

GloptiPoly

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The problem

$$\begin{aligned} f^* &:= \inf f(x) \\ & \quad g_1(x) \geq 0 \\ & \quad \vdots \\ & \quad g_m(x) \geq 0 \end{aligned}$$

If the feasible set S is compact and nonempty: $\inf = \min$.

Set $g_0 := 1$ and $M := \left\{ \sum_{i=0}^m \sigma_i g_i : \sigma_i \in \sum \mathbb{R}[x]^2 \right\}$.

General assumption: $\exists N : N - \sum_{i=1}^n x_i^2 \in M$

Convexification I

Points \rightarrow prob. measures: $f^* = \inf \left\{ \int f d\mu : \mu \in \mathcal{M}^1(S) \right\}$

Theorem (Putinar '93). For any map $L : \mathbb{R}[x] \rightarrow \mathbb{R}$ the following are equivalent:

1. L is linear, $L(1) = 1$ and $L(M) \subset [0, \infty)$.
2. $\exists \mu \in \mathcal{M}^1(S) : \forall p \in \mathbb{R}[x] \quad L(p) = \int p d\mu$.

$\Rightarrow f^* = \inf \{ L(f) : L : \mathbb{R}[x] \rightarrow \mathbb{R} \text{ lin.}, L(1) = 1, L(M) \subset [0, \infty) \}.$

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Example (n=2): L given by the moments

$$L(x_1^i x_2^j) = \int x_1^i x_2^j d\mu, \quad i, j \geq 0$$

Convexification II: Dual viewpoint

$$\begin{aligned} f^* &= \sup \{a \in \mathbb{R} : f - a \geq 0 \text{ on } S\} \\ &= \sup \{a \in \mathbb{R} : f - a > 0 \text{ on } S\} \end{aligned}$$

Putinar's Positivstellensatz ('93). If $p \in \mathbb{R}[x]$ satisfies $p > 0$ on S then $p \in M$.

$$\implies f^* = \sup \{a \in \mathbb{R} : f - a \in M\}.$$

Relaxation of order k (for $k \geq \max\{\deg g_i, \deg f\}$)

Let $M_k := \left\{ \sum_{i=0}^m \sigma_i g_i : \sigma_i \in \sum \mathbb{R}[x]^2, \deg(\sigma_i g_i) \leq k \right\}$.

$$\begin{aligned} (P_k :) \quad & \min L(f) \\ & L : \mathbb{R}[x]_k \rightarrow \mathbb{R} \text{ is linear} \\ & L(1) = 1 \\ & L(M_k) \subset [0, \infty) \end{aligned}$$

$$\begin{aligned} (D_k :) \quad & \max a \\ & f - a \in M_k \end{aligned}$$

Theorem (Lasserre 2001). $(D_k^*)_{k \in \mathbb{N}}$ and $(P_k^*)_{k \in \mathbb{N}}$ are increasing sequences that converge to f^* and satisfy $D_k^* \leq P_k^* \leq f^*$ for all admissible k .

Formulation as semidefinite program

Lemma. Let $L : \mathbb{R}[x]_k \rightarrow \mathbb{R}$ be a linear map. Then $L(M_k) \subset [0, \infty)$ if and only if the $m + 1$ matrices

$$(L(x^{\beta+\gamma} g_i))_{(\beta, \gamma) \in s(d_i) \times s(d_i)} \quad (0 \leq i \leq m)$$

are positive semidefinite, where

$d_i := \max\{d \in \mathbb{N}_0 : 2d + \deg g_i \leq k\}$ and

$s(d_i) := \{\alpha \in \mathbb{N}_0^n : |\alpha| \leq d_i\}$.

Example (for $g_0(x_1, x_2) = 1$, moment matrices, $y_{ij} := L(x_1^i x_2^j)$):

$$k = 2 : \left(\begin{array}{c|cc} 1 & y_{10} & y_{01} \\ \hline y_{10} & y_{20} & y_{11} \\ y_{01} & y_{11} & y_{02} \end{array} \right) \quad k = 4 : \left(\begin{array}{c|ccc|ccc} 1 & y_{10} & y_{01} & y_{20} & y_{11} & y_{02} \\ \hline y_{10} & y_{20} & y_{11} & y_{30} & y_{21} & y_{12} \\ y_{01} & y_{11} & y_{02} & y_{21} & y_{12} & y_{03} \\ \hline y_{20} & y_{30} & y_{21} & y_{40} & y_{31} & y_{22} \\ y_{11} & y_{21} & y_{12} & y_{31} & y_{22} & y_{13} \\ y_{02} & y_{12} & y_{03} & y_{22} & y_{13} & y_{04} \end{array} \right)$$

Example of second-order relaxation

$$\begin{aligned} \min \quad & 2x_1^2 - 3x_1x_2 \\ & -4x_1^2 + 7x_1 \geq 0 \\ & -x_1^2 - x_2^2 + 1 \geq 0 \end{aligned}$$

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Fourth-order relaxation of first constraint:

$$\left(\begin{array}{c|cc} -4y_{20} + 7y_{10} & -4y_{30} + 7y_{20} & -4y_{21} + 7y_{11} \\ \hline -4y_{30} + 7y_{20} & -4y_{40} + 7y_{30} & -4y_{31} + 7y_{21} \\ -4y_{21} + 7y_{11} & -4y_{31} + 7y_{21} & -4y_{22} + 7y_{12} \end{array} \right) \succeq 0$$

Remarks

- Solutions of the relaxations are proven lower bounds of the minimization problem.
- Sufficient criterion for global optimality:

$$\text{rank } M_k(y^*) = \text{rank } M_{k-d}(y^*) .$$

If the *equality* constraints define a 0-dim., radical ideal, this will hold for some k .

- In case rank condition holds, extraction of global optima possible by linear-algebra-techniques on polynomial equations.

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- by Didier Henrion and Jean B. Lasserre
- $k' := k/2$