Variational Quantum Machine Learning with Quantum Error Detection

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Quantum Machine Learning (QML) algorithms have recently emerged as an exciting solution to the increasing demand for computational power and efficiency across a wide range of complex tasks within the field of machine learning. QML algorithms are built upon the fundamental quantum phenomena of superposition and entanglement not available to classical machine learning algorithms. As such, they are expected to produce improvements in model performance compared to their classical counterparts for specific classes of problems. Indeed, QML has already demonstrated quantum advantage in various settings, such as speed-ups in supervised machine learning through quantum kernel estimation [1] and enhanced robustness of QML models to adversarial attacks [2,3].

However, before such enhancements can be exploited and made useful, there are significant barriers that must be overcome. As with most quantum algorithms, one of the key challenges we face is that QML algorithms are very prone to noise, producing meaningless output when run on noisy quantum devices, especially if circuit depths are high. Although error mitigation and suppression techniques may be used to address this problem, we require further techniques from Quantum Error Correction (QEC) theory to sufficiently overcome these challenges.

QEC protocols have been successfully applied to a small number of quantum algorithms; for example, the [[4,2,2]] stabiliser code with Variational Quantum Eigensolvers [4,5] and the Steane Code with a quantum Fourier Transform algorithm [6]. However, there has not yet been any experiment demonstrating the application of a quantum error correction or quantum error detection code to a quantum machine learning problem.

We will present the results of our experiment in applying the [[4,2,2]] stabiliser code to detect errors during the training of a Variational Quantum Classifier (VQC; see Fig 1). Specifically, we will demonstrate that the classifier can be trained with the [[4,2,2]] code to make accurate predictions on noisy quantum hardware, similar to the expected performance in an ideal, noiseless environment.

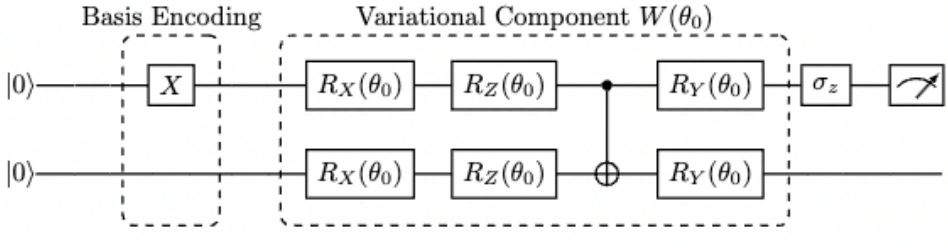

Fig 1. The structure of the Variational Quantum Classifier we trained with the [[4,2,2]] stabiliser code. The VQC outputs a parity classification for the 2 input qubits and requires only one rotational parameter to successfully train.

We will present a novel procedure for logically encoding rotation gates for [[*n*,*k*,*d*]] codes in general (see Fig 2), evaluate the performance of the VQC in the presence of gate errors and depolarising noise, quantify the maximum probability of gate errors that is tolerable for training a VQC with quantum error detection, and identify the limitations of the [[4,2,2]] code in protecting the training and prediction processes from random errors.

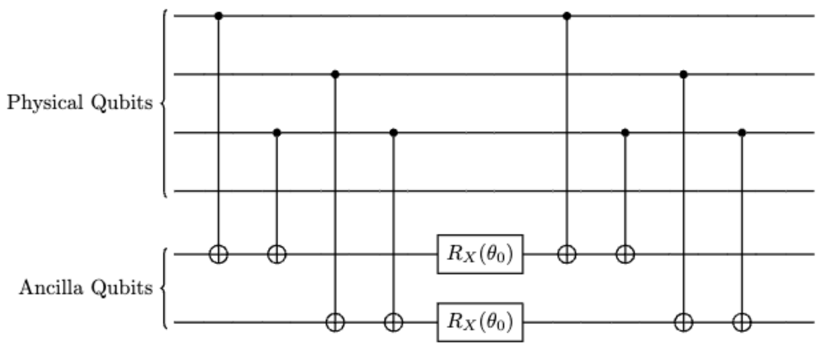

Fig 2. The logical encoding of the R_X gates, requiring one ancilla qubit per gate to implement for the [[4,2,2]] logical encoding.

We find that training the VQC with the [[4,2,2]] code under probabilistic gate errors or depolarising noise produces substantial improvements in accuracy compared to the case where no stabiliser code-based error detection is used. As an example, we display in Fig 3 the enhanced training accuracy of the VQC when trained with the stabiliser code, under a probabilistic gate error model with X, Y and Z error probabilities of 0.0025 (total gate error probability of 0.0075). The training accuracies shown are averages of 10 independent training runs, each simulated with 1000 shots.

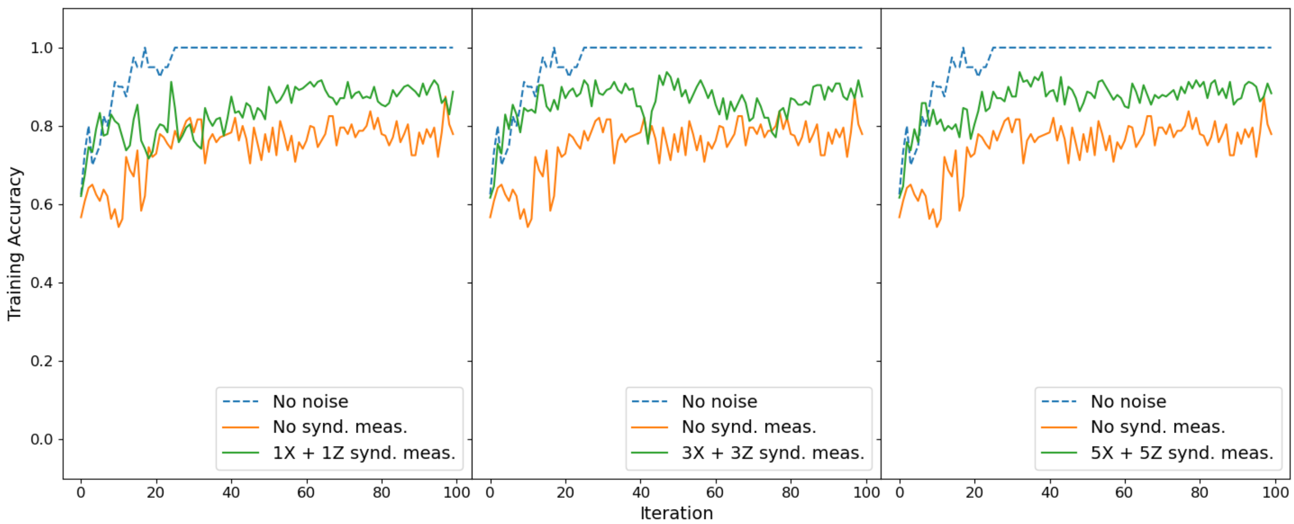

Fig 3. Comparison of the training accuracy of the VQC when trained with the [[4,2,2]] stabiliser code (green) and when trained without any stabiliser code (orange), under a probabilistic gate error model with X, Y and Z error probabilities of 0.0025 each. The training accuracy for a zero-noise environment is also displayed (blue dashed line). From left to right, we show the training accuracies when using 1, 3, and 5 pairs of X and Z stabiliser measurements. The accuracy improves as more stabiliser measurements are used to detect errors.

The results from this work are the first step in understanding how error detection and error correction impact QML model training and prediction in noisy environments. In future, we aim to build from these results to explore the implementation of more complex error detecting and error correcting codes with a variety of variational quantum machine learning architectures.

References:

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