Quantum Machine Learning: A Status Report

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On behalf of the Quantum Computing Team

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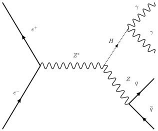
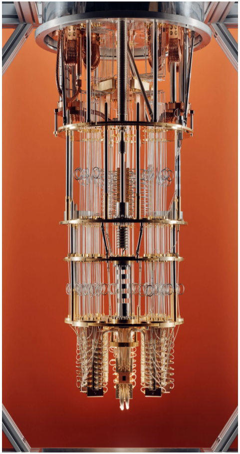
Overview

Introduction

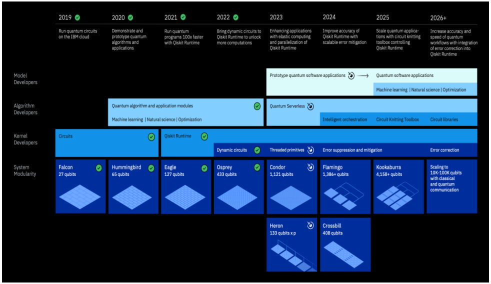
- ☐ Machine learning has blossomed in the last decades and becomes essential in many fields.
- ☐ It played a significant role in solving High Energy physics problems, such as reconstruction, particle identification.
- ☐ and handling high dimensional and complex problems using deep learning.
- ☐ Quantum computing is a new idea for our workstations to process data faster than currently achievable.
- ☐ Machine learning & quantum computing may:
  - locating more computationally complex feature spaces
  - better data classification
  - smarter algorithms that can give us accurate prediction.
- ☐ Companies such as Google, IBM and Origin are committed to accelerating the development of quantum technology.
- ☐ Objectives:
  - Apply quantum machine learning to high energy physics
  - Support-vector machine algorithm in quantum computers
  - Building the quantum algorithm using IBM quantum simulator
  - Comparing the performance in different real quantum computers

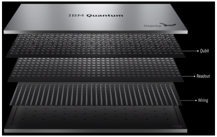


IBM quantum computer



Credited to Thomas Prior for TIME





IBM Quantum Osprey

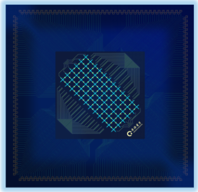
NY Quantum Computing Data Center

- ☐ IBM has ambitious pursuits:
  - 433-qubit IBM Quantum Osprey
  - three times larger than the Eagle processor
  - going up to 10k-100k qubits
- ☐ Taking quantum computing out of the lab:
  - NY provides over 20 quantum computing
  - Scales the processors with high availability

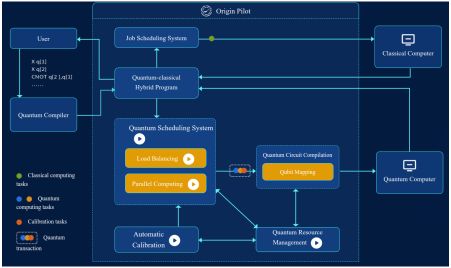
☐ IBM provides up to 7 qubits for free with an opportunity to apply for a researcher account with more qubits.

Origin quantum computer (Wuyuan)

- Origin Quantum 64-qubit superconductor QPU
  - single-qubit gate fidelity $> 99.9\%$
  - double-qubit gate fidelities $> 98\%$
  - readout fidelity $> 96\%$
- A quantum computing control system dedicated to superconducting quantum chips



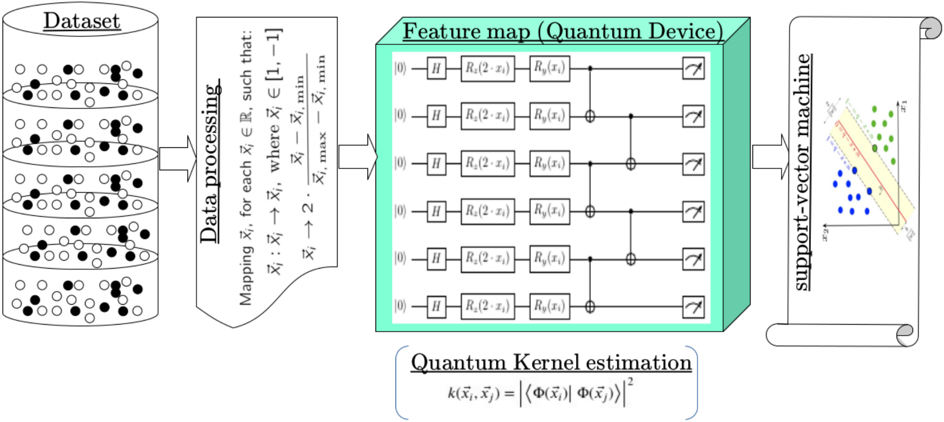
KF-C64-200



TJ-SQMC-300

- This is the first Quantum Computer Operating System in China. One could use up to 6 qubits for free.

Data encoding and processing



- ☐ Encoding the $e^+e^- \rightarrow ZH \rightarrow q\bar{q}\gamma\gamma$ and $e^+e^- \rightarrow (Z\gamma^*)\gamma\gamma$ datasets to high dimensional quantum dataset.
- ☐ Seven 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

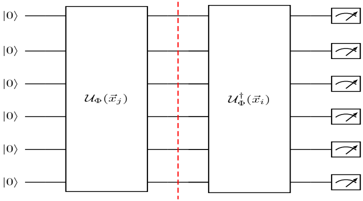
- Quantum feature map dictate the QSVM-Kernel:
  - two identical layers
  - single-qubit rotation gates
  - two-qubit CNOT entangling gates

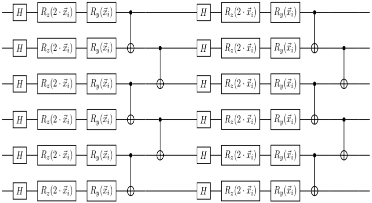
Rotation	Depth	Events	Best AUC	Variation
$R_z(2 \cdot \vec{x}_i) + R_y(\vec{x}_i)$	2	5000	0.935	0.009
$R_z(\vec{x}_i) + R_y(\vec{x}_i)$			0.933	0.015
$R_y(\vec{x}_i) + R_x(\vec{x}_i)$			0.932	0.015
$R_z(\vec{x}_i) + R_z(\vec{x}_i)$			0.932	0.014
$R_y(\vec{x}_i)$			0.928	0.008
$R_z(\vec{x}_i)$			0.928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

- QSVM-Kernel estimation:

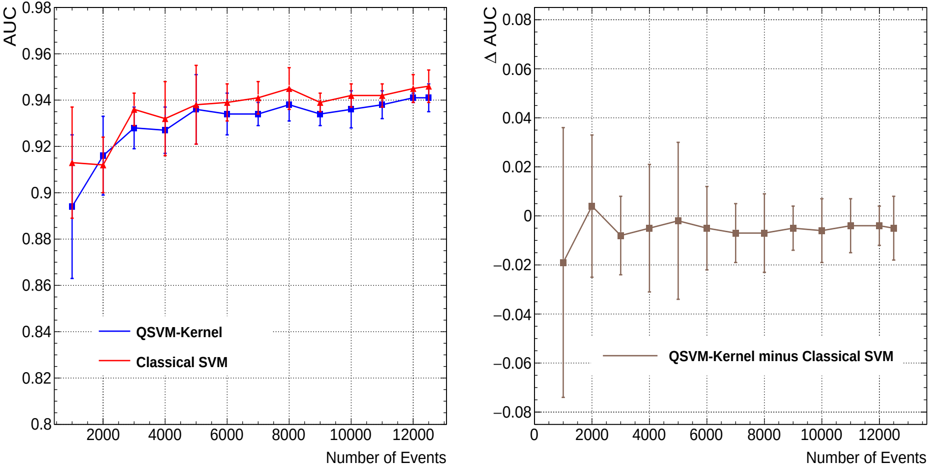
$$k(\vec{x}_i, \vec{x}_j) = \left| \langle 0^{\otimes N} \right| \mathcal{U}^{\dagger}_{\Phi(\vec{x}_i)} \mathcal{U}_{\Phi(\vec{x}_j)} \left| 0^{\otimes N} \rangle \right|^2$$

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



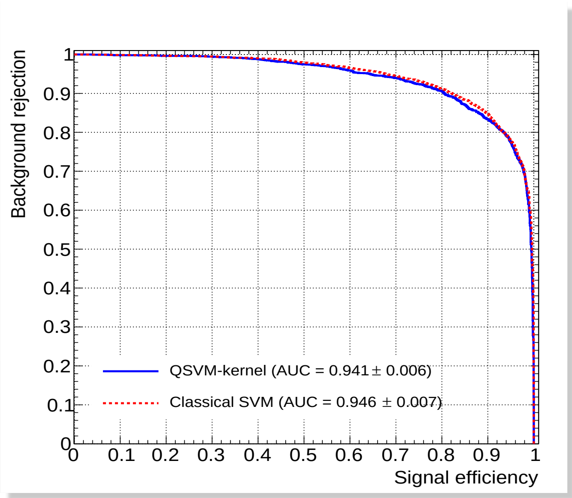


AUCs as function of the event



- ☐ 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



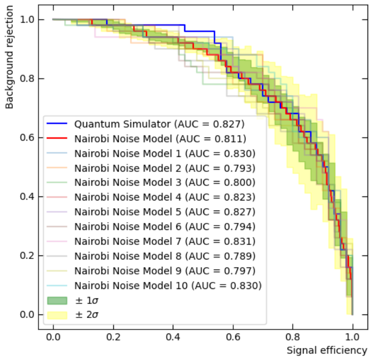
- The performance of the QSVM-Kernel and the SVM classification using StatevectorSimulator from IBM.

Nairobi Noise Model

Noise in quantum computers

Quantum computers are susceptible to all sort of noise sources: electromagnetic signal coming from a WiFi or a disturbance in the earth magnetic field etc. All these are considered as noise and can lead to error in the calculation.

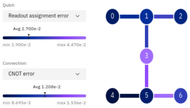
- ☐ The device noise model used automatically generate a simplified noise model for a real device.
- ☐ The noise model takes into account the following:
  - the gate error probability of each basis gate
  - the gate length of each basis gate
  - T_1 and T_2 relaxation time constant
  - the readout error probability
- ☐ The standard deviation of results generated using different seeds is taken as statistical fluctuations.
- ☐ The estimated noise in IBM Nairobi computer is 0.017.



The receiver operating characteristic curve

- ☐ The ROC curves of the QSVM-Kernel classifiers from the IBM Nairobi quantum computer,
- ☐ the Origin quantum computer (Wuyuan) and the state-vector quantum simulators from IBM.

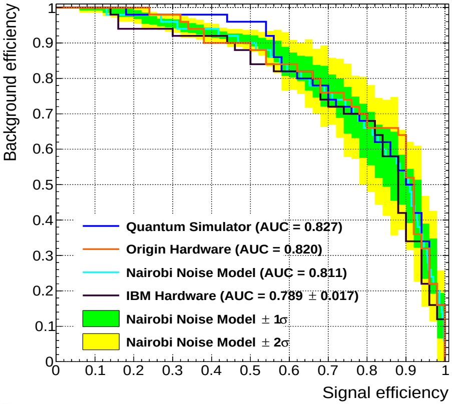
- ☐ Signal and Standard Model backgrounds:
  - $e^+e^- \to ZH \to q\bar{q}\gamma\gamma$
  - $e^+e^- \to (Z\gamma^*)\gamma\gamma$
- ☐ with 100 events for both signal and backgrounds
- ☐ 6-qubit superconducting quantum chip systems



IBM Nairobi quantum

Origin Wuyuan quantum

- ☐ Estimated uncertainties of:
  - Noise: ± 0.017
  - Statistical fluctuation: ± 0.022



Quantum Machine Learning documentation

Search the docs ...

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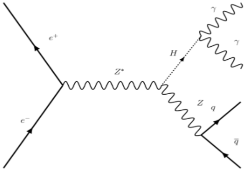
Contents

Tutorial for the application of quantum machine learning in HEP

This tutorial is a quick example of running support-vector machines in classical computers and a simulated quantum computer using a state vector simulator from IBM. Data samples from the Central Electron Positron Collider (CEPC) are used to demonstrate the performance of the support-vector machine.



The $e^+e^- \to ZH$ signal and its related backgrounds are utilised for the study where the $H \to \gamma\gamma$ and $Z \to q\bar{q}$. They are plenty of events for the signal and backgrounds, but for this tutorial, you can use up o 2k events.

By the end of the tutorial you will learn the following

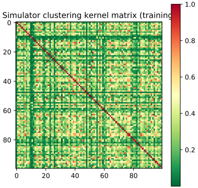
- Preparing the dataset from root fills as *NumPy* arrays
- Understand how to constuct a quantum feature map
- Run a support-vector machines algorithm in classical computers (SVM)
- Run a quantum support-vector machines in simulated computers (QSVM)

This tutorial is based on the results shown in this paper here on **inspirehep**. Before you run the tutorial, you need to download the following packages by uncommenting the lines in the cell below.

- ☐ Inspire further development in this exciting field, and identify opportunities for future research.
- ☐ We are developing this example in GitHub to help you get started (Still work in progress!)

Current and future plans

- ☐ Kernel-based QML with the $H \to b\bar{b}, c\bar{c}, gg$
  - Performed with MVA 2203.01469
  - Using about 16-24 variables
  - Collaborating with Origin Quantum
  - Granted 24-qubit for the analysis
- ☐ One-shot idea to speed the kernel calculation
  - Quafu offers up to 50-qubit



- ☐ Quantum transformer:
  - Deep learning quantum-based model
  - Adopts self-attention mechanism
- ☐ Manpower:
  - 3 seniors for IHEP, Peking University and Qujing Normal University
  - 2 postdocs so far from IHEP and Peking University
  - 3 PhD students from IHEP
  - Technical support from IHEP computing centre

Conclusion

- We studied the $e^+e^- \to ZH \to q\bar{q}\gamma\gamma$ signal optimisation using quantum/classical ML algorithm.
- Support-vector machines were compared:
  - Quantum support-vector machines (QSVM-Kernel) with IBM quantum simulator
  - Classical support-vector machines (SVM)
- Each QSVM and SVM algorithm is optimised to its best before comparing them.
- Real quantum computing system with 100 events for signal and background:
  - Wuyuan vs IBM
  - IBM vs IBM simulator
- We obtained a similar classification performance to the classical SVM algorithm with different dataset size.
- We also studied the effect of the noise based on a simple noise Model on IBM Nairobi.
- And providing a quick tutorial as an example for quantum machine learning using jupyter-lab.
- This talk is based on 2209.12788 [hep-ex]— submitted to Physics Letters B journal.