

Application of Quantum Machine Learning to High Energy Physics Analysis using Quantum Computer Simulator and Hardware

Jay Chan¹, Alkaid Cheng¹, Wen Guan¹, Tuan Pham¹, Shaojun Sun¹, Alex Wang¹,
Sau Lan Wu¹, Rui Zhang¹, Chen Zhou¹
Samuel Yen-Chi Chen², Shinjae Yoo², Chao Zhang²
Tzu-Chieh Wei³

1. University of Wisconsin-Madison
2. Brookhaven National Laboratory
3. State University of New York at Stony Brook

Primary contact: Sau Lan Wu (Sau.Lan.Wu@cern.ch)

One of the major objectives of the experimental programs for High Energy Physics is the discovery of new physics. This requires the identification of rare signals in immense backgrounds. Using machine learning algorithms greatly enhances our ability to achieve this objective.

With the progress of quantum technology, the intersection of quantum computing and machine learning can become a powerful tool for data analysis in high energy physics, leading to more powerful algorithms and applications. Furthermore, the use of quantum machine learning may offer a "speed up" advantage, which can be critical for the future of the high energy physics community. Our goal is to explore the potential of quantum machine learning on the current leading physics analyses and to demonstrate, as a proof of principle, the potential of quantum computers to become a new computational paradigm for big data analysis in high energy physics.

In our study, we employ quantum machine learning to high energy physics analyses, using gate-model quantum computers from commercial companies such as IBM and Google. Specifically, our goals are: (i) To perform research and development of quantum machine learning and data analysis techniques, with gate-model quantum computer simulator and hardware, to enhance efficiency and analysis methods for HEP. (ii) To enhance the software development of quantum machine learning for HEP to provide scalable quantum codes and tools for future HEP analysis.

Using 10 qubits on the IBM gate-model quantum computer simulator and hardware, we have obtained early results of employing the quantum variational algorithm [1] and quantum kernel algorithm [1]. With small training samples of 100 events, the quantum algorithms perform similarly to classical algorithms such as SVM (support vector machine) and BDT (boosted decision tree), which are often employed in LHC physics analyses.

We would like to further improve the quantum machine learning algorithms, to achieve better performance than classical machine learning in practice. By exploiting the high dimensional feature space defined by a larger number of qubits, quantum machine learning classifiers could possibly outperform classical classifiers. We plan to develop quantum circuits to extend our analysis to more qubits and larger sample sizes. We are also exploring different Quantum Machine Learning methods with the goal of enhancing their performance, including various quantum neural networks.

Application of quantum machine learning algorithms on quantum hardware is of great interest to our HEP community. It will be necessary to optimize the quantum circuits to best fit the constraints imposed by the hardware (e.g. qubit connectivity, gate set availability, and device noise). We are also exploring and applying quantum error mitigation in the context of quantum machine learning. It would give encouragement and inspiration to the HEP community when quantum computer hardware outperforms the result from classical computers in realistic high energy physics data analyses.

We look forward to the usage of quantum machine learning in physics analyses of future HEP experiments, including measurements of the Higgs boson self-couplings and searches for dark matter.

References:

[1] V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, Supervised learning with quantum-enhanced feature spaces. *Nature* 567, 209-212 (2019).