# ELE539A: Optimization of Communication Systems Lecture 3B: Network Flow Problems

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### **Lecture Outline**

- Network flow problems
- Problem 1: Maximum flow problem
- Ford Fulkerson algorithm
- Problem 2: Shortest path routing
- Bellman Ford algorithm
- Simple IP routing: RIP
- Dynamic Programming

### **Graph Theory Notation**

G = (V, E): directed graph with vertex set V and edge set E

 $b_i$ : external supply to each node  $i \in V$ 

 $u_{ij}$ : capacity of each edge  $(i,j) \in E$ 

 $c_{ij}$ : cost per unit flow on edge  $(i,j) \in E$ 

 $I(i) = \{j \in V | (j,i) \in E\}$ : set of start nodes of incoming edges to i

 $O(i) = \{j \in V | (i, j) \in E\}$ : set of end nodes of outgoing edges from i

Sources:  $\{i|b_i>0\}$ . Sinks:  $\{i|b_i<0\}$ 

#### Feasible flow f:

- Flow conservation:  $b_i + \sum_{j \in I(i)} f_{ji} = \sum_{j \in O(i)} f_{ij}, \ \forall i \in V$
- Capacity constraint:  $0 \le f_{ij} \le u_{ij}$

#### **Basic Formulation**

#### Network flow problem:

minimize 
$$\sum_{(i,j)\in E} c_{ij} f_{ij}$$
 subject to 
$$b_i + \sum_{j\in I(i)} f_{ji} = \sum_{j\in O(i)} f_{ij}, \ \forall i\in V$$
 
$$0\leq f_{ij}\leq u_{ij}$$

In matrix notation as a LP:

minimize 
$$c^T f$$
 subject to  $Af = b$  
$$0 \leq f \leq u$$

where  $A \in \mathbf{R}^{|V| \times |E|}$  is defined as

$$A_{ik} = \left\{ \begin{array}{ll} 1, & i \text{ is the start node of edge } k \\ -1, & i \text{ is the end node of edge } k \\ 0, & \text{otherwise} \end{array} \right.$$

### **Special Cases**

- Maximum flow problem (this lecture)
- Shortest path problem (this lecture)
- Transportation problem (uncapacitated bipartite graph)

minimize 
$$\sum_{i,j} c_{ij} f_{ij}$$
 subject to  $\sum_{i=1}^m f_{ij} = d_j, \ j=1,\ldots,n$   $\sum_{j=1}^n f_{ij} = s_i, \ i=1,\ldots,m$   $f_{ij} \geq 0, \ i=1,\ldots,m, j=1,\ldots,n$ 

Variables  $f_{ij}$ . Constants  $d_j, s_i, c_{ij}$ 

• Assignment problem (homework):

 $m=n, d_j=s_i=1$  in transportation problem

#### **Maximum Flow Problem**

maximize 
$$b_s$$
 subject to  $Af=b$  
$$b_t=-b_s$$
 
$$b_i=0, \ \forall i\neq s,t$$
 
$$0\leq f_{ij}\leq u_{ij}$$

Reformulated as network flow problem:

- Costs for all edges are zero
- ullet Introduce a new edge (t,s) with infinite capacity and cost -1
- ullet Minimize total cost is equivalent to maximize  $f_{ts}$

### Ford Fulkerson Algorithm

- 1. Start with feasible flow f
- 2. Search for an augmenting path P
- 3. Terminate if no augmenting path
- 4. Otherwise, if flow can be pushed, push  $\delta(P)$  units of flow along P and repeat Step 2
- 5. Otherwise, terminate

Q: How to find augmenting path?

Q: How much flow can be pushed?

### **Augmenting Path**

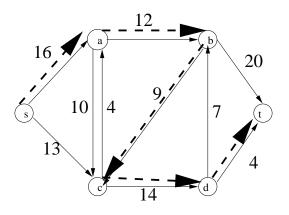
Idea: find a path where we can increase flow along every forward edge and decrease flow along backward edge by the same amount. Still satisfy constraints. Increase objective function

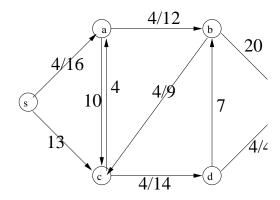
Augmenting path: a path from s to t such that  $f_{ij} < u_{ij}$  on forward edges and  $f_{ij} > 0$  on backward edges

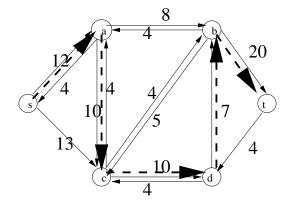
Augmenting flow amount along augmenting path P:

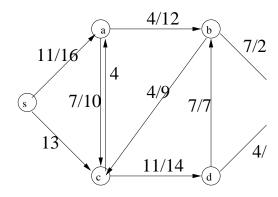
$$\delta(P) = \min \left\{ \min_{(i,j) \in F} (u_{ij} - f_{ij}), \min_{(i,j) \in B} f_{ij} \right\}$$

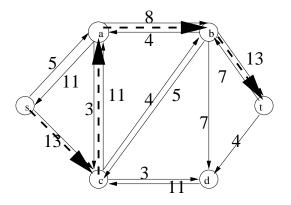
Can search for augmenting path by following possible paths leading from s and checking conditions above

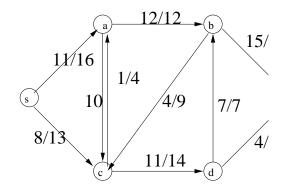


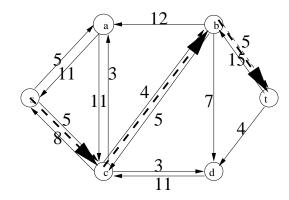


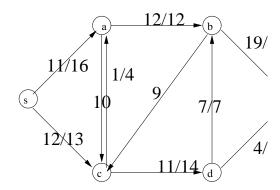


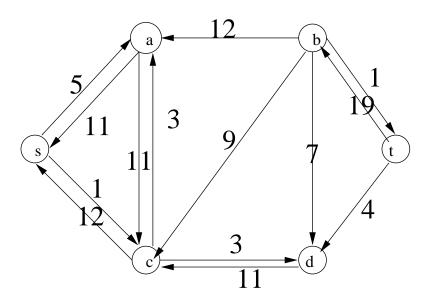












#### Max Flow Min Cut Theorem

Theorem: If optimal value is finite, Ford Fulkerson algorithm terminates with an optimal flow

Theorem: If edge capacities  $u_{ij}$  are integers, edge flow variables remain integer

Definition: cut S is a subset of V such that  $s \in S$  and  $t \notin S$ 

Definition: capacity of cut C(S) is sum of edge capacities on edges that cross from S to its complement:

$$C(S) = \sum_{(i,j)\in E|i\in S, j\notin S} u_{ij}$$

Theorem: Value of maximum flow  $\max b_s$  equals minimum cut capacity  $\min_S C(S)$ 

### **Shortest Path Routing**

Given a directed graph with vertex set V and edge set E

Each edge (i,j) has cost or length  $c_{ij}$ 

Allow negative length edges, but no negative length cycles

Our development follows DP algorithm

Other approaches (e.g., duality) and algorithms (e.g., Dijstrak) possible

Consider all-to-one shortest path routing with destination vertex n

### **Bellman Ford Algorithm**

Let  $p_i(t)$  be length of shortest path from i to n using at most t edges, with  $p_i(t) = \infty$  if no such path exists

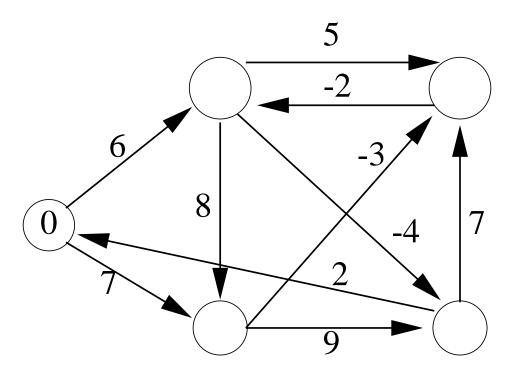
Let 
$$p_n(t) = 0$$
,  $\forall t$  and  $p_i(0) = \infty$ ,  $\forall i \neq n$ 

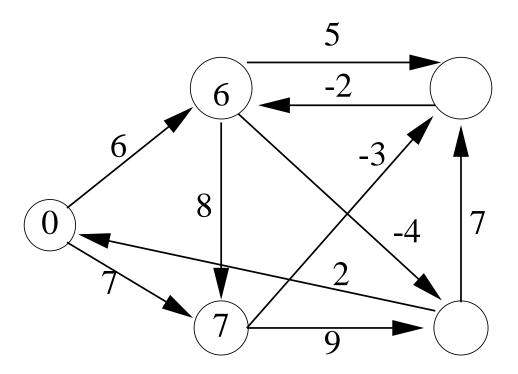
 $p_i(t+1)$  consists of two parts:

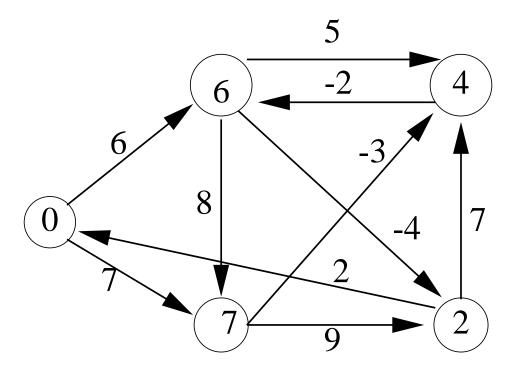
- ullet cost of getting from i to a neighboring k
- ullet cost of getting from k to destination n

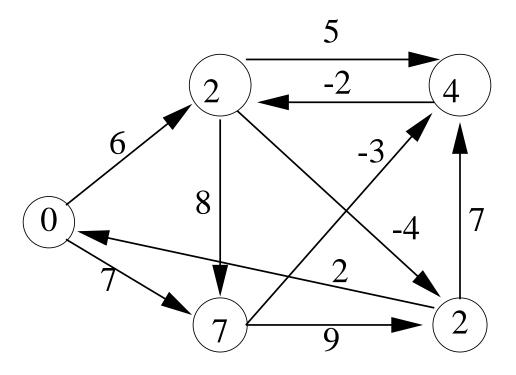
Pick the minimum total cost:

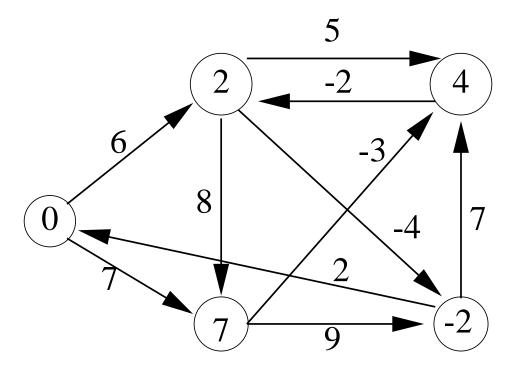
$$p_i(t+1) = \min_{k \in \mathcal{O}(i)} \{c_{ik} + p_k(t)\}$$











### **IP** Routing

#### Basic versions:

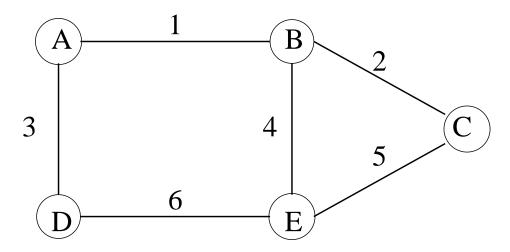
- IGP (e.g., RIP): distance-vector based
- IGP (e.g., OSPF, IS-IS): link-state based
- EGP (e.g., BGP4): across Autonomous Systems

#### Extensions:

- Multicast routing
- Mobile IP
- Mobile wireless ad hoc routing
- QoS routing

### **RIP Routing**

Simple example (homework):



#### Practical concerns:

- Loop avoidance
- Stability
- Speed of convergence
- Scalability

### **Sequential Optimization**

Additive cost in discrete time dynamic system:

$$x_{k+1} = f_k(x_k, u_k, w_k), \quad k = 0, \dots, N-1$$

State:  $x_k \in S_k$ 

Control:  $u_k \in U_k(x_k)$ 

Random disturbance:  $w_k \in D_k$  with distribution conditional on  $x_k, u_k$ 

Admissible policies:

$$\pi = \{\mu_0, \dots, \mu_{N-1}\}$$

where  $\mu_k(x_k) = u_k$  such that  $\mu_k(x_k) \in U_k(x_k)$  for all  $x_k \in S_k$ 

Given cost functions  $g_k, k = 0, ..., N$ , expected cost of  $\pi$  starting at  $x_0$ :

$$J_{\pi}(x_0) = \mathbf{E}\left(g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, \mu_k(x_k), w_k)\right)$$

Optimal policy  $\pi^*$  minimizes J over all admissible  $\pi$ , with optimal cost:

$$J^*(x_0) = J_{\pi^*}(x_0) = \min_{\pi \in \Pi} J_{\pi}(x_0)$$

### **Principle of Optimality**

Given optimal policy  $\pi^* = \{\mu_0^*, \dots, \mu_{N-1}^*\}$ . Consider subproblem where at time i and state  $x_i$ , minimize cost-to-go function from time i to N:

$$\mathbf{E}\left(g_N(x_N) + \sum_{k=i}^{N-1} g_k(x_k, \mu_k(x_k), w_k)\right)$$

Then truncated optimal policy  $\{\mu_i^*,\dots,\mu_{N-1}^*\}$  is optimal for subproblem

Tail of an optimal policy is also optimal for tail of the problem

### **DP Algorithm**

For every initial state  $x_0$ ,  $J^*(x_0)$  equals  $J_0(x_0)$ , the last step of the following backward iteration:

$$J_{N}(x_{N}) = g_{N}(x_{N})$$

$$J_{k}(x_{k}) = \min_{u_{k} \in U_{k}(x_{k})} \mathbf{E} \left( g_{k}(x_{k}, u_{k}, w_{k}) + J_{k+1}(f_{k}(x_{k}, u_{k}, w_{k})) \right), \quad k = 0, \dots, N-1$$

If  $\mu_k^*(x_k) = u_k^*$  are the minimizers of  $J_k(x_k)$  for each  $x_k$  and k, then policy

$$\pi^* = \{\mu_0^*, \dots, \mu_{N-1}^*\}$$

is optimal

Proof: induction and Principle of Optimality

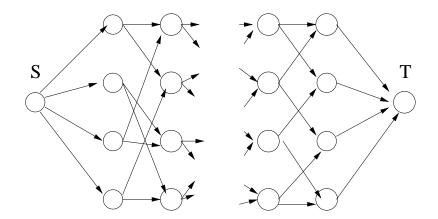
#### **Deterministic Finite-State DP**

• No stochastic perturbation:

$$x_{k+1} = f_k(x_k, \mu_k(x_k))$$

ullet Finite state space:  $S_k$  are finite for all k

Deterministic finite-state DP is equivalent to shortest path problem in trellis diagram



### **Lecture Summary**

- Network flow problems are special cases of LP that model a wide range of problems in networking and problems modelled by graphs.
- Maximum flow problems and shortest path problems are two important special cases of network flow problems that can be efficiently solved by special purpose distributed algorithms.
- DP principle is extremely powerful for sequential optimization.
- We will later study powerful generalizations of Network, Flow Problems to Network Utility Maximization.
- Practical issues in IP routing (IGP and BGP) to be taught in Rexford guest lecture.

Reading: Section 7.1, 7.2, 7.5, and 7.9 in Bertsimas and Tsitsiklis