Advancing Comprehension of Quantum Application Outputs: A Visualization Technique

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ABSTRACT

Noise in quantum computers presents a challenge for the users of quantum computing despite the rapid progress we have seen in the past few years in building quantum computers. Existing works have addressed the noise in quantum computers using a variety of mitigation techniques since error correction requires a large number of qubits which is infeasible at present. One of the consequences of quantum computing noise is that users are unable to reproduce similar output from the same quantum computer at different times, let alone from various quantum computers. In this work, we have made initial attempts to visualize quantum basis states for all the circuits that were used in quantum machine learning from various quantum computers and noise-free quantum simulators. We have opened up a pathway for further research into this field where we will be able to isolate noisy states from non-noisy states leading to efficient error mitigation. This is where our work provides an important step in the direction of efficient error mitigation. Our work also provides a ground for quantum noise visualization in the case of large numbers of qubits.

CCS CONCEPTS

• **Computer systems organization → Quantum computing**; • **Hardware → Quantum technologies**; • **Human-centered computing** → *Heat maps.*

KEYWORDS

quantum computing, quantum machine learning, quantum noise, noise visualization

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1 INTRODUCTION

Quantum computing is an emerging area of research that has attracted a lot of attention from academia and industry. Due to its unique characteristic of superposition, it has enormous potential to solve selective difficult classical problems that are unsolvable by present-day classical supercomputers. An example is that of Grover's algorithm [1] which has shown quadratic speed up on the unstructured search problem. We are also seeing rapid developments in building quantum computers with a much higher number of qubits than what we have seen a few years ago. More specifically, the number of the basic quantum data unit, qubits, has been scaled up from 5 to 127 in the past 5 years and is expected to achieve 1121 in 2023, according to the report of IBM [2].

Present-day quantum computers possess a serious challenge of noise. Due to the noise in present-day quantum computing, applications using quantum computers are constrained. Due to the noise, it is common to see unexpected results. An important consequence of noise in quantum computing is reproducibility. Reproducibility in classical computing is when we obtain similar results when an algorithm is tested on similar capable machines. On the contrary, a quantum algorithm will yield dissimilar results when tested on separate quantum computers. More precisely, a quantum algorithm may yield dissimilar results when tested on a specific quantum computer multiple times. Hence, it becomes imperative to reduce the noise in quantum computers or mitigate the effect of noise in quantum computers since the noise is detrimental to the effectiveness of quantum computing. To overcome the noise in quantum computers, a technique called error correction [4] is proposed aiming to create ideal qubits or noise-free qubits resulting in noise-free quantum computers. The problem with the error correction technique is that it requires a large number of qubits which is not present with quantum computers today. Another technique is a practical technique called error mitigation. In this technique, the effect of noise

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in quantum computers is reduced by various methods utilizing both classical and quantum computers. A very recent study of error mitigation in VQE using circuits controller is shown in [7]. Recent work provides a holistic picture of the noise of quantum computing through multiple interactively coordinated views [8]. However, there are few works on visualizing cumulative noise produced by a sequence of a large number of quantum machine learning jobs consisting of hundreds of circuits in each of those jobs.

Our paper is a novel approach in attempting to visualize the cumulative noise in quantum machine learning. In our work, we used multiple quantum computers and a noise-free quantum computer simulator to run our quantum machine learning algorithms. In our work, we have created raw data of the output states of all the quantum circuits that were used in our quantum machine learning algorithm. The raw output dataset is created from all the machines. We have provided a distribution visualization of all the basis states. We have also provided a heat map that shows KL-distance among all the quantum states for all the circuits. This visualizing technique is a crucial step toward understanding noise in quantum computing in general. When we will be able to access quantum computers with a very high number of qubits, key takeaways from our work will present users of noisy quantum computers with an understanding of noise visually. Research in this direction could provide us with crucial information on noisy and non-noisy basis states. With this information, we could mitigate the errors by isolating and suppressing the effect of noise in quantum computers.

2 RELATED WORK

Noise in Quantum Computing. There are multiple factors that lead to good accuracy in test results. They are (1) T_1, (2) T_2, (3) CNOT error and (4) readout error [3, 10]. T_1 is thermal relaxation time that is required by a qubit to move from an excited state to a ground state. It provides consistency for the qubits to stay in excited states for some time t. An excited state is usually state $|1\rangle$. This time is measured experimentally by first exciting a qubit in the ground state by using a pulse, then waiting for some time, and then measuring the same qubit. This will give us the thermal relaxation time of a qubit. T_2 is called dephasing time. It is the loss of a qubit's phase coherence time. It is measured by first applying a Hadamard gate H to a qubit in $|0\rangle$, which then transforms the qubit to a $|+\rangle = \frac{|0\rangle+|1\rangle}{\sqrt{2}}$ state which is a superposition of states $|0\rangle$ and $|1\rangle$. Then apply the Hadamard gate to the $|+\rangle$ and wait for some time t. Then we measure if it is in state $|0\rangle$. Readout error is the error that occurs when measurement times are much higher than coherence times [6]. A CNOT gate entangles two qubits. It involves two qubits, a source qubit, and a target qubit. If the source qubit is in state $|1\rangle$ then it applies a X gate to the target qubit. This gate produces similar error as that of single qubit gates except that the error involves error with two qubits.

3 GATHERING BASIS STATES DATA

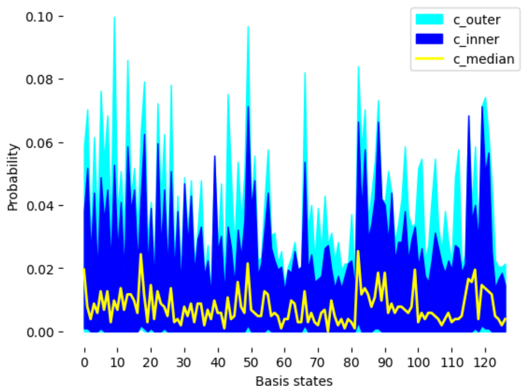
Our methodology of collecting the basis states distribution involves a series of steps. We start with training our QML model on MNIST images belonging to classes 3 and 6. The training is performed on a noisy quantum computer simulator. This noisy simulator emulates the NISQ machines used in our work. The training is performed on 2000 images. We train on a simulator because of the restrictions imposed on actual quantum computers through fair share job scheduling algorithms of IBMQ. The training schedule involves training our model once in a week and testing the model for the rest of the six days in a week on various machines. The accuracy of the model is tested on two devices IBM Nairobi and IBM Perth. The testing process involves testing 100 test images belonging to image classes 3 and 6. The raw data is collected for all the circuits from all jobs on the two machines. After preliminary analysis of the raw data, we found out that some of the test images were wrongly classified during testing by the ideal simulator. In order to remove noise from images, we adjusted our algorithm to skip those test images that were inaccurately predicted by the noise-free quantum computer simulator. We also test those images (post-skipping) on real quantum computers.

4 EXPERIMENTAL SETUP AND RESULTS

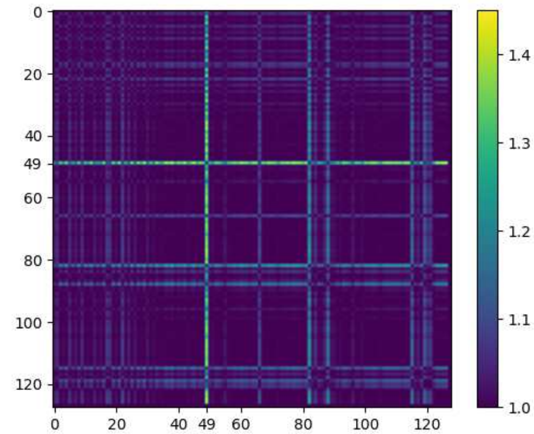
For this project, we compress the MNIST images from 28 by 28 pixels to 12 by 12 pixels so that they can be encoded onto 7 qubits, since 124 pixel values are encoded onto the amplitudes of 128 basis states using amplitude encoding. The batch size for our training and testing is set to 100 images and the learning rate is set to 0.005. We use the default optimization level for circuit transpilation. Our architecture is built on the architecture provided by torchquantum [9]. After the compressed images are encoded onto qubits, the qubits are subjected to a set of rotation gates and measurement gates. Post measurement, the qubits-wise probability is calculated which is further used in calculating the loss for each iteration.

After the testing is performed on both devices on those images which are predicted accurately by noise-free simulator, we collect the raw data of all the circuits from all the jobs that were executed by all the machines. This has resulted in thousands of rows of states distributions from all the executed circuits output. Figure 1a and Figure 2a shows the distribution of 128 states from the seven qubits from all the machines used in our work using the functional boxplot [5] method. These states reflect all the circuits that were used during the testing of images on two machines. The plots display the central 50% region by c_{inner}, the non-outlying region by c_{outer}, and the median region by c_{median}. Figure 1b and Figure 2b show the pairwise KL-distance among the 128 basis states distributions.

Figure 2a was produced from a much higher number of jobs than Figure 1a. One thing that is common among all the basis states distribution for all jobs is that not all the basis states are used for computation. From Figure 1b and Figure 2b, we can visualize the KL-distance among various basis states for each of the machines. Higher KL-distance refers to a higher degree of mismatch between two distributions, whereas lower KL-distance refers to a lower degree of mismatch between two distributions leading to a greater similarity between distributions. For instance, in Figure 1b, we see that there is one basis state 49 that has the brighter spectrum of colors which implies that state has the most significant mismatch in their distributions when compared to other states' distributions. This means basis state 50 has the highest KL-distance when compared with the rest of the states for the same machine. The figures presented in this paper lead us to expectations that the significant basis states distributions, i.e., basis states distributions with

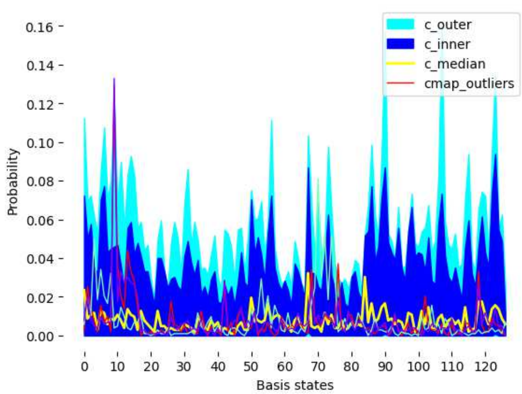


(a) Distribution displaying median, inner band, and outer band regions with yellow, dark blue, and cyan, respectively for basis states distribution of 7 qubits

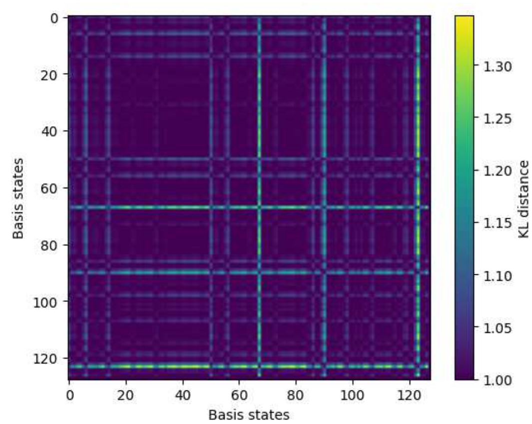


(b) Heat map of pairwise KL-distance for all jobs among the distributions for 128 basis states

Figure 1: Visualization of the distribution of the basis states and the KL-distance among basis states distribution for all jobs from IBM Nairobi



(a) Distribution displaying median, inner band, and outer band regions with yellow, dark blue, cyan, and red, respectively for basis states distribution of 7 qubits



(b) Heat map of pairwise KL-distance for all jobs among the distributions for 128 basis states

Figure 2: Visualization of the distribution of the basis states and the KL-distance among basis states distribution for all jobs from IBM Perth

higher KL-distance, could be the dominant basis states used by the quantum computer for calculation whereas the non-dominant basis states are a result of noise. This requires further study to prove our hypothesis. Also, some basis states are used for computation while the other excited basis states are a result of noise. With research in the direction of visualization, we hope to isolate the two types of basis states.

5 CONCLUSION

In this paper, we investigate the output noise from quantum computers using quantum machine learning as a case study. Our findings reveal that using quantum computers for quantum machine learning (QML) is challenging due to the noise that leads to uncertain fidelity. To find out the dominant states, we have deployed certain visualizing techniques to understand the dominant factors that lead to uncertain outputs due to noise. This is an important and crucial step toward visualizing and characterizing noise in quantum computing applications. This work is also a crucial step in the direction of visualizing the noise in the case when qubits are scaled from 5 to over 1000 qubits.

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