

# Linear and Integer Programming

- Time: Tuesdays and Thursdays, 16:15 - 17:55 (with 10 minutes break)
- Place: Gerhard-Konow-Hörsaal, Lennéstr. 2
- Website:  
`www.or.uni-bonn.de/lectures/ss19/lgo_ss19.html`
- **Lecture notes** and all **slides** can be found on the website.

## Final Examination

- Written examination
- Dates: Monday, July 15, 2019 and Saturday, September 21, 2019.
- There will be no third examination in this semester.

# Exercise Classes

- Exercise classes are **two hours per week**.
- **Assignments** are released every **Thursday**.
- There will be **programming exercises**.
- **50 % of all points** in the assignments are required to participate in the exam.
- Students can work in **groups of two**.
- All participants of a group have to be able to explain their solutions.
- Exercise classes begin in the **second week**.

# Possible Time Slots for the Exercise Classes

- ① Mo 10 - 12
- ② Tu 10 - 12
- ③ Tu 14 - 16
- ④ We 12 - 14
- ⑤ We 14 - 16
- ⑥ We 16 - 18
- ⑦ Th 10 - 12
- ⑧ Th 12 - 14
- ⑨ Th 14 - 16
- ⑩ Fr 10 - 12
- ⑪ Fr 14 - 16

We will choose four of these time slots.

**Application** for the exercise classes: Use the form on the website  
[www.or.uni-bonn.de/lectures/ss19/lgo\\_uebung\\_ss19.html](http://www.or.uni-bonn.de/lectures/ss19/lgo_uebung_ss19.html)

## Definition

- An **optimization problem** is a pair  $(I, f)$  with a set  $I$  and  $f : I \rightarrow \mathbb{R}$ .
- The elements of  $I$  are called **feasible solutions** of  $(I, f)$ .
- If  $I = \emptyset$ ,  $(I, f)$  is called **infeasible**, otherwise we call it **feasible**.
- The function  $f$  is called the **objective function** of  $(I, f)$ .
- We ask for an  $x^* \in I$  (called **optimum solution**) such that
  - for all  $x \in I$  we have  $f(x) \leq f(x^*)$  (then  $(I, f)$  is called a **maximization problem**)
  - for all  $x \in I$  we have  $f(x) \geq f(x^*)$  (then  $(I, f)$  is called a **minimization problem**).
- $(I, f)$  is **unbounded** if for all  $K \in \mathbb{R}$ , there is an  $x \in I$  with  $f(x) > K$  (for the maximization problem) or an  $x \in I$  with  $f(x) < K$  (for the minimization problem).
- An optimization problem is called **bounded** if it is not unbounded.

# Linear Programming

## LINEAR PROGRAMMING

*Instance:* A matrix  $A \in \mathbb{R}^{m \times n}$ , vectors  $c \in \mathbb{R}^n$  and  $b \in \mathbb{R}^m$ .

*Task:* Find a vector  $x \in \mathbb{R}^n$  with  $Ax \leq b$  maximizing  $c^t x$ .

**Example:**

$$\begin{aligned} & \max \quad (3, -2, 5) \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \\ \text{s.t.} \quad & \begin{pmatrix} -2 & 3 & 1 \\ 1 & 1 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \leq \begin{pmatrix} 5 \\ 2 \end{pmatrix} \end{aligned}$$

# Standard Forms

Standard inequality form:

$$\begin{array}{ll} \max & c^t x \\ \text{s.t.} & Ax \leq b \end{array} \quad (1)$$

Standard equational form:

$$\begin{array}{ll} \max & c^t x \\ \text{s.t.} & Ax = b \\ & x \geq 0 \end{array} \quad (2)$$

Both forms can be transformed into each other.

# Integer Linear Programming

## Integer LINEAR PROGRAMMING

*Instance:* A matrix  $A \in \mathbb{R}^{m \times n}$ , vectors  $c \in \mathbb{R}^n$  and  $b \in \mathbb{R}^m$ .

*Task:* Find a vector  $x \in \mathbb{Z}^n$  with  $Ax \leq b$  maximizing  $c^t x$ .

If only some variables have to be integral  $\Rightarrow$  MIXED INTEGER LINEAR PROGRAMMING (MILP)

# Modelling Optimization Problems as LPs

## Definition

Let  $G$  be a directed graph with capacities  $u : E(G) \rightarrow \mathbb{R}_{>0}$  and let  $s$  and  $t$  be two vertices of  $G$ . A feasible  **$s$ - $t$ -flow** in  $(G, u)$  is a mapping  $f : E(G) \rightarrow \mathbb{R}_{\geq 0}$  with

- $f(e) \leq u(e)$  for all  $e \in E(G)$  and
- $\Delta_f(v) := \sum_{e \in \delta_G^+(v)} f(e) - \sum_{e \in \delta_G^-(v)} f(e) = 0$  for all  $v \in V(G) \setminus \{s, t\}$ .

The **value** of an  $s$ - $t$ -flow  $f$  is  $\text{val}(f) = \Delta_f(s)$ .



# Modelling Optimization Problems as LPs

## MAXIMUM-FLOW PROBLEM

*Instance:* A directed Graph  $G$ , capacities  $u : E(G) \rightarrow \mathbb{R}_{>0}$ , vertices  $s, t \in V(G)$  with  $s \neq t$ .

*Task:* Find an  $s$ - $t$ -flow  $f : E(G) \rightarrow \mathbb{R}_{\geq 0}$  of maximum value.

LP-formulation:

$$\begin{array}{ll} \max & \sum_{e \in \delta_G^+(s)} x_e - \sum_{e \in \delta_G^-(s)} x_e \\ \text{s.t.} & x_e \geq 0 \quad \text{for } e \in E(G) \\ & x_e \leq u(e) \quad \text{for } e \in E(G) \\ & \sum_{e \in \delta_G^+(v)} x_e - \sum_{e \in \delta_G^-(v)} x_e = 0 \quad \text{for } v \in V(G) \setminus \{s, t\} \end{array}$$

# Modelling Optimization Problems as LPs

## BOTTLENECK MAXIMUM-FLOW PROBLEM WITH 2 SOURCES

*Instance:* A directed Graph  $G$ , capacities  $u : E(G) \rightarrow \mathbb{R}_{>0}$ , three vertices  $s_1, s_2, t \in V(G)$ .

*Task:* Find a mapping  $f : E(G) \rightarrow \mathbb{R}_{\geq 0}$  with

- $f(e) \leq u(e)$  for all  $e \in E(G)$  and
- $\Delta_f(v) = 0$  for all  $v \in V(G) \setminus \{s_1, s_2, t\}$

such that  $\min\{\Delta_f(s_1), \Delta_f(s_2)\}$  is maximized

How can this problem be modelled by an LP?

# Duality: Example

$$\begin{array}{ll} \text{(P)} & \max \quad 12x_1 + 10x_2 \\ & \text{s.t.} \quad 4x_1 + 2x_2 \leq 5 \\ & \quad \quad 8x_1 + 12x_2 \leq 7 \\ & \quad \quad 2x_1 - 3x_2 \leq 1 \end{array}$$

**Goal:** Find an upper bound on the optimum solution value.

Combine constraint 1 and 2:

$$12x_1 + 10x_2 = 2 \cdot (4x_1 + 2x_2) + \frac{1}{2}(8x_1 + 12x_2) \leq 2 \cdot 5 + \frac{1}{2} \cdot 7 = 13.5.$$

Combine constraint 2 and 3:

$$12x_1 + 10x_2 = \frac{7}{6} \cdot (8x_1 + 12x_2) + \frac{4}{3} \cdot (2x_1 - 3x_2) \leq \frac{7}{6} \cdot 7 + \frac{4}{3} \cdot 1 = 9.5.$$

# Duality: Example

$$\begin{array}{ll} \text{(P)} & \max \quad 12x_1 + 10x_2 \\ & \text{s.t.} \quad 4x_1 + 2x_2 \leq 5 \\ & \quad \quad 8x_1 + 12x_2 \leq 7 \\ & \quad \quad 2x_1 - 3x_2 \leq 1 \end{array}$$

General approach: Find numbers  $u_1, u_2, u_3 \in \mathbb{R}_{\geq 0}$  such that

$$12x_1 + 10x_2 = u_1 \cdot (4x_1 + 2x_2) + u_2 \cdot (8x_1 + 12x_2) + u_3 \cdot (2x_1 - 3x_2).$$

$\Rightarrow 5u_1 + 7u_2 + u_3$  is an **upper bound** on the value of any solution of (P).

$\Rightarrow$  Chose  $u_1, u_2, u_3$  such that  $5u_1 + 7u_2 + u_3$  is **minimized**.

# Duality: Example

$$\begin{array}{ll} \text{(P)} & \max \quad 12x_1 + 10x_2 \\ & \text{s.t.} \quad 4x_1 + 2x_2 \leq 5 \\ & \quad \quad 8x_1 + 12x_2 \leq 7 \\ & \quad \quad 2x_1 - 3x_2 \leq 1 \end{array}$$

Determine  $u_1$ ,  $u_2$ , and  $u_3$  by the following linear program:

$$\begin{array}{ll} \text{(D)} & \min \quad 5u_1 + 7u_2 + u_3 \\ & \text{s.t.} \quad 4u_1 + 8u_2 + 2u_3 = 12 \\ & \quad \quad 2u_1 + 12u_2 - 3u_3 = 10 \\ & \quad \quad u_1 \geq 0 \\ & \quad \quad \quad u_2 \geq 0 \\ & \quad \quad \quad \quad u_3 \geq 0 \end{array}$$

$\Rightarrow$  Any solution of (D) gives an upper bound for (P).

# Duality: Example

$$\begin{array}{ll} \text{(P)} & \max \quad 12x_1 + 10x_2 \\ & \text{s.t.} \quad 4x_1 + 2x_2 \leq 5 \\ & \quad \quad 8x_1 + 12x_2 \leq 7 \\ & \quad \quad 2x_1 - 3x_2 \leq 1 \end{array}$$

Determine  $u_1$ ,  $u_2$ , and  $u_3$  by the following linear program:

$$\begin{array}{ll} \text{(D)} & \min \quad 5u_1 + 7u_2 + u_3 \\ & \text{s.t.} \quad 4u_1 + 8u_2 + 2u_3 = 12 \\ & \quad \quad 2u_1 + 12u_2 - 3u_3 = 10 \\ & \quad \quad u_1 \geq 0 \\ & \quad \quad \quad u_2 \geq 0 \\ & \quad \quad \quad \quad u_3 \geq 0 \end{array}$$

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Determine  $u_1$ ,  $u_2$ , and  $u_3$  by the following linear program:

$$\begin{array}{ll} \text{(D)} & \min \quad 5u_1 + 7u_2 + 1u_3 \\ & \text{s.t.} \quad 4u_1 + 8u_2 + 2u_3 = 12 \\ & \quad \quad 2u_1 + 12u_2 - 3u_3 = 10 \\ & \quad \quad u_1 \geq 0 \\ & \quad \quad \quad u_2 \geq 0 \\ & \quad \quad \quad \quad u_3 \geq 0 \end{array}$$

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# Duality: Example

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Determine  $u_1$ ,  $u_2$ , and  $u_3$  by the following linear program:

$$\begin{array}{ll} \text{(D)} & \min \quad 5u_1 + 7u_2 + u_3 \\ & \text{s.t.} \quad 4u_1 + 8u_2 + 2u_3 = 12 \\ & \quad \quad 2u_1 + 12u_2 - 3u_3 = 10 \\ & \quad \quad u_1 \geq 0 \\ & \quad \quad \quad u_2 \geq 0 \\ & \quad \quad \quad \quad u_3 \geq 0 \end{array}$$

$\Rightarrow$  Any solution of (D) gives an upper bound for (P).



# Duality: Example

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Determine  $u_1$ ,  $u_2$ , and  $u_3$  by the following linear program:

$$\begin{array}{ll} \text{(D)} & \min \quad 5u_1 + 7u_2 + u_3 \\ & \text{s.t.} \quad 4u_1 + 8u_2 + 2u_3 = 12 \\ & \quad \quad 2u_1 + 12u_2 - 3u_3 = 10 \\ & \quad \quad u_1 \geq 0 \\ & \quad \quad \quad u_2 \geq 0 \\ & \quad \quad \quad \quad u_3 \geq 0 \end{array}$$

$\Rightarrow$  Any solution of (D) gives an upper bound for (P).

# Fourier-Motzkin Elimination I

Given a system of inequalities, check if a solution exists.

$$\begin{array}{rcccccc} 3x & + & 2y & + & 4z & \leq & 10 \\ 3x & & & + & 2z & \leq & 9 \\ 2x & - & y & & & \leq & 5 \\ -x & + & 2y & - & z & \leq & 3 \\ -2x & & & & & \leq & 4 \\ & & 2y & + & 2z & \leq & 7 \end{array}$$

First step: Get rid of variable  $x$ .

# Fourier-Motzkin Elimination II

$$\begin{array}{rccccrcr} 3x & + & 2y & + & 4z & \leq & 10 \\ 3x & & & + & 2z & \leq & 9 \\ 2x & - & y & & & \leq & 5 \\ -x & + & 2y & - & z & \leq & 3 \\ -2x & & & & & \leq & 4 \\ & & 2y & + & 2z & \leq & 7 \end{array}$$

is equivalent to

$$\begin{array}{rccccrcr} x & \leq & \frac{10}{3} & - & \frac{2}{3}y & - & \frac{4}{3}z \\ x & \leq & 3 & & & - & \frac{2}{3}z \\ x & \leq & \frac{5}{2} & + & \frac{1}{2}y & & \\ x & \geq & -3 & + & 2y & - & z \\ x & \geq & -2 & & & & \\ & & 2y & + & 2z & \leq & 7 \end{array}$$

# Fourier-Motzkin Elimination III

$$\begin{array}{rcllcl} x & \leq & \frac{10}{3} & - & \frac{2}{3}y & - & \frac{4}{3}z \\ x & \leq & 3 & & & - & \frac{2}{3}z \\ x & \leq & \frac{5}{2} & + & \frac{1}{2}y & & \\ x & \geq & -3 & + & 2y & - & z \\ x & \geq & -2 & & & & \\ & & & & 2y & + & 2z \leq 7 \end{array}$$

This system is feasible if and only if the following system has a solution:

$$\min \left\{ \frac{10}{3} - \frac{2}{3}y - \frac{4}{3}z, \quad 3 - \frac{2}{3}z, \quad \frac{5}{2} + \frac{1}{2}y \right\} \geq \max \left\{ -3 + 2y - z, \quad -2 \right\}$$
$$2y + 2z \leq 7$$

# Fourier-Motzkin Elimination IV

$$\min \left\{ \frac{10}{3} - \frac{2}{3}y - \frac{4}{3}z, \quad 3 - \frac{2}{3}z, \quad \frac{5}{2} + \frac{1}{2}y \right\} \geq \max \{-3 + 2y - z, \quad -2\}$$

$$2y + 2z \leq 7$$

This system can be rewritten in the following way:

$$\begin{array}{rccccccc} \frac{10}{3} & - & \frac{2}{3}y & - & \frac{4}{3}z & \geq & -3 & + & 2y & - & z \\ \frac{10}{3} & - & \frac{2}{3}y & - & \frac{4}{3}z & \geq & -2 & & & & \\ 3 & & & - & \frac{2}{3}z & \geq & -3 & + & 2y & - & z \\ 3 & & & - & \frac{2}{3}z & \geq & -2 & & & & \\ \frac{5}{2} & + & \frac{1}{2}y & & & \geq & -3 & + & 2y & - & z \\ \frac{5}{2} & + & \frac{1}{2}y & & & \geq & -2 & & & & \\ & & 2y & + & 2z & \leq & 7 & & & & \end{array}$$

# Fourier-Motzkin Elimination V

Conversion in standard form:

$$\begin{array}{rccccl} \frac{8}{3}y & + & \frac{1}{3}z & \leq & \frac{19}{3} \\ \frac{2}{3}y & + & \frac{4}{3}z & \leq & \frac{16}{3} \\ \frac{8}{3}y & - & z & \leq & 6 \\ & & \frac{2}{3}z & \leq & 5 \\ \frac{3}{2}y & - & z & \leq & \frac{11}{2} \\ -\frac{1}{2}y & & & \leq & \frac{9}{2} \\ 2y & + & 2z & \leq & 7 \end{array}$$

**Iterate** these steps and remove *all* variables.

# Farkas' Lemma

## Theorem (Farkas' Lemma, most general case)

For  $A \in \mathbb{R}^{m_1 \times n_1}$ ,  $B \in \mathbb{R}^{m_1 \times n_2}$ ,  $C \in \mathbb{R}^{m_2 \times n_1}$ ,  $D \in \mathbb{R}^{m_2 \times n_2}$ ,  $a \in \mathbb{R}^{m_1}$  and  $b \in \mathbb{R}^{m_2}$  exactly one of the two following systems has a feasible solution:

System 1:

$$\begin{array}{rclcl} Ax & + & By & \leq & a \\ Cx & + & Dy & = & b \\ x & & & \geq & 0 \end{array}$$

System 2:

$$\begin{array}{rclcl} u^t A & + & v^t C & \geq & 0^t \\ u^t B & + & v^t D & = & 0^t \\ u & & & \geq & 0 \\ u^t a & + & v^t b & < & 0 \end{array}$$

## Corollary

Let  $A, B, C, D, E, F, G, H, K$  be matrices and  $a, b, c, d, e, f$  be vectors of appropriate dimensions such that:

$$\begin{pmatrix} A & B & C \\ D & E & F \\ G & H & K \end{pmatrix} \text{ is an } m \times n\text{-matrix,}$$

$\begin{pmatrix} a \\ b \\ c \end{pmatrix}$  is a vector of length  $m$  and  $\begin{pmatrix} d \\ e \\ f \end{pmatrix}$  is a vector of length  $n$ . Then

$$\begin{aligned} & \max \left\{ \begin{array}{l} d^t x + e^t y + f^t z \\ x \\ z \end{array} : \begin{array}{l} Ax + By + Cz \leq a \\ Dx + Ey + Fz = b \\ Gx + Hy + Kz \geq c \\ x \geq 0 \\ z \leq 0 \end{array} \right\} \\ & = \\ & \min \left\{ \begin{array}{l} a^t u + b^t v + c^t w \\ u \\ w \end{array} : \begin{array}{l} A^t u + D^t v + G^t w \geq d \\ B^t u + E^t v + H^t w = e \\ C^t u + F^t v + K^t w \leq f \\ u \geq 0 \\ w \leq 0 \end{array} \right\}, \end{aligned}$$

provided that both sets are non-empty.



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provided that both sets are non-empty.

## Theorem (Strict Complementary Slackness)

Let  $\max\{c^t x \mid Ax \leq b\}$  and  $\min\{b^t y \mid A^t y = c, y \geq 0\}$  be a pair of a primal and a dual linear program that are both feasible. Then, for each inequality  $a_i^t x \leq b_i$  in  $Ax \leq b$  exactly one of the following two statements holds:

- (a) The primal LP  $\max\{c^t x \mid Ax \leq b\}$  has an optimum solution  $x^*$  with  $a_i^t x^* < b_i$ .
- (b) The dual LP  $\min\{b^t y \mid A^t y = c, y \geq 0\}$  has an optimum solution  $y^*$  with  $y_i^* > 0$ .

# Max-Flow Problem

**Assumption:** No edges enter  $s$  or leave  $t$ .

LP-formulation:

$$\begin{array}{ll} \max & \sum_{e \in \delta_G^+(s)} x_e \\ \text{s.t.} & x_e \geq 0 \quad \text{for } e \in E(G) \\ & x_e \leq u(e) \quad \text{for } e \in E(G) \\ & \sum_{e \in \delta_G^+(v)} x_e - \sum_{e \in \delta_G^-(v)} x_e = 0 \quad \text{for } v \in V(G) \setminus \{s, t\} \end{array}$$

Dual LP:

$$\begin{array}{ll} \min & \sum_{e \in E(G)} u(e)y_e \\ \text{s.t.} & y_e \geq 0 \quad \text{for } e \in E(G) \\ & y_e + z_v - z_w \geq 0 \quad \text{for } e = (v, w) \in E(G), \{s, t\} \cap \{v, w\} = \emptyset \\ & y_e + z_v \geq 0 \quad \text{for } e = (v, t) \in E(G), v \neq s \\ & y_e - z_w \geq 1 \quad \text{for } e = (s, w) \in E(G), w \neq t \\ & y_e \geq 1 \quad \text{for } e = (s, t) \in E(G) \end{array}$$

# Max-Flow Problem

**Assumption:** No edges enter  $s$  or leave  $t$ .

LP-formulation:

$$\begin{array}{ll} \max & \sum_{e \in \delta_G^+(s)} x_e \\ \text{s.t.} & x_e \geq 0 \quad \text{for } e \in E(G) \\ & x_e \leq u(e) \quad \text{for } e \in E(G) \\ & \sum_{e \in \delta_G^+(v)} x_e - \sum_{e \in \delta_G^-(v)} x_e = 0 \quad \text{for } v \in V(G) \setminus \{s, t\} \end{array}$$

Dual LP (simplified):

$$\begin{array}{ll} \min & \sum_{e \in E(G)} u(e)y_e \\ \text{s.t.} & y_e \geq 0 \quad \text{for } e \in E(G) \\ & y_e + z_v - z_w \geq 0 \quad \text{for } e = (v, w) \in E(G) \\ & z_s = -1 \\ & z_t = 0 \end{array}$$

# Max-Flow Problem

Assumption: No edges enter  $s$  or leave  $t$ .

LP-formulation:

$$\begin{array}{ll} \max & \sum_{e \in \delta_G^+(s)} x_e \\ \text{s.t.} & x_e \geq 0 \quad \text{for } e \in E(G) \\ & x_e \leq u(e) \quad \text{for } e \in E(G) \\ & \sum_{e \in \delta_G^+(v)} x_e - \sum_{e \in \delta_G^-(v)} x_e = 0 \quad \text{for } v \in V(G) \setminus \{s, t\} \end{array}$$

Dual LP:

$$\begin{array}{ll} \min & \sum_{e \in E(G)} u(e)y_e \\ \text{s.t.} & y_e \geq 0 \quad \text{for } e \in E(G) \\ & y_e + z_v - z_w \geq 0 \quad \text{for } e = (v, w) \in E(G) \\ & z_s = -1 \\ & z_t = 0 \end{array}$$



## Proposition

Let  $P = \{x \in \mathbb{R}^n \mid Ax \leq b\}$  be a polyhedron and  $F \subseteq P$ . Then, the following statements are equivalent:

- (a)  $F$  is a face of  $P$ .
- (b) There is a vector  $c \in \mathbb{R}^n$  such that  $\delta := \max\{c^t x \mid x \in P\} < \infty$  and  $F = \{x \in P \mid c^t x = \delta\}$ .
- (c) There is a subsystem  $A'x \leq b'$  of  $Ax \leq b$  such that  $F = \{x \in P \mid A'x = b'\} \neq \emptyset$ .

# Simplex Algorithm: Example I

$$\begin{array}{rcllclclcl}
 \max & x_1 & + & x_2 & & & & & \\
 \text{s.t.} & -x_1 & + & x_2 & + & x_3 & & & = & 1 \\
 & x_1 & & & & & + & x_4 & = & 3 \\
 & & & x_2 & & & & + & x_5 & = & 2 \\
 & x_1 & , & x_2 & , & x_3 & , & x_4 & , & x_5 & \geq & 0
 \end{array}$$

Initial basis:  $\{3, 4, 5\}$ .  $\Rightarrow A_B = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$

Simplex tableau:

$$\begin{array}{rclclcl}
 x_3 & = & 1 & + & x_1 & - & x_2 \\
 x_4 & = & 3 & - & x_1 & & \\
 x_5 & = & 2 & & & - & x_2 \\
 \hline
 z & = & & & x_1 & + & x_2
 \end{array}$$

Recent solution:  $(0, 0, 1, 3, 2)$

# Simplex Algorithm: Example I

$$\begin{array}{rclclcl} x_3 & = & 1 & + & x_1 & - & x_2 \\ x_4 & = & 3 & - & x_1 & & \\ x_5 & = & 2 & & & - & x_2 \\ \hline z & = & & & x_1 & + & x_2 \end{array}$$

Increase exactly one of the non-basic variables with positive coefficient in the objective function.

We choose  $x_2$ . How much can we increase it?

Constraints:

$x_3 = 1 + x_1 - x_2$ :  $x_2$  cannot get larger than 1.

$x_4 = 3 - x_1$  : no constraint on  $x_2$ .

$x_5 = 2 - x_2$ :  $x_2$  cannot get larger than 2.

Strictest constraint:  $x_3 = 1 + x_1 - x_2$

$\Rightarrow$  Replace 3 by 2 in  $B$ .

# Simplex Algorithm: Example I

First tableau:

$$\begin{array}{rclclcl} x_3 & = & 1 & + & x_1 & - & x_2 \\ x_4 & = & 3 & - & x_1 & & \\ x_5 & = & 2 & & & - & x_2 \\ \hline z & = & & & x_1 & + & x_2 \end{array}$$

Replace 3 by 2 in the basis  $B$ :  $B = \{2, 4, 5\}$ :

$$x_2 = 1 + x_1 - x_3.$$

Second tableau:

$$\begin{array}{rclclcl} x_2 & = & 1 & + & x_1 & - & x_3 \\ x_4 & = & 3 & - & x_1 & & \\ x_5 & = & 1 & - & x_1 & + & x_3 \\ \hline z & = & 1 & + & 2x_1 & - & x_3 \end{array}$$

Recent solution:  $(0, 1, 0, 3, 1)$

# Simplex Algorithm: Example I

Second tableau:

$$\begin{array}{rcccc} x_2 & = & 1 & + & x_1 & - & x_3 \\ x_4 & = & 3 & - & x_1 & & \\ x_5 & = & 1 & - & x_1 & + & x_3 \\ \hline z & = & 1 & + & 2x_1 & - & x_3 \end{array}$$

Only one candidate:  $x_1$

$x_5 = 1 - x_1 + x_3$  is critical. Replace 5 by 1 in  $B$ :  $B = \{1, 2, 4\}$ .

$$x_1 = 1 + x_3 - x_5.$$

Third tableau:

$$\begin{array}{rcccc} x_1 & = & 1 & + & x_3 & - & x_5 \\ x_2 & = & 2 & & & - & x_5 \\ x_4 & = & 2 & - & x_3 & + & x_5 \\ \hline z & = & 3 & + & x_3 & - & 2x_5 \end{array}$$

Recent solution:  $x = (1, 2, 0, 2, 0)$ .

# Simplex Algorithm: Example I

Third tableau:

$$\begin{array}{rccccr} x_1 & = & 1 & + & x_3 & - & x_5 \\ x_2 & = & 2 & & & - & x_5 \\ x_4 & = & 2 & - & x_3 & + & x_5 \\ \hline z & = & 3 & + & x_3 & - & 2x_5 \end{array}$$

Only one candidate:  $x_3$

$x_4 = 2 - x_3 + x_5$  is critical. Replace 4 by 3 in  $B$ :  $B = \{1, 2, 3\}$ .

$$x_3 = 2 - x_4 + x_5$$

Fourth tableau:

$$\begin{array}{rccccr} x_1 & = & 3 & - & x_4 & & \\ x_2 & = & 2 & & & - & x_5 \\ x_3 & = & 2 & - & x_4 & + & x_5 \\ \hline z & = & 5 & - & x_4 & - & x_5 \end{array}$$

Recent solution:  $x = (3, 2, 2, 0, 0)$ .

# Simplex Algorithm: Example I

Fourth tableau:

$$\begin{array}{rcccccc} x_1 & = & 3 & - & x_4 & & \\ x_2 & = & 2 & & & - & x_5 \\ x_3 & = & 2 & - & x_4 & + & x_5 \\ \hline z & = & 5 & - & x_4 & - & x_5 \end{array}$$

Recent solution:  $x = (3, 2, 2, 0, 0)$ .

This is an optimum solution!

## Second Example: Unboundedness





# Simplex Algorithm: Example II: Unboundedness

First Tableau:

$$\begin{array}{rclclcl} x_3 & = & 1 & - & x_1 & + & x_2 \\ x_4 & = & 2 & + & x_1 & - & x_2 \\ \hline z & = & & & x_1 & & \end{array}$$

Only one candidate:  $x_1$ .  $x_3 = 1 - x_1 + x_2$  is critical. Replace 3 by 1 in  $B$ :  $B = \{1, 4\}$ .

$$x_1 = 1 + x_2 - x_3.$$

Second Tableau:

$$\begin{array}{rclclcl} x_1 & = & 1 & + & x_2 & - & x_3 \\ x_4 & = & 3 & & & - & x_3 \\ \hline z & = & 1 & + & x_2 & - & x_3 \end{array}$$

Recent solution:

$$x = (1, 0, 0, 3).$$

# Simplex Algorithm: Example II: Unboundedness

Second Tableau:

$$\begin{array}{rcccccc} x_1 & = & 1 & + & x_2 & - & x_3 \\ x_4 & = & 3 & & & - & x_3 \\ \hline z & = & 1 & + & x_2 & - & x_3 \end{array}$$

Only one candidate:  $x_2$ . No constraint for it!

⇒ The LP is unbounded

## Second Example: Degeneracy

# Simplex Algorithm: Example III: Degeneracy

$$\begin{array}{rcllclclcl} \max & & & x_2 & & & & & \\ \text{s.t.} & -x_1 & + & x_2 & + & x_3 & & & = & 0 \\ & x_1 & & & & & + & x_4 & = & 2 \\ & x_1 & , & x_2 & , & x_3 & , & x_4 & \geq & 0 \end{array}$$

Initial basis:  $B = \{3, 4\}$

Simplex Tableau:

$$\begin{array}{rcllclcl} x_3 & = & & x_1 & - & x_2 & & \\ x_4 & = & 2 & - & x_1 & & & \\ \hline z & = & & & & & x_2 & \end{array}$$

$\Rightarrow x = (0, 0, 0, 2)$ : **degenerated solution.**

# Simplex Algorithm: Example III: Degeneracy

First Tableau:

$$\begin{array}{rclcl} x_3 & = & & x_1 & - & x_2 \\ x_4 & = & 2 & - & x_1 & \\ \hline z & = & & & & x_2 \end{array}$$

Want to increase  $x_2$ .  $x_3 = x_1 - x_2$  is critical. Replace 3 by 2 in  $B$ :  
 $B = \{2, 4\}$ .

$x_2 = x_1 - x_3$ . We will replace 3 by 2 in the basis.

But: We cannot increase  $x_2$ .

Second Tableau:

$$\begin{array}{rclcl} x_2 & = & & x_1 & - & x_3 \\ x_4 & = & 2 & - & x_1 & \\ \hline z & = & & x_1 & - & x_3 \end{array}$$

Recent solution:  $x = (0, 0, 0, 2)$ .

# Simplex Algorithm: Example III: Degeneracy

Second Tableau:

$$\begin{array}{rclcl} x_2 & = & & x_1 & - & x_3 \\ x_4 & = & 2 & - & x_1 & \\ \hline z & = & & x_1 & - & x_3 \end{array}$$

Increase  $x_1$ .  $x_4 = 2 - x_1$  is critical.  $x_1 = 2 - x_4$ . New base  $B = \{1, 2, 0, 0\}$ .

Third Tableau:

$$\begin{array}{rclcl} x_1 & = & 2 & & - & x_4 \\ x_2 & = & 2 & - & x_3 & - & x_4 \\ \hline z & = & 2 & - & x_3 & - & x_4 \end{array}$$

Optimum solution:  $x = (2, 2, 0, 0)$ .

# The Simplex Algorithm

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## Algorithm 1: Simplex Algorithm

---

**Input:**  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$ , and  $c \in \mathbb{R}^n$

**Output:**  $\tilde{x} \in \{x \in \mathbb{R}^n \mid Ax = b, x \geq 0\}$  maximizing  $c^t x$  or the message that  $\max\{c^t x \mid Ax = b, x \geq 0\}$  is unbounded or infeasible

- 1 Compute a feasible basis  $B$ ;
- 2 If no such basis exists, stop with the message “INFEASIBLE”;
- 3 Set  $N = \{1, \dots, n\} \setminus B$  and compute the feasible basic solution  $x$  for  $B$ ;
- 4 Compute the simplex tableau 
$$\begin{array}{rcl} x_B & = & p \quad + \quad Qx_N \\ z & = & z_0 \quad + \quad r^t x_N \end{array}$$
 for  $B$ ;
- 5 **if**  $r \leq 0$  **then**
  - └ **return**  $\tilde{x} = x$ ;
- 6 Choose  $\alpha \in N$  with  $r_\alpha > 0$ ;
- 7 **if**  $q_{i\alpha} \geq 0$  **for all**  $i \in B$  **then**
  - └ **return** “UNBOUNDED”;
- 8 Choose  $\beta \in B$  with  $q_{\beta\alpha} < 0$  and  $\frac{p_\beta}{q_{\beta\alpha}} = \max\{\frac{p_i}{q_{i\alpha}} \mid q_{i\alpha} < 0, i \in B\}$ ;
- 9 Set  $B = (B \setminus \{\beta\}) \cup \{\alpha\}$ ;
- 10 GOTO line 3;



# The Simplex Algorithm

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## Algorithm 2: Simplex Algorithm

---

**Input:**  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$ , and  $c \in \mathbb{R}^n$

**Output:**  $\tilde{x} \in \{x \in \mathbb{R}^n \mid Ax = b, x \geq 0\}$  maximizing  $c^t x$  or the message that  $\max\{c^t x \mid Ax = b, x \geq 0\}$  is unbounded or infeasible

- 1 **Compute a feasible basis  $B$ ;**
- 2 **If no such basis exists, stop with the message “INFEASIBLE”;**
- 3 Set  $N = \{1, \dots, n\} \setminus B$  and compute the feasible basic solution  $x$  for  $B$ ;
- 4 Compute the simplex tableau 
$$\frac{x_B = p + Qx_N}{z = z_0 + r^t x_N}$$
 for  $B$ ;
- 5 **if  $r \leq 0$  then**
  - └ **return  $\tilde{x} = x$ ;**
- 6 Choose  $\alpha \in N$  with  $r_\alpha > 0$ ;
- 7 **if  $q_{i\alpha} \geq 0$  for all  $i \in B$  then**
  - └ **return “UNBOUNDED”;**
- 8 Choose  $\beta \in B$  with  $q_{\beta\alpha} < 0$  and  $\frac{p_\beta}{q_{\beta\alpha}} = \max\{\frac{p_i}{q_{i\alpha}} \mid q_{i\alpha} < 0, i \in B\}$ ;
- 9 Set  $B = (B \setminus \{\beta\}) \cup \{\alpha\}$ ;
- 10 GOTO line 3;

# The Simplex Algorithm

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## Algorithm 3: Simplex Algorithm

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**Input:**  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$ , and  $c \in \mathbb{R}^n$

**Output:**  $\tilde{x} \in \{x \in \mathbb{R}^n \mid Ax = b, x \geq 0\}$  maximizing  $c^t x$  or the message that  $\max\{c^t x \mid Ax = b, x \geq 0\}$  is unbounded or infeasible

- 1 Compute a feasible basis  $B$ ;
- 2 If no such basis exists, stop with the message “**INFEASIBLE**”;
- 3 Set  $N = \{1, \dots, n\} \setminus B$  and compute the feasible basic solution  $x$  for  $B$ ;
- 4 Compute the simplex tableau 
$$\begin{array}{rcl} x_B & = & p \quad + \quad Qx_N \\ z & = & z_0 \quad + \quad r^t x_N \end{array}$$
 for  $B$ ;
- 5 **if**  $r \leq 0$  **then**
  - └ **return**  $\tilde{x} = x$ ;
- 6 **Choose**  $\alpha \in N$  with  $r_\alpha > 0$ ;
- 7 **if**  $q_{i\alpha} \geq 0$  **for all**  $i \in B$  **then**
  - └ **return** “**UNBOUNDED**”;
- 8 **Choose**  $\beta \in B$  with  $q_{\beta\alpha} < 0$  and  $\frac{p_\beta}{q_{\beta\alpha}} = \max\{\frac{p_i}{q_{i\alpha}} \mid q_{i\alpha} < 0, i \in B\}$ ;
- 9 Set  $B = (B \setminus \{\beta\}) \cup \{\alpha\}$ ;
- 10 GOTO line 3;

## Definition

Let  $G$  be a directed graph with capacities  $u : E(G) \rightarrow \mathbb{R}_{>0}$  and numbers  $b : V(G) \rightarrow \mathbb{R}$  with  $\sum_{v \in V(G)} b(v) = 0$ . A **feasible  $b$ -flow in  $(G, u, b)$**  is a mapping  $f : E(G) \rightarrow \mathbb{R}_{\geq 0}$  with

- $f(e) \leq u(e)$  for all  $e \in E(G)$  and
- $\sum_{e \in \delta_G^+(v)} f(e) - \sum_{e \in \delta_G^-(v)} f(e) = b(v)$  for all  $v \in V(G)$ .

## Notation:

- $b(v)$ : **balance** of  $v$ .
- If  $b(v) > 0$ , we call it the **supply** of  $v$ .
- If  $b(v) < 0$ , we call it the **demand** of  $v$ .
- Nodes  $v$  of  $G$  with  $b(v) > 0$  are called **sources**.
- Nodes  $v$  with  $b(v) < 0$  are called **sinks**.

## Minimum-Cost Flow Problem

- **Input:** A directed graph  $G$ , capacities  $u : E(G) \rightarrow \mathbb{R}_{>0}$ , numbers  $b : V(G) \rightarrow \mathbb{R}$  with  $\sum_{v \in V(G)} b(v) = 0$ , edge costs  $c : E(G) \rightarrow \mathbb{R}$ .
- **Task:** Find a  $b$ -flow  $f$  minimizing  $\sum_{e \in E(G)} c(e) \cdot f(e)$ .

## Definition

Let  $G$  be a directed graph.

- For  $e = (v, w)$  let  $\overleftarrow{e} = (w, v)$  its **reverse edge**.
- Define  $\overleftrightarrow{G}$  by  $V(\overleftrightarrow{G}) = V(G)$  and  $E(\overleftrightarrow{G}) = E(G) \dot{\cup} \{\overleftarrow{e} \mid e \in E(G)\}$ .
- Edge costs  $c : E(G) \rightarrow \mathbb{R}$  are extended to  $E(\overleftrightarrow{G})$  by  $c(\overleftarrow{e}) := -c(e)$ .
- Let  $(G, u, b, c)$  be a MINIMUM-COST FLOW instance and let  $f$  be a  $b$ -flow in  $(G, u)$ . The **residual graph**  $G_{u,f}$  is defined by  
 $V(G_{u,f}) := V(G)$  and  
$$E(G_{u,f}) := \{e \in E(G) \mid f(e) < u(e)\} \dot{\cup} \{\overleftarrow{e} \in E(\overleftrightarrow{G}) \mid f(e) > 0\}.$$
- For  $e \in E(G)$  we define the **residual capacity** by  
 $u_f(e) = u(e) - f(e)$  and by  $u_f(\overleftarrow{e}) = f(e)$ .

## Augmenting Flow

If  $P$  is a subgraph of the residual graph  $G_{u,f}$  then **augmenting  $f$  along  $P$  by  $\gamma$**  (for  $\gamma > 0$ ) means increasing  $f$  on forward edges in  $P$  (i.e. edges in  $E(G) \cap E(P)$ ) by  $\gamma$  and reducing it on reverse edges in  $P$  by  $\gamma$ .

## Definition

Let  $(G, u, b, c)$  be a MINIMUM-COST FLOW instance with  $G$  connected. A **spanning tree structure** is a quadruple  $(r, T, L, U)$  where  $r \in V(G)$ ,  $E(G) = T \dot{\cup} L \dot{\cup} U$ ,  $|T| = |V(G)| - 1$ , and  $(V(G), T)$  does not contain an undirected cycle. The  **$b$ -flow  $f$  associated to  $(r, T, L, U)$**  is defined by

- $f(e) = 0$  for  $e \in L$ ,
- $f(e) = u(e)$  for  $e \in U$ ,
- $f(e) = \sum_{v \in C_e} b(v) + \sum_{e' \in U \cap \delta^-(C_e)} u(e') - \sum_{e' \in U \cap \delta^+(C_e)} u(e')$  for  $e \in E(T)$  where  $C_e$  is vertex set of the the connected component for  $(V(G), T \setminus \{e\})$  containing  $v$  (for  $e = (v, w)$ ).

The structure  $(r, T, L, U)$  is called **feasible** if  $0 \leq f(e) \leq u(e)$  for all  $e \in E(T)$ . An edge  $(v, w) \in E(T)$  is called **downward** if  $v$  is on the undirected  $r$ - $w$ -path in  $T$ , otherwise is is called **upward**.

## Definition

A feasible spanning tree structure  $(r, T, L, U)$  is **strongly feasible** if  $0 < f(e)$  for every downward edge  $e \in E(T)$  and  $f(e) < u(e)$  for every upward edge  $e \in E(T)$ .

## Definition

Let  $(r, T, L, U)$  be a spanning tree structure. The unique function  $\pi : V(G) \rightarrow \mathbb{R}$  with  $\pi(r) = 0$  and  $c_\pi(e) := c(e) + \pi(v) - \pi(w) = 0$  for all  $e = (v, w) \in T$  is called the **potential associated to**  $(r, T, L, U)$ .



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## Algorithm 4: Network Simplex Algorithm

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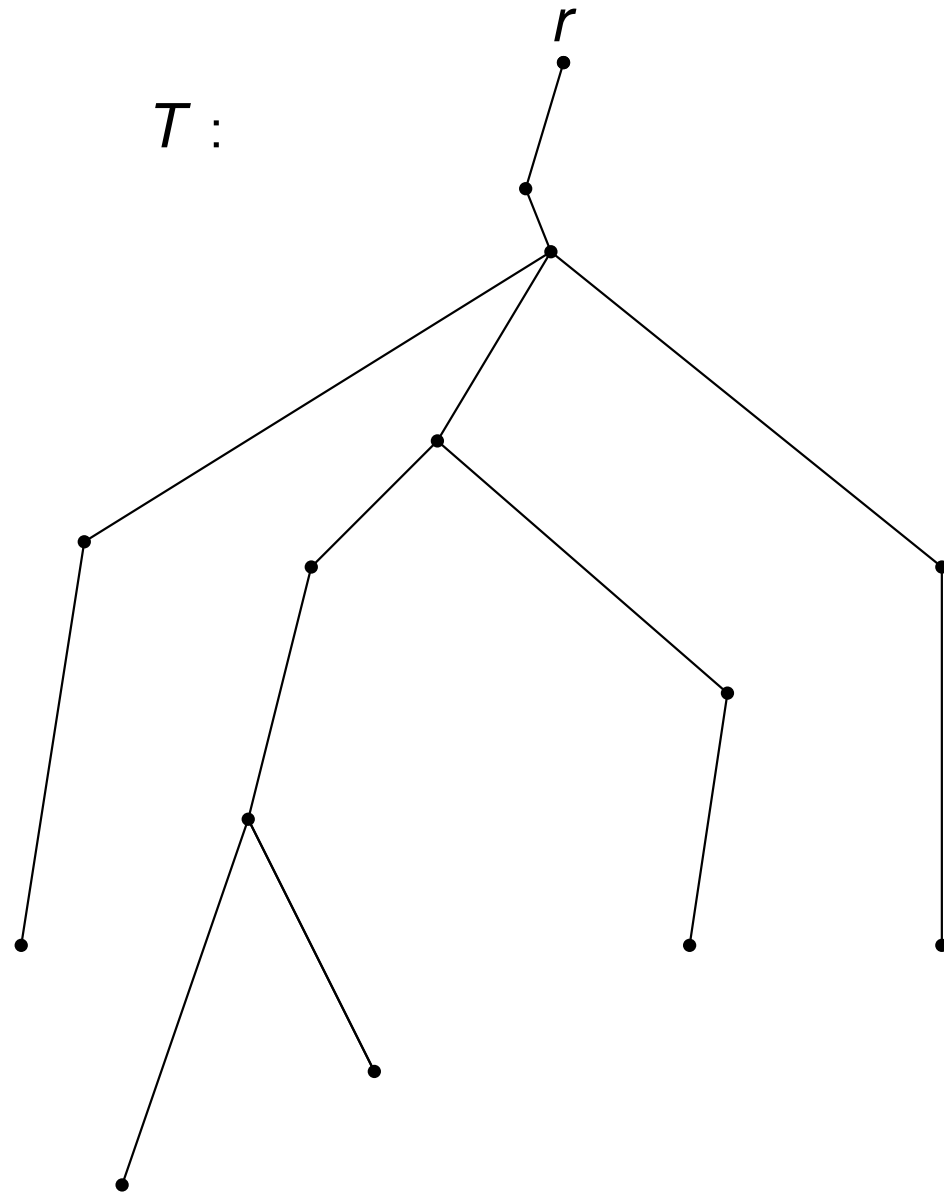
**Input:** A MIN-COST-FLOW instance  $(G, u, b, c)$ ;

A strongly feasible spanning tree structure  $(r, T, L, U)$ .

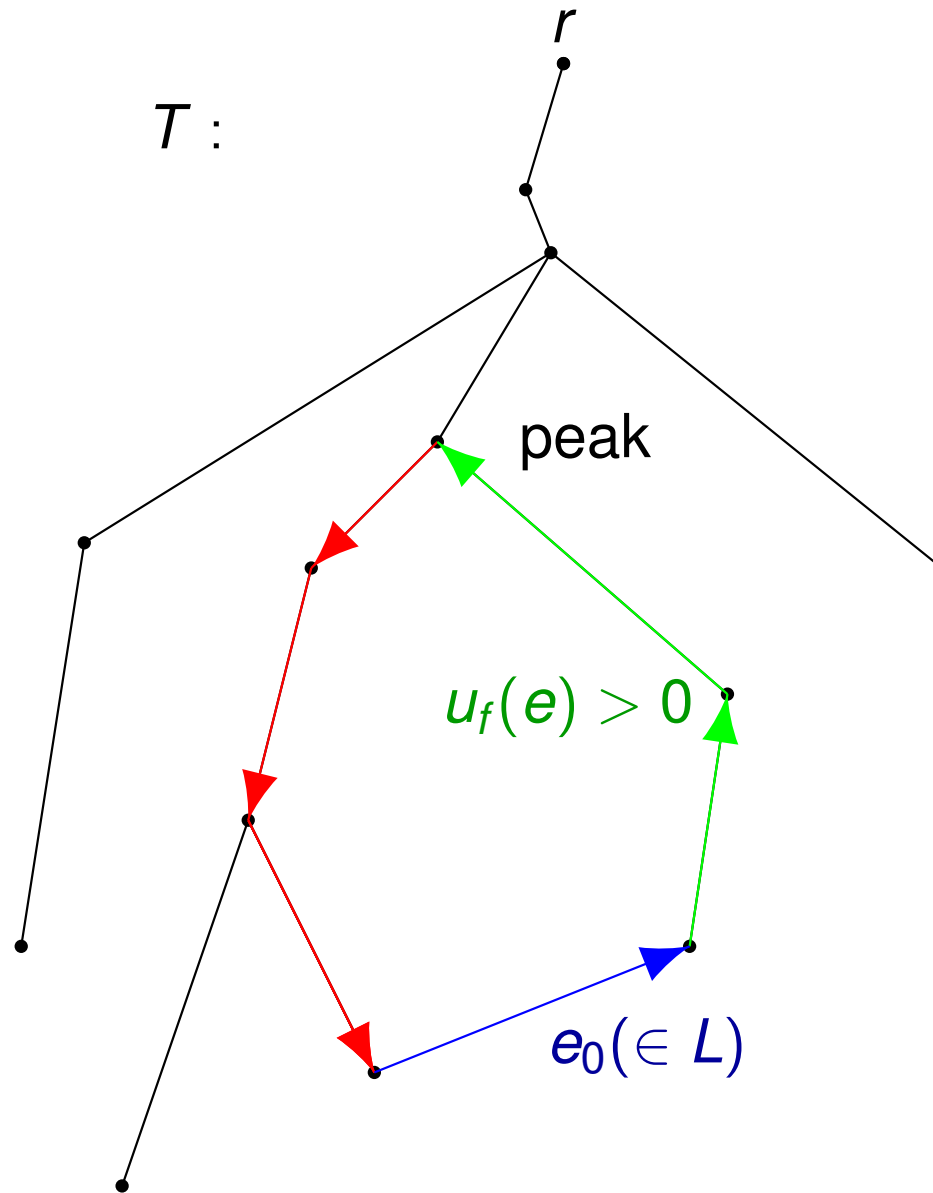
**Output:** A minimum-cost flow  $f$ .

- 1 Compute  $b$ -flow  $f$  and potential  $\pi$  associated to  $(r, T, L, U)$ ;
  - 2  $e_0 :=$  an edge with  $e_0 \in L$  and  $c_\pi(e_0) < 0$  or with  $e_0 \in U$  and  $c_\pi(e_0) > 0$ ;
  - 3 **if** (No such edge exists) **then return**  $f$
  - 4  $C :=$  the fund. circuit of  $e_0$  (if  $e_0 \in L$ ) or of  $\overleftarrow{e_0}$  (if  $e_0 \in U$ ) and let  $\rho = c_\pi(e_0)$ ;
  - 5  $\gamma := \min_{e' \in E(C)} u_f(e')$ .
  - 6  $e' :=$  last edge on  $C$  with  $u_f(e') = \gamma$  when  $C$  is traversed starting at the peak;
  - 7 Let  $e_1$  be the corresponding edge in  $G$ , i.e.  $e' = e_1$  or  $e' = \overleftarrow{e_1}$ ;
  - 8 Remove  $e_0$  from  $L$  or  $U$ ;
  - 9 Set  $T = (T \cup \{e_0\}) \setminus \{e_1\}$ ;
  - 10 **if**  $e' = e_1$  **then** Set  $U = U \cup \{e_1\}$ ;
  - 11 **else** Set  $L = L \cup \{e_1\}$ ;
  - 12 Augment  $f$  along  $\gamma$  by  $C$ ;
  - 13 Let  $X$  be the connected component of  $(V(G), T \setminus \{e_0\})$  that contains  $r$ ;
  - 14 **if**  $e_0 \in \delta^+(X)$  **then** Set  $\pi(v) = \pi(v) + \rho$  for  $v \in V(G) \setminus X$ ;
  - 15 **if**  $e_0 \in \delta^-(X)$  **then** Set  $\pi(v) = \pi(v) - \rho$  for  $v \in V(G) \setminus X$ ;
  - 16 **go to** line 2;
-

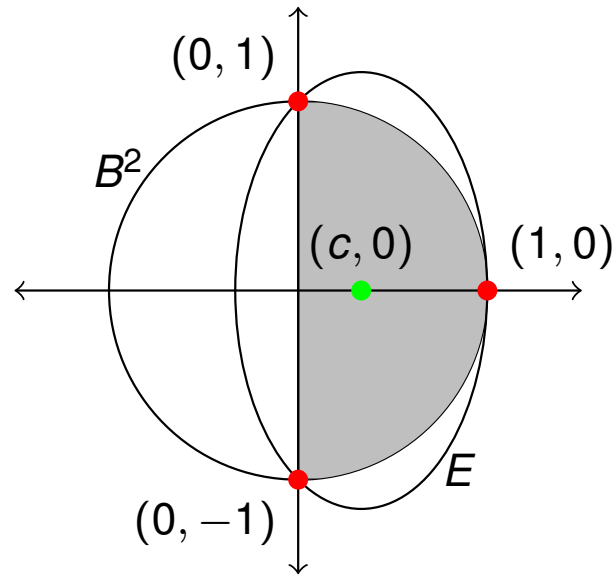
# Illustration:



# Illustration:



Cost of fundamental circuit =  $c_\pi(e_0)$ .



## Half-Ball Lemma

$$B^n \cap \{x \in \mathbb{R}^n \mid x_1 \geq 0\} \subseteq E$$

with

$$E = \left\{ x \in \mathbb{R}^n \mid \frac{(n+1)^2}{n^2} \left( x_1 - \frac{1}{n+1} \right)^2 + \frac{n^2-1}{n^2} \sum_{i=2}^n x_i^2 \leq 1 \right\}.$$

Moreover,  $\frac{\text{vol}(E)}{\text{vol}(B^n)} \leq e^{-\frac{1}{2(n+1)}}.$

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## Algorithm 5: Idealized Ellipsoid Algorithm

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**Input:** A separation oracle for a closed convex set  $K \subseteq \mathbb{R}^n$ , a number  $R > 0$  with  $K \subseteq \{x \in \mathbb{R}^n \mid x^t x \leq R^2\}$ , and a number  $\epsilon > 0$ .

**Output:** An  $x \in K$  or the message “ $\text{vol}(K) < \epsilon$ ”.

```
1  $p_0 := 0, A_0 := R^2 I_n;$ 
2 for  $k = 0, \dots, N(R, \epsilon) := \lfloor 2(n+1)(n \ln(2R) + \ln(\frac{1}{\epsilon})) \rfloor$  do
3   if  $p_k \in K$  then
4     return  $p_k;$ 
5   Let  $\bar{a} \in \mathbb{R}^n$  be a vector with  $\bar{a}^t y > \bar{a}^t p_k$  for all  $y \in K;$ 
6    $b_k := \frac{A_k \bar{a}}{\sqrt{\bar{a}^t A_k \bar{a}}};$ 
7    $p_{k+1} := p_k + \frac{1}{n+1} b_k;$ 
8    $A_{k+1} := \frac{n^2}{n^2-1} (A_k - \frac{2}{n+1} b_k b_k^t);$ 
9 return “ $\text{vol}(K) < \epsilon$ ”;
```

---

$\widetilde{p}_k$  and  $\widetilde{A}_k$ : exact values

$p_k$  and  $A_k$ : rounded values

Adjust  $\widetilde{A}_k$  by multiplying it by  $\mu = 1 + \frac{1}{2n(n+1)}$ .

$x \in K \Rightarrow$

- $(x - \widetilde{p}_k)^t \widetilde{A}_k^{-1} (x - \widetilde{p}_k) \leq 1 - \frac{1}{4n^2}$
- $(x - p_k)^t A_k^{-1} (x - p_k) \leq 1 - \frac{1}{4n^2} + 2\sqrt{n}\delta \|\widetilde{A}_k^{-1}\| (R + \|\widetilde{p}_k\|) + n\delta^2 \|\widetilde{A}_k^{-1}\| + (R + \|p_k\|)^2 \|A_k^{-1}\| \cdot \|\widetilde{A}_k^{-1}\| \cdot n\delta$

Goal is to choose  $\delta$  such that

- $2\sqrt{n}\delta \|\widetilde{A}_k^{-1}\| (R + \|\widetilde{p}_k\|) + n\delta^2 \|\widetilde{A}_k^{-1}\| + (R + \|p_k\|)^2 \|A_k^{-1}\| \cdot \|\widetilde{A}_k^{-1}\| n\delta < \frac{1}{4n^2}$
- $\delta \|\widetilde{A}_{k+1}^{-1}\| < \frac{1}{4(n+1)^3}$

## Proposition

Assume that  $\delta \leq \frac{1}{12n4^k}$  in iteration  $k$  of the ELLIPSOID METHOD. Then:

- (a)  $A_k$  is positive definite.
- (b)  $\|p_k\| \leq R2^k$ ,  $\|\widetilde{p}_k\| \leq R2^k$ .
- (c)  $\|A_k\| \leq R^22^k$ ,  $\|\widetilde{A}_k\| \leq R^22^k$ .
- (d)  $\|A_k^{-1}\| \leq R^{-2}4^k$ ,  $\|\widetilde{A}_k^{-1}\| \leq R^{-2}4^k$ .

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## Algorithm 6: Ellipsoid Algorithm

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**Input:** A separation oracle for a closed convex set  $K \subseteq \mathbb{R}^n$ , a number  $R > 0$  with  $K \subseteq \{x \in \mathbb{R}^n \mid x^t x \leq R^2\}$ , and a number  $\epsilon > 0$

**Output:** An  $x \in K$  or the message “ $\text{vol}(K) < \epsilon$ ”.

```
1  $p_0 := 0, A_0 := R^2 I_n;$ 
2 for  $k = 0, \dots, N(R, \epsilon) := \lceil 8(n+1)(n \ln(2R) + \ln(\frac{1}{\epsilon})) \rceil$  do
3   if  $p_k \in K$  then
4     return  $p_k;$ 
5   Let  $\bar{a} \in \mathbb{R}^n$  be a vector with  $\bar{a}^t y > \bar{a}^t p_k$  for all  $y \in K;$ 
6    $b_k := \frac{A_k \bar{a}}{\sqrt{\bar{a}^t A_k \bar{a}}};$ 
7    $p_{k+1}$  an approximation of  $\widetilde{p}_{k+1} := p_k + \frac{1}{n+1} b_k$  with maximum error
    $\delta < (2^{6(N(R, \epsilon)+1)} 16n^3)^{-1};$ 
8    $A_{k+1}$  a symmetric approximation of
    $\widetilde{A}_{k+1} := \left(1 + \frac{1}{2n(n+1)}\right) \frac{n^2}{n^2-1} (A_k - \frac{2}{n+1} b_k b_k^t)$  with maximum error  $\delta;$ 
9 return “ $\text{vol}(K) < \epsilon$ ”;
```

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## Theorem

Let  $P = \{x \in \mathbb{R}^n \mid Ax \leq b\}$  with  $A \in \mathbb{Q}^{m \times n}$  and  $b \in \mathbb{Q}^m$ . Then, the following statements are equivalent:

- (a)  $P$  is integral
- (b) Each face of  $P$  contains at least one integral vector.
- (c) Each minimal face of  $P$  contains at least one integral vector.
- (d) Each supporting hyperplane of  $P$  contains at least one integral vector.
- (e) Each rational supporting hyperplane of  $P$  contains at least one integral vector.
- (f)  $\max\{c^t x \mid x \in P\}$  is attained by an integral vector for each  $c$  for which the maximum is finite.
- (g)  $\max\{c^t x \mid x \in P\}$  is an integer for each integral vector  $c$  for which the maximum is finite.

## Theorem

A matrix  $A = (a_{ij})_{\substack{i=1,\dots,m \\ j=1,\dots,n}} \in \mathbb{Z}^{m \times n}$  is totally unimodular if and only if for each set  $R \subseteq \{1, \dots, n\}$  there is a partition  $R = R_1 \dot{\cup} R_2$  such that for each  $i \in \{1, \dots, m\}$ :  $\sum_{j \in R_1} a_{ij} - \sum_{j \in R_2} a_{ij} \in \{-1, 0, 1\}$ .

The **incidence matrix** of an undirected graph  $G$  is the matrix  $A_G = (a_{v,e})_{\substack{v \in V(G) \\ e \in E(G)}}$  which is defined by:

$$a_{v,e} = \begin{cases} 1, & \text{if } v \in e \\ 0, & \text{if } v \notin e \end{cases}$$

The **incidence matrix** of a directed graph  $G$  is the matrix  $A_G = (a_{v,e})_{\substack{v \in V(G) \\ e \in E(G)}}$  which is defined by:

$$a_{v,(x,y)} = \begin{cases} -1, & \text{if } v = x \\ 1, & \text{if } v = y \\ 0, & \text{if } v \notin \{x, y\} \end{cases}$$

## Definition

Let  $P \subseteq \mathbb{R}^n$  be a convex set. Let  $M$  be the set of all rational half-spaces  $H = \{x \in \mathbb{R}^n \mid c^t x \leq \delta\}$  with  $P \subseteq H$ . Then, we define

$$P' := \bigcap_{H \in M} H.$$

We set  $P^{(0)} := P$  and  $P^{(i+1)} := (P^{(i)})'$  for  $i \in \mathbb{N} \setminus \{0\}$ .  $P^{(i)}$  is the  $i$ -th **Gomory-Chvátal-truncation** of  $P$ .

## Lemma

Let  $H = \{x \in \mathbb{R}^n \mid c^t x \leq \delta\}$  be a rational half-space such that the components of  $c$  are relatively prime integers. Then

$$H_l = H' = \{x \in \mathbb{R}^n \mid c^t x \leq \lfloor \delta \rfloor\}.$$