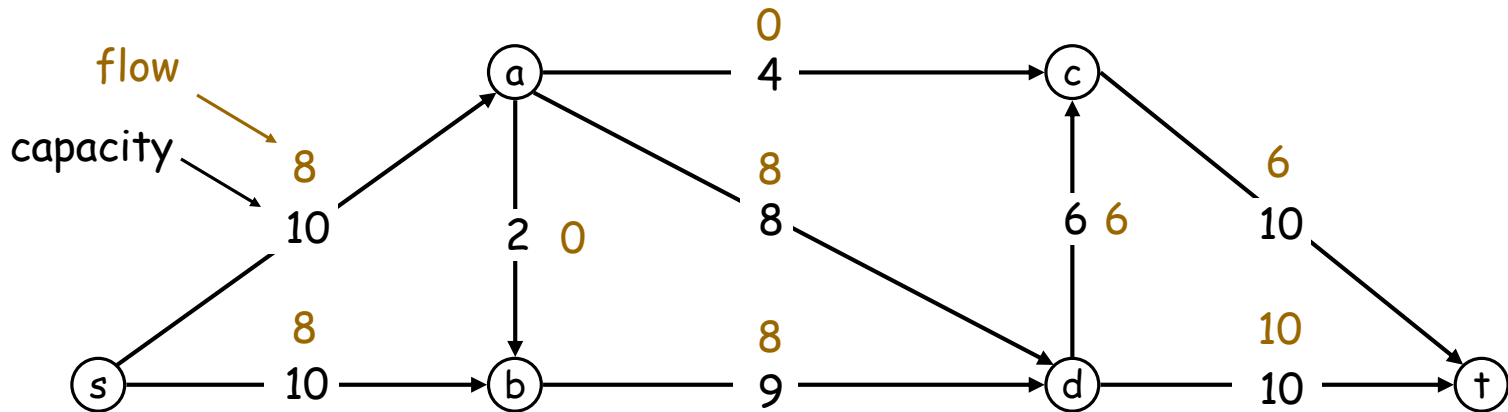

CSC3160: Design and Analysis of Algorithms

Week 8: Maximum Network Flow

Instructor: Shengyu Zhang

Transportation

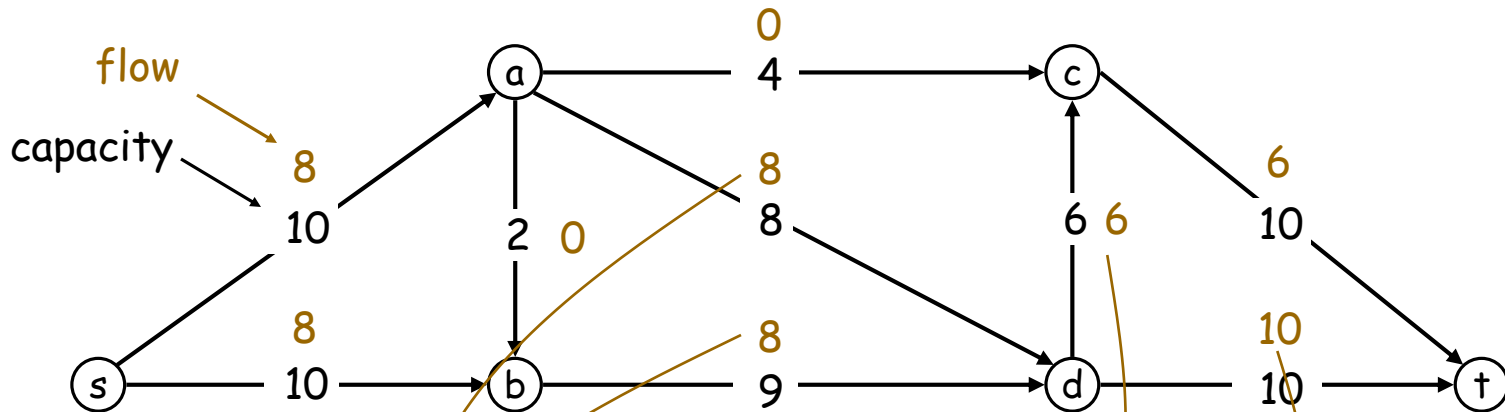
Total Flow: 16



- Suppose we want to transport commodity from s to t in a **directed** graph $G = (V, E)$.
- Each **directed** edge $(u, v) \in E$ has a **capacity**
 - Max amount of commodity allowed
- *Question: How much can we transport?*

Technically

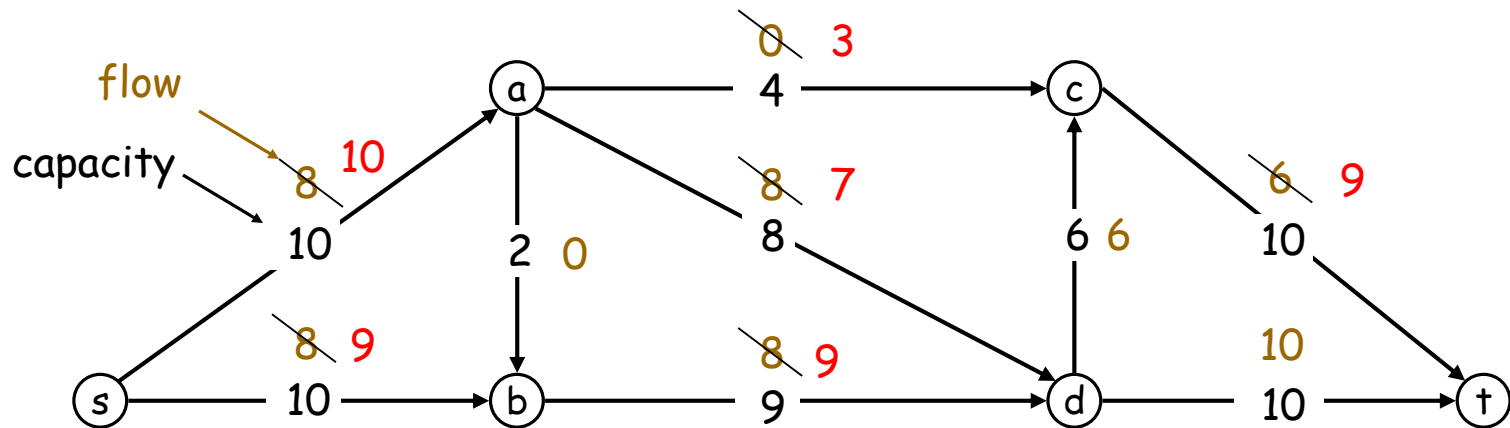
Total Flow: 16



- We have a capacity function $c: E \rightarrow \mathbb{R}^+$.
- We want a flow function $f: E \rightarrow \mathbb{R}^+$, s.t.
 - **Capacity constraint:** $\forall (u, v) \in E, f(u, v) \leq c(u, v)$.
 - **Flow conservation:** $\forall u \notin \{s, t\}$,
 - $\sum_{(v,u) \in E} f(v, u) = \sum_{(u,v) \in E} f(u, v)$
 - Incoming flow = outgoing flow
 - **Goal:** $\max_f \left(\sum_{(s,v) \in E} f(s, v) - \sum_{(u,s) \in E} f(u, s) \right)$
 - Net flow = flow going out of source - flow coming back into source

Improve it 😊

Total Flow: ~~16~~ 19



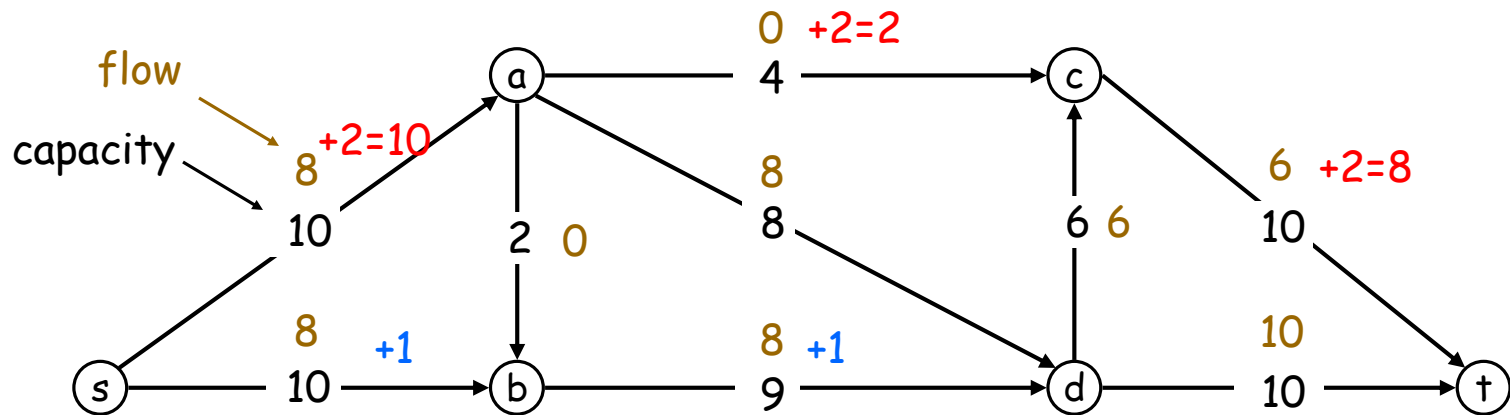
- Can we improve this?
 - For some edges: we gave too much.
 - For some other edges: we didn't give enough.
- Can we further improve this?

Network Flow

- Can you give a good algorithm?
- Methodology 5: Approach to the optimum by a sequence of improvements.

Improve it little by little

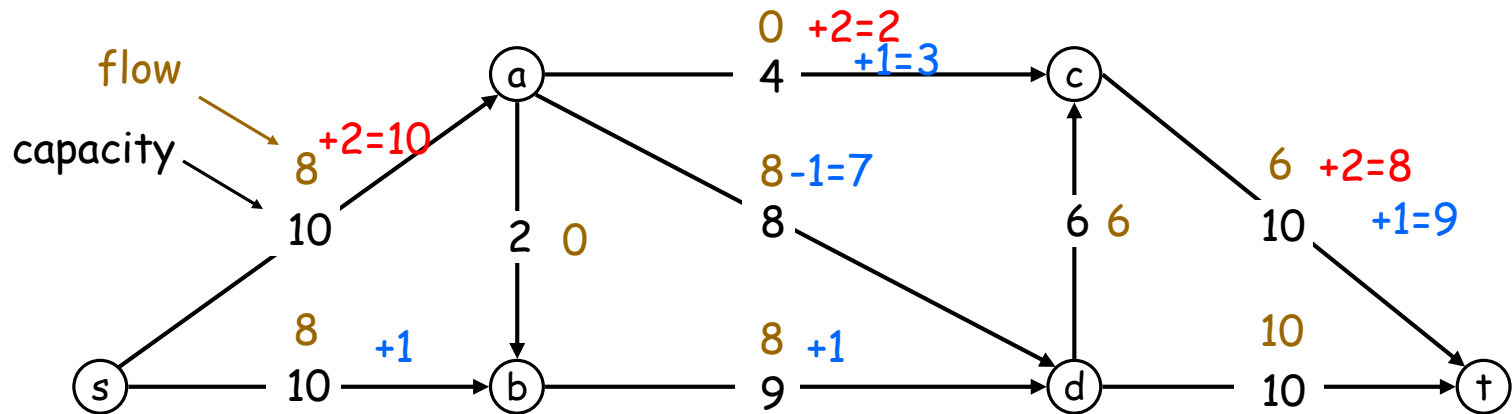
Total Flow: ~~16~~ 18



- We can find a path $s \rightarrow a \rightarrow c \rightarrow t$ on which we can add 2 (on every edge)
- Total flow becomes **18**.
- We also like to add 1 via $s \rightarrow b \rightarrow d \rightarrow t, \dots$
- but the edge $d \rightarrow t$ is a **bottleneck**.
 - Actually the edge $d \rightarrow c$ is as well.

Improve it little by little

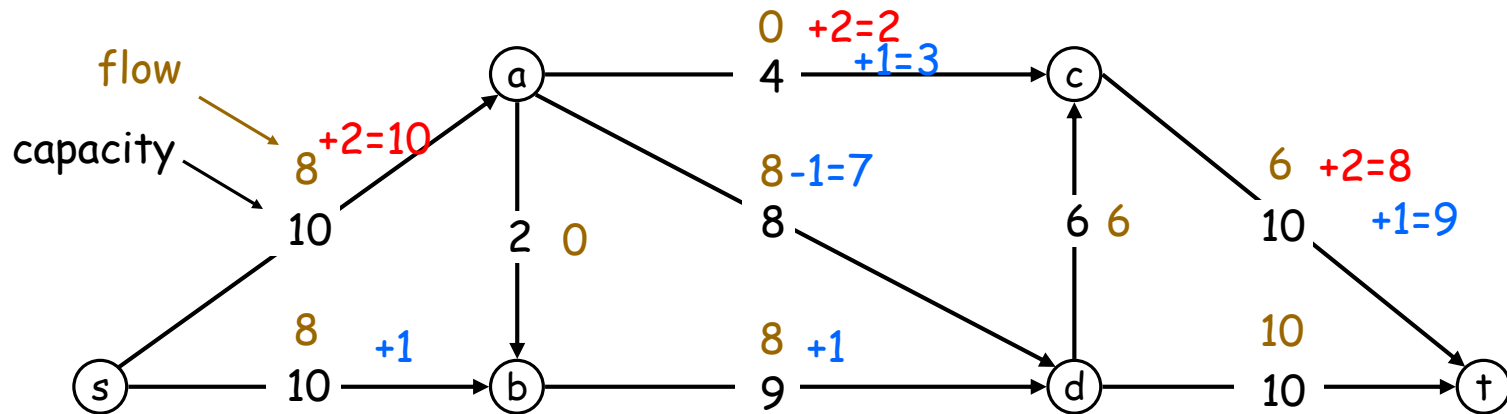
Total Flow: ~~16~~ ~~18~~ 19



- We can still squeeze some juice along the path $a \rightarrow c \rightarrow t$.
- But vertex a already allocates all its incoming 10 flow.
- Let's **withdraw** 1 unit on the edge $a \rightarrow d$ and assign it along $a \rightarrow c \rightarrow t$!
- Total flow becomes **19**.
- In some sense, it looks like we injected a unit of flow along $s \rightarrow b \rightarrow d \rightarrow a \rightarrow c \rightarrow t$.

Improve it little by little

Total Flow: ~~16~~ ~~18~~ 19



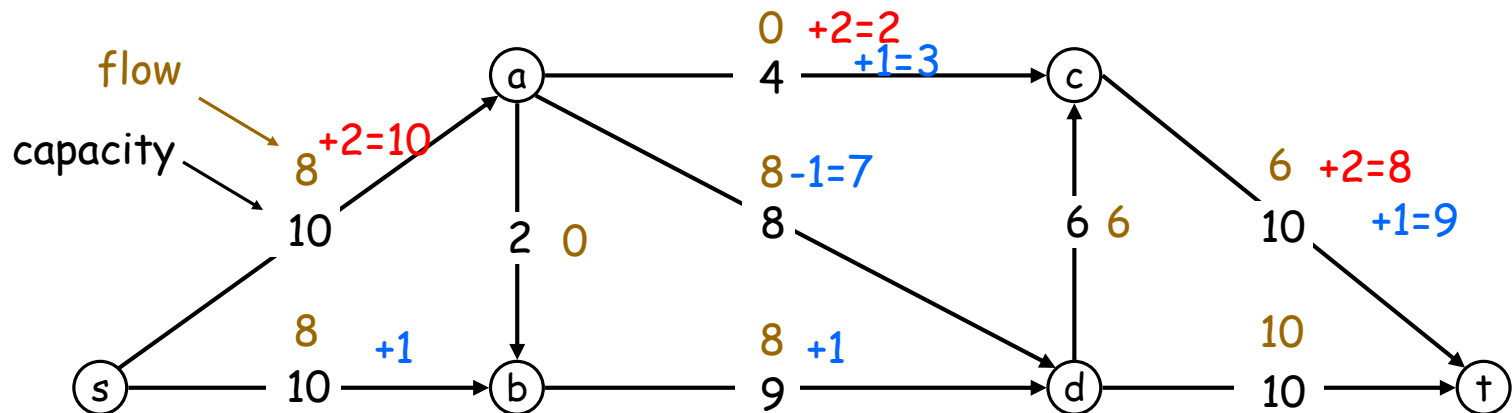
Ford-Fulkerson Algorithm:

- initialize flow f to 0
- **while** there exists an *augmenting path* p
 - Inject more flow along p (as much as possible)
- **return** f

- **Question 1**: What is an *augmenting path*?

Improve it little by little

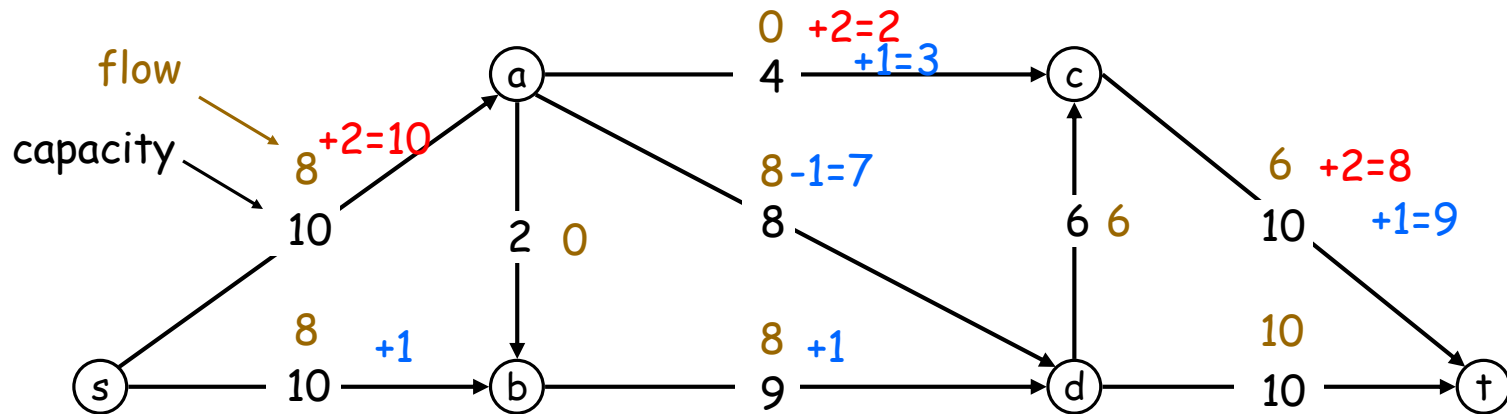
Total Flow: ~~16~~ ~~18~~ 19



- **Case 1:** if the capacity hasn't been used up for each edge on the path, then it's an augmenting path.
- **Case 2:** if some edge $u \rightarrow v$ already has a flow, then it amounts to a capacity in direction $v \rightarrow u$
 - By withdrawing the previously assigned flow.

Improve it little by little

Total Flow: ~~16~~ ~~18~~ 19

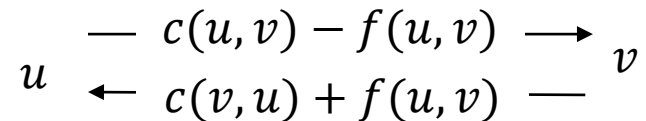
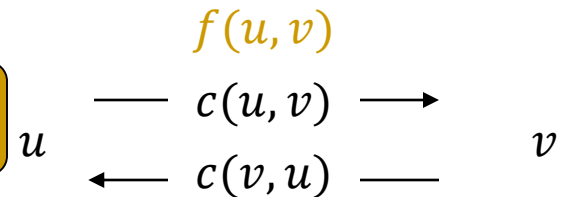


- **Question 2:** How to find an augmenting path?
- By *residual networks*.

Residual networks

- For a flow f , the **residual capacity** c_f is:
 - $c_f(u, v) = c(u, v) - f(u, v)$
 - $c_f(v, u) = c(v, u) + f(u, v)$
- **Residual network:**
 - $G_f = (V, E_f)$, where
 - $E_f = \{(u, v) \in V \times V : c_f(u, v) > 0\}$.
- Now an **augmenting path** is just a **path** from s to t in the **residual network**.

We can still inject up to $c(u, v) - f(u, v)$ flow from u to v



We can withdraw f flow from u to v first, and then inject up to $c(v, u)$ flow from v to u

Residual networks

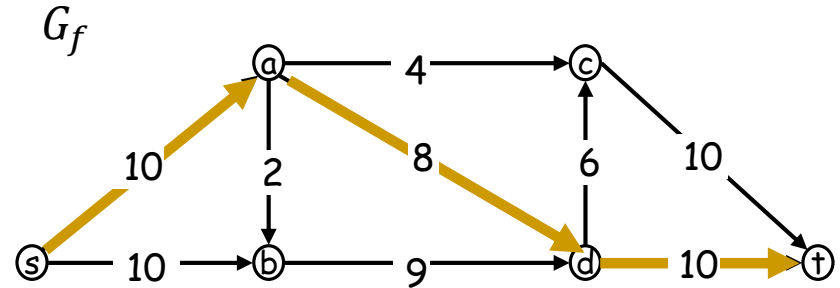
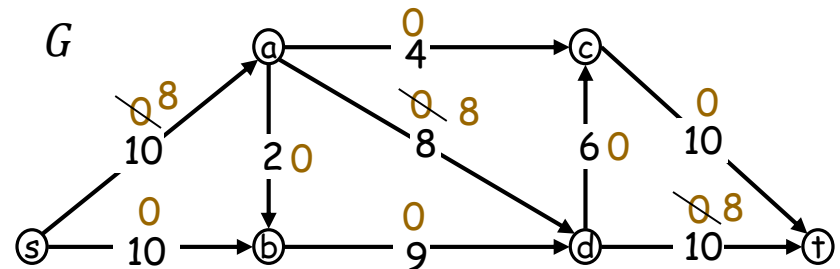
- The residual network gives the info of how we can get more flow from s to t in the graph.
 - And how much.
- So we define an **augmenting path** to be a path from s to t in the **residual network**.
- Now finding an augmenting path amounts to finding a path from s to t in the residual network,
- which we know how to do
 - e.g. BFS algorithm.

FORD-FULKERSON(G, s, t)

- **for** each edge $(u, v) \in E$ // Initialization
 - $f(u, v) \leftarrow 0, f(v, u) \leftarrow 0$
- $G_f = G$
- **while** there exists a path p from s to t in the residual network G_f
 - $c_f(p) \leftarrow \min\{c_f(u, v): (u, v) \text{ is in } p\}$ // max to inject on p
 - **for** each edge (u, v) in p // update flow
 - **if** $f(v, u) = 0$, // no backward flow on this edge
 - $f(u, v) \leftarrow f(u, v) + c_f(p)$
 - **else if** $c_f(p) \leq f(v, u)$ // has backward flow, withdraw part
 - $f(v, u) \leftarrow f(v, u) - c_f(p)$
 - **else** // has backward flow, withdraw all, add forward flow
 - $f(u, v) \leftarrow c_f(p) - f(v, u)$
 - $f(v, u) \leftarrow 0$
 - Update the residual network G_f .

FORD-FULKERSON(G, s, t)

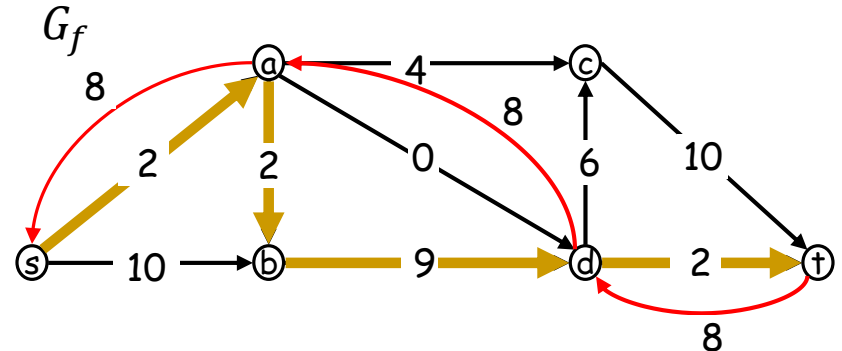
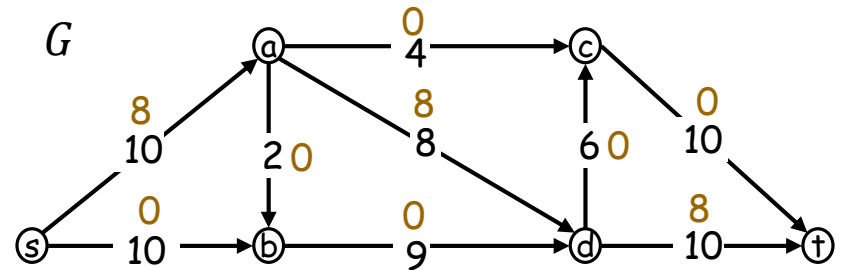
- **for** each edge $(u, v) \in E$
 - $f(u, v) \leftarrow 0, f(v, u) \leftarrow 0$
- $G_f = G$
- **while** there exists path p from s to t in residual network G_f
 - $c_f(p) \leftarrow \min\{c_f(u, v) : (u, v) \text{ is in } p\}$
 - **for** each edge (u, v) in p
 - **if** $f(v, u) = 0$,
 - $f(u, v) \leftarrow f(u, v) + c_f(p)$
 - **else if** $c_f(p) \leq f(v, u)$
 - $f(v, u) \leftarrow f(v, u) - c_f(p)$
 - **else**
 - $f(u, v) \leftarrow c_f(p) - f(v, u)$
 - $f(v, u) \leftarrow 0$
 - Update the residual network G_f .



$$c_f(p) = 8, \text{ flow} = 8$$

FORD-FULKERSON(G, s, t)

- **for** each edge $(u, v) \in E$
 - $f(u, v) \leftarrow 0, f(v, u) \leftarrow 0$
- $G_f = G$
- **while** there exists path p from s to t in residual network G_f
 - $c_f(p) \leftarrow \min\{c_f(u, v) : (u, v) \text{ is in } p\}$
 - **for** each edge (u, v) in p
 - **if** $f(v, u) = 0$,
 - $f(u, v) \leftarrow f(u, v) + c_f(p)$
 - **else if** $c_f(p) \leq f(v, u)$
 - $f(v, u) \leftarrow f(v, u) - c_f(p)$
 - **else**
 - $f(u, v) \leftarrow c_f(p) - f(v, u)$
 - $f(v, u) \leftarrow 0$
 - Update the residual network G_f .



$$c_f(p) = 8, \text{ flow} = 8$$

New $c_f(p)$? New flow? New G_f ?

Questions left

- **How** to find an augmenting path?
- What if, at some step, there is no augmenting path in the residual network?
 - Can we conclude that we've found the maximum flow?

Cut

- **Cut**: a partition of vertices into two parts S and T .
- **capacity** of cut (S, T) : $\sum_{u \in S, v \in T} c(u, v)$.
- Fact. Flow \leq capacity of any cut (S, T) .
- Proof.
 - flow value of f = net flow from S to T
 - = flow S to T – flow T to S // *conservation*
 - = $\sum_{u \in S, v \in T} f(u, v) - \sum_{u \in S, v \in T} f(v, u)$
 - $\leq \sum_{u \in S, v \in T} c(u, v)$
- How good is this upper bound of flow?

Max-flow min-cut Theorem.

- An important fact relating max flow and min cut: the previous upper bound is perfect
 - as long as we find a correct cut.
- [Theorem] The following are equivalent:
 1. f is a maximum flow in G
 2. G_f contains no augmenting paths.
- [Proof] $1 \Rightarrow 2$: trivial since otherwise f can be further increased.
- Next: $2 \Rightarrow 1$.
 - In the proof you'll see a cut with capacity achieving the max flow.

G_f contains no augmenting paths
 $\Rightarrow f$ is a maximum flow in G

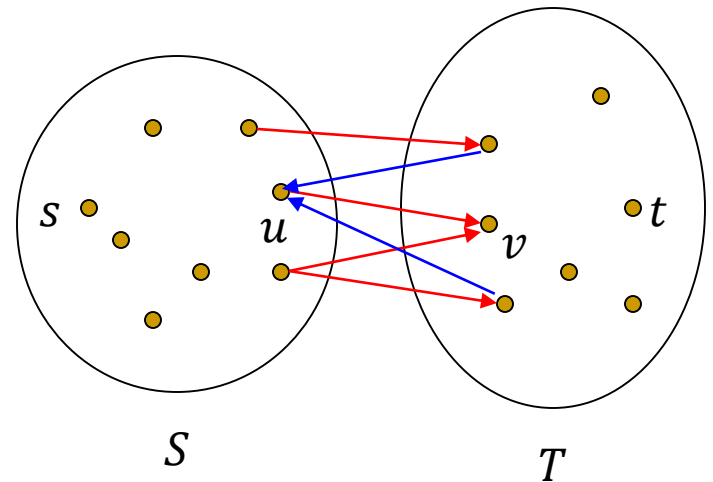
- Consider all vertices in G_f **reachable from s** .

- Call the set S .
- The rest is T .
- $s \in S, t \in T$.

- Consider this **cut (S, T)** :

- Two types of crossing edges in G
 - **Type 1:** $S \rightarrow T$. $(u, v): u \in S, v \in T$.
 - **Type 2:** $T \rightarrow S$. $(v, u): u \in S, v \in T$.

- For **type 1**: $f(u, v) = c(u, v)$
 - Otherwise v is reachable from s in G_f !



G_f contains no augmenting paths
 $\Rightarrow f$ is a maximum flow in G

- Consider all vertices in G_f **reachable from s** .

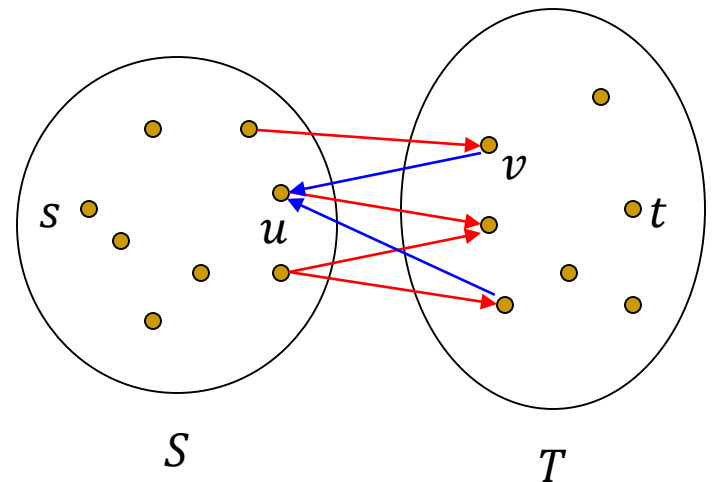
- Call the set S .
- The rest is T .
- $s \in S, t \in T$.

- Consider this **cut (S, T)** :

- Two types of crossing edges in G
 - **Type 1: $S \rightarrow T$** . $(u, v): u \in S, v \in T$
 - **Type 2: $T \rightarrow S$** . $(v, u): u \in S, v \in T$

- For **type 1**: $f(u, v) = c(u, v)$
 - Otherwise v is reachable from s in G_f !

- For **type 2**: $f(v, u) = 0$.
 - Otherwise v is also reachable from s in G_f !

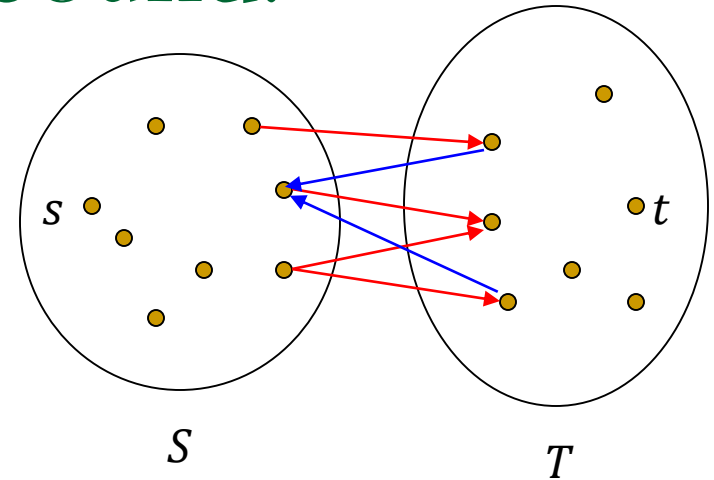


Done!

Why?

Any cut gives an upper bound!

- flow value of f
 - = flow “ $S \rightarrow T$ ” – flow “ $T \rightarrow S$ ”
 - = $\sum_{(u,v):\text{type 1}} f(u, v)$
– $\sum_{(u,v):\text{type 2}} f(v, u)$
 - $\leq \sum_{(u,v):\text{type 1}} c(u, v)$
- i.e. the best we can hope for f is to
 - use up full capacity of all **type 1** edges
 - not to use any capacity of any **type 2** edge.
- This essentially repeats the proof of **flow \leq cut capacity**.
- Last slide: If G_f has no augmenting path, then f already satisfies these two properties.
 - Thus f achieves $\sum_{(u,v):\text{type 1}} c(u, v)$ ---It is maximum.



Next

- **How** to find an augmenting path?
 - It matters. If we don't pick a good path, it may take forever and may not even converge to the optimum.
- [Edmonds-Karp] Use a **shortest path** will do.
 - Unweighted, thus BFS suffices.
- [Fact] At most $O(|V| \cdot |E|)$ augmenting path findings.
- Using BFS costs $O(|E|)$ for each path, thus $O(|V| \cdot |E|^2)$ for the total cost.

Edmonds-Karp Algorithm

- **for** each edge $(u, v) \in E$
 - $f(u, v) \leftarrow 0, f(v, u) \leftarrow 0$
- $G_f = G$
- **while** we can **use BFS to find a shortest path p** from s to t in the residual network G_f
 - $c_f(p) \leftarrow \min\{c_f(u, v): (u, v) \text{ is in } p\}$
 - Update the flow f
 - Update the residual network G_f .
- **Complexity?** Depends on how many iterations are executed in the **while** loop.
- [Thm] $O(|V| \cdot |E|)$ iterations.

Edmonds-Karp Algorithm

- **for** each edge $(u, v) \in E$
 - $f(u, v) \leftarrow 0, f(v, u) \leftarrow 0$
- $G_f = G$
- **while** we can **use BFS to find a shortest path p** from s to t in the residual network G_f
 - $c_f(p) \leftarrow \min\{c_f(u, v): (u, v) \text{ is in } p\}$
 - Update the flow f
 - Update the residual network G_f .
- An edge (u, v) is **critical** on an augmenting path p if the “min” in $c_f(p) \leftarrow \min\{c_f(u, v): (u, v) \text{ is in } p\}$ is achieved by (u, v)

Analysis

- [Lemma] Any (u, v) can be critical at most $|V|/2$ times.
- Once we prove this, we are done proving the theorem of “ $O(|V||E|)$ iterations”,
 - because there are $|E|$ edges, so at most $|V||E|/2$ iterations in total.

Proof of the lemma

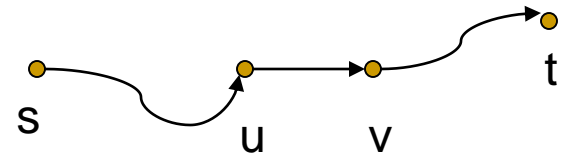
- We'll prove that each time (u, v) becomes critical, the distance $d(s, u)$ **increases by at least 2**.
 - $d(s, u)$: least number of edges on a path from s to u in graph G_f
- Since $0 < d(s, u) < |V|$, (u, v) is critical at most $|V|/2$ times.

Proof (continued)

- Since augmenting paths are shortest paths, when (u, v) is critical for the **first** time, we have

$$d_f(s, v) = d_f(s, u) + 1.$$

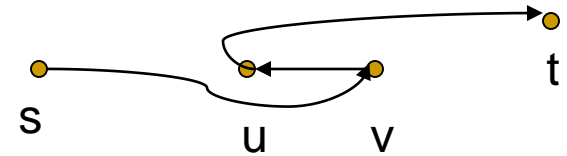
- d_f : distance on G_f .
- Once the flow is augmented, the edge (u, v) **disappears** from the residual network.
 - Critical: $f(u, v) = c(u, v)$,
 - So $c_f(u, v) = 0$, i.e. (u, v) disappears from the residual network.



Proof (continued)

- It cannot reappear later on another augmenting path **until** after the flow from u to v is decreased,
 - which occurs only if (v, u) appears on an augmenting path.
- If f' is the flow in G when this event occurs, then we have

$$d_{f'}(s, u) = d_{f'}(s, v) + 1.$$



Proof (continued)

- We've shown

- $d_f(s, v) = d_f(s, u) + 1$

- $d_{f'}(s, u) = d_{f'}(s, v) + 1$

- Now if $d_{f'}(s, v) \geq d_f(s, v) \dots$

Exercise!

- Then
$$\begin{aligned} d_{f'}(s, u) &= d_{f'}(s, v) + 1 \\ &\geq d_f(s, v) + 1 \\ &= d_f(s, u) + 2. \end{aligned}$$

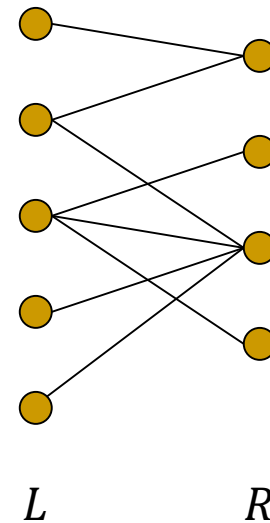
- Mission accomplished!

Application: Max bipartite matching

- We've learned maximum flow problem and algorithms.
- Next we apply it to solve the maximum bipartite matching problem.

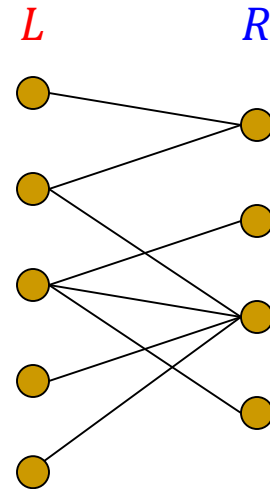
Maximum bipartite matching

- **Bipartite** graph: $G = (V, E)$ that can be partitioned into two parts with all edges crossing
 - $V = L \cup R$ with $L \cap R = \emptyset$,
 - All edges $(i, j) \in E$ have $i \in L$ and $j \in R$.
- **Matching**: a collection of edges (i_k, j_k) that are vertex disjoint
 - All i_k 's are distinct. So are all j_k 's.
- **Question**: Find a max matching in a bipartite graph.
 - Max matching: matching with maximum number of edges.

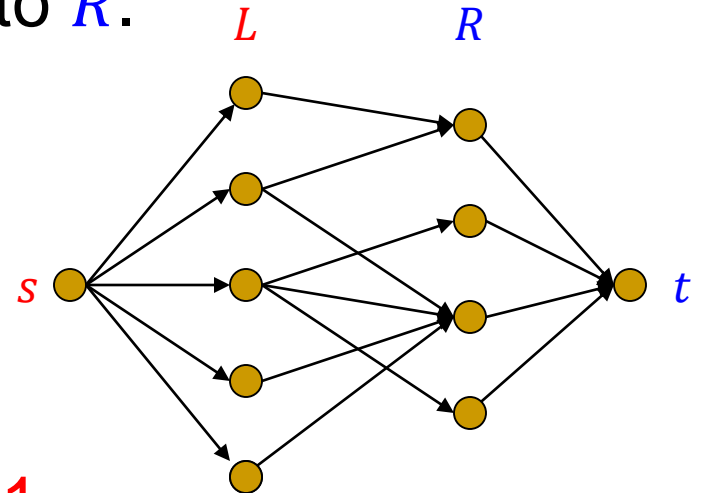


-
- Methodology 0: See whether the problem can be reduced to another one whose answer is known.
 - Very often, the problem that you are facing **appeared** to other people **before**.
 - Solutions are known.
 - Also very often, the problem is probably new, but it's very similar to, or essentially the same as an old one.
 - Then a simple transformation or reduction works.

- Orient existing edges from L to R .

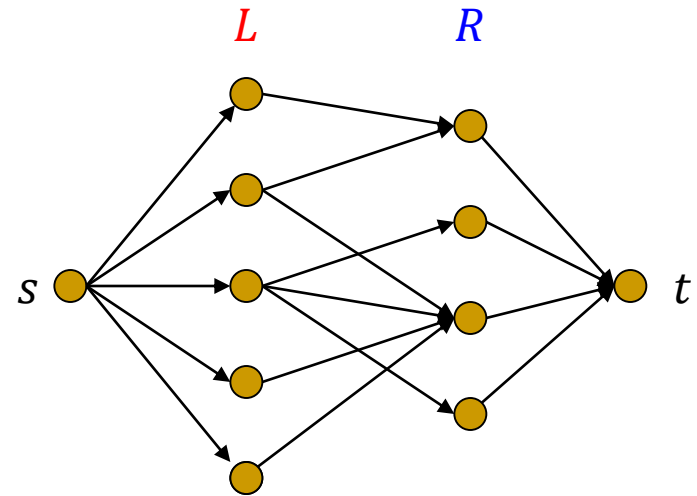


- Orient existing edges from L to R .
- Add one more node s .
- Link s to all vertices in L .
- Add one more node t .
- Link all vertices in R to t .
- All capacities (on edges) are 1 .



Equivalence

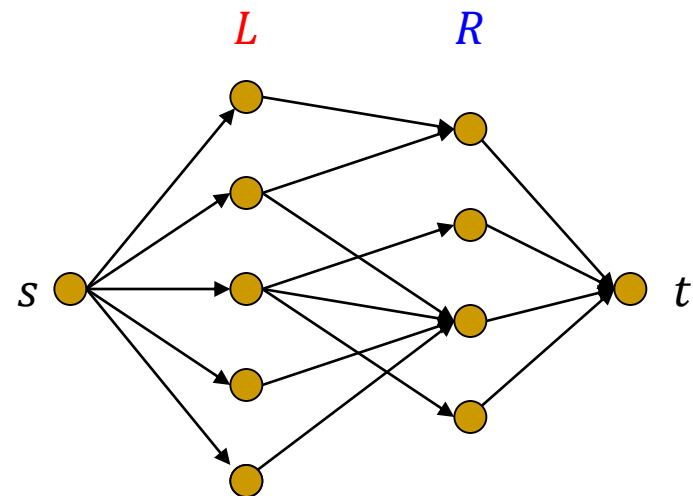
- [Fact] \exists **matching** of size m in original graph $\Leftrightarrow \exists$ **integral** flow of value m in the new graph
 - **Integral**: flow is **integer** on each edge
- \Rightarrow : For matching $\{(i_k, j_k) : k = 1, \dots, m\}$, give a unit flow to each edge (s, i_k) , (i_k, j_k) , and (j_k, t) .
- \Leftarrow : Since all capacities are 1 and flow is integral, flow on each edge is either 0 or 1.
 - So there are m “middle” edges (i_k, j_k) with flow 1.
 - And these edges are all vertex-disjoint because of the flow conservation.



- [Fact] \exists **matching** of size s in original graph $\Leftrightarrow \exists$ **integral** flow of value s in the new graph

- **Integral**: flow is **integer** on each edge

- [Fact] maximum matching in the original graph \Leftrightarrow maximum **integral flow** in the new graph.
- So it's sufficient to find a maximum **integral** flow in the new graph.
- We've learned how to find a maximum flow. But how to handle the integral constraint?
- Answer: We don't handle it.

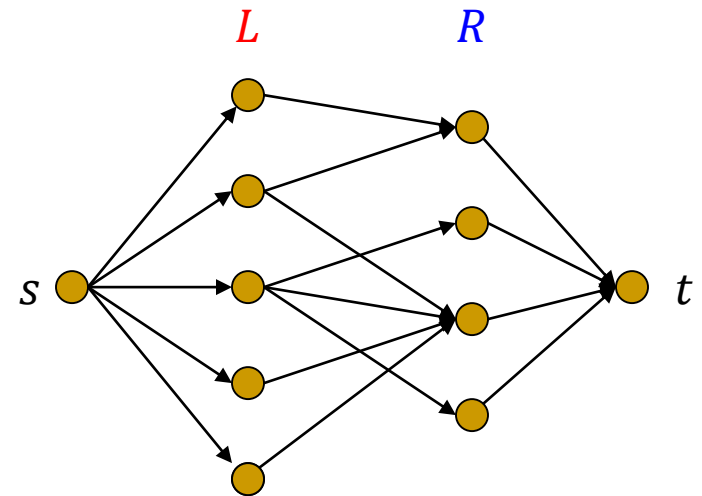


Integral constraint: automatic

- [Fact] In a graph with **integral capacities**, max flow is achieved by **integral flows**.
- **Why?** By our algorithm!
- Each time we follow an augmenting path to increase the flow ...
by how much?
 - $c_f(p) \leftarrow \min\{c_f(u, v): (u, v) \text{ is in } p\}$
 - It's an **integer**!
 - So the total flow is always an integer during the algorithm.
 - In particular, the final answer, i.e. a max flow, is an **integral flow**.

algorithm

- Overall, the algorithm is as follows.



- Create the new graph.
 - Orienting edges, adding s and t , giving unit capacity.
- Find a max flow of the new graph.
- Output middle edges with flow 1.

Summary

- Network flow **problem**.
- **Augmenting path** algorithm.
- Why **correct**? Max-flow Min-cut Theorem.
- **How** to find? One way: Shortest one by BFS.
- **Complexity**? $O(|V||E|^2)$ by analysis.
- One **application**: max bipartite matching