

INF562 – Géométrie Algorithmique et Applications

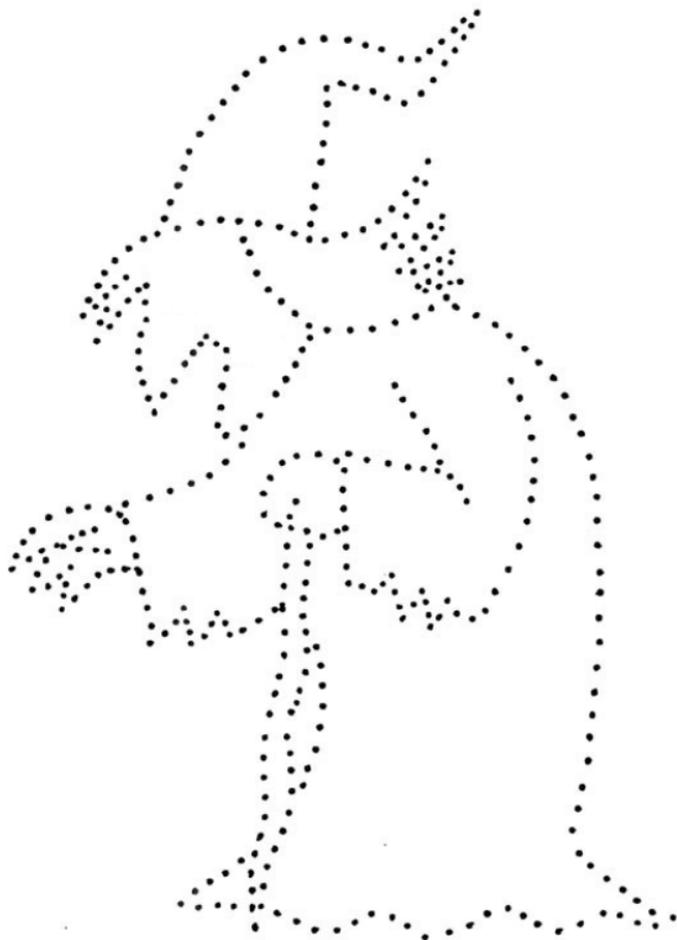
Curve and surface reconstruction

Steve Oudot

Reconstruction Paradigm

Q What do you see?

Why?



Reconstruction Paradigm

Q What do you see?

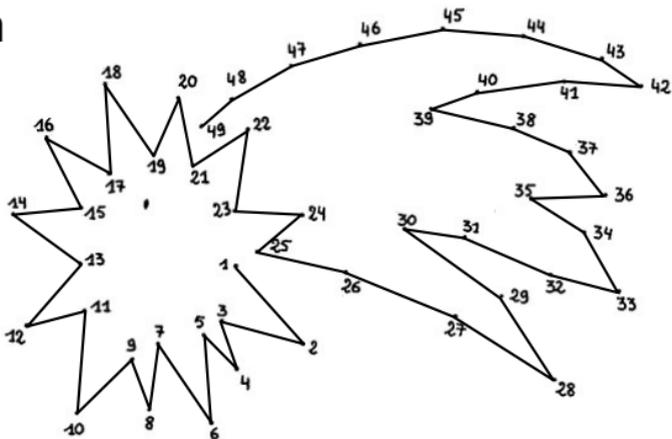
Why?



Reconstruction Paradigm

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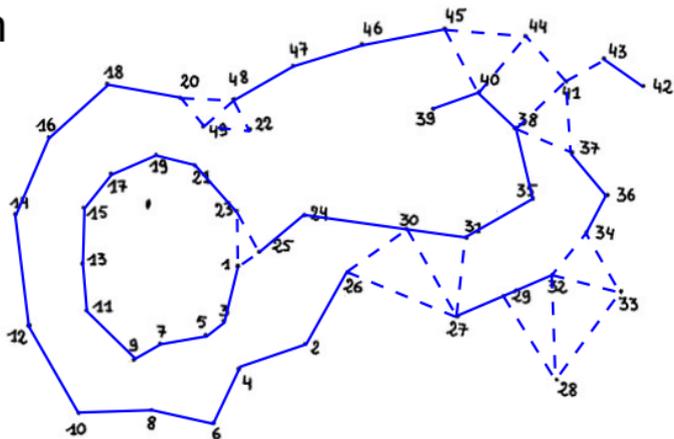


Reconstruction Paradigm

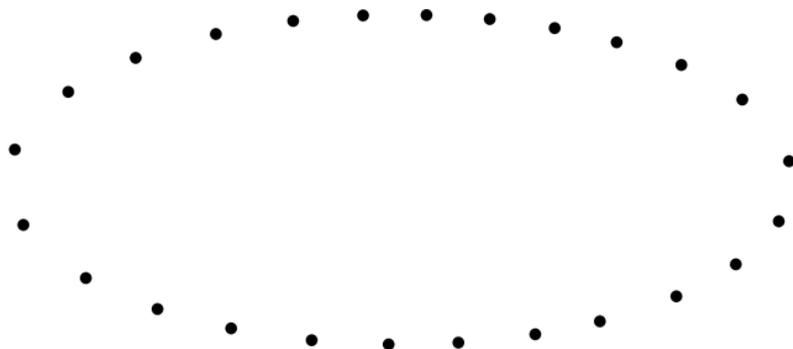
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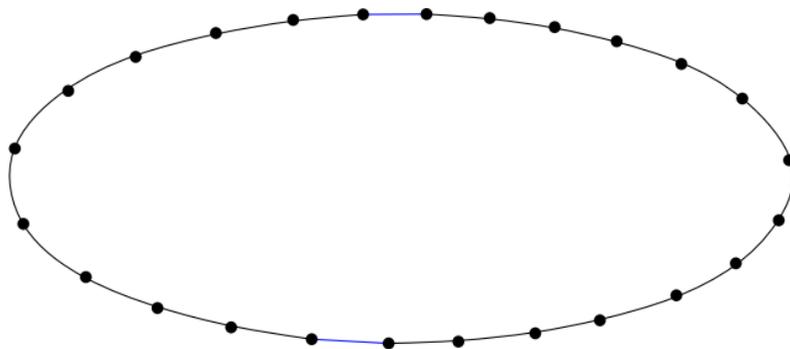
without the numbers...



Reconstruction Paradigm (Cont'd)

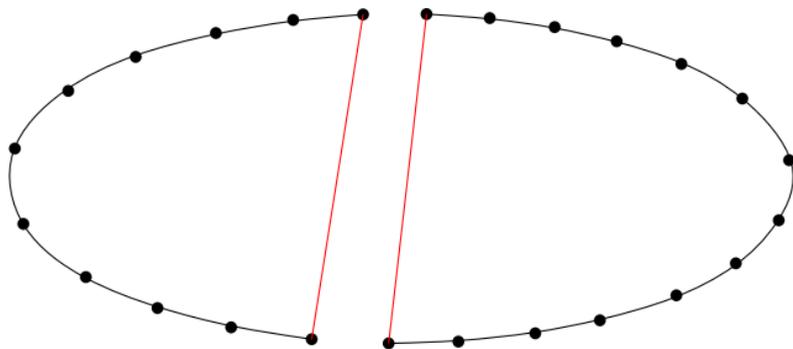


Reconstruction Paradigm (Cont'd)



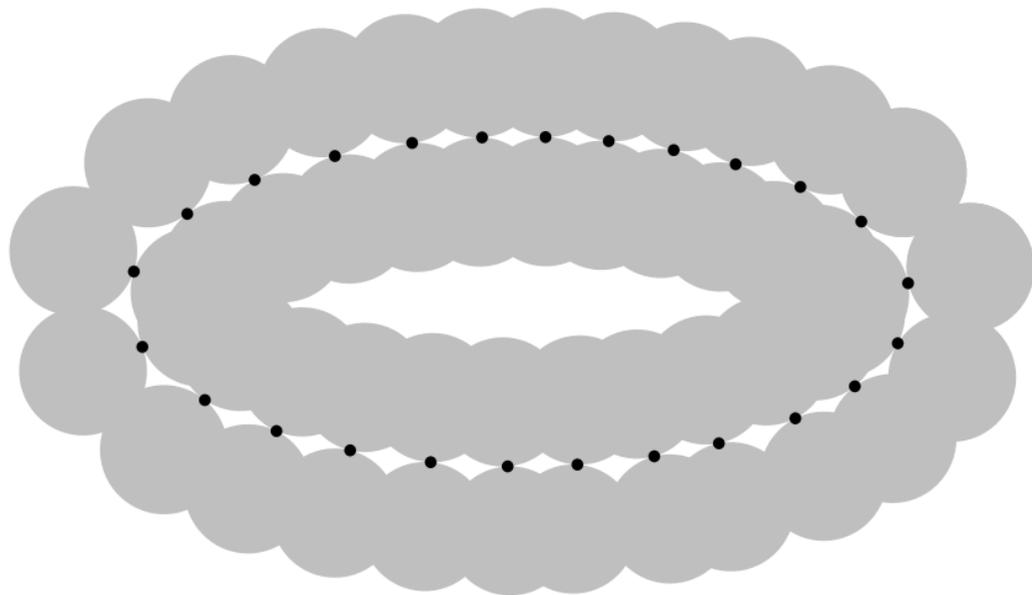
Q Given a point cloud, build a *faithful* (implicit, PL, ...) approximation of the shape underlying the data.

Reconstruction Paradigm (Cont'd)



Reconstruction problem is ill-posed by nature.

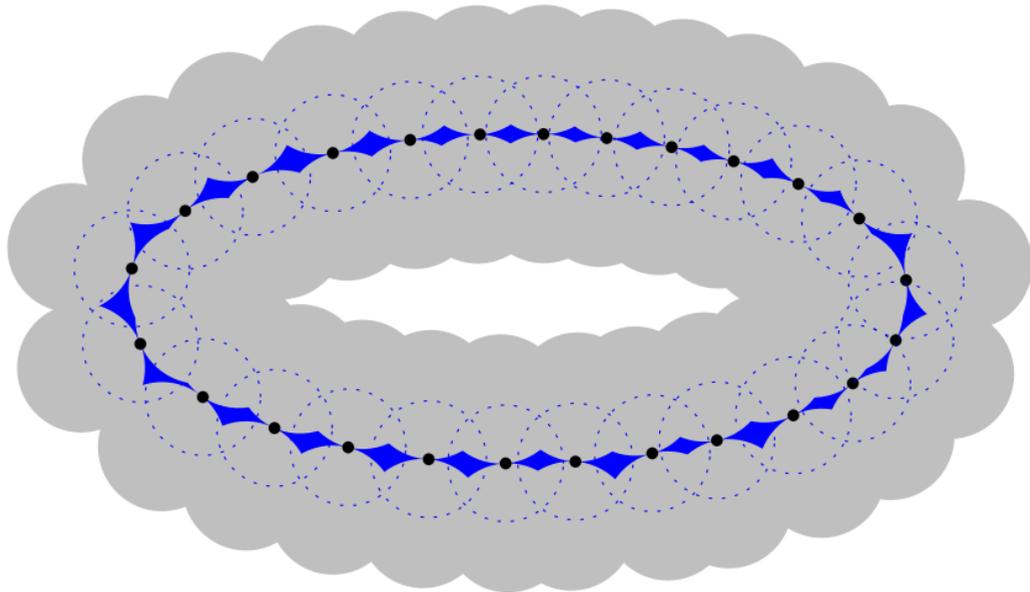
Reconstruction Paradigm (Cont'd)



Reconstruction problem is ill-posed by nature.

→ make assumptions on the underlying shape, *e.g.*: fix dimension, topological type, regularity (differentiability), Hausdorff distance to input...

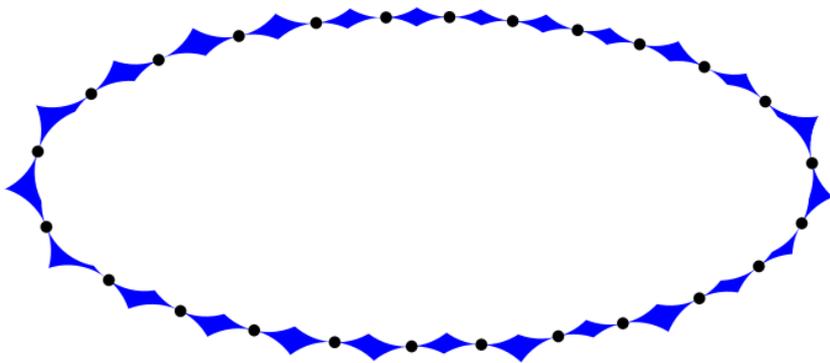
Reconstruction Paradigm (Cont'd)



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Reconstruction Paradigm (Cont'd)

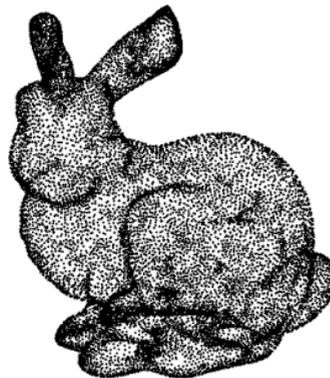
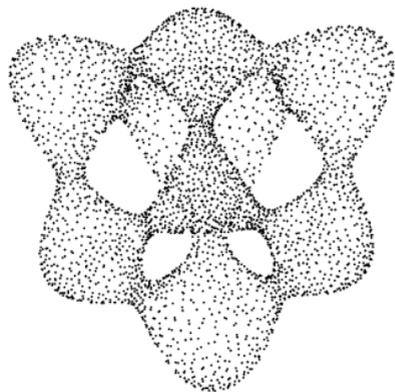


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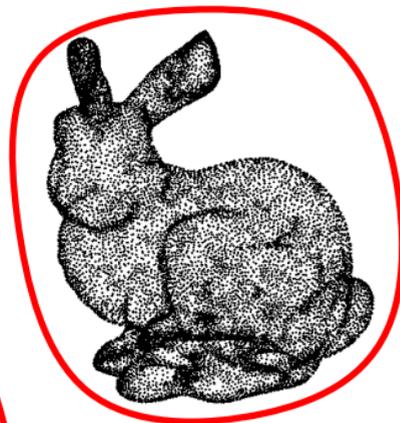
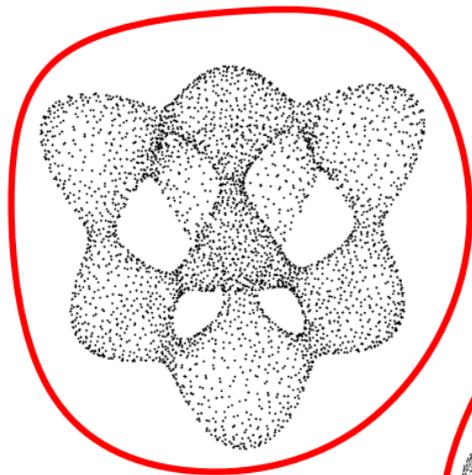
→ make assumptions on the underlying shape, *e.g.*: fix dimension, topological type, regularity (differentiability), Hausdorff distance to input...

→ for a suitable choice of hypotheses, the solution becomes unique **up to a set of local regular deformations** (solution never unique!)

Other (weaker) forms of reconstruction

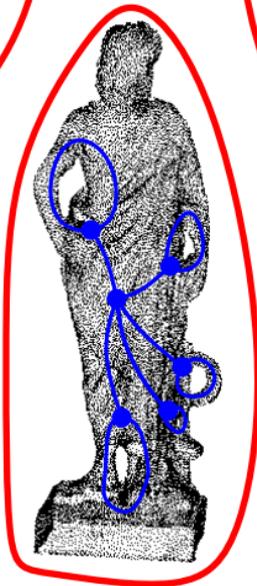
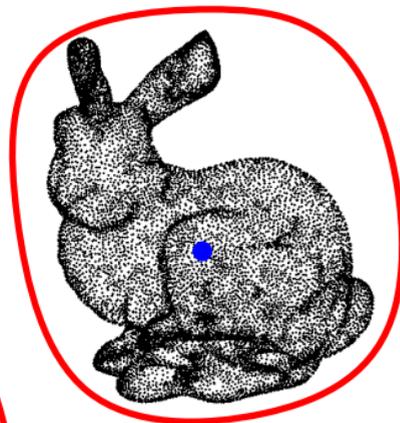
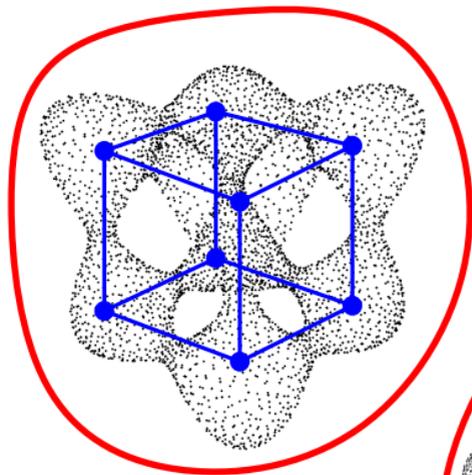


Other (weaker) forms of reconstruction



clustering

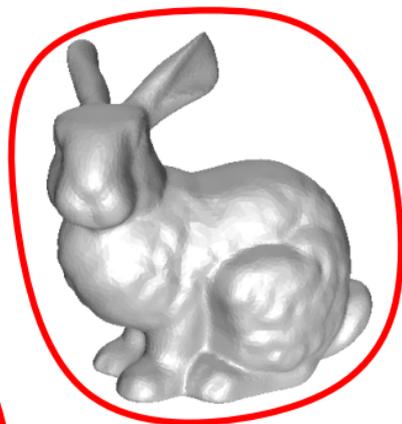
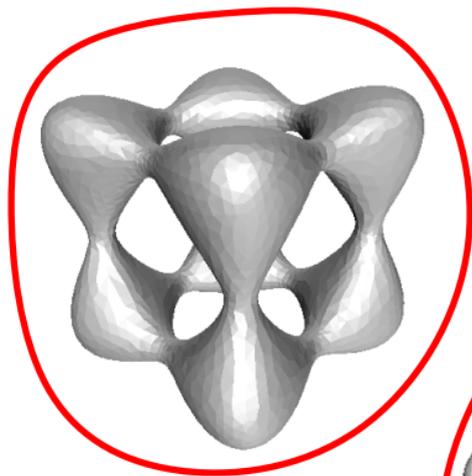
Other (weaker) forms of reconstruction



clustering

topological inference

Other (weaker) forms of reconstruction



clustering

topological inference

reconstruction

Where do the data come from?

3D scans

Sources

LASER

stereo vision

mechanical sensor

Applications

Reverse engineering

Prototyping

Quality control



Stanford Michelangelo Project

Where does the data come from?

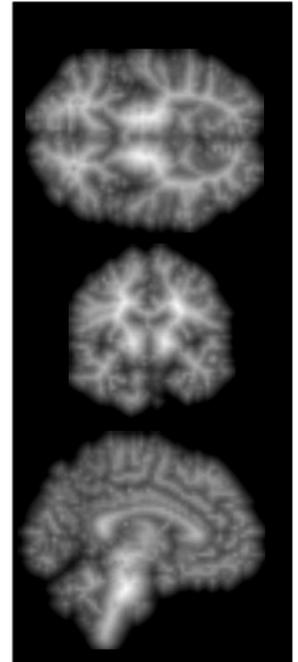
Medical Imaging

Sources

MRI scan
echograph
...

Applications

Diagnostic
Endoscopy simulation
Chirurgical intervention planning



Where does the data come from?

Geography, Geology

Sources

satellite/aerial images

ground probing

seismograph



Applications

Maps making / Terrain modeling

Prospection (tunnels, oil)

Where does the data come from?

Higher-Dimensions

Sources

Data bases
Simulations



Applications

Machine Learning
Path planning
Pattern recognition
Image processing

...



Various reconstruction techniques

Delaunay-based

- Crust / Power Crust
- Cocone
- Gabriel / α -shape / β -skeleton
- flow complex

Implicitization

- Local polynomial fitting
- Natural Neighbors (Voronoi-based)
- Radial Basis Functions

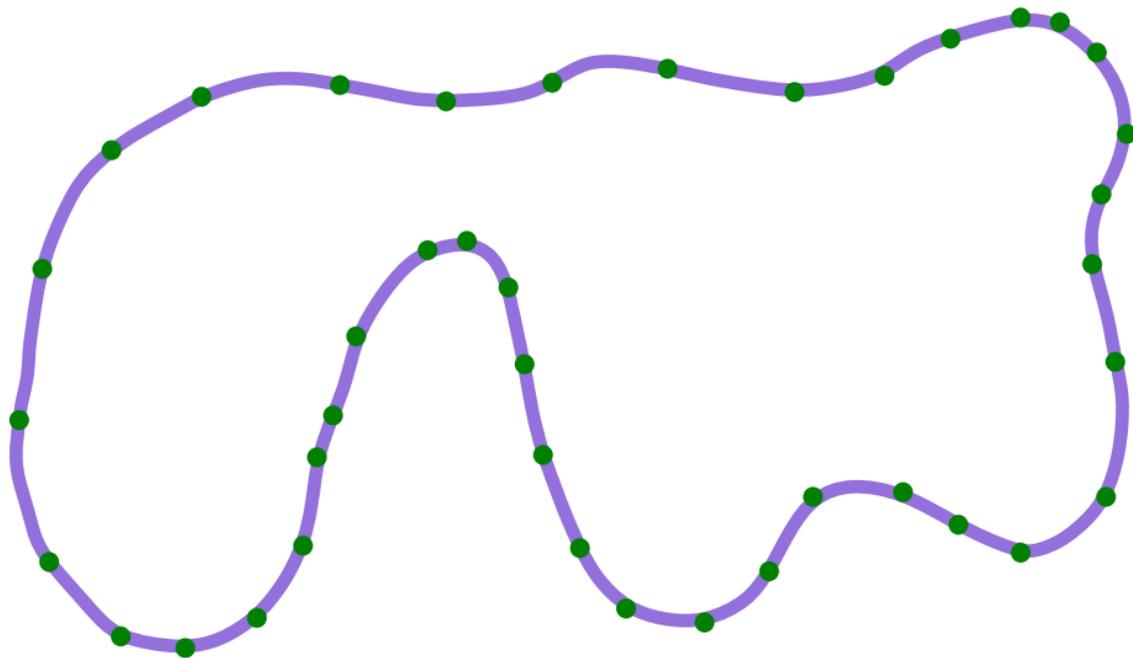
Projection operators

- Moving Least Squares
- Extremal surfaces

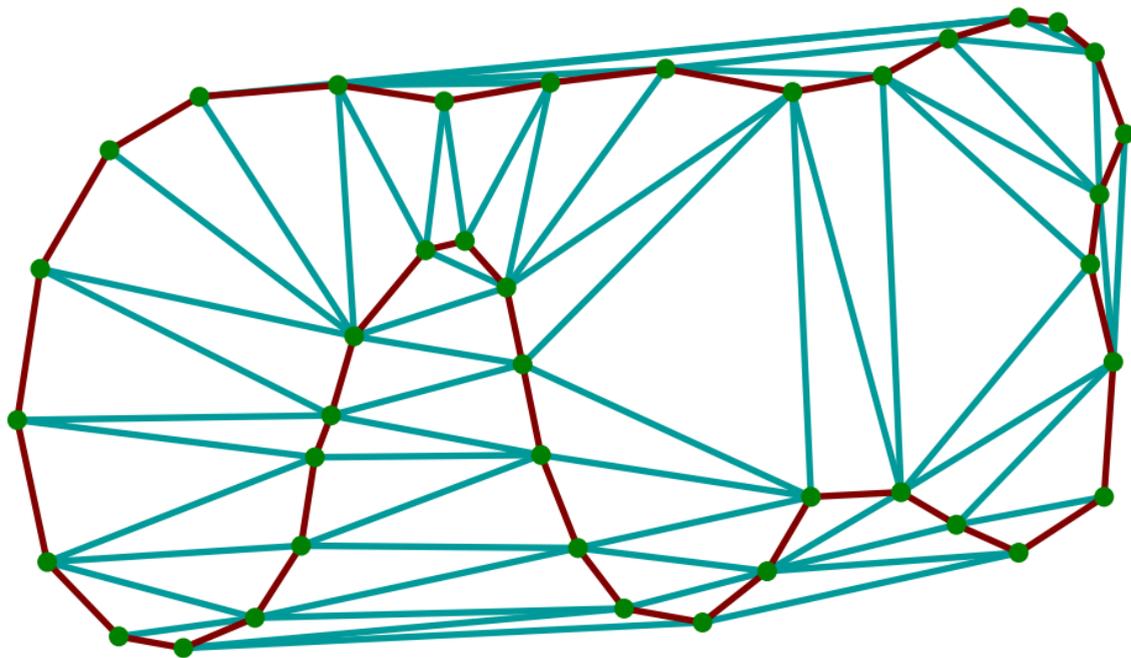
For arbitrary dimensions and co-dimensions

- Unions of balls / nerves
- Witness Complex

What Delaunay has to do with reconstruction



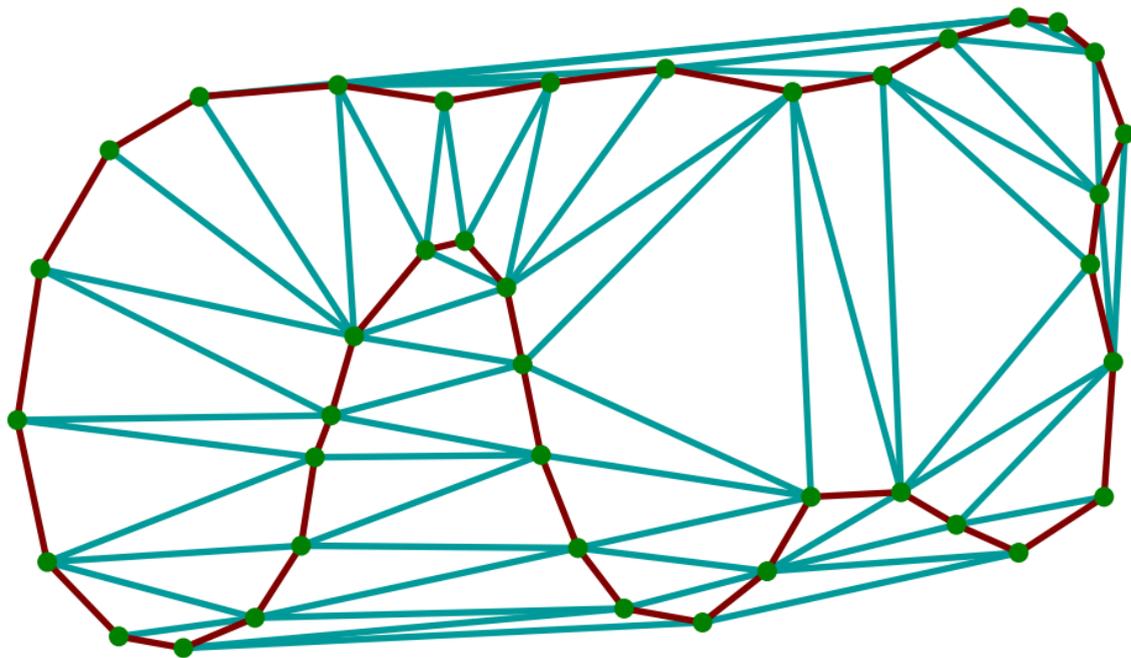
What Delaunay has to do with reconstruction



→ a faithful approximation of the curve appears as a subcomplex of the Delaunay

→ this should hold whenever the point cloud is sufficiently densely sampled along the curve

What Delaunay has to do with reconstruction

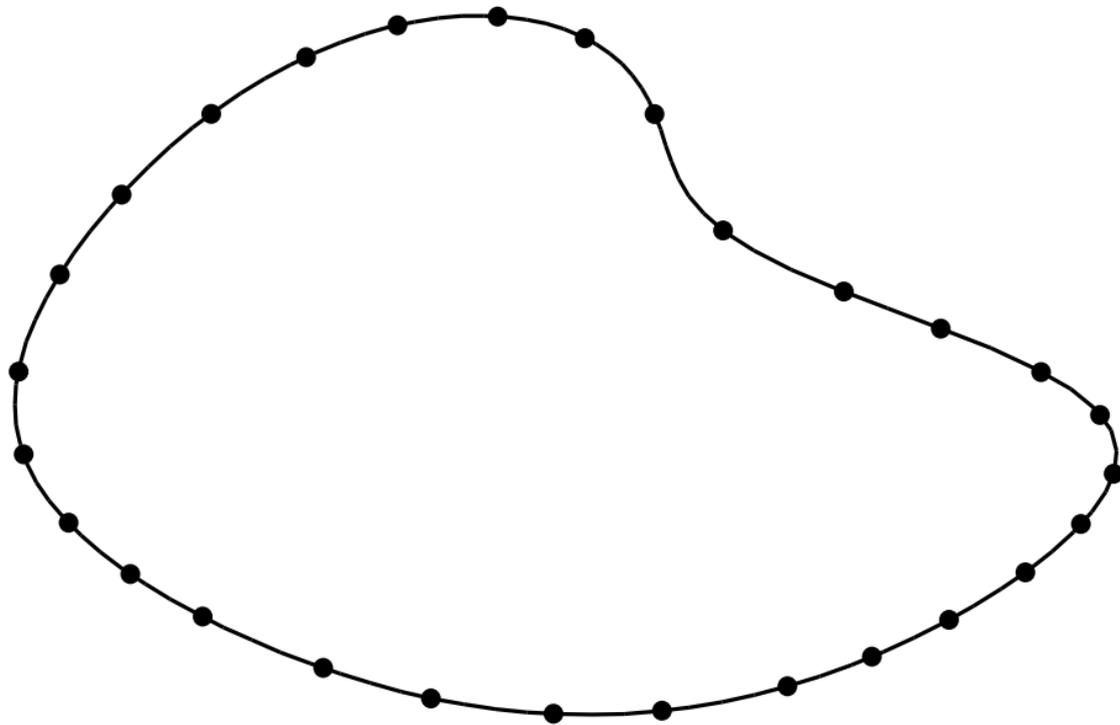


→ a faithful approximation of the curve appears as a subcomplex of the Delaunay

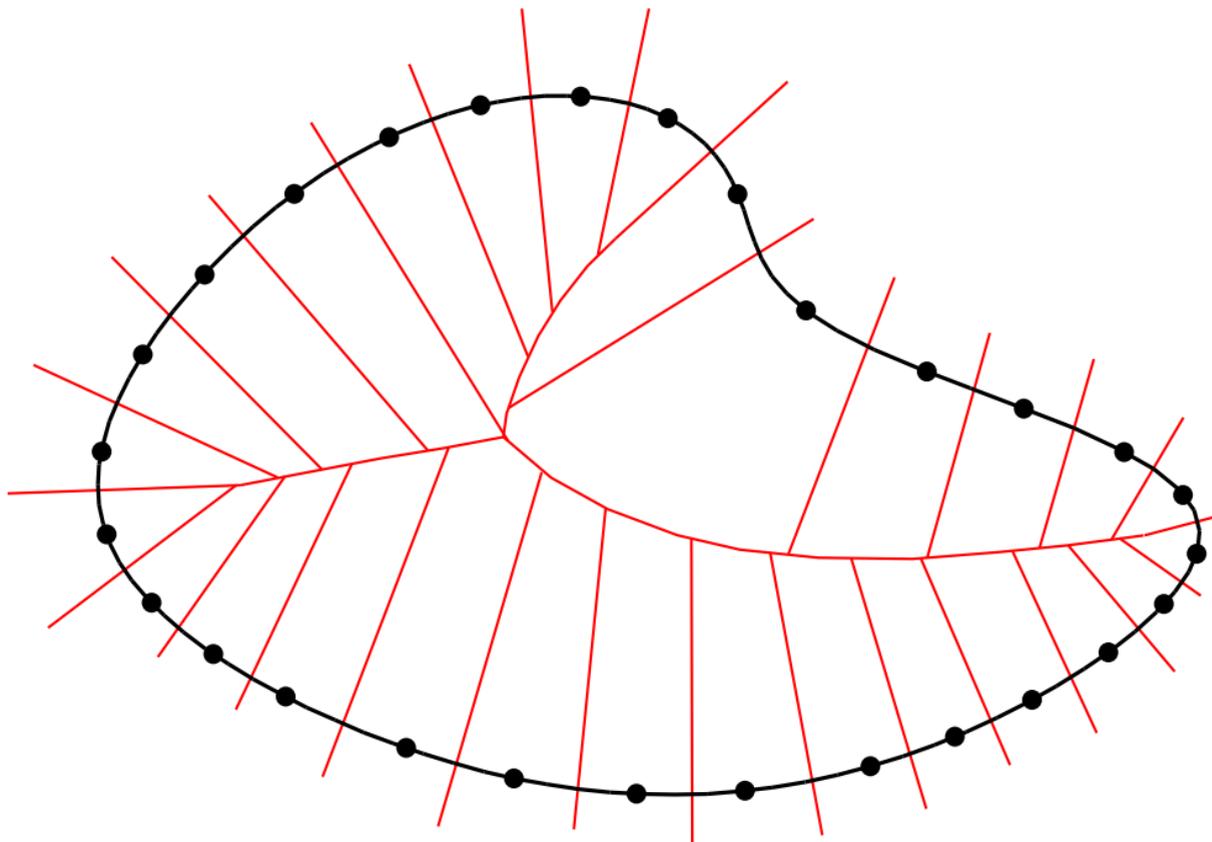
→ this should hold whenever the point cloud is sufficiently densely sampled along the curve

Q What is this *good* subcomplex? Can it be defined in some canonical way?

Restricted Delaunay triangulation

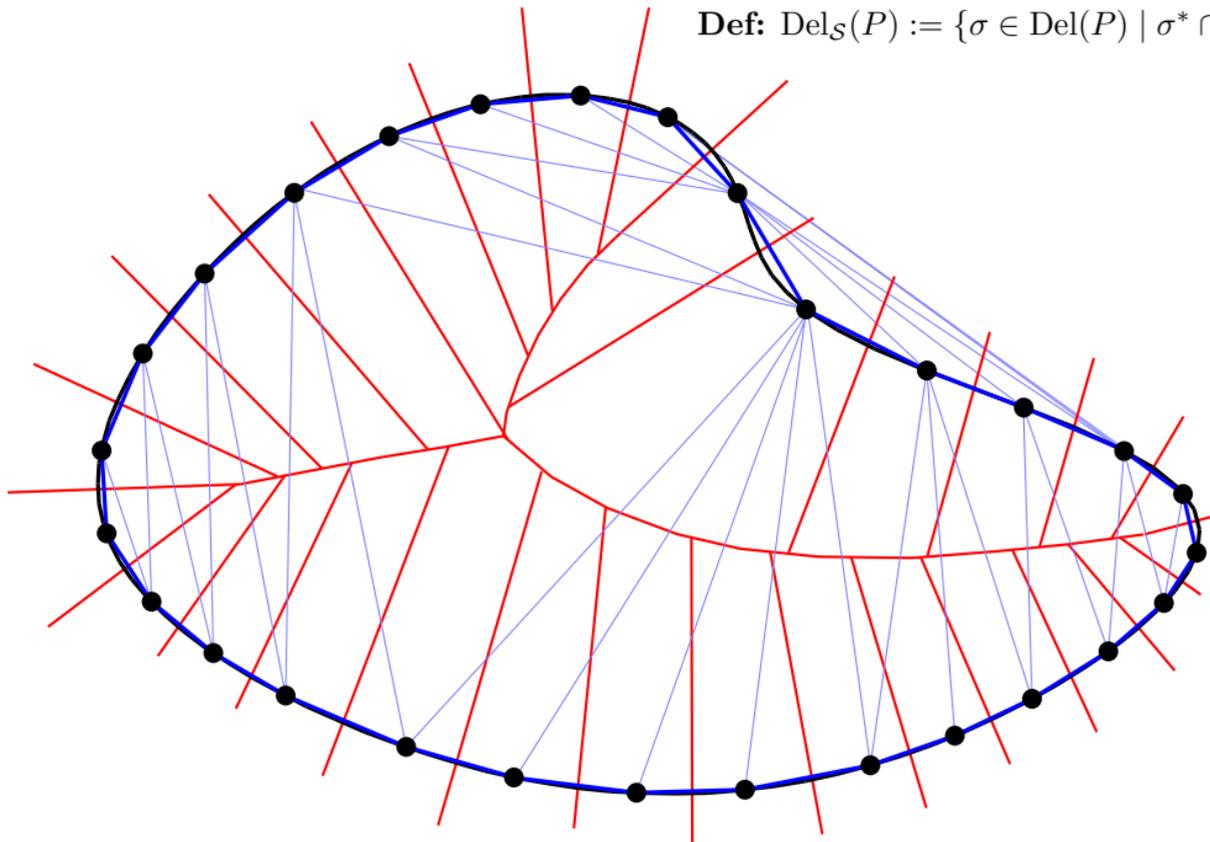


Restricted Delaunay triangulation



Restricted Delaunay triangulation

Def: $\text{Del}_S(P) := \{\sigma \in \text{Del}(P) \mid \sigma^* \cap S \neq \emptyset\}$



Approximation power of the restricted Delaunay

→ Our assumptions:

1. the underlying shape \mathcal{S} is a closed curve or surface with positive *reach* $\varrho_{\mathcal{S}}$
2. the point cloud P is an ε -*sample* of \mathcal{S} with $\varepsilon \in O(\varrho_{\mathcal{S}})$.

Approximation power of the restricted Delaunay

→ Our assumptions:

→ analogy with 1-d signal theory (Shannon's reconstruction theorem):

1. the underlying shape \mathcal{S} is a closed curve or surface with positive *reach* $\varrho_{\mathcal{S}}$
- 1'. the underlying signal is a weighted sum of sinusoids
2. the point cloud P is an ε -sample of \mathcal{S} with $\varepsilon \in O(\varrho_{\mathcal{S}})$.
- 2'. the sampling has ≥ 2 samples per period (signal has bounded bandwidth)

Approximation power of the restricted Delaunay

Theorem: [Amenta et al. 1998-99]

If \mathcal{S} is a curve or surface with positive *reach*, and if P is an ε -sample of \mathcal{S} with $\varepsilon < \rho_{\mathcal{S}}$ (curve) or $\varepsilon < 0.1\rho_{\mathcal{S}}$ (surface), then:

- $\text{Del}_{\mathcal{S}}(P)$ is homeomorphic to \mathcal{S} ,
- $d_{\text{H}}(\text{Del}_{\mathcal{S}}(P), \mathcal{S}) \in O(\varepsilon^2)$,
- $\forall f \in \text{Del}_{\mathcal{S}}(P), \forall v \in f, \angle n_f n_v \mathcal{S} \in O(\varepsilon)$,
- \dots (similar areas, curvature estimation, etc.)

Approximation power of the restricted Delaunay

Theorem: [Amenta et al. 1998-99]

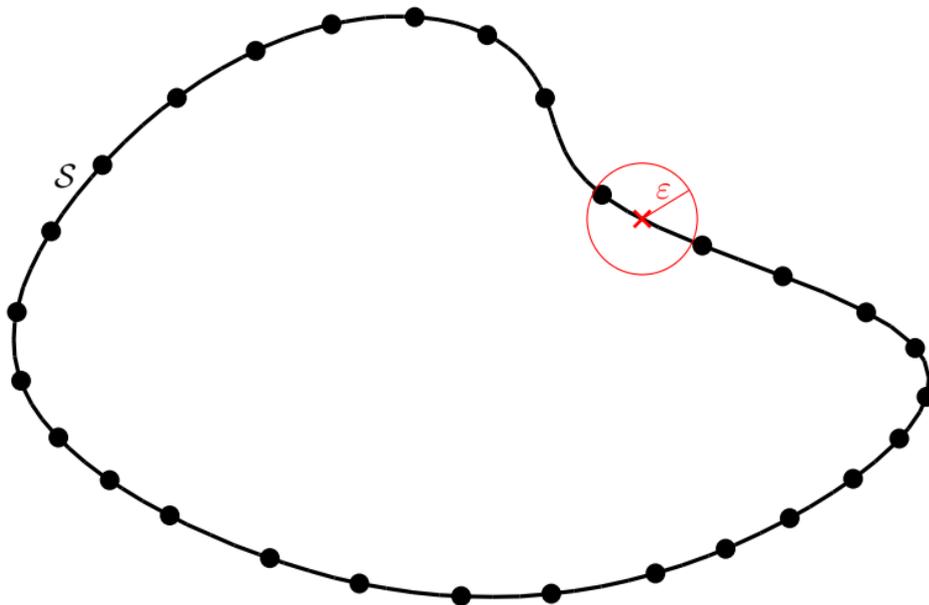
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\rightarrow to be explicated: ε -sampling, reach

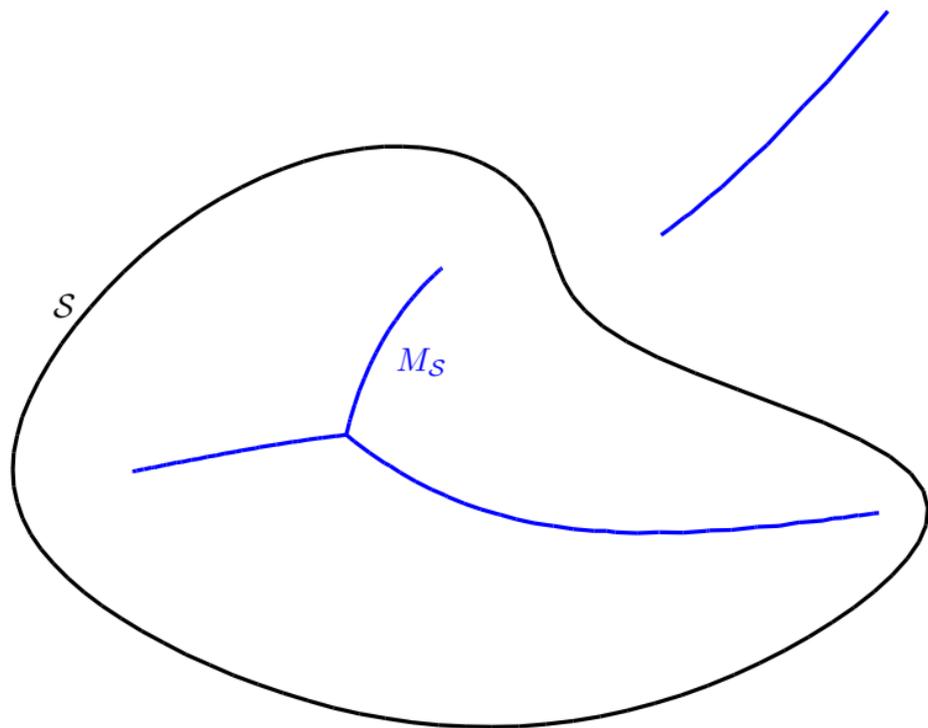
ε -samples

Def: P is an ε -sample of \mathcal{S} if $\forall x \in \mathcal{S}, \min\{\|x - p\| \mid p \in P\} \leq \varepsilon$.



Shapes with positive reach [Federer 1958]

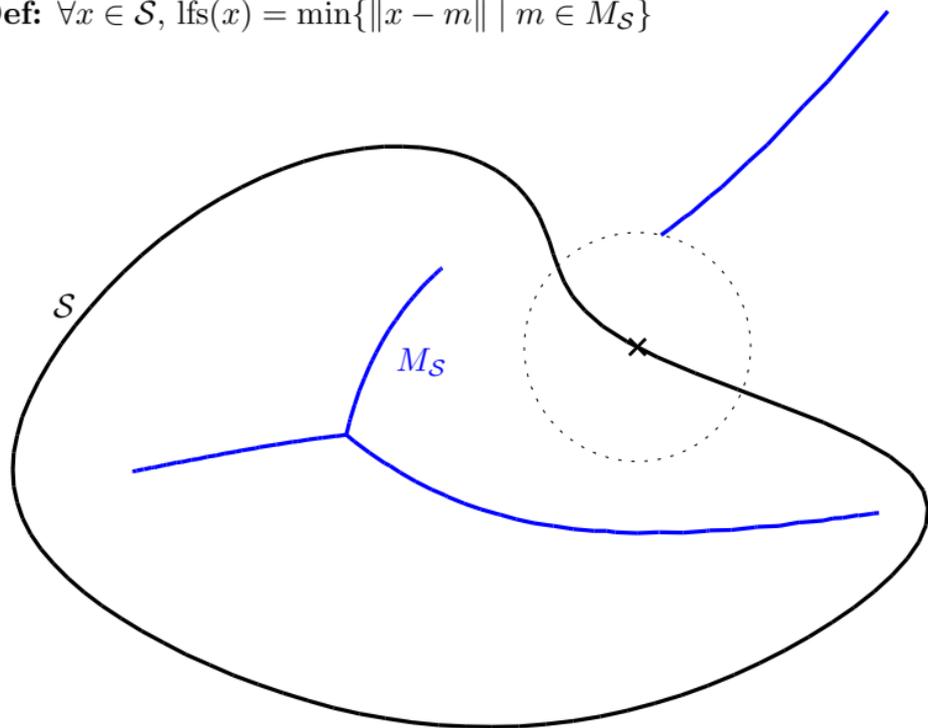
Def: M_S is the closure of the set of points of \mathbb{R}^d that have ≥ 2 nearest neighbors on S .



Shapes with positive reach [Federer 1958]

Def: $M_{\mathcal{S}}$ is the closure of the set of points of \mathbb{R}^d that have ≥ 2 nearest neighbors on \mathcal{S} .

Def: $\forall x \in \mathcal{S}$, $\text{lfs}(x) = \min\{\|x - m\| \mid m \in M_{\mathcal{S}}\}$

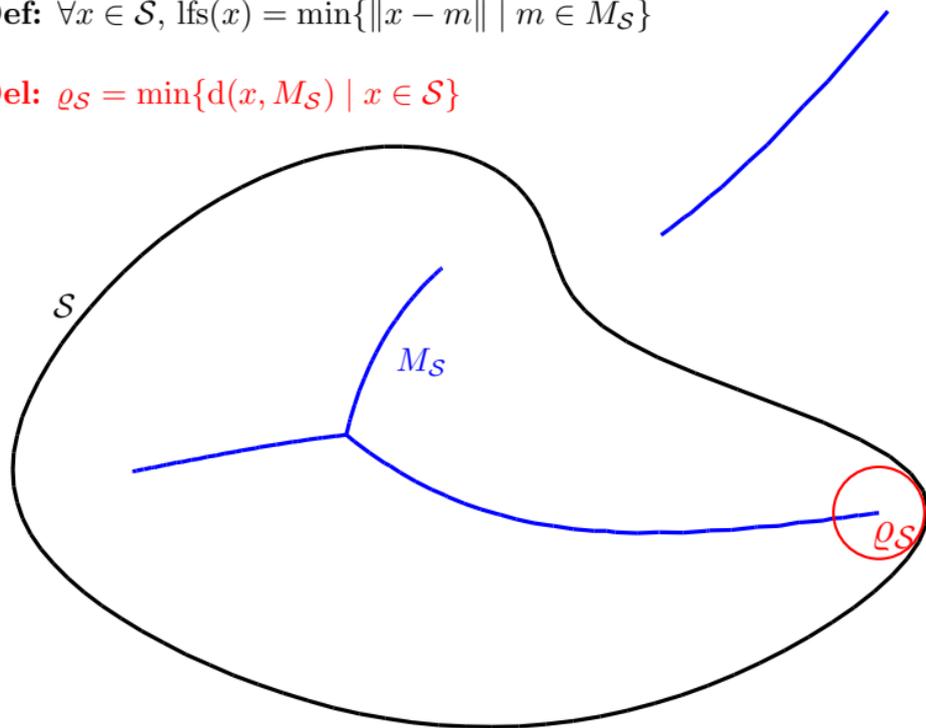


Shapes with positive reach [Federer 1958]

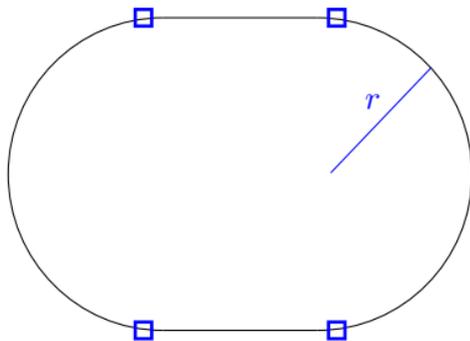
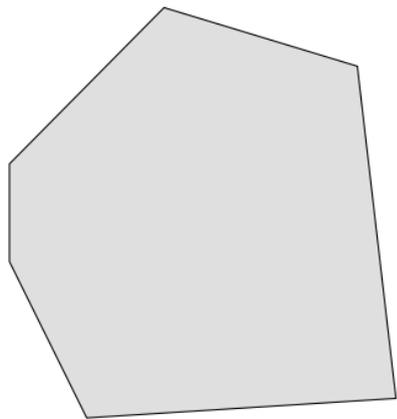
Def: M_S is the closure of the set of points of \mathbb{R}^d that have ≥ 2 nearest neighbors on S .

Def: $\forall x \in S$, $\text{lhs}(x) = \min\{\|x - m\| \mid m \in M_S\}$

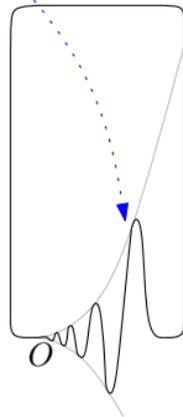
Def: $\varrho_S = \min\{d(x, M_S) \mid x \in S\}$



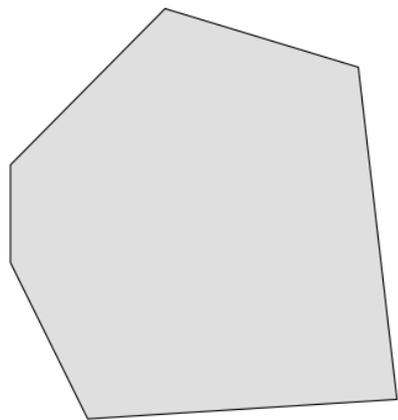
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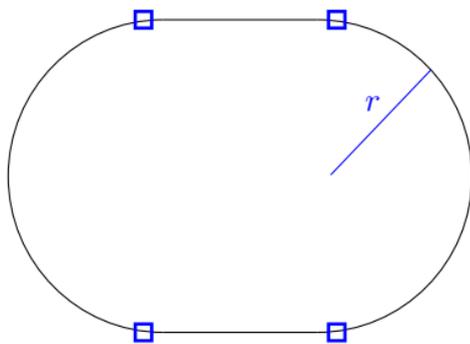
$$x \mapsto x^3 \sin \frac{1}{x}$$



Shapes with positive reach [Federer 1958]

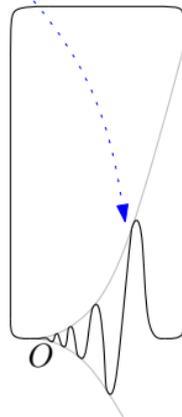


$\rho_S = +\infty$
(convex)



$\rho_S = r$
 $C^{1,1}$ but not C^2

$$x \mapsto x^3 \sin \frac{1}{x}$$

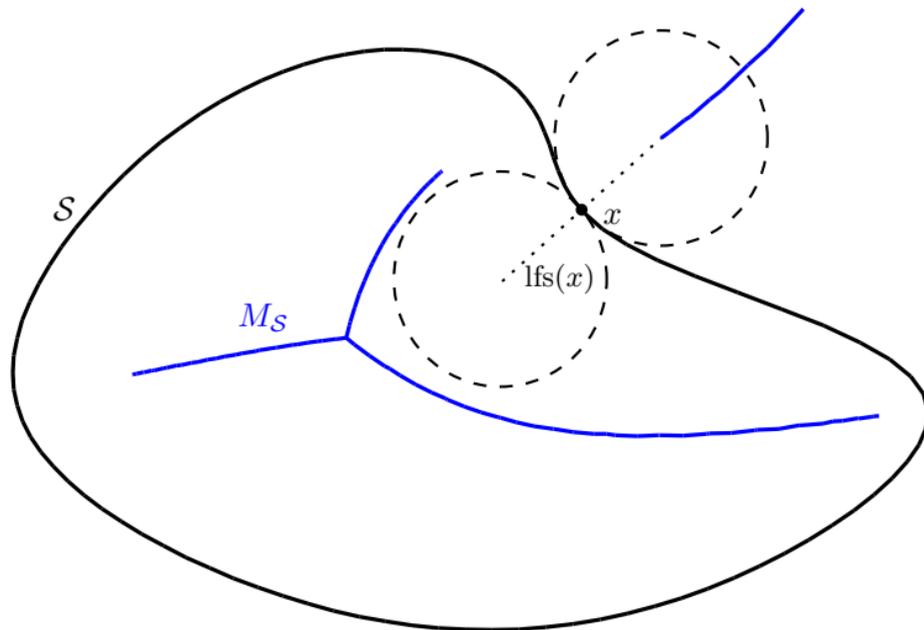


$\rho_S = 0$
(C^1 but not $C^{1,1}$)

Shapes with positive reach (Cont'd)

→ Fundamental properties: (see [Federer 1958])

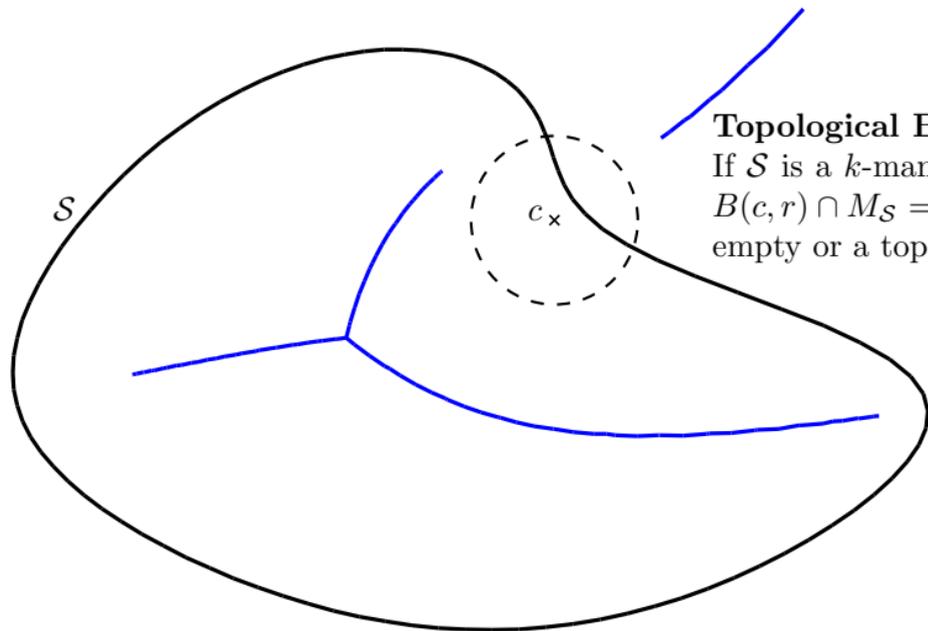
Tangent Ball Lemma: $\forall x \in \mathcal{S}, \forall c \in n_x \mathcal{S}, \|x - c\| < \text{lfs}(x) \Rightarrow B(c, \|x - c\|) \cap \mathcal{S} = \emptyset$.



Shapes with positive reach (Cont'd)

→ Fundamental properties: (see [Federer 1958])

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Topological Ball Lemma:

If \mathcal{S} is a k -manifold, then $\forall B(c, r)$ s.t. $B(c, r) \cap M_{\mathcal{S}} = \emptyset$, $B(c, r) \cap \mathcal{S}$ is either empty or a topological k -ball.

Approximation power of the restricted Delaunay

Theorem: [Amenta et al. 1998-99]

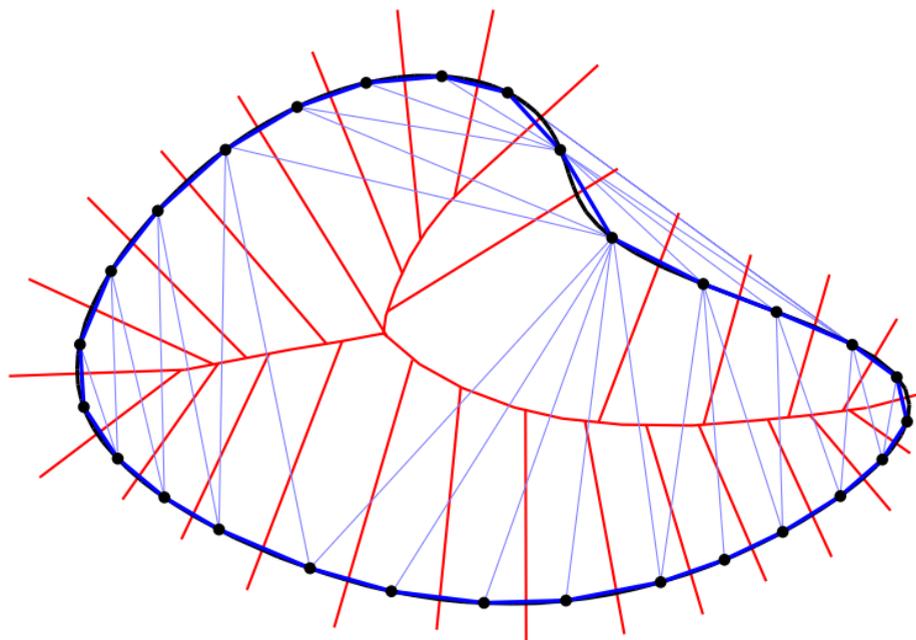
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- $\text{Del}_{\mathcal{S}}(P)$ is homeomorphic to \mathcal{S} ,
- $d_{\text{H}}(\text{Del}_{\mathcal{S}}(P), \mathcal{S}) \in O(\varepsilon^2)$,
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Approximation power of the restricted Delaunay

Proof for curves:

→ show that every edge of $\text{Del}_{\mathcal{S}}(P)$ connects consecutive points of P along \mathcal{S} , and vice-versa



Approximation power of the restricted Delaunay

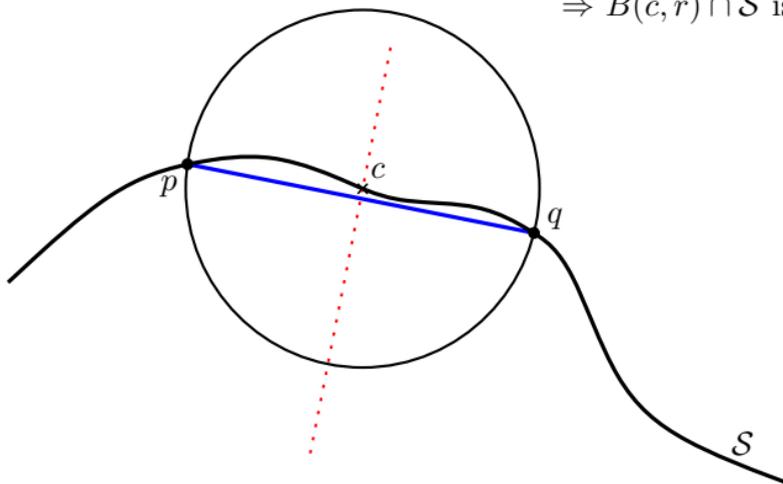
Proof for curves:

→ show that every edge of $\text{Del}_{\mathcal{S}}(P)$ connects consecutive points of P along \mathcal{S} , and vice-versa

Let $c \in pq^* \cap \mathcal{S}$.

$$r = \|c - p\| = \|c - q\| = d(c, P) \leq \varepsilon < \rho_{\mathcal{S}} \leq \text{lfs}(c)$$

$\Rightarrow B(c, r) \cap \mathcal{S}$ is a topological arc



Approximation power of the restricted Delaunay

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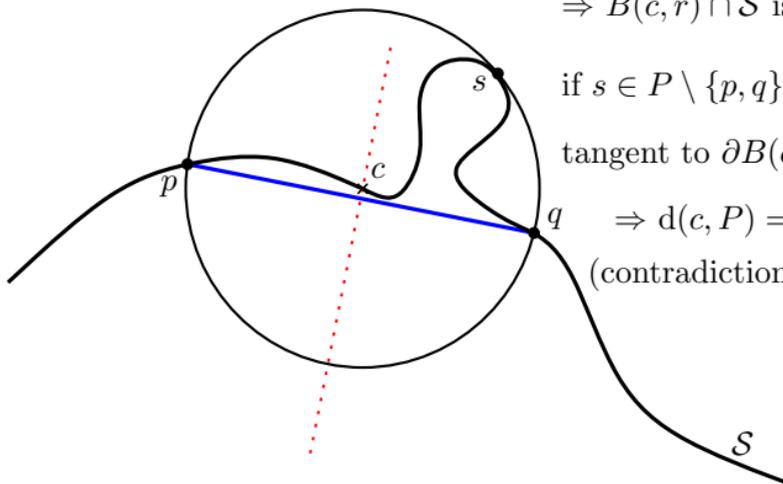
$$r = \|c - p\| = \|c - q\| = d(c, P) \leq \varepsilon < \varrho_{\mathcal{S}} \leq \text{lfs}(c)$$

$\Rightarrow B(c, r) \cap \mathcal{S}$ is a topological arc

if $s \in P \setminus \{p, q\}$ belongs to this arc, then the arc is tangent to $\partial B(c, r)$ in p, q or s (say s)

$$\Rightarrow d(c, P) = r = \|c - s\| \geq \text{lfs}(s) > \varepsilon.$$

(contradiction with the hypothesis of the theorem)



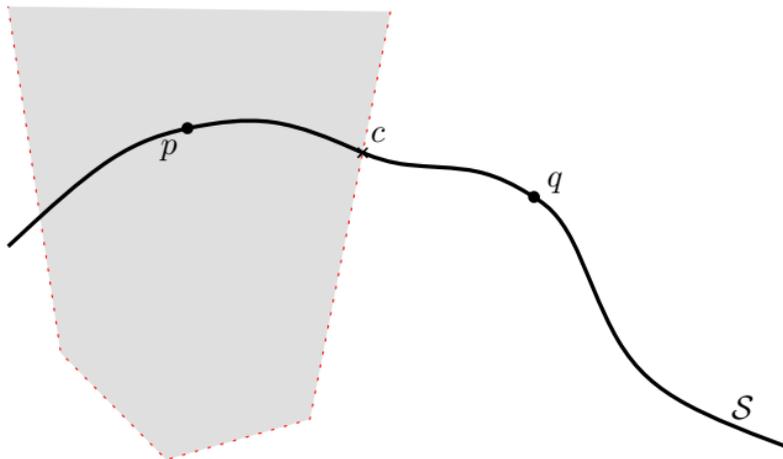
Approximation power of the restricted Delaunay

Proof for curves:

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Let $c \in \text{arc}_{\mathcal{S}}(pq) \cap \partial p^*$.

$c \in ps^*$ for some $s \in P \setminus \{p\}$



Approximation power of the restricted Delaunay

Proof for curves:

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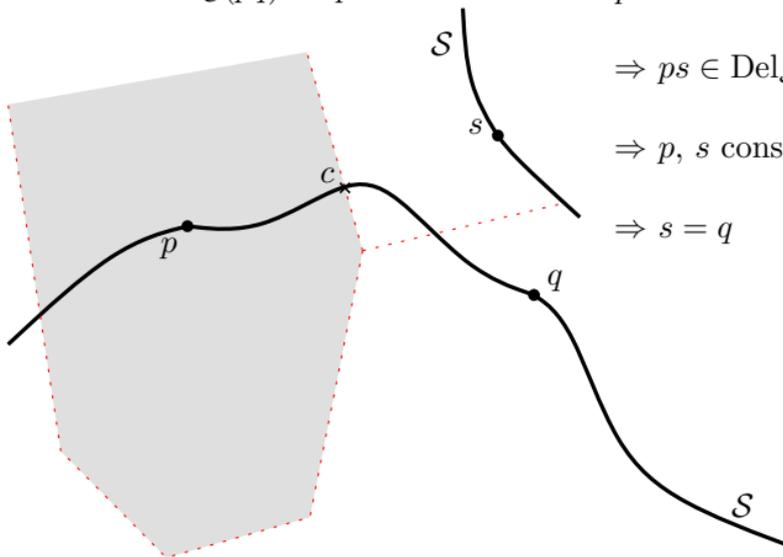
$c \in ps^*$ for some $s \in P \setminus \{p\}$

$\Rightarrow ps \in \text{Del}_{\mathcal{S}}(P)$

$\Rightarrow p, s$ consecutive along \mathcal{S} , with $c \in \text{arc}_{\mathcal{S}}(ps)$

$\Rightarrow s = q$

(by previous part of the proof)

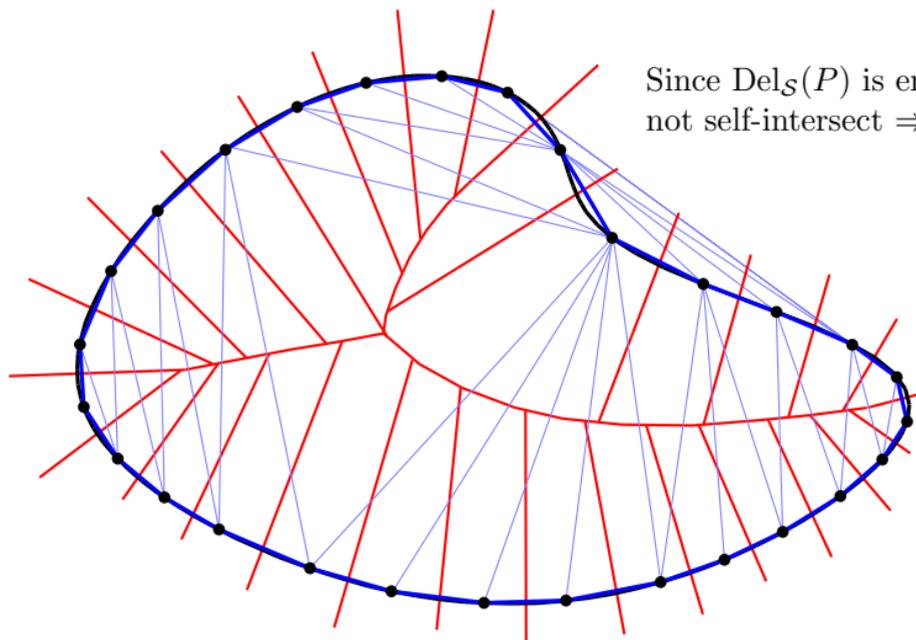


Approximation power of the restricted Delaunay

Proof for curves:

→ show that every edge of $\text{Del}_{\mathcal{S}}(P)$ connects consecutive points of P along \mathcal{S} , and vice-versa

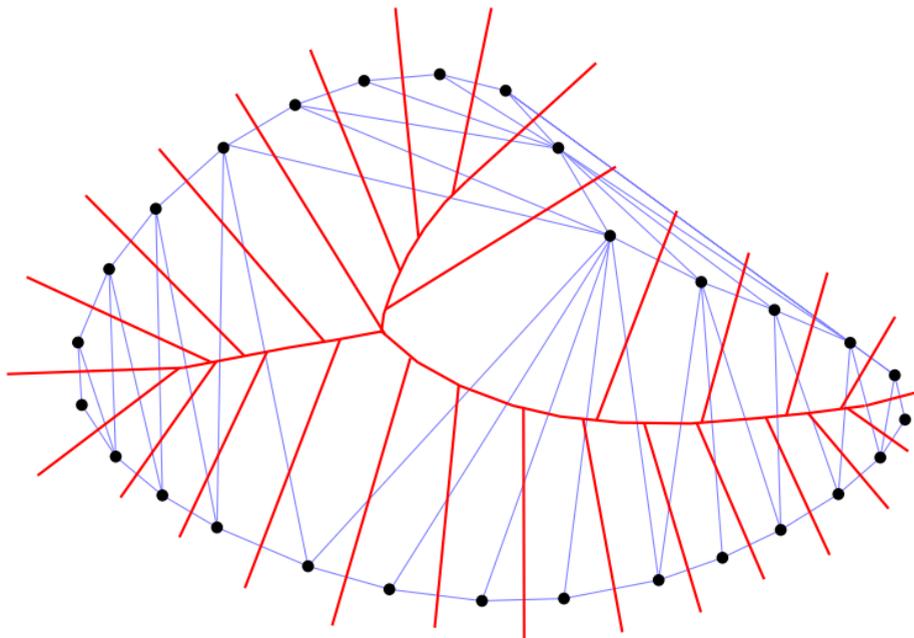
⇒ $\text{Del}_{\mathcal{S}}(P)$ is homeomorphic to \mathcal{S} between each pair of consecutive points of P



Since $\text{Del}_{\mathcal{S}}(P)$ is embedded in $\text{Del}(P)$, it does not self-intersect ⇒ global homeomorphism

Computing the restricted Delaunay

Q How to compute $\text{Del}_{\mathcal{S}}(P)$ when \mathcal{S} is unknown?

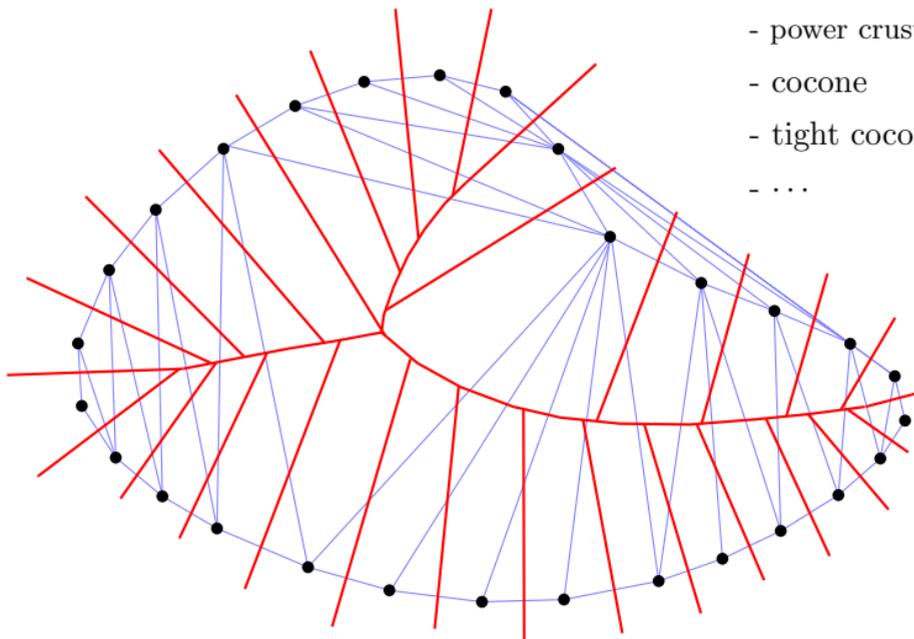


Computing the restricted Delaunay

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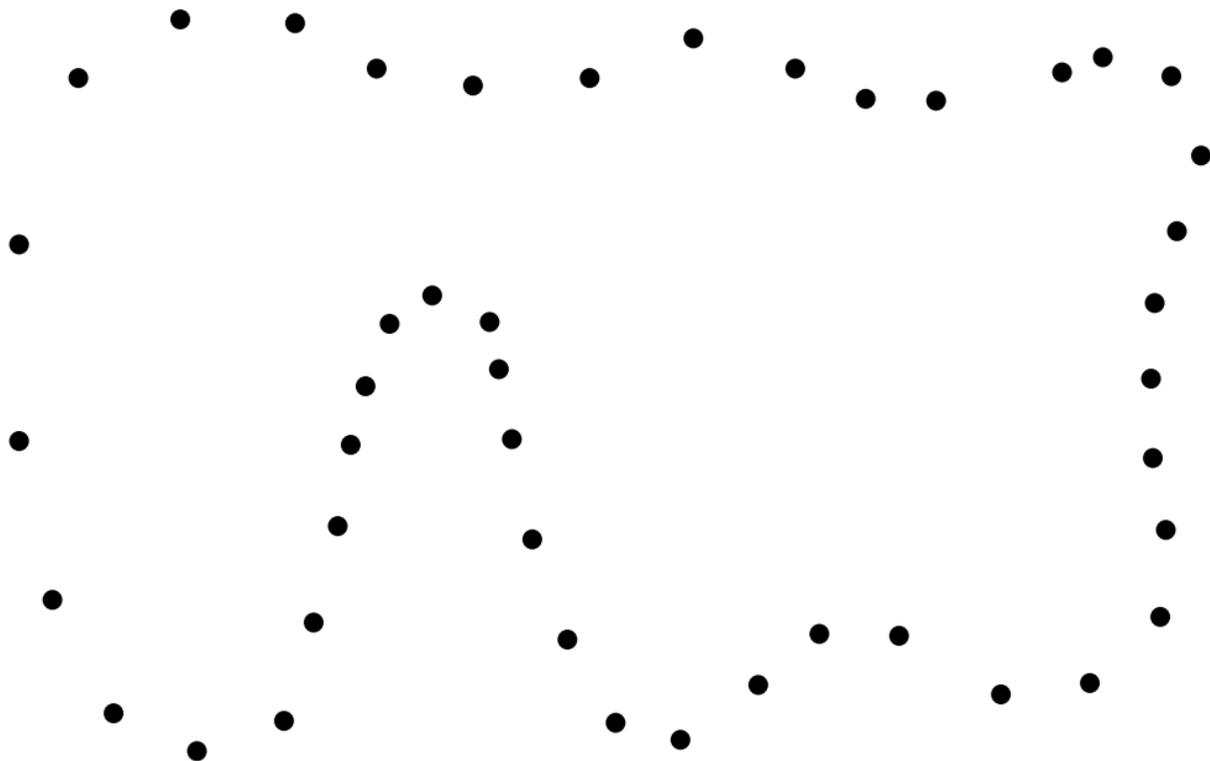
→ a whole family of algorithms use various Delaunay extraction criteria:

- crust
- power crust
- cocone
- tight cocone
- ...



Crust algorithm

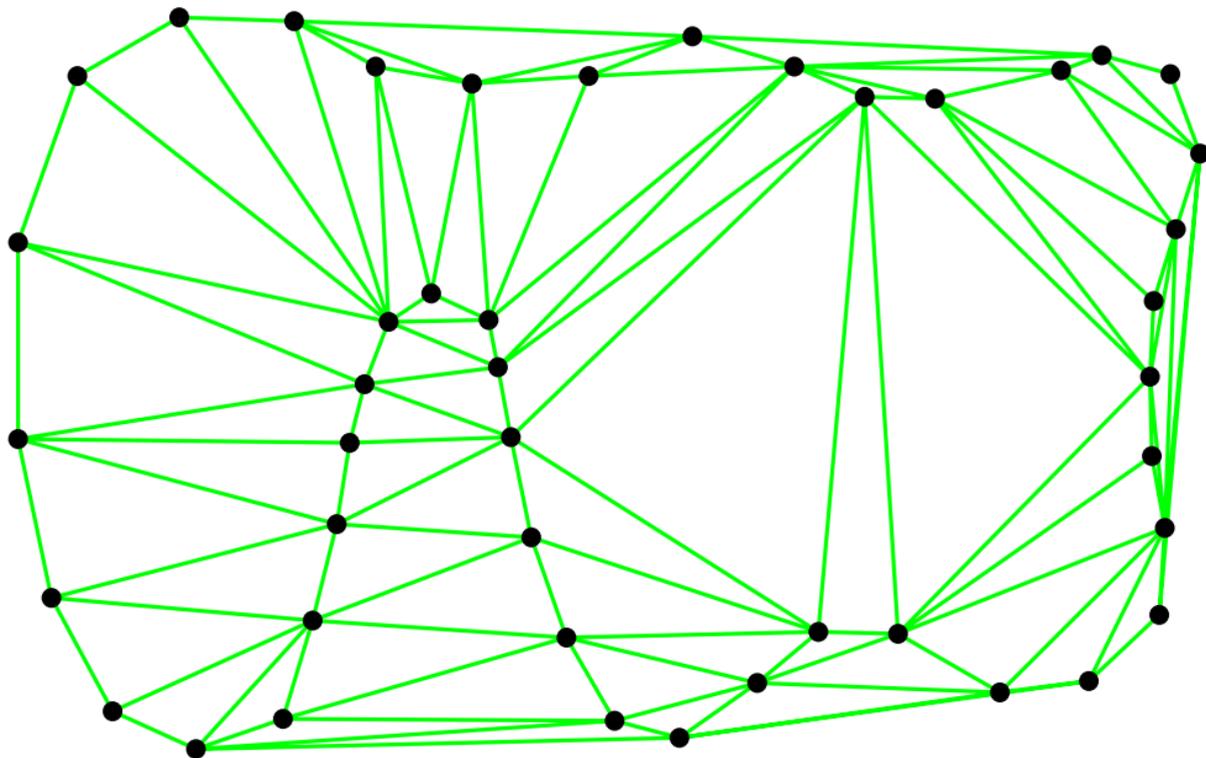
[Amenta et al. 1997-98]



Crust algorithm

[Amenta et al. 1997-98]

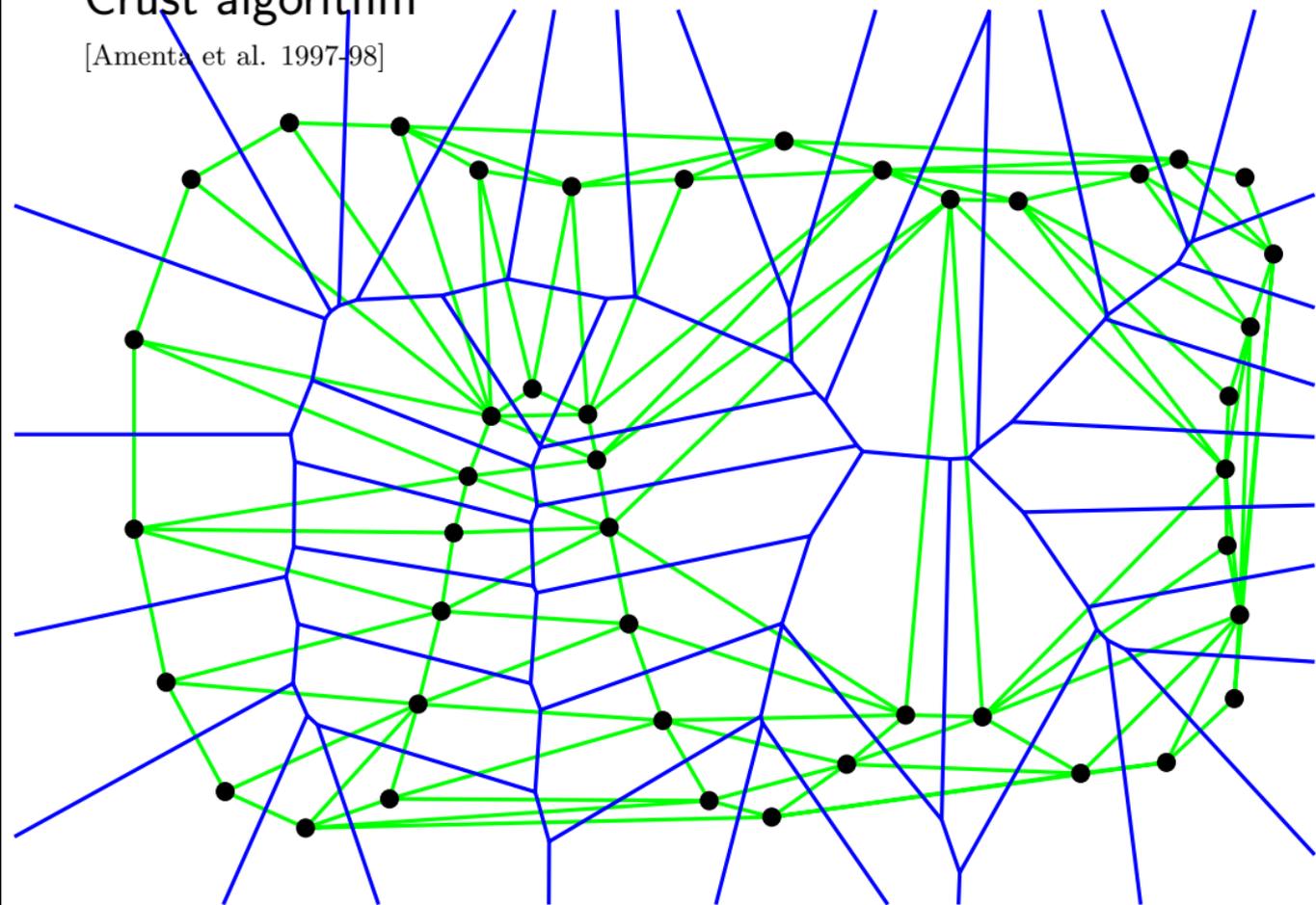
1. Compute Delaunay triangulation of P



Crust algorithm

[Amenta et al. 1997-98]

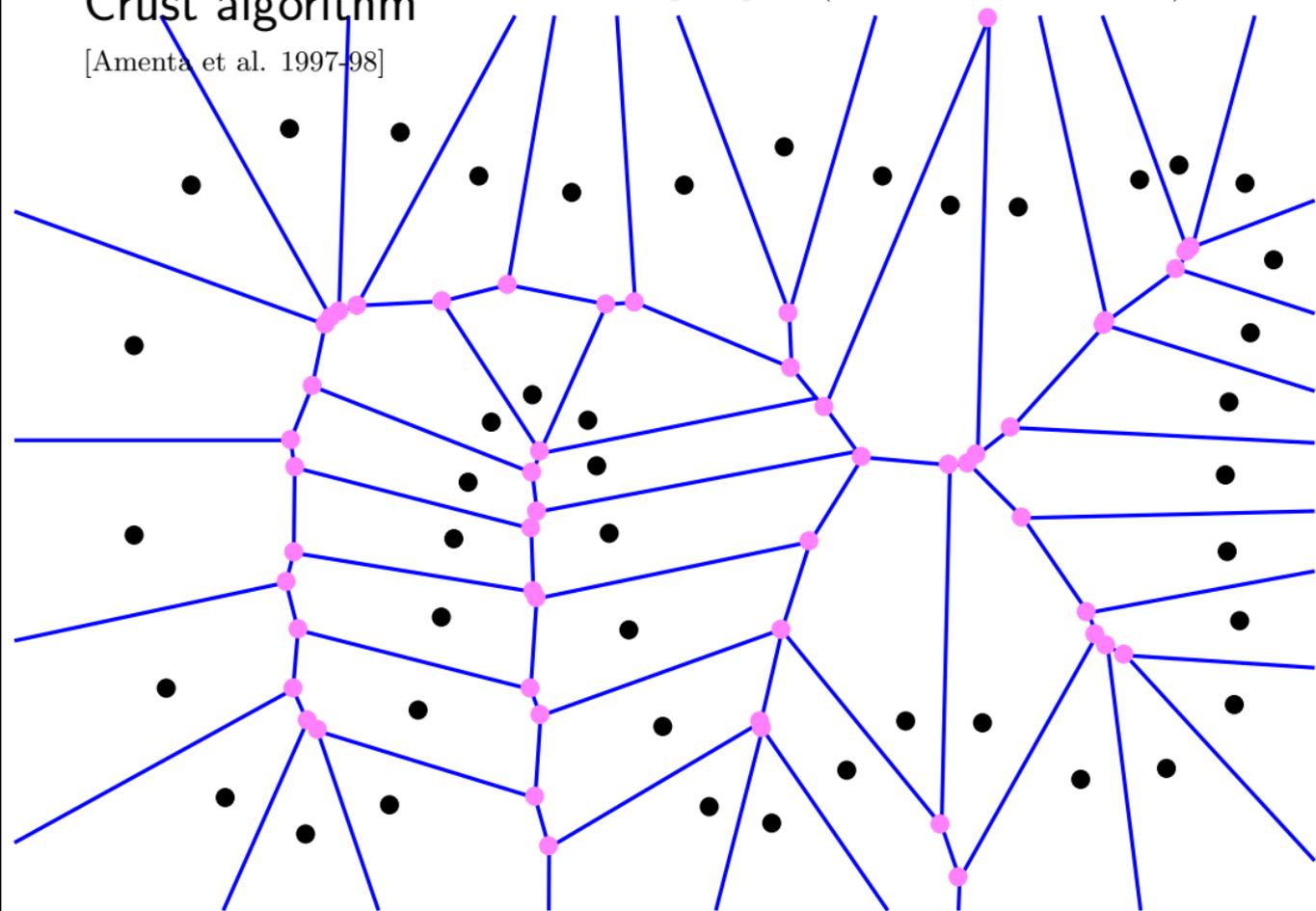
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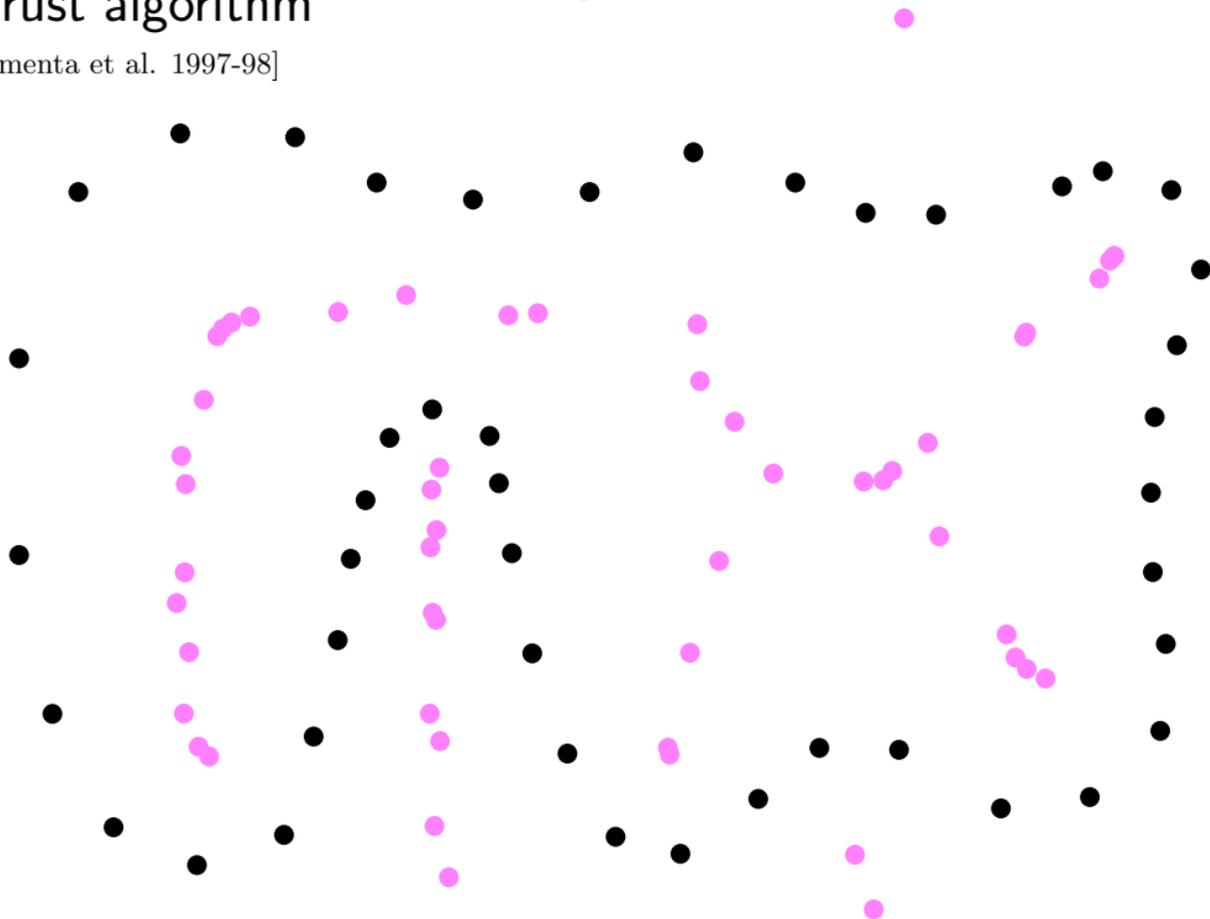
2. Compute *poles* (furthest Voronoi vertices)



Crust algorithm

[Amenta et al. 1997-98]

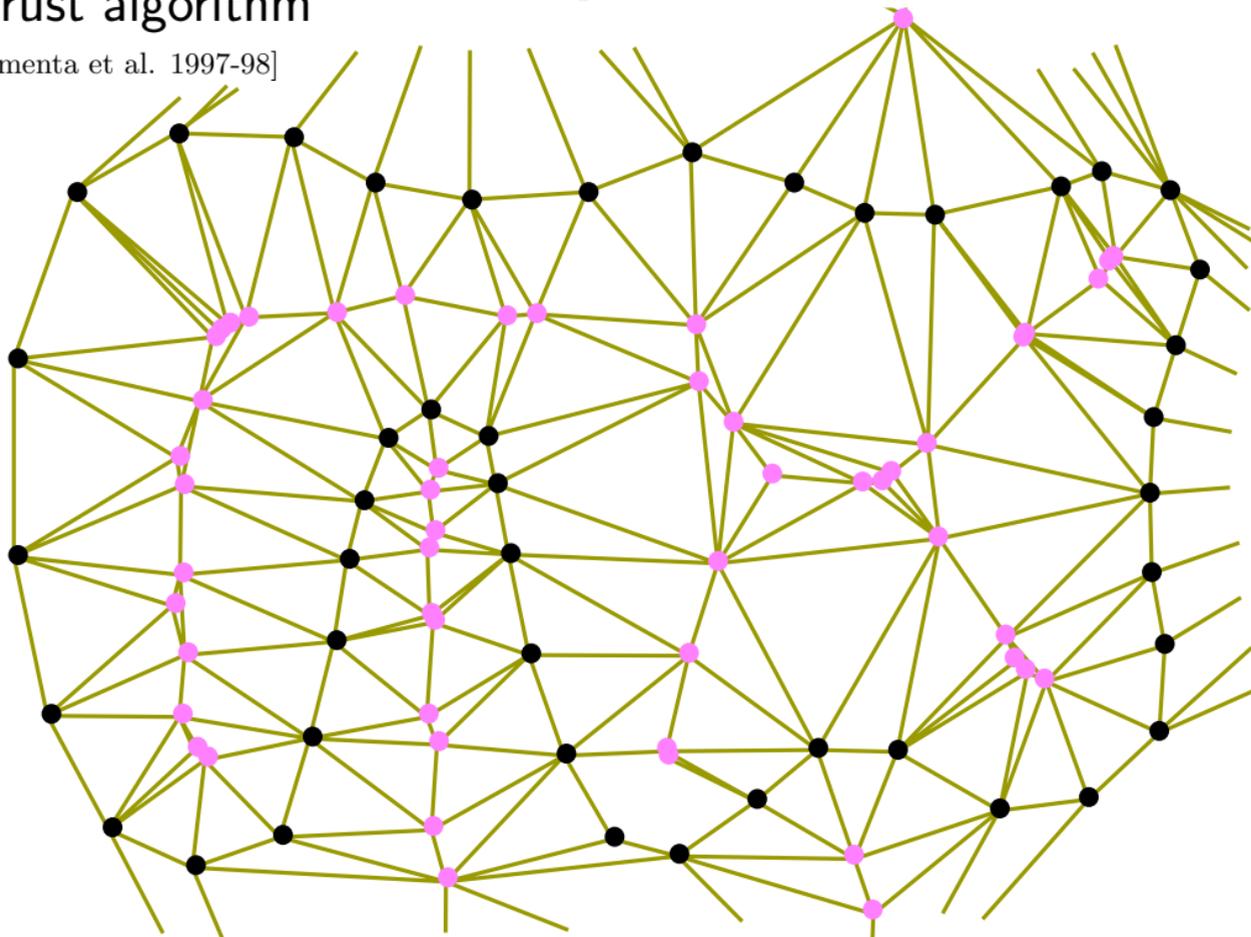
3. Add poles to the set of vertices



Crust algorithm

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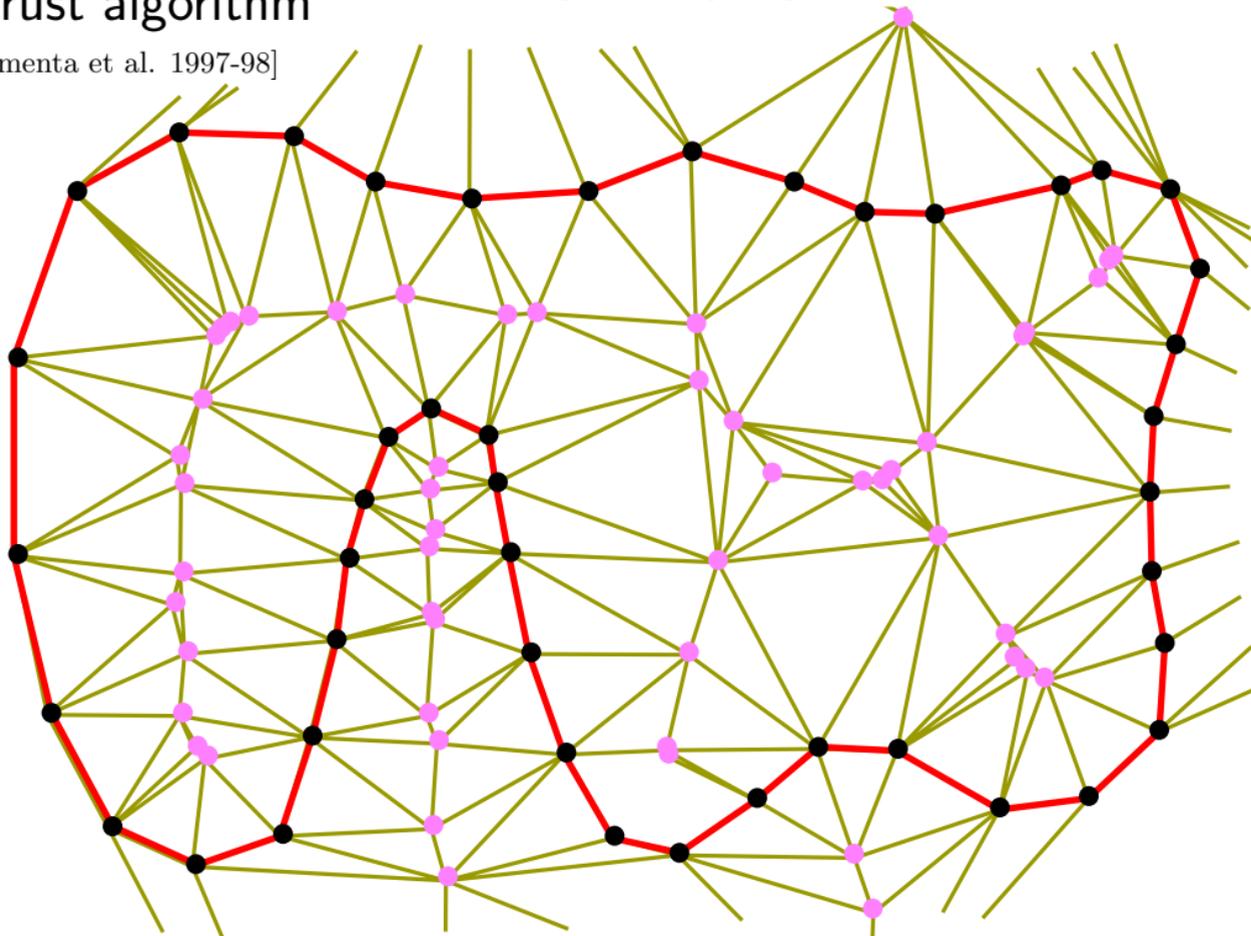
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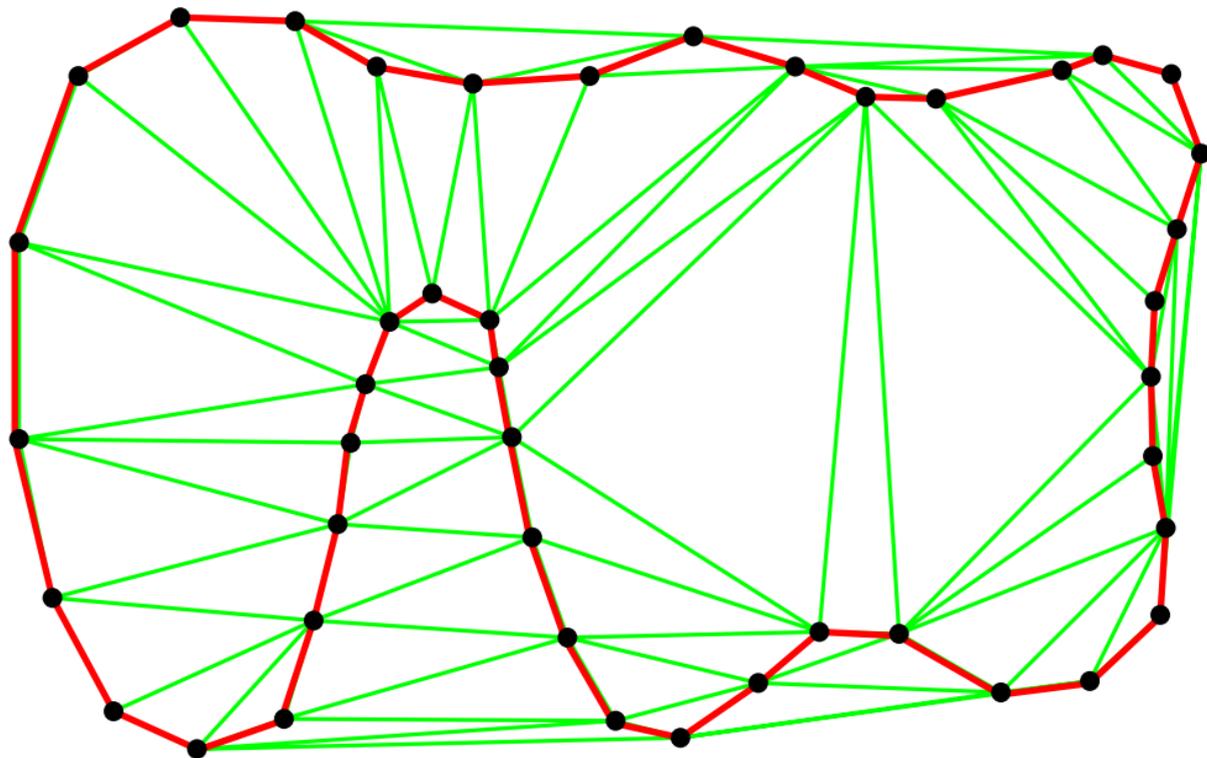
4. Keep Delaunay simplices whose vertices are in P



Crust algorithm

→ in 2-d, crust = $\text{Del}_S(P) \approx \mathcal{S}$

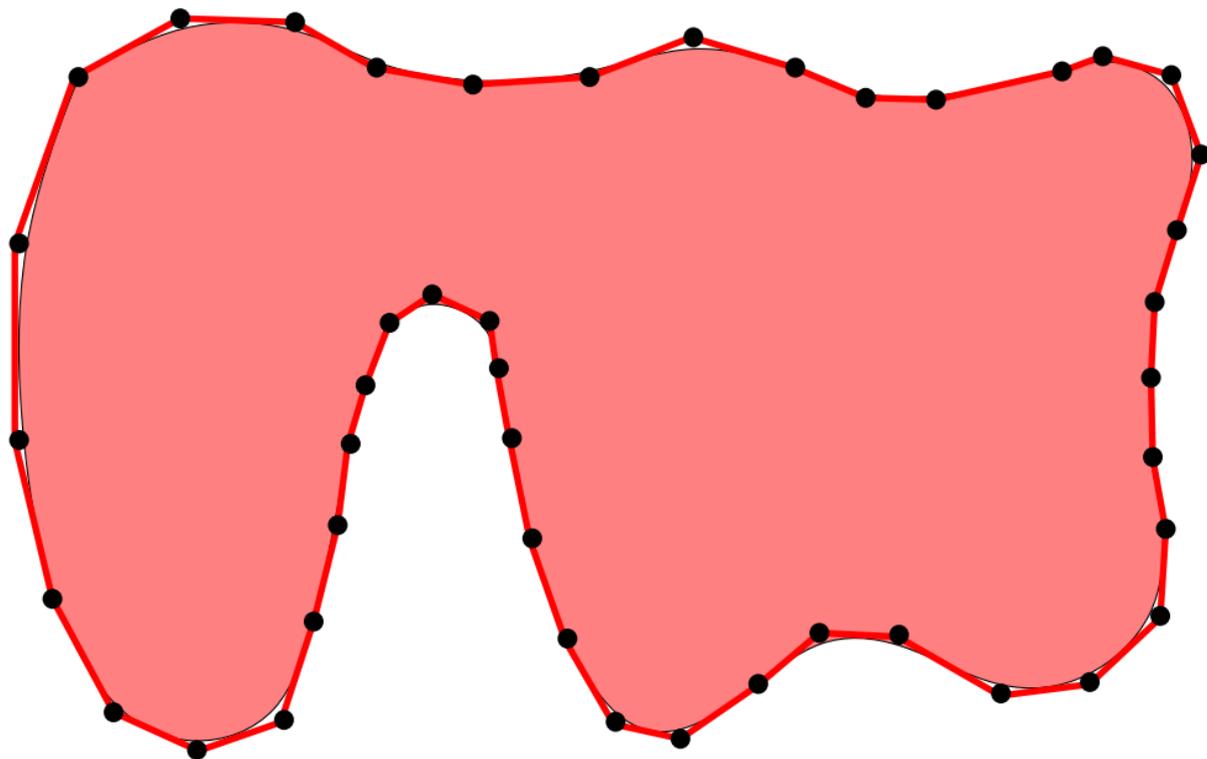
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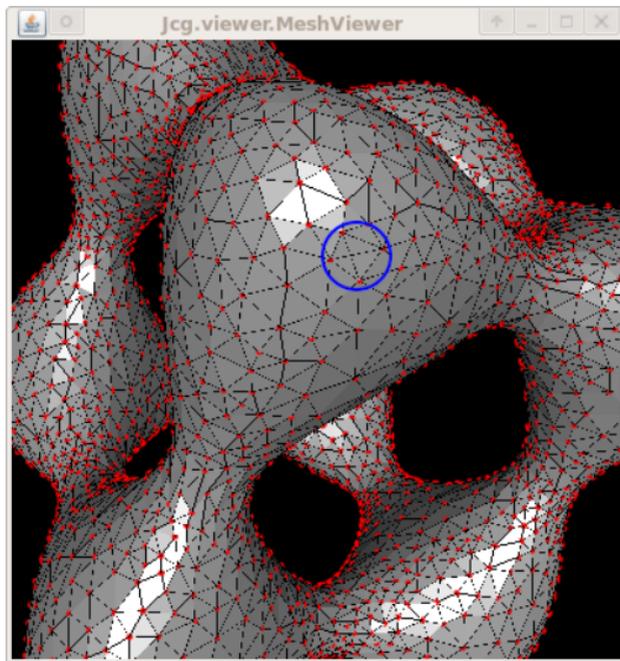
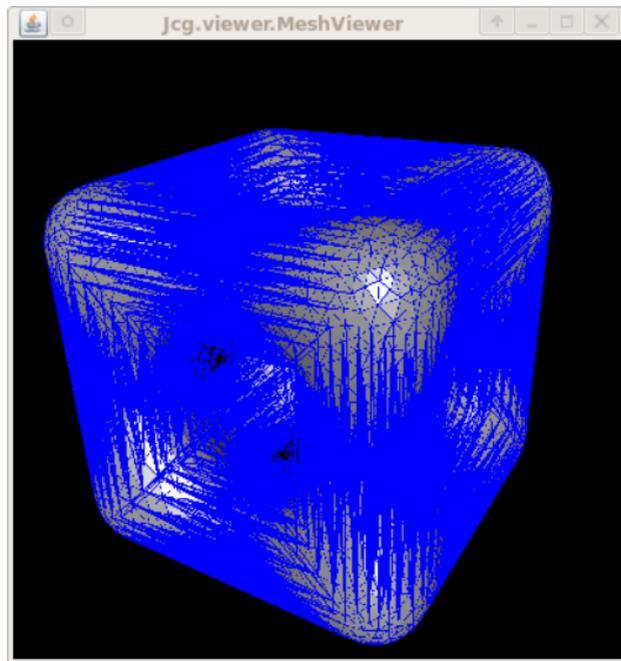


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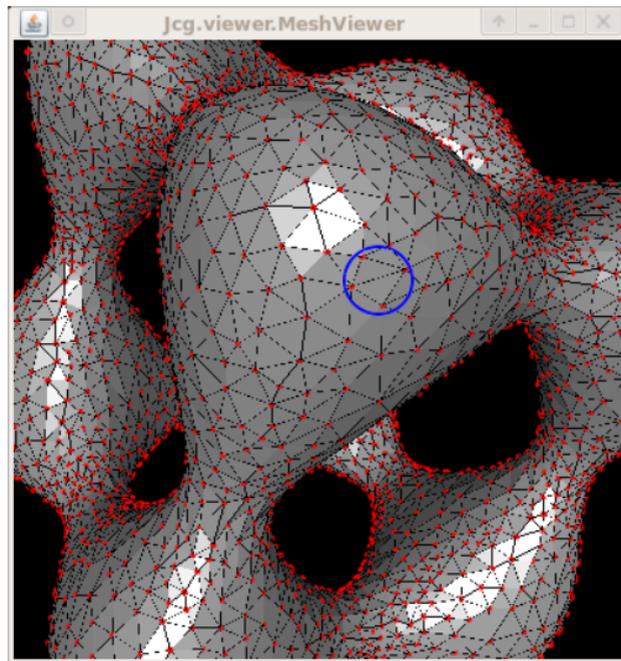
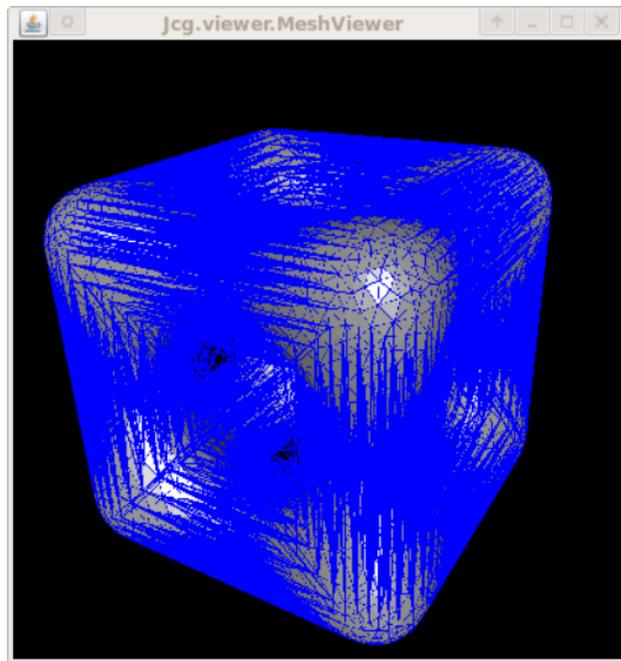
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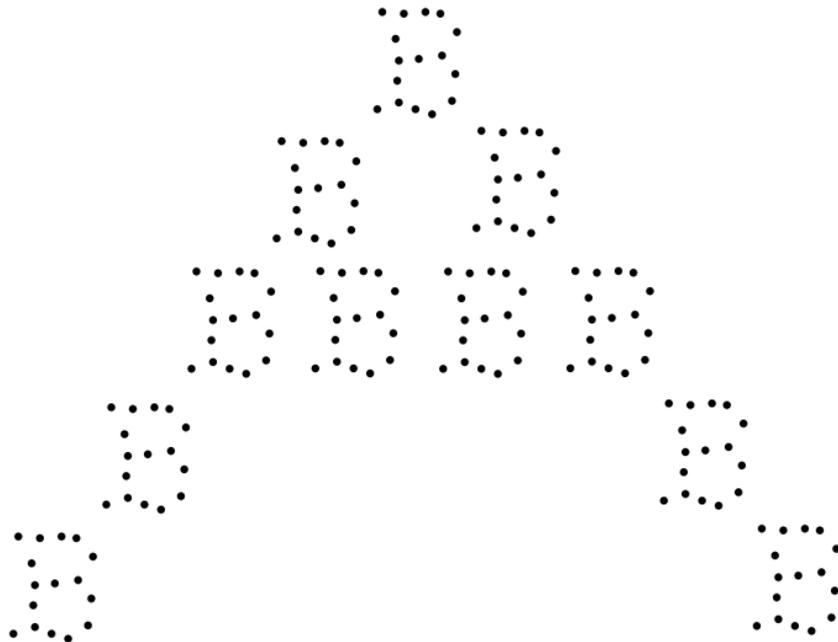
⇒ manifold extraction step in post-processing



Back to the reconstruction paradigm

Q What do you see?

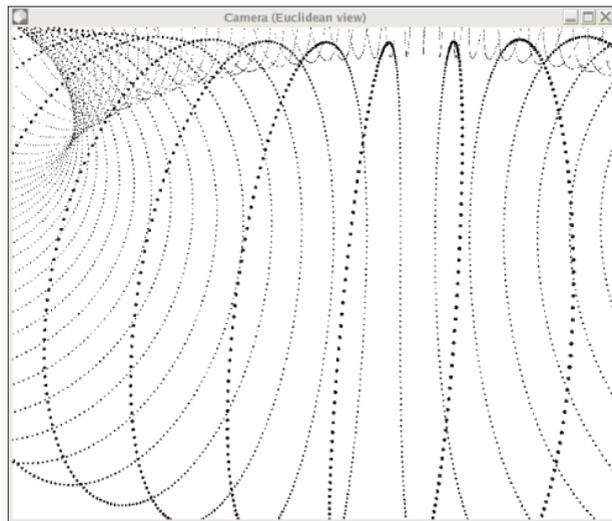
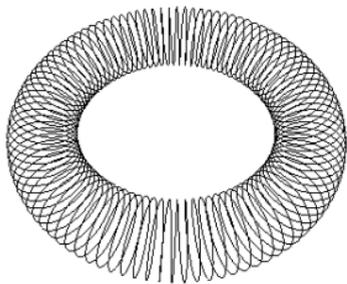
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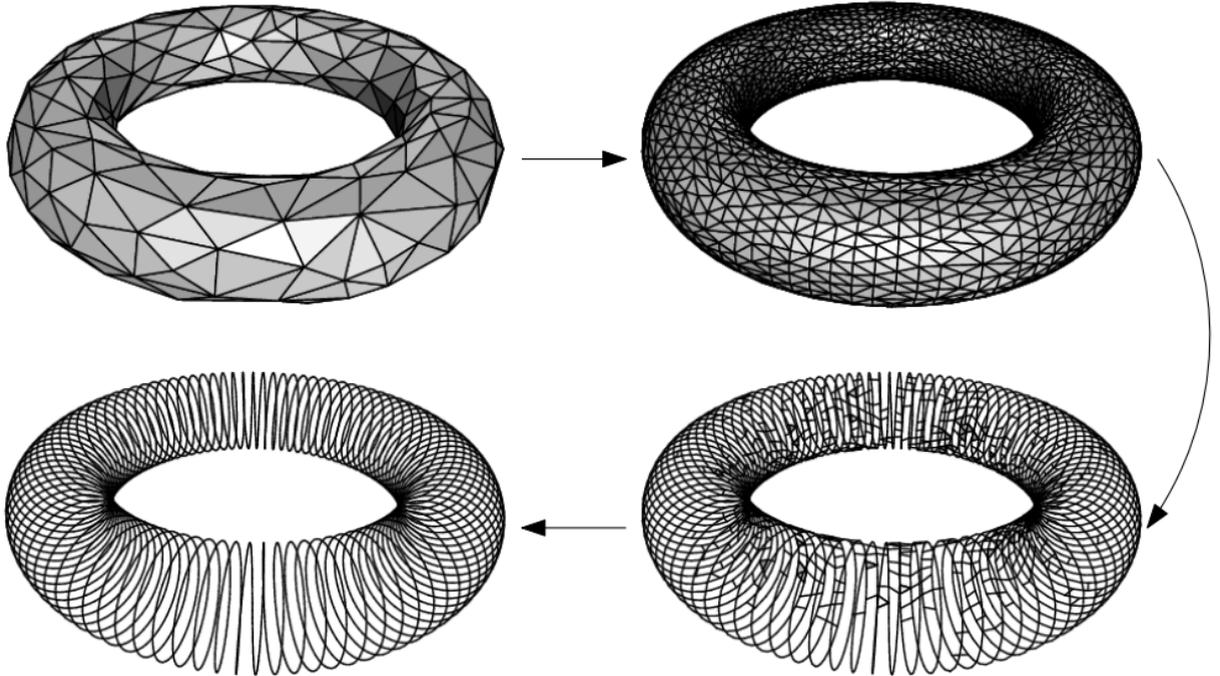
Back to the reconstruction paradigm

→ **When the dimensionality of the data is unknown or there is noise, the reconstruction result depends on the scale at which the data is looked at.**

→ need for multi-scale reconstruction techniques

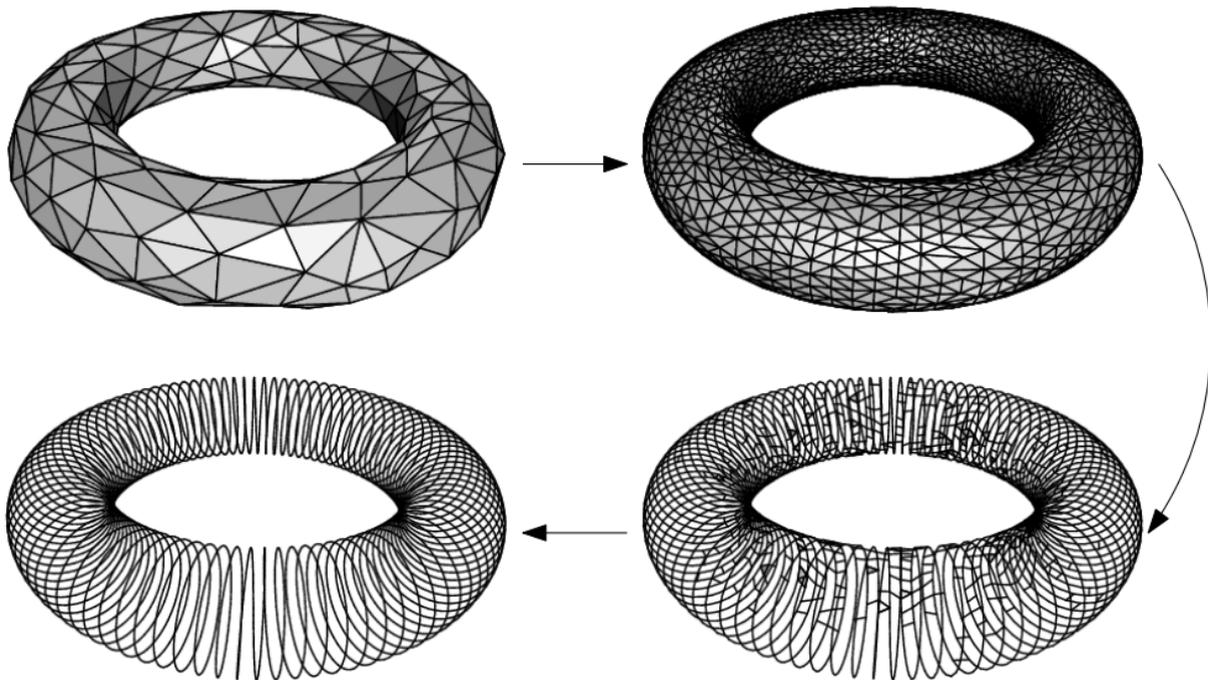
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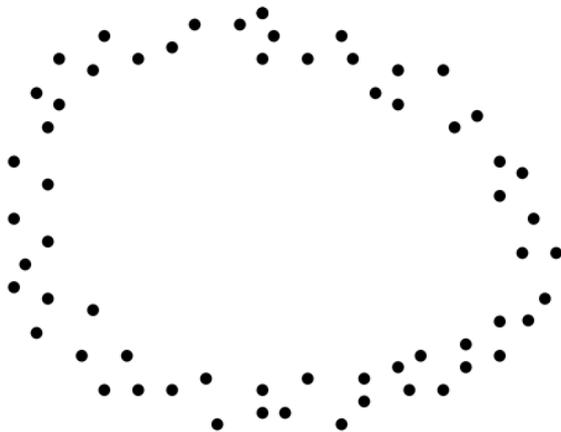


→ connections with manifold learning and topological persistence

Multi-scale algorithm [Guibas, Oudot 2007]

Input: a finite point set $W \subset \mathbb{R}^n$

→ resample W iteratively, and maintain a simplicial complex:

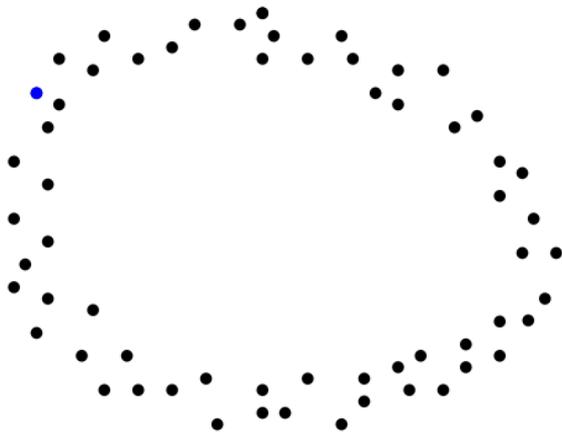


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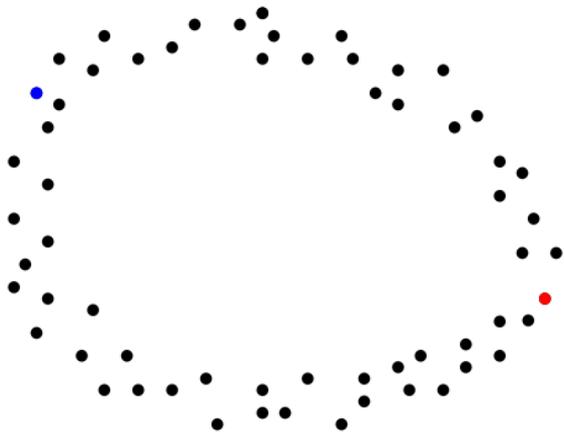
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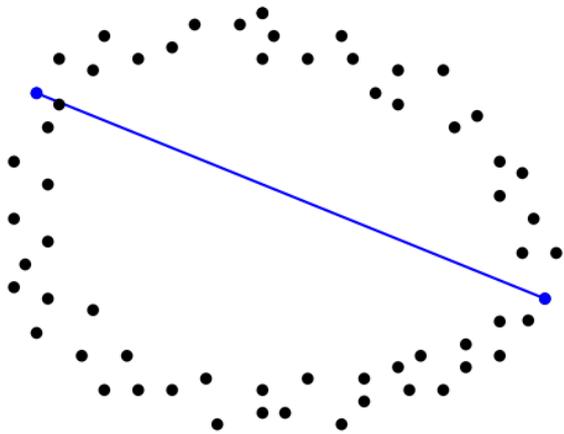
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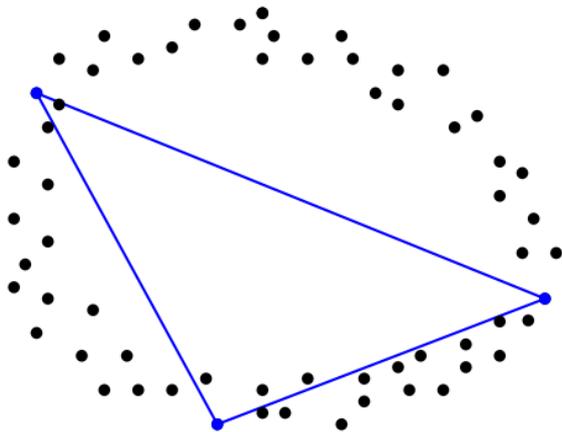
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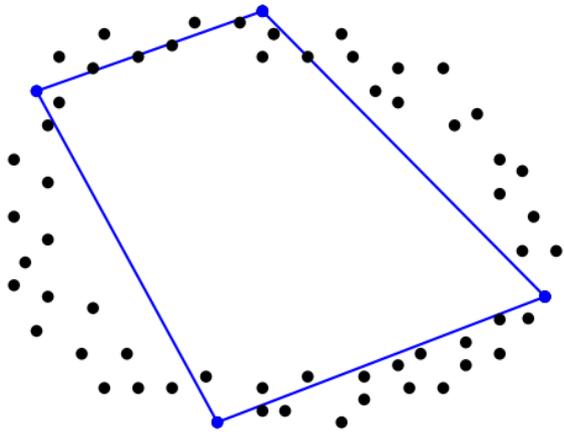
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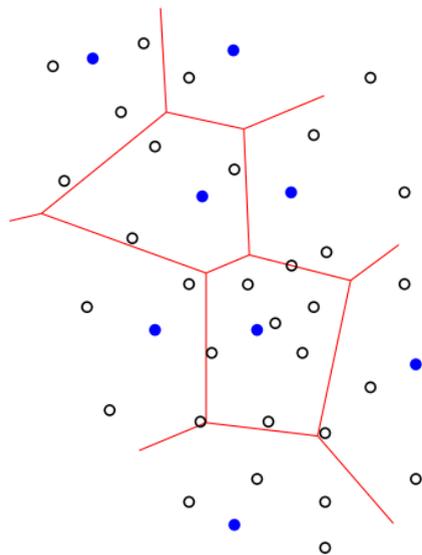
Output: the sequence of simplicial complexes



The simplicial complex to maintain

→ maintain the **witness complex** $C^W(L)$ [de Silva 2003]:

Let $L \subseteq \mathbb{R}^d$ (landmarks) s.t. $|L| < +\infty$ and $W \subseteq \mathbb{R}^d$ (witnesses)

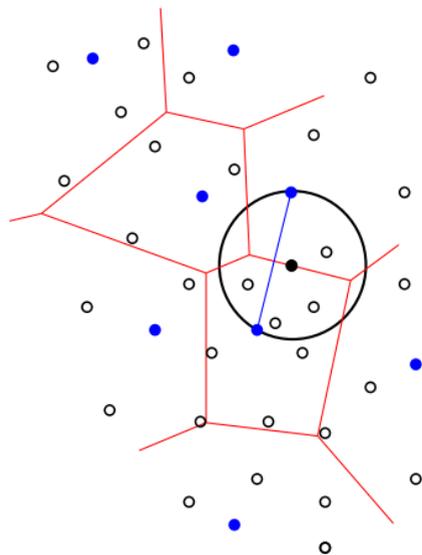


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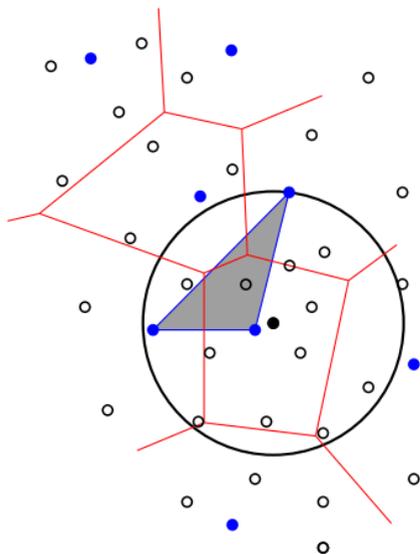
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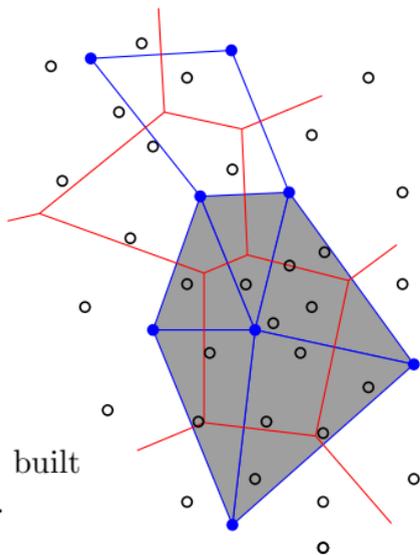
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Def. $C^W(L)$ is the largest abstract simplicial complex built over L , whose faces are weakly witnessed by points of W .

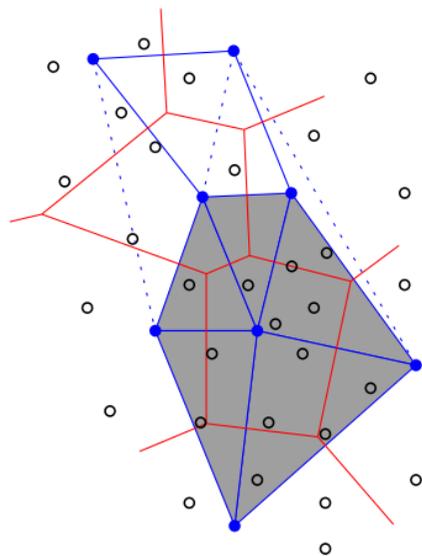


The witness complex (properties)

Thm. 1 [de Silva 2003] $\forall W, L, \forall \sigma \in C^W(L), \exists c \in \mathbb{R}^d$ that strongly witnesses σ .

$\Rightarrow C^W(L)$ is a subcomplex of $\text{Del}(L)$

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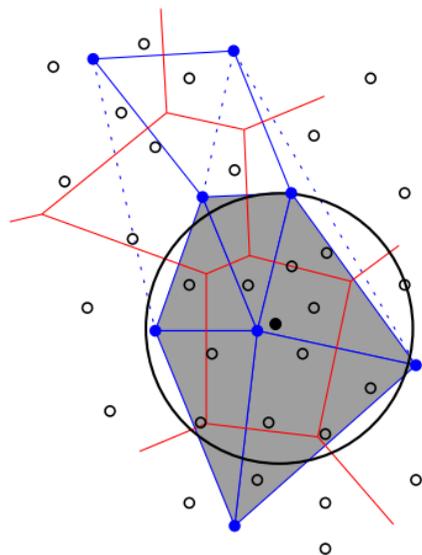
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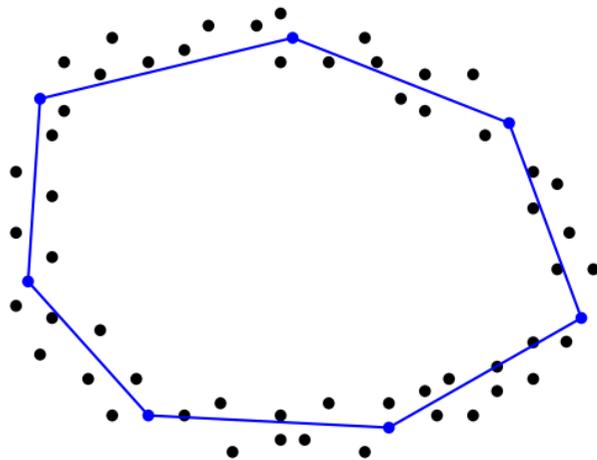
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Thm. 3 [Guibas, Oudot 2007]

[Attali, Edelsbrunner, Mileyko 2007]

Under some conditions, $C^W(L) = \text{Del}_{\mathcal{S}}(L) \approx \mathcal{S}$

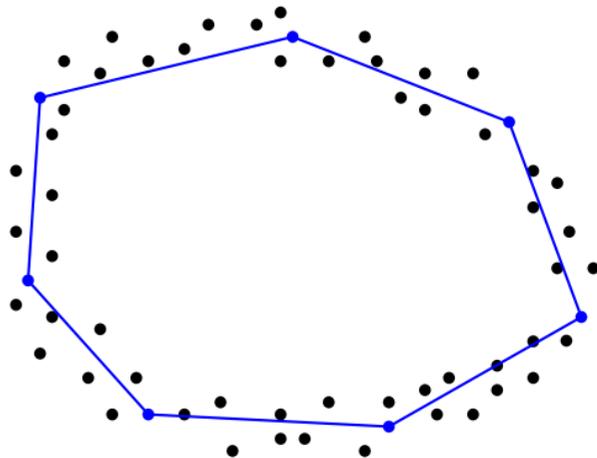


The witness complex (properties)

→ connection with reconstruction:

- $W \subset \mathbb{R}^d$ is given as input
- $L \subseteq W$ is generated
- underlying manifold \mathcal{S} unknown
- only distance comparisons

⇒ algorithm is applicable in any metric space



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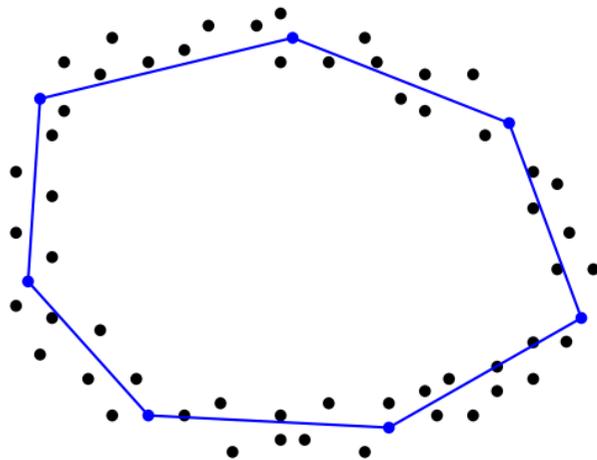
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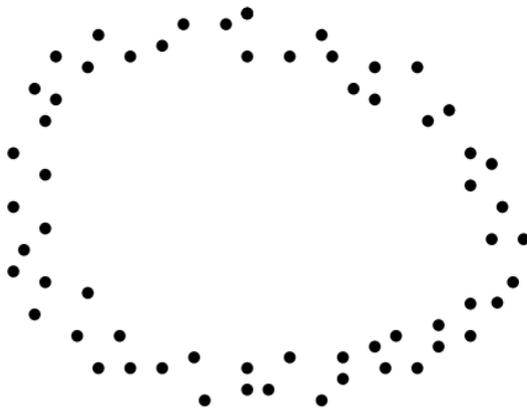
- In \mathbb{R}^d , $C^W(L)$ can be maintained by updating, for each witness w , the list of $d + 1$ nearest landmarks of w .

⇒ space $\leq O(d|W|)$
time $\leq O(d|W|^2)$



The full algorithm

Input: a finite point set $W \subset \mathbb{R}^d$.

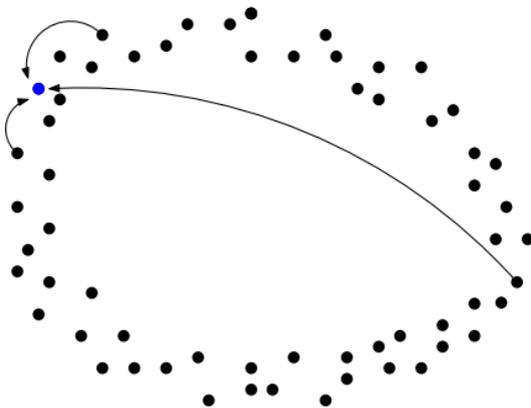


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Init: $L := \{p\}$; construct lists of nearest landmarks; $C^W(L) = \{[p]\}$;

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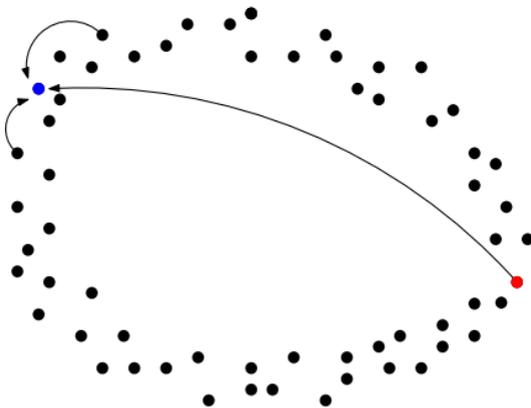
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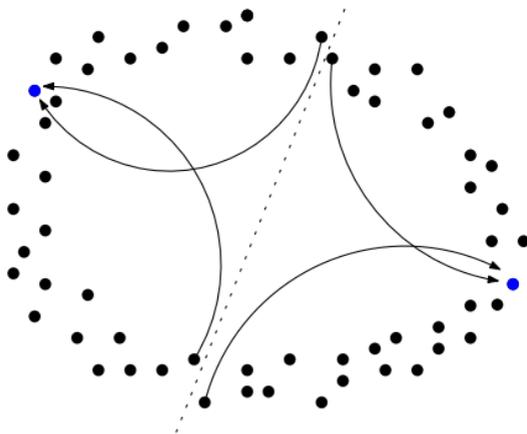
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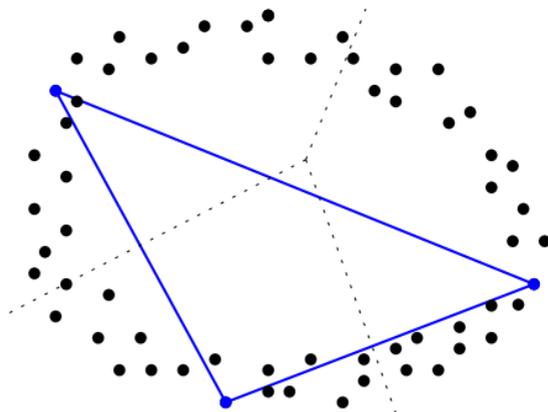
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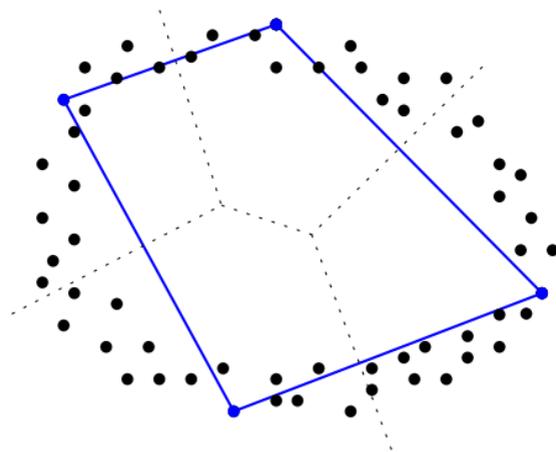
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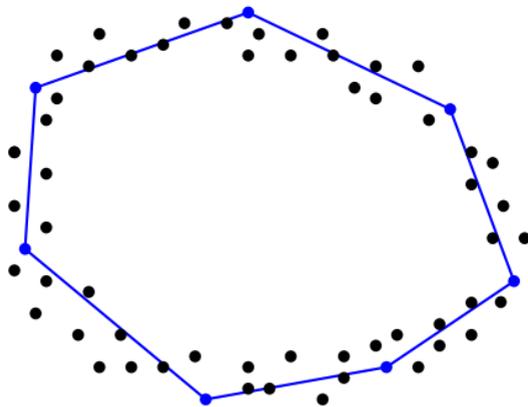
Output: the sequence of complexes $C^W(L)$



Theoretical guarantees

→ case of curves:

Conjecture [Carlsson, de Silva 2004]:
 $C^W(L)$ coincides with $\text{Del}_S(L)$...

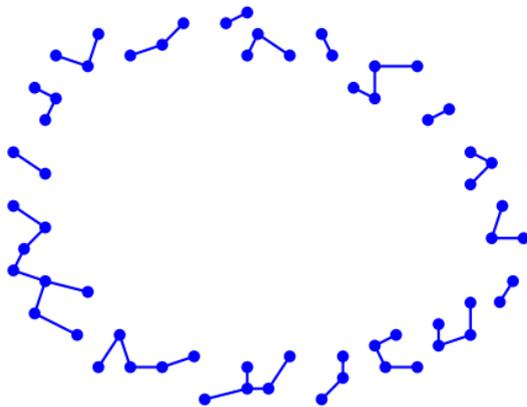


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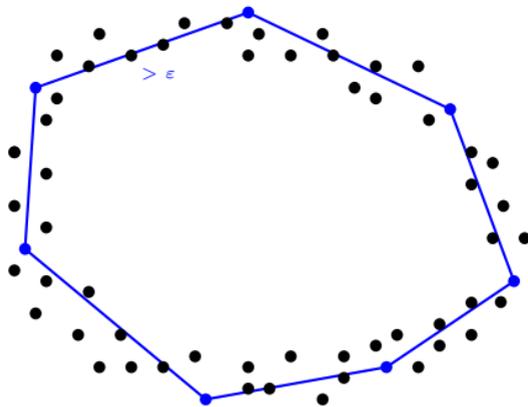
... under some conditions on W and L



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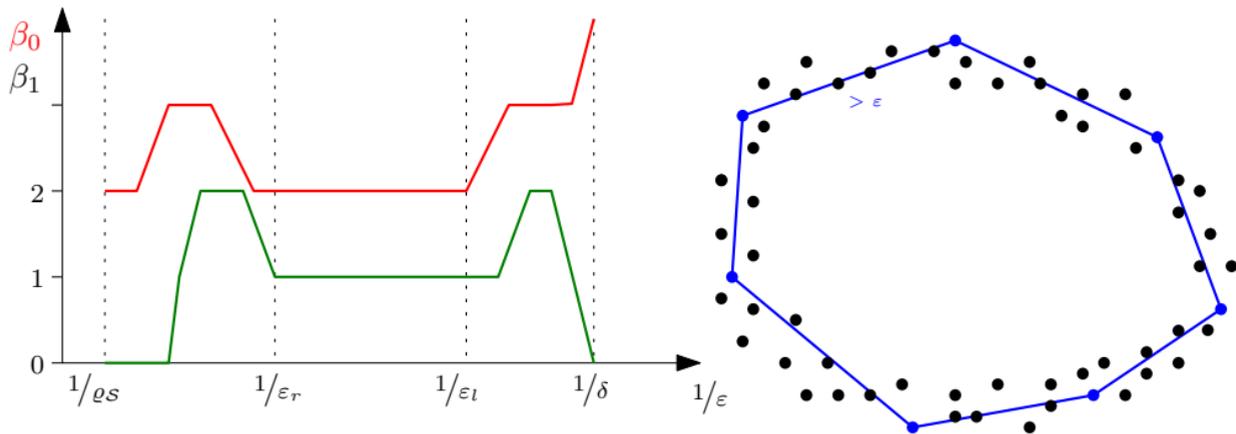
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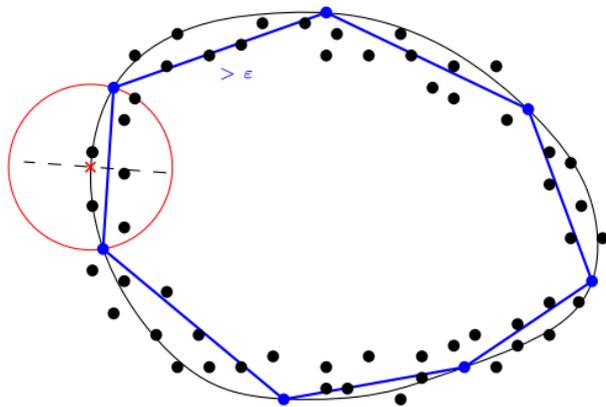
→ There is a plateau in the diagram of Betti numbers of $C^W(L)$.

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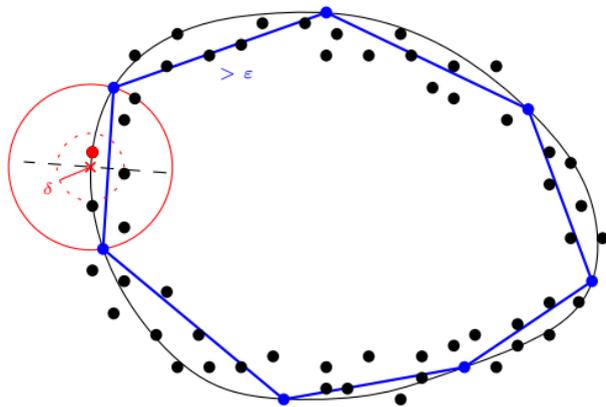


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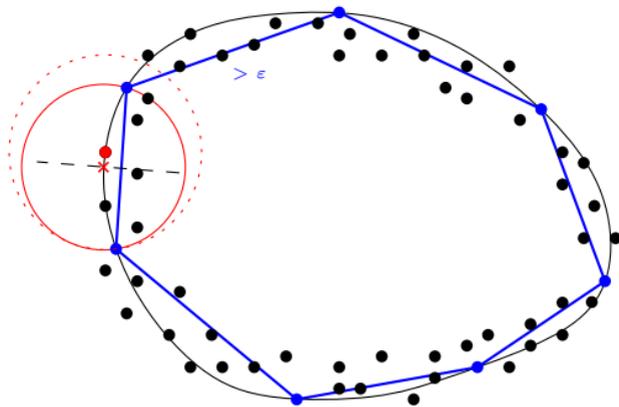


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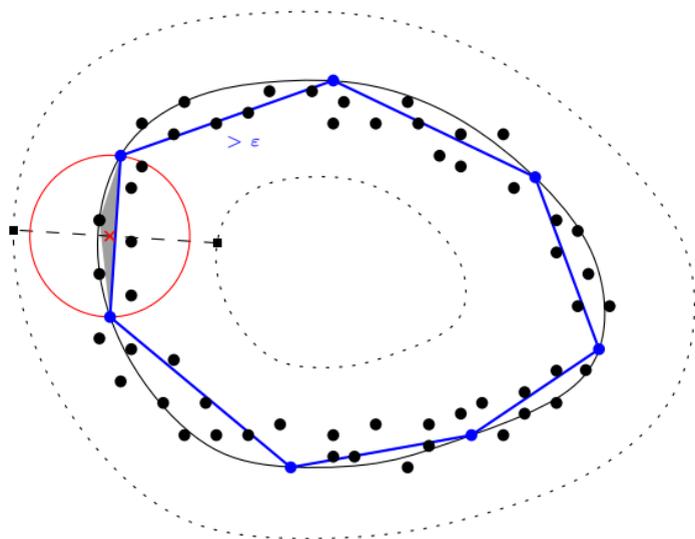


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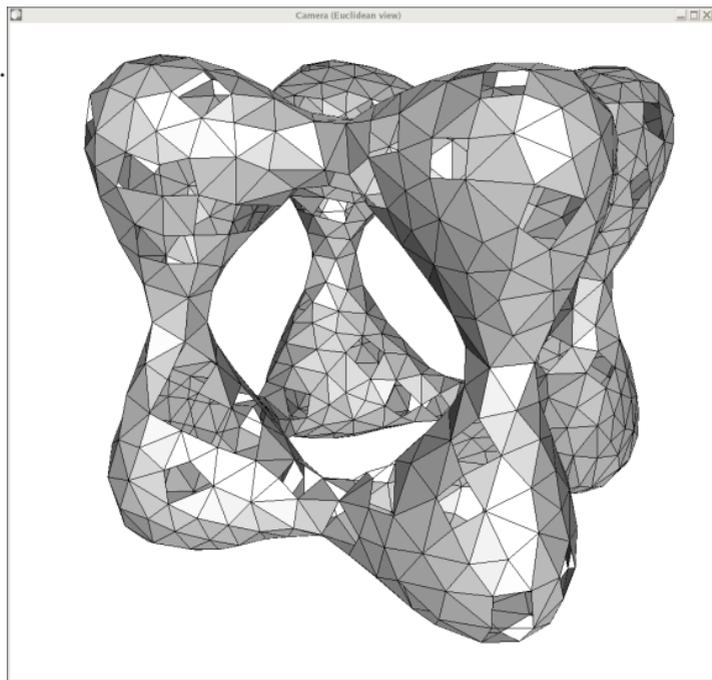
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Thm [Attali, Edelsbrunner, Mileyko]

If $\varepsilon \ll \varrho_S$, then $\forall W \subseteq S, C^W(L) \subseteq \text{Del}_S(L)$.

$\Rightarrow C^S(L) = \text{Del}_S(L)$



$\varepsilon = 0.2, \varrho_S \approx 0.25$

Theoretical guarantees

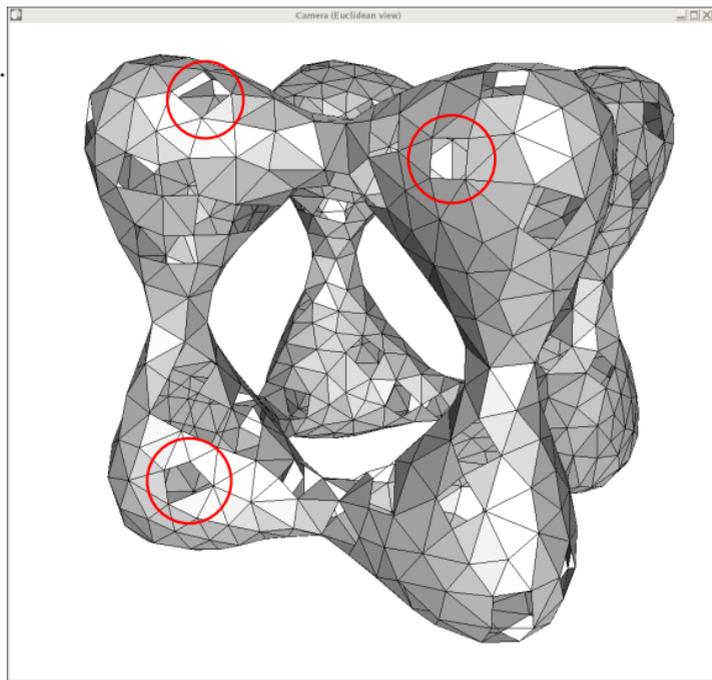
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$$\Rightarrow C^{\mathcal{S}}(L) = \text{Del}_S(L)$$

Pb $\text{Del}_S(L) \not\subseteq C^W(L)$ if $W \subsetneq \mathcal{S}$



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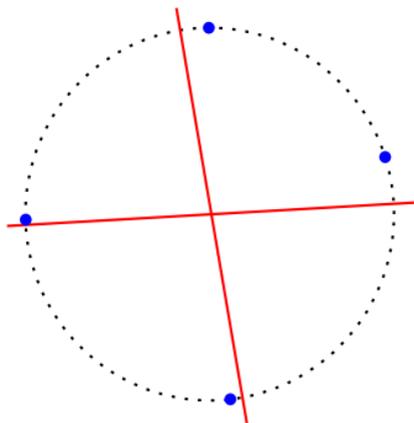
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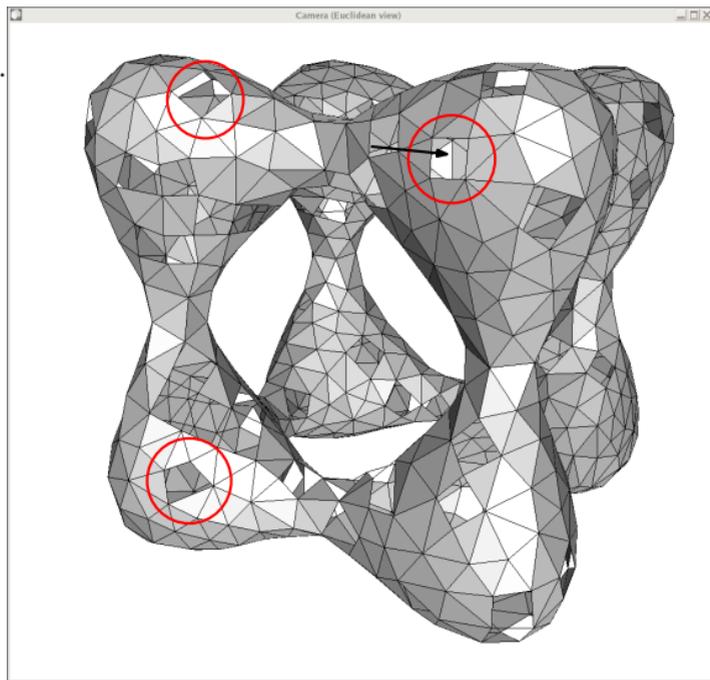
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order-2 Voronoi diagram



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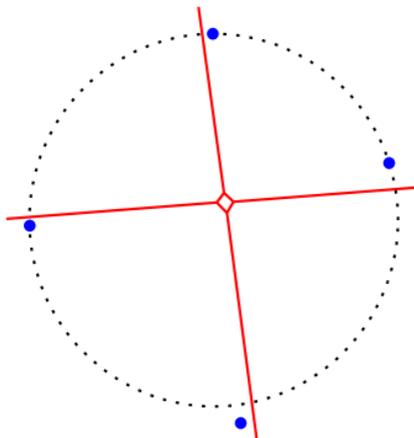
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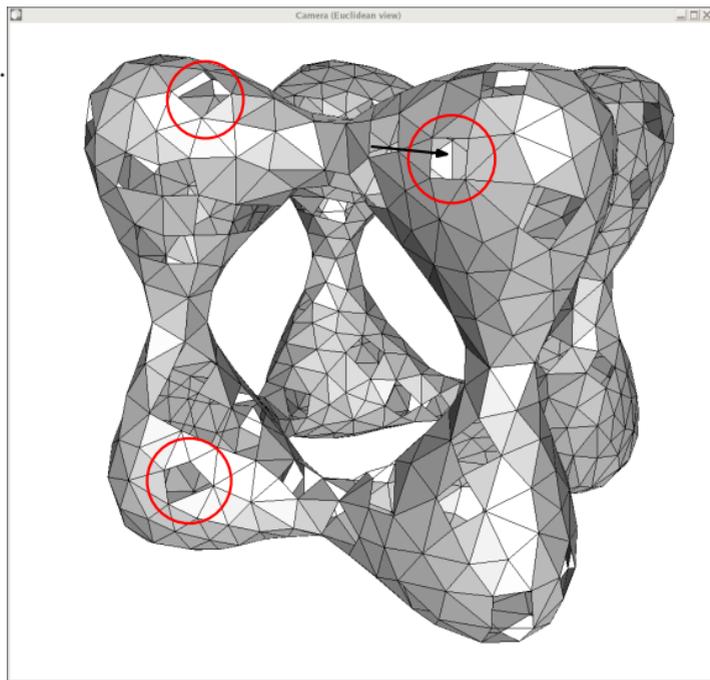
If $\varepsilon \ll \varrho_S$, then $\forall W \subseteq S, C^W(L) \subseteq \text{Del}_S(L)$.

$$\Rightarrow C^S(L) = \text{Del}_S(L)$$

Pb $\text{Del}_S(L) \not\subseteq C^W(L)$ if $W \subsetneq S$



order-2 Voronoi diagram



$$\varepsilon = 0.2, \varrho_S \approx 0.25$$

Theoretical guarantees

→ case of surfaces:

Thm [Attali, Edelsbrunner, Mileyko]

If $\varepsilon \ll \varrho_S$, then $\forall W \subseteq S, C^W(L) \subseteq \text{Del}_S(L)$.

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Solution relax witness test

[Guibas, Oudot]

$$\Rightarrow C_\nu^W(L) = \text{Del}_S(L) + \text{slivers}$$

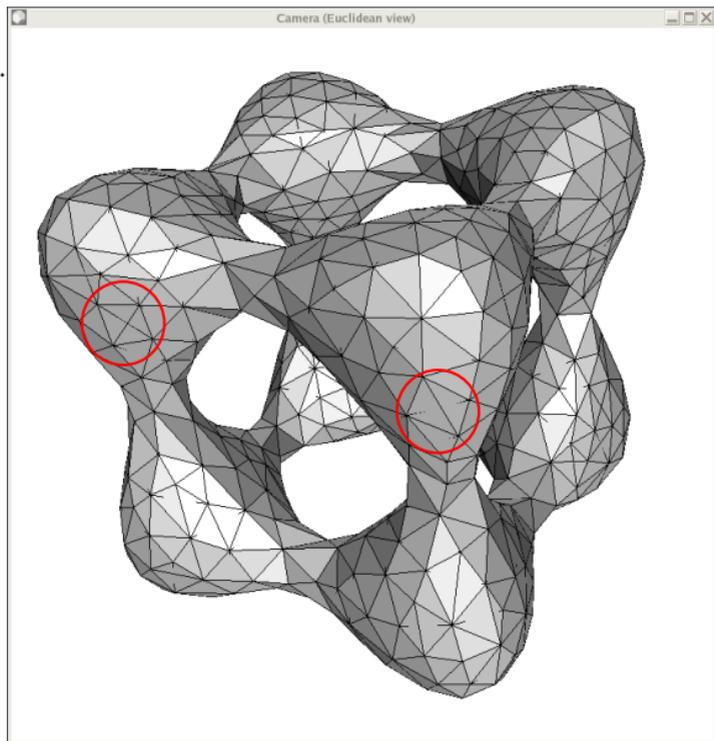
$$\Rightarrow C_\nu^W(L) \not\subseteq \text{Del}(L)$$

$$\Rightarrow C_\nu^W(L) \text{ not embedded.}$$

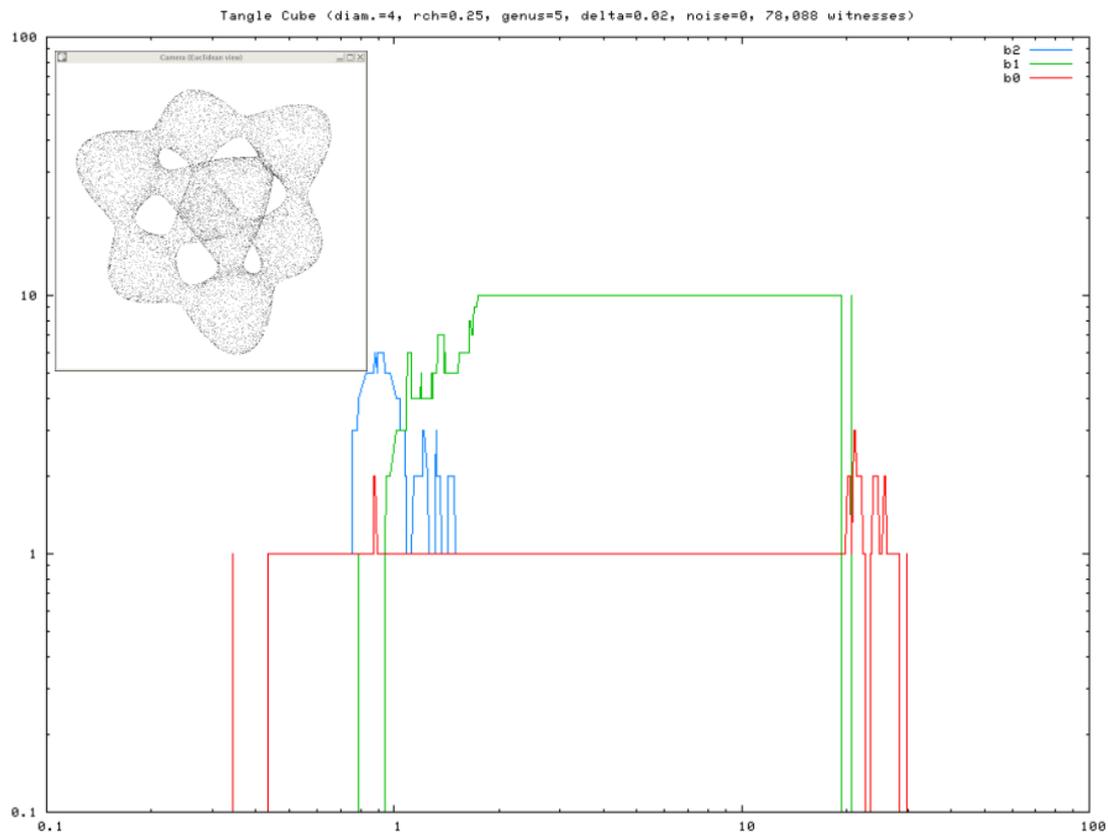
Post-process extract manifold M

from $C_\nu^W(L) \cap \text{Del}(L)$

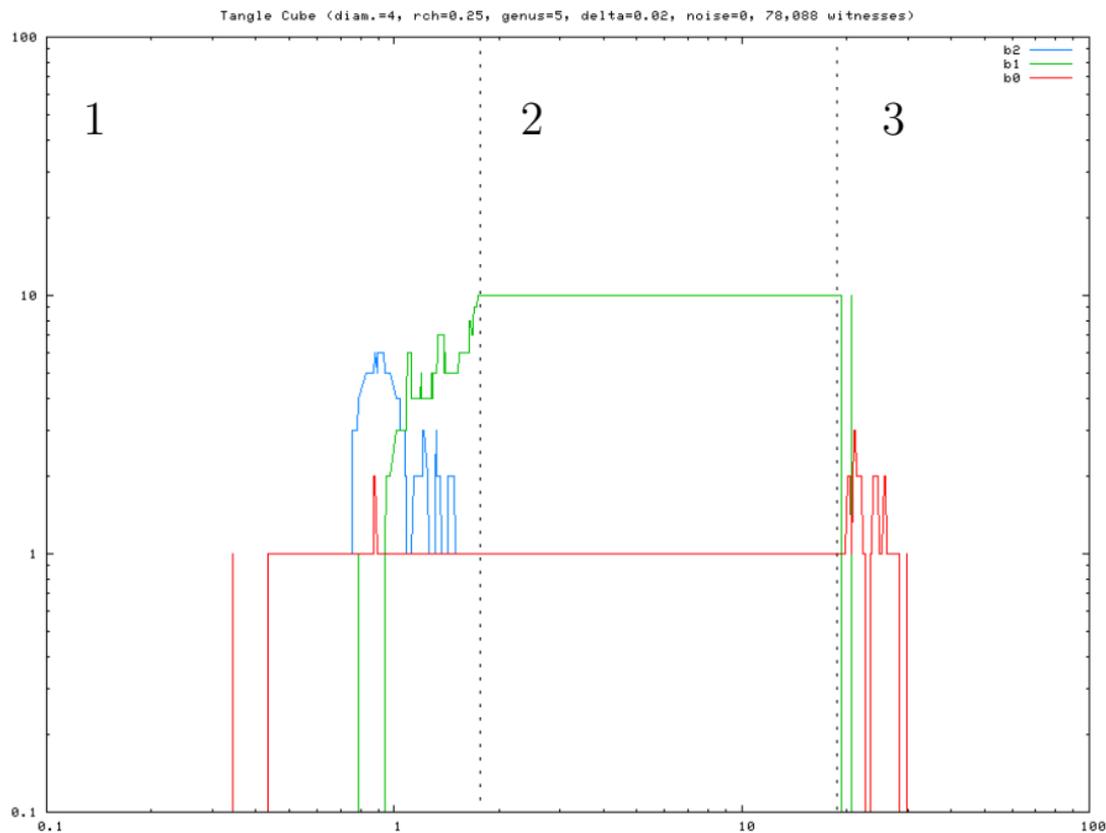
[Amenta, Choi, Dey, Leekha]



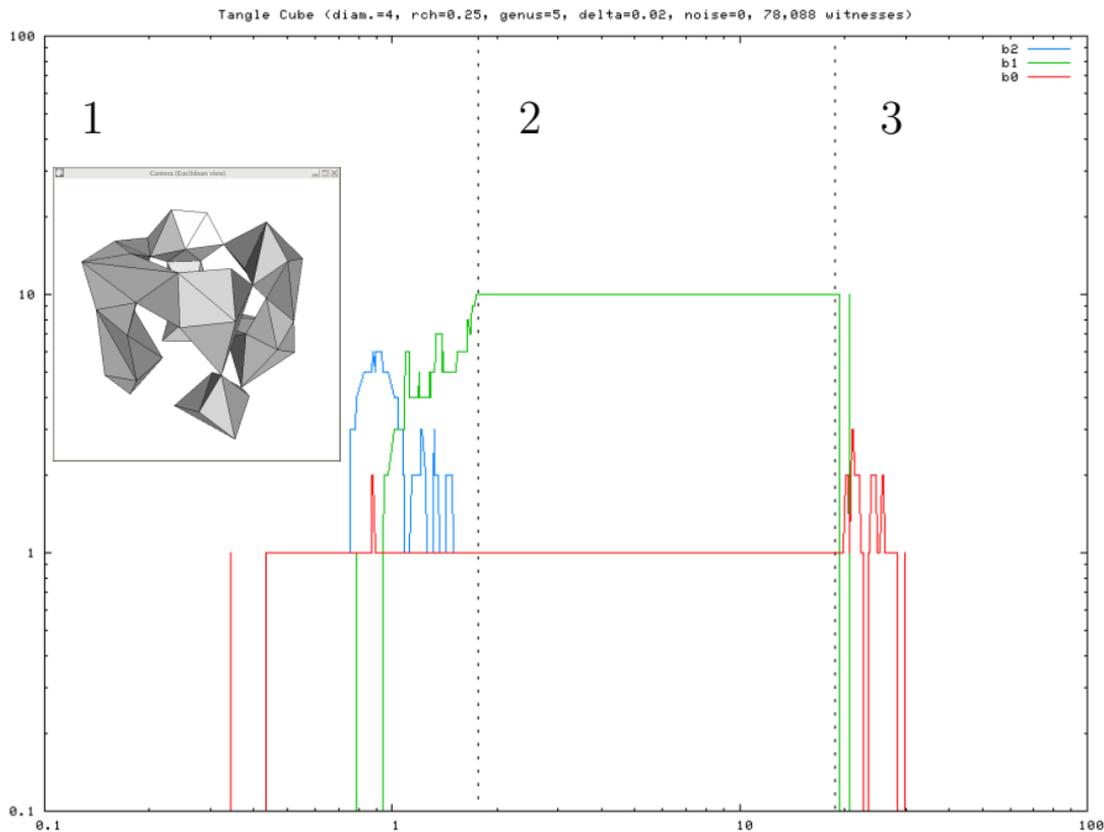
Some results



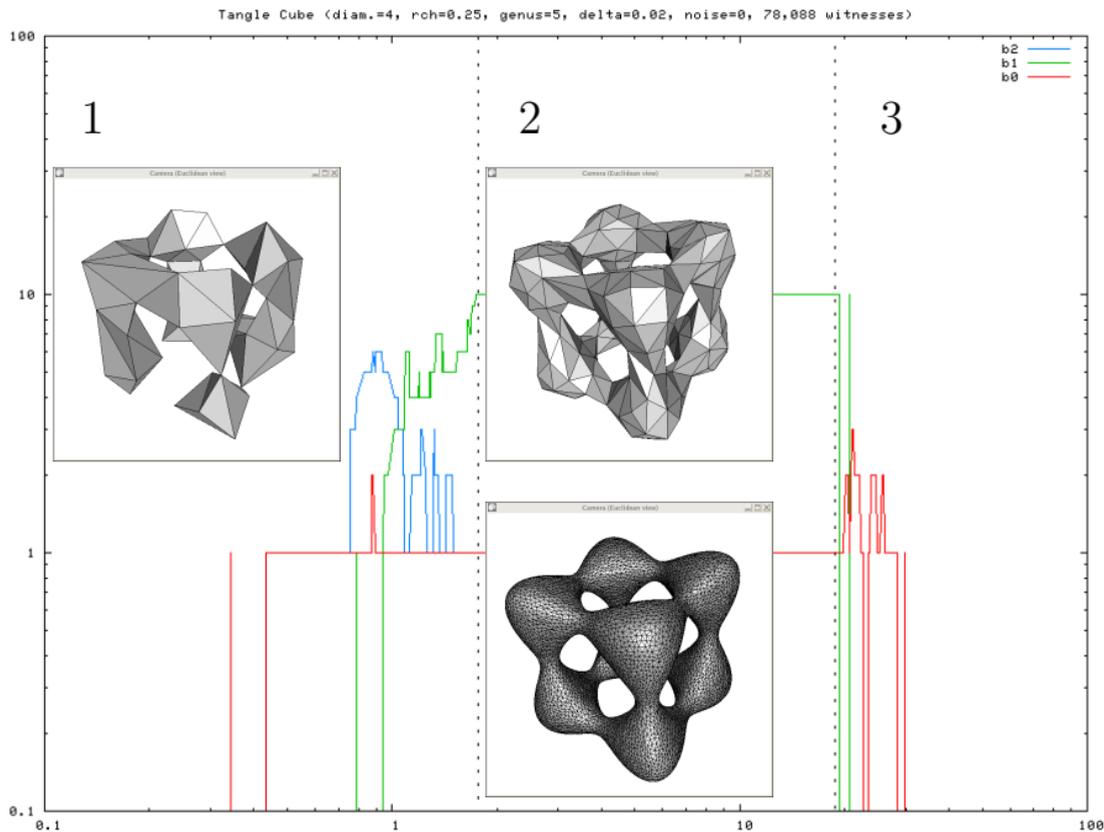
Some results



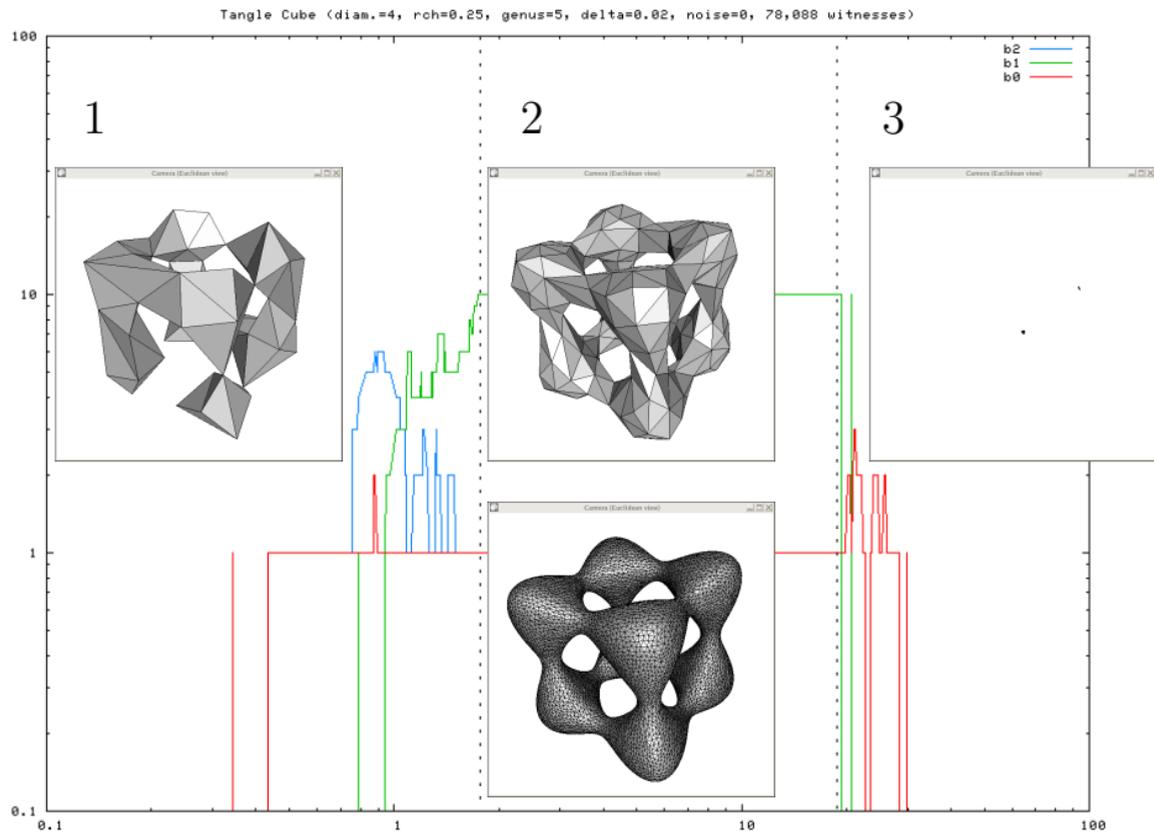
Some results



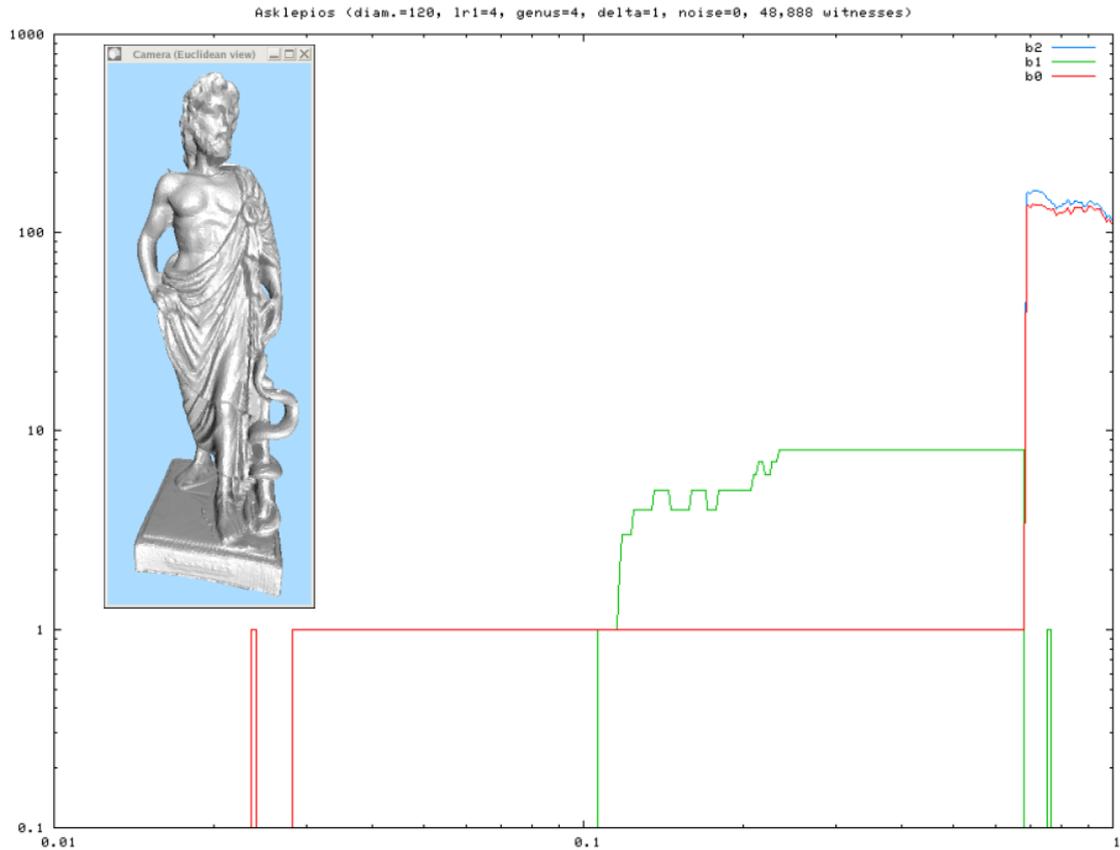
Some results



Some results

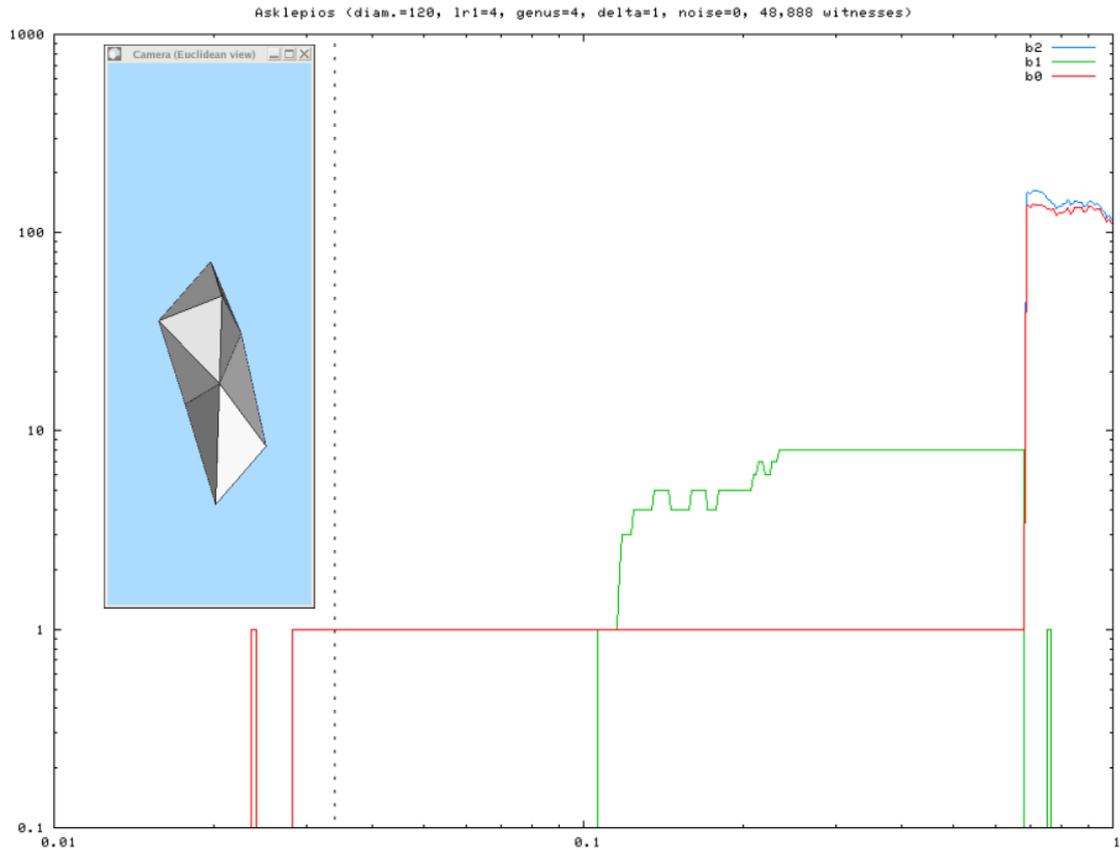


Some results (cont'd)



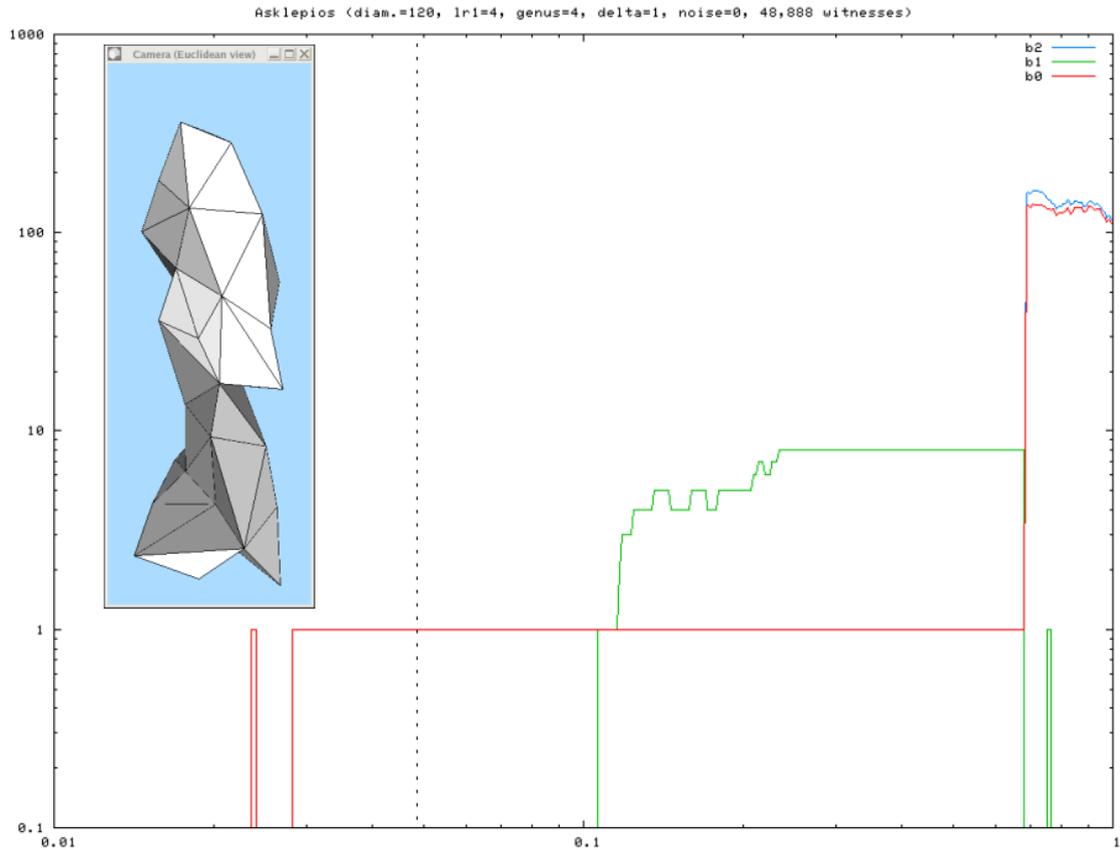
input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)



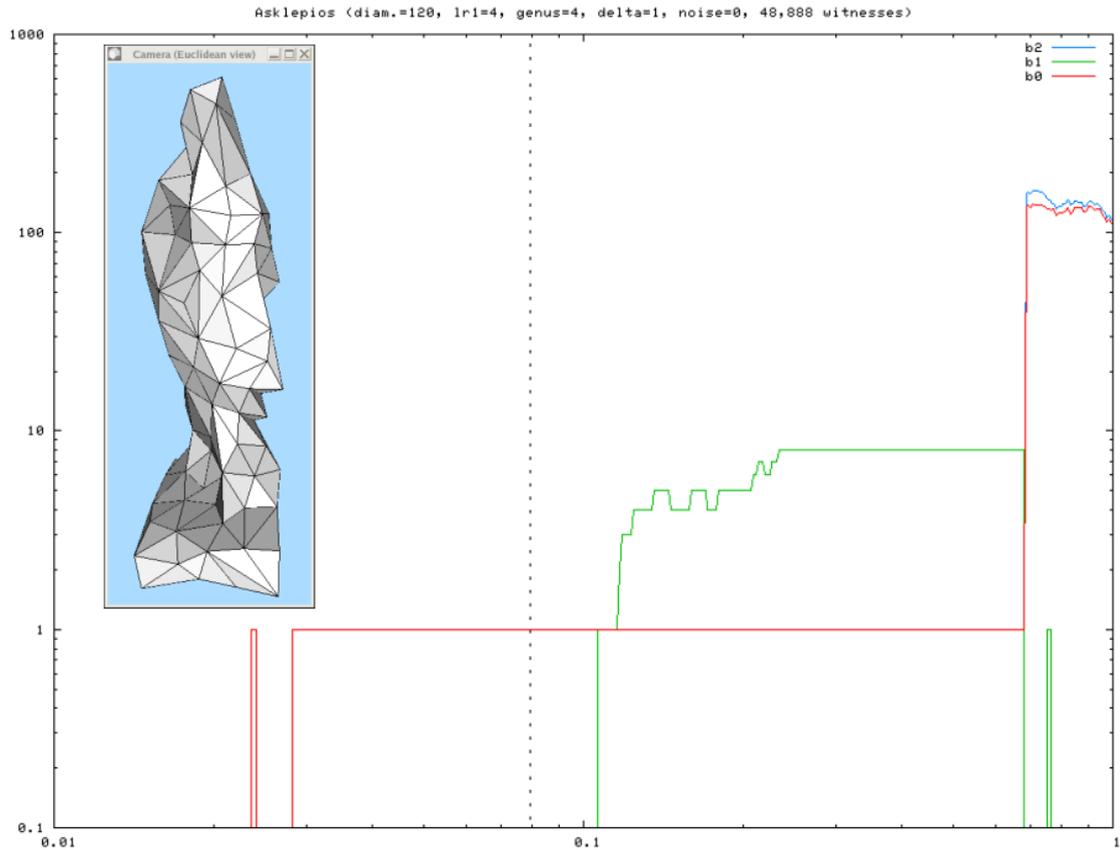
input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)



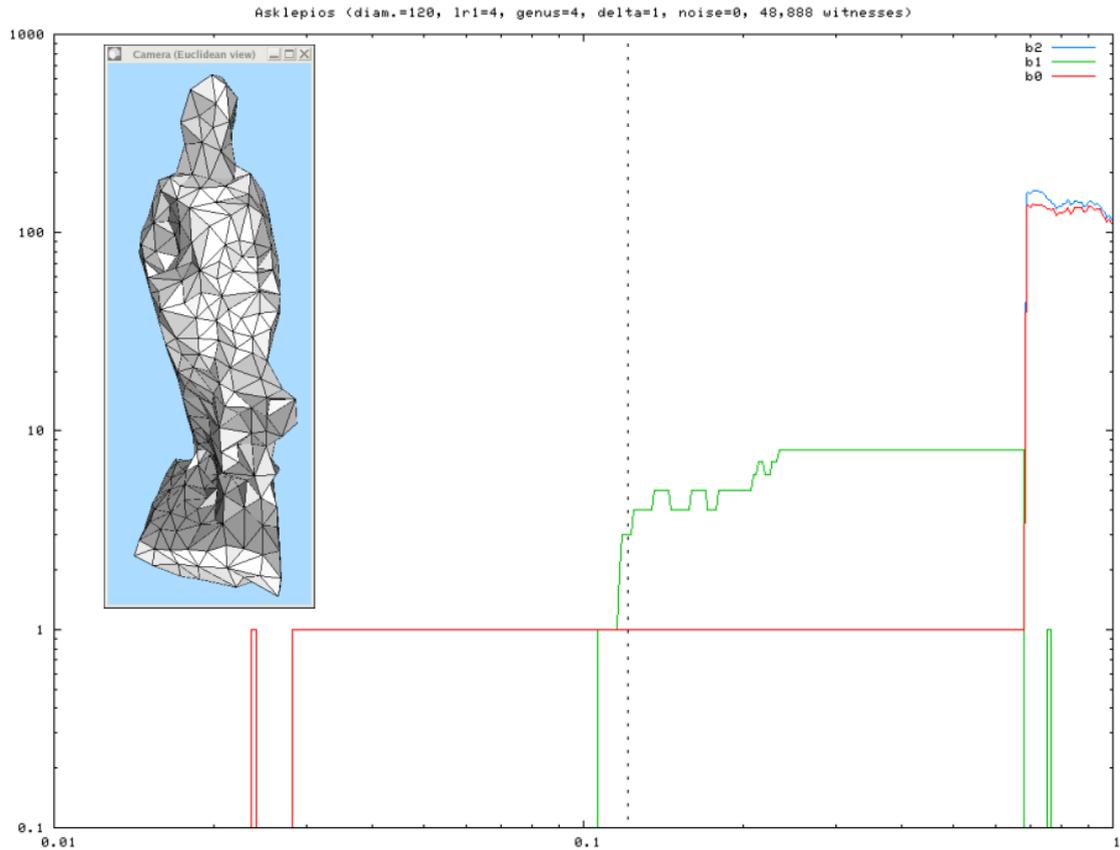
input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)



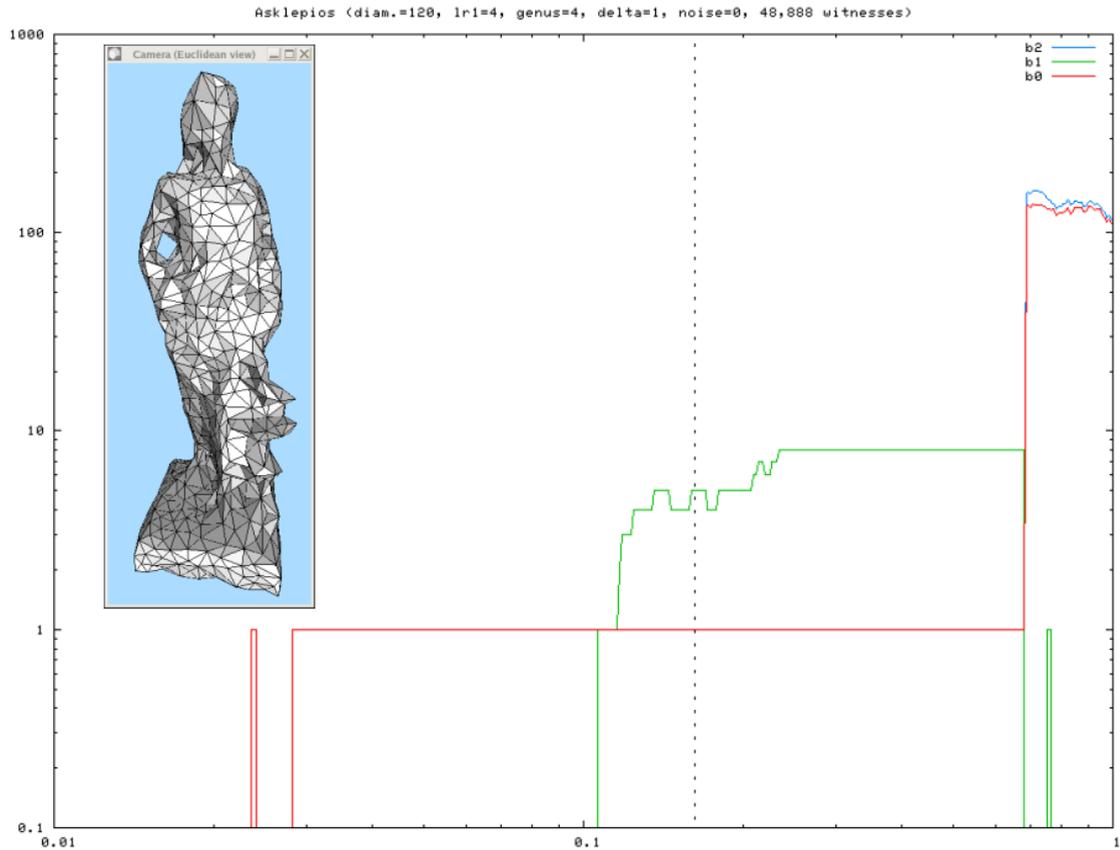
input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)



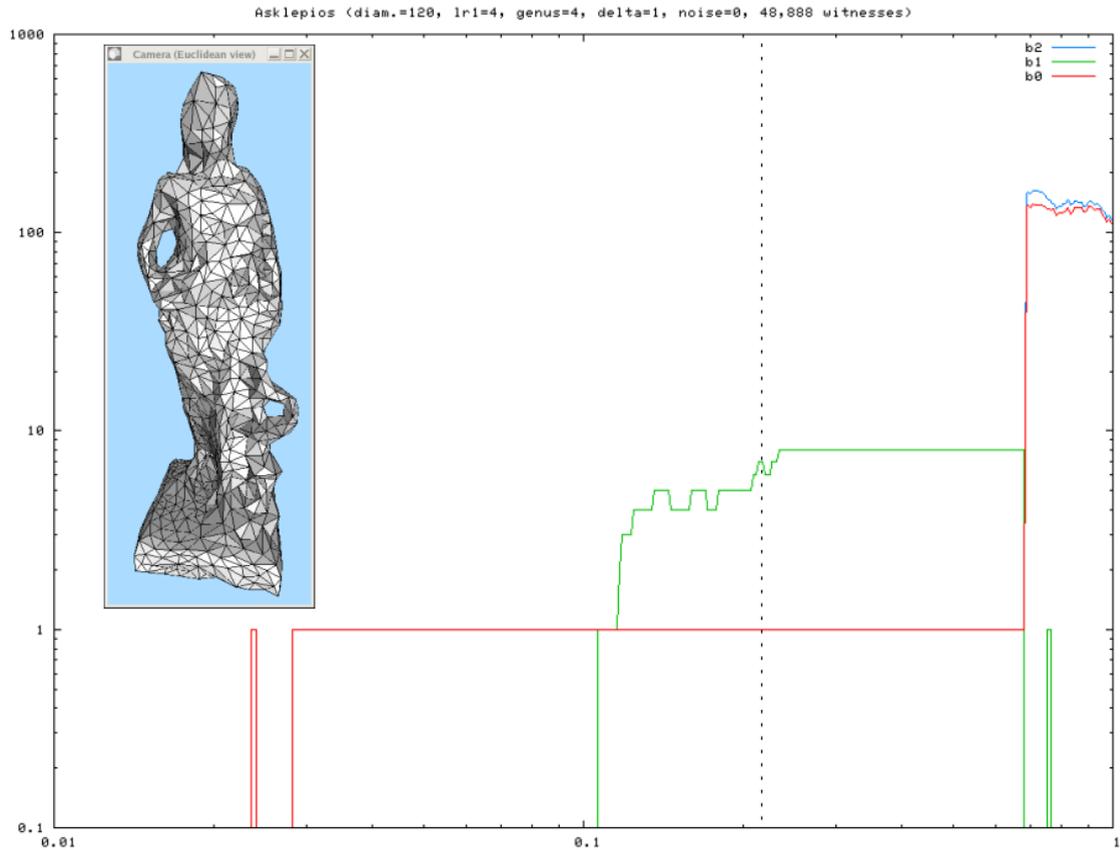
input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)



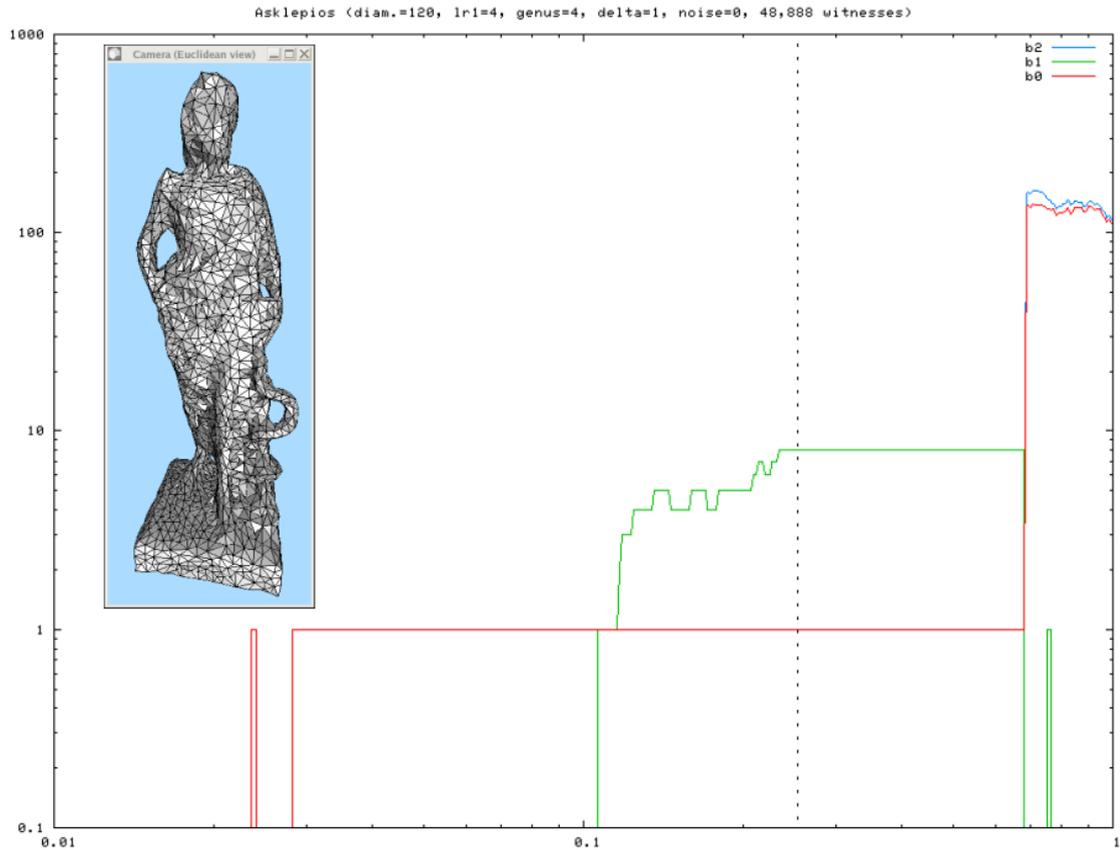
input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)



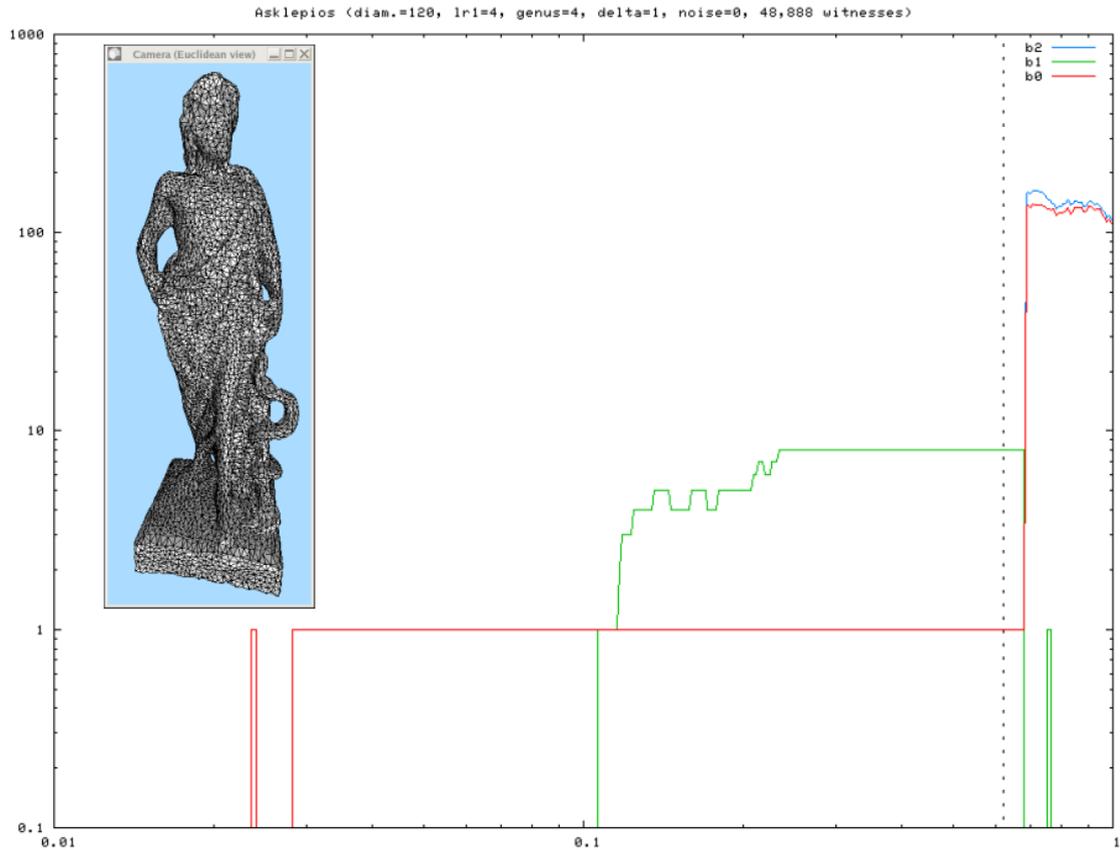
input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)



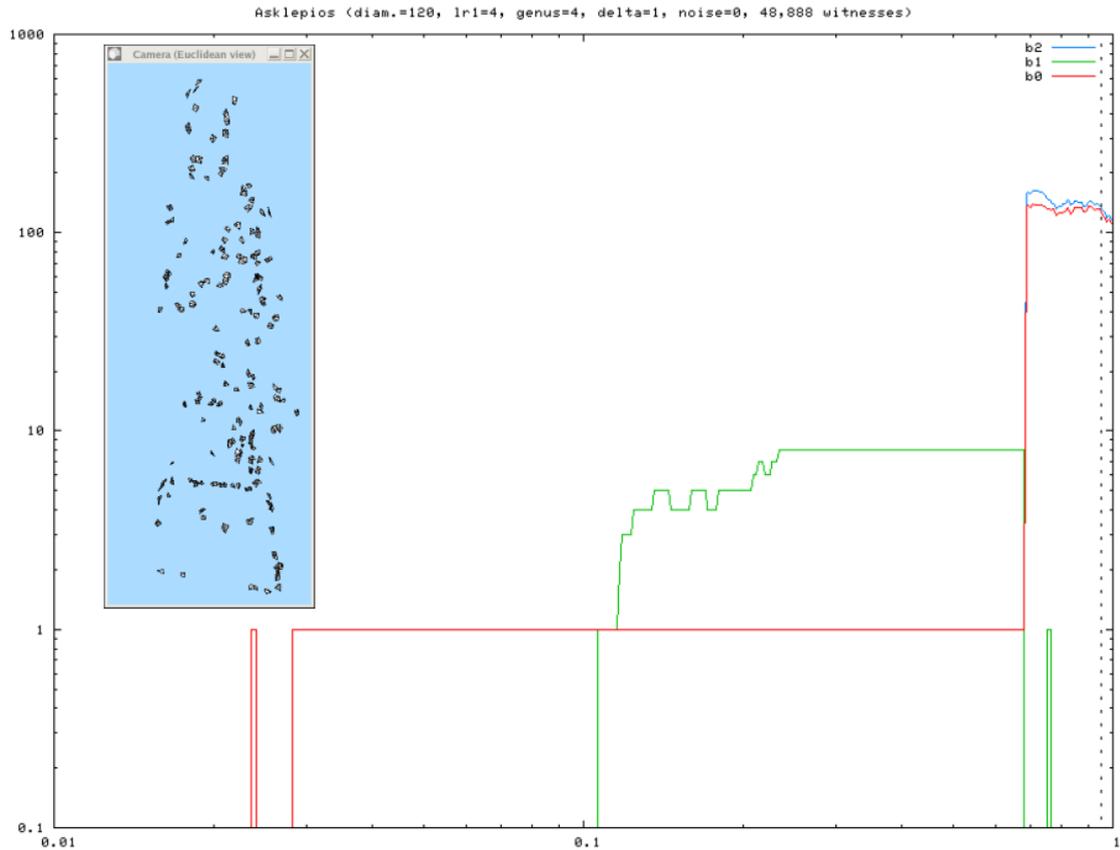
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Some results (cont'd)



input model provided courtesy of IMATI by the Aim@Shape repository

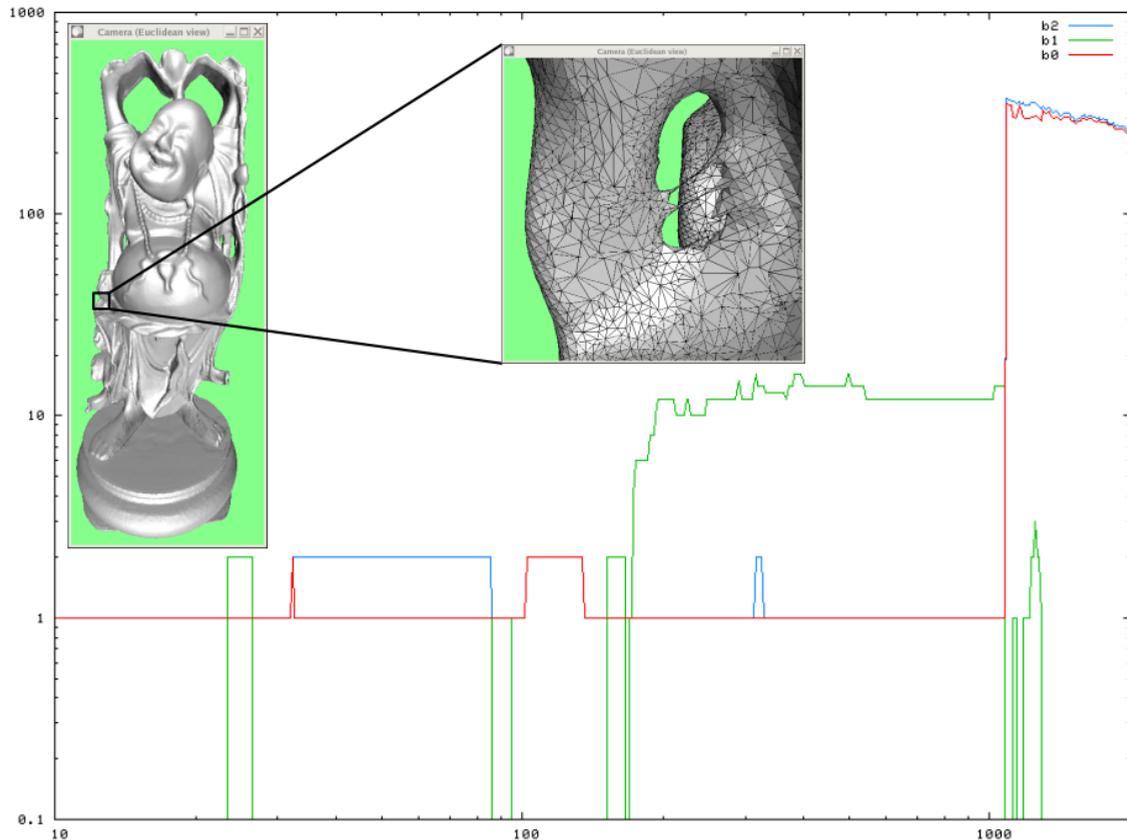
Some results (cont'd)



input model provided courtesy of IMATI by the Aim@Shape repository

Some results (cont'd)

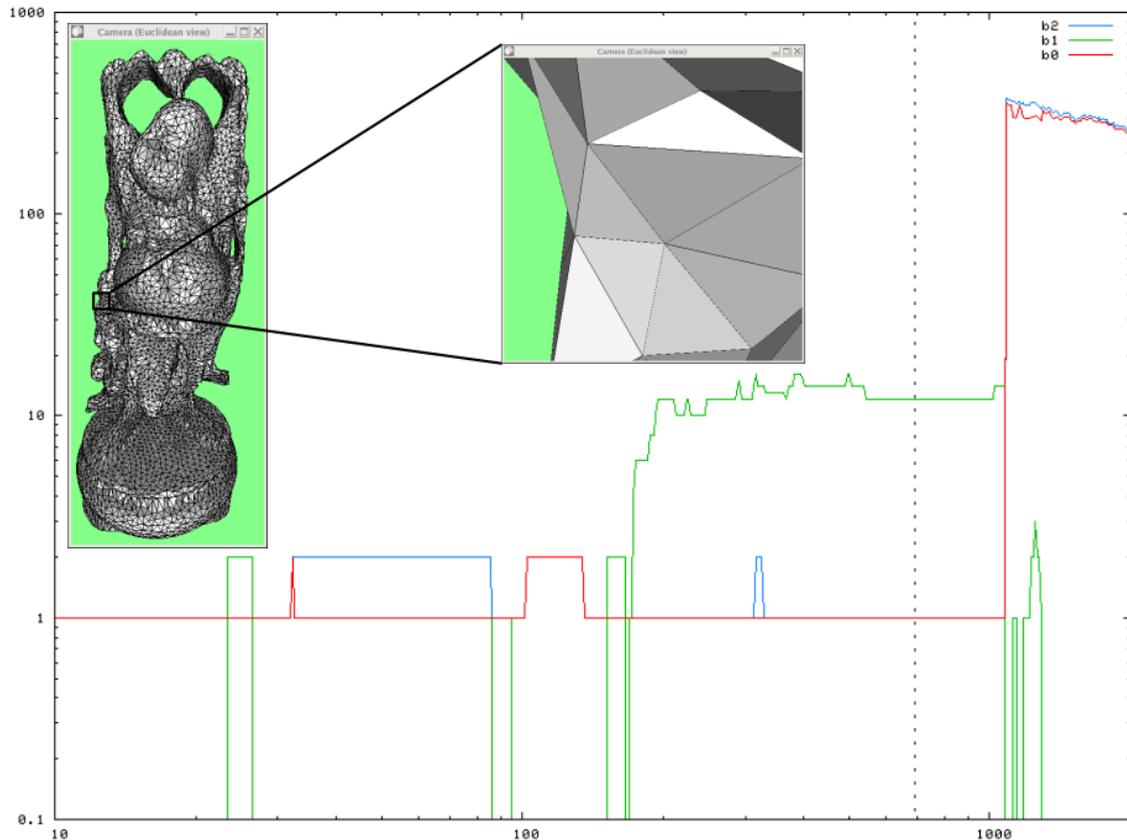
Happy Buddha (diam.=0.1, rch=?, genus=104, delta=?, noise=?, 1,631,368 witnesses)



input data set courtesy of the Graphics Lab@Stanford

Some results (cont'd)

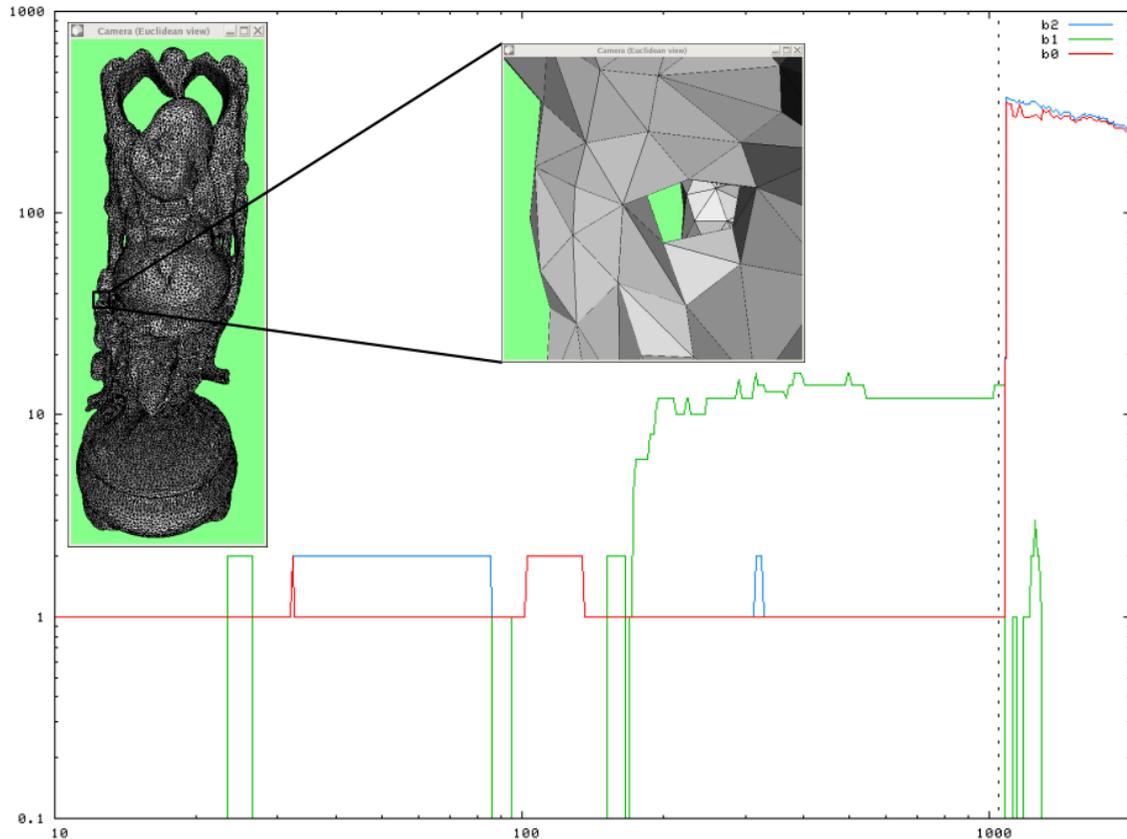
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Some results (cont'd)

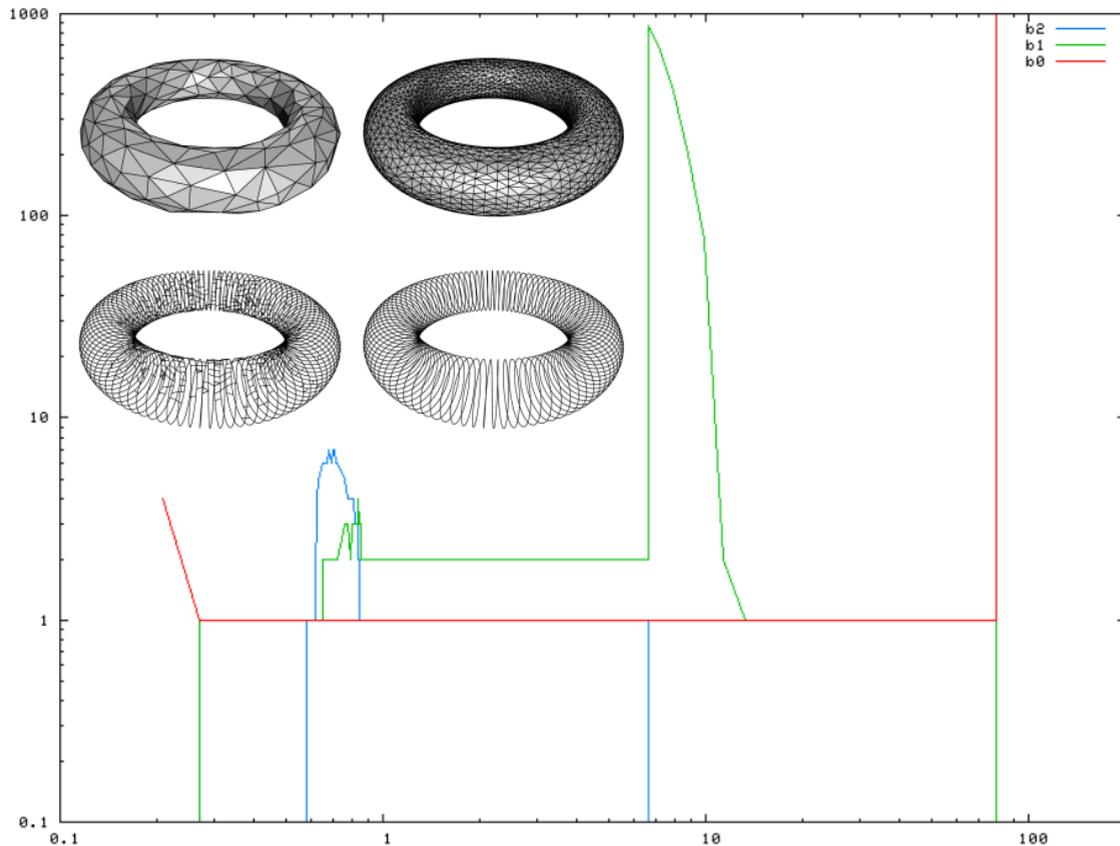
Happy Buddha (diam.=0.1, rch=?, genus=104, delta=?, noise=?, 1,631,368 witnesses)



input data set courtesy of the Graphics Lab@Stanford

Some results (cont'd)

Curve on Torus (diam.=10, rch=0.04:1, delta=0.01, noise=0, 50,000 witnesses)



Higher dimensions

→ Carlsson and de Silva's conjecture:

Under some sampling conditions, $C^W(L) = \text{Del}_{\mathcal{S}}(L) \approx \mathcal{S}$

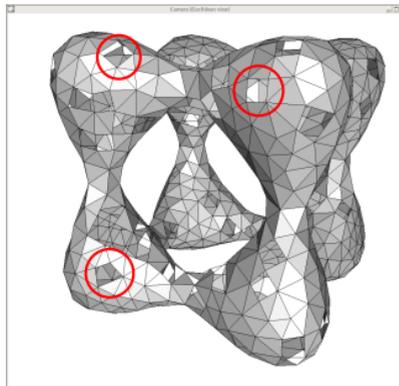
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non longer true

- $\text{Del}_S(L)$ may not be included in $C^W(L)$ on d -manifolds, $d \geq 2$ [Guibas, Oudot]



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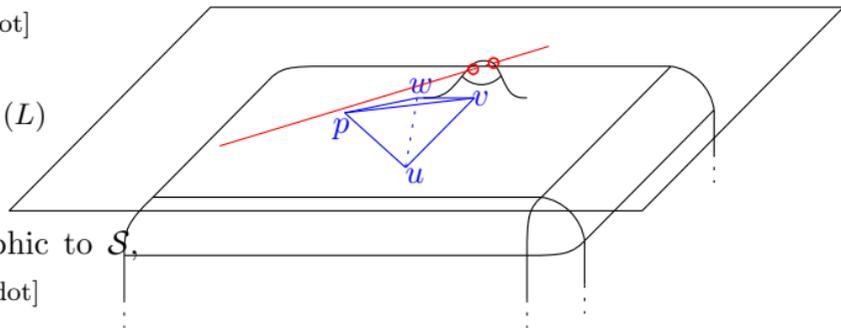
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on d -manifolds, $d \geq 2$ [Guibas, Oudot]
- $C^W(L)$ may not be included in $\text{Del}_S(L)$
on d -manifolds, $d \geq 3$ [Oudot]
- $\text{Del}_S(L)$ may not be homeomorphic to \mathcal{S} ,
nor even homotopy equivalent [Oudot]

→ source of problems: **slivers**



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Higher-dimensional reconstruction is still widely open