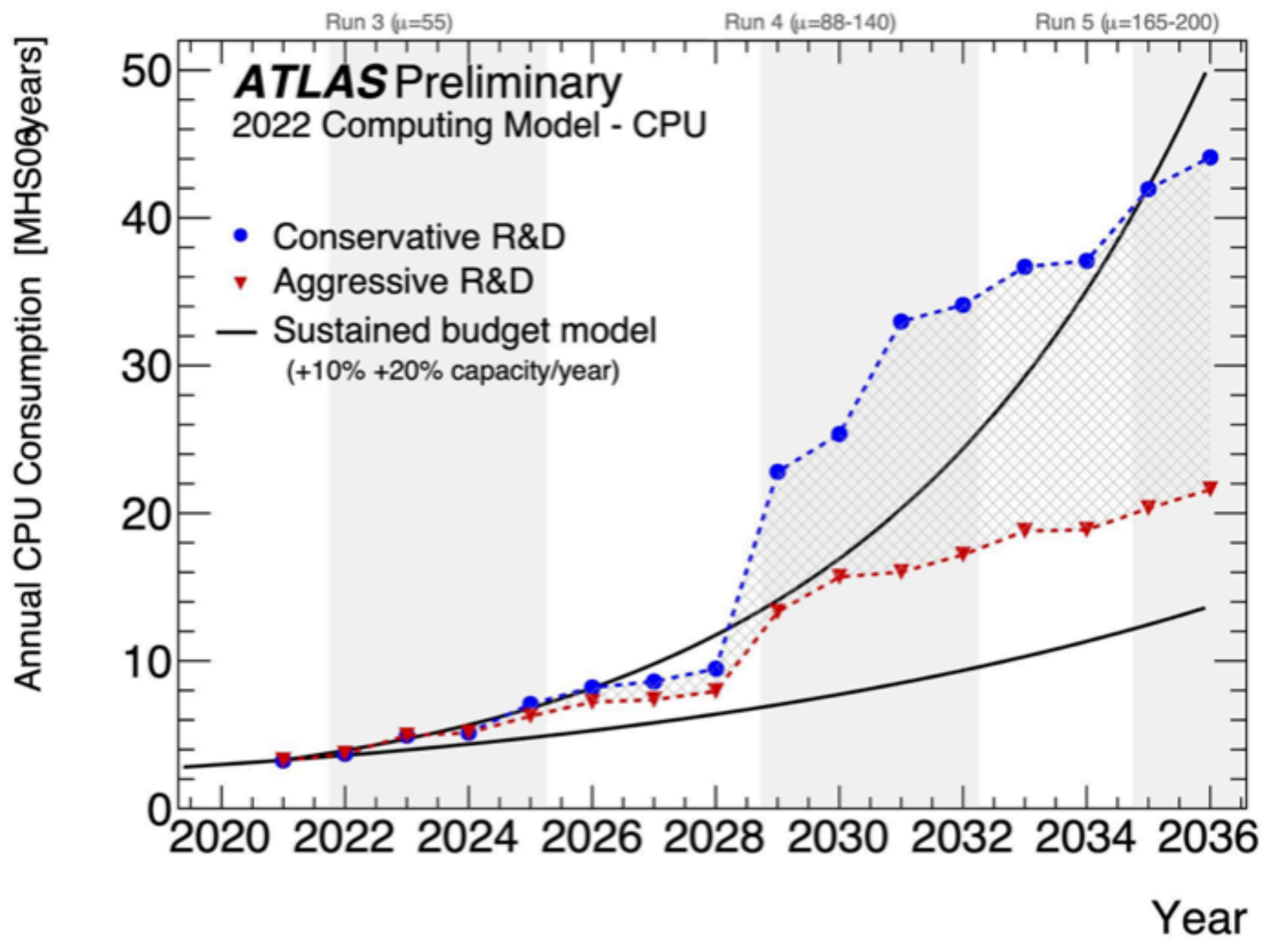
Quantum GAN for Fast Shower Simulation

Xiaozhong Huang, Weidong Li
IHEP

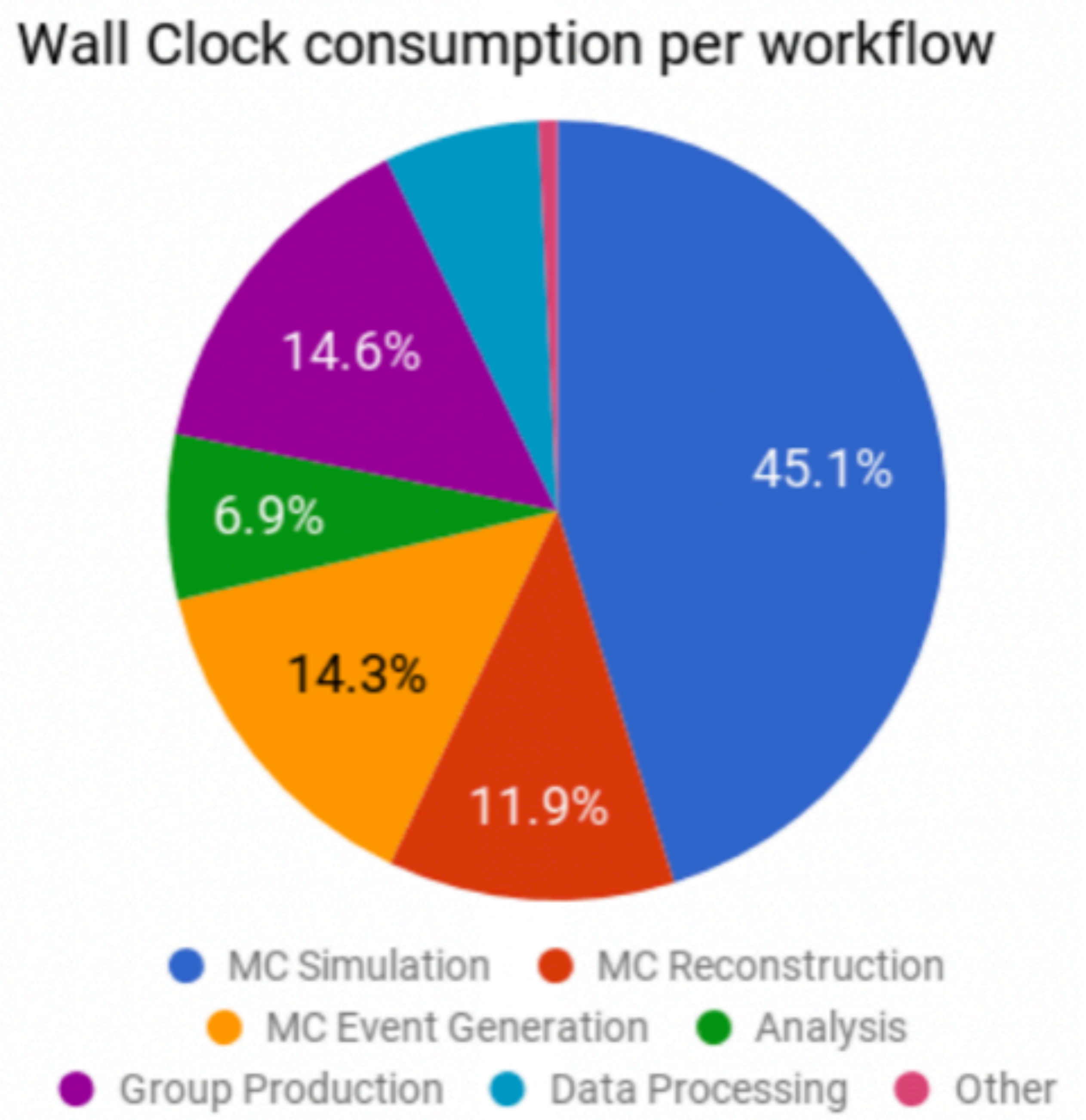
CEPC 2024
2024/10/26

Why Fast Shower Simulation?

- HL-LHC ⟶ huge computing resources
- MC simulation account for ～50%（dominated by shower simulation)
- Fast shower simulation: help overcome the computational challenge



ATLAS Software and Computing HL-LHC Roadmap

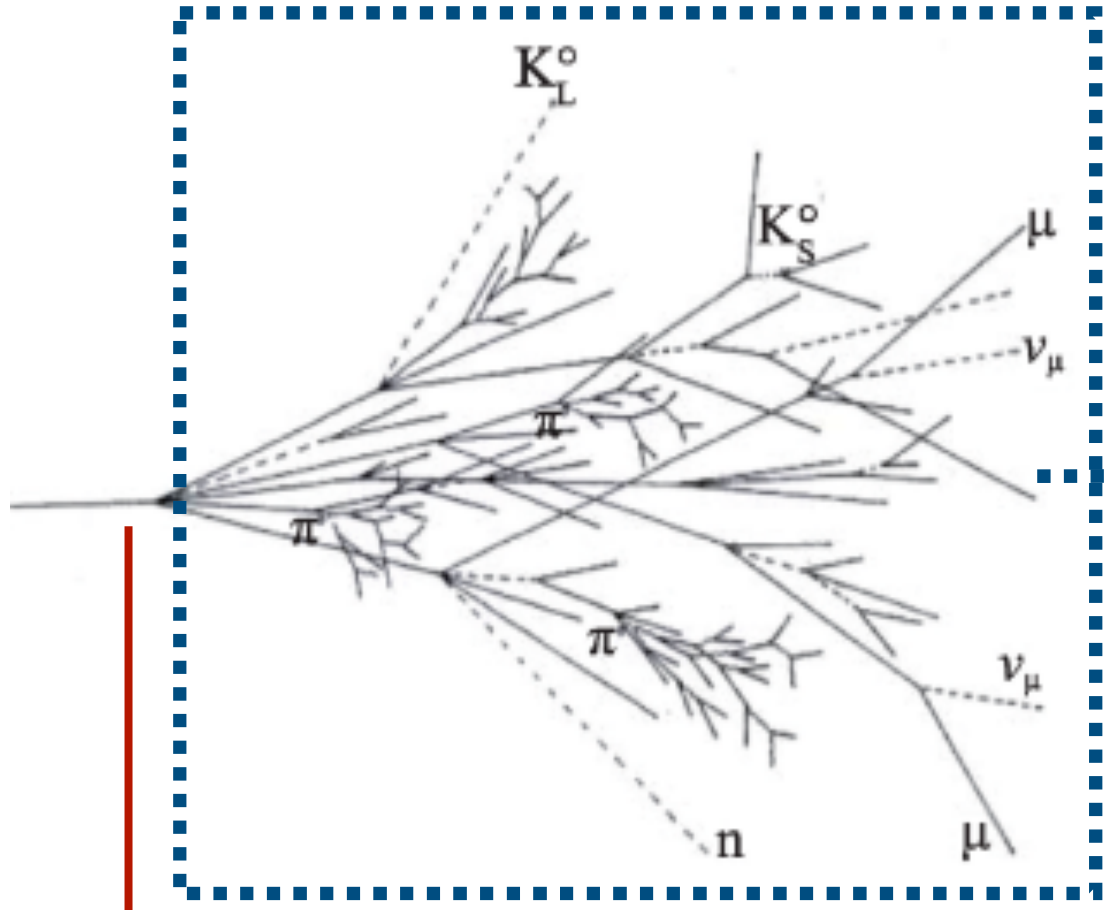


ATLAS 2017 number

Fast Shower Simulation

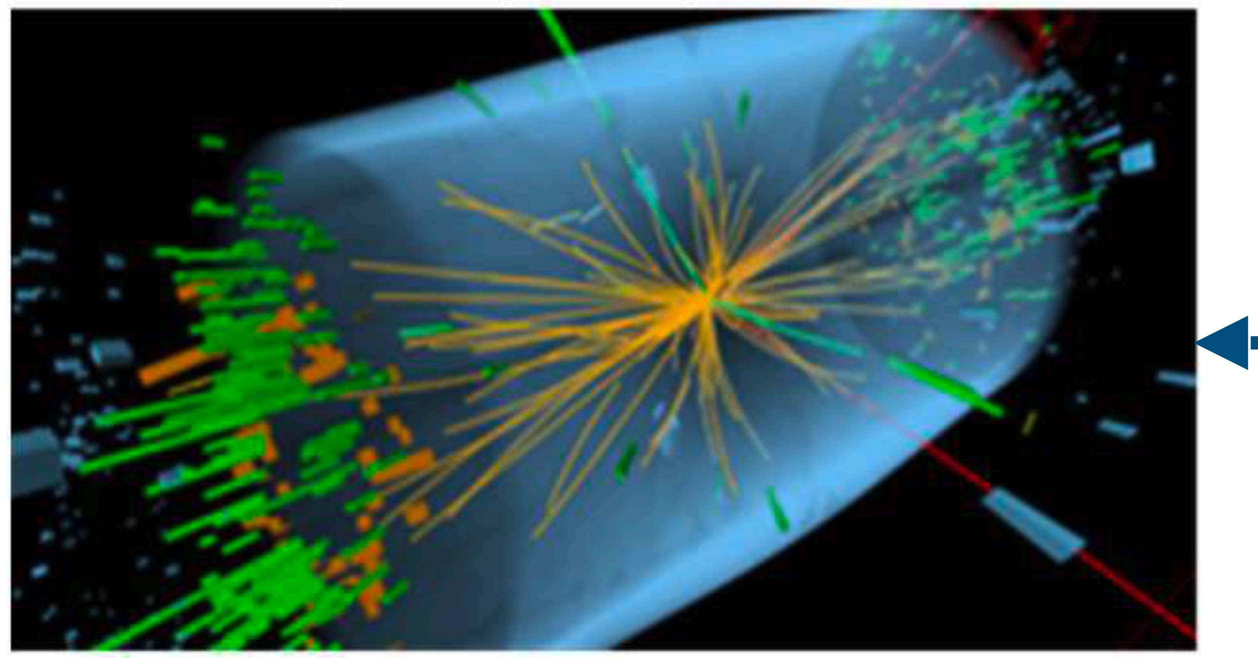
- Geant4: incoming particle → physics process in the detector → energy deposition
  - accurate results, but time-consuming
  - complex geometry
  - number of secondary particles grows quickly

Geant4



- Fast simulation: incoming particle → energy deposition
  - parameterization
  - **GAN (<u>ATLAS</u>)**
  - ……

fast simulation



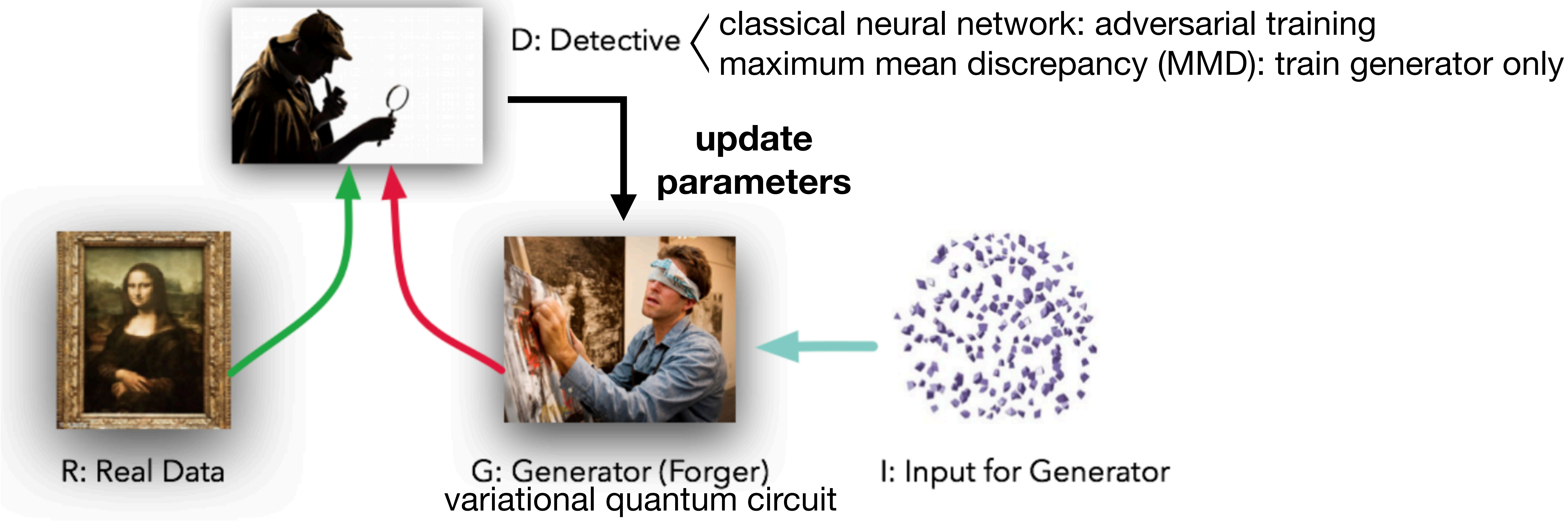
QC is an alternative to classical computing
QC + GAN: the potential to out-perform classical GAN

Quantum Generative Adversarial Network (GAN)

- Two kinds of quantum GAN
  - quantum generator + classical discriminator (choose the hybrid version for our study)
  - quantum generator + quantum discriminator

- NISQ (noisy intermediate-scale quantum era)
  - noisy and unstable qubit
  - number of qubits: [~10, ~10^2]

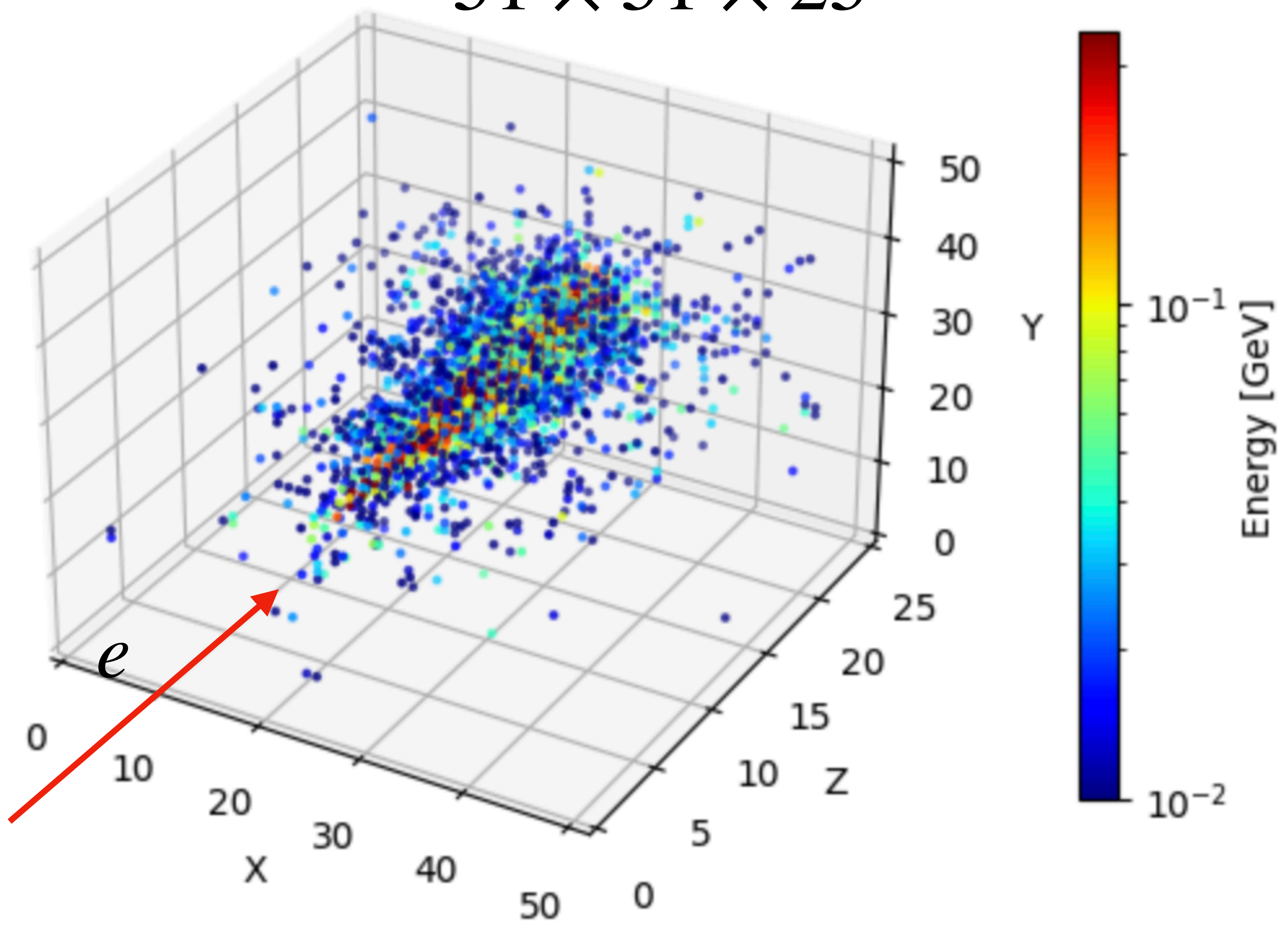
image source



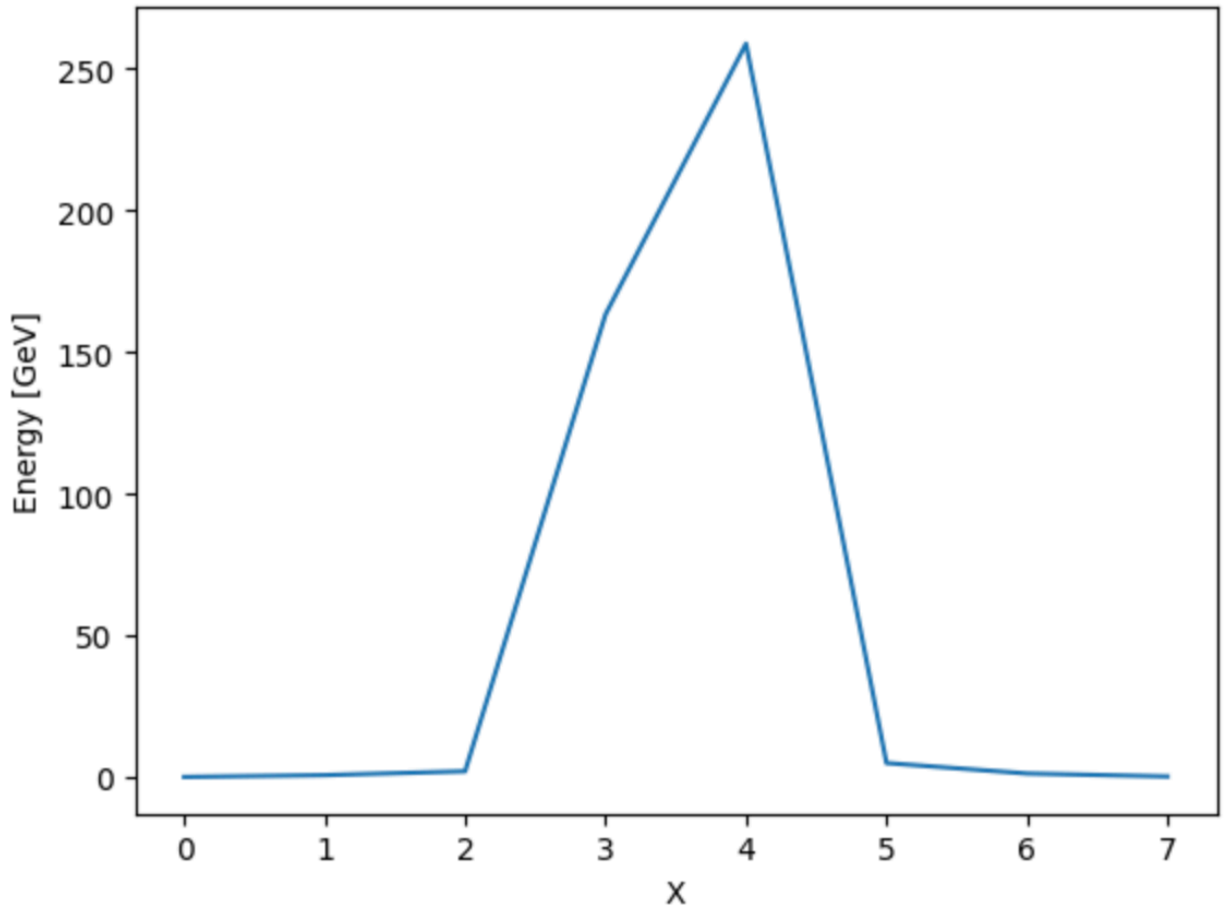
Data Sample

- CLIC Calorimeter images: energy deposits from electrons
- 3D ($51 \times 51 \times 25$): too large for the current quantum device
  - 60000 pixels downsampled to 8(64) pixels for prototype study
  - ATLAS classical GAN: ~180000 pixels downsampled to ~500 pixels
  - actual application: ~100 qubits

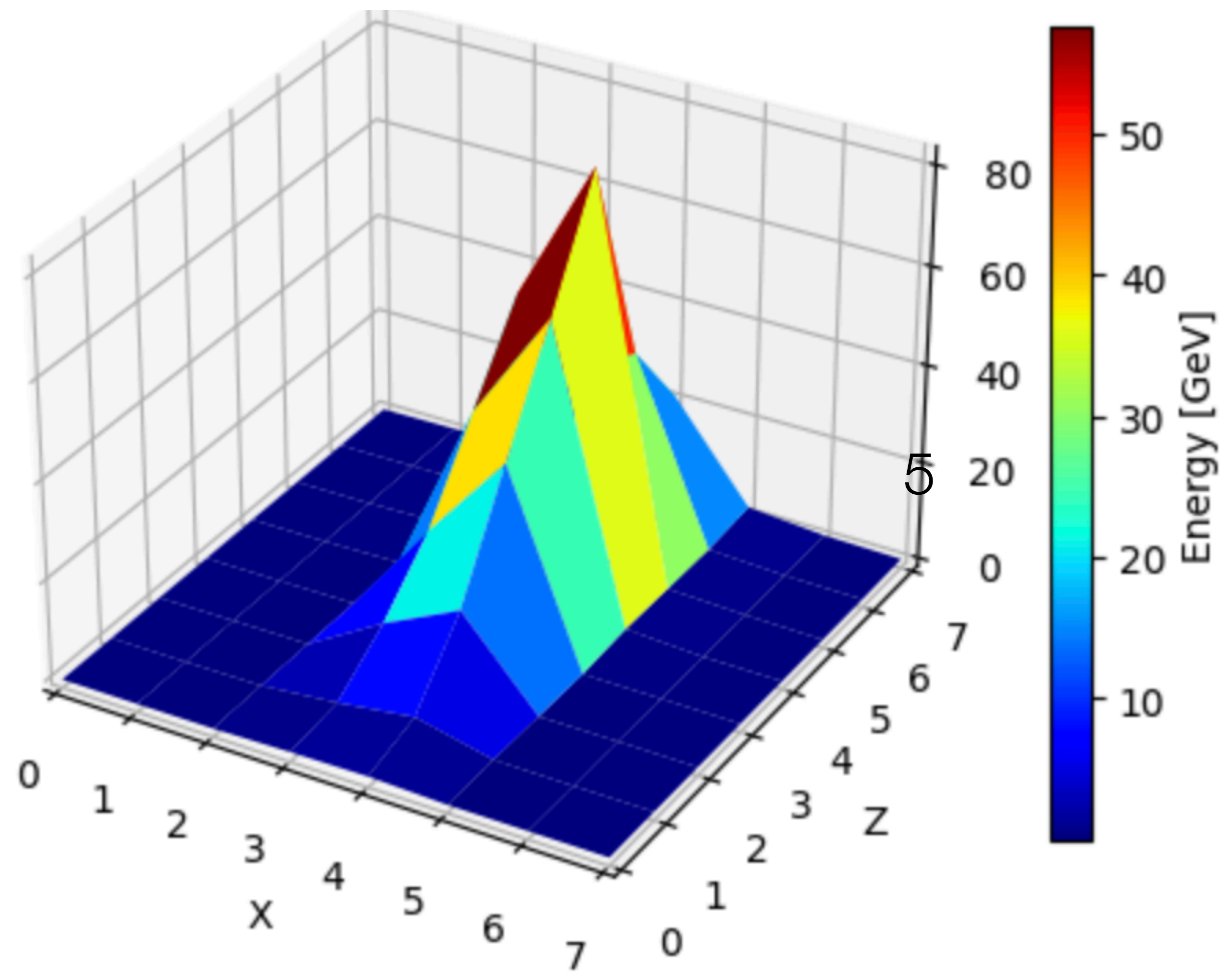
$51 \times 51 \times 25$



8



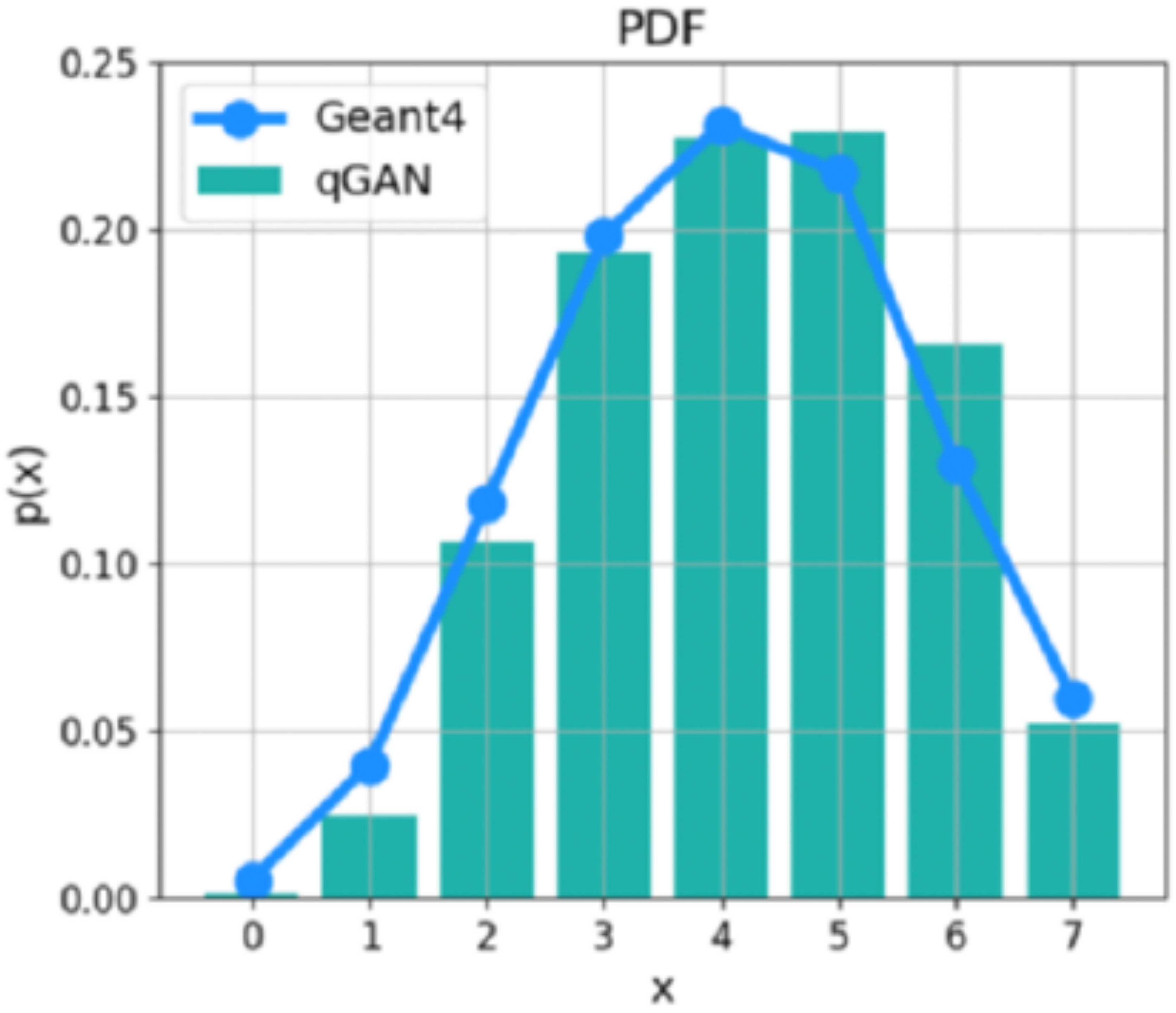
8×8



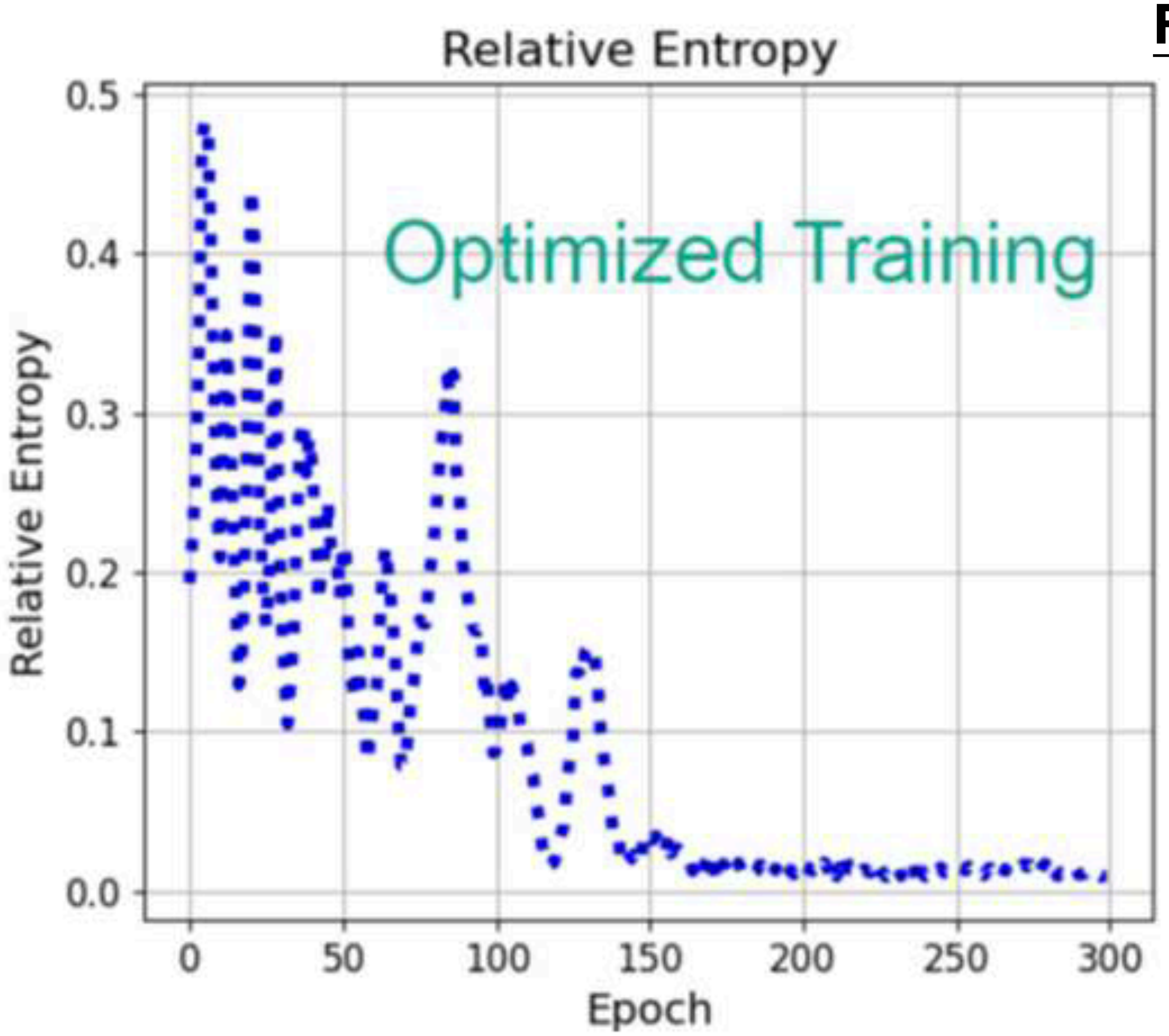
Average Shower Image (PDF)

Previous Studies

- DESY & CERN successfully generated the average shower image
  - 8 pixels: good performance
  - 64 pixels: training is unstable

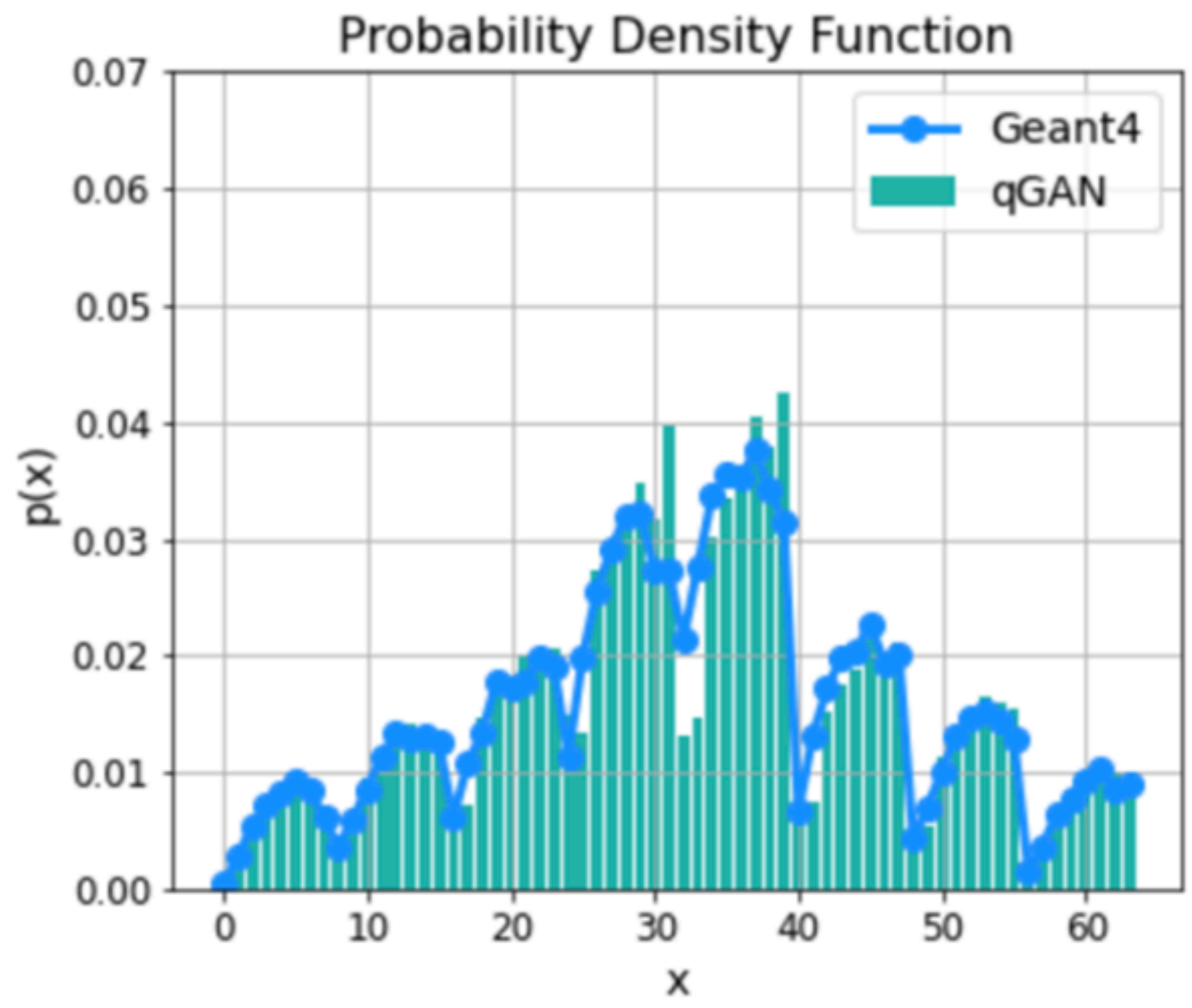


Florian Rehm

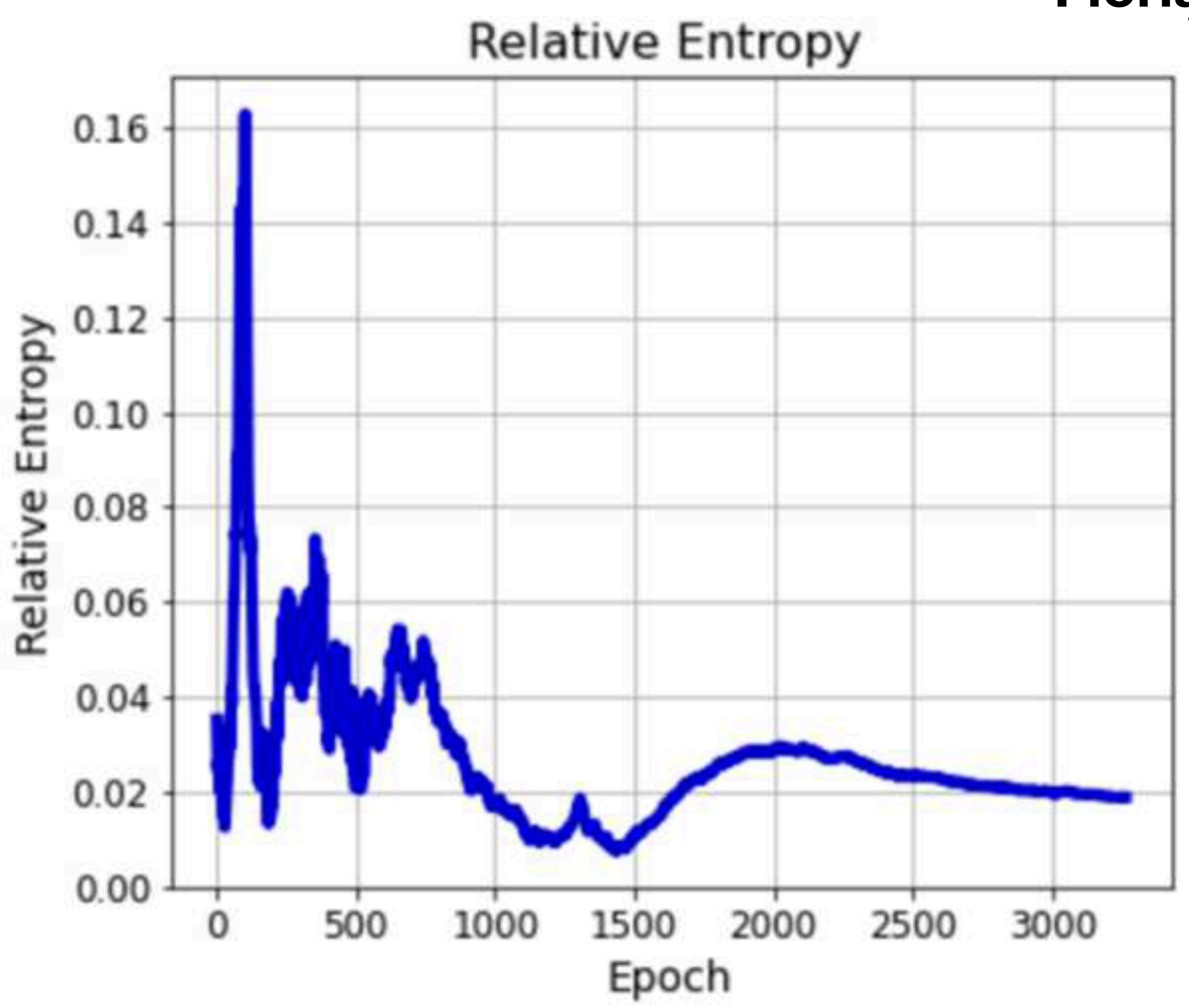


Previous Studies

- DESY & CERN successfully generated the average shower image
  - 8 pixels: good performance
  - 64 pixels: training is unstable

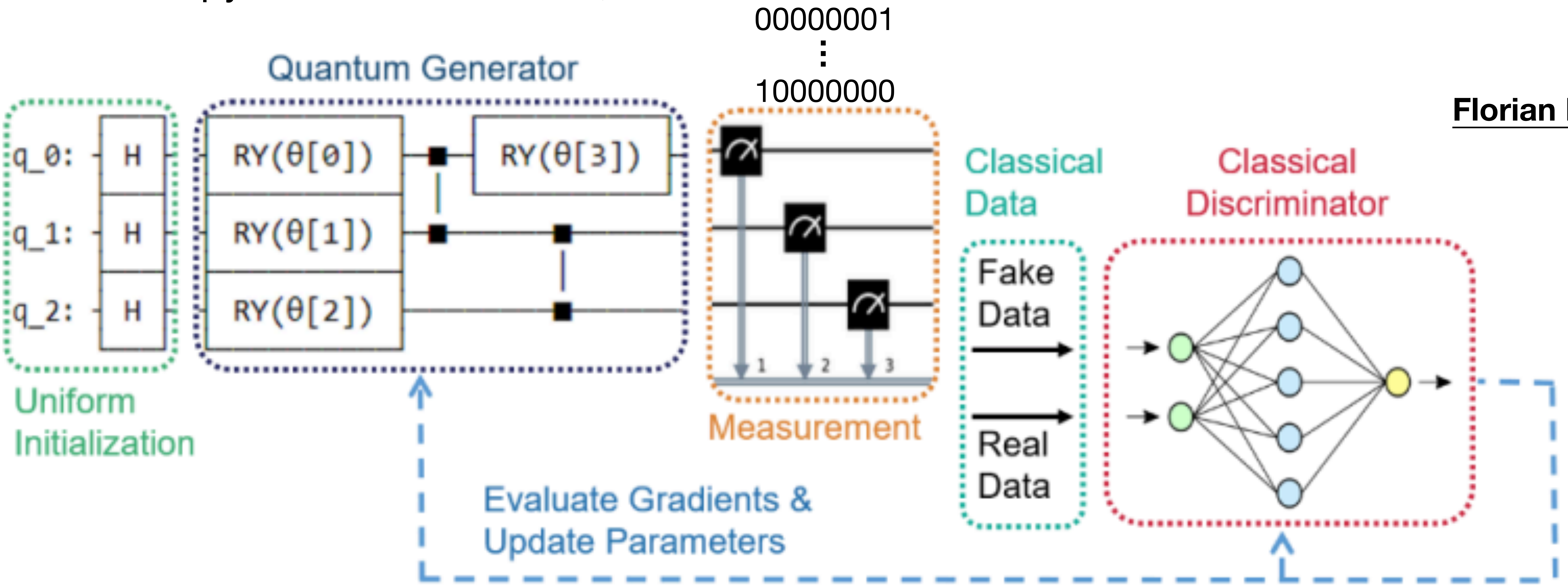


Florian Rehm



GAN Architecture (8 pixels)

- For each shot, we obtain one of the eight quantum states: $|000\rangle \rightarrow |111\rangle$
  - converted to classical data by one-hot encoding
- The input data of the classical discriminator is the sparse discrete data
  - not average shower image, hard to train
  - cross entropy as the loss function, known to be unstable in some cases

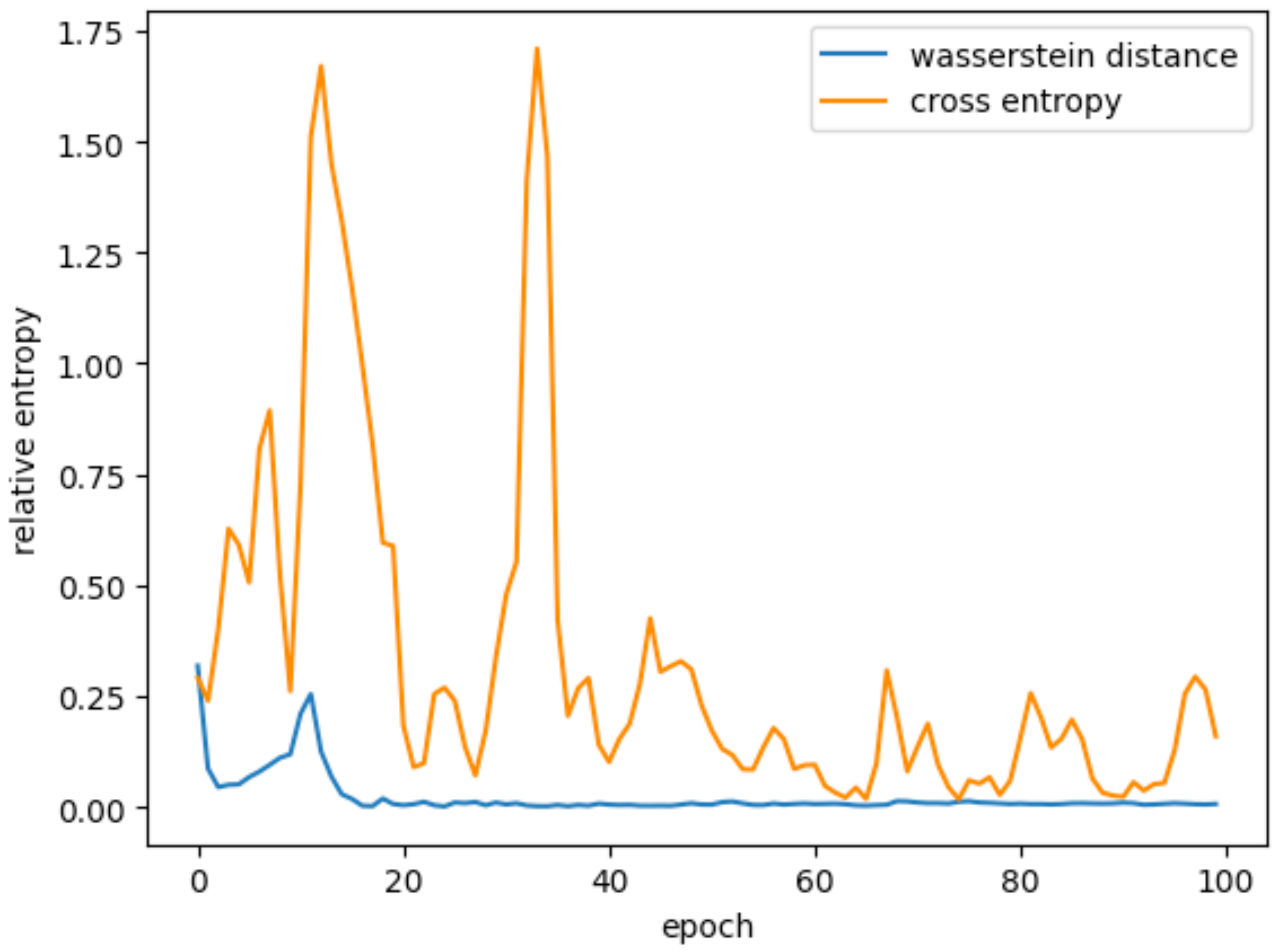


Florian Rehm

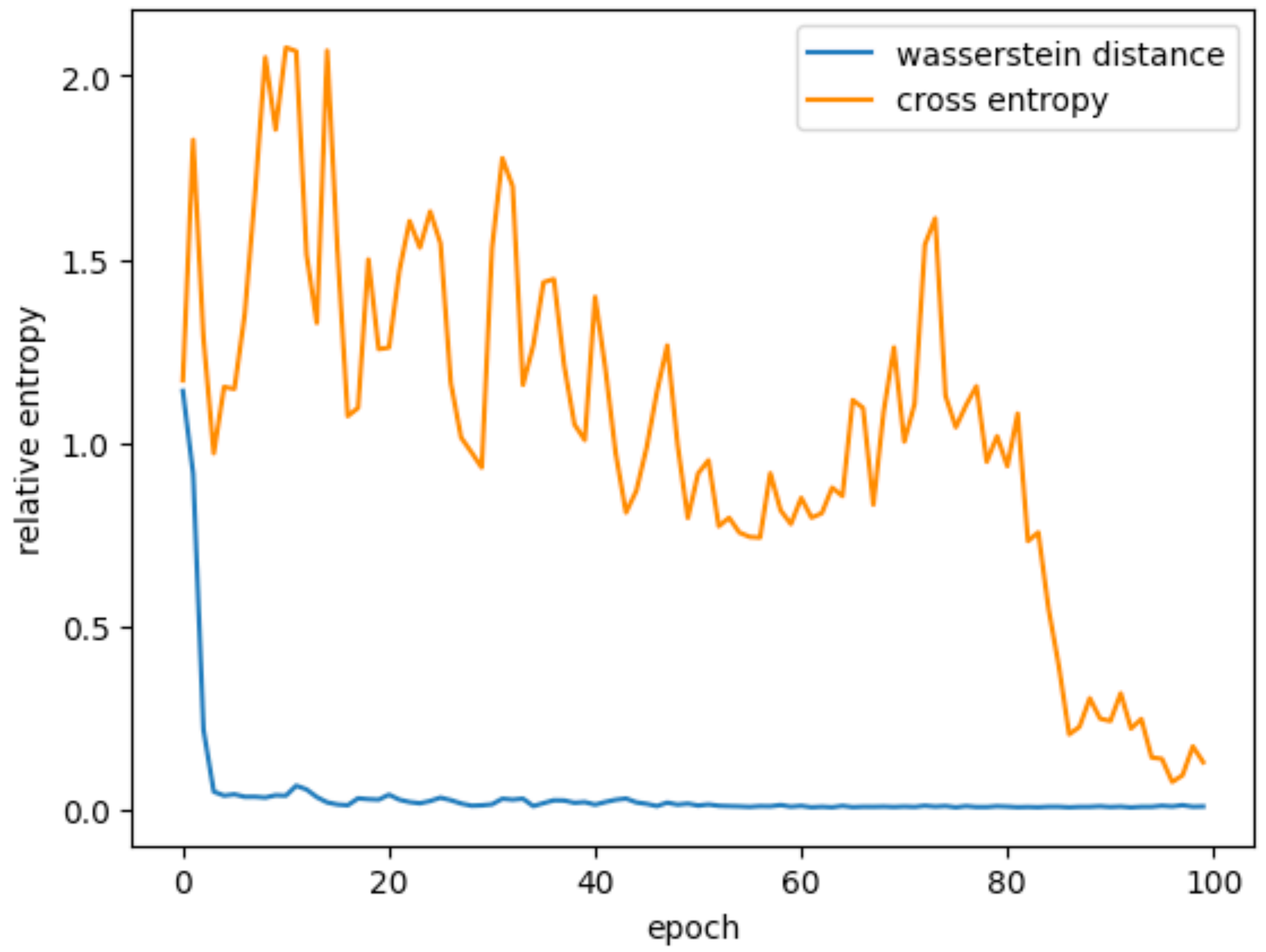
Modified Model

- Training data: sparse discrete data (one shot) → frequency of each quantum state (multiple shots)
- Loss function: cross entropy → Wasserstein distance

8 pixels

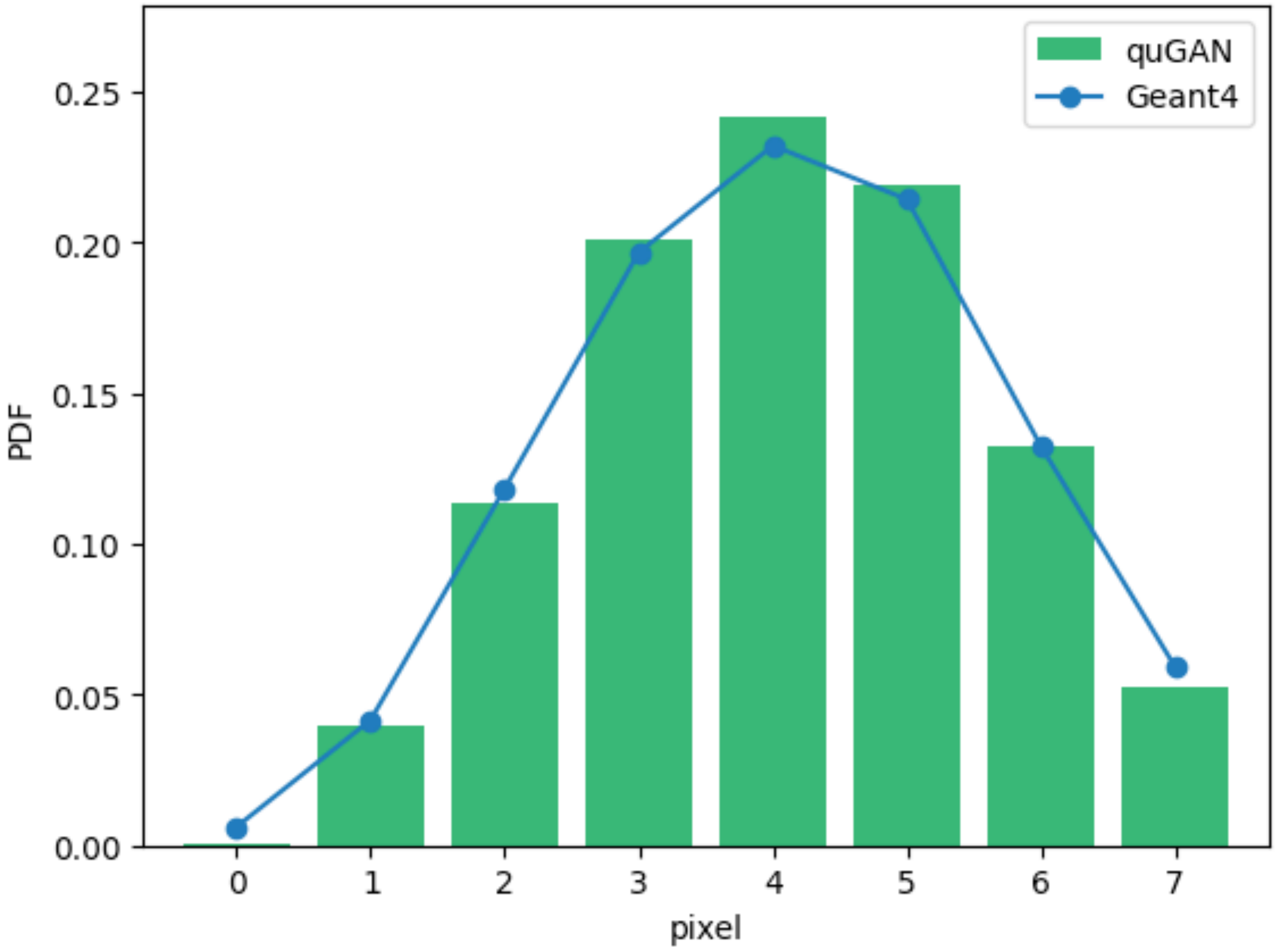


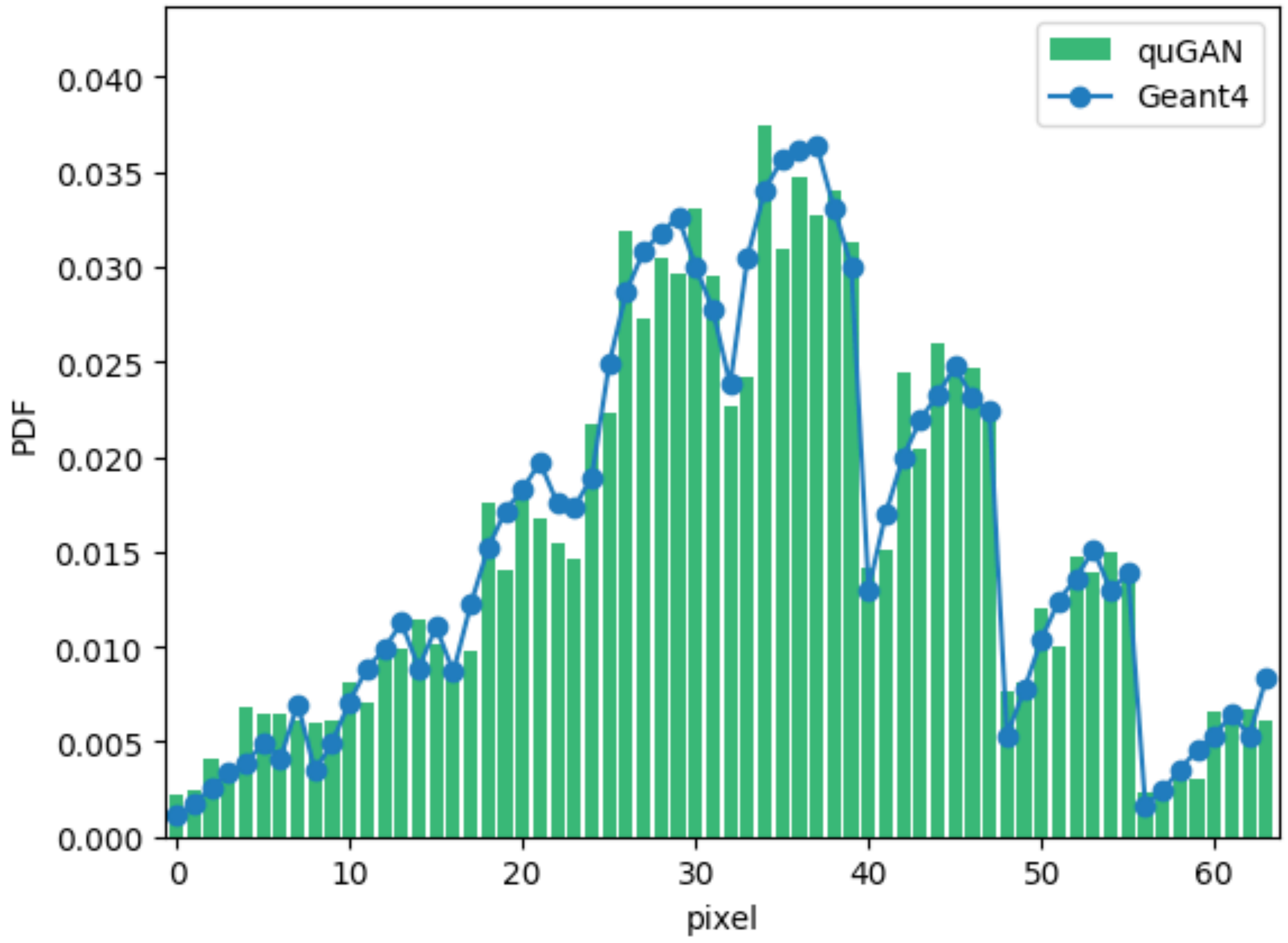
64 pixels



Performance（Ideal Simulator）

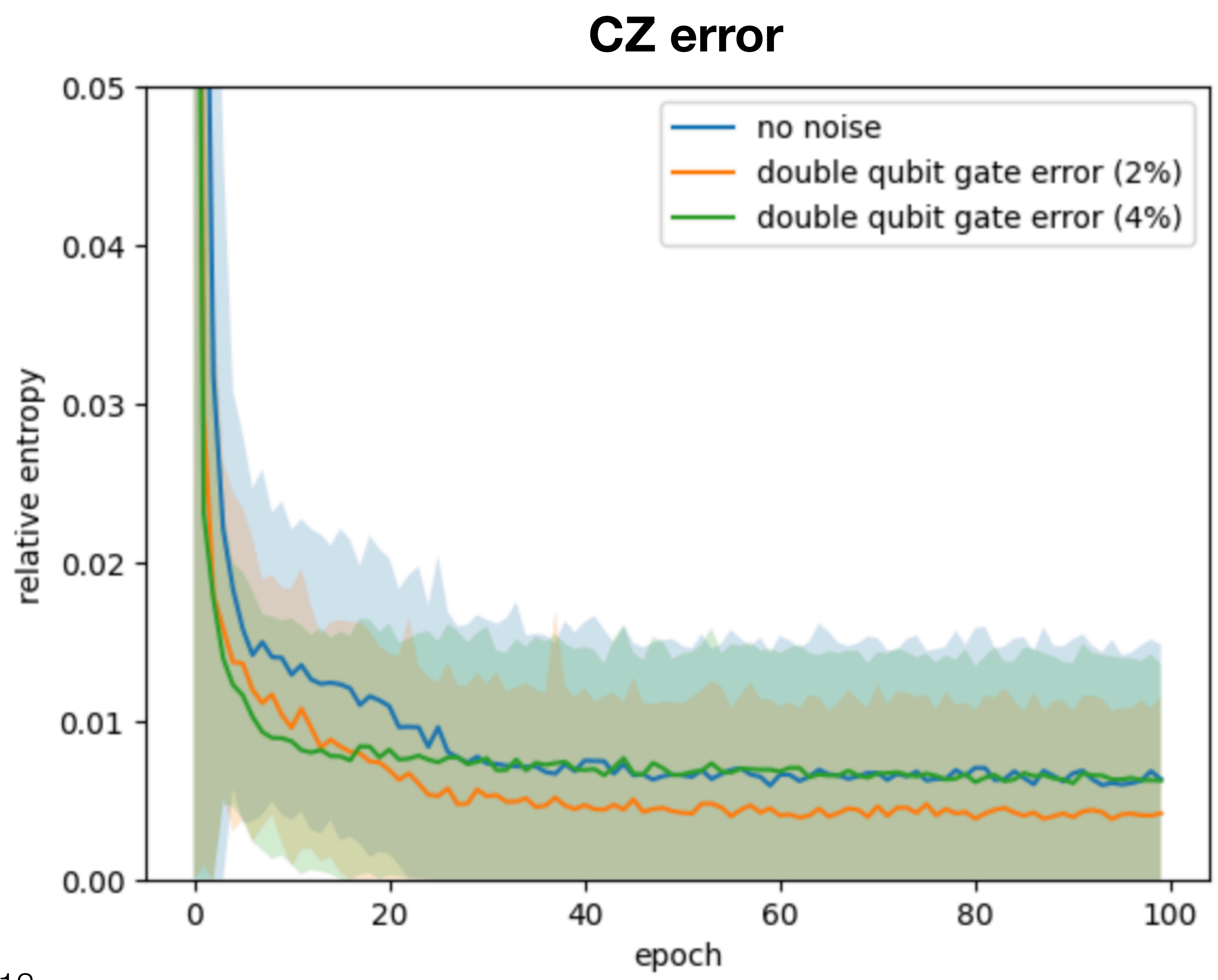
- Generated data is consistent with Geant4





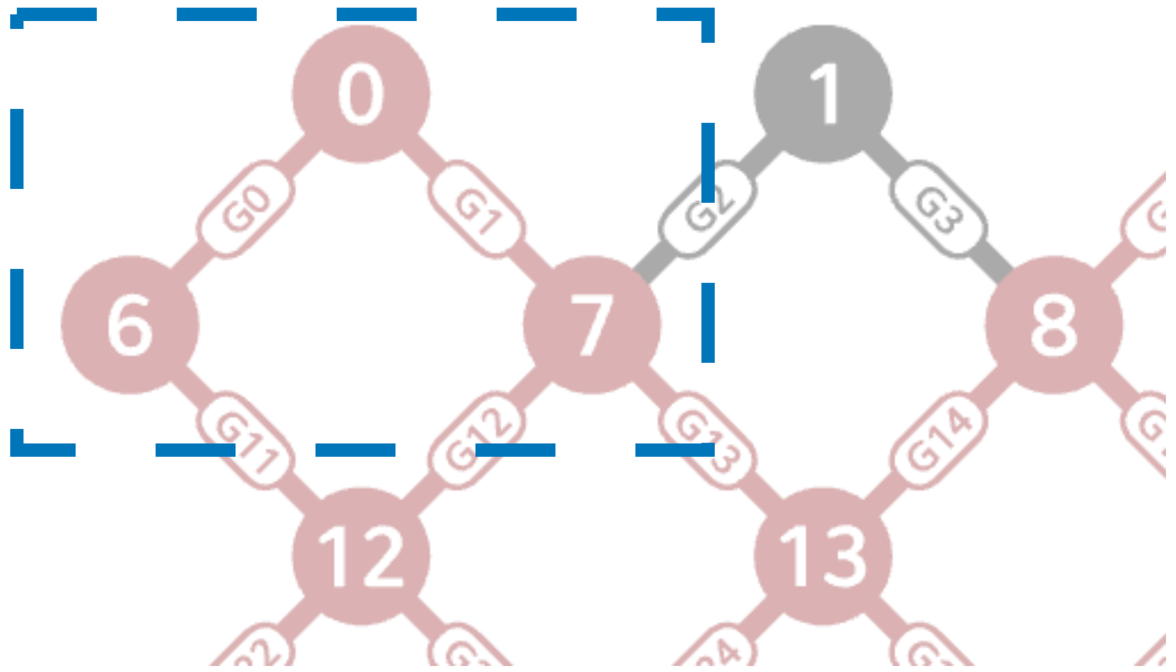
Impact of Noise: Training (8 pixels)

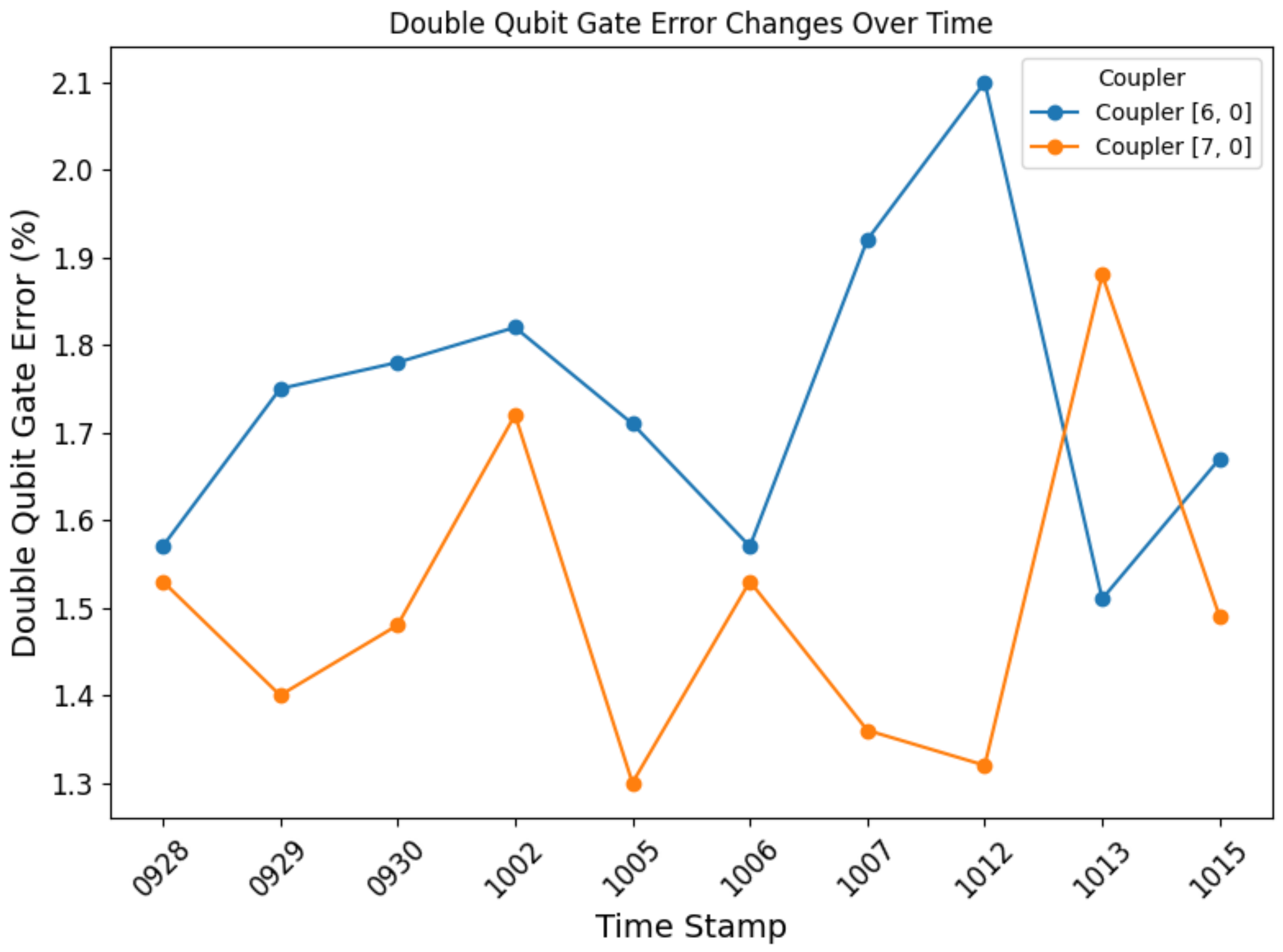
- Consider the impact of double qubit gate error and readout error
  - model performance depends on model initialization
  - mean (solid line) + std (error band)
  - model is robust against noise at the training stage

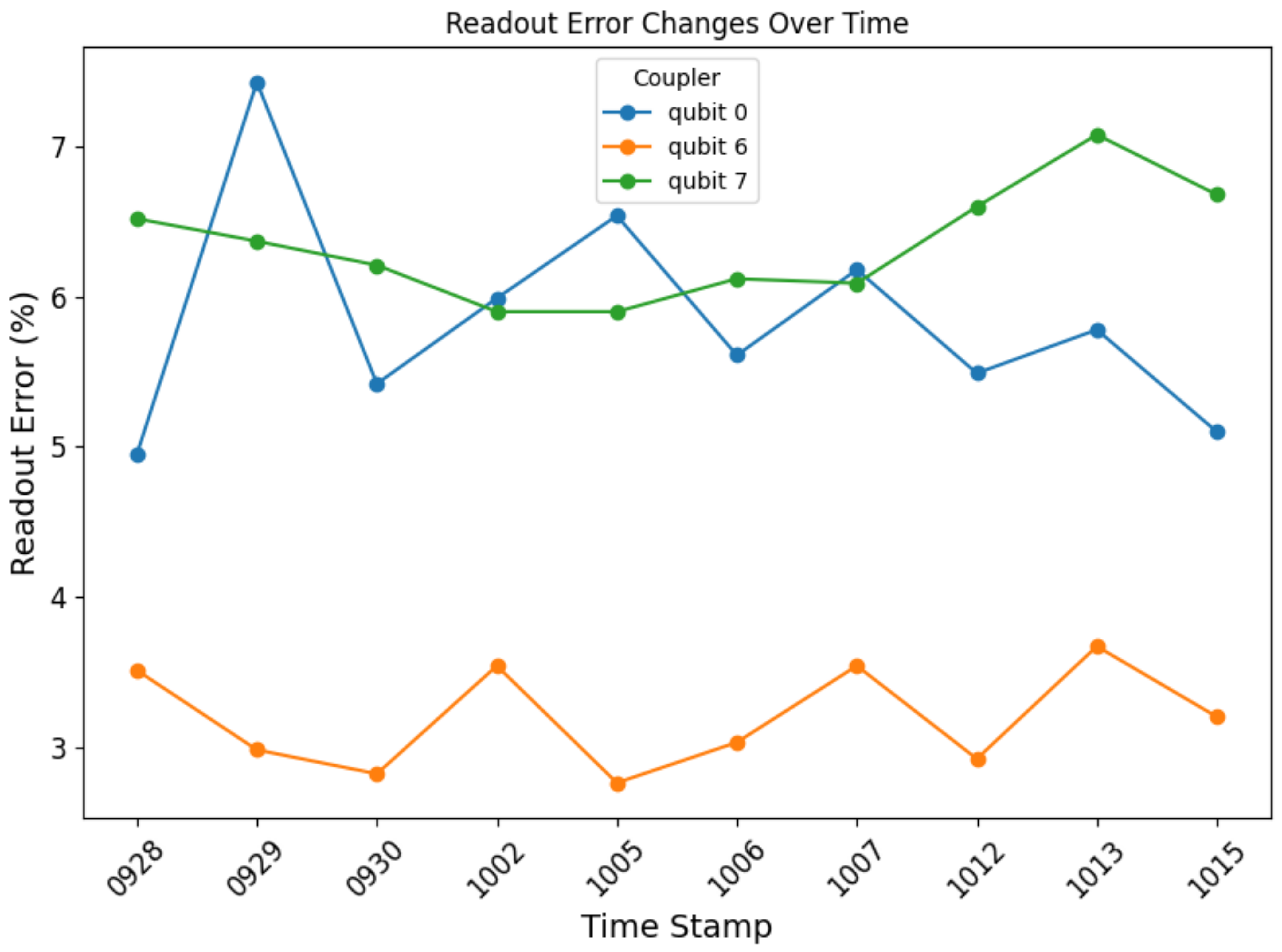


Impact of Noise: Inference (8 pixels)

- Qubit is not stable: noise level changes over time
  - change of CZ error: < 0.5%
  - change of readout error: < 2%

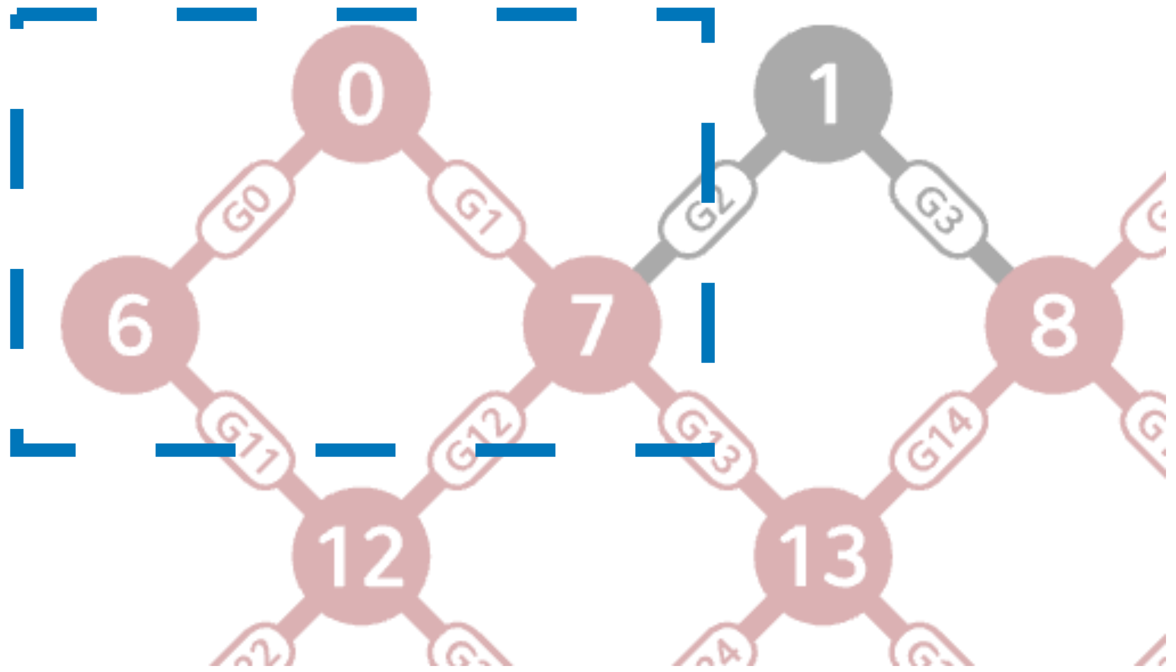


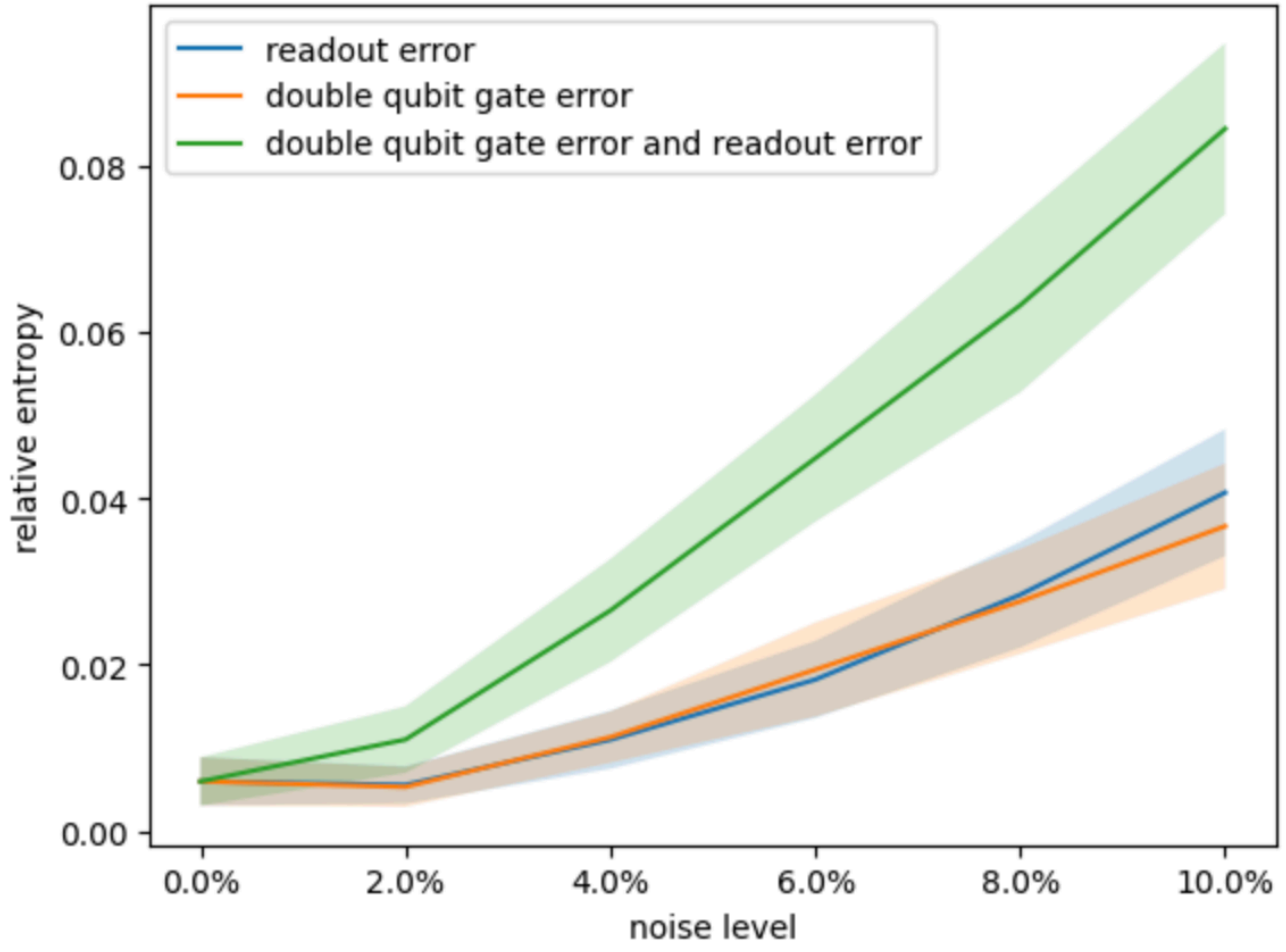




Impact of Noise: Inference (8 pixels)

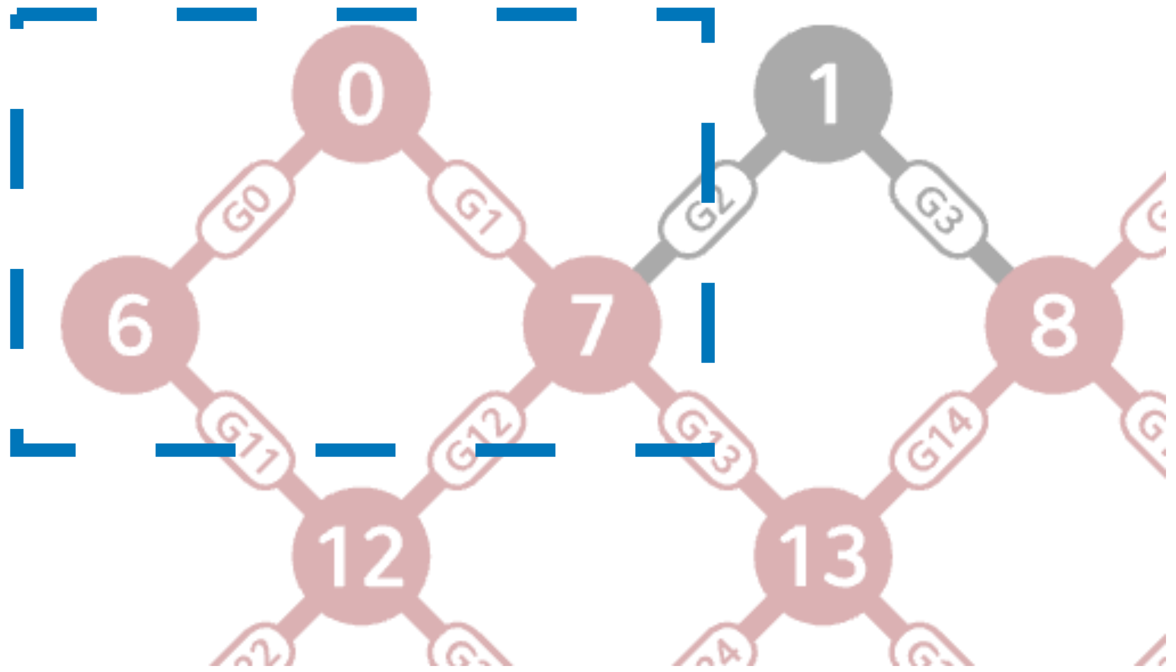
- Qubit is not stable: noise level changes over time
  - change of CZ error: < 0.5%
  - change of readout error: < 2%
  - model is robust when noise level < 2%



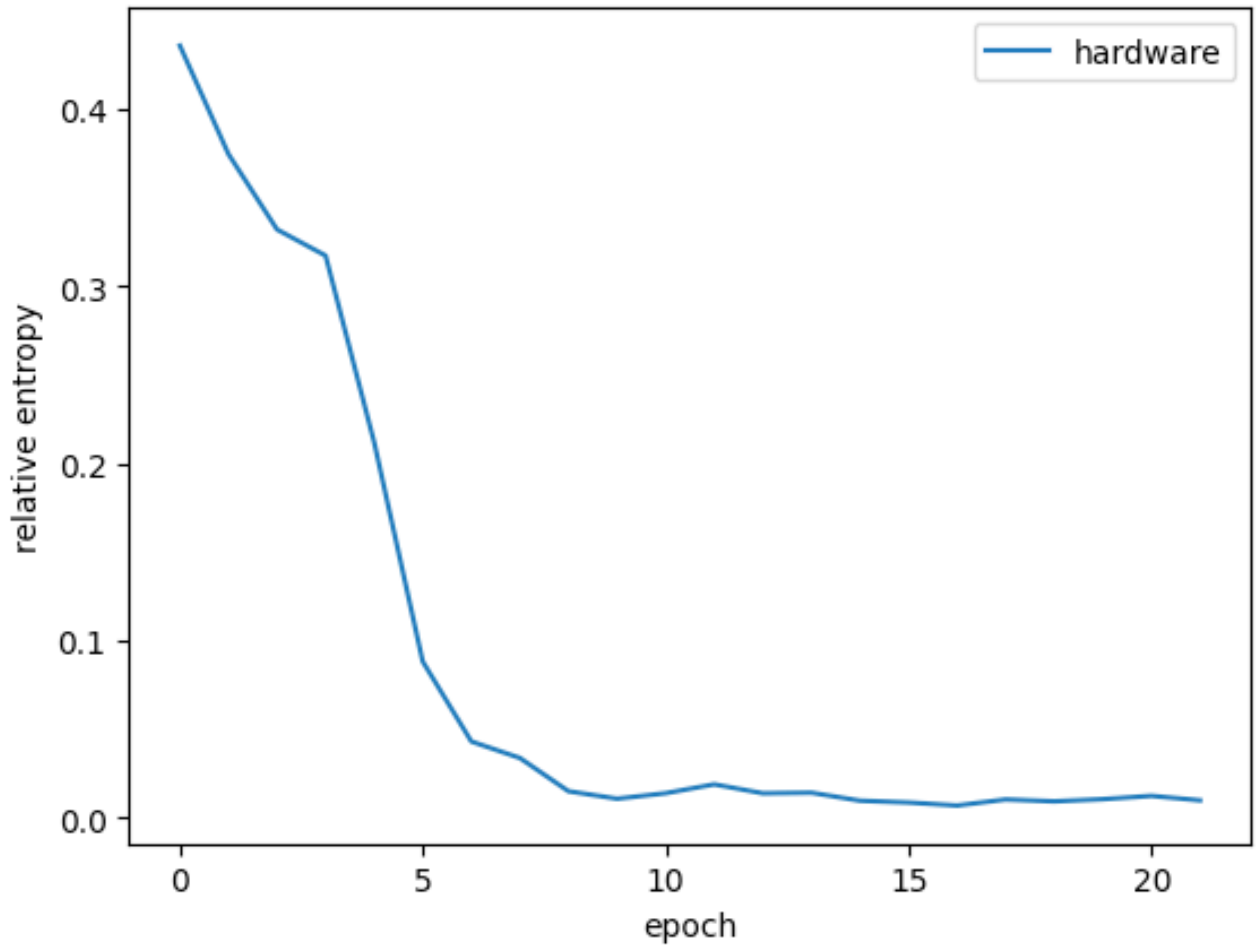


Results on the Hardware (8 pixels)

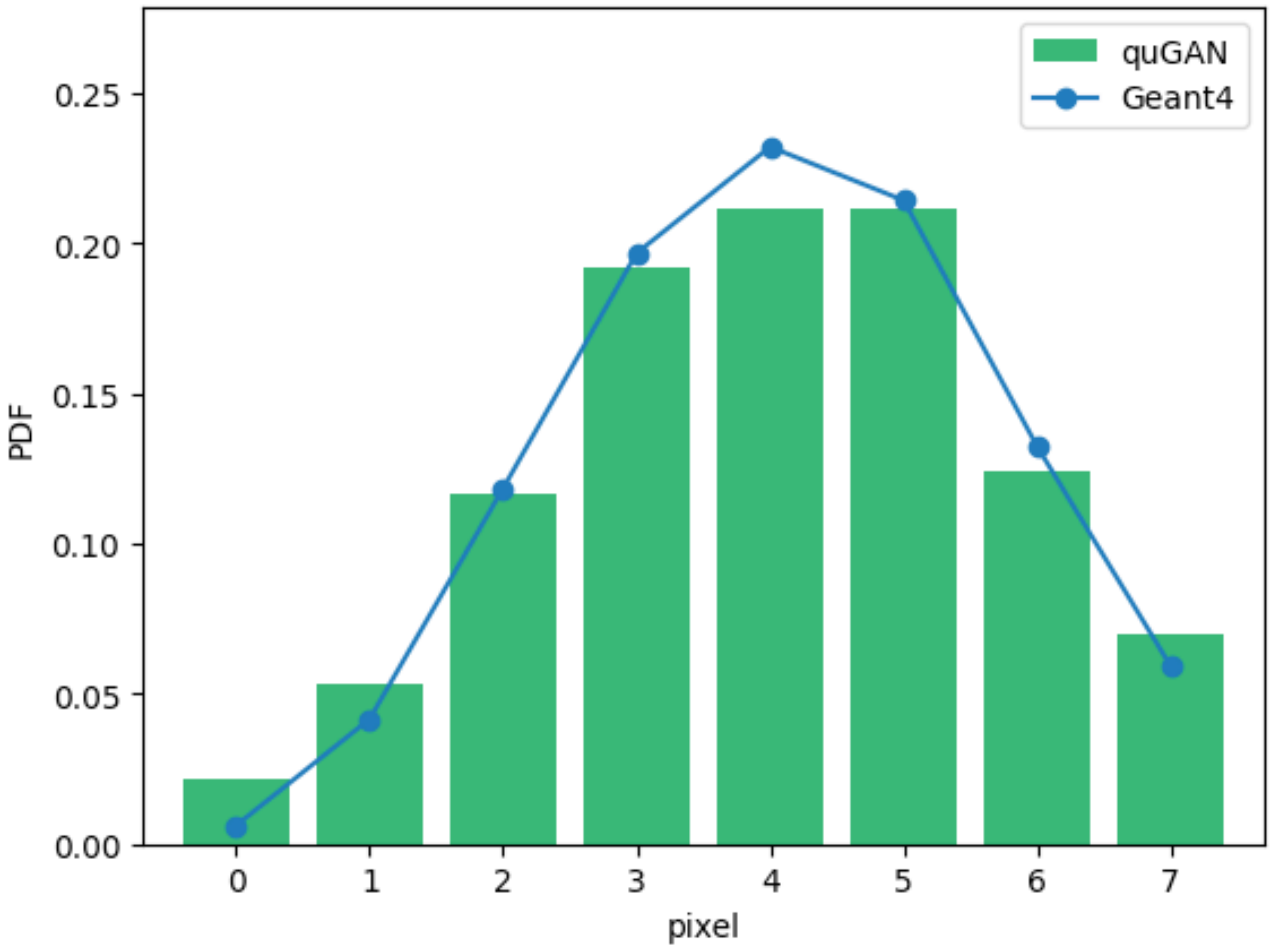
- Test the model on the hardware (Xiaohong: 骁鸿)



training process



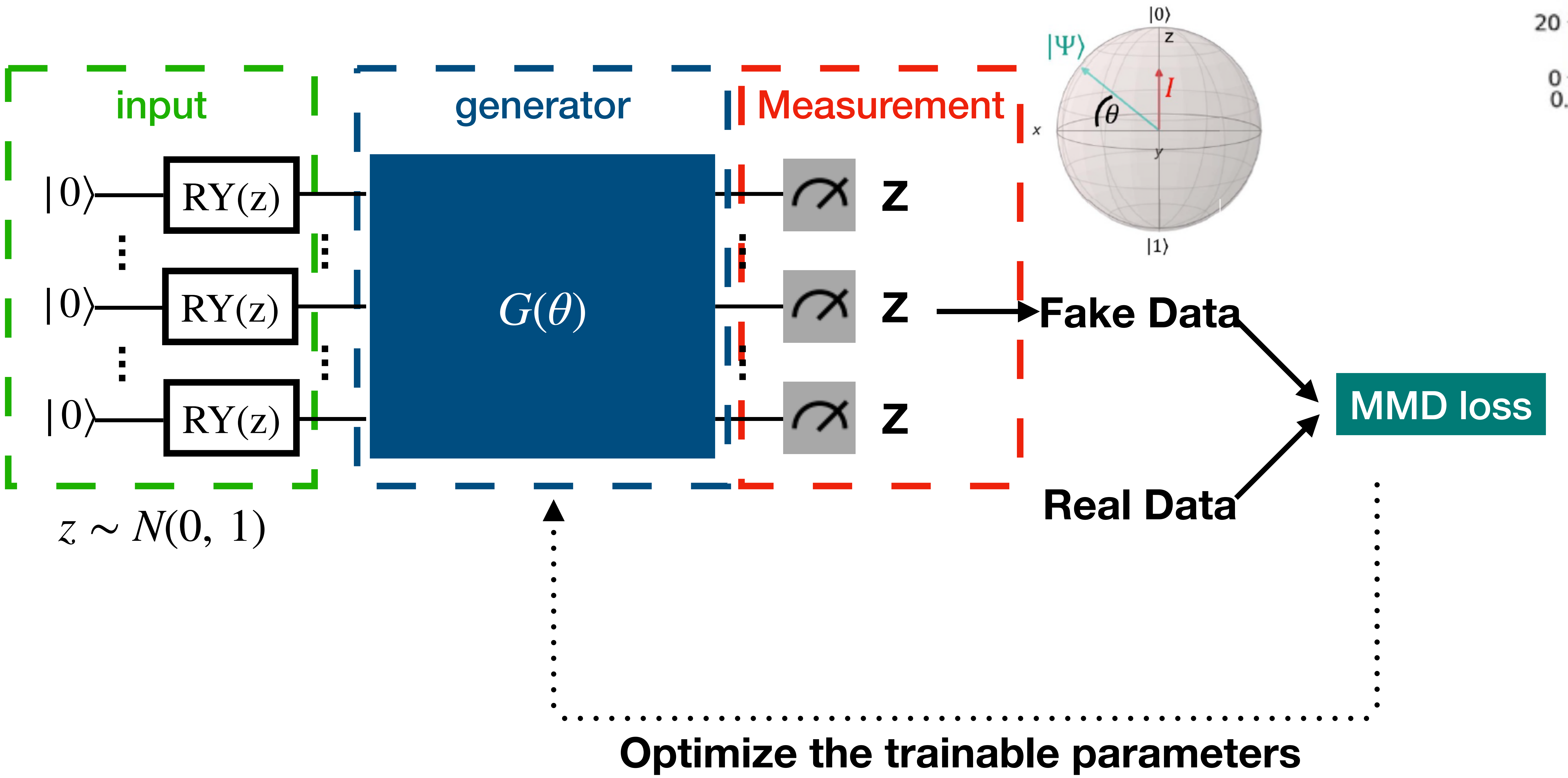
performance

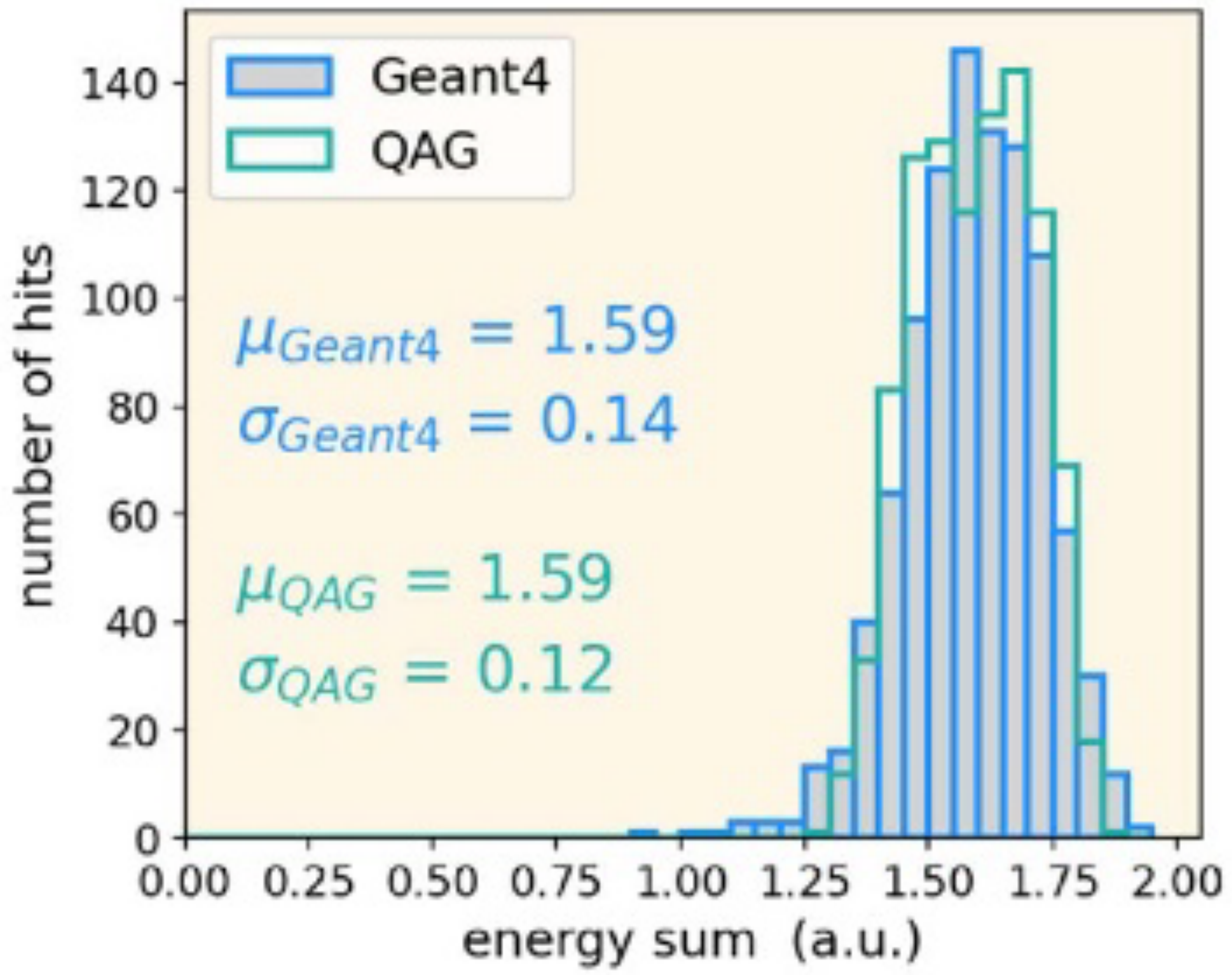


Pixel-wise Energy Distribution

Previous Studies

- CERN & DESY: Quantum angle generator (QAG)
  - discriminator： maximum mean discrepancy （MMD)
  - no trainable parameters in the discriminator
  - in general, the model could generate the data of 8 pixels

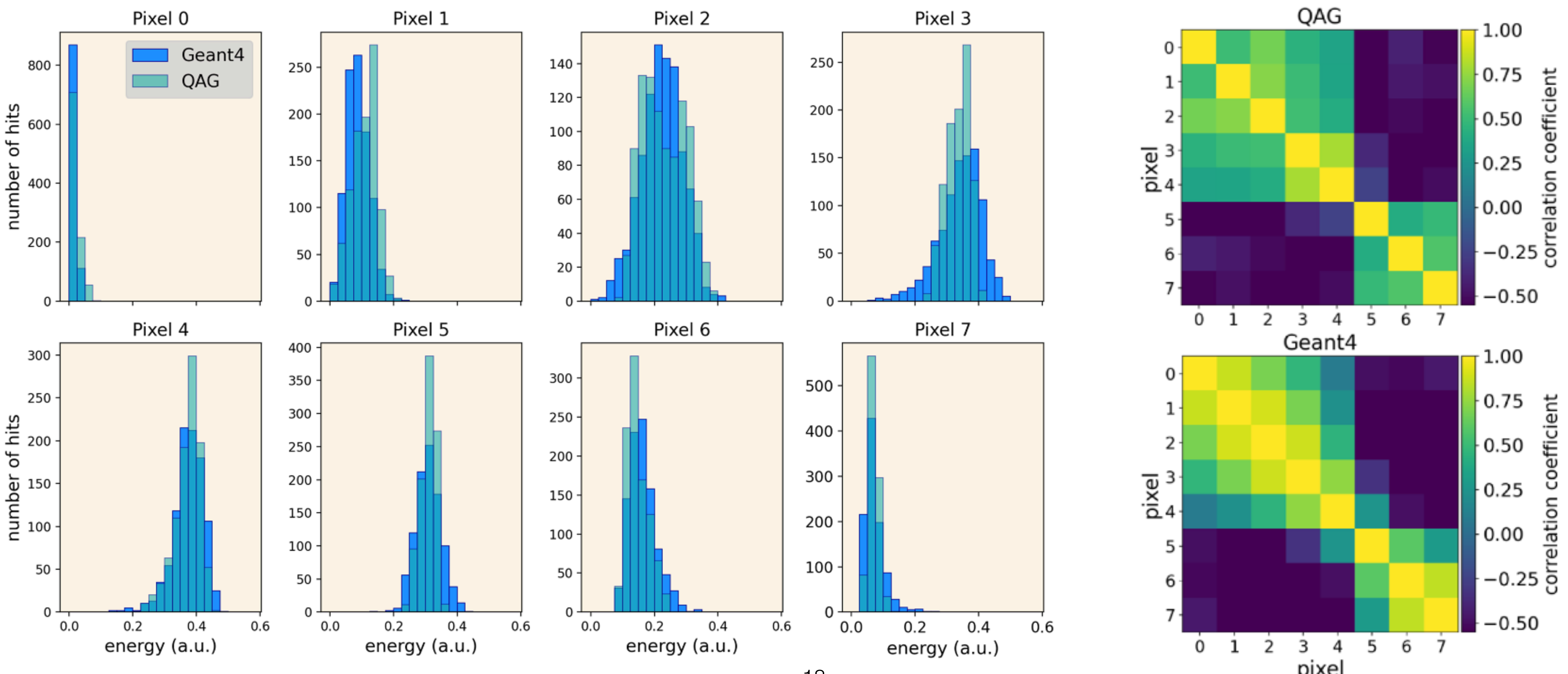




QAG
(CERN & DESY)

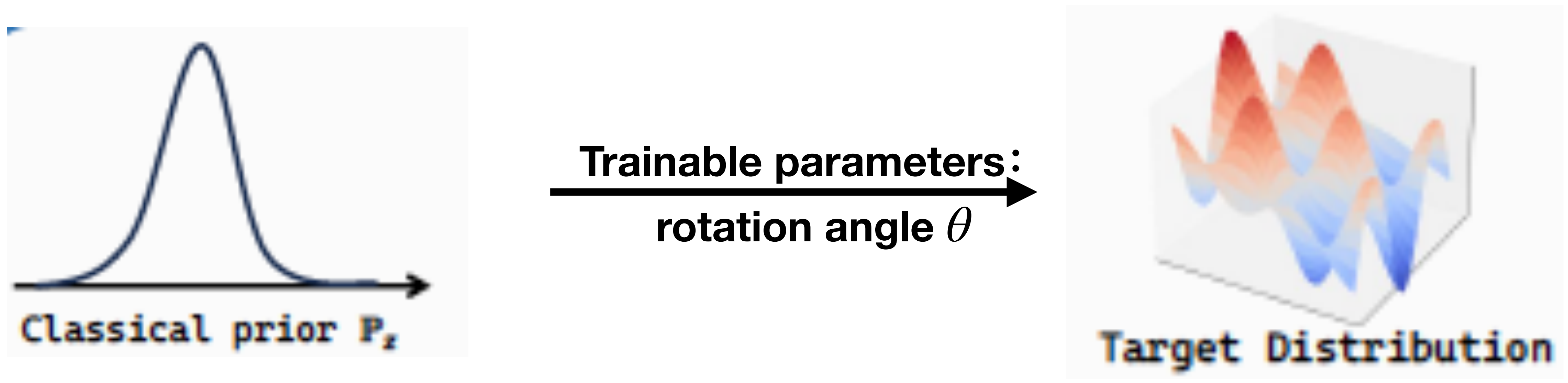
Performance of QAG

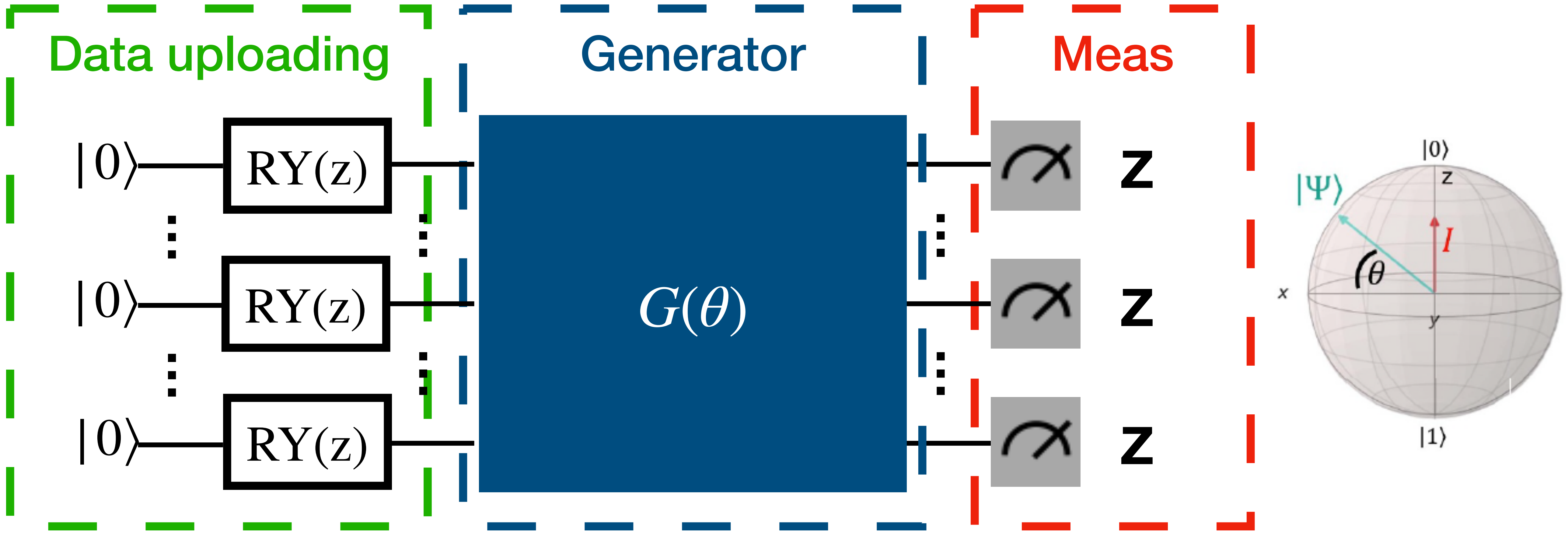
- Pixel-wise energy distribution (correlation coefficients)
  - in general, the distribution of QAG consists with that of Geant4
  - in detail: there are some differences.

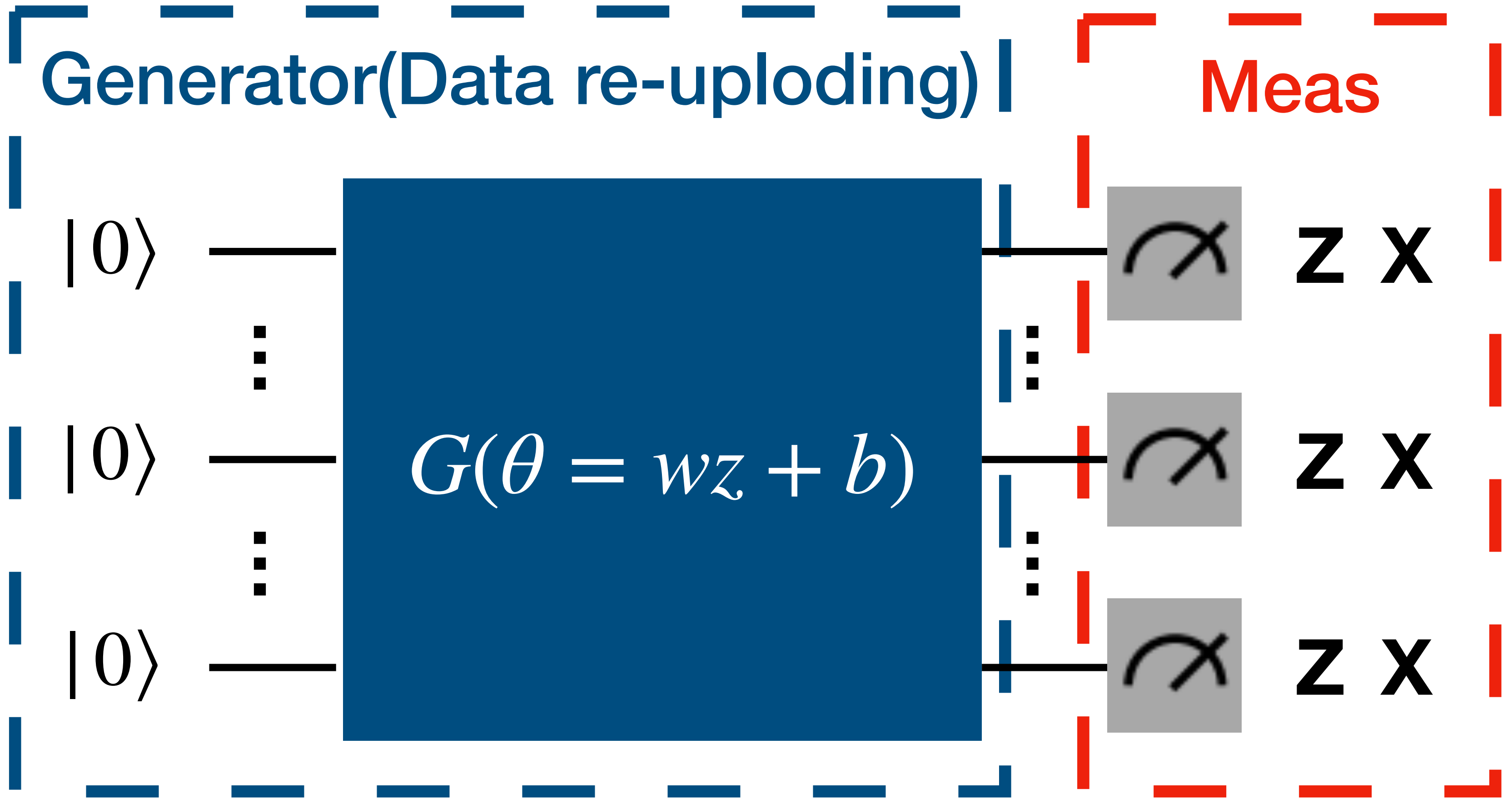


Modified Model

- CERN & DESY: QAG
  - data is only uploaded at the first layer
  - measure the expectations of PauliZ
  - 8 qubits to generate the data of 8 pixels
- Modified model
  - data re-uploading
  - measure the expectations of PauliZ and PauliX
  - 4 qubits to generate the data of 8 pixels

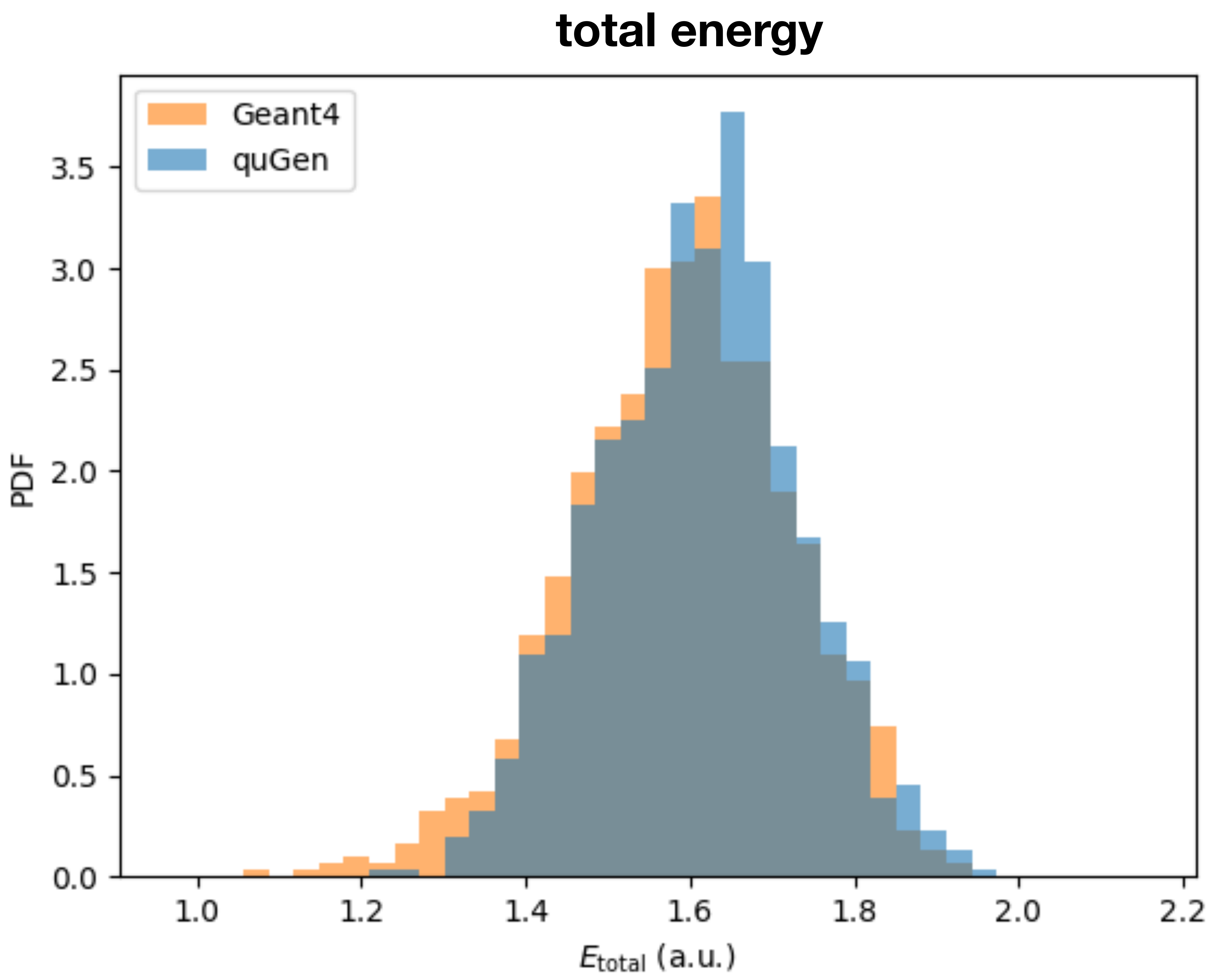


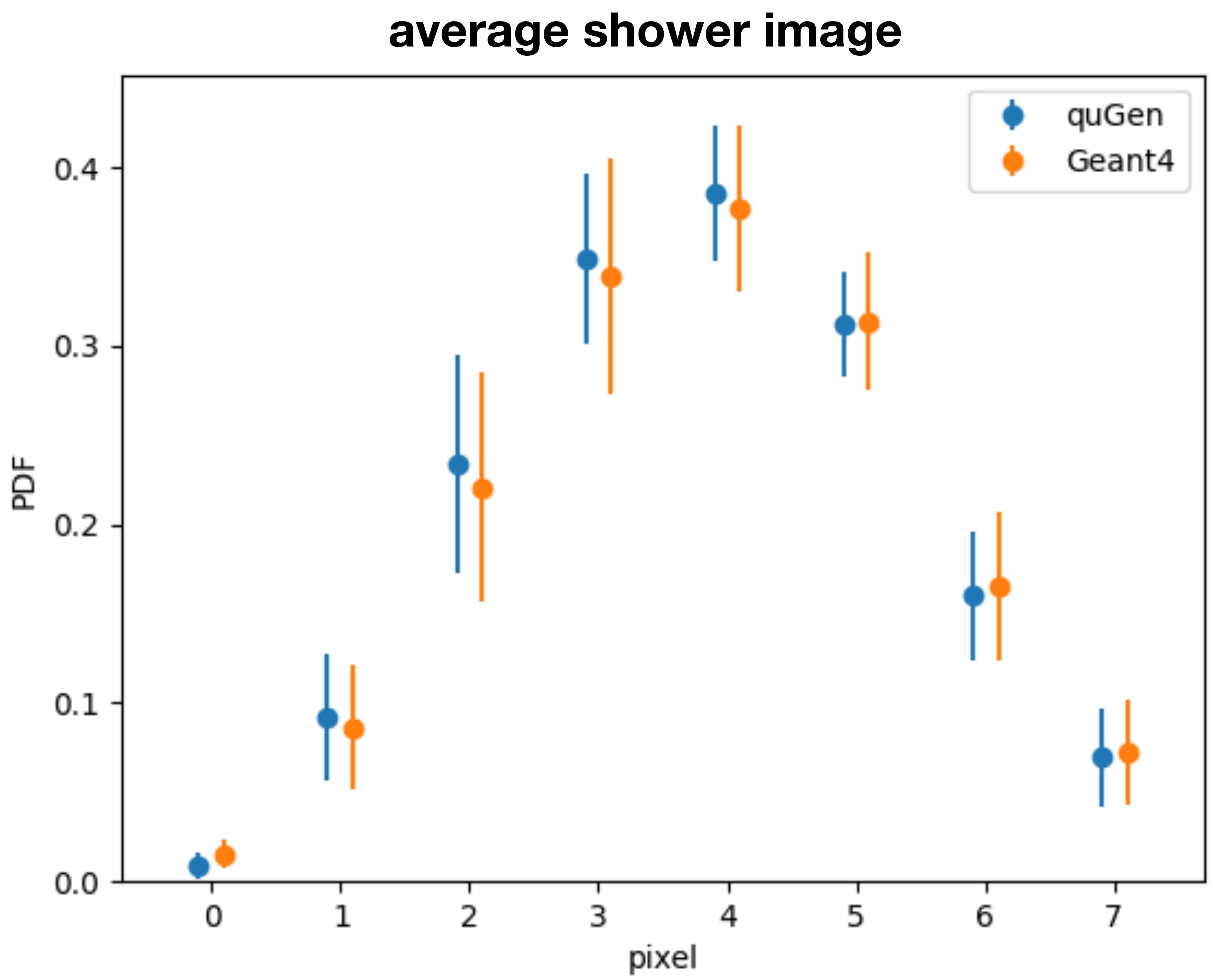




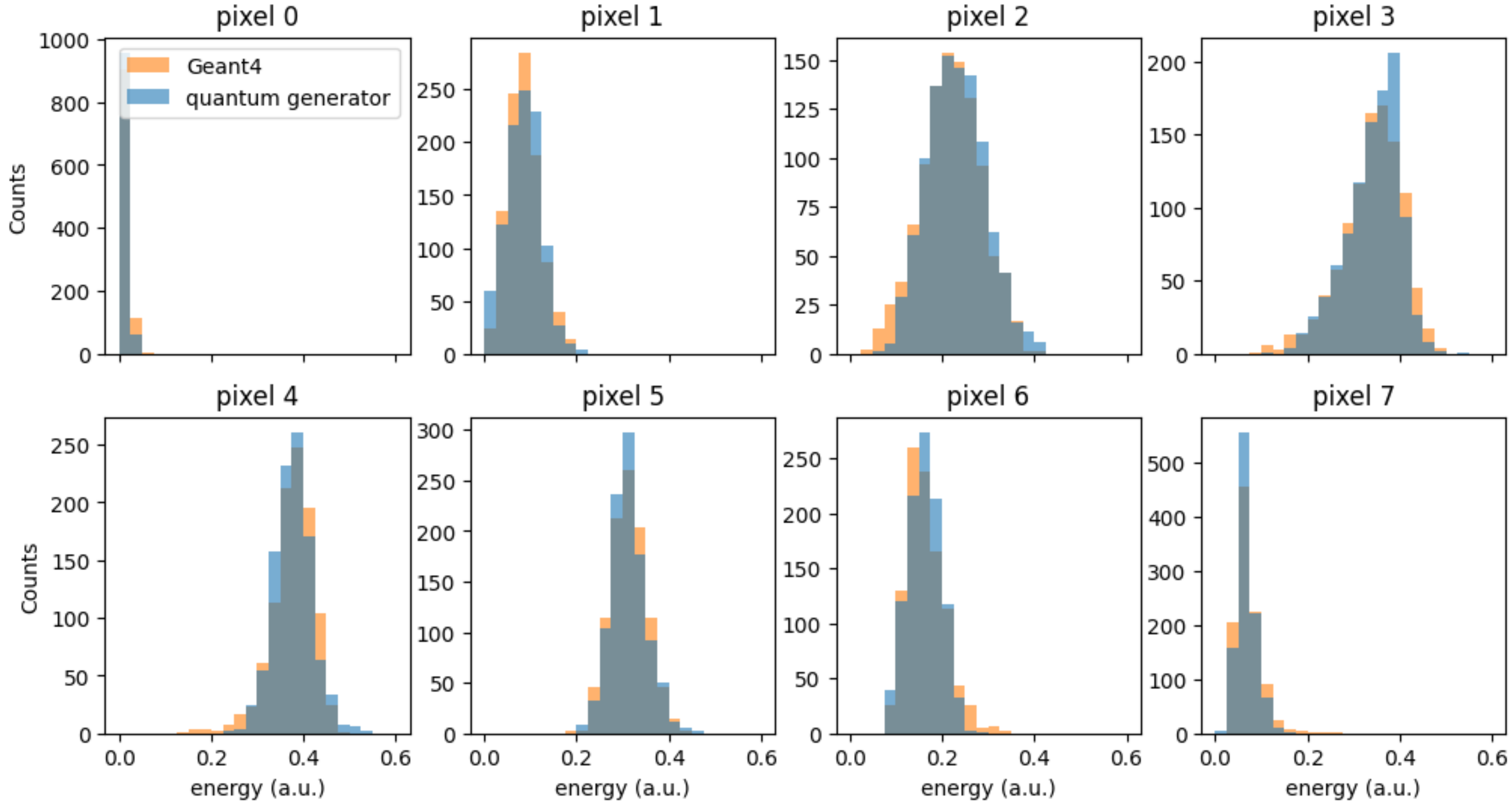
Overall Performance (Ideal Simulator)

- Consistent distribution between the generated data and Geant4

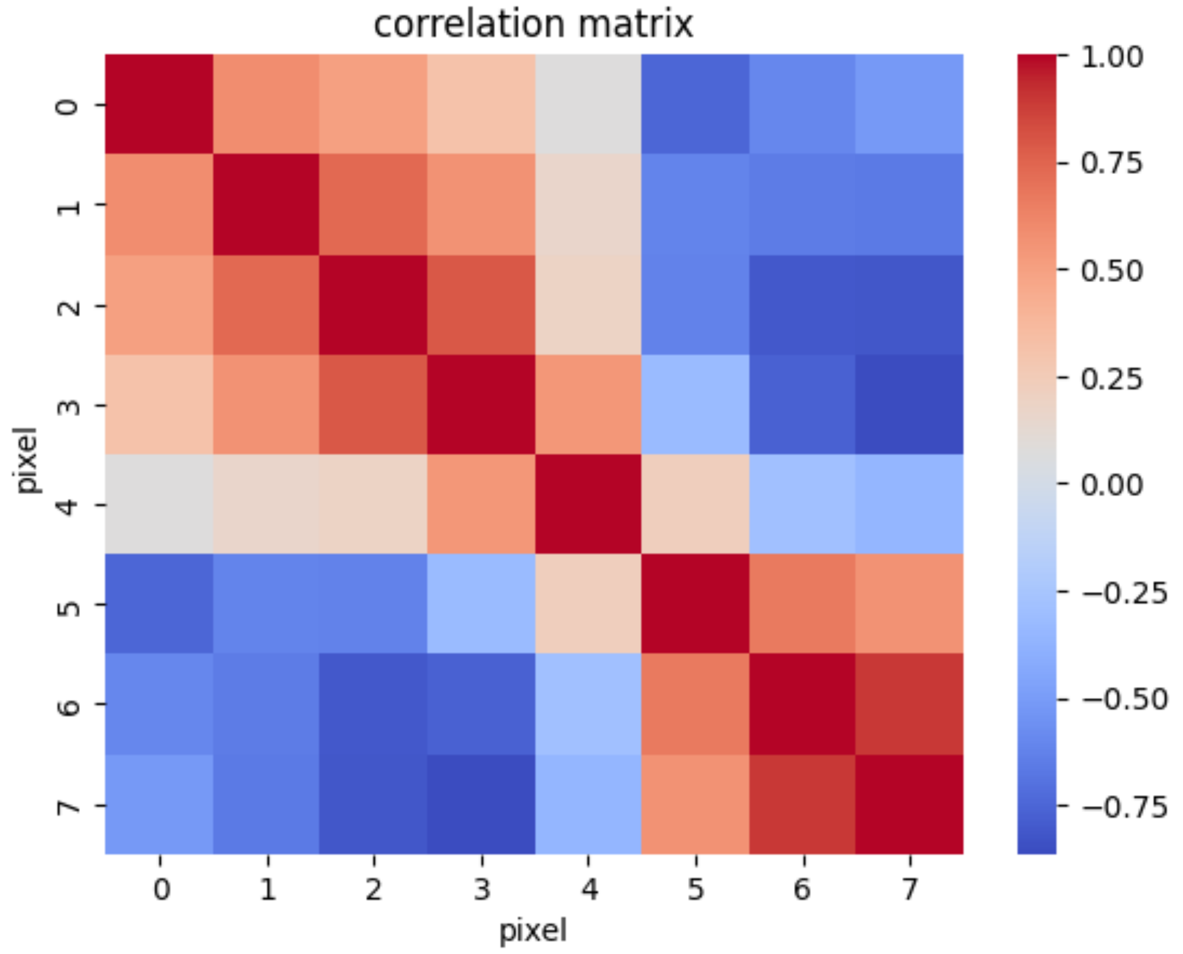




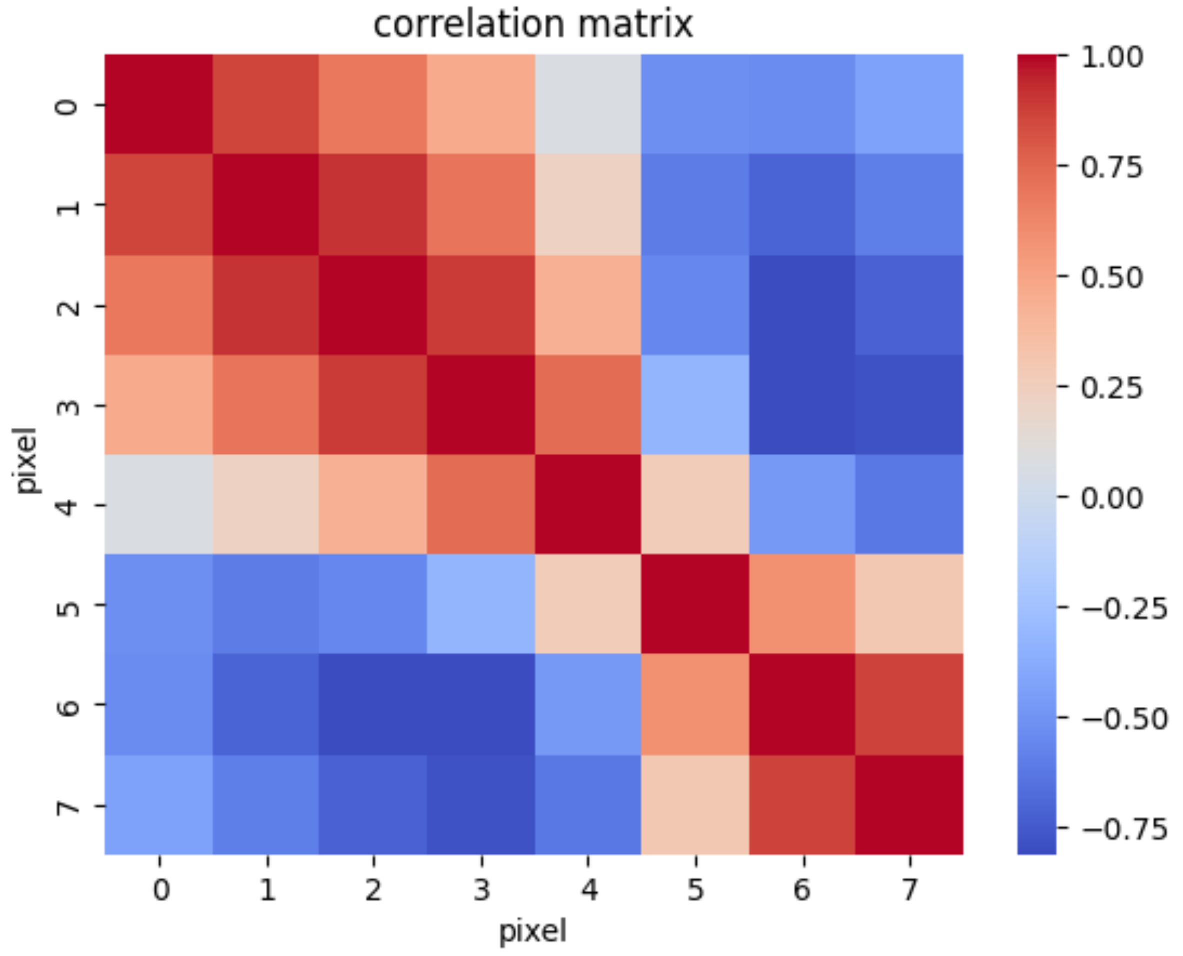
Performance (Ideal Simulator)



Quantum Generator



Geant4



Summary and Plan

Summary

- Shower simulation is one of the most CPU-intensive tasks in HEP
- Quantum computing brings us entirely new possibilities
- Average shower image:
  - improve the training stability
  - 64 pixels: 5d → less than 1h
- Pixel-wise energy distribution：
  - expressibility of the model is increased with data re-uploading
  - number of qubits is reduced by a factor of two

Plan

- Pixel-wise energy distribution: train the model on the real hardware

Thank you for your listening !

backup

Quantum Computing

- Quantum advantage: superposition, entanglement, …
  - N bits could represent 2^N states, and contain the information of one states
  - N qubits could represent 2^N states, but contain the information of 2^N states

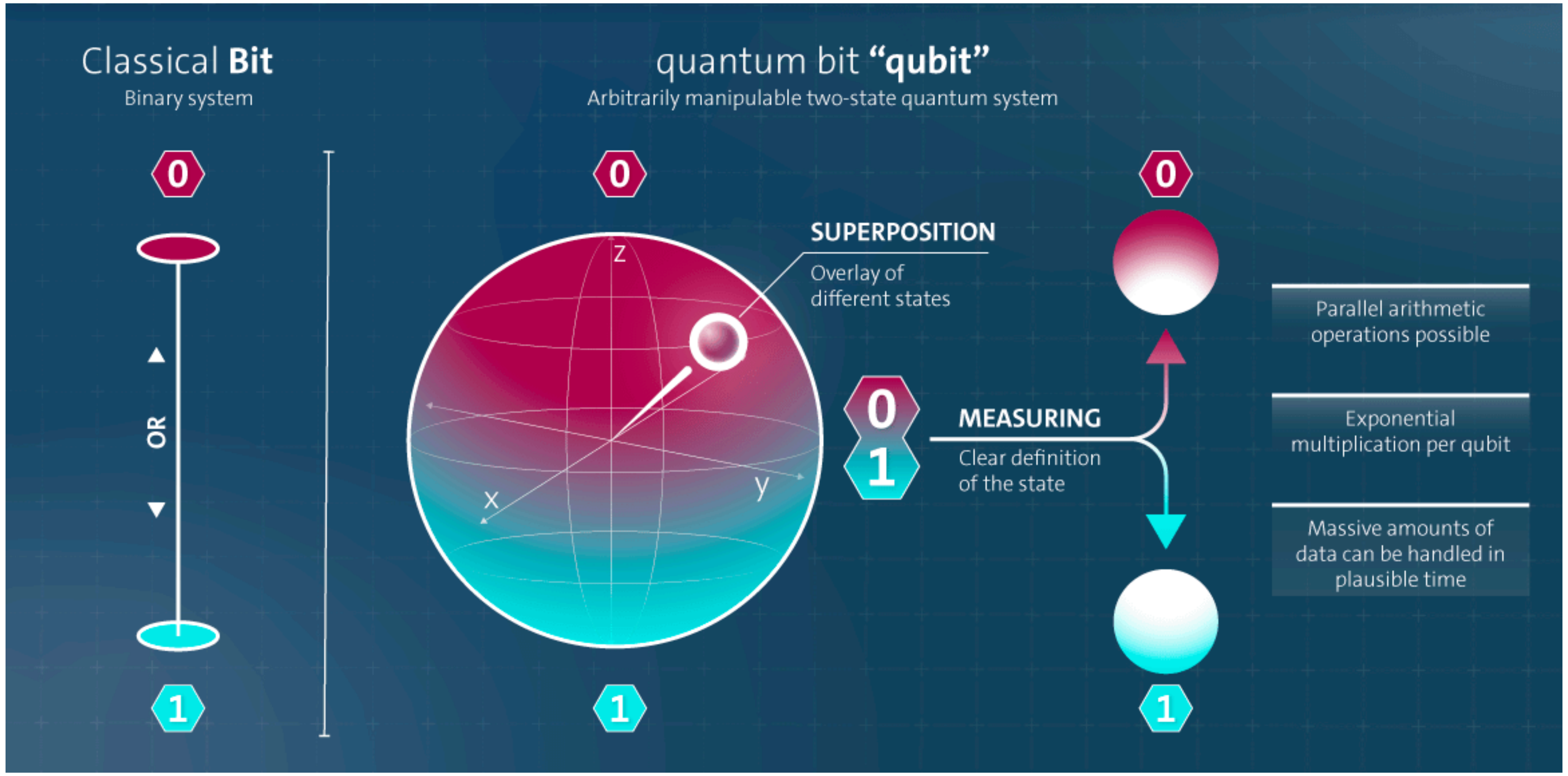
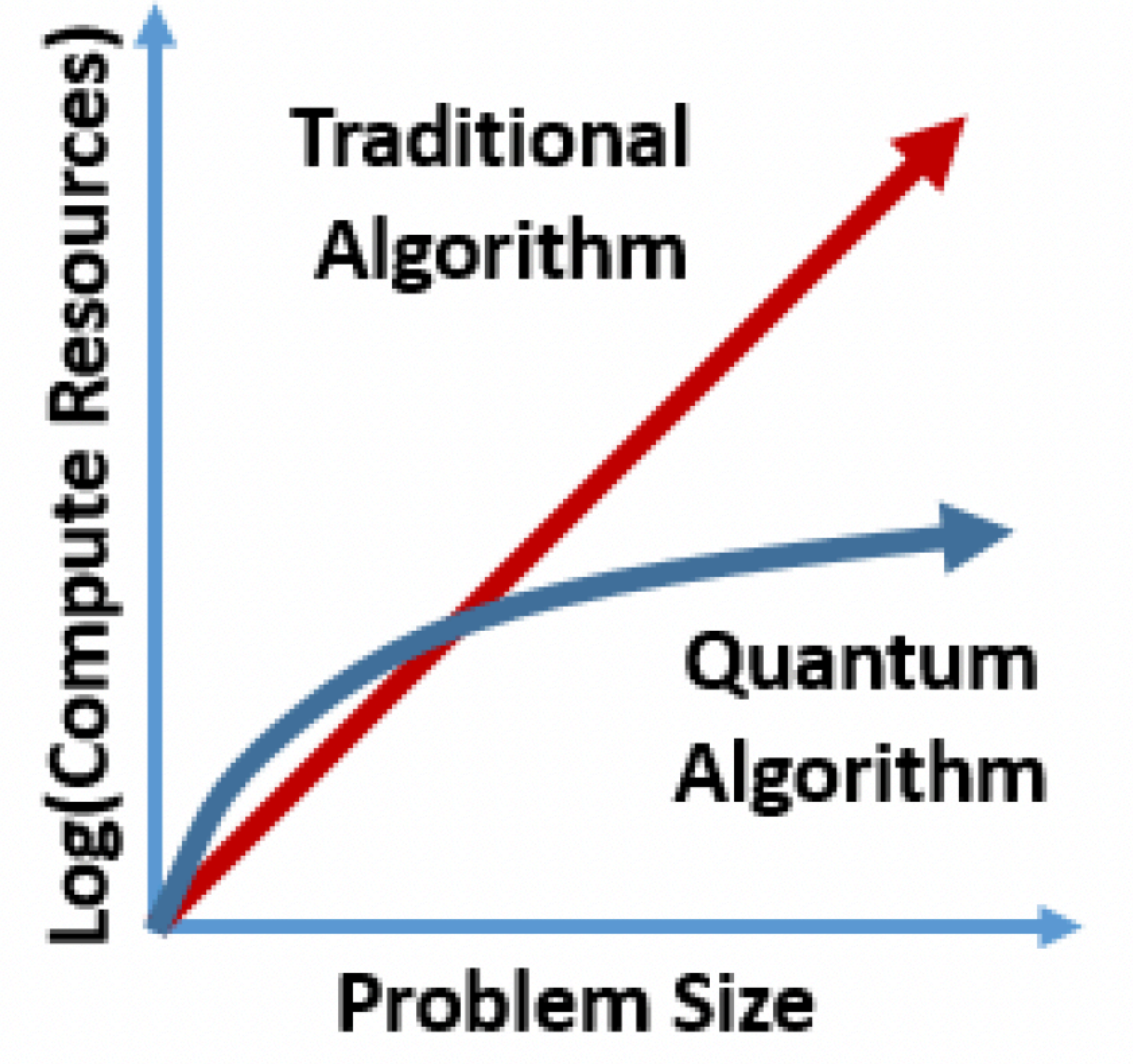
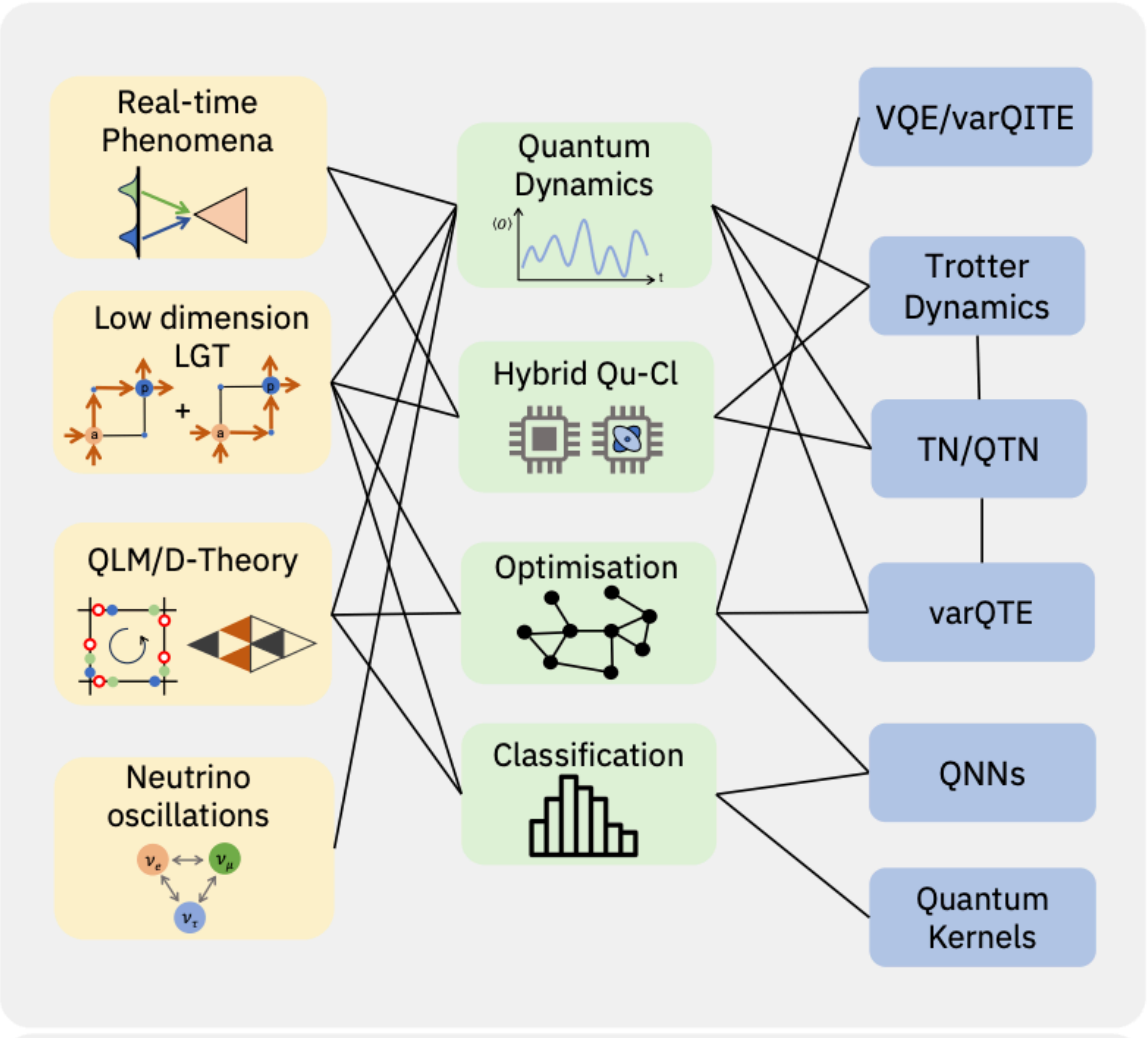


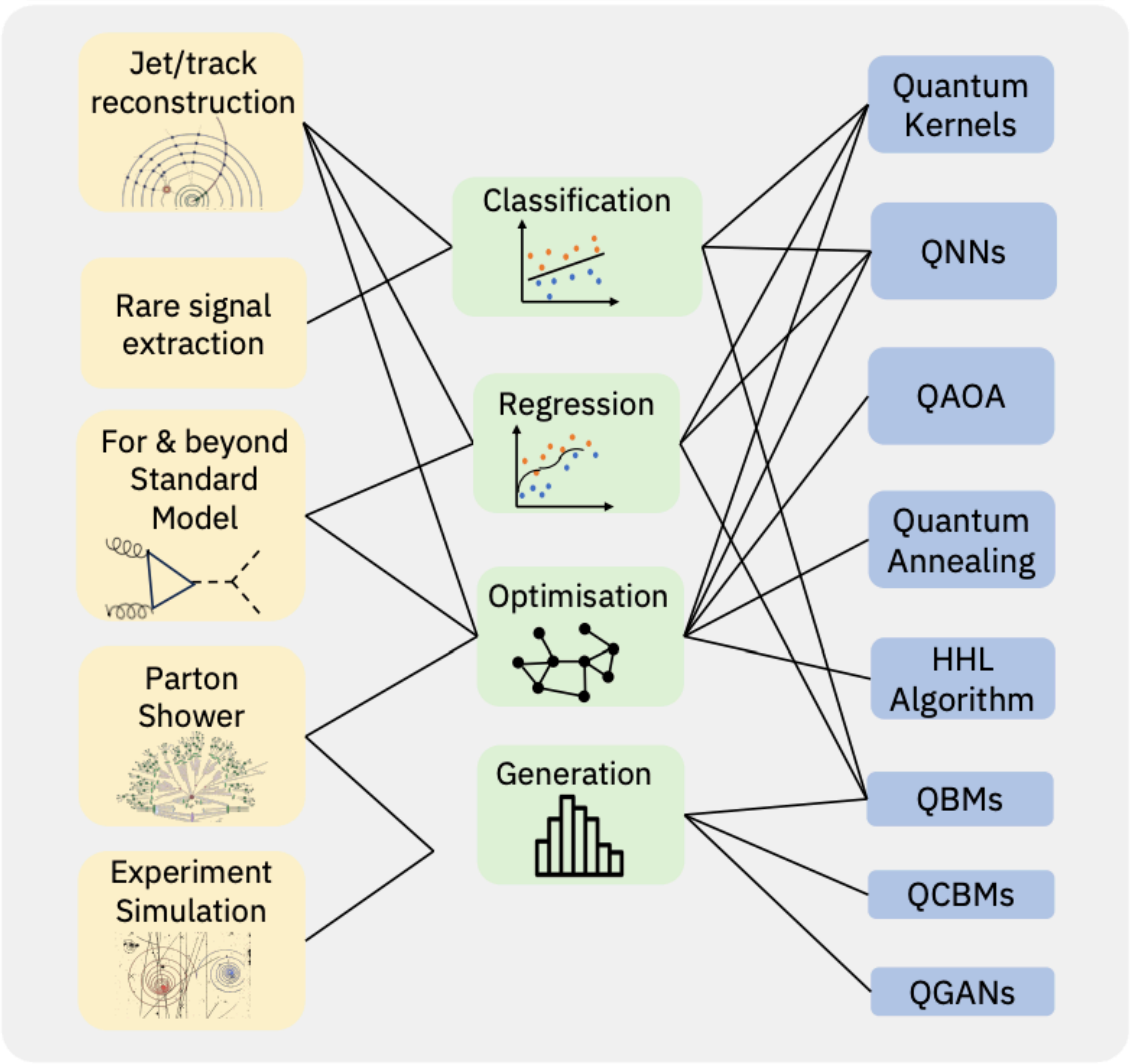
image source

suitable for complex and big data, e.g. fast calorimeter simulation



Quantum Computing in HEP

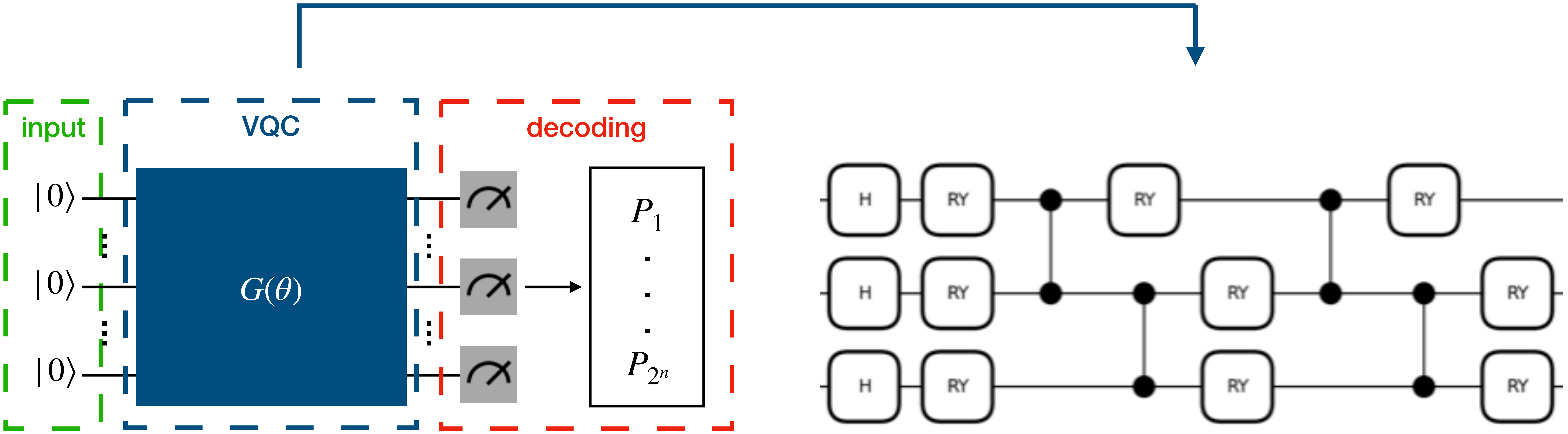




link

Generator model

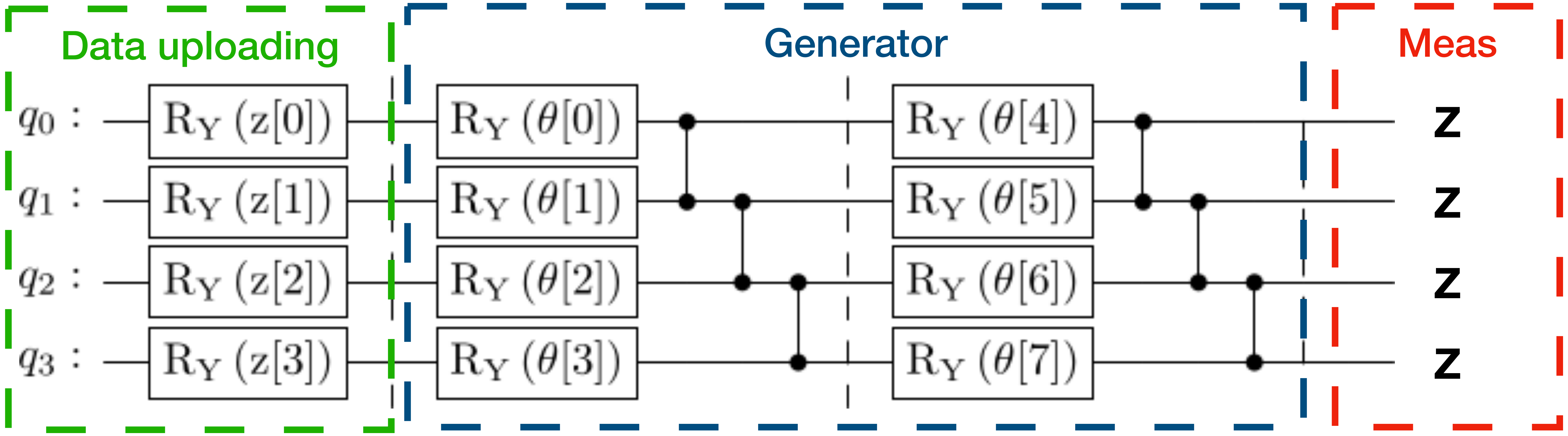
- Input states: $|0\rangle^{\otimes n}$
- Variational quantum circuits: $G(\theta)|0\rangle^{\otimes n} \rightarrow |\psi\rangle$
- Amplitude decoding: n qubits $\rightarrow 2^n$ amplitudes $\rightarrow 2^n$ PDF values
  - 8 pixels: 3 qubits
  - 64 pixels: 6 qubits



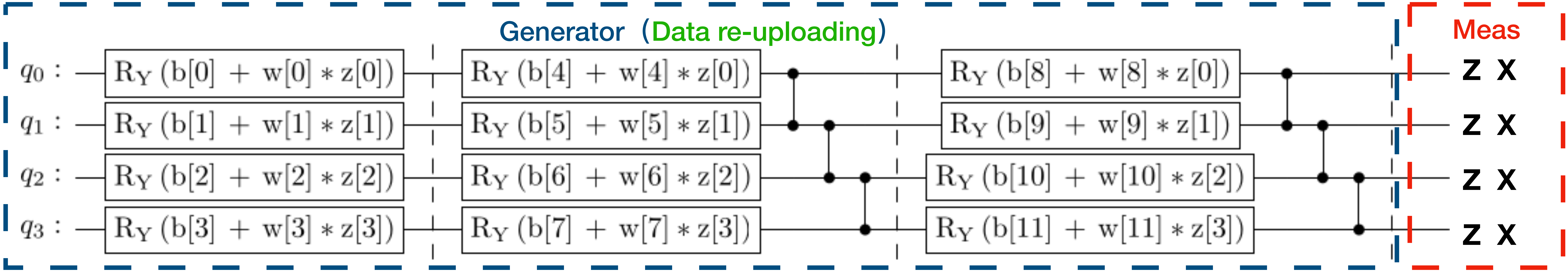
Architecture of the Quantum Generator

- Parameters to optimize:
  - rotation blocks: RY, RY+RX
  - entanglement blocks: CZ, CRY, CRY+CRX
  - number of layers: 1, 2, 3, 4, 5

QAG



Modified



On Stabilizing Generative Adversarial Training with Noise