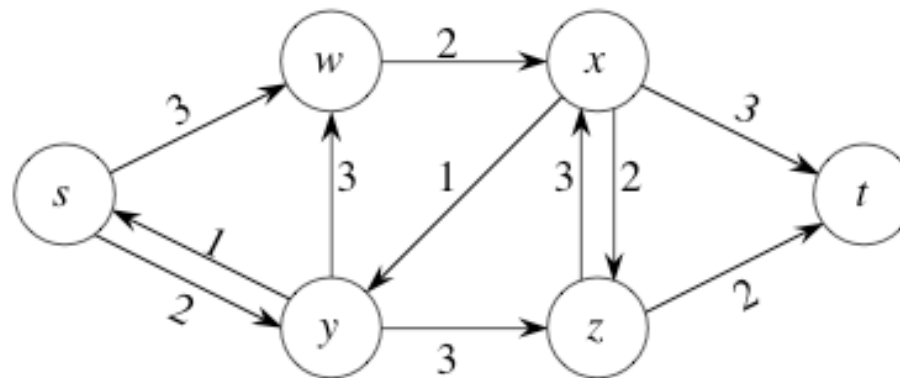




# **Graph Algorithms:** **Maximum Flow**

# Flow Network

- Directed graph  $G = (V, E)$  with non-negative edge weights  $c : E \rightarrow R$ 
  - $c(u, v)$ : nonnegative *capacity* of an edge  $(u, v) \in E$ 
    - ◆  $c(u, v) = 0$  if  $(u, v) \notin E$
  - $s$ : source of the network
  - $t$ : sink of the network

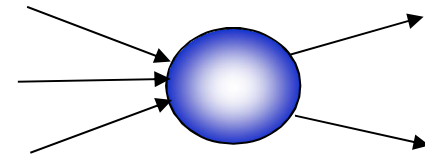


# Flow Network

- A *positive flow* is a function  $f: V \times V \rightarrow R$  s.t.,

- Capacity constraint:

- ◆ For all  $u, v \in V$ ,  $0 \leq f(u, v) \leq c(u, v)$

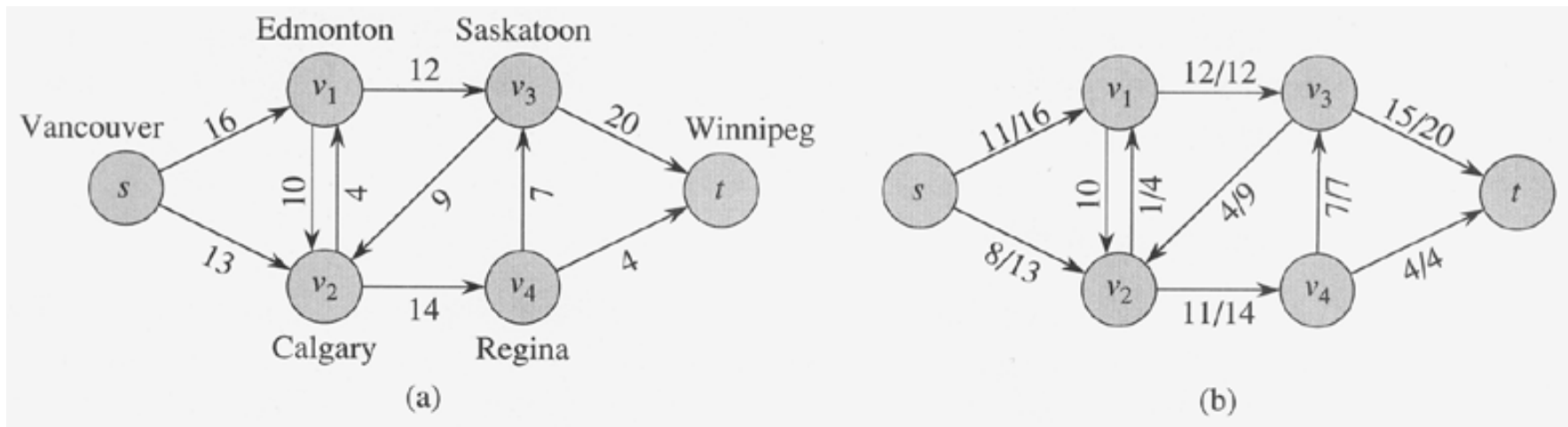


- Flow conservation constraint:

- ◆ For all  $u \in V - \{s, t\}$ ,

$$\sum_{v \in V} f(v, u) = \sum_{v \in V} f(u, v)$$

Flow-in equals flow-out

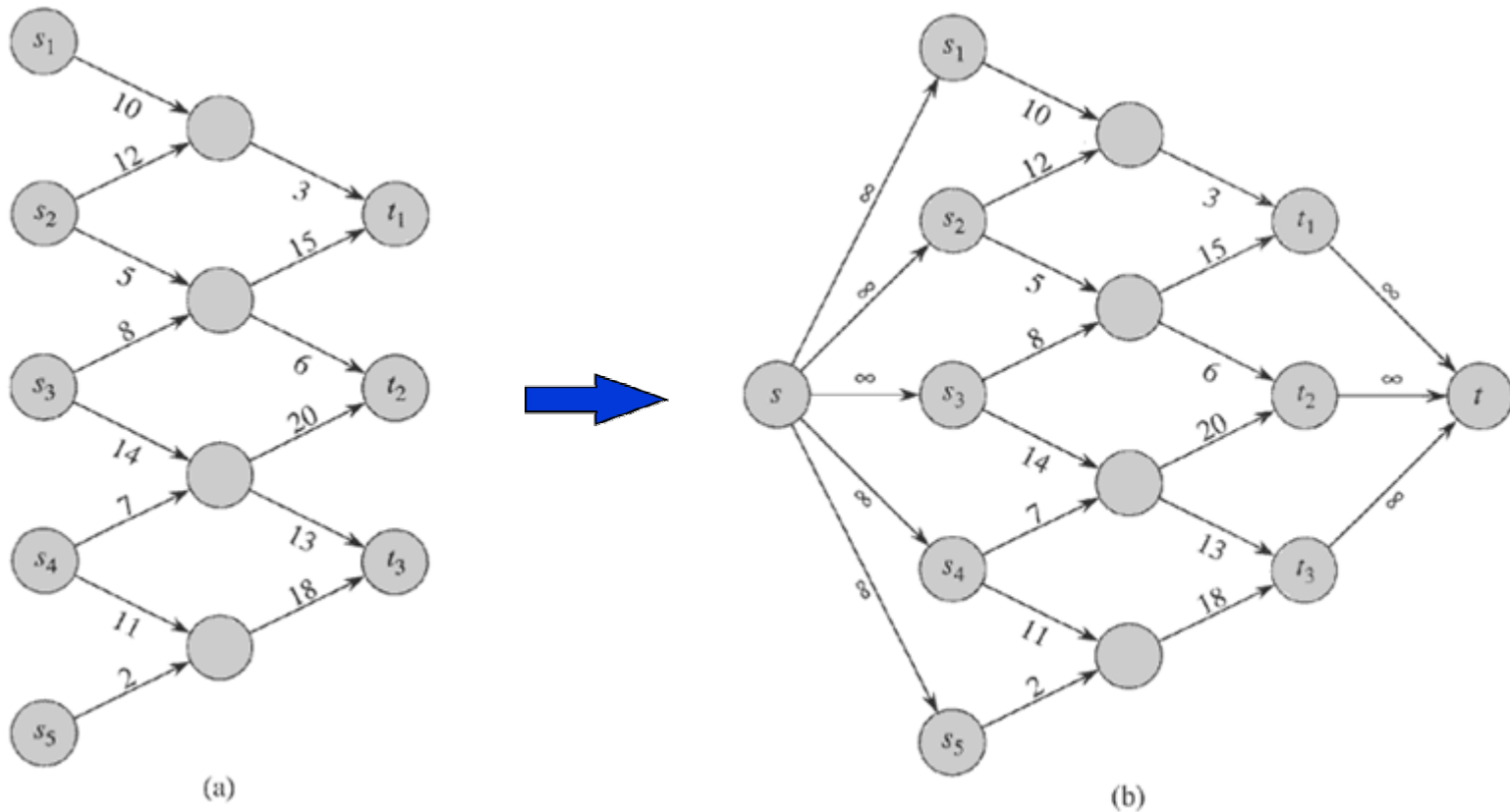


# Maximum-Flow Problem

- Given a flow  $f$ , the value of  $f$  is
  - $|f| = \sum f(s, u) : i.e.,$  total flow out of the source
- Maximum-flow problem:
  - Compute a flow of maximum value
- Multiple sources/sinks
  - Convert to single source/sink problem by adding one supersource and one supersink
- Anti-parallel edges or Two-way edges
  - Transform the network into an equivalent one containing no anti-parallel edges by adding a new vertex

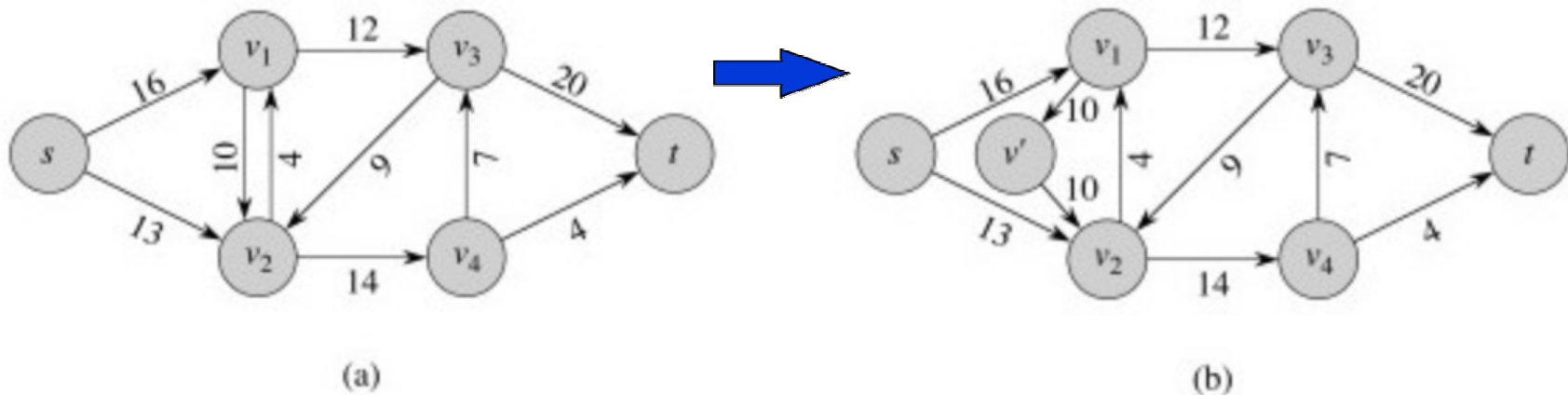
# Maximum-Flow Problem

- Multiple sources/sinks
  - Convert to single source/sink problem by adding one supersource and one supersink



# Maximum-Flow Problem

- Anti-parallel edges or Two-way edges
  - Transform the network into an equivalent one containing no anti-parallel edges by adding a new vertex and two edges having the same capacity as one of the anti-parallel edges.



- Flow networks without anti-parallel edges are easier to explain and process. It is not surprising if anti-parallel edges are avoided or excluded or disallowed for the sake of simplicity in many situations.

# Maximum-Flow Problem

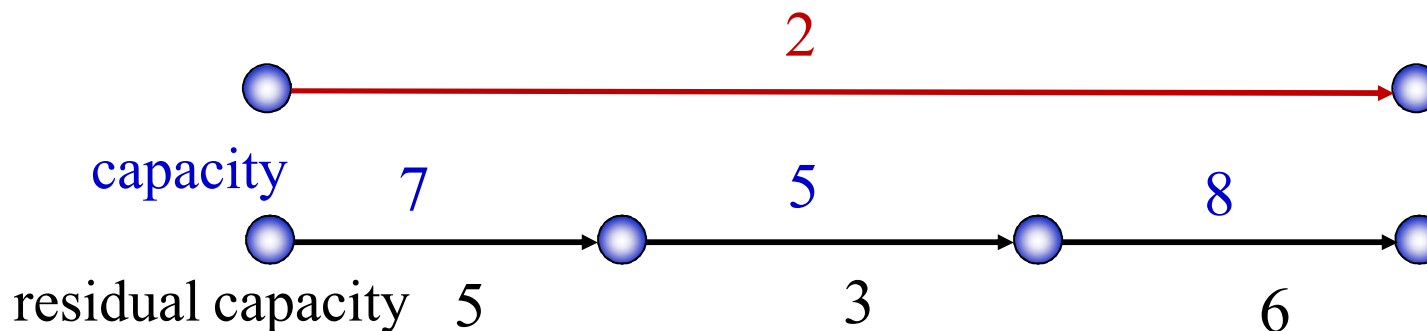
---

FORD-FULKERSON-METHOD( $G, s, t$ )

- 1 initialize flow  $f$  to 0
- 2 **while** there exists an augmenting path  $p$
- 3     **do** augment flow  $f$  along  $p$
- 4 **return**  $f$

# Residual Network

- Given a flow network and a flow, the **residual network** consists of edges that can admit more network flow.
- $G = (V, E)$ : a flow network with source  $s$  and sink  $t$
- $f$ : a flow in  $G$
- The amount of additional network flow from  $u$  to  $v$  before exceeding the capacity  $c(u, v)$  is the **residual capacity** of  $(u, v)$ , given by:  $c_f(u, v) = c(u, v) - f(u, v)$



The residual capacity of the path is 3

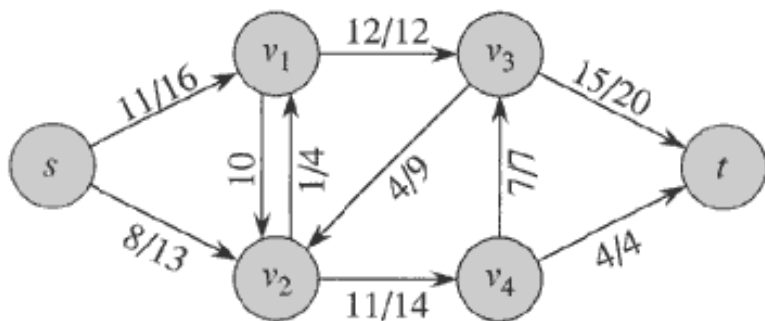


# Residual Network

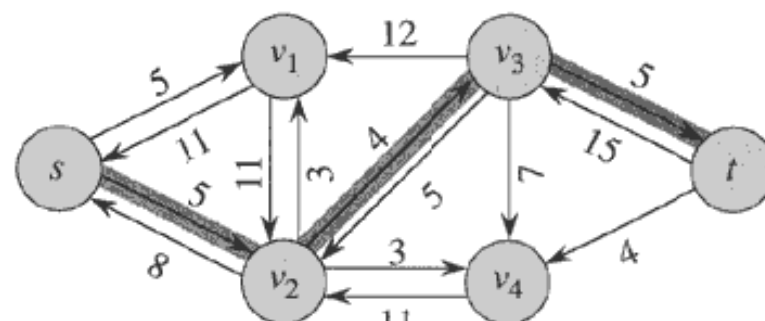
- Given a flow  $f$  in a network  $G = (V, E)$ 
  - The residual capacity between  $u, v \in V$ 
    - ◆  $c_f(u, v) = c(u, v) - f(u, v) \geq 0!$
  - Residual network  $G_f = (V, E_f)$ 
    - ◆ where  $E_f = \{(u, v) \in V \times V : c_f(u, v) > 0\}$
  - Residual network  $G_f$  may also contain edges that are not in  $G$
  - Residual capacity,  $c_f(u, v)$  is defined by

$$c_f(u, v) = \begin{cases} c(u, v) - f(u, v) & \text{if } (u, v) \in E \\ f(v, u) & \text{if } (u, v) \notin E \\ 0 & \text{otherwise} \end{cases}$$

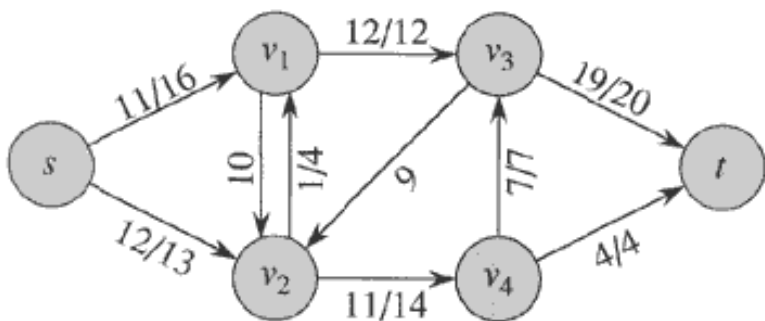
# Residual Network: Example



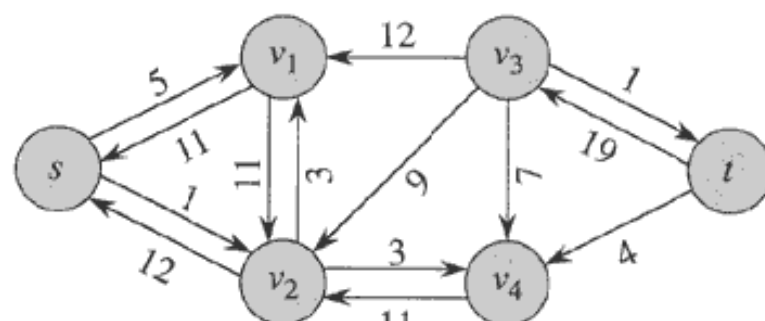
(a)



(b)



(c)



(d)

Each edge in  $G$  corresponds to at most two edges in residual network:  $|E_f| \leq 2|E|$

# Residual Network

- A flow in a residual network provides a roadmap for adding flow to the original flow network.
  - If  $f$  is a flow in  $G$  and  $f'$  is a flow in  $G_f$ , we define  $f \uparrow f'$ , the *augmentation of flow  $f$  by  $f'$*

$$(f \uparrow f')(u, v) = \begin{cases} f(u, v) + f'(u, v) - f'(v, u) & \text{if } (u, v) \in E \\ 0 & \text{otherwise} \end{cases}$$

- Pushing flow on the reverse edge in the residual network is known as *cancellation*.

# Residual Network

- Lemma

- Let  $G = (V, E)$  be a flow network with source  $s$  and sink  $t$ , and let  $f$  be a flow in  $G$ .
- Let  $G_f$  be the residual network of  $G$  induced by  $f$ , and let  $f'$  be a flow in  $G_f$ . Then the flow sum  $f + f'$  is a flow in  $G$  with value  $|f + f'| = |f| + |f'|$
- $f + f'$ : the flow in the same direction will be added.  
the flow in different directions will be cancelled.

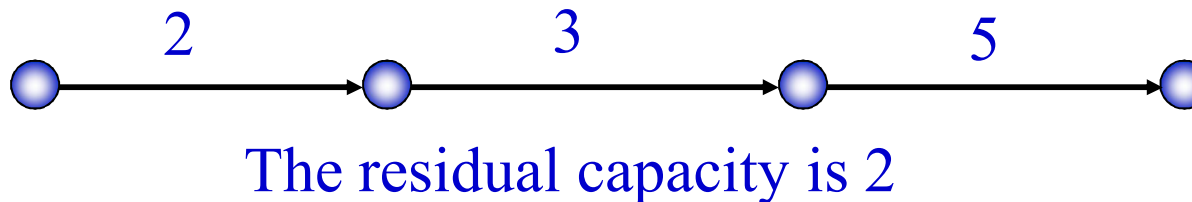
This suggests that we can improve current flow by computing a new flow for its residual network, and add it upon original one

# Augmenting Path

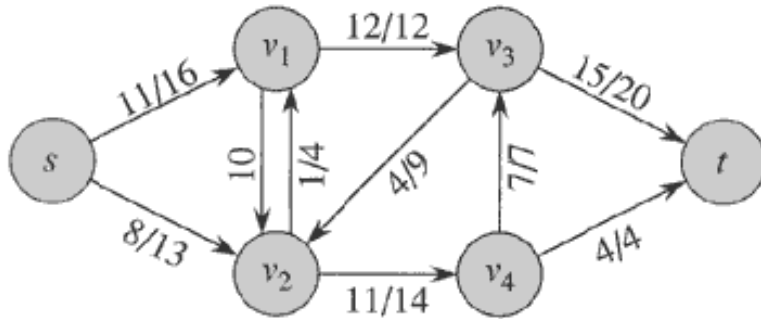
- Given a flow  $f$  in a flow network  $G = (V, E)$ , an *augmenting path*  $p$  is a simple path from source  $s$  to sink  $t$  in the residual network  $G_f$ .
- How much extra flow can we push on an augmenting path  $p$  ?

The maximum amount by which we increase the flow on each edge in an augmenting path  $p$  is the *residual capacity* of  $p$ , given by

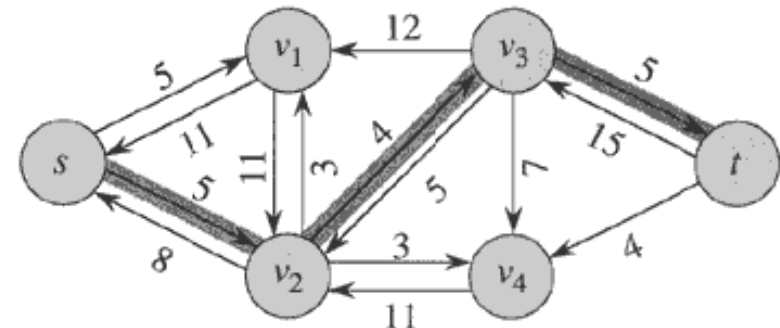
$$c_f(p) = \min \{c_f(u, v) : (u, v) \text{ is on } p\}$$



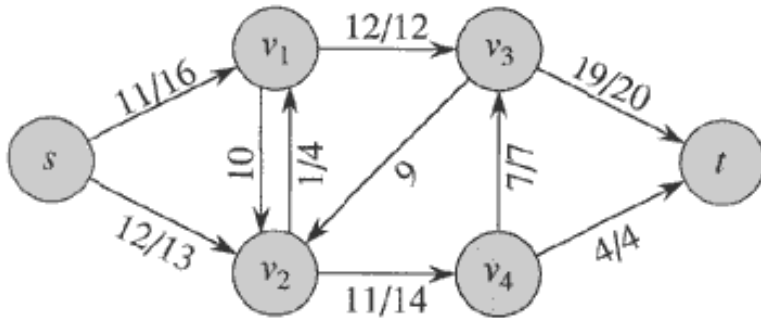
# Augmenting Path: Example



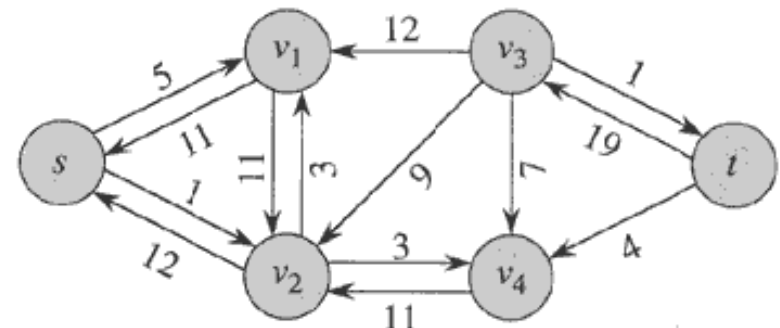
(a)



(b)



(c)



(d)

# Lemma: Augmenting $\rightarrow$ Flow

## *Lemma:*

Given flow network  $G$ , flow  $f$  in  $G$ , residual network  $G_f$ . Let  $p$  be an augmenting path in  $G_f$ . Define  $f_p : V \times V \rightarrow \mathbf{R}$ :

$$f_p(u, v) = \begin{cases} c_f(p) & \text{if } (u, v) \text{ is on } p, \\ -c_f(p) & \text{if } (v, u) \text{ is on } p, \\ 0 & \text{otherwise.} \end{cases}$$

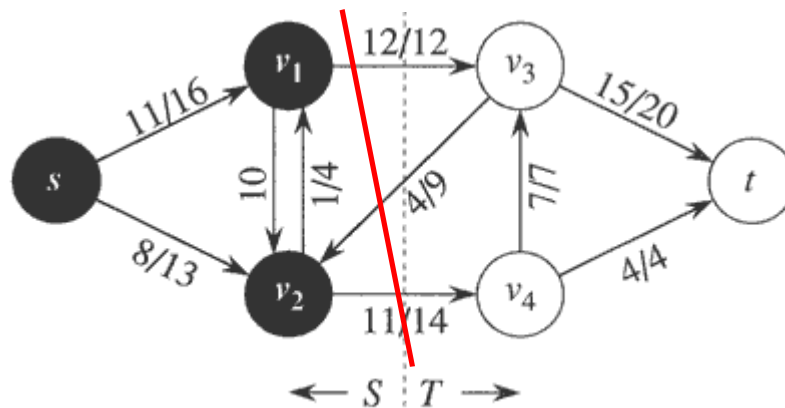
Then  $f_p$  is a flow in  $G_f$  with value  $|f_p| = c_f(p) > 0$ .

## *Corollary:*

Given flow network  $G$ , flow  $f$  in  $G$ , and an augmenting path  $p$  in  $G_f$ , define  $f_p$  as in lemma, and define  $f' : V \times V \rightarrow \mathbf{R}$  by  $f' = f + f_p$ . Then  $f'$  is a flow in  $G$  with value  $|f'| = |f| + c_f(p) > |f|$ .

# Cuts of Flow Networks

- A *cut*  $(S, T)$  of flow network  $G = (V, E)$ 
  - is a partition of  $V$  into  $S$  and  $T = V - S$ , s.t.  $s \in S$  and  $t \in T$
  - The net flow  $f(S, T)$  across cut  $(S, T)$  is
$$f(S, T) = \sum_{u \in S, v \in T} f(u, v) - \sum_{v \in T, u \in S} f(v, u)$$
  - The capacity  $c(S, T)$  of cut  $(S, T)$  is
$$c(S, T) = \sum_{u \in S, v \in T} c(u, v)$$
- A **minimum-cut** is a cut whose capacity is minimum over all cuts



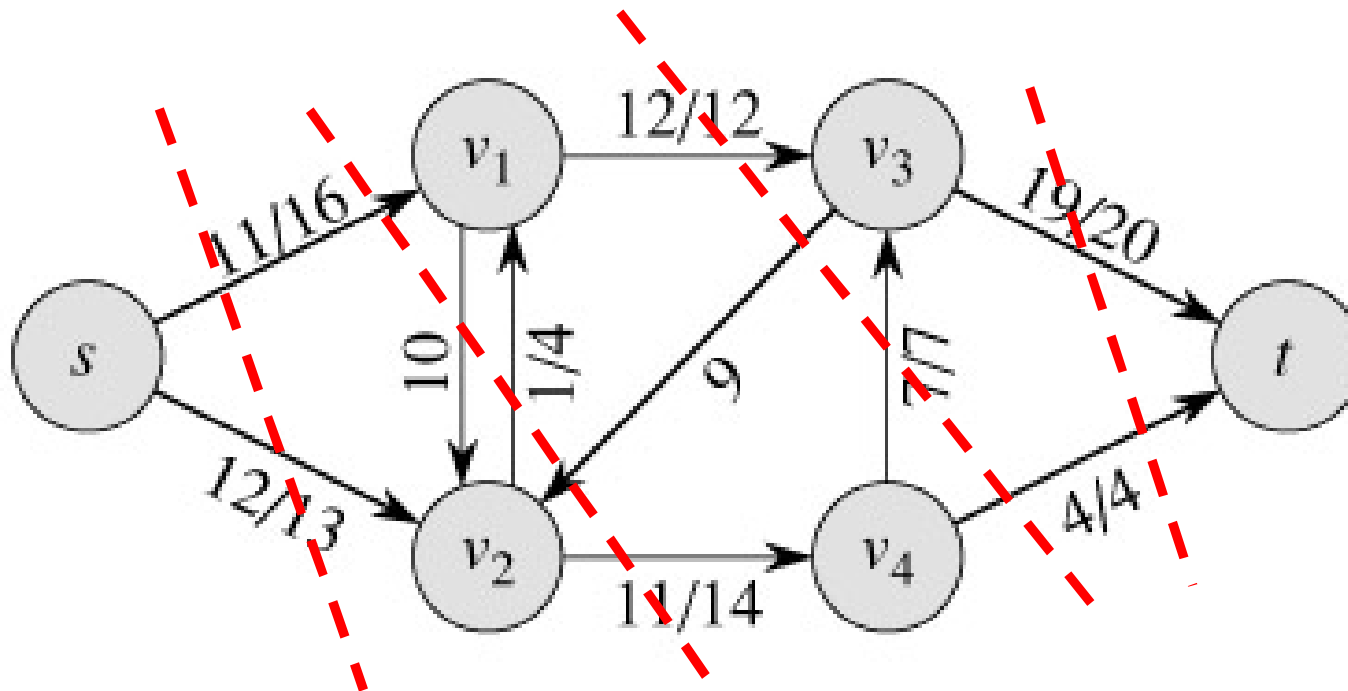
$$f(S, T) = 12 + 11 - 4 = 19$$

$$c(S, T) = 12 + 14 = 26$$



# Cuts of Flow Networks

- The net flow across any cut is the same and equal to the flow of the network  $|f|$ .



# Cuts of Flow Networks

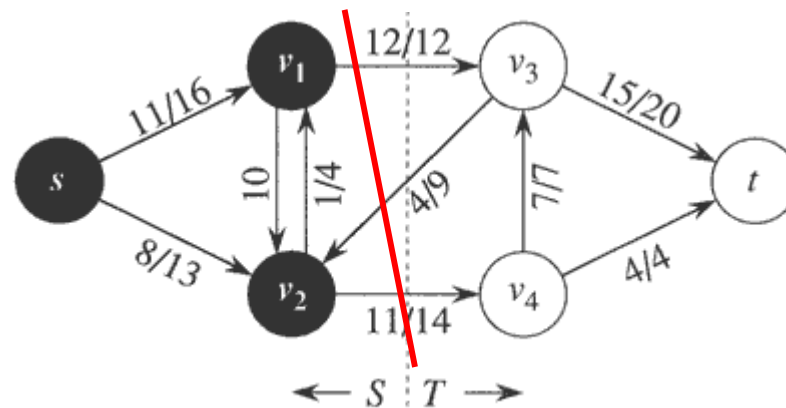
## *Lemma:*

Let  $f$  be a flow in a network  $G$  with source  $s$  and sink  $t$ , and let  $(S, T)$  be a cut of  $G$ . Then the net flow across  $(S, T)$  is  $f(S, T) = |f|$ .

## *Corollary:*

The value of any flow  $f$  in a flow network  $G$  is bounded from above by the capacity of any cut of  $G$ .

The value of any flow  $\leq$  the capacity of any cut

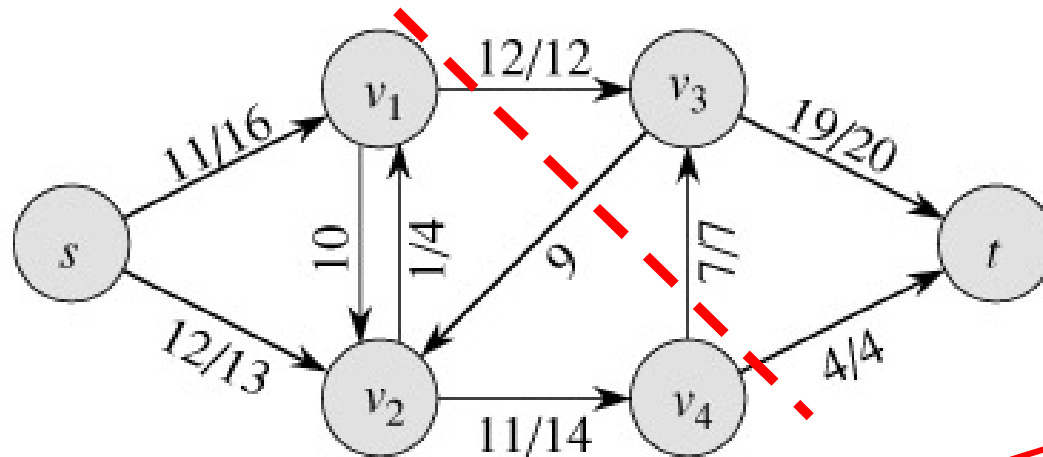


# Max-flow Min-cut Theorem

- If  $f$  is a flow in a flow network  $G = (V, E)$  with source  $s$  and sink  $t$ , then the following conditions are equivalent:
  - (1)  $f$  is a maximum flow in  $G$
  - (2) The residual network  $G_f$  contains no augmenting paths
  - (3)  $|f| = c(S, T)$  for some cut  $(S, T)$  in  $G$
- Proof:
  - (1)  $\Rightarrow$  (2)
  - (2)  $\Rightarrow$  (3)
  - (3)  $\Rightarrow$  (1)

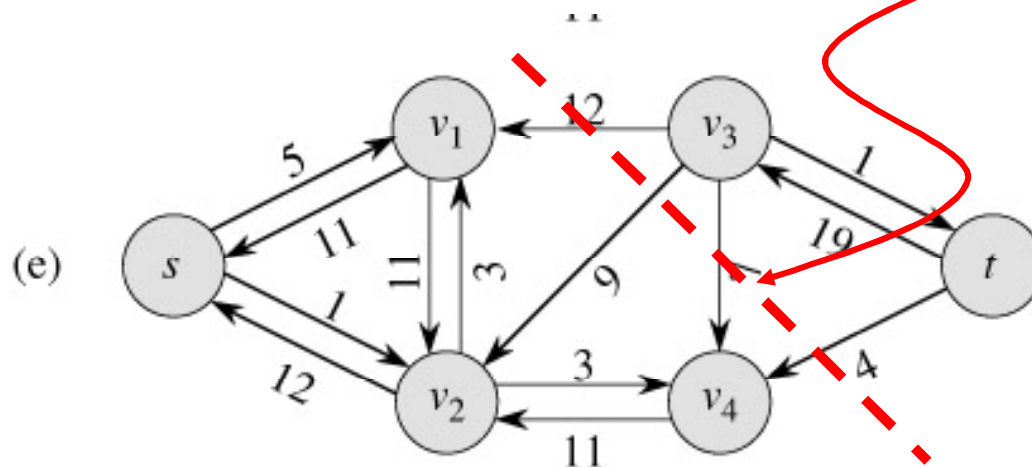
*The value of Maximum Flow =  
the Capacity of Minimum Cut*

# Max-flow Min-cut Theorem



Resulting Flow = 23

No augmenting path:  
Maxflow = 23



Residual Network

# Ford-Fulkerson Algorithm

FORD-FULKERSON( $G, s, t$ )

**for** each edge  $(u, v) \in E[G]$  **do**

$f[u, v] = 0$

$f[v, u] = 0$

$O(E)$

?

**while** there exists a path  $P$  from  $s$  to  $t$  in the residual network  $G_f$  **do**

$c_f(P) = \min\{c_f(u, v) : (u, v) \text{ is in } P\}$

**for** each edge  $(u, v)$  in  $P$  **do**

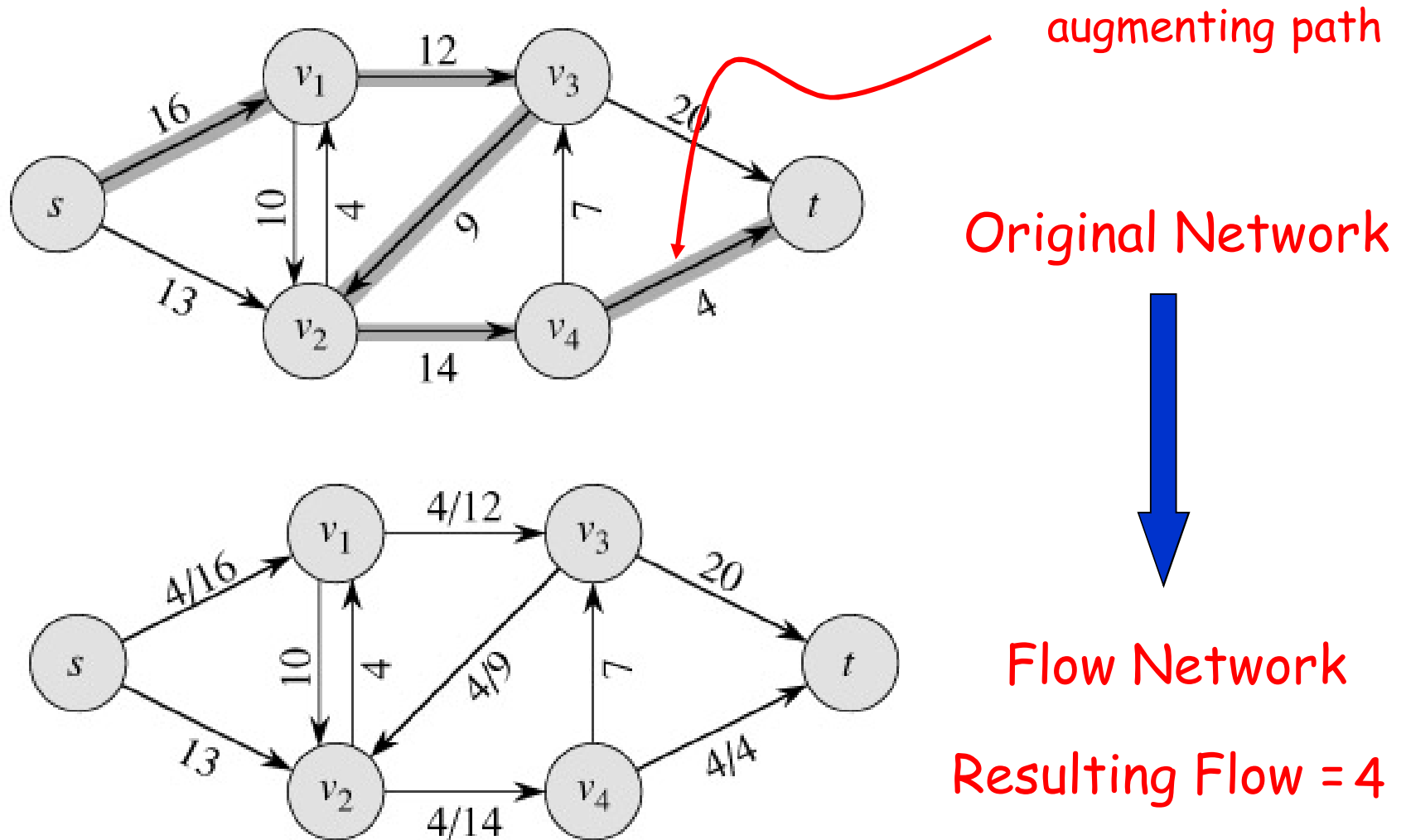
**if**  $(u, v) \in E[G]$

$f[u, v] = f[u, v] + c_f(P)$

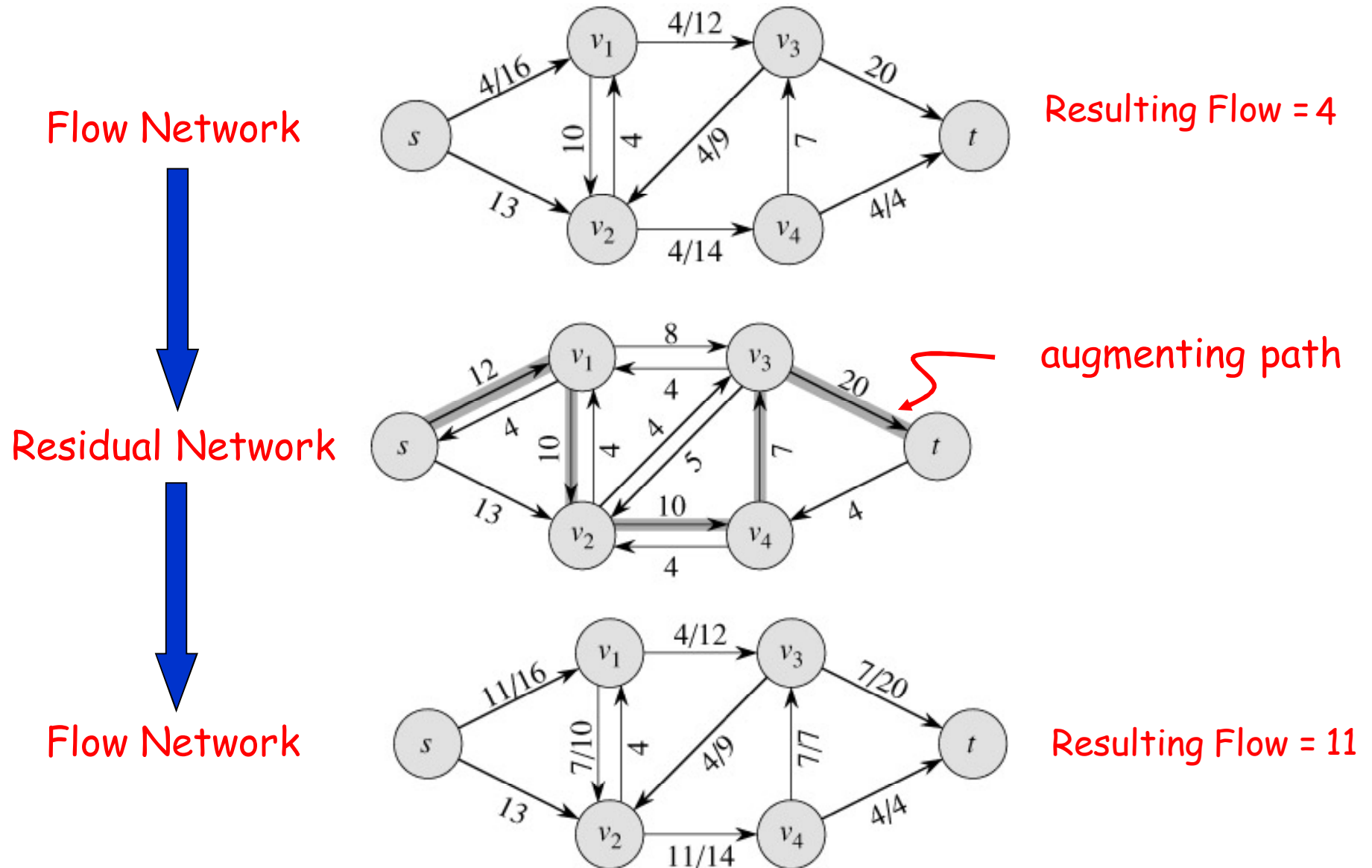
**else**  $f[v, u] = f[v, u] - c_f(P)$

$O(E)$

# Ford-Fulkerson Algorithm: Example

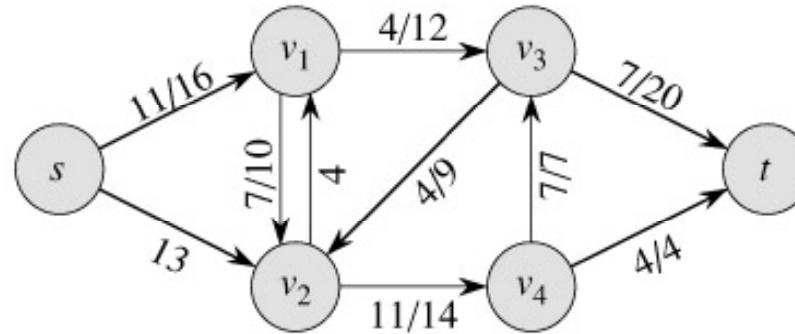


# Ford-Fulkerson Algorithm: Example



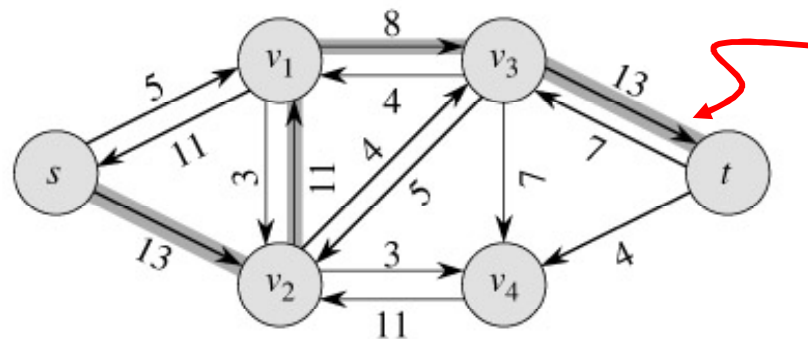
# Ford-Fulkerson Algorithm: Example

Flow Network



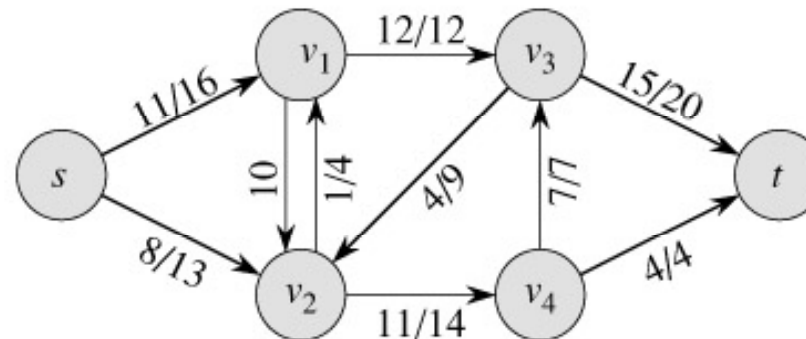
Resulting Flow = 11

Residual Network



augmenting path

Flow Network

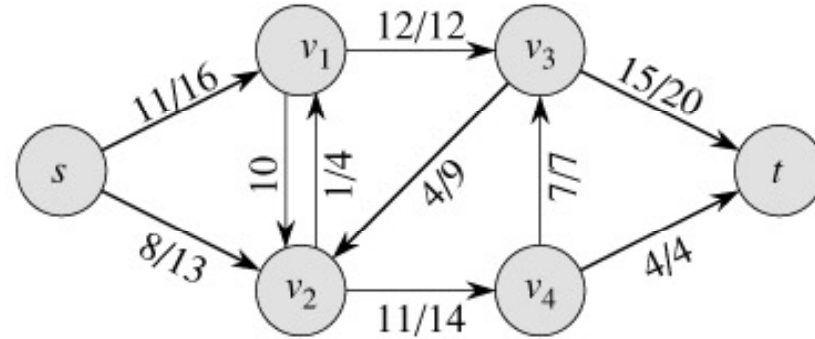


Resulting Flow = 19



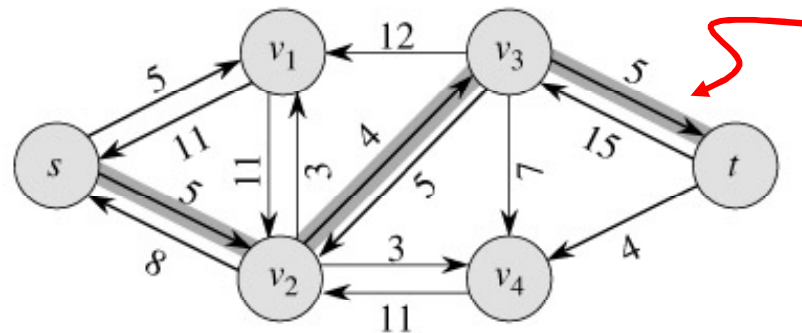
# Ford-Fulkerson Algorithm: Example

Flow Network



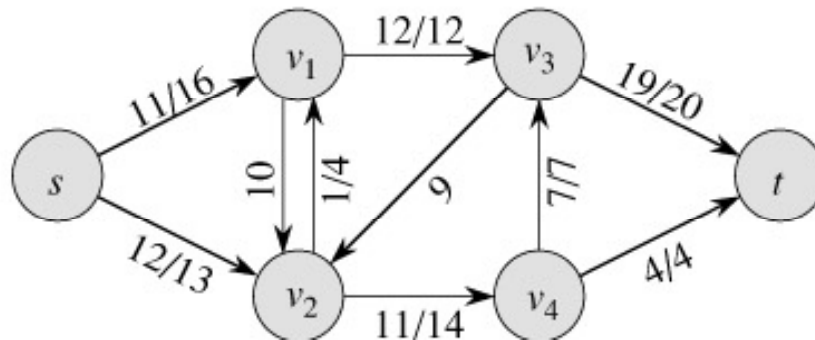
Resulting Flow = 19

Residual Network



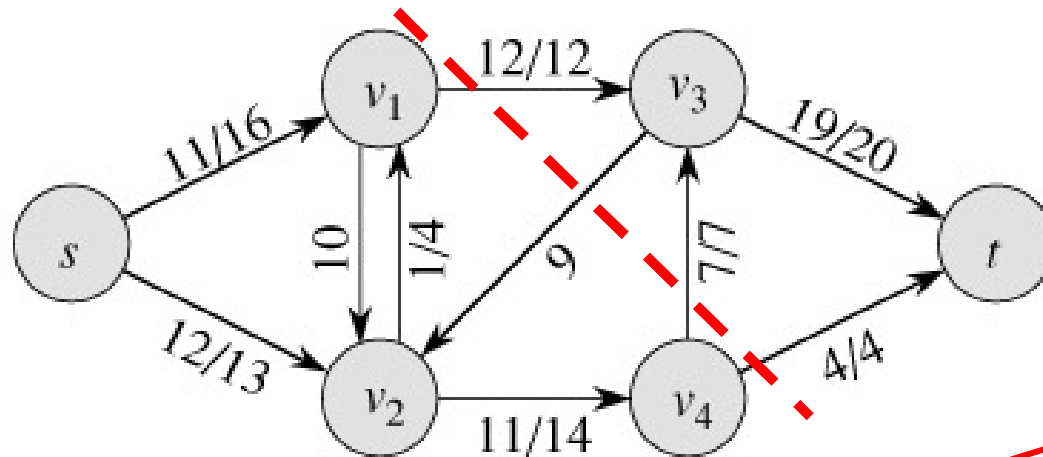
augmenting path

Flow Network



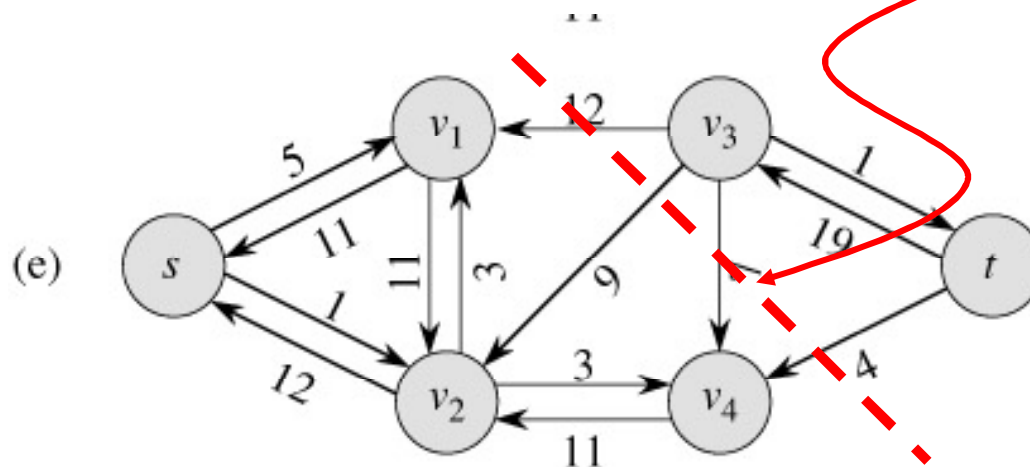
Resulting Flow = 23

# Ford-Fulkerson Algorithm: Example



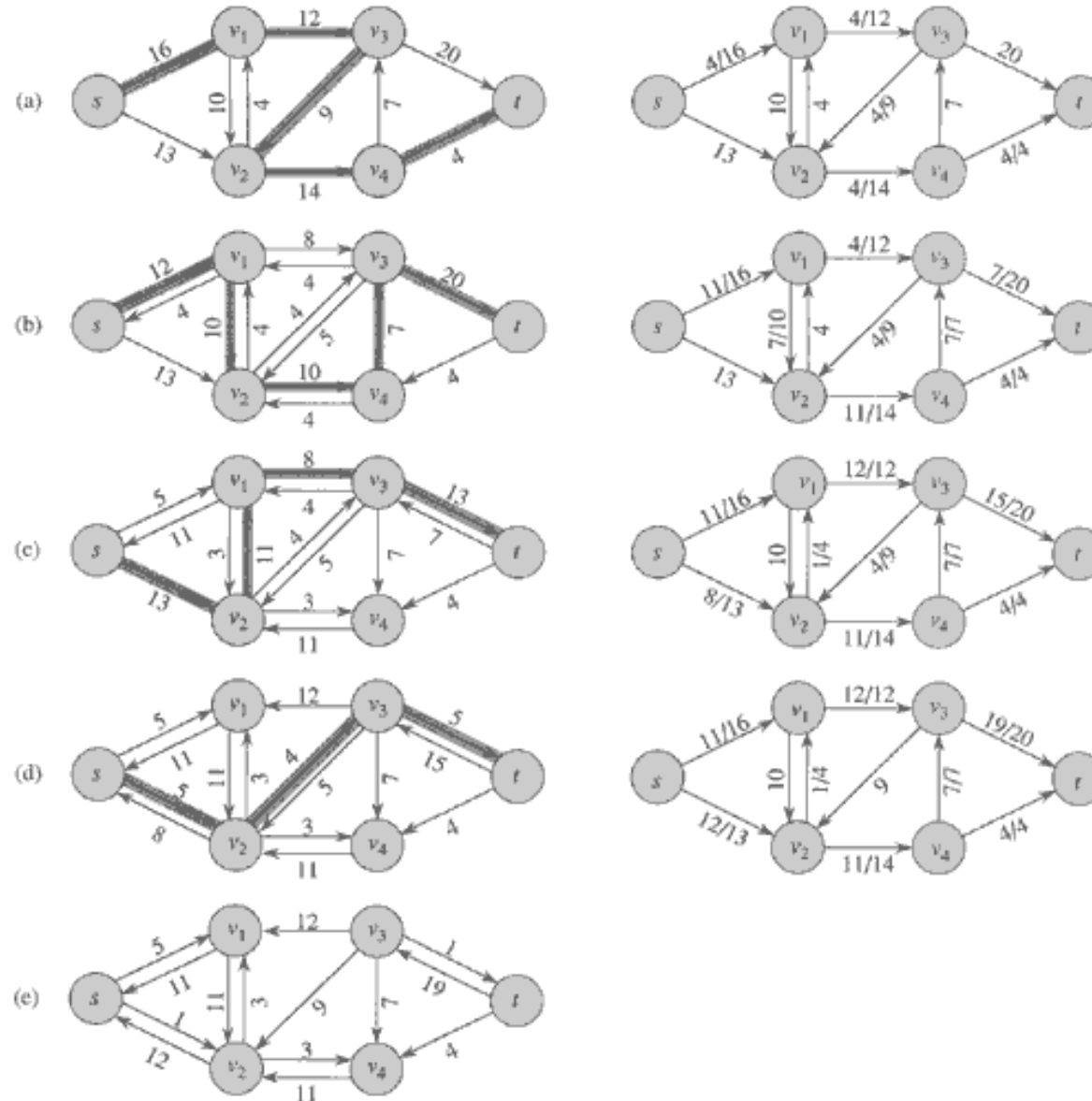
Resulting Flow = 23

No augmenting path:  
Maxflow = 23



Residual Network

# Ford-Fulkerson Algorithm: Example



# Ford-Fulkerson Algorithm: Analysis

---

- Performance obviously
  - depends on the augmenting paths found at each iteration
- If edge capacities are integers (or, rational numbers [*apply an appropriate scaling transformation to make them all integral*]):
  - Then the algorithm returns max-flow
  - The algorithm runs in polynomial time
- If edge capacities are irrational numbers:
  - Then the algorithm might not even terminate
  - It need not even converge to the maximum value

# Ford-Fulkerson Algorithm: Integral Capacities

```
FORD-FULKERSON( $G, s, t$ )
1  for each edge  $(u, v) \in E[G]$ 
2      do  $f[u, v] \leftarrow 0$ 
3       $f[v, u] \leftarrow 0$ 
4  while there exists a path  $p$  from  $s$  to  $t$  in the residual network  $G_f$ 
5      do  $c_f(p) \leftarrow \min \{c_f(u, v) : (u, v) \text{ is in } p\}$ 
6          for each edge  $(u, v)$  in  $p$ 
7              do  $f[u, v] \leftarrow f[u, v] + c_f(p)$ 
8               $f[v, u] \leftarrow -f[u, v]$ 
```

*Annotations:*

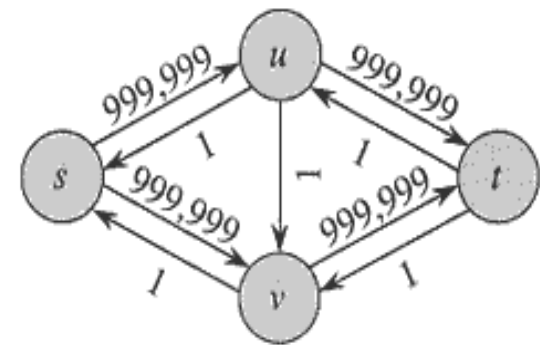
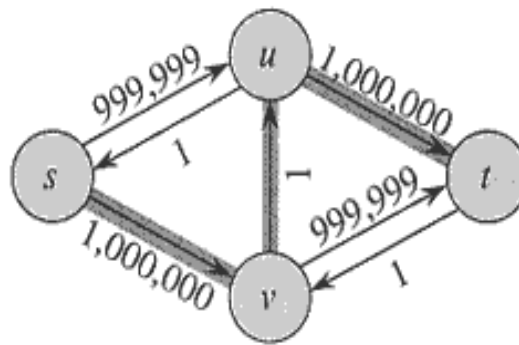
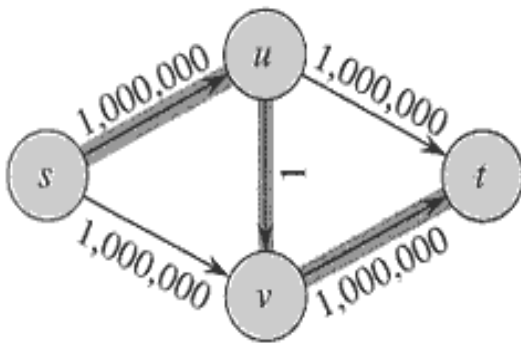
- Lines 1-3 are grouped by a red bracket labeled  $O(E)$ .
- Lines 4-8 are enclosed in a red dashed oval, with a red bracket on the right labeled  $O(E)$ .

If each  $c(e)$  is an *integer*, then time complexity is  $O(E |f^*|)$ , where  $f^*$  is the maximum flow found by the algorithm

- Lines 1-3 take  $O(E)$  time.
- The **while loop** of Line 4 is executed at most  $|f^*|$  times, since the value of the flow increases by at least 1 at each iteration.
  - ◆ Each iteration of the **while loop** takes  $O(E)$  time if either depth-first or breadth-first search is used to find a path in the residual network.
- Therefore, total time =  $O(E + E |f^*|) = O(E |f^*|)$ .

# Ford-Fulkerson Algorithm: Integral Capacities

- Ford-Fulkerson algorithm runs in  $O(E |f^*|)$  time, where  $f^*$  is the maximum flow found by the algorithm
- Not really polynomial in  $|V|$  and  $|E|$ 
  - Depends on  $|f^*|$



# Edmonds-Karp Algorithm

- A small fix to the Ford-Fulkerson algorithm makes it work in polynomial time.
- Select the augmenting path using **breadth-first search** on residual network.
- The augmenting path  $p$  is the shortest path from  $s$  to  $t$  in the residual network (treating all edge weights as 1).
- Runs in time  $O(V E^2)$ .

FORD-FULKERSON( $G, s, t$ )

```
1  for each edge  $(u, v) \in E[G]$ 
2      do  $f[u, v] \leftarrow 0$ 
3      do  $f[v, u] \leftarrow 0$ 
4  while there exists a path  $p$  from  $s$  to  $t$  in the residual network  $G_f$ 
5      do  $c_f(p) \leftarrow \min \{c_f(u, v) : (u, v) \text{ is in } p\}$ 
6      for each edge  $(u, v)$  in  $p$ 
7          do  $f[u, v] \leftarrow f[u, v] + c_f(p)$ 
8          do  $f[v, u] \leftarrow -f[u, v]$ 
```

# Edmonds-Karp Algorithm

---

- Use the Ford-Fulkerson framework
- Implement the computation of augmenting path
  - by using breadth-first search
  - *i.e.*, a shortest-linkage path (in no. of edges) from  $s$  to  $t$  in residual network
- Enable us to bound the time complexity
  - Mainly: the number of iterations
- Time complexity of Edmonds-Karp algorithm is  $O(V E^2)$ 
  - The number of iterations is  $O(V E)$
  - Each iteration needs  $O(E)$



# Edmonds-Karp Algorithm: Observations

- Lemma: If the Edmonds-Karp algorithm is run on a flow network  $G = (V, E)$  with source  $s$  and sink  $t$ , then for all vertices  $v \in V - \{s, t\}$ , the shortest distance  $\delta_f(s, v)$  in the residual network  $G_f$  increases monotonically with each flow augmentation.

Proof:

- Theorem: If the Edmonds-Karp algorithm is run on a flow network  $G = (V, E)$  with source  $s$  and sink  $t$ , then the total number of flow augmentations performed by the algorithm is  $O(V E)$ .

Proof:

- Time complexity of Edmonds-Karp algorithm is  $O(V E^2)$

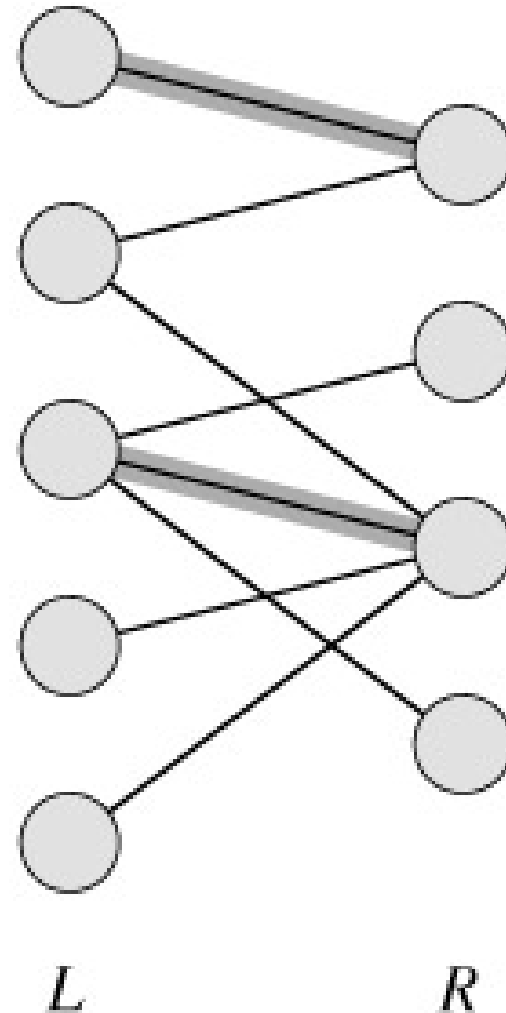


# **An Application of Max Flow:**

## **Maximum Bipartite Matching**

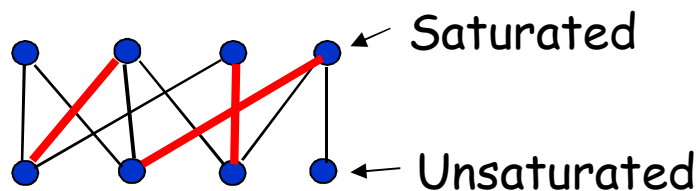
# Bipartite Graph

- A **bipartite graph** is a graph  $G = (V, E)$  in which  $V$  can be partitioned into two parts  $L$  and  $R$  such that every edge in  $E$  is between a vertex in  $L$  and a vertex in  $R$ .
- e.g. vertices in  $L$  represent skilled workers and vertices in  $R$  represent jobs. An edge connects workers to jobs they can perform.

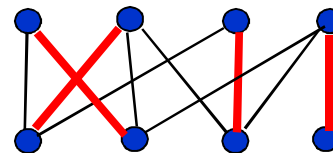


# Matching

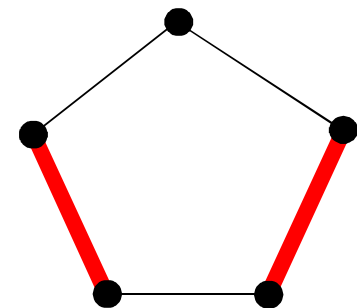
- A **matching** in a simple graph  $G$  is a set of edges with no shared endpoints.
- The vertices incident to the edges of a matching  $M$  are said to be **saturated** by  $M$ ; the others are **unsaturated**.
- A **perfect matching** in a graph is a matching that saturates every vertex.
- A **maximum matching** is a matching of maximum size among all matchings in the graph.



A matching



Perfect Matching

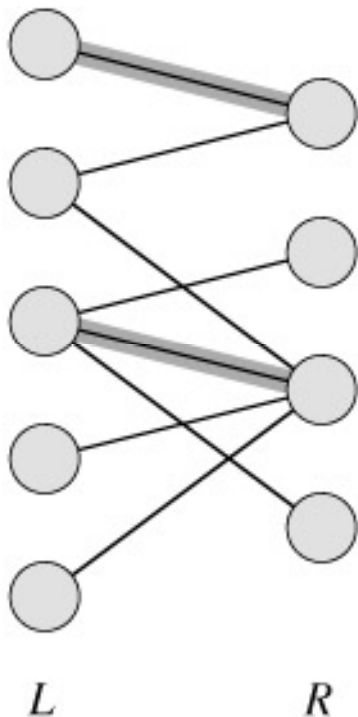


Maximum Matching  
Not a perfect matching

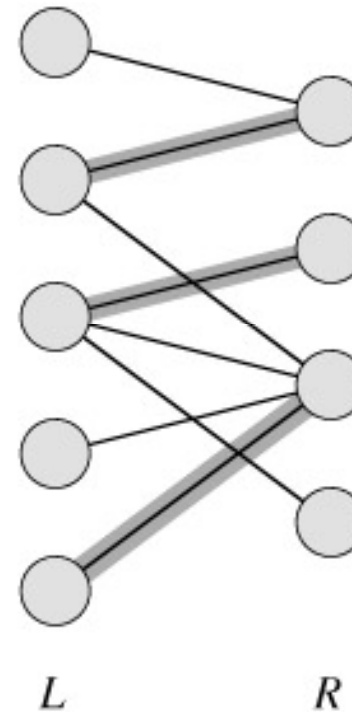
# Maximum Matching

- A **maximum matching** is a matching of maximum cardinality (maximum number of edges).

not maximum

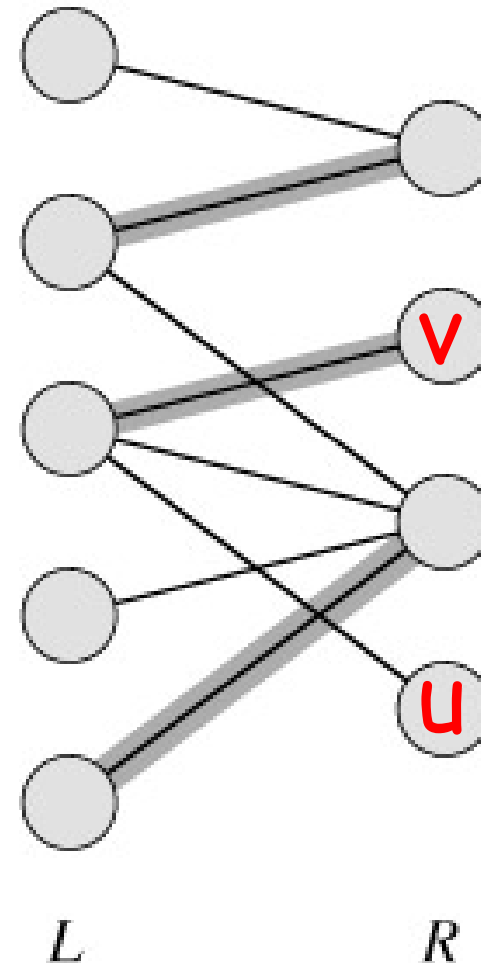


maximum



# Maximum Matching

- No matching of cardinality 4, because only one of  $v$  and  $u$  can be matched.
- In the workers-jobs example a max-matching provides work for as many people as possible.



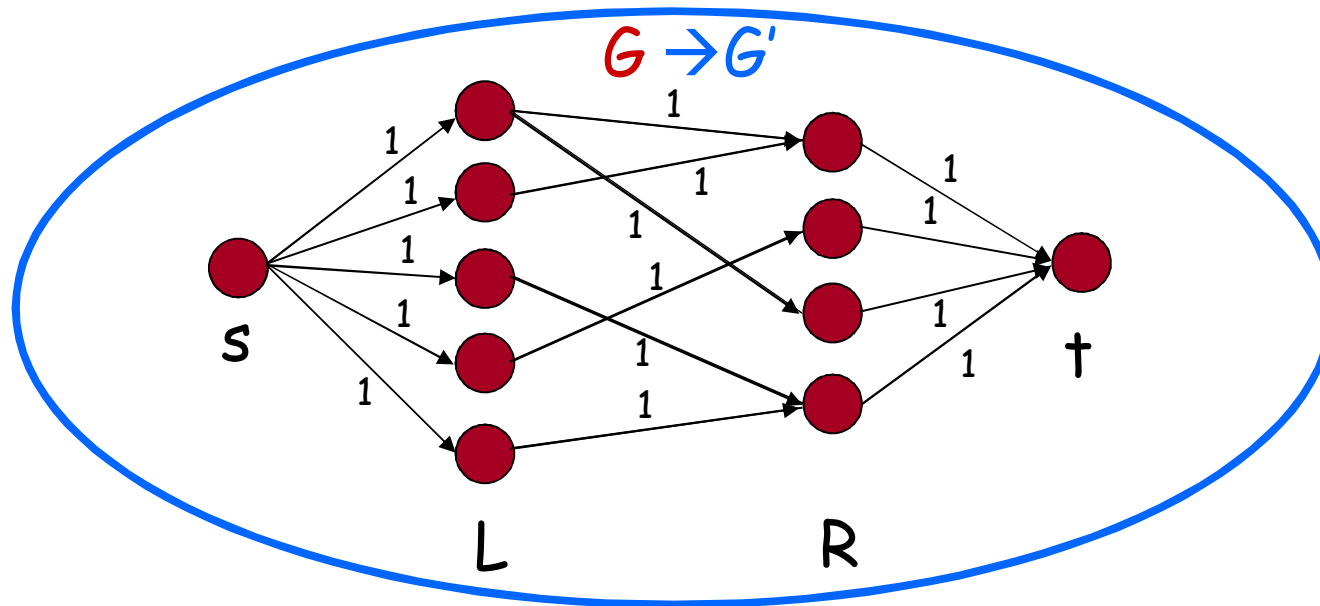
# Solving the Maximum Bipartite Matching Problem

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- Reduce the maximum bipartite matching problem on graph  $G$  to the max-flow problem on a corresponding flow network  $G'$ .
- Solve using Ford-Fulkerson algorithm.

# Corresponding Flow Network

- To form the corresponding flow network  $G'$  of the bipartite graph  $G$ :
  - Add a source vertex  $s$  and edges from  $s$  to  $L$ .
  - Direct the edges in  $E$  from  $L$  to  $R$ .
  - Add a sink vertex  $t$  and edges from  $R$  to  $t$ .
  - Assign a capacity of 1 to all edges.
- **Claim:** max-flow in  $G'$  corresponds to a max-bipartite-matching on  $G$ .





# Solving Bipartite Matching as Max Flow

Let  $G = (V, E)$  be a bipartite graph with vertex partition  $V = L \cup R$ .

Let  $G' = (V', E')$  be its corresponding flow network.

If  $M$  is a matching in  $G$ ,

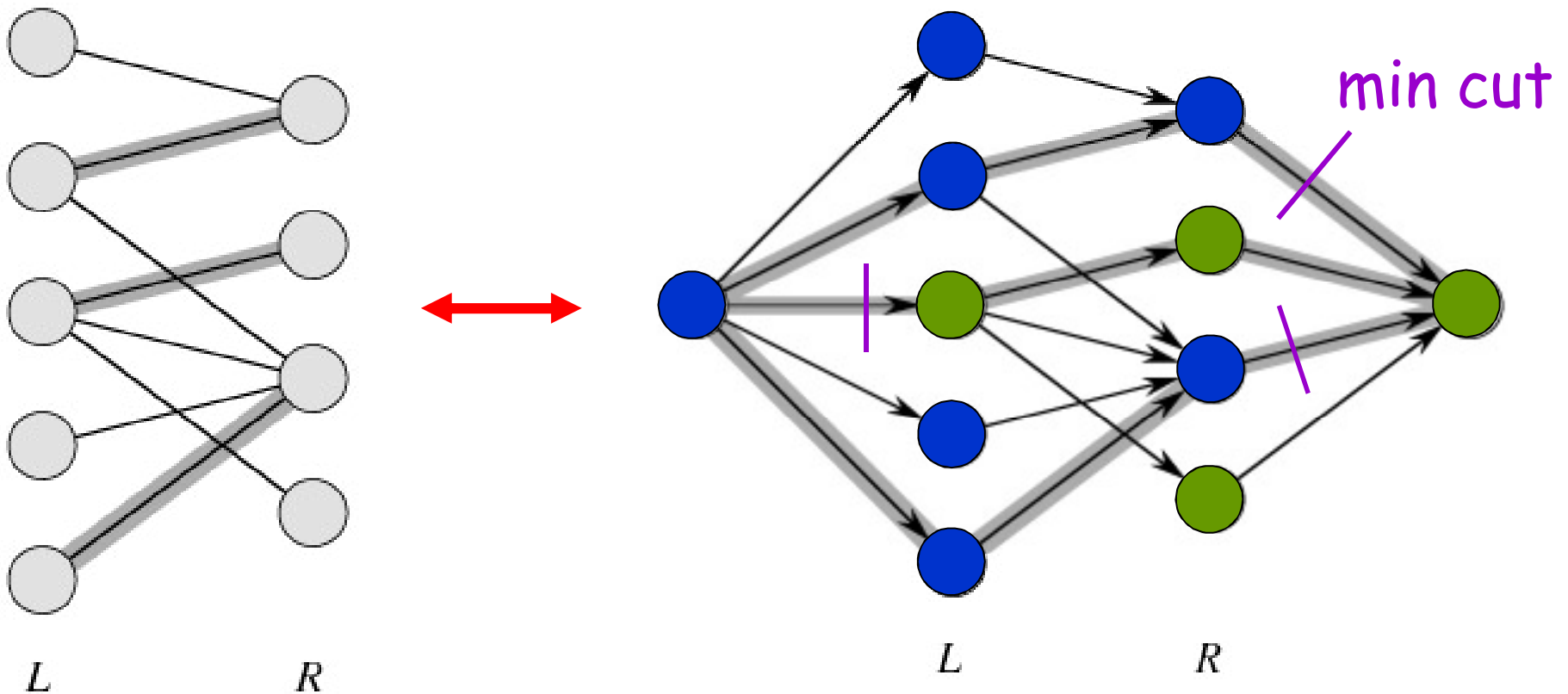
then there is an integer-valued flow  $f$  in  $G'$  with value  $|f| = |M|$ .

Conversely if  $f$  is an integer-valued flow in  $G'$ ,

then there is a matching  $M$  in  $G$  with cardinality  $|M| = |f|$ .

Thus  $\max |M| = \max(\text{integer } |f|)$

# Example

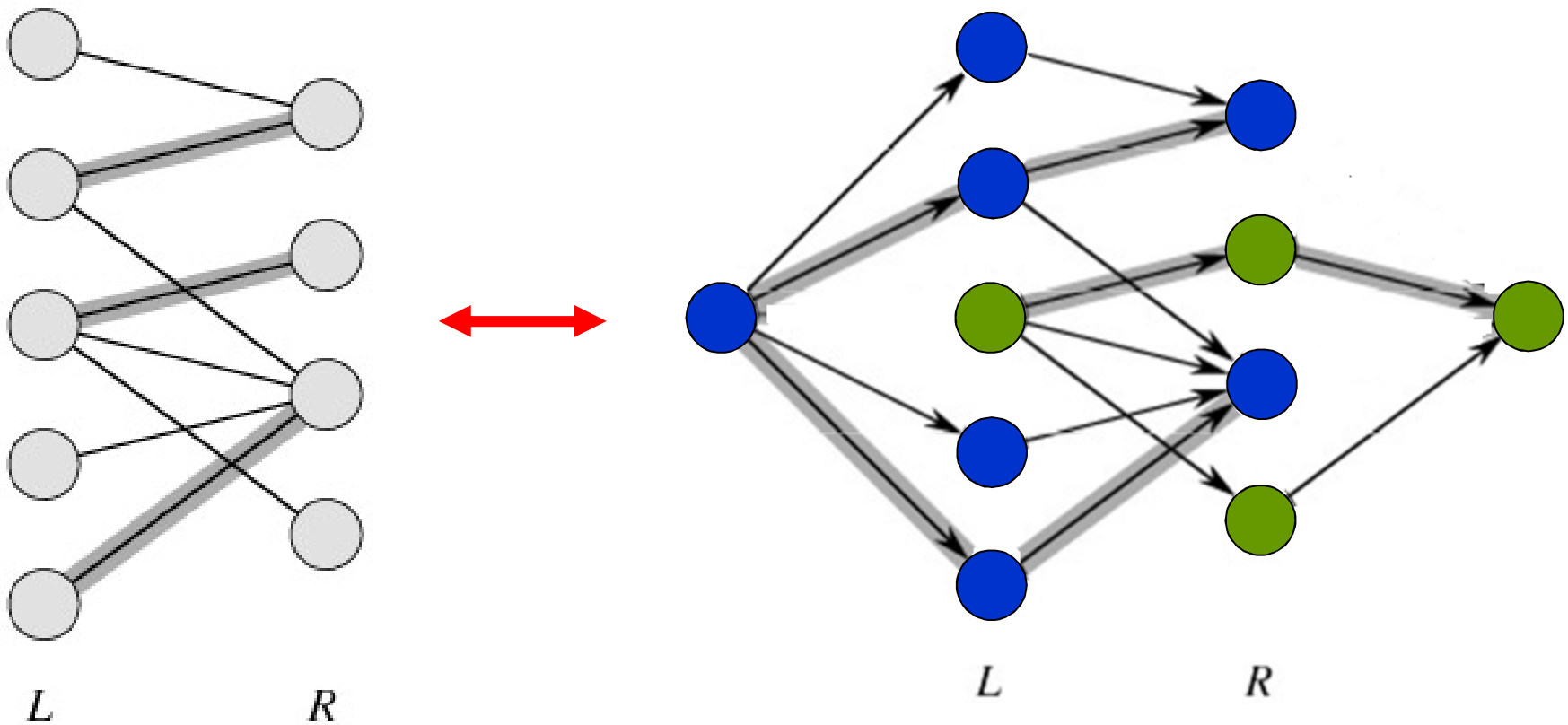


$$|M| = 3$$



$$\text{max flow} = |f| = 3$$

# Example



$$|M| = 3$$



$$\text{max flow} = |f| = 3$$

# Conclusion

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- Network flow algorithms allow us to find the maximum bipartite matching fairly easily.
- Similar techniques are applicable in other combinatorial design problems.