

Investigating Mixed-Integer Hulls using a MIP-Solver

Matthias Walter
Otto-von-Guericke Universität Magdeburg



Joint work with
Volker Kaibel (OvGU)

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1 Polyhedral Combinatorics

- 1 Introduction
- 2 Usual Approach
- 3 Limitations

2 Vision

3 Affine Hull

4 Facets

- 1 Polarity
- 2 Algorithm

5 Minimizing the 1-Norm of Basis Vectors

- 1 Problem
- 2 2 Vectors: Exact Approach
- 3 2 Vectors: Heuristic Approach

Problems in Question

We consider mixed-integer programs with rational data:

$$\max \langle c, x \rangle$$

s.t.

$$Ax \leq b$$

$$Cx = d$$

$$x_i \in \mathbb{Z}$$

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Denote by $R = \{x \in \mathbb{R}^n : Ax \leq b, Cx = d\}$ the relaxation polyhedron and by $P = \text{conv.hull} \{x \in R : x_i \in \mathbb{Z} \forall i \in I\}$ the **mixed-integer hull**.

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Facts

- ▶ P is a polyhedron again.
- ▶ For most (e.g., **NP**-hard) problems, P has **many** facets.
- ▶ Nevertheless, MIP-solvers are really fast these days.

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The time a MIP-solver needs for solving depends on the strength of the relaxation, i.e., how well P is approximated by R .

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Strengthening a Relaxation

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- ▶ Problem-specific inequalities: [Problem-dependent](#)

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Goals of Polyhedral Combinatorics

Given a MIP-model for a problem,

- ▶ find inequalities valid for P (but not for R),
- ▶ develop algorithms (exact or heuristics) to separate these inequalities if there are too many,
- ▶ determine the dimension of P , i.e., find valid equations,
- ▶ and prove if/when the inequalities define facets of P .

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There are quite a few tools (PORTA, Polymake, `azove`) and several algorithms:

- ▶ The [Beneath-and-Beyond](#) method
- ▶ The [Double-Description](#) method
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Step 3: Generalize Inequalities

There's only one main tool here: The mathematician.

Memory and Time

The dominant of the cut polytope (corresponds to MinCut problem) has among others **a facet per disjoint union of cycles joined together by any spanning tree!**

ALEVRAS ('99) enumerated the facets for this polyhedron for the complete graph on **8** nodes, including 2 billions of the above type.

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Specific Objective Functions

Which are the facets useful when optimizing **specific** objective functions?

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Goal of this work:

Use MIP-solvers to determine facets!

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Note: A rational number p/q with $p, q \in \mathbb{Z}$ is a **best approximation** for $x \in \mathbb{R}$ if $|x - p/q| \leq |x - p'/q'|$ holds for all $p', q' \in \mathbb{Z}$ with $q' \leq q$.

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Answer: SCIP* and some luck with the numerics!

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Algorithm:

- 1 Maintain known equations $Cx = d$ and points $x_1, x_2, \dots, x_\ell \subseteq P$.
- 2 Let A be matrix C with additional rows $x_i - x_1$ for $i = 2, \dots, \ell$.

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If $\langle c, q_i \rangle > \langle c, x_1 \rangle$, add row $x_{\ell+1} := q_i$, add row $x_{\ell+1} - x_1$ to A , and increment ℓ .
 - 2 Otherwise, compute an optimal solution q'_i by minimizing c_i over P .
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 - 3 Otherwise, $\langle c, x \rangle = \langle c, x_1 \rangle$ defines a valid equation for P and hence can be added to $Cx = d$. Add row c to A .

Remark

- ▶ We can initialize $Cx = g$ with equations from LP relaxation.
- ▶ Optimizing in unit directions is cheap but yields few points.
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Lemma

The rank of all matrices with rows $\{x_i - x_j : \{i, j\} \in T\}$ is constant over all edge sets T which span the node set $[\ell]$.

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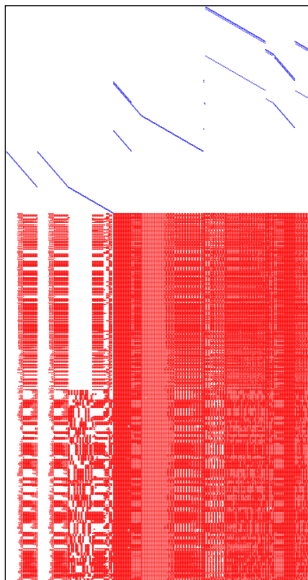
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Application

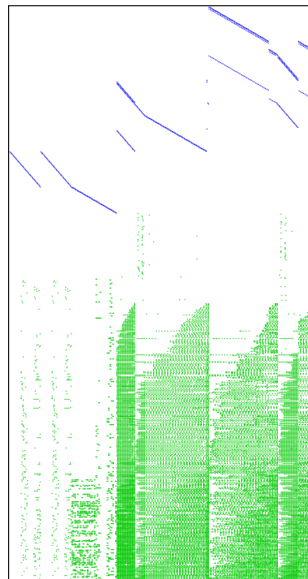
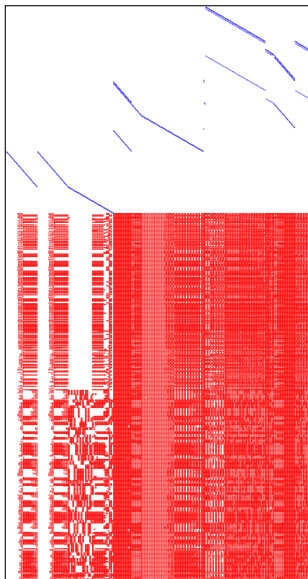
Instead of the rows $x_i - x_1$ for $i = 2, \dots, \ell$, we use $x_i - x_j$ for all minimum spanning tree edges $\{i, j\}$ where the weights are the number of nonzeros of $x_i - x_j$. This leads to a sparse (but equivalent) matrix A .

Example for Input Matrix

Polyhedral Comb. Vision Affine Hull Facets Min 1-Norm Final Slide
○○○ ○○ ○○● ○○○ ○○○ ○



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Let $P \subseteq \mathbb{R}^n$ be a polyhedron with \mathbb{O}_n in its relative interior. Then the set

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Since the polar dual has a lineality space if P is not full-dimensional, let

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Proposition (see SCHRIJVER '86)

- ▶ $(P^*)^* = P$
- ▶ x is a point in (vertex of) P if and only if $\langle x, y \rangle \leq 1$ defines an inequality for (facet of) P^* .
- ▶ P^* is bounded if and only if P contains \mathbb{O} in its relative interior.

Suppose \circ is in the relative interior of P .

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We are given a point $\hat{x} \in R \setminus P$. Find a facet $\langle y, x \rangle \leq 1$ of P cutting off \hat{x} !

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Very related work: [Target Cuts](#) by BUCHHEIM, LIERS & OSWALD, '08

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- ▶ Readability of produced equations & facets!
- ▶ $\langle a, x \rangle \leq \beta$ with $a \in \mathbb{Z}^n$ and $\beta \in \mathbb{Z}$ where (a^\top, β) is a **primitive** vector.

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Find $\lambda, \mu \in \mathbb{Q}$ with $\lambda \neq 0$ and $\lambda u + \mu v \in \mathbb{Z}^n$ minimizing $|\lambda u + \mu v|_1$.

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Then the sign-pattern of $\lambda u + \mu v$ is constant over all multiplier pairs λ, μ with $\lambda > 0$ for which λ/μ is in any fixed interval $[q_{j-1}, q_j]$.

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Final Step: In such an interval the 1-norm is linear and integer programming in dimension 2 can be solved efficiently (see EISENBRAND & LAUE, '03).

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Heuristic:

- 1 Let $w := u$.
- 2 For all $i \in [n]$ with $v_i \neq 0$ do:
 - 1 Let $w^{(i)} := v_i \cdot u - u_i \cdot v$.
 - 2 Divide $w^{(i)}$ by the g.c.d. of its entries.
 - 3 If $|w^{(i)}|_1 < |w|_1$, replace w by $w^{(i)}$.
- 3 Return w .

Problems to be tackled by help of MIP-solvers:

- ▶ Compute all valid equations / the dimension d .
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To be done:

- ▶ Finish basic code :-)
- ▶ Improve convergence for cutting plane procedure.
- ▶ Carry out computational study.
- ▶ Find some nice facets for interesting polytopes.