

Discrete Optimization

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Modeling techniques

We consider several concepts that can be well modeled by **integer programs**

Binary choice

A **choice** between 2 alternatives is modeled through a 0, 1-variable.

Example

The **knapsack problem**

$$\begin{aligned} & \text{maximize} && \sum_{i=1}^n c_i x_i \\ & \text{subject to} && \sum_{i=1}^n a_i x_i \leq b \\ & && x_i \in \{0, 1\} \text{ for all } i = 1, \dots, n. \end{aligned}$$

Forcing constraints

If decision B is taken **then** decision A must be taken.

$x = 1$ if decision A is taken
 $x = 0$ otherwise

$y = 1$ if decision B is taken
 $y = 0$ otherwise

The constraint reads

$$y \leq x$$

Example Facility location problem

Disjunctive constraints

Consider $x \geq 0, a \geq 0, c \geq 0$. We want to model an **OR** constraint :

$$a^T x \geq b \quad \text{or} \quad c^T x \geq d$$

We introduce a variable $y \in \{0, 1\}$ that represents whether **constraint 1** or **constraint 2** is satisfied.

$$a^T x \geq yb \quad \text{and} \quad c^T x \geq (1 - y)d.$$

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Modeling techniques

Restricted range of values

Suppose we want to formulate $x \in \{a_1, a_2, \dots, a_m\}$.

We introduce m **binary variables** y_j .

$$x = \sum_{j=1}^m a_j y_j, \quad \sum_{j=1}^m y_j = 1, \quad y_j \in \{0, 1\}$$

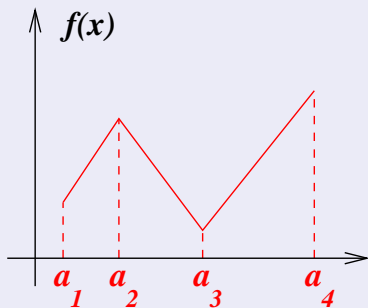
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Arbitrary piecewise linear cost functions

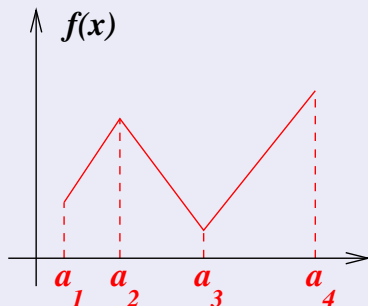


Introduce $y_i \in \{0, 1\}$ such that

$$y_i = 1 \quad \text{if } x \in [a_i, a_{i+1}]$$

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Guidelines for strong formulation

The linear relaxation

Given

$$\begin{aligned} \min \quad & c^T x + d^T y \\ \text{s.t.} \quad & Ax + By = b \\ & x, y \geq 0 \\ & x \in \mathbb{Z}^n. \end{aligned}$$

Its **linear relaxation** is defined as

$$\begin{aligned} \min \quad & c^T x + d^T y \\ \text{s.t.} \quad & Ax + By = b \\ & x, y \geq 0 \\ & x \in \mathbb{R}^n. \end{aligned}$$

The linear relaxation gives important information about the optimal value of an integer program.

Reminder : linear programming

If the objective is **linear** and the constraints are **linear**, we talk about **linear programming** (LP) or **linear optimization**.

LP in standard form

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \in \mathbb{R}_+^n \end{aligned}$$

Definition

A **polyhedron** is a set $\{x \in \mathbb{R}^n \mid Ax \geq b\}$

A set of the form $Ax \leq b$ is also a polyhedron.

A set $\{x \in \mathbb{R}^n \mid Ax = b, x \geq 0\}$ is a polyhedron in **standard form**.

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Graphic representation

We can represent a problem in two dimensions graphically.

Example :

$$\max x_1 + 2x_2 \quad (1)$$

$$-x_1 + 2x_2 \leq 1 \quad (2)$$

$$-x_1 + x_2 \leq 0 \quad (3)$$

$$4x_1 + 3x_2 \leq 12 \quad (4)$$

$$x_1, x_2 \geq 0 \quad (5)$$

Graphic representation

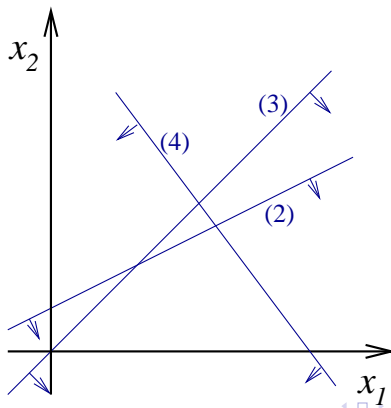
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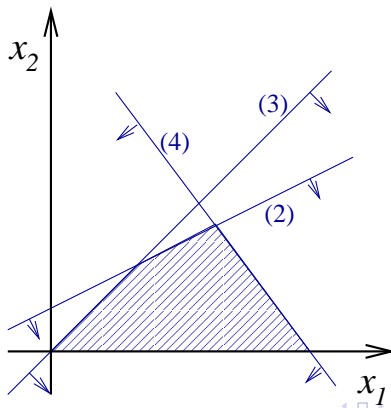
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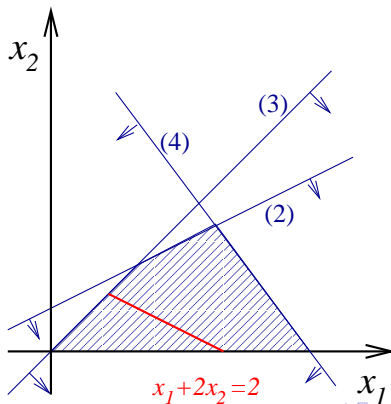
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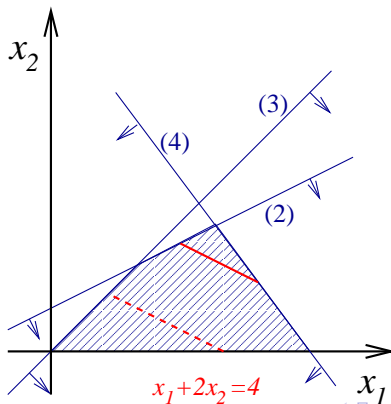
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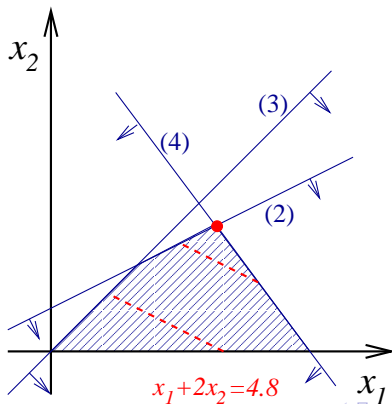
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Extreme points and vertices

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Let P be a polyhedron. A point $x \in P$ is an **extreme point** of P if there do not exist two points $y, z \in P$ such that x is a convex combination of y and z .

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Degenerate cases

In the example we had a **unique solution** at a **vertex** of the **polyhedron**.
Some degenerate cases can lead to different solutions.

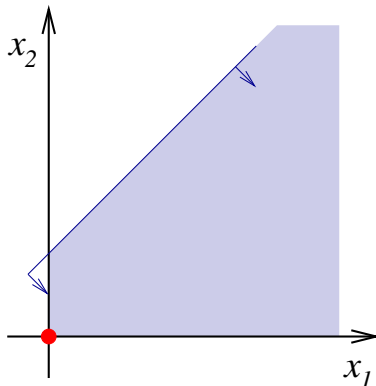
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$$\min x_1 + x_2$$

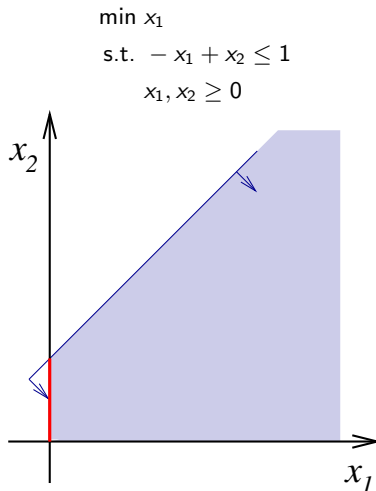
$$\text{s.t. } -x_1 + x_2 \leq 1$$

$$x_1, x_2 \geq 0$$



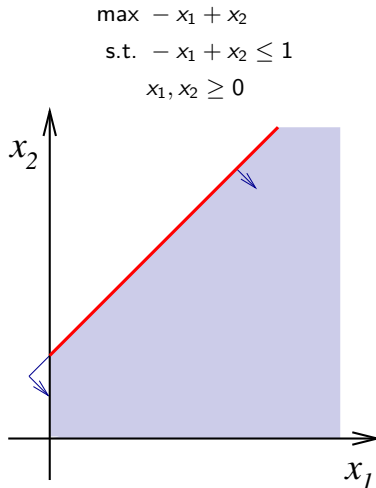
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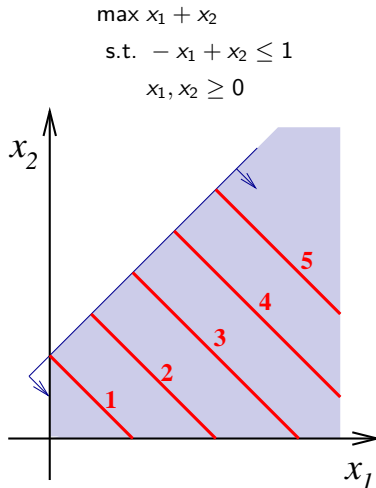
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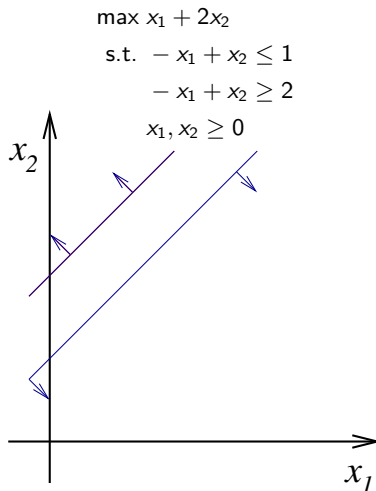
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Bases of a polyhedron

We subdivide the equalities and inequalities into three categories :

$$a_i^T x \geq b_i \quad i \in M_{\geq}$$

$$a_i^T x \leq b_i \quad i \in M_{\leq}$$

$$a_i^T x = b_i \quad i \in M_{=}$$

Definition

Let \bar{x} be a point satisfying $a_i^T \bar{x} = b_i$ for some $i \in M_{\geq}, M_{\leq}$ or $M_{=}$. The constraint i is said to be **active** or **tight**.

Bases of a polyhedron

Definition

Let P be a polyhedron and let $\bar{x} \in \mathbb{R}^n$.

(a) \bar{x} is a **basic solution** if

- ▶ all equalities ($i \in M_{=}$) are **active**
- ▶ among the active constraints, there are n **linearly independent**

(b) if \bar{x} is a basic solution **that satisfies all constraints**, then \bar{x} is a **feasible basic solution**.

Theorem

Let P be a polyhedron and let $\bar{x} \in P$. The three following statements are equivalent.

- (i) \bar{x} is a **vertex**
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Main messages

- The problem

$$\begin{aligned} \min \quad & c^T x \\ \text{subject to} \quad & a_{(i)}^T x \leq b_{(i)} \quad i = 1, \dots, m \\ & x \in \mathbb{R}_+^n \end{aligned}$$

can be solved efficiently both **in theory** and in **practice**.

Problems with **thousands** of variables and constraints can be solved in **seconds**.

- An optimal solution can always be found among **vertices**
- The **simplex algorithm** always outputs a **vertex** as an optimal solution.
- If you **add a new constraint to the problem**, you can **reoptimize** very quickly using the simplex algorithm.

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