

Section 7

Kissing Number Problem

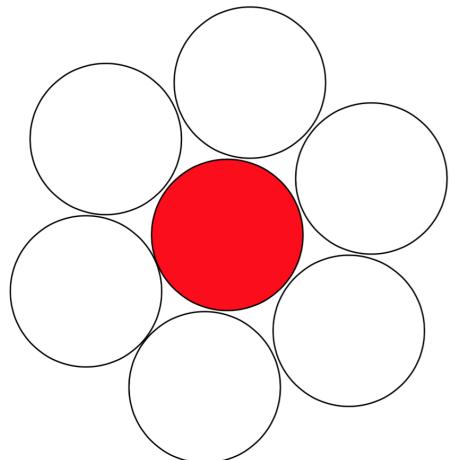
Definition

Given $n, K \in \mathbb{N}$, determine whether n unit spheres can be placed adjacent to a central unit sphere so that their interiors do not overlap

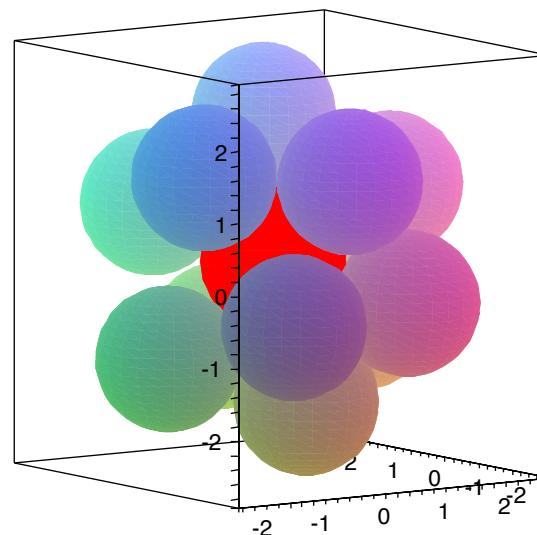
Funny story: *Newton and Gregory went down the pub...*

Some examples

$n = 6, K = 2$



$n = 12, K = 3$



more dimensions

| n | τ (lattice) | τ (nonlattice) |
|-----|------------------|---------------------|
| 0 | 0 | |
| 1 | 2 | |
| 2 | 6 | |
| 3 | 12 | |
| 4 | 24 | |
| 5 | 40 | |
| 6 | 72 | |
| 7 | 126 | |
| 8 | 240 | |
| 9 | 272 | (306)* |
| 10 | 336 | (500)* |
| 11 | 438 | (582)* |
| 12 | 756 | (840)* |
| 13 | 918 | (1130)* |
| 14 | 1422 | (1582)* |
| 15 | 2340 | |
| 16 | 4320 | |
| 17 | 5346 | |
| 18 | 7398 | |
| 19 | 10668 | |
| 20 | 17400 | |
| 21 | 27720 | |
| 22 | 49896 | |

Equivalent formulation

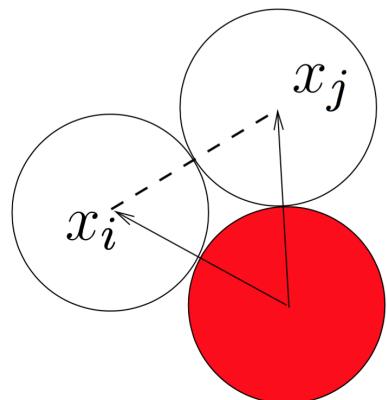
Given $n, K \in \mathbb{N}$, determine whether there exist n vectors $x_1, \dots, x_n \in \mathbb{R}^K$ such that:

$$\begin{aligned}\forall i \leq n \quad \|x_i\|_2^2 &= 1 \\ \forall i < j \leq n \quad \|x_i - x_j\|_2^2 &\geq 1.\end{aligned}$$

Spherical codes

- ▶ $\mathbb{S}^{K-1} \subset \mathbb{R}^K$ unit sphere centered at origin
- ▶ *K-dimensional spherical z-code:*
 - ▶ (finite) subset $\mathcal{C} \subset \mathbb{S}^{K-1}$
 - ▶ $\forall x \neq y \in \mathcal{C} \quad x \cdot y \leq z$
- ▶ non-overlapping interiors:

$$\forall i < j \quad \|x_i - x_j\| \geq 2 \iff x_i \cdot x_j \geq \cos\left(\frac{\pi}{3}\right) = \frac{1}{2}$$



...can use norm-1 projections
on \mathbb{S}^{K-1} instead

Lower bounds

- ▶ Construct spherical $\frac{1}{2}$ -code \mathcal{C} with $|\mathcal{C}|$ large
- ▶ Nonconvex NLP formulations
- ▶ SDP relaxations
- ▶ Combination of the two techniques

MINLP formulation

Maculan, Michelon, Smith 1995

Parameters:

- ▶ K : space dimension
- ▶ n : upper bound to $\text{kn}(K)$

Variables:

- ▶ $x_i \in \mathbb{R}^K$: center of i -th vector
- ▶ $\alpha_i = 1$ iff vector i in configuration

$$\begin{aligned} \max \quad & \sum_{i=1}^n \alpha_i \\ \forall i \leq n \quad & \|x_i\|^2 = \alpha_i \\ \forall i < j \leq n \quad & \|x_i - x_j\|^2 \geq \alpha_i \alpha_j \\ \forall i \leq n \quad & x_i \in [-1, 1]^K \\ \forall i \leq n \quad & \alpha_i \in \{0, 1\} \end{aligned} \quad \left. \right\}$$

Reformulating the binary products

- ▶ **Additional variables:** $\beta_{ij} = 1$ iff vectors i, j in configuration
- ▶ **Linearize** $\alpha_i \alpha_j$ by β_{ij}
- ▶ **Add constraints:**

$$\forall i < j \leq n \quad \beta_{ij} \leq \alpha_i$$

$$\forall i < j \leq n \quad \beta_{ij} \leq \alpha_j$$

$$\forall i < j \leq n \quad \beta_{ij} \geq \alpha_i + \alpha_j - 1$$

AMPL and Baron

- ▶ Certifying YES

- ▶ $n = 6, K = 2$: OK, 0.60s
- ▶ $n = 12, K = 3$: OK, 0.07s
- ▶ $n = 24, K = 4$: FAIL, CPU time limit (100s)

- ▶ Certifying NO

- ▶ $n = 7, K = 2$: FAIL, CPU time limit (100s)
- ▶ $n = 13, K = 3$: FAIL, CPU time limit (100s)
- ▶ $n = 25, K = 4$: FAIL, CPU time limit (100s)

Almost useless

Modelling the decision problem

$$\left. \begin{array}{lll} \max_{x,\alpha} & \alpha \\ \forall i \leq n & \|x_i\|^2 = 1 \\ \forall i < j \leq n & \|x_i - x_j\|^2 \geq \alpha \\ \forall i \leq n & x_i \in [-1, 1]^K \\ \alpha & \geq 0 \end{array} \right\}$$

- ▶ Feasible solution (x^*, α^*)
- ▶ *KNP instance is YES iff $\alpha^* \geq 1$*

[Kucherenko, Belotti, Liberti, Maculan, *Discr. Appl. Math.* 2007]

AMPL and Baron

- ▶ Certifying YES
 - ▶ $n = 6, K = 2$: FAIL, CPU time limit (100s)
 - ▶ $n = 12, K = 3$: FAIL, CPU time limit (100s)
 - ▶ $n = 24, K = 4$: FAIL, CPU time limit (100s)
- ▶ Certifying NO
 - ▶ $n = 7, K = 2$: FAIL, CPU time limit (100s)
 - ▶ $n = 13, K = 3$: FAIL, CPU time limit (100s)
 - ▶ $n = 25, K = 4$: FAIL, CPU time limit (100s)

Apparently even more useless

But more informative ($\arccos \alpha = \text{min. angular sep}$)

Certifying YES by $\alpha \geq 1$

- ▶ $n = 6, K = 2$: OK, 0.06s
- ▶ $n = 12, K = 3$: OK, 0.05s
- ▶ $n = 24, K = 4$: OK, 1.48s
- ▶ $n = 40, K = 5$: FAIL, CPU time limit (100s)

What about polar coordinates?

$$y = (y_1, \dots, y_K) \rightarrow (\rho, \vartheta_1, \dots, \vartheta_{K-1})$$

$$\rho = \|y\|$$

$$\forall k \leq K \quad y_k = \rho \sin \vartheta_{k-1} \prod_{h=k}^{K-1} \cos \vartheta_h$$

- ▶ Only need to decide $s_k = \sin \vartheta_k$ and $c_k = \cos \vartheta_k$
- ▶ Get polynomial program in s, c
- ▶ Numerically more challenging to solve
- ▶ *But maybe useful for bounds?*

SDP relaxation of Euclidean distances

- ▶ Linearization of scalar products

$$\forall i, j \leq n \quad x_i \cdot x_j \longrightarrow X_{ij}$$

where X is an $n \times n$ symmetric matrix

- ▶ $\|x_i\|_2^2 = x_i \cdot x_i = X_{ii}$
- ▶ $\|x_i - x_j\|_2^2 = \|x_i\|_2^2 + \|x_j\|_2^2 - 2x_i \cdot x_j = X_{ii} + X_{jj} - 2X_{ij}$
- ▶ $X = xx^\top \Rightarrow X - xx^\top = 0$ makes linearization exact
- ▶ Relaxation:

$$X - xx^\top \succeq 0 \Rightarrow \text{Schur}(X, x) = \begin{pmatrix} I_K & x^\top \\ x & X \end{pmatrix} \succeq 0$$

SDP relaxation of binary constraints

- ▶ $\forall i \leq n \quad \alpha_i \in \{0, 1\} \Leftrightarrow \alpha_i^2 = \alpha_i$
- ▶ Let A be an $n \times n$ symmetric matrix
- ▶ Linearize $\alpha_i \alpha_j$ by A_{ij} (hence α_i^2 by A_{ii})
- ▶ $A = \alpha \alpha^\top$ makes linearization exact
- ▶ **Relaxation:** $\text{Schur}(A, \alpha) \succeq 0$

SDP relaxation of [MMS95]

$$\begin{aligned}
 \max \quad & \sum_{i=1}^n \alpha_i \\
 \forall i \leq n \quad & X_{ii} = \alpha_i \\
 \forall i < j \leq n \quad & X_{ii} + X_{jj} - 2X_{ij} \geq A_{ij} \\
 \forall i \leq n \quad & A_{ii} = \alpha_i \\
 \forall i < j \leq n \quad & A_{ij} \leq \alpha_j \\
 \forall i < j \leq n \quad & A_{ij} \leq \alpha_i \\
 \forall i < j \leq n \quad & A_{ij} \geq \alpha_i + \alpha_j - 1 \\
 \forall i \leq n \quad & \text{Schur}(X, x) \succeq 0 \\
 \forall i \leq n \quad & \text{Schur}(A, \alpha) \succeq 0 \\
 \forall i \leq n \quad & x_i \in [-1, 1]^K \\
 \forall i \leq n \quad & \alpha \in [0, 1]^n \\
 \forall i \leq n \quad & X \in [-1, 1]^{n^2} \\
 \forall i \leq n \quad & A \in [0, 1]^{n^2}
 \end{aligned}
 \left. \right\}$$

Python, PICOS and Mosek

- ▶ bound always equal to n
- ▶ prominent failure :-)
- ▶ Why?
 - ▶ *can combine inequalities to remove A from SDP*
 - ▶ *integrality of α completely lost*

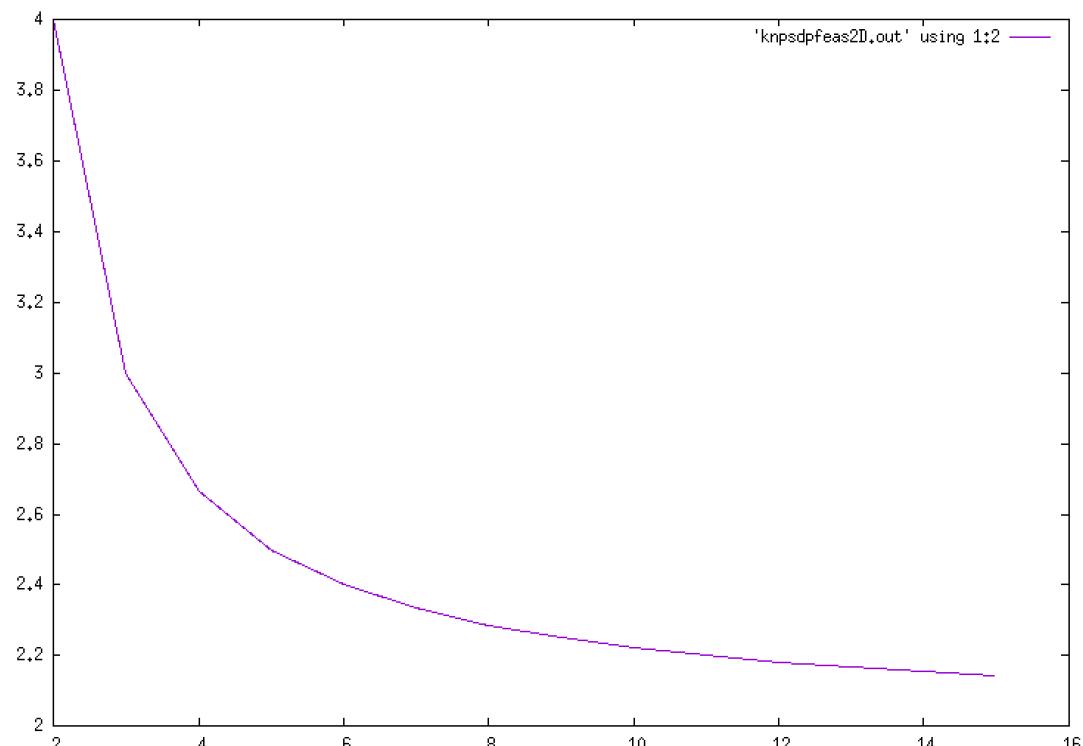
SDP relaxation of [KBLM07]

$$\begin{aligned} \max \quad & \alpha \\ \forall i \leq n \quad & X_{ii} = 1 \\ \forall i < j \leq n \quad & X_{ii} + X_{jj} - 2X_{ij} \geq \alpha \\ & X \in [-1, 1]^{n^2} \\ & X \succeq 0 \\ & \alpha \geq 0 \end{aligned} \left. \right\}$$

Python, PICOS and Mosek

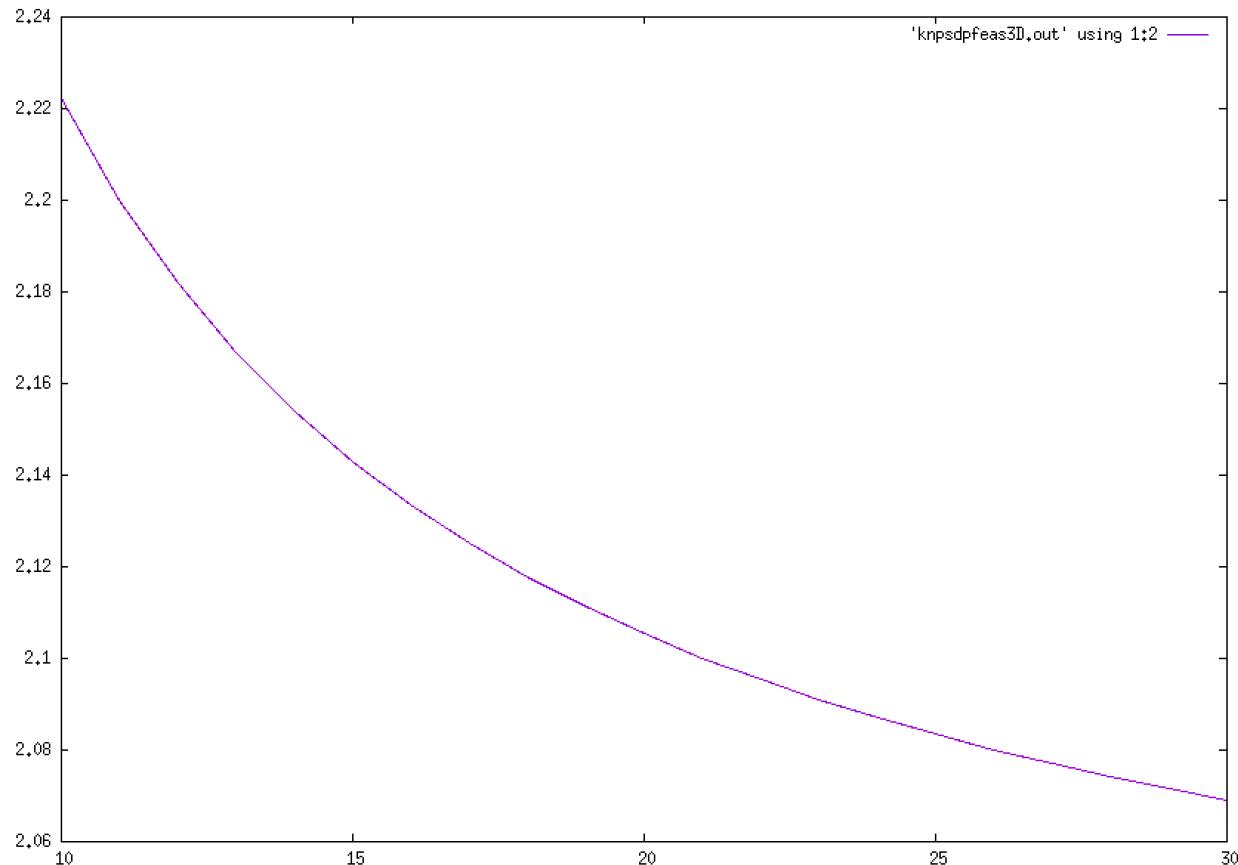
With $K = 2$

| n | α^* |
|-----|------------|
| 2 | 4.00 |
| 3 | 3.00 |
| 4 | 2.66 |
| 5 | 2.50 |
| 6 | 2.40 |
| 7 | 2.33 |
| 8 | 2.28 |
| 9 | 2.25 |
| 10 | 2.22 |
| 11 | 2.20 |
| 12 | 2.18 |
| 13 | 2.16 |
| 14 | 2.15 |
| 15 | 2.14 |



Python, PICOS and Mosek

With $K = 3$



Enforces some separation between “relaxed vectors”

An SDP-based heuristic

1. $X^* \in \mathbb{R}^{n^2}$: SDP relaxation solution of [KBLM07]
2. Perform *Principal Component Analysis (PCA)*, get $\bar{x} \in \mathbb{R}^{nK}$
 - ▶ concatenate K eigenvectors $\in \mathbb{R}^n$ corresponding to K largest eigenvalues
3. Use \bar{x} as starting point for local NLP solver on [KBLM07]

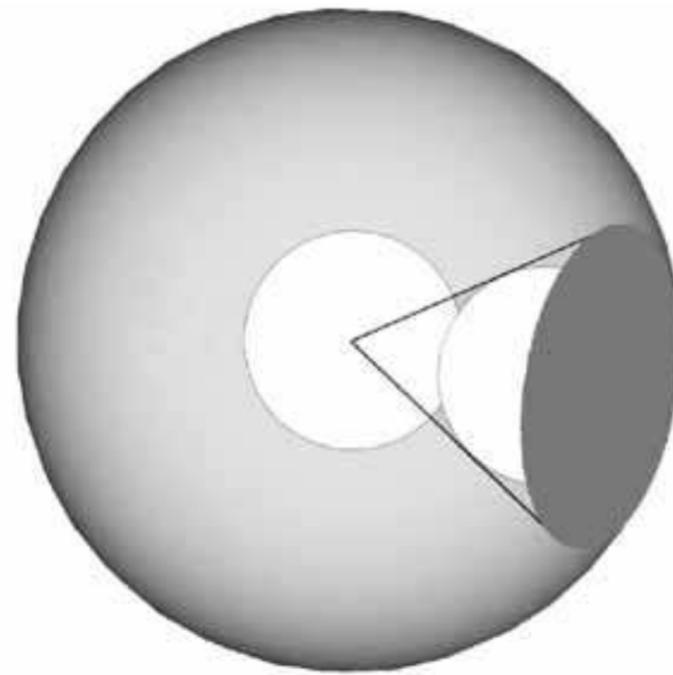
Python, PICOS, Mosek + AMPL, IPOPT

- ▶ $n = 6, K = 2$: **OK, 0.02s**
- ▶ $n = 12, K = 3$: **OK, 0.02s**
- ▶ $n = 24, K = 4$: **4% error, 0.32s**
- ▶ $n = 40, K = 5$: **5% error, 1.57s**
- ▶ $n = 72, K = 6$: **7% error, 12.26s**

Surface upper bound

Szpiro 2003, Gregory 1694

Consider a $kn(3)$ configuration inscribed into a super-sphere of radius 3. Imagine a lamp at the centre of the central sphere that casts shadows of the surrounding balls onto the inside surface of the super-sphere. Each shadow has a surface area of 7.6; the total surface of the super-ball is 113.1. So $\frac{113.1}{7.6} = 14.9$ is an upper bound to $kn(3)$.



At end of XVII century, yielded Newton/Gregory dispute

Another upper bound

Thm.

Let: $\mathcal{C}_z = \{x_i \in \mathbb{S}^{K-1} \mid i \leq n \wedge \forall j \neq i (x_i \cdot x_j \leq z)\}$; $c_0 > 0$; $f : [-1, 1] \rightarrow \mathbb{R}$ s.t.:
(i) $\sum_{i,j \leq n} f(x_i \cdot x_j) \geq 0$ **(ii)** $f(t) + c_0 \leq 0$ for $t \in [-1, z]$ **(iii)** $f(1) + c_0 \leq 1$

Then $n \leq \frac{1}{c_0}$

([Delsarte 1977]; [Pfender 2006])

Let $g(t) = f(t) + c_0$

$$\begin{aligned} n^2 c_0 &\leq n^2 c_0 + \sum_{i,j \leq n} f(x_i \cdot x_j) \quad \text{by (i)} \\ &= \sum_{i,j \leq n} (f(x_i \cdot x_j) + c_0) = \sum_{i,j \leq n} g(x_i \cdot x_j) \\ &\leq \sum_{i \leq n} g(x_i \cdot x_i) \quad \text{since } g(t) \leq 0 \text{ for } t \leq z \text{ and } x_i \in \mathcal{C}_z \text{ for } i \leq n \\ &= n g(1) \quad \text{since } \|x_i\|_2 = 1 \text{ for } i \leq n \\ &\leq n \quad \text{since } g(1) \leq 1. \end{aligned}$$

The Linear Programming Bound

- ▶ Condition (i) of **Theorem** valid for conic combinations of **suitable functions** $\mathcal{F} = \{f_1, \dots, f_H\}$:

$$f(t) = \sum_{h \leq H} c_h f_h(t) \quad \text{for some } c_h \geq 0$$

- ▶ Let $T = \{t_i \mid i \leq s \wedge t_1 = -1 \wedge t_s = z \wedge \forall i < j (t_i < t_j)\}$, get LP:

$$\left. \begin{array}{l} \max_{c \in \mathbb{R}^{K+1}} c_0 \\ \forall t \in T \quad \sum_{1 \leq h \leq H} c_h f_h(t) + c_0 \leq 0 \quad (\text{ii}) \\ \quad \sum_{1 \leq h \leq H} c_h f_h(1) + c_0 \leq 1 \quad (\text{iii}) \\ \forall 1 \leq h \leq H \quad c_h \geq 0 \quad (\text{conic comb.}) \end{array} \right\} \quad n = 1/c_0 \text{ smallest}$$

- ▶ E.g. \mathcal{F} = Gegenbauer polynomials [Delsarte 1977]
- ▶ $T \subseteq [-1, z]$, don't know how to solve infinite LPs so we discretize it

Some results

- ▶ *Gegenbauer polynomials* G_h^γ (**recursive definition**):

$$\begin{aligned} G_0^\gamma(t) &= 1, \quad G_1^\gamma(t) = 2\gamma t, \\ \forall h > 1 \quad hG_h^\gamma(t) &= 2t(h + \gamma - 1)G_{h-1}^\gamma(t) - (h - 2\gamma - 2)G_{h-2}^\gamma(t) \end{aligned}$$

(all normalized so $G_h^\gamma(1) = 1$)

- ▶ Special case $G_h^\gamma = P_h^{\gamma, \gamma}$ of *Jacobi polynomials*:

$$P_h^{\alpha, \beta} = \frac{1}{2^h} \sum_{i=0}^h \binom{h+\alpha}{i} \binom{h+\beta}{h-i} (t+1)^i (t-1)^{h-i}$$

- ▶ [Delsarte 1977, Odlyzko & Sloane 1998]
 $\text{kn}(3) \leq 12, \text{kn}(4) \leq 25, \text{kn}(5) \leq 46, \text{kn}(8) \leq 240, \text{kn}(24) \leq 196560$
- ▶ Used to prove the “Twelve spheres theorem” ($\text{kn}(3) = 12$)
- ▶ My test: works for $K > 4$, couldn’t make it work for $K = 3$

Where does K appear in the LP bound?

- ▶ \mathcal{F} containing Gegenbauer polynomials
- ▶ In $G_h^\gamma(t)$, $\gamma = \frac{K-3}{2}$
- ▶ K determined by *lowest* γ appearing in \mathcal{F}
- ▶ E.g. $\mathcal{F} = \{G_h^1(t), G_h^{1.5}(t) \mid h \leq 10\}$ yields bound
 $25.5581 \geq \text{kn}(4) = 24$