Dynamic State Change Detection Using Topological Data Analysis And Machine Learning

Contributed Talk

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Topological data analysis (TDA) has emerged as a potent tool for extracting the topological features in various fields. Specifically, persistent homology (PH) has shown promise in tracking the changing sub-cycles within dynamical systems as they bifurcate, thereby allowing us to map their period of oscillations. In this study, we leverage PH to characterize the system's bifurcation route to chaos in dynamical systems. However, this has two key challenges: manual validation of true features; and difficulty in deriving meaningful insights from features arising out of chaotic regimes. To counter the above-stated problems in using PH, we make use of a machine learning (ML) classifier to automate the process of identifying true features and noise from PH-extracted barcodes. We present two topological summaries that combine the ML-classified true features and noise, revealing distinct patterns that effectively distinguish the chaotic regimes and periodic regimes. Our proposed methodology is tested on three well-studied systems and benchmarked against the maximal Lyapunov exponent (MLE). The whole study is conducted on scanty phase space data, making it more relevant for experimentalists dealing with limited or inadequate (parsimonious) data. Additionally, we also propose a novel methodology to study the dynamical change state detection of irregularly sampled time series data. We make use of sublevel set homology from TDA to extract topological features. These features leave a distinctive noteworthy pattern that allows ML classifiers to demarcate the periodic and chaotic regimes. Our methodology was tested on three systems and benchmarked against the MLE. We anticipate that both these proposed methodologies help the practitioners dealing with real-world data that are irregularly sampled or parsimonious.