
Optimization over Polynomials with Moment Matrices and SOS: Further Topics

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IMA Tutorial: Algebraic Algorithms in Optimization

How to reduce the size of the SDP relaxations (MOMt) and (SOS_t)?

Exploit the structure of the problem:

- Equations
- Sparsity
- Symmetry

Exploit equations: The 0/1 instance

Assume the equations $h_i := x_i^2 - x_i = 0$ are present in the description of (POP)

On the moment side:

$$\begin{aligned} M_t(h_i \mathbf{y}) = 0 &\implies y_{\alpha+2e_i} = y_{\alpha} \quad \forall \alpha \\ &\implies y_{\alpha} = y_{\text{supp}(\alpha)} \quad \forall \alpha \end{aligned}$$

Hence: (MOM_t) involves only variables y_{α} with $\alpha \in \{0, 1\}^n$

\rightsquigarrow reduce number of variables and (MOM_t) is exact at $t = n$

On the SOS side: work in the quotient space $\mathbb{R}[\mathbf{x}]/I$

Extension to general ideal I - See [Lasserre, La, Jibetean-La, Parrilo,..]

Example: The Stable Set Problem

The **stability number** $\alpha(G)$ of graph $G = (V, E)$:

$$\max \sum_{i \in V} x_i \quad \text{s.t. } x_i x_j = 0 \ (ij \in E), \ x_i^2 = x_i \ (i \in V)$$

- **Moment relaxation of order 1** = Shor relaxation:

$$\max \sum_{i \in V} y_i \quad \text{s.t. } M_1(y) \succeq 0, \ y_{ij} = 0 \ (ij \in E), \ y_\emptyset = 1$$

\rightsquigarrow Lovász' **theta number**

- **Finite convergence** in $\alpha(G)$ steps

Example: The Max-Cut Problem

$G = (V, E)$ graph with edge weights $w \in \mathbb{R}^E$.

$$\text{Max-Cut: } \max \sum_{ij \in E} w_{ij} (1 - x_i x_j) \text{ s.t. } x_i^2 = 1 \ (i \in V)$$

● **Moment relaxation of order $t = 1$** = Shor relaxation:

$$\max \sum_{ij \in E} w_{ij} (1 - X_{ij}) \text{ s.t. } X \succeq 0, X_{ii} = 1 \ (i \in V)$$

↪ Goemans-Williamson 0.878-approximation algorithm

● **Finite convergence in n steps**

Proven: $n/2$ steps are necessary

Conjecture: $n/2$ steps are sufficient

Exploit sparsity

$$p = \sum_{\alpha} p_{\alpha} x^{\alpha}$$

\rightsquigarrow **Newton polytope:** $N(p) = \text{conv}(\alpha \mid p_{\alpha} \neq 0)$

Fact: [Reznick 1978] $p = \sum_i f_i^2 \implies N(f_i) \subseteq \frac{1}{2}N(p)$

\rightsquigarrow reduce the search space for the f_i 's

Example: $p = (x^4 + 1)(y^4 + 1)(z^4 + 1) + 2x - z + 5$

$N(p)$: cube with vertices $(0, 0, 0)$ and $(4, 4, 4)$

$\frac{1}{2}N(p)$: cube with vertices $(0, 0, 0)$ and $(2, 2, 2)$

Hence, f_i uses at most $3^3 = 27$ instead of $\binom{n+d}{d} = \binom{3+6}{6} = 84$

monomials

Exploit sparsity (continued)

$$\begin{aligned} \text{Minimize } p &= p_1(x_1 \dots x_3 \mathbf{x_4 x_5}) + p_2(\mathbf{x_4 x_5} x_6 \dots x_8) \\ \text{s.t. } x \in K &: \begin{cases} f_j(x_1 \dots x_3 \mathbf{x_4 x_5}) \geq 0 \quad (j \in J_1) \longrightarrow K_1 \\ g_j(\mathbf{x_4 x_5} x_6 \dots x_8) \geq 0 \quad (j \in J_2) \longrightarrow K_2 \end{cases} \end{aligned}$$

If Putinar's assumption holds for K_1, K_2 , one can give a more economical SOS certificate: $p > 0$ on $K \implies$

$$p = \underbrace{s_0 + \sum_j s_j f_j}_{s_0, s_j \text{ SOS in } \mathbb{R}[x_1 \dots x_3 \mathbf{x_4 x_5}]} + \underbrace{t_0 + \sum_j t_j g_j}_{t_0, t_j \text{ SOS in } \mathbb{R}[\mathbf{x_4 x_5} x_6 \dots x_8]}$$

See [Lasserre (06), Kojima, Kim, Waki, Muramatsu (05,06), Grimm, Netzer, Schweighofer (06), Nie (06), ...]

Exploit symmetry

Lot of recent work about symmetry reduction using invariant theory and block-diagonalization of matrix $*$ -algebras:

Gatermann-Parrilo (2004), J. Pure and Applied Algebra

de Klerk-Pasechnik-Schrijver (2006), Math. Programming

Schrijver (2005), IEEE Trans. Inform. Theory

La (2006), Math. Programming

Jansson-Lasserre-Riener-Theobald (2006)

Bachoc-Vallentin (2006)

Bosse (2006)

Many other interesting issues

- **How to improve the numerical stability ?**

Hankel matrices have a poor condition number ...

Idea: [Roh-Vandenberghe], [Löfberg-Parrilo], [de Klerk-den Hertog-Elabwabi]

Use another basis (instead of the monomial basis)

Use interpolation points for representing polynomials

- **Estimates on the quality of the MOM/SOS relaxations ?**

[de Klerk-La-Parrilo]: yes for minimization on the simplex

- **Degree bounds on the SOS relaxations ?**

Results by Schweighofer, Nie,..