

Distinguishing Chaos from Noise through Cross Prediction with Reservoir Computing

Jaesung Choi¹, Athokpam Langlen Chanu^{2,3}, and Jong-Min Park^{2,3}

¹*Center for Artificial Intelligence and Natural Sciences, Korea Institute for Advanced Study*

²*Asia Pacific Center for Theoretical Physics*

³*Department of Physics, Pohang University of Science and Technology*

Many time series observed in nature exhibit irregular and seemingly unpredictable fluctuations. Determining whether such behavior originates from chaotic dynamics or from intrinsic stochastic fluctuations is a longstanding challenge in nonlinear science and time-series analysis. Although a variety of methods have been developed for this purpose, reliable discrimination remains difficult because stochastic processes can often mimic characteristic signatures of chaos. In this talk, I will present a learning-based framework for distinguishing chaotic dynamics from stochastic processes using time-series data. The proposed approach is motivated by the observation that conventional short-term prediction methods can be misled by stochastic processes with strong temporal correlations, which may exhibit apparent predictability despite the absence of an underlying deterministic rule. To overcome this limitation, we introduce a cross-prediction strategy in which the future change of a variable is predicted from its current value. This prediction task requires not only short-term predictability but also the ability to infer the deterministic structure governing the dynamics, providing a more stringent test for chaos. Implemented using reservoir computing, the framework yields a simple quantitative criterion for distinguishing chaos from noise based on the coefficient of determination between true and predicted future changes. Applications to a wide range of synthetic chaotic and stochastic systems reveal a clear separation between the two classes. We further apply the method to several empirical datasets previously analyzed in the literature and obtain classifications largely consistent with existing evidence. These results demonstrate that the proposed approach provides a simple, robust, and broadly applicable tool for distinguishing chaos from noise in time-series observations.