Interfere: Intervention Response Simulation and Prediction for Stochastic Non-Linear Dynamics

D. J. Passey [ID] [1*] **and Peter J. Mucha** [ID] [2*]

1 University of North Carolina at Chapel Hill, United States ROR **2** Dartmouth College, United States ROR

* These authors contributed equally.

Summary

The vision of Interfere is simple: What if we used high quality scientific models to benchmark our causal prediction tools? When attempting to infer causal relationships from data, randomized experimental data and counterfactuals are key, but obtaining such datasets is expensive and difficult. Across many fields, like economics, neuroscience, ecology, systems biology and others, mechanistic models are developed to simulate scenarios and predict the response of systems to interventions. Because these models are painstaking calibrated with the real world, they have the ability to generate synthetic counterfactual data containing complexity characteristics of the real processes they emulate. With this vision in mind, Interfere offers the first steps towards such a vision: (1) A general interface for simulating the effect of interventions on dynamic simulation models, (2) a suite of predictive methods and cross validation tools, and (3) an initial benchmark set of dynamic counterfactual scenarios.

Statement of need

Over the past twenty years we've seen an emergence of multiple frameworks for identifying causal relationships (Imbens & Rubin, 2015), (Pearl, 2009), (Wieczorek & Roth, 2019). The most influential frameworks are probabilistic and while it is not a requirement of the frameworks, in practice, a static linear relationship is usually assumed. However, when attempting to anticipate the response of complex systems in the medium and long term, static linear models are insufficient. Thus there is a need for causal models with more complexity. (For example, static linear models cannot predict scenarios where things get worse before they get better.) Currently, there are very few techniques that are able to fit non-linear dynamic causal models to data. We see an opportunity to bring the insights from recent breakthroughs in causal inference to the world of mechanistic modeling. In order to facilitate this cross pollination, we chose a key causal problem, predicting how a complex system responds to a previously unobserved intervention in the medium and long term, and designed the Interfere package as a focal point for building and benchmarking tools that attempt to solve this problem.
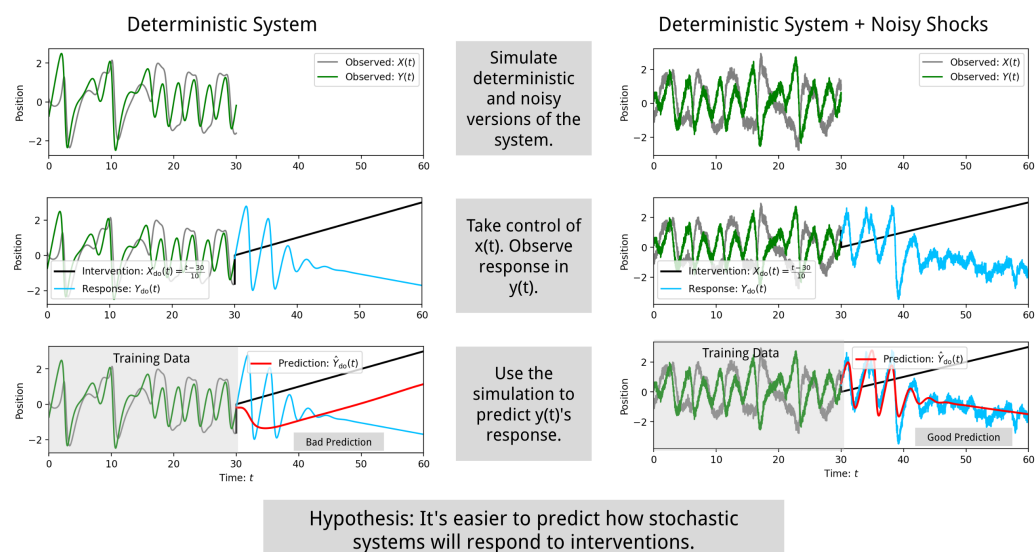
Figure 1: Comparing deterministic and stochastic systems.

Acknowledgements

References

Imbens, G. W., & Rubin, D. B. (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction* (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9781139025751

Pearl, J. (2009). *Causality* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511803161

Wieczorek, A., & Roth, V. (2019). Information Theoretic Causal Effect Quantification. *Entropy*, *21*(10), 975. https://doi.org/10.3390/e21100975