DY 22: Machine Learning in Dynamics and Statistical Physics II

Time: Tuesday 14:00–15:15 Location: ZEU 160

DY 22.1 Tue 14:00 ZEU 160

Reservoir Computing using Quantum Dot Lasers — •Huifang Dong, Lina Jaurigue, and Kathy Lüdge — Institute of Physik, Technische Universität Ilmenau, Weimarer Str. 32, 98684 Ilmenau, Germany.

Time-multiplexed reservoir computing is a machine-learning approach which is well suited for implementation using semiconductor lasers subject to optical feedback. In such a delay-based setup the feedback has two important roles; it directly influences the memory of the system and it generates the high dimensional transient dynamics needed for good computational performance [1]. However, commonly used and commercially available quantum well semiconductor lasers are dynamically very sensitive to optical feedback, which can make the implementation of such systems difficult. Implementation and on-chip integration of optical reservoir computing become feasible with quantum dot lasers, as they emit at the telecommunication wavelength and are less sensitive to unwanted reflections [2]. Using typical benchmark tasks for time series prediction we show that quantum dot lasers show good computing performance that can be further optimized by proper delay time tuning.

[1] T. Hülser, et al., Opt. Mater. Express 12, 3, 1214 (2022).
[2] C. Otto, et al., Int. J. Bifurc. Chaos 22, 10, 1250246 (2012).

DY 22.2 Tue 14:15 ZEU 160

Studying sequence property relationships with neural networks — •Huzaifa Shabbir[1], Jens Uwe Sommer[1,2], and Marco Werner[1] — [1]Leibniz Institute for Polymer Research Dresden, Germany. — [2]Technische Universität Dresden

In this work, we investigate the relationships between chemical sequence and property space for various sequence lengths with the help of neural networks (NN). Two different systems are investigated for this purpose: system I comprises copolymer sequences and their free energy of interaction with a lipid bilayer membrane. System II consists of metallic nanoparticle sequences and their plasmonic spectrum. We compare the performance of different neural network architectures such as feed-forward NNs and gated recurrent unit (GRU) networks in terms of their interpolation and extrapolation capacity between different sequence lengths. We show that the GRU is particularly suitable to transfer the learned patterns from smaller sequence lengths to enhance significantly the learning result for larger sequence lengths.

DY 22.3 Tue 14:30 ZEU 160

Modelling dynamic 3D-heat transfer for laser material processing using physics-informed neural networks (PINNs) — •Michael Moeckel and Jorrit Voigt — TH Aschaffenburg, Würzburger Str. 45, 63743 Aschaffenburg

Machine learning (ML) algorithms are increasingly applied to fit complex models to empirical data and to predict on dynamical system behaviour. However, such models are not intrinsically protected from violating causality or other, well-understood physical laws. Black-box ML models offer limited interpretability. Extending ML models by including physical knowledge in the optimization procedure is known as physics-based and data-driven modelling. A promising recent development are physics informed neural networks (PINN), which ensure consistency to physical laws and measured data via appropriately designed optimization routines. Here we model the 3D time-dependent temperature profile following the passage of a laser focus at the surface of some material using PINNs. In this setting, we discuss aspects of numerically efficient training for PINNs, e.g. on a set of varying collocation points. The results from the PINN agree with finite element simulations, proving the suitability of the approach. The proposed models can be smoothly integrated in monitoring systems and naturally extend to the joint analysis of measurement data and dynamical behaviour encoded in governing equations.

DY 22.4 Tue 14:45 ZEU 160

Optical convolutional neural network with atomic nonlinearity — •Mingwei Yang[1,2], Elizabeth Robertson[1,2], Luisa Esguerra[1,2], Kurt Busch[3,4], and Janik Wolters[1,2] — [1]Deutsches Zentrum für Luft- und Raumfahrt, Institute of Optical Sensor Systems, Berlin, Germany. — [2]Technische Universität Berlin, Berlin, Germany. — [3]Humboldt-Universität zu Berlin, Institut für Physik, AG Theoretische Optik & Photonik, Berlin, Germany. — [4]Max-Born-Institut, Berlin, Germany.

Due to their inherent parallelism, fast processing speeds and low energy consumption, free-space-optics implementations have been identified as an attractive possibility for analog computations of convolutions [1,2]. However, the efficient implementation of optical nonlinearities for such neural networks still remains challenging. In this work, we report on the realization and characterization of a three-layer optical convolutional neural network where the linear part is based on a 4f-imaging system and the optical nonlinearity is realized via the absorption profile of a cesium atomic vapor cell. This system classifies the handwritten digital dataset MNIST with 83.96% accuracy, which agrees well with corresponding simulations. [1] H. J. Caulfield and S. Dolev, *Why future supercomputing requires optics,* Nat. Photonics 4, 261*263 (2010). [2] M. Miscuglio, Z. Hu, S. Li, J. K. George, R. Capanna, H. Dalir, P. M. Bardet, P. Gupta, and V. J. Sorger, *Massively parallel amplitude-only fourier neural network,* Optica 7, 1812*1819 (2020).

DY 22.5 Tue 15:00 ZEU 160

Phase Diagram of the J_1-J_2 Ising Model from Unsupervised Learning: Neural Networks vs Image Comparison — •Burak Çivitcioğlu[1], Andreas Honecker[1], and Rudolf A. Römer[2] — [1]Laboratoire de Physique Théorique et Modélisation, CNRS UMR 8089, CY Cergy Paris Université, Cergy-Pontoise, France — [2]Department of Physics, University of Warwick, Coventry, CV4 7AL, United Kingdom

Machine learning methods have been shown to be one of the novel approaches in identifying the phases and phase transitions in models of statistical physics. Here, we study the performance of unsupervised learning in the J_1-J_2 Ising model. We benchmark the results for phase diagram reconstruction using variational autoencoders (VAEs) against straightforward image comparison. We show that such image comparison can result in accuracies that are akin to that of VAEs.