

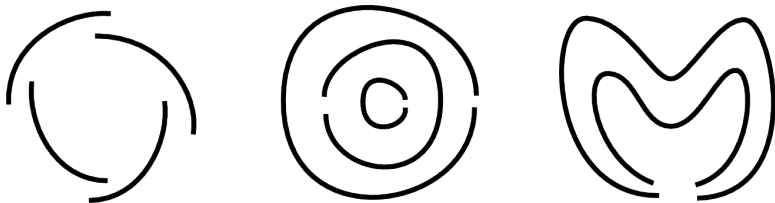
# Auto-completion of contours

## based on topological persistence

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Microsoft Research Cambridge  
and Durham University, UK

# Maps and hand-drawn sketches

**Problem:** complete all closed contours or paint all regions that they enclose (a segmentation).

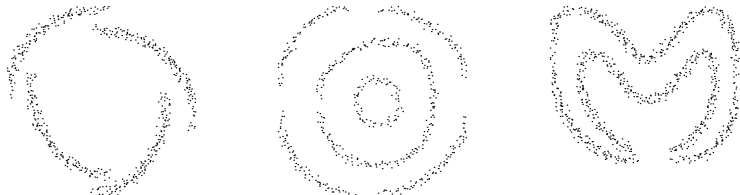


Saund. *Perceptually closed paths*. T-PAMI'03.

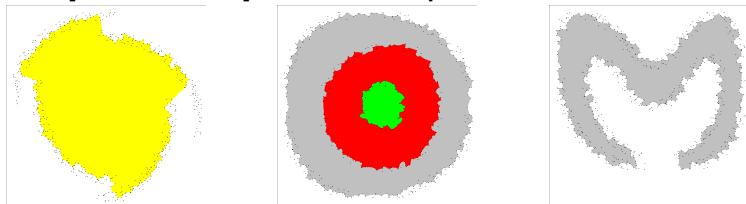
Past algorithms need ad-hoc parameters, e.g. a scale of closeness, weights for quality criteria.

# Auto-completion of contours

**Input:** a dotted 2D image of sparse points without any user-defined parameters, no scale.

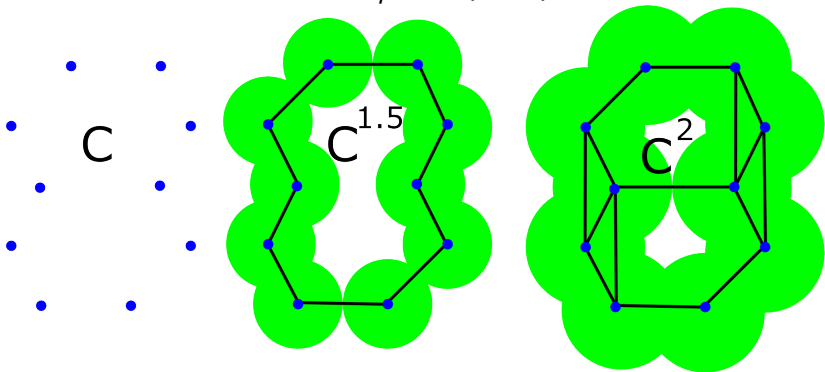


**Required output:** most 'persistent' contours.



# From a cloud to some shape

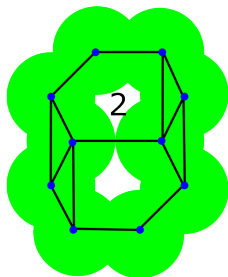
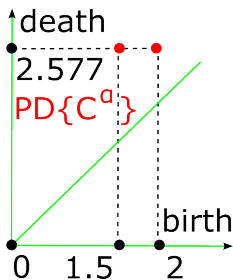
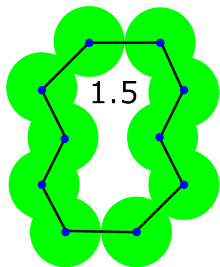
**Def :** the  $\alpha$ -offset of a cloud  $C \subset \mathbb{R}^2$  is the union of closed balls  $C^\alpha = \cup_{p \in C} B(p; \alpha)$  of a radius  $\alpha$ .



Homology group  $H_1$  counts independent cycles:  
 $C^{1.5}$  has 1 cycle,  $C^2$  has 2 cycles,  $C^{2.577}$  has 0.

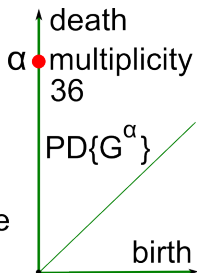
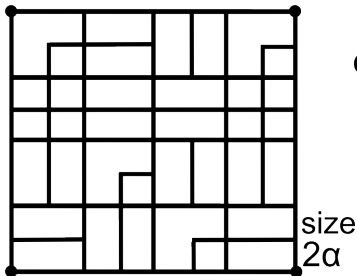
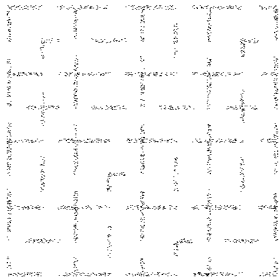
# Persistent homology

For any *filtration*  $\mathcal{S}(\alpha_1) \subset \mathcal{S}(\alpha_2) \subset \cdots \subset \mathcal{S}(\alpha_m)$ , the evolution of homology under linear maps  $H_1(\mathcal{S}(\alpha_1)) \rightarrow \cdots \rightarrow H_1(\mathcal{S}(\alpha_m))$  is described by pairs (birth, death) when a class *persists* from its **birth**  $\alpha = \text{birth}$  to its **death** at  $\alpha = \text{death}$ .



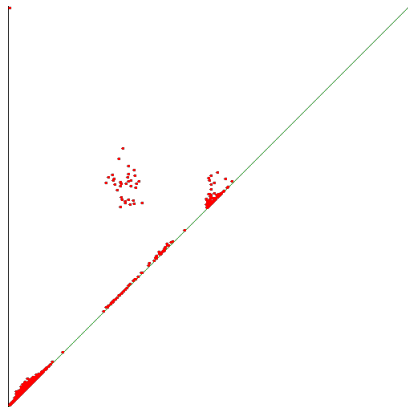
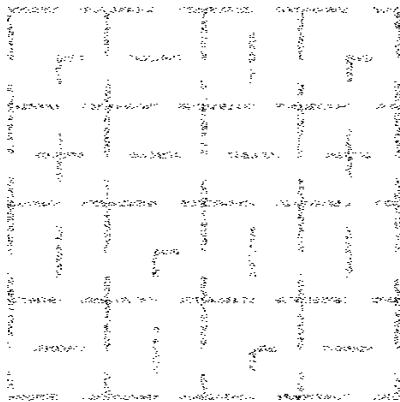
# A noisy $\varepsilon$ -sample $C$ of a graph

**Def:** a point cloud  $C$  is called a noisy  $\varepsilon$ -sample of a graph  $G \subset \mathbb{R}^2$  if  $C \subset G^\varepsilon$  and  $G \subset C^\varepsilon$ .



**Th** (Edelsbrunner et al. '07): any  $\varepsilon$ -sample  $C$  of  $G$  has the diagram  $PD\{C^\alpha\}$   $\varepsilon$ -close to  $PD\{G^\alpha\}$ .

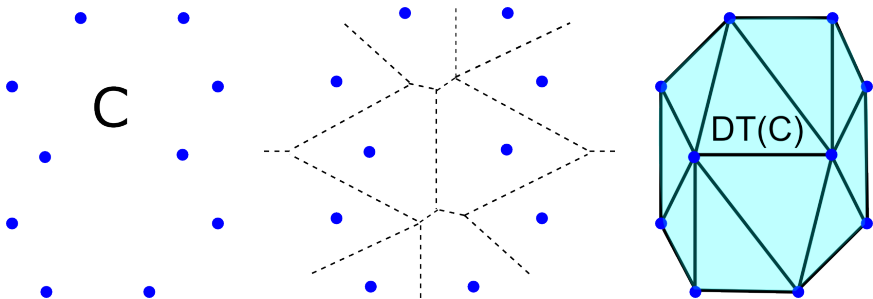
# Using stability of persistence



We can find the widest diagonal gap separating 36 points from the rest of persistence diagram.

# Delaunay triangulation $DT(C)$

**Def:** for  $C = \{p_1, \dots, p_n\} \subset \mathbb{R}^2$ , the **Voronoi cell** is  $V(p_i) = \{q \in \mathbb{R}^2 : d(q, p_i) \leq d(q, p_j), j \neq i\}$ .

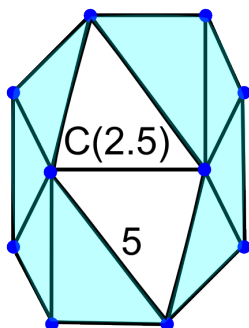
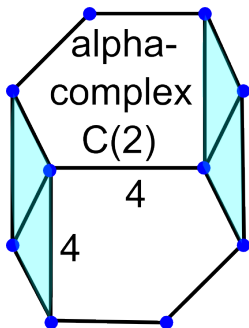
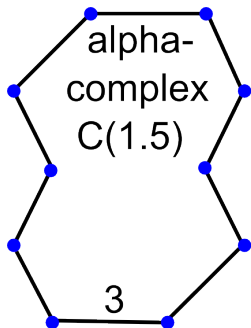


**Def:** a **Delaunay triangulation**  $DT(C)$  is dual to the Voronoi cells and is found in time  $O(n \log n)$ .



# $\alpha$ -complexes $C(\alpha)$ on a cloud $C$

**Def:** the  $\alpha$ -complex  $C(\alpha) \subset DT(C)$  has edges of length  $\leq 2\alpha$  and triangles of circumradius  $\leq \alpha$ .

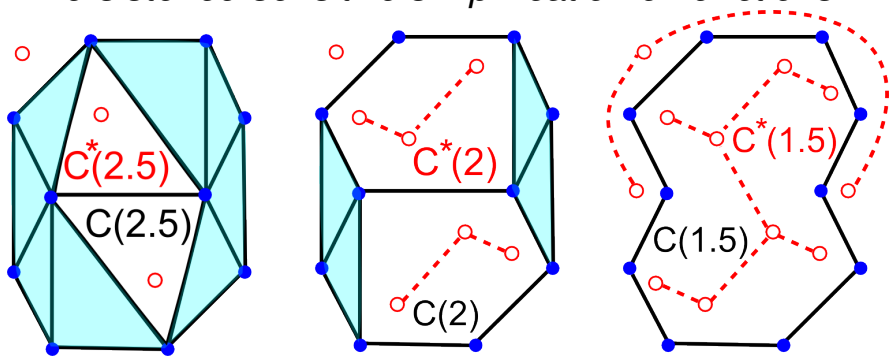


**Th** (Edelsbrunner '95): any  $C^\alpha$  deforms to  $C(\alpha)$ .

# Graphs $C^*(\alpha)$ dual to $\alpha$ -complexes

We extend algorithm Attali et al. TopoInVis'09.

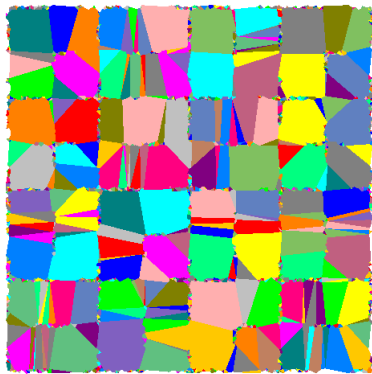
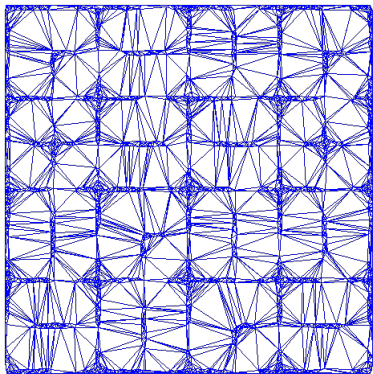
*Persistence-sensitive simplification of functions.*



Cycles of  $C(\alpha) \subset \mathbb{R}^2$  correspond to connected components of the graph  $C^*(\alpha)$  dual to  $C(\alpha)$ .

# Harder than counting cycles

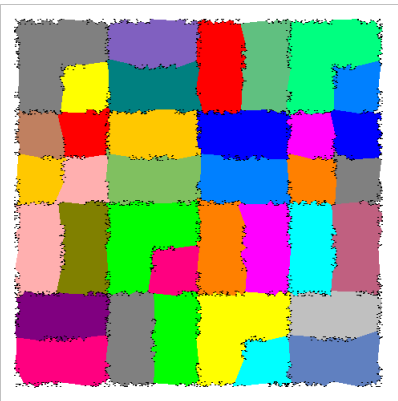
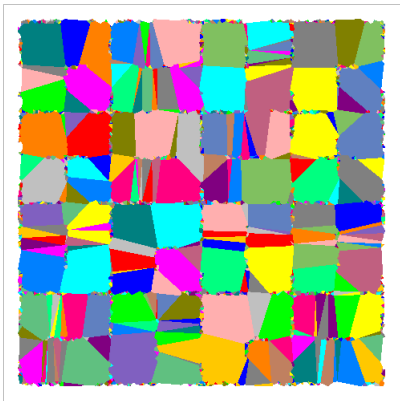
Acute Delaunay triangle is a 'center of gravity'.



We attach all adjacent non-acute triangles to get an initial segmentation on the right hand side.

# Merging initial regions

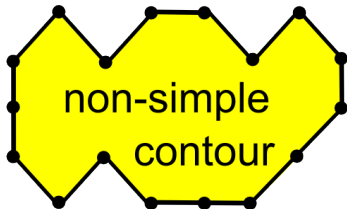
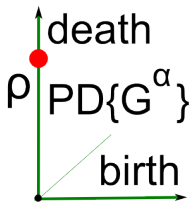
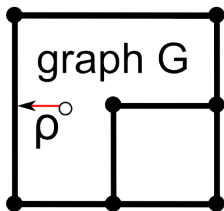
We maintain adjacency relations when a region merges another one with a higher persistence.



Merger: the older region absorbs the younger.

# Simple vs non-simple contours

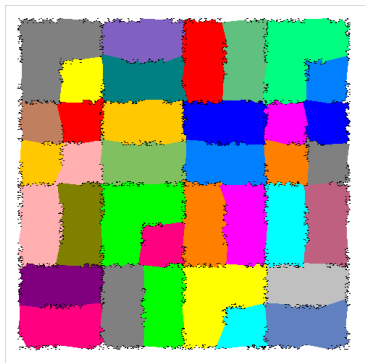
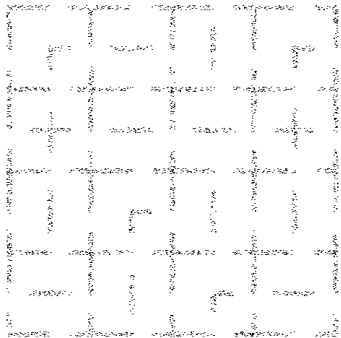
**Def:**  $G \subset \mathbb{R}^2$  is **simple** if the boundary  $L$  of any bounded region in  $\mathbb{R}^2 - G$  has a radius  $\rho(L)$  such that  $L^\alpha$  is circular for  $\alpha < \rho(L)$  and  $L^\alpha \sim \cdot$  for  $\alpha \geq \rho(L)$ , so the hole in  $L^\alpha$  dies at  $\alpha = \rho(L)$ .



The diagram  $PD\{G^\alpha\}$  of any simple graph has only  $(\text{birth}, \text{death}) = (0, \rho)$  in the vertical axis.

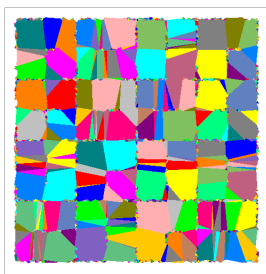
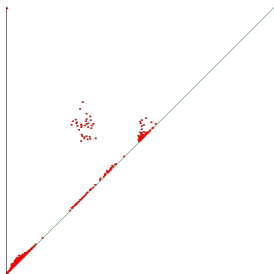
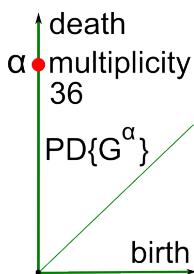
# Noisy input $\rightarrow$ correct output

**Th (VK'14):** let  $G \subset \mathbb{R}^2$  be a simple graph with  $0 < \rho_1 \leq \dots \leq \rho_m$  and  $\rho_1 > 8\varepsilon + \max\{\rho_{i+1} - \rho_i\}$ . For any  $\varepsilon$ -sample  $C$  of  $G$ , the algorithm finds  $m$  expected contours, they are **in the  $2\varepsilon$ -offset  $G^{2\varepsilon}$** .



# Idea: the widest gap survives

$\rho_1 > 8\varepsilon + \max\{\rho_{i+1} - \rho_i\}$  says that the diagonal gap  $\{0 < y - x < \rho_1\}$  is widest under noise.



Also  $\varepsilon \geq \max\{\text{birth}\}$  above the widest gap in  $PD\{C^\alpha\}$ , hence all edges in a persistent contour  $L \subset G$  have half-lengths  $\leq \varepsilon$ , so  $L \subset C^\varepsilon \subset G^{2\varepsilon}$ .

# Summary and further work

- **input:** 2D point cloud, no extra parameters
- **output:** most persistent closed contours
- **time:**  $O(n \log n)$  for any  $n$  points in 2D
- **$2\varepsilon$ -approximation** is guaranteed for a noisy  $\varepsilon$ -sample of a good unknown graph  $G \subset \mathbb{R}^2$
- any edge detector: image  $\rightarrow$  point cloud,  
*auto-completion*: cloud  $\rightarrow$  object contours
- *extend* to graphs with non-simple contours
- *collaboration* is welcome! [kurlin.org/blog](http://kurlin.org/blog)