

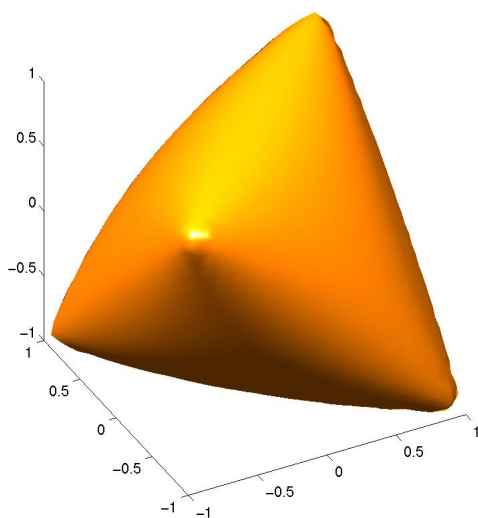
COURSE ON LMI OPTIMIZATION  
WITH APPLICATIONS IN CONTROL  
PART I.3

**GEOMETRY OF LMI SETS**

Denis Arzelier

[www.laas.fr/~arzelier](http://www.laas.fr/~arzelier)

[arzelier@laas.fr](mailto:arzelier@laas.fr)



January 2005

## Geometry of LMI sets

Given  $F_i \in \mathbb{S}^m$  we want to characterize the shape in  $\mathbb{R}^n$  of the LMI set

$$\mathcal{S} = \{x \in \mathbb{R}^n : F(x) = F_0 + \sum_{i=1}^n x_i F_i \succeq 0\}$$

Matrix  $F(x)$  is PSD iff its **diagonal minors**  $f_i(x)$  are nonnegative

Diagonal minors are multivariate **polynomials** of indeterminates  $x_i$

So the LMI set can be described as

$$\mathcal{S} = \{x \in \mathbb{R}^n : f_i(x) \geq 0, i = 1, \dots, n\}$$

which is a **semialgebraic** set

Moreover, it is a **convex** set

## Example of 2D LMI feasible set

$$F(x) = \begin{bmatrix} 1 - x_1 & x_1 + x_2 & x_1 \\ x_1 + x_2 & 2 - x_2 & 0 \\ x_1 & 0 & 1 + x_2 \end{bmatrix} \succeq 0$$

Feasible iff all principal minors nonnegative

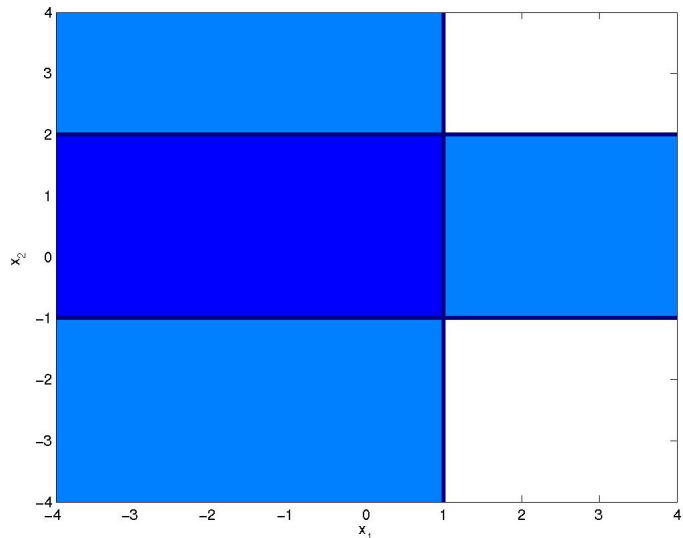
System of **polynomial inequalities**  $f_i(x) \geq 0$

1st order minors

$$f_1(x) = 1 - x_1 \geq 0$$

$$f_2(x) = 2 - x_2 \geq 0$$

$$f_3(x) = 1 + x_2 \geq 0$$

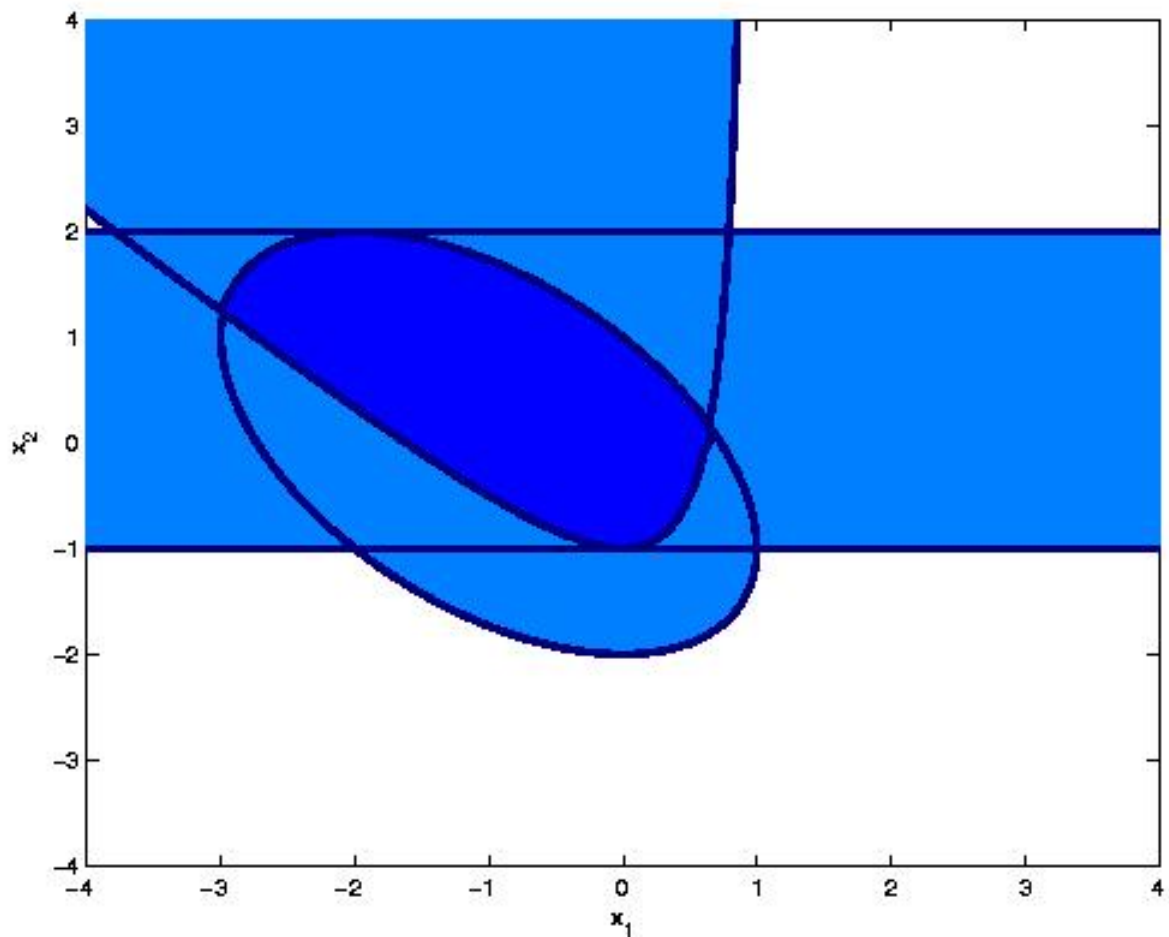


2nd order minors

$$f_4(x) = (1 - x_1)(2 - x_2) - (x_1 + x_2)^2 \geq 0$$

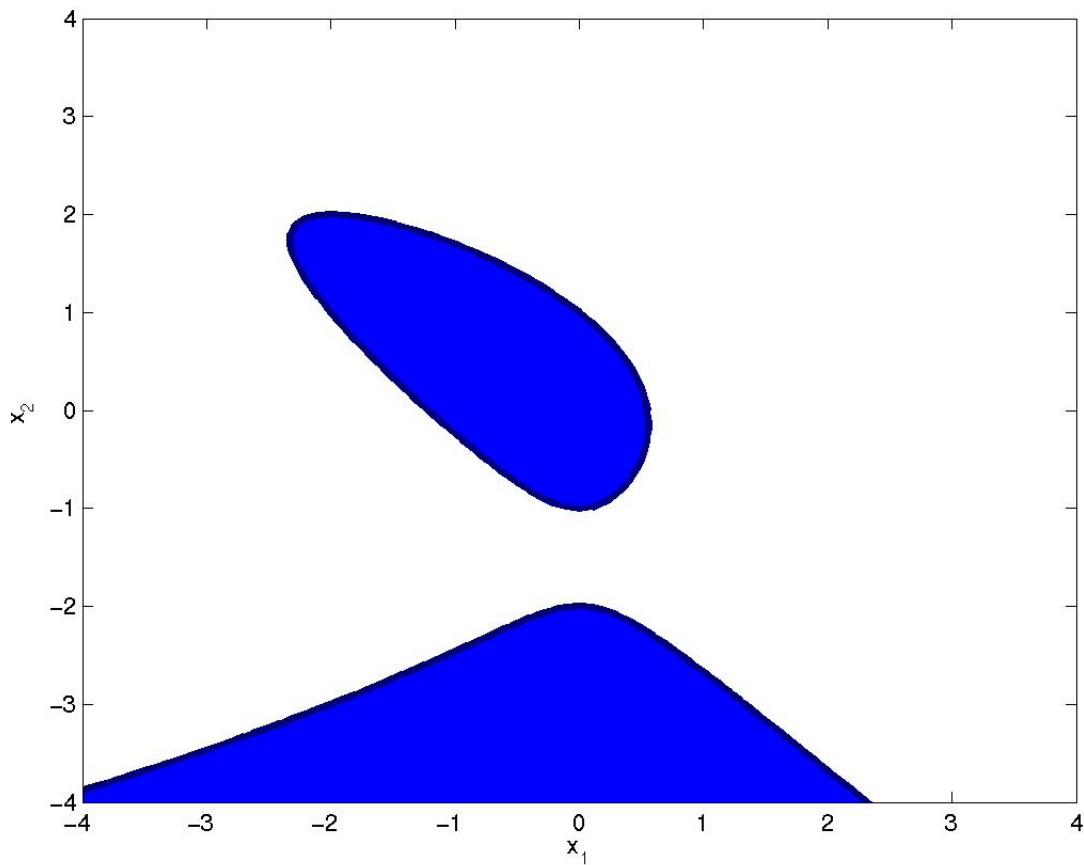
$$f_5(x) = (1 - x_1)(1 + x_2) - x_1^2 \geq 0$$

$$f_6(x) = (2 - x_2)(1 + x_2) \geq 0$$

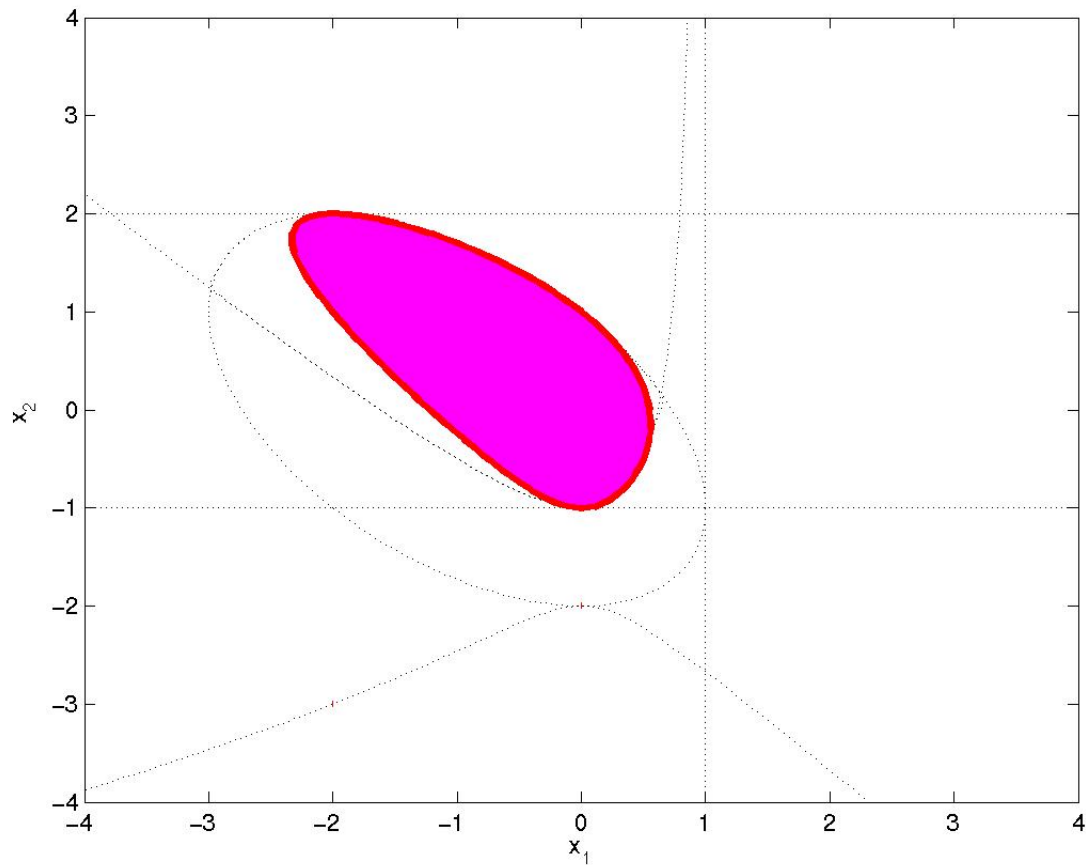


3rd order minor

$$f_7(x) = (1 + x_2)((1 - x_1)(2 - x_2) - (x_1 + x_2)^2) - x_1^2(2 - x_2) \geq 0$$



LMI feasible set = intersection of  
semialgebraic sets  $f_i(x) \geq 0$  for  $i = 1, \dots, 7$

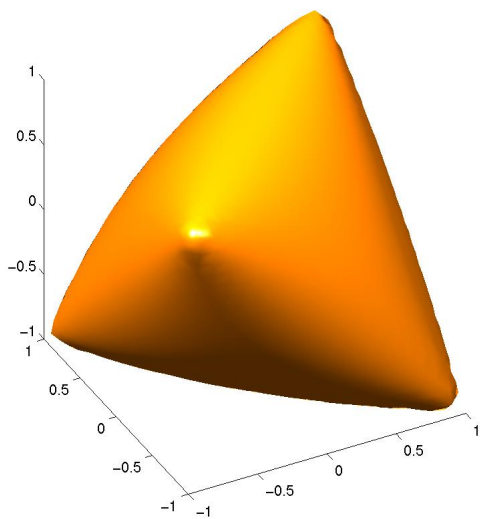


## Example of 3D LMI feasible set

LMI set

$$\mathcal{S} = \{x \in \mathbb{R}^3 : \begin{bmatrix} 1 & x_1 & x_2 \\ x_1 & 1 & x_3 \\ x_2 & x_3 & 1 \end{bmatrix} \succeq 0\}$$

arising in SDP relaxation of MAXCUT



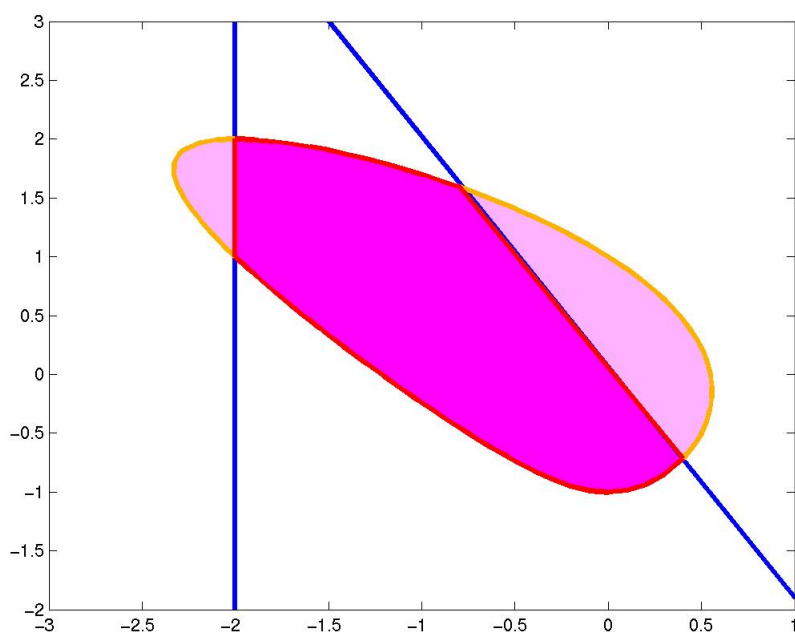
Semialgebraic set

$$\mathcal{S} = \{x \in \mathbb{R}^3 : 1 + 2x_1x_2x_3 - (x_1^2 + x_2^2 + x_3^2) \geq 0, \\ x_1^2 \leq 1, x_2^2 \leq 1, x_3^2 \leq 1\}$$

## Intersection of LMI sets

Intersection of LMI feasible sets

$$F(x) \succeq 0 \quad x_1 \geq -2 \quad 2x_1 + x_2 \leq 0$$



is also an LMI

$$\begin{bmatrix} F(x) & 0 & 0 \\ 0 & x_1 + 2 & 0 \\ 0 & 0 & -2x_1 - x_2 \end{bmatrix} \succeq 0$$



## Conic representability

LMI sets are **convex semialgebraic** sets.. but are all convex semialgebraic sets **representable** by LMIs ?

A set  $X \subset \mathbb{R}^n$  is **conic quadratic representable (CQR)** if there exist  $N$  affine mappings  $F_i(x, u)$  s.t.

$$x \in X \iff \begin{array}{l} \exists u : F_i(x, u) = A_i \begin{bmatrix} x \\ u \end{bmatrix} - b_i \succeq_{\mathbb{L}^{m_i}} 0 \\ i = 1, \dots, N \end{array}$$

A convex function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is **CQR** if its epigraph

$$\mathcal{E}pi = \{(x, t) \in \mathbb{R}^n \times \mathbb{R} : f(x) \leq t\}$$

is **CQR**

## SDP/LMI representability (1)

We say that a convex set  $X \subset \mathbb{R}^n$  is **SDP representable** if there exists an affine mapping  $F(x, u)$  such that

$$x \in X \iff \exists u : F(x, u) \succeq 0$$

In words, if  $X$  is the **projection** of the solution set of the LMI  $F(x, u) \succeq 0$  onto the  $x$ -space and  $u$  are **additional**, or **lifting** variables

We say that a convex set  $X \subset \mathbb{R}^n$  is **LMI representable** if there exists an affine mapping  $F(x)$  such that

$$x \in X \iff F(x) \succeq 0$$

In other words, additional variables  $u$  are **not allowed**

Similarly, a convex function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is **SDP** or **LMI** representable if its epigraph

$$\mathcal{E}_{pi} = \{(x, t) \in \mathbb{R}^n \times \mathbb{R} : f(x) \leq t\}$$

is an **SDP** or **LMI** representable set

## SDP/LMI representability (2) CQR and SDP representability

The Lorentz, or ice-cream cone

$$\mathbb{L}^{n+1} = \left\{ \begin{bmatrix} x \\ t \end{bmatrix} \in \mathbb{R}^{n+1} : \|x\|_2 \leq t \right\}$$

is SDP representable as

$$\mathbb{L}^{n+1} = \left\{ \begin{bmatrix} x \\ t \end{bmatrix} : \begin{bmatrix} tI_n & x \\ x' & t \end{bmatrix} \succeq 0 \right\}$$

As a result, all (convex quadratic) conic representable sets are also SDP representable

$$\mathbb{L}^n \subset \mathbb{S}_+^n$$

In the sequel we first give a list of conic representable sets (following Ben-Tal and Nemirovski 2000)

## SDP/LMI representability (3)

### Quadratic forms

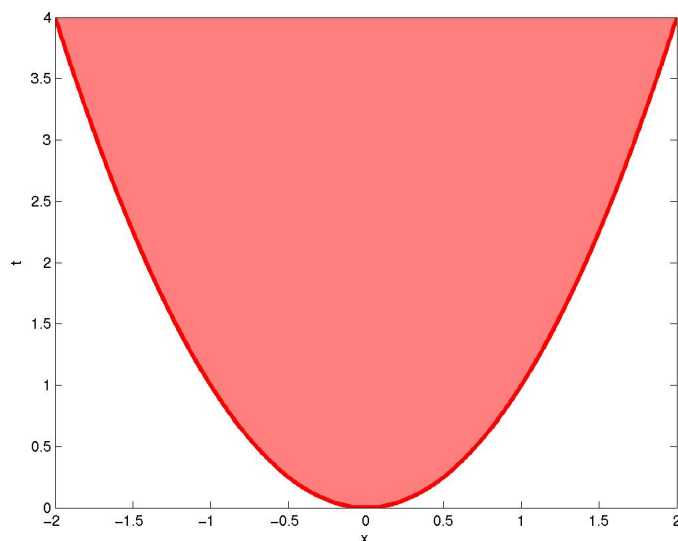
The **Euclidean norm**  $\{x, t \in \mathbb{R}^n \times \mathbb{R} : \|x\|_2 \leq t\}$  is **CQR** by definition

The **squared Euclidean norm**

$$\{(x, t) \in \mathbb{R}^n \times \mathbb{R} : x'x \leq t\}$$

is **CQR** as

$$\left\| \begin{bmatrix} x \\ \frac{t-1}{2} \end{bmatrix} \right\|_2 \leq \frac{t+1}{2}$$



## SDP/LMI representability (4)

### Quadratic forms (2)

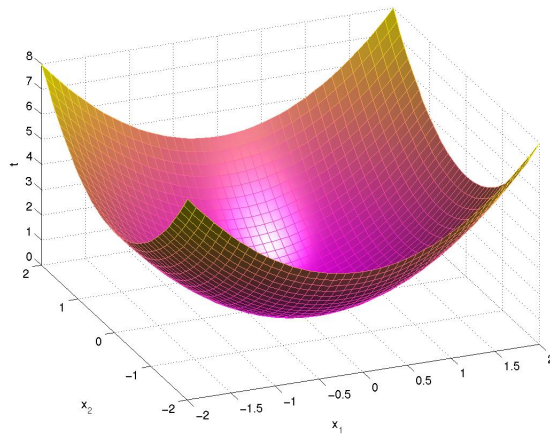
More generally, the **convex quadratic** set

$$\left\{x \in \mathbb{R}^n, t \in \mathbb{R} : x'Ax + b'x + c \leq 0\right\}$$

with  $A = A' \succeq 0$  is **CQR** as

$$\left\| \begin{bmatrix} Dx \\ \frac{t+b'x+c}{2} \end{bmatrix} \right\|_2 \leq \frac{t-b'x-c}{2}$$

where  $D$  is the **Cholesky factor** of  $A = D'D$



## SDP/LMI representability (5)

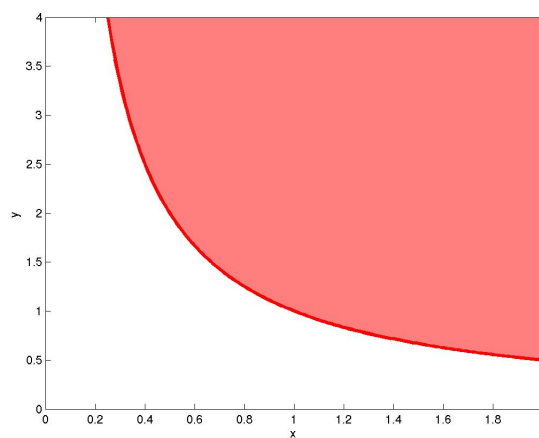
### Hyperbola

The branch of **hyperbola**

$$\{(x, y) \in \mathbb{R}^2 : xy \geq 1, x > 0\}$$

is **CQR** as

$$\left\| \begin{bmatrix} \frac{x-y}{2} \\ 1 \end{bmatrix} \right\|_2 \leq \frac{x+y}{2}$$



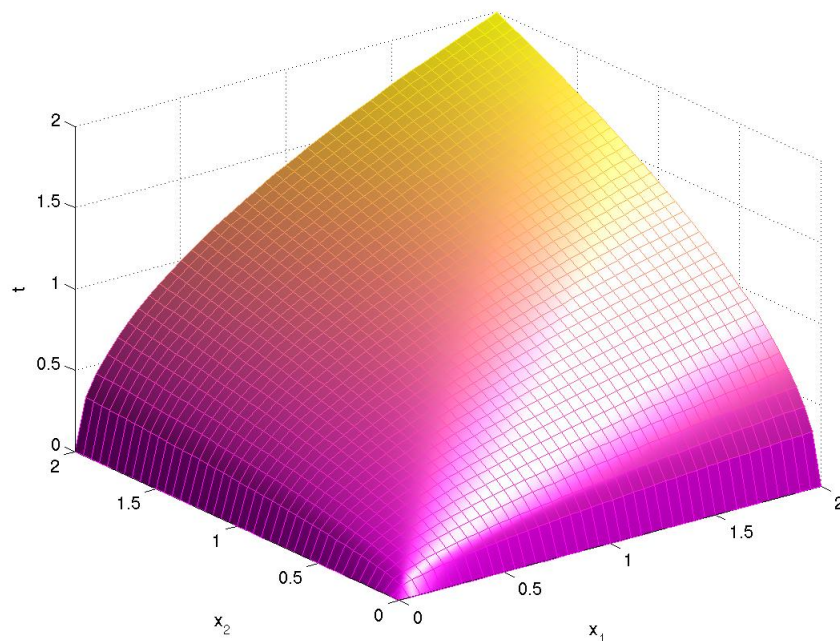
## SDP/LMI representability (6) Geometric mean of two variables

The hypograph of the **geometric mean**  
of 2 variables

$$\left\{ (x_1, x_2, t) \in \mathbb{R}^3 : x_1, x_2 \geq 0, \sqrt{x_1 x_2} \geq t \right\}$$

is **CQR** as

$$\exists u : u \geq t, \left\| \begin{bmatrix} u \\ \frac{x_1 - x_2}{2} \end{bmatrix} \right\|_2 \leq \frac{x_1 + x_2}{2}$$



## SDP/LMI representability (7)

### Geometric mean of several variables

The hypograph of the geometric mean of  $2^k$  variables

$$\left\{ (x_1, \dots, x_{2^k}, t) \in \mathbb{R}^{2^k+1} : x_i \geq 0, (x_1 \cdots x_{2^k})^{1/2^k} \geq t \right\}$$
 is also CQR

Proof: Iterate the previous construction

Example with  $k = 3$ :

$$\begin{array}{c}
 (x_1 x_2 \cdots x_8)^{1/8} \geq t \\
 \left. \begin{array}{l} \sqrt{x_{01} x_{02}} \geq x_{11} \\ \sqrt{x_{03} x_{04}} \geq x_{12} \\ \sqrt{x_{05} x_{06}} \geq x_{13} \\ \sqrt{x_{07} x_{08}} \geq x_{14} \end{array} \right\} \left. \begin{array}{l} \sqrt{x_{11} x_{12}} \geq x_{21} \\ \sqrt{x_{13} x_{14}} \geq x_{22} \end{array} \right\} \sqrt{x_{21} x_{22}} \geq x_{31} \geq t
 \end{array}$$

Useful idea in other SDP representability problems

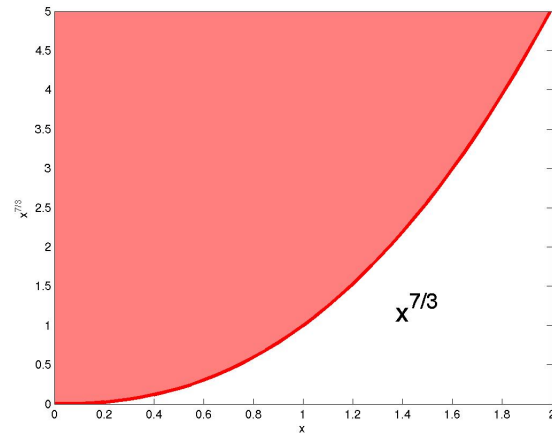


## SDP/LMI representability (8)

### Rational functions (1)

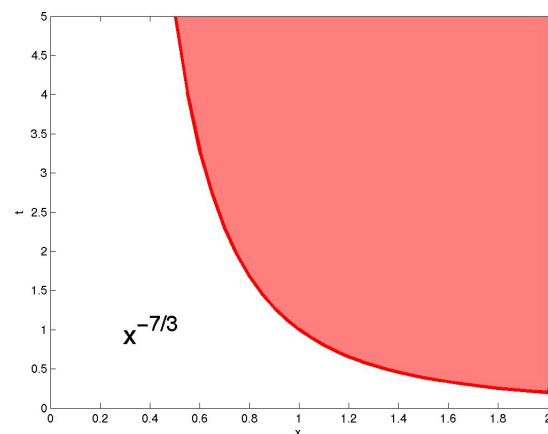
Using similar ideas, we can show that the increasing **rational power functions**

$$f(x) = x^{p/q}, \quad x \geq 0$$



with rational  $p/q \geq 1$ , as well as the decreasing

$$g(x) = x^{-p/q}, \quad x \geq 0$$



with rational  $p/q \geq 0$ , are both **CQR**

## SDP/LMI representability (9)

### Rational functions (2)

Example:

$$\{(x, t) \in \mathbb{R}^2 : x \geq 0, x^{7/3} \leq t\}$$

Start from conic representable

$$\hat{t} \leq (\hat{x}_1 \cdots \hat{x}_8)^{1/8}$$

and replace

$$\begin{aligned}\hat{t} &= \hat{x}_1 = x \geq 0 \\ \hat{x}_2 &= \hat{x}_3 = \hat{x}_4 = t \geq 0 \\ \hat{x}_5 &= \hat{x}_6 = \hat{x}_7 = \hat{x}_8 = 1\end{aligned}$$

to get

$$\begin{aligned}x &\leq x^{1/8}t^{3/8} \\ x^{7/8} &\leq t^{3/8} \\ x^{7/3} &\leq t\end{aligned}$$

Same idea works for any rational  $p/q \geq 1$

- **lift** = use additional variables, and
- **project** in the space of original variables

SDP/LMI representability (10)

Even power monomial (1)

The epigraph of **even power monomial**

$$\mathcal{E}_{pi} = \{x, t : x^{2p} \leq t\}$$

where  $p$  is a positive integer, is **CQR**

Note that

$$\{x, t : x^{2p} \leq t\}$$

$$\Longleftrightarrow$$

$$\begin{aligned} &\{x, y, t : x^2 \leq y\} \\ &\{x, y, t : y \geq 0, y^p \leq t\} \end{aligned}$$

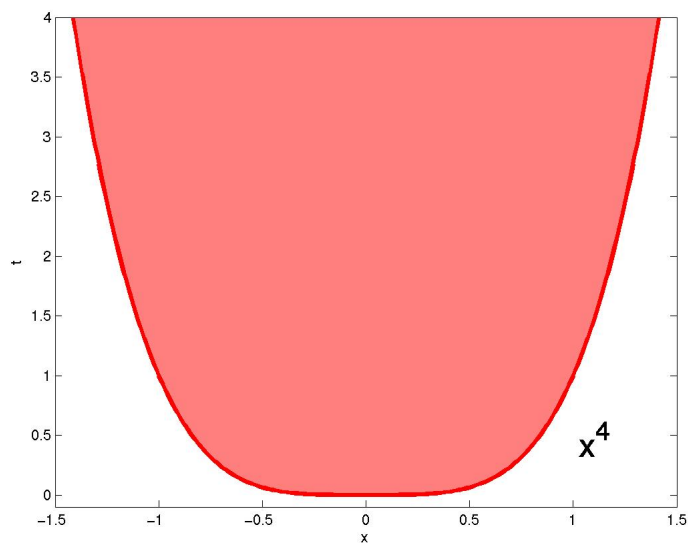
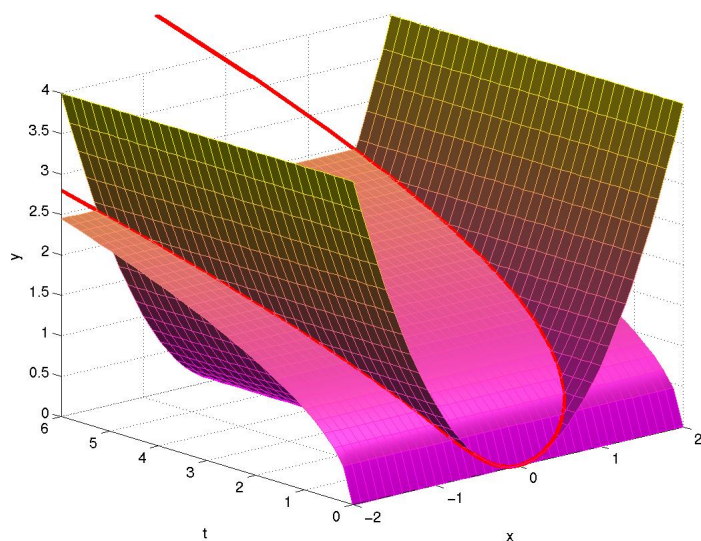
both CQR

Use **lifting**  $y$  and **project** back onto  $x, t$

Similarly, **even power polynomials** are **CQR** (combinations of monomials)

SDP/LMI representability (11)  
Even power monomial (2)

$$\mathcal{E}_{pi} = \{x, t : x^4 \leq t\}$$



## SDP/LMI representability (12)

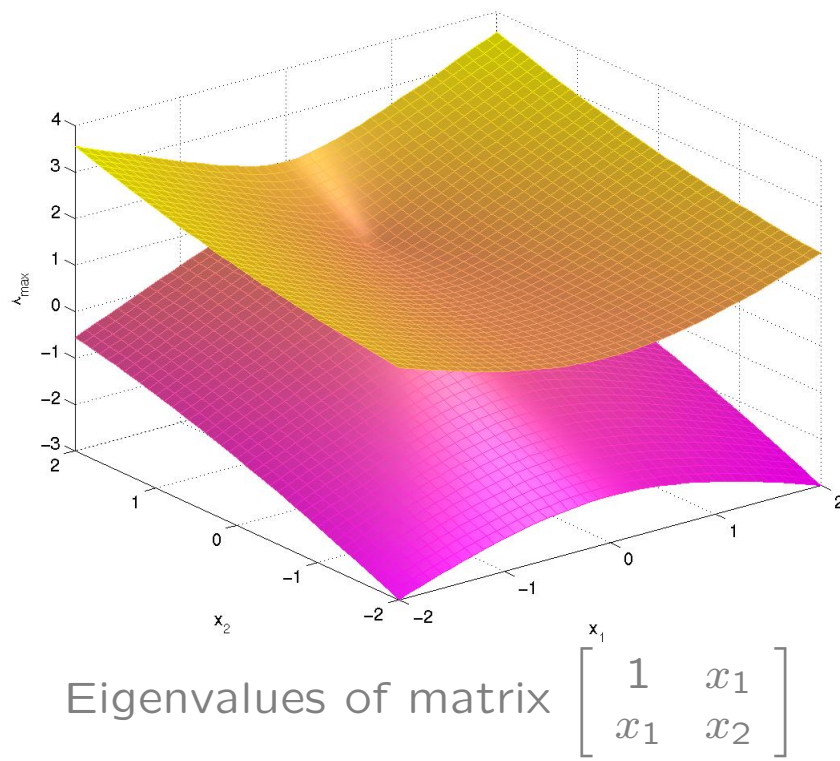
### Largest eigenvalue

The epigraph of the function **largest eigenvalue** of a symmetric matrix

$$\{X = X' \in \mathbb{R}^{n \times n}, t \in \mathbb{R} : \lambda_{\max}(X) \leq t\}$$

is **SDP (LMI) representable** as

$$X \preceq tI_n$$



## SDP/LMI representability (13)

### Sums of largest eigenvalues

Let

$$S_k(X) = \sum_{i=1}^k \lambda_i(X), \quad k = 1, \dots, n$$

denote the **sum of the  $k$  largest eigenvalues** of  $X \in \mathbb{S}^n$

The epigraph

$$\{X \in \mathbb{S}^{n \times n}, t \in \mathbb{R} : S_k(X) \leq t\}$$

is **SDP representable** as

$$\begin{aligned} t - k s - \text{trace } Z &\succeq 0 \\ Z &\succeq 0 \\ Z - X + s I_n &\succeq 0 \end{aligned}$$

where  $Z$  and  $s$  are additional variables

## Determinant of a PSD matrix

The **determinant**

$$\det(X) = \prod_{i=1}^n \lambda_i(X)$$

is not a convex function of  $X$ , but the function

$$f_q(X) = -\det^q(X), \quad X = X' \succeq 0$$

is convex when  $q \in [0, 1/n]$  is rational

The epigraph

$$\{f_q(X) \leq t\}$$

is **SDP representable** as

$$\begin{bmatrix} X & \Delta \\ \Delta' & \text{diag } \Delta \end{bmatrix} \succeq 0 \\ t \leq (\delta_1 \cdots \delta_n)^q$$

since we know that the latter constraint (hypograph of a concave monomial) is conic representable

Here  $\Delta$  is a lower triangular matrix of additional variables with diagonal entries  $\delta_i$

## Application: extremal ellipsoids

Various representations of an ellipsoid in  $\mathbb{R}^n$

$$\begin{aligned} E &= \{x \in \mathbb{R}^n : x'Px + 2x'q + r \leq 0\} \\ &= \{x \in \mathbb{R}^n : (x - x_c)'P(x - x_c) \leq 1\} \\ &= \{x = Qy + x_c \in \mathbb{R}^n : y'y \leq 1\} \\ &= \{x \in \mathbb{R}^n : \|Rx - x_c\| \leq 1\} \end{aligned}$$

where  $Q = R^{-1} = P^{-1/2} \succ 0$

Volume of ellipsoid  $E = \{Qy + x_c : y'y \leq 1\}$

$$\text{vol } E = k_n \det Q$$

where  $k_n$  is volume of  $n$ -dimensional unit ball

$$k_n = \begin{cases} \frac{2^{(n+1)/2} \pi^{(n-1)/2}}{n(n-2)!!} & \text{for } n \text{ odd} \\ \frac{2\pi^{n/2}}{n(n/2-1)!} & \text{for } n \text{ even} \end{cases}$$

$n$	1	2	3	4	5	6	7	8
$k_n$	2.00	3.14	4.19	4.93	5.26	5.17	4.72	4.06

Unit ball has maximum volume for  $n = 5$  !



## Outer and inner ellipsoidal approximations

Let  $S \subset \mathbb{R}^n$  be a **solid** = a closed bounded convex set with nonempty interior

- the largest volume ellipsoid  $E_{\text{in}}$  contained in  $S$  is unique and satisfies

$$E_{\text{in}} \subset S \subset nE_{\text{in}}$$

- the smallest volume ellipsoid  $E_{\text{out}}$  containing  $S$  is unique and satisfies

$$E_{\text{out}}/n \subset S \subset E_{\text{out}}$$

These are **Löwner-John** ellipsoids

Factor  $n$  reduces to  $\sqrt{n}$  if  $S$  is symmetric

How can these ellipsoids be computed ?

## Ellipsoids and polytopes (1)

Let the intersection of hyperplanes

$$S = \{x \in \mathbb{R}^n : a'_i x \leq b_i, i = 1, \dots, m\}$$

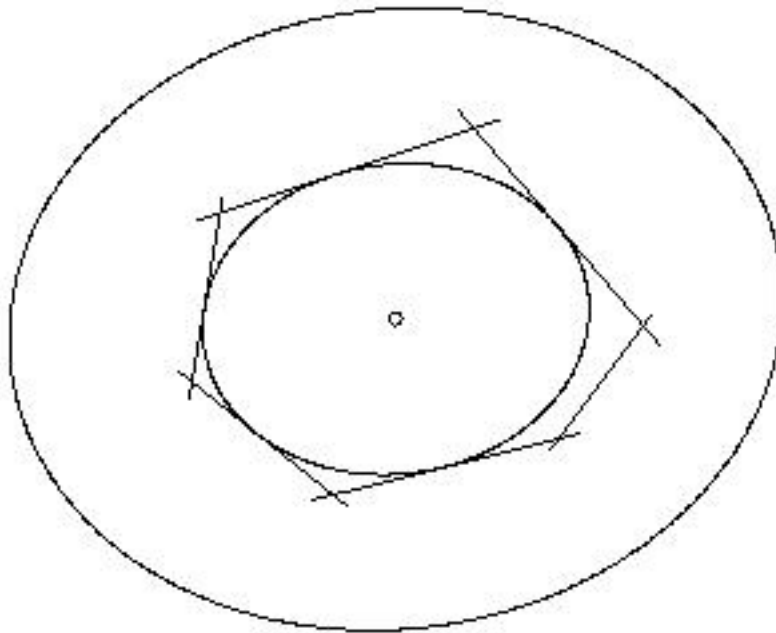
describe a **polytope**

The **largest volume ellipsoid contained** in  $S$  is

$$E = \{Qy + x_c : y'y \leq 1\}$$

where  $Q$ ,  $x_c$  are optimal solutions of the LMI

$$\begin{aligned} \max \quad & \det^{1/n} Q \\ & Q \succeq 0 \\ & \|Qa_i\|_2 \leq b_i - a'_i x_c, \quad i = 1, \dots, m \end{aligned}$$



## Ellipsoids and polytopes (2)

Let the convex hull of vertices

$$S = \text{co} \{x_1, \dots, x_m\}$$

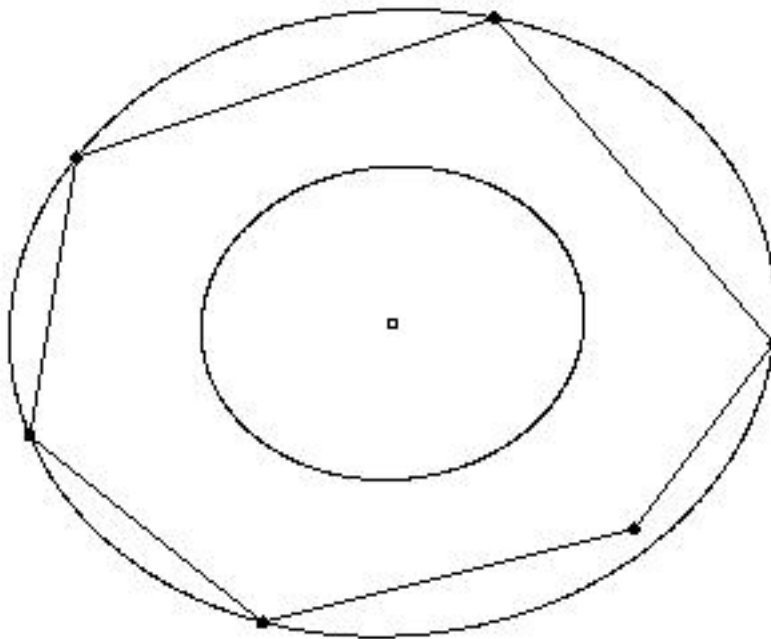
describe a polytope

The smallest volume ellipsoid containing  $S$  is

$$E = \{x : (x - x_c)' P (x - x_c) \leq 1\}$$

where  $P$ ,  $x_c = -P^{-1}q$  are optimal solutions of the LMI

$$\begin{aligned} \max \quad & t \\ & t \leq \det^{1/n} P \\ & \begin{bmatrix} P & q \\ q' & r \end{bmatrix} \succeq 0 \\ & x_i' P x_i + 2x_i' q + r \leq 1, \quad i = 1, \dots, m \end{aligned}$$



## SDP representability and singular values

Let

$$\Sigma_k(X) = \sum_{i=1}^k \sigma_i(X), \quad k = 1, \dots, n$$

denote the **sum of the  $k$  largest singular values** of  $X \in \mathbb{R}^{n \times n}$

Then the epigraph

$$\{X \in \mathbb{S}^n, t \in \mathbb{R} : \Sigma_k(X) \leq t\}$$

is **SDP representable** since

$$\sigma_i(X) = \lambda_i \left( \begin{bmatrix} 0 & X' \\ X & 0 \end{bmatrix} \right)$$

and the sum of largest eigenvalues of a symmetric matrix is **SDP representable**

## Nonlinear matrix inequalities (1)

### Schur complement

We can use the **Schur complement** to convert a non-linear matrix inequality into an LMI

$$\begin{aligned} A(x) - B(x)C^{-1}(x)B'(x) &\succeq 0 \\ C(x) &\succ 0 \end{aligned}$$

$$\iff$$

$$\begin{bmatrix} A(x) & B(x) \\ B(x) & C(x) \end{bmatrix} \succeq 0$$
$$C(x) \succ 0$$



Issai Schur  
(1875 Mogilyov - 1941 Tel Aviv)

## Nonlinear matrix inequalities (2)

### Elimination lemma

To remove decision variables we can use the **elimination lemma**

$$\begin{aligned} A(\boldsymbol{x}) + B(\boldsymbol{x})\boldsymbol{X}C(\boldsymbol{x}) + C'(\boldsymbol{x})\boldsymbol{X}'B'(\boldsymbol{x}) &> 0 \\ \iff \\ B^\perp(\boldsymbol{x})A(\boldsymbol{x})B^{\perp'}(\boldsymbol{x}) > 0 \quad C'^\perp(\boldsymbol{x})A(\boldsymbol{x})C'^{\perp'}(\boldsymbol{x}) > 0 \end{aligned}$$

where  $B^\perp$  and  $C'^\perp$  are orthogonal complements of  $B$  and  $C'$  respectively, and  $\boldsymbol{x}$  is a decision variable independent of matrix  $\boldsymbol{X}$

Can be shown with SDP duality and theorem of alternatives

## LMIR and Positive polynomials (1)

The set of univariate polynomials that are positive on the real axis is a **convex** set that is **LMI representable**

Can be proved with cone duality (Nesterov) or with theory of moments (Lasserre)

The even polynomial

$$p(s) = p_0 + p_1s + \cdots + p_{2n}s^{2n}$$

satisfies  $p(s) \geq 0$  for all  $s \in \mathbb{R}$  if and only if

$$\begin{aligned} p_k &= \sum_{i+j=k} X_{ij}, & k &= 0, 1, \dots, 2n \\ &= \text{trace } H_k X \end{aligned}$$

for some matrix  $X = X' \succeq 0$

## LMIR and Positive polynomials (2)

### Sum-of-squares decomposition

The expression of  $p_k$  with Hankel matrices  $H_k$  comes from

$$p(s) = [1 \quad s \quad \cdots \quad s^n] \mathbf{X} [1 \quad s \quad \cdots \quad s^n]^*$$

hence  $\mathbf{X} \succeq 0$  naturally implies  $p(s) \geq 0$

Conversely, existence of  $\mathbf{X}$  for any polynomial  $p(s) \geq 0$  follows from the existence of a **sum-of-squares** decomposition (with at most two elements) of

$$p(s) = \sum_k q_k^2(s) \geq 0$$

Matrix  $\mathbf{X}$  has entries  $\mathbf{X}_{ij} = \sum_k q_{k_i} q_{k_j}$



## Optimizing over polynomials (1)

### Primal and dual formulations

Global minimization of polynomial

$$p(s) = \sum_{k=0}^n p_k s^k$$

Global optimum  $p^*$ : maximum value of  $\hat{p}$  such that  $p(s) - \hat{p} \geq 0$  for all  $s \in \mathbb{R}$

Primal LMI

$$\begin{array}{ll} \max & \hat{p} = p_0 - \text{trace } H_0 \mathbf{X} \\ \text{s.t.} & \text{trace } H_k \mathbf{X} = p_k, \quad k = 1, \dots, n \\ & \mathbf{X} \succeq 0 \end{array}$$

Dual LMI

$$\begin{array}{ll} \min & p_0 + \sum_{k=1}^n p_k y_k \\ \text{s.t.} & H_0 + \sum_{k=1}^n H_k y_k \succeq 0 \end{array}$$

with **Hankel** structure (moment matrix)

## Optimizing over polynomials (2)

### Example

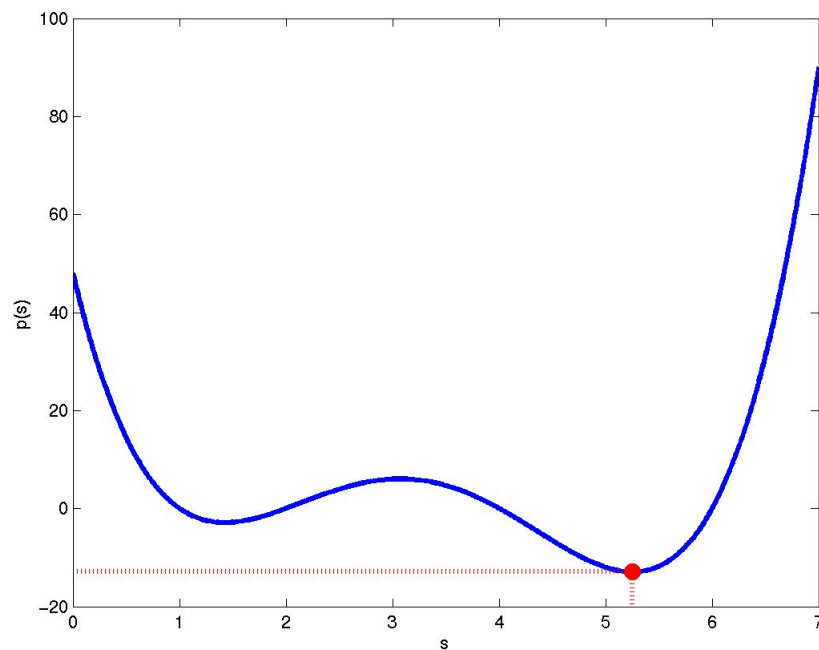
Global minimization of the polynomial

$$p(s) = 48 - 92s + 56s^2 - 13s^3 + s^4$$

We just have to solve the dual LMI

$$\begin{array}{ll} \min & 48 - 92y_1 + 56y_2 - 13y_3 + y_4 \\ \text{s.t.} & \begin{bmatrix} 1 & y_1 & y_2 \\ y_1 & y_2 & y_3 \\ y_2 & y_3 & y_4 \end{bmatrix} \succeq 0 \end{array}$$

to obtain  $p^* = p(5.25) = -12.89$



## Complex LMIs

The **complex** valued LMI

$$F(\boldsymbol{x}) = A(\boldsymbol{x}) + jB(\boldsymbol{x}) \succeq 0$$

is equivalent to the real valued LMI

$$\begin{bmatrix} A(\boldsymbol{x}) & B(\boldsymbol{x}) \\ -B(\boldsymbol{x}) & A(\boldsymbol{x}) \end{bmatrix} \succeq 0$$

If there is a complex solution to the LMI  
then there is a **real** solution to the same LMI

Note that matrix  $A(\boldsymbol{x}) = A'(\boldsymbol{x})$  is symmetric  
whereas  $B(\boldsymbol{x}) = -B'(\boldsymbol{x})$  is skew-symmetric

## Rigid convexity

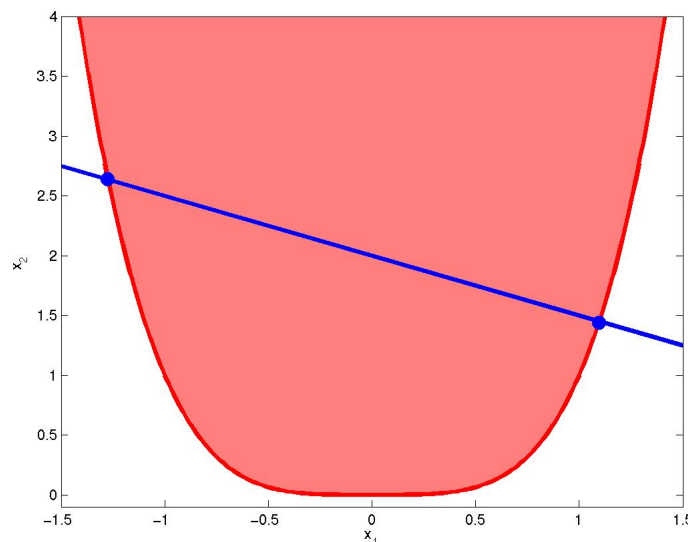
Helton & Vinnikov showed that a convex 2D set

$$\mathcal{F} = \{x \in \mathbb{R}^2 : p(x) \geq 0\}$$

defined by a polynomial  $p(x)$  of minimum degree  $d$  is LMI representable **without lifting variables** iff  $\mathcal{F}$  is **rigidly convex**, meaning that

for every point  $x \in X$  and almost every line through  $x$  then the line intersects  $p(x) = 0$  in exactly  $d$  points

Example:  $\mathcal{F} = \{(x_1, x_2) \in \mathbb{R}^2 : p(x) = x_2 - x_1^4 \geq 0\}$   
with 2 line intersections  
is not rigidly convex because  $2 < d = 4$



.. but it is LMI representable **with lifting variables**  
see the previous construction for even power monomials