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Graph Approximations to Geodesics on Metric Graphs

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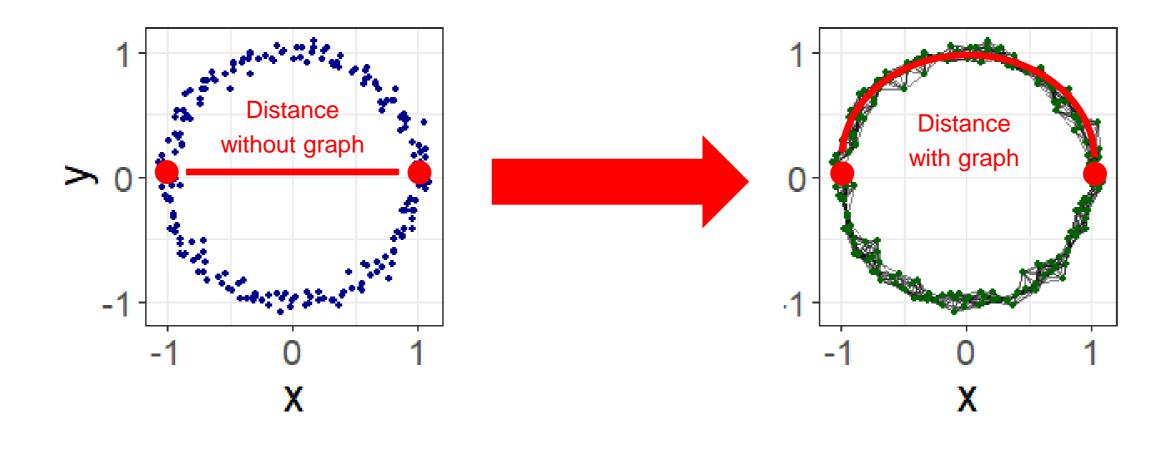






Proximity graphs are often used to approximate geodesics

- *k***NN**: connect each point to its *k* closest neighbors
- **Rips/unit disk:** connect every pair of points within distance ε



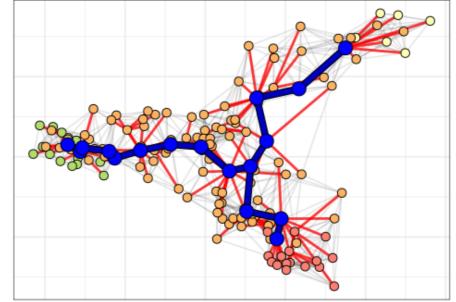


Proximity graphs are often used to approximate geodesics

- Used for various dimensionality reductions
 - Laplacian Eigenmaps
 - Locally Linear Embedding
 - **ISOMAP**
 - Maximum Variance Unfolding
 - Local Tangent Space Alignment
 - . . .
- More recently as intermediate representation for topological inference (after initial dimensionality reduction such as PCA, diffusion maps. ...)

Model = Metric Graph

E.g., Cell Trajectory Inference





group

- H1975 \circ
- H1975,H2228,HCC827
- H2228
- HCC827

Prior theory

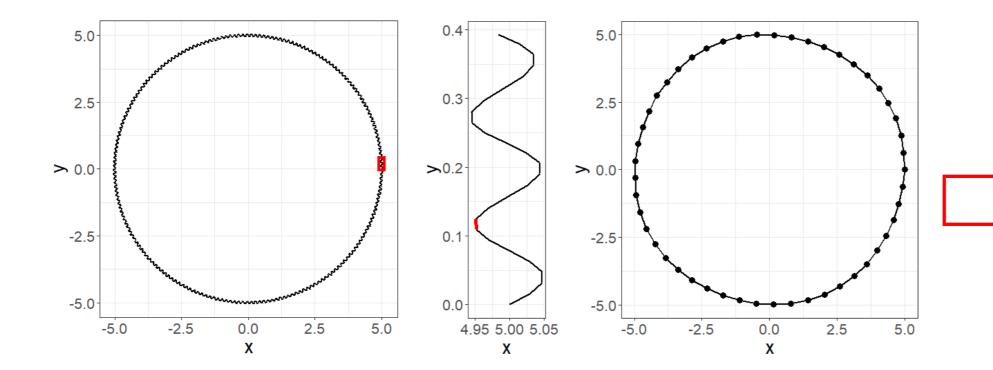
[1] M. Bernstein, V. D. Silva, J. C. Langford, and J. B. Tenenbaum, "Graph approximations to geodesics on embedded manifolds," 2000.

- Mainly serves as a theoretical justification of the ISOMAP dimensionality reduction
- Provides conditions under which shortest path distances in proximity graphs are close to true geodesics
- Restricted to smooth submanifolds of \mathbb{R}^n .



Prior theory – the issues

- Restricted to smooth submanifolds of $\mathbb{R}^n \rightarrow$ no singularities allowed
- Stringent conditions: all local patterns must be approximated well







Proximity graph fails to capture local
'wiggled' pattern
→ Violates conditions in [1]

Captures global cyclic pattern correctly

Our work – new and more flexible characteristics for metric graphs

Definition 3. Given a connected metric graph M. For any $\epsilon > 0$ we define the branch separation $s_{\epsilon}(M) \in \mathbb{R}^+ \cup \{\infty\}$ of M at resolution $1/\epsilon$ as

$$s_{\epsilon}(M) \coloneqq \sup \{s \in \mathbb{R} : ||x - y|| < s \implies d_M(x, y) \leq \epsilon$$
.

 $1/\epsilon$ and $1/\epsilon' \in \mathbb{R}^+ \cup \{\infty\}$ as

 $\lambda_{\epsilon',\epsilon}(M) \coloneqq \sup \{\lambda \in$

Specifies the scale of interest (solves flexibility)

Constrains from 'how close' we look at the data (necessary for extension to singularities)

Theorem 3. Let M be a connected metric graph in \mathbb{R}^d and let X be a finite set of data points in M. Suppose a graph G = (X, E) is given, defining the following three thresholds:

- 1) $||x y|| \ge \epsilon'$ for all $\{x, y\} \in E$,
- 2) $||x y|| < s_{\epsilon}(M)$ for all $\{x, y\} \in E$, with $\epsilon > 0$,

3) for all $x, y \in X$ with $||x - y|| \le \tau$, we have $\{x, y\} \in E$.

If for $0 < 4\delta < \tau$, X satisfies the δ -sampling condition, *i.e.*, for every $m \in M$ there is $x \in X$ with $d_M(m, x) \leq \delta$, then for all $x, y \in M$

 $\lambda_{\epsilon,\epsilon'}(M)d_M(x,y) \le d_G(x,y) \le (1+4\delta/\tau)d_M(x,y).$ (1)



Definition 4. Given a connected metric graph M. For any $0 \le \epsilon' < \epsilon$ we define the linearity of M between resolutions

$$\in \mathbb{R} : \epsilon' \leq d_M(x, y) \leq \epsilon \implies$$
$$\lambda d_M(x, y) \leq ||x - y|| \}.$$

Proof in paper

References

[2] Robin Vandaele, Yvan Saeys, and Tijl De Bie. "Mining Topological Structure in Graphs through Forest Representations," Journal of Machine Learning Research, 21(215):1–68, 2020.

Topological inference of metric graphs through proximity graphs

[3] Robin Vandaele. "Topological Data Analysis of Metric Graphs for Evaluating Cell Trajectory Data Representations," Master's thesis, Ghent University, 2020.

- Extension of current theoretical results (to probabilistic results and noise)
- Applications for evaluating cell trajectory data representation quality

[4] Robin Vandaele. "Topological Inference in Graphs and Images," Doctoral thesis, Ghent University, 2020.

Further applications of current results for comparing geometric patterns.







