Introduction to Focus Issue: When machine learning meets complex systems: Networks, chaos, and nonlinear dynamics

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Yang Tang, Jürgen Kurths, Wei Lin, Edward Ott, and Ljupco Kocarev

COLLECTIONS

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Note: This paper is part of the Focus Issue, "When Machine Learning Meets Complex Systems: Networks, Chaos and Nonlinear Dynamics."

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Yang Tang,[1,2] Jürgen Kurths,[3,4,a)] Wei Lin,[5,6] Edward Ott,[7] and Ljupco Kocarev[8,9,10]

AFFILIATIONS

[1] Key Laboratory of Advanced Control and Optimization for Chemical Processes, Ministry of Education, East China University of Science and Technology, Shanghai, China
[2] Department of Automation, East China University of Science and Technology, Shanghai, China
[3] Potsdam Institute for Climate Impact Research, Potsdam 14473, Germany
[4] Department of Physics, Humboldt University of Berlin, Berlin 12489, Germany
[5] Center for Computational Systems Biology of ISTBI and Research Institute of Intelligent Complex Systems, Fudan University, Shanghai 200433, China
[6] School of Mathematical Sciences, SCMS, SCAM, and LMNS, Fudan University, Shanghai 200433, China
[7] Department of Physics, University of Maryland, College Park, Maryland 20742, USA
[8] Macedonian Academy of Sciences and Arts, 1000 Skopje, Macedonia
[9] Faculty of Computer Science and Engineering, University "Sv Kiril i Metodij," 1000 Skopje, Macedonia
[10] BioCircuits Institute, University of California San Diego, La Jolla, California 92093, USA

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[a)] **Author to whom correspondence should be addressed:** juergen.kurths@pik-potsdam.de

INTRODUCTION

Machine learning (ML), a subset of artificial intelligence, refers to methods that have the ability to "learn" from experience, enabling them to carry out designated tasks. Examples of machine learning tasks are detection, recognition, diagnosis, optimization, and prediction. Machine learning can also often be used in different areas of complex systems research involving identification of the basic system structure (e.g., network nodes and links) and study of the dynamic behavior of nonlinear systems (e.g., determining Lyapunov exponents, prediction of future evolution, and inferring causality of interactions). Conversely, machine learning procedures, such as "reservoir computing" and "long short-term memory", are often dynamical in nature, and the understanding of when, how, and why they are able to function so well can potentially be addressed using tools from dynamical systems theory. For example, a recent consequence of this has been the realization of new optics-based physical realizations of reservoir computers. In the area of the application of machine learning to complex physical problems, it has been successfully used to construct and recover the complex structures and dynamics of climate networks, genetic regulatory systems, spatiotemporal chaotic systems, and neuronal networks. On the other hand, complex systems occur in a wide variety of practical settings, including engineering, neuroscience, social networks, geoscience, economics, etc. Since complex systems research and machine learning have a close relationship between each other, they provide a common basis for a wide range of cross-disciplinary interactions. Hence, exploring how machine learning works for issues involving complex systems has been a subject of significant research interest. With the advent of machine learning, it has become possible to develop new algorithms and strategies for identification, control, and data analytics of complex systems, thereby promoting the application of machine learning in many fields.

The main focus of this Focus Issue is on the new algorithms, strategies, and techniques with machine learning applied to complex systems and on applying complex system techniques to leverage the performance of machine learning techniques with high-efficiency. This Focus Issue provides a platform to facilitate interdisciplinary research and to share the most recent developments in various related fields. The specific areas represented include reservoir computing, modeling of complex systems, prediction and manipulations of complex systems, data-driven research, control and optimization, and applications.

For the Focus Issue, 58 papers were accepted for publication. In the following, we will divide the editorial into the following five parts, including reservoir computing, model of complex systems, prediction and manipulations of complex systems, data-driven research, control and optimization, and applications.

Reservoir computing

Reservoir computing is a type of machine learning in which an input **u** drives a dynamical system (the "reservoir"). The reservoir state vector **r** is then linearly mapped by a matrix Wout to an output **v**, **v** = Wout **r** [or **v** = Wout **r**′ for $\mathbf{r}' = \mathbf{f}(\mathbf{r})$]. The reservoir state vector **r** is high dimensional in the sense that its dimension is large compared to the number of output variables (the dimension of the vector **v**). The goal is to adjust ("train") the output weights (matrix elements of Wout) so that a desired functional relationship of **v** upon **u** is accurately achieved, and this is commonly found to be possible for large enough dimensions of **r** provided that a condition called the "echo state property" applies. For example, in the case of supervised learning, the desired functional dependence is specified through many examples of specific inputs **u**, along with the desired output **v** for each example. The key feature of reservoir computing is that only the output weights are trained, while parameters of the input couplings and the reservoir are held fixed. Thus, due to the linearity of the output mapping, the training can be done as a linear regression. The simplicity of the reservoir computing scheme is an attractive feature, for example, often enabling computationally rapid training and the possibility of flexibility in physical implementation. As a result, reservoir computing has attracted considerable attention as an alternative machine learning approach for tasks to which it can be applied. Thus, as described below, several of the papers in this special issue of *Chaos* concern reservoir computing, e.g., treating topics including physical implementation, principles of operation, and reservoir structure and optimization, as well as applications to a variety of different important tasks, etc.

The paper entitled "*Machine learning based on reservoir computing with time-delayed optoelectronic and photonic systems*" by Chembo[1] presents a review of research on the physical implementation of reservoir computing devices focusing on the use of time-delayed optoelectronic and photonic technologies. A basic idea highlighted in the review is that, by using a single time-delay nonlinear dynamical component, the required high dimensional reservoir dynamics can be achieved. These general types of devices appear to hold great promise for advantages in size, weight, power consumption, speed, and cost.

Moving from physical implementation of reservoir computing, several papers in this issue consider reservoir computing principles of operation and applications to various kinds of significant tasks. We notee that, unlike Chembo's paper,[1] all these other papers (to be described below) consider reservoirs implemented as recurrent neural networks simulated on digital computers.

Several papers consider training-data-enabled, model-free prediction tasks for chaotic systems, including both short-term prediction of system states, as well as long-term prediction replicating the system's ergodic properties. For example, the paper entitled "*Forecasting chaotic systems with very low connectivity reservoir computers*" by Griffith *et al.*[2] uses Bayesian optimization to search for good reservoirs for prediction tasks. Somewhat surprisingly, they find that the best results are often obtained for reservoir networks with very low connectivity. Similarly, the paper entitled "*Good and bad predictions: Assessing and improving the replication of chaotic attractors by means of reservoir computing*" by Haluszczynski and Räth[3] also considers prediction performance variation for different random reservoir network realizations, hyperparameters, and network topologies. One interesting result is that reservoir networks with scale-free topology display worse performance than other topologies tested. While the two papers just described consider prediction tasks for low dimensional chaotic systems (like the Lorenz '63 and Roessler systems), the paper entitled "*Combining machine learning with knowledge-based modeling for scalable forecasting and subgrid-scale closure of large, complex, spatiotemporal systems*" by Wikner *et al.*[4] is concerned with the task of machine learning applied to forecasting the state of very large, complex, spatiotemporally chaotic systems (e.g., a weather forecasting system). In this case the key issue is scalability, i.e., how can a machine learning system be configured so that performance of prediction of such large complex systems is practically possible? Wikner *et al.*[4] propose and demonstrate that scalability is promoted through a scheme that combines parallel operation of many reservoir computer units hybridized with a conventional global knowledge-based model.

The papers of Zhu *et al.*,[5] Cunillera *et al.*,[6] Banerjee *et al.*,[7] and Krishnagopal *et al.*[8] illustrate the use of reservoir computing to readily extract from data generated by unknown chaotic systems seemingly hard to obtain dynamical and system properties. In the case of the paper entitled "*Detecting unstable periodic orbits based only on time series: When adaptive delayed feedback control meets reservoir computing*" by Zhu *et al.*,[5] the goal is to find unstable periodic orbits embedded in a chaotic attractor—a task that could enable control of the system and is useful for basic understanding of chaotic attractors. Their method is to first use the reservoir computing to obtain a replication of the chaotic dynamical system generating the data and to then extract the unstable periodic orbits from this replication by using a technique that they call "adaptive delayed feedback control." For a situation where only a subset of the state variables of a dynamical system are measured, the paper entitled "*Cross-predicting the dynamics of an optically injected single-mode semiconductor laser using reservoir computing*" by Cunillera *et al.*[6] considers the problem of inferring the unmeasured state variables from the measured state variables. They give a machine learning method for doing this and test its application to the case of an optically injected single-mode semiconductor laser which has three state variables, two of which are difficult to measure, while the third is much easier to measure. The paper entitled "*Using machine learning to assess short term causal dependence and infer network links*" by Banerjee *et al.*[7] considers the problem of using state variable time series data to infer causal dependence between state variables of a continuous time dynamical system that is known to be of the form $dx(t)/dt = F(x(t))$ but is otherwise unknown. Banerjee *et al.*[7] approach this problem by first using a reservoir computer to replicate the dynamics of the unknown system $dx/dt = F(x)$ and then applying the "automatic differentiation" ability of machine learning to obtain an estimate of the Jacobian matrix of partial derivatives of F(x) following the orbit. Testing their method on an application to network link inference (for related work, see Refs. 9–11 in this issue), the authors present encouraging results of tests of their method, including the effects of dynamical noise (which can dramatically improve the results) and of observational noise (which degrades the results). The paper entitled "*Separation of chaotic signals by reservoir computing*" by Krishnagopal *et al.*[8] considers a situation where one is presented with a signal formed as a linear combination of two component signals, where each of the two component signals is a state variable time series originating from one of two different chaotic dynamical systems. The goal is to separate the presented signal into its two components based on training data time series of the separated components. Krishnagopal *et al.*[8] show that their nonlinear machine learning method is significantly better than the optimal linear method (the Weiner filter), especially when the frequency spectra of the component signals overlap.

While machine learning has been spectacularly successful, it seems fair to say that a sufficient understanding of the reasons for this success remains lacking. Three papers in this special issue address questions related to this problem in the context of reservoir computing. The paper entitled "*Collective dynamics of rate neurons for supervised learning in a reservoir computing system*" by Maslennikov and Nekorkin[12] considers a reservoir configured via feedback to act as a temporal pattern generator. Specifically, the reservoir is presented with a periodic function of time, and, by "listening" to it for a while, is able to learn weights that result in the reservoir feedback system replicating the presented time function. To gain insight into how the reservoir accomplishes this task, the authors examine the time dependence of the individual hidden variables (nodal state values) within the reservoir network before, during, and after training. They find that, through the training process, the state variation of individual nodes evolves to a situation where each nodal state varies periodically at the period of the presented signal. These individual orbits, however, all have different time variations, but, when linearly combined by the output weights, the desired signal is replicated. The paper entitled "*The reservoir's perspective on generalized synchronization*" by Lymburn *et al.*[13] explores reservoir computing with respect to the nonlinear dynamics concept of generalized synchronization (GS). The GS concept applies to attractor dynamics, where there are two identifiable subsystems, one with state x and one with state y, which are coupled together resulting in a functional relationship $[H(x,y) = 0]$ between x and y. When this relationship is smooth, "strong GS" is said to apply; when it is fractal, "weak GS" is said to apply. Lymburn *et al.* use reservoir computing to attempt reconstruction of a representation of a supposed GS relationship between x and y, thereby determining either the nonexistence of GS, or the existence of weak or strong GS. Furthermore, they also discuss the importance of the GS concept for basic understanding of reservoir computing itself. The paper entitled "*Dynamics of analog logic-gate networks for machine learning*" by Shani *et al.*[14] focuses on the continuous-time dynamics of networks implemented on field programable gate arrays (FPGAs) and use these FPGA networks as ultrafast machine-learning processors, using the technique of reservoir computing. Shani *et al.* study both the undriven dynamics and the input response of these networks, as we vary network design parameters and relate the dynamics to accuracy on two machine-learning tasks.

Model of complex systems

The reconstruction of system structure from data is a basic problem in complex network science and its various applications because some variables as well as possible connections among the nodes are often unavailable or even unknown.

The paper entitled "*Robust and optimal sparse regression for nonlinear PDE models*" by Gurevich *et al.*[15] addresses the question how models of spatiotemporal dynamics in the form of nonlinear partial differential equations can be identified directly from noisy data. By combining sparse regression and a weak formulation and employing the fourth-order Kuramoto–Sivashinsky equation for illustration, the authors show that their methodology is superior than existing techniques in the limits of low and high noise.

The paper entitled "*Discovering mean residence time and escape probability from data of stochastic dynamical systems*" by Wu *et al.*[16] learns the mean residence time and escape probability from data by a combination of machine learning and stochastic dynamics tools. They demonstrate that this algorithm is effective and robust by reproducing known dynamics and evaluating errors for several prototypical stochastic dynamical systems with Brownian motions.

By adapting a data-driven information-theoretic measure, the paper entitled "*How entropic regression beats the outliers problem in nonlinear system identification*" by AlMomani *et al.*[17] proposes a nonlinear system identification method. The method, referred as Entropic Regression, which shows robustness toward noise and outliers, is tested on various chaotic systems, including the Lorenz System, the Kuramoto–Sivashinsky equations, and the Double Well Potential, and compared with current state-of-the-arts methods.

The paper entitled "*Model reconstruction from temporal data for coupled oscillator networks*" by Panaggio *et al.*[18] demonstrates that, using sufficient observational data on the transient evolution of each oscillator, machine learning can restore the network and identify the intrinsic dynamics. Particularly for systems that synchronize, this paper designs an appropriate form of invasive perturbation to temporarily disrupt the synchronization and then realizes the network restoration by using the generated asynchronized transient data.

The paper entitled "*On learning Hamiltonian systems from data*" by Bertalan *et al.*[19] develops a data-driven, model free machine learning method to restore the Hamiltonian dynamics based on the observational data. This method trains jointly two neural networks, viz., an autoencoder neural network to approximate the transformation from observations to the phase space of a Hamiltonian system and a neural network to estimate the Hamiltonian function on this constructed space.

The paper entitled "*Coarse-scale PDEs from fine-scale observations via machine learning*" by Lee *et al.*[20] introduces a data-driven machine-learning-based methodology for dynamical system identification. In particular, employing Gaussian Processes, Artificial Neural Networks, and/or Diffusion Maps, identification of coarse-scale partial differential equations (PDEs) from microscopic observations has been documented, and a relation between the relevant macroscopic space fields and their time evolution has been provided. The methodology is illustrated with macroscopic, concentration-level PDEs for reaction/transport processes resulting from fine-scale observations, obtained from simulations of a Lattice Boltzmann mesoscopic model.

The paper entitled "*Cluster synchronization: From single-layer to multi-layer networks*" by Ma *et al.*[21] focuses on the cluster synchronization of an isolated network when it is influenced by an external network. The paper explores how the topology and the connection between the two layers impact the cluster synchronization of the layer of interest. The authors take three different patterns of connection into consideration, including typical positive correlation, negative correlation, and random correlation and find that they all have a certain influence.

The paper entitled "*Inferring causal relationship in coordinated flight of pigeon flocks*" by Chen *et al.*[22] proposes a causal inference method based on information theory to reveal individual intelligence and interagent interactions and the causal relationship among individuals. Particularly, they calculate mutual information by using a data mining algorithm named "k-nearest neighbor" and subsequently induce the transfer entropy to obtain the causality entropy quantifying the causal dependence of one individual on another subject to a condition set consisting of other neighboring ones.

Prediction and manipulations of complex systems

Machine Learning (ML) algorithms have provided great convenience in terms of analyzing and predicting the dynamics of chaotic and complex systems. Notably, the prediction of a complex system is of great significance in that it is the foundation of the subsequent manipulations and improvements.

By using a novel type of neural networks known as "attention-based sequence-to-sequence architecture," the paper entitled "*Sequence-to-sequence prediction of spatiotemporal systems*" by Shen *et al.*[23] proposes an efficient model-free prediction of high-dimensional complex systems from spatiotemporal systems. Among others, this technique enabled predict the evolution of solitary waves.

For various applications in engineering, climate, physiology, or epidemic, the early prediction of extreme events is a challenging task. The paper entitled "*Early detection of thermoacoustic combustion oscillations using a methodology combining statistical complexity and machine learning*" by Hachijo *et al.*[24] conducts an experimental study on early detection of thermoacoustic combustion oscillations using a method combining statistical complexity and machine learning, in particular, a support vector machine and the $\boldsymbol{k}$-means clustering method. The so constructed feature space in the complexity-entropy causality plane enables them to detect a precursor of combustion oscillations.

The paper entitled "*Machine learning algorithms for predicting the amplitude of chaotic laser pulses*" by Amil *et al.*[25] critically compares the predictive power of basic methods in machine learning, namely, deep learning, support vector machine, nearest neighbors, and reservoir computing for output signals of semiconductor lasers which generate a particular dynamical regime that can show ultra-high intensity pulses, reminiscent of rogue waves. This way the forecast of the laser amplitudes is possible with high accuracy even for extreme events and substantial stochastic contributions.

The paper entitled "*Using machine learning to predict extreme events in the Hénon map*" by Lellep *et al.*[26] applies an artificial neural network possessing classification function to predict extreme events in a typical chaotic dynamical system. This paper performs systematic analyses, illustrating that machine learning framework with an appropriate use of the mechanisms of dynamical systems could be beneficial to phase-space separation and dynamics prediction.

The paper entitled "*Predicting slow and fast neuronal dynamics with machine learning*" by Follmann and Rosa[27] employs reservoir computing to predict the neuronal activities produced by the physiological model of neurons. Numerical simulations show that although the reservoir computing model after training has a high predictability for tonic and bursting states but a low predictability for chaotic dynamics, it still has a high fidelity in recovering the bifurcation scenario of the neuronal model.

Link prediction plays a significant role in various applications of complex networks. The paper entitled "*Network embedding for link prediction: The pitfall and improvement*" by Cao *et al.*[9] compares structural similarity algorithms in network domain and network embedding algorithms in the field of machine learning and explores the intrinsic relationship between them, and studies the shortcomings of network embedding algorithms. Particularly, to address the pitfall of network embedding, a method which supplements network embedding algorithms with local structural information is proposed.

The paper entitled "*A novel complex network link prediction framework via combining mutual information with local naive Bayes*" by Chen *et al.*[10] utilizes local naïve Bayes, mutual information and an adjustable parameter to better quantify and balance the contributions caused by common neighbors and the interactions between neighbor sets. Furthermore, in order to improve the accuracy of prediction, the mutual information-based local naïve Bayes algorithm is proposed.

The paper entitled "*Generative dynamic link prediction*" by Chen *et al.*[11] presents a novel generative dynamic link prediction (GDLP) method, which is inspired by the widespread applications generative adversarial network in generating fake images. The model contains a generator and a discriminator. The main difference between the proposed GDLP and other DLP methods is to model the link prediction task as a network generation process.

The paper entitled "*Detecting network structures from measurable data produced by dynamics with hidden variables*" by Shi *et al.*[28] discusses and compares three reconstruction methods to solve the hidden variable problem, especially statistical characteristics of hidden variables, linearizable hidden variables, and white noise injection. Furthermore, the validity of theoretical derivations and the robustness of these methods are fully verified through numerical results.

The paper entitled "*Spectral forecast: A general purpose prediction model as an alternative to classical neural networks*" by Gagniuc *et al.*[29] describes a general-purpose prediction model and suggests a nonlinear model for the prediction of the occurrence of a disease. The approach is illustrated by showing that photon-pixel coupling data can be employed to indicate the predisposition to a disease, in particular, diabetes.

Data-driven research

Recently, machine learning and deep learning has taken part in the competition with traditional feature methods in complex networks and many deep learning based methods have achieved better results due to the plenty of data. Besides, the combination of traditional methods and deep learning techniques gradually received attention and some works in this part take advantage of them to obtain a breakthrough.

The paper entitled "*A recurrence network-based convolutional neural network for fatigue driving detection from EEG*" by Gao *et al.*[30] develops a two-stage machine learning framework integrating the recurrence network with the convolutional neural network. Using this framework, this paper successfully shows its exceptional efficacy in fatigue driving detection based on the EEG data set.

The paper entitled "*Network physiology in insomnia patients: Assessment of relevant changes in network topology with interpretable machine learning models*" by Jansen *et al.*[31] describes the human body as a complex network of interacting organ systems and applies the idea to determine topological changes in different sleep stages. In this paper, artificial neural networks (ANNs) are applied to build different models for the classification of insomnia and have been trained with 59 patients and age and gender matched controls. Feature relevance evaluation is employed for all methods.

The paper entitled "*Bayesian framework for simulation of dynamical systems from multidimensional data using recurrent neural network*" by Seleznev *et al.*[32] develops a new method for building data-driven dynamical models from observed multidimensional time series based on a recurrent neural network. Such a recurrent neural network enables the joint reconstruction of both a low-dimensional embedding for dynamical components in the data and an evolution operator. Specially, the key link of the method is a Bayesian optimization of both model structure and the hypothesis about the data generating law, which is needed for constructing the cost function for model learning.

The paper entitled "*Convolutional autoencoder and conditional random fields hybrid for predicting spatial-temporal chaos*" by Herzog *et al.*[33] introduces an algorithm for the data-driven prediction of high-dimensional chaotic time series generated by spatially extended systems. The approach employs a convolutional autoencoder for dimension reduction and feature extraction and a probabilistic prediction scheme operating in the feature space, consisting a conditional random field. Besides, the future evolution of the spatially extended system is predicted using a feedback loop and iterated predictions.

The paper entitled "*Identification of chimera using machine learning*" by Ganaie *et al.*[34] describes an approach using several machine learning techniques to characterize different dynamics and identify the chimera state from given spatial profiles of different underlying models for the identification of chimera. The experimental results demonstrate that the performance of the classification algorithms varies when different dynamical models are applied. It is notable that the presented work provides a direction for employing machine learning techniques to identify dynamical patterns arising in coupled non-linear units on a large-scale and for characterizing complex spatiotemporal phenomena in real-world systems for various applications.

The paper entitled "*Learning epidemic threshold in complex networks by convolutional neural network*" by Ni *et al.*[35] articulates a machine learning framework to learn the epidemic threshold in complex networks by utilizing the structural information and the dynamical information of finite states into the learning procedure. This framework, integrating the convolutional neural network with supervised and unsupervised learning schemes, is validated by synthetic and empirical network data sets.

The paper entitled "*Classification of close binary stars using recurrence networks*" by George *et al.*[36] uses the recurrent neural networks to learn different dynamics based solely on the observational time-series of light curves of close binary stars. Based on the characteristics of the trained network, this paper uses supervised and unsupervised classification methods to classify close binary stars into semidetached, overcontact, and ellipsoidal binaries.

The paper entitled "*Reconstructing directional causal networks with random forest: Causality meeting machine learning*" by Leng *et al.*[37] proposes a framework, inspired by the idea of decision tree, to realize causal network reconstruction based on the time-series from network systems. This framework, reducing the computational cost significantly, is validated by using the data sets produced by representative network systems.

The paper entitled "*Supervised chaotic source separation by a tank of water*" by Lu *et al.*[38] provides a framework where the sources are chaotic trajectories from independently evolving dynamical systems. The paper shows that the chaotic source separation problem can be considered as a nonlinear state-observer problem and proposes a model-independent, supervised framework to successfully solve this problem without knowing the explicit equations of the source systems.

The paper entitled "*Solving Fokker-Planck equation using deep learning*" by Xu *et al.*[39] develops a novel machine learning method to solve the general Fokker–Planck equations based on deep neural networks. Here, penalty factors are introduced to overcome the local optimization for the deep learning approach. It is shown for paradigmatic model systems that machine learning techniques outperform the corresponding classic methods.

Control and optimization

The following works address the consensus problem of the control and optimization in complex systems, which is a challenge issue in complex systems since they are multi-objective or high-dynamic. Besides, the game between the whole and the individual must be taken into consideration to achieve a satisfactory result.

The paper entitled "*Toward optimizing control signal paths in functional brain networks*" by Yao and Li[40] proposes a control signal path of the network and a local control centrality of the nodes to measure the efficiency of network structural control. Applying the designed iterative algorithms for searching the control signal path with maximal efficiency to the brain data set ADHD-200, the usefulness of the proposed measurement is fully demonstrated.

The consensus problem of multiagent systems (MASs) has obtained extensive attention nowadays. The paper entitled "*Sampled-based consensus for nonlinear multi-agent systems with average graph*" by Cui *et al.*[41] discusses the consensus problem for nonlinear MASs with sampled-data and switched topologies and proposes average graph based on the switching frequency. To guarantee the consensus of the MAS network, a sampled-based consensus protocol is proposed.

Different from Cui *et al.*,[42] the paper entitled "*An iterative Q-learning based global consensus of discrete-time saturated multi-agent systems*" by Long *et al.*[35] focuses on the consensus problem of discrete-time multiagent systems (DTMASs). To deal with the input saturation and the lack of the information of agent dynamics, the authors put forward a model-free Q-learning algorithm to obtain the low gain feedback matrices for the DTMASs achieving global consensus, motivated by the reinforcement learning method.

Moreover, the paper entitled "*Learned emergence in selfish collective motion*" by Algar *et al.*[43] focuses on the issue of many selfish individuals simultaneously optimizing their domains in order to reduce their personal risk of predation. Through an echo state network and data generated from the agent-based model, the authors demonstrate that this selfish movement can be learned with an appropriate representation of input and output states.

The paper entitled "*Heterogeneous cooperative leadership structure emerging from random regular graphs*" by Rong *et al.*[44] investigates the evolution of cooperation, the emergence of hierarchical leadership structure in random regular graphs. Additionally, directed game-learning skeleton is studied and the authors reveal some important structural properties, such as the heavy-tailed degree distribution and the positive in-degree correlation.

Motivated by the goal of enabling greatly improved performance for the deep brain stimulation (DBS) therapy for Parkinson's disease, the paper entitled "*Reinforcement learning for suppression of collective activity in oscillatory ensembles*" by Krylov *et al.*[45] considers the general problem of controlling an ensemble of many interacting dynamical units (neurons in the DBS application) to suppress unwanted synchronous oscillation of the ensemble. Their idea is to use reinforcement learning to create a data-driven method that determines efficient control. They demonstrate success of their method in numerical simulations employing globally coupled limit cycle Bonhoeffer–van der Pol oscillators and bursting Hindmarsh–Rose neurons.

The paper entitled "*Inference of chemical reaction networks based on concentration profiles using an optimization framework" by* Langary and Nokoloski[46] studies and analyzes chemical reaction networks. In particular, the authors propose an efficient and widely applicable methodology for inferring the stoichiometric subspace of a chemical reaction network from steady-state concentration data profiles obtained from a continuous isothermal reactor. The framework is tested using data from both synthetic reaction networks and biological models.

Applications

Additionally, neural networks have demonstrated their validity in solving practical problems, including depth estimation, visual odometry estimation, autonomous navigation, and so on. Some novel ideas have also emerged to mine the information in data to find the inner associations, and feature selection is an important problem in high-dimensional big data.

The paper entitled "*Cycle-SfM: Joint self-supervised learning of depth and camera motion from monocular image sequences*" by Sun *et al.*[47] presents a self-supervised framework which jointly estimates the monocular depth and camera's ego-motion from unlabeled, unstructured, and monocular video sequences. The main contribution is the novel forward–backward consistency constraint on view reconstruction to capture temporal relations across adjacent frames, which explores and makes full use of the bidirectional projection information.

The paper entitled "*Zermelo's problem: Optimal point-to-point navigation in 2D turbulent flows using reinforcement learning*" by Biferale *et al.*[48] designs a reinforcement learning approach to resolve Zermelo's problem in a 2D turbulent sea, finding quasi-optimal solutions for both time-free and chaotically evolving flow configurations. Compared with the continuous optimal navigation protocols in some typical situation, the designed approach shows more robustness against small changes in the initial conditions and against external noise.

The paper entitled "*Road traffic state prediction based on a graph embedding recurrent neural network under the SCATS*" by Xu *et al.*[49] represents the traffic road network as a graph and proposes a novel traffic flow prediction framework named graph embedding recurrent neural network (GERNN) to tackle the difficulty in the road traffic state prediction.

The paper entitled "*Fundamental aspects of noise in analog-hardware neural networks*" by Semenova *et al.*[50] analyzes the fundamental aspects, including management, mitigation, and propagation of noise, in both recurrent and deep multi-layer networks. This work not only shows that analog neural networks are robust against noisy neurons, but also identifies sensitive points of these computational systems.

The paper entitled "*Bayesian consensus clustering in multiplex networks*" by Jovanovski and Kocarev[51] combines models from sociology (stochastic block models) with tools from machine learning (Bayesian consensus clustering) to develop the Bayesian consensus stochastic block model for multiplex networks. The methodology provides integrated analysis of heterogeneous (social) relations, simultaneously addressing uncertainty in model parameters, and ensuring data-driven strength of relations.

The paper entitled "*Efficient community detection algorithm based on higher-order structures in complex networks"* by Huang *et al.*[52] provides an efficient algorithm as well as stochastic block models for detecting communities and their relations based on higher-order structures, including communities that can be detected via signed, colored, and/or weighted motifs. The algorithm is tested on the several real-world networks, including Florida Bay ecosystem food web, *E. coli* transcriptional regulation network, and friendship network of Zachary's Karate club.

The paper entitled "*Learning the tangent space of dynamical instabilities from data*" by Blanchard and Sapsis[53] utilizes neural networks to learn "pointwise" mapping from the phase space to optimally time-dependent space directly from data. The result of learning process can be viewed a cartography of directions which is relevant to strongest instabilities in the phase space, and then the paper discusses the implications for data-driven prediction and control of dynamical instabilities.

The paper entitled "*ChaosNet: A chaos based artificial neural network architecture for classification*" by Balakrishnan *et al.*[54] proposes a chaos based artificial neural network architecture for classification tasks, named ChaosNet. In the ChaosNet, a learning algorithm which exploits the topological transitivity property of the chaotic GLS neurons is introduced.

The paper entitled "*Predicting drug-disease associations with heterogeneous network embedding*" by Yang *et al.*[55] proposes a method to predict potential associations between drugs and diseases based on a drug-disease heterogeneous network, named Heterogeneous network Embedding for Drug–disease association (HED). Specifically, with the constructed heterogeneous network based on known drug–disease associations, HED trains a classifier to predict novel potential drug–disease associations.

The paper entitled "*Measuring similarity in co-occurrence data using ego-networks*" by Wang *et al.*[56] proposes a similarity measure based on the ego network of each entity, considering the change of an entity's centrality from one ego network to another. The proposed index is easy to calculate and has a clear physical meaning. Meanwhile, the measure by the new index has weak correlation with those by other methods, providing a different dimension to quantify similarities in co-occurrence data.

The paper entitled "*Percept-related EEG classification using machine learning approach and features of functional brain connectivity*" by Hramov *et al.*[57] uses a machine learning approach to identify hidden functional within a distributed network. By optimization of a feedforward multilayer perception, a substantial dimension reduction is reached. This way they classify the processing of ambiguous visual stimuli with an accuracy of 95% which cannot be distinguished by classic methods as time-frequency analysis.

The paper entitled "*Deep reinforcement learning in World-Earth system models to discover sustainable management strategies*" by Strnad *et al.*[58] presents a pipeline to combine deep reinforcement learning (DRL) with classical analysis of trajectories in the World–Earth system. The approach employs an agent that is generally able to act and learn in variable manageable environment models of the Earth system based on the concept of the agent–environment interface.

Finally, we would like to thank all the authors who submitted their work to this special section. We also would like to express our thanks to the experts in the field who voluntarily participated in the review process on a very tight schedule.

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