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Causal Discovery of Stochastic Dynamical Systems: A Markov Chain Approach

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Exploring causal relationships among stochastic dynamic systems based solely on observed time series of their states poses a challenging problem. In this context, we present a novel method for causal discovery within stochastic dynamic systems, specifically designed to overcome the limitations of existing methods, particularly in detecting hidden and common drivers. Our proposed approach is based on a straightforward observation: a process generated by a stochastic dynamical system follows a Markov chain if and only if all external influences are independent and identically distributed (i.i.d.). Consequently, the primary tool in our proposed causal discovery scheme involves testing whether the process generates a Markov chain, as opposed to relying on the "classical" causal Markov property or d-separation.

Our method is nonparametric, requiring no intervention, and is built on a reasonably small number of assumptions. We tested our model both on simulated Markov chains of finite state space and structural vector autoregressive processes. To demonstrate the efficacy of our model, we apply it to weather data consisting of solar irradiation and daily average air temperature. Through our method, we successfully identify the ground truth, revealing that irradiation drives temperature. Furthermore, we adeptly pinpoint the true lag while eliminating spurious lags in the autocorrelation function.