

INTEGER LINEAR PROGRAMMING

Mikaël Capelle

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Thales Alenia Space

- Lectures — 8h45 (7 sessions)
 - Instructor —
 - Mikaël Capelle — `mikael.capelle@insa-toulouse.fr`
 - Slides available at `https://pdf.typeface.fr`.
- Practical work — 11h (4 sessions)
 - Teaching assistants —
 - Marianne Desfrene - `marianne.defresne@insa-toulouse.fr`
 - Jupyter notebook — Be familiar with python!
- Grading — Written exam.

Reminders

- Complexity & Optimization

- Linear Programming (LP)

Integer Linear Programming

- Definition

- Why are Integer Linear Programs hard to solve?

- Examples

Solving Integer Linear Programs

- Relaxations

- Branch & Bound

- Cuts

- Decomposition methods

Modelling problems as integer linear programs

- Modeling elementary operations

- Examples

- **Linear Programming (LP)** is a paradigm for solving optimization problem where constraints are **linear inequalities**.
- Within linear programming, decision **variables** are **continuous**. The corresponding optimization problem can be solve in **polynomial** time.
- Within **Integer Linear Programming (ILP)**, decision variables are **discrete** (integers). The corresponding optimization problem is **hard** ($\in$ NP-HARD).
- Integer-Linear Programming is often used in practice to model industrial problems, even the ones that do not appear as linear, and then use off-the-shelf solvers to find (optimal) solutions.

REMINDERS

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COMPLEXITY & OPTIMIZATION

Optimization problem $Q = (X, f, m, g) : X \rightarrow \bigcup_{x \in X} f(x)$

- X is a set of **instances**.
- For any instance $x \in X$, $f(x)$ is the set of feasible solutions.
- $m : X \times f(X) \rightarrow \mathbb{R}$ is the **objective** function.
- $g \in \{\min, \max\}$
- $Q(x) = \arg_g \{m(x, y) : y \in f(x)\}$

Decision problem Q_D corresponding to $Q = (X, f, m, g)$

- **Inputs:** $x \in X, k \in \mathbb{R}$
- **Question:** Is there $y \in f(x)$ such that $m(x, y) \leq k$?

- $P = PTIME = \bigcup_{c \geq 0} TIME(n^c)$
 - Problems for which there exists a **polynomial**-time algorithm $\rightarrow$ “**easy**” problems.
 - Contains most of the problems you know of: shortest-path in a weighted-graph, sorting an array, finding maximum flow in a graph, ...
- $EXPTIME = \bigcup_{c \geq 0} TIME(2^{n^c})$
 - Contains P... $P \subseteq EXPTIME$,
 - ...and much more $P \subset EXPTIME$.

The NP complexity class — NP = Nondeterministic Polynomial

Class of problems for which we do not know if there exists a polynomial-time algorithm, but we cannot prove that none exist.

The NP-HARD complexity class

Class of problems that are “*at least as hard*” as the hardest problems in NP.

REMINDERS

LINEAR PROGRAMMING (LP)

Linear Programming

$$\max. \sum_{i=1}^n c_i x_i$$

$$\text{s.t. } \sum_{i=1}^n a_{ij} x_i \leq b_j, \quad 1 \leq j \leq m$$

$$x_i \geq 0, \quad 1 \leq i \leq n$$

<https://homepages.laas.fr/azelier/drupal/content/current-teaching-material>

Linear Programming

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Linear Programming — Short version

$$\begin{aligned} \max \quad & \{ c^T x \mid Ax \leq b, x \in \mathbb{R}^n, x \geq 0 \} \\ & c \in \mathbb{R}^n, \quad A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m \end{aligned}$$

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- If x is not constrained in sign ($x \in \mathbb{R}$), we can define two new variables $x^+ \geq 0$ and $x^- \geq 0$ and set $x = x^+ - x^-$.

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- If x is not constrained in sign ($x \in \mathbb{R}$), we can define two new variables $x^+ \geq 0$ and $x^- \geq 0$ and set $x = x^+ - x^-$.
- There can be no strict inequalities in a LP ($<$, $>$, $\neq$).

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Definition: Polyhedron of constraints

- Set of feasible solutions: subset $\mathcal{P}$ of $\mathbb{R}^n$ satisfying the $m + n$ constraints of the problem:
 - $\Rightarrow$ it is a **polyhedron**.
 - $\Rightarrow$ it is **convex**.
- If the polyhedron is bounded, it is a **polytope**.

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Theorem

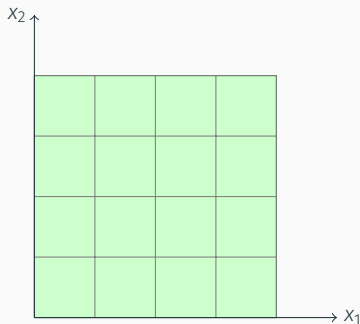
The optimum (maximum, minimum) of a linear program, if there is one, is found on at least one of the vertices of its polyhedron.

A linear program:

$$\max. \quad z = x_1 + 2x_2$$

s.t.

$$x_1, x_2 \in \mathbb{R}^+$$

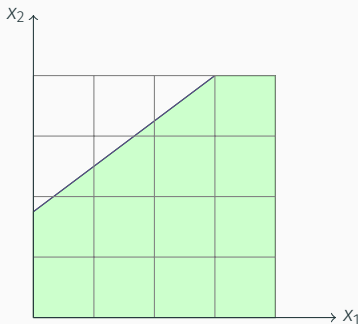


A linear program:

$$\max. \quad z = x_1 + 2x_2$$

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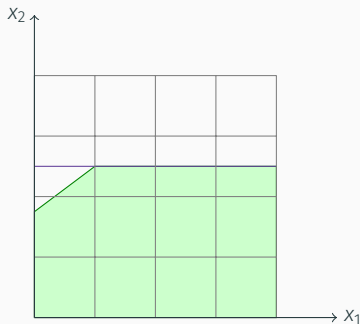
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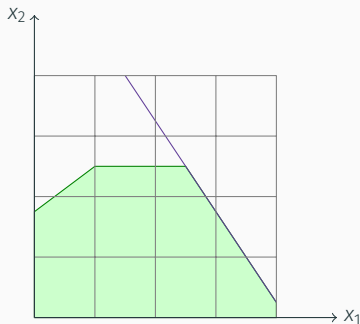
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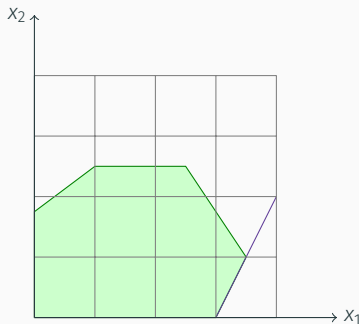
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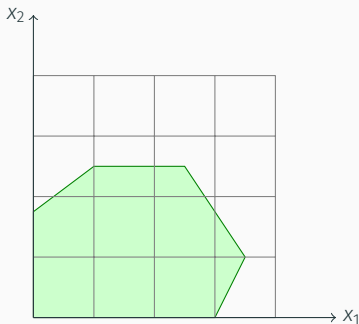
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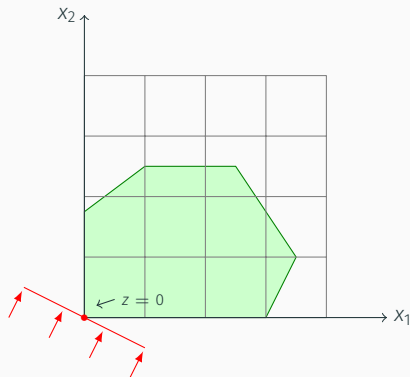
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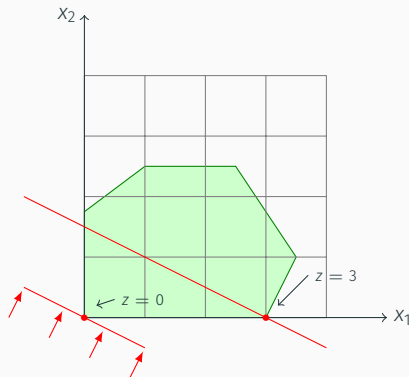
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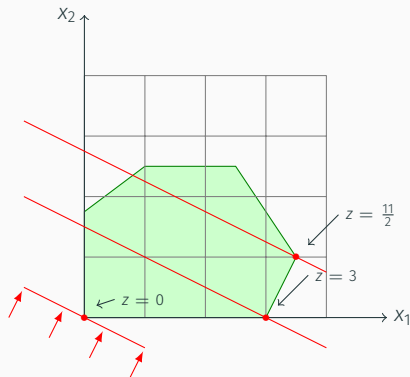
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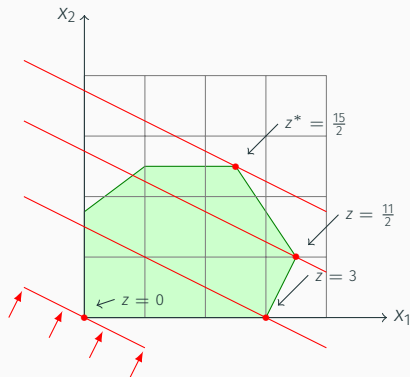
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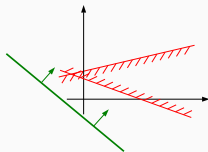
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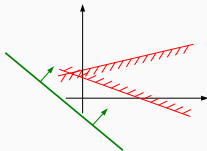
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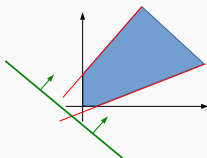




Empty polyhedron $\leftrightarrow$ No feasible solutions.

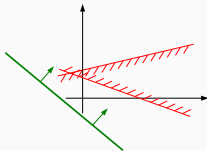


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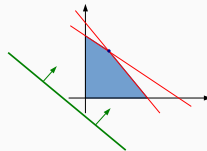


Non-bounded polyhedron — Problem is not bounded.

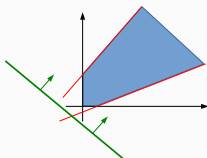
REMINDERS — LINEAR PROGRAMMING



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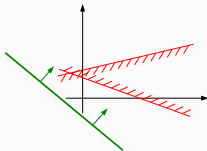


Polytope — Problem as a unique solution.

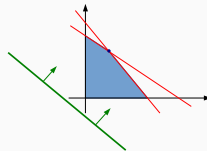


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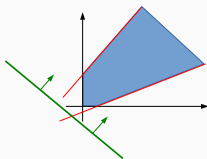
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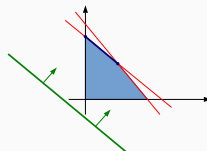
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Polytope — Problem as multiple solutions.

Linear Programming is a polynomial-time optimization problem

- **Simplex** algorithm — Exponential-time algorithm in theory, but very efficient in practice.
- **Interior point** (Barrier) methods — Polynomial-time algorithms, more and more used in practice.

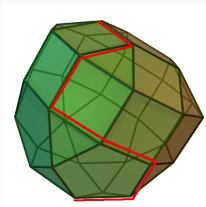


Illustration of the **Simplex** algorithm on a 3D polyhedron.

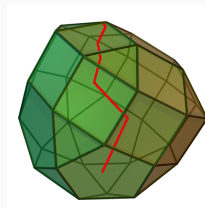


Illustration of an **Interior point** method on a 3D polyhedron.

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DEFINITION

Integer Linear Programming (ILP)

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Mixed-Integer Linear Programming (MILP)

Decision variables can be discrete or continuous:

$$\max \left\{ c^T x \mid Ax \leq b, x \in \mathbb{N}^q \times \mathbb{R}_+^{n-q} \right\}$$

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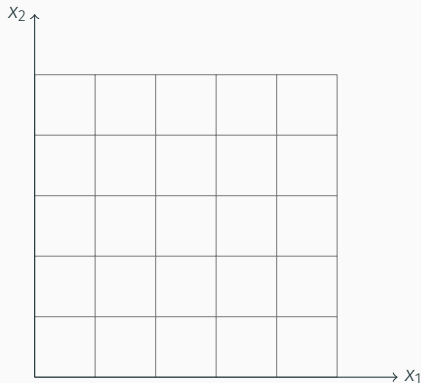
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A brute-force algorithm will quickly fail as the sets of solutions grow larger in size:

- There are too many feasible solutions to enumerate all of them.

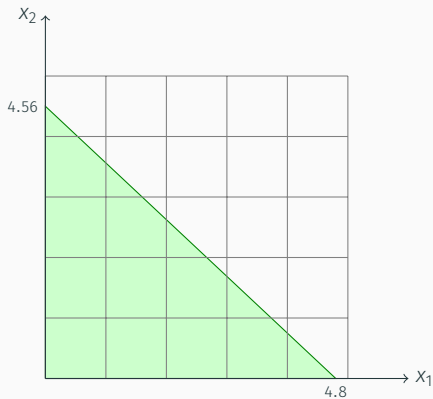
WHY ARE INTEGER LINEAR PROGRAMS HARD TO SOLVE? — EXAMPLE

$$\begin{array}{ll}\max. & z = 19x_1 + 20x_2 \\ \text{s.t.} & 15x_1 + 16x_2 \leq 72 \\ & x_1, x_2 \in \mathbb{N}\end{array}$$



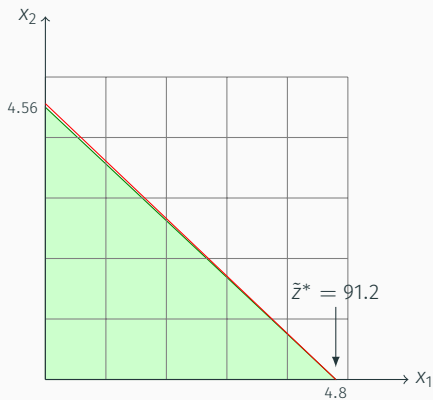
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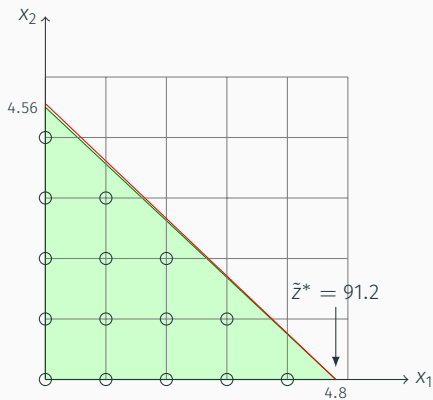
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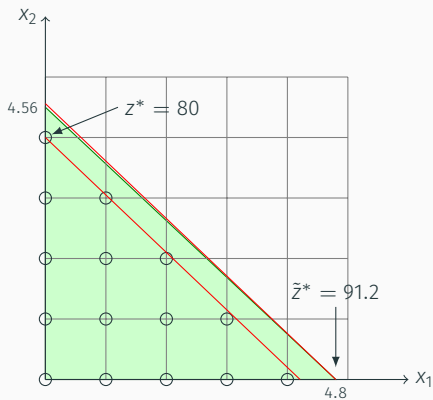
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ILP, 0-1 ILP and MILP are NP-HARD problems:

WHY ARE INTEGER LINEAR PROGRAMS HARD TO SOLVE?

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- using approximated algorithms — meta-heuristics, greedy heuristics, dedicated heuristics, ...

It is often not necessary to implement these methods ourselves because there are multiple off-the-shelf solvers available to solve mixed-integer linear program. A non-exhaustive list of these:

- IBM CPLEX (\$)
- GUROBI (\$)
- COIN-OR / CBC / CLP
- GLPK

Aside of these, various languages have been developped to model mixed-integer linear program in an easy way and then use one of the above mentioned solvers: AIMMS, AMPL, LINDO, MPL, OPL, ...

INTEGER LINEAR PROGRAMMING

EXAMPLES

Knapsack problem — We have a knapsack of capacity W and a set of n items with associated weights w_i and profits p_i . How can we maximize our profits while being limited by the capacity of the knapsack?

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The knapsack problem is **weakly NP-HARD**.

Warehouse allocations — A company needs to supply a set of n clients and needs to open new warehouses (from a set of m possible warehouses). Opening a warehouse j costs f_j and supplying a client i from a warehouse j costs c_{ij} per supply unit. All clients have the same unit demands. Which warehouses should be opened in order to satisfy all clients while minimizing the total cost?

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 \text{s.t.} \quad & \sum_{j=1}^m x_{ij} = 1, & \forall i \in \{1, \dots, n\} \\
 & \sum_{i=1}^n x_{ij} \leq n y_j, & \forall j \in \{1, \dots, m\} \\
 & y_j \in \{0, 1\}, & \forall j \in \{1, \dots, m\} \\
 & x_{ij} \geq 0, & \forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, m\}
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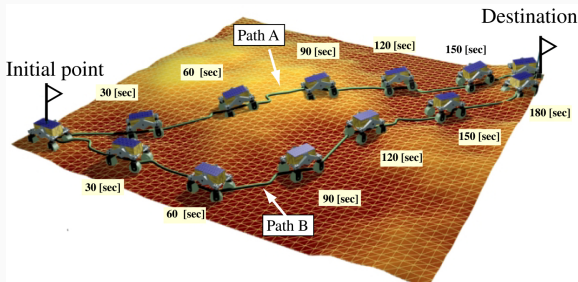
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Shortest-path — A road network is represented by a directed graph $\mathcal{G} = (V, A)$ with costs c_{ij} associated to each road (arc) $(i, j) \in A$. What is the shortest-path from s to t ?



Spatial application: Autonomous Mars rover navigation (Candaian Space Agency: [DRB⁺08], LAAS [HST02])

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Shortest-path is a polynomial problem, we will see later why we can solve this integer linear program in polynomial time using a linear relaxation.

Set cover — We want to check a set S of critical points in a system using a set T possible tests. Each test cover a subset of critical points ($a_{ij} = 1$ if test i covers critical point j) and costs c_i . Which tests should be set up in order to minimize the costs while ensuring that each critical points is tested?

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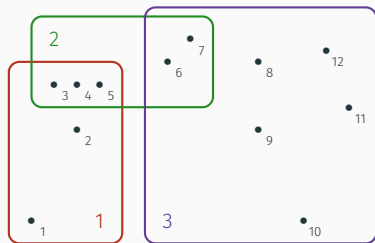
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The set-cover problem is **strongly NP-HARD**.

INTEGER LINEAR PROGRAMMING — SET COVER EXAMPLE

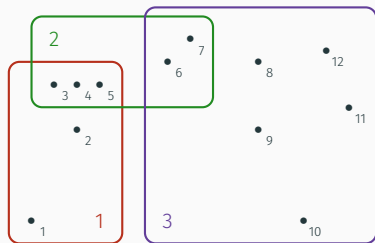
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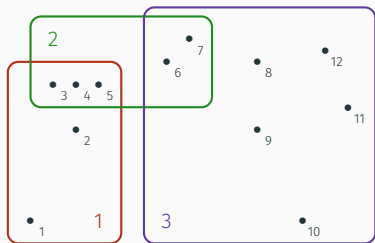
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$$6x_1 + 15x_2 + 7x_3$$

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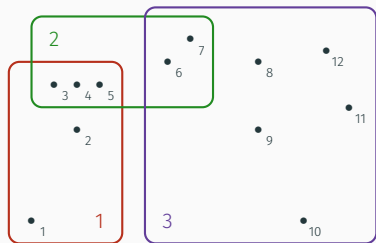
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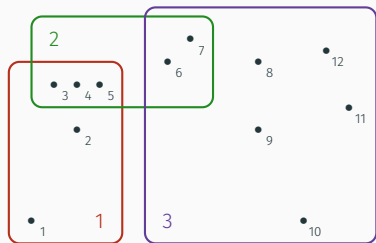
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$$x_1, x_2, x_3 \in \{0, 1\}$$

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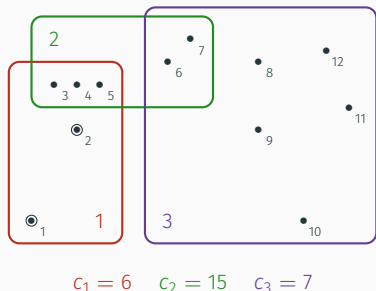


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$$\begin{array}{ll} \text{min.} & 6x_1 + 15x_2 + 7x_3 \\ \text{s.t.} & \left(\begin{array}{l} (x_1, x_2, x_3) \geq \mathbb{1}_{12} \\ x_1, x_2, x_3 \in \{0, 1\} \end{array} \right. \end{array}$$

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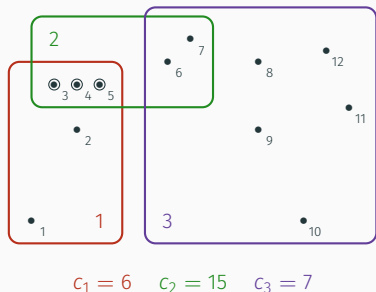
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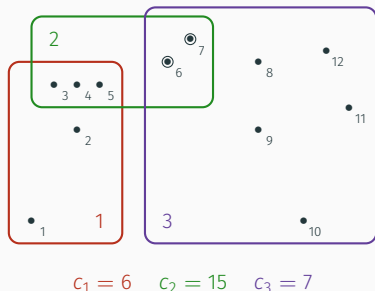
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$$\begin{array}{ll} \text{min.} & 6x_1 + 15x_2 + 7x_3 \\ \text{s.t.} & \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \end{pmatrix} (x_1, x_2, x_3) \geq \mathbb{1}_{12} \\ & x_1, x_2, x_3 \in \{0, 1\} \end{array}$$

INTEGER LINEAR PROGRAMMING — SET COVER EXAMPLE

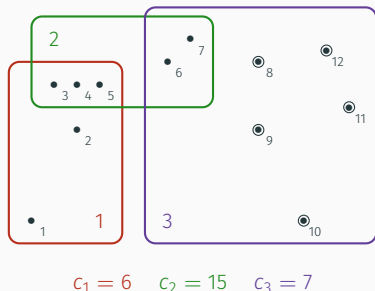
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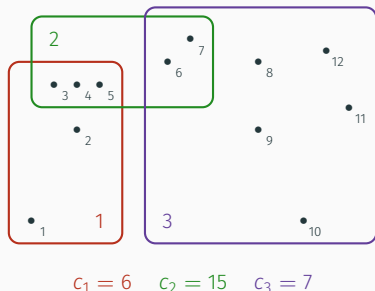
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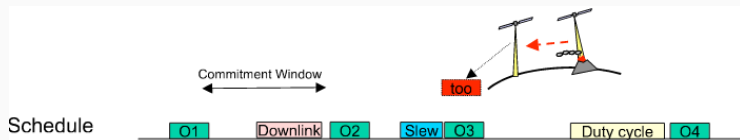


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Optimal solution is $x_1 = 1, x_2 = 0, x_3 = 1$ which covers all tests and cost $6 + 7 = 13$.

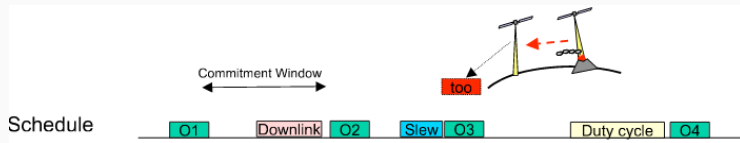
Single machine scheduling — A machine needs to produce a set L of n items. Each item i has a manufacturing time p_i , a release time r_i (time at which its components are available) and a deadline d_i (time at which the time should be manufactured). The factory can only produce **one item at a time**, and manufacturing process **cannot be interrupted** (non-preemptive machine), what is the schedule that minimize the overdue deliveries?

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The single machine scheduling problem is **strongly NP-HARD**.

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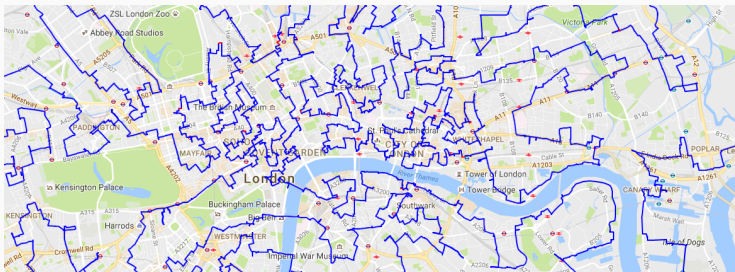
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The larger M , the harder the resolution will be, but if M is not big enough, the formulation may not be valid — We want to find a “good” value for M . Here we can choose $M = \max_{i \in L} r_i + \sum_{i \in L} p_i$.

Travelling salesman problem — Given a list of n cities and the distances c_{ij} between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?

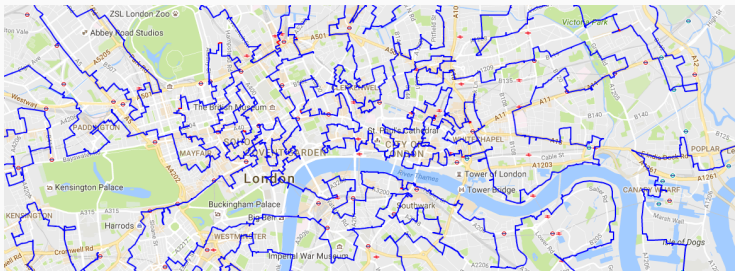
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- $x_{ij} \in \{0, 1\}$ — Binary variable indicating if we go directly from city i to city j .
- $u_i \in \{1, \dots, n\}$ — Subtour elimination variables — u_i is the position of city i in the tour.

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$$u_1 = 1 \quad (3d)$$

$$2 \leq u_i \leq n, \quad \forall i \in \{1, \dots, n\} \quad (3e)$$

$$u_i - u_j + 1 \leq (n-1)(1 - x_{ij}), \quad \forall i, j \in \{2, \dots, n\} \quad (3f)$$

$$x_{ij} \in \{0, 1\}, \quad u_i \in \mathbb{N} \quad \forall i, j \in \{1, \dots, n\} \quad (3g)$$

- (3b) We leave each city exactly once.
- (3c) We enter each city exactly once.
- (3d–3f) Subtour elimination — **arc-constraints**: $x_{ij} = 1 \Rightarrow u_j \geq u_i + 1$.

SOLVING INTEGER LINEAR PROGRAMS

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RELAXATIONS

Let (P) be an optimization problem $\max z = f(x)$ under $x \in \mathcal{X} \subseteq \mathbb{R}^n$.

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General definition

The optimization problem $(R) : \max z_R = \phi(x)$ under $x \in \mathcal{T} \subseteq \mathbb{R}^n$ is a relaxation of (P) if $\mathcal{X} \subseteq \mathcal{T}$ and $\forall x \in \mathcal{X}, \phi(x) \geq f(x)$.

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Theorem

If (R) is a relaxation of (P) , then $z_R^* \geq z^*$ (maximization) — (R) provides an **upper bound** for (P) .

Let (R) and (R') be two relaxations of (P) , (R) is **better** than (R') if:

$$z_R^* \leq z_{R'}^*$$

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Remove some or all constraints:

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Linear

Remove the integrity constraints on the variables:

$$\begin{aligned} \max \left\{ c^T x \mid Ax \leq b, x \in \mathbb{N}^n \right\} &\Rightarrow \max \left\{ c^T x \mid Ax \leq b, x \in \mathbb{R}_+^n \right\} \\ \max \left\{ c^T x \mid Ax \leq b, x \in \{0, 1\}^n \right\} &\Rightarrow \max \left\{ c^T x \mid Ax \leq b, x \in \mathbb{R}^n, 0 \leq x \leq 1 \right\} \end{aligned}$$

RELAXATIONS — LAGRANGIAN RELAXATION — DEFINITION

Consider an (integer) linear programs (P) containing $p + q$ constraints. A lagrangian relaxation of (P) is an (integer) linear program (L) similar to (P) where q constraints have been removed and **penalized** in the objective function.

Linear program (P)

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If we consider only **non-negative weights** $\lambda \geq 0$, we ensure that this is a **valid** relaxation:

$$\begin{aligned} \forall x \in \mathcal{P} : \quad & Ax \leq b \\ & c^T x \leq c^T x + \lambda^T (b - Ax) \end{aligned}$$

Generalized assignment problem — We want to assign n items to m bins. Assigning item i to bin j costs c_{ij} and uses a_{ij} space in the bin. Each bin j has a capacity b_j . Each item must be assigned to a bin. What is the assignment that minimizes the total assignment cost?

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Generalized assignment problem — We want to assign n items to m bins. Assigning item i to bin j costs c_{ij} and uses a_{ij} space in the bin. Each bin j has a capacity b_j . Each item must be assigned to a bin. What is the assignment that minimizes the total assignment cost?

- $x_{ij} \in \{0, 1\}$ — $x_{ij} = 1$ if we put item i in bin j .

$$\min. \quad z = \sum_{i=1}^n \sum_{j=1}^m c_{ij} x_{ij} \tag{4a}$$

$$\text{s.t.} \tag{4b}$$

$$\tag{4c}$$

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A possible lagrangian relaxation for the generalized assignment problem:

$$\min. \quad z = \sum_{i=1}^n \sum_{j=1}^m c_{ij} x_{ij} + \sum_{i=1}^n \lambda_i \left(\sum_{j=1}^m x_{ij} - 1 \right) \quad (5a)$$

$$\text{s.t.} \quad \sum_{i=1}^n a_{ij} x_{ij} \leq b_j, \quad \forall j \in \{1, \dots, m\} \quad (5b)$$

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Problem: How to find good λ_i ?

Constrained Shortest-Path — Consider a directed graph $\mathcal{G} = (V, A)$ where travel times t_{ij} and costs c_{ij} are associated to edges $(i, j) \in E$. What is the shortest path from node $s \in V$ to node $t \in V$ that costs less than K ?

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$$\min. \quad \sum_{(i,j) \in A} t_{ij} x_{ij}$$

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We can relax the last constraint $\sum_{(i,j) \in A} c_{ij} x_{ij} \leq K$.

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$$\begin{aligned}
 \min. \quad & \sum_{(i,j) \in A} t_{ij} x_{ij} - \mu (K - \sum_{(i,j) \in A} c_{ij} x_{ij}) \\
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We obtain a simple **shortest-path** problem on $\mathcal{G}$ with modified travel times $t_{ij} + \mu c_{ij}$.

Lagrangian relaxation (L_λ) of (P)

$$L(\lambda) = \max \left\{ c^T x - \lambda^T (b - Ax) \mid Dx \leq e, x \in \mathbb{N}^n \right\}$$

$L(\lambda)$ is an **upper bound** for (P), L^* is the tightest of all bounds:

Lagrangian dual

$$L^* = \min_{\lambda \geq 0} L(\lambda)$$

Problem: How to solve the lagrangian dual?

Subgradient method

- Choose a starting point λ^0 ($t = 0$), e.g. $\lambda^0 = 0$.
- Find the optimum x^t of (L_{λ^t}) and compute the subgradient $s^t = b - Ax^t$.
- If $s^t = 0$, then **stop**.
- Compute $\lambda^{t+1} = \max \{0, \lambda^t + \gamma^t s^t\}$, where γ^t denotes the step size.
- Increment t and **go to 2**.

Choosing a good step size γ^t is crucial for the method to converge quickly — Any γ^t series with the following properties guarantees convergence to L^* :

$$\sum_{t=0}^{+\infty} \gamma^t = +\infty \quad \text{and} \quad \lim_{t \rightarrow +\infty} \gamma^t = 0$$

One example for such a sequence is $\gamma^t = \frac{1}{t+1}$ — In practice this does not always lead to quick convergence, hence other step sizes are chosen.

The following γ^t sequence was proposed by **Held and Karp**:

$$\gamma^t = \mu^t \frac{z^* - L(\lambda_t)}{\|b - Ax\|_2}$$

Where:

- z^* is the value of the best solution for (P) found so far.
- μ^t is a decreasing adaptation parameter with $0 < \mu^0 < 2$ and:

$$\mu^{t+1} = \begin{cases} \alpha \mu^t & \text{if } L^* \text{ did not increase in the last } T \text{ iterations.} \\ \mu^t & \text{otherwise.} \end{cases}$$

Consider an integer linear programs (P) containing constraints. A linear relaxation of (P) is a linear program (R) similar to (P) where the integrity constraints on the decision variables have been replaced by positivity constraints.

Linear program (P)

$$\begin{array}{ll} \max. & z = c^T x \\ \text{s.t.} & Ax \leq b \\ & x \in \mathbb{N}^n \end{array}$$

A linear relaxation of (P)

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Linear relaxations can be used to find upper/lower **bounds** on the objective functions (*Branch & Bound*) or to generate **cuts** for the integer linear program (*Branch & Cuts*).

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If the optimal solution of the linear relaxation (P_R) is integral, it is also the optimal solution of the original program (P):

- most of the time, this will not be the case;
- there are some integer linear programs for which the optimal solution of the linear relaxation is **guaranteed** to be integral.

Proposition

Any integer linear program has an infinite number of linear relaxations.

Initial ILP (P):

$$\text{max.} \quad z = x_1 + 2x_2$$

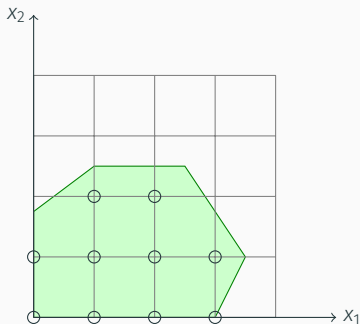
$$\text{s.t.} \quad -3x_1 + 4x_2 \leq 7$$

$$2x_2 \leq 5$$

$$6x_1 + 4x_2 \leq 25$$

$$2x_1 - x_2 \leq 6$$

$$x_1, x_2 \in \mathbb{N}$$



Proposition

Any integer linear program has an infinite number of linear relaxations.

Relaxation (R_1) of (P):

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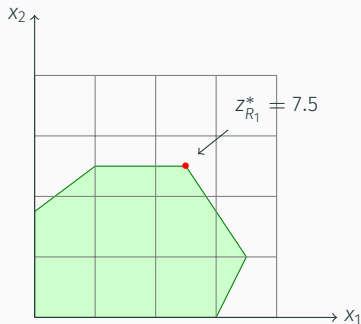
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$$x_1, x_2 \in \mathbb{R}^+$$

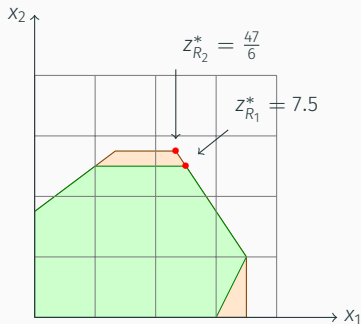


Proposition

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Relaxation (R_2) of (P):

$$\begin{array}{ll}
 \text{max.} & z = x_1 + 2x_2 \\
 \text{s.t.} & -3x_1 + 4x_2 \leq 7 \\
 & 4x_2 \leq 11 \\
 & 6x_1 + 4x_2 \leq 25 \\
 & 2x_1 \leq 7 \\
 & x_1, x_2 \in \mathbb{R}^+
 \end{array}$$

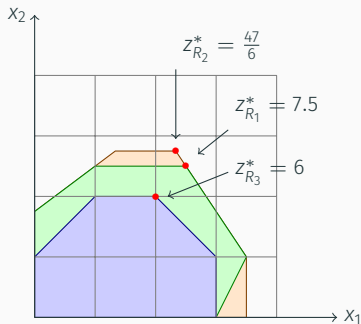


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Relaxation (R_2) of (P):

$$\begin{array}{ll}
 \text{max.} & z = x_1 + 2x_2 \\
 \text{s.t.} & -x_1 + x_2 \leq 1 \\
 & x_2 \leq 2 \\
 & x_1 + x_2 \leq 4 \\
 & x_1 \leq 3 \\
 & x_1, x_2 \in \mathbb{R}^+
 \end{array}$$

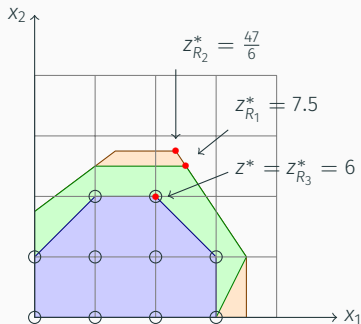


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Any integer linear program has an infinite number of linear relaxations.

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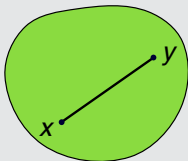
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 & x_1, x_2 \in \mathbb{N}
 \end{array}$$



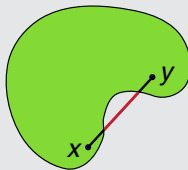
(R_3) is an ideal linear relaxation for (P) since $z^* = z_{R_3}^*$ — The polyhedron defined by (R_3) is the **convex hull** of (P).

Reminder: Convex set

A convex set is a set of points such that, given any two points x, y in that set, the line joining them lies entirely within that set.



Convex set.



Non-convex set.

Definition: Convex Hull

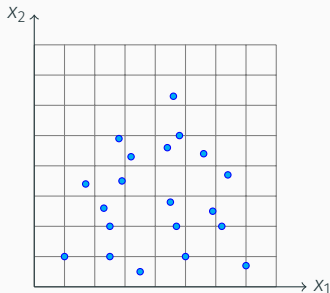
The convex hull (or convex envelope) of a set $\mathcal{X}$ of points is the **unique** smallest convex set that contains $\mathcal{X}$.

Let $\mathcal{X} = \{x_i, 1 \leq i \leq n\}$ be a set of points, its **convex hull** $\text{conv}(\mathcal{X})$ can be defined as:

$$\text{conv}(\mathcal{X}) = \left\{ \sum_{i=1}^k \lambda_i x_i : \lambda_i \geq 0, \sum_{i=1}^k \lambda_i = 1 \right\}$$

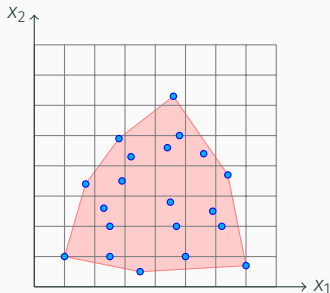
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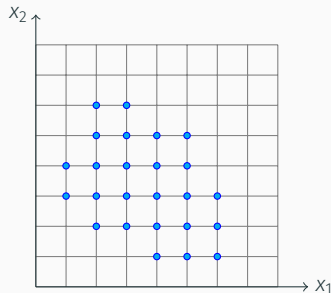
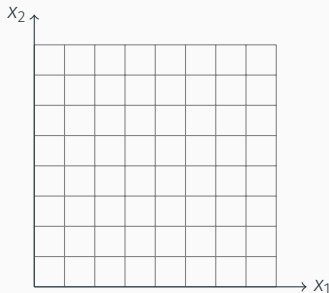
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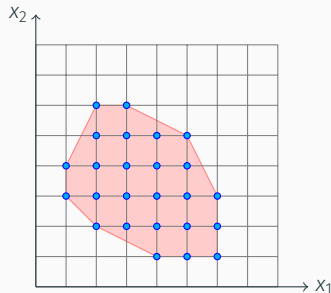
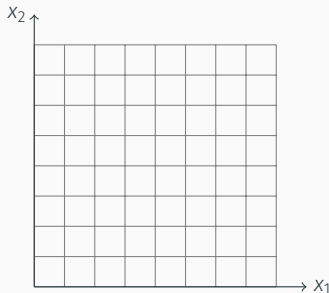
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Consider the following integer linear program:

$$(P) : \max \left\{ z = f(x), x \in \mathcal{X} \subseteq \mathbb{N}^n \right\}$$

And a general relaxation of its integrity constraints:

$$(R) : \max \left\{ z_R = f(x), x \in \mathcal{T} \subseteq \mathbb{R}^n \right\}$$

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Theorem

$$\mathcal{T} = \text{conv}(\mathcal{X}) \implies z_R^* = z^*$$

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Theorem

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Problem: Finding the **convex hull** of (P) is NP-HARD.

RELAXATIONS — LINEAR RELAXATION — EXAMPLE

We want to schedule two jobs J_1 and J_2 with known durations $p_1 = 3$ and $p_2 = 2$ on a single sequential machine. We need to find the starting time t_1 and t_2 of each task, such that $t_1 \in [0, 6]$ and $t_2 \in [1, 5]$. We want to minimize $f(t) = t_1 + t_2 + p_1 + p_2$.

min.

$$t_1 + t_2 + 5$$

s.t.

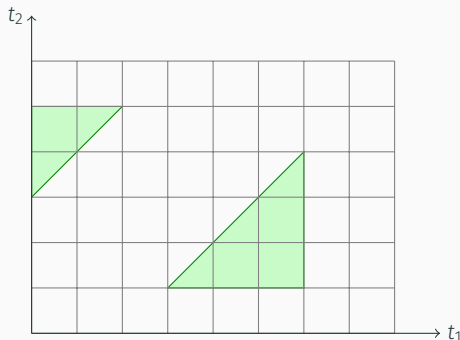
$$t_1 \geq 0$$

$$t_1 \leq 6$$

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$$(t_2 \geq t_1 + 3) \vee (t_1 \geq t_2 + 2)$$



□ $\mathcal{X}$

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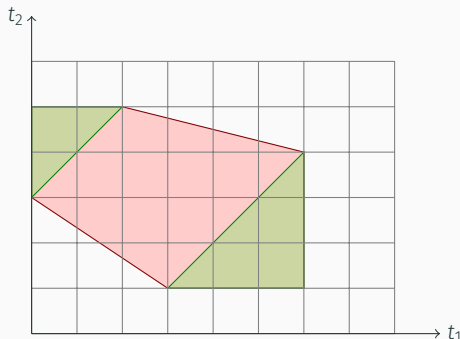
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□ $\text{conv}(\mathcal{X})$

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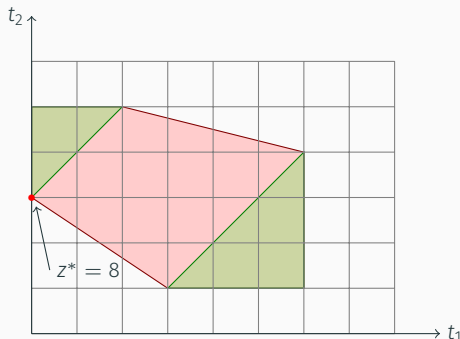
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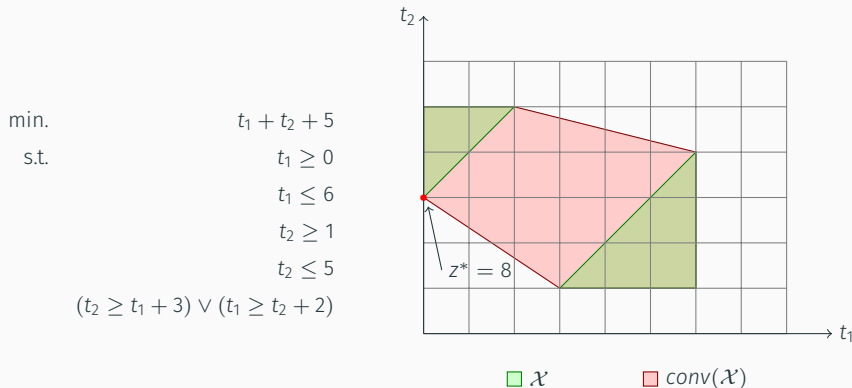


$\square \mathcal{X}$

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RELAXATIONS — LINEAR RELAXATION — EXAMPLE

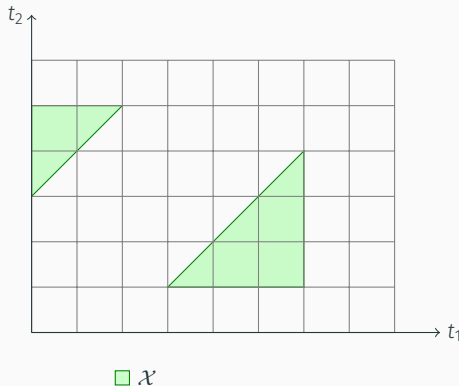
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Problem: How can we linearize the disjunctive constraint ($\vee$)?

We want to introduce a binary variable x to indicate which alternative is chosen: J_1 before J_2 or J_2 before J_1 . We get an integer linear program on $\mathcal{X}' \subseteq \mathbb{R} \times \mathbb{R} \times \{0, 1\}$:

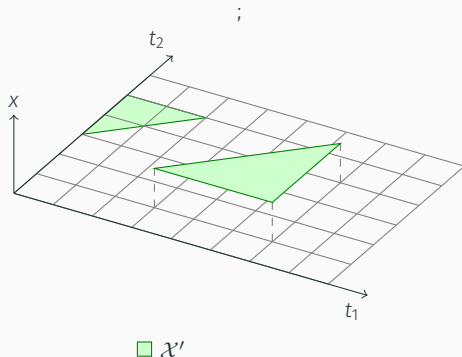
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 \min. & t_1 + t_2 + 5 \\
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 & t_2 \geq 1 \\
 & t_2 \leq 5 \\
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 & t_1 - t_2 + 7(1 - x) \geq 2 \\
 & x \in \{0, 1\}
 \end{array}$$



The formulation is **valid** because the projection of $\mathcal{X}'$ on $\mathbb{R}^2$ is $\mathcal{X}$.

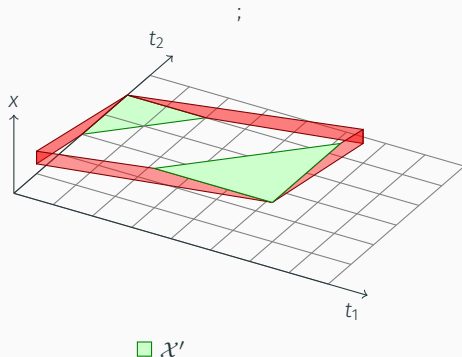
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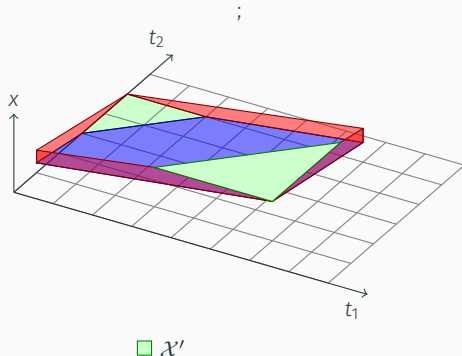
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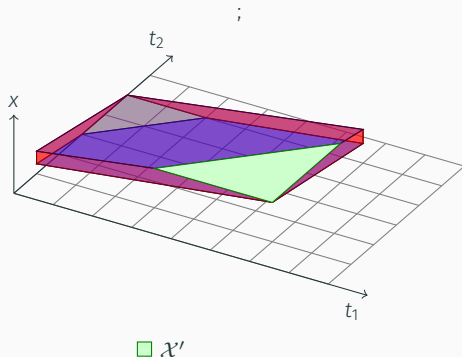
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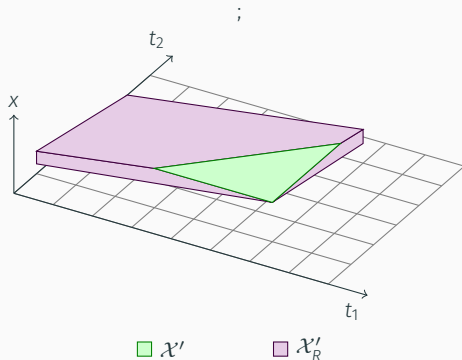
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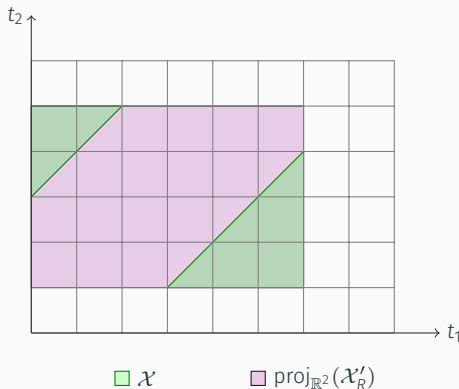
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RELAXATIONS — LINEAR RELAXATION — EXAMPLE

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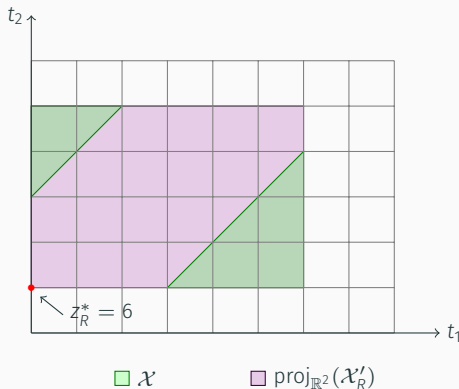
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This formulation is **valid** because the projection of $\mathcal{X}'$ on $\mathbb{R}^2$ is $\mathcal{X}$ **but** since the projection of its linear relaxation $\mathcal{X}'_R$ on $\mathbb{R}^2$ is far from $\text{conv}(\mathcal{X})$, it is a **weak** relaxation.

We want to find a formulation for (P) such that the linear relaxation of the formulation gives us the convex hull of (P) — This would be an **ideal** formulation.

$$\text{min.} \quad t_1 + t_2 + 5$$

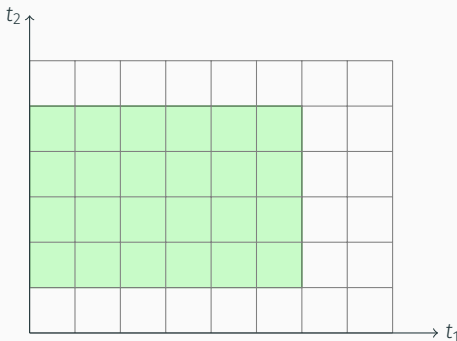
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■ $\mathcal{X}_{\mathcal{R}}$

RELAXATIONS — LINEAR RELAXATION — EXAMPLE

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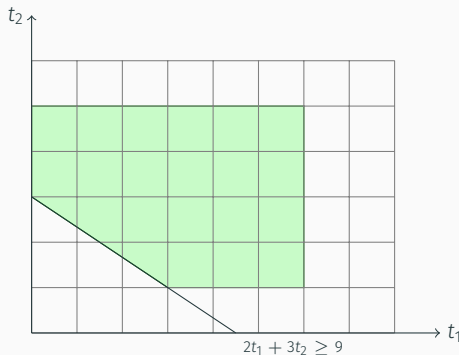
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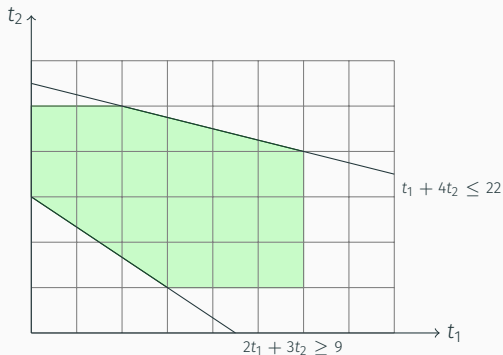
$$t_2 \geq 1$$

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$$t_1 + 4t_2 \leq 22$$

$$t_1, t_2 \in \mathbb{R}$$

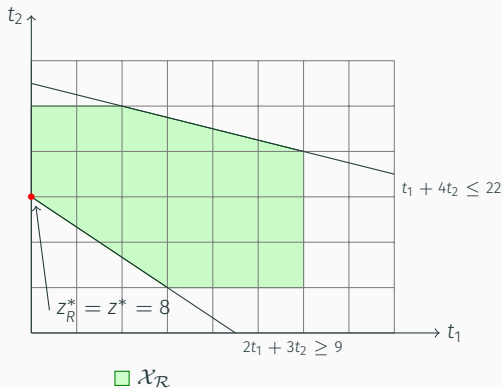


$\square \mathcal{X}_R$

RELAXATIONS — LINEAR RELAXATION — EXAMPLE

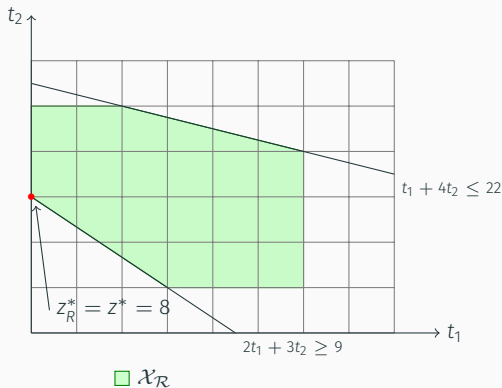
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Problem: Finding the **ideal** formulation for a problem is most of the time very difficult or impossible.

Theorem

Let $B \in \mathbb{Z}^{m \times m}$ be a non-singular matrix, then:

$$\text{Det}(B) = \pm 1 \iff \forall b \in \mathbb{Z}^m, B^{-1}b \in \mathbb{Z}^m$$

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A square matrix B is **unimodular** if $\text{Det}(B) = \pm 1$.

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Definition

A matrix $A \in \mathbb{Z}^{m \times n}$ is **totally unimodular** if every square non-singular submatrix of A is unimodular.

Let $(P) : \max \{ c^T x, Ax \leq b, x \in \mathbb{N}^n \}$ be an integer linear programs.

Corollary

*If A is **totally unimodular**, one of the solution of the linear relaxation of (P) is integral.*

https://www.ise.ncsu.edu/fuzzy-neural/wp-content/uploads/sites/9/2016/02/or766_TUM.pdf

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$$\forall j, \sum_{i=1}^m |a_{ij}| = 2 \implies \sum_{i \in M_1} a_{ij} = \sum_{i \in M_2} a_{ij}$$

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Example for $n = 3$:

x_{11}	x_{12}	x_{13}	x_{21}	x_{22}	x_{23}	x_{31}	x_{32}	x_{33}
1	0	0	1	0	0	1	0	0
0	1	0	0	1	0	0	1	0
0	0	1	0	0	1	0	0	1
1	1	1	0	0	0	0	0	0
0	0	0	1	1	1	0	0	0
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Example for $n = 3$:

x_{11}	x_{12}	x_{13}	x_{21}	x_{22}	x_{23}	x_{31}	x_{32}	x_{33}
1	0	0	1	0	0	1	0	0
0	1	0	0	1	0	0	1	0
0	0	1	0	0	1	0	0	1
1	1	1	0	0	0	0	0	0
0	0	0	1	1	1	0	0	0
0	0	0	0	0	0	1	1	1

M_1

M_2

The matrix satisfies the sufficient conditions for total unimodularity. We can find the optimum of (P) by solving its linear relaxation ($0 \leq x_{ij} \leq 1$) — The problem is **polynomial**.

Shortest-path — The integer linear program we found for the **shortest-path** problem satisfies the sufficient conditions.

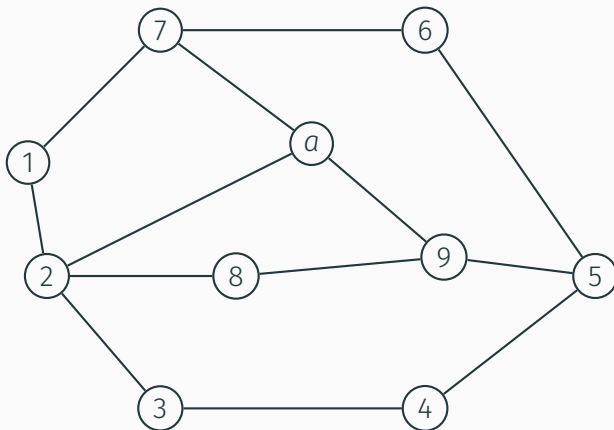
$$\begin{aligned}
 \min. \quad & \sum_{(i,j) \in A} x_{ij} c_{ij} \\
 \text{s.t.} \quad & \sum_{(s,k) \in A} x_{sk} - \sum_{(k,s) \in A} x_{ks} = 1 \\
 & \sum_{(i,k) \in A} x_{ik} - \sum_{(k,i) \in A} x_{ki} = 0, & \forall i \in V \setminus \{s, t\} \\
 & \sum_{(t,k) \in A} x_{tk} - \sum_{(k,t) \in A} x_{kt} = -1 \\
 & x_{ij} \in \{0, 1\}, & \forall (i,j) \in A
 \end{aligned}$$

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 \end{aligned}$$

We can replace constraints $x_{ij} \in \{0, 1\}$ by $0 \leq x_{ij} \leq 1$ and solve the resulting linear program in **polynomial time**.

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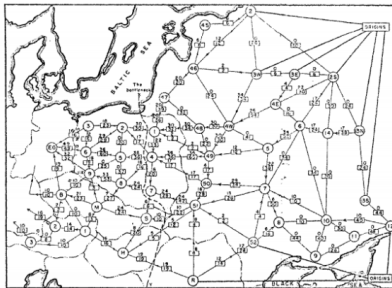
x_{12}	x_{17}	x_{21}	x_{23}	x_{28}	x_{2a}	x_{32}	x_{34}	x_{43}	x_{45}	x_{54}	x_{56}	x_{59}	x_{65}	x_{67}	x_{71}	x_{76}	x_{7a}	x_{82}	x_{89}	x_{95}	x_{98}	x_{9a}	x_{a2}	x_{a7}	x_{a9}
1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0
-1	0	1	1	1	1	-1	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0
0	0	0	-1	0	0	1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	-1	1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	-1	1	1	1	-1	0	0	0	0	0	0	-1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	-1	0	1	1	0	-1	0	0	0	0	0	0	0	0	0
0	-1	0	0	0	0	0	0	0	0	0	0	0	0	-1	1	1	1	0	0	0	0	0	0	-1	0
0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	-1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	-1	1	1	1	0	0	-1	0
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1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0
-1	0	1	1	1	1	-1	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0
0	0	0	-1	0	0	1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	-1	1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	-1	1	1	1	-1	0	0	0	0	0	0	-1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	-1	0	1	1	0	-1	0	0	0	0	0	0	0	0	0
0	-1	0	0	0	0	0	0	0	0	0	0	0	0	-1	1	1	1	0	0	0	0	0	0	-1	0
0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	-1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	-1	1	1	1	0	0	-1	0
0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	-1	1	1	1

Each column contains **exactly** one 1 and one -1 , so the set M_1 contains all the rows and the set M_2 is empty.

A transportation network is represented by a directed graph $\mathcal{G} = (V, A)$. To each node $i \in V$ is associated a value b_i representing supplies ($b_i > 0$), transit ($b_i = 0$) or demands ($b_i < 0$). Arcs $(i, j) \in A$ represent transport resources with limited capacities h_{ij} and unit costs c_{ij} . What is the least expensive plan that satisfies all demands?



Railway network — A. N. Tolstoi (1930s)

Minimum-cost flow — A transportation network is represented by a directed graph $\mathcal{G} = (V, A)$. To each node $i \in V$ is associated a value b_i representing supplies ($b_i > 0$), transit ($b_i = 0$) or demands ($b_i < 0$). Arcs $(i, j) \in A$ represent transport resources with limited capacities h_{ij} and unit costs c_{ij} . What is the least expensive plan that satisfies all demands?

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 \end{aligned}$$

The matrix is totally unimodular, if the demands and capacities are integral, the resulting flow will be integral and the linear relaxation will provide an integral solution.

SOLVING INTEGER LINEAR PROGRAMS

BRANCH & BOUND

Consider the following optimization problem:

$$(P) : \max z = f(x), x \in \mathcal{X}$$

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We can **separate** the set of feasible solutions $\mathcal{X}$ into k multiple (disjoint) sets $\mathcal{X}_i$:

$$\bigcup_{i=0}^k \mathcal{X}_i = \mathcal{X} \quad \text{and} \quad \mathcal{X}_i \cap \mathcal{X}_j = \emptyset, \forall i, j \in \{1, \dots, k\}$$

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We obtain a set (P_i) of problems — If we can find the optimal solution z_i of each problem (P_i) , we can compute the optimal solution of (P) :

$$Z = \max_i Z_i$$

Solving all the (P_i) is as hard as solving the original problem (P) . How can we reduce the number of problems to solve?

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- Maintain the best integral solution x^* we found (best objective value) — Update it each time a new integral solution is found.
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 - If the relaxation is worse than the current best solution, drop (P_i) .
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 - If the relaxation is worse than the current best solution, drop (P_i) .
 - Otherwise, re-apply the branch & bound procedure starting with (P_i) .

Drop problems that **cannot** lead to an optimal solution, re-apply the branch & bound procedure on problems that **may** lead to an optimal solution and update the best solution when an integral solution is found.

Algorithm Generic branch & bound algorithm — Version 1

```
1: procedure BRANCH & BOUND( $P$ )  
2:    $x^* \leftarrow -\infty$  ▷ Current best solution (assume maximization).  
3:    $L \leftarrow \{P\}$  ▷ List of problems to solve.  
4:   while  $L \neq \emptyset$  do  
  
  
  
  
  
  
  
  
  
  
14: end while  
15: return  $x^*$   
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8:       if  $x_R \in \mathbb{N}^n$  then                            ▷ If the solution is integral...
9:          $x^* \leftarrow x_R$                             ▷ ...update the current solution.

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9:          $x^* \leftarrow x_R$                             ▷ ...update the current solution.
10:      else
11:         $L \leftarrow L \cup \text{Separate}(P)$               ▷ Otherwise split the problem.
12:      end if
13:    end if
14:  end while
15:  return  $x^*$ 
16: end procedure
```

Algorithm Generic branch & bound algorithm – Version 2

```
1: procedure BRANCH & BOUND( $P$ )
```

$$2: \quad x^* \leftarrow -\infty$$

▷ Current best solution (assume maximization).

3: $L \leftarrow \{P\}$

- ▷ List of problems to solve.

```
4:   while  $L \neq \emptyset$  do
```

```
16:   end while
```

```
17:    return  $x^*$ 
```

18: end procedure

Algorithm Generic branch & bound algorithm — Version 2

```
1: procedure BRANCH & BOUND( $P$ )
2:    $x^* \leftarrow -\infty$ 
3:    $L \leftarrow \{P\}$ 
4:   while  $L \neq \emptyset$  do
5:      $P \leftarrow \text{Pop}(L)$ 
6:      $x^* \leftarrow \max(x^*, \text{Opt}(P))$ 
7:      $L \leftarrow L \cup \text{Branch}(P)$ 
8:      $\text{Prune}(L)$ 
9:      $\text{Update}(L)$ 
10:     $\text{Bound}(L)$ 
11:     $\text{Prune}(L)$ 
12:     $\text{Update}(L)$ 
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▷ Current best solution (assume maximization).
▷ List of problems to solve.
▷ Remove one of the problem from L .

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6:     for each  $P_i \in \text{Separate}(P)$  do

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11:        else
12:           $L \leftarrow L \cup \{P_i\}$                     ▷ Otherwise add the problem to  $L$ .
13:        end if
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There are **three** parts of the generic algorithm that are not specified and that we can customize in order to obtain an efficient algorithm:

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1. Which problem should be solved next? — $Pop(L)$
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2. Which relaxation to use?
3. How to separate a problem?

We also want to quickly find a solution in order to be able to prune the set of problems:

- Starting with $\pm\infty$ is generally not efficient.
- We can use a depth-first search approach at the beginning to quickly converge to a solution.
- We can use a custom heuristic to find a solution before starting the algorithm.

Consider a problem with a set x of binary variables — $x \in \{0, 1\}$.

We can branch:

- On a single variable — $x_i = 0$ and $x_i = 1$.
- On a pair of variables — $(x_i, x_j) = (0, 0)$, $(x_i, x_j) = (0, 1)$, $(x_i, x_j) = (1, 0)$ and $(x_i, x_j) = (1, 1)$.
- On a n -tuples of variables.

Branching on multiple binary variables does not reduce the number of branches but it may sometimes be useful:

- We often find better bounds when branching on multiple variables.
- Branching on a single variable may not update the bound of the current branch.

Problem

$$\text{max.} \quad z = x_1 + 2x_2$$

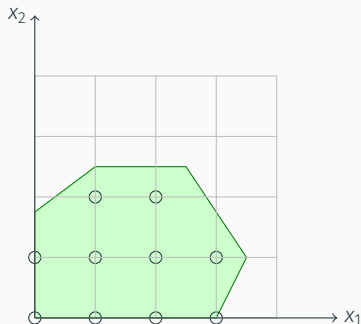
$$\text{s.t.} \quad -3x_1 + 4x_2 \leq 7$$

$$2x_2 \leq 5$$

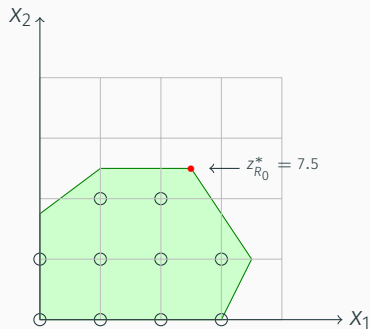
$$6x_1 + 4x_2 \leq 25$$

$$2x_1 - x_2 \leq 6$$

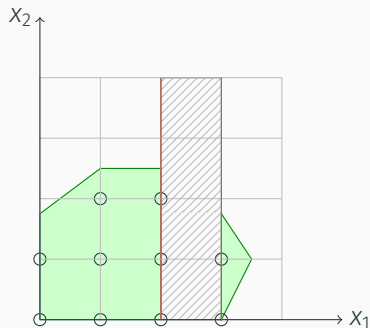
$$x_1, x_2 \in \mathbb{N}$$

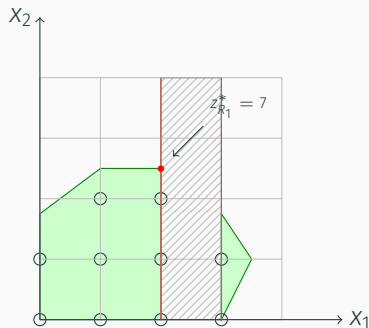
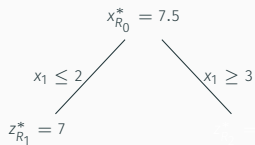


$$x_{R_0}^* = 7.5$$

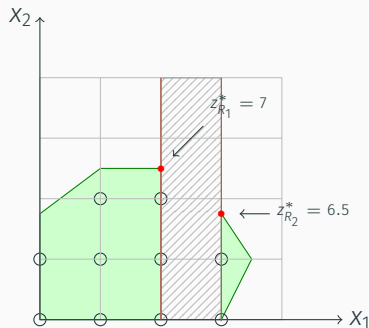
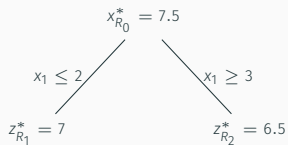


$$\begin{array}{c}
 x_{R_0}^* = 7.5 \\
 \swarrow \quad \searrow \\
 x_1 \leq 2 \quad x_1 \geq 3
 \end{array}$$

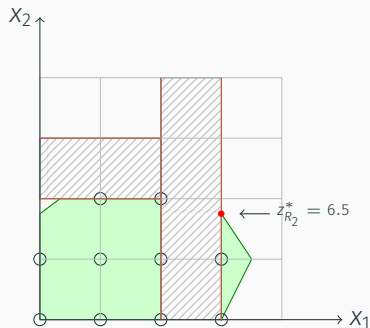
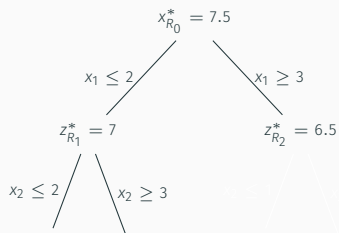




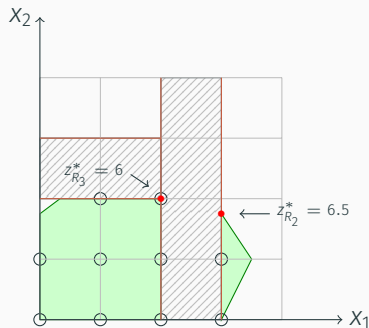
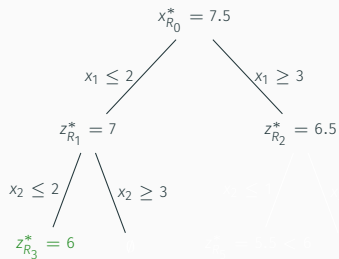
BRANCH & BOUND — EXAMPLE



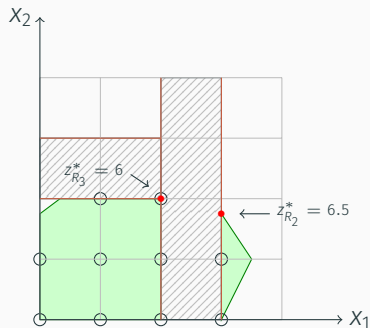
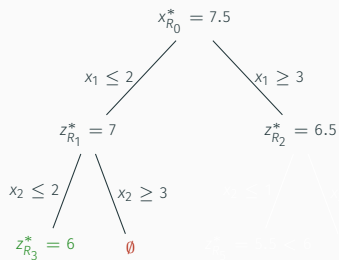
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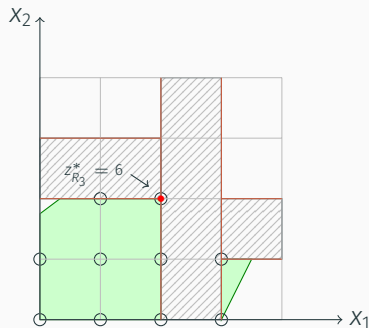
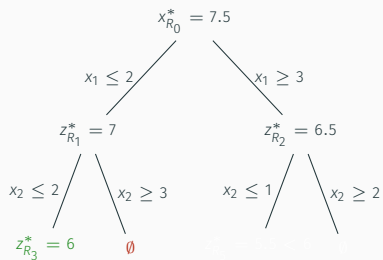
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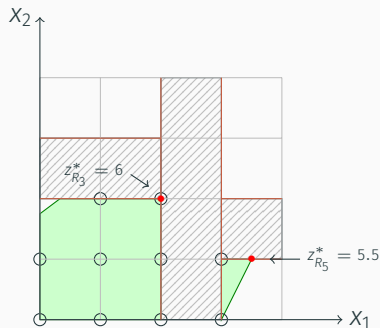
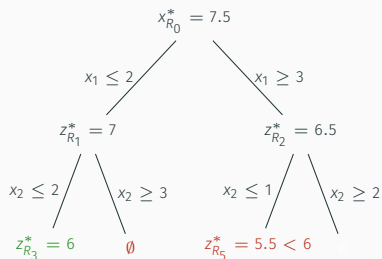
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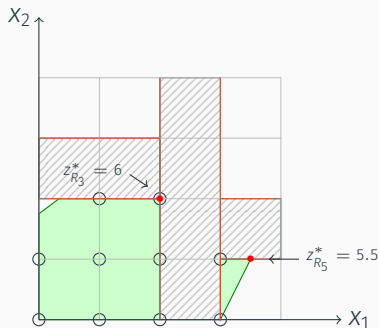
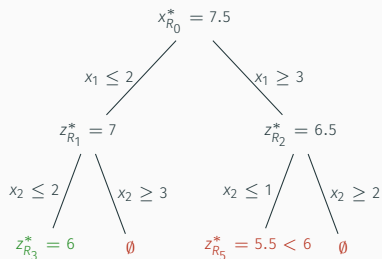


BRANCH & BOUND — EXAMPLE



$z_{R_5}^*$ is worse than the current best solution ($z_{R_3}^* = 6$) so it is not necessary to explore its branch further.

BRANCH & BOUND — EXAMPLE



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What is usually done for integer linear programs:

- Evaluate using linear relaxation ($x \in \mathbb{N}^n \rightarrow x \in \mathbb{R}^n$).
- Separate using intersecting planes — Find a fractional x_i in the current solution and set $x_i \leq k$ on one branch, $x_i \geq k + 1$ on the other.
- Add cuts to the problems: *Branch & Cut*

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What solvers usually add:

- Pre-processing: delete redundant variables or constraints, reduce domains of variables, detect sub-problems (graph, cliques, covers, ...), propagate constraints, ...
- Branching: simulate branching to find the best branch, remember past branching information, combine both, ...
- Multi-threading, detect infeasibility, find multiple solutions, ...

SOLVING INTEGER LINEAR PROGRAMS

CUTS

Cuts — Add constraints to the linear relaxation (R) of (P) until the optimum of (P) is on a vertex of (R).

Basic idea:

- The set of feasible solutions of the original problem (P) is unchanged.
- The current optimal solution z_R^* of the linear relaxation (R) is **excluded** using new constraints (cuts).

How to determine **valid** cuts?

1. Cuts from “rounding” objective function and constraints.
2. Cuts specific to a problem (clique, knapsack, ...).
3. Generic cuts: Gomory cuts.

Rounding cuts — Find cuts from rounding the right-hand side of existing constraints or the current value of the objective function.

Initial ILP (P):

$$\text{max.} \quad z = x_1 + 2x_2$$

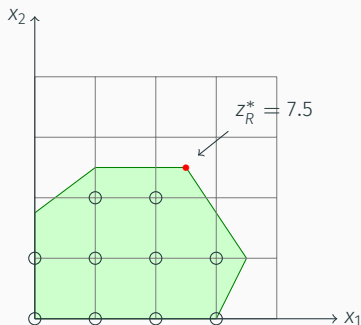
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Adding a cut from the objective:

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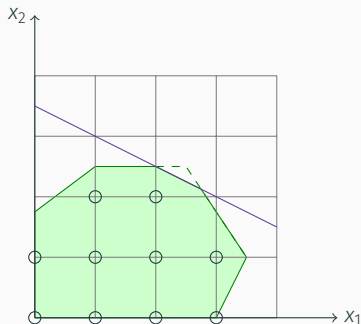
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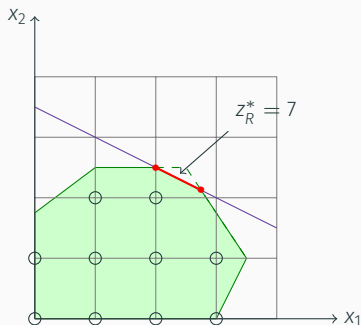
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Adding a cut from a constraint:

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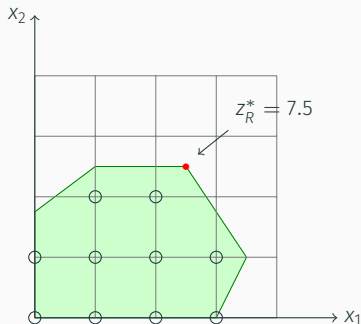
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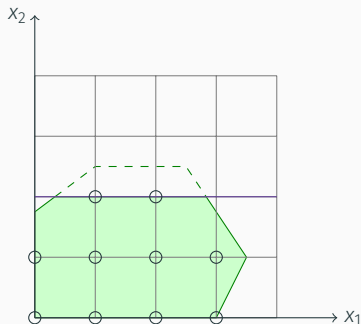
$$\text{s.t.} \quad -3x_1 + 4x_2 \leq 7$$

$$x_2 \leq \left\lfloor \frac{5}{2} \right\rfloor$$

$$6x_1 + 4x_2 \leq 25$$

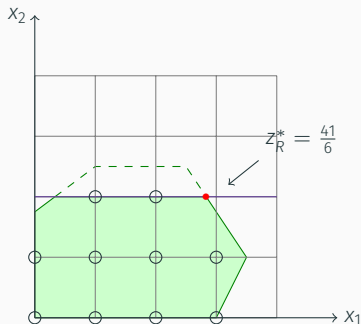
$$2x_1 - x_2 \leq 6$$

$$x_1, x_2 \in \mathbb{N}$$



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$$\begin{array}{ll}\max. & z = x_1 + 2x_2 \\ \text{s.t.} & -3x_1 + 4x_2 \leq 7 \\ & x_2 \leq 2 \\ & 6x_1 + 4x_2 \leq 25 \\ & 2x_1 - x_2 \leq 6 \\ & x_1, x_2 \in \mathbb{N}\end{array}$$



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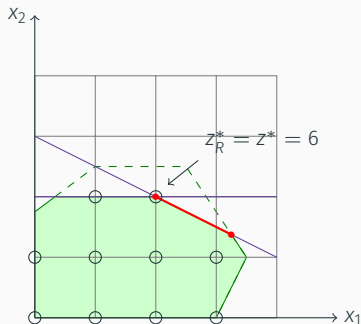
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Problem-specific cuts — Clique cuts

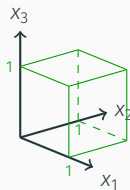
Clique: Set of **binary** variables $\mathcal{C} = \{x_1, \dots, x_k\}$ which are mutually exclusive:

$$x_i + x_j \leq 1, \quad \forall x_i, x_j \in \mathcal{C}$$

For any clique $\mathcal{C}$ of size k the following inequality is **valid**:

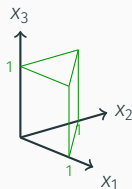
$$\sum_{i=1}^k x_i \leq 1$$

Example with 3 variables $x_1, x_2, x_3 \in \{0, 1\}$:



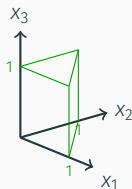
Domain of variables

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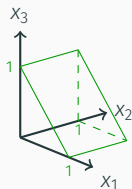


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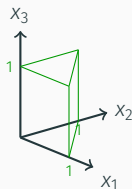


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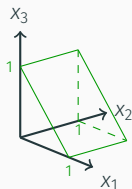


$$x_1 + x_3 \leq 1$$

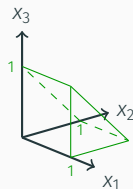
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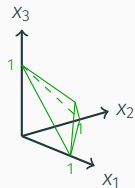


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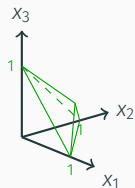
$$x_2 + x_3 \leq 1$$

Example with 3 variables $x_1, x_2, x_3 \in \{0, 1\}$:

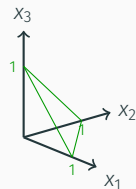


3 exclusion constraints

Example with 3 variables $x_1, x_2, x_3 \in \{0, 1\}$:



3 exclusion constraints



Clique cut

Reminder: Knapsack problem

Given a set of n items associated to profits and weights, and a knapsack of capacity K , find the set of items that maximize the total profit while ensuring the capacity constraint.

$$\max \left\{ p^T X \mid w^T X \leq K, X \in \{0, 1\}^n \right\}$$

With:

- $p \in \mathbb{N}^n$ the profits of item.
- $w \in \mathbb{N}^n$ the weights of items.
- $K \in \mathbb{N}^+$ the capacity of the knapsack.

A **minimal cover** $\mathcal{C} \subseteq X$ is a subset of the variables such that if all variables in the subset were set to one, the knapsack constraint would be violated, but if any one was excluded, the constraint would be satisfied:

$$\sum_{x_j \in \mathcal{C}} w_j > K$$

$$\sum_{x_j \in \mathcal{C}} w_j - w_j \leq K, \quad \forall x_j \in \mathcal{C}$$

For any **minimal cover** $\mathcal{C}$, the following inequality is **valid**:

$$\sum_{x_j \in \mathcal{C}} x_j \leq |\mathcal{C}| - 1$$

This inequality is called a **cover cut**.

Travelling salesman problem — Given a list of n cities and the distances c_{ij} between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?

Subtour formulation —

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- (6b) We leave each city exactly once.

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$$\sum_{i \in S} \sum_{\substack{j=1 \\ j \notin S}}^n x_{ij} \geq 1, \quad \forall S \subset \{1, \dots, n\}, S \neq \emptyset \quad (6d)$$

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- (6b) We leave each city exactly once.
- (6c) We enter each city exactly once.
- (6d) Subtour elimination.

Problem: There is an exponential number of subtour elimination constraints.

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Solution: Generate constraints only when necessary:

Algorithm Travelling Salesman Problem

```

1: procedure TSP( $\mathcal{G} = (V, E)$ )
2:    $P \leftarrow \text{RelaxTSP}(\mathcal{G})$                                 ▷ Create the problem without subtour constraints.
3:   while true do
4:      $x \leftarrow \text{Solve}(P)$ 
5:     if NumberOfSubtours( $x$ ) > 1 then
6:        $P \leftarrow P \cup \text{SubtourConstraints}(P, x)$ 
7:     else
8:       return  $x$ 
9:     end if
10:  end while
11: end procedure

```

For a graph $\mathcal{G}$, there exists a strict subset of subtour constraints that would be sufficient to reach the optimum. In practice, more constraints than necessary will be added — A trade-off needs to be found regarding the constraints we add to the model:

- if we add too many constraints, the ILP becomes larger and larger;
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Ref.: *Teaching Integer Programming Formulations Using the Traveling Salesman Problem*, 2003, Gábor Pataki —

<http://epubs.siam.org/doi/pdf/10.1137/S00361445023685>

How to find **generic** cuts?

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- Find **hyperplanes** that separate the current solution of the linear relaxation (if it is not integer) from the convex hull of $\mathcal{X}$.

How to find **generic** cuts?

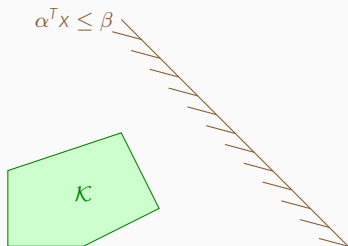
- Find **hyperplanes** that separate the current solution of the linear relaxation (if it is not integer) from the convex hull of $\mathcal{X}$.
- We need to find the most **efficient** cuts: cuts that allow the algorithm to converge to the solution as fast as possible.

Let $\mathcal{K} = \{x \in \mathbb{R}^n : Ax \leq b\}$ be a polyhedron in $\mathbb{R}^n$.

Definition

An inequality $\alpha^T x \leq \beta$ is **valid** for $\mathcal{K}$ if it is true for all $x \in \mathcal{K}$:

$$\mathcal{K} \subseteq \{x \in \mathbb{R}^n : \alpha^T x \leq \beta\}$$



Definition

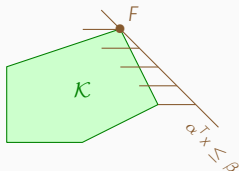
Let $\alpha^T x \leq \beta$ be a valid inequality for a polyhedron $\mathcal{P}$ in $\mathbb{R}^n$:

- $F = \{x \in \mathcal{P} : \alpha^T x = \beta\}$ is a **face** of $\mathcal{P}$.

Definition

Let $\alpha^T x \leq \beta$ be a valid inequality for a polyhedron $\mathcal{P}$ in $\mathbb{R}^n$:

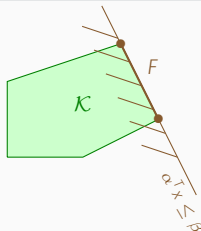
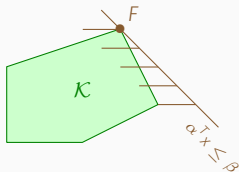
- $F = \{x \in \mathcal{P} : \alpha^T x = \beta\}$ is a **face** of $\mathcal{P}$.
- A **face** F of dimension k ($F \subseteq \mathbb{R}^k$) is a **k-face**.



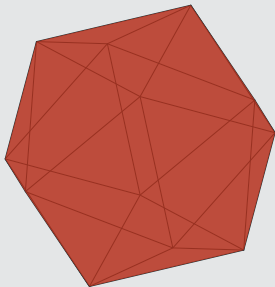
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- A **face** F of dimension k ($F \subseteq \mathbb{R}^k$) is a **k-face**.
- A **facet** of a polyhedron $\mathcal{K}$ in $\mathbb{R}^n$ is a **(n-1)-face**.



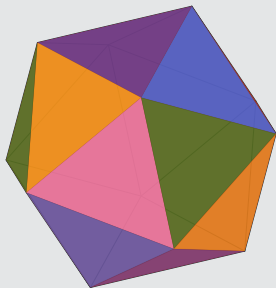
Example



Let $\mathcal{P}$ represent this 3D-polyhedron:

- $\mathcal{P}$ itself is the only **3-face** of $\mathcal{P}$
($0^T x = 0, \forall x \in \mathcal{P}$).

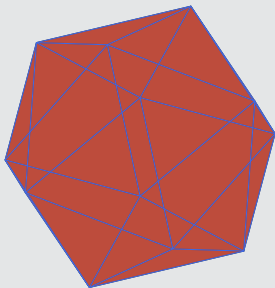
Example



Let $\mathcal{P}$ represent this 3D-polyhedron:

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- The triangles are the **facets** (or **2-faces**) of $\mathcal{P}$.

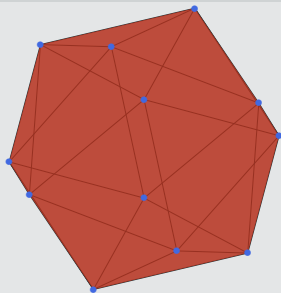
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- The edges are **1-faces** of $\mathcal{P}$.

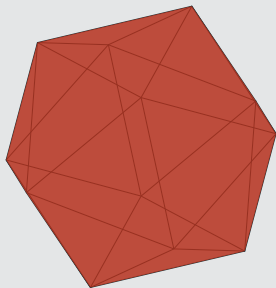
Example



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- The triangles are the **facets** (or **2-faces**) of $\mathcal{P}$.
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Example



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- The triangles are the **facets** (or **2-faces**) of $\mathcal{P}$.
- The edges are **1-faces** of $\mathcal{P}$.
- The vertices are **0-faces** of $\mathcal{P}$.
- The emptyset $\emptyset$ is the only **(-1)-face** of $\mathcal{P}$
(convention).

Theorem

Let $\mathcal{X}$ be a finite set of points in $\mathbb{R}^n$ and $x^0 \in \mathbb{R}^n \setminus \text{conv}(\mathcal{X})$. There exists $\alpha \in \mathbb{R}^n$ and $\beta \in \mathbb{R}$ such that:

$$\begin{aligned}\alpha^T x &\leq \beta, \quad \forall x \in \text{conv}(\mathcal{X}) \\ \alpha^T x_0 &> \beta\end{aligned}$$

Theorem

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$$\begin{aligned}\alpha^T x &\leq \beta, \quad \forall x \in \text{conv}(\mathcal{X}) \\ \alpha^T x_0 &> \beta\end{aligned}$$

$\alpha^T x - \beta$ defines a **hyperplane** that separates x_0 from the convex hull $\text{conv}(\mathcal{X})$ of $\mathcal{X}$.

Let (P) be the following linear programs (with m constraints):

$$\max \left\{ c^T x \mid Ax \leq b, x \in \mathbb{N}^n \right\}$$

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For all $1 \leq j \leq m$, $A_j x \leq b_j$ is a valid inequality for the convex hull of (P) .

Chvatál-Gomory inequality

Consider $y \in \mathbb{R}_+^m$ and:

$$\alpha^T = \lfloor \sum_{j=1}^m y_j A_j \rfloor \in \mathbb{Z}^n$$
$$\beta = \lfloor \sum_{j=1}^m y_j b_j \rfloor \in \mathbb{Z}$$

Then $\alpha^T x \leq \beta$ is a valid inequality for the convex hull of (P) .

In order to solve the linear relaxation (R) of an integer linear program (P), the simplex algorithm reformulate the problem by adding a set s of **slack** variables such that:

$$(R) = \max \left\{ c^T x \mid Ax + s = b, x \in \mathbb{R}^n, s \in \mathbb{R}^m \right\} = \max \left\{ c^T x \mid Du = b, u \in \mathbb{R}^{n+m} \right\}$$

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The simplex algorithm proceeds by pivoting at each iteration, transforming the original system of linear equations into another one:

$$\bar{D}u = \bar{b}, u \in \mathbb{R}^{n+m}$$

Consider constraint j of the final system (when the optimum of the linear relaxation has been found):

$$\sum_{i=1}^{n+m} \bar{d}_{ji} u_i = \bar{b}_j \quad (7)$$

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The following Gomory inequality is a **valid** inequality for the convex hull of (P) :

$$\sum_{i=1}^{n+m} x_i (\bar{d}_{ji} - \lfloor \bar{d}_{ji} \rfloor) \geq \bar{b}_j - \lfloor \bar{b}_j \rfloor$$

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We can create a **valid** Gomory inequality from (7) by dropping the integer parts (floor) of the coefficients $\bar{d}_{ji}$ and the right-hand-side $\bar{b}_j$, keeping only their **positive** fractional parts, and replacing the equality by an inequality $\geq$.

HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

Problem

$$\text{max.} \quad z = x_1 + 2x_2$$

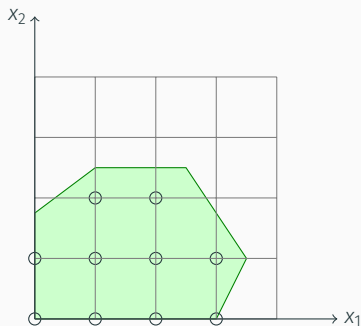
$$\text{s.t.} \quad -3x_1 + 4x_2 \leq 7$$

$$2x_2 \leq 5$$

$$6x_1 + 4x_2 \leq 25$$

$$2x_1 - x_2 \leq 6$$

$$x_1, x_2 \in \mathbb{N}$$



Linear relaxation

$$\max. \quad z = x_1 + 2x_2$$

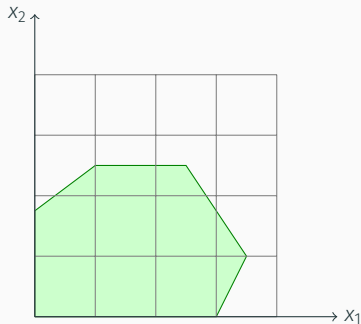
$$\text{s.t.} \quad -3x_1 + 4x_2 + s_3 = 7$$

$$2x_2 + s_4 = 5$$

$$6x_1 + 4x_2 + s_5 = 25$$

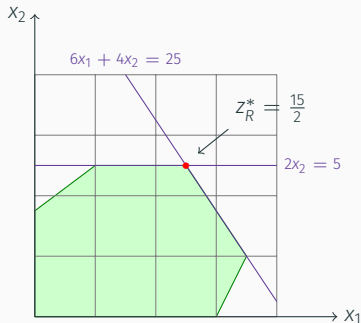
$$2x_1 - x_2 + s_6 = 6$$

$$x_1, x_2, s_3, s_4, s_5, s_6 \in \mathbb{R}^+$$



Linear relaxation

$$\begin{array}{ll}
 \max. & z = x_1 + 2x_2 \\
 \text{s.t.} & -3x_1 + 4x_2 + s_3 = 7 \\
 & 2x_2 = 5 \\
 & 6x_1 + 4x_2 = 25 \\
 & 2x_1 - x_2 + s_6 = 6 \\
 & x_1, x_2, s_3, s_4, s_5, s_6 \in \mathbb{R}^+
 \end{array}$$



The optimal solution of the relaxation is on the intersection of the second and third constraints, thus s_4 and s_5 are the **non-basic** variables and $s_4 = s_5 = 0$.

Final linear system (Simplex)

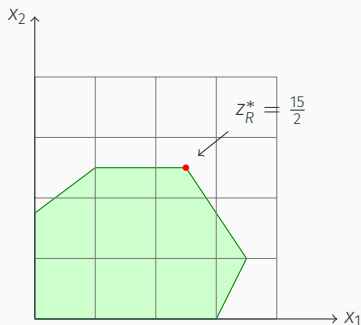
$$x_1 = \frac{5}{2} + \frac{1}{3}s_4 - \frac{1}{6}s_5$$

$$x_2 = \frac{5}{2} - \frac{1}{2}s_4 + 0s_5$$

$$s_3 = \frac{9}{2} + 3s_4 - \frac{1}{2}s_5$$

$$s_6 = \frac{15}{2} - \frac{7}{6}s_4 + \frac{1}{3}s_5$$

$$s_4 = s_5 = 0$$



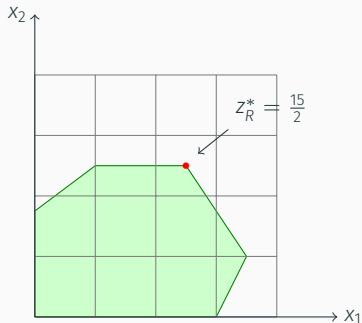
Note: x_1 , x_2 , s_3 , s_6 are the **basic** variables and s_4 , s_5 are the **non-basic** variables.

Gomory cut (1)

$$s_4 = 5 - 2x_2 \quad (R)$$

$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

$$x_1 = \frac{5}{2} + \frac{1}{3}s_4 - \frac{1}{6}s_5 \quad (S)$$



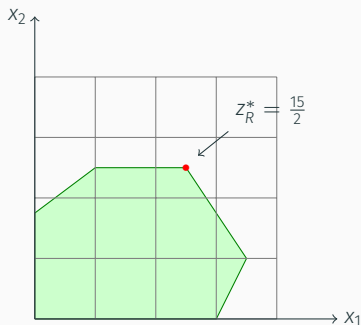
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$$\Leftrightarrow x_1 - \frac{1}{3}s_4 + \frac{1}{6}s_5 = \frac{5}{2}$$



Gomory cut (1)

$$s_4 = 5 - 2x_2 \quad (R)$$

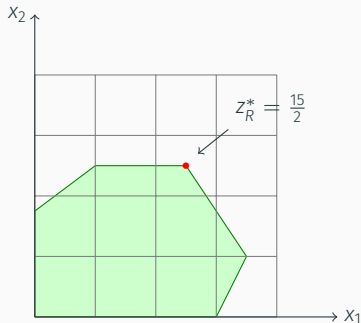
$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

$$x_1 = \frac{5}{2} + \frac{1}{3}s_4 - \frac{1}{6}s_5 \quad (S)$$

$$\Leftrightarrow x_1 - \frac{1}{3}s_4 + \frac{1}{6}s_5 = \frac{5}{2}$$

$$\Rightarrow \frac{2}{3}s_4 + \frac{1}{6}s_5 \geq \frac{1}{2}$$

$$\Rightarrow 4s_4 + s_5 \geq 3$$



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$$s_4 = 5 - 2x_2 \quad (R)$$

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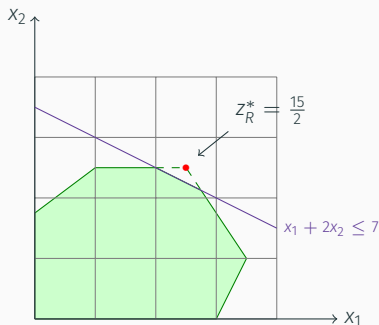
$$\Leftrightarrow x_1 - \frac{1}{3}s_4 + \frac{1}{6}s_5 = \frac{5}{2}$$

$$\Rightarrow \frac{2}{3}s_4 + \frac{1}{6}s_5 \geq \frac{1}{2}$$

$$\Rightarrow 4s_4 + s_5 \geq 3$$

$$\Rightarrow 45 - 6x_1 - 12x_2 \geq 3$$

$$\Rightarrow x_1 + 2x_2 \leq 7$$

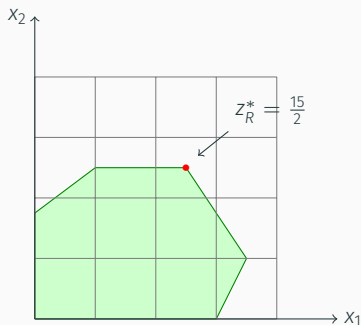


Gomory cut (2)

$$s_4 = 5 - 2x_2 \quad (R)$$

$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

$$x_2 = \frac{5}{2} - \frac{1}{2}s_4 - 0s_5 \quad (S)$$



HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

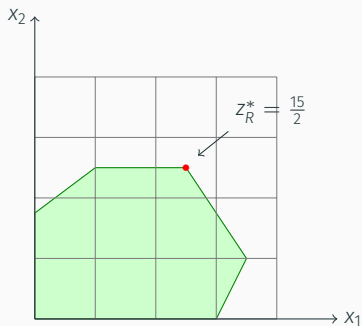
Gomory cut (2)

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$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

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$$\Leftrightarrow x_2 + \frac{1}{2}s_4 = \frac{5}{2}$$



Gomory cut (2)

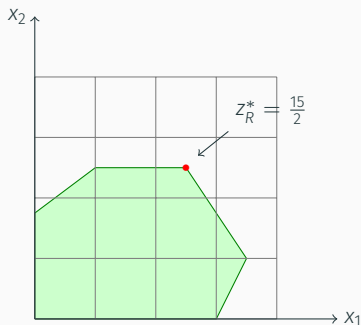
$$s_4 = 5 - 2x_2 \quad (R)$$

$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

$$x_2 = \frac{5}{2} - \frac{1}{2}s_4 - 0s_5 \quad (S)$$

$$\Leftrightarrow x_2 + \frac{1}{2}s_4 = \frac{5}{2}$$

$$\Rightarrow \frac{1}{2}s_4 \geq \frac{1}{2} \Rightarrow s_4 \geq 1$$



Gomory cut (2)

$$s_4 = 5 - 2x_2 \quad (R)$$

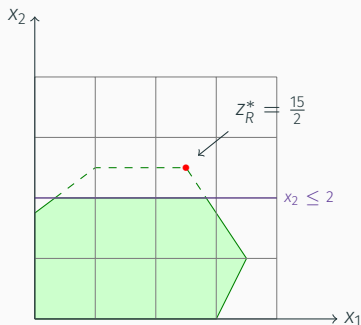
$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

$$x_2 = \frac{5}{2} - \frac{1}{2}s_4 - 0s_5 \quad (S)$$

$$\Leftrightarrow x_2 + \frac{1}{2}s_4 = \frac{5}{2}$$

$$\Rightarrow \frac{1}{2}s_4 \geq \frac{1}{2} \Rightarrow s_4 \geq 1$$

$$\Rightarrow 5 - 2x_2 \geq 1 \Rightarrow x_2 \leq 2$$



Gomory cut (3)

$$s_4 = 5 - 2x_2 \quad (R)$$

$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

$$s_3 = \frac{9}{2} + 3s_4 - \frac{1}{2}s_5 \quad (S)$$

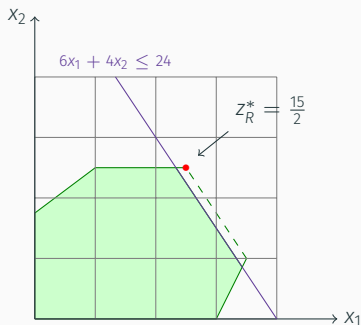
$$\Leftrightarrow s_3 - 3s_4 + \frac{1}{2}s_5 = \frac{9}{2}$$

$$\Rightarrow \frac{1}{2}s_5 \geq \frac{1}{2}$$

$$\Rightarrow s_5 \geq 1$$

$$\Rightarrow 25 - 6x_1 - 4x_2 \geq 1$$

$$\Rightarrow 6x_1 + 4x_2 \leq 24$$



Gomory cut (4)

$$s_4 = 5 - 2x_2 \quad (R)$$

$$s_5 = 25 - 6x_1 - 4x_2 \quad (R)$$

$$s_6 = \frac{7}{2} - \frac{7}{6}s_4 + \frac{1}{3}s_5 \quad (S)$$

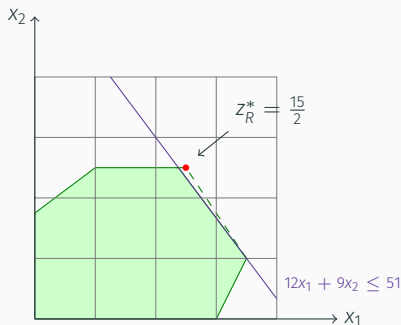
$$\Leftrightarrow s_6 + \frac{7}{6}s_4 - \frac{1}{3}s_5 = \frac{7}{2}$$

$$\Rightarrow \frac{1}{6}s_4 + \frac{2}{3}s_5 \geq \frac{1}{2}$$

$$\Rightarrow s_4 + 4s_5 \geq 3$$

$$\Rightarrow 105 - 24x_1 - 18x_2 \geq 3$$

$$\Rightarrow 12x_1 + 9x_2 \leq 51$$



Gomory cut (1-4)

$$-3x_1 + 4x_2 \leq 7$$

$$2x_2 \leq 5$$

$$6x_1 + 4x_2 \leq 25$$

$$2x_1 - x_2 \leq 6$$

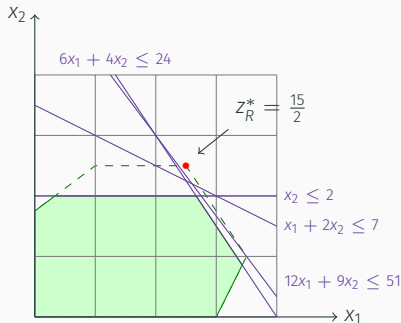
$$x_2 \leq 2$$

$$x_1 + 2x_2 \leq 7$$

$$6x_1 + 4x_2 \leq 24$$

$$12x_1 + 9x_2 \leq 51$$

$$x_1, x_2 \in \mathbb{R}$$



HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

New ILP formulation

$$\max. \quad z = x_1 + 2x_2$$

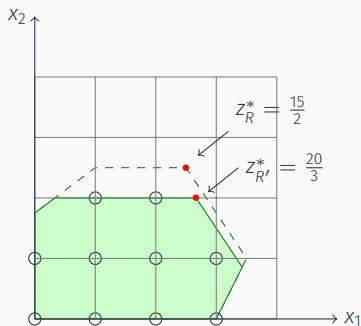
$$\text{s.t.} \quad -3x_1 + 4x_2 \leq 7$$

$$2x_1 - x_2 \leq 6$$

$$x_2 \leq 2$$

$$6x_1 + 4x_2 \leq 24$$

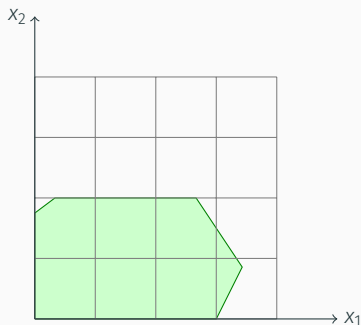
$$x_1, x_2 \in \mathbb{N}$$



HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

Linear relaxation

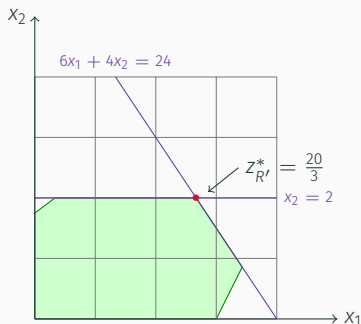
$$\begin{array}{ll}\text{max.} & z = x_1 + 2x_2 \\ \text{s.t.} & -3x_1 + 4x_2 + s_3 = 7 \\ & 2x_1 - x_2 + s_4 = 6 \\ & x_2 + s_5 = 2 \\ & 6x_1 + 4x_2 + s_6 = 24 \\ & x_1, x_2, s_3, s_4, s_5, s_6 \in \mathbb{R}^+\end{array}$$



HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

Linear relaxation

$$\begin{array}{ll}\text{max.} & z = x_1 + 2x_2 \\ \text{s.t.} & -3x_1 + 4x_2 + s_3 = 7 \\ & 2x_1 - x_2 + s_4 = 6 \\ & x_2 + s_5 = 2 \\ & 6x_1 + 4x_2 + s_6 = 24 \\ & x_1, x_2, s_3, s_4, s_5, s_6 \in \mathbb{R}^+\end{array}$$



HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

Linear relaxation

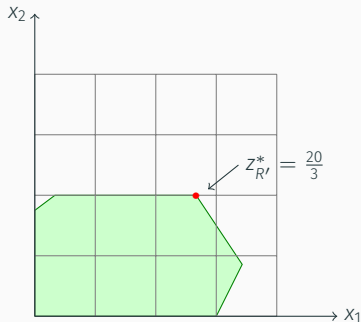
$$x_1 = \frac{8}{3} + \frac{2}{3}s_5 - \frac{1}{6}s_6$$

$$x_2 = 2 - s_5 + 0s_6$$

$$s_3 = 7 + 6s_5 - \frac{1}{2}s_6$$

$$s_4 = \frac{8}{3} - \frac{7}{3}s_5 + \frac{1}{3}s_6$$

$$s_5 = s_6 = 0$$



Linear relaxation

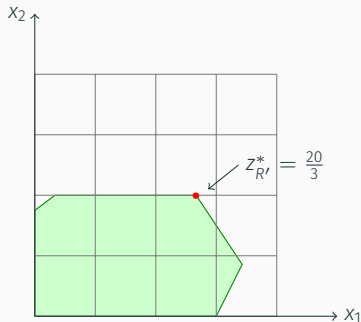
$$x_1 = \frac{8}{3} + \frac{2}{3}s_5 - \frac{1}{6}s_6$$

$$x_2 = 2 - s_5 + 0s_6$$

$$s_3 = 7 + 6s_5 - \frac{1}{2}s_6$$

$$s_4 = \frac{8}{3} - \frac{7}{3}s_5 + \frac{1}{3}s_6$$

$$s_5 = s_6 = 0$$



x_2 and s_3 do not have fractional part so no cuts can be generated from the two corresponding constraints.

HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

Linear relaxation

$$s_5 = 2 - x_2 \quad (R)$$

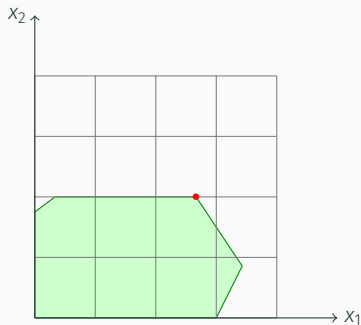
$$s_6 = 24 - 6x_1 - 4x_2 \quad (R)$$

$$x_1 = \frac{8}{3} + \frac{2}{3}s_5 - \frac{1}{6}s_6$$

$$x_2 = 2 - s_5 + 0s_6$$

$$s_3 = 7 + 6s_5 - \frac{1}{2}s_6$$

$$s_4 = \frac{8}{3} - \frac{7}{3}s_5 + \frac{1}{3}s_6$$



HOW TO GENERATE CUTS FOR GENERIC PROGRAMS? — GOMORY CUTS — EXAMPLE

Linear relaxation

$$s_5 = 2 - x_2 \quad (R)$$

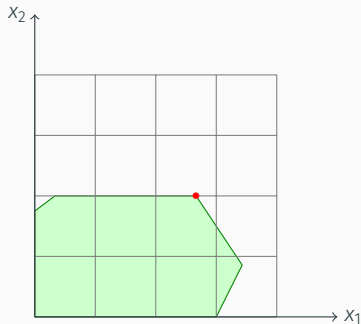
$$s_6 = 24 - 6x_1 - 4x_2 \quad (R)$$

$$2s_5 + s_6 \geq 4$$

$$x_2 = 2 - s_5 + 0s_6$$

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$$s_4 = \frac{8}{3} - \frac{7}{3}s_5 + \frac{1}{3}s_6$$



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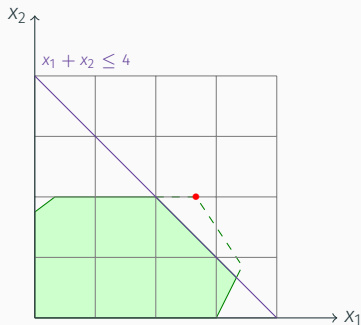
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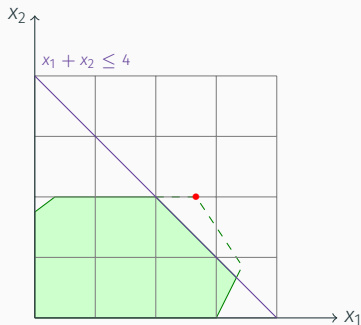
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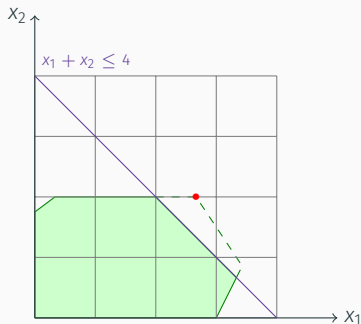
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- $s_3 = 7 + 6s_5 - \frac{1}{2}s_6$ generates $s_6 \geq 0$, which is equivalent to $6x_1 + 4x_2 \leq 24$, which is already a constraint.

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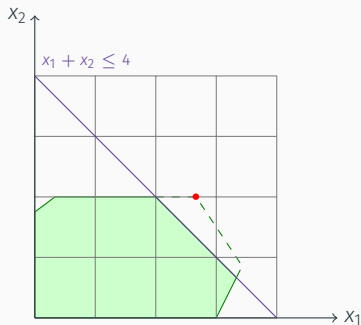
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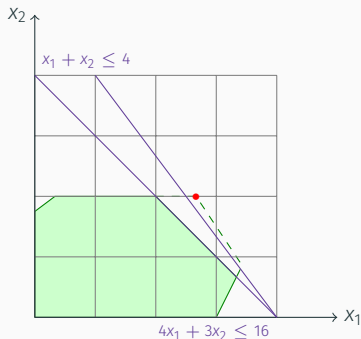
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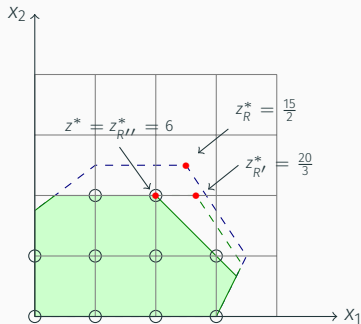
$$4x_1 + 3x_2 \leq 16$$



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New ILP formulation

$$\begin{array}{ll}
 \max. & z = x_1 + 2x_2 \\
 \text{s.t.} & -3x_1 + 4x_2 \leq 7 \\
 & 2x_1 - x_2 \leq 6 \\
 & x_2 \leq 2 \\
 & x_1 + x_2 \leq 4 \\
 & x_1, x_2 \in \mathbb{N}
 \end{array}$$



We can stop because the optimal solution of the linear relaxation $z_{R''}^*$ is in $\mathbb{N}^2$.

Algorithm Generic cut-based algorithm

```
1: procedure CUTS( $P$ )
2:    $x \leftarrow \text{null}$ 
3:   while  $x = \text{null}$  do
4:      $x_R \leftarrow \text{Simplex}(\text{Relax}(P))$ 
5:     if  $x_R \in \mathbb{N}^n$  then
6:        $x \leftarrow x_R$ 
7:     else
8:        $P \leftarrow P \cup \text{Gomory}(x_R)$ 
9:     end if
10:  end while
11:  return  $x$ 
12: end procedure
```

- ▷ Apply Simplex to the linear relaxation.
- ▷ Check if the solution is integral.
- ▷ The optimal solution has been found.
- ▷ Add cuts to the problem.

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▷ Apply Simplex to the linear relaxation.
▷ Check if the solution is integral.
▷ The optimal solution has been found.
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This algorithm is **guaranteed** to terminate in a finite number of steps, but it may takes a very long time to converge to the optimal solution.

SOLVING INTEGER LINEAR PROGRAMS

DECOMPOSITION METHODS

Integer linear programs can often be split in a **master problem** and a **subproblem** — These decompositions often depends on the form of the integer linear program.

- **Benders decomposition** — Constraints (rows) generation.
- **(Delayed) column generation** — Variables (columns) generation.
 - **Dantzig-Wolfe decomposition**

General idea:

1. Starts with a reduction of the original problem (P) → **Master problem**.
2. Solve the master problem.
3. Check the solution for optimality and feasibility in (P).
 - Check passed → The optimal solution has been found, **stop**.
 - Check failed → Create and solve the **subproblem** to generate new variables and/or constraints to add to the the **master problem**, and go bak to (2).

The reduced **master problem** and the **subproblem** must be “easy” to solve for the decomposition to be efficient.

Original problem (P)

$$\min \left\{ c^T x + f^T y : Ax + Fy = b, x \geq 0, y \in Y \right\}$$

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Primal subproblem $SP(\bar{y})$

$$h(\bar{y}) = \min \left\{ c^T x : Ax = b - F\bar{y}, x \geq 0 \right\}$$

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We need to select $\bar{y} \in Y$ such that $(SP(\bar{y}))$ admits feasible solutions:

- if $(SP(\bar{y}))$ is infeasible for all $\bar{y} \in Y$, then the original problem (P) is infeasible;
- if there exists $\bar{y}$ such that $SP(\bar{y})$ is unbounded, then the original problem (P) is unbounded;
- if (P) has an optimal solution (x^*, y^*) , then x^* is an optimal solution of $(SP(y^*))$.

Primal **subproblem** $SP(\bar{y})$

$$h(\bar{y}) = \min \left\{ c^T x : Ax = b - F\bar{y}, x \geq 0 \right\}$$

We can use Farkas' lemma —

- Given $\bar{y} \in Y$, there exists $x \geq 0$ such that $Ax = b - F\bar{y}$ if and only if $u^T(b - F\bar{y}) \leq 0$ for all u such that $u^T A \leq 0$.

The polar cone $\{u : u^T A \leq 0\}$ is polyhedral and generated by a **finite** number of “rays” (vectors) $\rho_r, r \in \Gamma$. These vectors are **independent from $\bar{y}$** .

The primal **subproblem** $SP(\bar{y})$ is feasible if

$$\bar{y} \in \bar{Y} = \{ \bar{y} : \rho_r^T(b - F\bar{y}) \leq 0, \quad \forall r \in \Gamma \}.$$

$\bar{Y} \subseteq Y$ is the set of solutions from the master problem for which the primal subproblem is feasible.

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If $\bar{y} \in \bar{Y} - (SP(\bar{y}))$ is feasible — then either

- $(SD(\bar{y}))$ is infeasible and $(SP(\bar{y}))$ is unbounded or;
- $(SD(\bar{y}))$ has a finite optimum, and does $(SP(\bar{y}))$.

We can reformulate (P) using the solution of $(SD(\bar{y}))$ ¹ –

$$\min_{y \in \bar{Y}} \left\{ \max_u \left\{ u^T (b - Fy) : u^T A \leq c \right\} + f^T y \right\}$$

¹We assign $-\infty$ to the $\max$ if $(SD(\bar{y}))$ is infeasible.

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$$\min_{\substack{y \in Y \\ \rho_r^T (b - Fy) \leq 0}} \left\{ \max_{p \in \Omega} \left\{ \omega_p^T (b - Fy) \right\} + f^T y \right\}$$

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Benders **master** problem:

$$\min. \quad z + f^T y \quad (8a)$$

$$\text{s.t.} \quad z \geq \omega_p^T (b - Fy), \quad p \in \Omega \quad (8b)$$

$$0 \geq \rho_r^T (b - Fy), \quad r \in \Gamma \quad (8c)$$

$$y \in S \quad (8d)$$

- (8b) — Optimality cuts.
- (8c) — Feasibility cuts, ensure that $(SP(y))$ is feasible.

There is a huge number of optimality (8b) and feasibility (8c) constraints — We start with a **subset** of these and add new ones when necessary.

Benders **master** problem (with only a subset of constraints):

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 - Otherwise, we add a new optimal cut to Ω_1 using the current solution ω_p of the dual — If this cut is not violated by the current solution $\bar{y}$, then the optimal solution of the original problem has been found, otherwise we go back to (1).

Warehouse allocations — A company needs to supply a set of n clients and needs to open new warehouses (from a set of m possible warehouses). Opening a warehouse j costs f_j and supplying a client i from a warehouse j costs c_{ij} per supply unit. Which warehouses should be opened in order to satisfy all clients while minimizing the total cost?

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$$\begin{aligned}
 \min. \quad & \sum_{i=1}^n \sum_{j=1}^m c_{ij} x_{ij} + \sum_{j=1}^m f_j y_j \\
 \text{s.t.} \quad & \sum_{j=1}^m x_{ij} = 1, & \forall i \in \{1, \dots, n\} \\
 & x_{ij} \leq y_j, & \forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, m\} \\
 & y_j \in \{0, 1\}, & \forall j \in \{1, \dots, m\} \\
 & x_{ij} \geq 0, & \forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, m\}
 \end{aligned}$$

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Dual subproblem — $SP(\bar{y})$

$$\begin{aligned}
 \max. \quad & \sum_{i=1}^n v_i - \sum_{i=1}^n \sum_{j=1}^m \bar{y}_j u_{ij} \\
 \text{s.t.} \quad & v_i - u_{ij} \leq c_{ij}, & \forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, m\} \\
 & v_i \in \mathbb{R}, u_{ij} \geq 0 & \forall i \in \{1, \dots, n\}, \forall j \in \{1, \dots, m\}
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Master problem —

$$\begin{aligned}
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 \text{s.t.} \quad & z \geq \sum_{i=1}^n v_i^p - \sum_{i=1}^n \sum_{j=1}^m u_{ij}^p y_j, & \forall p \in l_1 \\
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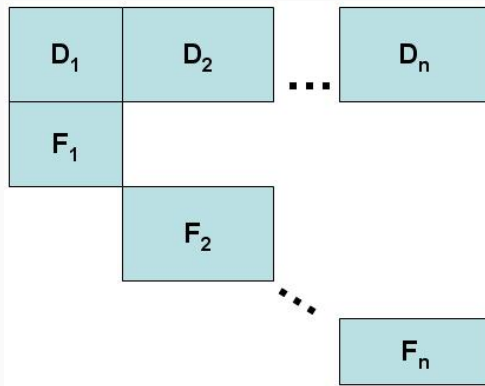
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- Adding optimality cuts is easy — We can retrieve v_i^p and u_{ij}^p from the solution of the dual subproblem.
- Adding feasibility cuts by hand is slightly more difficult — We need to find extreme directions along which the dual is unbounded, this may require solving another LP.

Dantzig-Wolfe decomposition can be used on integer linear program whose constraint matrix has the following block form:



The D matrix represent the **coupling** constraints and each F_i matrix represents an independent sub-matrix.

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The idea behind the **Dantzig-Wolfe** decomposition (and other column-generation methods) is that most variables will have a value of 0 in the optimal solution — We can start with a subset of the variables (columns) in the master problem and use solution(s) from the subproblem(s) to add new columns to the master problem as we go along.

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- **Dantzig-Wolfe** decomposition is a “generic” methods that can be used on any integer linear program whose constraint matrix has the correct form.
- There are problem-specific **Column-generation** method — We need to define columns (variables), sub-problems, and the way we generate columns from sub-problems.

Vehicle Routing Problem — Given a fleet of vehicles, a depot and a set of customers, what is the optimal set of routes that deliver to every customer?

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Let c_r be the cost of route r and $\alpha_{ir} = 1$ if customer i is served by route r .

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min.

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$$y_r \in \{0, 1\}, \quad \forall j \in \{1, \dots, R\}$$

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$$\min. \quad \sum_{r=1}^R c_r y_r$$

s.t.

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$$\begin{aligned}
 \min. \quad & \sum_{r=1}^R c_r y_r \\
 \text{s.t.} \quad & \sum_{r=1}^R \alpha_{ir} y_r \geq 1, & \forall i \in \{1, \dots, n\} \\
 & y_r \in \{0, 1\}, & \forall r \in \{1, \dots, R\}
 \end{aligned}$$

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 \end{aligned}$$

There is an exponential number of routes (columns) → We cannot enumerate all of them and solve the full program, we need to generate them as we go along.

Bin Packing Problem — Given a set of n items with associated weights w_i , and a set of n bins of capacity W , what is the packing of items into bins that minimizes the number of bins used?

- $x_{ik} - x_{ik} = 1$ if item i is put inside bin k .
- $y_k - y_k = 1$ if bin k is used.

$$\begin{aligned}
 \min. \quad & \sum_{k=1}^n y_k \\
 \text{s.t.} \quad & \sum_{k=1}^n x_{ik} \geq 1, & \forall i \in \{1, \dots, n\} \\
 & \sum_{i=1}^n w_i x_{ik} \leq W y_k, & \forall k \in \{1, \dots, n\} \\
 & x_{ik}, y_k \in \{0, 1\}, & \forall i, k \in \{1, \dots, n\}
 \end{aligned}$$

Bin Packing Problem — Given a set of n items with associated weights w_i , and a set of n bins of capacity W , what is the packing of items into bins that minimizes the number of bins used?

If we know all possible packing of any bin, we can reformulated the problem with an exponential number of variables.

A column x^t is a feasible solution of the (knapsack-like) problem:

$$\left\{ x^t \in \{0, 1\}^n : \sum_{i=1}^n w_i x_i^t \leq W \right\}$$

Let us assume there are T possible packings. For a packing t , $x_i^t = 1$ if item i is in the packing t .

Bin Packing Problem — Given a set of n items with associated weights w_i , and a set of n bins of capacity W , what is the packing of items into bins that minimizes the number of bins used?

- $\lambda_t - \lambda_t = 1$ if packing t is chosen.

Bin Packing Problem — Given a set of n items with associated weights w_i , and a set of n bins of capacity W , what is the packing of items into bins that minimizes the number of bins used?

- $\lambda_t - \lambda_t = 1$ if packing t is chosen.

$$\begin{aligned}
 \min. \quad & \sum_{t=1}^T \lambda_t \\
 \text{s.t.} \quad & \sum_{t=1}^T x_i^t \lambda_t \geq 1, & \forall i \in \{1, \dots, n\} \\
 & \lambda_t \in \{0, 1\}, & \forall t \in \{1, \dots, T\}
 \end{aligned}$$

Bin Packing Problem — Given a set of n items with associated weights w_i , and a set of n bins of capacity W , what is the packing of items into bins that minimizes the number of bins used?

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 & \lambda_t \in \{0, 1\}, & \forall t \in \{1, \dots, T\}
 \end{aligned}$$

The associated **subproblem** (used to generate new columns) is a well-known problem.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We start with a subset of possible packings — All packings that only put a single item per bin.

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$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \\ \lambda_5 \end{pmatrix} \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

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Optimal solution: $z_0 = 5$, $\lambda = (1, 1, 1, 1, 1)$.

The dual of the master problem (with S columns) is:

$$\begin{aligned}
 \max. \quad & \sum_{i=1}^n \pi_i \\
 \text{s.t.} \quad & \sum_{i=1}^n x_i^s \pi_i \leq 1 & 1 \leq s \leq S \\
 & \pi_i \geq 0 & 1 \leq i \leq n
 \end{aligned}$$

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 & \pi_i \geq 0 & 1 \leq i \leq n
 \end{aligned}$$

We want to find a column λ_s with negative reduced cost, i.e. whose corresponding constraints in the dual is violated:

$$\sum_{i=1}^n x_i^s \pi_i > 1 \iff \sum_{i=1}^n x_i^s \pi_i - 1 > 0$$

To find the column with maximum reduced cost, we want to solve:

$$\begin{aligned} \max. \quad & \sum_{i=1}^n x_i \pi_i^* - 1 \\ \text{s.t.} \quad & \sum_{i=1}^n w_i x_i \leq W \\ & x_i \in \{0, 1\} \end{aligned}$$

To find the column with maximum reduced cost, we want to solve:

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At each step, we get a new solution for the **primal master problem** and thus new values for the **dual variables** π^* . We can then construct a new **subproblem** from these dual values π^* . If the optimum of the **subproblem** is 0 (or negative), there is no column with reduced negative cost.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

The optimal dual solution for z_0 is $\pi^* = (1, 1, 1, 1, 1)$, thus the Knapsack subproblem associated with the solution is:

$$\begin{aligned} \max. \quad & x_1 + x_2 + x_3 + x_4 + x_5 - 1 \\ \text{s.t.} \quad & x_1 + 2x_2 + 2x_3 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\} \end{aligned}$$

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Optimal solution of the subproblem: $z_0^{SP} = 2$ — This generate a new column for our master problem $x = (1, 1, 1, 0, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We add the new column to the master problem:

$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

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$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Optimal solution: $z_1 = 3$, $\lambda = (0, 0, 0, 1, 1, 1)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution²:

$$\begin{array}{ll}\max. & x_3 + x_4 + x_5 - 1 \\ \text{s.t.} & 2x_3 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\}\end{array}$$

²We can drop the x_i variables not in the objective from the constraint.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution²:

$$\begin{aligned} \max. \quad & x_3 + x_4 + x_5 - 1 \\ \text{s.t.} \quad & 2x_3 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\} \end{aligned}$$

Optimal solution of the subproblem: $x_1^{SP} = 1$ — This generate a new column for our master problem $x = (0, 0, 1, 1, 0)$.

²We can drop the x_i variables not in the objective from the constraint.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We add the new column to the master problem:

$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Optimal solution: $z_2 = 3$, $\lambda = (0, 0, 0, 1, 1, 1, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution:

$$\begin{aligned} \max. \quad & x_1 + x_4 + x_5 - 1 \\ \text{s.t.} \quad & x_1 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\} \end{aligned}$$

Optimal solution of the subproblem: $z_2^{SP} = 1$ — This generate a new column for our master problem $x = (1, 0, 0, 1, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We add the new column to the master problem:

$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Optimal solution: $z_3 = 3$, $\lambda = (0, \frac{1}{2}, 0, 0, 1, \frac{1}{2}, \frac{1}{2}, \frac{1}{2})$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution:

$$\begin{array}{ll}\max. & x_2 + x_4 + x_5 - 1 \\ \text{s.t.} & 2x_2 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\}\end{array}$$

Optimal solution of the subproblem: $z_3^{SP} = 1$ — This generate a new column for our master problem $x = (0, 1, 0, 1, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We add the new column to the master problem:

$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 + \lambda_9$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Optimal solution: $z_4 = \frac{8}{3}$, $\lambda = (0, 0, 0, 0, 1, \frac{2}{3}, \frac{1}{3}, \frac{1}{3}, \frac{1}{3})$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution:

$$\begin{aligned} \max. \quad & \frac{1}{3}x_1 + \frac{1}{3}x_2 + \frac{1}{3}x_3 + \frac{2}{3}x_4 + x_5 - 1 \\ \text{s.t.} \quad & x_1 + 2x_2 + 2x_3 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\} \end{aligned}$$

Optimal solution of the subproblem: $z_4^{SP} = 2$ — This generate a new column for our master problem $x = (1, 1, 0, 1, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We add the new column to the master problem:

$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 + \lambda_9 + \lambda_{10}$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Optimal solution: $z_6 = 2.5$, $\lambda = (0, 0, 0, 0, 1, \frac{1}{2}, \frac{1}{2}, 0, 0, \frac{1}{2})$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution:

$$\begin{aligned} \max. \quad & \frac{1}{2}x_1 + \frac{1}{2}x_3 + \frac{1}{2}x_4 + x_5 - 1 \\ \text{s.t.} \quad & x_1 + 2x_3 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\} \end{aligned}$$

Optimal solution of the subproblem: $z_4^{SP} = 2$ — This generate a new column for our master problem $x = (1, 0, 1, 1, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We add the new column to the master problem:

$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11}$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Optimal solution: $z_6 = 2.5$, $\lambda = (0, 0, 0, 0, 1, \frac{1}{2}, \frac{1}{2}, 0, 0, \frac{1}{2}, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution:

$$\begin{aligned} \max. \quad & \frac{1}{2}x_2 + \frac{1}{2}x_3 + \frac{1}{2}x_4 + x_5 - 1 \\ \text{s.t.} \quad & 2x_2 + 2x_3 + 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\} \end{aligned}$$

Optimal solution of the subproblem: $z_4^{SP} = 1$ — This generate a new column for our master problem $x = (0, 1, 0, 0, 1)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

We add the new column to the master problem:

$$\min. \quad \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{12}$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \lambda \geq \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Optimal solution: $z_6 = 2$, $\lambda = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1)$

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution:

$$\begin{array}{ll}\max. & x_4 + x_5 - 1 \\ \text{s.t.} & 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\}\end{array}$$

Optimal solution of the subproblem: $z_4^{SP} = 0$ — This generate a new column for our master problem $x = (0, 0, 0, 1, 0)$.

Example: $W = 6$, $n = 5$, $w = (1, 2, 2, 3, 4)$.

Knapsack subproblem associated with the solution:

$$\begin{aligned} \max. \quad & x_4 + x_5 - 1 \\ \text{s.t.} \quad & 3x_4 + 4x_5 \leq 6 \\ & x_i \in \{0, 1\} \end{aligned}$$

Optimal solution of the subproblem: $z_4^{SP} = 0$ — This generate a new column for our master problem $x = (0, 0, 0, 1, 0)$.

The optimum of the **subproblem** is 0, thus the column x does not have a negative reduced-cost (in fact x is already in the master problem) $\rightarrow z_6$ is the optimal solution.

MODELLING PROBLEMS AS INTEGER LINEAR PROGRAMS

Linearization — A lots of elementary non-linear operations can be formulated as linear equations by adding variables and constraints to the model, but the resulting integer linear formulation may be pretty poor (weak relaxations).

Formulations — Most problems can be formulated in various way — For a given problem, most formulations have significant weaknesses and strengths, and should be solved in a suitable way.

In this section:

- How to “linearize” logical operators and simple non-linear operators?
- Examples of formulations for well-known problems (scheduling, travelling salesman, ...) — Tools and tips for modeling integer linear programs.
- Study case: **Resource-Constrained Project Scheduling Problem (RCPS)**.

MODELLING PROBLEMS AS INTEGER LINEAR PROGRAMS

MODELING ELEMENTARY OPERATIONS

We can model a logical proposition $P \in \{true, false\}$ by a binary variable $x_P \in \{0, 1\}$.

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- **Conjunction** — $A = B \wedge C$:

$$\begin{cases} x_A \leq x_B \\ x_A \leq x_C \\ x_A \geq x_B + x_C - 1 \end{cases}$$

We can model a logical proposition $P \in \{true, false\}$ by a binary variable $x_P \in \{0, 1\}$.

- **Conjunction** — $A = B \wedge C$:

$$\begin{cases} x_A \leq x_B \\ x_A \leq x_C \\ x_A \geq x_B + x_C - 1 \end{cases}$$

- **Disjunction** — $A = B \vee C$:

$$\begin{cases} x_A \geq x_B \\ x_A \geq x_C \\ x_A \leq x_B + x_C \end{cases}$$

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- **Implication** — $A \Rightarrow B$:

$$x_B \geq x_A$$

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- **Equivalence** — $A \Leftrightarrow B$:

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- **Implication** — $A \Rightarrow B$:

$$x_B \geq x_A$$

- **Equivalence** — $A \Leftrightarrow B$:

$$x_A = x_B$$

- **Negation** — $A = \neg B$:

$$x_A + x_B = 1$$

$$\bullet f : [0, C]^2 \rightarrow \{0, 1\}, z = f(x, y) = (x \leq y)$$

$$\left\{ \begin{array}{l} x \leq y + C(1 - z) \\ y \leq x + Cz \\ z \in \{0, 1\} \\ 0 \leq x, y \leq C \end{array} \right.$$

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$$\begin{cases} x \leq y + C(1 - z) \\ y \leq x + Cz \\ z \in \{0, 1\} \\ 0 \leq x, y \leq C \end{cases}$$

$$\cdot f : [0, C] \rightarrow \{0, 1\}, z = f(x) = (x > c)$$

$$\begin{cases} cz \leq x \\ x \leq Cz \\ z \in \{0, 1\} \\ 0 \leq x \leq C \end{cases}$$

Some non-linear functions can be formulated automatically in a linear way by adding some integer variables.

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$$\bullet f_1 : \{0, 1\}^2 \rightarrow \{0, 1\}, f_1(x, y) = xy$$

$$\left\{ \begin{array}{l} z \leq x \\ z \leq y \\ z \geq x + y - 1 \\ x, y, z \in \{0, 1\} \end{array} \right.$$

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$$\bullet f_1 : \{0, 1\}^2 \rightarrow \{0, 1\}, f_1(x, y) = xy$$

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$$\bullet f_2 : \{0, 1\} \times [0, a] \rightarrow \mathbb{R}, f_2(x, y) = xy$$

$$\left\{ \begin{array}{l} z \leq ax \\ z \leq y \\ z \geq y + y - (1 - x)a \\ x \in \{0, 1\} \\ 0 \leq y, z \leq a \end{array} \right.$$

$$\bullet f_3 : [0, C]^2 \rightarrow [0, C], f_3(x, y) = \min(x, y)$$

$$\left\{ \begin{array}{l} z \leq x \\ z \leq y \\ x \leq y + Cw \\ y \leq x + C(1 - w) \\ z \geq (1 - w)x + wy \\ w \in \{0, 1\} \\ 0 \leq x, y, z \leq C \end{array} \right.$$

If z has a positive coefficient in the objective function of a maximization problem (i.e. we want to maximize z), this formulation reduces to $z \leq x$ and $z \leq y$.

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If z has a positive coefficient in the objective function of a maximization problem (i.e. we want to maximize z), this formulation reduces to $z \leq x$ and $z \leq y$.

$$\bullet f_4 : [a, b] \rightarrow \mathbb{R}, f_4(x) = |x| \text{ with } a < 0 < b$$

$$\left\{ \begin{array}{l} z = x^+ + x^- \\ 0 \leq x^+ \leq by \\ 0 \leq x^- \leq |a|(1 - y) \\ a \leq x^+ - x^- \leq b \\ z \in \mathbb{R}, y \in \{0, 1\} \end{array} \right.$$

MODELLING PROBLEMS AS INTEGER LINEAR PROGRAMS

EXAMPLES

INTEGER LINEAR PROGRAMMING — SINGLE MACHINE SCHEDULING

Single machine scheduling — A machine needs to produce a set L of n items. Each item i has a manufacturing time p_i , a release time r_i (time at which its components are available) and a deadline d_i (time at which the time should be manufactured). The factory can only produce **one item at a time**, and manufacturing process **cannot be interrupted** (non-preemptive machine), what is the schedule that minimize the overdue deliveries?

- x_{ij} — Binary variable indicating if i is manufactured before j .
- s_i — Continuous variable indicating the starting time of task i .
- y_i — Binary variable indicating if the item i is overdue.

$$\min. \sum_{j=1}^n y_j \quad (10a)$$

$$\text{s.t. } s_j \geq s_i + p_i - M(1 - x_{ij}), \quad \forall i, j \in L, i \neq j \quad (10b)$$

$$s_i + p_i \leq d_i + My_i, \quad \forall i \in L \quad (10c)$$

$$x_{ij} + x_{ji} = 1, \quad \forall i, j \in L, i \neq j \quad (10d)$$

$$x_{ij} \in \{0, 1\}, \quad \forall i, j \in L \quad (10e)$$

$$y_i \in \{0, 1\}, \quad \forall i \in L \quad (10f)$$

$$s_i \geq r_i, \quad \forall i \in L \quad (10g)$$

- (10d) Two items must be ordered — i is before j or j is before i .
- (10c) $y_i = 1$ if $s_i + p_i > d_i - M$ must be big enough to inhibit the constraint when $y_i = 0$.
- (10b) If j is after i ($x_{ij} = 1$), then $s_j \geq s_i + p_i - M$ must be big enough to inhibit the constraint if j is before i ($x_{ij} = 0$).

Single machine scheduling —

We want to formulate a set of linear (in)-equalities that would enforce, for any pair of items/tasks i and j :

“If i is ordered before j , then j must start after the end of i .”

$$x_{ij} = 1 \Rightarrow s_j \geq s_i + p_i$$

- We can formulate this using the following linear equation:

$$s_j \geq s_i + p_i - M(1 - x_{ij})$$

- When $x_{ij} = 1$, we get $s_j \geq s_i + p_i$ as required. When $x_{ij} = 0$, we get:

$$s_j \geq s_i + p_i - M$$

- → We want that constraint to be **inhibited** when $x_{ij} = 0$, so we need to choose a correct value for M , e.g.:

$$M = \max_i r_i + \sum_i p_i$$

Single machine scheduling —

We want to formulate a set of linear (in)-equalities that would enforce, for any items/tasks i :

“If i is processed after its deadline, i is delayed.”

$$s_i + p_i > d_i \Leftrightarrow y_i = 1$$

- We can formulate one direction of the equivalence using the following linear equation:

$$s_i + p_i > d_i \Rightarrow y_i = 1 : s_i + p_i \leq d_i + M'y_i$$

- When $s_i + p_i > d_i$, we **have to** have $y_i = 1$, otherwise the constraint would be violated.
- What about the other direction?

$$(y_i = 1 \Rightarrow s_i + p_i > d_i) \iff (s_i + p_i \leq d_i \Rightarrow y_i = 0)$$

- We do not need an (in)-equality this because for each i , y_i has a **positive coefficient** in the objective function of a **minimization** problem, thus the model will try to set $y_i = 0$ whenever it is possible.

Aircraft landing scheduling problem — Given a fleet P of aircraft and a set of lanes R , what is the schedule that minimizes the fees due to plane landing too early or too late?

- e_i — Earliest landing time for aircraft i .
- d_i — Latest landing time for aircraft i .
- t_i — Desired landing time for aircraft i .
- s_{ij} — Separation time between aircraft i and j .

If a plane lands before or after its desired landing time, unit fees have to be paid — g_i for landing too early, h_i for landing too late.

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$$\min. \sum_{i \in P} (h_i E_i + g_i L_i)$$

$$\text{s.t. } e_i \leq T_i \leq d_i, \quad \forall i \in P$$

$$T_i, E_i, L_i \in \mathbb{R}^+, \quad \forall i \in P$$

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$$\text{s.t. } e_i \leq T_i \leq d_i,$$

$$\forall i \in P$$

$$L_i \geq T_i - t_i,$$

$$\forall i \in P$$

$$E_i \geq t_i - T_i,$$

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- $x_{ij} - x_{ji} = 1$ if aircraft j lands after aircraft i .

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$$L_i \geq T_i - t_i, \quad \forall i \in P$$

$$E_i \geq t_i - T_i, \quad \forall i \in P$$

$$T_j \geq T_i + s_{ij}x_{ij} - M_{ij}(1 - x_{ij}), \quad \forall i, j \in P$$

$$T_i, E_i, L_i \in \mathbb{R}^+, x_{ij} \in \{0, 1\}, \quad \forall i, j \in P$$

Aircraft landing scheduling problem — Given a fleet P of aircraft and a set of lanes R , what is the schedule that minimizes the fees due to plane landing too early or too late?

- T_i — Landing time of aircraft i .
- E_i, L_i — Advance and delay of aircraft i .
- $x_{ij} - x_{ji} = 1$ if aircraft j lands after aircraft i .
- $y_{ir} - y_{ir} = 1$ if aircraft i lands on lane r .

$$\begin{aligned}
 \min. \quad & \sum_{i \in P} (h_i E_i + g_i L_i) \\
 \text{s.t.} \quad & e_i \leq T_i \leq d_i, & \forall i \in P \\
 & L_i \geq T_i - t_i, & \forall i \in P \\
 & E_i \geq t_i - T_i, & \forall i \in P \\
 & T_j \geq T_i + s_{ij}x_{ij} - M_{ij}(1 - x_{ij}), & \forall i, j \in P \\
 & x_{ij} + x_{ji} \geq y_{ir} + y_{jr} - 1, & \forall i, j \in P, \forall r \in R \\
 & T_i, E_i, L_i \in \mathbb{R}^+, x_{ij} \in \{0, 1\}, y_{ir} \in \{0, 1\}, & \forall i, j \in P, \forall r \in R
 \end{aligned}$$

Aircraft landing scheduling problem — Given a fleet P of aircraft and a set of lanes R , what is the schedule that minimizes the fees due to plane landing too early or too late?

$$x_{ij} + x_{ji} \geq y_{ir} + y_{jr} - 1, \quad \forall i, j \in P, \forall r \in R$$

If both aircraft land on the same lane r , $y_{ir} = y_{jr} = 1$, they need to be scheduled:

$$\forall i, j \in P : \exists r \in R, y_{ir} = 1 \wedge y_{jr} = 1 \Rightarrow x_{ij} + x_{ji} = 1$$

Aircraft landing scheduling problem — Given a fleet P of aircraft and a set of lanes R , what is the schedule that minimizes the fees due to plane landing too early or too late?

$$T_j \geq T_i + s_{ij}x_{ij} - M_{ij}(1 - x_{ij})$$

If aircraft j lands after aircraft i , $x_{ij} = 1$, they must be separated by at least s_{ij} :

$$\forall i, j \in P : x_{ij} = 1 \Rightarrow T_j \geq T_i + s_{ij}$$

Aircraft landing scheduling problem — Given a fleet P of aircraft and a set of lanes R , what is the schedule that minimizes the fees due to plane landing too early or too late?

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To inhibit the constraint when $x_{ij} = 0$, we need the following to be always verified:

$$T_j \geq T_i - M_{ij}$$

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To inhibit the constraint when $x_{ij} = 0$, we need the following to be always verified:

$$M_{ij} \geq T_i - T_j$$

Since we know that for any plane i , $e_i \leq T_i \leq d_i$, we can choose:

$$M_{ij} = d_i - e_j \geq T_i - T_j$$

Most problems can be formulated as integer linear programs in multiple ways — Different formulations lead to different resolution techniques.

- Pseudo-polynomial or **extended** formulations:
 - Better *LP* relaxations, early node pruning in branch & bounds.
 - Large *MILP* — Possibly pseudo-polynomial or even exponential number of binary variables and/or constraints $\Rightarrow$ Needs of specific methods (column generation, branch & cuts, ...).
- Polynomial-size or **compact** formulations:
 - Fast node evaluation due to the small size of the relaxation.
 - Weaker relaxations, more nodes need to be explored, cuts need to be generated.

INTEGER LINEAR PROGRAMMING — TRAVELLING SALESMAN PROBLEM

Travelling salesman problem (TSP) — Given a list of n cities and the distances c_{ij} between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?

Miller-Tucker-Zemlin (MTZ) formulation —

- $x_{ij} \in \{0, 1\}$ — Binary variable indicating if we go directly from city i to city j .
- $u_i \in \{1, \dots, n\}$ — Subtour elimination variables — u_i is the position of city i in the tour.

$$\min. \quad \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij} \quad (11a)$$

$$\text{s.t.} \quad \sum_{\substack{j=1 \\ j \neq i}}^n x_{ij} = 1, \quad \forall i \in \{1, \dots, n\} \quad (11b)$$

$$\sum_{\substack{i=1 \\ i \neq j}}^n x_{ij} = 1, \quad \forall j \in \{1, \dots, n\} \quad (11c)$$

$$u_1 = 1 \quad (11d)$$

$$2 \leq u_i \leq n, \quad \forall i \in \{1, \dots, n\} \quad (11e)$$

$$u_i - u_j + 1 \leq (n-1)(1 - x_{ij}), \quad \forall i, j \in \{2, \dots, n\} \quad (11f)$$

$$x_{ij} \in \{0, 1\}, \quad u_i \in \mathbb{N} \quad \forall i, j \in \{1, \dots, n\} \quad (11g)$$

INTEGER LINEAR PROGRAMMING — TRAVELLING SALESMAN PROBLEM

Flow formulation —

- $x_{ij} \in \{0, 1\}$ — Binary variable indicating if we go directly from city i to city j .
- $y_{ij} \in \mathbb{R}_*^+$ — Subtour elimination variables — y_{ij} is the *flow* on arc (i, j) , each city produces one unit of flow.

$$\min. \quad \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij} \quad (12a)$$

$$\text{s.t.} \quad \sum_{\substack{j=1 \\ j \neq i}}^n x_{ij} = 1, \quad \forall i \in \{1, \dots, n\} \quad (12b)$$

$$\sum_{\substack{i=1 \\ i \neq j}}^n x_{ij} = 1, \quad \forall j \in \{1, \dots, n\} \quad (12c)$$

$$\sum_{j=2}^n y_{1j} = 1 \quad (12d)$$

$$\sum_{j=1}^n y_{ij} = \sum_{j=1}^n y_{ji} + 1, \quad \forall i \in \{2, \dots, n\} \quad (12e)$$

$$y_{ij} \leq n x_{ij}, \quad \forall i, j \in \{1, \dots, n\} \quad (12f)$$

$$x_{ij} \in \{0, 1\}, y_{ij} \in \mathbb{R}_*^+ \quad \forall i, j \in \{1, \dots, n\} \quad (12g) \quad 148/169$$

Subtour formulation —

- $x_{ij} \in \{0, 1\}$ — Binary variable indicating if we go directly from city i to city j .

$$\min. \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij} \quad (13a)$$

$$\text{s.t.} \quad \sum_{\substack{j=1 \\ j \neq i}}^n x_{ij} = 1, \quad \forall i \in \{1, \dots, n\} \quad (13b)$$

$$\sum_{\substack{i=1 \\ i \neq j}}^n x_{ij} = 1, \quad \forall j \in \{1, \dots, n\} \quad (13c)$$

$$\sum_{i \in S} \sum_{j \notin S} x_{ij} \geq 1 \quad S \subset \{1, \dots, n\}, S \neq \emptyset \quad (13d)$$

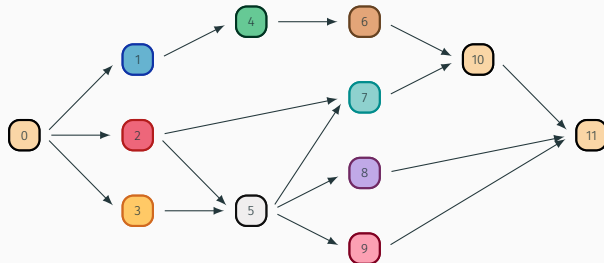
$$x_{ij} \in \{0, 1\} \quad \forall i, j \in \{1, \dots, n\} \quad (13e)$$

Resource-Constrained Project Scheduling Problem (RCPSP) —

- R — Set of resources with a **limited constant** availability $B_k \geq 0$.
- A — Set of activities with duration $p_i \geq 0$ and resource requirements $b_{ik} \geq 0$ for each resource $k \in R$.
- E — Set of precedence constraints (i, j) , $i, j \in A$, $i < j$, this can be represented as a *directed acyclic graph*.
- $\mathcal{T}$ — Time interval (scheduling horizon).

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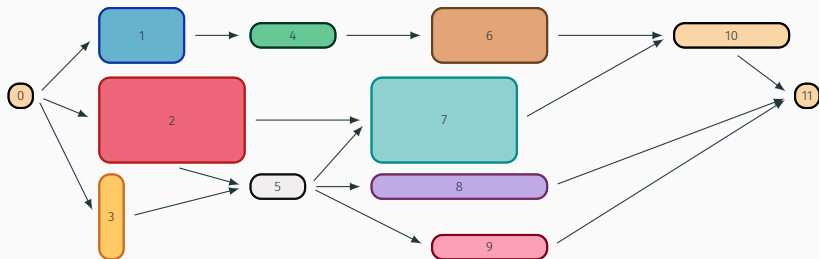
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$$R = \{1\}, B_1 = 4, \mathcal{T} = [0, 30).$$

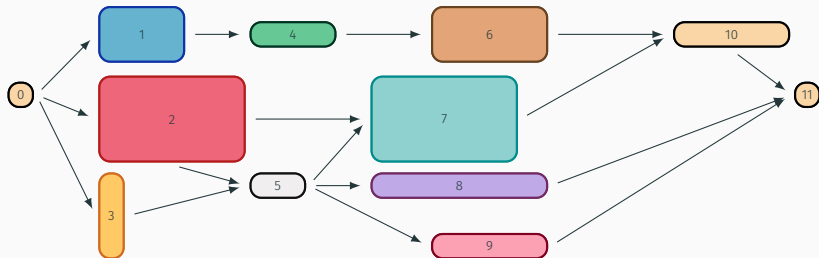
i	p_i	b_1
1	3	2
2	5	3
3	1	3
4	3	1
5	2	1
6	4	2
7	5	3
8	6	1
9	4	1
10	4	1

Example with $A = \{1, \dots, 10\}$ and a single resource B of capacity $B_1 = 4$:

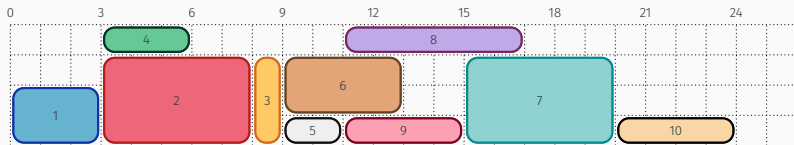


INTEGER LINEAR PROGRAMMING — RESOURCE CONSTRAINED SCHEDULING PROBLEM

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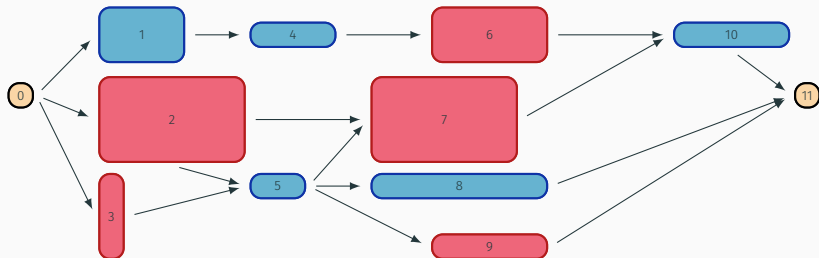


Feasible solution:



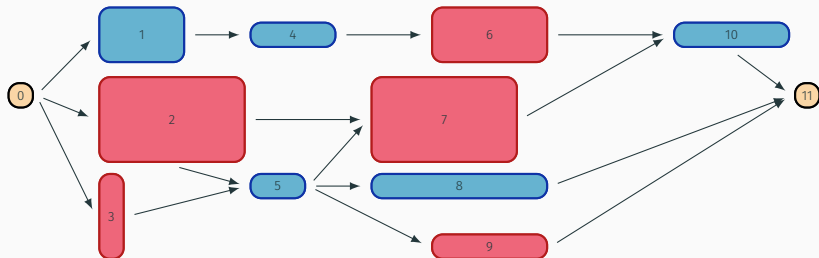
INTEGER LINEAR PROGRAMMING — RESOURCE CONSTRAINED SCHEDULING PROBLEM

Example with $A = \{1, \dots, 10\}$ and two resources of capacity $B_1 = B_2 = 3$:

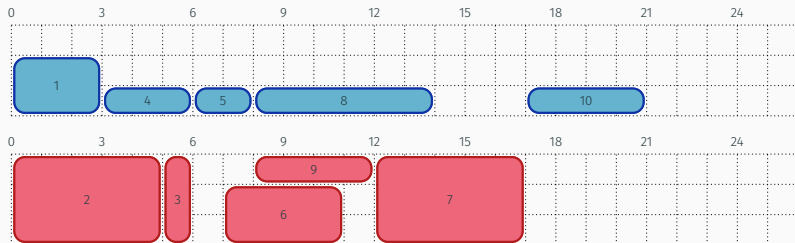


INTEGER LINEAR PROGRAMMING — RESOURCE CONSTRAINED SCHEDULING PROBLEM

Example with $A = \{1, \dots, 10\}$ and two resources of capacity $B_1 = B_2 = 3$:



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min. (14a)

s.t. (14b)

(14c)

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$$(14d)$$

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- (14c) — Resource constraints, $A(t) = \{j \in A : t \in [S_j, S_j + p_j)\}$.

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$$\sum_{i \in A(t)} b_{ik} \geq B_k, \quad \forall t \in \mathcal{T}, \forall k \in R \quad (14c)$$

$$S_j \geq 0, \quad \forall i \in A \quad (14d)$$

- (14b) — Precedence constraints.
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RCPSP — Aggregated time-indexed formulation [\[Pritsker, Waiters, et al. 1969\]](#)

For integer data (processing time), S_i is integral.

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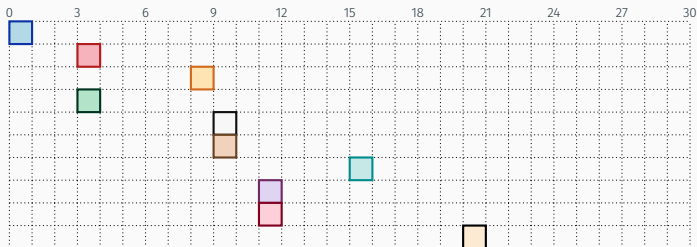
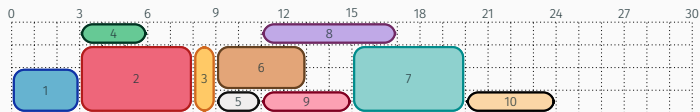
For integer data (processing time), S_i is integral.

- $x_{it} \in \{0, 1\} - x_{ij} = 1 \Leftrightarrow S_i = t, t \in T = \mathcal{T} \cap \mathbb{N}$, pseudo-polynomial number of variables ($|A| \cdot |T|$).

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Link with the conceptual formulation:

- $S_i = \sum_{t \in T} tx_{it}$
- $A(t) = \{i \in A : \exists \tau \in \{t - p_i + 1, \dots, t\}, x_{i\tau} = 1\}$

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min.

s.t.

$$x_{it} \in \{0, 1\}$$

$$\forall i \in A, \forall t \in T$$

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- $A(t) = \{i \in A : \exists \tau \in \{t - p_i + 1, \dots, t\}, x_{i\tau} = 1\}$

$$\min. \sum_{t \in T} tx_{n+1,t}$$

s.t.

$$x_{it} \in \{0, 1\}$$

$$\forall i \in A, \forall t \in T$$

RCPSP — Aggregated time-indexed formulation (DT) [Pritsker, Walters, et al. 1969]

- $x_{it} \in \{0, 1\} - x_{ij} = 1 \Leftrightarrow S_j = t, t \in T = \mathcal{T} \cap \mathbb{N}$, **pseudo-polynomial** number of variables ($|A| |T|$).

Link with the conceptual formulation:

- $S_i = \sum_{t \in T} tx_{it}$
- $A(t) = \{i \in A : \exists \tau \in \{t - p_i + 1, \dots, t\}, x_{i\tau} = 1\}$

$$\begin{aligned} \min. \quad & \sum_{t \in T} tx_{n+1,t} \\ \text{s.t.} \quad & \sum_{t \in T} tx_{jt} - \sum_{t \in T} tx_{it} \geq p_i, \quad \forall (i, j) \in E \end{aligned}$$

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$$\text{s.t.} \quad \sum_{t \in T} tx_{jt} - \sum_{t \in T} tx_{it} \geq p_i, \quad \forall (i, j) \in E$$

$$\sum_{i \in A} \sum_{\tau=t-p_i+1}^t b_{ik} x_{i\tau} \leq B_k, \quad \forall t \in T, \forall k \in R$$

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 & \sum_{i \in A} \sum_{\tau=t-p_i+1}^t b_{ik} x_{i\tau} \leq B_k, & \forall t \in T, \forall k \in R \\
 & \sum_{t \in T} x_{it} = 1, & \forall i \in A \\
 & x_{it} \in \{0, 1\} & \forall i \in A, \forall t \in T
 \end{aligned}$$

RCPSP — Disaggregated time-indexed formulation (DDT) [Christofides et al. 1987]

The relaxation of the **aggregated** time-indexed formulation is pretty weak — The lower bound on the makespan is often not better than a trivial lower bound.

The model can be reinforced by **disaggregation** of the precedence constraints, i.e. replacing precedence constraints by:

$$\sum_{\tau=0}^{t-p_j} x_{i\tau} - \sum_{\tau=0}^t x_{j\tau} \geq 0, \quad \forall (i,j) \in E, \forall t \in T$$

This model the set of constraints:

$$\forall (i,j) \in E, \forall t \in T : S_j \leq t \Rightarrow S_i \leq t - p_j$$

- The constraint matrix **without** resource constraints is **totally unimodular**.
- Total unimodularity is preserved by lagrangean relaxation of the resource constraints — Efficiently computable by a **max-flow** algorithm [Möhring et al. 2003].

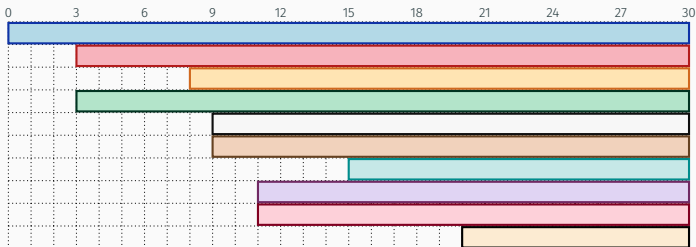
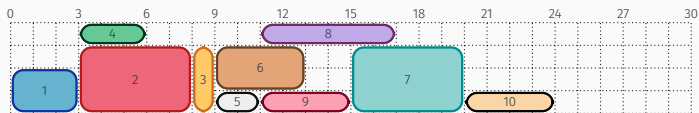
RCPSP — Time-indexed formulation with step variables (SDDT) [[Pritsker and Watters 1968](#)]

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- $\xi_{it} \in \{0, 1\} - x_{ij} = 1 \Leftrightarrow S_i \leq t, t \in T = \mathcal{T} \cap \mathbb{N}$, **pseudo-polynomial** number of variables ($|A| |T|$).

RCPSP — Time-indexed formulation with step variables (SDDT) [Pritsker and Watters 1968]

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RCPSP — Time-indexed formulation with step variables (SDDT) [[Pritsker and Watters 1968](#)]

The time-indexed formulation with step variables (SDDT) can be obtained by transforming the disaggregated time-indexed formulation with pulse variables (DDT) using the following:

$$\xi_{it} = \sum_{\tau=0}^t x_{i\tau}, \quad \forall i \in A, \forall t \in T$$

- This is a non-singular transformation (NST) — Formulations that can be obtained by a NST are strictly equivalent. They have the same set of feasible solutions and the same relaxation value.
- There is another formulation using $\xi' = 1 \Leftrightarrow S_i + p_i \leq t$ which is equivalent (by NST transformation) to (SDDT) [[Bianco et al. 2013](#)].

RCPSP — On/Off time-indexed formulation (OODDT) [Pritsker, Waiters, et al. 1969]

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- $\mu_{it} \in \{0, 1\} - \mu_{ij} = 1 \Leftrightarrow t \in [S_i, S_i + p_i[$, **pseudo-polynomial** number of variables ($|A| \cdot |T|$).

RCPSP — On/Off time-indexed formulation (OODDT) [Pritsker, Waiters, et al. 1969]

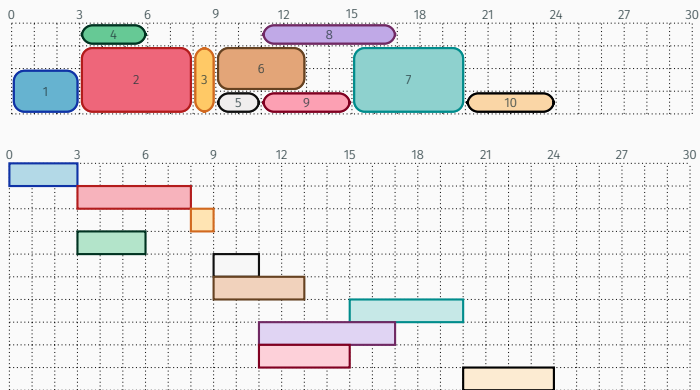
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It is possible to create a (OODDT) formulation equivalent to (DDT) using a non-singular transformation [Artigues 2013].

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RCPSP — Extended time-indexed formulations [Hardin et al. 2008; Christofides et al. 1987; Mingozzi et al. 1998].

- *Minimal Forbidden Set (MFS)*, F — Minimal set of activities that cannot be scheduled in parallel due to resource constraints.

$$\sum_{i \in F} b_{ik} > B_k \quad \text{and} \quad \forall j \in F, \quad \sum_{i \in F \setminus \{j\}} b_{ik} \leq B_k$$

We can create a **forbidden set-based** formulation by adding cover-like cuts for each MFS — This formulation would have an exponential number of constraints.

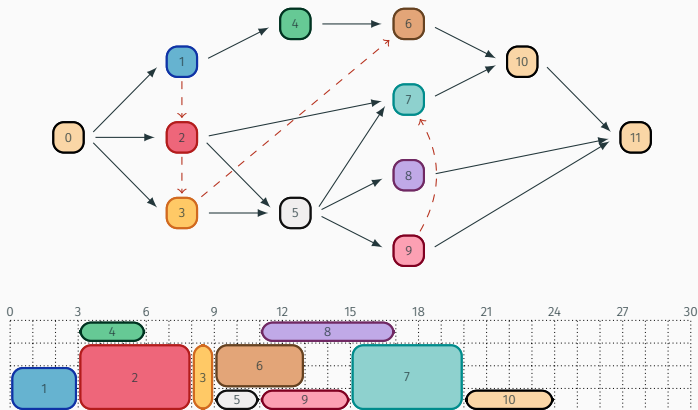
- *Feasible Set (FS)*— Set of activities that can be scheduled in parallel. A **feasible subset-based** formulation can be obtained from (DDT) by replacing the resource constraints by an exponential number of feasible set constraints.

Note: This is a non-exhaustive list of possible extended time-indexed formulations.

RCPSP — Sequencing (strict ordering) formulations.

Adding precedence constraints such that all resource conflicts are resolved —

$$z_{ij} = 1 \Leftrightarrow S_j \geq S_i + p_i, \quad \forall i, j \in A$$



RCPSP — Sequence formulation based on minimal forbidden sets [Olaguibel et al. 1993].

- S_i — Start time of task i .
- $z_{ij} \in \{0, 1\}$ — $z_{ij} = 1$ if task i is before j in the schedule.

min.

s.t.

$$z_{ij} \in \{0, 1\}$$

$$\forall i, j \in A$$

RCPSP — Sequence formulation based on minimal forbidden sets [Olaguibel et al. 1993].

- S_i — Start time of task i .
- $z_{ij} \in \{0, 1\}$ — $z_{ij} = 1$ if task i is before j in the schedule.

$$\begin{array}{ll} \min. & S_{n+1} \\ \text{s.t.} & \end{array}$$

$$z_{ij} \in \{0, 1\}$$

$$\forall i, j \in A$$

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- S_i — Start time of task i .
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$$\text{min. } S_{n+1}$$

$$\text{s.t. } z_{ij} + z_{ji} \leq 1,$$

$$z_{ij} + z_{jh} - z_{ih} \leq 1,$$

$$z_{ij} = 1,$$

$$\forall i, j \in A, i < j$$

$$\forall i, j, j \in A, i \neq j \neq h$$

$$\forall (i, j) \in E$$

$$z_{ij} \in \{0, 1\}$$

$$\forall i, j \in A$$

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- S_i — Start time of task i .
- $z_{ij} \in \{0, 1\}$ — $z_{ij} = 1$ if task i is before j in the schedule.

$$\begin{aligned}
 \min. \quad & S_{n+1} \\
 \text{s.t.} \quad & z_{ij} + z_{ji} \leq 1, & \forall i, j \in A, i < j \\
 & z_{ij} + z_{jh} - z_{ih} \leq 1, & \forall i, j, h \in A, i \neq j \neq h \\
 & z_{ij} = 1, & \forall (i, j) \in E \\
 & S_j + (1 - z_{ij})M_{ij} \geq S_i + p_i, & \forall i, j \in A, i \neq j \\
 & z_{ij} \in \{0, 1\} & \forall i, j \in A
 \end{aligned}$$

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 & z_{ij} = 1, & \forall (i, j) \in E \\
 & S_j + (1 - z_{ij})M_{ij} \geq S_i + p_i, & \forall i, j \in A, i \neq j \\
 & \sum_{\substack{i, j \in F \\ i \neq j}} z_{ij} \geq 1, & \forall F \in \mathcal{F} \\
 & z_{ij} \in \{0, 1\} & \forall i, j \in A
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 & z_{ij} \in \{0, 1\} & \forall i, j \in A
 \end{array}$$

We need an exponential number of forbidden sets constraints — This formulation is **extended**.

RCPSP — Sequence formulation based on **resource flow** [Artigues et al. 2003].

- S_i — Start time of task i .
- $z_{ij} \in \{0, 1\}$ — $z_{ij} = 1$ if task i is before j in the schedule.

RCPSP — Sequence formulation based on **resource flow** [Artigues et al. 2003].

- S_i — Start time of task i .
- $z_{ij} \in \{0, 1\}$ — $z_{ij} = 1$ if task i is before j in the schedule.
- Φ_{ij}^k — Units of resource k transferred from i to j .

RCPSP — Sequence formulation based on **resource flow** [Artigues et al. 2003].

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We can replace the forbidden set constraints in the previous formulation by:

$$\begin{aligned} \Phi_{ij}^k &\leq \min(b_{ik}, b_{jk})z_{ij}, & \forall i, j \in A, \forall k \in R, i \neq j \\ \sum_{j \in V \setminus \{i\}} \Phi_{ij}^k &= b_{ik}, & \forall i \in A, j \neq n+1 \\ \sum_{i \in V \setminus \{j\}} \Phi_{ij}^k &= b_{jk}, & \forall j \in A, j \neq 0 \\ 0 \leq \Phi_{ij}^k &\leq \min(b_{ik}, b_{jk}), & \forall i, j \in A, \forall k \in R, i \neq n+1, j \neq 0 \end{aligned}$$

RCPSP — Sequence formulation based on **resource flow** [Artigues et al. 2003].

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We need $\mathcal{O}(|A|^2 |R|)$ additional continuous variables and constraints — This formulation is **compact**.

RCPSP — **Event-based** formulations [Lasserre et al. 1992; Dautère-Pérès et al. 1995; Pinto et al. 1995].

Start and End event variables —

- ε — Set of remarkable events.
- $t_e \geq 0$ — Event date representing the start and end of at least one activity.
- $a_{ie}^- \in \{0, 1\}$ — Start assignment variables, $a_{ie}^- = 1 \Leftrightarrow S_i = t_e$.
- $a_{ie}^+ \in \{0, 1\}$ — End assignment variables, $a_{ie}^+ = 1 \Leftrightarrow S_i + p_i = t_e$.

We need $2(n + 1) |\varepsilon|$ binary variables.

RCPSP — Event-based formulations.

On/Off event variables (OOE) [Koné et al. 2011]. —

- ε — Set of remarkable events.
- $t_e \geq 0$ — Event date representing the **start** of at least one activity.
- $a_{ie} \in \{0, 1\}$ — On/off binary variables, $a_{ie} = 1 \Leftrightarrow [S_i, S_i + p_i] \cap [t_e, t_e + 1] \neq \emptyset$.

We need $n |\varepsilon|$ binary variables.

RCPSP — Event-based formulations — **On/Off** event variables (OOE) [Koné et al. 2011].

$$\min. C_{max}$$

$$\text{s.t. } C_{max} \geq t_e + (a_{ie} - a_{i,e-1})p_i \quad \forall e \in \varepsilon, \forall i \in A$$

$$t_{e+1} \geq t_e, \quad \forall e \in \varepsilon, e \neq n$$

$$t_0 = 0$$

$$t_f \geq t_e + (a_{ie} - a_{i,e-1} - a_{if} + a_{i,f-1} - 1)p_i, \quad \forall e, f \in \varepsilon, \forall i \in A, f > e \neq 0$$

$$\sum_{f=0}^{e-1} a_{if} \geq e(1 - a_{ie} + a_{i,e-1}) \quad \forall e \in \varepsilon, \forall i \in A$$

$$\sum_{f=e}^{n-1} a_{if} \geq e(1 + a_{ie} - a_{i,e-1}) \quad \forall e \in \varepsilon, \forall i \in A$$

$$\sum_{e \in \varepsilon} a_{ie} \geq 1, \quad \forall i \in A$$

$$a_{ie} + \sum_{f=0}^e a_{je} \leq 1 + (1 - a_{ie})e, \quad \forall e \in \varepsilon, \forall (i, j) \in E$$

$$\sum_{i=0}^{n-1} r_{ik} a_{ie} \leq B_k, \quad \forall e \in \varepsilon, \forall k \in R$$

$$t_e \geq 0, a_{ie} \in \{0, 1\}, \quad \forall e \in \varepsilon, \forall i \in A$$

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