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# Robust Causal Inference for Irregularly Sampled Time Series: Applications in Climate and Paleoclimate Data Analysis

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To predict and determine the major drivers of climate has become even more important now as climate change poses a big challenge to humankind and our planet earth. Different studies employ either correlation, causality methods or modelling approaches to study the interaction between climate and climate forcing variables (anthropogenic or natural). This includes the study of interaction between global surface temperatures and $CO_2$; rainfall in different locations and El Niño–Southern Oscillation (ENSO) phenomena. The results produced by different studies have been found to be different and debatable, presenting an ambiguous situation. In this work, we develop and apply a novel robust causality estimation technique for time-series data (to estimate causal influence between given observables), that can help to resolve the ambiguity. The discrepancy in existing results arises due to challenges with the acquired data and limitations of the causal inference/ modelling approaches. Our novel approach combines the use of a recently proposed causality method, Compression-Complexity Causality (CCC) [1], and Ordinal/ Permutation pattern-based coding [2]. CCC estimates have been shown to be robust for bivariate systems with low temporal resolution, missing samples, long-term memory and finite length data [1]. The use of ordinal patterns helps to extend bivariate CCC to the multivariate case by capturing the multidimensional dynamics of the given variables' systems in the symbolic temporal sequence of a single variable. This methodology is tested on dynamical systems data which are short in length and have been corrupted with missing samples or subsampled to different levels. The superior performance of 'Permutation CCC' on such data relative to other causality estimation methods, strengthens our trust in the method. We apply the method to study the interaction between $CO_2$-temperature recordings on three different time scales, $CH_4$-temperature on the paleoclimate scale, ENSO-South Asian monsoon on monthly and yearly time scales, North Atlantic Oscillation-surface temperature on daily and monthly time scales. These datasets are either short in length, have been sampled irregularly, have missing samples or have a combination of the above factors. Our results are interesting, which validate some existing studies while contradicting others. In addition, the development of the novel permutation-CCC approach opens the possibility of its application for making useful inferences on other challenging climate datasets.

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