Rogues Gallery VIP - Quantum Computing - Spring 2023

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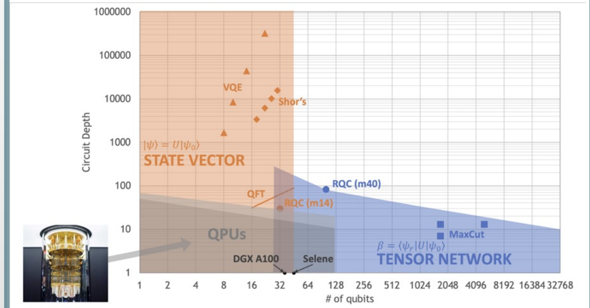
Semester Overview

Our past work has focused on training deep-reinforcement learning models for quantum circuit optimization via an action space of equivalent circuit substitutions (gate swaps). This has been constrained by a lack of a viable, generalizable theoretical noise model for simulating the operation of an arbitrary, real noisy intermediate scale quantum (NISQ) device, and further constrained by limitations on running circuits on these devices (previously with IBM Quantum framework). Our focus this semester has turned to implementing tensor network-based quantum circuit simulations, exploring how these can augment and expand our reinforcement learning capabilities for circuit optimization, and how tensor network simulations can be utilized in future semesters' work in the modeling of more complex physical systems on supercomputing hardware.

Toward Quantum Supremacy: Tensor Network Simulation



Plot from NVIDIA cuQuantum Brochure showing circuit depth and qubit count regions of simulation capabilities for NVIDIA cuQuantum state vector and tensor network simulations, respectively, compared to physical, state-of-the-art quantum processor units [4].

Simulation Results

- **All runs conducted on NVIDIA A100 GPU's using NVIDIA cuQuantum simulation framework.**
- **Random circuits with default cuQuantum noise models (simulating physical backends) were used.**

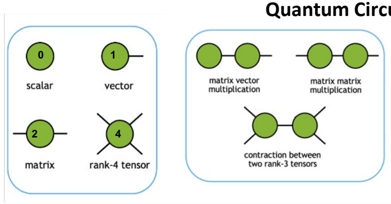
Initially attempted to use state vector simulation configuration.

- **Encountered a <u>qubit count</u> limitation of 32 qubits - though was able to handle <u>deep circuits</u> well.**

Pivoting to Tensor Network Simulations

- **Successfully reproduced the results of Google's quantum supremacy paper [5] and demonstrated our ability to surpass the 52-qubit "supremacy" benchmark (2019) by running a 100-qubit simulation on a Nvidia A100 GPU.**
- **Depth limitation is clear (chart). But our investigations encouraging.**

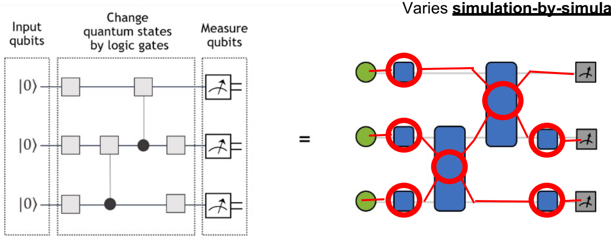
Tensor Network Representation: Quantum Circuits [6]



(Σ)

$$T_{abcd} = A_{aij} B_{bjk} C_{klc} D_{lid},$$

- **Contraction**: Sum over common Indexes (**edges**) [**Gates: Tensors**]
- Contraction Order (**which edges?**) Varies **<u>simulation-by-simulation</u>**



Future Work

- Expanding our work to utilize **multiple GPUs**, pushing qubit number and circuit depth limits further.
- Explore ways of approaching more recent supremacy benchmarks with both state vector and tensor network simulation.
- **Simulate quantum many-body systems** (e.g. solid state systems) to explore applicability to quantum information.
- **Scale Quantum Approximate Optimization Algorithm** (QAOA) to more qubits using tensor networks to perform complex combinatorial optimization.
- Upon gathering sufficient simulation data, begin developing an **RL optimization model** for noise reduction, as in [2].
- Train additional noise model as in [1, 3].

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. https://www.nersc.gov/assets/Uploads/11-cuQuantum-Kim.pdf
5. Arute, F., Arya, K., Babbush, R. et al. Quantum supremacy using a programmable superconducting processor. Nature 574, 505–510 (2019). https://doi.org/10.1038/s41586-019-1666-5
6. https://docs.nvidia.com/cuda/cuquantum/cutensornet/overview.html