Quantum Machine Learning for Quantum Many-Body Systems

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MOTIVATION

1. **Advancements in Traditional Machine Learning**: Traditional machine learning models have been successful in exploring chemical space by predicting molecular properties, helping to discover new chemical compounds based on desired characteristics.

2. **Quantum Machine Learning (QML) for Broader Exploration**: The rise of QML is expected to enhance the exploration of materials, speeding up the discovery of compounds with properties suited for sustainable and efficient technologies.

3. **Challenges in Studying Many-Body Systems**: Many-body systems, made up of many interacting particles, are governed by quantum mechanics, making them complex and difficult to predict. Classical algorithms struggle to handle the vast quantum state spaces involved.

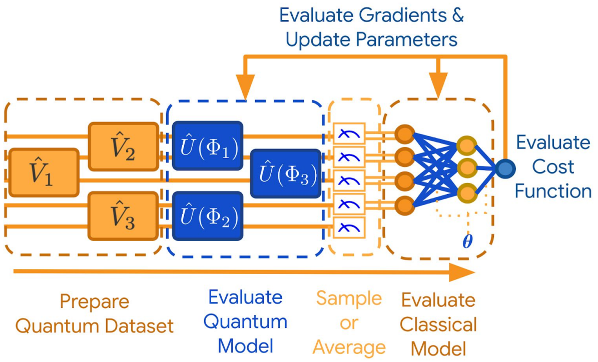
4. **Quantum Neural Networks in Condensed Matter Physics**: QML, using quantum neural networks, can efficiently analyze and classify quantum phases of matter (like superconductivity) by observing features such as magnetic fields, which could lead to breakthroughs in material science.

Quantum Machine Learning

- Quantum models represent and generalize data with quantum properties like superposition and entanglement, requiring significant classical resources to store.

- Quantum data can be generated or simulated on quantum processors, sensors, or networks.

- Applications include chemical simulation, quantum control, quantum communication networks, and quantum metrology.



Classifying topological and trivial phases in a superconducting system:

Topological vs. Trivial Phases:

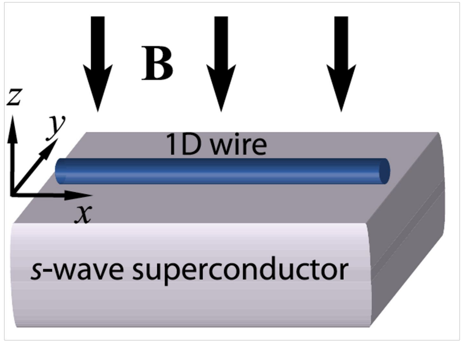
- Topological phase: Exhibits robust quantum properties, protected against small perturbations.
- Trivial phase: Conventional matter without these robust properties.

Majorana Modes:

- Quasiparticles that are their own antiparticles, appearing at the ends of a superconducting wire in the topological phase.

Requirements for a Topological Phase:

- A **gapped superconductor** (e.g., Aluminium).
- **Spin-orbit coupling** (e.g., InAs nanowire).
- An **external magnetic field**.



Phase Transition Condition:

- Topological phase occurs when $B_z^2 > \mu^2 + \Delta^2$, where Δ is the superconducting gap.

Key Outcome:

- Majorana modes are robust against perturbations, making them ideal for quantum computing applications.

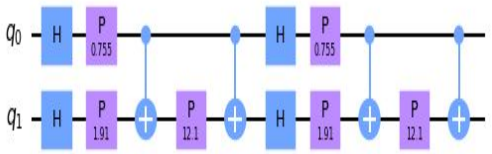
Quantum Neural Network Setup

1. **Data Preparation**
   Normalize Bz and μ w.r.t superconducting gap Δ

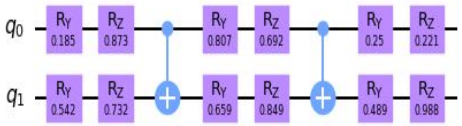
2. **Feature Mapping**
   ZZFeatureMap for data embedding into quantum circuit

3. **Variational Circuit**
   TwoLocal ansatz with customizable rotations and entanglement

4. **Measurement**
   Single-qubit or parity measurement for classification



ZZFeature Map



TwoLocal

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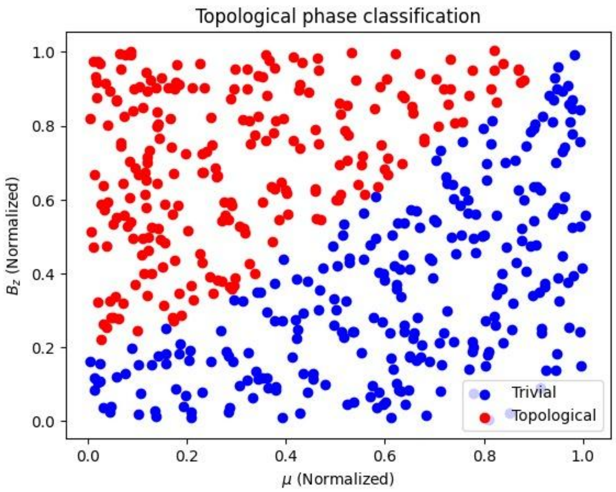
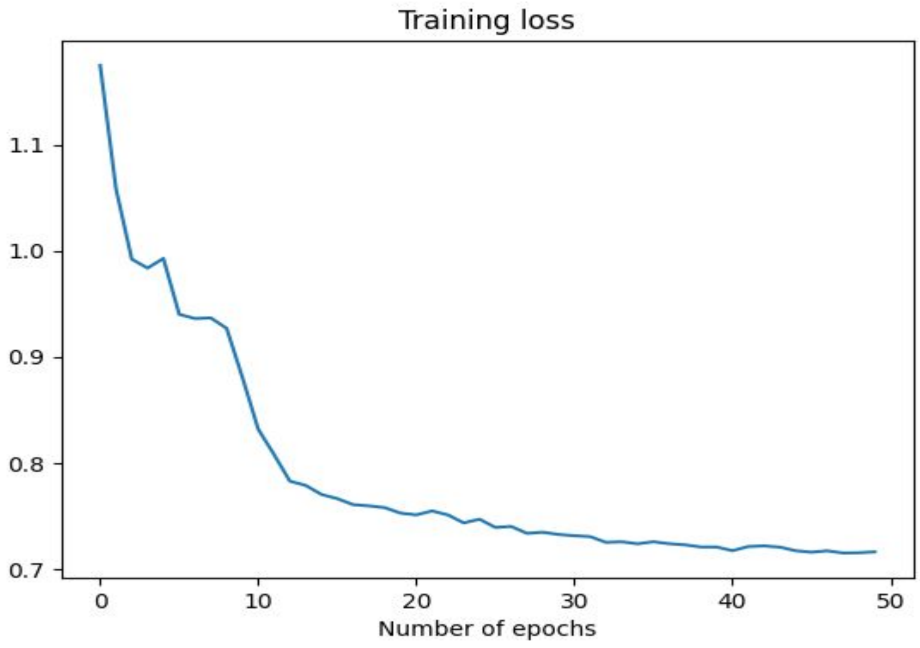
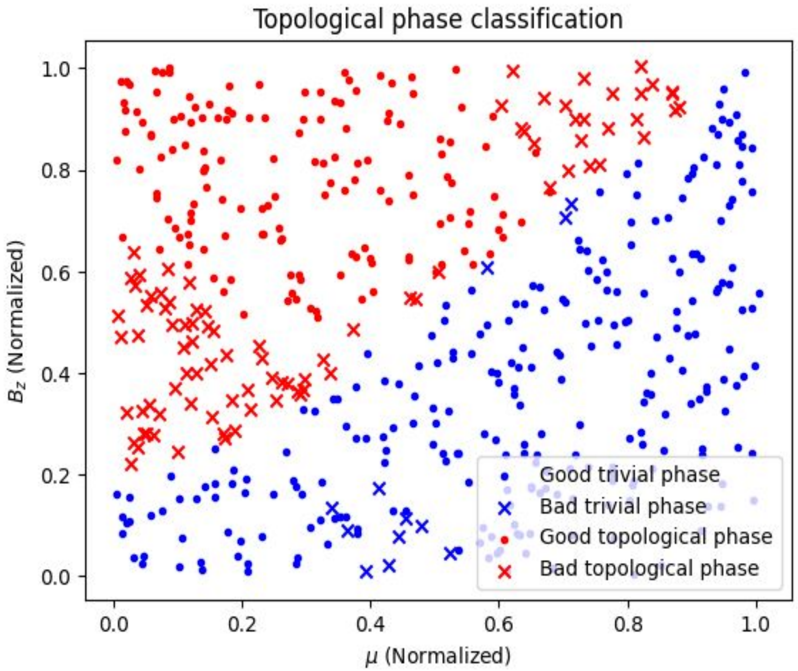


Results:


Training loss
1.1
1.0
0.9
0.8
0.7
0
10
20
30
40
50
Number of epochs


Topological phase classification
B_z (Normalized)
μ (Normalized)
0.0
0.2
0.4
0.6
0.8
1.0
Good trivial phase
Bad trivial phase
Good topological phase
Bad topological phase

Pros And Cons of QML:

Pros:

- **Potential for exponential speedups**
- **Handling high-dimensional data**
- **New model capabilities**
- **Probabilistic nature**

Cons:

- **Limited practical applications**
- **Training challenges**
- **Cost and accessibility**
- **Complexity in developing QML models**