AKPIK 5: AI Topical Day – Neural Networks and Computational Complexity (joint session MP/AKPIK)

Time: Wednesday 11:00–12:20 Location: ZEU/0250

AKPIK 5.1 Wed 11:00 ZEU/0250

A universal approach to state and operator complexities — •Souvik Banerjee[1] and Mohsen Alishahiha[2] — [1]Julius-Maximilians-Universität Würzburg, Würzburg, Germany — [2]IPM, Tehran, Iran

In this talk, I shall present a general framework in which both Krylov state and operator complexities can be put on the same footing. In our formalism, the Krylov complexity is defined in terms of the density matrix of the associated state which, for the operator complexity, lives on a doubled Hilbert space obtained through the channel-state map. This unified definition of complexity in terms of the density matrices enables us to extend the notion of Krylov complexity, to subregion or mixed state complexities and also naturally to the Krylov mutual complexity. We show that this framework also encompasses nicely, the holographic notions of complexity and explains the universal late-time growth of complexity, followed by a saturation.

Invited Talk AKPIK 5.2 Wed 11:30 ZEU/0250

Deep neural networks and the renormalization group — •Ro Jefferson[1], Johanna Erdmenger[2], and Kevin Grosvenor[3] — [1]Utrecht University — [2]University of Würzburg — [3]Leiden University

Despite the success of deep neural networks (DNNs) on an impressive range of tasks, they are generally treated as black boxes, with performance relying on heuristics and trial-and-error rather than any explanatory theoretical framework. Recently however, techniques and ideas from physics have been applied to DNNs in the hopes of distilling the underlying fundamental principles. In this talk, I will discuss some interesting parallels between DNNs and the renormalization group (RG). I will briefly reivew RG in the context of a simple lattice model, where subsequent RG steps are analogous to subsequent layers in a DNN, in that effective interactions arise after marginalizing hidden degrees of freedom/neurons. I will then quantify the intuitive idea that information is lost along the RG flow by computing the relative entropy in both the Ising model and a feedforward DNN. One finds qualitatively identical behaviour in both systems, in which the relative entropy increases monotonically to some asymptotic value. On the QFT side, this confirms the link between relative entropy and the c-theorem, while for machine learning, it may have implications for various information maximization methods, as well as disentangling compactness and generalizability.

AKPIK 5.3 Wed 12:00 ZEU/0250

Analytic continuation of Greens' functions using neural networks — Johanna Erdmenger, René Meyer, Martin Rackl, and •Yanick Thurn — JMU Würzburg

In quantum many-body physics, the analytic continuation of Greens' functions is a well-known problem. The problem is ill-posed in the sense that the transformation kernel becomes chaotic for large energies and thus small noise creates huge differences in the resulting spectral density function. Some techniques in the field of machine learning, in particular neural networks, are known for handling this kind of problem. Using a neural network and for the problem-optimized loss functions and hyperparameters, a network is trained to determine the spectral density from the imaginary part of the Greens function given by quantum Monte Carlo simulations. The network is able to recover the overall form of the spectral density function, even without adding constraints such as normalization and positive definiteness. There is no need to encode these constraints as regularizations since they are reflected automatically by the solution provided by the network. This indicates the correctness of the inversion kernel learned by the neural network. In the talk, I will explain the structure of the methods used to train the network and highlight the central results.