Quantum GAN for Fast Shower Simulation

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Introduction

The high luminosity upgrade of the LHC program in the next two decades and beyond will require enormous computing resources. As shown in Fig. 1, most computing resources in HEP are consumed by MC simulation ($\sim 50\%$) with GEANT4, especially calorimeter simulation. Fast calorimeter simulation is thus an important approach to help overcome this computational challenge.

Classical GANs will be used by the ATLAS experiment to perform the fast shower simulation [1]. However, the training of classical GANs is CPU intensive and the performance is not very well when simulating electrons and photons. Benefiting from quantum superposition and entanglement, quantum GANs could have more representational power with respect to classical GANs, and therefore present an advantage in terms of training sample size and/or final accuracy. In this work, we are investigating using the quantum GAN for fast shower simulation.

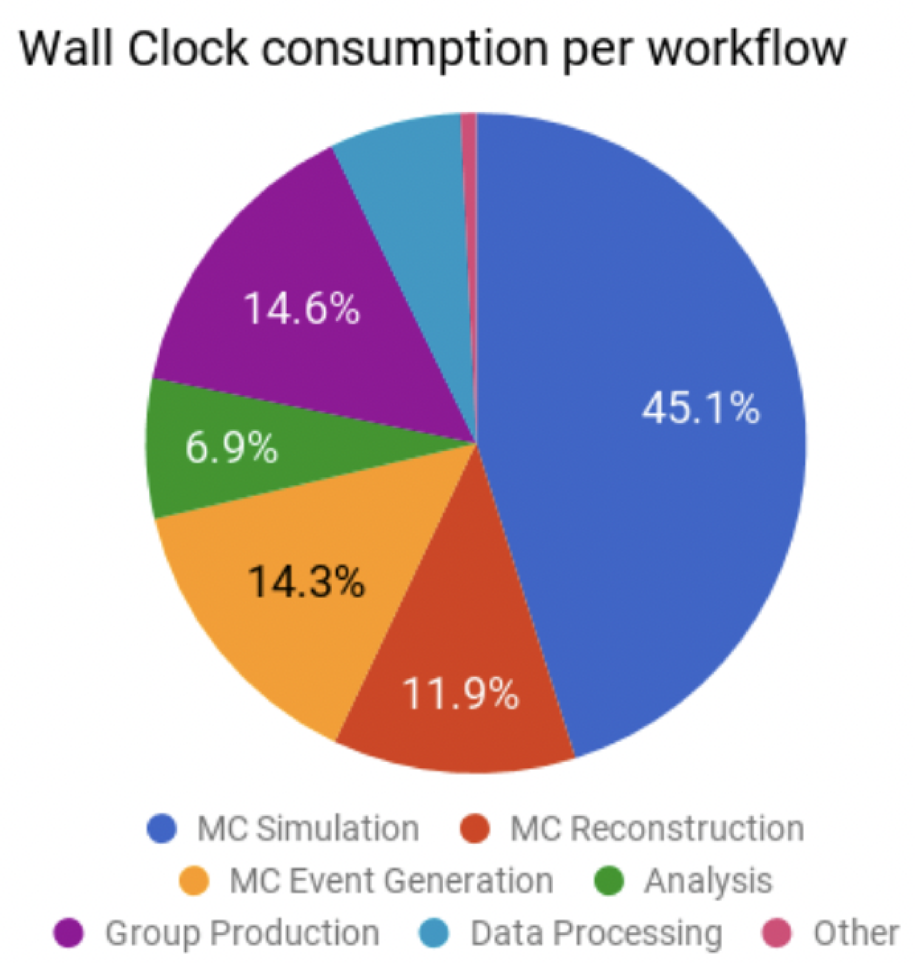

Fig. 1: CPU consumption per workflow

Methods

Similar as the classical GAN [2], the quantum GAN [4] has two models, i.e. a generator and a discriminator. The generator takes some random variables as input and creates fake data that looks like the real data; the discriminator takes the fake data and real data as input and tells their difference. The two models are trained against each other. In the ideal case, both generator and discriminator would perform better over time until the generator produces the same distribution as the real data. Figure 2 demonstrates the idea of GAN.

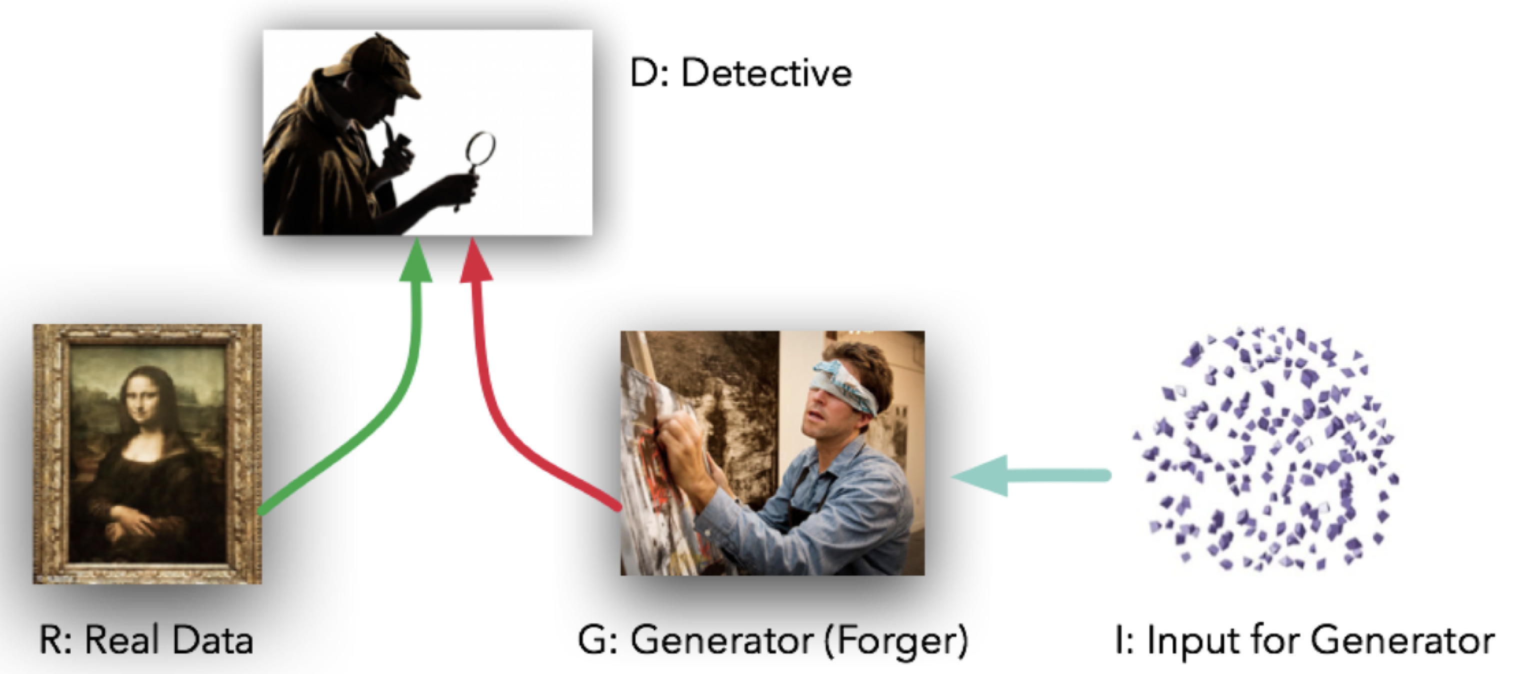

Fig. 2: Demonstration of GAN [5]

There are currently two possible approaches under the investigation of the HEP community:

- hybrid version: quantum generator and classical discriminator
- full quantum version: quantum generator and quantum discriminator

In the noisy intermediate-scale quantum (NISQ) era, the quantum computers contain only ten to a few hundred noisy qubits. Thus, the quantum circuits are limited in size and depth. As a starting point, we would use the hybrid version for fast shower simulation.

Preliminary Results

Fast shower simulation could be viewed as generating a 3D image. For simplicity, we first apply a hybrid GAN to generate 2D handwritten digits [3] as a proof of concept. The original dimension of the handwritten digits dataset is 32×32, which is too high for the current quantum devices. Thus, these images are divided into 4×4 blocks, which reduces the dimension to 8×8. The architecture of the hybrid GAN is shown in Fig. 3.

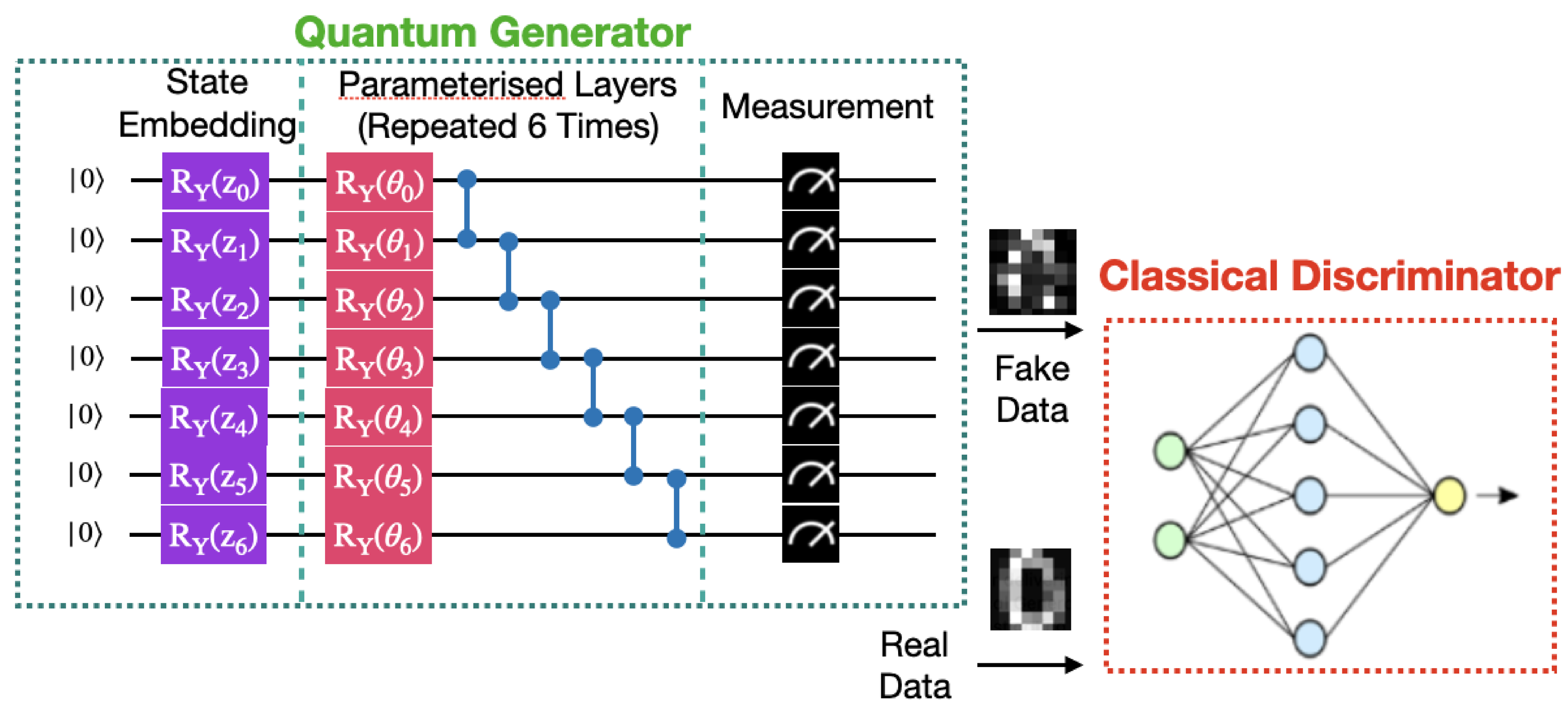

Fig. 3: Architecture of the hybrid GAN

The real images and the generated images using the quantum simulator for handwritten digits are shown in Fig. 4 to Fig. 6. As we can see from these images, the hybrid GAN could generate 2D hand-written digits.

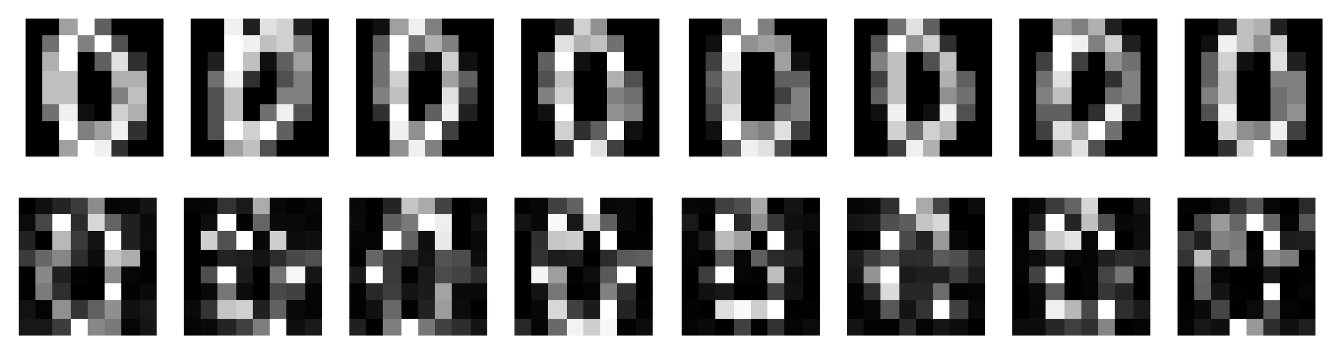

Fig. 4: Real images (upper plot) and generated images (bottom plot) for the handwritten digit '0'

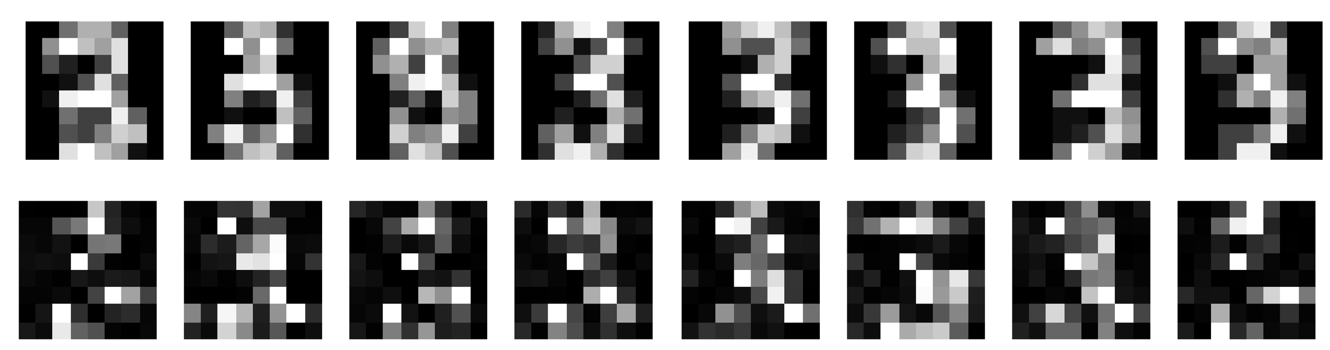

Fig. 5: Real images (upper plot) and generated images (bottom plot) for the handwritten digit '3'

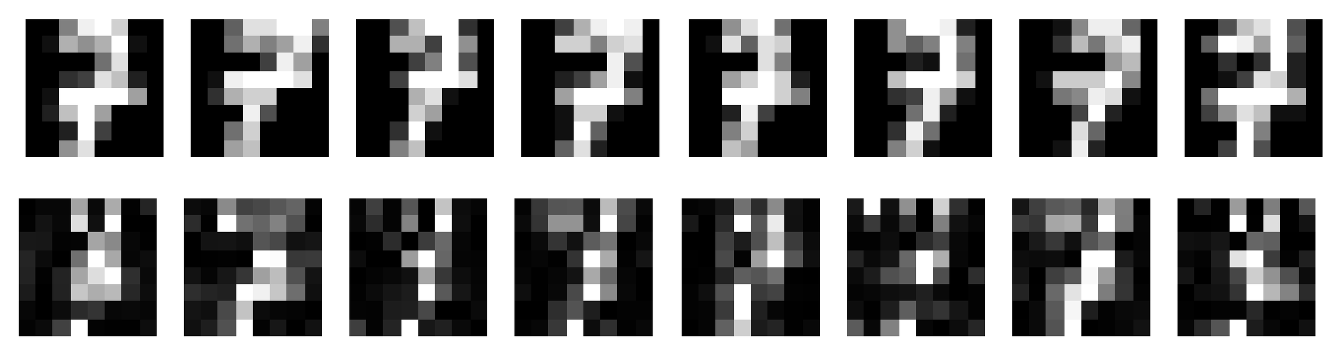

Fig. 6: Real images (upper plot) and generated images (bottom plot) for the handwritten digit '7'

Conclusion and Future Work

We implemented a hybrid classical-quantum GAN to generate hand-written digits on the quantum simulator. The results look promising. In the future, we plan to

- test the model using a real quantum computer
- implement a hybrid classical-quantum GAN for fast shower simulation
- investigate the impacts of data embedding, architecture, and noise

References

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[2] Ian J. Goodfellow et al. "Generative Adversarial Networks". In: *arXiv e-prints*, arXiv:1406.2661 (June 2014), arXiv:1406.2661. arXiv: `1406.2661 [stat.ML]`.

[3] He-Liang Huang et al. "Experimental Quantum Generative Adversarial Networks for Image Generation". In: *Physical Review Applied* 16.2, 024051 (Aug. 2021).

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