PhD proposal

Machine Learning for Disordered and Interacting Quantum Systems

Machine learning (ML) and deep learning (DL) are statistical analysis techniques that use strategies of artificial intelligence to characterize complex data and extract deep information [1]. In recent years, these techniques have begun to be used not only in traditional computer science test cases, but also in real world applications as well as, more recently, in areas of advanced physics [2]. In condensed matter systems, they have been shown to give useful insight into Ising/spin ice models, low dimensional topological systems, strongly correlated systems, as well as random systems. In particular, the interacting quantum many-body systems in one spatial dimension, the state-of-the-art approach has been for nearly 30 years the variational energy minimization of ground states based on matrix-product states (MPS). Such an optimization strategy is very reminiscent of the "learning" done in the deep neural network approach of ML. Indeed, it has been known for some years now that in principle, the ML paradigm can be used to "learn" the coefficients of an MPS in order to find energetically optimized ground states by variational methods. However, for disordered and interacting systems, it is not yet clear whether this approach will even work in principle. First, even the MPS approach has difficulties for disordered systems as the standard variational Ansatz does not converge as well as in the clean cases. Second, we recently showed that for disordered systems, a more renormalization group oriented approach might indeed be better suited – but how to translate this into the language of ML remains unexplored.

As a first step of the PhD work, we are planning to use the famous approach of Carleo et al. [3] to reconstruct an MPS states using the ML method for a clean, interacting system. The next step then will be to employ the same method but with a disordered quantum Hamiltonian. We expect this step to be numerically possible, but to lead to unsatisfactory convergence. Then we are planning to use the tree-tensor structure recently employed by us [4,5] to see if it, now recant using the methods of ML, also leads to a substantial improvement compared to the non-tree-like standard MPS approaches. Furthermore, in the tree-tensor approach, it might be that the ML methods allow an a-posteriori reconfiguration of the tree structure which might further improve the convergence, i.e. the "learning", of the ground state. This could lead to a completely new paradigm in constructing ground states of disordered and interacting quantum many-body systems. Conversely, it might lead to new ideas on the improvement of architectures for deep neural nets.

We note that work done in parallel at CY Paris by Prof. A. Honecker is investigating ML approaches to clean, interacting, low-dimensional quantum many-body systems.

For further information, see http://www.warwick.ac.uk/go/DisQS.

References:

[1] F. Chollet, *Deep Learning with Python* (IEEE, 2018).
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[3] G. Carleo and M. Troyer, Science **355**, 602 (2017).
[4] A. M. Goldsborough and R. A. Römer, Phys. Rev. B **89**, 214203 (2014).
[5] A. M. Goldsborough and G. Evenbly, Phys. Rev. B **96**, 155136 (2017).