

Grothendieck inequalities for semidefinite programs with rank constraints

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The logo for the Centrum voor Wiskunde en Informatica (CWI) is a red parallelogram with the letters 'CWI' in white, bold, sans-serif font.

The plain-vanilla-flavor SDP problem



Given: symmetric matrix $A \in \mathbb{R}^{n \times n}$ with $\text{diag}(A) = 0$

Find: unit vectors x_1, \dots, x_n that maximize the sum

$$\sum_{1 \leq i < j \leq n} A(i, j) \cdot \langle x_i, x_j \rangle$$

Can be solved in poly-time

SDPs with rank* constraint

Adding a little more structure...



Given: symmetric matrix $A \in \mathbb{R}^{n \times n}$ with $\text{diag}(A) = 0$
and positive integer r

Find: r -dimensional unit vectors x_1, \dots, x_n
that maximize the sum

$$\sum_{1 \leq i < j \leq n} A(i, j) \cdot \langle x_i, x_j \rangle$$

Denote this problem by SDP_r and its optimum by $\text{SDP}_r(A)$

SDP_∞ is the *SDP relaxation* of SDP_r : “drop the rank constraint”

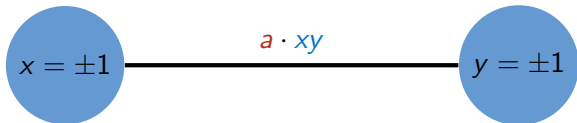
*The word *rank* appears because the matrix $X(i, j) = \langle x_i, x_j \rangle$ has rank r

A tiny example: $n = 2$

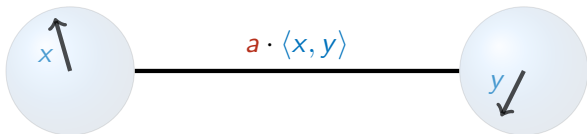
Given: $a \in \mathbb{R}$ and $r \in \mathbb{N}$

Find: $x, y \in S^{r-1}$ that maximize $a \cdot \langle x, y \rangle$

The rank-1 case has a combinatorial nature



Higher ranks have a more geometric flavor

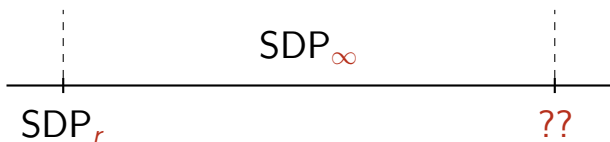


Applications of SDPs with rank constraint

- ▶ Combinatorial cases (rank-1):
 - ▶ MAX CUT
 - ▶ cut-norm of a matrix
 - ▶ statistical physics (Ising spin glasses)
 - ▶ communication complexity
- ▶ Geometrical cases (ranks ≥ 2):
 - ▶ quantum information theory
 - ▶ statistical physics (planar and Heisenberg spin glasses)

MAIN QUESTION

How close are $\text{SDP}_\infty(A)$ and $\text{SDP}_r(A)$?



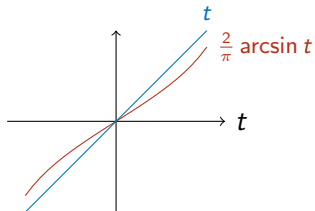
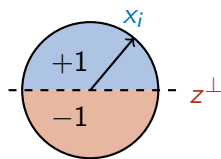
Inapproximability results are known for all ranks $r \geq 1$

“Hyperplane rounding” does not work

► Obvious strategy to approximate SDP_1 by SDP_∞

1. Solve SDP_∞ , get vectors $x_1, \dots, x_n \in S^{n-1}$
2. Sample vector $z \in \mathbb{R}^n$ with iid $N(0, 1)$ entries
3. Round: Set $y_i = \text{sign}\langle x_i, z \rangle$

► Grothendieck identity: $\mathbb{E}_z[y_i y_j] = \frac{2}{\pi} \arcsin(\langle x_i, x_j \rangle)$



► Coefficients $A(i, j)$ of $y_i y_j$ give bad cancellations

Approximation results for the rank-1 case

Positive result

- ▶ [N98, NRT99, Meg01, CW04]: $O(\log n)$ -approximation

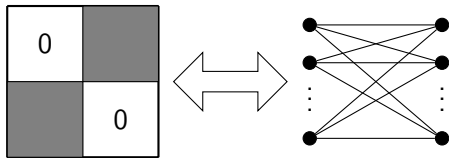


Negative results

- ▶ [KO'D09]: Matching $\Omega(\log n)$ lower bound
- ▶ [ABKHS05, KO'D09]: Hardness-of-approximation results

Better results hold for “bipartite matrices”...

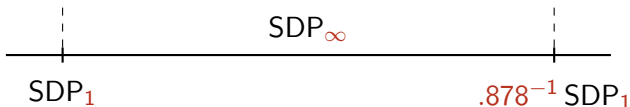
Matrices with bipartite support graph



- ▶ For graph $G = (V, E)$ and $W = \text{diag}(\text{deg}(V)) - \text{Adj}(G)$,

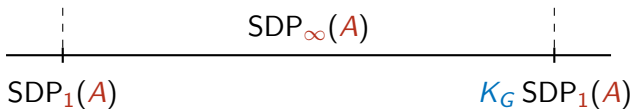
$$\text{SDP}_1 \left(\begin{bmatrix} 0 & W \\ W^T & 0 \end{bmatrix} \right) = 4|\text{MAX CUT}(G)|$$

- ▶ [GW95]: .878-approximation for these types of matrices



Grothendieck's inequality

- ▶ [AN04]: $O(1)$ -approximation of $\text{SDP}_1(A)$ for bipartite A
- ▶ Based on an algorithmic proof of *Grothendieck's inequality*:



$\text{SDP}_\infty(A)$

$\text{SDP}_1(A)$ $K_G \text{SDP}_1(A)$

for universal constant K_G and bipartite A [Grothendieck53]

- ▶ Exact value of K_G : **unknown**
- ▶ [Krivine79]: $K_G \leq 1.78\dots$, [BMMN11]: $K_G < 1.78\dots$
- ▶ [RS09]: Assuming UGC, $\nexists (K_G - \delta)$ -approximation for $\delta > 0$

Other support graphs? Higher ranks?

- ▶ Big contrast between complete and bipartite support graphs
- ▶ *Better approximation results for other support graphs??*
- ▶ *What about higher ranks??*

The graphical Grothendieck problem with rank- r constraint



Given: graph $G = (V, E)$,
symmetric matrix A with support graph G
and positive integer r

Find: r -dimensional unit vectors x_j
that maximize the sum

$$\sum_{i,j} A(i,j) \cdot \langle x_i, x_j \rangle$$

Application: spin glasses

Model of interacting particles introduced by Stanley (1968)

PHYSICAL REVIEW

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Spherical Model as the Limit of Infinite Spin Dimensionality

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(Received 20 April 1968)

The Berlin-Kac spherical model (or "spherical approximation to the Ising model")

$$\mathcal{H}^{\text{SM}} = -J \sum_{\langle ij \rangle} \mu_i \mu_j, \quad \text{with} \quad \sum_{i=1}^N u_i^2 = N,$$

is found to be equivalent to the $\nu \rightarrow \infty$ limit of the Hamiltonian

$$\mathcal{H}^{(\nu)} = -J \sum_{\langle ij \rangle} \mathbf{S}_i^{(\nu)} \cdot \mathbf{S}_j^{(\nu)},$$

where $\mathbf{S}_j^{(\nu)}$ are isotropically interacting ν -dimensional classical spins.

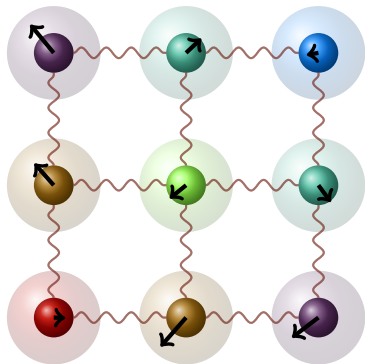
I. INTRODUCTION

THE Berlin-Kac spherical model¹ has received considerable attention, particularly because it is

Although it is perhaps not generally appreciated, it seems clear that $\mathcal{H}^{(\nu)}$ reduces to the $S = \frac{1}{2}$ Ising, classical planar, and classical Heisenberg models for $\nu = 1, 2,$

Geometric instances: spin glasses

Particles are located at vertices of an interaction graph



Particles are unit vectors

- ▶ 1D = Ising model
- ▶ 2D = planar model
- ▶ 3D = Heisenberg model

Edge weights $W : E \rightarrow \mathbb{R}$ give their interaction strength

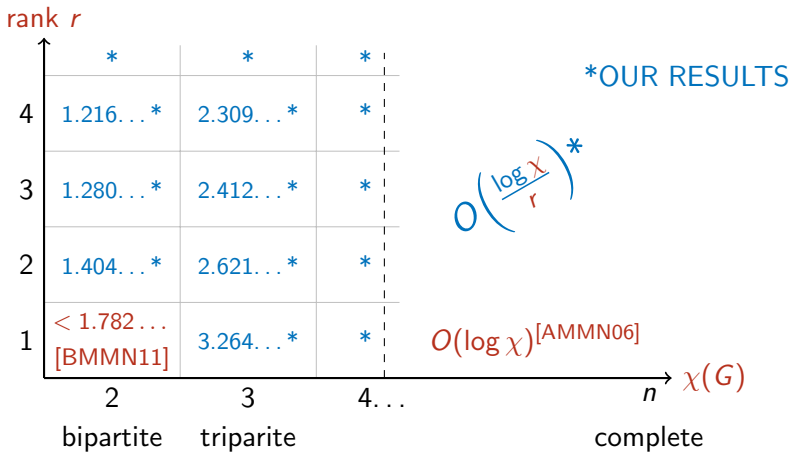
Problem: compute the *ground state* of the total system:

$$- \max_{\{u,v\} \in E} \sum W(u,v) \langle x_u, x_v \rangle$$

Approximation results

$$K(r, G) = \max \frac{\text{SDP}_\infty(A)}{\text{SDP}_r(A)} \text{ over matrices } A \text{ with support graph } G$$

upper bounds on $K(r, G)$ (“integrality gaps”)



Proof sketch for $\chi(G) = 2$, $\text{rank} \geq 1$

- ▶ Want to show: $\text{SDP}_r(A) \geq c \text{SDP}_\infty(A)$ for bipartite A
- ▶ **Transform** optimal SDP_∞ vectors x_i into r -dimensional y_i s.t.

$$\langle y_i, y_j \rangle = c \langle x_i, x_j \rangle$$

- ▶ y_i are *feasible* for SDP_r
- ▶ they give value

$$\sum A(i,j) \langle y_i, y_j \rangle = c \text{SDP}_\infty(A)$$

- ▶ Hence, $\text{SDP}_r(A) \geq c \text{SDP}_\infty(A)$
- ▶ $\leadsto K(r, G) \leq 1/c$

How to **transform** the SDP solution vectors??

Random “rounding” and a generalized Grothendieck identity

- ▶ Sample $Z \in \mathbb{R}^{r \times n}$ with iid $N(0, 1)$ entries
- ▶ For optimal SDP_∞ vector x , set $y = Zx / \|Zx\|_2$
- ▶ What we would like to hold: $\mathbb{E}_Z[\langle y_i, y_j \rangle] = c \langle x_i, x_j \rangle$

Theorem. $\mathbb{E}_Z[\langle y_i, y_j \rangle] = E_r(\langle x_i, x_j \rangle)$

$$\begin{aligned} &= \gamma(r) \times \left(\langle x_i, x_j \rangle + \frac{1}{2(r+2)} \langle x_i, x_j \rangle^3 + \right. \\ &\quad \left. \frac{9}{8(r+2)(r+4)} \langle x_i, x_j \rangle^5 + \frac{225}{48(r+2)(r+4)(r+6)} \langle x_i, x_j \rangle^7 + \right. \\ &\quad \left. \frac{11025}{384(r+2)(r+4)(r+6)(r+8)} \langle x_i, x_j \rangle^9 + \frac{893025}{3840(r+2)(r+4)(r+6)(r+8)(r+10)} \langle x_i, x_j \rangle^{11} + \dots \right) \end{aligned}$$

- ▶ Grothendieck's identity: $E_1 = \frac{2}{\pi} \arcsin$

Krivine's embedding technique

- ▶ Embed the SDP_∞ vectors x_i before rounding
- ▶ To embed, use the *inverse* of E_r

$$E_r^{-1}(t) = \alpha_1 t + \alpha_2 t^2 + \dots$$

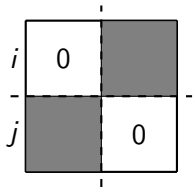
- ▶ Set $S(x) = [\sqrt{c|\alpha_1|x} \quad , \quad \sqrt{c^2|\alpha_2|x^{\otimes 2}} \quad , \dots]$
- ▶ $T(x) = [\text{sign}(\alpha_1)\sqrt{c|\alpha_1|x} \quad , \quad \text{sign}(\alpha_2)\sqrt{c^2|\alpha_2|x^{\otimes 2}} \quad , \dots]$
- ▶ Inner product of $S(x)$ and $T(y)$ *inverts* E_r

$$\langle S(x), S(y) \rangle = E_r^{-1}(c\langle x, y \rangle)$$

Putting things together: “Embed, then round”

1. Get optimal vectors x_i for SDP_∞
2. Krivine embedding
 - ▶ For “left” index i set $\tilde{x}_i = S(x_i)$
 - ▶ For “right” index j set $\tilde{x}_j = T(x_j)$
3. “Round”
 - ▶ Sample $Z \sim N(0, 1)^{r \times n}$
 - ▶ set $y_i = Z\tilde{x}_i / \|Z\tilde{x}_i\|_2$
4. We have

$$\begin{aligned}\mathbb{E}_Z[\langle y_i, y_j \rangle] &= E_r(\langle \tilde{x}_i, \tilde{x}_j \rangle) \text{ Grothenedieck identity} \\ &= E_r(E_r^{-1}(c\langle x_i, x_j \rangle)) \text{ Krivine's trick} \\ &= c\langle x_i, x_j \rangle\end{aligned}$$



Open problems

- ▶ [BMMN11] showed that Krivine's technique is *not* optimal for rounding SDP solutions to integer solutions
- ▶ *Can their rounding scheme be extended to higher ranks?*

- ▶ Krivine+ ϑ -type rounding and [AMMN06] rounding are favorable for small/large chromatic number resp.
- ▶ *Is there some hybrid scheme of these two?*