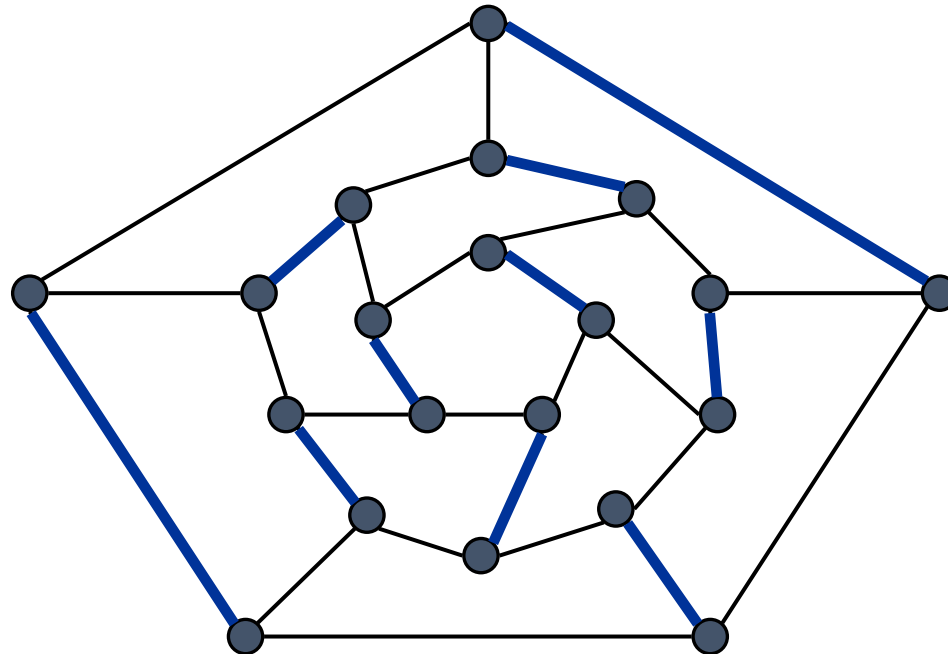


7. Bipartite Matching



Matching

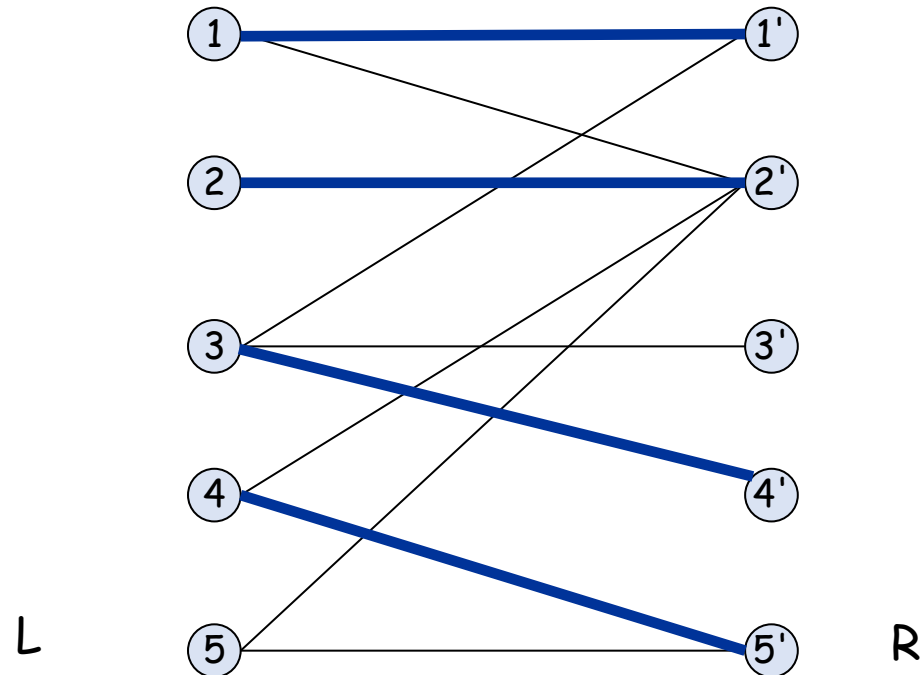
- **Def.** Given an undirected graph $G = (V, E)$, the subset of edges $M \subseteq E$ is a **matching** if each node appears in **at most one edge** in M .
- **Max matching.** Find **max-cardinality** matching.





Bipartite Matching

- **Def.** Given an undirected **bipartite** graph $G = (L \cup R, E)$, the subset of edges $M \subseteq E$ is a **matching** if each node appears in **at most one** edge in M .
- **Max bipartite matching.** Find **max-cardinality** matching in bipartite graph.

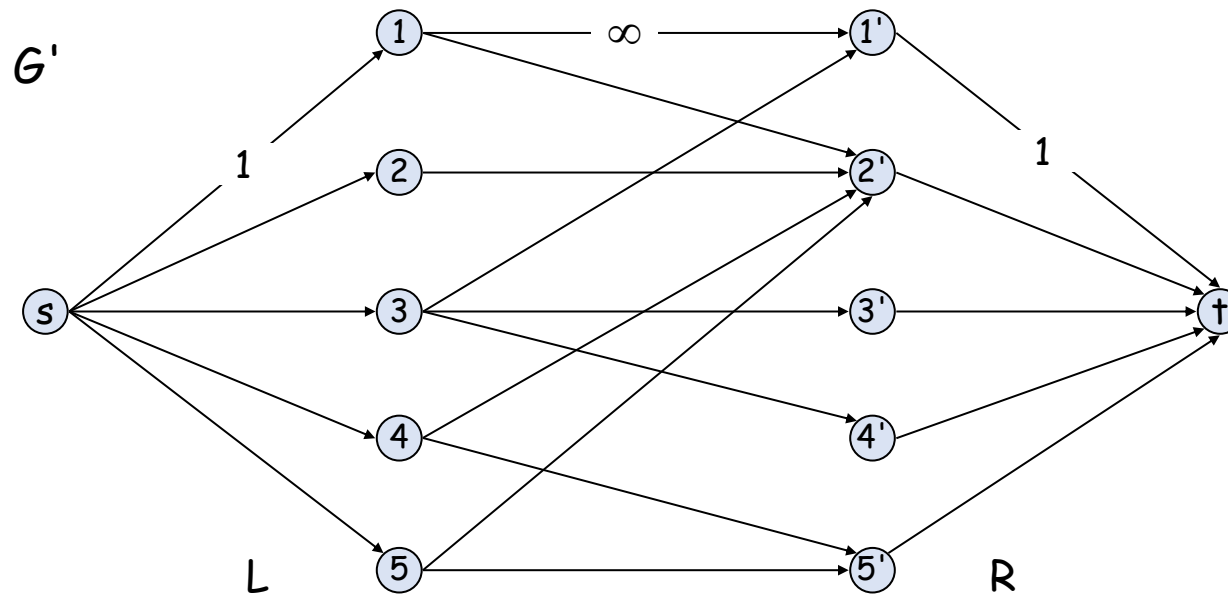




Bipartite Matching: Max-Flow Formulation

- **Max-flow formulation:**

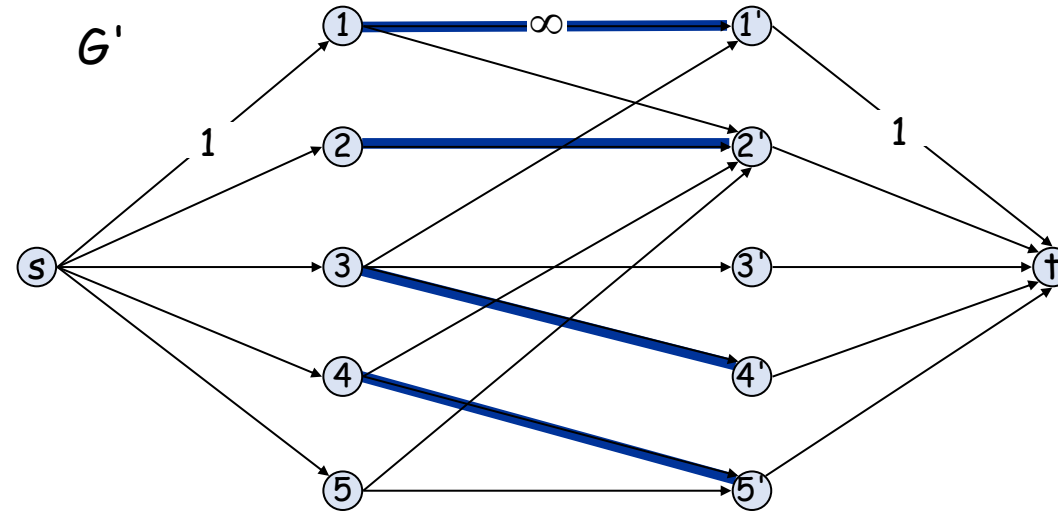
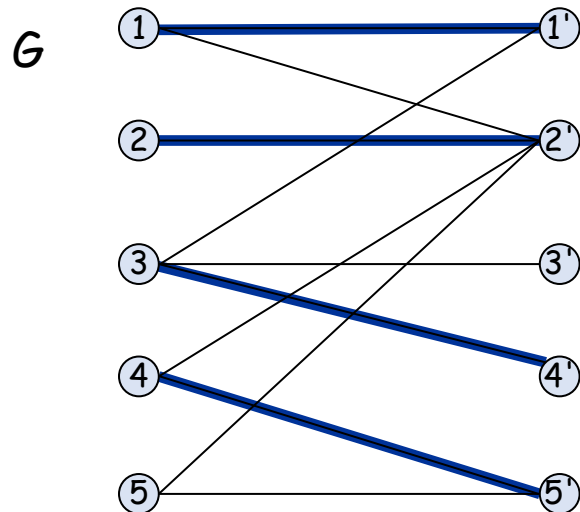
- Create a directed graph $G' = (L \cup R \cup \{s, t\}, E')$.
- Direct all edges from L to R , and assign **infinite** (or **unit**) capacity.
- Add source s , and **unit-capacity** edges from s to each node in L .
- Add sink t , and **unit-capacity** edges from each node in R to t .





Max-Flow Formulation: Correctness

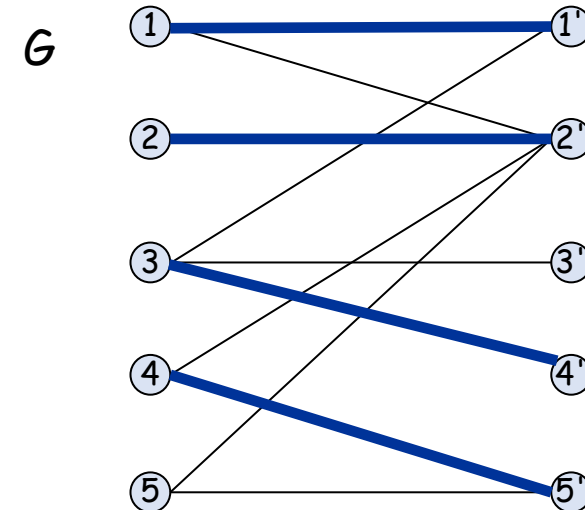
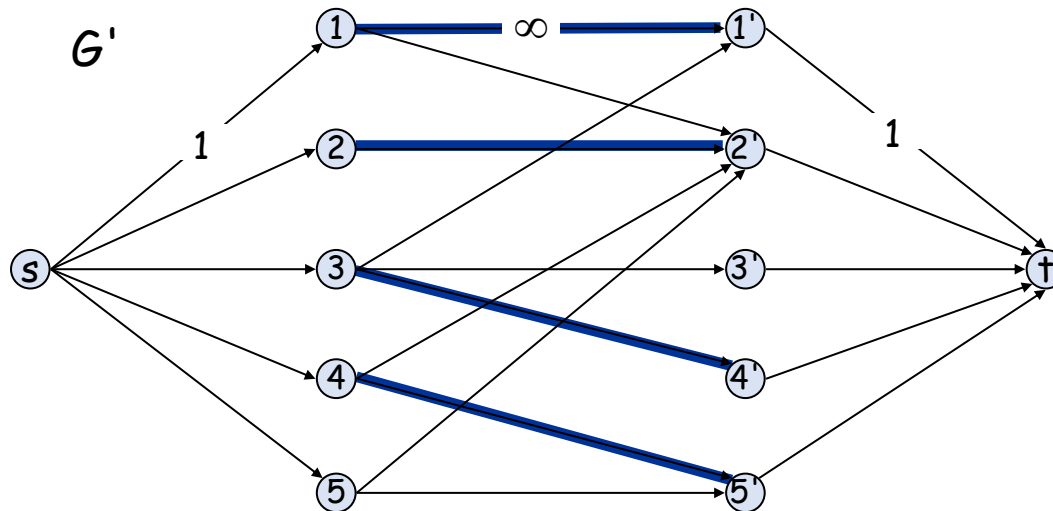
- **Theorem.** There exists a **1-1 correspondence** between matchings of cardinality k in G and integral flows of value k in G' .
- **Pf. \Rightarrow :** Let M be a matching in G of cardinality k .
 - Consider flow f that sends **1** unit flow on each of the k corresponding paths.
 - f is an integral flow of value k . ▀





Max-Flow Formulation: Correctness

- **Theorem.** There exists a **1-1 correspondence** between matchings of cardinality k in G and integral flows of value k in G' .
- **Pf. \Leftarrow :** Let f be an integral flow in G' of value k .
 - 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 .
 - ✓ $|M| = k$: apply **flow value lemma** to cut $(L \cup \{s\}, R \cup \{t\})$. ▀





Max-Flow Formulation: Correctness

- **Theorem.** There exists a **1-1 correspondence** between matchings of cardinality k in G and integral flows of value k in G' .
- **Corollary.** Can find **max bipartite matching** via max-flow formulation.
- **Pf.** (direct proof)
 - **Integrality theorem** \Rightarrow there exists a **max flow f^*** in G' that is integral.
 - **Theorem** $\Rightarrow f^*$ corresponds to **max-cardinality** matching. ■



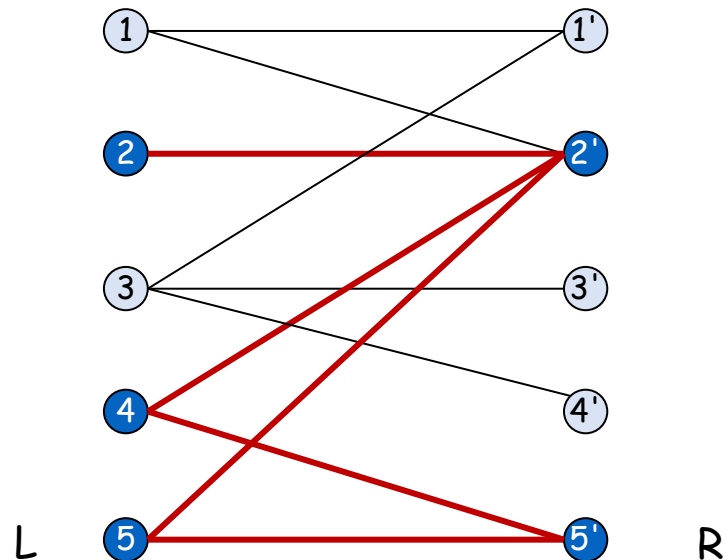
Perfect Matchings in Bipartite Graphs

- **Def.** Given a graph $G = (V, E)$, a subset of edges $M \subseteq E$ is a **perfect matching** if each node appears in **exactly one** edge in M .
- **Q.** When does a bipartite graph have a **perfect matching**?
- **Structure of bipartite graphs with perfect matchings:**
 - Clearly we must have $|L| = |R|$.
 - What other conditions are **necessary**?
 - What other conditions are **sufficient**?



Perfect Matchings in Bipartite Graphs

- **Notation.** Let S be a subset of nodes, and let $N(S)$ be the set of nodes adjacent to nodes in S .
- **Claim.** If a bipartite graph $G = (L \cup R, E)$ has a perfect matching, then $|N(S)| \geq |S|$ for all subsets $S \subseteq L$.
- **Pf.** Each node in S has to be matched to a different node in $N(S)$.
- **Example:**



No perfect matching exists:

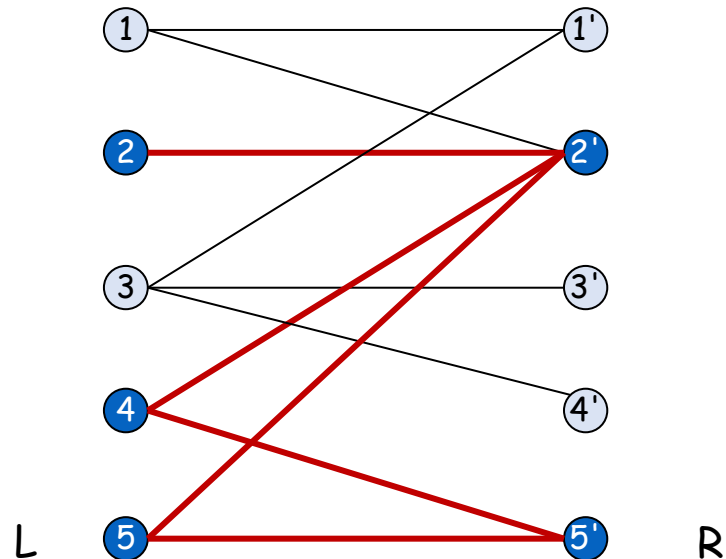
$$S = \{2, 4, 5\}$$

$$N(S) = \{2', 5'\}.$$



Hall's Marriage Theorem

- **Theorem.** [Frobenius 1917, Hall 1935] Let $G = (L \cup R, E)$ be a bipartite graph with $|L| = |R|$. G has a perfect matching if and only if $|N(S)| \geq |S|$ for all subsets $S \subseteq L$.
- **Pf.** “only if” \Rightarrow : This was the previous **Claim**.



No perfect matching exists:

$$S = \{ 2, 4, 5 \}$$

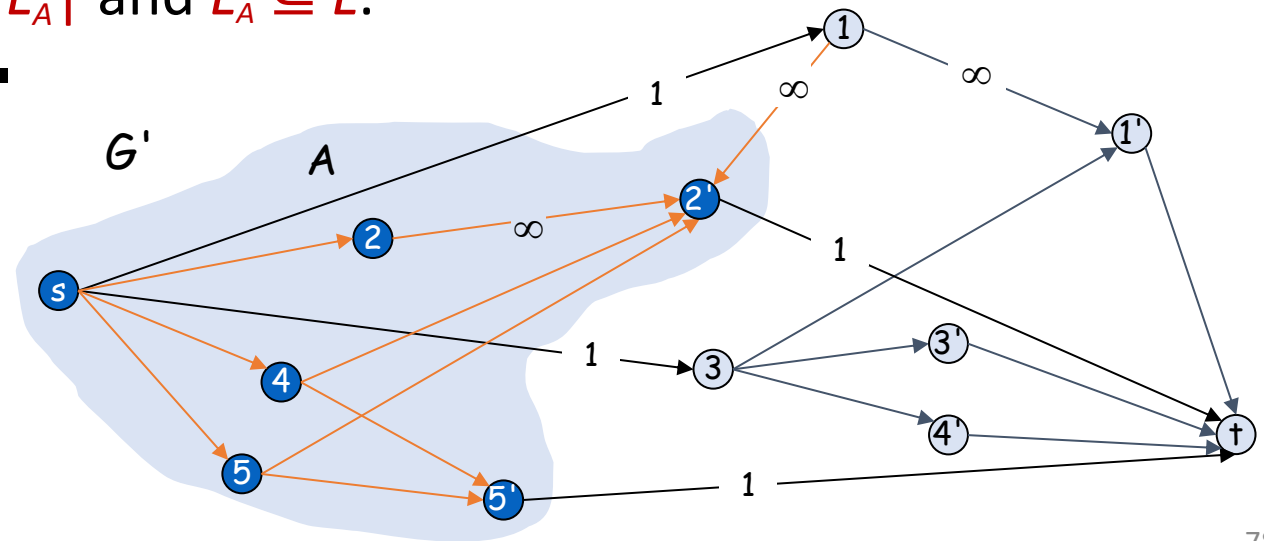
$$N(S) = \{ 2', 5' \}.$$



Hall's Marriage Theorem

- **Pf. “if” \Leftarrow :** Suppose G does **not** have a **perfect matching**. (contrapositive)
 - Formulate as a max flow problem and let (A, B) be a **min cut** in G' .
 - **Max-flow min-cut theorem** $\Rightarrow c(A, B) < |L|$
 - Define $L_A = L \cap A$, $L_B = L \cap B$, $R_A = R \cap A$.
 - Min cut cannot use ∞ edges $\Rightarrow N(L_A) \subseteq R \cap A = R_A$
 - $c(A, B) = |L_B| + |R_A| < |L| = |L_A| + |L_B| \Rightarrow |R_A| < |L_A|$
 - Together, $|N(L_A)| \leq |R_A| < |L_A|$ and $L_A \subseteq L$.
 - The contrapositive is true. ■

$$\begin{aligned} L_A &= \{2, 4, 5\} \\ L_B &= \{1, 3\} \\ R_A &= \{2', 5'\} \\ N(L_A) &= \{2', 5'\} \end{aligned}$$





Max Matching: Closing Remarks

- **Algorithms for bipartite matching:**

- Edmonds-Karp: $O(m^2n)$
 - Capacity-scaling: $O(m^2 \log C) = O(m^2)$
 - Ford-Fulkerson: $O(m v(f^*)) = O(mn)$
 - Dinitz: $O(mn^{1/2})$ [Even-Tarjan 1975]
 - Fast matrix multiplication: $O(n^{2.378})$ [Mucha-Sankowski 2003]
- learned max-flow algorithms

- **Non-bipartite matching:**

- Structure of **non-bipartite (undirected)** graphs is more complicated.
- But well-understood. [Tutte-Berge formula, Edmonds-Galai]
- Blossom algorithm: $O(n^4)$ [Edmonds 1965]
- Best known: $O(mn^{1/2})$ [Micali-Vazirani 1980, Vazirani 1994]



Historical Significance (Jack Edmonds 1965)

2. Digression. An explanation is due on the use of the words “efficient algorithm.” First, what I present is a conceptual description of an algorithm and not a particular formalized algorithm or “code.”

For practical purposes computational details are vital. However, my purpose is only to show as attractively as I can that there is an efficient algorithm. According to the dictionary, “efficient” means “adequate in operation or performance.” This is roughly the meaning I want—in the sense that it is conceivable for maximum matching to have no efficient algorithm. Perhaps a better word is “good.”

I am claiming, as a mathematical result, the existence of a *good* algorithm for finding a maximum cardinality matching in a graph.

There is an obvious finite algorithm, but that algorithm increases in difficulty exponentially with the size of the graph. It is by no means obvious whether *or not* there exists an algorithm whose difficulty increases only algebraically with the size of the graph.



Announcement

- **Assignment 5 has been released and the deadline is May 29.**

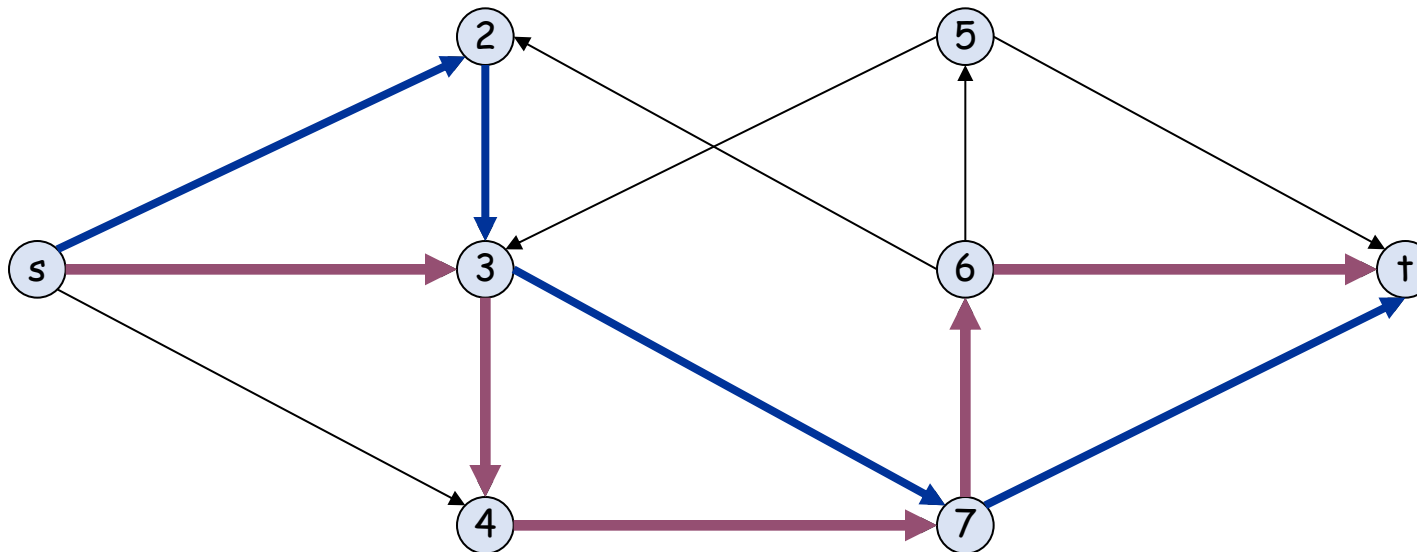


8. Disjoint Paths



Edge-Disjoint Paths

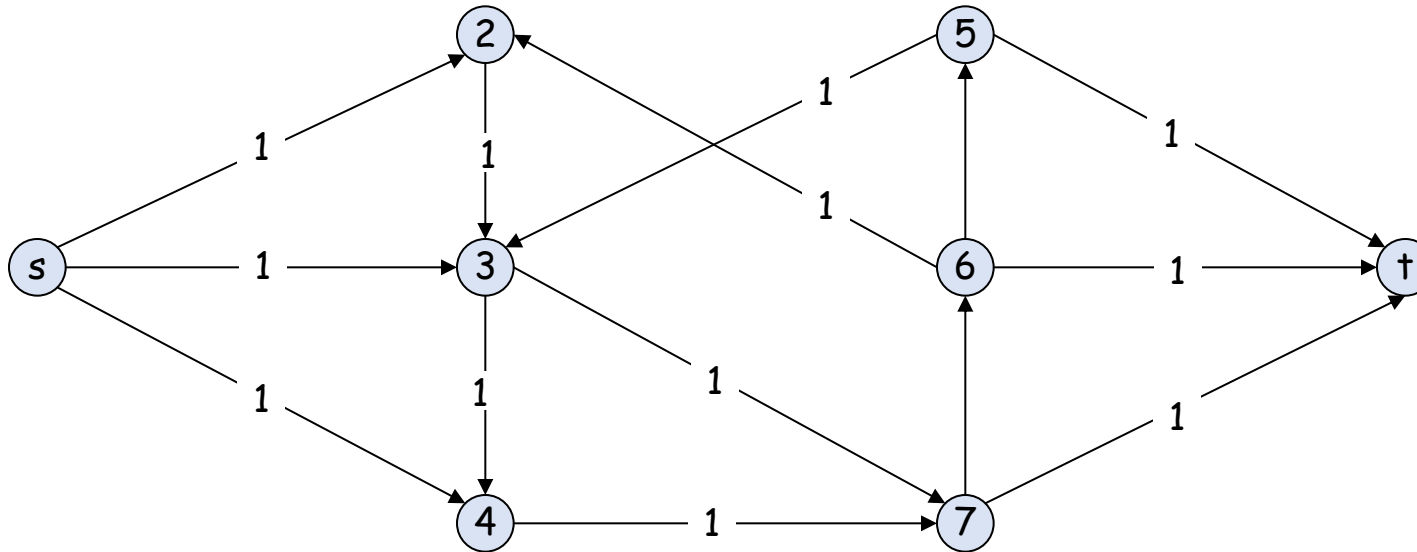
- **Def.** Two paths are **edge-disjoint** if they have no edge in common.
- **Edge-disjoint paths problem.** Given a directed graph $G = (V, E)$ and two nodes s and t , find the **max** number of **edge-disjoint s - t** paths.
- **Example.** Communication networks.





Edge-Disjoint Paths: Max-Flow Formulation

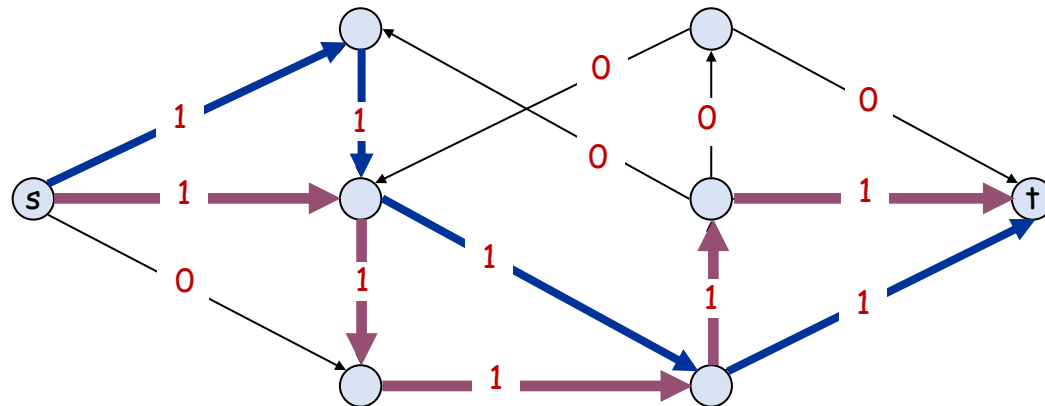
- **Def.** Two paths are **edge-disjoint** if they have no edge in common.
- **Edge-disjoint paths problem.** Given a directed graph $G = (V, E)$ and two nodes s and t , find the **max** number of **edge-disjoint s - t** paths.
- **Max-flow formulation.** Assign **unit capacity** to every edge.





Max-Flow Formulation: Correctness

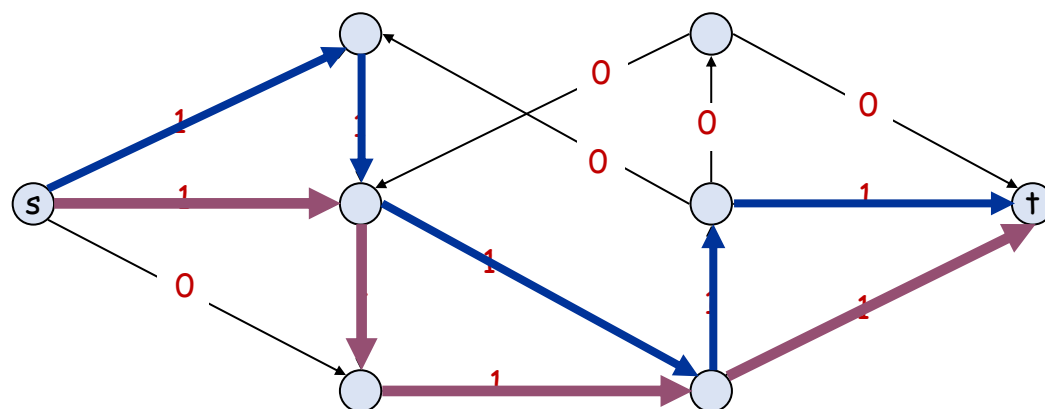
- **Theorem.** There exists a **1-1 correspondence** between k edge-disjoint s - t paths in G and integral flows of value k in G' .
- **Pf. \Rightarrow :**
 - Let P_1, \dots, P_k be k edge-disjoint paths in G .
 - Set $f(e) = 1$ if edge e participates in some path P_i ; else set $f(e) = 0$.
 - Since paths are edge-disjoint, f is a flow of value k . ▀





Max-Flow Formulation: Correctness

- **Theorem.** There exists a **1-1 correspondence** between k edge-disjoint s - t paths in G and integral flows of value k in G' .
- **Pf. \Leftarrow :**
 - Let f be an integral flow in G' of value k .
 - Consider edge (s, u) with $f(s, u) = 1$:
 - ✓ **flow conservation** \Rightarrow there exists an edge (u, v) with $f(u, v) = 1$
 - ✓ continue until reach t , always choosing a **new** edge
 - Produces k edge-disjoint paths (not necessarily simple) . ▀

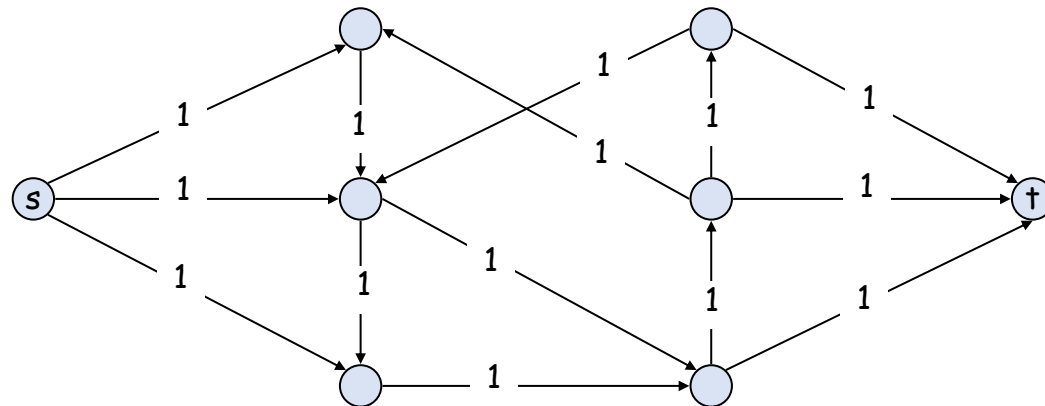


can eliminate cycles and get simple paths if desired



Max-Flow Formulation: Correctness

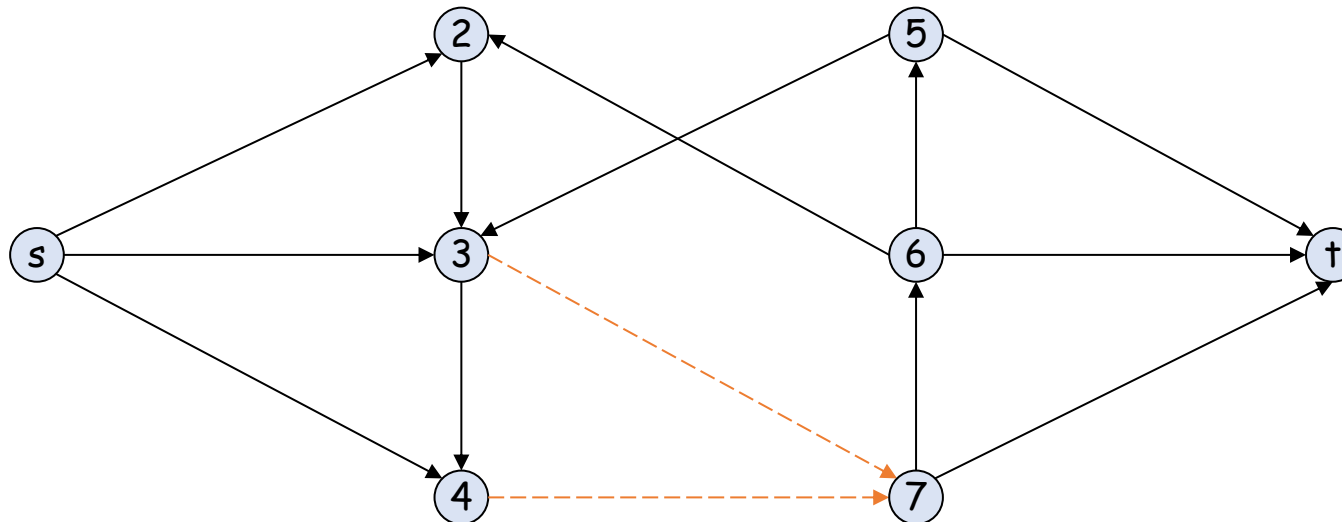
- **Max-flow formulation.** Assign **unit capacity** to every edge.
- **Theorem.** There exists a **1-1 correspondence** between **k** edge-disjoint **s - t** paths in **G** and integral flows of value **k** in **G'** .
- **Corollary.** Can solve edge-disjoint paths via max-flow formulation.
- **Pf. (direct proof)**
 - **Integrality theorem** \Rightarrow there exists a max flow **f^*** in **G'** that is integral.
 - **Theorem** $\Rightarrow f^*$ corresponds to **max** number of **edge-disjoint s - t** paths in **G** . ■





Network Connectivity

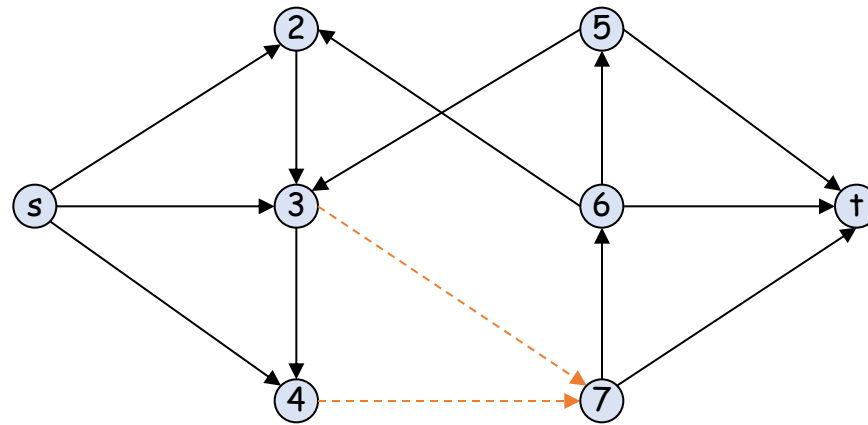
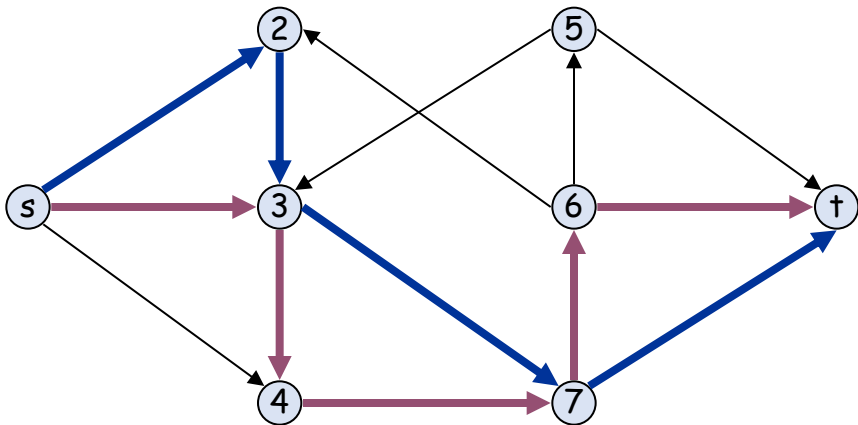
- **Def.** A set of edges $F \subseteq E$ disconnects t from s if every s - t path uses at least one edge in F .
- **Network connectivity.** Given a directed graph $G = (V, E)$ and two nodes s and t , find **min** number of edges whose removal disconnects t from s .





Menger's Theorem

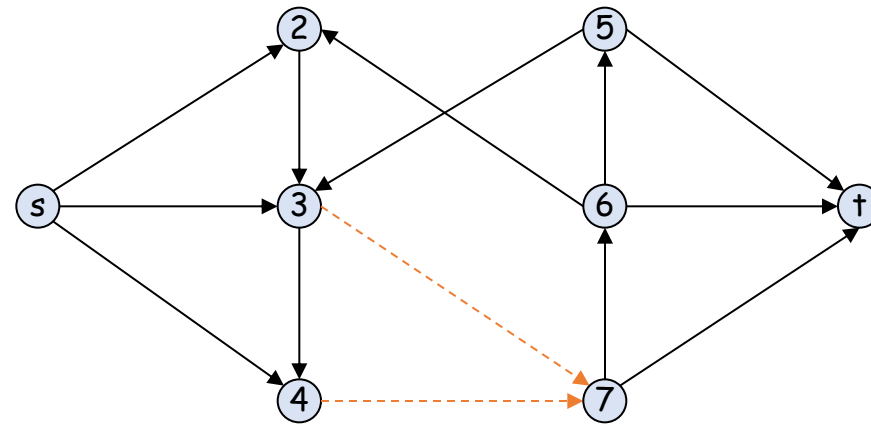
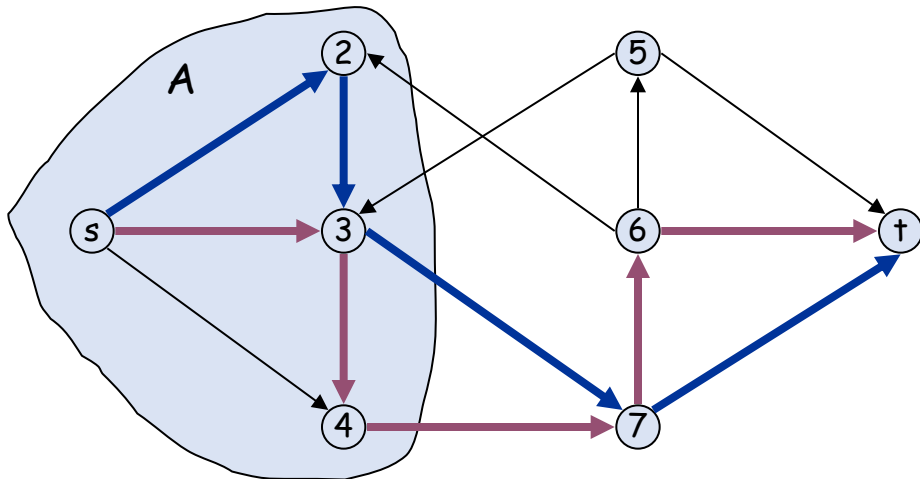
- **Theorem.** [Menger 1927] The **max** number of **edge-disjoint s - t** paths **equals** the **min** number of edges whose removal **disconnects t** from **s** .
- **Pf.** \leq :
 - Suppose the removal of $F \subseteq E$ disconnects t from s , and $|F| = k$.
 - Every s - t path uses **at least** one edge in F .
 - Hence, the number of **edge-disjoint** paths is $\leq k$. ▀





Menger's Theorem

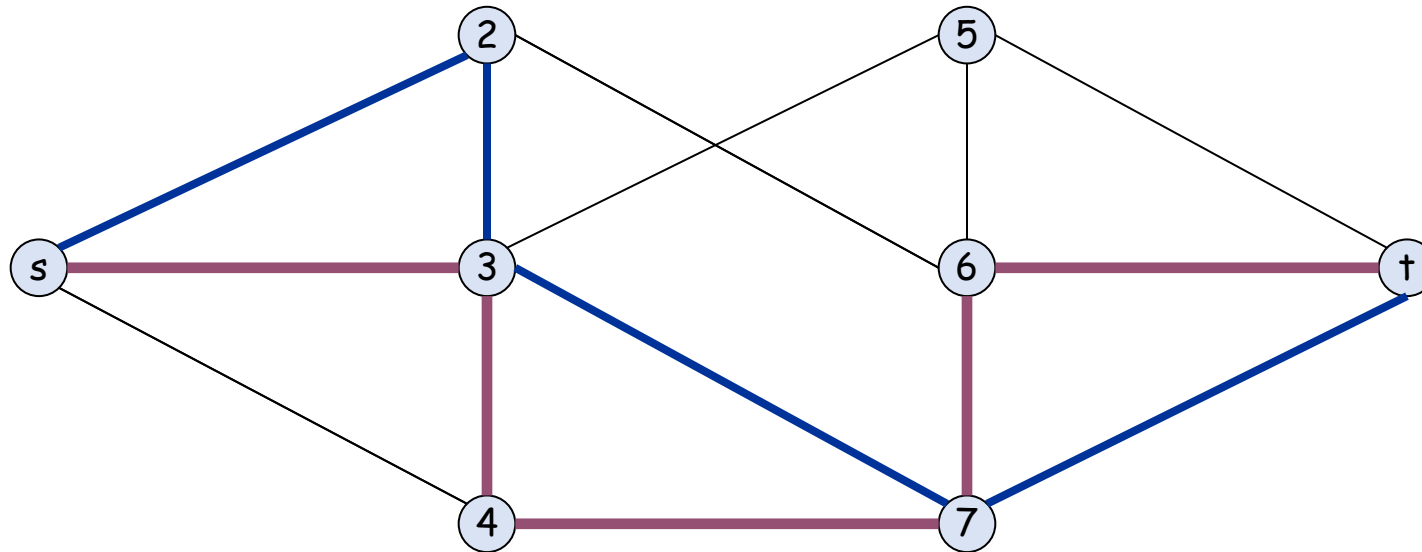
- **Theorem.** [Menger 1927] The **max** number of **edge-disjoint s - t** paths **equals** the **min** number of edges whose removal **disconnects t** from **s** .
- **Pf. \geq :**
 - Suppose max number of edge-disjoint s - t paths is k . Then, value of max flow = k .
 - **Max-flow min-cut theorem** \Rightarrow there exists a cut (A, B) of capacity k .
 - Let F be set of edges going from A to B .
 - $|F| = k$ and removing F disconnects t from s . ▀





Edge-Disjoint Paths in Undirected Graphs

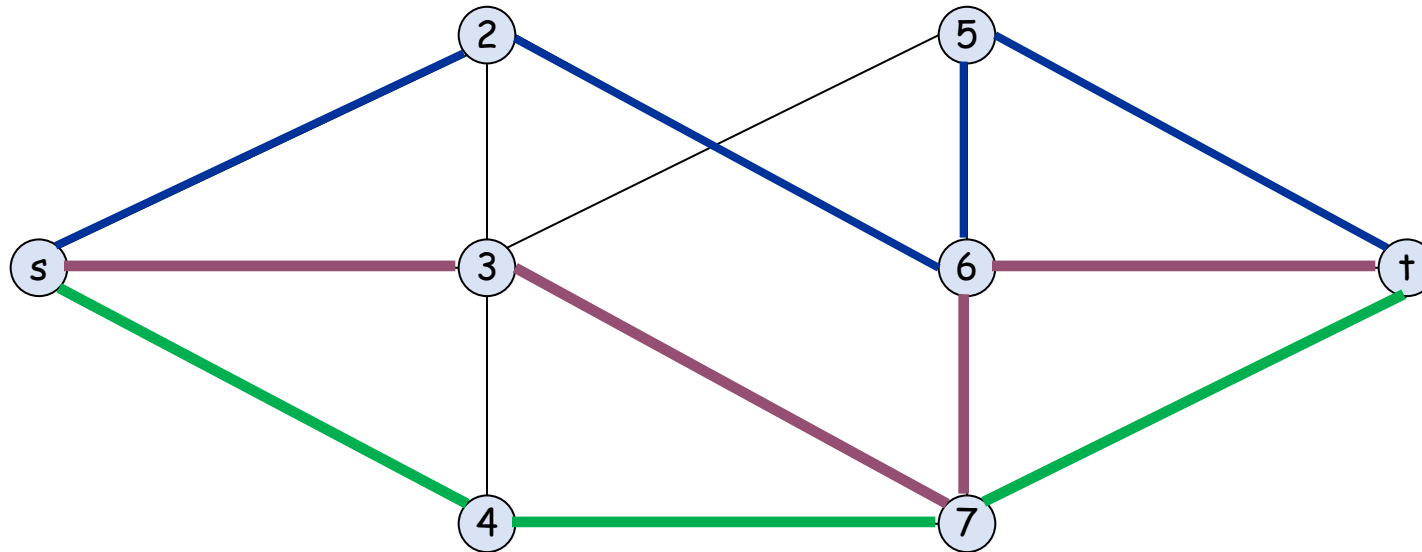
- **Edge-disjoint paths problem in undirected graphs.** Given an **undirected** graph $G = (V, E)$ and two nodes s and t , find **max** number of **edge-disjoint** s - t paths.
- **Example.** 2 edge-disjoint paths.





Edge-Disjoint Paths in Undirected Graphs

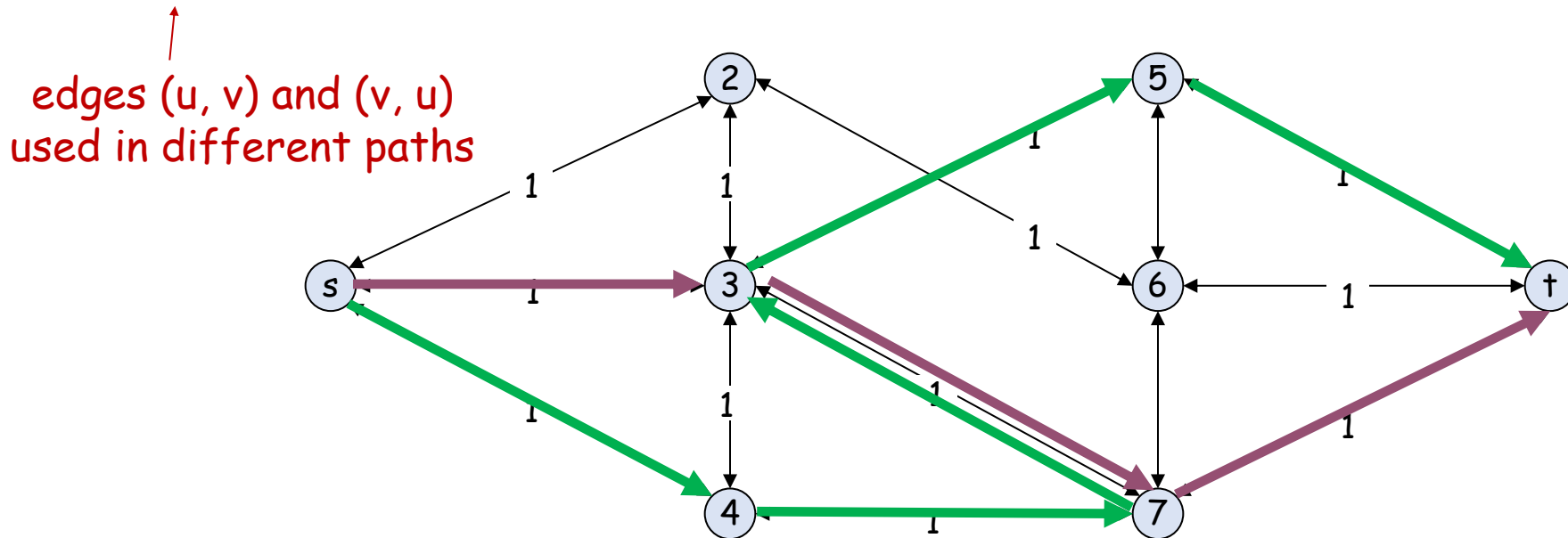
- **Edge-disjoint paths problem in undirected graphs.** Given an **undirected** graph $G = (V, E)$ and two nodes s and t , find **max** number of **edge-disjoint** s - t paths.
- **Example.** 3 edge-disjoint paths (max number).





Edge-Disjoint Paths: Max-Flow Formulation

- **Max-flow formulation.** Replace each edge with **two antiparallel edges** and assign **unit capacity** to every edge.
- **Caveat.** Two paths P_1 and P_2 may be edge-disjoint in the **directed** graph but **not** edge-disjoint in the **undirected** graph.





Max-Flow Formulation: Correctness

- **Max-flow formulation.** Replace each edge with **two antiparallel edges** and assign unit capacity to every edge.
- **Lemma.** In any flow network, there exists a **maximum** flow f in which for each pair of antiparallel edges e and e' : $f(e) = 0$ or $f(e') = 0$ or both. Moreover, **integrality theorem** still holds.
- **Pf.** (by induction on the number of such edge pairs)
 - Suppose $f(e) > 0$ and $f(e') > 0$ for a pair of **antiparallel** edges e and e' .
 - Set $f'(e) = f(e) - \delta$ and $f'(e') = f(e') - \delta$, where $\delta = \min\{f(e), f(e')\}$.
 - f' is still a flow of the **same** value but has **one fewer** such pair. ▀



Max-Flow Formulation: Correctness

- **Max-flow formulation.** Replace each edge with **two antiparallel edges** and assign unit capacity to every edge.
- **Lemma.** In any flow network, there exists a **maximum** flow f in which for each pair of antiparallel edges e and e' : $f(e) = 0$ or $f(e') = 0$ or both. Moreover, **integrality theorem** still holds.
- **Theorem.** **Max** number of edge-disjoint s - t paths = value of **max** flow.
- **Pf.** Similar to the proof in **directed** graphs. Use the above **Lemma**.



More Menger Theorems

- **Theorem.** Given an **undirected** graph and two nodes s and t , the **max** number of **edge-disjoint s - t** paths equals the **min** number of edges whose removal **disconnects s and t** .
- **Theorem.** Given an **undirected** graph and two **nonadjacent** nodes s and t , the **max** number of internally **node-disjoint s - t** paths equals the **min** number of internal nodes whose removal **disconnects s and t** .
- **Theorem.** Given a **directed** graph with two **nonadjacent** nodes s and t , the **max** number of internally **node-disjoint s - t** paths equals the **min** number of internal nodes whose removal **disconnects t from s** .



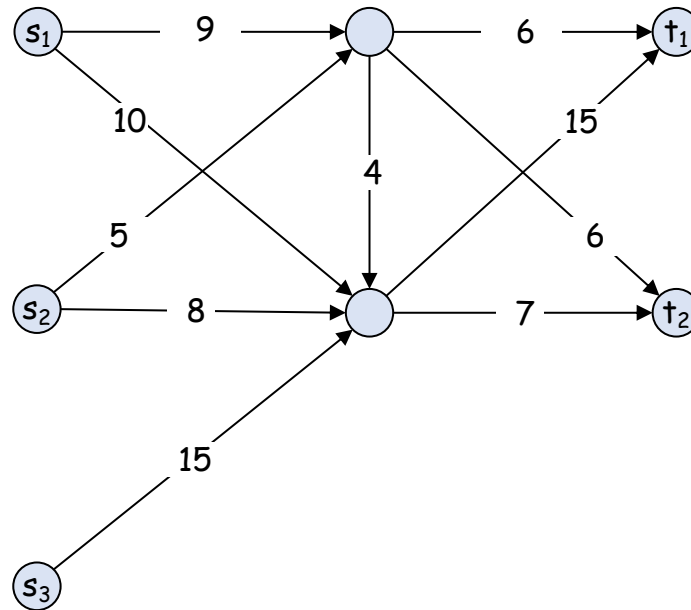
9. Extensions to Max Flow



Multiple Sources and Sinks

- **Def.** Given a directed graph $G = (V, E)$ with edge capacities $c(e) \geq 0$ and **multiple source nodes** and **multiple sink nodes**, find a **max flow** that can be sent from the source nodes to the sink nodes.

flow network G

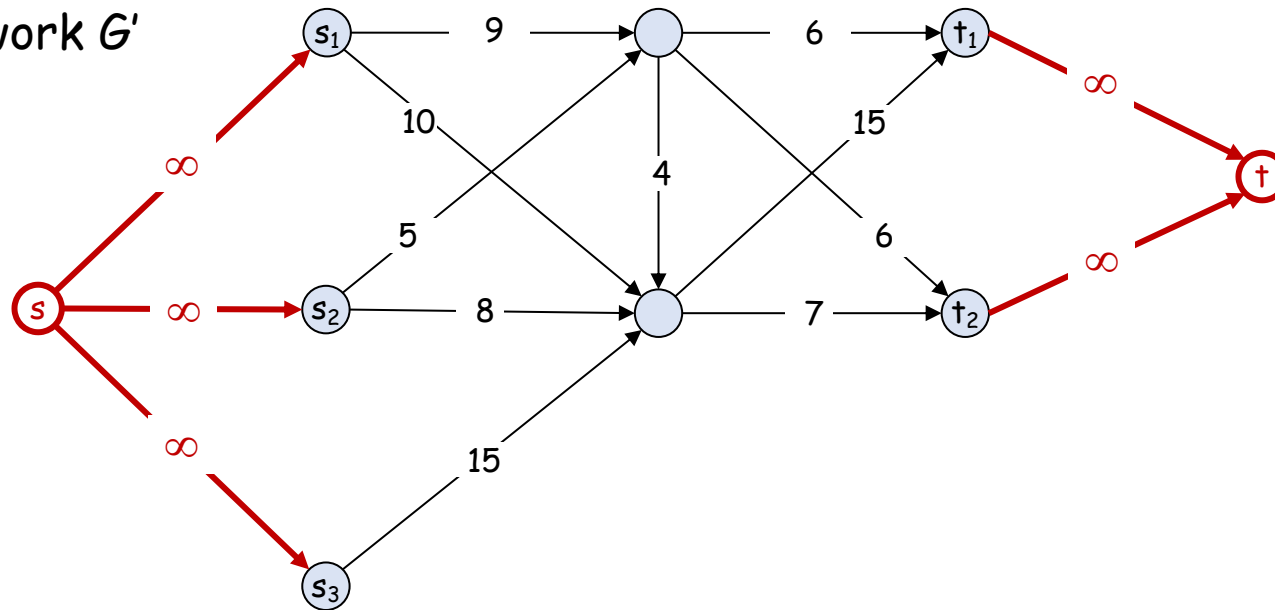




Multiple Sources and Sinks

- **Def.** Given a directed graph $G = (V, E)$ with edge capacities $c(e) \geq 0$ and **multiple source nodes** and **multiple sink nodes**, find a **max flow** that can be sent from the source nodes to the sink nodes.
- **Claim.** There exists a **1-1 correspondence** between flows in G and G' .

flow network G'



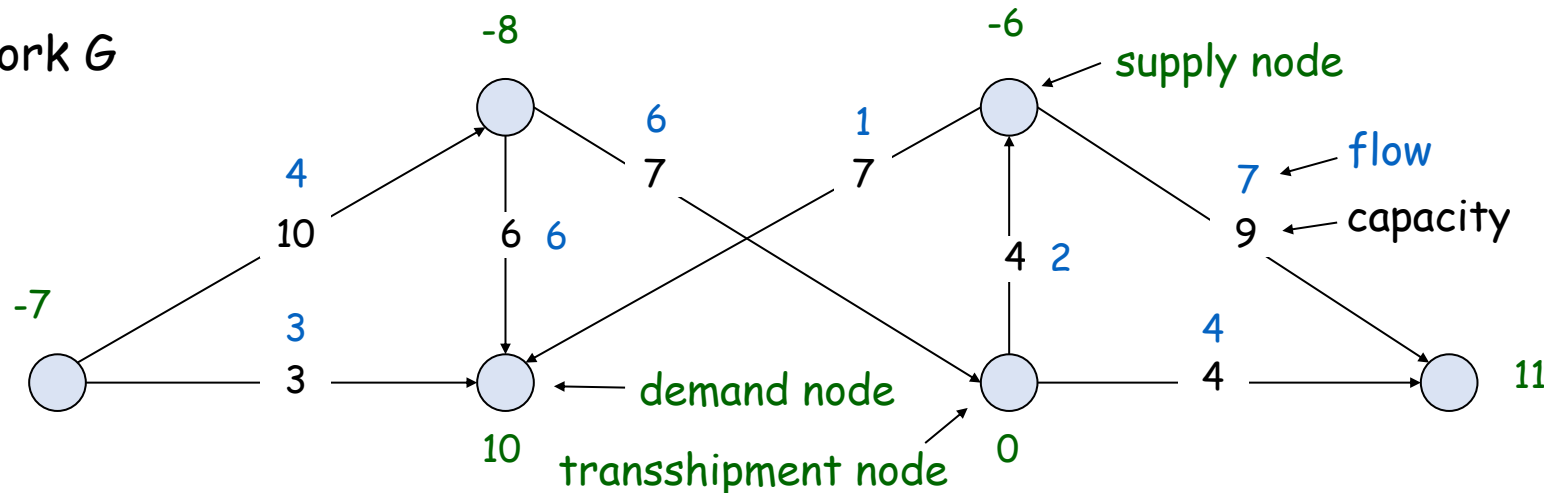


Circulation with Supplies and Demands

- **Def.** Given a directed graph $G = (V, E)$ with edge capacities $c(e) \geq 0$ and node demands $d(v)$, a **circulation** is a function $f(e)$ that satisfies:
 - [Capacity] For each $e \in E$: $0 \leq f(e) \leq c(e)$
 - [Flow conservation] For each $v \in V$: $\sum_{e \text{ into } v} f(e) - \sum_{e \text{ out of } v} f(e) = d(v)$
- **Circulation problem.** Given (V, E, c, d) , find a **circulation**.

simple notation:
 $f_{\text{in}}(v) - f_{\text{out}}(v) = d(v)$

flow network G

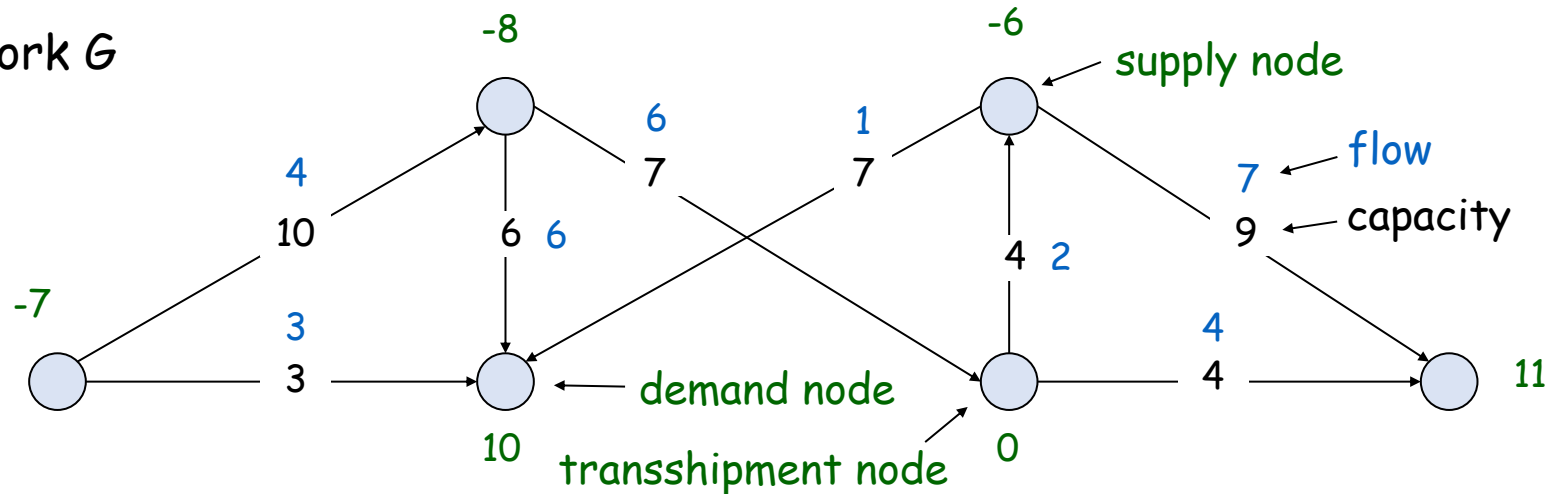




Circulation with Supplies and Demands

- **Circulation problem.** Given (V, E, c, d) , find a **circulation**.
- **Observation.** G has a circulation $\Rightarrow \sum_{v:d(v)>0} d(v) = \sum_{v:d(v)<0} -d(v)$
total demand = total supply
- **Pf.** (equivalent to show $\sum_v d(v) = 0$)
 - Sum **flow conservation** over all $v \in V$: $\sum_v f^{in}(v) - \sum_v f^{out}(v) = \sum_v d(v)$
 - Each $f(e)$ appears once in $\sum_v f^{in}(v)$ and once in $\sum_v f^{out}(v)$ so cancel out.
 - Therefore, $\sum_v d(v) = 0$.

flow network G

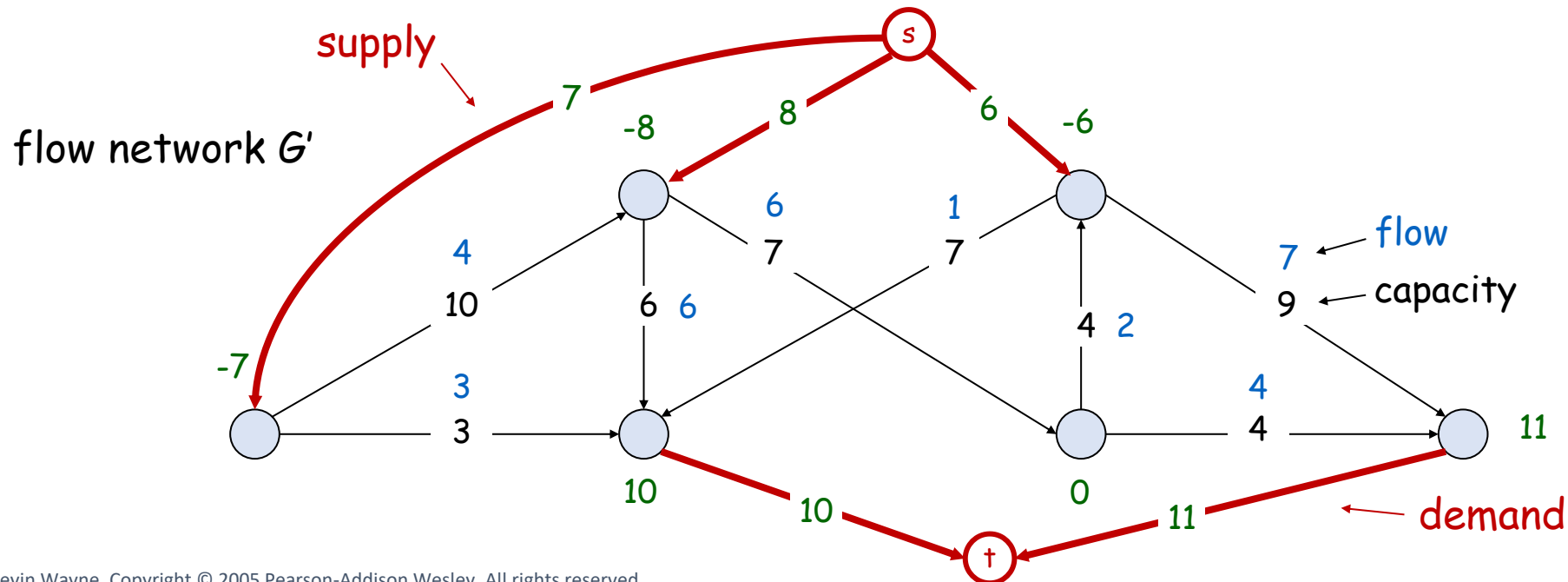




Circulation: Max-Flow Formulation

- **Max-flow formulation:**

- Add new source s and sink t .
- For each v with $d(v) < 0$, add edge (s, v) with capacity $-d(v)$.
- For each v with $d(v) > 0$, add edge (v, t) with capacity $d(v)$.



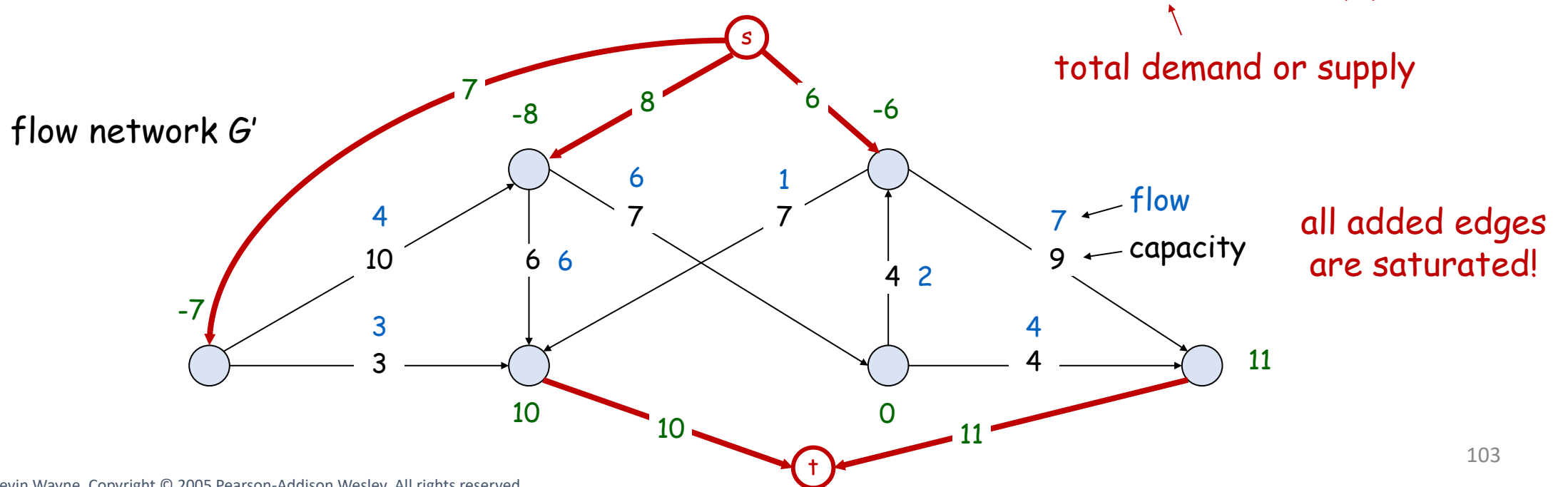


Circulation: Max-Flow Formulation

- **Max-flow formulation:**

- Add new source s and sink t .
- For each v with $d(v) < 0$, add edge (s, v) with capacity $-d(v)$.
- For each v with $d(v) > 0$, add edge (v, t) with capacity $d(v)$.

- **Claim.** G has a **circulation** iff G' has **max flow** of value $D = \sum_{v:d(v)>0} d(v)$.





Circulation with Supplies and Demands

- **Integrality theorem.** If all capacities and demands are integers, and there exists a **circulation**, then there exists one that is **integer-valued**.
- **Pf.** Follows from **integrality theorem** for max flow and previous **Claim**.
- **Theorem.** Given (V, E, c, d) , there does **not** exist a **circulation** iff there exists a **node partition** (A, B) such that $\sum_{v \in B} d(v) > c(A, B)$.
- **Pf idea.** Look at a **min cut** in G' .

↑
exploit the relation between
cut in G' and node partition in G

↑
demand by nodes in B exceeds
supply of nodes in B plus
max capacity of edges from A to B



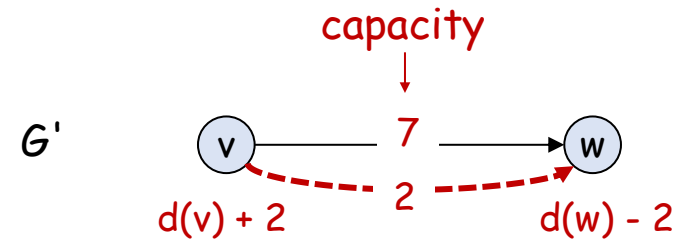
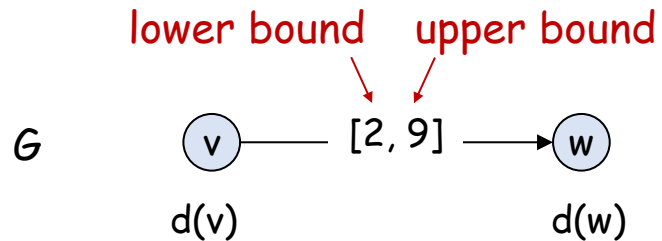
Circulation with Lower Bounds

- **Def.** Given a directed graph $G = (V, E)$ with edge capacities $c(e) \geq 0$, lower bounds $\ell(e) \geq 0$, and node demands $d(v)$, a **circulation** is a function $f(e)$ that satisfies:
 - [Capacity] For each $e \in E$: $\ell(e) \leq f(e) \leq c(e)$
 - [Flow conservation] For each $v \in V$: $\sum_{e \text{ into } v} f(e) - \sum_{e \text{ out of } v} f(e) = d(v)$
- **Circulation problem with lower bounds.** Given (V, E, ℓ, c, d) , does there exist a feasible circulation?



Circulation with Lower Bounds

- **Max-flow formulation.** Model **lower bounds** as circulation with **demands**.
 - Send $\ell(e)$ units of flow along edge e . ← this flow can be abstracted away from G'
 - Update demands of both endpoints.



- **Theorem.** There exists a circulation in G iff there exists a circulation in G' . Moreover, if all demands, capacities, and lower bounds in G are **integers**, then there exists a circulation in G that is **integer-valued**.
- **Pf idea.** $f(e)$ is a circulation in G iff $f'(e) = f(e) - \ell(e)$ is a circulation in G' .



10. Survey Design



Survey Design

- **Survey design:**

- Design survey asking n_1 consumers about n_2 products. ← one question per consumer-product
- Can survey consumer i about product j only if they own it.
- Ask consumer i between c_i and c_i' questions.
- Ask between p_j and p_j' consumers about product j .

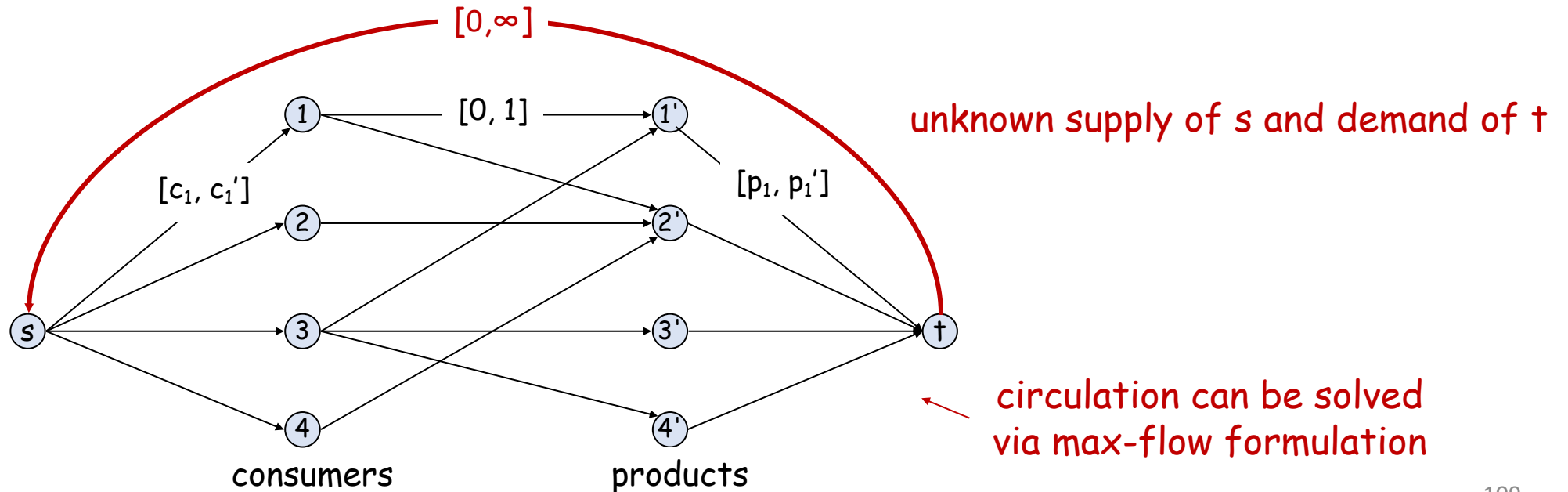
- **Goal.** Design a survey that meets these specs, if possible.

- **Bipartite perfect matching.** Special case when $c_i = c_i' = p_j = p_j' = 1$.



Survey Design: Circulation Formulation

- **Circulation formulation.** A circulation problem with **lower bounds**.
 - Add edge (i, j) if consumer i owns product j .
 - Add edge from s to consumer i . Add edge from product j to t .
 - Add edge from t to s with infinite capacity ∞ . All demands = 0.
- **Claim.** Integer circulation \Leftrightarrow feasible survey design.





11. Airline Scheduling



Airline Scheduling

- **Airline scheduling:**

- Complex computational problem faced by airline carriers.
- Must produce schedules that are efficient in terms of equipment usage, crew allocation, and customer satisfaction.
- One of largest consumers of high-powered algorithmic techniques.

← even in presence of unpredictable events, e.g., weather and breakdowns

- **“Toy problem”:**

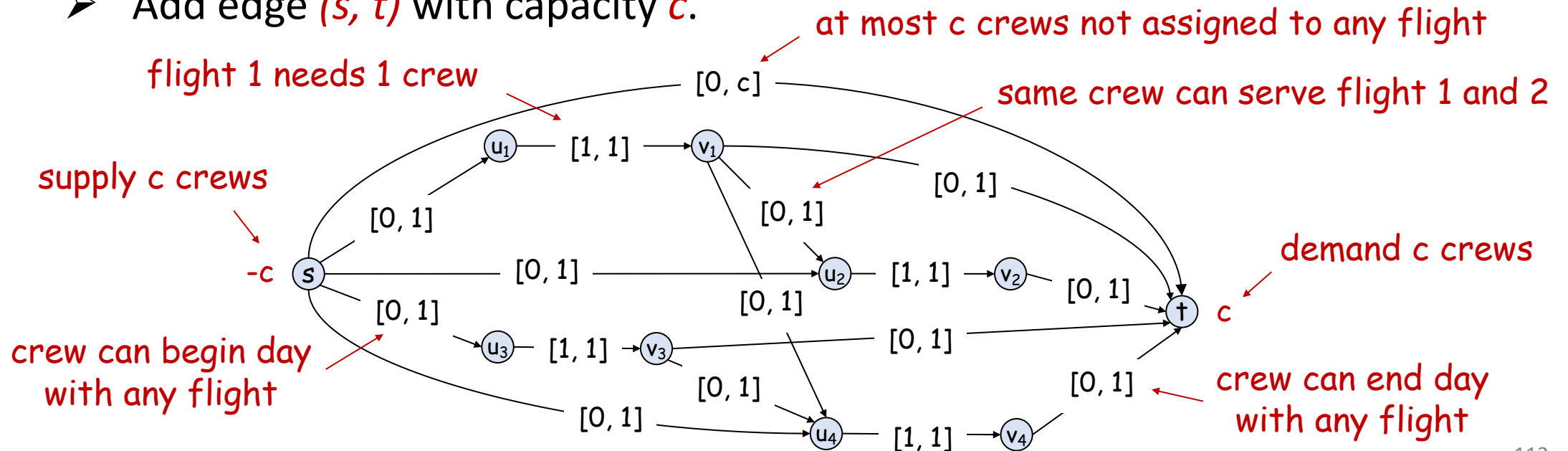
- Manage flight crews by reusing them over multiple flights.
- Input: set of k flights for a given day.
- Flight i leaves origin o_i at time s_i and arrives at destination d_i at time f_i .
- **Minimize** number of flight crews.

← one crew per flight



Airline Scheduling: Circulation Formulation

- **Circulation formulation.** (Check if c crews suffice.)
 - For flight i , add nodes u_i, v_i and edge (u_i, v_i) with lower bound and capacity 1 .
 - Add source s with demand $-c$, and edges (s, u_i) with capacity 1 .
 - Add sink t with demand c , and edges (v_i, t) with capacity 1 . $u_i = \text{start of flight } i$
 - If flight j reachable from i , add edge (v_i, u_j) with capacity 1 . $v_i = \text{end of flight } i$
 - Add edge (s, t) with capacity c .





Airline Scheduling: Running Time

- **Theorem.** Airline scheduling problem can be solved in $O(k^3 \log k)$ time.
- **Pf. (direct proof)**
 - k = number of flights
 - $O(k)$ nodes, $O(k^2)$ edges.
 - c = number of crews (unknown)
 - At most k crews needed \Rightarrow solve $\log_2 k$ circulation problems. binary search for min crew number c^*
 - Any flow value is between 0 and $k \Rightarrow \leq k$ augmentations per circulation problem.
 - Overall time = $O(k^3 \log k)$.
- **Note.** Can solve in $O(k^3)$ time by formulating as minimum-flow problem.



Airline Scheduling: Running Time

- **Remark.** We solved a toy version of a real problem.
- **Real-world problem models countless other factors:**
 - Flight crews can fly only a certain number of hours in a given time window.
 - Need optimal schedule over planning horizon, not just one day.
 - Flights don't always leave or arrive on schedule.
 - Simultaneously optimize both flight schedule and fare structure.
- **Take-away message:**
 - Our solution is a generally useful technique for efficient reuse of limited resources but trivializes real airline scheduling problem.
 - Flow techniques are useful for solving airline scheduling problems (and are widely used in practice).
 - Running an airline efficiently is a very difficult problem.



12. Image Segmentation



Image Segmentation

- **Image segmentation.** Divide image into coherent regions.
 - Central problem in image processing.
- **Example.** Separate human and robot from background scene.

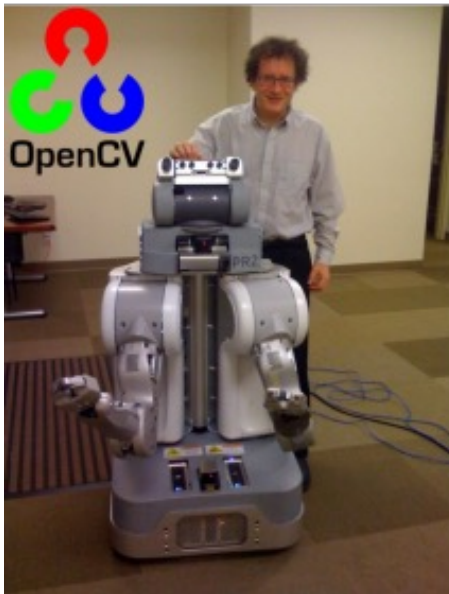
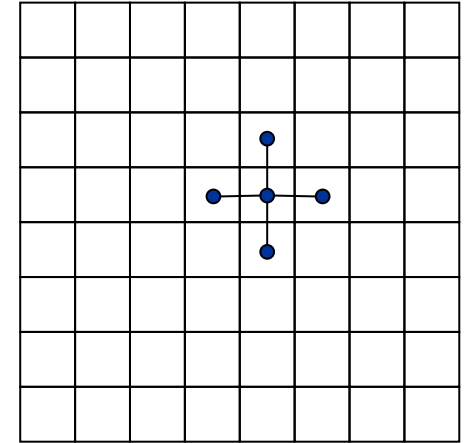




Image Segmentation

- **Foreground/background segmentation.** Label each pixel in picture as belonging to **foreground** or **background**.

- V = set of pixels, E = pairs of **neighboring** pixels.
- $a_i \geq 0$ is likelihood pixel i in foreground.
- $b_i \geq 0$ is likelihood pixel i in background.
- $p_{ij} \geq 0$ for each $(i, j) \in E$ is separation penalty for labeling one of i and j as foreground and the other as background.



- **Goals:**

- **Accuracy:** if $a_i > b_i$ in isolation, prefer to label i in foreground.
- **Smoothness:** if many neighbors of i are labeled foreground, we should be inclined to label i as foreground.

- Find **partition** (A, B) that **maximizes** $q(A, B) = \sum_{i \in A} a_i + \sum_{j \in B} b_j - \sum_{\substack{(i,j) \in E \\ |A \cap \{i,j\}| = 1}} p_{ij}$
- foregroundbackground



Image Segmentation

- **Formulate as min-cut problem:**

- No source or sink.
- **Undirected** graph.
- **Maximization.** ← how to convert max to min?

- **Turn into minimization problem:**

- **Maximizing** $q(A, B) = \sum_{i \in A} a_i + \sum_{j \in B} b_j - \sum_{\substack{(i,j) \in E \\ |A \cap \{i,j\}|=1}} p_{ij}$

is equivalent to **minimizing** $\left(\sum_{i \in A \cup B} a_i + \sum_{j \in A \cup B} b_j \right) - q(A, B) = \sum_{j \in B} a_j + \sum_{i \in A} b_i + \sum_{\substack{(i,j) \in E \\ |A \cap \{i,j\}|=1}} p_{ij}$

↑
constant

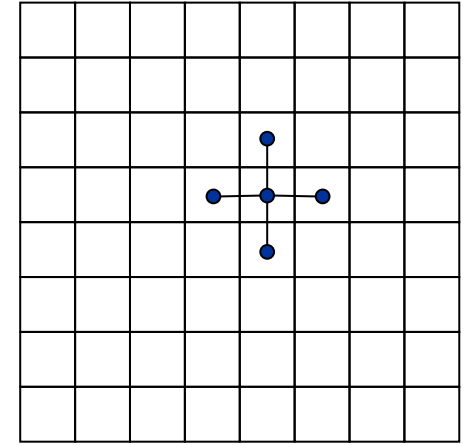




Image Segmentation

- **Formulate as min-cut problem $G' = (V', E')$:**

- Include node for each pixel.
- Use **two anti-parallel edges** instead of undirected edge.
- Add **source s** to represent **foreground**.
- Add **sink t** to represent **background**.

edge in G :



antiparallel edges in G' :

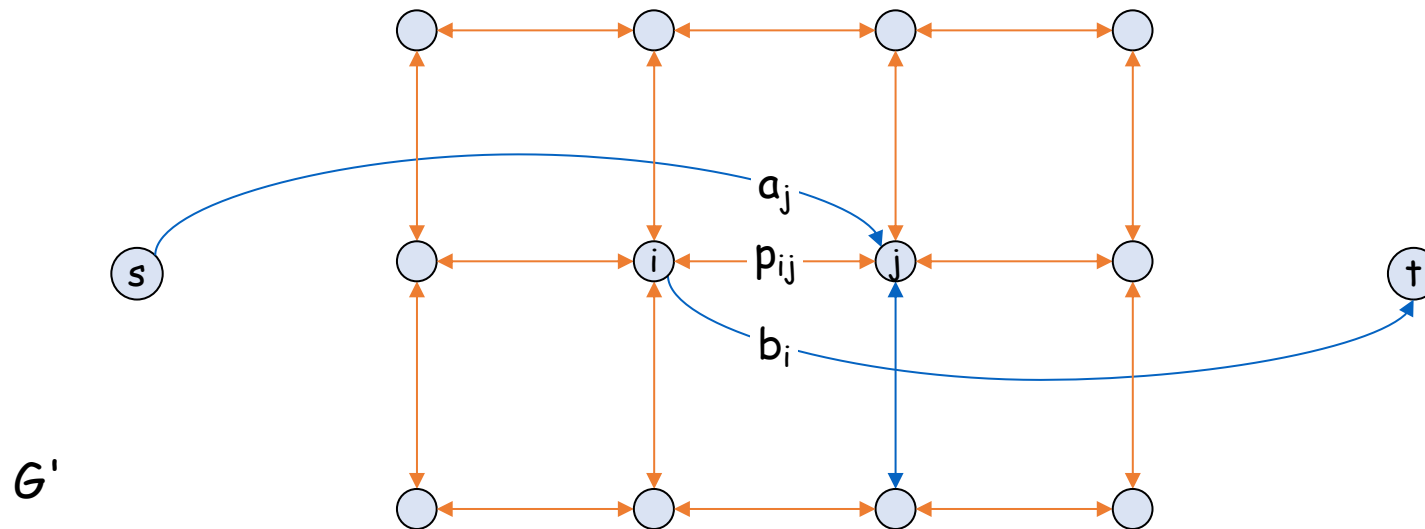
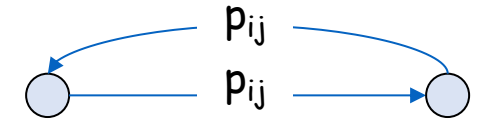
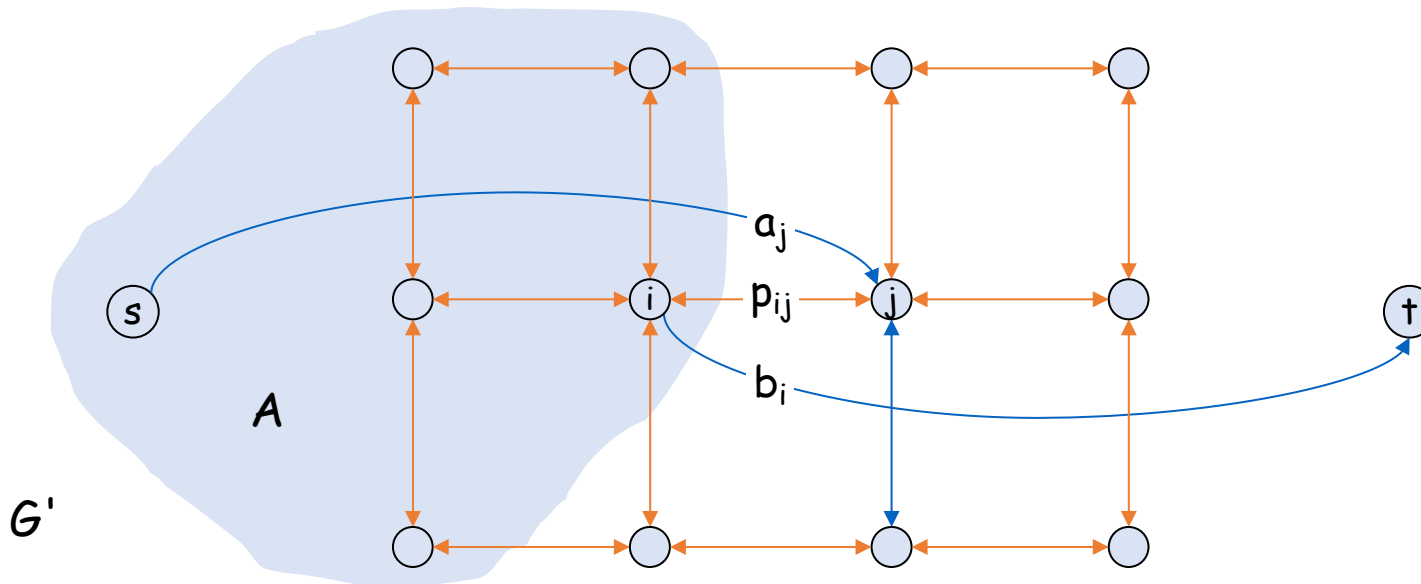




Image Segmentation

- **Min-cut formulation.** Consider a **cut** (A, B) in directed graph G' :

- $A = \text{foreground}$ $c(A, B) = \sum_{j \in B} a_j + \sum_{i \in A} b_i + \sum_{\substack{(i,j) \in E \\ i \in A, j \in B}} p_{ij}$ \leftarrow if i and j on different sides, p_{ij} counted exactly once
- Precisely the quantity we want to **minimize** in original undirected graph.





Network Flow: Closing Remarks

- **More applications:**

- Project selection (maximum weight closure problem). [section 7.11 of textbook]
- Baseball elimination. [section 7.12 of textbook]

- **Adding costs to max-flow problems:**

- **Min-cost max flow** (a natural extension to max-flow problems). [lab assignment]
- **Min-cost perfect matching** in **bipartite** graphs. [written assignment]