Graph Reconstruction via Discrete Morse Theory

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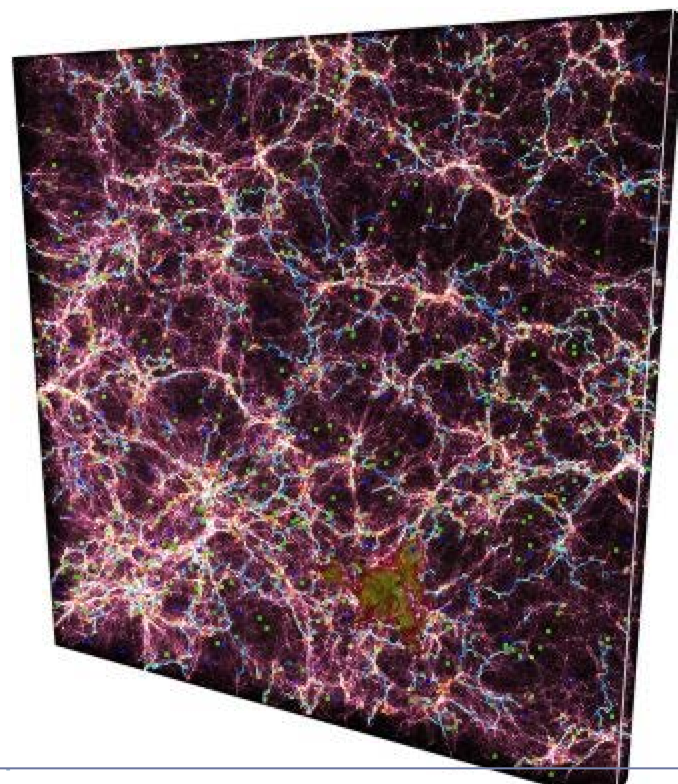
Introduction

- Graphs naturally occur in many applications
  - Hidden space: graph-like structures
  - Simple, non-linear structure behind data



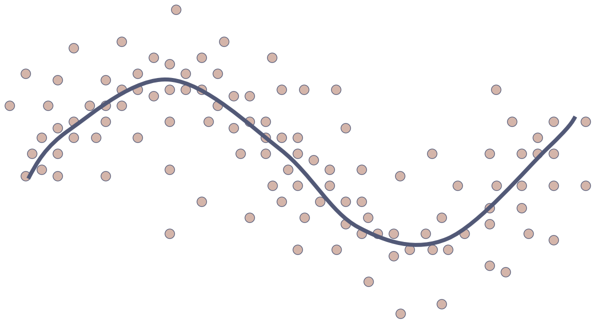
http://www2.iap.fr/users/sousbie/web/html/indexd41d.html

Overall Goal:

Using geometric and topological ideas to develop graph reconstruction algorithms for various settings with theoretical understanding / guarantees

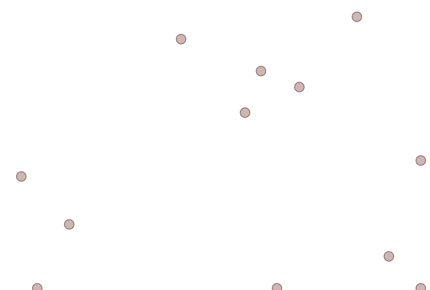
Some Related Work

- Principal curve based approaches
  - [Hastie, Stuetzle, 1989], [Kegl, Kryzak, 2002], [Ozertem, Erdogmus, 2011] …



Some Related Work

- Principal curve based approaches
  - [Hastie, Stuetzle, 1989], [Kegl, Kryzak, 2002], [Ozertem, Erdogmus, 2011] …
- Reeb graph based
  - [Natali et al., Graphical Models 2011], [Ge et al. W. , NIPS 2011], [Chazal et al, DCG 2015]…



This talk: an effective graph reconstruction algorithm to handle ambient noise

This Talk

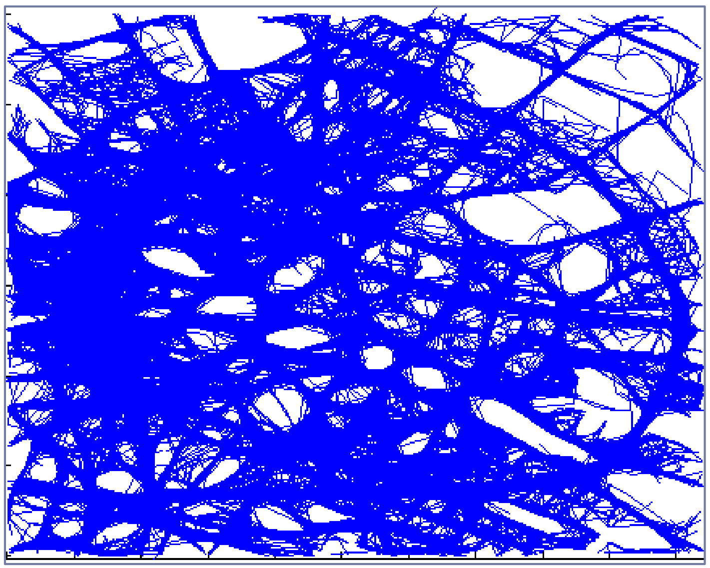
Overall Goal:

Using geometric and topological ideas to develop graph reconstruction algorithms for various settings with theoretical understanding / guarantees

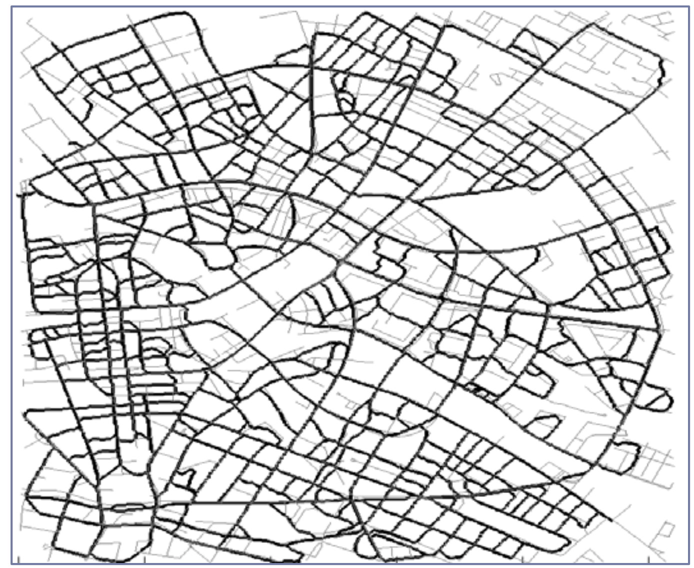
- Geometric graph reconstruction via discrete Morse + persistence
  - A motivating example from road-network reconstruction
  - Algorithms and theoretical understanding
  - [Wang, Li, W., SIGSPATIAL 2015], [Dey, Wang, W., SIGSPATIAL 2017, SoCG 2018]

A Motivating Application

- Automatic road network reconstruction



Input: GPS trajectories



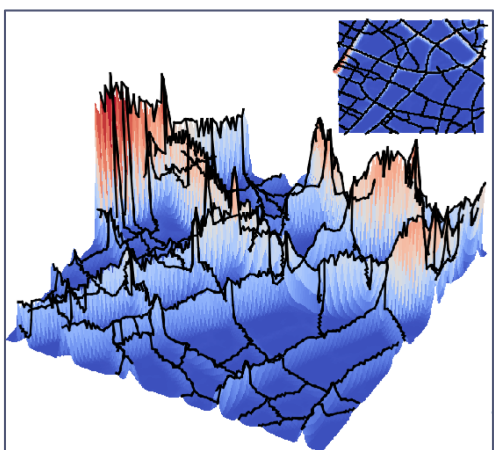
Goal: Road network

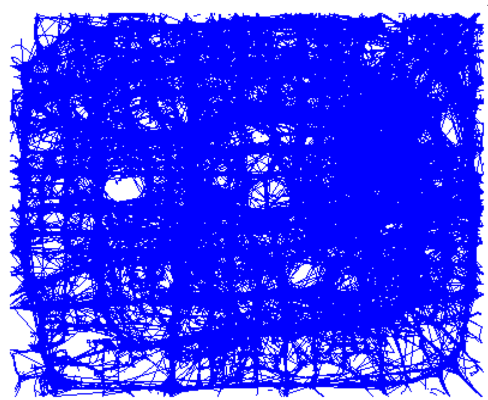
Motivation cont

- Reconstruction from satellite images

A Motivating Application

- Automatic road network reconstruction
- Two main challenges:
  - Noisy trajectories
  - Non-homogeneous distribution
- Previous methods:
  - Local information for decision making, sensitive to noise
  - Often thresholding involved, challenging in handling non-uniform input
  - Junction nodes identification and connectivity challenging





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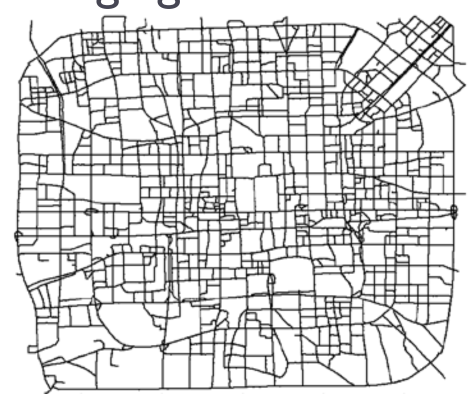
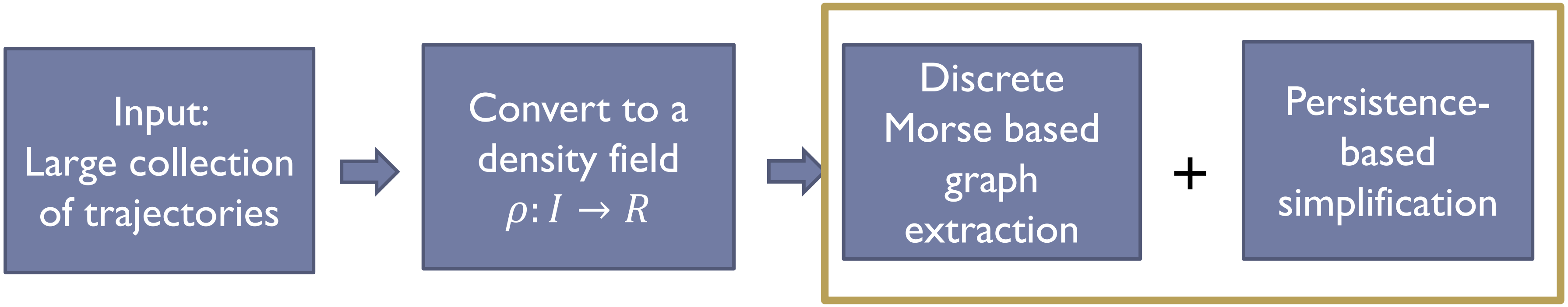


Goal: Road network

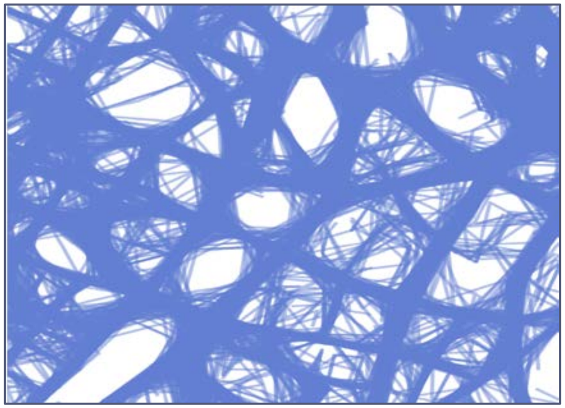
Morse-based Reconstruction

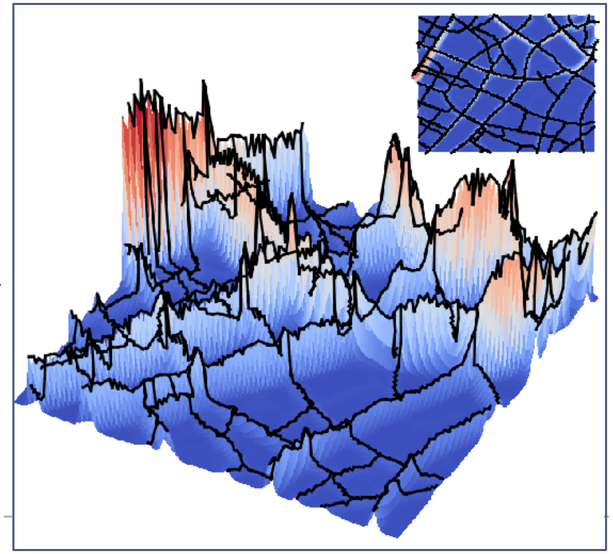


- Persistence-guided (discrete) Morse-based reconstruction framework for road network reconstruction
  - uses global structure behind data; robust against noise, small gaps, and non-uniformity in data
  - conceptually clean, easy to implement; also extension to map integration / augmentation
  - [Wang, Li, W., SIGSPATIAL 2015]
- [Gyulassy, PhD thesis 2008], [Robins et al. 2011], [Delgado-Friedrichs et al 2015], [Sousbie, 2015]

Main Idea

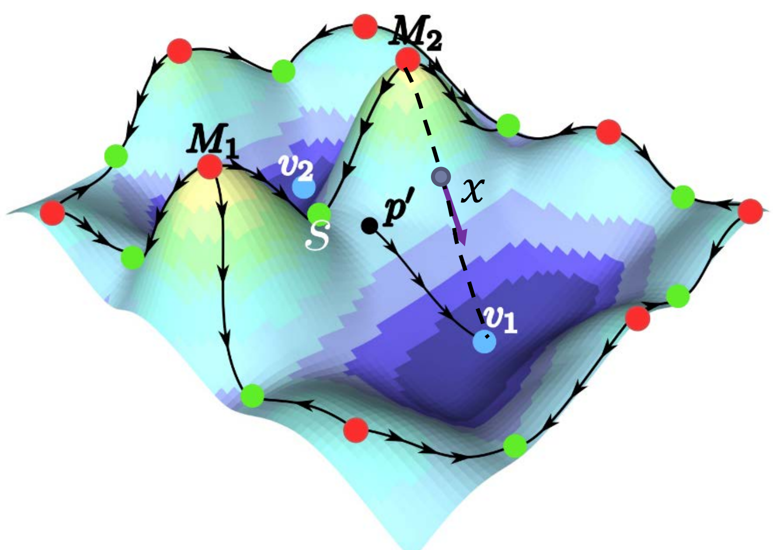
- Assume input is a scalar (density) field
  - $f: I \to R$, where high value of f indicates high signal value
- View graph of f as a terrain (mountain range) on $I \times R$
  - $I = [0,1]^2 \subset R^2$ for the case of road network reconstruction
- Road ≈ mountain ridge
  - Captured by 1-stable manifold of f



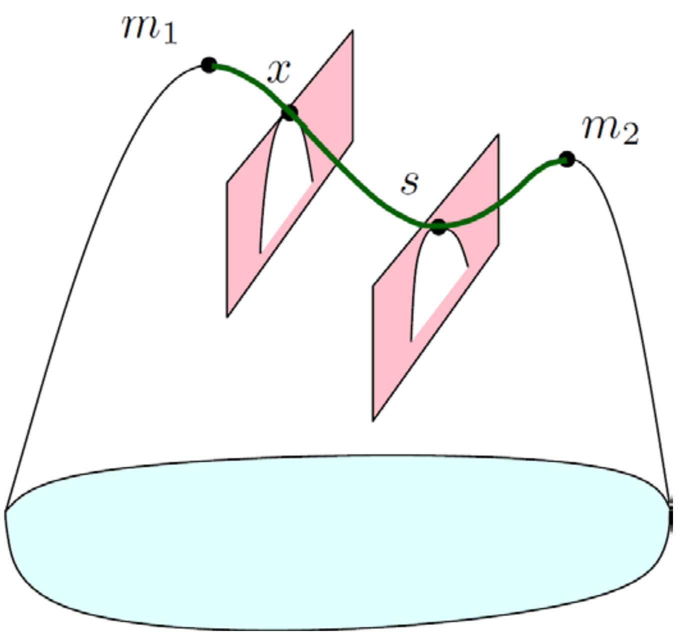


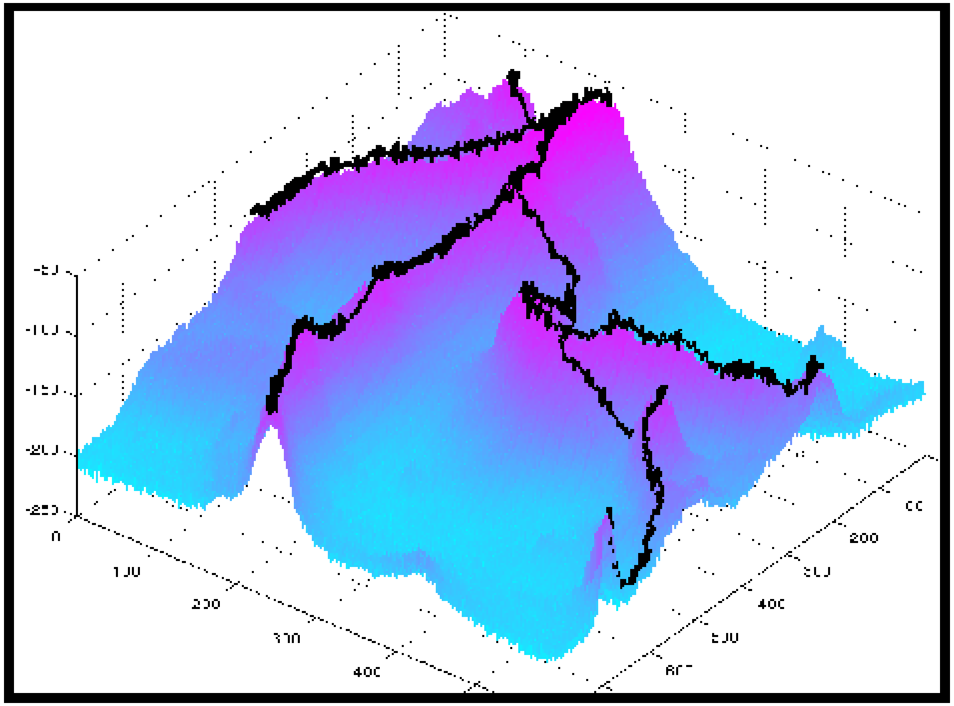
Morse Theory: Smooth Case

- Let $f: R^d \rightarrow R$ be a Morse function
- Gradient of f at x: $\nabla f(x) = -\left[\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \ldots, \frac{\partial f}{\partial x_d}\right]^T$
- Critical points of f: $\{\, x \in R^d \mid \nabla f(x) = 0 \,\}$
- An integral line $L: (0,1) \rightarrow R^d$:
  - a maximal path in R^d whose tangent vectors agree with gradient of f at every point of the path
  - origin/destination at critical points
    - $Dest(L) = \lim_{p \rightarrow 1} L(p)$
    - $Ori(L) = \lim_{p \rightarrow 0} L(p)$
- 1-stable manifolds
  - Integral lines ending at $(d-1)$-saddles



1-stable Manifold

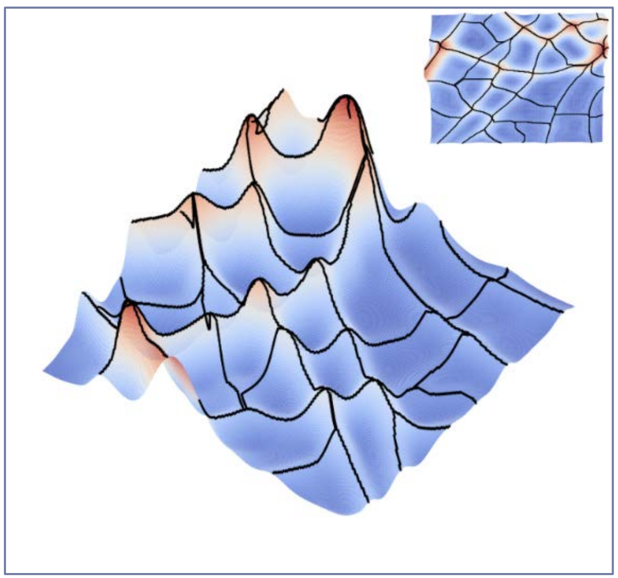




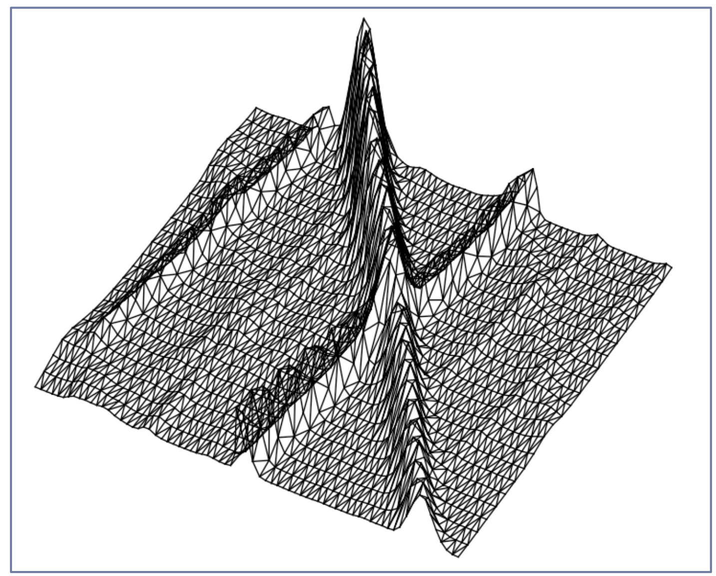
1-stable manifold (of index $d - 1$ saddle points) ≈ mountain ridges

Discrete Case

- Smooth case
  - 1-stable manifold from Morse theory



- Discrete case
  - Piecewise-linear (PL) approximation?



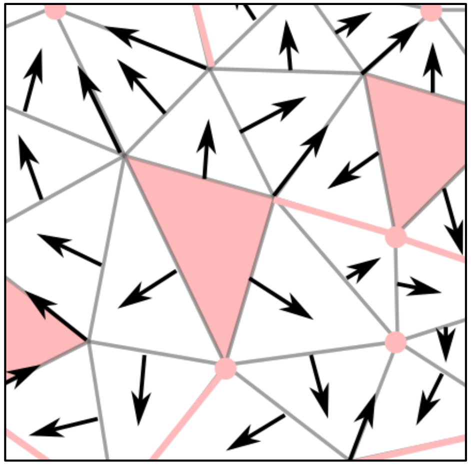
Discrete Morse Theory

- [Forman 1998, 2002]
- Combinatorial version of Morse theory
- Many results analogous to classical Morse theory
- Works for cell complexes

- Combinatorial, thus numerically stable
- Algorithmically often easy to handle, especially simplification

Discrete Gradient Vector Field

- Given a simplicial complex K, a discrete (gradient) vector
  - (σ, τ) s.t. $\sigma < \tau$ (*vertex-edge or edge-triangle pair in our case*)
- A Morse pairing $M(K)$ of K
  - A set of discrete vectors s.t. each simplex appears in at most one vector
- A simplex σ is critical, if
  - it does not appear in any pair in $M(K)$
- A V-path in $M(K)$
  - $\tau_0, \sigma_1, \tau_1, \sigma_2, \tau_2, \ldots, \tau_k, \sigma_{k+1}$ s.t. $(\sigma_i, \tau_i) \in M(K)$
  - cyclic: if $k > 0$, and $(\sigma_{k+1}, \tau_0) \in M(K)$
  - acyclic (gradient path) otherwise



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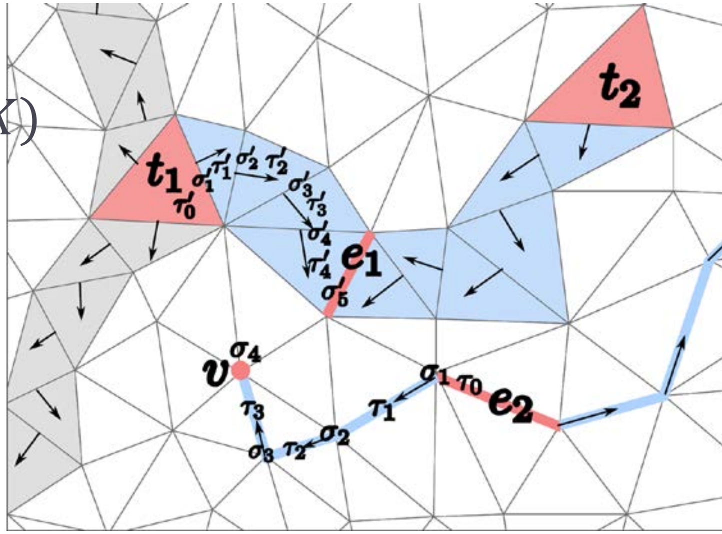
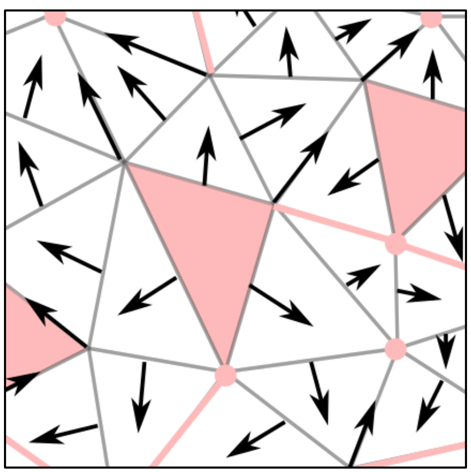
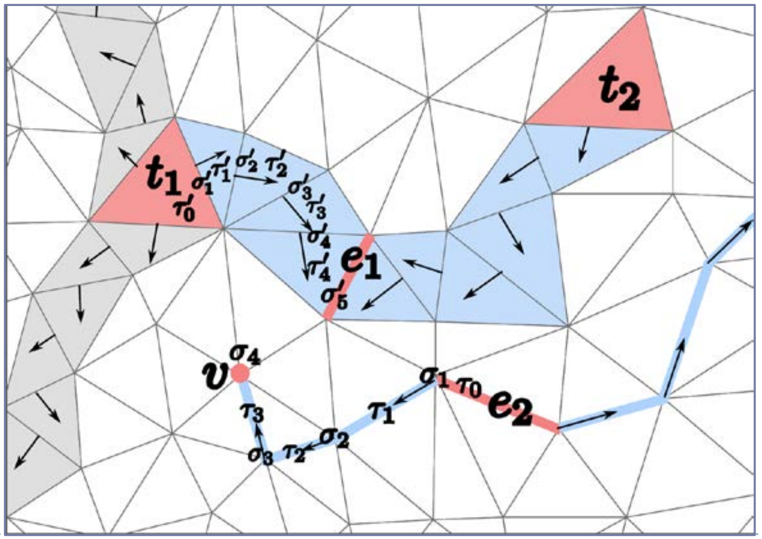
  - cyclic: if $k > 0$, and $(\sigma_{k+1}, \tau_0) \in M(K)$
  - acyclic (gradient path) otherwise
- $M(K)$: discrete gradient vector field
  - if there is no cyclic V-path in $M(K)$



Discrete Gradient Vector Field

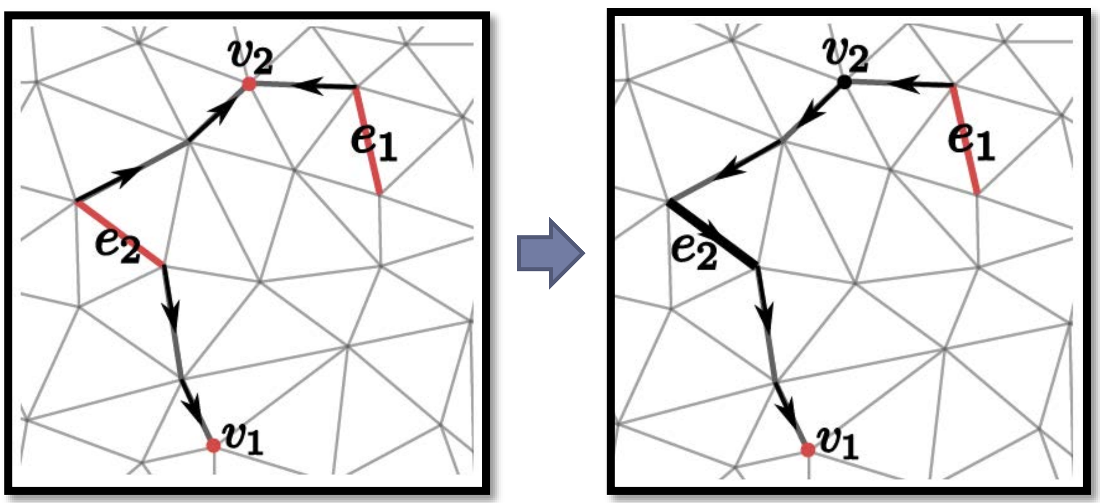
- Discrete Morse function ⟺ discrete gradient vector field
- A discrete Gradient Vector field ≈ gradient field for Morse functions
  - critical k-simplex ≈ index-k critical point
  - critical edge ≈ saddles for function on R^2
  - 1-stable manifolds: edge-triangle V-paths
  - 1-unstable manifolds: vertex-edge V-paths (``valley ridges'')



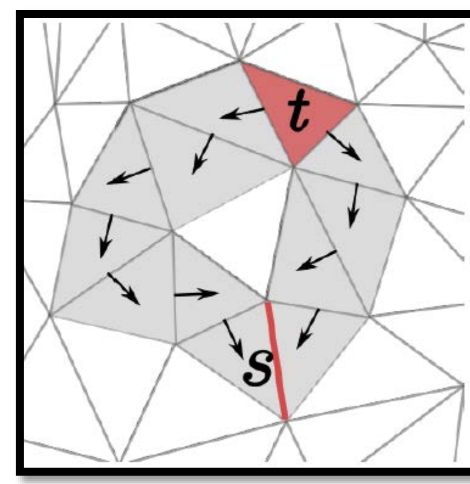


Simplification via Morse Cancellation

- Morse cancellation operation (to simplify the vector field):
  - A pair of critical simplices $\langle \sigma, \tau \rangle$ can be cancelled
    - if there is a unique gradient path between them
    - By reverting that gradient path



canceling $\langle v_2, e_2 \rangle$



$\langle s, t \rangle$ not cancellable

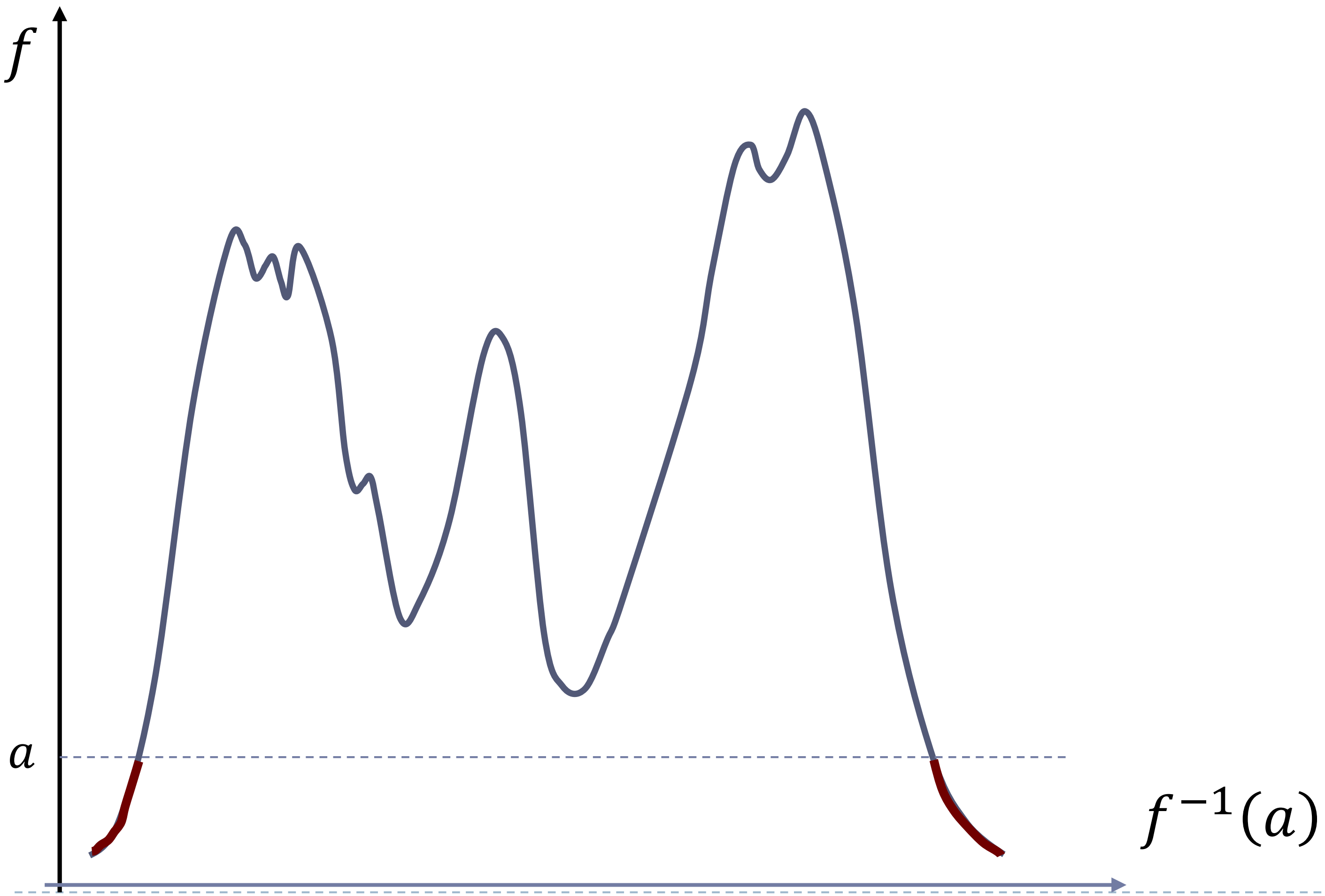
- Morse cancellation of critical pairs simplify the discrete gradient vector fields
  - which further simplifies 1-(un)stable manifolds

- But which critical pairs should we cancel?
  - intuitively: should respect input function! Less important ones corresponding to noise

- Persistence homology induced by the density function to guide the cancellation of critical pairs
  - ``persistence" capturing ``importance" of critical pairs
  - [Edelsbrunner, Letscher, Zomorodian 2002], [Zomorodian, Carlsson 2005], …

Sublevel-set Persistence – Simplified view

- Input: $f: R \to R$



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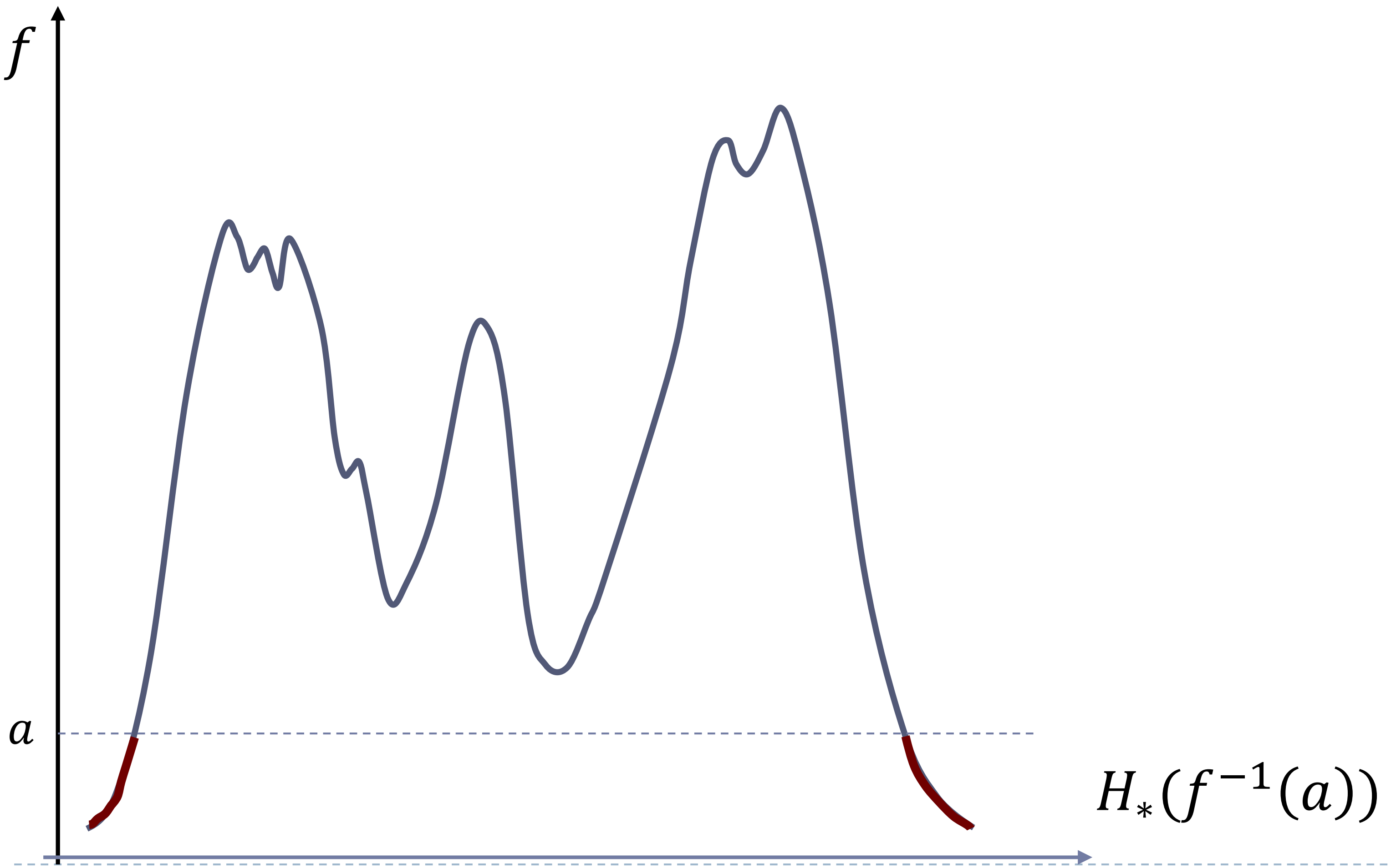

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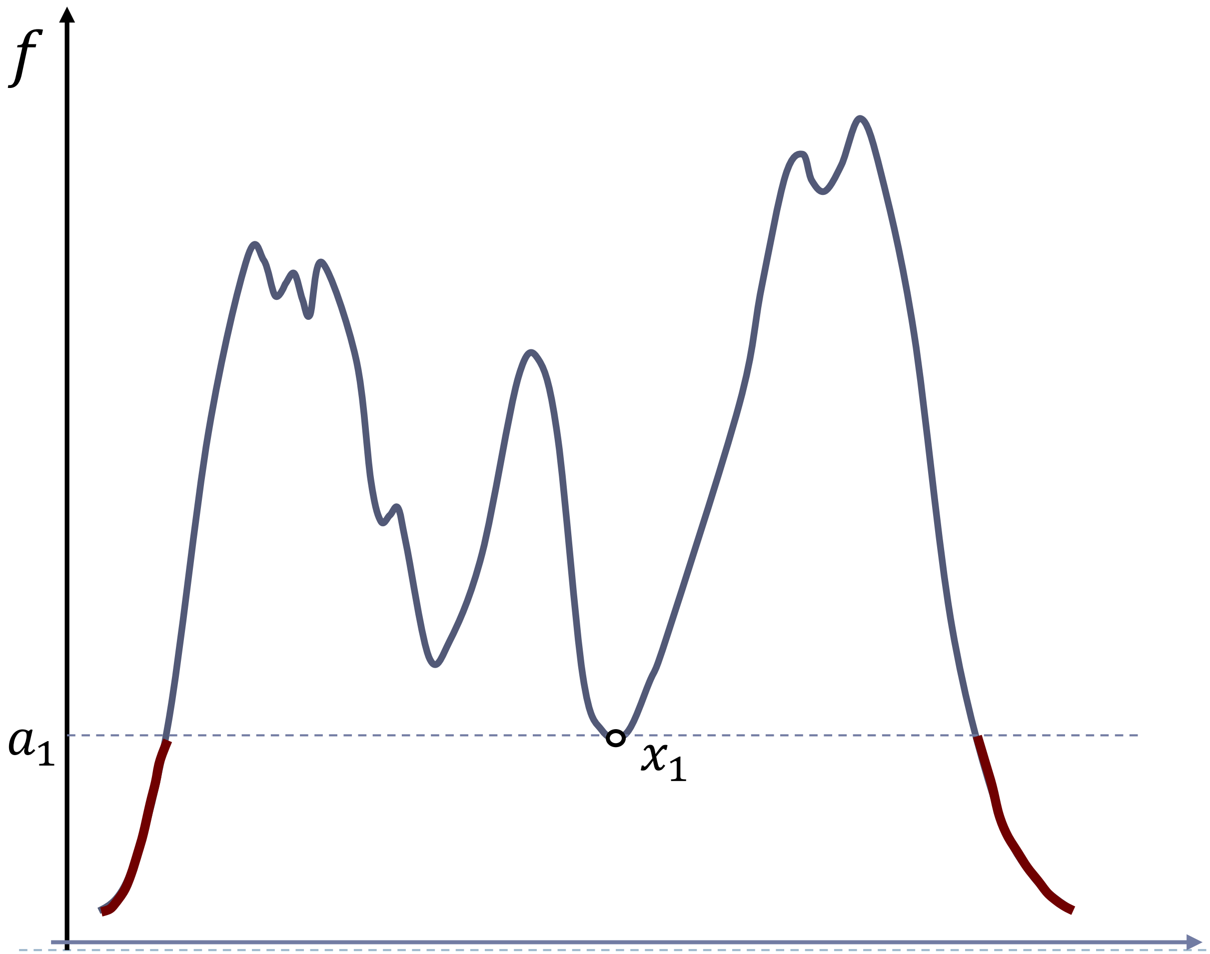

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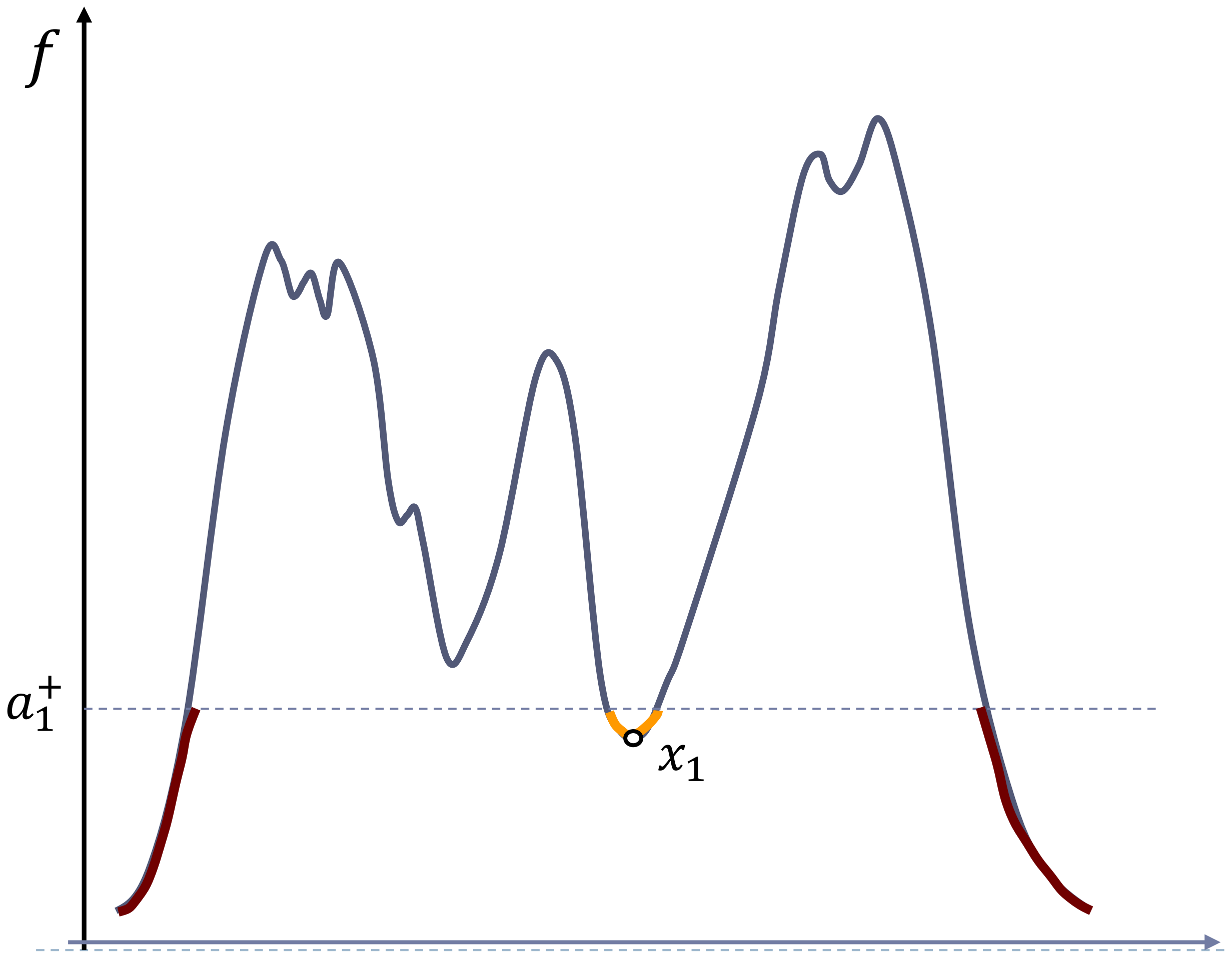

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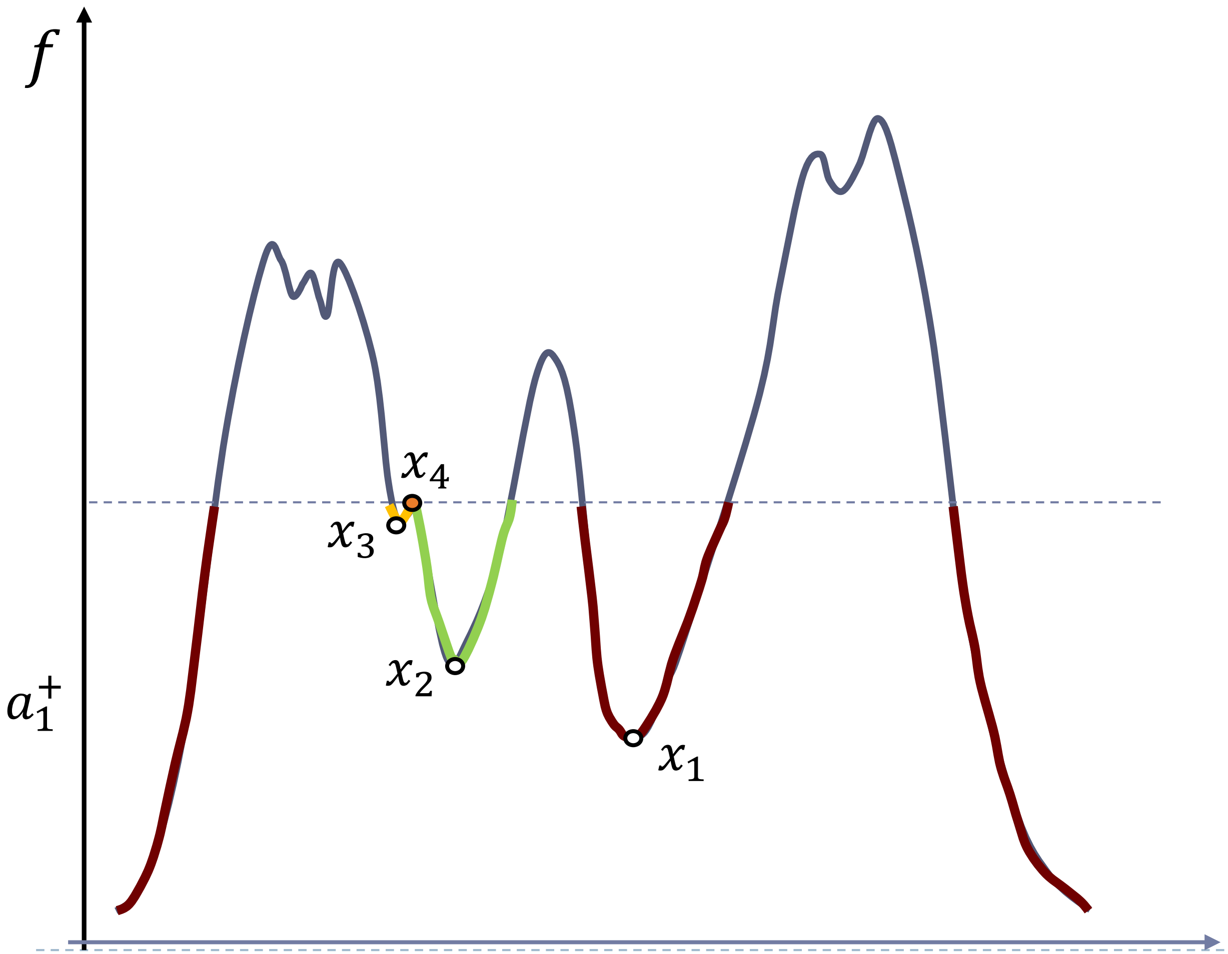

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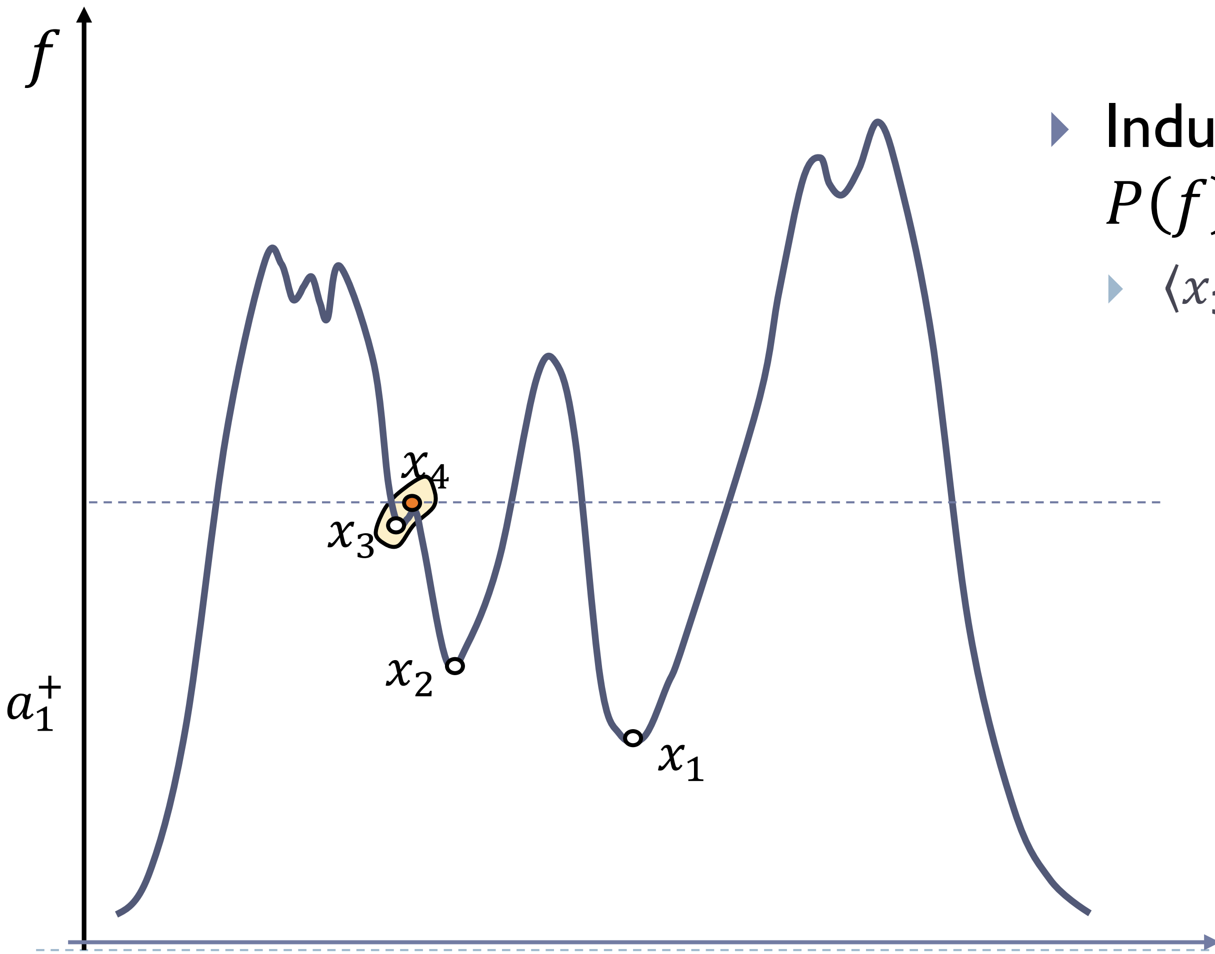
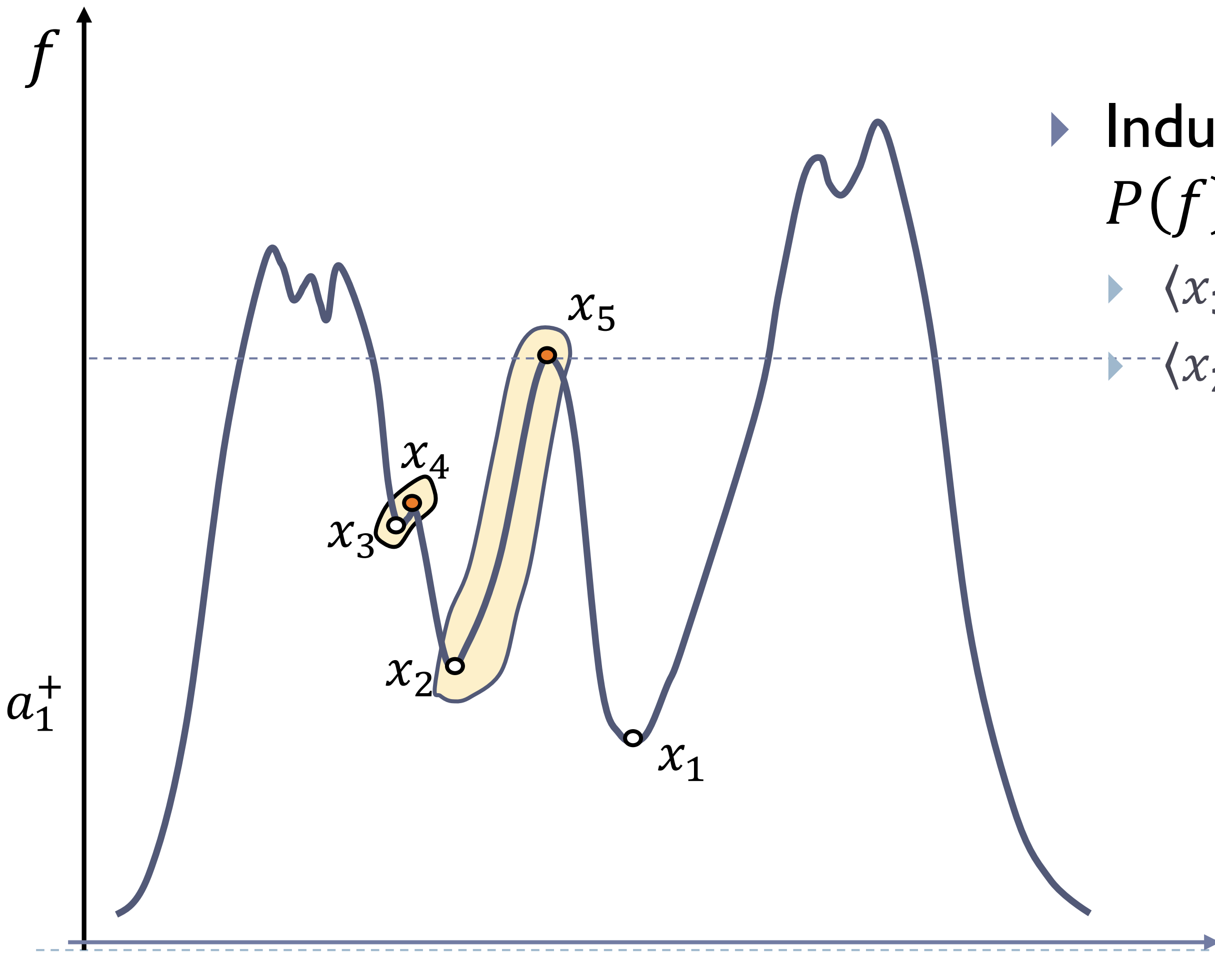


- Induced persistence pairings $P(f)$
  - $\langle x_3, x_4 \rangle, pers = f(x_4) - f(x_3)$

Sublevel-set Persistence – Simplified view

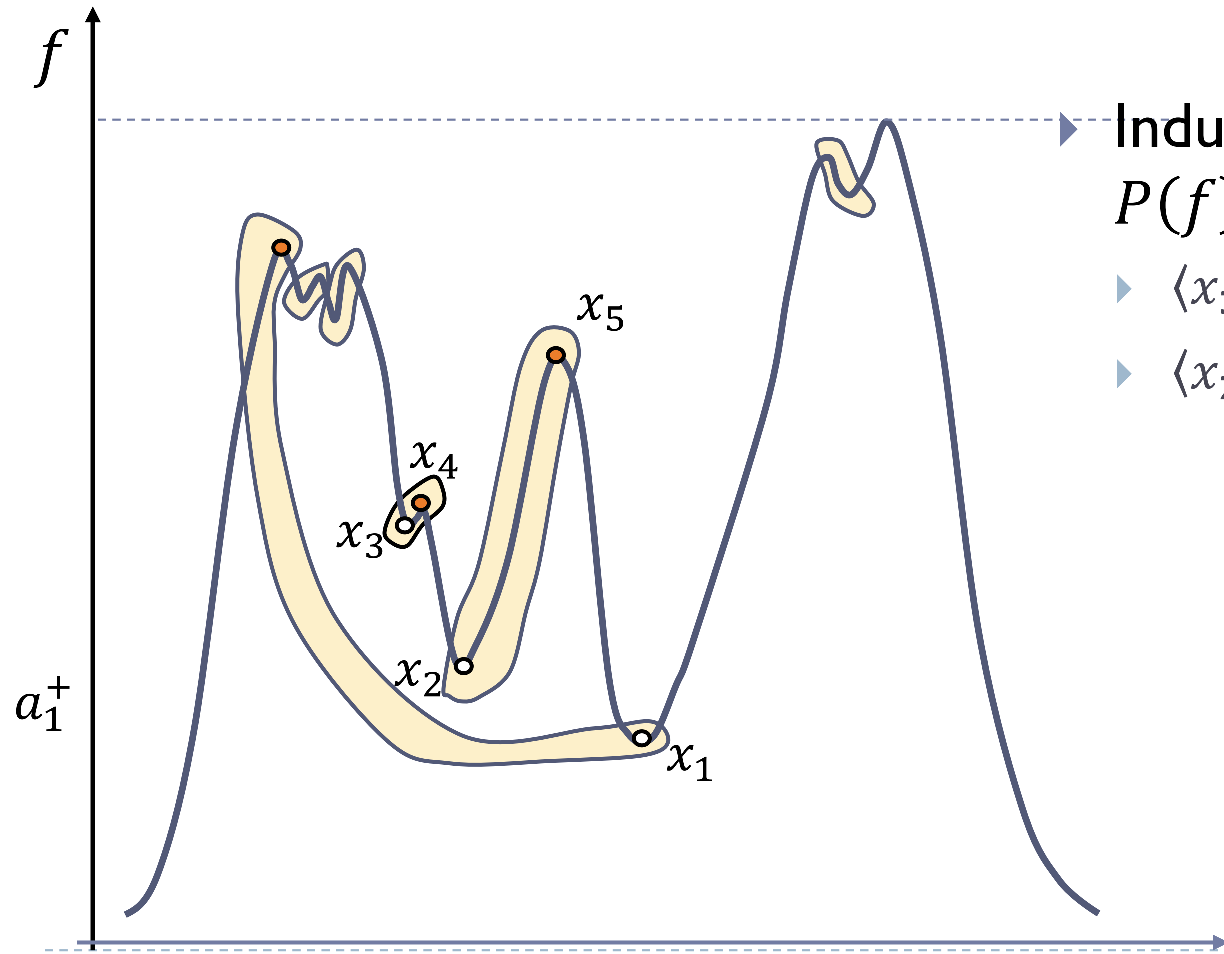
- Input: $f: R \to R$



- Induced persistence pairings $P(f)$
  - $\langle x_3, x_4 \rangle, pers = f(x_4) - f(x_3)$
  - $\langle x_2, x_5 \rangle$

Sublevel-set Persistence – Simplified view

- Input: $f : R \to R$

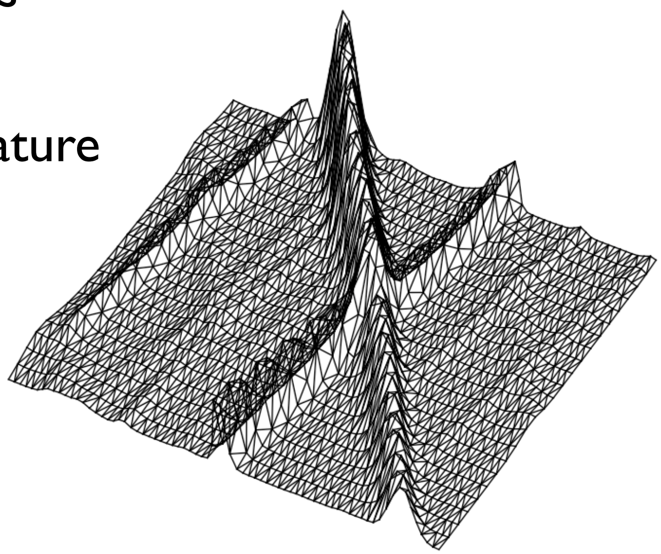


- Induced persistence pairings $P(f)$
  - $\langle x_3, x_4 \rangle, pers = f(x_4) - f(x_3)$
  - $\langle x_2, x_5 \rangle, \langle x_1, x_6 \rangle, \ldots$

Discrete Case

- A piecewise-linear (PL) function $\rho: |K| \to R$ defined on a simplicial complex domain K
- Persistence algorithm via lower-star filtration
  - *[Edelsbrunner, Letscher, Zomorodian 2002],*
  - A collection of persistence pairings:
  - $P_\rho(K) = \{ (\sigma, \tau)\}$, where $\mathrm{k} = \dim(\sigma) = \dim(\tau) - 1$
    - σ: creator, creating k-th homological features
    - τ: destroyer, killing feature created at σ
    - $per(\sigma, \tau) = \rho(\tau) - \rho(\sigma)$: life time of this feature

Intuitively, pairs of simplices with positive persistence corresponding to persistence pairing of critical points in the smooth case.

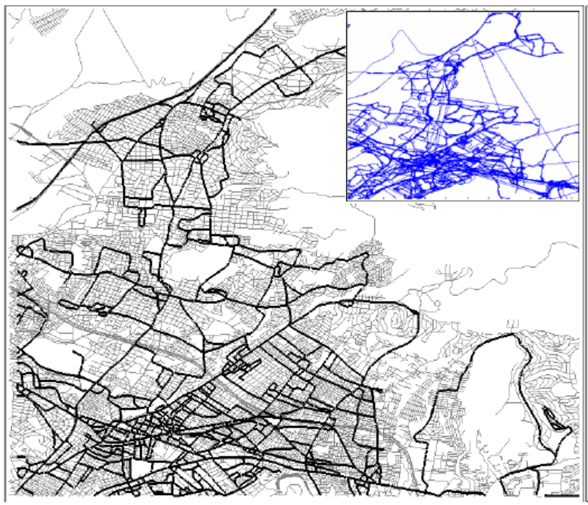


Main Algorithm

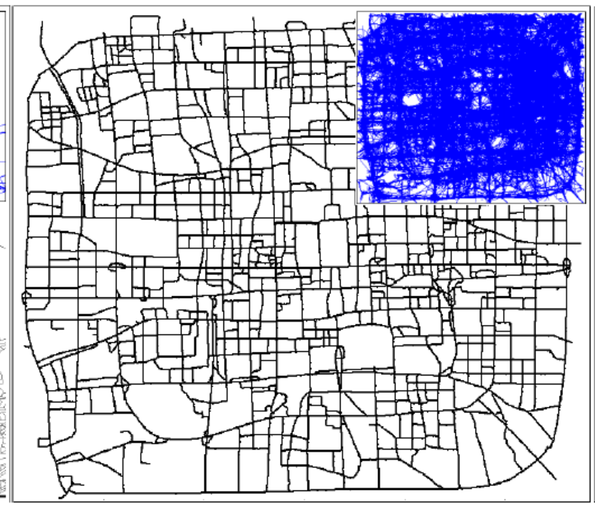
- Input:
  - Triangulation K of domain $I \subset R^d$, function $f: K \to R$, threshold δ
- Initialize discrete gradient vector field W on K to be the trivial one
- Step 1: *persistence computation*
  - Compute persistence pairings $P(K)$ induced by function $-f$
- Step 2: *Morse simplification*
  - Simplify W by performing Morse cancellation for all critical pairs from $P(K)$ with persistence $\leq \delta$, if possible
- Step 3: *collect output*
  - For all remaining critical edges with persistence $> \delta$

The algorithm works for any d-dimensional domain $I \subset R^d$
but only 2-skeleton of the triangulation K is needed

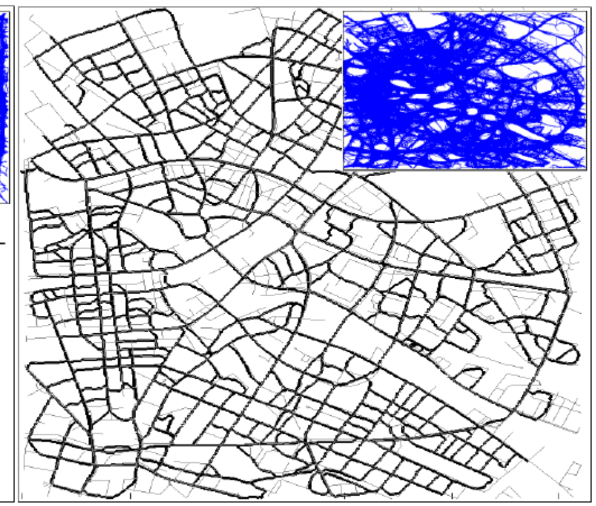
Results – Road network reconstruction



Athens

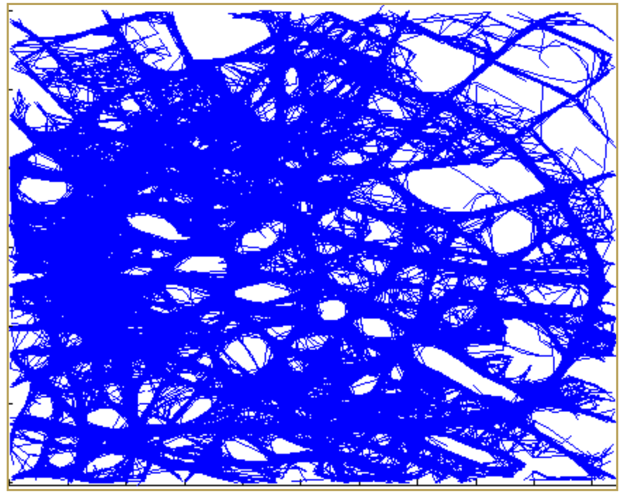


Beijing

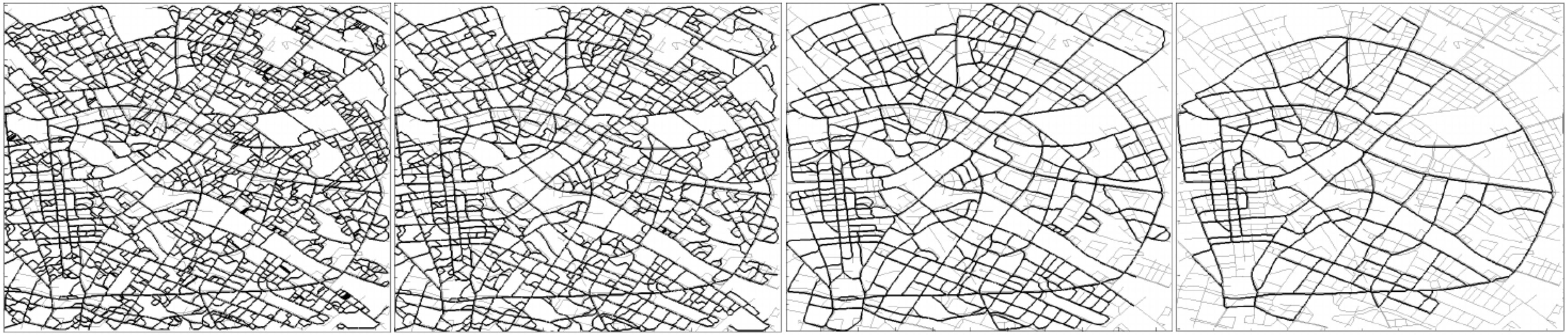


Berlin

Effect of Simplification

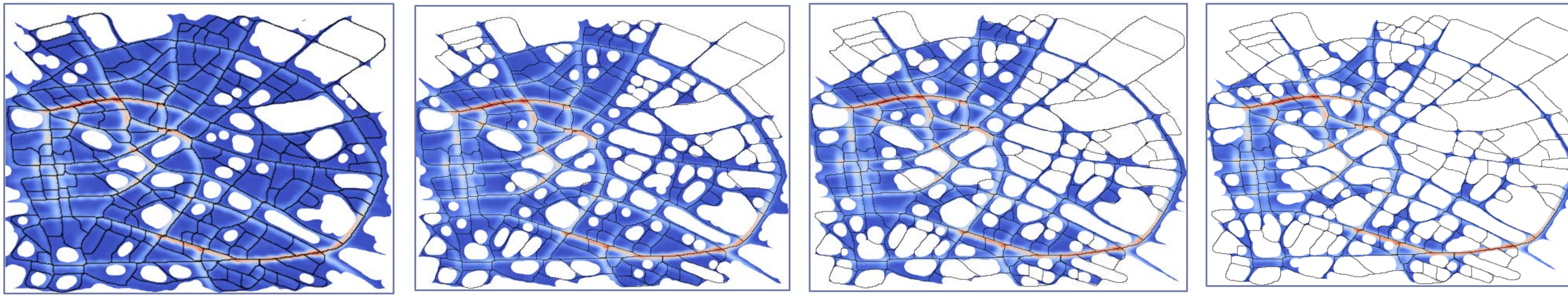


Berlin, 27189 trajectories

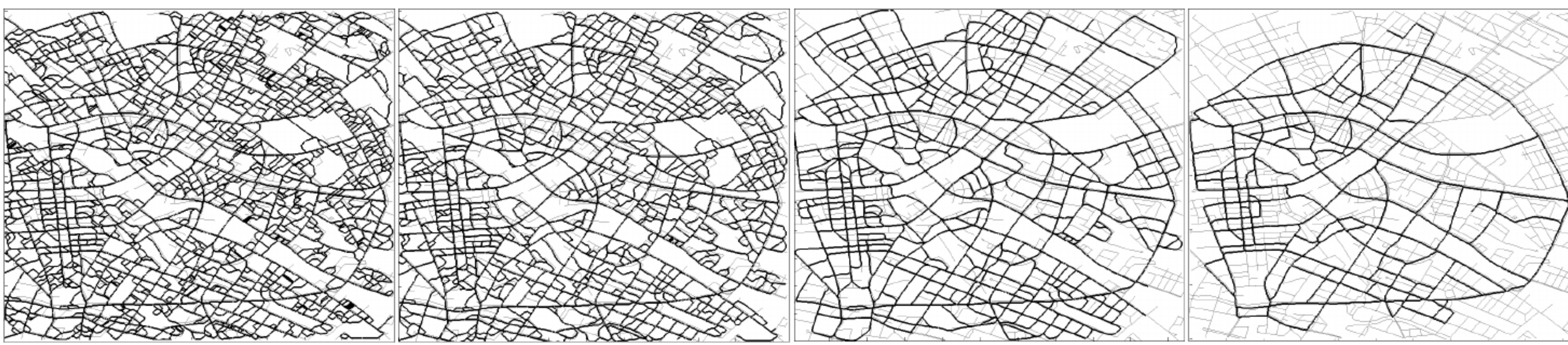


(a) Persistent 0.0001 (b) Persistent 0.001 (c) Persistent 0.01 (d) Persistent 0.1

Thresholding?



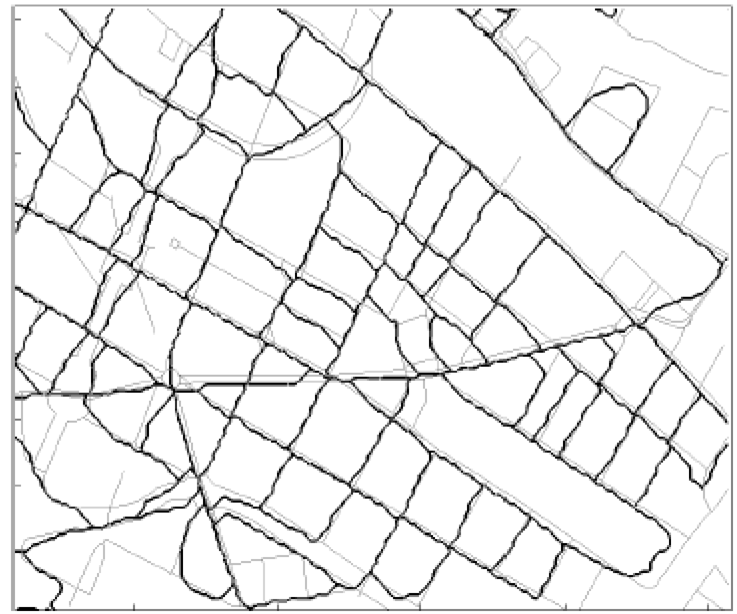
increasing threshold



(a) Persistent 0.0001 (b) Persistent 0.001 (c) Persistent 0.01 (d) Persistent 0.1

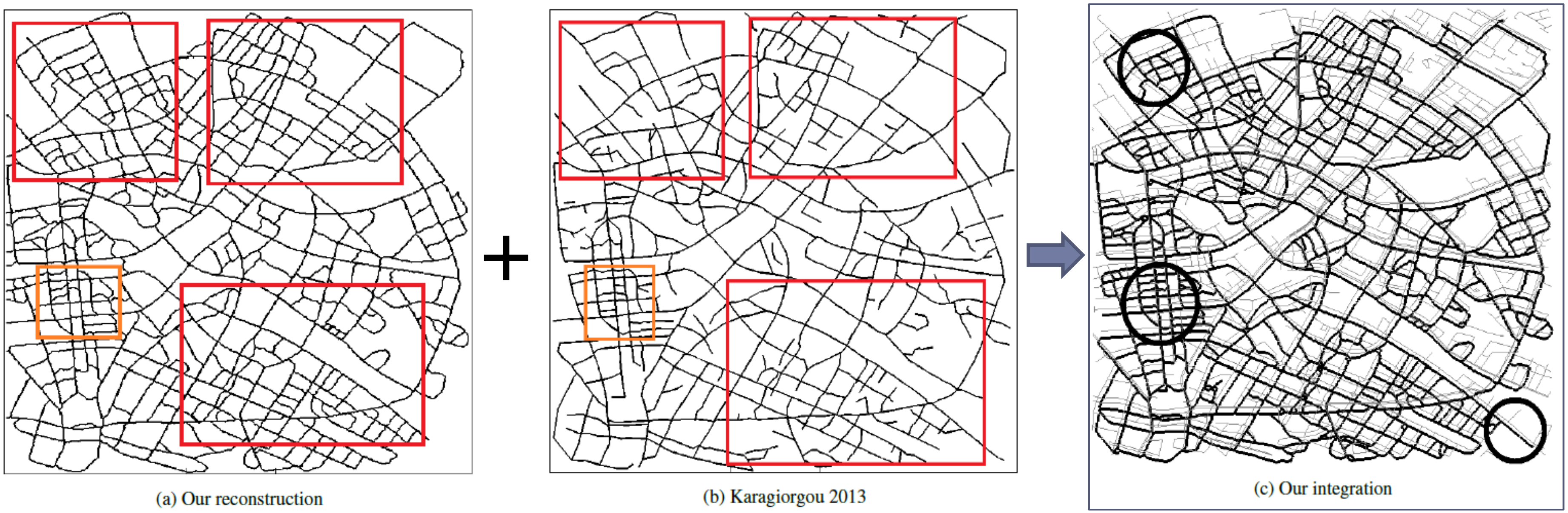
Comparison

(a) Karagiorgou(2013)



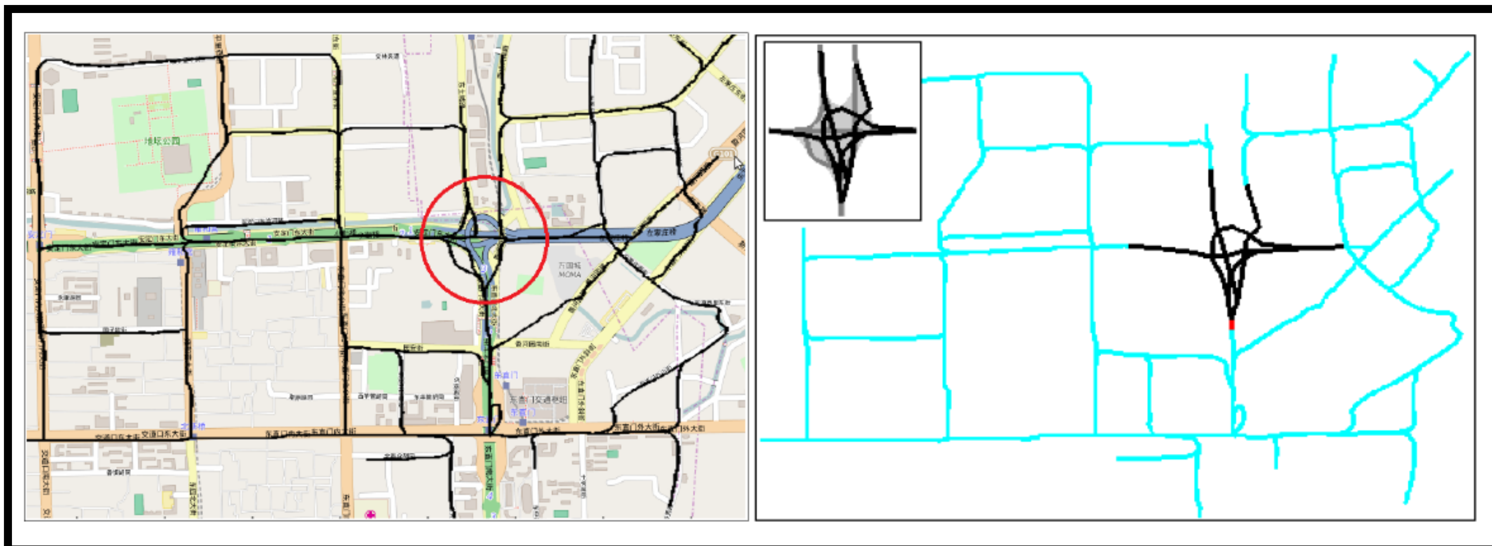
(b) Our result

Map Integration



(a) Our reconstruction (b) Karagiorgou 2013 (c) Our integration

Map Augmentation

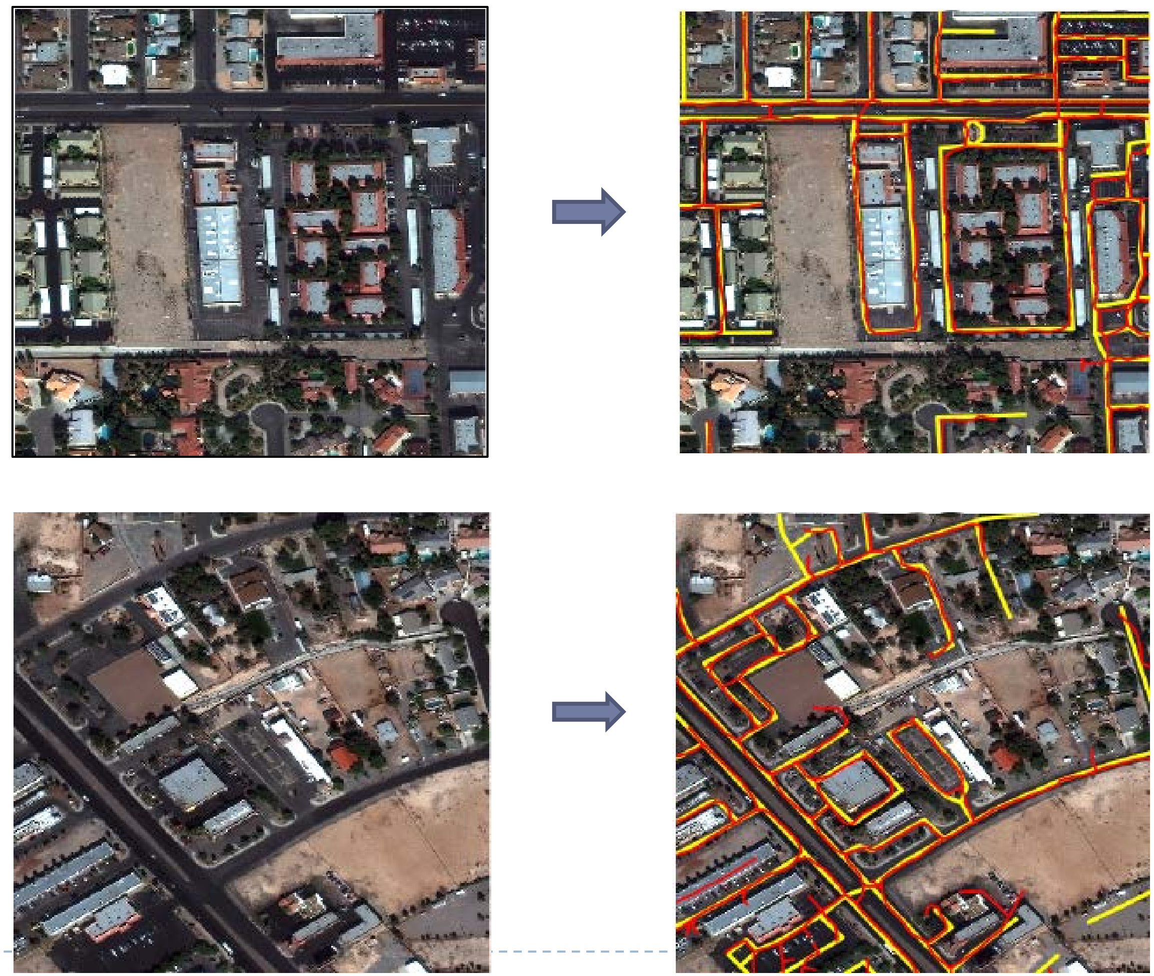


Reconstruction from Satellite Images

- CNN + reconstruction framework

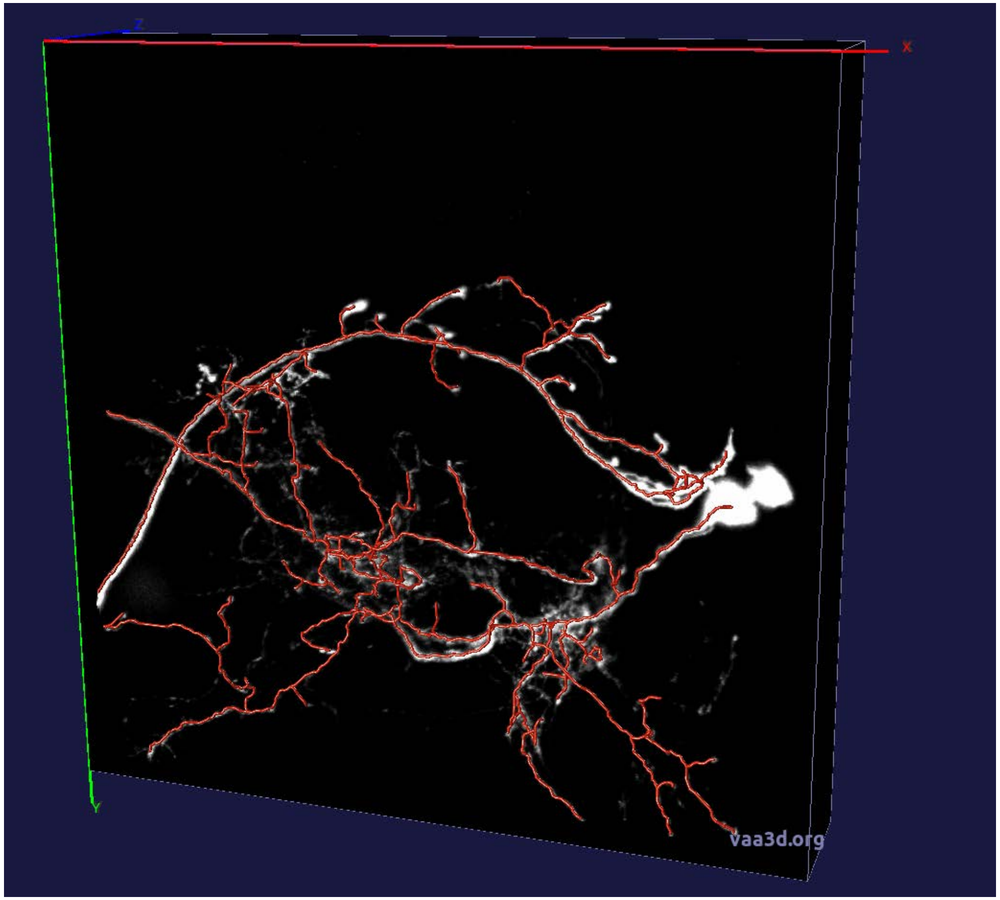
Reconstruction from Satellite Images

- CNN + reconstruction framework



Results – Neuron Reconstruction

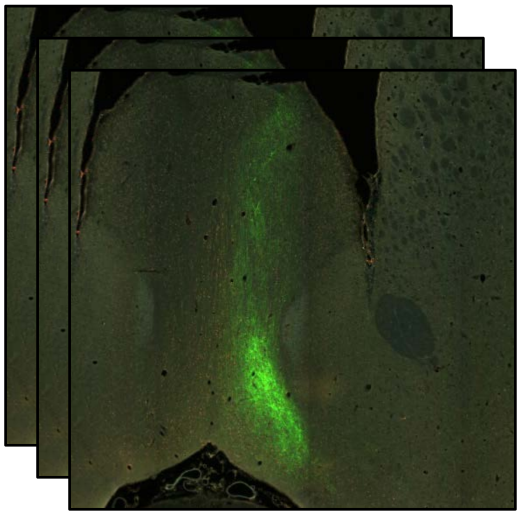
- Single neuron reconstruction

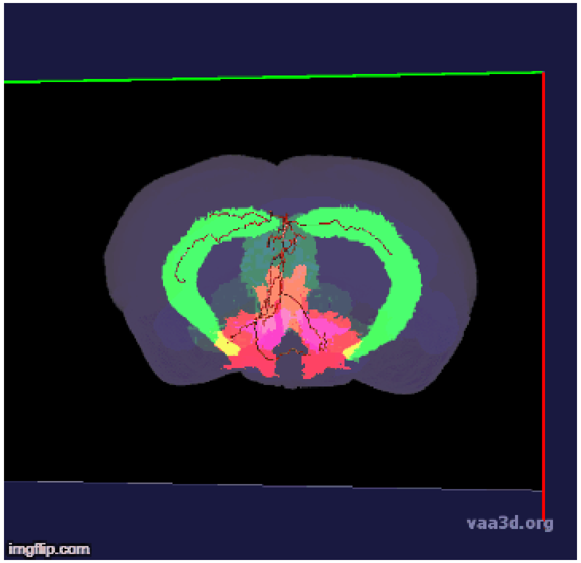


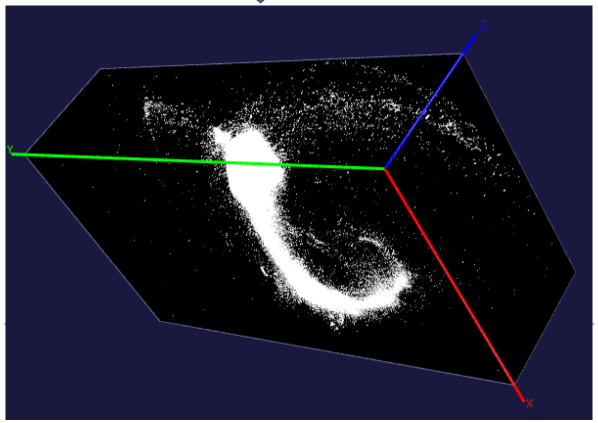
DIADAM dataset OP 2

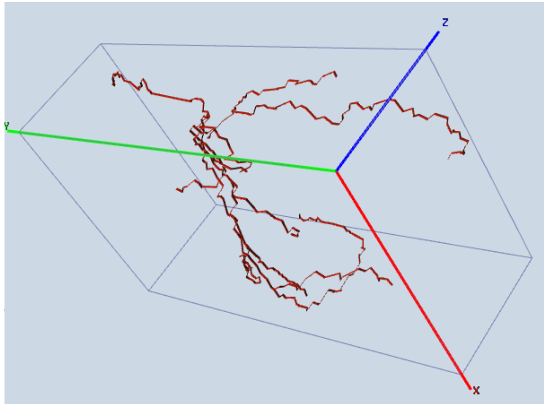
Results – Neuron reconstruction

- Mouse brain LM images from an AAV viral tracer-injection
  - from Mitra laboratory at CSHL









Great!

But what can we guarantee ?

Next

Provide theoretical justification / understanding for the persistence-guided discrete Morse-based graph reconstruction framework

- Further simplification of the algorithm/editing strategy
- Reconstruction guarantees under a (simple) noise model

- [Dey, Wang, W, ACM SIGSPATIAL 2017], [Dey, Wang, W., SoCG 2018]

Reconstruction Editing

- Simple strategies to allow adding missing parts
  - Enforce minima (vertices): allow adding missing free branches
  - Enforce maxima (triangles): allow adding missing loops

adding missing branches

adding missing loops

Main Algorithm

- Input:
  - Triangulation K of domain $I \subset R^d$, function $f: K \to R$, threshold δ

- Initialize discrete gradient vector field W on K
- Step 1: *persistence computation*
  - Compute persistence pairings $P(K)$ induced by function $-f$
- Step 2: *Morse simplification*
  - Simplify W by performing Morse cancellation for all critical pairs from $P(K)$ with persistence $\leq \delta$, if possible
- Step 3: *collect output*
  - For all remaining critical edges with persistence $> \delta$
  - collect their 1-unstable manifolds and output

Simplified Algorithms

- Step 2 (Morse simplification) is replaced by

Procedure PerSimpTree$(P(K), \delta)$

$\Pi :=$ the set of vertex-edge persistence pairs from $P = P(K)$

Set $\Pi_{\leq \delta} \subseteq \Pi$ to be $\Pi_{\leq \delta} = \{(v, e) \in \Pi \mid \mathrm{pers}(v, e) \leq \delta\}$

$\mathcal{T} := \bigcup_{(v,\sigma) \in \Pi_{\leq \delta}} \{\sigma = \langle u_1, u_2 \rangle, u_1, u_2\}$

return $(\mathcal{T})$

  - No need to cancel edge-triangle critical pair
  - No need to check whether cancellation is valid or not
  - No explicit cancellation operation is needed !
    - simply collect all ``negative" edges whose persistence is at most δ

Simplified Step 2:
Linear time to collect a set of edges, and they form a spanning forest that contain all necessary information of discrete gradient field

Simplified Algorithm – cont.

- Step 3 (collecting output) is replaced by:

Procedure Treebased-OutputG$(\mathcal{T})$

for *each critical edge* $e = \langle u, v \rangle$ *with* $\mathrm{pers}(e) \geq \delta$ **do**

    Let $\pi(u)$ be the unique path from u to the sink of the tree T_i containing u

    Define $\pi(v)$ similarly; Set $\widehat{G} = \widehat{G} \cup \pi(u) \cup \pi(v) \cup \{e\}$

  - No explicit discrete gradient vector field maintained!
  - Simplified algorithm even easier and faster
    - [Attali et al 2009], [Bauer et al 2012]

- Theorem

Time complexity of the simplified algorithms is $O(n + Time(Per))$ where n is the total number of vertices and edges in K.

This holds for any dimensions.

Next

Provide theoretical understanding / justification for the persistence-guided discrete Morse-based graph reconstruction framework

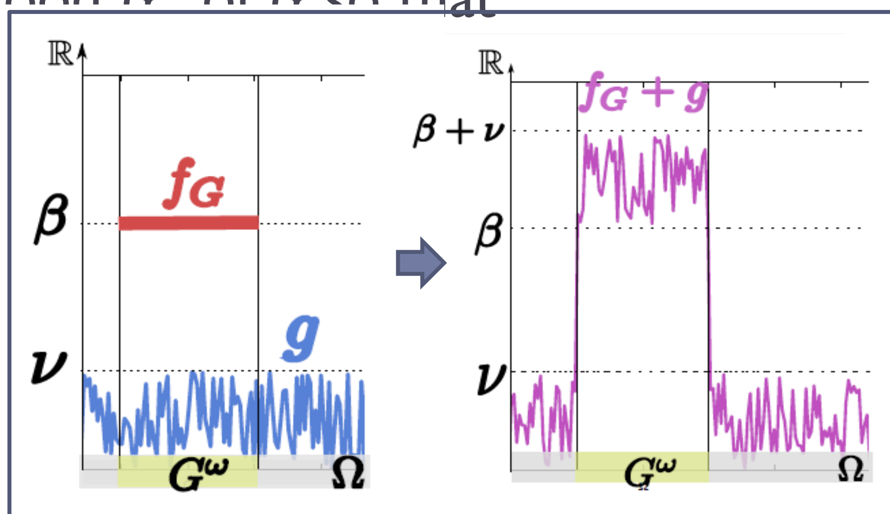
- Further simplification of the algorithm/editing strategy
- Reconstruction guarantees under a (simple) noise model

- [Dey, Wang, W, ACM SIGSPATIAL 2017], [Dey, Wang, W., 2018]

Noise Model

- True graph $G \subset \Omega := [0,1]^d$
- $G^\omega \subset \Omega$: an ω-neighborhood of G
  - such that for (i) any $x \in G^\omega$, $d(x, G) \leq \omega$; and (ii) G^ω deformation retracts to G

- A function $\rho: \Omega \to R$ is (β, μ, ω)-approximation of G
  - if there exists an ω-neighborhood G^ω of G so that
    - $\rho(x) \in [\beta, \beta + \mu]$, for any $x \in$
    - $\rho(x) \in [0, \mu]$, otherwise
    - $\beta > 2\mu$



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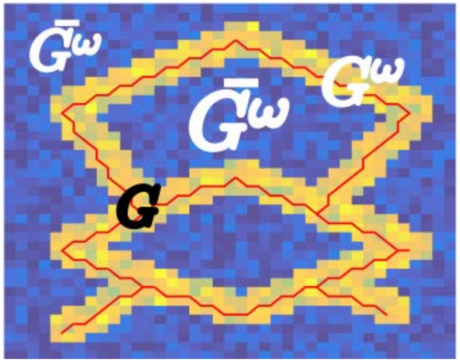


- In discrete case,
  - K a triangulation of Ω, $G^\omega \subset K$, ρ defined at vertices of K

Main Results

Theorem (Geometry)

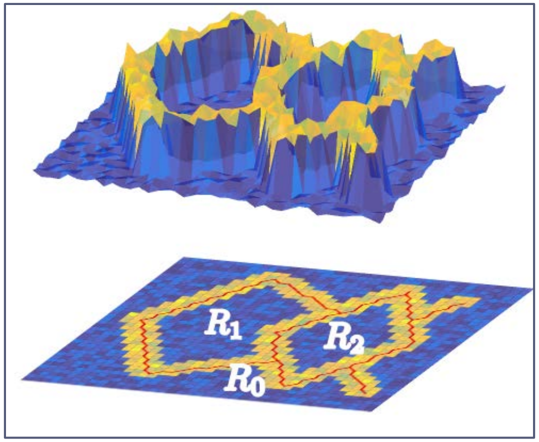
For any dimension d, under our noise model and for appropriate δ, the output graph $\hat{G}$ satisfies $\hat{G} \subset G^{\omega}$.

Theorem (Topology)

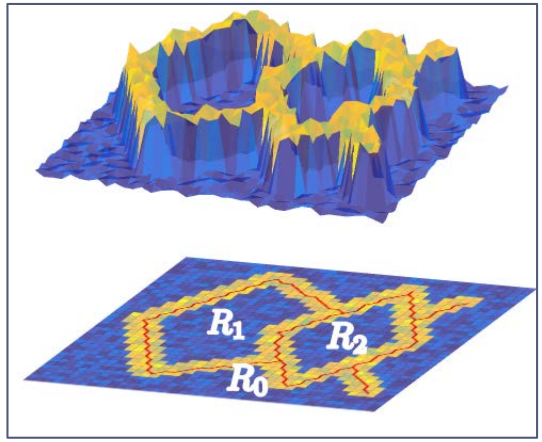
For any dimension d, under our noise model and for appropriate δ, the output graph $\hat{G}$ is homotopy equivalent to G.

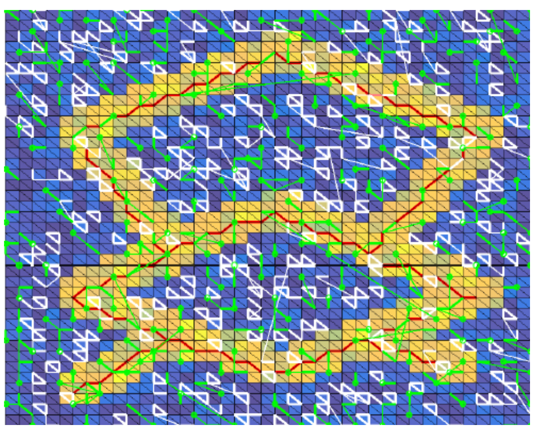
Theorem (Topology in 2D)

For $d = 2$, under our noise model and for appropriate δ, there is a deformation retraction from G^{ω} to $\hat{G}$.

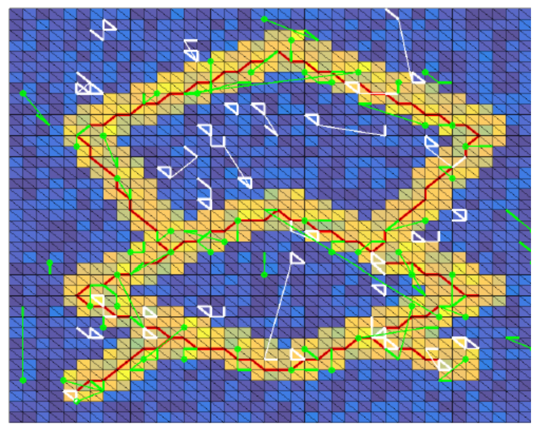


R_1
R_2
R_0

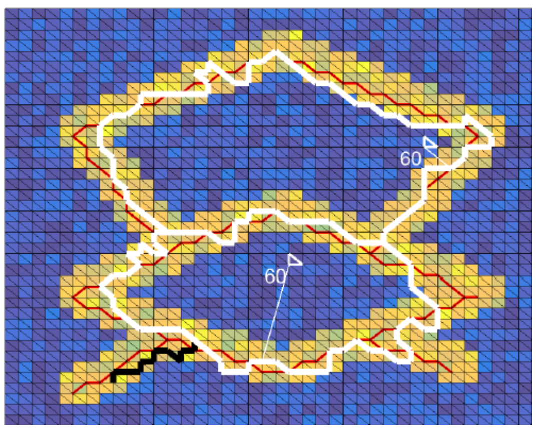




$\delta = 0.0001$



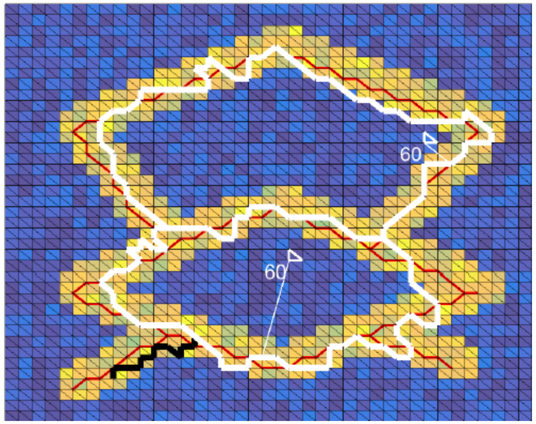
$\delta = 5$



$\delta = 20$

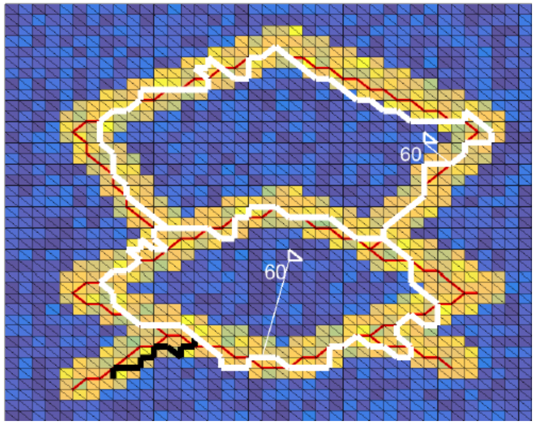
Proof Ideas

- Suppose true graph G has g independent loops
- Lemma A:
  - Under the noise model, after δ-simplification for appropriate δ, exactly 1 critical vertex (global minimum), g critical edges and g critical triangles are left.

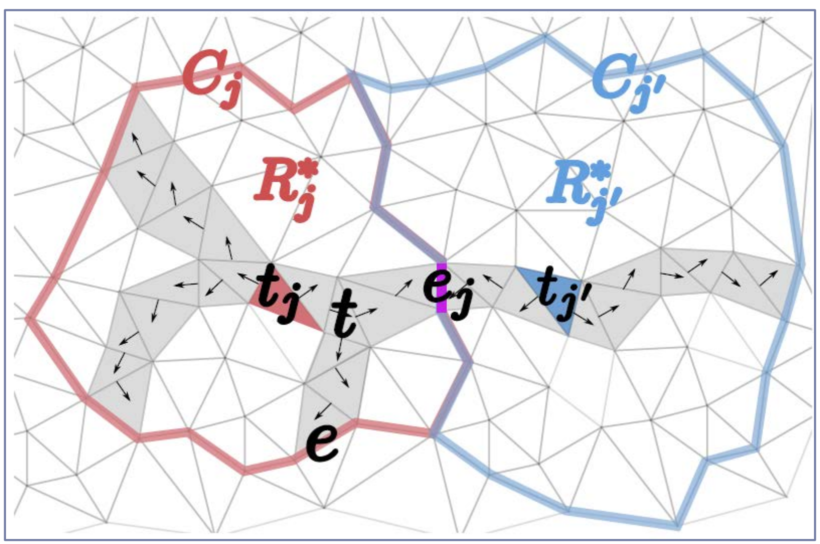


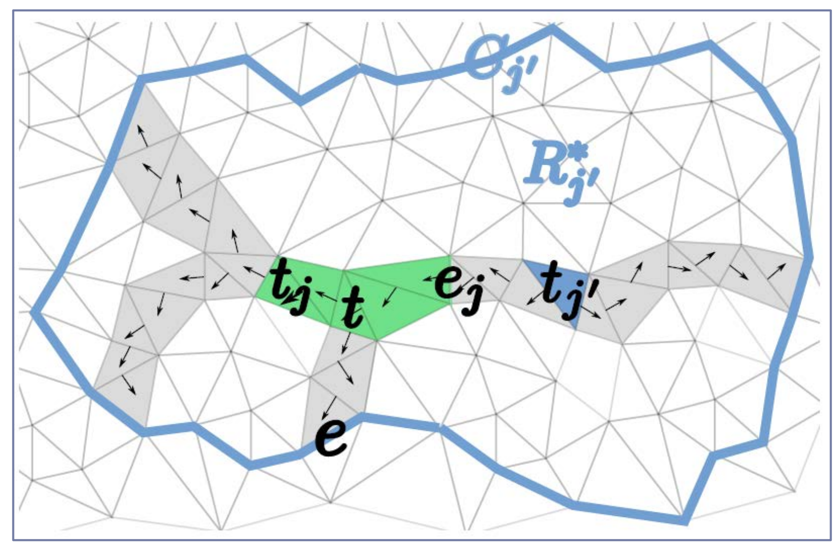
Proof Ideas

- Suppose the true graph G has g independent loops
- Lemma A:
  - Under the noise model, after δ-simplification for appropriate δ, exactly 1 critical vertex (global minimum), g critical edges and g critical triangles are left.
- Lemma B:
  - All critical edges are in the region G^{ω},
  - and all critical triangles are outside it.



- Each critical triangle t
  - corresponds to a region spanned by triangles reachable from t via discrete gradient paths
- Simplification process
  - merges such regions





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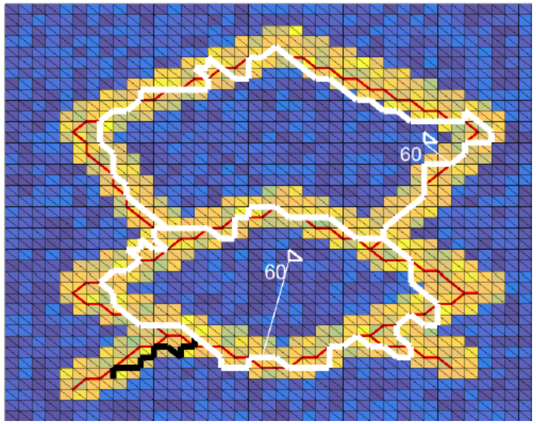
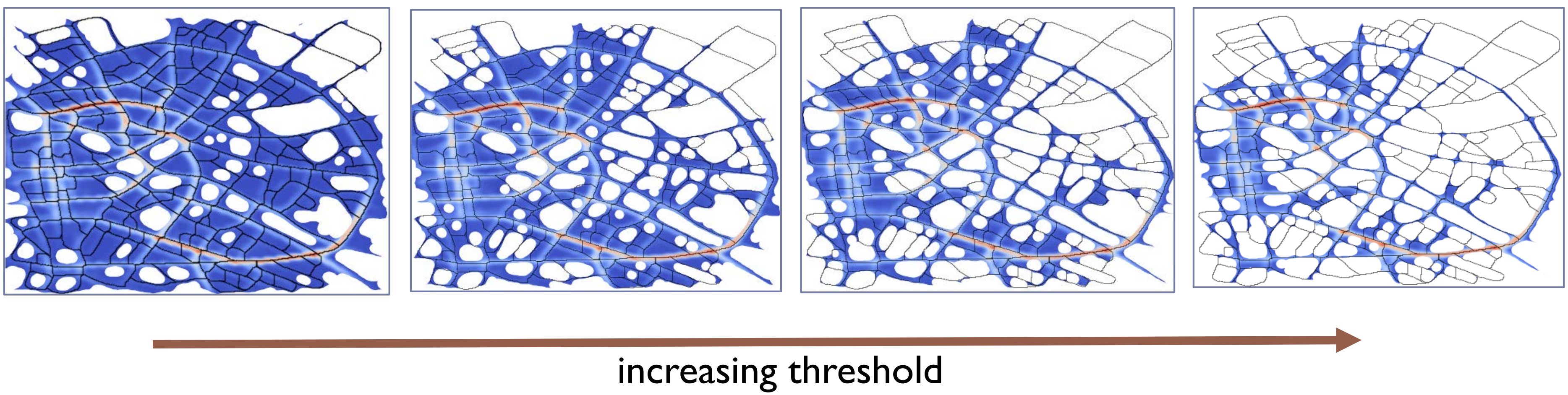


- Lemma C:
  - In R^2, at the end of simplification, the boundary of the g regions corresponding to the remaining critical triangles form a subset of output graph $\hat{G}$.
  - The associated edge-triangle discrete gradient vectors inside each region lead to a deformation retraction from G^{ω} to $\hat{G}$.

Remarks

- Noise model simple
  - Thresholding-based approach may potentially work for this model
  - However, not for real data



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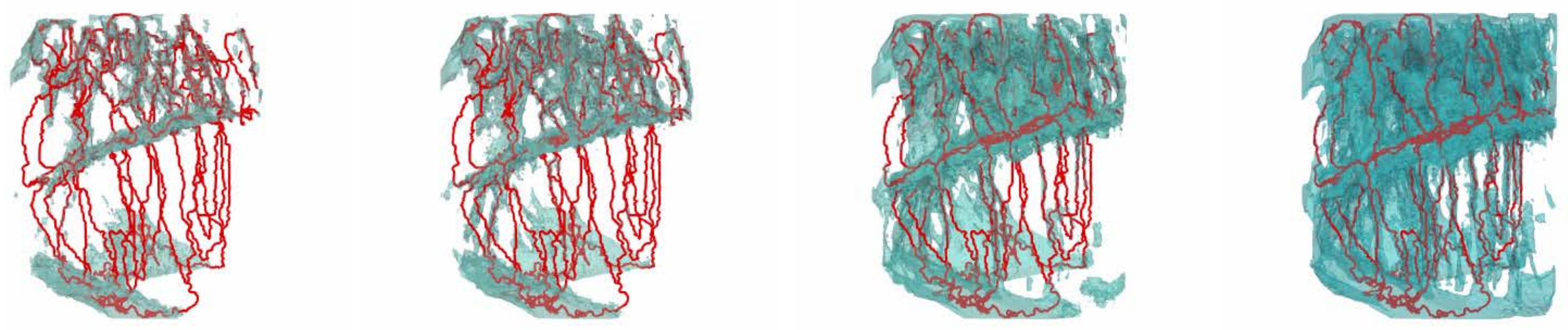

decreasing thresholds

Concluding Remarks

- Explored the power of a discrete Morse+persistence based framework for graph reconstruction
  - Application to both 2D (road network) and 3D (neuron reconstruction)
- Provided theoretical understanding and justification of its reconstruction ability
- Only a first step!
  - More general noise models
  - High dimensional points data input


THANK YOU!