Scalable Quantum Error Decoding With Sparse Graph Neural Networks

Wang, Kuan Yi (School: Marianopolis College)

Xu, Bill (School: Marianopolis College)

Quantum computers encode information in qubits, which are susceptible to physical noise. To protect information, quantum systems use error correction codes like the surface code, detecting errors through repeated syndrome measurements. Decoders must interpret syndromes accurately and quickly; approaches range from classical algorithms like minimum weight perfect matching to neural networks. Neural decoders take fixed-size inputs tied to one code size, requiring a new model for every larger processor. This project investigated whether graph neural networks (GNNs) on sparse graphs can outperform standard neural decoders and generalize to unseen code sizes. Syndrome data were generated with Google's Stim simulator for six code sizes (d = 3 through 13, where larger d protects against more errors) at eight physical error rates. Measurements were converted into sparse graphs where only triggered detectors became nodes, producing inputs that scale with error count, not processor size. Among four GNN architectures tested, GraphSAGE achieved the best accuracy. GraphSAGE achieved the lowest logical error rate among neural decoders. GraphSAGE outperformed the neural baseline at every code size, achieving 4-7× lower logical error rate at large d, using five to seven times fewer parameters. In extrapolation tests, models trained only on small codes (d = 3, 5, 7) were evaluated on unseen codes (d = 9, 11, 13). GraphSAGE significantly outperformed a non-graph baseline at all extrapolation distances (p less than 0.001), confirming that graph structure drives generalization. Sparse GNN decoders offer favorable scaling in logical error rate, efficiency, and generalization, essential for scaling real-time quantum error decoding.

Awards Won:

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