

# Limitations on representing SOS cones with bounded size PSD blocks

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December 12, 2017

# Sums of squares

$$p(x) = \sum_i [p_i(x)]^2 \implies p(x) \geq 0 \text{ for all } x$$

- ▶ sufficient condition for global nonnegativity
- ▶ generic tool for constructing convex optimization formulations/relaxations
- ▶ **Key observation:**  $\text{SOS}_{n,2d}$  has semidefinite description

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- ▶ generic tool for constructing convex optimization formulations/relaxations
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# Scalability: use SDPs with only small blocks

Inner approximations to SOS cone:

- ▶ DSOS: linear programming formulation ( $1 \times 1$  blocks)
- ▶ SDSOS: second-order cone formulation ( $2 \times 2$  blocks)

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**Equivalently:** there exist  $2 \times 2$  psd matrices  $G_{\{i,j\}}$  s.t.

$$G = \sum_{i < j} E_{\{i,j\}} G_{\{i,j\}} E_{\{i,j\}}^T$$

Solution time for SDPs with (small) bounded blocks  
more like LP than general SDP

# Challenge: what can be done with small blocks?



## DSOS and SDSOS:

- ▶ particular strategies for approximating SOS cones with sets that can be described using small SDP blocks

Can we find

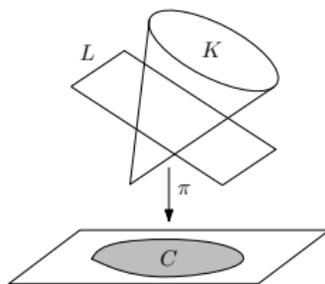
- ▶ Better approximations with fewer small blocks?
- ▶ Exact formulations of SOS cones using only small blocks?

How to reason about all possible SDP formulations with small blocks?

# Lifts of convex sets

**Definition:** A convex set  $C$  has a  $K$ -lift if there is an affine subspace  $L$  and linear map  $\pi$  such that

$$C = \pi(K \cap L)$$



If  $C$  has a  $K$ -lift then linear optimization problems over  $C$  can be formulated as conic programs over  $K$ .

# Lifts with small blocks: $(\mathcal{S}_+^2)^p$ -lifts

**Cone:** product of  $2 \times 2$  PSD cones

$$(\mathcal{S}_+^2)^p := \mathcal{S}_+^2 \times \cdots \times \mathcal{S}_+^2 \quad (p \text{ terms})$$

For a convex set:

$$(\mathcal{S}_+^2)^p\text{-lift} \iff \text{LMI description with } 2 \times 2 \text{ blocks}$$

All basic ideas generalize to bounded block size case

**Examples:**

- ▶  $n \times n$  scaled diag. dominant matrices: has  $(\mathcal{S}_+^2)^{\binom{n}{2}}$ -lift
- ▶  $\{X \in \mathcal{S}_+^3 : X_{11} = X_{22}\}$  has  $(\mathcal{S}_+^2)^2$ -lift  
(chordal sparsity after congruence transformation)

# Some related work

Lifts using  $1 \times 1$  blocks  $\longleftrightarrow$  linear prog. descriptions

- ▶ Existence easy:  $C$  has LP lift if and only if  $C$  a polyhedron
- ▶ Main effort: lower bounds on size of lifts
  - ▶ Connection with nonnegative rank: Yannakakis (1991)
  - ▶ Correlation/CUT/TSP polytope: Fiorini et al. (2012)
  - ▶ Matching polytope: Rothvoß (2013)

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**No restriction on block size**  $\longleftrightarrow$  general SDP descriptions

- ▶ Many constructions (including SOS cones)
- ▶ Scheiderer (2017)

$\text{PSD}_{n,d}$  has  $\mathcal{S}_+^P$ -lift if and only if  $\text{PSD}_{n,d} = \text{SOS}_{n,d}$

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Very little known about obstructions to representability with small blocks

# Fawzi's result

**Question:** For which  $(n, d)$  does  $\text{SOS}_{n,d}$  have an  $(\mathcal{S}_+^2)^p$ -lift?

- ▶  $(n, d) = (1, 2)$  (trivial)
- ▶ Are there any other cases with  $(\mathcal{S}_+^2)^p$ -lifts?

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**Fawzi (2016)** The cone of non-negative univariate quartics does not have a  $(\mathcal{S}_+^2)^p$ -lift.

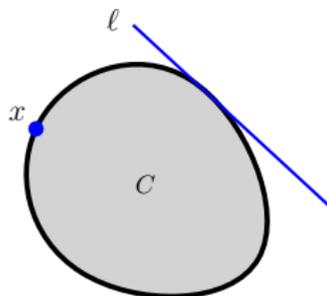
**Corollaries:** cannot describe using  $2 \times 2$  PSD blocks:

- ▶  $\text{SOS}_{n,d}$  unless  $(n, d) = (1, 2)$
- ▶  $n \times n$  PSD cone for  $n \geq 3$

# Slack matrix

Associate **slack matrix** with convex cone  $C$

$$S_{x,\ell} = \langle \ell, x \rangle$$



where

- ▶  $\ell$  linear functional non-negative on  $C$
- ▶  $x$  an element of  $C$

The slack matrix is entry-wise nonnegative.

Lifts of  $C$  correspond to structured factorizations of  $S$

# Lifts of convex sets and $\mathcal{S}_+^2$ -rank

A nonnegative matrix  $S$  has  $\mathcal{S}_+^2$ -rank one if  $\exists A_i, B_j \in \mathcal{S}_+^2$  s.t.

$$S = \begin{bmatrix} \langle A_1, B_1 \rangle & \langle A_1, B_2 \rangle & \cdots & \langle A_1, B_b \rangle \\ \langle A_2, B_1 \rangle & \langle A_2, B_2 \rangle & \cdots & \langle A_2, B_b \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle A_a, B_1 \rangle & \langle A_a, B_2 \rangle & \cdots & \langle A_a, B_b \rangle \end{bmatrix}$$

**Definition:** The  $\mathcal{S}_+^2$ -rank of an entrywise nonnegative matrix  $S$  is the smallest  $p$  such that  $S = S_1 + S_2 + \cdots + S_p$  where each  $S_k$  has  $\mathcal{S}_+^2$ -rank one.

**Theorem** [Gouveia, Parrilo, Thomas 2013]

If  $C$  has a proper  $(\mathcal{S}_+^2)^p$ -lift then (any submatrix of) its slack matrix has  $\mathcal{S}_+^2$ -rank at most  $p$ .

# Slack matrix of non-negative univariate quartics

Indexed by non-neg. polynomials  $p \in \text{SOS}_{1,4}$  and points  $t \in \mathbb{R}$ :

$$S_{p,t} = p(t) \geq 0$$

If  $\text{SOS}_{1,4}$  had  $(\mathcal{S}_+^2)^p$ -lift then for any non-negative quartics  $p_1, \dots, p_a$  and any points  $t_1, \dots, t_b \in \mathbb{R}$ , could write

$$\begin{bmatrix} p_1(t_1) & p_1(t_2) & \cdots & p_1(t_b) \\ p_2(t_1) & p_2(t_2) & \cdots & p_2(t_b) \\ \vdots & \vdots & \ddots & \vdots \\ p_a(t_1) & p_a(t_2) & \cdots & p_a(t_b) \end{bmatrix} = S_1 + S_2 + \cdots + S_p$$

where each  $S_i$  has  $\mathcal{S}_+^2$ -rank **one**

# Define sequence of submatrices

For positive integers  $1 \leq i_1 < i_2$  define

$$p_{\{i_1, i_2\}}(t) = [(i_1 - i_2)(i_1 - t)(i_2 - t)]^2$$

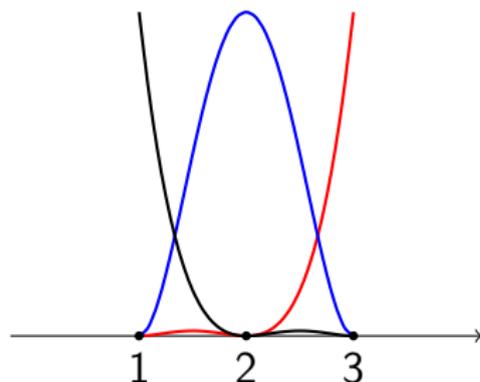
Define  $\binom{k}{2} \times k$  submatrices of  $S$  by

$$S_{\{i_1, i_2\}, j}^{(k)} = p_{\{i_1, i_2\}}(j)$$

for  $1 \leq i_1 < i_2 \leq k$  and  $1 \leq j \leq k$

Example:

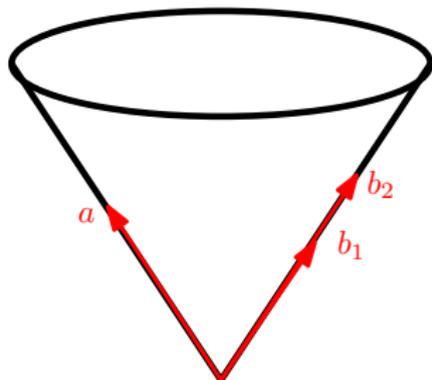
$$S^{(3)} = \begin{matrix} p_{\{1,2\}} \\ p_{\{1,3\}} \\ p_{\{2,3\}} \end{matrix} \begin{bmatrix} 1 & 2 & 3 \\ 0 & 0 & 4 \\ 0 & 4 & 0 \\ 4 & 0 & 0 \end{bmatrix}$$



# Show that $\mathcal{S}_+^2$ -rank of $S^{(k)}$ grows without bound

## Key ingredients:

- ▶ if  $k' < k$  then  $S^{(k')}$  a submatrix of  $S^{(k)}$
- ▶ if  $S_{ij} = 0$  and  $S = S_1 + \cdots + S_p$  with non-negative terms then  $[S_k]_{ij} = 0$  for all  $k$
- ▶ if  $\mathcal{S}_+^2$ -rank one matrix has two zeros in a non-zero row then the corresponding columns are scalings of each other



# Approximations?

- ▶ How well can we **approximate** SOS cones with cones having SDP representations with few small blocks?
- ▶ Even for **polyhedral approximations** ( $1 \times 1$  blocks) how do approximation quality and size of lift relate?
- ▶ Can we find **quantitative** lower bounds? What do obstructions look like?

# Sum of squares optimization

**Useful:** in control, combinatorial optimization, analysis of games, quantum information, . . .

**Challenge:** Natural SDP formulation scales poorly with increasing degree/number of variables

**Possibilities:**

- ▶ Algorithms that exploit structure (e.g., sparsity)
- ▶ Alternative certificates of non-negativity: DSOS, SDSOS can search for these via LP/SOCP
- ▶ Iterative methods based on DSOS and SDSOS
- ▶ Better approximations with small blocks(?)

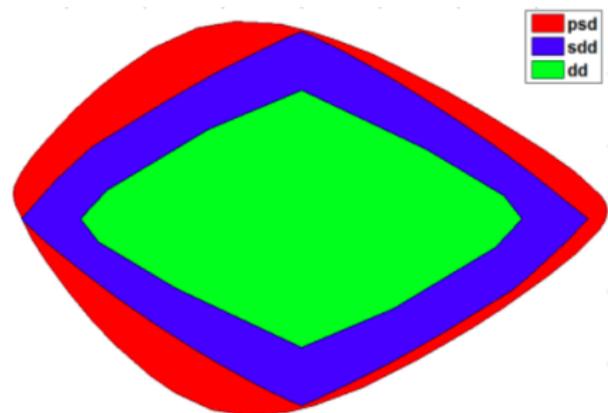
# Exploiting sparsity in first-order methods

## SOS programs:

- ▶ Coefficient matching constraints very sparse
- ▶ Have additional 'partial orthogonality' structure
- ▶ Can solve and exploit this structure using ADMM-based first-order methods

CDCS: open-source MATLAB solver for partially decomposable conic programs (including SOS)

# DSOS and SDSOS



Search over inner approximations to SOS cone:

- ▶ DSOS: diag. dominant Gram matrix (LP)
- ▶ SDSOD: scaled diag. dominant Gram matrix (SOCP)

## Trade-off

- ▶ (S)DSOS inner approx.  $\implies$  'weaker' than regular SOS
- ▶ BUT can solve problems 'higher' in  $r$ -(S)DSOS hierarchy

# Adaptive non-negativity certificates

## Classical SOS:

- ▶ choose subspace(s) of functions to take sums of squares from (e.g., polynomials of degree at most  $d$ )
- ▶ Search for DSOS/SDSOS/SOS certificates

## (S)DSOS column generation:

- ▶ Large dictionary of small subspaces of functions to take sums of squares from
- ▶ Each iteration, add useful subspace to the dictionary

## (S)DSOS Cholesky change of basis:

- ▶ Each iteration, update subspace(s) of functions to take sums of squares from
- ▶ Don't increase size of subspace, but improve it

Systematic study of such adaptive certificates?

# References

## Fawzi's paper

H. Fawzi, 'On representing the positive semidefinite cone using the second-order cone' [arxiv.org/abs/1610.04901](https://arxiv.org/abs/1610.04901), 2016.

## CDC tutorial paper

'Improving Efficiency and Scalability of Sum of Squares Optimization: Recent Advances and Limitations'  
[arxiv.org/abs/1710.01358](https://arxiv.org/abs/1710.01358)

Thank you!