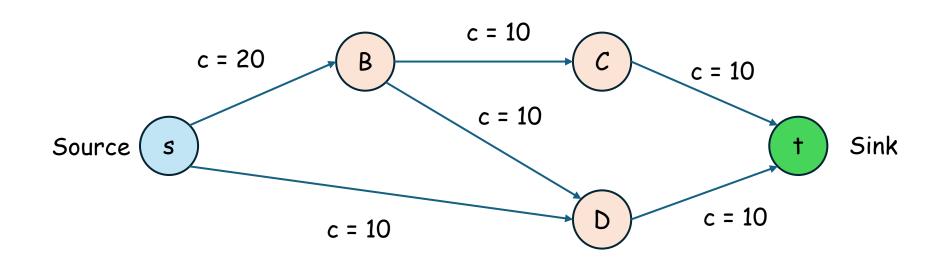
Max-Flow Problem

Fakultas Ilmu Komputer Universitas Indonesia

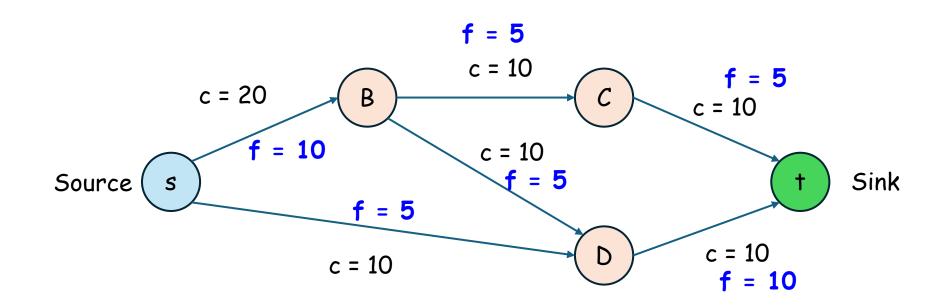
Compiled by Alfan F. Wicaksono from multiple sources

Suppose we consider a directed graph G = (V, E), where each edge has a flow capacity (how much this edge can carry?); and there is a single source node and a sink node.



Suppose we consider a directed graph G = (V, E), where each edge has a flow capacity (how much this edge can carry?); and there is a single source node and a sink node.

A flow is an "abstract entity" that is generated at a source node, transmitted across edges, and absorbed at a sink node.



Flow Networks

- > Assumptions:
 - no edge enters the source s and no edge leaves the sink t;
 - there is at least one edge incident to each node;
 - all capacities are integers.
- These assumptions make things cleaner to think about, and while they eliminate a few pathologies, they preserve all the important issues.

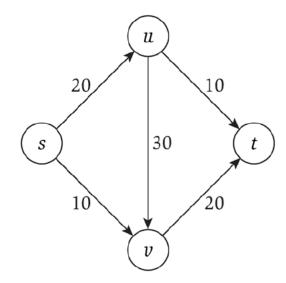


Figure 7.2 A flow network, with source *s* and sink *t*. The numbers next to the edges are the capacities.

Flow

- What does it mean for a network to carry traffic, or flow?
- An s-t flow is a function f that maps each edge e to a nonnegative real number, $f:E \to \mathbb{R}^+$; the value f(e) intuitively represents the amount of flow carried by edge e.
- > A flow f must satisfy the following two properties:
 - (i) (Capacity conditions) For each $e \in E$, we have $0 \le f(e) \le c(e)$.
 - (ii) (Conservation conditions) For each node v other than s and t, we have

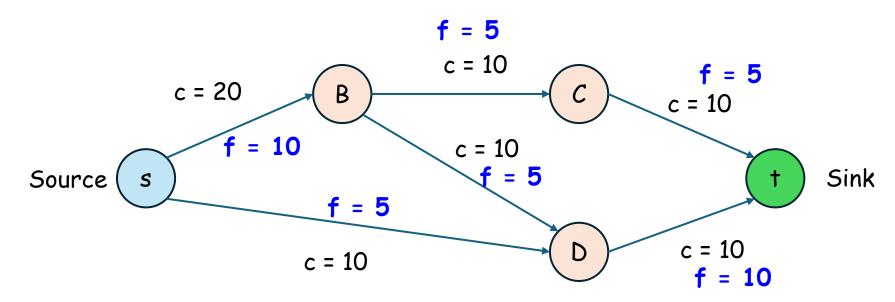
$$\sum_{e \text{ into } v} f(e) = \sum_{e \text{ out of } v} f(e).$$

Flow

The value of a flow f, denoted v(f), is defined to be the amount of flow generated at the source:

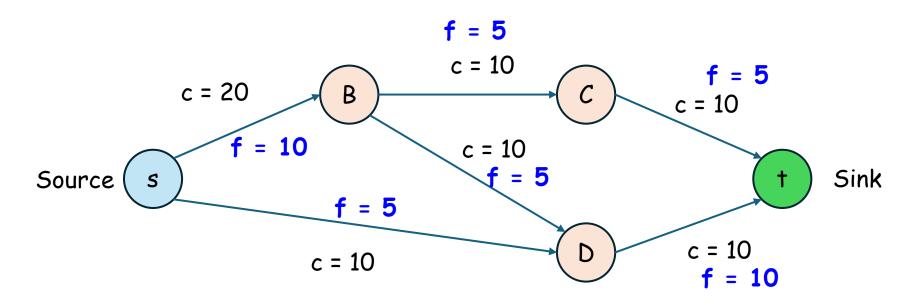
$$v(f) = \sum_{e \text{ out of } s} f(e)$$

In the following example, v(f) = 10 + 5 = 15



Given a flow network, a goal is to arrange the flow so as to make as efficient use as possible of the available capacity.

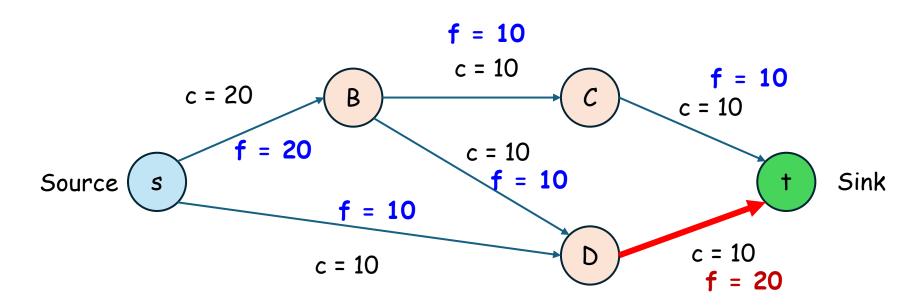
--> Goal: Find a flow of maximum possible value!



v(f) = 15, is this an optimal flow? NO

Given a flow network, a goal is to arrange the flow so as to make as efficient use as possible of the available capacity.

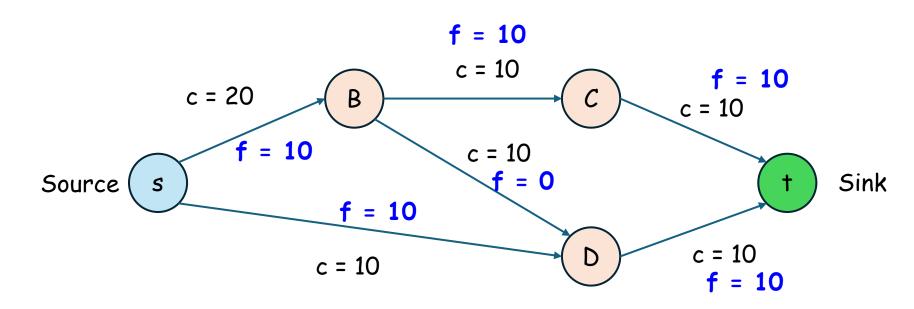
--> Goal: Find a flow of maximum possible value!



v(f) = 30, is this an optimal flow? NO ... A flow @ edge (D, t) is over capacity!

Given a flow network, a goal is to arrange the flow so as to make as efficient use as possible of the available capacity.

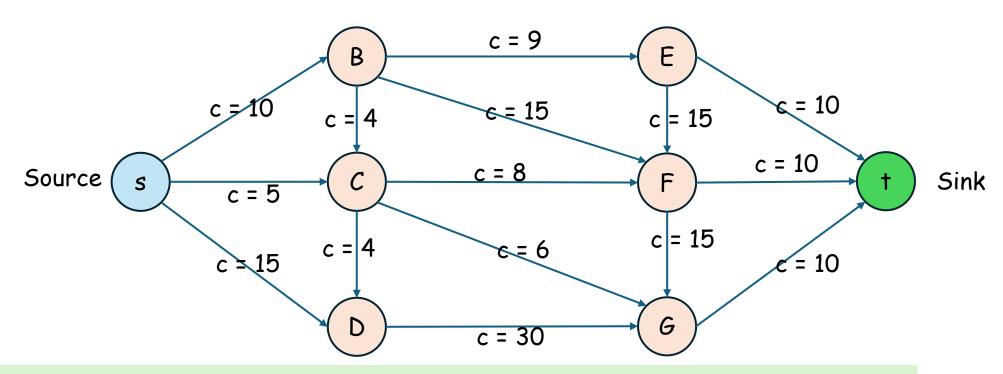
--> Goal: Find a flow of maximum possible value!



v(f) = 20, is this an optimal flow? YES

Given a flow network, a goal is to arrange the flow so as to make as efficient use as possible of the available capacity.

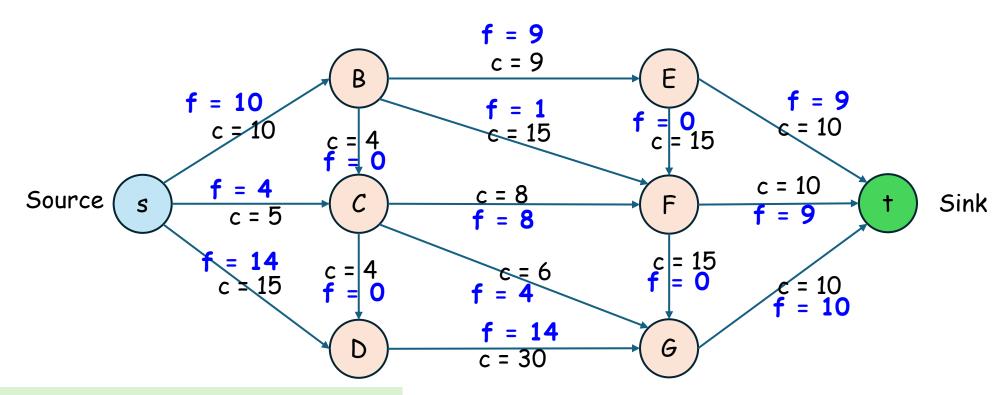
--> Goal: Find a flow of maximum possible value!



What if the flow graph is a bit more complex ©, Can you guess?

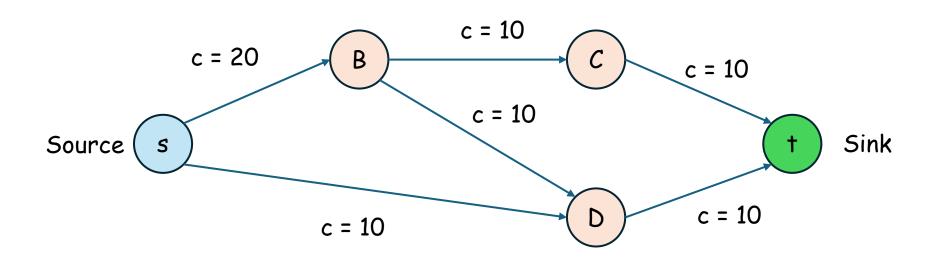
Given a flow network, a goal is to arrange the flow so as to make as efficient use as possible of the available capacity.

--> Goal: Find a flow of maximum possible value!

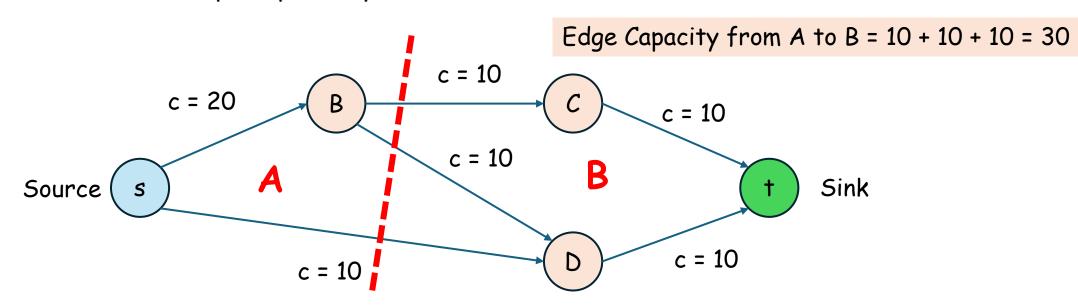


The maximum flow --> v(f) = 28

- A basic obstacle to the existence of large flows is as follows: Suppose we divide the nodes of the graph into two sets, A and B, so that $s \in A$ and $t \in B$. Then, intuitively, any flow that goes from s to t must cross from A into B at some point, and thereby use up some of the edge capacity from A to B. This suggests that each such division (cut) of the graph puts a bound on the maximum possible flow value.
- We will learn later that the maximum-flow value equals the minimum capacity of any such division, called the minimum cut.

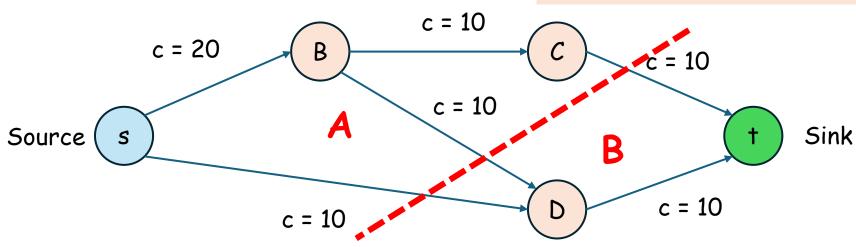


- A basic obstacle to the existence of large flows is as follows: Suppose we divide the nodes of the graph into two sets, A and B, so that $s \in A$ and $t \in B$. Then, intuitively, any flow that goes from s to t must cross from A into B at some point, and thereby use up some of the edge capacity from A to B. This suggests that each such division (cut) of the graph puts a bound on the maximum possible flow value.
- We will learn later that the maximum-flow value equals the minimum capacity of any such division, called the minimum cut.

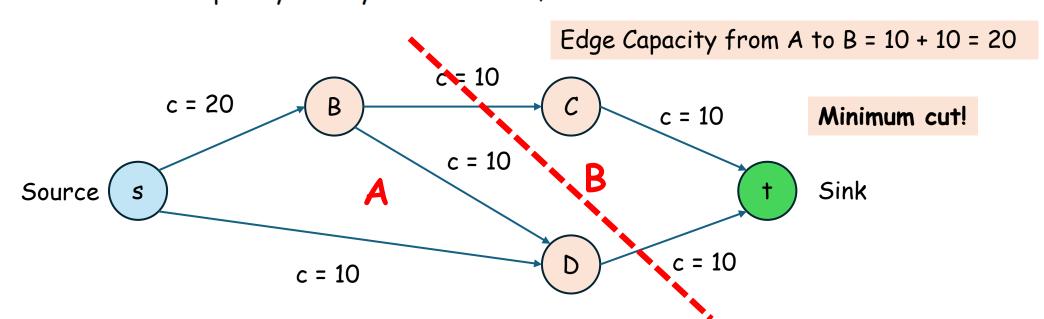


- A basic obstacle to the existence of large flows is as follows: Suppose we divide the nodes of the graph into two sets, A and B, so that $s \in A$ and $t \in B$. Then, intuitively, any flow that goes from s to t must cross from A into B at some point, and thereby use up some of the edge capacity from A to B. This suggests that each such division (cut) of the graph puts a bound on the maximum possible flow value.
- We will learn later that the maximum-flow value equals the minimum capacity of any such division, called the minimum cut.

Edge Capacity from A to B = 10 + 10 + 10 = 30



- A basic obstacle to the existence of large flows is as follows: Suppose we divide the nodes of the graph into two sets, A and B, so that $s \in A$ and $t \in B$. Then, intuitively, any flow that goes from s to t must cross from A into B at some point, and thereby use up some of the edge capacity from A to B. This suggests that each such division (cut) of the graph puts a bound on the maximum possible flow value.
- We will learn later that the maximum-flow value equals the minimum capacity of any such division, called the minimum cut.



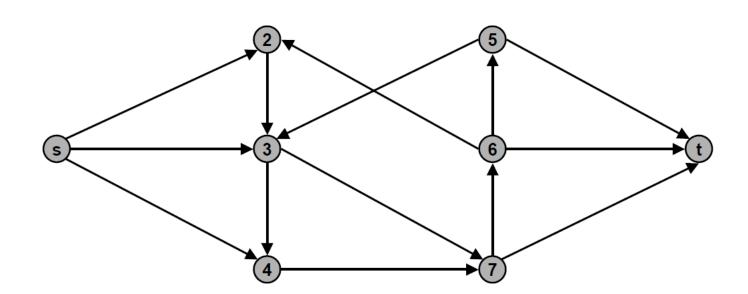
Max-Flow Problem?

Is this an "abstract hypothetical problem" or what? What are the applications of Max-Flow Problem?

Application of "Max-Flow" for Communication Networks

Disjoint path problem:

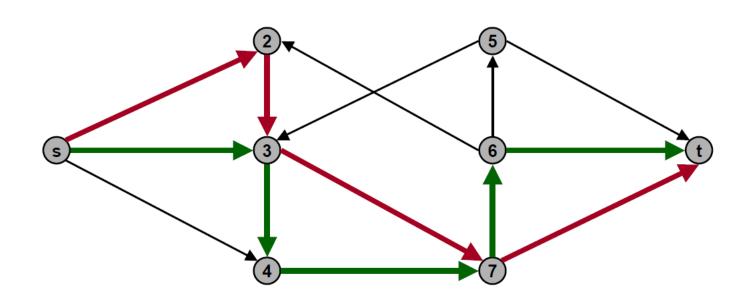
find max number edge-disjoint s-t path



Application of "Max-Flow" for Communication Networks

Disjoint path problem:

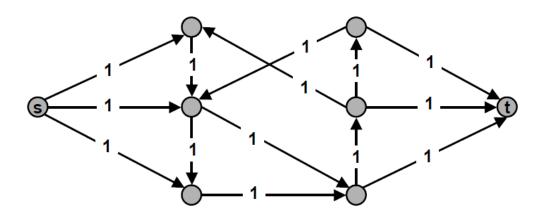
find max number edge-disjoint s-t path



Application of "Max-Flow" for Communication Networks

Disjoint path problem:

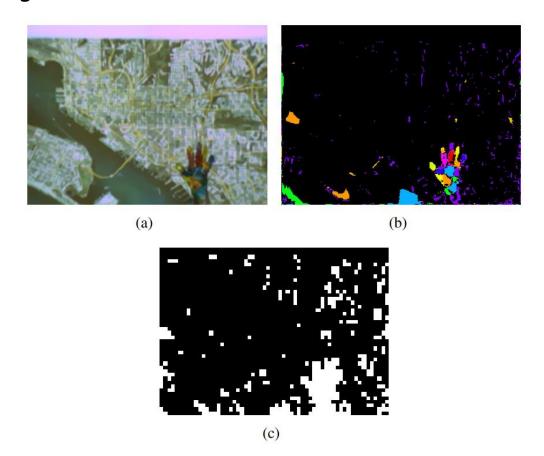
find max number edge-disjoint s-t path
Max-Flow Formulation: assign unit capacity to every edge



Theorem: There are k edge-disjoint s-t paths if and only if the max flow value is k. We will study this problem later on ...

Application of "Max-Flow" for (Binary) Image Segmentation

Example: Given a binary image, the purpose of the segmentation is to track the position of the hand in camera images for gestural interaction.



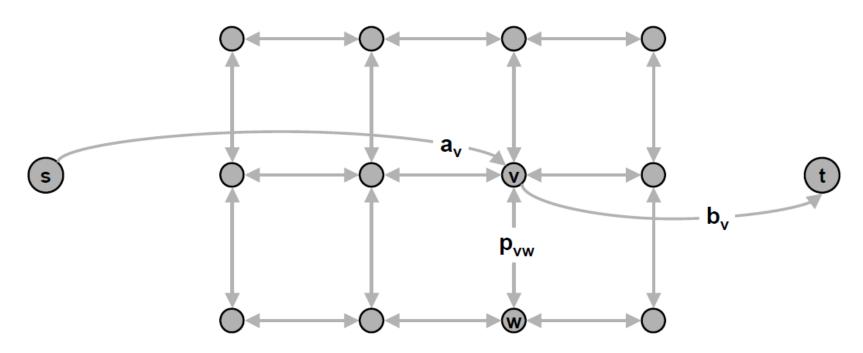
Application of "Max-Flow" for (Binary) Image Segmentation

Max-Flow Formulation:

a_v = likelihood pixel v in foreground

b_v = likelihood pixel v in background

 P_{vw} = separation penalty for labeling one of v and w as foreground, and the other as background



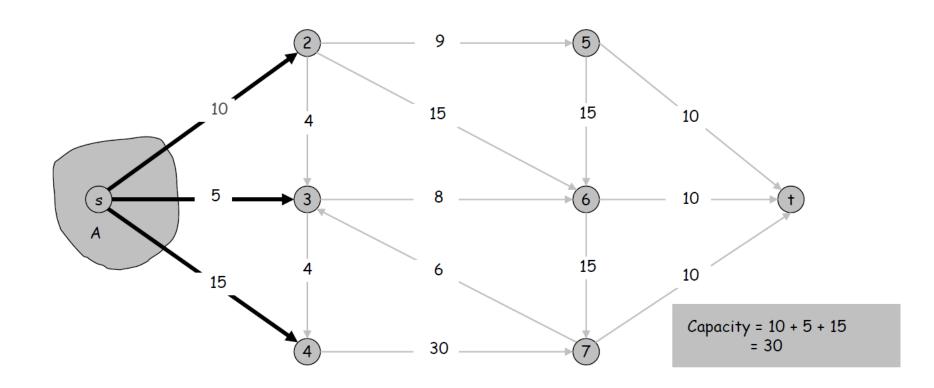
Algorithm for Finding Max-Flow?

Just be patient... before we learn an algorithm, we must understand basic terminologies and definitions

Flow Network and Cuts

Definition. An s-t cut is a partition (A, B) of V with $s \in A$ and $t \in B$.

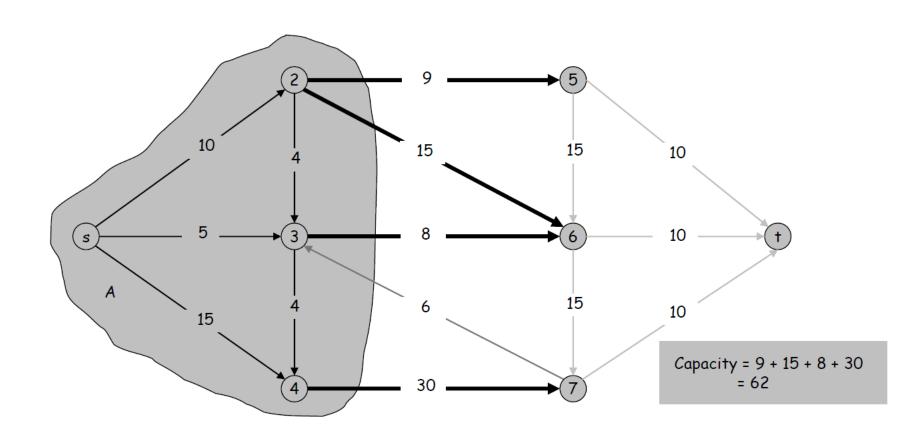
Definition. The capacity of a cut (A, B) is: $cap(A,B) = \sum_{e \text{ out of } A} c(e)$



Flow Network and Cuts

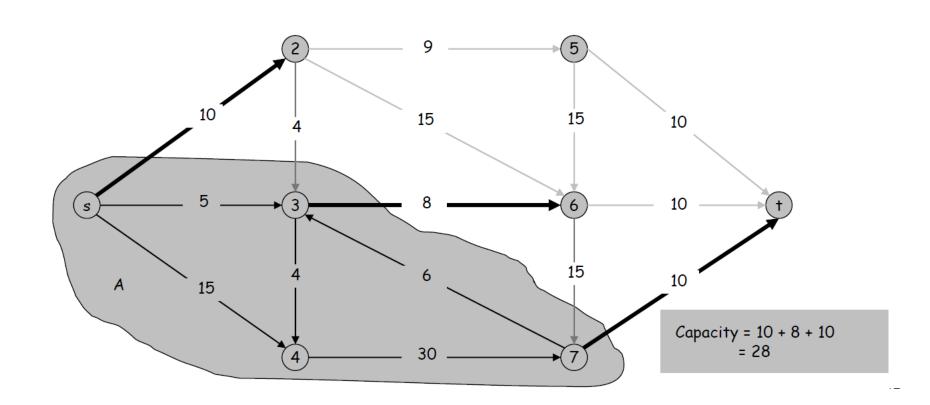
Definition. An s-t cut is a partition (A, B) of V with $s \in A$ and $t \in B$.

Definition. The capacity of a cut (A, B) is: $cap(A,B) = \sum_{e \text{ out of } A} c(e)$



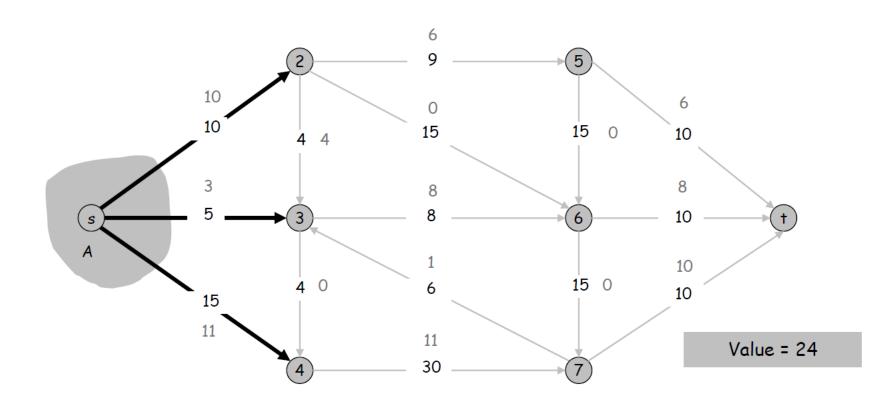
Minimum Cut Problem

Min s-t cut problem. Find an s-t cut of minimum capacity.



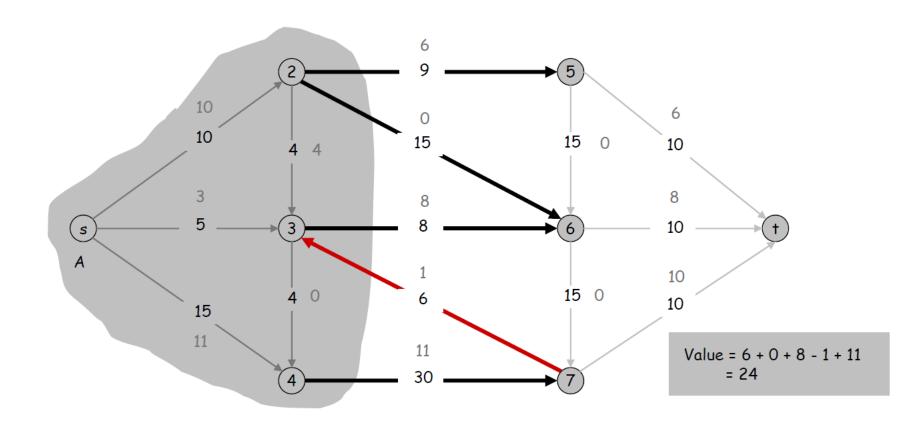
Flow value lemma. Let f be any flow, and let (A, B) be any s-t cut. Then, the net flow sent across the cut is equal to the amount leaving s.

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



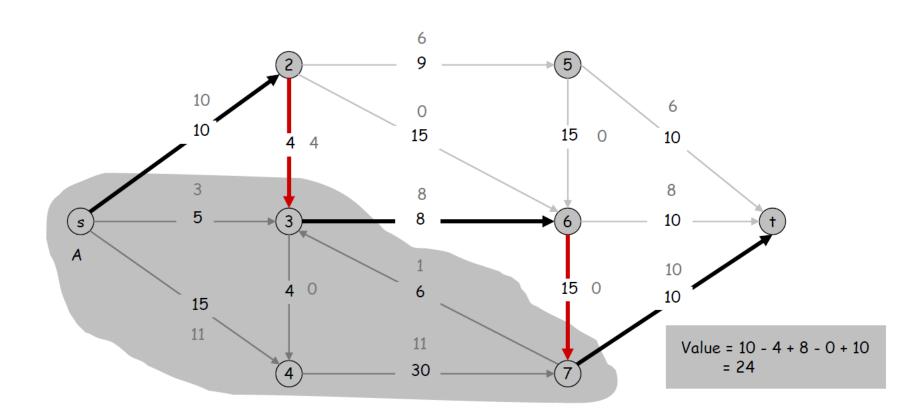
Flow value lemma. Let f be any flow, and let (A, B) be any s-t cut. Then, the net flow sent across the cut is equal to the amount leaving s.

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



Flow value lemma. Let f be any flow, and let (A, B) be any s-t cut. Then, the net flow sent across the cut is equal to the amount leaving s.

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



Flow value lemma. Let f be any flow, and let (A, B) be any s-t cut. Then

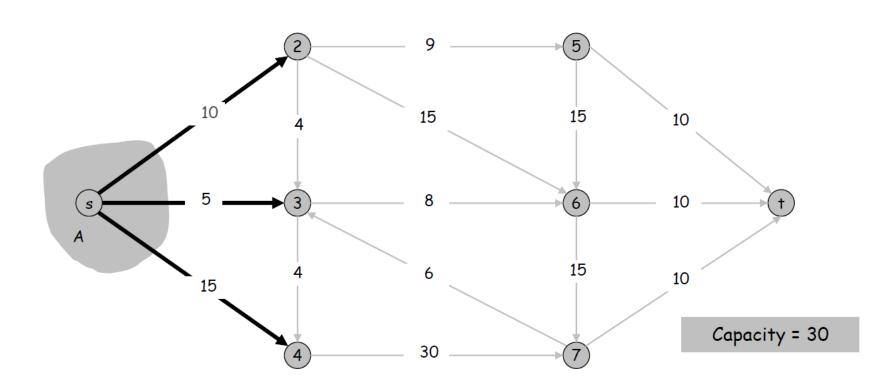
$$\sum_{e \text{ out of } A} f(e) - \sum_{e \text{ in to } A} f(e) = v(f).$$

Proof.
$$v(f) = \sum_{e \text{ out of } s} f(e)$$
by flow conservation, all terms
$$= \sum_{v \in A} \left(\sum_{e \text{ out of } v} f(e) - \sum_{e \text{ in to } v} f(e) \right)$$

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

Weak duality. Let f be any flow, and let (A, B) be any s-t cut. Then the value of the flow is at most the capacity of the cut.

Cut capacity = $30 \Rightarrow \text{Flow value} \leq 30$



Weak duality. Let f be any flow. Then, for any s-t cut (A, B) we have $v(f) \le cap(A, B)$.

Proof.

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

$$\leq \sum_{e \text{ out of } A} f(e)$$

$$\leq \sum_{e \text{ out of } A} c(e)$$

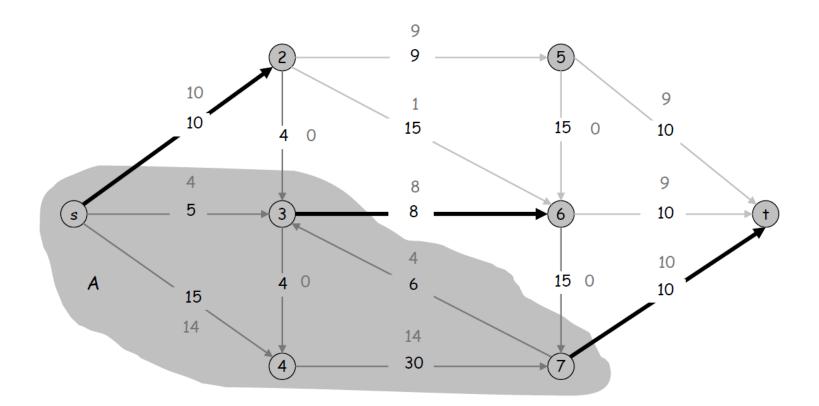
$$\leq \sum_{e \text{ out of } A} c(e)$$

$$= cap(A, B) \quad \blacksquare$$

Certificate of Optimality

Corollary. Let f be any flow, and let (A, B) be any cut. If v(f) = cap(A, B), then f is a max flow and (A, B) is a min cut.

Value of flow = 28 Cut capacity = 28 \Rightarrow Flow value \leq 28



OK, Let's Discuss an Algorithm

First, it is necessary to understand what "Residual Graph" is

Residual Graph

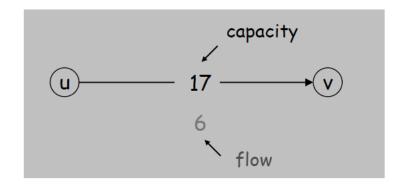
Given a flow network G, and a flow f on G, we define the residual graph G_f of G with respect to f as follows:

- The node set of G_f is the same as that of G;
- For each edge **e** of **G** on which **f(e)** < **c(e)**, there are **c(e) f(e)** "leftover" units of capacity on which we can try pushing flow forward. These are **forward edges**.
- For each edge e of G on which f(e) > 0, there are f(e) units of flow that we can "undo" if we want to, by pushing flow backward. So we include the edge e^R in G_f , with a capacity of f(e).

Residual Graph

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

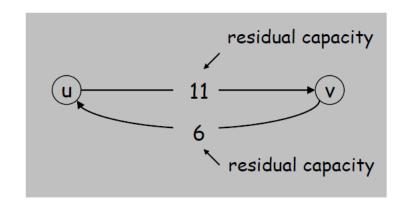
Flow f(e), capacity c(e).



Residual edge.

- "Undo" flow sent.
- $_{u}$ e = (u, v) and e^{R} = (v, u).
- Residual capacity:

$$\begin{cases} c(e) - f(e) & \text{for forward edge} \\ f(e) & \text{for backward edge} \end{cases}$$



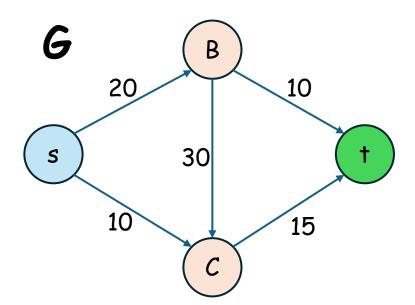
Residual graph: $G_f = (V, E_f)$.

- Residual edges with positive residual capacity.
- $_{\circ}$ E_f = {e} \cup {e^R}.

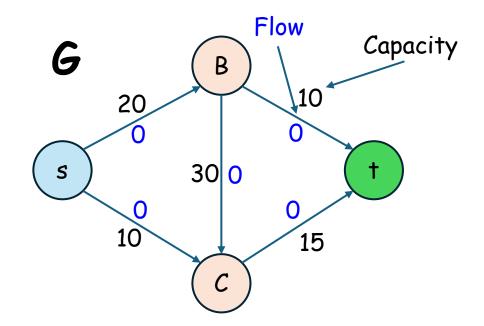
Residual Capacity

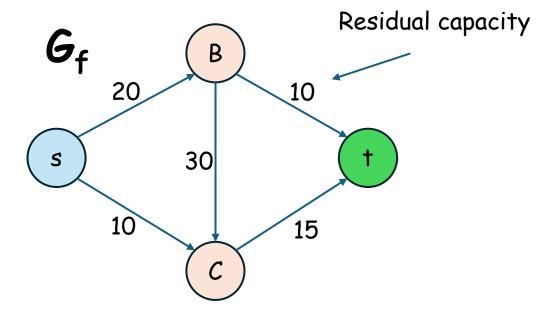
- Note that each edge e in G can give rise to one or two edges in G_f . If O < f(e) < c(e) it results in both a forward edge and a backward edge being included in G_f ;
 - Thus, G_f has at most twice as many edges as G
- We will refer to the capacity of an edge in the residual graph as a residual capacity.

- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - · Repeat until no new path P is found.

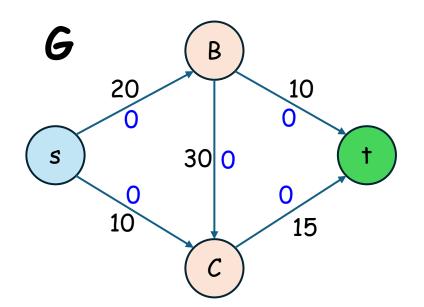


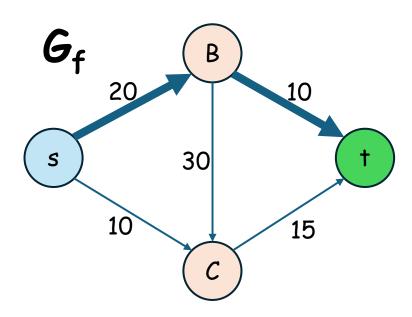
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - · Repeat until no new path P is found.



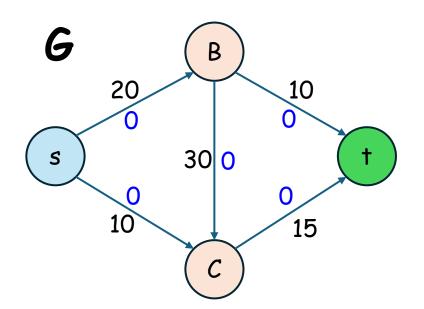


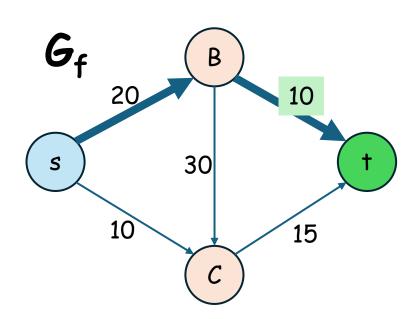
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - · Repeat until no new path P is found.



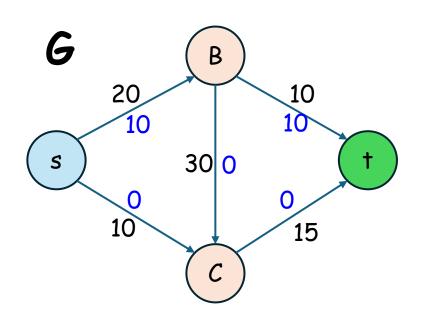


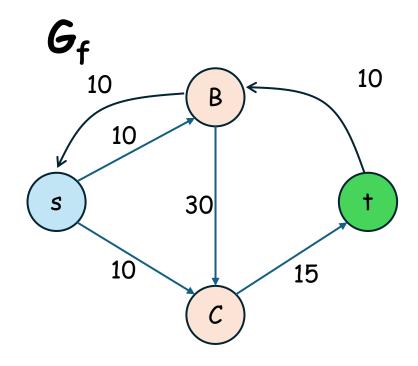
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - · Repeat until no new path P is found.



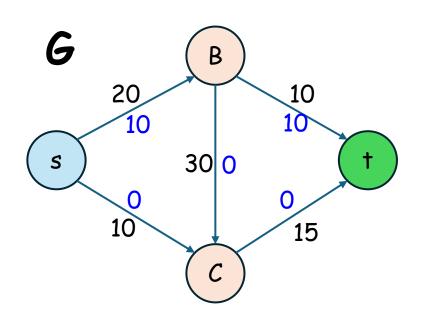


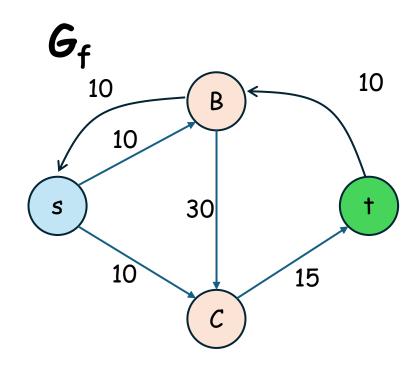
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - · Repeat until no new path P is found.





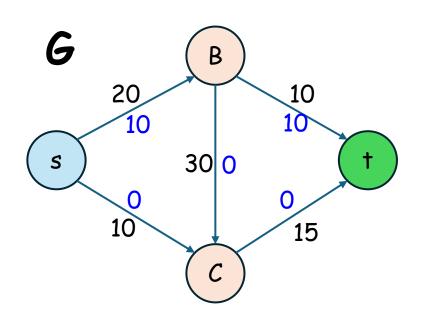
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - Repeat until no new path P is found.

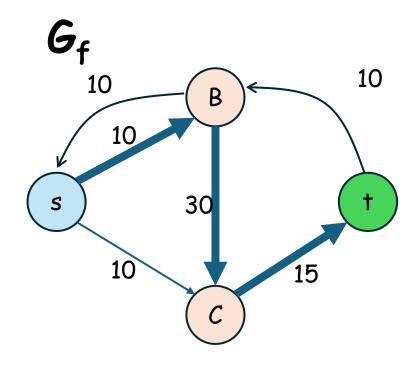




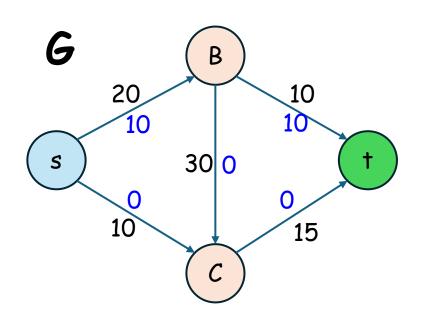
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;

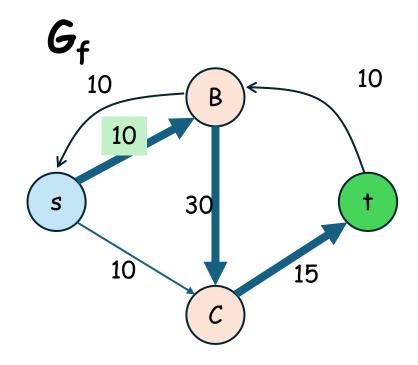
· Repeat until no new path P is found.



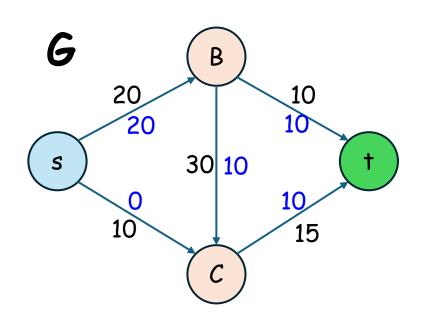


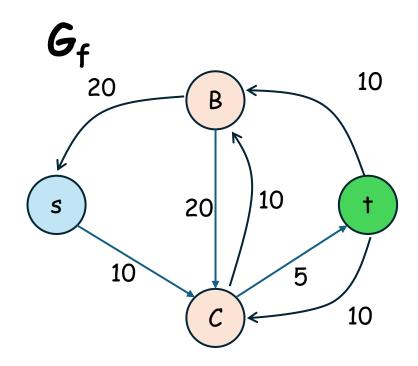
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - · Repeat until no new path P is found.



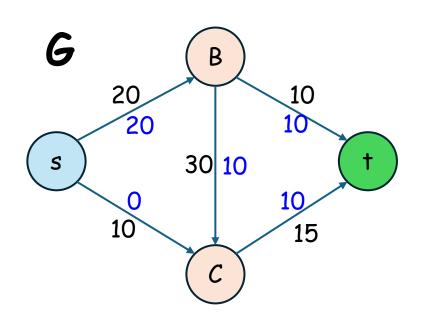


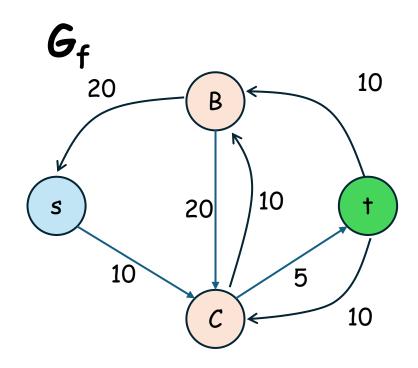
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - Repeat until no new path P is found.





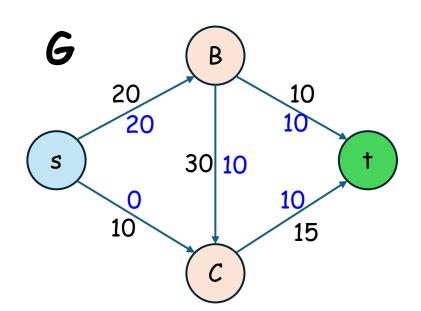
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - Repeat until no new path P is found.

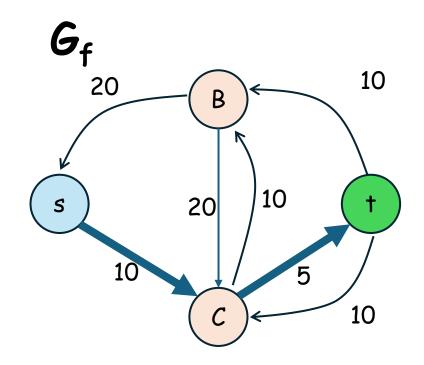




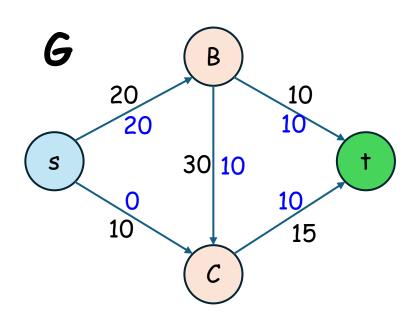
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;

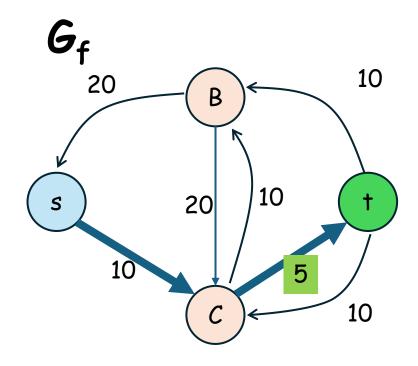
• Repeat until no new path P is found.



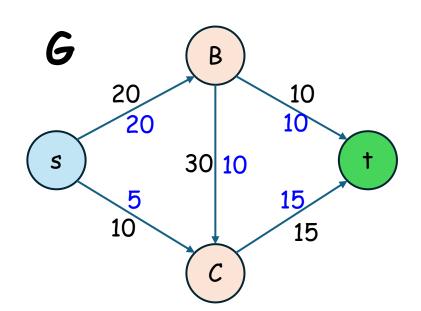


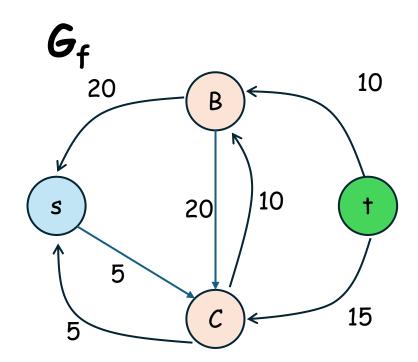
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - Repeat until no new path P is found.





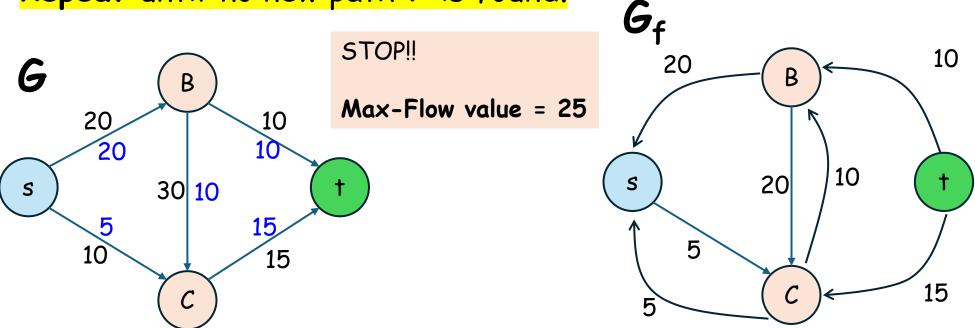
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;
 - · Repeat until no new path P is found.





- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;
 - Find s-t path P on G_f ;
 - Find the minimum residual capacity of any edge on P;
 - Augment flow along path P --> set a new flow in G and update G_f ;

Repeat until no new path P is found.



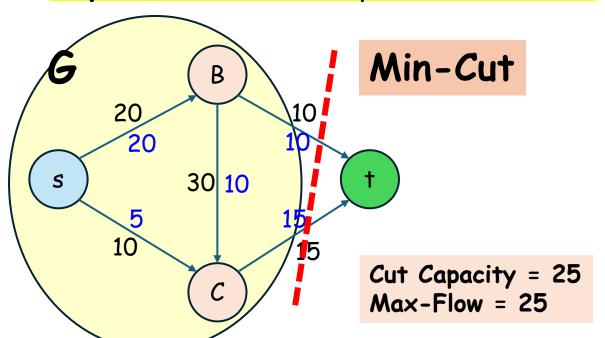
- Algorithm for finding Max-Flow
 - Start with f(e) = 0 for all edge in G;

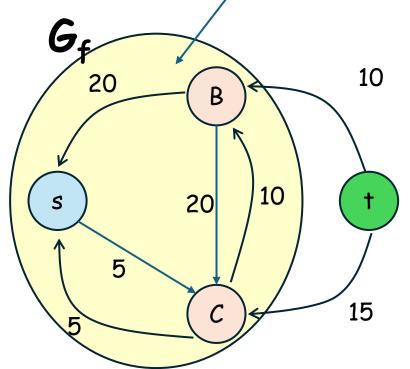
• Find s-t path P on G_f ;

• Find the minimum residual capacity of any edge on P;

• Augment flow along path P --> set a new flow in G and update G_f :

Repeat until no new path P is found.





All nodes reachable from s

Augmenting Paths in a Residual Graph

- \triangleright Now we want to make precise the way in which we push flow from s to t in G_f .
- \triangleright Let P be a simple s-t path in G_f that is, P does not visit any node more than once.
- We define bottleneck(P, f) to be the minimum residual capacity of any edge on P, with respect to the flow f.
- Next we define the operation augment(f, P), which yields a new flow f' in G.
- > It was purely to be able to perform this operation that we defined the residual graph.
- To reflect the importance of augment, one often refers to any s-t path in the residual graph as an augmenting path.
- This augmentation operation captures the type of forward and backward pushing of flow in the Ford-Fulkerson algorithm for computing an s-t flow in G.

Ford-Fulkerson Algorithm

Forward edge

Yes, you've just seen Ford-Fulkerson Algorithm!

```
Fold-Fulkerson(G, s, t):
  for e \in G.E:
     f(e) \leftarrow 0
  G_f \leftarrow Residual - Graf(G)
  while there exist augmenting s-t path P on G_f:
      f \leftarrow Augment(f, P)
      G_f \leftarrow \text{Residual-Graf}(G) // update G_f
  return f
```

```
Augment(f, P):
  b \leftarrow Bottleneck(P, f)
  for e \in P:
     if e \in G.E then
         f(e) \leftarrow f(e) + b
     else
         f(e^R) \leftarrow f(e^R) - b
  return f
```

Reverse edge

```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-}G\text{raf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

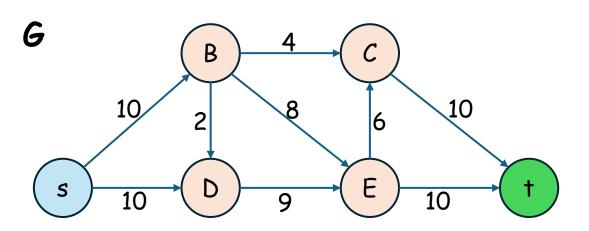
G_f \leftarrow \text{Residual-}G\text{raf}(G) // update G_f

return f
```

Augment(f, P):

$$b \leftarrow Bottleneck(P, f)$$

for $e \in P$:
if $e \in G.E$ then
 $f(e) \leftarrow f(e) + b$
else
 $f(e^R) \leftarrow f(e^R) - b$
return f



```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

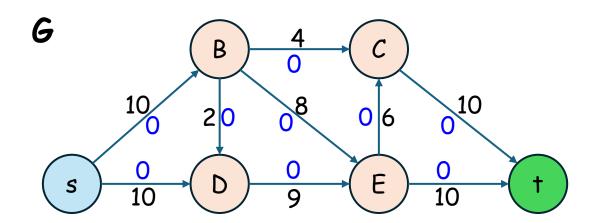
while there exist augmenting s-t path P on G_f:

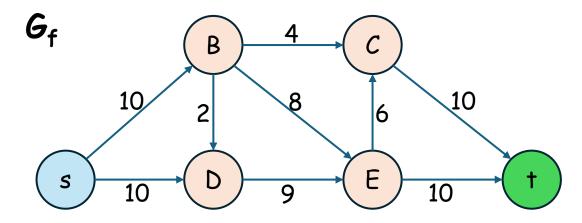
f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):
b \leftarrow Bottleneck(P, f)
for e \in P:
if e \in G.E then
f(e) \leftarrow f(e) + b
else
f(e^R) \leftarrow f(e^R) - b
return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

for e \in P:

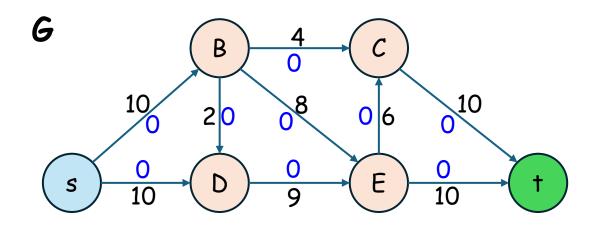
if e \in G.E then

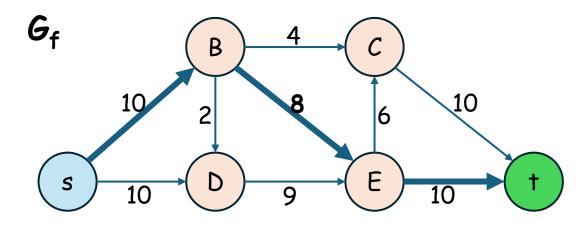
f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b

return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

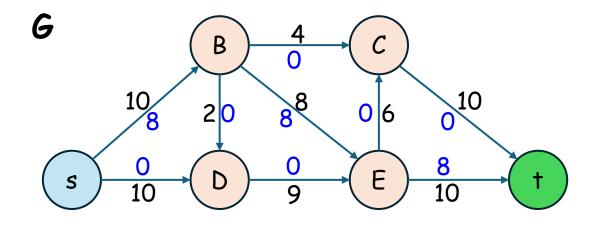
while there exist augmenting s-t path P on G_f:

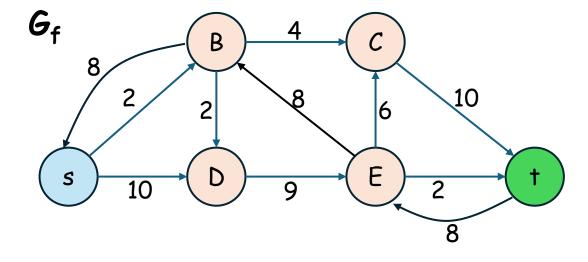
f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):
b \leftarrow Bottleneck(P, f)
for e \in P:
if e \in G.E then
f(e) \leftarrow f(e) + b
else
f(e^R) \leftarrow f(e^R) - b
return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

for e \in P:

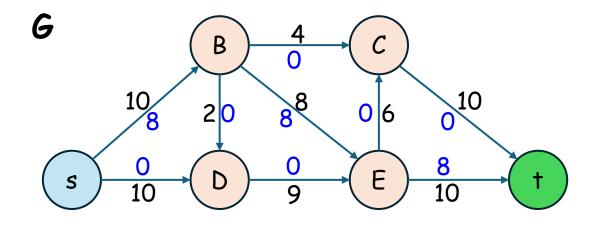
if e \in G.E then

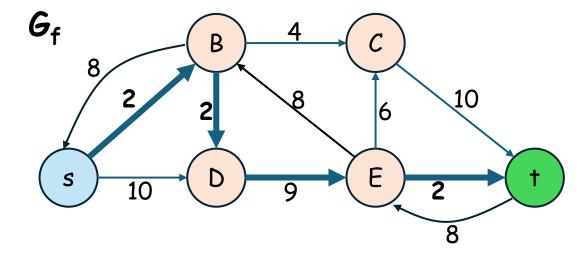
f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b

return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

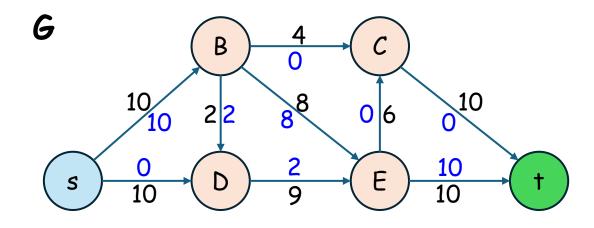
for e \in P:

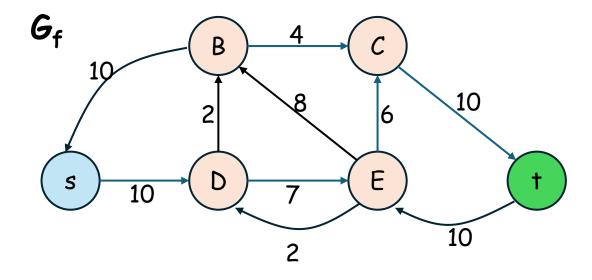
if e \in G.E then

f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

for e \in P:

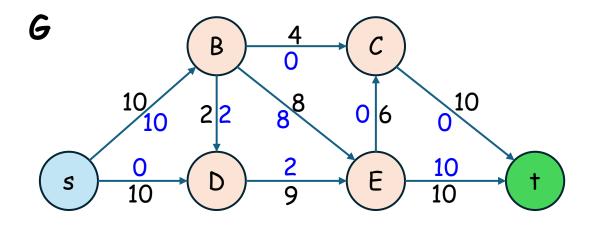
if e \in G.E then

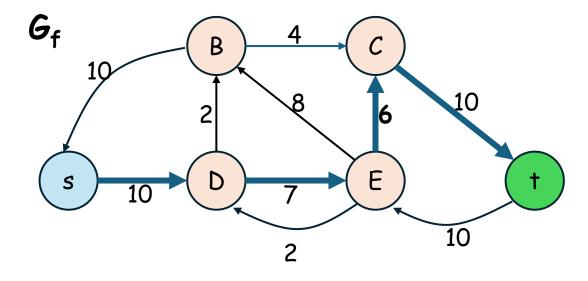
f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b

return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

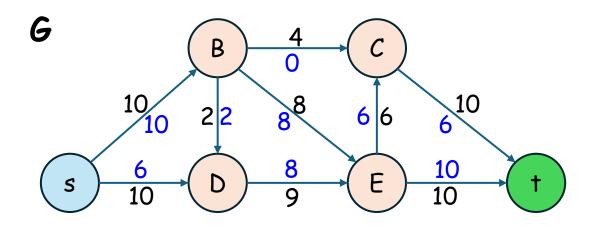
for e \in P:

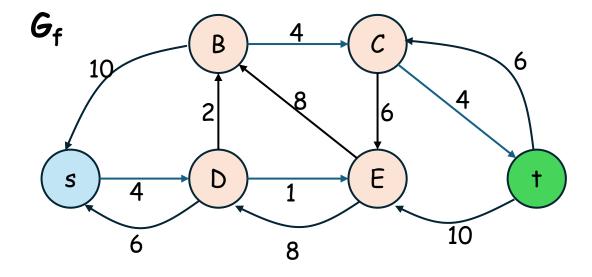
if e \in G.E then

f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

for e \in P:

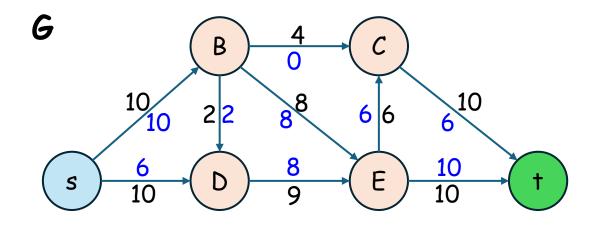
if e \in G.E then

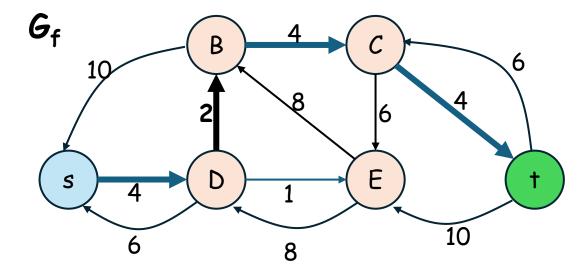
f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b

return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)
while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)
G_f \leftarrow \text{Residual-Graf}(G)
// update G_f
return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

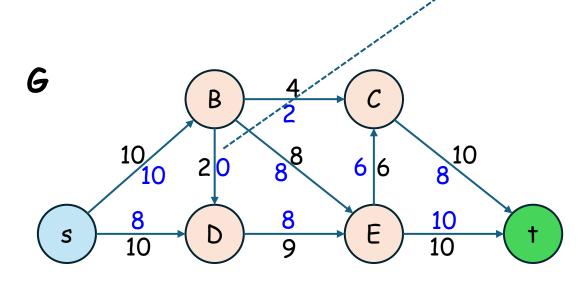
for e \in P:

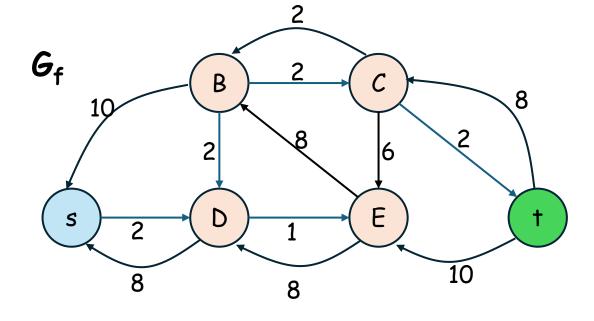
if e \in G.E then

f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

for e \in P:

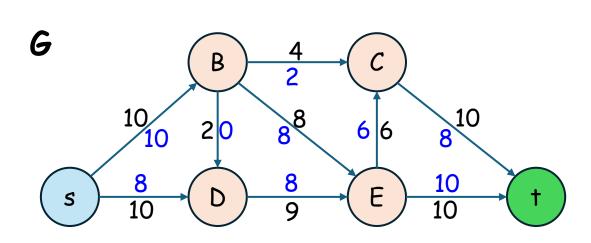
if e \in G.E then

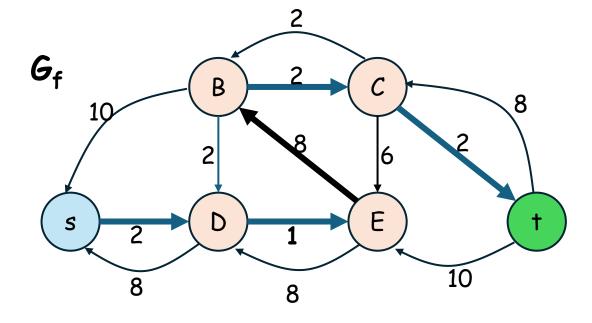
f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b

return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

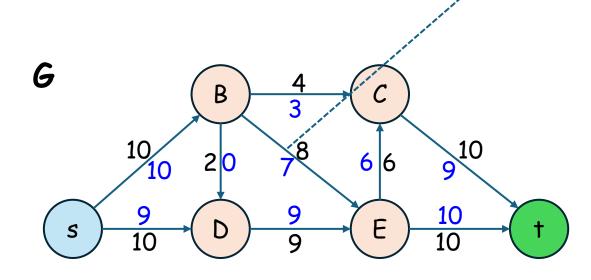
while there exist augmenting s-t path P on G_f:

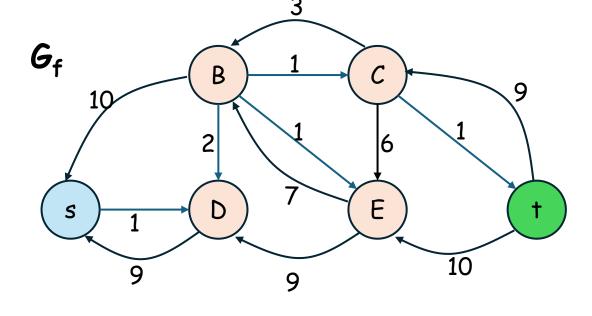
f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):
b \leftarrow Bottleneck(P, f)
for e \in P:
if e \in G.E then
f(e) \leftarrow f(e) + b
else
f(e^R) \leftarrow f(e^R) - b
return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

False

while there exist augmenting s-t path P on G_f:

f \leftarrow Augment(f, P)

G_f \leftarrow Residual-Graf(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

for e \in P:

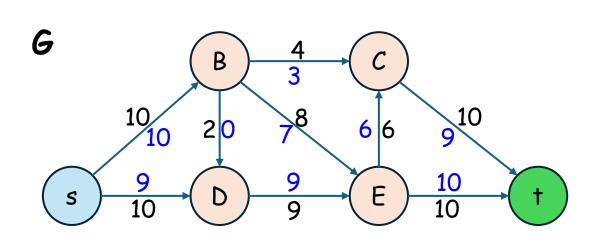
if e \in G.E then

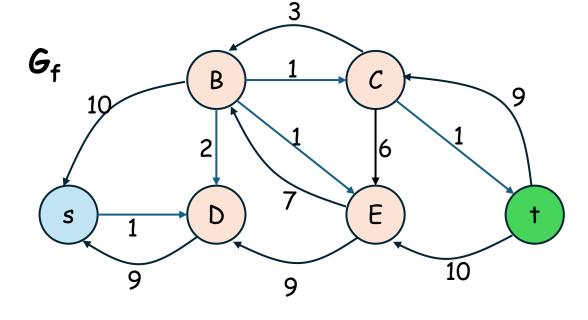
f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b

return f
```





```
Fold-Fulkerson(G, s, t):

for e \in G.E:

f(e) \leftarrow 0

G_f \leftarrow \text{Residual-Graf}(G)

while there exist augmenting s-t path P on G_f:

f \leftarrow \text{Augment}(f, P)

G_f \leftarrow \text{Residual-Graf}(G) // update G_f

return f
```

```
Augment(f, P):

b \leftarrow Bottleneck(P, f)

for e \in P:

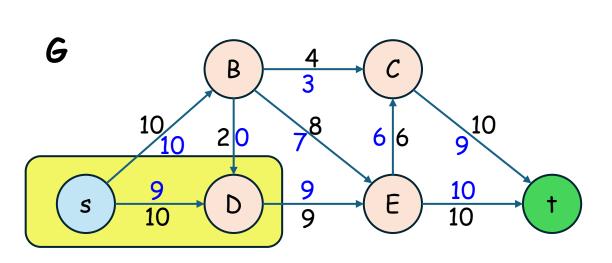
if e \in G.E then

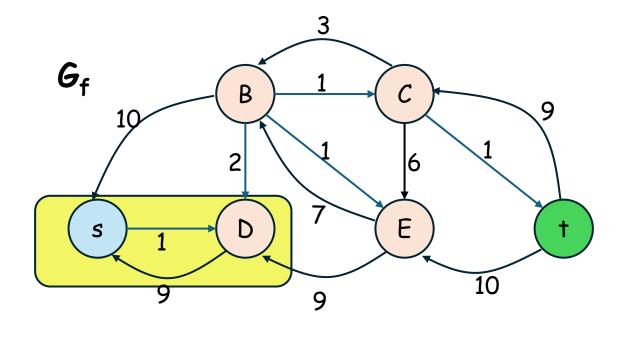
f(e) \leftarrow f(e) + b

else

f(e^R) \leftarrow f(e^R) - b
```

Flow value = 19 (max) Cut Capacity = 19





```
int fordFulkerson(int graph[V][V], int s, int t) {
   int u, v;
    int residualGraph[V][V];
   for (u = 0; u < V; u++)
                                                  Initially, residual Graph = Graph
        for (v = 0; v < V; v++)
            residualGraph[u][v] = graph[u][v];
    int parent[V];
                                                  This is useful for storing path; this is filled by bfs()
    int max flow = 0;
   while (bfs(residualGraph, s, t, parent)) {
        int path flow = INT MAX;
                                                       Bottleneck(P, f): Finding minimum residual capacity
        for (v = t; v != s; v = parent[v]) {
            u = parent[v];
            path flow = min(path flow, residualGraph[u][v]);
        for (v = t; v != s; v = parent[v]) {
            u = parent[v];
            residualGraph[u][v] -= path_flow;
                                                   Update residual graph
            residualGraph[v][u] += path flow;
       max flow += path flow;
    return max_flow;
```

```
bool bfs(int residualGraph[V][V], int s, int t, int parent[]) {
   bool visited[V];
   memset(visited, 0, sizeof(visited));
   queue<int> q;
   q.push(s);
                                             BFS is used to find augmenting s-t path!
   visited[s] = true;
   parent[s] = -1;
   while (!q.empty()) {
       int u = q.front();
       q.pop();
       for (int v = 0; v < V; v++) {
           if (visited[v] == false && residualGraph[u][v] > 0) {
               if (v == t) {
                   parent[v] = u;
                   return true:
               q.push(v);
               parent[v] = u;
               visited[v] = true;
   return false;
```

Correctness & Analysis

Yes, you are not taking "the DAA course" if you don't learn these stuffs ☺

This is where the interesting part will start ©

Max-Flow Min-Cut Theorem

Augmenting path theorem. Flow f is a max flow iff there are no augmenting paths.

Max-flow min-cut theorem. [Ford-Fulkerson 1956] The value of the max flow is equal to the value of the min cut.

Proof strategy. We prove both theorem simultaneously by showing the equivalence of the following conditions:

- (i) There exists a cut (A^*, B^*) such that $v(f) = cap(A^*, B^*)$.
- (ii) Flow f is a max flow.
- (iii) There is no augmenting path relative to f.
- (i) \Rightarrow (ii) This was the corollary to weak duality lemma.
- (ii) \Rightarrow (iii) We show contrapositive.
- Let f be a flow. If there exists an augmenting path, then we can improve f by sending flow along the path.

Proof of Max-Flow Min-Cut Theorem

(iii)
$$\Rightarrow$$
 (i)

- Let f be a flow with no augmenting paths.
- Let A* be set of vertices reachable from s in residual graph.
- By definition of A^* , $s ∈ A^*$.
- By definition of f, f ∉ f and f ∈ f.
- So, (A^*,B^*) is indeed an s-t cut.

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

$$= \sum_{e \text{ out of } A^*} c(e) - 0$$

$$= cap(A^*, B^*) \quad \blacksquare$$
Residual graph
$$(u, v) \text{ is saturated with flow.}$$

$$(u', v') \text{ carries no flow.}$$

Running Time

Assumption. Let C denote $\sum_{e \text{ out of } s} c(e)$.

All capacities are integers between 1 and C.

Invariant. Every flow value f(e) and every residual capacities $c_f(e)$ remains an integer throughout the algorithm.

Theorem. The algorithm terminates in at most C iterations. Proof. Each augmentation increase value by at least 1. •

m = |V| = banyaknya nodes

Theorem. The Ford-Fulkerson algorithm runs in O(mC) time.

Integrality theorem. If all capacities are integers, then there exists a max flow f for which every flow value f(e) is an integer.

Proof. Since algorithm terminates, theorem follows from invariant.

Computing a minimum s-t cut from a maxflow

Theorem

Given a flow f of maximum value, we can compute an s-t cut of minimum capacity in O(m) time.

Proof

We simply follow the construction in the proof of the Max-Flow Min-Cut Theorem. We construct the residual graph G_f , and perform breadth-first search or depth-first search to determine the set A^* of all nodes that s can reach. We then define $B^* = V - A^*$, and return the cut (A^*, B^*) .

Ford-Fulkerson --> O(mC)

• Do you think that O(mC) is polynomial?

Ford-Fulkerson --> O(mC)

• Do you think that O(mC) is polynomial?

- · No, it's exponential in terms of input size!
- C is integer, and the number of bits for representing C is log_2 C = size(C).

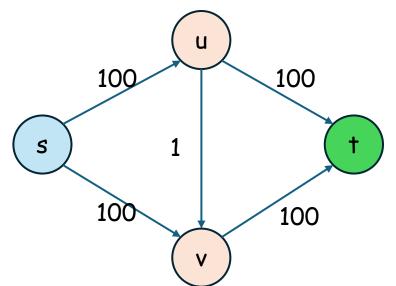
 $\bullet O(mC) = O(m2^{size(C)})$

Bonus Stuffs

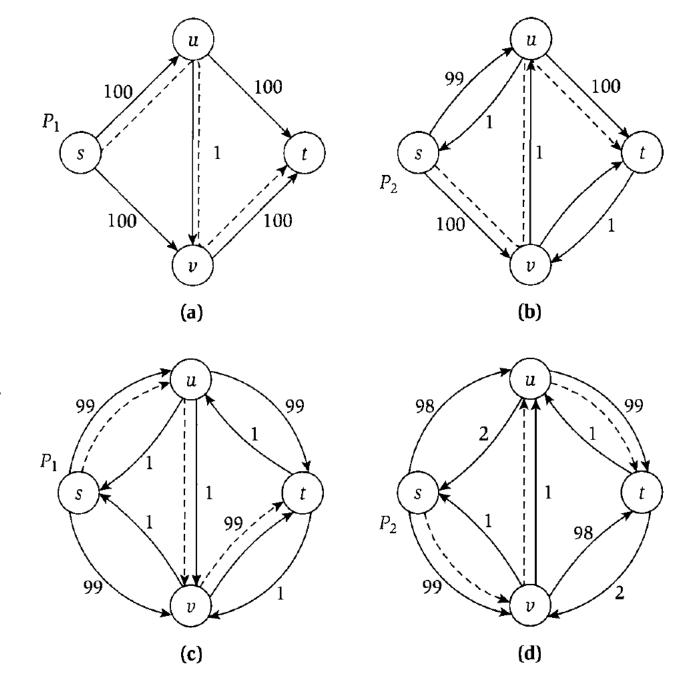
Can we still improve the algorithm?

Choosing Good Augmenting Paths

- In the Ford-Fulkerson Algo., any way of choosing an augmenting path increases the value of the flow;
- How to select augmenting paths so as to avoid the potential bad behavior of the algorithm?
- To get a sense for how bad the algorithm can be with pathological choices for the augmenting paths, consider the following graph:



(a) through (d) depict four iterations of the Ford-Fulkerson Algorithm using a bad choice of augmenting paths: The augmentations alternate between the path P₁ through nodes s, u, v, t and the path P₂ through the nodes s, v, u, t



It is easy to see that the maximum flow has value 200, and has f(e) = 100 for the edges (s, v), (s, u), (v,t) and (u,t) and value 0 on the edge (u, v). This flow can be obtained by a sequence of two augmentations, using the paths of nodes s, u, t and path s, v, t.

- Suppose we start with augmenting path P1 of nodes s, u, v, t. This path has bottleneck(P_1 , f) = 1. After this augmentation, we have f(e) = 1 on the edge e = (u, v), so the reverse edge is in the residual graph.
- For the next augmenting path, we choose the path P_2 of the nodes s, v, u, t. In this second augmentation, we get bottleneck(P_2 , f) = 1 as well. After this second augmentation, we have f(e) = 0 for the edge e = (u, v), so the edge is again in the residual graph.
- ➤ Suppose we alternate between choosing P₁ and P₂ for augmentation. In this case, each augmentation will have 1 as the bottleneck capacity, and it will take 200 augmentations to get the desired flow of value 200.

Choosing Good Augmenting Paths

Use care when selecting augmenting paths.

- Some choices lead to exponential algorithms.
- Clever choices lead to polynomial algorithms.
- If capacities are irrational, algorithm not guaranteed to terminate!

Goal: choose augmenting paths so that:

- Can find augmenting paths efficiently.
- Few iterations.

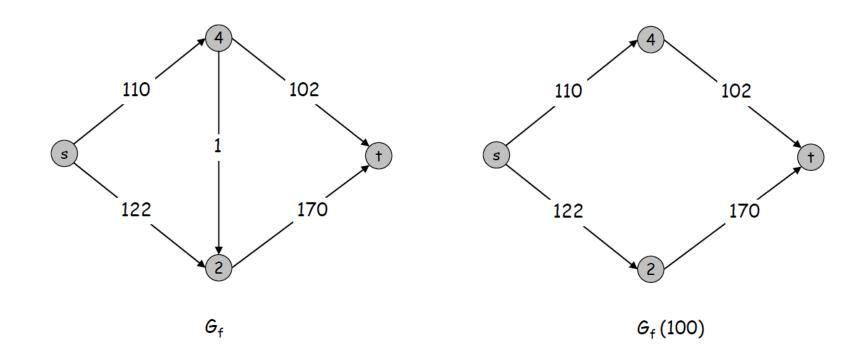
Choose augmenting paths with: [Edmonds-Karp 1972, Dinitz 1970]

- Max bottleneck capacity.
- Sufficiently large bottleneck capacity.
- Fewest number of edges.

Capacity Scaling

Intuition. Choosing path with highest bottleneck capacity increases flow by max possible amount.

- Don't worry about finding exact highest bottleneck path.
- \Box Maintain scaling parameter Δ .
- Let $G_f(\Delta)$ be the subgraph of the residual graph consisting of only edges with capacity at least Δ .



Ford-Fulkerson Algorithm with Capacity Scaling

```
Scaling Max-Flow
  Initially f(e) = 0 for all e in G
  Initially set \Delta to be the largest power of 2 that is no larger
          than the maximum capacity out of s: \Delta \leq \max_{e \text{ out of } s} c_e
     While \Delta > 1
        While there is an s-t path in the graph G_f(\Delta)
            Let P be a simple s-t path in G_f(\Delta)
            f' = \operatorname{augment}(f, P)
            Update f to be f' and update G_f(\Delta)
        Endwhile
         \Delta = \Delta/2
                                                     Theorem:
     Endwhile
```

Return f

The scaling max-flow algo. finds a max flow in $O(m \log C)$ augmentations. It can be implemented to run in $O(m^2 \log C)$ time.