Benchmarking Quantum Convolutional Neural Networks for Classification and Data Compression Tasks

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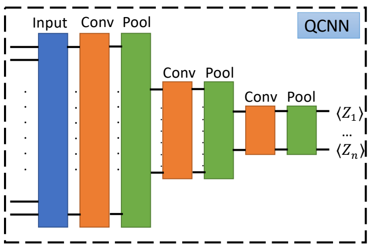
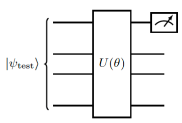
Introduction

Quantum machine learning leverages on quantum parallelism and entanglement to enhance classical machine learning algorithms performance. Quantum Convolutional Neural Networks (QCNNs) have shown significant potential in classification tasks by exploiting quantum parallelism and entanglement to process quantum data with short range entanglement structure, and avoids the notorious barren plateau problem by construction due to its logarithmic circuit depth. Here we [1] compare the efficiency of QCNN with that of the hardware-efficient ansatz (HEA) in classifying the ground states of two quantum models. We have also studied the compression capabilities of the ground states of one quantum model.

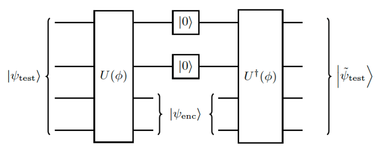
Methodology

- HEA consists of alternating layers of single-qubit rotations and entangling gates
- HEA RX-RZ-RX gates replaced by HEA RY gates achieves good performance
- QCNN [2] extends the classical CNNs to quantum data
- We replace the default complex QCNN to RY and real variants with a smaller number of parameters for shorter run time





Quantum phase classification



Quantum data compression

Ground states of the Transverse Field Ising (TFI) model and XXZ model are used for classification and data compression

$$\mathscr{H}_{\text{TFI}} = -\sum_{j=1}^{N-1} \sigma_j^z \sigma_{j+1}^z - h \sum_{j=1}^{N} \sigma_j^x, \quad (1)$$

$$\mathscr{H}_{\text{XXZ}} = -\sum_{j=1}^{N-1} \left(\sigma_j^x \sigma_{j+1}^x + \sigma_j^y \sigma_{j+1}^y + h \sigma_j^z \sigma_{j+1}^z\right). \quad (2)$$

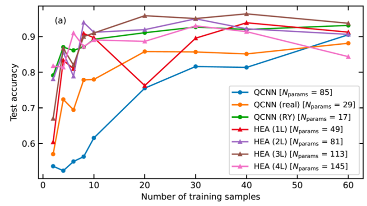
Phase classification

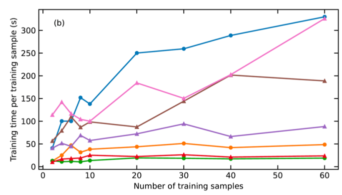
We adopt the conventional quantum classifier setup, in which the test state $|\psi_{test}\rangle$ with label $l = \pm 1$ is passed into the trained model $U(\theta)$ with optimized parameters θ. The label p predicted by the model is given by $p = sign\langle\psi_{test}|U^\dagger(\theta) Z_0 U(\theta)|\psi_{test}\rangle$

Data compression

In the encoding phase, the test state $|\psi_{test}\rangle$ is passed into the trained encoder $U(\phi)$ with optimized parameters ϕ, and finally applying reset gates to the qubits to be discarded to obtain the encoded state $|\psi_{enc}\rangle$ of the remaining qubits. In the decoding phase, $|\psi_{enc}\rangle$ is passed with $|0\rangle$ states of the discarded quibits into the trained decoder $U^\dagger(\phi)$ to obtain the decoded test state $|\psi'_{test}\rangle$. The quality of encoder can be determined by the overlap $|\langle\psi'_{test}|\psi_{test}\rangle|^2$

Results & Discussions





Best Models	Test Accuracy	Training Time / sample	N_{params}
QCNN (RY)	0.931	18.7s	17
HEA (3L)	0.938	188.7s	113

- For the same number of trainable parameters, QCNN with RY gates is the most efficient architecture for classifying the quantum ground states
  - Great reduction in training times due to much fewer trainable parameters
- HEAs show an increasing performance with expressibility (number of layers) but with a corresponding increasing run time per training data
- For compression tasks, we obtain high reconstruction fidelities implying that all evaluated models are capable of compressing TFI model ground states
  - .QCNNs demonstrated faster training convergence
  - This demonstrates one key advantage of QCNN architecture --- lower number of training parameters leading to faster convergence and less trainability issues, with minimal tradeoff in compression capability

Conclusions

We demonstrated the effectiveness of QCNNs (with RY gates) in quantum phase classification and data compression tasks. Consistent across both tasks, we find that QCNNs not only achieve similar performance to HEAs but also also benefit from shorter training time due to a simpler structure. The simulation results will be compared against the implementation on hardware using the Qibolab software.

[1] https://arxiv.org/abs/2411.13468
[2] I. Cong, S. Choi, M. D. Lukin, "Quantum Convolutional Neural Network", *Nat. Phys.* 15, 1273 (2019)

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