LEARNING QUANTUM STRUCTURES IN COMPACT LOCALIZED EIGENSTATES

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Application of machine learning techniques for complex quantum systems provides new numerical tools to probe quantum phenomena [1, 2]. These tools can potentially outperform traditional methods due to their high tunability and efficient information encoding. The faithful representability of many-body states by artificial neural networks (ANNs), given a sufficient number of parameters, is now becoming established as an empirical fact and is supported by analytical evidence [3]. On the other hand, the optimizability of a neural net remains an open issue: it is not *a priori* clear which models and features are well suited for machine learning techniques.

We apply ANNs to study the emergence of quantum structures in interacting bosonic systems on a lattice. We focus on the simplest one- and two-dimensional geometries that support dispersionless energy bands and the the formation of compact localized states [4] spanning just a few neighboring sites. In the presence of interactions and at suitable values of the filling, these systems demonstrate a transition to a charge density wave. Inspired by a successful machine learning treatment of the paradigmatic superfluid-Mott insulator [2] and magnetic [1] transitions, we set out to explore how successful ANNs can be in learning quantum structures defined by compact localized states. We find that while being guided only by the noisy signal of Monte-Carlo estimates of the ground-state energy, ANNs are able to learn the defining features of quantum structures with the accuracy comparable or even superior to that of ground-state energy itself.

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