Abstract: Many data sets from across the sciences collect sequences of matrix- and tensor-structured data; we refer to such data as tensor time series. To explore and highlight the main dynamic structure of a set of multivariate time series, we extend the use of standard variance-covariance matrices for non-time series data in principal component analysis. This is also achieved by combining the principles of both canonical correlation analysis and principal component analysis for time series to obtain a new type of covariance/correlation matrix for a principal component analysis to produce a so-called “principal component time series”.

Another application, we are particularly motivated by electrophysiology studies in which electrical activity at multiple locations in the brain is measured over time. It is typical to pre-process such data to obtain tensors for each short time interval representing the level of coherence between each pair of brain regions at each spectral frequency. We propose a flexible class of nonparametric factor models for tensor time series data, which reduce dimensionality and maintain interpretability through the incorporation of sparsity constraints. The ability to accurately infer dynamically changing subnetworks is shown through simulations, and the methods are applied to mouse electrophysiology data.