EVALUATION OF DIRECT CAUSALITY MEASURES AND LAG ESTIMATIONS IN MULTIVARIATE TIME SERIES

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1. INTRODUCTION

The detection and characterization of causal effects among simultaneously observed systems provides knowledge about the underlying network, and is a topic of interests in many scientific areas such as EEG analysis and network physiology. Over the years different causality measures have been developed, each with their advantages and disadvantages. However, in most studies their performance is evaluated only on one or two simulation models, that often don't correspond to the characteristics of real-world observed signals, and an extensive evaluation study is missing.

In this work we examine the behavior of several measures on a wide range of simulation models, to see how well they work in- as well as outside of their "comfort zone". Their performance is assessed on multivariate simulation models with distinct generative processes and connectivity characteristics.

Furthermore, as the lag between communicating nodes can have a significant impact on the network dynamics, mere detection of the connectivity pattern is not enough to fully describe the behavior of the system. These lags could hold essential information, but are often forgotten and we lack proper tools to estimate them. We propose 3 new methods for lag estimation in multivariate time series, based on autoregressive modelling and information theory.

2. MATERIALS AND METHODS

We compare the performance of six well-known methods for detecting directed causal interactions: cross-correlation, (conditional) Granger causality index (CGCI), partial directed coherence (PDC), directed transfer function (DTF) and partial mutual information on mixed embedding (PMIME).

CGCI is calculated from the coefficients of a multivariate autoregressive (MVAR) model fitted to the time series. Both PDC and DTF are related to the same MVAR model, but are defined in the frequency domain. Based on AR models, these measures can only detect linear relationships. Information theory sets a natural framework for non-parametric methodologies of statistical dependencies, which opens the possibility to detecting all types of interaction. To this end we also implement PMIME, which is based on conditional mutual information. [1]

All considered coupling measures are computed on 100 realizations of stochastic and chaotic coupled and uncoupled systems, with general or frequency-specific (non-)linear interaction terms.

Three new lag estimation methods are proposed based on AR models in time- and frequency domain, and the PMIME measure.

3. RESULTS AND DISCUSSION

CGCI, PDC and DTF perform well on linearly coupled systems and significantly outperform cross-correlation. In cases where non-linear interaction terms are present, their sensitivity and precision drop, as was expected. PMIME is able to reliably detect non-linear interactions, but works slightly worse than the AR-based measures for systems with only linear couplings.

The AR-based lag estimation method in time domain shows to reliably estimate the delays in linear multivariate systems for different embedding dimensions.

Advanced causality measures prove to outperform simpler method. However it should be noted that the accuracy is never perfect and varies strongly depending on the simulation model, indicating the importance of choosing the best fitting method depending on the expected type of couplings. Estimation of the lag between multivariate time series is possible with our novel AR-based method.

References

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