

Manifold learning via Fréchet maps

Demetrio Labate

Department of Mathematics, University of Houston

This work is motivated by neuroimaging applications, where correlation matrices derived from functional Magnetic Resonance Imaging (fMRI) data model neural connection strengths to evaluate brain function. Because these matrices are typically high-dimensional (e.g., 2000 x 2000), they impose a significant computational burden on downstream clustering and classification tasks. Current approaches often address this challenge either by disregarding the underlying non-Euclidean geometry or by employing rank-reduction techniques that incur significant information loss. To bridge this gap, we introduce a novel framework for dimensionality reduction on a large class of Riemannian manifolds, including the space of correlation matrices. The core innovation of our approach is the application of Fréchet maps - a class of nonlinear transformations tailored to achieve substantial dimensionality reduction while preserving the intrinsic geometry of the data. In this presentation, I will detail the mathematical foundations of this framework, address parameter optimization, and demonstrate its performance through numerical experiments. This is joint work with Robert Azencott, Nicolas Charon, Andreas Mang, and Ji Shi.