Extended Formulations for Quadratic Mixed Integer Programming

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IP for Lunch,
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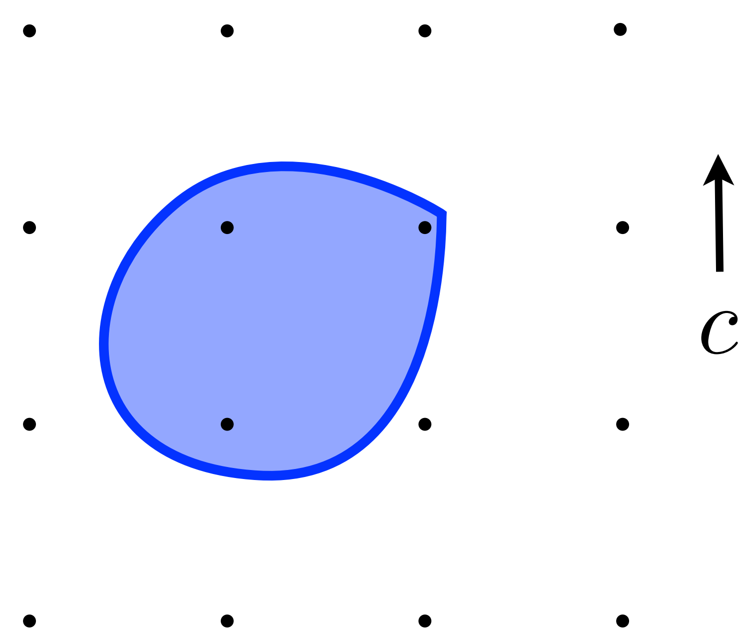
Nonlinear MIP B&B Algorithms

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

$$s.t.$$

$$g_i(x) \leq 0,\ i \in I, \quad x \in \mathbb{Z}^n$$

$$x \in \mathbb{Z}^{n_1} \times \mathbb{R}^{n_2}$$



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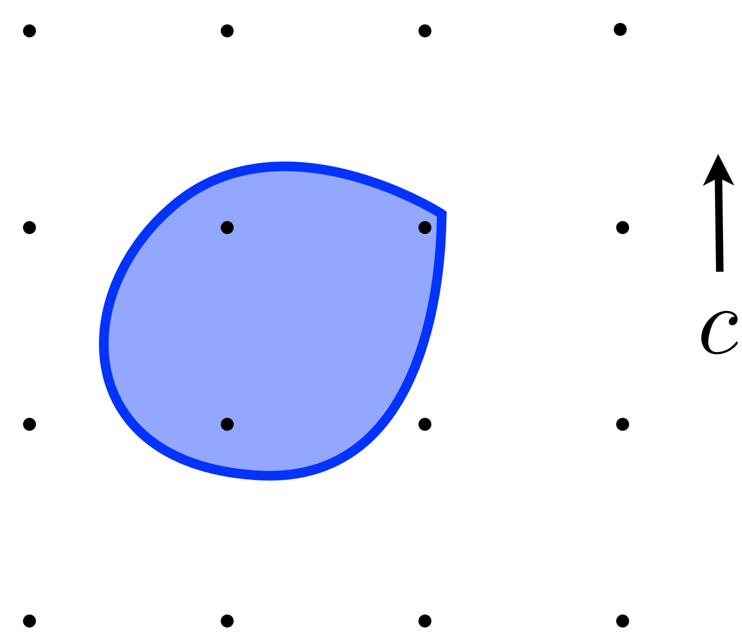

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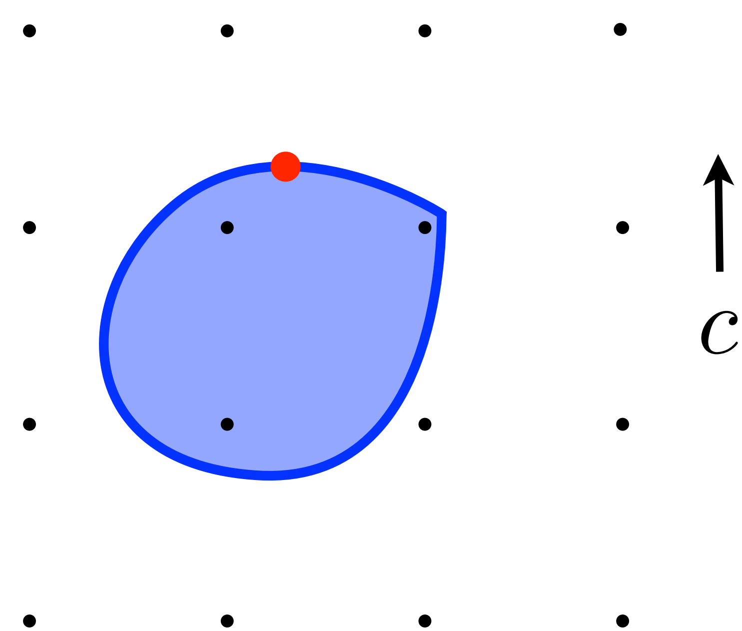

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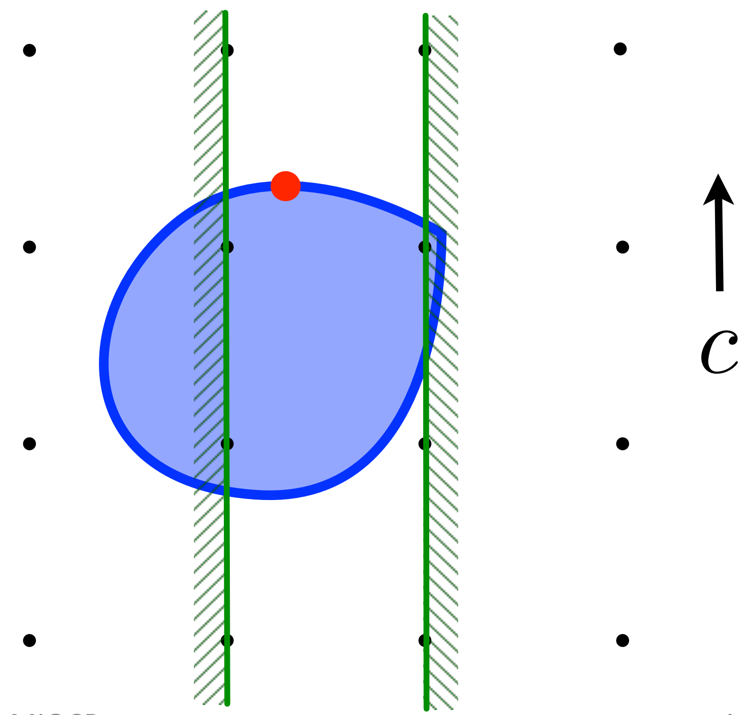

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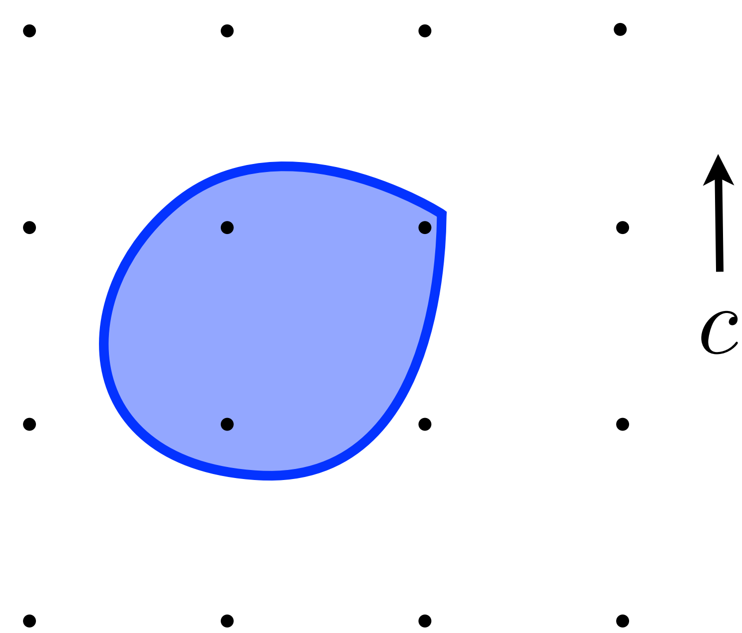

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- NLP (QCP) Based B&B
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  - Few cuts = high speed.
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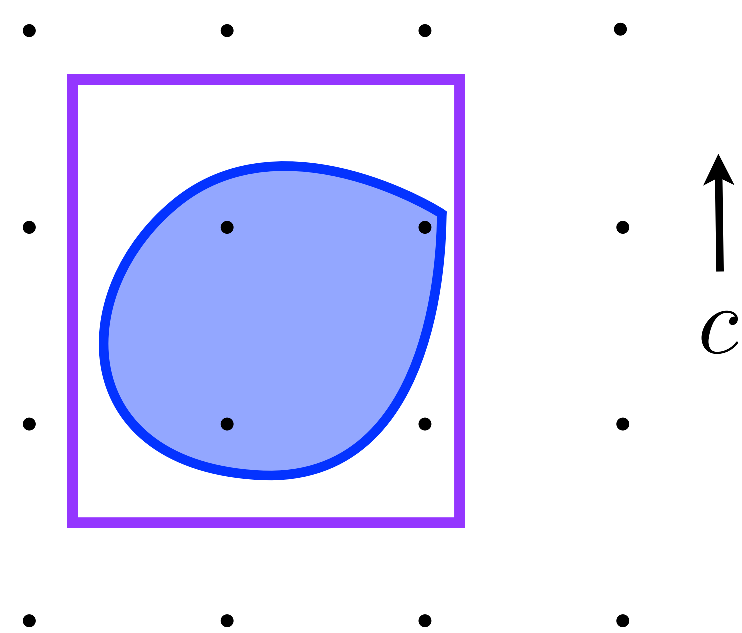

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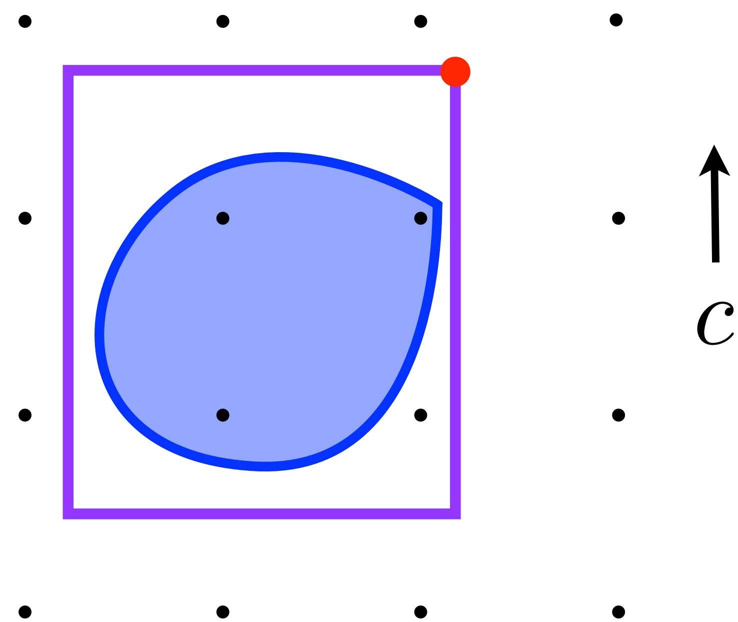

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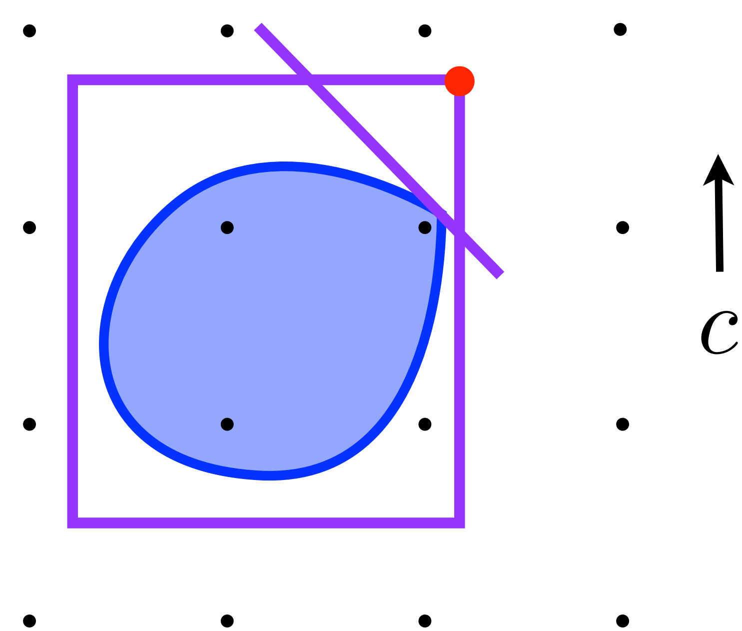

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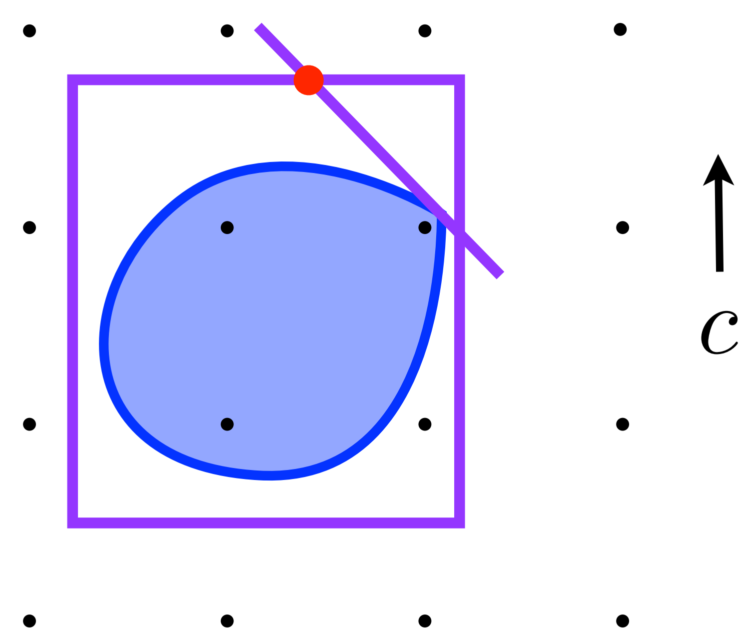

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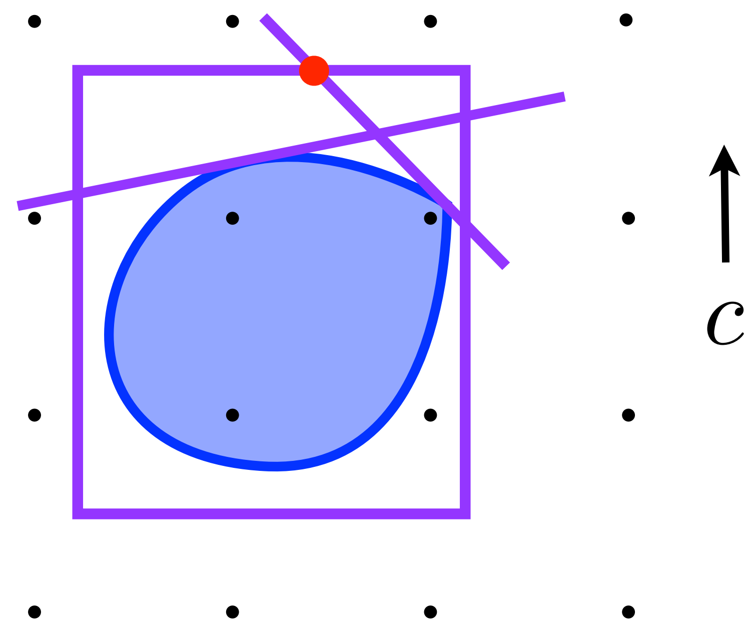

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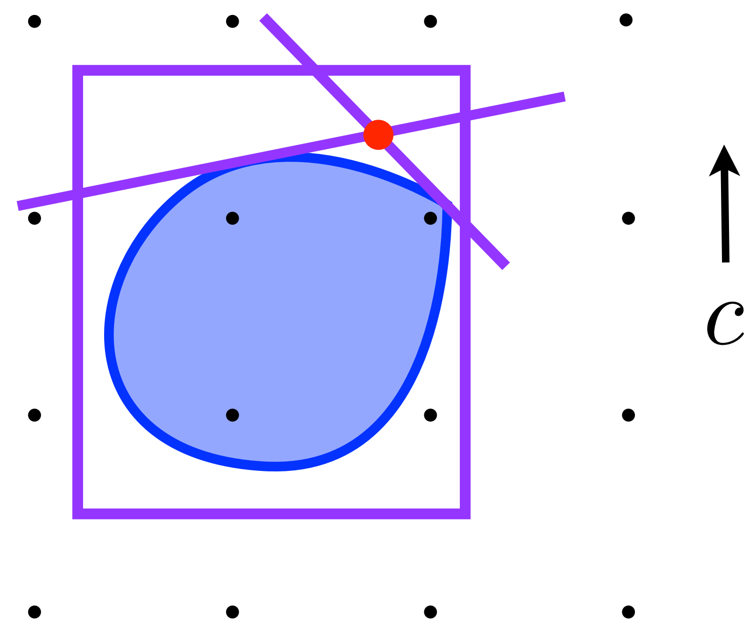

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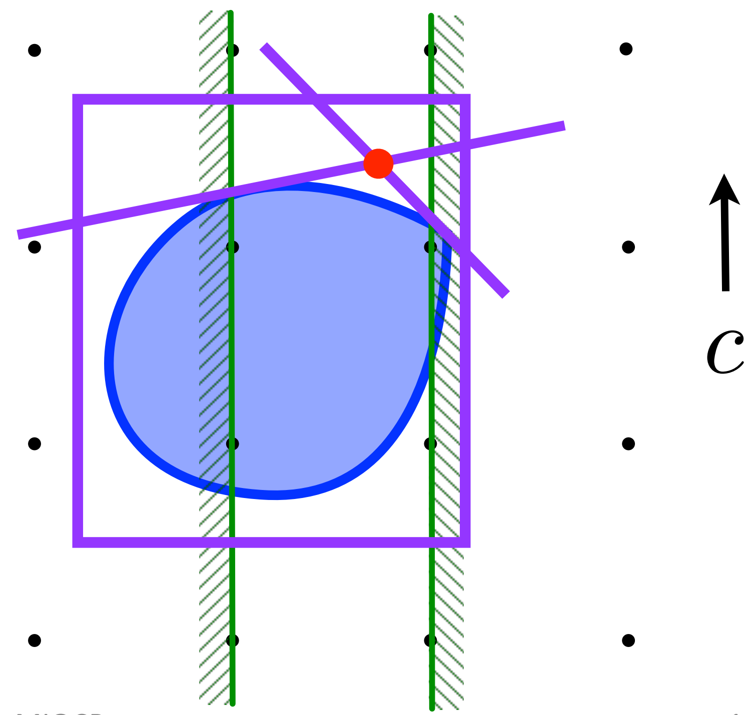

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- NLP (QCP) Based B&B
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- Lifted LP B&B
  - Extended or Lifted relaxation.
  - Static relaxation
    - Mimic NLP B&B.
  - Dynamic relaxation
    - Standard LP B&B

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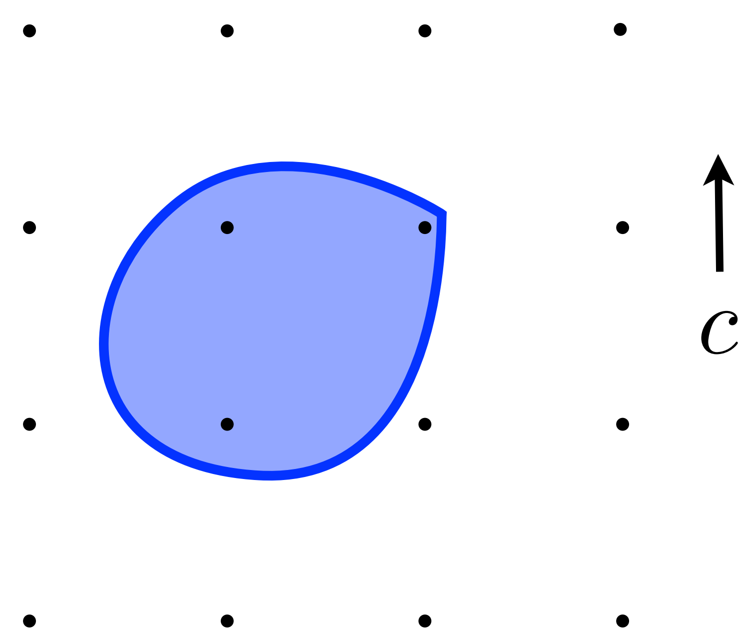

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$$s.t. \quad Ax + Dz \leq b,$$

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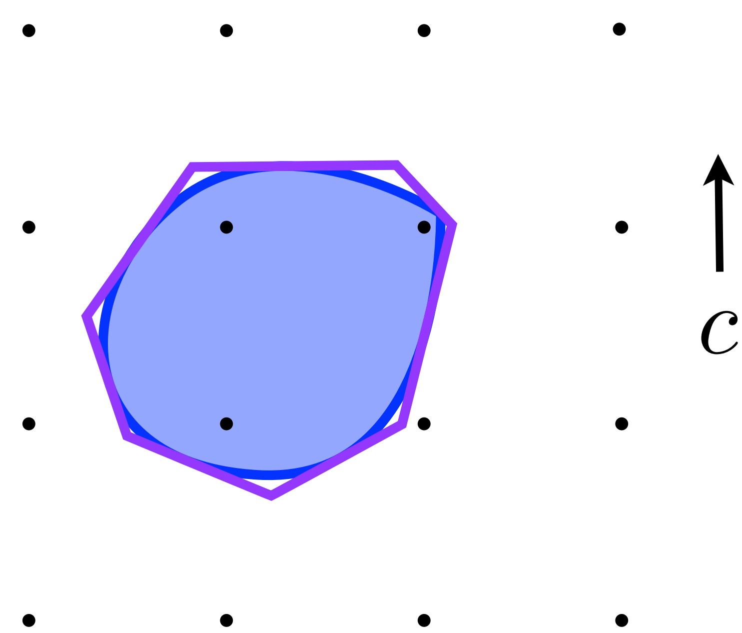
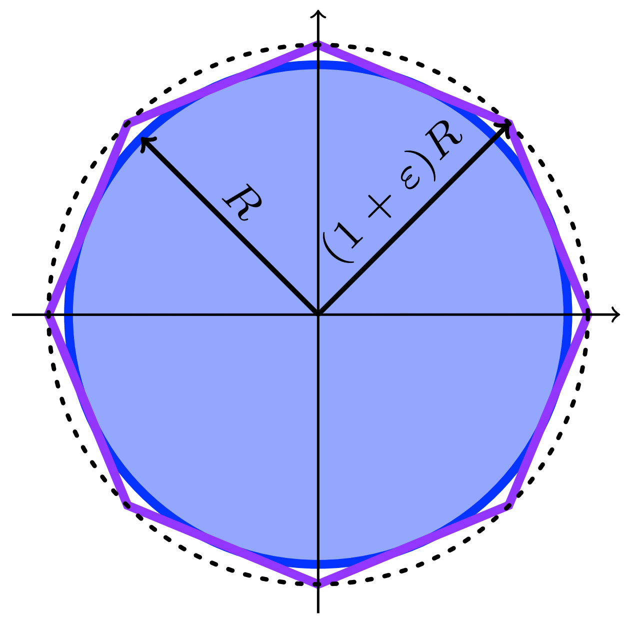


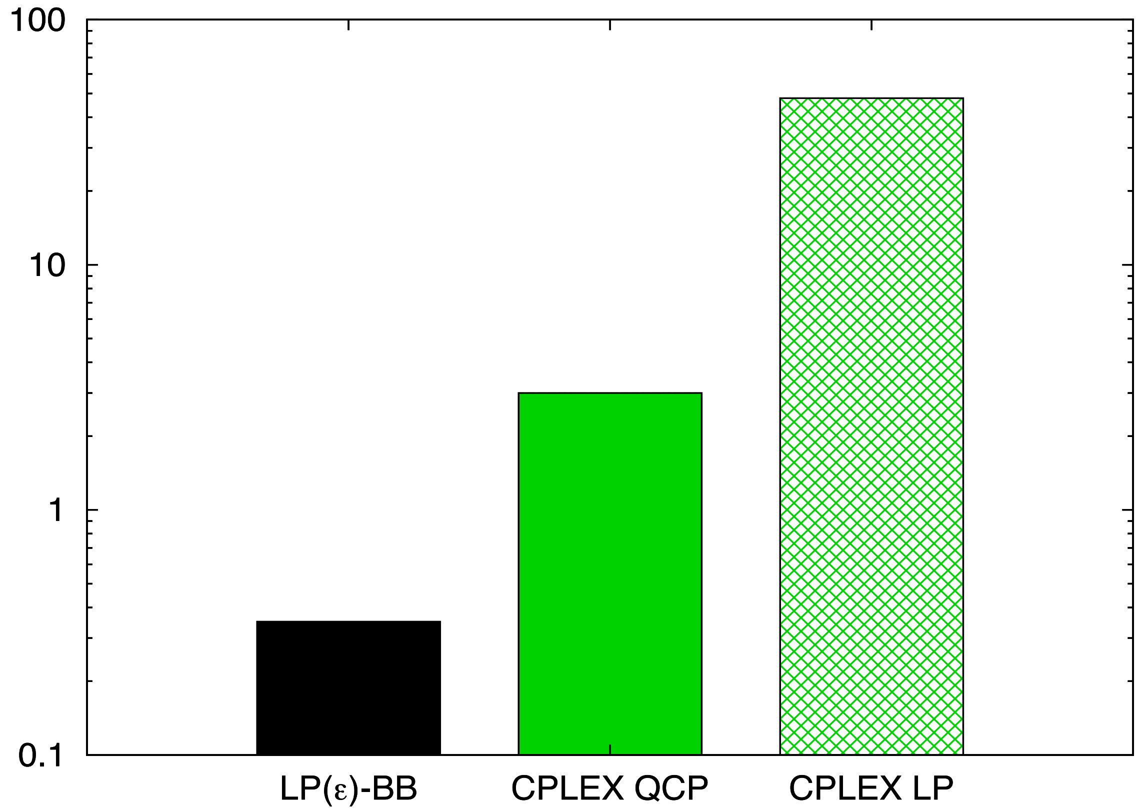
Static Lifted LP for Conic Quadratic MIP

- Approximation of Second Order Cone of dimension n by Ben-Tal and Nemirovski (Glineur).
- $O(n \log(1/\varepsilon))$ variables and constraints for quality ε.
  - Exponential increment in # of constraints through projection.
- Problem:
  - Fixed a-priori quality: no dynamic improvement (e.g. $\varepsilon = 0.01$ best for some portfolio optimization problems)



Correct Quality = Significant Improvement

- Results from V., Ahmed and Nemhauser '08.



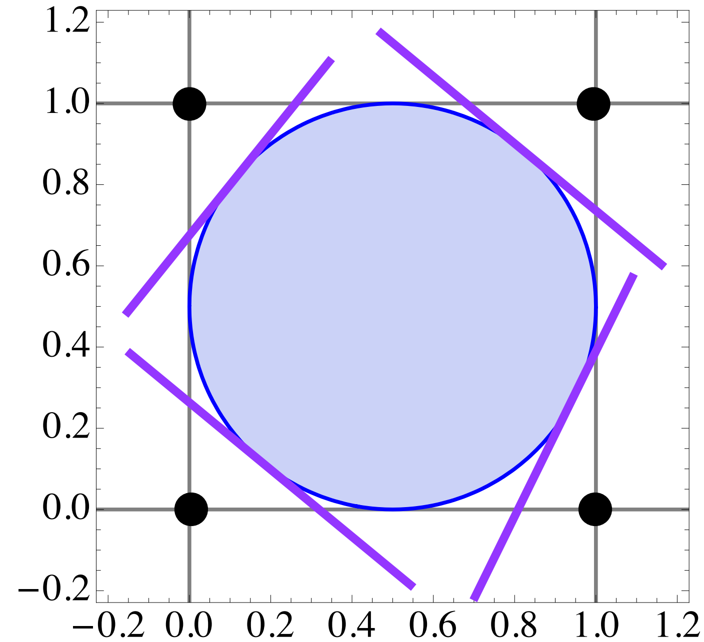
Average Solve Times [s]

Dynamic Lifted LP for Separable Problems

- Motivating example from Hijazi et al. '14

$$F^n := \left\{ x \in \mathbb{R}^n \; : \; \sum_{i=1}^{n} \left(x_i - \frac{1}{2} \right)^2 \leq \frac{n-1}{4} \right\}$$

Showing $F^n \cap \mathbb{Z}^n = \emptyset$ requires 2^n cuts.



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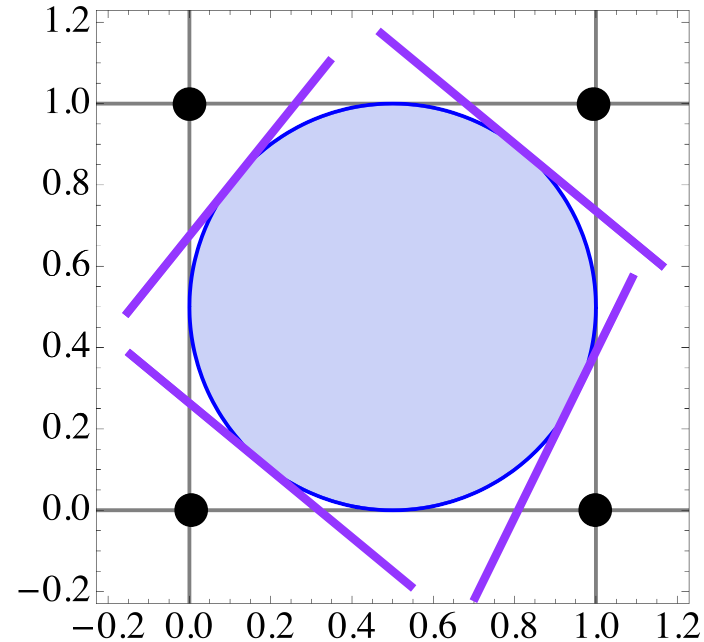
Extended formulation of F^n:

$$\left(x_i - \frac{1}{2} \right)^2 \leq z_i \qquad \forall i \in [n]$$

$$\sum_{i=1}^{n} z_i \leq \frac{n-1}{4}$$



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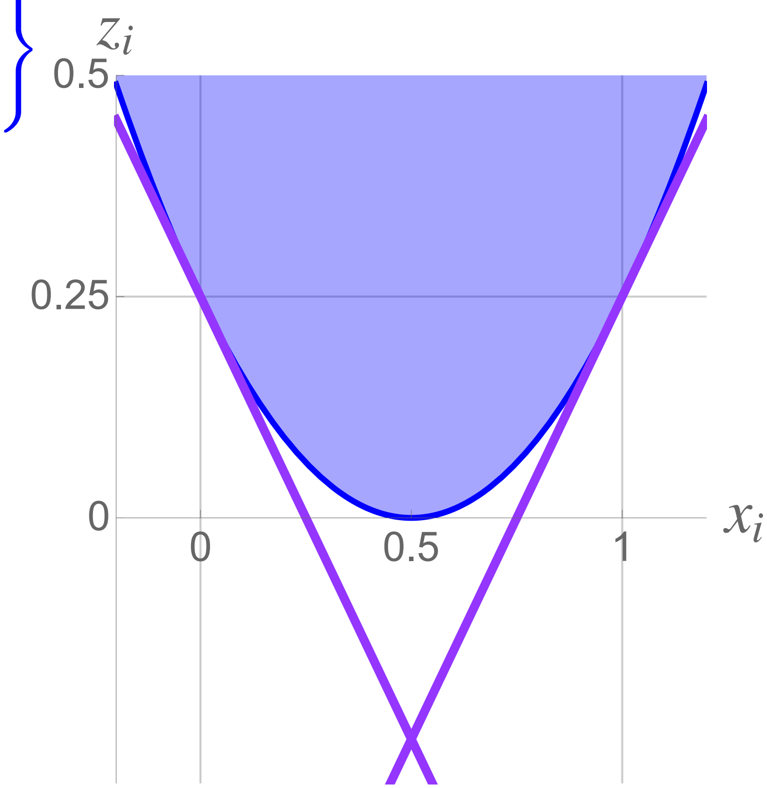

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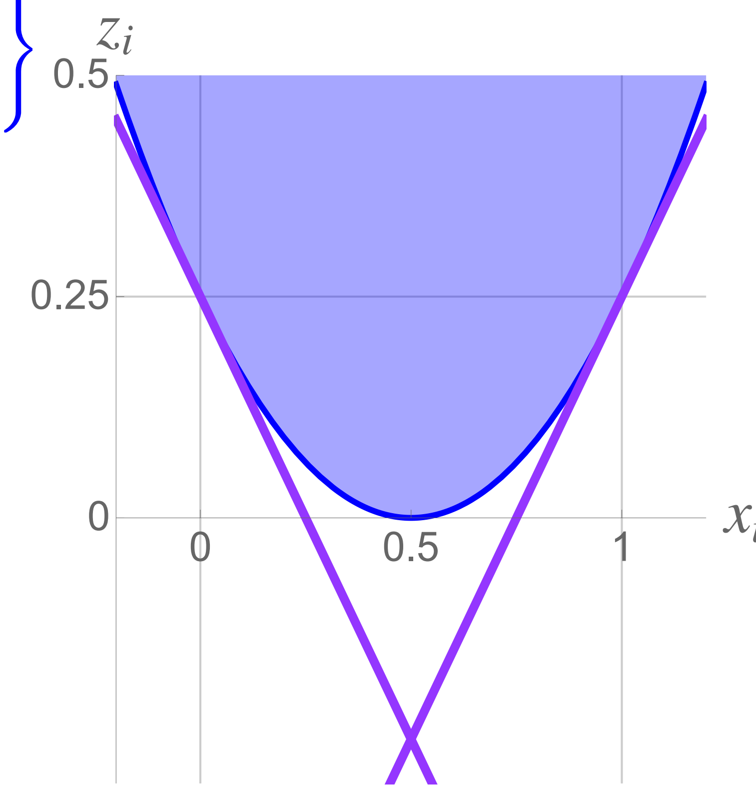

$B^n \cap \mathbb{Z}^n = \emptyset$ with only $2n$ cuts on extended formulation.

Significant Improvement For Many Problems

- Tawarmalani and Sahinidis '05:

$$f_j : \mathbb{R} \to \mathbb{R} \text{ convex differentiable}$$

Lifted Relaxation of $F := \left\{ (y_0, y) \in \mathbb{R}^{n+1} \ : \ \sum_{j=1}^n f_j(y_j) \leq y_0 \right\}$:

$$f_j(\gamma) + f_j'(\gamma)(y_j - \gamma) \leq w_j \quad \forall \gamma \in \Gamma_j, \quad j \in [n]$$
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- Polynomial (degree n) increment in # of constraints through projection

Separable Approach for Conic Quadratic?

- "Separable Sets" include many quadratics:
  - Euclidean Ball

$$B^n := \left\{ y \in \mathbb{R}^n \ : \ \sum_{j=1}^n y_j^2 \leq 1 \right\}$$

  - Paraboloids

$$Q^n := \left\{ (y_0, y) \in \mathbb{R}^{n+1} \ : \ \sum_{j=1}^n y_j^2 \leq y_0 \right\}$$

- Does not include Lorentz/SOCP cone:

$$L^n := \left\{ (y_0, y) \in \mathbb{R}^{n+1} \ : \ \sqrt{\sum_{j=1}^n y_j^2} \leq y_0 \right\}$$

Separable to Conic: Homogenize

- From Euclid to Lorentz

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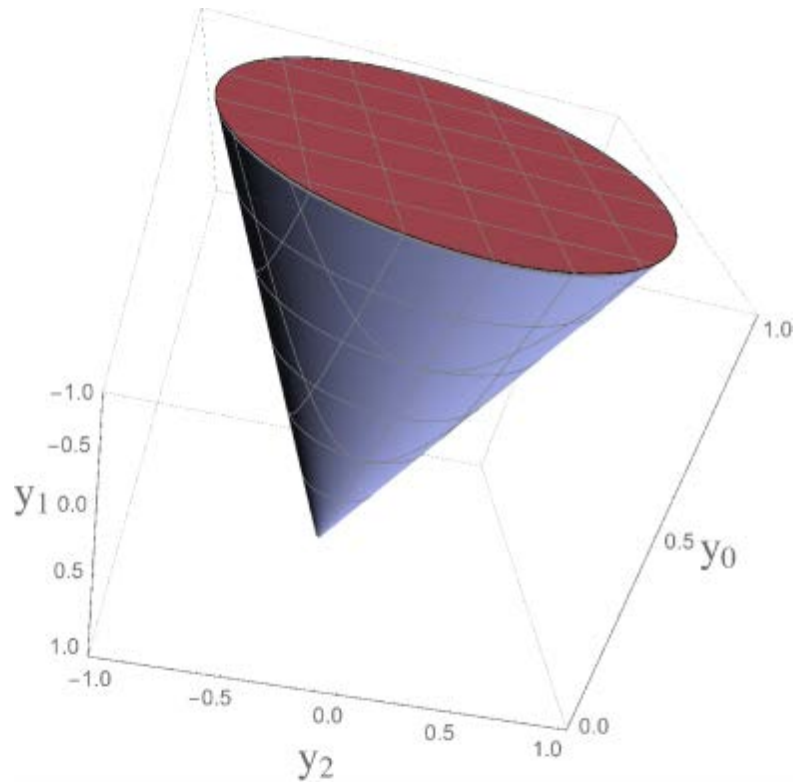

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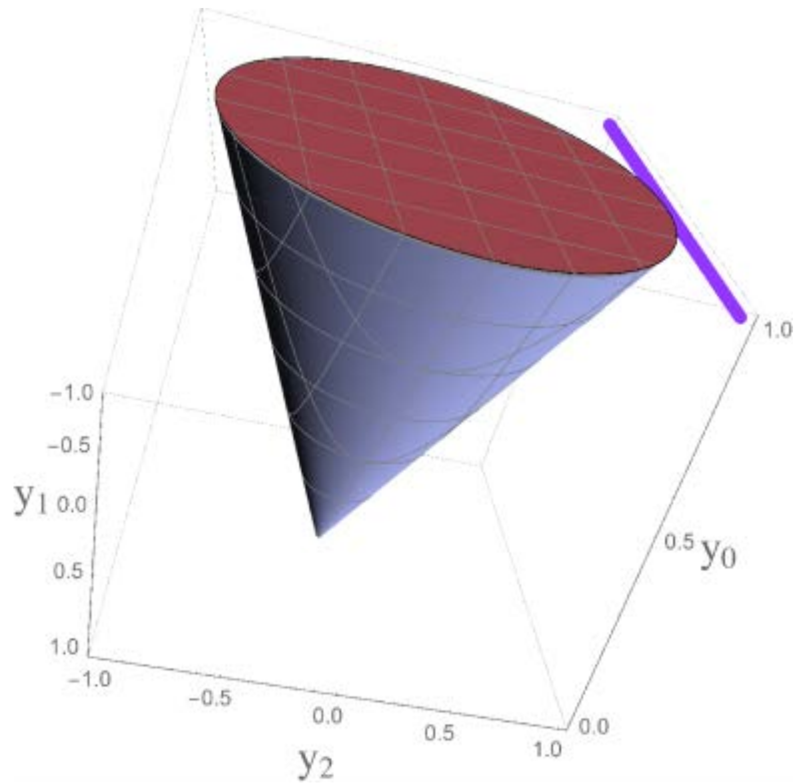
$$B^n \subseteq P$$



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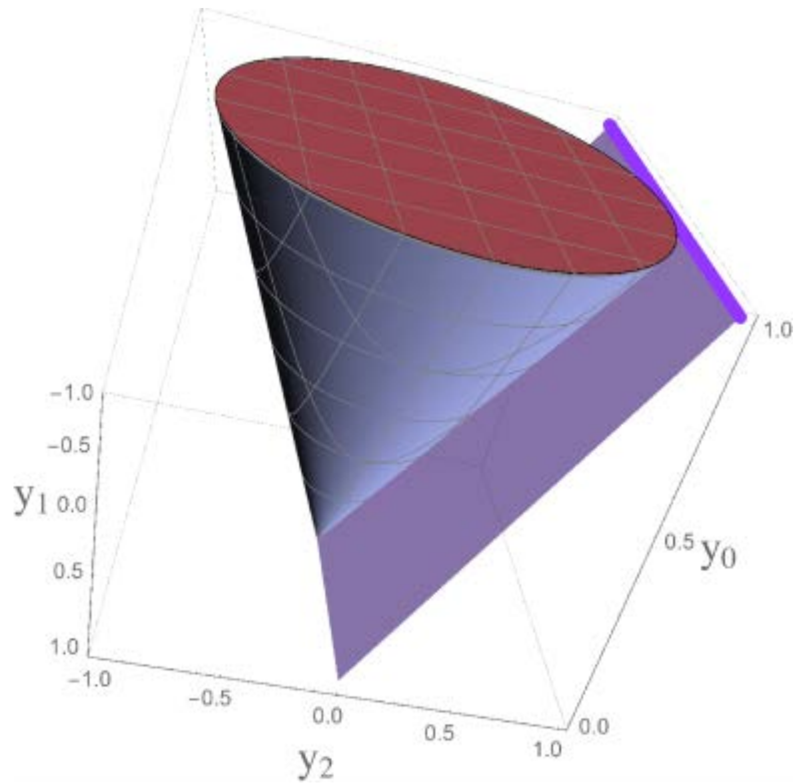

$$B^n \subseteq P \Rightarrow L^n \subseteq \operatorname{cone}\left(\{1\} \times P\right)$$

Lifted Relaxation for Separable Conic Sets

$f_j : \mathbb{R} \to \mathbb{R}$ convex, differentiable and 1-coercive

$$C := \left\{ y \in \mathbb{R}^n \; : \; \sum_{j=1}^{n} f_j(y_j) \leq 1 \right\}$$

Lifted Relaxation of $\operatorname{cone}\left(\{1\} \times C\right)$:

$$\left(f\left(\gamma\right) - \gamma f'\left(\gamma\right)\right) y_0 + f'\left(\gamma\right) y \leq w_j \quad \forall \gamma \in \Gamma_j,\; j \in [n]$$

$$\sum_{j=1}^{n} w_j \leq y_0$$

$$0 \leq y_0$$

Lifted Reformulation for Conic Quadratic Sets

- Lifted Reformulation of $L^n := \left\{(y_0, y) \in \mathbb{R}^{n+1} \ : \ \|y\|_2 \leq y_0\right\}$:

$$y_i^2 \leq z_i \cdot y_0 \qquad \forall i \in [n]$$

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Rotated SOCP cone

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Rotated SOCP cone

- Lifted polyhedral relaxation automatic from standard polyhedral approximation of (rotated) SOCP cone:
  – Dynamic Lifted LP-based algorithm:
    1. Replace every SOCP cone with lifted reformulation
    2. Solve with standard LP-based algorithm

Computational Experiments 1: Solvers

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  - **CPLEXCP** : MIQCPSTRAT = 1
  - **GurobiCP** : MIQCPMethod = 0

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- Dynamic Lifted LP-based Branch-and-Bound:
  - **CPLEXSepLP** : CPLEXLP on lifted reformulation
  - **GurobiSepLP**: GurobiLP on lifted reformulation

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- CPLEX v 12.6 and Gurobi v 5.6.3
- Time limit of 3,600 s on i7-3770 3.40GHz

Computational Experiments 1: Instances

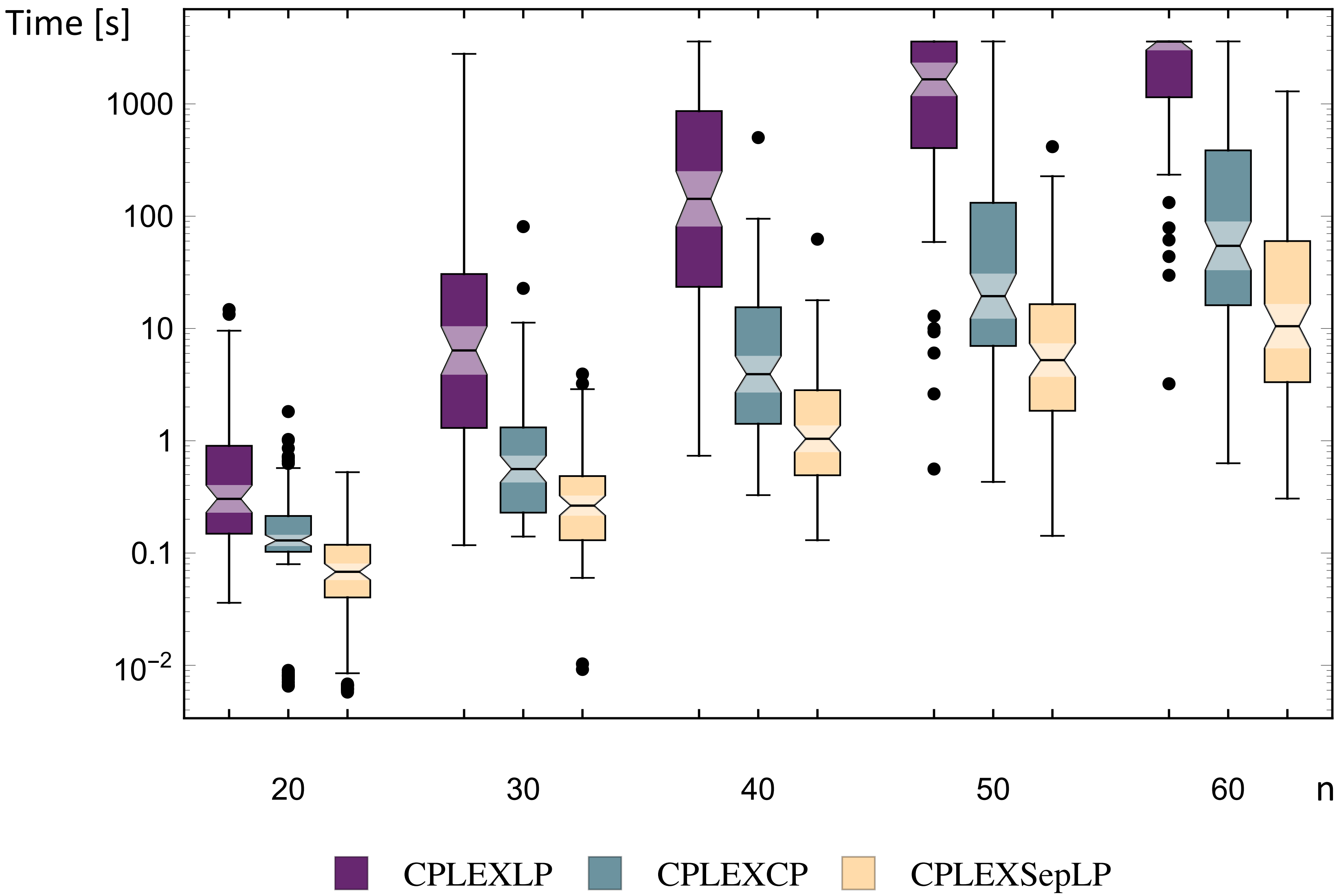
- Portfolio optimization problems:

Classical:

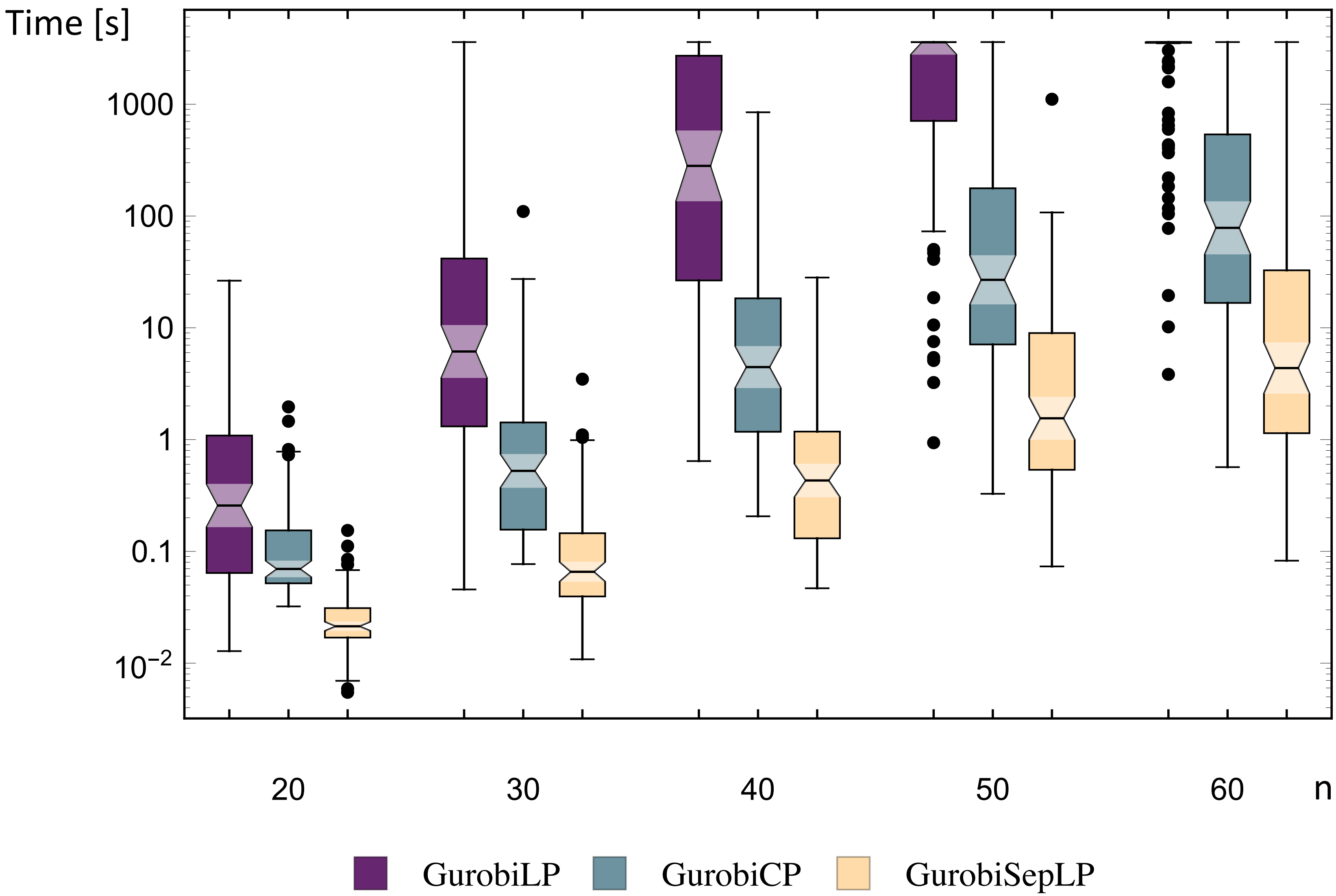
$$
\begin{aligned}
\max \quad & \bar{a}x \\
s.t. \quad & \\
& \left\| Q^{1/2} x \right\|_2 \leq \sigma \\
& \sum_{j=1}^{n} x_j = 1, \quad x \in \mathbb{R}^n_+ \\
& x_j \leq z_j \quad \forall j \in [n] \\
& \sum_{j=1}^{n} z_j \leq K, \quad z \in \{0,1\}^n
\end{aligned}
$$

- $\bar{a}$ expected returns.
- $Q^{1/2}$ square root of covariance matrix.
- K maximum number of assets.
- σ maximum risk.

Results for CPLEX: 100 instances per n



Results for Gurobi: 100 instances per n



Computational Experiments 2: More Solvers

- Static Lifted LP-based Branch-and-Bound:
  - **LiftedLP**: from V., Ahmed and Nemhauser '08
  - Fixed approximation by Ben-Tal and Nemirovski (Glineur)
  - No refinement: integer nodes = solve NLP and process
  - Heuristic: Correct integral solutions (fix integers, solve NLP)
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- ~ 400 lines of JuMP code in about a week

JuMP : Julia for Mathematical Programming

- Developed by ORC students: Iain Dunning, Joey Huchette and Miles Lubin.
- "As easy as AMPL and faster than C++" (JPV 2014).
- Linear/Quadratic MIP and general nonlinear
  - Cbc/Clp, CPLEX, ECOS, GLPK, Gurobi, Ipopt, KNITRO, MOSEK, and Nlopt.
- Automatic differentiation, solver independent MIP callbacks, etc.
- https://github.com/JuliaOpt/JuMP.jl

Computational Experiments 2 : More Instances

- Portfolio optimization problems:

Classical:

$$
\begin{aligned}
\max \quad & \bar{a}x \\
s.t. \quad & \\
& \left\| Q^{1/2} x \right\|_2 \leq \sigma \\
& \sum_{j=1}^{n} x_j = 1, \quad x \in \mathbb{R}^n_+ \\
& x_j \leq z_j \quad \forall j \in [n] \\
& \sum_{j=1}^{n} z_j \leq K, \quad z \in \{0,1\}^n
\end{aligned}
$$

- $\bar{a}$ expected returns.
- $Q^{1/2}$ square root of covariance matrix.
- K maximum number of assets.
- σ maximum risk.

Computational Experiments 2 : More Instances

- Portfolio optimization problems:

Shortfall:

$$
\begin{aligned}
\max \quad & \bar{a}x \\
s.t. \quad & \\
& \Phi^{-1}(\eta_i)\left\|Q^{1/2}y\right\|_2 \le \bar{a}y - W_i^{low} \qquad i \in \{1,2\} \\
& \sum_{j=1}^{n} x_j = 1, \quad x \in \mathbb{R}_+^n \\
& x_j \le z_j \quad \forall j \in [n] \\
& \sum_{j=1}^{n} z_j \le K, \quad z \in \{0,1\}^n
\end{aligned}
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- $\bar{a}$ expected returns.
- $Q^{1/2}$ square root of covariance matrix.
- K maximum number of assets.
- $\approx \mathbb{P}\left(\bar{a}x \ge W_i^{low}\right) \ge \eta_i$

Computational Experiments 2 : More Instances

- Portfolio optimization problems:

Robust:

$$
\begin{aligned}
\max \quad & \bar{a}x - \alpha \left\| R^{1/2} y \right\|_2 \\
s.t. \quad & \\
& \left\| Q^{1/2} x \right\|_2 \leq \sigma \\
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- $\bar{a}$ expected returns.
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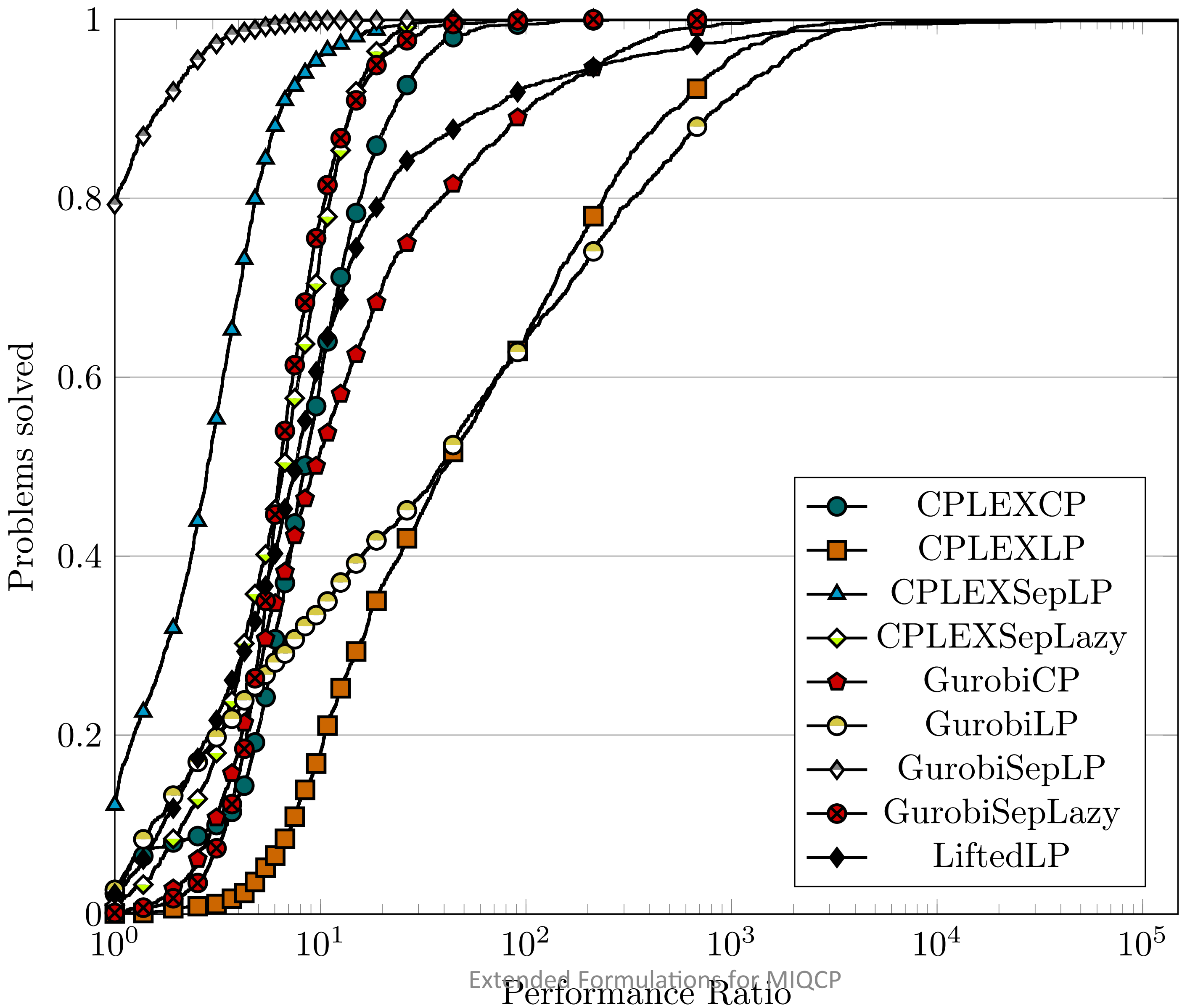
- Robust objective.

Performance Profile for n “=“ 20-60, 100 and 200



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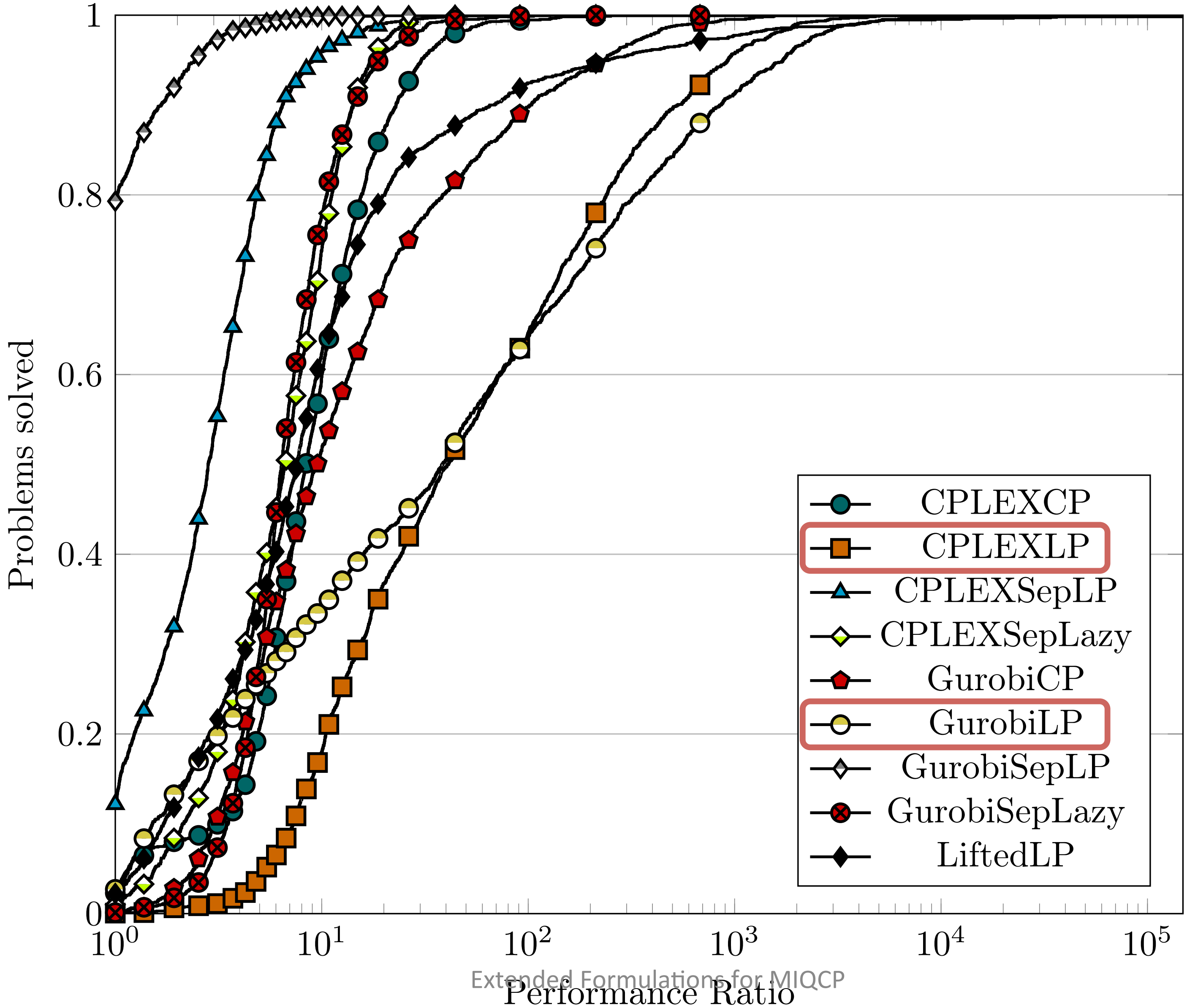

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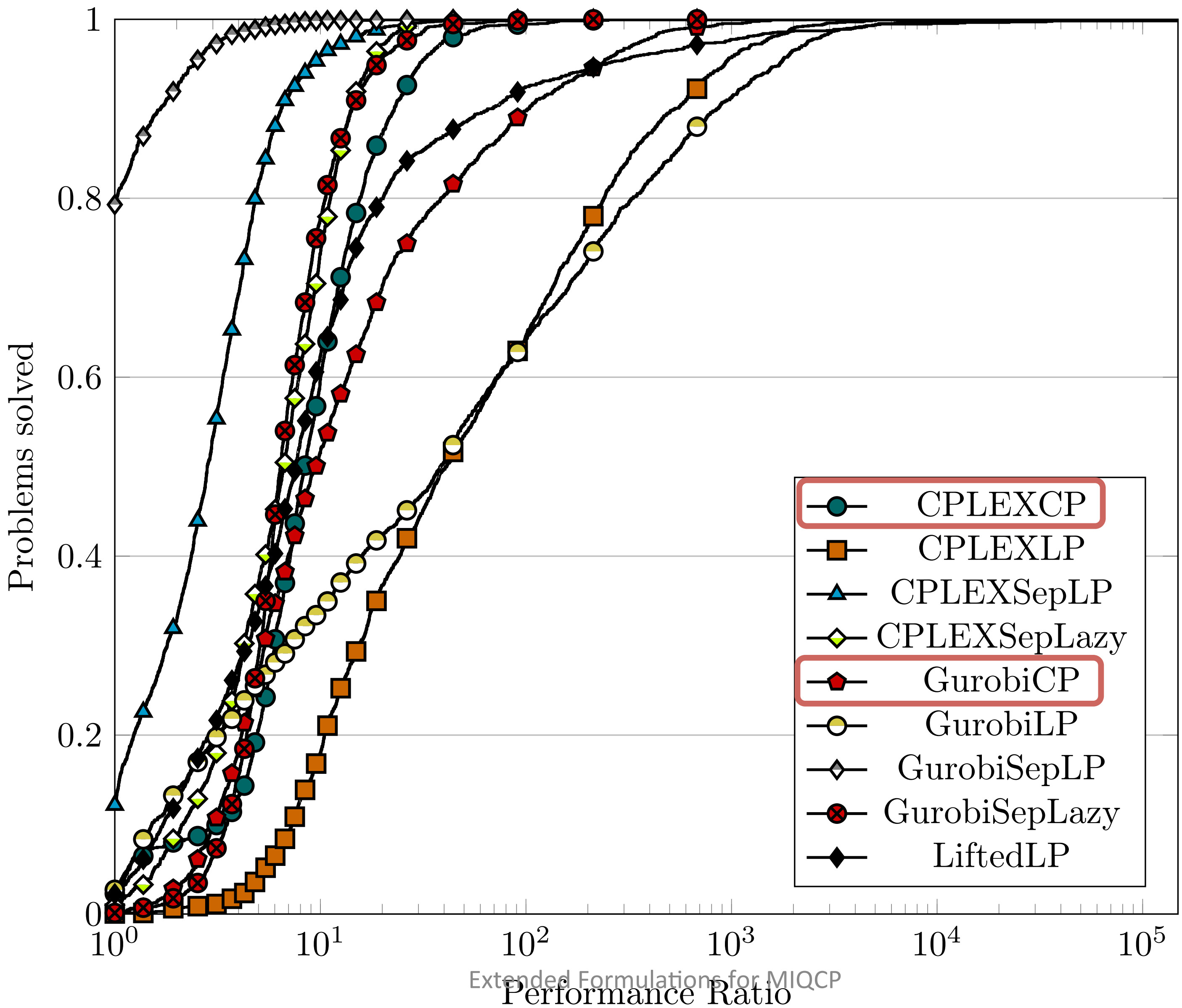

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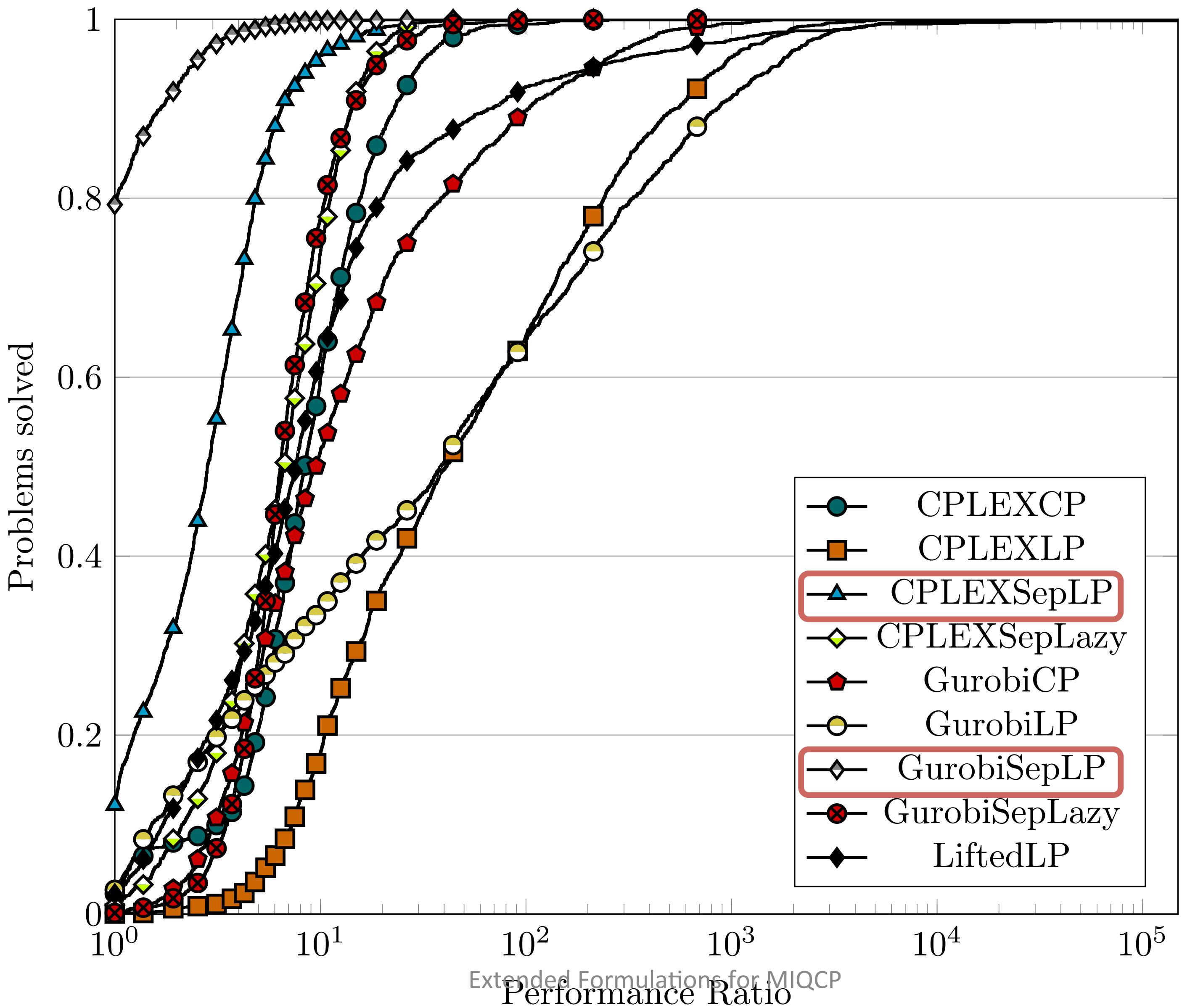

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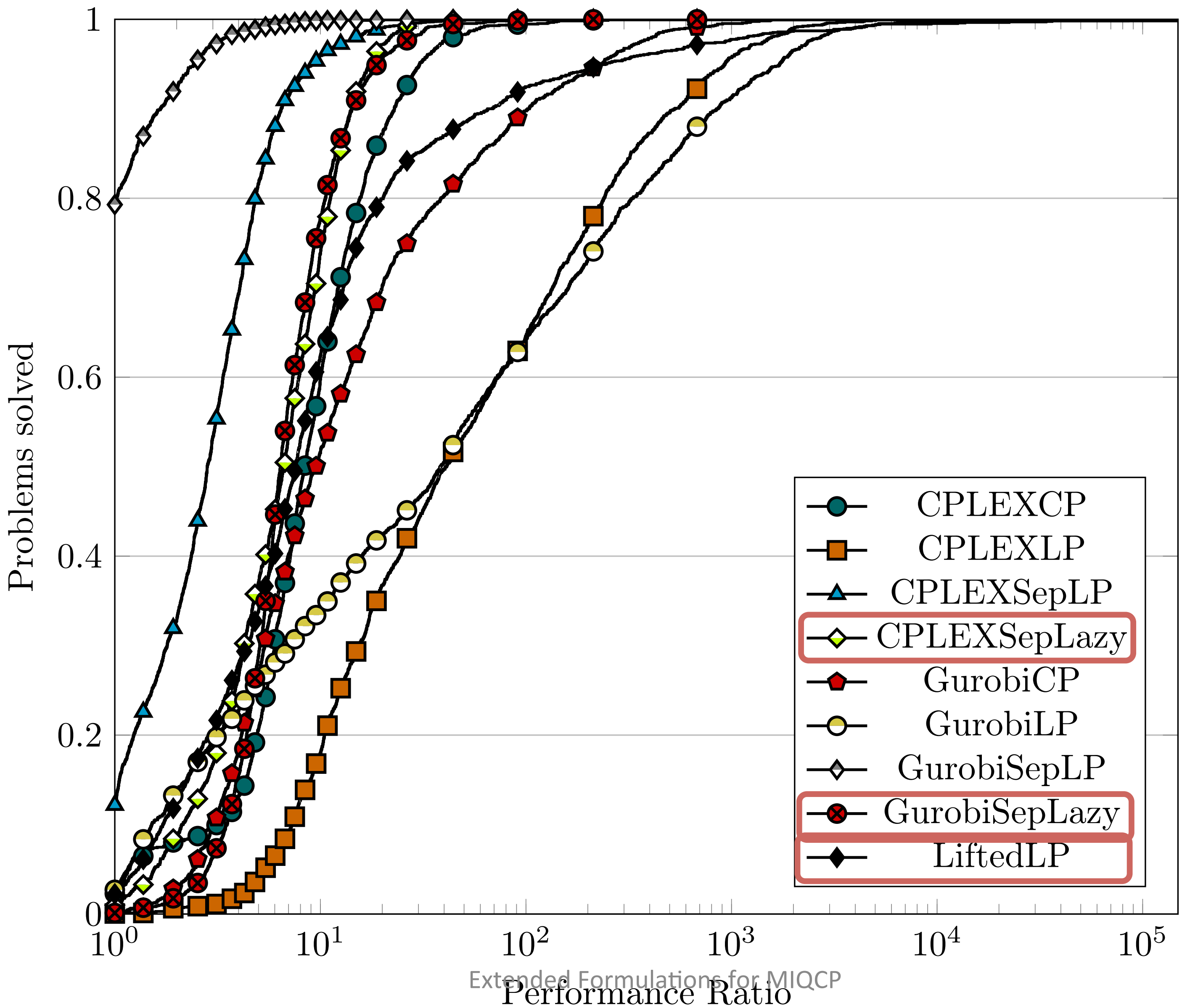

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Summary

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  - LP-based B&B: Both in theory and practice.
- Most ideas can be extended beyond quadratic
  - p-order cones almost directly
  - General nonlinear through perspective functions
- You should definitely try:

JuMP