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A SHORT REVIEW ON QUANTUM MACHINE LEARNING

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ABSTRACT. Quantum Machine Learning (QML) integrates two prosperous scientific fields: quantum computing and artificial intelligence. We will review recent developments in QML-based methods, their theoretical foundations, algorithmic progress, practical applications, and remaining issues. By analyzing contemporary QML literature, we will identify its main strengths and weaknesses that guide the pursuit of achieving quantum advantage in machine learning tasks.

Keywords: quantum computing, machine learning, quantum advantage, quantum-inspired algorithms.

INTRODUCTION

Machine learning and neural networks have been the focus of intensive scientific research for several decades. A noticeable advancement of computing power has enabled the practical implementation of theoretical frameworks established in the 20th century, driving significant advancements in artificial intelligence in recent years. In recognition of the pioneering work that laid the foundation for modern machine learning models, John J. Hopfield and Geoffrey Hinton were awarded the 2024 Nobel Prize in Physics.

Quantum physics has fundamentally altered our understanding of Nature, where quantum computing is a computational paradigm based on the principles of quantum mechanics. The basic idea for using physical systems in efficiently simulating some complex tasks was introduced by Richard Feynman (FEYNMAN, 1999). His proposal was inspired by the limitations of classical computational methods in modeling quantum systems. Key quantum phenomena such as superposition and entanglement are the basis for exotic quantum algorithms, which enable quantum computers to perform complex parallel computations and encode information in fundamentally new ways. From theoretical point of view, these unique properties offer potential advantages in computational speed and efficiency, particularly for problems intractable for classical computers due to their exponential complexity. Quantum Machine Learning (QML) aims to leverage these capabilities to improve or redefine classical learning algorithms, promising faster and more efficient data processing integrated into advanced artificial intelligence systems.

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CLASSIFICATION OF QUANTUM MACHINE LEARNING APPROACHES

Most literature usually recognizes four characteristic approaches on which QML is based. These approaches differ according to whether the data or the algorithms for their processing are classical (C) or quantum (Q). A traditional schematic view of combining quantum computing and machine learning is displayed in Fig. 1.

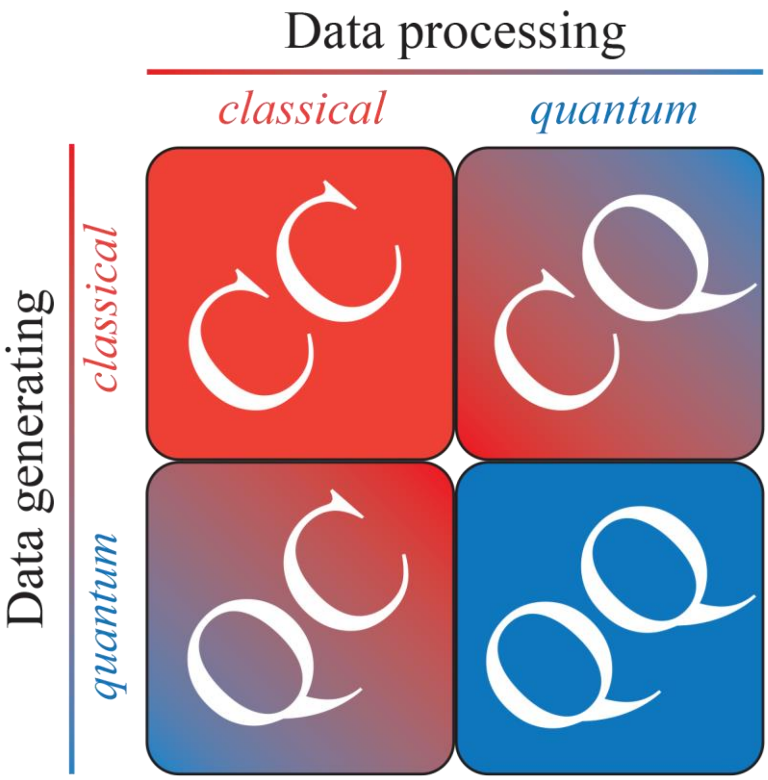

Figure 1. A schematic view of combining quantum computing and machine learning (The figure is adapted from https://commons.wikimedia.org/wiki/File:Qml_approaches.tif?page=1 (CC BY-SA 4.0) by Maria Schuld).

The CC approach relies on both classical data and computational techniques. In this context, machine learning is based on quantum mechanical principles, hence, it is commonly referred to as 'quantum-inspired' (or 'quantum-like') machine learning algorithms. The idea of utilizing quantum mechanics in classical computing was introduced by MOORE and NARAYANAN (1995). First successful quantum-inspired (Qi) algorithms include optimization techniques such as evolutionary algorithms (QiEA) (HAN and KIM, 2013), genetic algorithms (QiGA) (NARAYANAN and MOORE, 1996; HAN *et al*., 2001), Particle Swarm Optimization (QiPSO) (SUN *et al.*, 2004) and Quantum Simulated Annealing (QSA) (SOMMA *et al.*, 2007). A detailed review of such quantum-inspired metaheuristic algorithms can be found in (GHAREHCHOPOGH, 2022). In recent years, several quantum-inspired techniques have been developed beyond optimization. Most found inspiration in quantum algorithms, imposing classical counterparts to quantum-based machine learning methods. These methods, implemented on classical hardware, circumvent some main drawbacks of genuine quantum computing, such as limited number and connectivity of noise-prone physical qubits and costly requirements for quantum state preparation. Consequently, a few quantum-inspired algorithms harvesting benefits of quantum speedup are developed, such as *dequantized algorithms* (SCHULD and PETRUCCIONE, 2021; TANG, 2022), *tensor networks* (CARRASQUILLA, 2020; ALCHIERI *et al.*, 2021), *classical simulations of quantum variational algorithms* and alternative methods that incorporate quantum phenomena and adapt it to classical settings (HUYNH *et al.*, 2023).

The QC methods use quantum data and classical processing. They are usually utilized to analyze the measurement data employing conventional machine learning (AARONSON, 2007). These are particularly useful for manipulating data obtained via quantum experiments (SASAKI and CARLINI, 2002; BISIO *et al.*, 2010).

The CQ systems explore classical data using quantum systems. The most common objective of this methodology is to use existing or create new quantum algorithms to be used in data mining. Classical input data originating from text or images is appropriately encoded and fed to the quantum computer for further evaluation and analysis (ZEGUENDRY *et al.*, 2023).

Finally, the QQ techniques use algorithms and data, which are both quantum in nature. This category examines the processing of quantum data using quantum devices, either by inputting experimental measurements into a quantum computer or by employing a quantum computer to simulate and analyze the behavior of quantum systems. In the former case, a quantum computer simulates the behavior of analyzed quantum system and uses its state as input for a quantum machine learning algorithm executed on the same computer (JIANG, 2023).

Due to the progressive evolution of QML in many practical areas, a more suitable contemporary categorization scheme is proposed (ABOHASHIMA *et al.*, 2020; HUYNH *et al.*, 2023):

- **Quantum Machine Learning** that includes various quantum adaptations of classical machine learning algorithms that require quantum computation for their execution.
- **Quantum-inspired Machine Learning**, which integrates quantum computing concepts to enhance traditional machine learning algorithms, without the actual necessity for quantum computation.
- **Hybrid Classical-Quantum Machine Learning**, which combines classical and quantum algorithms to optimize performance and minimize learning costs by exploiting the strengths of both approaches.

To explain the benefits of this new classification, let us consider the CQ and QQ systems. Here, CQ uses classical input data that should be encoded and fed into a quantum circuit. In this case, QQ can be seen as part of the CQ system. Moreover, some conventional algorithms may be executed before data encoding, thus making this approach hybrid. Using similar arguments and examples, one may show that the traditional classification does not make a clear boundary between ML models based on quantum mechanics. Therefore, an overview of QML methods will be given according to the above contemporary categorization.

QUANTUM MACHINE LEARNING ALGORITHMS

Quantum machine learning mainly leverages the inherent parallelism of quantum computing to enhance the efficiency and performance of classical machine learning algorithms. The basic principle of this approach is translating information (data) into quantum states, followed by applying unitary transformations to perform computational tasks. Realizing the potential speedups offered by quantum mechanics demands systematically adapting conventional algorithms to conform with fundamental constraints and operational principles of quantum computation.

Data encoding is a critical process in machine learning since it transforms "raw data" into a format that can be easily, precisely, and effectively processed by an algorithm. This is crucial in cases where the initial data format is unsuitable for direct use in computations or applications (e.g., for categorical variables). Instead of a conventional data fed to the input of an algorithm and generated at the output in classical machine learning, quantum machine learning deals with quantum states (data). Therefore, QML requires more intricate encoding. There are several strategies to encode conventional data into quantum (SCHULD and KILLORAN, 2019), where the three most important are (ZEGUENDRY *et al*., 2023):

- *Basic encoding* is the traditional bit-wise conversion of a binary string into equivalent state of a quantum system. One may use quantum superposition of a few (or all) states to perform parallel computing on all of them.
- *Amplitude encoding* is an approach in which normalized input vectors of dimension $N=2^n$ are associated with the amplitudes of a n qubit state.
- *Qsample encoding* is a hybrid quantum data representation that integrates amplitude and basis encoding, combining real-valued amplitude vectors with classical binary probability distributions.

More complex quantum QML circuits are based on elementary algorithms, such as Grover's (GROVER, 1997), Quantum Phase Estimation (KITAEV, 1995; NIELSEN and CHUANG, 2000), Harrow-Hassidim-Lloyd (HHL) algorithm (HARROW *et al.*, 2009), and Variational Quantum Circuit (VQC) (CEREZO *et al.*, 2021). The notable examples of QML applications are Quantum Support Vector Machines (QSVM) (ANGUITA *et al.*, 2003; REBENTROST *et al.*, 2014), Quantum Principal Component Analysis (QPCA) (LLOYD *et al.*, 2014), Quantum Linear Regression (SCHULD *et al.*, 2016), and Quantum Neural Network (DA SILVA *et al.*, 2016).

Quantum Support Vector Machines

Support Vector Machines (SVM) are a class of supervised learning algorithms commonly employed to address problems involving linear classification. The fundamental principle of SVM lies in constructing an optimal hyperplane that separates two distinct classes within a feature space. This hyperplane acts as a decision boundary for classifying new data points and its position in hyperspace is based on the principle of maximizing the margin between the hyperplane and the nearest data points from each class, known as support vectors. The optimization objective in SVM varies in convexity depending on the choice of the kernel function. In cases involving non-convex objective functions, optimization may converge to local optima, potentially compromising both efficiency and classification accuracy.

Quantum Support Vector Machines (QSVM) integrate Grover's algorithm (GA) as a quantum subroutine for optimization, enabling convergence to global optima even in the presence of non-convex cost functions (ANGUITA *et al.*, 2003). Therein, GA reduces the temporal (time) complexity of the SVM optimization task, particularly in the computation of the kernel matrix, which is typically among computationally the most expensive tasks. In this quantum framework, the objective function is assumed to be accessible via a quantum oracle. Additionally, an alternative quantum SVM method proposed in REBENTROST *et al.* (2014) exhibits exponential speedup over classical counterparts, without imposing constraints on the optimization problem.

Quantum Principal Component Analysis

Classical Principal Component Analysis (C-PCA) is one technique for dimensionality reduction in machine learning tasks. It performs the transposition of the covariance matrix into diagonal form. The covariance matrix summarizes the relations between various data elements. Principal components refer to the few relatively large eigenvalues (that are, *primary* or *principal*) compared to the rest, which are selected as the new feature vectors.

Conventional PCA exhibits a runtime complexity of $O(d^2)$, where d denotes the dimensionality of the Hilbert space. In contrast, the quantum PCA algorithm (LLOYD *et al.*, 2014) offers a significant improvement in computational efficiency. The procedure begins by encoding classical data into quantum states via Quantum Random Access Memory (QRAM), which allows the preparation of quantum states corresponding to randomly sampled data vectors. Subsequently, a density matrix is constructed from the ensemble of quantum states. Applying density matrix exponentiation in conjunction with quantum phase estimation and continuous data sampling, the quantum algorithm executes the decomposition of input data into its principal components. That is, this approach enables the extraction of dominant eigenvectors associated with the data's covariance structure. The quantum PCA algorithm achieves a runtime complexity of $O((\log d)^2)$, which is an exponential speedup as a function of dimensionality over its classical counterpart.

Quantum Linear Regression

Quantum Linear Regression (QLR) is a quantum algorithm that aims to perform linear regression using quantum computing principles, potentially offering speed advantages over classical methods. It leverages the quantum analog of classical linear regression, typically solving the equation $w = (X^TX)^{-1}X^Ty$, where X is the input matrix and y is the output vector. Data points are encoded into amplitude-encoded quantum states, which allows the processing of exponentially large datasets using few qubits.

The core component of QLR often involves the HHL algorithm (HARROW *et al.*, 2009) to solve linear systems efficiently on a quantum computer. HHL outputs a quantum state proportional to the solution vector rather than the explicit classical values. Inner products are then computed via quantum techniques such as the Hadamard test. QLR assumes efficient quantum access to data via quantum RAM, which is a strong and currently impractical requirement. It can achieve exponential speedups in theory but only under specific and restrictive conditions such as low-rank data matrices and well-conditioned systems. Practical use remains limited due to current hardware constraints and overhead in preparing quantum states when applying algorithms to a genuine quantum device. However, QLR is an important theoretical step in exploring the power of quantum machine learning.

Quantum Neural Networks

Quantum Neural Networks (QNNs) represent an emerging paradigm that combines principles of quantum theory with the properties of an artificial neural network (NN). The main advantage over classical neural networks that operate on binary data is that QNNs employ qubit superposition, which enables exponentially larger state spaces for information processing. This allows QNNs to outperform classical models in complex pattern recognition, optimization, and similar machine learning tasks in high-dimensional spaces. Another key advantage of QNNs is their ability to explore multiple computational paths simultaneously through quantum parallelism, which may lead to significant speedups for specific classes of problems. Additionally, quantum entanglement can be used to model complex correlations between inputs in ways that classical networks cannot replicate efficiently (SCHULD *et al.*, 2014).

However, the practical implementation of QNNs is also limited by the quantum hardware constraints that significantly restrict real-world applications. Moreover, QNN usually suffers from vanishing gradient problems, when the gradient tends to zero during supervised training. This problem is known as *barren plateau* (BP) and its dominance in quantum architectures makes it a key factor in choosing appropriate circuit (McClean *et al.*, 2018). In contrast to conventional NN, where gradients vanish exponentially with the number of layers, in QNN similar trend of gradient disappearance happens with an increase in the number of qubits. However, recent research has shown that deep QNN circuits, although employing only a few qubits, can flatten the loss landscape due to noise accumulation in deep circuits (Wang *et al.*, 2021). Nevertheless, designing effective quantum circuits that can generalize like classical deep learning models remains a fundamental research challenge.

QUANTUM-INSPIRED MACHINE LEARNING TECHNIQUES

Quantum-inspired machine learning (QiML) refers to a broad class of machine learning algorithms inspired by quantum phenomena or quantum computing. However, it is founded on the principles of classical machine learning and incorporates the ability to simulate quantum hardware using classical representation and computation techniques. Three distinctive categories have been identified based on underlying methodologies, such as *dequantized algorithms*, *tensor networks*, and *simulation of quantum variational algorithms*. One should note that some methods do not fall into either category, although they are classified as quantum-inspired (Huynh *et al.*, 2023).

Dequantized algorithms aim to determine if the QML algorithms' speedups are attributed to the power of quantum computation or are the consequence of specific input and output encoding/decoding inherent to the underlying quantum counterpart. A seminal work in this area was presented by Ewin Tang (Tang, 2019). Analyzing a state-of-the-art quantum recommendation system (Kerenidis and Prakash, 2017), the authors devised a classical algorithm with an execution runtime approaching the quantum one. They showed that the specific data structure used to quickly prepare quantum states also fulfills the classical L_2-norm sampling assumption, thus allowing efficient SQ ("sample and query") access to the data. An extension of this work is formalized to dequantize quantum algorithms for supervised clustering (SC) and principal component analysis (PCA) (Tang, 2021). A benefit of the dequantization approach for solving linear systems is demonstrated by the low-rank inversion algorithms (Gilyén *et al.*, 2018; Chia *et al.*, 2018). Significant results are also achieved for the Least Squares Support Vector Machine (LS-SVM) optimizations (Ding *et al.*, 2021), Linear Discriminant Analysis (LDA) (Cong and Duan, 2016), Hamiltonian simulations (Chia *et al.*, 2022), and similar quantum-related algorithms (Huynh *et al.*, 2023).

Contemporary QiML research focuses on *tensor networks* (TN) applications as powerful machine learning models. This direction builds on years of classical research, both inside and outside the machine learning field, that can be easily adapted to quantum problems. It was demonstrated that tensor networks provide a principled framework that bridges classical neural network methodologies and quantum computing. A recent study (Huggings *et al.*, 2019) implies a formal correspondence between specific tensor network structures and quantum circuits, wherein many TN architectures admit direct mappings to equivalent quantum circuits. One of the main motivations for employing TNs is their proven efficiency in classically simulating many-body quantum wavefunctions, which are based on higher-order tensor decompositions and representations (Ran and Su, 2023).

The effective emulation of quantum computations on classical hardware critically depends on the ability to simulate qubits and their associated capacity for exponential information encoding. Resources needed for classical simulations scale exponentially with the number of qubits and the depth of the quantum circuit. Some classical strategies, such as data compression, optimized circuit parametrization, and batching methods, can reduce emulation complexity. However, these methods are effective only for simulations of a system composed of up to ten qubits, which defines the current lower limit for supremacy of quantum algorithms over classical. The most typical emulated quantum algorithms are quantum kernels and quantum variational methods (GUJJU *et al.*, 2023). A detailed study of the significant challenges in simulating these quantum algorithms is provided in XU *et al.*, (2023).

Miscellaneous quantum-inspired methods such as classifiers, quantum-based feature representation in machine learning tasks etc., are overviewed in HUYNH *et al.*, (2023). Understanding contemporary advancements in QiML techniques requires mastering the theoretical foundations of key algorithms such as Quantum-inspired Binary Classifier (TIWARI and MELUCCI, 2019), Helstrom Quantum Centroid (SERGIOLI *et al.*, 2019) which is a Quantum-inspired Binary Supervised Learning Classification, Quantum-inspired Support Vector Machines (DING *et al.*, 2021), Quantum Nearest Mean Classifier (SERGIOLI *et al.*, 2018), Quantum-inspired K Nearest-Neighbor (CHEN *et al.*, 2015), quantum algorithms for ridge regression (YU *et al.*, 2019), and Quantum-inspired Neural Networks (SAGHEER, *et al.*, 2019).

HYBRID CLASSICAL-QUANTUM MACHINE LEARNING

Hybrid classical-quantum machine learning is the approach that merges classical and quantum algorithms to improve performance and reduce the cost of learning. Using this combined approach, novel methods are proposed, such as a variational quantum classifier (ADHIKARY *et al.*, 2020), variational quantum SVM and SVM supported by quantum kernel-based algorithm (HAVLÍČEK *et al.*, 2019), hybrid K Nearest-Neighbor algorithm (RUAN *et al.*, 2017), a hybrid quantum computer-based quantum version of nonlinear regression (ZHANG *et al.*, 2018), hybrid quantum-classical neural networks (LIANG *et al.*, 2021; ARTHUR and DATE, 2022), and many others.

In recent study (ADHIKARY *et al.*, 2020), the advantages of hybrid variational quantum classifiers (hVQCs) over purely quantum classifiers are explored. The authors demonstrated that a hybrid approach, which combines quantum circuits with classical optimization techniques, can outperform a purely quantum classifier in terms of accuracy and efficiency. Their experiments on the MNIST dataset show that the hybrid model achieves a test accuracy of 96.05%, significantly higher than the 67% achieved by the purely quantum classifier with a small bond dimension. This indicates that integrating classical components can enhance the performance of quantum classifiers by leveraging the strengths of both quantum and classical computing.

Variational Quantum SVMs (VQ-SVMs) and Quantum Kernel-based SVMs (QK-SVMs) combine quantum feature encoding with classical optimization or classification, offering advantages over purely classical or purely quantum approaches. VQ-SVMs use parameterized quantum circuits to map data into complex quantum spaces, while QK-SVMs grasps on quantum circuits to compute kernel functions that capture rich data correlations. Compared to classical SVMs, these methods can potentially access higher-dimensional feature spaces more efficiently, and unlike fully quantum models, they are more resilient to hardware limitations due to their hybrid structure (HAVLÍČEK *et al.*, 2019).

A hybrid quantum-classical k-nearest neighbors (KNN) algorithm combines quantum computing techniques with classical methods to enhance performance over purely classical approaches. The quantum enhancement is based on the circuit that calculates the Hamming distance, while classical methods are used for preparing datasets. By leveraging potentials of classical and quantum computations, this algorithm outperforms quantum Centroid and QNN approach on time performance and classification accuracy (RUAN *et al.*, 2017).

Recently proposed hybrid quantum-classical approach to nonlinear regression offers distinct advantages over existing classical or quantum methods. Utilizing quantum computing's ability to encode and process high-dimensional data efficiently, this hybrid model can capture highly complex patterns in data more effectively than state-of-the-art classical systems alone (ZHANG *et al.*, 2018). Additionally, integrating classical optimization techniques allows for more practical and scalable implementations, circumventing current constraints in quantum hardware.

Hybrid quantum-classical neural networks (hQCNNs) integrate quantum computing's high-dimensional feature mapping with classical optimization techniques, thus outperforming conventional or quantum models. Usually, classical components handle tasks like data preprocessing and optimization, making the hybrid model more scalable and adaptable to larger datasets (LIANG *et al.*, 2021). On the other hand, quantum circuits can encode data into high-dimensional Hilbert spaces, enabling the capture of complex patterns that classical networks might miss or disregard (LIANG *et al.*, 2021; ARTHUR and DATE, 2022). By integrating quantum and classical components, hQCNNs can be deployed on existing quantum hardware, bridging the gap between the theoretical potential of quantum computing and its practical applications on current noisy intermediate-scale quantum hardware.

CHALENGES AND FUTURE DIRECTIONS

Despite the promising future of QML, several significant challenges for full potential in practical applications remain. Quantum hardware is still in an early developmental stage, with issues like qubit coherence times and error rates hindering practical implementations. Developing algorithms that can outperform classical counterparts in real-world applications is a very tedious task. Currently, there are only a few useful quantum algorithms and finding new efficient algorithms is in focus of an ongoing area of research. Future directions include improving quantum hardware, developing error-correction techniques, and creating hybrid quantum-classical algorithms to bridge the gap between theoretical potential and practical application. Combining the strengths of both paradigms could lead to more practical and efficient solutions. Finally, the criteria proving the advantage of quantum over classical machine learning are *open topics*. Establishing standardized benchmarking for QML algorithms will facilitate more realistic and sustainable progress in the QML field.

CONCLUSIONS

Quantum Machine Learning represents a frontier in computational science, offering the possibility of transforming how machines learn from data. It stands at the confluence of quantum computing and artificial intelligence, offering transformative potential across various domains. While significant challenges persist, ongoing research and advancements in quantum technology hold promise for significant breakthroughs in various domains, including artificial intelligence, data analysis, and beyond. A concerted effort across various disciplines will be crucial in unlocking the full capabilities of current QML techniques. Moreover, it may happen in the future that a novel approach that diverges from classical machine learning background may potentially elevate QML to an entirely new level.

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