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Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware

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ABSTRACT

Our group pioneers the use of Quantum Machine Learning (QML) on High Energy Physics analysis at LHC. We have successfully employed several QML classification algorithms in the ttH (Higgs production in association with a top quark pair) and Higgs to two muons (Higgs coupling to second generation fermions), two recent LHC flagship physics analysis, on gate-model quantum computer simulators and hardware. The simulation studies have been performed with the IBM Quantum Framework, Google Tensorflow Quantum Framework, and Amazon Braket Framework, and we have achieved good classification performance that is similar to the performances of the classical machine learning methods currently used in LHC physics analyses, classical SVM, classical BDT, and classical deep neural network for example. We have also performed our studies using IBM superconducting quantum computer hardware and the performance is promising and is approaching the performance from IBM quantum simulators. Moreover, we extend our studies to other QML areas such as quantum anomaly detection and quantum generative adversarial, and some preliminary results have been obtained. Also, we have overcome the challenges of intensive computing resources in the cases of large qubits (25 qubits or more) and large numbers of events using NVIDIA cuQuantum with NERSC Perlmutter HPC.

Our studies give an example that Quantum Machine Learning performs as well as its classical counterpart for realistic High Energy Physics analysis datasets. Furthermore, our result on noisy quantum hardware provides important validation for the result on noiseless quantum simulators.

SECTION 1: OUR MAJOR GOALS OF THE PROJECT

The ambitious HL-LHC program will require enormous computing resources in the next two decades. New technologies are being sought after to replace the present computing infrastructure. A burning question is whether quantum computers can solve the ever growing demand of computing resources in High Energy Physics (HEP) in general and physics at LHC in particular. Our goal was to explore and to demonstrate that Quantum Computing can be the new paradigm for HEP data analysis (Proof of Principle).

The experimental programs of PI Wu at the LHC revolve around one major objective: 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. Our group in the ATLAS/LHC is one of the groups which have pioneered the use of machine learning in high profile physics analyses. We have used classical machine learning algorithms on the measurement of Higgs coupling to top quark pairs (ttH). However, with a rapidly increasing volume of data in the future HL-LHC program, applying Quantum Machine Learning methods may well be a new direction to go.

Specifically, our goals of this project are:

(i) To Perform Research and Development of Quantum Machine Learning and Data Analysis Techniques, with Qubit Platform, using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware, to enhance efficiency and analysis methods for HEP. Additionally, we extend our studies to Google Tensorflow Quantum framework and Amazon Braket framework so that we gain the ability to perform the data analysis with all possible resources.

(ii) To Enhance the Software Development of Quantum Machine Learning for HEP at the LHC to provide Scalable Quantum Codes and Tools for Future HEP Analysis

SECTION 2: OUR ACCOMPLISHMENTS

We have assembled a team of HEP physicists, quantum physicists and computer scientists from Wisconsin, CERN openlab, IBM Research Zurich, IBM T.J. Watson Research Center, Fermilab Quantum Institute, and Computational Science Initiative of BNL. We have made promising progress in application of Quantum Machine Learning algorithms with IBM Quantum Computer Simulators and Quantum Computer Hardware to two LHC flagship physics channels: ttH (Higgs production in association with a top quark pair) and Higgs to two muons (Higgs coupling to second generation fermions).

2.1 Quantum Machine Learning Algorithms

The intersection between machine learning and quantum computing has been referred to as Quantum Machine Learning. With the progress of quantum technologies, the application of Quantum Machine Learning emerges as a possible powerful tool for data analysis in HEP in the future. We have explored the following Quantum Machine Learning algorithms:

(a) Quantum Variational Classification

Following Nature 567 (2019) 209, we look into the quantum variational algorithm to classify physics events of interest from background events. This quantum approach exploits the mapping of input physics data to an exponentially large Hilbert quantum state space (feature map) to enhance the ability to find an optimal classification solution. The quantum variational approach is summarized in four main steps as shown in Figure 1, which is taken from the supplementary information of the Nature publication.

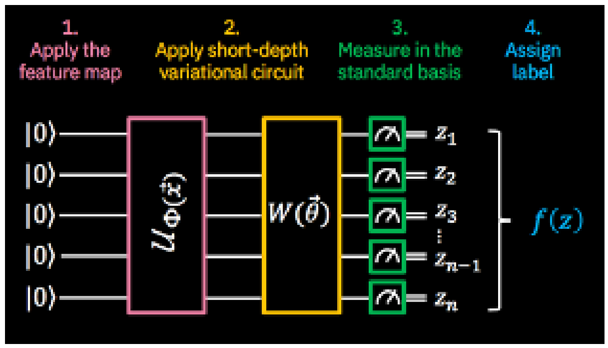


Figure 1. Sketch of the quantum variational algorithm with its steps: 1. Loading of the data by means of the feature map; 2. Application of the variational circuit; 3. Read out of the final qubit state, and 4. Assignment to the different classes.

To classify the signal and dominant background processes for the ttH analysis and H → μ+μ− analysis, we employ the quantum variational classifier with 10 qubits on the ibmq QasmSimulator. For 10 qubits, using ttH analysis dataset (100 events) and H → μ+μ− analysis dataset (100 events), Quantum Variational Classifier on IBM simulator (red) performs similarly with classical BDT (green) and classical SVM (blue).

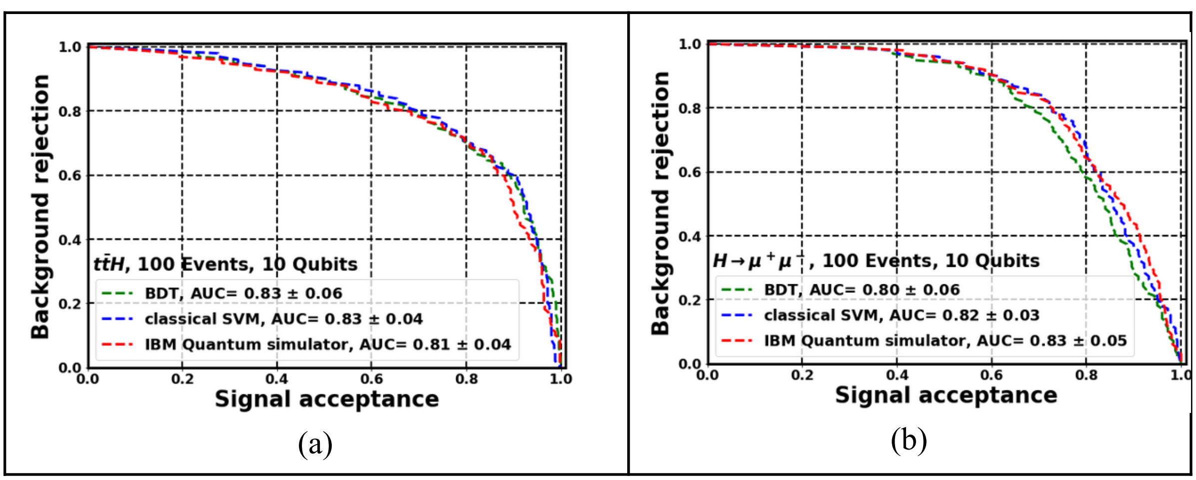
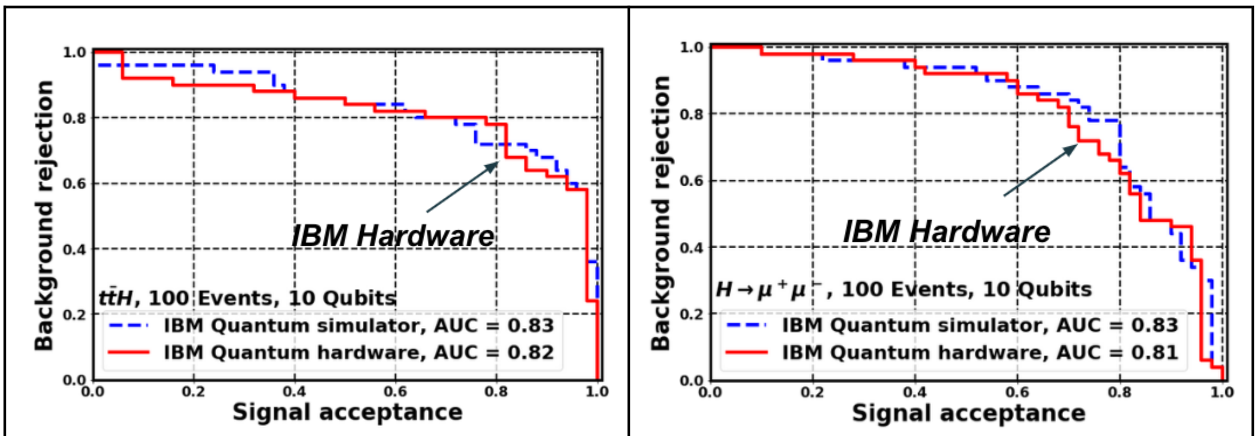


Figure 2: The ROC curves (as a benchmark in the plane of background rejection versus signal efficiency) of the quantum variational classifier method on the ibmq QasmSimulator (red), the classical SVM (Support Vector Machine) (blue), and the BDT (Boosted Decision Tree) (green) for (a) the ttH analysis and (b) the H → μ+μ− analysis. In each analysis, the classifiers are

constructed using ten independent datasets, each consisting of 100 events for training and 100 events for testing. All classifiers are trained with the same 10 variables processed with the PCA (Principal Component Analysis) method.

In Figure 2, 10 qubits are employed on the quantum computer simulator. To visualize the discrimination power of each algorithm, the testing events of the ten datasets are combined to make the ROC curves. We observe that the quantum variational classifier method on the ibmq QasmSimulator performs similarly to the classical SVM and the BDT for both the ttH analysis and the H → μ+μ− analysis.

We also employ the quantum variational algorithm with 10 qubits on the IBM quantum computer hardware 'ibmq_boeblingen' and 'ibmq_paris'. 'ibmq_boeblingen' is a 20-qubit quantum processor and 'ibmq_paris' is a 27-qubit quantum processor. Both are based on superconducting electronic circuits. Due to current limitation of the access time to the quantum processors, the quantum variational classifier algorithm is only applied to one of the ten datasets for each physics analysis. We pick the dataset whose simulator AUC (Area Under the Curve) is closest to the average simulator AUC of the ten datasets. We made a major effort to make sure that the circuit, optimizer, and error mitigation configuration on the hardware is kept the same as for the simulator jobs.



(a) (b)

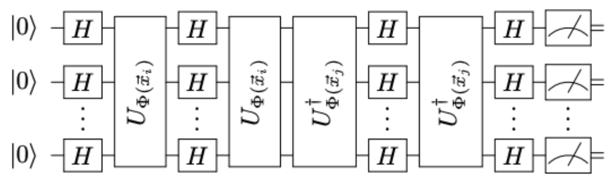
Figure 3: The ROC curves of the quantum variational classifier method with the IBM quantum computer hardware (red) and with the ibmq QasmSimulator (blue) for (a) the ttH analysis (using 'ibmq_boeblingen') and (b) the H → μ+μ− analysis (using 'ibmq_paris').

For each physics analysis, one dataset consisting of 100 events for training and 100 events for testing is utilized to construct the classifiers. This dataset is one of the ten datasets used in figure 3. All classifiers are trained with the same 10 variables processed with the PCA method. In this study, 10 qubits are employed on the quantum computer hardware and the quantum computer simulator. To visualize the discrimination power of both the quantum simulator and quantum hardware, the testing events of the dataset are used to make the ROC curves. We observe that, for the quantum variational classifier method, the quantum simulator and quantum hardware results appear to be in good agreement.

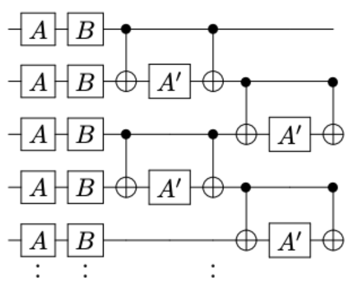
The result of this study, as shown in Figure 2 and 3, has been published in 2021 J. Phys. G: Nucl. Part. Phys. 48 125003.

(b) Quantum Support Vector Machine (QSVM) Kernel Estimation

The support vector machine (SVM) is one of the most commonly used supervised machine learning algorithms for data classification. Following the same paper: Nature 567 (2019) 209, we propose to look for new mapping of the classical Support Vector Machine (SVM) approach into a quantum algorithm in which the feature map is evaluated in the Hilbert space of the N-qubit system. A quantum version of the SVM with a quantum kernel estimator leverages the quantum state space as a feature space to efficiently compute kernel entries. This algorithm maps the classical data event non-linearly to a quantum state of N qubits by applying a quantum feature map circuit $U_{\phi(\vec{x}_i)}$ to the initial state. It then calculates the kernel entry for data events based on the inner product of their quantum states. The calculated kernel matrix will be used to optimize a hyperplane that separates signal events from background events.



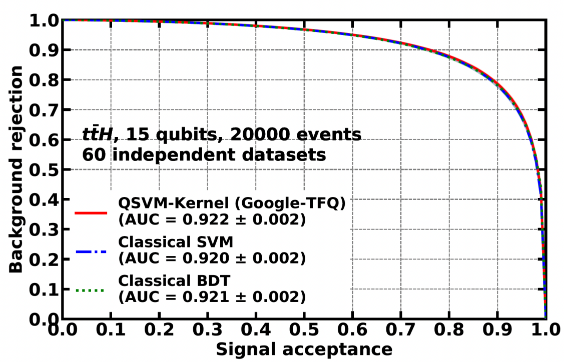
(a)



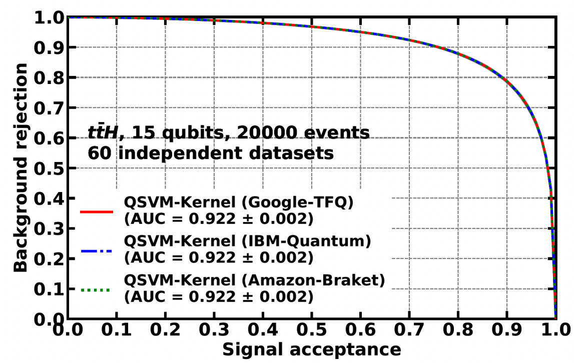
(b)

Figure 4: (a) Quantum circuit for evaluating the kernel entry for data events $\vec{x}_i$ and $\vec{x}_j$ used in our study. H is a Hadamard gate and $U_{\phi(\vec{x}_i)}$ is a unitary operator that encodes data from a classical event in its parameters. (b) Quantum circuit of the unitary operator $U_{\phi(\vec{x}_i)}$. It is constituted by single-qubit rotation gates (A, B and A’), as well as two-qubit CNOT entangling gates.

To classify the signal and dominant background processes for the ttH analysis, we employ the QSVM Kernel algorithm using up to 20 qubits on the qsim Simulator from the StatevectorSimulator from the IBM Quantum framework. For comparison, we also performed the same studies using the Google TensorFlow Quantum framework and the Local Simulator from the Amazon Braket framework. As shown in Figure 5, with 15 qubits and 20000 events, QSVM Kernel on simulator achieves similar performances with classical SVM and classical BDT. Furthermore, the three quantum computer simulators, from the IBM framework, Google framework, and Amazon framework, provide identical classification performances using the QSVM-Kernel algorithm.



(a)



(b)

Figure 5. ROC curves of various classifiers using the ttH analysis datasets of 20000 events and 15 input variables. Each curve represents results averaged over 60 statistically independent datasets. (a) Overlays the results of the Quantum Kernel algorithm (on the qsim Simulator from the Google TensorFlow Quantum framework) (red), the classical SVM algorithm (blue) and the classical BDT algorithm (green). (b) Overlays the QSVM-Kernel results on the qsim Simulator from the Google TensorFlow Quantum framework (red), the StatevectorSimulator from the IBM Quantum framework (blue) and the Local Simulator from the Amazon Braket framework (green). Here the QSVM-Kernel classifiers employ 15 qubits on the quantum simulators.

We also studied the AUC for various classifiers as a function of the ttH analysis dataset size (10000 to 50000 events) and as a function of the number of qubits – see Figure 6. We found that the performance of the QSVM-Kernel algorithm is similar to that of the classical SVM algorithm and classical BDT.

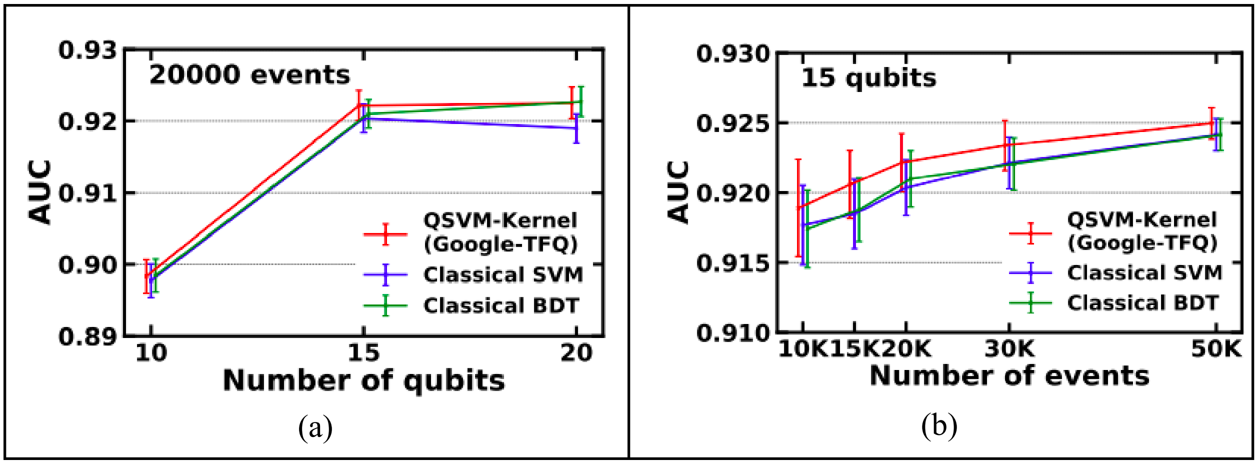


Figure 6: (a) AUCs of the QSVM-Kernel algorithm as a function of the number of qubits (10 to 20 qubits). (b)The AUC for various classifiers as a function of the ttH analysis dataset size (10000 to 50000 events). Both show the results of the QSVM-Kernel (on the qsim Simulator from the Google TensorFlow Quantum framework), the classical SVM and the classical BDT.

After the studies using simulation of the ideal quantum simulators, we also apply the QSVM-Kernel method to today's noisy quantum computer hardware to assess its performance. As shown in Figure 7, with small training samples of 100 events, the performance achieved by the "ibmq paris" quantum computer hardware is promising and approaching the noiseless quantum computer simulator.

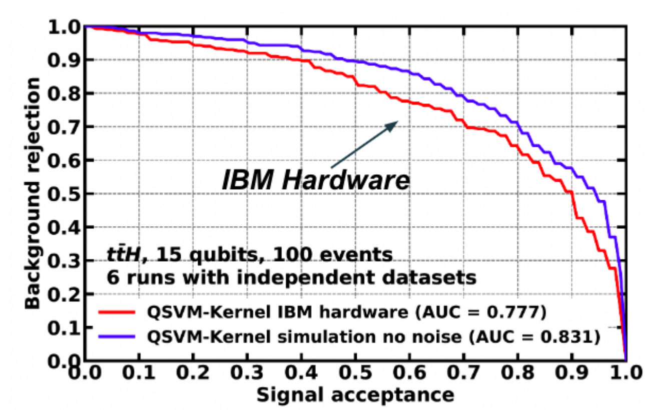


Figure 7: ROC curve with the "ibmq paris" quantum computer hardware and ROC curve with the StatevectorSimulator from the IBM Quantum framework.

The result of this study, shown in Figure 5, 6 and 7, has been published in Phys. Rev. Research 3 (2021), 033221.

(c) Quantum Neural Network (QNN)

Quantum Neural Networks (QNNs) are a class of neural networks that perform computations on quantum states. QNNs are constructed by mapping classical neural network architectures to quantum circuits, with qubits acting as the neurons. The large latent space represented by the qubits in QNNs may potentially lead to a better global minimum than the classical neurons in classical NNs. To fit the Noisy Intermediate-Scale Quantum (NISQ) devices, hybrid QNNs of three layers have been explored. Figure 8 (a) shows a comparison of the performance between classical NN and quantum NN on the signal-background separation in the ttH analysis. Very close performance is achieved with 15 qubits and 200K events, showing great potential of the QNN. The use of hardware confirms the potency of QNN (b).

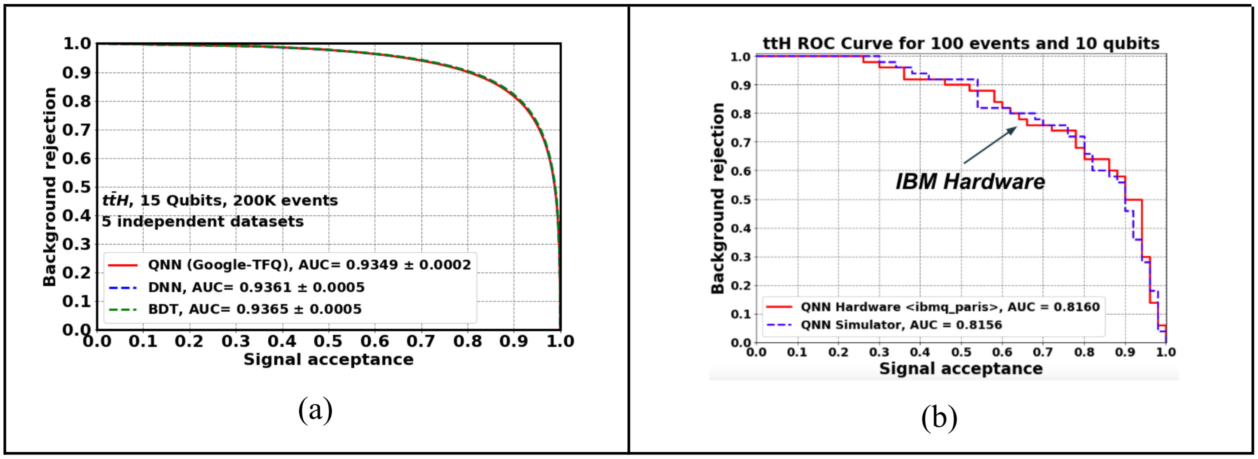


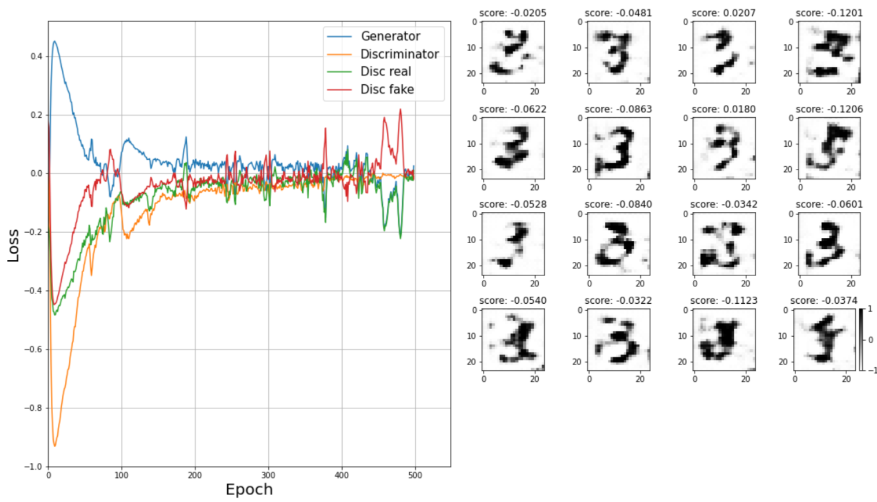
Figure 8: (a) ROC of Quantum NN, classical NN, and BDT trained on 200K events. Comparable performance is achieved with QNN showing good potential to QNN. (b) Performance of QNN using quantum computers.

The result of this study, shown in Figure 8, has been presented in the International conferences European Physics Society conference on High Energy Physics 2021 and International Symposium on Lepton Photon Interactions at High Energies 2021 by PI Wu.

(d) Quantum Generative Adversarial Network (QGAN)

Quantum machine learning can be used to construct generative models. Our objective was to develop a quantum version of the Generative Adversarial Network (QGAN) by replacing its generator and/or discriminator neural networks with quantum neural networks. To achieve this, we developed a quantum convolutional network layer that uses a quantum filter as its fundamental building block. This quantum filter replaces the classical filter with a Parameterised Quantum Circuit (PQC). The PQC scans local regions of an image, transforms classical pixel values into quantum states, and processes them through the rest of the quantum convolutional layers. We can train the quantum filters using gradient descent to optimize the parameters of the quantum convolutional network.

Using the Quantum convolutional layer, we also successfully built a Quantum GAN. Figure 9 illustrates the output of the QGAN we developed, which was trained on the MNIST dataset to generate images of the digit "3". After training for 100 iterations, the QGAN was able to produce acceptable images of the digit “3”. Our findings suggest that Quantum Machine Learning can be used to construct generative models.



Digit 3

Figure 9: Performance of Quantum GAN trained using MNIST dataset. The QGAN consists of a classical generator and a quantum discriminator. The left plot shows the loss values as a function of training iterations and the right plot shows some examples of generated images of the digit “3”.

(e) Quantum Anomaly Detection

Quantum anomaly detection is an emerging field in quantum computing that aims to detect anomalies in complex data sets using quantum algorithms. Anomalies are often defined as data points that deviate significantly from the expected behavior of the system. Detecting anomalies can be critical in many applications, including cybersecurity, finance, and healthcare. Here we studied a quantum autoencoder as an anomalous detector to “re-discover” the Higgs boson in the LHC dataset.

We train a quantum autoencoder using the sideband data of the di-photon mass distribution, in which the Higgs signal events are negligible. Results are shown in Figure 10. Upon completion of the training process, the quantum autoencoder exhibits varied responses to different processes as depicted in (a). In the anomalous region, defined by Ln(loss) > 5 (shown in red in (b)), a more prominent peak of the Higgs boson signal emerges on the distribution of the di-photon invariant mass (yy_m).

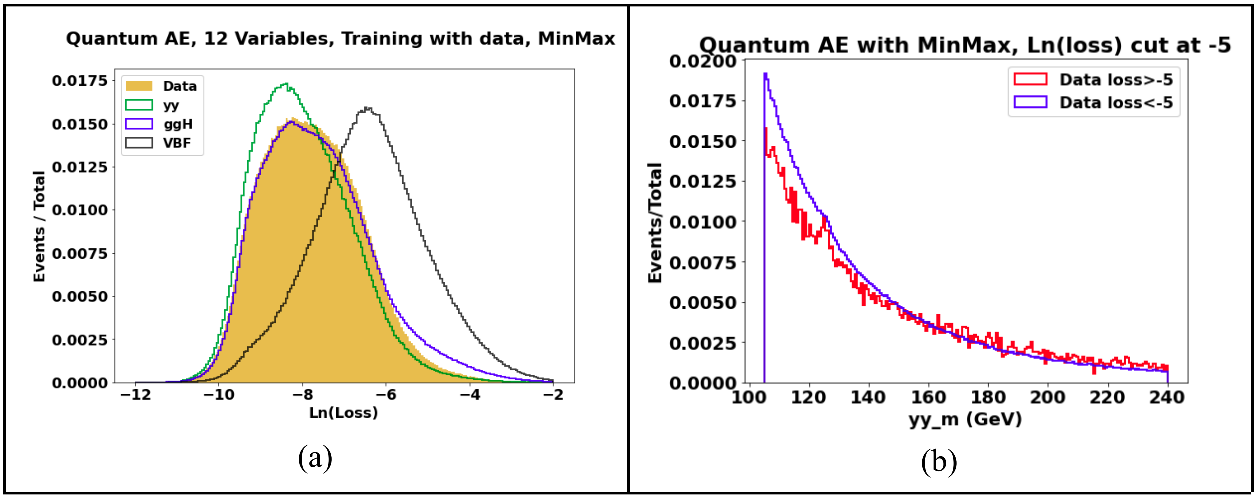


Figure 10: Using a quantum autoencoder as an anomalous detector to “re-discover” the Higgs boson. The quantum autoencoder is trained on the sideband data of the di-photon mass distribution that do not contain Higgs signal events. After training, the quantum autoencoder shows different responses on different processes in (a). In the anomalous region that is defined with Ln(loss) > 5 (red), a more visible Higgs boson signal peak emerges (b).

2.2 Large Qubit Simulation with Distributed Training on NERSC Perlmutter HPC (GPUs)

The primary goal of LHC Quantum Machine Learning physics is to unite High Energy Physics analysis techniques with cutting-edge quantum computing advances to explore quantum advantages. We aim to show that Quantum Machine Learning can outperform classical machine learning in classification power by exploiting a large number of qubits (25 qubits or more) and a large number of events. To achieve this, we need a large amount of computational power to perform quantum simulations.

With the QIS @ Perlmutter Award, we have access to the NERSC Perlmutter HPC system. We have been communicating with the NVIDIA cuQuantum team. With their help, we managed to run large qubit simulations (for example, 26 qubits) with distributed training techniques and NVIDIA cuQuantum on Perlmutter GPUs. We are now able to use multiple nodes and multiple GPUs on each node for the QNN training. Figure 11 shows the GPU Utilization rate (~60%) for a QNN training with 26 qubits and 5000 events. In this study, Fifteen Perlmutter nodes were used and each node has four NVIDIA A100 (Ampere) GPUs. We will investigate further the large qubit simulation by increasing the GPU utilization rate and by improving the training time. We will extend this study to the training of other Quantum Machine Learning models.

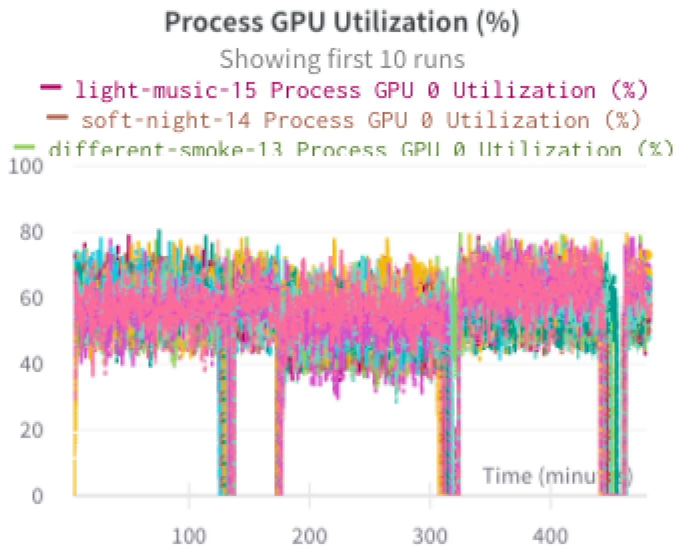


Figure 11: GPU Utilization rate for QNN training with 26 qubits and 5000 events. Fifteen Perlmutter nodes were used and each work node has four NVIDIA A100 (Ampere) GPUs.

SECTION 3: EDUCATION

Education is one of the primary missions of PI Sau Lan Wu. In the era of rapid advancement of technological innovation, it is crucial to prepare our graduate students and young research associates for their scientific and technical careers. Conducting research and development in the area of Quantum Machine Learning will fulfill this goal, which is critically important to the mission of education for the younger generation.

Sixty one graduate students have obtained their Ph.D. degrees under the supervision of PI Sau Lan Wu, including 10 theses from the TASSO collaboration, 23 from the ALEPH collaboration, 9 from the BaBar collaboration, and 19 from the ATLAS collaboration. In all cases, PI Wu points out the right research direction and creates a platform for her students to perform. Forty of her former postdocs and graduate students are now faculty members in major U.S. universities and worldwide. In addition, eighteen are permanent staff members at major High Energy Physics laboratories. An interesting development is that high-energy physicists are entering the workforce of well-known industries, providing successfully the functionality of technology transfer. Having been well trained in the high technology environment of large international physics collaborations, members of Wu's group are eminently suited to provide this functionality of technology transfer, always on the leading edge. Some of her former postdocs and former graduate students hold challenging positions in industries. In the last several years, eight graduate students have received PhD degrees from PI Sau Lan Wu; two of them was awarded the prestigious Chamberlain Fellowship from Berkeley, one has joined Google, one is at Amazon, one is at Facebook, one is at Ernst & Young and one is at Accenture Entreprise (big data sciences). The eighth former graduate student is a High Performance Computing Postdoctoral Scholar at Berkeley.

Contribution to the Google Summer of Code Program

Under the umbrella of the ML4SCI organization, 4 of our group members have served as mentors for the Google Summer of Code projects related to Quantum Machine Learning in 2020 and 2021. We helped the students in the projects to develop Quantum Machine Learning libraries for High Energy Physics.

SECTION 4: IMPACT TO COMMUNITIES OF INTEREST

Results from this project are typically disseminated via refereed publications and conference talks and proceedings. Our team has published two journal publications to summarize the accomplishments: Phys. Rev. Research 3 (2021), 033221 and J. Phys. G: Nucl. Part. Phys. 48 (2021) 125003. Furthermore, postdoctoral research associate Wen Guan was invited to write a review article on “Quantum Machine Learning in High Energy Physics” together with other experts and this review article (2021 Mach. Learn.: Sci. Technol. 2 011003) has been published in “Machine Learning: Science and Technology”.

On November 4, 2020, PI Sau Lan Wu was honored to be one of the two inaugural speakers of the QuantHEP seminar – a platform open to scientists around the world, which aims to bring the Quantum Computation and High-Energy Physics communities closer together, discuss recent scientific work on the relations between the two communities, and sparking a strong interest from CERN. The title of the presentation is “Application of Quantum Machine Learning to HEP Analysis at LHC using Quantum Computer Simulators and Quantum Computer Hardware”.

In addition, PI Sau Lan Wu was invited to write by Nature and has published a review article for Nature Review Physics on “Challenges and opportunities in quantum machine learning for high-energy physics”, Nature Rev. Phys. 4 (2022), 143–144.

Our team has published 4 journal publications in total related to Quantum Machine Learning and has given 21 presentations in conferences and workshops including EPS-HEP (European Physical Society Conference on High Energy Physics) 2019 and EPS-HEP 2021, and LP (International Symposium on Lepton Photon Interactions at High Energies) 2019 and LP 2021, ICHEP (International Conference on High Energy Physics) 2020 and QTech (Quantum Technology International Conference) 2020.

SECTION 5: PUBLICATIONS

PI Sau Lan Wu and our Wisconsin group are the leading authors of the following journal publications and proceedings of the major international conferences:

1. S. L. Wu, S. Yoo, “Challenges and opportunities in quantum machine learning for high-energy physics”, Nature Rev. Phys. 4 (2022), 143–144 (Sau Lan Wu was the corresponding author)
2. S. L. Wu et al., “Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC”, Phys. Rev. Research 3 (2021), 033221 (Sau Lan Wu was the corresponding author)
3. S. L. Wu et al., “Application of quantum machine learning using the quantum variational classifier method to high energy physics analysis at the LHC on IBM quantum computer simulator and hardware with 10 qubits”, 2021 J. Phys. G: Nucl. Part. Phys. 48 125003
4. W. Guan et al., “Quantum Machine Learning in High Energy Physics”, 2021 Mach. Learn.: Sci. Technol. 2 011003
5. S. L. Wu et al., “Application of Quantum Artificial Intelligence / Machine Learning to High Energy Physics Analyses at LHC Using Quantum Computer Simulators and Quantum Computer Hardware”, Proceeding of “30th International Symposium on Lepton Photon Interactions at High Energies (Lepton Photon 2021)”
6. S. L. Wu et al., “Application of Quantum Machine Learning to HEP Analysis at LHC using Quantum Computer Simulators and Quantum Computer Hardware”. Proceedings of “European Physical Society Conference for High Energy Physics (EPS-HEP) 2021”.
7. S. L. Wu et al., “Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware”. Proceedings of “40th International Conference on High Energy Physics - ICHEP2020”
8. S. L. Wu et al., “Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware”. Proceedings of "XXIX International Symposium on Lepton Photon Interactions at High Energies (LeptonPhoton2019)"
9. S. L. Wu et al., “Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware”. Proceedings of "European Physical Society Conference on High Energy Physics (EPS-HEP) 2019”

SECTION 6: CONFERENCE TALKS

We gave 21 conference talks in various international conferences in HEP or Quantum machine learning fields.

Speaker	Talk title	Conference	Dates
Postdoc Wen Guan	Application of Quantum Machine Learning to High Energy Physics Analysis at LHC	Quantum Technology International Conference 2020	Nov 4, 2020
Postdoc Wen Guan	Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware	4th ATLAS Machine Learning Workshop, Geneva, Switzerland	Nov 15, 2019
Postdoc Wen Guan	Applying IBM quantum computing to LHC physics analysis Higgs coupling to two top quarks	CERN Graph Net::work::shop, Geneva, Switzerland	Jun 19, 2019
Postdoc Wen Guan	Application on LHC High Energy Physic data analysis with IBM Quantum Computing	19th International Workshop on Advanced Computing and Analysis Techniques in Physics Research	Mar 10, 2019
Postdoc Wen Guan	Application of IBM Quantum Computing to LHC High Energy Physics Data Analysis	European Quantum Technologies Conference (EQTC19) in Grenoble, France, the First International Conference of the QT Flagship(2019)	Feb 20, 2019
Postdoc Wen Guan	Applying IBM Quantum Computing to LHC Physics Analysis of HiggsCoupling to Top Quarks	CERN openlab Technical Workshop, CERN, Geneva, Switzerland(2019)	Jan 24, 2019
Postdoc Wen Guan	Preliminary Development on HEPData Analysis Using Quantum Computing Based on IBM Qiskit	Quantum Computing for High EnergyPhysics workshop, CERN, Geneva, Switzerland(2018)	Nov 6, 2018
Software Engineer S. J. Sun	Application of Quantum Machine Learning using the Quantum Kernel Algorithm on High Energy Physics Analysis at the LHC	DPF 2021, Virtual Conference	July 14, 2021
Software Engineer S. J. Sun	Application of Quantum Machine Learning to HEP Analysis at LHC using IBM Quantum Simulator and Quantum Hardware	Quantum Technology International Conference 2020	Nov. 4, 2020
Software Engineer S. J. Sun	Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum	CERN openlab Technical Workshop, Geneva, Switzerland	Jan. 22, 2020

	Computer Simulators and IBM Quantum Computer Hardware		
Software Engineer S. J. Sun	Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware	IBM Workshop: Quantum Computing for chemistry and physics applications, Zurich, Switzerland	Oct. 30, 2019
Grad. Student A. Wang	Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware	29th International Symposium on Lepton Photon Interactions at High Energies, Toronto, CA	Aug 8, 2019
Grad. Student A. Wang	Application of Quantum Machine Learning to High Energy Physics Analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware	DPF 2019, Northeastern University, USA	Aug 1, 2019
PI Prof. S.L. Wu	Application of Quantum Machine Learning to HEP Analysis at LHC using Quantum Computer Simulators and Quantum Computer Hardware: Challenges and Opportunities	30th International Symposium on Lepton Photon Interactions at High Energies, Manchester, UK	Jan 12, 2022
PI Prof. S.L. Wu	Application of quantum machine learning to High Energy Physics analysis at LHC using Quantum Computer Simulators and Quantum Computer Hardware	European Physics Society Conference on High Energy Physics	July 29, 2021
PI Prof. S.L. Wu	Application of quantum machine learning to High Energy Physics analysis at LHC using Quantum Computer Simulators and Quantum Computer Hardware	CERN TH Institute Workshop “Perspectives on Quantum Sensing and Computing for Particle Physics”	July 15, 2021
PI Prof. S.L. Wu	Application of quantum machine learning to High Energy Physics analysis at LHC using Quantum Computer Simulators and Quantum Computer Hardware	“QuantHEP – Quantum Computing Solutions for High-Energy Physics” Inaugural Seminar	Nov 4, 2020

Postdoc C. Zhou	Application of quantum machine learning to High Energy Physics analysis at LHC using IBM Quantum Computer Simulators and Hardware	40th international conference on High Energy Physics, virtual conference	July 28, 2020
Postdoc C. Zhou	Application of quantum machine learning to High Energy Physics analysis at LHC using IBM Quantum Computer Simulators and Hardware	ATLAS Software & Computing Week	Feb 10, 2020
Postdoc C. Zhou	Application of quantum machine learning to High Energy Physics analysis at LHC using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware	EPS-HEP 2019	July 12, 2019
Postdoc R. Zhang	Application of Quantum Machine Learning to HEP Analysis at LHC using Quantum Computer Simulators and Quantum Computer Hardware – Challenges and Opportunities	XI International Conference on New Frontiers in Physics (ICNFP 2022)	Sep 7, 2022