

# Geometric Methods in Data Analysis

## Manifold Learning

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# Reference

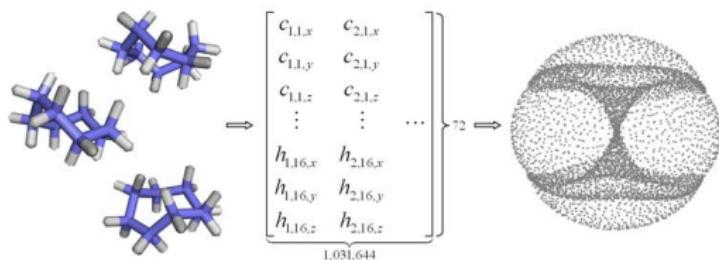
J-D. Boissonnat, F. Chazal, M. Yvinec

*Geometric and Topological Inference*

Cambridge University Press. 2018

- 1 The shape of data
- 2 The manifold model
- 3 Quality criteria
- 4 Discrete models
- 5 Reconstruction of submanifolds
  - Distance functions and homotopic reconstruction
  - Delaunay triangulation of submanifolds of  $\mathbb{R}^d$

# The shape of data



**Geometrisation :** Data = points + distances between points

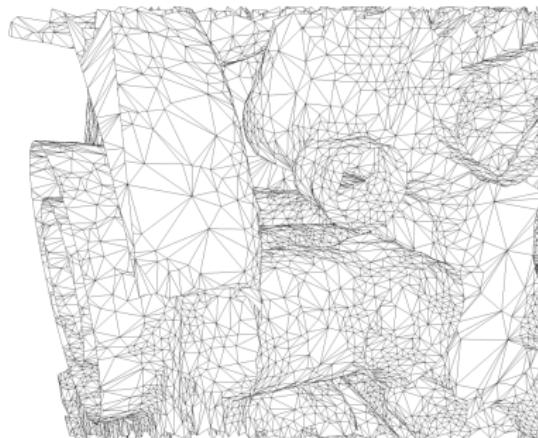
**Hypothesis :** Data lie close to a structure of  
“small” intrinsic dimension

**Problem :** Infer the structure from the data

# Geometric models and approaches

- Dimensionality reduction either linear (PCA, MDS) or non-linear (ISOMAP, LLE)
- Computation of topological and/or geometric invariants
  - ▶ Clustering
  - ▶ Persistent homology
- Shape reconstruction

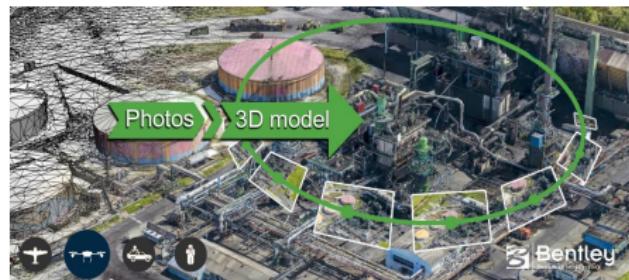
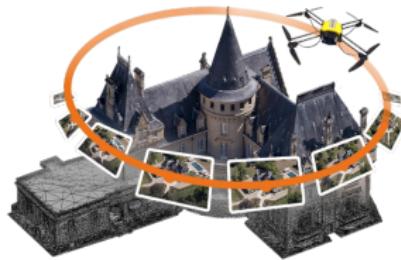
# Reconstructing surfaces from point clouds



One can reconstruct a surface from  $10^6$  points within 1mn

[CGAL]

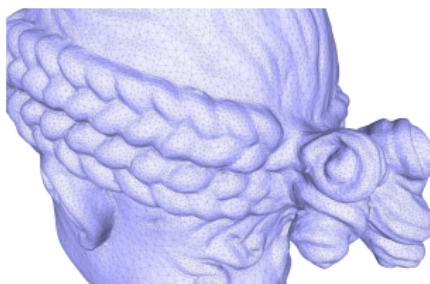
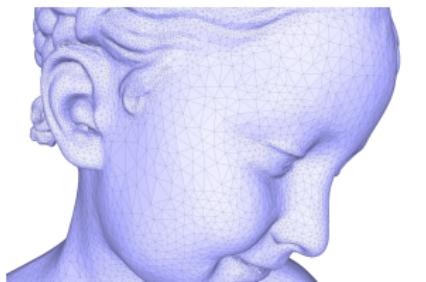
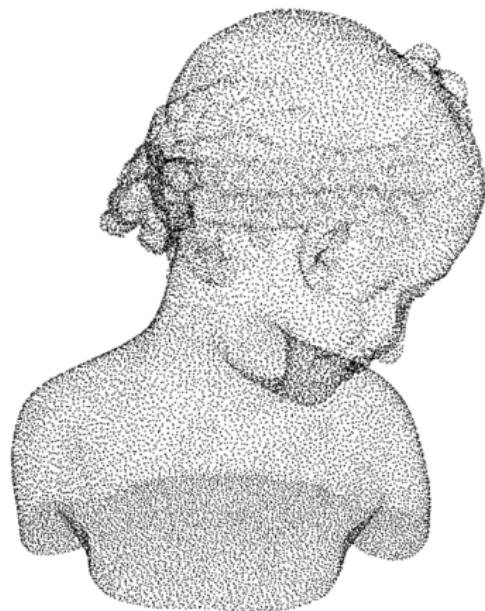
# Reconstructing surfaces from images



Acute3D, Bentley Systems

# Geometric shape reconstruction

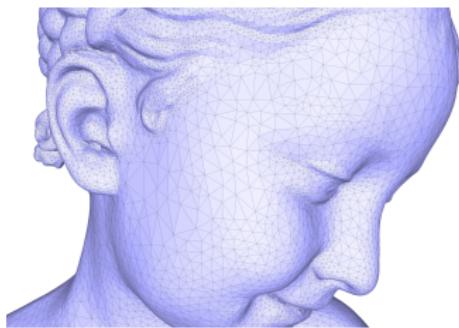
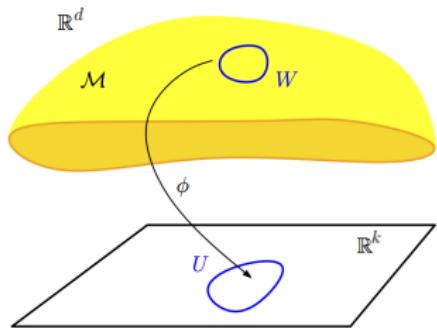
Towards a sampling theory for geometric objects



- What spaces ?
- Quality criteria
- Discrete models
- Curse of dimensionality

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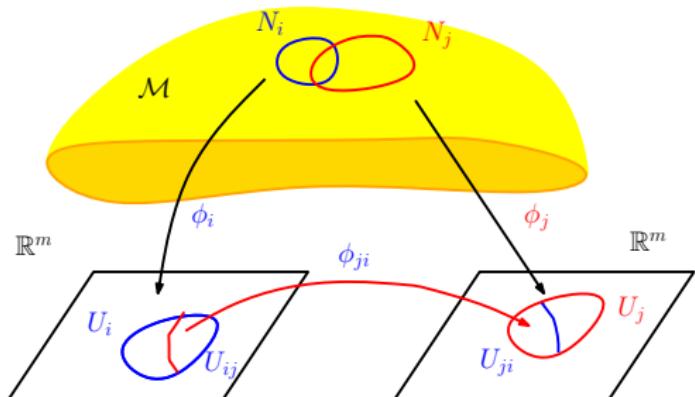
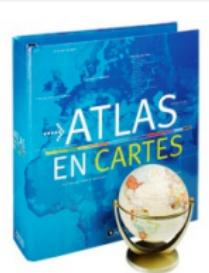
# The manifold model



A manifold of dimension  $m$  is a topological space that locally looks like (is homeomorphic to)  $\mathbb{R}^m$

**Examples :** curves and surfaces, isomanifolds (zero set of  $f : \mathbb{R}^d \rightarrow \mathbb{R}^{d-m}$ ), configuration spaces of mechanisms, time series

# Charts and atlases

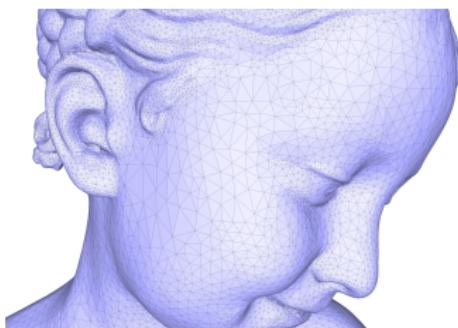
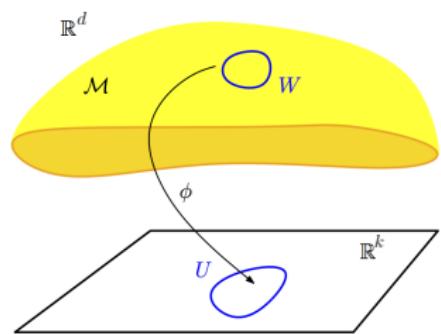


$\phi_{ij}$  : transition functions between charts

# Submanifolds of $\mathbb{R}^d$

Intrinsic and ambient dimensions

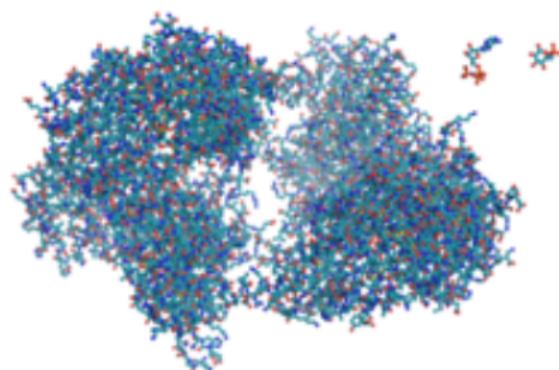
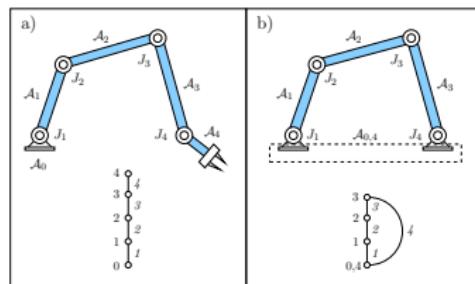
A submanifold of dimension  $m$  is a subset of  $\mathbb{R}^d$  that locally looks like (is homeomorphic to)  $\mathbb{R}^m$



The manifold hypothesis :  $m \ll d$

# Configuration spaces

Associate a point (a vector of parameters) to each configuration



# Embedding theorems

## Intrinsic and ambient dimensions

**Definition :**  $f : X \rightarrow Y$  embeds  $X$  in  $Y$  iff  $X$  and  $f(X) \subset Y$  are topologically equivalent

**Example :** The usual sphere is a manifold of intrinsic dimension 2 that cannot be embedded in  $\mathbb{R}^2$

### Whitney's embedding theorem

Any manifold  $M$  of intrinsic dimension  $m$  can be embedded as a submanifold of  $\mathbb{R}^{2m+1}$

# Dimensionality reduction

## Variant of the Johnson Lindenstrauss lemma for manifolds

[Baraniuk & Wakin 2007] [Clarkson 2007]

Let  $\mathbb{M}$  be a  $m$ -submanifold of  $\mathbb{R}^d$  of bounded geometry and  $\epsilon \in (0, 1)$ . If one projects and scale  $\mathbb{M}$  on a random flat  $H$  of dimension

$$k = \Omega\left(\frac{m}{\varepsilon^2} \log \frac{1}{\varepsilon} + \frac{1}{\varepsilon^2} \log \frac{1}{\delta}\right),$$

then, with probability  $1 - \delta$ ,

$$\forall p, q \in \mathbb{M}, \quad (1 - \epsilon) \|p - q\|^2 \leq \|f(p) - f(q)\|^2 \leq (1 + \epsilon) \|p - q\|^2$$

where  $f(p) = \sqrt{\frac{d}{k}} \pi_H(p)$

# Time series

Delay Embedding Theorem (Takens 1981)

Dynamical system :  $\phi : \mathbb{R} \times X \rightarrow X$        $X \in \mathbb{R}^d$  is the state space

We look for stable manifolds  $M \subset X$  :  $\phi(\mathbb{R}, M) = M$

Typically     $m = \dim(M) \ll d = \dim(X)$ .

In practice, we don't have access to  $M$  but we observe the system at regular time intervals using an observation function  $\alpha : M \rightarrow \mathbb{R}$  :

$$\psi(x) = (\alpha(x), \alpha(\phi(x)), \dots, \alpha(\phi^{k-1}(x))) \in \mathbb{R}^k$$

Takens's theorem

if  $k \geq 2m + 1$ , then  $\psi$  is (generically) an embedding of  $M$  in  $\mathbb{R}^k$

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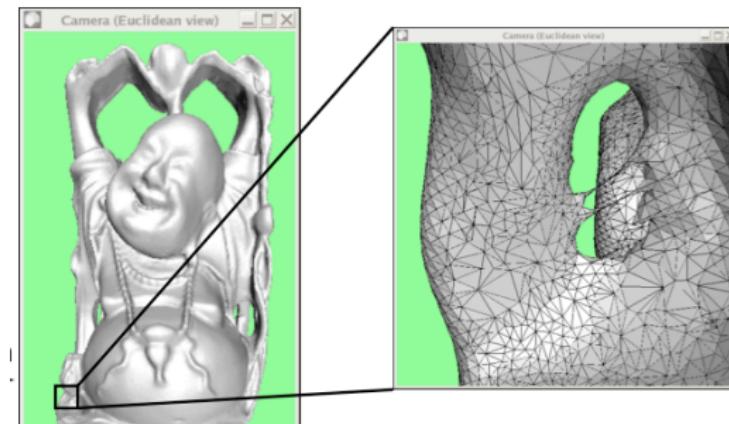
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# Topological quality criteria for approximations

Homeomorphism (topological equivalence)

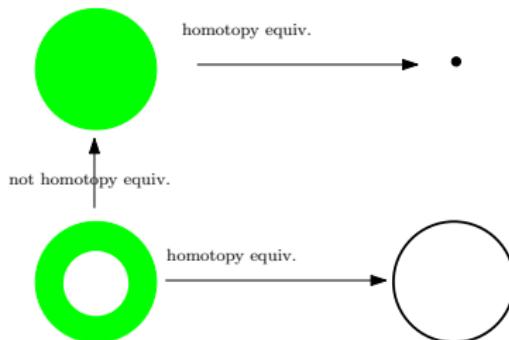
$f : X \rightarrow Y$  is a continuous bijective mapping  
whose inverse is continuous

$$X \approx Y$$



# Homotopy equivalence

A weaker notion of topological equivalence



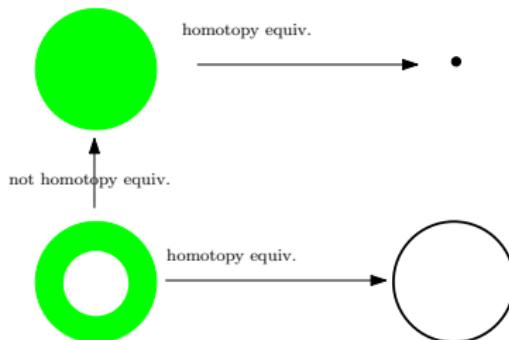
Intuitively, two spaces  $X$  and  $Y$  are **homotopy equivalent** if they can be transformed into one another

by bending, shrinking and expanding operations  
but not by cutting or tearing

$X$  is **contractible** if it is homotopy equivalent to a point

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A weaker notion of topological equivalence



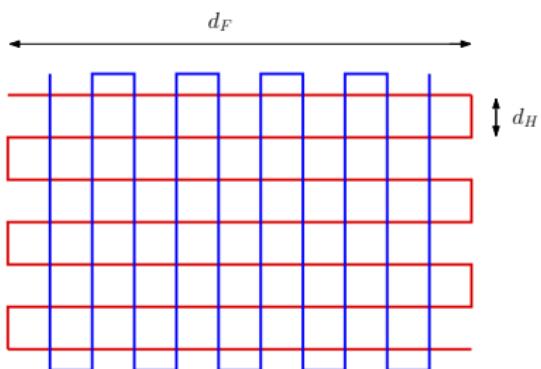
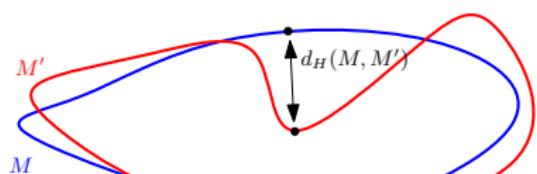
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# Geometric quality criteria

## 1. Hausdorff distance / Fréchet distance



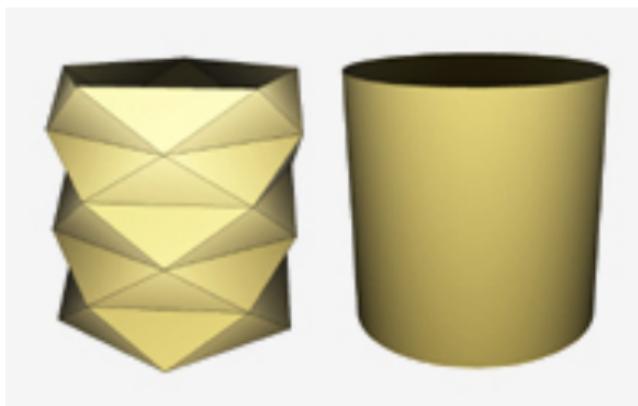
$$d_H(M, M') = \max(\sup_{x \in M} \inf_{x' \in M'} \|x - x'\|, \sup_{x \in M} \inf_{x' \in M'} \|x - x'\|)$$

$$= \min\{r : M \subset M'^{+r} \text{ et } M' \subset M^{+r}\}$$

$$d_F(M, M') = \inf_{f \in \mathcal{H}(M, M')} \sup_{x \in M} \|x - f(x)\|$$

# Geometric quality criteria

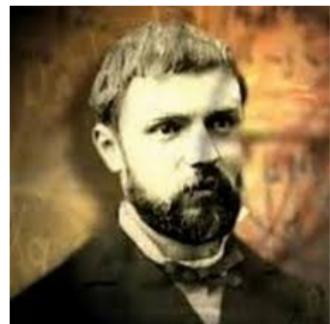
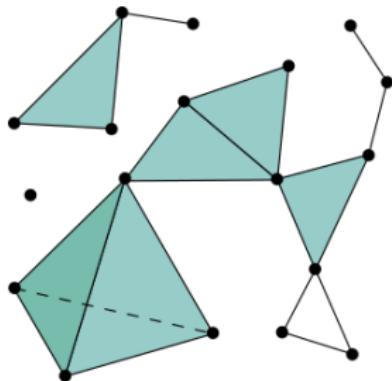
## 2. Tangent spaces approximation



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# Discrete models

## Simplicial complexes



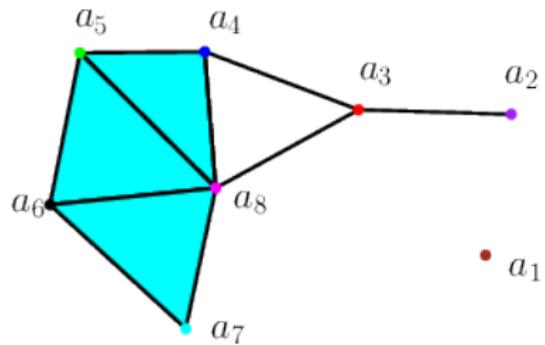
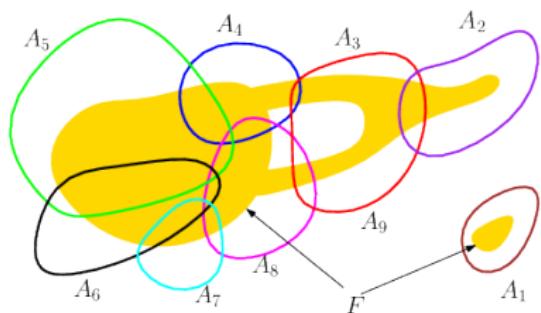
H. Poincaré (1854-1912)

Let  $V$  be a finite set. A simplicial complex (abstract) on  $V$  is a finite set of subsets of  $V$  called the **simplexes or faces** of  $K$  that satisfy :

- ① The elements of  $V$  belong to  $K$       (vertices)
- ② If  $\tau \in K$  and  $\sigma \subseteq \tau$ , then  $\sigma \in K$

# Nerve of a good cover

A simplicial complex to represent the topology of an object



## Nerve theorem

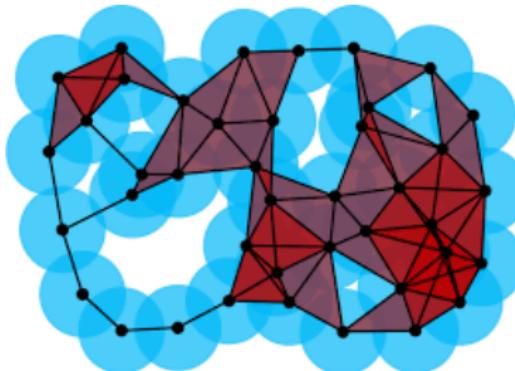
(J. Leray, 1945)

If the intersection of any subset of elements in the cover is contractible, then the nerve and the union of the elements of the cover have the same homotopy type.

# Čech complex

Nerve of a set of balls

A finite set of points  $\mathcal{P} \in \mathbb{R}^d$



J. Leray

(1906-1998)

Corollary of the nerve theorem

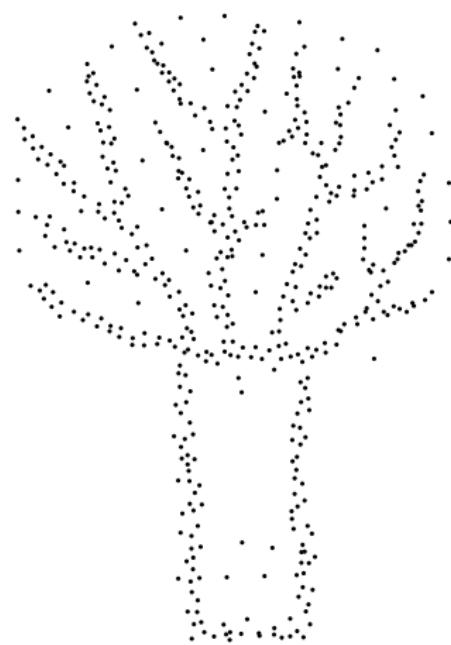
(J. Leray, 1945)

The Čech complex has the same homotopy type as the union of balls

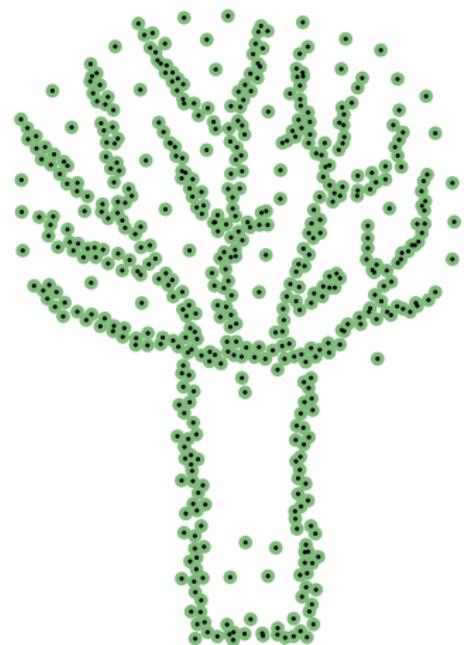
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# Reconstruction of geometric shapes

Union of balls and distance functions



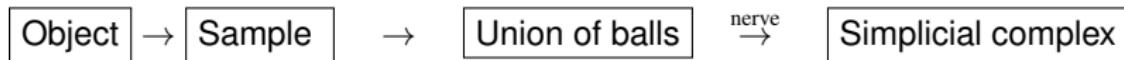
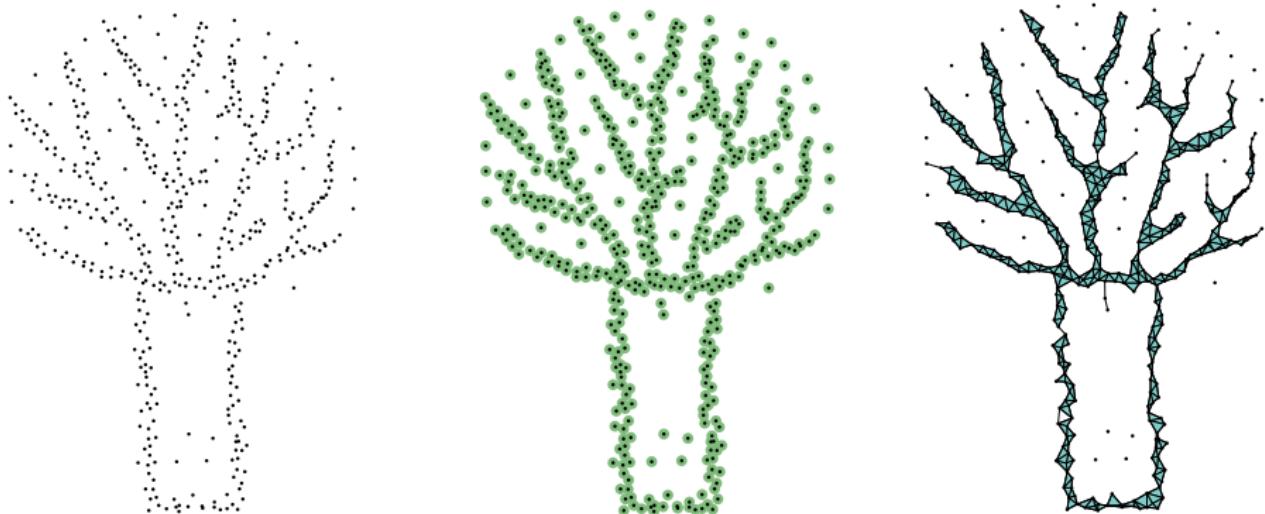
Sample  $P$



Union of balls  $P^{+\alpha}$

# Shape reconstruction

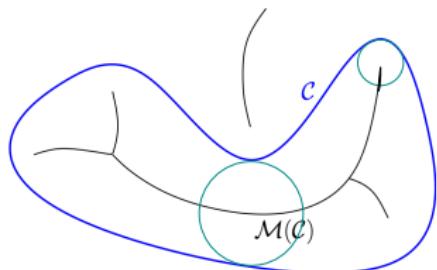
Discrete approximation of continuous spaces



# Reconstruction theorems

Niyogi, Smale, Weinberger [2008]

If  $\mathbb{M}$  is a submanifold of positive reach  $\tau$ ,  
 $P$  an  $\varepsilon$ -dense sample of  $\mathbb{M}$ ,  
then, for all  $\alpha \in [\sim \varepsilon, \sim \tau]$ ,  $P^{+\alpha} \simeq \mathbb{M}$

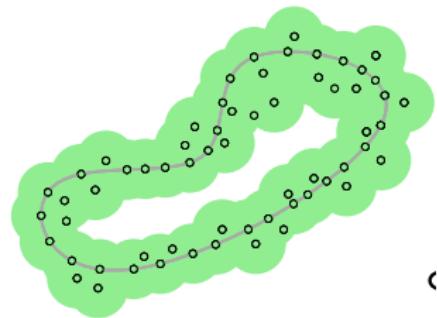


Chazal, Cohen-Steiner, Lieutier [2009]

Extension to general compact sets

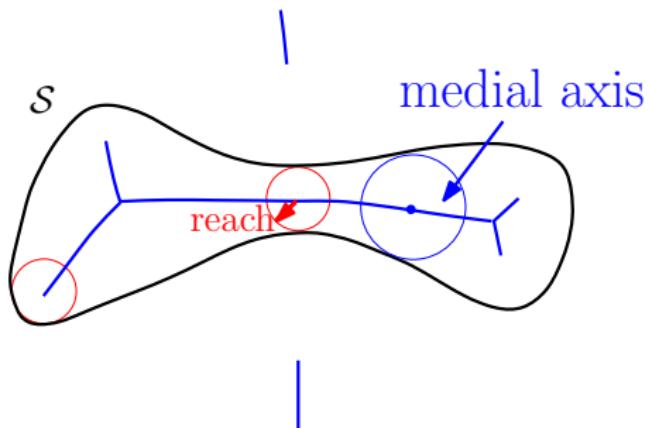
Chazal, Cohen-Steiner, Mérigot [2011]

Extension to points sets with outliers



# Regularity condition : bounded reach

[Federer 1958], [Amenta & Bern 1998]



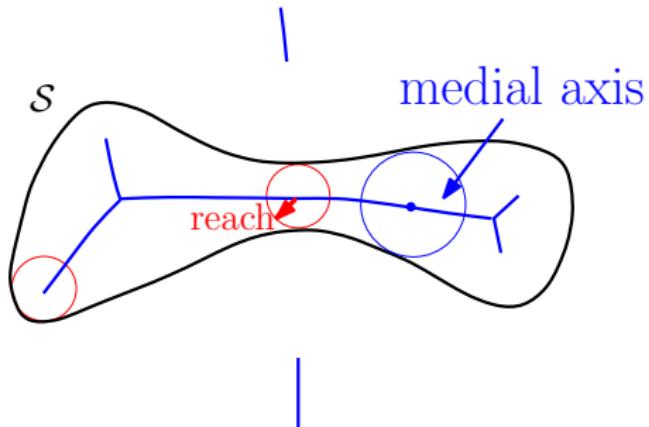
## Local feature size

$$\forall x \in \mathcal{S}, \text{ lfs}(x) = d(x, \text{axis}(\mathcal{S}))$$

(1-Lipschitz :  $|f(x) - f(y)| \leq \|x - y\|$ )

$$\text{rch}(\mathcal{S}) = \inf_{x \in \mathcal{S}} \text{lfs}(x)$$

## Sampling condition : $\varepsilon$ -nets



$(\epsilon, \bar{\eta})$ -net of  $\mathcal{S}$

- ① **Covering :**  $\mathcal{P} \subset \mathcal{S}, \forall x \in \mathcal{S}, d(x, \mathcal{P}) \leq \epsilon \text{lfs}(x)$
- ② **Packing :**  $\forall p, q \in \mathcal{P}, \|p - q\| \geq \bar{\eta}\varepsilon \min(\text{lfs}(p), \text{lfs}(q))$

## Two questions

### Complexity

The Čech complex is **big** ( $\Theta(n^d)$ ) and difficult to compute  
(reduces to computing smallest enclosing balls)

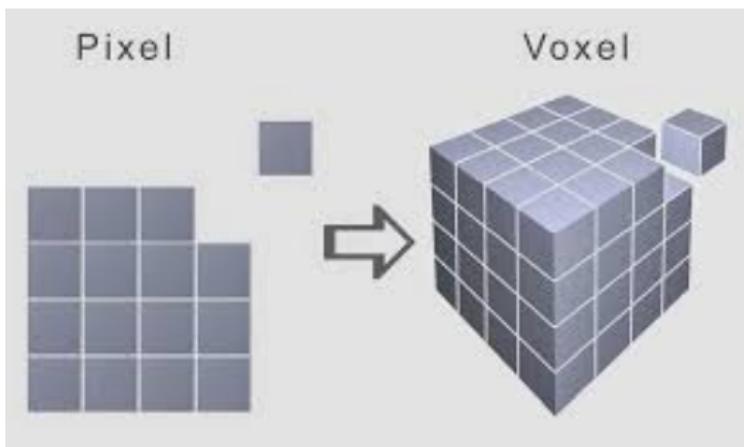
- Can/when we avoid the exponential dependence on  $d$ ?

### Quality of approximation

The Čech complex is **not** (in general) homeomorphic to  $X$  and cannot be **embedded** in the same space as  $X$

# The curse of dimensionality

Subdividing the ambient space is impossible in high dimensions



$$\text{Resolution} = 1/N$$



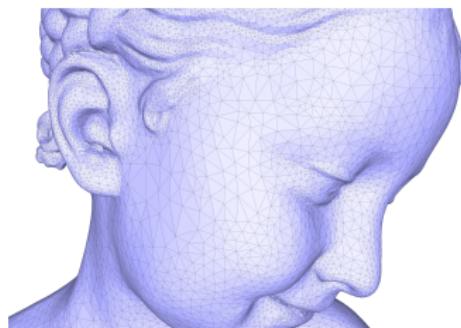
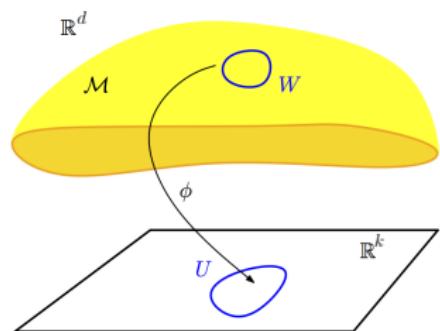
$$\text{Number of cells} = N^d$$

$$N = 1000$$

$$N^2 = 1 \text{ million} \quad N^3 = 1 \text{ billion} \quad N^6 = 1.000.000.000.000.000$$

# Shape model

Smooth manifolds of low intrinsic dimensions

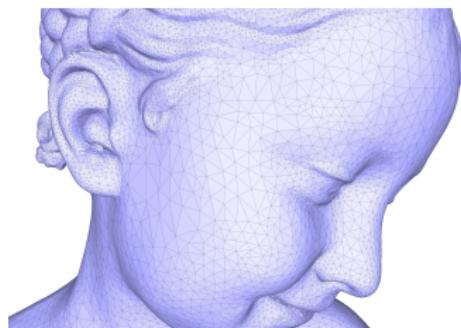
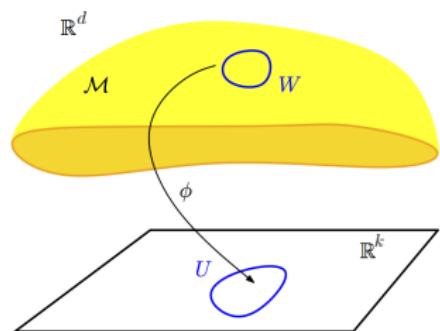


Manifold Hyp. :  $m \ll d$

- Can we bound the combinatorial complexity as a function of the intrinsic dimension ?
- Can we reconstruct a simplicial complex **homeomorphic** to the manifold, i.e. a **triangulation** of the manifold ?

# Shape model

Smooth manifolds of low intrinsic dimensions



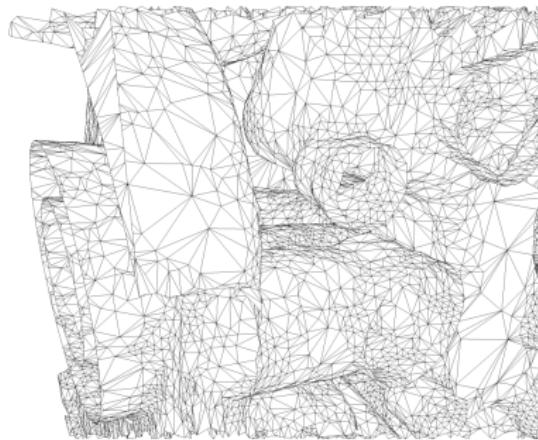
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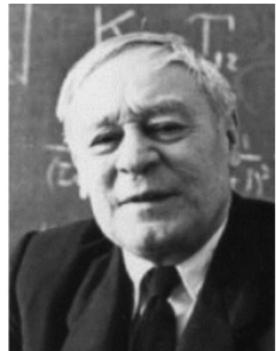
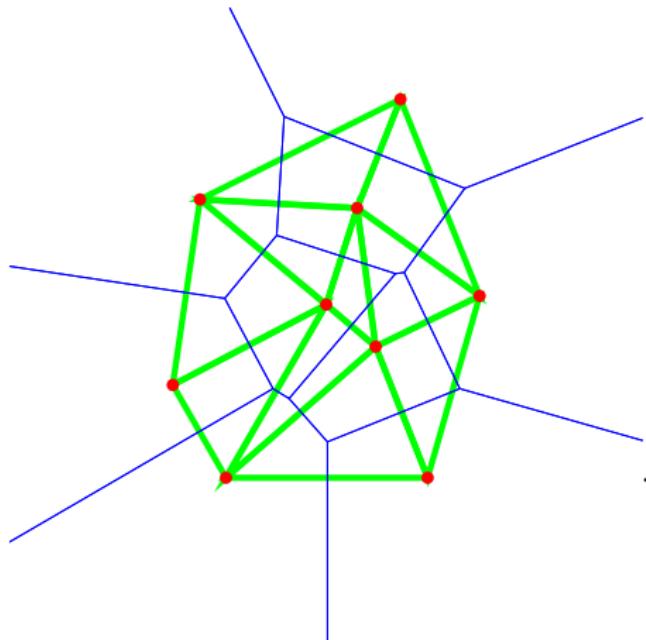
# Delaunay triangulation of manifolds

Can we extend the techniques developed for surfaces ?



# Delaunay Triangulations

*Sur la sphère vide (On the empty sphere)*, Boris Delaunay (1934)



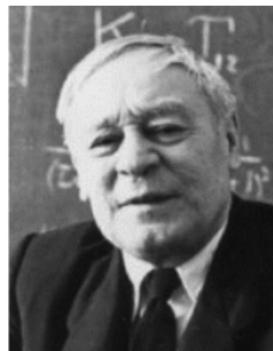
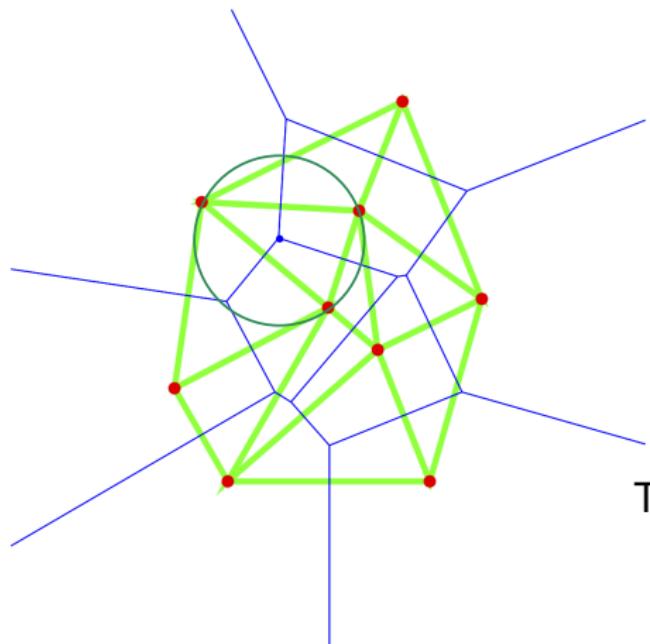
The Delaunay complex  $\text{Del}(\mathcal{P})$  is  
the **nerve** of  $\text{Vor}(\mathcal{P})$

## Theorem

If  $\mathcal{P}$  contains no subset of  $d + 2$  points on a same hypersphere, then  
 $\text{Del}(\mathcal{P})$  can be realized as a **triangulation** of  $\mathcal{P}$  in  $\mathbb{R}^d$

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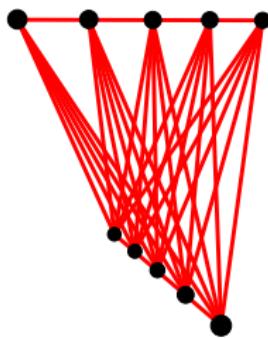
# Combinatorial and algorithmic complexity

The complexity of the Delaunay triangulation of  $n$  points of  $\mathbb{R}^d$  is exponential

$$\Theta(n^{\lceil \frac{d}{2} \rceil})$$

[Mc Mullen 1970]

Worst-case : points on the moment curve  $\Gamma(t) = \{t, t^2, \dots, t^d\} \subset \mathbb{R}^d$



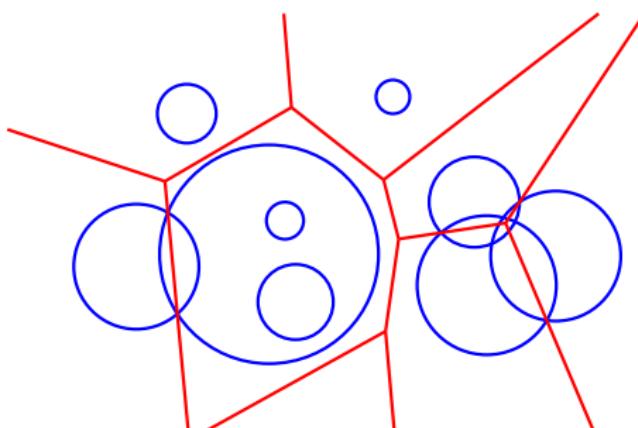
Construction :  $\Theta(n \log n + n^{\lceil \frac{d}{2} \rceil})$

[Clarkson & Shor 1989] [Chazelle 1993]

## Laguerre (power, weighted) diagrams

Weighted points :  $\mathcal{B} = \{b_1, \dots, b_n\}$

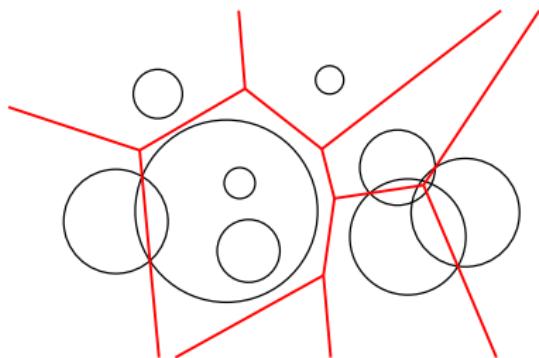
$$D(x, b_i) = (x - p_i)^2 - r_i^2$$



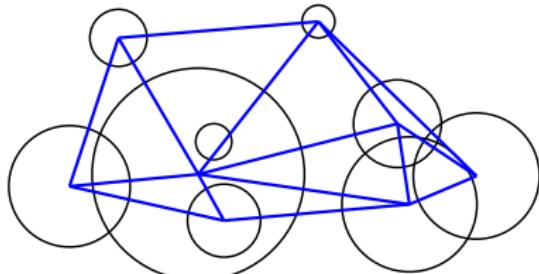
Voronoi cell :  $\text{Vor}(b_i) = \{x : D(x, b_i) \leq D(x, b_j) \forall j\}$

Voronoi diagram of  $\mathcal{B}$  : = { set of cells  $\text{Vor}(b_i)$ ,  $b_i \in \mathcal{B}$  }

# Delaunay triangulations of weighted points



$\text{Vor}(\mathcal{B})$



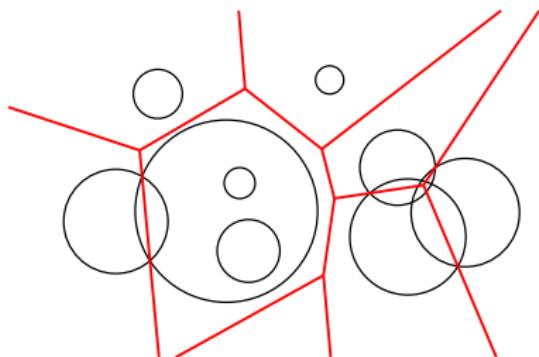
$\text{Del}(\mathcal{B})$  is the **nerve** of  $\text{Vor}(\mathcal{B})$

## Theorem

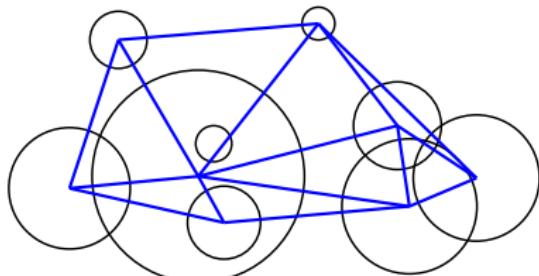
If  $\mathcal{B}$  is in general position, then  $\text{Del}(\mathcal{B})$  is a triangulation of a subset  $\mathcal{P}' \subseteq \mathcal{P}$  of the points

General position : no point of  $\mathbb{R}^d$  is at the same distance  $D$  to  $d + 2$  balls

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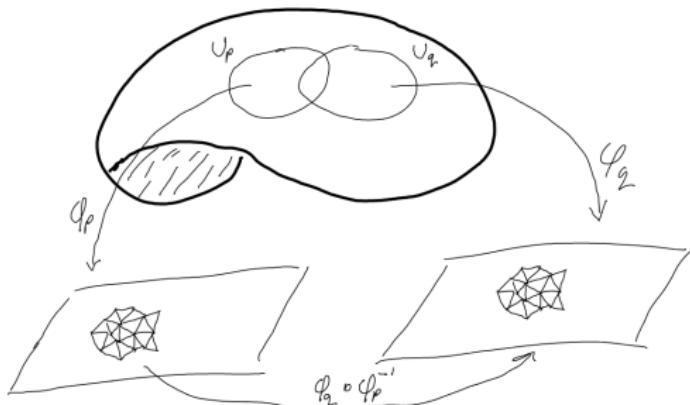
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# Delaunay triangulation of submanifolds of $\mathbb{R}^d$

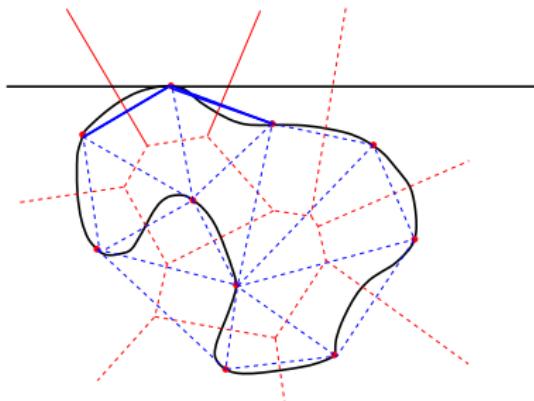
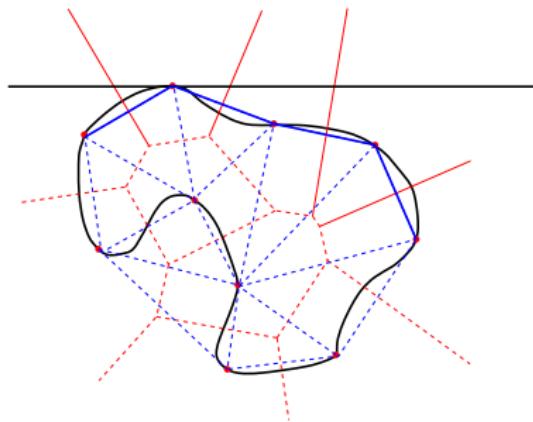
Euclidean charts and local triangulations



- ① Construct **local** Delaunay triangulations (stars)
- ② Make the local triangulations **compatible** by perturbing the input point set
  - ⇒ a simplex belongs to the stars of all its vertices
- ③ Stitch the stars ⇒ a **combinatorial manifold**  $\hat{M}$
- ④ Exhibit a **homeomorphism**  $\hat{M} \rightarrow M$

# The tangential Delaunay complex

[Freedman 2002], [B.& Flottoto 2004], [B. Ghosh 2014]

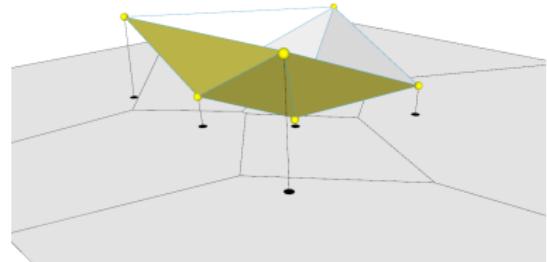


Local triangulations

$$\forall p \in \mathcal{P} : T_p(\mathcal{P}) = \text{star}(p, \text{Del}|_{T_p}))$$

Tangential complex

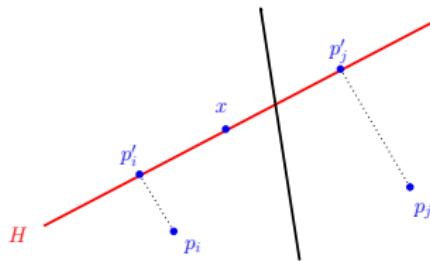
$$TC(\mathcal{P}) = \{T_p(\mathcal{P}), p \in \mathcal{P}\} \subset \text{Del}(\mathcal{P})$$



# Construction of $\text{Del}_{T\mathbb{M}}(\mathcal{P})$

Complexity linear in  $d$ , exponential in  $k$

If  $H \subset \mathbb{R}^d$  is a  $k$ -flat,  $\text{Vor}(\mathcal{P}) \cap H$  is a **weighted Voronoi diagram** in  $H$



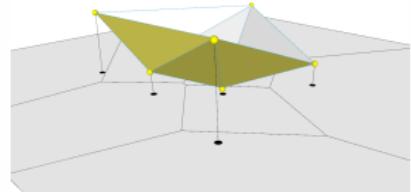
$$\|x - p_i\|^2 \leq \|x - p_j\|^2 \\ \Leftrightarrow \|x - p'_i\|^2 + \|p_i - p'_i\|^2 \leq \|x - p'_j\|^2 + \|p_j - p'_j\|^2$$

$$\psi_p(p_i) = (p'_i, -\|p_i - p'_i\|^2) \quad (\text{weighted point})$$

$$\text{Vor}(\mathcal{P}) \cap H = \text{Vor}(\psi_p(\mathcal{P})) \quad (\text{Laguerre diag.})$$

Corollary : construction of  $\text{Del}_{T_p}(\mathcal{P})$

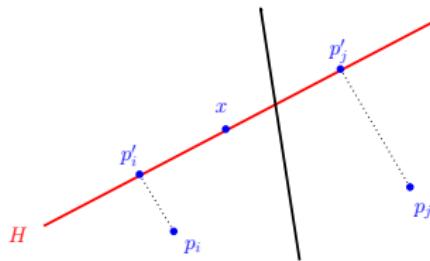
- 1 project  $\mathcal{P}$  in  $T_p$  in time  $O(dn)$
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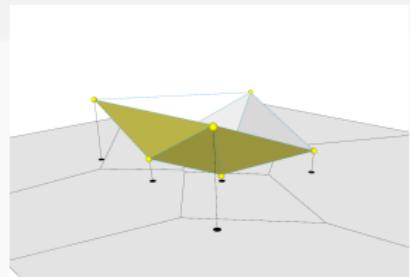
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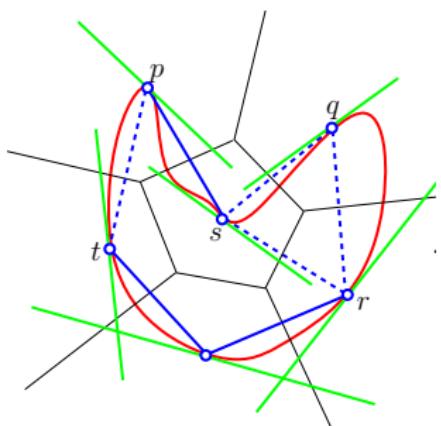
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# Conflicting stars

A 2-dimensional example



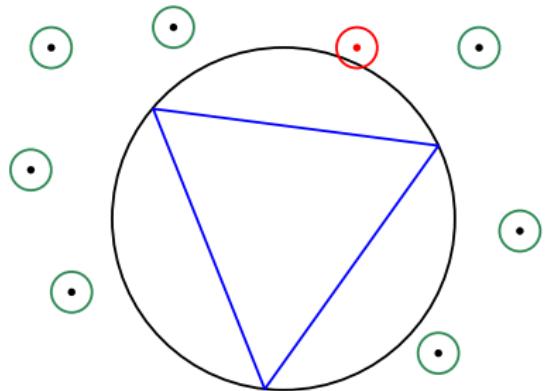
$\text{Vor}(p, t)$  intersects  $T_t$  but not  $T_p$

$\Rightarrow p \in \text{star}(t)$

$\Rightarrow t \notin \text{star}(p)$

# Conflicting stars

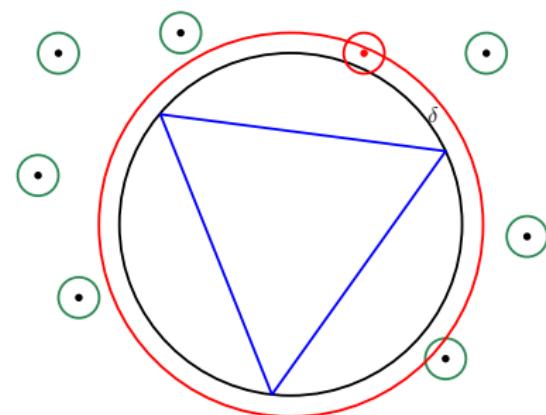
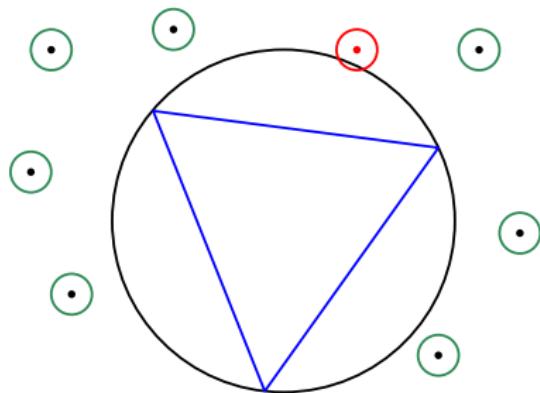
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We need the simplices to be **protected** !

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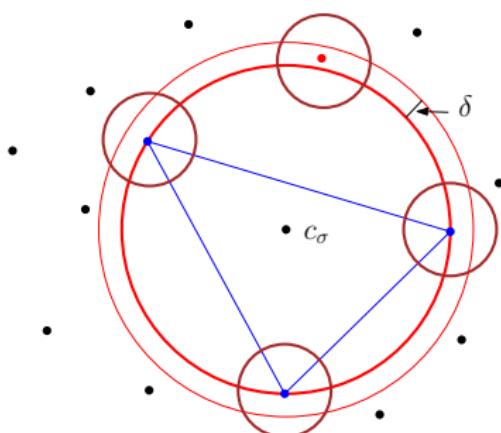
We need the simplices to be **protected** !

# Protection via Random perturbations

A geometric application of the constructive version of the Local Lovasz Lemma  
[Moser and Tardos 2010]

Random variables :  $\mathcal{P}'$  a set of random points  $\{p'_1, \dots, p'_n\}$

$$p'_i \in B(p_i, \rho), p_i \in \mathcal{P}$$



## Algorithm

**Input :** an  $\varepsilon$ -net  $\mathcal{P}$  of  $\mathbb{T}^d$ ,  $\rho$ ,  $\delta$

**while**  $\exists \phi' = (\sigma', p')$  unprotected **do**

resample the points of  $\phi'$

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

**Return**  $\mathcal{P}'$  and  $\text{Del}(\mathcal{P}')$

# Analysis of the algorithm

## The Local Lovasz Lemma

Let  $A_1, \dots, A_N$  be a set of bad events  
each occurs with  $\text{proba}(A_i) \leq p < 1$

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

The (easy) case of independent events

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

What happens if the events are weakly dependent ?

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# Lovász local lemma

[Lovász & Erdős 1975]

If, for  $i = 1, \dots, N$ ,

- ①  $A_i$  is independent from all events except  $\leq \Gamma$  of them
- ②  $\text{proba}(A_i) \leq \frac{1}{e(\Gamma+1)}$        $e = 2.718\dots$

then

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

# A constructive version of LLL

[Moser and Tardos 2010]

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

$\mathcal{A}$  a finite set pf events determined by the values of some of the variables of  $\mathcal{P}$

Two events are independent iff they don't share any variable

## Algorithm

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

$v_p \leftarrow$  random evaluation of  $p$ ;

while some events of  $\mathcal{A}$  occur for ( $p = v_p, p \in \mathcal{P}$ ) do

choose one such event  $A$  uniformly at random;

choose one variable  $x$  in  $A$  uniformly at random;

choose one value  $y$  for  $x$  uniformly at random;

return  $(v_p)_{p \in \mathcal{P}}$ ;

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$v_p \leftarrow$  random evaluation of  $p$ ;

**while** some events of  $\mathcal{A}$  occur for  $(p = v_p, p \in \mathcal{P})$  **do**

    select (arbitrarily) such an event  $A \in \mathcal{A}$ ;

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

$v_p \leftarrow$  a new random evaluation of  $p$ ;

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

# Moser and Tardos theorem

Hypothesis : for all events  $A_i, i \in [1, N]$

- ①  $A_i$  is independent from all events except  $\leq \Gamma$  of them
- ②  $\text{proba}(A_i) \leq \frac{1}{e(\Gamma+1)}$        $e = 2.718\dots$

## Theorem

- The algorithm assigns values to the variables  $\mathcal{P}$  s.t. no event of  $\mathcal{A}$  occurs
- The algorithm resamples an event  $A \in \mathcal{A}$  at most  $\boxed{\frac{1}{\Gamma}}$  times on expectation before finding such an assignment
- The expected total number of resamplings is at most  $\boxed{\frac{N}{\Gamma}}$

# Removing conflicts among stars

## Summary

### Hypotheses

- $\mathbb{M}$  : a differential submanifold of **positive reach** of dim.  $m \subset \mathbb{R}^d$
- $\mathcal{P}$  : an  $\varepsilon$ -net of  $\mathbb{M}$  for some sufficiently small  $\varepsilon$
- we know the tangent space  $T_p$  at each point  $p \in \mathcal{P}$  (of dim.  $m$ )

### Main result

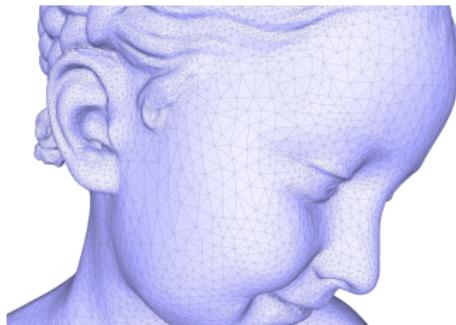
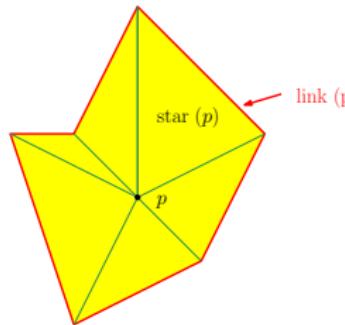
Under those hypotheses, one can choose  $\delta$  and  $\rho$  so that the algorithm terminates and removes all conflicts among stars

Complexity :  $O(d2^m)$ , i.e. linear in  $d$  and only exponential in  $m$   
(almost optimal)

# Reconstruction of smooth submanifolds

- ① For each vertex  $p$ , compute its star in  $\text{Del}_p(\mathcal{P})$ ,  $\text{star}(p)$
- ② Remove conflicts among stars
- ③ Stitch the stars  $\rightarrow \hat{\mathbb{M}}$

$\hat{\mathbb{M}}$  is a **PL manifold of dimension  $m$** , i.e. the **link** of each vertex is PL-homeomorphic to a topological sphere of dimension  $m$



The underlying space of a PL manifold is a topological manifold

# $\hat{\mathbb{M}}$ is a PL simplicial $k$ -manifold

## Lemma

Let  $\mathcal{P}$  be an  $\varepsilon$ -sample of a manifold  $\mathbb{M}$  and let  $p \in \mathcal{P}$ . The link of any vertex  $p$  in  $\hat{\mathbb{M}}$  is a topological  $(k - 1)$ -sphere

## Proof :

- 1 Since  $\hat{\mathbb{M}}$  contains no conflicting stars, the star of any vertex  $p$  of  $\hat{\mathbb{M}}$  is identical to  $\text{star}_p(p)$ , the star of  $p$  in  $\text{Del}_p(\mathcal{P})$
- 2  $\text{star}(p) \xleftrightarrow{1-1} \text{star}_p(p)$
- 3  $\text{star}_p(p)$  is a  $m$ -dimensional triangulated topological ball (general position)
- 4  $p$  cannot belong to the boundary of  $\text{star}_p(p)$   
(the Voronoi cell of  $p = \psi_p(p)$  in  $\text{Vor}(\psi_p(\mathcal{P})) = \text{Vor}(p) \cap T_p$ , which is bounded)

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# Reconstruction of submanifolds

## Summary of results

### Guarantees on the quality of approximation

For  $\varepsilon$  small enough, there exists  $\Theta_0$  s.t.

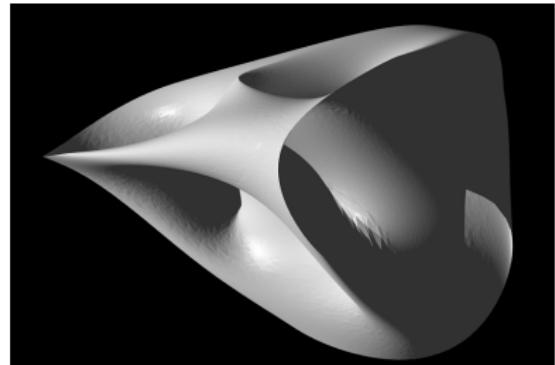
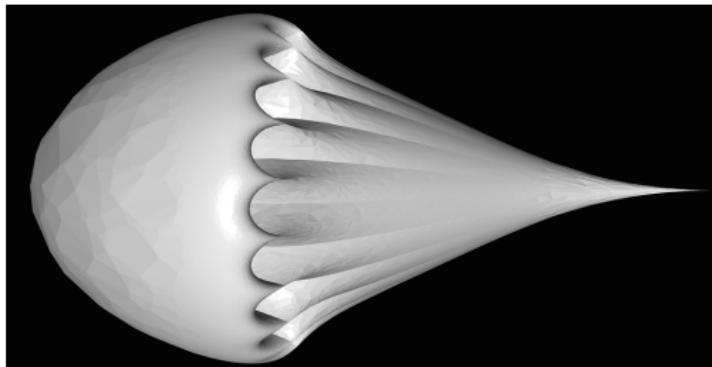
- $\hat{M}$  is a PL submanifold of dimension  $m$
- $\hat{M} \subset \text{tub}(M, 4\varepsilon^2 \text{rch}(M))$
- Angles between facets of  $\hat{M}$  and tangent spaces of  $M \leq \frac{2\varepsilon}{\Theta_0}$
- All simplices of  $\hat{M}$  are  $\Theta_0$ -thick
- $\text{proj} : \hat{M} \rightarrow M$  is a homeomorphism  
 $\Rightarrow \hat{M}$  is a **triangulation** of  $M$

### Complexity of the algorithm

- linear in  $d$
- exponential in  $m$

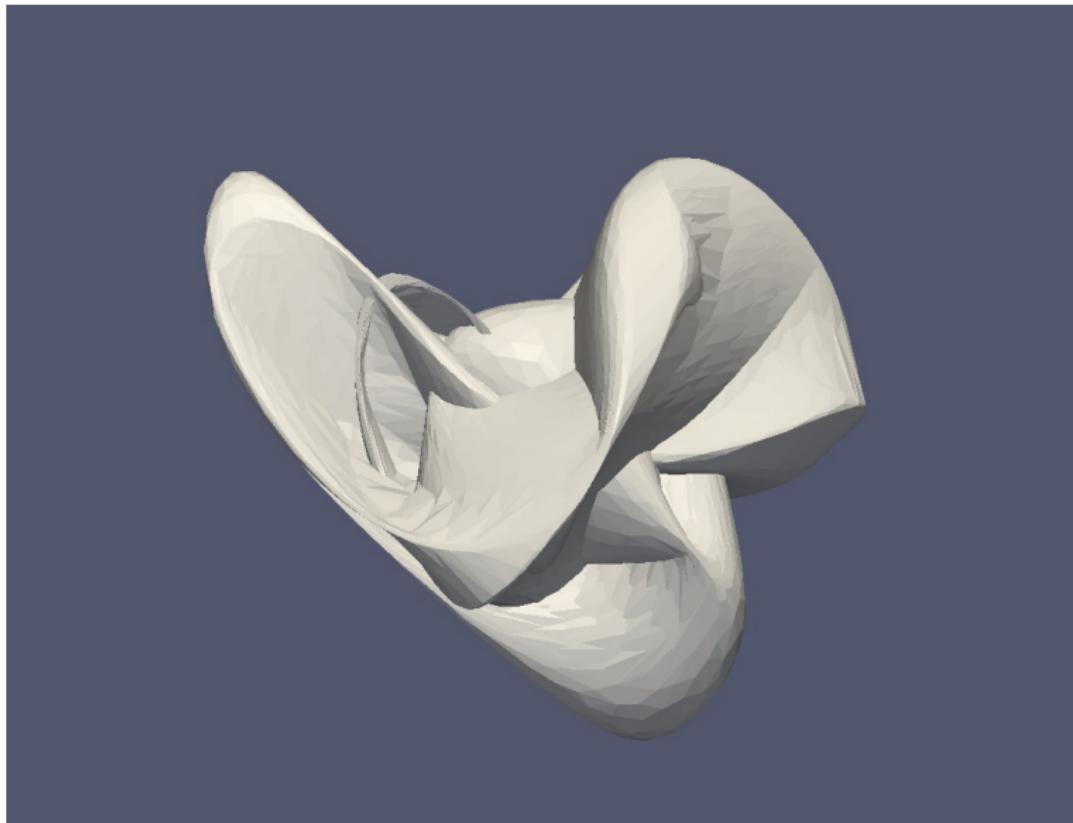
# Reconstruction of Rieman surfaces of $\mathbb{R}^8$

Gudhi implementation [Jamin 2016]



Data provided by A. Alvarez

# Triangulation of the space of conformations of $C_8H_{16}$



# Take home messages

## Mathematical and algorithmic tools for Geometric Data Analysis

- Manifolds, atlas and charts, reach, nets, manifold hypothesis
- Distance functions, Čech and Delaunay complexes
- Sampling theory and reconstruction algorithms
- Randomized algorithms : RIC, Moser-Tardos algorithm

## Good news and questions

- Complexity linear in  $d$  : got around the curse of dimensionality
- Practicality is questionable
- Statistical point of view