

Duality of sum of nonnegative circuit polynomials and optimal SONC bounds

Dávid Papp

MEGA 2021 (Tromsø/virtual). June 7–11, 2021.

NC STATE UNIVERSITY

Nonnegativity certificates

Let $p \in \mathbb{R}[x_1, \dots, x_n]_d$ be a polynomial and $S \subseteq \mathbb{R}^n$.

Definition (nonnegativity certificate)

A certificate of nonnegativity (usually) is a representation of p that makes its nonnegativity over S apparent.

- Sum-of-squares (SOS)
- *Sum-of-nonnegative-circuit-polynomials (SONC)*
- etc.
- Different: dual certificates (see Maria Macaulay's talk)

Optimization = certified upper bound (a point $\mathbf{x} \in S$) + **certified lower bound** (nonnegativity certificate for some $p - c$).

SONC polynomials

- Polynomials certifiably nonnegative by the AM/GM inequality. (“agiforms”, [Reznick 1989])
- Systematically/computationally studied by de Wolff et al. [2016–]
- Related: Ghasemi and Marshall; Chandrasekaran and Shah (SAGE)

Basic idea (example):

- the Motzkin polynomial $m(x, y) = x^4y^2 + x^2y^4 - 3x^2y^2 + 1$ is not SOS but is nonnegative,
- because each monomial is nonnegative and $\frac{x^4y^2+x^2y^4+1}{3} \geq x^2y^2$.
- Easily generalized to weighted AM/GM.

SONC polynomials

- Polynomials certifiably nonnegative by the AM/GM inequality. (“agiforms”, [Reznick 1989])
- Systematically/computationally studied by de Wolff et al. [2016–]
- Related: Ghasemi and Marshall; Chandrasekaran and Shah (SAGE)

Basic idea (example):

- the Motzkin polynomial $m(x, y) = x^4y^2 + x^2y^4 - 3x^2y^2 + 1$ is not SOS but is nonnegative,
- because each monomial is nonnegative and $\frac{x^4y^2+x^2y^4+1}{3} \geq x^2y^2$.
- Easily generalized to weighted AM/GM.

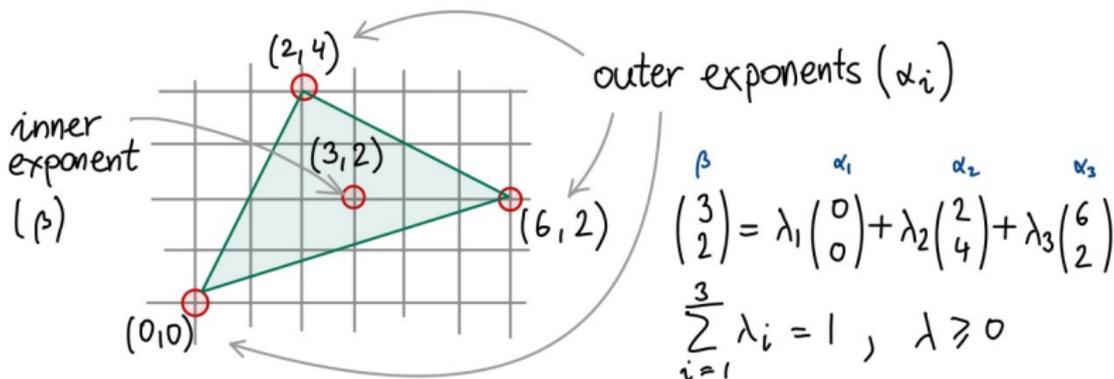
SONC polynomials

Definition (circuit polynomial)

An n -variate polynomial p is a **circuit polynomial** if it is given by

$$p(\mathbf{x}) = \sum_{i=1}^r p_{\alpha_i} \mathbf{x}^{\alpha_i} + p_{\beta} \mathbf{x}^{\beta}, \text{ where}$$

- $\text{supp}(p) = \{\alpha_1, \dots, \alpha_r, \beta\}$ is minimally affinely dependent and
- $\beta \in \text{conv}(\{\alpha_1, \dots, \alpha_r\})$.



SONC polynomials

Proposition (Illman & de Wolff, 2016)

Let p be an n -variate circuit polynomial satisfying $p(\mathbf{x}) = \sum_{i=1}^r p_{\alpha_i} \mathbf{x}^{\alpha_i} + p_{\beta} \mathbf{x}^{\beta}$ for some real coefficients p_{α_i} and p_{β} and suppose that $\beta = \sum_{i=1}^r \lambda_i \alpha_i$ with some $\lambda_i > 0$ satisfying $\sum_{i=1}^r \lambda_i = 1$.

Then p is nonnegative if and only if $\alpha_i \in (2\mathbb{N})^n$ and $p_{\alpha_i} > 0$ for each i , and at least one of the following two alternatives holds:

1. $\beta \in (2\mathbb{N})^n$ and $p_{\beta} \geq 0$, or
2. $|p_{\beta}| \leq \prod_{i=1}^r \left(\frac{p_{\alpha_i}}{\lambda_i} \right)^{\lambda_i}$.

- Makes the recognition of a nonnegative circuit polynomial straightforward.
- SONC = Minkowski sum of nonnegative circuit polynomials with different supports.
- Optimal SONC bounds and certificates?

$$\inf\{p(\mathbf{x}) \mid \mathbf{x} \in \mathbb{R}^n\} = \sup\{c \mid p - c \text{ is nonnegative}\} \geq \sup\{c \mid p - c \text{ is SONC}\}.$$

SONC polynomials and convex conic representations

$$|p_\beta| \leq \prod_{i=1}^r \left(\frac{p_{\alpha_i}}{\lambda_i} \right)^{\lambda_i} \quad (\lambda > 0, \sum_{i=1}^r \lambda_i = 1)$$

- This inequality is **convex** in the coefficients of p .
 - (Dressler et al. 2017): it can be represented using $O(r)$ relative entropy and linear constraints.
 - (Wang & Magron, 2020): it can be represented using second-order cone constraints.
 - Lifted SOCP representation also follows from (Alizadeh & Goldfarb, 2003).
- In this talk: treat it as a single convex (dual power) cone constraint (no lifting).

SONC polynomials and power cones

Definition (the power cone and its dual)

The (*generalized*) *power cone* with *signature* $\lambda = (\lambda_1, \dots, \lambda_r) \in (0, 1)^r$ is the convex cone defined as

$$\mathcal{P}_\lambda \stackrel{\text{def}}{=} \left\{ (\mathbf{v}, w) \in \mathbb{R}_+^r \times \mathbb{R} \mid |w| \leq \prod_{i=1}^r v_i^{\lambda_i} \right\}.$$

The dual of this (closed, pointed, full-dimensional) convex cone is

$$\mathcal{P}_\lambda^* \stackrel{\text{def}}{=} \left\{ (\mathbf{v}, w) \in \mathbb{R}_+^r \times \mathbb{R} \mid |w| \leq \prod_{i=1}^r \left(\frac{v_i}{\lambda_i} \right)^{\lambda_i} \right\}.$$

In other words, $|p_\beta| \leq \prod_{i=1}^r \left(\frac{p_{\alpha_i}}{\lambda_i} \right)^{\lambda_i} \iff ((p_{\alpha_1}, \dots, p_{\alpha_r}), p_\beta) \in \mathcal{P}_\lambda^*$.

- Note that the cone depends on the circuit $\text{supp}(p) = \{\alpha_1, \dots, \alpha_r, \beta\}$ only through its λ vector.

Theoretical consequences

The conic formulation allows for simple (convex) analysis on the SONC cone.

Theorem (P., 2019)

*Every SONC polynomial p has a SONC decomposition in which every nonnegative circuit polynomial is **supported on a subset of $\text{supp}(p)$** .*

- A generalization of (Wang, 2019).
- Proof is an elementary application of convex programming duality.

Support of SONC decompositions

- Fix a set of circuits $\mathcal{C} = \{C^1, \dots, C^N\}$ covering $\text{supp}(p)$.
- Let $\mathcal{S}(\mathcal{C})$ be the set of SONC polynomials corresponding to \mathcal{C} .
- Let V be the vertices of $\text{New}(p)$, and consider the optimization problem

$$\begin{aligned}
 & \underset{\gamma \in \mathbb{R}_+^V}{\text{minimize}} && \sum_{\alpha \in V} \gamma_{\alpha} \\
 & \text{subject to} && (\mathbf{x} \mapsto p(\mathbf{x}) + \sum_{\alpha \in V} \gamma_{\alpha} \mathbf{x}^{\alpha}) \in \mathcal{S}(\mathcal{C}).
 \end{aligned} \tag{P}$$

- Its dual can be written as

$$\begin{aligned}
 & \underset{\mathbf{y} \in \mathbb{R}^{\text{supp}(p)}}{\text{maximize}} && -\mathbf{p}^T \mathbf{y} \\
 & \text{subject to} && (y_{\alpha})_{\alpha \in C^j} \in \mathcal{P}_{\lambda(C^j)} \quad j = 1, \dots, N \\
 & && y_{\alpha} \geq 0 \quad \alpha \in \text{supp}(p) \cap (2\mathbb{N})^n, \\
 & && y_{\alpha} \leq 1 \quad \alpha \in V.
 \end{aligned} \tag{D}$$

Support of SONC decompositions

- Both the primal and dual problem have optimal solutions, and strong duality holds ($\min = \max$).
- Consider two instances of these primal-dual pairs:
 1. where \mathcal{C} is the set of all circuits $\subseteq \text{supp}(p)$, and
 2. where \mathcal{C} is the set of all circuits $\subseteq \text{New}(p) \cap \mathbb{N}^n$.
- The optimal solutions of the first pair are optimal solutions of the second pair, proving that $f \in \mathcal{S}(\mathcal{C})$ holds either for both set of circuits or for neither.
- The proof of the last statement uses linear(!) programming to argue that the extra power cone constraints are redundant.

Computational consequences

- To find the optimal SONC bound (using all possible circuits), we need to solve

$$\inf\{\gamma \mid p + \gamma \in \mathcal{S}(\mathcal{C})\}.$$

- The previous theorem helps reduce \mathcal{C} .
- The number of circuits (and dual power cone constraints) is still exponential!
- Various heuristics have been proposed for a selection of “good” circuits. (Seidler, de Wolff, Dressler, etc.)
- The proof suggests a different approach:
 - Iteratively identify and add the “useful” circuits using the dual problem.
 - Stop with a certificate that no circuits can improve the bound.

Computational consequences

Algorithm 1: Optimal SONC bound with iterative circuit generation

input : A polynomial p .

outputs: The optimal SONC lower bound for p and a SONC decomposition certifying the bound.

- 1 initialize $\mathcal{C} = \{C^1, \dots, C^N\}$
- 2 repeat
- 3 solve (P)-(D) for the optimal SONC bound γ^* and dual vector \mathbf{y}^*
- 4 find circuits $C \subseteq \text{supp}(p)$ whose power cone constraint is violated
- 5 if *no such circuit exists* then
- 6 return γ^* and the SONC decomposition of $p + \gamma^*$
- 7 else
- 8 add the circuit(s) C found in Step 4 to \mathcal{C}
- 9 end if
- 10 until *false*

Step 4 amounts to solving $< |\text{supp}(p)|$ small linear programs. (No enumeration.)

Example

Consider the polynomial p given by

$$p(x_1, x_2) = 1 + x_2^2 - x_1^2 x_2^2 + x_1^2 x_2^6 + x_1^6 x_2^2.$$

- p clearly has a SONC lower bound that we can get by taking $\mathcal{C} = \{C_1\} = \{(0, 0), (2, 6), (6, 2), (2, 2)\}$.
- Solving the (P)-(D) problems, we obtain $\gamma^* = -\frac{7}{8}$ and the SONC decomposition

$$p(x_1, x_2) - \frac{7}{8} = (x_2)^2 + \underbrace{\left(\frac{1}{8} + x_1^2 x_2^6 + x_1^6 x_2^2 - x_1^2 x_2^2 \right)}_{\text{nonneg. circuit poly.}}$$

- The dual optimal solution is $\mathbf{y}^* = (1, 0, \frac{1}{4}, \frac{1}{16}, \frac{1}{16})$.
- Circuit generation: (next slide)

Example cont'd

- Circuit generation:
 1. No circuit with $(0, 2)$ as an inner exponent can violate its corresponding power cone constraint.
 2. $C_2 = \{(0, 2), (6, 2), (2, 2)\}$, with signature $\lambda(C_2) = (\frac{2}{3}, \frac{1}{3})$ violates its power cone constraint.
- Reoptimize with $\mathcal{C} = \{C_1, C_2\}$: $\gamma^* = -1$, the new SONC decomposition is

$$p(x_1, x_2) - 1 = x_1^2 x_2^6 + \underbrace{(x_2^2 + x_1^6 x_2^2 - x_1^2 x_2^2)}_{\text{nonneg. circuit poly}(C_2)}.$$

- The new dual solution is $\mathbf{y}^* = (1, 0, 0, 0, 0)$.
- Circuit generation: no circuits violate their power cone constraint.
- This is the optimal SONC bound. (In this case, 1 is also the global minimum.)

Implementation

Some practical consideration for the implementation:

- We can solve the (P)-(D) instances in each iteration using an SOCP (following Wang & Magron), which allows for an “off-the-shelf” implementation.
 - Reconstructing the optimal dual vector from the lifted dual vector isn't obvious, though!
- We can also optimize directly over Cartesian products of power cones (and their duals) using **interior-point methods of non-symmetric cone programming**.
- We used `alfonso` (open source, Matlab) for the conic programs.
 - Avoids the lifting necessary to represent the problems as an SOCP.
 - Efficient: same complexity of solving linear programs of the same size.

Numerical experiments

Questions of interest:

1. How many circuit generation iterations are needed?
2. How many circuits until the algorithm stops?

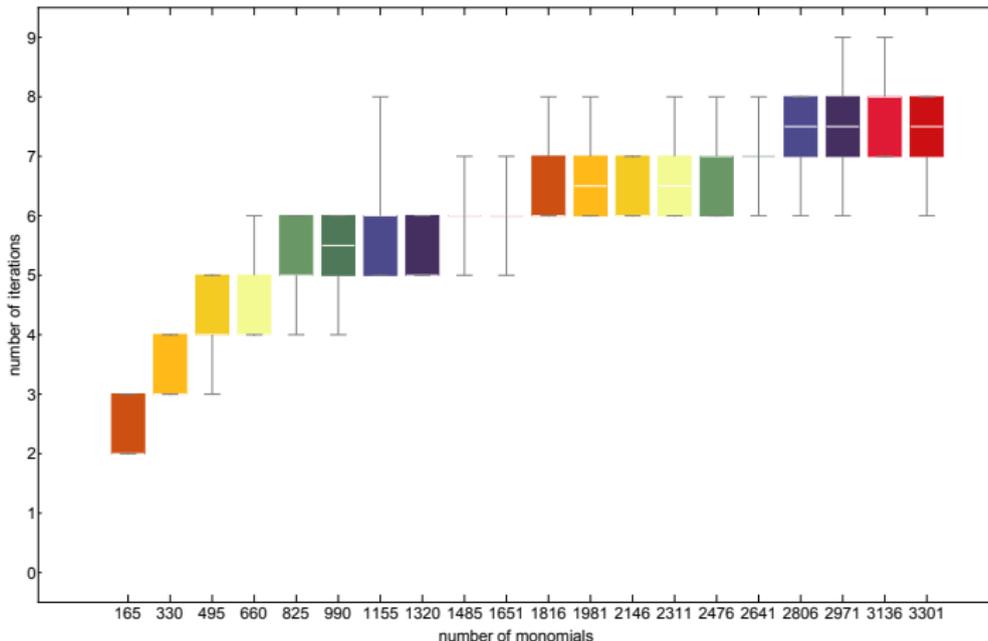
Used two sets of test problems:

1. The largest problems of (Seidler & de Wolff, 2018) with general (not simplex) Newton polytopes.
(438 instances; $4 \leq n \leq 40$, $6 \leq d \leq 60$; sparse.)
2. Random instances with $n = 25$, $d = 8$, all exponents even, with varying $|\text{supp}(p)|$ up to the maximum.

Numerical experiments

How many circuit generation iterations are needed?

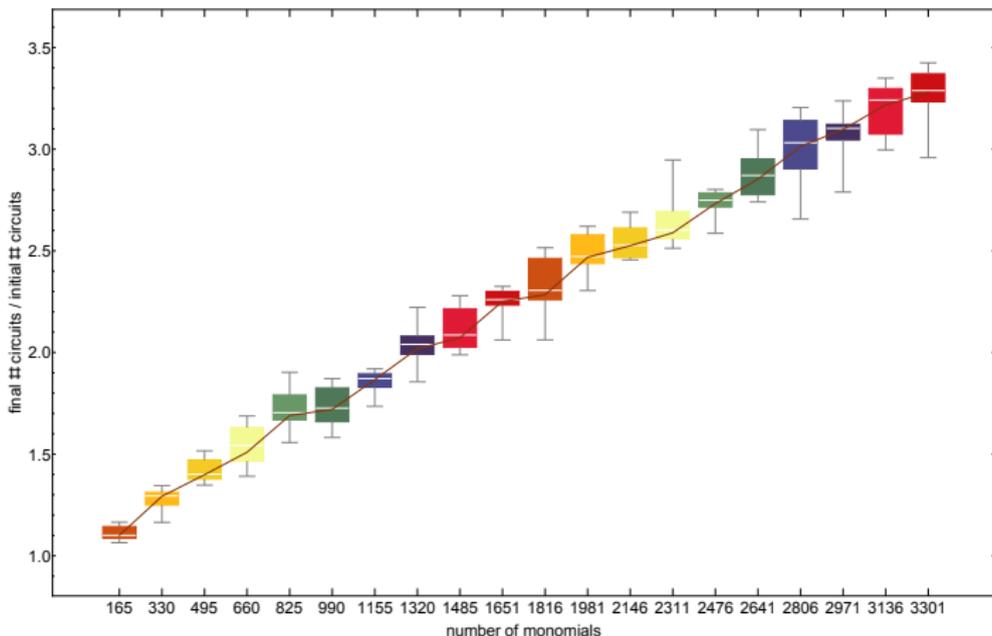
- Appears clearly sublinear in $|\text{supp}(p)|$.
- The largest number encountered was 9.



Numerical experiments

How many circuits until the algorithm stops?

- The final/initial set of circuits appears to increase linearly with $|\text{supp}(p)|$



Summary and references

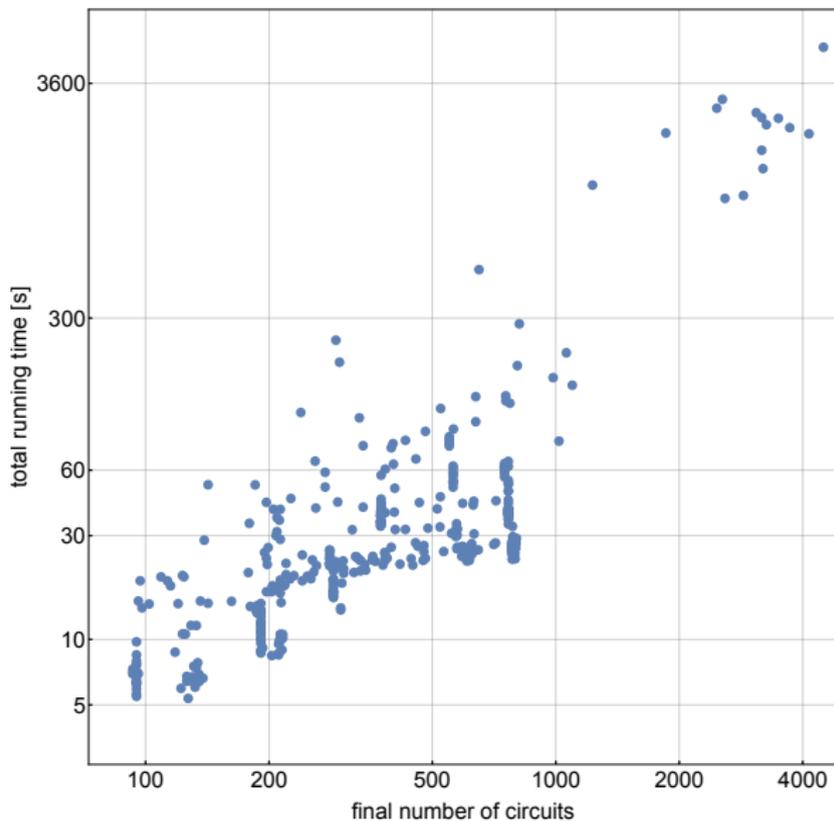
- Optimal SONC bounds can be computed quickly without resorting to approximations or circuit selection heuristics.
- The circuit generation algorithm identifies the “right” circuits efficiently.
- For a given set of circuits, the SONC decomposition can be computed using non-symmetric cone optimization, circumventing costly characterizations of the SONC cone as the projection of “simpler” high-dimensional cones.

 D.P.: Duality of sum of nonnegative circuit polynomials and optimal SONC bounds. <https://arxiv.org/abs/1912.04718>

 D.P. and S. Yıldız: alfonso: Matlab package for nonsymmetric conic optimization. *INFORMS Journal on Computing*.
<https://arxiv.org/abs/2101.04274>

 Matlab code: <https://github.com/dpapp-github/alfonso>

Running time / number of circuits (Seidler-de Wolff)



Running time / number of circuits (larger instances)

