Resource efficient transfer learning approach for error mitigation of quantum circuits at scale

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Large-scale fault-tolerant quantum computers are likely to enable new solutions for problems known to be hard for classical computers. This potential is tempered by the reality that hardware is exceptionally fragile and error-prone, forming a bottleneck in the development of novel applications. While error suppression techniques can dramatically boost algorithmic performance, inherent and irreversible errors, such as T1 processes, limit the ability of achieving quantum utility at scale. Error mitigation techniques provide a route to go beyond that limit at the price of additional resources overhead [1]. Some of these approaches, such as probabilistic error cancellation (PEC), aim to collect a full description of the noise model to facilitate noise suppression. However, this requires over-sampling which is costly to acquire and scales poorly as the number of qubits increases. Recently, machine learning methods have been successfully used for the mitigation of errors in noisy quantum devices [2, 4] and can, depending on the approach, be designed to scale to large circuits.

In this work, building upon the suggestions presented in [3], we develop such a technique for problems where the quantity of interest is a set of expectation values such as quantum simulations or variational quantum eigensolvers (VQE). Using non-parametric ensemble models, we machine-learn the approximate inverse noise map for a subset of quantum observables. This is achieved by training models on a closely-related family of circuits which are efficiently simulable, and then using transfer learning to apply the learned inverse noise map to the circuits of interest. We observe that models are easily subject to overfitting and that simpler models such as linear regressions offer better results over more sophisticated models. To demonstrate this approach, we estimate Pauli observables and show a consistent ability to mitigate errors with a significantly reduced runtime compared to established mitigation techniques such as PEC and zero-noise extrapolation (ZNE).

References

[1] Y. Kim, A. Eddins, S. Anand, K. X. Wei, E. van den Berg, S. Rosenblatt, H. Nayfeh, Y. Wu, M. Zaletel, K. Temme, and A. Kandala. Evidence for the utility of quantum computing before fault tolerance. *Nature*, 618(7965):500–505, June 2023. Publisher: Nature Publishing Group.

[2] H. Liao, D. S. Wang, I. Sitdikov, C. Salcedo, A. Seif, and Z. K. Minev. Machine Learning for Practical Quantum Error Mitigation, Sept. 2023. arXiv:2309.17368 [quant-ph].

[3] S. H. Sack and D. J. Egger. Large-scale quantum approximate optimization on non-planar graphs with machine learning noise mitigation. *Physical Review Research*, 6(1):013223, Mar. 2024.

[4] A. Strikis, D. Qin, Y. Chen, S. C. Benjamin, and Y. Li. Learning-based quantum error mitigation. *PRX Quantum*, 2(4):040330, Nov. 2021.