



Quantum data learning of phase transitions

Tanmoy Bhattacharya (tanmoy@lanl.gov)

Los Alamos National Laboratory

**(with Shamminuj Aktar, Andreas Bärtschi, Rishabh Bharadwaj,
and Stephan Eidenbenz)**

July 29, 2026

43rd International Symposium on Lattice Field Theory

LA-UR-25-30864



Managed by Triad National Security, LLC, for the U.S. Department of Energy's NNSA.

Jul 29, 2026

Abstract

Quantum data learning (QDL) provides a framework for extracting physical insights directly from quantum states. In this presentation we develop QDL techniques for detecting the phase transition in the 2+1-dimensional toric-code loop-gas model in a magnetic field. Our unsupervised QDL approach recovers the phase structure and locates the phase transition with a small offset as expected in finite volumes; both supervised and unsupervised QDL methods outperform classical alternatives. These findings establish QDL as an effective framework for characterizing topological quantum matter, studying finite volume effects, and probing phase diagrams. (arXiv:2511.16851 [quant-ph])

Outline

Introduction

Supervised Learning

Unsupervised Learning

Conclusions

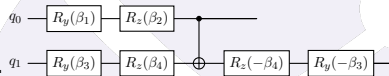
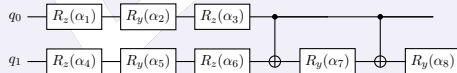
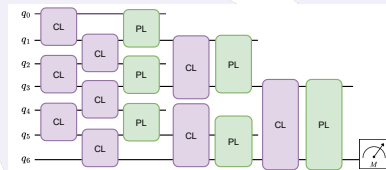
Introduction

Quantum Data Learning

- QDL is a type of Quantum Machine Learning
- It is a quantum circuit
 - that takes a quantum state as input
 - that ends with a measurement
 - whose parameters are trained
- Training is a classical choice of parameters
- We use a QCNN that alternates
 - Convolutional Layers (two-qubit gates)
 - Pooling layers (single-qubit rotations + controlled not + discard)

followed by single-qubit rotation and measurement.

- $y_{\text{out}}^{\phi} = \text{Tr } Z_{\text{out}} U_{\text{QCNN}}(\phi) \rho U_{\text{QCNN}}(\phi).$



Introduction

Toric Code Model

- The qubits live on links on a 2-dimensional square lattice.

$$H_{\text{TCM}} = - \sum_{\text{site}} \prod_{\text{link} \ni \text{site}} \sigma_{\text{link}}^x - \sum_{\text{plaq}} \prod_{\text{link} \in \text{plaq}} \sigma_{\text{link}}^z$$

- Open boundary conditions stop degenerate superposition of Wilson line states.
- OBC produces anyons, but maintains long-range topological order.
- We study the ferromagnetic perturbation that produces aligned spins.

$$H(x) = (1 - x)H_{\text{TCM}} - x \sum_{\text{link}} \sigma_{\text{link}}^z$$

- The infinite system has a phase transition at $x_c \approx 0.25$.
- Order parameter: Magnetization $m_z = \langle \sigma_{\text{link}}^z \rangle_{\text{average}}$.

Introduction

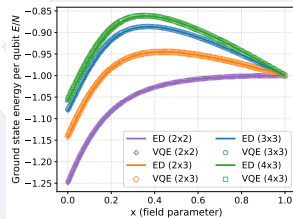
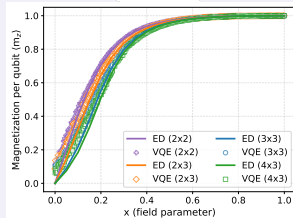
Ground State Preparation

- Use Variational Quantum Eigensolver technique
- Use the ansatz

$$|\psi(\theta)\rangle = \prod_p \left[\cos \frac{\theta_p}{2} + \sin \frac{\theta_p}{2} \prod_{i \in p} \sigma_i^x \right] \bigotimes_i |0\rangle$$

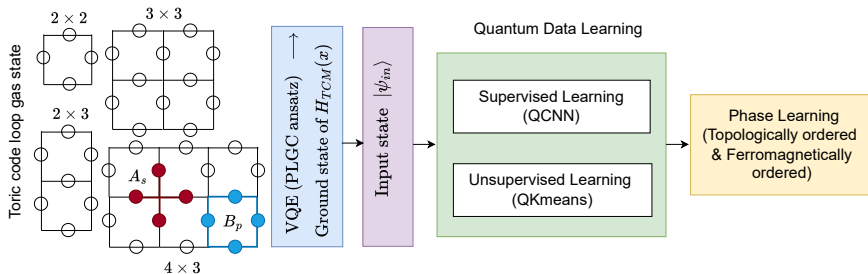
that creates a superposition of loops.

- Use classical minimization of measured energy.



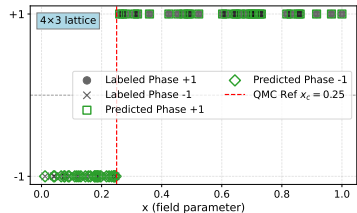
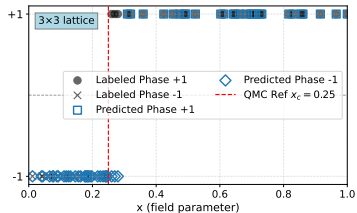
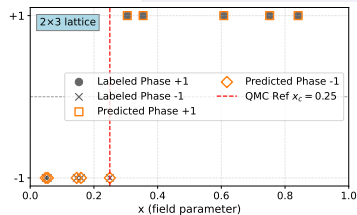
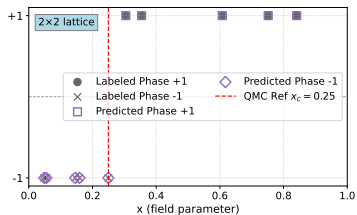
Introduction

Overall strategy



Supervised Learning Classification

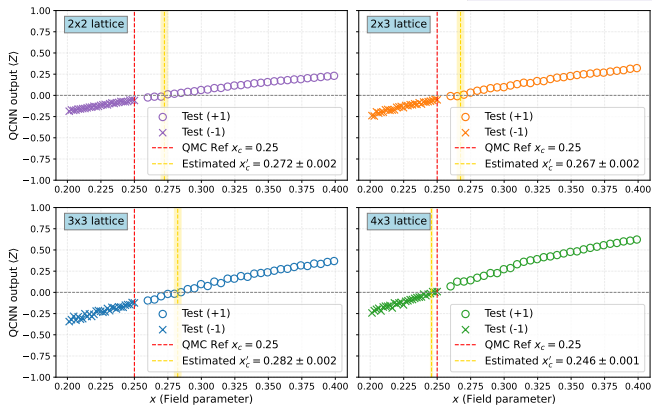
Define $x = 0.25$ as the phase boundary and train.



Supervised Learning

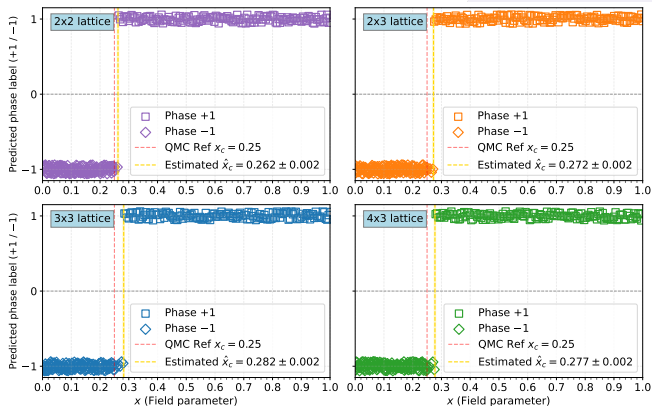
Determining phase boundary

Train only on samples $x \notin [0.2, 0.4]$.



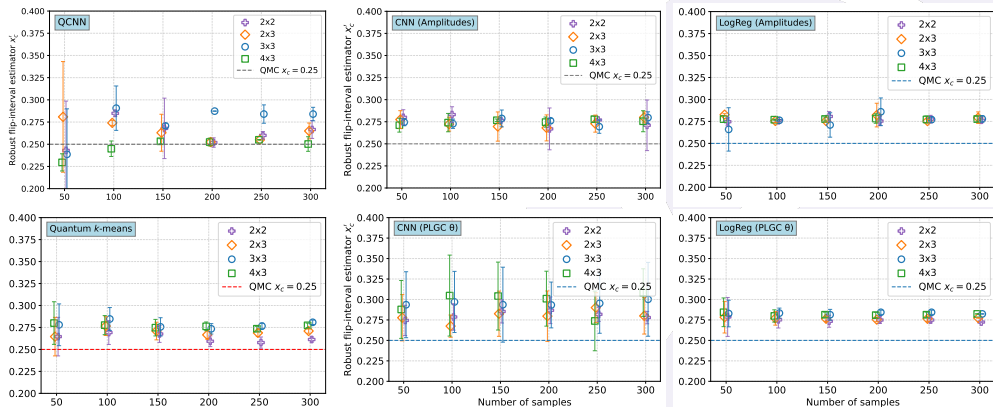
Unsupervised Learning Results

k -means clustering into two sets based on Hilbert-Schmidt metric: $\sqrt{2(1 - F)}$.



Conclusions

Comparison between quantum and classical results



Further studies needed to understand finite size effects.