

Exploratory Causal Analysis with Time Series Data

Synthesis Lectures on Data Mining and Knowledge Discovery

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Exploratory Causal Analysis with Time Series Data

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*SYNTHESIS LECTURES ON DATA MINING AND KNOWLEDGE
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ABSTRACT

Many scientific disciplines rely on observational data of systems for which it is difficult (or impossible) to implement controlled experiments. Data analysis techniques are required for identifying causal information and relationships directly from such observational data. This need has led to the development of many different time series causality approaches and tools including transfer entropy, convergent cross-mapping (CCM), and Granger causality statistics.

A practicing analyst can explore the literature to find many proposals for identifying drivers and causal connections in time series data sets. Exploratory causal analysis (ECA) provides a framework for exploring potential causal structures in time series data sets and is characterized by a myopic goal to determine which data series from a given set of series might be seen as the primary driver. In this work, ECA is used on several synthetic and empirical data sets, and it is found that all of the tested time series causality tools agree with each other (and intuitive notions of causality) for many simple systems but can provide conflicting causal inferences for more complicated systems. It is proposed that such disagreements between different time series causality tools during ECA might provide deeper insight into the data than could be found otherwise.

KEYWORDS

time series causality, leaning, exploratory causal analysis

To Angel, whose patience I have tested often but never broken

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Preface

Consider a scientist wishing to find the driving relationships among a collection of time series data. The scientist probably has a particular problem in mind, e.g., comparing the potential driving effects of different space weather parameters, but a quick search of the data analysis literature would reveal that this problem is found in many different fields. They would find proposals for different approaches, most of which are justified with philosophical arguments about definitions of causality and are only applicable to specific types of data. However, the scientist would not find any consensus of which tools consistently provide intuitive causal inferences for specific types of systems. The literature seems to lack straightforward guidance for drawing causal inferences from time series data. Many of the proposed approaches are tested on a small number of data sets, usually generated from complex dynamics, and most authors do not discuss how their techniques might be used as part of a general causal analysis.

This work was developed from the realization that drawing causal inferences from time series data is subtle. The study of causality in data sets has a long history, so the first step is to develop a loose taxonomy of the field to help frame the specific types of approaches an analyst may be seeking (e.g., time series causality). Then, the philosophical causality studies must be carefully and deliberately divorced from the data causality studies, which is done here with the introduction of *exploratory causal analysis* (ECA). Finally, examples need to be presented where the different approaches are compared on identical data sets that have strongly intuitive driving relationships. Using such an approach, the analyst can develop an understanding of how a causal analysis might be performed, and how the results of that analysis can be interpreted. This work presents all three of these steps and is intended as an introduction and guide to such analysis.

James M. McCracken
March 2016

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James M. McCracken
March 2016