Bit-Flip Error Mitigation Using Deep Learning

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***Abstract*—In this paper, the use of deep learning is investigated for quantum state tomography on noisy measurements. For this paper, we acquired data from experimental measurements based on the noisy models provided by IBM cloud quantum computers. We have introduced varying degrees of bit-flip error into the data and trained a quantum-aware neural network. The results show that for varying degrees of noise, a generalized neural network can be trained which can learn the noise and help us generate the pure quantum states with higher Fidelity.**

I. Introduction

Quantum information theory is a new area that offers unique algorithms and computational speedups due to its separate computing paradigm. Quantum computing operates on physical rules such as superposition and entanglement. Although it has the potential to transform several sectors of research, it is still in its early stages and prone to mistakes which end up in noisy data. Quantum tomography is used to check the accuracy of the measurement findings produced from experiments using quantum computers since the results one receive from this error-prone technology are probabilistic (QT). With applications in quantum communication, quantum sensing, quantum computing, and other areas, noisy-intermediate scale quantum (NISQ) devices are benchmarked using the post-measurement approach known as QT. In this paper, we examine the two-step quantum state tomography (QST) process. i) Measuring an unknown quantum state supplied in order to obtain the classical data. ii) using post-processing techniques to the data that has been collected in order to reconstruct the unknown quantum state.

Maximum likelihood estimation (MLE), Bayesian mean estimation (BME), and linear inversion are the most common methods for QST in the literature[1], [2]. However, MLE and BME both need a lot of resources and are more noise-sensitive. As a result, a lot of study has been done on estimating unknown quantum states when there is noise. The quantum state estimation method is suggested in this research utilizing a simple and reliable deep learning model. We demonstrate that, even in the presence of noise in NISQ devices, the trained deep learning model guides us to the true pure quantum state.

II. Method

Any single qubit quantum state can be experimentally reconstructed using the Stokes parameters as [3]

$$\rho = \frac{1}{2}\sum_{i=0}^{3} s_i \sigma_i, \tag{1}$$

where s_i represents the Stokes parameters, σ_0, σ_1, σ_2, and σ_3 are the Identity, Pauli X, Pauli Y, and Pauli Z matrices, respectively. In general, we require d^2 parameters to reconstruct any n-qubit state, where $d = 2^n$.

A. Dataset Generation and Model Training

As in this paper we wanted to show that a generalized model for varying noise can be made, so for dataset generation, 500 pure quantum states through a noise model on IBM cloud-based quantum computer (IBM Nairobi) is generated. For input features of the neural network, we used the stokes parameters that we inferred from the measurements data on real quantum computer and our model returns us theoretical expectation values in Pauli bases as output. We divided our dataset into 5 sets of 100 data points each and added bit-flip error ranging from 0.05 to 0.25 with a step of 0.05 in subsequent sets. Then this dataset is combined again in order to generate a 500 pure quantum states dataset with varying bit-flip error. We split the dataset into 70% training dataset and 30% test dataset with stratification on the bit-flip error so we have an equal number of samples for each bit-flip error value. 30% of our training dataset is used for validation. Datasets for both single qubit as well as two qubits are generated in the similar fashion.

B. Model Configuration

1) Evaluation Metrics: we use mean squared error (MSE) as our loss function, which is given by

$$J(w) = \sum_{i=1}^{D} (w^T \tilde{S}_i - S_i)^2 \tag{2}$$

where W is the weight matrix learned by the model, $\tilde{S}_i$ are the input stokes parameter vector, and S_i is the actual state expectation values vector. Moreover, we evaluate the learning performance of the model by a metric known as Fidelity which is defined as;

$$F(\rho, \sigma) = \mathrm{tr}\left(\sqrt{\sqrt{\rho}\sigma\sqrt{\rho}}\right)^2. \tag{3}$$

2) Optimizer: We uses the RMSProp [4] as our optimizer. In RMSprop, we adjust the learning rate by dividing it by the root of the squared gradient, but because we only know an estimate of the gradient on the current mini-batch, we must instead use its moving average.

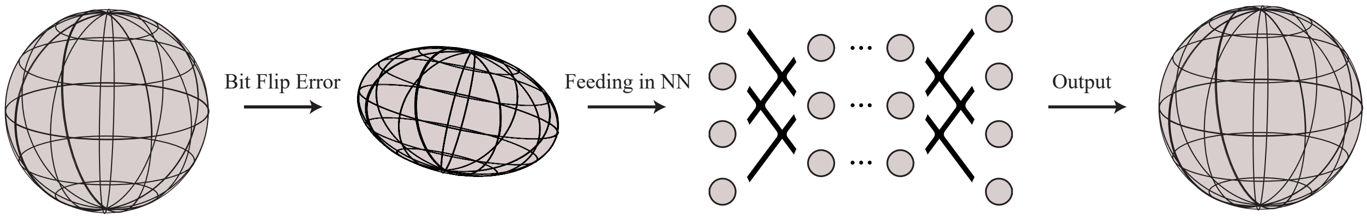

Figure 1. Our proposed methodology takes the parameters with bit flip error and feed it to a neural network which can vary based on the number of qubits n. The neural network returns expectation values as output with which we reconstruct the state.

C. State Validation

We reconstruct the density matrix from the prediction using the (1) In order to deal with non-positive eigenvalues, which make our predictions physically invalid, we perform single value decomposition (SVD) on our predicted density matrix and select the eigenvector whose eigenvalue is the maximum and then take its outer product with itself for the final state.

III. Results

We calculated the mean Fidelity after state validation of our 150 test quantum states from the parameters that we predicted from the neural network trained on 350 quantum states for 1000 epochs in both single qubit as well as two qubits cases. Then we compare this mean Fidelity with the mean Fidelity of the noisy test dataset. Results indicate that a generalized neural network can be trained for varying noise which can learn the noise and help us achieve the pure quantum states with higher Fidelity.

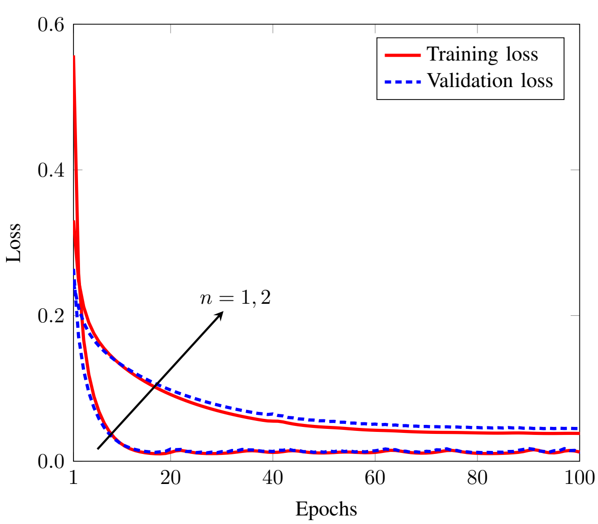

Figure 2. An illustration of training and validation loss on n qubit data while training.

Method	Single Qubit Mean Fidelity	Two Qubit Mean Fidelity
Without Deep Learning	0.92	0.76
With Deep Learning	0.99	0.97

IV. Conclusion

The noise model of IBM quantum computers illustrates the robust reconstruction of the pure quantum state. The provided approach can be used as a standard for noise removal in quantum measurements data obtained from noisy quantum computers. We exhibit results on single as well as two-qubit data, which gives us an indication that this strategy may be used for multi-qubit data for any noise model of a quantum device because deep learning algorithms have been theoretically shown to approximate any function.

V. Acknowledgement

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2019R1A2C2007037 and 2022R1A4A3033401) and by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2021-0-02046) supervised by the IITP (Institute for Information Communications Technology Planning Evaluation).

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