Quantum Machine Learning on Near-term Hardware

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***Abstract*—Machine learning has revolutionized data analysis and prediction, but quantum computing offers the potential to unlock entirely new capabilities beyond classical limits. Though powerful, today's quantum hardware remains in the noisy intermediate-scale quantum (NISQ) stage, with noise and qubit count constraints limiting practical applications. This paper reviews the framework of parametrized quantum circuits (PQCs), a flexible approach designed to achieve quantum advantages within the constraints of near-term quantum devices. Despite their promise, PQCs face many open questions regarding use case-specific design, data encoding, training efficiency, and robustness, making them an active area of research in quantum machine learning.**

***Index Terms*—quantum machine learning, parametrized quantum circuit, NISQ hardware, review**

I. INTRODUCTION

Machine learning has reshaped fields such as computer vision, natural language processing, and scientific research by uncovering complex patterns in data and providing tools for high-quality predictions. However, as datasets grow and tasks increase in complexity, classical machine learning faces limitations in computational efficiency and scalability. Quantum computing — a paradigm that leverages quantum mechanics principles like superposition and entanglement — has the potential to overcome some of these barriers, offering advantages in speed, memory efficiency, and model complexity beyond classical limits. [1]

Despite the theoretical promise of quantum machine learning (QML), practical solutions are constrained by the limitations of current noisy intermediate-scale quantum (NISQ) devices. These constraints require innovative strategies to achieve quantum advantage, with parametrized quantum circuits (PQCs) being one of the leading approaches [2]. PQCs enable the construction of QML models that leverage quantum properties but can be trained classically, akin to neural networks, thus relaxing hardware requirements. This paper explores PQCs as a foundational approach for advancing QML in the NISQ era [3, 2].

II. WHY QUANTUM?

The quantum advantage stems from the fundamental differences between classical and quantum information. While classical bits are limited to states of either **0** or **1**, qubits can exist in superpositions of both: $a_0|\mathbf{0}\rangle + a_1|\mathbf{1}\rangle$, where $a_0^2 + a_1^2 = 1$. This extends to systems of multiple qubits, enabling an n-qubit register to store all 2^n possible states simultaneously. In the context of QML, this has two key implications: first, quantum systems can encode data using exponentially fewer memory resources, potentially addressing big data challenges intractable on classical hardware. Second, superposition enables quantum parallelism, allowing quantum algorithms to achieve speedups over classical ones. An example is Grover's algorithm for unsorted database searches, which provides a quadratic speedup and can be applied to accelerate model optimization in QML.

Another key aspect of quantum computing is its probabilistic nature. While both classical and quantum operations are deterministic, measuring a quantum system collapses its state into one of the basis states, with a probability proportional to the square of its coefficient (for a single qubit the outcome is either $|\mathbf{0}\rangle$ with probability a_0^2 or $|\mathbf{1}\rangle$ with probability a_1^2). This introduces a layer of complexity that distinguishes quantum from classical computing. A fundamental consequence is quantum entanglement, where quantum states become correlated in ways that exponentially increase their expressive power. This enables quantum systems to uncover correlations in data that would be difficult or impossible for classical algorithms to detect. Additionally, quantum entanglement allows for a richer feature space and more expressive models, as the mathematical space describing quantum systems scales exponentially. It is up to quantum software engineers and researchers to develop innovative methods to exploit these additional dimensions. [1]

III. NEAR-TERM QUANTUM HARDWARE

NISQ devices, with neutral atoms and superconducting qubits as leading physical platforms, face significant limitations that affect algorithm design. High levels of quantum noise and short coherence times — the period a quantum system retains its quantum state before it decoheres into classical information — restrict computation duration and complexity. An additional problem is the limited number of qubits, typically tens to a few hundred, and poor qubit connectivity, which restricts the types of entangled states that can be created and limits the expressive power of quantum algorithms. [1, 2]

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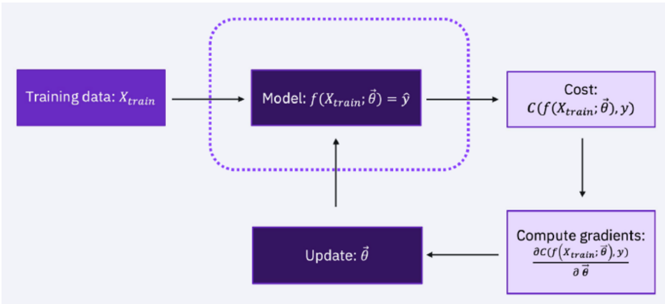

Fig. 1: Near-term QML framework. Training data is passed through the PQC model, a cost function is calculated, and parameters are updated via optimization methods. Only computing the PQC model requires quantum resources, while all other calculations are performed on classical hardware. Image credit: [6]

Designing noise-resilient algorithms that rely on noise suppression and mitigation, rather than on full error correction, is essential for making practical use of current NISQ devices. Quantum neural networks (QNNs) implemented as PQCs are a key example, as they leverage quantum properties like superposition and entanglement while being able to operate effectively in noisy environments [4, 2, 5]. In general, many theoretical quantum algorithms have unrealistic requirements, such as long coherence times, high qubit counts and full connectivity, that are far beyond what is achievable with today's hardware. There is a growing need to bridge this gap by developing algorithms that can function within the constraints of current NISQ devices, such as the framework of QML with PQC discussed in the following section. [1, 2]

IV. Quantum Machine Learning

Near-term QML largely follows the classical machine learning framework. Following Fig. 1, the training data is passed through a parametrized model, and a cost function is calculated based on the difference between predicted and true values. Due to the probabilistic nature of quantum computing, the PQC runs multiple times to get an accurate expectation value for the cost function. Optimization methods like gradient descent then update the model parameters, and the cycle is repeated until optimal accuracy. The key is that only the model (PQC) requires quantum resources; all other calculations, such as cost evaluation and parameter updates, are performed on classical hardware. This hybrid approach leverages quantum circuits to process data in a quantum-enhanced feature space while maintaining efficiency by handling optimization and auxiliary tasks on classical systems. This design keeps computation times compatible with the coherence limits of NISQ devices, enabling the model to exploit quantum advantages without requiring prolonged, noise-sensitive quantum operations. All steps of the process are active areas of research. [1, 3, 2]

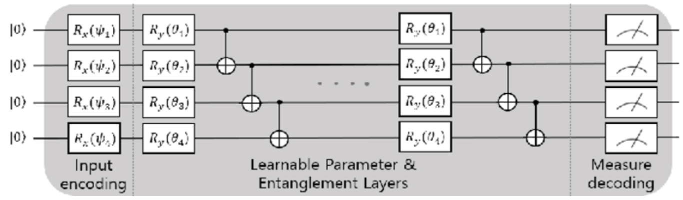

Fig. 2: Parametrized quantum circuit (PQC). The main elements are single-qubit parametrized rotations (here $R_y(\theta)$) and entangling gates that exploit quantum correlations (here $CNOT$). Image credit: [8]

A. Input Encoding

Data encoding is crucial in QML, translating classical data into quantum states [1]. A good example of the trade-off between memory efficiency and speed is provided by amplitude encoding, which efficiently represents 2^n data points with only n qubits, but is too time-intensive for NISQ devices, as encoding times often surpass qubit coherence limits [7]. This challenge drives active research, especially for tasks like image classification, where current schemes don't account for spatial structure, underscoring the need for encoding methods that balance fidelity with realistic hardware constraints [2, 4].

B. The model: Parametrized Quantum Circuits

As shown in Fig. 2, PQCs feature two main components: learnable parameters via single-qubit parametrized rotations and entangling gates that exploit quantum correlations [8]. Arranged in layers, these elements form quantum neural networks (QNNs) that can parallel classical architectures [4]. Research indicates that QNNs may offer enhanced generalization capabilities and resilience to noise, making them well-suited for NISQ devices [5]. Notably, QNNs have been successfully run on hardware without error correction, demonstrating practical feasibility [2]. However, scaling QNNs to larger systems relevant to real-world applications and establishing rigorous benchmarks for quantum advantage remain significant challenges [1].

A recurrent issue in training PQC-based QML models is the formation of barren plateaus, where the optimization landscape flattens as circuit depth or qubit count grows, leading to vanishing gradients and hindering parameter updates by classical optimization methods [5]. This challenge can, however, be mitigated through careful data encoding, the design of improved quantum model architectures — such as quantum convolutional neural networks (QCNNs), which have structures that reduce the occurrence of barren plateaus [9] — or by using gradient-free optimization techniques [2].

V. Conclusion

QML with PQCs is a promising approach for near-term practical applications, as it offloads the optimization process to classical hardware, thus alleviating the hardware constraints of current quantum devices [3]. To realize its full potential, it is essential to bridge the gap between theoretical models and the limitations of existing hardware, providing proof of practical quantum advantage. Further research into end-to-end solutions, noise-resilient models, and even exploiting quantum noise as a resource [10, 11] is critical for advancing the field. Additionally, given the maturity gap between classical and quantum technologies, it is crucial to explore diverse sources of quantum advantage beyond just quantum speedup, considering other aspects such as model expressiveness and resilience, to maximize the impact of QML in real-world applications. [1]

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