Topological inference of hidden common driver dynamics by anisotropic self-organizing neural networks

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In this talk, we are introducing a novel approach to infer the underlying dynamics of hidden common drivers, based on analyzing time series data from two driven dynamical systems. The new method is builds on dimensional causality analysis that can reveal the presence of a hidden common driver behind the observed time series. The inference relies on time-delay embedding, estimation of the intrinsic dimension of the observed systems, and their mutual dimension.

We demonstrate the topological properties of the attractor manifolds that our method leverages, and introduce the new anisotropic training algorithm necessary for the self-organizing neural map to accurately learn the topological structure of these manifolds to provide estimation for the hidden common driver time series.

The method is rigorously tested on simulated time series from nonlinearly coupled chaotic systems, where it demonstrates superior performance compared to several established methods. These include linear techniques such as PCA and ICA, as well as nonlinear approaches like slow-feature analysis, dynamical component analysis, canonical correlation analysis, and deep canonical correlation analysis.