Machine-Learning Assisted Quantum Control in Random Environment

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Machine learning (ML), which enables computers to learn automatically from available task-specific data, is reshaping modern approaches in physical sciences. In quantum science, ML is one of the most useful and powerful approaches in particle physics, many-body physics, and quantum computing among others. Recently developed learning architectures such as convolution neural networks (CNN), having a considerable success in object detection and image classification, were beneficial to classify phases of matter, study non-equilibrium glasses, find hidden order in electronic-quantum-matter imaging data and identify the thermodynamic time arrow in quantum systems.

Figures

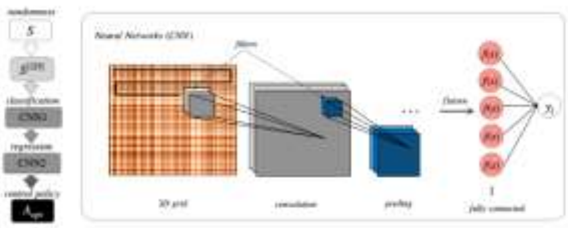

Figure 1: Schematic diagram (left) of supervised learning with two CNNs and working flow (right) of CNN.

Disorder in condensed matter and atomic physics is responsible for a great variety of fascinating quantum effects [1,2]. Many of these effects, being still challenging for understanding, make highly demanded dynamical control of quantum disordered systems hard, which requires novel tools to tackle the relevant issue. Particularly, as the size of the stochastic sample increases dramatically, the higher power of ML is demanding in such complexity.

To work out this problem, here we establish the ML approach for identifying and controlling dynamics of a quantum system with disorder. For this purpose, we use deep learning with two CNNs, see Fig. 1, for high-fidelity control of a quantum particle in a time-varying trapping potential embedded in a random environment.

Figures

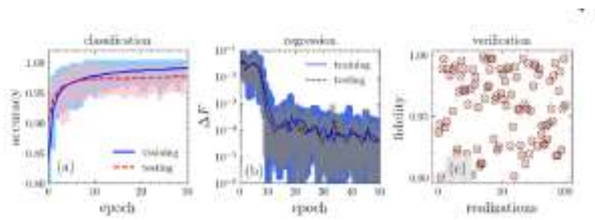

Figure 2: Performance of the accuracy in CNN1 (a) and the fidelity deviation (b) are displayed for classification and regression, where the dashed and solid lines represent the test and training batch of database. The shadow area indicates the average of every batch. (c) The outputs from two trained CNNs (red crosses) compared with the numerical results (black circles) for 100 testing realizations of random potential.

Consider a quantum particle, located at the sum of time-dependent harmonic potential and a random potential of impurities [3,4]. We show first an important result: training the CNN can efficiently preselect the relevant type of the disorder realization from tens of thousands of stochastic samples. Then, we introduce the second CNN to find the optimal control policy such as the time-dependent potential shape, in a training regression model, see Fig. 2. To make the optimization more efficient, the randomness classification from deep learning is an essential pretraining for disordered system under control, thus removing the redundant data. Thus, the supervised learning with CNNs provides the ability to generalize to tasks beyond their original design, applicable to any realization of random potential.

Figures

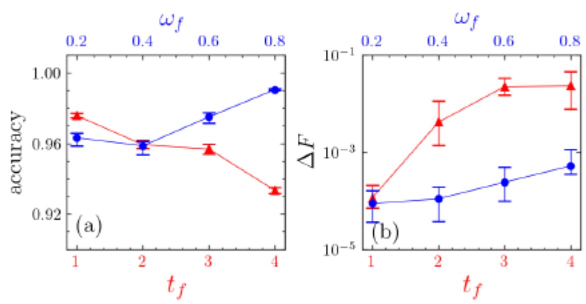

Figure 3: The average accuracy in CNN1 (a) and the average fidelity deviation in CNN2 (b) for the last ten epochs are illustrated for the different values of time and trap frequency, where the error bar represents their deviations.

To illustrate the generality of proposed method, we apply different values of time and trap frequency to the trained CNNs. Fig. 3 indicates the average accuracy in CNN1 and the average fidelity deviation in CNN2 for the last ten epochs by using the same structure and hyperparameter as before. On the one hand, when final trap frequency is increased, the random realizations are much easier to recognize, thus resulting in higher accuracy. It makes sense that the influence of random potentials on the fidelity can be negligible, when the trap potential is strong enough to localize the state near the origin. However, the more realizations as the inputs of CNN2 finally lead to the larger fidelity derivation as shown in Fig. 3. On the other hand, according to the time-energy trade-off, larger t_f (still far away from the adiabaticity) increase the area corresponding to condition for input power. The fidelity deviation in CNN2 becomes larger because of worse classification, depending on the distribution and number of the selected realizations in CNN1, see Fig. 3. In a word the combined effects of the trapping potential and disorder plays an important role in dynamical control, characterized by the fidelity and the required energy cost, e.g., the laser power for optical trap or the electrical power for quantum dots.

In practice, impurities, noise, and other imperfections are ubiquitous and unavoidable in condensate matter physics and their simulated counterparts. Our methods pave an efficient way for the robust optimal control, i.e., cooling, transporting, trapping the neutral atoms [4,5] or charged particles (ions and electrons) [6], by taking into account environmental noise and randomness.

References

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