Assimilative Causal Inference

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Causal inference is fundamental across scientific disciplines, yet state-of-the-art methods often struggle to capture instantaneous and time-evolving causal relationships in complex, high-dimensional systems. This work introduces assimilative causal inference (ACI), a paradigm-shifting framework that reframes causality as a Bayesian inverse problem using data assimilation. Rather than measuring forward influence from causes to effects, ACI instead traces causality backwards by quantifying how incorporating future information about observed effects reduces uncertainty in the estimated system state. In this sense, effects are interpolated onto causes, contrasting classical predictive approaches that extrapolate causes to identify effects. ACI determines dynamic causal interactions without requiring observations of candidate causes, accommodates short and incomplete datasets, and scales efficiently to high dimensions. Crucially, it provides online tracking of causal roles, which may reverse intermittently, and facilitates the development of mathematically rigorous criteria for the causal influence range (CIR) of a relationship. The ACI-based CIR metric is objectively defined, without empirical thresholds, and admits both forward- and backward-in-time formulations. The forward CIR quantifies the temporal reach of a cause, while the backward CIR traces the onset of triggers for an observed effect, enabling causal predictability and attribution in transient regimes. The effectiveness of ACI has been demonstrated on nonlinear dynamical systems in geophysics showcasing intermittency and extreme events.

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