Ensemble-learning error mitigation for variational quantum algorithms

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Quantum computers are rapidly emerging in various physical platforms. Several machine learning algorithms have been generalized to be adopted on quantum computers, including distance-based quantum classifier, quantum support vector machine, quantum k-nearest-neighbor algorithm, quantum decision tree classifiers, and quantum neural networks. However, current noisy intermediate-scale quantum (NISQ) computers are far away from achieving fault-tolerant quantum computing and thus most of these algorithms cannot be realized on such noisy hardware. In fact, outperforming classical computers with NISQ devices is still a hotly debated subjected. Indeed, in the absence of error correction, error mitigation algorithms are crucial for demonstrating practical quantum advantage.

A promising approach towards achieving such advantage is variational quantum algorithms (VQAs). In these algorithms, the complexity is divided between a quantum circuit and a classical computer, allowing a complex task to be achieved using a shallow quantum circuit. So far, VQAs have been exploited to solve a wide range of problems, including eigenvalue solvers, quantum neural networks, quantum adversarial machine learning, quantum approximate optimization algorithms and linear equation solvers. Variational Quantum Classification (VQC) algorithms, as typical VQAs, have also been developed to solve classification problems on NISQ computers, with some of them being experimentally demonstrated. Nonetheless, the imperfect nature of NISQ computers restricts the achievable accuracy of VQCs. In the absence of error correction, error mitigation techniques are essential for achieving practical quantum advantage using near-term quantum computers. Zero-noise extrapolation algorithm is possibly the most widely used error mitigation technique. In this algorithm, one can systematically enhance the noise power and then extrapolate the results to the limit of zero noise. Despite its success, the zero-noise extrapolation algorithm has its own limitations. One open problem is whether one can combine successful ensemble learning techniques, developed in classical machine learning, with VQCs to enhance the precision of classifiers for both classical and quantum datasets.

Here, we develop two ensemble-learning error mitigation techniques, namely bootstrap aggregating (Bagging) and adaptive boosting (AdaBoost), for VQCs to combine a few weak quantum classifiers and make a strong one with enhanced accuracy. This allows to use of shallow circuits for each of the classifiers and improves noise resilience. The results have recently been published in Ref. [1]. In the Bagging algorithm, an ensemble of weak classifiers are trained in parallel. For any given new input, one can perform a majority vote to decide the class of the input. In the AdaBoost algorithm, however, the classifiers are trained sequentially. After training one classifier, those data samples which have been wrongly classified are given a larger weight in the training of the next classifier. This forces the subsequent classifiers to improve their performance over those data samples which were wrongly classified by the previous classifier. After training the whole ensemble of classifiers, any new test data is given to all these classifiers. Their results are weighted by the precision of each classifier to compute the final class of the data.

To demonstrate the performance of AdaBoost and Bagging, we consider both classical and quantum data sets. For the case of classical data, we focus on classification of standard hand-writing data. For quantum data, we consider phase discrimination of a complex many-body system prepared in its ground state. We find that both proposed protocols significantly outperform the ZNE method in classification tasks. In the two protocols, the AdaBoost shows stronger performance, namely, higher accuracy and more noise resilience, than the Bagging. Since our ensemble learning algorithms can achieve accurate classification with only shallow circuits, they are NISQ-friendly and feasible for applications using existing quantum-computing technologies.

Reference

[1] Q. Li, Y. Huang, X. Hou, Y. Li, X. Wang, and A. Bayat, Phys. Rev. Research 6, 013027 (2024)