

Introduction to Linear and Combinatorial Optimization (ADM I)

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based on the 2011/12 course by Martin Skutella

TU Berlin

WS 2013/14

Dates for Tutorien:

Wednesday: 8-10, ...

(2 out of those)

16-18

General Remarks

- ▶ new flavor of ADM II — continuation of “new ADM I” from last semester
- ▶ lectures (Rolf Möhring):
Thursday, 14:15 – 15:45, MA 043
Friday, 14:15 – 15:45, MA 041
- ▶ exercise session (Torsten Gellert):
Wednesday, 14:15 – 15:45, MA 041 (starting next week)
- ▶ tutorial sessions (Antje Lehmann), [details see web page](#)
- ▶ homework: set of problems every week (solve in groups of at most 3), sometimes programming exercises (details t.b.a.)
- ▶ “Scheinkriterium”: 50 % of points from problem sets 1–6 and 7–12
- ▶ final oral exam (Modulabschlussprüfung) in summer during the semester break (details t.b.a.), written exam if 50 or more students take the course

!

Outline

- 0 Introduction
- 1 Linear Programming Basics
- 2 The Geometry of Linear Programming
- 3 The Simplex Method
- 4 Duality Theory
- 5 Optimal Trees and Paths
- 6 Maximum Flow Problems
- 7 Minimum-Cost Flow Problems
- 8 NP-Completeness

- 9 Linear Programming and Polyhedral Theory
- 10 Sensitivity Analysis for Linear Programs
- 11 Large-Scale Linear Programming
- 12 Interior Point Methods
- 13 Optimal Matchings
- 14 Integer Linear Programming
- 15 The Traveling Salesperson Problem
- 16 Matroids
- 17 Approximation Algorithms

ADM I



ADM II



LP Theorie

Graphen also

Gauzzahlige Lin Opt

Verbindung zu algebraischen Konzeption

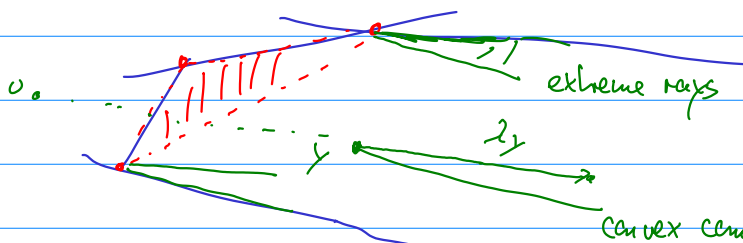
↑ schnelle Näherungslösungen für NP-vollst. Probleme

Chapter 9:

Linear Programming & Polyhedral Theory

(cp. Bertsimas & Tsitsiklis, Chapters 2.8, 4.6–4.9)

First Goal: Representation Theorem for general polyhedra



every $y \in P$ has a representation as convex comb. of extreme points + non-neg comb. of extreme rays

Fourier-Motzkin Elimination

Let $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$. It follows from Gaussian elimination that

$$\exists x \in \mathbb{R}^n : A \cdot x = b \iff \exists y \in \mathbb{R}^m : y^T \cdot A = 0^T, y^T \cdot b = -1$$

Aim: Derive analogous characterization for existence of x with $A \cdot x \leq b$.

Idea: Rewrite $A \cdot x \leq b$ equivalently (multiply rows by positive scalars) as

$$\begin{aligned} x_1 + (a'_i)^T \cdot x' &\leq b_i && \text{for all } i = 1, \dots, m' \\ -x_1 + (a'_i)^T \cdot x' &\leq b_i && \text{for all } i = m' + 1, \dots, m'' \\ (a'_i)^T \cdot x' &\leq b_i && \text{for all } i = m'' + 1, \dots, m \end{aligned}$$

with $x' = (x_2, \dots, x_n)^T$ and $(a'_i)^T = i$ th row of A with first entry deleted.

This system has a solution (x_1, x') if and only if there is $x' \in \mathbb{R}^{n-1}$ with

$$\begin{aligned} (a'_j)^T \cdot x' - b_j &\leq b_i - (a'_i)^T \cdot x' && \text{for all } i = 1, \dots, m', j = m' + 1, \dots, m'' \\ (a'_i)^T \cdot x' &\leq b_i && \text{for all } i = m'' + 1, \dots, m \end{aligned}$$

Example:

$$\begin{aligned} x_1 - \frac{1}{4}x_2 &\leq -1 && \left. \begin{array}{l} \\ \\ \\ \end{array} \right\} \text{"+"} \quad \text{coeff of } x_1 \text{ is positive} \\ x_1 + 2x_2 - x_3 &\leq -5 && \\ -x_1 - \frac{1}{2}x_2 - \frac{1}{2}x_3 &\leq -4 && \left. \begin{array}{l} \\ \\ \end{array} \right\} \text{"-" } \quad \text{"negative"} \\ -x_1 - \frac{2}{3}x_2 &\leq -1 && \\ &-x_2 - x_3 &\leq -1 && \left. \begin{array}{l} \\ \end{array} \right\} \text{"0"} \quad \text{"-"} \quad \text{"0"} \end{aligned}$$

all combinations of adding a "-" inequality to a "+" ineq

$$\begin{aligned} -\frac{3}{4}x_2 - \frac{1}{2}x_3 &\leq -2 \\ \frac{3}{2}x_2 + \frac{1}{2}x_3 &\leq -6 \\ -\frac{11}{12}x_2 &\leq -2 \\ \frac{4}{3}x_2 - x_3 &\leq -6 \\ &-x_2 - x_3 &\leq -1 && \left. \begin{array}{l} \\ \\ \\ \end{array} \right\} \text{"0"} \text{ ineq} \end{aligned}$$

combinations

new system $\hat{=}$ $UA \leq Ub \quad U \geq 0$

models elementary row operations

Problem: # of inequalities may grow exponentially when this process is repeated

Farkas' Lemma

The system $A \cdot x \leq b$ has a solution x if and only if there is $x' \in \mathbb{R}^{n-1}$ with

$$(a'_i + a'_j)^T \cdot x' \leq b_i + b_j \quad \text{for all } i = 1, \dots, m', j = m' + 1, \dots, m''$$

$$(a'_i)^T \cdot x' \leq b_i \quad \text{for all } i = m'' + 1, \dots, m$$

The following theorem is known as Farkas' Lemma:

Theorem 9.1.

The system $A \cdot x \leq b$ has a solution x , if and only if there is no vector y satisfying $y \geq 0$, $y^T \cdot A = 0$ and $y^T \cdot b < 0$.

Proof: ... □

Corollary 9.2. *standard form used by Simplex algo*

The system $A \cdot x = b$ has a non-negative solution $x \geq 0$, if and only if there is no vector y satisfying $y^T \cdot A \geq 0$ and $y^T \cdot b < 0$. □

Remark: Farkas' Lemma also follows immediately from LP duality.

Proof: Theorem 9.1

" \Rightarrow " let $x \in \mathbb{R}^n$ with $Ax \leq b$

suppose there is $y \geq 0$ with $y^T A = 0$, $y^T b < 0$

$$\text{Then } 0 > y^T b \geq y^T Ax = (y^T A) \cdot x = 0$$

" \Leftarrow " Suppose that $Ax \leq b$ has no solution

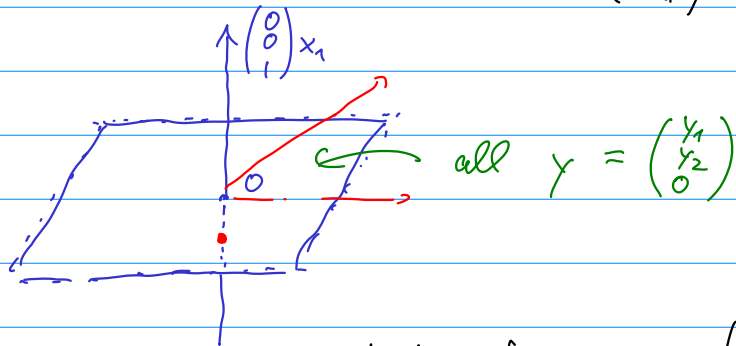
Show by induction on # columns of A

that $\exists y \geq 0$ with $y^T A = 0$ and $y^T b < 0$

$$\underline{n=1} \quad \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} x_1 \leq \begin{pmatrix} b_1 \\ \vdots \\ b_m \end{pmatrix} \quad \text{no solution}$$

$$y^T \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} = 0 \quad \hat{=} \quad \text{subspace of } \mathbb{R}^m \text{ orthogonal to } \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix}$$

$x_1 \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} \hat{=} \text{line in } \mathbb{R}^m \text{ through } 0$
 \Rightarrow (coordinate transformation) $\begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} \rightarrow \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}$



no solution $\Rightarrow b \notin$ subspace $x_1 \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix}$

and $\begin{pmatrix} b_1 \\ \vdots \\ b_m \end{pmatrix} \neq 0$

\sqsubset otherwise $\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix} = -1 \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} \leq b$

$\Rightarrow \exists i_0$ with $b_{i_0} < 0$ $i_0 \in \{1, \dots, m-1\}$

\Rightarrow set $y_{i_0} = 1$, $y_i = 0$ otherwise $\Rightarrow y^T b < 0$
 $y_i \geq 0$

inductive step $n-1 \rightarrow n$

$Ax \leq b$ has no solution

\Rightarrow system $A'x' \leq b'$ with $n-1$ columns has no solution

\uparrow

Farkas Lemma

$\Rightarrow \exists y' \geq 0$ with $y'^T A' = 0$ $y'^T b' < 0$
 ind. hypothesis

Note that $A' = U \cdot A$ for some $U \geq 0$ and $b' = Ub$

Set $y^T := y'^T \cdot U \geq 0$

$\Rightarrow y^T A = (y'^T U) A = y'^T (UA) = y'^T A' = 0$

$y^T b = (y'^T U) b = y'^T (Ub) = y'^T b' < 0 \quad \square$

Proof Corollary 9.2

Existence of $x \geq 0$ $\Rightarrow \underbrace{y^T A x}_{\geq 0} = \underbrace{y^T b}_{< 0}$ not satisfied by any $x \geq 0$
 $\sqsubset Ax = b$

Assume there is no $x \geq 0$ with $Ax = b$

\Rightarrow the LP $\max c^T x$ is infeasible
s.t. $Ax = b$
 $x \geq 0$

dual is $\min y^T b$
s.t. $y^T A \geq c^T$
 y unrestricted

dual is feasible, $y = 0$ is a solution

\Rightarrow dual is unbounded

$\Rightarrow y$ with $y^T A \geq c^T$ and $y^T b < 0$ \square

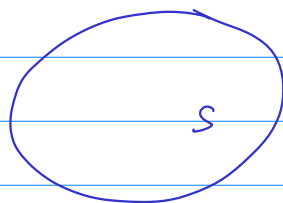
Separating Hyperplane Theorem

Another possible approach to Farkas' Lemma is the following separating hyperplane theorem:

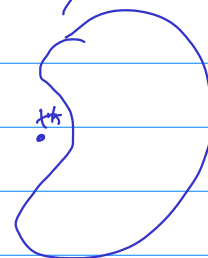
Theorem 9.3.

Let S be a non-empty, closed, convex subset of \mathbb{R}^n and let $x^* \in \mathbb{R}^n$ be a vector that does not belong to S . Then there exists some vector $c \in \mathbb{R}^n$ such that $c^T \cdot x^* < c^T \cdot x$ for all $x \in S$.

Proof: ... \square



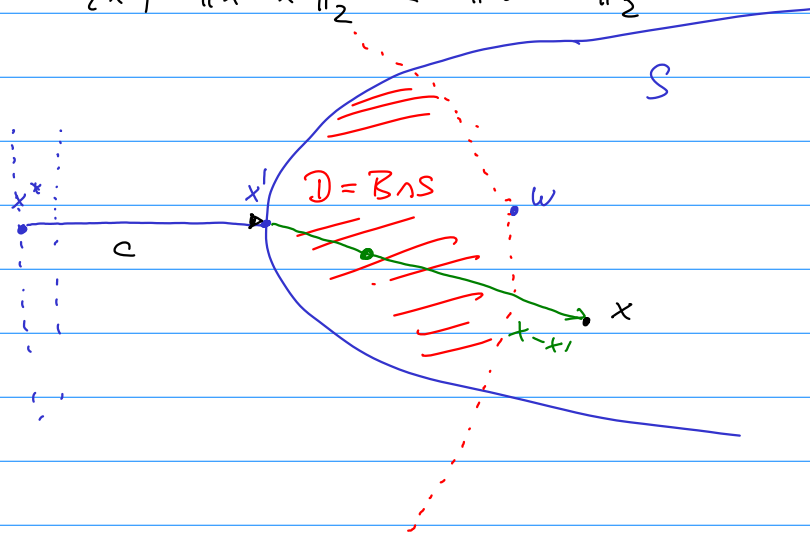
needs convexity



Proof Thm. 9.3

let $w \in S$ arbitrary

$$\text{Set } \mathcal{B} := \{x \mid \|x - x^*\|_2 \leq \|w - x^*\|_2\}$$



\mathcal{D} is bounded, closed, $\neq \emptyset$

$\Rightarrow f(x) := \|x - x^*\|_2$ attains its minimum on \mathcal{D} , say in x'

$$\Rightarrow \|x' - x^*\|_2 \leq \|x - x^*\|_2 \quad \forall x \in \mathcal{D}, \text{ even } \forall x \in S$$

$$\text{set } c := x' - x^*$$

let $x \in S$ and $\lambda \in]0, 1[$ with $\underbrace{x' + \lambda(x - x')} \in S$

$$\|x' - x^*\|_2^2 \leq \|x' + \lambda(x - x') - x^*\|_2^2$$

\leq

\uparrow

$$\|a+b\|^2 = (a+b)^T(a+b) = a^T a + 2a^T b + b^T b$$

$$\|a\|^2$$

$$\|b\|^2$$

$$= \|x' - x^*\|^2 + 2\lambda \underbrace{(x' - x^*)^T}_{b} \underbrace{(x - x')}_{b} + \lambda^2 \|x - x'\|^2$$

$$\Rightarrow 0 \leq 2\lambda (x' - x^*)^T (x - x') + \lambda^2 \|x - x'\|^2$$

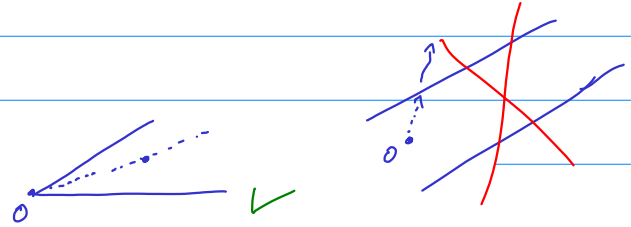
$$\lambda \rightarrow 0 \Rightarrow \underbrace{(x' - x^*)^T}_{c^T} (x - x') \geq 0$$

$$\Rightarrow c^T (x - x') \geq 0 \Rightarrow c^T x \geq c^T x'$$

$$\begin{aligned} \Rightarrow c^T x &\geq c^T x^1 = c^T x^* + c^T (x^1 - x^*) \\ &= c^T x^* + \underbrace{\|c\|^2}_{>0} \end{aligned}$$

$$\Rightarrow c^T x > c^T x^*$$

↑
∈ S arbitrary



Cones

Definition 9.4.

- a** A set $C \subseteq \mathbb{R}^n$ is a **cone** if $\lambda \cdot x \in C$ for all $\lambda \geq 0$ and all $x \in C$.
- b** A polyhedron of the form $P = \{x \in \mathbb{R}^n \mid A \cdot x \geq 0\}$ is called **polyhedral cone**.

Remark: $0 \in P$ is the only possible vertex of a polyhedral cone P .
If $0 \in P$ is a vertex, then P is called **pointed**.

Theorem 9.5.

Let $C \subseteq \mathbb{R}^n$ be the polyhedral cone defined by the constraints $a_i^T \cdot x \geq 0$, $i = 1, \dots, m$. Then, the following are equivalent:

- i** The zero vector is an extreme point of C .
- ii** The cone C does not contain a line.
- iii** There exist n vectors out of the family a_1, \dots, a_m , which are linearly independent.

Proof: Follows from Theorem 2.23. □