

Positive spectrahedra:

Invariance principles and PRGs

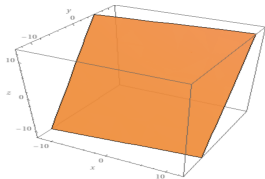
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- Optimizing a linear function over a **polytope**
- A general LP has the form: $w^1; \dots; w^k; c \in \mathbb{R}^n$ and $i \in \mathbb{R}$

$$\text{OPT} = \max_{x \in \mathbb{R}^n} f^T c^T x : w^1 x \leq 1; \dots; w^k x \leq k g$$

- **E**asily solvable!



- **Halfspace** in \mathbb{R}^n is a constraint that divides the space, i.e., $h_1 : \mathbb{R}^n \rightarrow \{0, 1\}$
- Let $w \in \mathbb{R}^n$ and $x \in \mathbb{R}^n$, then a halfspace $h_1(x) = 1$ if $w \cdot x \leq g$, or $h_1(x) = w \cdot x \leq g$
- **Polytope** is an **intersection** of halfspaces
- Let $w^i \in \mathbb{R}^n$, $i \in \mathbb{R}$, a **k-facet polytope** is

$$P = \{x : h_1(x) \wedge h_2(x) \wedge \dots \wedge h_k(x)\}$$

$$\text{where } h_i = [w^i \cdot x \leq g^i]$$

Applications: Optimization, combinatorics, geometry, computational complexity, ...

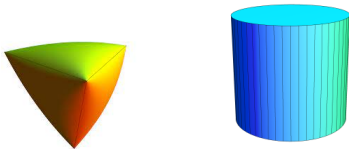
What is an SDP?

- Optimizing a **linear function** over a **spectrahedron**
- A general SDP has the form: $W^1; \dots; W^k; B \succeq \text{Sym}_n$

$$\text{OPT} = \max_{x \in \mathbb{R}^n} f^T x : x_1 W^1 + \dots + x_n W^n \preceq B;$$

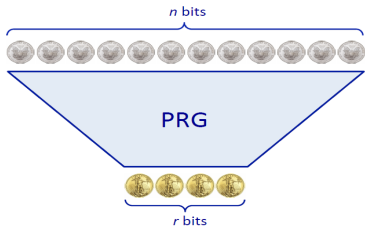
where $C \preceq D$ means $D - C$ is PSD (i.e., all eigenvalues are ≥ 0)

How does it look?



- Generalizes linear programs and still **efficiently solvable!**
- Unfortunately, spectrahedra are **not very well understood!**
- But SDPs have found applications in approximation theory, SoS hierarchy, quantum computing

A PRG is a function that "expands" randomness



PRGs for a class of functions

An r -PRG for C is a function $G : \{0,1\}^r \rightarrow \{0,1\}^n$ such that

$$\text{for every } F \in C; \quad \mathbb{E}_x [F(G(x))] \approx \mathbb{E}_u [F(u)]$$

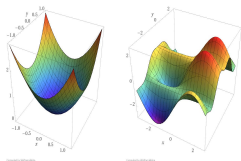
The **seed length** of G is r . **Goal** is to have $r = \text{polylog}(n)$ in all relevant parameters

Holy grail. Can we design a PRG against the class of polynomial sized circuits unconditionally? If so, would imply $BPP = P$

PRGs for geometric objects. Constructing PRGs using geometric properties has been a rich area of study this work.

Halfspaces

- Diakonikolas et al.'09
- Meka, Zuckerman'09
- Karnin, Rabani, Shpilka'11
- Kothari, Meka'15
- Gopalan, Kane, Meka'15



Polytopes

- Harsha, Klivans, Meka'13
- Gopalan et al.'13
- Servedio, Tan'17
- O'Donnell, Servedio, Tan'19

Polynomial Threshold function

$T(x) = \text{sign}(p(x_1; \dots; x_n))$ where p is a polynomial

- Meka, Zuckerman'09
- Diakonikolas'10
- Kane'11, Kane'12, Kane'13
- Kane, Meka'14
- O'Donnell, Servedio, Tan'20

Spectrahedra: generalization of halfspaces, polytopes and PTFs in one framework

In this work: Can we construct PRGs for spectrahedra?

Recall. Spectrahedron is the set $S = \{x \in \mathbb{R}^n : \sum_{i=1}^k x_i A^i \succeq B\}$.

- 1 **Positive:** A^1, \dots, A^n, B are $k+1$ PSD matrices
- 2 **Bounded width:** $\sum_{i=1}^k (A^i)^2 \preceq M I$
- 3 **Regular:** $A^i \succeq I$ for every i

Main Theorem

There exists a PRG $G : \{0,1\}^r \rightarrow \mathbb{R}^n$ with seed length

$$r = (\log n) \text{ poly}(\log k, M, \epsilon^{-1});$$

that ϵ -fools the class of positive bounded width regular spectrahedron S , i.e.,

$$\mathbb{E}_x [G(x) \in S] \approx \mathbb{E}_u [u \in S] \pm \epsilon;$$

Main technical contributions: Rest of this talk

An invariance principle for *positive regular spectrahedra*

Punchline: Invariance principles give pseudorandom generators.

What is an invariance principle? Generalization of **Berry-Esseen theorem**

Standard **central limit theorem** states: suppose $x_1; \dots; x_n$ are random variables satisfying $E[x] = 0$ and $\text{Var}[x^2] = 1$, then

$$\frac{x_1 + \dots + x_n}{\sqrt{n}} \approx g(0;1);$$

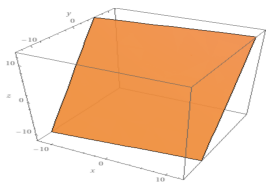
where $g(0;1)$ is a Gaussian

But what about convergence? Berry-Esseen states that for every $u \in \mathbb{R}$

$$\Pr \left[\frac{x_1 + \dots + x_n}{\sqrt{n}} \leq u \right] - \Pr [g(0;1) \leq u] \leq \frac{C}{\sqrt{n}};$$

for "C-nice" $x_1; \dots; x_n$. Proved using the Lindeberg method'22 (aka hybrid method)

Invariance principles: understanding in the Gaussian space is similar to Boolean space



Halfspace (Meka-Zuckerman'09)

- Halfspace is
$$x \geq f + \sum_i w_i x_i$$
- For smooth $w \in \mathbb{R}^n$
$$x \in \bigcap_i \{x \mid w_i x_i \leq g_i\}$$

Polytope (Harsha-Klivans-Meka'13)

- Polytope is
$$x \geq f + \sum_i w_i^1 x_i + \dots + \sum_k w_k^k x_k$$
- Let $w^1, \dots, w^k \in \mathbb{R}^n$ all be smooth, then
$$\begin{matrix} 2 & - & w^1 & - & 3 & 2 & 3 \\ & & & & x_1 & & g_1 \\ 6 & - & w^2 & - & 7 & 6 & 7 \\ & & & & x_2 & & g_2 \\ 4 & - & \vdots & - & 5 & 4 & 5 \\ & & & & \vdots & & \vdots \\ & - & w^k & - & x_n & & g_k \end{matrix}$$

- Recently OST'19 removed regularity

Recall: Polytope $F(x) = w^1 x_1 \wedge \dots \wedge w^k x_k$ or $W x \sim$

Main result of HKM'13 Invariance principle for k -regular polytopes (i.e., $k w^i k \sim$)

$$\mathbb{E}_x \mathbb{E}_{U_n} [Wx] \approx \mathbb{E}_g \mathbb{E}_{G^n} [Wg] \quad \text{polylog } k \quad (1)$$

How to prove this?

1. **Smooth invariance.** Establish (1) for smooth functions $O: \mathbb{R}^k \rightarrow \mathbb{R}$, i.e.,

$$\mathbb{E}_x \mathbb{E}_{U_n} [O(Wx)] \approx \mathbb{E}_g \mathbb{E}_{G^n} [O(Wg)] \quad \log k \quad k O^{(3)} k_1$$

- **Lindeberg method:** Write out Taylor series for $O: \mathbb{R}^k \rightarrow \mathbb{R}$, since U_n and G^n have matching first and second moments, we get 3rd derivatives, hence $k O^{(3)} k_1$
- Since O is smooth, all derivatives are "small" so $k O^{(3)} k_1$ is also "small"

Main result of HKM'13 Invariance principle for d -regular polytopes

$$\mathbb{E}_x \mathbb{E}_{U_n} [W(x)] \approx \mathbb{E}_g \mathbb{E}_{G^n} [W(g)] \quad \text{polylog } k \quad (2)$$

How to prove this?

1. **Smooth invariance.** Establish (2) for smooth mollifiers $O: \mathbb{R}^n \rightarrow \mathbb{R}$, i.e.,

$$\mathbb{E}_x \mathbb{E}_{U_n} [O(W(x))] \approx \mathbb{E}_g \mathbb{E}_{G^n} [O(W(g))] \quad \log k \leq k O^{(3)} k_1 \quad (3)$$

2. **Bentkus mollifier.** Care about $[W(x)]$ **not** $O(W(x))$. Bentkus'90 established a mollifier $B: \mathbb{R}^k \rightarrow \mathbb{R}$ that approximates the orthant function, i.e.,

$$B(z_1, \dots, z_k) \approx \max_i z_i \quad \text{and} \quad k B^{(3)} k_1 \leq \log^{-2} k$$

3. **Anti-concentration.** From above B "approximately agrees" with O .

- Around the "boundary" of the polytope is where B and O disagree
- If probability of $x \in G^n$ lying in boundary is "small", maybe it is ok? YES
- Gaussian surface area! Nazarov'03 showed GSA of k -facet polytopes is $\sqrt{\log k}$

Putting everything together. All dependence are logarithmic factors, so (3) \Rightarrow (2).

A halfspace $F(x) = \sum_j w_j x_j$. Spectrahedron is $F(x) = x_1 A^1 + \dots + x_n A^n \succeq B$



1. Hybrid method?

- ① Spectrahedron naturally deals with eigenvalues of matrices
- ② Unknown if Lindeberg-type argument works for spectral mollifiers (i.e., smooth functions acting on the eigenspectrum of matrices)

An invariance principle for the Bentkus mollifier of arbitrary regular spectrahedra

2. Anti-concentration? Even if GSA of spectrahedra are small, they are "funky" geometric objects, not clear how to go from mollifier-closeness to CDF closeness

Prove a Littlewood-Ord theorem for positive regular spectrahedra

- 1 **Spectral function** $f : \mathbb{R}^n \rightarrow \mathbb{R}$ acts on the eigenvalues of matrices:

$$f(M) = g(\lambda_1(M), \dots, \lambda_n(M))$$

for some $g : \mathbb{R}^n \rightarrow \mathbb{R}$. **Examples** include determinants, trace, matrix norms

- 2 **Derivatives of matrix-valued functions** $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$.

Taylor series. Let $h : \mathbb{R} \rightarrow \mathbb{R}$, then **Taylor series** of h is

$$h(x) = h(a) + \frac{h'(a)}{1!}(x-a) + \frac{h''(a)}{2!}(x-a)^2 + \frac{h'''(a)}{3!}(x-a)^3 + \dots;$$

where

$$h^{(k)}(a) = \lim_{s \rightarrow 0} \frac{1}{s^k} (h(a+s) - h(a))$$

Fréchet derivatives. Derivatives in **Banach spaces**. "Similar" to standard calculus. For $A, B \in \mathbb{R}^n$, we have

$$Df(A)[B] = \lim_{s \rightarrow 0} \frac{1}{s} (f(A+sB) - f(A));$$

$$D^t f(A)[B] = \lim_{s \rightarrow 0} \frac{1}{s^t} (D^{t-1} f(A+sB)[B] - D^{t-1} f(A)[B])$$

Fréchet derivatives are **hard to compute**. **Poorly understood**: basic properties as continuity, Lipschitz continuity, differentiability proven in last 2 decades.

Goal: Invariance principle for Bentkus mollifier B

$$\Pr_{U_n}[(B)(\sum_i x_i A^i) \in B] \approx \Pr_{G^n}[(B)(\sum_i g_i A^i) \in B] \quad \text{polylog } k$$

1. **Hybrid method.** Hash the sum over $[n]$ into t blocks: let $Q_x = \sum_{i=1}^{n/t} x_i A^i$,

$$\mathbb{E}_{x;g}[(B)(Q_x + P_{x;g})] \approx \mathbb{E}_{x;g}[(B)(Q_g + P_{x;g})] \quad (4)$$

2. **Taylor expansion.** Write out Frechet series for both these terms.

$$\mathcal{B}_\lambda(Q_x + P_{x,g}) = \mathcal{B}_\lambda(P_{x,g}) + D\mathcal{B}_\lambda(P_{x,g})[Q_x] + \frac{1}{2}D^2\mathcal{B}_\lambda(P_{x,g})[Q_x, Q_x] + \frac{1}{6}D^3\mathcal{B}_\lambda(P'_{x,g})[Q_x, Q_x, Q_x]$$

$$\mathcal{B}_\lambda(Q_g + P_{x,g}) = \mathcal{B}_\lambda(P_{x,g}) + D\mathcal{B}_\lambda(P_{x,g})[Q_g] + \frac{1}{2}D^2\mathcal{B}_\lambda(P_{x,g})[Q_g, Q_g] + \frac{1}{6}D^3\mathcal{B}_\lambda(R'_{x,g})[Q_g, Q_g, Q_g]$$

Same colour terms are equal in expectation

So bounding Eq (4) amounts to proving. **Goal:** upper bound

$$\mathbb{E}_{x;g}^h D^3\mathcal{B}(P_{x;g}^0)[Q_x; Q_x; Q_x] \approx \mathbb{E}_{x;g}^i D^3\mathcal{B}(R_{x;g}^0)[Q_g; Q_g; Q_g] \quad \text{polylog } k$$

3. **Sendov to the rescue.** For us, Sendov provided a tensorial representation of Frechet series for spectral functions

Recall: Goal is to upper bound

$$\mathbb{E}_{x;g}^h D^3 B (P_{x;g}^0)[Q_x; Q_x; Q_x] \quad D^3 B (R_{x;g}^0)[Q_g; Q_g; Q_g]^i$$

Hope: use Sendov's tensor-result. BUT, if you write it out, we get:

$H = VQV^T$. Then $D^3 F(P)[Q, Q, Q]$ is the summation of the following terms.

$$1. \sum_{i_1} \nabla_{i_1, i_1, i_1}^3 f(x) H_{i_1, i_1}^3$$

$$2. \sum_{i_1 \neq i_2} \nabla_{i_1, i_2, i_1}^3 f(x) H_{i_1, i_1}^2 H_{i_2, i_2}$$

$$3. \sum_{i_1 \neq i_2 \neq i_3} (\nabla_{i_1, i_2, i_2}^3 f(x)) \cdot H_{i_1, i_1} H_{i_2, i_2} H_{i_3, i_3}$$

DIAGONAL ELEMENTS

$$4. \sum_{i_1 \neq i_2} \left(\frac{\nabla_{i_2, i_2}^2 - \nabla_{i_1, i_2}^2}{x_{i_2} - x_{i_1}} - \frac{\nabla_{i_2, i_2} - \nabla_{i_1, i_2}}{(x_{i_2} - x_{i_1})^2} \right) f(x) H_{i_2, i_2} H_{i_2, i_1}^2$$

$$5. \sum_{i_1 \neq i_2 \neq i_3} \frac{\nabla_{i_2, i_3}^2 - \nabla_{i_1, i_3}^2}{x_{i_2} - x_{i_1}} f(x) H_{i_1, i_2}^2 H_{i_3, i_3}$$

$$6. \sum_{i_1 \neq i_2 \neq i_3} \left(\frac{\nabla_{i_3, i_3} - \nabla_{i_1, i_3}}{(x_{i_3} - x_{i_2})(x_{i_3} - x_{i_1})} - \frac{\nabla_{i_2, i_3} - \nabla_{i_1, i_3}}{(x_{i_3} - x_{i_2})(x_{i_2} - x_{i_1})} \right) f(x) H_{i_1, i_2} H_{i_2, i_3} H_{i_3, i_1}$$

$$7. \sum_{i_1 \neq i_2 \neq i_3} \left(\frac{\nabla_{i_2, i_3} - \nabla_{i_1, i_3}}{(x_{i_3} - x_{i_1})(x_{i_2} - x_{i_3})} - \frac{\nabla_{i_2, i_3} - \nabla_{i_1, i_3}}{(x_{i_3} - x_{i_1})(x_{i_2} - x_{i_1})} \right) f(x) H_{i_1, i_3} H_{i_2, i_1} H_{i_3, i_2},$$

Recall: Goal is to upper bound

$$\mathbb{E}_{x;g}^h D^3 B(P_{x;g}^0)[Q_x; Q_x; Q_x] \quad D^3 B(R_{x;g}^0)[Q_g; Q_g; Q_g]$$

Technical contribution.

- Bound each of the 7 terms by polylog k times norms of $Q_g; Q_x; P_{x;g}^0; R_{x;g}^0$.
- Completely **open up** the Bentkus **molli er** (prior works used it as a blackbox)

4. Final step. Understand $\mathbb{E}_x[kQ_x k_4^4]$ and similar quantities.

- We use **matrix Rosenthal's** inequality (proved "recently") gives good **concentration for Schatten norms** of $k \sum_i x_i A^i k_p^p$
- Also matrix Rosenthal is true when $(x_1; \dots; x_n)$ is **p -wise independent**

Putting everything together.

$$\Pr_{x, U_n} [(B) (\sum_i x_i A^i) (B)] \quad \Pr_{g, G^n} [(B) (\sum_i g_i A^i) (B)] \quad \text{polylog } k$$

Recall: positive spectrahedron $S = \{x : x_1 A^1 + \dots + x_n A^n \succeq B\}$ where $A^i, B \succeq 0$

So far.

$$\Pr_{x \in U_n} \left(\sum_i x_i A^i \succeq B \right) \approx \Pr_{g \in G^n} \left(\sum_i g_i A^i \succeq B \right) \approx \text{polylog } k \quad (5)$$

But we care about CDF distance

$$\Pr_{x \in U_n} \left(\sum_i x_i A^i \succeq B \right) \approx \Pr_{g \in G^n} \left(\sum_i g_i A^i \succeq B \right) \approx \text{polylog } k \quad (6)$$

Intuition for this approximation: What does $\sum_i x_i A^i \succeq B$ mean?

If $x_1, \dots, x_k \in [1/100, 100]$; then $\sum_i x_i A^i \succeq B \approx \sum_i x_i A^i \succeq B$

Else $x_1, \dots, x_k \notin [1/100, 100]$; then $\sum_i x_i A^i \succeq B \approx \sum_i x_i A^i \succeq B$

For uniform x , $\Pr \left(\sum_i x_i A^i \succeq B \right) \approx \left[\frac{1}{100}, \frac{1}{100} \right]$ with tiny probability

Recall: positive spectrahedron $S = \{x : x_1 A^1 + \dots + x_n A^n \preceq B\}$ where $A^i, B \succeq 0$

So far.

$$\Pr_{x \in U_n} \left(\sum_i x_i A^i \preceq B \right) \quad \Pr_{g \in G^n} \left(\sum_i g_i A^i \preceq B \right) \quad \text{polylog } k \quad (7)$$

But we care about CDF distance

$$\Pr_{x \in U_n} \left(\sum_i x_i A^i \preceq B \right) \quad \Pr_{g \in G^n} \left(\sum_i g_i A^i \preceq B \right) \quad \text{polylog } k \quad (8)$$

Our result: Littlewood-Offord for spectrahedra

Let A^1, \dots, A^n be positive matrices s.t. $\sum_i k A^i \preceq k^2 I$. 1. For every

$$\Pr_{x \in U_n} \max_i \sum_j x_j A^j \preceq B \geq \frac{1}{k} \Rightarrow O(k^{-1})$$

Prior: Littlewood-O'Leary '43, Erdős '45 proved it for halfspaces, OST'19 for polytopes

Hence (7) implies (8) except tiny probability. Done!

Recall: positive spectrahedron $F(x) = x_1 A^1 + \dots + x_n A^n \succeq B$ where $A^i; B \succeq 0$

A PRG that ϵ -fools the class of positive width- M spectrahedra with seed length $\text{poly}(\log n; \log k; M; 1/\epsilon)$

Open questions:

- 1 Remove regularity?
- 2 Remove positivity?
- 3 What is the Gaussian surface area of spectrahedron?
- 4 Improve the $1/\epsilon$ dependence?
- 5 A general invariance principle for spectral functions?

THANK YOU