Variational Quantum Regression on NISQ Hardware with Error Mitigation

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At the intersection of two promising technologies, machine learning (ML) and quantum computing (QC), Quantum Machine Learning (QML) emerges. However, while QC is still in an early stage of development, QML is even more so. In this study, the Auto-MPG dataset [1] has been used to examine the state of the art of QML models in regression problems [2]. To this end, a preliminary analysis was conducted using a classical model as a reference point for subsequent evaluation. The XGBoost algorithm has proven to be a powerful ML algorithm that can be used for this task obtaining un R2 of 0.874 in the training phase and a 0.872 in the 20% of the data reserved for validation. Also, XGBoost can measure the contribution of each variable, which can be key when it comes to reducing the problem's dimensionality in the quantum approach. After that, the quantum experimentation was carried out in two phases. First, the model was trained in a perfect simulator of Pennylane to determine the best hyperparameters of the model. The best result achieved an R^2 of 0.860 for the training and 0.896 for the testing. Then, the best model was run against a simulator that include the noisy model extracted from the IBM Brisbane device using different error mitigation techniques. Among all of them, Zero Noise Extrapolation technique [3] was chosen as it yielded the most suitable results according to the selected simulator. To conclude, the QML model outperformed classical methods, demonstrating robustness with minimal R^2 reduction in the noisy simulator (by 0.001) during training and achieving consistent test performance using error mitigation.

References

[1] Quinlan,R.. (1993). Auto MPG. UCI Machine Learning Repository.
[2] Hirai, H., 2023. Application of quantum neural network model to a multivariate regression problem.
[3] He, A., Nachman, B., de Jong, W. A., & Bauer, C. W. (2020). Zero-noise extrapolation for quantum-gate error mitigation with identity insertions. *Physical Review A*, *102*(1), 012426.

Figures

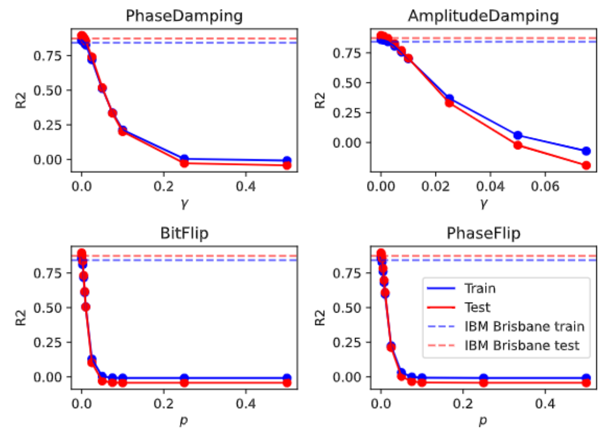

Figure 1: Study of the effect of different types of noise in the performance of the model

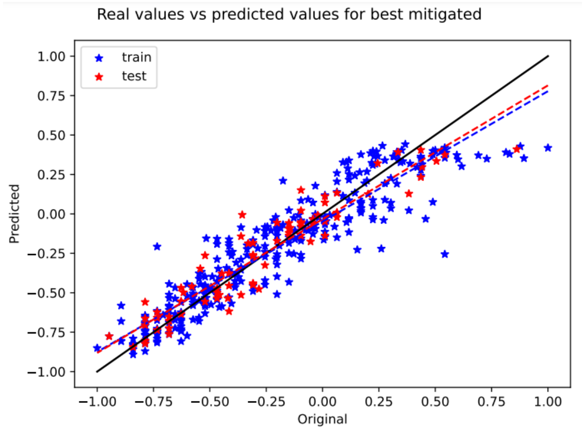

Figure 2: Comparison of predicted values and original values in train and test sets obtained by a noisy quantum circuit with the best error mitigation strategy.