LPCMCI: Causal Discovery in Time Series with Latent Confounders

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The quest to understand cause and effect relationships is at the basis of the scientific enterprise. In cases where the classical approach of controlled experimentation is not feasible, methods from the modern framework of causal discovery provide an alternative way to learn about cause and effect from observational, i.e., non-experimental data. Recent years have seen an increasing interest in these methods from various scientific fields, for example in the climate and Earth system sciences (where large scale experimentation is often infeasible) as well as machine learning and artificial intelligence (where models based on an understanding of cause and effect promise to be more robust under changing conditions.)

In this contribution we present the novel LPCMCI algorithm for learning the cause and effect relationships in multivariate time series. The algorithm is specifically adapted to several challenges that are prevalent in time series considered in the climate and Earth system sciences, for example strong autocorrelations, combinations of time lagged and contemporaneous causal relationships, as well as nonlinearities. It moreover allows for the existence of latent confounders, i.e., it allows for unobserved common causes. While this complication is faced in most realistic scenarios, especially when investigating a system as complex as Earth’s climate system, it is nevertheless assumed away in many existing algorithms. We demonstrate applications of LPCMCI to examples from a climate context and compare its performance to competing methods.

Related reference: