

A semidefinite program for least distortion embeddings of flat tori into Hilbert spaces

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based on joint work with
Arne Heimendahl, Moritz Lücke, Marc Christian Zimmermann

CWI Workshop
Semidefinite and Polynomial Optimization
August 29, 2022

The beginning of the story

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<https://www.cwi.nl/events/past/Diamantseminars>

The screenshot shows a web browser window displaying the CWI (Centrum Wiskunde & Informatica) website. The browser's address bar shows the URL <https://www.cwi.nl>. The website's header includes the CWI logo and the text "Centrum Wiskunde & Informatica". A navigation menu is visible with links: Home, About CWI, News, Calendar, Research, Industry & Society, Output, and Working at CWI. The "Calendar" link is highlighted. On the left side, there is a sidebar with a list of categories: CALENDAR, CWI RESEARCH SEMESTER PROGRAMME, CWI LECTURES, CWI IN BEDRIJF, VAN WIJNGAARDEN AWARDS, DIJKSTRA FELLOWSHIPS, CWI SEMINARS, CWI SCIENTIFIC MEETINGS, and PHD DEFENCES. The main content area is titled "DIAMANT SEMINARS COMBINATORICS AND OPTIMIZATION". Below the title, a paragraph states: "The seminar is organized by the research group [Algorithms, Combinatorics and Optimization](#) on a bi-weekly basis and takes place at CWI. For information you may contact Monique Laurent or Lex Schrijver." Below this, a section titled "2008" lists several seminars with their speakers, titles, and dates/locations. The seminars listed are:

- Speaker: Gunnar Klau (CWI)
Title: Three combinatorial optimization problems in the life sciences
Date/Location: Friday January 23, 14h00, CWI-Amsterdam
- Speaker: Janina Brenner (TU Berlin)
Title: Cooperative cost sharing via singleton mechanisms
Date/Location: Thursday December 11, 13h00, room M280, CWI-Amsterdam
- Speaker: Florian Horn (CWI)
Title: The complexity of Muller games

On the right side of the page, there is a list of seminars with their titles, dates, and locations:

- Title: Approximation Algorithms for Fair Allocation of Indivisibles
Date/Location: Tuesday July 3, 10h00, CWI-Amsterdam, M280
- Speaker: Vangelis Markakis
Title: Algorithms for Approximate Nash Equilibria
Date/Location: Friday June 22, 13h00, CWI-Amsterdam, M280
- Speaker: Benny Mounits
Title: Lower bounds on the minimum average distance of bipartite graphs
Date/Location: Thursday June 7, 10h00, CWI-Amsterdam, H3
- Speaker: Arantza Estevez-Fernandez
Title: Sequencing games: an introduction to OR games
Date/Location: Friday May 25, 13h00, CWI-Amsterdam, M280
- Speaker: Nicole Immorlica
Title: Secretary Problems and Online Auction Design

The beginning of the story

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CWI Centrum Wiskunde & Informatica [Log in](#)

<p>Title: Realizability of oriented matroids Date/Location: Friday November 2, 13h00, CWI-Amsterdam, M280.</p> <p>Speaker: Nicole Immorlica (CWI) Title: Revenue maximization in digital goods auctions Date/Location: Friday October 12, 13h00, CWI-Amsterdam, M280.</p> <p>Speaker: Frank McSherry (Microsoft Research) Title: Mechanism Design via Differential Privacy Date/Location: Monday October 1st, 16h00, CWI-Amsterdam, M279.</p> <p>Speaker: Jarek Byrka and Steven Kelk Title: Worst-case optimal approximation algorithms for maximizing triplet consistency within phylogenetic networks Date/Location: Monday October 1st, 10h00, CWI-Amsterdam, M279.</p> <p>Speaker: Erik Jan van Leeuwen Title: Domination in Geometric Intersection Graphs Date/Location: Friday September 7, 10h00, CWI-Amsterdam, M280.</p> <p>Speaker: Gyula Pap Title: Packing A-paths subject to node-capacities Date/Location: Friday August 24, 13h00, CWI-Amsterdam, M279.</p> <p>Speaker: Gyula Karolyi Title: The Combinatorial Nullstellensatz and the Polynomial Method Date/Location: Friday August 24, 10h00, CWI-Amsterdam, M279.</p> <p>Speaker: Amin Saberi</p>	<p>Title: Fast matrix multiplication (II) Date/Location: 20-01-2006, 11h00, CWI-Amsterdam, Room M280.</p> <p>2005</p> <p>Speaker: Fernando de Oliveira Filho, CWI Title: Fast matrix multiplication (I) Date/Location: 16-12-2005, 13h00, CWI-Amsterdam, Room M279.</p> <p>Speaker: Benny Mounits, Technion, Haifa. Title: Upper bounds on sizes of codes via association schemes and linear programming Date/Location: 02-12-2005, 10h00, CWI-Amsterdam, Room M279.</p> <p>Speaker: Erik Jan van Leeuwen, CWI Title: Better approximation schemes on disk graphs Date/Location: 04-11-2005, 13h00, CWI-Amsterdam, Room M279.</p> <p>Speaker: Frank Vallentin, CWI Title: Computing the minimum distortion for embedding distance-transitive graphs in the Euclidean space Date/Location: 21-10-2005, 13h00, CWI-Amsterdam, Room H220 (NIKHEF building).</p> <p>Speaker: Nebojsa Gvozdenovic, CWI Title: Approximating the chromatic number of a graph by semidefinite programming Date/Location: 07-10-2005, 13h00, CWI-Amsterdam, Room M27.</p>
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Notes from October 21, 2005

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OPTIMAL EMBEDDINGS OF DISTANCE TRANSITIVE GRAPHS INTO EUCLIDEAN SPACES

FRANK VALLENTIN

1. PROBLEM, MOTIVATION AND SOME BACKGROUND

1.1. Problem. Let (X, d) be a finite metric space. Find an *isometric embedding* into n -dimensional Euclidean space. This is a map $\varrho : X \rightarrow \mathbb{R}^n$ with

$$\forall x, y \in X : d(x, y) = \|\varrho(x) - \varrho(y)\|,$$

where the norm of $(x_1, \dots, x_n) \in \mathbb{R}^n$ is

$$\|(x_1, \dots, x_n)\| = \sqrt{x_1^2 + \dots + x_n^2}.$$

1.2. Applications. Visualization of DNA data, Voronoi cells for fingerprint data, Design of approximation algorithms for the sparsest cut problem, ...

1.3. Bad News. There is no isometric embedding into any n -dimensional Euclidean space for $X = \{\alpha, \beta, \gamma, \delta\}$ with

$$d(\alpha, \beta) = d(\beta, \gamma) = d(\gamma, \delta) = d(\delta, \alpha) = 1$$

and

$$d(\alpha, \gamma) = d(\beta, \delta) = 2.$$

1.4. Good News.

Definition 1.1. Let $\varrho : X \rightarrow \mathbb{R}^n$ an embedding. The embedding has *distortion* $D = \frac{\beta}{\alpha}$ if

$$\forall x, y \in X : \alpha d(x, y) \leq \|\varrho(x) - \varrho(y)\| \leq \beta d(x, y).$$

Denote by $c_2(X, d)$ the minimal possible distortion of (X, d) into any n -dimensional Euclidean space. An embedding of (X, d) attaining distortion $c_2(X, d)$ is called *optimal embedding*.

Example 1.2. The “square embedding” has distortion $\sqrt{2}$ where $\beta = 1$ and $\alpha = \frac{2}{\sqrt{2}}$. We shall

I. Least distortion embeddings
of (finite) metric spaces

II. Flat tori

III. SDP perspective

Recap

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given: (X, d) metric space

goal: find Hilbert space H and injective map $\varphi : X \rightarrow H$
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$$\text{distortion}(\varphi) = \text{expansion}(\varphi) \cdot \text{contraction}(\varphi)$$

$$\text{expansion}(\varphi) = \sup_{\substack{x, y \in X \\ x \neq y}} \frac{\|\varphi(x) - \varphi(y)\|}{d(x, y)}$$

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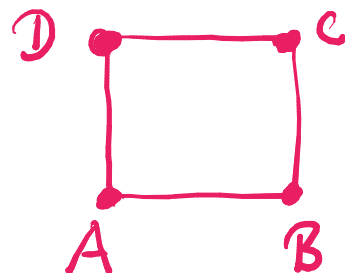
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natural embedding
of square graph



$$d(A, C) = 2$$

$$\|\varphi(A) - \varphi(C)\| = \sqrt{2}$$

$$\text{expansion}(\varphi) = 1$$

$$\text{contraction}(\varphi) = 2/\sqrt{2} = \sqrt{2}.$$

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least distortion: $c_2(X, d) = \inf_{\varphi: X \rightarrow H} \text{distortion}(\varphi)$

good news: $c_2(X, d) = O(\log |X|)$ if $|X| < \infty$ (Bourgain, 1985)

High-level motivation

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Least distortion is central to the “Ribe program” in functional analysis:
Relate Banach space concepts (linear, normed, complete) to metric space concepts (fascinating surveys by Ball, Naor)

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Least distortion is central to the “Ribe program” in functional analysis: Relate Banach space concepts (linear, normed, complete) to metric space concepts (fascinating surveys by Ball, Naor)

Applications to data science and algorithm design: Data sets come equipped with a natural similarity metric but not with a linear structure. Now embed the data into Banach space with least distortion and exploit the linear structure.

Linial, London, Rabinovich, 1995

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Can determine $c_2(X, d)$ efficiently by a semidefinite program

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primal SDP

Scale φ so that $\text{contraction}(\varphi) = 1$ and set $\varphi(x) \cdot \varphi(y) = Q_{xy}$

$$c_2(X, d)^2 = \inf \{ C : C \in \mathbb{R}_+, Q \in \mathcal{S}_+^X, \\ d(x, y)^2 \leq Q_{xx} - 2Q_{xy} + Q_{yy} \leq Cd(x, y)^2 \text{ for } x, y \in X \},$$

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dual SDP: systematic way to derive lower bounds for $c_2(X, d)$

$$c_2(X, d)^2 = \sup \left\{ \frac{\sum_{i,j=1:n}^{Y_{ij} > 0} Y_{ij} d(x_i, x_j)^2}{-\sum_{i,j=1:n}^{Y_{ij} < 0} Y_{ij} d(x_i, x_j)^2} : Y \in \mathcal{S}_+^n, Y\mathbf{e} = 0 \right\}.$$

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weak duality: $Y_{ij} > 0$ only for most contracted pairs

$Y_{ij} < 0$ only for most expanded pairs

Using the dual

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Linial, Magen, 2000: If (X, d) comes from a graph, then most expanded pairs come from adjacent vertices, but most contracted pairs are mysterious.

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The positive semidefinite matrix

$$Y = \begin{pmatrix} 1 & -1 & 1 & -1 \\ -1 & 1 & -1 & 1 \\ 1 & -1 & 1 & -1 \\ -1 & 1 & -1 & 1 \end{pmatrix} = (1, -1, 1, -1)^t (1, -1, 1, -1)$$

proves that the “square embedding” is optimal. We have $c_2(X, d)^2 \leq 2$ due to the existence of the embedding and we have

$$c_2(X, d)^2 \geq \frac{\sum_{i,j=1:4}^{Y_{ij}>0} Y_{ij} d(x_i, x_j)^2}{-\sum_{i,j=1:4}^{Y_{ij}<0} Y_{ij} d(x_i, x_j)^2} = \frac{4 \cdot 2^2 \cdot 1}{8 \cdot 1^2 \cdot (-(-1))} = 2.$$

Using the dual: References

dual SDP has been used to find least distortion embeddings of several graph classes:

Linial, Magen, 2000: product of cycles and expander graphs (in particular Bourgain's result is tight)

Linial, Magen, Naor, 2002: graphs of high girth

Vallentin, 2008: strongly regular graphs, distance regular graphs
(extended by Kobayashi, Kondo, 2015,
Cioabă, Gupta, Ihringer, Kurihara, 2021)

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Flat tori: Definition

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b_1, \dots, b_n basis of \mathbb{R}^n

$L = \mathbb{Z}b_1 + \dots + \mathbb{Z}b_n$ lattice

$T = \mathbb{R}^n / L$ flat torus

$$d_{\mathbb{R}^n / L}(x, y) = \min_{v \in L} |x - y - v|.$$

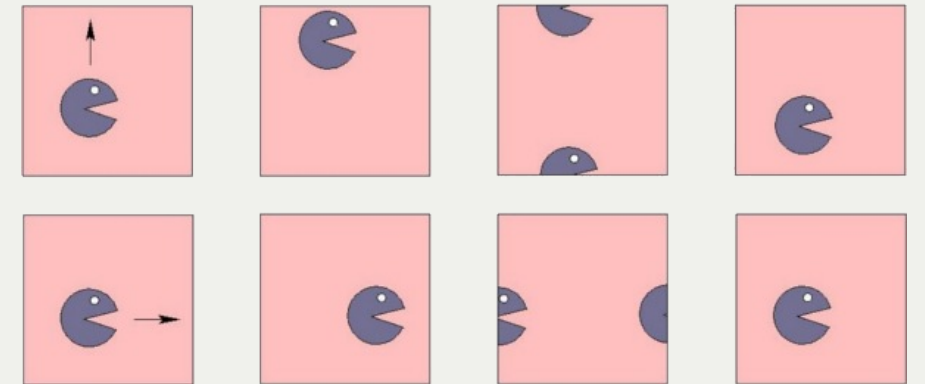
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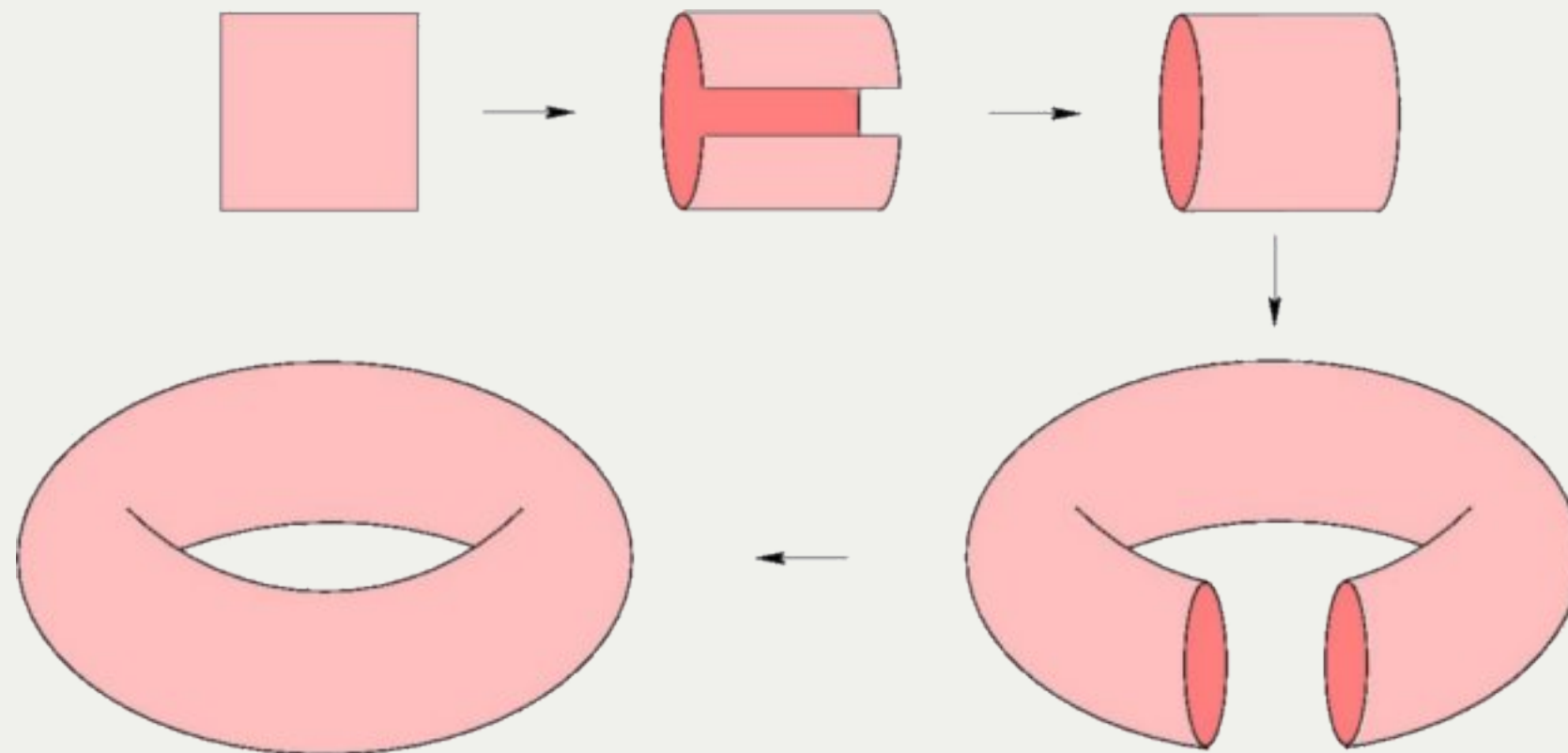
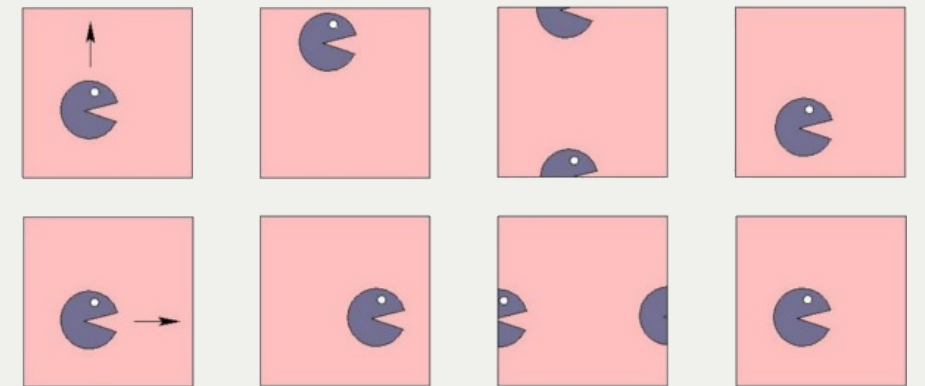
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from: <http://hevea-project.fr>

Flat tori: Euclidean embeddings

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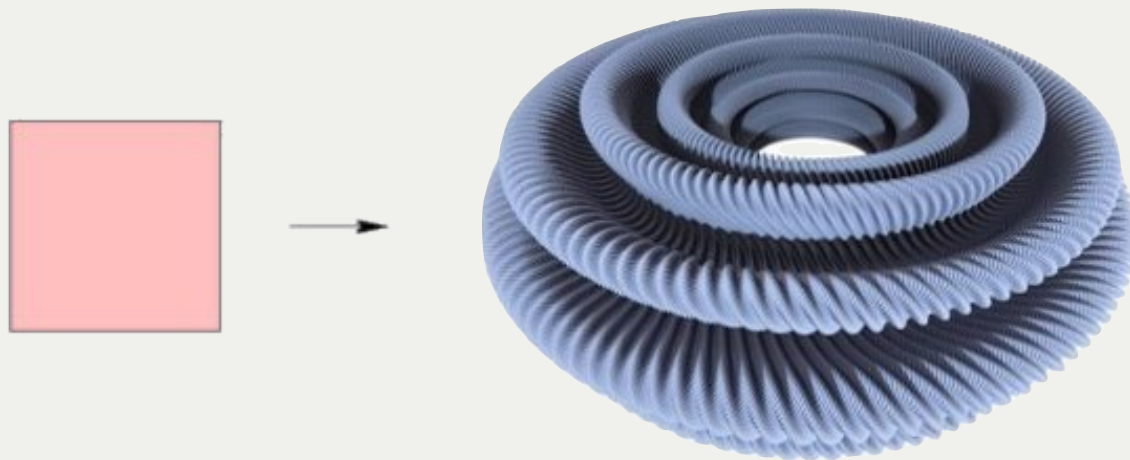
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in contrast to Nash's embedding theorem



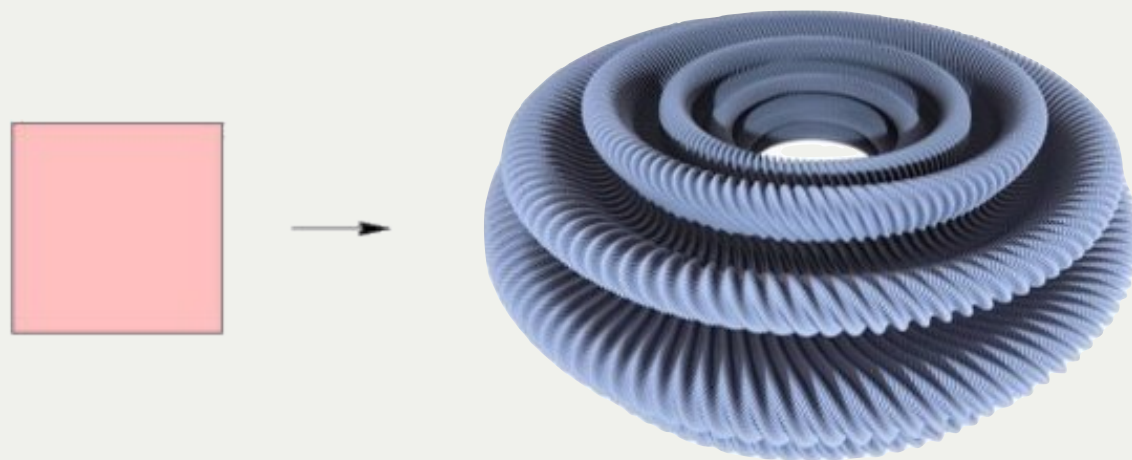
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Potential applications: complexity of lattice problems, like closest vector problem

Standard embedding of standard torus

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$$\varphi : \mathbb{R}^n / \mathbb{Z}^n \rightarrow \mathbb{R}^{2n}$$

$$\varphi(x_1, \dots, x_n) = (\cos 2\pi x_1, \sin 2\pi x_1, \dots, \cos 2\pi x_n, \sin 2\pi x_n).$$

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$$n = 1$$



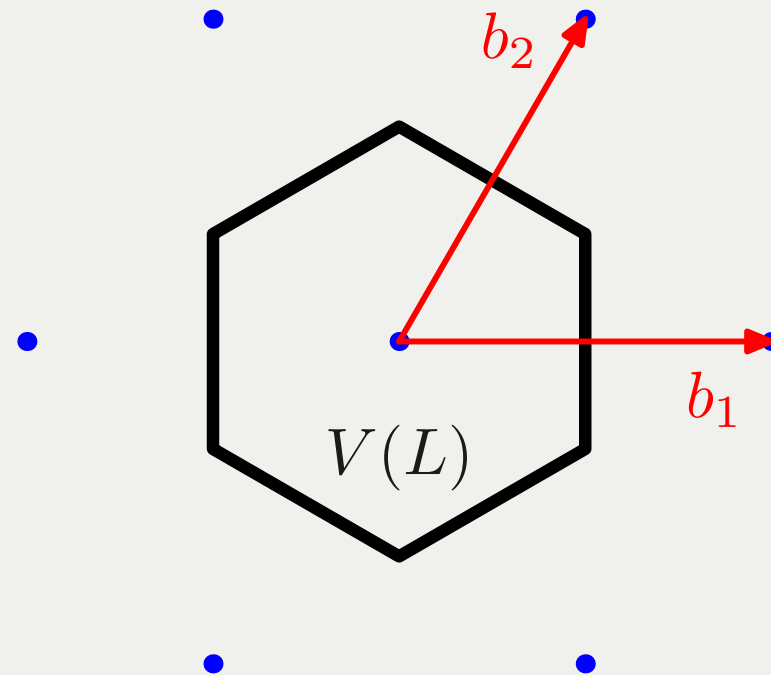
$$\text{contraction}(\varphi) = \frac{1/2}{\|\varphi(0) - \varphi(1/2)\|} = 1/4$$

$$\text{expansion}(\varphi) = \frac{\|\varphi(0) - \varphi(\varepsilon)\|}{\varepsilon} = \frac{\sqrt{2 - 2\cos(2\pi\varepsilon)}}{\varepsilon} \rightarrow 2\pi$$

Flat tori can be highly non-Euclidean

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$L = \mathbb{Z}b_1 + \cdots + \mathbb{Z}b_n$ lattice



$V(L)$ = Voronoi cell

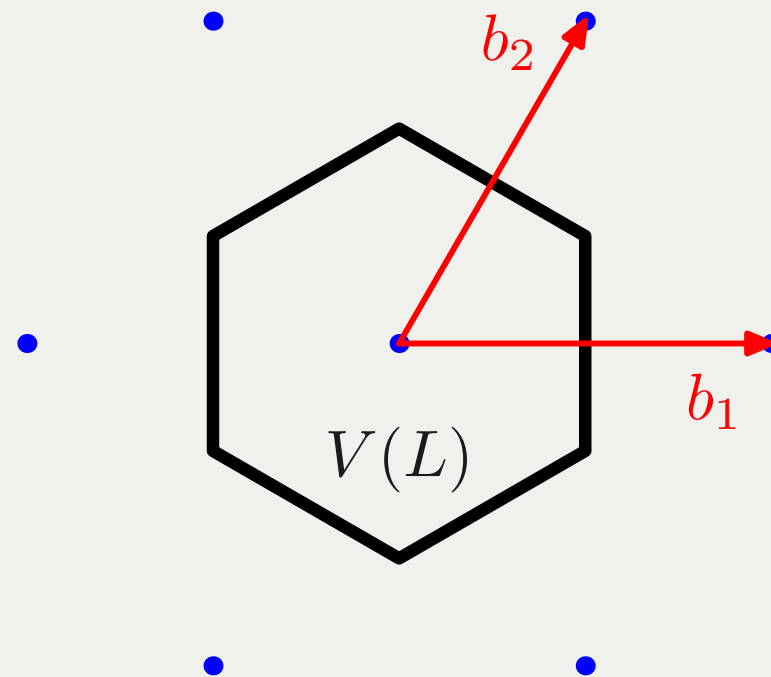
$\lambda(L) = 2 \cdot \text{inradius of } V(L)$

$\mu(L) = \text{circumradius of } V(L)$

$L^* = \{y \in \mathbb{R}^n : x \cdot y \in \mathbb{Z} \text{ for all } x \in L\}$ dual lattice

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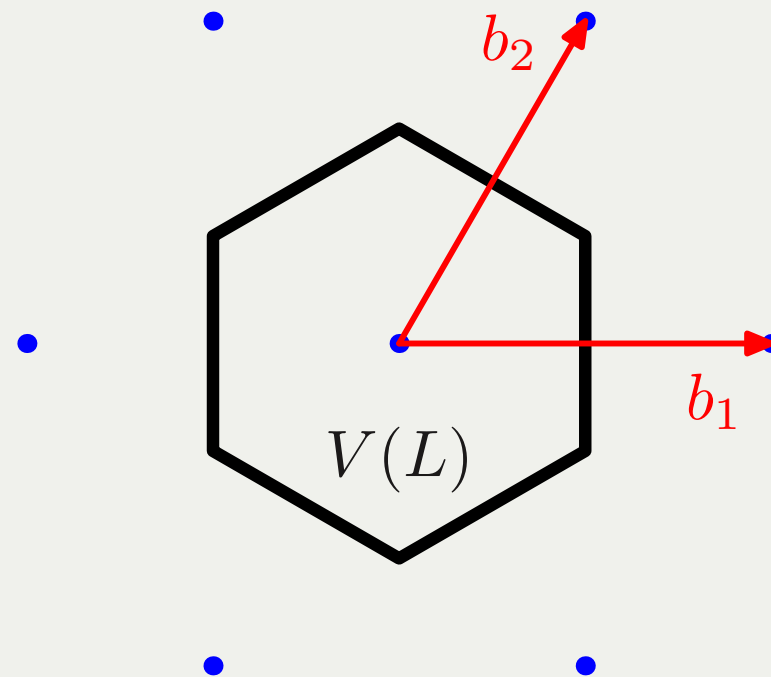
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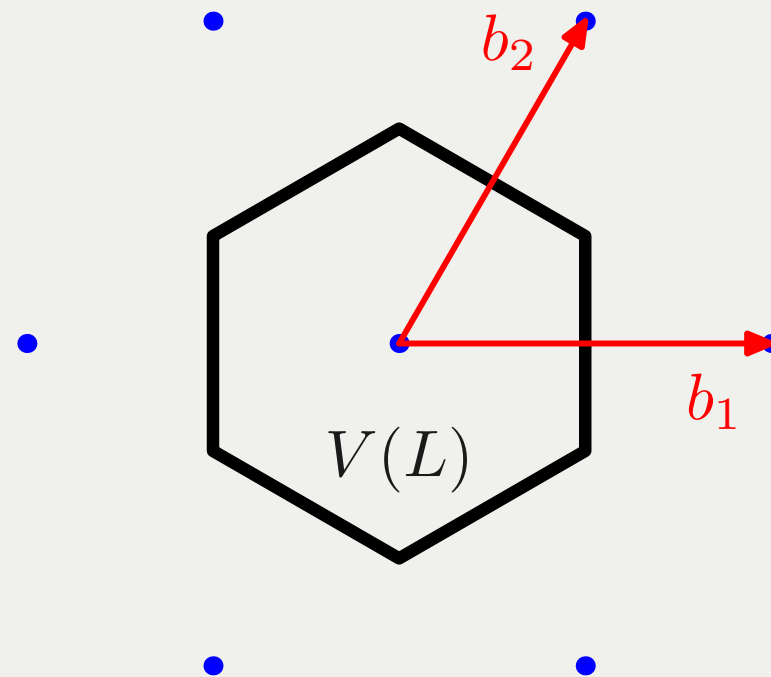
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Theorem. (Butler, 1973) $\exists L_n$ with $\lambda(L_n)/\mu(L_n) = \text{const}$

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Corollary. $c_2(\mathbb{R}^n/L_n) = \Omega(\sqrt{n})$

More about Euclidean embeddings of flat tori

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Theorem. Haviv, Regev, 2010

$$c_2(\mathbb{R}^n / L) \geq \frac{\lambda(L^*)\mu(L)}{4\sqrt{n}},$$

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Theorem. Haviv, Regev, 2010 $c_2(\mathbb{R}^n/L) \geq \frac{\lambda(L^*)\mu(L)}{4\sqrt{n}},$

improvement over $c_2(\mathbb{R}^n/L) = \Omega\left(\frac{\lambda(L^*)\sqrt{n}}{\mu(L^*)}\right).$

because $\mu(L)\mu(L^*) \geq \Omega(n)$

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More about Euclidean embeddings of flat tori

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almost tight lower bound

Theorem. Agarwal, Regev, Tang, 2020 $c_2(\mathbb{R}^n / L) = O(\sqrt{n \log n})$

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Recall: SDP for finite metric spaces

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Recall: SDP for finite metric spaces

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Want: similar SDP for flat torus

$$c_2(\mathbb{R}^n/L) = \inf \{ \text{distortion}(\varphi) : \varphi : \mathbb{R}^n/L \rightarrow H \text{ for some Hilbert space } H, \varphi \text{ injective} \}.$$

First problem: How do we optimize over all Hilbert spaces?

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Moore's theorem (1916): There exist a Hilbert space H and a map $\varphi : \mathbb{R}^n/L \rightarrow H$ if and only if there is a positive definite kernel Q so that

$$Q : \mathbb{R}^n/L \times \mathbb{R}^n/L \rightarrow \mathbb{C} \text{ so that } Q(x, y) = (\varphi(x), \varphi(y)) \text{ for all } x, y \in \mathbb{R}^n/L.$$

Kernel Q is called positive definite if and only if for all $N \in \mathbb{N}$ and for all $x_1, \dots, x_N \in \mathbb{R}^n/L$ the matrix $(Q(x_i, x_j))_{1 \leq i, j \leq N} \in \mathbb{C}^{N \times N}$ is Hermitian and positive semidefinite.

First problem: How do we optimize over all Hilbert spaces?

Moore's theorem (1916): There exist a Hilbert space H and a map $\varphi : \mathbb{R}^n/L \rightarrow H$ if and only if there is a positive definite kernel Q so that

$$Q : \mathbb{R}^n/L \times \mathbb{R}^n/L \rightarrow \mathbb{C} \text{ so that } Q(x, y) = (\varphi(x), \varphi(y)) \text{ for all } x, y \in \mathbb{R}^n/L.$$

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This gives:

$$c_2(\mathbb{R}^n/L)^2 = \inf\{C : C \in \mathbb{R}_+, Q \text{ positive definite},$$

$$\begin{aligned} d_{\mathbb{R}^n/L}(x, y)^2 &\leq Q(x, x) - 2\Re(Q(x, y)) + Q(y, y) \\ &\leq C d_{\mathbb{R}^n/L}(x, y)^2 \text{ for all } x, y \in \mathbb{R}^n/L \} \end{aligned}$$

Our favorite trick: Symmetry reduction

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- \overline{Q} depends only on $x - y$

so: \exists continuous positive type function $f : \mathbb{R}^n/L \rightarrow \mathbb{R}$

with $\overline{Q}(x, y) = f(x - y)$

$c_2(\mathbb{R}^n/L)^2 = \inf\{C : C \in \mathbb{R}_+, f : \mathbb{R}^n/L \rightarrow \mathbb{R} \text{ continuous and of positive type},$
 $|x|^2 \leq 2(f(0) - f(x)) \leq C|x|^2 \text{ for all } x \in V(L)\}.$

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This gives: infinite-dimensional LP

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- understand principal structure of Euclidean embeddings

A feasible solution of the above minimization problem (C, z) determines a Euclidean embedding φ of \mathbb{R}^n/L with distortion $\leq \sqrt{C}$ by

$$\varphi : \mathbb{R}^n/L \rightarrow \ell^2(L^*), \quad x \mapsto \left(\sqrt{z(u)} e^{2\pi i u^\top x} \right)_{u \in L^*},$$

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- inf is max

because bounded, continuous, positive type functions are weak* compact

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infinite-dimensional linear program

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equivalent to finite SDP condition

$$CI - 4\pi^2 \sum_{u \in L^*} z(u)uu^\top \in \mathcal{S}_+^n,$$

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dual SDP

$$c_2(\mathbb{R}^n/L)^2 = \sup \left\{ 2\pi^2 \int_{V(L)} |x|^2 d\nu(x) : \right. \\ \left. \nu \in \mathcal{M}_+(V(L)), Y \in \mathcal{S}_+^n, \text{Tr}(Y) = 1, \right. \\ \left. \int_{V(L)} (1 - \cos(2\pi u^\top x)) d\nu(x) \leq u^\top Y u \text{ for all } u \in L^* \right\}$$

$\mathcal{M}_+(V(L))$ is the cone of Borel measures on $V(L)$

First application: Constant factor improvement of lower bound

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Theorem. Let L be an n -dimensional lattice, then

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Proof. Let y be a vertex of the Voronoi cell $V(L)$ which realizes the covering radius, that is $|y| = \mu(L)$.

Choose $\nu = \frac{\lambda(L^*)^2}{2n} \delta_y$ to be a point measure supported at y and set $Y = \frac{1}{n}I$.

Then (Y, ν) is feasible for dual.

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Second application: Least distortion embedding of standard torus

$$\varphi : \mathbb{R}^n / \mathbb{Z}^n \rightarrow \mathbb{R}^{2n}$$

$$\varphi(x_1, \dots, x_n) = (\cos 2\pi x_1, \sin 2\pi x_1, \dots, \cos 2\pi x_n, \sin 2\pi x_n).$$

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Theorem. $c_2(\mathbb{R}^n / \mathbb{Z}^n) = \pi/2$

$$c_2(\mathbb{R}^n / L) \geq \frac{\pi \lambda(L^*) \mu(L)}{\sqrt{n}} \quad \text{is tight for } L = \mathbb{Z}^n$$
$$\lambda(\mathbb{Z}^n) = 1 \text{ and } \mu(\mathbb{Z}^n) = \sqrt{n/4}$$

Third application: Least distortion embedding of 2-d flat tori

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Suppose $\exists u_1, \dots, u_k \in L^*, z_1, \dots, z_k \geq 0$ such that $\sum_{i=1}^k z_i u_i u_i^\top = I$.

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$$\varphi : \mathbb{R}^n / L \rightarrow \mathbb{C}^k, \quad H(x)_r = (2\pi^2 D z_r e^{2i\pi u_r^\top x})$$

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$$D = \max_{v \in V(L) \setminus \{0\}} \frac{|x|^2}{\sum_{i=1}^k z_i (1 - \cos(2\pi u_i^\top x))}$$

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Drawback: somewhat indirect, D seems hard to determine.

The end of the story: Questions and speculations

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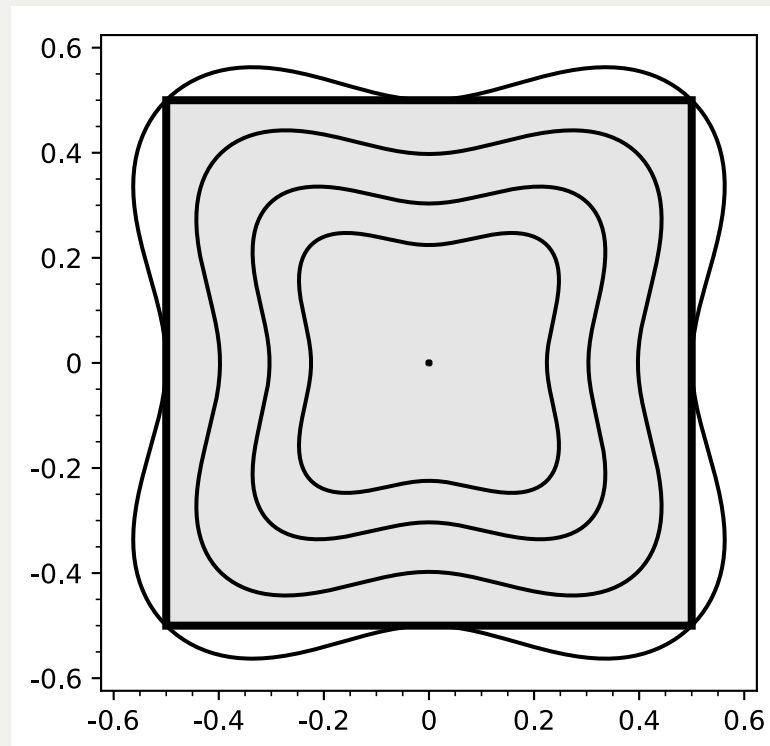
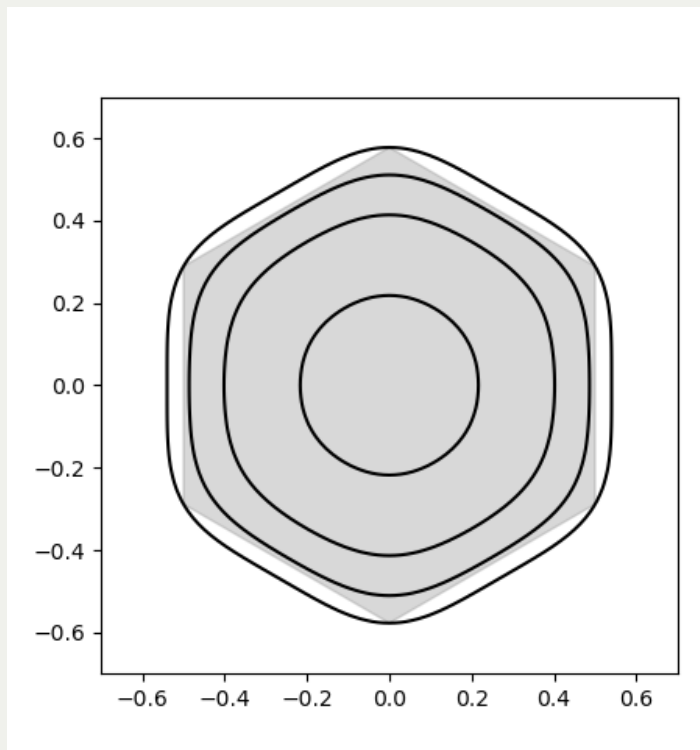
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Seems to be $(0, y)$ where y vertex of Voronoi cell

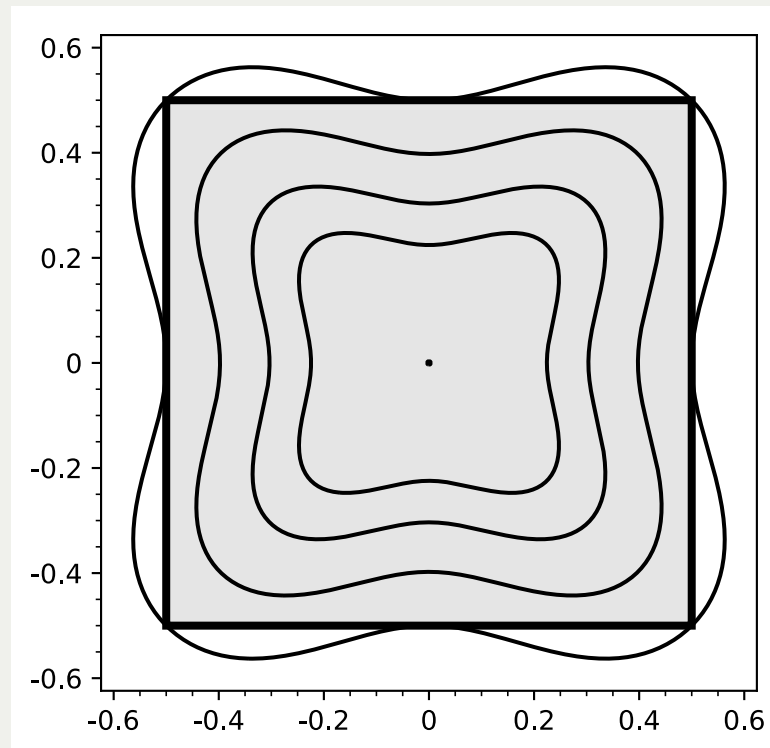
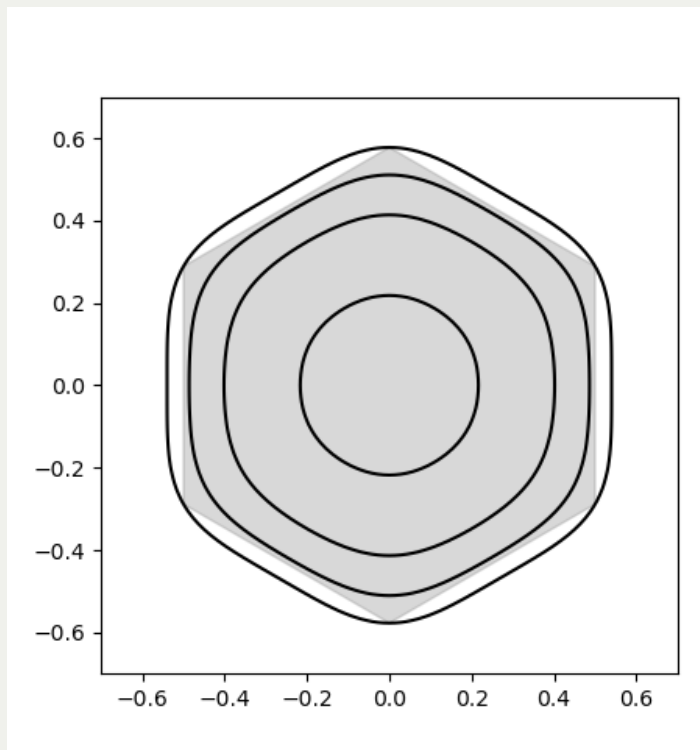


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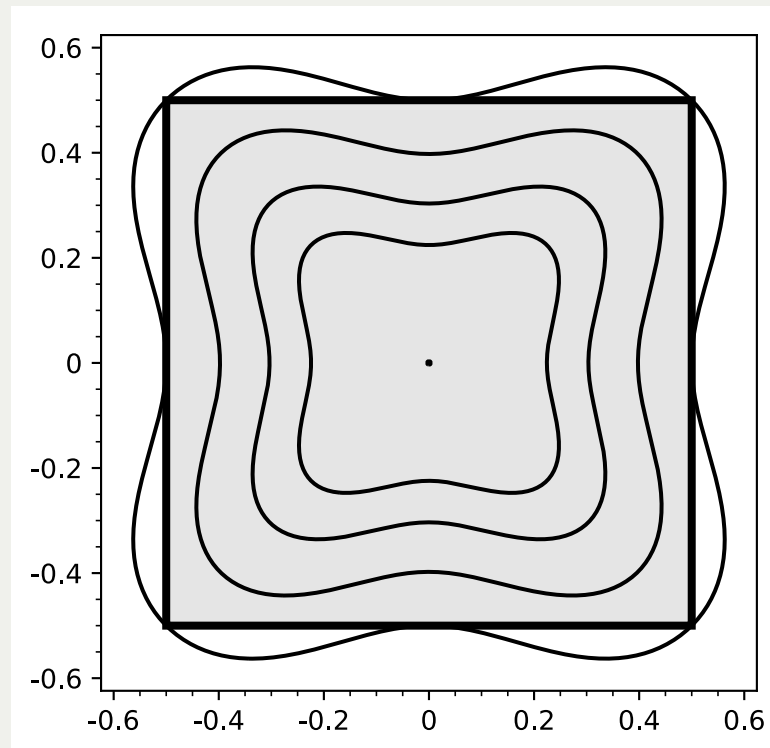
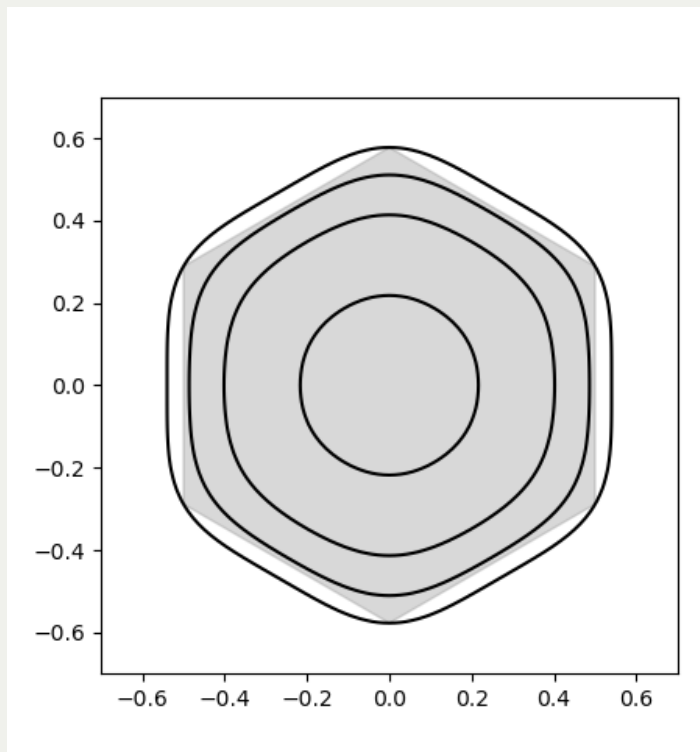
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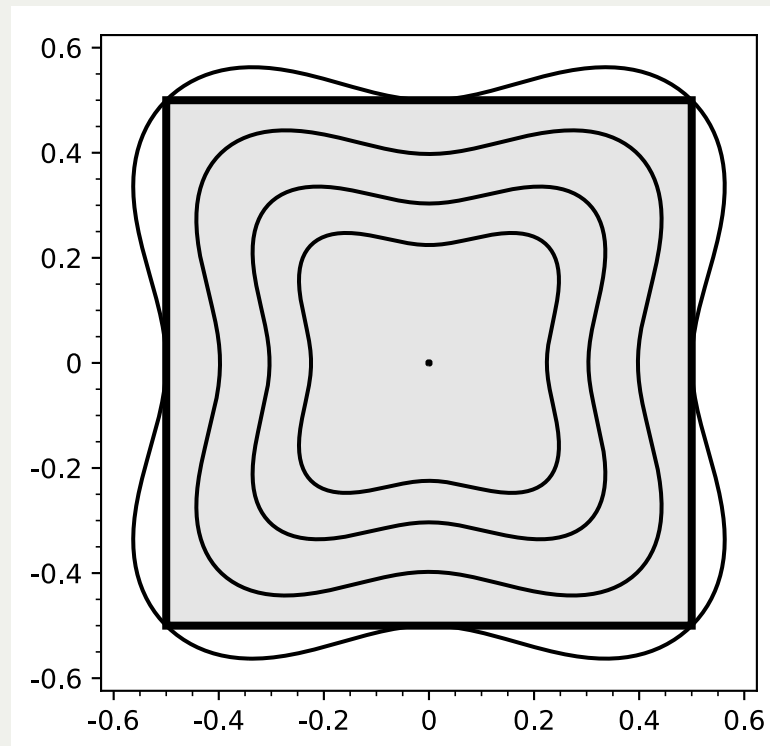
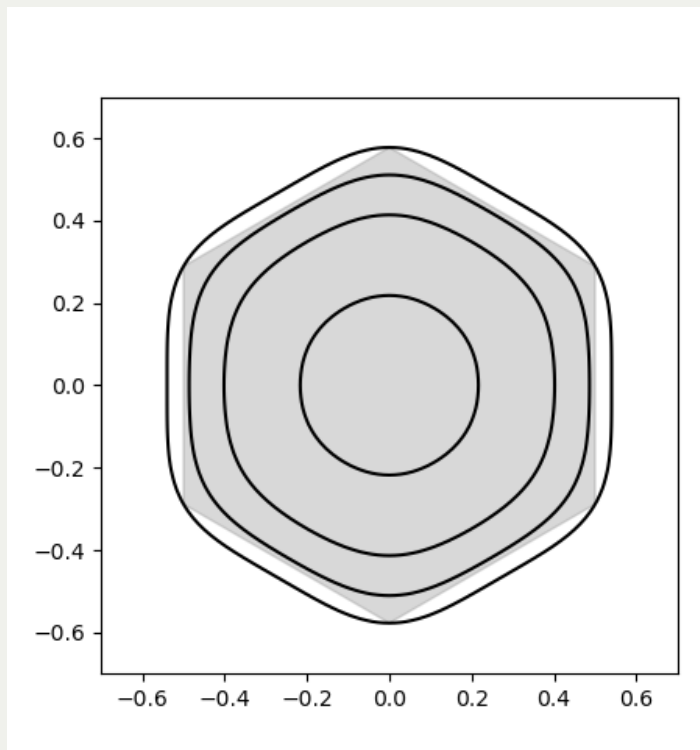
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If both are true: SDP perspective would provide a finite algorithm