

# Good Triangulations

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# Definition and existence of nets

## Definition

Let  $\Omega$  be a bounded subset of  $\mathbb{R}^d$ . A finite set of points  $P$  is called an  $(\varepsilon, \bar{\eta})$ -net of  $\Omega$  iff

**Density** :  $\forall x \in \Omega, \exists p \in P : \|x - p\| \leq \varepsilon$

**Separation** :  $\forall p, q \in P : \|p - q\| \geq \bar{\eta} \varepsilon$

**Lemma**  $\Omega$  admits an  $(\varepsilon, 1)$ -net.

**Proof.** While there exists a point  $p \in \Omega, d(p, P) \geq \varepsilon$ , insert  $p$  in  $P$

# Size of a net

**Lemma** The number of points of an  $(\varepsilon, \bar{\eta})$ -net is at most

$$n(\varepsilon, \bar{\eta}) \leq \frac{\text{vol}_d(\Omega_{\frac{\eta}{2}})}{\text{vol}_d(B(\frac{\eta}{2}))} = O\left(\frac{1}{\varepsilon^d}\right)$$

where the constant in the  $O$  depends on the geometry of  $\Omega$  and on  $\bar{\eta}^d$ .

**Proof.** Consider the balls  $B(p, \frac{\eta}{2})$  of radius  $\frac{\eta}{2}$  that are centered at the points  $p \in P$ . These balls are disjoint by definition of an  $(\varepsilon, \bar{\eta})$ -sample and they are all contained in  $\Omega_{\frac{\eta}{2}}$

## Delaunay complex of a net

**lemma** Let  $\Omega$  be a bounded subset of  $\mathbb{R}^d$ ,  $P$  an  $(\varepsilon, \bar{\eta})$ -net of  $\Omega$ , and assume that  $d$  and  $\bar{\eta}$  are positive constants. The restriction of the Delaunay triangulation of  $P$  to  $\Omega$  has linear size  $O(n)$  where  $n = |P| = O(\frac{1}{\varepsilon^d})$

**Proof.** 1. First bound the number of neighbours of  $p$  is  $n_p = O(1)$  using a volume argument

2. Bound the number of simplices incident on a vertex is at most

$$\sum_{i=1}^{d+1} \binom{n_p}{i} \leq \sum_{i=0}^{n_p} \binom{n_p}{i} = 2^{n_p}.$$

3. For the construction, use a grid  $G_\varepsilon$  of resolution  $\varepsilon$  and compute, for each  $p \in P$ , the subset  $N(p) \subset P$  of points that lie at distance at most  $2\varepsilon$  from the cell that contains  $p$ . We have

$$|N(p)| = O(1) \quad \text{and} \quad \text{star}(p, \text{Del}_{|\Omega}(P)) = \text{star}(p, \text{Del}_{|\Omega}(N(p)))$$

# Nets in discrete metric spaces

We are only given the distance of interpoint distances (not the locations of the points)

**Lemma** Let  $W$  be a finite set of points such that the distance of any point  $q \in W$  to  $W \setminus \{q\}$  is at most  $\varepsilon$  and let  $\lambda \geq \varepsilon$ . One can extract from  $W$  a subsample  $L$  that is a  $(\lambda, 1)$ -net of  $W$ .

# Farthest point insertion

**Input:** the distance matrix of a finite point set  $W$  and either a positive constant  $\lambda$  (Case 1) or an integer  $k$  (Case 2)

1.  $L := \emptyset$
2.  $L(w) := p_\infty$  for all  $w \in W$
3.  $\lambda^* := \max_{w \in W} \|w - L(w)\|$
4.  $w^* :=$  a point  $p \in W$  such that  $\|p - L(p)\| = \lambda^*$
5. **while** either  $\lambda^* > \lambda$  (Case 1) or  $|L| < k$  (Case 2)
  - 5.1 add  $w^*$  to  $L$
  - 5.2 **for** each point  $w$  of  $W$  such that  $\|w - w^*\| < \|w - L(w)\|$  **do**
    - 5.2.1  $L(w) := w^*$
    - 5.2.2 update  $w^*$
6. **Output :**  $L \subseteq W$ , a  $(\lambda, 1)$ -net of  $W$  (Case 1), an approximate solution to the  $k$ -centers problem (Case 2)

# Analysis of the algorithm

For any  $i > 0$ ,  $L_i = \{p_1, \dots, p_i\}$  and  $\lambda_i = d(p_i, L_{i-1})$

Since  $L_i$  grows with  $i$ :  $j \geq i \Rightarrow \lambda_j \leq \lambda_i$

**Lemma** At each iteration  $i > 0$ ,  $L_i$  is a  $(\lambda_i, 1)$ -net of  $W$ .

## Proof

1.  $L_i$  is  $\lambda_i$ -dense in  $W$  ...
2.  $L_i$  is  $\lambda_i$ -separated:  $p_a p_b$  closest par in  $L_i$ ,  $\|p_a - p_b\| = \lambda_b \geq \lambda_i$

# The $k$ -centers problem

**Problem :** Select from  $W$  a subset  $L$  of  $k$  points so as to maximize the minimum pairwise distance between the points of  $L$ .

**Lemma** The farthest insertion algorithm (Case 2) provides a 2-approximation to the  $k$ -centers problem.

## Proof

- $W \subset \bigcup_{i=1}^{k-1} B(l_i, \lambda_k)$ 
  - $\Rightarrow$  Two points of  $L_{\text{opt}}$  lie in the same ball  $B(l_i, \lambda_k)$ ,  $i \leq k - 1$
  - $\Rightarrow \exists p, q \in L_{\text{opt}}$  s.t.  $\|p - q\| \leq 2\lambda_k$
- The distance between any two points of  $L$  is at least  $\lambda_k$ .



# Some optimality properties of Delaunay triangulations

Among all possible triangulations of  $\mathcal{P}$ ,  $\text{Del}(\mathcal{P})$

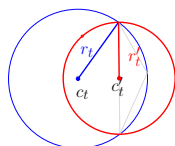
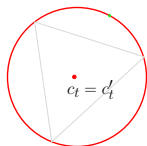
1 (2d) maximizes the smallest angle [Lawson]

2 (2d) Linear interpolation of  $\{(p_i, f(p_i))\}$  that minimizes [Rippa]

$$R(T) = \sum_i \int_{T_i} \left( \left( \frac{\partial \phi_i}{\partial x} \right)^2 + \left( \frac{\partial \phi_i}{\partial y} \right)^2 \right) dx dy \quad (\text{Dirichlet energy})$$

$\phi_i =$  linear interpolation of the  $f(p_j)$  over triangle  $T_i \in T$

3 minimizes the radius of the maximal smallest ball enclosing a simplex ) [Rajan]



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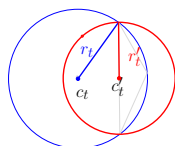
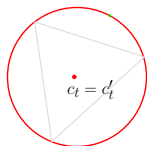
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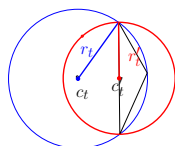
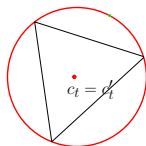
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# Optimizing the angular vector ( $d = 2$ )

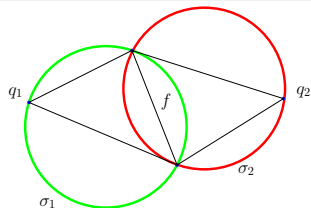
Angular vector of a triangulation  $T(\mathcal{P})$

$$\text{ang}(T(\mathcal{P})) = (\alpha_1, \dots, \alpha_{3t}), \quad \alpha_1 \leq \dots \leq \alpha_{3t}$$

**Optimality** Any triangulation of a given point set  $\mathcal{P}$  whose angular vector is maximal (for the lexicographic order) is a Delaunay triangulation of  $\mathcal{P}$

Good for matrix conditioning in FE methods

# Local characterization of Delaunay complexes



Pair of regular simplices

$$\sigma_2(q_1) \geq 0 \quad \text{and} \quad \sigma_1(q_2) \geq 0$$

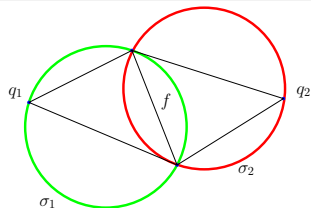
$$\Leftrightarrow \hat{c}_1 \in h_{\sigma_2}^+ \quad \text{and} \quad \hat{c}_2 \in h_{\sigma_1}^+$$

**Theorem** A triangulation  $T(P)$  such that all pairs of simplexes are regular is a Delaunay triangulation  $\text{Del}(P)$

**Proof** The PL function whose graph  $G$  is obtained by lifting the triangles is locally convex and has a convex support

$$\Rightarrow G = \text{conv}^-(\hat{Q}) \quad \Rightarrow T(Q) = \text{Del}(Q)$$

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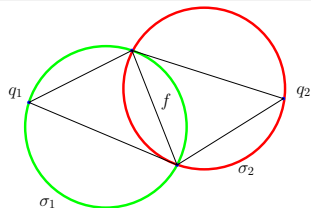
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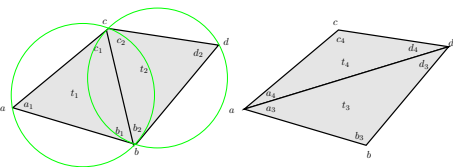
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# Lawson's proof using flips



While  $\exists$  a non regular pair  $(t_3, t_4)$

/\*  $t_3 \cup t_4$  is convex \*/

replace  $(t_3, t_4)$  by  $(t_1, t_2)$

Regularize  $\Leftrightarrow$  improve  $\text{ang}(T(\mathcal{P}))$

$$\text{ang}(t_1, t_2) \geq \text{ang}(t_3, t_4)$$

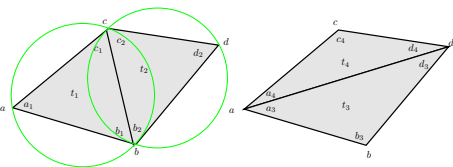
$$a_1 = a_3 + a_4, \quad d_2 = d_3 + d_4,$$

$$c_1 \geq d_3, \quad b_1 \geq d_4, \quad b_2 \geq a_4, \quad c_2 \geq a_3$$

- ▶ The algorithm terminates since the number of triangulations of  $\mathcal{P}$  is finite and  $\text{ang}(T(\mathcal{P}))$  cannot decrease
- ▶ The obtained triangulation is a Delaunay triangulation of  $\mathcal{P}$  since all its edges are regular



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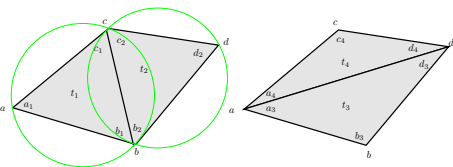
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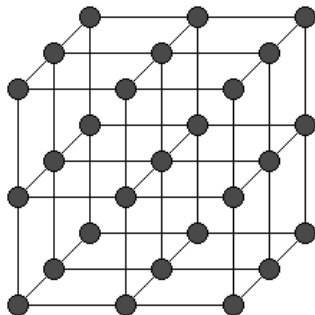
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## Flat simplices may exist in higher dimensional DT



- Each square face can be circumscribed by an empty sphere
- This remains true if the grid points are slightly perturbed therefore creating flat tetrahedra

# The long quest for thick triangulations

Differential Topology

[Cairns], [Whitehead], [Whitney], [Munkres]

Differential Geometry

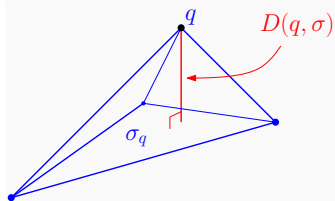
[Cheeger et al.]

Geometric Function Theory

[Peltonen], [Saucan]

# Simplex quality

## Altitudes



If  $\sigma_q$ , the face opposite  $q$  in  $\sigma$  is protected, The *altitude* of  $q$  in  $\sigma$  is

$$D(q, \sigma) = d(q, \text{aff}(\sigma_q)),$$

where  $\sigma_q$  is the face opposite  $q$ .

## Definition (Thickness

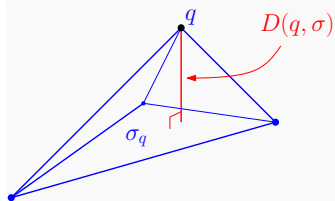
[Cairns, Whitney, Whitehead et al.] )

The *thickness* of a  $j$ -simplex  $\sigma$  with diameter  $\Delta(\sigma)$  is

$$\Theta(\sigma) = \begin{cases} 1 & \text{if } j = 0 \\ \min_{p \in \sigma} \frac{D(p, \sigma)}{j \Delta(\sigma)} & \text{otherwise.} \end{cases}$$

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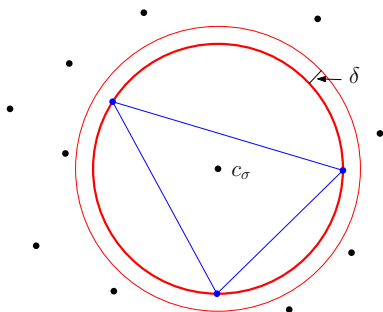
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**$\delta$ -protection** We say that a Delaunay simplex  $\sigma \subset L$  is  $\delta$ -protected if

$$\|c_\sigma - q\| > \|c_\sigma - p\| + \delta \quad \forall p \in \sigma \text{ and } \forall q \in L \setminus \sigma.$$

# Protection implies separation and thickness

Let  $P$  be a  $(\varepsilon, \bar{\eta})$ -net, i.e.

- $\forall x \in \Omega, \quad d(x, P) \leq \varepsilon$
- $\forall p, q \in P, \quad \|p - q\| \geq \bar{\eta}\varepsilon$

if all  $d$ -simplices of  $\text{Del}(P)$  are  $\bar{\delta}\varepsilon$ -protected, then

- **Separation** of  $P$  :  $\bar{\eta} \geq \bar{\delta}$
- **Thickness** :  $\forall \sigma \in \text{Del}(P), \quad \Theta(\sigma) \geq \frac{\bar{\delta}^2}{8d}$



# The Lovász Local Lemma

## Motivation

**Given:** A set of (bad) events  $A_1, \dots, A_N$ ,  
each happens with  $\text{proba}(A_i) \leq p < 1$

**Question :** what is the probability that none of the events occur?

The case of independent events

$$\text{proba}(\neg A_1 \wedge \dots \wedge \neg A_N) \geq (1 - p)^N > 0$$

What if we allow a limited amount of dependency among the events?

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Under the assumptions

- 1  $\text{proba}(A_i) \leq p < 1$
- 2  $A_i$  depends of  $\leq \Gamma$  other events  $A_j$
- 3  $\text{proba}(A_i) \leq \frac{1}{e^{(\Gamma+1)}}$        $e = 2.718\dots$

then

$$\text{proba}(\neg A_1 \wedge \dots \wedge \neg A_N) > 0$$

# Moser and Tardos' constructive proof of the LLL [2010]

$\mathcal{P}$  a finite set of mutually independent random variables

$\mathcal{A}$  a finite set of events that are determined by the values of  $S \subseteq \mathcal{P}$

Two events are independent iff they share no variable

## Algorithm

**for all**  $P \in \mathcal{P}$  **do**

$v_P \leftarrow$  a random evaluation of  $P$ ;

**while**  $\exists A \in \mathcal{A} : A$  happens when  $(P = v_P, P \in \mathcal{P})$  **do**

pick an arbitrary happening event  $A \in \mathcal{A}$ ;

**for all**  $P \in \text{variables}(A)$  **do**

$v_P \leftarrow$  a new random evaluation of  $P$ ;

**return**  $(v_P)_{P \in \mathcal{P}}$ ;

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# Moser and Tardos' theorem

if

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**then**  $\exists$  an assignment of values to the variables  $\mathcal{P}$  such that no event in  $\mathcal{A}$  happens

The randomized algorithm resamples an event  $A \in \mathcal{A}$  at most expected times before it finds such an evaluation

$$\frac{1}{\Gamma}$$

The expected total number of resampling steps is at most

$$\frac{N}{\Gamma}$$

- Read the proof of Moser & Tardos (or Spencer's nice note)
- Learn about the parallel and the derandomized versions
- Listen to a talk by Aravind Srinivasan on further extensions  
<https://video.ias.edu/csdm/2014/0407-AravindSrinivasan>



# Protecting Delaunay simplices via perturbation

Picking regions : pick  $p'$  in  $B(p, \rho)$     Hyp.     $\rho \leq \frac{\eta}{4}$  ( $\leq \frac{\varepsilon}{2}$ )

Sampling parameters of a perturbed point set

If  $P$  is an  $(\varepsilon, \bar{\eta})$ -net,     $P'$  is an  $(\varepsilon', \bar{\eta}')$ -net, where

$$\varepsilon' = \varepsilon(1 + \bar{\rho}) \quad \text{and} \quad \bar{\eta}' = \frac{\bar{\eta} - 2\bar{\rho}}{1 + \bar{\rho}} \geq \frac{\bar{\eta}}{3}$$

Notation :  $\bar{x} = \frac{x}{\varepsilon}$

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# The LLL framework

**Random variables :**  $P'$  a set of random points  $\{p', p' \in B(p, \rho), p \in P\}$

**Event:**  $\exists \phi' = (\sigma', p')$  (Bad configuration)  
 $\sigma'$  is a  $d$  simplex with  $R_{\sigma'} \leq \varepsilon + \rho$   
 $p' \in Z_\delta(\sigma') \quad Z_\delta(\sigma') = B(c_{\sigma'}, R_{\sigma'} + \delta) \setminus B(c_{\sigma'}, R_{\sigma'})$

## Algorithm

**Input:**  $P, \rho, \delta$

**while** an event  $\phi' = (\sigma', p')$  occurs **do**

resample the points of  $\phi'$

update  $\text{Del}(P')$

**Output:**  $P'$  and  $\text{Del}(P')$

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## Algorithm

**Input:**  $P, \rho, \delta$

**while** an event  $\phi' = (\sigma', p')$  occurs **do**

    resample the points of  $\phi'$

    update  $\text{Del}(P')$

**Output:**  $P'$  and  $\text{Del}(P')$

# Bounding $\Gamma$

**Lemma** : An event is independent of all but at most  $\Gamma$  other bad events where  $\Gamma$  depends on  $\bar{\eta}$ ,  $\bar{\rho}$ ,  $\bar{\delta}$  and  $d$

**Proof** :

- Let  $\phi' = (\sigma', p')$  be a bad configuration.

$$\forall p' \in \phi', \quad \|p' - c_{\sigma'}\| \leq R_{\sigma'} + \delta = R = \varepsilon + \rho + \delta = \varepsilon (1 + \bar{\rho} + \bar{\delta})$$

- the number of events that may not be independent from an event  $(\sigma', p')$  is at most the number of subsets of  $(d + 1)$  points in  $B(c_{\sigma'}, 3R)$ .
- Since  $P'$  is  $\eta'$ -sparse,

$$\Gamma = \left( \frac{3R + \frac{\eta'}{2}}{\frac{\eta'}{2}} \right)^{d(d+1)} = \left( 1 + 6 \frac{(1 + \bar{\rho} + \bar{\delta})(1 + \bar{\rho})}{\bar{\eta} - 2\bar{\rho}} \right)^{d(d+1)}$$

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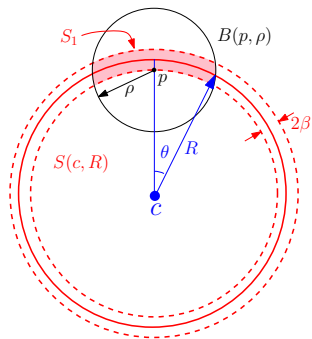
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# Bounding $\text{proba}(\sigma, p)$ be a bad configuration



$S(c, R)$  a hypersphere of  $\mathbb{R}^d$

$$T_\delta = B(c, R + \delta) \setminus B(c, R)$$

$B_\rho$  any  $d$ -ball of radius  $\rho < R$

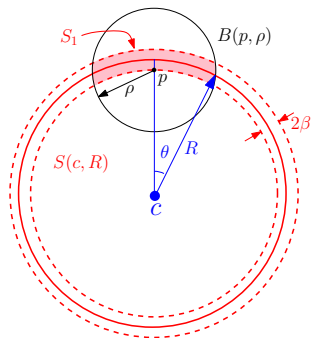
$$\text{vol}_d(T_\delta \cap B_\rho) \leq U_{d-1} (R\theta)^{d-1} \delta,$$

$$\frac{2}{\pi} \theta \leq \sin \theta \leq \frac{\rho}{R} \quad (\theta < \frac{\pi}{2} \Leftrightarrow \rho < R)$$

$$\Rightarrow R\theta \leq \frac{\pi}{2} \rho$$

$$\text{proba}(p' \in Z_\delta(\sigma')) \leq \varpi = \frac{U_{d-1}}{U_d} \frac{2}{\pi} \frac{\delta}{\rho} \leq \frac{C}{\sqrt{d}} \frac{\delta}{\rho}$$

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# Main result

Under condition

$$\frac{2^{d+1}e}{\pi} (\Gamma + 1) \delta \leq \rho \leq \frac{\eta}{4}$$

the algorithm terminates.

## Guarantees on the output

- ▶  $d_H(P, P') \leq \rho$
- ▶ the  $d$ -simplices of  $\text{Del}(P')$  are  $\delta$ -protected
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## Bound on the number of events

$\Sigma(p')$  : number of  $d$ -simplices that can possibly make a bad configuration with  $p' \in P'$  for some perturbed set  $P'$

$$R = \varepsilon + \rho + \delta$$

$$\begin{aligned} \sum_{p' \in P'} \Sigma(p') &\leq n \times |P' \cap B(p', 2R)|^{d+1} \\ &\leq n \left( \frac{2(1 + \bar{\rho} + \bar{\delta} + \frac{\bar{\eta}'}{2})}{\frac{\bar{\eta}'}{2}} \right)^{d(d+1)} \\ &= C' n \end{aligned}$$

# Complexity of the algorithm

- The number of resamplings executed by the algorithm is at most

$$\frac{Cn}{\Gamma} \leq C'' n$$

where  $C''$  depends on  $\bar{\eta}$ ,  $\bar{\rho}$ ,  $\bar{\delta}$  and (exponentially)  $d$

- Each resampling consists in perturbing  $O(1)$  points
- Updating the Delaunay triangulation after each resampling takes  $O(1)$  time
- The expected complexity is **linear in the number of points**