Quantum GAN-Based Fast Calorimeter Simulation

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Outline

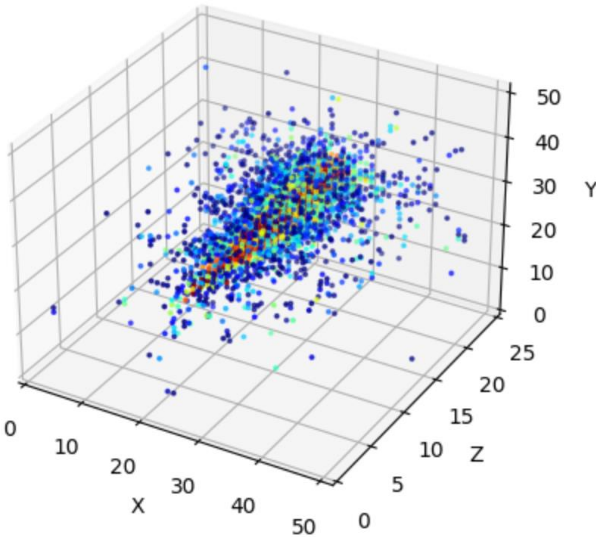
- Motivation
- Quantum Generative Adversarial Network (GAN)
- Methods
- Training Result
- Summary

Motivation

❖ Calorimeter Simulation

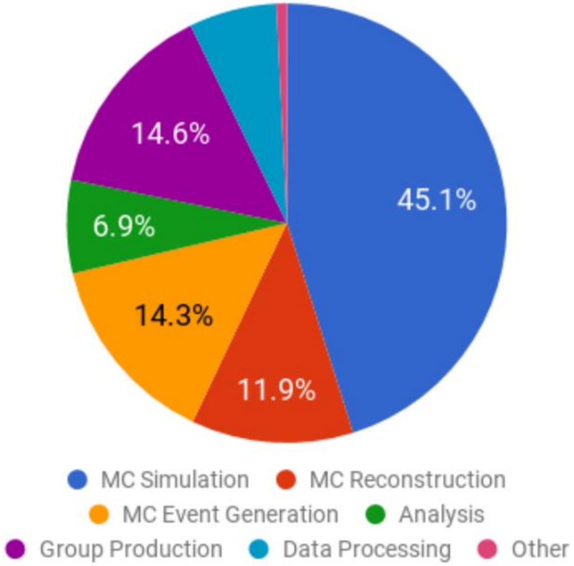
- Modeling of high-energy particles inducing cascade showers and depositing energy in the calorimeter
- Shower spatial distribution & energy deposition pattern

  → particle identification & energy measurement



❖ Geant4: Monte Carlo (MC) Method

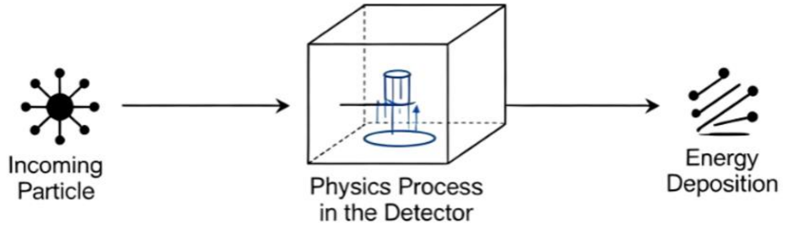
- MC method: step-by-step tracking of particle generation, transport, and energy deposition
- Accurate results, complex geometry
- Enormous computational cost

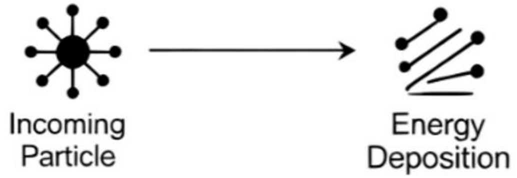


Motivation

❖ Fast Calorimeter Simulation

- Incoming particle → energy deposition
- Methods: Parametric models、GAN、DiT. . .



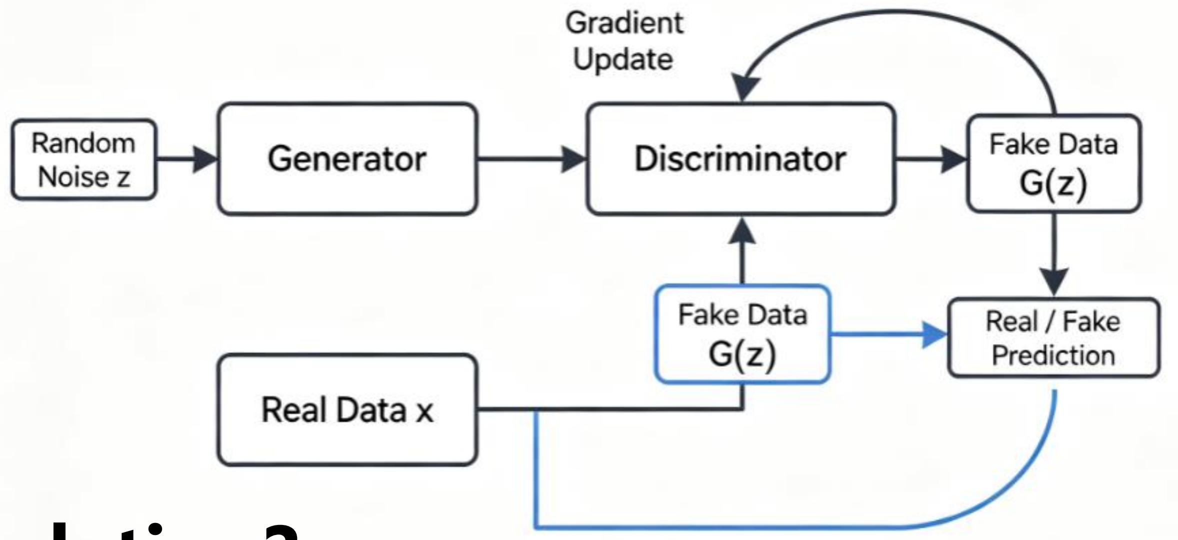


❖ Why Quantum Machine Learning (ML)?

- GANs proven: similar accuracy, orders-of-magnitude speedup
- Quantum ML: superposition & entanglement → exponentially larger representational space
- Can quantum ML match Geant4 fidelity at even lower computational cost?

Quantum GAN

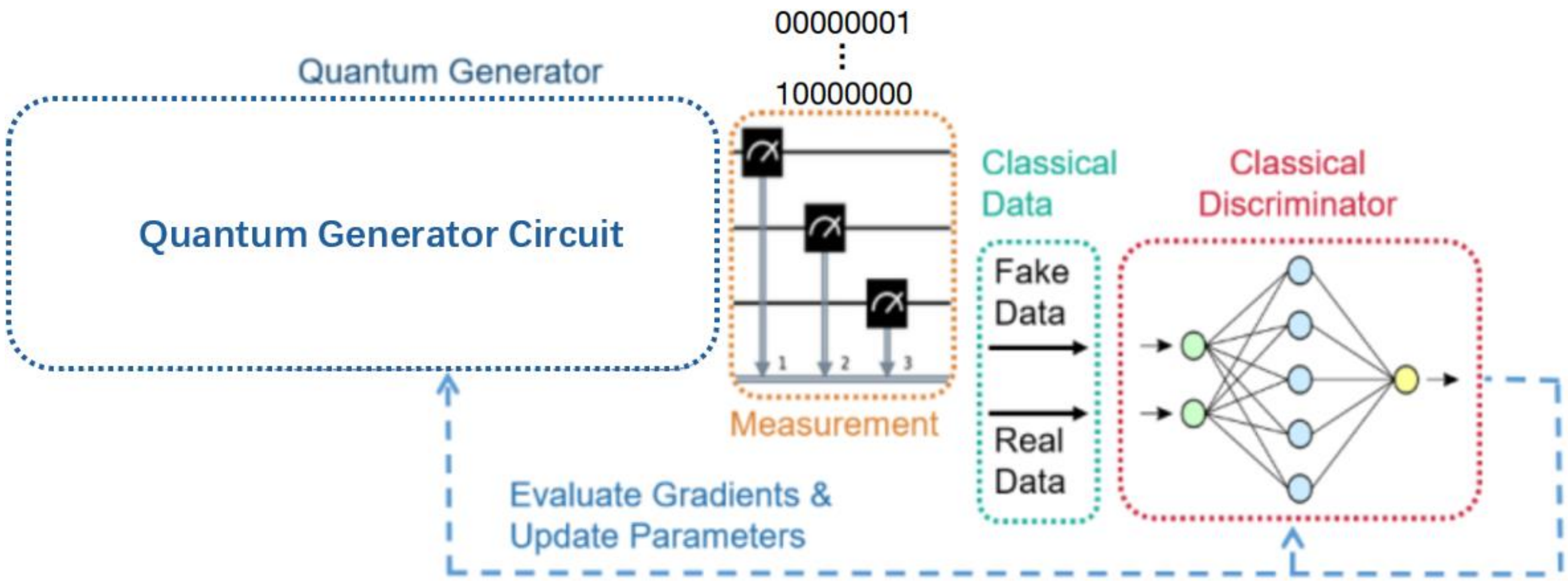
- **Generative Adversarial Network (GAN):** GAN is a deep learning framework where two neural networks compete to learn and generate realistic new data
  - **Generator:** creates fake data to fool the discriminator
  - **Discriminator:** learns to tell real data from fake



- **Why GAN for calorimeter simulation?**
  - Learns complex distributions through adversarial competition
  - No need for explicit physical modeling

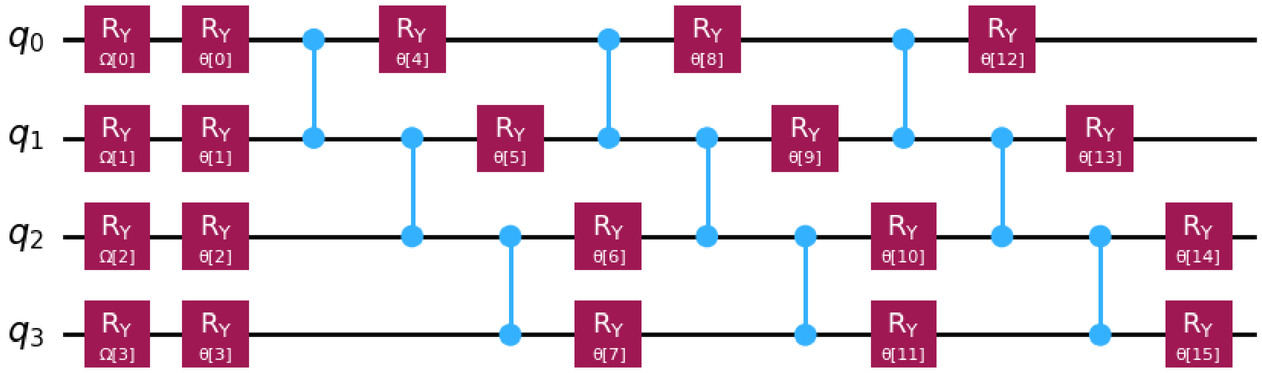
Quantum GAN

- **NISQ (Noisy Intermediate-Scale Quantum)-Era Constraints**
  - Limited qubits, high error rates, short coherence times
  - Full quantum GANs impractical → Hybrid approach necessary
- **Hybrid Architecture:** quantum generator + classical discriminator



Quantum GAN

- **Parameterized Quantum Circuit:** 4 qubits
  - Statevector simulation cost ∝ 2^n → exponential in qubit count



- **Two-part circuit structure**
  - Feature Map: encodes classical noise into quantum state

    single-qubit RY rotations per qubit
  - Ansatz: trainable variational circuit

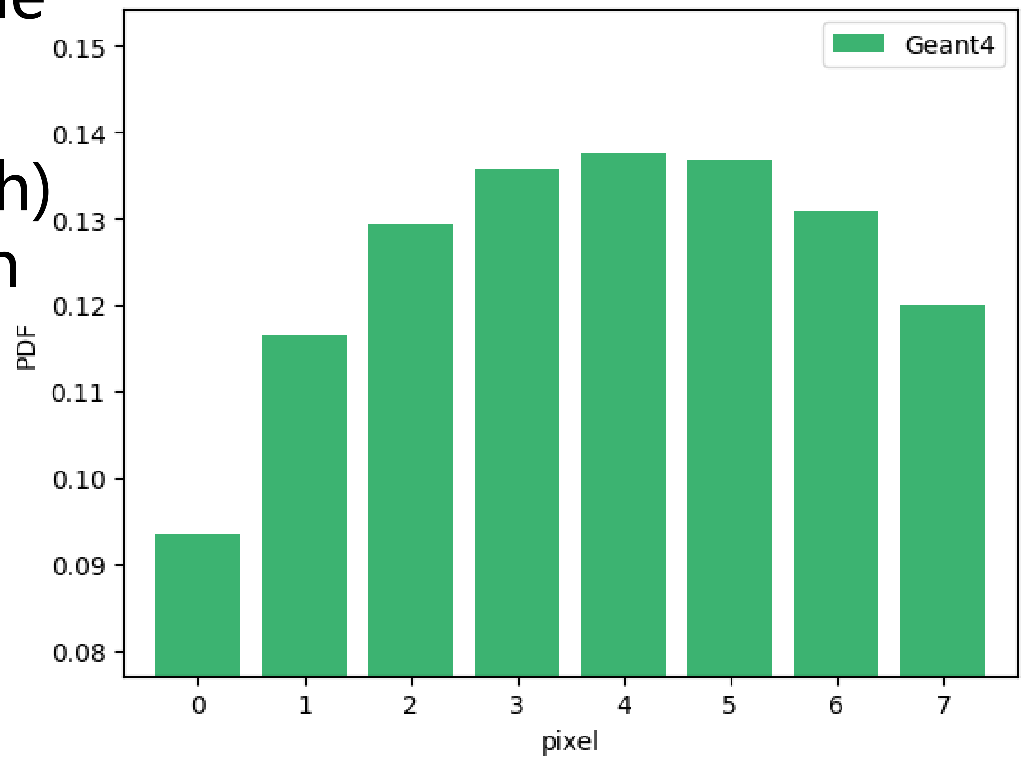
    RY rotation gates + CZ entangling gates

Methods

❖ Data Reduction

- Raw data: Electron showers at Fixed Angle by Geant4, 3D voxel grid
- Shower develops primarily along z (depth) → Average over all x and y voxels at each z-layer
- 25 original z-layers compressed into 8 representative layers:

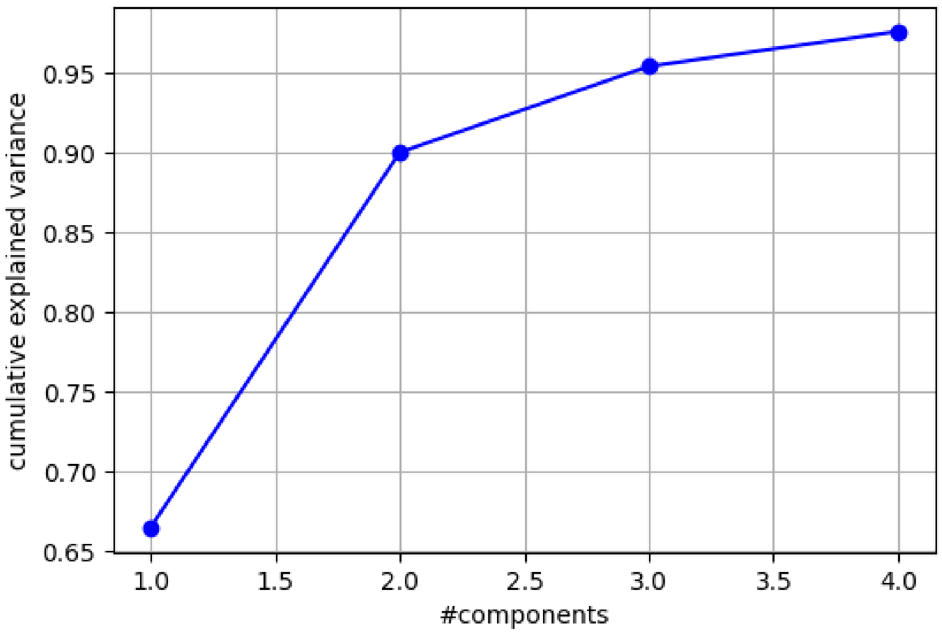
z-direction binning → 8 pixels

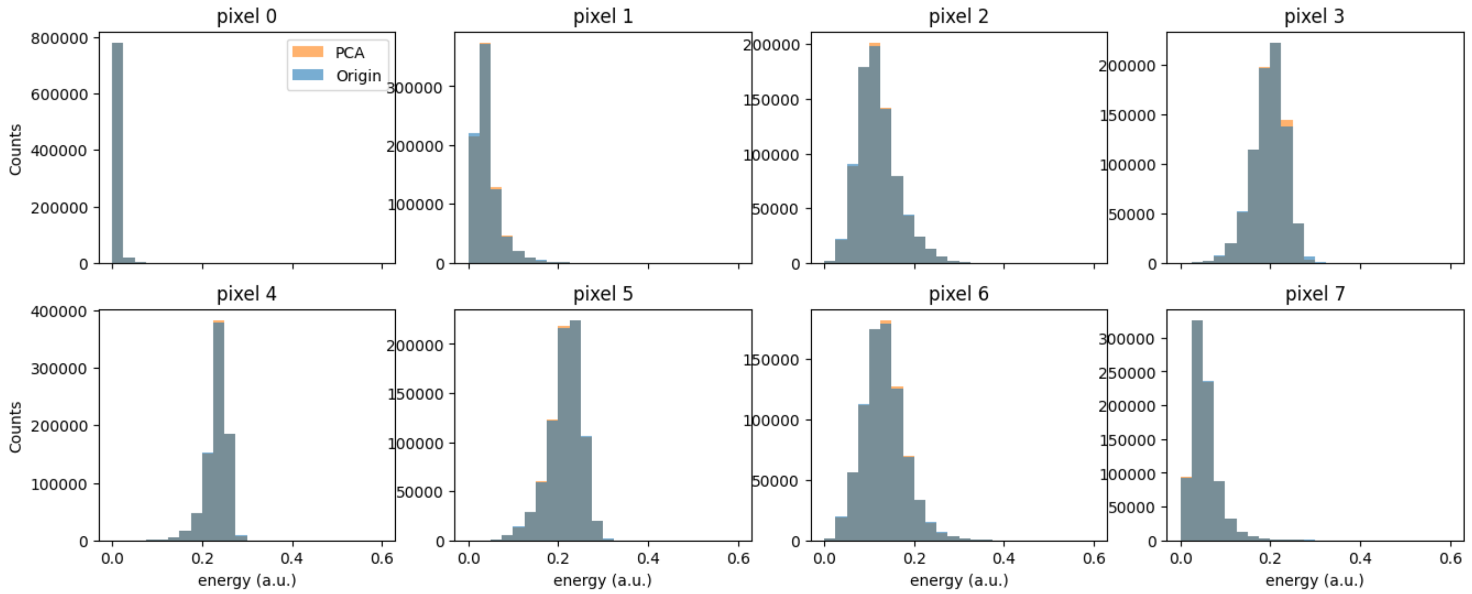


Methods

Principal Component Analysis (PCA)

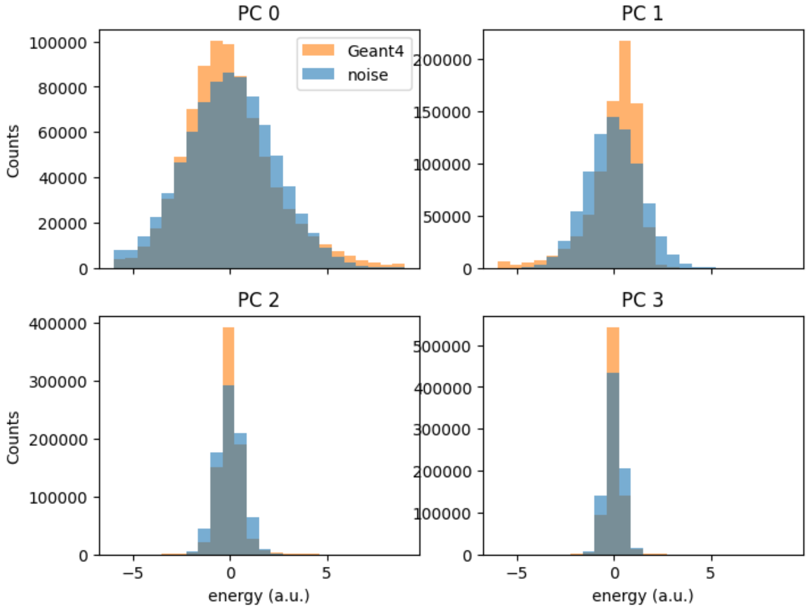
- Linear dimensionality reduction methods, Computes eigenvectors of the covariance matrix of the 8 pixels
- 4 components retain dominant shower shape information





Methods

Training Strategy



- Data encoding: Energy → Bloch sphere angle

  $E_i \rightarrow$ linear transform $\rightarrow$ Angle $\in [0, \pi] \rightarrow \theta_i$

- Gaussian noise prior in θ-space: Noise drawn as $\theta \sim \mathcal{N}(\mu\_pixel, \sigma\_pixel)$, feeds into the Feature Map as input

- Loss function: Wasserstein GAN & Gradient penalty (WGAN-GP)

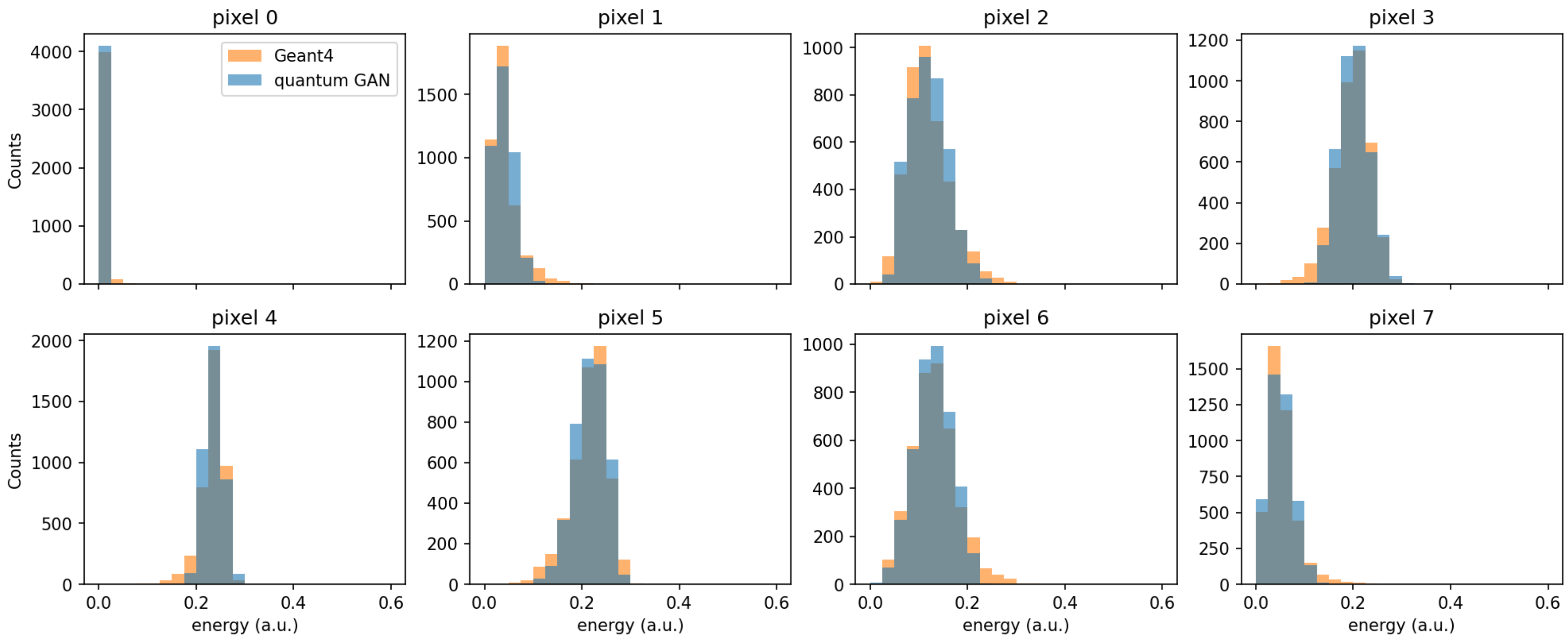
  $L\_D = E[D(G(z))] - E[D(x)] + \lambda \cdot GP, \quad L\_G = -E[D(G(z))], \quad \lambda = 10$

- Training configuration: lr_gen = 0.008, lr_disc = 0.001,

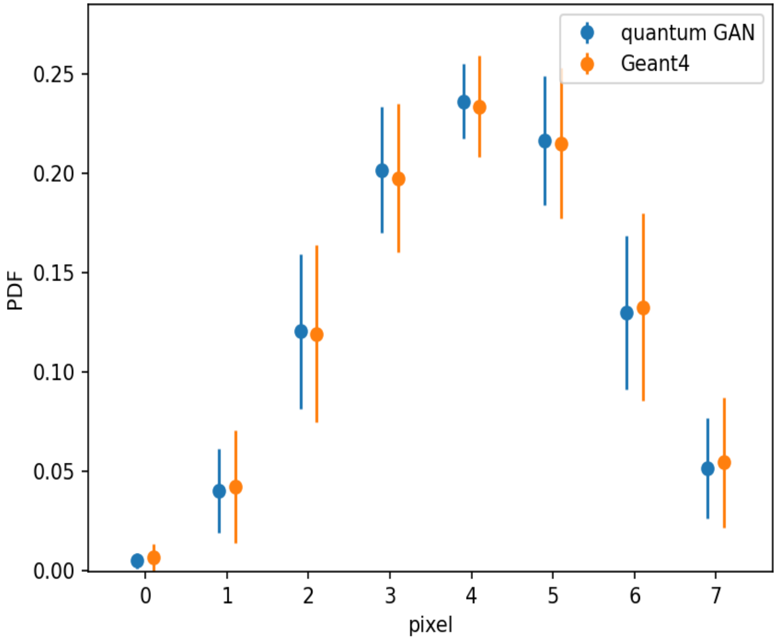
  γ (lr decay) = 0.995/epoch, disc:gen = 10:1

Training Result

❖ Quantum GAN vs Geant4 Shower Distributions



Per-Pixel Distribution



Average Pixel Distribution

Training Result

❖ Correlation Structure

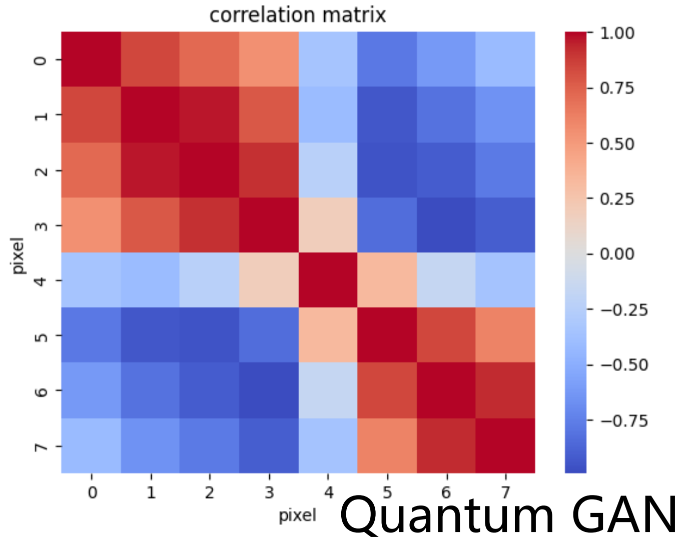
- Visually consistent patterns

  → GAN captures inter-pixel shower correlations

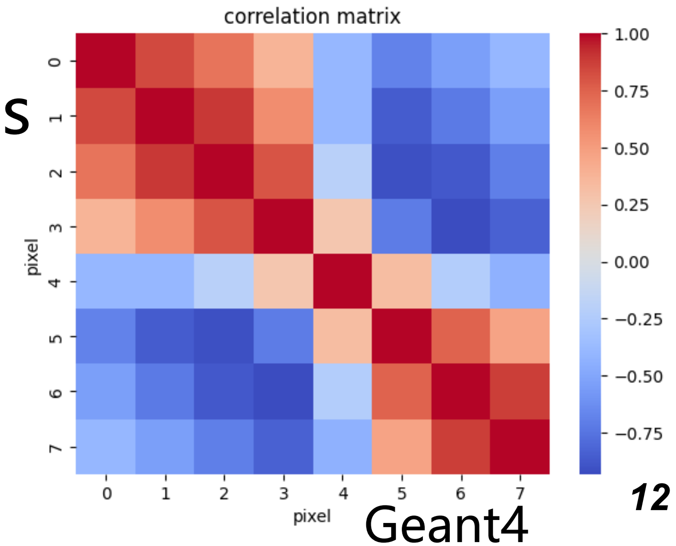
❖ Parameter Efficiency

- Quantum GAN generator: 16 parameters
- Classical generator: typically thousands to millions
- Expressivity comes from superposition and entanglement, not parameter volume

pixel correlation matrices



Quantum GAN



Geant4

Summary

Summary

- Quantum GAN successfully learns Geant4 calorimeter shower distributions
- Hybrid quantum-classical architecture + WGAN-GP training is viable

Limitations

- Quantum GAN suffer from training instability
- Statevector simulation runs slowly on the CPU

Plan

- Add realistic noise models
- Deploy on real quantum hardware
- Explore alternative architectures(RNN, Transformers...)

Thank you for your listening !