CSE 421 Winter 2025
Lecture 15: Bellman-Ford
Max Flow

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Single-source shortest paths, with negative edge weights

Given: an (un)directed graph $\boldsymbol{G = (V, E)}$ with each edge $\boldsymbol{e}$ having a weight $\boldsymbol{w(e)}$ and a vertex $\boldsymbol{s}$

Find: (length of) shortest paths from $\boldsymbol{s}$ to each vertex in $\boldsymbol{G}$, **or else indicate that there is a negative-cost cycle**

Called the Bellman-Ford algorithm

(The original DP algorithm!)

(Also, the original shortest path algorithm!)

Bellman Ford– Four Steps

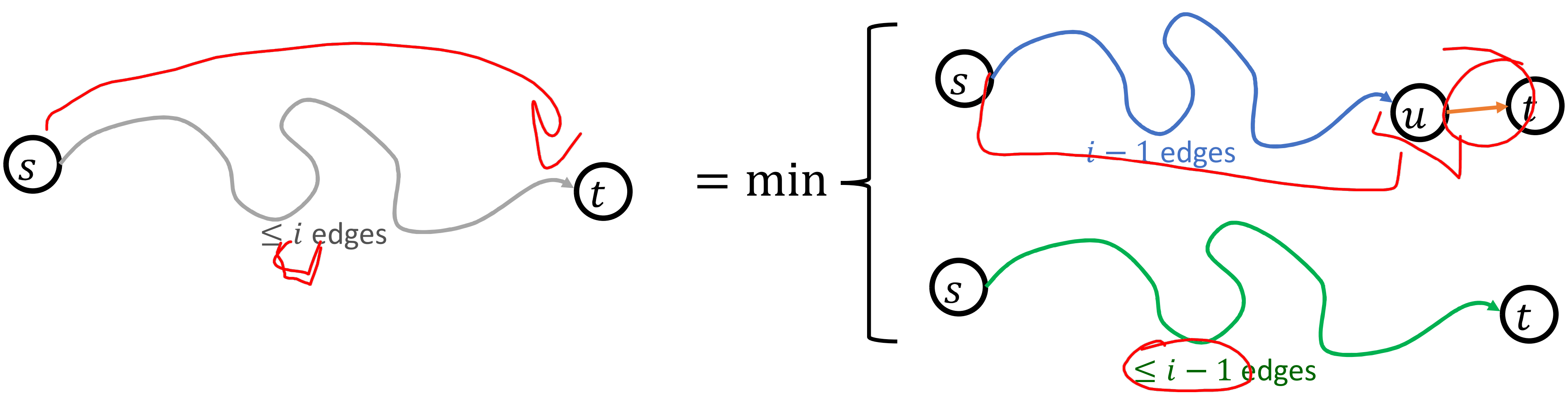
1. Formulate the answer with a recursive structure
   - What are the options for the last choice?
   - For each such option, what does the subproblem look like? How do we use it?
2. Choose a memory structure.
   - Figure out the possible values of all parameters in the recursive calls.
   - How many subproblems (options for last choice) are there?
   - What are the parameters needed to identify each?
   - How many different values could there be per parameter?
3. Specify an order of evaluation.
   - Want to guarantee that the necessary subproblem solutions are in memory when you need them.
   - With this step: a “Bottom-up” (iterative) algorithm
   - Without this step: a “Top-down” (recursive) algorithm
4. See if there’s a way to save space
   - Is it possible to reuse some memory locations?

Final Recursive Structure

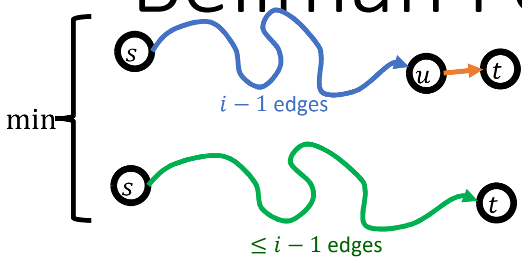
$OPT(i, t)$ = the weight of the shortest path from s to t with at most i edges

$$OPT(i, t) = \begin{cases} 0 \text{ if } i = 0 \text{ and } s = t \\ \infty \text{ if } i = 0 \text{ and } s \neq t \\ \min \begin{cases} \min\limits_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{cases} \end{cases}$$

Where $w(u, t)$ is the weight of the edge from u to t if it exists and ∞ if not.



Bellman Ford– Four Steps



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Identifying the Memory Structure

$$OPT(i,t) = \begin{cases} 0 \text{ if } i = 0 \text{ and } s = t \\ \infty \text{ if } i = 0 \text{ and } s \neq t \\ \min \begin{cases} \min_{u \in V}\{OPT(i-1,u) + w(u,t)\} \\ OPT(i-1,t) \end{cases} \end{cases}$$

- How many parameters?
  - 2
- What does each represent?
  - i: the length of the path
  - t: a node
- How many different values?
  - i: $|V|$ (from length 0 up to $|V|-1$ if the path is simple)
  - t: $|V|$ (one value per node)

	1	2	3	4	5	6	7
0							
1							
2							
3							
4							
5							
6							

Top-Down Bellman-Ford

This algorithm correctly finds shortest paths when there are no negative-cost cycles
How can we check for negative cost cycles?

BF(i, t):

    if OPT$[i][t]$ not blank: // Check if we've solved this already

        return OPT$[i][j]$

    if $i == 0$: // Check if this is a base case

        solution = 0 ? $t == s$: ∞

        OPT$[i][t]$ = solution // Always save your solution before returning

        return solution

    solution = ∞

    for each $u \in V$:

        solution = min(solution, BF$(i-1, u)$+$w(u, t)$) // solve each subproblem, pick which to use

    solution = min(solution, BF$(i-1,t)$) // solve each subproblem, pick which to use

    OPT$[i][t]$ = solution // Always save your solution before returning

    return solution

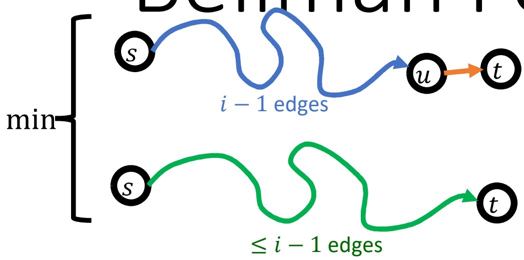
Checking for Negative Cycles

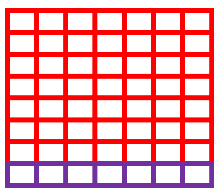
$$OPT(i,t) = \begin{cases} 0 \text{ if } i = 0 \text{ and } s = t \\ \infty \text{ if } i = 0 \text{ and } s \neq t \\ \min \begin{cases} \min_{u \in V}\{OPT(i-1,u) + w(u,t)\} \\ OPT(i-1,t) \end{cases} \end{cases}$$

- How many parameters?
  - 2
- What does each represent?
  - i: the length of the path
  - t: a node
- How many different values?
  - $\boldsymbol{i}$: $|\boldsymbol{V}|$**+1**
    - **a path of $|V|$ edges is not simple, so if any $|V|$-edge path is shorter than one with fewer edges, there must be a negative cycle!**
  - t: $|V|$ (one value per node)

	1	2	3	4	5	6	7
0							
1							
2							
3							
4							
5							
6							
7							

Bellman Ford– Four Steps





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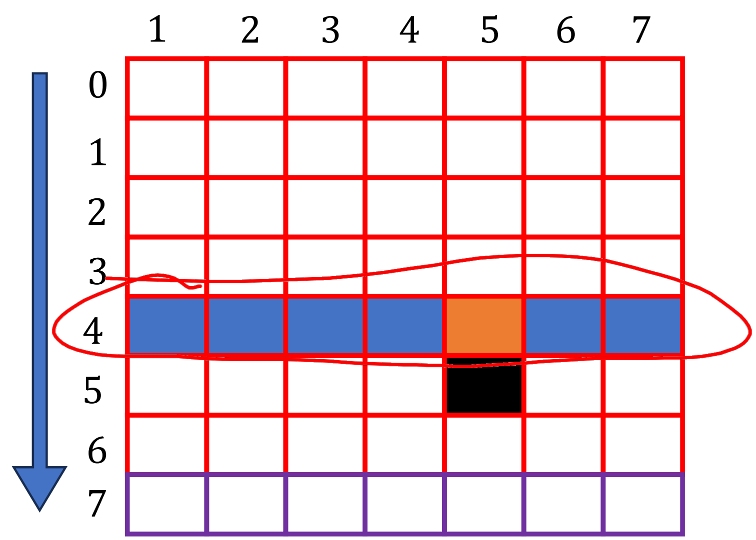
Order of Evaluations

$$OPT(i,t) = \begin{cases} 0 \text{ if } i = 0 \text{ and } s = t \\ \infty \text{ if } i = 0 \text{ and } s \neq t \\ \min \begin{cases} \min_{u \in V}\{OPT(i-1,u) + w(u,t)\} \\ OPT(i-1,t) \end{cases} \end{cases}$$

Each cell depends on every value in the previous row

Solve in order of i



Bottom-Up Bellman-Ford

BF(s, t):

OPT[0][s] = 0 // Solve and save base cases   1

for $u \in V \setminus \{s\}$:

    OPT[0][u] = ∞ // Solve and save base cases $|V|$

$|V|$

for $i = 0$ up to $|V|$:

    for $u \in V$:

        for $v \in$ neighbors(u):

            $OPT[i][u] = \min(OPT[i][u], OPT[i-1][v])$ // solve and pick $+ w(u,v)$

E

        $OPT[i][u] = \min(OPT[i][u], OPT[i-1][u])$ // solve and pick

for $u \in V$:

    if $OPT[|V|][u] < OPT[|V|-1][u]$: // check for negative cycles

        return “negative cycle”

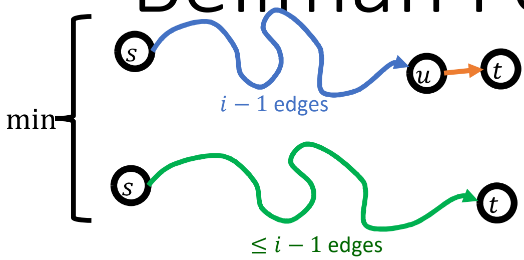
return OPT[s][t] // return the final answer

Bottom-Up Bellman-Ford

BF(s, t):

```
OPT[0][s] = 0   // Solve and save base cases      Θ(1)
for u ∈ V \ {s}:
        OPT[0][u] = ∞   // Solve and save base cases      Θ(|V|)
for i = 0 up to |V|:
        for u ∈ V:
                for v ∈ neighbors(u):                                     Θ(|V||E|)
                        OPT[i][u] = min(OPT[i][u], OPT[i − 1][v]) // solve and pick
                OPT[i][u] = min(OPT[i][u], OPT[i − 1][u]) // solve and pick
for u ∈ V:
        if OPT[|V|][u] < OPT[|V| − 1][u]: // check for negative cycles      Θ(|V|)
                return "negative cycle"
return OPT[s][t] // return the final answer      Θ(1)
```

Bellman Ford– Four Steps



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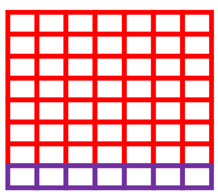

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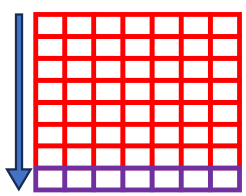

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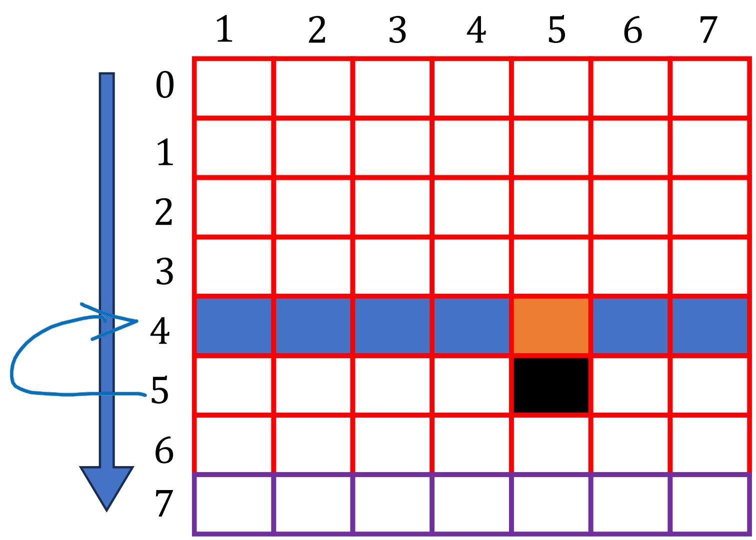
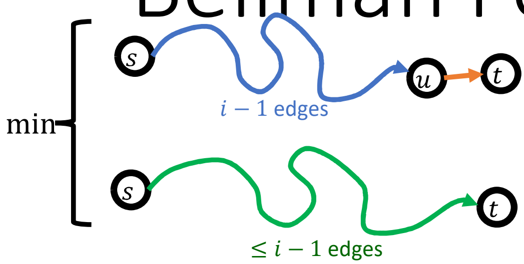
Each cell depends *only* on values in the previous row

We only need two rows!



Bellman Ford– Four Steps



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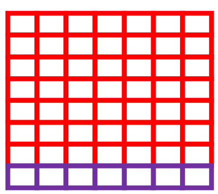

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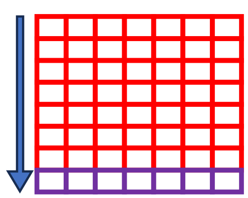

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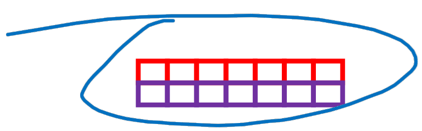

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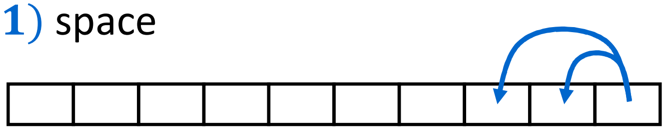
Dynamic Programming Patterns

Fibonacci pattern:

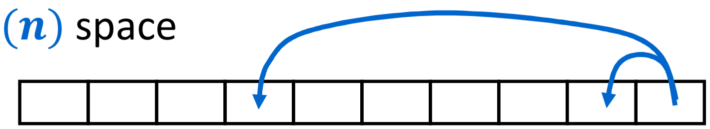
- 1-D, $O(\mathbf{1})$ immediately prior
- $O(\mathbf{1})$ space



$O(\boldsymbol{n})$

Weighted interval scheduling pattern:

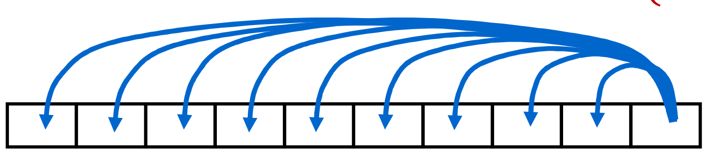
- 1-D, $O(\mathbf{1})$ arbitrary prior
- $O(\boldsymbol{n})$ space



$O(\boldsymbol{n})$

Longest increasing subsequence pattern:

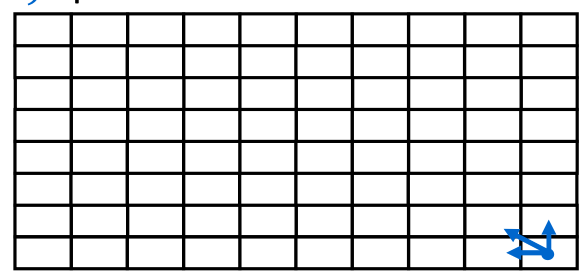
- 1-D, all $\boldsymbol{n}-\mathbf{1}$ prior
- $O(\boldsymbol{n})$ space



$O(\boldsymbol{n^2})$

Alignment pattern:

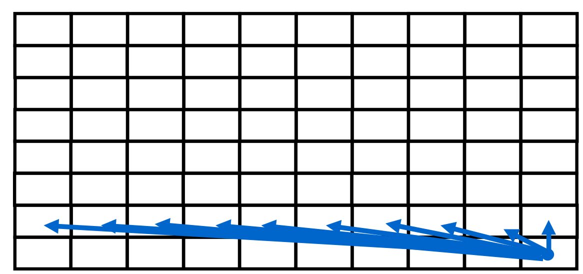
- 2-D, O(**1**) in previous row, above, left, diagonal
- $O(\boldsymbol{n}\cdot\boldsymbol{m})$ space



$O(\boldsymbol{nm})$

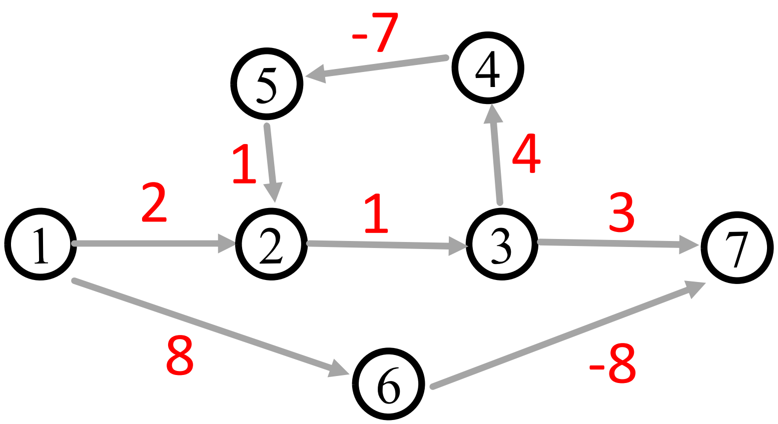
Bellman Ford pattern:

- 2-D, O(**|V|**) in previous row,
- $O(|V|)$ space



$O(|V||E|)$

Example Execution



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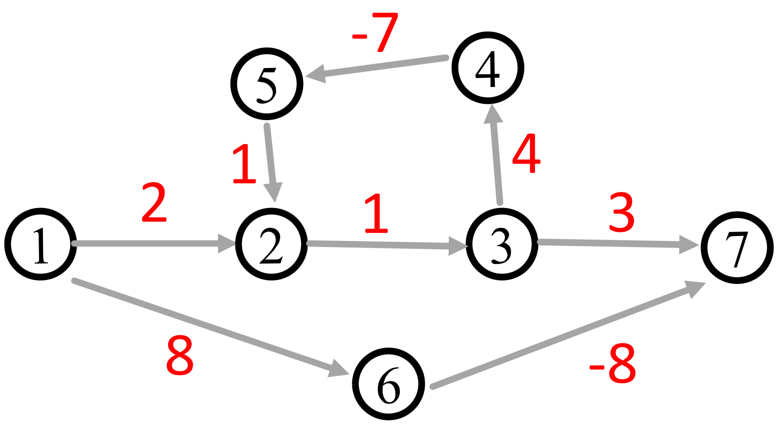
	1	2	3	4	5	6	7
0	0	∞	∞	∞	∞	∞	∞
1							
2							
3							
4							
5							
6							
7							

Example Execution



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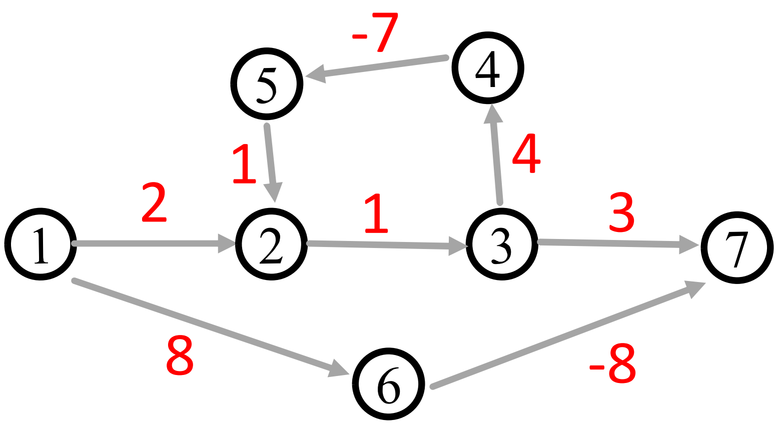
	1	2	3	4	5	6	7
0	0	∞	∞	∞	∞	∞	∞
1	0	2	∞	∞	∞	8	∞
2							
3							
4							
5							
6							
7							

Example Execution



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	1	2	3	4	5	6	7
0	0	∞	∞	∞	∞	∞	∞
1	0	2	∞	∞	∞	8	∞
2	0	2	3	∞	∞	8	0
3							
4							
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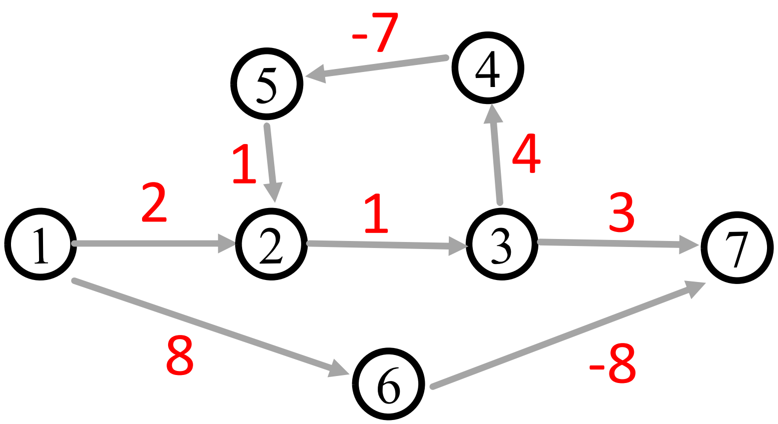
6							
7							

Example Execution



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1	0	2	∞	∞	∞	8	∞
2	0	2	3	∞	∞	8	0
3	0	2	3	7	∞	8	0
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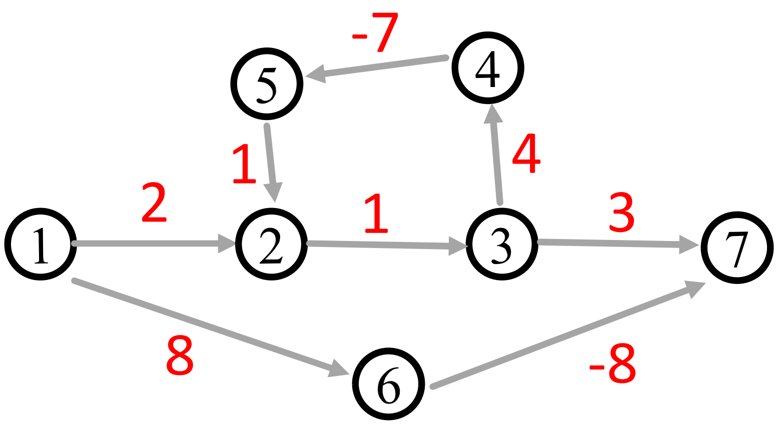

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1	0	2	∞	∞	∞	8	∞
2	0	2	3	∞	∞	8	0
3	0	2	3	7	∞	8	0
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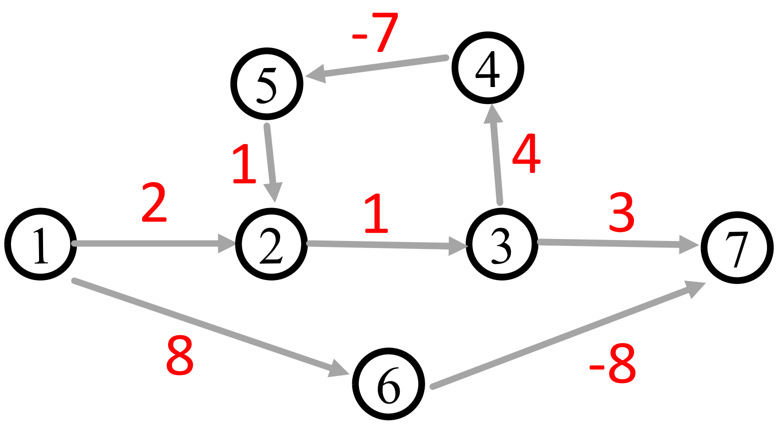

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3	0	2	3	7	∞	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6							
7							

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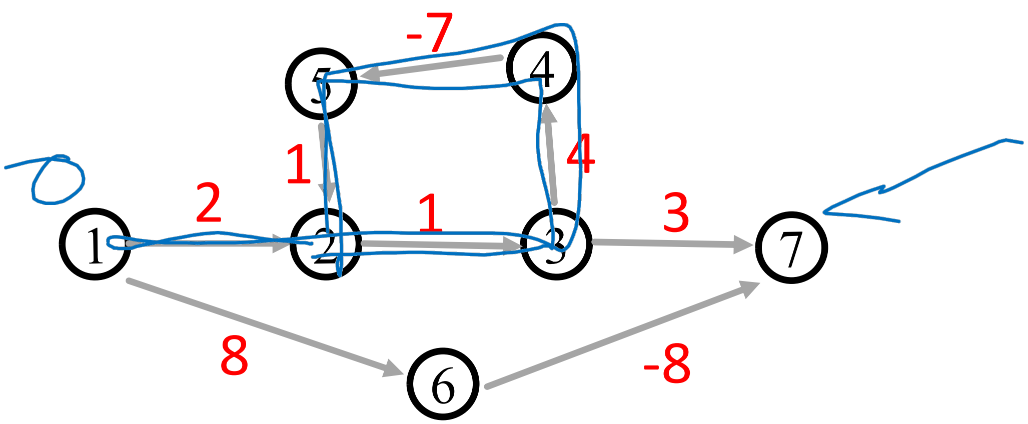

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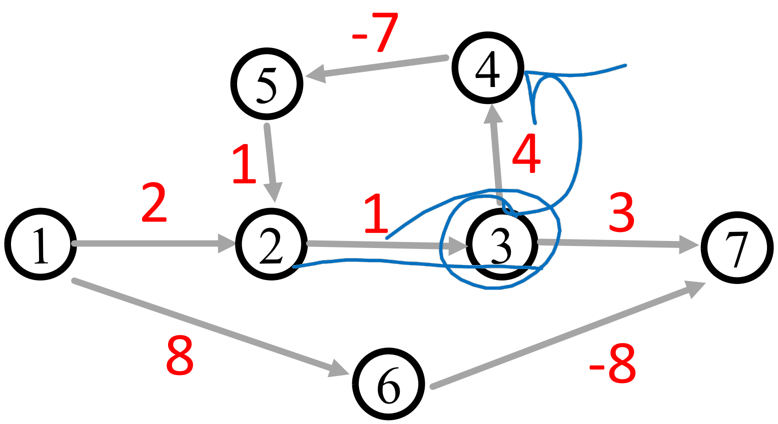
1	0	2	∞	∞	∞	8	∞
2	0	2	3	∞	∞	8	0
3	0	2	3	7	∞	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6	0	1	2	7	0	8	0
7							

Example Execution



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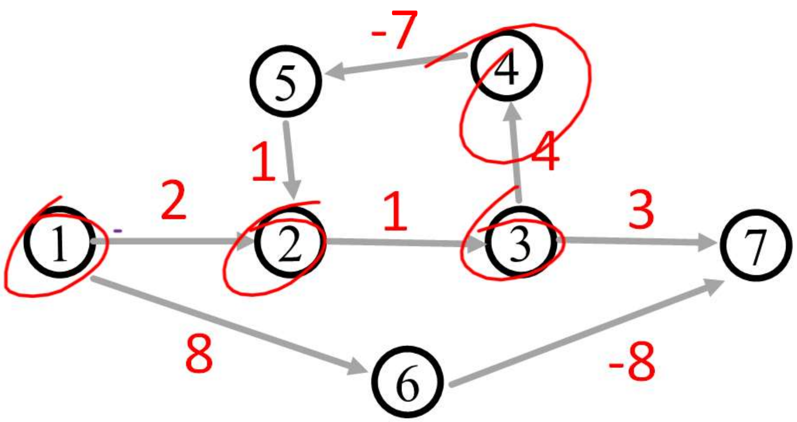
2	0	2	3	∞	∞	8	0
3	0	2	3	7	∞	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6	0	1	2	7	0	8	0
7	0	1	2	~~3~~	0	8	0

6

Example Execution



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1	0	2	∞	∞	∞	8	∞
2	0	2	3	∞	∞	8	0
3	0	2	3	~~7~~	∞	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6	0	1	2	7	0	8	0
7	0	1	2	3	0	8	0

Negative Cycle Found!

Origins of Max Flow and Min Cut Problems

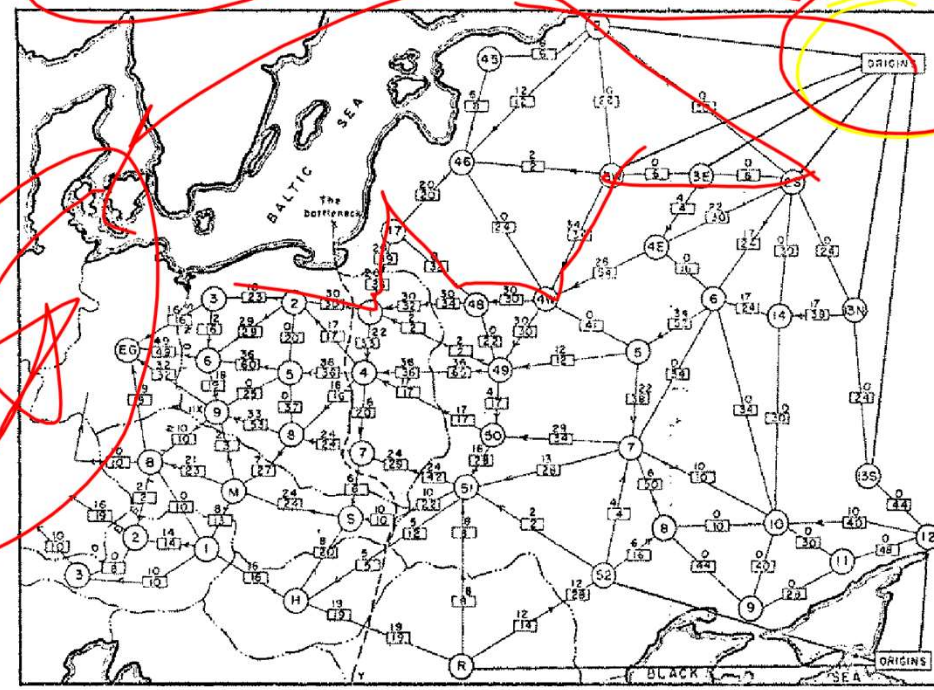
Max Flow problem formulation:

- [Tolstoy 1930] Rail transportation planning for the Soviet Union

Min Cut problem formulation:

- Cold War: US military planners want to find a way to cripple Soviet supply routes
- [Harris 1954] Secret RAND corp report for US Air Force

[Ford-Fulkerson 1955] Problems are equivalent

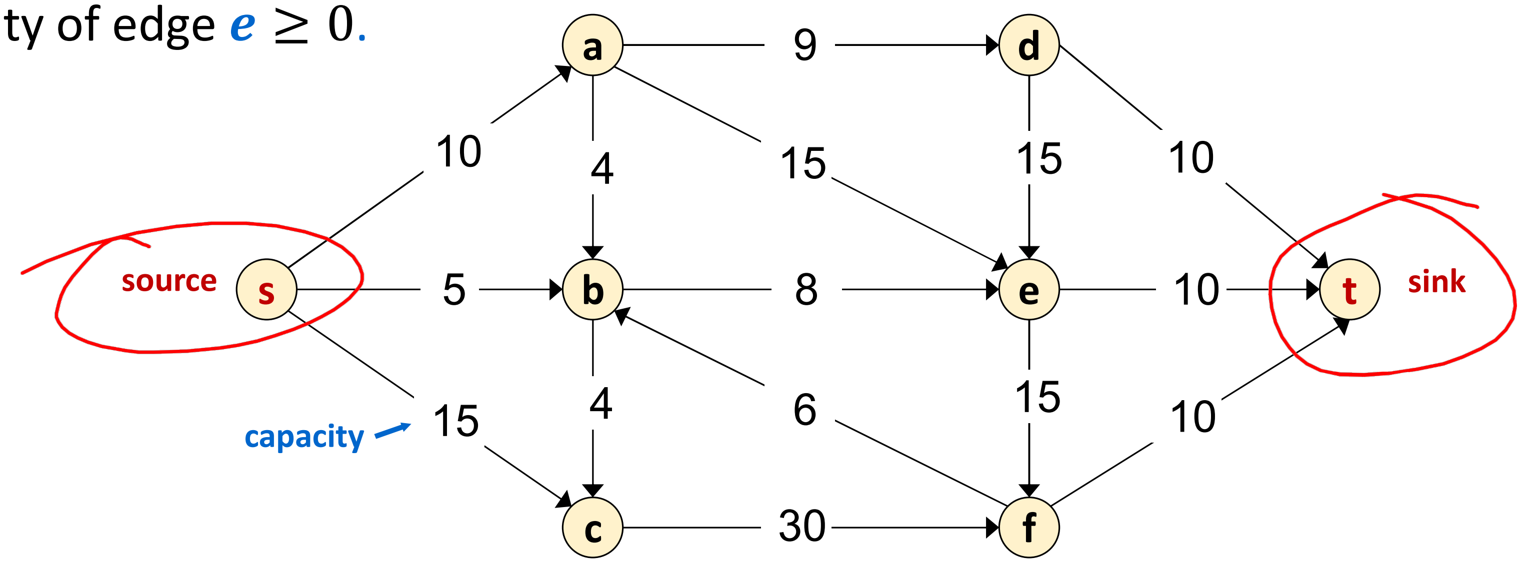


Reference: *On the history of the transportation and maximum flow problems*. Alexander Schrijver in Math Programming, 91: 3, 2002.

Flow Network

Flow network:

- Abstraction for material *flowing* through the edges.
- $\boldsymbol{G = (V, E)}$ directed graph, no parallel edges.
- Two distinguished nodes: $\boldsymbol{s}$ = source, $\boldsymbol{t}$ = sink.
- $\boldsymbol{c(e)}$ = capacity of edge $\boldsymbol{e} \geq 0$.



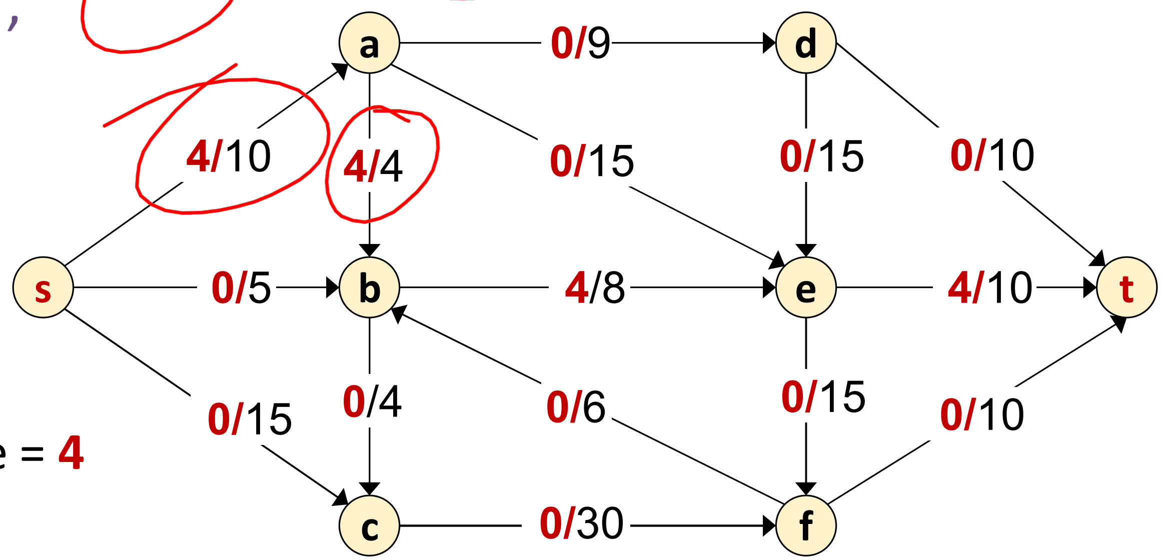
Flows

Defn: An s-t flow in a flow network is a function $f\colon\ E \to \mathbb{R}$ that satisfies:

- For each $e \in E$: $0 \leq\ f(e) \leq\ c(e)$ [capacity constraints]
- For each $v \in V - \{s,t\}$: $\sum_{e \text{ into } v} f(e) = \sum_{e \text{ out of } v} f(e)$ [flow conservation]

Defn: The value of flow f,

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



value = 4

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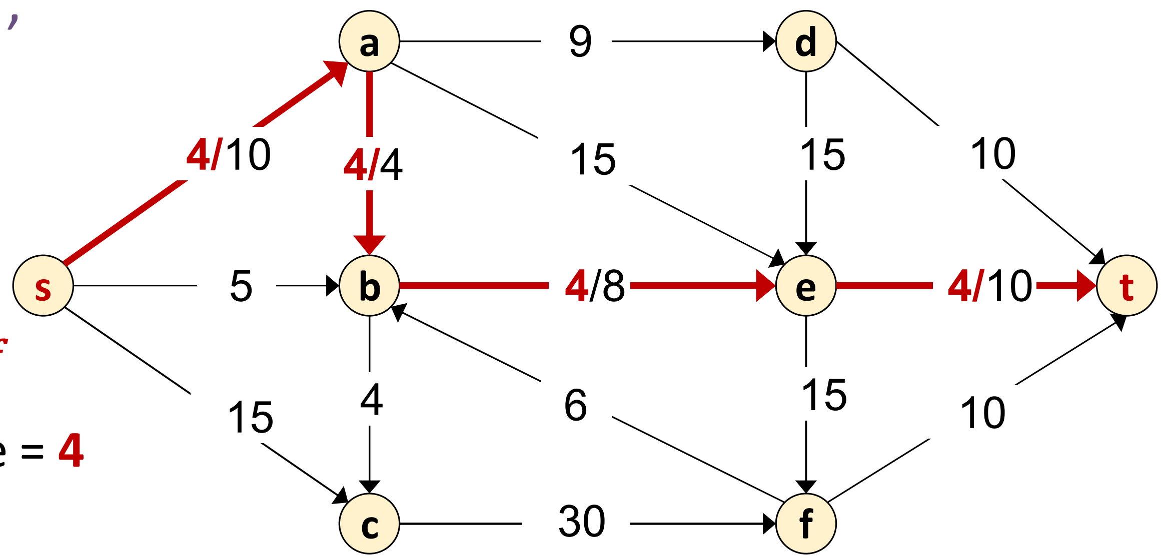

Only show non-zero values of f

value = 4

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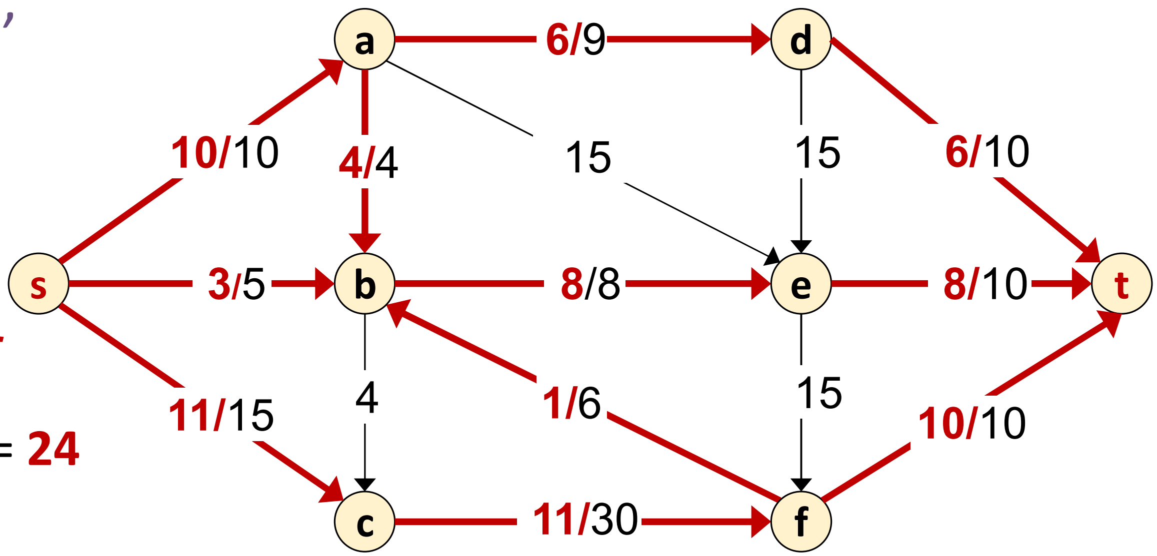


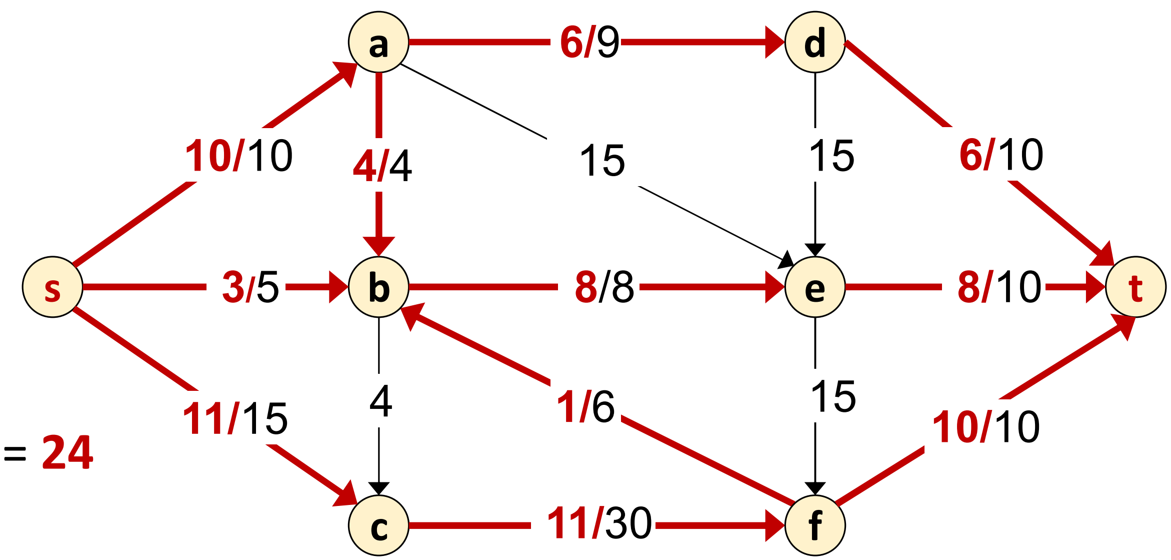
Only show non-zero values of f

value = **24**

Maximum Flow Problem

Given: a flow network

Find: an s-t flow of maximum value



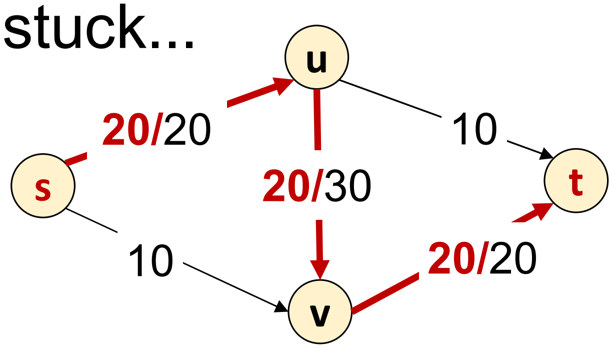
value = **24**

Towards a Max Flow Algorithm

What about the following greedy algorithm?

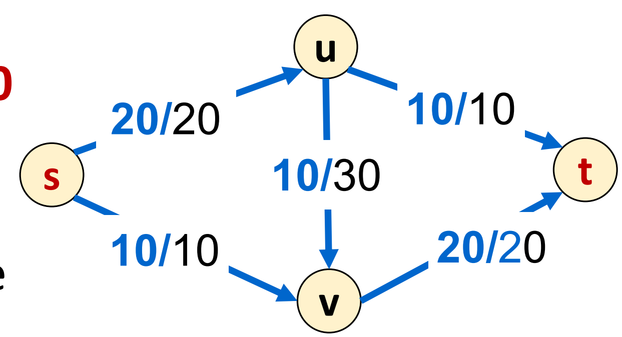
- Start with $f(e) = 0$ for all edges $e \in E$.
- While there is an s-t path P where each edge has $f(e) < c(e)$.
  - "Augment" flow along P; that is:
    - Let $\alpha = \min_{e \in P} (c(e) - f(e))$
    - Add α to flow on every edge e along path P. (Adds α to $v(f)$.)

Can get stuck...



Has flow value **20** and no path P

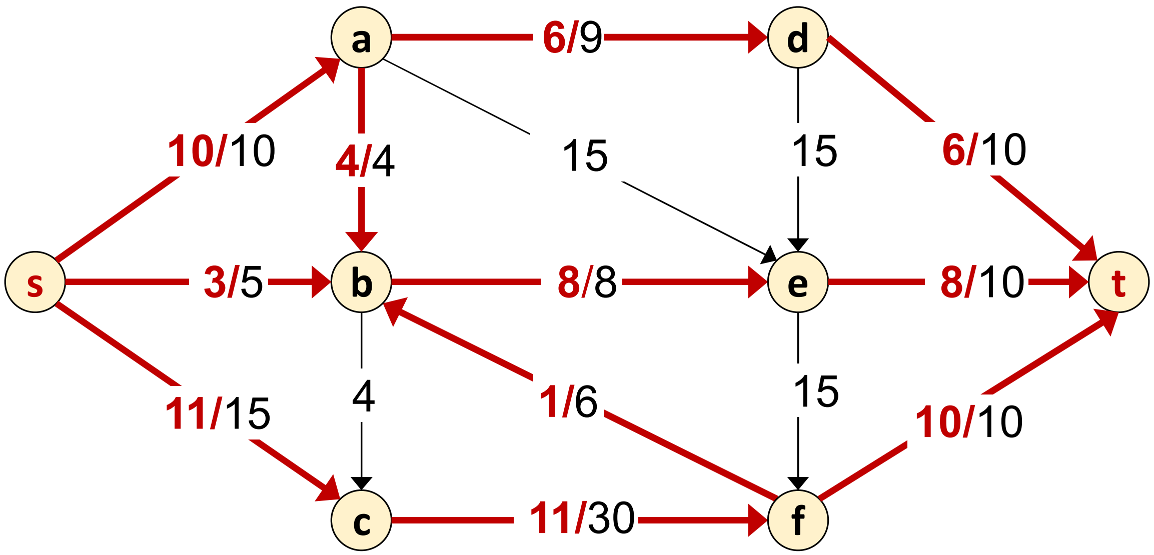
but **30** is possible



Another "Stuck" Example

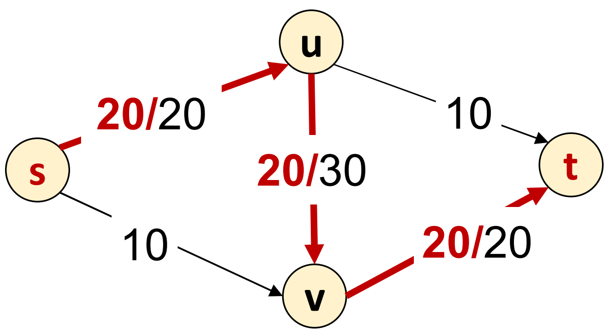
On every s-t path there is some edge with $f(e) = c(e)$:

Value of flow = **24**



Next idea: Ford-Fulkerson Algorithm, which applies greedy ideas to a "residual graph" that lets us reverse prior flow decisions from the basic greedy approach to get optimal results!

Greed Revisited: Residual Graph & Augmenting Paths

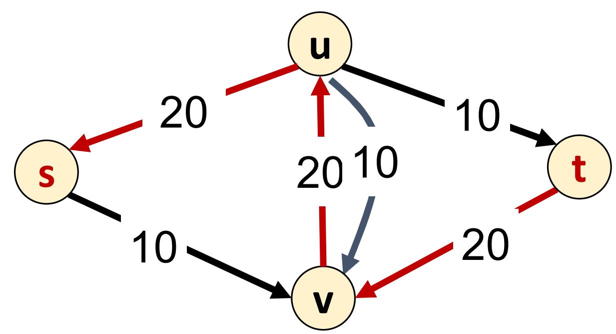


The only way we could route more flow from **s** to **t** would be to reduce the flow from **u** to **v** to make room for that amount of extra flow from **s** to **v**.
But to conserve flow we also would need to increase the flow from **u** to **t** by that same amount.

Suppose that we took this flow $\boldsymbol{f}$ as a baseline, what changes could each edge handle?

- We could add up to 10 units along **sv** or **ut** or **uv**
- We could reduce by up to 20 units from **su** or **uv** or **vt**

This gives us a residual graph $\boldsymbol{G_f}$ of possible changes where we draw reducing as “sending back”.



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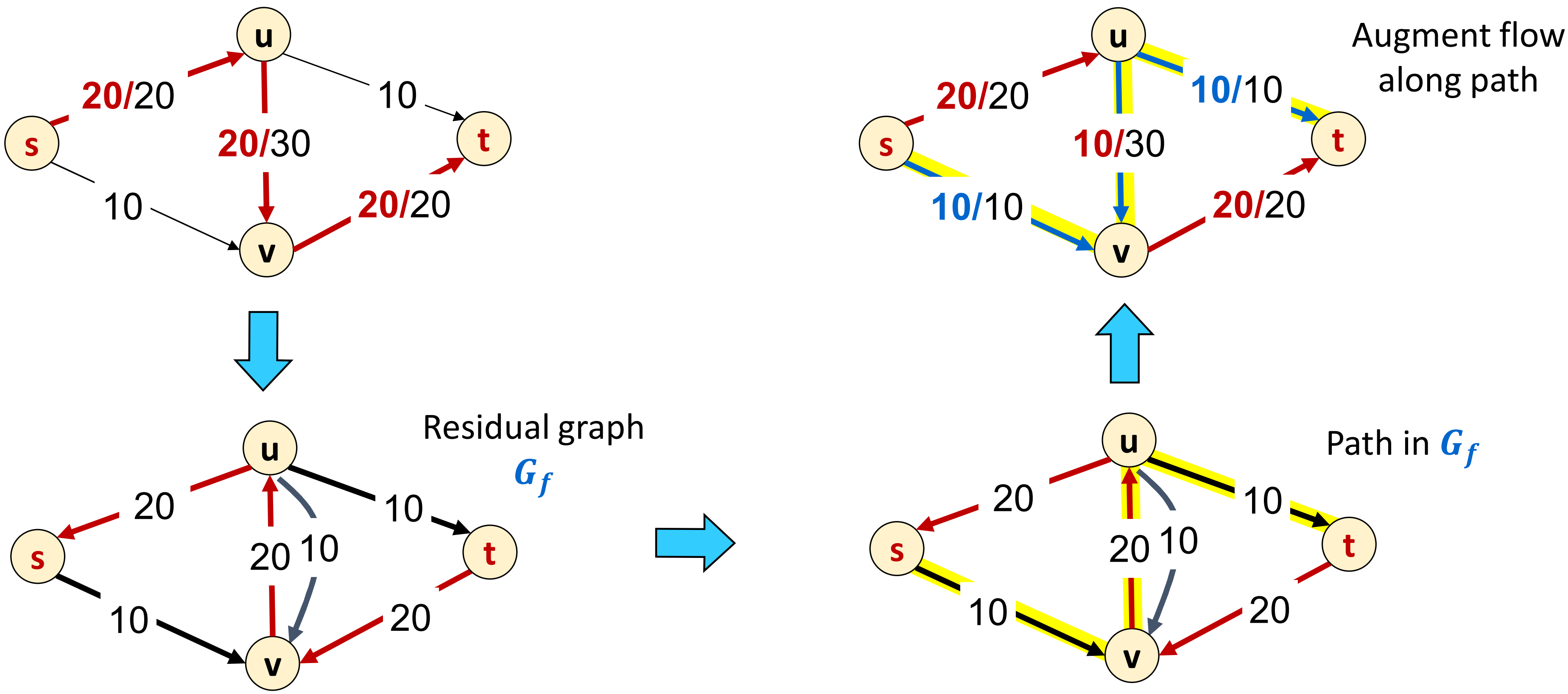

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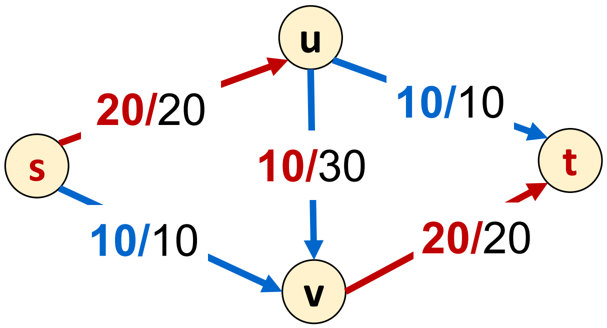
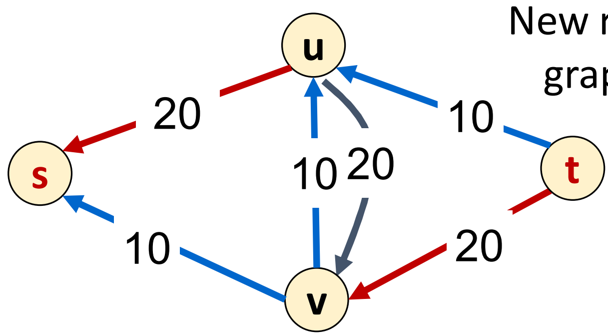


New residual graph G_f



No path can even leave s!

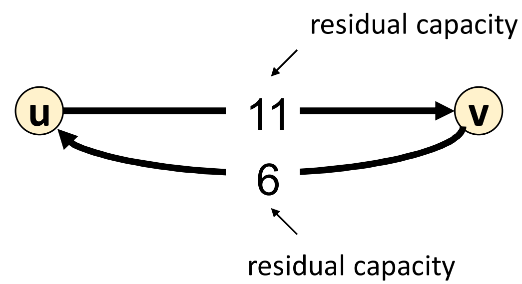
Residual Graphs

An alternative way to represent a flow network

- Represents the net available flow between two nodes

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

- Flow $\boldsymbol{f(e)}$, capacity $\boldsymbol{c(e)}$.



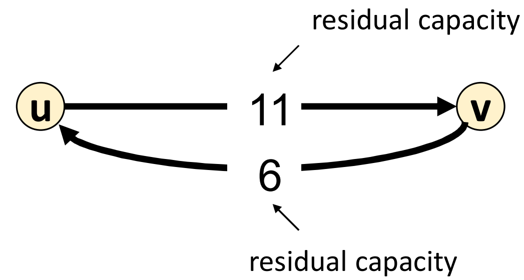
Residual edges of two kinds:

- Forward: $\boldsymbol{e = (u, v)}$ with capacity $\boldsymbol{c_f(e) = c(e) - f(e)}$
  - Amount of extra flow we can add along $\boldsymbol{e}$
- Backward: $\boldsymbol{e^{\mathrm{R}} = (v, u)}$ with capacity $\boldsymbol{c_f(e) = f(e)}$
  - Amount we can reduce/undo flow along $\boldsymbol{e}$

Residual graph: $\boldsymbol{G_f = (V, E_f)}$.

- Residual edges with residual capacity $\boldsymbol{c_f(e) > 0}$.
- $\boldsymbol{E_f = \{e : f(e) < c(e)\} \cup \{e^{\mathrm{R}} : f(e) > 0\}}$.

Residual Graphs and Augmenting Paths



Residual edges of two kinds:

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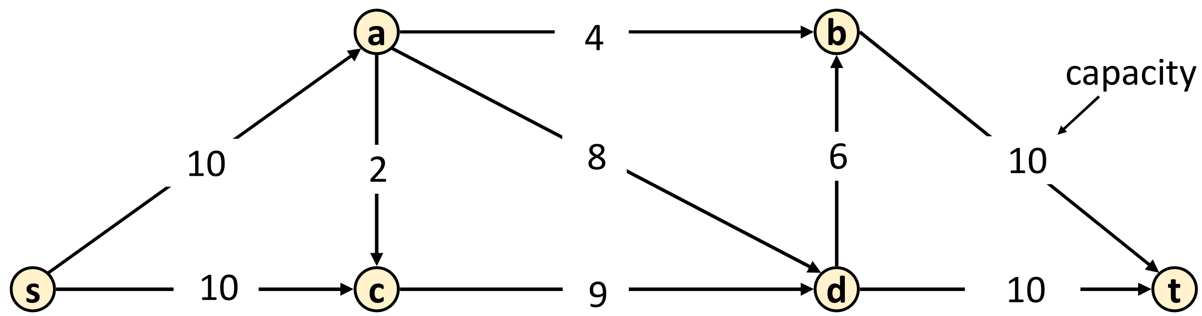
Augmenting Path: Any $\boldsymbol{s}$-$\boldsymbol{t}$ path $\boldsymbol{P}$ in $\boldsymbol{G_f}$. Let **bottleneck**$(\boldsymbol{P}) = \min_{\boldsymbol{e \in P}} \boldsymbol{c_f(e)}$.

Ford-Fulkerson idea: Repeat "find an augmenting path $\boldsymbol{P}$ and increase flow by **bottleneck**$(\boldsymbol{P})$" until none left.

38

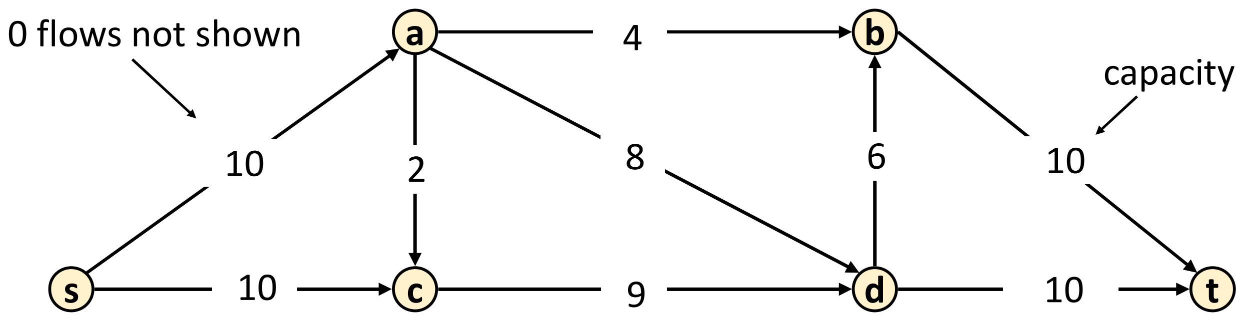
Ford-Fulkerson Algorithm

$\boldsymbol{G}$:



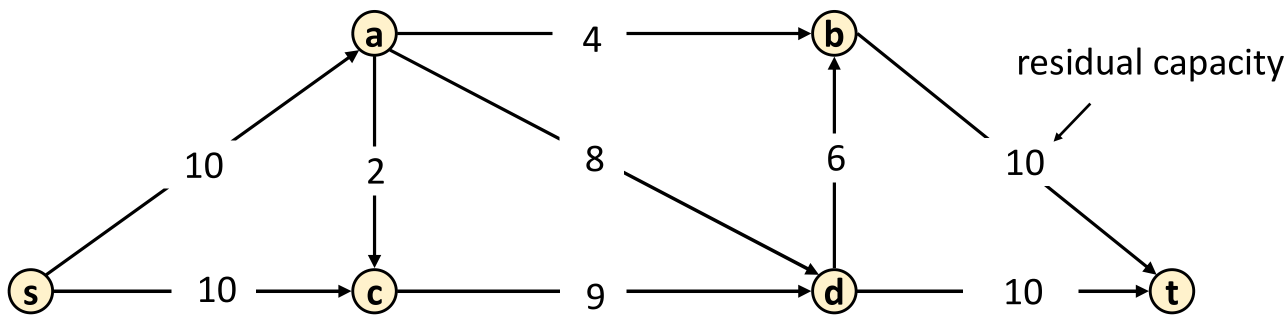
Ford-Fulkerson Algorithm

G:

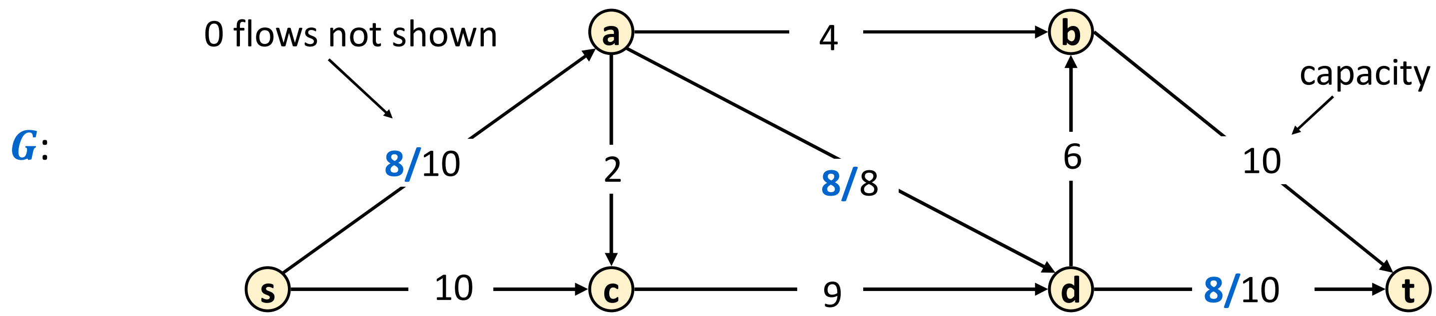


Flow value = **0**

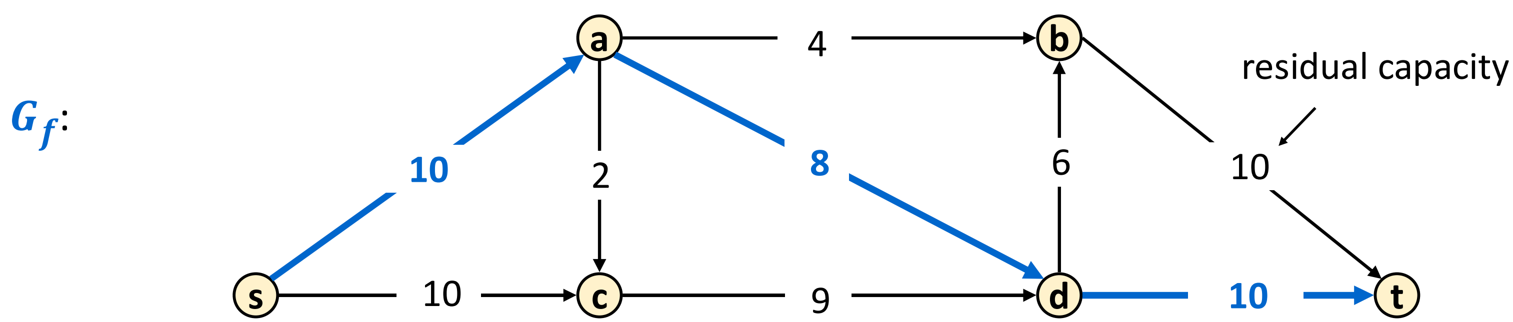
G_f:



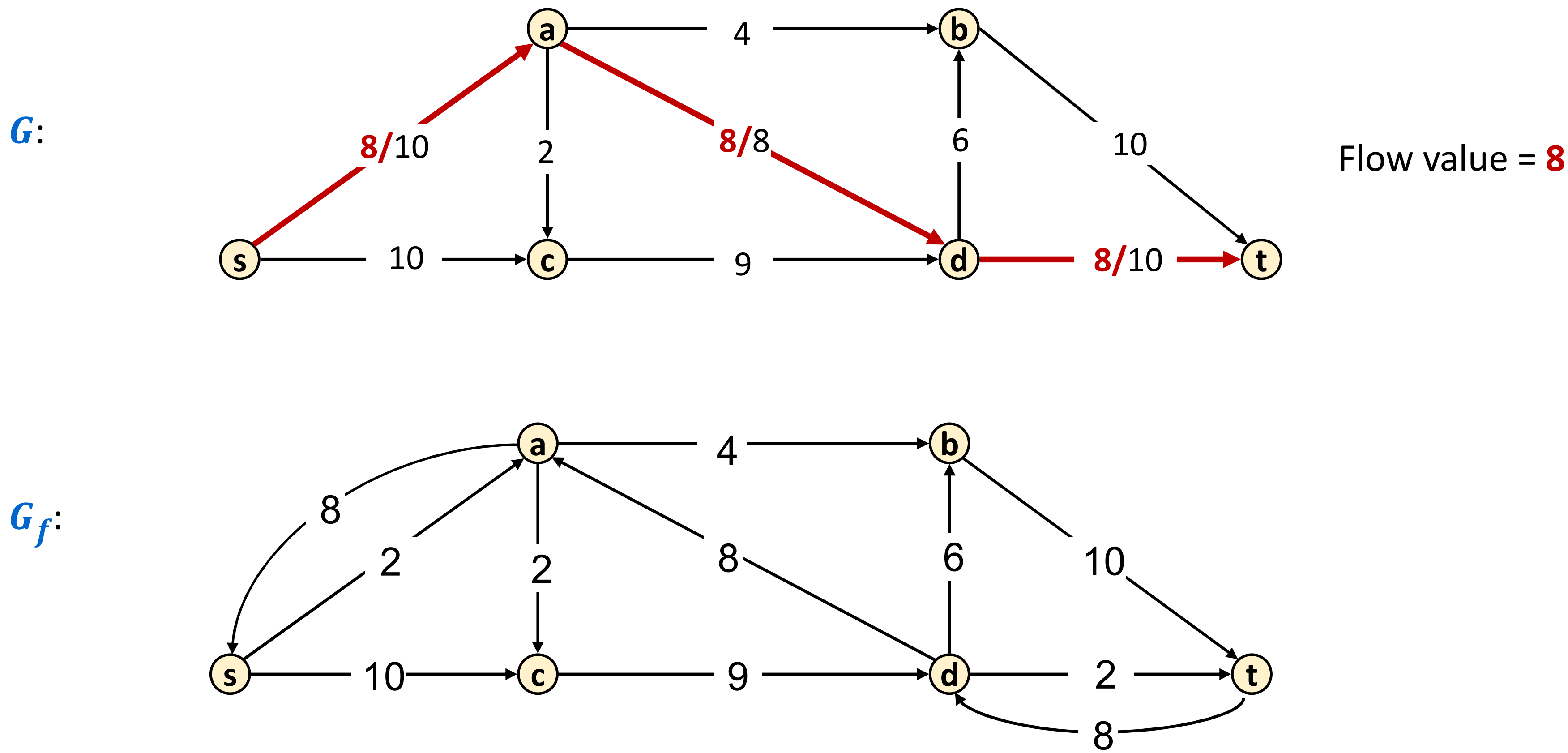
Ford-Fulkerson Algorithm



Flow value = 0
+8=8



Ford-Fulkerson Algorithm



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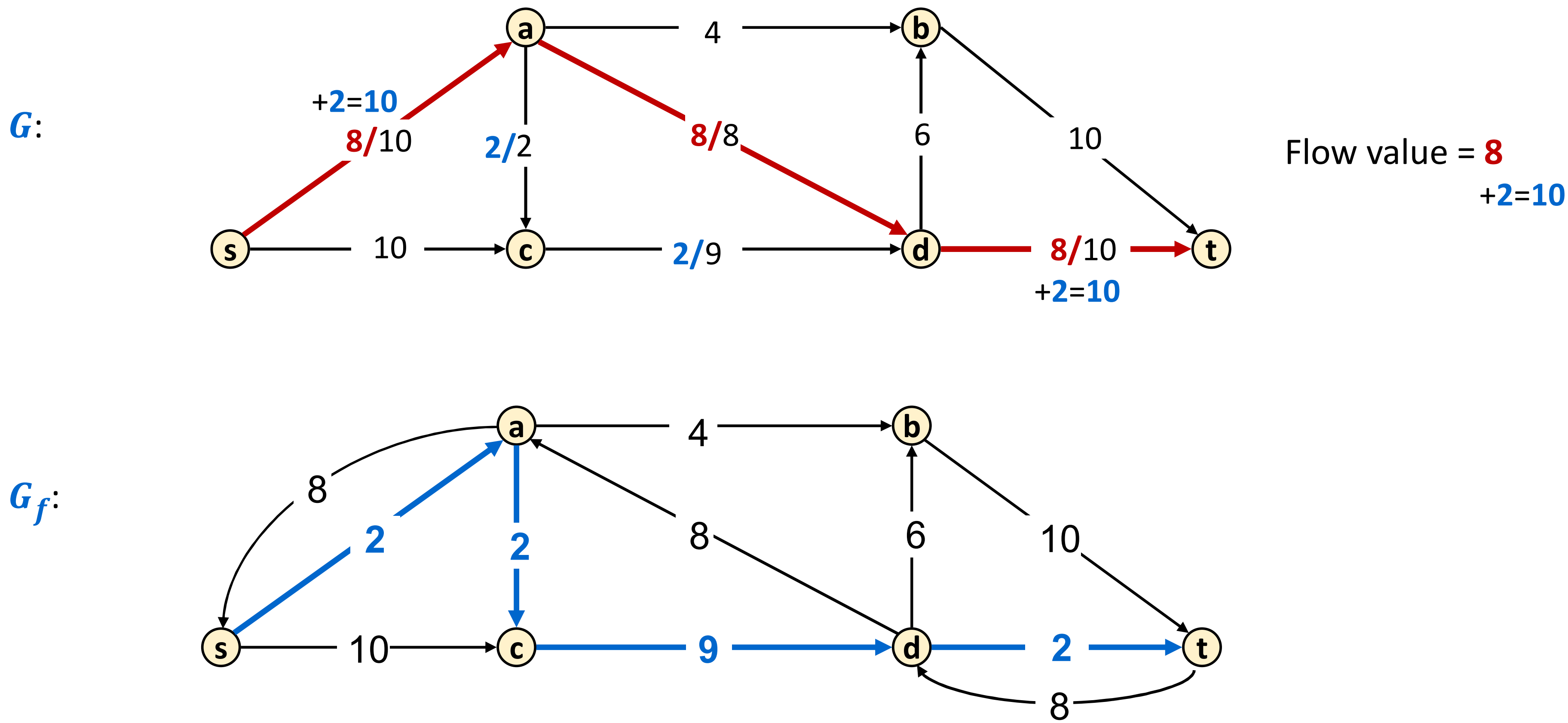
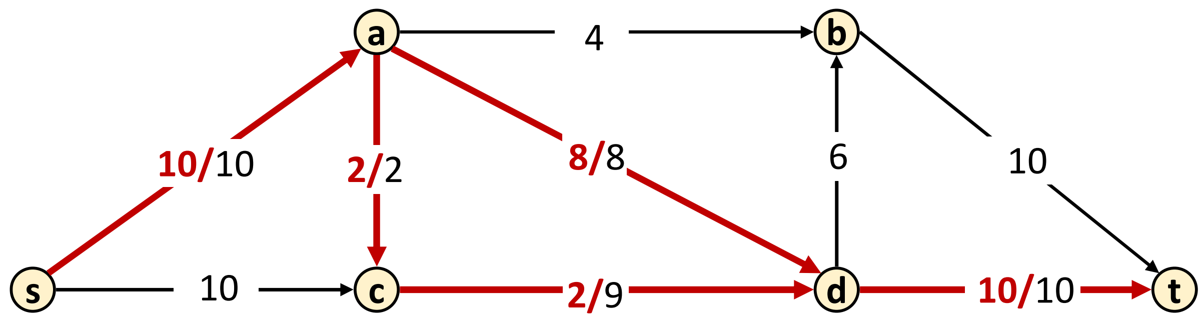


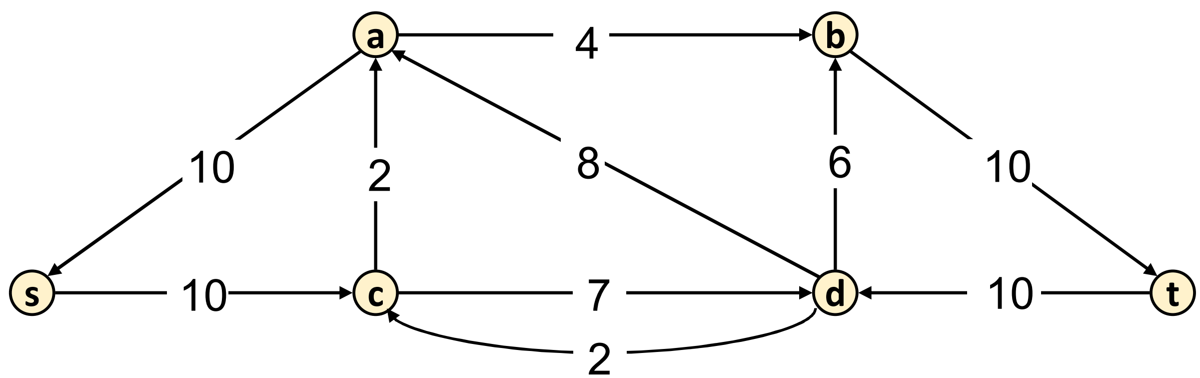
Ford-Fulkerson Algorithm

G:



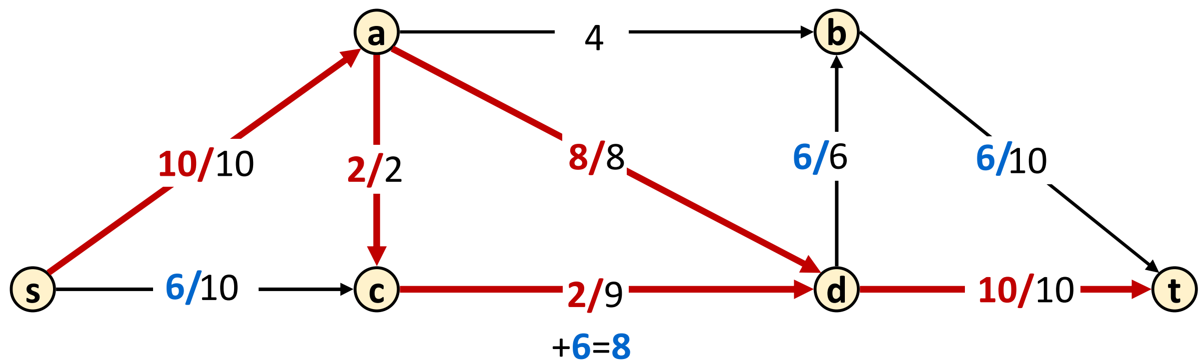
Flow value = **10**

G_f:



Ford-Fulkerson Algorithm

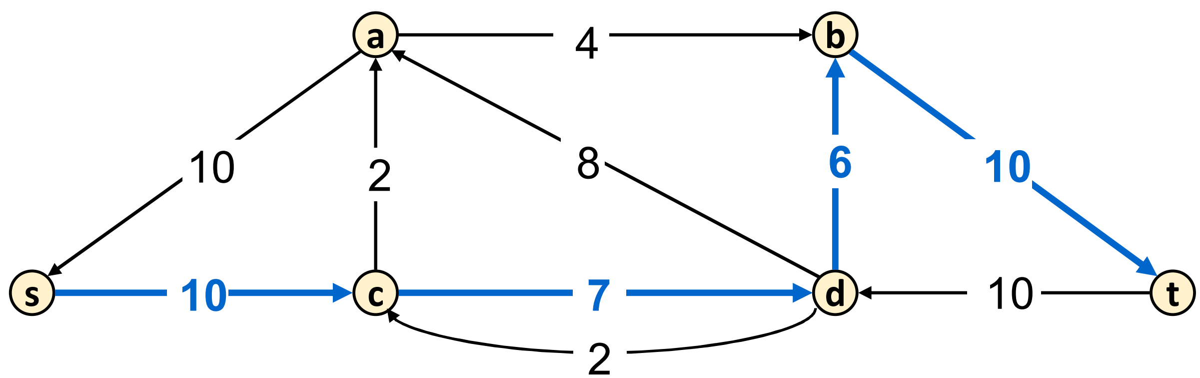
G:



Flow value = 10

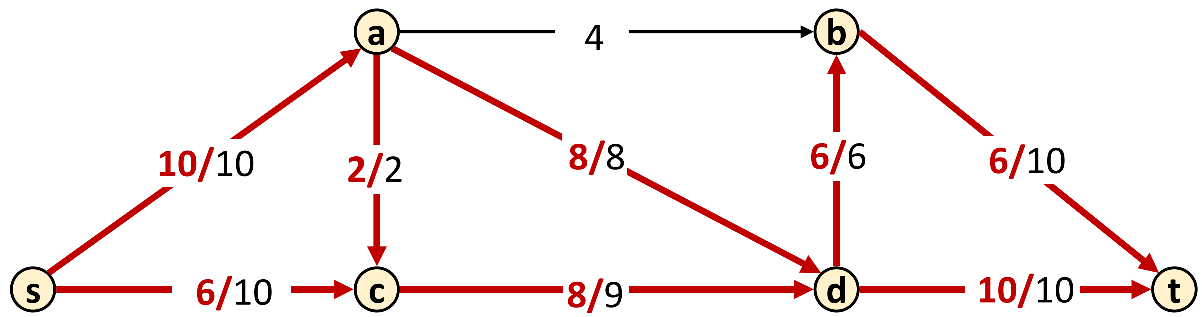
+6=16

G_f:



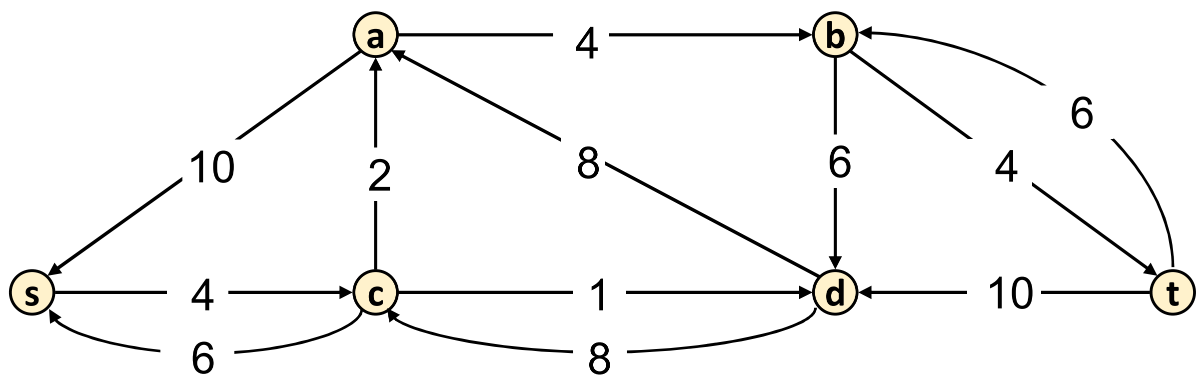
Ford-Fulkerson Algorithm

G:



Flow value = **16**

G_f:



Ford-Fulkerson Algorithm

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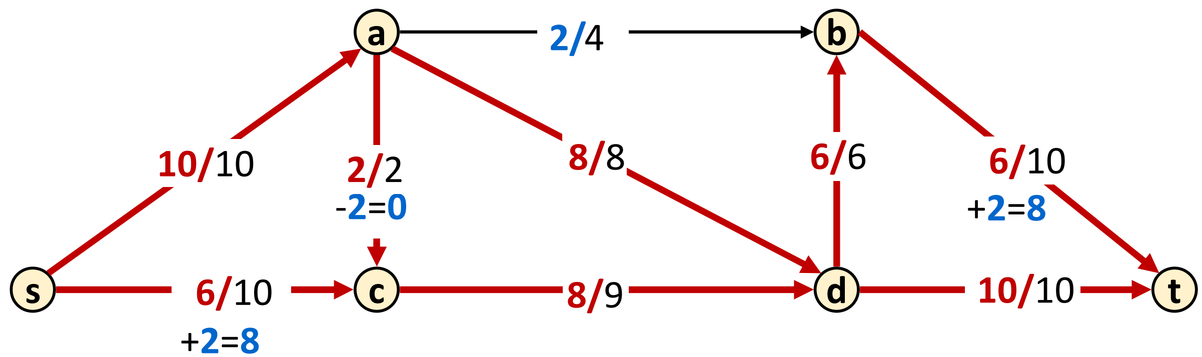
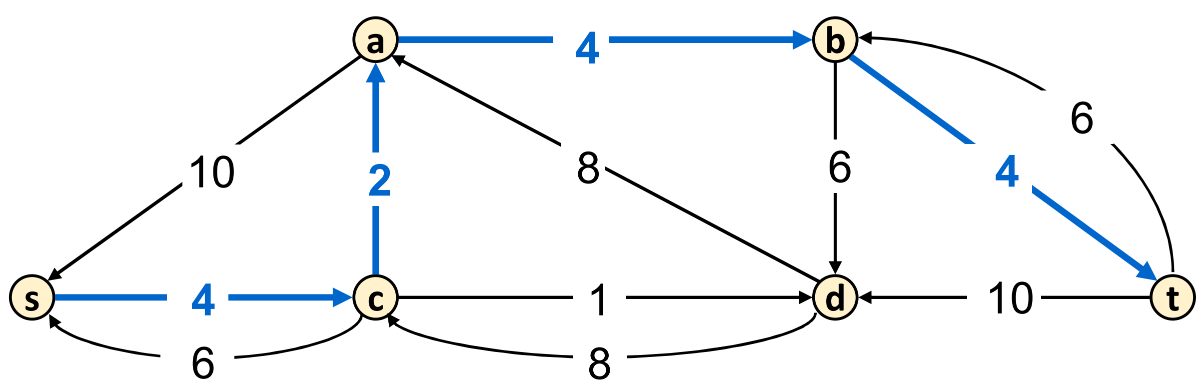


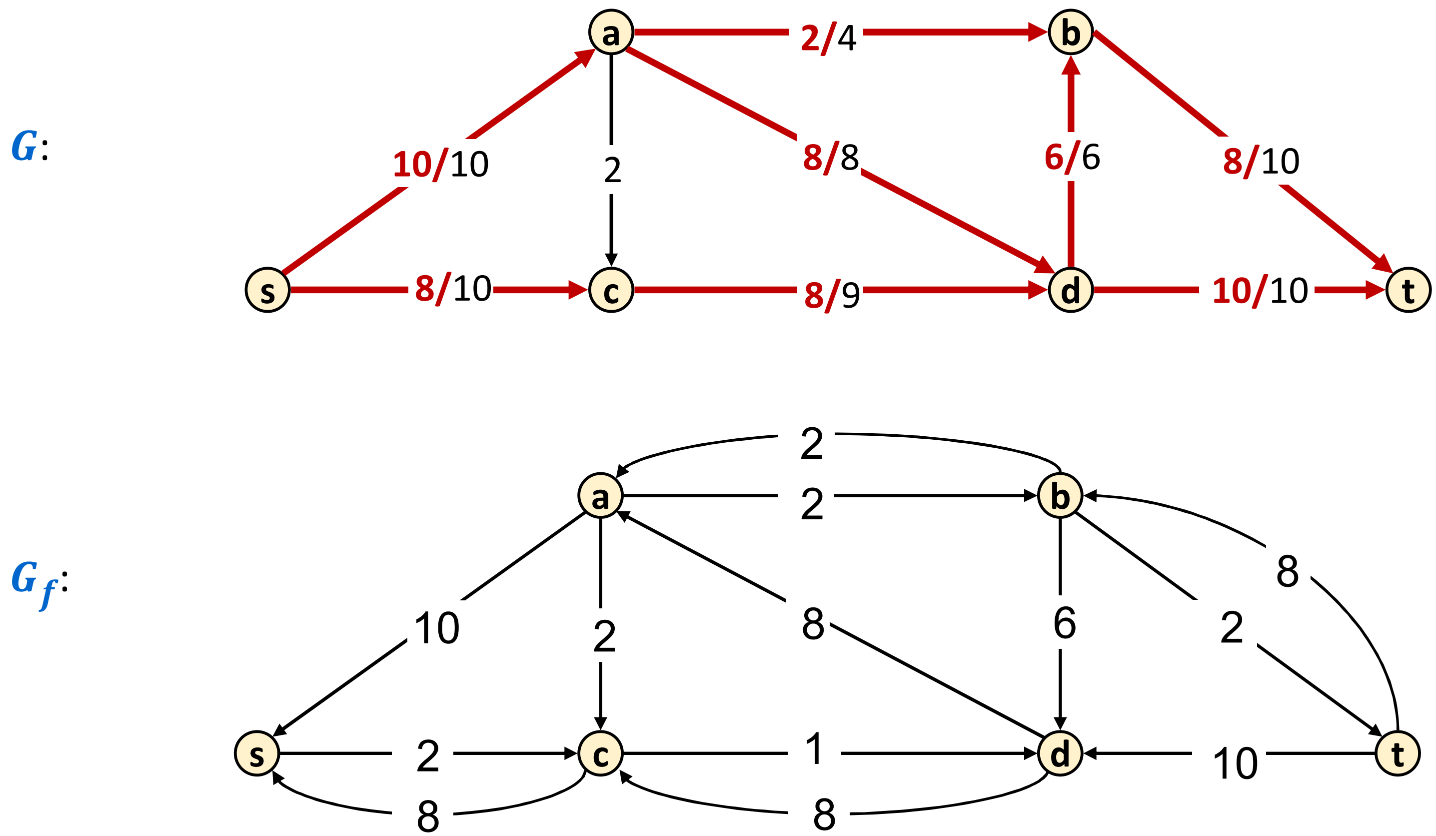
Flow value = **16**

+2=18

G_f:



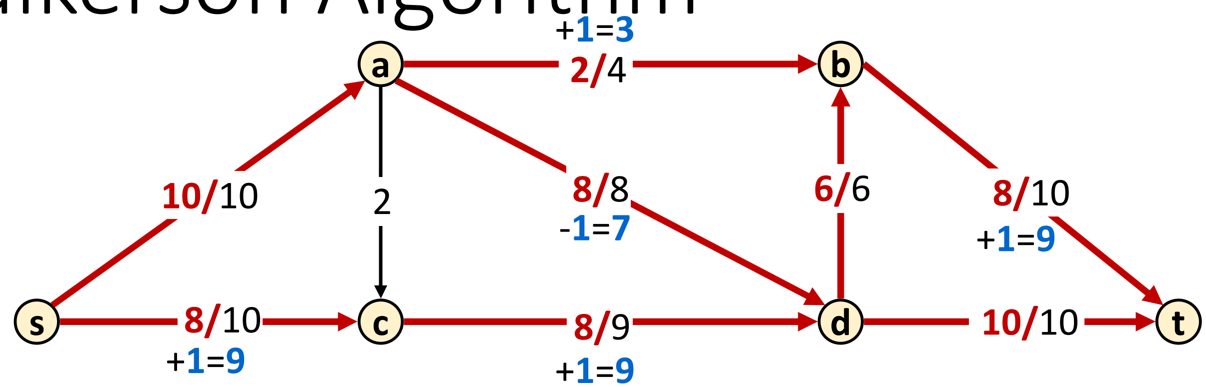
Ford-Fulkerson Algorithm



Flow value = **18**

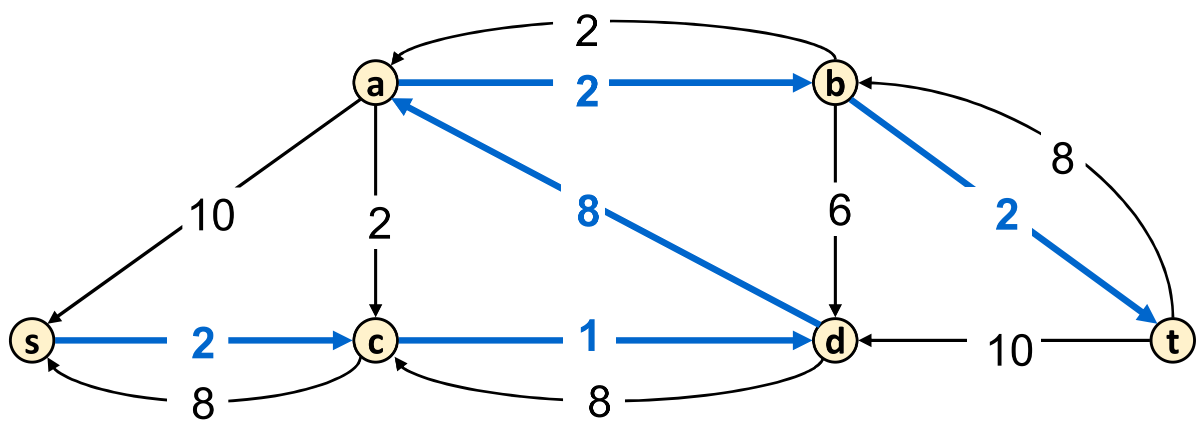
Ford-Fulkerson Algorithm

G:



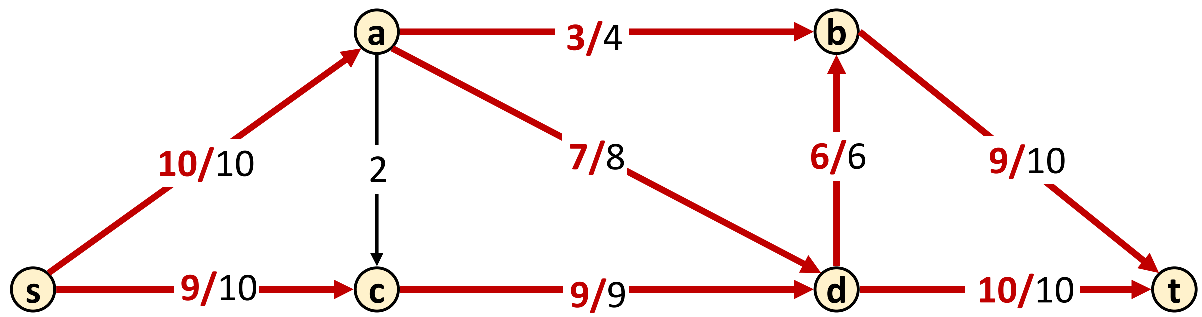
Flow value = 18
+1=19

G_f:



Ford-Fulkerson Algorithm

G:



Flow value = **19**

G_f: