## Algorithms for Programming Contests - Week 05

Prof. Dr. Javier Esparza
Pranav Ashok, A. R. Balasubramanian,
Tobias Meggendorfer, Philipp Meyer,
Mikhail Raskin,
conpra@in.tum.de

20. Mai 2020

## Flow Network

## Definition (Flow network)

A flow network is a directed graph G=(V,E), where each edge (u,v) is assigned a nonnegative capacity  $c(u,v)\geq 0$  and there are two designated vertices, the source s and the target t.

W.l.o.g., we will only consider flow networks without antiparallel edges, i.e. if  $(u, v) \in E$ , then  $(v, u) \notin E$ .

## Definition (Flow)

For a given flow network G=(V,E) with capacity function c, a flow is a function  $f\colon E\to\mathbb{R}$  satisfying

$$\forall (u,v) \in E: \quad 0 \le f(u,v) \le c(u,v)$$

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

## Maximum Flow Problem

## Definition (Flow value)

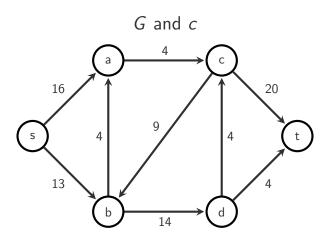
The value |f| of a flow f is defined as

$$|f| = \sum_{\{v: (s,v) \in E\}} f(s,v) - \sum_{\{v: (v,s) \in E\}} f(v,s)$$

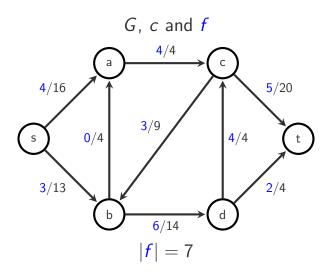
## Definition (Maximum Flow Problem)

For a given flow network G with source s and target t, what is a flow f with maximal value |f| over all flows?

# Example: Flow network



# Example: Flow network with flow



### Reductions to maximum flow

#### Hints

- Minimum flow: send no flow at all.
- Multiple sources/sinks: add super-source/sink and edges with infinite capacity to other sources/sinks.
- Sources/sinks with supply constraints: add super-source/sink with edges to sources/sinks with corresponding capacity.
- · Demands for sinks: check value of maximum flow.
- Vertex capacities: Split up vertex with edge of that capacity in between.
- Antiparallel edges: Insert vertex in between one edge (or use multi-edges when necessary).
- Undirected edges: Convert to two antiparallel directed edges.

## Max-flow min-cut

## Definition (Cut)

For a given flow network G with source s and target s, a cut C = (S, T) is a partititon of V into two subsets S and T such that  $s \in S$  and  $t \in T$ . The capacity c(S, T) of a cut (S, T) is defined as

$$c(S,T) = \sum_{(u,v)\in(S\times T)\cap E} c(u,v)$$

## Theorem (Min-cut max-flow theorem)

The maximum value |f| over all flows f is equal to the minimum capacity c(S,T) over all cuts (S,T).

## Residual network

## Definition (Residual capacity and residual network)

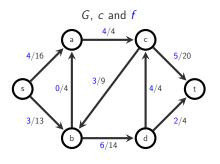
For a given flow network G and a flow f, and a pair of vertices  $u, v \in V$ , the *residual capacity*  $c_f(u, v)$  is defined by

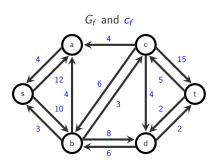
$$c_f(u,v) = egin{cases} c(u,v) - f(u,v) & ext{if } (u,v) \in E \ f(v,u) & ext{if } (v,u) \in E \ 0 & ext{otherwise} \end{cases}$$

The *residual network* of G induced by f is  $G_f = (V, E_f)$ , where

$$E_f = \{(u, v) \in V \times V : c_f(u, v) > 0\}$$

# Example: Residual network





# Augmenting flow

## Definition (Augmenting flows)

If f is a flow in a flow network G and f' is a flow in the corresponding residual network  $G_f$ , then the augmentation  $f \uparrow f'$  of f by f' is a flow of G defined as

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

#### Lemma

If f is a flow in a flow network G and f' is a flow in the corresponding residual network  $G_f$ , then  $f \uparrow f'$  is also a flow in G and

$$|f \uparrow f'| = |f| + |f'|$$

## Augmenting path

## Definition (Augmenting path)

Given a flow network G and a flow f, an augmenting path p is a simple path in the residual network  $G_f$  from s to t.

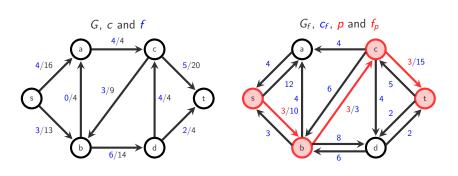
The residual capacity of an augmenting path p is given by

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

The flow  $f_p$  of an augmenting path p in  $G_f$  is defined as

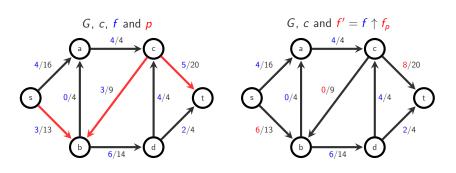
$$f_p(u,v) = \begin{cases} c_f(p) & \text{if } (u,v) \text{ is on } p \\ 0 & \text{otherwise} \end{cases}$$

# Example: Augmenting path



$$p = \text{sbct}$$
 $c_f(p) = 3$ 

# Example: Augmenting flow



$$p = \text{sbct}$$
 $c_f(p) = 3$ 

# Augmenting path algorithm (Ford-Fulkerson algorithm)

### Algorithm 1 Ford-Fulkerson algorithm

```
\triangleright Initial flow is 0 (f \leftarrow 0)
for (u, v) \in E do
    f(u,v) \leftarrow 0
end for
while there exists a path p from s to t in the residual network G_f do
    \triangleright Augment f by f_n (f \leftarrow f \uparrow f_n)
     c_f(p) \leftarrow \min\{c_f(u,v): (u,v) \text{ is on } p\}
    for each edge (u, v) in p do
         if (u, v) \in E then
              f(u, v) \leftarrow f(u, v) + c_f(p)
         else
              f(v, u) \leftarrow f(v, u) - c_f(p)
         end if
     end for
end while
```

# **Analysis**

How to decide with augmenting path to choose?

- Any path (with DFS): Ford-Fulkerson algorithm. Complexity
   O(|E|U) with integer capacities, where U is the value of the
   maximum flow. Possibly non-terminating for irrational capacities.
- Shortest path by number of edges (with BFS): Edmonds-Karp algorithm. Complexity  $\mathcal{O}(|V||E|^2)$ .
- All shortest paths (blocking flows): Dinic's algorithm. Complexity  $\mathcal{O}(|V|^2|E|)$ .

## Blocking flow

## Definition (Level graph)

Given a residual network  $G_f = (V, E_f)$ , let  $d_{G_f}(s, v)$  be the length of the shortest path from s to v in  $G_f$  (by number of edges).

The *level graph* of  $G_f$  is the graph  $G_L = (V, E_L, c_L)$ , where

$$E_L = \{(u,v) \in E_f \colon d_{G_f}(s,v) = d_{G_f}(s,u) + 1\}$$
  $c_L(u,v) = egin{cases} c_f(u,v) & ext{if } (u,v) \in E_L \ 0 & ext{otherwise} \end{cases}$ 

## Definition (Blocking flow)

A blocking flow in the level graph  $G_L$  is a flow f such that every path from s to t in  $G_L$  contains a saturated edge, i.e., an edge (u, v) with  $f(u, v) = c_L(u, v)$ .

## Dinic's algorithm

### Algorithm 2 Dinic's algorithm

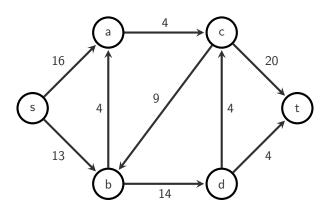
 $f\leftarrow 0$  while there exists a blocking flow f' in  $G_L$  with |f'|>0 do  $f\leftarrow f\uparrow f'$  end while

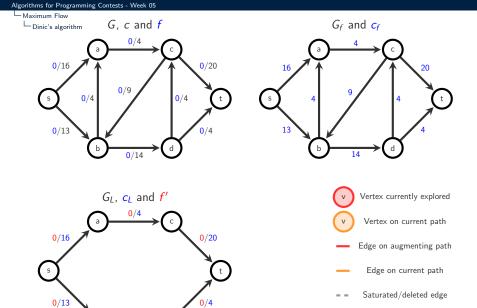
# Finding a blocking flow

#### **Algorithm 3** Finding blocking flows via DFS

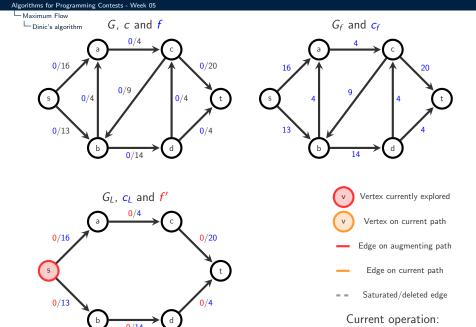
```
f' \leftarrow 0: p \leftarrow s: u \leftarrow s
while u \neq t do
    while there is an edge (u, v) \in E_I with f'(u, v) < c_I(u, v) do
         p \leftarrow pv
         II \leftarrow V
    end while
    if \mu = t then
         f' \leftarrow f' \uparrow f_p; p \leftarrow s; u \leftarrow s
     else if \mu = s then
         return f'
    else
         let (v, w) be the last edge on p; delete w from p
         delete (v, w) from E_l: u \leftarrow v
    end if
end while
```

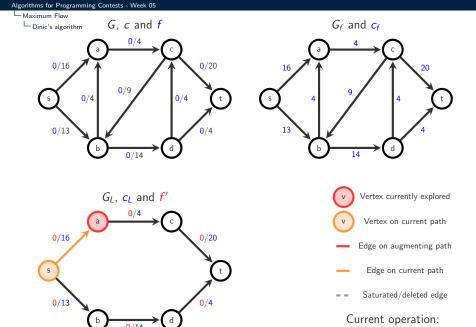
# Dinic's algorithm (example)

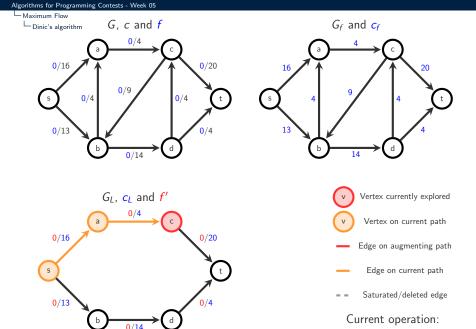


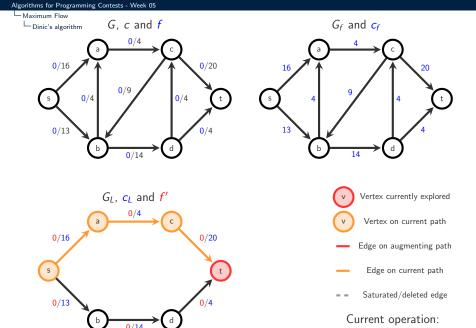


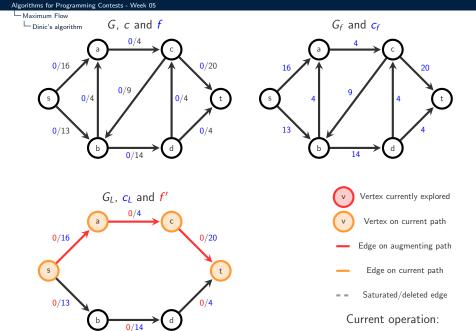
Current operation: Find blocking flow







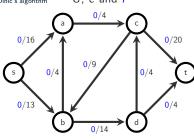


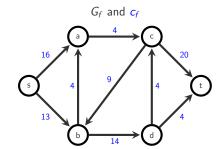


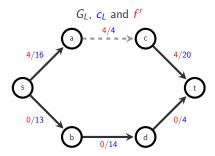
Augment f' by  $f_p$ 







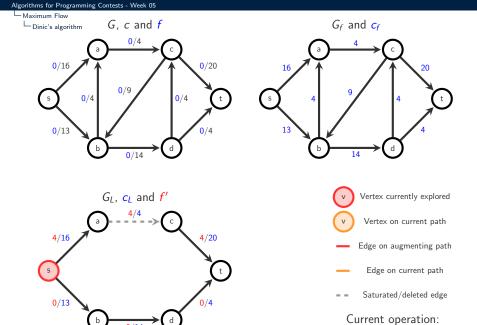


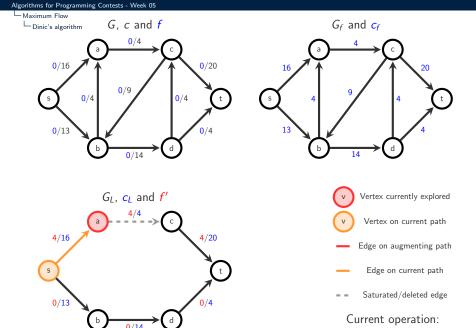


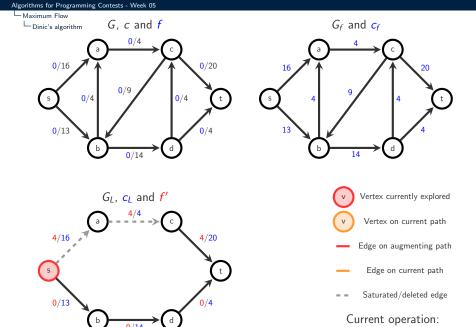
- v Vertex currently explored
- V Vertex on current path
- Edge on augmenting path
- Edge on current path
  - Saturated/deleted edge

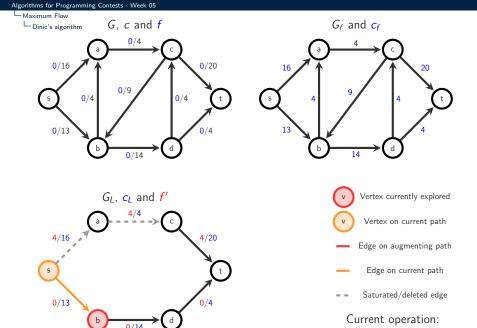
Current operation:

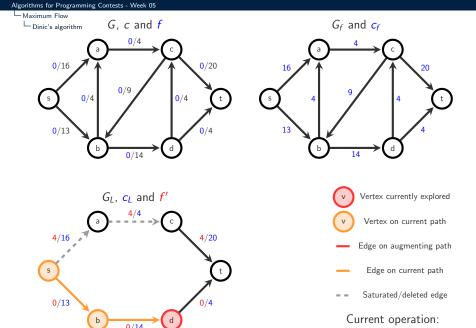
Augment f' by  $f_p$ 

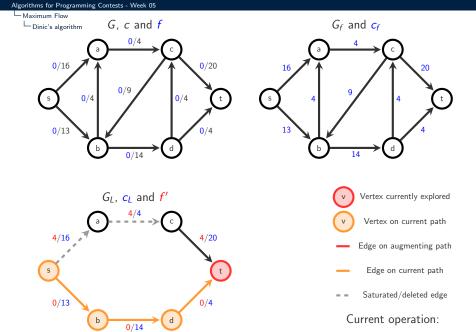


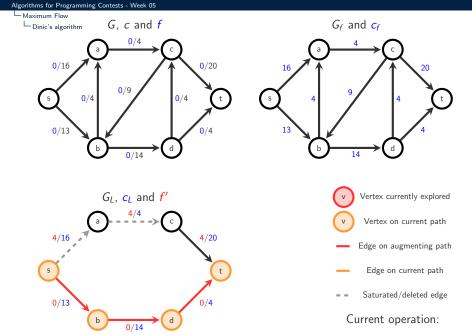




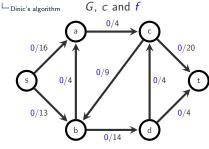


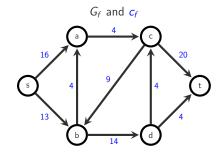


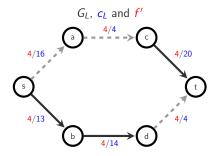




Augment f' by  $f_p$ 



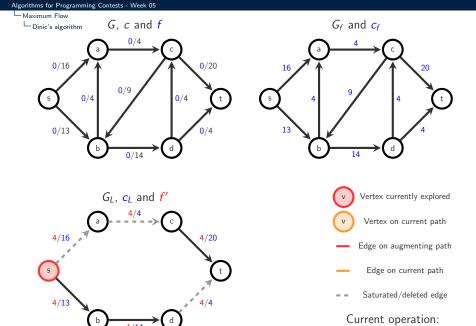


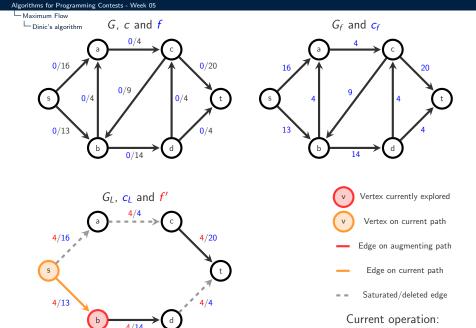


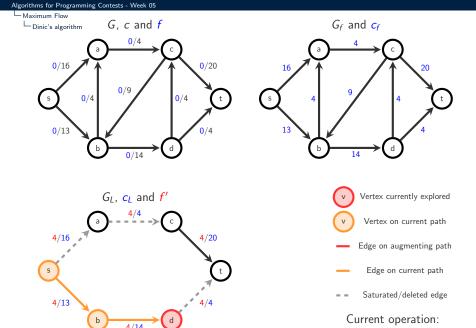
- V Vertex currently explored
- V Vertex on current path
- Edge on augmenting path
- Edge on current path
  - Saturated/deleted edge

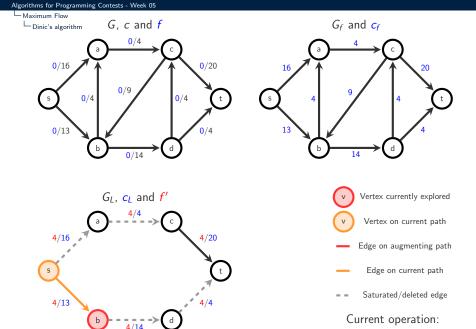
Current operation:

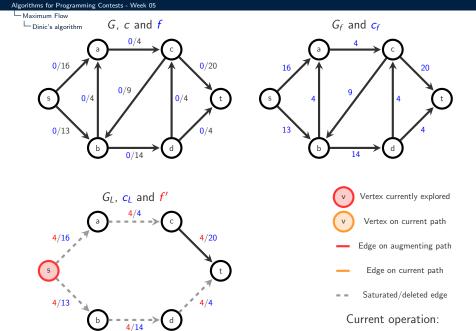
Augment f' by  $f_p$ 

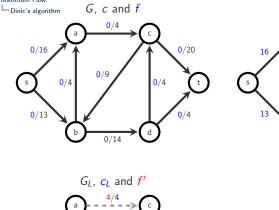


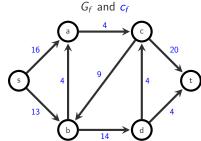


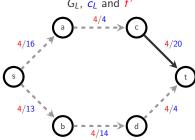










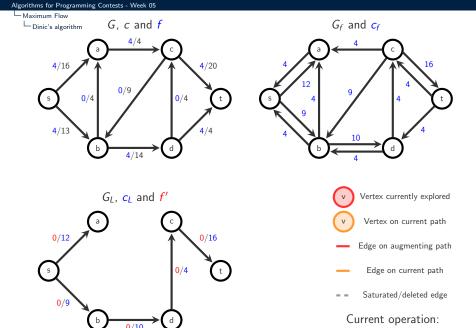


- v Vertex currently explored
- v Vertex on current path
- Edge on augmenting path
- Edge on current path
  - Saturated/deleted edge

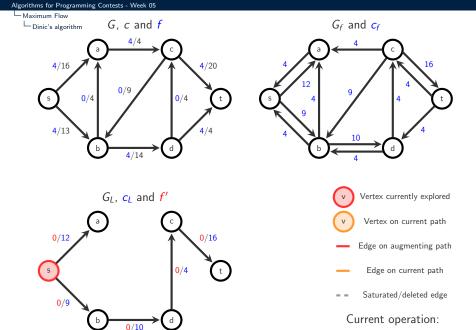
Current operation:

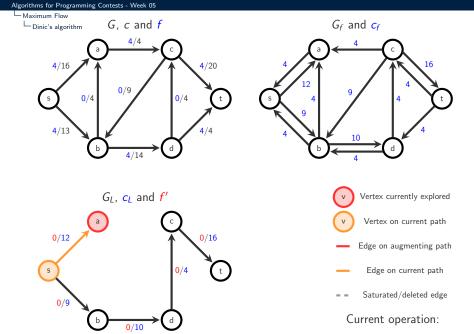
Augment f by f'

Current operation: **Augment** *f* **by** *f'* 

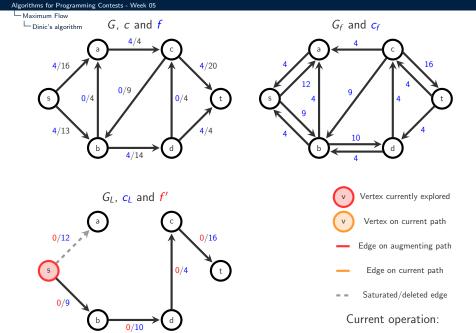


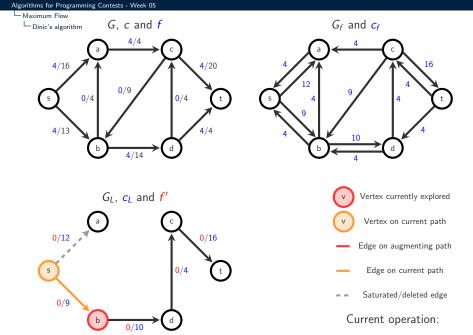
Find blocking flow

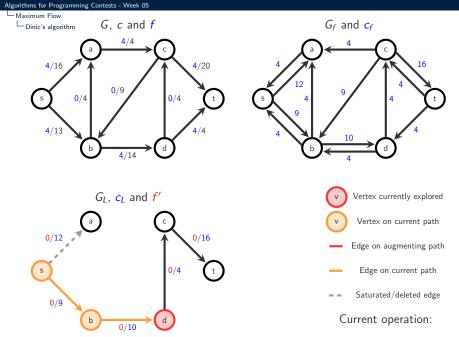


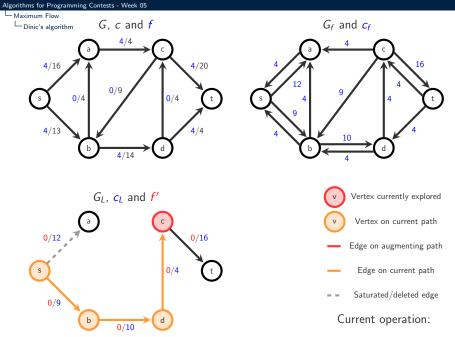


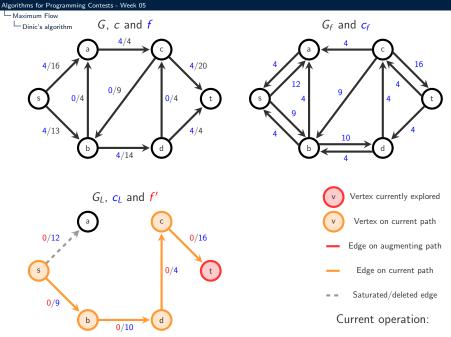
Find augmenting path

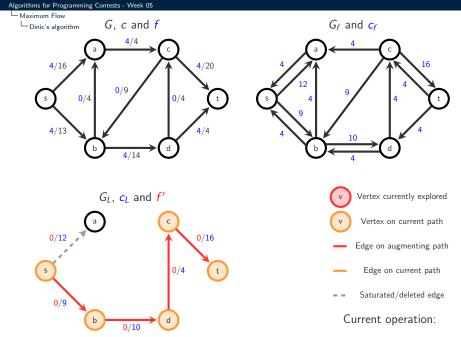




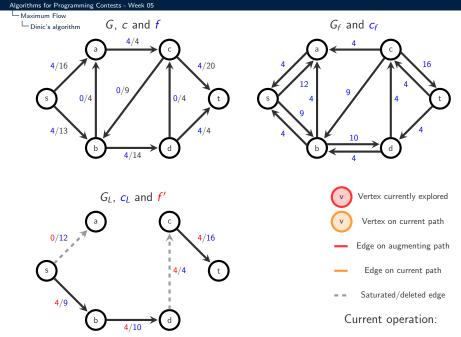




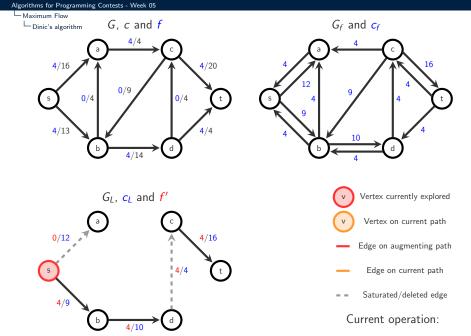


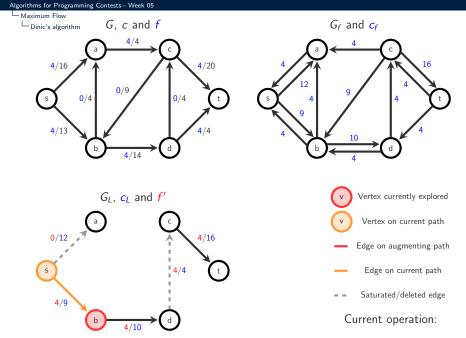


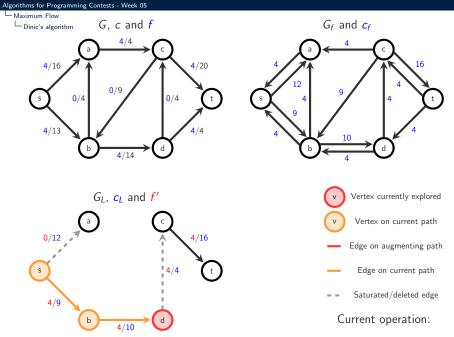
Augment f' by  $f_p$ 

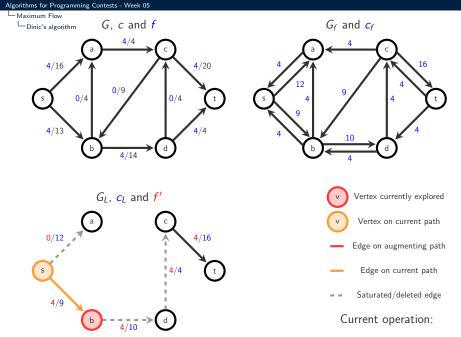


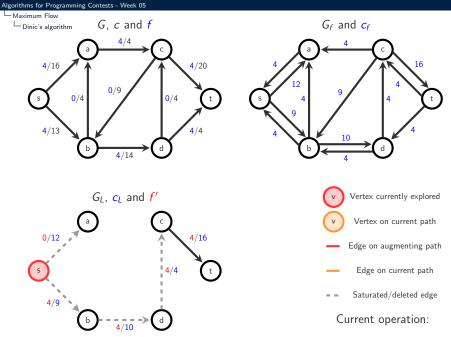
Augment f' by  $f_p$ 



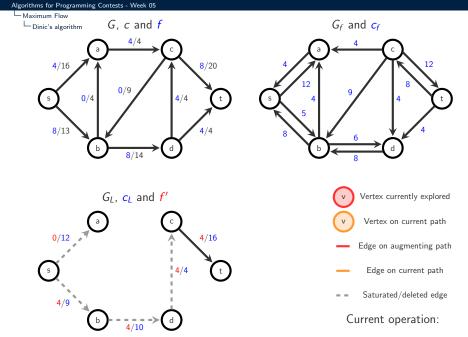




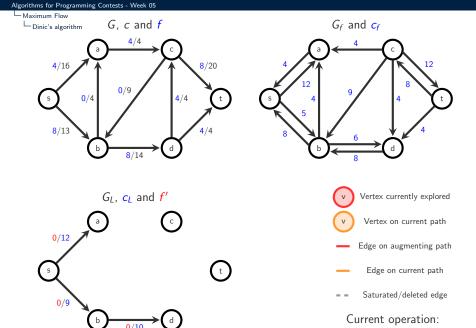




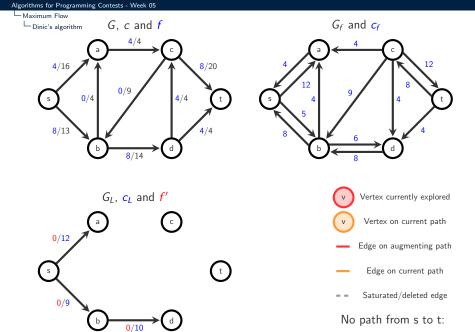
Augment f by f'



Augment f by f'



Find blocking flow



Maximum flow found

### Push-relabel algorithms: Preflow

The class of *push-relabel* algorithms for maximum flow work by maintaining a *preflow* and pushing it along edges, while (re-)labeling vertices to determine where flow can be pushed.

### Definition (Preflow)

For a given flow network G = (V, E) with capacity function c, a preflow is a function  $f : E \to \mathbb{R}$  satisfying

$$\forall (u,v) \in E: \quad 0 \le f(u,v) \le c(u,v)$$

$$\forall u \in V \setminus \{s,t\}: \quad \sum_{\{v: (v,u) \in E\}} f(v,u) - \sum_{\{v: (u,v) \in E\}} f(u,v) \ge 0$$

## Push-relabel algorithms: Excess flow and height labels

### Definition (Excess flow)

For a given flow network G and a preflow f, the excess flow e(u) of a vertex u is given by

$$e(v) = \sum_{\{v: (v,u) \in E\}} f(v,u) - \sum_{\{v: (u,v) \in E\}} f(u,v)$$

A vertex  $u \in V \setminus \{s, t\}$  is said to be *overflowing* if e(u) > 0.

### Definition (Height function)

For a given flow network G and a flow f, a function  $h \colon V \to \mathbb{N}$  is a height function if h(s) = |V|, h(t) = 0 and  $h(u) \le h(v) + 1$  for every residual edge  $(u, v) \in E_f$ .

## Push and relabel operations

#### Algorithm 4 Push operation

Applies to 
$$(u, v) \in E_f$$
 when  $u$  is overflowing and  $h(u) = h(v) + 1$ 

$$\Delta_f(u, v) \leftarrow \min(e(u), c_f(u, v))$$
if  $(u, v) \in E$  then
$$f(u, v) \leftarrow f(u, v) + \Delta_f(u, v)$$
else
$$f(v, u) \leftarrow f(v, u) - \Delta_f(u, v)$$
end if
$$e(u) \leftarrow e(u) - \Delta_f(u, v)$$

$$e(v) \leftarrow e(v) + \Delta_f(u, v)$$

#### Algorithm 5 Relabel operation

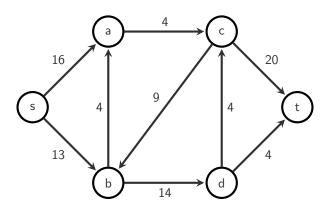
▷ Applies to u when u is overflowing and  $h(u) \le h(v)$  for all  $(u, v) \in E_f$  $h(u) \leftarrow 1 + \min\{h(v) : (u, v) \in E_f\}$ 

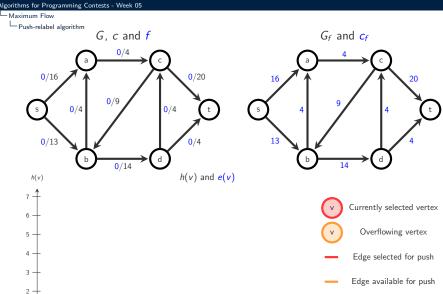
# Push-relabel algorithm (Goldberg-Tarjan algorithm)

#### Algorithm 6 Push-relabel algorithm

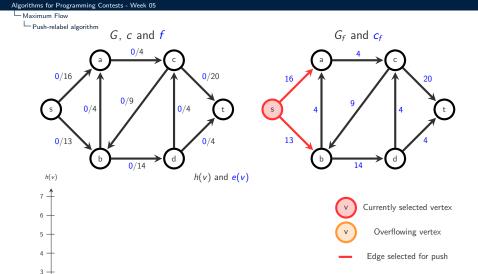
for each vertex 
$$v \in V$$
 do  $h(v) \leftarrow 0$ ;  $e(v) \leftarrow 0$  end for for  $(u,v) \in E$  do  $f(u,v) \leftarrow 0$  end for  $h(s) \leftarrow |V|$  for each vertex  $v \in sE$  do  $f(s,v) \leftarrow c(s,v)$   $e(v) \leftarrow e(v) + c(s,v)$   $e(s) \leftarrow e(s) - c(s,v)$  end for while there is an applicable push or relabel operation do select an applicable push or relabel operation and perform it end while

## Push-relabel algorithm (example)





Current operation:



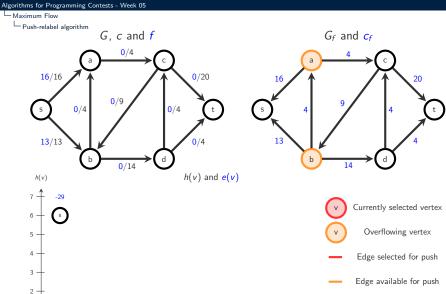
2 +

Edge available for push

Current operation: Initialize preflow

1 +

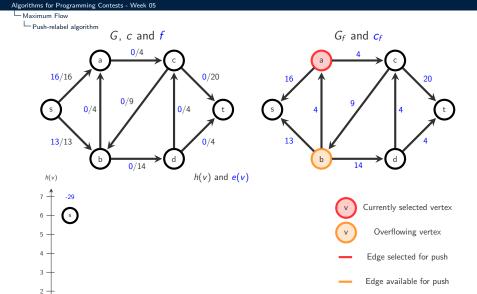
0 +



13

16

Current operation:



13

16

1 +

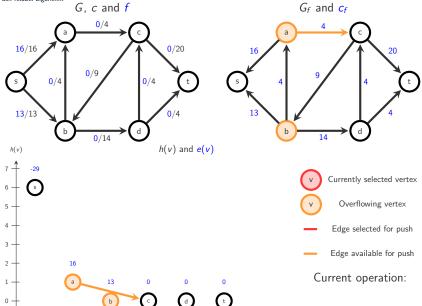
0 +

Relabel a

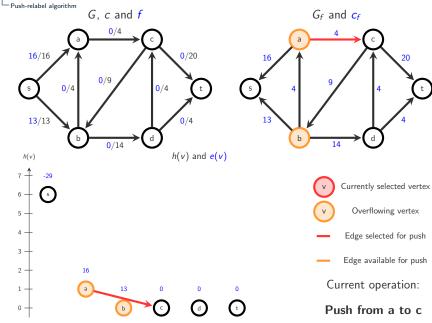
Current operation:

Maximum Flow

Push-relabel algorithm







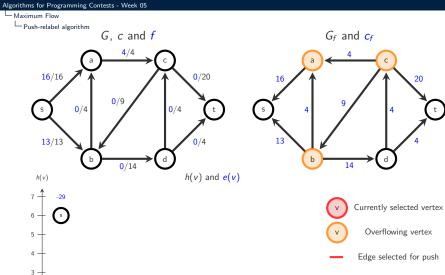
2 +

1 + 0 + 12

a

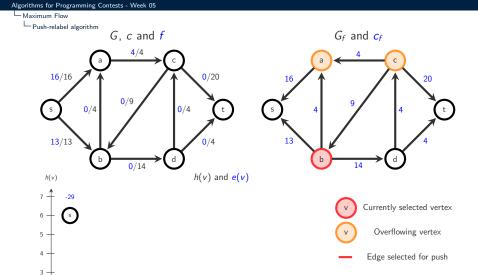
13

Ь



Edge available for push

Current operation:



2 +

1 +

0 +

12

a

13

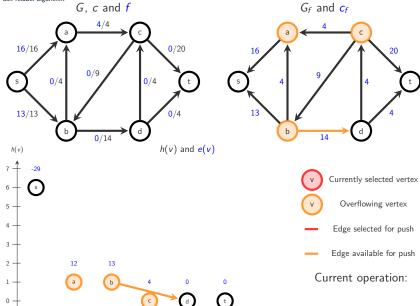
Ь

Relabel b

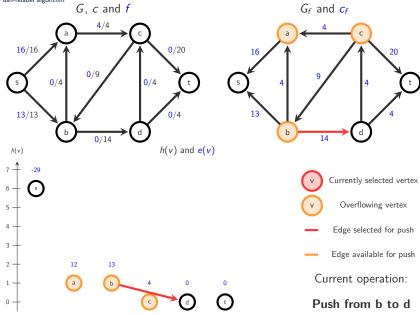
Edge available for push

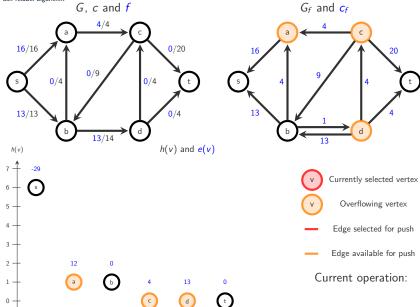
Current operation:

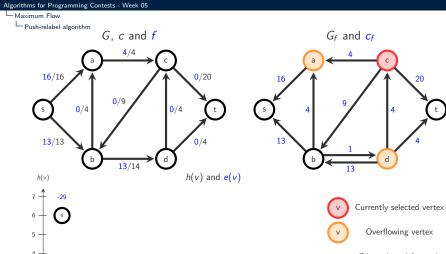


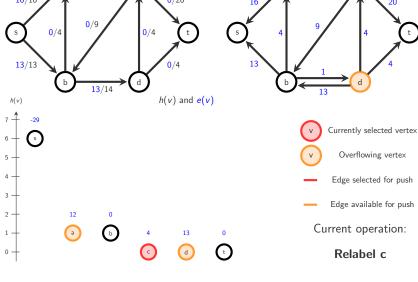


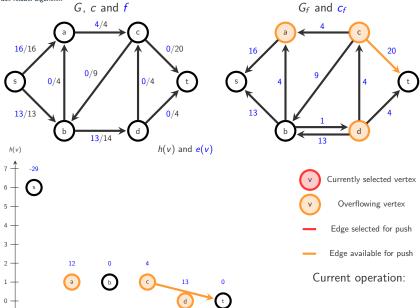




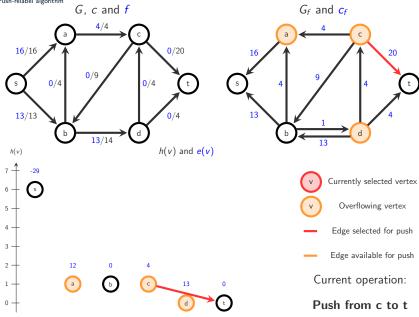




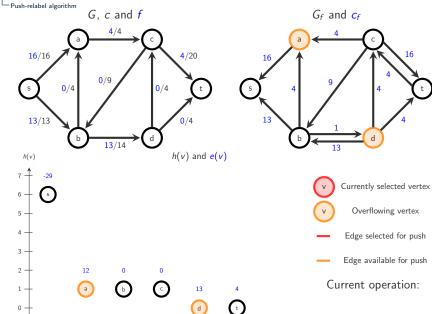


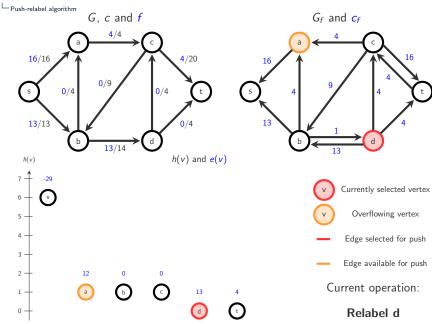




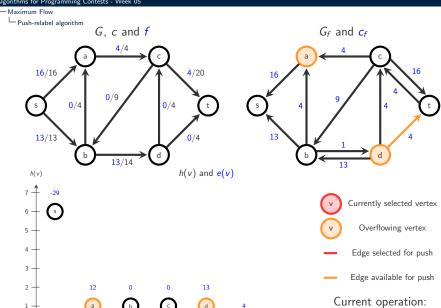


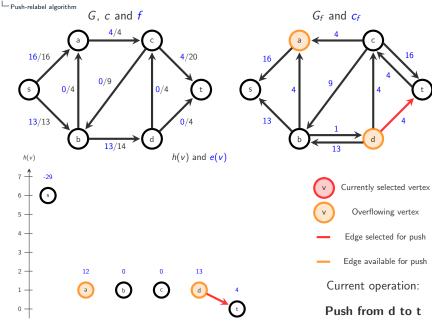


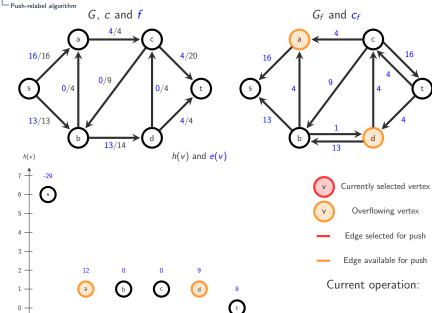


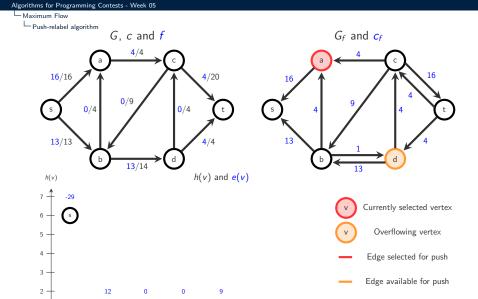


1 + 0 +









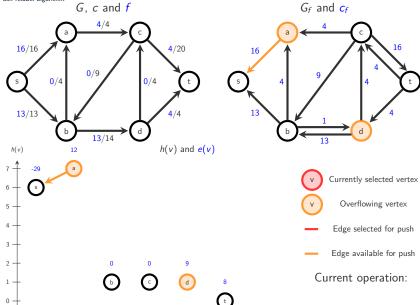
 $^{\circ}+$  Relabel a

d

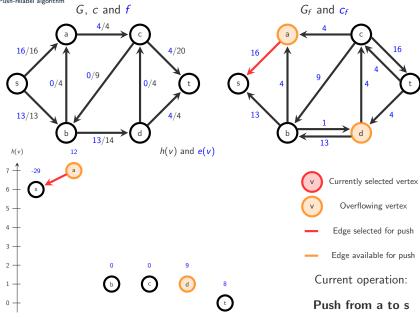
1 +

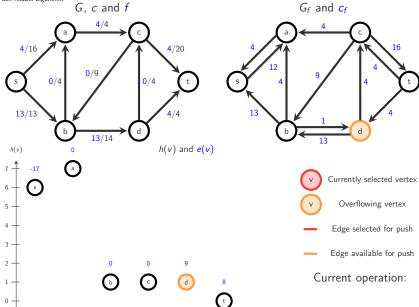
Current operation:



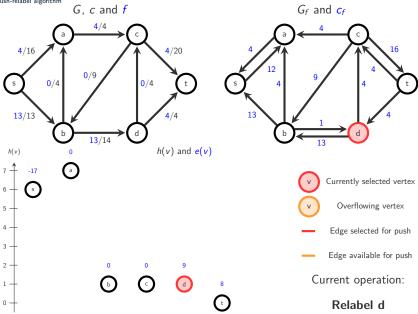


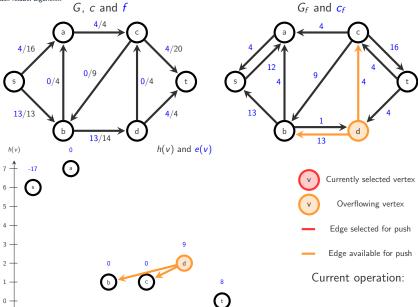


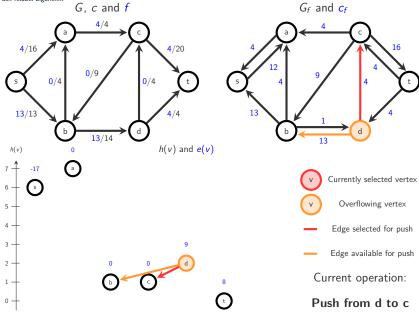


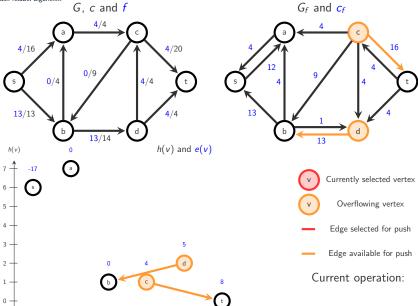


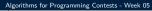




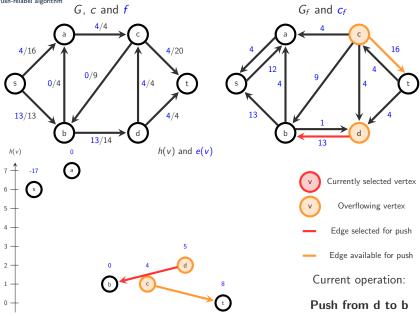


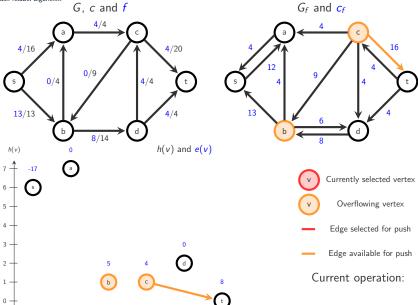




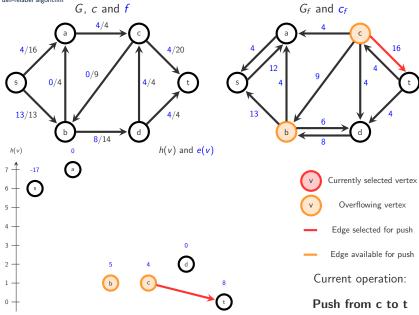


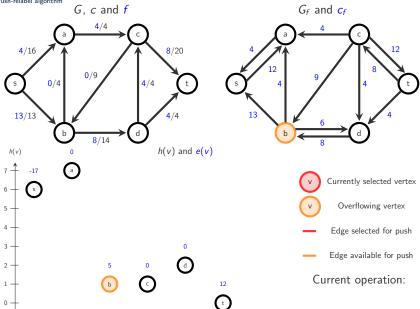




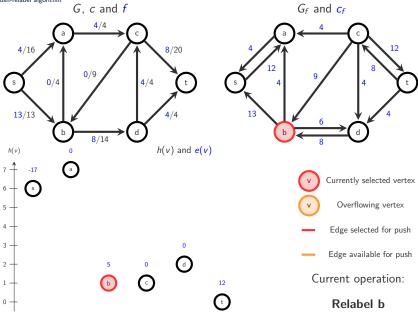


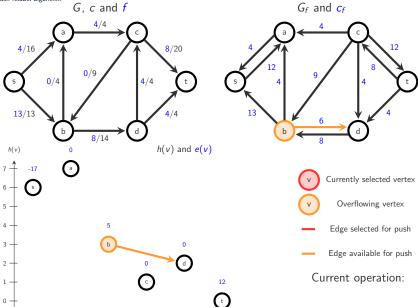






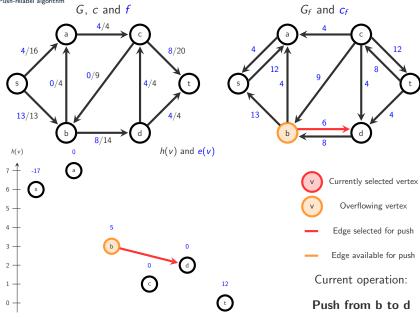


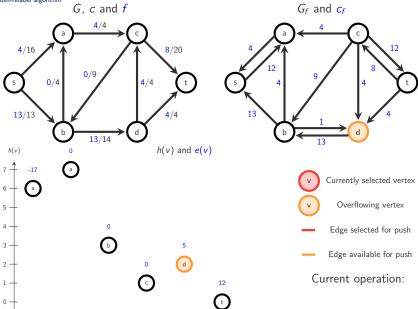


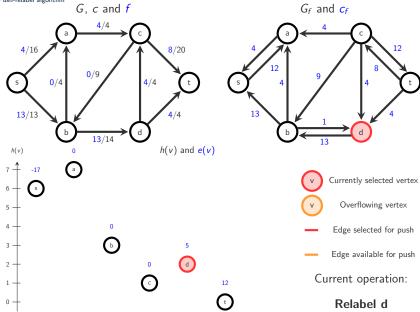


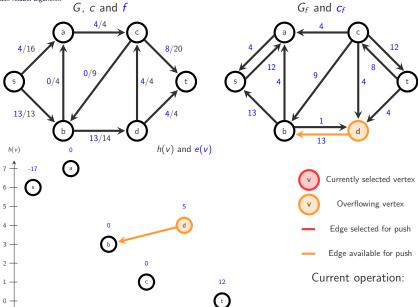






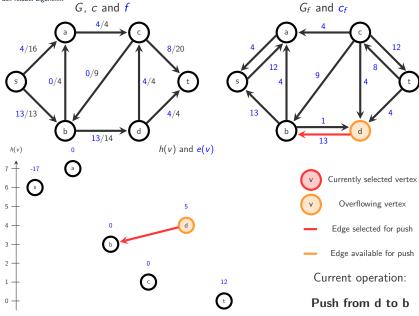


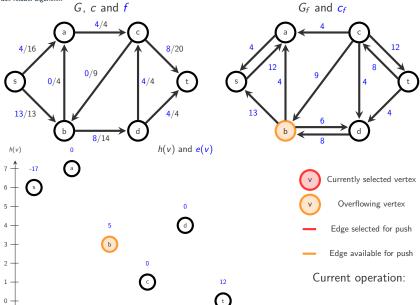




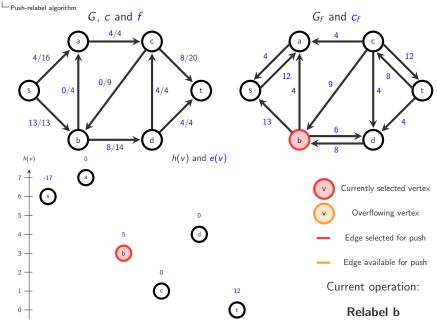


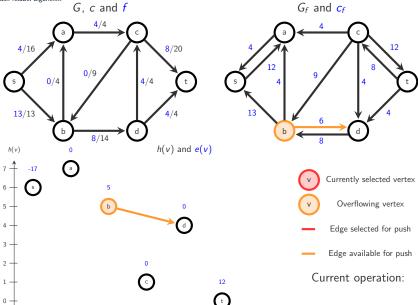


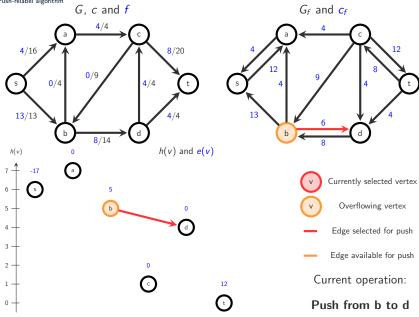


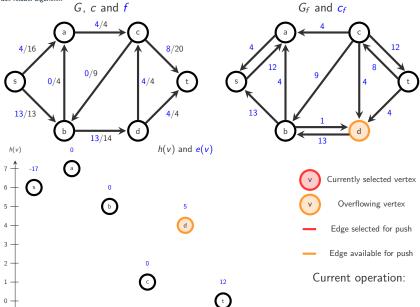


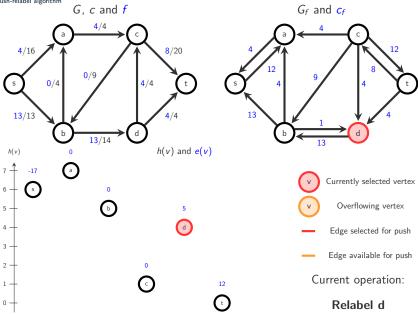


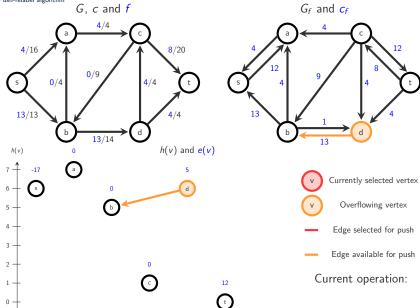


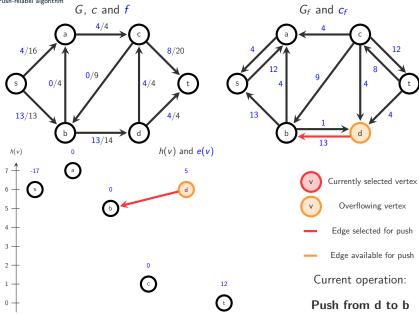


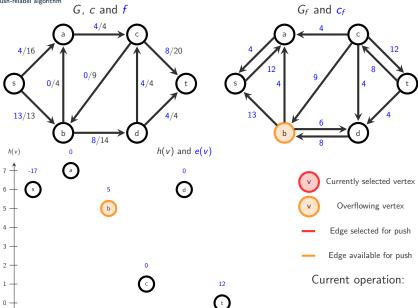


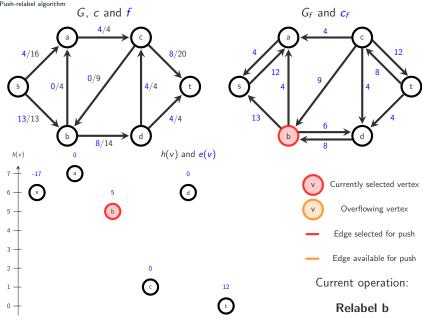


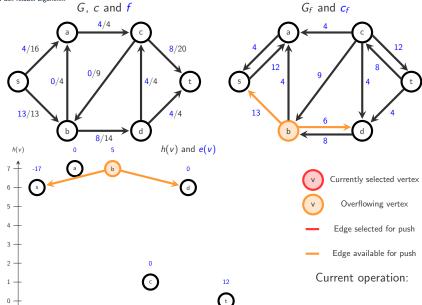






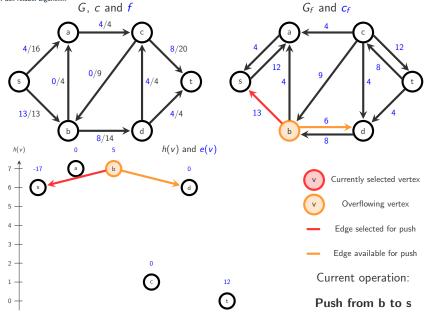


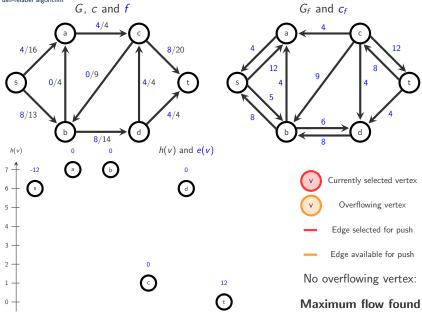












Push-relabel algorithm

#### Correctness

Why it even works?

 $h(\cdot)$  stays height function Path of k residual edges reduces h by at most k Acyclic path has  $\leqslant |V|-1$  edges h(s)-h(t)=|V|, therefore cut exists

# Analysis

Order for choosing next operation?

- Any order (e.g. with stack): Goldberg-Tarjan algorithm,  $\mathcal{O}(|V|^2|E|)$ .
- FIFO (with a queue):  $\mathcal{O}(|V|^3)$ .
- Highest label (with buckets):  $\mathcal{O}(|V|^2 \sqrt{|E|})$ .

Keep list of overflowing vertices in appropriate data structure and update accordingly after each operation!

### Heuristics for the push-relabel algorithm

#### Two-phase algorithm

- In first phase, only push/relabel vertices with h(v) < |V|.
- Does not compute complete flow, but value of maximum flow at t.
- ullet Remaining excess flow may be pushed back to s in second phase.

#### Initial labeling heuristic

- Compute initial heights as minimal distance to t by backwards BFS, computing  $h(v) \leftarrow d_G(v, t)$ .
- Avoids unnecessary initial relabeling operations.
- Can also compute labeling for second phase with  $h(v) \leftarrow d_{G_r}(v,s) + |V|$ .

### Heuristics for the push-relabel algorithm

#### Gap heuristic

- After each relabeling, check if there is a height k with 0 < k < |V| such that there is no vertex v with h(v) = k (keep a count array).
- If yes, all vertices u with k < h(u) < |V| are disconnected from t in  $G_f$  and can be disregarded (set  $h(u) \leftarrow |V|$ ).
- One of the most efficient heuristics, crucial for improving the performance.

### Further reading

#### Several improved algorithms available:

- Orlin: Max flows in  $\mathcal{O}(nm)$  time, or better, 2013:  $\mathcal{O}(|V||E|)$
- Sidford and Lee: Path-Finding Methods for Linear Programming, 2014:  $\widetilde{\mathcal{O}}(|E|\sqrt{|V|}\log^{\mathcal{O}(1)}U)$  (where  $\widetilde{\mathcal{O}}$  hides polylog(|V|, |E|)).

#### Additional literature on flow problems and algorithms:

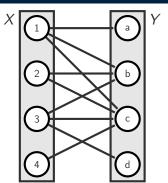
- T. H. Cormen et al.: Introduction to Algorithms. MIT press, 2009.
- R. Ahuja, T. Magnanti and J. B. Orlin: Network Flows: Theory, Algorithms and Applications. Prentice Hall, 1993.
- B. Korte, J. Vygen: Combinatorial Optimization: Theory and Algorithms. Springer, 2012.

Maximum Flow
Bipartite Matching

### Application: Bipartite Matching

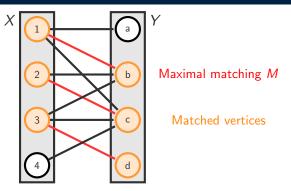
### Definition (Bipartite Matching / Maximum Matching Problem)

Given two disjoint sets of vertices X and Y and a set of edges  $E \subseteq X \times Y$ , a matching  $M \subseteq E$  is a subset of edges such that each node of  $X \cup Y$  appears in at most one edge of M. The maximum matching problem is finding a matching M such that |M| is maximal.



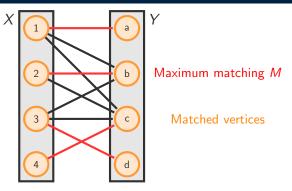
### Definition (Bipartite Matching / Maximum Matching Problem)

Given two disjoint sets of vertices X and Y and a set of edges  $E \subseteq X \times Y$ , a matching  $M \subseteq E$  is a subset of edges such that each node of  $X \cup Y$  appears in at most one edge of M. The maximum matching problem is finding a matching M such that |M| is maximal.



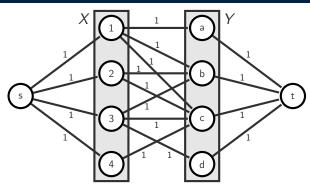
### Definition (Bipartite Matching / Maximum Matching Problem)

Given two disjoint sets of vertices X and Y and a set of edges  $E \subseteq X \times Y$ , a matching  $M \subseteq E$  is a subset of edges such that each node of  $X \cup Y$  appears in at most one edge of M. The maximum matching problem is finding a matching M such that |M| is maximal.



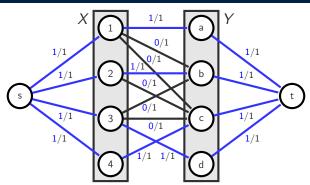
### Matching problem as a flow problem

Given a bipartite matching problem, construct flow network G = (V, E') with  $V = \{s, t\} \cup X \cup Y$  and  $E' = E \cup (\{s\} \times X) \cup (Y \times \{t\})$  and c(e) = 1 for all  $e \in E'$ . Then the value of the maximum flow is equal to the size of the maximum matching.



### Matching problem as a flow problem

Given a bipartite matching problem, construct flow network G = (V, E') with  $V = \{s, t\} \cup X \cup Y$  and  $E' = E \cup (\{s\} \times X) \cup (Y \times \{t\})$  and c(e) = 1 for all  $e \in E'$ . Then the value of the maximum flow is equal to the size of the maximum matching.



# Notes on performance

#### General

- Better asymptotic complexity in general means nothing check the constraints
- Constants matter

JIT 
$$(non-C++)$$
 languages

- We have Python (PyPy3) solutions to everything
- For JIT, many small functions are often easier to optimise than a single large one
- Data structure allocation also has a cost
- Recalculating can be cheaper than caching