QUANTUM COMPUTING

# Circuit Complexity Links Fidelity, Entanglement in Many-Body Unsupervised Machine Learning

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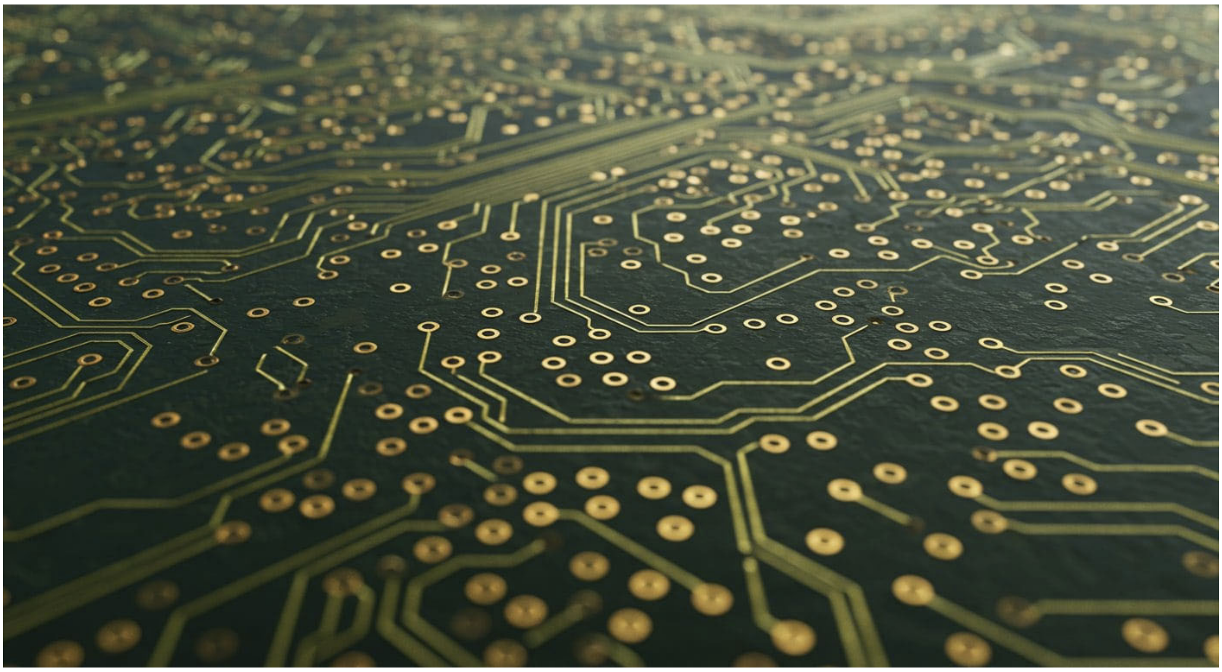

The challenge of identifying hidden order within complex physical systems receives a boost from new research exploring the link between quantum circuit complexity and unsupervised machine learning. Yanming Che from the University of Michigan, Clemens Gneiting and Franco Nori from RIKEN, along with Xiaoguang Wang from Zhejiang Sci-Tech University, demonstrate how measuring the complexity of quantum circuits can improve the efficiency and interpretability of algorithms designed to uncover patterns in many-body systems. The team establishes a direct connection between circuit complexity and measurable quantities like fidelity and entanglement, allowing them to formulate practical similarity measures for use in machine learning. Through numerical experiments on various quantum models, including the bond-alternating XXZ spin chain and Kitaev's toric code, they show these new methods outperform existing approaches, offering a powerful new tool for understanding and classifying quantum phases of matter.

In machine learning, researchers explore quantum circuit complexity, a key concept in quantum computation and quantum information science, to build interpretable and efficient unsupervised machine learning methods for understanding quantum many-body systems exhibiting topological order. To bridge the gap between theoretical concepts and practical applications, the team presents two theorems that connect Nielsen's quantum circuit complexity with changes in fidelity and the generation of entanglement, enabling the creation of fidelity-based and entanglement-based similarity measures, known as kernels, more readily implemented in practical algorithms.

## Quantum Machine Learning Landscape and References

This collection of references covers a broad range of topics within quantum machine learning, many-body physics, quantum error correction, and related fields, demonstrating a growing interest in using quantum algorithms to improve machine learning tasks and applying machine learning techniques to enhance quantum systems. Foundational work by Biamonte and colleagues introduces the field of quantum machine learning, while Bartkiewicz and colleagues demonstrate experimental kernel-based quantum machine learning. Recent studies explore quantum neural networks, such as the QKAN introduced by Ivashkov and colleagues, and the use of reinforcement learning for preparing quantum ground states, optimizing circuits, and performing error correction. The references also highlight significant progress in understanding and simulating complex quantum systems, with tensor networks, a dominant technique in this area, explored by Schollwoeck and colleagues, and Vermersch and colleagues demonstrating their use for enhanced estimation of quantum properties.

Studies on entanglement and area laws, led by Bravyi and colleagues, explore the relationship between entanglement, the size of quantum systems, and the stability of quantum states, while key papers by Pollmann and Turner investigate symmetry-protected topological phases, and Elben and colleagues demonstrate the detection of topological invariants using randomized measurements. Recent work by Granet and colleagues explores entanglement transitions in measurement-only circuits, and a growing body of research focuses on mixed-state topological order. Albash and Lidar provide a comprehensive review of adiabatic quantum computation, a promising approach to solving complex optimization problems. The collection also covers essential aspects of quantum error correction and quantum information theory, with Liu and colleagues focusing on quantum Fisher information and multiparameter estimation, and Taddei and colleagues discussing the quantum speed limit for physical processes. Foundational texts by Helstrom and Holevo lay the groundwork for quantum detection and estimation theory, and studies by Hutter and Wehner, and Van Acoleyen and colleagues, explore the limits on entanglement generation and the stability of quantum states. Emerging trends include hybrid quantum-classical machine learning, reinforcement learning for quantum control, topological order in mixed states, and the continued development of quantum simulation techniques using tensor networks, all aiming to demonstrate a quantum advantage for specific tasks.

## Quantum Circuits Reveal Topological Phase Transitions

Researchers have established a new connection between quantum complexity and the ability to identify and categorize different phases of matter, particularly those exhibiting complex topological order, addressing a significant challenge in physics: detecting topological phases defined by global properties. Existing methods often struggle with strongly interacting quantum systems, where traditional approaches become inefficient. The team proposes a novel approach based on the idea that topologically equivalent quantum states can be connected by relatively simple quantum circuits, building on the concept of quantum circuit complexity, which measures the cost of transforming one quantum state into another. By using this complexity as a measure of distance between states, researchers developed new kernels, mathematical tools that allow machine learning algorithms to identify patterns and group similar states together.

Experiments demonstrate that these new kernels significantly outperform existing methods in clustering different quantum phases, including the bond-alternating XXZ spin chain, the ground state of Kitaev’s toric code, and random quantum states. The improved performance stems from the ability of the new approach to capture the intricate entanglement patterns characteristic of topological order at multiple scales, offering a potentially optimal solution for unsupervised machine learning and establishing a link between quantum complexity and classifying quantum phases of matter. By framing the problem in terms of minimal quantum circuit cost, researchers provide a theoretically grounded approach to unsupervised learning, opening new avenues for both fundamental research and potential applications in materials science and quantum technologies.

## Quantum Kernels Reveal Hidden Quantum Order

This research establishes a connection between quantum circuit complexity and unsupervised machine learning, offering a new approach to identifying order in complex quantum systems. By leveraging Nielsen's quantum circuit complexity, the team developed practical kernels, mathematical functions that measure similarity, based on fidelity and entanglement. Numerical experiments demonstrate these kernels effectively cluster different quantum phases, outperforming existing methods in clarity and interpretability, particularly when applied to the bond-alternating XXZ spin chain. The study's significance lies in its ability to provide both accurate and understandable results, a crucial combination for advancing the field of topological quantum order. The entanglement-based kernel proved robust against noise and offered insights into the relationship between long-range entanglement and topological phases. While the current work focuses on pure and gapped ground states, the authors acknowledge limitations and suggest promising avenues for future research, including applications to gapless systems, entanglement transitions, and mixed-state topological order, as well as exploring quantum machine learning techniques and combining their approach with reinforcement learning for quantum state generation, potentially leading to even more powerful tools for understanding and manipulating complex quantum systems.

👉 More information
🗞 *Quantum circuit complexity and unsupervised machine learning of topological order*
🧠 ArXiv: https://arxiv.org/abs/2508.04486

CIRCUIT COMPLEXITY | ENTANGLEMENT | FIDELITY | MANY-BODY SYSTEMS | SHADOW KERNEL LEARNING | SIMILARITY MEASURES | TORIC CODE | UNSUPERVISED MACHINE LEARNING | XXZ SPIN CHAIN