

The Lasserre hierarchy for binary polynomial optimization

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MINOA

MIXED-INTEGER NON-LINEAR OPTIMISATION:
ALGORITHMS AND APPLICATIONS

Polynomial optimization on the binary cube

We consider the problem of computing:

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

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:

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

- ▶ BPOP is NP-hard in general
- ▶ Many techniques exist for approximation
- ▶ Today: two semidefinite hierarchies due to Lasserre

The outer Lasserre hierarchy

Observation

We can rewrite:

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

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 SDP

Question

What can be said of the quality of $f_{(r)}$, i.e., can we bound $f_{\min} - f_{(r)}$?

- ▶ **Finite convergence:** $f_{(r)} = f_{\min}$ when $r \geq \frac{n+d-1}{2}$
[Fawzi, Saunderson, Parrilo 2016 ($d = 2$)] [Sakaue et al. 2017 ($d > 2$)]
- ▶ But, nothing is known for $r < \frac{n+d-1}{2}$, when the bound is **not exact**.

Analysis of the outer hierarchy

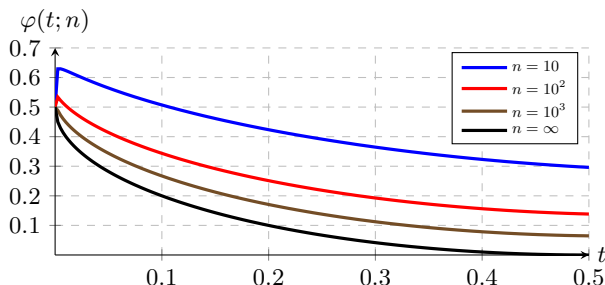
Theorem (Main result on the outer hierarchy)

Let $f \in \mathbb{R}[x]_d$ and choose $r \in \mathbb{N}$ such that $t := r/n \in [0, 1/2]$. Then:

$$\frac{f_{\min} - f(r)}{\|f\|_{\infty}} \leq C_d \underbrace{\left(1/2 - \sqrt{t(1-t)} + \frac{t^{1/6} \sqrt{1-t}}{n^{1/3}} \right)}_{\varphi(t;n)}$$

when $d(d+1) \cdot \varphi(t;n) \leq 1/2$.

- ▶ This analysis applies in the regime $r \approx t \cdot n$, and becomes sharper as $n \rightarrow \infty$



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

Theorem (Main result on the inner hierarchy)

Let $f \in \mathbb{R}[x]_d$ and choose $r \in \mathbb{N}$ such that $t := r/n \in [0, 1/2]$. Then:

$$\frac{f^{(r)} - f_{\min}}{\|f\|_{\infty}} \leq \frac{1}{2} C_d \left(1/2 - \sqrt{t(1-t)} + \frac{t^{1/6} \sqrt{1-t}}{n^{1/3}} \right)$$

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:

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

- ▶ We wish to bound:

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

- ▶ We focus on the **outer** hierarchy, but the **inner** hierarchy will play an important role in the proof

Key steps for analyzing the outer hierarchy

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)

Observation

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

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

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

- ▶ If we assume $\mathbf{K}(1) = 1$, we know that $\mathbf{K}^{-1}(f + \lambda) \geq 0$ on \mathbb{B}^n if:

$$\|\mathbf{K}^{-1}p - p\|_\infty \leq \lambda \text{ for all } p \in \mathbb{R}[x]_d \text{ with } \|p\|_\infty = 1.$$

- ▶ We will bound this quantity by considering the **eigenvalues of \mathbf{K}**

Funk-Hecke formula

The eigenvalues of $K(x, y) = q^2(d(x, y))$ are given by the coefficients λ_i in the expansion of q^2 into the **Krawtchouk** polynomials \mathcal{K}_i :

$$q^2(t) = \sum_{i=0}^{2r} \lambda_i \mathcal{K}_i(t)$$

Step 2. Fourier analysis on \mathbb{B}^n and symmetry reduction

Characters and Krawtchouk polynomials

- ▶ For $a \in \mathbb{B}^n$ define the **character** $\chi_a(x) := (-1)^{a \cdot x}$
- ▶ The characters form an ONB for the space $\mathcal{R}[x] := \mathbb{R}[x]/(x_i^2 = x_i)$ of polynomials on \mathbb{B}^n .
- ▶ Then, $\mathcal{R}[x]$ decomposes as:

$$\mathcal{R}[x] = H_0 \perp H_1 \perp \cdots \perp H_n, \quad H_i = \{\chi_a : |a| = i\}$$

The components H_i are **invariant** and **irreducible** under the symmetries of \mathbb{B}^n (**permutations** and **bit-flips**)

- ▶ We can write $p \in \mathcal{R}[x]_d$ as (**harmonic decomposition**):

$$p = p_0 + p_1 + \cdots + p_d \quad (p_i \in H_i)$$

- ▶ The **Krawtchouk** polynomials \mathcal{K}_i are the orthogonal polynomials w.r.t. the measure $\omega = \sum_{t=0}^n \binom{n}{t} \delta_t$, with $\langle f, g \rangle_\omega = \int_0^n f \cdot g d\omega = \sum_{t=0}^n \binom{n}{t} f(t)g(t)$.
- ▶ **Key fact:** For $x, y \in \mathbb{B}^n$ with $d(x, y) = k$, we have:

$$\sum_{|a|=i} \chi_a(x)\chi_a(y) = \mathcal{K}_i(k)$$

Step 2. Fourier analysis on \mathbb{B}^n and symmetry reduction

Theorem (Funk-Hecke)

Let $q \in \mathbb{R}[t]_r$, and decompose q^2 as $q^2(t) = \sum_{i=0}^{2r} \lambda_i \mathcal{K}_i(t)$. Then the kernel $K(x, y) = q^2(d(x, y))$ satisfies:

$$\mathbf{K}p = \lambda_0 p_0 + \lambda_1 p_1 + \cdots + \lambda_d p_d \quad \text{for } p \in \mathcal{R}[x]_d$$

Proof.

Apply the **key fact** to show that $\mathbf{K}\chi_a = \lambda_{|a|}\chi_a$ for all $a \in \mathbb{B}^n$ □

Recall

We want to choose q such that $\mathbf{K}(1) = 1$ and

$$\|\mathbf{K}^{-1}p - p\|_\infty \text{ is small for all } p \in \mathbb{R}[x]_d \text{ with } \|p\|_\infty = 1$$

Upshot

Using **Funk-Hecke**, we find that if $\lambda_0 = 1$, then $\mathbf{K}(1) = 1$ and:

$$\|\mathbf{K}^{-1}p - p\|_\infty \leq \max_{k=0}^d \|p_k\|_\infty \cdot \sum_{i=1}^d |1 - \lambda_i^{-1}| \leq 2C_d \sum_{i=1}^d (1 - \lambda_i)$$

So we want a q with $\lambda_0 = 1$, and λ_i as close as possible to 1.

Step 3. Connection to the inner hierarchy

Goal

Find a univariate $q \in \mathbb{R}[t]_r$ for which the coefficients in $q^2(t) = \sum_{i=0}^{2r} \lambda_i \mathcal{K}_i(t)$ satisfy:

$$\lambda_0 = 1 \text{ and } \sum_{i=1}^d (1 - \lambda_i) \text{ is small}$$

- ▶ Recall that the \mathcal{K}_i are orthogonal w.r.t. $\omega = \sum_{t=0}^n \binom{n}{t} \delta_t$ and so we have

$$\lambda_i = \langle \widehat{\mathcal{K}}_i, q^2 \rangle_\omega := \int_0^n \widehat{\mathcal{K}}_i \cdot q^2 d\omega,$$

where $\widehat{\mathcal{K}}_i := \mathcal{K}_i / \|\mathcal{K}_i\|_\omega^2 = \mathcal{K}_i / \mathcal{K}_i(0)$.

- ▶ We thus achieve our goal by solving:

$$\inf_{q \in \mathbb{R}[t]_r} \left\{ \int_0^n g \cdot q^2 d\omega : \int_0^n q^2 d\omega = 1 \right\}, \text{ with } g(t) := d - \sum_{i=1}^d \widehat{\mathcal{K}}_i(t).$$

- ▶ This is just the **inner** Lasserre hierarchy for minimizing g on $[0, n]$ w.r.t. the measure ω !
- ▶ To summarize, we have: $f_{\min} - f_{(r)} \leq 2C_d(g_\omega^{(r)} - g_{\min})$

Step 4. Analyzing the inner hierarchy

Theorem (special case of de Klerk, Laurent 2020)

Let $\hat{g}(t) = ct$, $c > 0$ be a **linear** polynomial. Then:

$$\hat{g}_\omega^{(r)} - \hat{g}_{\min} = c \cdot \xi_{r+1},$$

where ξ_{r+1} is the least root of \mathcal{K}_{r+1} .

- ▶ **Problem:** $g(t) = d - \sum_{i=1}^d \hat{\mathcal{K}}_i(t)$ is not linear!
- ▶ But, it is **upper estimated** by its linear approximation at $t = 0$:

$$g(t) \leq \hat{g}(t) := d(d+1) \cdot (t/n) \quad (t = 0, 1, \dots, n)$$

- ▶ We may conclude:

$$g_\omega^{(r)} - g_{\min} \leq \hat{g}_\omega^{(r)} - \hat{g}_{\min} = d(d+1) \cdot (\xi_{r+1}/n)$$

Theorem (Levenshtein 1995)

The least root ξ_r of \mathcal{K}_r satisfies:

$$\xi_r^n/n \leq \frac{1}{2} - \sqrt{(1-t)t} + \frac{t^{1/6}\sqrt{1-t}}{n^{1/3}}$$

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 $r \in \mathbb{N}$**
- ▶ The entire analysis carries over the **q -ary cube** $Q^n = \{0, 1, \dots, q-1\}^n$
- ▶ **Open question:** is it possible to add (linear) constraints?

Some references



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