Evaluating Noise Resilience of a Variational Quantum Classifier

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***Abstract*—This project report presents an empirical study examining the noise resilience of Variational Quantum Algorithms (VQAs), with a specific focus on the Variational Quantum Classifier (VQC). This experiment focuses on the performance of VQCs under various simulated noise conditions, including depolarizing, amplitude damping, and measurement noises. The findings of this experiment reveal that VQCs exhibit considerable robustness against quantum noise, maintaining high accuracy levels even in moderately noisy scenarios, thus aligning with and reinforcing similar findings in the field. These findings not only affirm the potential of VQAs as a valuable tool in quantum machine learning but also establish a foundation for future enhancements and optimizations, showcasing their practical utility in addressing the inherent imperfections of current quantum hardware.**

***Index Terms*—quantum machine learning, variantional quantum classifiers, variational quantum algorithms, NISQ**

I. Introduction

With the escalating exploration of quantum algorithms that promise exponential and quadratic speedups, there is a pressing need to deploy them on Noisy Intermediate Scale Quantum (NISQ) devices [1]. Variational Quantum Algorithms (VQAs) emerge as a particularly promising class, displaying resilience to noise [2]. A notable example is the Variational Quantum Eigensolver (VQE), designed to determine the ground state energy of a quantum system. Their variational nature renders them applicable to quantum machine learning tasks. Variational Quantum Classifiers [3], in particular, exemplify the implementation of such algorithms, showcasing their potential utility in addressing quantum machine learning challenges amidst the constraints of current quantum hardware.

Noise effects on Variational Quantum Algorithms (VQAs) have been extensively investigated, both theoretically and experimentally, across various domains and considering different underlying hardware architectures of quantum computers. In a review paper on VQAs [2], the authors highlighted that the impact of noise depends on multiple factors, including the choice of cost function, ansatz, parameter initialization, and optimization method. One notable empirical study showcased that VQAs can partially mitigate quantum noise by optimizing parameters in its presence [4]. The study demonstrates that incorporating redundant parameterized gates can lead to states with heightened resilience to noise.

Another empirical study illustrated the robustness of variational quantum compiling to various sources of incoherent noise, such as measurement noise, gate noise, and decoherence noise [5]. These findings collectively contribute to our understanding of how VQAs can effectively navigate and mitigate the challenges posed by quantum noise in different contexts.

The subsequent sections delineate the experiment setup, encompassing the classifier algorithm, employed noise models, simulation environment, dataset details, and the results of testing and training, drawing comparisons between the noisy and ideal circuit configurations.

II. Experiment

A. Variational Quantum Classifier

The Variational Quantum Classifier (VQC) employed in this study is referenced from the Qiskit machine learning examples [6]. The VQC encompasses four stages:

1) **Data Loading**: Classical data is loaded onto the circuit using encoding mechanisms such as basis encoding, amplitude encoding, and angle encoding.
2) **Ansatz Application**: A parameterized unitary operation, denoted as $U(\theta)$ and referred to as the ansatz, is applied to the encoded data. The parameters θ are ecoded in an arbitrary unitary as the following.
$$\rho(\theta) = U_l(\theta_l)\dots U_2(\theta_2)U_1(\theta_1)$$
3) **Measurement**: The expectation value measured during this stage serves as the output of the classifier. The cost function $C(\theta)$ is computed after the measurement and is represented as follows, for some set of functions $\{f_k\}$.
$$C(\theta) = \sum_k f_k\left(\text{Tr}\left[O_k U(\theta)\rho_k U^\dagger(\theta)\right]\right)$$
4) **Optimization**: A classical optimizer function compares the predicted outcomes against the actual labels and minimizes the error using techniques like gradient descent. This process generates updated values for the parameters θ, and a new iteration is initiated with these updated values. The following equation shows how the analytical gradient is calculated.
$$\nabla_j f(\theta) = \frac{f(\theta + se_j) - f(\theta - se_j)}{2\sin(s)}$$

This iterative process continues until convergence is achieved, refining the model's parameters and optimizing its performance.

B. Noise Models

The experimented noise models include depolarizing noise, amplitude damping noise, measurement noise, and noise models derived from the fake IBM backend snapshots. *Depolarizing Noise* is commonly encountered in quantum computing architectures. This type of noise acts by randomly flipping or depolarizing the states of qubits, which can be thought of as the quantum equivalent of bit-flip errors in classical computing. For Depolarizing Noise, the Kraus operators K_j are defined as:

$$K_0 = \sqrt{1 - \frac{3\lambda}{4}} I, K_1 = \sqrt{\frac{\lambda}{4}} X$$

$$K_2 = \sqrt{\frac{\lambda}{4}} Y, K_3 = \sqrt{\frac{\lambda}{4}} Z$$

where λ is the depolarizing parameter.

Amplitude Damping Noise describes the process by which a qubit loses energy to its surrounding environment, resulting in a damping of its amplitude. This phenomenon is a primary source of decay and loss of coherence in quantum systems and is mathematically represented by the parameter $\gamma = 1 - e^{-t/T_1}$, where t is the circuit time and T_1 is the relaxation time of the qubit. For Amplitude Damping Noise, the operators K_0 and K_1 take the matrix forms:

$$K_0 = \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{1-\rho} \end{pmatrix}, \quad K_1 = \begin{pmatrix} 0 & \sqrt{\rho} \\ 0 & 0 \end{pmatrix},$$

with ρ representing the probability of the qubit remaining in the excited state.

Measurement Noise generally refers to errors that occur during the measurement process of qubits, leading to incorrect readouts. Finally, the *Noise from Fake IBM Backend Snapshots* is incorporated into the experiment to simulate real noise deltas. This refers to noise that is simulated based on snapshots from IBM's quantum computing backends, allowing for a more realistic emulation of operational quantum computers.

C. Problem Setup

The problem formulated for this experiment revolves around an exploratory data analysis task. The classical dataset selected for this purpose is the renowned Iris flower dataset. Comprising 150 samples, each with four features, the dataset entails the prediction of three distinct labels. Prior to loading the dataset into the Variational Quantum Classifier, traditional data preprocessing and normalization tasks are performed. The data preparation and ansatz stages utilize ZZFeatureMap and EfficientSU2 from the Qiskit library. Circuits representing these components are illustrated in Figures 1 and 2.

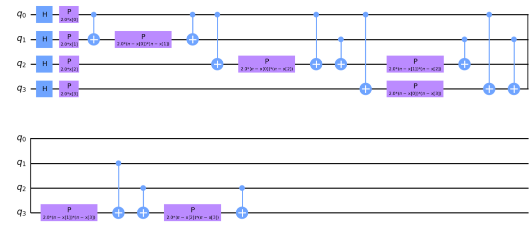

Figure 1: ZZFeatureMap in Qiskit

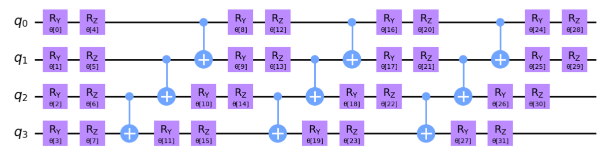

Figure 2: EfficientSU2 ansatz in Qiskit

D. Results

The baseline model, without any noise simulation, yielded training and testing accuracies of approximately 85% and 87%, respectively. These accuracies establish a baseline for assessing the performance of noisy simulations. Throughout the plots in Figures 3, 4, and 5, these base train and test accuracies are depicted as dashed red and blue lines.

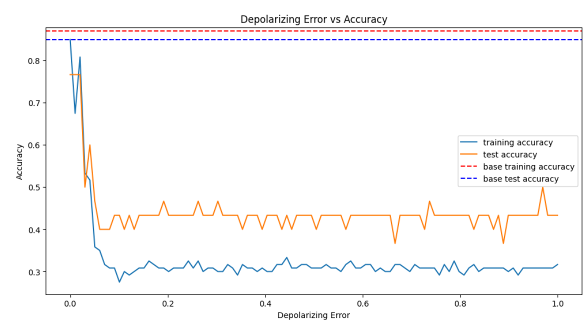

Figure 3: Depolarizing error probability vs test & train accuracy

From the figure 3 we can observe that there is a *sharp decline* in both training (solid blue line) and test (solid orange line) accuracies when the depolarizing error increases from 0, but the decline stabilizes shortly after. Further investigation can be conducted to analyze the relationship between the 5% error delta and understand how the depolarizing error influences performance within that range.

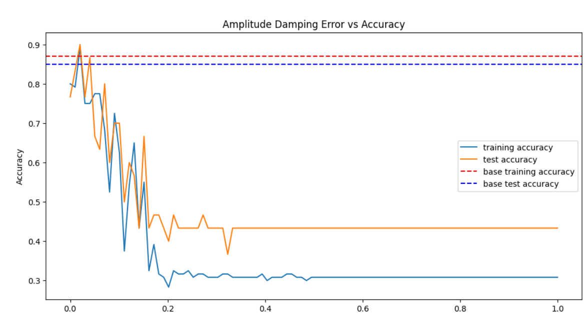

Figure 4: Amplitude damping error probability (λ) vs test & train accuracy

From the figure 4 we can observe that as the amplitude damping error increases from 0 to 1, there is a noticeable decrease in both training accuracy (solid blue line) and test accuracy (solid orange line). This suggests that the model's performance degrades with the increase in error introduced by the noise.

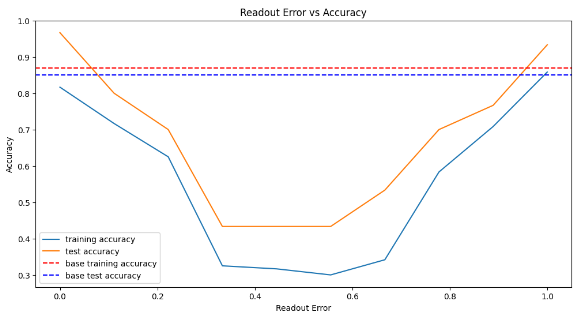

Figure 5: Readout error probability vs test & train accuracy

In the figure 5 both the training accuracy (solid blue line) and test accuracy (solid orange line) exhibit a symmetrical pattern, decreasing and then increasing as the readout error varies from 0 to 1. The symmetrical nature of the curve is unusual for noise models and might suggest that the variational model learns the inverse relation of the classification. It's important to note that very high noise levels, as seen in this experiment, are primarily for experimental purposes. Real-world noise typically falls within a 10% range, as demonstrated in the experiments with fake IBM backends in Figure 6.

Figure 6: Readout error probability from fake IBM backend vs test & train accuracy

The scatter plot in Figure 6 illustrates individual data points representing test scores at different levels of readout error, derived from fake IBM quantum computer backends. Observations from this plot indicate that at lower readout error rates, there is a considerable variation in test scores, spanning from approximately 0.55 to 0.90. This variability may suggest that factors beyond readout error are impacting accuracy at these lower error probabilities, or it could imply inherent variability the variational algorithm's performance at these levels.

III. Navigating the Project

This section elucidates the project structure and aids in navigating through the files. The project folder encompasses multiple Jupyter notebook files. The baseline model and IBM fake backend readout noise calculations are detailed in the *baseline_vqc.ipynb* file. Amplitude damping noise simulations are present in the *amp_damp_vqa.ipynb* file, depolarizing noise simulations in the *var_dep_vqa.ipynb* file, and readout error simulations in the *readout_vqa.ipynb* file. Each notebook file is accompanied by an HTML counterpart, providing snapshots of the simulations.

IV. Conclusion & Future Work

The outcomes of this experiment largely align with the hypothesis, indicating a potential to delve deeper into the relationship between performance within very small noise errors. We can see that VQCs exhibit considerable robustness against quantum noise, maintaining high accuracy levels even in moderately noisy scenarios, thus aligning with and reinforcing similar findings in the field. This exploration holds significant promise for the future of quantum machine learning tasks in general. The demonstrated potential of Variational Quantum Algorithms (VQAs) underscores their significance as valuable tools in quantum machine learning. This exploration serves as a foundation for future enhancements and optimizations, highlighting their practical utility in addressing the inherent imperfections of current quantum hardware.

In future research, there is an opportunity to investigate simulations incorporating error mitigation strategies and explore the effectiveness of hybrid quantum-classical algorithms. These algorithms can harness classical computing resources to enhance resilience against quantum noise. Additionally, the development of tailored noise models for specific quantum applications could improve the efficiency of noise mitigation techniques. These observations and findings might be extended to deterministic quantum algorithms, such as Shor's factoring and Grover's search, challenging the notion that they are incompatible with Noisy Intermediate-Scale Quantum (NISQ) devices [7].

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