# Limitations of monogamy, Tsirelson-type bounds, and other SDPs in quantum information

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QMA(2) Workshop, UMD



#### **SDPs in Quantum Information**

Semidefinite Programmings (SDPs) admit *polynomial time* solvers and plays an important role in quantum information.

- Consistency of reduced states, Quantum conditional min-entropy, local Hamiltonians
- QIP=PSPACE, QRG=EXP, ......

This talk is, however, about its limitation in

- Separability or entanglement detection,
- Approximation of Bell-violation (non-local game values).

Result: unconditional limitations of SOS/SDPs comparable to existing computational hardness.



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# **Problem 1: Separability**

#### **Definition (Separable and Entangled States)**

A bi-partitie state  $\rho \in D(\mathcal{X} \otimes \mathcal{Y})$  is *separable* if  $\exists$  dist.  $\{p_i\}$ ,

$$\rho = \sum p_{i}\sigma_{X}^{i}\otimes\sigma_{Y}^{i}, \text{ s.t. } \sigma_{X}^{i}\in \mathrm{D}\left(\mathcal{X}\right), \sigma_{Y}^{i}\in \mathrm{D}\left(\mathcal{Y}\right).$$

Otherwise,  $\rho$  is *entangled*. Let Sep  $\stackrel{\text{def}}{=}$  { separable states }.

#### **Definition (Entanglement Detection**

A KEY problem: given the description of  $\rho \in D(\mathcal{X} \otimes \mathcal{Y})$ , decide

Either  $ho\in\mathsf{Sep}$ , or ho is far away from  $\mathsf{Sep}$ .



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### **Alternative Formulation**

#### **Definition (Weak Membership)**

WMem $(\epsilon, \|\cdot\|)$ : for any  $\rho \in D(\mathcal{X} \otimes \mathcal{Y})$ , decide either  $\rho \in Sep$  or  $\|\rho - Sep\| \ge \epsilon$ .

Via standard techniques in convex optimization, equivalent to

#### **Definition (Weak Optimization)**

 $\mathsf{WOpt}(M, \epsilon)$ : for any  $M \in \mathsf{Herm}\,(\mathcal{X} \otimes \mathcal{Y})$ , estimate the value of

$$h_{\mathsf{Sep}(d,d)}(\mathit{M}) := \max_{
ho \in \mathsf{Sep}} \left\langle \mathit{M}, 
ho 
ight
angle,$$

with additive error  $\epsilon$ .



# $h_{\text{Sep}(d,d)}(M)$

$$h_{\mathsf{Sep}(d,d)}(M) := \max_{\substack{x,y \in \mathbb{C}^d \\ \|x\|_2 = \|y\|_2 = 1}} \sum_{i,j,k,l \in [d]} M_{ij,kl} x_i^* x_j y_k^* y_l. \tag{1}$$

**REMARK**: this is an instance of *polynomial optimization* problems with a homogenous degree 4 objective polynomial and a degree 2 constraint polynomial.

#### **Quantum Information:**

- Mean-field approximation in statistical quantum mechanics.
- Positivity test of quantum channels
- Data hiding, Channel capacities, Privacy, ......
- 17 more examples in quantum information in [HM10].

#### Quantum Complexity:

Quantum Merlin-Arthur Game with Two-Provers (QMA(2))

#### Classical Complexity:

• Unique Game Conjecture and Small-set Expansion.  $(\ell_2 \rightarrow \ell_4 \text{ norm})$ 



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#### **Separability Criterions:**

- Positive Partial Transpose (PPT) :  $\rho^{T_y} = \rho$ ? [PH]
- Reduction Criterions:  $I_X \otimes \rho_Y \geq \rho$ ? [HH]
- FAILURE: any such test has arbitrarily large error. [BS]

#### Doherty-Parrilo-Spedalieri (DPS) hierarchy:

•  $\rho$  is k-extendible if  $\exists$  symmetric  $\sigma \in D(\mathcal{X} \otimes \mathcal{Y}_1 \otimes \cdots \otimes \mathcal{Y}_k)$ ,  $\forall i, \rho = \sigma_{XY}$ .

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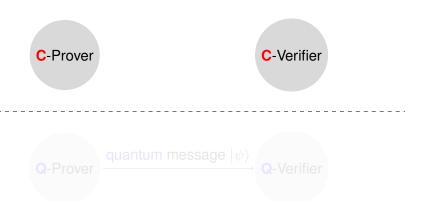
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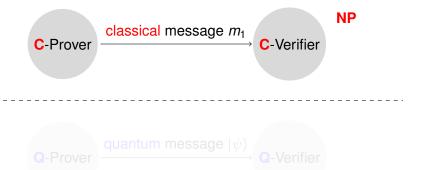


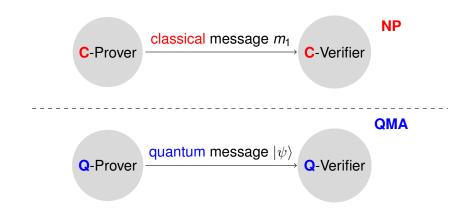


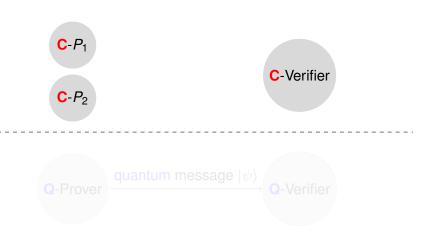


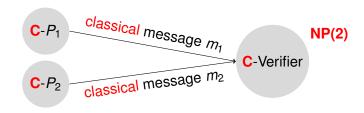


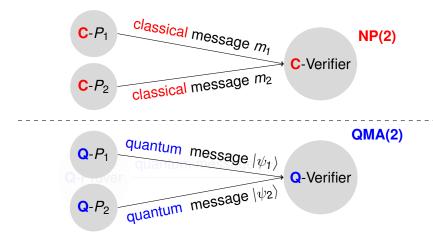


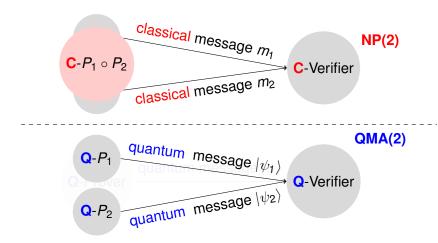


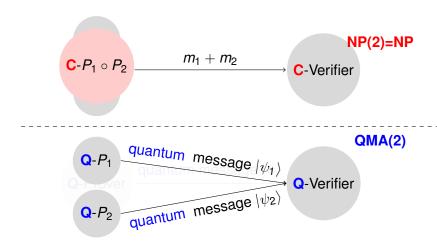


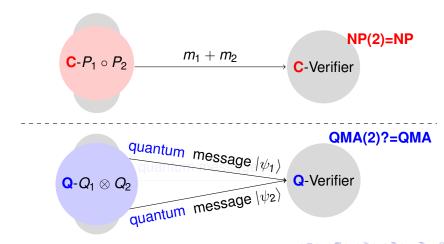












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- QMA(2) solves 3SAT (constant gaps) with  $O(\sqrt{n})$ -qubit proofs [ABD+, CD].
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# **History about QMA(2)**

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reference	k	С	s	n
GNN12	2	1	$1 - \frac{1}{d \cdot \operatorname{poly} \log(d)}$	<i>O</i> ( <i>d</i> )
Per12	2	1	$1-\frac{1}{\operatorname{poly}(d)}$	O(d)
AB+08	$\sqrt{d}$ · poly log(d)	1	0.99	O(d)
CD10	$\sqrt{d}$ · poly log(d)	$1 - 2^{-d}$	0.99	O(d)
HM13	2	1	0.01	$\frac{\log^2(d)}{\text{poly log}(d)}$

**Table:** Hardness results for  $h_{Sep^k(d)}$  (k-partitle  $h_{Sep(d,d)}$ ).

Hardness: determining satisfiability of 3-SAT instances with n variables and O(n) clauses can be reduced to distinguishing between  $h_{\operatorname{Sep}^k(d)} \geq c$  and  $\leq s$  as above.



### **Exponential Time Hypothesis (ETH)**

The 3-SAT problem with *n* variables requires  $2^{\Omega(n)}$  time to solve.

 $h_{\text{Sen}(d)}$  with constant precision requires  $d^{\Omega(\log(d))}$  time.

• A matching upper bound: DPS to  $O(log(d)/c^2)$  level for  $1.1 \, OCC \, M$ ; time  $dO(log(d)/c^2) = dO(log(d))$ 



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### Will the hardness of $h_{Sep(d)}$ for const $\epsilon$ hold w/o ETH?

#### Theorem (Main I.1)

The DPS hierarchy (or general Sum-of-Squares SDP) requires  $\Omega(\log(d))$  levels to solve  $h_{\text{Sep}(d)}$  with constant precision.

#### Theorem (Main I.2)

Any SDP relaxation that estimates  $h_{Sep(d)}(M)$  with  $O(1/d^2)$  errors requires size  $d^{\overline{\Omega}(\log(d))}$ .



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- Input dimension  $\dim(\mathcal{H}) = \infty$  for  $\epsilon = \delta = 0$  [AB+09]
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- Two physically separated players Alice and Bob. No communication once the game starts.
- Sets of questions S, T and answers A, B and a distribution
   π : S × T → [0, 1].
- Sample  $(s, t) \in S \times T \sim \pi$  and ask Alice and Bob respectively. Obtain answers  $a \in A, b \in B$ .
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# **Problem 2: Non-local Games (cont'd)**

### Strategies:

- Denote by P[a, b|s, t] the probability of answering (a, b) upon receiving (s, t).
- Quantum strategies: share a quantum state  $|\psi\rangle \in \mathcal{H}_A \otimes \mathcal{H}_E$  and answer w.r.t measurements  $\{A_s^a\}$  and  $\{B_t^b\}$ ,

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# **Problem 2: Non-local Games (cont'd)**

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### **Definition (Game Value)**

$$\omega(G) = \max_{P} \sum_{a.b.s.t} \pi(s,t) V(a,b|s,t) P(a,b|s,t).$$

Example: CHSH game

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$$A = B = S = T = \{0, 1\}$$
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$$\omega^*(\textit{G}) = \lim_{\textit{d} \to \infty} \max_{|\psi\rangle \in \mathbb{C}^{\textit{d} \times \textit{d}}} \max_{\textit{A}_{\textit{s}}^{\textit{a}}, \textit{B}_{t}^{\textit{b}}} \sum_{\textit{a},\textit{b},\textit{s},\textit{t}} \pi(\textit{s},\textit{t}) \textit{V}(\textit{a},\textit{b}|\textit{s},\textit{t}) \left\langle \psi \right| \textit{A}_{\textit{s}}^{\textit{a}} \otimes \textit{B}_{t}^{\textit{b}} \left| \psi \right\rangle.$$

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reference	k	С	s	n
KK+11	3	1	$1 - \frac{1}{\operatorname{poly}(Q)}$	O(Q)
IKM09	2	1	$1 - \frac{1}{\operatorname{poly}(Q)}$ $2^{-Q^{\Omega(1)}}$	O(Q)
IV12	4	1	$2^{-Q^{\Omega(1)}}$	$Q^{\Omega(1)}$
Vid13	3	1	$2^{-Q^{\Omega(1)}}$	$Q^{\Omega(1)}$

**Table:** Hardness results for  $\omega^*(G)$  where G is a one-round k-prover interactive proof protocol with question alphabet size Q. Hardness in the following sense: determining satisfiability of 3-SAT instances with n variables and O(n) clauses can be reduced to distinguishing between  $\omega^*(G) \geq c$  and  $\leq s$  as above.

### Will the hardness of $\omega^*(G)$ hold w/o ETH?

#### Theorem (Main II.1)

There exists a family of games  $\{G_n\}$  s.t. the NPA hierarchy requires  $\Omega(n)$  levels to distinguish  $\omega^*(G) = 1$  from  $\omega^*(G) = 1 - \Omega(1/n^2)$ .

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- Introduce hardness of SDPs/SoS into quantum problems.
  - Deal with their limitations, such as boolean domains, pattern matrices, and non-commutative problems.

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Formulate a framework of reductions for this purpose.
 Other applications, e.g., Nash's equilibria [HNW16].



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# **Principle of Sum-of-Squares**

One way to show that a polynomial f(x) is *nonnegative* could be

$$f(x)=\sum a_i(x)^2\geq 0.$$

### **Example**

$$f(x) = 2x^2 - 6x + 5$$
  
=  $(x^2 - 2x + 1) + (x^2 - 4x + 4)$   
=  $(x - 1)^2 + (x - 2)^2 \ge 0$ .

Such a decomposition is called a *sum of squares (SOS)* certificate for the non-negativity of f. The min degree,  $deg_{sos}$ .



# Principle of SoS: constrained domain

### **Definition (Variety)**

A set  $V \subseteq \mathbb{C}^n$  is called an *algebraic variety* if  $V = \{x \in \mathbb{C}^n : g_1(x) = \dots = g_k(x) = 0\}.$ 

Non-negativity of f(x) on V could be shown by

$$f(x) = \sum a_i(x)^2 + \sum b_j(x)g_j(x) \ge 0.$$

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# **SoS in Optimization**

is equivalent to (justified by *Positivstellensatz*)

min 
$$\nu$$
 such that  $\nu - f(x) = \sigma(x) + \sum_{i} b_i(x)g_i(x)$ , (3)

where  $\sigma(x)$  is SOS and  $b_i(x)$  is any polynomial.

## **Pseudo-distribution**

#### **Dual of the SOS cone**

- Let  $\Sigma_{n,2D}$  be the cone of all PSD matrices representing SOS polynomials with degree up to 2D.
- The dual cone  $\Sigma_{n,2D}^*$  is moment  $M_D(x) \geq 0$ , where entry  $(\alpha,\beta)$  of  $M_D(x)$  is  $\int x^{\alpha+\beta}\mu(dx), |\alpha|, |\beta| \leq D$ .

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A degree-2*d* pseudo-expectation  $\tilde{\mathbb{E}}$  is an element of  $\mathcal{R}[x]_{2d}^*$  (i.e. a linear map from  $\mathcal{R}[x]_{2d}$  to  $\mathcal{R}$ ) satisfying

- Normalization.  $\tilde{\mathbb{E}}[1] = 1$ .
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# Recall $h_{Sep(d,d)}(M)$

$$h_{\text{Sep}(d,d)}(M) := \max_{\substack{x,y \in \mathbb{C}^d \\ \|x\|_2 = \|y\|_2 = 1}} \sum_{i,j,k,l \in [d]} M_{ij,kl} x_i^* x_j y_k^* y_l.$$
 (6)

Its SOS hierarchy is the DPS hierarchy with full symmetry.

$$\rho \propto \sum_{\substack{i_1 i_2 \dots i_d \\ i_1 i_2 \dots i_d}} \tilde{\mathbb{E}}_{x}[x_{i_1} \dots x_{i_d} x_{j_1} \dots x_{j_d}] |i_1 \dots i_d\rangle \langle j_1 \dots j_d|.$$

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### Lee-Raghavendra-Steurer

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# **Integrality Gaps**

## What constitutes an integrality gap?

- An instance  $\Phi$  that has  $f_{\text{opt}}(\Phi)$  is small.
- But  $f_{SoS}^d(\Phi)$  is large for some  $d \Rightarrow$  lower bound at level d.

### Example

- 3XOR: O(n) clauses on n boolean variables:
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- **Pseudo-completeness**:  $f_{SoS}^{d_A}(\Phi^A)$  large  $\Rightarrow f_{SoS}^{d_B}(\Phi^B)$  large,  $d_B$  is not too smaller than  $d_A$ .

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## More on the low-degree reduction

#### Lemma

Let  $A \subset \mathbb{R}^n$ ,  $B \subset \mathbb{R}^m$  be algebraic varieties, meaning that

$$A = \{x \in \mathbb{R}^n : g_1(x) = \cdots = g_{n'}(x) = 0\}$$

$$B = \{x \in \mathbb{R}^m : h_1(x) = \cdots = h_{m'}(x) = 0\},\$$

for some polynomials  $\{g_i\}, \{h_i\}.$ 

Suppose that p is a degree- $\frac{d}{d}$  polynomial map from  $\mathbb{R}^n \to \mathbb{R}^m$  such that  $p(A) \subseteq B$ .

Let  $\tilde{\mathbb{E}}_A \in \mathbb{R}[x_1, \dots, x_n]_\ell^*$  be a degree- $\ell$  pseudo-expectation (compatible with the constraints  $g_1, \dots, g_{n'}$ )  $\Rightarrow$  a degree- $\ell/d$  pseudo-expectation  $\tilde{\mathbb{E}}_B \in \mathbb{R}[y_1, \dots, y_m]_{\ell/d}^*$  (compatible with the constraints  $h_1, \dots, h_{m'}$ ).

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SDP lower bounds (LRS)



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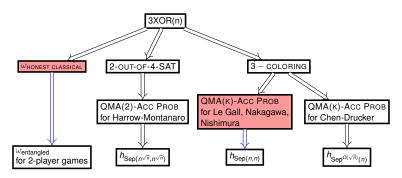
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# Real reductions for $h_{Sep}$ and $\omega^*(G)$



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# Reduction for $h_{Sep}$ : Inspired by Aaronson et al.

$$3SAT \underset{R_1}{\Longrightarrow} 2$$
-OUT-OF-4-SAT  $\underset{R_2}{\Longrightarrow} QMA(2)$ -ACC PROB $\underset{R_3}{\Longrightarrow} h_{Sep}$ 

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## SDP lower bound: the tricky condition

#### LRS core technical object: the pattern matrix

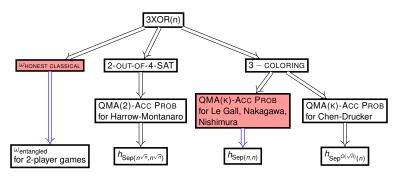
$$M_f^n : [n]^m \times \{0,1\}^n \mapsto \mathbb{R}_{\geq 0}, M_f^n(S,x) = c - f(x_S).$$

#### Lemma (Theorem 3.8 of LRS)

Suppose  $\Phi$  is an instance of an optimization problem over m variables, and  $\deg_{SoS}(c-f_{\Phi}(x)) \geq d$ . Then for  $n \geq m^{d/4}$ ,  $\operatorname{rk}_{psd}(M_f^n) \geq \Omega(m^{d^2/8})$ .

Make  $M_f^n$  a sub-matrix of the slack-matrix of your optimization problem. The tricky condition.

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### **Summary**

#### Results

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- Match ETH-based bounds for h<sub>Sep</sub>.
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#### Technical Contribution

- A reduction framework. Already find an application to the Nash equilibria.
- Reductions for general domains and non-commutative problems.



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#### **Question And Answer**

Thank you! Q & A

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#### Observation

- Any p(x) (of degree 2D) =  $m^T Qm$ , where m is the vector of monomials of degree up to 2D and Q is the coefficients.
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