Solving Mixed Integer Linear Programs with Cutting Planes

Tobias Kohler

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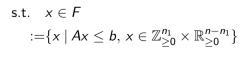
- Optimize linear objective function s.t. linear constraints and some integer constraints.
- Sometimes, decision variables are discrete: Distribution of patients/supplies/vehicles... or binary/logical variables.

Mixed Integer Linear Program and Linear Program Relaxation



$$\min_{x} c^{\top} x$$

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



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LP Relaxation

$$\min_{x} c^{\top}x$$

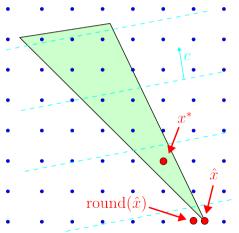
s.t.
$$x \in P$$

$$:= \{x \mid Ax \le b, \, x \in \mathbb{R}^n_{\ge 0}\}$$

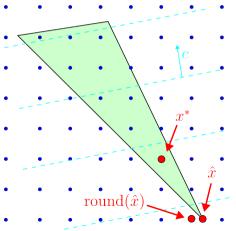
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Notation

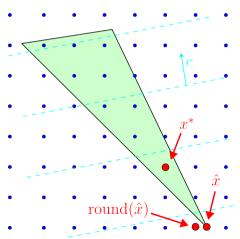
- $x_1, ..., x_n$: Integer variables
- $x_{n_1}, ..., x_n$: Real variables
- F, x^* : Feasible region and optimal solution of the MILP
- P, \hat{x} : Feasible region and optimal solution of the LP-relaxation $(F = P \cap \mathbb{Z}_{>0}^{n_1} \times \mathbb{R}_{>0}^{n-n_1})$
- $n_1 = 0 \Rightarrow \text{Linear Program (LP)}$
- $n_1 = n \Rightarrow \text{Integer Linear Program (ILP)}$
- $x_i \in \{0, 1\} \Rightarrow (Mixed)$ Binary Program ((M)BP)



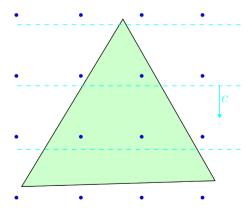
 \hat{x} can be found at a vertex of P (Simplex Algorithm).

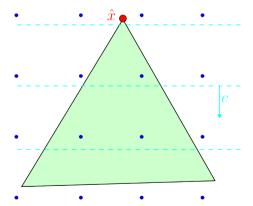


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- In general, round(\hat{x}) $\neq x^*$

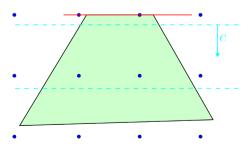


- \hat{x} can be found at a vertex of P (Simplex Algorithm).
- In general, round(\hat{x}) $\neq x^*$
- If \hat{x} is already feasible, then $c^{\top}\hat{x} = c^{\top}x^*$.

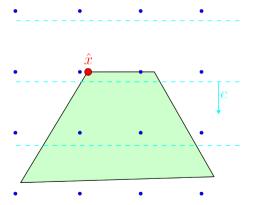


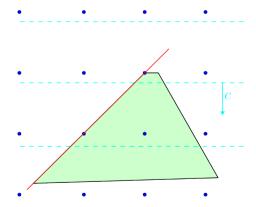




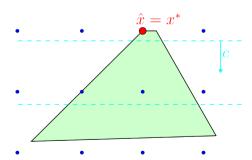


Cutting Planes









Valid Inequalities and Cuts

■ An inequality $a^{\top}x \leq r$ is valid for a set F if $a^{\top}x \leq r$ is satisfied for all $x \in F$.

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 - For example: $x \le 2$ is a valid inequality for $\{x \in \mathbb{Z}_{>0} \mid x \le 2.718\}$
- A <u>cutting plane</u> (or cut) w.r.t. $\hat{x} \in P \setminus F$ is any valid inequality $a^{\top}x \leq r$ for F such that:

$$a^{\top}\hat{x} > r$$

```
1: LP \leftarrow Relaxation of the MILP

2: repeat

3: \hat{x} \leftarrow Optimal solution of the LP

4: if (\hat{x}_1, ..., \hat{x}_{n_1}) \notin \mathbb{Z}^{n_1} then

5: Add a cut w.r.t. \hat{x} to the LP

6: until (\hat{x}_1, ..., \hat{x}_{n_1}) \in \mathbb{Z}^{n_1}

7: return \hat{x}
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Question: How to generate "good" and useful cuts?

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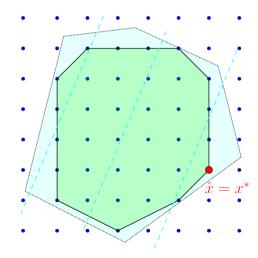
Cutting Strategy

Question: How to generate "good" and useful cuts?

- Good: Cut away as much as possible (while staying feasible)
- Useful: Cut away the optimal solution of the relaxation

Convex Hull

- The relaxed solution \hat{x} in conv(F) also solves the MILP.
- But computing the convex hull is infeasible.
- Our goal is instead to approximate the convex hull in a neighborhood of x*.



Any real number $a \in \mathbb{R}$ can be expressed as

$$a = |a| + f_a$$

for some unique $\lfloor a \rfloor \in \mathbb{Z}$ and $f_a \in [0, 1)$.

- $\lfloor a \rfloor = \max\{z \in \mathbb{Z} \mid z \leq a\}$ is the integer part of a.
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 $f_a = 0 \Leftrightarrow a = |a| \Leftrightarrow a \in \mathbb{Z}$

Integer Part and Fractional Part

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■
$$\lfloor -a \rfloor = -\lceil a \rceil$$
 where $\lceil a \rceil = \min\{z \in \mathbb{Z} \mid z \geq a\}$

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- $\lfloor -a \rfloor = -\lceil a \rceil$ where $\lceil a \rceil = \min\{z \in \mathbb{Z} \mid z \geq a\}$
- lacksquare $a \in \mathbb{Z}$ and $a \leq b \Rightarrow a \leq \lfloor b \rfloor$

Integer Part and Fractional Part

Any real number $a \in \mathbb{R}$ can be expressed as

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- \bullet $f_a = a |a|$ is the fractional part of a.

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- |-a| = -[a] where $\lceil a \rceil = \min\{z \in \mathbb{Z} \mid z > a\}$
- $\blacksquare a \in \mathbb{Z}$ and $a < b \Rightarrow a < |b|$
- \blacksquare $a \in \mathbb{Z}$ and $a > b \Rightarrow a > \lceil b \rceil$

Let $\sum_{j=1}^{n} a_{ij} x_j \leq b_i$ for an Integer Linear Program $(x \in \mathbb{Z}_{\geq 0}^n)$. Then the following inequalities are valid for any $\alpha > 0$:

$$\alpha \geq \mathbf{0}$$

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$$\sum_{j=1}^{n} \lfloor \alpha a_{ij} \rfloor x_j \leq \alpha b_i$$

$$x_i \geq 0$$

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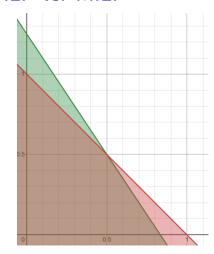
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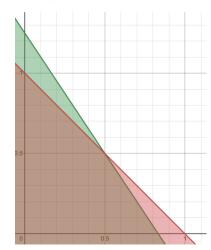
$$x_j \in \mathbb{Z}$$

ILP vs. MILP



- $\min_{x,y} -y$ s.t. $\frac{3}{2}x + y \le \frac{5}{4}$, $(x, y) \in \mathbb{Z}_{\ge 0}^2$
- $(x^*, y^*) = (0, 1)$

ILP vs. MILP



- $\min_{x,y} -y$ s.t. $\frac{3}{2}x + y \le \frac{5}{4}$, $(x, y) \in \mathbb{Z}_{\ge 0} \times \mathbb{R}_{\ge 0}$
- $(x^*, y^*) = (0, \frac{5}{4})$
- lacksquare $\lfloor rac{3}{2}
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 floor \cdot rac{5}{4} = rac{5}{4} > \lfloor rac{5}{4}
 floor$ X

Let
$$x \in \mathbb{Z}_{>0}$$
, $y \in \mathbb{R}_{>0}$, $b \in \mathbb{R}_{>0} \setminus \mathbb{Z}$. Then

$$x \le \lfloor b \rfloor$$
 is a valid inequality for $\{x + y \le b\}$ (1)

and

$$x \ge \lceil b \rceil$$
 is a valid inequality for $\{-x + y \le -b\}$ (2)

Let $x \in \mathbb{Z}_{>0}$, $y \in \mathbb{R}_{>0}$, $b \in \mathbb{R}_{>0} \setminus \mathbb{Z}$. Then

$$x - \frac{1}{f_b - 1} \le \lfloor b \rfloor \text{ is a valid inequality for } \{x - y \le b\}$$
 (1)

and

$$x + \frac{1}{f_b} \ge \lceil b \rceil$$
 is a valid inequality for $\{-x - y \le -b\}$ (2)

General Mixed Integer Rounding Inequality

Let $F_{MIR} = \{(x, y) \in \mathbb{Z}^2_{\geq 0} \times \mathbb{R}_{\geq 0} \mid a_1x_1 + a_2x_2 - y \leq b\}$ where $a \in \mathbb{R}^2$, $b \in \mathbb{R} \setminus \mathbb{Z}$ and assume that $f_1 \leq f_b \leq f_2$. Then the inequality

$$\lfloor a_1 \rfloor x_1 + \left(\lfloor a_2 \rfloor + \frac{f_2 - f_b}{1 - f_b} \right) x_2 - \frac{1}{1 - f_b} y \le \lfloor b \rfloor$$

is valid for F_{MIR} .

Simplex Algorithm

Simplex finds $\hat{x} \in P \times \mathbb{R}^{N-n}_{\geq 0}$ and creates the optimal simplex tableau:

i—th row in the simplex tableau

$$x_{B_i} + \sum_{j \in NB} \bar{a}_{ij} x_j = \bar{b}_i$$

- $x_1, ..., x_{n_1}$: Integral decision variables
- $x_{n_1+1}, ..., x_n$: Real decision variables
- $x_{n+1}, ..., x_N$: (Real) slack variables

- $B = \{B_1, ..., B_m\}$: Basic variables
- $NB = \{1, ..., N\} \setminus B$: Nonbasic variables $(\hat{x}_j = 0 \text{ for } j \in NB)$

Let $N_1 = NB \cap \{1, ..., n_1\}$, $N_2 = NB \cap \{n_1 + 1, ..., N\}$. Consider the i-th row in the optimal simplex tableau

$$x_{B_i} + \sum_{j \in \mathcal{N}_1} \bar{a}_{ij} x_j + \sum_{j \in \mathcal{N}_2} \bar{a}_{ij} x_j = \bar{b}_i$$

and assume $B_i \leq n_1$ but $\hat{x}_{B_i} = \bar{b}_i \notin \mathbb{Z}$. Then the Gomory Mixed Integer Cut

$$x_{B_i} + \sum_{\substack{j \in N_1 \\ f_{ij} \le f_i}} \lfloor \bar{a}_{ij} \rfloor x_j + \sum_{\substack{j \in N_1 \\ f_{ij} > f_i}} \left(\lfloor \bar{a}_{ij} \rfloor + \frac{f_{ij} - f_i}{1 - f_i} \right) x_j + \sum_{\substack{j \in N_2 \\ \bar{a}_{ij} < 0}} \left(\frac{\bar{a}_{ij}}{1 - f_i} \right) x_j \le \lfloor \bar{b}_i \rfloor$$

is a valid inequality for F that is not satisfied by \hat{x} .

■ Let a MILP be given with feasible region $F = \{x \in \mathbb{Z}_{\geq 0}^{n_1} \times \mathbb{R}_{\geq 0}^{n_{-n_1}} \mid Ax \leq b\}$ for some $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$.

- The relaxation is the LP obtained by removing the integer constraints, so its feasible region is the polyhedron $P = \{x \in \mathbb{R}^n_{>0} \mid Ax \leq b\}$.
- Repeat the following two steps until $\hat{x} \in F$:
 - **1** Solve the LP using the Simplex Algorithm and obtain $\hat{x} \in P$
 - 2 If the problem is infeasible $(P = \emptyset)$, return INEASIBLE. If the problem is unbounded and no integer constraints are violated, return UNBOUNDED
 - If $\hat{x} \notin F$, pick $i \in \{1, ..., n_1\}$ s.t. $\hat{x}_i \notin \mathbb{Z}$ and add the corresponding GMI-Cut to the LP.

- Simplex Solver
- Mixed Integer Gomory Cut
- 2D Visualisation

Only adding an arbitrary, single cutting plane is very inefficient if the problem dimension is large.

Cutting Planes Selection

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 - Evaluate the efficiency of a cutting plane based on some heuristics (for example euclidean distance to \hat{x}).

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- Other cutting plane strategies exist:

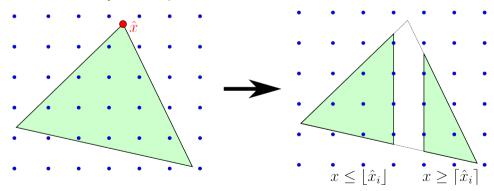
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- Other cutting plane strategies exist:
 - Knapsack Covers or GUB (generalized upper bound) covers for binary programs.

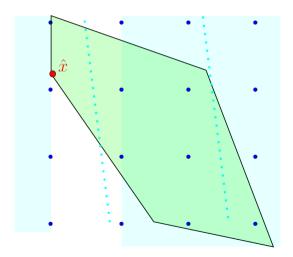
- Like Cutting Planes, we solve the problem relaxation and add constraints until an optimal solution has been found.
- Divide & Conquer approach

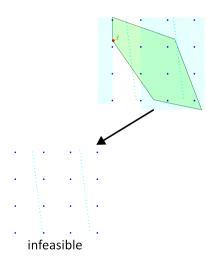
Branching

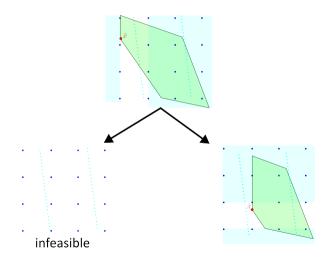
Cut off the non-integer neighborhood of $\hat{x}_i \notin \mathbb{Z}$ and obtain two new relaxation problems, one with $x_i \leq |\hat{x}_i|$ and one with $x_i \geq [\hat{x}_i]$. The resulting data structure is a binary tree of problems.

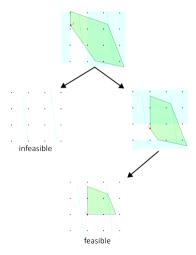


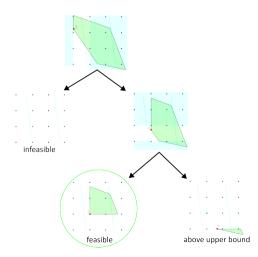
- Initially, we only know that $-\infty < c^{\top}x^* < \infty$ (not very helpful).
- Improve bounds:
 - Lower Bound: For any LP-Relaxation, we have $c^{\top}\hat{x} \leq c^{\top}x^*$
 - Upper Bound: By definition, $c^{\top}x^* \leq c^{\top}x$ for any feasible $x \in F$
- For an optimal solution \hat{x} of a subproblem:
 - if $c^{\top}\hat{x} \geq$ upper bound, prune tree (stop branching).
 - if \hat{x} is feasible, update upper bound and prune.
 - if \hat{x} is infeasible, update lower bound and branch.
 - stop if tree is completely pruned or upper bound lower bound $< \epsilon$.











Subproblem and Branching Variable Selection Strategies

- Subproblem selection:
 - Depth-First: Descend quickly to obtain a good upper bound (obtain a feasible solution fast).
 - Best-First: Pick the active node with the current lower bound (obtain a good lower bound).
- Branching variable selection:
 - Most fractional: $i = \arg\max_{1 \le i \le n_1} \min(f_i, 1 f_i)$ (f_i close to $\frac{1}{2}$).
 - Multiple variables at once.

- Cutting Planes or Branch & Bound on their own are inefficient in practice.
- Combine the two to Branch & Cut. This works like Branch & Bound but with additionally adding cuts before branching.
- Used most often in practice.

Questions?

References



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