Using Machine Learning To Anticipate Tipping Points and To Extrapolate To Post-Tipping Point Dynamics of Non-Stationary Dynamical Systems

Dhruvit Patel, and Edward Ott

The Institute for Research in Electronics and Applied Physics, University of Maryland, College Park, Maryland 26742, USA

Abstract

On the one hand, machine-learning- (ML) based methods have recently seen tremendous success in various tasks involving forecasting the short-term behavior of physical systems, such as in weather forecasting, and on the other hand, the applicability of such methods to the problem of forecasting the long-term behavior of such systems has received relatively little attention. When the system of interest is *non-stationary* (e.g., the terrestrial climate with increasing greenhouse gasses), the latter problem may require the ML-based models to extrapolate to situations outside of the range spanned by their training data since future trajectories of the system may explore regions of state space which were not explored in past time-series measurements used as training data. We develop ML-based methods for the general problem of predicting the long-term time evolution of non-stationary dynamical systems, and we explore the question: to what extent can such methods be used to anticipate potential future tipping points and to extrapolate to the post-tipping-point dynamics? We find that ML-based methods are surprisingly effective at anticipating future tipping point transitions, and in some cases, are even able to predict the post-tipping-point dynamics. Not surprisingly, when the "amount of extrapolation" from the training data becomes too much, we find that the ML is unable to predict the post-tipping-point dynamics. In such cases, we find that a hybrid model combining the data-driven ML model with an available, but inaccurate, knowledge-based model can still yield useful predictions of the post-tipping-point dynamics.