frontiers in Applied Mathematics and Statistics

EDITORIAL
published: 24 March 2022
doi: 10.3389/fams.2022.869999

Editorial: Machine Learning in Natural Complex Systems

Axel Hutt[1]*, *André Grüning*[2], *Alex Hansen*[3], *Thomas Hartung*[4] *and Raina Robeva*[5]

[1] Université de Strasbourg, CNRS, INRIA, ICube, MLMS, MIMESIS, Strasbourg, France, [2] Mathematics and Computational, Intelligence Faculty of Electrical Engineering and Computer Science, Stralsund University of Applied Sciences, Stralsund, Germany, [3] Department of Physics, Faculty of Natural Sciences, Norwegian University of Science and Technology, Trondheim, Norway, [4] Bloomberg School of Public Health, Johns Hopkins University, Baltimore, MD, United States, [5] Department of Mathematics, Randolph-Macon College, Ashland, VA, United States

Keywords: model improvement, learning rules, deep learning, data assimilation, big data

Editorial on the Research Topic

Machine Learning in Natural Complex Systems

For many decades, scientists strive to develop intelligent machines to reproduce or improve human intelligent actions. Machine Learning (ML), a research branch of artificial intelligence, aims to learn and simulate specific intelligent human actions and has been applied to a large variety of artificial and natural systems. At first glance, it is tempting to automize solving complex problems by machines. Specifically, in ML this is done by learning features of a data training data set, i.e., learning hidden relations in the data. Since the learned patterns and the subsequent prediction is based on the training set, the success of ML heavily depends on the training data. This renders the application of ML to natural systems rather challenging, since natural systems' dynamics are complex, and the training data set has to reflect the diverse dynamics. Typically, this renders the data set huge in size and thus such methods apply well to so-called *Big Data*. Examples for applications are visual pattern recognition, language processing and signal processing. Moreover, ML techniques compete with model approaches, which have built-in relations between system elements and which do not depend on specific training sets. In certain research fields, such as meteorology, system models and corresponding techniques are already so powerful that a benefit of ML is still unclear. However, recent techniques combine ML and models to achieve the best insight into the dynamics of systems. The present Research Topic collects work from a large variety of research fields on natural complex systems and provides a good up-to-date overview of the field of ML.

An important percentage of ML applications focuses on classification of datasets. In medical science, a combination of different data types has proven to improve patient classification and prediction. In Zhu et al., the authors have shown that a deep learning classification of both patient and radiograph variables allow to predict osteonecrosis and thus may prevent its aggravation at an early stage. Similarly, Xue et al. shows that the combination of diverse patient variables, such as level of cholesterol and patient age, permits to predict pulmonary complications after gastrointestinal surgery by ML techniques. The latter studies demonstrate that ML techniques permit predictions in patients with a very high success rate. In line with this approach, Liu G. et al. reviews ML techniques for epilepsy detection in electroencephalographic signals (EEG). Such latter techniques involve the additional complexity of a temporal sequence in the data compared to the temporally static data in the studies mentioned earlier. The authors of Liu J. et al. also consider EEG signals and demonstrate how to classify emotions by ML techniques. A different application is considered in Peng et al. considering observed time series in a meteorological model. Here, the authors successfully find relationships between the climate variables using ML on the basis of precipitation observations.

Edited and reviewed by:
Ulrich Parlitz,
Max Planck Society, Germany

***Correspondence:**
Axel Hutt
axel.hutt@inria.fr

Specialty section:
This article was submitted to Dynamical Systems, a section of the journal Frontiers in Applied Mathematics and Statistics

Received: *05 February 2022*
Accepted: *21 February 2022*
Published: *24 March 2022*

Citation:
Hutt A, Grüning A, Hansen A, Hartung T and Robeva R (2022) Editorial: Machine Learning in Natural Complex Systems. Front. Appl. Math. Stat. 8:869999. doi: 10.3389/fams.2022.869999

Although classification tasks play an important role in current ML research, existing ML techniques may also serve as tools to achieve a different research goal. For instance, Wang et al. shows how ML techniques may assist to learn time-dependent neural activity in order to understand better the relation of neural activity to behavior. ML may also help to understand complex systems on the basis of incomplete observations. Herzog et al. demonstrate how to complete sparsely sampled mechanical cardiac dynamics to predict electric heart activity by employing a dynamical model. The combination of ML techniques and mathematical models, as in this latter work, is especially powerful and promises to boost theoretical models of complex systems. This is shown nicely as well in Kigure, where the author demonstrates a numerical speed-up in a computational fluid dynamics model by employing ML.

In recent years, experimental observation techniques have been improved and are providing more and more data with increased temporal and spatial resolution. This progress demands advanced analysis techniques. For instance, today it is possible to observe neural activity in brain tissue by electrode grids with a high spatial resolution. Since the corresponding observed time series are correlated by virtue of the increased resolution, Geddes et al. propose a new data analysis technique for multivariate signals to extract novel underlying dynamic features. However, an improved temporal resolution of observations also requests improved analysis techniques that take into account multiple time scales. To this end, Manneschi et al. propose an extended reservoir computing technique to better learn computationally observed time series. Moreover, new observational data may also exhibit sparse dynamics that represents an important challenge to existing ML techniques. Nascimento et al. investigates how various sparse dynamics models can be combined with a graphical approach on the basis of EEG data to retrieve valuable insights into the brain's network connectivity. These latter data evolve on a certain grid in space and/or time and may be used to identify hidden patterns of functional and effective connectivity of brain networks. However, this is more difficult in other data, such as the temporally-changing positions of single objects in an environment. The authors Fromreide and Hansen address such data and present a method to predict the motion of moving ships. They demonstrate how to introduce movement patterns dependent on the land/sea environment.

In data analysis, a first step identifies data properties which are then examined in subsequent steps. In order to extract knowledge from a dataset and learn more about the system under study, it may be beneficial to look for structural patterns in the data. For instance, certain symmetries in datasets may immediately indicate pieces of redundant information and permit a simplifying dimensionality reduction. Capobianco addresses this issue and argues that data symmetries may enhance ML performance. Moreover, it may be promising to define novel similarity measures in life science data which are adapted to the respective data type (e.g., genetic sequences, chromosome data or chemical structure formulas). In Münch et al., the authors present strategies and concepts how to employ data-driven similarity measures in ML.

In conclusion, the Research Topic *Machine Learning in Natural Complex Systems* showcases the powerful impact of ML on the study of complex systems and the enormous potential this approach holds for gaining further knowledge about the complexities of their dynamics. We trust that the readers will enjoy these articles as much as we did and hope that the collection will help generate further discussion and inspire further discoveries.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.