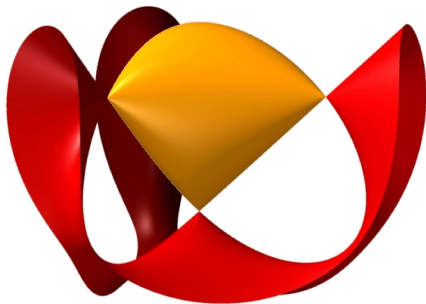


# The Geometry of Semidefinite Programming

Bernd Sturmfels  
UC Berkeley



# Positive Semidefinite Matrices

For a real symmetric  $n \times n$ -matrix  $A$  the following are equivalent:

- ▶ All  $n$  eigenvalues of  $A$  are positive real numbers.
- ▶ All  $2^n$  principal minors of  $A$  are positive real numbers.
- ▶ Every non-zero vector  $x \in \mathbb{R}^n$  satisfies  $x^T A \cdot x > 0$ .

A matrix  $A$  is *positive definite* if it satisfies these properties, and it is *positive semidefinite* if the following equivalent properties hold:

- ▶ All  $n$  eigenvalues of  $A$  are non-negative real numbers.
- ▶ All  $2^n$  principal minors of  $A$  are non-negative real numbers.
- ▶ Every vector  $x \in \mathbb{R}^n$  satisfies  $x^T A \cdot x \geq 0$ .

The set of all positive semidefinite  $n \times n$ -matrices is a *convex cone* of full dimension  $\binom{n+1}{2}$ . It is *closed* and *semialgebraic*.

The interior of this cone consists of all positive definite matrices.

# Semidefinite Programming

A *spectrahedron* is the intersection of the cone of positive semidefinite matrices with an affine-linear space. Its algebraic representation is a linear combination of symmetric matrices

$$A_0 + x_1 A_1 + x_2 A_2 + \cdots + x_m A_m \succeq 0 \quad (*)$$

Engineers call this is a *linear matrix inequality*.

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*Semidefinite programming* is the computational problem of maximizing a linear function over a spectrahedron:

$$\text{Maximize } c_1 x_1 + c_2 x_2 + \cdots + c_m x_m \text{ subject to } (*)$$

**Example:** *The smallest eigenvalue of a symmetric matrix  $A$  is the solution of the SDP* Maximize  $x$  subject to  $A - x \cdot \text{Id} \succeq 0$ .

# Convex Polyhedra

*Linear programming* is semidefinite programming for diagonal matrices. If  $A_0, A_1, \dots, A_m$  are diagonal  $n \times n$ -matrices then

$$A_0 + x_1 A_1 + x_2 A_2 + \dots + x_m A_m \succeq 0$$

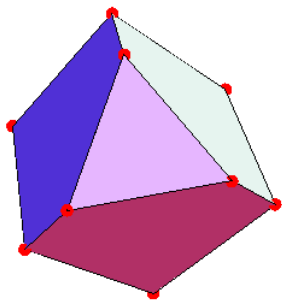
translates into a system of  $n$  linear inequalities in the  $m$  unknowns.

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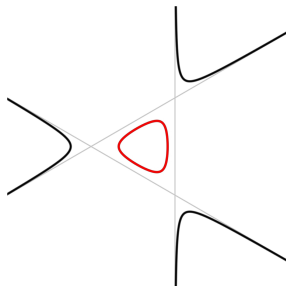
$$A_0 + x_1 A_1 + x_2 A_2 + \dots + x_m A_m \succeq 0$$

translates into a system of  $n$  linear inequalities in the  $m$  unknowns. A spectrahedron defined in this manner is a **convex polyhedron**:



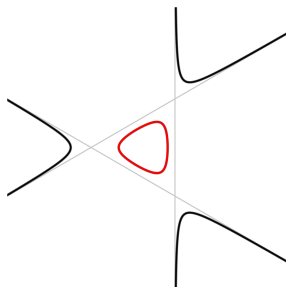
## Pictures in Dimension Two

Here is a picture of a spectrahedron for  $m = 2$  and  $n = 3$ :

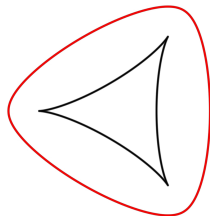


## Pictures in Dimension Two

Here is a picture of a spectrahedron for  $m = 2$  and  $n = 3$ :



**Duality** is important in convex optimization:





## Example: Multifocal Ellipses

Given  $m$  points  $(u_1, v_1), \dots, (u_m, v_m)$  in the plane  $\mathbb{R}^2$ , and a radius  $d > 0$ , their  **$m$ -ellipse** is the convex algebraic curve

$$\left\{ (x, y) \in \mathbb{R}^2 : \sum_{k=1}^m \sqrt{(x-u_k)^2 + (y-v_k)^2} = d \right\}.$$

The 1-ellipse and the 2-ellipse are algebraic curves of degree 2.

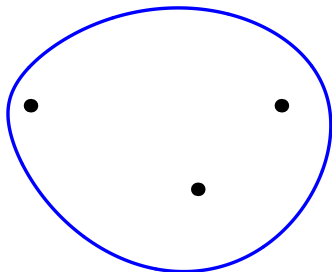
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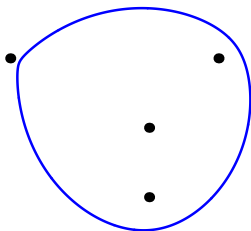
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The 3-ellipse is an algebraic curve of degree 8:

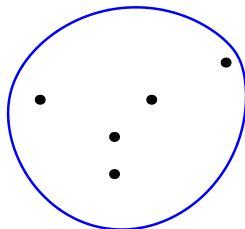


2, 2, 8, 10, 32, ...

The 4-ellipse is an algebraic curve of degree 10:



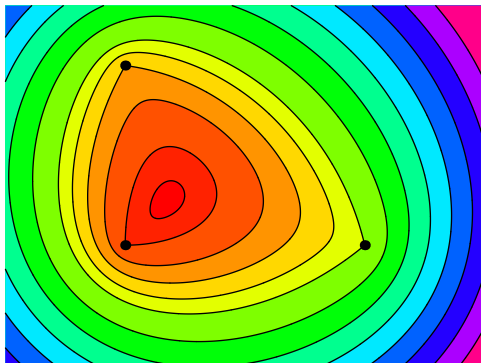
The 5-ellipse is an algebraic curve of degree 32:



# Concentric Ellipses

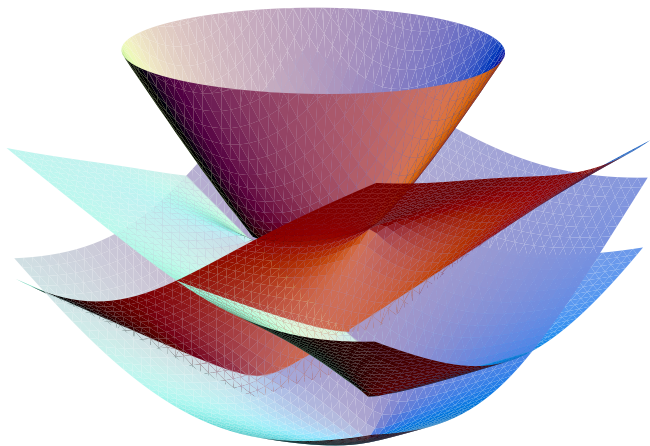
What is the algebraic degree of the  $m$ -ellipse?

How to write its equation?



What is the smallest radius  $d$  for which the  $m$ -ellipse is non-empty? How to compute the **Fermat-Weber point**?

## 3D View



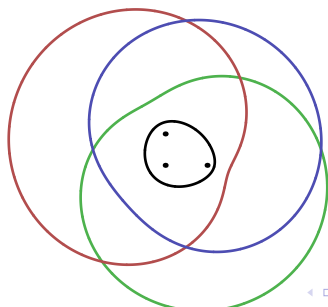
$$\mathcal{C} = \left\{ (x, y, d) \in \mathbb{R}^3 : \sum_{k=1}^m \sqrt{(x-u_k)^2 + (y-v_k)^2} \leq d \right\}.$$

## Ellipses are Spectrahedra

The 3-ellipse with foci  $(0, 0)$ ,  $(1, 0)$ ,  $(0, 1)$  has the representation

$$\begin{bmatrix} d+3x-1 & y-1 & y & 0 & y & 0 & 0 & 0 \\ y-1 & d+x-1 & 0 & y & 0 & y & 0 & 0 \\ y & 0 & d+x+1 & y-1 & 0 & 0 & y & 0 \\ 0 & y & y-1 & d-x+1 & 0 & 0 & 0 & y \\ y & 0 & 0 & 0 & d+x-1 & y-1 & y & 0 \\ 0 & y & 0 & 0 & y-1 & d-x-1 & 0 & y \\ 0 & 0 & y & 0 & y & 0 & d-x+1 & y-1 \\ 0 & 0 & 0 & y & 0 & y & y-1 & d-3x+1 \end{bmatrix}$$

The ellipse consists of all points  $(x, y)$  where this symmetric  $8 \times 8$ -matrix is **positive semidefinite**. Its boundary is a curve of **degree eight**:



2, 2, 8, 10, 32, 44, 128, ...

**Theorem:** *The polynomial equation defining the  $m$ -ellipse has degree  $2^m$  if  $m$  is odd and degree  $2^m - \binom{m}{m/2}$  if  $m$  is even. We express this polynomial as the determinant of a symmetric matrix of linear polynomials. Our representation extends to weighted  $m$ -ellipses and  $m$ -ellipsoids in arbitrary dimensions .....*

[J. Nie, P. Parrilo, B.St.: [Semidefinite](#) representation of the  $k$ -ellipse, in *Algorithms in Algebraic Geometry*, I.M.A. Volumes in Mathematics and its Applications, 146, Springer, New York, 2008, pp. 117-132]

In other words,  $m$ -ellipses and  $m$ -ellipsoids are spectrahedra.  
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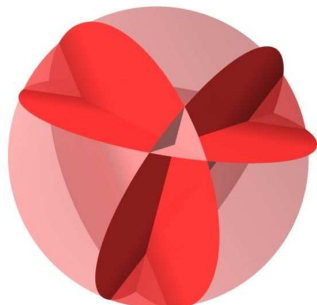
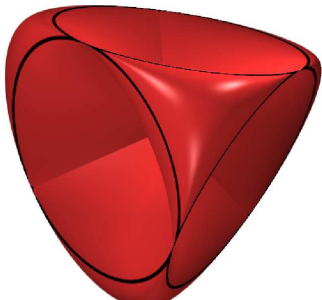
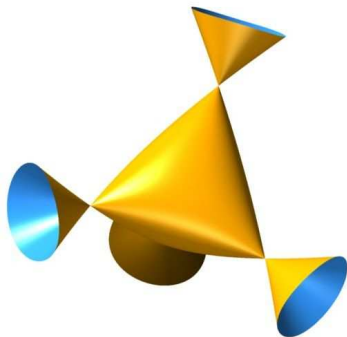
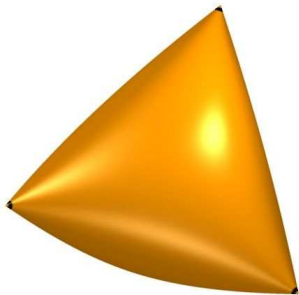
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Let's now look at some spectrahedra in dimension three. Our next picture shows the typical behavior for  $m = 3$  and  $n = 3$ .

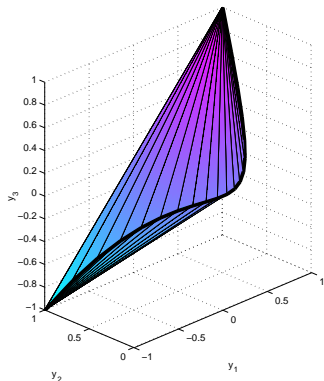


# A Spectrahedron and its Dual



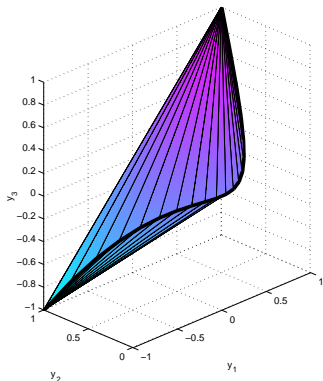
# Non-Linear Convex Hull Computation

**Input :**  $\{(t, t^2, t^3) \in \mathbb{R}^3 : -1 \leq t \leq 1\}$



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The convex hull of the moment curve is a spectrahedron.

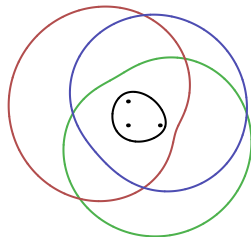
**Output :** 
$$\begin{pmatrix} 1 & x \\ x & y \end{pmatrix} \pm \begin{pmatrix} x & y \\ y & z \end{pmatrix} \succeq 0$$

# Characterization of Spectrahedra

A convex hypersurface of degree  $d$  in  $\mathbb{R}^n$  is *rigid convex* if every line passing through its interior meets (the Zariski closure of) that hypersurface in  $d$  *real* points.

**Theorem (Helton–Vinnikov (2006))**

*Every spectrahedron is rigid convex. The converse is true for  $n = 2$ .*

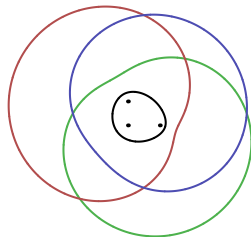


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**Open problem:** Is every compact convex basic semialgebraic set  $\mathcal{S}$  the projection of a spectrahedron in higher dimensions?

Theorem (Helton–Nie (2008))

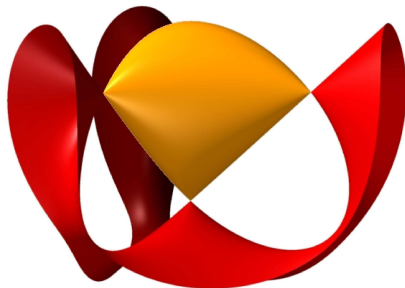
*The answer is yes if the boundary of  $\mathcal{S}$  is “sufficiently smooth”.*

## Questions about 3-Dimensional Spectrahedra

What are the edge graphs of spectrahedra in  $\mathbb{R}^3$ ?

How can one define their *combinatorial types*?

Is there an analogue to Steinitz' Theorem for polytopes in  $\mathbb{R}^3$ ?



Consider 3-dimensional spectrahedra whose boundary is an irreducible surface of degree  $n$ . Can such a spectrahedron have  $\binom{n+1}{3}$  isolated singularities in its boundary? How about  $n = 4$ ?

## A Pinch of Statistics

Every positive definite  $n \times n$ -matrix  $\Sigma = (\sigma_{ij})$  is the covariance matrix of a multivariate normal distribution. A **Gaussian graphical model** is specified by requiring that some entries of  $\Sigma^{-1}$  are zero.

Maximum likelihood estimation is a *matrix completion problem*.

For example, under which condition on the visible entries  $\sigma_{ij}$  can we find  $x$  and  $y$  which make the following matrix positive definite?

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & x & \sigma_{14} \\ \sigma_{12} & \sigma_{22} & \sigma_{23} & y \\ x & \sigma_{23} & \sigma_{33} & \sigma_{34} \\ \sigma_{14} & y & \sigma_{34} & \sigma_{44} \end{pmatrix}$$

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The MLE is the point  $(\hat{x}, \hat{y})$  which maximizes the determinant. In optimization, this is the *analytic center* of the spectrahedron.

[C. Uhler, B.St.: Multivariate Gaussians, Semidefinite Matrix Completion and Convex Algebraic Geometry, 2009]



# Minimizing Polynomial Functions

Let  $f(x_1, \dots, x_m)$  be a polynomial of even degree  $2d$ .

We wish to compute the global minimum  $x^*$  of  $f(x)$  on  $\mathbb{R}^m$ .

This optimization problem is equivalent to

Maximize  $\lambda$  such that  $f(x) - \lambda$  is non-negative on  $\mathbb{R}^m$ .

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Empirically, the optimal value of the SDP almost always agrees with the global minimum. In that case, the optimal matrix of the dual SDP has rank one, and the optimal point  $x^*$  can be recovered from this. **How to reconcile this with Blekherman's results?**

## SOS Programming: A Univariate Example

Let  $m = 1$ ,  $d = 2$  and  $f(x) = 3x^4 + 4x^3 - 12x^2$ . Then

$$f(x) - \lambda = \begin{pmatrix} x^2 & x & 1 \end{pmatrix} \begin{pmatrix} 3 & 2 & \mu - 6 \\ 2 & -2\mu & 0 \\ \mu - 6 & 0 & -\lambda \end{pmatrix} \begin{pmatrix} x^2 \\ x \\ 1 \end{pmatrix}$$

Our problem is to find  $(\lambda, \mu)$  such that the  $3 \times 3$ -matrix is positive semidefinite and  $\lambda$  is maximal. The optimal solution of this SDP is

$$(\lambda^*, \mu^*) = (-32, -2).$$

Cholesky factorization reveals the SOS representation

$$f(x) - \lambda^* = \left( (\sqrt{3}x - \frac{4}{\sqrt{3}}) \cdot (x+2) \right)^2 + \frac{8}{3}(x+2)^2.$$

We see that the global minimum is  $x^* = -2$ .

This approach works for many polynomial optimization problems.

# Hankel Matrices

Consider the intersection of the cone of  $6 \times 6$  PSD matrices with the 15-dimensional linear space consisting of all Hankel matrices

$$H = \begin{pmatrix} \lambda_{400} & \lambda_{220} & \lambda_{202} & \lambda_{310} & \lambda_{301} & \lambda_{211} \\ \lambda_{220} & \lambda_{040} & \lambda_{022} & \lambda_{130} & \lambda_{121} & \lambda_{031} \\ \lambda_{202} & \lambda_{022} & \lambda_{004} & \lambda_{112} & \lambda_{103} & \lambda_{013} \\ \lambda_{310} & \lambda_{130} & \lambda_{112} & \lambda_{220} & \lambda_{211} & \lambda_{121} \\ \lambda_{301} & \lambda_{121} & \lambda_{103} & \lambda_{211} & \lambda_{202} & \lambda_{112} \\ \lambda_{211} & \lambda_{031} & \lambda_{013} & \lambda_{121} & \lambda_{112} & \lambda_{022} \end{pmatrix}.$$

Dual to this intersection is the projection

$$\text{Sym}_2(\text{Sym}_2(\mathbb{R}^3)) \rightarrow \text{Sym}_4(\mathbb{R}^3)$$

taking a  $6 \times 6$ -matrix to the ternary quartic it represents. Its image is a cone whose **algebraic boundary** is a **discriminant** of degree 27.

**Problem:** Determine the variety of all Bézout matrices  $H^{-1}$ .

# Orbitopes

An *orbitope* is the convex hull of an orbit under a real algebraic representation of a compact Lie group. Primary examples are the groups  $SO(n)$  and their products. Orbitopes for their adjoint representations are continuous analogues of *permutohedra*.

Many of these special orbitopes are projections of spectrahedra.

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**Quiz:** Is this orbitope a spectrahedron?

**Answer:** Yes, it is the set of psd Hankel matrices  $H$  that satisfy

$$\lambda_{400} + \lambda_{040} + \lambda_{004} + 2\lambda_{220} + 2\lambda_{202} + 2\lambda_{022} = 9.$$

**Problem.** Classify all  $\mathrm{SO}(n)$ -orbitopes that are spectrahedra.



# Tautological Orbitopes

... are obtained by taking the convex hull of a matrix group.

**Example** (P. Parrilo):  $\text{conv}(SO(3))$  is the set of  $3 \times 3$ -matrices

$$\begin{pmatrix} u_{11} + u_{22} - u_{33} - u_{44} & 2u_{23} - 2u_{14} & 2u_{13} + 2u_{24} \\ 2u_{23} + 2u_{14} & u_{11} - u_{22} + u_{33} - u_{44} & 2u_{34} - 2u_{12} \\ 2u_{24} - 2u_{13} & 2u_{12} + 2u_{34} & u_{11} - u_{22} - u_{33} + u_{44} \end{pmatrix}$$

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where  $U = (u_{ij})$  runs over all  $4 \times 4$  psd matrices having trace 1.

*Proof:* Psd matrices having both trace 1 and rank 1 are of the form

$$U = \frac{1}{a^2 + b^2 + c^2 + d^2} \begin{pmatrix} a^2 & ab & ac & ad \\ ab & b^2 & bc & bd \\ ac & bc & c^2 & cd \\ ad & bd & cd & d^2 \end{pmatrix}$$

Their images under the linear map parametrize the group  $SO(3)$ .

## Barvinok-Novik Orbitopes

Consider the  $SO(2) \times SO(2)$ -orbitope  $BN_4$  determined by the curve

$$\theta \mapsto (\cos(\theta), \sin(\theta), \cos(3\theta), \sin(3\theta)) \in \mathbf{R}^4.$$

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$$\begin{pmatrix} 1 & x_1 & x_2 & x_3 \\ y_1 & 1 & x_1 & x_2 \\ y_2 & y_1 & 1 & x_1 \\ y_3 & y_2 & y_1 & 1 \end{pmatrix} \quad \text{where} \quad \begin{aligned} x_j &= c_j + \sqrt{-1} \cdot s_j, \\ y_j &= c_j - \sqrt{-1} \cdot s_j, \end{aligned}$$

under the map  $(c_1, c_2, c_3, s_1, s_2, s_3) \mapsto (c_1, c_3, s_1, s_3)$ . Here the unknown  $c_j$  represents  $\cos(j\theta)$ , the unknown  $s_j$  represents  $\sin(j\theta)$ .

The curve is cut out by the  $2 \times 2$ -minors of the Toeplitz matrix.

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This is the projection of a 6-dimensional **Hermitian spectrahedron**:

$$\begin{pmatrix} 1 & x_1 & x_2 & x_3 \\ y_1 & 1 & x_1 & x_2 \\ y_2 & y_1 & 1 & x_1 \\ y_3 & y_2 & y_1 & 1 \end{pmatrix} \quad \text{where} \quad \begin{aligned} x_j &= c_j + \sqrt{-1} \cdot s_j, \\ y_j &= c_j - \sqrt{-1} \cdot s_j, \end{aligned}$$

under the map  $(c_1, c_2, c_3, s_1, s_2, s_3) \mapsto (c_1, c_3, s_1, s_3)$ . Here the unknown  $c_j$  represents  $\cos(j\theta)$ , the unknown  $s_j$  represents  $\sin(j\theta)$ .

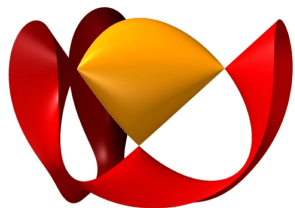
The curve is cut out by the  $2 \times 2$ -minors of the Toeplitz matrix.

The **faces** of  $\text{BN}_4$  are certain edges and triangles. Its **algebraic boundary** is the threefold defined by the degree 8 polynomial

$$\begin{aligned} &x_3^2 y_1^6 - 2x_1^3 x_3 y_1^3 y_3 + x_1^6 y_3^2 + 4x_1^3 y_1^3 - 6x_1 x_3 y_1^4 - 6x_1^4 y_1 y_3 + 12x_1^2 x_3 y_1^2 y_3 \\ &- 2x_3^2 y_1^3 y_3 - 2x_1^3 x_3 y_3^2 - 3x_1^2 y_1^2 + 4x_3 y_1^3 + 4x_1^3 y_3 - 6x_1 x_3 y_1 y_3 + x_3^2 y_3^2. \end{aligned}$$

# Conclusion

Spectrahedra and orbitopes deserve to be studied in their own right, independently of their important uses in applications.



A true understanding of these convex bodies will require the integration of three different areas of mathematics:

- ▶ Classical Convexity
- ▶ Algebraic Geometry
- ▶ Optimization Theory