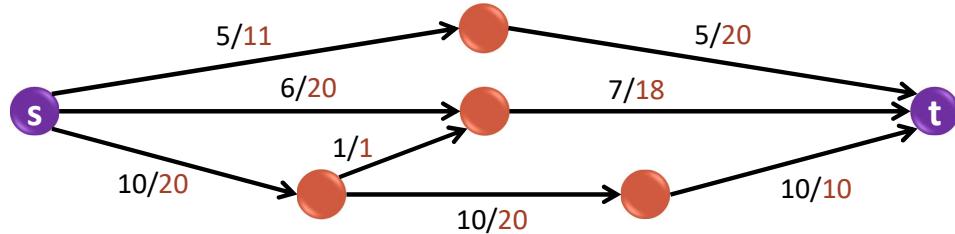


# Network Flow

EECS 336: Design and Analysis of Algorithms.  
Konstantin Makarychev

## Network

- Network:
  - Directed graph  $G = (V, E)$ .
  - Two designated nodes (terminals):  $s$ -source and  $t$ -sink.
  - Every edge  $e$  has a capacity  $c(e)$ .

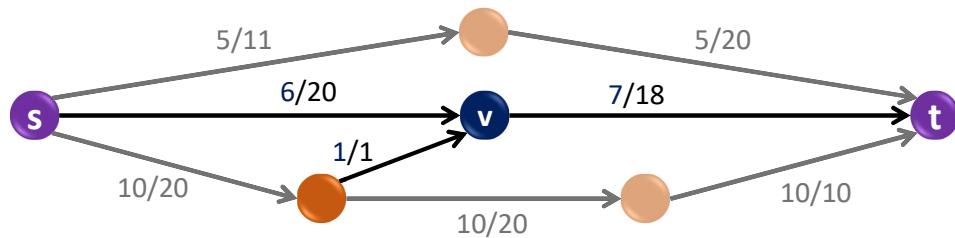


## Feasible Flow

Flow  $f: E \rightarrow \mathbb{R}^+$ . We route  $f(e)$  units of flow over each edge  $e$ .

- Flow conservation constraints: for all vertices  $v$  but  $s$  and  $t$ ,

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



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- a. Flow conservation constraints: for all vertices  $v$  but  $s$  and  $t$ ,

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

- b. Capacity constraints: for all edges  $e$ :

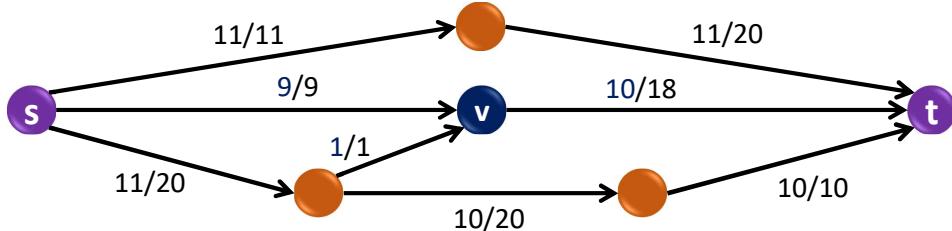
$$f(e) \leq c(e)$$

The value of the flow  $f$  equals

$$\sum_{s \rightarrow v \in E} f(s \rightarrow v) - \sum_{s \rightarrow v \in E} f(s \rightarrow v)$$

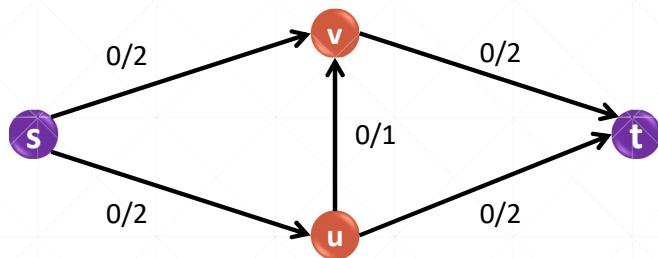
## Maximum Flow Problem

Given a network  $G = (V, E)$ , find the maximum feasible flow from  $s$  to  $t$ .

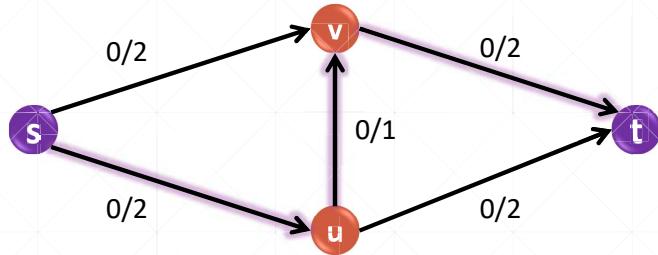


## Ford–Fulkerson algorithm

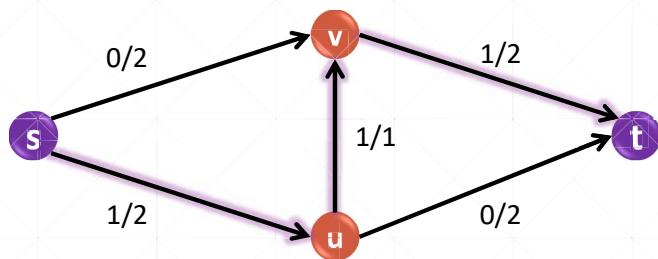
## Naïve Greedy Algorithm Fails



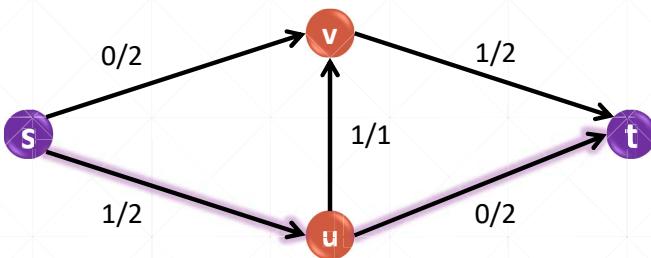
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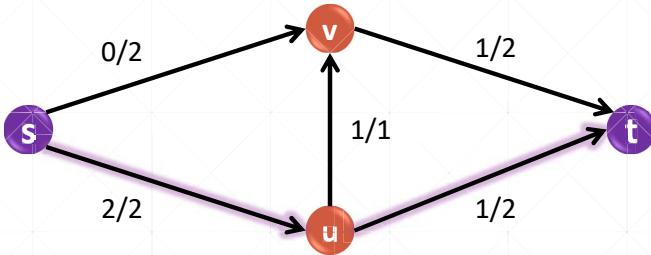
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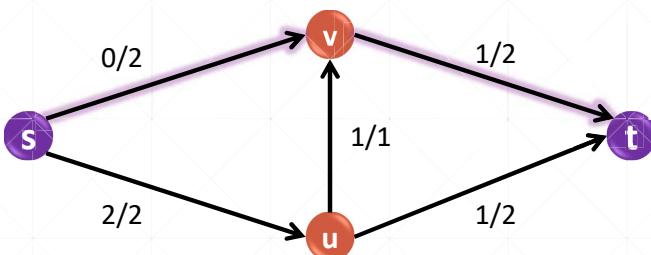
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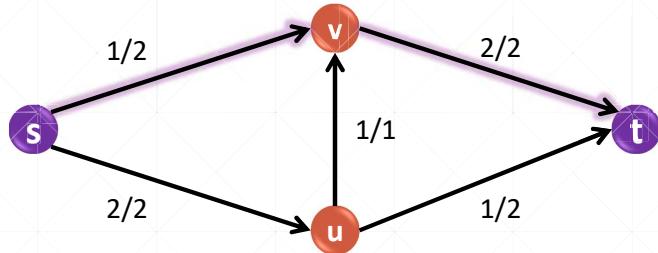
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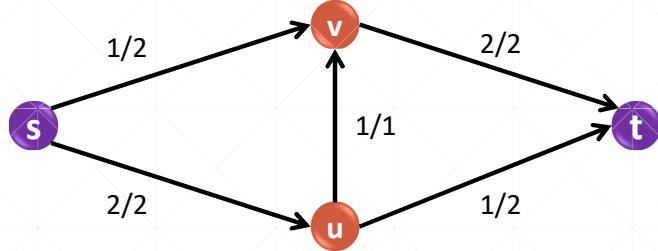
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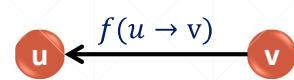
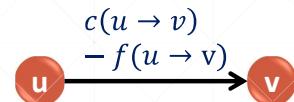


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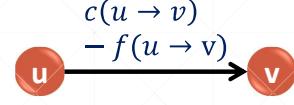
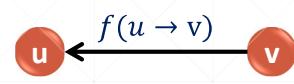


## Residual network $G_f$

- Residual network is a graph on the same set of vertices as the original network  $G$ .
- For every original edge  $u \rightarrow v$ ,  
 $G_f$  has edge  $u \rightarrow v$  if  $f(u \rightarrow v) < c(u \rightarrow v)$ .  
➤  $c_f(u \rightarrow v) = c(u \rightarrow v) - f(u \rightarrow v)$
- For every original edge  $u \rightarrow v$ ,  
 $G_f$  has edge  $v \rightarrow u$  if  $f(u \rightarrow v) > 0$ .  
➤  $c_f(v \rightarrow u) = f(u \rightarrow v)$

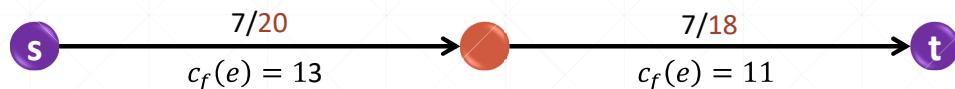


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- 

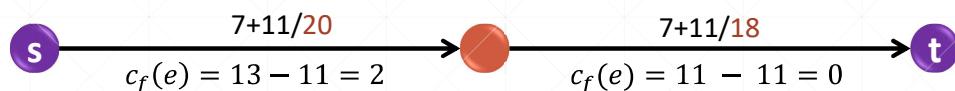
## Bottleneck Edge

- Bottleneck edge in  $P$  is the edge with the min residual capacity.
- After augmenting the flow along  $P$ , the bottleneck edge disappears.



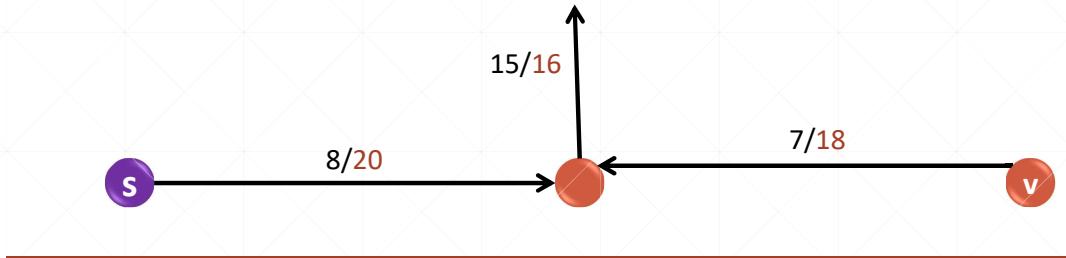
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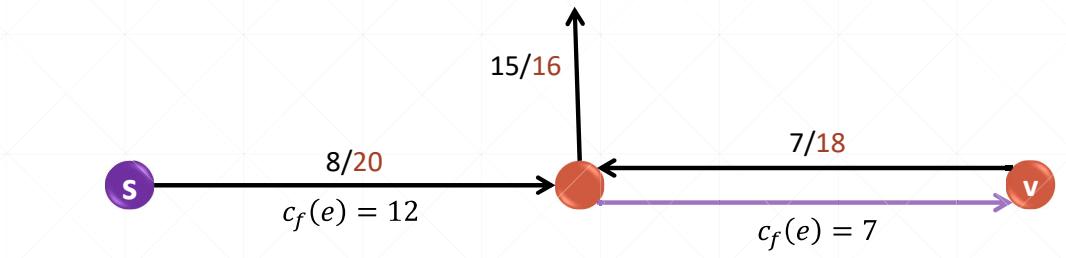
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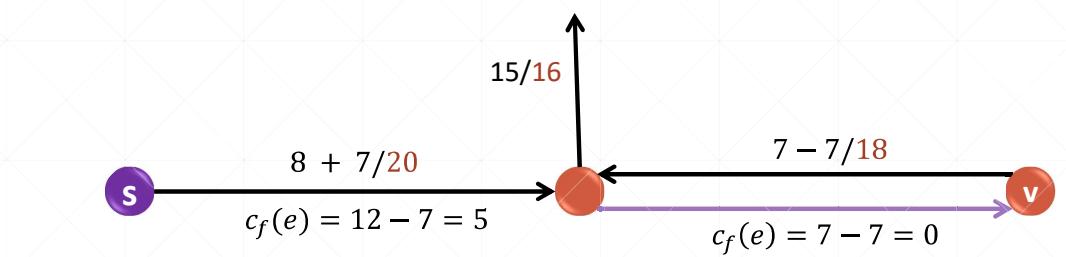
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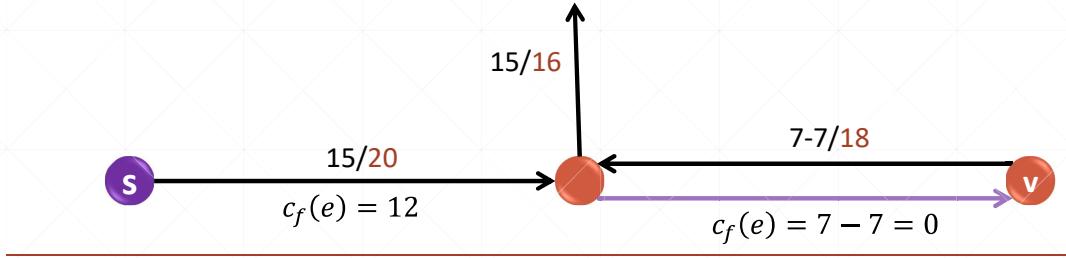
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## Ford–Fulkerson algorithm

**Input:** network  $G = (V, E)$  with capacities  $c$ , source node  $s$ , sink node  $t$

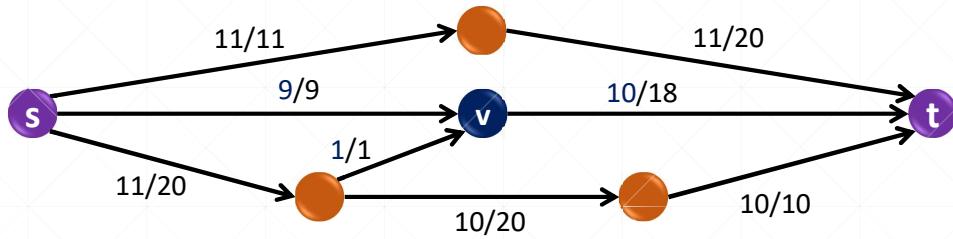
- Initialize flow: Let  $f(u, v) = 0$  for all  $(u, v) \in E$
- **Repeat:**
  - Compute residual flow  $G_f$ .
  - Find\* a path  $P$  from  $s$  to  $t$  in  $G_f$ .
  - Augment the flow along  $P$  by the bottleneck capacity.
  - If there is no path from  $s$  to  $t$  in  $G_f$  return  $f$ .

## Ford–Fulkerson algorithm

- **Claim:** If all capacities are integral, then Ford–Fulkerson algorithm eventually terminates and outputs a flow in  $G$ .
- Is this flow maximum possible?

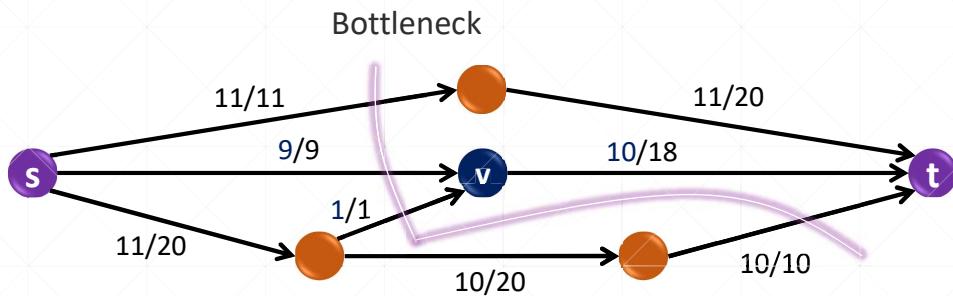
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Given a network  $G = (V, E)$ , find the maximum feasible flow from  $s$  to  $t$ .



## Maximum Flow Problem

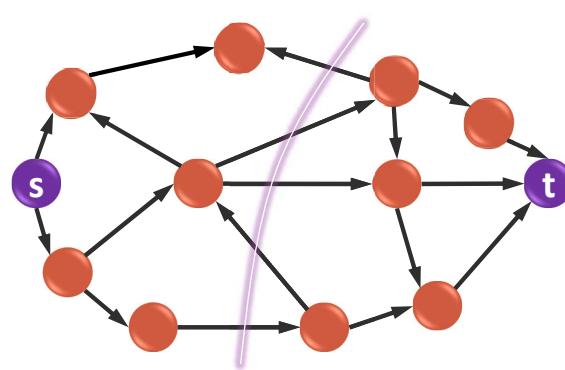
Given a network  $G = (V, E)$ , find the maximum feasible flow from  $s$  to  $t$ .



## st-Cuts

- Cut  $(A, B)$  is partitioning of the set of all vertices into two sets  $A$  and  $B$  s.t.  $s \in A$  and  $t \in B$ .
- Capacity of the cut:

$$cut(A, B) = \sum_{e \in A \rightarrow B} c(e)$$



## Min Cut = Max Flow = Ford-Fulkerson

- We prove that

$$\text{Min Cut} \geq \text{Max Flow} \geq \text{Ford - Fulkerson} \geq \text{Min Cut}$$

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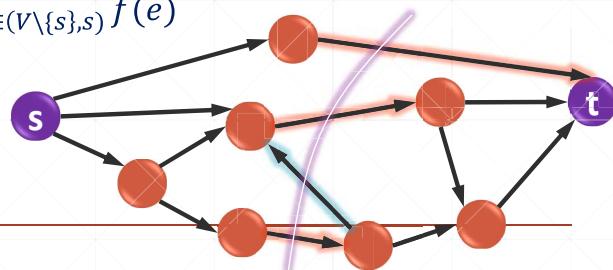
## Flow-value Lemma

Network  $G = (V, E)$ . Feasible flow  $F$  from  $s$  to  $t$ .  $st$ -Cut  $(S, \bar{S})$ .

$$\text{val}(f) = \sum_{e \in (S, \bar{S})} f(e) - \sum_{e \in (\bar{S}, S)} f(e)$$

where

- $\text{val}(f) = \sum_{e \in (S, V \setminus \{s\})} f(e) - \sum_{e \in (V \setminus \{s\}, S)} f(e)$
- $f(e) = 0$ , if  $e \notin E$



## Flow-value Lemma

Network  $G = (V, E)$ . Feasible flow  $F$  from  $s$  to  $t$ .  $st$ -Cut  $(S, \bar{S})$ .

$$\text{val}(f) = \sum_{e \in (S, \bar{S})} f(e) - \sum_{e \in (\bar{S}, S)} f(e) = (*)$$

**Proof:**

$$\text{val}(f) = \sum_{u \in S} \left[ \sum_{v: (u, v) \in E} f(e) - \sum_{v: (v, u) \in E} f(e) \right] = (*)$$

Details are on the board.

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## Min Cut = Max Flow = Ford-Fulkerson

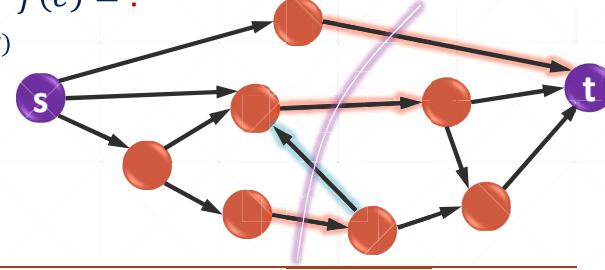
We prove that

- a. **Min Cut  $\geq$  Max Flow:** By the flow-value lemma, the value of the flow equals the flow across the min cut, which is upper bounded by **Min Cut**.
  - b. **Max Flow  $\geq$  Ford – Fulkerson:** Ford-Fulkerson gives a feasible solution to the Max Flow Problem.
  - c. **Ford – Fulkerson  $\geq$  Min Cut** (next slide)
- 

## Ford–Fulkerson $\geq$ Min Cut

Let  $f$  be the flow returned by Ford-Fulkerson and  $S$  be the set of nodes reachable from  $s$  in  $G_f$ . By the flow-value lemma:

$$\text{val}(f) = \sum_{e \in (S, \bar{S})} f(e) - \sum_{e \in (\bar{S}, S)} f(e) = ?$$

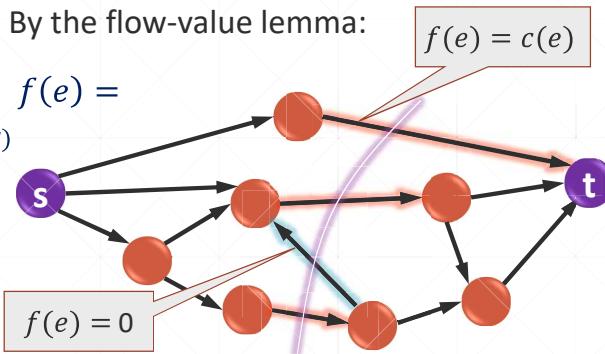


## Ford–Fulkerson $\geq$ Min Cut

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$$\text{val}(f) = \sum_{e \in (S, \bar{S})} f(e) - \sum_{e \in (\bar{S}, S)} f(e) =$$

$$= \sum_{e \in (S, \bar{S})} c(e) \geq \text{Min Cut}$$



- Min cut – the minimum  $st$ -cut.
- Max flow – max flow from  $s$  to  $t$ .

## Max-flow min-cut theorem:

The value of max flow = The capacity of min cut

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## Integral flow theorem:

If each edge in a flow network has integral capacity, then there exists an integral maximum flow.

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## Edmonds-Karp Algorithm

- Start with a feasible flow  $f = 0$ .
  - while ( $f$  is not max flow)
    - Construct residual network  $G_f$  wrt flow  $f$ .
    - Find the *shortest path*  $P$  from  $s$  to  $t$  in  $G_f$ .
    - Push/augment flow along path  $P$ .
  - return  $f$

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### Lemma 1

- Throughout the algorithm, the length of a shortest augmenting path never decreases.

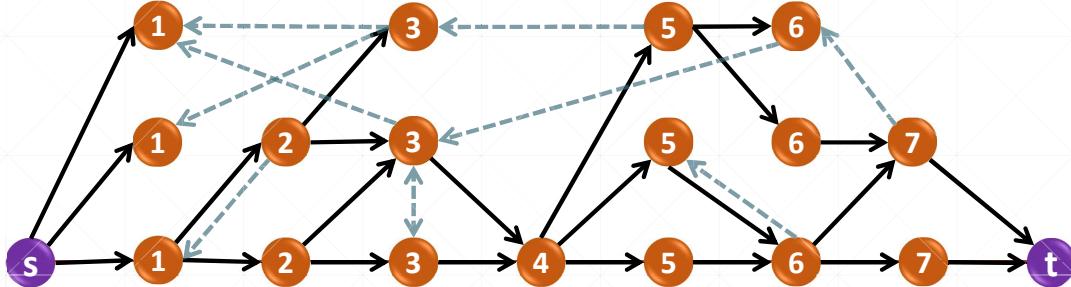
### Lemma 2

- After at most  $m$  shortest-path augmentations, the length of a shortest augmenting path strictly increases.

**Lemma 1 + Lemma 2** imply the Edmonds-Karp algorithm terminates in  $mn$  steps.

## Level Graph

- Let  $d(u)$  be the shortest path distance from  $s$  to  $u$ . Let  $L = d(t)$ .
- Place vertex  $u$  in row  $d(u)$ .
- Forward edges go from  $i$  to  $j \geq i$ . Backward edges go from  $j$  to  $i < j$ .

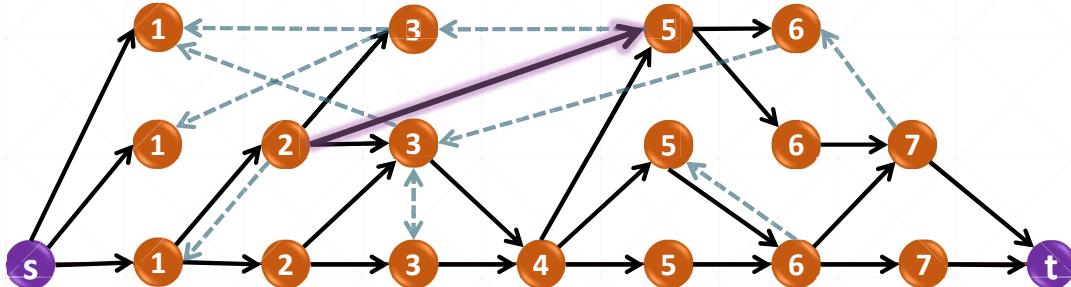


## Level Graph

**Claim A:** If  $u \rightarrow v$  is a forward edge, then

$$\text{level of } v = \text{level of } u + 1$$

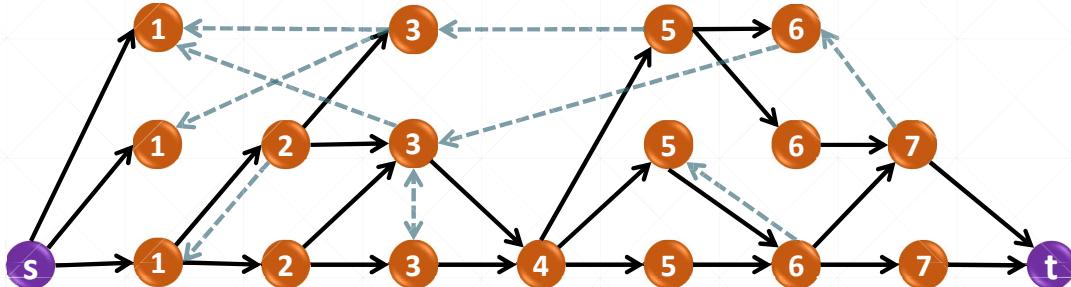
**If graph satisfies (A) then:** Every path  $s \rightarrow t$  of length  $L$  consists only of forward edges, where  $L$  is the level of  $t$ . Distance from  $s$  to  $t$  is  $\geq L$ .



## Level Graph

**Claim B:** If we add arbitrary **backward** edges and remove arbitrary edges, then the distance from  $s$  to  $t$  will still be  $\geq L$ .

**Proof:** After the update, the graph still satisfies **(A)** (note: we don't change the positions of vertices).



## Lemma 1

- Throughout the algorithm, the length of the shortest augmenting path never decreases.

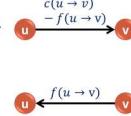
### Proof:

- $f$  and  $f'$  — flow before and after a shortest-path augmentation along path  $P$ .
- $G_f$  and  $G_{f'}$  — corresponding residual networks.

Consider the level graph for  $G_f$ . We update capacities in  $f$  along the path  $P$ . Hence, only edges from  $\text{reverse}(P)$  may get added to  $G_{f'}$ . Hence, we don't add forward edges. Lemma 1 follows from Claim B.

### Residual network $G_f$

- Residual network is a graph on the same set of vertices as the original network  $G$ .
- For every original edge  $u \rightarrow v$ ,  $G_f$  has edge  $u \rightarrow v$  if  $f(u \rightarrow v) < c(u \rightarrow v)$ .  
➢  $c_f(u \rightarrow v) = c(u \rightarrow v) - f(u \rightarrow v)$
- For every original edge  $u \rightarrow v$ ,  $G_f$  has edge  $v \rightarrow u$  if  $f(u \rightarrow v) > 0$ .  
➢  $c_f(v \rightarrow u) = f(u \rightarrow v)$



## Lemma 2

- After at most  $m$  shortest-path augmentations, the length of the shortest augmenting path strictly increases.

**Proof:** Consider the phase of ALG when  $d(s, t) = L$ .

- Fix the level graph at the first step when  $d(s, t) = L$ .
- At every step, in this phase, all shortest paths  $s \rightarrow t$  consist only of forward edges.
- Thus, no forward edges are added, but at least one forward edge – the bottleneck edge – is deleted.
- After  $m$  steps all forward edges are deleted or  $d(s, t)$  increases.

## Lemma 1

- Throughout the algorithm, 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.

**Lemma 1 + Lemma 2** imply the Edmonds-Karp algorithm terminates in  $mn$  steps.

## **Applications of Max Flow and Min Cut**

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### **Routing**

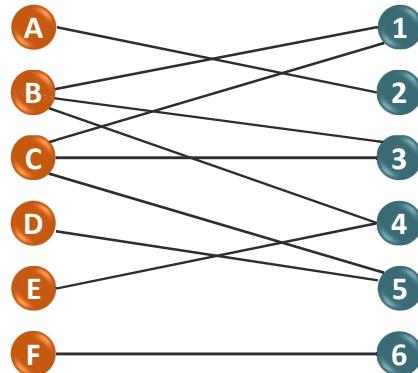
- Routing vehicles on the road.
  - Routing electricity.
  - Routing internet traffic.
- 

## **Bipartite Matching**

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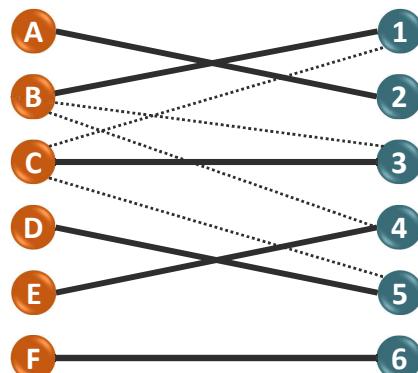
## Bipartite Matching

- Alice, Bob, Carol, Dan, Eve, and Frank want to organize a party. They would like to prepare dishes 1,...,6. Each of them knows how to cook some subset of these dishes. What dish should each person prepare?
- Need to find a matching.



## Bipartite Matching

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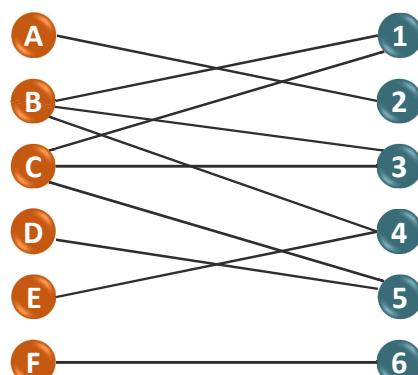


## Bipartite Matching

**Given:** Bipartite graph

$$G = (L, R, E)$$

**Goal:** Find a perfect matching i.e., a subset of edges  $M \subset E$  s.t. each vertex is incident to exactly one edge in  $M$ .

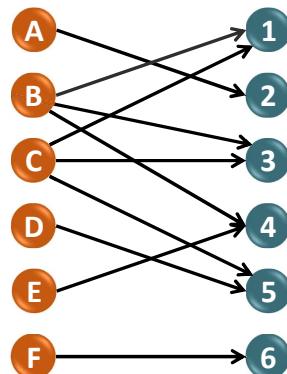


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## Bipartite Matching

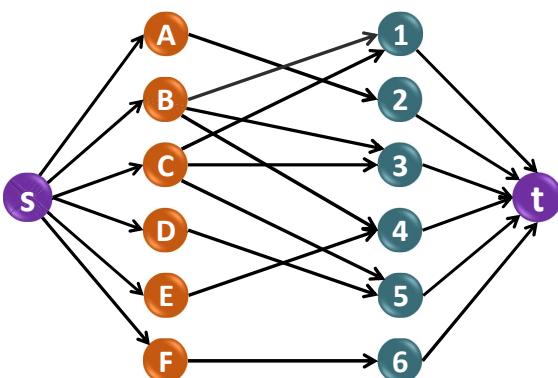
**Given:** Bipartite graph

$$G = (L, R, E)$$

**Goal:** Find a perfect matching i.e., a subset of edges  $M \subset E$  s.t. each vertex is incident to exactly one edge in  $M$ .

Consider a flow network with edges of capacity 1 and  $\infty$ .

$c = 1$       capacity = 1  
capacity =  $\infty$        $c = 1$



## Bipartite Matching

**Given:** Bipartite graph  $G$ .

**Goal:** Find a perfect matching.

$n$  = #vertices on each side

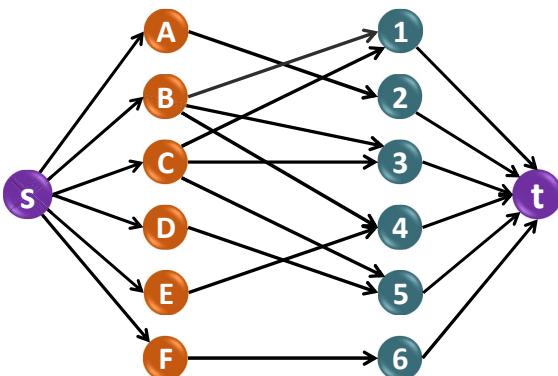
**Thm:**

There is perfect matching in  $G$



the max flow equals  $n$

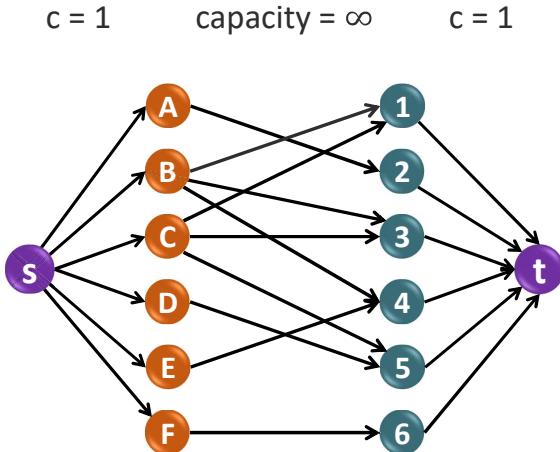
$c = 1$       capacity =  $\infty$        $c = 1$



## Bipartite Matching

### Proof:

⇒ If there is a perfect matching in  $G$ , then we can route the flow via this matching.

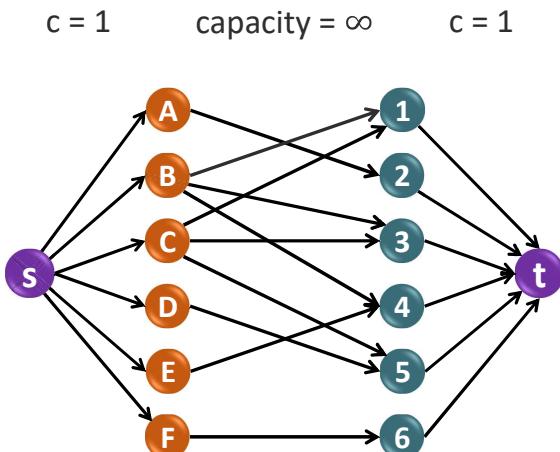


## Bipartite Matching

### Proof:

⇒ If there is a perfect matching in  $G$ , then we can route the flow via this matching.

⇐ Since all capacities are integral, there exists an integral max flow ( $f(e) \in \mathbb{Z}$ ). Drop all edges with  $f(e) = 0$ .

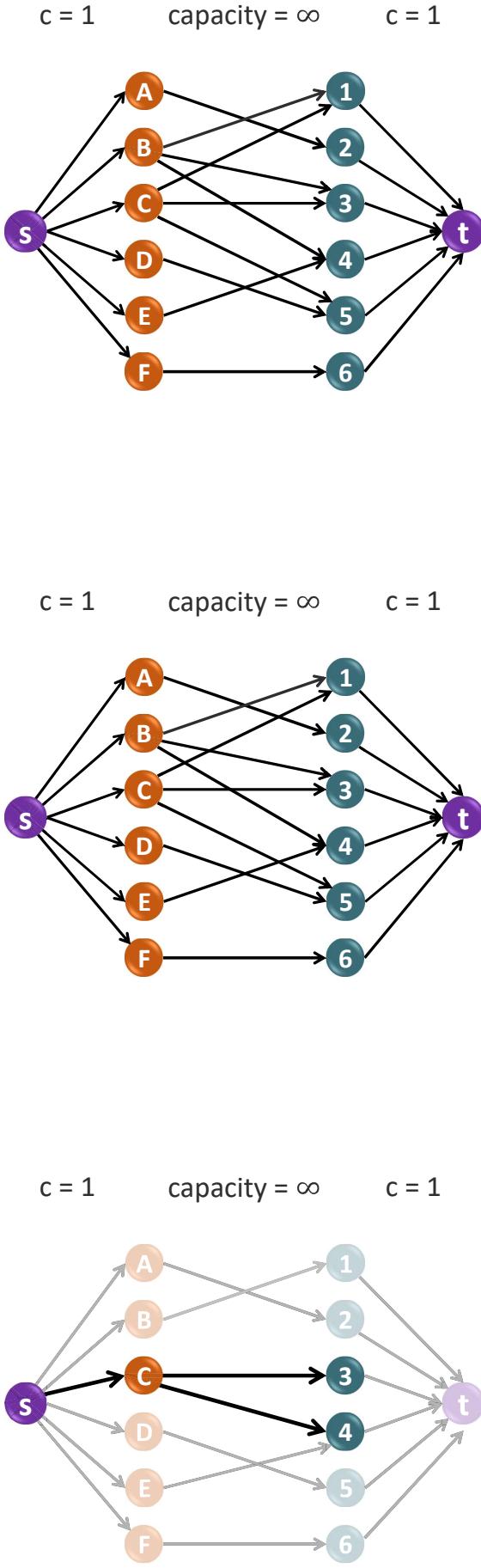


## Bipartite Matching

### Proof:

⇐ Since all capacities are integral, there exists an integral max flow ( $f(e) \in \mathbb{Z}$ ). Drop all edges with  $f(e) = 0$ .

The flow to each vertex on the left  $\leq 1$ . It is 1 because max flow =  $n$ . Hence, flow out of each vertex must be also 1.

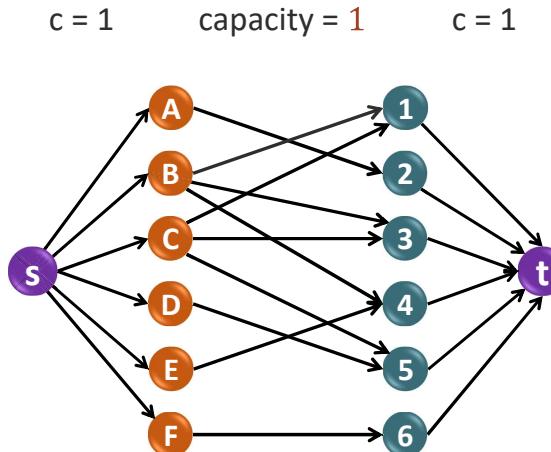


## Algorithm

- Solve the Max Flow problem.
- Return all edges  $e$  between  $L$  and  $R$  with  $f(e) = 1$ .

When does the algorithm succeed?

Min cut = Max flow =  $n$ .



## Maximum Matching

### Algorithm for Maximum Matching

- Solve the Max Flow problem.
- Return all edges  $e$  between  $L$  and  $R$  with  $f(e) = 1$ .



# Hall's Theorem

## Hall's Theorem

There is a perfect matching in  $G$

$c = 1$

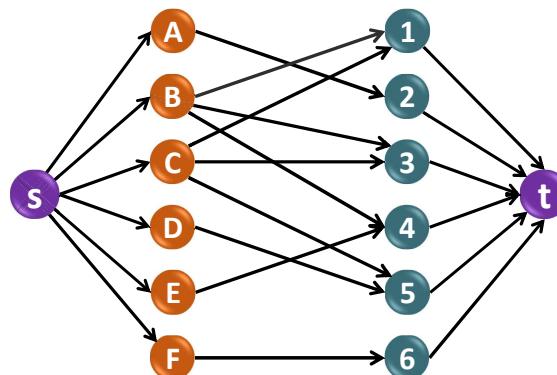
capacity =  $\infty$

$c = 1$



for every  $S \subset L$ , we have  
 $|N(S)| \geq |S|$

Here,  $N(S)$  is the set of  
neighbors of  $S$ .



## Hall's Theorem

There is a perfect matching in  $G$

$c = 1$

capacity =  $\infty$

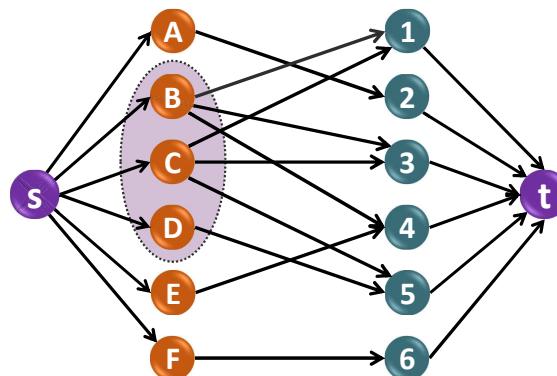
$c = 1$



for every  $S \subset L$ , we have  
 $|N(S)| \geq |S|$

Here,  $N(S)$  is the set of  
neighbors of  $S$ .

⇒ If there is a perfect matching in  $G$ , then “the image of  $S$ ”  
contains at least  $|S|$  elements.



## Hall's Theorem

There is a perfect matching in  $G$

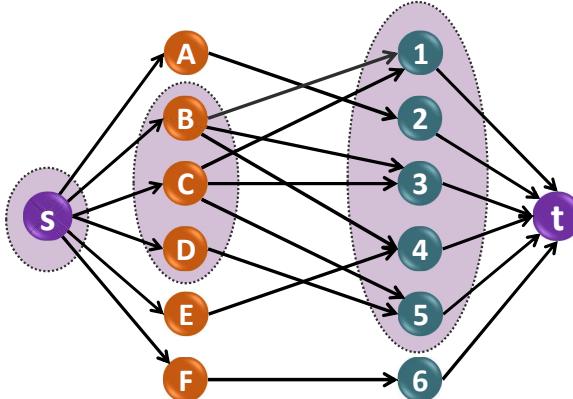
$\Updownarrow$   
for every  $S \subset L$ , we have  
 $|N(S)| \geq |S|$

$\Leftarrow$  Consider min cut  $(A, B)$ . Its capacity  $< \infty$ . Thus, edges between  $L$  and  $R$  cannot cross it. Let  $S = A \cap L$ ;  $T = A \cap R$ .

Then,  $N(S) \subset T$ . We get

$$\begin{aligned} \text{cut}(A, B) &= n - |S| + |T| \\ &\geq n - |S| + |N(S)| \geq n \end{aligned}$$

$c = 1$       capacity =  $\infty$        $c = 1$

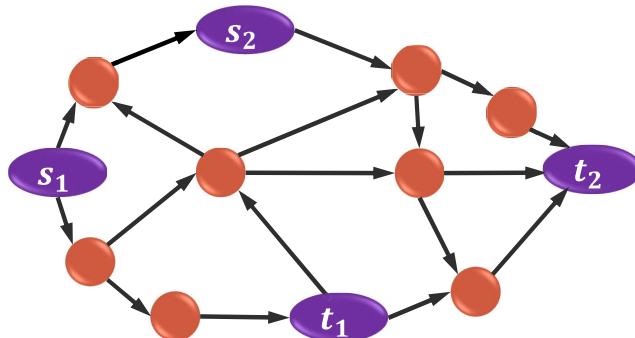


## Multiple Sources & Sinks

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**Given:** Flow network w/ many sources:  $s_1, \dots, s_{k'}$  and many sinks:  $t_1, \dots, t_{k''}$ .

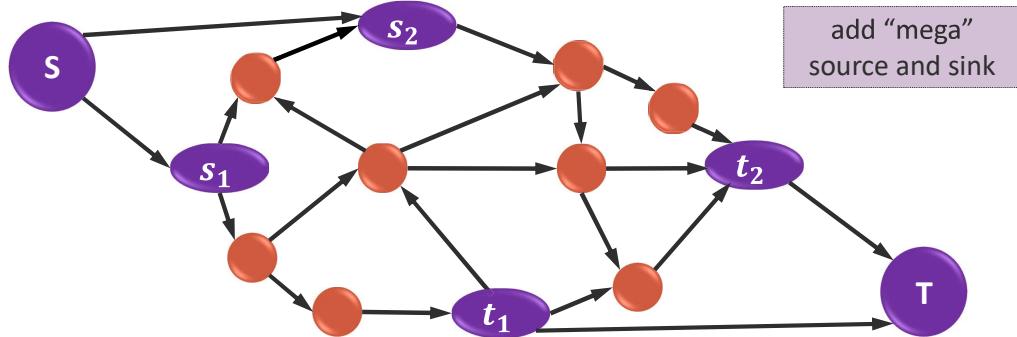
**Goal:** Maximize the total amount of flow from all sources to all sinks.



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## Questions