Application of machine learning for analysis of nonlinear dynamical systems with the classification of chaotic and periodic time series

Abstract

The subject of this thesis is the application of machine learning techniques to identify chaotic and periodic time series, as well as the reconstruction of two-parameter bifurcation diagrams derived from nonlinear dynamical systems. Although such classification can initially be treated as a binary task, the underlying sensitivity to initial conditions and parameter changes introduces a *concept drift* problem, which presents significant challenges for traditional supervised methods. To address these issues, various machine learning models are developed and evaluated against traditional non-machine learning techniques.

This thesis commences with establishing foundational concepts in dynamical systems and chaos theory and includes a review of existing numerical techniques for system analysis and classification. Using the Pentegov-Sydorets electrical arc model as a foundational dataset, various supervised learning frameworks, such as multilayer perceptrons, deep neural networks, time series forests, and k-nearest neighbors, are used to reconstruct bifurcation diagrams. To improve model generalization and address the issue of *concept drift*, signal decomposition methods are introduced, which enhances the robustness of the neural networks.

Building on these findings, the research explores unsupervised and semi-supervised methods, such as the Gaussian mixture models and k-means clustering, to reduce the reliance on large labeled datasets. These methods show improved performance in challenging classification scenarios. Furthermore, the study investigates self-supervised learning techniques, including SimCLR, VICReg, and SimSiam. It also examines novel modules like Temporal Contrastive and extends it to non-contrastive self-supervised methods. Lastly, a Confidence Retraining method is proposed to further enhance generalization and accuracy, with potential applications extending beyond time series classification tasks.

The thesis concludes with a summary of key outcomes and offers insights into possible future research directions. The presented strategies demonstrate a strong potential for integrating advanced machine learning models in the analysis of nonlinear dynamical systems.