ACAT 2021
29 Nov - 03 Dec, Daejeon, South Korea

Quantum Classifiers Hybrids with Advanced Data Compression Methods for Higgs Identification on Noisy Simulations

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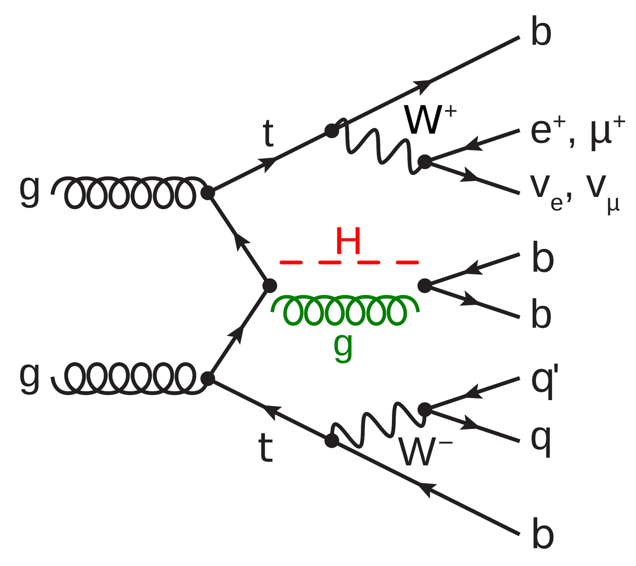
Introduction

NISQ devices demand that quantum algorithms use a limited number of qubits. We use conventional and more complex dimensionality reduction techniques to investigate the performance of quantum machine learning algorithms in identifying the Higgs boson.

The Studied Process

Extremely challenging Signal vs. Background discrimination.

67 final state observables:
8x7 (jets) + 7 (lepton) + 4 (MET)

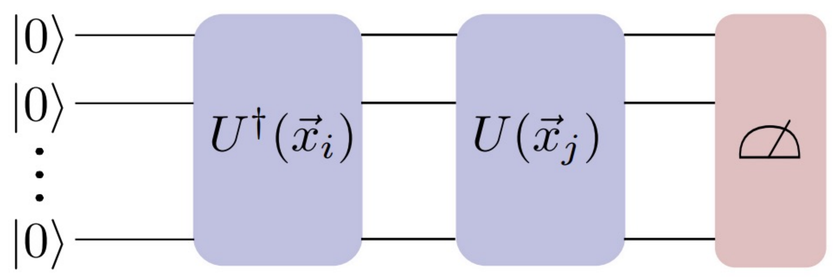


Conventional methods: Boosted Decision Trees, Neural Networks, high-level observables (MEM).
Best classification performance on our data using conventional methods (DNN): <u>AUC = 0.740 ± 0.001</u>.

Quantum Machine Learning Models

Quantum Support Vector Machine (QSVM)

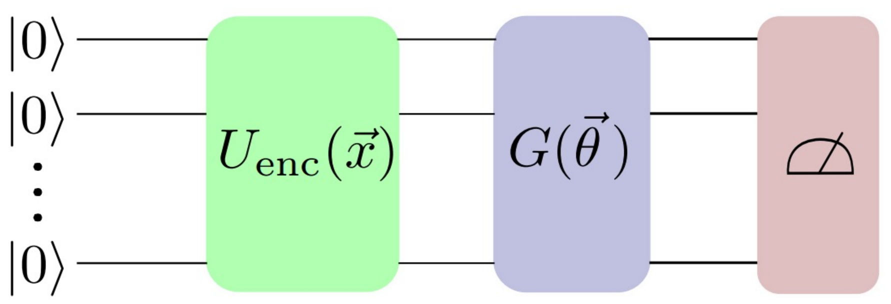
- Compute the quantum kernel and minimize the objective function on a classical computer.



$$\Rightarrow K_{ij} = |\langle 0|U^\dagger(\vec{x}_i)U(\vec{x}_j)|0\rangle|^2$$

Variational Quantum Circuits

- Architectures with 8 qubits and a hybrid network.



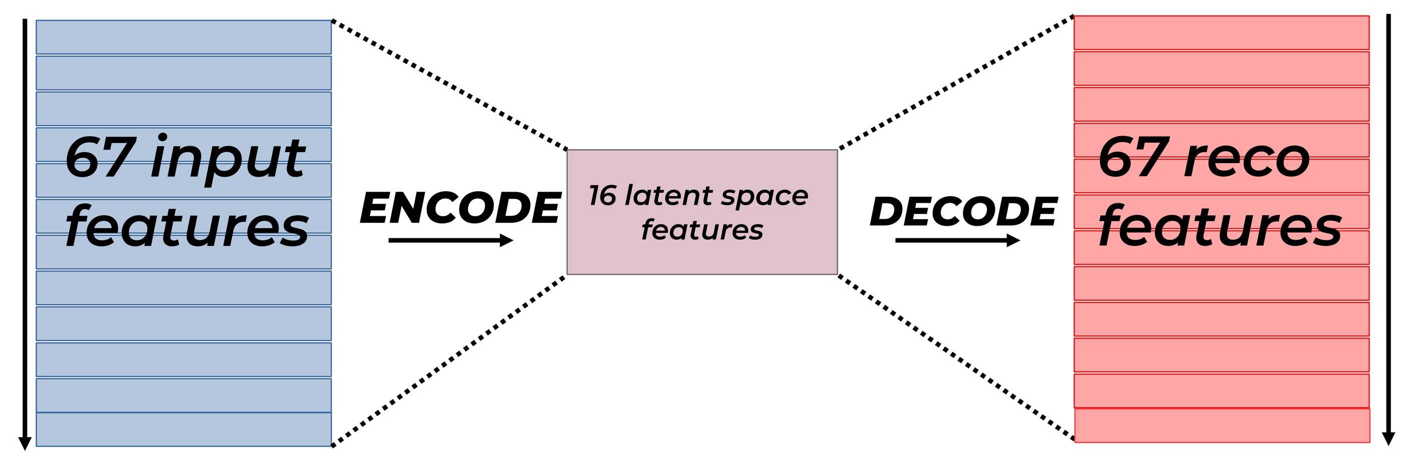
$$\Rightarrow f(\vec{x};\vec{\theta}) = \langle \mathcal{O}_{\vec{x},\vec{\theta}} \rangle$$

Feature Reduction Methods

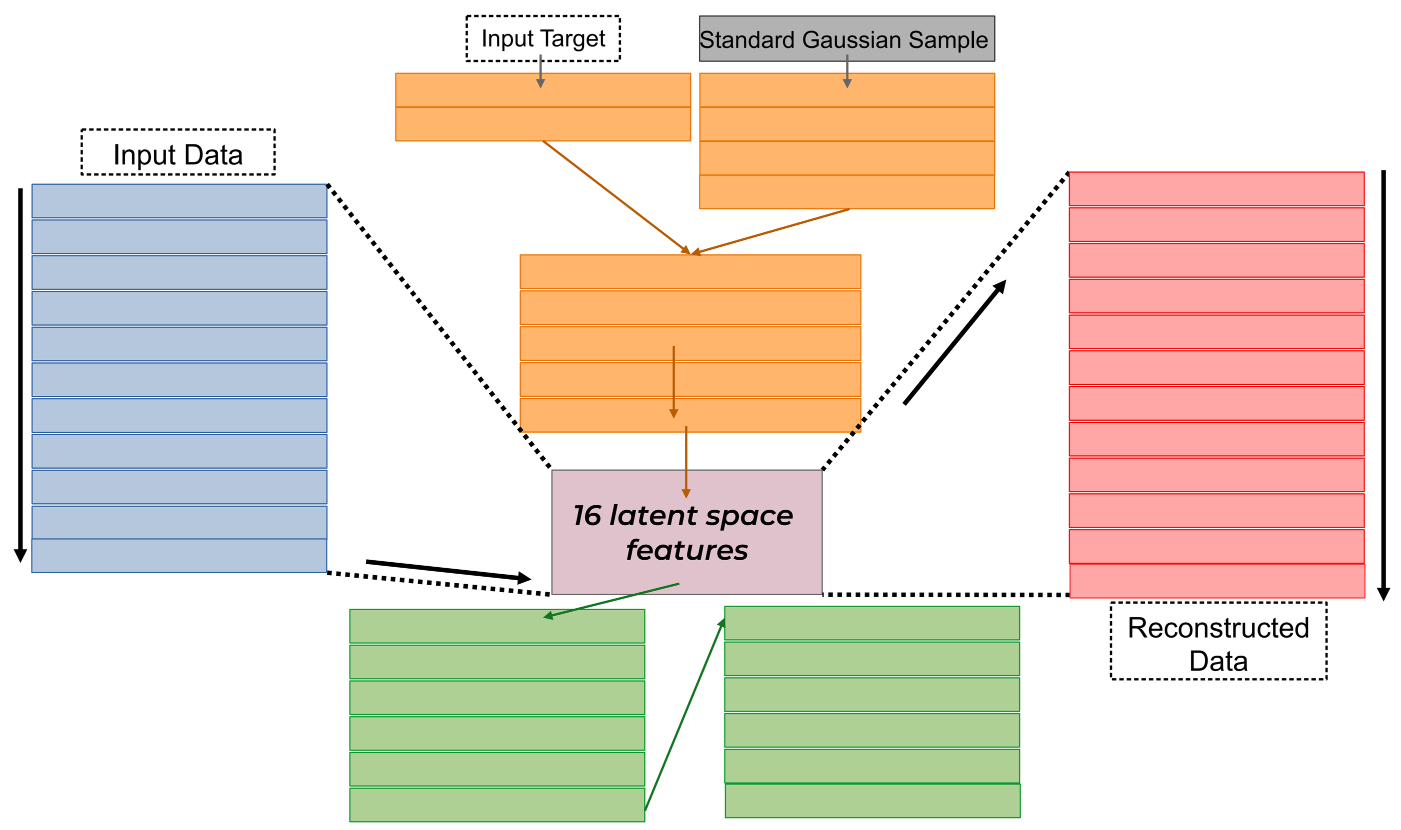
- To accommodate NISQ limitations of the quantum classifiers, feature reduction is needed.
- 7 auto-encoder models and 6 conventional feature extraction methods were tested for dim. reduction.
- Feed the latent space or extracted features as **input** to the Quantum Machine Leaning (QML) models.

Encoder Decoder Noise Classifier

The Vanilla Autoencoder



The Sinkclass Autoencoder



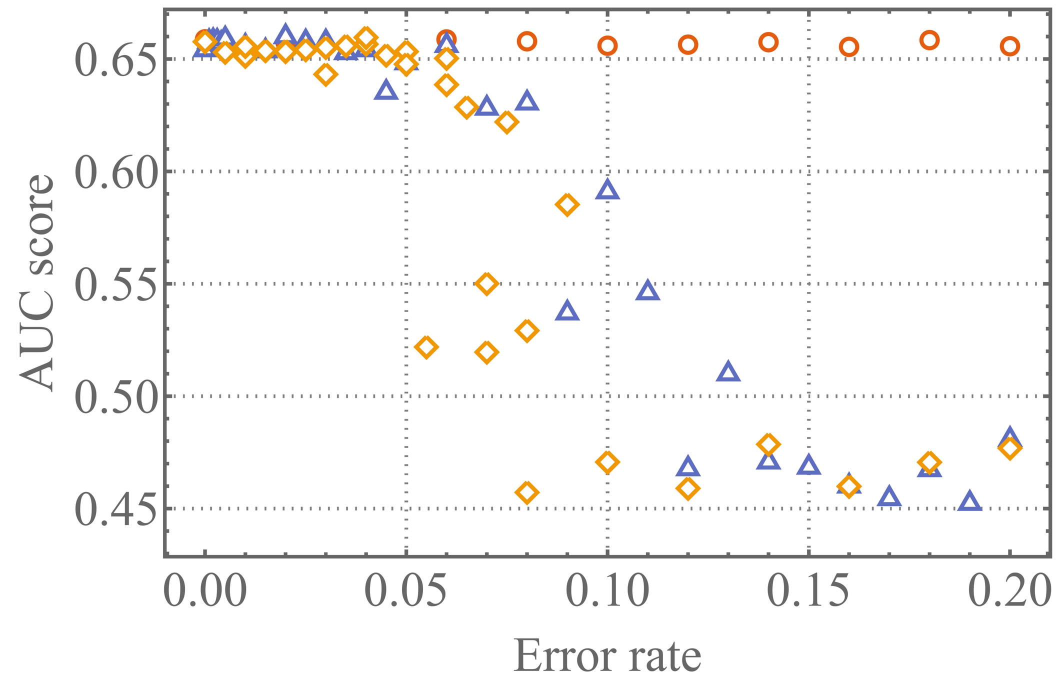
References

[1] V. Belis et. al., *Higgs Analysis with Quantum Classifiers*, EPJ Web Conf. 25103070 (2021), DOI: 10.1051/epjconf/202125103070.
[2] M. Schuld, N. Killoran, *Quantum Machine Learning in Feature Hilbert Spaces*, Phys. Rev. Lett.122, 040504 (2019).

Results

Model	AUC	C	Feature Extraction Type
Bernoulli Restricted Boltzmann Machine	0.651 ± 0.016	0.01	Neural Network
Locally Linear Embedding	0.533 ± 0.014	0.01	Manifold Learning
Spectral Embedding	0.526 ± 0.013	0.1	Manifold Learning
Independent Component Analysis	0.528 ± 0.006	0.01	Linear
Non-negative Matrix Factorisation	0.599 ± 0.013	0.001	Linear
Principal Component Analysis	0.541 ± 0.015	10	Linear

Autoencoder	HP Optimisation	MSE Loss $\times 10^{-4}$	BCE Loss	Classifier AUC	QSVM AUC
Vanilla	-	4.77	-	-	0.56± 0.01
Variational	MSE	4.49	-	-	0.56± 0.02
Classifier	MSE	5.47	0.63	0.700± 0.001	0.56± 0.02
	BCE	62.97	0.61	0.734± 0.002	0.72± 0.01
Sinkhorn	MSE	9.65	-	-	0.51± 0.01
Sinkclass	MSE	26.41	0.65	0.642± 0.003	0.50± 0.01
	BCE	24.69	0.61	0.734± 0.002	0.74± 0.01



Model	BCE Loss	AUC
Encoder + VQC	0.61	0.702± 0.004

One-gate Error
CNOT Error
Readout Error

Conclusions

- We conclude that most developed models are suitable for NISQ devices: the main limitation is the *circuit depth*.
- One way cooperation between reconstruction and classification tasks is manifest in the classifier AEs.
- Within the context of HEP data, the novel AE architectures produce lower dimensional spaces that are more suitable for NISQ classifiers than conventional feature extraction methods.