# Lecture 16: Max-Flow \& Min-Cut 

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## Overview

- Paths, Flows \& Cuts
- Paths
- Flows
- Cuts
- Ford-Fulkerson Algorithm
- Residual Graph
- Main Algorithm
- Acknowledgements


## Paths: Measure of "Resilience"

- Given (directed) graph $G(V, E)$, we would like to know how "resilient" it may be
- Is $G$ (strongly) connected?
- How many edges does one need to remove to disconnect it?
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- More generally, can consider weighted directed graphs
- networks: edge weights are how much data can go through
- traffic system: edge weights are how much traffic can go through Weighted version is (almost) the maximum flow problem.


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Weighted version is (almost) the maximum flow problem.

- How to generalize notion of edge-disjoint in weighted version?


## Flows

- We will now think of a weighted graph $G(V, E, c)$, where
$c: E \rightarrow \mathbb{R}_{>0}$ (the weight function) is giving the capacity of an edge
If we have $c: E \rightarrow \mathbb{N}$ then
- Think of capacity as number of lanes in a street/highway
- Or think of $G(V, E, c)$ as unweighted graph with $c((u, v))$ being the number of distinct $u \rightarrow v$ edges


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- An $s \rightarrow t$ flow is a function $f: E \rightarrow \mathbb{R}_{\geq 0}$ with the properties:
(1) Capacity constraints: $0 \leq f(e) \leq c(e)$ for all $e \in E$
(2) Flow conservation: $f_{\text {in }}(u)=f_{\text {out }}(u)$ for each $u \in V \backslash\{s, t\}$, where

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f_{\text {in }}(u):=\sum_{w \in N_{\text {in }}(u)} f(w, u), \quad \text { and } f_{\text {out }}(u):=\sum_{w \in N_{\text {out }}(u)} f(u, w)
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- The value of a flow $f$ is value $(f):=f_{\text {out }}(s)-f_{\text {in }}(s)$

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- Max-flow problem:
- Input: directed graph $G(V, E, c)$, with $c: E \rightarrow \mathbb{R}_{>0}$, vertices $s, t \in V$
- Output: an $s \rightarrow t$ flow with maximum value.


## Example (from Jeff Erickson's book)



SECRET $\begin{aligned} & \substack{506-1973 \\ 10-24-95 \\-33-}\end{aligned}$

Fig. 7 - Traffic pattern: entire network available

Legend:
-... International boundary
(B) Railway operating division

- 12 - Copacity: 12 each way per doy. atauired flow of 9 per day toward destinations (in direction of arrow) with equivalent numbar of returning
trains in opposite direction

All eapacifies in trains $\left.\begin{array}{c}\text { troon's of tons }\end{array}\right\}$ each way per day
Origins: Divisions $2,3 \mathrm{~W}, 3 \mathrm{E}, 25,13 \mathrm{~N}, 13 \mathrm{~s}$,
12,52 (USSR), and Roumania
Pestinctions: Divisions 3, 6,9 (Poland);
B (Czechaslovavakio); and 2, 3 (Austr la)
Alternativa destinations: Germany or Eas? Germany

Note IIX at Dívision 9, Polanid

Figure 10.1. Harris and Ross's map of the Warsaw Pact rail network. (See Image Credits at the end of the book.)

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- Think of capacity as number of lanes in a street/highway
- Or think of $G(V, E, c)$ as unweighted graph with $c((u, v))$ being the number of distinct $u \rightarrow v$ edges
Integral flow $f$ (i.e. $f: E \rightarrow \mathbb{N}$ ) with value $(f)=k$ corresponds to $k$ edge-disjoint paths in the unweighted graph $G(V, E, c)$ above
- Think of edge $e$ with $f(e)=h$ as the collections of paths using $h$ lanes in highway
- flow conservation $\leftrightarrow \#$ cars entering vertex $u=$ \# cars leaving vertex $u$
- capacity constraints $\leftrightarrow$ each car gets one lane in highway


## Example

(aloo in Jeffés book)


Path decomposition lemma

Lemma (Path Decomposition Lemma)
Let $G$ be a weighted DAG with integral weights. Let $f$ be an integral $s \rightarrow t$ flow, with $f_{\text {in }}(s)=0$ and value $(f)=k$. Then, there are $s \rightarrow t$ paths $P_{1}, \ldots, P_{k}$ such that each edge $e$ appears in $f(e)$ of these paths.

Remark: for full "flow decomposition theorem" see Jeff Erickson's book, chapter 10.

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- an $s-t$ cut is a cut $(S, V \backslash S)$ such that $s \in S$ and $t \notin S$.
- Capacity of cut:

$$
C_{\text {out }}(S):=\sum_{e \in \delta_{\text {out }}(S)} c(e)
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where $\delta_{\text {out }}(S)=\{(u, v) \in E \mid u \in S, v \notin S\}$

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- By path decomposition lemma or flow conservation, can prove that

$$
\operatorname{value}(f) \leq C_{\text {out }}(S)
$$

for any flow $f$ and cut $S$.

Example

note that st cut $\{s, a, b, u\}$ gives better upper bound than $\{s\}$.

## Max-Flow Min-Cut Theorem

- Capacity of cuts are an upper bound for flows. Is this a tight upper bound?


## Theorem (Max-Flow Min-Cut Theorem)

The value of the maximum $s-t$ flow equals the minimum capacity among all cuts.

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\max _{f-t \text { flow }} \operatorname{value}(f)=\min _{S \text { is } s-t \text { cut }} C_{\text {out }}(S)
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- We will give an algorithmic proof of this theorem, that solves the max-flow and the min-cut problem at the same time.
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- Flows
- Cuts
- Ford-Fulkerson Algorithm
- Residual Graph
- Main Algorithm


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- Natural (greedy) strategy: by path decomposition lemma, we could just keep finding $s \rightarrow t$ paths in the graph
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Main idea behind Ford-Fulkerson.

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Main idea behind Ford-Fulkerson.

- Augment the flow by finding "augmenting path" which increases total amount of flow

Example
(bad greedy example)

all capacities 1 .
Shortest path in red would block max flow in green

## Residual Graph

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- The residual graph is the object we will study to find augmenting paths
- Given $G(V, E, c)$ and $s \rightarrow t$ flow $f$ on $G$, define the residual graph $G_{f}$ as follows:
- $V\left(G_{f}\right)=V(G)$
- For each $(u, v)=: e \in E$ add edges
- $(u, v)$ to $G_{f}$ with capacity $c(e)-f(e)$
- $(v, u)$ to $G_{f}$ with capacity $f(e)$
(forward edges)
(backward edges)

Example


## Augmenting Path

- An augmenting path with respect to a flow $f$ is simply an $s \rightarrow t$ path ${ }^{1}$ in $G_{f}$

[^0]
## Augmenting Path

- An augmenting path with respect to a flow $f$ is simply an $s \rightarrow t$ path ${ }^{1}$ in $G_{f}$
- Given augmenting path $P$ in $G_{f}$, want to push as much flow as possible through it:
bottleneck $(P, f):=$ minimum capacity of edge of $P$ in $G_{f}$

[^1]Example
In previous residual graph, have following

$$
\operatorname{bottlenech}(P, p)=1
$$ augmenting path.



## Improving the Flow

- Input: flow $f$ and an augmenting path $P$ in $G_{f}$
- Output: improved flow $f^{\prime}$


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- Input: flow $f$ and an augmenting path $P$ in $G_{f}$
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augment $(f, P)$ :
- Let $b:=\operatorname{bottleneck}(P, f)$ and $f^{\prime}(e)=f(e)$ for all $e \in E$
- for each $e:=(u, v) \in P$ :
- If $e$ forward edge:

$$
f^{\prime}(e)=f^{\prime}(e)+b
$$

- If $e$ backward edge:

$$
f^{\prime}(v, u)=f^{\prime}(v, u)-b
$$

(decrease reversed edge)

- return $f^{\prime}$


## Improving Flow

## Lemma (Flow Improvement)

Let $f$ be a flow in $G$ with $f_{\text {in }}(s)=0$ and $P$ an augmenting path with respect to $f$. If $f^{\prime}$ is the output from augment $(f, P)$, then $f^{\prime}$ is a flow with

$$
\operatorname{value}\left(f^{\prime}\right)=\operatorname{value}(f)+\operatorname{bottleneck}(P, f)
$$

and $f_{\mathrm{in}}^{\prime}(s)=0$.

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- To check that $f^{\prime}$ is a flow, need to check capacity constraint and flow conservation constraint.


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- Let $b:=\operatorname{bottleneck}(P, f)$.
- Capacity constraint: given $e \in E\left(G_{f}\right)$, we have
- e forward edge in $G_{f}$, then

$$
f^{\prime}(e)=f(e)+b \leq f(e)+(c(e)-f(e))=c(e)
$$

- $e:=(u, v)$ backward edge in $G_{f}$, then

$$
f^{\prime}(v, u)=f(v, u)-b \leq f(v, u) \leq c(v, u)
$$

and

$$
f^{\prime}(v, u)=f(v, u)-b \geq f(v, u)-f(v, u) \geq 0
$$

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and $f_{\text {in }}^{\prime}(s)=0$.

- Let $b:=\operatorname{bottleneck}(P, f)$.
- Flow Conservation: let $u \in V$ be a vertex.
- if $u \notin P$ then flow in and out of $u$ doesn't change.


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- Let $b:=\operatorname{bottleneck}(P, f)$.
- Flow Conservation: let $u \in V$ be a vertex.
- if $u \in P$, have 4 cases to analyze. Let $e_{1}:=(w, u)$ and $e_{2}:=(u, z)$ be the edges in $P$ passing through $u$ in $G_{f}$.
(1) $e_{1}, e_{2}$ forward edges: both incoming and outgoing flow increase by $b$
(2) $e_{1}, e_{2}$ backward edges: both incoming and outgoing flow decrease by $b$
(3) $e_{1}$ forward, $e_{2}$ backward: both incoming and outgoing flow unchanged
(4) $e_{1}$ backward, $e_{2}$ forward: both incoming and outgoing flow unchanged


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and $f_{\text {in }}^{\prime}(s)=0$.

- Let $b:=\operatorname{bottleneck}(P, f)$.
- Value of flow $f^{\prime}$ and $f_{\text {in }}^{\prime}(s)$ :
- $f_{\text {in }}(s)=0 \Rightarrow$ no backward edges incident to $s$ in $G_{f}$

$$
f_{\mathrm{in}}^{\prime}(s)=f_{\mathrm{in}}(s)+0=f_{\mathrm{in}}(s)=0
$$

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- Let $b:=\operatorname{bottleneck}(P, f)$.
- Value of flow $f^{\prime}$ and $f_{\text {in }}^{\prime}(s)$ :
- Value of $f^{\prime}$ : by previous bullet, only forward edges out of $s$, thus:

$$
\operatorname{value}\left(f^{\prime}\right)=f_{\text {out }}^{\prime}(s)=f_{\text {out }}(s)+b=\operatorname{value}(f)+b
$$

## Ford-Fulkerson Algorithm

Now that we know that augmenting paths can only improve our flow, we can describe Ford-Fulkerson, which simply applies the augmenting operation until we can no longer do it.

- Ford-Fulkerson $(G)$ :
(1) Initialize $f(e)=0$ for all $e \in E$, and initialize $G_{f}$ accordingly
(2) While there is $s \rightarrow t$ path $P \in G_{f}$ :
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Next lecture: runtime analysis and proof of correctness.

## Acknowledgement

## Based on

- Prof. Lau's Lecture 15
https://cs.uwaterloo.ca/~lapchi/cs341/notes/L15.pdf
- Jeff Erickson's book, Chpater 10
https://jeffe.cs.illinois.edu/teaching/algorithms/book/ 10-maxflow.pdf


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