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Submitted on 1 Sep 2023

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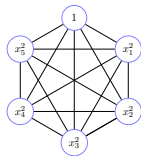
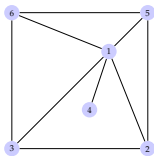
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# Exploiting sparsity in polynomial optimization

Victor Magron  
LAAS CNRS

<https://homepages.laas.fr/vmagron/SparsePOPJNCF23.pdf>

Journées Nationales de Calcul Formel 6-10 March 2023



# What is sparse polynomial optimization?

---

Looks like a regular polynomial optimization problem (POP):

$$\begin{aligned} \text{inf} \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{x} \in \mathbf{X} = \{\mathbf{x} \in \mathbb{R}^n : g_j(\mathbf{x}) \geq 0\} \end{aligned}$$

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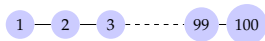
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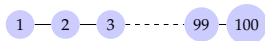
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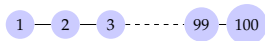
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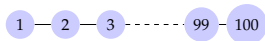
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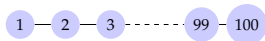
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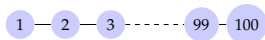
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PERFORMANCE



VS



ACCURACY

# Where do we find sparse POPs?

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Everywhere (almost)!

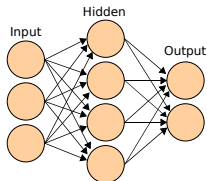
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## Deep learning

~> robustness, computer vision



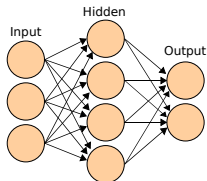
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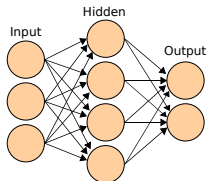
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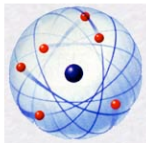
## Power systems

↪ AC optimal power-flow, stability



## Quantum Systems

↪ condensed matter, entanglement





# The Moment-SOS Hierarchy for POP

NP-hard NON CONVEX Problem  $f_{\min} = \inf f(\mathbf{x})$

## Theory

(Primal)		(Dual)
$\inf \int f d\mu$		$\sup \lambda$
with $\mu$ proba $\Rightarrow$	<b>INFINITE LP</b>	$\Leftarrow$ with $f - \lambda \geq 0$

# The Moment-SOS Hierarchy for POP

NP-hard NON CONVEX Problem  $f_{\min} = \inf f(x)$

## Practice

(Primal **Relaxation**)

moments  $\int x^\alpha d\mu$

finite number  $\Rightarrow$



**SDP**

(Dual **Strengthening**)

$f - \lambda =$  sum of squares

$\Leftarrow$  fixed degree

LASSERRE'S HIERARCHY of **CONVEX PROBLEMS**  $\uparrow f_{\min}$

[Lasserre '01]

degree  $r$  &  $n$  vars  $\implies \binom{n+2r}{n}$  **SDP** VARIABLES



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HOW TO OVERCOME THIS **NO-FREE LUNCH** RULE?

# An example

---

**NP hard General Problem:**  $f_{\min} := \min_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x})$

Semialgebraic set  $\mathbf{X} = \{\mathbf{x} \in \mathbb{R}^n : g_j(\mathbf{x}) \geq 0\}$

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$$\underbrace{x_1 x_2}_f = -\frac{1}{8} + \frac{1}{2} \overbrace{\left(x_1 + x_2 - \frac{1}{2}\right)^2}^{\sigma_0} + \frac{1}{2} \overbrace{x_1(1 - x_1)}^{g_1} + \frac{1}{2} \overbrace{x_2(1 - x_2)}^{g_2}$$

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$$\text{Quadratic module: } \mathcal{M}(\mathbf{X})_r = \left\{ \sigma_0 + \sum_j \sigma_j g_j, \deg \sigma_j g_j \leq 2r \right\}$$



# The Moment-SOS Hierarchy for POP

**NP-hard NON CONVEX Problem**  $f_{\min} = \inf_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x})$

- space  $\mathcal{M}_+(\mathbf{X})$  of probability measures supported on  $\mathbf{X}$
- quadratic module  $\mathcal{Q}(\mathbf{X}) = \left\{ \sigma_0 + \sum_j \sigma_j g_j, \text{ with } \sigma_j \text{ SOS} \right\}$

Infinite-dimensional linear programs (LP)

(Primal)	=	(Dual)
$\inf \int_{\mathbf{X}} f d\mu$		$\sup \lambda$
s.t. $\mu \in \mathcal{M}_+(\mathbf{X})$		s.t. $\lambda \in \mathbb{R}$
		$f - \lambda \in \mathcal{Q}(\mathbf{X})$

# The Moment-SOS Hierarchy for POP

**NP-hard NON CONVEX Problem**  $f_{\min} = \inf_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x})$

- Pseudo-moment sequences  $\mathbf{y}$  up to order  $r$
- Truncated quadratic module  $\mathcal{Q}(\mathbf{X})_r$

Finite-dimensional semidefinite programs (SDP)

(Moment)	=	(SOS)
$\inf \sum_{\alpha} f_{\alpha} y_{\alpha}$		$\sup \lambda$
s.t. $\mathbf{M}_{r-r_j}(g_j \mathbf{y}) \succcurlyeq 0$		s.t. $\lambda \in \mathbb{R}$
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Primal-dual “SPARSE” variants?

Sparse SDP

Correlative sparsity

Term sparsity

Ideal sparsity

Tutorial session

Sparse SDP

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# Sparse matrices

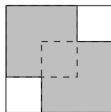
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Symmetric matrices indexed by graph vertices

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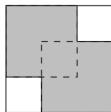


💡 no edge between 1 and 3  $\iff$  0 entry in the (1,3) entry

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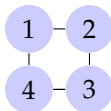
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cycle =

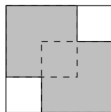




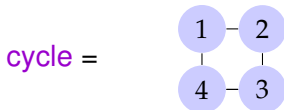
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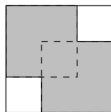


chord = edge between two nonconsecutive vertices in a cycle

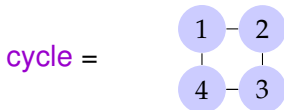
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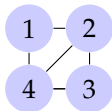


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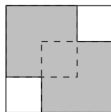
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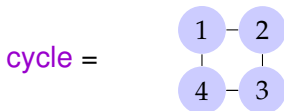
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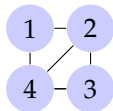
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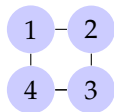
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clique = a fully connected subset of vertices



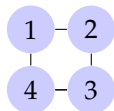
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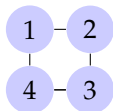


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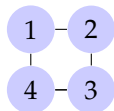


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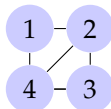
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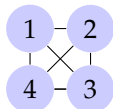
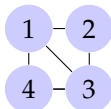
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approximately minimal



maximal

**Theorem [Gavril '72, Vandenberghe & Andersen '15]**

The maximal cliques of a chordal graph can be enumerated in linear time in the number of nodes and edges.

# Running intersection property (RIP)

---

RIP Theorem for chordal graphs [Blair & Peyton '93]

For a chordal graph with maximal cliques  $I_1, \dots, I_p$ :

$$(RIP) \quad \forall k < p \quad I_{k+1} \cap \bigcup_{j \leq k} I_j \subseteq I_i \quad \text{for some } i \leq k$$

(possibly after reordering)



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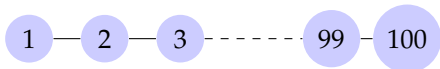
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💡 RIP holds for chains



# Running intersection property (RIP)

RIP Theorem for chordal graphs [Blair & Peyton '93]

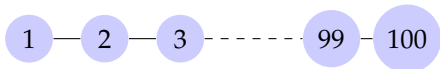
For a chordal graph with maximal cliques  $I_1, \dots, I_p$ :

$$(RIP) \quad \forall k < p \quad I_{k+1} \cap \bigcup_{j \leq k} I_j \subseteq I_i \quad \text{for some } i \leq k$$

(possibly after reordering)

💡 RIP always holds for  $p = 2$

💡 RIP holds for chains



💡 RIP holds for numerous applications!

# Semidefinite Programming (SDP)

---

$$\begin{aligned} \min_{\mathbf{y}} \quad & \mathbf{c}^\top \mathbf{y} \\ \text{s.t.} \quad & \sum_i \mathbf{F}_i y_i \succcurlyeq \mathbf{F}_0 \end{aligned}$$

- Linear cost  $\mathbf{c}$
- Symmetric matrices  $\mathbf{F}_0, \mathbf{F}_i$
- Linear matrix inequalities “ $\mathbf{F} \succcurlyeq 0$ ”  
( $\mathbf{F}$  has nonnegative eigenvalues)



**Spectrahedron**

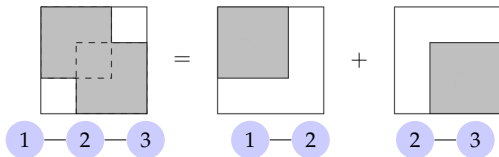
# Sparse SDP matrices

Theorem [Griewank Toint '84, Agler et al. '88]

Chordal graph  $G$  with  $n$  vertices & maximal cliques  $I_1, I_2$

$Q_G \succcurlyeq 0$  with nonzero entries corresponding to edges of  $G$

$\implies Q_G = P_1^T Q_1 P_1 + P_2^T Q_2 P_2$  with  $Q_k \succcurlyeq 0$  indexed by  $I_k$



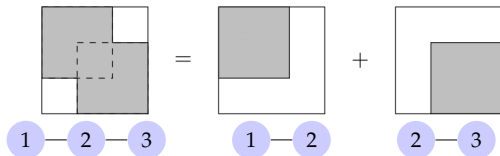
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What are  $P_1, P_2$ ?

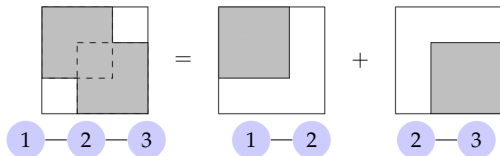
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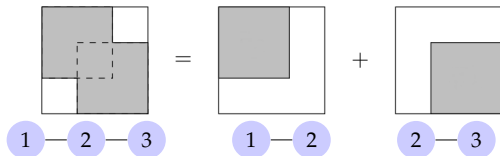
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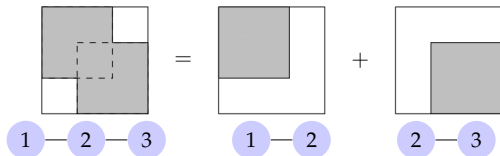
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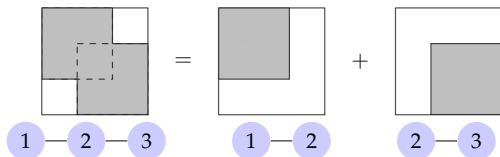
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💡  $P_1^T Q_1 P_1$  inflates a  $|I_1| \times |I_1|$  matrix  $Q_1$  into a sparse  $n \times n$  matrix

Sparse SDP

**Correlative sparsity**

Term sparsity

Ideal sparsity

Tutorial session

# What is correlative sparsity?

---

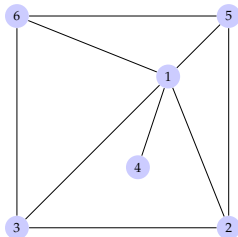
💡 Exploit few links between **variables** [Lasserre, Waki et al. '06]

$$f(\mathbf{x}) = x_2x_5 + x_3x_6 - x_2x_3 - x_5x_6 + x_1(-x_1 + x_2 + x_3 - x_4 + x_5 + x_6)$$

Correlative sparsity pattern (csp) graph  $G$

Vertices =  $\{1, \dots, n\}$

$(i, j) \in \text{Edges} \iff x_i x_j$  appears in  $f$



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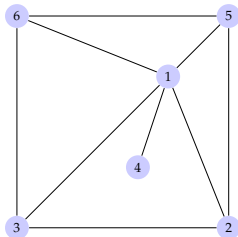
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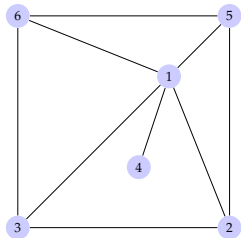
Similar construction with constraints  $\mathbf{X} = \{\mathbf{x} \in \mathbb{R}^n : g_j(\mathbf{x}) \geq 0\}$

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Chordal graph after adding edge (3,5)

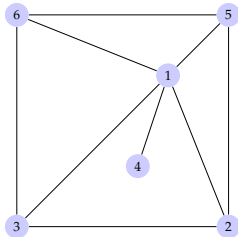


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Chordal graph after adding edge (3,5)



maximal cliques  $I_1 = \{1,4\}$     $I_2 = \{1,2,3,5\}$     $I_3 = \{1,3,5,6\}$

$f = f_1 + f_2 + f_3$  where  $f_k$  involves **only** variables in  $I_k$

💡 Let us index moment matrices and SOS with the cliques  $I_k$

# A sparse variant of Putinar's Positivstellensatz

---

Convergence of the Moment-SOS hierarchy is based on:

Theorem [Putinar '93] Positivstellensatz

If  $\mathbf{X}$  contains a ball constraint  $N - \sum_i x_i^2 \geq 0$  then

$f > 0$  on  $\mathbf{X} = \{\mathbf{x} : g_j(\mathbf{x}) \geq 0\} \implies f = \sigma_0 + \sum_j \sigma_j g_j$  with  $\sigma_j$  SOS



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Theorem: Sparse Putinar's representation [Lasserre '06]

$f = \sum_k f_k$ ,  $f_k$  depends on  $\mathbf{x}(I_k)$

$f > 0$  on  $\mathbf{X}$

Each  $g_j$  depends on some  $I_k$

RIP holds for  $(I_k)$

ball constraints for each  $\mathbf{x}(I_k)$

$$\boxed{f = \sum_k (\sigma_{0k} + \sum_{j \in I_k} \sigma_j g_j)}$$

$\implies$  SOS  $\sigma_{0k}$  "sees" vars in  $I_k$   
 $\sigma_j$  "sees" vars from  $g_j$

# A first key message

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**SUMS OF SQUARES PRESERVE SPARSITY**



# A proof of sparse Putinar's Positivstellensatz

---

Let  $\mathbf{X} = \{\mathbf{x} : g_j(\mathbf{x}) \geq 0\}$  be compact and  $f = \sum_k f_k$ , with  $f_k$  depends on  $\mathbf{x}(I_k)$ , and  $f > 0$  on  $\mathbf{X}$

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If RIP holds for  $(I_k)$  then

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💡 Then apply Putinar to each  $h_k$

# Sparse moment matrices

---

For each subset  $I_k$ , submatrix of  $\mathbf{M}_r(\mathbf{y})$  corresponding of rows & columns indexed by monomials in  $\mathbf{x}(I_k)$



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$$I_1 = \{1, 4\} \implies \text{monomials in } x_1, x_4$$

$$\mathbf{M}_1(\mathbf{y}, I_1) = \begin{pmatrix} 1 & | & y_{1,0,0,0,0,0} & y_{0,0,0,1,0,0} \\ \hline y_{1,0,0,0,0,0} & | & y_{2,0,0,0,0,0} & y_{1,0,0,1,0,0} \\ y_{0,0,0,1,0,0} & | & y_{1,0,0,1,0,0} & y_{0,0,0,2,0,0} \end{pmatrix}$$

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💡 same for each localizing matrix  $\mathbf{M}_r(\mathbf{g}_j\mathbf{y})$

# Sparse primal-dual Moment-SOS hierarchy

$$f_{\min} = \inf_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x}) \text{ with } \mathbf{X} = \{\mathbf{x} : g_j(\mathbf{x}) \geq 0\}$$

## Dense Moment-SOS hierarchy

(Moment)	=	(SOS)
$\inf \sum_{\alpha} f_{\alpha} y_{\alpha}$		$\sup \lambda$
s.t. $\mathbf{M}_r(\mathbf{y}) \succeq 0$		s.t. $\lambda \in \mathbb{R}$
$\mathbf{M}_{r-r_j}(g_j \mathbf{y}) \succeq 0$		$f - \lambda = \sigma_0 + \sum_j \sigma_j g_j$
$y_0 = 1$		

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$$\text{s.t. } \mathbf{M}_r(\mathbf{y}, I_k) \succeq 0$$

$$\mathbf{M}_{r-r_j}(g_j \mathbf{y}, I_k) \succeq 0, j \in J_k, \forall k$$

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RIP holds for  $(I_k)$  + ball constraints for each  $\mathbf{x}(I_k) \implies$  Primal and dual optimal value converge to  $f_{\min}$  by sparse Putinar

# Computational cost

$$f_{\min} = \inf_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x}) \text{ with } \mathbf{X} = \{\mathbf{x} : g_j(\mathbf{x}) \geq 0, j \leq m\}$$

$$\tau = \max\{|I_1|, \dots, |I_p|\}$$

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$(m + p)$  SOS in at most  $\tau$  vars of degree  $\leq 2r$



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💡  $(m + p) \mathcal{O}(r^{\tau})$  SDP vars

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💡  $(m + p) \mathcal{O}(r^{\tau})$  SDP vars vs  $(m + 1) \mathcal{O}(r^n)$  in the dense SDP

# Sparse linear program over measures

---

In the dense setting:

$$\begin{aligned} f_{\min} &= \inf_{\mu} \int_{\mathbf{X}} f d\mu \\ \text{s.t. } &\mu \in \mathcal{M}_+(\mathbf{X}) \end{aligned}$$

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In the sparse setting:

$\mathbf{X}_k = \{\mathbf{x}(I_k) : g_j(\mathbf{x}) \geq 0 : j \in J_k\}$  = the subspace of  $\mathbf{X}$  which only “sees” variables indexed by  $I_k$

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Sparse moment SDPs relax the sparse LP over measures:

$$f_{\text{CS}} = \inf_{\mu_k} \sum_k \int_{\mathbf{X}_k} f_k d\mu_k$$

s.t.  $\pi_{jk}\mu_j = \pi_{kj}\mu_k, \quad \mu_k \in \mathcal{M}_+(\mathbf{X}_k)$

# The dual of sparse Putinar's Positivstellensatz

Theorem [Lasserre '06]

$$\begin{aligned} \text{RIP holds for } (I_k) \implies f_{\min} = f_{\text{CS}} = \inf_{\mu_k} & \sum_k \int_{\mathbf{X}_k} f_k d\mu_k \\ \text{s.t.} & \pi_{jk}\mu_j = \pi_{kj}\mu_k \\ & \mu_k \in \mathcal{M}_+(\mathbf{X}_k) \end{aligned}$$

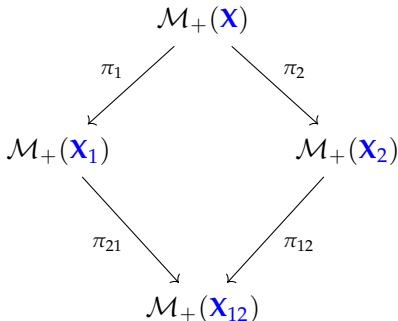


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💡 Proof: there exists  $\mu \in \mathcal{M}_+(\mathbf{X})$  with marginal  $\mu_k$  on  $\mathbf{X}_k$



# A first (dual) key message

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**THE MEASURE LP PRESERVES SPARSITY**



# Extracting minimizers: the dense case

---

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Extraction possible with the Gloptipoly software

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💡 RIP is not required!

💡 Extract  $\mathbf{x}(k)$  from  $\mathbf{M}_r(\mathbf{y}, I_k) \implies$  minimizer  $\mathbf{x}$  with  $(x_i)_{i \in I_k} = \mathbf{x}(k)$

# Application to rational functions

---

$$f_{\min} = \inf_{\mathbf{x} \in \mathbf{X}} \sum_i \frac{p_i(\mathbf{x})}{q_i(\mathbf{x})}, \quad q_i > 0 \text{ on } \mathbf{X}, \quad p_i, q_i \text{ depends only on } I_i$$

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3: Bound  $\ell(\mathbf{x}, \mathbf{e})$  with **SPARSE SUMS OF SQUARES**

💡  $I_k \rightarrow \{\mathbf{x}, e_k\} \implies \boxed{m r^{n+1} \text{ instead of } r^{n+m}}$  SDP vars

# Application to roundoff errors

---

$$f = x_2x_5 + x_3x_6 - x_2x_3 - x_5x_6 + x_1(-x_1 + x_2 + x_3 - x_4 + x_5 + x_6)$$

$$\mathbf{x} \in [4.00, 6.36]^6, \quad \mathbf{e} \in [-\epsilon, \epsilon]^{15}, \quad \epsilon = 2^{-53}$$

**Dense SDP:**  $\binom{6+15+4}{6+15} = 12650$  variables  $\leadsto$  **Out of memory**

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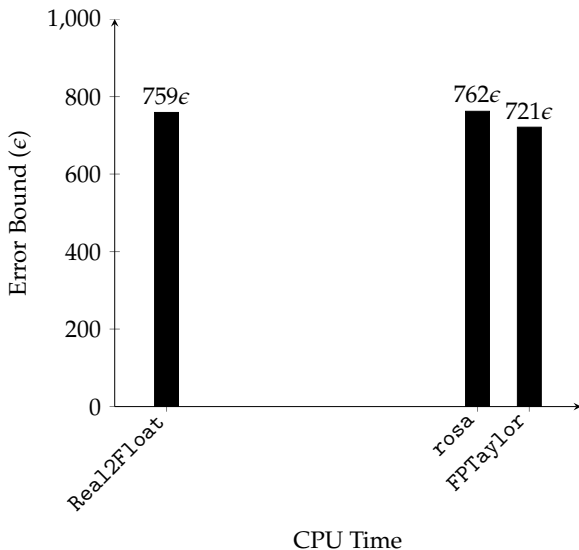
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**SMT-based** rosa tool:  $762\epsilon$  (19  $\times$  more CPU)



# Application to roundoff errors

---



# Extension to noncommutative optimization

---

Self-adjoint noncommutative variables  $a_i, b_j \in \mathcal{B}(\mathcal{H})$

$$f = a_1(b_1 + b_2 + b_3) + a_2(b_1 + b_2 - b_3) + a_3(b_1 - b_2) - b_1 - 2b_2 - b_3$$

with  $a_1 a_2 \neq a_2 a_1$ , **involution**  $(a_1 b_3)^* = b_3 a_1$

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Ball constraint  $N - \sum_i x_i^2 \succcurlyeq 0$  in  $\mathbf{X}$

Theorem: NC Putinar's representation [Helton & McCullough '02]

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NC variant of Lasserre's Hierarchy for  $\lambda_{\min}$ :

💡 replace " $f - \lambda \mathbf{I} \succcurlyeq 0$  on  $\mathbf{X}$ " by  $f - \lambda \mathbf{I} = \sum_i s_i^* s_i + \sum_j \sum_i t_{ji}^* g_j t_{ji}$   
with  $s_i, t_{ji}$  of **bounded** degrees = SDP 🎯

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Self-adjoint noncommutative (NC) variables  $x = (x_1, \dots, x_n)$

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[Klep Magron Povh '21]

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Theorem: Sparse NC Positivstellensatz [Klep Magron Povh '21]

$f = \sum_k f_k$ ,  $f_k$  depends on  $x(I_k)$

$f > 0$  on  $\{x : g_j(x) \geq 0\}$

chordal graph with cliques  $I_k \implies$

ball constraints for each  $x(I_k)$

$$f = \sum_{k,i} (s_{ki}^* s_{ki} + \sum_{j \in J_k} t_{ji}^* g_j t_{ji})$$

$s_{ki}$  "sees" vars in  $I_k$

$t_{ji}$  "sees" vars from  $g_j$

# Application to violation of Bell inequalities

---

I<sub>3322</sub> Bell inequality (entanglement in quantum information)

$$f = a_1(b_1 + b_2 + b_3) + a_2(b_1 + b_2 - b_3) + a_3(b_1 - b_2) - a_1 - 2b_1 - b_2$$

Maximal violation levels  $\rightarrow$  **upper bounds** on  $\lambda_{\max}$  of  $f$  on  $\{a, b : a_i^2 = a_i \quad b_i^2 = b_i \quad a_i b_j = b_j a_i\}$

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3	0.2511592	0.2508756
3'		0.2508754 (1 day)
4	0.2508917	
5	0.2508763	
6	0.2508753977180	(1 hour)

PERFORMANCE



VS



ACCURACY

# Application to SOS of bounded degrees

---

Theorem: sparse BSOS representation [Weisser et al. '18]

If  $0 \leq g_j \leq 1$  on  $\mathbf{X}$ ,  $f > 0$  on  $\mathbf{X}$  & RIP holds for  $(I_k)$  then

$$f = \sum_k \left( \sigma_k + \sum_{\alpha, \beta} c_{k, \alpha \beta} \prod_{j \in I_k} g_j^{\alpha_j} (1 - g_j)^{\beta_j} \right),$$

with  $\sigma_k$  SOS of degree  $\leq 2r$

# Application to sparse positive definite forms

Theorem: [Reznick '95] Positivstellensatz

$$\text{pd form } f \implies f = \frac{\sigma}{\|\mathbf{x}\|_2^{2r}} \text{ with } \sigma \text{ SOS, } r \in \mathbb{N}$$

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Sparse  $f \sum_k f_k$ , with  $f_k$  only depends on  $I_k$

RUNNING INTERSECTION PROPERTY (RIP)

$$\forall k \quad \underbrace{I_k \cap \bigcup_{j < k} I_j}_{\hat{I}_k} \subseteq I_{s_k} \quad \text{for some } s_k < k$$



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Theorem: sparse Reznick [Mai Lasserre Magron '20]

$$\text{RIP} \implies f = \sum_k \frac{\sigma_k}{H_k^r} \text{ with } \sigma_k \text{ SOS only depends on } I_k$$

Uniform  $H_k$  involve products  $\|\mathbf{x}(I)\|_2^2$  for  $I \in \{I_k, \hat{I}_k, \hat{I}_i : s_i = k\}$

# More and more applications!

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Robust Geometric Perception [Yang & Carlone '20]

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# More and more applications!

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Volume computation [Tacchi et al. '21]

Robustness of implicit deep networks [Chen et al. '21]

Sparse SDP

Correlative sparsity

**Term sparsity**

Ideal sparsity

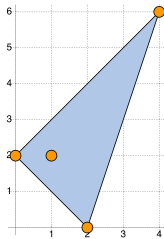
Tutorial session

# Term sparsity via Newton polytope

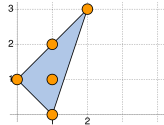
$$f = 4x_1^4x_2^6 + x_1^2 - x_1x_2^2 + x_2^2$$

$$\text{spt}(f) = \{(4,6), (2,0), (1,2), (0,2)\}$$

Newton polytope  $\mathcal{B} = \text{conv}(\text{spt}(f))$



Squares in SOS decomposition  $\subseteq \frac{\mathcal{B}}{2} \cap \mathbb{N}^n$   
 [Reznick '78]



$$f = \left( x_1 \quad x_2 \quad x_1x_2 \quad x_1x_2^2 \quad x_1^2x_2^3 \right) \underbrace{Q}_{\succeq 0} \begin{pmatrix} x_1 \\ x_2 \\ x_1x_2 \\ x_1x_2^2 \\ x_1^2x_2^3 \end{pmatrix}$$



# Term sparsity: the unconstrained case

---

$$f = x_1^2 - 2x_1x_2 + 3x_2^2 - 2x_1^2x_2 + 2x_1^2x_2^2 - 2x_2x_3 \\ + 6x_3^2 + 18x_2^2x_3 - 54x_2x_3^2 + 142x_2^2x_3^2$$

[Reznick '78]  $\rightarrow f = (1 \quad x_1 \quad x_2 \quad x_3 \quad x_1x_2 \quad x_2x_3)$

$\rightsquigarrow \frac{6 \times 7}{2} = 21$  “unknown” entries in  $\mathcal{Q}$

$$\underbrace{\mathcal{Q}}_{\succeq 0} \begin{pmatrix} 1 \\ x_1 \\ x_2 \\ x_3 \\ x_1x_2 \\ x_2x_3 \end{pmatrix}$$

# Term sparsity: the unconstrained case

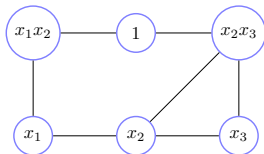
$$f = x_1^2 - 2x_1x_2 + 3x_2^2 - 2x_1^2x_2 + 2x_1^2x_2^2 - 2x_2x_3 \\ + 6x_3^2 + 18x_2^2x_3 - 54x_2x_3^2 + 142x_2^2x_3^2$$

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💡 **Term sparsity pattern graph  $G$**



# Term sparsity: the unconstrained case

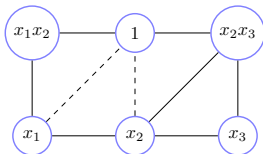
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+ chordal extension  $G'$



# Term sparsity: the unconstrained case

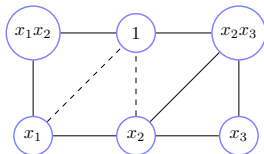
$$f = x_1^2 - 2x_1x_2 + 3x_2^2 - 2x_1^2x_2 + 2x_1^2x_2^2 - 2x_2x_3 + 6x_3^2 + 18x_2^2x_3 - 54x_2x_3^2 + 142x_2^2x_3^2$$

[Reznick '78]  $\rightarrow f = (1 \ x_1 \ x_2 \ x_3 \ x_1x_2 \ x_2x_3) \underbrace{Q}_{\neq 0}$

$\rightsquigarrow \frac{6 \times 7}{2} = 21$  "unknown" entries in  $Q$

$$\begin{pmatrix} 1 \\ x_1 \\ x_2 \\ x_3 \\ x_1x_2 \\ x_2x_3 \end{pmatrix}$$

💡 **Term sparsity pattern graph  $G$**   
+ chordal extension  $G'$



Replace  $Q$  by  $Q_{G'}$  with nonzero entries at edges of  $G'$

$\rightsquigarrow 6 + 9 = 15$  "unknown" entries in  $Q_{G'}$

## Term sparsity: the constrained case

---

At step  $r$  of the hierarchy,  $\text{tsp}$  graph  $G$  has

Nodes  $V =$  monomials of degree  $\leq r$

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Edges  $E$  with

$$\{\alpha, \beta\} \in E \Leftrightarrow \alpha + \beta \in \text{supp } f \cup \bigcup_{|\alpha| \leq r} \text{supp } g_j \cup 2\alpha$$

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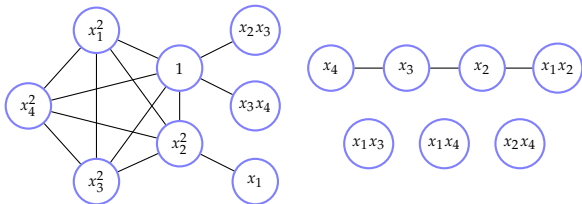
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An example with  $r = 2$

$$f = x_1^4 + x_1x_2^2 + x_2x_3 + x_3^2x_4^2$$

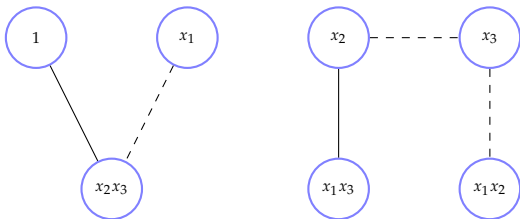
$$g_1 = 1 - x_1^2 - x_2^2 - x_3^2 \quad g_2 = 1 - x_3x_4$$



# Term sparsity: support extension

---

$$\alpha' + \beta' = \alpha + \beta \text{ and } (\alpha, \beta) \in E \Rightarrow (\alpha', \beta') \in E$$





## Term sparsity: the constrained case

---

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At step  $r$  of the hierarchy, **tsp** graph  $G$  has

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$\rightsquigarrow$  **support extension**

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$\rightsquigarrow$  support extension  $\rightsquigarrow$  chordal extension  $G'$

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$\rightsquigarrow$  **support extension**  $\rightsquigarrow$  **chordal extension**  $G'$

By iteratively performing **support extension** & **chordal extension**

$$G^{(1)} = G' \subseteq \dots \subseteq G^{(s)} \subseteq G^{(s+1)} \subseteq \dots$$

💡 Two-level hierarchy of lower bounds for  $f_{\min}$ , indexed by sparse order  $s$  and relaxation order  $r$

# Term sparsity: primal moment relaxations

---

Let  $G'$  be a chordal extension of  $G$  with maximal cliques  $(C_i)$

$$C_i \longmapsto \mathbf{M}_{C_i}(\mathbf{y})$$

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$$\mathbf{M}_r(\mathbf{y}) \succeq 0 \longrightarrow \mathbf{M}_{C_i}(\mathbf{y}) \succeq 0$$

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Similarly for the localizing matrices  $\mathbf{M}_{r-r_j}(\mathbf{g}_j \mathbf{y})$

💡 Each constraint  $G_j \rightsquigarrow G_j^{(s)} \rightsquigarrow \text{cliques } C_{j,i}^{(s)}$



# Term sparsity: primal moment relaxations

---

Let  $C_{j,i}^{(s)}$  be the maximal cliques of  $G_j^{(s)}$ . For each  $s \geq 1$

$$\begin{aligned} f_{\text{ts}}^{r,s} &= \inf \sum_{\alpha} f_{\alpha} y_{\alpha} \\ \text{s.t. } & \mathbf{M}_{C_{0,i}^{(s)}}(\mathbf{y}) \succeq 0 \\ & \mathbf{M}_{C_{j,i}^{(s)}}(\mathbf{g}_j \mathbf{y}) \succeq 0 \\ & y_0 = 1 \end{aligned}$$

💡 dual yields the **TSSOS** hierarchy

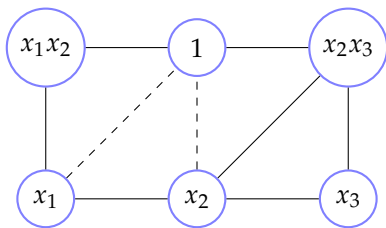
# A two-level hierarchy of lower bounds

---

$$\begin{array}{cccc} f_{\text{ts}}^{r_{\min},1} \leq & f_{\text{ts}}^{r_{\min},2} \leq & \dots \leq & f^{r_{\min}} \\ \wedge | & \wedge | & & \wedge | \\ f_{\text{ts}}^{r_{\min}+1,1} \leq & f_{\text{ts}}^{r_{\min}+1,2} \leq & \dots \leq & f^{r_{\min}+1} \\ \wedge | & \wedge | & & \wedge | \\ \vdots & \vdots & \vdots & \vdots \\ \wedge | & \wedge | & & \wedge | \\ f_{\text{ts}}^{r,1} \leq & f_{\text{ts}}^{r,2} \leq & \dots \leq & f^r \\ \wedge | & \wedge | & & \wedge | \\ \vdots & \vdots & \vdots & \vdots \end{array}$$

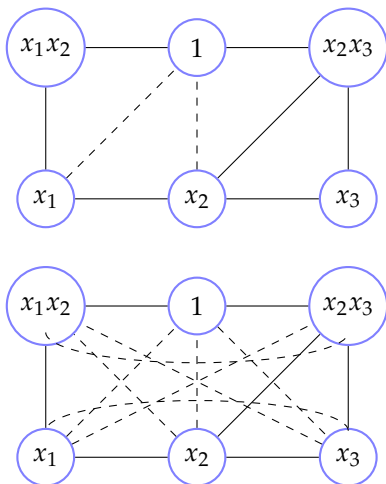
# Different choices of chordal extensions

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# Different choices of chordal extensions

---



# Term sparsity: convergence guarantees

---

Theorem [Lasserre Magron Wang '21]

Fixing a sparse order  $s$ , the sequence  $(f_{ts}^{r,s})_{r \geq r_{\min}}$  is monotonically non-decreasing.

# Term sparsity: convergence guarantees

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💡 The block structures converge to the one determined by the **sign symmetries** if the **maximal chordal extension** and monomial basis are used.

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Newton polytope  $\rightsquigarrow \mathcal{B} = (1 \quad x_1 x_2 \quad x_1 x_2^2 \quad x_1^2 x_2 \quad x_1^2 x_2^2)$



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$$x_2 \mapsto -x_2$$

Sign-symmetries blocks



$$(1 \quad x_1 x_2^2 \quad x_1^2 x_2^2) \quad (x_1 x_2 \quad x_1^2 x_2)$$

**TSSOS** blocks

$$(1 \quad x_1 x_2^2 \quad x_1^2 x_2^2) \quad (x_1 x_2) \quad (x_1^2 x_2)$$

## A second key message

---

 **TSSOS preserves the block structure  
related to sign-symmetries** 

# Comparison with (S)DSOS

---

Let  $f$  be a nonnegative polynomial of degree  $2d$

$f$  is SOS  $\Leftrightarrow f = \mathbf{v}^T \mathbf{Q} \mathbf{v}$  with  $\mathbf{Q} \succeq 0 \rightsquigarrow$  semidefinite program

where  $\mathbf{v}$  contains  $1, x_1, \dots, x_n, x_1^2, \dots, x_n^d$

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To reduce the number of “unknown” entries in  $\mathbf{Q}$ , one can force:

[Ahmadi & Majumdar '14]

- 1  $\mathbf{Q}$  diagonally dominant:  $Q_{ii} \geq \sum_{j \neq i} Q_{ij} \rightsquigarrow$  linear program
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**Theorem [Lasserre Magron Wang '21]**

The first TSSOS relaxation is always more accurate than the SDSOS relaxation

# Combining correlative & term sparsity

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  - 2 For each subsystem involving variables from one maximal clique, apply TSSOS
- 💡 a two-level CS-TSSOS hierarchy of lower bounds for  $f_{\min}$

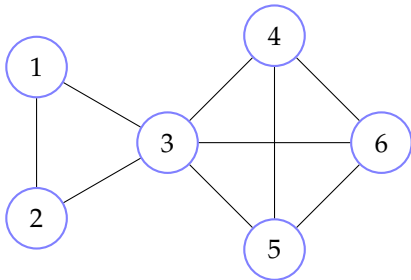


# Combining correlative & term sparsity

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$$f = 1 + \sum_{i=1}^6 x_i^4 + x_1x_2x_3 + x_3x_4x_5 + x_3x_4x_6 + x_3x_5x_6 + x_4x_5x_6$$

csp graph

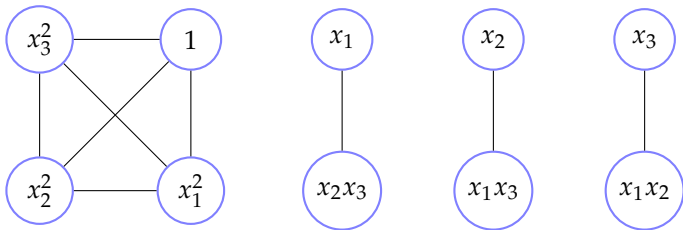


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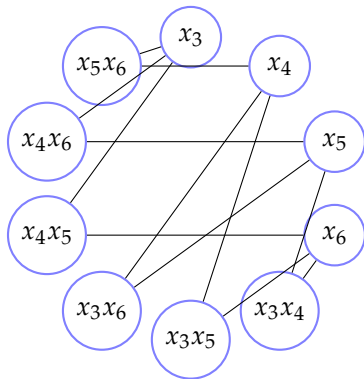
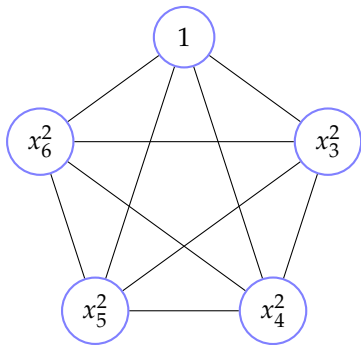
tsp graph for the first clique



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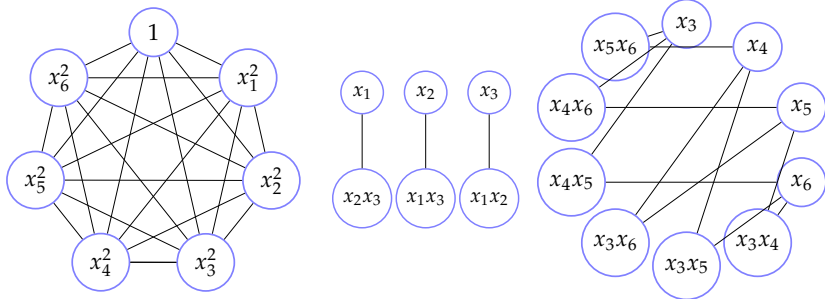
tsp graph for the second clique



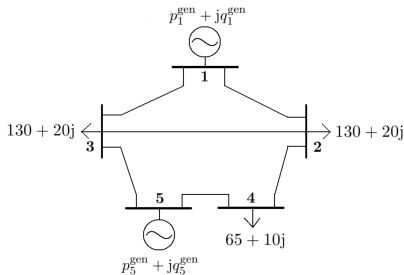
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tsp graph without correlative sparsity



# Application to optimal power-flow



Optimal Powerflow  $n \simeq 10^3$   
[Josz et al. '18]

$$\left\{ \begin{array}{l} \inf_{V_i, S_s^g, S_{ij}} \quad \sum_{s \in G} (\mathbf{c}_{2s} (\Re(S_s^g))^2 + \mathbf{c}_{1s} \Re(S_s^g) + \mathbf{c}_{0s}) \\ \text{s.t.} \quad \angle V_{\text{ref}} = 0, \\ \mathbf{S}_s^{gl} \leq \mathbf{S}_s^g \leq \mathbf{S}_s^{gu} \quad \forall s \in G, \quad \mathbf{v}_i^l \leq |V_i| \leq \mathbf{v}_i^u \quad \forall i \in N \\ \sum_{s \in G_i} \mathbf{S}_s^g - \mathbf{S}_i^d - \mathbf{Y}_i^s |V_i|^2 = \sum_{(i,j) \in E_i \cup E_i^R} S_{ij}, \quad \forall i \in N \\ S_{ij} = (\mathbf{Y}_{ij}^* - \mathbf{i} \frac{\mathbf{b}_{ij}^c}{2}) \frac{|V_i|^2}{|\mathbf{T}_{ij}|^2} - \mathbf{Y}_{ij}^* \frac{V_i V_j^*}{\mathbf{T}_{ij}}, \quad S_{ji} = \dots \\ |S_{ij}| \leq \mathbf{s}_{ij}^u, \quad \theta_{ij}^{\Delta l} \leq \angle(V_i V_j^*) \leq \theta_{ij}^{\Delta u}, \quad \forall (i,j) \in E \end{array} \right.$$

# Application to optimal power-flow

---

mb = the maximal size of blocks

$m$  = number of constraints

$n$	$m$	CS ( $r = 2$ )			CS+TS ( $r = 2, s = 1$ )		
		mb	time (s)	gap	mb	time (s)	gap
114	315	66	5.59	0.39%	31	2.01	0.73%
348	1809	253	—	—	34	278	0.05%
766	3322	153	585	0.68%	44	33.9	0.77%
1112	4613	496	—	—	31	410	0.25%
4356	18257	378	—	—	27	934	0.51%
6698	29283	1326	—	—	76	1886	0.47%

# Application to noncommutative optimization

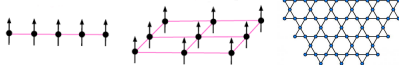
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Ground-state energy  $\Leftrightarrow$  minimal eigenvalue of an Hamiltonian

$$H = \sum_{\langle i,j \rangle} (x_i x_j + y_i y_j + z_i z_j)$$

spin states  $(x_i, y_i, z_i)$ , constraints

Lattices: 1D 2D Kagome



# Application to noncommutative optimization

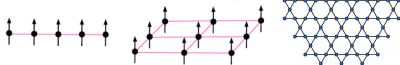
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First neighbors interactions :  $H = \sum_{i=1}^n x_i x_{i+1} + y_i y_{i+1} + z_i z_{i+1}$



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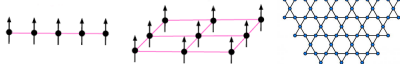
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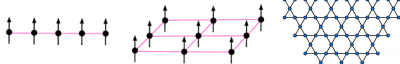
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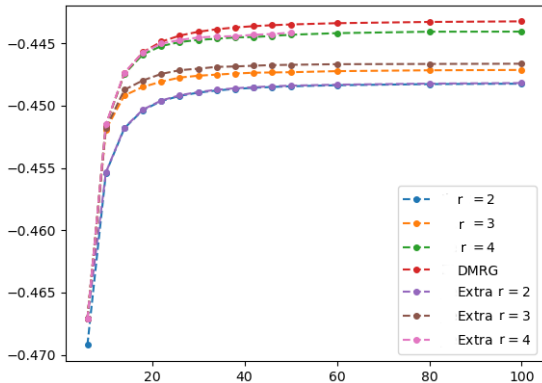
periodic boundary conditions  $\Rightarrow$   $n + 1 = 1$

Existing  $\pm$  efficient techniques: quantum Monte Carlo & variational algorithms  $\Rightarrow$  **upper bounds** on minimal energy

# Application to noncommutative optimization

Lower bounds of the energy

1D lattice

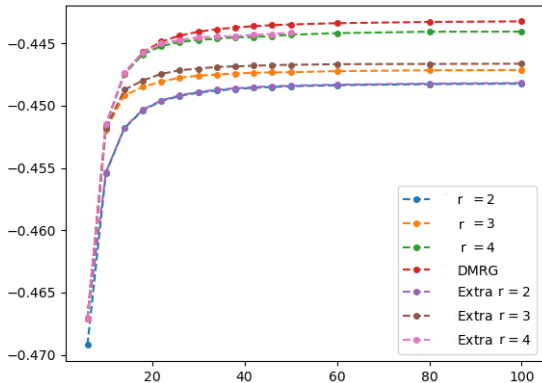


Dense  $r = 4, n = 10^2 \Rightarrow 10^{11}$  variables (solvers handle  $\simeq 10^4$ )

# Application to noncommutative optimization

Lower bounds of the energy

1D lattice



**Dense**  $r = 4, n = 10^2 \Rightarrow 10^{11}$  variables (solvers handle  $\simeq 10^4$ )

**Sparse** solved within 1 hour on PFCALCUL at LAAS

# Application to noncommutative optimization

---

## CLASSICAL WORLD

$$\psi^*(A_1 \otimes B_1 + A_1 \otimes B_2 + A_2 \otimes B_1 - A_2 \otimes B_2)\psi \leq 2$$

for separable states  $\psi \in \mathbb{C}^k \otimes \mathbb{C}^k$  and matrices  $A_j, B_j$  satisfying  $A_j^* = A_j, A_j^2 = I, B_j^* = B_j, B_j^2 = I$

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$$2\sqrt{2} = \text{tr}_{\max}\{a_1b_1 + a_1b_2 + a_2b_1 - a_2b_2 : a_j^2 = b_j^2 = 1\}$$

# Application to noncommutative optimization

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## COVARIANCES OF QUANTUM CORRELATIONS

$$\text{cov}_\psi(A, B) = \psi^*(A \otimes B)\psi - \psi^*(A \otimes I)\psi \cdot \psi^*(I \otimes B)\psi$$



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💡 2nd sparse SDP gives also 5 ... **10 times faster**

# Application to networked systems stability

---

## Lyapunov function

$$f = \sum_{i=1}^N a_i (x_i^2 + x_i^4) - \sum_{i,k=1}^N b_{ik} x_i^2 x_k^2 \quad a_i \in [1, 2] \quad b_{ik} \in \left[\frac{0.5}{N}, \frac{1.5}{N}\right]$$

$\rightsquigarrow \binom{N+2}{2} (\binom{N+2}{2} + 1) / 2$  “unknown” entries in  $Q = 231$  for  $N = 5$

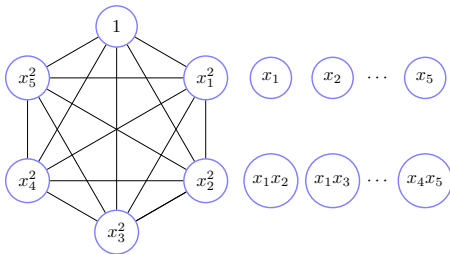
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💡 **tsp** graph  $G$



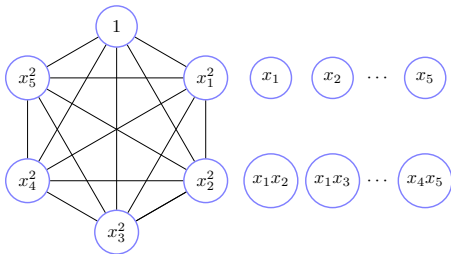
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$\rightsquigarrow (N+1)^2$  “unknown” entries in  $Q_G = 36$  for  $N = 5$

Proof that  $f \geq 0$  for  $N = 80$  in  $\sim 10$  seconds!



# Application to networked systems stability

---

Duffing oscillator Hamiltonian  $V = \sum_{i=1}^N a_i \left( \frac{x_i^2}{2} - \frac{x_i^4}{4} \right) + \frac{1}{8} \sum_{i,k=1}^N b_{ik} (x_i - x_k)^4$

On which domain  $V > 0$ ?  $f = V - \sum_{i=1}^N \underbrace{\lambda_i}_{>0} x_i^2 (g - x_i^2) \geq 0$

$$\implies V > 0 \text{ when } x_i^2 < g$$

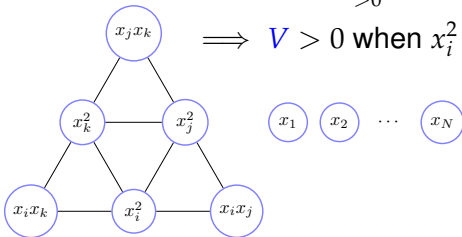
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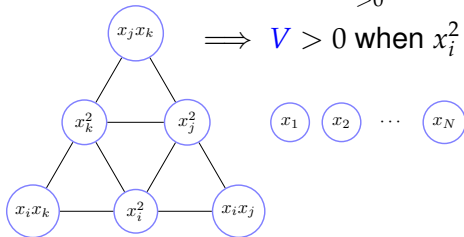
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$\rightsquigarrow \frac{N(N+1)}{2} + 6\binom{N}{2} + N$  “unknown” entries in  $Q_G = 80$  for  $N = 5$

Proof that  $f \geq 0$  for  $N = 50$  in  $\sim 1$  second!

# Application to joint spectral radius (JSR)

---

Given  $\mathcal{A} = \{A_1, \dots, A_m\} \subseteq \mathbb{R}^{n \times n}$ , the JSR is

$$\rho(\mathcal{A}) := \lim_{k \rightarrow \infty} \max_{\sigma \in \{1, \dots, m\}^k} \|A_{\sigma_1} A_{\sigma_2} \cdots A_{\sigma_k}\|^{1/k}$$

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Tons of applications:

- stability of switched linear systems
- continuity of wavelet functions
- trackability of graphs
- ...

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... NP-hard to compute/approximate

# Application to joint spectral radius (JSR)

Theorem [Parrilo & Jadbabaie '08]

Given  $\mathcal{A} = \{A_1, \dots, A_m\} \subseteq \mathbb{R}^{n \times n}$ , if a positive definite form  $f$  of degree  $2r$  satisfies

$$f(A_i \mathbf{x}) \leq \gamma^{2r} f(\mathbf{x}) \quad \forall i, \mathbf{x}$$

Then  $\rho(\mathcal{A}) \leq \gamma$

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$$\begin{aligned} \text{💡 } \rho(\mathcal{A}) \leq \rho^r(\mathcal{A}) &= \inf_{f \in \mathbb{R}[\mathbf{x}]_{2r}, \gamma} \gamma \\ \text{s.t. } &\begin{cases} f(\mathbf{x}) - \|\mathbf{x}\|_2^{2r} \text{ SOS} \\ \gamma^{2r} f(\mathbf{x}) - f(A_i \mathbf{x}) \text{ SOS} \end{cases} \end{aligned}$$



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Theorem [Parrilo & Jadbabaie '08]

Given  $\mathcal{A} = \{A_1, \dots, A_m\} \subseteq \mathbb{R}^{n \times n}$ , if a positive definite form  $f$  of degree  $2r$  satisfies

$$f(A_i \mathbf{x}) \leq \gamma^{2r} f(\mathbf{x}) \quad \forall i, \mathbf{x}$$

Then  $\rho(\mathcal{A}) \leq \gamma$

$$\begin{aligned} \text{💡 } \rho(\mathcal{A}) \leq \rho^r(\mathcal{A}) &= \inf_{f \in \mathbb{R}[\mathbf{x}]_{2r, \gamma}} \gamma \\ \text{s.t. } &\begin{cases} f(\mathbf{x}) - \|\mathbf{x}\|_2^{2r} \text{ SOS} \\ \gamma^{2r} f(\mathbf{x}) - f(A_i \mathbf{x}) \text{ SOS} \end{cases} \end{aligned}$$

Bisection on  $\gamma$  + SDP

# Application to joint spectral radius (JSR)

---

💡 At fixed  $r$ , replace  $f$  by a “term sparse”  $f$

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**Theorem: Sparse JSR [Maggio Magron Wang '21]**

$$\begin{aligned} \text{💡 } \rho(\mathcal{A}) \leq \rho^r(\mathcal{A}) \leq \rho^{r,s}(\mathcal{A}) &= \inf_{f \in \mathbb{R}[\mathcal{A}^{(s)}], \gamma} \gamma \\ \text{s.t. } &\begin{cases} f(\mathbf{x}) - \|\mathbf{x}\|_2^{2r} \text{ SOS}(\mathcal{A}^{(s)}) \\ \gamma^{2r} f(\mathbf{x}) - f(A_i \mathbf{x}) \text{ SOS}(\mathcal{A}_i^{(s)}) \end{cases} \end{aligned}$$

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Closed-loop system evolves according to either a **completed** or a **missed** computation ( $A_H$  or  $A_M$ ):  $\mathcal{A} = \{A_H A_M^i \mid i < m\}$

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💡 takes less than 10 seconds with the Sparse JSR!

Sparse SDP

Correlative sparsity

Term sparsity

**Ideal sparsity**

Tutorial session

# Ideal sparsity

---

$$f_{\min} = \inf\{f(x_1, x_2) : x_1 x_2 = 0\}$$

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**Theorem [Korda-Laurent-Magron-Steenkamp '22]**

Ideal-sparse hierarchies provide better bounds than the dense ones



ACCURACY

# Application to matrix ranks

---

Given a symmetric nonnegative matrix  $A$ , find the smallest  $r_+$  s.t.

$$A = \sum_{\ell=1}^{r_+} a_\ell a_\ell^T \quad \text{for } a_\ell \geq 0$$

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$$K_A = \{ \mathbf{x} : \sqrt{A_{ii}} x_i - x_i \geq 0, \ A_{ij} - x_i x_j \geq 0 \ (i, j) \in E_A, \\ x_i x_j = 0 \ (i, j) \in \bar{E}_A, \ A - \mathbf{x}\mathbf{x}^T \succeq 0 \}$$

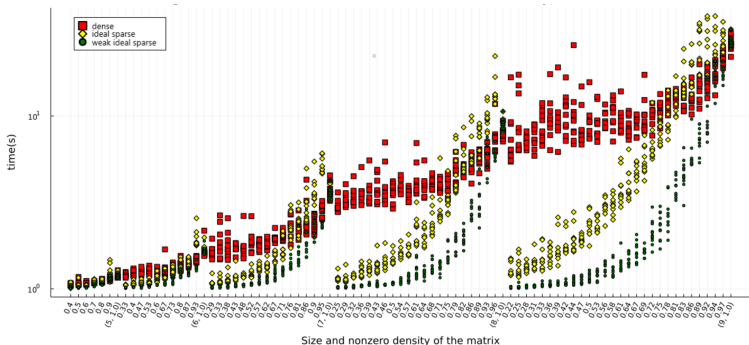
# Application to matrix ranks

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Random instances, order 2

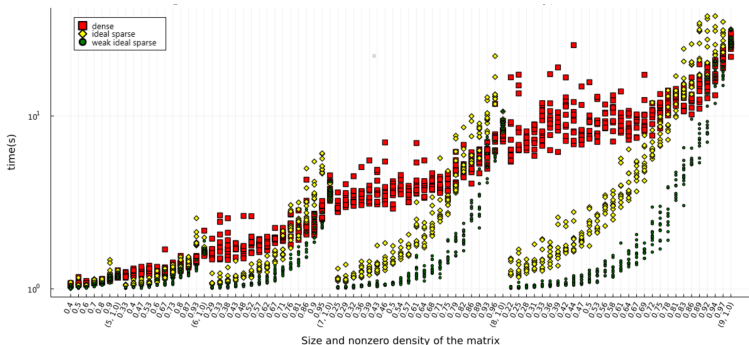
# Application to matrix ranks

## Random instances, order 2



# Application to matrix ranks

Random instances, order 2



PERFORMANCE



AND



ACCURACY



# Conclusion

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SPARSITY EXPLOITING **CONVERGING HIERARCHIES** to minimize polynomials, eigenvalue/trace, joint spectral radii

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FAST IMPLEMENTATION IN JULIA: **TSSOS**, **NCTSSOS**, **SparseJSR**

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 **Combine** correlative & term sparsity for problems with  $n = 10^3$

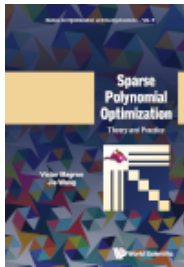
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# Further topics

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**Correlative** sparsity: Convergence rate?



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**Term** sparsity: Smart solution extraction?



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**Ideal** sparsity: tensor (nonnegative, symmetric) ranks?

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**Correlative** sparsity: Convergence rate?



**Term** sparsity: Smart solution extraction?

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Numerical conditioning of sparse SDP?



# Further topics

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**Correlative** sparsity: Convergence rate?

**Term** sparsity: Smart solution extraction?

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Numerical conditioning of sparse SDP?

Combination with symmetries?

# Further topics

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**Correlative** sparsity: Convergence rate?

**Term** sparsity: Smart solution extraction?

**Ideal** sparsity: tensor (nonnegative, symmetric) ranks?

Numerical conditioning of sparse SDP?

Combination with symmetries?

💡 Tons of applications!

# Thank you for your attention!






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`https://homepages.laas.fr/vmagron`

`GITHUB:TSSOS`








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Sparse SDP

Correlative sparsity

Term sparsity

Ideal sparsity

**Tutorial session**

# Newton polytope

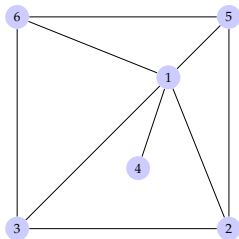
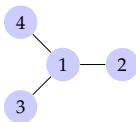
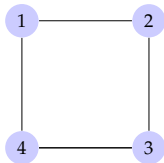
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Motzkin  $f = x_1^4 x_2^2 + x_1^2 x_2^4 - 3x_1^2 x_2^2 + 1$

- 1 Compute the Newton polytope of  $f$
- 2 Show that  $f$  is not SOS

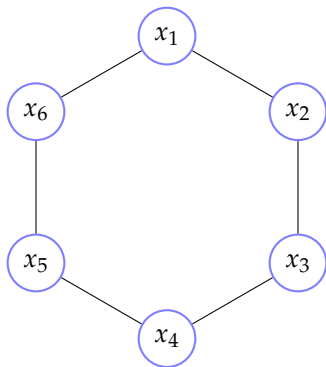
# Chordal or not chordal?

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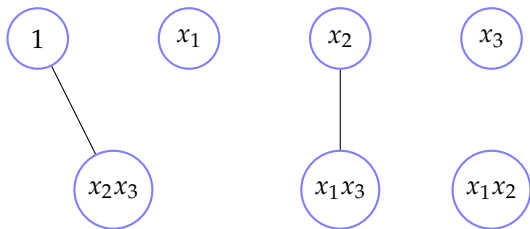
# Chordal extension

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# Support extension

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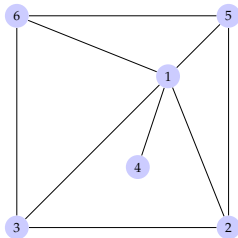


# How big is CS?

---

$$f(\mathbf{x}) = x_2x_5 + x_3x_6 - x_2x_3 - x_5x_6 + x_1(-x_1 + x_2 + x_3 - x_4 + x_5 + x_6)$$

Chordal graph after adding edge (3,5)

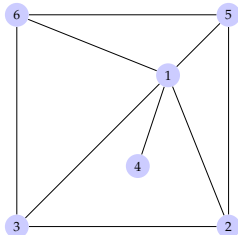


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How many SDP variables in the dense and sparse relaxation at order  $r = 1, 2, 3$ ?

# Moment matrix

---

Write the first (correlative) sparse moment relaxation of

$$\begin{aligned} \inf_x \quad & x_1x_2 + x_1x_3 + x_1x_4 \\ \text{s.t.} \quad & x_1^2 + x_2^2 \leq 1 \\ & x_1^2 + x_3^2 \leq 1 \\ & x_1^2 + x_4^2 \leq 1 \end{aligned}$$



# Measure LP preserves sparsity

---

$f = f_1 + f_2$ ,  $f_k$  depends on  $I_k$ ,  $\mathbf{X}$  compact & each  $g_j$  depends either on  $I_1$  or  $I_2$ .

# Measure LP preserves sparsity

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$$f_{\min} = \inf_{\mu \in \mathcal{M}_+(\mathbf{X})} \int_{\mathbf{X}} f d\mu = f_{\text{CS}} = \inf_{\mu_1, \mu_2} \int_{\mathbf{X}_1} f_1 d\mu_1 + \int_{\mathbf{X}_2} f_2 d\mu_2$$

s.t.  $\pi_{12}\mu_1 = \pi_{21}\mu_2$   
 $\mu_1 \in \mathcal{M}_+(\mathbf{X}_1), \quad \mu_2 \in \mathcal{M}_+(\mathbf{X}_2)$

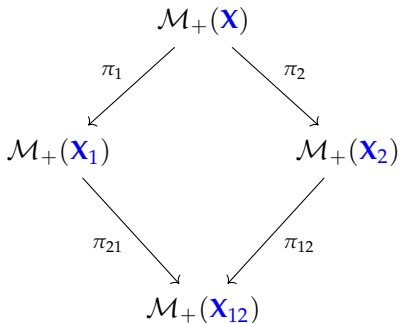
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💡  $(\mu_k)$  feasible for  $f_{\text{CS}} \implies \exists \mu \in \mathcal{M}_+(\mathbf{X})$  with marginal  $\mu_k$  on  $\mathbf{X}_k$



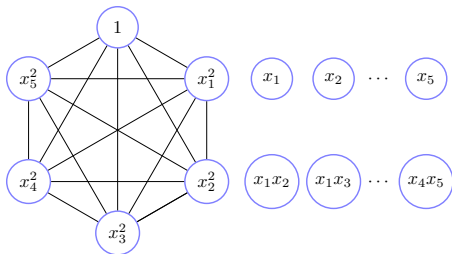
$$f = \sum_{i=1}^N (x_i^2 + x_i^4) - \sum_{i,k=1}^N x_i^2 x_k^2$$

How many entries in the dense & sparse SOS/moment matrices?

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💡 **tsp** graph  $G$



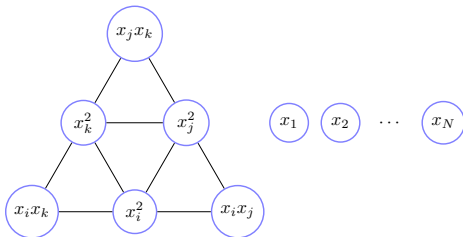
$$f = \sum_{i=1}^N \left( \frac{x_i^2}{2} - \frac{x_i^4}{4} \right) + \sum_{i,k=1}^N (x_i - x_k)^4$$

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Compute the dense relaxation  $f^2$

Compare with the correlative sparse relaxation  $f_{cs}^2$

Compare with the term sparse relaxation  $f_{ts}^{2,s}$  for  $s = 1, 2, \dots$

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💡 Install and run TSSOS:

```
] add https://github.com/wangjie212/TSSOS  
using TSSOS, DynamicPolynomials
```

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💡 Install and run TSSOS:

```
] add https://github.com/wangjie212/TSSOS
using TSSOS, DynamicPolynomials
@polyvar x1 x2 x3; x=[x1;x2;x3];
f1 = x1^4+(x1*x2-1)^2; f2 = x2^2*x3^2+(x3^2-1)^2;
f = f1+f2
```

$$f_1 = x_1^4 + (x_1x_2 - 1)^2 \quad f_2 = x_2^2x_3^2 + (x_3^2 - 1)^2 \quad f = f_1 + f_2$$

Compute the dense relaxation  $f^2$

Compare with the correlative sparse relaxation  $f_{CS}^2$

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f = f1+f2
dense2,sol,data=cs_tssos_first([f], x, 2,
CS=false,TS=false);
```

Download from <https://homepages.laas.fr/vmagron/ncball>:

$$f = f_1 + f_2 \quad \mathbb{B}_{nc} = \{x : 1 - x_1^2 - x_2^2 - x_3^2 \succcurlyeq 0, 1 - x_2^2 - x_3^2 - x_4^2 \succcurlyeq 0\}$$

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Compute  $\lambda_{\min}(f)$  on  $\mathbb{B}_{nc}$  with 2nd dense relaxation

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Compute  $\lambda_{\min}(f)$  on  $\mathbb{B}_{nc}$  with 2nd dense relaxation

```
cs_nctssos_first([f;ncball],x,2,CS=false, TS=false,  
obj="eigen");
```

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```

Compare with the correlative and term sparse relaxations