Epsilon Machines and Randomness, Structure and Complexity: Predicting Complex Systems

Author

Alexandra Jurgens[1]

[1] *INRIA Bordeaux, France*

Abstract

Even simply defined, finite-state generators produce stochastic processes that require tracking an uncountable infinity of probabilistic features for optimal prediction. For processes generated by hidden Markov chains, the consequences are dramatic. Their optimal predictive models, known as epsilon machines, are generically infinite state. Until recently, one could determine neither their intrinsic randomness nor structural complexity. However, new methods have been developed to accurately calculate the Shannon entropy rate (randomness) and to constructively determine their minimal set of predictive features. We also address the complementary challenge of determining how structured hidden Markov processes are by calculating their statistical complexity dimension—the information dimension of the minimal set of predictive features. This introduces a scaling law for the minimal memory resources required to optimally predict a broad class of truly complex processes.

References/Recommended reading

Jurgens, A. M., and Crutchfield, J. P.: Divergent predictive states: The statistical complexity dimension of stationary, ergodic hidden Markov processes, Chaos: An Interdisciplinary Journal of Nonlinear Science, 31, 10.1063/5.0050460, 2021.