Persistent homology for characterizing brain connectivity networks: promises, pitfalls, revelations

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Analyzing the patterns of dependencies between the dynamics of nodes in complex systems (such as interacting brain regions) using topological data analysis (TDA) is a rapidly growing field of interest. Recent research has demonstrated that TDA is sensitive to alterations in brain-disease-related changes in both functional connectivity (instantaneous statistical dependencies) and effective connectivity (directed causal interactions). However, the detectability of these alterations depends on their topological and topographical specificity [Caputi et al., 2021].

In this contribution, we discuss the practical use of TDA to characterize the hidden geometry of brain dynamics and provide methodological approaches for qualitative insights. We investigate the underlying curvature of data through topology [Caputi et al., 2023], using Persistent Homology and topological features derived from Betti curves. Analyzing random and geometric matrices (distance matrices of points on manifolds of constant sectional curvature), we show that Betti curves effectively distinguish between Euclidean, spherical, and hyperbolic spaces. We then analyze brain dynamics data (compared with financial and climate data) and find that their topological features suggest a hyperbolic underlying geometry. This supports the belief that their data manifold has non-positive curvature, but we also consider alternative explanations related to data sampling, processing, and complex hidden geometries. Building on previous work [Giusti et al.], we show that Betti curves effectively distinguish these spaces. Thus, we can use manifolds of constant curvature as comparison models to infer properties of the underlying curvature of real data.