A Theoretical Framework for Mapper

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Introduction

 $\ensuremath{\mathsf{Goal}}$: provide theoretical treatment and guarantees on the Mapper algorithm



Introduction

Several attempts have been made to bring theory to Mapper:

- Bakken-Stovner (2012) express Mapper as a functor
- Dey et al (2013) introduced MultiScale Mapper, a construction tailored for stability

Background

Mapper Persistence Diagrams Reeb Graphs

MultiNerve Mapper

Telescope

Stability

Background

- Famous algorithm widely used in TDA
- Input:
 - \blacktriangleright Topological Space $\mathbb X$
 - Continuous $f : \mathbb{X} \to \mathbb{R}$,
 - Covering $\mathcal{I} = \{I\}$ s.t. $\operatorname{im}(f) \subseteq \bigcup_{I \in \mathcal{I}} I$
- ► Output: Simplicial Complex M_f(X, I)

- Nodes in M_f(X, I) are given by the path-connected components (cc) of each f⁻¹(I), I ∈ I
- Create k-simplex between nodes v₀, ..., v_k iff the corresponding cc intersect
- ► Equivalently, take the *nerve* of the pullback covering U = cc(f⁻¹(I)):

$$\mathcal{N}(\mathcal{U}) = \{A \subseteq \mathcal{U} \mid \bigcap_A \neq \emptyset\}$$



- **Definition:** Small intervals of a covering: $I = I_{\cap}^- \sqcup I_p \sqcup I_+$
- Definition: A covering is minimal if there is no element included in the others' union
- Lemma: \mathcal{I} is minimal $\Longrightarrow M_f(\mathbb{X}, \mathcal{I})$ is a graph

Proof: No more than 2 elements can intersect \Rightarrow 1-simplices only



- Persistence Diagrams (PD) are useful tools to characterize the topological information of a space
- Given function *f*, observe the space through:
 - sublevel sets $F_{\alpha} = f^{-1}((-\infty, \alpha])$
 - surlevel sets $\mathbb{X} \setminus (F^{\alpha} = f^{-1}([\alpha, +\infty)))$



- ▶ PD record birth and death times *b*, *d* of topological features
- PD distinguish between:
 - Ordinary topological features (b, d sublevel)
 - Extended topological features (b sublevel, d surlevel)
 - Relative topological features (b, d surlevel)



- Mapper is deeply related to Reeb Graphs
- $\mathsf{R}_f(\mathbb{X}) = \mathbb{X}/\sim$ where $x \sim y \iff f(x) = f(y) \text{ and } x, y \in \text{same cc of } f^{-1}(f(x))$
- Notation: $\tilde{f} : \mathsf{R}_f(\mathbb{X}) \to \mathbb{R}$



Definition: $f : \mathbb{X} \to \mathbb{R}$ is of Morse type if:

- (i) ∃a₁ < ... < a_n s. t. for every
 I ∈ {(-∞, a₁), (a_i, a_{i+1}), (a_n, +∞)}, X^I = f⁻¹(I)
 homeomorphic to Y_i × I and f = projection onto the second factor π₂
- ► (*ii*) $\exists \phi_i : \mathbb{Y}_i \times \{a_i\} \to \mathbb{X}^{a_i}, \psi_i : \mathbb{Y}_i \times \{a_{i+1}\} \to \mathbb{X}^{a_{i+1}}$ continuous
- (*iii*) \mathbb{X}^t has finitely-generated homology





- Includes Morse functions, PL functions...
- Reeb Graph behaves nicely: multi-graph
- **Theorem:** If *f* is of Morse type:

$$\begin{aligned} \mathsf{Dg}_0(\tilde{f},\mathsf{R}_f(\mathbb{X})) &= \mathsf{Dg}_0(f,\mathbb{X})\\ \mathsf{Dg}_1(\tilde{f},\mathsf{R}_f(\mathbb{X})) &= \mathsf{Dg}_1(f,\mathbb{X}) \setminus \mathsf{Ext}_1^{+\Delta}(f,\mathbb{X})\\ \mathsf{Dg}_p(\tilde{f},\mathsf{R}_f(\mathbb{X})) &= \emptyset, p \geq 2 \end{aligned}$$

- Variant of Mapper naturally related to the Reeb graph
- Same inputs
- Outputs a multigraph $\overline{\mathsf{M}}_{f}(\mathbb{X},\mathcal{I})$

• **Definition:** The MultiNerve of a covering \mathcal{U} is:

$$\mathcal{M}(\mathcal{U}) = \left\{ (C,A) | \ A \subseteq \mathcal{U} \ \text{and} \ C \in \mathsf{cc} \ igcap_A
ight\}$$

- MultiNerve Mapper takes the MultiNerve of the pullback covering
- Mapper is the simple graph obtained by gluing edges of MultiNerve Mapper



- We filter the multigraph to have a Dg
- Notation: $\overline{f} : \overline{M}_f(\mathbb{X}, \mathcal{I}) \to \mathbb{R}$

$$\blacktriangleright \forall v_I \in V(\overline{\mathsf{M}}_f(\mathbb{X},\mathcal{I})), \overline{f}(v_I) \in I_p$$

• Ordinary part of filtration: lower-star of \bar{f}

$$\forall e = (v_I, v_J) \in E(\overline{\mathsf{M}}_f(\mathbb{X}, \mathcal{I})), \overline{f}(e) = \max(\overline{f}(v_I), \overline{f}(v_J))$$

• Relative part of filtration: upper-star of \bar{f}

$$\forall e = (v_I, v_J) \in E(\overline{\mathsf{M}}_f(\mathbb{X}, \mathcal{I})), \overline{f}(e) = \min(\overline{f}(v_I), \overline{f}(v_J))$$

PD encodes multigraph structure and function behaviour

- MultiNerve Mapper is a coarse version of Reeb Graph
- ▶ **Goal:** Conditions on *I* for equality ?
- ▶ **Theorem:** If no interval of *I* contains paired critical values:
 - ▶ ∃ bijection between $Dg(\overline{f}, \overline{M}_f(\mathbb{X}, \mathcal{I}))$ and $Dg(\widetilde{f}, R_f(\mathbb{X}))$
 - R_f(X) and M
 _f(X, I) have same homology (⇒ same homotopy type e.g. X is connected)
- ► To prove this, we slightly modify (X, f) into (X', f') (according to I) without changing M_f(X, I) s.t.
 - $\overline{\mathsf{M}}_{f}(\mathbb{X},\mathcal{I}) \simeq \overline{\mathsf{M}}_{f'}(\mathbb{X}',\mathcal{I}) \simeq \mathsf{R}_{f'}(\mathbb{X}')$ combinatorially
 - same Dg



We define three operations on $\mathbb X$ that *preserve* MultiNerve Mapper but *change* the Reeb Graph:

- Merge
- Split
- Shift



Definition: The telescope of f is:

 $(\mathbb{Y}_0 \times (a_0, a_1]) \cup (\mathbb{X}^{a_1} \times \{a_1\}) \cup (\mathbb{Y}_1 \times [a_1, a_2]) \cup \ldots \cup (\mathbb{Y}_n \times [a_n, a_{n+1}))$

 (\mathbb{X}, f) is equivalent to (telescope, π_2)

► A Merge operation between a < b gives the same value ā to all points whose function value belongs to [a, b]:

$$\begin{split} \dots(\mathbb{Y}_{i-1}\times[a_{i-1},a_i])\cup(\mathbb{X}^{a_i}\times\{a_i\})\dots(\mathbb{X}^{a_j}\times\{a_j\})\cup(\mathbb{Y}_j\times[a_j,a_{j+1}])\dots\\ \downarrow\\ \dots(\mathbb{Y}_{i-1}\times[a_{i-1},\bar{a}])\cup(\mathbb{X}^{[a,b]}\times\{\bar{a}\})\cup(\mathbb{Y}_j\times[\bar{a},a_{j+1}])\dots \end{split}$$



Effect on PD:



Given \mathcal{I} , Merge_{\mathcal{I}} collapses all critical values inside the same small interval $I_{\cap}^{-}, I_{p}, I_{\cap}^{+}$:





• A Split operation of size ϵ at a_i extrudes the levelset \mathbb{X}^{a_i} :



• A Split operation of size ϵ at a_i extrudes the levelset \mathbb{X}^{a_i} :

- MultiNerve Mapper is unchanged
- ▶ Definition: a_i is a down-fork if φ_i homeomorphism and an up-fork if ψ_{i-1} homeomorphism

• A Split operation of size ϵ at a_i extrudes the levelset \mathbb{X}^{a_i} :

Lemma: $a_i - \epsilon$ is a down-fork; $a_i + \epsilon$ is an up-fork.

Lemma:

down-forks
$$\in$$
 $b(Ord), d(Ord), b(Ext)$
up-forks \in $b(Rel), d(Rel), d(Ext)$

Effect on PD:



Given $\mathcal I, \, {\sf Split}_{\mathcal I} \,$ extrudes all critical values s.t. the extrusion stays in the same small interval:





A Shift operation of size *ϵ* at *a_i* moves the critical value to *a_i* + *ϵ*:

$$\begin{array}{c} \dots (\mathbb{Y}_{i-1} \times [a_{i-1}, a_i]) \cup (\mathbb{X}^{a_i} \times \{a_i\}) \cup (\mathbb{Y}_i \times [a_i, a_{i+1}]) \dots \\ \downarrow \\ \dots (\mathbb{Y}_{i-1} \times [a_{i-1}, a_i + \epsilon]) \cup (\mathbb{X}^{a_i} \times \{a_i + \epsilon\}) \cup (\mathbb{Y}_i \times [a_i + \epsilon, a_{i+1}]) \dots \end{array}$$



Effect on PD:



Given $\mathcal I,$ Shift_{\mathcal I} moves all up-forks in an intersection upward and all down-forks in an intersection downward:





Let $T := \mathsf{Merge}_{\mathcal{I}} \circ \mathsf{Shift}_{\mathcal{I}} \circ \mathsf{Split}_{\mathcal{I}} \circ \mathsf{Merge}_{\mathcal{I}}$ and $\mathbb{X}' = T(\mathbb{X})$









Let Q_O, Q_E, Q_R denote the following *staircases*:



- Theorem: $Dg(\overline{f}', \overline{M}_{f'}(\mathbb{X}', \mathcal{I})) = Dg(\widetilde{f}', R_{f'}(\mathbb{X}'))$
- **Theorem:** Bijection between:

$$\begin{aligned} & \operatorname{Ext}^{+\Delta}(\tilde{f}', \mathsf{R}_{f'}(\mathbb{X}')) \text{ and } \operatorname{Ext}^{+\Delta}(\tilde{f}, \mathsf{R}_{f}(\mathbb{X})) \\ & \operatorname{Ext}^{-\Delta}(\tilde{f}', \mathsf{R}_{f'}(\mathbb{X}')) \text{ and } \operatorname{Ext}^{-\Delta}(\tilde{f}, \mathsf{R}_{f}(\mathbb{X})) \setminus Q_{E} \\ & \operatorname{Ord}(\tilde{f}', \mathsf{R}_{f'}(\mathbb{X}')) \text{ and } \operatorname{Ord}(\tilde{f}, \mathsf{R}_{f}(\mathbb{X})) \setminus Q_{O} \\ & \operatorname{Rel}(\tilde{f}', \mathsf{R}_{f'}(\mathbb{X}')) \text{ and } \operatorname{Rel}(\tilde{f}, \mathsf{R}_{f}(\mathbb{X})) \setminus Q_{R} \end{aligned}$$

We can consider either

•
$$\mathsf{Dg}(\overline{\mathsf{M}}_{f}(\mathbb{X},\mathcal{I})) = \mathsf{Dg}(\tilde{f}) \setminus Q$$

• $\mathsf{Dg}'(\overline{\mathsf{M}}_{f}(\mathbb{X},\mathcal{I})) = \mathsf{Dg}(\bar{f})$

▶ Definition: Let S ⊆ ℝ². The bottleneck distance between two multisets P, Q ⊆ ℝ² is:

$$d_{\mathcal{S}}(\mathsf{P}, \mathsf{Q}) = \mathsf{inf}_{\gamma} \, \sup_{(\mathsf{p}, q) \in \gamma} \, \|\mathsf{p} - q\|_{\infty}$$

where γ is a partial matching between P and Q that can match points to their projection on ${\cal S}$

- ▶ Lemma: For $Q \in \{Q_E, Q_R, Q_O\}$, $d_Q(D_1, D_2) \le d_\Delta(D_1, D_2)$
- Definition: Pseudo-metric between MultiNerve Mapper:

$$\begin{split} d(\mathsf{Dg}(\overline{\mathsf{M}}_{f}(\mathbb{X},\mathcal{I})),\mathsf{Dg}(\overline{\mathsf{M}}_{g}(\mathbb{X},\mathcal{I}))) &:= \max\{d_{Q_{O}}(\mathsf{Ord}(\tilde{f}),\mathsf{Ord}(\tilde{g})), \\ & d_{\Delta}(\mathsf{Ext}^{+\Delta}(\tilde{f}),\mathsf{Ext}^{+\Delta}(\tilde{g})), \\ & d_{Q_{E}}(\mathsf{Ext}^{-\Delta}(\tilde{f}),\mathsf{Ext}^{-\Delta}(\tilde{g})), \\ & d_{Q_{R}}(\mathsf{Rel}(\tilde{f}),\mathsf{Rel}(\tilde{g}))\} \end{split}$$

▶ Definition: Let S ⊆ ℝ². The bottleneck distance between two multisets P, Q ⊆ ℝ² is:

$$d_{\mathcal{S}}(P,Q) = \mathsf{inf}_{\gamma} \, \sup_{(p,q) \in \gamma} \, \|p-q\|_{\infty}$$

where γ is a partial matching between P and Q that can match points to their projection on S

- ▶ Lemma: For $Q \in \{Q_E, Q_R, Q_O\}$, $d_Q(D_1, D_2) \le d_\Delta(D_1, D_2)$
- **Definition:** Pseudo-metric between MultiNerve Mapper:

$$\begin{aligned} d(\mathsf{Dg}'\overline{\mathsf{M}}_{f}(\mathbb{X},\mathcal{I})),\mathsf{Dg}'(\overline{\mathsf{M}}_{g}(\mathbb{X},\mathcal{I}))) &:= \max\{d_{Q_{O}}(\mathsf{Ord}(\bar{f}),\mathsf{Ord}(\bar{g})), \\ & d_{\Delta}(\mathsf{Ext}^{+\Delta}(\bar{f}),\mathsf{Ext}^{+\Delta}(\bar{g})), \\ & d_{Q_{E}}(\mathsf{Ext}^{-\Delta}(\bar{f}),\mathsf{Ext}^{-\Delta}(\bar{g})), \\ & d_{Q_{P}}(\mathsf{Rel}(\bar{f}),\mathsf{Rel}(\bar{g}))\} \end{aligned}$$

Theorem: Stability

$$egin{aligned} &d(\mathsf{Dg}(\overline{\mathsf{M}}_f(\mathbb{X},\mathcal{I})),\mathsf{Dg}(\overline{\mathsf{M}}_g(\mathbb{X},\mathcal{I}))) \leq d_\Delta(\mathsf{Dg}(\widetilde{f},\mathsf{R}_f(\mathbb{X})),\mathsf{Dg}(\widetilde{g},\mathsf{R}_g(\mathbb{X}))) \ &\leq d_\Delta(\mathsf{Dg}(f,\mathbb{X}),\mathsf{Dg}(g,\mathbb{X})) \ &\leq \|f-g\|_\infty \end{aligned}$$

► Corollary: If
$$\mathcal{I}$$
 is of size $\lambda > 0$:
 $d(\mathsf{Dg}'(\overline{\mathsf{M}}_{f}(\mathbb{X}, \mathcal{I})), \mathsf{Dg}'(\overline{\mathsf{M}}_{g}(\mathbb{X}, \mathcal{I})))$
 $\leq \lambda + d(\mathsf{Dg}(\overline{\mathsf{M}}_{f}(\mathbb{X}, \mathcal{I})), \mathsf{Dg}(\overline{\mathsf{M}}_{g}(\mathbb{X}, \mathcal{I})))$

Implementation: Point-based Version

- Available Python code: danifold.net/mapper/
- Discrete Case: Input = Point Cloud
- CC found with Hierarchical Clustering (need parameters: cutoff, threshold...)
- 2 CC intersect iff they have at least 1 point in common (in practice threshold again...)

Implementation: Edge-based Version

- Input = Graph e.g. δ -Neighborhood Graph
- CC naturally defined
- ► 2 CC intersect iff there is at least 1 edge connecting the CC → Graph-induced Simplicial Complex
- Only 1 parameter δ

Open Questions

- Sampling conditions for which discrete case = continuous case?
- Functoriality of the mapping?
- Extension to $f : \mathbb{X} \to \mathbb{R}^d$?

Thank you !