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Machine Learning Techniques for Quantum State Prediction

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ABSTRACT: We also provide an overview of the challenges, potential, and limitations of QML, both in these specific areas and more broadly across the field. This review study examines state-of-the-art algorithms and techniques in quantum machine learning with potential applications in finance. We also provide an overview of the challenges, potential, and limitations of QML, both in these specific areas and more broadly across the field. Fuelled by increasing computer power and algorithmic advances, machine learning techniques have become powerful tools for finding patterns in data. The field of quantum machine learning explores how to devise and implement quantum software that could enable machine learning that is faster than that of classical computers. Quantum machine learning by utilizing the concepts of superposition and entanglement promises a solution to this problem. Quantum machine learning algorithms are in surface for the past few years and majority of the current research has dealt with the two machine learning problems namely classification and clustering. Machine learning (ML) has emerged as a formidable force for identifying hidden but pertinent patterns within a given data set with the objective of subsequent generation of automated predictive behavior.

KEYWORDS: Machine learning techniques, Quantum machine learning, resource-intensive process, machine learning algorithms, potential applications.

I. INTRODUCTION

The fields of machine learning and quantum technologies have much in common: Both started out with an amazing vision of applications went through a series of challenges, and are currently extremely hot research topics. Of these two, machine learning has firmly taken hold beyond academia and beyond prototypes, triggering a revolution in technological applications during the past decade. This perspective study will be concerned with shining a spotlight on how techniques of classical machine learning (ML) and artificial intelligence (AI) hold great promise for improving quantum technologies in the future. With the present review, we aim to take physicists with a background in quantum technologies on a tour of this rapidly growing area at the interface to classical machine learning. The readers are not expected to have a background in machine learning and will get a state-of-the-art view into how machine learning techniques are applied to quantum physics. We hope that after seeing the examples discussed in our review, the reader will appreciate how useful machine learning techniques could be for quantum technologies. Machine learning techniques create patterns in data, while quantum systems produce informal patterns and investigate how to create and implement quantum software for faster machine learning. In the 20th century, computers were built to analyze mathematical models using several techniques and methods. Quantum computers excel at solving complex algebraic expressions, such as the factorization of large integers and the computation of discrete logarithms, leveraging their computational power. These impressive capabilities stem from the unique axioms and characteristics of quantum mechanics, such as quantum bits (qubits), interpolation, superposition, and entanglement.

II. LITERATURE REVIEW

Florian Marquardt (2023) In recent years the dramatic progress in machine learning has begun to impact many areas of science and technology significantly. In the present perspective article, we explore how quantum technologies are benefiting from this revolution. We showcase in illustrative examples how scientists in the past few years have started to use machine learning and more broadly methods of artificial intelligence to analyze quantum measurements, estimate

the parameters of quantum devices, discover new quantum experimental setups, protocols, and feedback strategies, and generally improve aspects of quantum computing, quantum communication, and quantum simulation.

George A. Papakostas (2023) Quantum computing has been proven to excel in factorization issues and unordered search problems due to its capability of quantum parallelism. This unique feature allows exponential speed-up in solving certain problems. However, this advantage does not apply universally, and challenges arise when combining classical and quantum computing to achieve acceleration in computation speed. This study aims to address these challenges by exploring the current state of quantum machine learning and benchmarking the performance of quantum and classical algorithms in terms of accuracy. Specifically, we conducted experiments with three datasets for binary classification, implementing Support Vector Machine (SVM) and Quantum SVM (QSVM) algorithms.

Jarrod R. McClean (2021) The use of quantum computing for machine learning is among the most exciting prospective applications of quantum technologies. However, machine learning tasks where data is provided can be considerably different than commonly studied computational tasks. In this work, we show that some problems that are classically hard to compute can be easily predicted by classical machines learning from data. Using rigorous prediction error bounds as a foundation, we develop a methodology for assessing potential quantum advantage in learning tasks. The bounds are tight asymptotically and empirically predictive for a wide range of learning models. These constructions explain numerical results showing that with the help of data, classical machine learning models can be competitive with quantum models even if they are tailored to quantum problems.

Manik Kapil (2021) Quantum machine learning is at the intersection of two of the most sought after research areas—quantum computing and classical machine learning. Quantum machine learning investigates how results from the quantum world can be used to solve problems from machine learning. The amount of data needed to reliably train a classical computation model is ever growing and reaching the limits which normal computing devices can handle. In such a scenario, quantum computation can aid in continuing training with huge data. Quantum machine learning looks to devise learning algorithms faster than their classical counterparts. Classical machine learning is about trying to find patterns in data and using those patterns to predict further events. Quantum systems, on the other hand, produce atypical patterns which are not producible by classical systems, thereby postulating that quantum computers may overtake classical computers on machine learning tasks.

Ashish Mani (2020) The support vector clustering algorithm is a well-known clustering algorithm based on support vector machines using Gaussian or polynomial kernels. The classical support vector clustering algorithm works well in general, but its performance degrades when applied on big data. In this paper, we have investigated the performance of support vector clustering algorithm implemented in a quantum paradigm for possible runtime improvements. We have developed and analyzed a quantum version of the support vector clustering algorithm. The proposed quantum version of the support vector clustering method demonstrates a significant speedup gain on the overall runtime complexity as compared to the classical counterpart.

III. QUANTUM MACHINE LEARNING

Quantum machine learning uses algorithms run on quantum devices, such as quantum computers, to supplement, expedite, or support the work performed by a classical machine learning program. Also called quantum-enhanced machine learning, quantum machine learning leverages the information processing power of quantum technologies to enhance and speed up the work performed by a machine learning model. While classical computers are constrained by limited storage and processing capacities, quantum-enabled ones allow for exponentially more storage and processing power. This ability to store and process huge amounts of information means that quantum computers can analyze massive data sets that would take classical methods significantly longer to perform.

Machine learning with quantum computers

Quantum-enhanced machine learning refers to quantum algorithms that solve tasks in machine learning, thereby improving and often expediting classical machine learning techniques. Such algorithms typically require one to encode the given classical data set into a quantum computer to make it accessible for quantum information processing. Subsequently, quantum information processing routines are applied and the result of the quantum computation is read out by measuring the quantum system. For example, the outcome of the measurement of a qubit reveals the result of a binary classification task. While many proposals of quantum machine learning algorithms are still purely theoretical

and require a full-scale universal quantum computer to be tested, others have been implemented on small-scale or special purpose quantum devices.

Quantum machine learning algorithms based on Grover search

Another approach to improving classical machine learning with quantum information processing uses amplitude amplification methods based on Grover's search algorithm, which has been shown to solve unstructured search problems with a quadratic speedup compared to classical algorithms. These quantum routines can be employed for learning algorithms that translate into an unstructured search task, as can be done, for instance, in the case of the k-medians and the k-nearest neighbors algorithms. Other applications include quadratic speedups in the training of perceptron and the computation of attention. An example of amplitude amplification being used in a machine learning algorithm is Grover's search algorithm minimization.

Statistical learning theory

A core objective of a learner is to generalize from its experience. Generalization in this context is the ability of a learning machine to perform accurately on new, unseen examples/tasks after having experienced a learning data set. The training examples come from some generally unknown probability distribution (considered representative of the space of occurrences) and the learner has to build a general model about this space that enables it to produce sufficiently accurate predictions in new cases. The computational analysis of machine learning algorithms and their performance is a branch of theoretical computer science known as computational learning theory via the Probably Approximately Correct Learning (PAC) model. Because training sets are finite and the future is uncertain, learning theory usually does not yield guarantees of the performance of algorithms. Instead, probabilistic bounds on the performance are quite common. The bias-variance decomposition is one way to quantify generalization error.

IV. RESEARCH METHODOLOGY

The first one is the state preparation circuit for the n-qubit data register and is applied to encode the inputs in a quantum state. Lastly, we present three baseline models taken from the literature, in particular we will introduce two quantum neural network classifiers and a quantum support vector classifier, all proposed by qiskit as basic quantum machine learning models. An implementation of a non-linear activation function is beyond the scope of this thesis, and for this reason, in the practical implementation, we set a single unitary matrix as a placeholder. As we discussed in the previous sections the parametric quantum circuit of a quantum single layer perceptron is composed of four parts: state preparation, linear parametric gate operators or ansatz, activation function, and measurement operation. The MAQA framework introduces an exponential scaling in the number of the aggregated function with respect to a classical machine learning approach. Furthermore, it opens the possibility to implement many quantum machine learning models not yet present in the literature. Second we discuss the theoretical foundations of a quantum single layer perceptron and how it can be utilised as a quantum variational algorithm. It holds the theoretical ability to reproduce all machine learning models that can be represented, providing advantages over classical models. Here we propose a short description of the algorithm, for a more in-depth.

V. RESULTS AND DISCUSSIONS

The performances on the test set (in table 1) highlight the potential of the proposed models since they achieve high test accuracy in almost all datasets (94% on MNIST09, 82% on MNIST38 100% on SeVe and SeVi, and only 65% on ViVe). The accuracy is, in most cases, on par with the best performing baseline (QSVC) except for the ViVe dataset.

Table 1: Accuracy on the test set for each model for each dataset, performed with a simulated quantum processor. The best results for each dataset are highlighted.

	MNIST09	MNIST38	SeVe	SeVi	ViVe
QSVC	.94	.8	1.0	1.0	1.0
QNNC v1	.86	.46	.85	1.0	1.0
QNNC v2	.83	.8	.95	.95	.8
pad qSLP 1	.93	.82	1.0	1.0	.65
pad qSLP 2	.89	.81	1.0	1.0	.65
pad qSLP 3	.94	.81	1.0	1.0	.6
sdq qSLP 1	.81	.81	1.0	1.0	.65
sdq qSLP 2	.83	.76	1.0	1.0	.65
sdq qSLP 3	.83	.78	1.0	1.0	.6

One great achievement is the ability of the qSLP of reaching more than 80% of accuracy on the MNIST38 dataset, outperforming all baselines on the dataset with the smaller explained variance. In all experiments the test accuracy is in line with the training accuracy, hence the models are not affected by overfitting.

Table 2: List and specifics of the real devices on which the models could be tested the choice was made at test time considering the availability of each device

Device	Qubits	QV	CLOPS
ibmq_manila	5	32	2.8K
ibmq_bogota	5	32	2.3K
ibmq_quito	5	16	2.5K
ibmq_belem	5	16	2.5K
ibmq_lima	5	8	2.7K

Lastly, we tested our models on the real devices that IBM lends to the general public. Many of the devices mentioned in the previous section have restricted access and can be utilized only by members of the IBM quantum network. For this reason, we only used processors from the Falcon family with five qubits and with a QV up to 32, since they can be accessed by everyone. Each test chooses the device to use depending on their availability from the list presented in table 2.

Table 3: Accuracy of the models tested on a real device. We can observe a negative correlation between the complexity of the tested circuit and the accuracy

	MNIST09	MNIST38	SeVe	SeVi	ViVe
QSVC	-	-	1.0	1.0	.95
QNNC v1	.81	.51	.95	1.0	.95
QNNC v2	.85	.83	1.0	1.0	.89
pad qSLP1	.68	.51	.60	.50	.60
pad qSLP2	.63	.69	.65	.70	.55
pad qSLP3	.51	.51	.50	.60	.5
sdq qSLP1	.83	.79	1.0	1.0	.55
sdq qSLP2	.84	.78	1.0	1.0	.70
sdq qSLP3	.76	.80	1.0	1.0	.65

From these experiments, we can also conclude that with the current technology, the single data qubit sQLP is a more reliable choice when running on a real device, because, even if it has slightly worse performance on the simulation compared with the padded version, in a real processor the smaller depth produces less noise derived errors, preserving the simulated accuracy.

VI. CONCLUSION

Quantum machine learning (qML) is a very promising branch of quantum computation, where rich possibilities are offered by just a small amount of qubits. However, the computational advantages over classical machine learning have yet to be proven, and qML techniques are limited by the state preparation phase and by the application of an arbitrary number of gates. The key idea behind the proposal is to take advantage of properties of quantum computation like entanglement, superposition, and interference, to create a more efficient version of the classical algorithm. This amalgamation of machine learning and quantum computers allows us to run classical algorithms significantly faster in many cases. We attempt to solve the link prediction problem in dynamic networks using an enlarged feature set which represents different levels of node information in this research. We propose an implementation of qSLP as an aggregator of multiple functions $g(x, \cdot)$ where each function propagates the input on a different quantum trajectory, all of which are in superposition with each other. The speedup provided by our model derives from the ability to create an exponentially large number of neurons in a linear number of steps and from the possibility of propagating a function to each quantum state by applying it only once. We presented the implementation for a general model with a variable number of control qubits, which allows great flexibility when dealing with the small size of modern quantum hardware. Furthermore, the resulting quantum circuit is modular and it gives the possibility to change the ansatz's parametric gates, the activation function and the state preparation circuit, making it able to exploit more advanced techniques as soon as they are found.

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