

Grothendieck inequalities for SDPs with rank constraint

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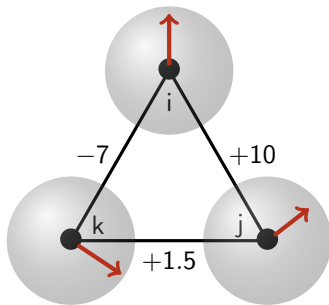
Joint work with **Fernando de Oliveira Filho (FU Berlin)**
and **Frank Vallentin (TU Delft)**

Phenomena in high dimensions in geometric analysis,
random matrices and computational geometry

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The Grothendieck problem

- Given a weighted graph and dimension d , find an optimal configuration of unit vectors in \mathbb{R}^d associated to the vertices



$$10 x_i \cdot x_j - 7 x_i \cdot x_k + 1.5 x_j \cdot x_k$$

- An optimal configuration **maximizes the weighted sum of dot products** between the vectors on the edges

$$\sum_{ij \in E} W_{ij} x_i \cdot x_j$$

Example 1: Ground-state energy of a spin glass

- Model of interacting particles introduced by Stanley (1968)
- Particles form the vertices of a weighted interaction graph

Particles are unit vectors $x_i \in \mathbb{R}^d$

d=1: Ising model $x_i \in \{-1, 1\}$

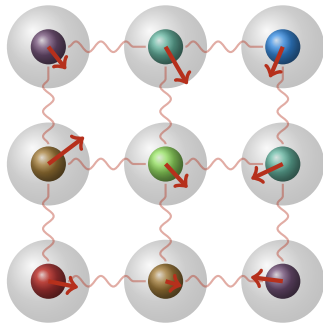
d=2: planar model

d=3: Heisenberg model

Edge weights W_{ij} give their interaction type and strength

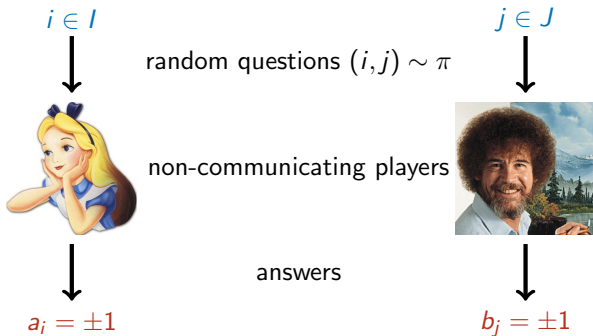
The **ground-state energy** is given by

$$\min \sum_{ij \in E} W_{ij} x_i \cdot x_j$$



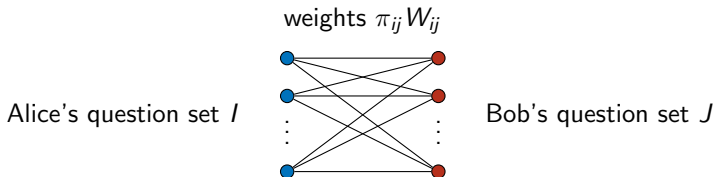
Example 2: XOR games

- Abstract model of the simplest physics experiments used to test predictions of quantum mechanics
- $W \in \{-1, 1\}^{I \times J}$, probability distribution π over $I \times J$



- The players win if $W_{ij}a_i b_j = +1$ and lose if $W_{ij}a_i b_j = -1$
- The goal: Maximize the bias $\mathbb{E}[W_{ij}a_i b_j]$

XOR games are bipartite instances



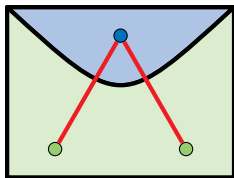
- **(Tsirelson).** For any quantum strategy there exist unit vectors x_i, y_j such that for all i, j

$$\mathbb{E}[a_i b_j] = x_i \cdot y_j$$

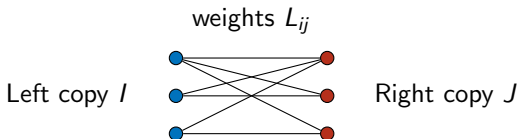
- The bias is of the form $\sum_{ij} \pi_{ij} W_{ij} x_i \cdot y_j$
- Dimension of the vectors is related to the quantum systems used in the strategy

Example 3: The maximum cut problem

- Given a graph, partition its vertices such that the number of edges crossing the cut is maximized



- Combinatorial ($d = 1$) instance of the Grothendieck problem



- Max $\sum_{i \in I, j \in J} L_{ij} x_i y_j$ over $x_i, y_j \in \{-1, 1\}$ gives a max cut

Computational perspective

- If $P \neq NP$, then MaxCut cannot be solved in polynomial time
- Hence, worst-case instances of the Grothendieck problem are likely to be intractable

Then, can we efficiently find d -dimensional unit vectors that achieve a value very close to the optimum?

- **(Håstad)** In general, no! If $P \neq NP$, then MaxCut cannot even be approximated to within a factor $16/17 - \epsilon$ in poly-time
- But if the required dimension is greater than the number of vectors, we *can*!
- Since N vectors span a space of dimension at most N , there is no effective constraint on the dimension

SDP formulation of the Grothendieck problem

- A matrix $X \in \mathbb{R}^{N \times N}$ is **positive semidefinite** iff there exist vectors x_1, \dots, x_N such that $X_{ij} = x_i \cdot x_j$
- The Grothendieck problem as a **semidefinite program (SDP)** with **rank constraint**:

$$\begin{array}{ll} \text{Maximize} & \sum_{ij \in E} W_{ij} X_{ij} \\ \text{Subject to} & X \text{ is positive semidefinite} \\ & X_{ii} = 1 \text{ for all vertices } i \\ & \del{\text{rank } X \leq d} \end{array}$$

- Without the rank constraint, this problem can be solved (approximated arbitrarily well) in poly-time

SDP-based approximation algorithms

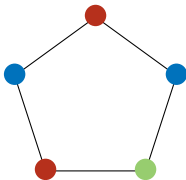
- To approximate the **optimum value** of the Grothendieck problem, drop the rank constraint and solve the SDP

Def. The maximum **ratio** of this optimum and the SDP value, $K(d, G)$, is the **rank- d Grothendieck constant of the graph G**

$$K(d, G) = \sup_W \frac{\text{SDP}_\infty(W, G)}{\text{SDP}_d(W, G)}$$

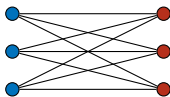
- How large $K(d, G)$ is highly depends on the **chromatic number $\chi(G)$** of the graph G

Def. $\chi(G)$ = the least number of colors with which the vertices can be colored, such that **adjacent vertices get different colors**



$$\chi(C_5) = 3$$

Previous results for bipartite graphs



- **(Grothendieck, Alon-Naor).** \exists universal constant K_G such that $K(1, G) \leq K_G$ for all bipartite graphs G
- **(Braverman-Makarychev-Makarychev-Naor).**
 $K_G < \frac{\pi}{2 \ln(1+\sqrt{2})} = 1.782\dots$
- **(Goemans-Williamson).** For MaxCut this upper bound can be improved to $1/0.878\dots = 1.138\dots$
- **(Davie-Reeds).** $K_G \geq 1.676\dots$
- **(Raghavendra-Steurer).** Assuming the Unique Games Conjecture, K_G is the poly-time approximation threshold

Previous results for general graphs

- **(Alon-Makarychev-Makarychev-Naor).** $K(1, G) \leq O(\log \vartheta(\overline{G}))$

$$\begin{aligned} \vartheta(\overline{G}) = \text{Min} \quad & \lambda \\ \text{Subject to} \quad & Z_{ij} = \lambda - 1 \text{ and positive semidefinite} \\ & Z_{ij} = -1 \text{ for all edges } ij \end{aligned}$$

- The Lovász theta number satisfies $\vartheta(\overline{G}) \leq \chi(G)$
- **(AMMN, Arora-Berger-Hazan-Kindler-Safra, Khot-O'Donnell).** $K(1, K_N) = \Theta(\log N)$
- **(Alon-Berger).** $K(1, G(N, p)) = \Theta(\log Np)$ almost surely.

Our main results

- **(B-de Oliveira Filho-Vallentin)**. New upper bounds on $K(1, G)$ for graphs with small chromatic number

$$K(1, G) \leq \frac{\pi}{2 \operatorname{arcsinh}((\vartheta(\overline{G}) - 1)^{-1})}$$

- This bound grows **linearly** with $\vartheta(\overline{G})$, but is favorable over the $O(\log \vartheta(\overline{G}))$ when $\vartheta(\overline{G})$ is small

Our main results

- For higher dimensions, we give numeric upper bounds

d	<i>bipartite G</i>	<i>tripartite G</i>
1	1.782213...	3.264251...
2	1.404909...	2.621596...
3	1.280812...	2.412700...
4	1.216786...	2.309224...
5	1.177179...	2.247399...
6	1.150060...	2.206258...
7	1.130249...	2.176891...
8	1.115110...	2.154868...
9	1.103150...	2.137736...
10	1.093456...	2.124024...

- (Naor-Regev)**. The first column goes as $1 + O(1/d)$
- (B-Buhrman-Toner)**. $1 + \Omega(1/d)$ lower bound for bipartite graphs
- So our first column is asymptotically optimal

High chromatic numbers

- **(B-de Oliveira Filho-Vallentin)**. If the graph has large chromatic number the method of [AMMN] gives the better bound

$$K(d, G) \leq O\left(\frac{\log \vartheta(\overline{G})}{d}\right)$$

Proof outline

The Grothendieck problem

$$\text{Maximize} \quad \sum_{ij \in E} W_{ij} x_i \cdot x_j$$

$$\text{Subject to} \quad x_1, \dots, x_N \in \mathbb{R}^d$$

$$\|x_i\|_2 = 1 \text{ for all vertices } i \in [N]$$

- If we let $\text{SDP}_d(W, G)$ be the optimum, then

$$K(d, G) = \sup_W \frac{\text{SDP}_N(W, G)}{\text{SDP}_d(W, G)}$$

- To upper bound $K(d, G)$, we convert N -dimensional SDP vectors x_i into random d -dimensional unit vectors y_i such that

$$\mathbb{E}[y_i \cdot y_j] = c x_i \cdot x_j$$

for all adjacent vertices i and j , for some $c = c(G)$

- ... implying $K(d, G) \leq 1/c$ by the averaging principle

Gaussian dimension reduction

- For a random $d \times N$ matrix G with i.i.d. $\mathcal{N}(0, 1/d)$ entries,

$$\mathbb{E} \left[\begin{array}{|c|} \hline G^T \\ \hline \end{array} \begin{array}{|c|} \hline G \\ \hline \end{array} \right] = \begin{array}{|c|} \hline 1 & & 0 \\ & \ddots & \\ 0 & & 1 \\ \hline \end{array}$$

- If we use G to map the N -dimensional SDP vectors x_1, \dots, x_N to d -dimensional vectors

$$\begin{array}{|c|} \hline y_i \\ \hline \end{array} = \begin{array}{|c|} \hline G \\ \hline \end{array} \begin{array}{|c|} \hline x_i \\ \hline \end{array}$$

- then $\mathbb{E}[y_i \cdot y_j] = x_i^T \mathbb{E}[G^T G] x_j = x_i \cdot x_j$ for all vertices i, j
- Great! But these new vectors may not have unit norm...

Can't we just normalize the new vectors?

- Suppose we normalize the new vectors

$$d \begin{array}{|c} \hline y_i \\ \hline \end{array} = \begin{array}{|c} \hline G \\ \hline \end{array} \begin{array}{|c} \hline x_i \\ \hline \end{array} / \sqrt{\|Gx_i\|_2}$$

- Gives **unit** vectors of the desired dimension, but their expected dot products depends **non-linearly** on the original dot products
- For example, if $d = 1$ we have **Grothendieck's identity**:

$$\mathbb{E}[y_i \cdot y_j] = \frac{2}{\pi} \arcsin(x_i \cdot x_j)$$

- If the SDP value is high, the new vectors can give a low (expected) value due to non-linear scaling of the dot products

A generalized Grothendieck identity

Lemma (B-de Oliveira Filho-Vallentin). For

$$d \begin{array}{|c|} \hline y_i \\ \hline \end{array} = \begin{array}{|c|} \hline G \\ \hline \end{array} \begin{array}{|c|} \hline x_i \\ \hline \end{array} / \sqrt{\|Gx_i\|_2}$$

we have $\mathbb{E}[y_i \cdot y_j] = E_d(x_i \cdot x_j)$, where

$$E_d(t) = \sum_{k=0}^{\infty} \underbrace{\frac{2}{d} \left(\frac{\Gamma(\frac{d+1}{2})}{\Gamma(\frac{d}{2})} \right)^2 \prod_{\ell=1}^k \frac{(2\ell-1)^2}{2\ell(d-2\ell)}}_{\text{Taylor coefficients}} t^{2k+1}$$

- Grothendieck's identity: $E_1(t) = (2/\pi) \arcsin t$

Krivine's method: Preprocess before embedding

- Main idea: Preprocess the SDP vectors $x_i \mapsto \tilde{x}_i$ so that

$$E_d(\tilde{x}_i \cdot \tilde{x}_j) = c x_i \cdot x_j$$

for all adjacent vertices i and j , and some $c = c(G)$

- Then, rounding the preprocessed vectors as before

$$d \begin{array}{|c|} \hline y_i \\ \hline \end{array} = \begin{array}{|c|} \hline G \\ \hline \end{array} \begin{array}{|c|} \hline \tilde{x}_i \\ \hline \end{array} / \sqrt{\|G\tilde{x}_i\|_2}$$

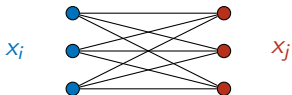
gives d -dimensional unit vectors with expected dot product

$$\mathbb{E}[y_i \cdot y_j] \stackrel{\uparrow}{=} E_d(\tilde{x}_i \cdot \tilde{x}_j) = c x_i \cdot x_j$$

(by our lemma)

Preprocessing for bipartite graphs

- To preprocess the SDP vectors for a bipartite graph, we group them according to a 2-coloring



- It suffices to find maps **BLUE**, **RED** that send unit vectors to unit vectors and satisfy

$$E_d(\text{BLUE}(x_i) \cdot \text{RED}(x_j)) = c x_i \cdot x_j$$

for some $c > 0$

The maps BLUE and RED

- Take the Taylor coefficients a_0, a_1, a_2, \dots of the *inverse* E_d^{-1} of E_d (can be computed from those of E_d)
- By the tensor-power trick: $x^{\otimes k} \cdot y^{\otimes k} = (x \cdot y)^k$, the vectors

$$\begin{bmatrix} \sqrt{|a_0|} \\ \sqrt{|a_1|} c x_i \\ \sqrt{|a_2|} (c x_i)^{\otimes 2} \\ \vdots \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} \text{sgn}(a_0) \sqrt{|a_0|} \\ \text{sgn}(a_1) \sqrt{|a_1|} c x_j \\ \text{sgn}(a_2) \sqrt{|a_2|} (c x_j)^{\otimes 2} \\ \vdots \end{bmatrix}$$

have dot product $a_0 + a_1(c x_i \cdot x_j) + a_2(c x_i \cdot x_j)^2 + \dots$

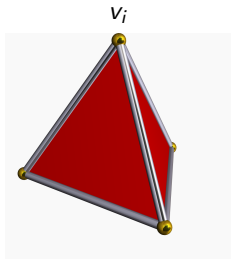
- This equals $E_d^{-1}(c x_i \cdot x_j)$ since the Taylor series converges
- $E_d(\text{BLUE}(x_i) \cdot \text{RED}(x_j)) = E_d(E_d^{-1}(c x_i \cdot x_j)) = c x_i \cdot x_j$
- Set c such that $\text{BLUE}(x_i)$ and $\text{RED}(x_j)$ are unit vectors

Dealing with larger chromatic numbers

- For graphs with chromatic number larger than 2, we preprocess using linear combinations of the BLUE and RED maps

$$x_i \mapsto \text{BLUE}(x_i) \otimes s_i + \text{RED}(x_i) \otimes t_i$$

- The vectors s_i are t_i are “orthogonal tails”
- Can be obtained from a feasible solution for $\vartheta(\overline{G})$
- For example if G is k -colorable, we can use vertices of a $(k - 1)$ -dimensional simplex of radius $\sqrt{k - 1}$



$$t_i = (v_i, 0, 1)$$

$$s_i = (v_i, 1, 0)$$

A better method for very large chromatic numbers

- The main problem was to turn the d -dimensional vectors

$$\boxed{y_i} = \boxed{G} \boxed{x_i}$$

into [unit vectors](#)

- However, $\|y_i\|_2$ is large with only tiny probability
- The [AMMN] method:
 - Scale y_i to y_i/R if y_i lies in the ball of radius R
 - Set $y_i = 0$ otherwise
- Optimizing over R shows that there exist vectors in the [unit ball](#) giving value $1/R^2 \approx d/\log \vartheta(G)$ times the SDP value

Open problems and future/current work

- The Krivine and AMMN methods are favorable for small/large chromatic number resp.
- *Is there some hybrid scheme of these two?*
- Extend the known $\Omega(\log \omega(G))$ lower bound on $K(1, G)$ [AMMN] to the higher-dimensional cases

Thank you!

arXiv:1011.1754 [math.OC]