Computational, combinatorial, and geometric aspects of linear optimization



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based on joint works with:

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Linear optimization

Given an *n*-dimensional vector *b* and an *n* x *d* matrix *A* find, in any, a *d*-dimensional vector *x* such that :

$$Ax = b \qquad Ax = b, \ x \ge 0$$

linear algebra

linear optimization

"Can linear optimization be solved in strongly polynomial time?" is listed by Smale as one of the top problems for the XXI century

Strongly polynomial *:* algorithm *independent* from the *input data length* and polynomial in *n* and *d*.



Linear optimization algorithms simplex methods

Given an *n*-dimensional vector **b** and an *n* x **d** (full row-rank) matrix **A** and a **d**-dimensional cost vector **c**, solve : max { $c^Tx : Ax = b, x \ge 0$ }

- start from a *feasible basis*
- ➤ use a *pivot rule*
- find an optimal solution after a *finite number* of iterations
- most known pivot rules are known to be *exponential* (worst case); *efficient* implementations exist



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> $\delta(d, n)$ largest diameter over all (d, n)-polytopes: lower bound on the number of simplex pivots required in the **worst case**. > $\delta(4, 12) = \delta(5, 12) = 7$ [Bremner-Deza-Hua-Schewe 2013], ...

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- random spherical polytopes [Bonnet, Dadush, Grupel, Huiberts, Livshyts 2021], smooth analysis [Huiberts, Lee, Zhang 2024], ...

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- > $\delta(d, k)$ largest diameter over all **lattice** (d, k)-polytopes: **V** lower bound on the number of simplex pivots in the **worst case.**
- > [Del Pia-Michini 2022] preprocessing and scaling algorithm yielding simplex paths that are short relative to $\delta(d, k)$

Linear optimization algorithms (central path following) interior point methods

Given an *n*-dimensional vector **b** and an *n* x **d** (full row-rank) matrix **A** and a **d**-dimensional cost vector **c**, solve : max { $c^Tx : Ax = b, x \ge 0$ }

Interior Point Methods:

path-following, polynomial, efficient in practice

- start from the analytic center
- follow the central path
- > converge to an optimal solution in $O(\sqrt{nL})$ iterations
 - (L: input data length)



$$- \mu \sum_{i} \ln(b - Ax)_{i}$$

 μ : central path parameter $x \in \mathbf{P}$: $Ax \leq b$

 $\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x}$

Linear optimization diameter and curvature

Diameter (of a polytope) :

lower bound for the number of iterations for *pivoting* **simplex methods**

Curvature (of the central path associated to a polytope) :

large curvature indicates large number of iterations for *path following* **interior point methods**





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- [Dedieu-Malajovich-Shub 2005]
 Average curvature of the central path is bounded by 2πd (analogue of Haimovich (Borgwardt 1987) analysis of the simplex)
- Conjecture [Dedieu-Malajovich 2005]
 Curvature of the central path is O(d)
- [Deza-Terlaky-Zinchenko 2008]
 Counterexample to Dedieu-Malajovich conjecture
- Conjecture [Deza-Terlaky-Zinchenko 2008]
 Curvature of the central path is O(n,d)
 (continuous analogue of the Hirsch conjecture)



Linear optimization

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- [Allamigeon, Benchimol, Gaubert, Joswig 2018] (logarithmic barrier) *Interior point methods* are *not strongly polynomial* (tropical counterexample to continuous Hirsch conjecture)
- [Allamigeon, Gaubert, Vandame 2022] (self-concordant barrier) *Interior point methods* are *not strongly polynomial*



Further results: [Allamigeon-Dadush-Loho-Natura-Végh 2024],

Kissing Polytopes

Q. How close can two disjoint *d*-dimensional 0/1-polytopes be?



Motivation: this minimal distance appears in complexity bounds of algorithms such as **von Neumann's alternating projections**

Complexity of certifying that $P \cap Q = \emptyset$ is

$$O\left(\frac{1}{d(P,Q)^2}\right)$$

Alternating Linear Minimization: Revisiting von Neumann's alternating projections [Braun-Pokutta-Weismantel 2022]

Main question, motivation, related works

Related works: \mathcal{V} : vertex set of a polytope P

• Facial distance of *P* is:

 $\Phi(P) = \min \left\{ d \left(F, \operatorname{conv}(\mathcal{V} \setminus F) \right) : F \text{ proper face of } P \right\}$ [Peña-Rodriguez 2018], [Gutman-Peña 2018], [Peña 2019]

• Vertex-facet distance of P is:

 $\Delta(P) = \min \left\{ d \left(\operatorname{aff}(F), \operatorname{conv}(\mathcal{V} \setminus F) \right) : F \text{ facet of } P \right\}$ [Beck-Shtern 2017]

• Minimal vertex-facet distance of all *d*-dimensional **0/1-simplex** S

$$\frac{1}{\sqrt{2}^{d\log d - 2d + o(d)}} \le \min \, \Delta(\mathbf{S}) \le \frac{1}{\sqrt{2}^{d\log d - 4d + o(d)}}$$
[Alon-Vũ 1997]

Main results

• If P and Q are **disjoint** d-dimensional 0/1-polytopes, then

$$\frac{1}{\sqrt{d}^{3d+2}} \le d(P, Q)$$

For any large enough d, there exist two disjoint d-dimensional
 0/1-polytopes P and Q such that

$$d(P, Q) \leq \frac{1}{\sqrt{d}\sqrt{d}}$$

Main results

• **Theorem**: For any large enough *d*, there exist two **disjoint** *d*dimensional **0/1**-polytopes *P* and *Q* such that

$$rac{1}{\sqrt{d}^{3d+2}} \leq d(P,Q) \leq rac{1}{\sqrt{d}^{\sqrt{d}}}$$

- ⇒ Similar bounds for lattice (d, k)-polytope (that is, convex hull of points drawn from $\{0, 1, ..., k\}^d$)
- ⇒ New bounds for the minimal facial distance $\Phi(P)$ over of all lattice (d, k)-polytopes P
- ⇒ Similar bounds for rational polytopes in terms of binary encoding length and dimension

 $\Rightarrow \varepsilon(d, 1) = \min\{d(P, Q) : P, Q \text{ disjoint } d\text{-dimensional } 0/1\text{-polytopes}\}$ What about dimension 2 ?



$$d(P,Q) = 0, \frac{1}{\sqrt{2}}, 1 \text{ or } \sqrt{2} \qquad \Rightarrow \quad \varepsilon(2,1) = \frac{1}{\sqrt{2}}$$

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- $\varepsilon(2,1)$ achieved as $d(p^*,q^*)$ with q^* not a vertex of Q
- If P or Q is reduced to a vertex, $d(P,Q) \ge \frac{1}{\sqrt{d}}$ for any d

 $\Rightarrow \varepsilon(d, 1) = \min\{d(P, Q) : P, Q \text{ disjoint } d\text{-dimensional } 0/1\text{-polytopes}\}$ What about dimension 3 ?



 $d(P,Q) = 0, \frac{1}{\sqrt{6}}, \frac{1}{\sqrt{3}}, \frac{2}{\sqrt{3}}, \frac{1}{\sqrt{2}}, \frac{2}{\sqrt{6}}, 1, \frac{3}{\sqrt{6}}, \sqrt{2} \text{ or } \sqrt{3} \quad \Rightarrow \quad \varepsilon(3,1) = \frac{1}{\sqrt{6}}$

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• $\varepsilon(3,1)$ achieved as $d(p^*,q^*)$ with both p^* and q^* **not** vertices of P,Q

• If both P and Q are segments, $d(P,Q) \ge \frac{1}{\sqrt{6}}$ for any d

 $\Rightarrow \varepsilon(d, 1) = \min\{d(P, Q) : P, Q \text{ disjoint } d\text{-dimensional } 0/1\text{-polytopes}\}$ What about dimension d?



P: segment [(0, 0, ..., 0), (1, 1, ..., 1)]

Q: (d-2)-simplex with vertices (1, 0, ..0, 0), (0, 1, ..0, 0), ..., (0, 0, ..1, 0)

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 $\begin{array}{l} P: \text{ segment } [(0,0,\ldots,0),(1,1,\ldots,1)]\\ Q: \ (d-2)\text{-simplex with vertices } (1,0,\ldots,0),(0,1,\ldots,0),\ldots,(0,0,\ldots,1,0)\\ p^* = \frac{1}{d}(1,1,\ldots,1), \ q^* = \frac{1}{d-1}(1,1,\ldots,1,0), \ d(p^*,q^*) = \frac{1}{\sqrt{d(d-1)}} \end{array}$

 $\Rightarrow \varepsilon(d, 1) = \min\{d(P, Q) : P, Q \text{ disjoint } d\text{-dimensional } 0/1\text{-polytopes}\}$

- Obtaining a non-trivial upper bound on ε(d, 1) requires to exhibit two disjoint polytopes that are very close
- Obtaining a lower bound on $\varepsilon(d, 1)$ requires investigating the geometric setup

Remark: If P and Q are rational polytopes then $d(P,Q)^2$ is rational

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Direct geometric proof yields a lower bound:



d(P,Q) achieved as $d(p^*,q^*)$ with $(p^* - q^*)$ orthogonal to a unique face of P (resp. Q) containing p^* (resp. q^*) in its relative interior

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- (essentially) Cramer's rule yields $(p^* q^*)$ is rational
- (in addition) d(P,Q) can be achieved with **both** p^* and q^* rational

Remark: If P and Q are rational polytopes then $d(P,Q)^2$ is rational

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Direct geometric proof yields a lower bound:



d(P,Q) achieved as $d(p^*,q^*)$ with $(p^* - q^*)$ orthogonal to a unique face of P (resp. Q) containing p^* (resp. q^*) in its relative interior

- (essentially) Cramer's rule yields $(p^* q^*)$ is rational
- (essentially) Hadamard's inequality yields $d(p^*, q^*) \ge \frac{1}{\sqrt{d^{3d+2}}}$.

 $\varepsilon(d, 1) = \min\{d(P, Q) : P, Q \text{ disjoint } d\text{-dimensional } 0/1\text{-polytopes}\}$

$$rac{1}{\sqrt{d}^{3d+2}} \leq arepsilon(d, \mathbf{1}) \leq \quad ?$$

 Obtaining a non-trivial upper bound on ε(d, 1) requires to exhibit two disjoint polytopes that are very close

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 Obtaining a non-trivial upper bound on ε(d, 1) requires to exhibit two disjoint polytopes that are very close

• Intuition: d(P,Q) might be not too different from d(aff(P), aff(Q))

Example: For $i \leq d-1$, consider two consecutive hyper-simplices:

 $P = \text{convex hull of all } x \in \{0, 1\}^d \text{ such that } x_1 + x_2 + \dots + x_d = i$ $Q = \text{convex hull of all } x \in \{0, 1\}^d \text{ such that } x_1 + x_2 + \dots + x_d = i + 1$

$$\mathbf{a} = (1, 1, ..., 1)$$
 orthogonal to both $\operatorname{aff}(P)$ and $\operatorname{aff}(Q)$
 $\Rightarrow \quad d(P, Q) = d(\operatorname{aff}(P), \operatorname{aff}(Q)) = \frac{1}{\sqrt{d}} = \frac{1}{||\mathbf{a}||}$

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a = (1, 1, ..., 1) orthogonal to both aff(P) and aff(Q)

$$\Rightarrow \quad d(P,Q) = d(\operatorname{aff}(P),\operatorname{aff}(Q)) = \frac{1}{\sqrt{d}} = \frac{1}{||\mathbf{a}||}$$

• Can we make $||\mathbf{a}||$ larger while maintaining d(P,Q) = d(aff(P), aff(Q))?

 $\varepsilon(d, 1) = \min\{d(P, Q) : P, Q \text{ disjoint } d\text{-dimensional } 0/1\text{-polytopes}\}$

Consider much larger ||a||

•
$$\mathbf{a} \approx (\underbrace{1, \dots, 1}_{\sqrt{d} \text{ times}}, \underbrace{-\sqrt{d}, \dots, -\sqrt{d}}_{\sqrt{d} \text{ times}}, \dots, \underbrace{(-\sqrt{d})^{\sqrt{d}}, \dots, (-\sqrt{d})^{\sqrt{d}}}_{\sqrt{d} \text{ times}})$$

- $P = \text{convex hull of all } x \in \{0,1\}^d \text{ such that } \mathbf{a} \cdot x = \mathbf{0}$
- $Q = \text{convex hull of all } x \in \{0,1\}^d \text{ such that } \mathbf{a} \cdot x = \mathbf{1}$

Maintaining d(P,Q) = d(aff(P), aff(Q)): (careful) convex combination of (carefully) chosen vertices in P (resp. Q) yields a point $p^* \in P$ (resp. $q^* \in Q$) such that, for d large enough

$$d(p^*, q^*) pprox rac{1}{||\mathbf{a}||} pprox rac{1}{\sqrt{d}}$$

 $\varepsilon(d, 1) = \min\{d(P, Q) : P, Q \text{ disjoint } d\text{-dimensional } 0/1\text{-polytopes}\}$

$$\frac{1}{\sqrt{d}^{3d+2}} \le \varepsilon(d, \mathbf{1}) \le \frac{1}{\sqrt{d}^{\sqrt{d}}}$$

 $\varepsilon(d, \mathbf{k}) = \min\{d(P, Q) : P, Q \text{ disjoint lattice } (d, \mathbf{k}) \text{-polytopes}\}$

$$rac{1}{k^{2d-1}\sqrt{d}^{3d+2}} \leq arepsilon(d,k) \leq rac{1}{(k\sqrt{d})^{\sqrt{d}}}$$

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Q. How to **compute** the minimal distance between disjoint lattice polytopes for small dimension d and small range k?

 $\varepsilon(d, \mathbf{k}) = \min\{d(P, Q) : P, Q \text{ disjoint lattice } (d, \mathbf{k}) \text{-polytopes}\}$

Exploiting the **symmetries** of the cube, proving that one can assume that P is a simplex such that $1 \leq \dim(P) \leq \lfloor \frac{d}{2} \rfloor$, and Q is a simplex such that $\dim(Q) = d+1-\dim(P)$, significantly reduce the huge search space and allow for the **computation** of $\varepsilon(d, \mathbf{k})$ for small (d, \mathbf{k}) :

(d, \mathbf{k})	1	2	3	4	5	6
$\frac{1}{\varepsilon(2,k)}$	$\sqrt{2}$	$\sqrt{5}$	$\sqrt{13}$	$\sqrt{25}$	$\sqrt{41}$	$\sqrt{61}$
$\frac{1}{\varepsilon(3,k)}$	$\sqrt{6}$	$\sqrt{50}$	$\sqrt{299}$			
$\frac{1}{\varepsilon(4,k)}$	$\sqrt{18}$					
$\frac{1}{\varepsilon(5,k)}$	$\sqrt{58}$					

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[Deza-Liu-Pournin 2024]

•
$$\varepsilon(2, \mathbf{k}) = \frac{1}{\sqrt{(\mathbf{k}-1)^2 + \mathbf{k}^2}}$$
 for $\mathbf{k} \ge 2$

•
$$\varepsilon(3, k) = \frac{1}{\sqrt{2(2k^2 - 4k + 5)(2k^2 - 2k + 1)}}$$
 for $k \ge 4$

Determination of $\varepsilon(3, \mathbf{k})$ amounts to minimize

$$\frac{|\mathbf{f}(x)|}{\sqrt{\mathbf{g}(x)}}$$

$$f(x) = x_1(x_6x_8 - x_5x_9) + x_2(x_4x_9 - x_6x_7) + x_3(x_5x_7 - x_4x_8)$$
$$g(x) = (x_1x_5 - x_2x_4)^2 + (x_1x_6 - x_3x_4)^2 + (x_2x_6 - x_3x_5)^2$$

such that $f(x) \neq 0$, $g(x) \neq 0$, $-k \leq x_i \leq k$, x_i integer for i = 1, 2, ..., 9

 $\varepsilon(d, \mathbf{k}) = \min\{d(P, Q) : P, Q \text{ disjoint lattice } (d, \mathbf{k}) \text{-polytopes}\}$

(<i>d</i> , <i>k</i>)	1	2	3	4	• • •	k
$\frac{1}{\varepsilon(2,k)}$	$\sqrt{2}$	$\sqrt{5}$	$\sqrt{13}$	$\sqrt{25}$		$\sqrt{(k-1)^2 + k^2}$
$\frac{1}{\varepsilon(3,k)}$	$\sqrt{6}$	$\sqrt{50}$	$\sqrt{299}$	$\sqrt{1050}$	•••	$\sqrt{2(2k^2-4k+5)(2k^2-2k+1)}$
$\frac{1}{\varepsilon(4,k)}$	$\sqrt{18}$					
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(<i>d</i> , <i>k</i>)	1	2	3	4	•••	k
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$\frac{1}{\varepsilon(5,\boldsymbol{k})}$	$\sqrt{58}$					

Thanks