Quantum GANs for HEP Detector Simulations

CERN openlab Technical Workshop 2022

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23.03.2022

Future Simulations

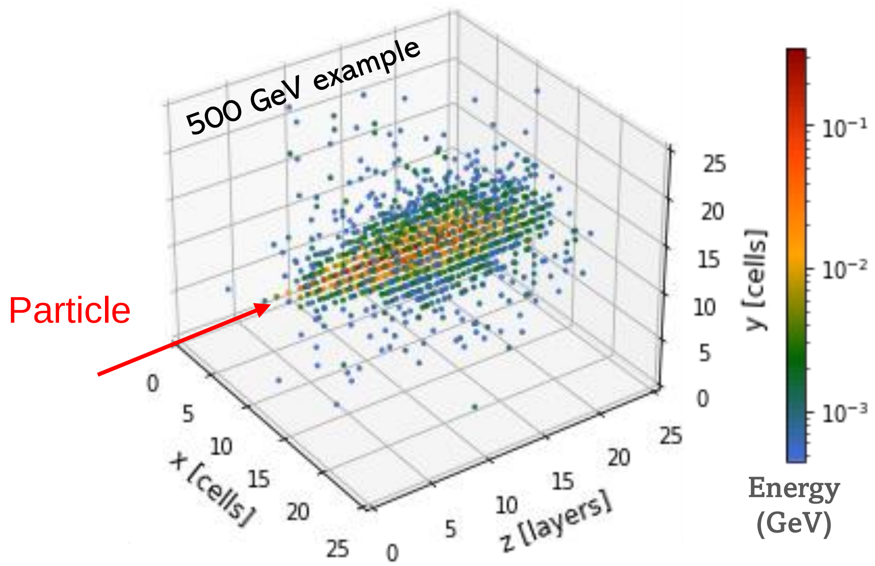
Alternative to Calorimeter Monte Carlo Simulations

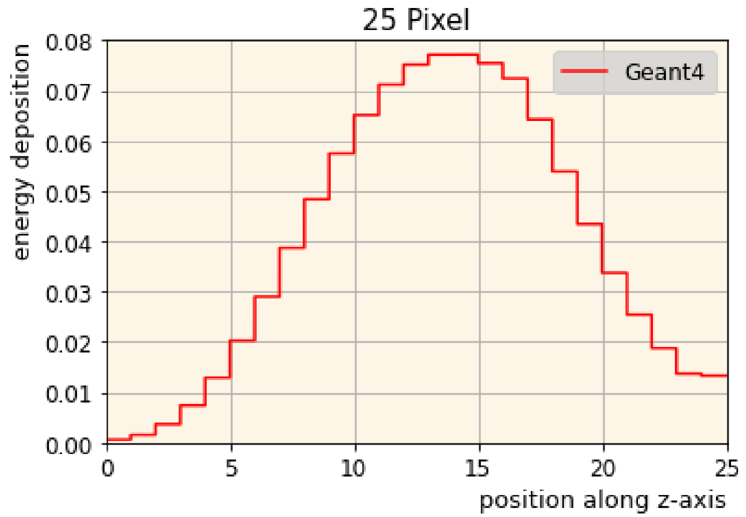
- Previously: **Deep Learning**
  - → Developed a Deep Learning (DL) approach for calorimeter simulations which requires fewer computing resources compared to Geant4
    - DL GAN (up to 160 000x speed up)

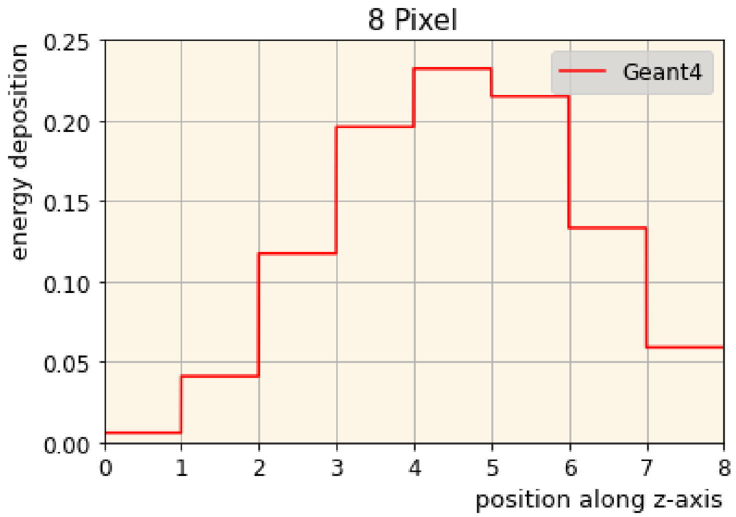
- Now: **Explore Potential of Quantum Computing**
  - Hope to solve problems faster and / or more accurately
  - “Quantum Advantage” not yet reached → only initial investigations
    - Using simplified models
    - Understanding advantages and challenges

Calorimeter Training Data

- 3D particle shower images
- Average over z-axis → 1D image
- Down sample to only 8 pixel
- Average of all input energies



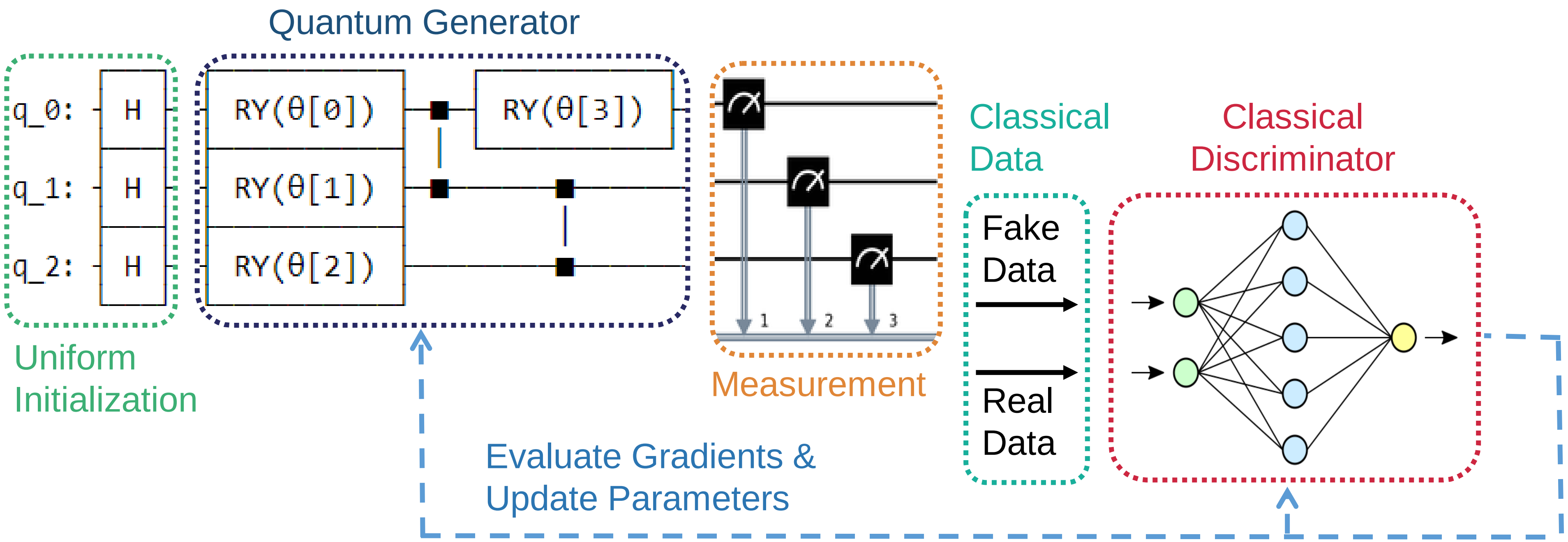




Hybrid qGAN

Quantum Generative Adversarial Networks

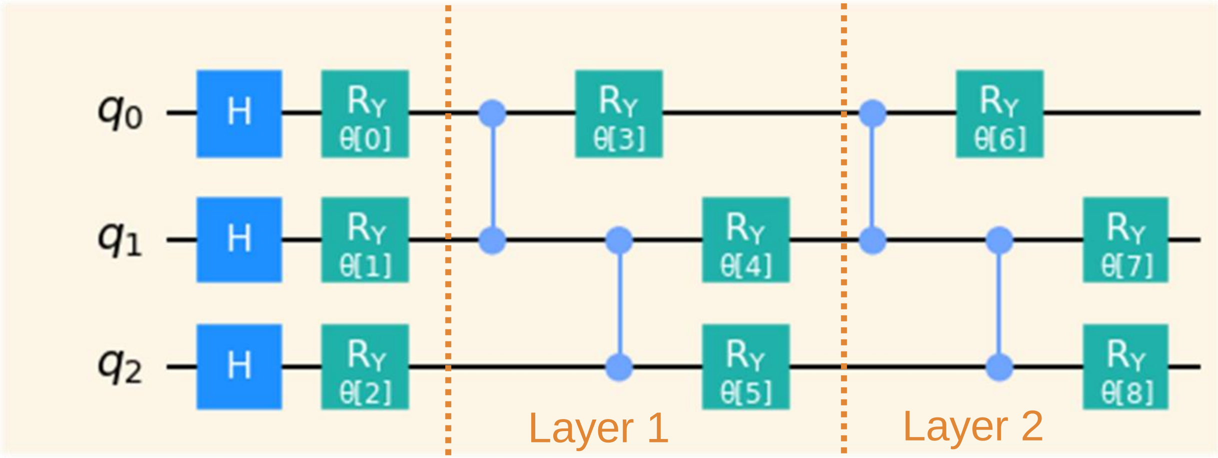
- Hybrid quantum – classical ansatz for generating shower images



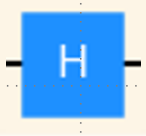
1D Quantum Generator Circuit

- Modified a Qiskit qGAN model developed by IBM
- 1D 8-pixel images
  - Amplitude encoding: 3 qubits ($2^3 = 8$ states)

Quantum Generator Circuit

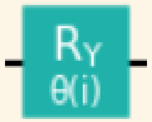


Hadarmard Gate



$$= \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

Y-Rotational Gate



$$= \begin{pmatrix} cos\left(\frac{\theta}{2}\right) & -sin\left(\frac{\theta}{2}\right) \\ sin\left(\frac{\theta}{2}\right) & cos\left(\frac{\theta}{2}\right) \end{pmatrix}$$

Controlled-Z Gate

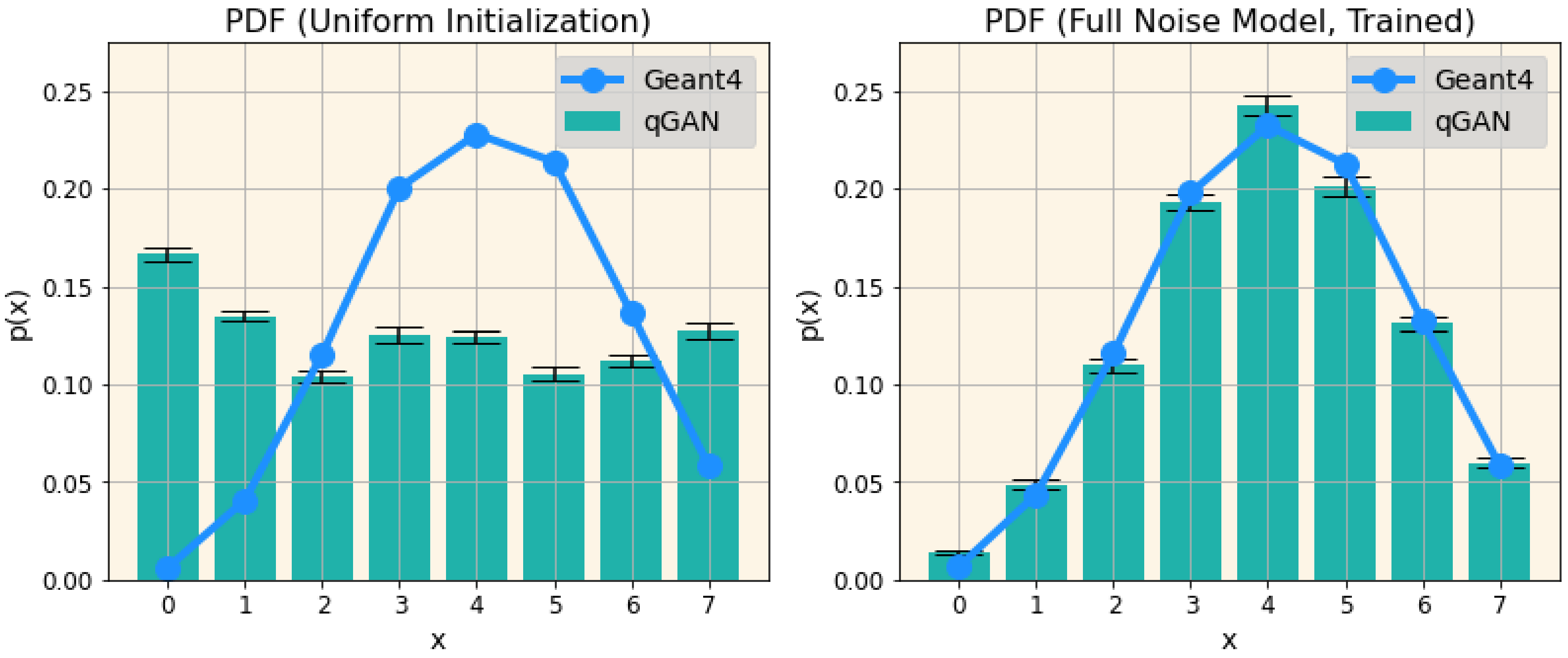
$$= \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 \end{pmatrix}$$

1D Training without Noise

- Simulating the quantum computer on a classical computer

Run on olgpu-01 node:
- Only CPUs used
- Intel(R) Xeon(R) Gold 6130 CPU
- Training time per trial ~8h

- Hyperparameter search reduced training time and increased accuracy



Uniform Initialization

Trained Model

→ Good results

Proceedings:
http://ceur-ws.org/Vol-3041/363-368-paper-67.pdf

qGAN Noise Study

- Perform tests with NISQ quantum hardware noise
- Does the quantum machine learning training benefit from the noise?
- Are error mitigation techniques beneficial?

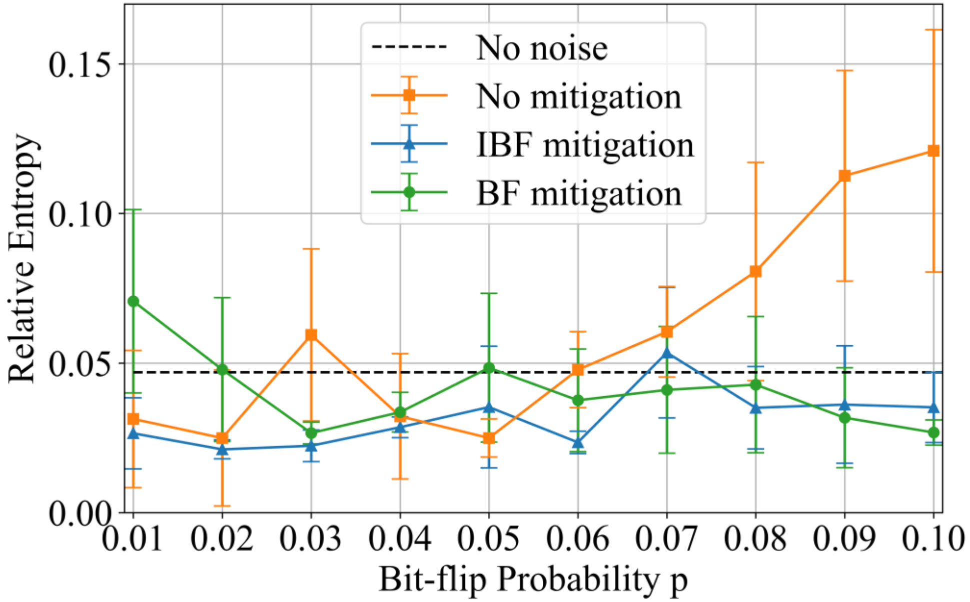
Noise Study and Error Mitigation

Readout Noise Only

- Train qGAN with readout noise
  - Training tolerant up to ~6% readout noise
- Test two error mitigation methods:
  - Conventional bit-flip (BF) mitigation
  - Independent bit-flip (IBF) mitigation

→ Error mitigation becomes important for higher readout noise level

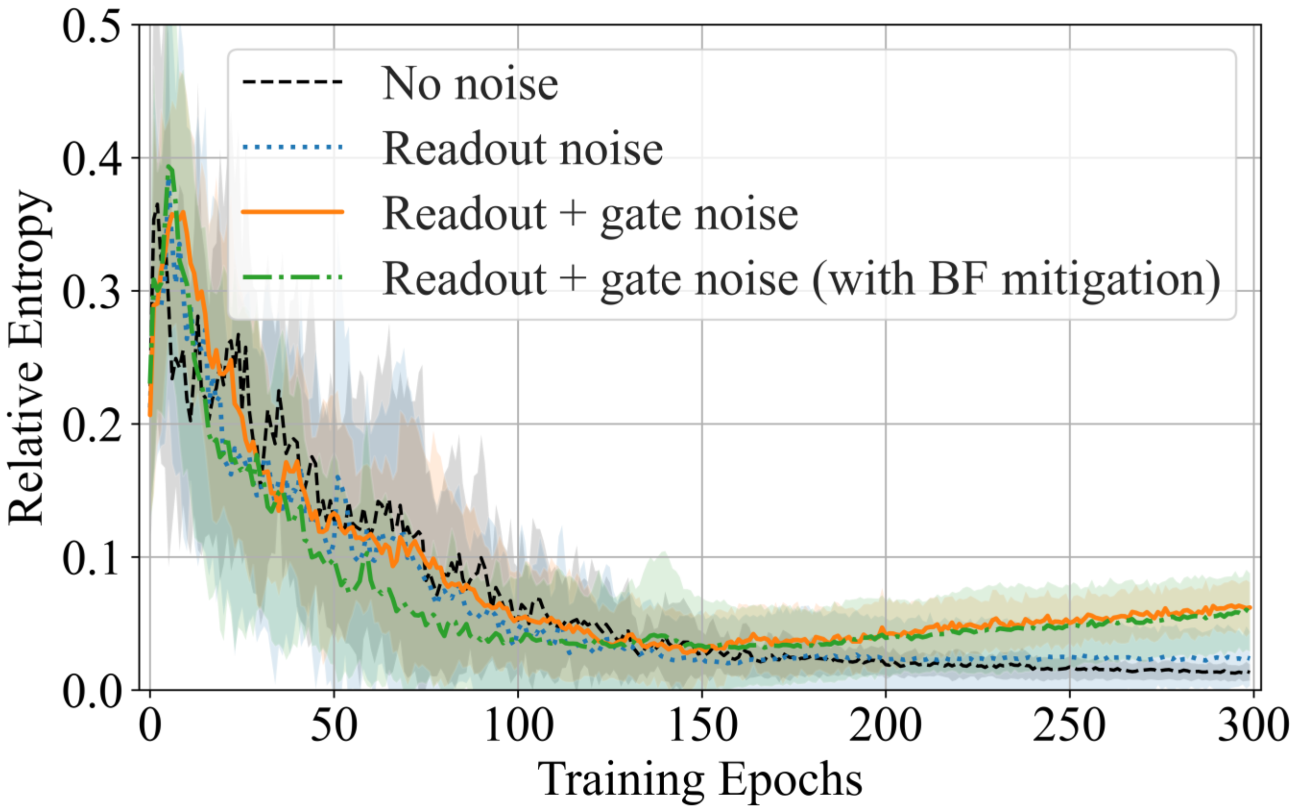
→ BF and IBF perform similar



Paper:
https://arxiv.org/abs/2203.01007

Full Noise Model

- Readout + gate level noise:
  - 2.5% readout noise
  - 1.5% two-qubit gate noise



→ All configurations converge
→ The configurations with gate level noise are not stable

Paper:
https://arxiv.org/abs/2203.01007

Summary

- qGAN training is tolerant to readout noise up to a certain level
    - In our case ~6%

- For higher readout noise error mitigation becomes relevant

- Two-qubit gate errors seem to decrease accuracy of qGAN training

Future Work

- The recent qGAN model only generates probability distributions, no real samples
  - → move to another model
- Develop qGAN model with different data encoding
  - Test a full qGAN model (generator and discriminator quantum circuits)
    - Convergence issues
- (q)GAN training is resource consuming and instable
  - → develop a completely different generative model
- Goal: Run training on real IBMQ quantum hardware

Thanks for Listening

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