

Semidefinite optimization for polynomials in noncommuting variables




Networks & Optimization
Algorithm & Complexity


Scientific Meeting, June 2014

Sabine Burgdorf


What are we up to?

- ▶ Generalize polynomial optimization over scalar variables 
- ▶ Want to optimize polynomials evaluated in matrices $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$


What do we need?

- ▶ Polynomials in noncommuting variables $EAT \neq TEA$
- ▶ Approximation technique using semidefinite programs 



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What do I need it for?

- ▶ Applications in quantum physics 
 - ▶ quantum chemistry: ground state electronic energy of atoms
 - ▶ quantum theory: upper bounds for violation of Bell inequalities
 - ▶ quantum information: multi prover games/quantum correlation
- ▶ Application in systems control 
 - ▶ Systematic strategy to compute stabilizing feedback for closed loop systems

- ▶ $p \in \mathbb{R}[\underline{x}]$ polynomial
- ▶ Find

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Example

A matrix M is copositive if $p_{min} \geq 0$ for $p = \sum_{i,j} M_{ij} x_i^2 x_j^2$.

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Problem

Calculating p_{min} is in general NP-hard 😞

- ▶ Find a way to make it easier → approximation
- ▶ Involves sums of squares and semidefinite programs 😊

$$\begin{aligned} \max \quad & \langle C, X \rangle \\ \text{s.t.} \quad & \langle A_j, X \rangle = b_j, \quad j = 1, \dots, m \\ & X \succeq 0 \end{aligned}$$

$$\max \langle C, X \rangle$$

$$\text{s.t. } \langle A_j, X \rangle = b_j, \quad j = 1, \dots, m$$

$$X \succeq 0$$

← linear function

- Optimization of a **linear function**

$$\max \langle C, X \rangle$$

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← affine space

- Optimization of a **linear function** over an **affine space**

$$\begin{array}{l} \max \langle C, X \rangle \\ \text{s.t. } \langle A_j, X \rangle = b_j, \quad j = 1, \dots, m \\ X \succeq 0 \end{array}$$

← psd matrix

- Optimization of a **linear function** over an **affine space** intersected with the set of **positive semidefinite matrices**:

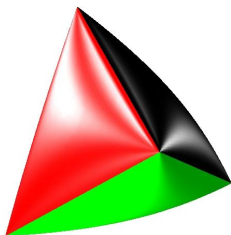
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} spectrahedron

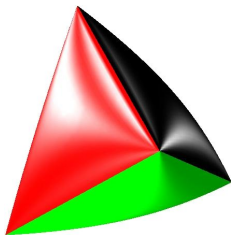
- Optimization of a **linear function** over an **affine space** intersected with the set of **positive semidefinite matrices**: a *spectrahedron*



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- ▶ Optimization of a **linear function** over an **affine space** intersected with the set of **positive semidefinite matrices**: a *spectrahedron*

poly in $\log(1/\varepsilon)$
for precision ε



- ▶ Essentially solvable in polynomial time using interior point algorithms, e.g. SeDuMi, SDPT3, SDPA, Mosek,...

Idea: Replace \underline{a} with $a_i \in \mathbb{R}$ by \underline{A} with A_i symmetric matrices

► Model NC polynomials

- Polynomials in noncommuting variables $\underline{X} = (X_1, \dots, X_n)$
- Like usual polynomials, only difference $X_1 X_2 \neq X_2 X_1$ **EAT \neq TEA**

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► Evaluation in symmetric matrices

- $p = 1 + 2X_1^2 + X_2 X_1 - X_1 X_2,$
 - $\underline{A} = (A_1, A_2) \in (S\mathbb{R}^{s \times s})^2$
- } $p(\underline{A}) = \mathbf{1}_s + 2A_1^2 + A_2 A_1 - A_1 A_2$

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► NC polynomial optimization

$$p_{min} = \min_{(\varphi, \underline{A})} \{ \langle \varphi, p(\underline{A})\varphi \rangle \mid \|\varphi\| = 1 \}$$

- p_{min} is the **smallest eigenvalue** $p(\underline{A})$ can attain over all \underline{A}

We can add polynomial constraints like $g(\underline{A}) \succeq 0$ to define a region where we want to optimize p

- ▶ We can reformulate our nc optimization problem

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using nc sums of squares

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But first, let's look at applications
of nc polynomial optimization

Compute ground state energy of atoms

- ▶ Molecule of N electrons that can occupy M orbitals
- ▶ Each orbital associated with creation/annihilation operators a_i^\dagger, a_i
- ▶ Pairwise interaction described by h_{ijkl}

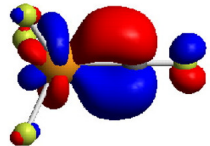
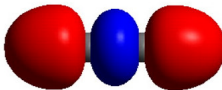
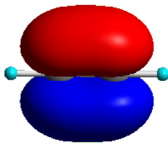
$$\min_{(a, a^\dagger, \varphi)} \left\langle \varphi, \sum_{ijkl} h_{ijkl} a_i^\dagger a_j^\dagger a_k a_l \varphi \right\rangle$$

s.t. $\|\varphi\| = 1$

$$\{a_i, a_j\} = \{a_i^\dagger, a_j^\dagger\} = 0$$

$$\{a_i^\dagger, a_j\} = \delta_{ij}$$

$$\left(\sum_i a_i^\dagger a_i - N \right) \varphi = 0$$



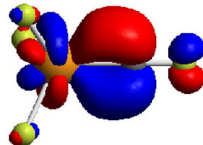
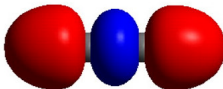
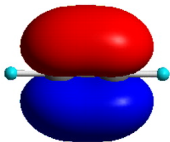
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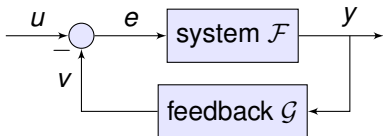
$$\min_{(a, a^\dagger, \varphi)} \left\langle \varphi, \sum_{ijkl} h_{ijkl} a_i^\dagger a_j^\dagger a_k a_l \varphi \right\rangle \leftarrow \langle \varphi, p(a, a^\dagger) \varphi \rangle$$

$$\text{s.t. } \|\varphi\| = 1 \leftarrow \|\varphi\| = 1$$

$$\left. \begin{aligned} \{a_i, a_j\} &= \{a_i^\dagger, a_j^\dagger\} = 0 \\ \{a_i^\dagger, a_j\} &= \delta_{ij} \\ \left(\sum_i a_i^\dagger a_i - N \right) \varphi &= 0 \end{aligned} \right\} \text{additional constraints}$$



- ▶ Linear closed loop system with unknown feedback \mathcal{G}

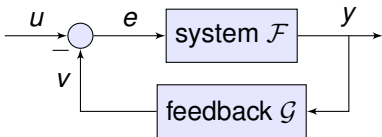


Math. System

$$\begin{aligned}\dot{\vec{x}}(t) &= \mathcal{A}\vec{x}(t) + \mathcal{B}\vec{u}, \\ \vec{y}(t) &= \mathcal{C}\vec{x}(t)\end{aligned}$$

- ▶ **Goal** Find \mathcal{G} which stabilizes the system

- ▶ Linear closed loop system with unknown feedback \mathcal{G}



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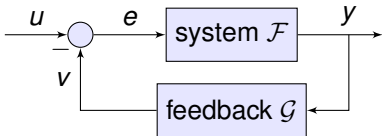
NC polynomial with
matrix coefficients

Lyapunov¹⁸⁹²

A system $\dot{x}(t) = Ax(t)$ is stable if there is a $P \succeq 0$ with $A^t P + PA \prec 0$

- ▶ Lyapunov's idea can be extended to our problem: Riccati equations

- ▶ Linear closed loop system with unknown feedback \mathcal{G}



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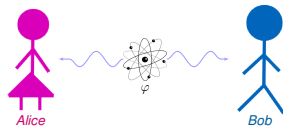
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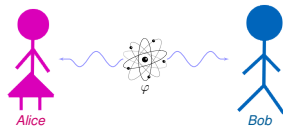
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- ▶ Lyapunov's idea can be extended to our problem: Riccati equations
- ▶ Optimization problem is first a feasibility problem
- ▶ Can be refined by optimizing a specific singular value
- ▶ For a uniform strategy to get \mathcal{G} we have to work free of dimensions

- ▶ Two separated systems $A = M_1 \cup \dots \cup M_n$ and $B = M_{n+1} \cup \dots \cup M_N$
- ▶ Measurements of M_i described by operators E_i performed on a joint quantum state φ
- ▶ Correlations between A and B : Joint probabilities $P(i, j) = \langle \varphi, E_i E_j \varphi \rangle$



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- ▶ Violation of Bell inequalities
 - ▶ Linear combination of (joint) probabilities
 - ▶ Get inequalities by considering classical random variables
 - ▶ Want to find violations using quantum setup



$\max_{(E, \varphi)} \left\langle \varphi, \sum_{i,j} c_{ij} E_i E_j \varphi \right\rangle$ $\text{s.t. } \ \varphi\ = 1$ $E_i E_j = \delta_{ij} \text{ for } i, j \in M_k$ $\sum_{i \in M_k} E_i = 1$ $[E_i, E_j] = 0 \text{ for } i \in A, j \in B$	$\leftarrow \langle \varphi, p(E) \varphi \rangle$ $\leftarrow \ \varphi\ = 1$ $\left. \begin{array}{l} \text{measurement} \\ \text{] } A/B \text{ separated} \end{array} \right\}$
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