

# Optimization over trace polynomials

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Joint work with Igor Klep and Jurij Volcic

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$S \subset \text{Sym } \mathbb{T}$   $X_j$  operators from finite von Neumann algebra


Constraints  $\mathcal{D}_S = \{ \underline{X} = (X_1, \dots, X_n) : s(\underline{X}) \succcurlyeq 0, \quad \forall s \in S \}$



# Optimization over $\mathbb{T}$ : special cases

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- **Eigenvalue** optimization  no traces [Helton-McCallough 04, Navascuez-Pironio-Acin 08]


 Bounded self-adjoint operators on Hilbert spaces  $\rightsquigarrow \mathcal{D}_S^\infty$

$$\begin{aligned}\lambda_{\min} &= \inf \{ \langle a(\underline{X}) \mathbf{v}, \mathbf{v} \rangle : \underline{X} \in \mathcal{D}_S^\infty, \|\mathbf{v}\| = 1 \} \\ &= \sup \{ \lambda \mid a(\underline{X}) - \lambda \mathbf{I} \succcurlyeq 0, \quad \forall \underline{X} \in \mathcal{D}_S^\infty \}\end{aligned}$$

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- Finite-dimensional matrices [Klep-Spenko-Volcic 18]:  
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- Univ case [Klep-Pascoe-Volcic]:  $a \succcurlyeq 0 \Rightarrow a = \text{SOHS/SOHS}$
- Multilinear case [Huber]

# Motivation: quantum information

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Entanglement in quantum mechanics

→ **upper bounds** for violation levels of Bell inequalities

[Fukuda-Nechita 14] limit output states with input having specific parameters → bounds for generalized tensor traces

[Pozas et al 19] “scalar extension” of NPA hierarchy → identify correlations not attainable in entanglement-swapping scenario

NC operators  $A_i, C_k$  satisfy causal constraints:

$$\mathrm{tr}(A_{i_1} \cdots A_{i_m} C_{k_1} \cdots C_{k_m}) - \mathrm{tr}(A_{i_1} \cdots A_{i_m}) \mathrm{tr}(C_{k_1} \cdots C_{k_m}) = 0.$$

💡 Additional variables for each  $\mathrm{tr}(w)$  but no convergence proof

# Contribution

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## Theorem: T variant of Helton-McCullough Psatz

Let  $S \subset \text{Sym } \mathbb{T}$  and  $a \in \mathbb{T}$ . The Positivstellensatz-induced hierarchy of semidefinite programs produces a convergent increasing sequence with limit  $\inf_{\mathcal{D}_S^{\text{II}_1}} a$ .

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💡 Also a cyclic Positivstellensatz for  $\mathbb{T}$  (not enough time today)



Moment-sums of squares hierarchies

Non-cyclic Psatz for T

SDP hierarchies

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# Commutative Polynomial Optimization

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**NP hard General Problem:**  $f^* := \min_{\mathbf{x} \in \mathcal{D}_S} f(\mathbf{x})$

Semialgebraic set  $\mathcal{D}_S = \{\mathbf{x} \in \mathbb{R}^n : s_j(\mathbf{x}) \geq 0\}$

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$$\underbrace{x_1 x_2}_f = -\frac{1}{8} + \frac{1}{2} \overbrace{\left(x_1 + x_2 - \frac{1}{2}\right)^2}^{\sigma_0} + \frac{1}{2} \overbrace{x_1(1 - x_1)}^{\sigma_1} + \frac{1}{2} \overbrace{x_2(1 - x_2)}^{\sigma_2}$$

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

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Can be computed with SDP solvers (CSDP, SDPA, MOSEK)

**“No Free Lunch” Rule:**  $\binom{n+2r}{n}$  SDP variables

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$\mathcal{M}(S)$  Archimedean quadratic module:  $N - \sum_i x_i^2 \succcurlyeq 0$

Theorem: NC Putinar's Psatz [Helton-McCullough 02]

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

💡 replace " $a - \lambda \mathbf{I} \succcurlyeq 0$  on  $\mathcal{D}_S^\infty$ " by  $a - \lambda \mathbf{1} \in \mathcal{M}(S)_r$

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$a - \lambda \mathbf{1} = \sum_i h_i^* h_i + \sum_j \sum_i t_{ji}^* s_j t_{ji}$  with  $h_i, t_{ji}$  of **bounded** degrees

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$\mathrm{tr}_{\min}^{\mathrm{II}_1}$  = minimal trace over the union of type  $\mathrm{II}_1$  vN algebras

💡 Disproving Connes' embedding conjecture:  $\mathrm{tr}_{\min}^{\mathrm{II}_1} < \mathrm{tr}_{\min}$

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Converging hierarchy with cyclic quadratic modules:

💡 replace " $\text{tr}(a - m) \geq 0$  on  $\mathcal{D}_S^{\text{II}_1}$ " by  $a - m\mathbf{1} \in \mathcal{M}^{\text{cyc}}(S)_r$

$\mathcal{M}^{\text{cyc}}(S)_r$  = polynomials with same trace as some from  $\mathcal{M}(S)_r$

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# Kadison-Dubois representation theorem

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$$\chi_{\mathcal{M}} := \{ \varphi : \mathbb{T} \rightarrow \mathbb{R} \mid \varphi \text{ homomorphism, } \varphi(\mathcal{M}) \subseteq \mathbb{R}_{\geq 0}, \varphi(1) = 1 \}$$

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**Theorem: Kadison-Dubois [Marshall 08]**

Given an Archimedean quadratic module  $\mathcal{M} \subseteq \mathbb{T}$  &  $a \in \mathbb{T}$ :

$$\forall \varphi \in \chi_{\mathcal{M}} \quad \varphi(a) \geq 0 \quad \Leftrightarrow \quad \forall \varepsilon > 0 \quad a + \varepsilon \in \mathcal{M}$$

# Non-cyclic Psatz for T

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For  $S \subseteq T$ , “augment”  $S$  with traces of hermitian squares:

$$S(N) = S \cup \{\operatorname{tr}(pp^*) \mid p \in \mathbb{R}\langle \underline{x} \rangle\} \cup \{N^k - \operatorname{tr}(x_j^{2k}) \mid k \in \mathbb{N}\} \subseteq T$$

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**Lemma [Klep-M.-Volcic 20]**

$\mathcal{M}(S(N))$  is archimedean



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**Proof**

By induction:  $\forall w \in \langle \underline{x} \rangle$ ,  $m \pm \operatorname{tr}(w) \in \mathcal{M}(S(N))$  for some  $m > 0$

$$w = x_j^{2k} \implies N^k + 1 + 2 \operatorname{tr}(x_j^k) = (N^k - \operatorname{tr}(x_j^{2k})) + \operatorname{tr}((x_j^k + 1)^2)$$

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**Theorem: Non-cyclic Psatz for T [Klep-M.-Volcic 20]**

$$a \geq 0 \text{ on } \mathcal{D}_{S[N]}^{\Pi_1} \iff a + \varepsilon \in \mathcal{M}(S(N)) \text{ for all } \varepsilon > 0$$

Moment-sums of squares hierarchies

Non-cyclic Psatz for T

**SDP hierarchies**

## Tracial words & moment matrices

---

$\mathbb{T}$ -words =  $\{\prod_i \text{tr}(u_i)v \mid u_i, v \in \langle \underline{x} \rangle\}$  and T-words  
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$\mathbf{W}_r^{\mathbb{T}}$  = vector of  $\mathbb{T}$ -words of with tracial degree  $\leq r$   
 $n = 1$ :  $\mathbf{W}_2^{\mathbb{T}}$  contains  $1, x_1, x_1^2, \text{tr}(x_1), \text{tr}(x_1^2), \text{tr}(x_1)x_1$

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Tracial moment matrix  $\mathbf{M}_r^{\mathbb{T}}(L)$  for a linear functional  $L : \mathbb{T} \rightarrow \mathbb{R}$ :

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# SDP hierarchy for $\mathbf{T}$

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Reminder:

$$S(N) = S \cup \{\operatorname{tr}(pp^*) \mid p \in \mathbb{R}\langle \underline{x} \rangle\} \cup \{N^k - \operatorname{tr}(x_j^{2k}) \mid k \in \mathbb{N}\} \subseteq \mathbf{T}$$



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Elements of  $\mathcal{M}(\mathcal{S}(N))_r$  are

$$a_1^2 s \quad a_2^2 (N^k - \operatorname{tr}(x_j^{2k})) \quad \operatorname{tr}(ff^*)$$

for  $s \in \mathcal{S}$ ,  $a_i \in \mathbb{T}$ ,  $f \in \mathbb{T}$

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**Theorem [Klep-M.-Volcic 20]**

There is no duality gap and  $a_r \rightarrow a_{\min}^{\text{II}_1}$  as  $r \rightarrow \infty$

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$S \subset \text{Sym } \mathbb{T}$

💡 Reduction from the general trace setting to the pure trace

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# Linear Bell inequalities

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## 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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 $\psi^*(X \otimes Y)\psi = \text{tr}(XY)$

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

# Polynomial Bell inequalities

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## COVARIANCES OF QUANTUM CORRELATIONS

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

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for separable states but ...

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💡 2nd SDP relaxation of the corresponding trace problem outputs 5

⇒ The max value is 5 for **all** maximally entangled state

# Conclusion and perspectives

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CONVERGING HIERARCHIES to minimize pure trace polynomials

**Implementation** in progress



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Exploiting SPARSITY of cost and constraints?

# Thank you for your attention!

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



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[NCSOStools](#) [NCTSSOS](#)