# Sums of squares in polynomial binary optimization 

## Greg Blekherman ${ }^{1}$ João Gouveia ${ }^{2}$ James Pfeiffer ${ }^{3}$

${ }^{1}$ Georgia Tech<br>${ }^{2}$ Universidade de Coimbra<br>${ }^{3}$ University of Washington

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## Sums of squares certificates

## Polynomial Optimization over Algebraic Varieties

$p_{\text {min }}=\min p(x)$ over all $x$ such that

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x \in\left\{x \mid p_{i}(x)=0, i=1, \ldots, t\right\} .
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$p_{\text {min }}=\max \lambda$ such that

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p(x)-\lambda \geq 0 \text { for all } x \in \mathcal{V}(I)
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$p_{\text {min }} \leq p_{\text {sos }}=\max \lambda$ such that

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p(x)-\lambda=\sum h_{i}^{2} \bmod I
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$p_{\min } \leq p_{\mathrm{sos}}^{l, k}=\max \lambda$ such that

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This is not a linear SDP anymore, but is still doable.

## Example

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Multipliers make the relaxations less sensitive to singularities.

## The $n$-cube

We are interested in the $n$-cube:

$$
C_{n}=\{0,1\}^{n}=\left\{x \in \mathbb{R}^{n}: x_{i}^{2}-x_{i}=0, i=1, \cdots, n\right\}=\mathcal{V}\left(I_{n}\right) .
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Cube $C_{3}$
$S_{n}$ acts on $C_{n}$ by permuting coordinates, and if $p$ is symmetric, it will be completely characterized by its evaluation at the levels $T_{k}$ of the cube:

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T_{k}=\left\{x \in C_{n}: \sum x_{i}=k\right\} .
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## Main Result 1 - Bad news

Let $p$ be a symmetric square-free polynomial attaining its minimum over $C_{n}$ at level $T_{k}$, with $\operatorname{deg} p \leq k \leq n / 2$.

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## Theorem

If $T_{k}$ is not a local extreme of $p$ over $\mathbb{R}^{n}$ (seen as a polynomial in $\sum x_{i}$ ) then $p_{\text {min }}>p_{\text {sos }}^{k-r, k}$, where $r=\lceil(\operatorname{deg} p) / 2\rceil$.

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This means that if the minimizer of $p$ is "simple enough" and is close to the central levels of the cube, we need high level sos relaxations.

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The proof reduces to this lemma.

## Lemma

If $p$ has degree $d$ and vanishes at $T_{k}$ with $d \leq k \leq n-d$ then

$$
p=\left(k-\sum x_{i}\right) q \bmod I_{n},
$$

with $\operatorname{deg} q<\operatorname{deg} p$.

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\mathbb{R}[]_{k}=\mathbb{R}[/]_{=0} \oplus \mathbb{R}[I]_{=1} \oplus \mathbb{R}[I]_{=2} \oplus \oplus \cdots c \mid \mathbb{R}[]_{=k}
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## Sketch of Proof:

Consider the action of $S_{n}$ in $\mathbb{R}[]_{k}$. It decomposes:

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\begin{aligned}
& H_{n, 0} \\
& \begin{array}{c}
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\oplus
\end{array} \\
& H_{n-1,1} \\
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H_{n, 0} & H_{n, 0} & H_{n, 0} & & \cdots & \mathbb{R}[I]_{=k} \\
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Let $M_{j}$ be the first copy of $H_{n-j, j}$ to appear, then

$$
\mathbb{R}[I]_{k}=\bigoplus_{j=0}^{k} M_{j} \oplus\left(k-\sum x_{i}\right) M_{j} \oplus \cdots \oplus\left(k-\sum x_{i}\right)^{k-j} M_{j}
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and is enough to check that $M_{j}$ does not vanish at $T_{k}$.

## Application 1 - MaxCut

Recall that the maxcut problem over $K_{n}$ can be reduced to

## Binary polynomial formulation of MaxCut

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\max p(x)=\sum_{i \neq j}\left(1-x_{i}\right) x_{j} \text { s.t. } x \in C_{n}
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For $n=2 k+1, p_{\text {sos }}^{k}>p_{\text {max }}$.
Note that $p$ attains its maximum in $C_{n}$ at $T_{k}$ and $T_{k+1}$, which are not local maxima of $p$ over $\mathbb{R}^{n}$.

## First corollary of main result 1

For $n=2 k+1, p_{\mathrm{sos}}^{k-1, k}>p_{\text {max }}$.

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Let $p$ be any polynomial in $\mathbb{R}^{n}$.

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For some $I, k, p_{\mathrm{sos}}^{l, k}=p_{\text {min }}$.

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For any $k$ there is a degree 4 polynomial in $\mathbb{R}^{2 k+1}$ for which $p_{\text {min }}<p_{\mathrm{sos}}^{k-2, k}$.

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This is proven by a perturbed extension of the polynomial on the previous example.

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We have showed lower bounds to the effectiveness of sos for binary polynomial programming. Luckily we also can show some upper bounds.

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Let $p$ be a non constant quadratic polynomial in $\mathbb{R}^{2 k+1}$, then $p_{\min }=p_{\mathrm{sos}}^{k+1, k+2}$.

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Theorem
Let $p$ be a non constant quadratic polynomial in $\mathbb{R}^{2 k+1}$, then $p_{\mathrm{min}}=p_{\mathrm{sos}}^{k+1, k+2}$.

The proof is based in dimension counting.

## Application - MaxCut revisited

Consider the weighted maxcut formulation.
Binary polynomial formulation of MaxCut

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\max p_{\omega}(x)=\sum_{i \neq j} \omega_{i j}\left(1-x_{i}\right) x_{j} \text { s.t. } x \in C_{n},
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where $\omega_{i j}$ is the weight of edge $\{i, j\}$.
The negative result proved by Laurent has an opposed positive conjecture.

## Conjecture (Laurent)

If $n=2 k+1,\left(p_{\omega}\right)_{\min }=\left(p_{\omega}\right)_{\mathrm{sos}}^{k+1}$ for all weights.

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## Conjecture (Laurent)

If $n=2 k+1,\left(p_{\omega}\right)_{\min }=\left(p_{\omega}\right)_{\mathrm{sos}}^{k+1}$ for all weights.
A weaker version can now be proved.
Corollary of main result 2
If $n=2 k+1,\left(p_{\omega}\right)_{\min }=\left(p_{\omega}\right)_{\text {sos }}^{k+1, k+2}$ for all weights.

## The End

## Thank You

