A practical use case for Quantum Generative Adversarial Networks in High Energy Physics

Generating top squark events decaying via the four-body mode in single-lepton final states in proton-proton collisions at $\sqrt{s} = 13$ TeV

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Abstract

This is a simple paragraph at the beginning of the document. A brief introduction about the main subject.

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Glossary

CERN QTI CERN Quantum Technology Initiative. 1

CMS Compact Muon Solenoid. 1

HEP High Energy Physics. 1

MC Monte Carlo. 1

NISQ Noisy Intermediate-Scale Quantum. 1

QC Quantum Computing. 1

qGAN quantum Generative Adversarial Network. 1

QML Quantum Machine Learning. 1

1 Introduction

One of the main objectives of CERN Quantum Technology Initiative (CERN QTI) is to investigate if Quantum Computing (QC) can be used in the field of High Energy Physics (HEP) in the Noisy Intermediate-Scale Quantum (NISQ) era. Noisy means that, currently, we have imperfect control over qubits. Intermediate refers to the number of qubits our present quantum computers have. They range from 50 to a few hundred. In order to fully fulfill the promise of quantum computing, the challenges of noise and scalability (millions of qubits) needs to be solved. Nonetheless, we can already use the available quantum computers and algorithms to tackle present challenges.

Quantum Machine Learning (QML) is a growing research area that explores the interplay of ideas from QC and machine learning. This project explores the use of quantum Generative Adversarial Networks (qGANs) [4], a QML algorithm, to learn the kinematic distributions of stop four-body decays [3] in Compact Muon Solenoid (CMS) data. the Feynman diagram for such process is represented in Figure 1. In HEP, to simulate such distributions, Monte Carlo (MC) simulations are used in a very convoluted and computational resources hungry process that can take up months. As we will see, the method presented in this project could speed up this process significantly when run on quantum computers. This method could also be used for data augmentation of the MC generated samples which would be helpful in the training of the classification algorithms in many HEP searches improving the sensitivity of such searches.

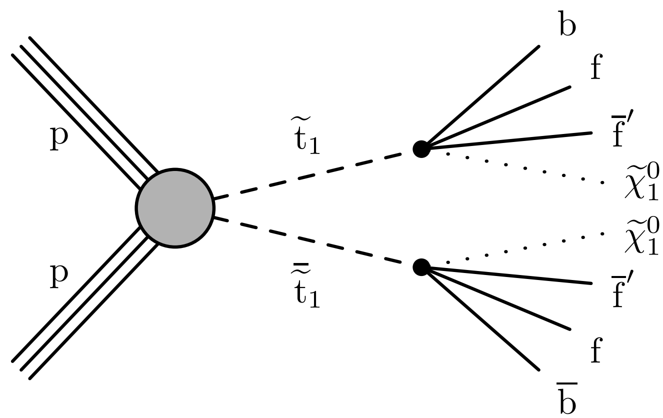

Figure 1: Diagram of top squark pair production $\widetilde{t}_1\bar{\widetilde{t}}_1$ in pp collisions, with a four-body decay of each top squark.

This project will be run on a classical computer (my personal laptop) simulating a quantum computer with 5 qubits using pennylane [2] to train and optimize the quantum algorithm, and cirq [1] for writing, manipulating, and running the quantum simulator.

References

[1] *Cirq*. 2022. URL: https://quantumai.google/cirq.

[2] *Pennylane*. 2022. URL: https://pennylane.ai/.

[3] *Searching for top squarks with CMS data*. 2022. URL: https://cms.cern/news/searching-top-squarks-cms-data.

[4] Christa Zoufal, Aurélien Lucchi, and Stefan Woerner. "Quantum Generative Adversarial Networks for learning and loading random distributions". In: *npj Quantum Information* 5.1 (Nov. 2019). DOI: 10.1038/s41534-019-0223-2. URL: https://doi.org/10.1038%2Fs41534-019-0223-2.