Book of Abstracts

Workshop on Characterizing Interactions in Complex Systems

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Contents

1 Holger Kantz: Power law error growth rates - a dynamical mechanism for a strictly finite prediction horizon in weather forecasts

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We first recall some essential aspects of nonlinear dynamics, chaos, and information theory. Our main issue is to answer two questions related to weather forecasting: If the true Lyapunov exponent of the system is if the order of 1/s (which is plausible from considering the instability of small scale motion), why then can one predict weather on the time scale of days? And how far could one push the weather predictions into the future, assuming perfect models and increasing accuracy of initial conditions? We present an answer to both questions by introducing an error growth rate which depends on the error magnitude as an inverse power law, i.e, the smaller the error the faster it grows. Integration over time shows that then the error itself will grow like a power of time (opposed to exponential error growth of conventional chaotic systems) and that improved accuracy of the initial condition will not extend the prediction horizon beyond a constant time interval which is determined by the tolerable forecast error. Inspired by the coupling of length and time scales of atmospheric phenomena, we introduce a class of hierarchically coupled low-dimensional chaotic systems which, due to proper scaling of length and time scales, exhibits exactly this power law error growth. We then re-analyse data of an error growth experiment performed 15 years ago by the Maryland-group with an operational weather forecast system (general circulation model) and show that on a log-log representation, their data support the idea of a power law divergence of the error growth rate at small scale. The fitted parameters then reveal an average maximal prediction horizon of about 15 days for weather forecasts.

2 Dimitris Kugiumtzis: Dimension Reduction for Causality in High-dimensional Time Series

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The overall objective of the analysis of multivariate time series generated by coupled dynamical systems, termed also complex systems, is to learn the dynamics and make predictions. For the former, the focus is on estimating the coupling structure by means of a complex network. The network has nodes the observed variables (subsystems) and directed connections determined by an inter-dependence measure, termed often as measure of Granger causality, connectivity and coupling (simply termed here as causality measure). To this respect, direct causality measures are more appropriate for the formation of networks to assign only for direct connections and couplings. However, estimating only direct causality effects is a hard task, particularly for high-dimensional time series, i.e. large number of observed variables or subsystems. The way to handle high-dimension is dimension reduction.

We will first discuss two main approaches our research team has developed for dimension reduction in the formation of the causality measure. The first is for the Granger causality index defined in terms of the vector autoregressive (VAR) model and suggests building a sparse VAR using a backward-in-time selection of lagged variables. This approach gives the restricted conditional Granger causality index (RCGCI) in the time domain and the restricted generalized partial directed coherence (RGPDC) in the frequency domain. The second approach estimates a sparse lagged structure using information criteria, termed partial mixed embedding from mutual information (PMIME). We will show the superiority of measures making use of dimension reduction (RCGCI, RGPDC, PMIME) in estimating the coupling structure of the generating system and compare them to other standard measures in simulations with low and high-dimensional time series of 5 and 25 coupled subsystems or variables. We will then move to higher dimensions and show that PMIME can still capture the original coupling structure with high accuracy.

3 Lionel Barnett: Granger Causality and Nonlinear Dynamics - A personal perspective and some future directions

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The somewhat glib statement "Of course, Granger causality [based on linear modelling] can only infer linear causal interactions" will be familiar to anyone working in the field of causal interactions in time series. But is it actually true? Or, more pertinently, when is it true - and why? I'll give a personal perspective on these questions, illustrated by simple examples, and, drawing on my own work, how they speak to the frequently-misunderstood relationship between Granger causality and transfer entropy. I'll conclude with a few suggestions for future research directions.

4 Bjarte Hannisdal, David Diego, Kristian Agasøster Haaga: Making transfer entropy work: new causality methods for short and noisy time series

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From a paleogeoscience perspective, the prospect of detecting causal interactions from observed time series without recourse to modelling is highly attractive, yet controversial. Here we briefly discuss some new approaches that show promise for causal analysis of short and noisy time series. First, we present a method for computing the transfer entropy between time series using the transfer operator associated with the map generating the dynamics. Here, the invariant measure is estimated not directly from the data points but from the invariant distribution of the transfer operator approximated from those points. We find that our approach is robust against the presence of moderate levels of dynamical noise, especially for time series with a few hundred observations. Secondly, we introduce a new, simple, yet high-performance causality test that dramatically improves the performance of transfer entropy as a causality estimator. Our test quantifies a difference between forwards-in-time ("causal") prediction and backwards-in-time ("non-causal") prediction, which yields predictive asymmetries characteristic of the drive-response interaction. We show that this predictive asymmetry is related to the flow of the underlying dynamical system.

5 Jakub Kořenek: Causal Network Discovery by Iterative Conditioning

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The study of complex networks is a growing area of research with applications in multiple fields ranging from neuroscience through genetics, ecology, social anthropology, informatics, economy and energetics to climate research. A key principle in complex network research is viewing the system at hand as a network of interacting subsystems, with one of the central questions being that of estimating the pattern of mutual or causal interactions of these. While in some cases (computer or social networks) the existence of connections can be naturally defined, in other systems (neuroscience, climatology) it is often problematic to determine this structure by direct observation. For this reason, methods for inference of causal structure using only knowledge of time series have been developed. Recently, several methods based on iterative procedures for assessment of conditional dependencies have been developed to mitigate this problem. Based on analysis of the current algorithms, we have proposed a new hybrid Fast Approximate Causal Discovery Algorithm (FACDA), designed for optimized performance and accuracy. Unlike the other studied algorithms, FACDA appears on simulated data to be computationally effective also for estimation of causality in complex systems with hundreds elements.

6 Anna Pidnebesna: Brain Network Analysis By Mixture Component Inference Deconvolution

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Brain is one of the most complex systems known. The common way to characterise brain activity is to estimate the connectivity of the neuronal system. One of the most popular and useful methods for measuring the neuronal activity is functional magnetic resonance imaging (fMRI), that uses the blood-oxygen-level-dependent (BOLD) contrast to detect changes associated with blood flow. However, the BOLD signal does not measure the neuronal activity directly, but it can be approximately represented as a linear convolution of the brain neuronal signal and the hemodynamic response function.

The connectivity structure estimated from the BOLD signal is not equivalent to the one of the original neuronal signal. Thus, to obtain the correct causality network, the analysis should be performed on the estimation of the source signal. In this talk, we present a new method of neuronal signal estimation. The proposed the Mixture Components Inference (MCI) approach is based on the idea of mixing random variables coming from two distributions: true activations and noise. The theory of mixtures with varying concentrations is used for the estimation of distributions. Finally, a Bayes classifier is applied to obtain the final estimate.

7 Martina Chvosteková: Testing linear Granger causality

Institute of Measurement Science, Slovak Academy of Sciences

The linear Granger causality analysis commonly used F-test for statistical testing a causal connection between variables. Low sensitivity of the F-test, even for large sample sizes, leads to false detections. We analyzed two different techniques for testing linear Granger causality. The application of time reversal for inferring causal interaction is considered in the first technique. The statistical significance of the presence of a causal connection is assessed by bootstrapping the residuals from a linear regression model in the second procedure.

8 Anna Krakovská: Causal analysis in reconstructed state spaces

Institute of Measurement Science, Slovak Academy of Sciences

It is increasingly evident that causal analysis of dynamical systems requires different approaches than, for example, causal analysis of interconnected autoregressive processes. In this presentation, two approaches to detect causality in reconstructed state spaces are presented: one is based on estimates of correlation dimension, the other on evaluating predictability. If deterministic dynamics plays a dominant role in data, then these methods, unlike many other causal approaches, reveal the presence and the direction of the coupling well, even for very weak links. Use of correlation dimension can even identify cases of uncoupled systems that are causally affected by a hidden common driver.