

# **FIT2004**

## **Algorithms and Data Structures**

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Referencing materials by  
Nathan Companeze, Aamir Cheema, Arun Konagurthu and Lloyd Allison



# Faculty of Information Technology, Monash University

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Ready?

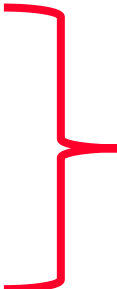
# Agenda

- Network Flow

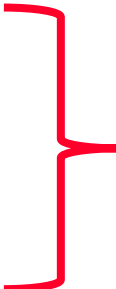
# Agenda

- Network Flow
- The maximum flow problem
- The residual network
- Path augmentation    multiple BFS to augment path

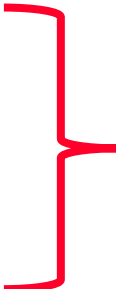
# Agenda

- Network Flow
  - The maximum flow problem
  - The residual network
  - Path augmentation
- 
- Ford-Fulkerson  
Method**

# Agenda

- Network Flow
  - The maximum flow problem
  - The residual network
  - Path augmentation
  - Min-cut Max-flow Theorem
- 
- Ford-Fulkerson  
Method**

# Agenda

- Network Flow
  - The maximum flow problem
  - The residual network
  - Path augmentation
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- Ford-Fulkerson  
Method**
- Min-cut Max-flow Theorem
  - Then we have Bipartite Graph



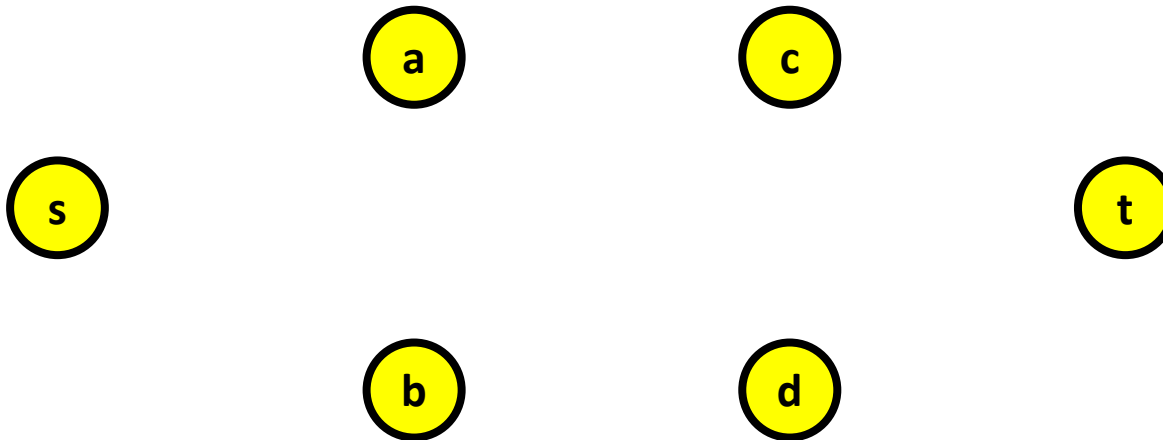
# Agenda

- Network Flow
  - The maximum flow problem
  - The residual network
  - Path augmentation
  - Min-cut Max-flow Theorem
  - Then we have Bipartite Graph
    - Matching optimally =)
- Ford-Fulkerson Method  
with extra optimization  
from FIT3155**

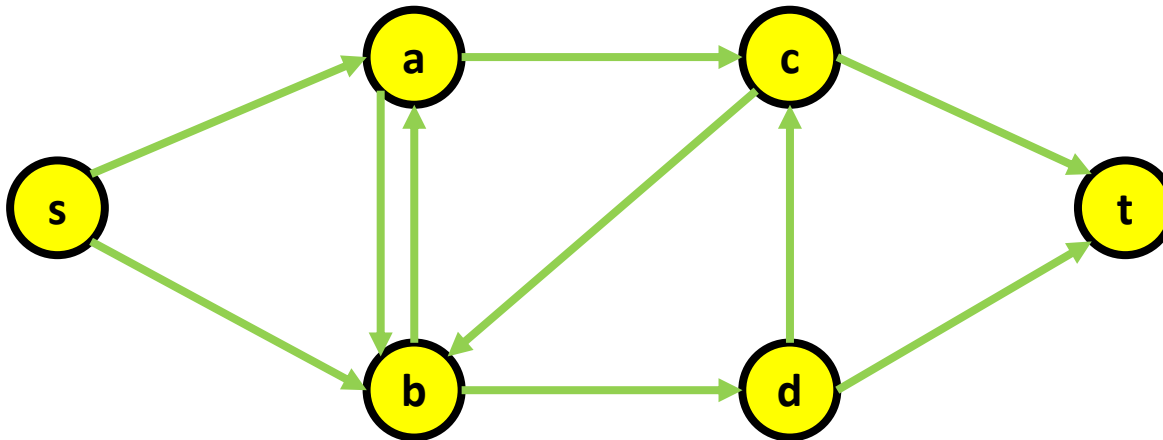
Let us begin...

- What is it?

- What is it?
  - It is a graph
    - With vertices



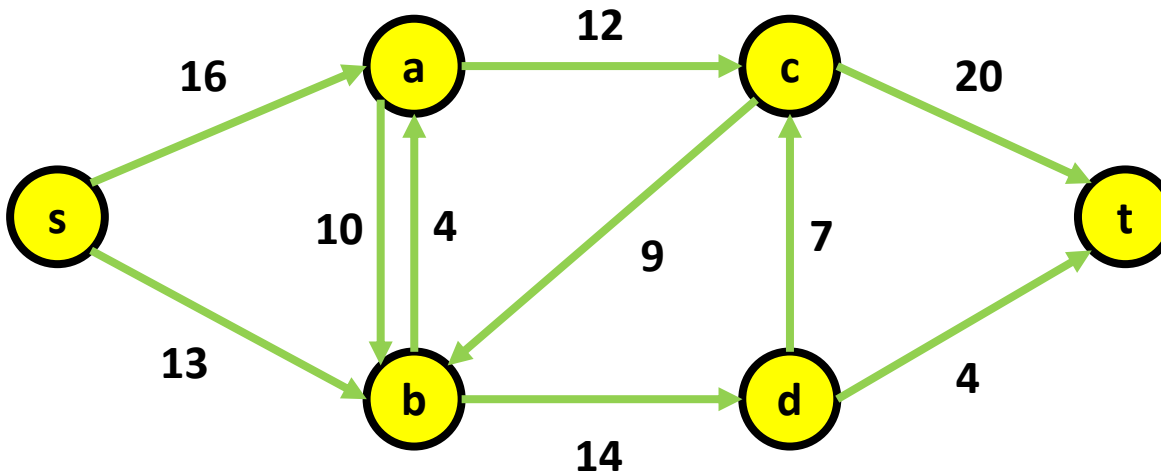
- What is it?
  - It is a graph
    - With vertices
    - With edges (directed)



# Flow Network

## Transfer of content

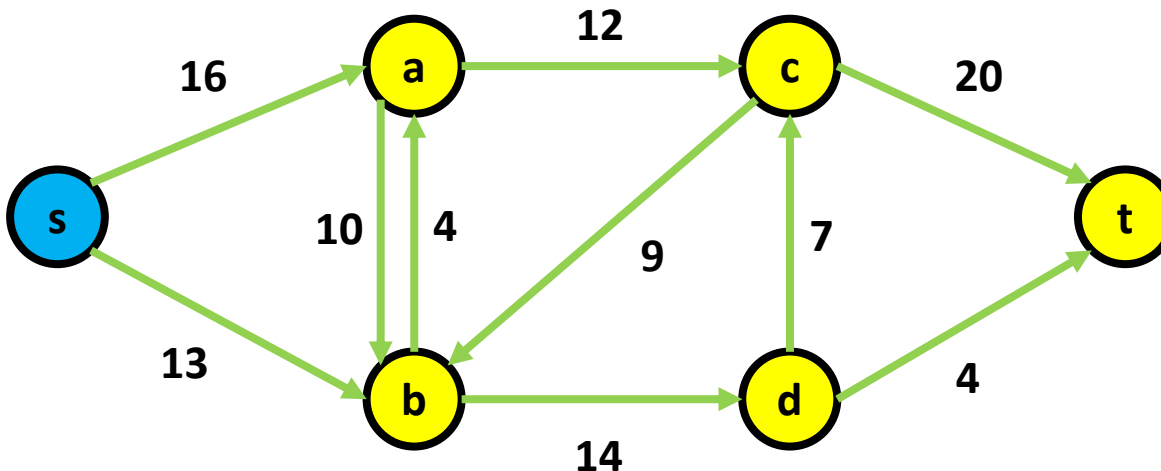
- What is it?
  - It is a graph
    - With vertices
    - With edges (directed and weighted)



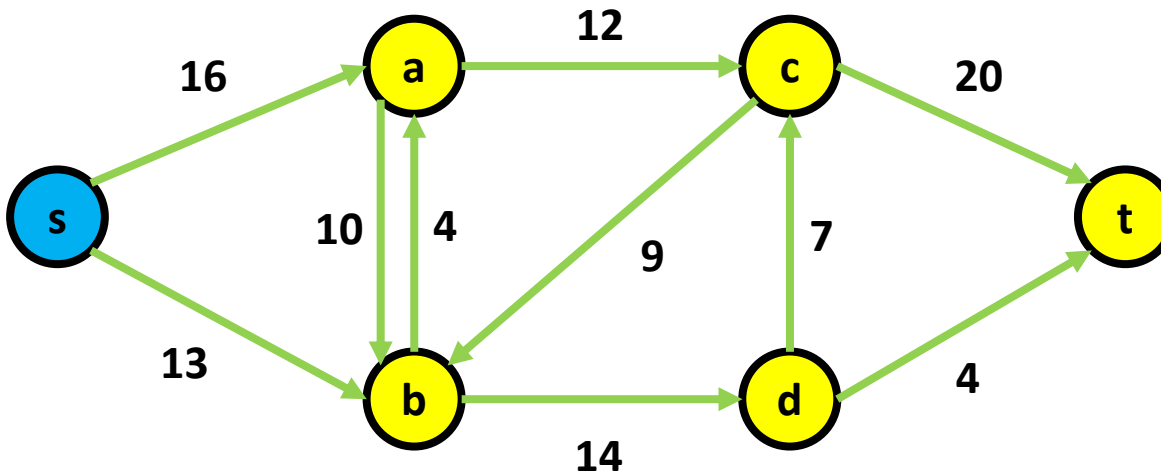
# Flow Network

## Transfer of content

- What is it?
  - It is a graph
    - With vertices
    - With edges (**directed** and **weighted**)
    - A vertex without incoming edges

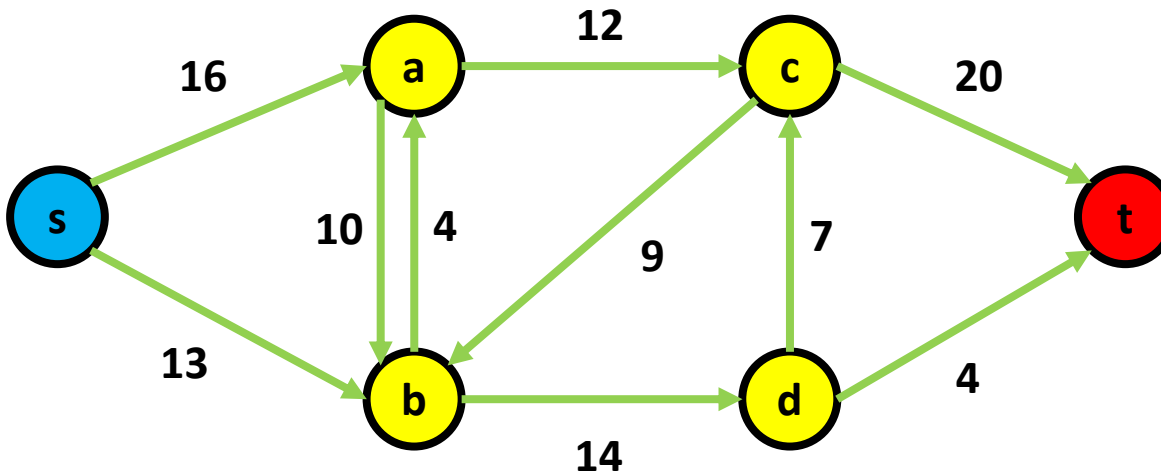


- What is it?
  - It is a graph
    - With vertices
    - With edges (directed and weighted)
    - A vertex without incoming edges know as the **source**





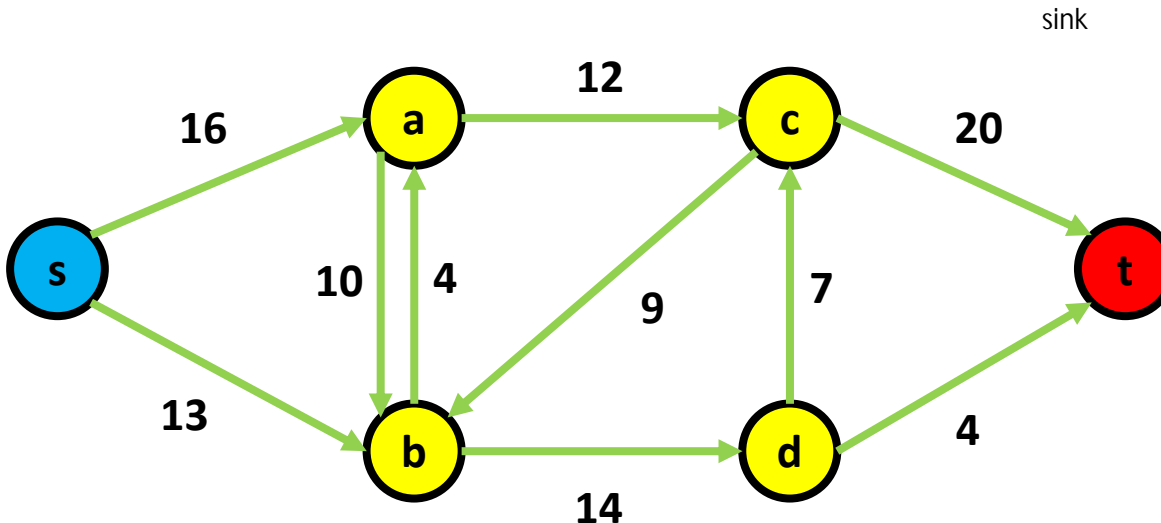
- What is it?
  - It is a graph
    - With vertices
    - With edges (directed and weighted)
    - A vertex without incoming edges known as the **source**
    - A vertex without outgoing edges



# Flow Network

## Transfer of content

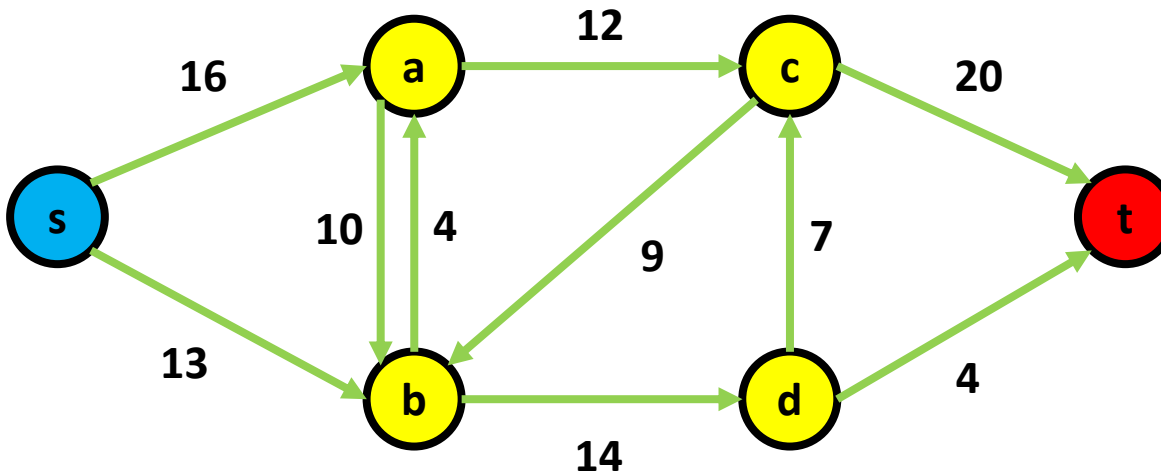
- What is it?
  - It is a graph
    - With vertices
    - With edges (directed and weighted)
    - A vertex without incoming edges known as the **source**
    - A vertex without outgoing edges known as the **target**/ destination



# Flow Network

## Transfer of content

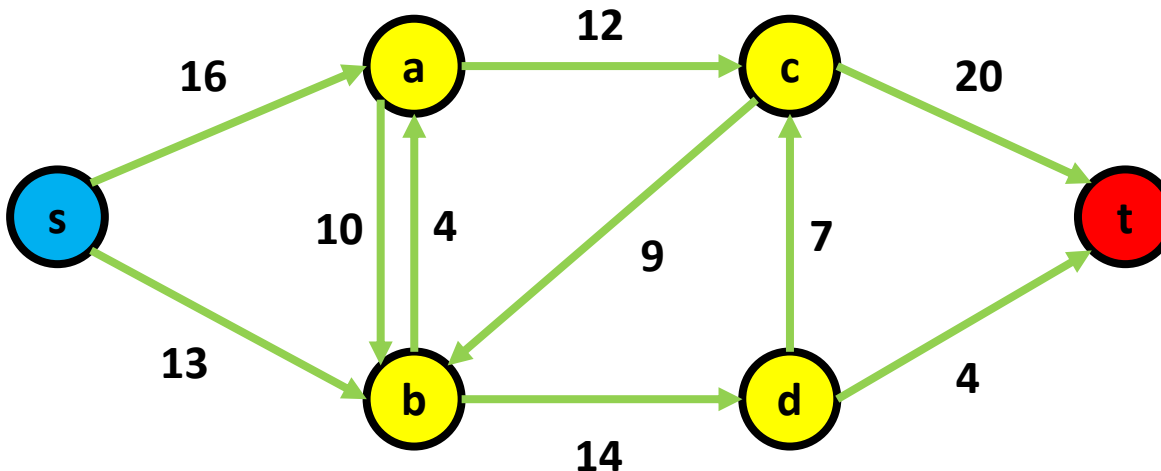
- What is it?
  - It is a graph
    - With vertices
    - With edges (directed and weighted non-negative known as capacity)
    - A vertex without incoming edges known as the source
    - A vertex without outgoing edges known as the target/ destination



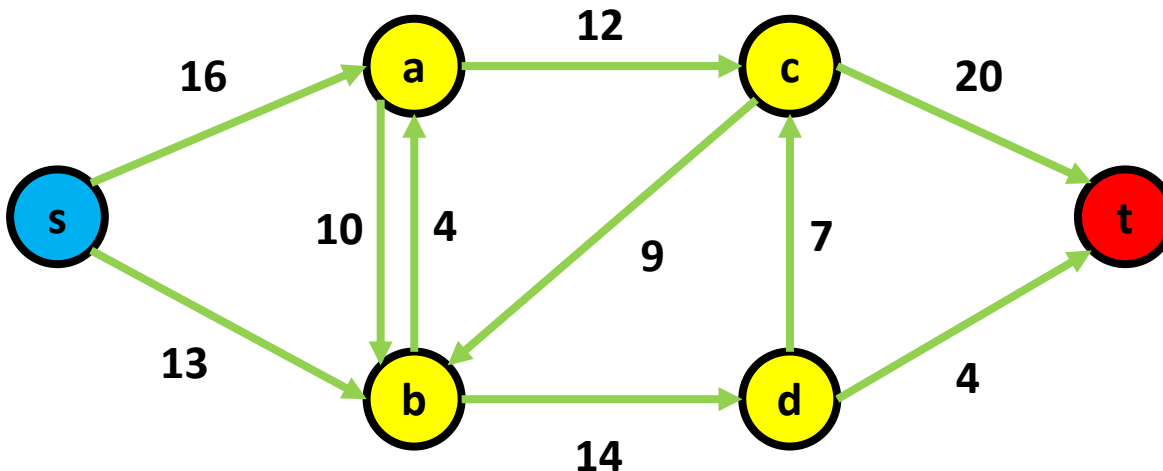
# Flow Network

## Transfer of content

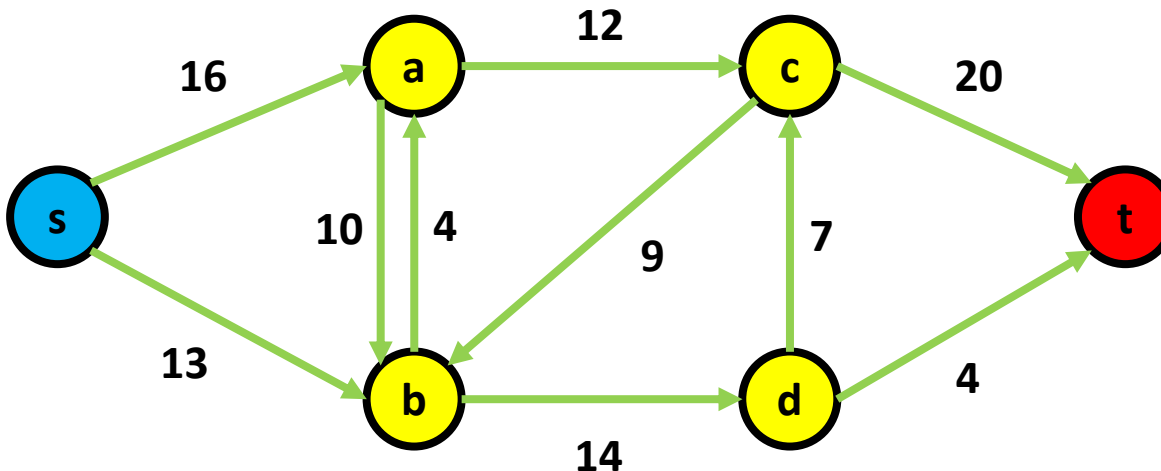
- What is it?
  - Explore the real world problem of transfer
    - From source
    - To destination



- What is it?
  - Explore the real world problem of transfer
    - From source
    - To destination
    - Within the capacity (which can be bottlenecks)



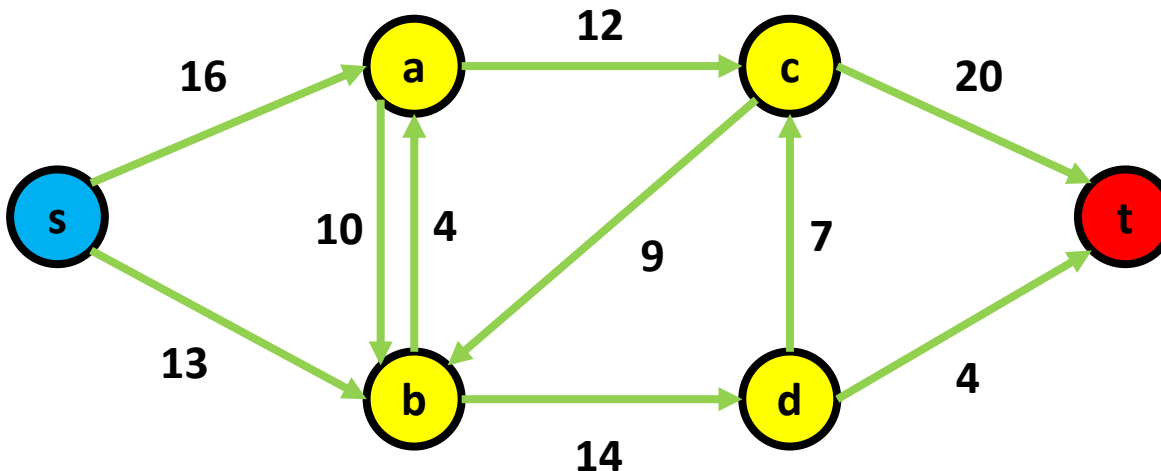
- What is it?
  - Explore the real world problem of transfer
    - From source
    - To destination
    - Within the capacity (which can be bottlenecks)
    - What is the maximum possible transfer of content?



# Flow Network

## Transfer of content

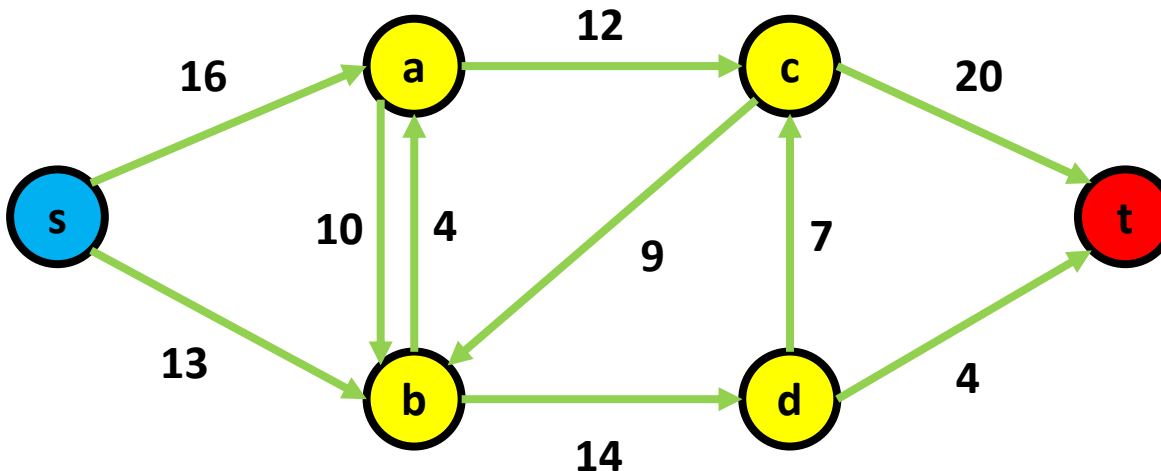
- What is it?
  - Explore the real world problem of transfer
    - From source
    - To destination
    - Within the capacity (which can be bottlenecks)
    - What is the maximum possible transfer of content? **Goal here**



# Flow Network

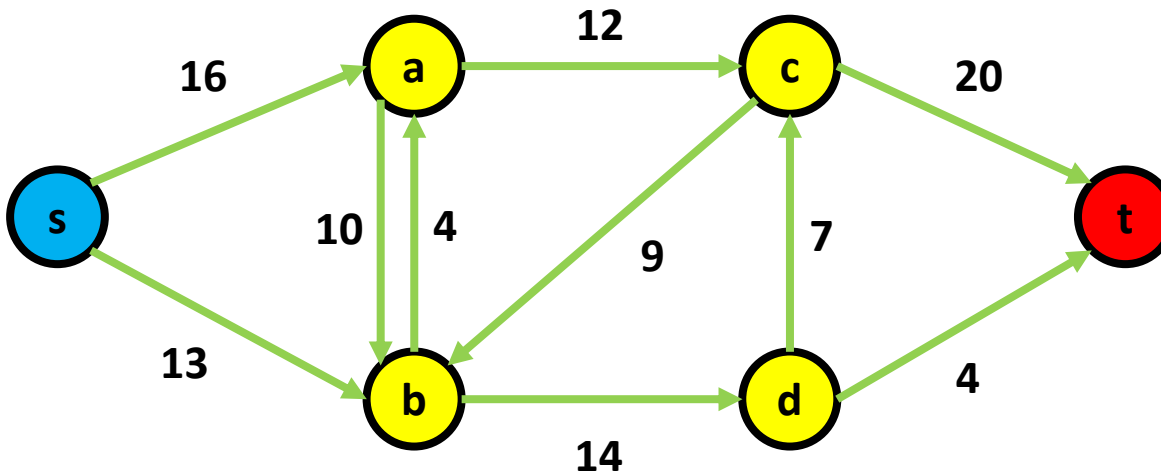
## Transfer of content

- We can get details from this graph
  - $E_{in}(b)$  = edges incoming to b
  - $E_{out}(b)$  = edges outgoing from b





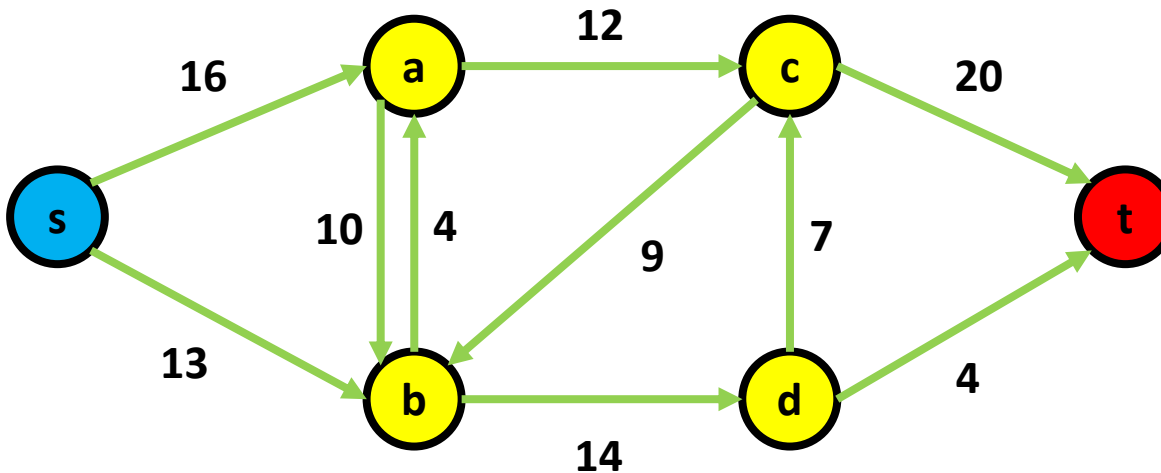
- We can get details from this graph
  - $E_{in}(b)$  = edges incoming to  $b$  =  $\langle s, b, 13 \rangle \langle a, b, 10 \rangle \langle c, b, 9 \rangle$
  - $E_{out}(b)$  = edges outgoing from  $b$  =  $\langle b, a, 4 \rangle \langle b, d, 14 \rangle$



# Flow Network

## Transfer of content

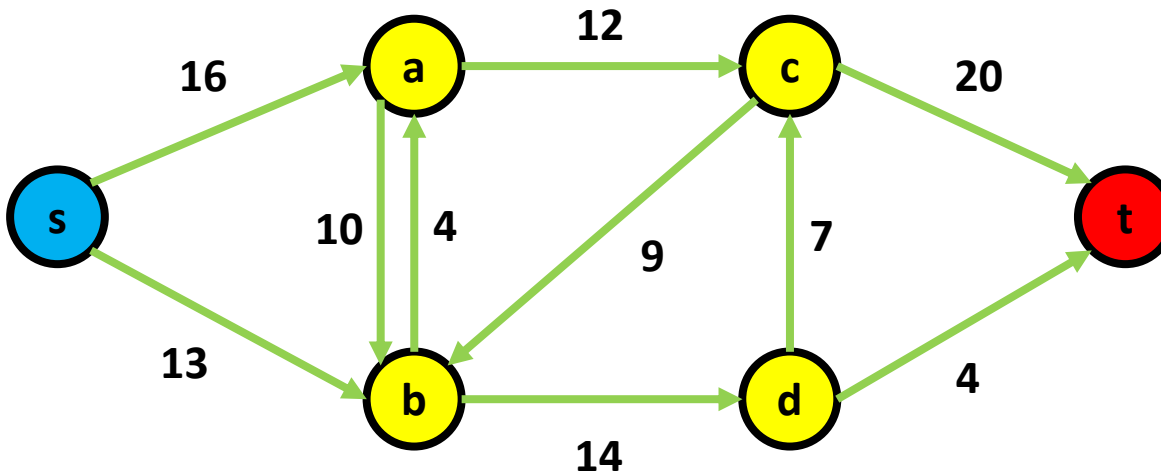
- Flow network model in real world



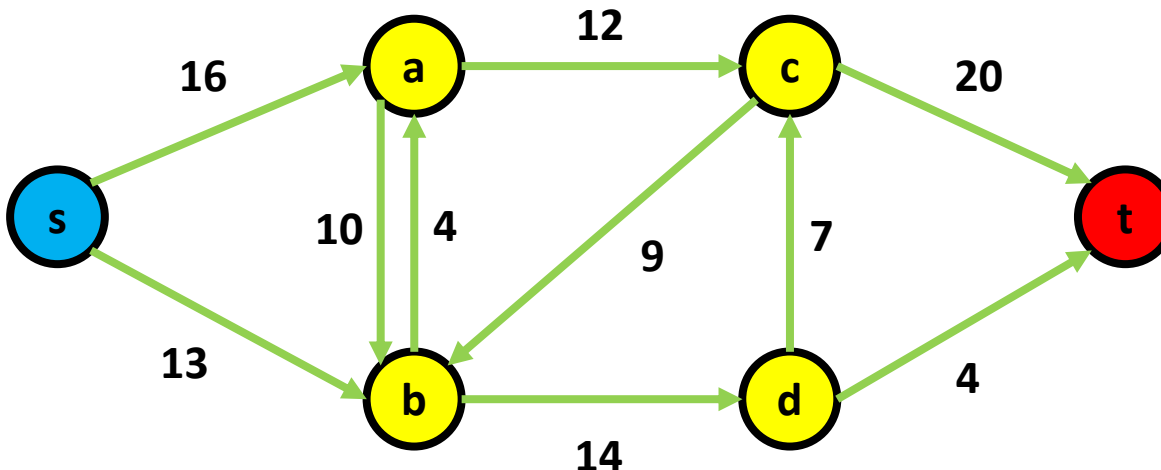
# Flow Network

## Transfer of content

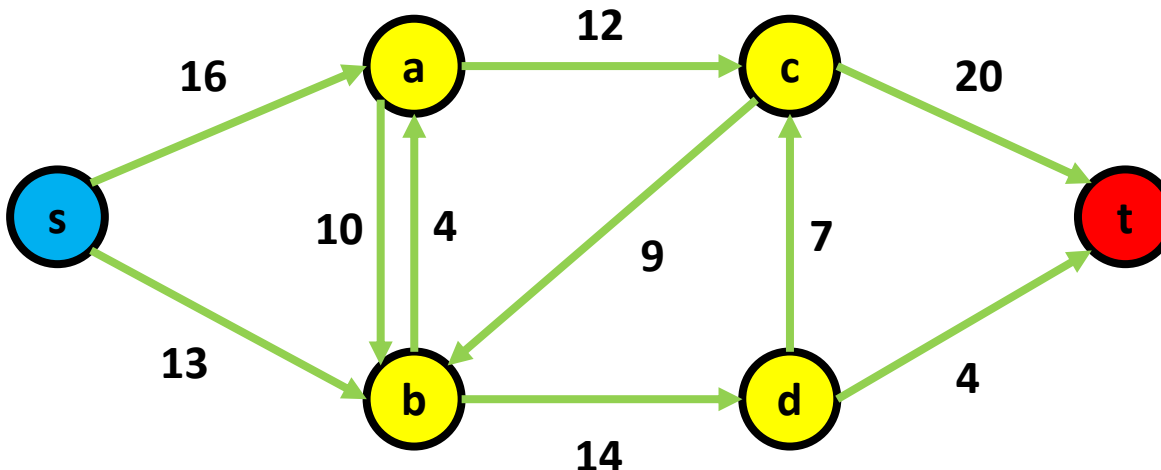
- Flow network model in real world
  - Water flow through pipes
  - Electric through electrical circuits
  - Information flow through communication network



- Flow network model in real world
  - Water flow through pipes
  - Electric through electrical circuits
  - Information flow through communication network
  - And many more! We can design good networks #engineered



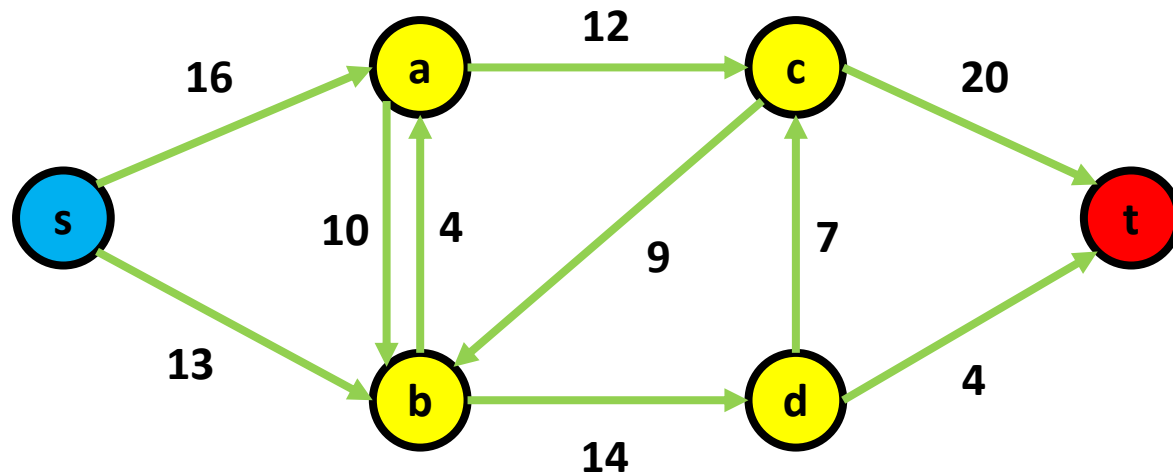
- Flow network model in real world
  - Water flow through pipes
  - Electric through electrical circuits
  - Information flow through communication network
  - And many more! We can design good networks #engineered
  - Was mainly used in WW2 to **disrupt enemy supply lines**



Questions?

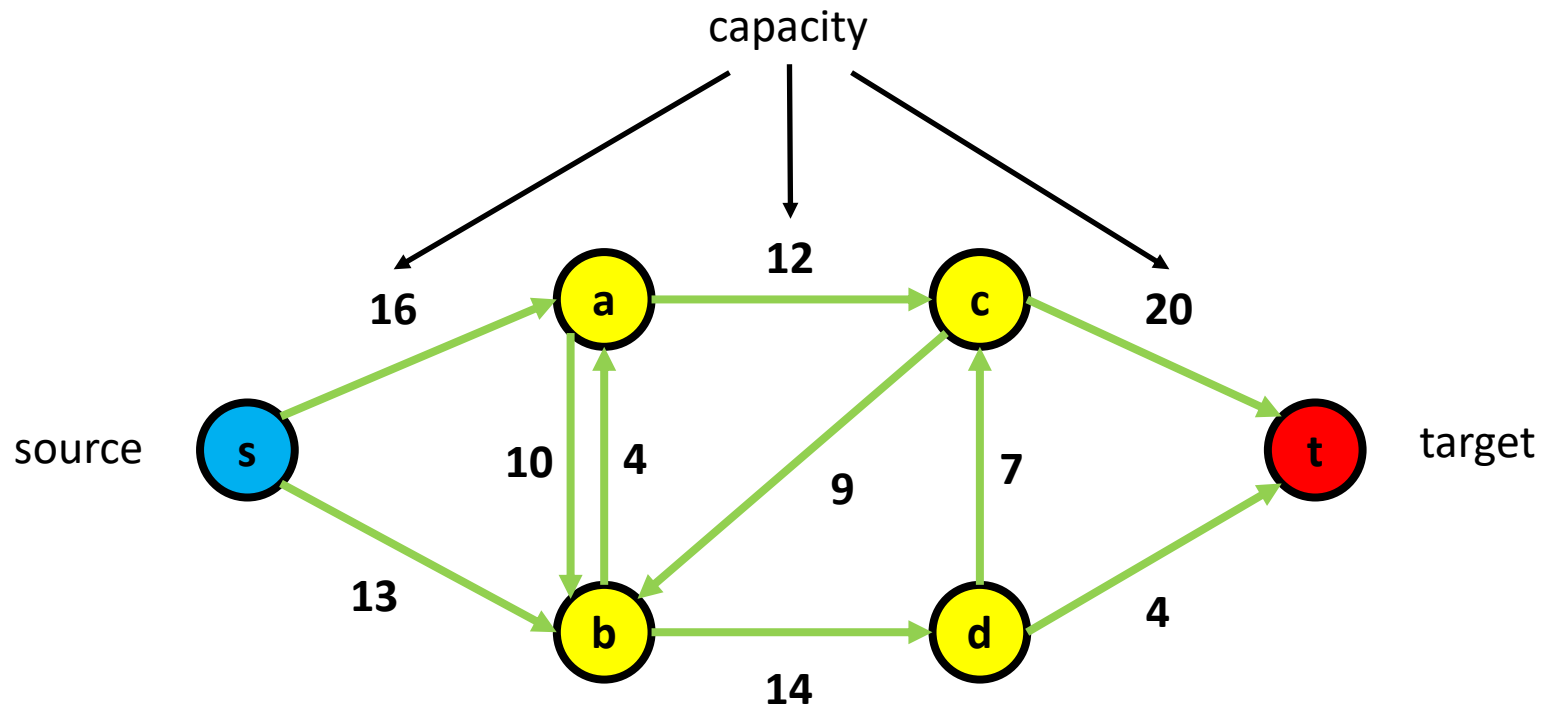
# Recap

## Of flow network



# Recap

## Of flow network

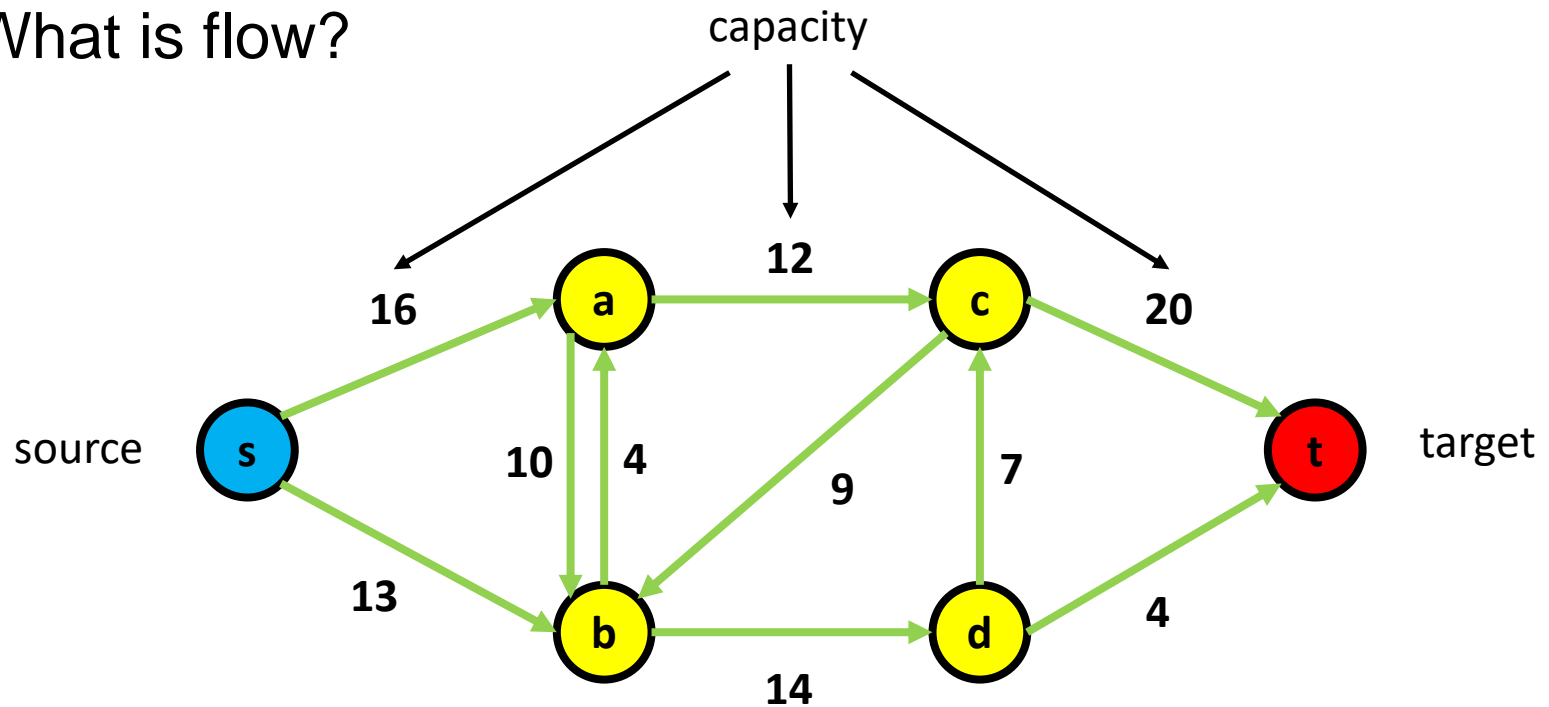




# Flow Network

## Transfer of content

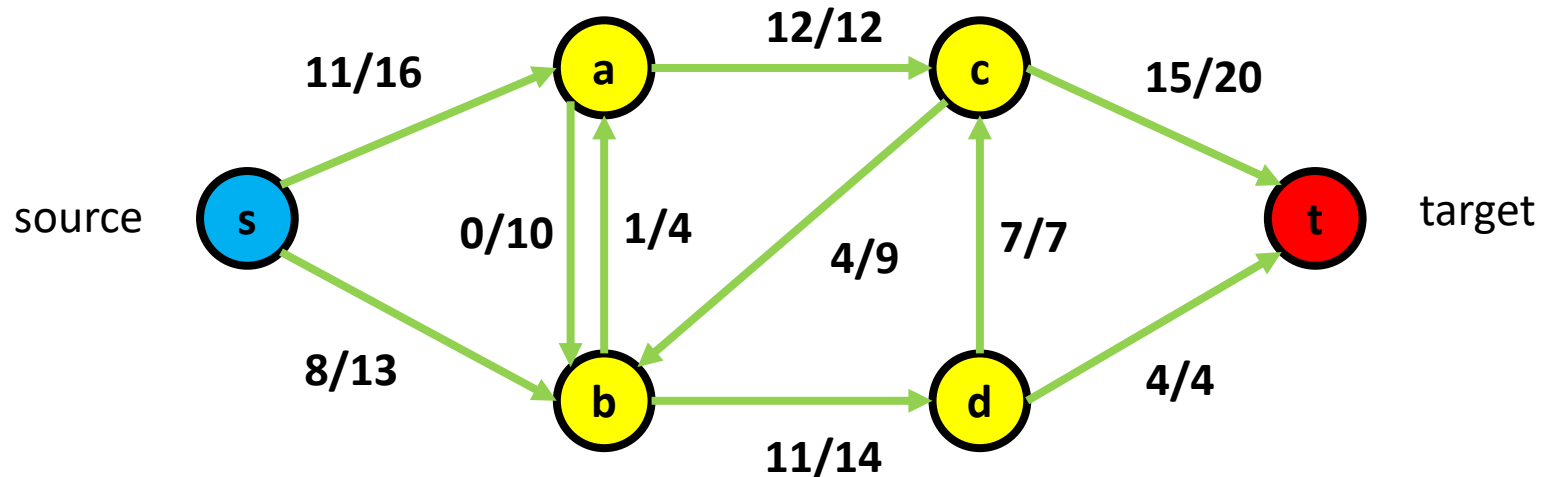
- What is flow?



# Flow Network

## Transfer of content

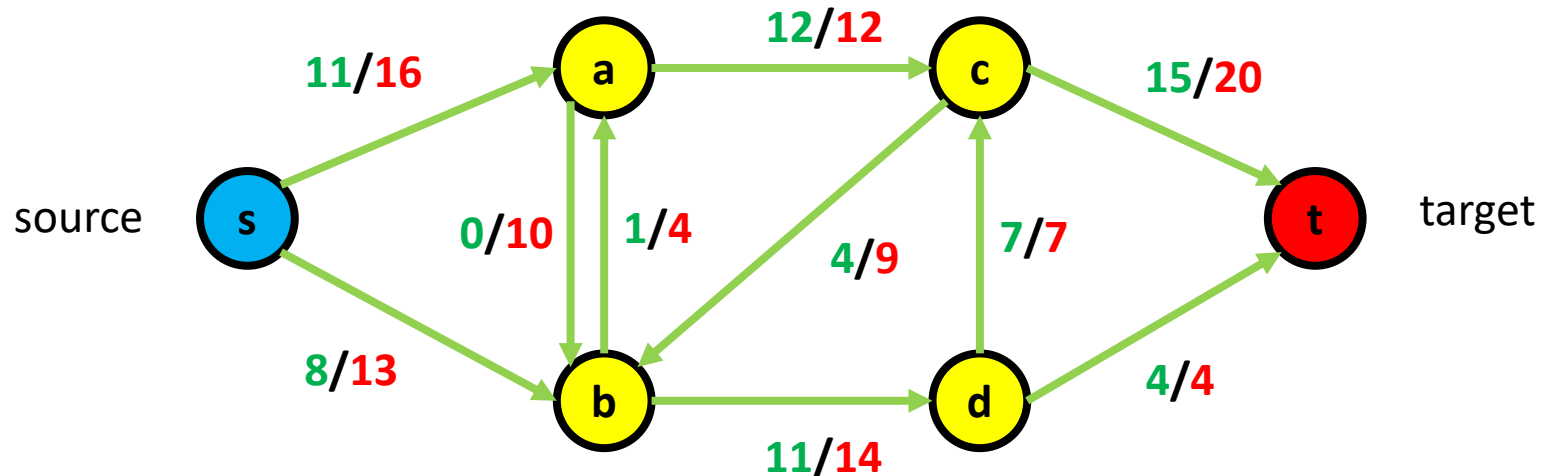
- What is **flow**?
- What is **capacity**?



# Flow Network

## Transfer of content

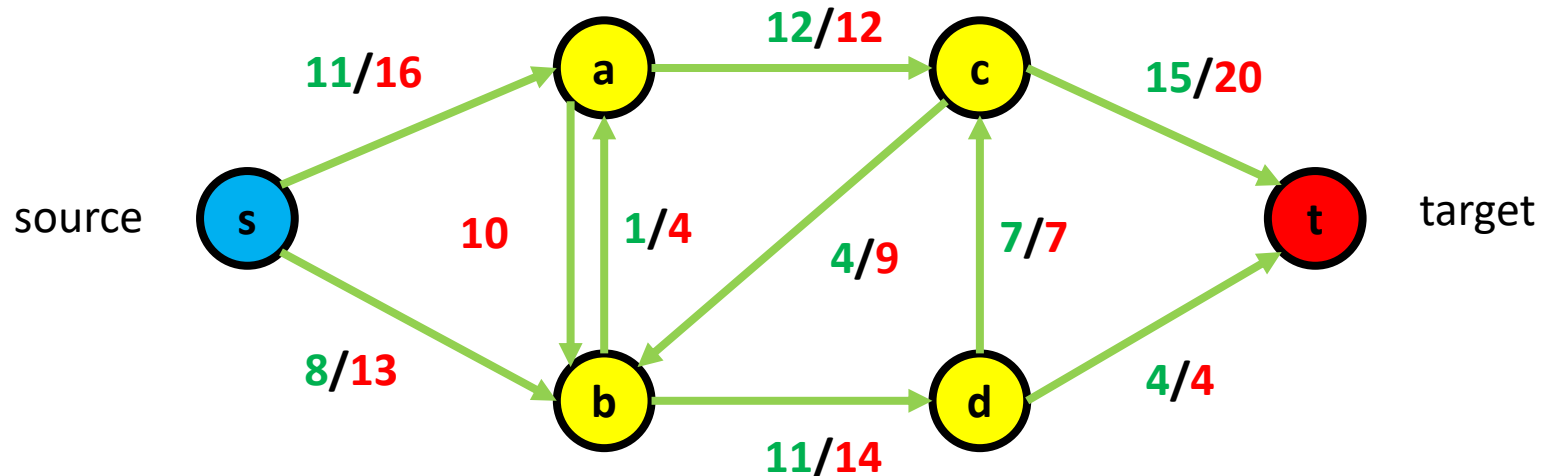
- What is **flow**?
- What is **capacity**?



# Flow Network

## Transfer of content

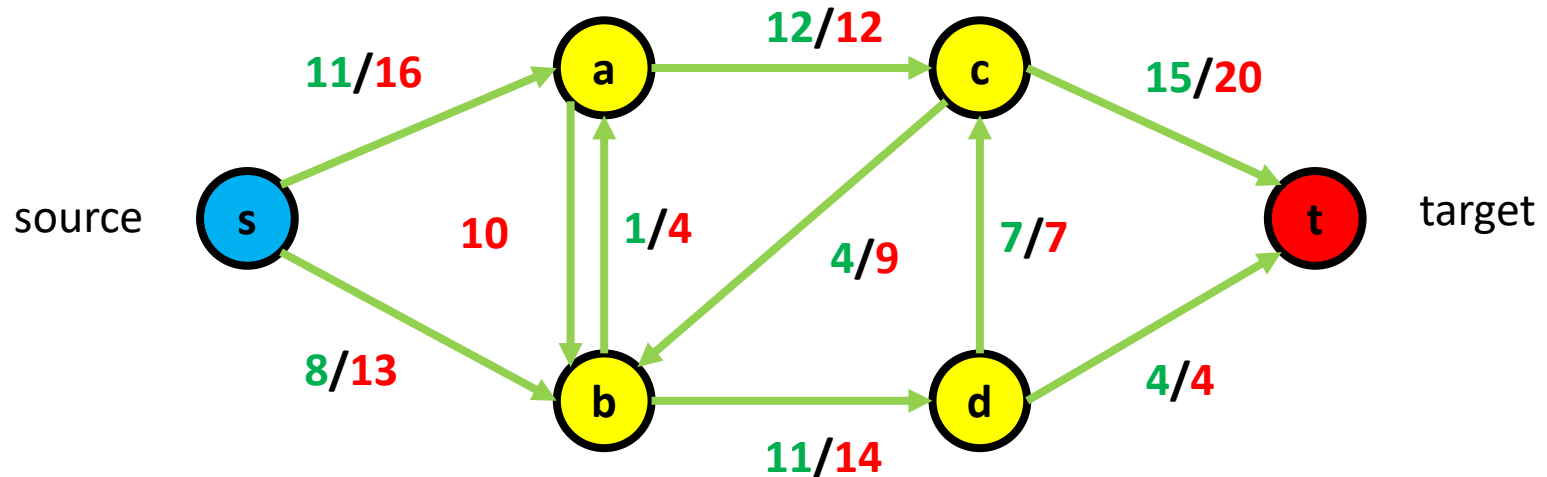
- What is **flow**?
  - If there is **no flow**, you can **exclude it**
  - It is how **much material flowing through each edge**
- What is **capacity**?



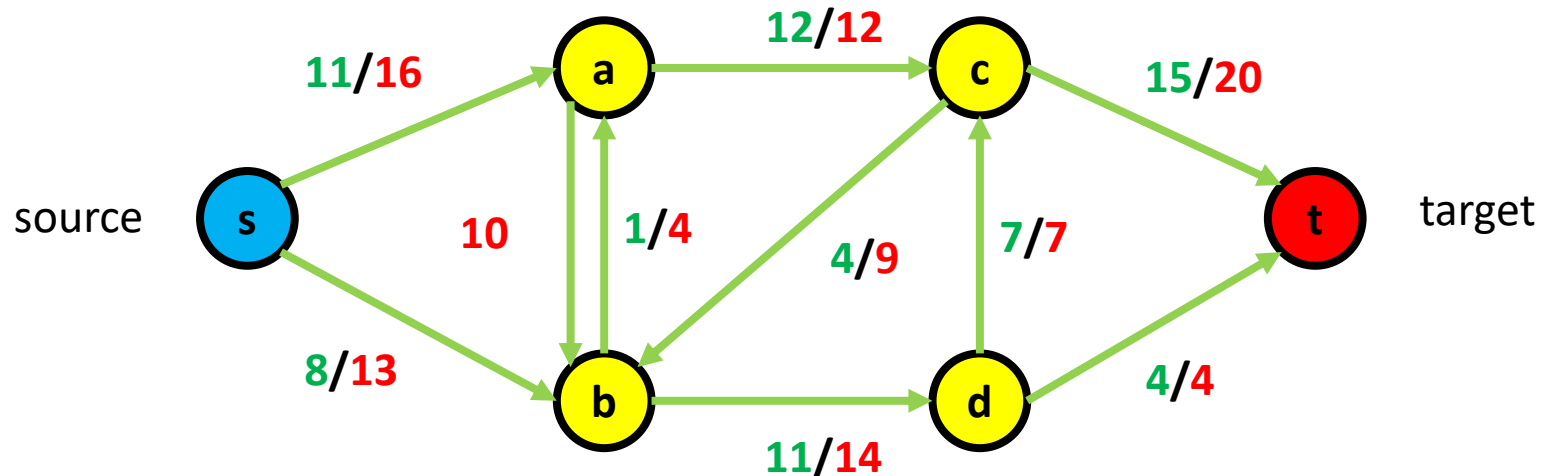
# Flow Network

## Transfer of content

- Flow constraint property



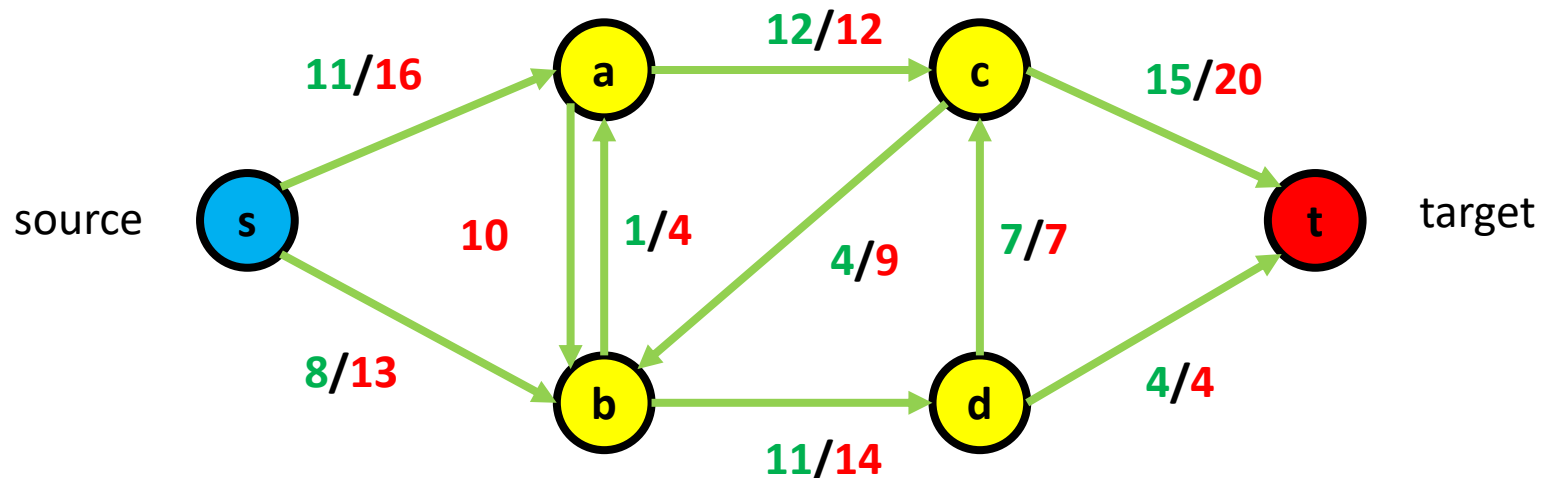
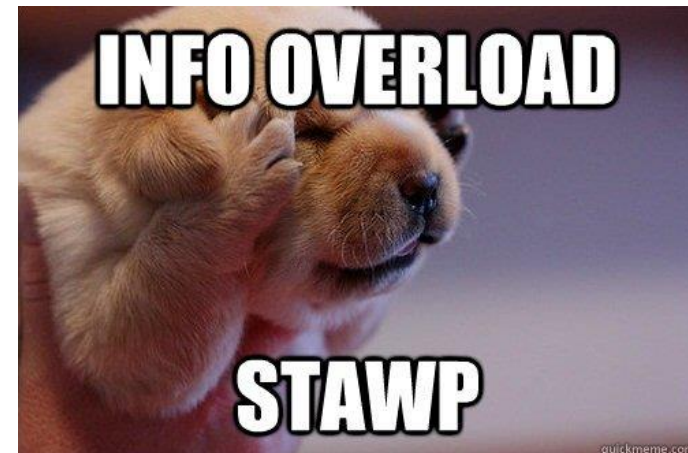
- Flow constraint property
  - For each edge, the flow can't be more than the capacity of the edge



# Flow Network

## Transfer of content

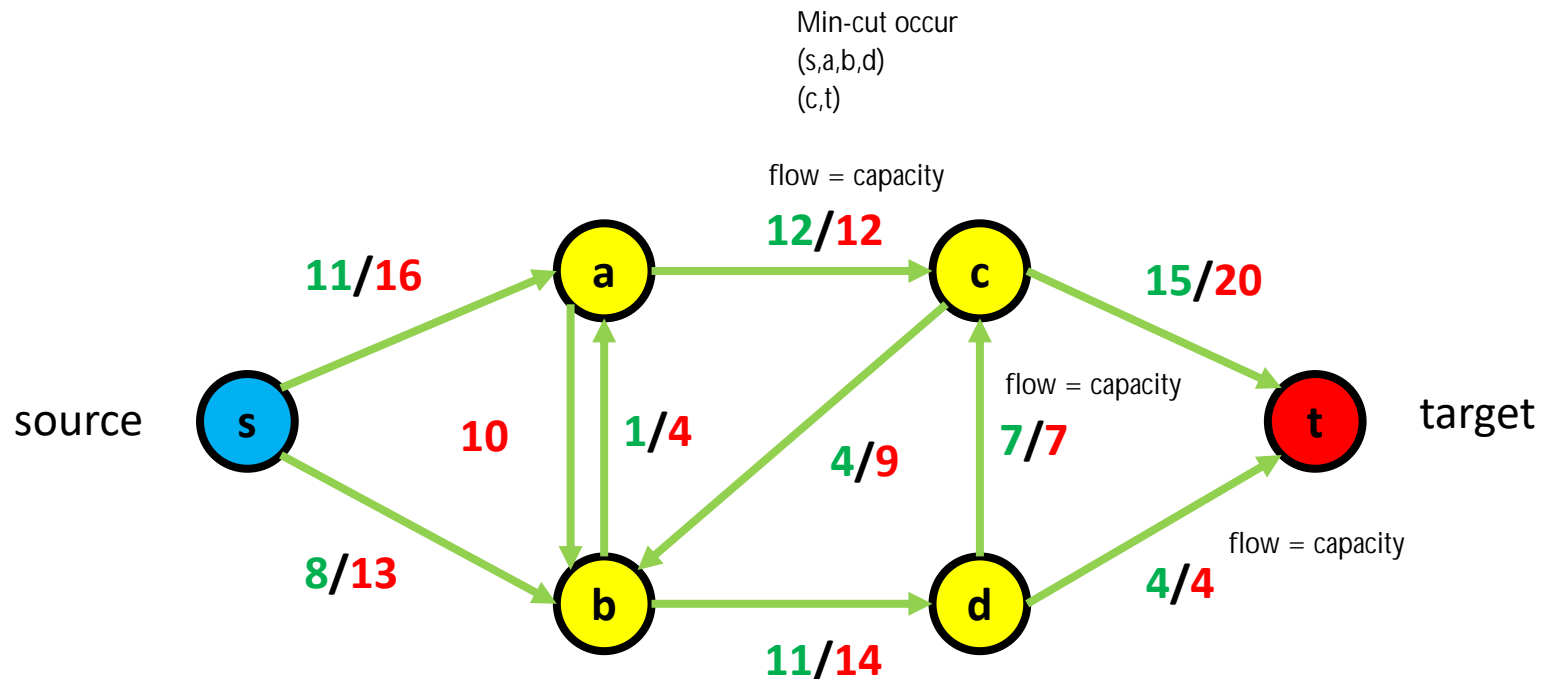
- Flow constraint property
  - For each edge, the flow can't be more than the capacity of the edge
  - In other words, you can't overload



# Flow Network

## Transfer of content

- Flow conservation property

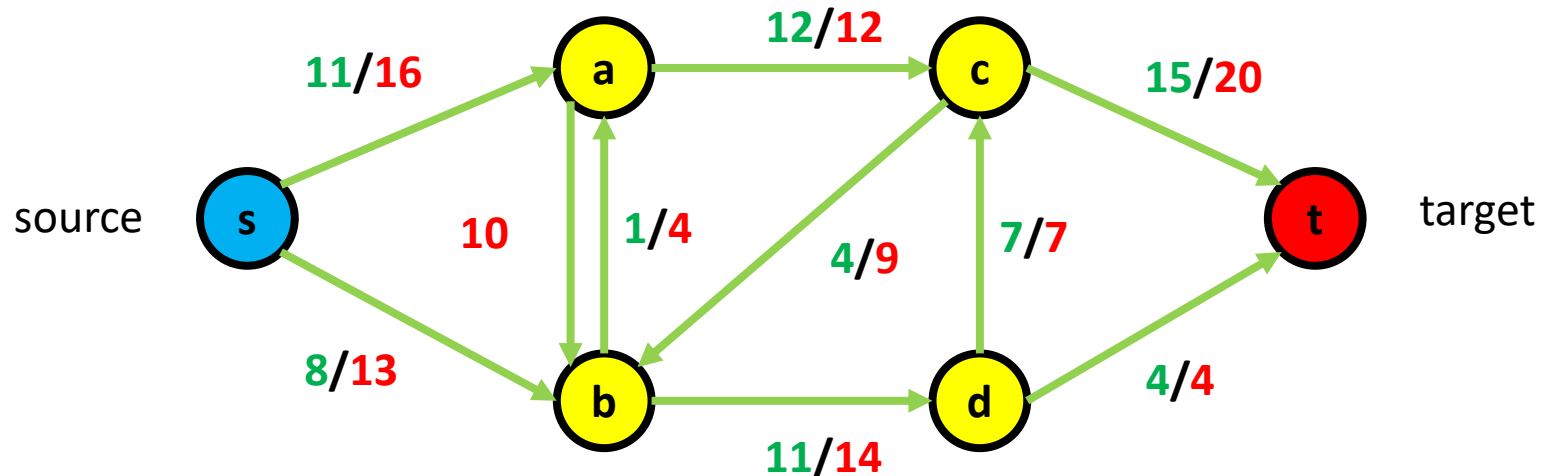




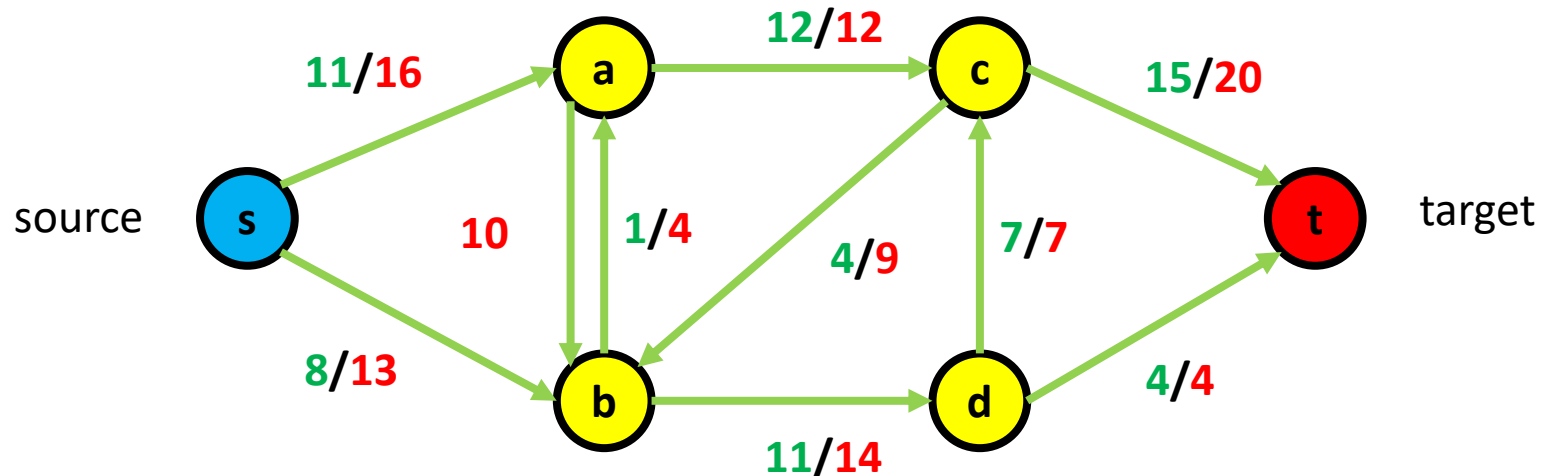
# Flow Network

## Transfer of content

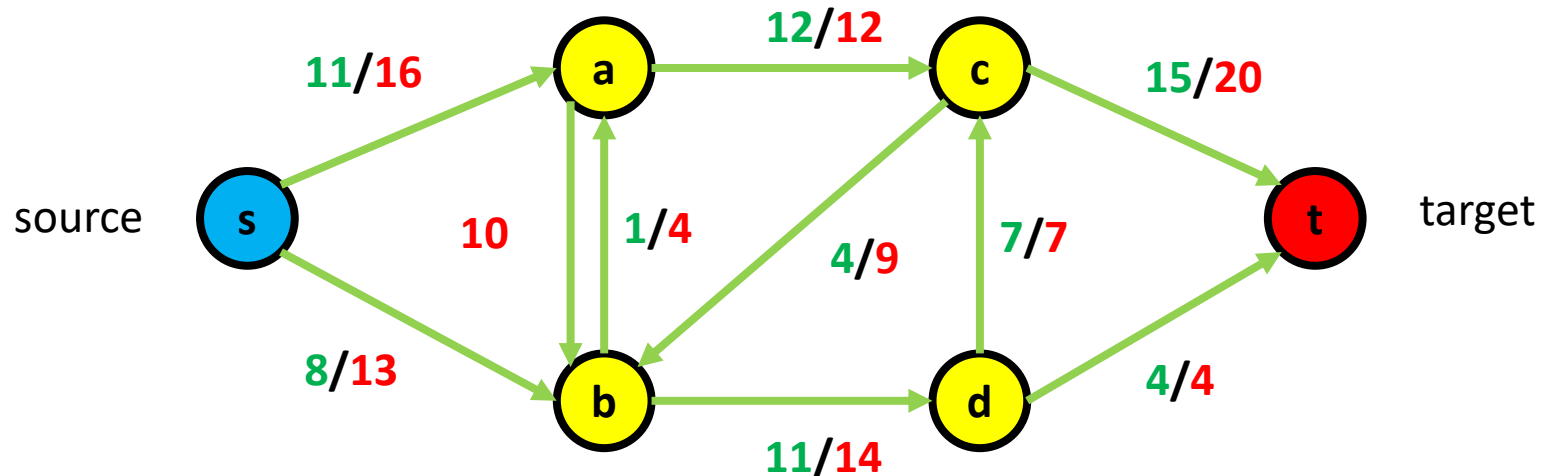
- Flow conservation property
  - For every vertex in the graph (except source and target)
  - incoming flow == outgoing flow



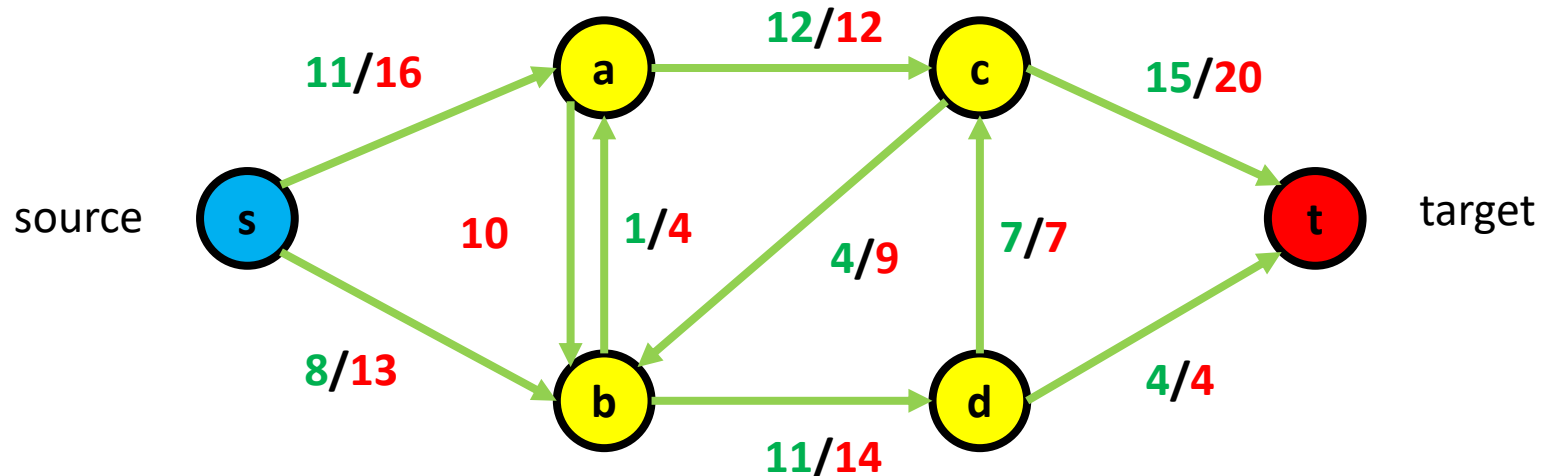
- Flow conservation property
  - For every vertex in the graph (except source and target)
  - total incoming flow == total outgoing flow



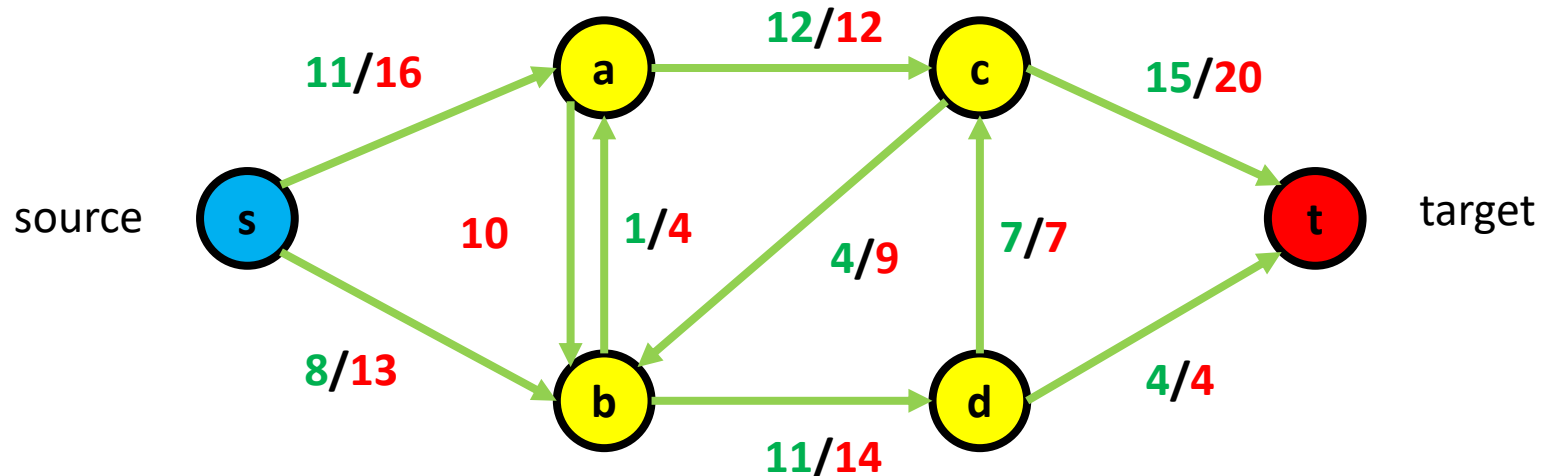
- Flow conservation property
  - For every vertex in the graph (except source and target)
  - total incoming flow == total outgoing flow
  - What is the total incoming flow to vertex b?



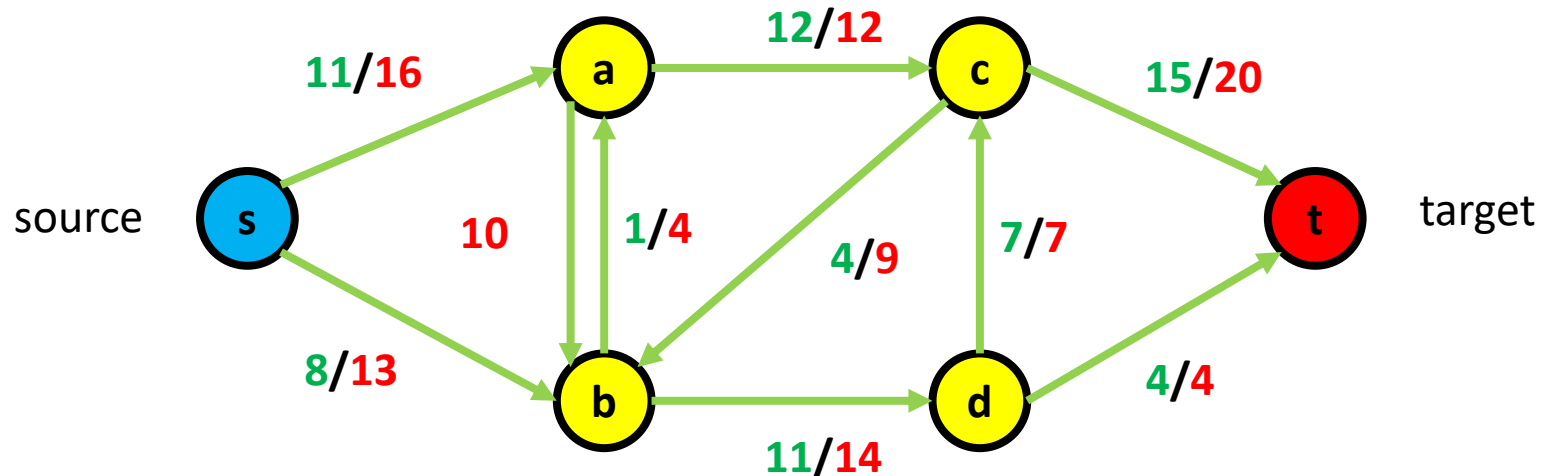
- Flow conservation property
  - For every vertex in the graph (except source and target)
  - total incoming flow == total outgoing flow
  - What is the total incoming flow to vertex b? 12



- Flow conservation property
  - For every vertex in the graph (except source and target)
  - total incoming flow == total outgoing flow
  - What is the total incoming flow to vertex b? 12
  - What is the total outgoing flow to vertex b?



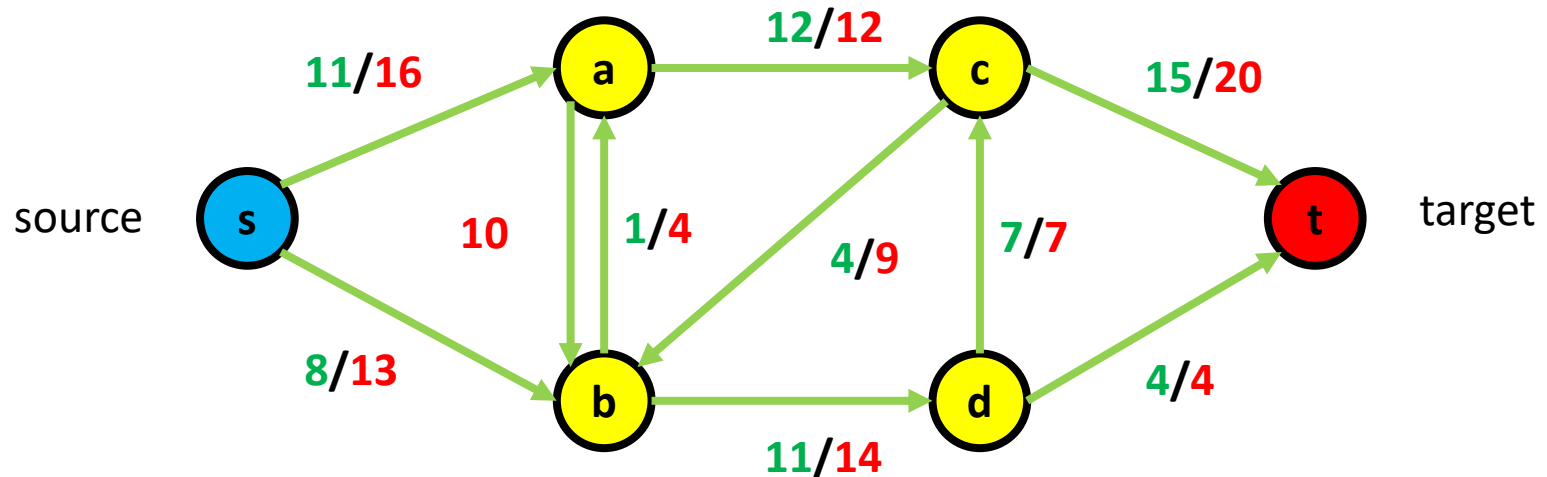
- Flow conservation property
  - For every vertex in the graph (except source and target)
  - total incoming flow == total outgoing flow
  - What is the total incoming flow to vertex b? 12
  - What is the total outgoing flow to vertex b? 12



# Flow Network

## Transfer of content

- Capacity constraint
- Flow conservation property



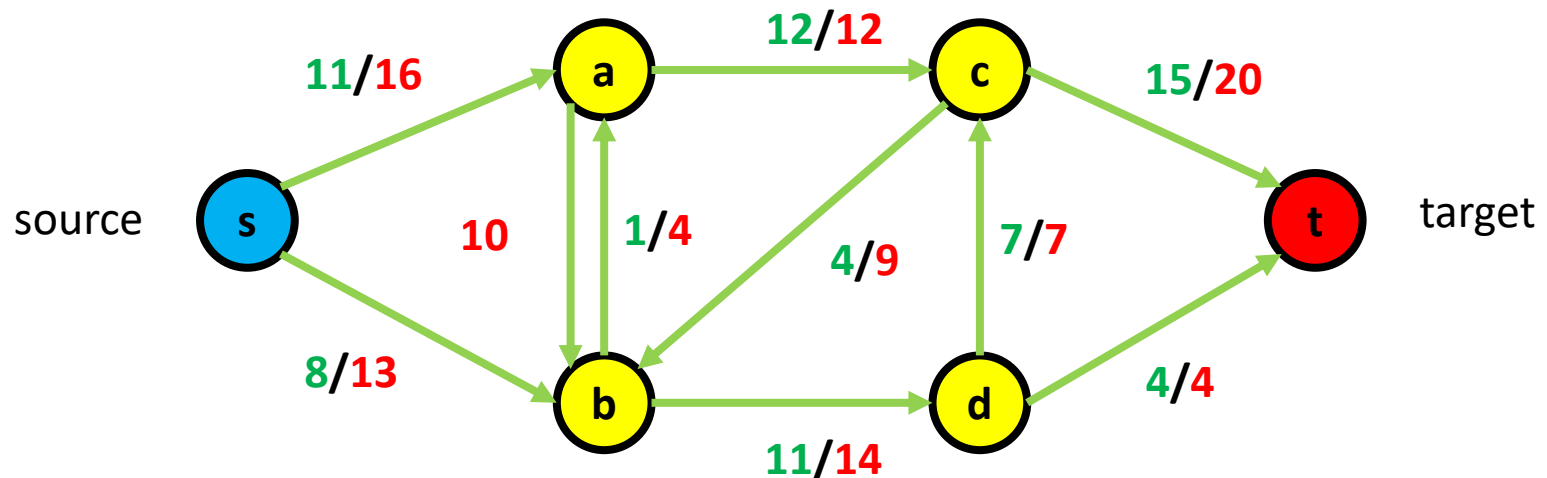
Questions?



# Maximum-Flow Problem

Best network?

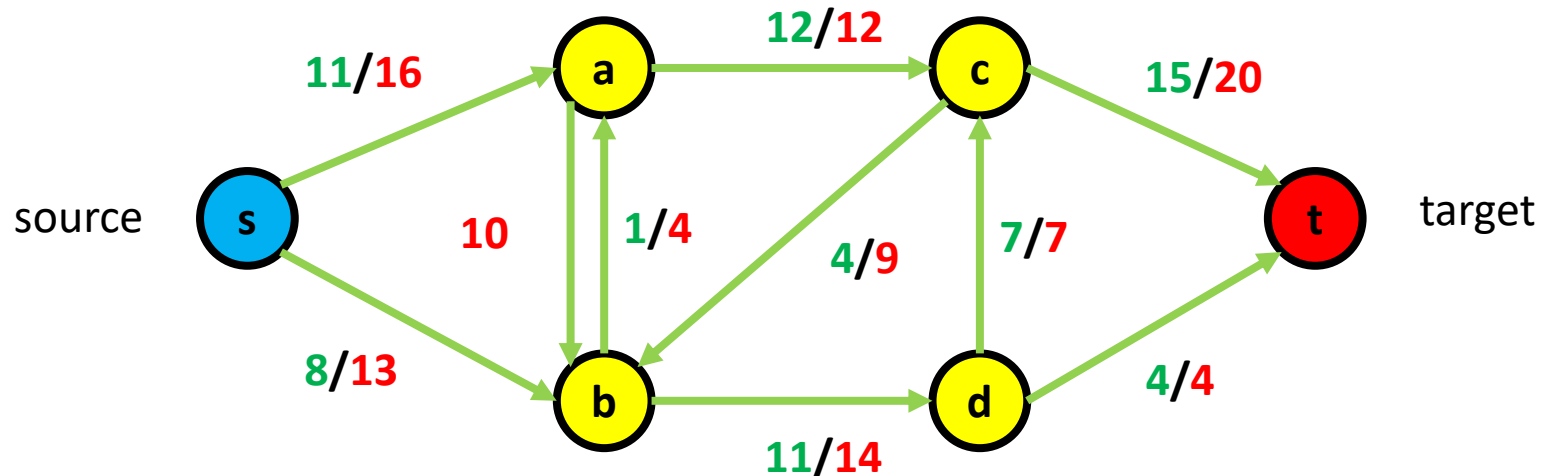
- What is the flow of the network?



# Maximum-Flow Problem

Best network?

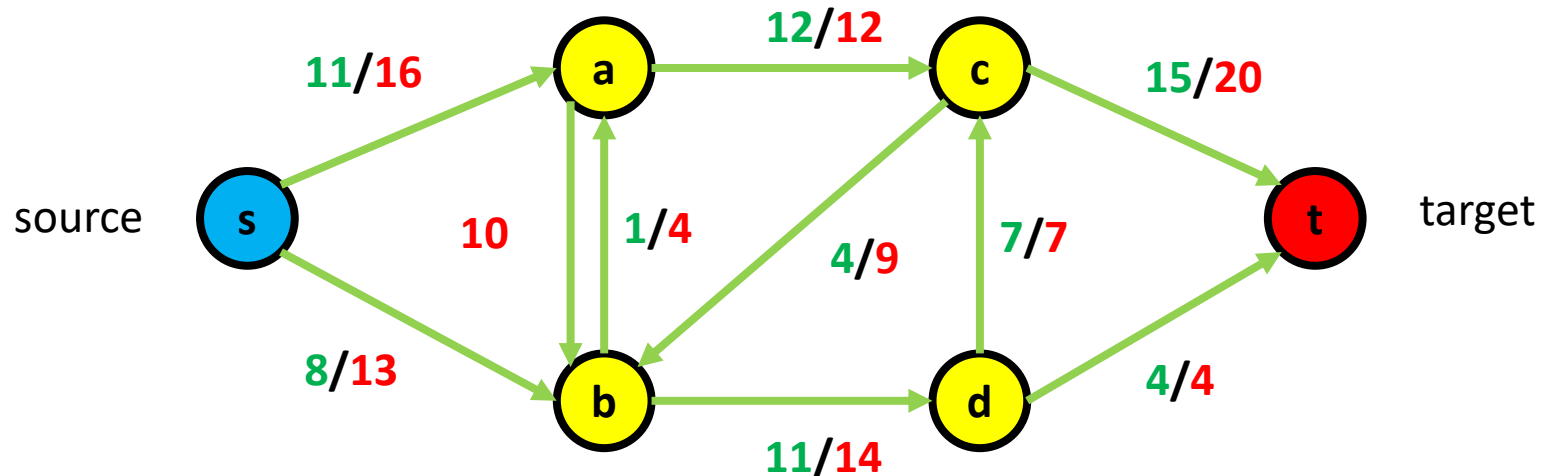
- What is the flow of the network? **19**
  - Total flow out of source vertex
  - Total flow into target vertex



# Maximum-Flow Problem

## Best network?

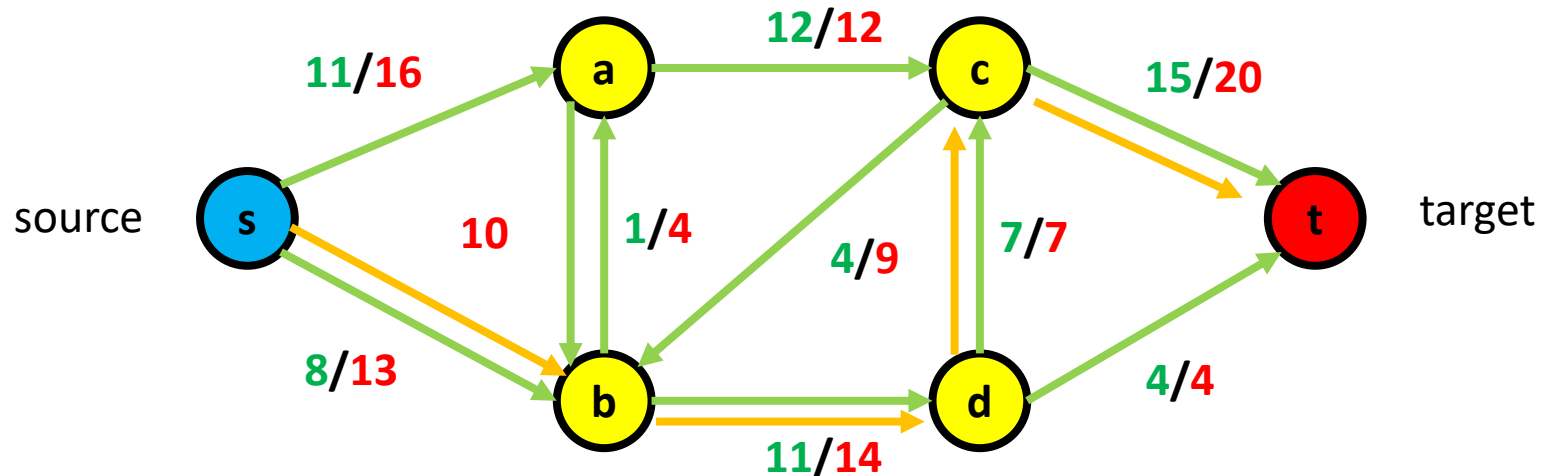
- What is the flow of the network? 19
  - Total flow out of source vertex
  - Total flow into target vertex
- Is this the maximum possible flow for this network?



# Maximum-Flow Problem

## Best network?

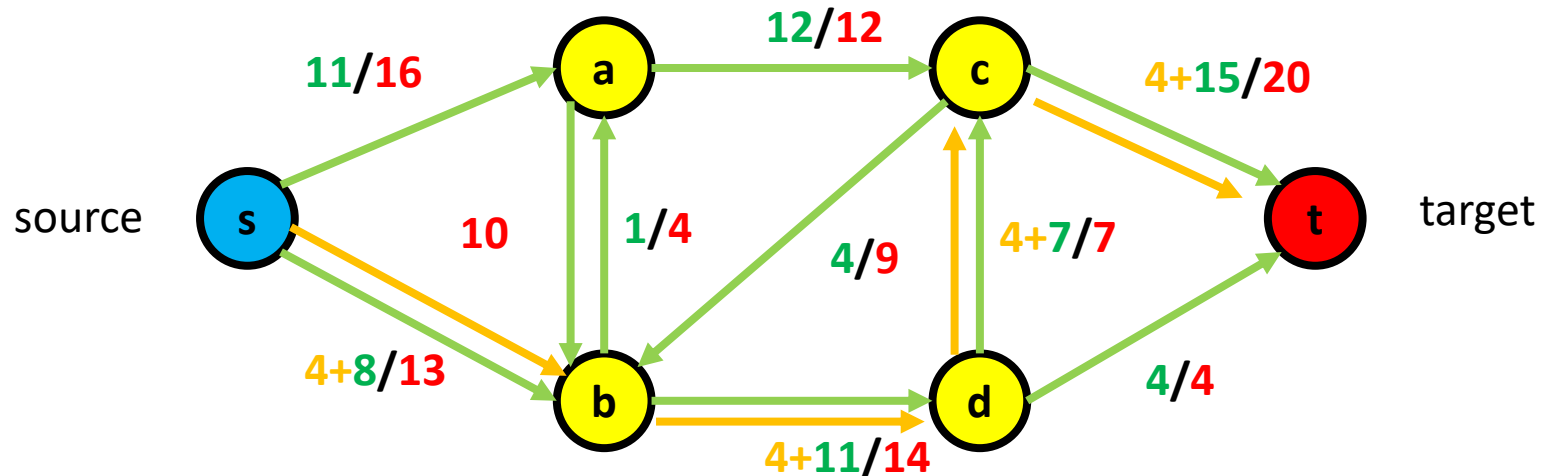
- Is this the maximum possible flow for this network?
  - We can push in 4 more through the following route...



# Maximum-Flow Problem

## Best network?

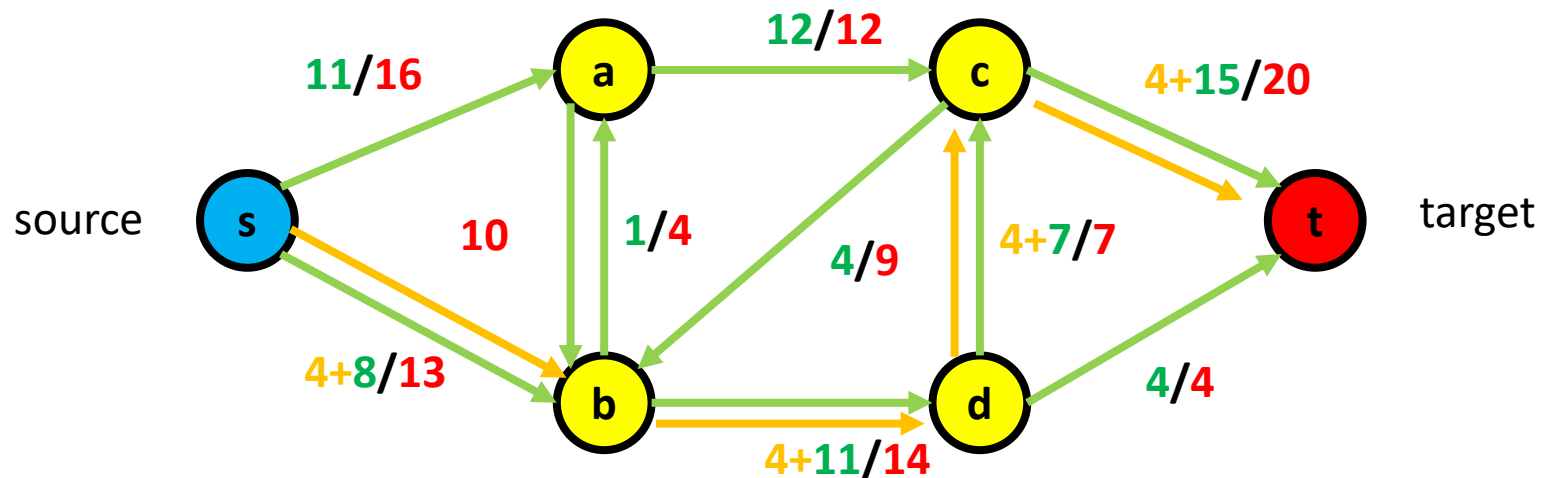
- Is this the **maximum possible flow** for this network?
  - We can push in 4 more through the following route...



# Maximum-Flow Problem

## Best network?

- Is this the maximum possible flow for this network?
  - We can push in 4 more through the following route... we cant! Cause over capacity...

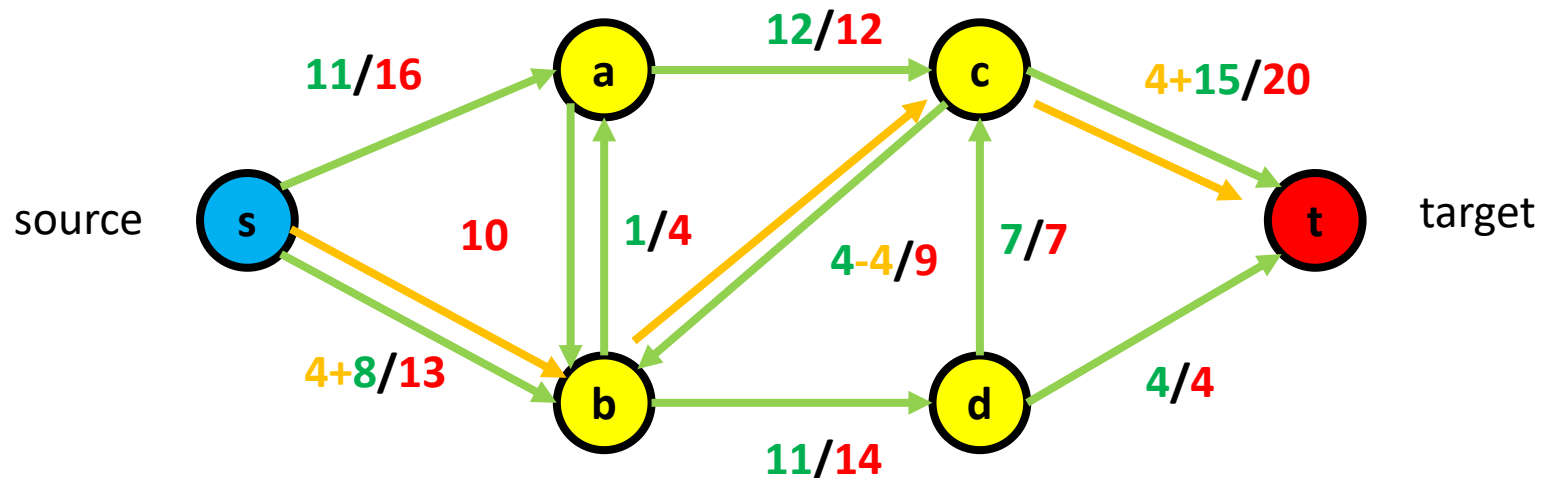


15 > 14 , capacity constraint principle

# Maximum-Flow Problem

## Best network?

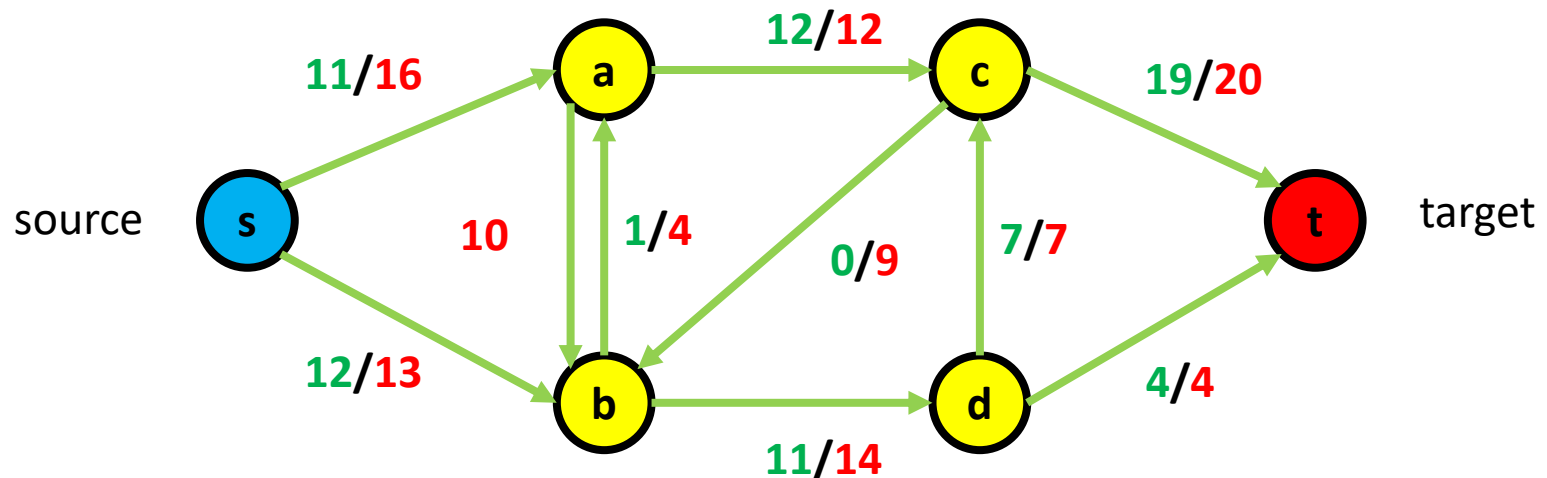
- Is this the maximum possible flow for this network?
  - We can push in 4 more through the following route... but we can do this, **not accepting the opposite...**



# Maximum-Flow Problem

## Best network?

- Is this the maximum possible flow for this network? 23!
  - We can push in 4 more through the following route... but we can do this, not accepting the opposite...

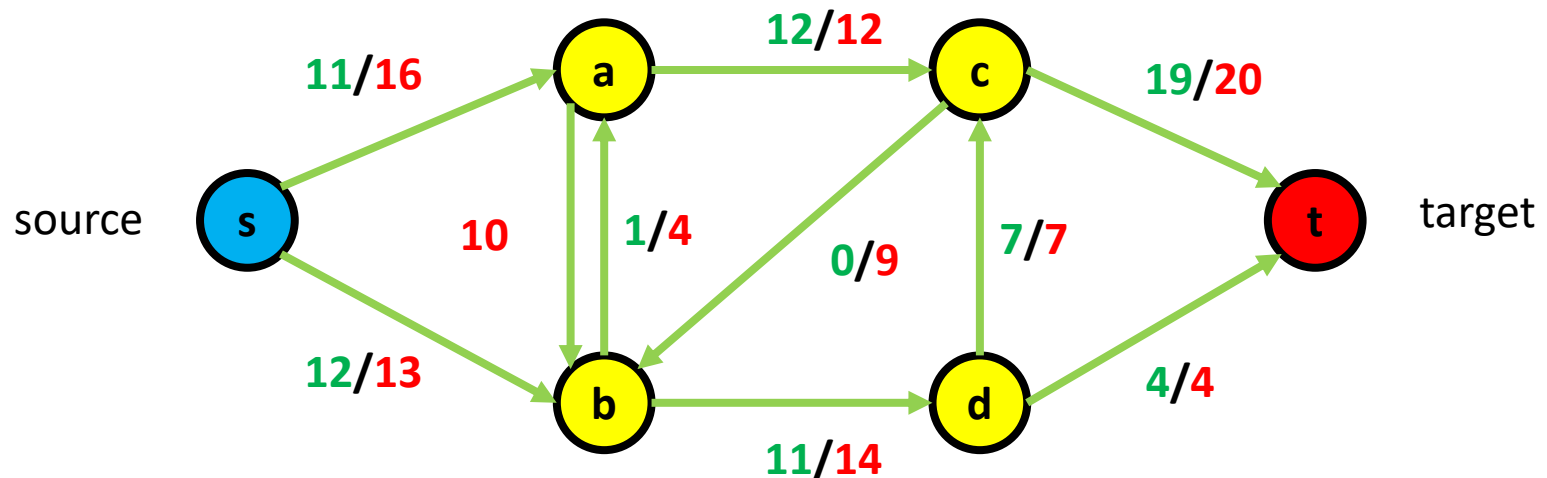




# Maximum-Flow Problem

## Best network?

- Is this the maximum possible flow for this network? 23!
  - We can push in 4 more through the following route... but we can do this, not accepting the opposite...
- Is this easy to do?
  - No of course, but we in CS to make it easy!



Questions?

# Ford-Fulkerson Method

## Finding the maximum flow of network

- What we use to find the maximum flow



# Ford-Fulkerson Method

## Finding the maximum flow of network

- What we use to find the maximum flow



# Ford-Fulkerson Method

## Finding the maximum flow of network

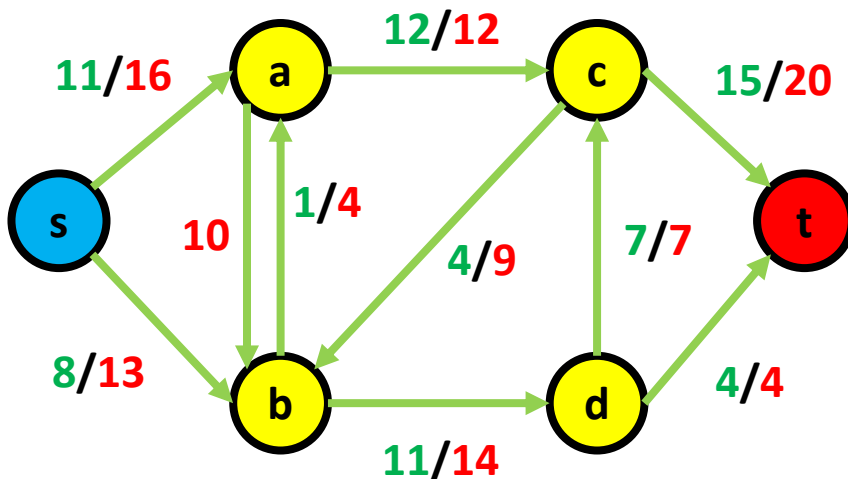
- Residue network first...



# Residual network

Another freaking network

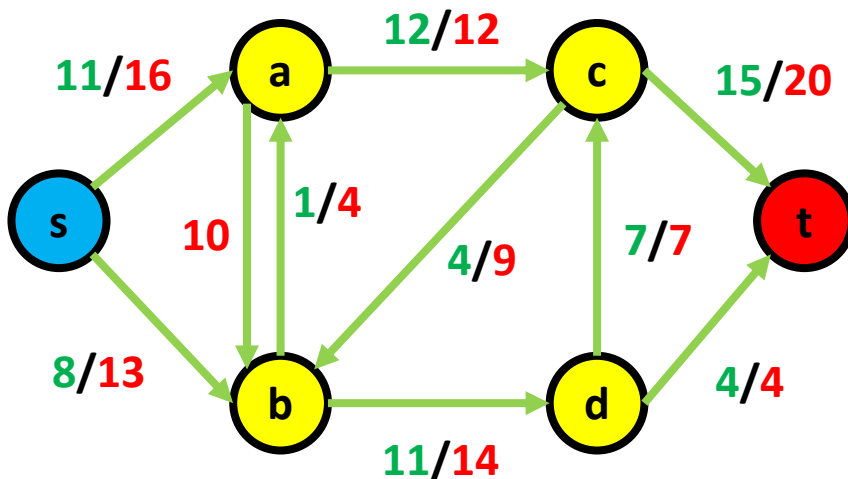
- Consider the following graph (same as earlier)



# Residual network

## Another freaking network

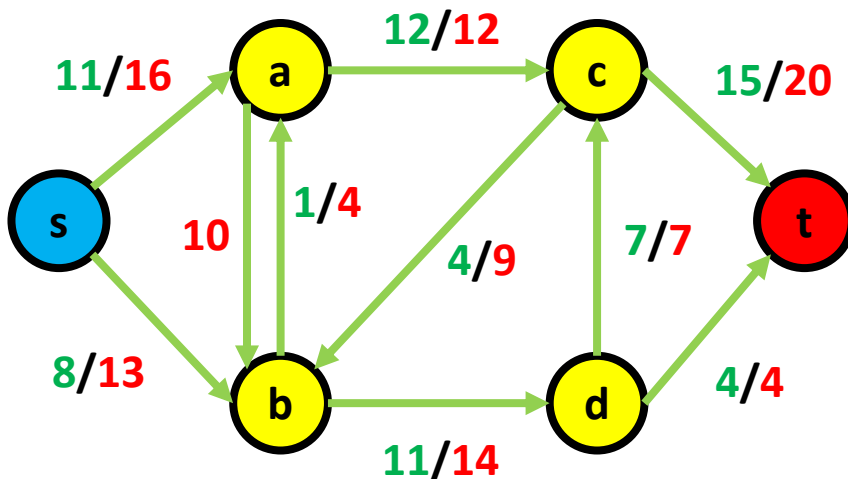
- Consider the following graph (same as earlier)
  - Can you make a residual network?



# Residual network

Another freaking network

- What is a residual network?

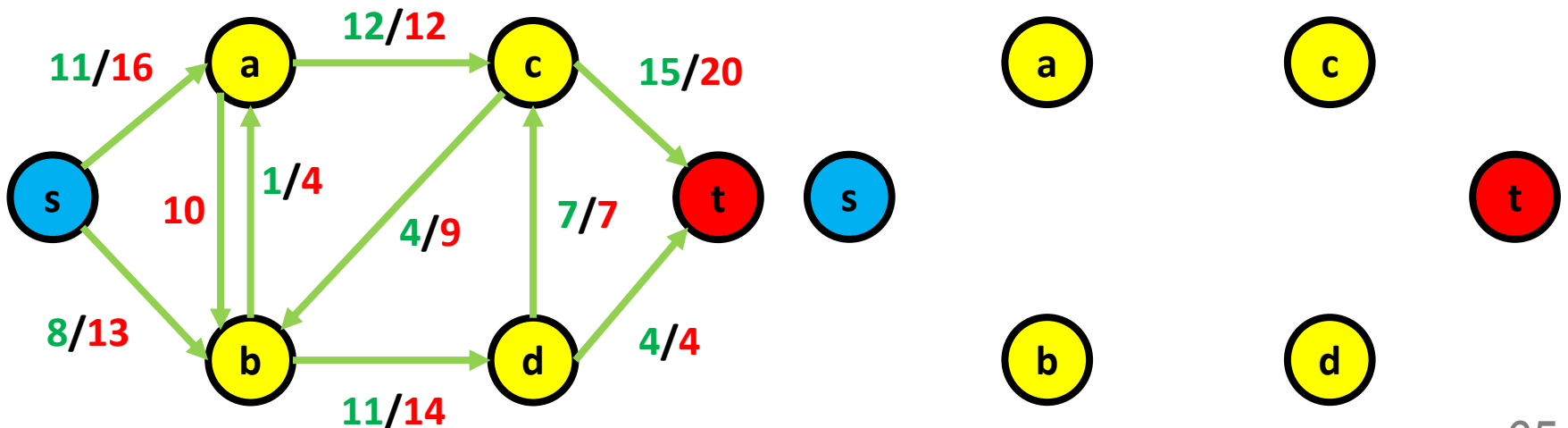




# Residual network

## Another freaking network

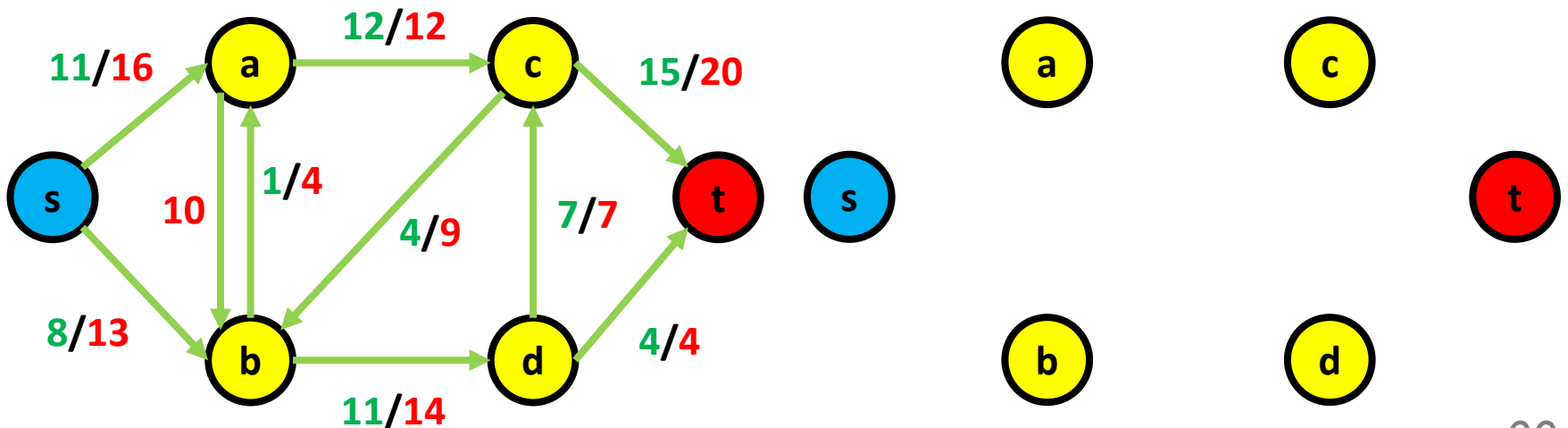
- What is a residual network?
  - Same vertices



# Residual network

## Another freaking network

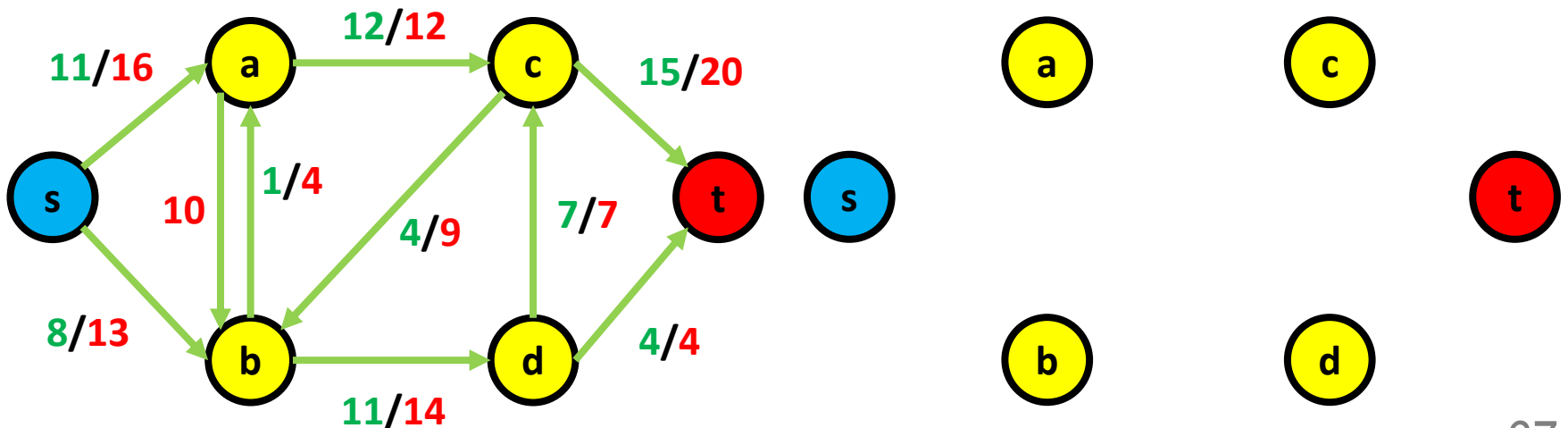
- What is a residual network?
  - Same vertices
  - Forward edge/ residual edge



# Residual network

## Another freaking network

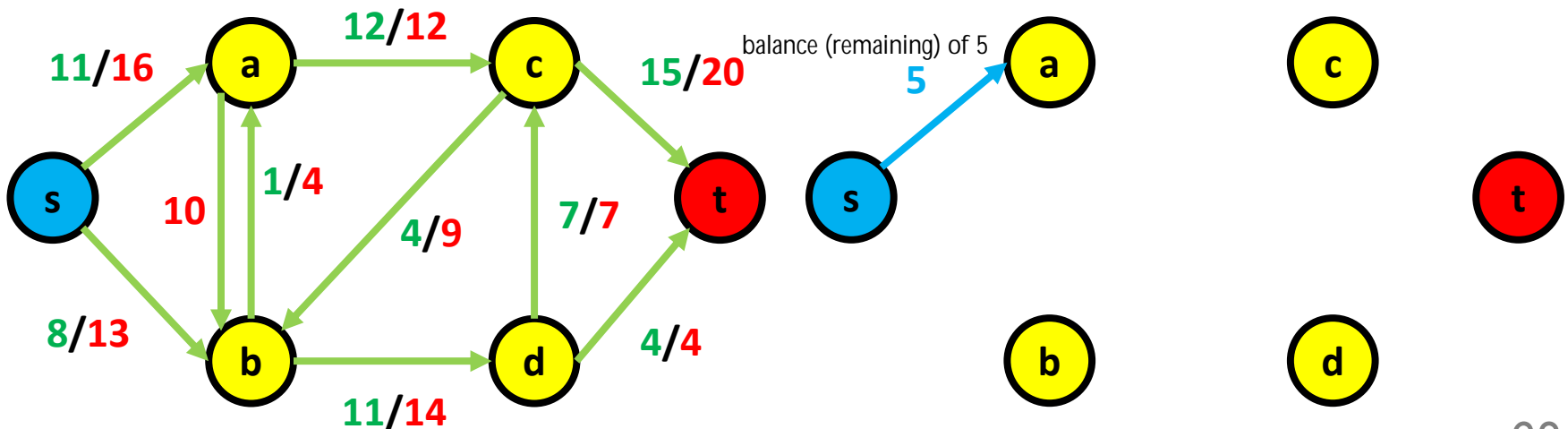
- What is a residual network?
  - Same vertices
  - Forward edge/ residual edge for remaining capacity



# Residual network

## Another freaking network

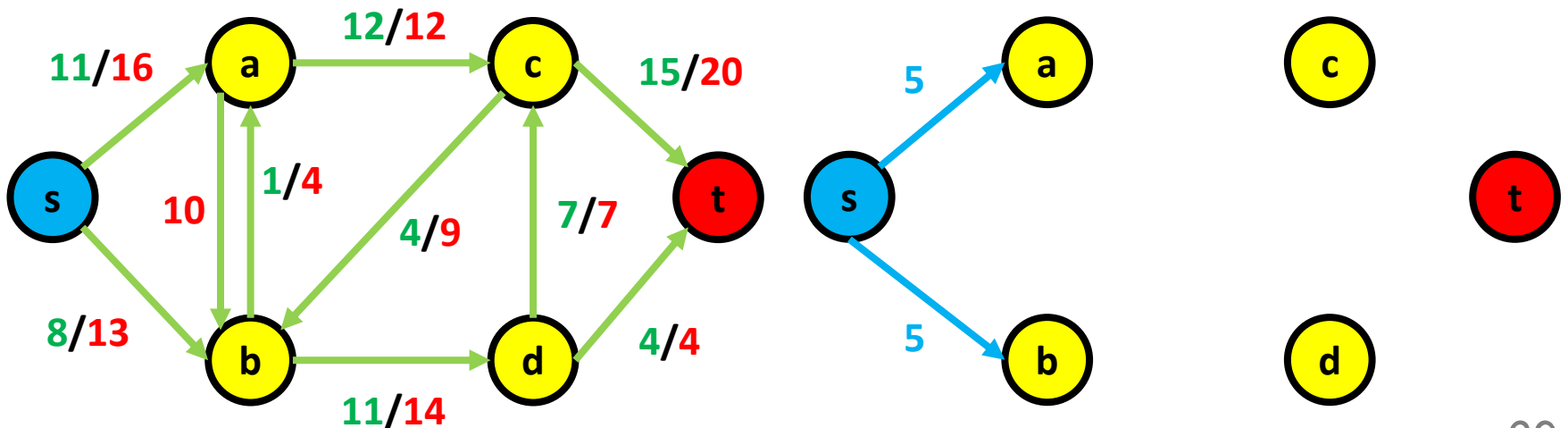
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# Residual network

## Another freaking network

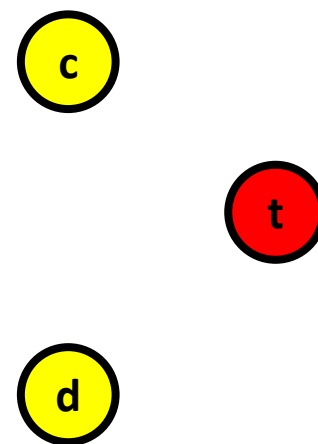
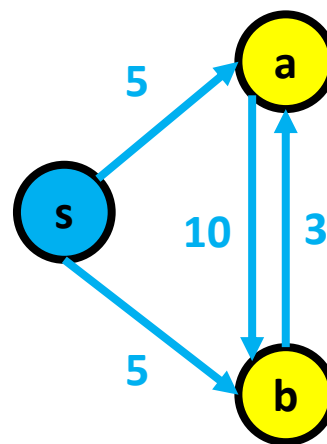
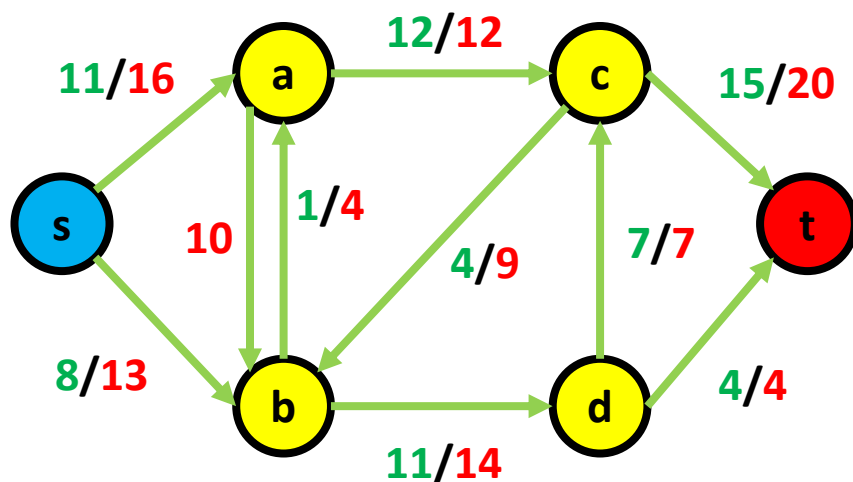
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# Residual network

## Another freaking network

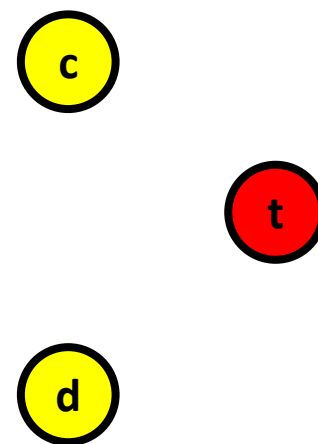
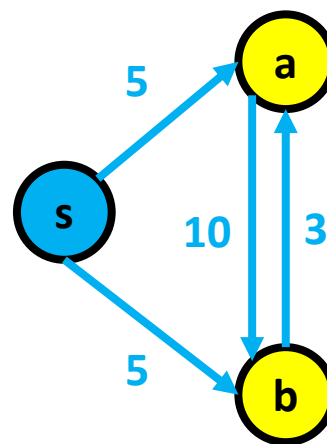
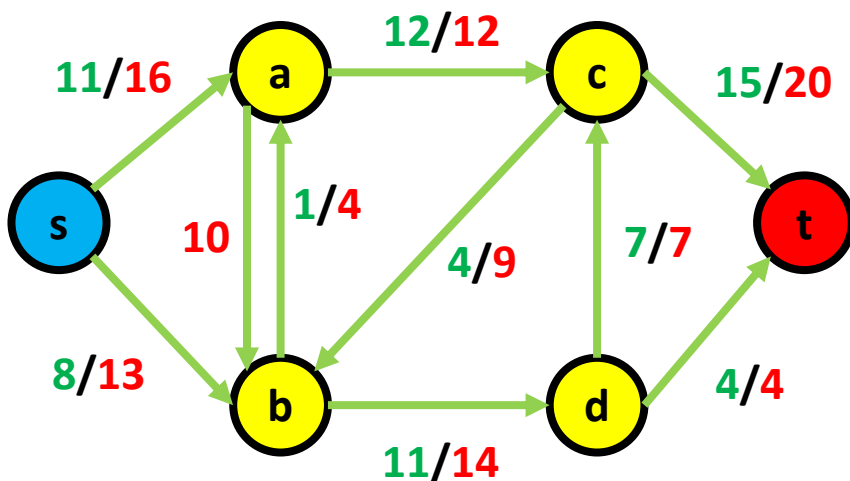
- What is a residual network?
  - Same vertices
  - Forward edge/ residual edge for remaining capacity
    - What about the one between a and b?



# Residual network

## Another freaking network

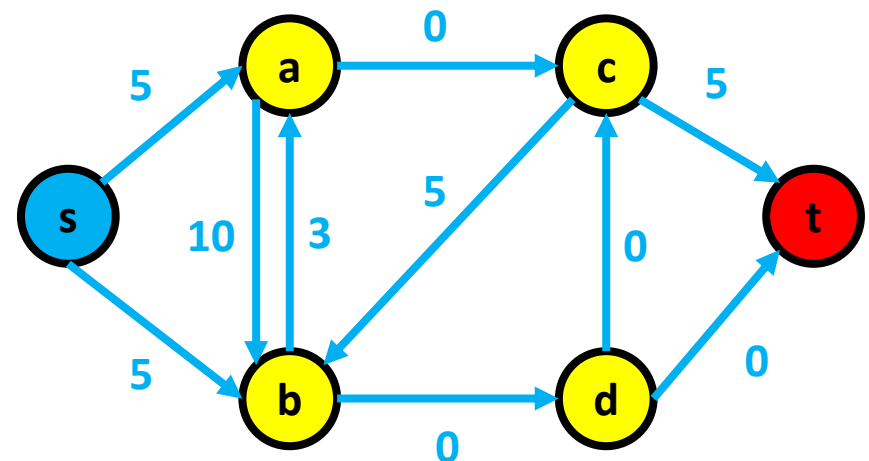
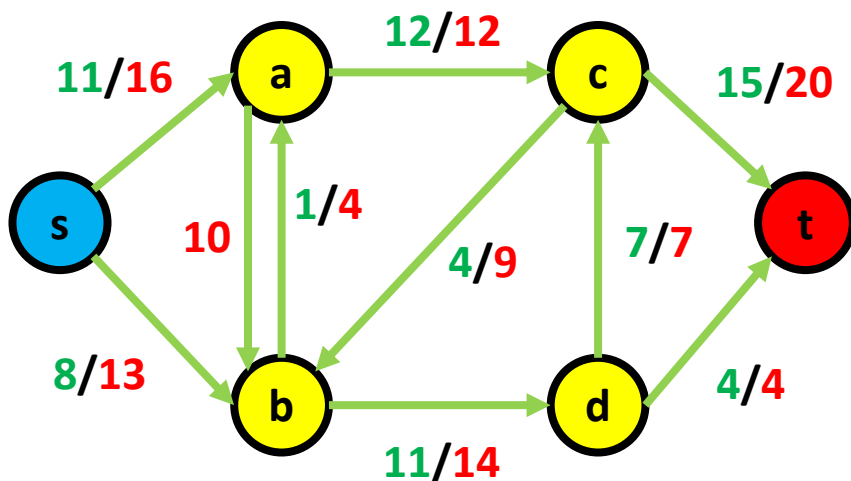
- What is a residual network?
  - Same vertices
  - Forward edge/ residual edge for remaining capacity
    - What about the one between a and b? We will come back to this later...



# Residual network

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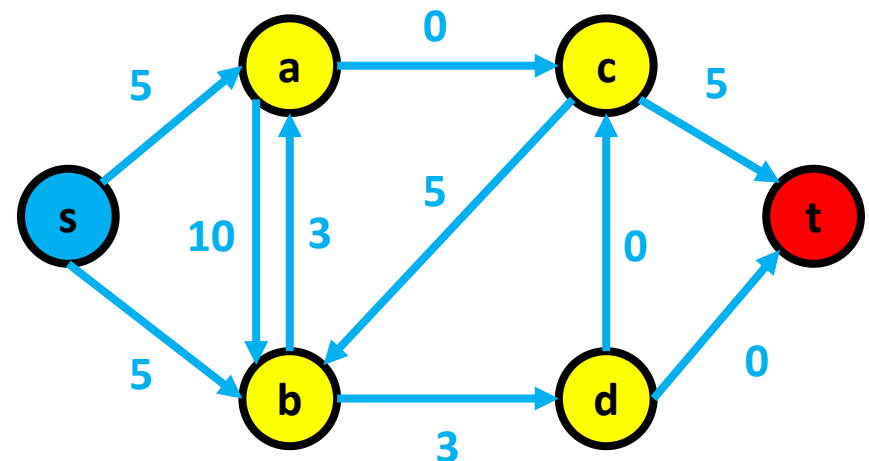
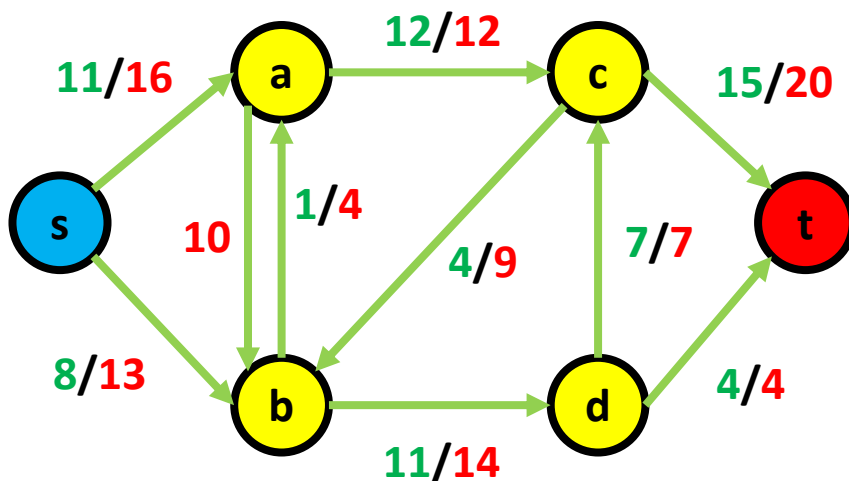




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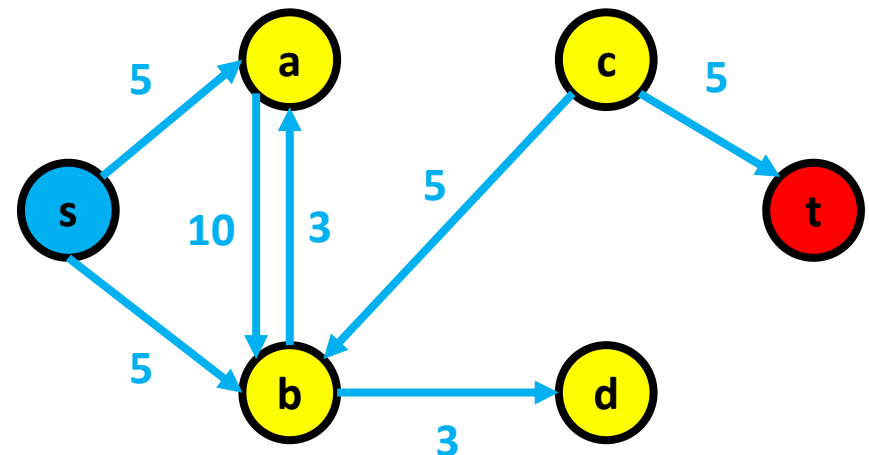
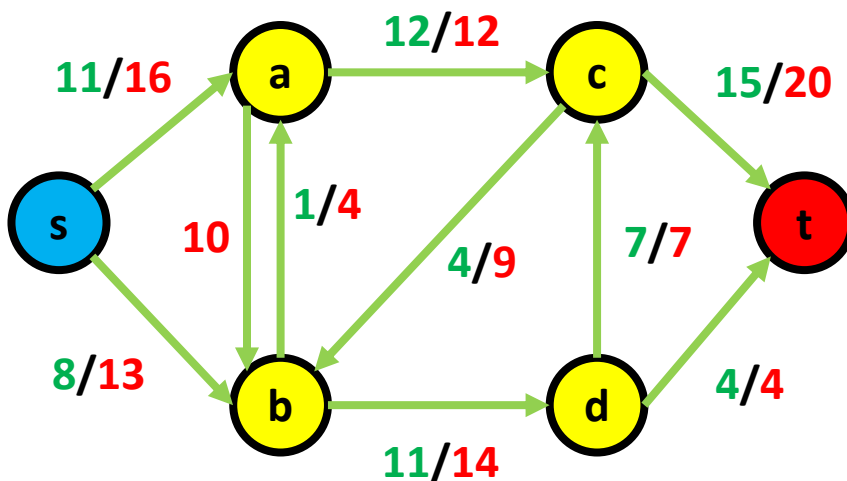
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    - We can delete the ones with 0



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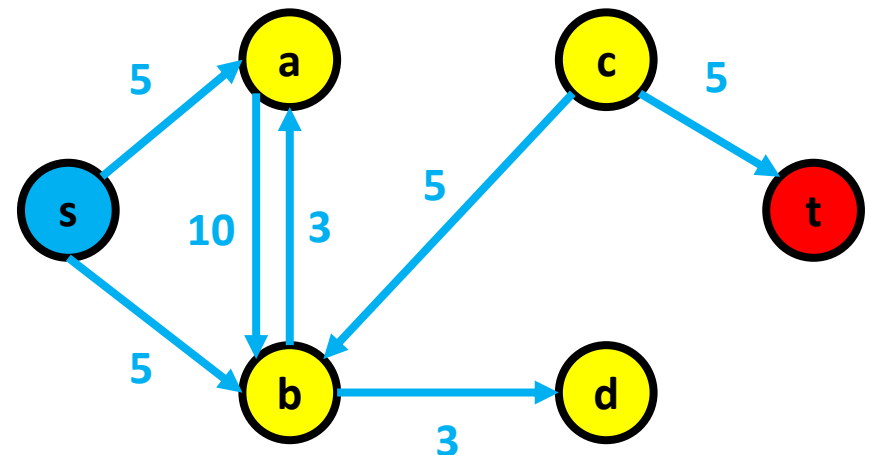
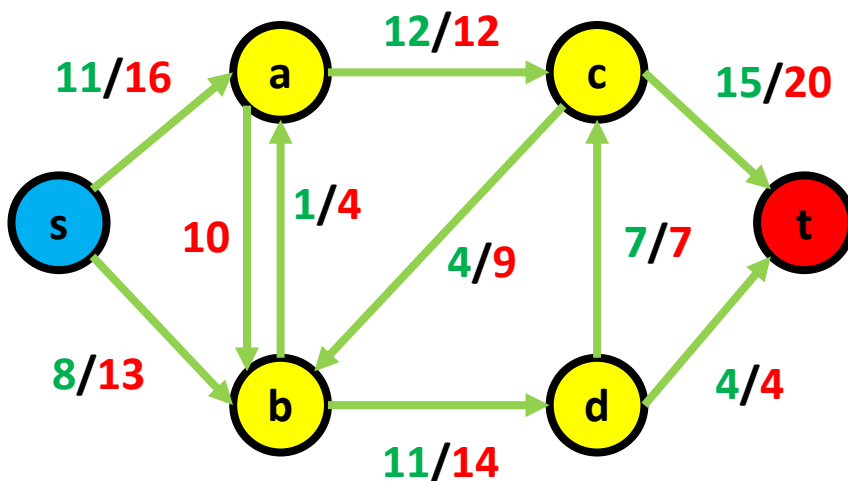
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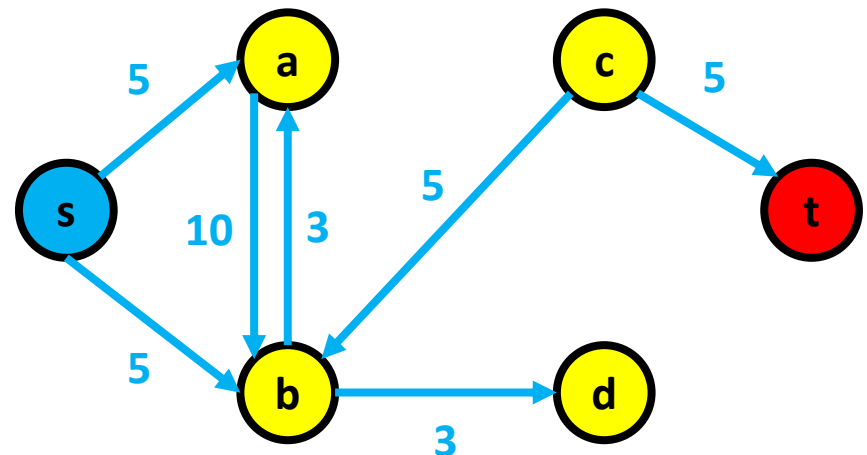
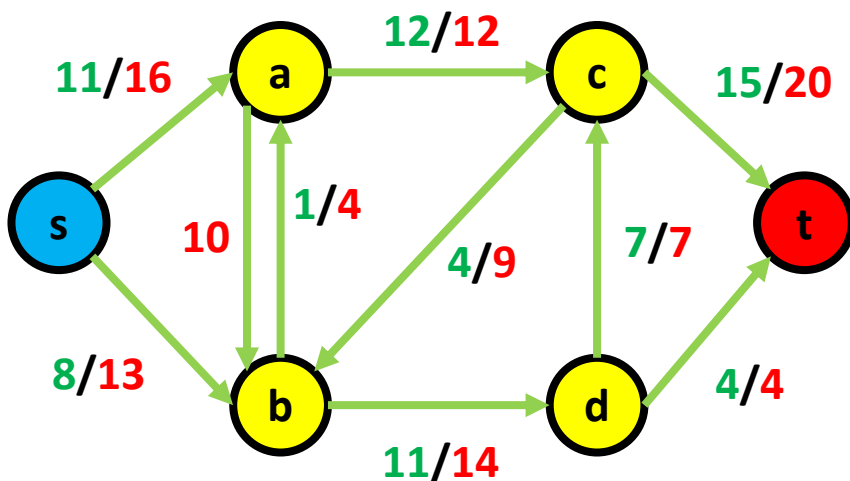
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# Residual network

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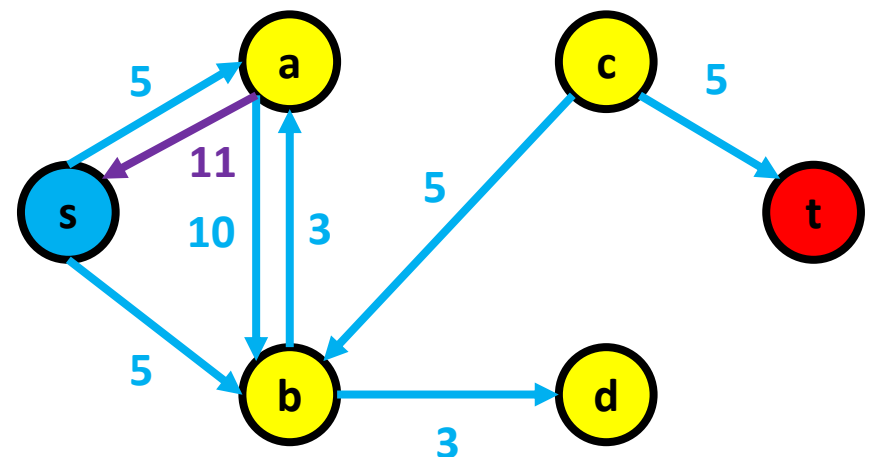
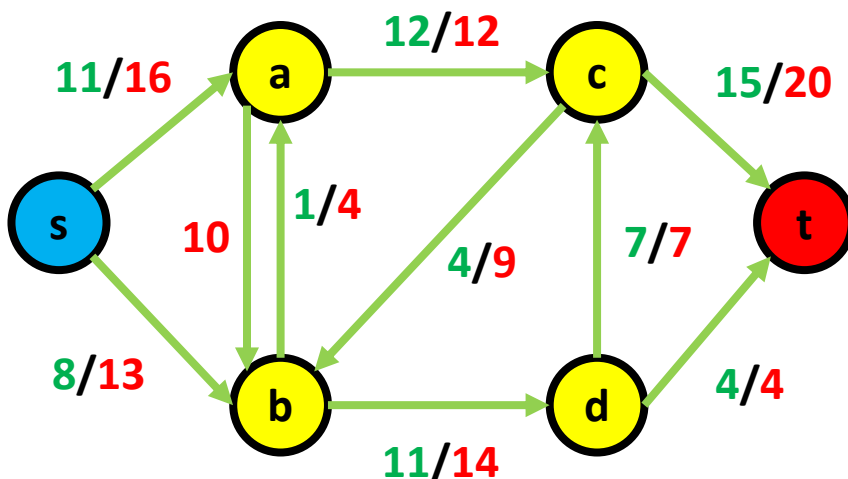
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    - Provided they have been allocated



# Residual network

## Another freaking network

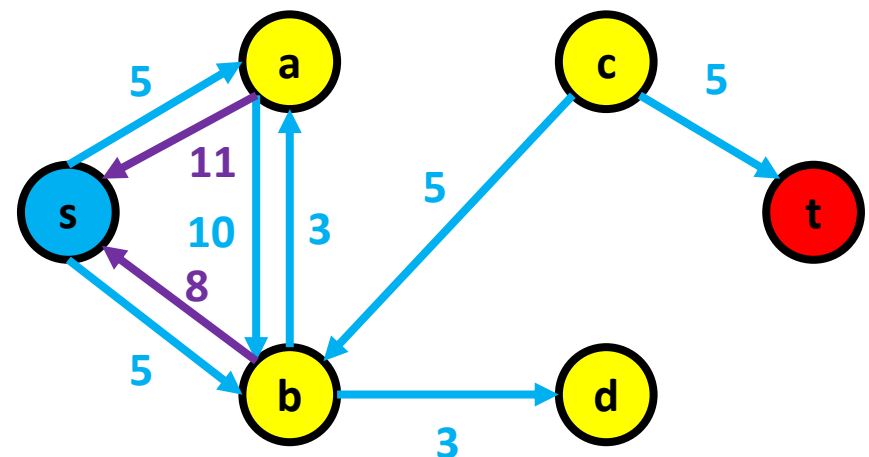
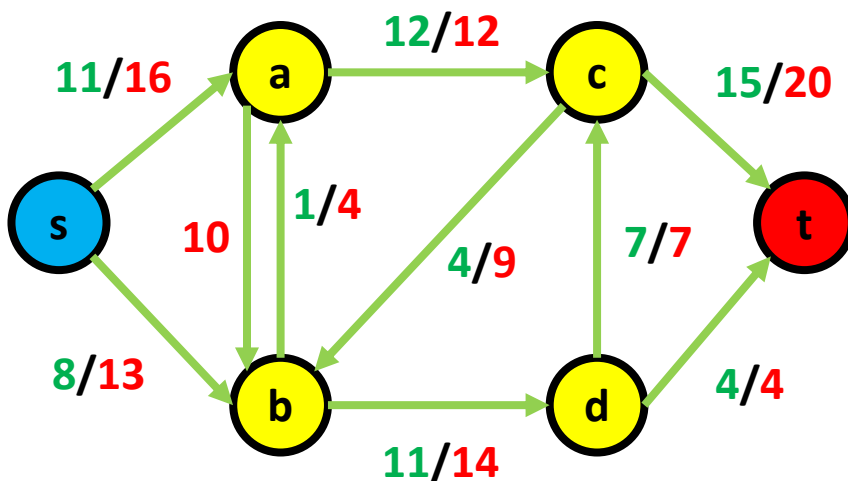
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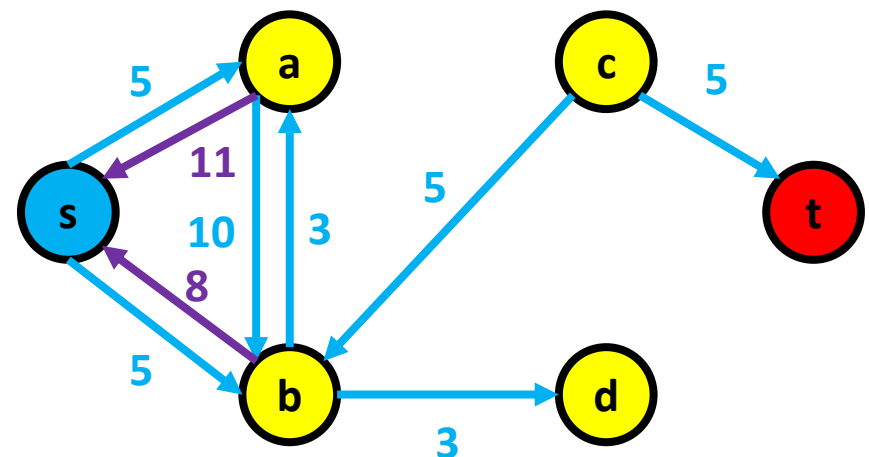
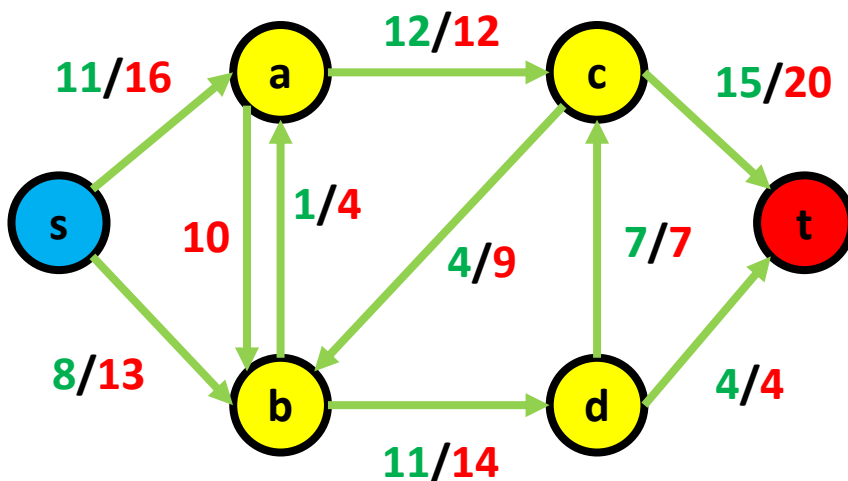
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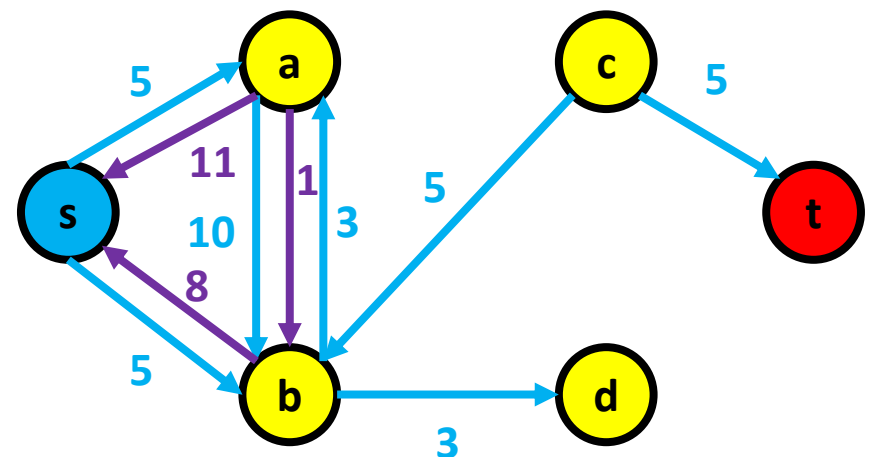
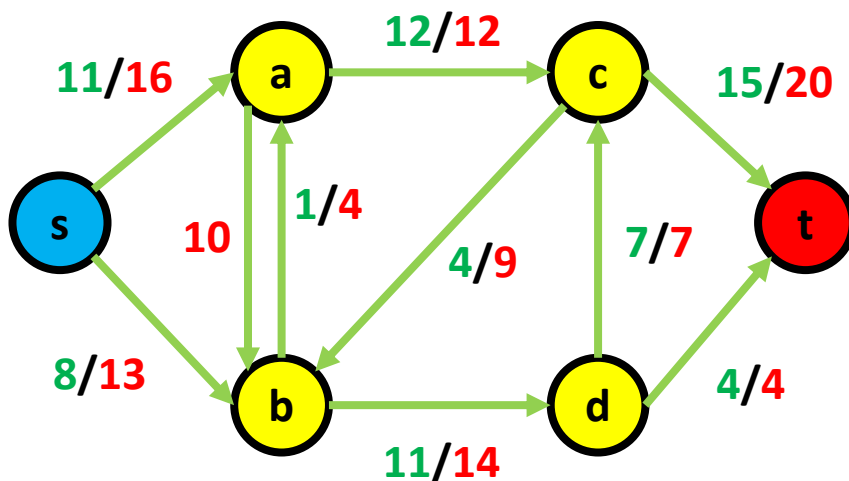
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# Residual network

## Another freaking network

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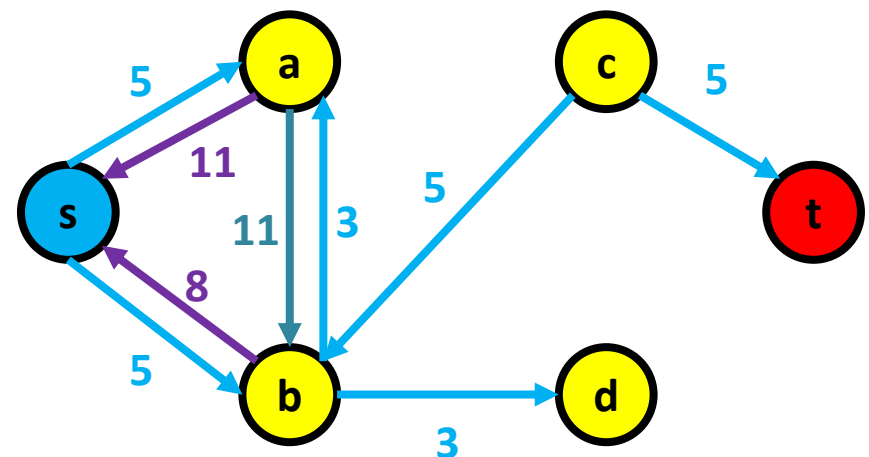
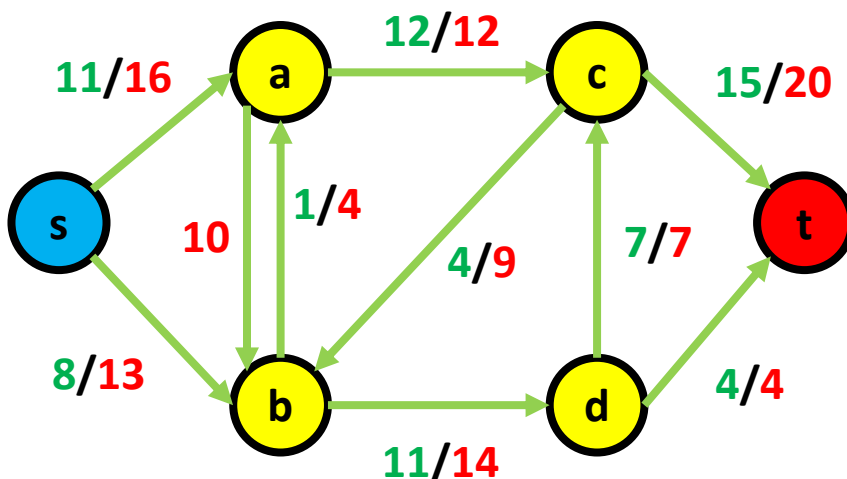




# Residual network

## Another freaking network

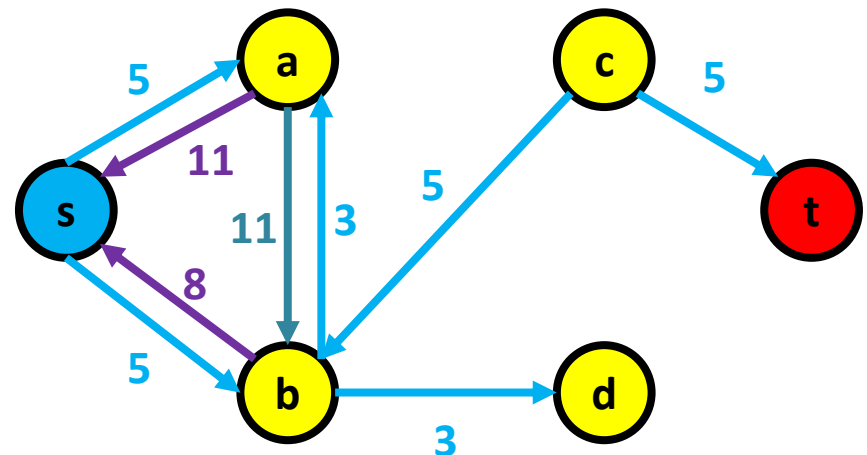
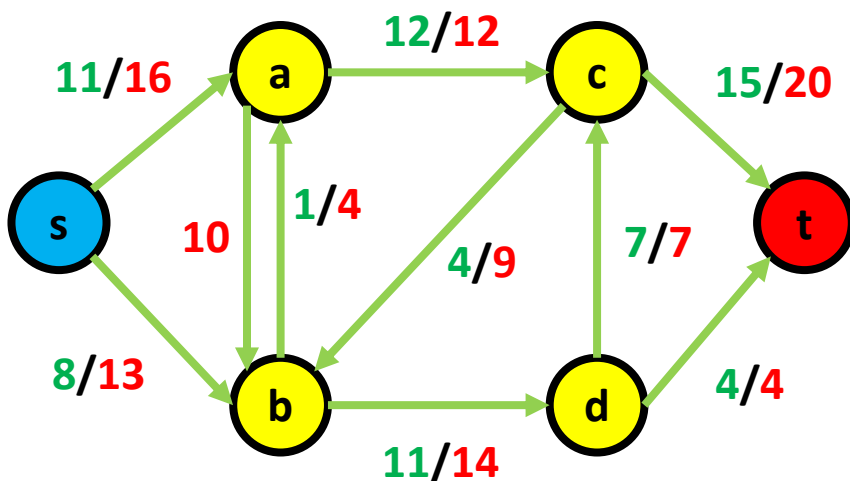
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    - What about the one between a and b? We have 2 in the same direction, so we combine both



# Residual network

## Another freaking network

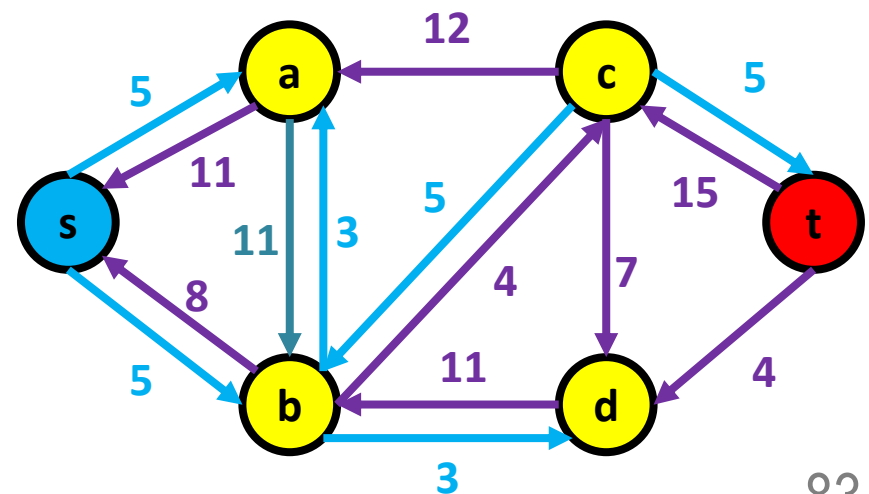
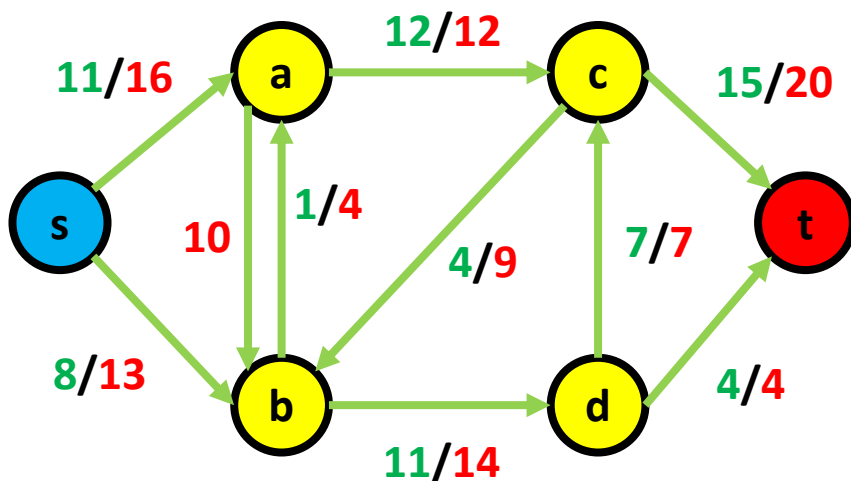
- What is a residual network?
  - Same vertices
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  - Backward edge/ reversible edge for flow that can be cancelled
    - What about the one between a and b? We have 2 in the same direction, so we combine both. The other side is 0, so nothing to combine



# Residual network

## Another freaking network

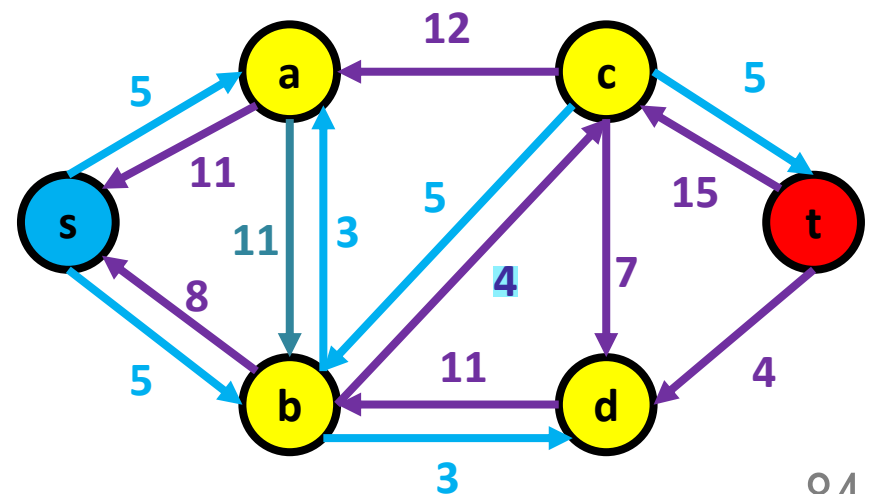
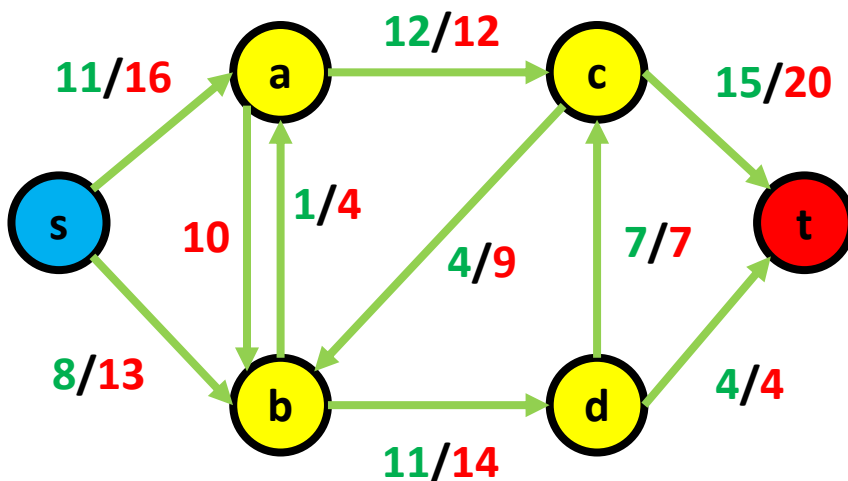
- What is a residual network?
  - Same vertices
  - Forward edge/ residual edge for remaining capacity
  - Backward edge/ reversible edge for flow that can be cancelled
    - And we add for all



# Residual network

## Another freaking network

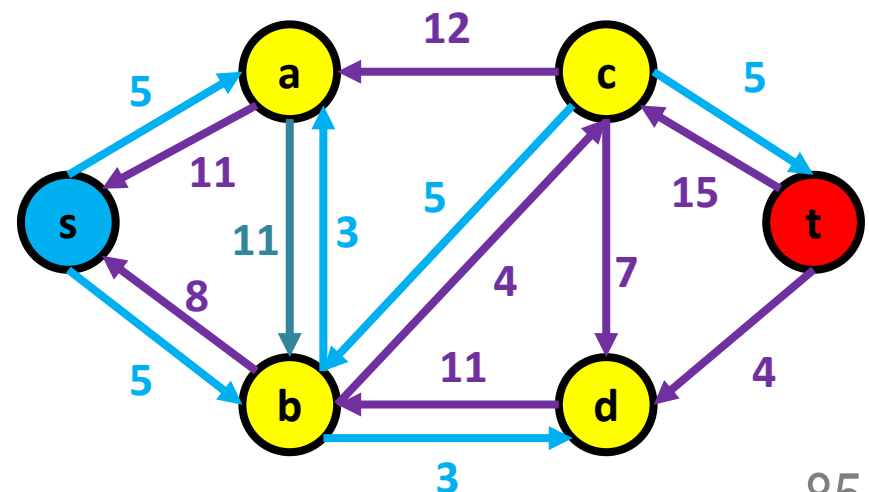
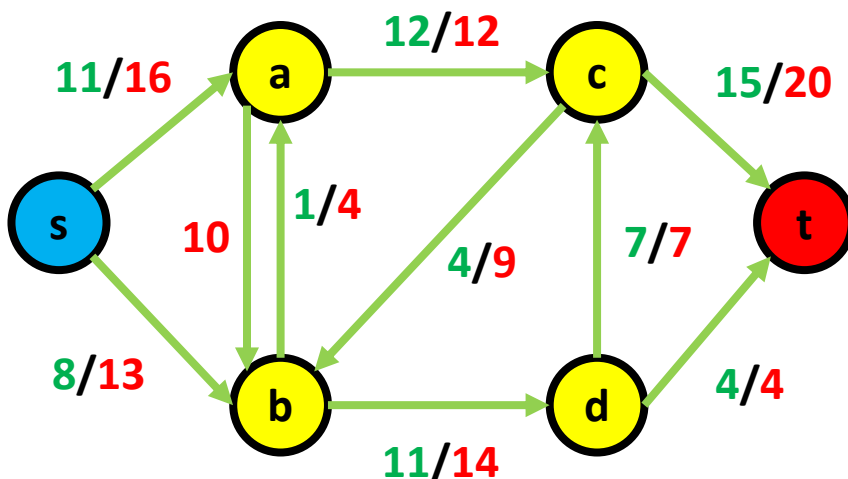
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# Residual network

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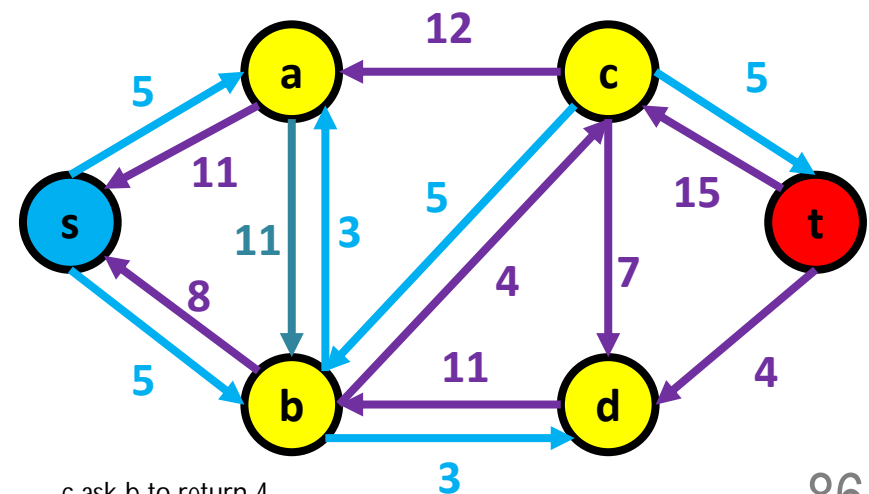
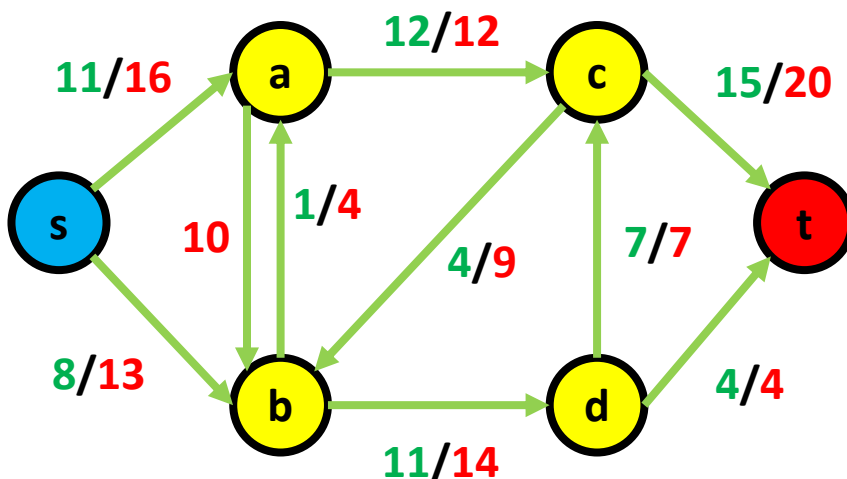
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  - Same vertices
  - Forward edge/ residual edge for remaining capacity
  - Backward edge/ reversible edge for flow that can be cancelled
  - Simple graph, so multi edges are merged together



# Residual network

## Another freaking network

- What is a residual network?
  - Same vertices
  - Forward edge/ residual edge for remaining capacity
  - Backward edge/ reversible edge for flow that can be cancelled
  - Simple graph, so multi edges are merged together
  - Also note, sum of the edge between 2 vertices same as the edge capacity

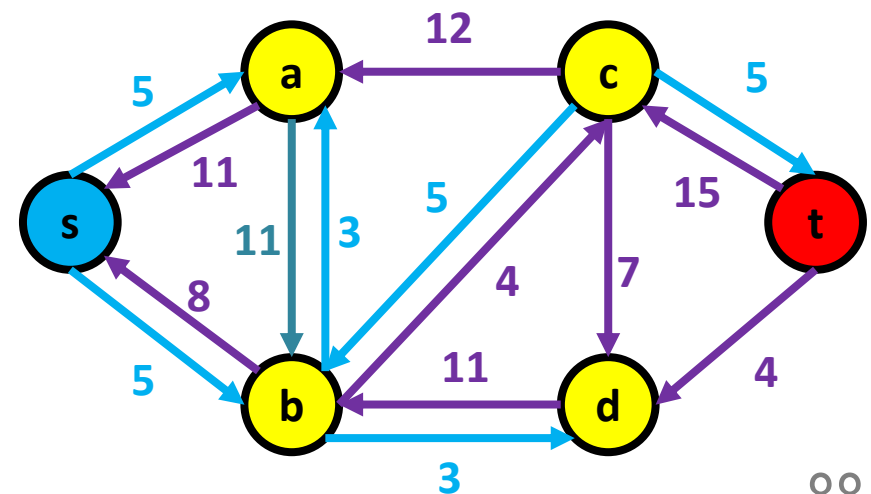
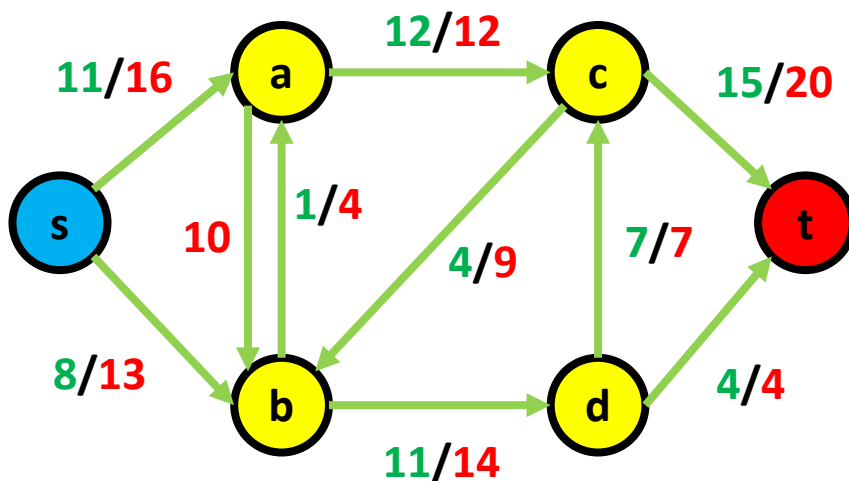


c ask b to return 4  
so it can pass 4 flow then flow from c to t

Questions?

# Residual network

So what is the purpose?

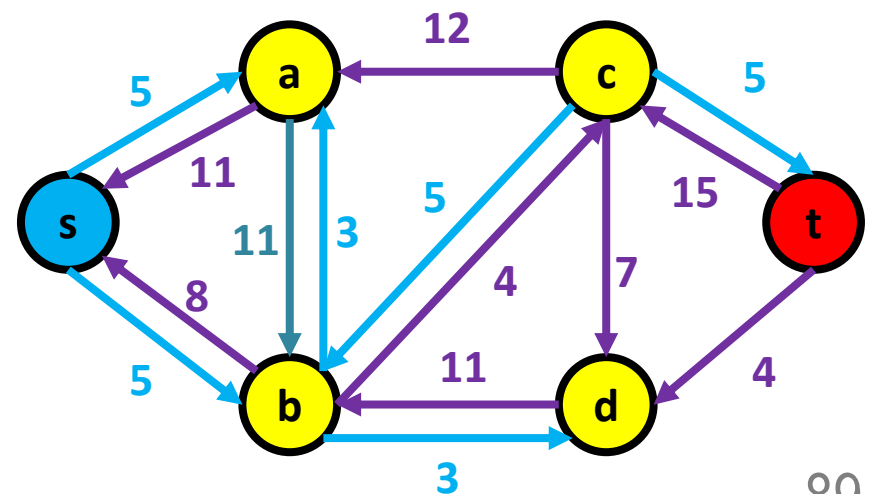
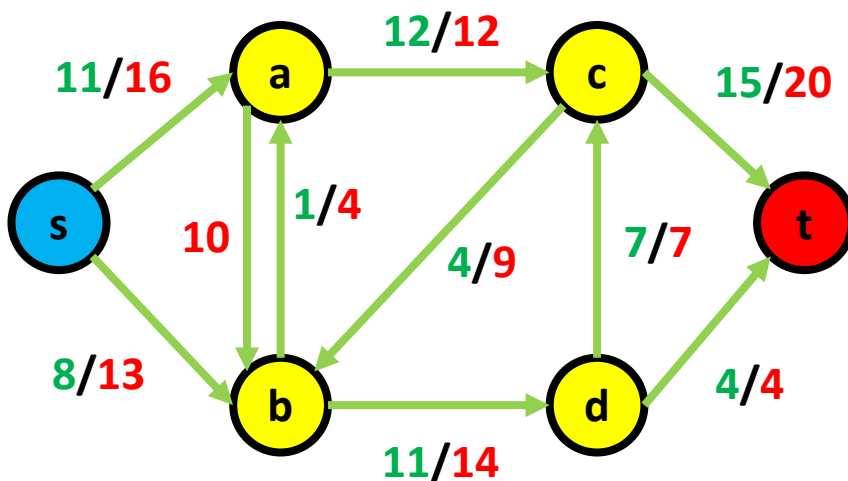




# Residual network

Measuring the **potential** of a network

- Stores the network potential

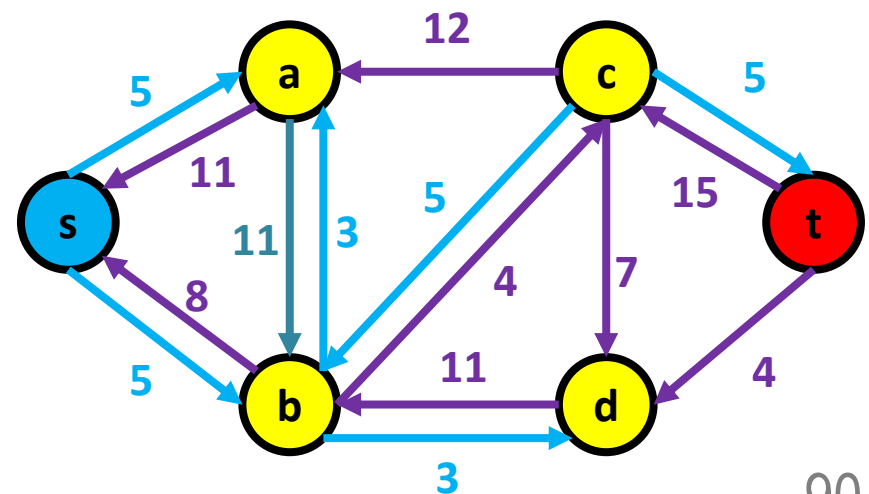
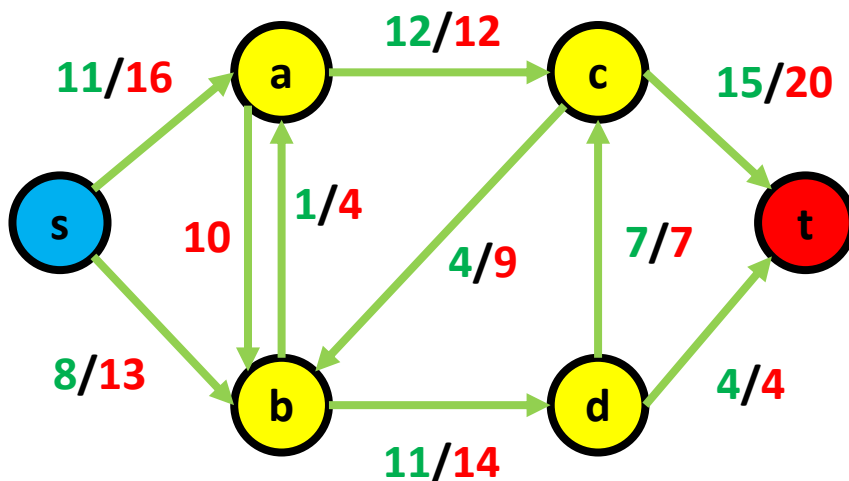


# Residual network

## Measuring the potential of a network

- Stores the network potential
  - Which we will unleash...

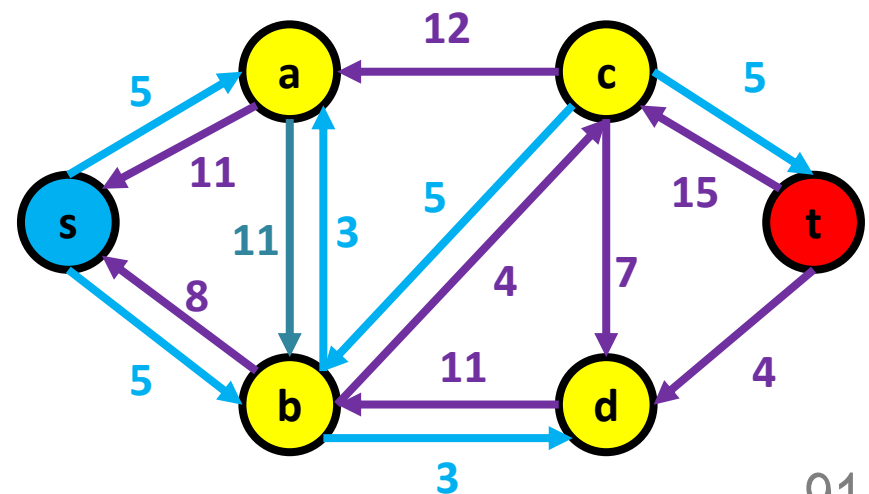
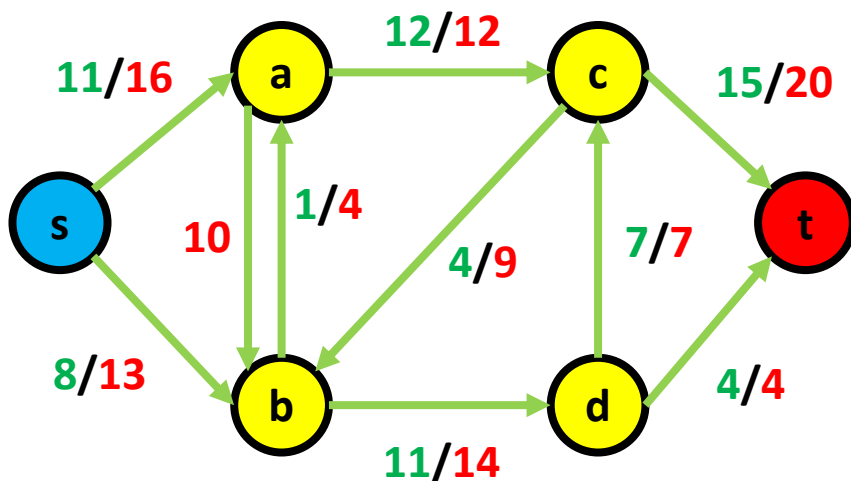
When you stop chasing your tail and start chasing your dreams



# Residual network

## Measuring the potential of a network

- Stores the network potential
  - Which we will unleash... via path augmentation!

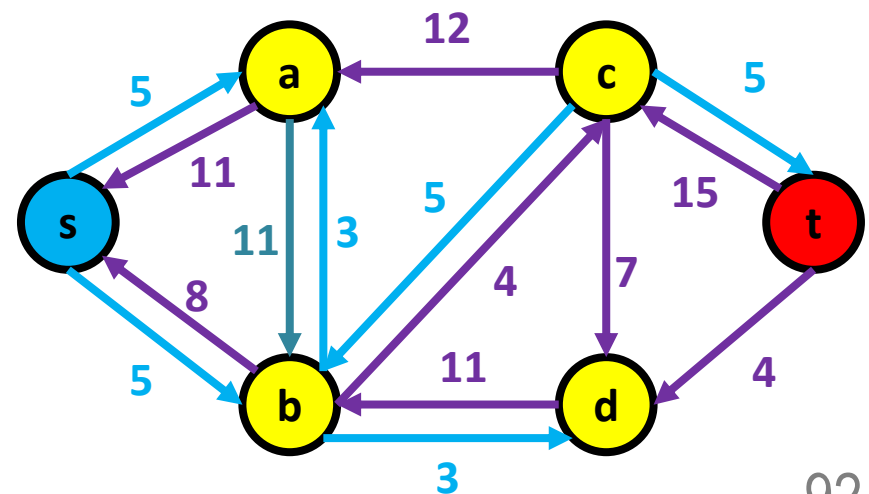
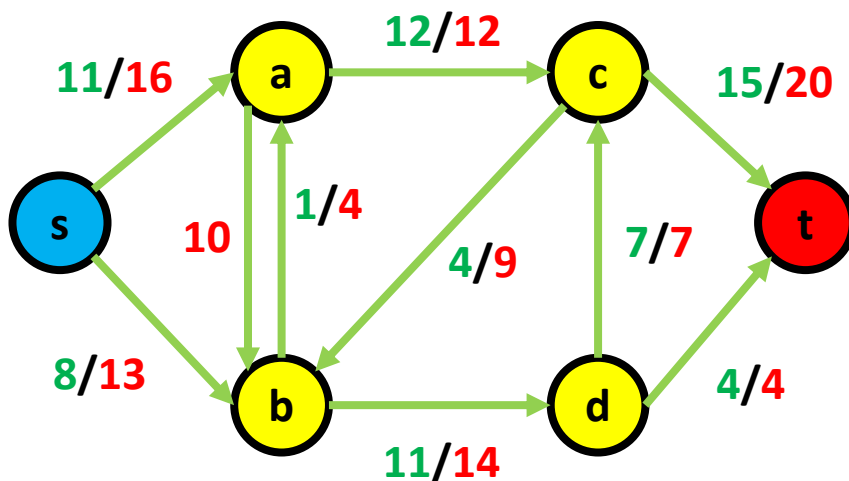


# Residual network

## Measuring the potential of a network

increase the path flow

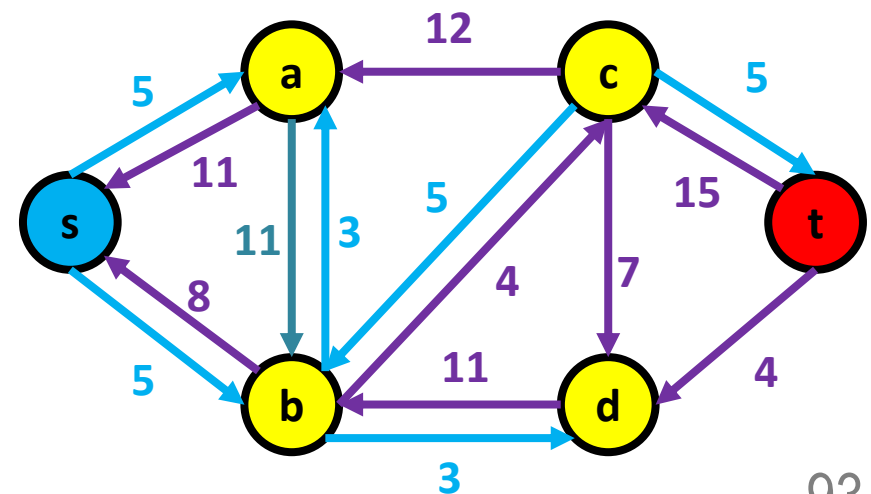
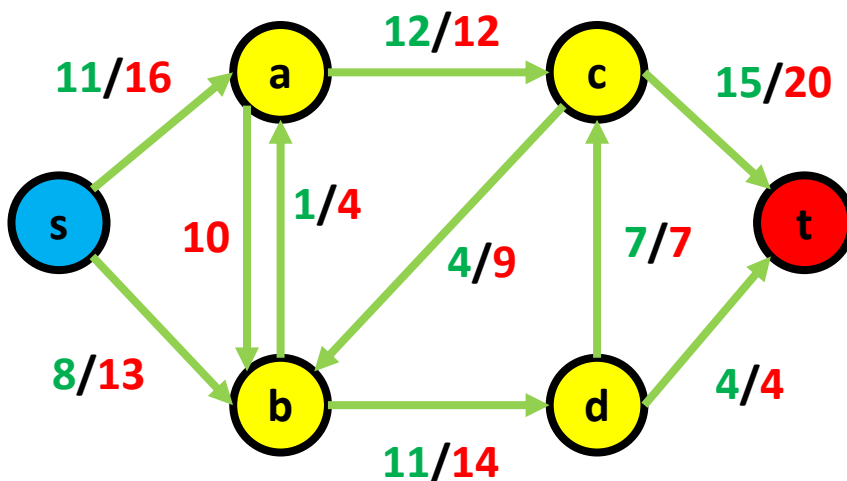
- So what is path augmentation?



# Path Augmentation

## Traversal in residual network

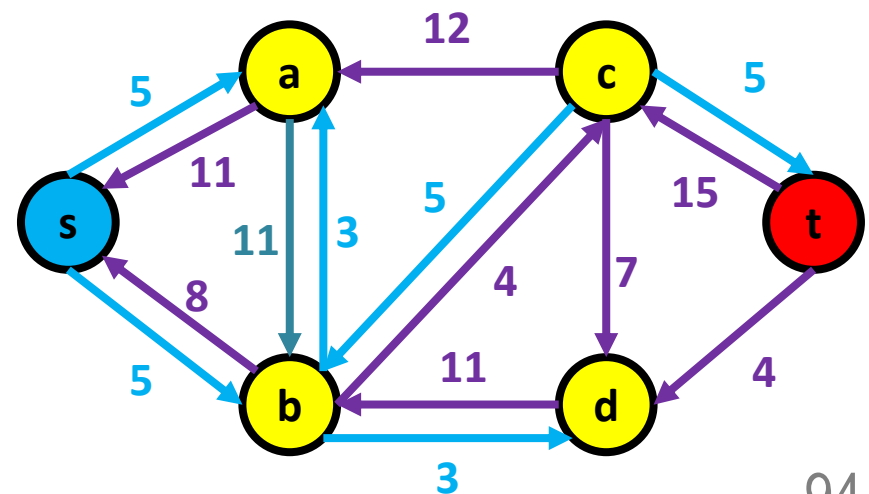
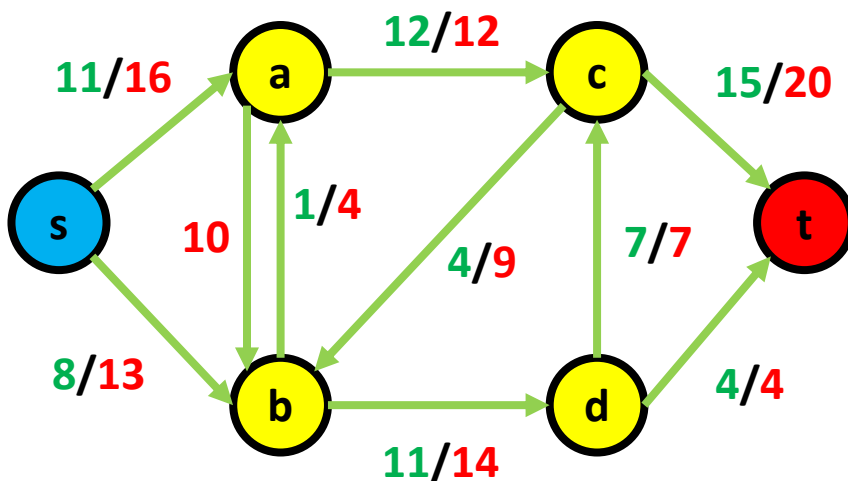
- So what is path **augmentation**?
  - A **traversal** in the **residual network**



# Path Augmentation

## Traversal in residual network

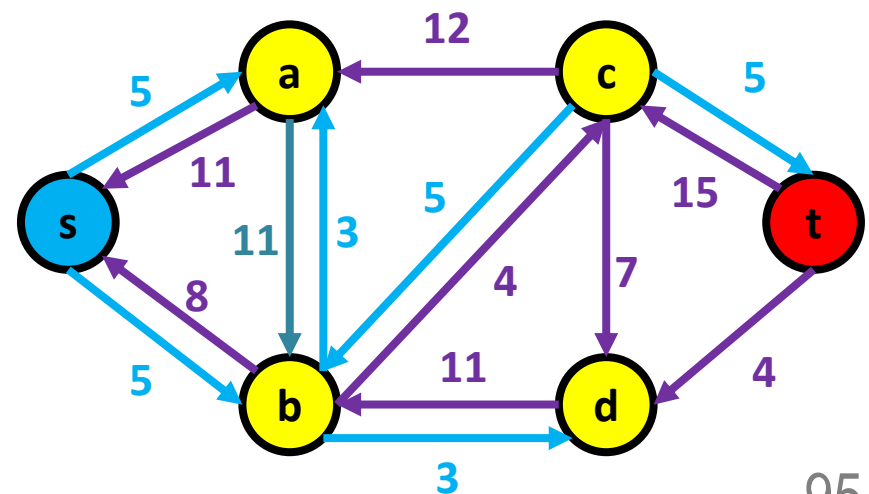
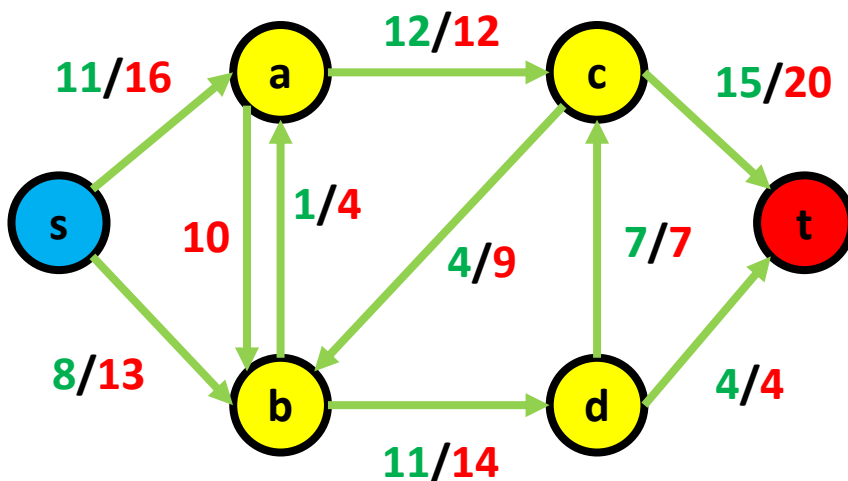
- So what is path augmentation?
  - A traversal in the residual network
  - From source, to target



# Path Augmentation

## Traversal in residual network

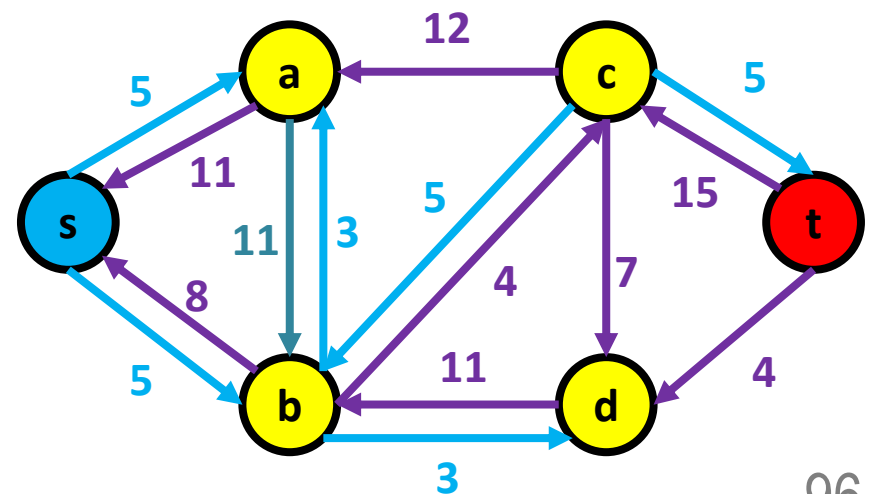
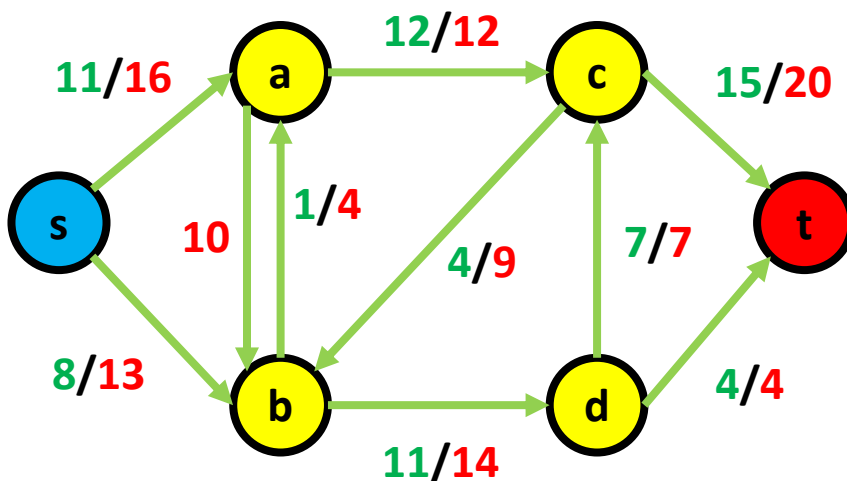
- So what is path augmentation?
  - A traversal in the residual network
  - From source, to target
  - Following the edges in the residual network



# Path Augmentation

## Traversal in residual network

- So what is path augmentation?
  - A traversal in the residual network
    - BFS! Or DFS!
  - From source, to target
  - Following the edges in the residual network

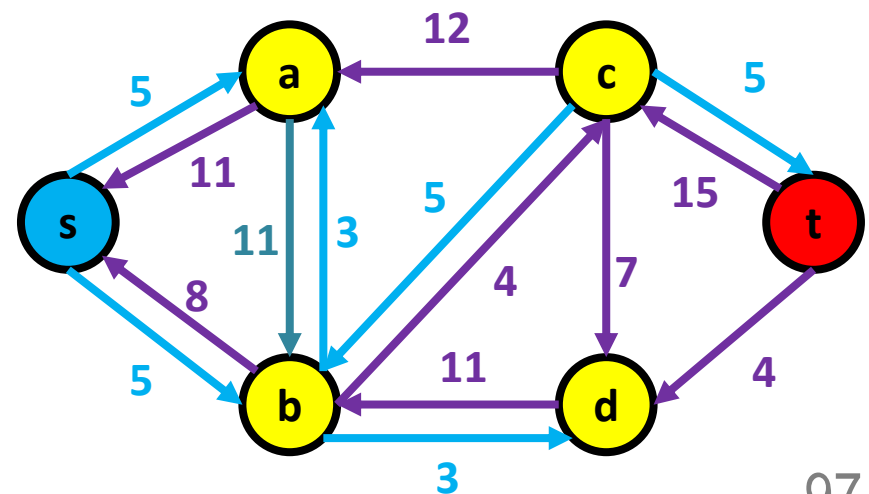
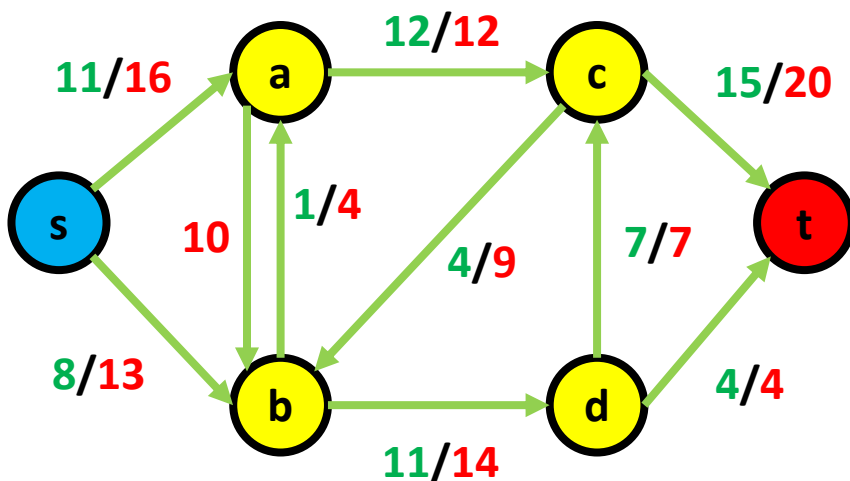




# Path Augmentation

## Traversal in residual network

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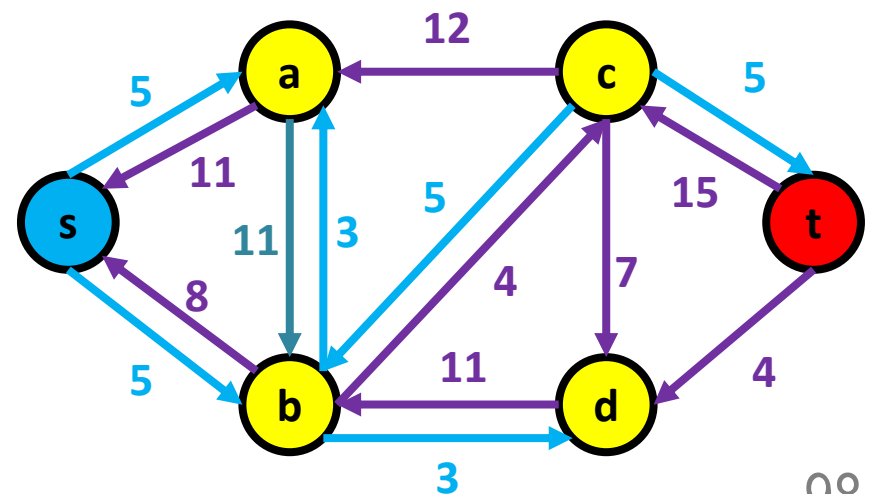
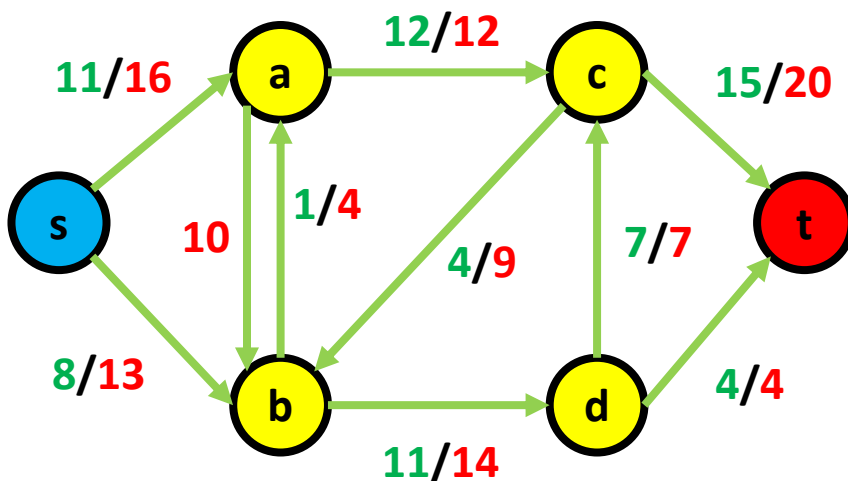


# Path Augmentation

## Traversal in residual network

- Is there a path here?

–  $s \rightarrow b \rightarrow c \rightarrow t$

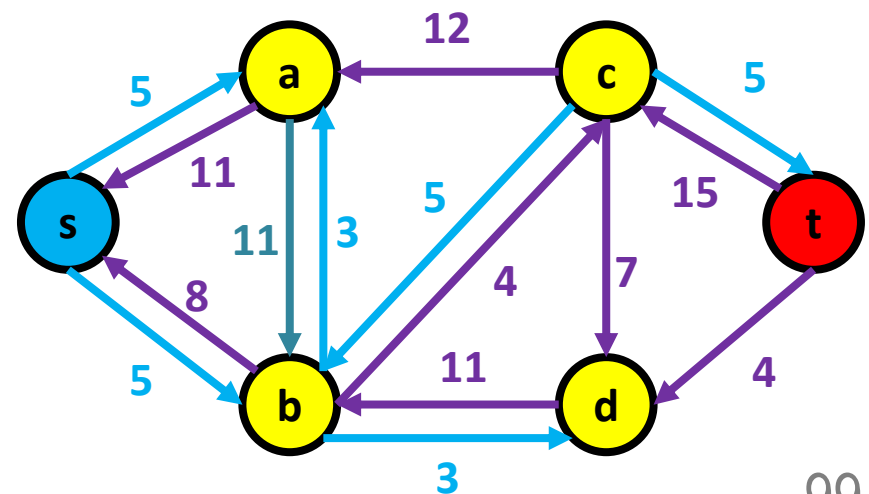
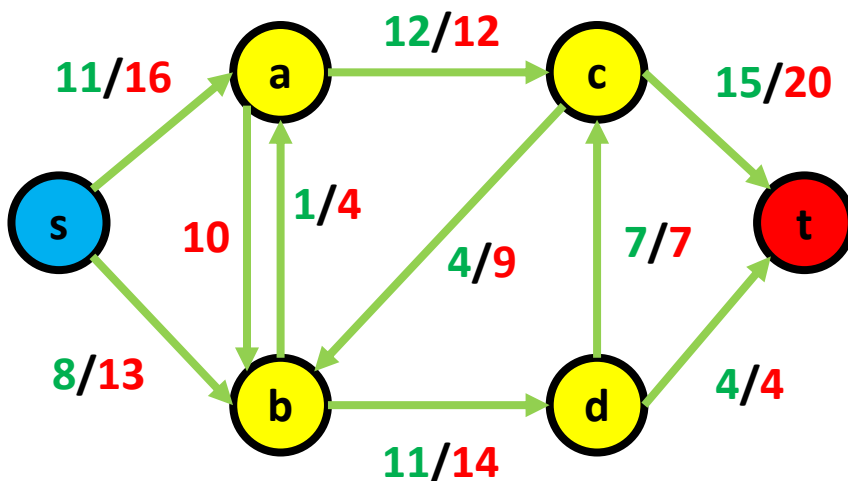


# Path Augmentation

## Traversal in residual network

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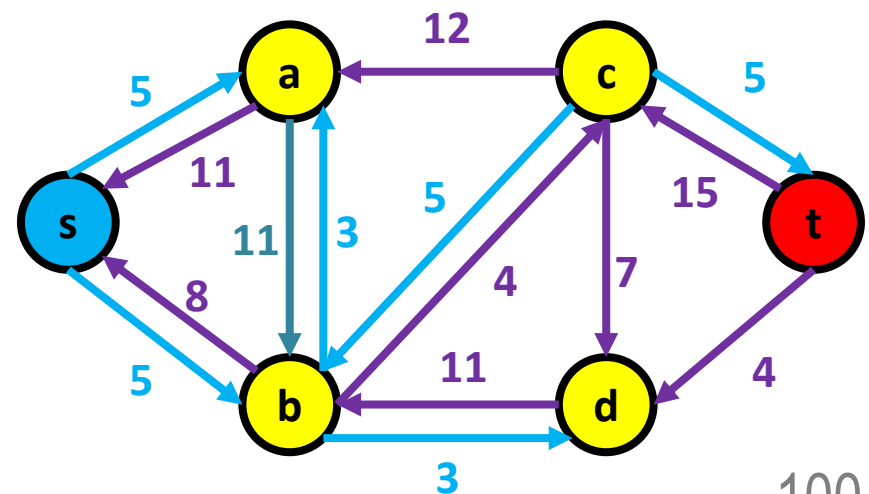
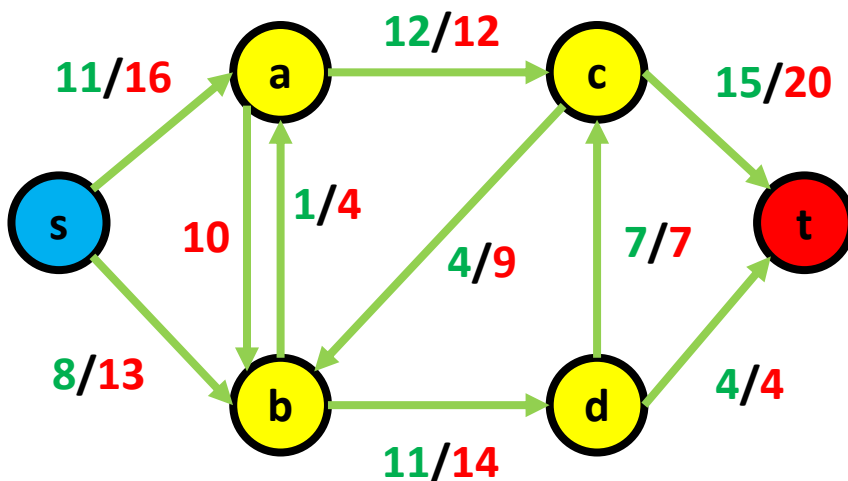
- $s \rightarrow b \rightarrow c \rightarrow t$       either BFS or DFS  
find a path from source to destination
- $s \rightarrow a \rightarrow b \rightarrow c \rightarrow t$



# Path Augmentation

## Traversal in residual network

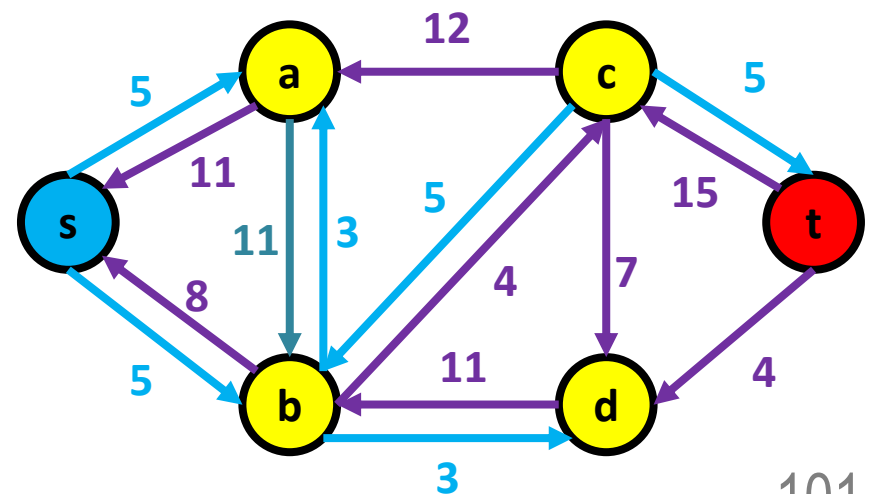
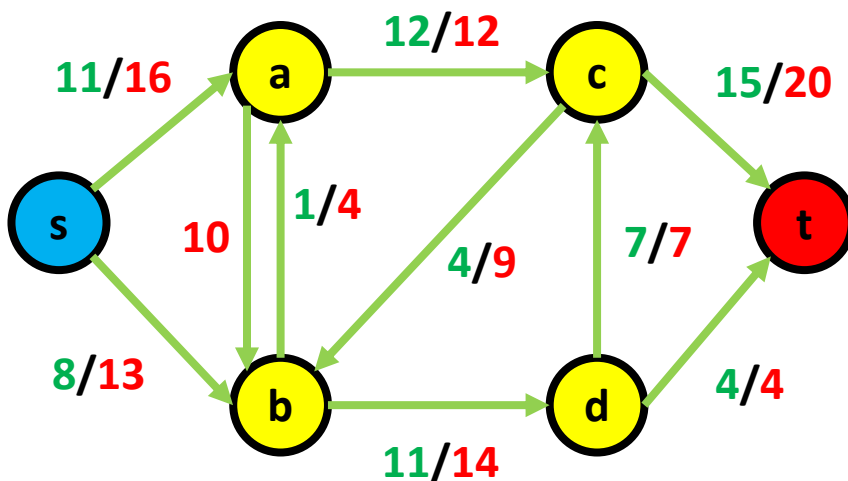
- Is there a path here?
  - $s \rightarrow b \rightarrow c \rightarrow t$ ... let us look at this one first
  - $s \rightarrow a \rightarrow b \rightarrow c \rightarrow t$



# Path Augmentation

## Traversal in residual network

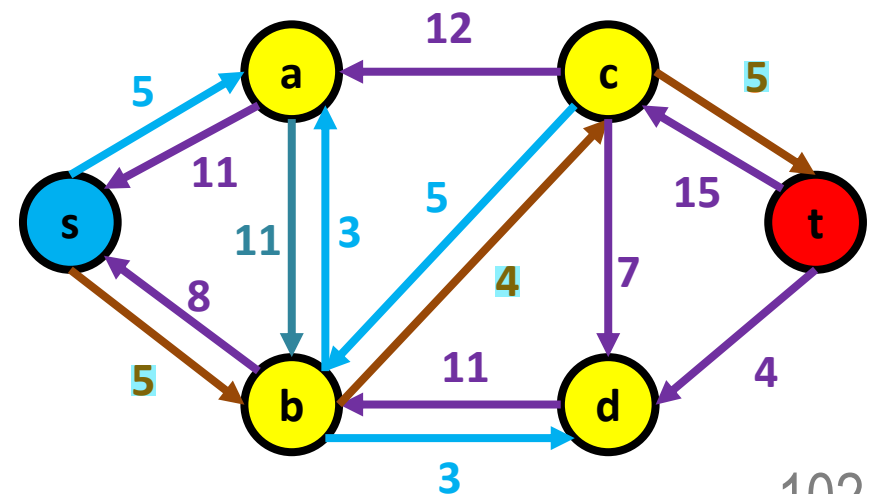
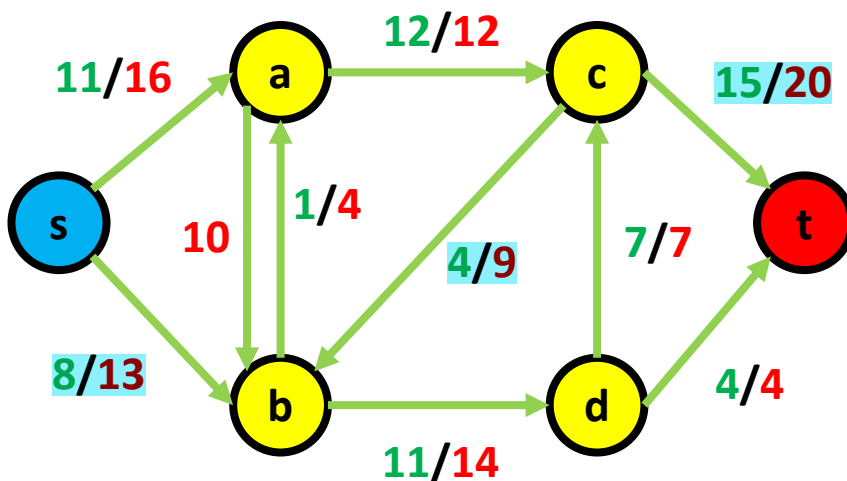
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# Path Augmentation

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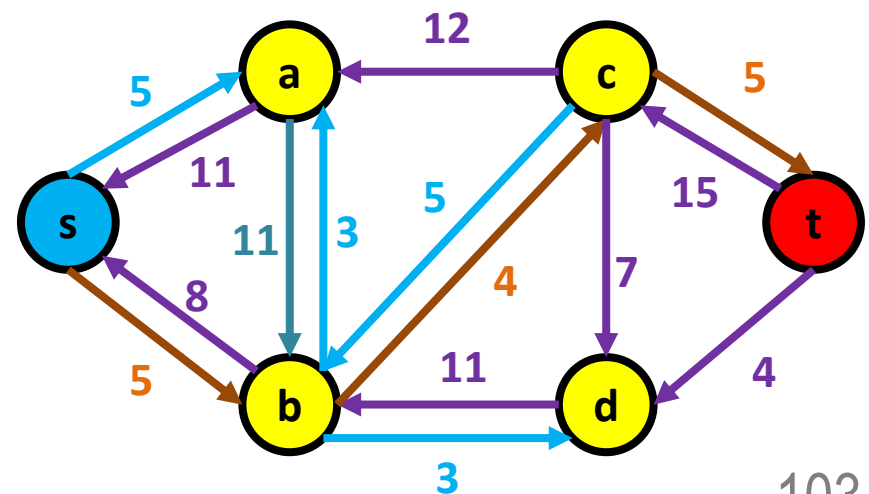
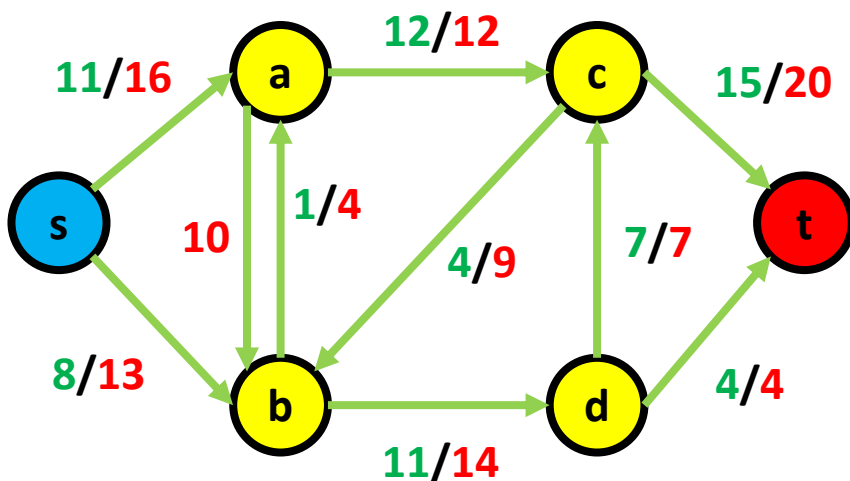
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# Path Augmentation

## Traversal in residual network

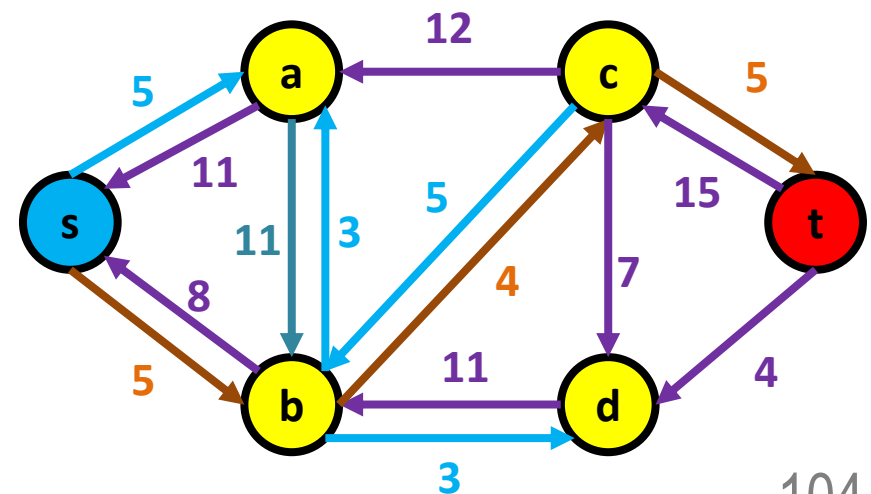
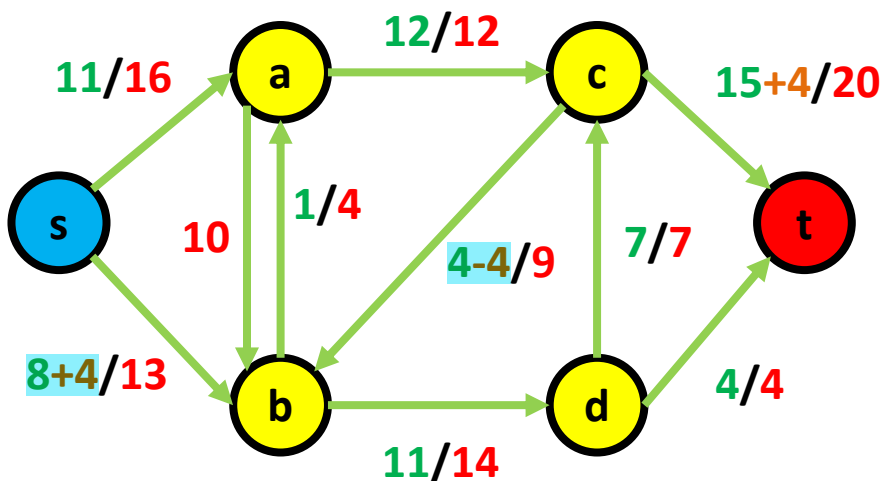
- Is there a path here?
  - $s \rightarrow b \rightarrow c \rightarrow t$ ... let us look at this one first
  - That the smallest value which is 4
    - This value can flow from source to target



# Path Augmentation

## Traversal in residual network

- Is there a path here?
  - $s \rightarrow b \rightarrow c \rightarrow t$ ... let us look at this one first
  - That the smallest value which is 4
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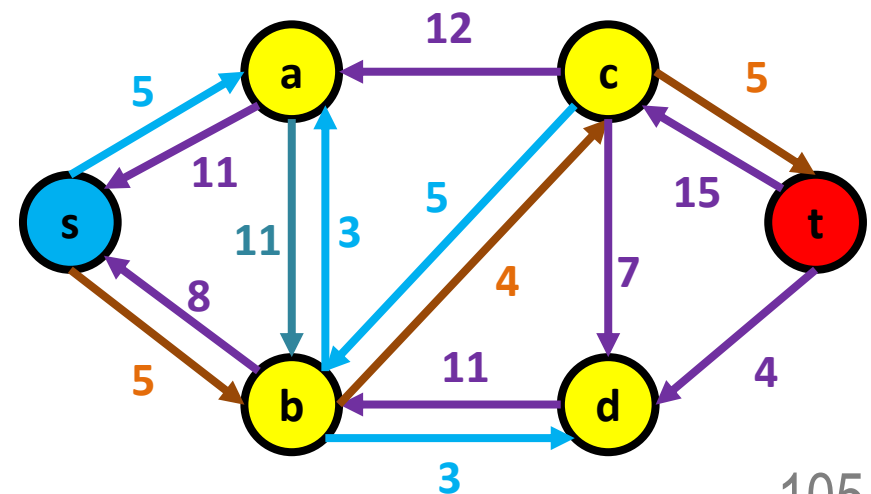
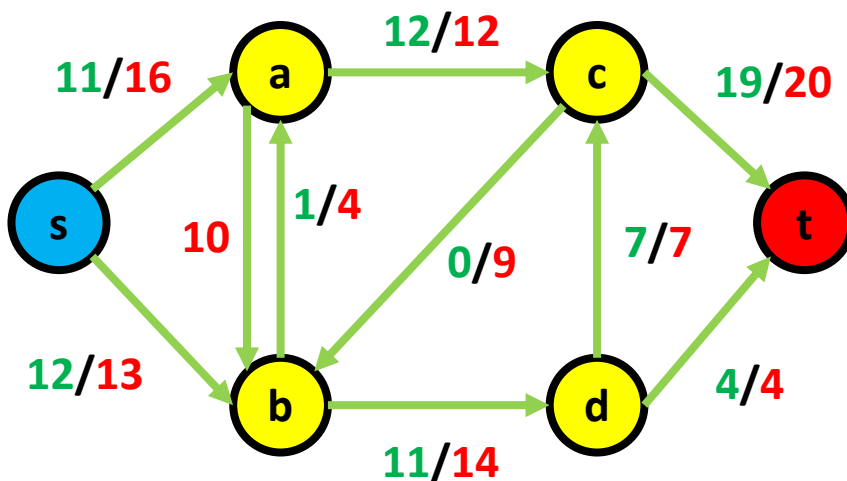




# Path Augmentation

## Traversal in residual network

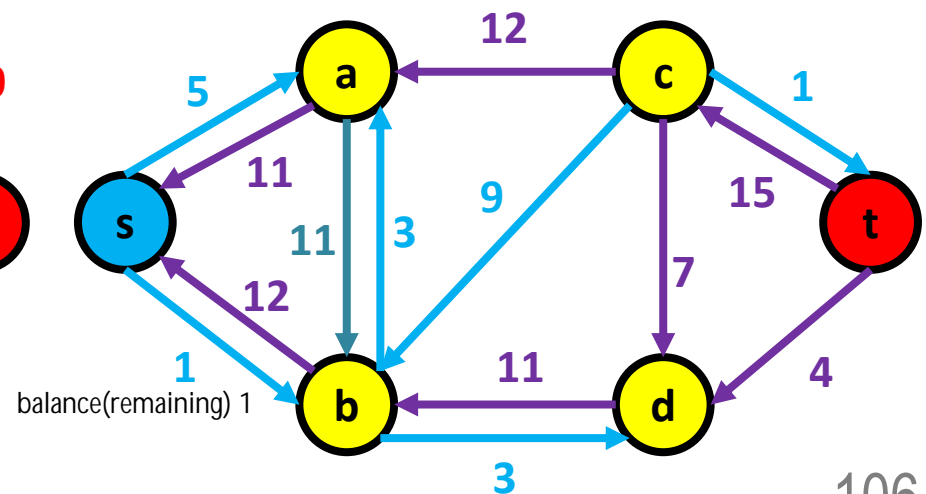
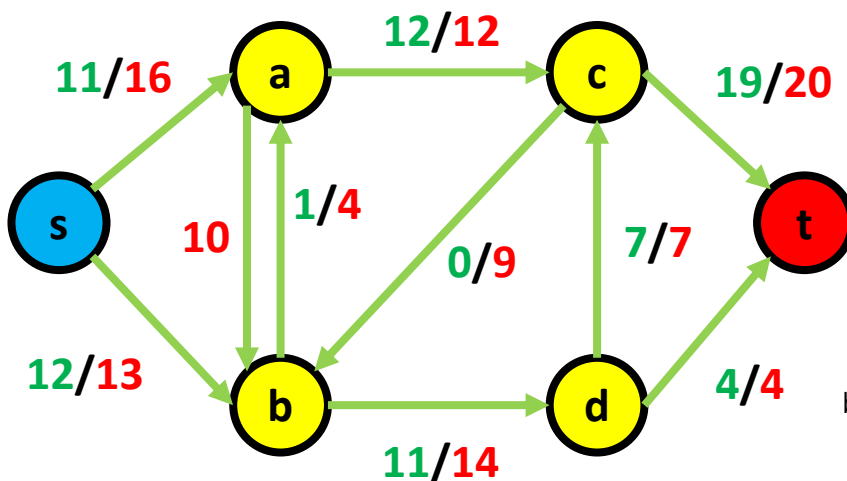
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  - $s \rightarrow b \rightarrow c \rightarrow t$ ... let us look at this one first
  - That the smallest value **which is 4**
    - This value can flow from source to target



# Path Augmentation

## Traversal in residual network

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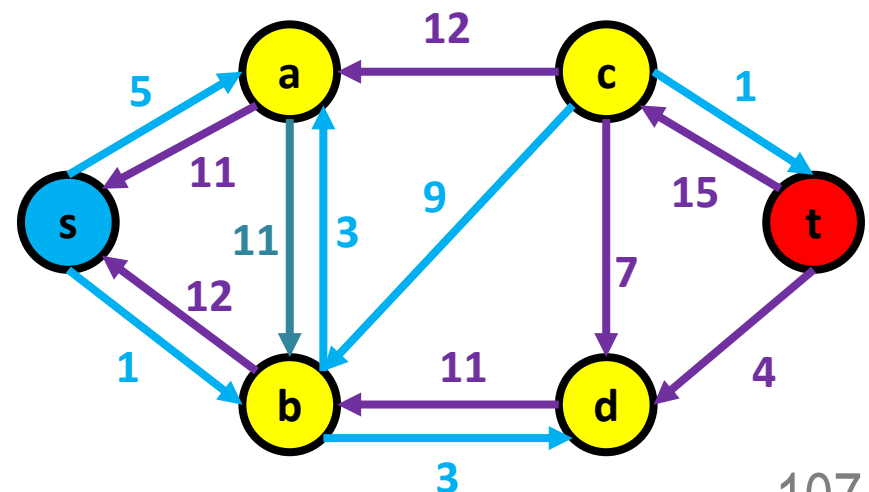
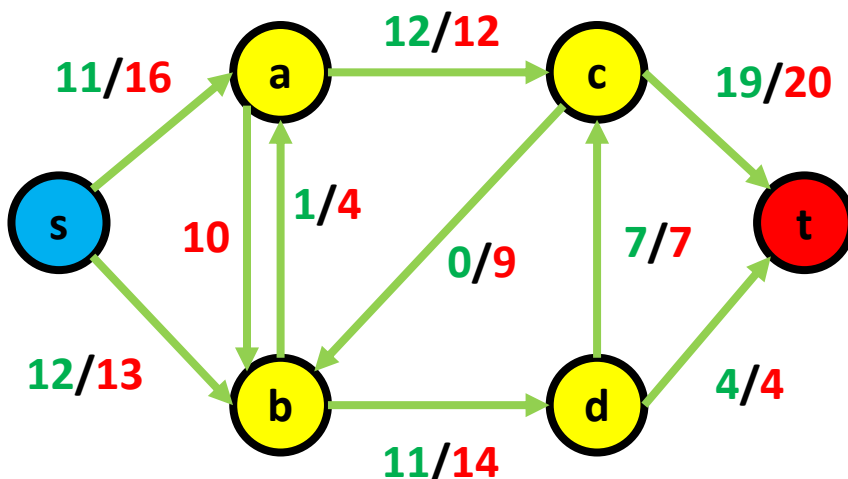


# Path Augmentation

## Traversal in residual network

- Is there a path here?
  - $s \rightarrow b \rightarrow c \rightarrow t$ ... let us look at this one first
  - That the smallest value which is 4
    - This value can flow from source to target
- With this, the flow in the network goes from 19 to 23!

BFS on residual network,  
to find the path from  $s$  to  $t$   
backtrack path to find the previous edge  
remember minimum flow value  
update on the original network  
then due to update on original network  
then update residual network



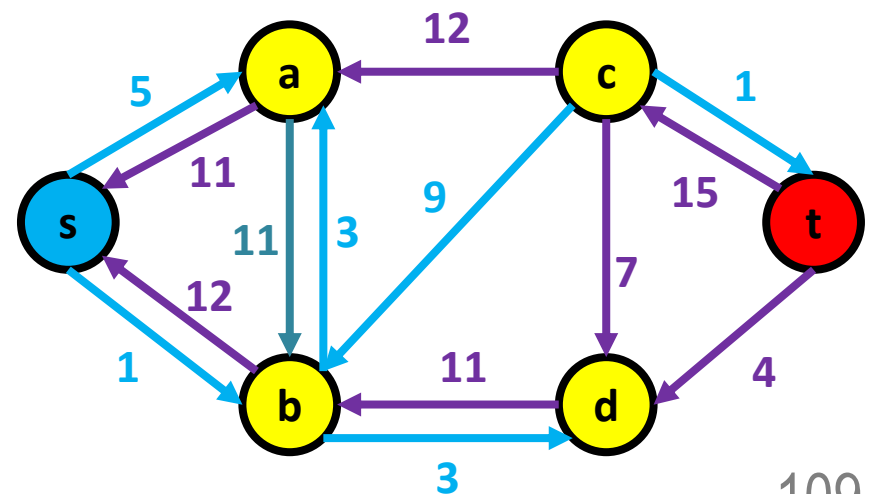
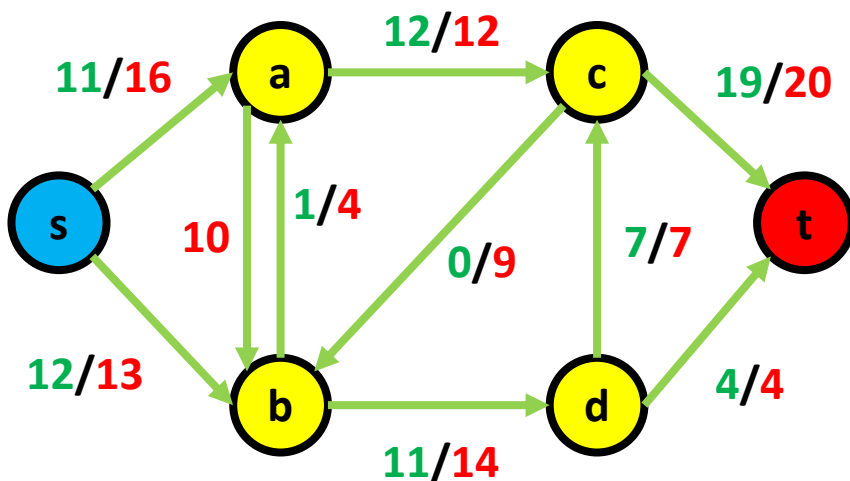
Questions?

# Path Augmentation

## Traversal in residual network

- Is there another path here?

finish when residual network has not path from s to t

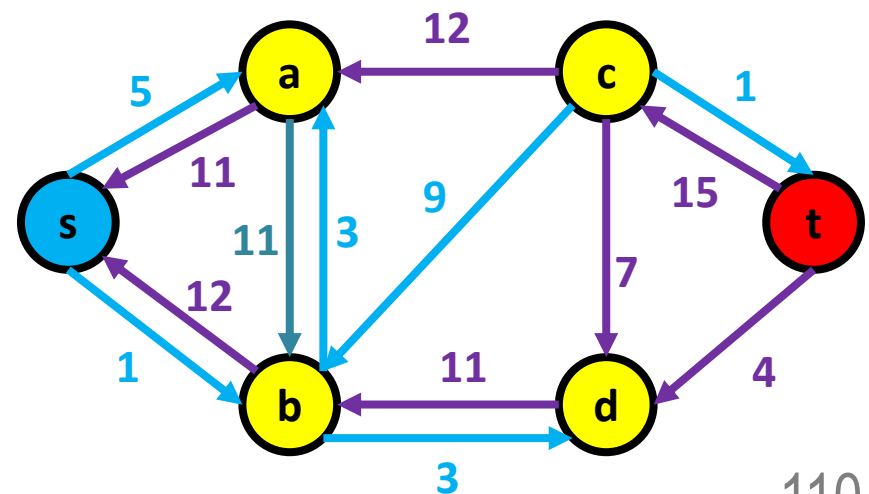
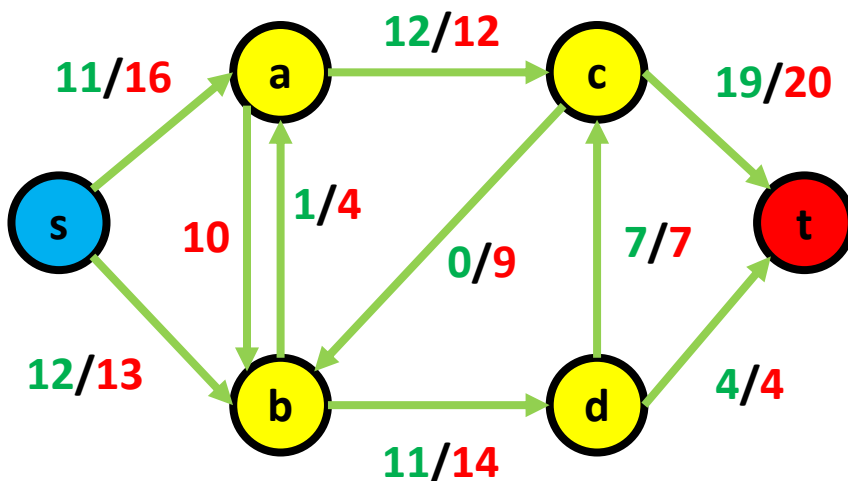
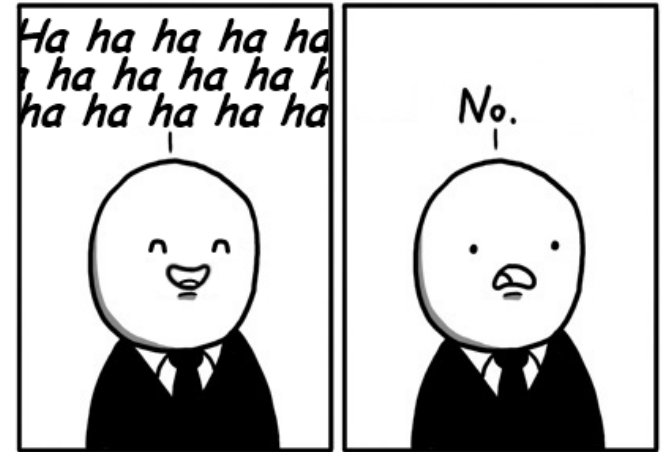


# Path Augmentation

## Traversal in residual network

- Is there another path here?
  - NO!

reach the point that has no another path



Questions?

# Ford-Fulkerson Method

## Finding the maximum flow

- So we have learnt all the components for the Ford-Fulkerson Method...



# Ford-Fulkerson Method

## Finding the maximum flow

- So we have learnt all the components for the Ford-Fulkerson Method...
  - Residual network
  - Path augmentation

# Ford-Fulkerson Method

## Finding the maximum flow

- So we have learnt all the components for the Ford-Fulkerson Method...
  - Residual network
  - Path augmentation
- Now let us look at the algorithm...

Break?

# Ford-Fulkerson Method

## Finding the maximum flow

- Let break it down slowly...

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
7      while residual_network.has_AugmentingPath():
8          # take the path
9          path = residual_network.get_AugmentingPath()
10         # augment the flow equal to the residual capacity
11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

build residual network from graph  
see 62

repeat until there is no path  
from s to t  
if there is a path,  
meaning: flow can be increased  
corresponding path can be  
augmented


see slide 88 to 107  
update flow with capacity

# Ford-Fulkerson Method

## Finding the maximum flow

- Let break it down slowly...

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
7      while residual_network.has_AugmentingPath():
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9          path = residual_network.get_AugmentingPath()
10         # augment the flow equal to the residual capacity
11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```



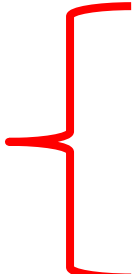
See slide  
62 to 86

# Ford-Fulkerson Method

## Finding the maximum flow

- Let break it down slowly...

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
7      while residual_network.has_AugmentingPath():
8          # take the path
9          path = residual_network.get_AugmentingPath()
10         # augment the flow equal to the residual capacity
11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```




See slide  
88 to 107

# Ford-Fulkerson Method

## Finding the maximum flow

- Let break it down slowly...

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is a augmenting path
7      while residual_network.has_AugmentingPath():
8          # take the path
9          path = residual_network.get_AugmentingPath()
10         # augment the flow equal to the residual capacity
11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```



Ends when  
it is like slide  
109 to 110

# Ford-Fulkerson Method

## Finding the maximum flow

- And that's all...

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
7      while residual_network.has_AugmentingPath():
8          # take the path
9          path = residual_network.get_AugmentingPath()
10         # augment the flow equal to the residual capacity
11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```



Questions?

# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?

# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?

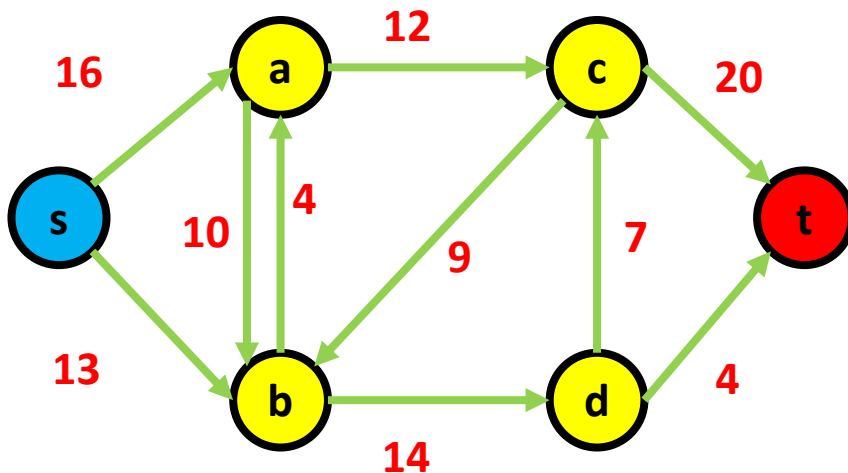
```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
7      while residual_network.has_AugmentingPath():
8          # take the path
9          path = residual_network.get_AugmentingPath()
10         # augment the flow equal to the residual capacity
11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

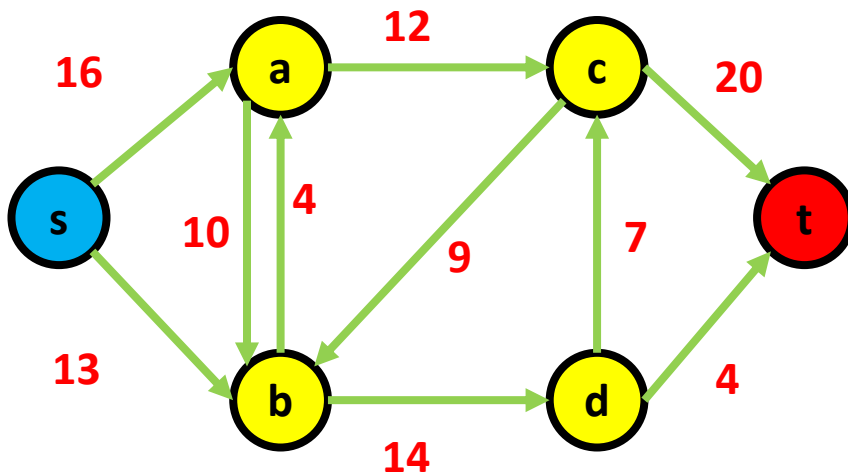


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 0

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

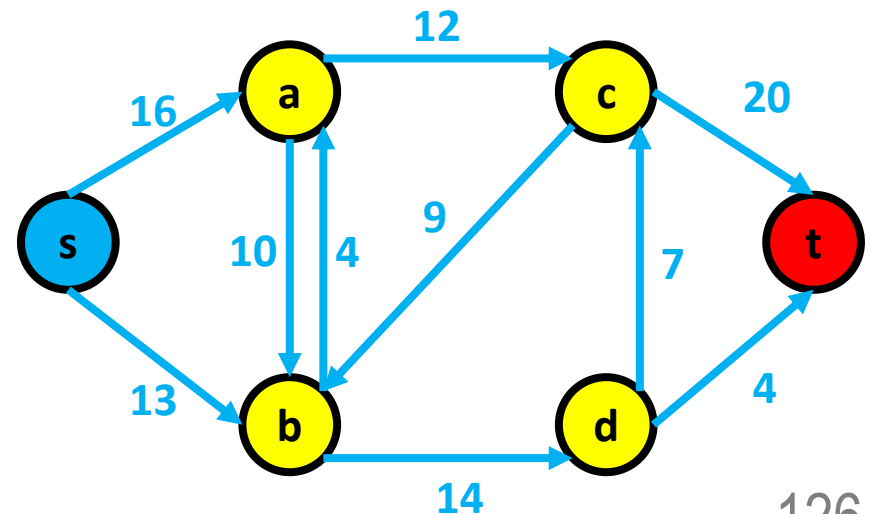
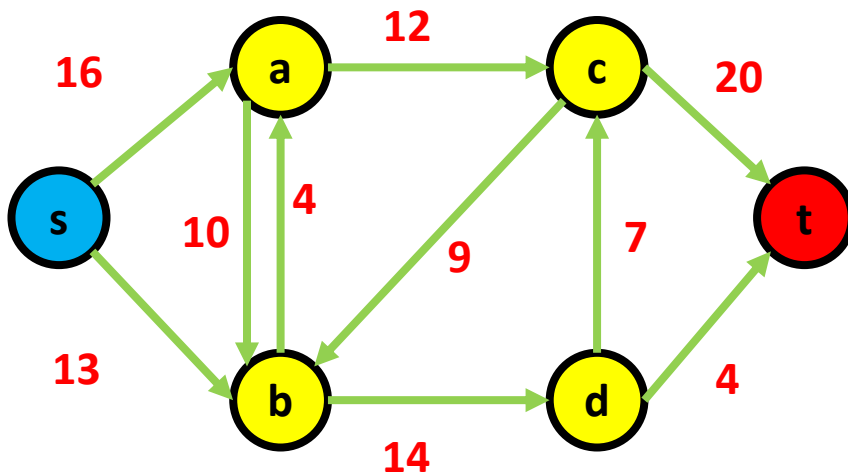


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 0
  - Make residual network

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
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10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

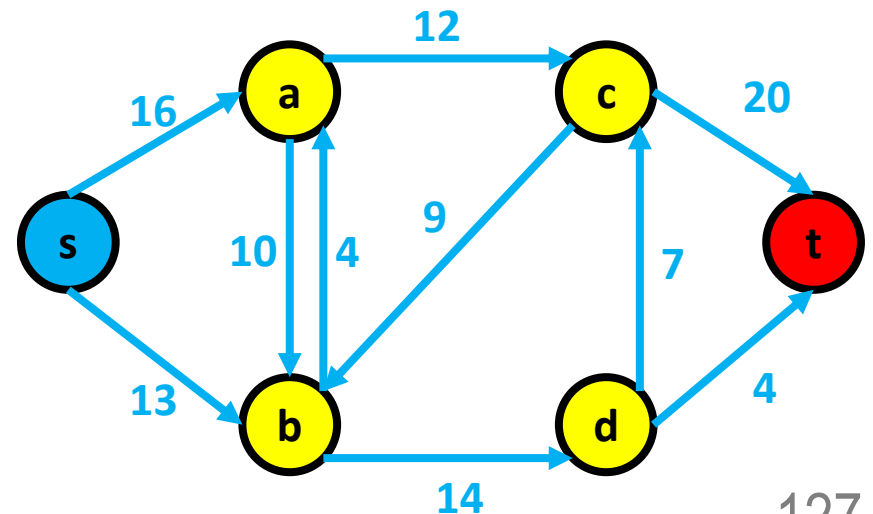
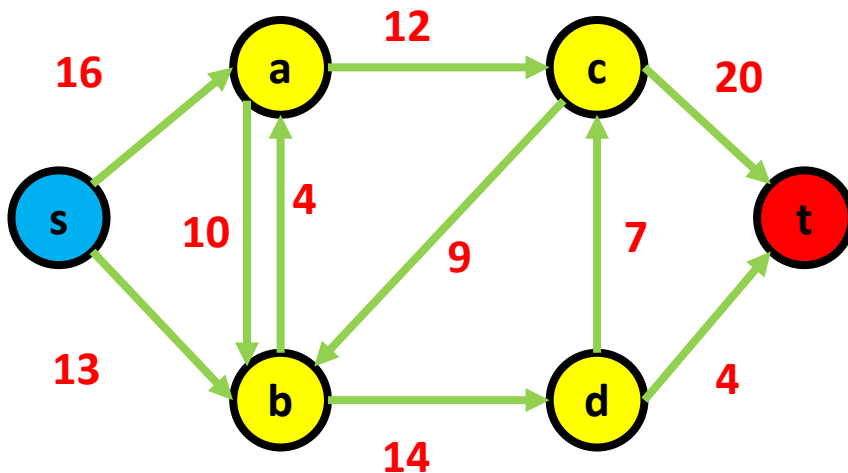


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 0
  - Make residual network
  - Do we have an augmenting path?

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

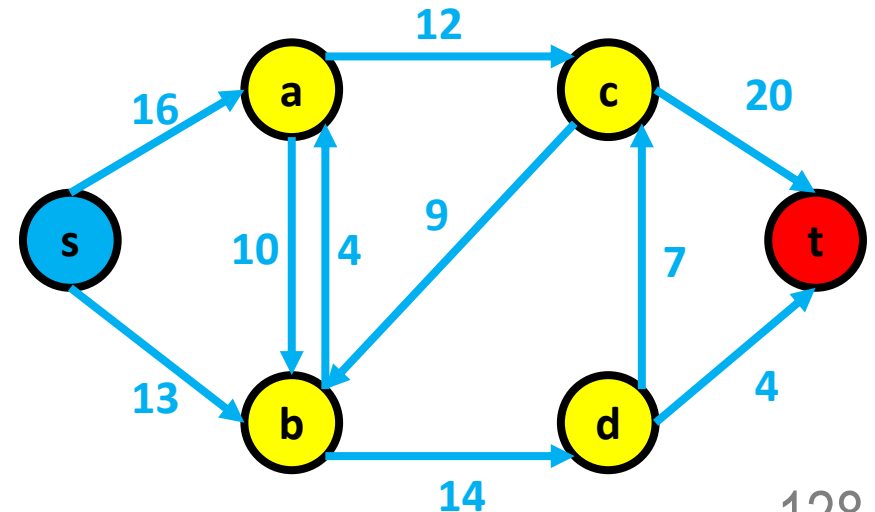
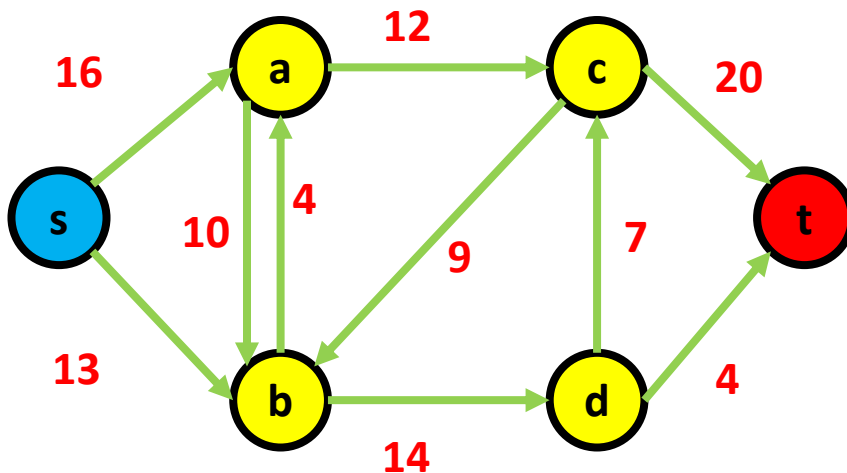


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 0
  - Make residual network
  - Do we have an augmenting path?
    - Yes! What is the path?

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



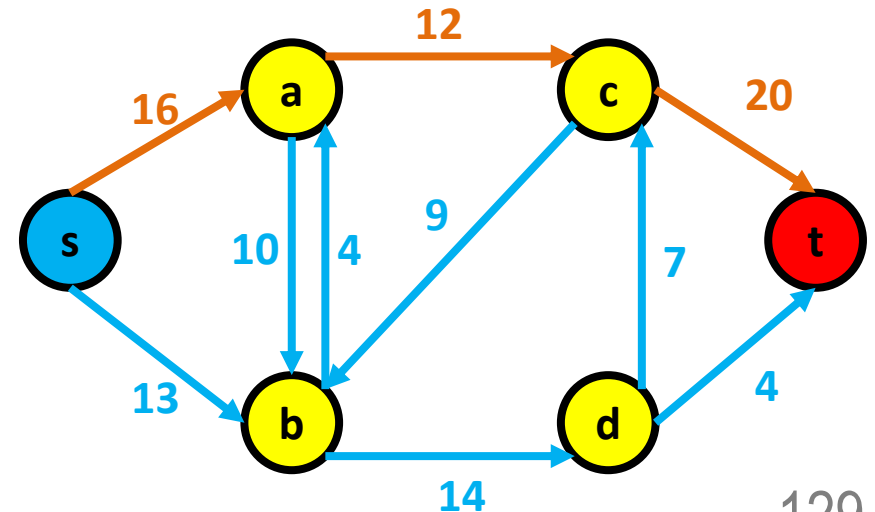
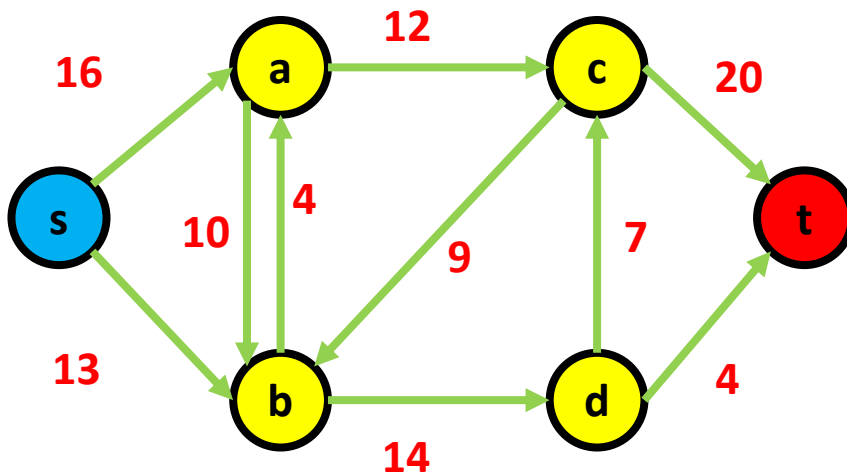


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 0
  - Make residual network
  - Do we have an augmenting path?
    - Yes! What is the path?  $s \rightarrow a \rightarrow c \rightarrow t$

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
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9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

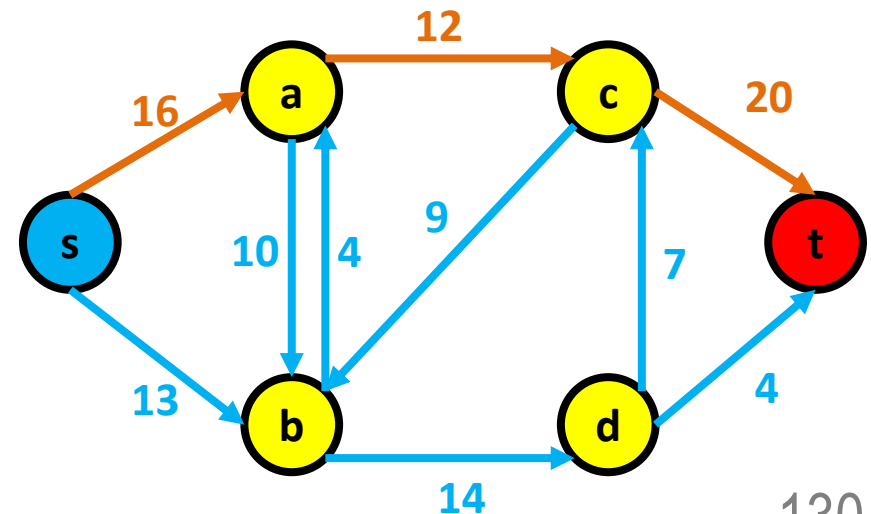
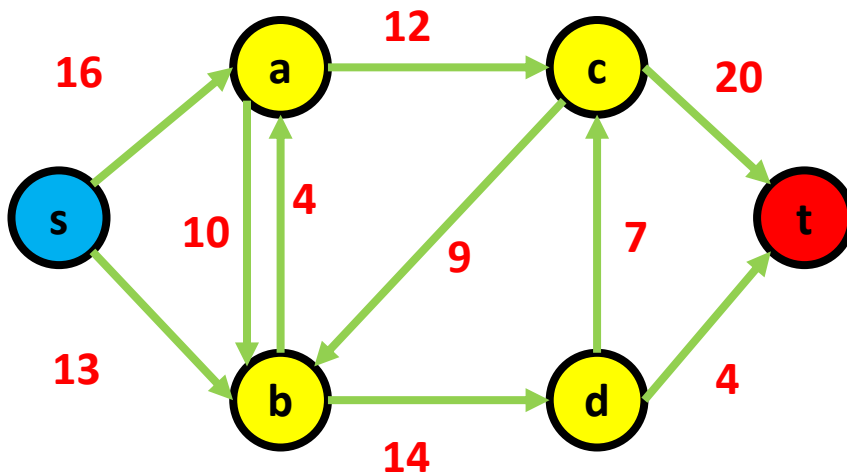


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 0
  - Make residual network
  - Do we have an augmenting path?
    - Yes! What is the path?  $s \rightarrow a \rightarrow c \rightarrow t$
    - Take the smallest value, 12

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



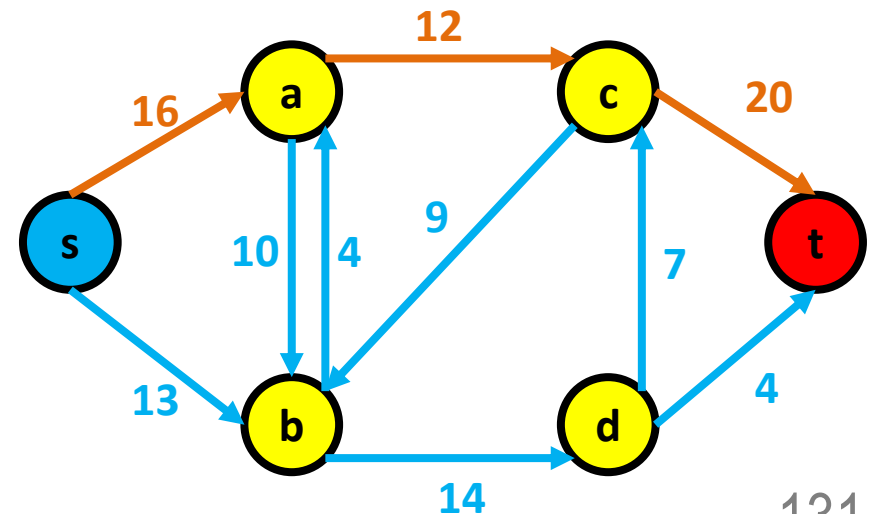
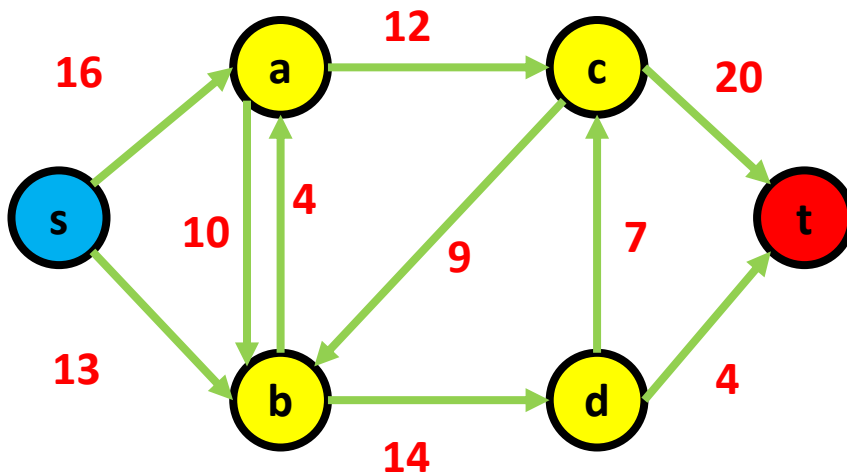
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?

- Flow = 0
- Make residual network
- Do we have an augmenting path?
  - Yes! What is the path?  $s \rightarrow a \rightarrow c \rightarrow t$
  - Take the smallest value, 12 and update the network

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



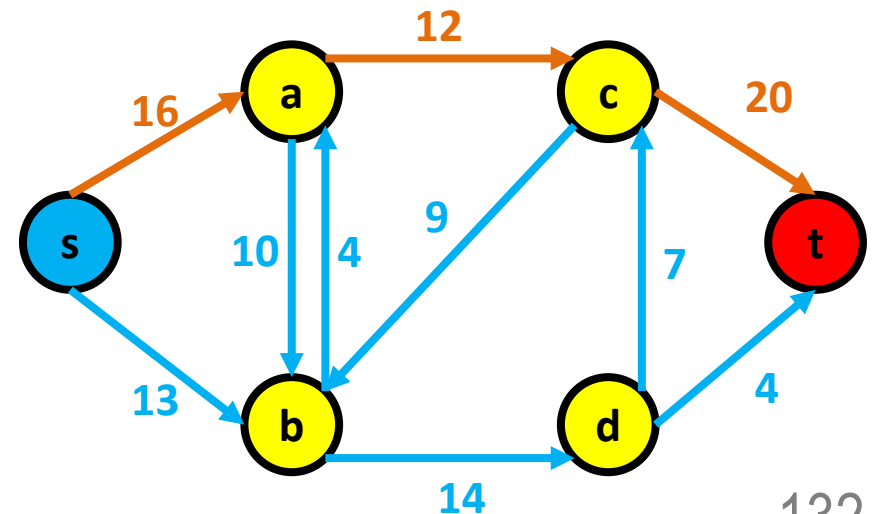
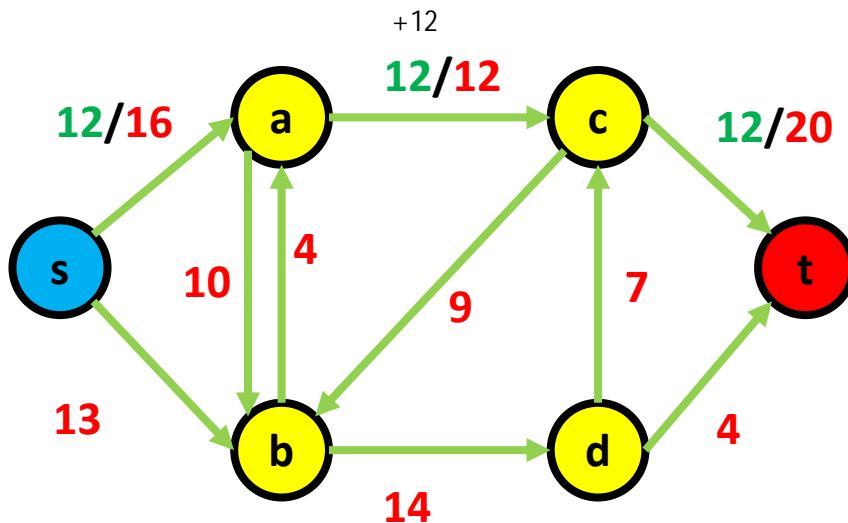
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?

- Flow = 0
- Make residual network
- Do we have an augmenting path?
  - Yes! What is the path?  $s \rightarrow a \rightarrow c \rightarrow t$
  - Take the smallest value, 12 and update the network

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
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12        # updating the residual network
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14    return flow
```



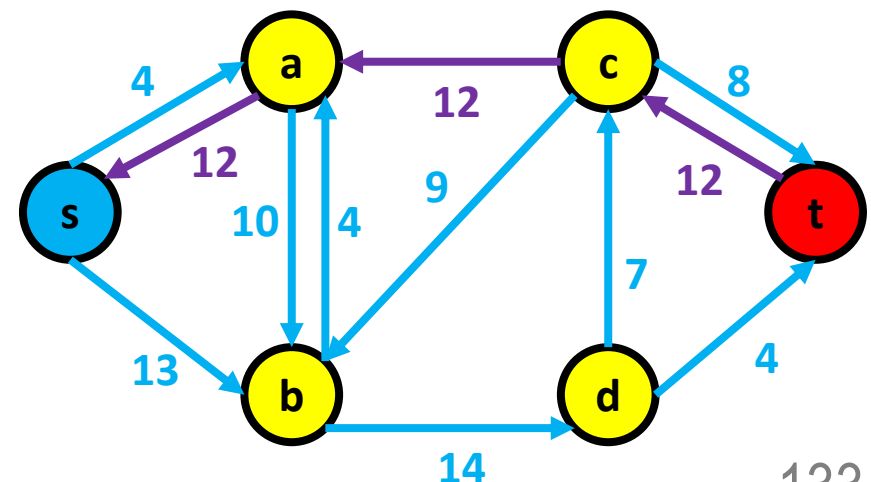
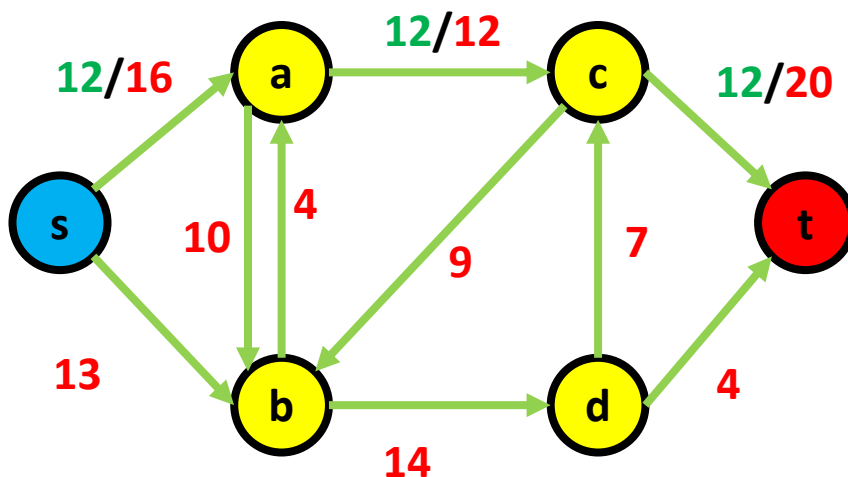
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?

- Flow = 0
- Make residual network
- Do we have an augmenting path?
  - Yes! What is the path?  $s \rightarrow a \rightarrow c \rightarrow t$
  - Take the smallest value, 12 and update the network
  - Update the residual network as well

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



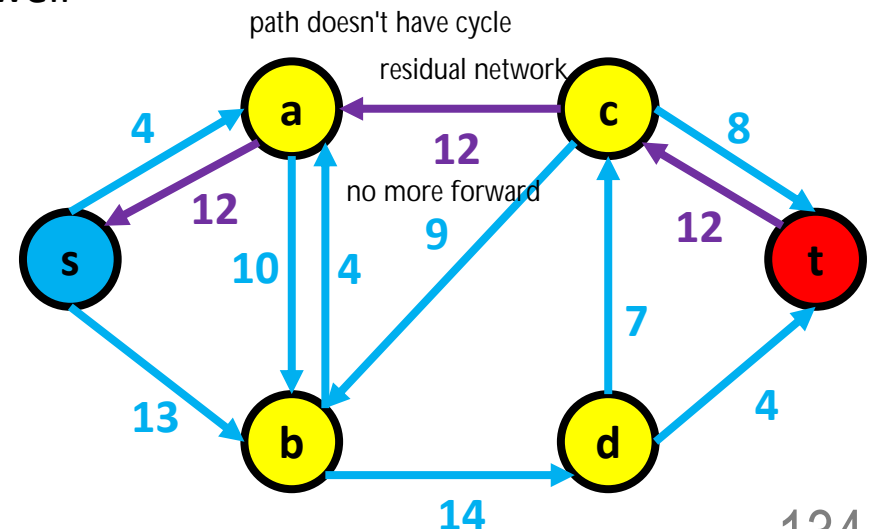
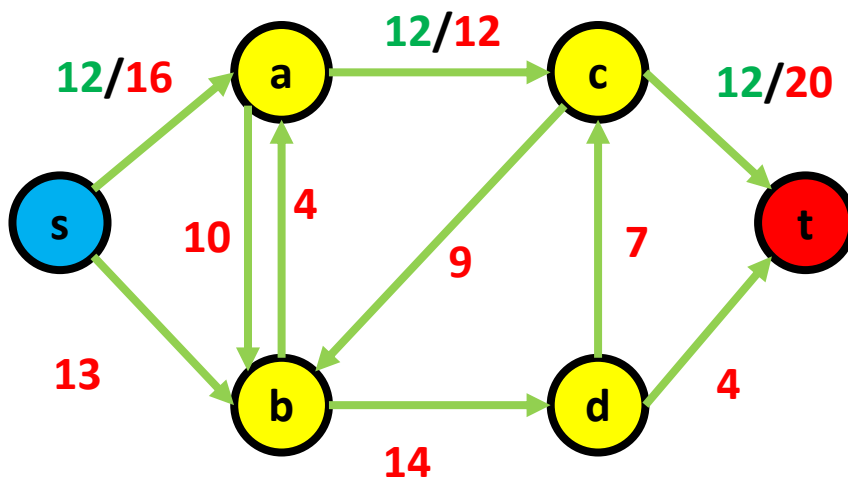
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?

- Flow =  $0 + 12 = 12$
- Make residual network
- Do we have an augmenting path?
  - Yes! What is the path?  $s \rightarrow a \rightarrow c \rightarrow t$
  - Take the smallest value, 12 and update the network
  - Update the residual network as well

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
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11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



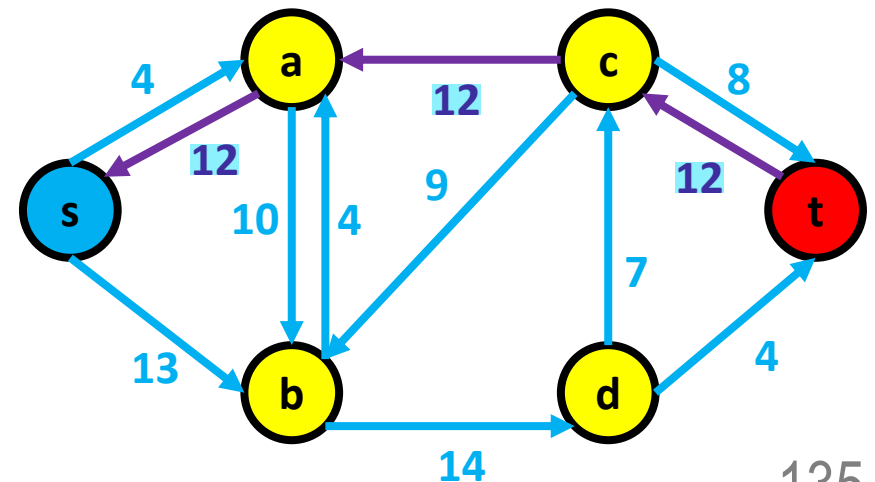
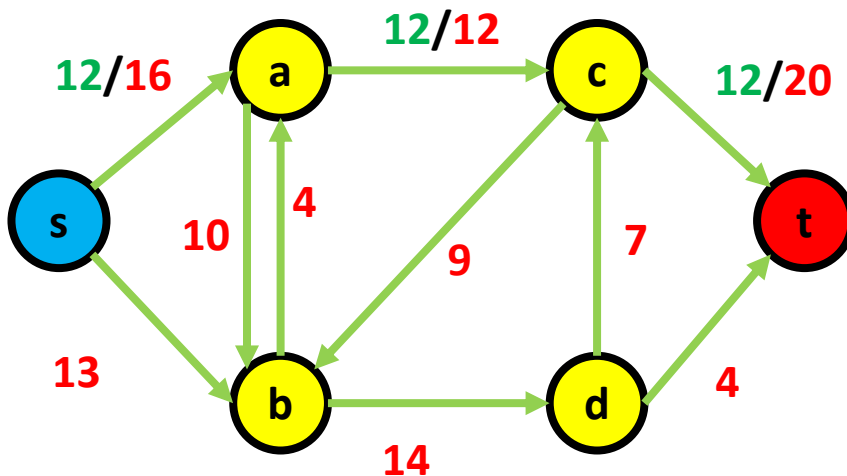
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 12
  - So we just repeat it

path does not have duplicate

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
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11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

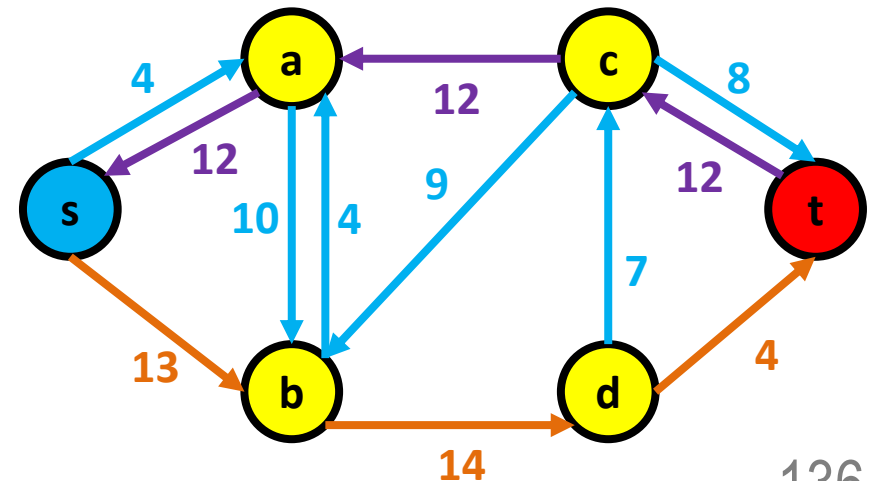
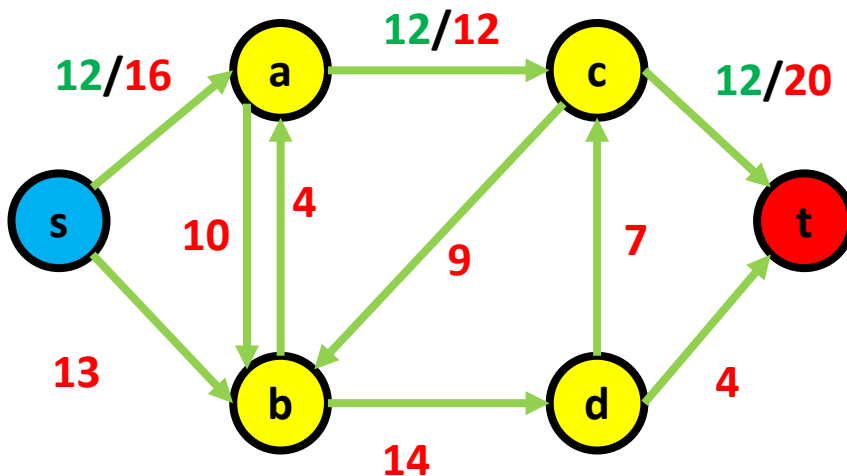


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 12
  - So we just repeat it with path SBDT

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```





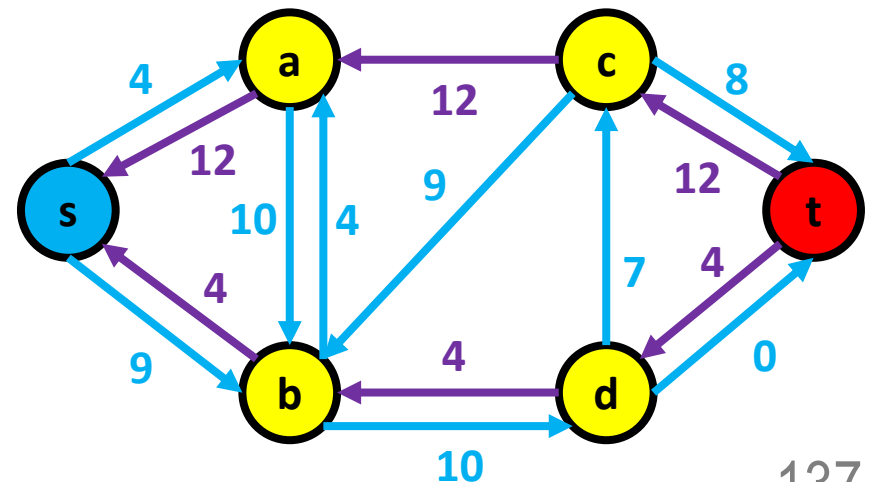
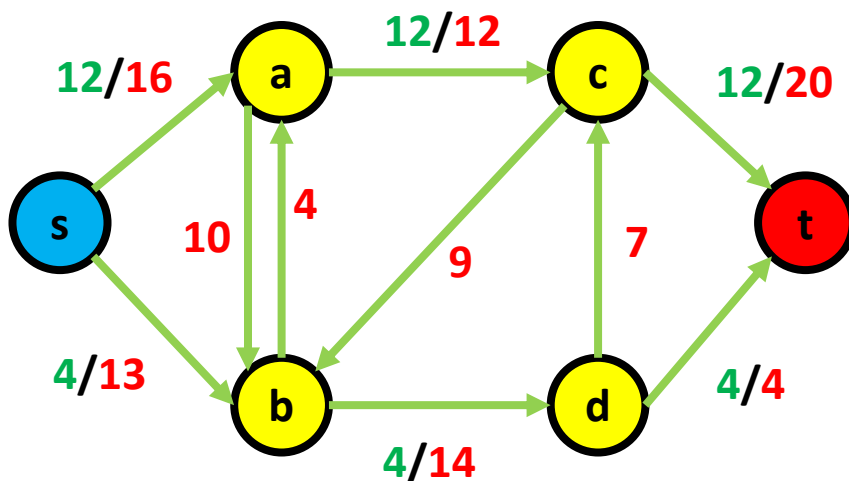
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow =  $12+4 = 16$
  - So we just repeat it with path SBDT

another path

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

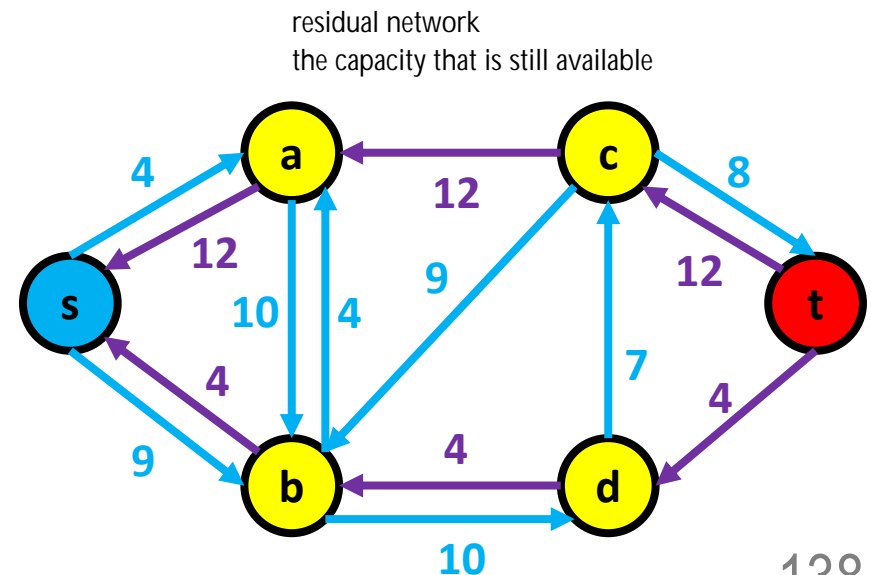
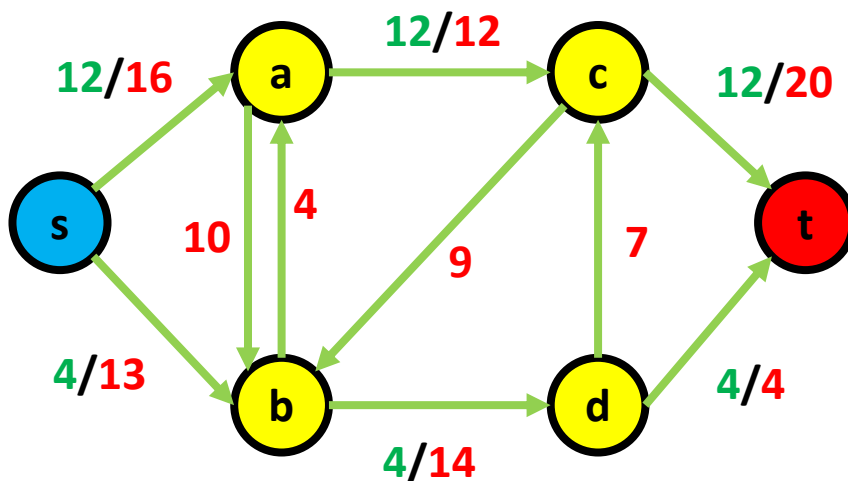


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 16

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

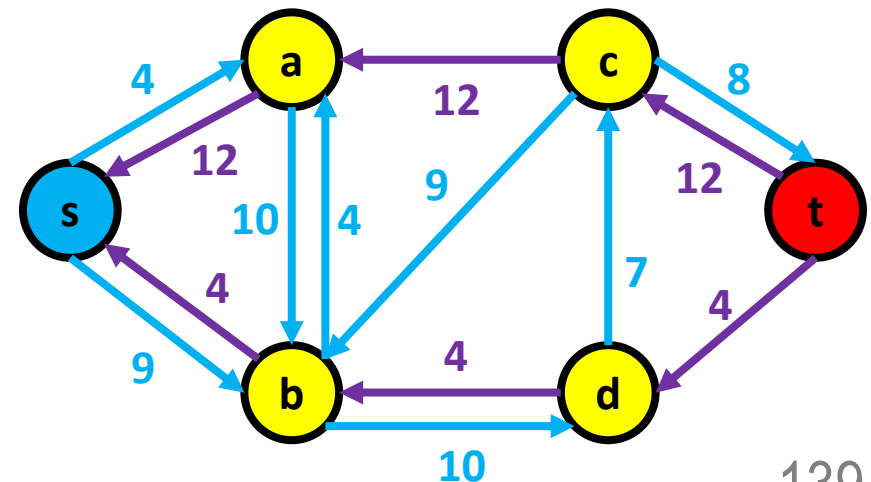
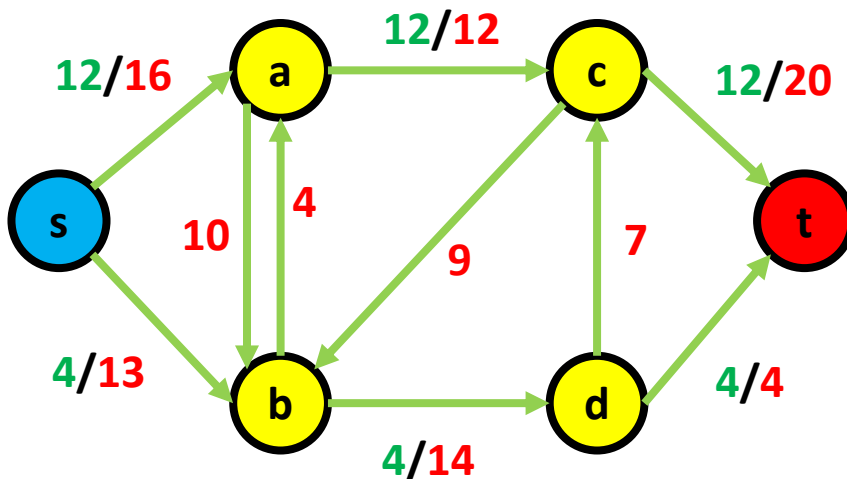


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 16
  - So now we repeat again

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

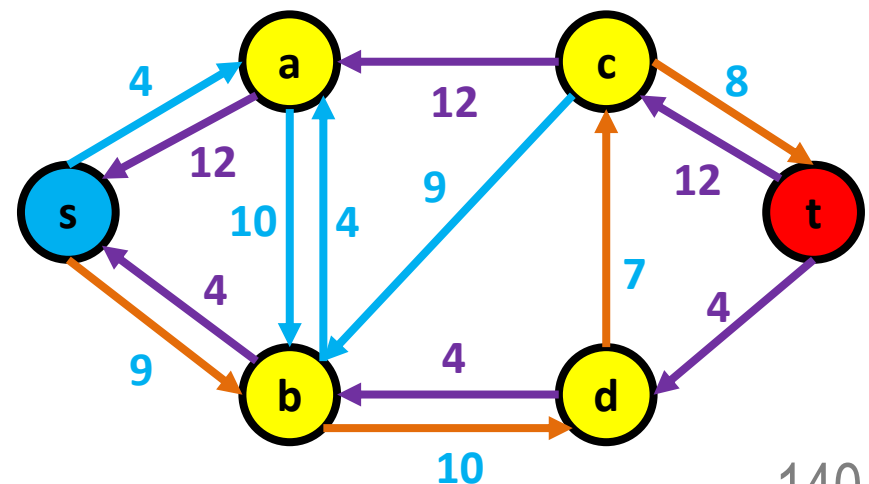
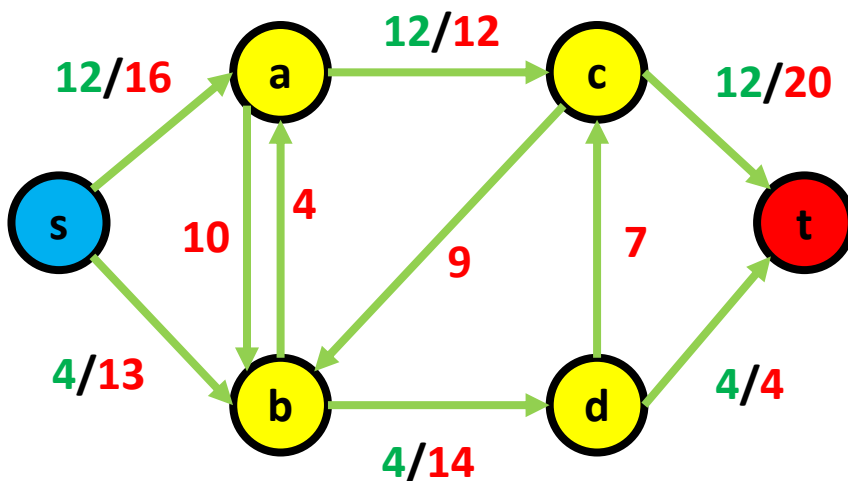


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 16
  - So now we repeat again with path SBDCT

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

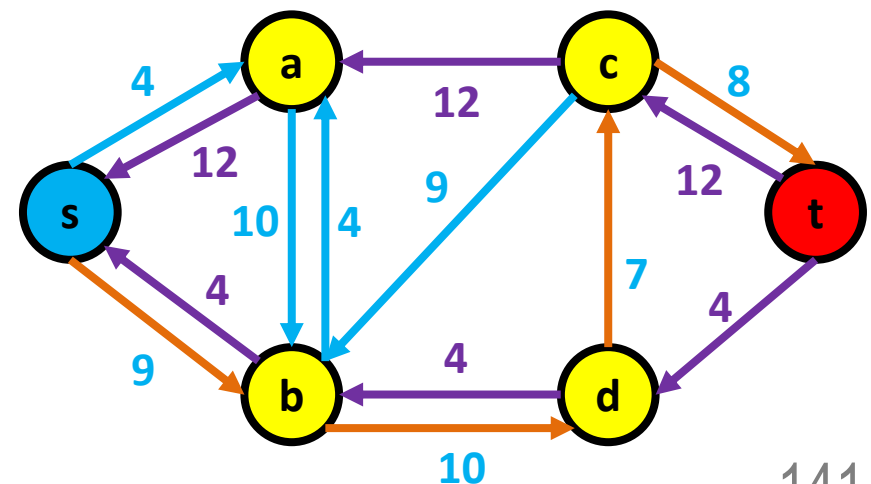
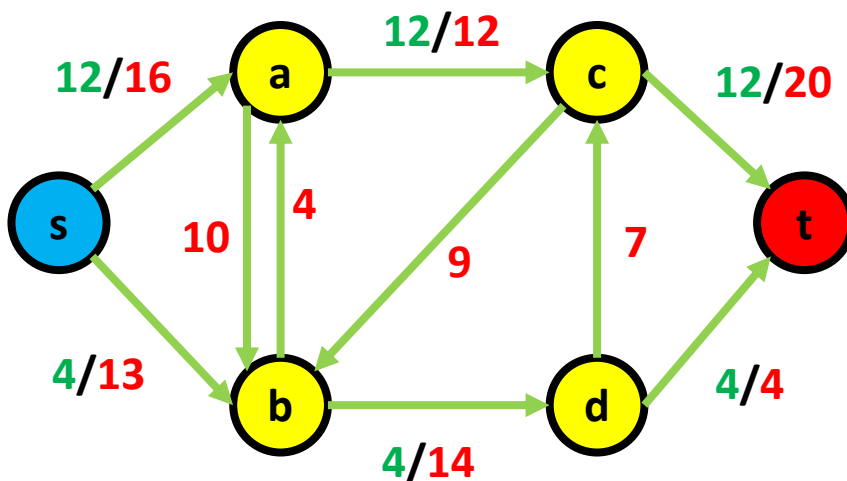


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 16+7
  - So now we repeat again with path SBDCT

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is a augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

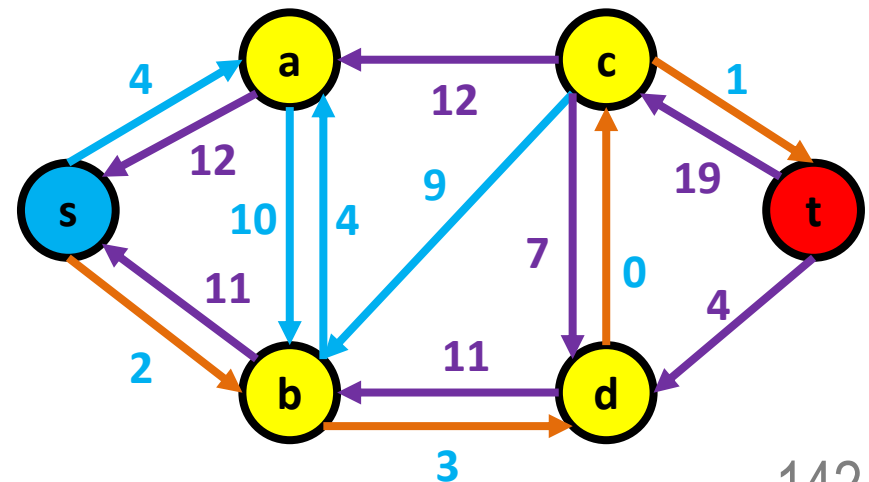
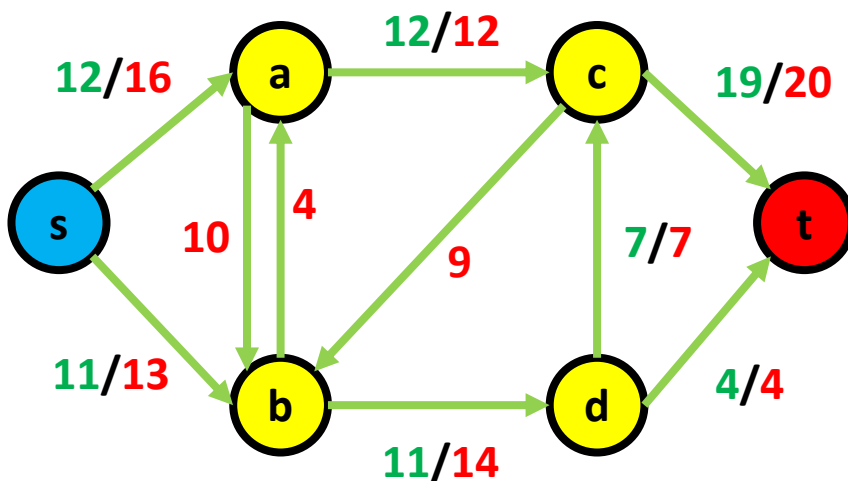


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 16+7
  - So now we repeat again with path SBDCT

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
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13        residual_network.augmentFlow(path)
14    return flow
```

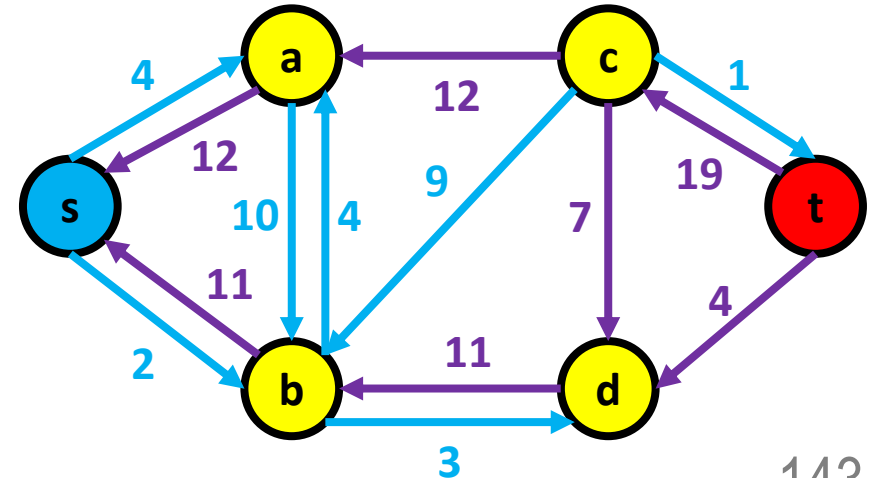
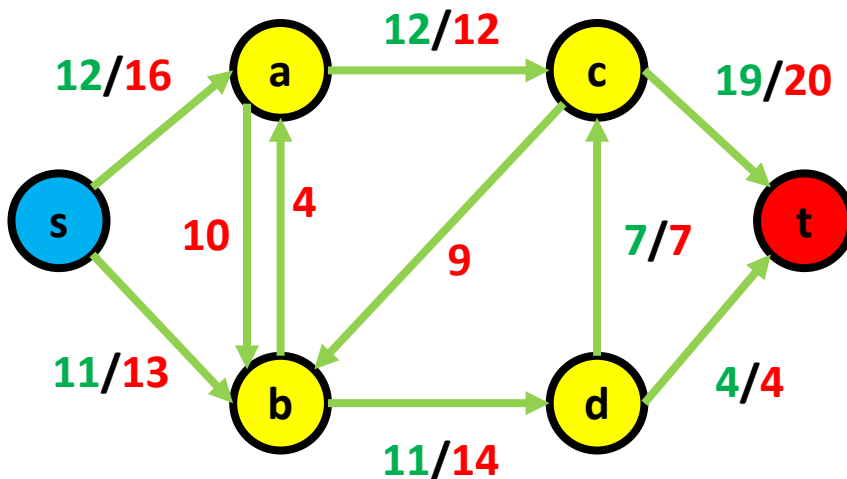


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 23

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

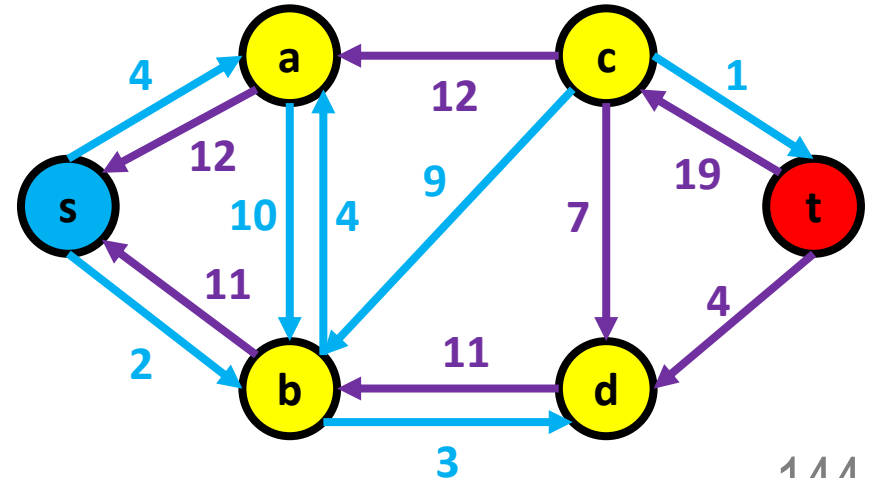
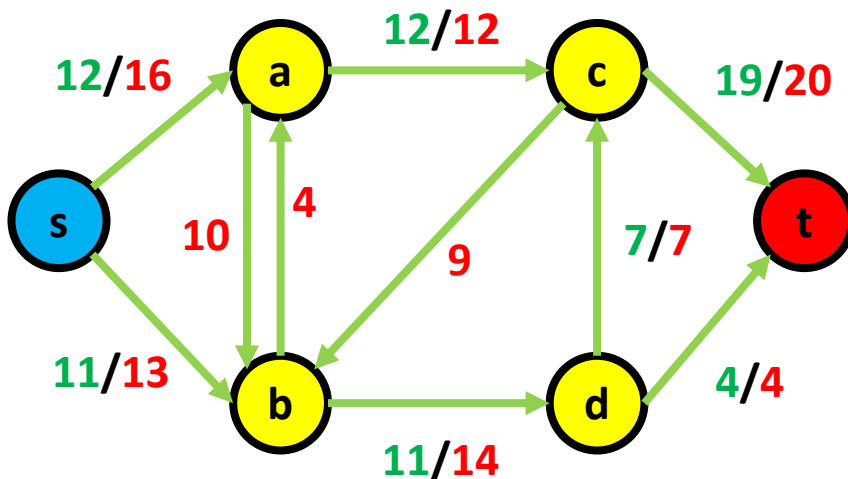


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 23
  - Do we still have a path?

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is a augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
9         path = residual_network.get_AugmentingPath()
10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



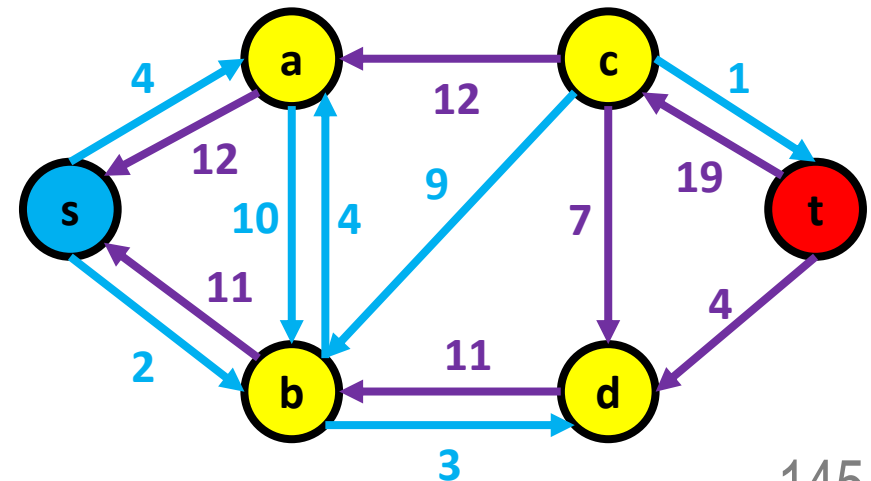
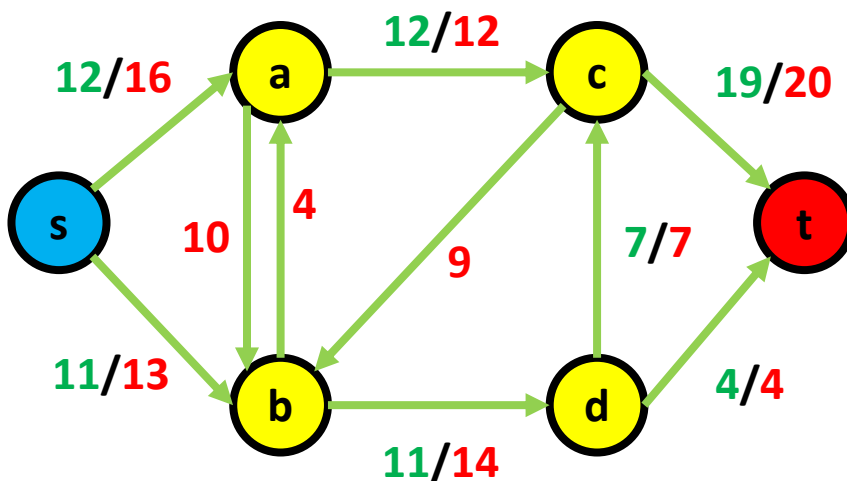


# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 23 max, run out of possible routes
  - Do we still have a path?  
No more, so we are done!

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
8         # take the path
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10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



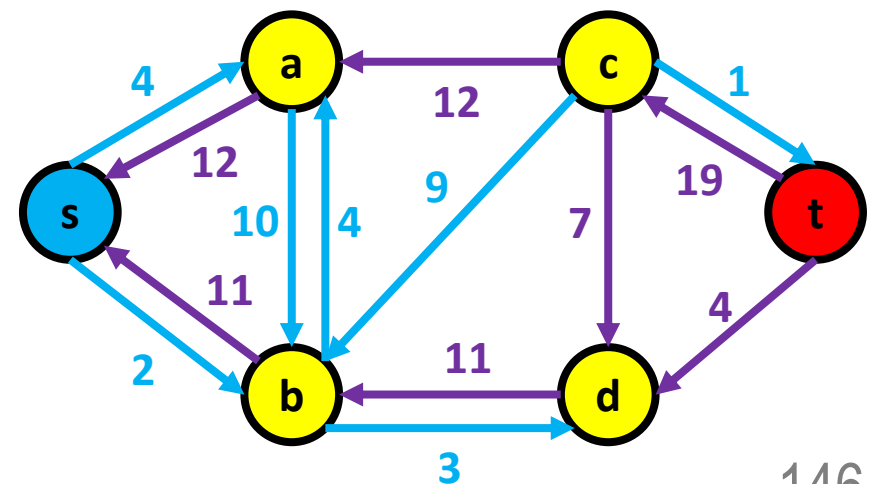
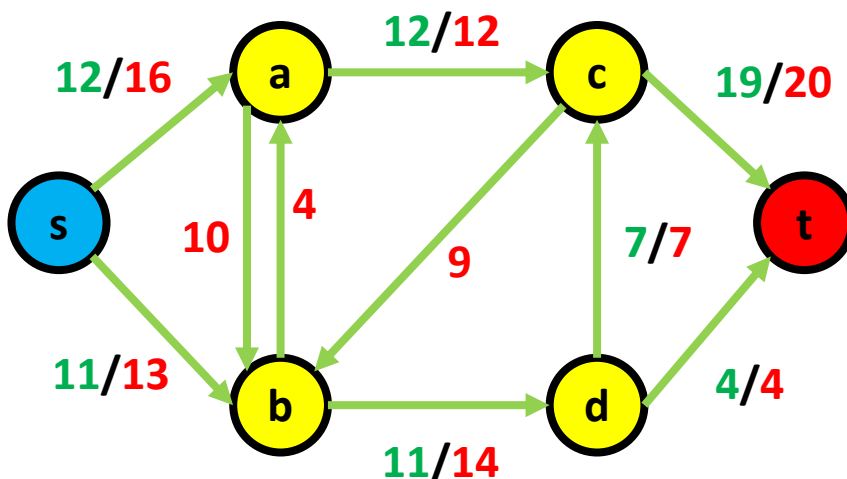
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 23
  - Do we still have a path?  
No more, so we are done!

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
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5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
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10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

- Note: The answer in MUA's slide is same value, but different network flow



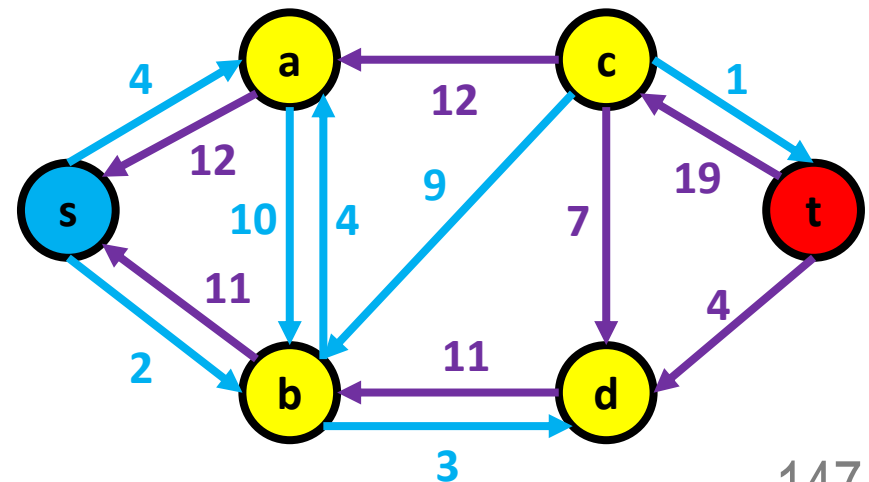
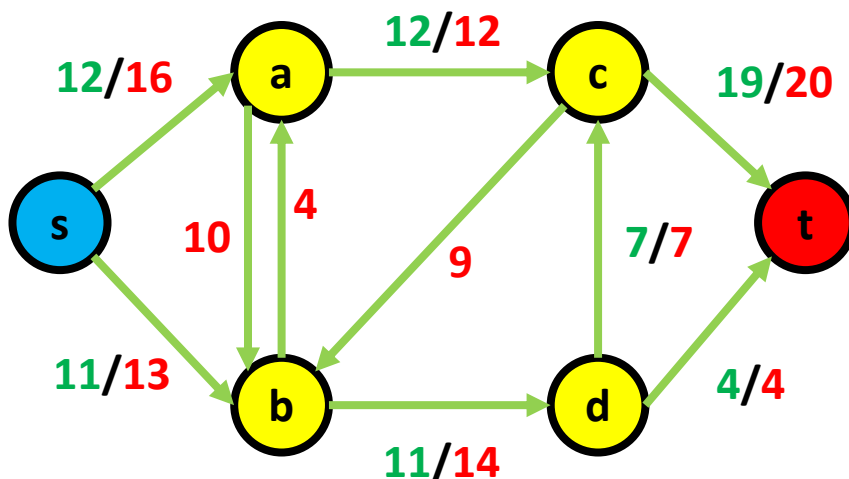
# Ford-Fulkerson Method

## Finding the maximum flow

- Want a trial run?
  - Flow = 23 unique maximum flow
  - Do we still have a path?  
No more, so we are done!

```
1 def ford_fulkerson(my_graph):
2     # initialize flow
3     flow = 0
4     # initialize the residual network
5     residual_network = ResidualNetwork(my_graph)
6     # as long as there is an augmenting path
7     while residual_network.has_AugmentingPath():
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10        # augment the flow equal to the residual capacity
11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```

- Note: The answer in MUA's slide is same value, but different network flow. Thus, answer not unique!

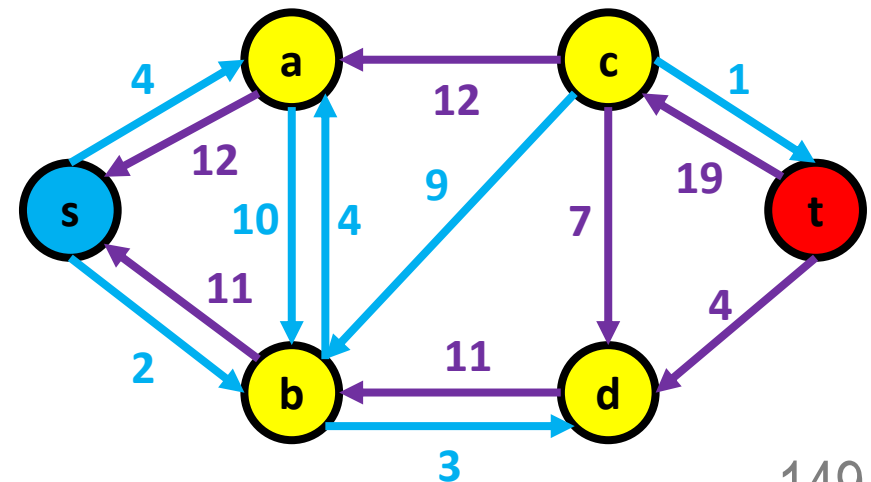
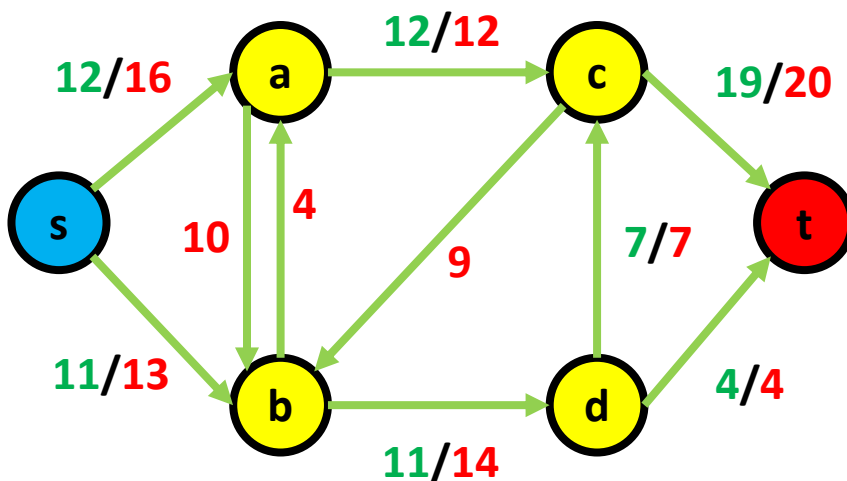


Questions?

# Ford-Fulkerson Method

## Finding the maximum flow

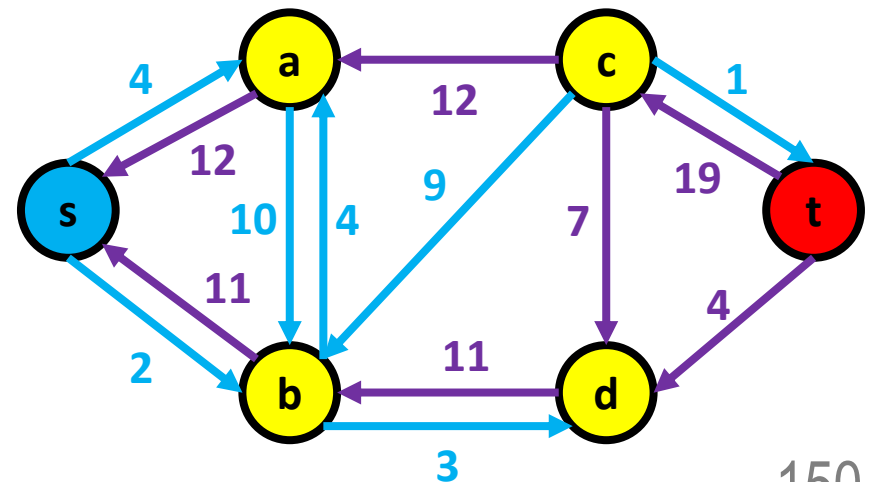
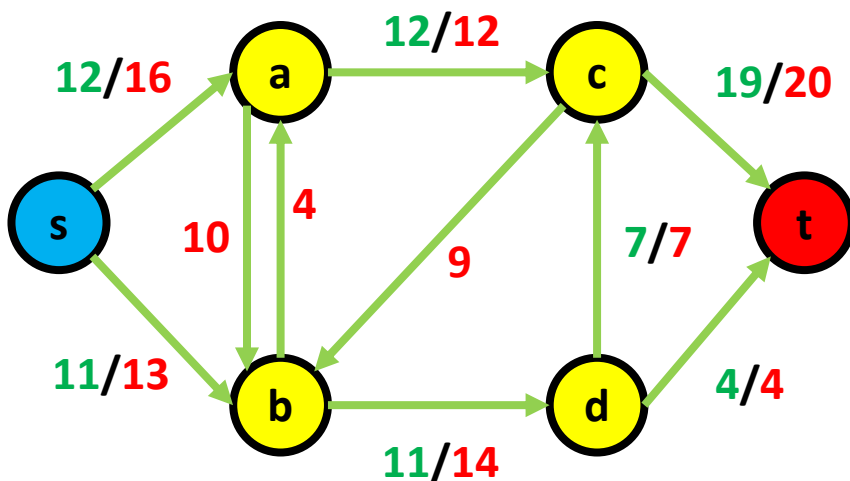
- Also remember, we maintain all of the properties!



# Ford-Fulkerson Method

## Finding the maximum flow

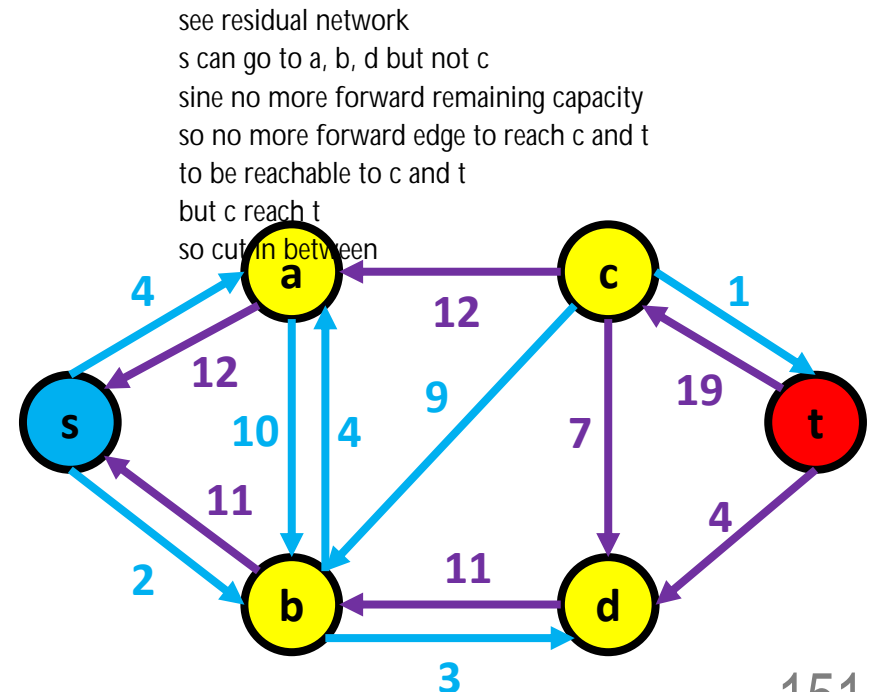
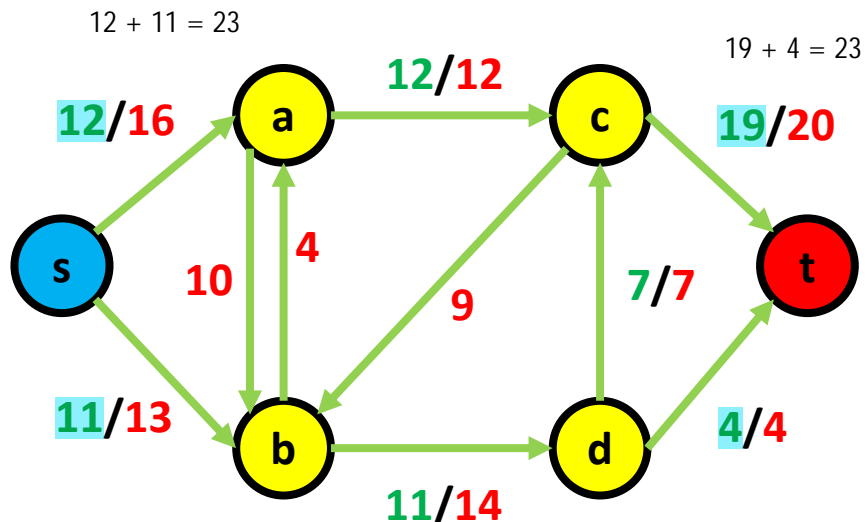
- Also remember, we maintain all of the properties!
  - The flow doesn't exceed capacity
  - Incoming to a vertex is the same as outgoing to a vertex



# Ford-Fulkerson Method

## Finding the maximum flow

- Also remember, we maintain all of the properties!
  - Capacity constraint: The flow doesn't exceed capacity
  - Flow conservation: Incoming to a vertex is the same as outgoing to a vertex  
outgoing from source = incoming to destination



Questions?



# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
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8          # take the path
9          path = residual_network.get_AugmentingPath()
10         # augment the flow equal to the residual capacity
11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?
  - Residual network have a total of  $2E$  edges, thus  $O(E)$

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is a augmenting path
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12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

  $O(E)$

# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?
  - Everything with augmenting path is  $O(V+E)$ . Why?

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
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4      # initialize the residual network
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6      # as long as there is an augmenting path
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12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?
  - Everything with augmenting path is  $O(V+E)$ . Why? Cause everything is just BFS! Or DFS if you wish to be hipster...

recommend BFS

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is a augmenting path
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13         residual_network.augmentFlow(path)
14     return flow
```


$O(V+E)$

# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?
  - But how many times do the loop repeat?

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
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6      # as long as there is an augmenting path
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11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```



# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?
  - But how many times do the loop repeat? **Total** of  $O(F)$  where **F** is the **flow itself**.

number of augmentation path

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
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5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is a augmenting path
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13         residual_network.augmentFlow(path)
14     return flow
```



$O(F)$

# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?
  - But how many times do the loop repeat? Total of  $O(F)$  where  $F$  is the flow itself. Why?

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is a augmenting path
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11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

  $O(F)$

# Ford-Fulkerson Method

## Complexity analysis

- So what is the complexity?
  - But how many times do the loop repeat? Total of  $O(F)$  where  $F$  is the flow itself. Why? Because we increase the flow in each iteration till we can't anymore. Minimum increment is  $F = F + 1$

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is a augmenting path
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11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

  $O(F)$



# Ford-Fulkerson Method

## Complexity analysis

- Total?

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
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4      # initialize the residual network
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6      # as long as there is an augmenting path
7      while residual_network.has_AugmentingPath():
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13         residual_network.augmentFlow(path)
14     return flow
```

# Ford-Fulkerson Method

## Complexity analysis

- Total?  $O(FV + FE) = O(FE)$

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
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4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
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11         flow += path.residual_capacity
12         # updating the residual network
13         residual_network.augmentFlow(path)
14     return flow
```

# Ford-Fulkerson Method

## Complexity analysis

- Total?  $O(FV + FE) = O(FE)$ 
  - This is **pseudo-polynomial** since  $F$  can be very very large...

```
1  def ford_fulkerson(my_graph):
2      # initialize flow
3      flow = 0
4      # initialize the residual network
5      residual_network = ResidualNetwork(my_graph)
6      # as long as there is an augmenting path
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12         # updating the residual network
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14     return flow
```

# Ford-Fulkerson Method

## Complexity analysis

- Total?  $O(FV + FE) = O(FE)$ 
  - This is pseudo-polynomial since  $F$  can be very very large...
  - But can be proven to be  $O(VE^2)$  via Edmonds-Karp (in FIT3155)

```
1  def ford_fulkerson(my_graph):
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14     return flow
```

# Ford-Fulkerson Method

## Complexity analysis

- Total?  $O(FV + FE) = O(FE)$ 
  - This is pseudo-polynomial since  $F$  can be very very large...
  - But can be proven to be  $O(VE^2)$  via Edmonds-Karp (in FIT3155)

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11        flow += path.residual_capacity
12        # updating the residual network
13        residual_network.augmentFlow(path)
14    return flow
```



Questions?

Break?

# Ford-Fulkerson Method

## Proof of correctness

- But does it work???





# Ford-Fulkerson Method

## Proof of correctness

- Assume every capacity is integer



# Ford-Fulkerson Method

## Proof of correctness

- Assume every capacity is integer
- Flow always **increase by 1** at **each iteration** and we know **flow** is **finite**



# Ford-Fulkerson Method

## Proof of correctness

- Assume every capacity is integer
- Flow always <sup>until max Flow</sup> increase by 1 at each iteration and we know flow is finite
- Therefore the algorithm do terminate!  
finitely reach compacity of the some necessary edge in the path



# Ford-Fulkerson Method

## Proof of correctness

- Assume every capacity is integer
  - Flow always increase by 1 at each iteration and we know flow is finite
  - Therefore the algorithm do terminate!
- 
- But does it terminate with the max flow?



# Ford-Fulkerson Method

## Proof of correctness

- Assume every capacity is integer
- Flow always increase by 1 at each iteration and we know flow is finite
- Therefore the algorithm do terminate!



- But does it terminate with the max flow?
  - That is why we need the min-cut max-flow theorem to finish our proof

Questions?

# Cut

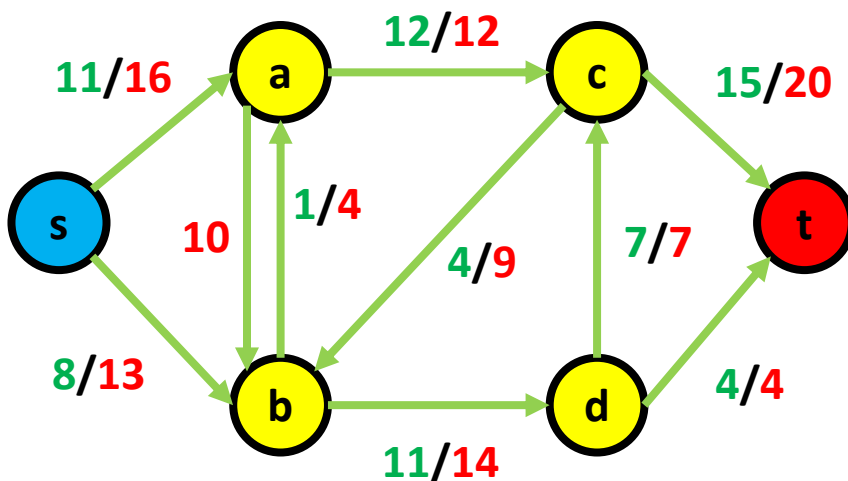
## Flow and Capacity

- What is a cut?

# Cut

## Flow and Capacity

- What is a cut?

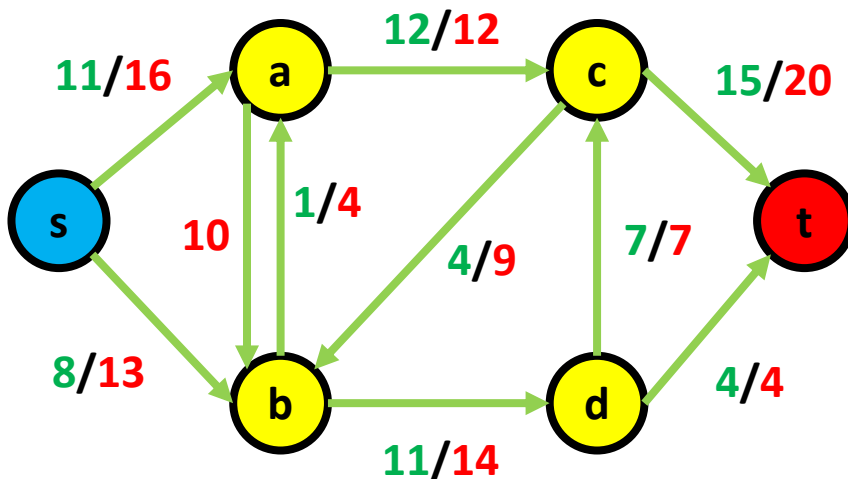




# Cut

## Flow and Capacity

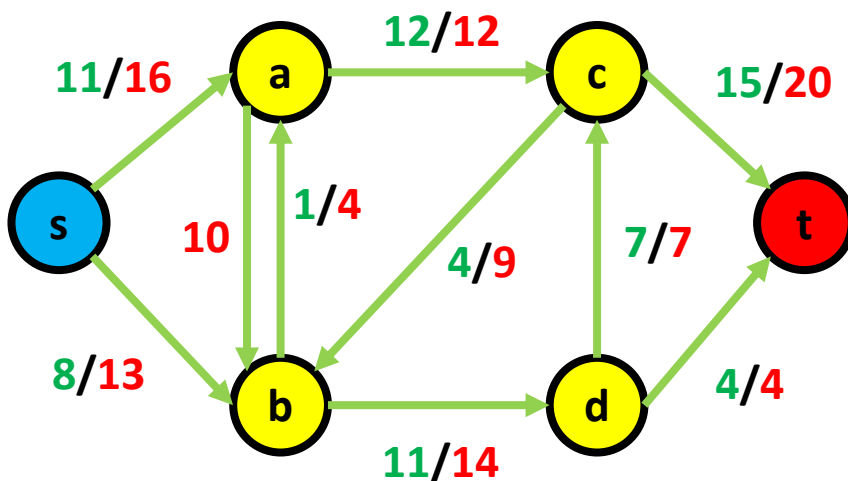
- What is a cut?
  - A cut (S,T)



# Cut

## Flow and Capacity

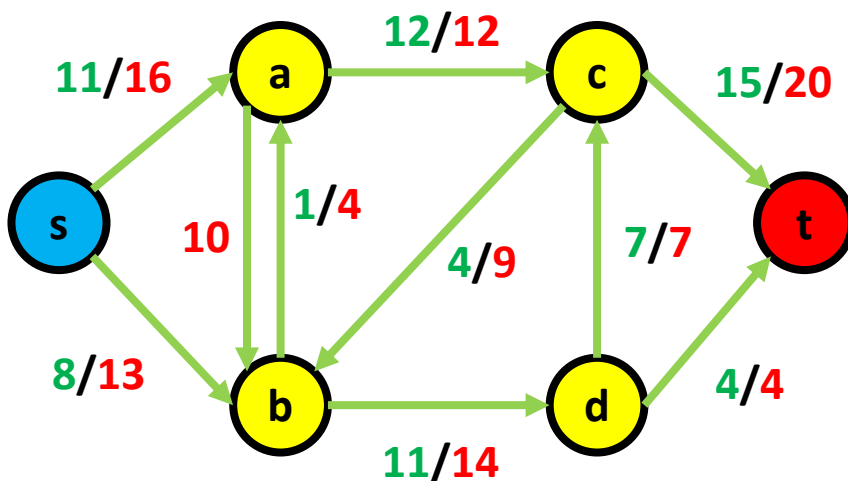
- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$
    - $T$  must contain vertex  $t$



# Cut

## Flow and Capacity

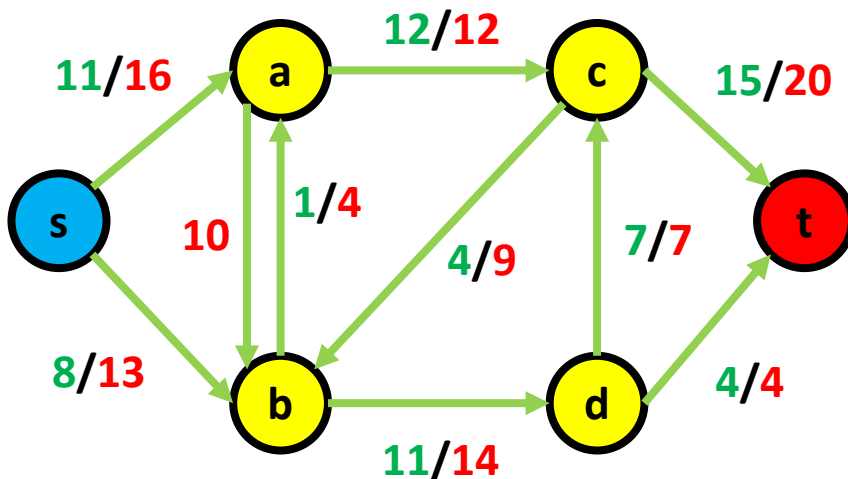
- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$
    - $T$  must contain vertex  $t$



# Cut

## Flow and Capacity

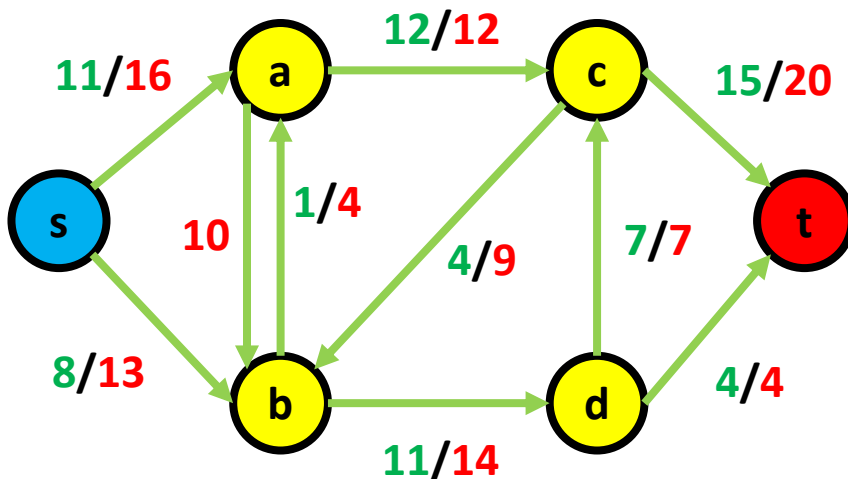
- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$
    - $T$  must contain vertex  $t$
  - Thus we can do the following...



# Cut

## Flow and Capacity

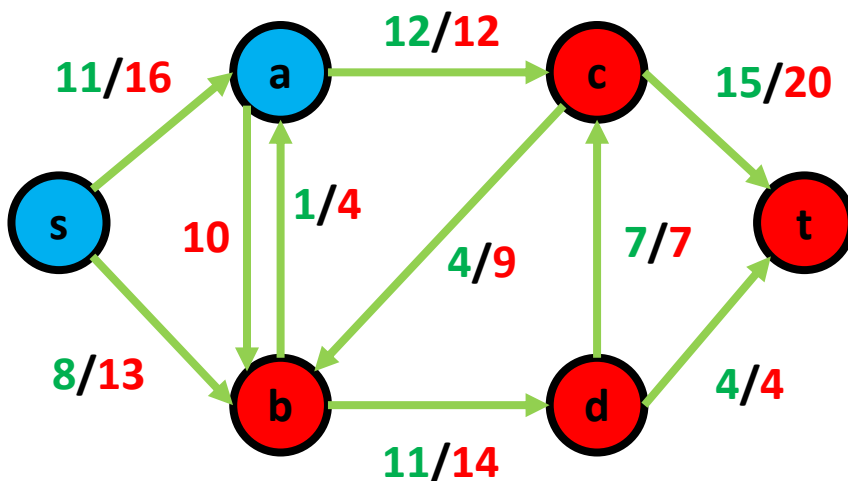
- What is a cut?
  - A cut ( $S, T$ )
    - cut into two parts: source in one part, destination in another
    - $S$  must contain vertex  $s$ .  $S = (s, a)$
    - $T$  must contain vertex  $t$ .  $T = (b, c, d, t)$
  - Thus we can do the following...



# Cut

## Flow and Capacity

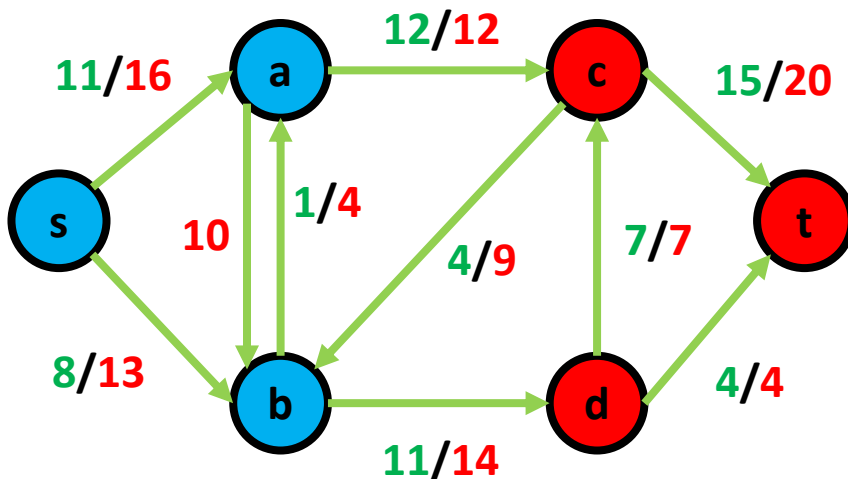
- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a)$
    - $T$  must contain vertex  $t$ .  $T = (b, c, d, t)$
  - Thus we can do the following...



# Cut

## Flow and Capacity

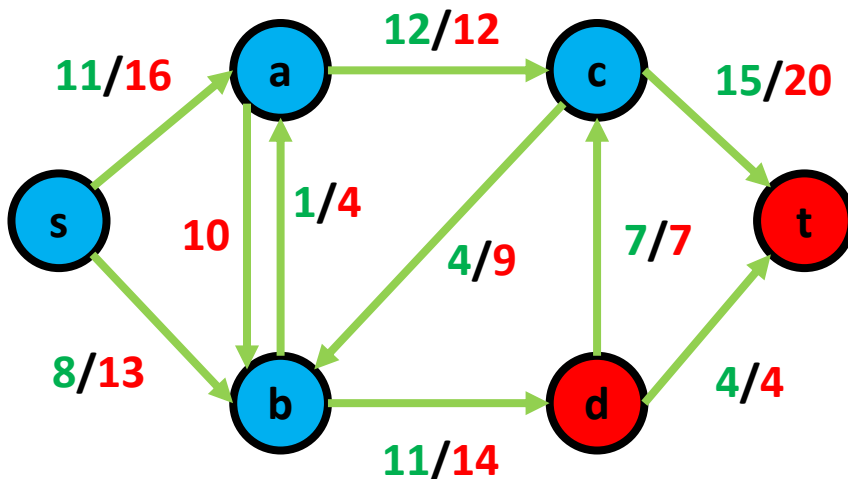
- What is a cut?
  - A cut  $(S, T)$  Min Cut = Max Flow
    - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
    - $T$  must contain vertex  $t$ .  $T = (c, d, t)$
  - Thus we can do the following...



# Cut

## Flow and Capacity

- What is a cut?
  - A cut ( $S, T$ )
    - $S$  must contain vertex  $s$ .  $S = (s, a, b, c)$   
a, b, c must connect to  $s$  (start)
    - $T$  must contain vertex  $t$ .  $T = (d, t)$   $t$  must connect to  $t$  (sink)
  - Thus we can do the following...

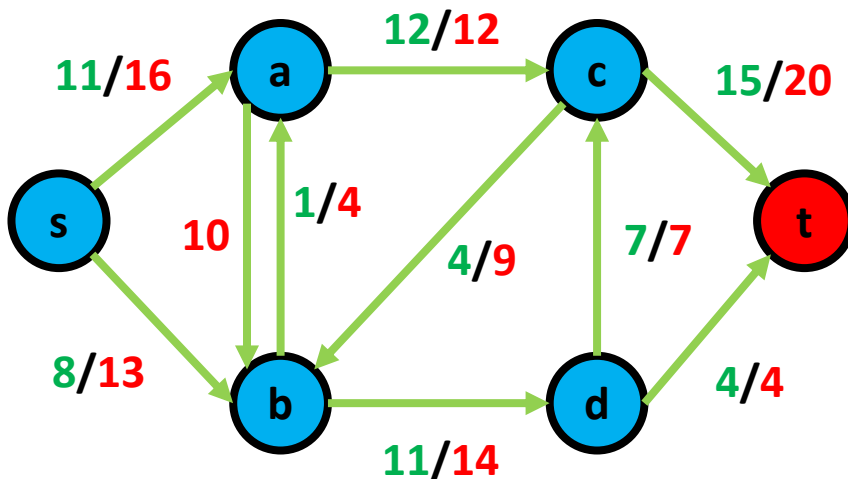




# Cut

## Flow and Capacity

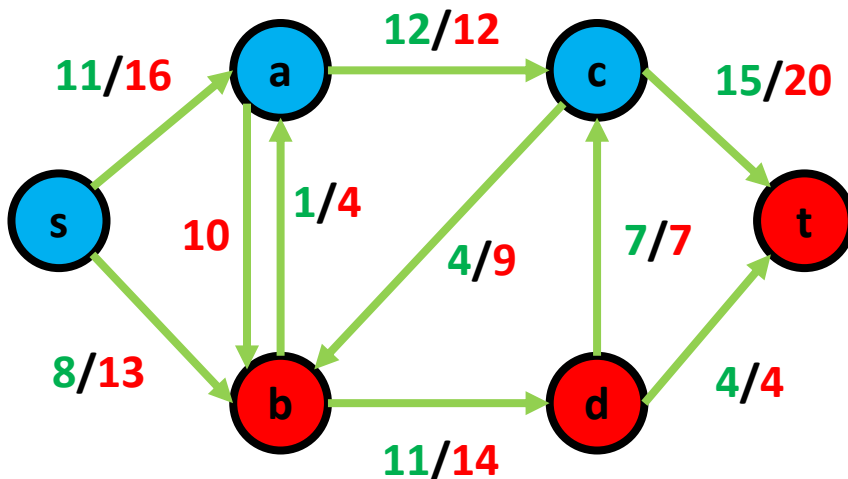
- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, b, c, d)$
    - $T$  must contain vertex  $t$ .  $T = (t)$
  - Thus we can do the following...



# Cut

## Flow and Capacity

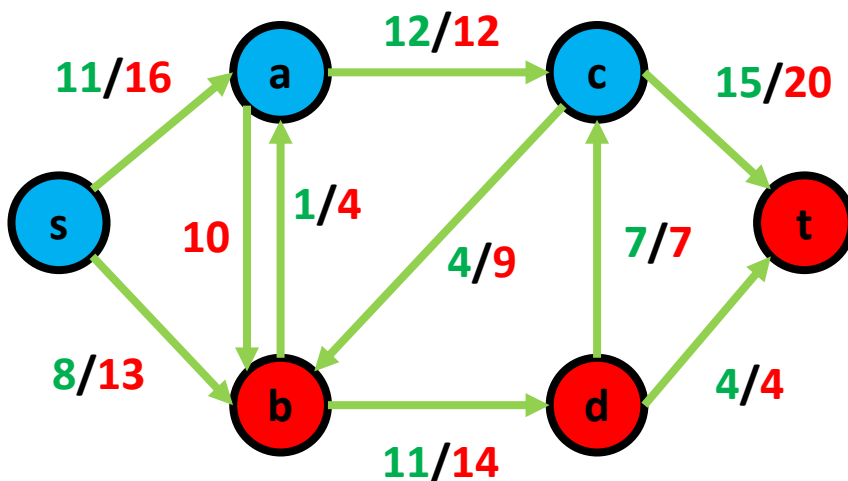
- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, c)$
    - $T$  must contain vertex  $t$ .  $T = (b, d, t)$
  - Thus we can do the following...
  - And more!!!



# Cut

## Flow and Capacity

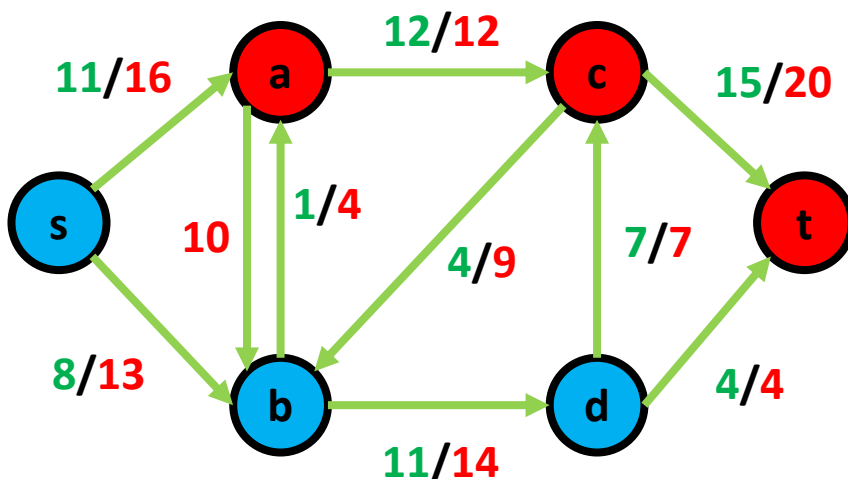
- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, c)$  reachable from  $s$  to  $a, c$
    - $T$  must contain vertex  $t$ .  $T = (b, d, t)$  vertex reachable to  $t$
  - Thus we can do the following...
  - And more!!! Because the  $S$  and  $T$  are still connected with path from  $s$  and path to  $t$



# Cut

## Flow and Capacity

- What is a cut?
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, c)$
    - $T$  must contain vertex  $t$ .  $T = (b, d, t)$
  - Thus we can do the following...
  - And more!!! Because the  $S$  and  $T$  are still connected with path from  $s$  and path to  $t$

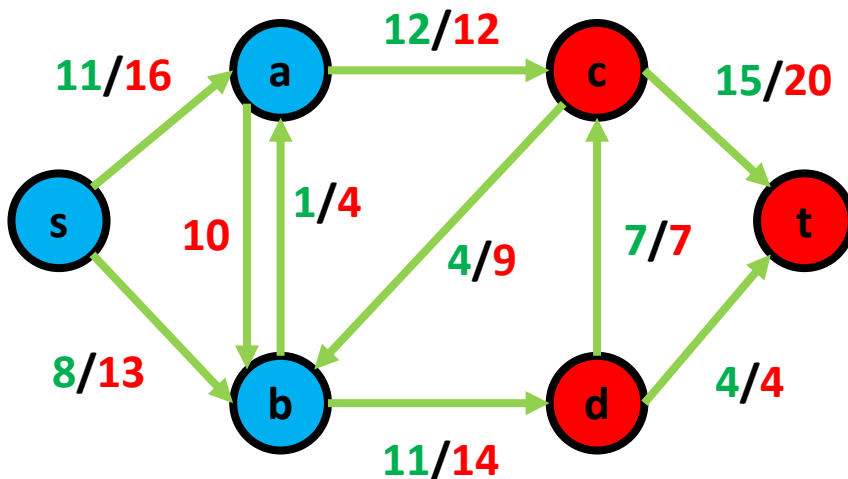


Questions?

# Cut

## Flow and Capacity

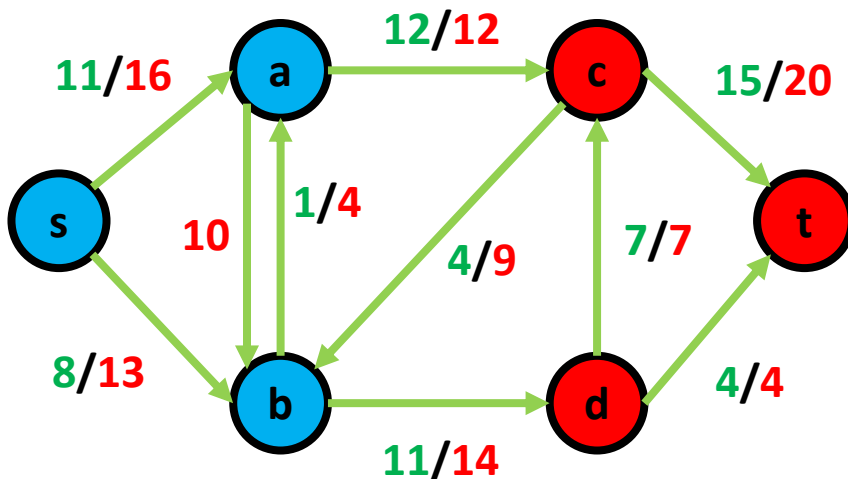
- Let us use this example
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
    - $T$  must contain vertex  $t$ .  $T = (c, d, t)$



# Cut

## Flow and Capacity

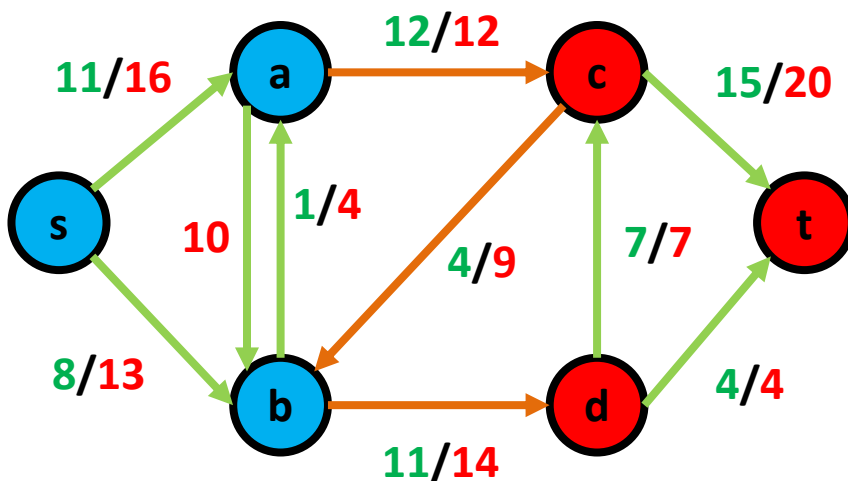
- Let us use this example
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
    - $T$  must contain vertex  $t$ .  $T = (c, d, t)$
  - We have edges **crossing** the cut



# Cut

## Flow and Capacity

- Let us use this example
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
    - $T$  must contain vertex  $t$ .  $T = (c, d, t)$
  - We have edges crossing the cut

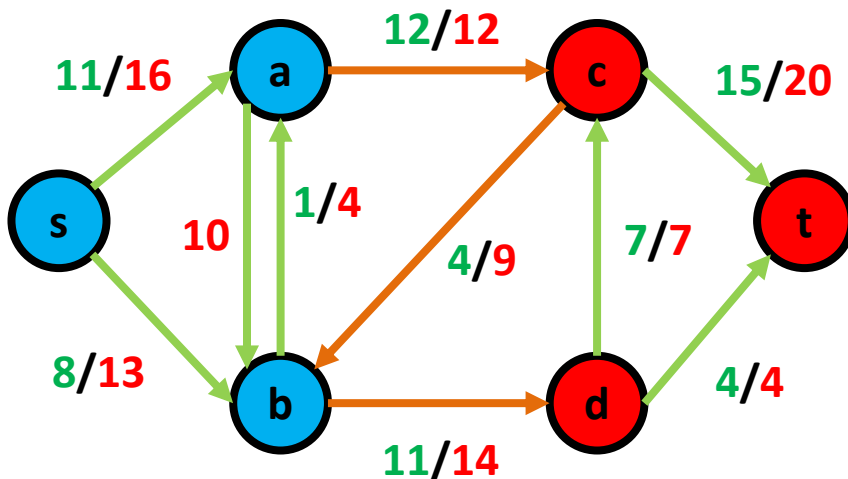




# Cut

## Flow and Capacity

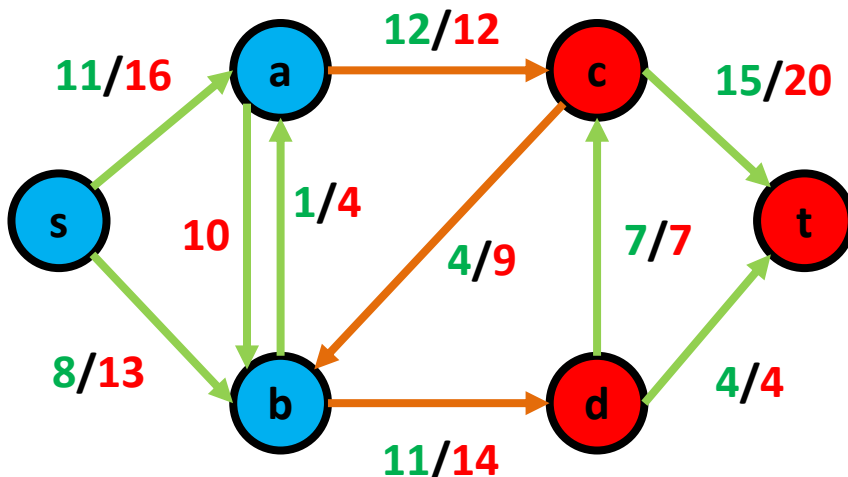
- Let us use this example
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
    - $T$  must contain vertex  $t$ .  $T = (c, d, t)$
  - We have edges **crossing** the cut
  - Capacity of a cut  $(S, T) =$
  - Flow of a cut  $(S, T) =$



# Cut

## Flow and Capacity

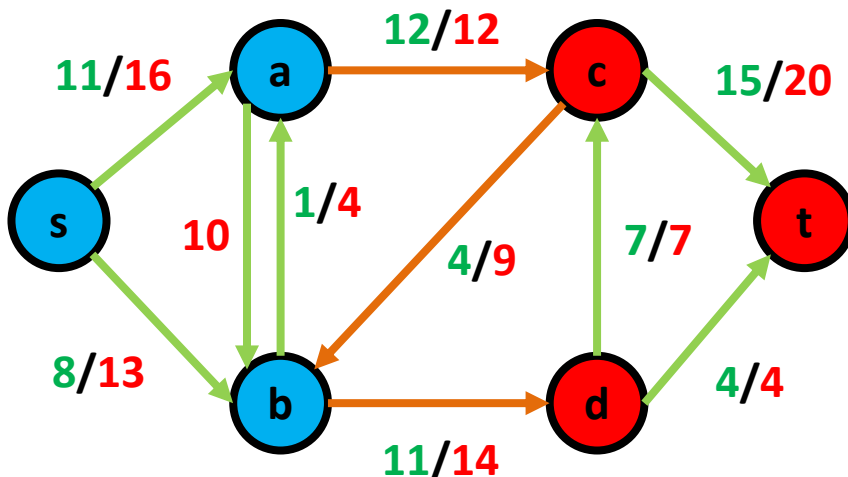
- Let us use this example
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
    - $T$  must contain vertex  $t$ .  $T = (c, d, t)$
  - We have edges **crossing** the cut
  - Capacity of a cut  $(S, T) =$  **capacity** of **outgoing edges**
  - Flow of a cut  $(S, T) =$



# Cut

## Flow and Capacity

- Let us use this example
  - A cut  $(S, T)$ 
    - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
    - $T$  must contain vertex  $t$ .  $T = (c, d, t)$
  - We have edges **crossing** the cut
  - Capacity of a cut  $(S, T)$  = capacity of outgoing edges =  $12 + 14 = 26$
  - Flow of a cut  $(S, T)$  =

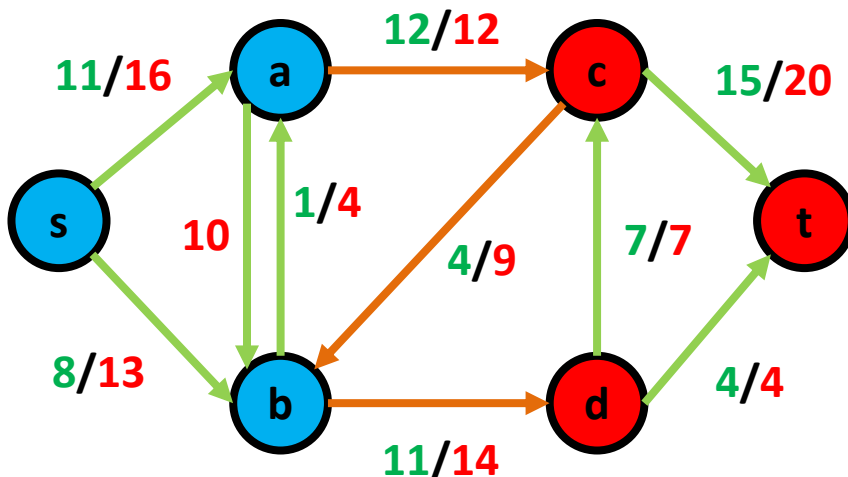


# Cut

## Flow and Capacity

- Let us use this example

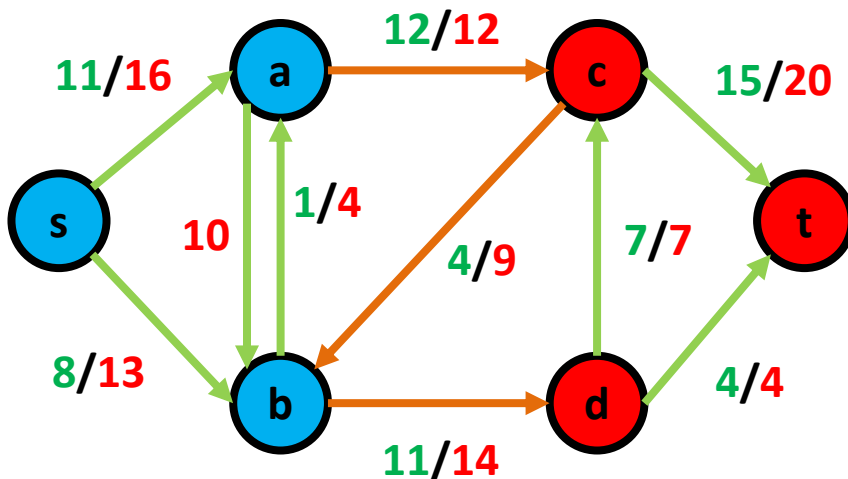
- A cut  $(S, T)$ 
  - $S$  must contain vertex  $s$ .  $S = (s, a, b)$
  - $T$  must contain vertex  $t$ .  $T = (c, d, t)$
- We have edges **crossing** the cut
- Capacity of a cut  $(S, T)$  = capacity of outgoing edges =  $12 + 14 = 26$
- Flow of a cut  $(S, T)$  = flow of outgoing edges – flow of incoming edges



# Cut

## Flow and Capacity

- Let us use this example
  - A cut (S,T)
  - We have edges **crossing** the cut
  - Capacity of a cut (S,T) = capacity of outgoing edges =  $12+14 = 26$
  - Flow of a cut (S,T) = flow of outgoing edges – flow of incoming edges

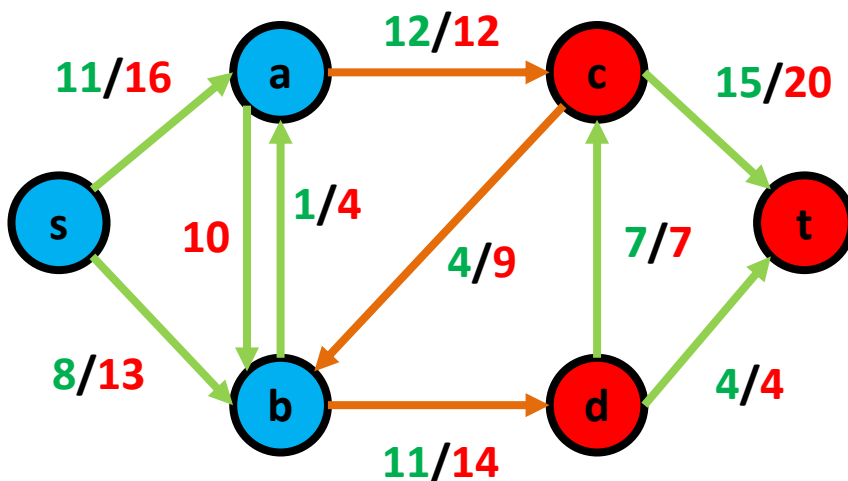


# Cut

## Flow and Capacity

### ■ Let us use this example

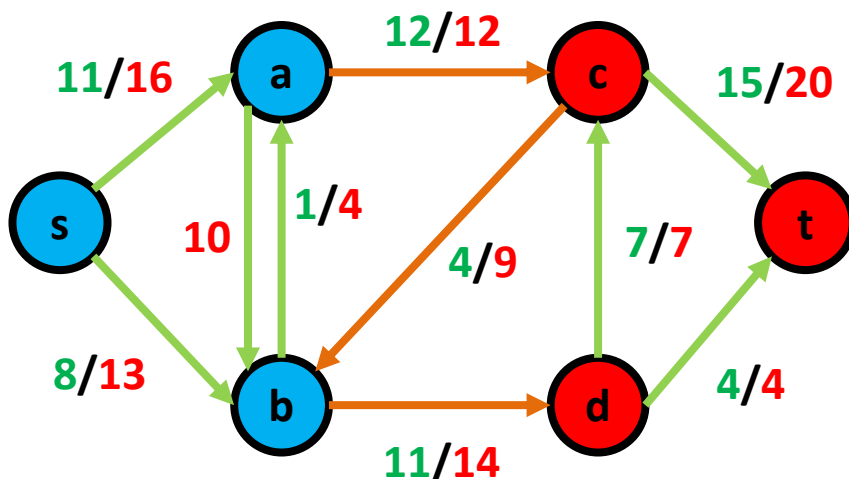
- A cut (S,T)
- We have edges **crossing** the cut
- Capacity of a cut (S,T) = capacity of outgoing edges =  $12 + 14 = 26$
- Flow of a cut (S,T) = flow of outgoing edges – flow of incoming edges  
 $= 12 + 11 - 4$       capacity = 26, flow = 19 = 19/24



# Cut

## Flow and Capacity

- Let us use this example
  - A cut (S,T)
  - We have edges **crossing** the cut
  - Capacity of a cut (S,T) = capacity of outgoing edges =  $12 + 14 = 26$
  - Flow of a cut (S,T) = flow of outgoing edges – flow of incoming edges  
 $= 12 + 11 - 4 = 19$



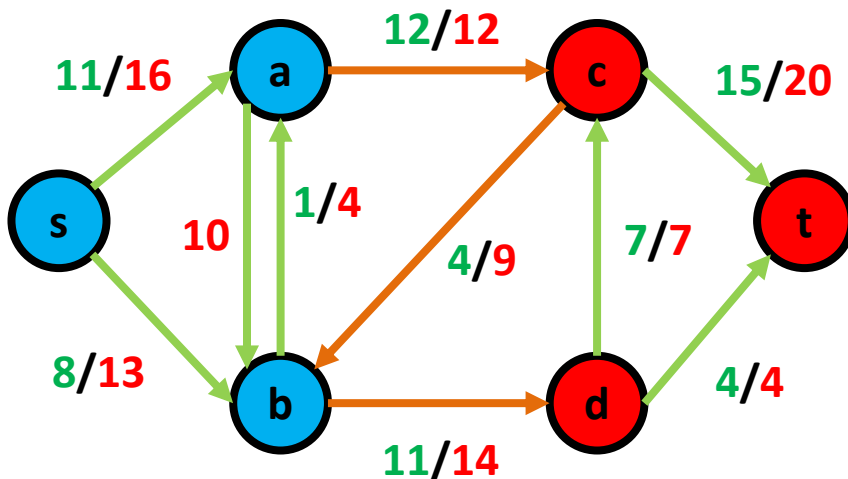
Questions?



# Cut

## Flow and Capacity

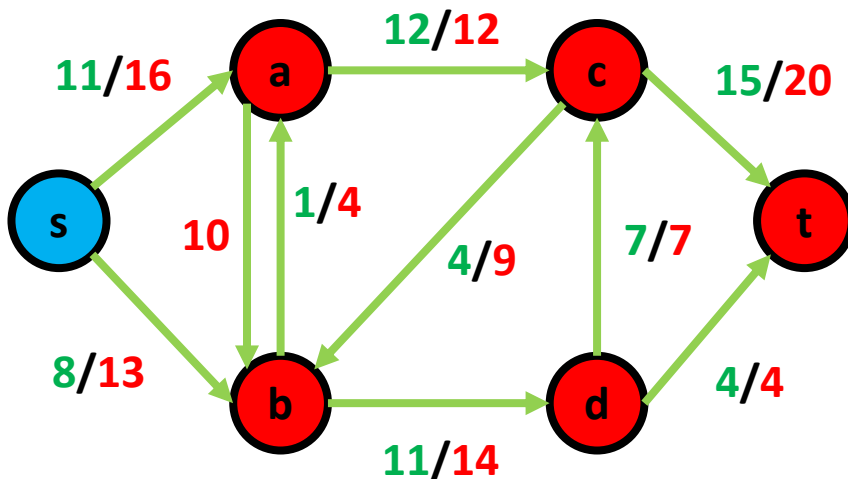
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19  
potential 7 outgoing flow -> another route



# Cut

## Flow and Capacity

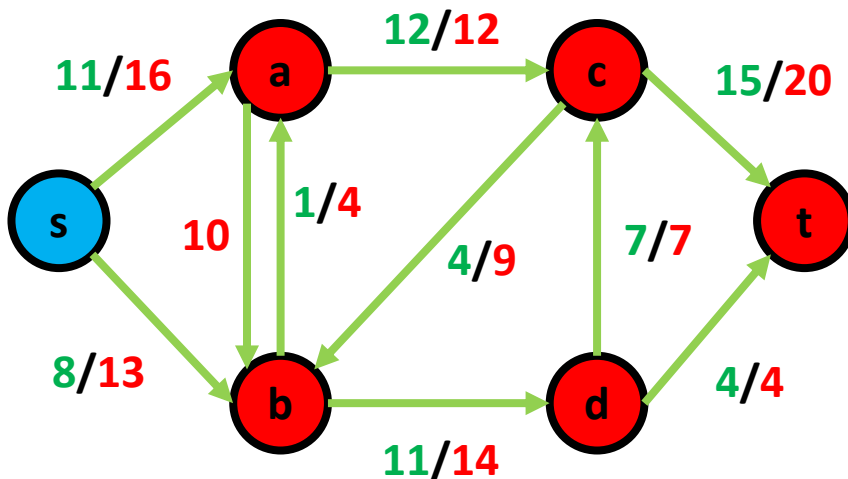
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about **other way** of cutting?



# Cut

## Flow and Capacity

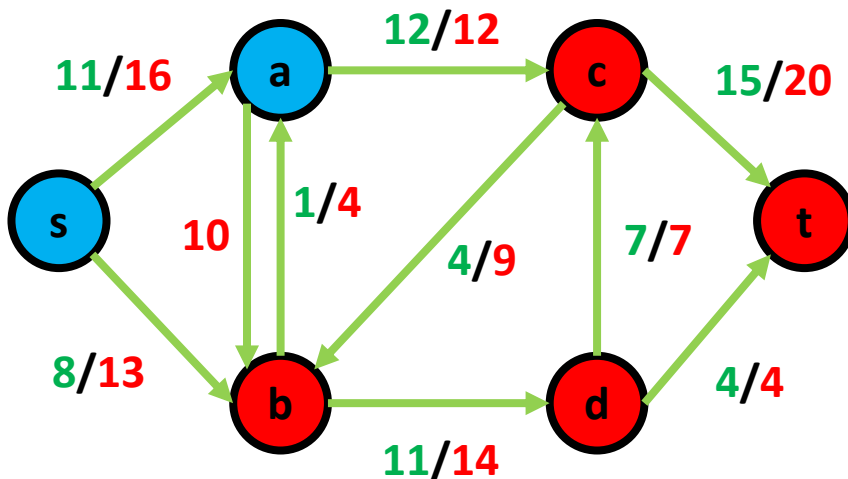
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 29
    - Flow = 19



# Cut

## Flow and Capacity

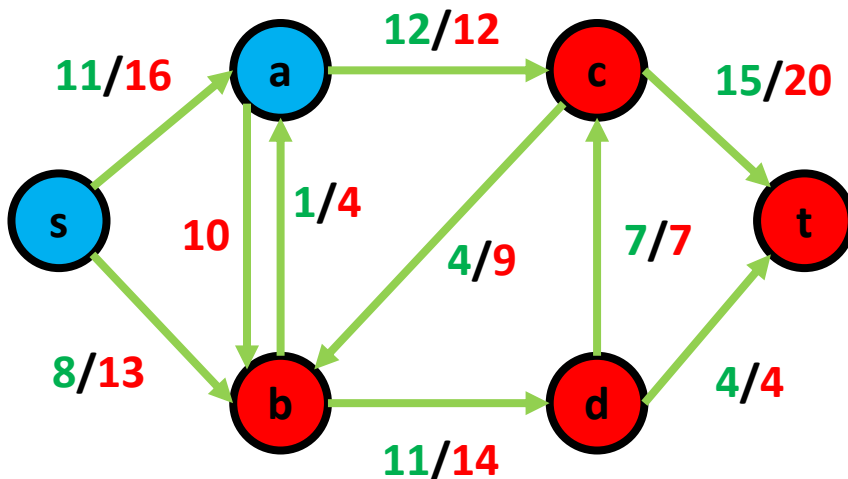
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = ?
    - Flow = ?



# Cut

## Flow and Capacity

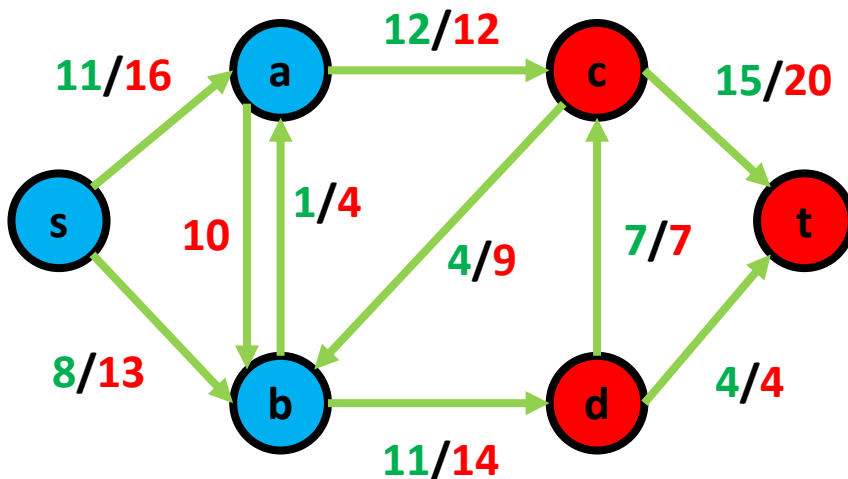
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 35
    - Flow = 19



# Cut

## Flow and Capacity

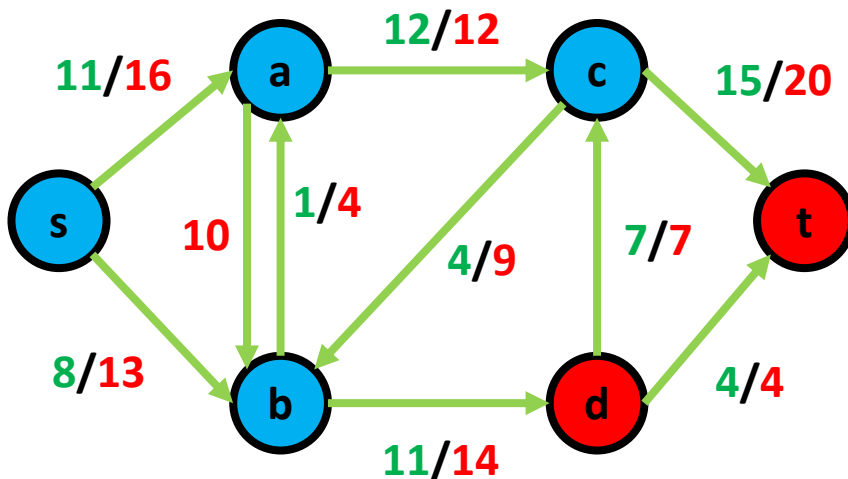
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 26
    - Flow = 19



# Cut

## Flow and Capacity

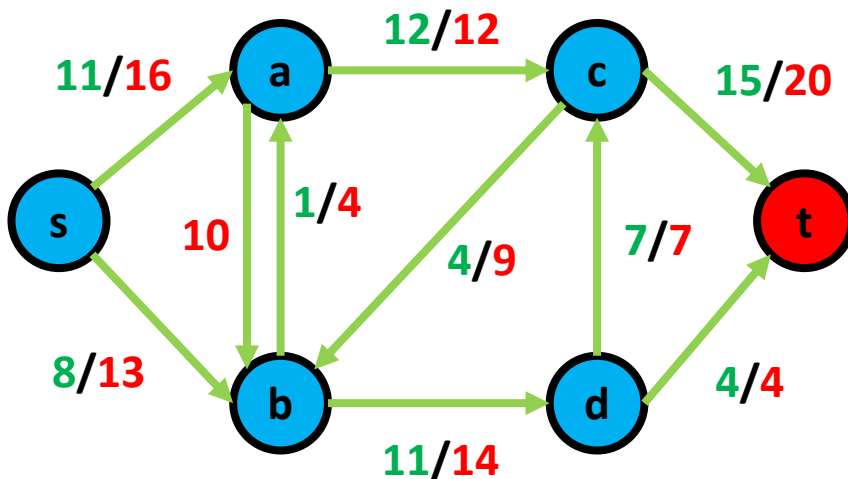
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 34
    - Flow = 19



# Cut

## Flow and Capacity

- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 24
    - Flow = 19

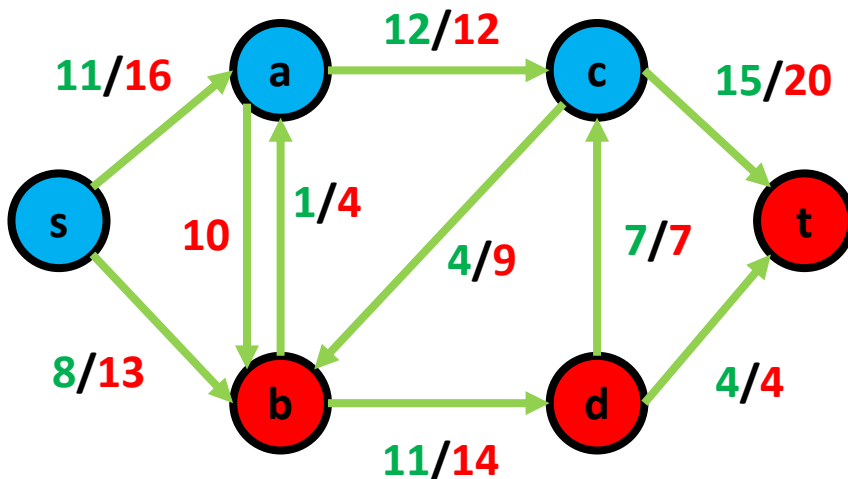




# Cut

## Flow and Capacity

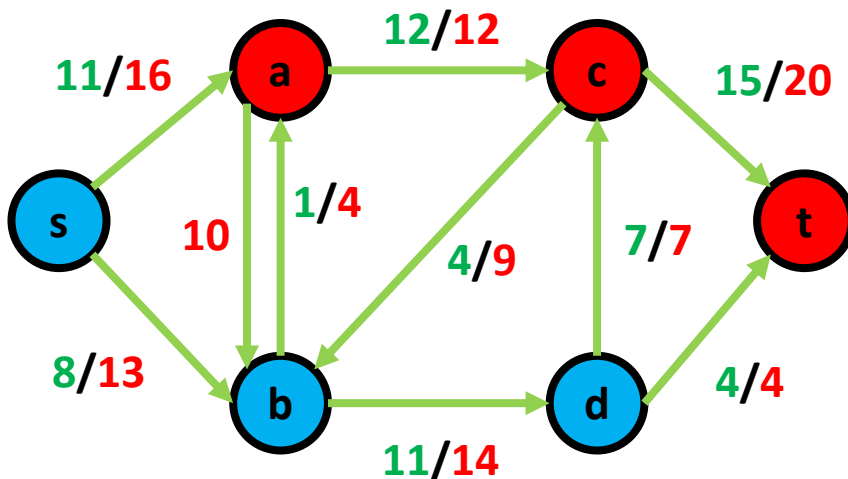
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 52
    - Flow = 19



# Cut

## Flow and Capacity

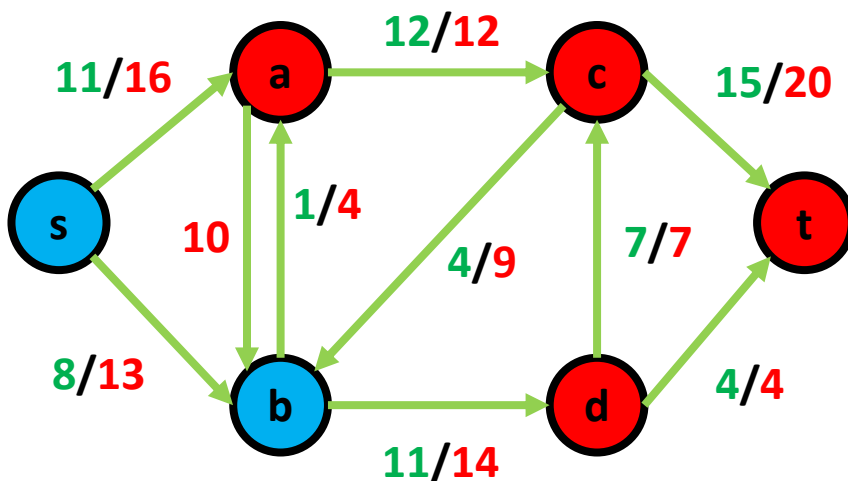
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 31
    - Flow = 19



# Cut

## Flow and Capacity

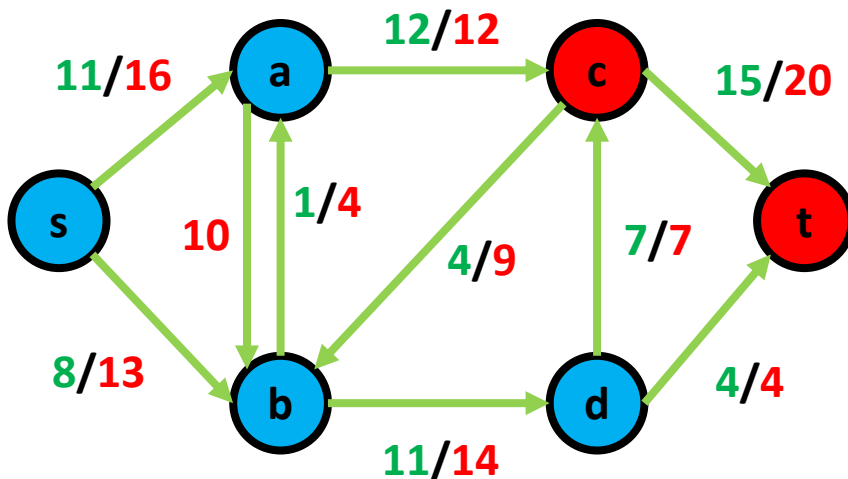
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 34
    - Flow = 19



# Cut

## Flow and Capacity

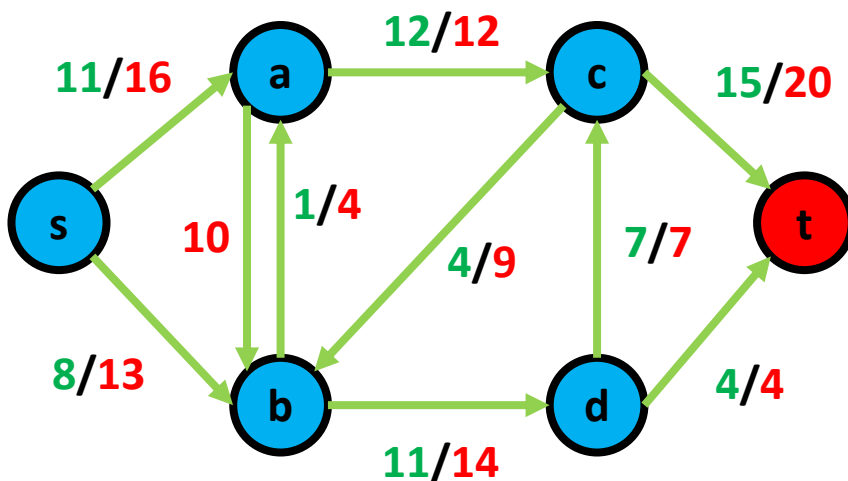
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity = 23
    - Flow = 19



# Cut

## Flow and Capacity

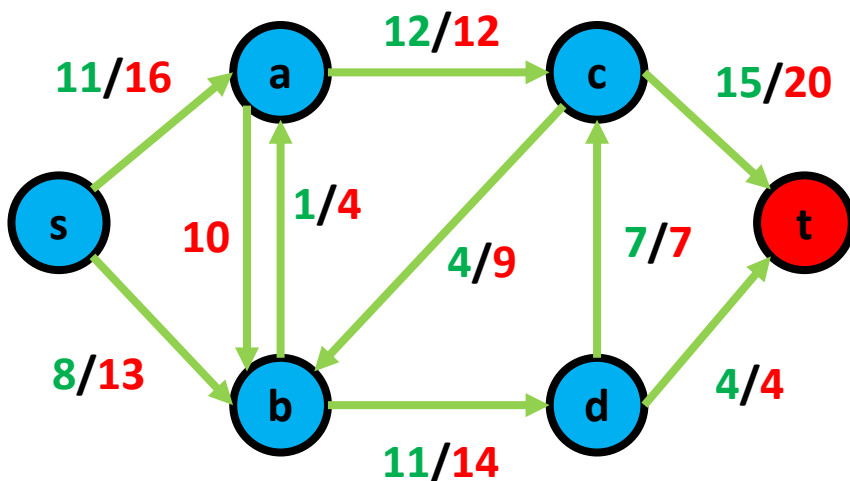
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity differs
    - Flow the same



# Cut

## Flow and Capacity

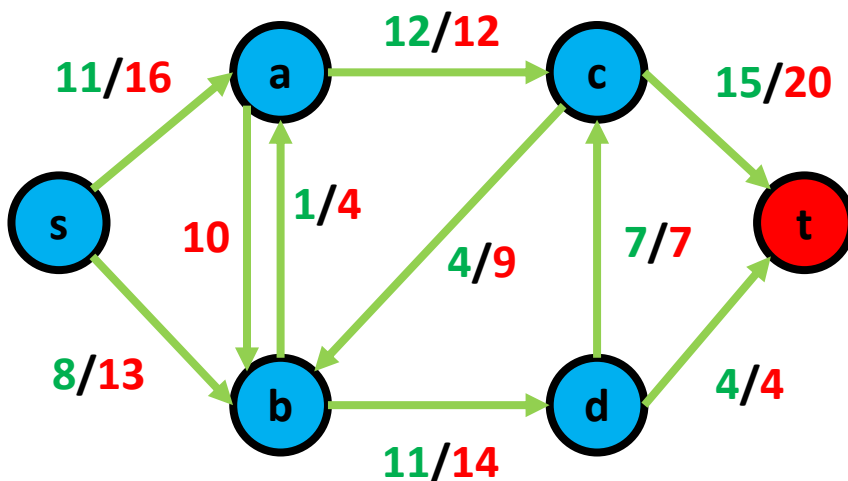
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity differs
    - Flow the same
    - But we know  $\text{flow} \leq \text{capacity}$



# Cut

## Flow and Capacity

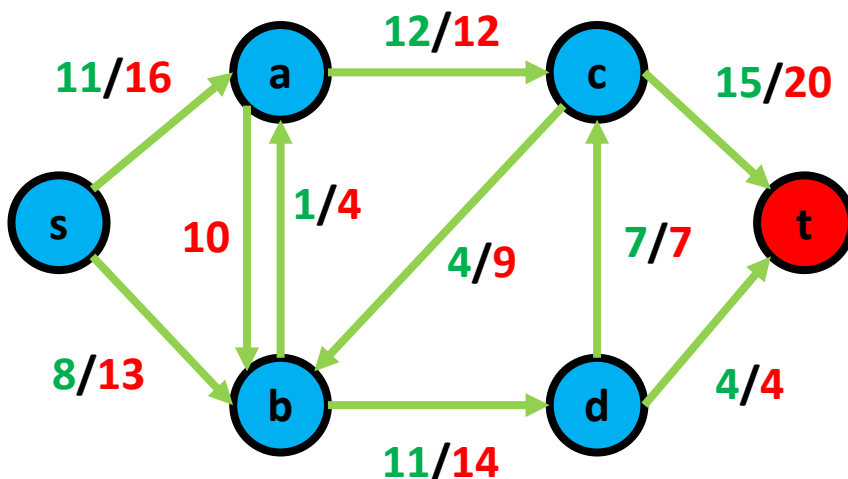
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting?
    - Capacity differs
    - Flow the same
    - But we know  $\text{flow} \leq \text{capacity}$
    - Thus **smallest capacity is the upper bound of flow?**



# Cut

## Flow and Capacity

- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting? **Flow of every cut = flow of network**
    - Capacity differs
    - Flow the same
    - But we know  $\text{flow} \leq \text{capacity}$
    - Thus **smallest capacity** is the **upper bound** of **flow**?

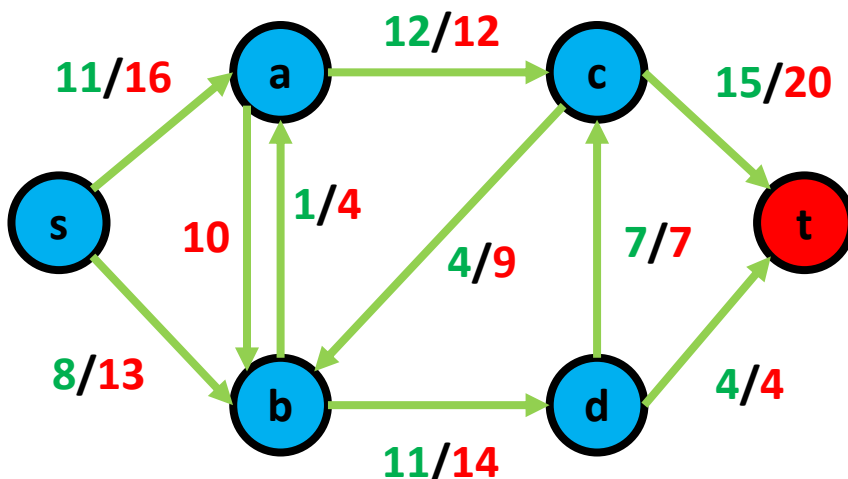




# Cut

## Flow and Capacity

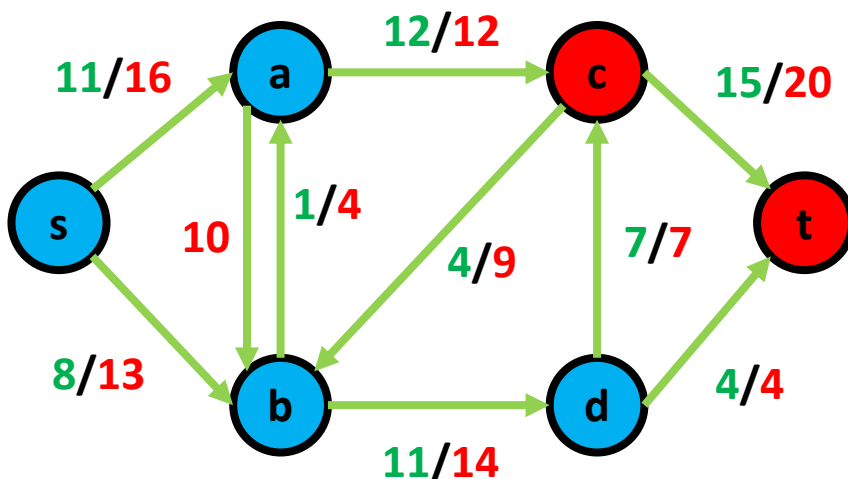
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting? **Flow of every cut = flow of network**
    - Capacity differs, **smallest** is **23**!
    - Flow the same
    - But we know  $\text{flow} \leq \text{capacity}$
    - Thus smallest capacity is the upper bound of flow?



# Cut

## Flow and Capacity

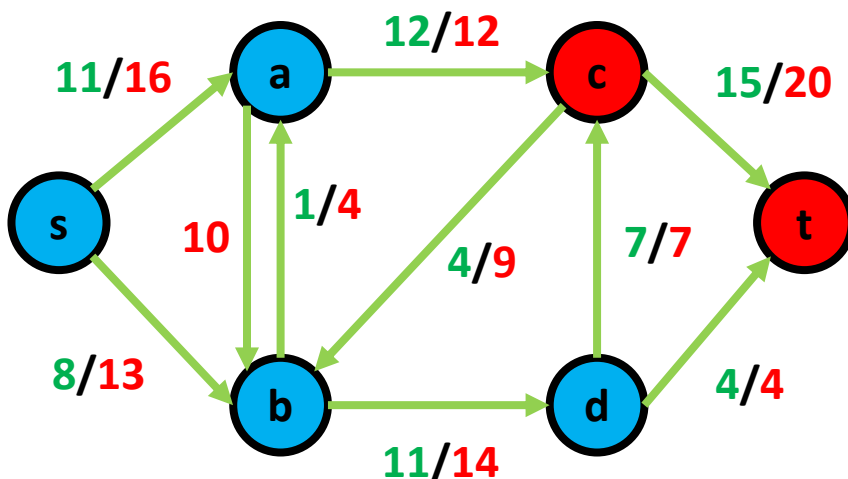
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting? **Flow of every cut = flow of network**
    - Capacity differs, smallest is 23!
    - Flow the same
    - But we know  $\text{flow} \leq \text{capacity}$
    - Thus smallest capacity is the upper bound of flow?



# Cut

## Flow and Capacity

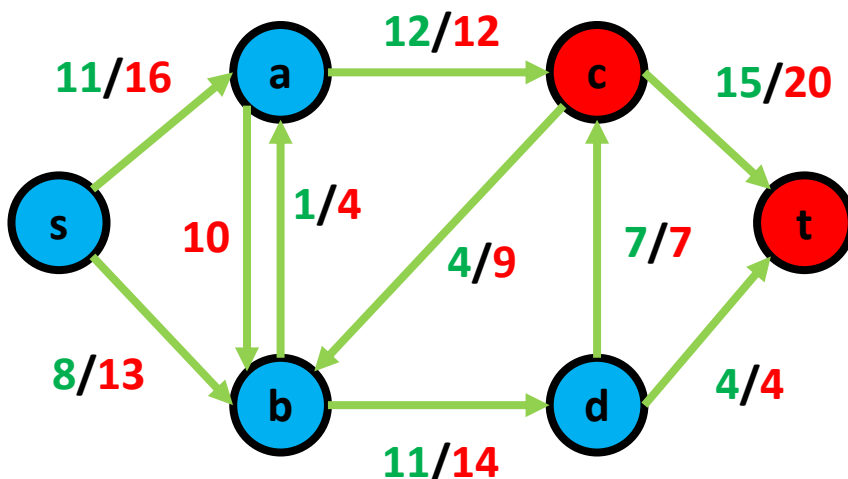
- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting? **Flow of every cut = flow of network**
    - Capacity differs, smallest is 23!
    - Flow the same, so max flow is 23!
    - But we know  $\text{flow} \leq \text{capacity}$
    - Thus smallest capacity is the upper bound of flow?



# Cut

## Flow and Capacity

- Now we realize something....
  - Remember our earlier cut have capacity of 26 and flow of 19
  - What about other way of cutting? **Flow of every cut = flow of network**
    - Capacity differs, smallest is 23!
    - Flow the same, so max flow is 23! And we saw earlier when we run Ford-Fulkerson that the maximum flow is 23!
    - But we know flow  $\leq$  capacity

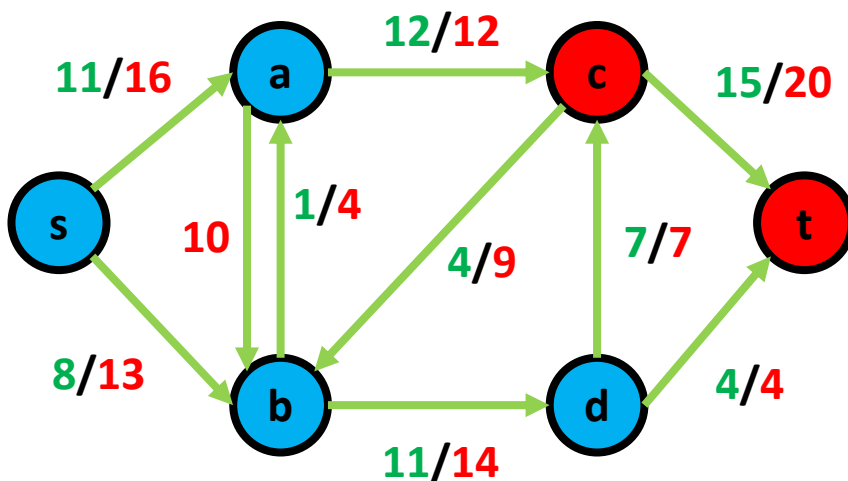


Questions?

# Min-Cut Max-Flow Theorem

The key to this...

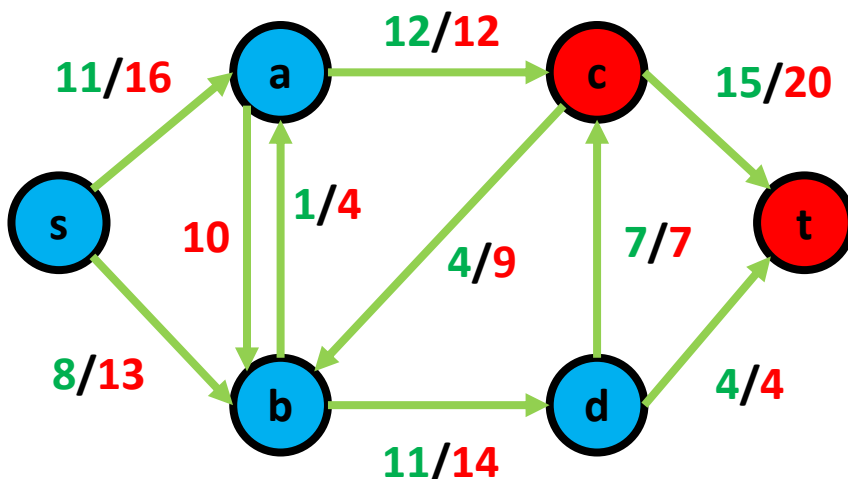
- Minimum capacity of all cut is 23
- Flow of cut  $\leq$  capacity of cut
- Flow of a cut  $=$  flow of a network



# Min-Cut Max-Flow Theorem

The key to this...

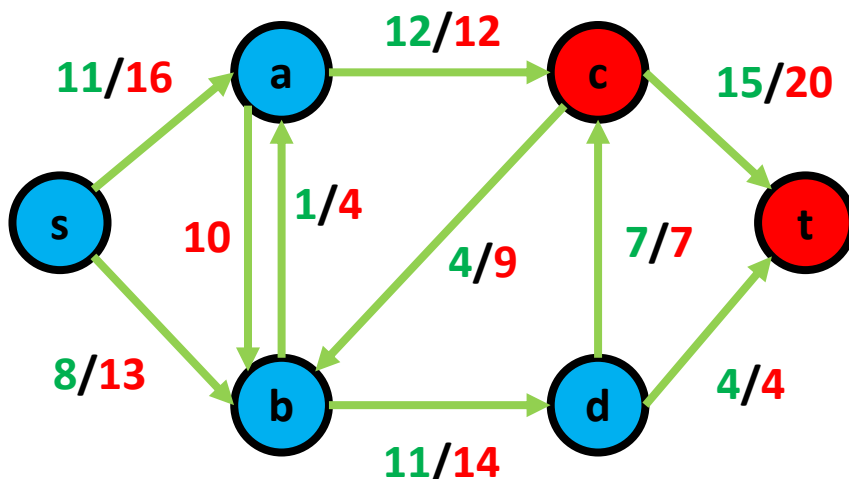
- Minimum capacity of all cut is 23
- Flow of cut  $\leq$  capacity of cut
- Flow of a cut  $=$  flow of a network
- Therefore, capacity of a min-cut = max-flow of a network



# Min-Cut Max-Flow Theorem

The key to this...

- Minimum capacity of all cut is 23
- Flow of cut  $\leq$  capacity of cut
- Flow of a cut  $=$  flow of a network
- Therefore, capacity of a min-cut  $=$  max-flow of a network





# Min-Cut Max-Flow Theorem

The key to this...

- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:

# Min-Cut Max-Flow Theorem

The key to this...

- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson **terminates** when **there is a cut**:
  - **Flow** on **each outgoing edge cut** is **equal** to the **capacity** of the **edge**

# Min-Cut Max-Flow Theorem

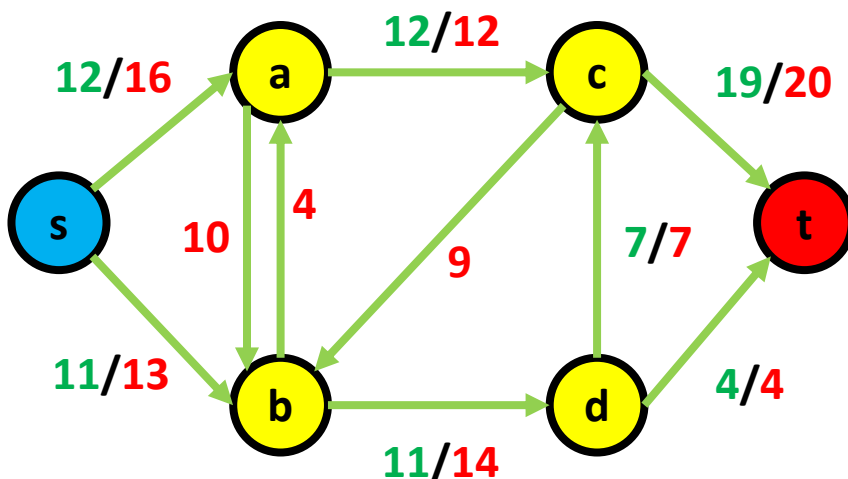
The key to this...

- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
  - Flow on each outgoing edge cut is equal to the capacity of the edge
  - Flow on each incoming edge to the cut is zero

# Min-Cut Max-Flow Theorem

The key to this...

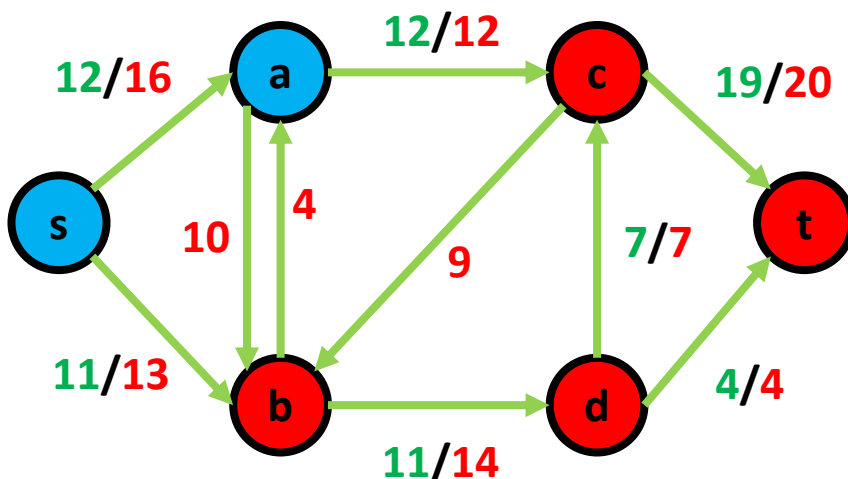
- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
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  - Flow on each incoming edge to the cut is zero



# Min-Cut Max-Flow Theorem

The key to this...

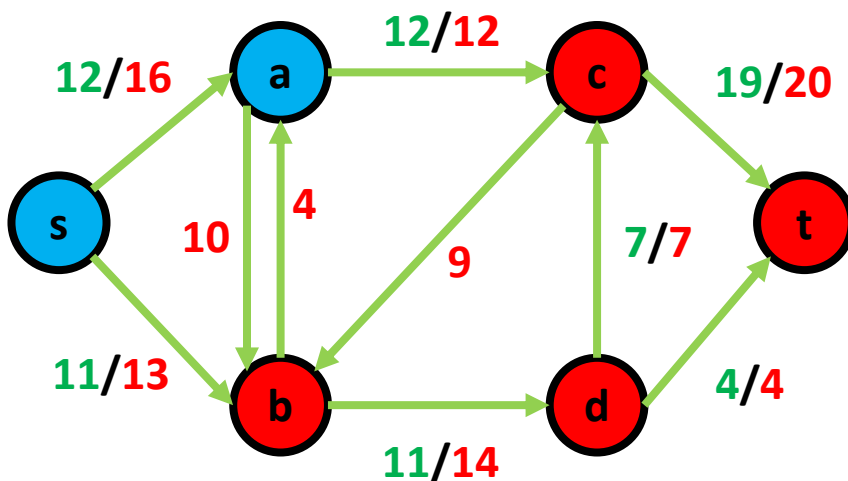
- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
  - Flow on each outgoing edge cut is equal to the capacity of the edge
  - Flow on each incoming edge to the cut is zero
  - This meets the requirement above right?



# Min-Cut Max-Flow Theorem

The key to this...

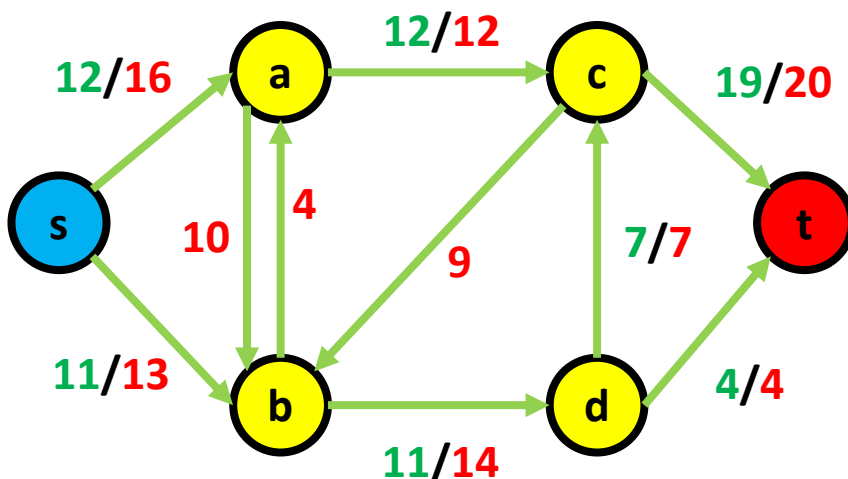
- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
  - Flow on each outgoing edge cut is equal to the capacity of the edge
  - Flow on each incoming edge to the cut is zero
  - This meets the requirement above right? NO!



# Min-Cut Max-Flow Theorem

The key to this...

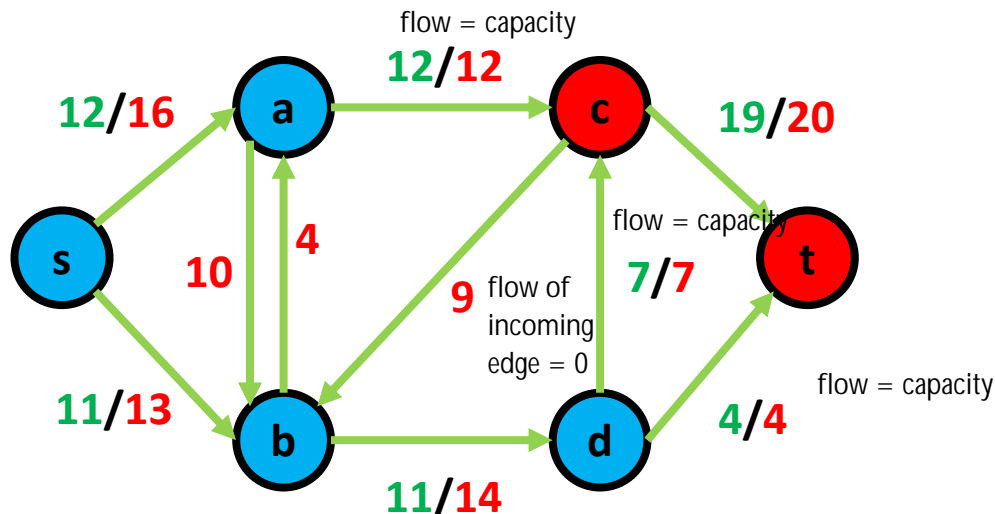
- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
  - Flow on each outgoing edge cut is equal to the capacity of the edge
  - Flow on each incoming edge to the cut is zero
  - This meets the requirement above right? Which one meet the requirement above?



# Min-Cut Max-Flow Theorem

The key to this...

- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
  - Flow on each **outgoing edge** cut is **equal** to the **capacity** of the **edge**
  - **Flow** on each **incoming edge** to the **cut** is **zero**
  - This meets the requirement above right? Which one meet the requirement above? This one!

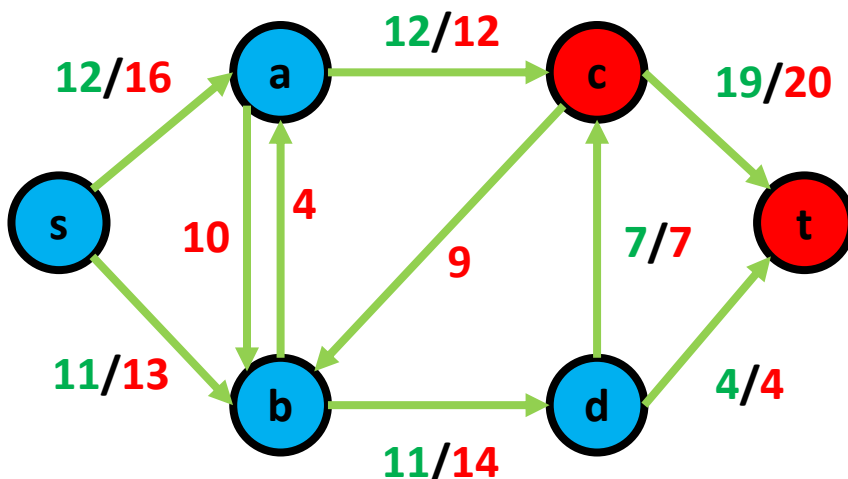




# Min-Cut Max-Flow Theorem

The key to this...

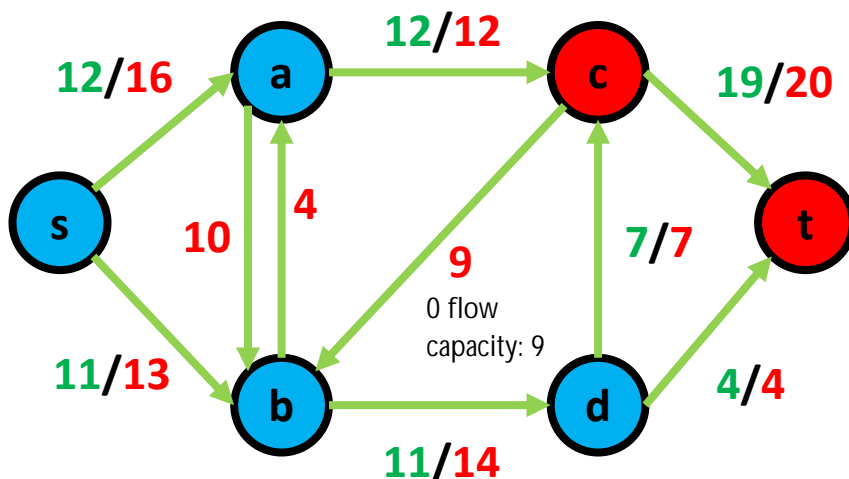
- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
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# Min-Cut Max-Flow Theorem

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Min-cut

$S = (s, a, b, d)$

$T = (c, t)$

cross of cut: still have capacity and has incoming flow to return  
due to Ford-Fulkerson find cut that  
flow on each outgoing = capacity  
flow on incoming edge = 0, so no longer  
have forward edge (outgoing edge  
in residual network and no incoming flow  
to return (purple color)

short cut  
cut(S,T) set of vertices reachable by S  
reachable: has a edge directly to that vertex

everything else falls on T

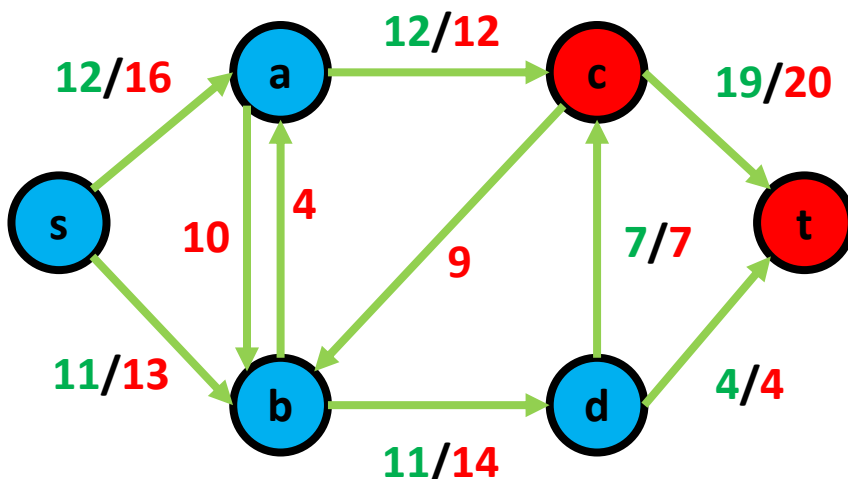
# Min-Cut Max-Flow Theorem

The key to this...

from residual network, start can reach a, b, d, rest to destination, so cut between them -> Mincut

find min-cut lead to max-flow

- Therefore, capacity of a min-cut = max-flow of a network
- Ford-Fulkerson terminates when there is a cut:
  - Flow on each outgoing edge cut is equal to the capacity of the edge no forward edge
  - Flow on each incoming edge to the cut is zero no flow to be undone  
so no backward edge to return to sink
  - This meets the requirement above right? Which one meet the requirement above? This one! This is called the min-cut



Go through MUA's slides where his final network differs but still max flow of 23. Can you find such a cut?

Questions?

# Optimization

## Finding max-flow quicker...

- We know the following...

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  - Complexity is  $O(FE)$  where  $F$  is the maximum flow

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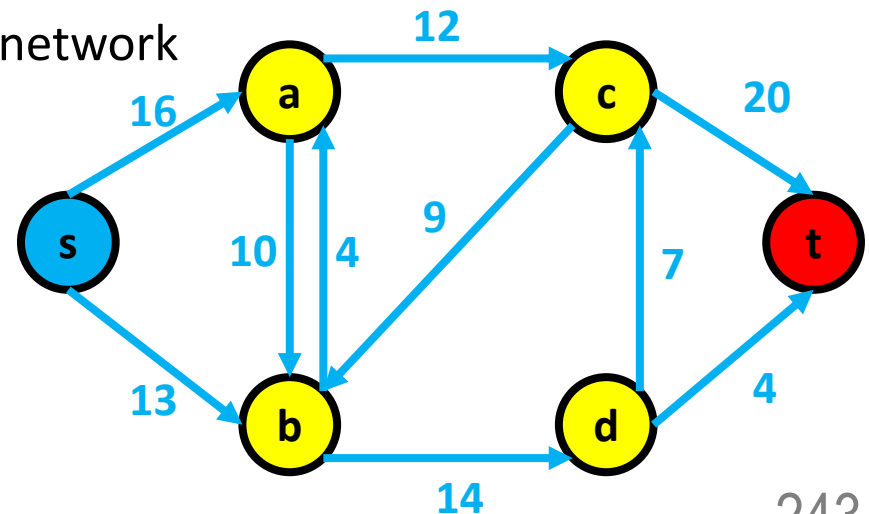
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# Optimization

## Finding max-flow quicker...

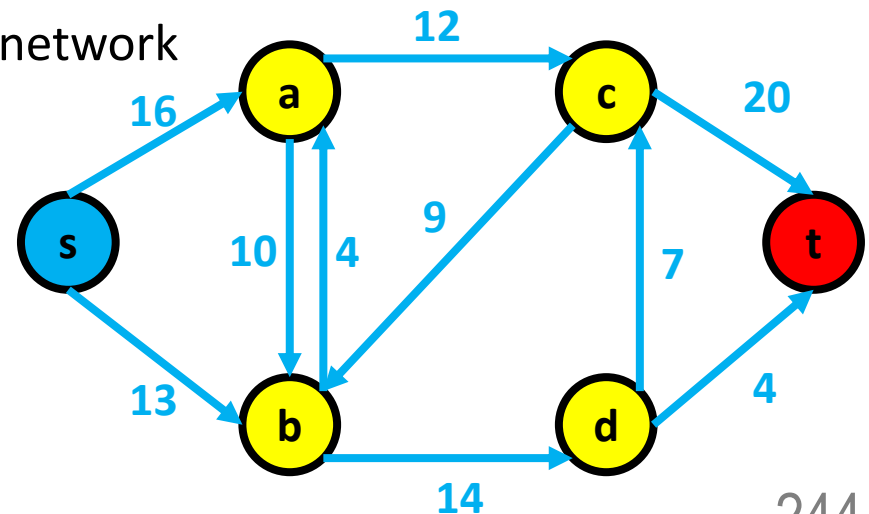
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# Optimization

## Finding max-flow quicker...

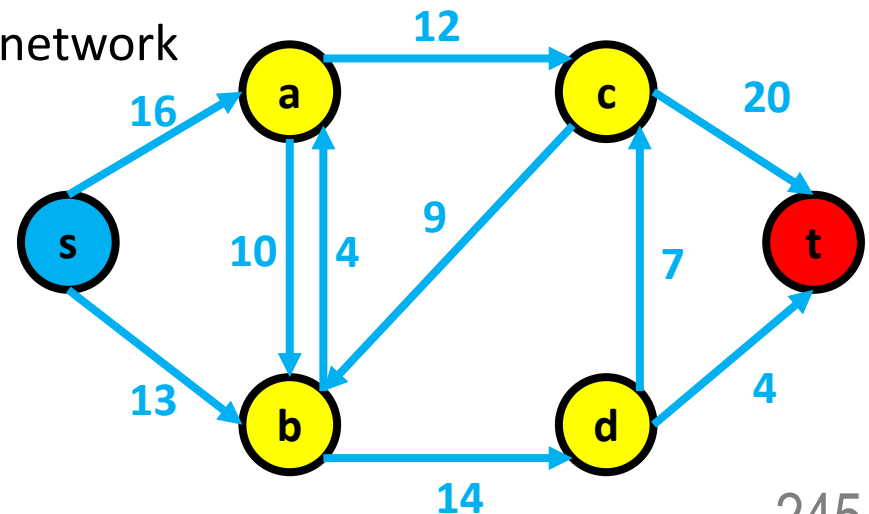
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    - We used BFS/ DFS
    - Can we choose a better path?



# Optimization

## Finding max-flow quicker...

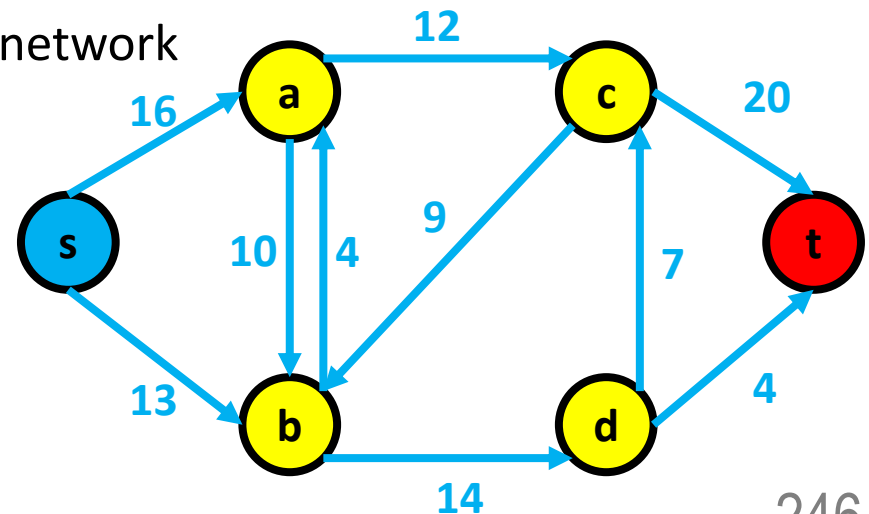
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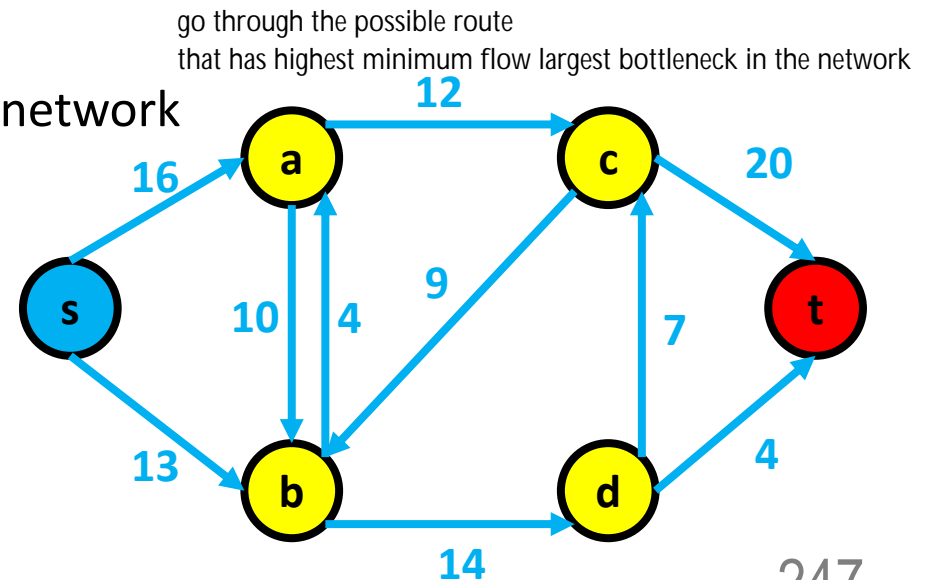
# Optimization

## Finding max-flow quicker...

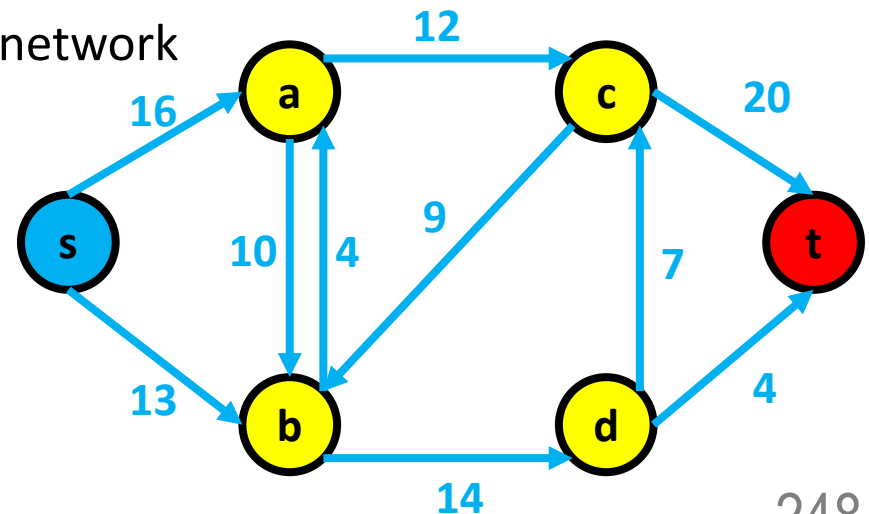
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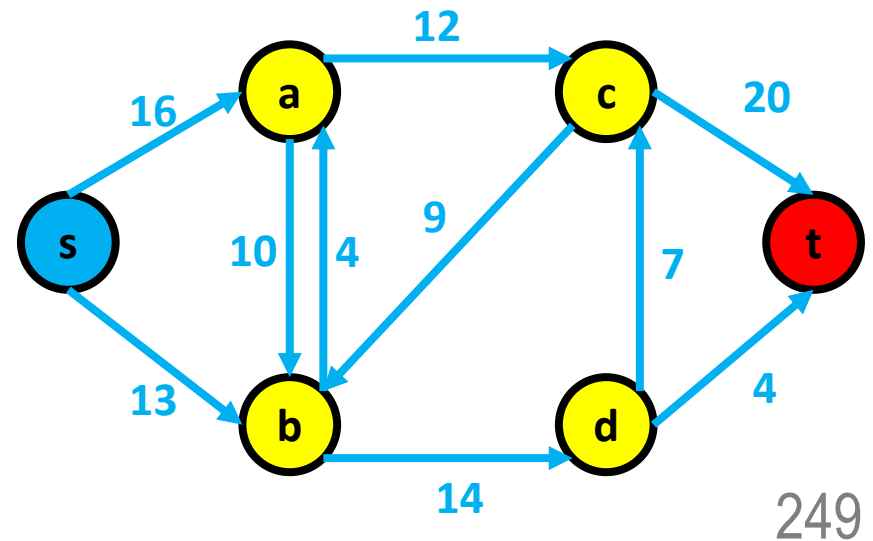


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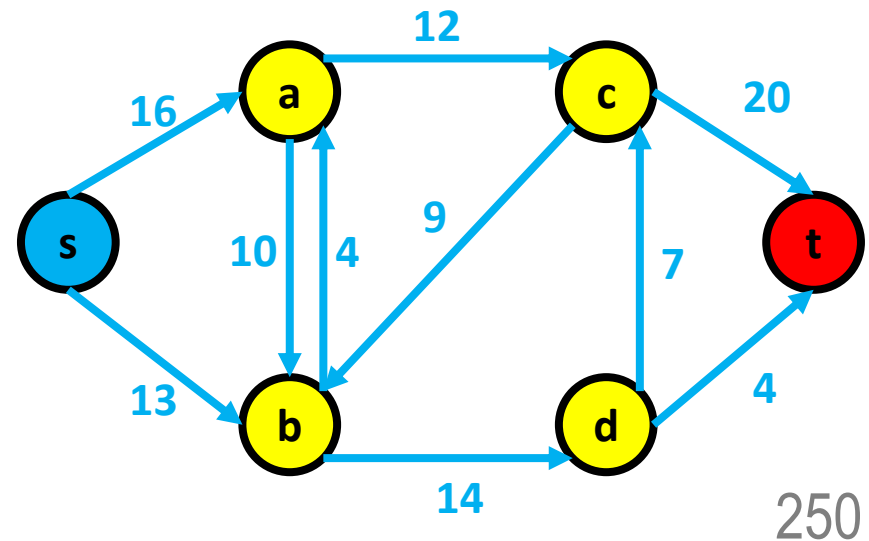
- Consider the following:



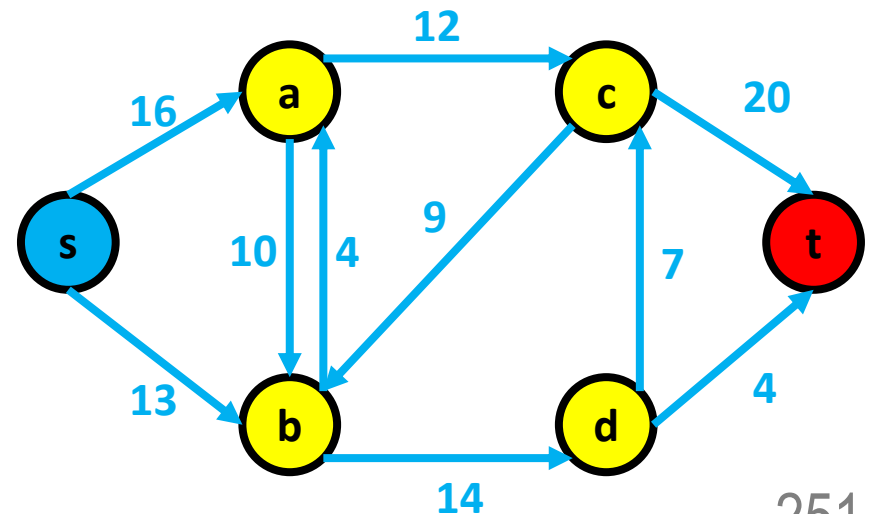
# Edmond-Karp

Finding max-flow quicker...

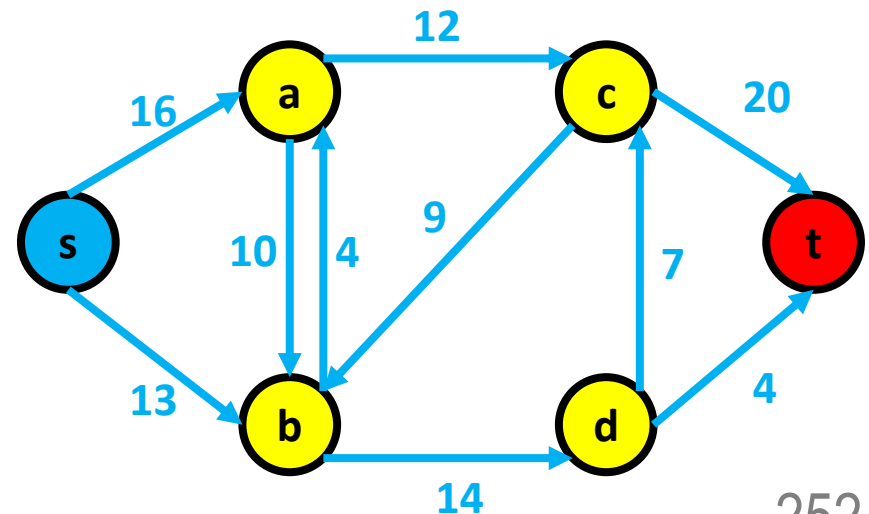
- Consider the following:
  - Dinic/ Edmonds-Karp = choose path with fewest edge
  - Edmonds-Karp = choose path with largest bottle neck



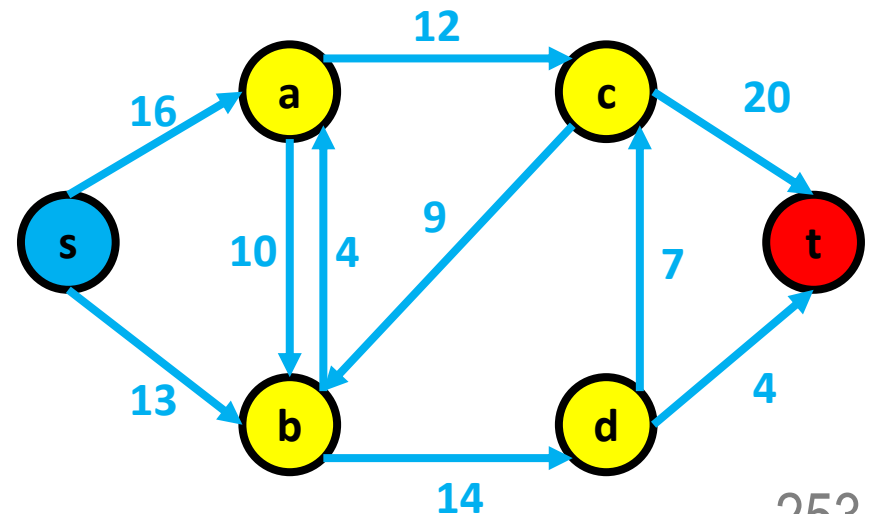
- Consider the following:
  - Dinic/ Edmonds-Karp = choose path with fewest edge
  - Edmonds-Karp = choose path with largest bottle neck
  - How?



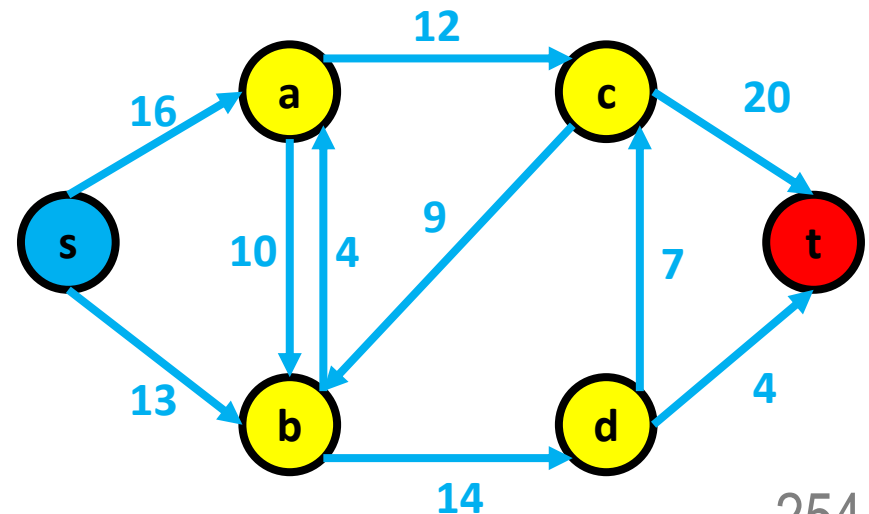
- Consider the following:
  - Dinic/ Edmonds-Karp = choose path with fewest edge
    - Running BFS ensure this isn't it?
  - Edmonds-Karp = choose path with largest bottle neck



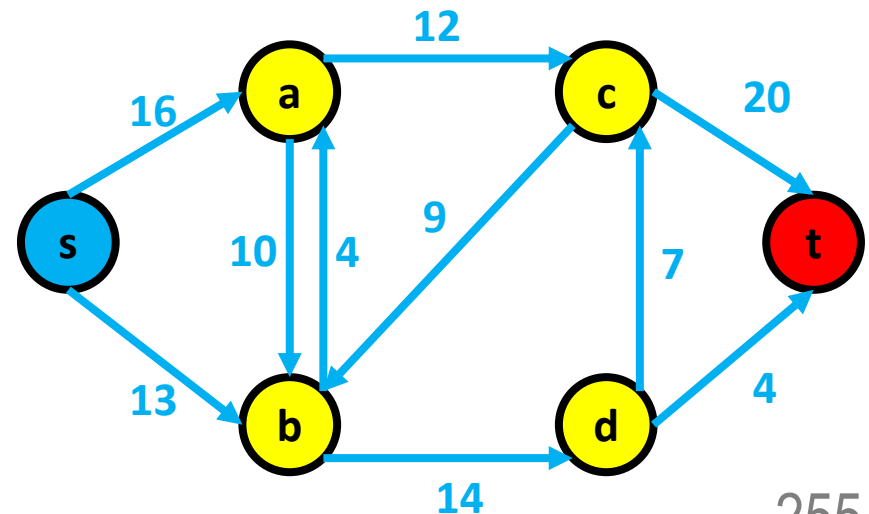
- Consider the following:
  - Dinic/ Edmonds-Karp = choose path with fewest edge
    - Running BFS ensure this isn't it?
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- Consider the following:
  - Dinic/ Edmonds-Karp = choose path with fewest edge
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    - Find a maximum spanning tree! convert minimum spanning tree into maximum spanning tree



- Consider the following:
  - Dinic/ Edmonds-Karp = choose path with fewest edge
    - Running BFS ensure this isn't it?
    - Less edge, lower chance to get smaller weights
  - Edmonds-Karp = choose path with largest bottle neck
    - Find a **maximum spanning tree**! convert minimum spanning tree in previous unit to max spanning tree by negating weight in prim's and Kruskal's -> edge with largest bottleneck
    - Recall we discuss a little in FIT2004 Tutorial 10 about bottleneck...



Questions?



# Bipartite Graph

An application of network flow...

- Consider the situation...

# Bipartite Graph

An application of network flow...

- Arranged marriage agency...

# Bipartite Graph

An application of network flow...

- Arranged marriage agency...
  - A list of men
  - A list of women

# Bipartite Graph

## An application of network flow...

- Arranged marriage agency...
  - A list of men
  - A list of women
  - Their preferences

# Bipartite Graph

## An application of network flow...

- Arranged marriage agency...
  - A list of men
  - A list of women
  - Their preferences
  - Each match you get, you earn \$\$\$

# Bipartite Graph

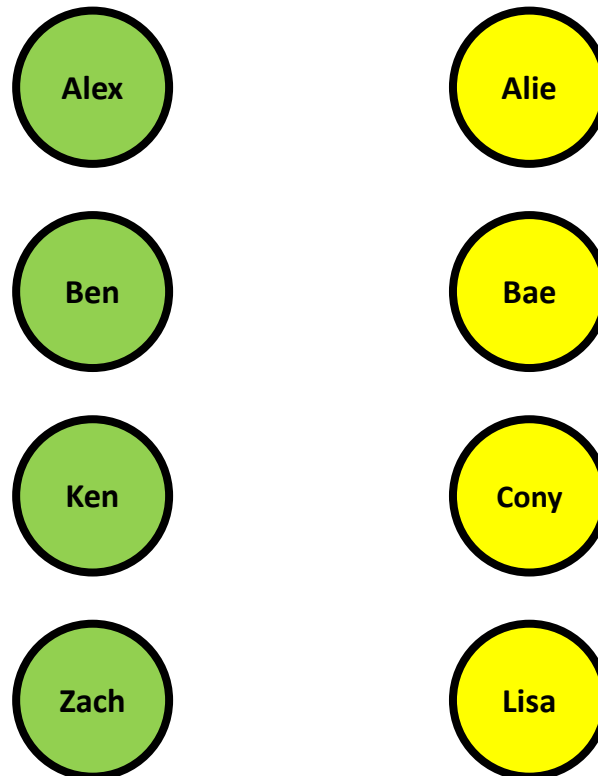
## An application of network flow...

- Arranged marriage agency...
  - A list of men
  - A list of women
  - Their preferences
  - Each match you get, you earn \$\$\$
  - So we want the most matches!

# Bipartite Graph

An application of network flow...

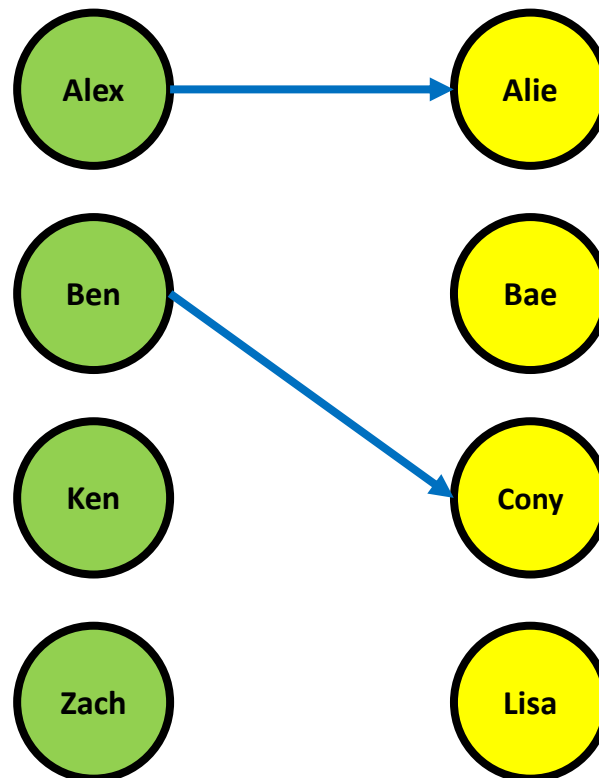
- Arranged marriage agency...



# Bipartite Graph

An application of network flow...

- Arranged marriage agency...
  - Can you max profit?

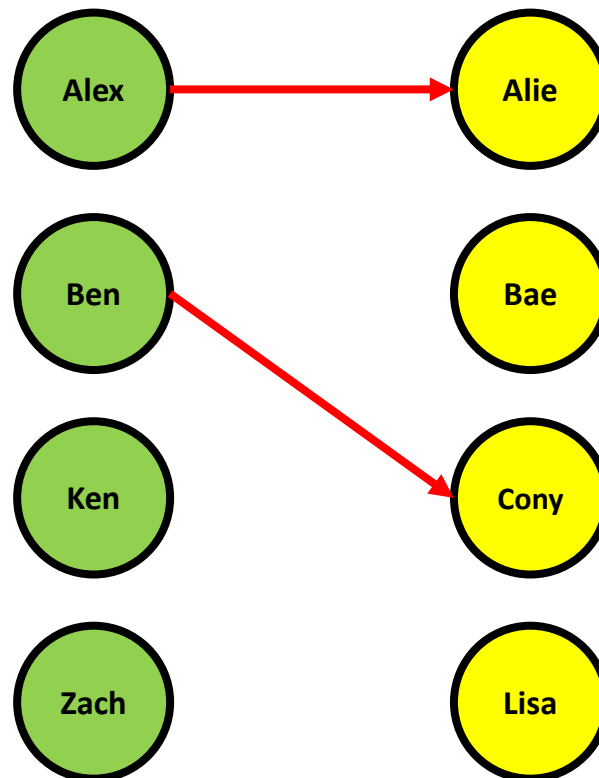




# Bipartite Graph

An application of network flow...

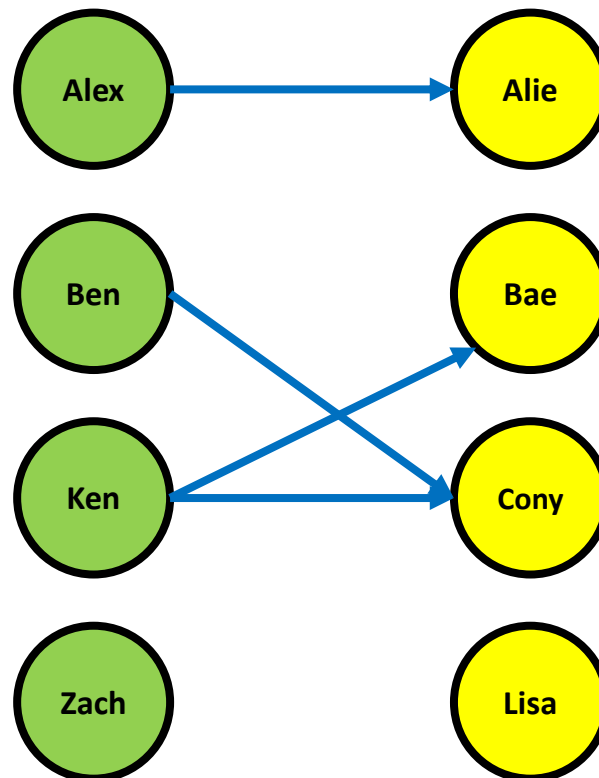
- Arranged marriage agency...
  - Can you max profit?



# Bipartite Graph

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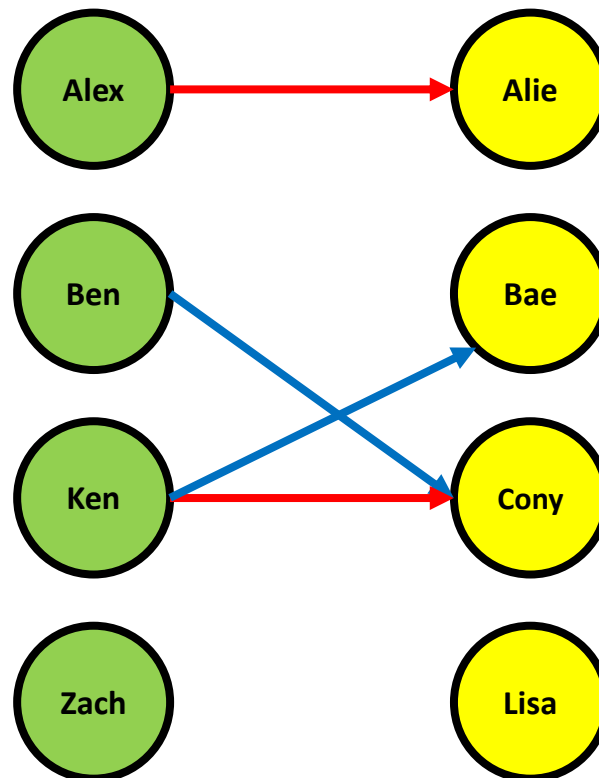
- Arranged marriage agency...
  - Can you max profit? What about now?



# Bipartite Graph

An application of network flow...

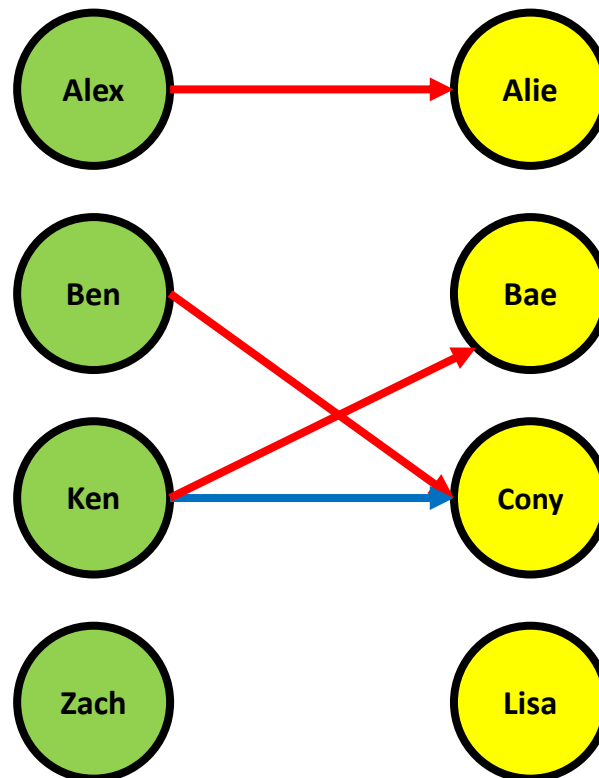
- Arranged marriage agency...
  - Can you max profit? What about now? Only 2...



# Bipartite Graph

An application of network flow...

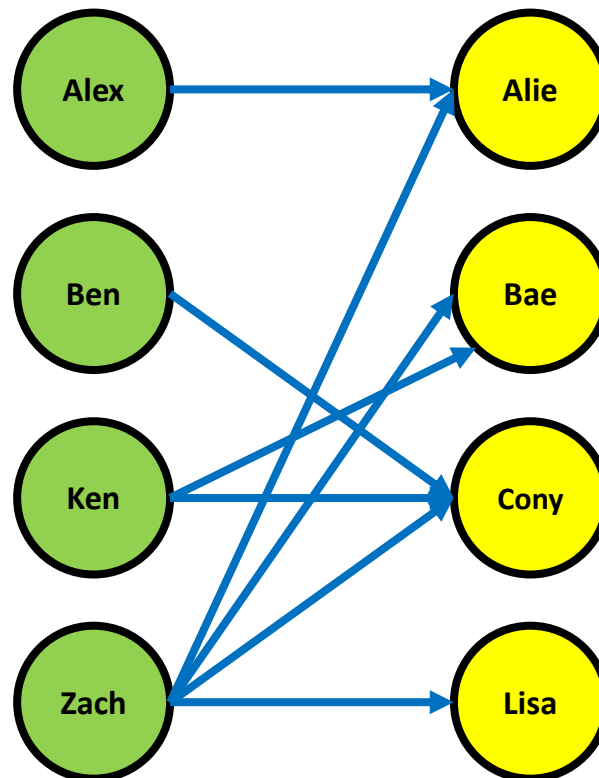
- Arranged marriage agency...
  - Can you max profit? What about now? We can do better with 3



# Bipartite Graph

An application of network flow...

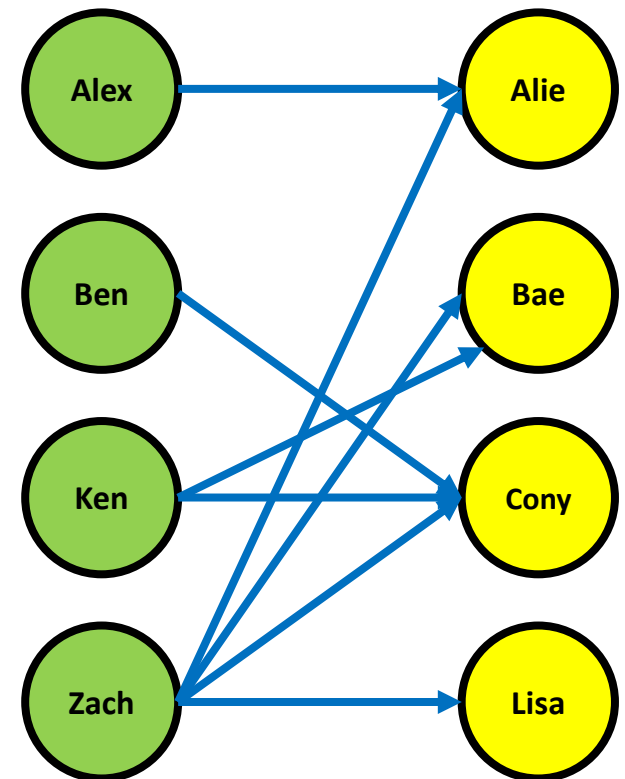
- Arranged marriage agency...
  - What about now???



# Bipartite Graph

An application of network flow...

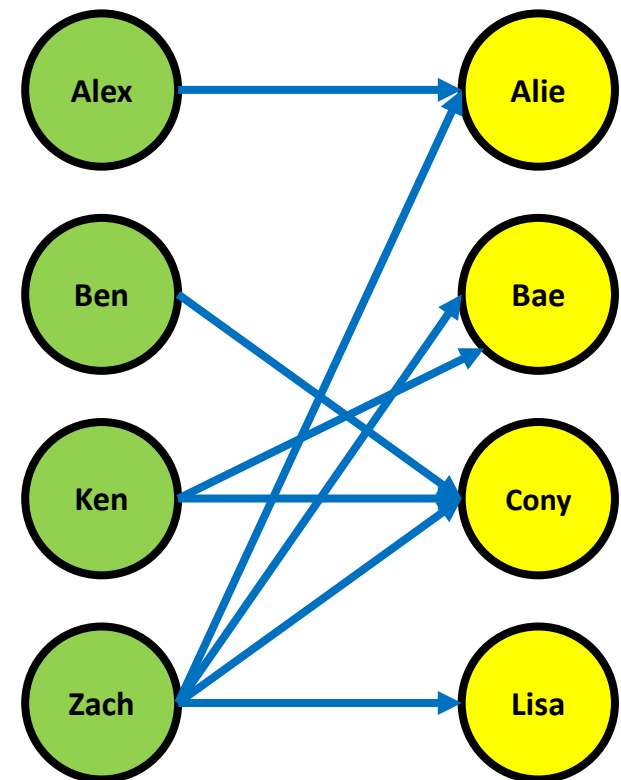
- Arranged marriage agency...
  - What about now???



# Bipartite Graph

An application of network flow...

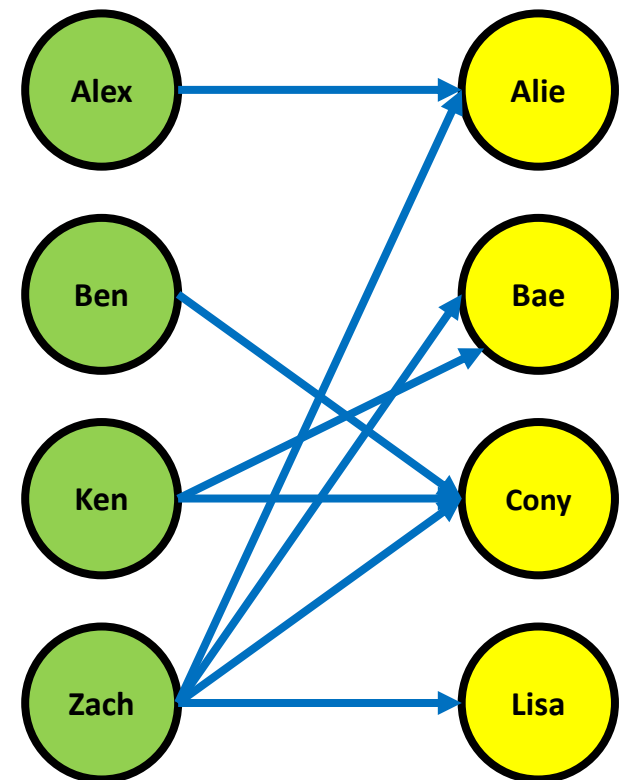
- Arranged marriage agency...
  - What about now???
  - Imagine you run a bigger agency!
    - 100s of eligible bachelor
    - 100s of eligible ladies



# Bipartite Graph

An application of network flow...

- Arranged marriage agency...
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    - 100s of eligible bachelor
    - 100s of eligible ladies
    - Or **Tinder**!

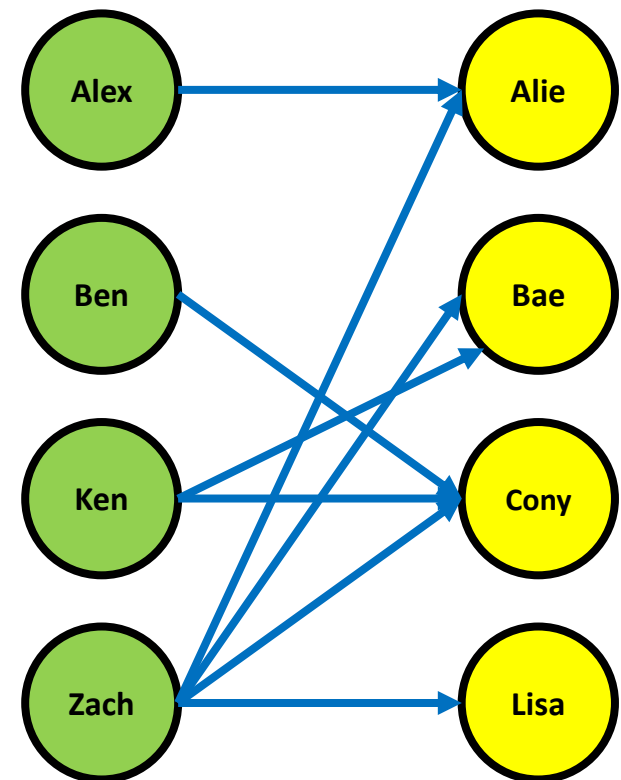




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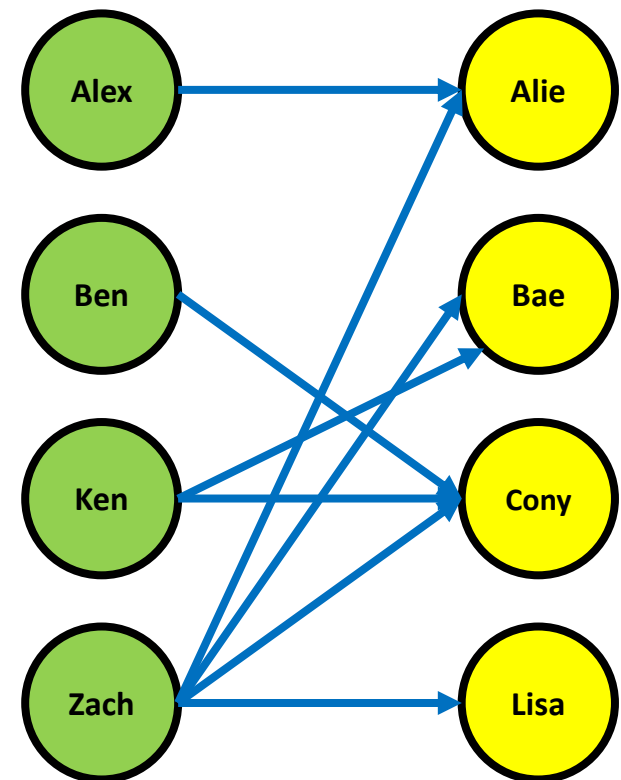
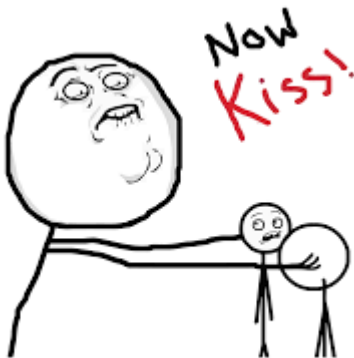
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  - What about now???
  - Imagine you run a bigger agency!
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    - 100s of eligible ladies
    - Or **Tinder**!
  - What would you do?



# Bipartite Graph

An application of network flow...

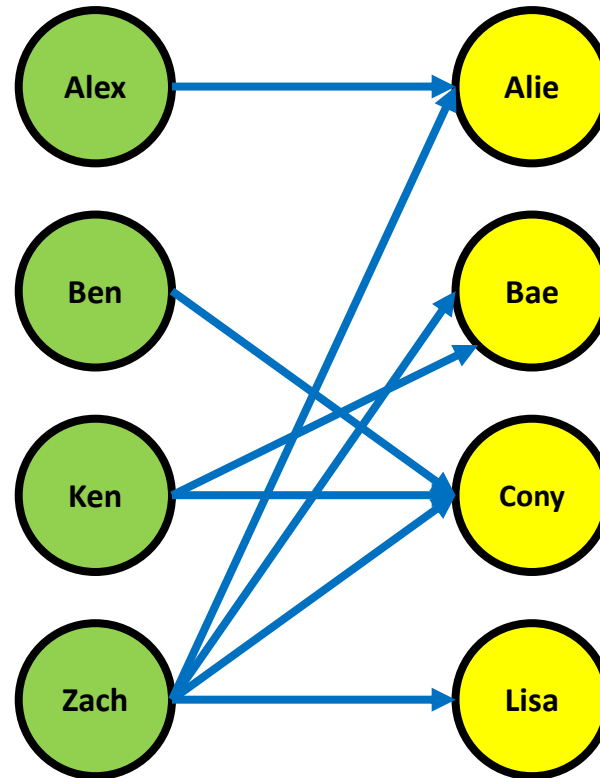
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    - Or **Tinder**!
  - What would you do? Maximize the flow!



# Bipartite Graph

An application of network flow...

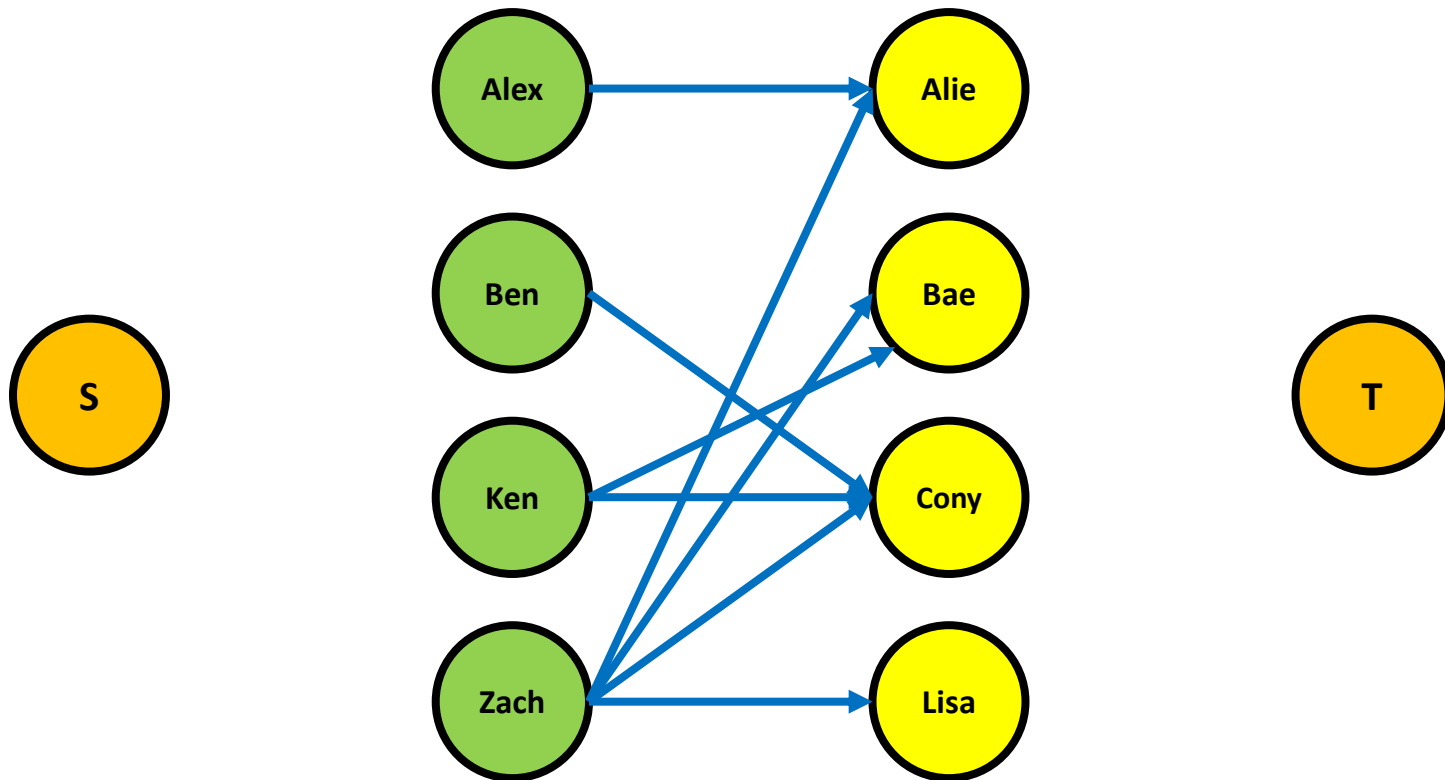
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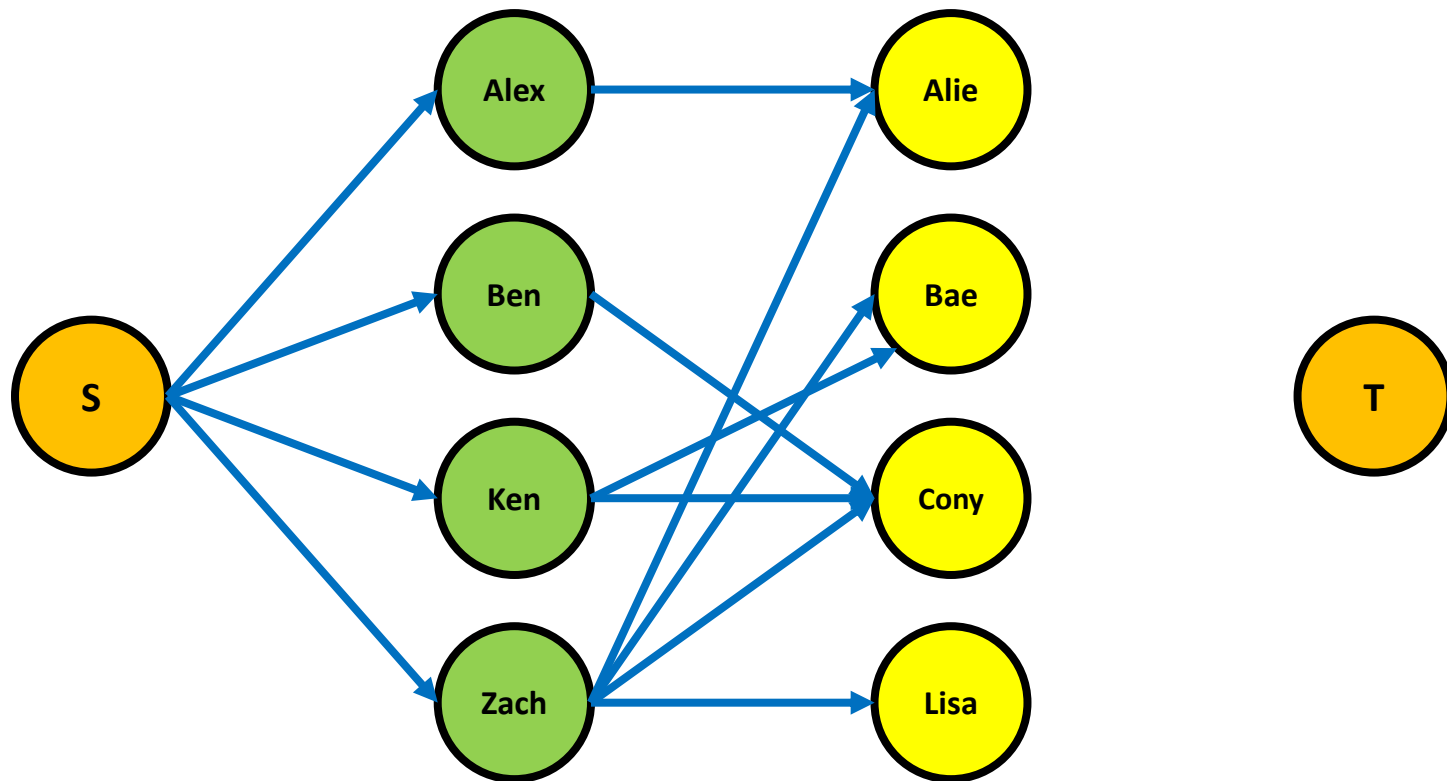
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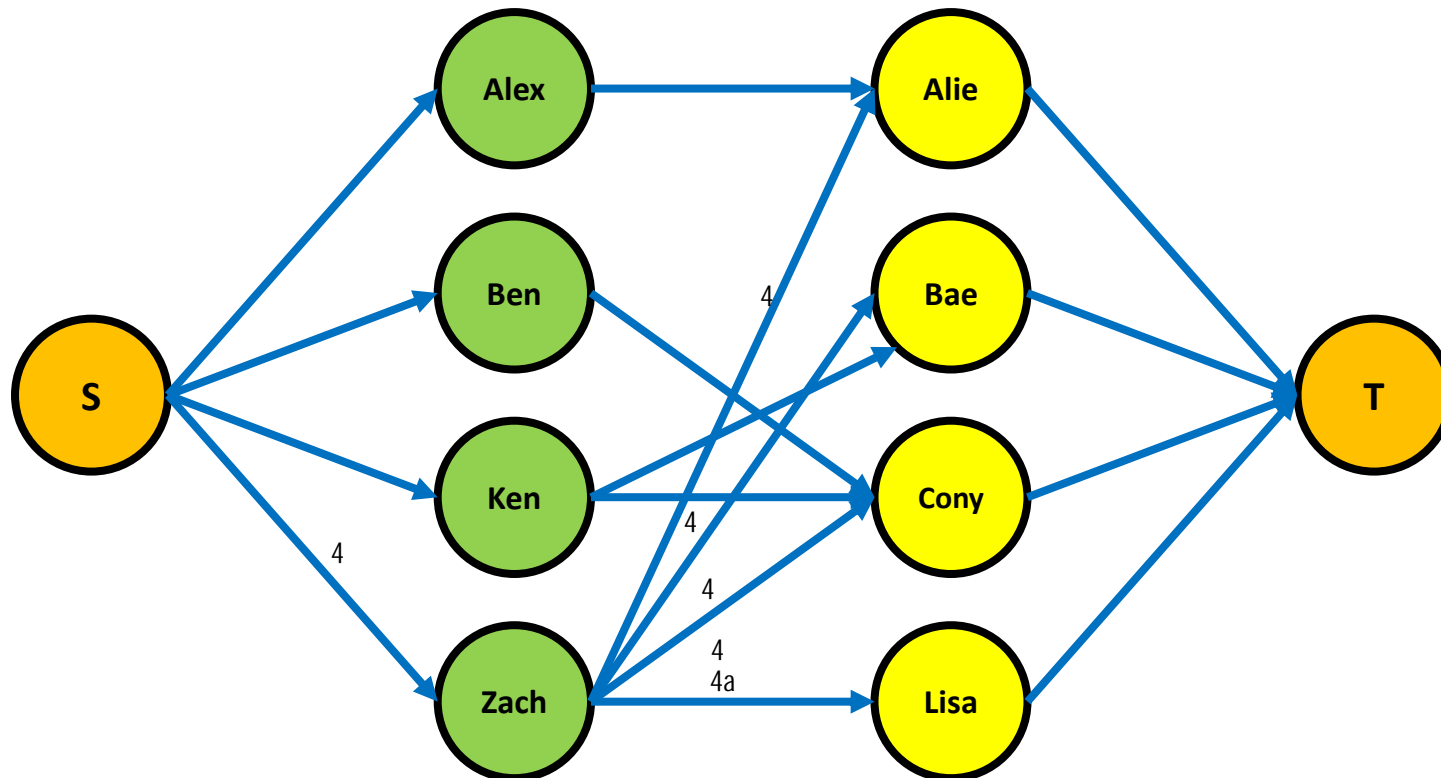


# Bipartite Graph

An application of network flow...

- Arranged marriage agency...
  - What would you do? Maximize the flow!

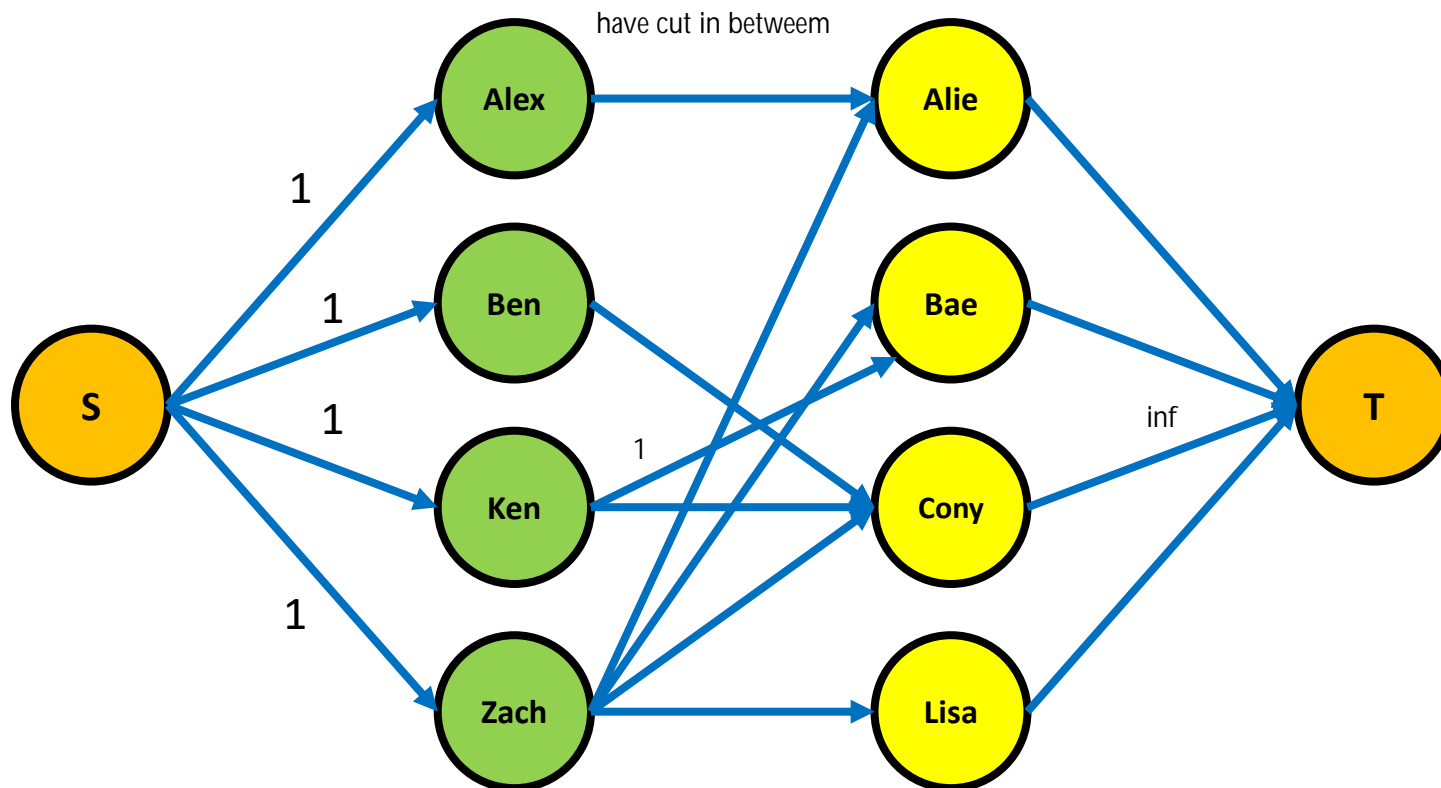
Max money = Max flow = Min Cut



# Bipartite Graph

An application of network flow...

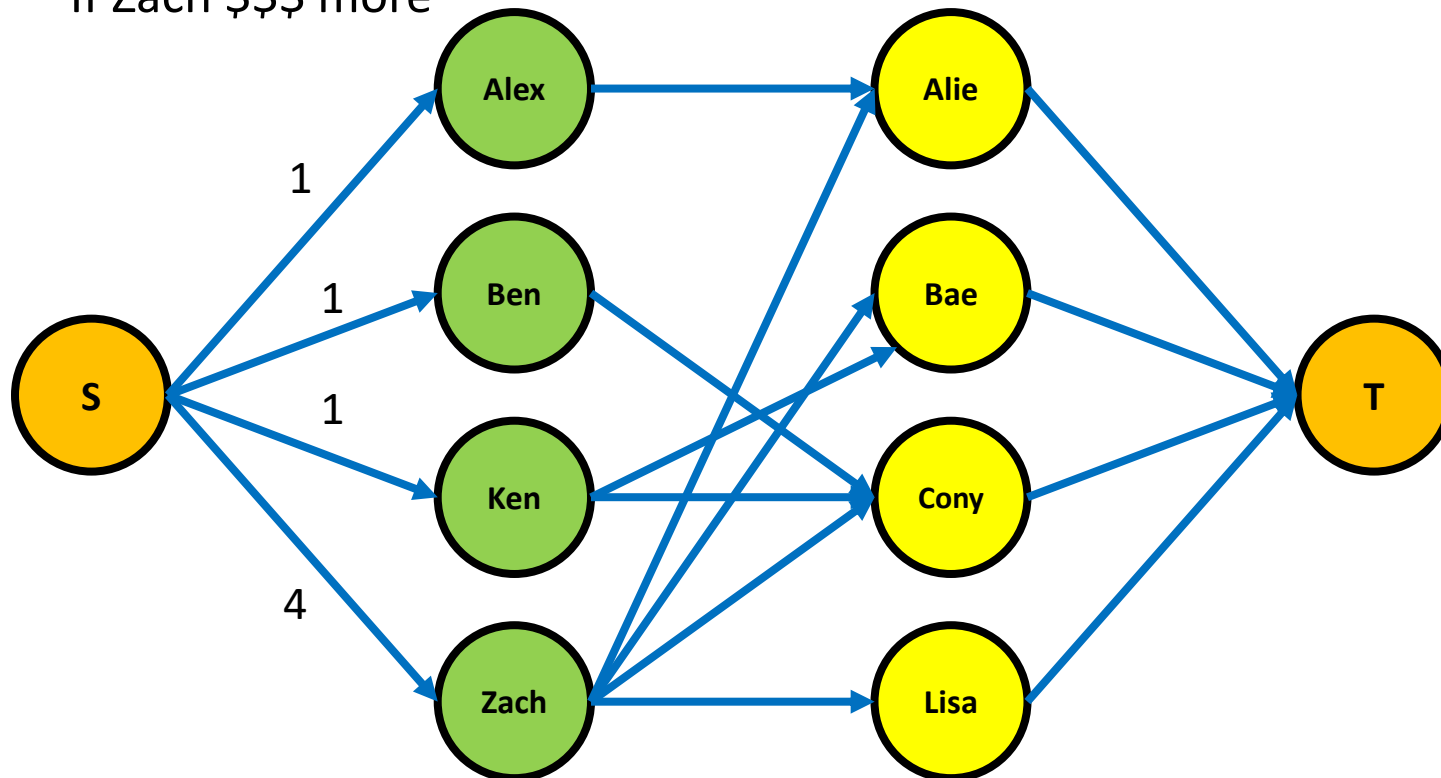
- Arranged marriage agency...
  - What would you do? Maximize the flow! ... I won't finish this #lazy2draw



# Bipartite Graph

An application of network flow...

- Arranged marriage agency...
  - What would you do? Maximize the flow! ... I won't finish this #lazy2draw
  - If Zach \$\$\$ more





Questions?

# Bipartite Graph

## An application of network flow...

- Arranged marriage agency...
  - A list of men
  - A list of women
  - Their preferences
  - Each match you get, you earn \$\$\$
  - So we want the most matches!
  
- Can you think of other applications?

# Bipartite Graph

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  - Each match you get, you earn \$\$\$
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- Can you think of other applications?
  - Think of Monash

Questions?

Thank You