

Semester Overview

This semester focused on gathering and cleaning data in preparation for training a noise model to enable reinforcement learning for noise reduction. In particular, we focused on (1) reviewing deepq methodology, (2) generating equivalent test circuits/gathering noise data.

Circuit Generation

We generated circuits with VX , VY , VW in one layer and CNOT gates in another layer then inverted them so that the result should be that the qubits are unchanged. Any deviations would be the result of noise.

Data Collection

Since noise models are hardware specific, we ran our circuits on `ibm_kyoto` to gather realistic test data.

DeepQ Paper

Paper Objectives

- Learning a noise model for a given circuit.
- Introduction of noise mitigation strategies focusing on two methods:
 - *Randomized compiling*: Conversion of coherent errors to Pauli errors (error correction)
 - *Padding*: Reduce “not busy” qubits at risk of error (noise mitigation)

Present Progress

- We used methods outlined in the DeepQ paper to generate trainable circuit data. These circuits were all “0” circuits, with different noise parameters.
- The circuits were created by performing a number of unitary operations and then inverting all of these operations.
- Set up data pipeline, with preliminary test dataset generated.

Preliminary Results

- 1000 supremacy style identity circuits generated
- 1000 runs over 100 equivalent circuits (continuing to run jobs based on IBM rate limit)
- Data visualization to better understand dataset
- Convolutional Neural Network Architecture with 2 conv layers, padding, and fully connected dense layers

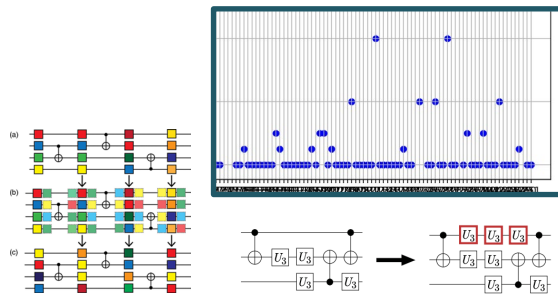


Fig. 1 (1) Randomized Compiling

Fig. 2 (2) Idle Qubit Reduction (Padding)

Fig. 3 Data Generation Pipeline

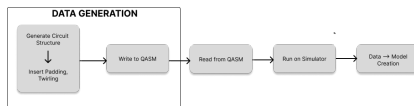
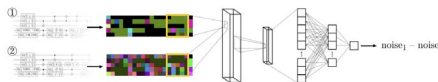


Fig. 4 Eventual Objective: Noise Model



Challenges

- Understanding existing code on circuit generation, data cleaning, and modeling
- Deprecated Qiskit packages, versions
- Limited compute time/long queue time
- Converting noise data into trainable data

Future Work

- Expanded dataset with more circuits and computations
- Test different ML models for noise model construction (simpler, more efficient)
- Alternative, more spatially aware methods of training
- Explore alternative noise mitigation and error correction strategies

References

1. Wallman, Joel J., and Joseph Emerson. “Noise tailoring for scalable quantum computation via randomized compiling.” *Physical Review A*, vol. 94, no. 5, 18 Nov. 2016, <https://doi.org/10.1103/physrev.94.052325>.
2. Zlokapa, Alexander, and Alexandru Gheorghiu. “A deep learning model for noise prediction on near-term quantum devices.” *arXiv*, 2020, <https://doi.org/10.48550/arXiv.2005.10811>.