Semidefinite programming bounds for the kissing number

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Master's thesis defense São Paulo, 21 February 2017

Spherical codes

$$\begin{split} x \cdot y &:= \sum_{i=1}^{n} x_i y_i \\ S^{n-1} &:= \{ x \in \mathbb{R}^n : x \cdot x = 1 \} \\ d(x,y) &:= \arccos(x \cdot y) \\ A(n,\theta) &:= \max\{ |C| : C \subset S^{n-1}, \\ d(x,y) \geq \theta \text{ for } x, y \in C, x \neq y \} \end{split}$$



Find upper bounds for the size of spherical codes with minimum angular distance θ .

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Find upper bounds for the size of spherical codes with minimum angular distance θ .

The kissing number (case $\theta = \pi/3$)











n	lower bound	upper bound]	n	lower bound	upper bound
3	12	12	1	14	1606	3177
4	24	24	1	15	2564	4866
5	40	44	1	16	4320	7355
6	72	78	1	17	5346	11014
7	126	134	1	18	7398	16469
8	240	240	1	19	10668	24575
9	306	363	1	20	17400	36402
10	500	553	1	21	27720	53878
11	582	869	1	22	49896	81376
12	840	1356	1	23	93150	123328
13	1154	2066	1	24	196560	196560

Table 1. Lower and upper bounds for the kissing number $A(n, \pi/3)$ in dimensions $3, \ldots, 24$.

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Representation theory Continuous, positive and invariant kernels Conic programming

Preliminaries

- Representation theory
- Continuous, positive and invariant kernels
- Conic programming

Representation theory Continuous, positive and invariant kernels Conic programming

Basic definitions from representation theory

A representation of a group G on a vector space V is a homomorphism $\rho\colon G\to \operatorname{GL}(V).$

A *G*-homomorphism between two representations $\rho: G \to \operatorname{GL}(V)$ and $\tau: G \to \operatorname{GL}(W)$ is a homomorphism that commutes with the representations. That is, $T: V \to W$ linear such that

$$T\rho(g) = \tau(g)T$$

for every $g \in G$. If T is invertible, the representations are said to be *equivalent*.

Representation theory Continuous, positive and invariant kernels Conic programming

Basic definitions from representation theory

We say that a representation space V is *irreducible* if there is no proper and nonzero invariant subspace W of V (in the sense that $\rho(g)w \in W$ for every $w \in W$ and $g \in G$).

Every finite dimensional representation space V can be written as a direct sum of invariant and irreducible subspaces.

 $V = V_1 \oplus \cdots \oplus V_m.$

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Representation theory Continuous, positive and invariant kernels Conic programming

Basic definitions from representation theory

Every finite dimensional representation space V can be written as a direct sum of invariant and irreducible subspaces.

 $V = V_1 \oplus \cdots \oplus V_m.$

The main result of this section is that a G-homomorphism $T: V \rightarrow V$ can be block-diagonalized with respect to the way that V decomposes as a direct sum of invariant and irreducible subspaces.

Representation theory Continuous, positive and invariant kernels Conic programming

Continuous and positive kernels

Consider a compact Hausdorff space X with a positive Radon measure $\omega.$ The vector space $L^2(X)$ of square-integrable functions on X is a Hilbert space with inner product

$$(f,g) := \int_X f(x)\overline{g(x)} \,\mathrm{d}\omega(x).$$

A (Hilbert-Schmidt) kernel is a function $K \in L^2(X \times X)$. To a kernel is associated the integral operator $T_K : L^2(X) \to L^2(X)$:

$$(T_K f)(x) := \int_X K(x, y) f(y) \,\mathrm{d}\omega(y).$$

Representation theory Continuous, positive and invariant kernels Conic programming

Continuous and positive kernels

A hermitian kernel (i.e. such that $K(x,y) = \overline{K(y,x)}$ for every $x,y \in X$) is *positive* if for every $f \in L^2(X)$ we have

 $(T_K f, f) \ge 0.$

When a kernel is continuous, the following result is very useful:

A continuous and hermitian kernel K is positive if and only if for every finite subset $\{x_1, ..., x_N\}$ of X, the matrix $(K(x_i, x_j))_{i,j=1}^N$ is positive semidefinite.

Representation theory Continuous, positive and invariant kernels Conic programming

Invariant kernels

Consider that there is a compact group G which acts continuously on X and that ω is G-invariant (i.e., $\omega(gA) = \omega(A)$ for every $g \in G$ and $A \subset X$ measurable).

A continuous kernel K is *invariant* if K(gx, gy) = K(x, y) for any $x, y \in X$ and $g \in G$. It can be verified that this condition is equivalent to that the associated operator T_k is a G-homomorphism with respect the representation of G in $L^2(X)$ defined by

$$(\rho(g)f)(x) = f(g^{-1}x).$$

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Invariant kernels

A continuous kernel K is *invariant* if K(gx, gy) = K(x, y) for any $x, y \in X$ and $g \in G$. It can be verified that this condition is equivalent to that the associated operator T_k is a G-homomorphism with respect the representation of G in $L^2(X)$ defined by

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It is possible to represent continuous, positive and invariant kernels using positive semidefinite matrices and the block diagonalization of G-homomorphisms given by the representation theory.

Representation theory Continuous, positive and invariant kernels Conic programming

Conic programming

A *duality* between two real vector spaces E and F is a nondegenerate bilinear form $\langle,\rangle: E \times F \to \mathbb{R}$ (non-degenerate means that $\langle e, f \rangle = 0$ for every $e \in E$ implies f = 0 and $\langle e, f \rangle = 0$ for every $f \in F$ implies e = 0).

Let $\langle, \rangle_1 \colon E_1 \times F_1 \to \mathbb{R}$ and $\langle, \rangle_2 \colon E_2 \times F_2 \to \mathbb{R}$ be two dualities. The *adjoint* of a linear transformation $A \colon E_1 \to E_2$ is a linear transformation $A^* \colon F_2 \to F_1$ such that

$$\left\langle Ae, f \right\rangle_2 = \left\langle e, A^*f \right\rangle_1 \quad \text{for all } e \in E_1, \ f \in F_2.$$

Representation theory Continuous, positive and invariant kernels Conic programming

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A subset K of a vector space E is a *cone* if $\alpha x + \beta y \in K$ for every $\alpha, \beta \geq 0$ and $x, y \in K$. If $\langle, \rangle \colon E \times F \to \mathbb{R}$ is a duality, then the *dual cone* $K^* \subset F$ is defined as

$$K^* := \{ y \in F : \langle x, y \rangle \ge 0 \text{ for all } x \in K \}.$$

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Pair of problems primal and dual

Let $\langle, \rangle_1 \colon E_1 \times F_1 \to \mathbb{R}$ and $\langle, \rangle_2 \colon E_2 \times F_2 \to \mathbb{R}$ be two dualities, $K_1 \subset E_1, K_2 \subset E_2$ two convex cones and $A \colon E_1 \to E_2$ a linear transformation. For $c \in F_1$ and $b \in E_2$, we have:



The linear programming bound The semidefinite programming bound Polynomial optimization with sum of squares and symmetries Application to the semidefinite programming bound



Bounds for the kissing number

- The linear programming bound
- The semidefinite programming bound
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The linear programming bound

- The linear programming bound was proposed by Delsarte, Goethals and Seidel (1977) and used by Odlyzko and Sloane (1979) and, independently, Levenshtein (1979) to derive upper bounds for the kissing number in $n \leq 24$.
- It solves the cases $A(8, \pi/3) = 240$ and $A(24, \pi/3) = 196560$.
- It relies on the following property satisfied by the Gegenbauer polynomials P_k^n :

$$\sum_{x,y\in C} P^n_k(x\cdot y) \geq 0, \ \text{ for every } C\subset S^{n-1} \text{ finite.}$$

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Continuous, positive and $O(\mathbb{R}^n)$ -invariant kernels on S^{n-1}

The space $\operatorname{Pol}_{\leq d}(S^{n-1})$ decomposes as a direct sum of invariant and irreducible subspaces:

$$\operatorname{Pol}_{\leq d}(S^{n-1}) = H_0^n \perp H_1^n \perp \dots \perp H_d^n,$$

where

$$H^n_k := \big\{ f \in \operatorname{Pol}_{\leq d}(S^{n-1}) : f \text{ homogeneous}, \deg f = k, \ \sum_{j=1}^n \frac{\partial^2}{\partial x_j^2} f = 0 \big\}$$

is the space of spherical harmonic polynomials of degree k.

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Gegenbauer polynomials

Addition formula

If $\{R_1, \ldots, R_{h_k^n}\}$ is an orthonormal basis of H_k^n , then for any $x, y \in S^{n-1}$:

$$P_k^n(x \cdot y) = \frac{1}{h_k^n} \sum_{i=1}^{h_k^n} \overline{R_i(x)} R_i(y).$$

 P_k^n is a univariate polynomial of degree k such that $P_k^n(1) = 1$.

Orthogonality relation:

$$\int_{-1}^{1} P_k^n(t) P_l^n(t) (1-t^2)^{(n-3)/2} dt = 0,$$

if $k \neq l$.





$$n = 3$$

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The linear programming bound

If a_1, \ldots, a_d is a feasible solution for the following program:

$$\begin{array}{ll} \min & 1+\sum_{k=1}^d a_k \\ \text{subject to} & \displaystyle \sum_{k=1}^d a_k P_k^n(t) \leq -1 & \text{ for } t \in [-1,\cos\theta], \\ & a_k \geq 0 & \text{ for } k=1,2,\ldots,d. \end{array}$$

Then $A(n,\theta) \leq 1 + \sum_{k=1}^{d} a_k$.

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$$\begin{array}{ll} \min & 1+\sum\limits_{k=1}^d a_k \\ \text{s. t.} & \sum\limits_{k=1}^d a_k P_k^n(t) \leq -1 & \text{ for } t \in [-1,\cos\theta], \\ & a_k \geq 0 & \text{ for } k=1,2,\ldots,d. \end{array}$$

If a_1, \ldots, a_d is a feasible solution for the program, then

$$A(n,\theta) \le 1 + \sum_{k=1}^d a_k.$$

If $C \subset S^{n-1}$, $C \neq \emptyset$, is a spherical code of minimum angular distance θ ,

$$\sum_{x,y\in C} \left(1 + \sum_{k=1}^{d} a_k P_k^n(x \cdot y) \right) = |C|^2 + \sum_{k=1}^{d} a_k \sum_{x,y\in C} P_k^n(x \cdot y) \ge |C|^2.$$

$$\sum_{x,y\in C} \left(1 + \sum_{k=1}^{d} a_k P_k^n(x \cdot y) \right) = \sum_{x\in C} \left(1 + \sum_{k=1}^{d} a_k P_k^n(x \cdot x) \right) + \sum_{\substack{x,y\in C, \\ x \neq y}} \left(1 + \sum_{k=1}^{d} a_k P_k^n(x \cdot y) \right)$$

$$\leq |C| \left(1 + \sum_{k=1}^{d} a_k \right).$$
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- The semidefinite programming bound was proposed by Bachoc and Vallentin (2008) and is responsible for all the upper bounds currently known for the kissing number.
- It improves the linear programming bound with constraints based on relations between triples of points.
- It relies on the following property satisfied by the zonal matrices S_k^n whose coefficients are symmetric polynomials in three variables:

$$\sum_{x,y,z\in C}S_k^n(x\cdot z,y\cdot z,x\cdot y)\succeq 0, \text{ for every } C\subset S^{n-1} \text{ finite.}$$

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Continuous positive and H-invariant kernels on S^{n-1}

Fix one point $e \in S^{n-1}$ and consider the subgroup H that stabilizes e under the action of $O(\mathbb{R}^n)$:

$$H := \{T \in \mathcal{O}(\mathbb{R}^n) : Te = e\},\$$

writing $\mathbb{R}^n = \mathbb{R}^{n-1} \perp \mathbb{R}^e$, we have that $H \simeq O(\mathbb{R}^{n-1})$.

The spaces H_k^n are not irreducible with respect to the action of the subgroup H. They can be decomposed as a direct sum of smaller invariant and irreducible subspaces:

$$H_k^n = H_{0,k}^{n-1} \perp H_{1,k}^{n-1} \perp \dots \perp H_{k,k}^{n-1},$$

where the representation of H in $H_{i,k}^{n-1}$ is equivalent to the representation of $O(\mathbb{R}^{n-1})$ in H_i^{n-1} .

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where the representation of H in $H^{n-1}_{i,k}$ is equivalent to the representation of $\mathcal{O}(\mathbb{R}^{n-1})$ in $H^{n-1}_i.$

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$$\begin{array}{rcl} Pol_{\leq d}(S^{n-1}) &=& H_0^n \quad \bot \quad H_1^n \quad \bot \quad \cdots \quad \bot \quad H_d^n \\ &=& H_{0,0}^{n-1} \quad \bot \quad H_{0,1}^{n-1} \quad \bot \quad \cdots \quad \bot \quad H_{0,d}^{n-1} \\ & & \bot \quad H_{1,1}^{n-1} \quad \bot \quad \cdots \quad \bot \quad H_{1,d}^{n-1} \\ & & & \bot \quad \cdots \quad \bot \quad \cdots \\ & & & & \bot \quad H_{d,d}^{n-1} \end{array}$$

The representations of H in the subspaces of a same line are equivalent to each other and using an expression similar to the addition formula, one can define the matrices S_k^n of dimension $(d-k+1) \times (d-k+1)$ for each line $k = 0, \ldots, d$.

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$$\begin{array}{ll} \min & 1 + \sum_{k=1}^{d} a_k + b_{11} + \left\langle F_0, J_{d+1} \right\rangle \\ \text{subject to} & (\mathbf{a}) & \sum_{k=1}^{d} a_k P_k^n(u) + 2b_{12} + b_{22} \\ & + 3 \sum_{k=0}^{d} \left\langle F_k, S_k^n(u, u, 1) \right\rangle \leq -1 \quad \text{for } u \in [-1, \cos \theta], \\ & (\mathbf{b}) & b_{22} + \sum_{k=0}^{d} \left\langle F_k, S_k^n(u, v, t) \right\rangle \leq 0 \quad \text{ for } (u, v, t) \in \Delta, \\ & a_k \geq 0 \quad \text{ for } k = 1, \dots, d, \\ & B = \begin{pmatrix} b_{11} & b_{12} \\ b_{12} & b_{22} \end{pmatrix} \succeq 0, \\ & F_k \in \mathbb{R}^{(d-k+1) \times (d-k+1)}, \quad F_k \succeq 0 \quad \text{ for } k = 0, \dots, d. \end{array}$$

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The semidefinite programming bound

Where

$$\Delta = \{ (u, v, t) \in \mathbb{R}^3 : g_i(u, v, t) \ge 0 \text{ for } i = 1, \dots, 4 \},\$$

with

$$\begin{split} g(u) &:= (u+1)(\cos \theta - u), \\ g_1(u,v,t) &:= g(u), \quad g_2(u,v,t) := g(v), \\ g_3(u,v,t) &:= g(t), \quad g_4(u,v,t) := 1 + 2uvt - u^2 - v^2 - t^2. \end{split}$$

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Polynomial optimization with sum of squares

Write a real polynomial p(x) (with $x \in \mathbb{R}^n$) in the form

$$p = r + \sum_{i=1}^{s} r_i g_i$$

with r,r_1,\ldots,r_s sum of squares is a sufficient condition for p to be non-negative in the semialgebraic set

 $\{x \in \mathbb{R}^n : g_1(x) \ge 0, g_2(x) \ge 0, \dots, g_s(x) \ge 0\}.$

A polynomial r of degree 2d can be expressed as a sum of squares if and only if there exists a matrix $Q\succeq 0$ such that

$$r = z^t Q z = \left\langle Q, z z^t \right\rangle,$$

where z is a vector with a basis for $\mathbb{R}[x]_{\leq d}$ in its entries.

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$$\begin{array}{ll} \min & 1 + \sum_{k=1}^{d} a_k + b_{11} + \left\langle F_0, J_{d+1} \right\rangle \\ \text{s. t.} & (\textbf{a}) - 1 - \sum_{k=1}^{d} a_k P_k^n(u) - 2b_{12} - b_{22} \\ & - 3 \sum_{k=0}^{d} \left\langle F_k, S_k^n(u, u, 1) \right\rangle = q(u) + p(u)q_1(u), \\ & (\textbf{b}) - b_{22} - \sum_{k=0}^{d} \left\langle F_k, S_k^n(u, v, t) \right\rangle = r(u, v, t) + \sum_{i=1}^{4} r_i(u, v, t)g_i(u, v, t), \\ & a_k \ge 0 \quad \text{for } k = 1, \dots, d, \\ & B = \begin{pmatrix} b_{11} & b_{12} \\ b_{12} & b_{22} \end{pmatrix} \succeq 0, \\ & F_k \in \mathbb{R}^{(d-k+1) \times (d-k+1)}, \quad F_k \succeq 0 \quad \text{for } k = 0, 1, \dots, d, \\ & q, q_1, r, r_1, \dots, r_4 \text{ sum of squares.} \end{array}$$

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Sum of squares with invariant polynomials

(b)
$$-b_{22} - \sum_{k=0}^{d} \langle F_k, S_k^n(u, v, t) \rangle = r(u, v, t) + \sum_{i=1}^{4} r_i(u, v, t) g_i(u, v, t)$$

$$r = \langle Q, zz^t \rangle, \qquad \dim \mathbb{R}[u, v, t]_{\leq d} = \begin{pmatrix} d+3\\ 3 \end{pmatrix}$$

When r is invariant with respect to the action of the group of permutations of three elements, Q can be block-diagonalized in three blocks of sizes m_1, m_2 and m_3 such that

$$m_1 + m_2 + 2m_3 = \binom{d+3}{3}.$$

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When r is invariant with respect to the action of the group of permutations of three elements, Q can be block-diagonalized in three blocks of sizes m_1, m_2 and m_3 such that

$$m_1 + m_2 + 2m_3 = \binom{d+3}{3}.$$

The linear programming bound The semidefinite programming bound Polynomial optimization with sum of squares and symmetries Application to the semidefinite programming bound

n	lower bound	previous upper bound	new upper bound
3	12	12.381810	12.368591
4	24	24.066284	24.056903
5	40	44.998997	44.981067
6	72	78.240613	78.187761
7	126	134.448817	134.270201
8	240	240.000000	240.000010
9	306	364.091929	<u>363</u> .675154
10	500	554.507549	553.827497
11	582	870.883116	869.244985
12	840	1357.889300	1356.603728
13	1154	2069.587585	2066.405173
14	1606	3183.133169	<u>3177</u> .917052
15	2564	4866.245659	4858.505436
16	4320	7355.809036	<u>7332</u> .776399
17	5346	11072.37543	<u>11014</u> .183845
18	7398	16572.26478	<u>16469</u> .090329
19	10668	24812.30254	24575.871259
20	17400	36764.40138	<u>36402</u> .675795
21	27720	54584.76757	53878.722941
22	49896	82340.08003	81376.459564
23	93150	124416.9796	123328.397290
24	196560	196560.0000	196560.000465

Table 3. New upper bounds for the kissing number.

Rigorous verification with interval arithmetic

The computation of the block-diagonalization and the solver use floating point arithmetic and so the obtained solution is just an approximation. It is possible to obtain a feasible solution and verify it with the following steps:

• Find an approximate solution with matrices positive definite together with lower bounds to their eigenvalues.

•
$$\langle X, A \rangle = b, \ X \succeq 0 \rightarrow \langle X', A \rangle = b - \langle \lambda_{\min}I, A \rangle, \ X' \succeq 0.$$

• $X' = LL^t + \lambda_X I$

• Use interval arithmetic to find a bound for the violation in the constraints of the problem.

3 Extension to topological packing graphs

- Topological packing graphs
- Moment matrix and k-point bounds for finite graphs
- 3-point bound for topological packing graphs
- The semidefinite programming bound revisited

Topological packing graphs

Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

Topological packing graphs

Definition: a graph whose vertex set is a Hausdorff topological space is a *topological packing graph* if every finite clique is contained in an open clique.

Note that if the vertex set is compact, the topological packing condition implies that the independence number of the graph is finite.

Topological packing graphs Moment matrix and *k*-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

Denote as $\operatorname{sub}_t(V)$ the family of subsets with at most t vertices, as I_t the family of independent subsets with at most t vertices, $I_{=t}$ the family of independent subsets with exactly t vertices and $I'_t = I_t \setminus \{\emptyset\}.$

Topology on the family of subsets with at most t vertices $sub_t(V)$

We can associate a topology to the family of subsets with at most t vertices $sub_t(V)$ using the product topology in V^t and then the quotient topology to the image of V^t under the map

$$q:(v_1,...,v_t) \to \{v_1,...,v_t\}$$

and finally adding $\{\emptyset\}$ with the disjoint union topology.

If V is compact, one can show with the topological packing condition that I_t is compact and $I_{=r}$ is open and closed in I_t for all $r = 1, \ldots, t$.

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Moment matrix and k-point bounds for finite graphs

For $y: \operatorname{sub}_{2t}(V) \to \mathbb{R}$, the truncated moment matrix $M_t(y): \operatorname{sub}_t(V) \times \operatorname{sub}_t(V) \to \mathbb{R}$ is the matrix defined as: $[M_t(y)]_{S,S'} := y_{S\cup S'}.$

The moment matrix can be used to define optimization programs that upper bounds the independence number of a graph. For instance, the t-th step of the Lasserre's hierarchy is:

$$\max \sum_{u \in V} y_{\{u\}}$$
s. t. $y : \operatorname{sub}_{2t}(V) \to \mathbb{R},$
 $y_{\emptyset} = 1,$
 $y_S = 0 \text{ if } S \notin I_{2t},$
 $M_t(y) \succeq 0.$

The denomination "k-point bound" refers to the size k of the biggest subset considered. This program is a 2t-point bound.

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$$\begin{array}{ll} \max & \sum_{u \in V} y_{\{u\}} \\ \text{s. t.} & y \colon \mathrm{sub}_{2t}(V) \to \mathbb{R}, \\ & y_{\emptyset} = 1, \\ & y_{S} = 0 \text{ if } S \notin I_{2t}, \\ & M_{t}(y) \succeq 0. \end{array}$$

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The extended Lovász theta number $\vartheta'_t(G)$

Replace $\operatorname{sub}_t(V)$ by $\operatorname{sub}'_t(V) = \operatorname{sub}_t(V) \setminus \{\emptyset\}$ and denote by $M'_t(y)$ the corresponding truncate moment matrix without the row and column associated to $\{\emptyset\}$.

$$\begin{array}{ll} \max & \sum_{u,v \in V} y_{\{u,v\}} \\ \text{s. t.} & y \colon \mathrm{sub}_{2t}'(V) \to \mathbb{R}_{\geq 0}, \\ & \sum_{u \in V} y_{\{u\}} = 1, \\ & y_S = 0 \text{ if } S \notin I_{2t}', \\ & M_t'(y) \succeq 0. \end{array}$$

To see that $\alpha(G) \leq \vartheta'_t(G)$, given $I \subseteq V$ independent, consider y defined as $y_S = \frac{1}{|I|}$ if $S \subseteq I$ and $y_S = 0$ otherwise.

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3-point bound for finite graphs

For $u \in V,$ consider the matrix $M'_u(y) \colon V \times V \to \mathbb{R}$ defined as:

$$[M'_u(y)]_{v,w} := y_{\{u,v,w\}}.$$



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3-point bound for topological packing graphs

$$\begin{array}{ll} \max & \displaystyle \sum_{u,v \in V} y_{\{u,v\}} \\ \text{s. t.} & \displaystyle y \colon \mathrm{sub}_3'(V) \to \mathbb{R}_{\geq 0}, \\ & \displaystyle \sum_{u \in V} y_{\{u\}} = 1 \\ & \displaystyle y_S = 0 \text{ if } S \notin I_3', \\ & \displaystyle M_1'(y) \succeq 0, \\ & \displaystyle M_u'(y) \succeq 0 \text{ for all } u \in V. \end{array}$$

 $\begin{array}{ll} \max & \lambda(I_{=1}) + 2\lambda(I_{=2}) \\ \text{s. t.} & \lambda \in \mathcal{M}(I'_3)_{\geq 0}, \\ & \lambda(I_{=1}) = 1, \\ & A_1^* \lambda \in \mathcal{M}(V \times V)_{\geq 0}, \\ & A_{3\mathrm{PB}}^* \lambda \in \mathcal{M}(V \times V \times V)_{\geq 0}. \end{array}$

Where the operators $A_1 : \mathcal{C}(V \times V)_{sym} \to \mathcal{C}(I'_3)$ and $A_{3PB} : \mathcal{C}(V \times V \times V)_{sym} \to \mathcal{C}(I'_3)$ are defined as:

$$A_1K(S) := \sum_{\substack{u,v \in V: \\ \{u,v\} = S}} K(u,v), \qquad A_{3\text{PB}}T(S) := \sum_{\substack{u,v,t \in V: \\ \{u,v,t\} = S}} T(u,v,t).$$

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Primal and dual formulations

$$\begin{array}{ll} \max & \lambda(I_{=1}) + 2\lambda(I_{=2}) \\ \text{s. t.} & \lambda \in \mathcal{M}(I'_3)_{\geq 0}, \\ & \lambda(I_{=1}) = 1, \\ & A_1^* \lambda \in \mathcal{M}(V \times V)_{\succeq 0}, \\ & A_{3\mathrm{PB}}^* \lambda \in \mathcal{M}(V \times V \times V)_{\succeq 0}. \end{array}$$

$$\begin{array}{ll} \min & a \\ \text{s. t.} & a \in \mathbb{R}, \quad K \in \mathcal{C}(V \times V)_{\succeq 0}, \\ & T \in \mathcal{C}(V \times V \times V)_{\succeq 0}, \\ & A_1K(S) + A_{3\mathrm{PB}}T(S) \leq a-1 & \quad \text{if } S \in I_{=1}, \\ & A_1K(S) + A_{3\mathrm{PB}}T(S) \leq -2 & \quad \text{if } S \in I_{=2}, \\ & A_1K(S) + A_{3\mathrm{PB}}T(S) \leq 0 & \quad \text{if } S \in I_{=3}. \end{array}$$

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Symmetrization for homogeneous graphs

A graph G is *homogeneous* if there exists a compact group Γ , subgroup of the group of automorphisms of G, that acts continuously in V and such that the action of Γ in V is transitive.

Fixing $e \in V$ and letting H be the subgroup that stabilizes e under the action of Γ , there is a one-to-one correspondence Φ between $\mathcal{C}(V \times V \times V)_{\geq 0}^{\Gamma}$ and $\mathcal{C}(V \times V)_{\geq 0}^{H}$ given by:

$$\Phi(T)(x,y) = T(x,y,e),$$

whose inverse is

$$\Phi^{-1}(R)(x, y, z) = R(\psi_z^{-1}x, \psi_z^{-1}y),$$

where for each $z \in V$, $\psi_z \in \Gamma$ is such that $\psi_z e = z$.

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The semidefinite programming bound revisited

A kernel of $\mathcal{C}(S^{n-1} \times S^{n-1})^H_{\succeq 0}$ can be written in terms of the zonal matrices in such way that for $T \in \mathcal{C}(S^{n-1} \times S^{n-1} \times S^{n-1})^{\mathcal{O}(\mathbb{R}^n)}_{\succeq 0}$, $A_{3\mathrm{PB}}T$ can be approximated by expressions of the form

$$A_{3\text{PB}}T(\{x, y, z\}) = \sum_{k=0}^{d} \langle F_k, S_k^n(x \cdot z, y \cdot z, x \cdot y) \rangle.$$

and, after the substitutions, the three point bound applied to the kissing number problem becomes equal to the semidefinite programming bound.

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References I

[AAR99]	George E. Andrews, Richard Askey and Ranjan Roy. <i>Special functions</i> , volume 71 of <i>Encyclopedia of Mathematics and its Applications</i> Cambridge University Press, Cambridge, 1999.
[ABR01]	Sheldon Axler, Paul Bourdon and Wade Ramey. <i>Harmonic function theory</i> , volume 137 of <i>Graduate Texts in Mathematics</i> . Springer-Verlag, New York, second edition, 2001.
[AT07]	Charalambos D. Aliprantis and Rabee Tourky. <i>Cones and duality</i> , volume 84 of <i>Graduate Studies in Mathematics</i> . American Mathematical Society, Providence, RI, 2007.
[AW01]	George B. Arfken and Hans J. Weber. <i>Mathematical methods for physicists.</i> Harcourt/Academic Press, Burlington, MA, quinta edição, 2001.
[Bar02]	Alexander Barvinok. <i>A course in convexity</i> , volume 54 of <i>Graduate Studies in Mathematics</i> . American Mathematical Society, Providence, RI, 2002.
[BCR84]	Christian Berg, Jens P. R. Christensen and Paul Ressel. Harmonic analysis on semigroups, volume 100 of Graduate Texts in Mathematics. Springer-Verlag, New York, 1984. Theory of positive definite and related functions.

Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

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References II

[BGSV12]	Christine Bachoc, Dion C. Gijswijt, Alexander Schrijver and Frank Vallentin. Invariant semidefinite programs. In Handbook on semidefinite, conic and polynomial optimization, volume 166 de Internat. Ser. Oper. Res. Management Sci., páginas 219–269. Springer, New York, 2012.
[BNdOFV09]	Christine Bachoc, Gabriele Nebe, Fernando M. de Oliveira Filho and Frank Vallentin. Lower bounds for measurable chromatic numbers. <i>Geom. Funct. Anal.</i> , 19(3):645–661, 2009.
[Boc41]	Salomon Bochner. Hilbert distances and positive definite functions. Ann. of Math. (2), 42:647–656, 1941.
[BS81]	Eiichi Bannai and Neil J. A. Sloane. Uniqueness of certain spherical codes. <i>Canad. J. Math.</i> , 33(2):437–449, 1981.
[BV08]	Christine Bachoc and Frank Vallentin. New upper bounds for kissing numbers from semidefinite programming. J. Amer. Math. Soc., 21(3):909–924, 2008.
[Con90]	John B. Conway. <i>A course in functional analysis</i> , volume 96 of <i>Graduate Texts in Mathematics</i> . Springer-Verlag, New York, segunda edição, 1990.
[Cox62]	Harold S. M. Coxeter. The problem of packing a number of equal nonoverlapping circles on a sphere. <i>Transactions of the New York Academy of Sciences</i> , 24(3 Series II):320–331, 1962.

Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

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References III

[CS99]	John H. Conway and Neil J. A. Sloane. Sphere packings, lattices and groups, volume 290 de Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences]. Springer-Verlag, New York, third edition, 1999. With additional contributions of E. Bannai, R. E. Borcherds, J. Leech, S. P. Norton, A. M. Odlyzko, R. A. Parker, L. Queen and B. B. Venkov.
[DGdOFV17]	Maria Dostert, Cristóbal Guzmán, Fernando M. de Oliveira Filho and Frank Vallentin. New upper bounds for the density of translative packings of three-dimensional convex bodies with tetrahedral symmetry. <i>Accepted in Discrete Comput. Geom.</i> , 2017. arXiv:1510.02331.
[DGS77]	Philippe Delsarte, Jean-Marie Goethals and Johan J. Seidel. Spherical codes and designs. Geometriae Dedicata, 6(3):363–388, 1977.
[dLV15]	David de Laat and Frank Vallentin. A semidefinite programming hierarchy for packing problems in discrete geometry. <i>Math. Program.</i> , 151(2, Ser. B):529–553, 2015.
[FH91]	William Fulton and Joe Harris. <i>Representation theory</i> , volume 129 of <i>Graduate Texts in Mathematics</i> . Springer-Verlag, New York, 1991. A first course, Readings in Mathematics.

Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

References IV

[Fol16]	Gerald B. Folland. <i>A course in abstract harmonic analysis.</i> Textbooks in Mathematics. CRC Press, Boca Raton, FL, second edition, 2016.
[GP04]	Karin Gatermann and Pablo A. Parrilo. Symmetry groups, semidefinite programs, and sums of squares. J. Pure Appl. Algebra, 192(1-3):95–128, 2004.
[Han00]	David Handel. Some homotopy properties of spaces of finite subsets of topological spaces. <i>Houston J. Math.</i> , 26(4):747–764, 2000.
[Hil88]	David Hilbert. Über die Darstellung definiter Formen als Summe von Formenquadraten. <i>Math. Ann.</i> , 32(3):342–350, 1888.
[KKLS16]	Rob Kusner, Wöden Kusner, Jeffrey C. Lagarias and Senya Shlosman. The twelve spheres problem. <i>arXiv preprint</i> , 2016. arXiv:1611.10297.
[KL78]	Grigorii A. Kabatiansky and Vladimir I. Levenshtein. Bounds for packings on the sphere and in space. Problemy Peredachi Informacii, 14(1):3–25, 1978.
[Knu94]	Donald E. Knuth. The sandwich theorem. <i>Electron. J. Combin.</i> , 1:Article 1, approx. 48 pp. (electronic), 1994.



Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

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References V

[Las02]	Jean B. Lasserre. An explicit equivalent positive semidefinite program for nonlinear 0-1 programs. SIAM J. Optim., 12(3):756–769, 2002.
[Lau03]	Monique Laurent. A comparison of the Sherali-Adams, Lovász-Schrijver, and Lasserre relaxations for 0-1 programming. <i>Math. Oper. Res.</i> , 28(3):470–496, 2003.
[Lev79]	Vladimir I. Levenshtein. Boundaries for packings in <i>n</i> -dimensional Euclidean space. <i>Dokl. Akad. Nauk SSSR</i> , 245(6):1299–1303, 1979.
[Lov79]	László Lovász. On the Shannon capacity of a graph. IEEE Trans. Inform. Theory, 25(1):1–7, 1979.
[LS91]	László Lovász and Alexander Schrijver. Cones of matrices and set-functions and 0-1 optimization. <i>SIAM J. Optim.</i> , 1(2):166–190, 1991.
[MdOF17]	Fabrício C. Machado and Fernando M. de Oliveira Filho. Improving the semidefinite programming bound for the kissing number by exploiting polynomial symmetry. <i>Accepted in Experiment. Math.</i> , 2017. arXiv:1609.05167.

Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

45/48

References VI

[Meg98]	Robert E. Megginson. An introduction to Banach space theory, volume 183 of Graduate Texts in Mathematics. Springer-Verlag, New York, 1998.
[Mus08]	Oleg R. Musin. The kissing number in four dimensions. Ann. of Math. (2), 168(1):1–32, 2008.
[MV10]	Hans D. Mittelmann and Frank Vallentin. High-accuracy semidefinite programming bounds for kissing numbers. Experiment. Math., 19(2):175–179, 2010.
[Nak10]	Maho Nakata. A numerical evaluation of highly accurate multiple-precision arithmetic version of semidefinite programming solver: SDPA-GMP,-QD and-DD. In Computer-Aided Control System Design (CACSD), 2010 IEEE International Symposium on, páginas 29–34. IEEE, 2010.
[OS79]	Andrew M. Odlyzko and Neil J. A. Sloane. New bounds on the number of unit spheres that can touch a unit sphere in n dimensions. J. Combin. Theory Ser. A, 26(2):210–214, 1979.
[Put93]	Mihai Putinar. Positive polynomials on compact semi-algebraic sets. Indiana Univ. Math. J., 42(3):969–984, 1993.

Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

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References VII

[PZ04]	Florian Pfender and Günter M. Ziegler. Kissing numbers, sphere packings, and some unexpected proofs. Notices Amer. Math. Soc., 51(8):873–883, 2004.
[RR05]	Nathalie Revol and Fabrice Rouillier. Motivations for an arbitrary precision interval arithmetic and the MPFI library. <i>Reliab. Comput.</i> , 11(4):275–290, 2005.
[RS72]	Michael Reed and Barry Simon. <i>Methods of modern mathematical physics. I. Functional analysis.</i> Academic Press, New York-London, 1972.
[Rud87]	Walter Rudin. <i>Real and complex analysis.</i> McGraw-Hill Book Co., New York, third edition, 1987.
[Sch42]	Isaac J. Schoenberg. Positive definite functions on spheres. Duke Math. J., 9:96–108, 1942.
[Sch79]	Alexander Schrijver. A comparison of the Delsarte and Lovász bounds. IEEE Trans. Inform. Theory, 25(4):425–429, 1979.
[Ser77]	Jean-Pierre Serre. Linear representations of finite groups. Springer-Verlag, New York-Heidelberg, 1977. Translated from the french edition by Leonard L. Scott, Graduate Texts in Mathematics, Vol. 42.

Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

47/48

References VIII

[Sim63]	George F. Simmons. <i>Introduction to topology and modern analysis.</i> McGraw-Hill Book Co., Inc., New York-San Francisco, CalifToronto-London, 1963.
[Slo81]	Neil J. A. Sloane. Tables of sphere packings and spherical codes. IEEE Trans. Inform. Theory, 27(3):327–338, 1981.
[Stu08]	Bernd Sturmfels. Algorithms in invariant theory. Texts and Monographs in Symbolic Computation. Springer Wien New York, Vienna, segunda edição, 2008.
[SvdW53]	Kurt Schütte and Bartel L. van der Waerden. Das Problem der dreizehn Kugeln. <i>Math. Ann.</i> , 125:325–334, 1953.
[Sze39]	Gabor Szegő. <i>Orthogonal Polynomials.</i> American Mathematical Society, New York, 1939. American Mathematical Society Colloquium Publications, v. 23.
[Vil68]	Neil Ja. Vilenkin. <i>Special functions and the theory of group representations.</i> Translated from the russian by V. N. Singh. Translations of Mathematical Monographs, Vol. 22. American Mathematical Society, Providence, R. I., 1968.

References IX

Topological packing graphs Moment matrix and k-point bounds for finite graphs 3-point bound for topological packing graphs The semidefinite programming bound revisited

[Wyn65] Aaron D. Wyner. Capabilities of bounded discrepancy decoding. Bell Systems Tech. J., 44:1061–1122, 1965.

[ZE99] Victor A. Zinov'ev and Thomas Ericson. New lower bounds for contact numbers in small dimensions. Problemy Peredachi Informatsii, 35(4):3–11, 1999.