

# **Algorithms**

**Lecture Topic: Maximum Flow (Part 2)**

**Anxiao (Andrew) Jiang**

Roadmap of this lecture:

1. Maximum Flow.

1.1 Analyze the correctness and time complexity of the Ford-Fulkerson Method.

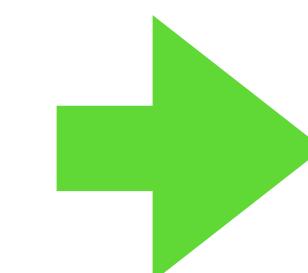
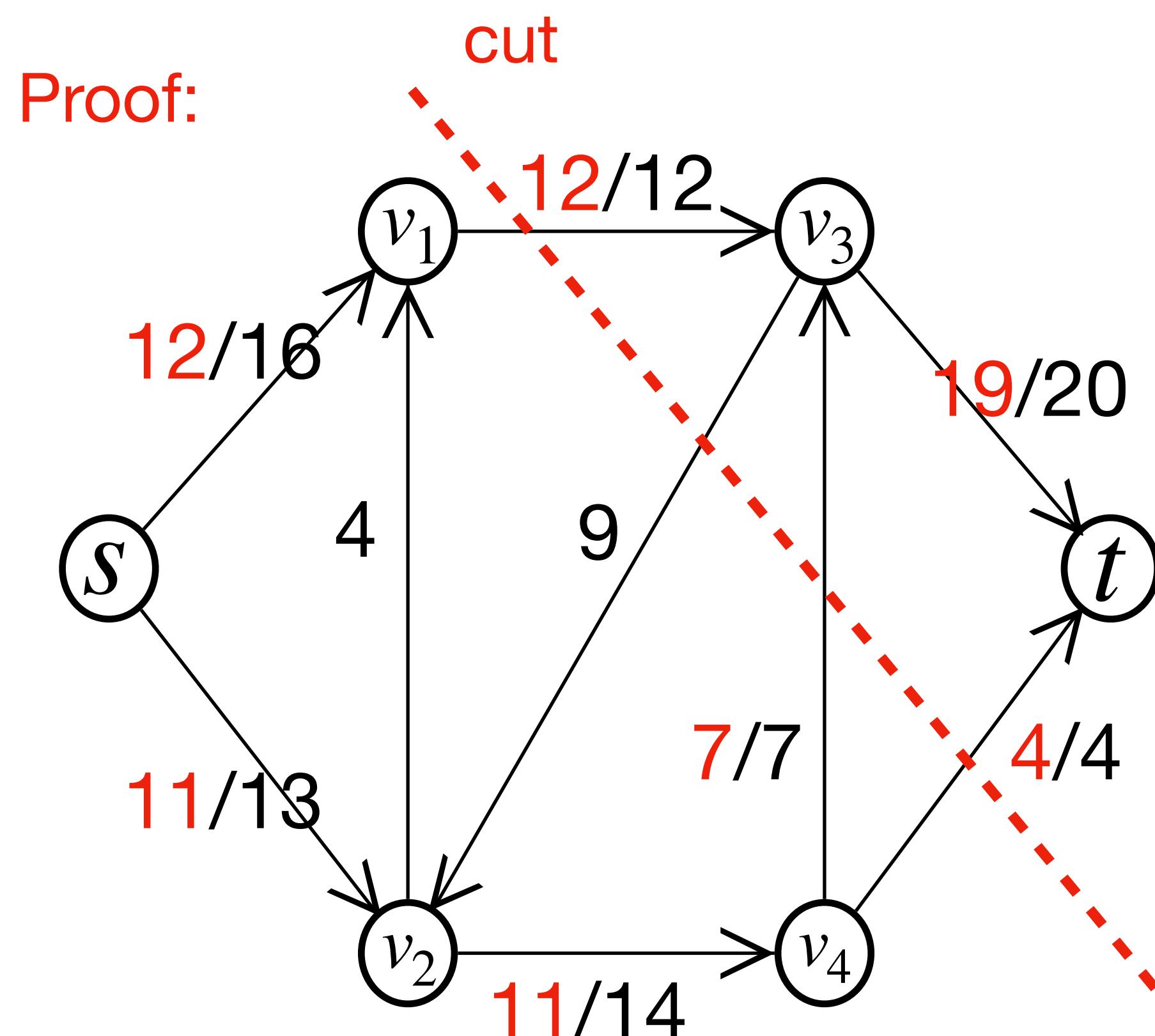
1.2 Edmonds-Karp Algorithm for maximum flow.

1.3 Use maximum flow to solve the "Maximum Bipartite Matching Problem".

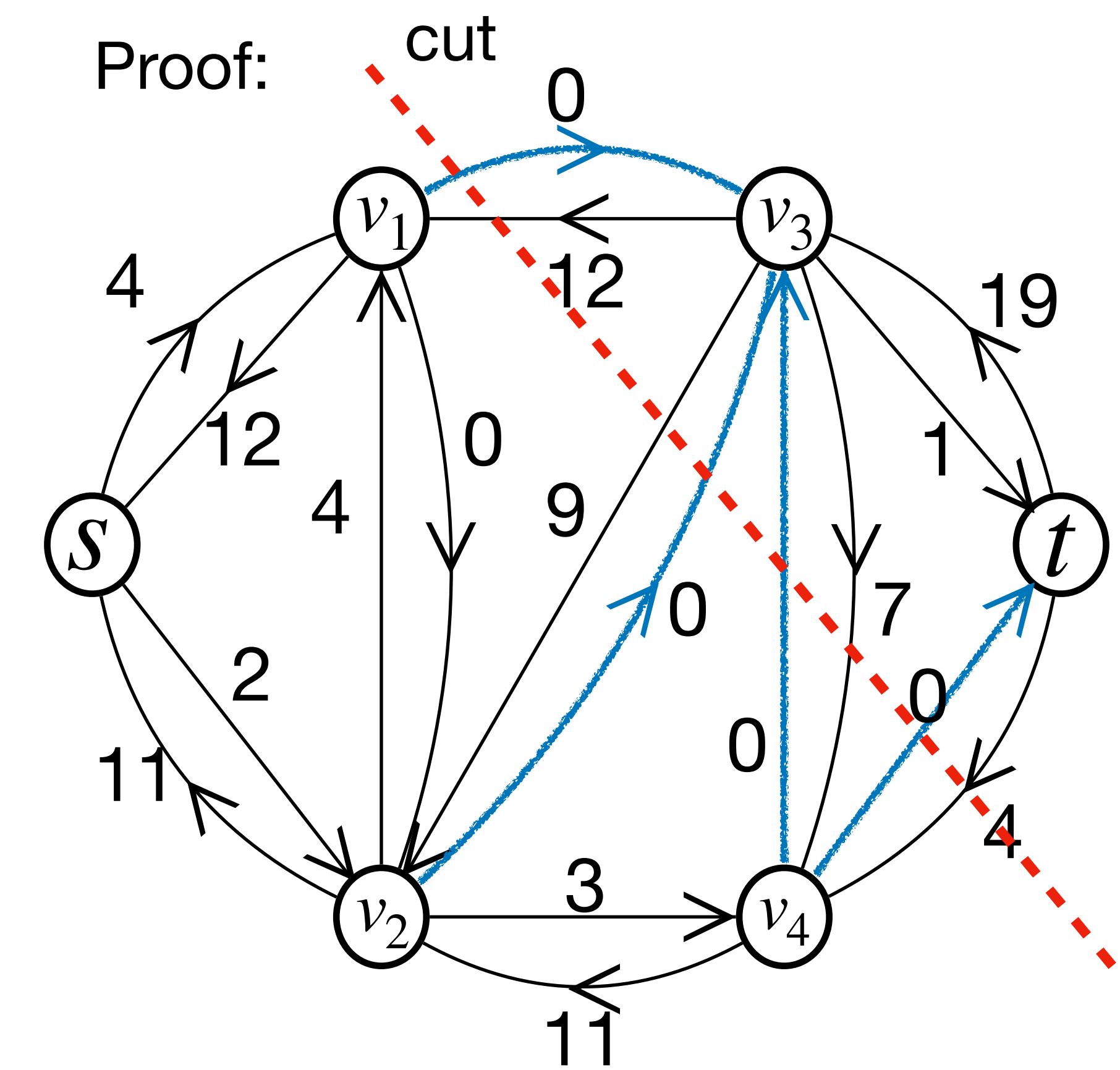
# Maximum Flow

## Ford-Fulkerson Method

Original network



Residual network



Size of flow:  $12+11=19+4=23$

Is it optimal? YES.

Is there still a path from  $s$  to  $t$  of residual capacity  $> 0$ ?

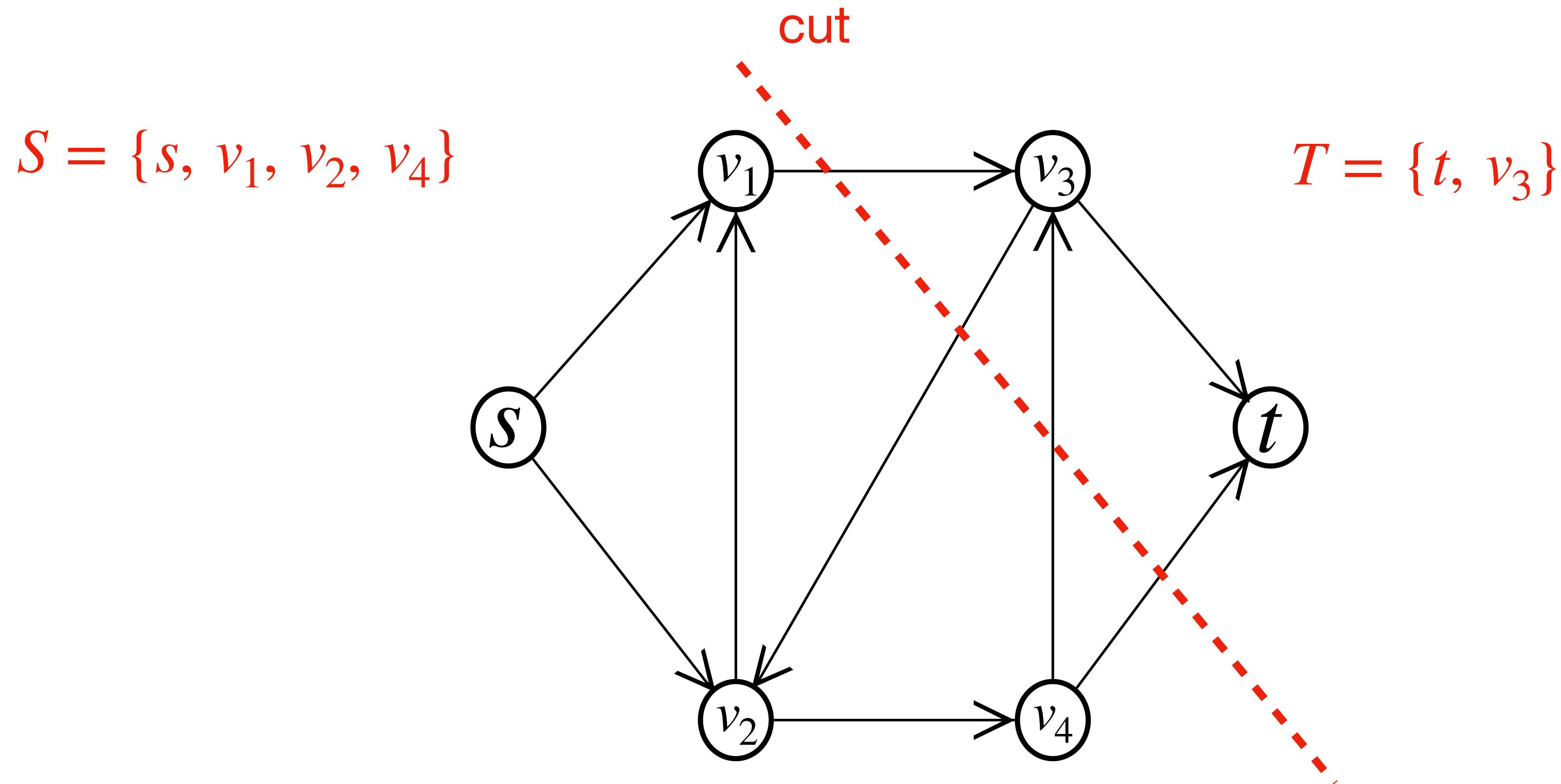
NO

**Theorem:** The Ford-Fulkerson Method finds a maximum flow.

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**Cut:** A partition of the nodes in the network  $G=(V,E)$  into two sets  $S$  and  $T$ , such that  $s \in S$  and  $t \in T$ .

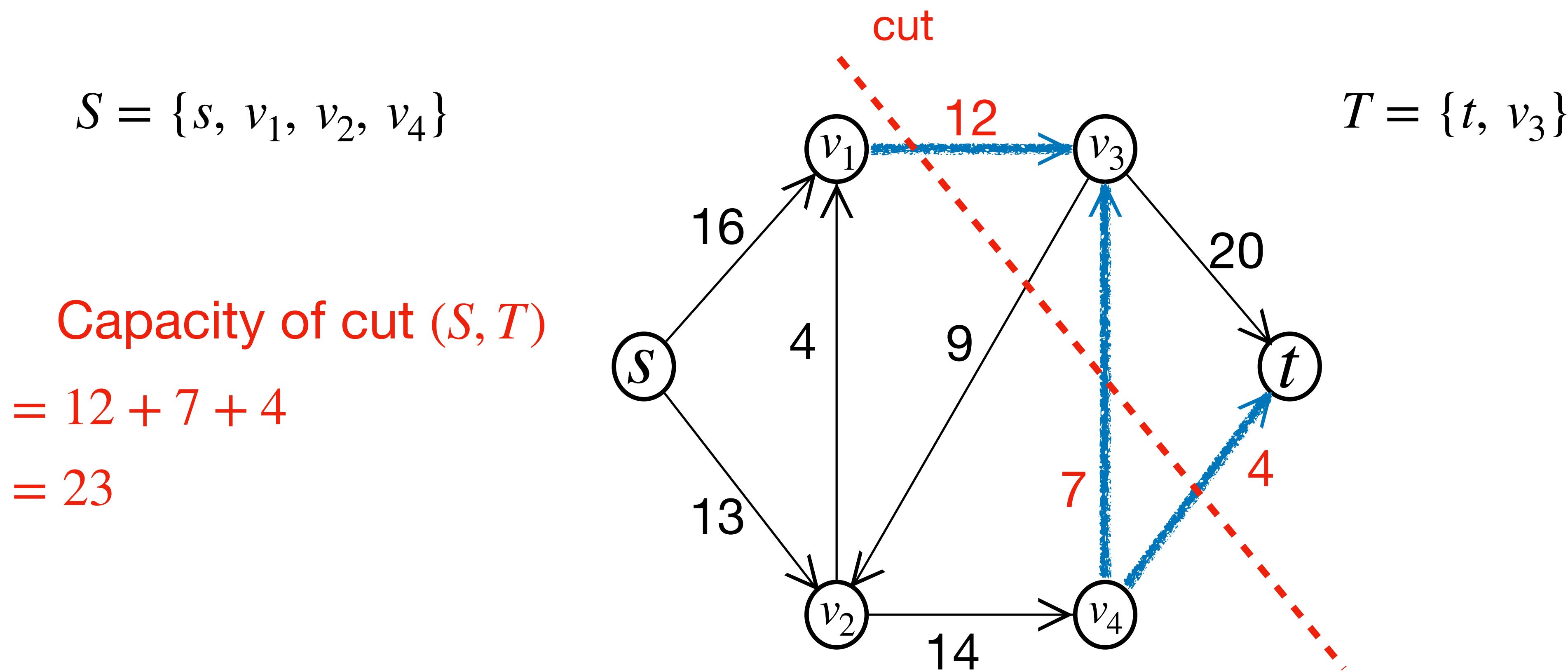


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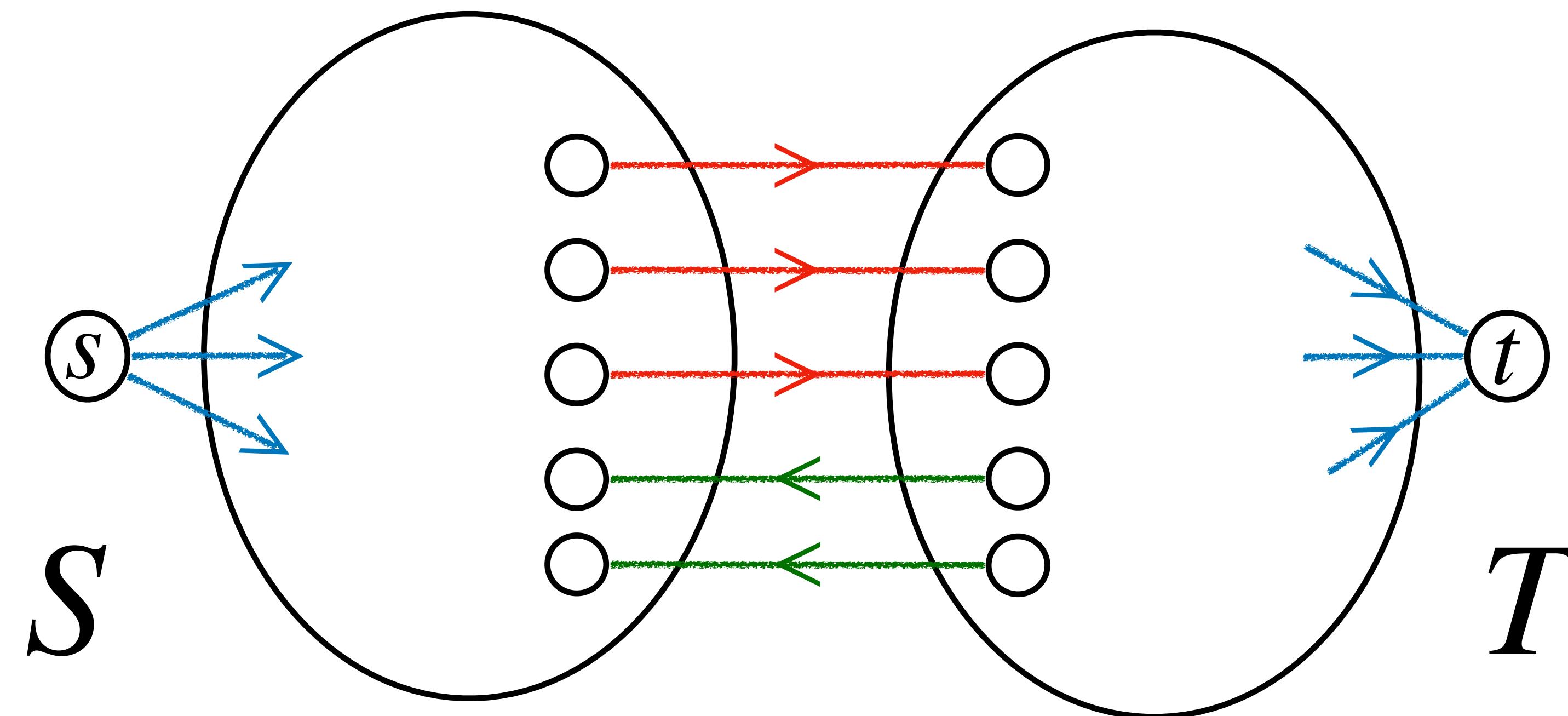
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**Cut:** A partition of the nodes in the network  $G=(V,E)$  into two sets  $S$  and  $T$ , such that  $s \in S$  and  $t \in T$ .

**Capacity of Cut ( $S, T$ )**: the total capacity of the edges from  $S$  to  $T$ .



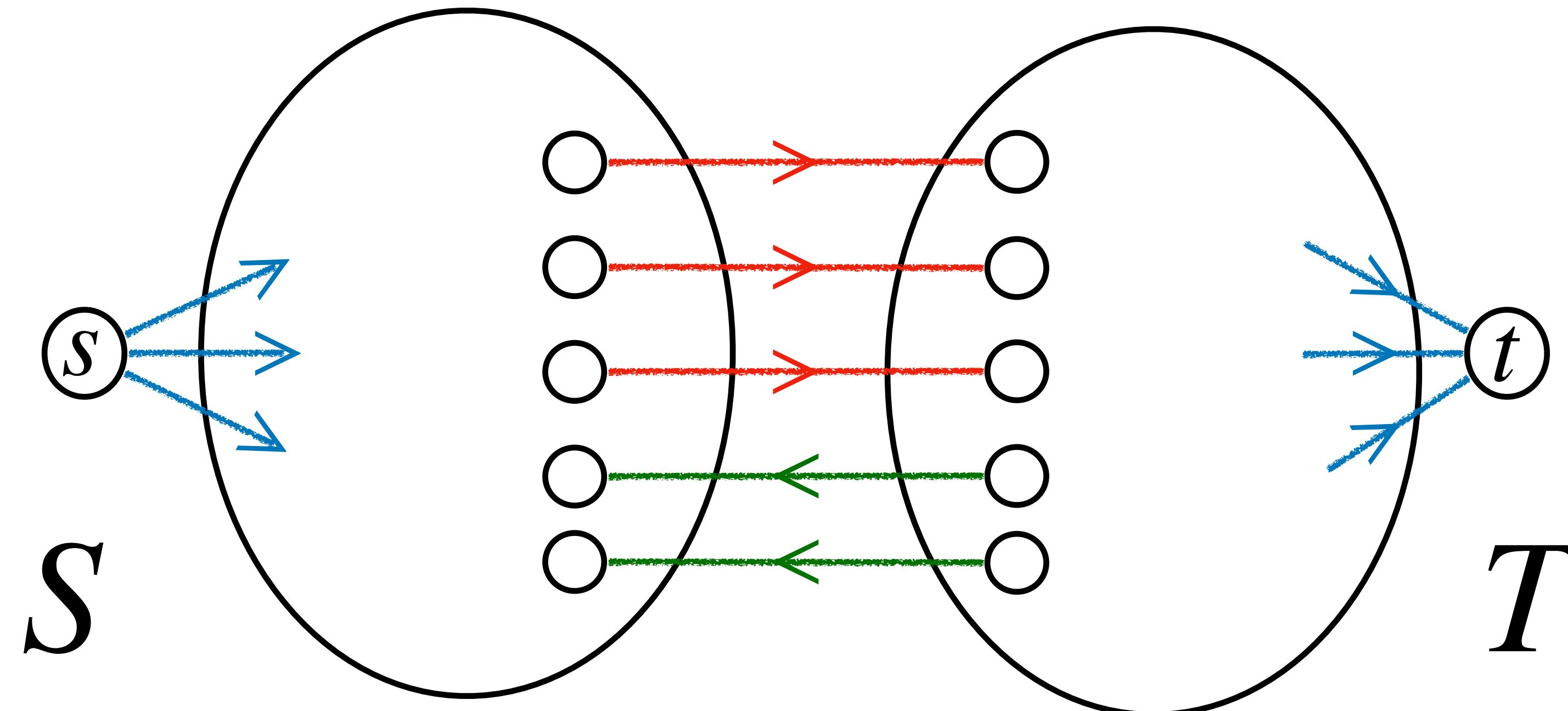
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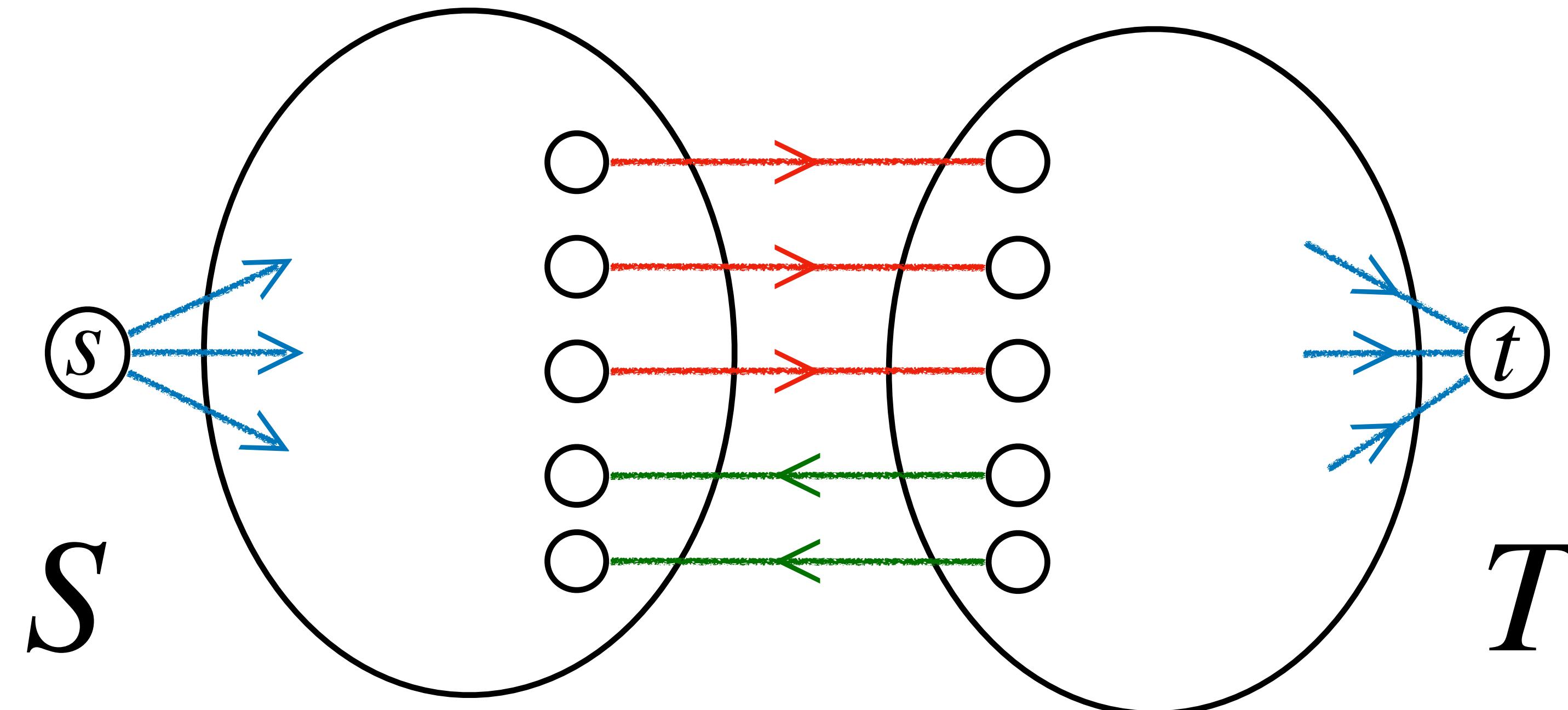


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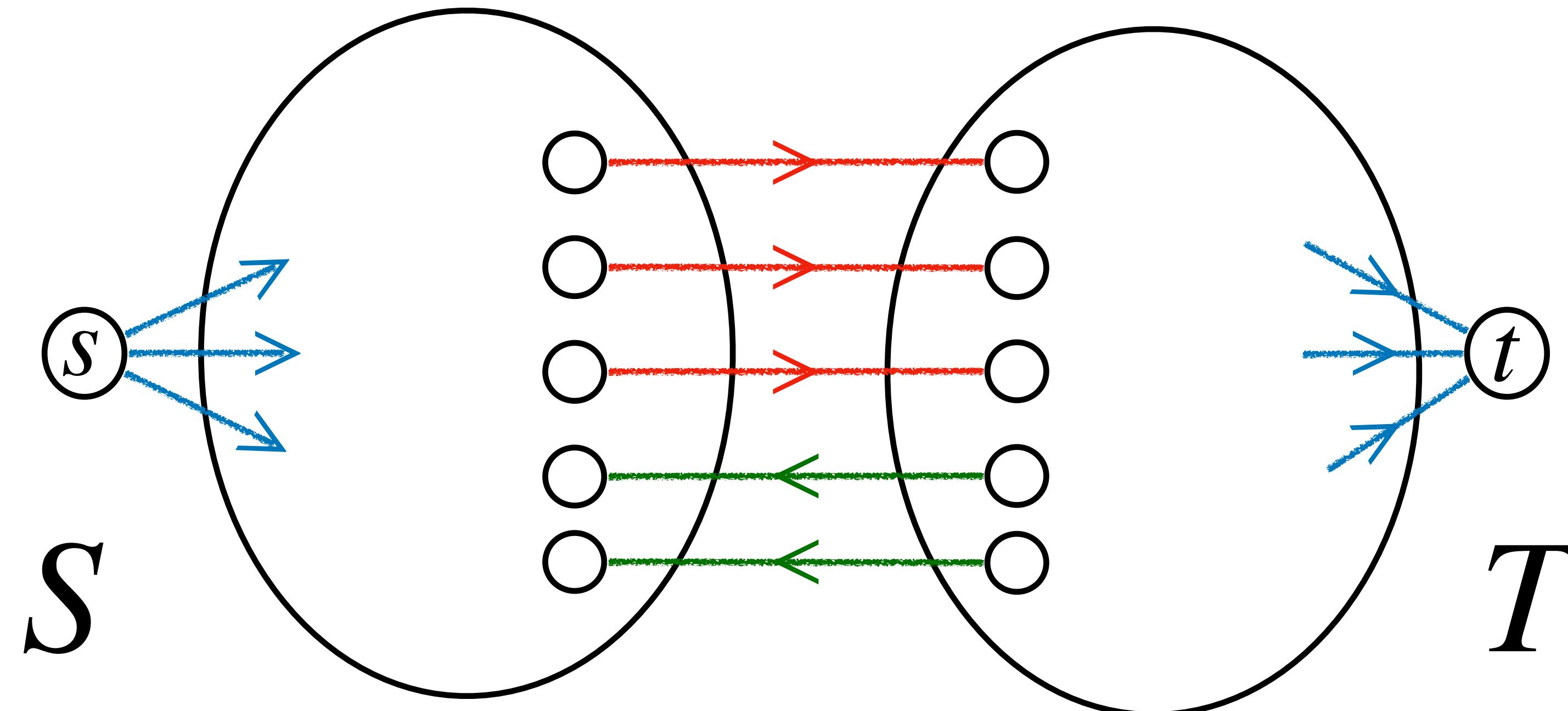
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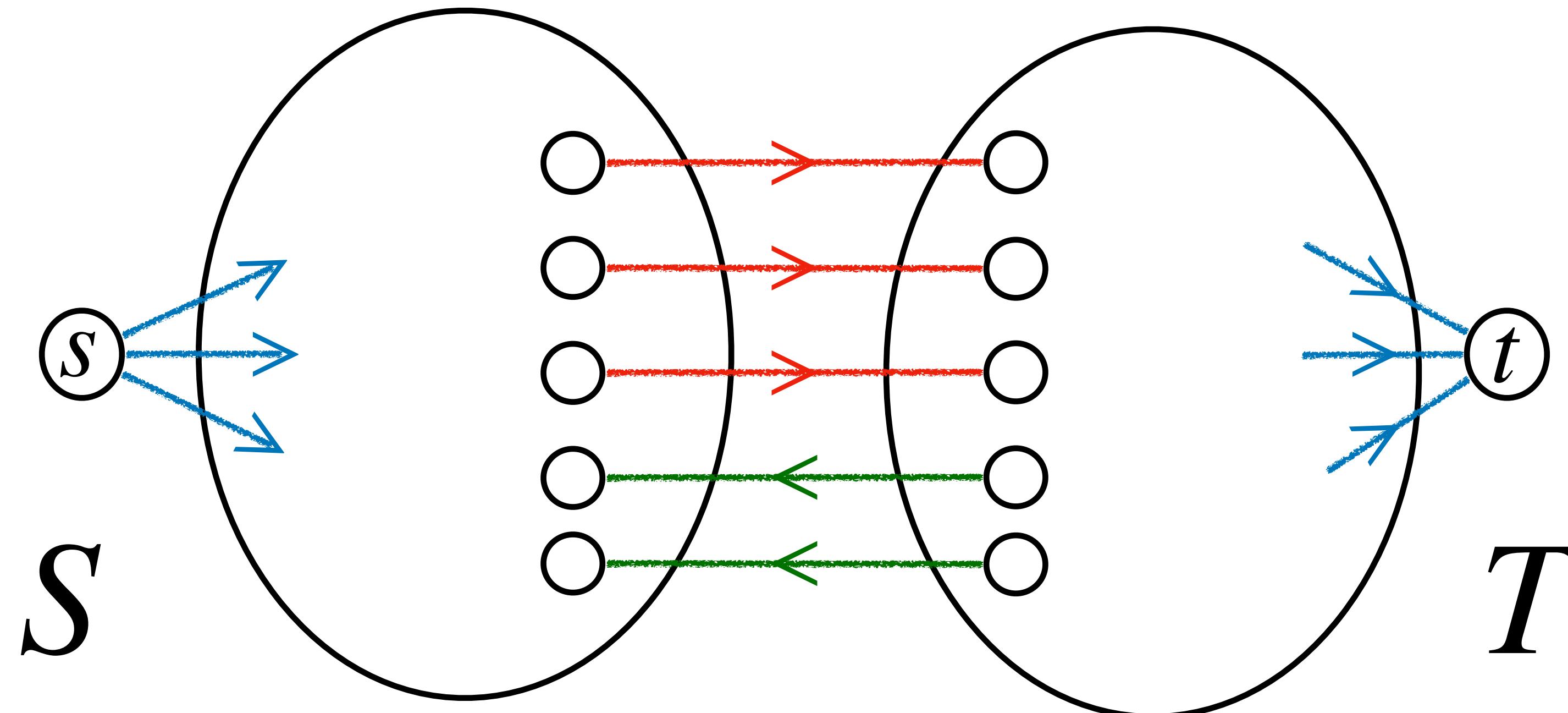
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**Lemma:** The size of **any flow** is less than or equal to the capacity of **any cut**.

**Maximum flow:** a flow from  $s$  to  $t$  of maximum size.

**Minimum cut:** a cut  $(S, T)$  of minimum capacity.

$$\text{size of maximum flow} \leq \text{capacity of minimum cut}$$

**Question:** is it true that

$$\text{size of maximum flow} = \text{capacity of minimum cut}$$

**Answer:** Yes. We will prove that.

**Theorem:** Let  $f$  be a flow in a network  $G = (V, E)$  with source  $s$  and sink  $t$ .

Then these three conditions are equivalent:

1.  $f$  is a maximum flow in  $G$ .
2. The residual network  $G_f$  has no path from  $s$  to  $t$  with positive residual capacity.
3. The size of the flow  $f$  equals the capacity of some cut  $(S, T)$ .

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**Proof:**  $1 \rightarrow 2$  : By contradiction.

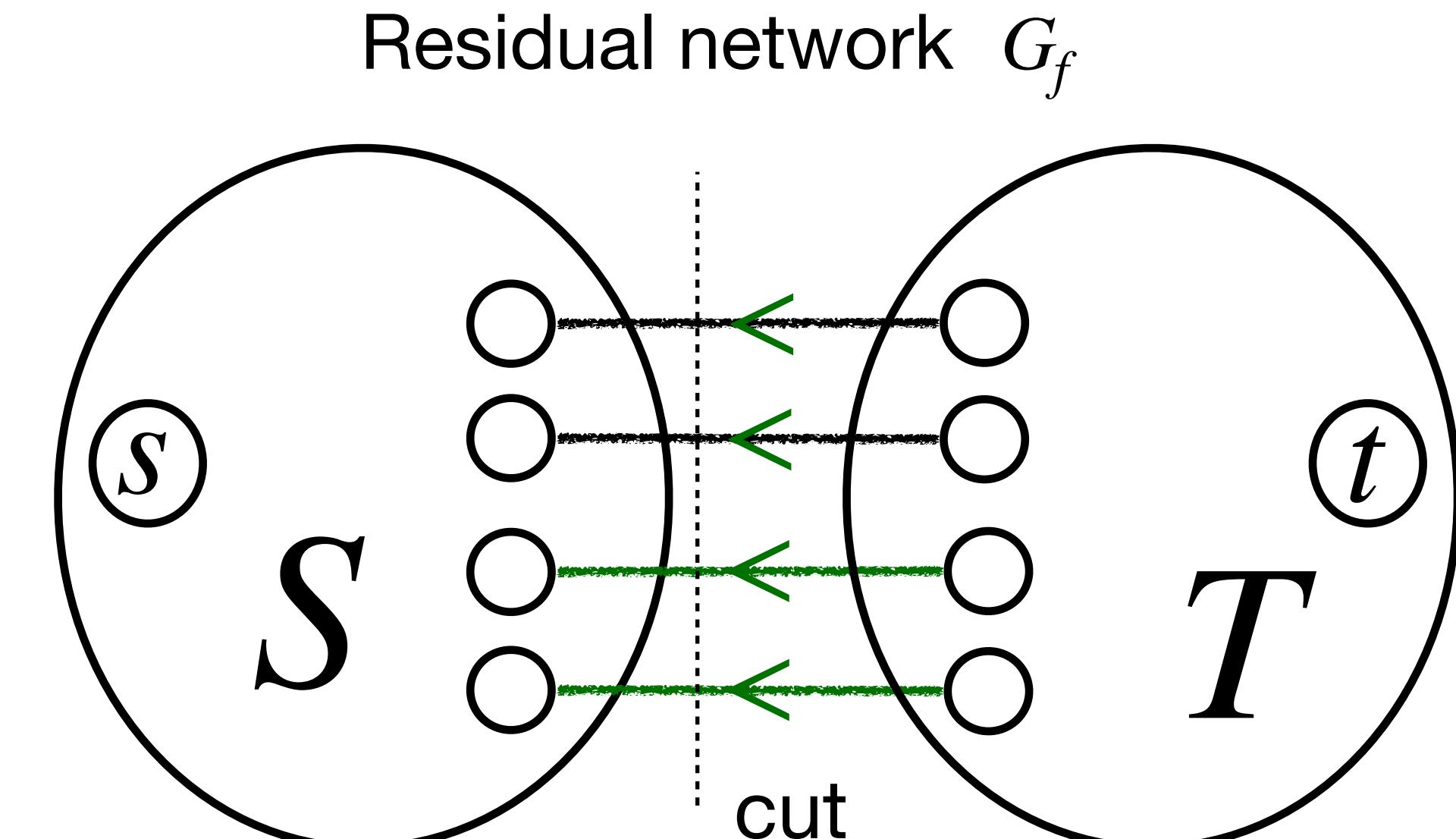
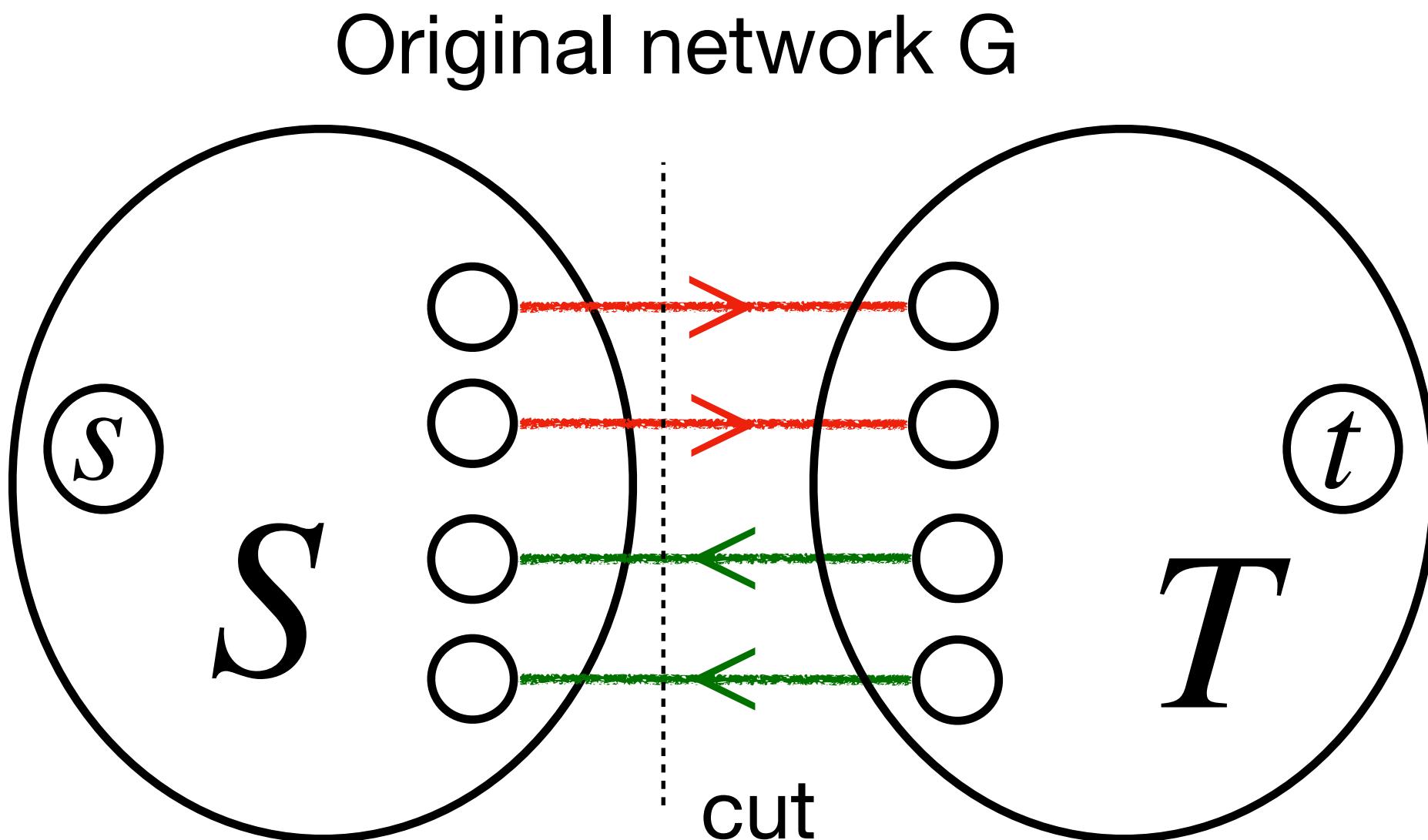
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Proof:  $1 \rightarrow 2$  : By contradiction.

$2 \rightarrow 3$  :  $S$  : the set of nodes that the source  $s$  can reach in the residual network  $G_f$   
 $T$  : the remaining nodes

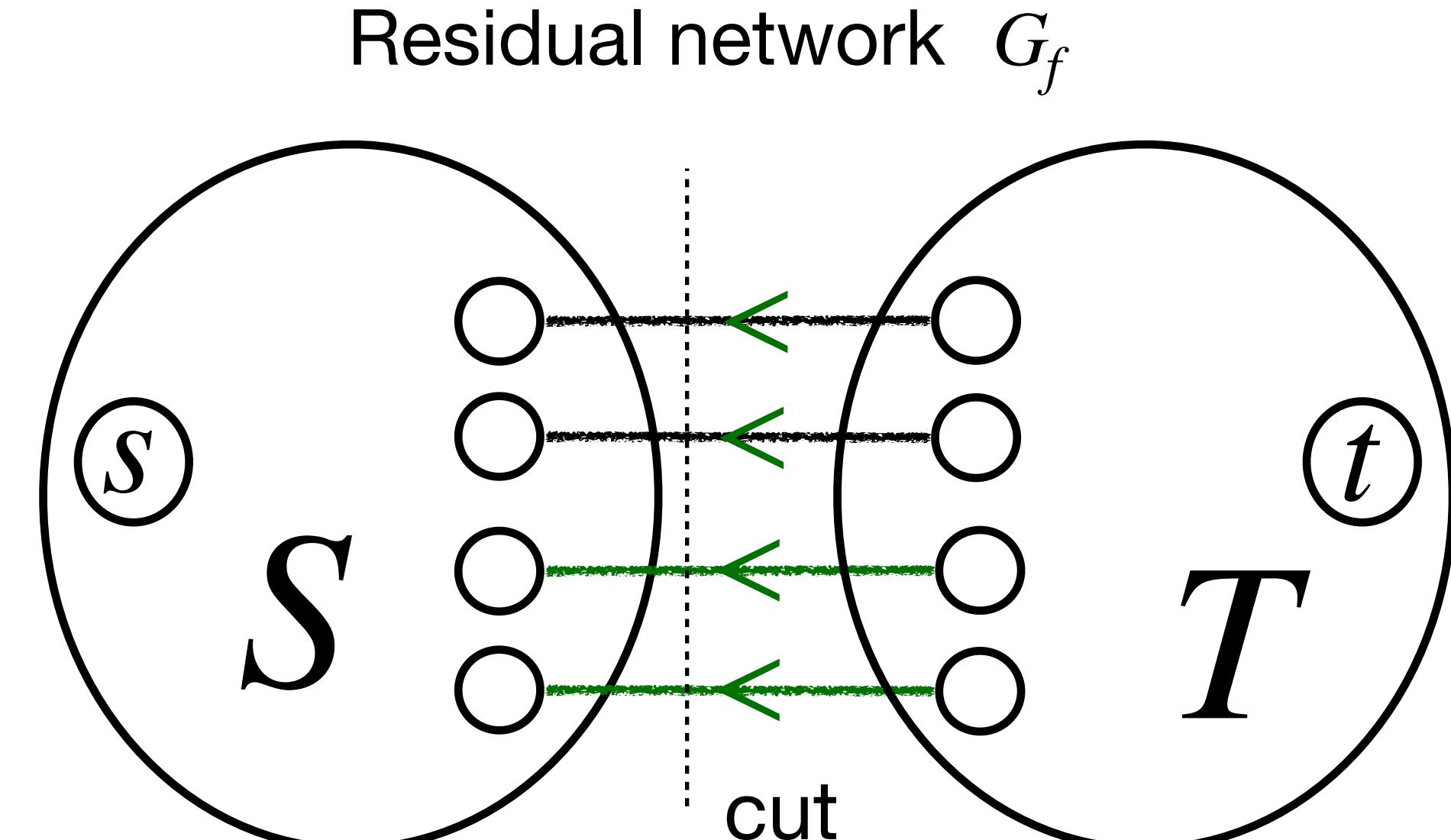
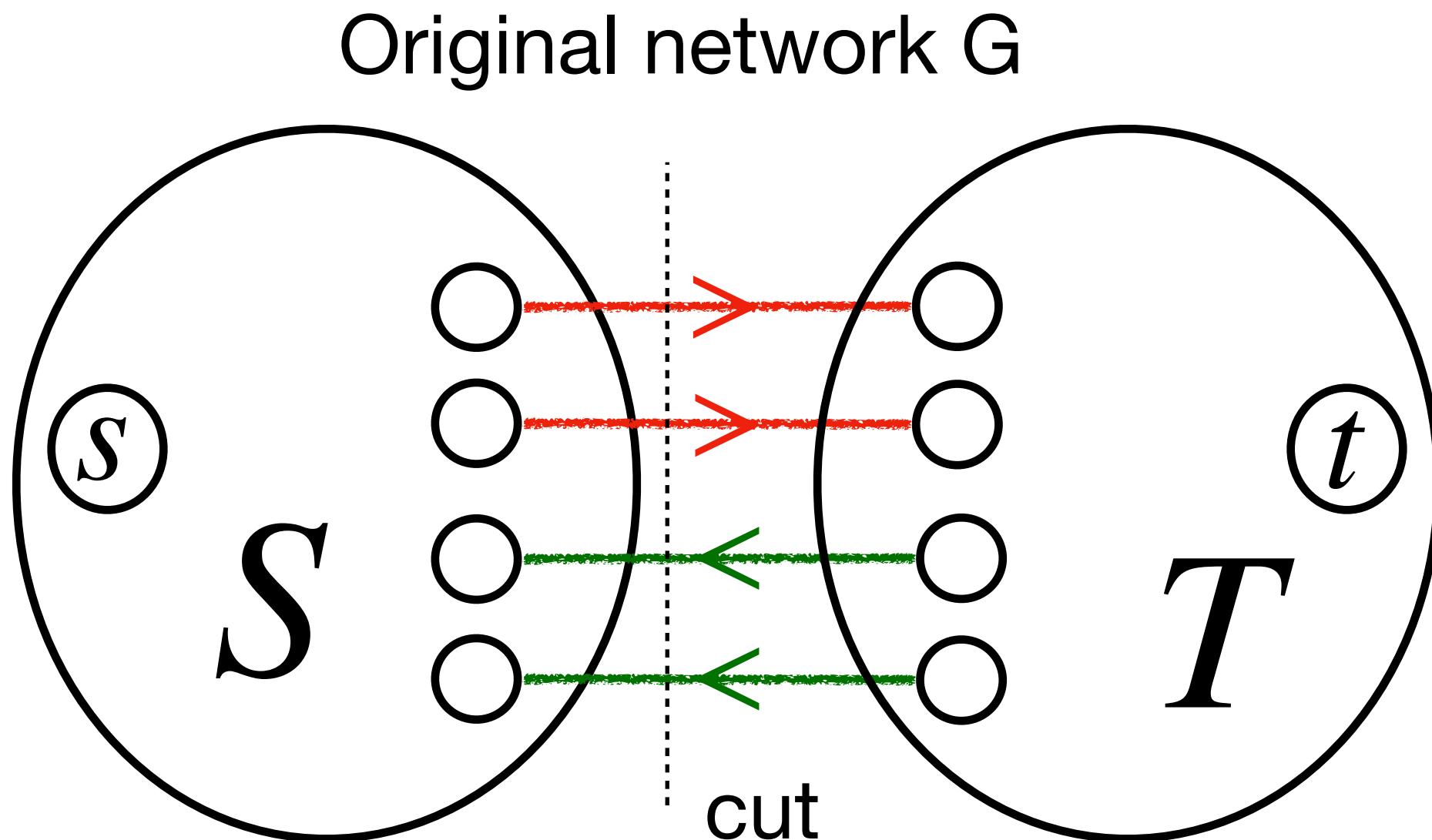


In the original network  $G$ :

“Forward” edges from  $S$  to  $T$  are saturated by flow

“Backward” edges from  $T$  to  $S$  have no flow at all

Therefore, the size of the flow  $f$  equals the capacity of this cut  $(S, T)$ .



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$2 \rightarrow 3$  : Done.

$3 \rightarrow 1$  : Because we already know

$$\text{size of any flow} \leq \text{capacity of any cut}$$

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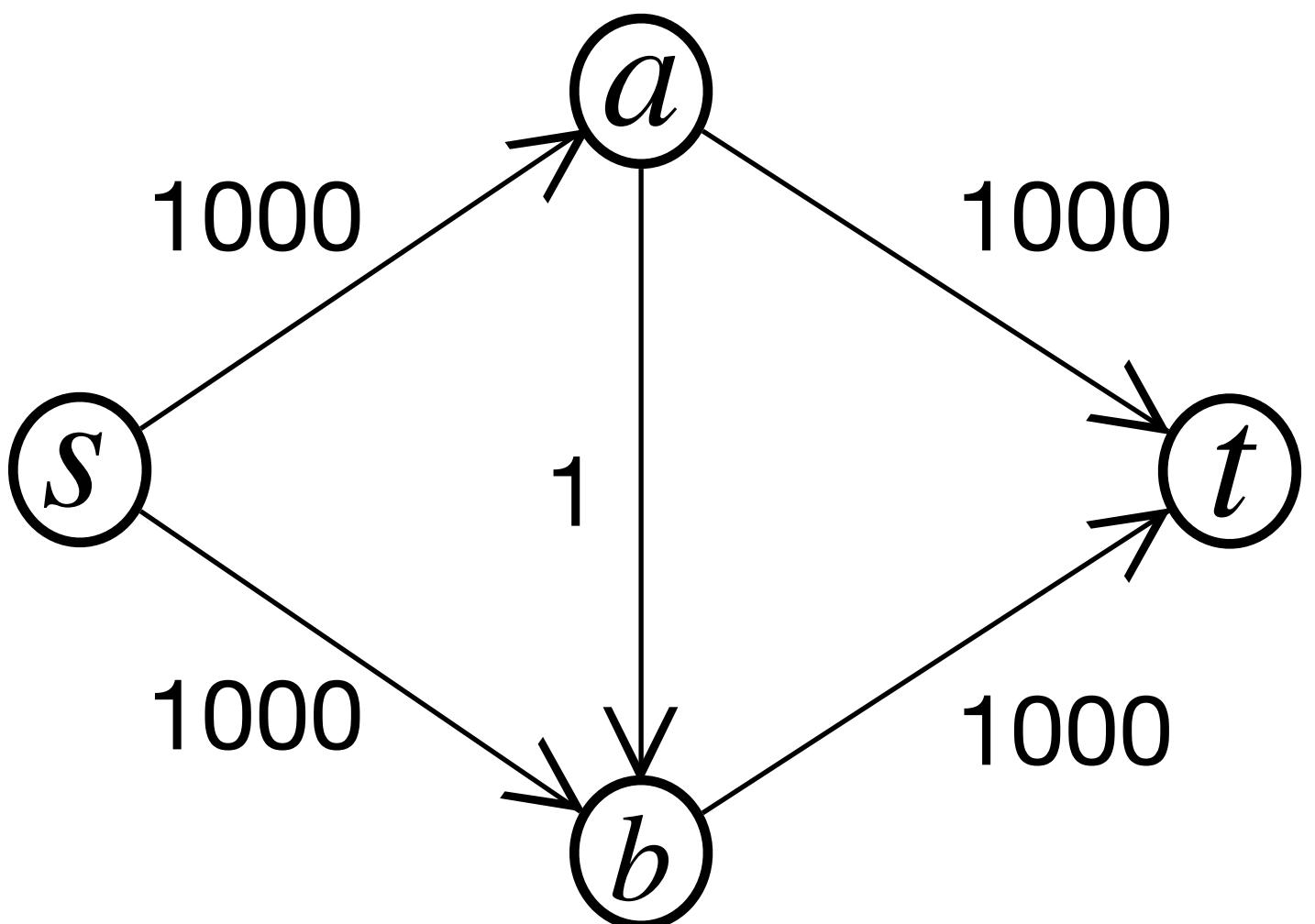
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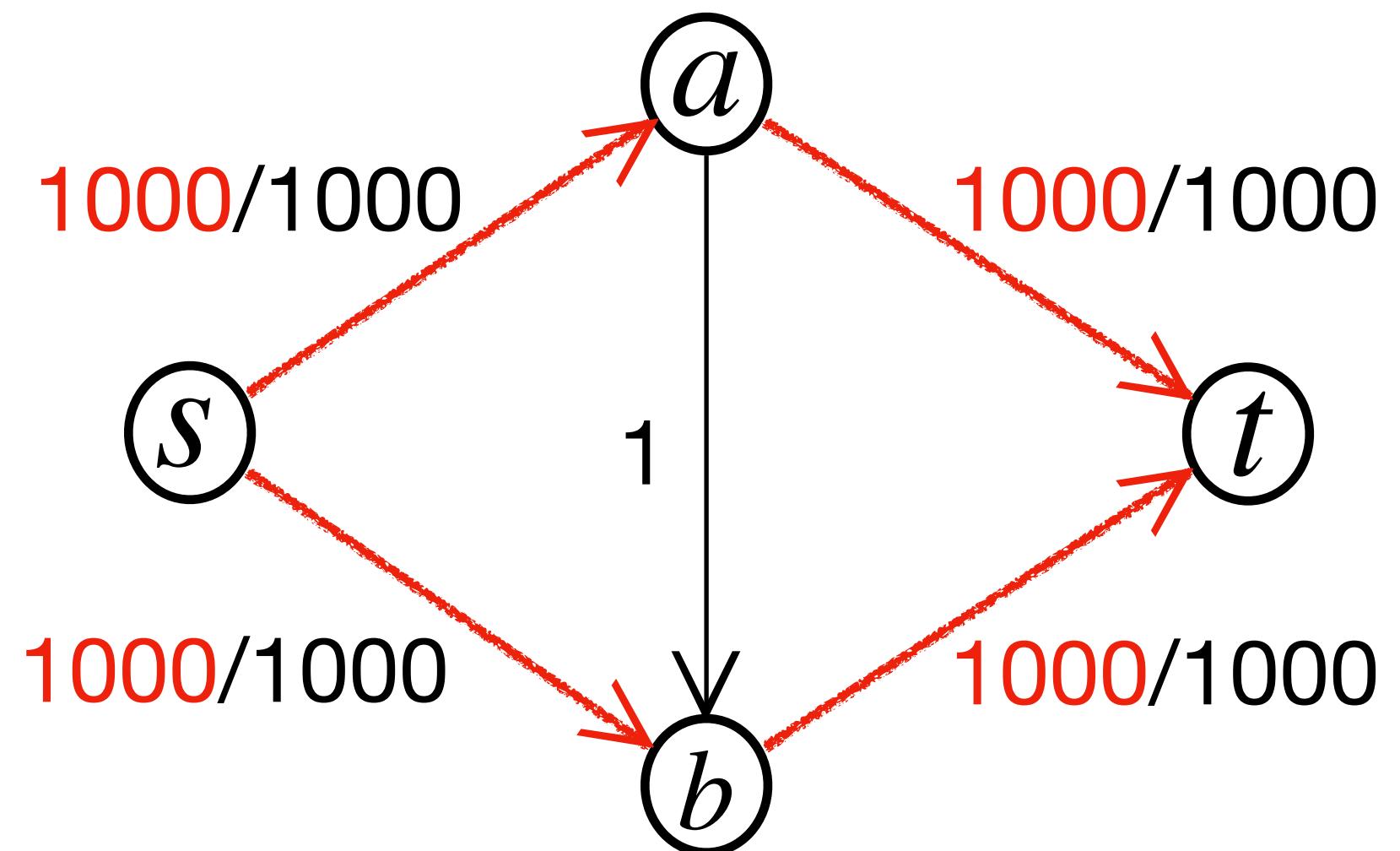
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## Time complexity of the Ford-Fulkerson Method



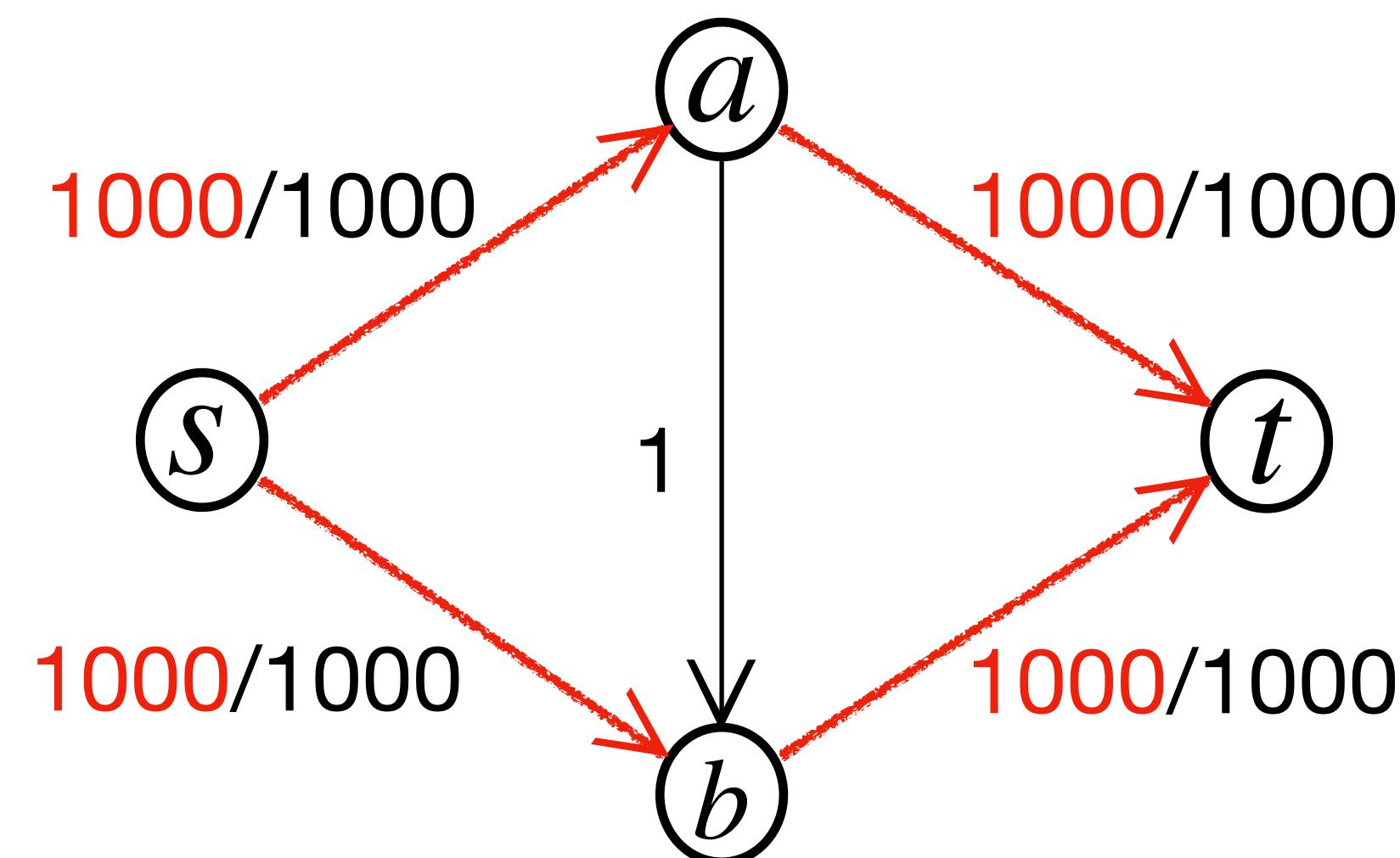
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Maximum Flow: 2000

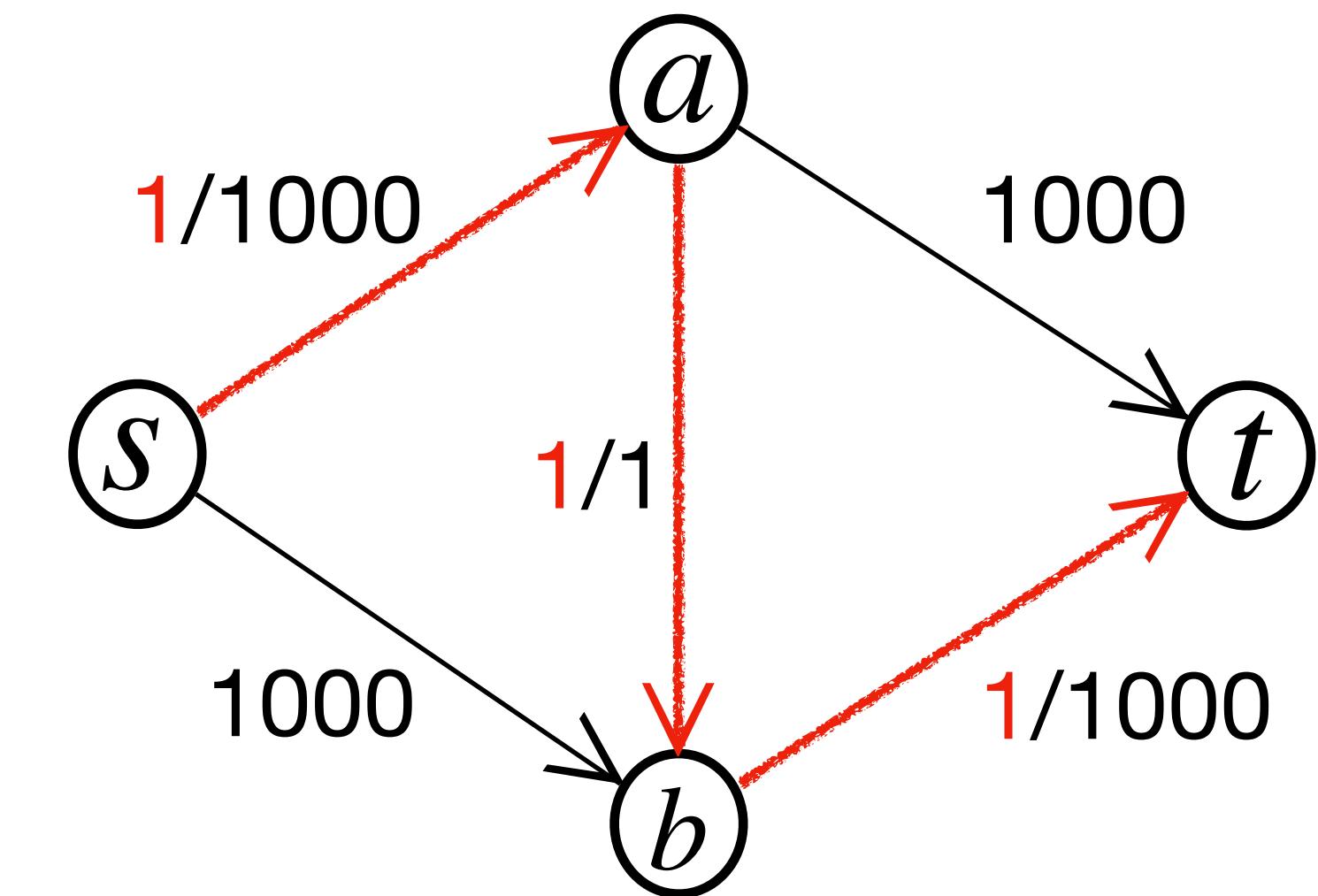


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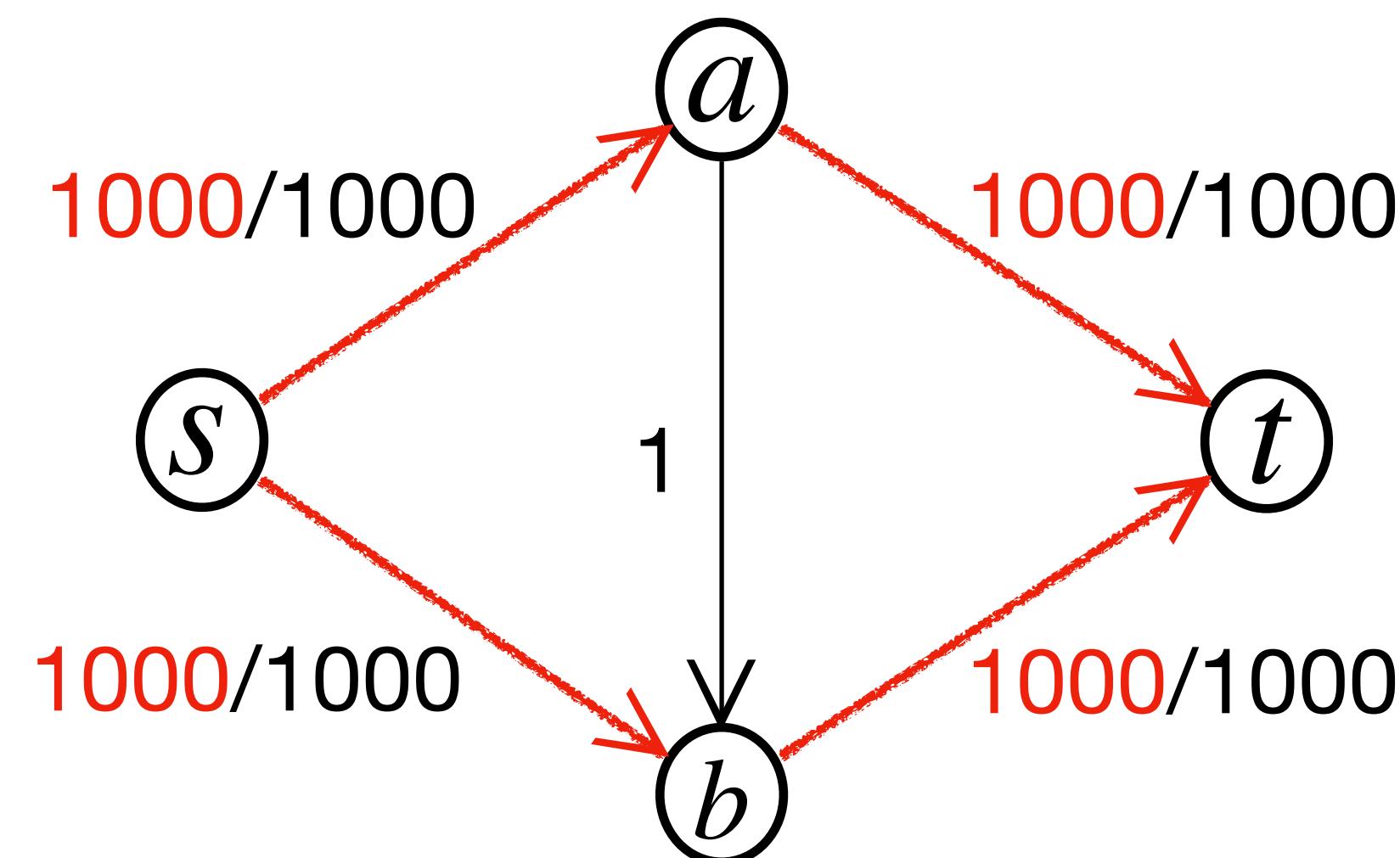
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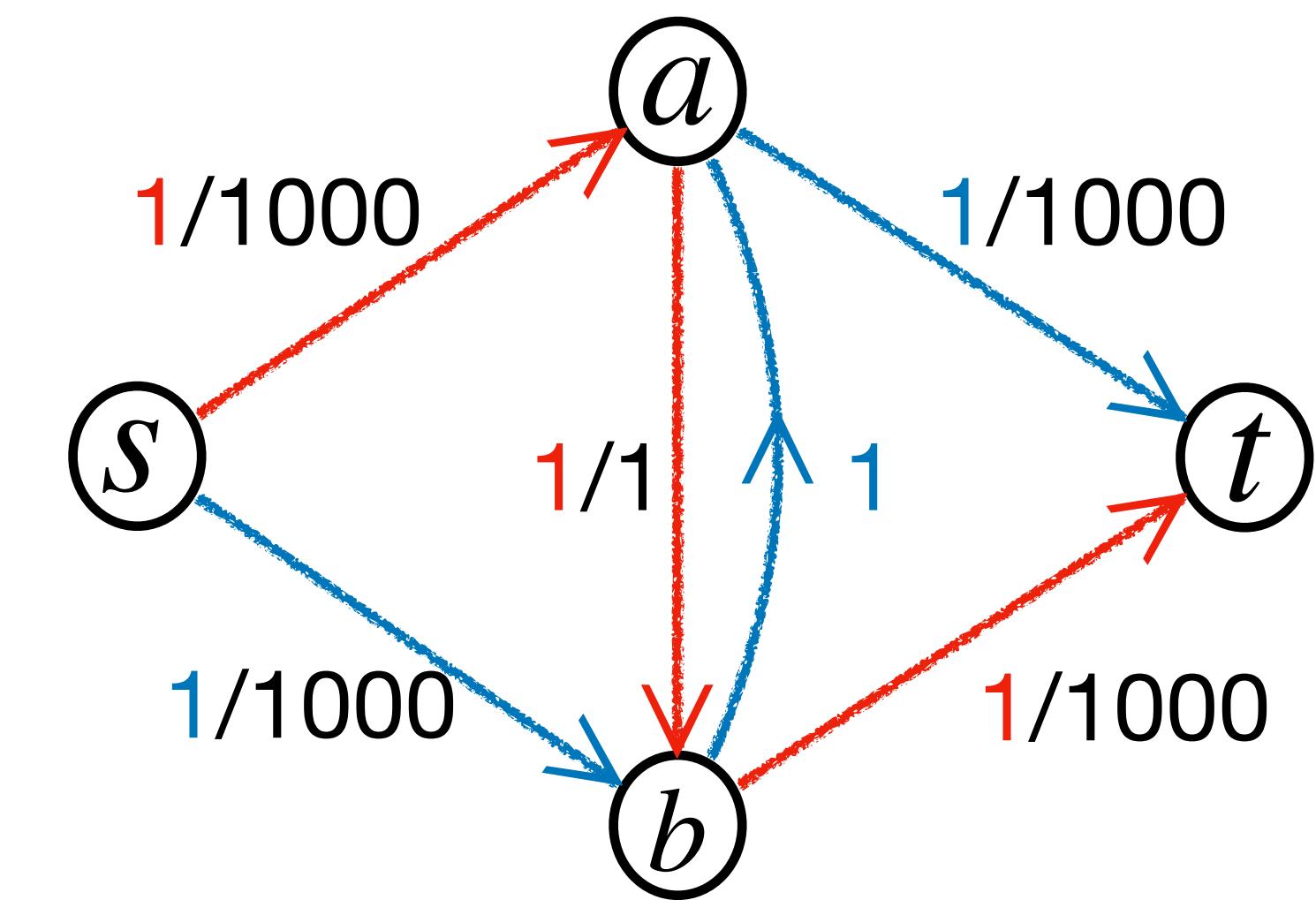
Current flow size = 1

## Time complexity of the Ford-Fulkerson Method

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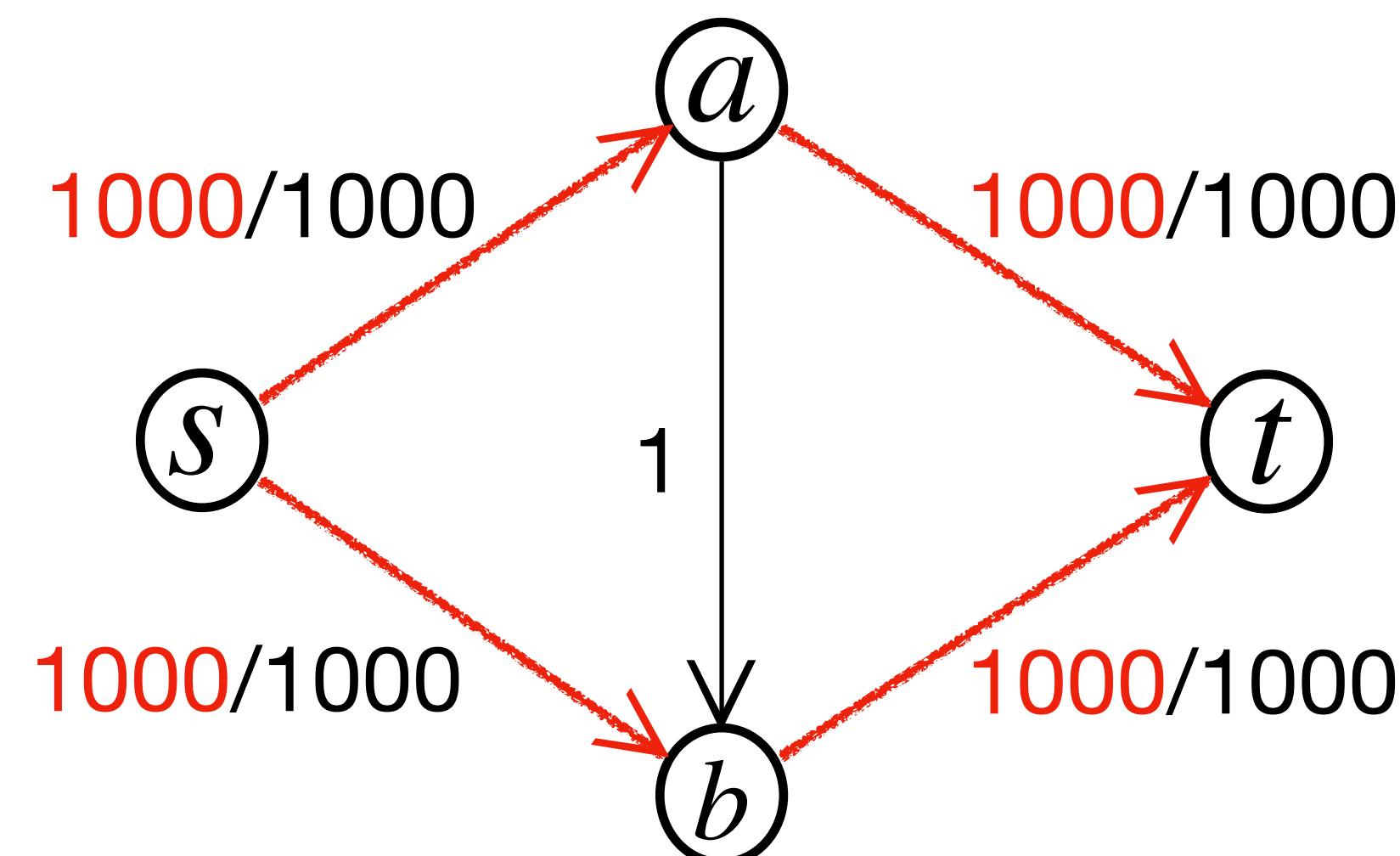
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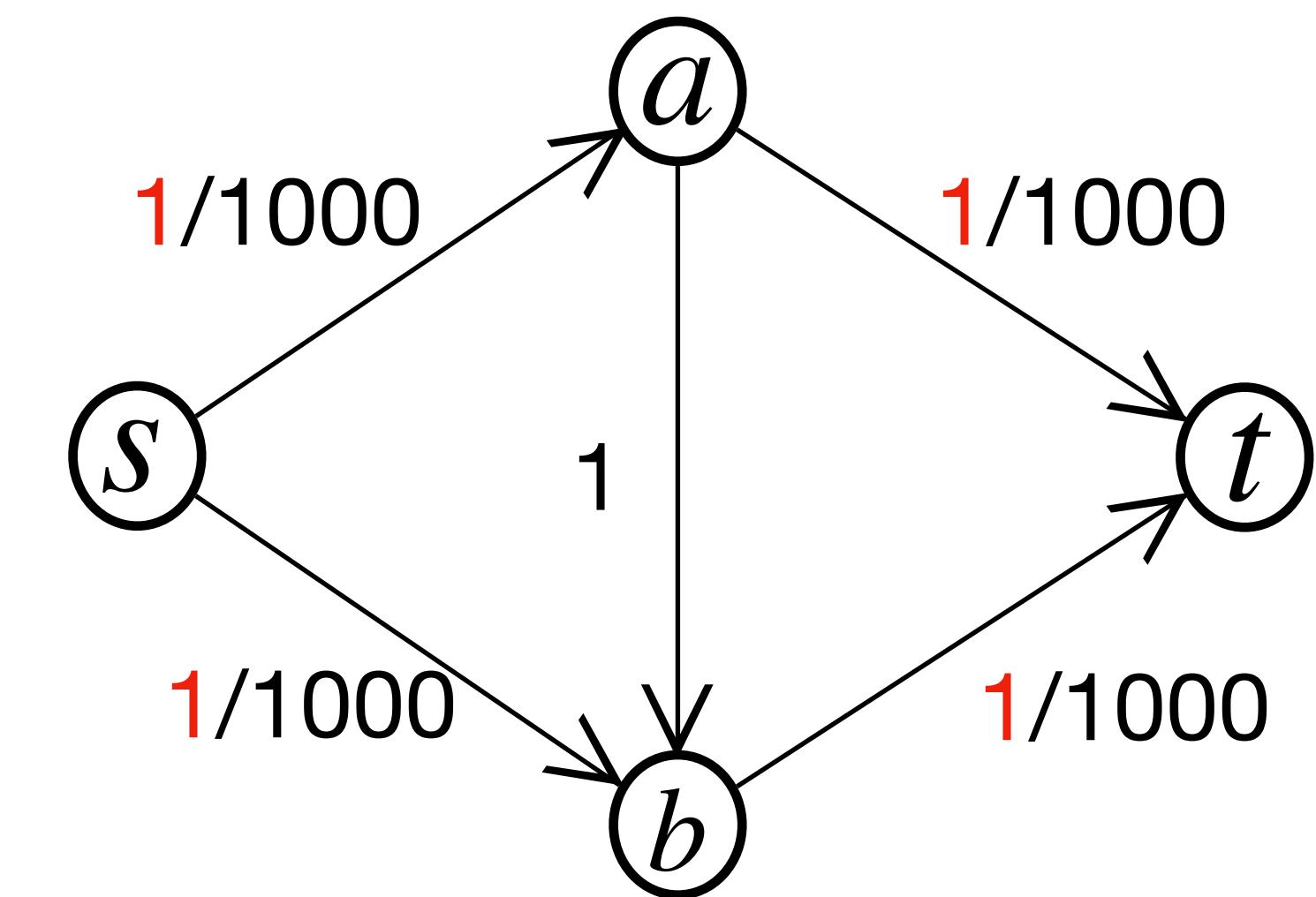
Current flow size = 2

## Time complexity of the Ford-Fulkerson Method

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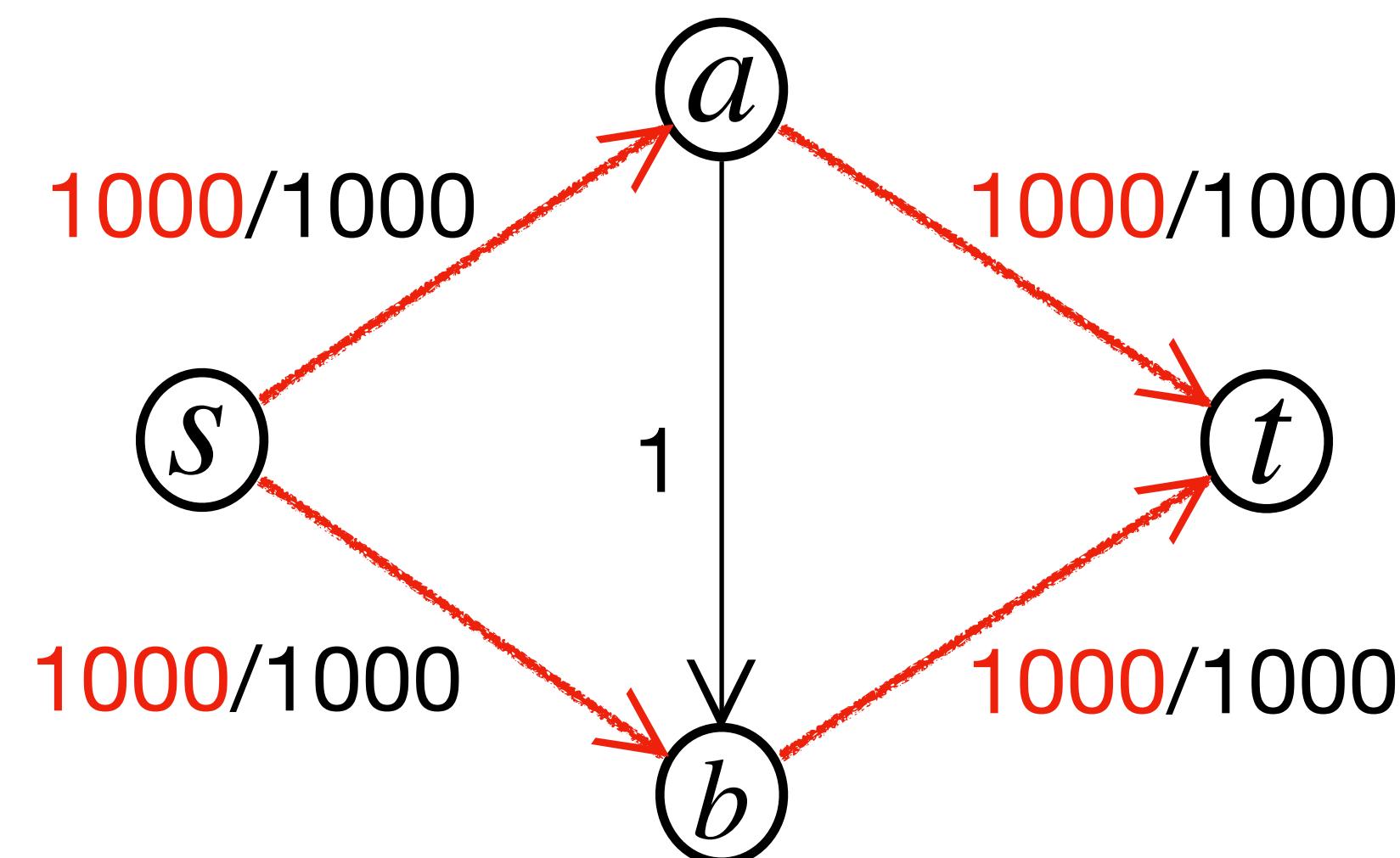
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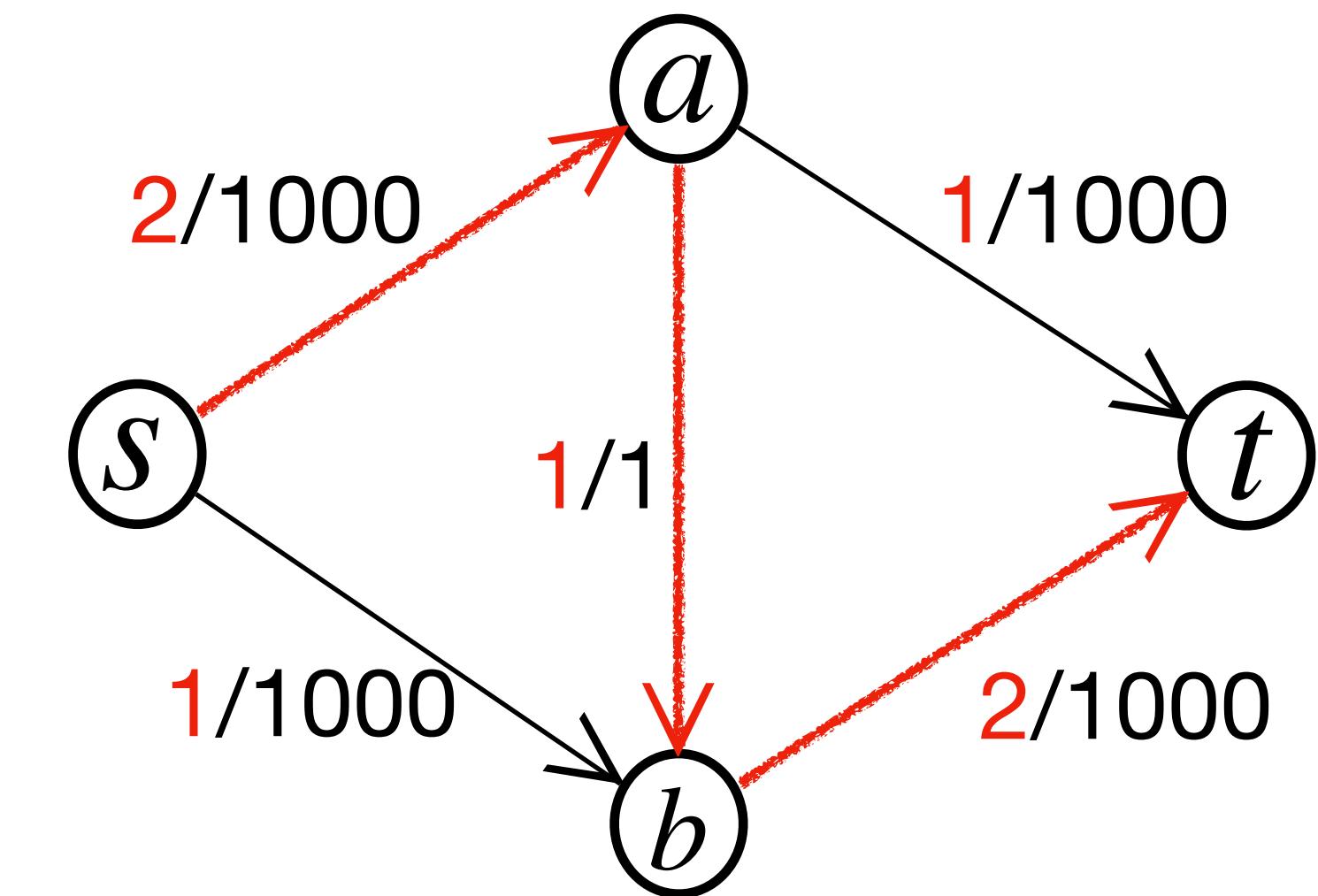
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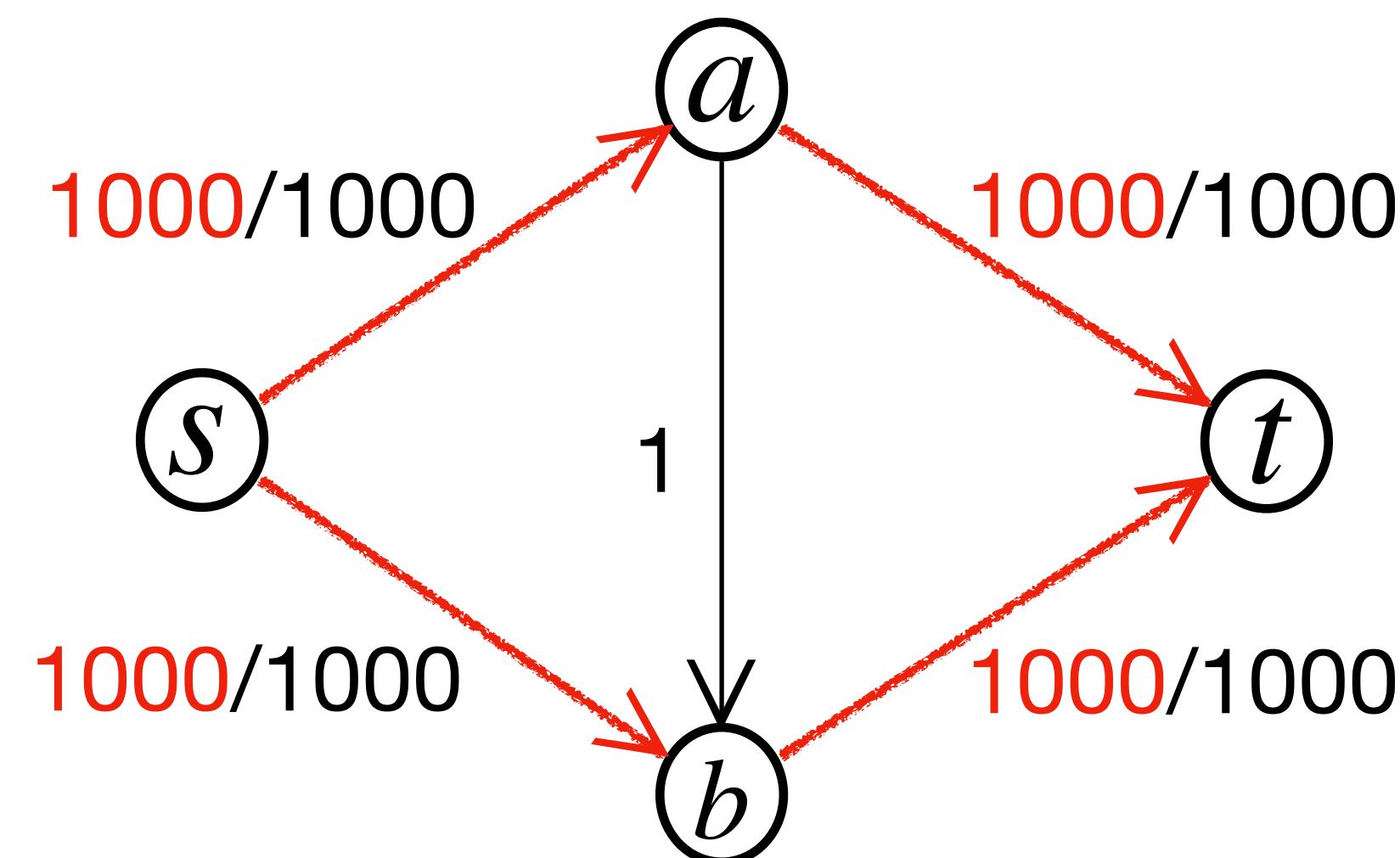
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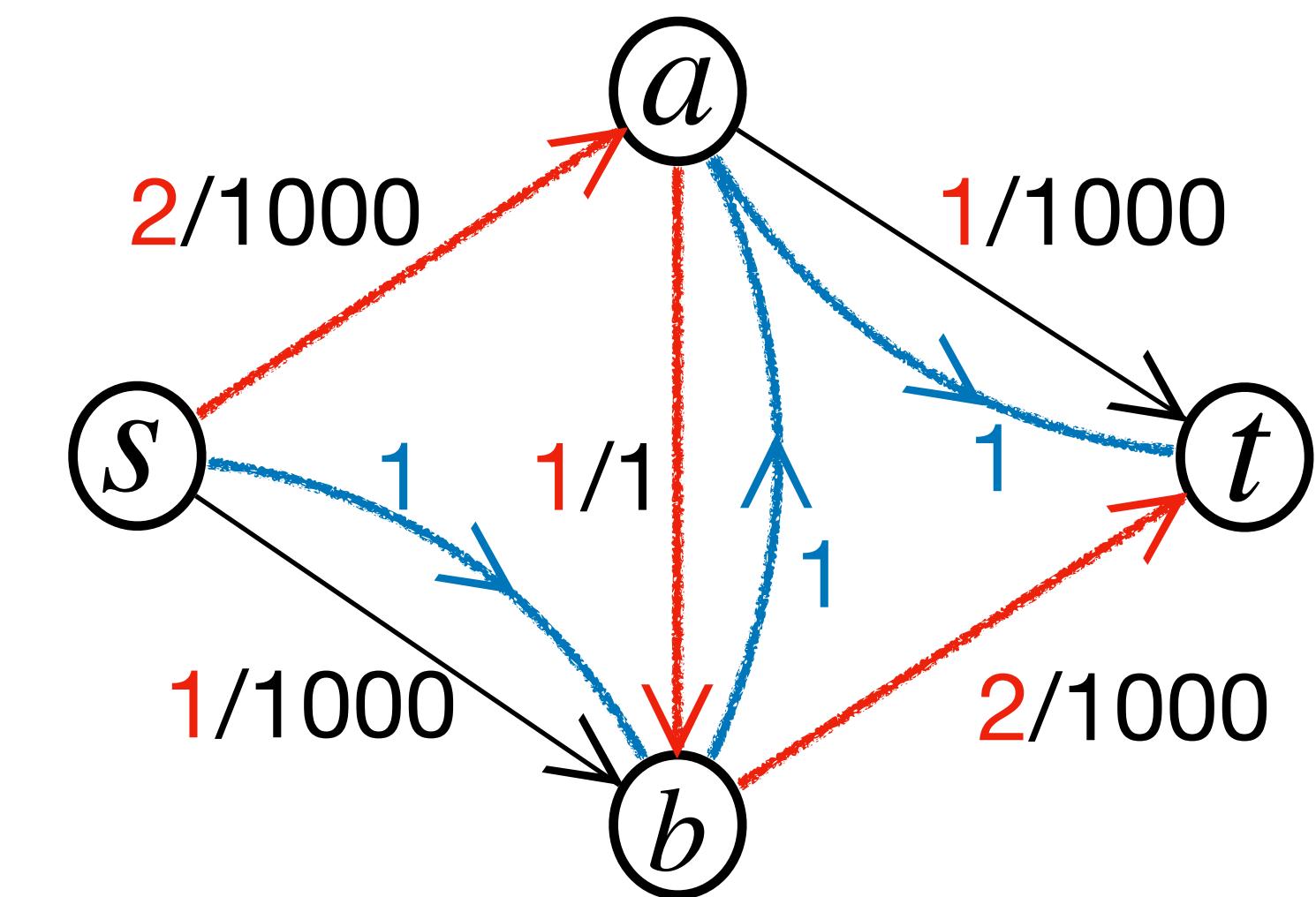
Current flow size = 3

## Time complexity of the Ford-Fulkerson Method

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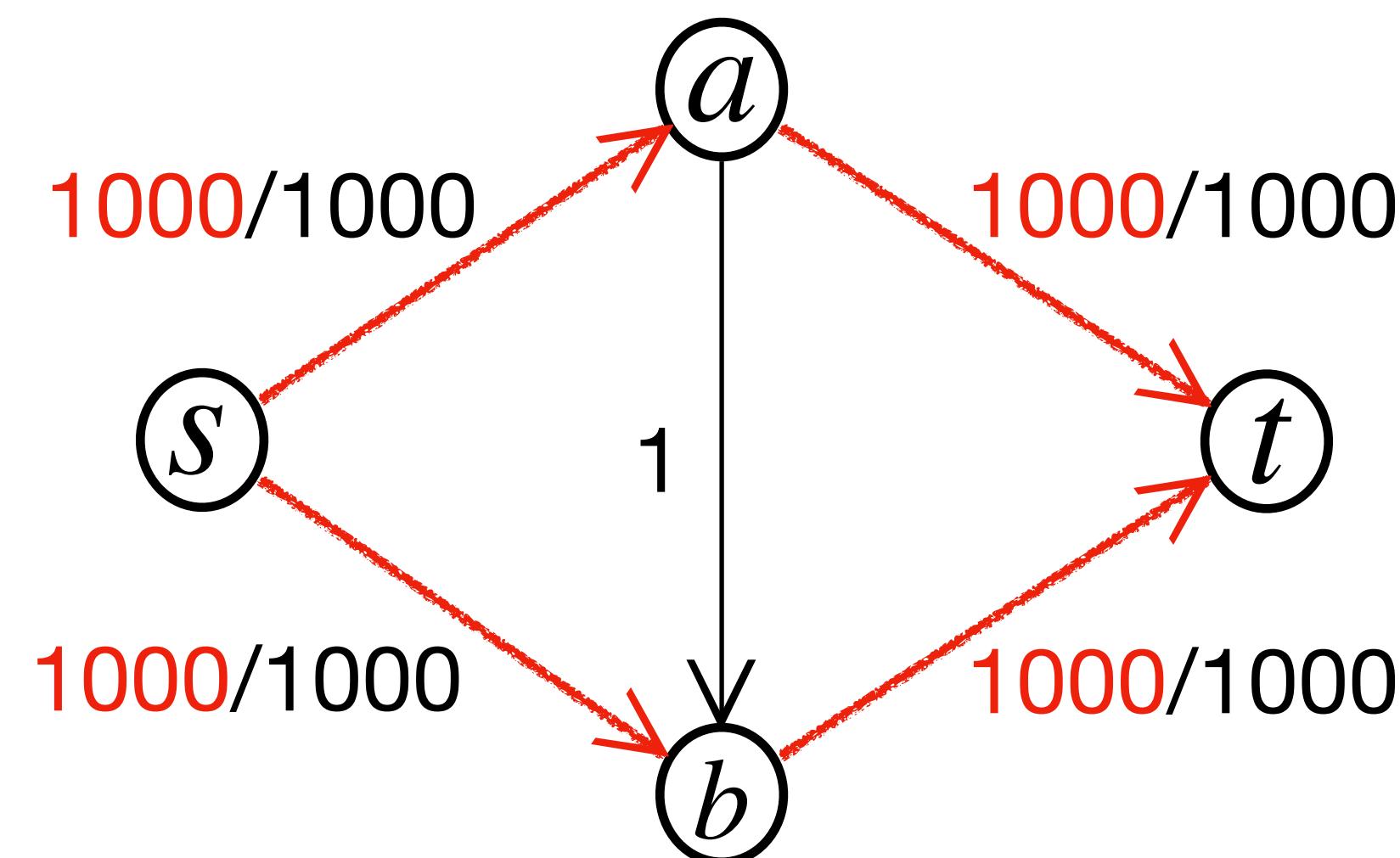
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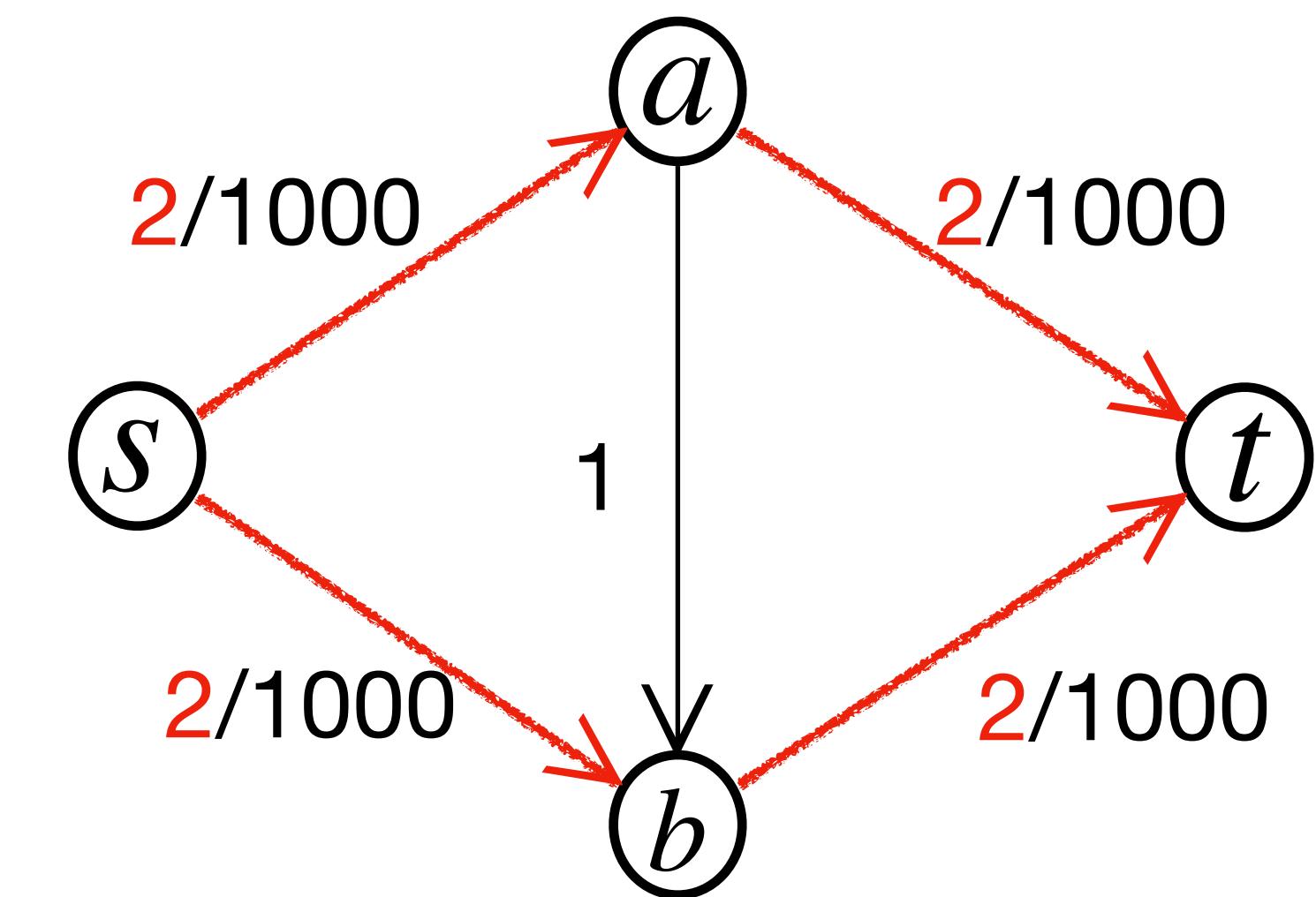
Current flow size = 4

## Time complexity of the Ford-Fulkerson Method

Maximum Flow: 2000



Naive way to run Ford-Fulkerson Method:



Current flow size = 4

Time complexity: too high

## Quiz questions:

1. What does the “Max-Flow Min-Cut” Theorem tell us?
2. Why does the Ford-Fulkerson Method have high time complexity?

Roadmap of this lecture:

**1. Maximum Flow.**

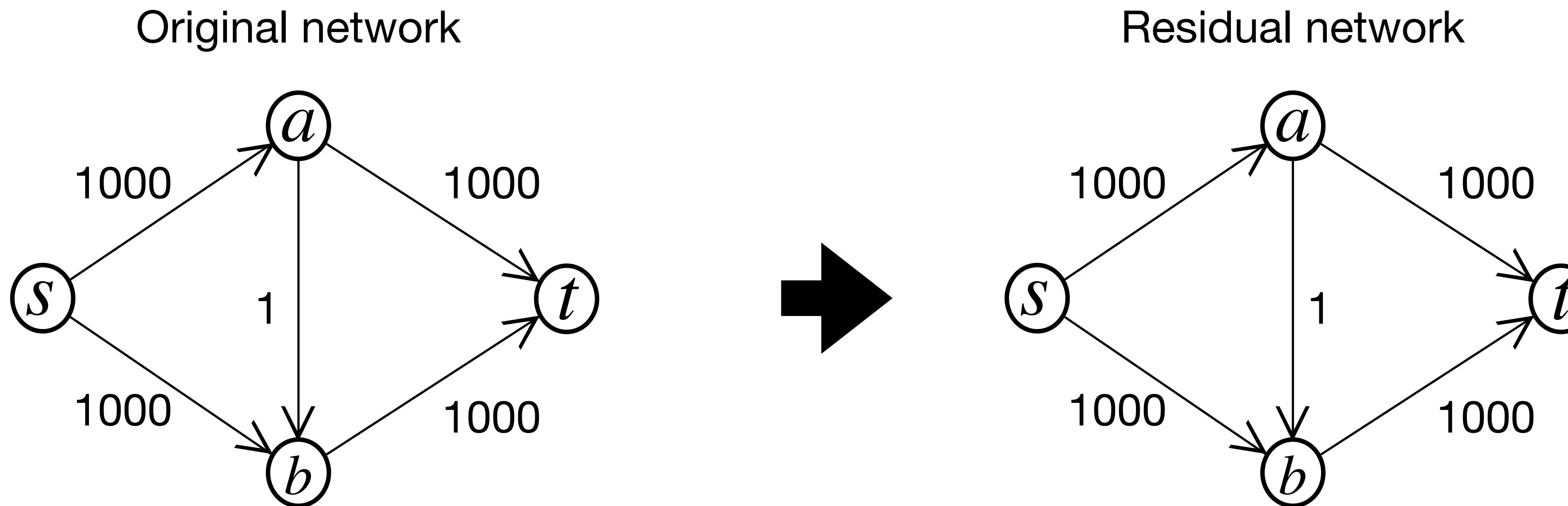
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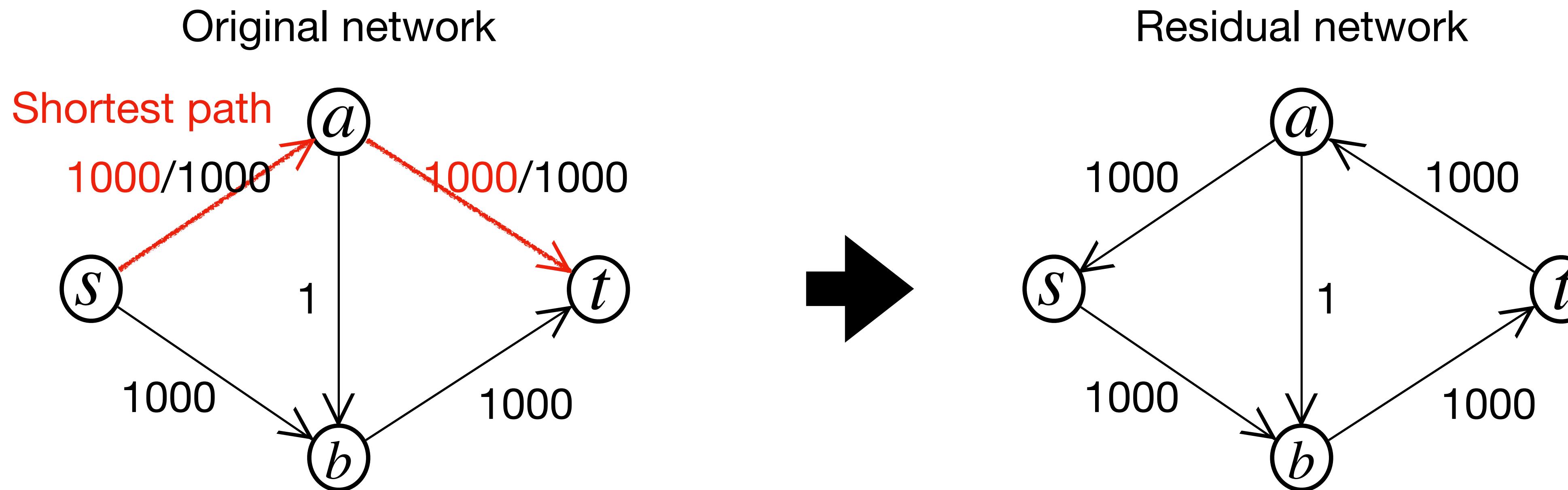
**Edmonds-Karp Algorithm** (an efficient way to implement the Ford-Fulkerson Method):

Each time, pick the **shortest path** from  $s$  to  $t$  in the residual network,  
and augment the flow along that path.



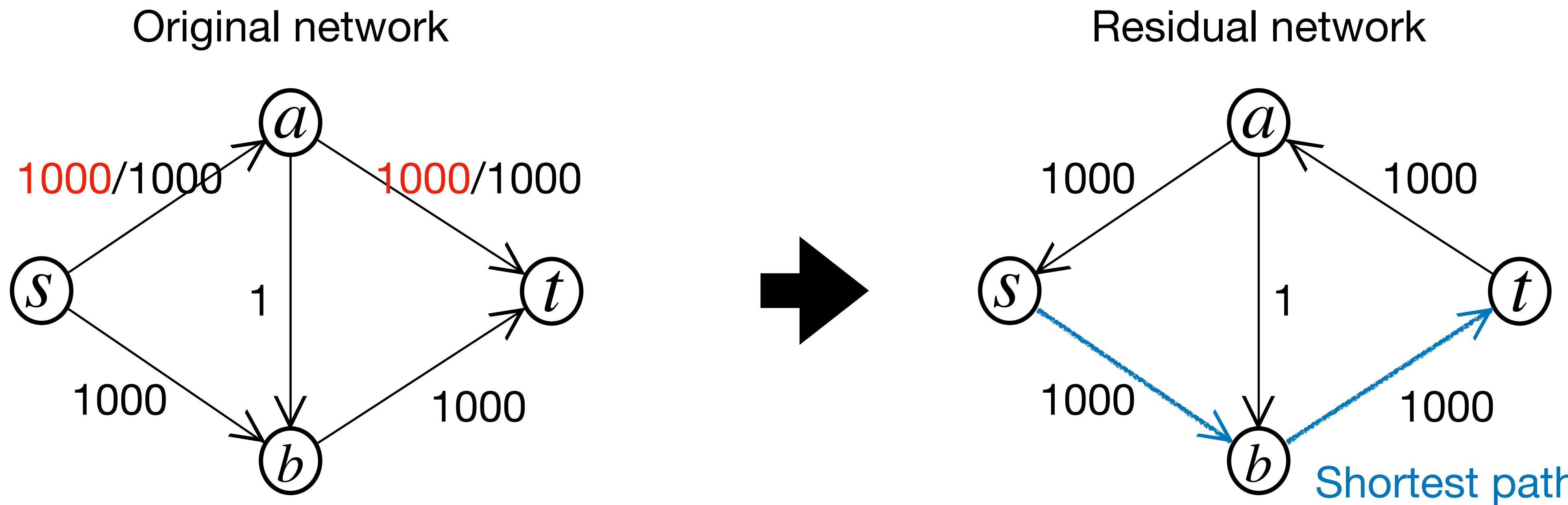
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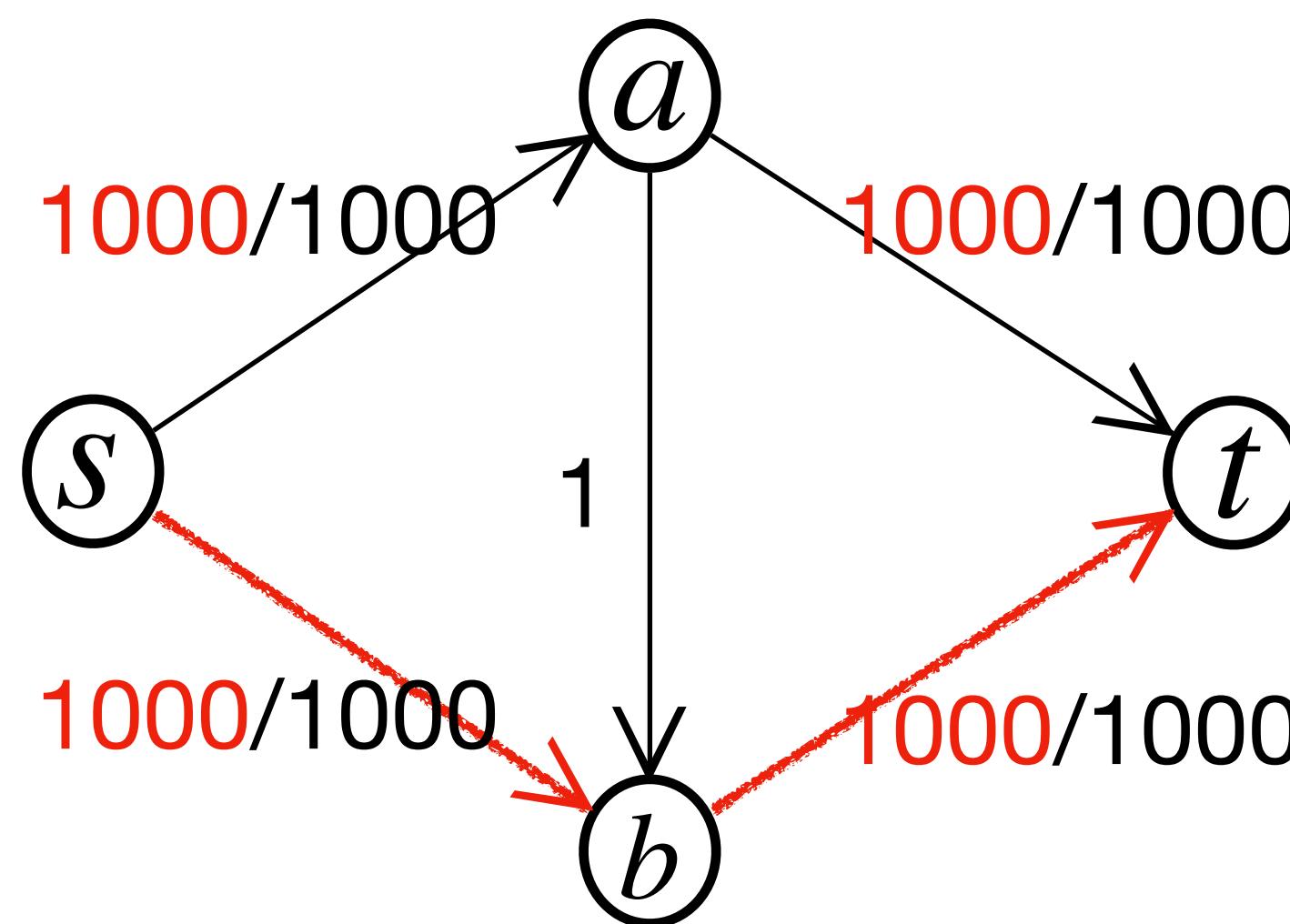
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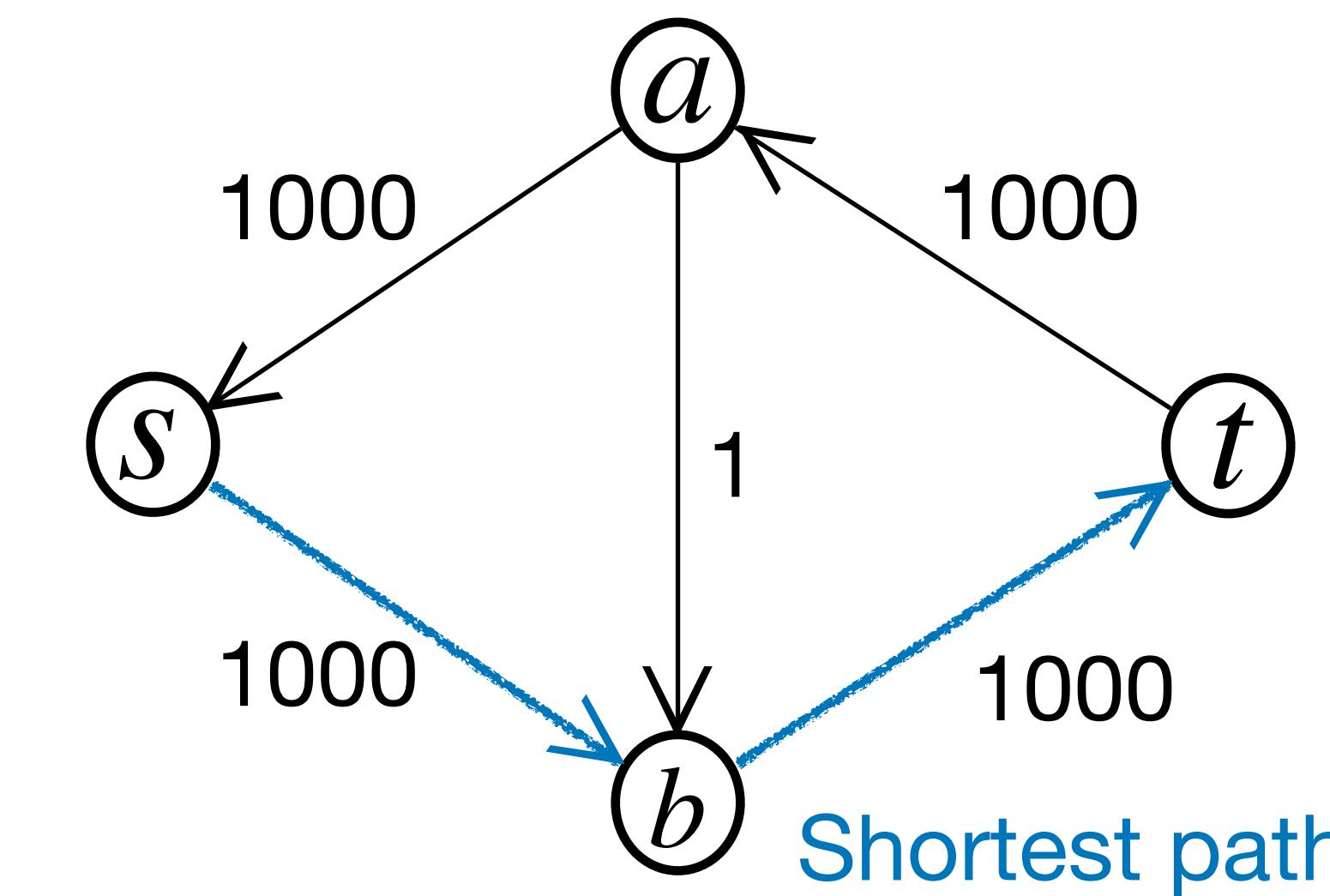
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Original network



Residual network



It works!

**Edmonds-Karp Algorithm** (an efficient way to implement the Ford-Fulkerson Method):

Each time, pick the shortest path from  $s$  to  $t$  in the residual network,  
and augment the flow along that path.

Time Complexity:  $O(VE^2)$

Quiz question:

- I. What is the difference between the “Edmonds-Karp Algorithm” and the “Ford-Fulkerson Method”?

## Roadmap of this lecture:

### 1. Maximum Flow.

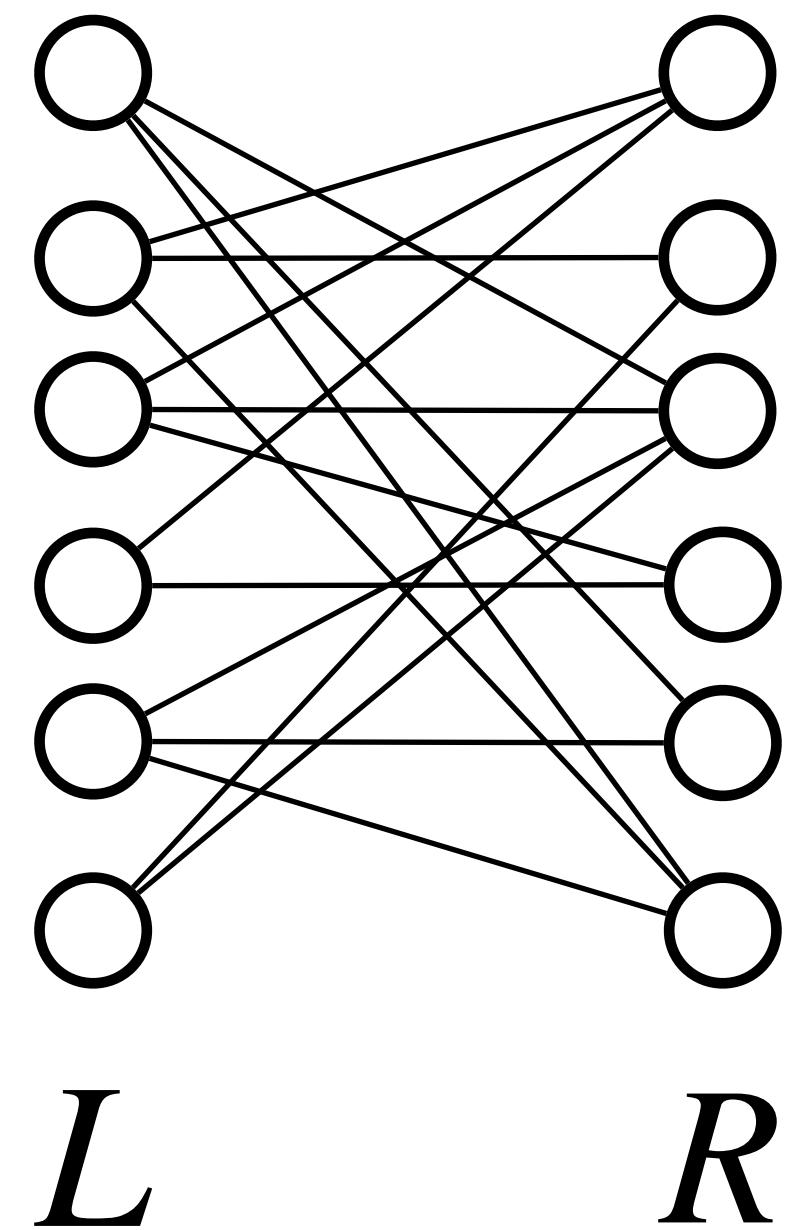
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## Application: Maximum Bipartite Matching

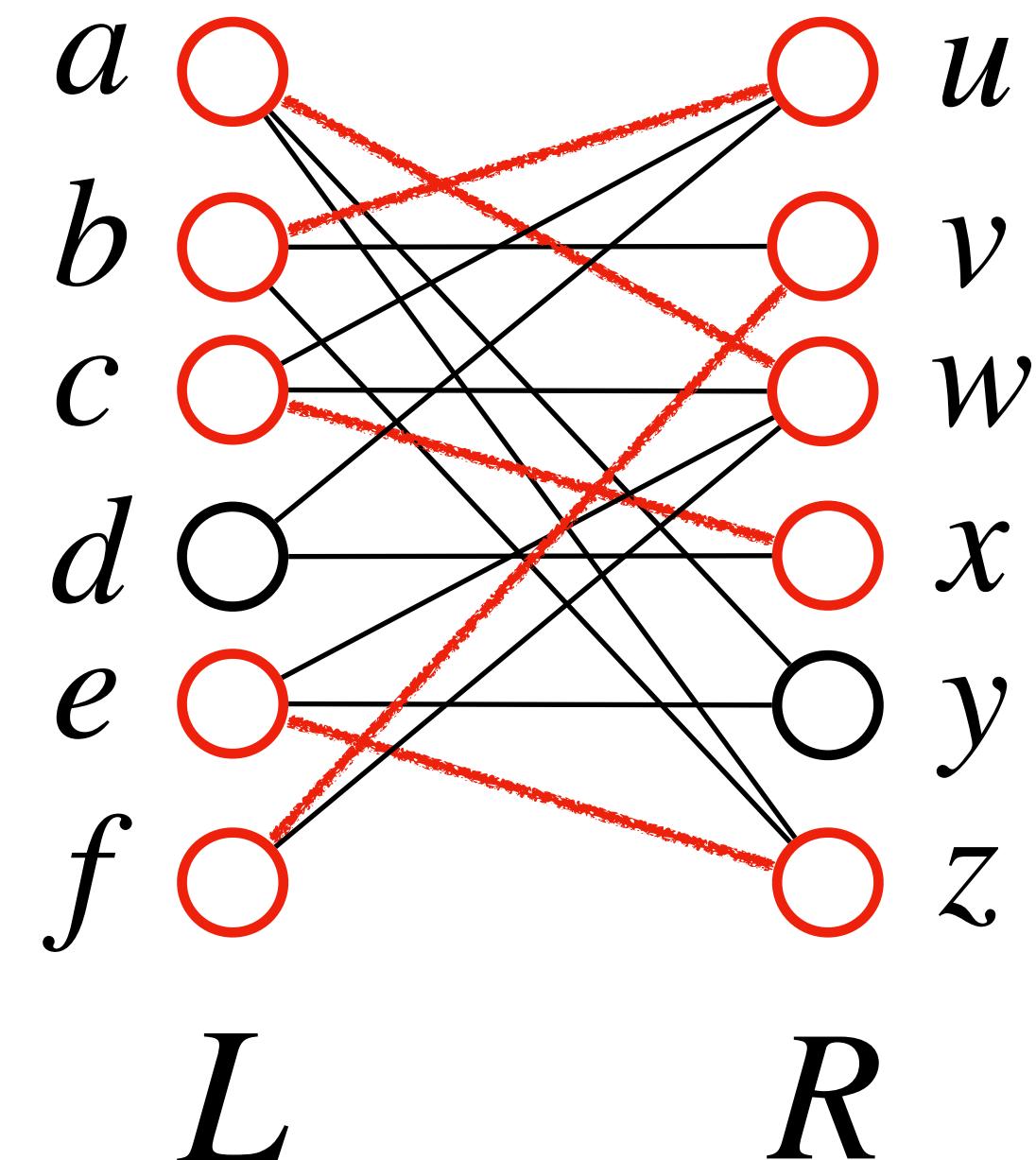
**Bipartite Graph:** A graph  $G = (V, E)$  is bipartite if we can partition the nodes into  $L$  and  $R$ , such that every edge is between a node in  $L$  and a node in  $R$ .



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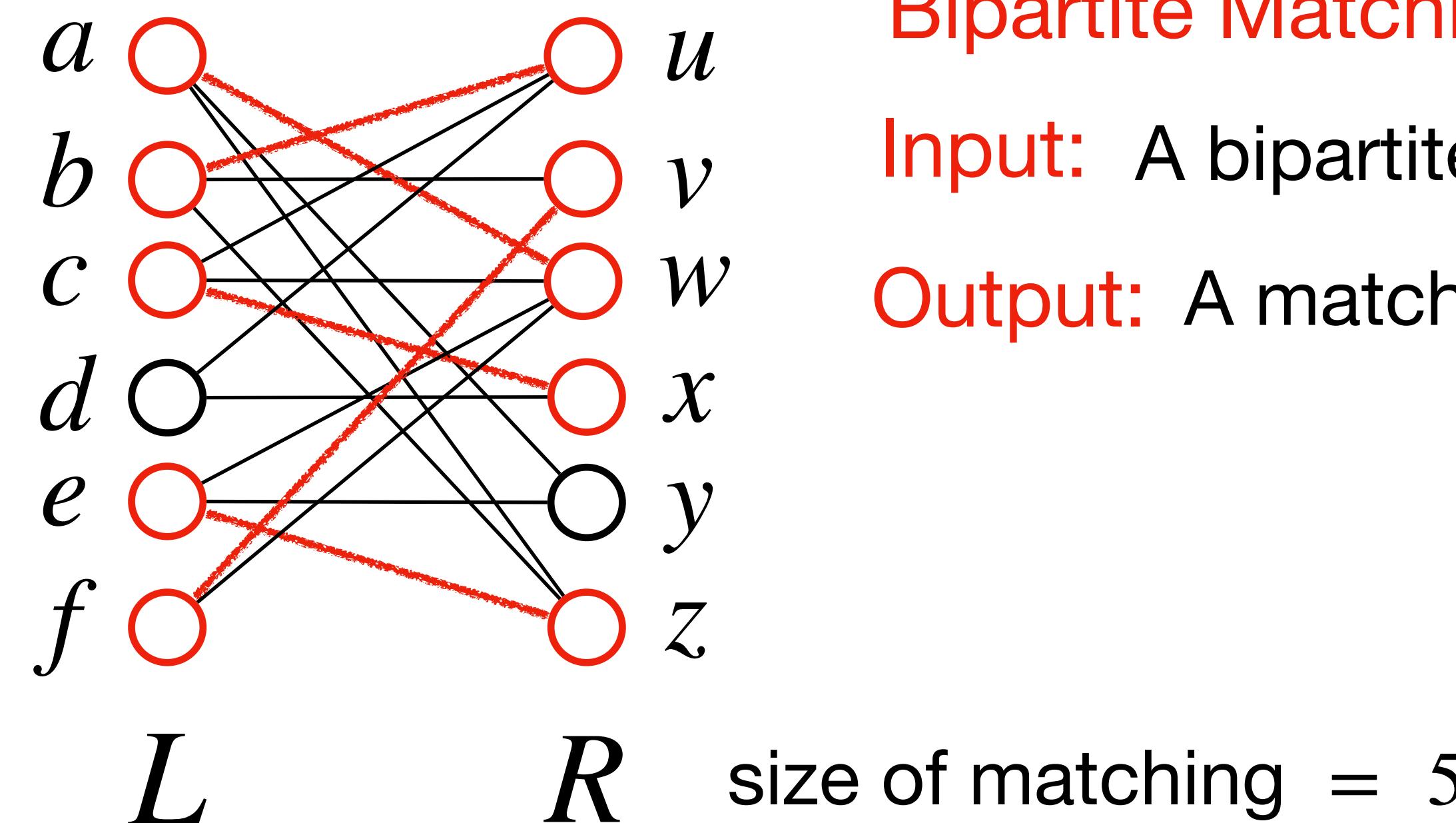
**Matching:** Given an undirected graph  $G = (V, E)$ , a matching is a subset of edges  $S \subseteq E$  such that every node  $v \in V$  is an endpoint of at most one edge in  $S$ .



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**Bipartite Matching Problem:**

**Input:** A bipartite graph  $G = (L \cup R, E)$ .

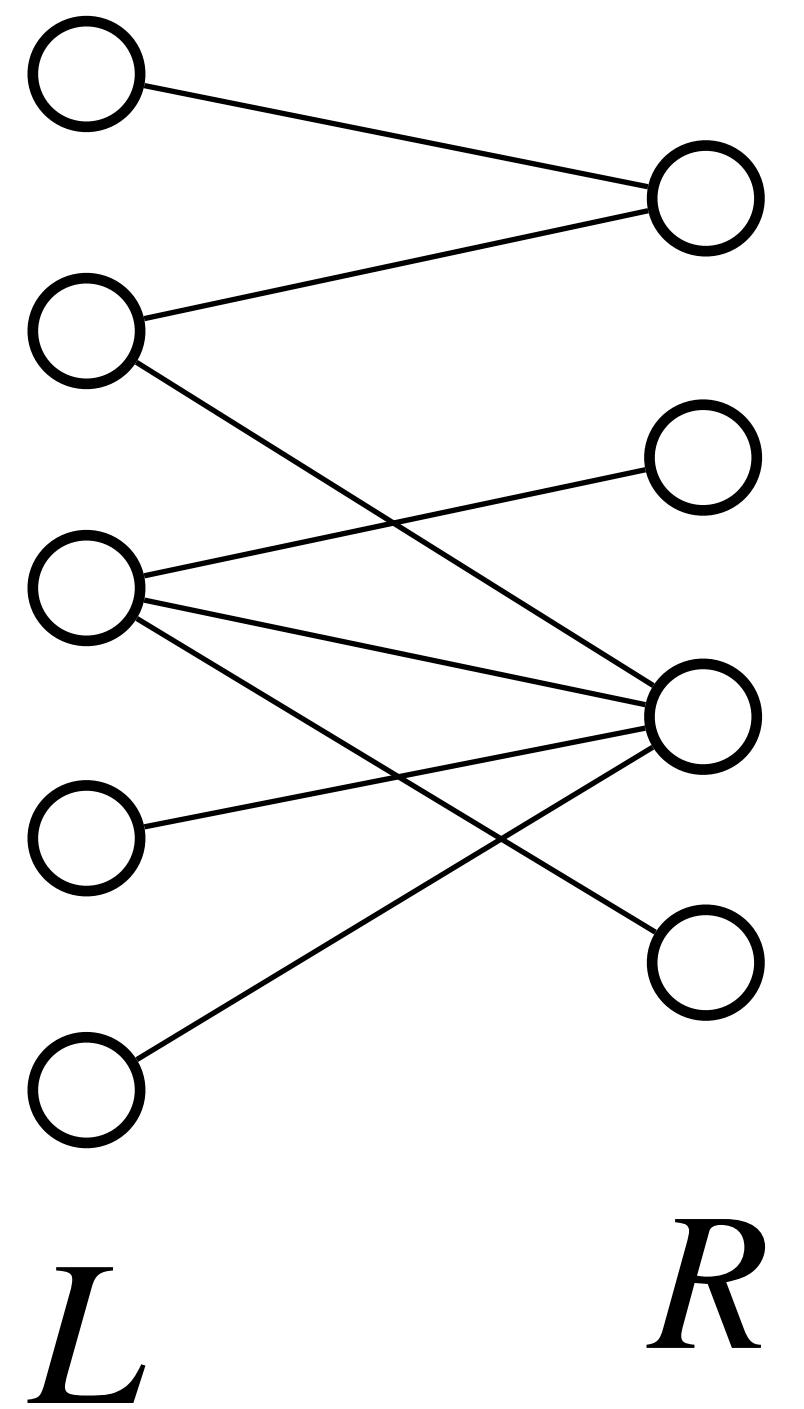
**Output:** A matching of maximum size.

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Example instance:

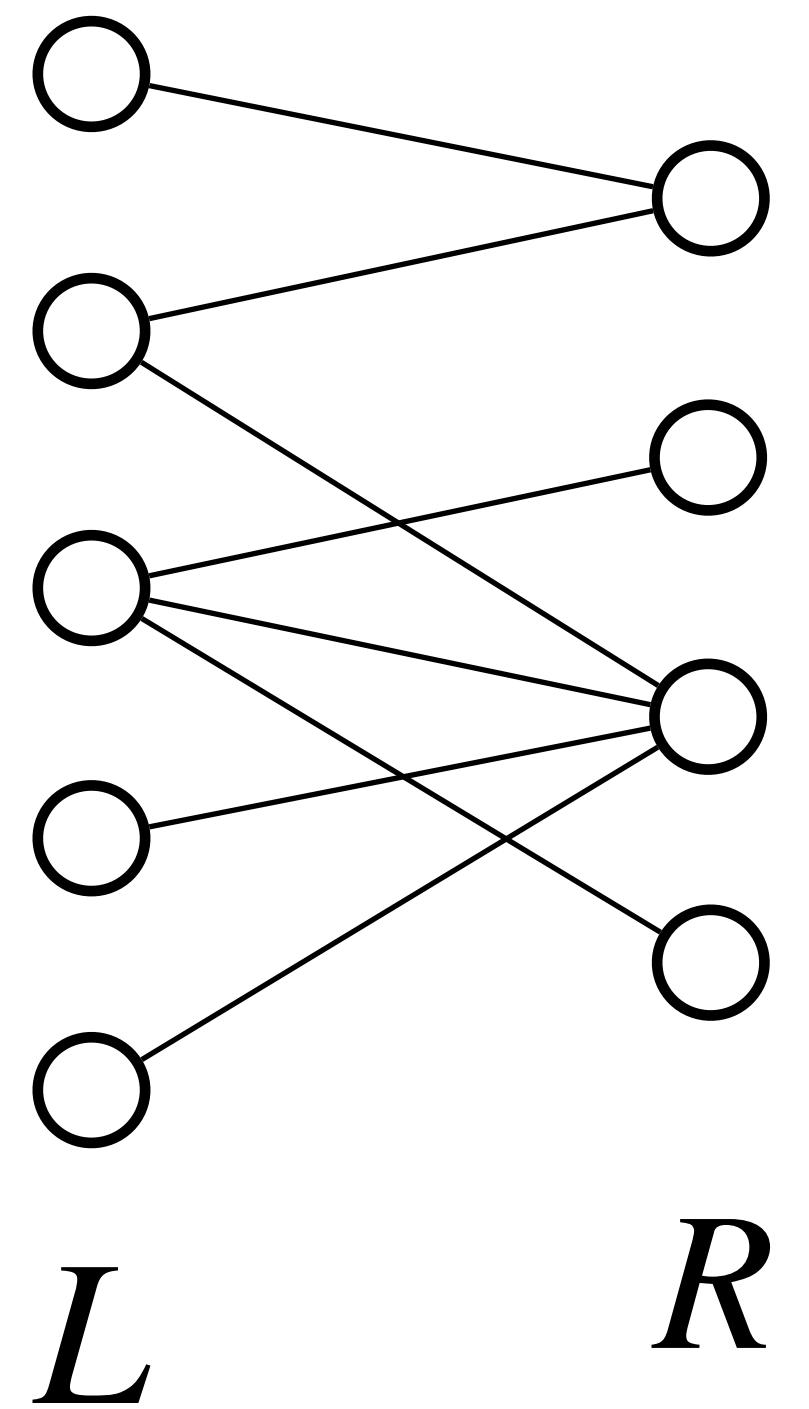


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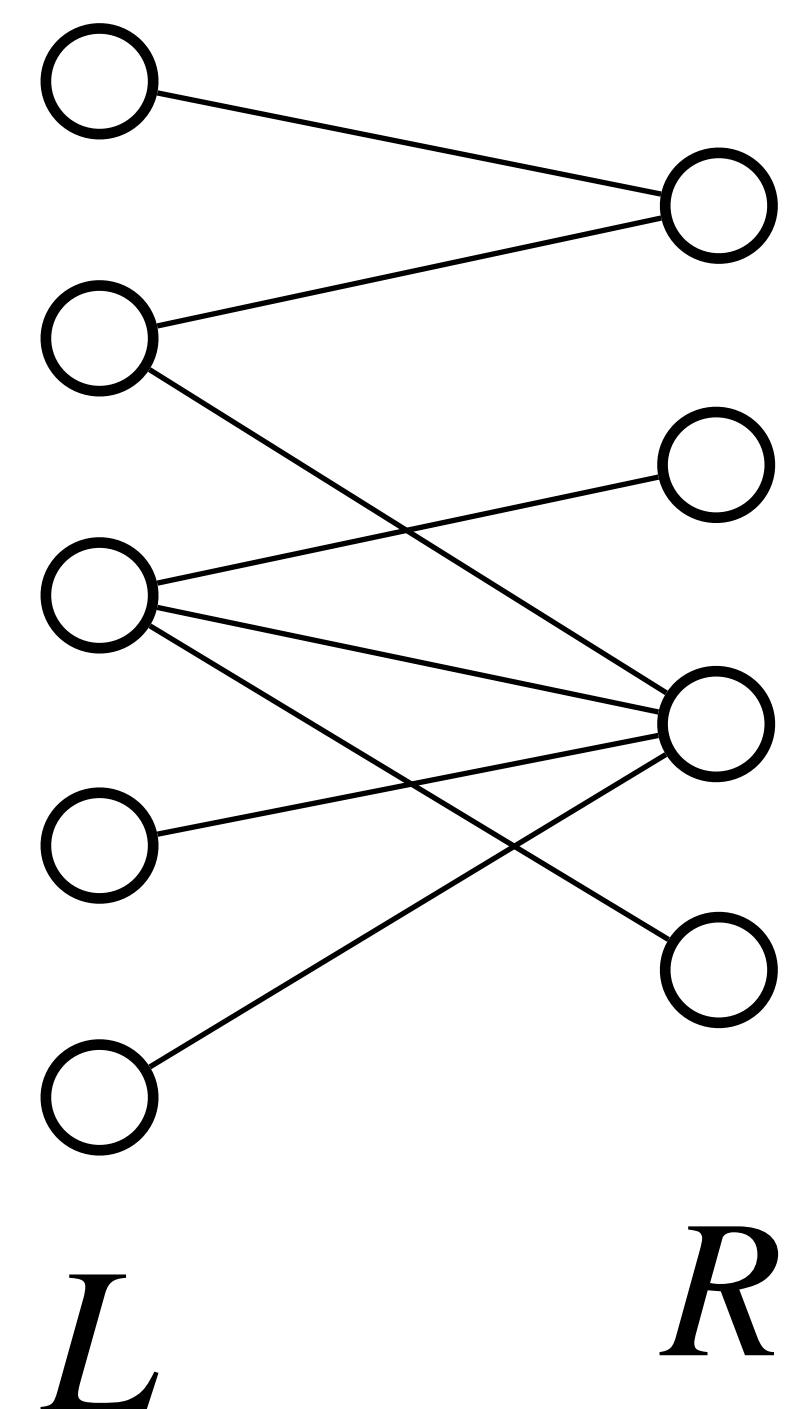
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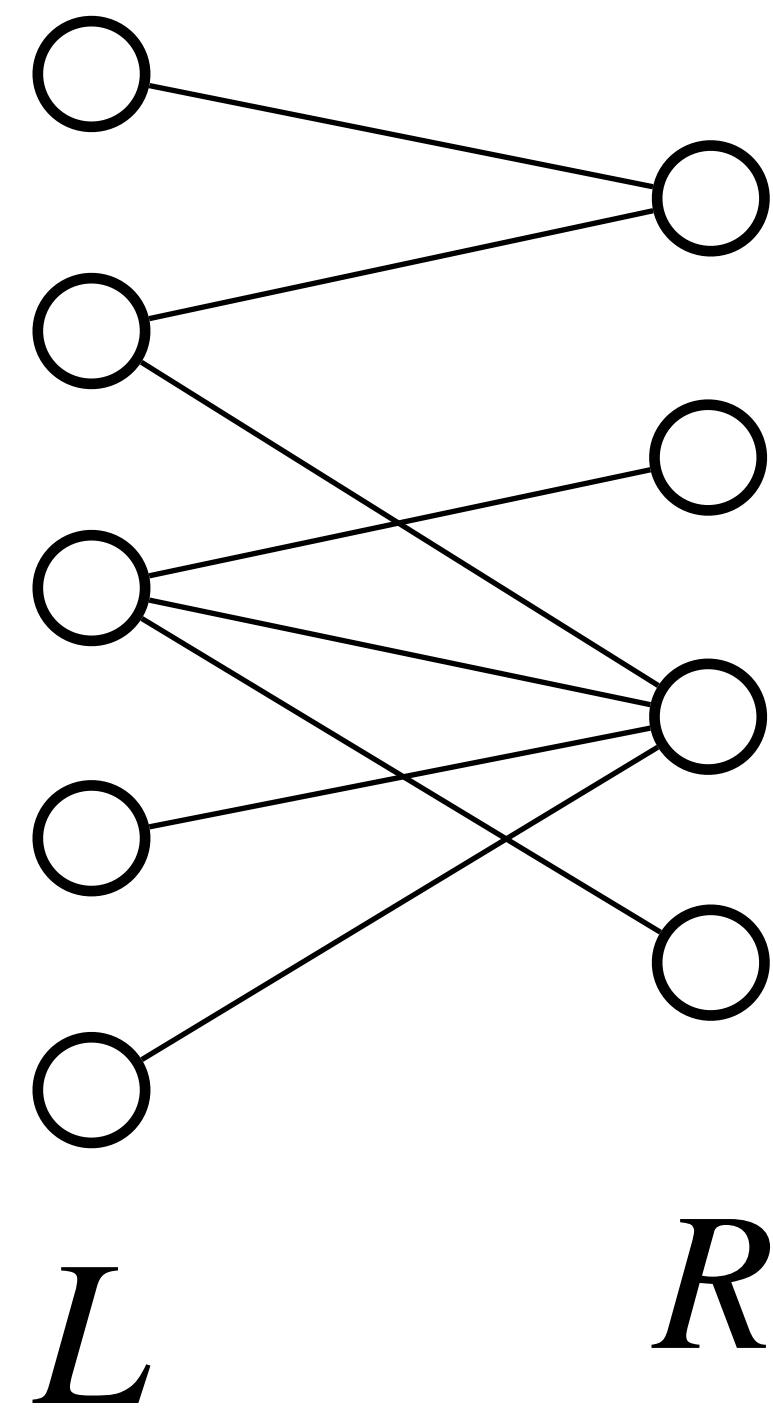


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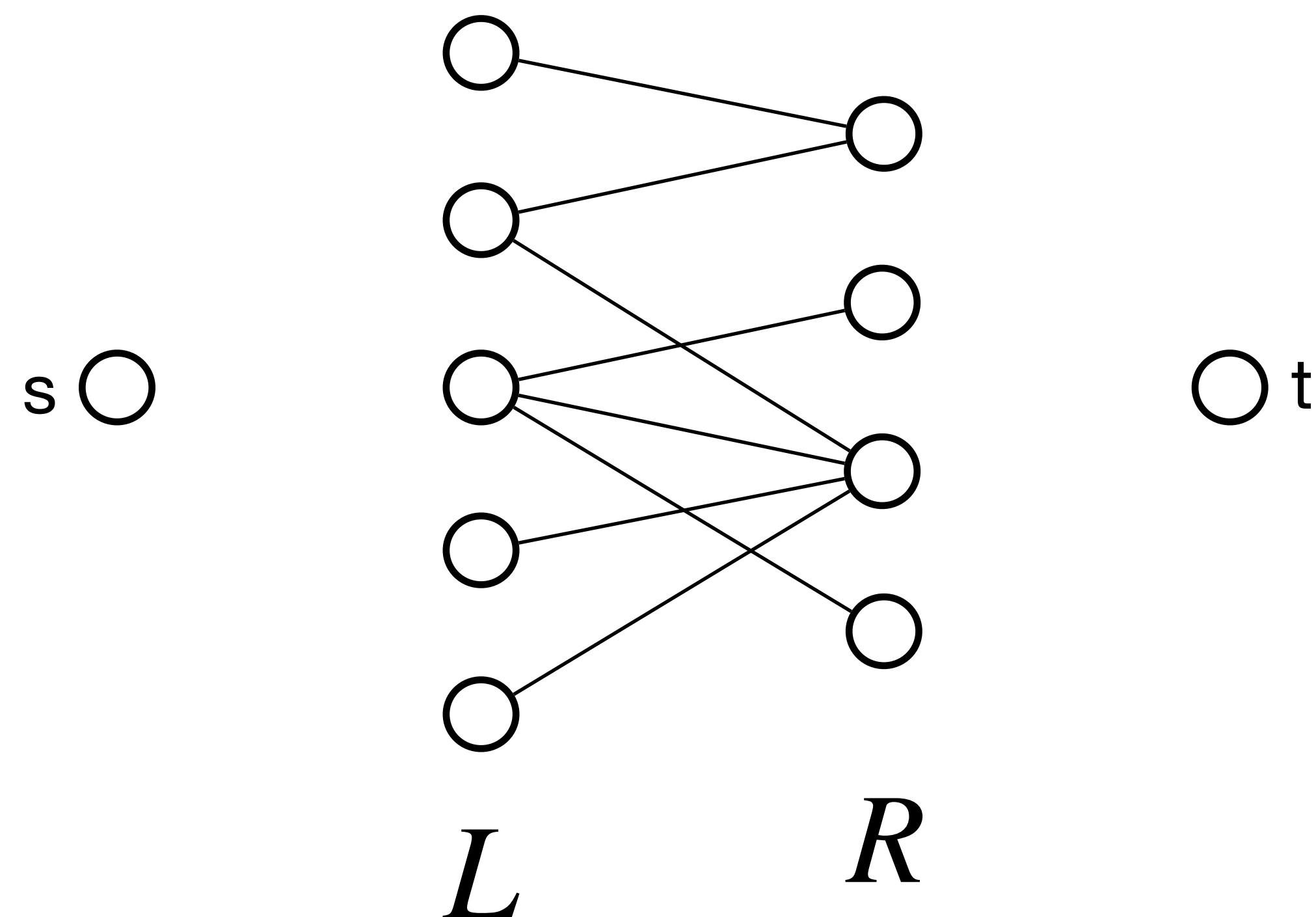
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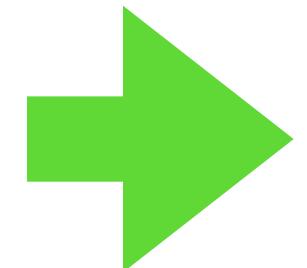
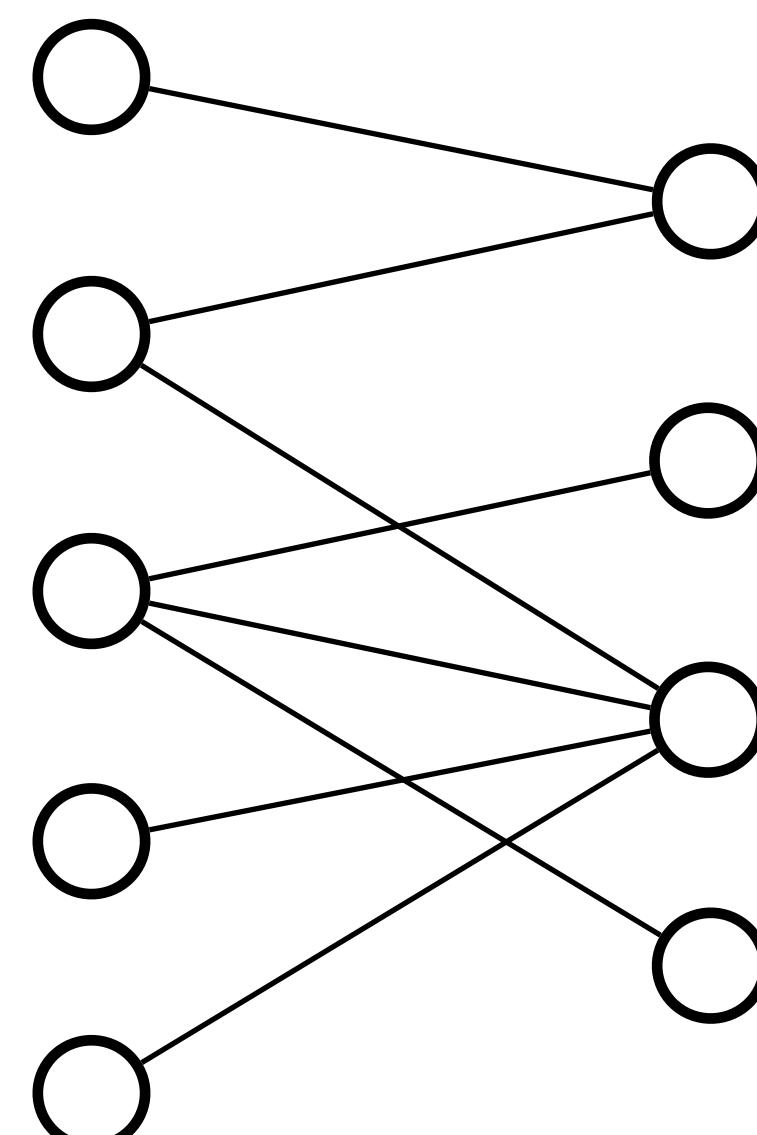


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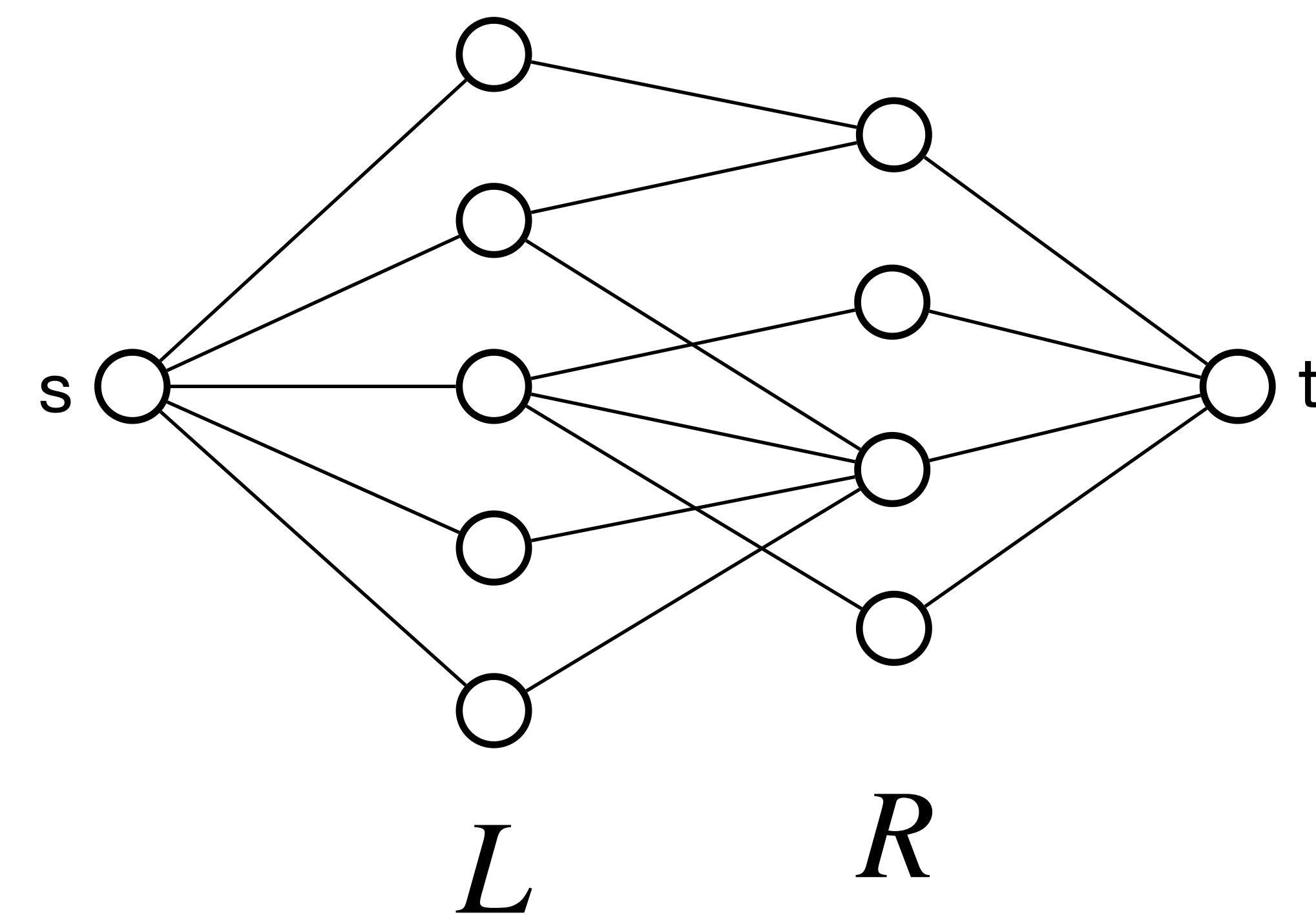
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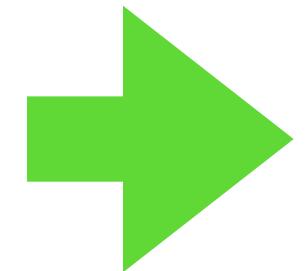
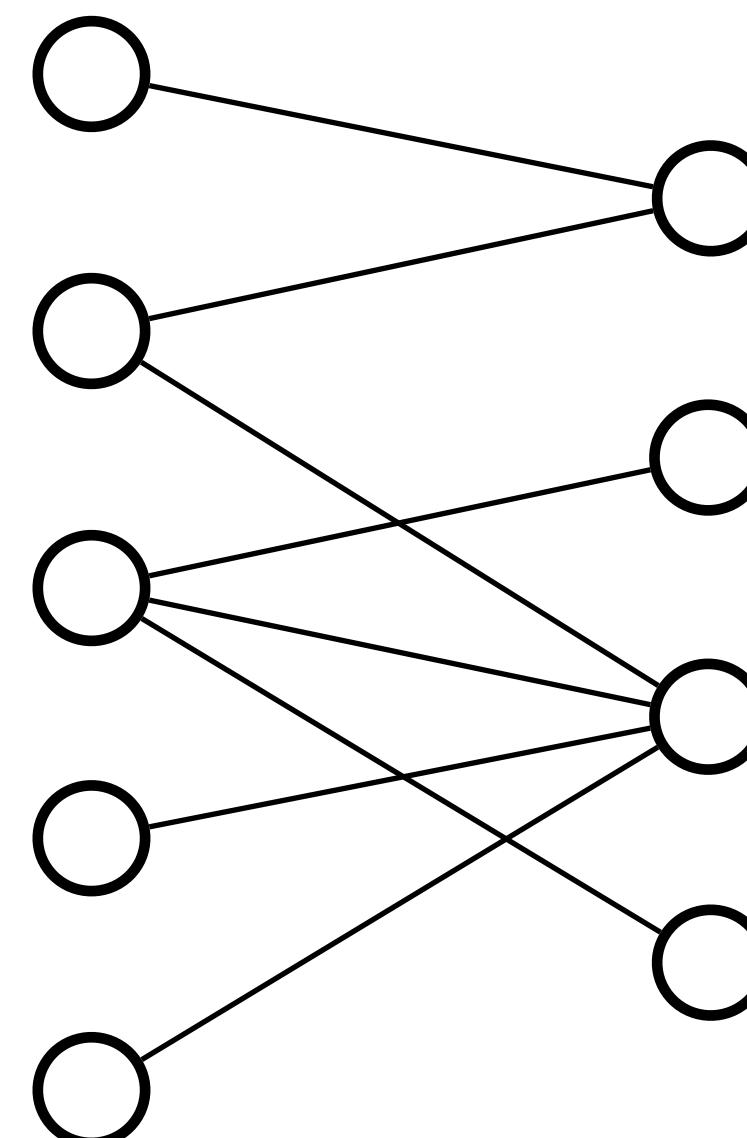


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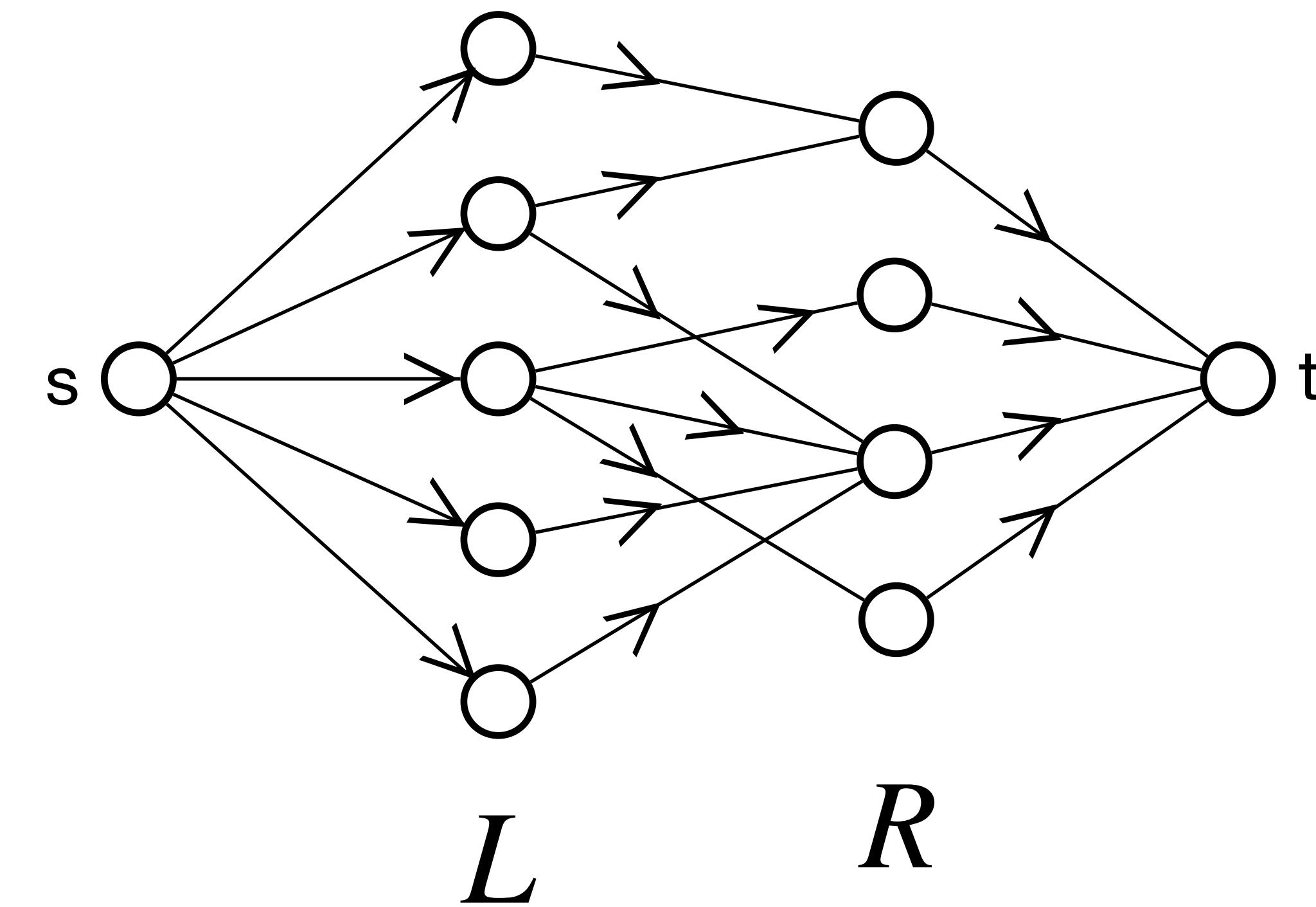
Example instance:



$L$        $R$

Maximum Flow Problem:

All edges have capacity 1

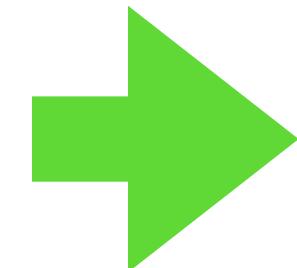
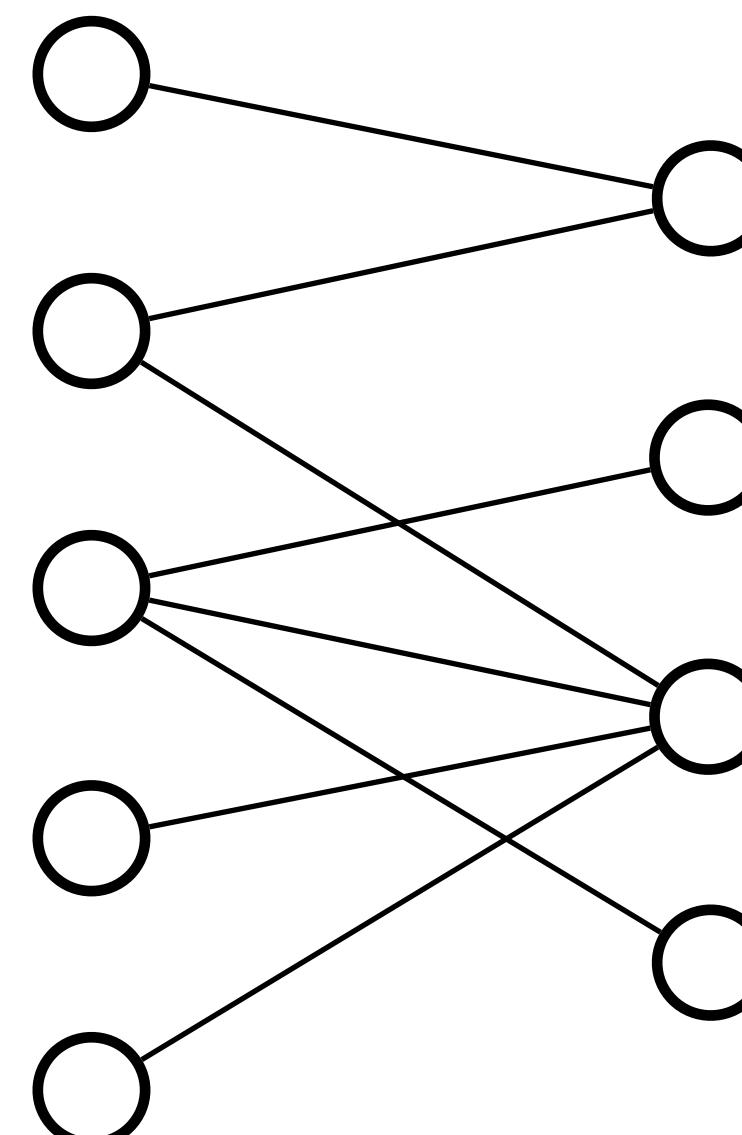


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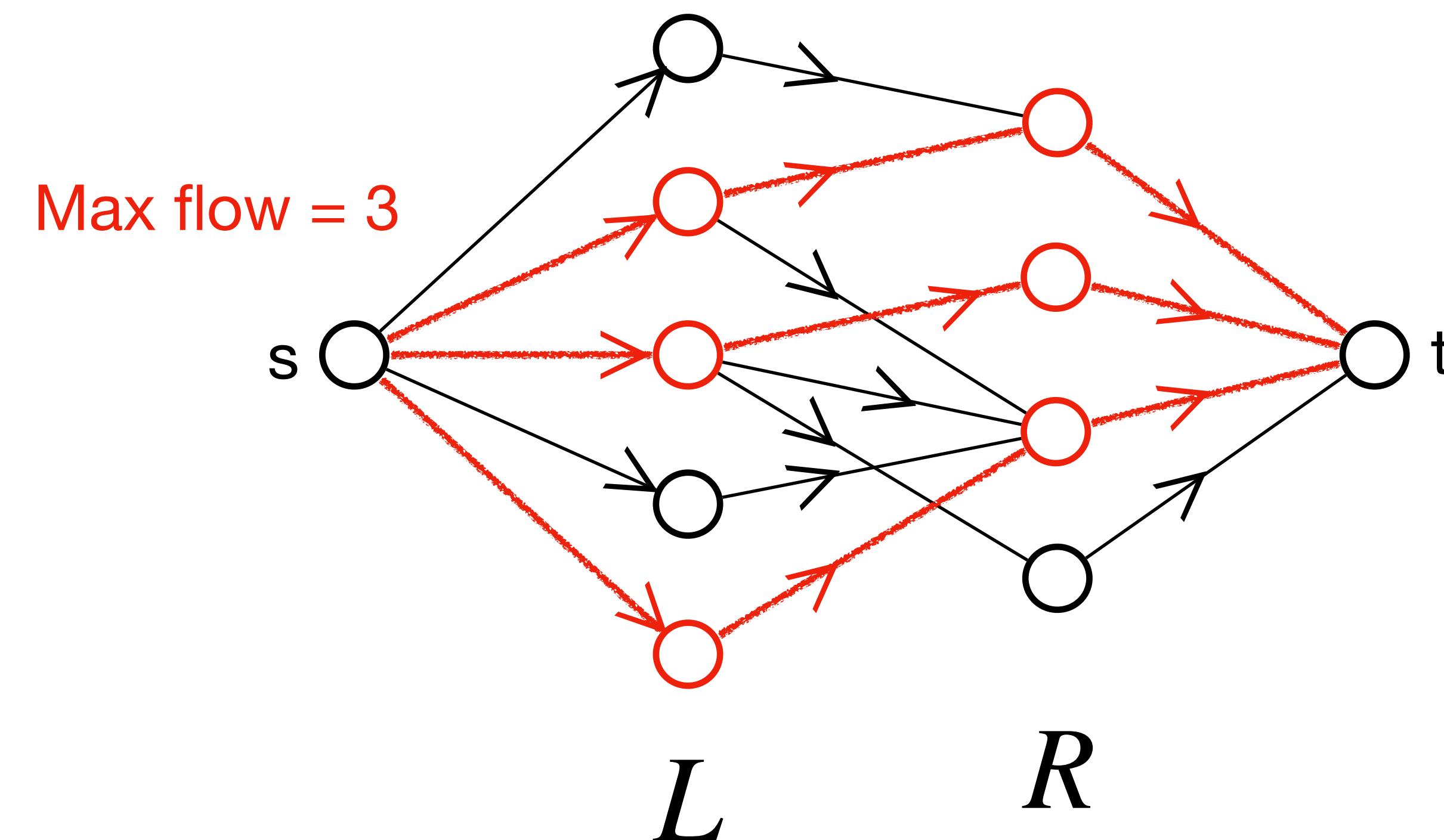
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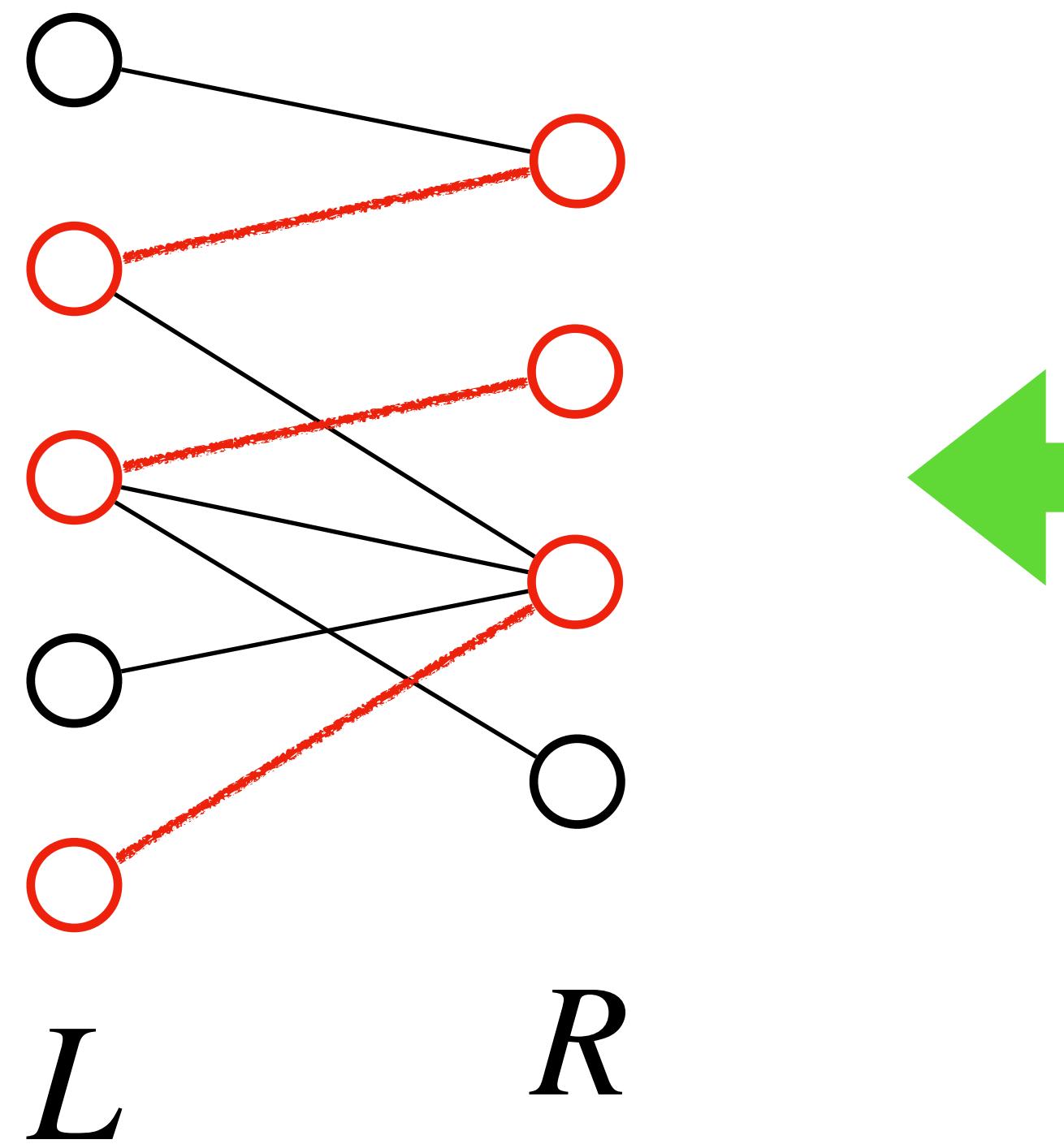
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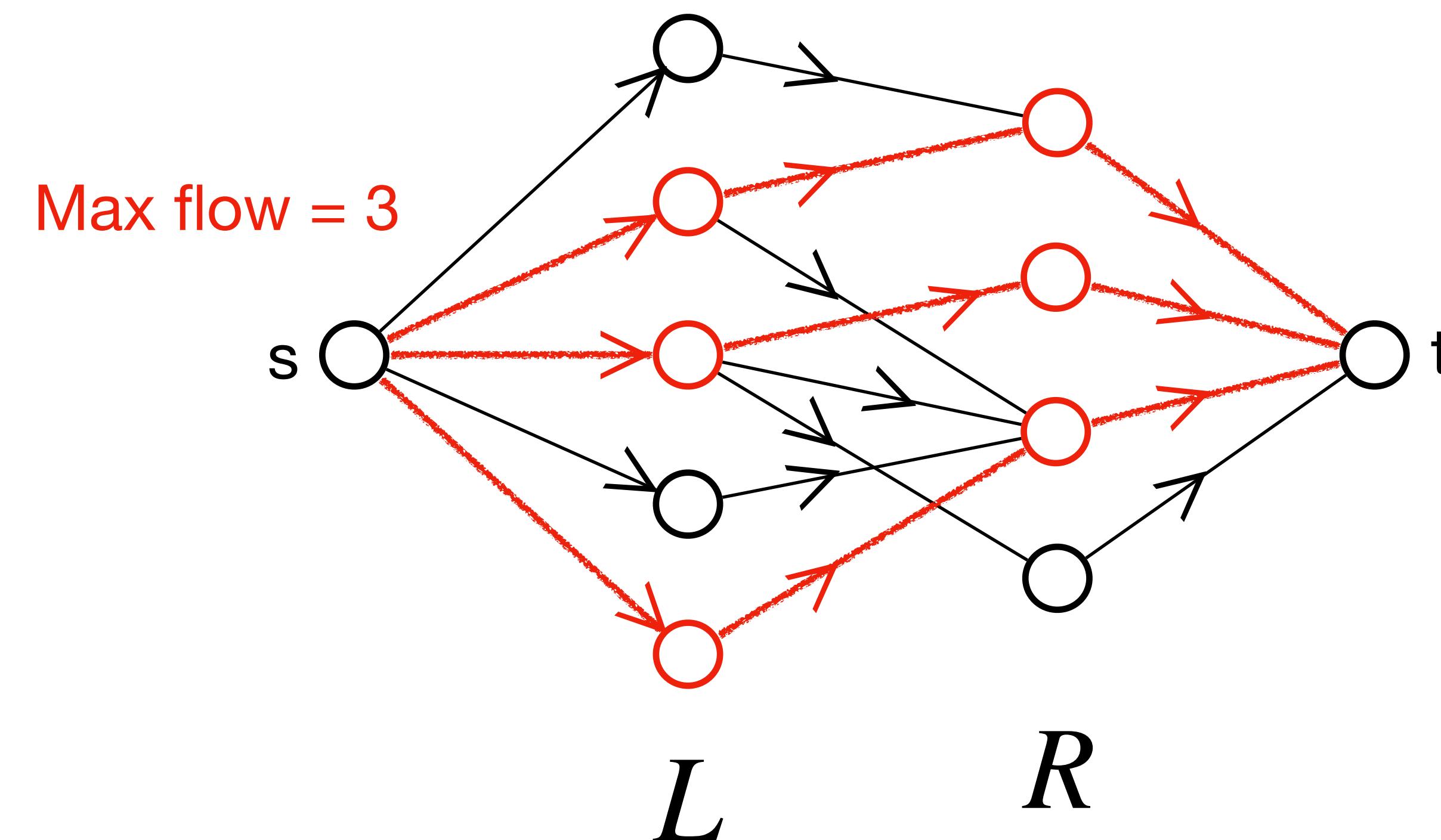
Example instance:

Max matching = 3



Maximum Flow Problem:

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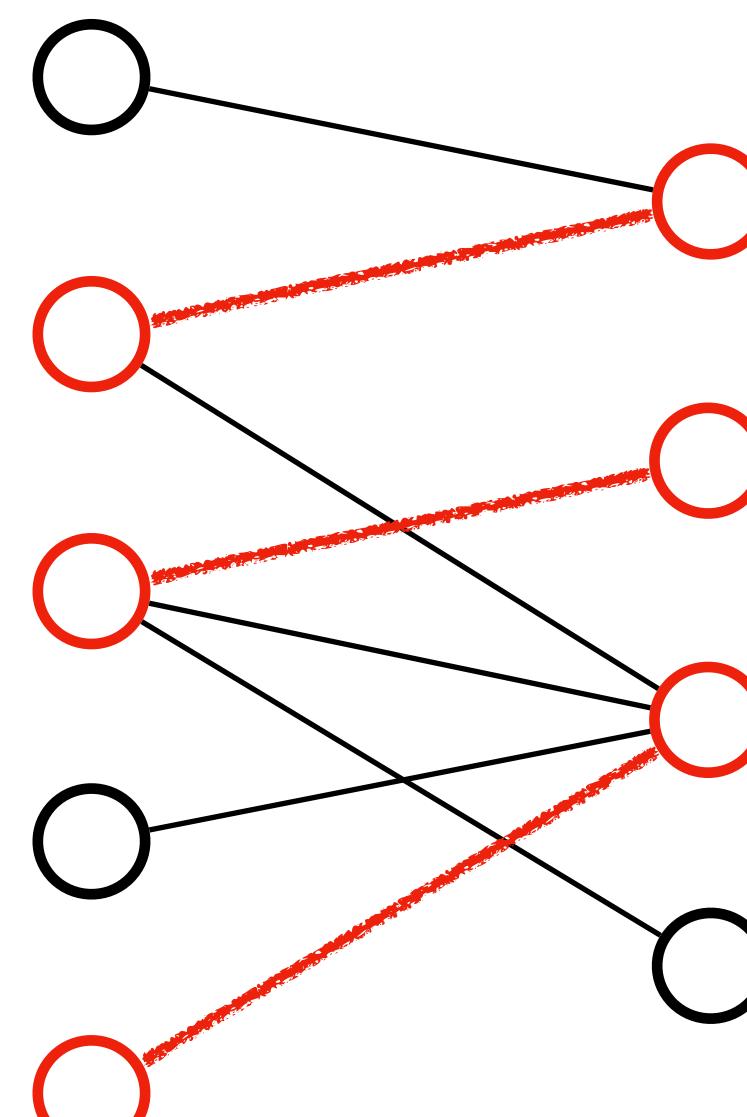
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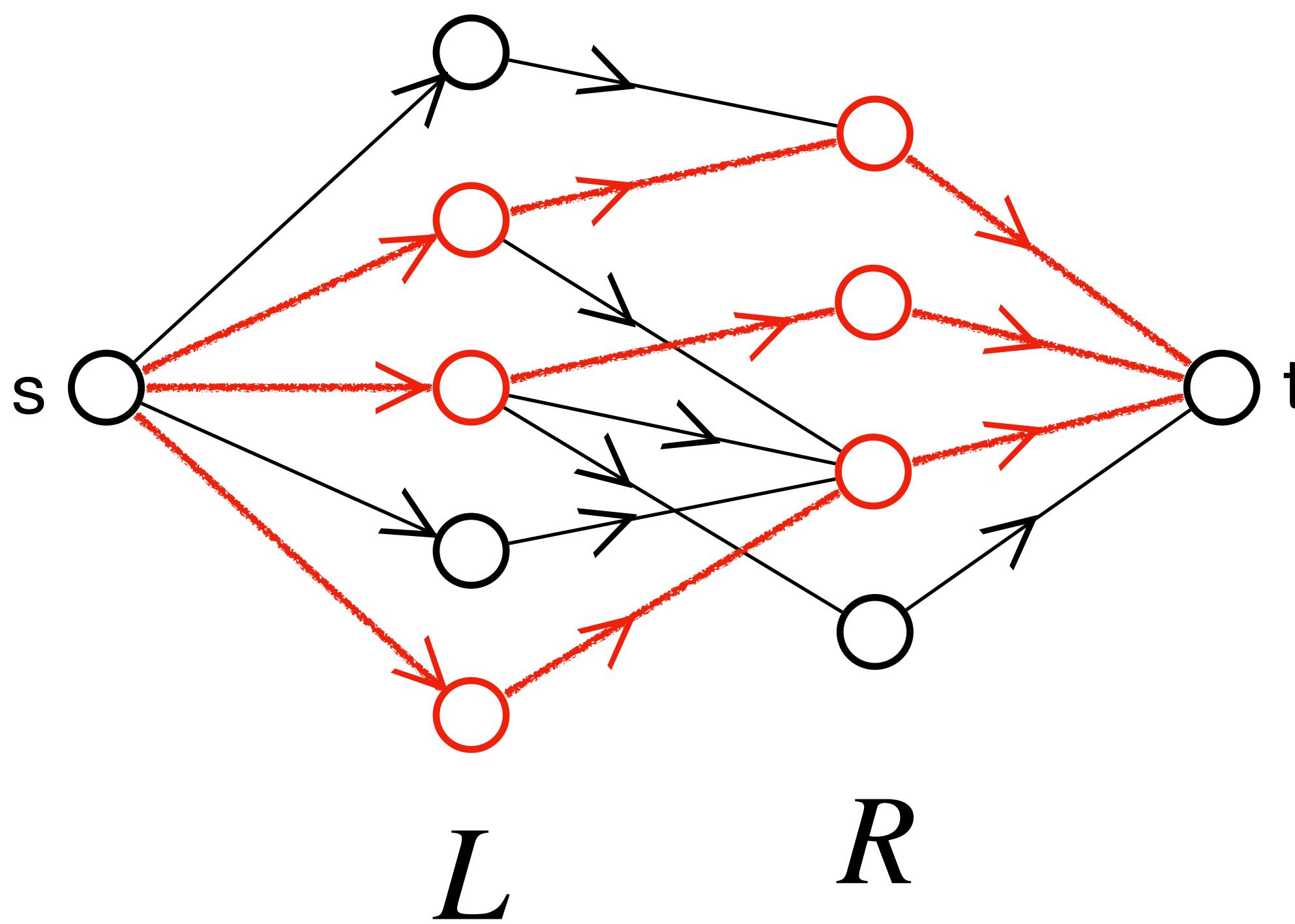
Output: A matching of maximum size.

Theorem:  $G$  has a matching of size  $k$   
if and only if  
 $G'$  has a flow of size  $k$ .

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



$$G'$$



## Bipartite Matching Problem:

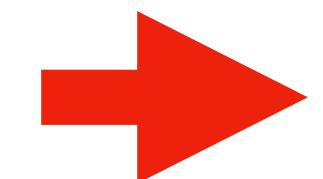
Input: A bipartite graph  $G = (L \cup R, E)$ .

Output: A matching of maximum size.

Theorem:  $G$  has a matching of size  $k$   
if and only if

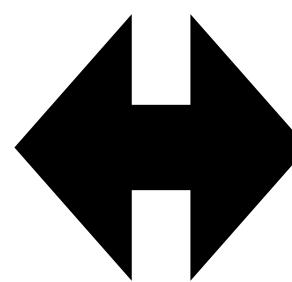
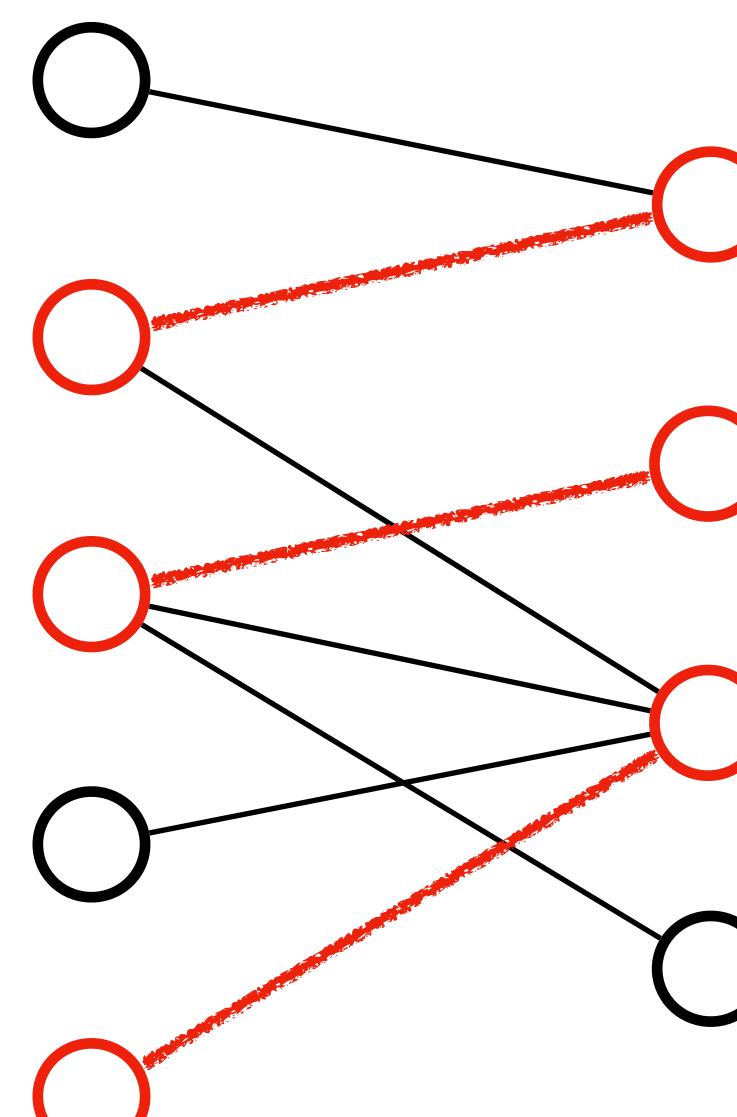
$G'$  has a flow of size  $k$ .

Proof:

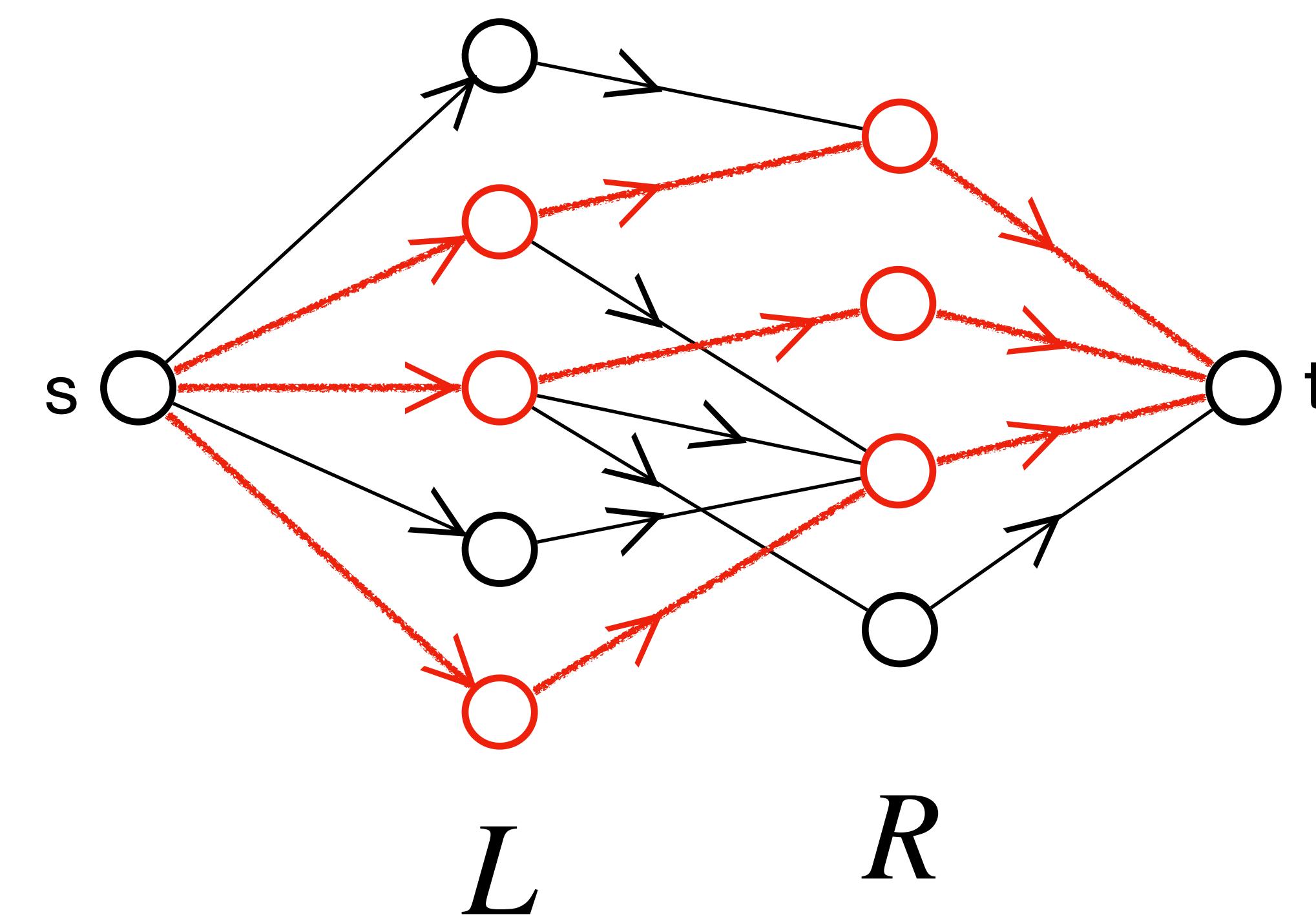


Construct flow from matching.

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



$$G'$$



## Bipartite Matching Problem:

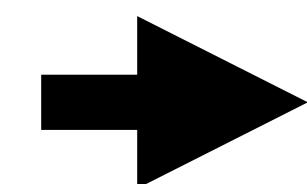
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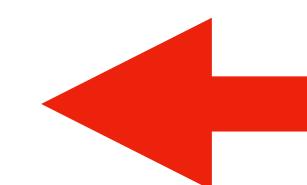
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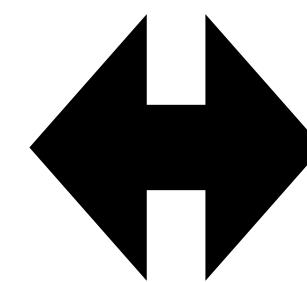
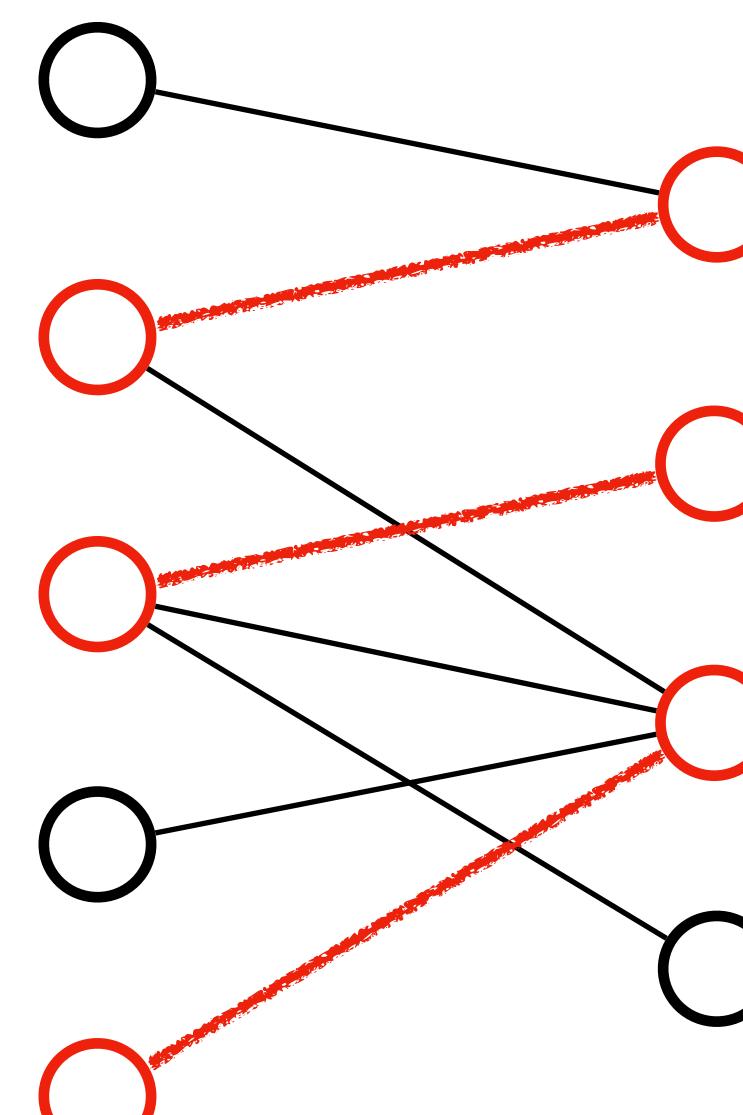


Construct flow from matching.

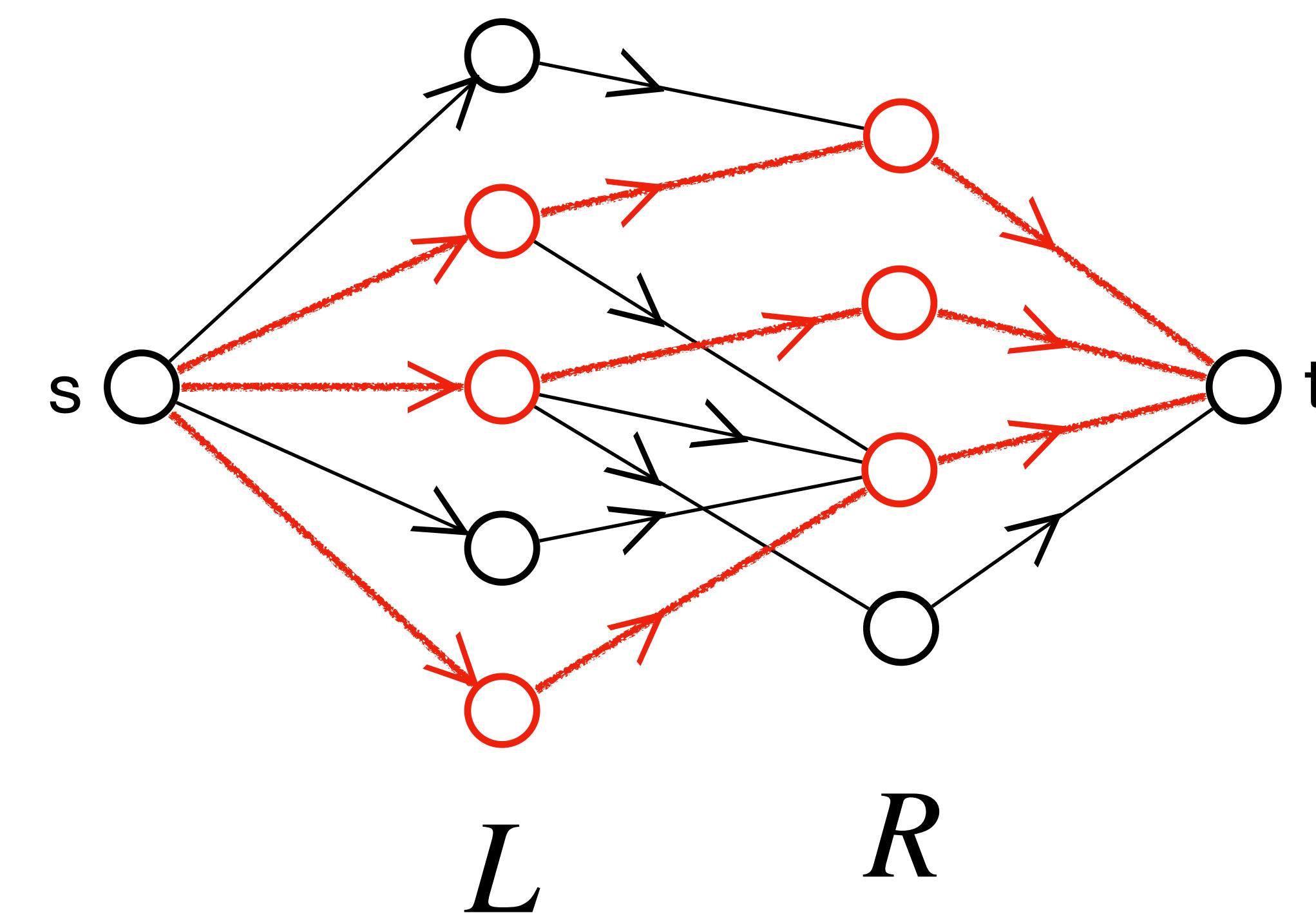


$G'$  has an integer flow of size  $k$ .

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



$$G'$$



$L$

$R$

$L$

$R$

# Bipartite Matching Problem:

**Input:** A bipartite graph  $G = (L \cup R, E)$ .

**Output:** A matching of maximum size.

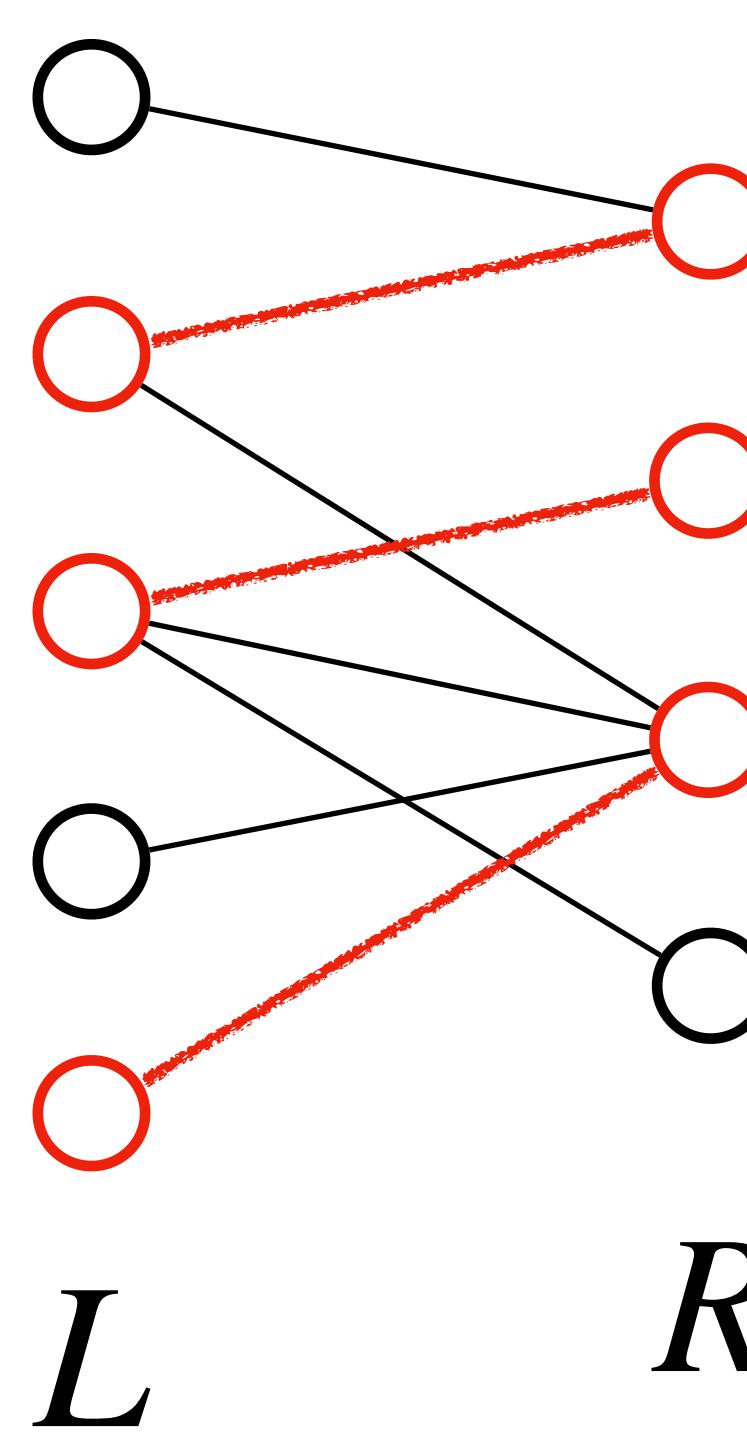
Theorem:  $G$  has a matching of size  $k$   
if and only if  
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# Proof

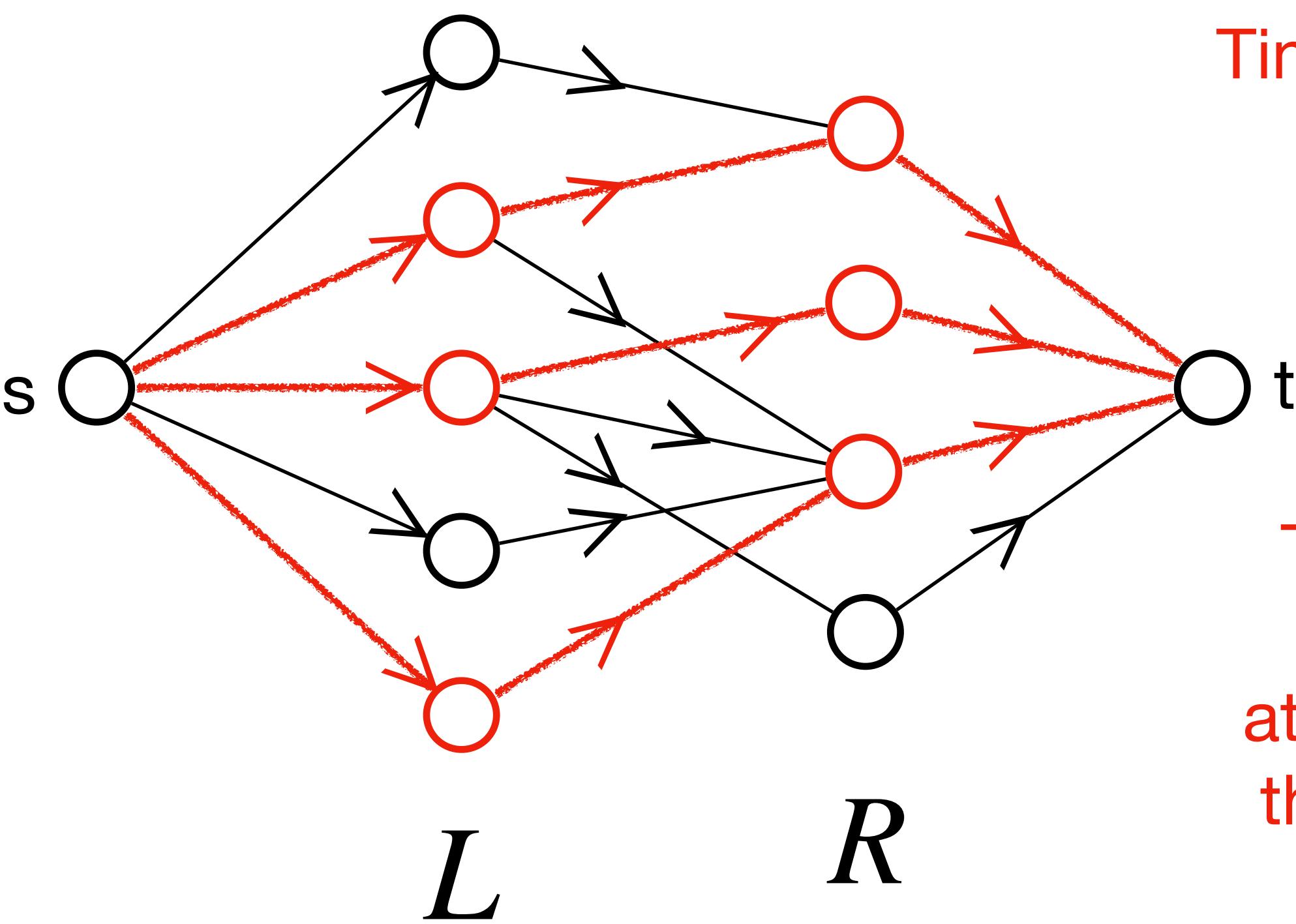
# Construct flow from matching.

■  $G'$  has an integer flow of size  $k$ .

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



G'



Time complexity:  $O(VE)$

$$|f| \leq |L| \leq |V|$$

The Edmonds-Karp algorithm needs to augment the flow at most  $|V|$  times, and each time the BFS algorithm uses  $O(V+E)$  time to find a shortest path.

## Formulate Maximum Flow Problem as a Linear Program

**Input:** A directed graph  $G = (V, E)$ , where every edge  $(u, v) \in E$  has a positive capacity  $c(u, v)$ .

Let  $s \in V$  be a source node, and let  $t \in V$  be a sink node.

**Output:** A maximum flow from  $s$  to  $t$ .

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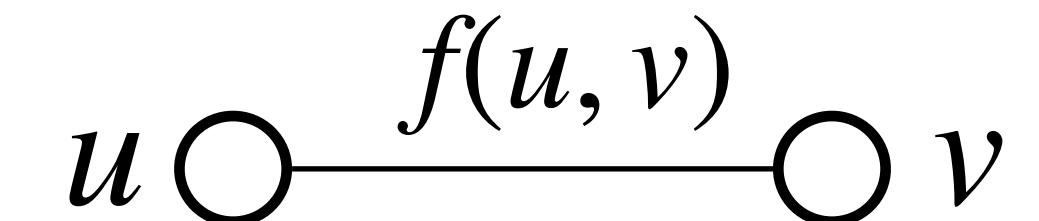
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1) variables:  $\forall$  edge  $(u, v) \in E$ , the flow  $f(u, v)$  on it is a variable.



## Formulate Maximum Flow Problem as a Linear Program

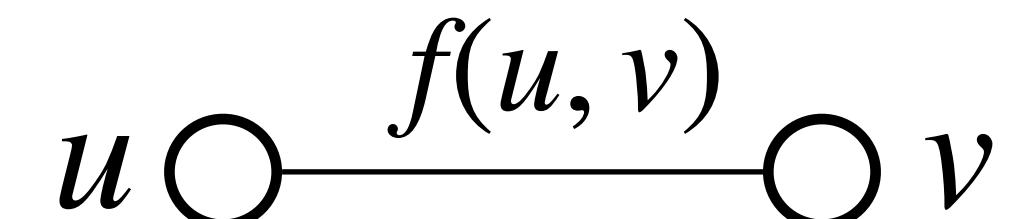
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Objective function and constraints:

$$\text{maximize} \quad \sum_{(s,v) \in E} f(s, v)$$

$$\text{subject to: } 0 \leq f(u, v) \leq c(u, v), \quad \forall (u, v) \in E$$

$$\sum_{(u,v) \in E} f(u, v) = \sum_{(v,u) \in E} f(v, u), \quad \forall v \in V - \{s, t\}$$

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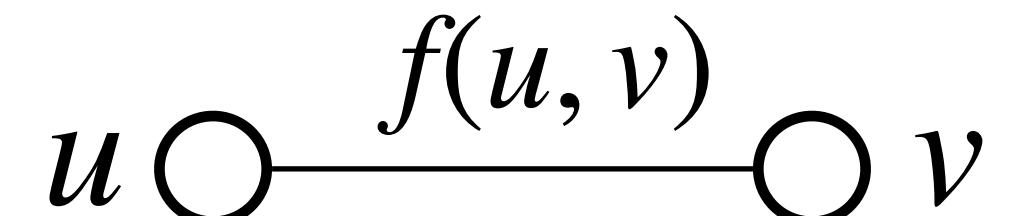
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Why do we still need  
Edmonds-Karp Algorithm?  
Lower time complexity.

## Quiz questions:

1. How do we map the “Maximum Bipartite Matching Problem” to a “Maximum Flow Problem”?
2. What is the benefit of designing a specialized algorithm for a more special problem than using a more general algorithm for a more general problem?