Real-time error mitigation fights barren plateaus

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Abstract

We present a real-time error mitigation strategy to aid the training of Quantum-Hardware Machine Learning (QML) models under gradient-based optimization.

In the era of Noisy Intermediate Scale Quantum (NISQ) [1, 2] devices, Variational Quantum Algorithms (VQA) are the QML models that appear more promising in the near future as they have several concrete applications today already, such as electronic structure modelization in quantum chemistry [3, 4, 5, 6] for instance. Different VQA ansatze have been proposed, such as the QAOA [7], but they all share as foundation a Variational Quantum Circuit (VQC) consisting of several parametrized gates whose parameters are updated during training. Since hardware errors and large execution times severely hinder NISQ [1, 2] devices' applicability in practice, this ability of VQC based models to adapt their parameters and accomodate for the noise makes them appealing.

However, despite their improved robustness against noise, VQC models are known to suffer from the presence of plateaus (barren plateaus) in the optimization space that lead to vanishing gradients. In particular, these plateaus are naturally present for VQAs but [8] proved that the noise can induce them (NIBP, *i.e.* Noise-Induced-Barren-Plateaus), making vain their advantage in noise mitigation.

To overcome these limitations we either have to build fault tolerant architectures carrying an usable amount of logical qubits, or exploit as better as we can the available NISQ hardware by cleaning its results. While the first solution might require significant technical advances, the second one is often achieved with the help of quantum error mitigation (QEM). Therefore, we define here an algorithm to perform real-time quantum error mitigation (RTQEM) alongside a VQA-based QML training process.

In this work, we use in particular the Clifford Data Regression [9] (CDR) QEM algorithm, which is used to map noisy expected values into cleaned ones through a linear map $E_{\text{clean}} = \alpha E_{\text{noisy}} + \beta$. The two mitigation parameters $\boldsymbol{\theta} = (\alpha, \beta)$ are learned during training and depend on the hardware device and on the quantum circuit's architecture considered.

We select a specific QML problem inspired by [10]. We train a VQC to fit the u quark Parton Density Function (PDF) using a reuploading ansatz [11] to build the model. We implement an hardware-compatible Adam [12] optimizer for the training, in which we calculate gradients with respect to the variational parameters using the Parameter Shift Rule [13, 14] (PSR). This setup is then used to perform the full gradient descent on a 1-qubit device hosted in the Quantum Research Centre (QRC) of the Technology Innovation Institute (TII) and controlled using the `Qibo` [15] framework. Exploiting the full-stack environment provided by `Qibo`, we implement a training routine with realtime mitigation where the $\boldsymbol{\theta}$ parameters required by the CDR algorithm are gradually updated. This choice is useful for at least two reasons. Firstly, since the noisy-to-clean map only depends on the device and the VQC, in this case (and more in general in QML applications) we can consider the map structure fixed for any data we encode into the circuit. Secondly, the CDR map can be easily computed at any desired moment of the training procedure.

Therefore, we decide to update $\boldsymbol{\theta}$ periodically during the optimization, re-calculating the CDR fit every $N_{\rm cdr}$ epochs only.

In this talk, we show how this strategy can be used to generalize the final results, reduce the number of optimization iterations and fight against barren plateaus (see Fig. 1). We discuss both the cases of noisy simulations and real hardware deployment on superconducting qubits.

References

[1] John Preskill. Quantum computing in the NISQ era and beyond. *Quantum*, 2:79, aug 2018. 1

[2] Kishor Bharti, Alba Cervera-Lierta, Thi Ha Kyaw, Tobias Haug, Sumner Alperin-Lea, Abhinav Anand, Matthias Degroote, Hermanni Heimonen, Jakob S. Kottmann, Tim Menke, Wai-Keong Mok, Sukin Sim, Leong-Chuan Kwek, and Alá n Aspuru-Guzik. Noisy intermediate-scale quantum algorithms. *Reviews of Modern Physics*, 94(1), feb 2022. 1

[3] Alberto Peruzzo, Jarrod McClean, Peter Shadbolt, Man-Hong Yung, Xiao-Qi Zhou, Peter J. Love, Alán Aspuru-Guzik, and Jeremy L. O'Brien. A variational eigenvalue solver on a photonic quantum processor. *Nature Communications*, 5(1), jul 2014. 1

[4] Jarrod R McClean, Jonathan Romero, Ryan Babbush, and Alá n Aspuru-Guzik. The theory of variational hybrid quantum-classical algorithms. *New Journal of Physics*, 18(2):023023, feb 2016. 1

[5] Bela Bauer, Dave Wecker, Andrew J. Millis, Matthew B. Hastings, and Matthias Troyer. Hybrid quantum-classical approach to correlated materials. *Phys. Rev. X*, 6:031045, Sep 2016. 1

[6] Tyson Jones, Suguru Endo, Sam McArdle, Xiao Yuan, and Simon C. Benjamin. Variational quantum algorithms for discovering hamiltonian spectra. *Phys. Rev. A*, 99:062304, Jun 2019. 1

[7] Edward Farhi and Aram W Harrow. Quantum supremacy through the quantum approximate optimization algorithm, 2019. 1

[8] Samson Wang, Enrico Fontana, M. Cerezo, Kunal Sharma, Akira Sone, Lukasz Cincio, and Patrick J. Coles. Noise-induced barren plateaus in variational quantum algorithms. *Nature Communications*, 12(1):6961, nov 2021. 1

[9] Piotr Czarnik, Andrew Arrasmith, Patrick J. Coles, and Lukasz Cincio. Error mitigation with clifford quantum-circuit data. *Quantum*, 5:592, nov 2021. 1

[10] Adriá n Pérez-Salinas, Juan Cruz-Martinez, Abdulla A. Alhajri, and Stefano Carrazza. Determining the proton content with a quantum computer. *Physical Review D*, 103(3), feb 2021. 1

[11] Adrián Pérez-Salinas, Alba Cervera-Lierta, Elies Gil-Fuster, and José I. Latorre. Data re-uploading for a universal quantum classifier. *Quantum*, 4:226, feb 2020. 1

[12] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2017. 1

[13] K. Mitarai, M. Negoro, M. Kitagawa, and K. Fujii. Quantum circuit learning. *Physical Review A*, 98(3), sep 2018. 1

[14] Maria Schuld, Ville Bergholm, Christian Gogolin, Josh Izaac, and Nathan Killoran. Evaluating analytic gradients on quantum hardware. *Physical Review A*, 99(3), mar 2019. 1

[15] Stavros Efthymiou, Sergi Ramos-Calderer, Carlos Bravo-Prieto, Adrián Pérez-Salinas, Diego García-Martín, Artur Garcia-Saez, José Ignacio Latorre, and Stefano Carrazza. Qibo: a framework for quantum simulation with hardware acceleration. *Quantum Science and Technology*, 7(1):015018, dec 2021. 1

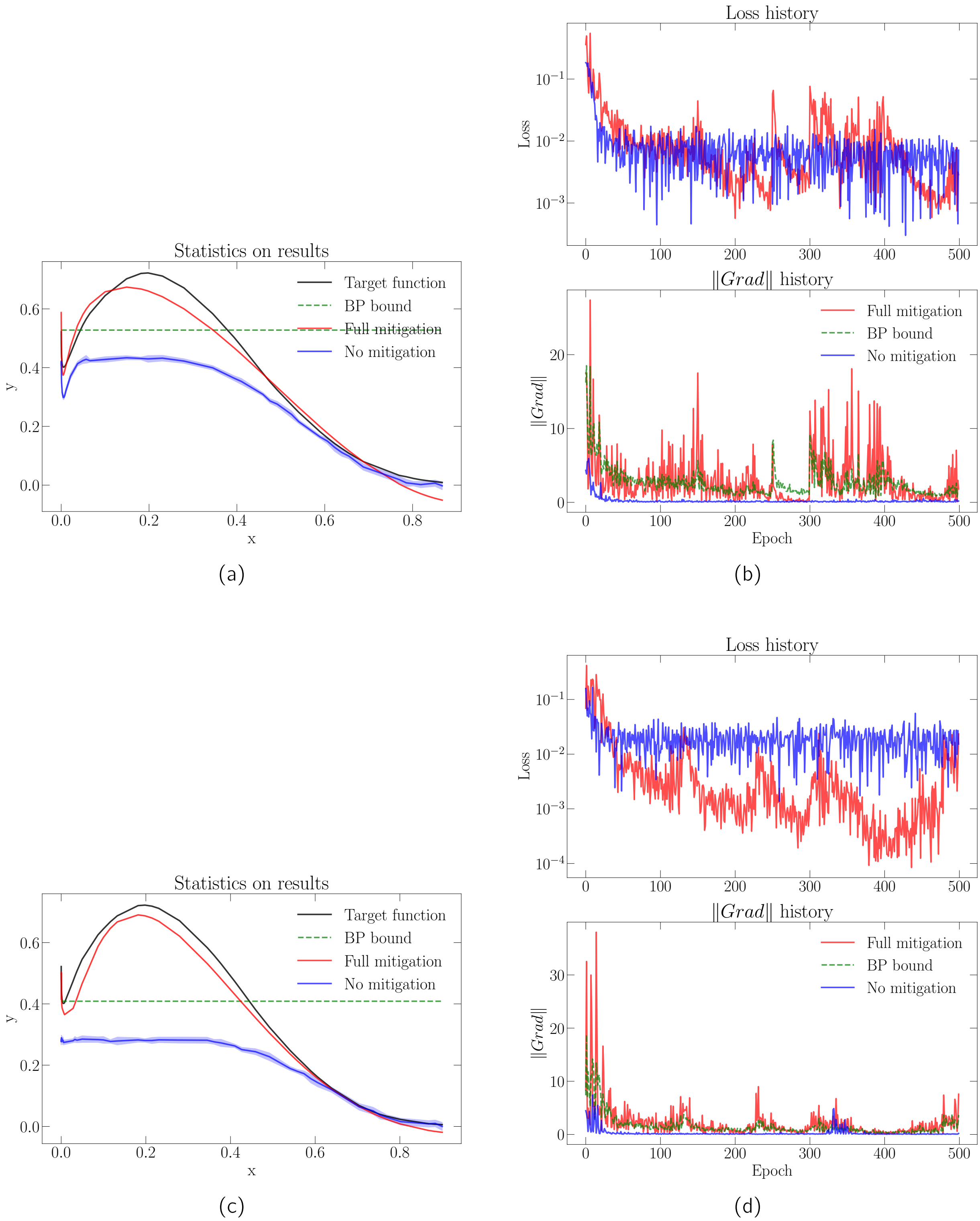

Figure 1: u PDF fit using a single-qubit quantum circuit with 4 (a, b) and 6 (c, d) layers, respectively. At the end of each layer, we introduce Pauli noise that induces barren plateaus during the training. This phenomenon is characterized by gradients that decay exponentially with the number of layers, as well as an upper bound for the cost function. We observe that this prevents the reproduction of the PDF in regions where it is close to one. By employing error mitigation during the training, it is possible to overcome these barriers, thereby enabling better training.