

Sum-of-squares hierarchies for binary polynomial optimization

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Polynomial optimization on the binary cube

We consider the problem of computing:

$$f_{\min} := \min_{x \in \mathbb{B}^n} f(x),$$

where

- ▶ $f \in \mathbb{R}[x]$ is a **polynomial** of degree d .
- ▶ $\mathbb{B}^n := \{0, 1\}^n \subseteq \mathbb{R}^n$ is the **boolean hypercube**.

Example (MAXCUT)

For the complete graph K_n with edge-weights $w_{ij} \geq 0$, we have:

$$\text{MAXCUT}(w) = \max_{x \in \mathbb{B}^n} \sum_{1 \leq i < j \leq n} w_{ij} (x_i - x_j)^2.$$

Example (STABLESET)

The stability number of a graph $G = (V, E)$ can be computed as:

$$\text{STAB}(G) = \max_{x \in \mathbb{B}^{|V|}} \sum_{i \in V} x_i - \sum_{\{i, j\} \in E} x_i x_j.$$

Any binary polynomial optimization problem **with linear constraints** can be reformulated as an **unconstrained** binary optimization problem.

Semidefinite hierarchies for polynomial optimization

- ▶ (Binary) polynomial optimization is generally **intractable**
- ▶ This motivates the search for efficient **bounds** on the optimum
- ▶ Many such bounds have been proposed based on **lift-and-project** methods
- ▶ Today: two **semidefinite hierarchies** due to Lasserre

The outer Lasserre hierarchy (sum-of-squares hierarchy)

Observation

We can rewrite:

$$f_{\min} = \max\{\lambda \in \mathbb{R} : f - \lambda \geq 0 \text{ on } \mathbb{B}^n\}$$

- ▶ The nonnegativity condition can be relaxed to a sum-of-squares condition:

$$\max\{\lambda \in \mathbb{R} : f - \lambda \text{ is a sum-of-squares on } \mathbb{B}^n\},$$

meaning $f(x) - \lambda = \sum_i p_i^2(x)$ for all $x \in \mathbb{B}^n$ for certain $p_i \in \mathbb{R}[x]$

- ▶ We can then put a bound on the degree of the p_i :

$$f_{(r)} = \max\{\lambda \in \mathbb{R} : f - \lambda \text{ is a sum-of-squares of degree } \leq 2r \text{ on } \mathbb{B}^n\},$$

meaning $f(x) - \lambda = \sum_i p_i^2(x)$ for all $x \in \mathbb{B}^n$ for certain $p_i \in \mathbb{R}[x]$ of degree at most r

The outer Lasserre hierarchy (sum-of-squares hierarchy)

Definition (Lasserre, 2001)

For $r \in \mathbb{N}$, define:

$$f_{(r)} = \max\{\lambda \in \mathbb{R} : f - \lambda \text{ is a sum-of-squares of degree } \leq 2r \text{ on } \mathbb{B}^n\}$$

- ▶ $f_{(r)} \leq f_{(r+1)} \leq f_{\min}$
- ▶ For fixed r , $f_{(r)}$ can be computed efficiently using **semidefinite programming**
- ▶ There is a one-to-one correspondence between semidefinite matrices and sum-of-squares polynomials:

$$p(x) \text{ is a sum-of-squares} \iff \exists M \succeq 0 \text{ with } p(x) = [x]^\top M[x],$$

where $[x] = (x^\alpha)_\alpha$ is the vector of monomials up to degree $\deg(p)/2$

The inner (measure-based) Lasserre hierarchy

Observation

We can rewrite:

$$f_{\min} = \min_{\nu} \left\{ \int_{\mathbb{B}^n} f d\nu : \int_{\mathbb{B}^n} d\nu = 1 \right\}$$

Definition (Lasserre, 2010)

Let μ be the uniform measure on \mathbb{B}^n . For $r \in \mathbb{N}$, define:

$$f^{(r)} = \min_{s \in \Sigma_r[x]} \left\{ \int_{\mathbb{B}^n} f \cdot s d\mu : \int_{\mathbb{B}^n} s d\mu = 1 \right\}$$

- ▶ $f^{(r)} \geq f^{(r+1)} \geq f_{\min}$
- ▶ For fixed r , $f^{(r)}$ can be computed efficiently using SDP
- ▶ In principle we could choose a different **reference measure** μ .

Summary

We have the hierarchies:

$$\text{(outer)} \quad f_{(r)} = \max\{\lambda \in \mathbb{R} : f - \lambda \text{ is sos of degree } \leq 2r \text{ on } \mathbb{B}^n\}$$

$$\text{(inner)} \quad f^{(r)} = \min_{s \in \Sigma_r[x]} \left\{ \int_{\mathbb{B}^n} f \cdot s d\mu : \int_{\mathbb{B}^n} s d\mu = 1 \right\}$$

satisfying:

$$f_{(r)} \leq f_{\min} \leq f^{(r)} \leq f_{\max}$$

Question

What can be said about the quality of these hierarchies? That is, can we bound:

$$\frac{f_{\min} - f_{(r)}}{\|f\|_{\infty}} \quad \text{and} \quad \frac{f^{(r)} - f_{\min}}{\|f\|_{\infty}} \quad ?$$

(here, $\|f\|_{\infty} := \max_{x \in \mathbb{B}^n} |f(x)|$)

Some broader context

Both hierarchies can be defined more generally for polynomial optimization over sets $K \subseteq \mathbb{R}^n$ **other than the cube**. Depending on K , their quality has been investigated:

$$\text{(inner)} \quad \frac{f^{(r)} - f_{\min}}{\|f\|_{\infty}} = \begin{cases} O(1/r^2) & \text{if } K = [-1, 1]^n \quad (\text{de Klerk, Laurent}) \\ O(1/r^2) & \text{if } K = S^{n-1} \quad (\text{de Klerk, Laurent}) \\ O(1/r^2) & \text{if } K = B^n, \Delta^n, \text{'nice'} \quad (\mathbf{S.}, \text{Laurent}) \\ O(\log^2 r/r^2) & \text{for 'general' } K \quad (\mathbf{S.}, \text{Laurent}) \end{cases}$$

$$\text{(outer)} \quad \frac{f_{\min} - f(r)}{\|f\|_{\infty}} = \begin{cases} O(1/\log(r/c)^{1/c}) & \text{if } K \text{ 'compact'} \quad (\text{Nie, Schweighofer}) \\ O(1/r) & \text{if } K = S^{n-1} \quad (\text{Doherty, Wehner}) \\ O(1/r^2) & \text{if } K = S^{n-1} \quad (\text{Fang, Fawzi}) \end{cases}$$

Note: The inner hierarchy is much better understood than the outer hierarchy

Back to the binary cube

(outer) $f_{(r)} = \max\{\lambda \in \mathbb{R} : f - \lambda \text{ is sos of degree } \leq 2r \text{ on } \mathbb{B}^n\}$

(inner) $f^{(r)} = \min_{s \in \Sigma_r[x]} \left\{ \int_{\mathbb{B}^n} f \cdot s d\mu : \int_{\mathbb{B}^n} s d\mu = 1 \right\}$

Known results

- ▶ **Finite convergence** for the outer hierarchy:

$$f_{(r)} = f_{\min} \text{ when } r \geq \frac{n+d-1}{2} \approx \frac{1}{2}n$$

[Fawzi, Saunderson, Parrilo 2016 ($d = 2$)] [Sakaue et al. 2017 ($d > 2$)]

- ▶ **Finite convergence** for the inner hierarchy:

$$f^{(r)} = f_{\min} \text{ when } r \geq n$$

- ▶ But, nothing is known when the bounds are **not exact**

Theorem (Main result on the outer hierarchy)

Let $f \in \mathbb{R}[x]_d$. Let ξ_{r+1}^n be the *least root* of the degree $r + 1$ *Krawtchouk polynomial* (with parameter n). Then for any n and $r \leq \frac{1}{2}n$ large enough, we have:

$$\frac{f_{\min} - f^{(r)}}{\|f\|_{\infty}} \leq C_d \cdot (\xi_{r+1}^n/n)$$

Theorem (Main result on the inner hierarchy)

For any n and $r \leq \frac{1}{2}n$, we have:

$$\frac{f^{(r)} - f_{\min}}{\|f\|_{\infty}} \leq \frac{1}{2} C_d \cdot (\xi_{r+1}^n/n)$$

Main new results

Theorem (Levenshtein)

For $t \in [0, 1/2]$, write:

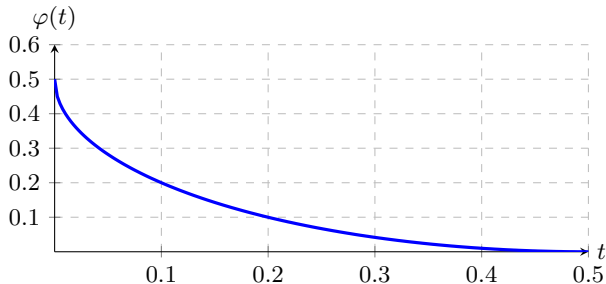
$$\varphi(t) = 1/2 - \sqrt{t(1-t)}.$$

Then the least root ξ_r^n of the degree $r + 1$ Krawtchouk polynomial satisfies:

$$\xi_r^n/n \leq \varphi(r/n) + c \cdot (r/n)^{-1/6} \cdot n^{-2/3}$$

► So, roughly:

$$\frac{f_{\min} - f(r)}{\|f\|_{\infty}} \lesssim \varphi(r/n)$$



Key steps of the proof for the outer hierarchy

Observation

We may assume for the proof that $f_{\min} = f(0) = 0$ and $\|f\|_{\infty} = 1$.

Goal: Show that there exists a small $\lambda > 0$ such that $f + \lambda$ is a sum-of-squares on \mathbb{B}^n of degree at most $2r$.

1. Use the **polynomial kernel technique** to produce sum-of-squares representations [Fang, Fawzi 2020]
2. Perform a symmetry reduction using **classical Fourier analysis** on \mathbb{B}^n
3. Link the reduced problem to an analysis of the **inner hierarchy** in a **univariate** setting
4. Exploit a known connection between the inner hierarchy and **extremal roots of orthogonal polynomials** (Krawtchouk)

Our result for the **inner hierarchy** can be extrapolated from steps 3 and 4.

Step 1: The polynomial kernel technique (Fang, Fawzi 2020)

Goal: Find a sum-of-squares representation of $f + \lambda$ for some small $\lambda > 0$.

- ▶ Consider a **polynomial kernel** of the form:

$$K(x, y) := q^2(d_{ham}(x, y)) \quad (x, y \in \mathbb{B}^n),$$

with $q \in \mathbb{R}[t]_r$ a **univariate** polynomial to be chosen later

- ▶ The kernel K induces a **linear operator** on $\mathbb{R}[x]$ by:

$$\mathbf{K}p(x) := \int_{\mathbb{B}^n} p(y)K(x, y)d\mu(y) = \frac{1}{2^n} \sum_{y \in \mathbb{B}^n} p(y)K(x, y)$$

- ▶ When $p \geq 0$ on \mathbb{B}^n , then $\mathbf{K}p$ is **sos of degree** $\leq 2r$ on \mathbb{B}^n (!)
- ▶ If we choose λ big enough s.t. $\mathbf{K}^{-1}(f + \lambda) \geq 0$ on \mathbb{B}^n , we find that

$$f + \lambda = \underbrace{\mathbf{K} \mathbf{K}^{-1}(f + \lambda)}_{\geq 0} \text{ is sos of degree } \leq 2r \text{ on } \mathbb{B}^n$$

- ▶ This immediately implies $f_{\min} - f_{(r)} \leq \lambda$

Step 2, 3 and 4:

Problem: How do we ensure that $\mathbf{K}^{-1}(f + \lambda) \geq 0$ on \mathbb{B}^n ?

- ▶ We want the eigenvalues of \mathbf{K} to be as close as possible to 1 (so that $\mathbf{K} \approx \text{Id}$).
- 2. If $K(x, y) = q^2(d(x, y))$, then the eigenvalues λ_i of \mathbf{K} are given by the decomposition:

$$q^2(t) = \sum_{i=0}^{2r} \lambda_i \mathcal{K}_i(t) \quad \text{where } \mathcal{K}_i \text{ is the Krawtchouk polynomial}$$

- 3. Selecting the **univariate** polynomial q so that the λ_i are as close as possible to 1 corresponds to a univariate instance of the **inner hierarchy**
- 4. In the univariate case, the inner hierarchy is well understood, and the behaviour can be described using **orthogonal polynomials**
[de Klerk, Laurent 2020]

Concluding remarks

- ▶ We have shown a guarantee on the **outer** hierarchy $f_{\min} - f_{(r)}$ using a connection to (a special case of) the **inner** hierarchy
- ▶ The treatment of this special case can be extended to obtain our result on the inner hierarchy
- ▶ As far as we know, this is the first analysis in the setting $r < \frac{n+d-1}{2}$
- ▶ But, our results apply only in the setting $r \approx t \cdot n$. In particular they give **no information for fixed $r \in \mathbb{N}$**
- ▶ **Open question:** is it possible to add (linear) constraints?

Some references



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