### **CSEP 521 Applied Algorithms** Spring 2005

Maximum Flow

### Reading

• Chapter 26

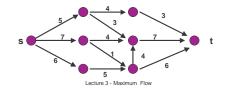
Lecture 3 - Maximum Flow

### Outline:

- · Properties of flow
- · Augmenting paths
- · Max-flow min-cut theorem
- Ford-Fulkerson method
- Edmonds-Karp method
- · Applications, bipartite matching and more.
- · Variants: min cost max flow

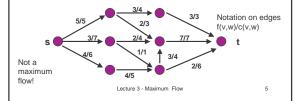
### Maximum Flow

- Input: a directed graph (network) G
  - each edge (v,w) has associated capacity c(v,w)
  - a specified source node s and target node t
- Optimization Problem: What is the maximum flow you can route from s to t while respecting the capacity constraint of each edge?



### Properties of Flow: f(v,w) - flow on edge (v,w)

- **Edge condition:**  $0 \le f(v,w) \le c(v,w)$  : the flow through an edge cannot exceed the capacity of an edge.
- **Vertex condition:** for all v except s,t:  $\Sigma_u f(u,v) = \Sigma_w f(v,w)$  the total flow entering a vertex is equal to total flow exiting this vertex.
- total flow leaving s = total flow entering t.



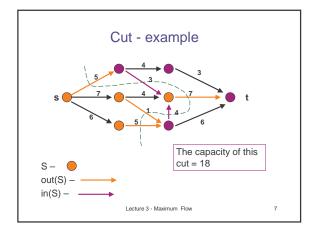
### Cut

- Cut a set of edges that separates s from t.
- A cut is defined by a set of vertices, S. This set includes s and maybe additional vertices reachable from s. The sink t is not in S.
- The cut is the set of edges (u,v) such that  $u \in S$  and v∉S, or v∈S and u∉S.



- out(S) edges in the cut directed from S to V-S
- in(S) edges in the cut directed from V-S to S

Lecture 3 - Maximum Flow



### Value of a Flow:

- A flow function f is an assignment of a real number f(e) to each edge e such that the edge and vertex conditions hold for all the vertices/edges.
- Definition: The value of the flow is the flow net flow from s

$$F = \sum_{e \in out(s)} f(e) - \sum_{e \in in(s)} f(e).$$

Lecture 3 - Maximum Flow

### Flow

• Theorem: The net flow into t equals the net flow out of s.

$$F = \sum_{e \in out(s)} \!\! f(e) - \sum_{e \in in(s)} \!\! f(e) \! = \sum_{e \in in(t)} \!\! f(e) - \sum_{e \in out(t)} \!\! f(e)$$

Lecture 3 - Maximum Flow

### Capacity of a cut

For a cut S, the capacity of S is  $c(S) = \sum_{e \in out(S)} c(e)$ .

**Claim:** For every flow function f with total flow F, and every cut S,  $F \le c(S)$ .

 $\mbox{\bf Proof: We know that} \qquad \mbox{\bf F} = \sum_{e \in \mbox{out}(S)} \!\! f(e) - \sum_{e \in \mbox{in}(S)} \!\! f(e).$ 

By the edge condition,  $0 \leq f(e) \leq c(e), \ \ \text{for all } e \in E.$  Thus,

$$F \leq \sum_{e \in out(S)} \!\! c(e) \! - 0 = c(S) \! .$$

Lecture 3 - Maximum Flow

10

### Max-flow Min-Cut Theorem

The value of a maximum flow in a network is equal to the minimum capacity of a cut.

### Proof:

max flow ≤ min cut: follows from the previous lemma.

max flow ≥ min cut: we will see an algorithm that

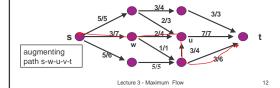
produces a flow in which some cut is saturated.

Lecture 3 - Maximum Flow

## An augmenting path with respect to a given flow f:

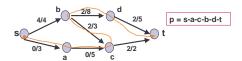
A directed path from s to t which consists of edges from G, but **not necessarily in the original direction**.

forward edge: (w,u) in same direction as G and f(w,u) < c(w,u). (c(w,u)-f(w,u) is called slack) à has room for more flow. backward edge: (u,v) in opposite direction in G (i.e., (v,u) in E) and f(v,u) > 0 à can 'take back' flow from such an edge.



### Using an augmenting path to increase flow

 Push flow forward on forward edges, deduct flow from backward edges.



•The amount of flow we can push: minimum { slacks along the forward edges on the path flow along the backward edges on the path

Lecture 3 - Maximum Flow

13

### The Ford-Fulkerson Method

- Initialize flow on all edges to 0.
- While there is an augmenting path, improve the flow along this path.

To implement F&F, we need a way to detect augmenting paths.

We build a residual graph with respect to the current flow.

Lecture 3 - Maximum Flow

Maniana Elem

14

### Residual Graph w.r.t. flow f

- Given f, we build the residual graph: a network flow R=(V,E')
- An edge (v,w)∈E' if either
  - (v,w) is a forward edge, and then its capacity in R is c(v,w)-f(v,w)
  - or (v,w) is a backward edge (that is, (w,v) is an edge with positive flow in G), and then its capacity in R is f(w,v).
- An augmenting path is a regular directed path from s to t in R.

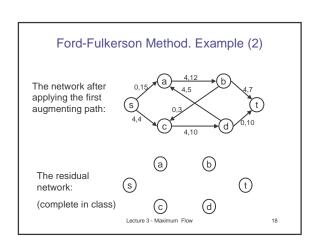
Lecture 3 - Maximum Flow

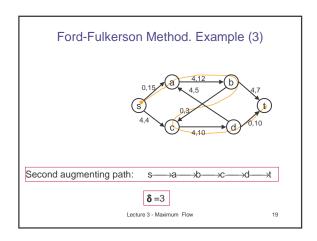
### Ford-Fulkerson Method (G,s,t)

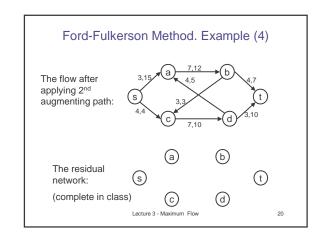
- Initialize flow on all edges to 0.
- While there is a path p from s to t in residual network R
  - $-\delta$  = minimum capacity along p in R
  - augment  $\delta$  units of flow along p and update R.

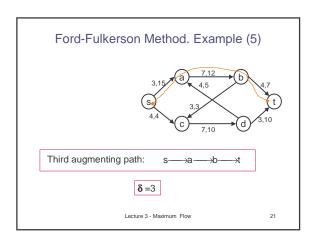
Lecture 3 - Maximum Flow

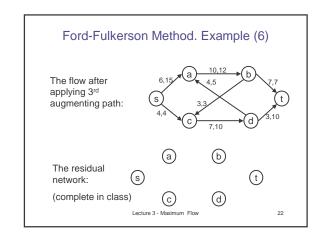
# Ford-Fulkerson Method. Example (1) Example taken from the book Graph Algorithms by Shimon Even The given network, with initial all-0 flow. First augmenting path: $s \to c \to d \to a \to b \to t$ Remark: in the first iteration R=G.

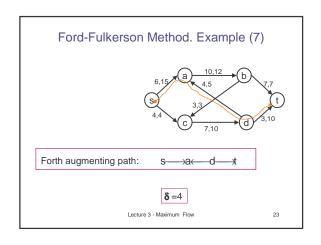


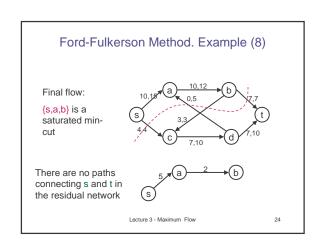












### Proof of Ford-Fulkerson Method.

Claim: The flow after each iteration is legal

Proof: The initial assignment (of f(e)=0 for all e) is clearly legal.

Let p be an augmenting path. Let d be the minimum capacity along p in R.

Vertex condition: For each v∉p, the flow that passes v does not change. For each  $v \in p$  ( $v \neq s,t$ ), exactly one edge of p enters v and exactly one edge of p goes out of v. In each of these edges the flow increase by &. The value of the flow in and out of v remains 0.

Egde condition: preserved by the selection of  $\delta$ 

Lecture 3 - Maximum Flow

25

### Proof of Ford-Fulkerson Method.

Theorem: A flow f is maximum if and only if it admits no augmenting path

- Already saw that if an augmenting path exists, then the flow is not maximum (can be improved).
- Suppose f admits no augmenting path. We need to show that f is maximum.
- We use the min-cut max-flow theorem: we will see that when no augmenting path exists, some cut is saturated.

Lecture 3 - Maximum Flow

### Proof of Ford-Fulkerson Method.

- Let A be the vertices such that for each v∈ A. there is an augmenting path from s to v.
- The set A defines a cut.
- Claim: for all edges in cut, f(v,w)=c(v,w).
- Proof: if f(v,w)< c(v,w) then w should join A.
- · Therefore: The value of the flow is the capacity of the cut defined by A à (min cut theorem) f is maximum.

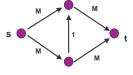
### Running time of Ford-Fulkerson

Each iteration (building R and detecting an augmenting path) takes O(|E|) (how?).

How many iterations are there?

Could be f\* when f\* is the value of the maximum flow.





The time complexity of F&F is O(|E|f\*), when f\* is the value of the maximum flow.

### Edmonds-Karp Algorithm:

- · Use F&F method. Search for augmenting path using breadth-first search, i.e., the augmenting path is always a shortest path from s to t in the residual network.
- Theorem: This way, the number of augmentations is O(|V||E|).
- The resulting complexity: O(|V||E|2) each iteration takes O(|E|)

Lecture 3 - Maximum Flow

29

### Greedy augmenting path Selection:

- Use F&F method. In each iteration select an augmenting path with the maximal  $\delta$  value.
- · The time complexity of this algorithm is  $O(|E|\log_2 f^*)$ .

Lecture 3 - Maximum Flow

# Some applications of max-flow and max-flow min-cut theorem

- · Bipartite matching
- · Network connectivity
- Video on demand
- Many many more...

Lecture 3 - Maximum Flow

31

### Matching

- Definition: a matching in a graph G is a subset M of E such that the degree of each vertex in G'=(V'.M) is 0 or 1.
- Example: M={(a,d),(b,e)} is a matching.
   S={(a,d), (c,d)} is not a matching.



32

### **Bipartite Matching**

- Example 1: In a party there are n<sub>1</sub> boys and n<sub>2</sub> girls.
   Each boy tells the DJ the girls with whom he is ready to dance with.
   Each girl tells the DJ the boys with whom she is ready to dance with.
- DJ's goal: As many dancing pairs as possible.
- Note: This has nothing to do with the stable pairing problem. No preferences. Some participants can remain lonely (even if  $n_1=n_2$ ).
- Example 2 (production planning) :  $n_2$  identical servers need to serve  $n_1$  clients. Each client specifies the subset of servers that can serve him.
- Goal: Serve as many clients as possible.

Lecture 3 - Maximum Flow

### **Bipartite Matching**

Graph representation: G=(V,E).

 $V = V_1 \cup V_2$ .

In  $1^{st}$  problem  $(u,v) \in E$ , if u is ready to dance with v and vice versa.

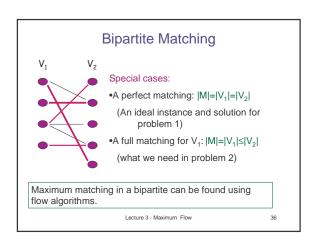
In  $2^{nd}$  problem  $(u,v) \in E$ , if u can be served by v.

This is a bipartite!

We are looking for the largest possible matching.

Lecture 3 - Maximum Flow

# Bipartite Matching Input: a bipartite graph G=(V₁ ∪ V₂, E) Goal: A matching of maximal size. A matching A maximal matching − can not be extended. Lecture 3 - Maximum Flow Our goal! 35



### Using Flow for Bipartite Matching

Input: A bipartite  $G=(V_1 \cup V_2, E)$ 

Output: Maximum matching McE.

### Algorithm:

1. Build a network flow N=(V',E')

 $\mathsf{V'} = \mathsf{V_1} \cup \mathsf{V_2} \cup \{\mathsf{s},\mathsf{t}\}$ 

 $E' = E \cup \{(s \rightarrow u) | \forall u \in V_1\} \cup \{(v \rightarrow t) | \forall v \in V_2\}$ 

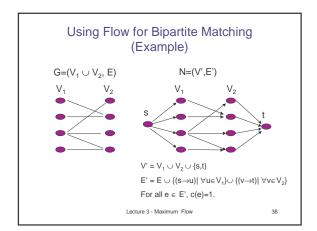
All  $e \in E'$  have the capacity c(e)=1.

Vertices of E are directed from V<sub>1</sub> to V<sub>2</sub>

- 2. Find a maximum flow in N.
- 3. M = saturated edges in the cut defined by  $\{s,V_1\}$ .

Lecture 3 - Maximum Flow

37



### Using Flow for Bipartite Matching (proof)

Theorem: G includes a matching of size  $k \Leftrightarrow N$  has flow with value k.

### Proof:

- 1.  $(\Rightarrow)$  Given a matching of size k, define the flow f(u,v)=1 for all (u,v) in M, all all (s,u) and (v,t) such that u or v are matched. For all the other edges f=0.
- F is legal (proof in class)
- The value of f is k (consider the cut  $\{s\} \cup V_1$ ).
- 2. (⇐) Similar. Based on the capacities of the edges (s,u), (v,t), and the fact that f is legal.

Lecture 3 - Maximum Flow

### **Network Connectivity**

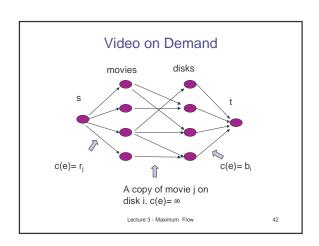
- What is the minimum number of links in the network such that if that many links go down, it is possible for nodes s and t to become disconnected?
- Solution using flow:

Lecture 3 - Maximum Flow

### Video on Demand

- m storage devices (e.g., disks), The i-th disk is capable of supporting b<sub>i</sub> simultaneous streams.
- k movies, one copy of each on some of the disks (this assignment is given as input).
- Given set of R movie requests, (r<sub>j</sub> requests to movie j) how would you assign the requests to disks so that no disk is assigned more than bi requests and the maximum number of requests is served?

Lecture 3 - Maximum Flow



### Other network flow problems:

- 1. Lower bounds on flow.
  - For each (v,w):  $0 \le lb(v,w) \le f(v,w) \le c(v,w)$
  - Not always possible:



### 2. Minimum flow

 Want to send minimum amount of flow from source to sink, while satisfying certain lower and upper bounds on flow on each edge.

Lecture 3 - Maximum Flow

43

### Other network flow problems:

3. Min-cost max-flow

Input: a graph (network) G where each edge (v,w) has associated capacity c(v,w), and **a cost** cost(v,w).

Goal: Find a maximum flow of minimum cost. The cost of a flow :

 $\Sigma_{f(v,w)>0}$  cost (v,w)f(v,w)

Out of all the maximum flows, which has minimal cost?

Lecture 3 - Maximum Flow

44

### Weighted Assignment - Min-cost maxflow example

**Production planning**:  $n_2$  servers need to serve  $n_1$  clients. Each client specifies for each server how much he is ready to pay in order to be served by this server (this is given by revenue(client, server)).

Goal: Maximize the profit.

