Breaking Barriers in Quantum Circuit Optimization With Efficient and Noise-Resilient Real-Time Adaptation

Tomar, Yash (School: West Lafayette Junior/Senior High School)

Due to the inherently noisy and error-prone nature of modern quantum hardware, optimizing quantum circuit (QC) layouts is a fundamental challenge in quantum computing. Modern industrial optimization tools often overlook devices' calibration fluctuations, leading to suboptimal solutions & increased error rates during execution. To address this, this project presents the first reinforcement learning (RL)-based algorithm that adapts to quantum devices' calibration shifts & hardware constraints. The algorithm was trained in an online learning-based environment, which continuously updates qubit error rates, coherence times, & connectivity constraints using a custom noise built from real calibration data (e.g., "ibm_torino") & was dynamically updated at each timestep. Using a custom reward function, the algorithm optimizes the QC with respect to coherence & connectivity constraints, reduces overall circuit depth, & maintains high state fidelity. Using Monte-Carlo validation, the developed algorithm achieved 49.34% depth reduction ($p = 0.0004$) & 50.30% fidelity increase ($p = 0.0021$) when optimizing QCs. When benchmarking against standard optimization tools (Qiskit Optimizer Level 3, PassManager, Tket, PyZX), the algorithm outperformed each tool by an average of 79.03% on random circuits ($p < 0.0001$, sample size = 30). This project successfully implements 1) a novel QC optimizer tool that respects calibration shifts and is 125-300X more cost-efficient than current algorithms 2) a realistic, online learning-based environment for future algorithm development. This project ultimately identifies & solves a problem neglected by experts in the field, leading to breakthrough-level results & coming closer to more error-resilient computations.

Awards Won: