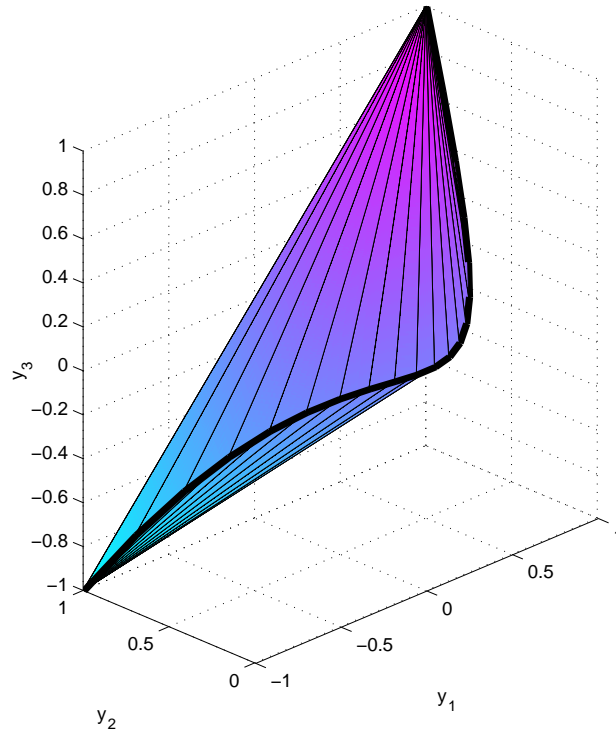


# Convex Algebraic Geometry

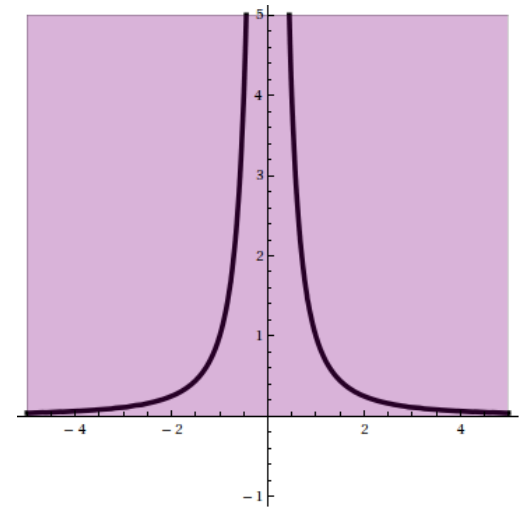


**Rekha R. Thomas**

*University of Washington, Seattle*

# CAG = study of convex hulls of real algebraic varieties

- $I \subseteq \mathbb{R}[x_1, \dots, x_n] =: \mathbb{R}[\mathbf{x}]$  ideal
- $\mathcal{V}_{\mathbb{R}}(I) := \{\mathbf{p} \in \mathbb{R}^n : f(\mathbf{p}) = 0 \forall f \in I\}$   
real variety of  $I$ , closed, semi-algebraic
- $\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$  convex hull of  $\mathcal{V}_{\mathbb{R}}(I)$   
convex, semi-algebraic



$$I = \langle x^2y - 1 \rangle$$

$\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$  open

(1)  $S \subseteq \mathbb{R}^n$  is (basic) semi-algebraic if

$$S = \{\mathbf{p} \in \mathbb{R}^n : f_1(\mathbf{p}) \triangleright_1 0, \dots, f_s(\mathbf{p}) \triangleright_s 0\},$$

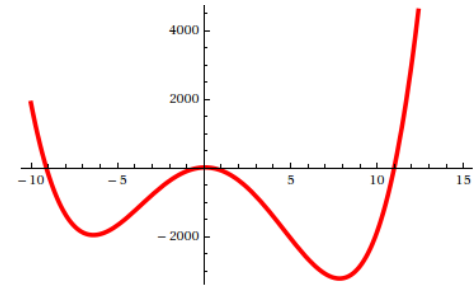
$$f_i \in \mathbb{R}[\mathbf{x}], \quad \triangleright_i \in \{\geq, \leq, =, \neq\}$$

(2) semi-algebraic set = union of basic semi-algebraic sets

# I. Why should anyone care?

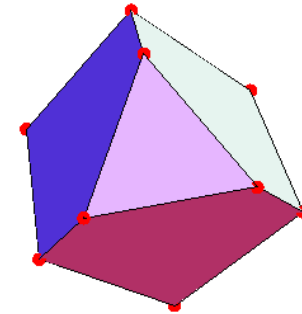
(1) **univariate ideals**:  $I = \langle f \rangle$

$\text{conv}(\mathcal{V}_{\mathbb{R}}(f))$  – **min** and **max real roots** of  $f$



(2)  $\mathcal{V}_{\mathbb{R}}(I)$  **finite**:

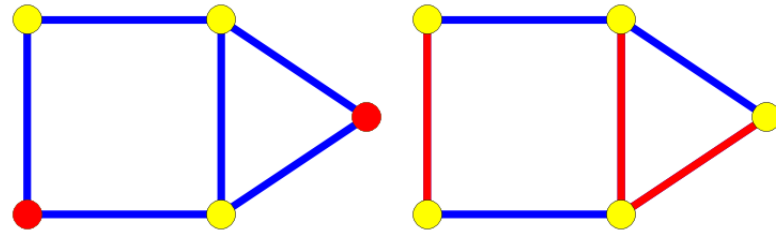
- $\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$  is a **polytope**
- allows **linear optimization** over  $\mathcal{V}_{\mathbb{R}}(I)$



contains **0/1 integer programming**:  $\max\{\mathbf{c} \cdot \mathbf{x} : A\mathbf{x} \leq \mathbf{b}, \mathbf{x} \in \{0, 1\}^n\}$

Ex:  $G = ([n], E)$  **graph** on  $n$  nodes

- (i) **max stable set problem** in  $G$
- (ii) **max cut problem** in  $G$



(3) **Polynomial Optimization**:  $p^* := \inf\{p(\mathbf{x}) : \mathbf{x} \in K\}$ ,  $K$  semi-algebraic

$$p(\mathbf{x}) = \sum_{\alpha \in S} p_{\alpha} \mathbf{x}^{\alpha}, \quad |S| = s, \quad p_{\alpha} \in \mathbb{R}$$

•  $K = \mathbb{R}^n$  (unconstrained poly optimization):

$\phi : \mathbb{R}^n \longrightarrow \mathbb{R}^s, \quad \mathbf{t} \mapsto (\mathbf{t}^{\alpha_1}, \dots, \mathbf{t}^{\alpha_s})$  toric variety

$p^* = \min\{\sum p_{\alpha} y_{\alpha} : y \in \text{conv}(\phi(\mathbb{R}^n))\}$  linear objective!

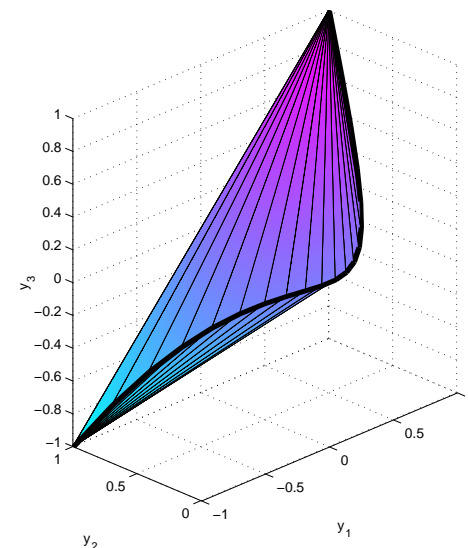
$n = 1$  &  $\deg(p) = d$ :  $\Rightarrow$

$\phi(t) = (1, t, t^2, \dots, t^d)$

rational normal curve

• **Constrained Optimization**:

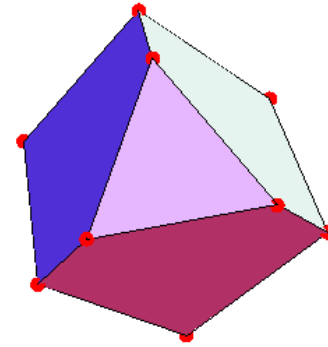
similar, extensive applications



## II. Representing $\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$

★ finite real varieties:

$\text{conv}(\mathcal{V}_{\mathbb{R}}(I)) = \{\mathbf{x} \in \mathbb{R}^n : A\mathbf{x} \leq \mathbf{b}\}$  polytope



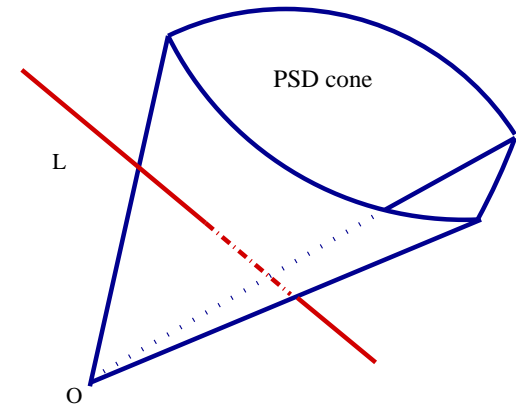
- linear programming (**polynomial time**)
- duality theory / separation theorem (**Farkas lemma**)
- projection algorithms (**Fourier-Motzkin elimination**)
- well developed computational methods

What is a useful representation in other cases?

Driven by available algorithms & their inputs

# Semidefinite programming

- $A, B \in \text{Symm}(\mathbb{R}^{n \times n})$ ,  $A \cdot B := \text{trace}(AB)$
- $A \succeq 0$  (positive semi-definite)
  - $\Leftrightarrow$  all eigenvalues of  $A$  are non-negative
  - $\Leftrightarrow \mathbf{v}^t A \mathbf{v} \geq 0 \quad \forall \mathbf{v} \in \mathbb{R}^n$
  - $\Leftrightarrow$  all principal subdeterminants  $\geq 0$
  - $\Leftrightarrow A = BB^t$  for some  $B \in \mathbb{R}^{n \times m}$



semidefinite program (sdp):

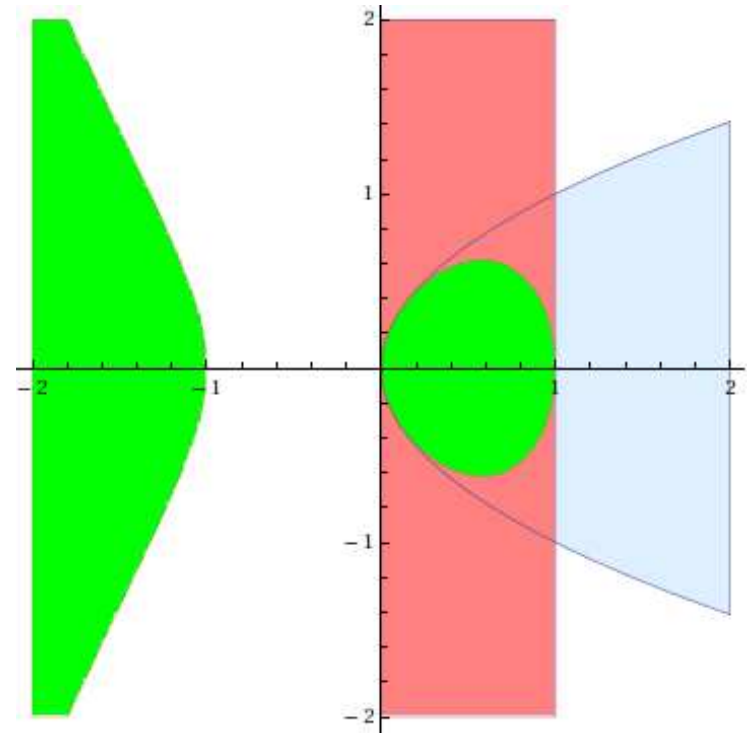
$$\sup\{C \cdot X : A_j \cdot X = b_j, j = 1, \dots, m, X \succeq 0\}$$

- convex optimization, polynomial time algorithms
- Linear programming is SDP over diagonal matrices
- feasible region – spectrahedron – convex, semi-algebraic

**Example:**

$$\left\{ (x, y) \in \mathbb{R}^2 : \begin{bmatrix} x & 0 & y \\ 0 & 1 & -x \\ y & -x & 1 \end{bmatrix} \succeq 0 \right\}$$

$$= \left\{ (x, y) \in \mathbb{R}^2 : \begin{array}{l} 0 \leq x \leq 1, \\ x \geq y^2, \\ x - x^3 - y^2 \geq 0 \end{array} \right\}$$



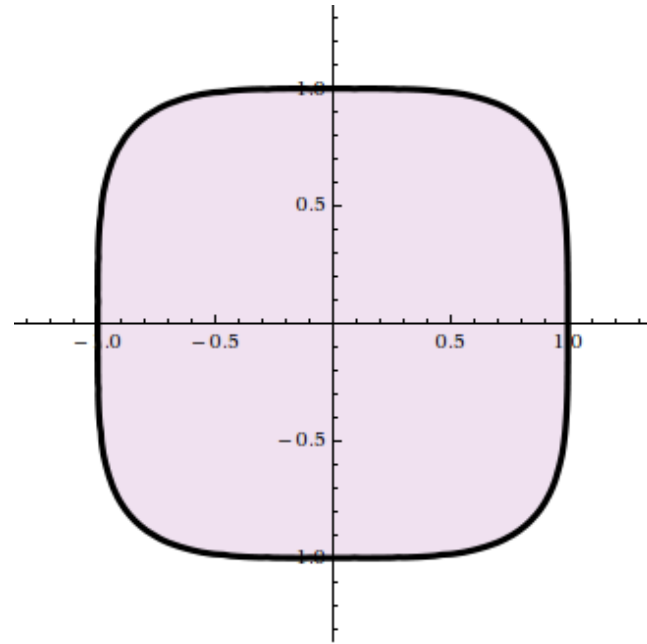
**Open Problem:** Can every convex semi-algebraic set be written as a spectrahedron or a projection of one?

Exact conditions known in  $\mathbb{R}^2$  (**Helton-Vinnikov**)

no obstructions known when  $n > 2$ .

TV screen :  $I = \langle x^4 + y^4 - 1 \rangle$

$\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$  is not a spectrahedron but is the projection of one. (Helton-Vinnikov)



In many more cases  $\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$  is the projection of a spectrahedron:

- $\mathcal{V}_{\mathbb{R}}(I)$  finite (Parrilo, Lasserre, Laurent)
- $\mathcal{V}_{\mathbb{R}}(I)$  compact with certain smoothness & curvature (Helton-Nie)
- non-compact examples with  $\dim(\mathcal{V}_{\mathbb{R}}(I)) \leq 2$  (Scheiderer)
- some ideals generated by convex quadrics (Gouveia, Parrilo, T.)
- rationally parametrized curves & some hypersurfaces (Didier)



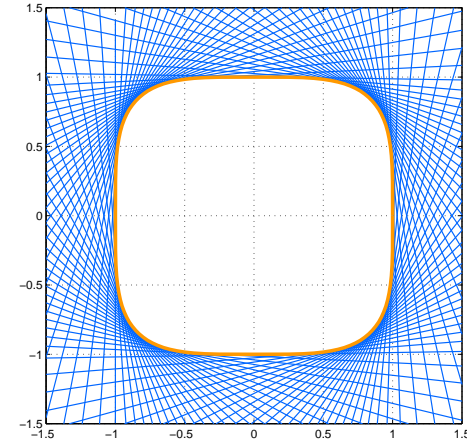
### III. Approximating $\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$ via SDP

★  $\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$  cut out by all **linear**  $f \in \mathbb{R}[\mathbf{x}]$ ,

**non-negative** on  $\mathcal{V}_{\mathbb{R}}(I)$

★  $f \equiv \sum h_j^2 \pmod{I} \Rightarrow f \geq 0$  on  $\mathcal{V}_{\mathbb{R}}(I)$ ; say  $f$  is

**sum of squares (sos)** mod  $I$  &  **$k$ -sos** if  $\deg(h_j) \leq k$



Definitions:  $f \in \mathbb{R}[\mathbf{x}]$

•  $I$  is  **$k$ -sos** if  $f \geq 0$  on  $\mathcal{V}_{\mathbb{R}}(I) \Rightarrow f$   $k$ -sos mod  $I$

•  $I$  is  **$(1, k)$ -sos** if  $f \geq 0$  on  $\mathcal{V}_{\mathbb{R}}(I)$  &  $f$  **linear**  $\Rightarrow f$   $k$ -sos mod  $I$

**Lovász: Which ideals are  $(1, 1)$ -sos,  $(1, k)$ -sos?**

☺ (Parrilo)  $I$  **zero-dim & radical**  $\Rightarrow I$  is  $|\mathcal{V}_{\mathbb{C}}(I)|$ -sos  $\Rightarrow (1, |\mathcal{V}_{\mathbb{C}}(I)|)$ -sos.

☹  $\langle x^2 \rangle$  not  $(1, k)$ -sos for any  $k$

# Theta bodies of polynomial ideals (Gouveia-Parrilo-T)

$$\text{TH}_k(I) := \{\mathbf{x} \in \mathbb{R}^n : f(\mathbf{x}) \geq 0 \forall f \text{ linear \& } k\text{-sos mod } I\}$$

$$\text{TH}_1(I) \supseteq \text{TH}_2(I) \supseteq \cdots \supseteq \overline{\text{conv}(\mathcal{V}_{\mathbb{R}}(I))} \text{ ---} (*)$$

Theorem (GPT):  $\text{TH}_k(I)$  is the projection of a spectrahedron

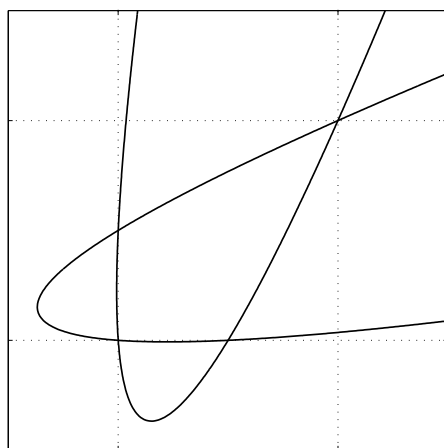
Definition:  $I$  is

- **TH<sub>k</sub>-exact** if  $\text{TH}_k(I) = \text{cl}(\text{conv}(\mathcal{V}_{\mathbb{R}}(I)))$  (finite convergence)
- **TH-exact** if there is convergence in (\*)
- \*  $\langle x^2y - 1 \rangle$  is (1, 2)-sos and TH<sub>2</sub>-exact
- \*  $\langle x^2 \rangle$  is TH<sub>1</sub>-exact
- \*  $\mathcal{V}_{\mathbb{R}}(I)$  compact  $\Rightarrow I$  is TH-exact (Schmüdgen) eg. tv screen
- \* ideal of rational normal curve of degree  $d$  is TH <sub>$d$</sub> -exact

## Geometry of theta bodies

Theorem (GPT):  $\text{TH}_1(I) = \bigcap \{\text{conv}(\mathcal{V}_{\mathbb{R}}(F)) : F \text{ convex quadric in } I\}$

Ex.  $I = \text{Vanishing ideal of } \{(0,0), (1,0), (0,1), (2,2)\}$



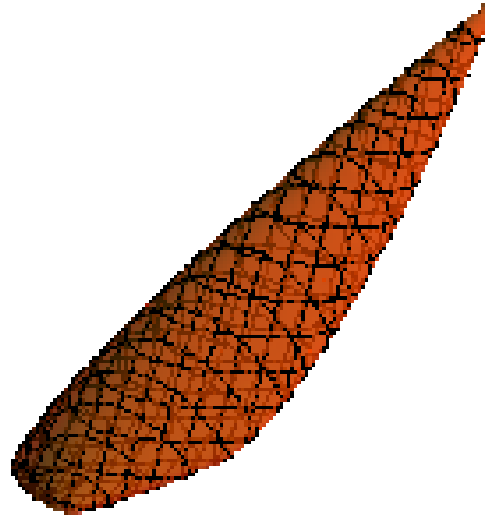
Corollary:  $J_n := \langle \sum_{i=1}^n x_i^2 - 1 \rangle$  is  $(1,1)$ -sos &  $\text{TH}_1$ -exact.

By Scheiderer  $\exists f \geq 0 \text{ mod } J_n, n \geq 4$  that is not sos mod  $J_n$ .

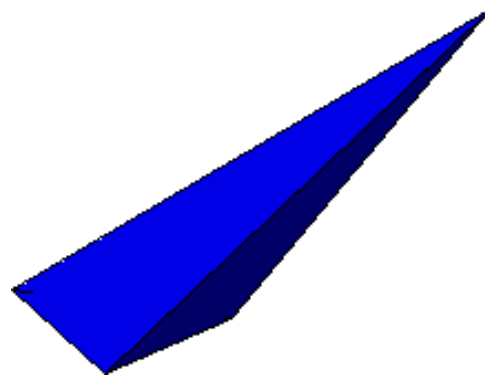
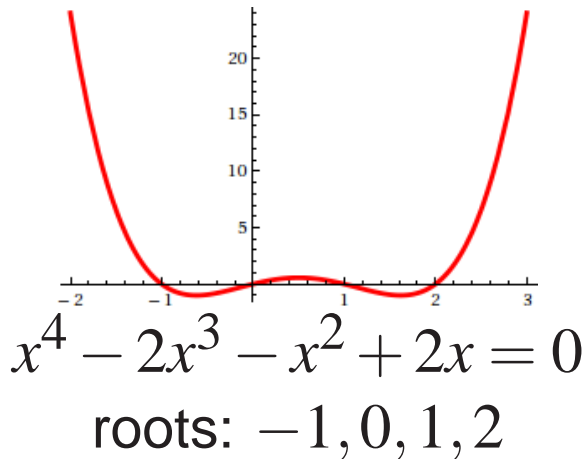
Question: What is the geometry of higher theta bodies?

# The spectrahedra upstairs

$$y_2 \geq y_1^2$$



- $y_2 \geq y_1^2$
- $y_2 y_4 \geq y_3^2$
- $y_4 \geq y_2^2,$
- $2y_3 y_2 + y_2^2$   
 $- 2y_2 y_1 - y_3^2$   
 $- 2y_3 y_1^2 - y_2 y_1^2$   
 $+ 2y_1^3 + 2y_3 y_2 y_1$   
 $- y_2^3 \geq 0$



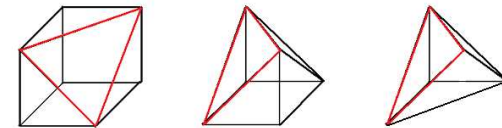
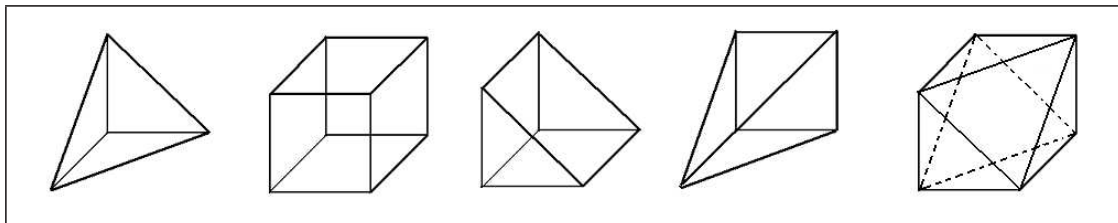
**tetrahedron**

conv(roots lifted to  
 $(1, x, x^2, x^3)$ )

# Real radical ideals

Definition:  $I$  **real radical** if it is the vanishing ideal of  $\mathcal{V}_{\mathbb{R}}(I)$

- Theorem (**GPT**):  $I$  real radical  $\Rightarrow I$  is  $(1, k)$ -sos  $\Leftrightarrow I$  is  $\text{TH}_k$ -exact
- Theorem (**GPT**):  $I$  **real radical & 0-dimensional**. Then TFAE:
  - $I$  is  $\text{TH}_1$ -exact
  - $\text{conv}(\mathcal{V}_{\mathbb{R}}(I))$  has a (finite) linear inequality description in which  $\forall f(\mathbf{x}) \geq 0, f \equiv f^2 \pmod I$
  - $\dots \forall f(\mathbf{x}) \geq 0, \mathcal{V}_{\mathbb{R}}(I) \subseteq \{f(\mathbf{x}) = 0\} \cup \{f(\mathbf{x}) = 1\}$



## IV. Computation

via Combinatorial Moment Matrices (Laurent, Lasserre)

$\mu$  probability measure supported on  $K \subseteq \mathbb{R}^n$ :

- $y_\alpha := \int \mathbf{x}^\alpha d\mu$  moment of order  $\alpha$
- $\mathbf{y} := (y_\alpha : \alpha \in \mathbb{N}^n)$  moment sequence of  $\mu$
- $M(\mathbf{y}) \in \mathbb{R}^{\mathbb{N}^n \times \mathbb{N}^n}$ :  $M(\mathbf{y})_{(\alpha, \beta)} := y_{\alpha + \beta}$  moment matrix ( $M(\mathbf{y}) \succeq 0$ )

$\mathcal{B}$  linear basis for  $\mathbb{R}[\mathbf{x}]/I$  containing  $1, x_1, \dots, x_n$  (use Gröbner bases)

• Combinatorial moment matrix:  $\mathbf{y} = (y_\gamma : \mathbf{x}^\gamma \in \mathcal{B}) \longrightarrow M_{\mathcal{B}}(\mathbf{y})$

$$\mathbf{x}^\alpha \mathbf{x}^\beta \equiv \sum_{\mathbf{x}^\gamma \in \mathcal{B}} \lambda_\gamma \mathbf{x}^\gamma; \quad M_{\mathcal{B}}(\mathbf{y})_{\alpha, \beta} := \sum_{\mathbf{x}^\gamma \in \mathcal{B}} \lambda_\gamma y_\gamma$$

Theorem (GPT):  $\text{TH}_k(I)$  is the closure of the projn onto  $(y_1, \dots, y_n)$  of

$$\left\{ \mathbf{y} \in \mathbb{R}^{\mathcal{B}_{2k}} : M_{\mathcal{B}_k}(\mathbf{y}) \succeq 0, y_0 = 1 \right\} \quad (\text{sdp})$$

# Duality

$\mathbb{R}[\mathbf{x}]^* \cong \{\mathbf{y} := (y_\alpha \in \mathbb{R} : \alpha \in \mathbb{N}^n)\}$  dual vector space of  $\mathbb{R}[\mathbf{x}]$

$$\begin{array}{ccc}
 \mathcal{P} = \{p : p(\mathbf{x}) \geq 0, \forall \mathbf{x} \in \mathbb{R}^n\} & \supseteq & \Sigma = \{\sum h_j^2 : h_j \in \mathbb{R}[\mathbf{x}]\} \\
 \downarrow * & & \downarrow * \\
 \mathcal{M} := \{\mathbf{y} \in \mathbb{R}^{\mathbb{N}^n} : \mathbf{y} \text{ mom seq in } \mathbb{R}^n\} & \subseteq & \mathcal{M}_{\succeq} := \{\mathbf{y} \in \mathbb{R}^{\mathbb{N}^n} : M(\mathbf{y}) \succeq 0\}
 \end{array}$$

Haviland 1935  $\mathcal{P} = \mathcal{M}^*, \mathcal{P}^* = \mathcal{M}$

Berg, Christensen, Jensen 1979:  $\Sigma = \mathcal{M}_{\succeq}^*, \Sigma^* = \mathcal{M}_{\succeq}$

- $(n = 1) \Rightarrow \begin{array}{l} \mathcal{M} = \mathcal{M}_{\succeq} \\ \mathcal{P} = \Sigma \end{array}$  Hamburger's theorem  
pre Hilbert

## V. Why does Lovász care?

- $G = ([n], E)$  graph,
- $S \subseteq [n]$  **stable set** in  $G$  if  $\forall i, j \in S, \{i, j\} \notin E$

**max stable set problem:**  $\max\{|S| : S \text{ stable in } G\}$

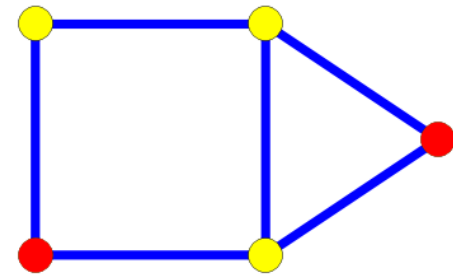
geometric approach:  $\text{STAB}(G) := \text{conv}\{\chi^S : S \text{ stable set in } G\}$

**max stable set problem:**  $\max\{\sum x_i : \mathbf{x} \in \text{STAB}(G)\}$  (NP-hard)

$$I_G := \langle x_i - x_i^2 : i \in [n], x_i x_j : ij \in E \rangle \Rightarrow \mathcal{V}(I_G) = \{\chi^S : S \text{ stable in } G\}$$

Lovász 1980: introduced  $\text{TH}_1(I_G)$  (Lovász theta body of  $G$ )

- $\text{STAB}(G) = \text{TH}_1(I_G) \Leftrightarrow G$  perfect
- poly time algorithm when  $G$  perfect
- initiated sdp relaxations in combinatorial opt





# Max Cut Problem

$C \subseteq E$  cut in  $G$  if  $\exists V_1 \cup V_2 = [n] : \forall ij \in E, i \in V_1 \text{ \& } j \in V_2$  or vice-versa

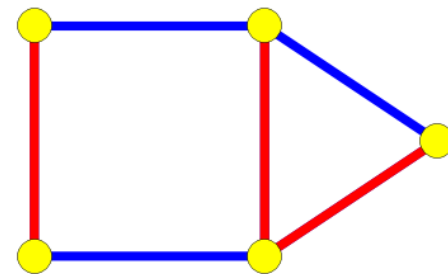
max cut problem:  $\max\{|C| : C \text{ cut in } G\}$

$$\chi^C : (\chi^E)_e = \begin{cases} -1 & \text{if } e \in C \\ 1 & \text{if } e \notin C \end{cases} \quad \text{CUT}(G) := \text{conv}\{\chi^C : C \text{ cut in } G\}$$

max cut problem:  $\max\{\sum \frac{1}{2}(1 - x_{ij}) : \mathbf{x} \in \text{CUT}(G)\}$  (NP-hard)

$$IG := I(\{\chi^C : C \text{ cut in } G\})$$

$$\text{GB: } \{x_{ij}^2 - 1\} \cup \{\mathbf{x}^A - \mathbf{x}^B : A \cup B \text{ circuit in } G\}$$



Theorem (GPT+Laurent):  $G$  is cut-perfect (i.e.,  $\text{CUT}(G) = \text{TH}_1(IG)$ )  $\Leftrightarrow$

$G$  has no  $K_5$ -minor and chordless circuits of length  $\geq 5$ . (a Lovász qn)

# Bigger context in which CAG lives

**Real algebraic geometry:** study of semi-algebraic sets in  $\mathbb{R}^n$ , preorders in  $\mathbb{R}[\mathbf{x}]$ , non-negative polynomials, sos polynomials, positivstellensatz

**Analysis:** moment problems, functional analysis

**Optimization:** semidefinite programming, polynomial optimization, control theory, combinatorial optimization

**FRG project (2008-11):**

Semidefinite Optimization and Convex Algebraic Geometry

Helton, Nie, Parrilo, Sturmfels, T., Rostalski, Klep, Gouveia, Vinzant,

Diwedi ...