

Title

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(Dated: April 27, 2021)

Abstract ...

Quantum entanglement has been shown to be a ubiquitous phenomenon in fundamental studies of quantum physics and take indispensable roles in varied quantum applications ranging from ultraprecise sensing, provably secure communication and quantum computing. Despite such prevalence, experts have found it extremely non-trivial to find a universal yet computationally efficient entanglement measure, or a categorization for multipartite quantum correlations in general. In most cases, the computational burden grows exponentially with the number of particles N . Such difficulty is highlighted in the field of condensed matter physics where N usually tends to be incredibly large. As a result, instead of making a full classification of all possible entanglement patterns, researchers focus on the asymptotic behavior of entanglement properties and switch between different measures when dealing with different problems. Under this line of thought, Morimae et al. [1] proposed a characterizing index, or index p following their notation, which was demonstrated to capture the existence of macroscopic entanglement—that is, intuitively, the superposition of macroscopically distinct states—and have a close relationship to the stability of quantum states against local measurements.

As is pointed out in [1], there is an efficient algorithm of computing the index p for pure states of quantum spins on a lattice, as long as one has obtained all the two-local covariance information of the state. However, this would not be helpful in identifying macroscopic entanglement unless combined with a method to efficiently estimate the correlations of local observables on up to two distant lattice sites. Although we may not expect tractability for general states due to the exponential dimension of the Hilbert space, machine learning provides a solution to this problem under the justified assumption that the physically interesting quantum states live in a much smaller subspace. Machine learning techniques, best known for real-world applications such as facial recognition and machine translation [2], have also been widely adopted in condensed matter physics with unprecedented success, mainly attributed to their abil-

ity of feature extraction and dimensionality reduction [3–7]. In this work, we adopt the restricted Boltzmann machine (RBM) based reinforcement learning to learn, as a concrete example, an approximate representation of the ground state of the transverse field Ising model (TFIM) on a hypercubic lattice up to three dimension. By making use of the advantage that local observables are readily estimated out of RBM representations, we showcase the capability of reinforcement learning in detecting macroscopic entanglement. Importantly, the approximation power of RBMs is confirmed by showing that the index p results are in perfect alignment with exact diagonalization (ED) method in small-sized low-dimensional cases and agree largely on quantum phase transition behaviors predicted by our numerical calculations based on order parameters.

Discussion and conclusion—Discussion and conclusion

Acknowledgment—Acknowledgment

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