

Linear Matrix Inequalities vs Convex Sets

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Advertisement: Try noncommutative computation

NCAIgebra¹

NCSOStools²

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² Igor Klep

Ingredients of Talk: LMIs and Convexity

A **Linear Pencil** is a matrix valued function L of the form

$$L(\mathbf{x}) := L_0 + L_1 \mathbf{x}_1 + \cdots + L_g \mathbf{x}_g,$$

where $L_0, L_1, L_2, \dots, L_g$ are symmetric matrices and $\mathbf{x} := \{\mathbf{x}_1, \dots, \mathbf{x}_g\}$ are g real parameters.

A **Linear Matrix Inequality (LMI)** is one of the form:

$$L(\mathbf{x}) \succ 0 \quad \text{means} \quad L(\mathbf{x}) \text{ is PosDef.}$$

Normalization: a **monic LMI** is one with $L_0 = I$.

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The set of solutions

$$\mathcal{G} := \{(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_g) : L_0 + L_1 \mathbf{x}_1 + \cdots + L_g \mathbf{x}_g \succ 0\}$$

is a **convex set**. Solutions can be found numerically for problems of modest size. This is called

Semidefinite Programming **SDP**

Ingredients of Talk: Noncommutative polynomials

$\mathbf{x} = (x_1, \dots, x_g)$ algebraic noncommuting variables

Noncommutative polynomials: $p(\mathbf{x})$:

Eg.
$$p(\mathbf{x}) = x_1x_2 + x_2x_1$$

Evaluate p : on matrices $\mathbf{X} = (X_1, \dots, X_g)$ a tuple of matrices.

Substitute a matrix for each variable $x_1 \rightarrow X_1, x_2 \rightarrow X_2$

Eg.
$$p(\mathbf{X}) = X_1X_2 + X_2X_1.$$

Noncommutative inequalities: p is positive means:

$p(\mathbf{X})$ is PSD for all \mathbf{X}

Outline

Ingredients: Polynomials and LMIs with Matrix Unknowns

Linear Systems give NonCommutative Polynomial Inequalities

Dimension Free Convexity vs NC LMIs

Comparison to LMIs in Scalar Unknowns

Free RAG

- Convex Positivstellensatz

- Randstellensatz for Defining Polynomials

Examples of NC Polynomials

The Riccati polynomial

$$r((a, b, c), \mathbf{x}) = -\mathbf{x}b^T\mathbf{b}\mathbf{x} + a^T\mathbf{x} + \mathbf{x}a + c$$

Here $m = (a, b, c)$ and $\mathbf{x} = (x)$.

Evaluation of NC Polynomials

r is naturally evaluated on a $1 + 3 = 4$ tuple of matrices

$$M = (A, B, C) \in (\mathbb{R}^{n \times n})^3 \quad \mathbf{X} = (X) \in \mathbb{S}^{n \times n}$$

$$r((A, B, C), \mathbf{X}) = -\mathbf{X}B^T\mathbf{B}\mathbf{X} + A^T\mathbf{X} + \mathbf{X}A + C \in \mathbb{S}_n(\mathbb{R}).$$

Note that the form of the Riccati is independent of n .

POLYNOMIAL MATRIX INEQUALITIES

Polynomial or Rational function of matrices are PosSDef.

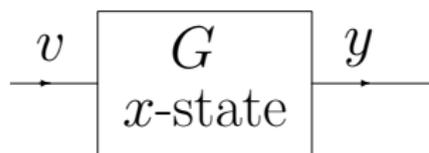
Example: Get Riccati expressions like

$$\mathbf{AX} + \mathbf{XA}^T - \mathbf{XBB}^T\mathbf{X} + \mathbf{CC}^T \succ 0$$

OR Linear Matrix Inequalities (LMI) like

$$\begin{pmatrix} \mathbf{AX} + \mathbf{XA}^T + \mathbf{C}^T\mathbf{C} & \mathbf{XB} \\ \mathbf{B}^T\mathbf{X} & \mathbf{I} \end{pmatrix} \succ 0$$

which is equivalent to the Riccati inequality.



$$\begin{aligned} & \frac{dx(t)}{dt} = Ax(t) + Bv(t) \\ & y(t) = Cx(t) + Dv(t) \\ & A, B, C, D \text{ are matrices} \\ & x, v, y \text{ are vectors} \end{aligned}$$

Asymptotically stable

$$\begin{aligned} & \operatorname{Re}(\text{eigvals}(A)) < 0 \iff \\ & A^T \mathbf{E} + \mathbf{E}A < 0 \quad \mathbf{E} \succ 0 \end{aligned}$$

Energy dissipating

$$\begin{aligned} & G : L^2 \rightarrow L^2 \\ & \int_0^T |v|^2 dt \geq \int_0^T |Gv|^2 dt \\ & \quad x(0) = 0 \end{aligned}$$

$$\begin{aligned} & \exists \mathbf{E} = \mathbf{E}^T \succeq 0 \\ & H := A^T \mathbf{E} + \mathbf{E}A + \\ & \quad + \mathbf{E}BB^T \mathbf{E} + C^T C \preceq 0 \\ & \mathbf{E} \text{ is called a storage function} \end{aligned}$$

Linear Systems Problems \rightarrow Matrix Inequalities



Many such problems Eg. H^∞ control

The problem is **Dimension free**: since it is given **only** by signal flow diagrams and L^2 signals.

Linear Systems Problems \rightarrow Matrix Inequalities



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A Dim Free System Prob is **Equivalent** to **Noncommutative Polynomial Inequalities**

Linear Systems Problems \rightarrow Matrix Inequalities



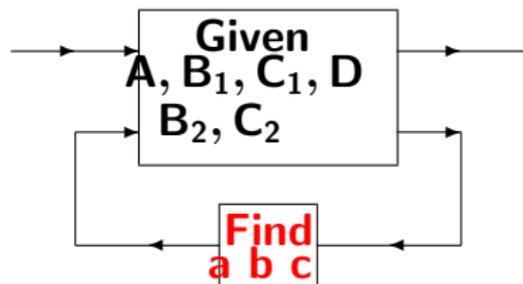
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A Dim Free System Prob is **Equivalent** to **Noncommutative Polynomial Inequalities**

Example:

GET ALGEBRA



$$D = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

DYNAMICS of "closed loop" system: BLOCK matrices

$A \quad B \quad C \quad D$

ENERGY DISSIPATION:

$$H := \mathcal{A}^T E + E \mathcal{A} + E B B^T E + C^T C \preceq 0$$

$$E = \begin{pmatrix} E_{11} & E_{12} \\ E_{21} & E_{22} \end{pmatrix}$$

$$E_{12} = E_{21}^T$$

$$H = \begin{pmatrix} H_{xx} & H_{xy} \\ H_{yx} & E_{yy} \end{pmatrix}$$

$$H_{xy} = H_{yx}^T$$

H^∞ Control

ALGEBRA PROBLEM:

Given the polynomials:

$$H_{xx} = E_{11} A + A^T E_{11} + C_1^T C_1 + E_{12}^T b C_2 + C_2^T b^T E_{12}^T + E_{11} B_1 b^T E_{12}^T + E_{11} B_1 B_1^T E_{11} + E_{12} b b^T E_{12}^T + E_{12} b B_1^T E_{11}$$

$$H_{xz} = E_{21} A + \frac{a^T (E_{21} + E_{12}^T)}{2} + c^T C_1 + E_{22} b C_2 + c^T B_2^T E_{11}^T + \frac{E_{21} B_1 b^T (E_{21} + E_{12}^T)}{2} + E_{21} B_1 B_1^T E_{11}^T + \frac{E_{22} b b^T (E_{21} + E_{12}^T)}{2} + E_{22} b B_1^T E_{11}^T$$

$$H_{zx} = A^T E_{21}^T + C_1^T c + \frac{(E_{12} + E_{21}^T) a}{2} + E_{11} B_2 c + C_2^T b^T E_{22}^T + E_{11} B_1 b^T E_{22}^T + E_{11} B_1 B_1^T E_{21}^T + \frac{(E_{12} + E_{21}^T) b b^T E_{22}^T}{2} + \frac{(E_{12} + E_{21}^T) b B_1^T E_{21}^T}{2}$$

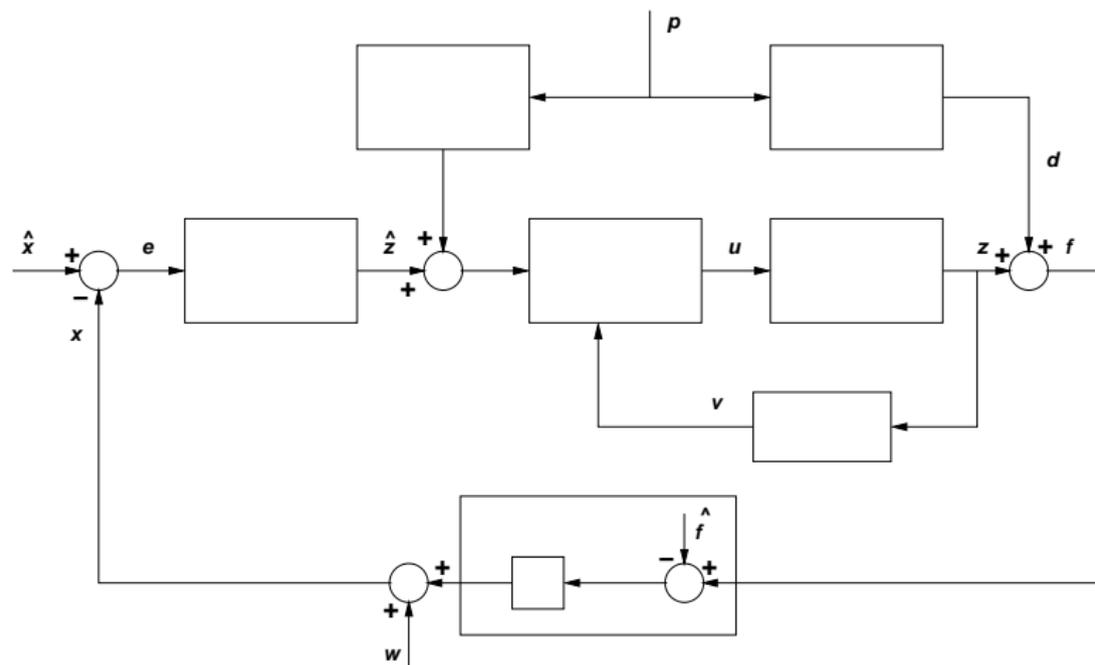
$$H_{zz} = E_{22} a + a^T E_{22}^T + c^T c + E_{21} B_2 c + c^T B_2^T E_{21}^T + E_{21} B_1 b^T E_{22}^T + E_{21} B_1 B_1^T E_{21}^T + E_{22} b b^T E_{22}^T + E_{22} b B_1^T E_{21}^T$$

(PROB) A, B_1, B_2, C_1, C_2 are knowns.

Solve the inequality $\begin{pmatrix} H_{xx} & H_{xz} \\ H_{zx} & H_{zz} \end{pmatrix} \preceq 0$ for unknowns

a, b, c and for E_{11}, E_{12}, E_{21} and E_{22}

More complicated systems give fancier nc polynomials



**Engineering problems defined
entirely by signal flow diagrams
and L^2 performance specs
are equivalent to
Polynomial Matrix Inequalities**

A more precise statement is on the next slide

Linear Systems and Algebra Synopsis

A Signal Flow Diagram with L^2 based performance, eg H^∞ gives precisely a nc polynomial

$$p(\mathbf{a}, \mathbf{x}) := \begin{pmatrix} p_{11}(\mathbf{a}, \mathbf{x}) & \cdots & p_{1k}(\mathbf{a}, \mathbf{x}) \\ \vdots & \ddots & \vdots \\ p_{k1}(\mathbf{a}, \mathbf{x}) & \cdots & p_{kk}(\mathbf{a}, \mathbf{x}) \end{pmatrix}$$

Such linear systems problems become exactly:

Given matrices \mathbf{A} .

Find matrices \mathbf{X} so that $P(\mathbf{A}, \mathbf{X})$ is PosSemiDef.

BAD Typically p is a mess, until a hundred people work on it and maybe **convert it to CONVEX in \mathbf{x} Matrix Inequalities**.

All known **successes**³ do more: They **convert to a LMI in \mathbf{x}** .

³about 20, plus a few thousand ad hoc compromises

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Convexity vs LMIs

QUESTIONS (Vague) :

WHICH DIM FREE PROBLEMS "ARE" LMI PROBLEMS.

Clearly, such a problem must be convex and "semialgebraic".

Which convex nc problems are NC LMIS?

WHICH PROBLEMS ARE TREATABLE WITH LMI's?

This requires some kind of **change of variables theory.**

The first is the main topic of this talk

A cleaner problem

Consider a cleaner problem we consider $p(\mathbf{x}, \mathbf{a})$ but with no \mathbf{a} :

$$p(\mathbf{x}) := \begin{pmatrix} p_{11}(\mathbf{x}) & \cdots & p_{1k}(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ p_{k1}(\mathbf{x}) & \cdots & p_{kk}(\mathbf{x}) \end{pmatrix}$$

WHICH DIM FREE PROBLEMS "ARE" LMI PROBLEMS?

Linear Pencil

RECALL

- ▶ For symmetric matrices $L_0, L_1, \dots, L_g \in \mathbb{S}^{s \times s}$ and $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_g)$, the expression

$$L(\mathbf{x}) = L_0 + L_1 \mathbf{x}_1 + \dots + L_g \mathbf{x}_g$$

is called a $s \times s$ **linear pencil**.

If $L_0 = I$, we say that $L(\mathbf{x})$ is **monic**.

Linear Pencil, Linear Matrix Inequality (LMI)

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If $L_0 = I$, we say that $L(\mathbf{x})$ is **monic**.

- ▶ A **linear matrix inequality (LMI)** is of the form $L(\mathbf{x}) \succeq 0$.
Its **solution set**

$$\begin{aligned} \mathcal{D}_L(1) &= \{ \mathbf{x} \in \mathbb{R}^g \mid L(\mathbf{x}) \succeq 0 \} \\ &= \{ \mathbf{x} \in \mathbb{R}^g \mid L_0 + L_1 \mathbf{x}_1 + \dots + L_g \mathbf{x}_g \succeq 0 \} \end{aligned}$$

is called a **spectrahedron** or also an **LMI domain**.

Pencils in Matrix Variables

Given a $s \times s$ linear pencil

$$L(\mathbf{x}) = L_0 + L_1x_1 + \cdots + L_gx_g,$$

it is natural to substitute **symmetric matrices** X_j for the **variables** x_j .

Pencils in Matrix Variables

Given a $s \times s$ linear pencil

$$L(\mathbf{x}) = L_0 + L_1 \mathbf{x}_1 + \cdots + L_g \mathbf{x}_g,$$

it is natural to substitute **symmetric matrices** \mathbf{X}_j for the **variables** x_j :

- ▶ For $\mathbf{X} = (\mathbf{X}_1, \dots, \mathbf{X}_g) \in (\mathbb{S}^{n \times n})^g$, the **evaluation** $L(\mathbf{X})$ is

$$L(\mathbf{X}) := L_0 \otimes I_n + L_1 \otimes \mathbf{X}_1 + \cdots + L_g \otimes \mathbf{X}_g \in \mathbb{S}^{sn \times sn}.$$

The **tensor product** in this expression is the standard **(Kronecker)** tensor product of matrices.

- ▶ The **positivity set** of L is

$$\mathcal{D}_L(n) := \{\mathbf{X} \in (\mathbb{S}^{n \times n})^g : L(\mathbf{X}) \succ 0\} \quad \mathcal{D}_L := \cup_n \mathcal{D}_L(n)$$

Convex Matrix Inequalities vs Linear Matrix Inequalities

Let p be a symmetric nc polynomial denote the principal component of the positivity domain

$$\mathcal{D}_p(n) := \{\mathbf{X} \in (\mathbb{S}^{n \times n})^g : p(\mathbf{X}) \succ 0\}.$$

by $\mathcal{D}_p^\circ(n)$.

Theorem H-McCullough (Annals 2012)

SUPPOSE p is a nc symmetric noncommutative polynomial with $p(0) = 1$ and \mathcal{D}_p^0 bounded.

THEN

\mathcal{D}_p^0 is a convex set for each n

if and only if

there is a monic linear pencil L such that $\mathcal{D}_p^\circ = \mathcal{D}_L$.

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This is also true if p is a symmetric matrix of nc polynomials.

The (SAD) MORAL OF THE STORY

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**Advice to engineers from this (and other theorems).
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It looks like:**

**A CONVEX problem specified entirely by a signal flow diagram
and L^2 performance of signals is equivalent to some LMI.**

**Looking for LMIs is what they already do. SAD there is no
other way to get convexity.**

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Scalar Unknowns: LMI representations

**Comparison to the case
when all unknowns are
scalars.**

Which Sets in \mathbb{R}^g have LMI REPRESENTATIONS?

QUESTION (Vague):

ARE CONVEX PROBLEMS ALL TREATABLE WITH LMI's?

DEFINITION: A set $\mathcal{C} \subset \mathbb{R}^g$

has an **Linear Matrix Inequality (LMI) Representation**

provided that there are sym matrices L_1, L_2, \dots, L_g

for which the **monic Linear Pencil**,

$L(x) := I + L_1 x_1 + \dots + L_g x_g$, has positivity set,

$$\mathcal{D}_L := \{x : L_0 + L_1 x_1 + \dots + L_g x_g \text{ is PosSD}\} \subset \mathbb{R}^g$$

equals the set \mathcal{C} ; that is,

$$\mathcal{C} = \mathcal{D}_L.$$

EXAMPLE

$$\mathcal{C} := \{(\mathbf{x}_1, \mathbf{x}_2) : 1 + 2\mathbf{x}_1 + 3\mathbf{x}_2 - (3\mathbf{x}_1 + 5\mathbf{x}_2)(3\mathbf{x}_1 + 2\mathbf{x}_2) > 0\}$$

has the LMI Rep

$$\mathcal{C} = \{\mathbf{x} : \mathbf{L}(\mathbf{x}) \succ 0\} \quad \text{here } \mathbf{x} := (\mathbf{x}_1, \mathbf{x}_2)$$

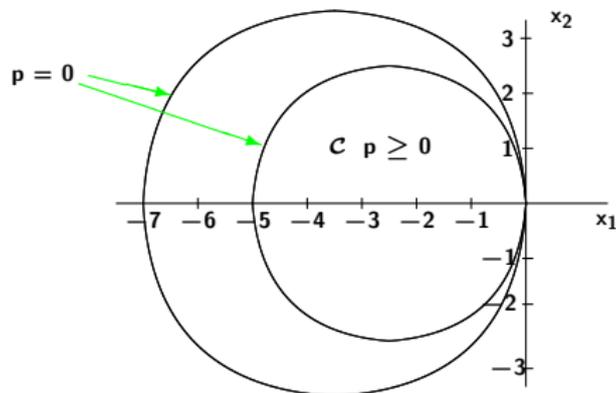
with

$$\mathbf{L}(\mathbf{x}) = \begin{pmatrix} 1 + 2\mathbf{x}_1 + 3\mathbf{x}_2 & 3\mathbf{x}_1 + 5\mathbf{x}_2 \\ 3\mathbf{x}_1 + 2\mathbf{x}_2 & 1 \end{pmatrix}$$

Pf: The determinant of $\mathbf{L}(\mathbf{x})$ is pos iff $\mathbf{L}(\mathbf{x})$ is PosDef.

QUESTION 1

Does this set \mathcal{C} which is the inner component of



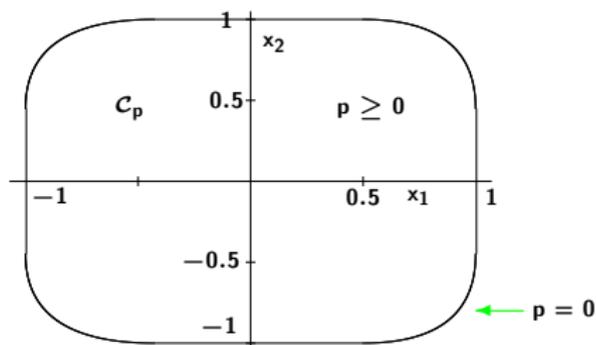
have an LMI representation?

$$p(\mathbf{x}_1, \mathbf{x}_2) = (\mathbf{x}_1^2 + \mathbf{x}_2^2)(\mathbf{x}_1^2 + \mathbf{x}_2^2 + 12\mathbf{x}_1 - 1) + 36\mathbf{x}_1^2 > 0$$

$$\mathcal{C} := \text{inner component of } \{\mathbf{x} \in \mathbb{R}^2 : p(\mathbf{x}) > 0\}$$

QUESTION 2

Does this set have an LMI representation?



$$p(x_1, x_2) = 1 - x_1^4 - x_2^4 > 0$$

$C_p := \{x \in \mathbb{R}^2 : p(x) > 0\}$ has degree 4.

Rigid Convexity-Line Test

DEFINITION: A convex set \mathcal{C} in \mathbb{R}^g with **minimal degree defining polynomial** p passes the **the “line test”** means:

For every point x^0 in \mathcal{C} and almost every line ℓ through x^0 **the line ℓ intersects the the zero set**

$$\{x \in \mathbb{R}^g : p(x) = 0\} \text{ of } p$$

in exactly d points⁴ where $d = \text{degree of } p$.

⁴In this counting one ignores lines which go thru x^0 and hit the boundary of \mathcal{C} at ∞ .

IN \mathbb{R}^2 THE LINE TEST RULES

THM [Vinnikov + H, CPAM 2007].

IF \mathcal{C} is a bounded open convex set in \mathbb{R}^g with an LMI representation, **THEN** \mathcal{C} must pass the line test.

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When $g = 2$, the converse is true, namely, a convex set which passes the line test has a LMI representation with symmetric matrices $L_j \in \mathbb{R}^{d \times d}$ and $L_0 = I$.

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When $g = 2$, the converse is true, namely, a convex set which passes the line test has a LMI representation with symmetric matrices $L_j \in \mathbb{R}^{d \times d}$ and $L_0 = I$.

Lewis-Parrilo-Ramana showed our **determinantal representation** solves a conjecture (1958) by Peter Lax about constant coefficient linear hyperbolic PDE, one time and 2 space dim.

Free RAG

Snippets of Free RAG.

Convex (perfect) Positivstellensatz

Suppose:

- ▶ $L(x)$ is a monic linear pencil;
- ▶ $q(x)$ is a **noncommutative** polynomial.

Is $q(X)$ PosSemiDef if $L(X)$ is PosSemiDef?

Convex (perfect) Positivstellensatz

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THEOREM (H-Klep- McCullough; Advances 2012)

$q \succeq 0$ where $L \succeq 0$ if and only if

$$q(\mathbf{x}) = s(\mathbf{x})^*s(\mathbf{x}) + \sum_j v_j(\mathbf{x})^*L(\mathbf{x})v_j(\mathbf{x}),$$

where s, v_j are vectors of polynomials each of degree $\leq \left\lfloor \frac{\deg(q)}{2} \right\rfloor$.

If \mathcal{D}_L is bounded, then we may take $s = 0$.

Arveson -Stinespring vs PosSS

Convex PosSS: Suppose L monic linear pencil and \mathcal{D}_L is bounded.

$q \succeq 0$ on \mathcal{D}_L iff

$$q(\mathbf{x}) = \sum_j f_j(\mathbf{x})^* L(\mathbf{x}) f_j(\mathbf{x}),$$

where f_j are vectors of polynomials each of degree $\leq \left\lfloor \frac{\deg(q)}{2} \right\rfloor$.

Take $q(\mathbf{x}) = \tilde{L}(\mathbf{x})$ an affine linear nc function, $q(0) = 1$.

Then $\left\lfloor \frac{\deg(\tilde{L})}{2} \right\rfloor = 0$, so f_j are constants. The PosSS becomes:

Free LMI domination Theorem:

$\tilde{L} \succeq 0$ on \mathcal{D}_L if and only if $\tilde{L}(\mathbf{x}) = \sum_j^\mu V_j^* L(\mathbf{x}) V_j$

if and only if $\tilde{L}(\mathbf{x}) = V^* (I_\mu \otimes L(\mathbf{x})) V$ V isometry

(**EQUIVALENT** to finite dim Arveson Extension plus Steinspring.)

Recall Real Nullstellensatz addresses

$$q(\mathbf{X})\mathbf{v} = 0 \text{ if } p(\mathbf{X})\mathbf{v} = 0$$

**Now there is good theory of it: Cimpric, McCullough , Nelson -H
(Proc London Math Soc – to appear)**

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For classical polynomials on \mathbb{R}^g there is an algebraic certificate **equivalent** to any list of polynomial inequalities-equalities.

For NC polynomials **open**.

Currently doing mixtures of PosSS and NullSS.

Randstellensatz for Defining Polynomials: Zariski Nice

Given \mathbf{p} a $d \times d$ matrix of nc polynomials defining a domain by

$$\mathcal{D}_p^\circ := \text{principal component of } \{\mathbf{X} : \mathbf{p}(\mathbf{X}) \succ 0\}$$

with (detailed) boundary

$$\widehat{\partial}\mathcal{D}_p^\circ := \{(\mathbf{X}, \mathbf{v}) : \mathbf{X} \in \text{closure } \mathcal{D}_p^\circ, \mathbf{p}(\mathbf{X})\mathbf{v} = 0\}$$

Theorem in preparation

SUPPOSE:

$\mathbf{p}(\mathbf{x})$ is a $d \times d$ symmetric nc polynomial, and

$\mathbf{L}(\mathbf{x})$ is a $d \times d$ monic linear pencil for which

“the free Zariski closure” of $\widehat{\partial}\mathcal{D}_L^\circ$ equals “the Zero Set of \mathbf{L} ”,

THEN

Randstellensatz for Defining Polynomials: Zariski Nice ... continued

Theorem (continued)

$$\mathcal{D}_L \subseteq \mathcal{D}_p \quad \text{and} \quad \widehat{\partial}\mathcal{D}_L^\circ \subseteq \widehat{\partial}\mathcal{D}_p^\circ$$

if only if

$$p = L \left(\sum_i \mathbf{q}_i^* \mathbf{q}_i \right) L + \sum_j (\mathbf{r}_j L + \mathbf{C}_j)^* L (\mathbf{r}_j L + \mathbf{C}_j),$$

where $\mathbf{q}_i, \mathbf{r}_j$ are matrices of polynomials, and \mathbf{C}_j are real matrices satisfying $\mathbf{C}_j L = L \mathbf{C}_j$.

Current ventures

Free convex hulls of free semialgebraic sets

Free change of variables to achieve free convexity. – Obsession
(Motivates recent PosSS work)

MANY THANKS

from

Igor Klep Math Dept NewZealand

Scott McCullough Math Dept University of Florida

Chris Nelson Math Dept UCSD → NSA

Victor Vinnikov Ben Gurion U of the Negev

Bill

Polys in \mathbf{a} and \mathbf{x}

Partial Convexity of NC Polynomials

The polynomial $p(\mathbf{a}, \mathbf{x})$ is **convex** in \mathbf{x} for all \mathbf{A} if for each \mathbf{X}, \mathbf{Y} and $0 \leq \alpha \leq 1$,

$$p(\mathbf{A}, \alpha\mathbf{X} + (1 - \alpha)\mathbf{Y}) \preceq \alpha p(\mathbf{A}, \mathbf{X}) + (1 - \alpha)p(\mathbf{A}, \mathbf{Y}).$$

The Riccati $r(\mathbf{a}, \mathbf{x}) = c + \mathbf{a}^T \mathbf{x} + \mathbf{x} \mathbf{a} - \mathbf{x} \mathbf{b}^T \mathbf{b} \mathbf{x}$ is concave, meaning $-r$ is convex in \mathbf{x} (everywhere).

Can **localize** \mathbf{A} to an nc semialgebraic set.

Structure of Partially Convex Polys

THM (Hay-Helton-Lim- McCullough)

SUPPOSE $p \in \mathbb{R}\langle a, x \rangle$ is convex in x **THEN**

$$p(a, x) = L(a, x) + \tilde{L}(a, x)^T Z(a) \tilde{L}(a, x),$$

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Structure of Partially Convex Polys

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where,

- $L(a, x)$ has degree at most one in x ;
- $Z(a)$ is a symmetric matrix-valued NC polynomial;
- $Z(A) \succeq 0$ for all A ;
- $\tilde{L}(a, x)$ is linear in x . $\tilde{L}(a, x)$ is a (column) vector of NC polynomials of the form $x_j m(a)$.

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-

This also works fine if p is a **matrix of nc polynomials**.

This also works fine if A only belongs to an **open nc semi-algebraic set** (will not be defined here) .

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COR SUPPOSE $p \in \mathbb{R}\langle a, x \rangle$ is convex in x

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The (SAD) MORAL OF THE STORY

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The (SAD) MORAL OF THE STORY

A CONVEX problem specified entirely by a signal flow diagram and L^2 performance of signals is equivalent to some LMI.

Context: Related Areas

Convex Algebraic Geometry (mostly commutative)

NSF FRG: Helton -Nie- Parrilo- Strumfels- Thomas

One aspect: Convexity vs LMIs.

Now there is a **roadmap** with some theorems and conjectures.

Three branches:

1. Which convex semialgebraic sets in \mathbb{R}^g have an LMI rep?
(Line test) Is it necessary and sufficient? **Ans:** Yes if $g \leq 2$.
2. Which convex semialgebraic sets in \mathbb{R}^g lift to a set with an LMI representation? **Ans:** Most do.
3. Which noncommutative semialgebraic convex sets have an LMI rep? **Ans:** All do. (like what you have seen.), see Helton-McCullough Annals of Mathematics Sept 2012.

NC Real Algebraic Geometry (since 2000)

We have a good body of results in these areas.

Eg. Positivstellensatz – Saw in Tuesday Morning Tutorial session.