The Joint Workshop of the CEPC Physics, Software and New Detector Concept

Application of quantum computing at Higgs measurements

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Contents

- ☐ 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 and IBM are committed to accelerating the development of quantum technology.

Objective

- ☐ Apply quantum machine learning in high energy physic.
- ☐ We compare quantum support-vector machine to classical support-vector machine.
- ☐ The comparison is demonstrated in terms of process from different CEPC and LHC:
  - CEPC: $e^+e^- \to Z(\to q\bar{q})H(\to \gamma\gamma)$ & $e^+e^- \to Z(\to \mu^-\mu+)H(\to \nu\nu qq)$
  - LHC: (VBF) $H \to \gamma\gamma$
- ☐ We use IBM quantum simulator " qasm_simulator "
- ☐ The simulator is build using Qiskit packages

Support-vector machines

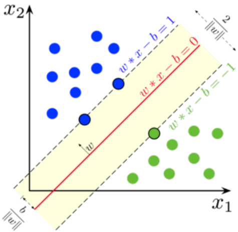
SVM

- ☐ SVMs are supervised machine learning algorithms for classifications.

$$(\vec{x}_i, y_i) \ldots (\vec{x}_n, y_n)$$

- ☐ $\vec{x}_i$ is n-dimensional vector and y_i is class label of each data point.

- ☐ SVM tries to maximize the margin between hyperplanes.
- ☐ Useful if the training dataset is linearly separable.
- ☐ It'll hard to separate non-linear datasets.
- ☐ So a trick called kernel machine is introduced.



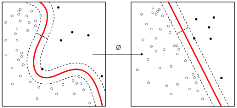
Support-vector machines

Kernel trick

- ☐ The dot product of a feature $\vec{x}_i$ and $\vec{x}_j$, after being transferred to a higher dimension via a function f, is called kernel.

$$k_{ij}(\vec{x}_i, \vec{x}_j) = \langle f(\vec{x}_i), f(\vec{x}_j) \rangle$$

- ☐ Non-leaner futures can then mapped to a liner ones.
- ☐ The function $f(\vec{x})$ could be:
  - linear
  - polynomial
  - Radial basis function
  - sigmoid



- ☐ In our case, we'll be using a linear function;
- ☐ and we call the SMV a classical SVM.

Quantum support-vector machines

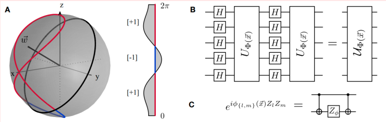
Quantum kernel

- ☐ In a quantum kernel, a classical feature $\vec{x}$ is mapped to higher dimension Hilbert space like $|\phi(\vec{x})\rangle\langle\phi(\vec{x})|$ in such a way that:

$$k_{ij}(\vec{x}_i, \vec{x}_j) = |\langle\phi(\vec{x}_i)|\phi(\vec{x}_j)\rangle|^2$$

- ☐ Feature map quantum circuits:
  - ZZFeatureMap
  - ZFeatureMap
  - PauliFeatureMap
- ☐ Many more in Qiskit packages.

arXiv:1804.11326v2

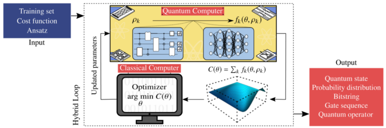


Variational quantum algorithm

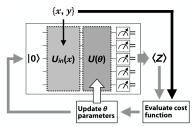
VQA

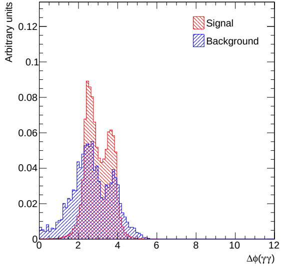
- ☐ VQA uses a classical optimizer to train a parametric quantum circuit.
- ☐ It takes advantage of quantum parallelism, the superposition of quantum states that allows a circuit to simultaneously process 2^n eigenstates.
- ☐ For the classical machine learning algorithm, the model is such as a neural network running on the classical computer.
- ☐ For the variational quantum algorithm, the model is a quantum circuit running on a quantum computer.

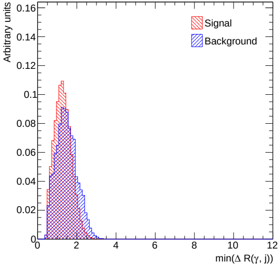
arXiv:2012.09265

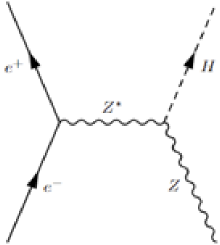


arXiv:2002.09935







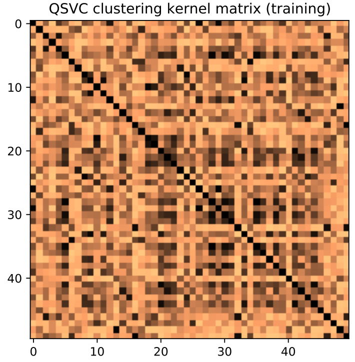


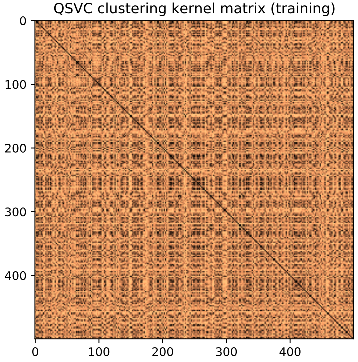
Training and testing strategy

- Two variables as inputs, so the number of qubit is 2 for the QSVM.
- Then training with different dataset size like 50, 100, 150, 200, 500

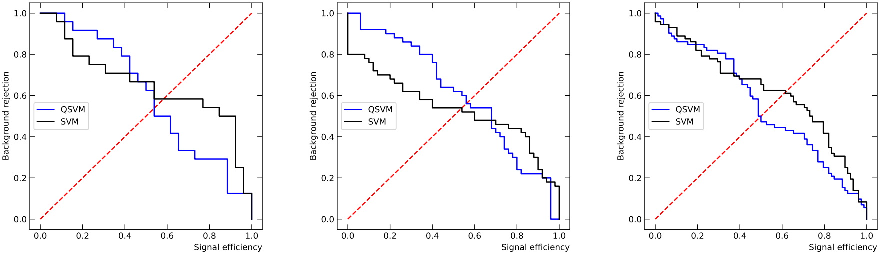
CEPC: $e^+e^- \to Z(\to q\bar{q})H(\to \gamma\gamma)$

Shape of the training kernel matrix in QSVM

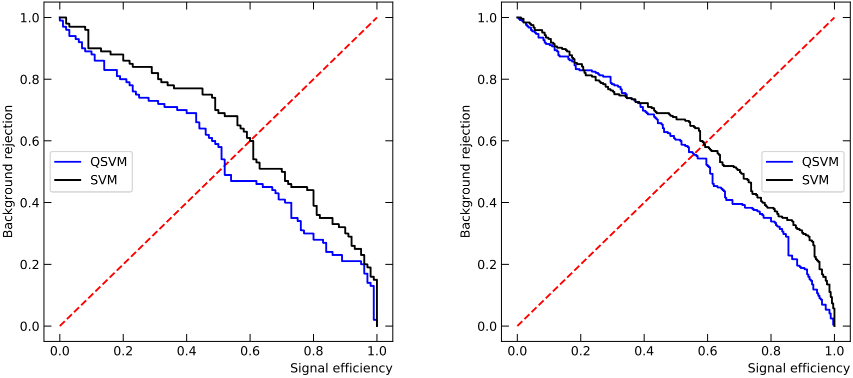




- ☐ The more clustered features the better the kernel.
- ☐ Quantum kernel, slide 6, from 50 to 500 training dataset.



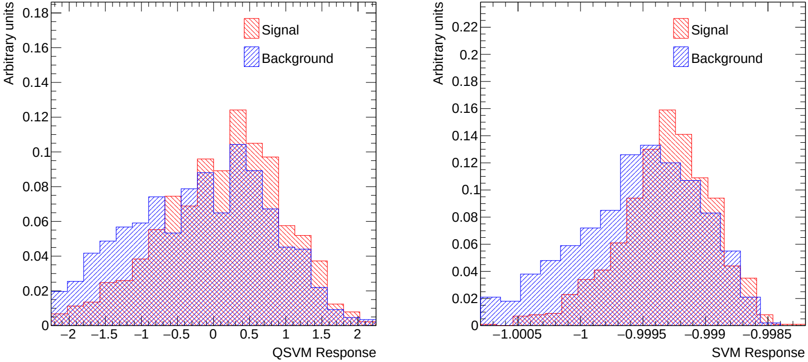
☐ ROC with 50, 100, 150 events fort both training and testing dataset.



☐ ROC for 200 and 500 events for both training and testing dataset.

CEPC: $e^+e^- \to Z(\to q\bar{q})H(\to \gamma\gamma)$

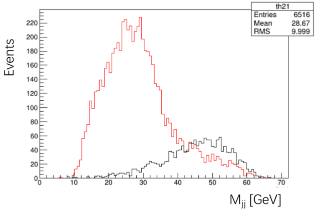
Checking the separation power

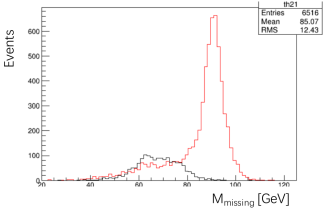


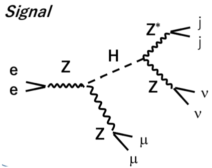
- ☐ 1000 events (training = 500, testing = 500)
- ☐ Unlike the TMVA, it's the separation margin between the classes.

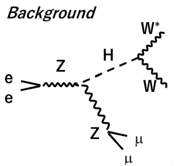
CEPC: $e^+e^- \to Z(\to \mu^-\mu+)H(\to \nu\nu qq)$

Input datasets





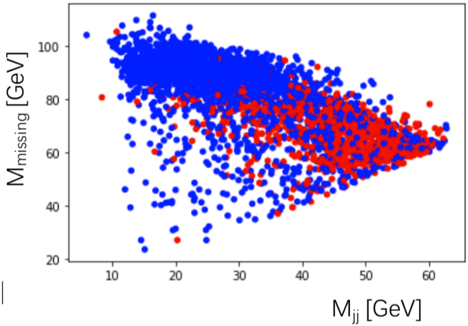




- ☐ Preliminary cut on di-muon invariant mass $80 < M_{\mu\mu} < 100$ GeV
- ☐ 837 background and 3263 signal events
- ☐ Taking the half from each data set for training and testing.

CEPC: $e^+e^- \to Z(\to \mu^-\mu+)H(\to \nu\nu qq)$

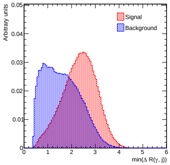
Training and testing output

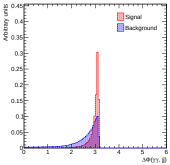


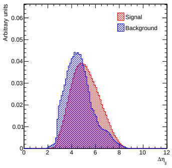
- ☐ VQA with a classical optimiser in IBM simulator.
- ☐ Result of the training and testing:
  - 67.21% signal efficiency
  - Reject 32.42% of the background

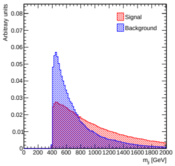
LHC: (VBF) $H \to \gamma\gamma$

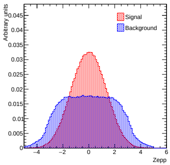
Training and testing strategy

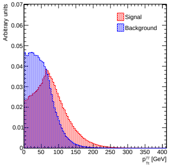


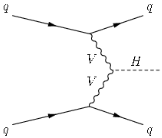










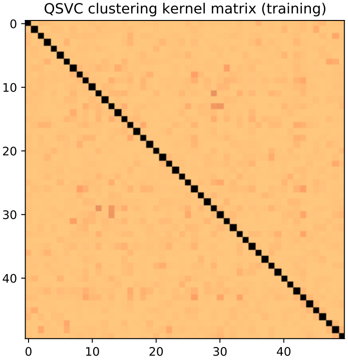


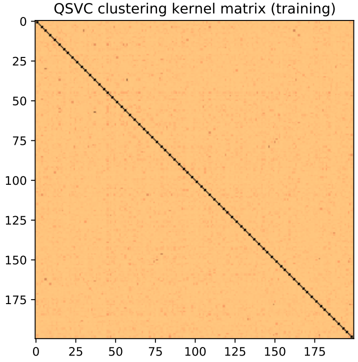
Training and testing strategy

- ☐ Six variables as inputs, so the number of qubit is 6 for the QSVM.
- ☐ Then training with different dataset size like 50, 100, 150, 200, 500

LHC: (VBF) $H \to \gamma\gamma$

Shape of the training kernel matrix in QSVM

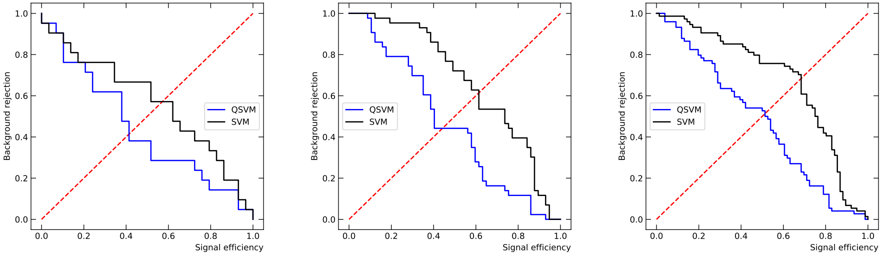




- ☐ The more clustered features the better the kernel.
- ☐ Quantum kernel, slide 6, from 50 to 500 training dataset.

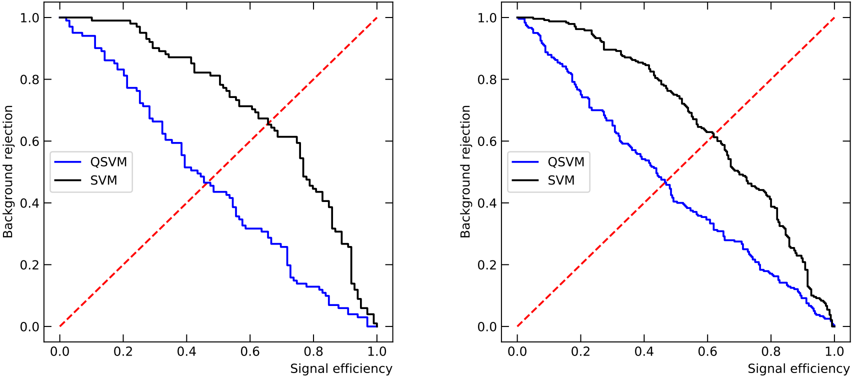
LHC: (VBF) $H \to \gamma\gamma$

ROC



- ☐ ROC with 50, 100, 150 events fort both training and testing dataset.

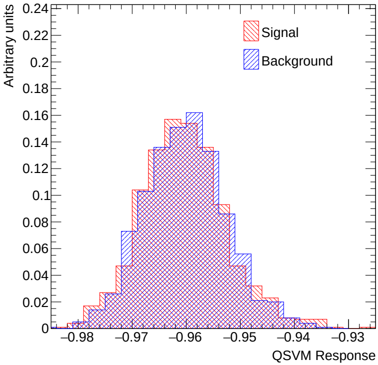
LHC: (VBF) $H \to \gamma\gamma$
ROC

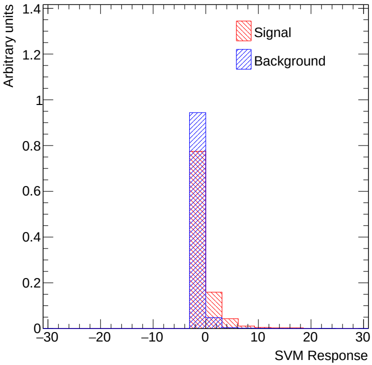


- ☐ ROC for 200 and 500 events for both training and testing dataset.

LHC: (VBF) $H \to \gamma\gamma$

Checking the separation power

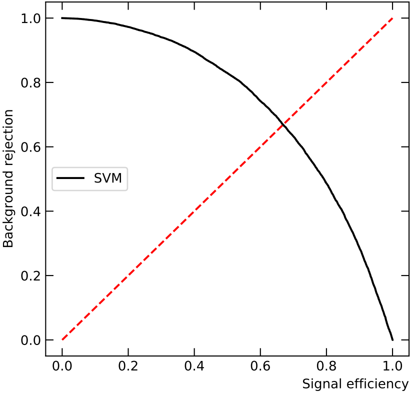




- ☐ 1000 events (training = 500, testing = 500)
- ☐ Unlike the TMVA, it’s the separation margin between the classes.

LHC: (VBF) $H \to \gamma\gamma$

SVM with more stats



- ☐ 20k events (training = 10k, testing = 10k)

Summary

- ☐ QSMV and SVM are compared using few events up to 500 using the qsam simulator:
  - Using 2 qubits $e^+e^- \rightarrow ZH \rightarrow \gamma\gamma q\bar{q}$ (CEPC)
  - Using 6 qubits $pp \rightarrow H \rightarrow \gamma\gamma$ (LHC)
- ☐ CEPC: $e^+e^- \rightarrow Z(\rightarrow \mu^-\mu+)H(\rightarrow \nu\nu qq)$ using VQA.
- ☐ We test the performance of QSVM and SVM using ROCs and SB separation.
- ☐ The computational is time expensive specially when running locally.

TO DO . . .

- Optimizing QSVM, SVM and QVA for better results.
- Train more events after setting the framework in the server.
- Train and test the same algorithm in real IBM quantum computer.

- ☐ We are open to any comments and suggestions as we still learning.

Thank you!

Additional slides

Hadamard $= H = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$	CNOT $= CX = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$
$I = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \ S = \begin{pmatrix} 1 & 0 \\ 0 & i \end{pmatrix}$	$CZ = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 \end{pmatrix}$
$T = \begin{pmatrix} 1 & 0 \\ 0 & e^{i\pi/4} \end{pmatrix}$	Controlled-U $= CU = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & U_{00} & U_{01} \\ 0 & 0 & U_{10} & U_{11} \end{pmatrix}$

NOT $= X = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$	SWAP $= \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$
$Y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}, Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$	Toffoli (CCNOT) $= \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$
$R(\theta) = P(\theta) = \begin{pmatrix} 1 & 0 \\ 0 & e^{i\theta} \end{pmatrix}$	

- ☐ Commonly used single- and multi-qubit quantum gates