Prediction of complex spatiotemporal evolution through machine learning methods improved with the addition of observers

Abstract:
Can we use machine learning (ML) to predict the evolution of complex, chaotic systems? Recent work has shown that the answer is conditionally affirmative provided we use some additional “help” through a random bath and observers, as defined through reservoir computing (RC) [1]. What about using other “standard” ML methods in forecasting the future of complex systems? It is shown that long-short-term-memory (LSTM) method may work in general spatiotemporal evolution of the Kuramoto type [2]. We focused on the following question: Under what circumstances ML can predict spatiotemporal structures that emerge in complex evolution that involves nonlinearity as well as some form of stochasticity? To address this question we used two extreme phenomena, one being turbulent chimeras while the second involves stochastic branching. The former phenomenon generates partially coherent structures in highly nonlinear oscillators interacting through short or long range coupling while the latter appears in wave propagation in weakly disordered media. Examples of the former include biological networks, SQUIDs (superconducting quantum interference devices), coupled lasers, etc while the latter geophysical waves, electronic motion in a graphene surface and other similar wave propagation configurations.

We applied and compared three ML methods, viz. LSTM, RC as well as the standard Feed-Forward neural networks (FNNs) in the two extreme spatiotemporal phenomena dominated by coherence, i.e. chimeras, and stochasticity, i.e. branching, respectively [3]. In order to increase the predictability of the methods we augmented LSTM (and FNNs) with observers; specifically we assigned one LSTM network to each system node except for “observer” nodes which provide continual “ground truth” measurements as input; we refer to this method as “Observer LSTM” (OLSTM). We found that even a small number of observers greatly improves the data-driven (model-free) long-term forecasting capability of the LSTM networks and provide the framework for a consistent comparison between the RC and LSTM methods. We find that RC requires smaller training datasets than OLSTMs, but the latter requires fewer observers. Both methods are benchmarked against Feed-Forward neural networks (FNNs), also trained to make predictions with observers (OFNNs). This work targets the general direction of “physics informed neural networks” [4].


Bio:
Giorgos P. Tsironis is Professor of Physics at the Physics Department of the University of Crete and also leads the Nonlinear and Statistical Physics Group at the IESL-FORTH. He obtained his PhD in Theoretical Condensed Matter and Statistical Physics from the University of Rochester (USA) in 1987. He was a postdoctoral associate at the University of California San Diego (1987-89) and the Fermi National Accelerator Laboratory (1989-91) and assistant professor of Physics at the University of North Texas (1991-96) while also affiliated with the Superconducting Super Collider
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He has served as director of the University of Crete Computer Center (2003-09) and chairman of the Department of Physics of the University of Crete (2007-2011), acting chair of the Department of Physics, Nazarbayev University (2014-15) and deputy rector of the University of Crete (2016-17). In recent years, he established the Crete Center for Quantum Complexity and Nanotechnology which at its initial stage (2013-2017) it was funded from EU via an FP7-REGPOT grant.