

Two-player games between polynomial optimizers and semidefinite solvers

Victor Magron, CNRS–LAAS

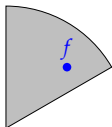
Joint work with

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Mohab Safey El Din (Sorbonne Université)

Mosek Aps, Copenhagen, 21 January 2020



Σ



SDP for Polynomial Optimization

NP-hard NON CONVEX Problem $f^* = \inf f(x)$

Theory

(Primal)		(Dual)
$\inf \int f d\mu$		$\sup \lambda$
with μ proba \Rightarrow	INFINITE LP	\Leftarrow with $p - \lambda \geq 0$

SDP for Polynomial Optimization

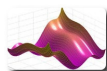
NP-hard NON CONVEX Problem $f^* = \inf f(x)$

Practice

(Primal **Relaxation**)

moments $\int x^\alpha d\mu$

finite number \Rightarrow



SDP

(Dual **Strengthening**)

$f - \lambda =$ sum of squares

\Leftarrow fixed degree

LASSERRE'S HIERARCHY of **CONVEX PROBLEMS** $f_d^* \uparrow f^*$

[Lasserre/Parrilo 01]

degree d

n vars

**Numeric
Solvers**

$\Rightarrow \binom{n+d}{n}$ **SDP** VARIABLES

\Rightarrow **Approx Certificate**

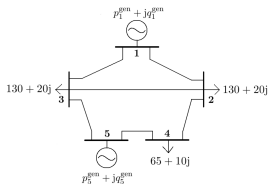


Success Stories: Lasserre's Hierarchy

MODELING POWER: Cast as ∞ -dimensional LP over measures

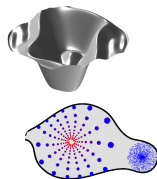
💡 **STATIC Polynomial Optimization**

Optimal Powerflow $n \simeq 10^3$ [Josz et al 16]



Roundoff Error $n \simeq 10^2$ [Magron et al 17]

💡 **DYNAMICAL Polynomial Optimization**
Regions of attraction [Henrion et al 14]



Reachable sets [Magron et al 19]



APPROXIMATE OPTIMIZATION BOUNDS!

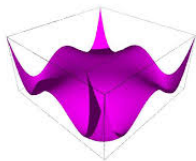
Two-player Games: Optimizers vs Solvers

MOTZKIN POLYNOMIAL

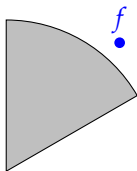
sums of squares = Σ

$$f = \frac{1}{27} + x^2y^4 + x^4y^2 - x^2y^2$$

$f \geq 0$ but $f \notin \Sigma$



Σ



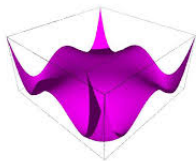
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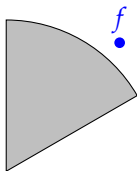
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$$f^* = \min_{(x,y) \in \mathbb{R}^2} f(x,y) = 0 \text{ for } |x^*| = |y^*| = \frac{\sqrt{3}}{3}$$

Lasserre's hierarchy:

■ order 3 $\rightsquigarrow f_3^* = -\infty$ unbounded SDP $\implies f \notin \Sigma$

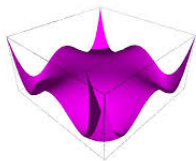
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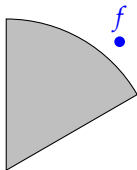
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- order 4 $\rightsquigarrow f_4^* = -\infty$

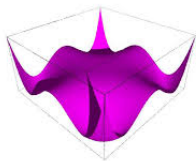
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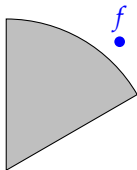
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Lasserre's hierarchy:

- order 3 $\rightsquigarrow f_3^* = -\infty$ unbounded SDP $\implies f \notin \Sigma$
- order 4 $\rightsquigarrow f_4^* = -\infty$
- order 5 $\rightsquigarrow f_5^* \simeq -0.4$

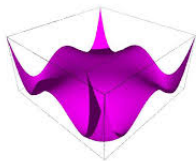
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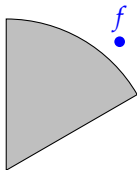
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Lasserre's hierarchy:

- order 3 $\rightsquigarrow f_3^* = -\infty$ unbounded SDP $\implies f \notin \Sigma$
- order 4 $\rightsquigarrow f_4^* = -\infty$
- order 5 $\rightsquigarrow f_5^* \simeq -0.4$
- order 8 $\rightsquigarrow f_8^* \simeq -10^{-8} \oplus$ extraction of x^*, y^* **Paradox** ?!

Two-player Games: Optimizers vs Solvers

APPROXIMATE SOLUTIONS

sum of squares of $a^2 - 2ab + b^2$?



$(1.00001a - 0.99998b)^2!$



$$a^2 - 2ab + b^2 \simeq (1.00001a - 0.99998b)^2$$

$$a^2 - 2ab + b^2 \neq 1.0000200001a^2 - 1.9999799996ab + 0.9999600004b^2$$

$$\boxed{\simeq \rightarrow = ?}$$

SDP for Polynomial Optimization

Optimization Game

Certification Game

Inaccurate SDP do Robust Optimization

$$f^* = \inf \sum_{\alpha} f_{\alpha} \mathbf{x}^{\alpha}$$

Moment matrix $\mathbf{M}_d(\mathbf{y})_{\alpha,\beta} = y_{\alpha+\beta}$

Accurate SDP Relaxations

(Primal **Relaxation**)

$$\inf_{\mathbf{y}} \sum_{\alpha} f_{\alpha} y_{\alpha}$$

s.t. $\mathbf{M}_d(\mathbf{y}) \succcurlyeq 0$

$$y_0 = 1$$

(Dual **Strengthening**)

$$\sup \lambda$$

$$f - \lambda = \sigma$$

$$\sigma \in \Sigma_d$$

Inaccurate SDP do Robust Optimization

$$f^* = \inf \sum_{\alpha} f_{\alpha} \mathbf{x}^{\alpha}$$

Moment matrix $\mathbf{M}_d(\mathbf{y})_{\alpha,\beta} = y_{\alpha+\beta}$

$$\mathbf{M}_d(\mathbf{y}) = \sum_{\alpha} \mathbf{B}_{\alpha} y_{\alpha}$$

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$$\sup \lambda$$

$$f_{\alpha} - \lambda 1_{\alpha=0} = \langle \mathbf{B}_{\alpha}, \mathbf{Q} \rangle$$

$$\mathbf{Q} \succcurlyeq 0$$

Inaccurate SDP do Robust Optimization

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Inaccurate SDP Relaxations

(Primal **Relaxation**)

(Dual **Strengthening**)

$$\sup \lambda$$

$$| f_{\alpha} - \lambda 1_{\alpha=0} - \langle \mathbf{B}_{\alpha}, \mathbf{Q} \rangle | \leq \varepsilon$$

$$\mathbf{Q} \succcurlyeq -\eta \mathbf{I}$$

Inaccurate SDP do Robust Optimization

$$f^* = \inf \sum_{\alpha} f_{\alpha} \mathbf{x}^{\alpha}$$

Moment matrix $\mathbf{M}_d(\mathbf{y})_{\alpha,\beta} = y_{\alpha+\beta}$

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Inaccurate SDP Relaxations

(Primal **Relaxation**)

(Dual **Strengthening**)

$$\inf_{\mathbf{y}} \sum_{\alpha} f_{\alpha} y_{\alpha} + \eta \langle \mathbf{M}_d(\mathbf{y}), \mathbf{I} \rangle + \varepsilon \|\mathbf{y}\|_1$$

$$\sup \lambda$$

$$\text{s.t. } \mathbf{M}_d(\mathbf{y}) \succcurlyeq 0$$

$$|f_{\alpha} - \lambda 1_{\alpha=0} - \langle \mathbf{B}_{\alpha}, \mathbf{Q} \rangle| \leq \varepsilon$$

$$y_0 = 1$$

$$\mathbf{Q} \succcurlyeq -\eta \mathbf{I}$$

Priority to Trace Equalities: $\varepsilon = 0$

$$\tilde{f} = f + \eta \sum_{\beta} \mathbf{x}^{2\beta}$$

Inaccurate SDP Relaxations

(Primal **Relaxation**)

$$\inf_{\mathbf{y}} \sum_{\alpha} f_{\alpha} y_{\alpha} + \eta \langle \mathbf{M}_d(\mathbf{y}), \mathbf{I} \rangle$$

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(Dual **Strengthening**)

$$\sup \lambda$$

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Inaccurate SDP Relaxations

(Primal Relaxation)	(Dual Strengthening)
$\inf_{\mathbf{y}} \sum_{\alpha} f_{\alpha} y_{\alpha} + \eta \langle \mathbf{M}_d(\mathbf{y}), \mathbf{I} \rangle$	$\sup \lambda$
s.t. $\mathbf{M}_d(\mathbf{y}) \succcurlyeq 0$	$f_{\alpha} - \lambda 1_{\alpha=0} - \langle \mathbf{B}_{\alpha}, \mathbf{Q} - \eta \mathbf{I} \rangle = 0$
$y_0 = 1$	$\mathbf{Q} \succcurlyeq 0$

Priority to Trace Equalities: $\varepsilon = 0$

$$\tilde{f} = f + \eta \sum_{\beta} \mathbf{x}^{2\beta}$$

Inaccurate SDP Relaxations

(Primal **Relaxation**)

$$\begin{aligned} \inf_{\mathbf{y}} \sum_{\alpha} \tilde{f}_{\alpha} y_{\alpha} \\ \text{s.t. } \mathbf{M}_d(\mathbf{y}) \succcurlyeq 0 \\ y_0 = 1 \end{aligned}$$

(Dual **Strengthening**)

$$\begin{aligned} \sup \lambda \\ \tilde{f} - \lambda = \sigma \\ \sigma \in \Sigma_d \end{aligned}$$

Priority to Trace Equalities: $\varepsilon = 0$

$$\mathbf{B}_\infty(f, \eta) := \left\{ f + \theta \sum_{\beta} x^{2\beta} : |\theta| \leq \eta \right\}$$

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Theorem [Lasserre-Magron 19]

Inaccurate SDP relaxations of the **robust** problem

$$\max_{\tilde{f} \in \mathbf{B}_\infty(f, \eta)} \min_{\mathbf{x}} \tilde{f}(\mathbf{x})$$

Priority to Trace Equalities: $\varepsilon = 0$

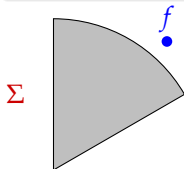
Theorem [Lasserre 06]

For fixed n , any $f \geq 0$ can be approximated arbitrarily closely by SOS polynomials.

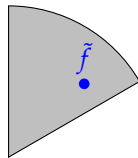
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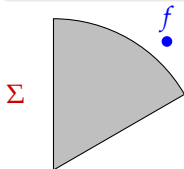
$$\tilde{f} = f + \eta \sum_{|\beta| \leq d} \mathbf{x}^{2\beta}$$



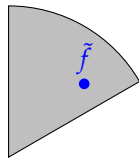
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Theorem [Lasserre 06]

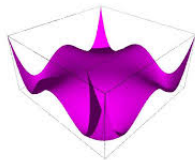
For fixed n , any $f \geq 0$ can be approximated arbitrarily closely by SOS polynomials.



$$\tilde{f} = f + \eta \sum_{|\beta| \leq d} x^{2\beta} \quad \Sigma$$



At fixed η , when $d \nearrow$, $\tilde{f} \in \Sigma!$



$$f + 10^{-7} \sum_{|\beta| \leq 4} x^{2\beta} \in \Sigma$$

Paradox Explanation

Priority to SDP Inequalities: $\eta = 0$

Inaccurate SDP Relaxations

(Primal **Relaxation**)

$$\inf_{\mathbf{y}} \sum_{\alpha} f_{\alpha} y_{\alpha} + \varepsilon \|\mathbf{y}\|_1$$

$$\text{s.t. } \mathbf{M}_d(\mathbf{y}) \succeq 0$$

$$y_0 = 1$$

(Dual **Strengthening**)

$$\sup \lambda$$

$$|f_{\alpha} - \lambda 1_{\alpha=0} - \langle \mathbf{B}_{\alpha}, \mathbf{Q} \rangle| \leq \varepsilon$$

$$\mathbf{Q} \succeq 0$$

Priority to SDP Inequalities: $\eta = 0$

$$\mathbf{B}_\infty(f, \varepsilon) := \{\tilde{f} : \|\tilde{f} - f\|_\infty \leq \varepsilon\}$$

Inaccurate SDP Relaxations

(Primal **Relaxation**)

$$\inf_{\mathbf{y}} \sum_{\alpha} f_{\alpha} y_{\alpha} + \varepsilon \|\mathbf{y}\|_1$$

$$\text{s.t. } \mathbf{M}_d(\mathbf{y}) \succeq 0$$

$$y_0 = 1$$

(Dual **Strengthening**)

$$\sup_{\lambda, \tilde{f}} \lambda$$

$$|\tilde{f}_{\alpha} - f_{\alpha}| \leq \varepsilon$$

$$\tilde{f} - \lambda \in \Sigma_d$$

Priority to SDP Inequalities: $\eta = 0$

Theorem (Lasserre-Magron)

Inaccurate SDP relaxations of the **robust** problem

$$\max_{\tilde{f} \in \mathbf{B}_\infty(f, \varepsilon)} \min_{\mathbf{x}} \tilde{f}(\mathbf{x})$$

A Two-player Game Interpretation



max – min ROBUST OPTIMIZATION

Player 1 (solver) picks $\tilde{f} \in \mathbf{B}_\infty(f) \rightsquigarrow$ **SDP leads**

Player 2 (optimizer) picks an SOS \rightsquigarrow **User follows**

A Two-player Game Interpretation



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Convex SDP relaxations \implies $\max - \min = \min - \max$

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min – max ROBUST OPTIMIZATION

Player 1 (robust optimizer) picks an SOS \rightsquigarrow **User leads**

Player 2 (solver) picks $\tilde{f} \in \mathbf{B}_\infty(f) \rightsquigarrow$ **SDP follows**

SDP for Polynomial Optimization

Optimization Game

Certification Game

From Approximate to Exact Solutions

Win TWO-PLAYER GAME



sum of squares of f ?



\approx Output!



From Approximate to Exact Solutions

Win TWO-PLAYER GAME



💡 **Hybrid** Symbolic/Numeric Algorithms

sum of squares of $f - \varepsilon$?

\simeq Output!



Error Compensation



$\simeq \rightarrow =$

Rational SOS Decompositions

- $f \in \mathbb{Q}[X] \cap \overset{\circ}{\Sigma}[X]$ (interior of the SOS cone)

Existence Question

Does there exist $f_i \in \mathbb{Q}[X], c_i \in \mathbb{Q}^{>0}$ s.t. $f = \sum_i c_i f_i^2$?

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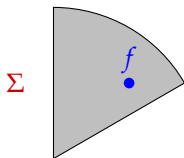
Does there exist $f_i \in \mathbb{Q}[X], c_i \in \mathbb{Q}^{>0}$ s.t. $f = \sum_i c_i f_i^2$?

Examples

$$1 + X + X^2 = \left(X + \frac{1}{2}\right)^2 + \left(\frac{\sqrt{3}}{2}\right)^2 = 1 \left(X + \frac{1}{2}\right)^2 + \frac{3}{4}(1)^2$$

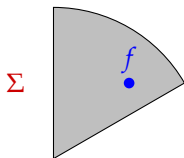
$$1 + X + X^2 + X^3 + X^4 = \left(X^2 + \frac{1}{2}X + \frac{1 + \sqrt{5}}{4}\right)^2 + \left(\frac{\sqrt{10 + 2\sqrt{5}} + \sqrt{10 - 2\sqrt{5}}}{4}X + \frac{\sqrt{10 - 2\sqrt{5}}}{4}\right)^2 = ???$$

Round & Project Algorithm [Peyrl-Parrilo 08]




$$f \in \mathring{\Sigma}[X] \text{ with } \deg f = 2D$$

Round & Project Algorithm [Peyrl-Parrilo 08]



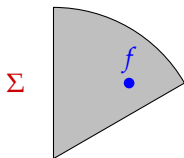
$$f \in \overset{\circ}{\Sigma}[X] \text{ with } \deg f = 2D$$

 Find \tilde{Q} with SDP at tolerance $\tilde{\delta}$ satisfying

$$f(X) \simeq \mathbf{v}_D^T(X) \tilde{Q} \mathbf{v}_D(X) \quad \tilde{Q} \succ 0$$

$\mathbf{v}_D(X)$: vector of monomials of $\deg \leq D$

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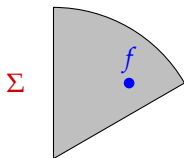
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💡 Exact $Q \implies f_{\alpha+\beta} = \sum_{\alpha'+\beta'=\alpha+\beta} Q_{\alpha',\beta'}$

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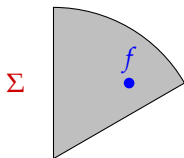
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 Exact $Q \implies f_{\alpha+\beta} = \sum_{\alpha'+\beta'=\alpha+\beta} Q_{\alpha',\beta'}$

1 Rounding step $\hat{Q} \leftarrow \text{round}(\tilde{Q}, \hat{\delta})$

Round & Project Algorithm [Peyrl-Parrilo 08]




$$f \in \mathring{\Sigma}[X] \text{ with } \deg f = 2D$$

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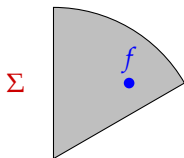
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1 Rounding step $\hat{Q} \leftarrow \text{round}(\tilde{Q}, \hat{\delta})$

2 Projection step

$$Q_{\alpha,\beta} \leftarrow \hat{Q}_{\alpha,\beta} - \frac{1}{\eta(\alpha+\beta)} \left(\sum_{\alpha'+\beta'=\alpha+\beta} \hat{Q}_{\alpha',\beta'} - f_{\alpha+\beta} \right)$$

Round & Project Algorithm [Peyrl-Parrilo 08]



$$f \in \mathring{\Sigma}[X] \text{ with } \deg f = 2D$$

🔍 Find \tilde{Q} with SDP at tolerance $\tilde{\delta}$ satisfying

$$f(X) \simeq \mathbf{v}_D^T(X) \tilde{Q} \mathbf{v}_D(X) \quad \tilde{Q} \succ 0$$

$\mathbf{v}_D(X)$: vector of monomials of $\deg \leq D$

💡 Exact $Q \implies f_{\alpha+\beta} = \sum_{\alpha'+\beta'=\alpha+\beta} Q_{\alpha',\beta'}$

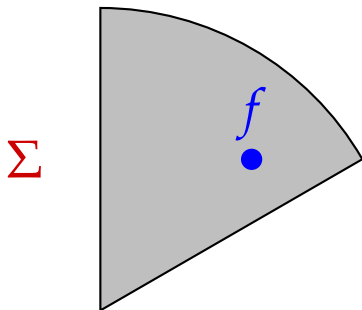
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$$Q_{\alpha,\beta} \leftarrow \hat{Q}_{\alpha,\beta} - \frac{1}{\eta(\alpha+\beta)} (\sum_{\alpha'+\beta'=\alpha+\beta} \hat{Q}_{\alpha',\beta'} - f_{\alpha+\beta})$$

💡 Small enough $\tilde{\delta}, \hat{\delta} \implies f(X) = \mathbf{v}_D^T(X) Q \mathbf{v}_D(X)$ and $Q \succcurlyeq 0$

Our Alternative Approach



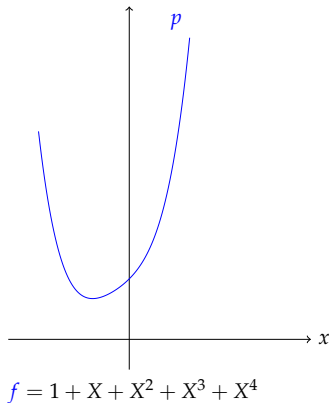
PERTURBATION idea

💡 Approximate SOS Decomposition

$$f(X) - \varepsilon \sum_{\alpha \in \mathcal{P}/2} X^{2\alpha} = \tilde{\sigma} + u$$

RealCertify with $n = 1$ [Chevillard et. al 11]

$$f \in \mathbb{Q}[X], \deg f = d = 2k, f > 0$$

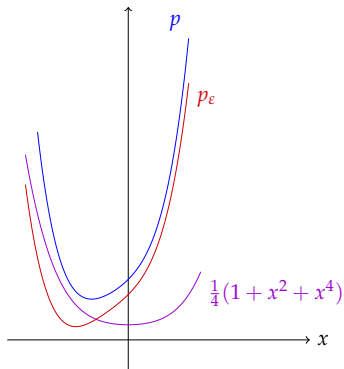


RealCertify with $n = 1$ [Chevillard et. al 11]

$$f \in \mathbb{Q}[X], \deg f = d = 2k, f > 0$$

💡 **PERTURB:** find $\varepsilon \in \mathbb{Q}$ s.t.

$$f_\varepsilon := f - \varepsilon \sum_{i=0}^k X^{2i} > 0$$



$$f = 1 + X + X^2 + X^3 + X^4$$

$$\varepsilon = \frac{1}{4}$$

$$f > \frac{1}{4}(1 + X^2 + X^4)$$

RealCertify with $n = 1$ [Chevillard et. al 11]

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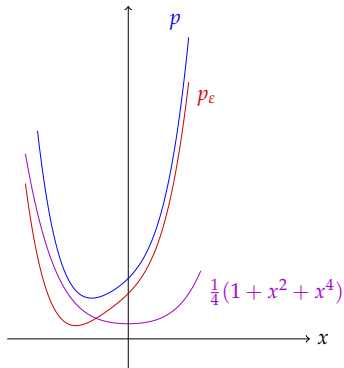
$$f_\varepsilon := f - \varepsilon \sum_{i=0}^k X^{2i} > 0$$

💡 **SDP Approximation:**

$$f - \varepsilon \sum_{i=0}^k X^{2i} = \tilde{\sigma} + u$$

💡 **ABSORB:** small enough u_i

$$\implies \varepsilon \sum_{i=0}^k X^{2i} + u \text{ SOS}$$

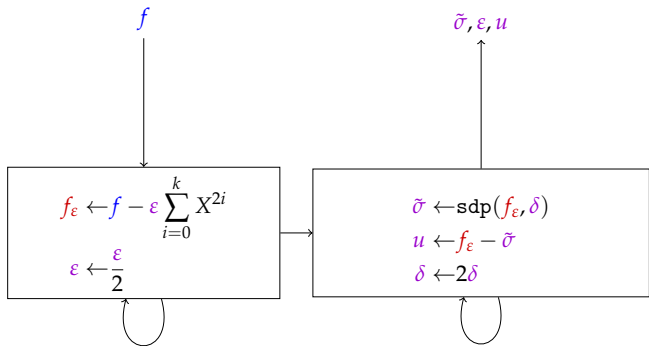


$$f = 1 + X + X^2 + X^3 + X^4$$

$$\varepsilon = \frac{1}{4}$$

$$f > \frac{1}{4}(1 + X^2 + X^4)$$

RealCertify with $n = 1$: SDP Approximation



while
 $f_\epsilon \leq 0$

while
 $\epsilon < \frac{|u_{2i+1}| + |u_{2i-1}|}{2} - u_{2i}$

RealCertify with $n = 1$: Absorbion

$$\text{💡 } X = \frac{1}{2}[(X + 1)^2 - 1 - X^2]$$

$$\text{💡 } -X = \frac{1}{2}[(X - 1)^2 - 1 - X^2]$$

RealCertify with $n = 1$: Absorbtion

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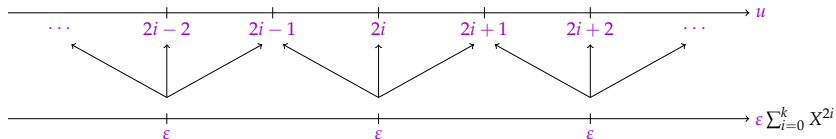
$$u_{2i+1} X^{2i+1} = \frac{|u_{2i+1}|}{2} [(X^{i+1} + \text{sgn}(u_{2i+1})X^i)^2 - X^{2i} - X^{2i+2}]$$

RealCertify with $n = 1$: Absorbion

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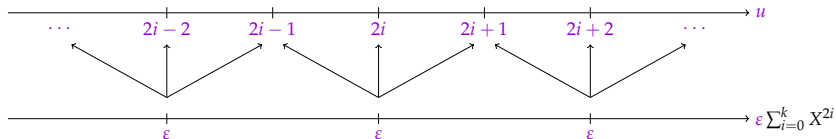


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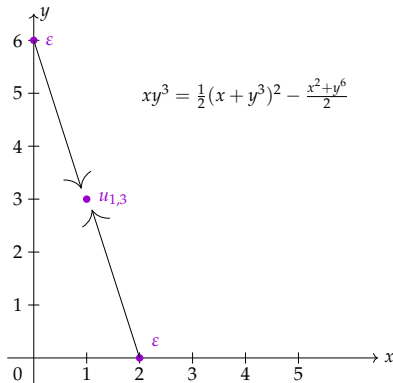


$$\epsilon \geq \frac{|u_{2i+1}| + |u_{2i-1}|}{2} - u_{2i} \implies \epsilon \sum_{i=0}^k X^{2i} + u \quad \text{SOS}$$

RealCertify with $n \geq 1$: Absorbtion

$$f(X) - \varepsilon \sum_{\alpha \in \mathcal{P}/2} X^{2\alpha} = \tilde{\sigma} + u$$

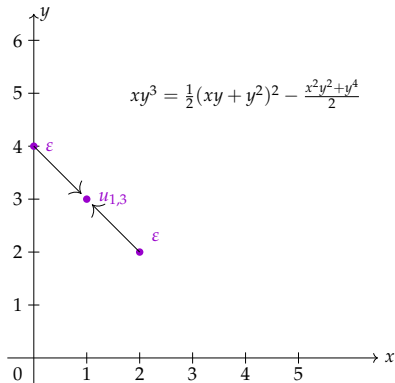
Choice of \mathcal{P} ?



RealCertify with $n \geq 1$: Absorbtion

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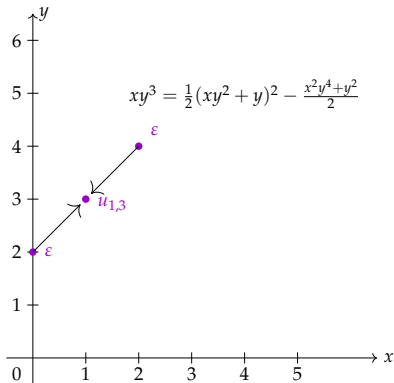
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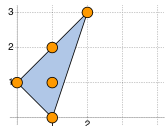
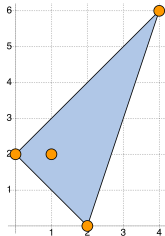
Choice of \mathcal{P} ?

$$f = 4x^4y^6 + x^2 - xy^2 + y^2$$

$$\text{spt}(f) = \{(4, 6), (2, 0), (1, 2), (0, 2)\}$$

Newton Polytope $\mathcal{P} = \text{conv}(\text{spt}(f))$

Squares in SOS decomposition $\subseteq \frac{\mathcal{P}}{2} \cap \mathbb{N}^n$
[Reznick 78]



RealCertify: Benchmarks

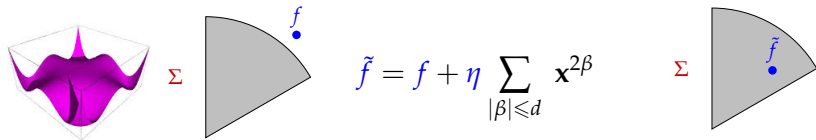
- RAGLib (critical points) [Safey El Din]
- SamplePoints (CAD) [Moreno Maza-Alvandi et al.]

Id	n	d	RealCertify		RoundProject		RAGLib	CAD
			τ_1 (bits)	t_1 (s)	τ_2 (bits)	t_2 (s)	t_3 (s)	t_4 (s)
f_{20}	2	20	745 419	110.	78 949 497	141.	0.16	0.03
M	3	8	17 232	0.35	18 831	0.29	0.15	0.03
f_2	2	4	1 866	0.03	1 031	0.04	0.09	0.01
f_6	6	4	56 890	0.34	475 359	0.54	598.	—
f_1	10	4	344 347	2.45	8 374 082	4.59	—	—

Two-player Games: Perspectives

OPTIMIZATION GAME

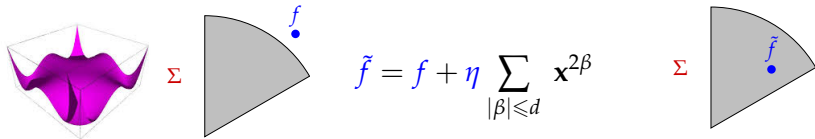
Solvers **OUTPUT** inaccurate certificates \Rightarrow extract solutions



Two-player Games: Perspectives

OPTIMIZATION GAME

Solvers **OUTPUT** inaccurate certificates \Rightarrow extract solutions



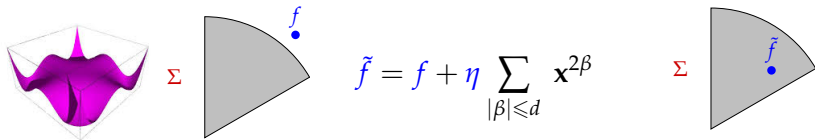
CERTIFICATION GAME

Optimizers **INPUT** inaccurate $\tilde{f} = f - \eta \sum_{|\beta| \leq d} \mathbf{x}^{2\beta}$
 \Rightarrow exact certificates

Two-player Games: Perspectives

OPTIMIZATION GAME

Solvers **OUTPUT** inaccurate certificates \Rightarrow extract solutions



CERTIFICATION GAME

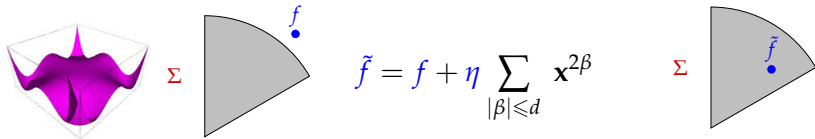
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- 💡 Better arbitrary-precision SDP solvers
- 💡 Extension to other relaxations, sums of hermitian squares

Two-player Games: Perspectives

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Crucial need for polynomial systems certification
Available PhD/Postdoc Positions



End

Thank you for your attention!

[gricad-gitlab:RealCertify](https://gitlab.com/RealCertify)

<https://homepages.laas.fr/vmagron>



Lasserre & Magron. In SDP relaxations, inaccurate solvers do robust optimization, *SIOPT*. arxiv:1811.02879



Magron & Safey El Din. On Exact Polya and Putinar's Representations, *ISSAC'18*. arxiv:1802.10339



Magron & Safey El Din. RealCertify: a Maple package for certifying non-negativity, *ISSAC'18*. arxiv:1805.02201