Rogues Gallery VIP - Quantum Computing - Fall 2022

Andrew Asper, Shirley Benedict, Andrew Luo, Herman Rogers, Ashwin Srivastava, Jack Sullivan, Stefan Talpa, Victor Ung, Jon Wang

Semester Overview

This semester, we re-evaluated our reinforcement learning approach for optimizing variational quantum circuits (VQC). We found that building our own feasible theoretical noise models is likely beyond our grasp. We are now primed, however, to dive into quantum circuit optimization strategies utilizing deep reinforcement learning for quantum circuit noise reduction. To this end, we modularized our codebase for building an open-source quantum circuit database gathering platform, via the IBMQ. Future additional project avenues will be opened in the vein of quantum simulations testing, and our work expanded in utilizing both existing deep noise computing and circuit optimization methods.

Machine Learning Objectives

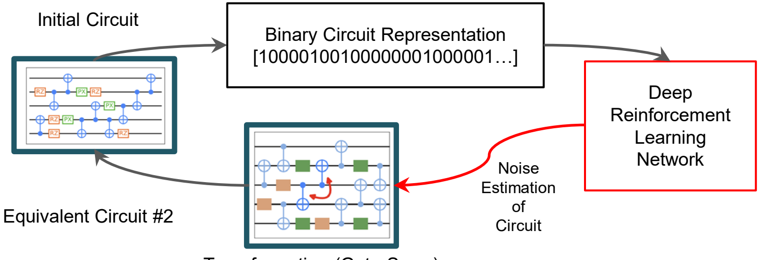
- Conducted literature review of existing deep learning-based methods for ideal quantum circuit optimization and quantum circuit mapping.
  - Using a single IBM back end architecture per model is optimal [1, 2].
  - Using additional deep model modules to resolve a hardware backend's benchmarked noise values may lead to better circuit optimizations in the reinforcement learning (RL) setting [3].
  - Existing operator-sum noise models within reach **of our testing** using tensor network architectures [4, 5]
- Using vectorized gate swaps as the RL action, plan on beginning reinforcement learning-based optimization (<u>using available data</u>) in the coming months.

Quantum Information Theory Subgroup

- In attempt to devise or understand circuit noise modeling: Conducted weekly problem sessions, following assigned reading in Nielsen & Chuang, to learn fundamentals of quantum information theory:
- **Conclusion:** <u>Devising</u> theoretical models are not within our grasp on a useful level.
- Will pivot this subgroup's focus to testing quantum computing simulations, applicable to modeling noise and other relevant phenomena.

IBM Quantum: "Circuit Mining" Library

- **<u>Goal</u>: Accommodate building larger datasets needed for deep neural network training.**
- Modularized scripts generating and testing random quantum circuits, on IBMQ backends.
- Adapting algorithms from previous semesters to find all possible ideal circuit gate swaps and execute them in our current binary circuit vector representation: **<u>optimized for deep reinforcement models</u>**.



Circuit graphics utilized from [2]

Next Steps

- **Dataset:** Finalize scheduled data generation pipeline on a local RG cluster.
- **Verify existence of larger circuit datasets** than we have assembled [3].
- Continue to evaluate performance of our existing DNN **noise model**. Compare with that of published neural networks that capture alternative representation of quantum circuit [2, 3].
  - **Also:** compare to analytically-driven simulations computing noise.
- Begin testing circuit optimization (different **noise models) via** reinforcement learning (classical Q-learning, Deep-Q) with existing input structure [2].
  - <u>Potentially explore existing RL architectures suited to graph structure.</u>
- **Pivot theory group: Test Existing Quantum Simulations.**

References

1. Zlokapa, Alexander, and Alexandru Gheorghiu. "A deep learning model for noise prediction on near-term quantum devices." arXiv preprint arXiv:2005.10811 (2020).
2. Fösel, Thomas, et al. "Quantum circuit optimization with deep reinforcement learning." arXiv preprint arXiv:2103.07585 (2021).
3. Wang, Hanrui, et al. "QuEst: Graph Transformer for Quantum Circuit Reliability Estimation." *arXiv preprint arXiv:2210.16724* (2022).
4. Hong, Xin, et al. "A tensor network based decision diagram for representation of quantum circuits." *(TODAES)* 27.6 (2022): 1-30.
5. Roberts, Chase, et al. "Tensornetwork: A library for physics and machine learning." *arXiv:1905.01330* (2019).