

# From approximate factorizations to approximate lifts

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# Linear Lifts

A linear lift of a polytope  $P$  of size  $k$  is a description

$$P = \left\{ x \in \mathbb{R}^n \mid \exists y \text{ s.t. } a_0 + \sum a_i x_i + \sum b_j y_j \geq 0 \right\}$$

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where  $a_i$  and  $b_j$  are in  $\mathbb{R}^k$ .

Equivalently, it is a polytope  $Q$  with  $k$  facets such that  $L(Q) = P$  for some affine map  $L$ .

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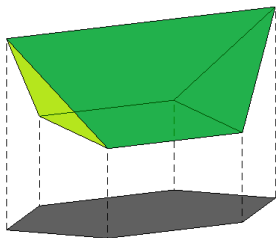
$$\begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ -1 \\ 0 \\ 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ -1 \end{bmatrix} y + \begin{bmatrix} 1 \\ 1 \\ 1 \\ -1 \\ -1 \end{bmatrix} z \geq 0$$

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Linear lift of size 5

# Slack Matrix

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Given a nonnegative matrix  $M \in \mathbb{R}_+^{n \times m}$  a  **$k$ -nonnegative factorization**, is a pair of matrices  $A \in \mathbb{R}_+^{k \times n}$  and  $B \in \mathbb{R}_+^{k \times m}$  such that

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The slack matrix of an hexagon has nonnegative rank 5

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More precisely, let  $P = \{x : H^t x \leq \mathbb{1}\}$  and  $S_P = A^t \cdot B$  be a  $k$ -nonnegative factorization.

$$P = \left\{ x \in \mathbb{R}^n : \exists y \in \mathbb{R}_+^k \text{ s.t. } H^t x + A^t y = \mathbb{1} \right\}$$

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This formulation is very overdetermined, any perturbation of  $A$  makes it unfeasible. We need a more robust version.

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These are robust formulations, but too big.

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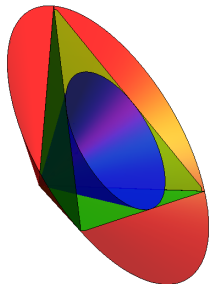
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Then  $\mathcal{O}_{in}^n \subseteq \mathbb{R}_+^n \subseteq \mathcal{O}_{out}^n$ , and furthermore,  $(\mathcal{O}_{in}^n)^* = (\mathcal{O}_{out}^n)$ .

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$$P = \text{Out}_P(B) = \left\{ Vz : z \in \mathcal{O}_{out}^v, \quad \mathbb{1}^t z \leq 1, \quad Bz \in \mathbb{R}_+^k \right\}$$

Both  $\text{Inn}_P(A)$  and  $\text{Out}_P(B)$  are actually  $\mathbb{R}_+^k \times \text{SOC}_{k+n+1}$  lifts, so we gain robustness and don't lose effectiveness.

# Containment

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For any  $A$  and  $B$  nonnegative

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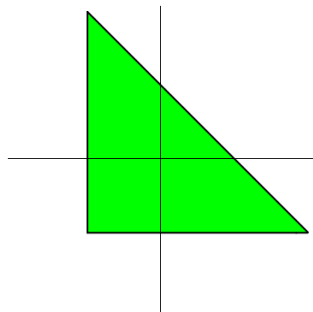
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## Polar Property

$$(\text{Inn}_P(A))^\circ = \text{Out}_{P^\circ}(A) \text{ and } (\text{Out}_P(B))^\circ = \text{Inn}_{P^\circ}(B).$$

## Example

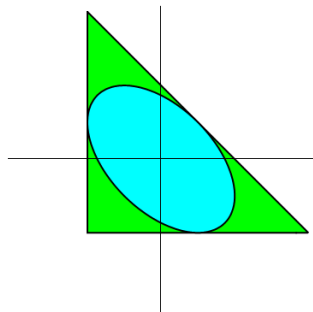
$$\text{Let } P = \left\{ (x, y) : \begin{bmatrix} -1 & 0 & 1 \\ 0 & -1 & 1 \end{bmatrix}^t \begin{bmatrix} x \\ y \end{bmatrix} \leq \mathbb{1} \right\}$$



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$$\text{Inn}_P(\mathbf{0}) = \left\{ (x, y) : 3(x + y)^2 + (x - y)^2 \leq 3 \right\}$$

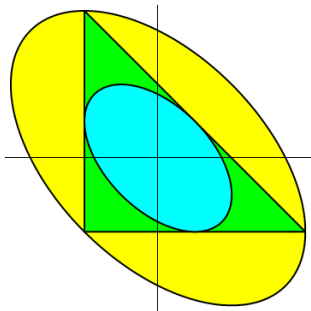


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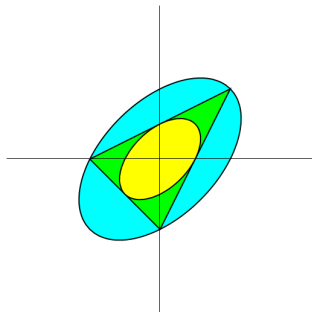
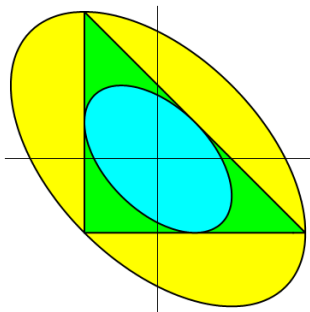


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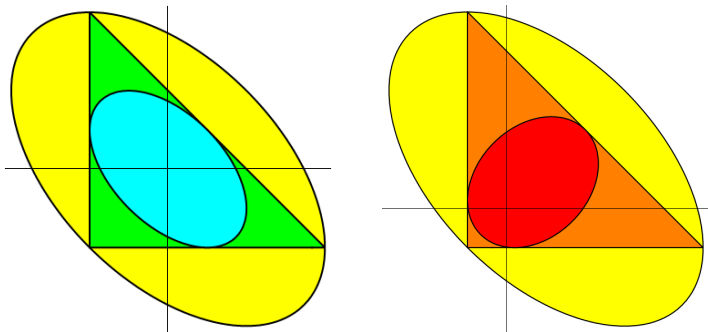
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# Translation (In)variance

Note that the inner approximations depend on the choice of the center, while the outer is invariant.



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Good factorizations give good approximations.

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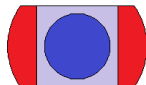


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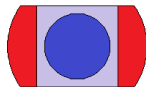


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$$S_P = \begin{bmatrix} 2 & 2 & 0 & 0 \\ 0 & 2 & 2 & 0 \\ 0 & 0 & 2 & 2 \\ 2 & 0 & 0 & 2 \end{bmatrix} \quad \tilde{S} = A^t \cdot B = \begin{bmatrix} 4/3 & 4/3 & 4/3 & 0 \\ 4/3 & 4/3 & 4/3 & 0 \\ 4/3 & 0 & 4/3 & 4/3 \\ 4/3 & 0 & 4/3 & 4/3 \end{bmatrix}$$

$$\varepsilon_1 = 2/3\sqrt{10}; \quad \varepsilon_2 = 2/3\sqrt{6}$$

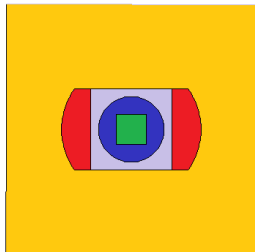


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- ▶ **More on the session tomorrow afternoon: WED.C.11**

THE END

THANK YOU