CSE 421 Introduction to Algorithms

Lecture 15: Network Flow

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Announcements

Midterm Reminder:

- Date:
 - Next Monday, November 4, 6:00 7:30 pm in this room
 - Exam designed for a regular class time-slot but this includes extra time to finish.
- Coverage:
 - Up to the end of last Thursday's section on Dynamic Programming
- Sample midterm for practice problems and length posted yesterday.
 - Includes "summary sheet" available to you on the midterm.
- This week's section will focus on review problems.
- Zoom review session for Q&A on Sunday Nov 3 at 4:45 pm. (No conflict with the Seahawks game.)

Maximum Flow and Minimum Cut

Max flow and min cut:

- Two very rich algorithmic problems.
- Cornerstone problems in combinatorial optimization.
- Beautiful mathematical duality.

Nontrivial applications / reductions:

- Data mining.
- Project selection.
- Airline scheduling.
- Bipartite matching.
- Baseball elimination.
- Image segmentation.
- Network connectivity.
- Strip mining.
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- Network reliability.
- Distributed computing.
- Egalitarian stable matching.
- Security of statistical data.
- Network intrusion detection.
- Multi-camera scene reconstruction.
- many many more ...

Origins of Max Flow and Min Cut Problems

Max Flow problem formulation:

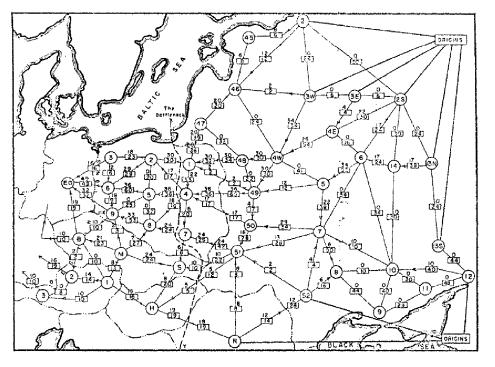
• [Tolstoy 1930] Rail transportation planning for the Soviet Union

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

Soviet Rail Network 1955

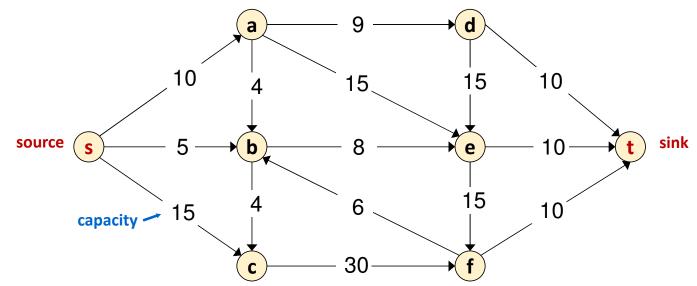


Reference: On the history of the transportation and maximum flow problems. Alexander Schrijver in Math Programming, 91: 3, 2002.

Flow Network

Flow network:

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

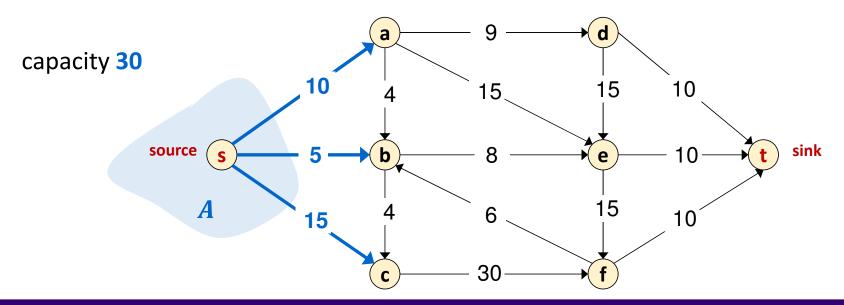




Cuts

Defn: An *s*-*t* cut is a partition (A, B) of *V* with $s \in A$ and $t \in B$. The capacity of cut (A, B) is

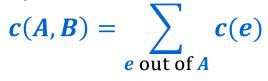


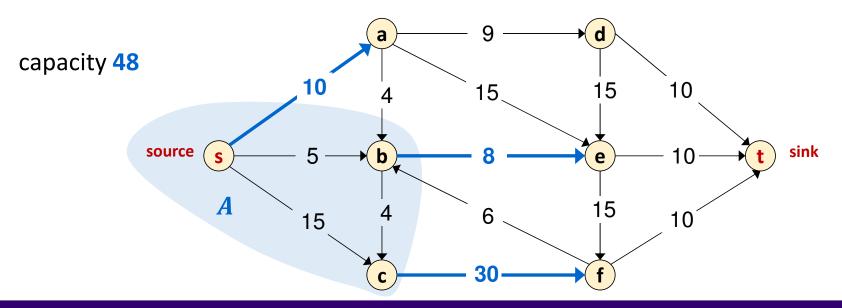




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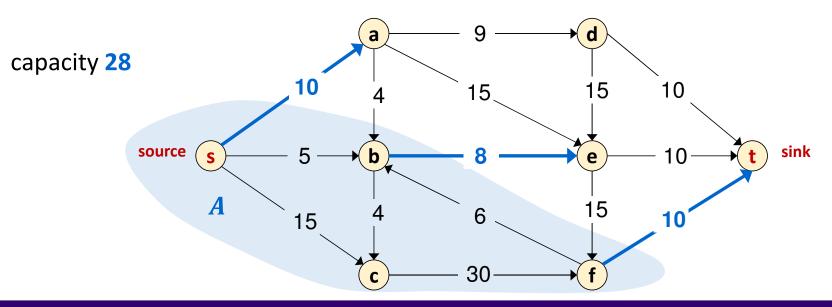


Minimum Cut Problem

Minimum s-t cut problem:

Given: a flow network

Find: an *s*-*t* cut of minimum capacity



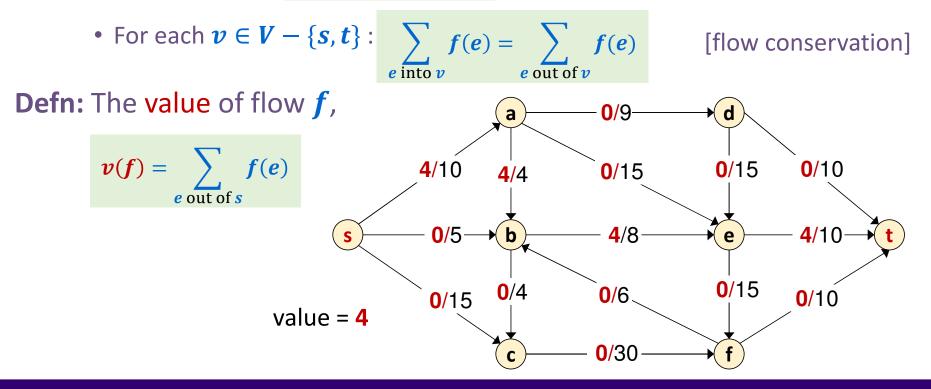


Flows

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

• For each $e \in E$: $0 \leq f(e) \leq c(e)$

[capacity constraints]



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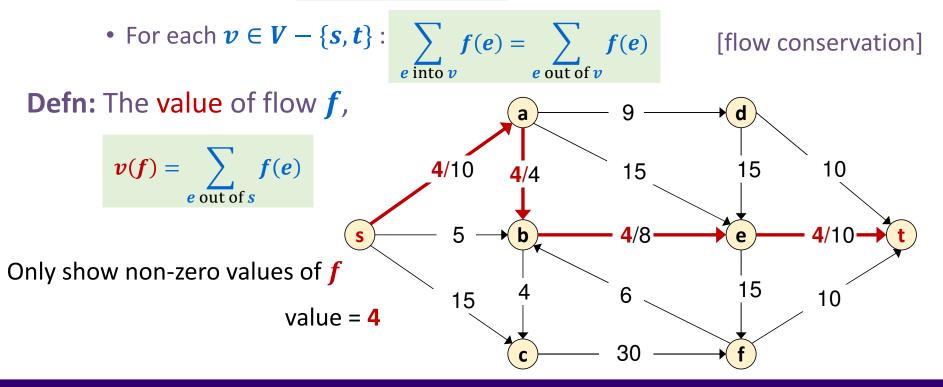
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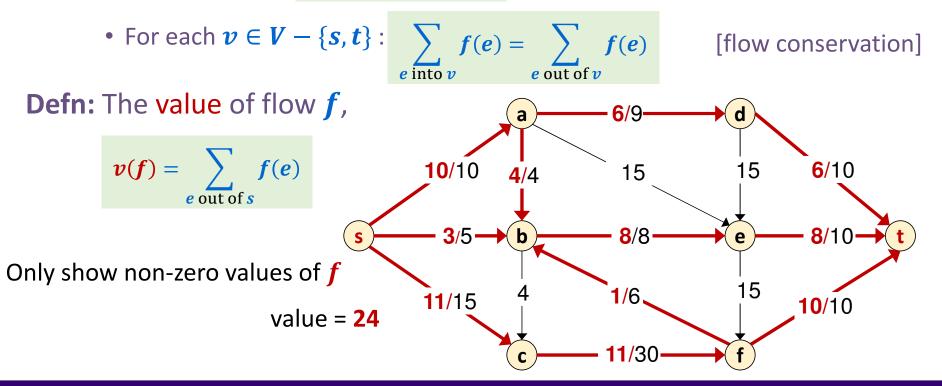


Flows

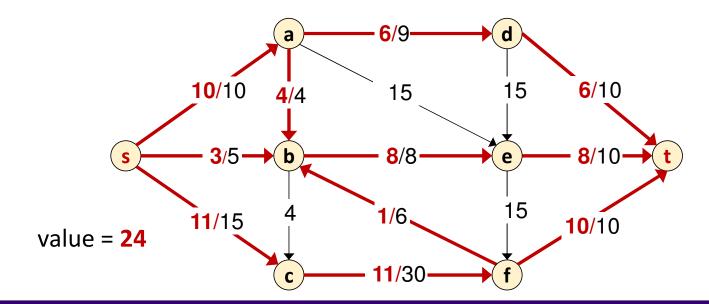
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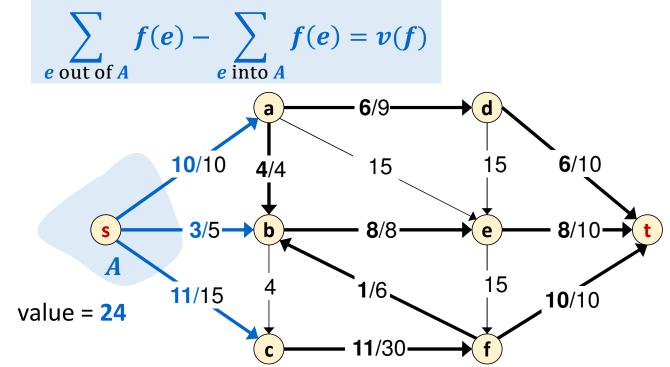
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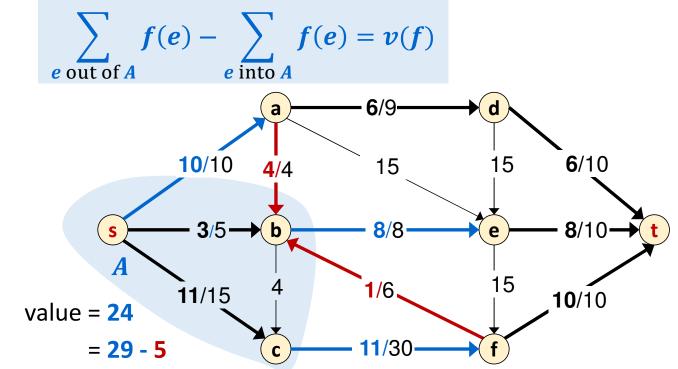
Given: a flow network **Find:** an *s*-*t* flow of maximum value



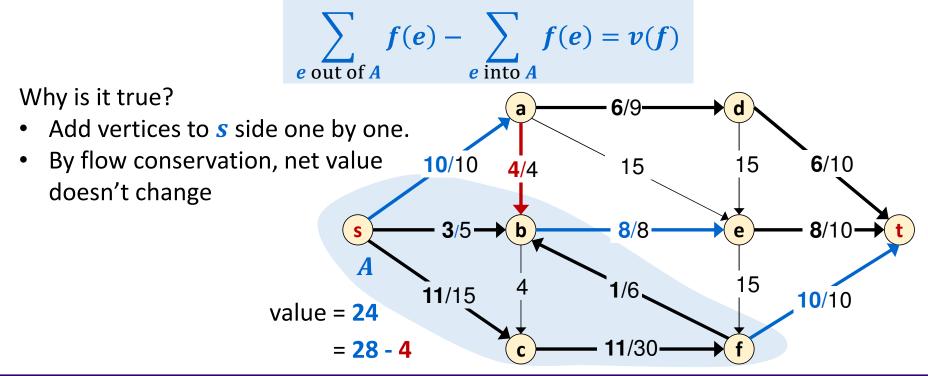


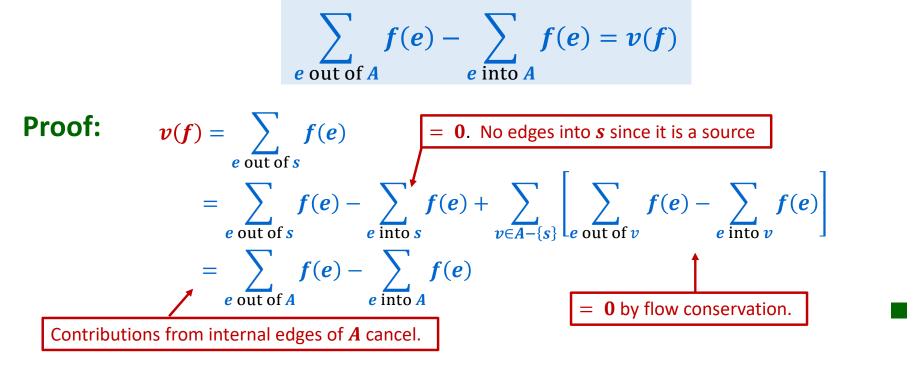






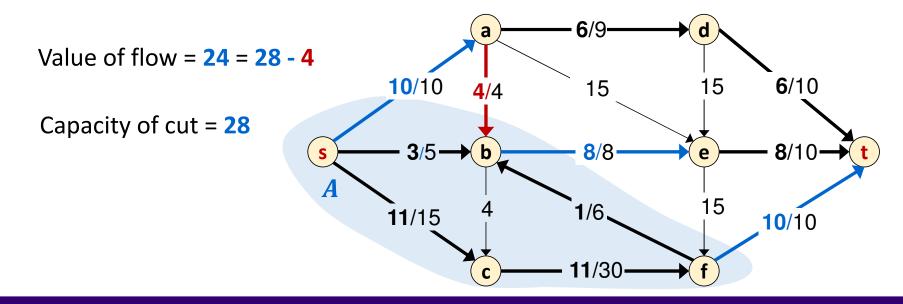






Flows and Cuts

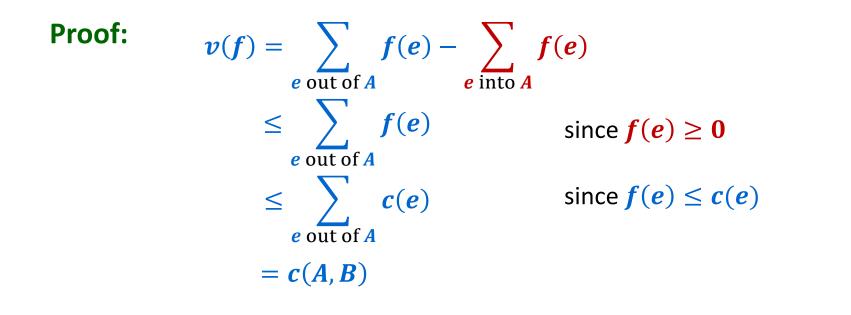
Weak Duality: Let f be any s-t flow and (A, B) be any s-t cut. The value of the flow is at most the capacity of the cut; i.e., $v(f) \le c(A, B)$:



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Flows and Cuts

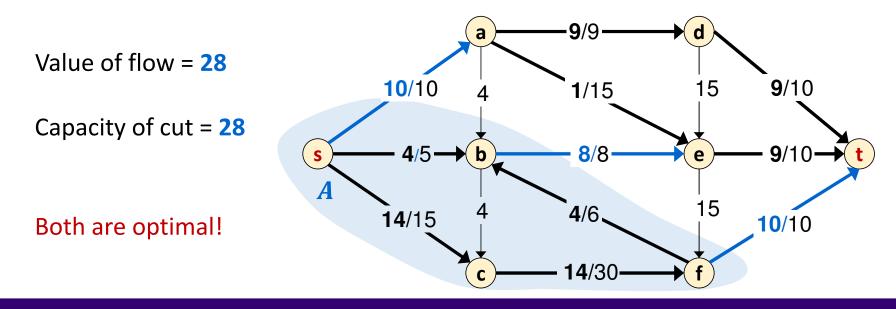
Weak Duality: Let f be any s-t flow and (A, B) be any s-t cut. The value of the flow is at most the capacity of the cut; i.e., $v(f) \le c(A, B)$.



Certificate of Optimality

Corollary: Let **f** be any **s**-**t** flow and (**A**, **B**) be any **s**-**t** cut.

If v(f) = c(A, B) then f is a max flow and (A, B) is a min cut.



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Towards a Max Flow Algorithm

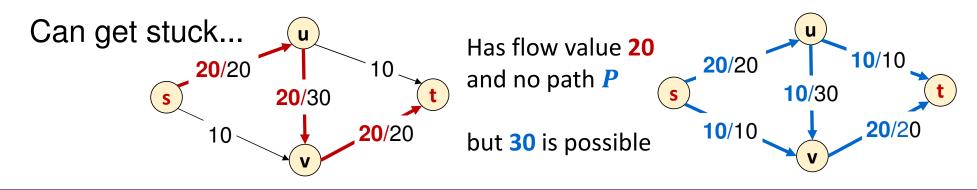
What about the following greedy algorithm?

- 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 $\nu(f)$.)

Towards a Max Flow Algorithm

What about the following greedy algorithm?

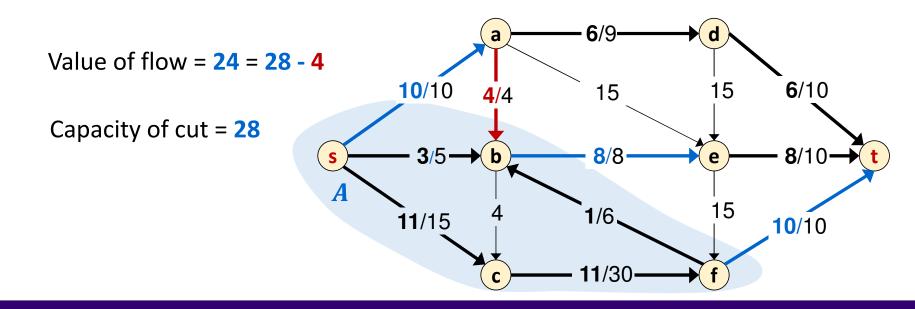
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 - Add α to flow on every edge e along path P. (Adds α to v(f).)



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Another Stuck Example

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



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Flows and cuts so far

Let **f** be any **s**-**t** flow and (**A**, **B**) be any **s**-**t** cut:

Flow Value Lemma: The net value of the flow sent across (A, B) equals v(f).

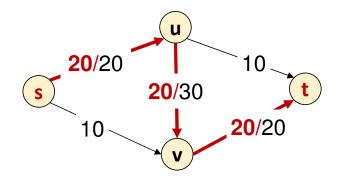
Weak Duality: The value of the flow is at most the capacity of the cut; i.e., $v(f) \le c(A, B)$.

Corollary: If v(f) = c(A, B) then f is a maximum flow and (A, B) is a minimum cut.

Augmenting along paths using a greedy algorithm can get stuck.

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!

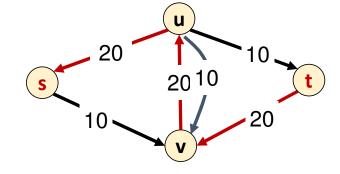
Greed Revisited: Residual Graph & Augmenting Paths



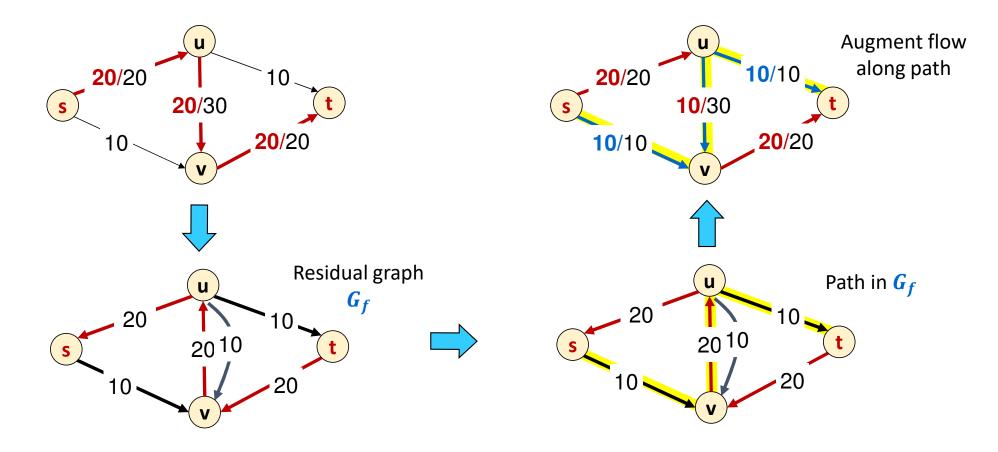
The only way we could route more flow from **s** to **t** would be to reduce the flow from **u** to **v** to make room for that amount of extra flow from **s** to **v**. But to conserve flow we also would need to increase the flow from **u** to **t** by that same amount.

Suppose that we took this flow **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 G_f of possible changes where we draw reducing as "sending back".



Greed Revisited: Residual Graph & Augmenting Paths



Greed Revisited: Residual Graph & Augmenting Paths

