

# **LP and SOCP-based Approximations to SOS**

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# Optimization over nonnegative polynomials

Is  $p(x) \geq 0$  on  $\{g_1(x) \geq 0, \dots, g_m(x) \geq 0\}$ ?

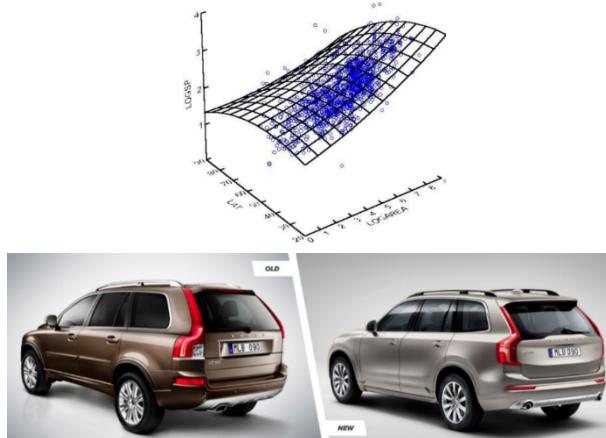
## Optimization

- Lower bounds on polynomial optimization problems

$$\begin{aligned} \min_x \quad & p(x) \\ \text{s.t. } & g_i(x) \geq 0 \end{aligned}$$

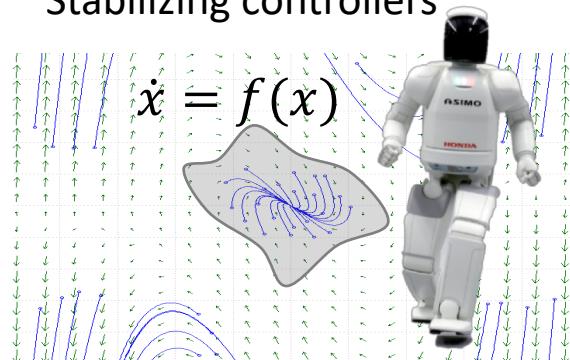
## Statistics/ML

- Fitting a polynomial to data subject to shape constraints (e.g., convexity, or monotonicity)



## Control

- Stabilizing controllers



$$\begin{aligned} V(x) > 0, \\ V(x) \leq \beta \Rightarrow \nabla V(x)^T f(x) < 0 \end{aligned}$$

Implies that  
 $\{x \mid V(x) \leq \beta\}$   
is in the region of attraction

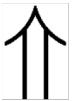
$$\frac{\partial p(x)}{\partial x_j} \geq 0, \forall x \in B$$

# How to prove nonnegativity?

$$p(x) = x_1^4 - 6x_1^3x_2 + 2x_1^3x_3 + 6x_1^2x_3^2 + 9x_1^2x_2^2 - 6x_1^2x_2x_3 - 14x_1x_2x_3^2 + 4x_1x_3^3 + 5x_3^4 - 7x_2^2x_3^2 + 16x_2^4$$

Nonnegative

$$p(x) = (x_1^2 - 3x_1x_2 + x_1x_3 + 2x_3^2)^2 + (x_1x_3 - x_2x_3)^2 + (4x_2^2 - x_3^2)^2.$$



SOS

- Optimization over sum of squares (SOS) polynomials is a semidefinite program (SDP)!
- SDPs can be solved in poly-time to arbitrary accuracy.

# Practical limitations of SOS

- **Scalability** is a nontrivial challenge!

A polynomial  $p$  of degree  $2d$  is SOS if and only if  $\exists Q \geq 0$  such that

$$p(x) = \mathbf{z}(x)^T Q \mathbf{z}(x)$$

where  $\mathbf{z} = [1, x_1, \dots, x_n, x_1 x_2, \dots, x_n^d]^T$  is the vector of monomials of degree up to  $d$ .

- The size of the Gram matrix is:

$$\binom{n+d}{d} \times \binom{n+d}{d}$$

- Polynomial in  $n$  for fixed  $d$ , but grows quickly
  - **The semidefinite constraint is expensive**
- E.g., local stability analysis of a 20-state cubic vector field is typically an SDP with  $\sim 1.2M$  decision variables and  $\sim 200k$  constraints

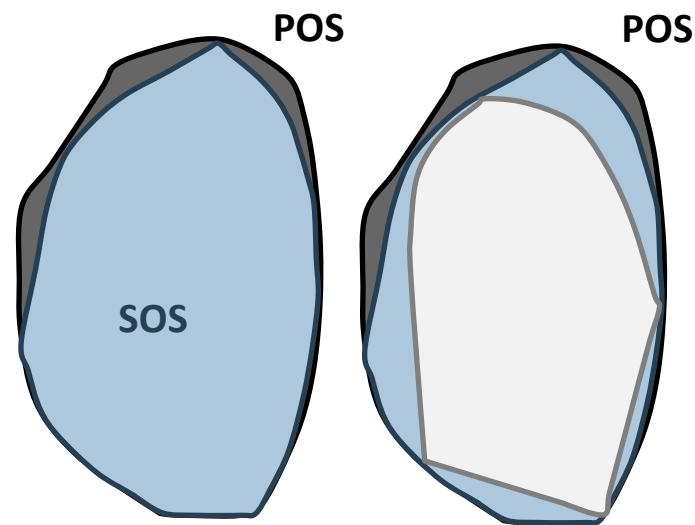
# Simple idea...

- Let's not work with SOS...
- Give other sufficient conditions for nonnegativity that are **perhaps stronger than SOS, but hopefully cheaper**

Not any set inside SOS would work!

- 1) sums of 4<sup>th</sup> powers of polynomials
- 2) sums of 3 squares of polynomials

Both sets are clearly inside the SOS cone,  
but linear optimization over them is **intractable**.



# dsos and sdsos polynomials (1/3)

**Defn.** A polynomial  $p$  is *diagonally-dominant-sum-of-squares (dsos)* if it can be written as:

$$p(x) = \sum_i \alpha_i m_i^2(x) + \sum_{i,j} \beta_{ij}^+ (m_i(x) + m_j(x))^2 + \sum_{i,j} \beta_{ij}^- (m_i(x) - m_j(x))^2,$$

for some monomials  $m_i, m_j$   
and some nonnegative constants  $\alpha_i, \beta_{ij}^+, \beta_{ij}^-$ .

**Defn.** A polynomial  $p$  is *scaled-diagonally-dominant-sum-of-squares (sdsos)* if it can be written as:

$$p(x) = \sum_i \alpha_i m_i^2(x) + \sum_{i,j} (\hat{\beta}_{ij}^+ m_i(x) + \tilde{\beta}_{ij}^+ m_j(x))^2 + \sum_{i,j} (\hat{\beta}_{ij}^- m_i(x) - \tilde{\beta}_{ij}^- m_j(x))^2,$$

for some monomials  $m_i, m_j$   
and some constants  $\alpha_i, \hat{\beta}_{ij}^+, \tilde{\beta}_{ij}^+, \hat{\beta}_{ij}^-, \tilde{\beta}_{ij}^-$  with  $\alpha_i \geq 0$ .

# dsos and sdsos polynomials (2/3)

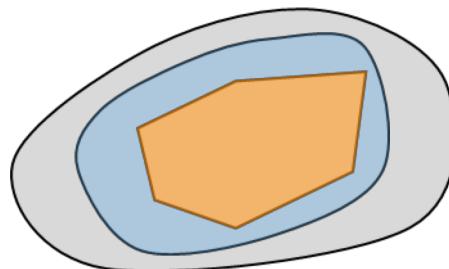
Sum of squares (sos)

$$p(x) = z(x)^T Q z(x), Q \geq 0$$

SDP

$$\text{DD cone} := \{Q \mid Q_{ii} \geq \sum_{j \neq i} |Q_{ij}|, \forall i\}$$

$$\text{PSD cone} := \{Q \mid Q \geq 0\}$$



$$\text{SDD cone} := \{Q \mid \exists \text{ diagonal } D \text{ with } D_{ii} > 0 \text{ s.t. } D Q D \text{ dd}\}$$

Diagonally dominant sum of squares (dsos)

$$p(x) = z(x)^T Q z(x), Q \text{ diagonally dominant (dd)}$$

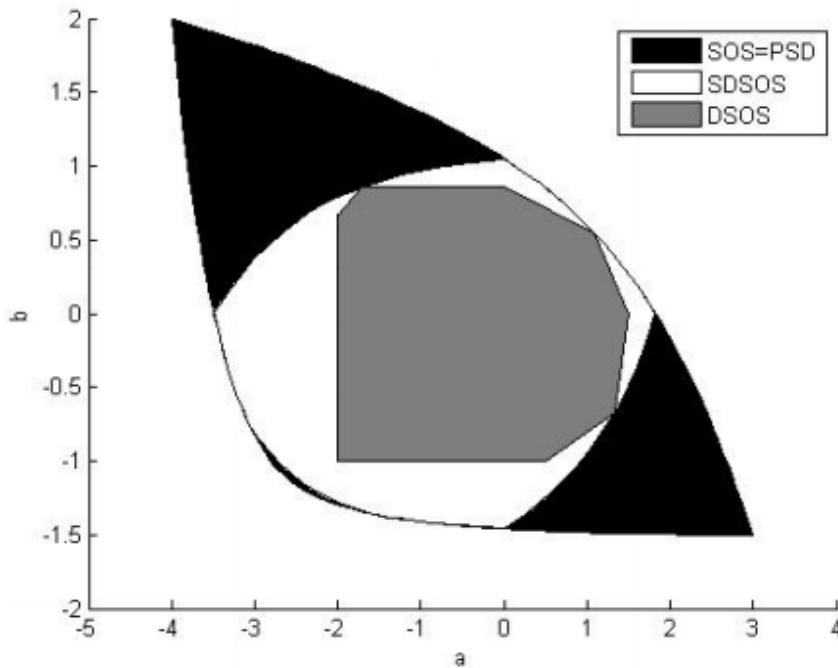
LP

Scaled diagonally dominant sum of squares (sdsos)

$$p(x) = z(x)^T Q z(x), Q \text{ scaled diagonally dominant (sdd)}$$

SOCP

# dsos and sdsos polynomials (3/3)



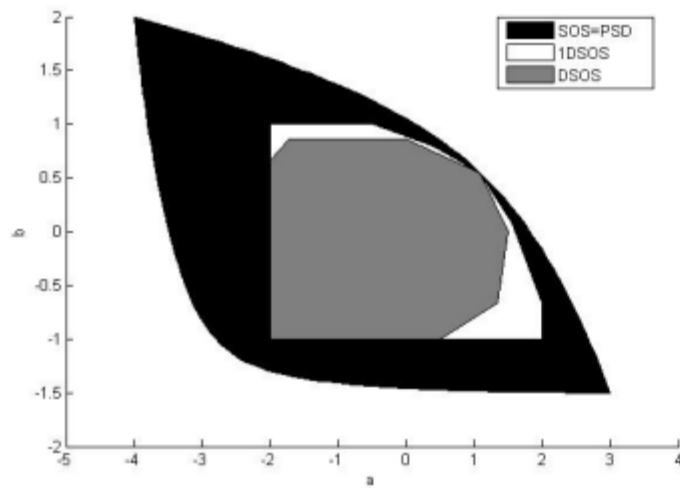
$$p(x_1, x_2) = x_1^4 + x_2^4 + ax_1^3x_2 + \left(1 - \frac{1}{2}a - \frac{1}{2}b\right)x_1^2x_2^2 + 2bx_1x_2^3$$

How to do better?

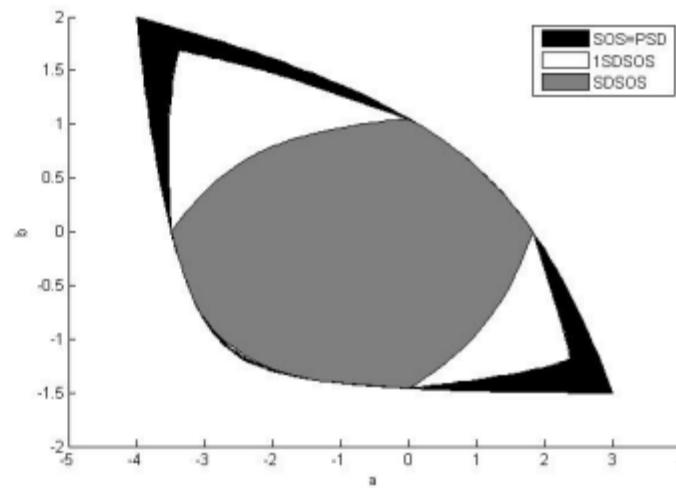
# Method #1: r-dsos and r-sdsos polynomials (1/2)

## Defn.

- A polynomial  $p$  is **r-dsos** if  $p(x) \cdot (\sum_i x_i^2)^r$  is dsos.
- A polynomial  $p$  is **r-sdsos** if  $p(x) \cdot (\sum_i x_i^2)^r$  is sdsos.



(a) The LP-based r-dsos hierarchy.



(b) The SOCP-based r-sdsos hierarchy.

$$p(x_1, x_2) = x_1^4 + x_2^4 + ax_1^3x_2 + \left(1 - \frac{1}{2}a - \frac{1}{2}b\right)x_1^2x_2^2 + 2bx_1x_2^3$$

# Method #1: r-dsos and r-sdsos polynomials (2/2)

- r-dsos can outperform sos!

$$p(x) = x_1^4x_2^2 + x_2^4x_3^2 + x_3^4x_1^2 - 3x_1^2x_2^2x_3^2$$

is 1-dsos but not sos.

**Theorem:** Any even positive definite form is r-dsos for some r.

- Even forms include *copositive programming* (*and all problems in NP*).

**Theorem:** Any form can be made even, while preserving positivity, by doubling the number of variables and degree.

- Leads to arbitrarily tight lower bounds on any polynomial optimization problem (with a compact feasible set).

## Method #2: dsos/sdsos + change of basis (1/2)

$$p(x) = x_1^4 - 6x_1^3x_2 + 2x_1^3x_3 + 6x_1^2x_2^2 + 9x_1^2x_2^2 - 6x_1^2x_2x_3 - 14x_1x_2x_3^2 + 4x_1x_3^3 \\ + 5x_3^4 - 7x_2^2x_3^2 + 16x_2^4$$

$$p(x) = z^T(x)Qz(x)$$

$$Q = \begin{pmatrix} 1 & -3 & 0 & 1 & 0 & 2 \\ -3 & 9 & 0 & -3 & 0 & -6 \\ 0 & 0 & 16 & 0 & 0 & -4 \\ 1 & -3 & 0 & 2 & -1 & 2 \\ 0 & 0 & 0 & -1 & 1 & 0 \\ 2 & -6 & 4 & 2 & 0 & 5 \end{pmatrix}$$

$$z(x) = (x_1^2, x_1x_2, x_2^2, x_1x_3, x_2x_3, x_3^2)^T$$

$$p(x) = \tilde{z}^T(x) \begin{pmatrix} \frac{1}{2} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 4 \end{pmatrix} \tilde{z}(x)$$

$$\tilde{z}(x) = \begin{pmatrix} 2x_1^2 - 6x_1x_2 + 2x_1x_3 + 2x_3^2 \\ x_1x_3 - x_2x_3 \\ x_2^2 - \frac{1}{4}x_3^2 \end{pmatrix}$$

**Goal:** iteratively improve  $z(x)$

# Method #2: dsos/sdsos + change of basis (2/2)

LP

$$\max_{\vec{P}, Q} l(\vec{P})$$

s.t.  $P(x) = \vec{z}^T(x) Q \vec{z}(x) \forall x$

$Q \text{ dd}$

→ Optimal soln.  $Q^*$

→ Cholesky:  $Q^* = U^T U$

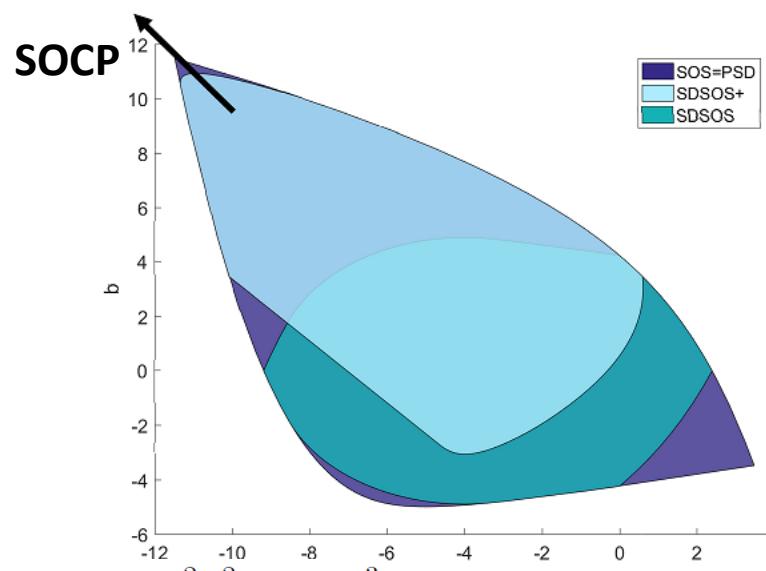
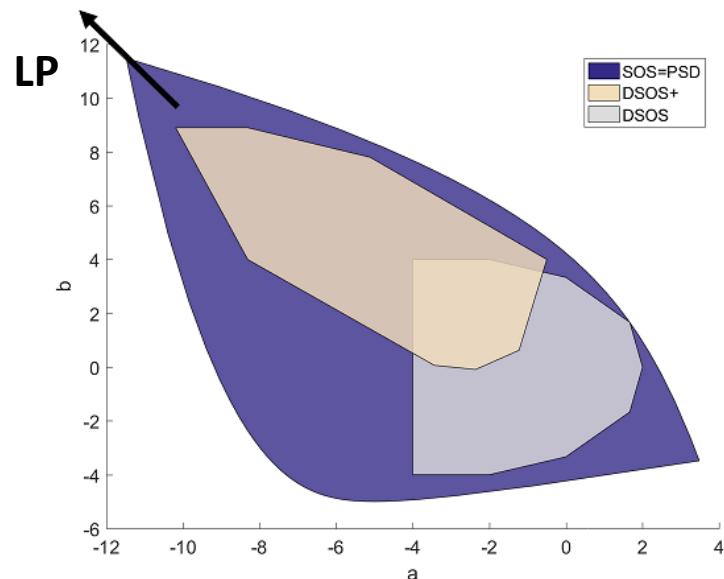
LP<sub>+</sub>

$$\max_{\vec{P}, Q} l(\vec{P})$$

s.t.  $P(x) = \vec{z}^T(x) U^T Q U \vec{z}(x) \forall x$

$Q \text{ dd}$

Works beautifully!



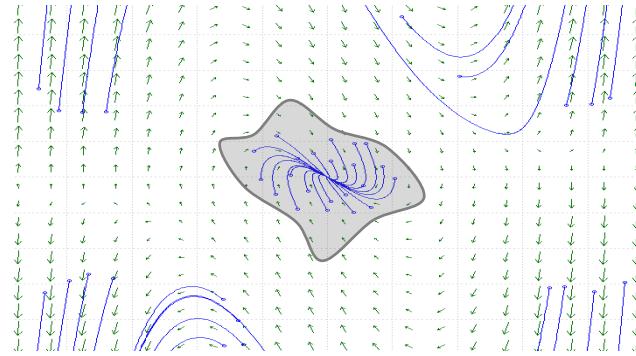
# Applications in control

(see paper for applications in statistics, finance, combinatorial and polynomial optimization)

## Reminder

$$\dot{x} = f(x, u)$$

### Stability of equilibrium points



$$V(x) > 0, \\ V(x) \leq \beta \Rightarrow \dot{V}(x) < 0$$

implies  $\{x \mid V(x) \leq \beta\}$  is in the region of attraction (ROA)

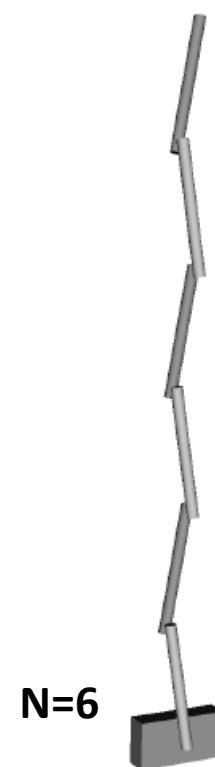
# Stabilizing the inverted N-link pendulum (2N states)



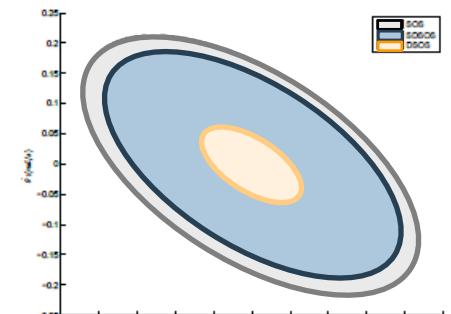
**N=1**



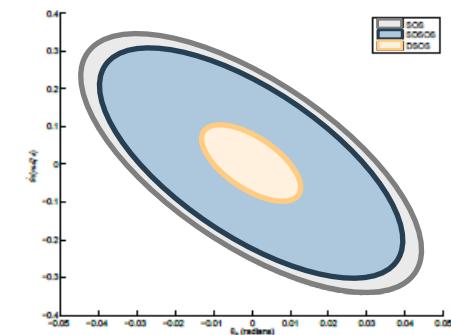
**N=2**



**N=6**



(a)  $\theta_1 - \dot{\theta}_1$  subspace.



(b)  $\theta_6 - \dot{\theta}_6$  subspace.

**Runtime:**

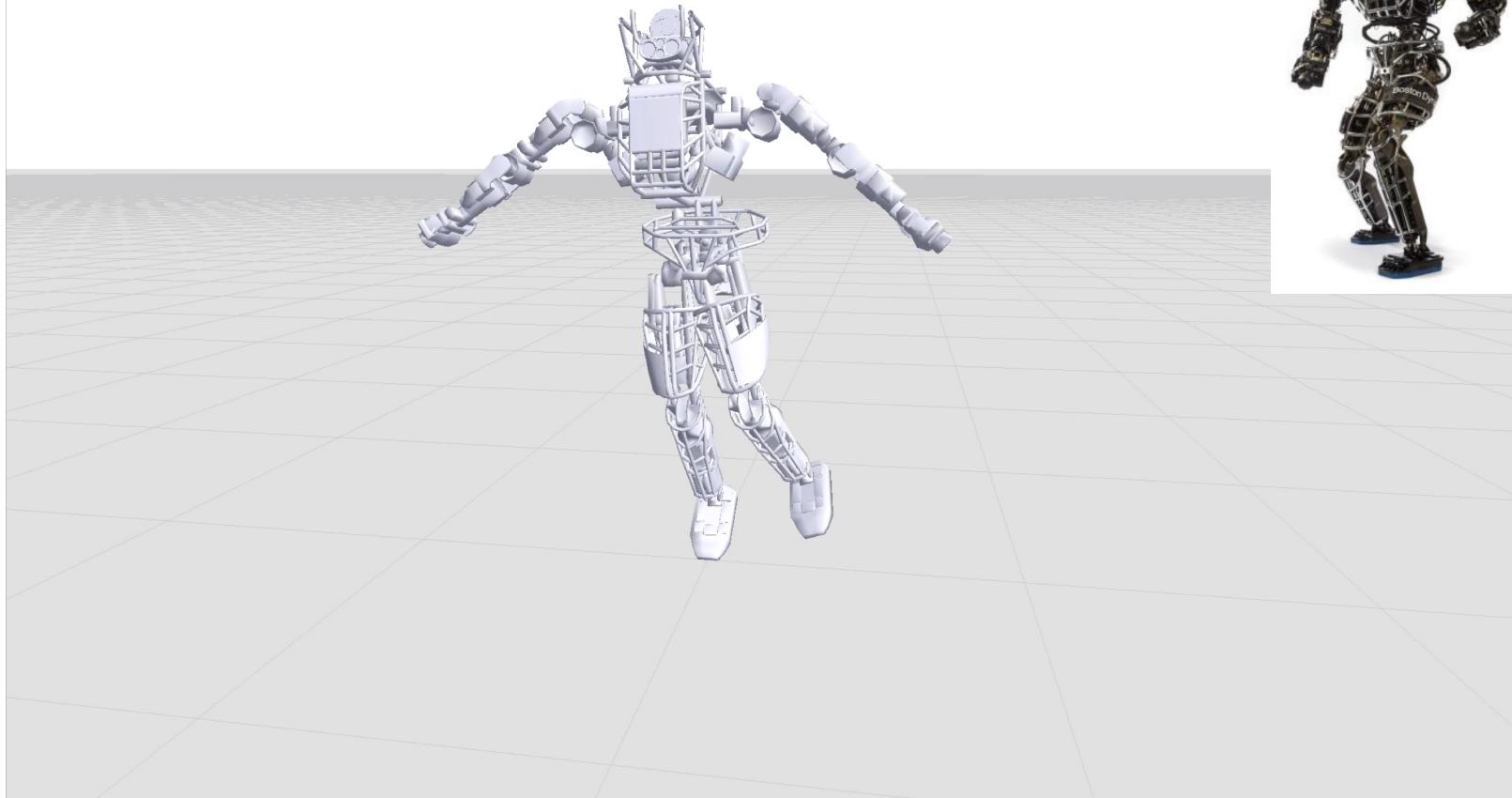
2N (# states)	4	6	8	10	12	14	16	18	20	22
DSOS	< 1	0.44	2.04	3.08	9.67	25.1	74.2	200.5	492.0	823.2
SDSOS	< 1	0.72	6.72	7.78	25.9	92.4	189.0	424.74	846.9	1275.6
SOS (SeDuMi)	< 1	3.97	156.9	1697.5	23676.5	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
SOS (MOSEK)	< 1	0.84	16.2	149.1	1526.5	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$

**ROA volume ratio:**

2N (states)	4	6	8	10	12
$\rho_{dsos}/\rho_{sos}$	0.38	0.45	0.13	0.12	0.09
$\rho_{sdsos}/\rho_{sos}$	0.88	0.84	0.81	0.79	0.79

# Stabilizing ATLAS

- 30 states    14 control inputs    Cubic dynamics



Done by SDSOS Optimization

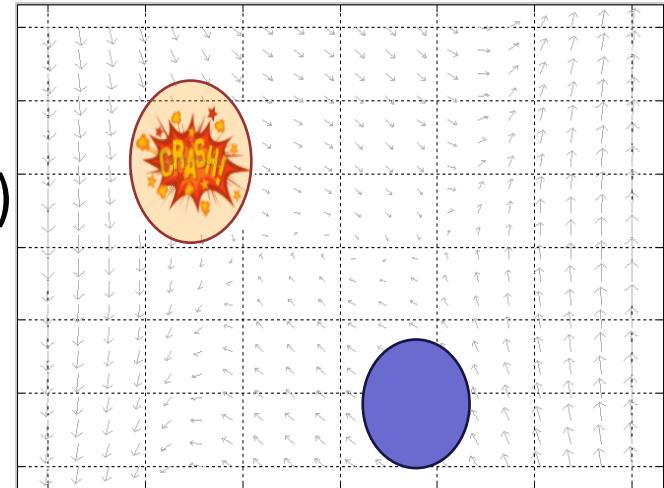
[Majumdar, AAA, Tedrake, CDC]

<https://github.com/spot-toolbox/spotless>

# Real-time barrier certificates

## Collision avoidance

$$\begin{aligned}\dot{x} &= f(x) \\ (f: \mathbb{R}^n &\rightarrow \mathbb{R}^n)\end{aligned}$$



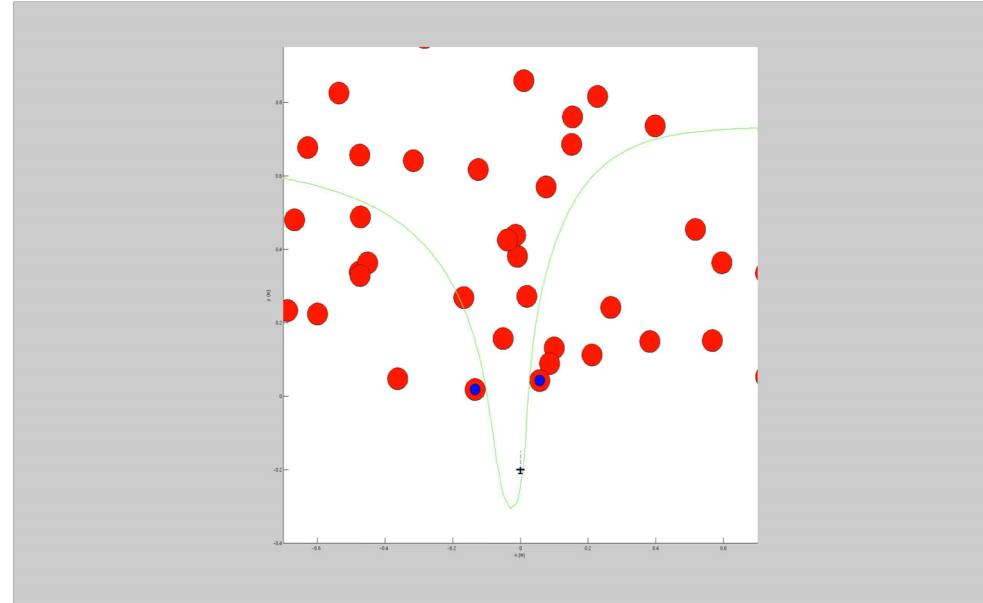
**S:** needs safety verification

**U:** unsafe (or forbidden) set

$$(V: \mathbb{R}^n \rightarrow \mathbb{R}) \quad V(x) < 0, \forall x \in S$$

$$V(x) > 0, \forall x \in U$$

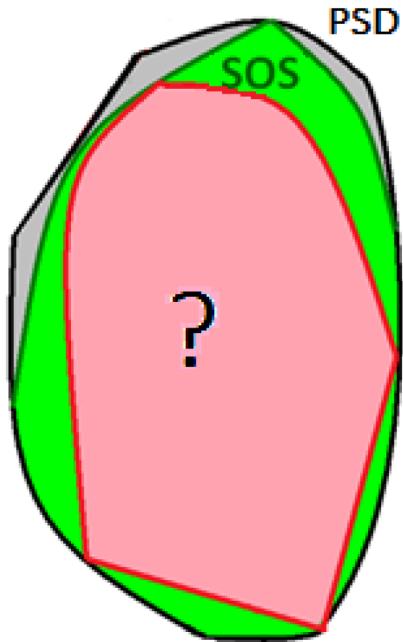
$$\dot{V}(x) = \langle \nabla V(x), f(x) \rangle \leq 0$$



SDOS run time: ~ms

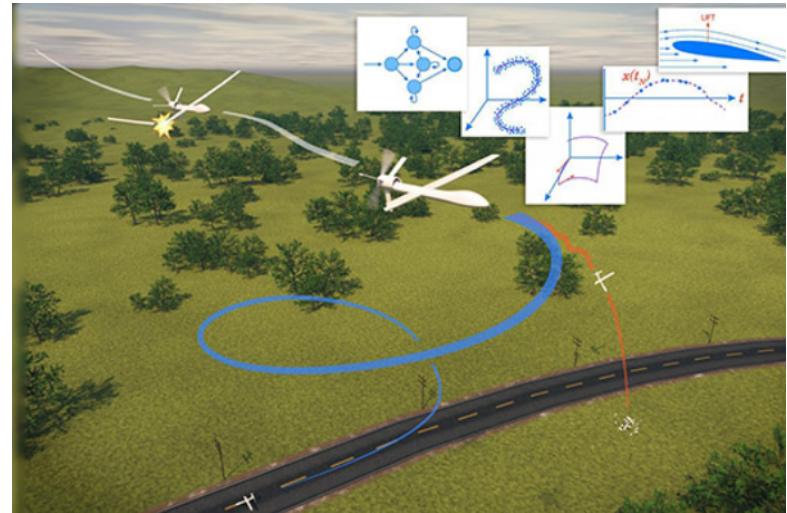
[AAA, Majumdar, *Optimization Letters*]

# Take-away message



**There is plenty of room inside the SOS cone!**

**But we have a long way to go!**



- Trade-offs between the different approximations?
- What algorithm to use when? Can ML tell us?
- How to exploit sparsity, symmetry, etc. on top of this?
- Real-time implementations?

# Backup slides...

# What can DSOS/SDSOS do in theory?

$$p(x) > 0, \forall x \in \{x \in \mathbb{R}^n \mid g_i(x) \geq 0, i = 1, \dots, m\}$$

- Is there always an SOS proof?

Yes, e.g. based on Putinar's Psatz.  
(under a compactness assumption)

Putinar



If  $p(x) > 0, \forall x \in S$ ,  
then  $p(x) = \sigma_0(x) + \sum_i \sigma_i(x)g_i(x)$ ,  
where  $\sigma_0, \sigma_i$  are sos

- Is there always an SDSOS proof?
- Is there always an DSOS proof?

Yes! In fact, a much stronger statement is true.

# An optimization-free Positivstellensatz (1/2)

$$p(x) > 0, \forall x \in \{x \in \mathbb{R}^n \mid g_i(x) \geq 0, i = 1, \dots, m\}$$

$2d$  = maximum degree of  $p, g_i$

$\Updownarrow$  Under compactness assumptions,  
i.e.,  $\{x \mid g_i(x) \geq 0\} \subseteq B(0, R)$

$\exists r \in \mathbb{N}$  such that

$$\left( f(v^2 - w^2) - \frac{1}{r} \left( \sum_i (v_i^2 - w_i^2)^2 \right)^d + \frac{1}{2r} \left( \sum_i (v_i^4 + w_i^4) \right)^d \right) \cdot \left( \sum_i v_i^2 + \sum_i w_i^2 \right)^{r^2}$$

has **nonnegative coefficients**,

where  $f$  is a form in  $n + m + 3$  variables and of degree  $4d$ , which can be explicitly written from  $p, g_i$  and  $R$ .

# An optimization-free Positivstellensatz (2/2)

$$p(x) > 0 \text{ on } \{x \mid g_i(x) \geq 0\} \Leftrightarrow$$
$$\exists r \in \mathbb{N} \text{ s.t. } \left( \mathbf{f}(\mathbf{v}^2 - \mathbf{w}^2) - \frac{1}{r} \left( \sum_i (\mathbf{v}_i^2 - \mathbf{w}_i^2)^2 \right)^d + \frac{1}{2r} \left( \sum_i (\mathbf{v}_i^4 + \mathbf{w}_i^4) \right)^d \right) \cdot \left( \sum_i \mathbf{v}_i^2 + \sum_i \mathbf{w}_i^2 \right)^{r^2}$$

has  $\geq 0$  coefficients

- $p(x) > 0$  on  $\{x \mid g_i(x) \geq 0\} \Leftrightarrow f$  is pd

- **Result by Polya (1928):**

$f$  even and pd  $\Rightarrow \exists r \in \mathbb{N}$  such that  $f(z) \cdot \left( \sum_i z_i^2 \right)^r$  has nonnegative coefficients.

- Make  $f(z)$  even by considering  $\mathbf{f}(\mathbf{v}^2 - \mathbf{w}^2)$ . We lose positive definiteness of  $f$  with this transformation.
- Add the positive definite term  $\frac{1}{2r} \left( \sum_i (\mathbf{v}_i^4 + \mathbf{w}_i^4) \right)^d$  to  $f(\mathbf{v}^2 - \mathbf{w}^2)$  to make it positive definite. **Apply Polya's result.**
- The term  $-\frac{1}{r} \left( \sum_i (\mathbf{v}_i^2 - \mathbf{w}_i^2)^2 \right)^d$  ensures that the converse holds as well.

As a corollary, gives LP/SOCP-based converging hierarchies...  
(Even forms with nonnegative coefficients are trivially dsos.)