Implementation of Quantum Machine Learning in $H \to \gamma\gamma$ analysis at CEPC

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Overview

Introduction

Data encoding and processing

Feature map and quantum kernel estimation

Performance of the quantum simulator

Performance of the real quantum computers

Conclusion and outlook

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Application of Quantum Machine Learning in a Higgs Physics Study at the CEPC

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ABSTRACT

Machine learning has blossomed in recent decades and has become essential in many fields. It significantly solved some problems for particle physics—particle reconstruction, event classification, etc. However, it is now time to break the limitation of conventional machine learning with quantum computing. A support-vector machine algorithm with a quantum kernel estimator (QSVM-Kernel) leverages high-dimensional quantum state space to identify a signal from backgrounds. In this study, we have employed this quantum machine learning algorithm to study the $e^+e^- \rightarrow ZH$ process at the Circular Electron-Positron Collider (CEPC), a Higgs factory proposed by Chinese scientists. Using 6-qubits on quantum computer simulators, we have optimized the QSVM-Kernel algorithm and obtained a similar classification performance to the classical support-vector machine algorithm. We have also validated the QSVM-Kernel algorithm using 6-qubits on quantum computer hardware from both IBM and Origin Quantum (a quantum technology company in China), where the classification performance is approaching noiseless quantum computer simulators. Our study is one of the few examples that apply state-of-the-art quantum computing technologies to particle physics, a branch of fundamental science that relies on big experimental data.

1. Introduction

The discovery of the Higgs boson [1, 2] by the ATLAS and CMS experiments at the Large Hadron Collider (LHC) in 2012 was a significant milestone in particle physics. It confirmed the fundamental particle spectrum of the Standard Model and opened a new window to refine our understanding of particle physics (also known as high energy physics). Since then, the LHC experiments have performed extensive studies on the Higgs boson properties: clues for new physics would emerge if any measurement disagrees with the Standard Model prediction. Furthermore, Higgs factories [3, 4, 5, 6] based on lepton colliders have been proposed to perform more precise measurements of the Higgs boson properties and study the deeper structure of particle physics. The Circular Electron-Positron Collider (CEPC), presented by Chinese scientists, is one of such collider that acts as a Higgs factory. It will be located in a tunnel with a circumference of approximately 100 km colliding electron-positron pairs at a centre-of-mass energy of up to 240 GeV, upgradable to 360 GeV as well as Super Proton Proton Collider (SPPC).

Machine learning has enjoyed widespread success in detector simulation, particle reconstruction and data analyses of experimental particle physics and dramatically enhances the ability to achieve physics discovery. For instance, machine learning algorithms are used in ATLAS and CMS experiments to help separate signals from backgrounds in the observation of the Higgs boson production in association with a top quark pair ($t\bar{t}H$), which directly establishes the Higgs boson couplings to the top quarks [7, 8].

Another essential tool for experimental particle physics could be quantum machine learning. It uses quantum computing to perform machine learning tasks that tackle large data dimensions. Quantum machine learning enables effective operations in high-dimensional quantum state spaces where computers operate with qubits instead of classical bits. Therefore, it could provide fast computing speed and better learning ability than classical machine learning. As an example of quantum machine learning, a support-vector machine algorithm with a quantum kernel estimator (QSVM-Kernel) [9, 10] encodes classical data into quantum state space and makes accurate classifications for certain artificial data sets.

In recent years, the field of quantum computing has developed rapidly. Superconducting quantum and optical quantum computers have been successfully fabricated and have demonstrated capabilities far beyond today's supercomputers in certain computing tasks [11, 12]. In the following decades, this field will likely increase the number of qubits, improve execution time, and reduce device noise for quantum computers. These developments will lay a foundation for the practical application of quantum computing.

Studying quantum machines to utilize the potential of quantum advantage for future particle physics research is important. There have already been proof-of-principle studies that apply quantum machine learning algorithms to detector

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Introduction

Machine learning has blossomed in the last decades and becomes essential in many fields.

- It played a significant role in solving High Energy physics problems, such as reconstruction, particle identification.
- We can use deep learning to handle some high dimensional and complex problems.

Quantum computer is a new tool that offers faster processing capabilities compared to traditional computers.

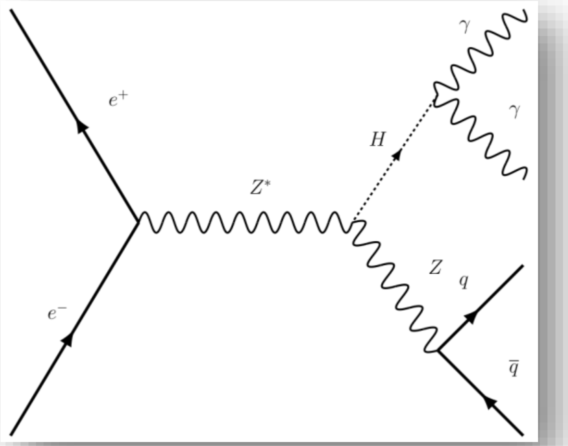
Quantum machine learning:

- Enhanced computing speed: Quantum computing's parallel computing capability improves prediction accuracy.
- Improved generalization ability: QML algorithms effectively handle large- scale data and process multiple data sources, leading to better generalization in practical applications.

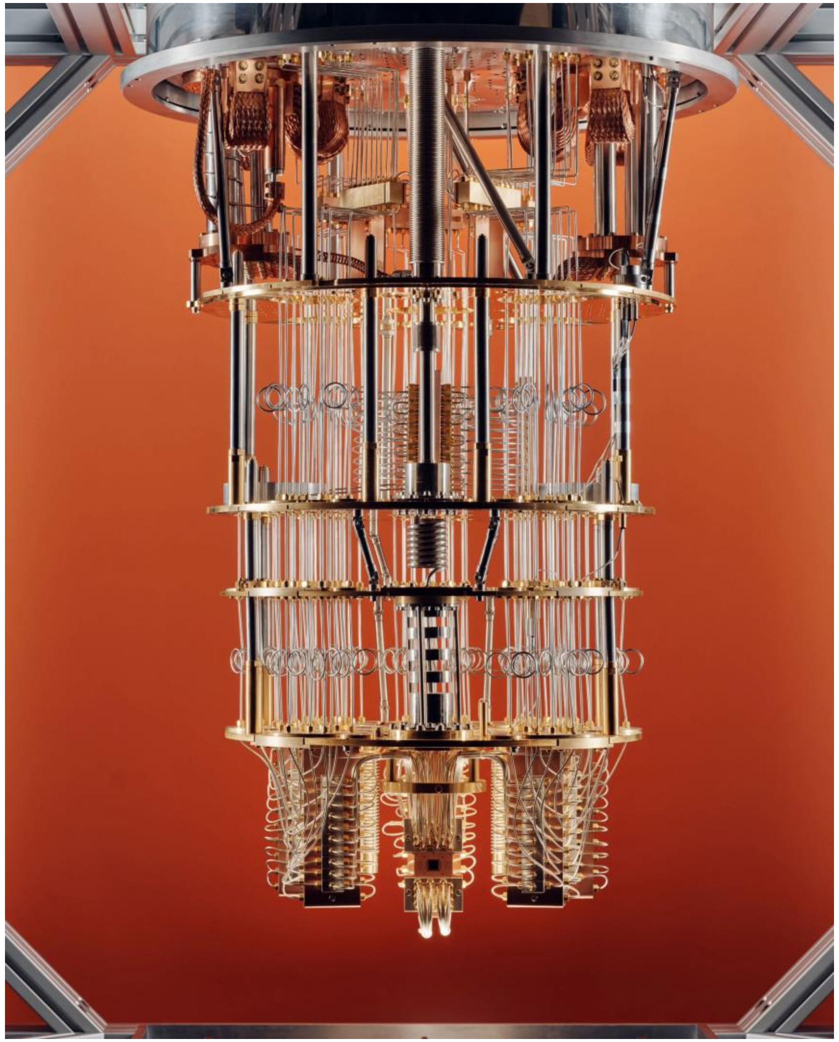
Many companies, including Google, IBM, are actively devoted to accelerating the development of quantum technology.

Objectives:

- Apply quantum machine learning to high energy physics.
- Using quantum algorithm to classify the CEPC signal and background in quantum computer.
- Make the algorithm work in both quantum simulators and real quantum computers.



Introduction---IBM Quantum Computer



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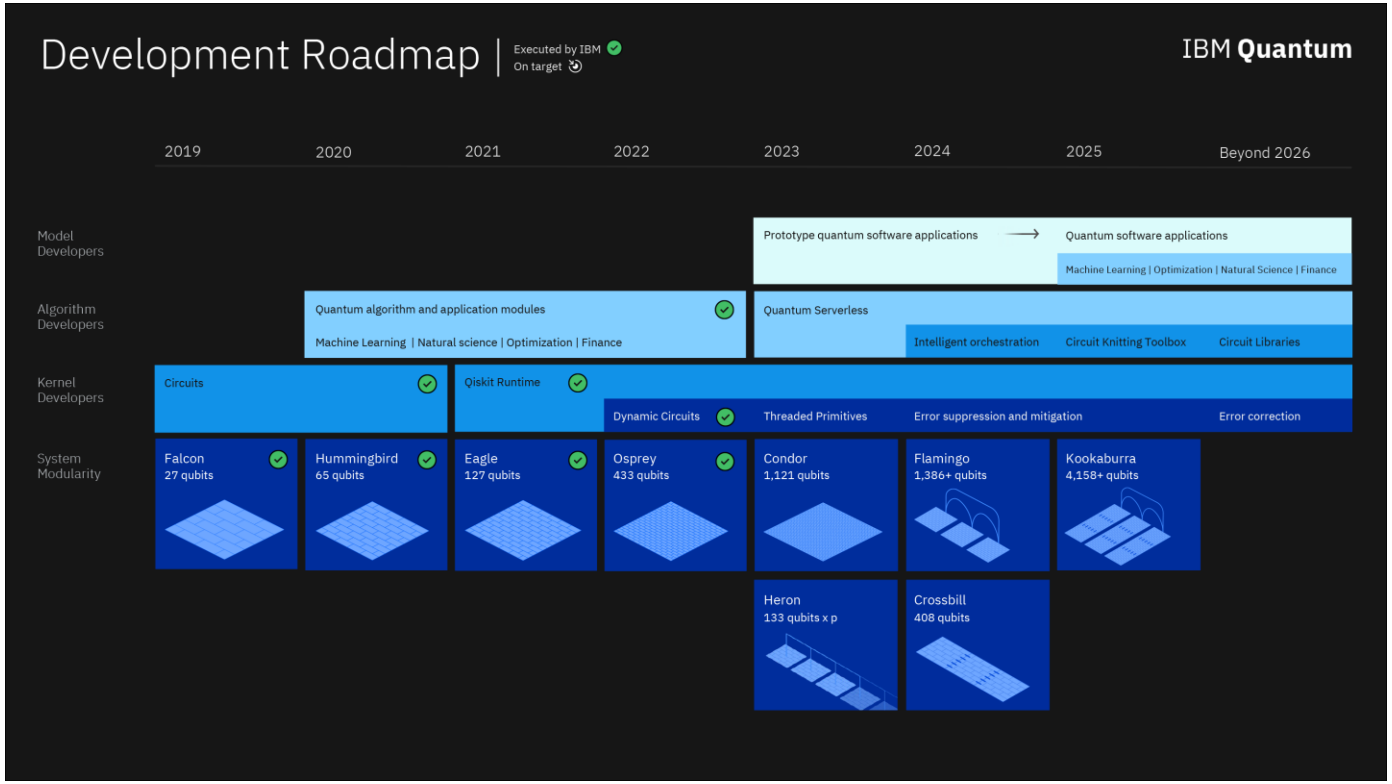
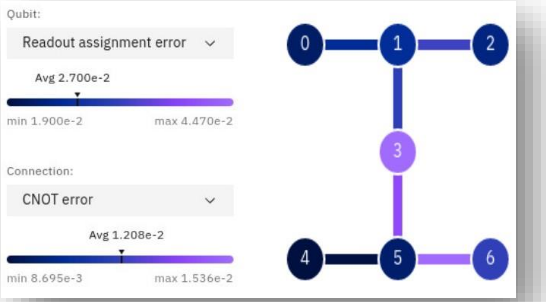


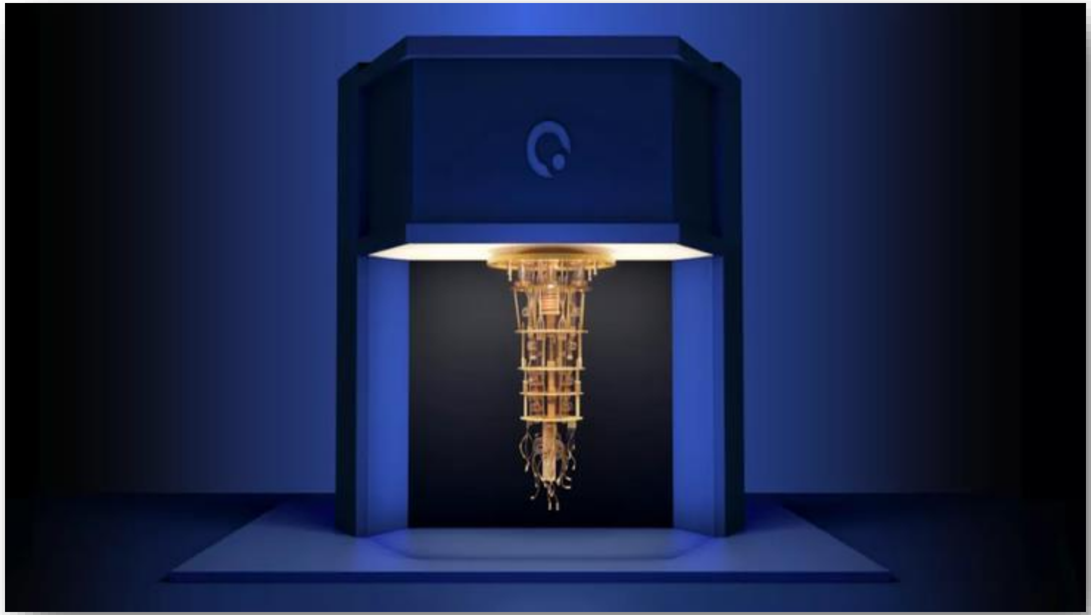
IBM has ambitious pursuits:

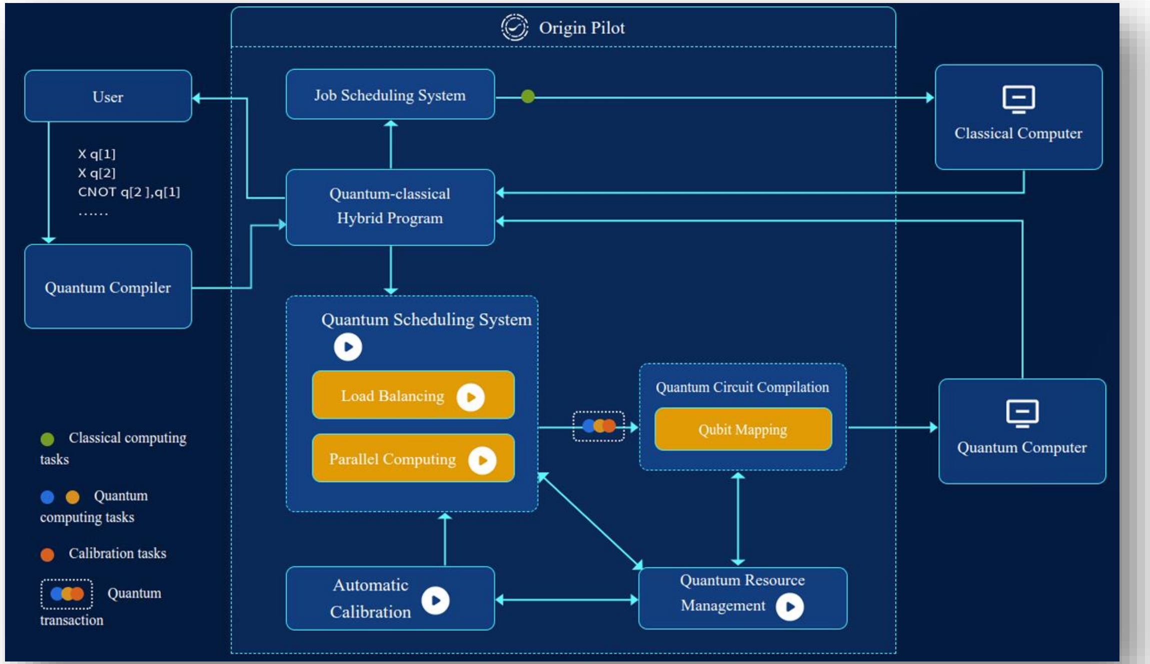
- 433-qubits IBM Quantum Osprey
- Three times larger than the Eagle processor (127-qubits)
- Going up to 10k-100k qubits.

Now, IBM provides up to 7 qubits for free.



Introduction---Origin Quantum Computer



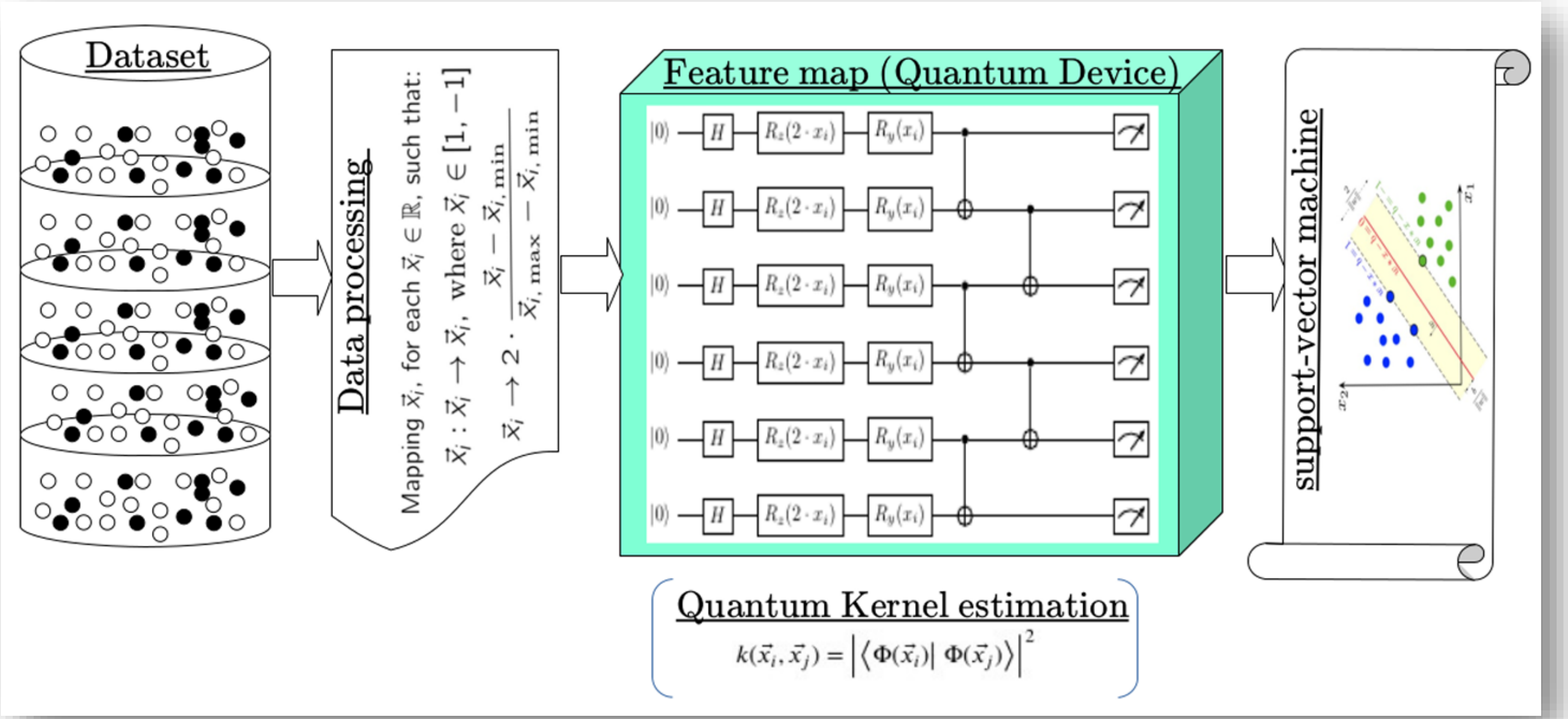


Origin wuyuan:

- The first “practical quantum computer” in China.
- 24-qubits with own control system.

Origin wuyuan provide up to 6 qubits for free.

Data encoding and processing



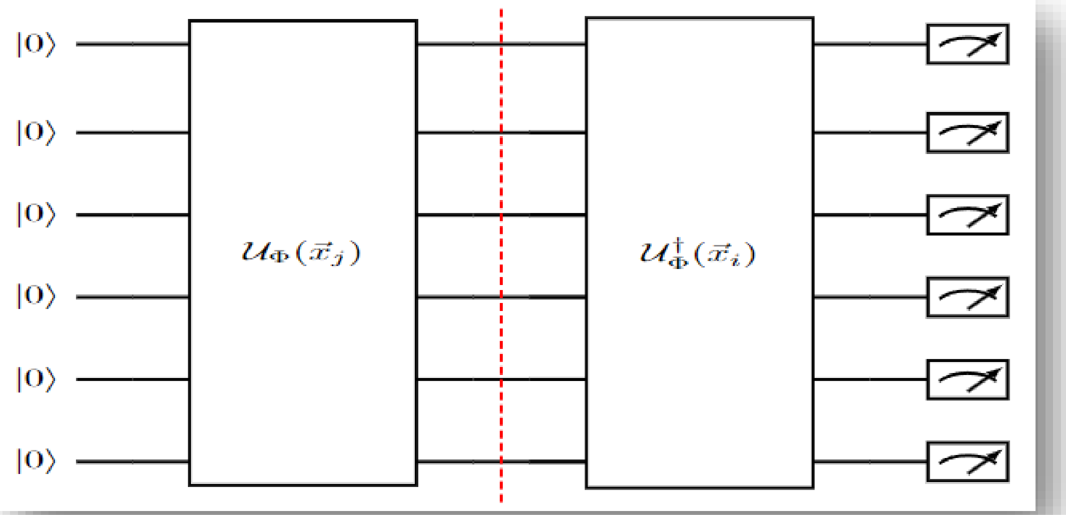
- Encoding the $e^+e^- \to ZH \to q\bar{q}\gamma\gamma$ (signal) and $e^+e^- \to (Z/\gamma^*)\gamma\gamma$ (background)
- Six variables are passed through preliminary mapping and then passed to a quantum circuit for evaluation.
- The Quantum support-vector machines kernel (QSVM-Kernel) is evaluated for each data point and the rest.

Feature map and quantum kernel estimation

Quantum feature map determines the QSVM-Kernel:

- Two identical layers
- Single-qubit rotation gates
- Two-qubits CNOT entangling gates

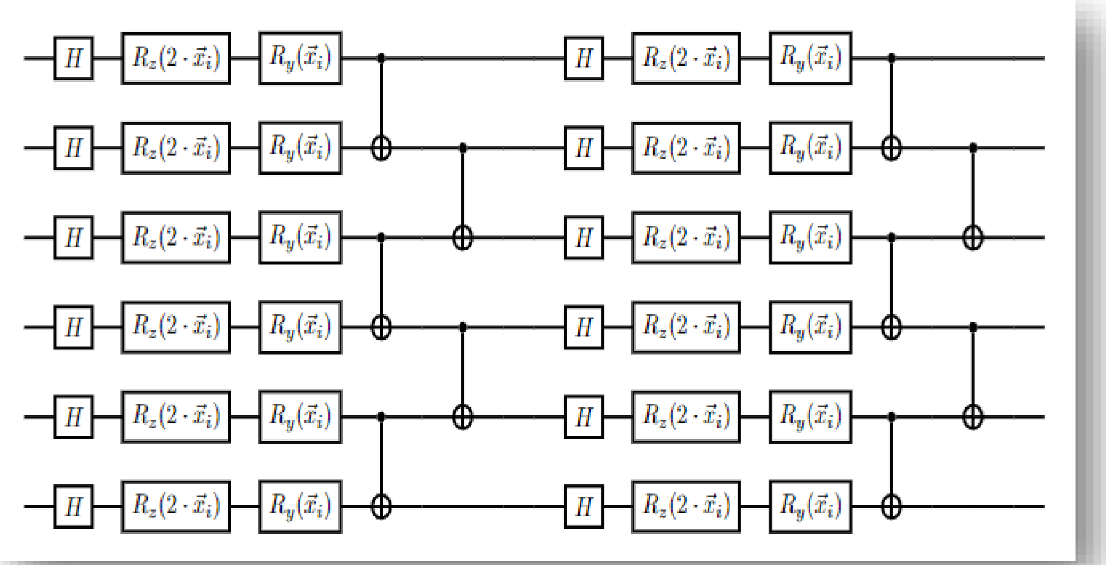
Rotation	Depth	Events	Best AUC	Variation
$R_z(2 \cdot \vec{x_i}) + R_y(\vec{x_i})$	2	5000	0.935	0.009
$R_z(\vec{x_i}) + R_y(\vec{x_i})$			0.933	0.015
$R_y(\vec{x_i}) + R_x(\vec{x_i})$			0.932	0.015
$R_z(\vec{x_i}) + R_z(\vec{x_i})$			0.932	0.014
$R_y(\vec{x_i})$			0.928	0.008
$R_z(\vec{x_i})$			0.928	0.008



QSVM-Kernel estimation:

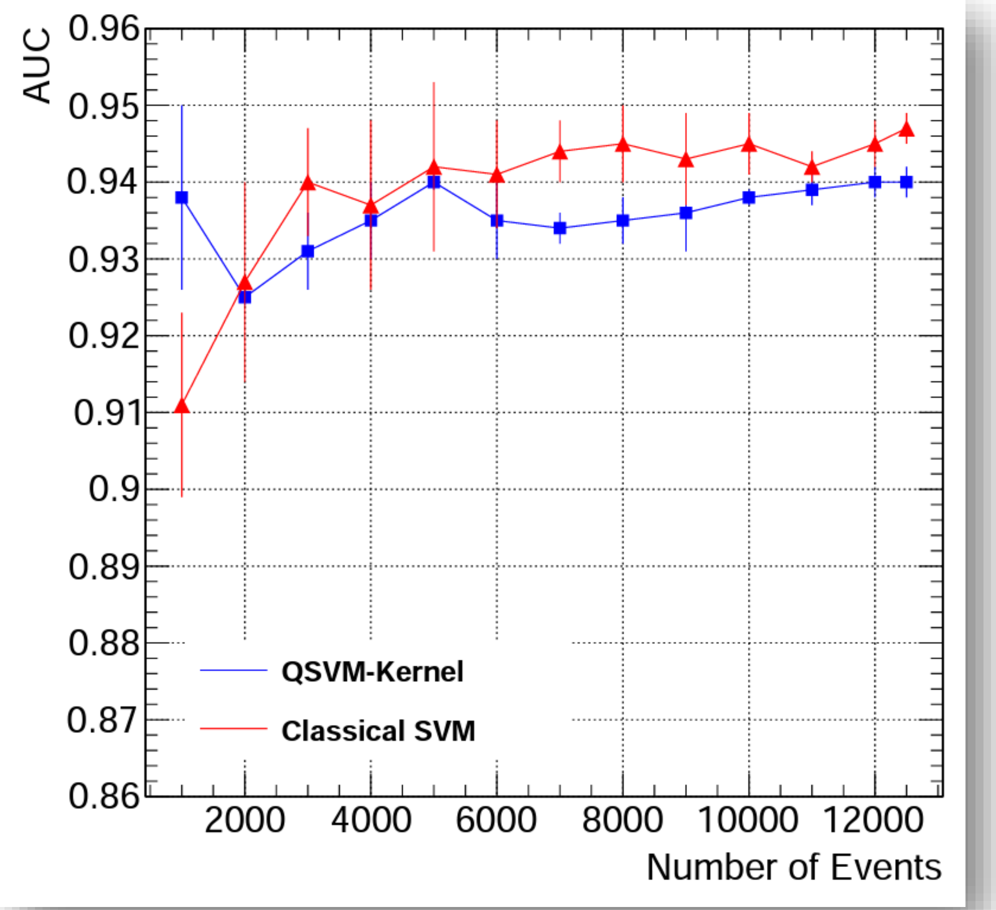
- Using 6 variables mapped to 6-qubit
- The expectation of each data point

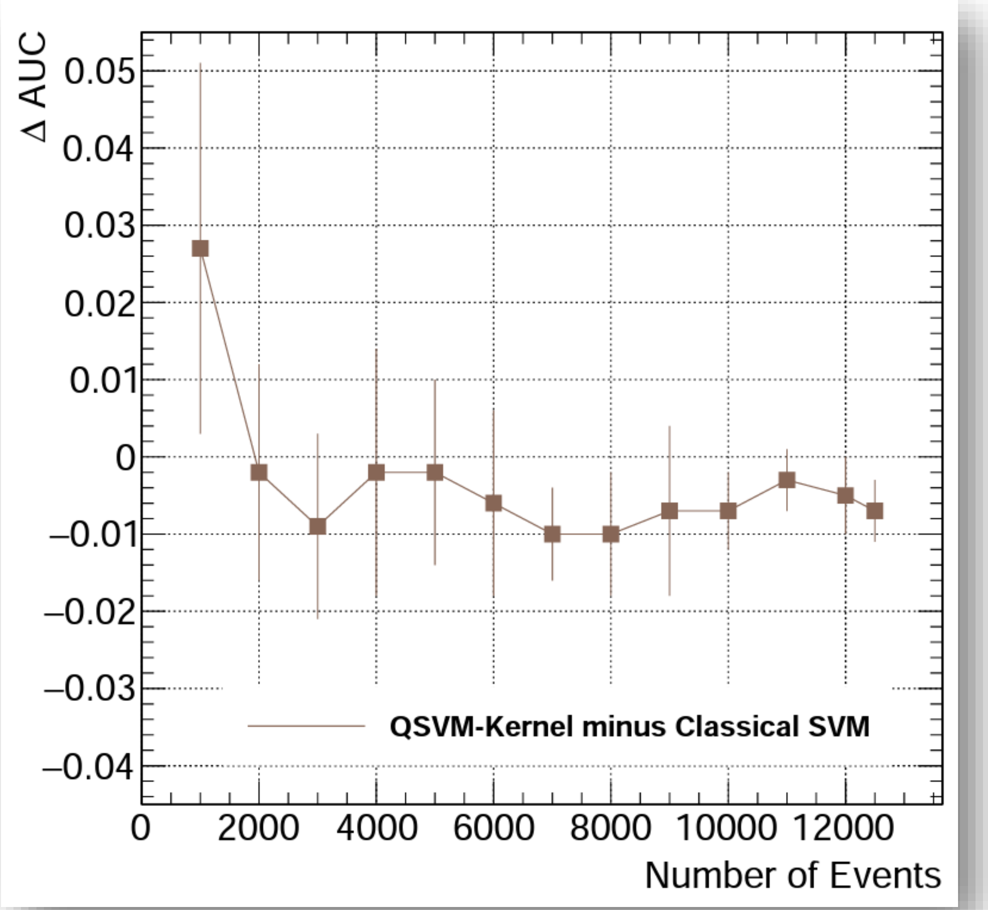
$$k(\vec{x_i}, \vec{x_j}) = \left| \langle 0^{\otimes N} | \mathcal{U}^\dagger_{\Phi(\vec{x_i})} \mathcal{U}_{\Phi(\vec{x_j})} | 0^{\otimes N} \rangle \right|^2$$



AUCs as function of the event

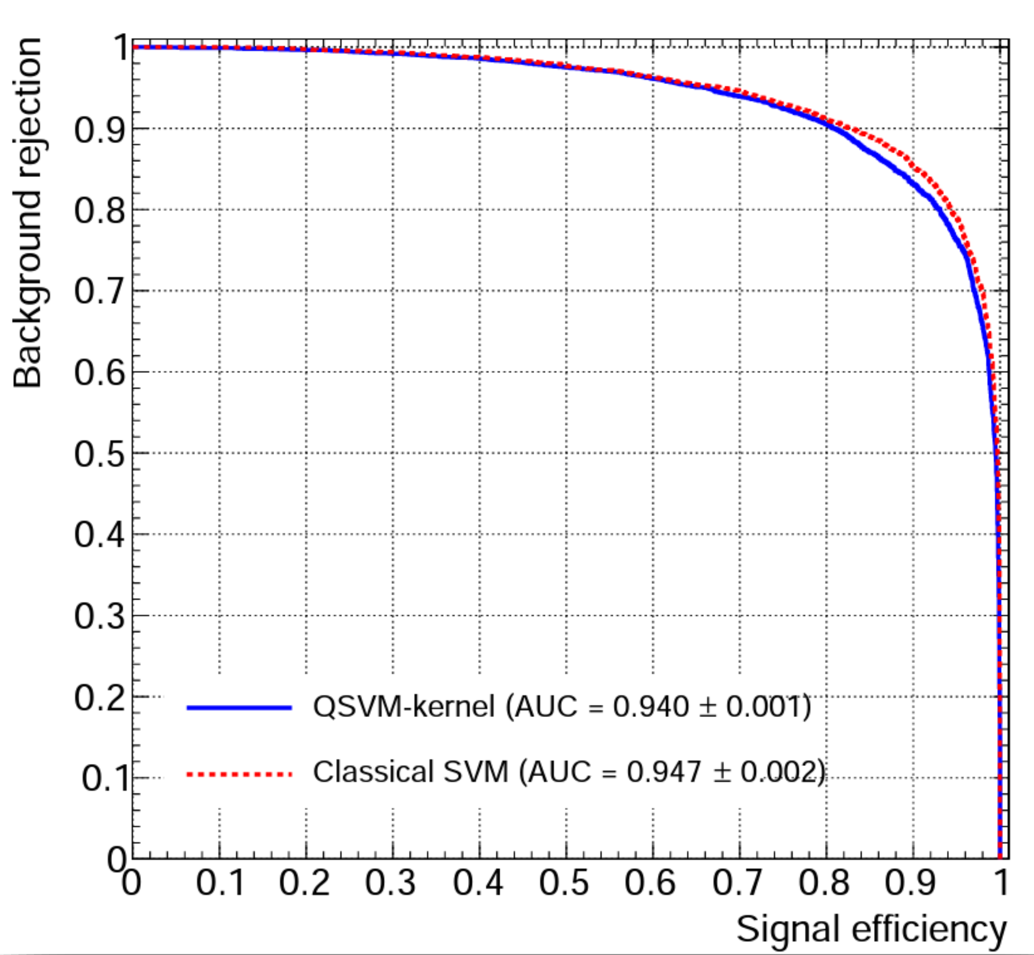
- The QSVM-Kernel and classical SVM classifiers with different dataset size from 1000 to 12500 events.
- The quoted errors are the standard deviations for AUCs calculated from several shuffles of the dataset.





Performance of the quantum simulator

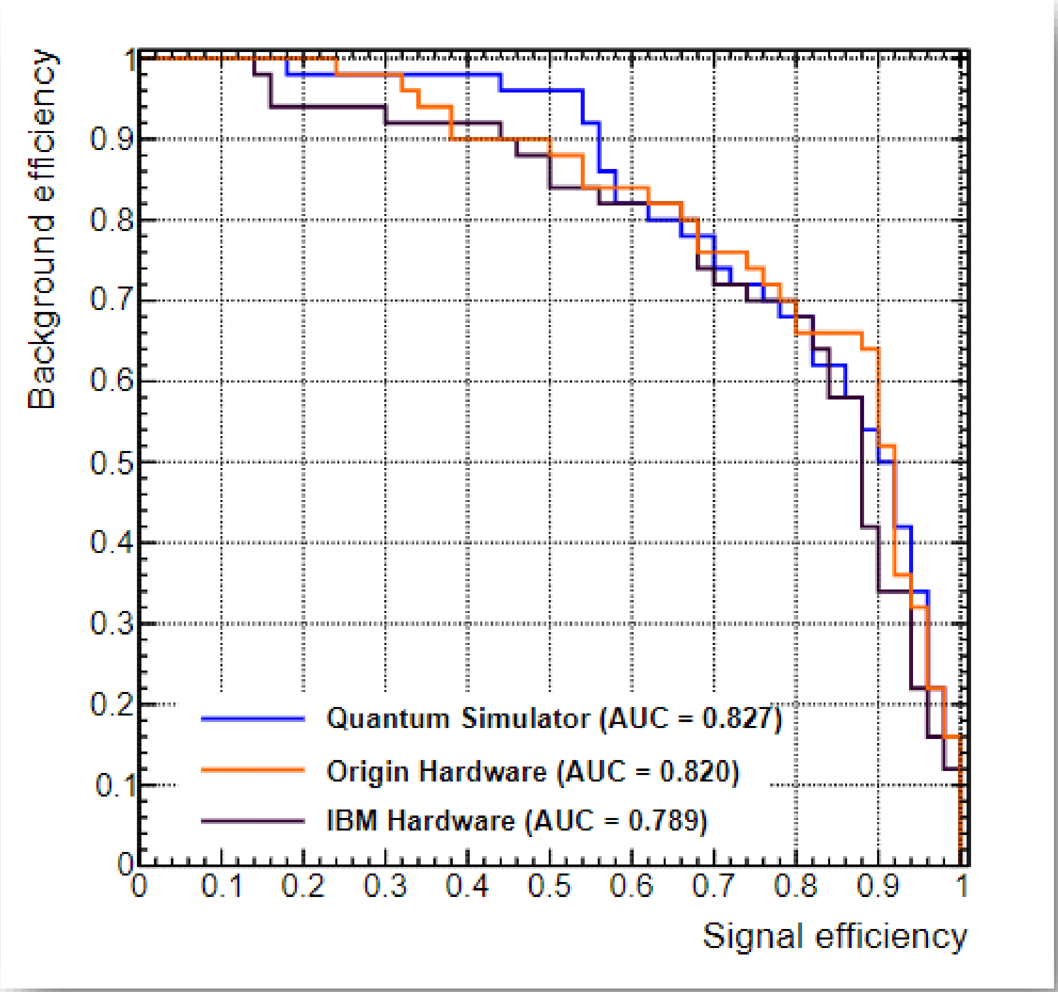
- The performance of the QSVM-Kernel using State-vector-simulator from IBM and the classical SVM.
- Use 12500 events for both signal and backgrounds.



Performance of the real quantum computers

- IBM Nairobi & Origin Wuyuan quantum computer hardware
- Use 100 events for both signal and backgrounds.
- Use 6 qubits.

IBM Nairobi quantum   Origin Wuyuan quantum



Conclusion and outlook

- We studied the signal/background classification using quantum/classical ML algorithm.
- We compared QSVM-kernel with quantum simulator (state-vector) and classical SVM.
- Each QSVM and SVM algorithm is optimized to its best before comparing them
- Real quantum computing systems with 100 events for signal and background:
  - Wuyuan v.s IBM
- We obtained a similar classification performance to the classical SVM algorithm with different dataset size.

Conclusion and outlook

For next step, we are working on the classification using different algorithms and build a corresponding quantum algorithms, like Quantum transformer and Quantum particle transformer.

- For example, using Quantum feature map to replace the linear layer of Q,K,V in the self-attention