# Lecture 17 Network flow optimization

- minimum cost network flows
- total unimodularity
- examples

## Networks

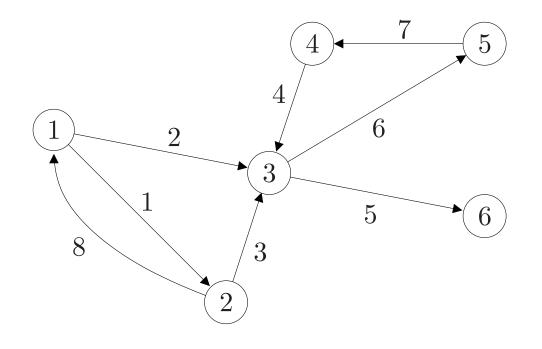
**network** (directed graph, digraph): m nodes connected by n directed arcs

- arcs are ordered pairs (i, j) of nodes
- we assume there is at most one arc from node i to node j
- there are no loops (arcs (i, i))

#### arc-node incidence matrix: $m \times n$ matrix A with entries

$$A_{ij} = \begin{cases} 1 & \text{if arc } j \text{ starts at node } i \\ -1 & \text{if arc } j \text{ ends at node } i \\ 0 & \text{otherwise} \end{cases}$$

# Example



$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & -1 \\ -1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & -1 & -1 & -1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \end{bmatrix}$$

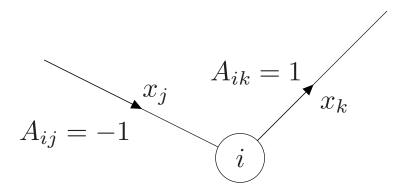
### **Network flow**

flow vector  $x \in \mathbf{R}^n$ 

- $x_j$ : flow (of material, traffic, charge, information, . . . ) through arc j
- positive if in direction of arc; negative otherwise

total flow leaving node *i*:

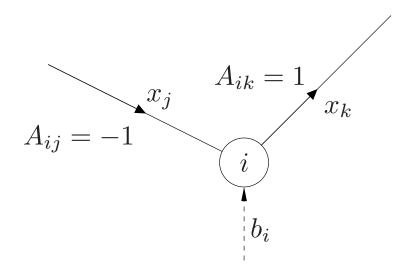
$$\sum_{j=1}^{n} A_{ij} x_j = (Ax)_i$$



# **External supply**

#### supply vector $b \in \mathbf{R}^m$

- $b_i$  is external supply at node i (negative  $b_i$  represents external demand)
- must satisfy  $\mathbf{1}^T b = 0$  (total supply = total demand)



#### balance equations:

### Minimum cost network flow problem

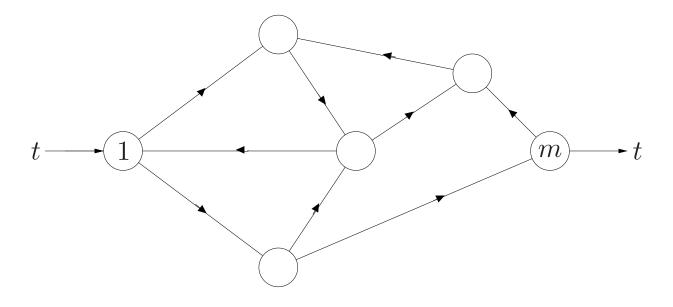
$$\begin{array}{ll} \text{minimize} & c^T x\\ \text{subject to} & Ax = b\\ & l \leq x \leq u \end{array}$$

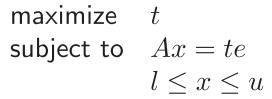
- $c_i$  is unit cost of flow through arc i
- $l_j$  and  $u_j$  are limits on flow through arc j (typically,  $l_j \leq 0$ ,  $u_j \geq 0$ )
- we assume  $l_j < u_j$ , but allow  $l_j = -\infty$  and  $u_j = \infty$  to simplify notation

includes many network optimization problems as special cases

# Maximum flow problem

maximize flow from node 1 (source) to node m (sink) through the network

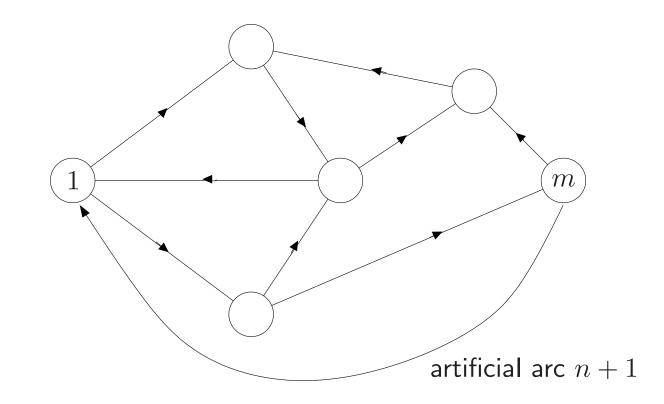




where  $e = (1, 0, \dots, 0, -1)$ 

Network flow optimization

### Formulation as minimum cost flow problem



 $\begin{array}{ll} \text{minimize} & -t \\ \text{subject to} & \left[ \begin{array}{c} A & -e \end{array} \right] \left[ \begin{array}{c} x \\ t \end{array} \right] = 0 \\ & l \leq x \leq u \end{array}$ 

# Outline

- minimum cost network flows
- total unimodularity
- examples

# **Totally unimodular matrix**

a matrix is **totally unimodular** if all its minors are -1, 0, or 1 (a minor is the determinant of a square submatrix)

#### examples

• the matrix

$$\left[\begin{array}{rrrrr} 1 & 0 & -1 & 0 & 1 \\ 0 & -1 & 1 & -1 & -1 \\ 0 & 0 & 0 & 1 & 1 \end{array}\right]$$

• node-arc incidence matrix of a directed graph (proof on next page)

**properties** of a totally unimodular matrix A

- the entries  $A_{ij}$  (*i.e.*, its minors of order 1) are -1, 0, or 1
- the inverse of any nonsingular square submatrix of A has entries  $\pm 1,\,0$

*proof:* let A be an  $m \times n$  node-arc incidence matrix

- the entries of A are -1, 0, or 1
- A has exactly two nonzero entries (-1 and 1) per column

consider a  $k \times k$  submatrix B of A

- if B has a zero column, its determinant is zero
- if all columns of B have two nonzero entries, then  $\mathbf{1}^T B = 0$ , det B = 0
- otherwise B has a column, say column j, with one nonzero entry  $B_{ij}$ , so

$$\det B = (-1)^{i+j} B_{ij} \det C$$

C is square of order k-1, obtained by deleting row i and column j of B

hence, can show by induction on k that all minors of A are  $\pm 1$  or 0

# **Integrality of extreme points**

let P be a polyhedron in  $\mathbf{R}^n$  defined by

$$Ax = b, \qquad l \le x \le u$$

where

- A is totally unimodular
- *b* is an integer vector
- the finite lower bounds  $l_k$  and finite upper bounds  $u_k$  are integers

then all the extreme points of P are integer vectors

*proof:* apply rank test to determine whether  $\hat{x} \in P$  is an extreme point

• partition  $\{1, 2, \ldots, n\}$  in three sets  $J_0$ ,  $J_-$ ,  $J_+$  with

$$\begin{aligned} l_k &< \hat{x}_k < u_k & \text{ for } k \in J_0 \\ \hat{x}_k &= l_k & \text{ for } k \in J_- \\ \hat{x}_k &= u_k & \text{ for } k \in J_+ \end{aligned}$$

let  $A_0$ ,  $A_-$ ,  $A_+$  be the submatrices of A with columns in  $J_0$ ,  $J_-$ ,  $J_+$ 

•  $\hat{x}$  is an extreme point if and only if

$$\operatorname{rank} \begin{bmatrix} 0 & I & 0 \\ 0 & 0 & -I \\ A_0 & A_- & A_+ \end{bmatrix} = n \quad \iff \quad A_0 \text{ has full column rank}$$

integrality of  $\hat{x}$  then follows from  $A_0 \hat{x}_{J_0} = b - A_- \hat{x}_{J_-} - A_+ \hat{x}_{J_+}$ 

- right-hand side is an integral vector ( $\hat{x}_k$  is integer for  $k \in J_- \cup J_+$ )
- inverse of any nonsingular submatrix of  $A_0$  has integer entries

## Implications for combinatorial optimization

$$\begin{array}{ll} \text{minimize} & c^T x\\ \text{subject to} & Ax = b\\ & l \leq x \leq u\\ & x \in \mathbf{Z}^n \end{array}$$

- an integer linear program, very difficult in general
- equivalent to its linear program relaxation

$$\begin{array}{ll} \text{minimize} & c^T x\\ \text{subject to} & Ax = b\\ & l \leq x \leq u \end{array}$$

if A is totally unimodular and b, l, u are integer vectors (extreme optimal solution of the relaxation is optimal for the integer LP)

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# Shortest path problem

**shortest path** in directed graph with node-arc incidence matrix A

• (forward) paths from node 1 to m can be represented by vectors x with

$$Ax = (1, 0, \dots, 0, -1), \qquad x \in \{0, 1\}^n$$

• shortest path is solution of

$$\begin{array}{ll} \mbox{minimize} & \mathbf{1}^T x\\ \mbox{subject to} & Ax = (1,0,\ldots,0,-1)\\ & x \in \{0,1\}^n \end{array}$$

### **LP** formulation

$$\begin{array}{ll} \text{minimize} & \mathbf{1}^T x\\ \text{subject to} & Ax = (1,0,\ldots,0,-1)\\ & 0 \leq x \leq \mathbf{1} \end{array}$$

extreme optimal solutions satisfy  $x_i \in \{0, 1\}$ 

### **Birkhoff theorem**

**doubly stochastic matrix:**  $N \times N$  matrices X with  $0 \le X_{ij} \le 1$  and

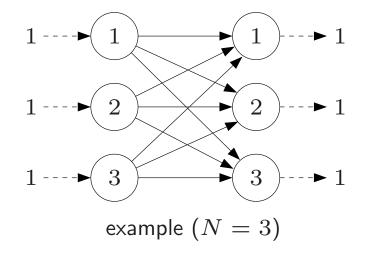
$$\sum_{i=1}^{N} X_{ij} = 1, \quad j = 1, \dots, N, \qquad \sum_{j=1}^{N} X_{ij} = 1, \quad i = 1, \dots, N$$

set of doubly stochastic matrices is a polyhedron P in  $\mathbf{R}^{N imes N}$ 

**theorem** (p.3–29): the extreme points of P are the permutation matrices

proof: interpret  $\boldsymbol{X}$  as network flow

- $\bullet~N$  input nodes, N output nodes
- $X_{ij}$  is flow from input i to output jhence extreme X has integer entries



# Weighted bipartite matching

- $\bullet \mbox{ match } N$  persons to N tasks
- each person assigned to one task; each task assigned to one person
- cost of matching person i to task j is  $A_{ij}$

### LP formulation

minimize 
$$\sum_{\substack{i,j=1\\N}}^{N} A_{ij}X_{ij}$$
subject to 
$$\sum_{\substack{i=1\\N}}^{N} X_{ij} = 1, \quad j = 1, \dots, N$$
$$\sum_{\substack{j=1\\0 \le X_{ij} \le 1, \quad i, j = 1, \dots, N}$$

integrality: extreme optimal solution X has entries  $X_{ij} \in \{0, 1\}$