QUANTUM MACHINE LEARNING FOR REAL-WORLD, LARGE SCALE DATA SETS WITH APPLICATIONS IN EARTH OBSERVATION

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1. ABSTRACT

Quantum machine learning is the synergy between quantum computing resources and machine learning methods. In particular, quantum machine learning refers to quantum algorithms promising to compute some machine learning methods and optimization problems (exponentially) faster than conventional algorithms. Quantum algorithms for computing any problems are algorithms using a quantum computer. This work (**I**) identifies intractable real-world problems of practical significance which can be computed efficiently on a quantum computer, (**II**) provides an encoding strategy of real-world, large scale problems in a small-scale quantum computer, and (**III**) invents so-called hybrid classical-quantum (HPC-nQC) learning networks and analyses their performance in comparison to conventional machine (deep) learning methods in order to gain quantum advantage as early and efficiently as possible; here, HPC-nQC is referred to as high performance computing and n quantum computers, where "n" stands for n different types of quantum computers.

2. INTRODUCTION

Current real-world problems involve big datasets obtained from dedicated experiments, internet, and distinct sensor devices. Modern supercomputers (HPC) allow us to analyse and to recognize hidden patterns in these big datasets by leveraging Machine Learning (ML) and Deep Learning (DL) techniques faster than ever before while their computing power including floating-point and matrix operations increases [11], [4]. In particular, an increase of computing power of a supercomputer made it possible to employ ML and DL techniques on real-world big datasets. However, there is the indication that even the most powerful supercomputer in the world cannot solve efficiently a certain class of problems in science, engineering, and industry. These problems are called NP-hard problems in computational complexity when efficient classical algorithms are not known for finding their solutions [12], [2].

NP-hard problems motivated generations of scientists to study and employ a quantum algorithm while quantum algorithms using a quantum computer are exponentially faster than conventional algorithms for some intractable

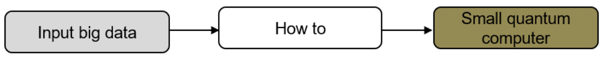

Figure 1: **Input big data**: Real-world large scale datasets, **How to**: Embedding strategy, and **Small quantum computer**: NISQ computers.

problems [6], [20]. For example, Grover's search [7] and Shor's factorization [20] show polynomial speedup over their classical counterparts. There are even a quite few quantum algorithms exhibiting quantum advantage over classical algorithms, and hence, for interested readers on speedup improvements of quantum algorithms, we would like to refer to the website cited in [17].

Several kinds of quantum computers for executing quantum algorithms, that is, a quantum annealer and universal, general-purpose quantum computers, recently become accessible via online [5], [9]. These quantum computers has a limited error-prone quantum bits (around 50-100 qubits), and such quantum computers are called *Noisy Intermediate-Scale Quantum* (NISQ) computers [16]. Thus, finding potential applications for NISQ computers becomes an on-going research study. And quantum ML is one of the most promising applications for NISQ computers due to its probabilistic methodology. Quantum ML (QML) studies quantum variational algorithms for speeding up some ML and DL techniques. Several QML algorithms surpass their classical counterparts, and these quantum algorithms include quantum principal component analysis (qPCA), quantum support vector machine (qSVM), a Harrow-Hassidim-Lloyd (HHL) algorithm for a least squares fitting, and a quantum neural network (qNN) [10], [18], [8], [3], [1]. Even some advantages of QML and quantum sampling algorithms are experimentally demonstrated in laboratories [22], [19]. There are, however, no demonstrated quantum advantages using universal, general-purpose quantum computers for solving real-world problems due to their very few noisy qubits and quantum gates. Even there is the bottleneck of encoding classical, large scale datasets in imperfect small quantum computers.

3. CONCLUSION

In this talk, we (I) identify intractable real-world problems which can be computed on a quantum computer [14], (II)

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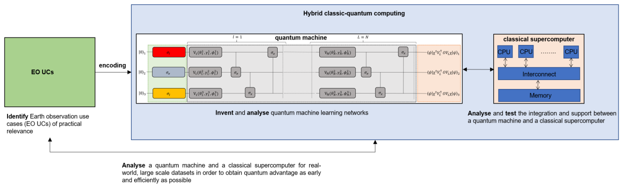

Figure 2: A hybrid classic-quantum model: HPC+nQC

develop novel methodologies to encode real-world, large scale datasets in limited error-prone qubits [13], and (III) invent hybrid classical-quantum (HPC-nQC) networks and benchmark their performance on real-world big datasets in comparison to classical machine and deep learning methods [15]. In particular, we develop novel methods to map large scale images (in our case, remotely-sensed satellite images) to small quantum computers (see **Figure** 1), and we propose novel hybrid classical-quantum models (HPC-nQC) for processing real-world big datasets and problems (see **Figure** 2), since we do not know that when we have a programmable universal quantum computer a so-called fault-tolerant quantum computer (FTQC) with perfect $n \geq 100$ qubits and quantum gates [21]. The proposed hybrid classical-quantum models in this talk, indeed, help us to tackle two main challenges encountered in NISQ-era computers: 1) encoding real-world, large scale datasets in small quantum computers, and 2) benchmarking QML methods against each other and conventional ML methods. More importantly, the studies presented here broaden our perspectives on using small-scale quantum computers and will help us to design QML models with quantum advantages as early and efficiently as possible for practically significant problems.

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