

Optimization problems

Optimization problem is pair $(\mathcal{F}, f)$

- $\mathcal{F}$ is set of feasible solutions
- $f : \mathcal{F} \rightarrow \mathbb{R}$ objective or cost function.

Task: Find $x \in \mathcal{F}$ s.t.

$$f(x) \geq f(y) \text{ holds for all } y \in \mathcal{F}$$

Such $x \in \mathcal{F}$ is optimal solution

We also write

$$\max\{c(x) : x \in \mathcal{F}\}.$$

Minimization

If minimize $f(x)$, i.e.

find $x \in \mathcal{F}$ with

$$f(x) \leq f(y) \text{ for all } y \in \mathcal{F}$$

This is optimization problem $(\mathcal{F}, -f)$
since

$$-f(x) \geq -f(y) \text{ for all } y \in \mathcal{F}$$

if and only if

$$f(x) \leq f(y) \text{ for all } y \in \mathcal{F}.$$

Example: Maximizing quadratic form over sphere

$$A \in \mathbb{R}^{n \times n}$$

$$S^{(d-1)} : \text{  }$$

Max. $x^T A x$ over domain

$$\mathcal{F} = S^{(d-1)}$$

$$f(x) = x^T A x$$

$$f: \mathcal{F} \rightarrow \mathbb{R}.$$

$$S^{(d-1)} = \{x \in \mathbb{R}^d : \|x\| = 1\} \subseteq \mathbb{R}^d$$

$A \in \mathbb{R}^{d \times d}$ symmetric

$$x^T \cdot A \cdot x = x^T \underbrace{\left(\frac{1}{2} A + \frac{1}{2} A^T \right)}_{\text{symmetric}} \cdot x$$

$$\max \{x^T A x : x \in S^{(d-1)}\}.$$

$x_{\max}^*$ is EV corresponding
to $\lambda_{\max}$ of A
then x^* is an optimal solution
of $(\mathcal{F}, f)$

Example: Minimizing quadratic form over sphere

Min $x^T A x$ over domain

$$S^{(d-1)} = \{x \in \mathbb{R}^d : \|x\| = 1\} \subseteq \mathbb{R}^d$$

$A \in \mathbb{R}^{d \times d}$ symmetric

$$\mathcal{F} = S^{(d-1)}$$

$$f(x) = x^T (-A) x$$

$$\min \{x^T A x : x \in S^{(d-1)}\}.$$

$$\sim \max \{x^T (-A) x : x \in S^{(d-1)}\}$$

Example: Shortest path in directed graph

Directed graph: Tuple $G = (V, A)$

V : finite set of **vertices**

$A \subseteq V \times V$: **arcs**

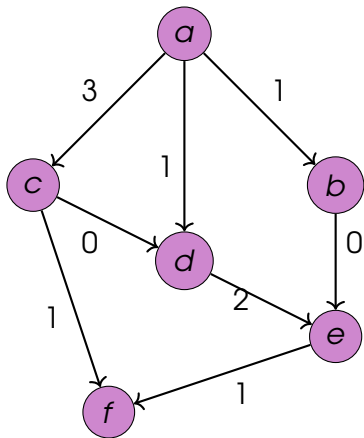
$w : A \rightarrow \mathbb{R}$: **weights**

Simple path: $P = v_1, v_2, \dots, v_k$ s.t.

v_i distinct and

$(v_i, v_{i+1}) \in A \quad i \in \{1, \dots, k-1\}$

length: $\ell(P) = \sum_{i=1}^{k-1} w(v_i, v_{i+1})$



Directed Graph:

$$G = (V, A)$$

V : finite set, the vertices of G .

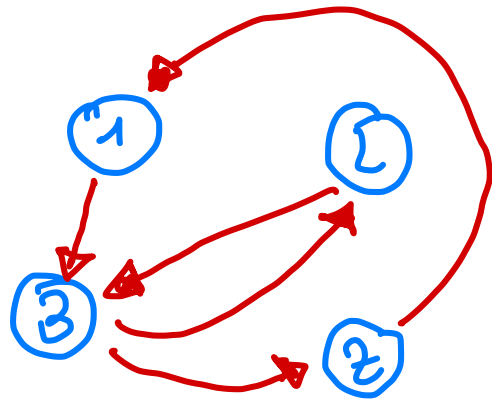
$A \subseteq V \times V$, the arcs (edges) of G .

Example:

$$G = (V, A)$$

$$V = \{1, 2, 3, z\}$$

$$A = \{(1, 3), (2, 3), (3, 2), (3, z), (z, 1), (z, 2)\}$$



Example:

3, z, 1

Simple path: $v_1, \dots, v_k$ sequence of distinct vertices

$$v_i \neq v_j \text{ if } i \neq j.$$

s.th. $(v_i, v_{i+1}) \in A$
 $\forall i \in \{1, \dots, k-1\}$

Shortest path

Given: $G = (V, A)$

$w : A \rightarrow \mathbb{R}$

$s, t \in V$

Shortest path problem:

$(\mathcal{P}, f)$

$\mathcal{P} = \{ P \subseteq V : P \text{ is simple path connecting } s \text{ with } t \}$



$$f(P) = -l(P)$$

$|\mathcal{P}|$ can be exponential in $|V|$

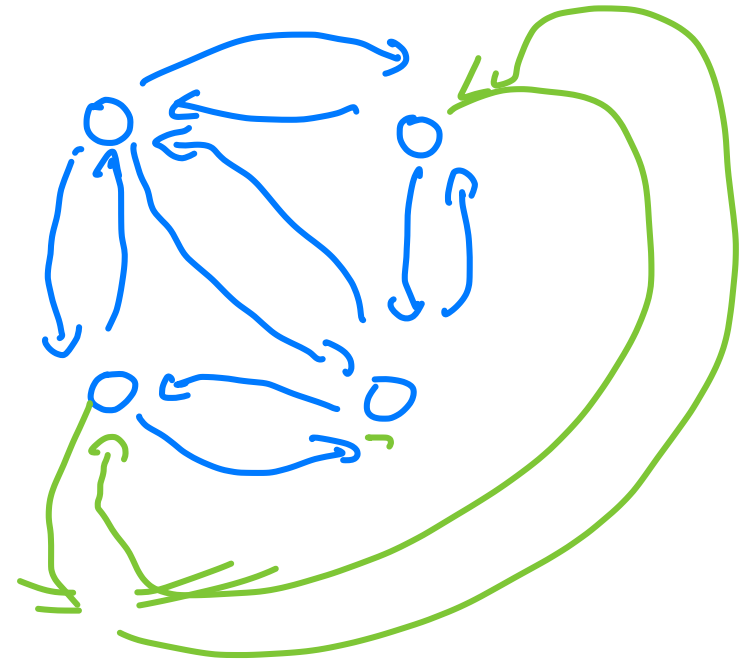
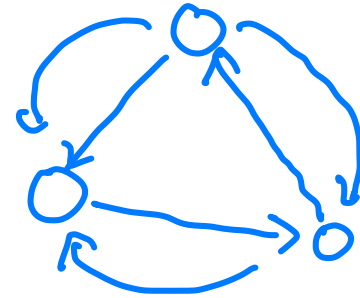
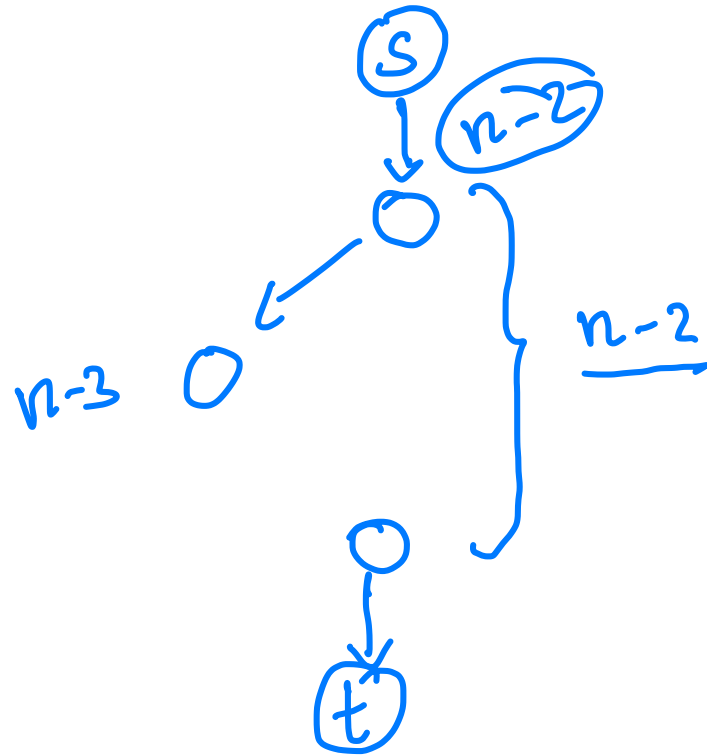
There are graphs for which
 $|\mathcal{P}| \geq (n-2)! = \frac{(n-2)(n-1)\dots(2)(1)}{2^{n-2}}$

Example:

$$G = (\{1, \dots, n\}, A)$$

$$A = \{(i, j) : i \neq j \in \{1, \dots, n\}\}$$

$$|A| \leq n^2$$



$$Z \geq (n-2)! \geq 2^{n-3}$$

exponential in n .

Linear Programming

(G, f) $\swarrow$ system of inequalities

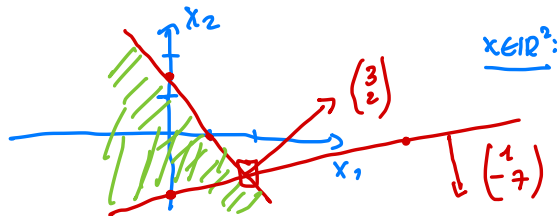
$$\mathcal{F} = \{x \in \mathbb{R}^n : Ax \leq b\},$$

$$A \in \mathbb{R}^{m \times n} \quad b \in \mathbb{R}^m$$

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ linear, i.e.,

$$f(x) = c^T x \text{ for } c \in \mathbb{R}^n$$

$$\begin{aligned} \max x_1 \\ = \begin{pmatrix} 1 \\ 0 \end{pmatrix}^T \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \end{aligned}$$



Example:

$$A = \begin{pmatrix} 3 & 2 \\ 1 & -7 \end{pmatrix} \quad b = \begin{pmatrix} 3 \\ 4 \end{pmatrix}$$

$\Downarrow$ feasible.

$$3 \cdot x_1 + 2 \cdot x_2 \leq 3 \quad (1)$$

$$x_1 - 7 \cdot x_2 \leq 4 \quad (2)$$

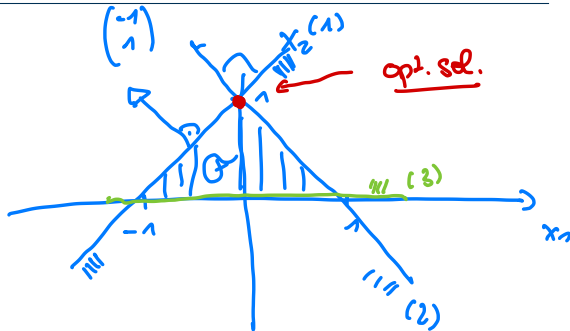
Linear programming: Example

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

$$b = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$$

$$\mathcal{F} = \{x \in \mathbb{R}^2 : Ax \leq b\}$$

$$\underline{f(x) = x_2}$$



$$-x_1 + x_2 \leq 1 \quad (1) \quad \uparrow \quad \text{why } (0,1) \text{ optimal.}$$

$$x_1 + x_2 \leq 1 \quad (2) \quad \downarrow \quad \rightarrow 2x_2 \leq 2$$

$$x_2 \geq 0 \quad (3) \quad \Leftrightarrow x_2 \leq 1 \text{ is satisfied by each } x \in \mathcal{F}.$$

Linear programming – Focus of this course

- Geometry
- Efficient algorithms
- Duality
- Convexity

Certificates: An algorithmic paradigm

- Algorithms computes solution
- How can we be sure of correctness?
- Philosophy: Checking a certificate might be easy

$$\begin{pmatrix} 1 & 0 \\ -2 & 1 \end{pmatrix} \cdot \begin{pmatrix} \overbrace{2 \quad 3 \quad 4}^A & \underbrace{1}_{\tilde{b}} \\ 4 \quad 5 \quad 6 & 1 \end{pmatrix} \rightsquigarrow$$

Example: Linear systems solving

$$Ax = b \quad (1)$$

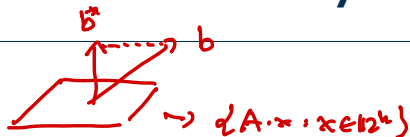
$$A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$$

If solvable, then solution $x^* \in \mathbb{R}^n$ serves as certificate.

you can be form.

$$\left[\begin{array}{ccc|c} 2 & 3 & 4 & 1 \\ 0 & -1 & -2 & -1 \end{array} \right]$$

Linear systems – Certificate for unsolvability



Theorem

(1) has no solution if and only if there exists $q \in \mathbb{R}^m$ with

$$q^T A = 0 \text{ and } q^T b \neq 0.$$

Proof: " $\Rightarrow$ " if $q^T A = 0$ and $q^T b \neq 0$ suppose $x^* \in \mathbb{R}^n$
 $\Rightarrow 0 \neq 0 \quad \downarrow$
is solution: $\left[A \cdot x^* = b \mid \cdot q^T \right] \Rightarrow \underbrace{q^T A \cdot x^*}_{=0} = \underbrace{q^T b}_{\neq 0}$

⇐

$$[A \mid b]$$

Gaussian elimination: $U \in \mathbb{R}^{n \times n}$
non-singular s.t.

$$U[A \mid b] = \left(\begin{array}{c|c} \text{staircase} & \end{array} \right)$$

2 cases:

Case 1:

$$\left(\begin{array}{c|c} \text{staircase} & \end{array} \right)$$

$Ax = b$ has solution x^*

We want: $q \in \mathbb{R}^n$ s.t.

$$q^T \cdot A = 0 \quad \text{and} \quad q^T \cdot b \neq 0$$

Case 2:

$$m \left(\begin{array}{c|c} \text{staircase} & \end{array} \right) \rightarrow \text{row } i$$

$1 - q^T \cdot A$ (green line) $\rightarrow$ (red circle)

$$\boxed{q?}$$

q^T : i -th row of U
 $c^*(i) = q^T \cdot b \neq 0$

Systems of linear inequalities – Deriving consequences

$$\begin{array}{rcl} 2x_1 + 3x_2 & \leq & 5 \\ 4x_1 + 1x_2 & \leq & 3 \end{array} \quad \begin{array}{l} \times \frac{1}{2} \\ \times \frac{1}{2} \end{array} \quad \begin{array}{l} \downarrow \\ \downarrow \end{array} \quad (2)$$

$$\Rightarrow \textcircled{4} \quad 3x_1 + 2x_2 \leq 4$$

If $x^* \in \mathbb{R}^2$ satisfies (2), then x^* satisfies

$$3x_1 + 2x_2 \leq 4$$

Derivation proves

Systems of linear inequalities – Deriving consequences

Let $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$ and $\lambda \in \mathbb{R}_{\geq 0}^m$. If $x^* \in \mathbb{R}^n$ satisfies

$$Ax \leq b$$

the x^* satisfies

$$\lambda^T Ax \leq \lambda^T b.$$



One inequality derived from $Ax \leq b$ with $\lambda \in \mathbb{R}_{\geq 0}^m$

$a_1^T, \dots, a_m^T$ rows of A

$$\begin{aligned} & (\lambda^T A) \cdot x^* \\ &= \underbrace{\lambda_1 a_1^T \cdot x^*}_{\leq \lambda_1 \cdot b_1} + \underbrace{\lambda_2 a_2^T \cdot x^*}_{\leq \lambda_2 \cdot b_2} + \dots + \underbrace{\lambda_m a_m^T \cdot x^*}_{\leq \lambda_m \cdot b_m} \\ & \qquad \qquad \qquad \underbrace{\hspace{10em}}_{= \lambda^T \cdot b} \end{aligned}$$

$Ax \leq b$: Certifying infeasibility

Theorem (Farkas' lemma)

$Ax \leq b$ is infeasible if and only if there exists $\lambda \in \mathbb{R}_{\geq 0}^m$ such that

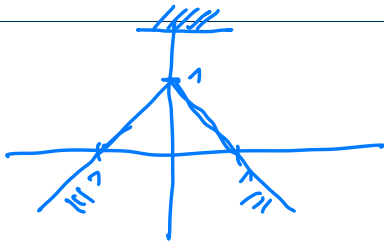
$$\lambda^T A = 0 \text{ and } \lambda^T b = -1.$$

proof: $\Leftarrow$ if x^* sat. $A \cdot x \leq b$ then x^* satisfies.

$$(\lambda^T A) x \leq (\lambda^T b) \Leftrightarrow 0^T x \leq -1 \Rightarrow \text{f.e.s. } x^* \text{ does not exist.}$$

Example: Infeasible system of inequalities

$$\underbrace{A}_{\begin{pmatrix} -1 & 1 \\ 1 & 1 \\ 0 & -1 \end{pmatrix}} x \leq \begin{pmatrix} 1 \\ 1 \\ -2 \end{pmatrix} \quad \Leftrightarrow x_2 \geq 2$$



$$\lambda = \begin{pmatrix} 1 \\ 1 \\ 2 \end{pmatrix}$$

$$\lambda \in \mathbb{R}_{\geq 0}^3 \quad \text{s.t.} \quad \lambda^T A = 0 \quad \lambda^T \cdot b = (0, 0)$$

$$\lambda = \begin{pmatrix} 1/2 \\ 1/2 \\ 1 \end{pmatrix} \quad \text{s.t.} \quad \lambda^T \cdot A = 0 \quad \lambda^T \cdot b = -1$$

$$\lambda^T \cdot b = -2$$

Example: Production planning

Spring and Nebsi

		A	B	Profit
Per 100l:	Spring	3l	8l	100 CHF
	Nebsi	6l	4l	125 CHF

In stock: 30l of A; 44l of B

Capacity of transport barrels:

Spring: 500l Nebsi: 400l

Production plan: (x_1, x_2)



100 l

3l A

6l B

$$\max \quad 100 \cdot x_1 + 125 \cdot x_2$$

$$A: \quad 3 \cdot x_1 + 6 \cdot x_2 \leq 30$$

$$B: \quad 8 \cdot x_1 + 4 \cdot x_2 \leq 44$$

$$x_1 \leq 5$$

$$x_2 \leq 4$$

$$x_1, x_2 \geq 0$$



Example: Production planning

Spring and Nebsi

	A	B	Profit
Per 100ℓ: Spring	3ℓ	8ℓ	100 CHF
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In stock: 30ℓ of A; 44ℓ of B

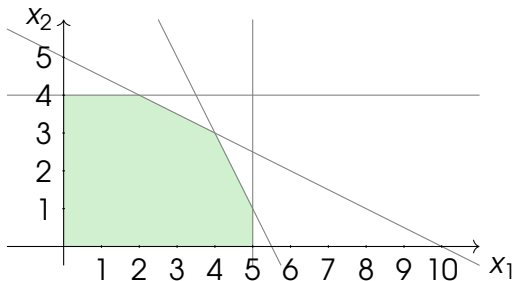
Capacity of transport barrels:

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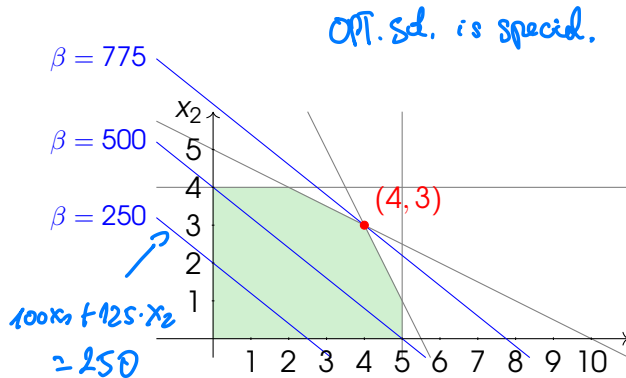
The linear program

$$\begin{array}{llll} \text{max.} & 100 \cdot x_1 + 125 \cdot x_2 & & \\ \text{s.t.:} & 3 \cdot x_1 + 6 \cdot x_2 & \leq & 30 \\ & 8 \cdot x_1 + 4 \cdot x_2 & \leq & 44 \\ & x_1 & \leq & 5 \\ & x_2 & \leq & 4 \\ & x_1 & \geq & 0 \\ & x_2 & \geq & 0 \end{array}$$



The linear program

$$\begin{array}{llll} \text{max.} & 100 \cdot x_1 + 125 \cdot x_2 & & \\ \text{s.t.:} & 3 \cdot x_1 + 6 \cdot x_2 & \leq & 30 \\ & 8 \cdot x_1 + 4 \cdot x_2 & \leq & 44 \\ & x_1 & \leq & 5 \\ & x_2 & \leq & 4 \\ & x_1 & \geq & 0 \\ & x_2 & \geq & 0 \end{array}$$



Proving optimality

$$3 \cdot x_1 + 6 \cdot x_2 \leq 30$$

$$8 \cdot x_1 + 4 \cdot x_2 \leq 44.$$

multiplied by $50/3$ and $25/4$
respectively:

$$50 \cdot x_1 + 100 \cdot x_2 \leq 500$$

$$50 \cdot x_1 + 25 \cdot x_2 \leq 275$$