

Volume and edge-skeleton computation in high dimensions

Vissarion Fisikopoulos

Computer Science Department, Algorithms Group



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Outline of the talk

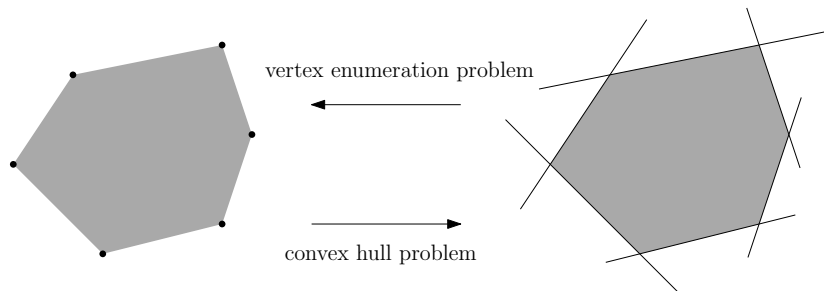
Edge-skeleton computation [Emiris-F-Gaertner]

Practical volume approximation [Emiris-F]

Classical Polytope Representations

A convex **polytope** $P \subseteq \mathbb{R}^d$ can be represented as the

1. convex hull of a pointset $\{p_1, \dots, p_n\}$ (**V-representation**)
2. intersection of halfspaces $\{h_1, \dots, h_m\}$ (**H-representation**)



- These problems are equivalent by polytope **duality**.

Algorithmic Issues

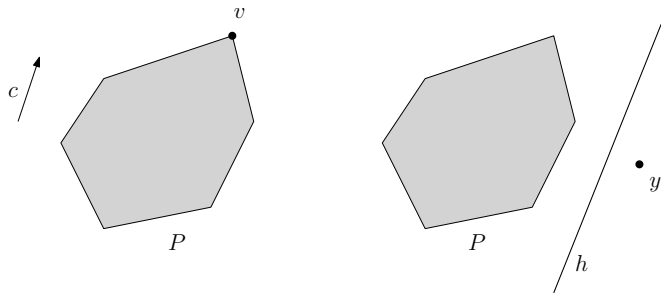
- ▶ For general dimension d there is no polynomial algorithm for the convex hull (or vertex enumeration) problem since m can be $O(n^{\lfloor d/2 \rfloor})$ [McMullen'70].
- ▶ It is **open** whether there exist a **total** poly-time algorithm for the convex hull (or vertex enumeration) problem, *i.e. runs in poly-time in n, m, d .*
- ▶ Vertex enumeration special cases
 1. Simple polytopes: $O(n m d)$ [Avis, Fukuda'92]
 2. 0/1 polytopes: $O(n d T_{LP})$ [Bussieck, Lubbecke'98]

Polytope Oracles

Implicit representation for a polytope $P \subseteq \mathbb{R}^d$.

OPT_P: Given direction $c \in \mathbb{R}^d$ return the vertex $v \in P$ that maximizes $c^T v$.

SEP_P: Given point $y \in \mathbb{R}^d$, return yes if $y \in P$ otherwise a hyperplane h that separates y from P .



Well-described polytopes and oracles

Definition

A rational polytope $P \subseteq \mathbb{R}^d$ is **well-described** (with a parameter φ) if there exists an H-representation for P in which every inequality has encoding length at most φ . The encoding length of P is $\langle P \rangle = d + \varphi$.

Proposition (Grötschel et al.'93)

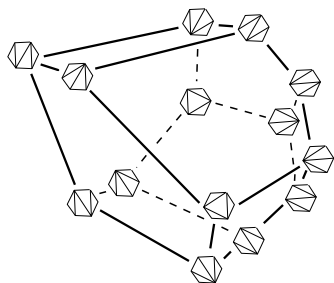
For a well-described polytope, we can compute OPT_P from SEP_P (and vice versa) in oracle polynomial-time. The runtime (polynomially) depends on d and φ .

Why oracles?

- ▶ Polynomial time algorithms for combinatorial optimization problems using the ellipsoid method [Grötschel-Lovász-Schrijver'93]
- ▶ Randomized polynomial-time algorithm for approximating the volume of convex bodies [Dyer-Frieze-Kannan '90]

Original Motivation

(1) Secondary, Resultant polytopes



- ▶ Vertices \rightarrow **reg. triangulations** of a pointset's convex hull
- ▶ OPT_P is available via a triangulation computation
[\[Emiris-F-Konaxis-Peñaranda '12\]](#)

(2) Minkowski sums

- ▶ Applications in Computational Algebraic Geometry, Geometric Modelling, Combinatorics

Vertex enumeration with edge-directions

Given OPT_P and a superset D of the edge directions $D(P)$ of $P \subseteq \mathbb{R}^d$, compute the vertices P .

Proposition (Rothblum-Onn '07)

Let $P \subseteq \mathbb{R}^d$ given by OPT_P , and $D \supseteq D(P)$. All vertices of P can be computed in

$O(|D|^{d-1})$ calls to $\text{OPT}_P + O(|D|^{d-1})$ arithmetic operations.

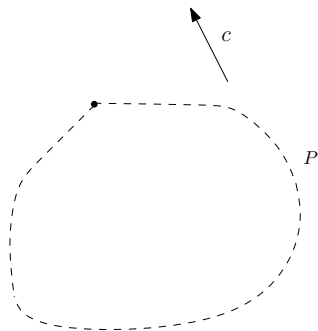
The edge-skeleton algorithm

Input:

- ▶ OPT_P
- ▶ Edge vec. P (dir. & len.): D

Output:

- ▶ Edge-skeleton of P



Sketch of **Algorithm**:

- ▶ Compute a vertex of P ($x = \text{OPT}_P(c)$ for arbitrary $c^T \in \mathbb{R}^d$)

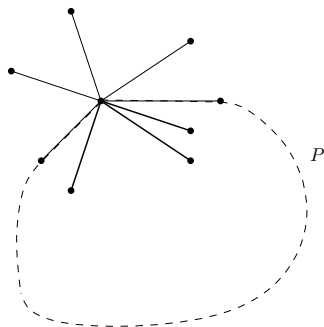
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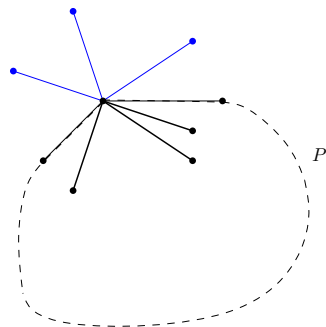
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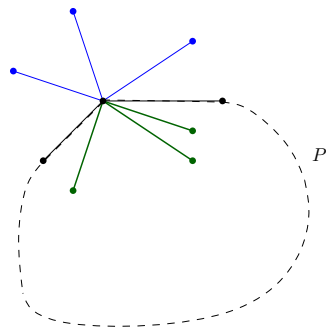
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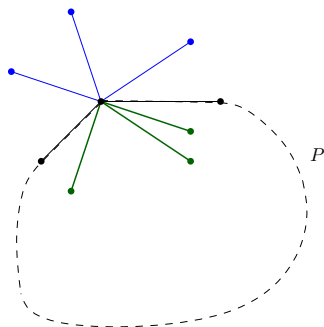
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Can be altered to work with **edge directions only**

Complexity

Theorem

Given OPT_P and a superset of edge directions D of a well-described polytope $P \subseteq \mathbb{R}^d$, the edge skeleton of P can be computed in oracle *total polynomial-time*

$$O\left(n |D| (T + \mathbb{LP}(d^3 |D| \langle B \rangle) + d \log n)\right),$$

- ▶ n the number of vertices of P ,
- ▶ T : runtime of oracle conversion algorithm for P and D ,
- ▶ $\langle B \rangle$ is the binary encoding length of the vector set D and P ,
- ▶ $\mathbb{LP}(\langle A \rangle + \langle b \rangle + \langle c \rangle)$ runtime of $\max c^T x$ over $\{x : Ax \leq b\}$.

Applications

Corollary

The edge skeleton of resultant, secondary polytopes and signed Minkowski sums (knowing the edge directions of the summands) can be computed in oracle total polynomial-time.

Corollary

*The edge skeletons of polytopes appearing in **convex combinatorial optimization** [Rothblum-Onn '04] and **convex integer programming** [De Loera et al. '09] problems can be computed in oracle total polynomial-time.*

Outline

Edge-skeleton computation [Emiris-F-Gaertner]

Practical volume approximation [Emiris-F]

The volume computation problem

Input: Polytope $P := \{x \in \mathbb{R}^d \mid Ax \leq b\}$ $A \in \mathbb{R}^{m \times d}$, $b \in \mathbb{R}^m$

Output: Volume of P

- ▶ #-P hard for vertex and for halfspace repres. [DyerFrieze'88]

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- ▶ open if both vertex & halfspace representation is available
- ▶ no deterministic poly-time algorithm can compute the volume with less than exponential relative error [Elekes'86]
- ▶ randomized poly-time algorithm approximates the volume of a convex body with high probability and arbitrarily small relative error [DyerFriezeKannan'91] $O^*(d^{23}) \rightarrow O^*(d^4)$ [LovVemp'04]

Implementations

Exact: VINCI [Bueler et al'00], Latte [deLoera et al], Qhull [Barber et al], LRS [Avis], Normaliz [Bruns et al]

- ▶ triangulation, sign decomposition methods
- ▶ cannot compute in high dimensions (e.g. > 15)

Randomized:

- ▶ [LovàszDeàk'12] cannot compute in > 10 dimensions
- ▶ Matlab code by Cousins & Vempala based on [LovVemp'04]
- ▶ **Ours:** based on [DyerFriezeKannan'91], . . . , [KannanLovàszSimon.'97]

Goal: compute accurate estimations in about 100 dimensions

How do we compute a random point in a polytope P ?

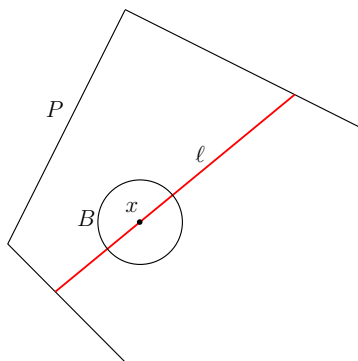
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- ▶ BUT for arbitrary polytopes we need *random walks*
e.g. grid walk, ball walk, **hit-and-run**

Random Directions Hit-and-Run (RDHR)



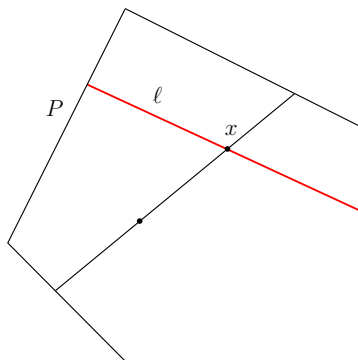
Input: point $x \in P$ and polytope $P \subset \mathbb{R}^d$

Output: a new point in P

1. line ℓ through x , uniform on $B(x, 1)$
2. set x to be a uniform distributed point on $P \cap \ell$

Iterate this for W steps and return x .

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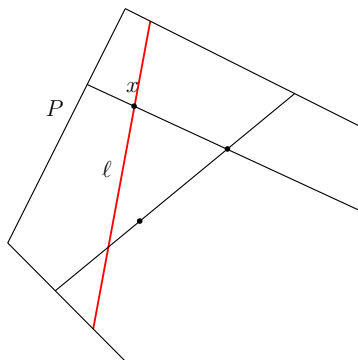
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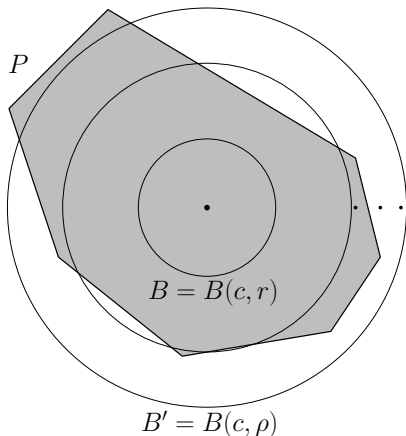
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- ▶ x is unif. random distrib. in P after $W = O^*(d^3)$ steps, where $O^*(\cdot)$ hides log factors [[LovaszVempala'06](#)]
- ▶ to generate many random points iterate this procedure

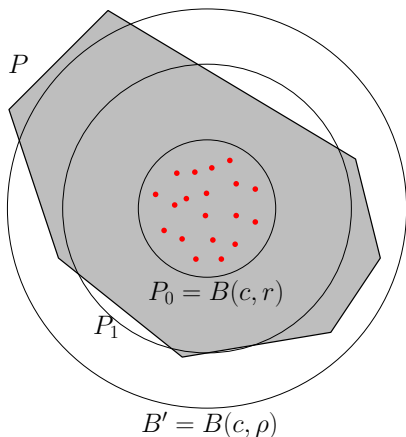
Multiphase Monte Carlo (Sequence of balls)



▶ $B(c, 2^{i/d})$, $i = \alpha, \alpha + 1, \dots, \beta$,
 $\alpha = \lfloor d \log r \rfloor$, $\beta = \lceil d \log \rho \rceil$

▶ $P_i := P \cap B(c, 2^{i/d})$, $i = \alpha, \alpha + 1, \dots, \beta$,
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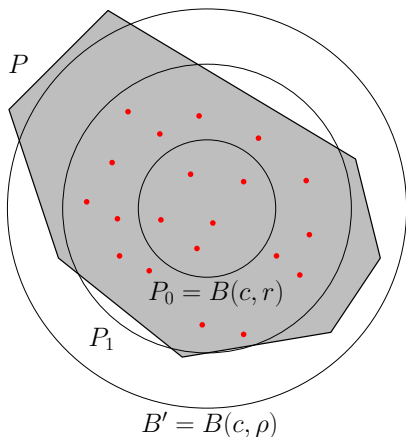


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1. Generate rand. points in P_i
2. Count how many rand. points in P_i fall in P_{i-1}

$$\text{vol}(P) = \text{vol}(P_\alpha) \prod_{i=\alpha+1}^{\beta} \frac{\text{vol}(P_i)}{\text{vol}(P_{i-1})}$$

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Complexity [KannanLS'97]

Assuming $B(c, 1) \subseteq P \subseteq B(c, \rho)$, the volume algorithm returns an estimation of $\text{vol}(P)$, which lies between $(1 - \epsilon)\text{vol}(P)$ and $(1 + \epsilon)\text{vol}(P)$ with probability $\geq 3/4$, making

$$O^*(d^5)$$

oracle calls, where ρ is the radius of a bounding ball for P .

Isotropic sandwiching: $\rho = O^*(\sqrt{d})$ and **ball walk**.

Runtime

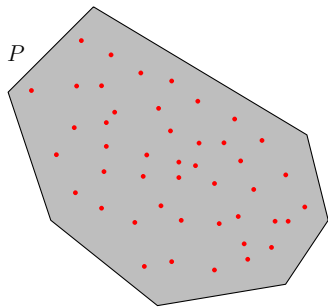
- ▶ generates $d \log(\rho)$ balls
- ▶ generate $N = 400\epsilon^{-2}d \log d$ random points in each ball $\cap P$
- ▶ each point is computed after $O^*(d^3)$ random walk steps

Modifications towards practicality

- ▶ $W = \lfloor 10 + d/10 \rfloor$ random walk steps (vs. $O^*(d^3)$ which hides constant 10^{11}) achieve $< 1\%$ error in up to 100 dim.
- ▶ sample **partial generations** of $\leq N$ points in each ball $\cap P$ (starting from the largest ball)
- ▶ coordinate (vs. random) directions hit-and-run (**CDHR**)
- ▶ implement **boundary oracles** with $O(m)$ runtime in CDHR

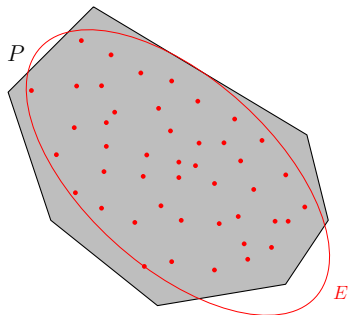
Iterative rounding

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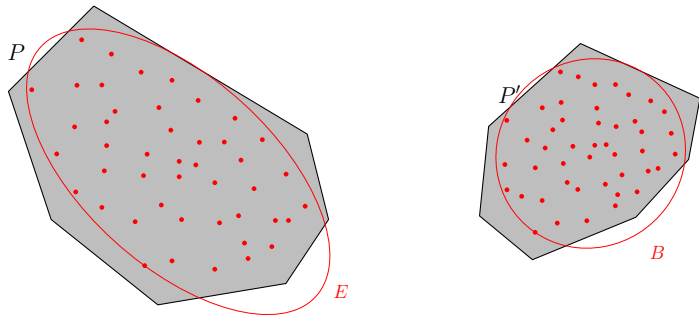
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3. compute L that maps E to the unit ball B and apply L to P

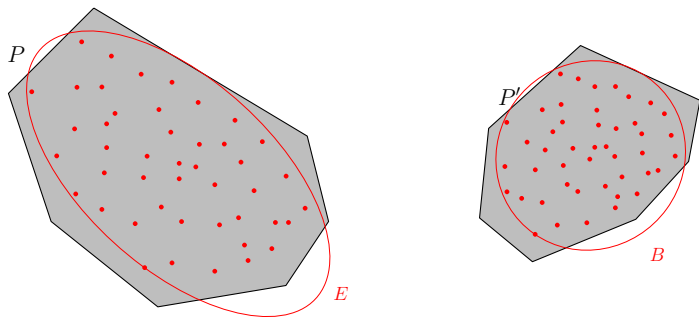
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Efficiently handle skinny polytopes in practice.

Experimental results

- ▶ approximate the volume of a **series of polytopes** (cubes, random, cross, birkhoff) up to dimension 100 in less than 2 hours with mean approximation error at most 1%

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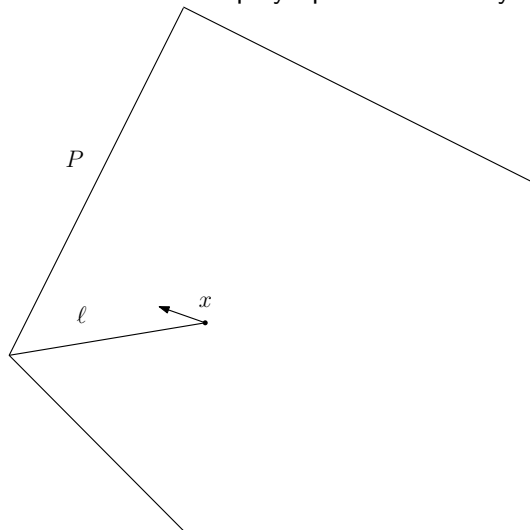
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- ▶ **CDHR** faster and more accurate than RDHR
- ▶ Compute the volume of Birkhoff polytopes B_{11}, \dots, B_{15} in few hrs whereas exact methods have **only computed that of B_{10}** by specialized software in ~ 1 year of parallel computation

Volumes of Birkhoff polytopes

n	d	estimation	asymptotic <small>[CanfieldMcKay09]</small>	<u>estimation</u> <u>asymptotic</u>	exact	<u>exact</u> <u>asymptotic</u>
3	4	1.12E+000	1.41E+000	0.7932847	1.13E+000	0.7973923
4	9	6.79E-002	7.61E-002	0.8919349	6.21E-002	0.8159296
5	16	1.41E-004	1.69E-004	0.8344350	1.41E-004	0.8341903
6	25	7.41E-009	8.62E-009	0.8598669	7.35E-009	0.8527922
7	36	5.67E-015	6.51E-015	0.8713891	5.64E-015	0.8665047
8	49	4.39E-023	5.03E-023	0.8729497	4.42E-023	0.8778632
9	64	2.62E-033	2.93E-033	0.8960767	2.60E-033	0.8874117
10	81	8.14E-046	9.81E-046	0.8305162	8.78E-046	0.8955491
11	100	1.40E-060	1.49E-060	0.9342584	???	???
12	121	7.85E-078	8.38E-078	0.9370513	???	???
13	144	1.33E-097	1.43E-097	0.9331517	???	???
14	169	5.96E-120	6.24E-120	0.9550089	???	???
15	196	5.70E-145	5.94E-145	0.9593786	???	???

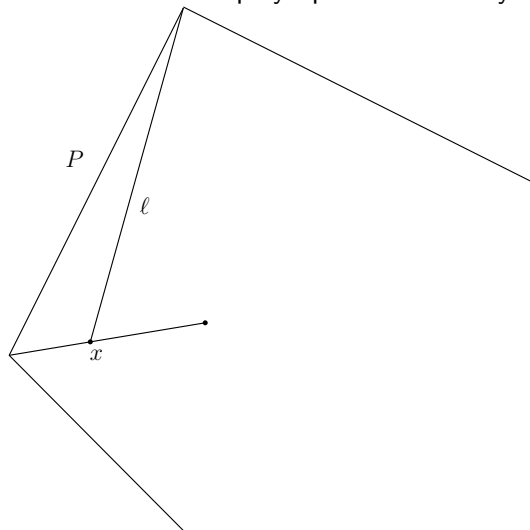
Open problem

Random walks for polytopes described by optimization oracles



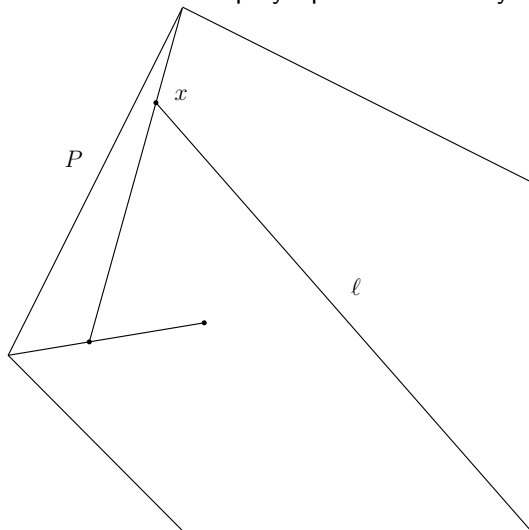
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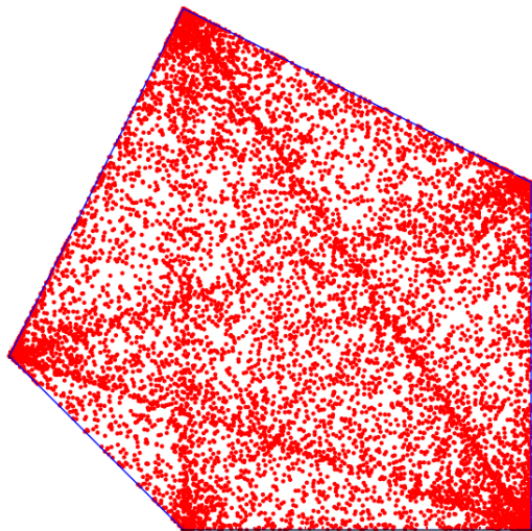
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Random walks for polytopes described by **optimization oracles**



Ongoing and future work

1. **Lattice point enumeration** using random walks
(joint with R.Yoshida, A.Campo)
2. Volume of more general convex bodies
e.g. **spectahedra**
3. Other $\#P$ -hard problems
e.g. counting **linear extensions** of posets
4. Use **approximate** oracles (utilizing approximate NN)

Conclusion

- ▶ Output-sensitive vertex enumeration for special cases of polytopes
- ▶ Practical volume estimation in high dimensions (e.g. 100)
- ▶ Software framework for testing theoretical ideas (e.g. new geometric random walks)

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