

# Lecture 9

Connectivity: Dijkstra's algorithm.

Flow networks: Maximum flow algorithms

December, 7 2015

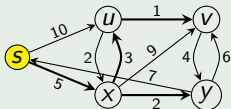
- ① The problem of lightest paths from a single source in a weighted digraph
  - **Dijkstra's algorithm**
- ② Flow networks and flows
  - Maximum flow
  - Residual networks, augmenting paths
  - **Ford-Fulkerson algorithm**
  - Applications

# Lightest paths from a given source node

**Given** a simple weighted digraph  $G = (V, E)$  with  $w : E \mapsto \mathbb{R}^+$  and a source node  $s \in V$

**Find** for every node  $x \in V$  accessible from  $s$ , a lightest path  $\rho : s \rightsquigarrow x$ , and its weight  $w(\rho)$

## Example



$[s]$  with  $w([s]) = 0$ ;       $[s, x, u]$  with  $w([s, x, u]) = 8$

$[s, x]$  with  $w([s, x]) = 5$ ;  $[s, x, u, v]$  with  $w([s, x, u, v]) = 9$

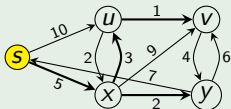
$[s, x, y]$  with  $w([s, x, y]) = 7$ .

# Lightest paths from a given source node

**Given** a simple weighted digraph  $G = (V, E)$  with  $w : E \mapsto \mathbb{R}^+$  and a source node  $s \in V$

**Find** for every node  $x \in V$  accessible from  $s$ , a lightest path  $\rho : s \rightsquigarrow x$ , and its weight  $w(\rho)$

## Example



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$[s, x]$  with  $w([s, x]) = 5$ ;  $[s, x, u, v]$  with  $w([s, x, u, v]) = 9$

$[s, x, y]$  with  $w([s, x, y]) = 7$ .

## Remark

- The problem can be solved with **Warshall's algorithm**:
  - Computes the lightest paths that exist between every pair of nodes
  - Runtime complexity  $O(|V|^3)$ ; it computes more than needed

Is there a better algorithm, if the source node is fixed?

# Dijkstra's Algorithm

## Informal description

Proposed by E. Dijkstra in 1956 to solve the previous problem

1 Assign

- A tentative weight  $d(x)$  for a lightest path from source to  $x$ .
- a predecessor node  $\pi(x)$  of every node  $x$  on a lightest path from  $s$  to  $x$ .

Initially, we have  $d(x) = \begin{cases} 0 & \text{if } x = s, \\ \infty & \text{if } x \neq s \end{cases}$      $\pi(x) = \begin{cases} \text{undef} & \text{if } x = s \\ s & \text{if } x \neq s \end{cases}$

where *undef* is a special value: it indicates the inexistence of a predecessor.

- 2 Create a set  $Q$  of **unvisited nodes**. Initially,  $Q := V$ , and keep track of a **current node**  $crt$ .
- 3 choose  $crt :=$  a node from  $Q$  with  $d(crt) = \min\{d(x) \mid x \in Q\}$ , and remove  $crt$  from  $Q$ .
- 4 For every neighbor  $x \in Q$  of  $crt$  update the tentative values of  $d(x)$  and  $\pi(x)$  as follows:

If  $d(crt) + w((crt, x)) < d(x)$  then  $d(x) := d(crt) + w((crt, x))$   
and  $\pi(x) := crt$ .

This updating step is called **relaxation step** of the arc  $(crt, x) \in E$ .

- 5 If  $Q = \emptyset$  then **stop**, else **goto** 3.

# Dijkstra's algorithm

Pseudocode for the auxiliary operations

## ► Initialization

**SINGLESOURCEINIT**( $G, s$ )

**for** each  $v \in V$

$d(v) := \infty$

$\pi(v) := s$

$d(s) := 0$

$\pi(s) := \text{undef}$

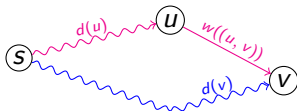
## ► Relaxation step for an arc $(u, v)$

**RELAX**( $u, v$ )

**if**  $d(v) > d(u) + w((u, v))$

$d(v) := d(u) + w((u, v))$

$\pi(v) := \pi(u)$



# Dijkstra's algorithm

## Pseudocode

**DIJKSTRA**( $G, w, s$ )

1 **SINGLESOURCEINIT**( $G, s$ )

2  $Q := V$

3 **while**  $Q \neq \emptyset$

4      $u := \text{EXTRACTMIN}(Q)$

5     **for** every neighbor  $v$  of  $u$  for which  $v \notin Q$

6          $\text{RELAX}(u, v)$

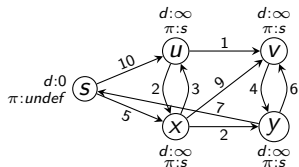
### Runtime complexity:

- ▶ Original algorithm:  $O(|V|^2)$
- ▶ Algorithm improved with a min-priority queue:  
 $O(|E| + |V| \cdot \log |V|)$

# Dijkstra's algorithm

Illustrated example: first **while** loop

**CONVENTION:** The nodes not marked yet (those from  $Q$ ) are white; the others are gray

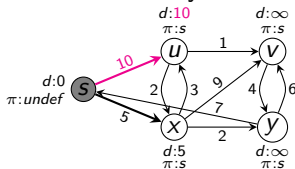
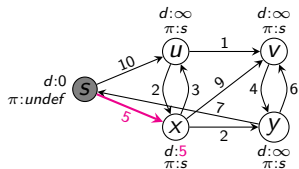


Configuration produced by `INITIALIZE_SINGLE_SOURCE( $G, s$ )`:

$Q = \{s, x, y, u, v\}$

Select  $s = \text{EXTRACT\_MIN}(Q)$

Relax all arcs from  $s$  to nodes not visited yet:

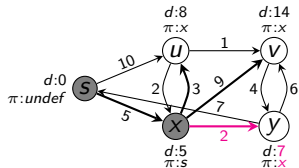
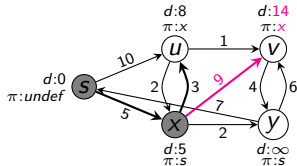
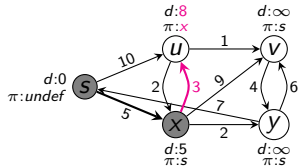




# Dijkstra's algorithm

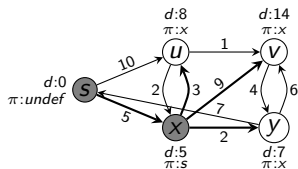
Illustrated example: the second **while** loop

Select and mark  $x$ , and relax all arcs from  $x$  to unmarked nodes:

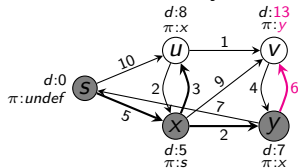


# Dijkstra's algorithm

Illustrated example: the third **while** loop

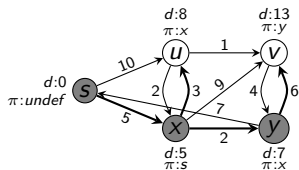


Select and mark  $y$ , and relax all arcs from  $y$  to unmarked nodes:

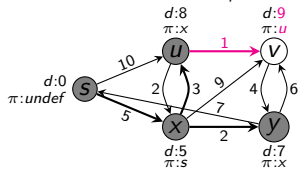


# Dijkstra's algorithm

Illustrated example: the fourth **while** loop

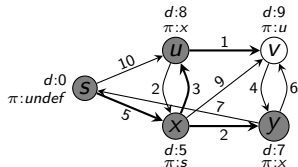


Select and mark  $u$ , and relax all arcs from  $u$  to unmarked nodes:



# Dijkstra's algorithm

Illustrated example: the fifth **while** loop



$d(s) = 0$	$\pi(s) = undef$
$d(x) = 5$	$\pi(x) = s$
$d(u) = 8$	$\pi(u) = x$
$d(y) = 7$	$\pi(y) = x$
$d(v) = 9$	$\pi(v) = u$

- Select and mark  $v$
- There are no arcs left to relax  $\Rightarrow$  the algorithm stops.

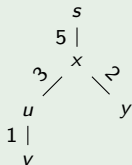
From the values of  $\pi$  and  $d$  we can retrieve lightest paths from  $s$  to all other nodes:

- ▶ to  $s$ :  $[s]$  with weight  $w([s]) = d(s) = 0$
- ▶ to  $x$ :  $[s, x]$  with weight  $w([s, x]) = d(x) = 5$
- ▶ to  $u$ :  $[s, x, u]$  with weight  $w([s, x, u]) = d(u) = 8$
- ▶ to  $y$ :  $[s, x, y]$  with weight  $w([s, x, y]) = d(y) = 7$
- ▶ to  $v$ :  $[s, x, u, v]$  with weight  $w([s, x, u, v]) = d(v) = 9$

# The tree of lightest paths from source to all other nodes

The function  $\pi$  computed by Dijkstra's algorithm determines a tree  $G_\pi$  with root  $s$ , in which every node  $x \neq s$  has parent  $\pi(x)$ .

Example (The tree  $G_\pi$  for the illustrated weighted digraph  $G$ )



## Remark

Every branch of  $G_\pi$  from the source node  $s$  to a node  $x$  is a lightest path from  $s$  to  $x$ .

- 1 T. H. Cormen, C. E. Leiserson, R. L. Rivest. Section **25.2** from *Introduction to Algorithms*. MIT Press, 2000.
- 2 A C++ implementation of Dijkstra's algorithm can be downloaded from the website of this lecture (click [here](#))

# Flow networks and flows

Intuitive (informal) definitions

**Flow network:** Oriented graph in which arch represent flows of material between nodes (volume of liquid, electricity, a.s.o.)

- Every edge has a **maximum capacity**.
- We wish to determine a **flow** from a **source** node (the **producer**) to a **sink** node (the **consumer**).

**Flow**  $\approx$  the rate of flow of resources along arcs .

**The problem of maximum flow:** What is the maximum possible flow of resources from source to destination, without violating any maximum capacity constraint of the arcs?

# Flow networks

## The mathematical model

### Definition (Flow network)

An oriented graph  $G = (V, E)$ , where every arc  $(u, v) \in E$  has a **capacity**  $c(u, v) \geq 0$ , and two special nodes:

- a **source**  $s$  and
- a **sink**  $t$ .

If  $(u, v) \notin E$ , we assume  $c(u, v) = 0$ .

We write  $u \rightsquigarrow v$  to indicate the existence of a path from  $u$  to  $v$ , and assume that **every node  $v \in G$  is on a path from  $s$  to  $t$** , i.e., there is a path  $s \rightsquigarrow v \rightsquigarrow t$ .

### Remark

A flow network is a connected graph, thus  $|E| \geq |V| - 1$ .



## Definition

A **flow** in a flow network  $G$  is a function  $f : V \times V \rightarrow \mathbb{R}$  that fulfils the following constraints:

**Capacity constraint:** For all  $u, v \in V$ ,  $f(u, v) \leq c(u, v)$ .

**Skew symmetry:** For all  $u, v \in V$ ,  $f(u, v) = -f(v, u)$ .

**Flow conservation:** For all  $u \in V - \{s, t\}$ ,  $\sum_{v \in V} f(u, v) = 0$ .

$f(u, v)$  is called the **net flow** from node  $u$  to  $v$ . The **value** of a flow  $f$  is defined as  $|f| = \sum_{v \in V} f(s, v)$ , that is, the total net flow out of the source.

## The maximum-flow problem

**Given** a flow network  $G$

**Find** a flow of maximum value from  $s$  to  $t$ .

# Flow networks and flows

## Auxiliary notions

- The **positive net flow entering a node**  $v$  is

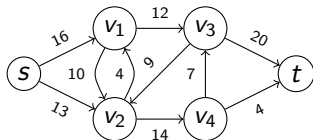
$$\sum_{\substack{u \in V \\ f(u,v) > 0}} f(u, v)$$

- The **positive net flow leaving a node**  $v$  is

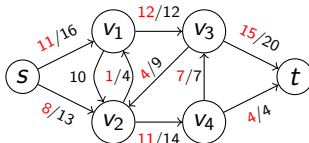
$$\sum_{\substack{u \in V \\ f(v,u) > 0}} f(v, u)$$

⇒ by flow conservation property: for all nodes  $v$ , the positive net flow entering node  $v$  = the positive net flow leaving node  $v$ .

# Network flow example



(a)



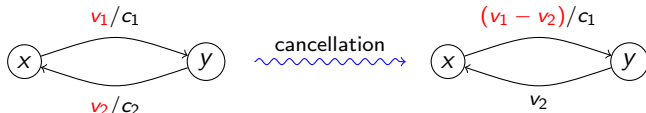
(b)

- (a) A flow network  $G = (V, E)$  with edges labeled with their capacities. The source is  $s$ , and destination is  $t$ .
- (b) A flow  $f$  in the flow network  $G$  with value  $|f| = 19$ . Only positive flows are shown. If  $f(u, v) > 0$ , edge  $(u, v)$  is labeled with  $f(u, v)/c(u, v)$ . (The slash notation is used merely to separate the flow and capacity; it does *not* indicate division.) If  $f(u, v) \leq 0$ , edge  $(u, v)$  is labeled only by its capacity.

# Network flows

Removing all negative net flows – the cancellation rule

If  $v_1 \geq v_2$  then

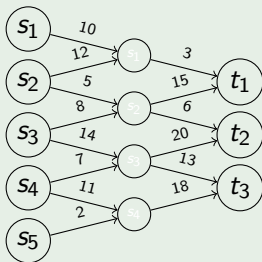


- Only positive net flows represent actual shipments.
- Applications of the cancellation rule
  - eliminate negative net flows.
  - do not violate the 3 requirements of a network flow:
    - 1 capacity constraint
    - 2 skew symmetry
    - 3 flow conservation

# Multiple sources and sinks

- A maximum-flow problem can have several sources  $s_1, \dots, s_m$  and sinks  $t_1, \dots, t_m$ .
- Such a problem can be reduced to an equivalent single-source single-sink maximum-flow problem:
  - add a **supersource**  $s$  and a **supersink**  $t$
  - add directed edges  $(s, s_i)$  with  $c(s, s_i) = \infty$  for  $i = 1..m$
  - add directed edges  $(t_j, t)$  with  $c(t_j, t) = \infty$  for  $j = 1..n$

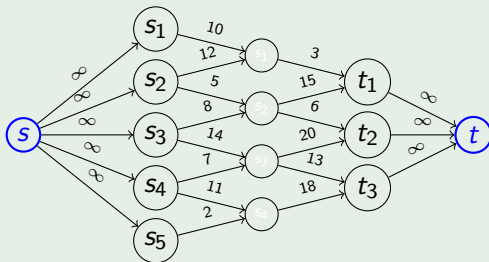
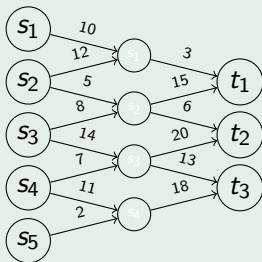
## Example



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  - add directed edges  $(t_j, t)$  with  $c(t_j, t) = \infty$  for  $j = 1..n$

## Example



# Working with flows

## Convention of notation

- Assume we know:
  - a flow network  $G = (V, E)$
  - a function  $f$  from  $V \times V$  to  $\mathbb{R}$
  - sets of nodes  $X, Y$  (that is,  $X \subseteq V, Y \subseteq V$ )
  - node  $u \in V$ .
- Then
  - $f(X, Y)$  represents the sum  $\sum_{x \in X} \sum_{y \in Y} f(x, y)$ .
  - $f(u, X)$  represents the sum  $\sum_{x \in X} f(u, x)$ .
  - $f(Y, u)$  represents the sum  $\sum_{y \in Y} f(y, u)$ .
  - $X - u$  represents the set  $X - \{u\}$ .

**Remark.** If  $f$  is a flow for  $G = (V, E)$  then  $f(u, V) = 0$  for all  $u \in V - \{s, t\}$ . This follows from the flow conservation constraint  $\Rightarrow f(V - \{s, t\}, V) = 0$ .

# Properties of flow networks

## Lemma

Let  $G = (V, E)$  be a flow network and  $f$  a flow in  $G$ . Then

- $f(X, X) = 0$  for all  $X \subseteq V$ .
- $f(X, Y) = -f(Y, X)$  for all  $X, Y \subseteq V$ .
- $f(X \cup Y, Z) = f(X, Z) + f(Y, Z)$  and  $f(Z, X \cup Y) = f(Z, X) + f(Z, Y)$  for all  $X, Y, Z \subseteq V$  with  $X \cap Y = \emptyset$ .

Note that:

$ f  = f(s, V)$	by definition
$= f(V, V) - f(V - s, V)$	by previous lemma
$= f(V, V - s)$	by previous lemma
$= f(V, t) + f(V, V - \{s, t\})$	by previous lemma
$= f(V, t)$	by flow conservation



## Definition

If  $f_1, f_2$  are flows in a flow network  $G$  and  $\alpha \in \mathbb{R}$ , then

- the **flow sum**  $f_1 + f_2$  of  $f_1$  and  $f_2$  is the function from  $V \times V$  to  $\mathbb{R}$  defined by

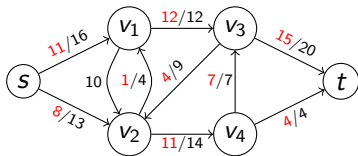
$$(f_1 + f_2)(u, v) := f_1(u, v) + f_2(u, v) \quad \text{for all } u, v \in V.$$

- the **scalar flow product**  $\alpha f_1$  is the function from  $V \times V$  to  $\mathbb{R}$  defined by

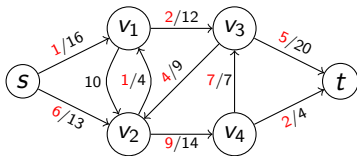
$$(\alpha f_1)(u, v) := \alpha f_1(u, v) \quad \text{for all } u, v \in V.$$

# Operations with flows

## Examples



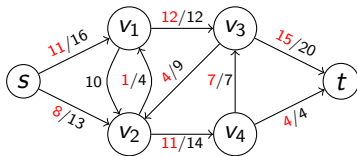
(a)  $G$  and  $f_1$



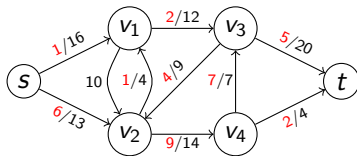
(b)  $G$  and  $f_2$

# Operations with flows

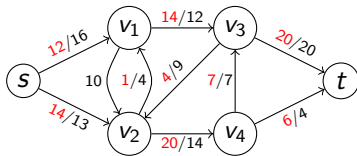
## Examples



(a)  $G$  and  $f_1$



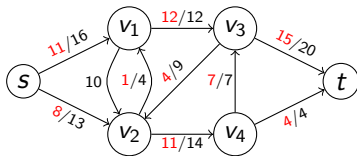
(b)  $G$  and  $f_2$



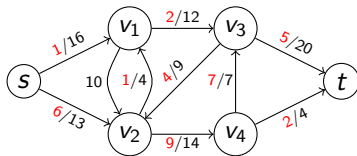
(c)  $G$  and  $f_1 + f_2$

# Operations with flows

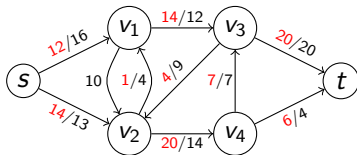
## Examples



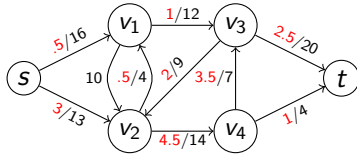
(a)  $G$  and  $f_1$



(b)  $G$  and  $f_2$



(c)  $G$  and  $f_1 + f_2$



(d)  $G$  and  $\alpha f_2$  when  $\alpha = \frac{1}{2}$

# Operations with flows

## Quizzes

A flow must satisfy 3 requirements: capacity constraint, skew symmetry, and flow conservation.

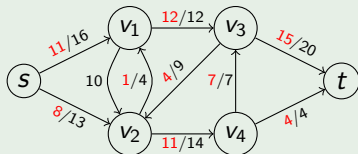
- 1 Which properties are not preserved by flow sums?
- 2 Which properties are not preserved by scalar flow products?
- 3 Show that, if  $f_1, f_2$  are flows and  $0 \leq \alpha \leq 1$ , then  $\alpha f_1 + (1 - \alpha) f_2$  is a flow.

# Residual networks

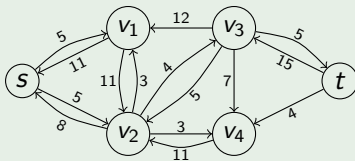
Assumptions: a flow network  $G = (V, E)$ ; flow  $f$  in  $G$ .

- The **residual capacity** of an edge  $(u, v)$  is  $c_f(u, v) := c(u, v) - f(u, v)$ .
- The **residual network** of  $G$  induced by  $f$  is the flow network  $G_f = (V, E_f)$  where  $E_f = \{(u, v) \in V \times V \mid c_f(u, v) > 0\}$ , and the capacity of every edge  $(u, v)$  is  $c_f(u, v)$ .

## Example



(a)  $G$  and  $f$



(b)  $G_f$

**Remark.** In general,  $|E_f| \leq 2|E|$ .

# Flows in residual networks

## Properties

Assume a flow network  $G$ , a flow  $f$  in  $G$ , and the residual network  $G_f$ . If  $f'$  is a flow in  $G_f$  then  $f + f'$  is a flow in  $G$  with value  $|f + f'| = |f| + |f'|$ .

PROOF.

- **Skew symmetry** holds because  $(f + f')(u, v) = f(u, v) + f'(u, v) = -f(v, u) - f'(v, u) = -(f(v, u) + f'(v, u)) = -(f + f')(v, u)$ .
- For the **capacity constraints**, note that  $f'(u, v) \leq c_f(u, v)$  for all  $u, v \in V$ , therefore  $(f + f')(u, v) = f(u, v) + f'(u, v) \leq f(u, v) + (c(u, v) - f(u, v)) = c(u, v)$ .
- For **flow conservation**, we note that

$$\begin{aligned}\sum_{v \in V} (f + f')(u, v) &= \sum_{v \in V} (f(u, v) + f'(u, v)) \\ &= \sum_{v \in V} f(u, v) + \sum_{v \in V} f'(u, v) = 0 + 0 = 0.\end{aligned}$$

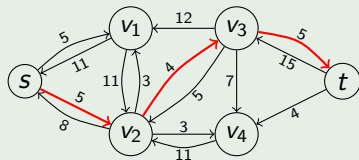
Finally, we have

$$|f + f'| = \sum_{v \in V} (f + f')(s, v) = \sum_{v \in V} (f(s, v) + f'(s, v)) = \sum_{v \in V} f(s, v) + \sum_{v \in V} f'(s, v) = |f| + |f'|.$$

# Augmenting paths

An **augmenting path** for a flow network  $G$  and a flow  $f$  is a simple path from  $s$  to  $t$  in the residual network  $G_f$ .

## Example (Augmented path)



## REMARKS.

- Each edge  $(u, v)$  of an augmenting path admits additional positive net flow without violating the capacity of the edge.
- In this example, we could ship up to 4 units more from  $s$  to  $t$  along the highlighted augmenting path, without violating any capacity constraint (Note: the smallest residual capacity on the highlighted augmenting path is 4).



## Augmenting paths (continued)

- The **residual capacity** of an augmenting path  $p$  is given by

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

### Lemma

Let  $G = (V, E)$  be a flow network with flow  $f$ ,  $p$  an augmenting path in  $G_f$ , and  $f_p : V \times V \rightarrow \mathbb{R}$  defined by

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

Then  $f_p$  is a flow in  $G_f$  with value  $|f_p| = c_f(p) > 0$ .

### Corollary

Let  $G = (V, E)$  be a flow network with flow  $f$ , and  $p$  be an augmenting path in  $G_f$ . Let  $f_p$  be the flow defined as in the previous lemma. Then  $f + f_p$  is a flow in  $G$  with value  $|f'| = |f| + |f_p| > |f|$ .

# The Ford-Fulkerson method

Yields a maximum flow for a given flow network  $G$ :

FORD-FULKERSON-METHOD( $G, s, t$ )

1 initialize flow  $f$  to 0

2 **while** there exists an augmenting path  $p$

3     augment flow  $f$  along  $p$

4 **return**  $f$

- The Ford-Fulkerson method works because the following result holds:

**A flow is maximum if and only if its residual network contains no augmenting path.**

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- ▷ We shall prove this fact.

**Auxiliary notions:** cut, capacity of a cut.



# Properties of cuts

## Lemma

The net flow across a cut  $(S, T)$  is  $f(S, T) = |f|$ .

## Corollary

For any flow  $f$  and any cut  $(S, T)$ , we have  $|f| \leq c(S, T)$ .

## Max-flow min-cut theorem

If  $f$  is a flow in a flow network  $G = (V, E)$  with source  $s$  and sink  $t$ , then the following conditions are equivalent:

- 1  $f$  is a maximum flow in  $G$ .
- 2  $G_f$  contains no augmenting paths.
- 3  $|f| = c(S, T)$  for some cut  $(S, T)$  of  $G$ .

# The max-flow min-cut theorem

## Proof

- (1)  $\Rightarrow$  (2) By contradiction: Assume  $f$  is a maximum flow in  $G$  and that  $G_f$  has an augmenting path  $p$ . Then  $f + f_p$  would be a flow in  $G$  with value strictly larger than  $|f|$ , contradicting the assumptions.
- (2)  $\Rightarrow$  (3) Suppose  $G_f$  has no augmenting path from  $s$  to  $t$ . Let
- $$S = \{v \in V \mid \text{there exists a path from } s \text{ to } v \text{ in } G_f\}$$
- and  $T = V - S$ . Then  $(S, T)$  is a cut because  $s \in S$  and  $t \notin S$ . For each pair of nodes  $(u, v) \in S \times T$  we have  $v(u, v) = c(u, v)$  because otherwise  $(u, v) \in E_f$  and  $v \in S$ . It follows that  $|f| = f(S, T) = c(S, T)$ .
- (3)  $\Rightarrow$  (1) We know that  $|f| \leq c(S, T)$  for all cuts  $(S, T)$  of  $G$ . Therefore, the condition  $|f| = c(S, T)$  implies that  $f$  is a maximum flow.

# The max-flow min-cut theorem

Why is this theorem called “max flow min-cut”?

Assume

- ①  $G = (V, E)$  is a flow network,
- ②  $f$  is a maximum flow in  $G$ ,
- ③  $(S, T)$  is a cut of  $G$  with minimum capacity.

Then

- $|f| = c(S', T')$  for some cut  $(S', T')$  of  $G$ . Since  $c(S, T) \leq c(S', T')$  (by assumption 3), we have  $c(S, T) \leq |f|$ .
- By Previous corollary,  $|f| \leq \text{capacity of any cut}$ ; in particular  $|f| \leq |c(S, T)|$ .

$\Rightarrow |f| = c(S, T)$ . This means that

- ▷ Value of maximum flow in  $G$  = minimum capacity of cut of  $G$ .

# The basic Ford-Fulkerson algorithm

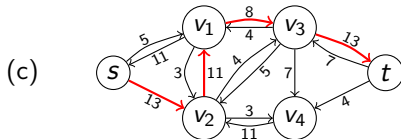
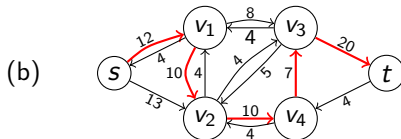
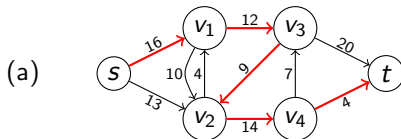
```
FORD-FULKERSON( $G, s, t$ )  
1 for each edge  $(u, v) \in E(G)$   
2    $f(u, v) := 0$   
3    $f(v, u) := 0$   
4 while  $\exists$  path  $p$  from  $s$  to  $t$  in  $G_f$   
5    $c_f := \min\{c_f(u, v) \mid (u, v) \text{ is in } p\}$   
6   for each edge  $(u, v)$  in  $p$   
7      $f(u, v) := f(u, v) + c_f(p)$   
8      $f(v, u) := -f(u, v)$ 
```



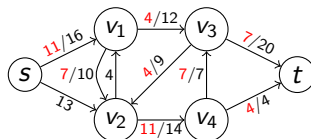
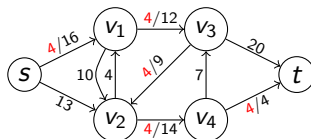
# The basic Ford-Fulkerson algorithm

## Running example

Residual network  $G_f$  with augmented path (line 4)



New flow that results from adding  $f_p$  to  $f$



...

**Exercise:** draw the graphs for the remaining steps of Ford-Fulkerson algorithm.

# The basic Ford-Fulkerson algorithm

## Complexity analysis

- The running time depends on how the augmenting path  $p$  is computed in line 4 of the algorithm.

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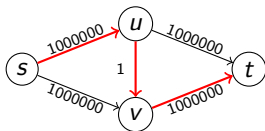
## Complexity analysis

- The running time depends on how the augmenting path  $p$  is computed in line 4 of the algorithm.
- ASSUMPTION: all edge capacities are integral numbers (that is,  $0, 1, 2, \dots$ ).
  - If the capacities are rational numbers, we can make them all integer, with an appropriate scaling transformation.
- A straightforward implementation of FORD-FULKERSON algorithm runs in time  $O(|E| \cdot |f^*|)$  where  $f^*$  is the maximum flow found by the algorithm.

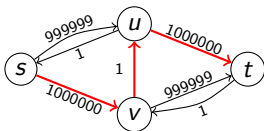
**Reason:** the **while** loop of lines 4-8 is executed at most  $|f^*|$  times, because the flow values increase by at least 1 in each iteration.

# Complexity analysis

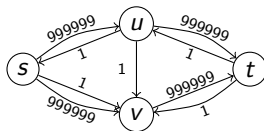
An example which takes  $\Theta(E \cdot |f^*|)$  time



(a)



(b)

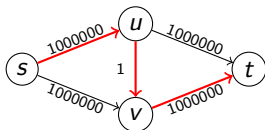


(c)

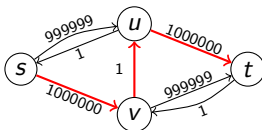
- A maximum flow  $f^*$  in flow network (a) has  $|f^*| = 2000000$ . A poorly chosen augmented path, with capacity 1, is highlighted.
- (b) and (c) illustrate resulting residual networks, after augmenting with the previously highlighted augmenting path.

# Complexity analysis

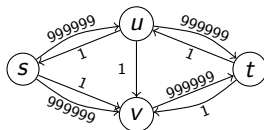
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(a)



(b)



(c)

- A maximum flow  $f^*$  in flow network (a) has  $|f^*| = 2000000$ . A poorly chosen augmented path, with capacity 1, is highlighted.
- (b) and (c) illustrate resulting residual networks, after augmenting with the previously highlighted augmenting path.
- Time complexity is improved if  $p$  in line 4 is computed with a breadth-first search, that is, if  $p$  is a *shortest* path from  $s$  to  $t$  in the residual network, where each edge has unit distance (weight)  $\Rightarrow$  **Edmonds-Karp algorithm** with runtime complexity  $O(|V| \cdot |E|^2)$ .

# Applications and extensions

## Application 1: Maximum bipartite matching

Let  $B = (V_1 \cup V_2, E)$  be a bipartite graph between subsets  $V_1$  and  $V_2$  of  $V$  (Note:  $V_1 \cap V_2 = \emptyset$ .)

### Definition

A **matching** in  $B$  is a set of edges  $M \subseteq E$  such that for all nodes  $v$  of  $G$ , at most one edge of  $M$  is incident on  $v$ . A **maximum matching** is a matching of maximum cardinality, that is, a matching  $M$  such that for any matching  $M'$ , we have  $|M| \geq |M'|$ .



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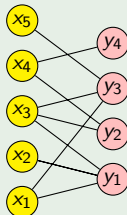
A maximum bipartite matching of  $B = (V_1 \cup V_2, E)$  can be found as follows:

- 1 Extend  $B$  with 2 new nodes:  $s$  (**supersource**) and  $t$  (**supersink**). Orient all edges of  $G$  from  $V_1$  to  $V_2$ . Add edges from  $s$  to all sources of  $G$ , and from all sinks of  $G$  to  $t$ . All edges in the extended network have capacity 1.
- 2 Compute a maximum flow in the newly constructed flow network with source  $s$  and sink  $t$ .

# Applications and extensions

## Application 1: Maximum bipartite matching

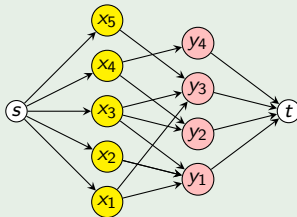
### Example



# Applications and extensions

## Application 1: Maximum bipartite matching

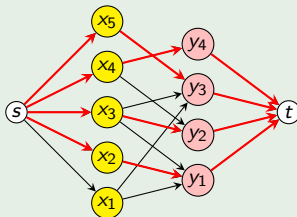
### Example



# Applications and extensions

## Application 1: Maximum bipartite matching

### Example

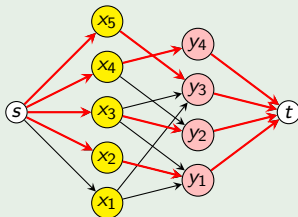


Maximum matching  $C = \{(x_2, y_1), (x_3, y_2), (x_4, y_4), (x_5, y_3)\}$

# Applications and extensions

## Application 1: Maximum bipartite matching

### Example



Maximum matching  $C = \{(x_2, y_1), (x_3, y_2), (x_4, y_4), (x_5, y_3)\}$

### Theorem

*Let  $G$  be the flow network constructed for a bipartite graph  $B = (V_1 \cup V_2, E)$ , and  $f$  a maximum flow in  $G$  computed with Ford-Fulkerson logarithm. Then the set of edges  $(u, v)$  of  $f$  with  $u \in V_1$ ,  $v \in V_2$  and  $f(u, v) = 1$  is a maximum matching of  $B$ .*

# Applications and extensions

## Application 2: Maximum flow with minimum cost

### Problem

$G = (V, E)$ : flow network in which every edge  $(u, v)$  has a capacity  $c(u, v)$  and a unit cost  $k(u, v) \geq 0$ .

A **maximum flow with minimum cost** in  $G$  is a maximum flow  $f$  in  $G$  such that the sum

$$\sum_{(u,v) \in E} f(u, v) \cdot k(u, v)$$

is minimum.

# Applications and extensions

## Application 2: Maximum flow with minimum cost

### Solution: Adjustment of Edmonds-Karp algorithm

- Attach costs to all edges of the residual networks of a flow  $f$ :
  - edge  $(u, v)$  has cost  $k(u, v)$  if  $c(u, v) > f(u, v)$  in the original flow network
  - edge  $(u, v)$  has cost  $-k(u, v)$  if  $f(u, v) < 0$  in the original flow network
- Instead of shortest simple path from source  $s$  to sink  $t$ , this algorithm finds a path  $p$  from  $s$  to  $t$  with minimum cost in the residual network.
  - $p$  can be found with Bellman-Ford algorithm.
- Next, the flow is incremented along path  $p$  with the maximum possible value (=minimum of the differences between capacity and flow, for every arc of  $p$ ).

Chapter 27 from

- T. H. Cormen, C. E. Leiserson, R. L. Rivest. *Introduction to Algorithms*. MIT Press, 2000.