Learning Predictive Models for Nonlinear Dynamical Systems Using Neural Networks

Vlad-Flavius Misăilă,[1, a)] Robert-Daniel Man,[1, b)] and Sebastian-Adrian Mărginean[1, c)]
Department of Computer Science, West University of Timișoara, Romania

(Dated:)

RESEARCH QUESTION

How accurately can neural network models predict future trajectories of nonlinear dynamical systems—specifically chaotic and oscillatory systems—using only observed time-series data, without explicit knowledge of the governing differential equations?

MOTIVATION

Nonlinear dynamical systems govern a wide spectrum of natural and engineered processes, yet many such systems lack tractable analytical solutions and exhibit sensitive dependence on initial conditions. Traditional modeling requires explicit equations; however, in many real-world settings the governing laws are unknown or difficult to derive. Inspired by recent advances in machine learning for dynamical systems, particularly the pedagogical work of Roy and Rana (2020), this project evaluates neural networks as data-driven predictors capable of learning system evolution directly from observations.

OBJECTIVES (PLANNED STEPS)

- Train neural network models to learn and forecast trajectories of nonlinear dynamical systems.
- Evaluate short- and medium-term prediction accuracy for chaotic and oscillatory regimes.
- Analyze the effects of noise, window length, and neural architecture on prediction performance.
- Optionally compare feed-forward neural networks with recurrent architectures or reservoir computing.

SYSTEMS UNDER STUDY

- **Chaotic dynamics:** Lorenz or Rössler system.
- **Oscillatory dynamics:** Van der Pol or Duffing oscillator.

Synthetic time-series data will be generated using numerical solvers (e.g., fourth-order Runge–Kutta), with controlled noise to simulate measurement uncertainty.

METHODOLOGY

- **Data Preparation:** Numerical simulation, sliding-window embedding, normalization, train-test split.
- **Modeling:** Feed-forward neural networks trained via stochastic gradient descent in TensorFlow/PyTorch; optional RNN/LSTM.
- **Evaluation:** RMSE, prediction horizon, sensitivity to initial conditions, robustness under noise.
- **Analysis:** Compare performance across systems and hyperparameter settings.

EXPECTED OUTCOMES

- Accurate short-term prediction of nonlinear trajectories.
- Characterization of prediction degradation in chaotic systems.
- Insight into architectural and hyperparameter effects on forecasting quality.
- Plots, error curves, and reproducible code for all models.

REFERENCES

- S. Roy and D. Rana, *Machine Learning in Nonlinear Dynamical Systems*, 2020.

[a)]Electronic mail: vlad.misaila02@e-uvt.ro
[b)]Electronic mail: robert.man01@e-uvt.ro
[c)]Electronic mail: sebastian.marginean02@e-uvt.ro