

A linear-time algorithm for the generalized TRS based on a convex quadratic reformulation

Alex L. Wang

Based on joint work with Fatma Kılınç-Karzan

① Introduction

② Convex hull result

③ Convex quadratic reformulation of the GTRS and algorithms

The Generalized Trust Region Subproblem (GTRS)

$$\text{Opt} := \inf_{x \in \mathbb{R}^n} \{q_0(x) \mid q_1(x) \leq 0\}$$

- q_0 and q_1 are nonconvex quadratic functions

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- q_0 and q_1 are nonconvex quadratic functions
- Applications: nonconvex quadratic integer programs, signal processing, compressed sensing, robust optimization, trust-region methods

Motivation

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 - S-lemma \implies the semidefinite-programming relaxation is tight \implies polynomial-time algorithm
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 - Special instance of QCQP

Results/Outline

Under “mild assumptions”

- Convex hull result \implies convex quadratic reformulation

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- Convex hull result \implies convex quadratic reformulation
- New linear-time algorithm for approximating the GTRS

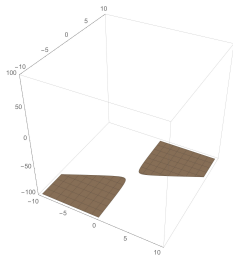
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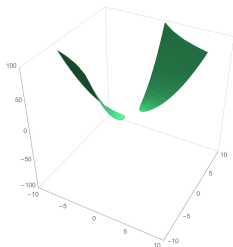
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$$\inf_{x \in \mathbb{R}^n} \{q_0(x) \mid q_1(x) \leq 0\}$$



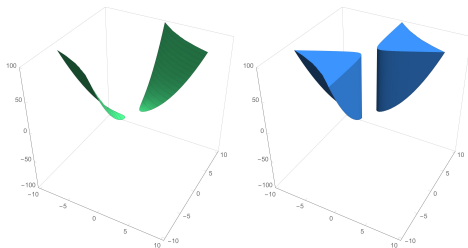
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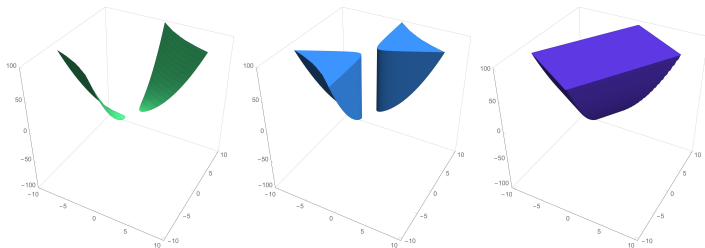
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- Main object of analysis

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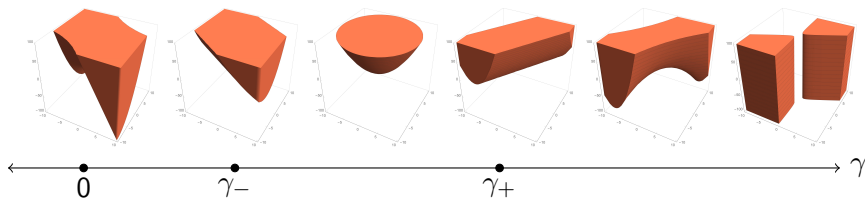
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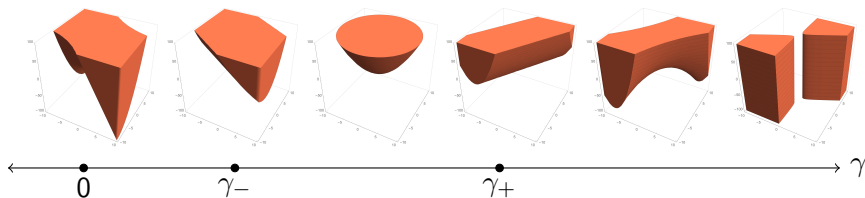
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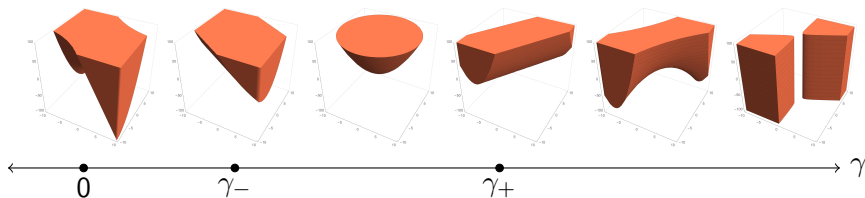
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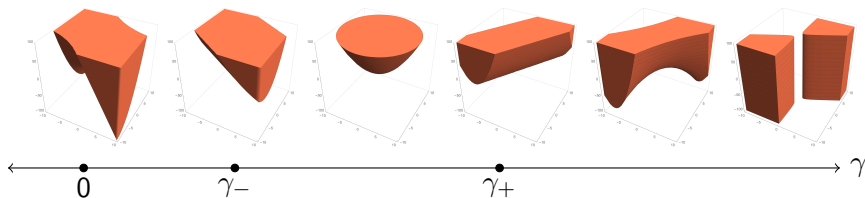
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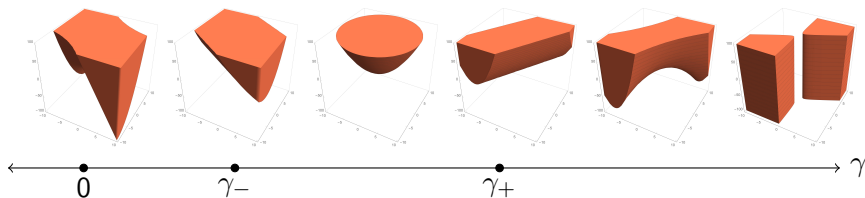
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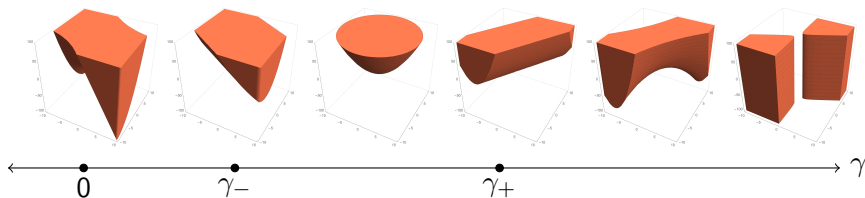
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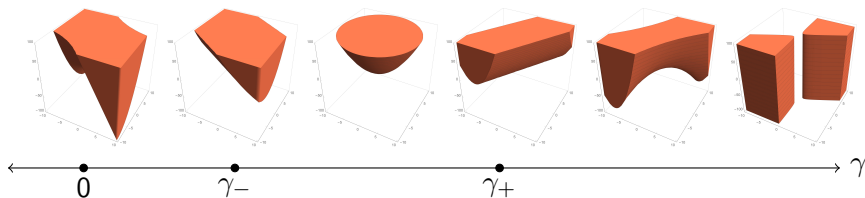
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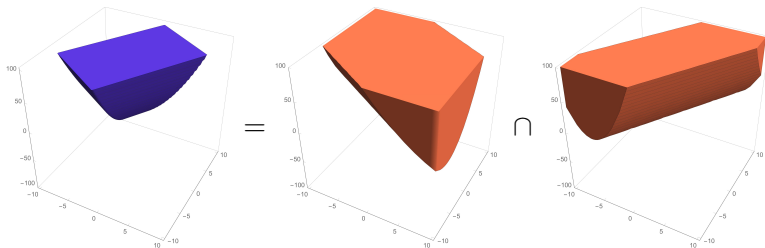
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 - $\overline{\text{conv}}(\mathcal{S}) = \mathcal{S}(\gamma_-) \cap \mathcal{S}(\gamma_+)$

Convex hull result

Theorem

Suppose q_0 and q_1 are both nonconvex and Γ is nonempty. Then Γ can be written $\Gamma = [\gamma_-, \gamma_+]$ and

$$\overline{\text{conv}}(\mathcal{S}) = \mathcal{S}(\gamma_-) \cap \mathcal{S}(\gamma_+) = \left\{ (x, t) \mid \begin{array}{l} q(\gamma_-, x) \leq t \\ q(\gamma_+, x) \leq t \end{array} \right\}$$



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Theorem (“informally”)

There exists an algorithm, ALG, such that if q_0 and q_1 satisfy some “mild assumptions,” then ALG outputs an ϵ -approximate optimizer to the GTRS with probability $\geq 1 - p$. ALG runs in time $\approx \tilde{O}\left(\frac{N}{\sqrt{\epsilon}}\right)$.

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- Gave an explicit description of $\overline{\text{conv}}(\mathcal{S})$
- Convex quadratic reformulation!
- Gave a linear (in N) time algorithm for solving the GTRS

Questions?