CS 6170: Computational Topology, Spring 2019 Lecture 17 Topological Data Analysis for Data Scientists

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Stability of Persistence Diagrams: Continued Edelsbrunner and Harer (2010), C.VIII

Tame functions

- A *triangulation* of a topological space X is a simplicial complex K together with a homeomorphism between X and |K|, the support of K.
- Let X be *triangulable* (i.e., if it has a triangulation) and $f : X \to \mathbb{R}$ continuous.
- Define *sublevel set*

$$\mathbb{X}_a = f^{-1}(-\infty, a],$$

for $a \in \mathbb{R}$ and for $a \leq b$

$$f_p^{a,b}: \mathsf{H}_p(\mathbb{X}_a) \to \mathsf{H}_p(\mathbb{X}_b).$$

• The *p*-th persistent homology group is defined to be

$$\mathsf{H}_p^{a,b} = \operatorname{im} \, f_p^{a,b}.$$

• The *p-th persistent Betti number* is

$$\beta_p^{a,b} = \operatorname{rank} \mathsf{H}_p^{i,j}.$$

- A a group *isomorphism* is a function between two groups that sets up a one-to-one correspondence between the elements of the groups that respects the given group operations/relations among the elements.
- Greek: iso means "equal", and morphosis means "to shape".
- $a \in \mathbb{R}$ is a *homological critical value* if there is no $\epsilon > 0$ for which $f_p^{a-\epsilon,a+\epsilon}$ is an isomorphism for each p.
- *f* is *tame* if it has only finitely many homological critical values and all homology groups of all sub level sets have finite rank.

Theorem (Stability Theorem for Filtrations)

Let X be a triangulable topological space, $f, g : X \to \mathbb{R}$ two tame functions. For each dimension p, the bottleneck distance between the diagrams $X = Dgm_p(f)$ and $Y = Dgm_p(g)$ is bounded from above by the L_{∞} distance between the functions (Edelsbrunner and Harer, 2010, Page 183), that is,

 $W_{\infty}(X,Y) \leq ||f-q||_{\infty}.$

(Edelsbrunner and Harer, 2010, Page 183)

Degree-q Wasserstein distance

- $\bullet\,$ Given two persistence diagrams X and Y
- The degree-q Wasserstein distance is

$$W_q(X,Y) = \left[\inf_{\eta: X \to Y} \sum_{x \in X} ||x - \eta(x)||_{\infty}^q\right]^{1/q}$$

- Think about assignment problem
- Hungarian algorithm: find a perfect matching (in a bipartite graph) with a minimum total cost
- Software: https://bitbucket.org/grey_narn/hera
- Kerber et al. (2016)

• A function $f: \mathbb{X} \to \mathbb{R}$ is *Lipschitz* if there is a constant C such that

$$|f(x) - f(y)| \le c||x - y||$$

for all points $x, y \in \mathbb{X}$.

- mesh: max distance between two points in $\sigma \in K$
- N(r): minimum number of simplices whose mesh $\leq r$.
- A triangulation of X grows polynomially if there are constants c and j such that $N(r) \leq \frac{c}{r^{j}}$.

Theorem (Stability Theorem for Lipschitz Functions)

Let $f, g: \mathbb{X} \to \mathbb{R}$ be two tame Lipschitz functions on a metric space whose triangulations grow polynomially with constant j. Then there are constants C and k > j no smaller than 1 such that the degree-q Wasserstein distance between $X = \text{Dgm}_p(f)$ and $Y = \text{Dgm}_p(g)$ is

$$W_q(X,Y) \le C \cdot ||f-g||_{\infty}^{1-k/q}$$

for every $q \ge k$.

- Given a weighted bipartite graph G with n + n vertices (n vertices on each side), find a *perfect matching* with minimal cost.
- A common cost function is the minimum of the sum of the q-th power of weights of the matching edges for some $q \leq 1$.
- The solution: q-Wasserstein distance
- Kerber et al. (2016): https://bitbucket.org/grey_narn/hera
- Bottleneck distance computation: Hopcroft + Karp using k-d tree
- Wasserstein distance computation: Bertsekas using weighted k-d tree

Kernels for barcodes

- Let H be a vector space over $\mathbb R$
- A function $\langle \cdot, \cdot \rangle_H : H \times H \to \mathbb{R}$ is an *inner product* on H if
 - Linear: $\langle \alpha_1 f_1 + \alpha_2 f_2, g \rangle_H = \alpha_1 \langle f 1, g \rangle_H + \alpha_2 \langle f_2, g \rangle_H.$
 - Symmetric: $\langle f, g \rangle_H = \langle g, h \rangle_H$.
 - $\langle f, f \rangle_H \ge 0.$
 - $\langle f, f \rangle_H = 0$ iff f = 0.
- Norm induced by the inner product

$$||f||_H := \sqrt{\langle f, f \rangle_H}.$$

- Hilbert space: an inner product space that contains a Cauchy sequence.
- Wait a minute...
- A *Hilbert space* is an abstract vector space with the structure of an inner product that allows lengths and angles to be measured.
- A generalizes the notion of Euclidean space.

Kernel

• Given a set X, a function $K: X \times X \to \mathbb{R}$ is a *kernel* if there exists a Hilbert space H called a *feature space* such that

$$K(x,y) = \langle \Phi(x), \Phi(y) \rangle_H$$

for all $x, y \in X$.

- Alternatively, K is a kernel if it is symmetric and positive definite.
- A symmetric function $K: X \times X \to \mathbb{R}$ is *positive definite* if $\forall n \ge 1$, $\forall a_1, \dots, a_n \in \mathbb{R}^n$, $\forall x_1, \dots, x_n \in X^n$,

$$\sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j K(x_i, x_j) \ge 0.$$

- Kernels are positive definite
 - Let H be a Hilbert space, X is a nonempty set and $\Phi : \mathbb{X} \to H$, then $K(x,y) := \langle \Phi(x), \Phi(y) \rangle_H$ is positive definite.

TDA Kernels and Vectorizations

- https://github.com/MathieuCarriere/sklearn_tda
- Kernels:
 - Persistence scale space kernel, Reininghaus et al. (2015)
 - Persistence weighted Gaussian kernel
 - Sliced Wasserstein kernel
 - Persistence Fisher kernel
- Vectorizations:
 - Persistence Image, Adams et al. (2017)
 - Persistence landscape
 - Betti Curve
 - Silhouette

TDA Kernels in applications



Reininghaus et al. (2015)

Persistence scale space kernel

- Let F, G be two persistence diagram (of a fixed dimension p)
- The persistence scale space kernel is

$$K_{\sigma}(F,G) = \frac{1}{8\pi\sigma} \sum_{p \in F, q \in G} \left(e^{-\frac{||p-q||^2}{8\sigma}} - e^{-\frac{||p-\bar{q}||^2}{8\sigma}} \right)$$

• \bar{p} is p mirrored at the diagonal.



- $\bullet \ \mathcal{D}:$ set of persistence diagrams
- Parameter: σ
- $L_2(\Omega)$: set of L_2 functions (square integrable) on $\Omega \subset \mathbb{R}^2$
- Feature map: $\Phi_{\sigma} : \mathcal{D} \to L_2(\Omega)$
- $K_{\sigma}(F,G) = \langle \Phi_{\sigma}(F), \Phi_{\sigma}(G) \rangle_{L_2(\Omega)}$
- Stability of the persistence scale space kernel:

$$||\Phi_{\sigma}(F) - \Phi_{\sigma}(G)||_{L_2(\Omega)} \le \frac{1}{\sigma\sqrt{8\pi}} W_1(F,G)$$

• $W_1(F,G)$: degree-1 Wasserstein distance.

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