Voronoi Diagrams and Delaunay Triangulations

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Outline

- Euclidean Voronoi diagrams
- Delaunay triangulations
- Convex hulls

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Voronoi diagrams in nature





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The solar system (Descartes)



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Growth of merystem



Euclidean Voronoi diagrams



Voronoi cell
$$V(p_i) = \{x : \|x - p_i\| \le \|x - p_j\|, \forall j\}$$

Voronoi diagram (\mathcal{P}) = { cell complex whose cells are the $V(p_i)$ and their faces, $p_i \in \mathcal{P}$ }

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Polyhedra and cell complexes

Polyhedron

The intersection of a finite collection of half-spaces :

 $\mathcal{V} = \bigcap_{i \in I} h_i^+$

Polyhedra and cell complexes

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Faces of a polyhedron

$$F_J = \bigcap_{j \in J} h_j^+ \bigcap_{i \in I \setminus J} h_i$$

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Cell complex

A finite collection C of polyhedra called the faces of C such that

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$$f \in C$$
, $g \subset f \Rightarrow g \in C$

▶ $\forall f, g \in C$, either $f \cap g = \emptyset$ or $f \cap g \in C$



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Vor $(p_1, ..., p_n)$ is the minimization diagram of the *n* functions $\delta_i(x) = (x - p_i)^2$



Image: A (1)

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 $\arg\min(\delta_i) = \arg\max(h_i)$ where $h_{p_i}(x) = 2 p_i \cdot x - p_i^2$

The minimization diagram of the δ_i is also the maximization diagram of the affine functions $h_i(x)$



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The faces of Vor(\mathcal{P}) are the projection of the faces of $\mathcal{V}(\mathcal{P}) = \bigcap_i h_{p_i}^+$ $h_{p_i}^+ = \{x : x_{d+1} > 2p_i \cdot x - p_i^2\}$





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Note !

 $h_{p_i}(x) = 0$ is the hyperplane tangent to $Q: x_{d+1} = x^2$ at (x, x^2)





Lifting map

The faces of $\operatorname{Vor}(\mathcal{P})$ are the projection of the faces of the

polyhedron $\mathcal{V}(\mathcal{P}) = \bigcap_i h_{p_i}^+$

where h_{p_i} is the hyperplane tangent to paraboloid Qat the lifted point (p_i, p_i^2)

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Corollaries

- ► The size of Vor(P) is the same as the size of V(P)
- Computing Vor(P) reduces to computing V(P)

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Delaunay Triangulations

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Dual triangulation





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Convex hull of a finite point set ${\mathcal P}$



Definition

$$\operatorname{conv}(\mathcal{P}) = \{ \sum \lambda_i \boldsymbol{\rho}_i, \quad \lambda_i \ge \mathbf{0}, \quad \sum_i \lambda_i = \mathbf{1} \}$$

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k-dimensional simplex (k-simplex for short)

The convex hull of k + 1 points that are affinely independent

1-simplex = line segment 2-simplex = triangle 3-simplex = tetrahedron



Geometric simplicial complexes

Definition

A finite collection of simplices C called the faces of C such that

- $\forall f \in C, f \text{ is a simplex}$
- ▶ $f \in C, f \subset g \Rightarrow g \in C$
- ▶ $\forall f, g \in C$, either $f \cap g = \emptyset$ or $f \cap g \in C$

The dimension of the complex is the max dimension of its simplices

Abstract simplicial complexes

Given a finite set of points \mathcal{P} (not necessarily from a Euclidean space) a subset $C = \{\sigma_1, ..., \sigma_m\}$ is a simplicial complex if

1.
$$\forall i, \quad \sigma_i \subset \mathcal{P}$$

2. $\forall i$, all the subsets of σ_i are in *C*

3.
$$\forall i, j, \sigma_i \cap \sigma_j \in C$$

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Theorem

Any simplicial complex of dimension k can be embedded in \mathbb{R}^{2k+1}

Nerve of the Voronoi diagram of $\mathcal{P} = \{p_1, ..., p_n\} \subset \mathbb{R}^d$

If *j* Voronoi cells $V(p_{i_1}), ..., V(p_{i_j})$ have a non empty intersection, $conv(p_{i_1}, ..., p_{i_j})$ is a simplex of the Delaunay triangulation Del(P)



Note : $Del(\mathcal{P})$ is not always embedded in \mathbb{R}^d

Empty circumballs

- An (open) *d*-ball *B* circumscribing a simplex $\sigma \subset \mathcal{P}$ is called empty if
 - 1. $\sigma \subset \partial B$
 - **2**. $B \cap \mathcal{P} = \emptyset$

 $\mathrm{Del}(\mathcal{P})$ is the collection of simplices admitting an empty circumball



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Generic point sets

 $\mathcal{P} = \{p_1, p_2 \dots p_n\}$ is said to be generic if $\not\exists d + 1$ points of \mathcal{P} lying on a same sphere

If \mathcal{P} is generic, $t \subset \mathcal{P}$ is a Delaunay simplex iff \exists a sphere $\sigma_t = \{x, \sigma_t(x) = 0\}$ s.t.

 $\sigma_t(\boldsymbol{p}) = \mathbf{0} \ \forall \boldsymbol{p} \in t \\ \sigma_t(\boldsymbol{q}) > \mathbf{0} \ \forall \boldsymbol{q} \in \mathcal{P} \setminus t$

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$$\sigma_t(p) = 0 \ \forall p \in t$$

 $\sigma_t(q) > 0 \ \forall q \in \mathcal{P} \setminus t$

Theorem [Delaunay 1936]

If \mathcal{P} is generic, $Del(\mathcal{P})$ is embedded in \mathbb{R}^d

Proof of Delaunay's theorem

Linearization $\sigma(x) = x^2 - 2c \cdot x + s, \ s = c^2 - r^2$



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Proof of Delaunay's theorem

Linearization $\sigma(x) = x^2 - 2c \cdot x + s, \ s = c^2 - r^2$



$$egin{aligned} \sigma(x) < 0 &\Leftrightarrow \left\{ egin{aligned} z < 2c \cdot x - s & (h_\sigma^-) \ z = x^2 & (\mathcal{P}) \ & \Leftrightarrow \hat{x} = (x, x^2) \in h_\sigma^- \end{aligned}
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Proof of Delaunay's th.

t a simplex, σ_t its circumscribing sphere

$$t \in \mathrm{Del}(\mathcal{P}) \Leftrightarrow orall i, \hat{p}_i \in h_{\sigma_t}^+$$

 $\Leftrightarrow \hat{t} ext{ is a face of } ext{conv}^-(\hat{\mathcal{P}})$

Proof of Delaunay's theorem

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$$t \in \mathrm{Del}(\mathcal{P}) \Leftrightarrow orall i, \hat{p}_i \in h^+_{\sigma_t}$$

$$\Leftrightarrow \hat{t}$$
 is a face of $\operatorname{conv}^-(\hat{\mathcal{P}})$

 $\operatorname{Del}(\mathcal{P}) = \operatorname{proj}(\operatorname{conv}^{-}(\hat{\mathcal{P}}))$

Combinatorial complexity

The combinatorial complexity of the Delaunay triangulation diagram of *n* points of \mathbb{R}^d is the same as the combinatorial complexity of a convex hull of *n* points of \mathbb{R}^{d+1}



Quadratic in \mathbb{R}^3

Constructing $Del(\mathcal{P}), \quad \mathcal{P} = \{p_1, ..., p_n\} \subset \mathbb{R}^d$ Algorithm

- 1 Lift the points of \mathcal{P} onto the paraboloid $x_{d+1} = x^2$ of \mathbb{R}^{d+1} : $p_i \rightarrow \hat{p}_i = (p_i, p_i^2)$
- 2 Compute $conv(\{\hat{p}_i\})$
- 3 Project the lower hull $\operatorname{conv}^{-}(\{\hat{p}_i\})$ onto \mathbb{R}^d

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Constructing $\text{Del}(\mathcal{P}), \quad \mathcal{P} = \{p_1, ..., p_n\} \subset \mathbb{R}^d$ Algorithm

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Convex Hulls

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Set of all possible convex combinations of points in \mathcal{P} $\sum \lambda_i p_i, \quad \lambda_i \ge 0, \quad \sum_i \lambda_i = 1$

We call polytope the convex hull of a finite set of points

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Cell complex

A finite collection of polytopal cells C called the faces of C such that

▶
$$f \in C, g \subset f \Rightarrow g \in C$$

▶ $\forall f, g \in C$, either $f \cap g = \emptyset$ or $f \cap g \in C$

Simplicial complex

all faces are simplices

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Facial structure of a polytope

Supporting hyperplane

 $H \cap C \neq \emptyset$ and *C* is entirely contained in one of the two half-spaces defined by *H*



Facial structure of a polytope

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Faces

The faces of *P* are the polytopes $P \cap h$, *h* support. hyp.

Facial structure of a polytope

Supporting hyperplane

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Faces

The faces of *P* are the polytopes $P \cap h$, *h* support. hyp.

The face complex

The faces of *P* form a cell complex *C*

General position

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A point set \mathcal{P} is said to be in general position iff no subset of k + 2 points lie in a *k*-flat

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A point set \mathcal{P} is said to be in general position iff no subset of k + 2 points lie in a k-flat

Boundary complex

If $\mathcal P$ is in general position, all the faces of $\operatorname{conv}(\mathcal P)$ are simplices

The boundary of $conv(\mathcal{P})$ is a simplicial complex

Two ways of defining polyhedra



Convex hull of *n* points Intersection of *n* half-spaces

Duality between points and hyperplanes

hyperplane $h: x_d = a \cdot x' - b$ of $\mathbb{R}^d \longrightarrow$ point $h^* = (a, b) \in \mathbb{R}^{d-1} \times \mathbb{R}$

point
$$p = (p', p_d) \in \mathbb{R}^d$$
 \longrightarrow hyperplane $p^* \subset \mathbb{R}^d$
= { $(a, b) \in \mathbb{R}^d : b = p' \cdot a - p_d$ }

The mapping *

preserves incidences :

$$\begin{array}{ccc} p \in h & \Longleftrightarrow & p_d = a \cdot p' - b \Longleftrightarrow b = p' \cdot a - p_d \Longleftrightarrow h^* \in p^* \\ p \in h^+ & \Longleftrightarrow & p_d > a \cdot p' - b \Longleftrightarrow b > p' \cdot a - p_d \Longleftrightarrow h^* \in p^{*+} \end{array}$$

▶ is an involution and thus is bijective : $h^{**} = h$ and $p^{**} = p$

Duality between polytopes

Let h_1, \ldots, h_n be *n* hyperplanes de \mathbb{R}^d and let $P = \cap h_i^+$



A vertex *s* of *P* is the intersection of $k \ge d$ hyperplanes h_1, \ldots, h_k lying above all the other hyperplanes

$$\implies s^*$$
 is a hyperplane $\ni h_1^*, \dots, h_k^*$
supporting $P^*=\operatorname{conv}^-(h_1^*, \dots, h_k^*)$

General position

s is the intersection of d hyperplanes

 \implies supports a (d - 1)-face (simplex) de P*

More generally and under the general position assumption, if *f* is a (d - k)-face of *P* and $aff(f) = \bigcap_{i=1}^{k} h_i$

$$p \in f \quad \Leftrightarrow \quad h_i^* \in p^* \text{ for } i = 1, \dots, k$$
$$h_i^* \in p^{*+} \text{ for } i = k+1, \dots, n$$

$$\Leftrightarrow \quad \boldsymbol{p}^* \text{ support. hyp. of } \quad \boldsymbol{P}^* = \operatorname{conv}(h_1^*, \dots, h_n^*)$$
$$\boldsymbol{p}^* \ni h_1^*, \dots, h_k^*$$

$$\Leftrightarrow f^* = \operatorname{conv}(h_1^*, \ldots, h_k^*) \text{ is a } (k-1) - \text{face of } P^*$$

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More generally and under the general position assumption, if *f* is a (d - k)-face of *P* and $aff(f) = \bigcap_{i=1}^{k} h_i$

$$p \in f \iff h_i^* \in p^* \text{ for } i = 1, \dots, k$$

 $h_i^* \in p^{*+} \text{ for } i = k+1, \dots, r$

$$\Leftrightarrow \quad p^* \text{ support. hyp. of } P^* = \operatorname{conv}(h_1^*, \dots, h_n^*)$$
$$p^* \ni h_1^*, \dots, h_k^*$$

$$\Leftrightarrow f^* = \operatorname{conv}(h_1^*, \ldots, h_k^*) \text{ is a } (k-1) - \text{face of } P^*$$

Duality between P and P^*

- The correspondence between the faces of P and P* is involutive and therefore bijective
- ► It reverses inclusions : $\forall f, g \in P, f \subset g \Rightarrow g^* \subset f^*$

Algorithmic consequences

- Computing the intersection of *n* upper half-spaces or the lower convex hull of *n* points are equivalent problems
- Depending on the application, the primal or the dual setting may be more appropriate

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Euler formula for 3-polytopes

The numbers of vertices *s*, edges *a* and facets *f* of a polytope of \mathbb{R}^3 satisfy

s – *a* + *f* = 2

Schlegel diagram



Euler formula for 3-polytopes : s - a + f = 2

Incidences edges-facets

$$2a \ge 3f \implies a \le 3s-6$$

 $f < 2s-4$

with equality when all facets are triangles

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Beyond the 3rd dimension

Upper bound theorem

[McMullen 1970]

If *P* is the intersection of *n* half-spaces of \mathbb{R}^d

nb faces of
$$P = \Theta(n^{\lfloor \frac{d}{2} \rfloor})$$

Beyond the 3rd dimension

Upper bound theorem

[McMullen 1970]

If *P* is the intersection of *n* half-spaces of \mathbb{R}^d

nb faces of
$$P = \Theta(n^{\lfloor \frac{d}{2} \rfloor})$$

General position

- all vertices of P are incident to d edges (in the worst-case) and have distinct x_d
- the convex hull of k < d edges incident to a vertex p is a k-face of P
- ► any k-face is the intersection of d k hyperplanes defining P

Proof of the upper bound th.

Bounding the number of vertices

- 1. $\geq \lceil \frac{d}{2} \rceil$ edges incident to a vertex *p* are in $h_{\rho}^+ : x_d \geq x_d(p)$ or in h_{ρ}^-
 - \Rightarrow *p* is a *x_d*-max or *x_d*-min vertex of at least one $\lceil \frac{d}{2} \rceil$ -face of *P*
 - \Rightarrow # vertices of $P \leq 2 \times \# \lfloor \frac{d}{2} \rfloor$ -faces of P

Proof of the upper bound th.

Bounding the number of vertices

 \Rightarrow ≥ $\lceil \frac{d}{2} \rceil$ edges incident to a vertex *p* are in *h*⁺_{*p*} : *x*_{*d*} ≥ *x*_{*d*}(*p*) or in *h*⁻_{*p*}

 $\Rightarrow p \text{ is a } x_d \text{-max or } x_d \text{-min vertex of at least one } \lceil \frac{d}{2} \rceil \text{-face of } P$

 \Rightarrow # vertices of $P \le 2 \times \# \lfloor \frac{d}{2} \rfloor$ -faces of P

2. A k-face is the intersection of d - k hyperplanes defining P

$$\Rightarrow \# k \text{-faces} = \binom{n}{d-k} = O(n^{d-k})$$
$$\# \lceil \frac{d}{2} \rceil \text{-faces} = O(n^{\lfloor \frac{d}{2} \rfloor})$$

Proof of the upper bound th.

Bounding the number of vertices

 \Rightarrow ≥ $\lceil \frac{d}{2} \rceil$ edges incident to a vertex *p* are in *h*⁺_{*p*} : *x*_{*d*} ≥ *x*_{*d*}(*p*) or in *h*⁻_{*p*}

⇒ *p* is a *x_d*-max or *x_d*-min vertex of at least one $\lceil \frac{d}{2} \rceil$ -face of *P* ⇒ # vertices of *P* ≤ 2×# $\lceil \frac{d}{2} \rceil$ -faces of *P*

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Bounding the total number of faces

The number of faces incident to p depends on d but not on n

Representation of a convex hull

Adjacency graph (AG) of the facets

In general position, all the facets are (d - 1)-simplexes



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Incremental algorithm

 \mathcal{P}_i : set of the *i* points that have been inserted first

 $conv(\mathcal{P}_i)$: convex hull at step *i*



 $f = [p_1, ..., p_d]$ is a red facet iff its supporting hyperplane separates p_i from conv(\mathcal{P}_i)

 $\iff \texttt{orient}(p_1,...,p_d,p_i) \times \texttt{orient}(p_1,...,p_d,O) < 0$

orient
$$(p_0, p_1, ..., p_d) = \begin{vmatrix} 1 & 1 & ... & 1 \\ p_0 & p_1 & ... & p_d \end{vmatrix} = \begin{vmatrix} 1 & 1 & ... & 1 \\ x_{01} & x_{11} & ... & x_{d1} \\ \vdots & \vdots & ... & \vdots \\ x_{0d} & x_{1d} & ... & x_{dd} \end{vmatrix}$$

Update of $conv(\mathcal{P}_i)$

red facet = facet whose supporting hyperplane separates o and p_{i+1}

horizon : (d - 2)-faces shared by a blue and a red facet

Update $conv(\mathcal{P}_i)$:

- 1. find the red facets
- 2. remove them and create the new facets

 $[p_{i+1}, g], \forall g \in horizon$



Update of $conv(\mathcal{P}_i)$

red facet = facet whose supporting hyperplane separates o and p_{i+1}

horizon : (d - 2)-faces shared by a blue and a red facet

Update $conv(\mathcal{P}_i)$:

- 1. find the red facets
- 2. remove them and create the new facets

 $[p_{i+1}, g], \forall g \in horizon$

Complexity

proportional to the nb of red facets



Complexity analysis

- update proportionnal to the number of red facets
- ► # new facets = $|\operatorname{conv}(i, d-1)|$ = $O(i^{\lfloor \frac{d-1}{2} \rfloor})$
- fast locate : insert the points in lexicographic order and search a 1st red facet in star(p_{i-1}) (which necessarily exists)



Complexity analysis

- update proportionnal to the number of red facets
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- fast locate : insert the points in lexicographic order and search a 1st red facet in star(p_{i-1}) (which necessarily exists)



$$T(n,d) = O(n\log n) + \sum_{i=1}^{n} i^{\lfloor \frac{d-1}{2} \rfloor}$$

= $O(n\log n + n^{\lfloor \frac{d-1}{2} \rfloor})$

Worst-case optimal in even dimensions

Lower bound



 $\operatorname{conv}(\{p_i\}) \Longrightarrow \operatorname{tri}(\{x_i\})$

the orientation test reduces to 3 comparisons

orient
$$(p_i, p_j, p_k) = \begin{vmatrix} x_i - x_j & x_i - x_k \\ x_i^2 - x_j^2 & x_i^2 - x_k^2 \end{vmatrix}$$

$$= (x_i - x_j)(x_j - x_k)(x_k - x_i)$$

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 \implies Lower bound : $\Omega(n \log n)$

Lower bound for the incremental algorithm



No incremental algorithm can compute the convex hull of *n* points of \mathbb{R}^3 in less than $\Omega(n^2)$

Randomized incremental algorithm

o a point inside $conv(\mathcal{P})$

 \mathcal{P}_i : the set of the first *i* inserted points

 $\operatorname{conv}(\mathcal{P}_i)$: convex hull at step *i*



Randomized incremental algorithm

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Conflict graph

bipartite graph $\{p_j\} \times \{\text{facets of } \operatorname{conv}(\mathcal{P}_i)\}$

$$p_j \dagger f \Longleftrightarrow j > i$$
 (p_j not yet inserted), $f \cap op_j \neq \emptyset$

Hyp. : points are inserted in random order

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Hyp. : points are inserted in random order

Notations

- R : random sample of size r of \mathcal{P}
- $F(R) = \{ \text{ subsets of } d \text{ points of } R \}$

 $F_0(R) = \{ \text{ elements of } F(R) \text{ with 0 conflict in } R \}$

(i.e. $\in \operatorname{conv}(R)$)

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 $F_1(R) = \{ \text{ elements of } F(R) \text{ with 1 conflict in } R \}$

 $C_i(r, \mathcal{P}) = E(|F_i(R)|)$ (expectation over all random samples $R \subset \mathcal{P}$ of size r)

Hyp. : points are inserted in random order

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Lemma

$$C_1(r,\mathcal{P}) = C_0(r,\mathcal{P}) = O(r^{\lfloor \frac{\alpha}{2} \rfloor})$$

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Proof of the lemma : $C_1(r, \mathcal{P}) = C_0(r, \mathcal{P}) = O(r^{\lfloor \frac{d}{2} \rfloor})$ $R' = R \setminus \{p\}$

$$\begin{array}{ll} f \in F_0(R') \text{ if } & f \in F_1(R) \text{ and } p \dagger f & (\text{proba} = \frac{1}{r}) \\ \text{or } & f \in F_0(R) \text{ and } R' \ni \text{the } d \text{ vertices of } f & (\text{proba} = \frac{r-d}{r}) \end{array}$$

Taking the expectation,

$$\begin{array}{lll} C_0(r-1,R) &=& \frac{1}{r} \, |F_1(R)| + \frac{r-d}{r} \, |F_0(R)| \\ C_0(r-1,\mathcal{P}) &=& \frac{1}{r} \, C_1(r,\mathcal{P}) + \frac{r-d}{r} \, C_0(r,\mathcal{P}) \\ C_1(r,\mathcal{P}) &=& d \, C_0(r,\mathcal{P}) - r \, (C_0(r,\mathcal{P}) - C_0(r-1,\mathcal{P})) \\ &\leq& d \, C_0(r,\mathcal{P}) \\ &=& O(r^{\lfloor \frac{d}{2} \rfloor}) \end{array}$$

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Updating the convex hull + memory space

Expected number N(i) of facets created at step *i*

$$N(i) = \sum_{f \in F(\mathcal{P})} \operatorname{proba}(f \in F_0(\mathcal{P}_i)) \times \frac{d}{i}$$
$$= \frac{d}{i} O\left(i^{\lfloor \frac{d}{2} \rfloor}\right)$$
$$= O(n^{\lfloor \frac{d}{2} \rfloor - 1})$$

Expected total number of created facets = $O(n^{\lfloor \frac{d}{2} \rfloor})$ O(n) if d = 2, 3

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Updating the conflict graph

Cost proportional to the total number of conflicts between facets that have been created and points not yet inserted

$$\begin{split} & \textit{N}(i,j) = \text{expected number of conflicts } f \dagger \textit{p}_j \\ & \textit{f face of conv}(\mathcal{P}_i) \text{ created at step } i \\ & \textit{j} > i \end{split}$$

$$\begin{array}{l} \mathcal{P}_i : \text{a random subset of } \mathcal{P} \\ p_j : \text{a random point of } \mathcal{P} \setminus \mathcal{P}_i \\ \mathcal{P}_i^+ = \mathcal{P}_i \cup \{p_j\} : \text{a random subset of } i+1 \text{ points of } \mathcal{P} \\ N(i,j) = \sum_{f \in \mathcal{F}(\mathcal{P})} \operatorname{proba}(f \in \mathcal{F}_1(\mathcal{P}_i^+)) \times \frac{d}{i} \times \frac{1}{i+1} = \frac{d C_1(i+1)}{i(i+1)} \end{array}$$

Expected total cost of updating the conflict graph

$$\sum_{i=1}^{n} \sum_{j=i+1}^{n} N(i,j) = O(n \log n + n^{\lfloor \frac{d}{2} \rfloor})$$

Ξ.

Theorem

- ► The convex hull of *n* points of \mathbb{R}^d can be computed in time $O(n \log n + n^{\lfloor \frac{d}{2} \rfloor})$ using $O(n^{\lfloor \frac{d}{2} \rfloor})$ space
- ► The same bounds hold for computing the intersection of n half-spaces of ℝ^d
- The randomized algorithm can be derandomized

[Chazelle 1992]

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► The same results hold for Voronoi diagrams and Delaunay triangulations provided that d → d + 1



You know my methods. Apply them ! Sherlock Holmes