The study of statistical features of the evolution of complex physical systems using adaptive machine learning methods

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Abstract. In this work, we discuss various machine learning methods and their implementation in the field of complex physical systems for the analysis of experimental data. These methods: classical machine learning, neural nets and deep learning allow greatly outperforming classical analysis methods by giving the algorithm the ability to “learn” and perform tasks adapting to the data provided and search. Neural nets and deep learning approaches are used to search for hidden patterns of the suggested input data that can’t be analyzed using common methods. This variety of methods can be applied to study collective phenomena in plasma and thermonuclear fusion on the basis of experimental data of physical experiments with a higher level of performance than classical approaches.

1. Introduction

Nowadays, one of the most relevant and remarkable areas in physics is the physics of complex systems. Such systems are widely distributed in nature on scales from a group of cells to plasma in stars and stellar cluster systems. A complex system is a composite object, the parts of which relate to each other by certain relationships, as a result of which such a system acquires new properties that cannot be reduced to the properties of its parts. Complex systems are distinguished by the following properties: non-linearity, limited predictability, evolutionary dynamics, self-organization, openness, and adaptability [1, 2].

Machine learning is one of the new and actively developing methods of analysis, combining approaches that can “learn” based on the received data, which allows you to perform a wide range of different tasks. Machine learning can be used to solve problems of detection, recognition, prediction, diagnosis, and optimization. In the area of physics of complex systems machine learning methods are widely used in the study of complex systems structure and for analysis of the dynamic behavior of nonlinear physical complex systems: forecasting of the future evolution of the systems and establishing a causal relationship [3].

2. Application of machine learning methods in the analysis of the dynamic behavior of complex physical systems

In this paper, we discuss the prospects for applying the latest methods of machine learning, neural networks and deep learning for the analysis of experimental data from physical experiments in modern science.
2.1. Machine Learning methods

Figure 1 shows the relationship between machine learning and other learning methods within artificial intelligence technologies [4].

Figure 1. The relationship among different types of machine learning methods.

Machine learning is a rapidly growing area and one of the latest technologies being used in the modern information technology field. Machine learning is a set of techniques that will allow computer algorithms to be able to learn [5]. It is based on the input and required output of the algorithms, some of which are based on the way how humans can carry out a task [6]. Machine learning is usually classified into the following categories: reinforcement learning, ensemble methods, supervised and unsupervised learning. In reinforcement learning the algorithm needs not just to analyze data, but to act independently in real conditions. The task is to minimize errors, for which it gets the opportunity to continue working without obstacles and failures [7]. Ensemble methods are groups of algorithms that use several machine learning methods at once and correct each other's errors. Supervised learning is a type of algorithm where the method is supplied with example inputs along with the required output, which then allows it to learn a rule that maps inputs to outputs [8]. In unsupervised learning, on the contrary, only the inputs are supplied, and the learning algorithm is required to determine the structure of the input and perform according to unknown characteristics [9].

These algorithms are widely used by scientists in different areas. For example, in the area of construction of accurate density functionals for realistic molecular systems [10]. Figure 2 shows the principle of the authors’ method to directly learn the Hohenberg-Kohn map.
Figure 2. The principle of forecasting machine learning Hohenberg-Kohn map.

Besides, in the field of complex physical systems, machine learning methods are used in plasma physics. In [11] the supervised and unsupervised learning methods are used to predict matrix effects severity and analyte recovery prediction in plasma optical emission spectrometry. The study used non-analyte signals as inputs. The authors declare that the efficiency of collecting and interpreting responses from plasma species may be based on this analysis workflow. Moreover, machine learning methods are also widely used in the tasks of thermonuclear fusion. In the study [12] the authors compare two machine learning tools: Gaussian Mixture Models and Support Vector Machine to carry out the classification task – distinguishing neutrons and gamma-rays in thermonuclear fusion. As a result, the authors declare that the approaches are in very good agreement and these methods greatly outperform previously used classification algorithms, by providing the probability of each example being a neutron or a gamma-ray.

2.2. Neural Nets and Deep Learning methods
The next group of methods is neural nets and deep learning approaches. It is a more complex level of learning algorithm than machine learning. Neural nets are designed in a way that resembles the way the neurons work in the human brain [13]. Neurons form layers through which the signal passes consistently. All this is connected by neural connections – channels for which data is transmitted. Each channel has its own “weight” – a parameter that affects the data it transmits. The input layer takes input, which then is processed in the hidden layer and the output layer sends out the calculated output. Neural nets are a powerful tool for image, speech and signal processing and are widely used in modern science [14]. Deep learning is a set of learning algorithms that can be used to learn complex forecasting models, e.g., multi-layer neural networks with many hidden layers. Figure 3 shows the variety of neural nets and deep learning methods.

Both sets of methods are recently being used in the field of physics of complex systems for the analysis of experimental data. For example, in [15] the authors develop a new method to produce a predictive model for turbulent fluxes in drift-wave turbulence systems, which can be applied to forecasting of turbulence behavior in plasma. Authors use a supervised deep learning methodology that infers a mean-field model for the cross-phases from direct numerical simulation. As a result, the authors develop a model for the drift-wave/zonal flow system directly from numerical solution data. The method reproduces analytical results for the Reynolds stress, such as negative viscosity effects and terms regularizing it.
3. Conclusion

In this paper, we discuss recently developed methods of analyzing data of various nature: machine learning [16], neural nets and deep learning approaches. We describe different approaches, their meaning and their implementation in modern science. These methods are applied in different fields, including information technologies and physics. In the area of physics of complex systems, the methods are actively used to study experimental data of experiments, e.g., in plasma physics and thermonuclear fusion, in order to replace classical analysis methods due to the higher level of performance.

These approaches are not the only ones that can outperform classical analysis methods: in the study of collective phenomena in physical complex systems, Memory Functions Formalism [17] and Flicker-Noise Spectroscopy [18] are also can show significant results. These methods can be applied to analyze autocorrelations, cross-correlations and statistical memory effects in the recorded experimental data [19], which reflect the manifestation of collective phenomena in plasma and during thermonuclear fusion [20, 21].

Acknowledgments

This paper has been supported by the Kazan Federal University Strategic Academic Leadership Program (PRIORITY–2030). The authors express gratitude to D.Sc. (Physics and Mathematics), Prof. S.F. Timashev for discussing some of the results of the present work.

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