Quantum GAN for Fast Shower Simulation

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IHEP

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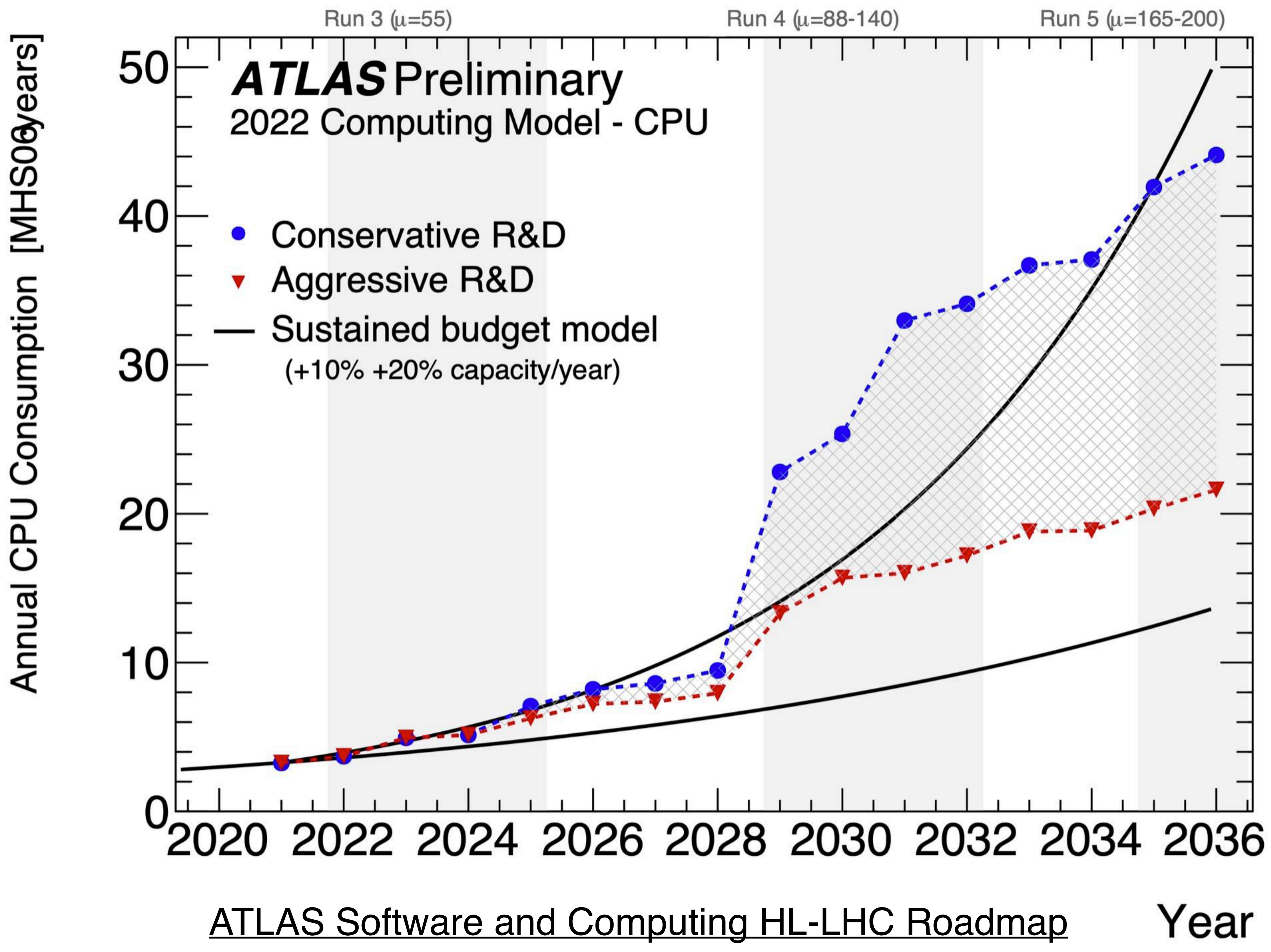
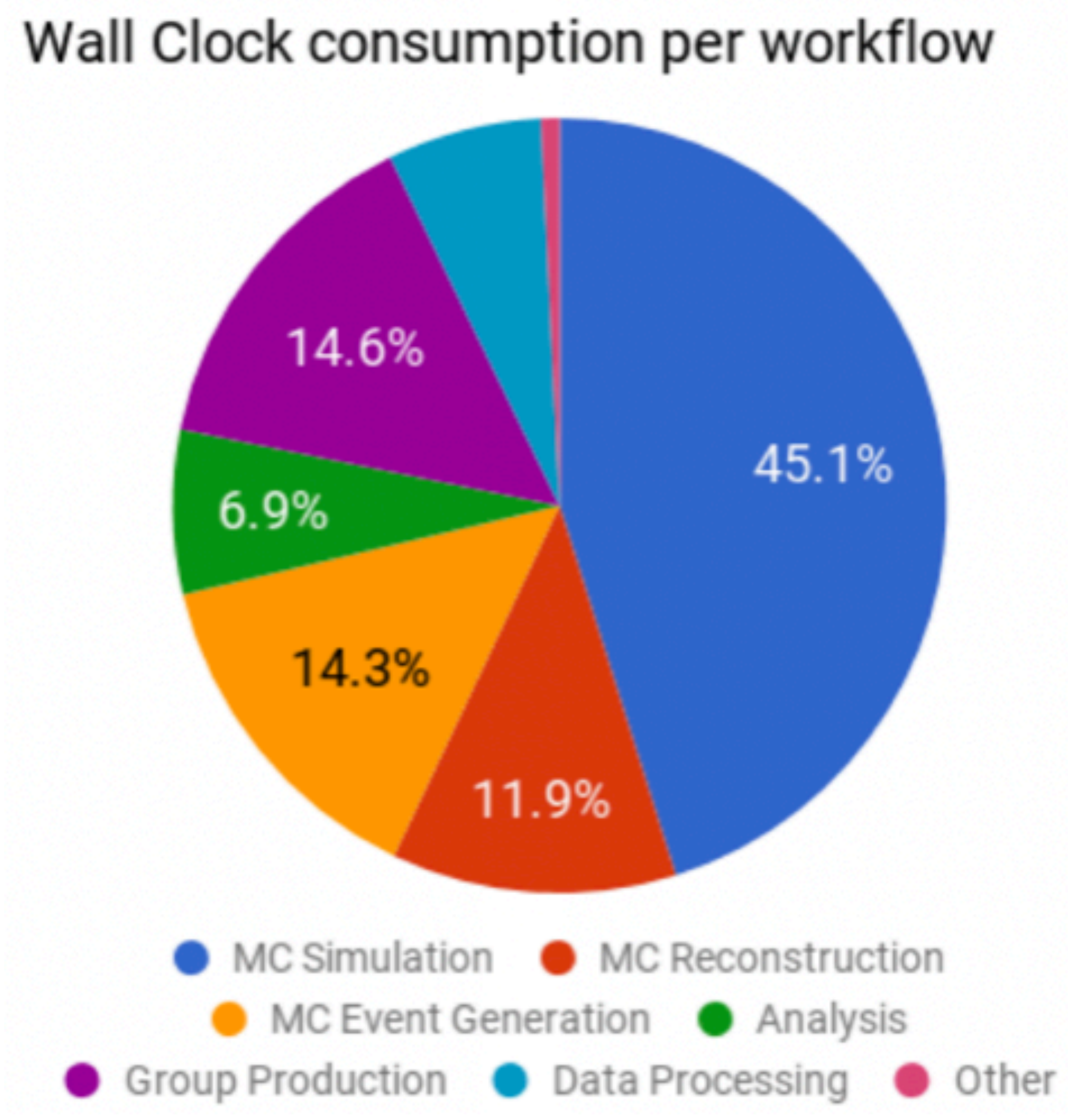
Why Fast Shower Simulation?

- 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

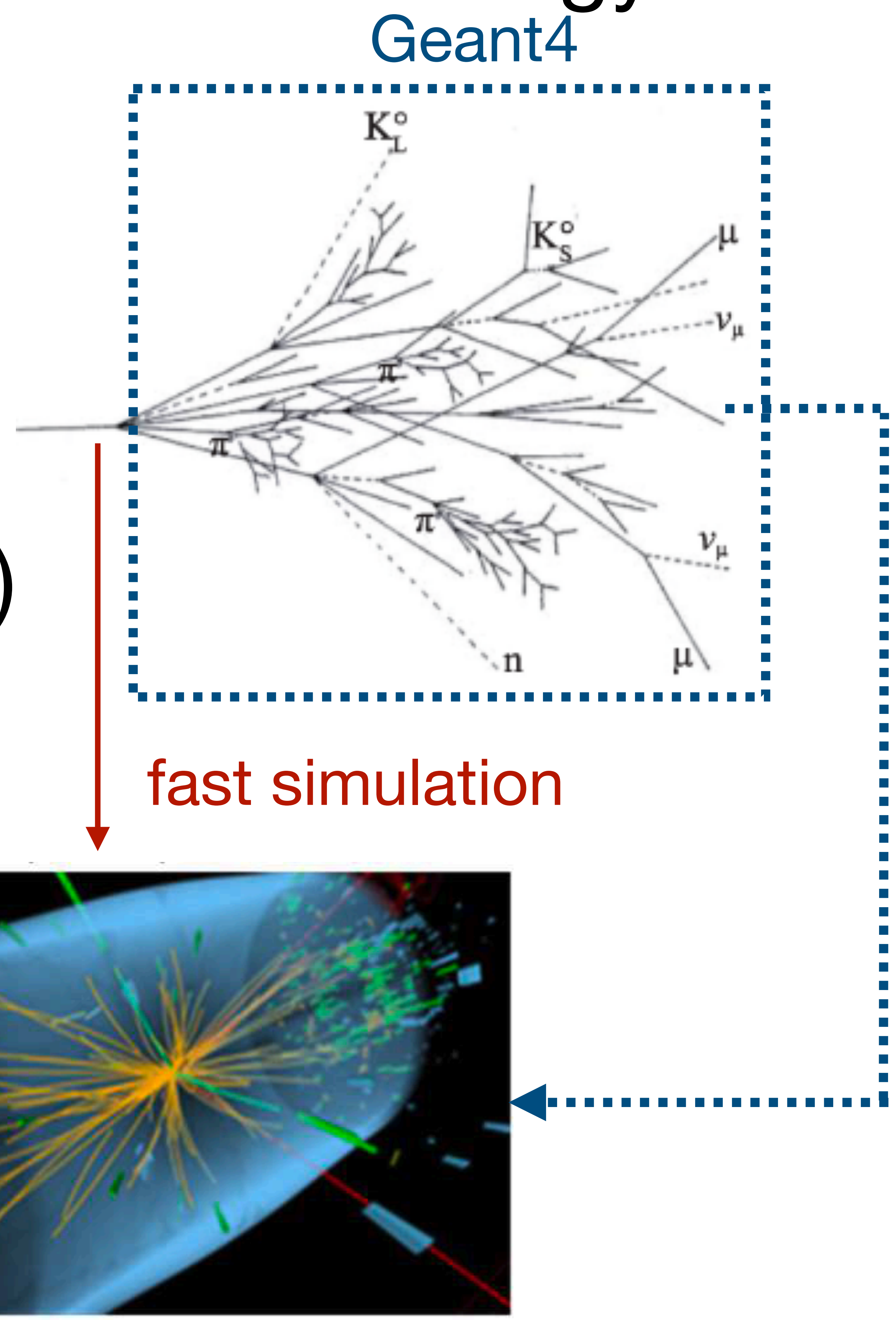


ATLAS 2017 number

Fast Simulation

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

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



QC is an alternative to classical computing
QC + GAN: the potential to outperform classical GAN

Quantum GAN

- Two versions 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, $\sim 10^2$]

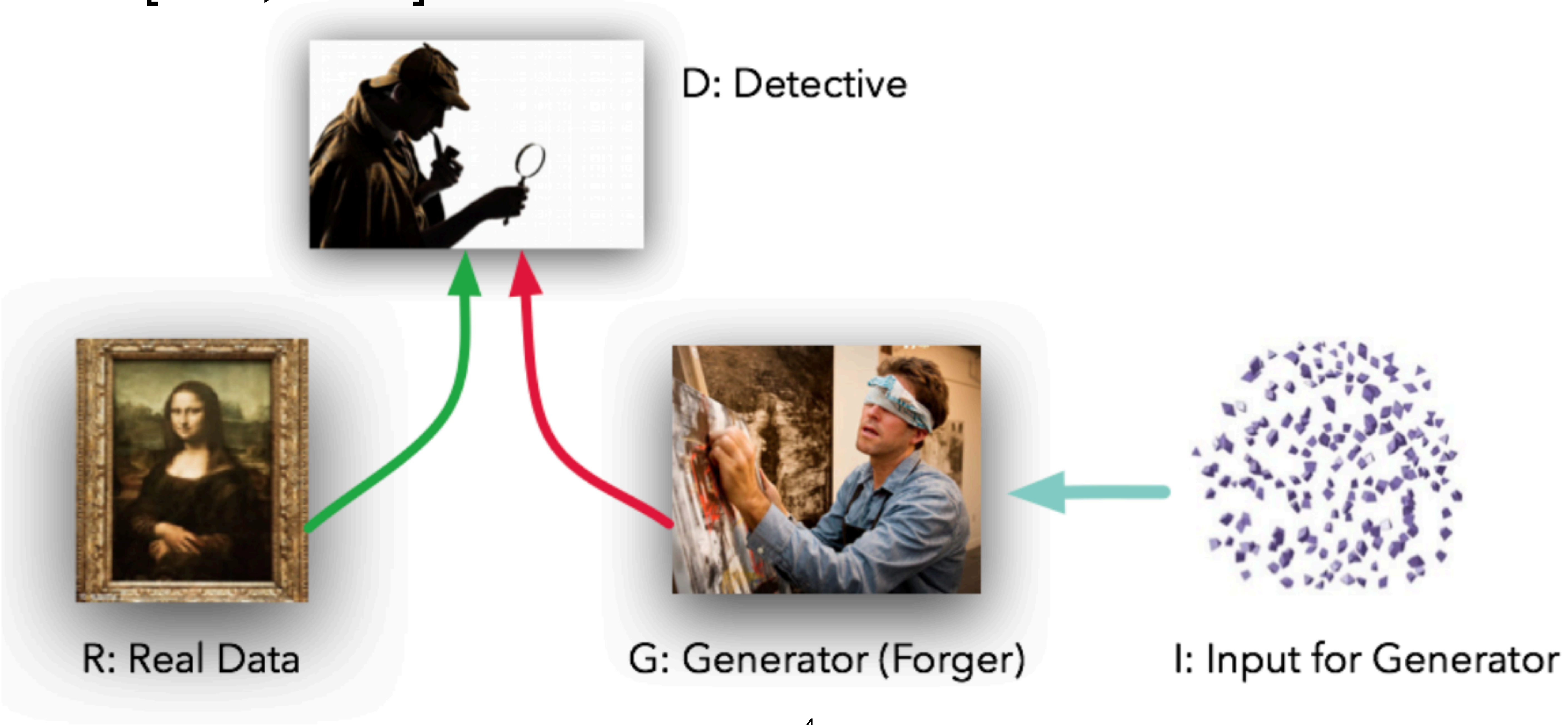
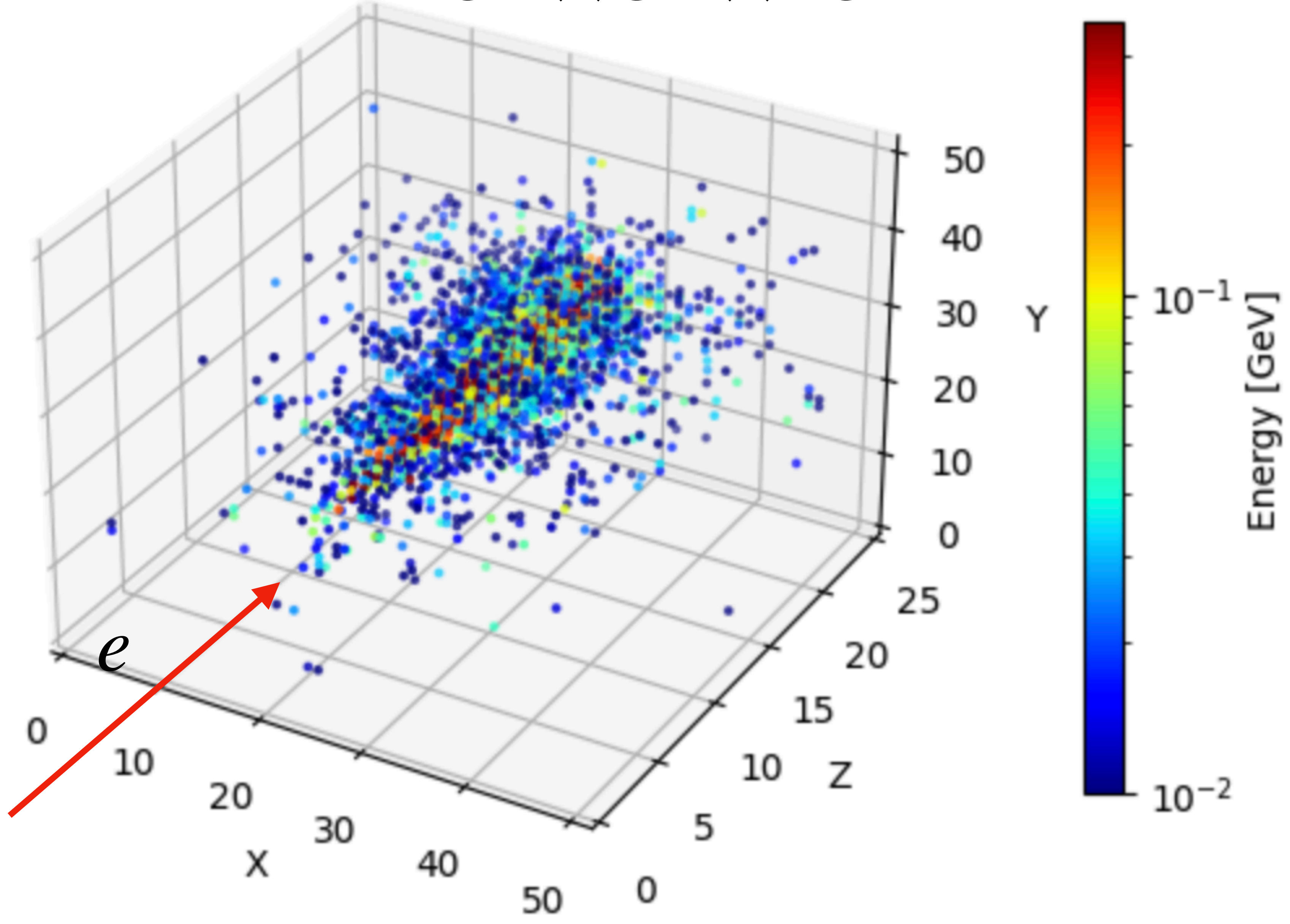


image source

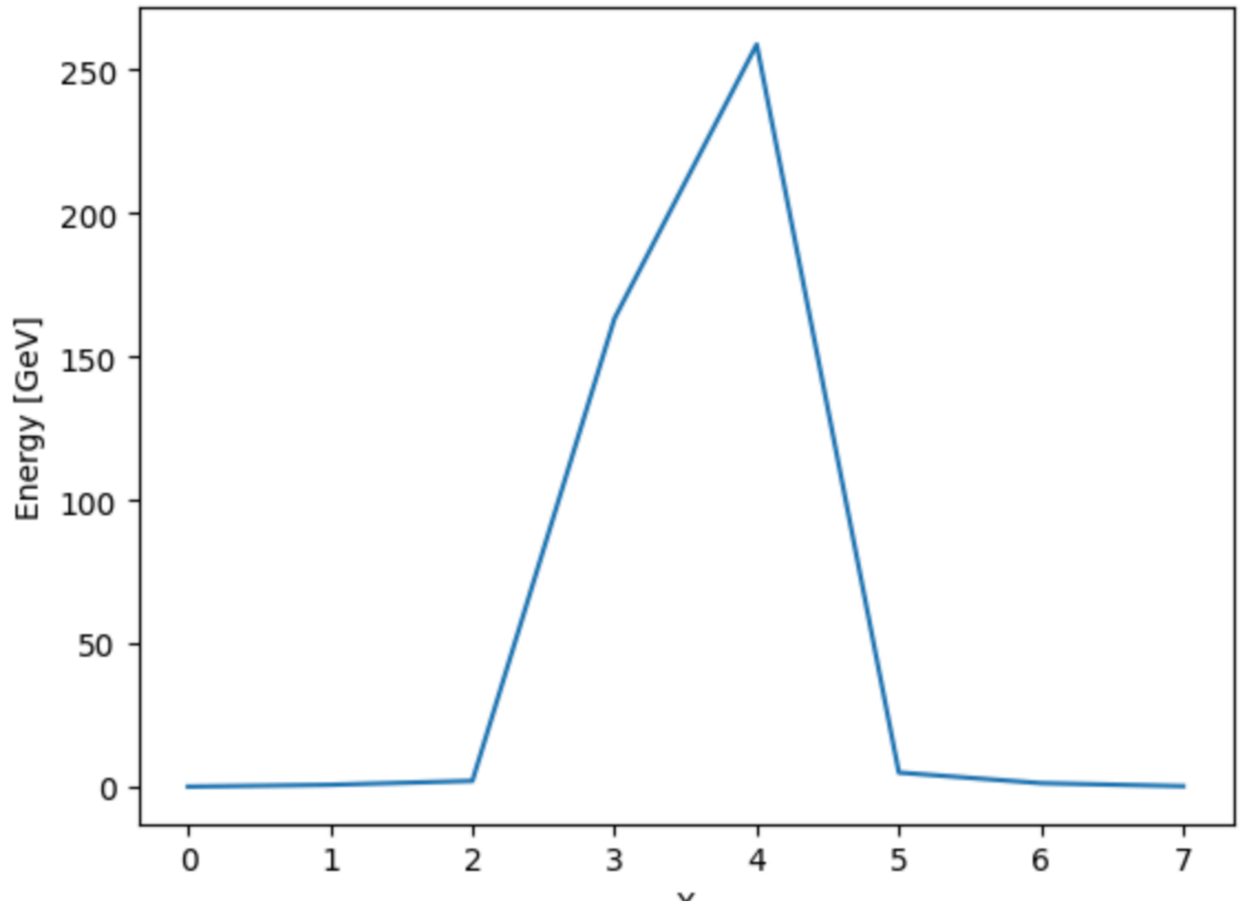
Data Sample

- CLIC Calorimeter images: energy deposits from electrons
- 3D ($51 \times 51 \times 25$): too large for the current quantum device
  - downsampled to 8 pixels
  - downsampled to 64 pixels (8×8)

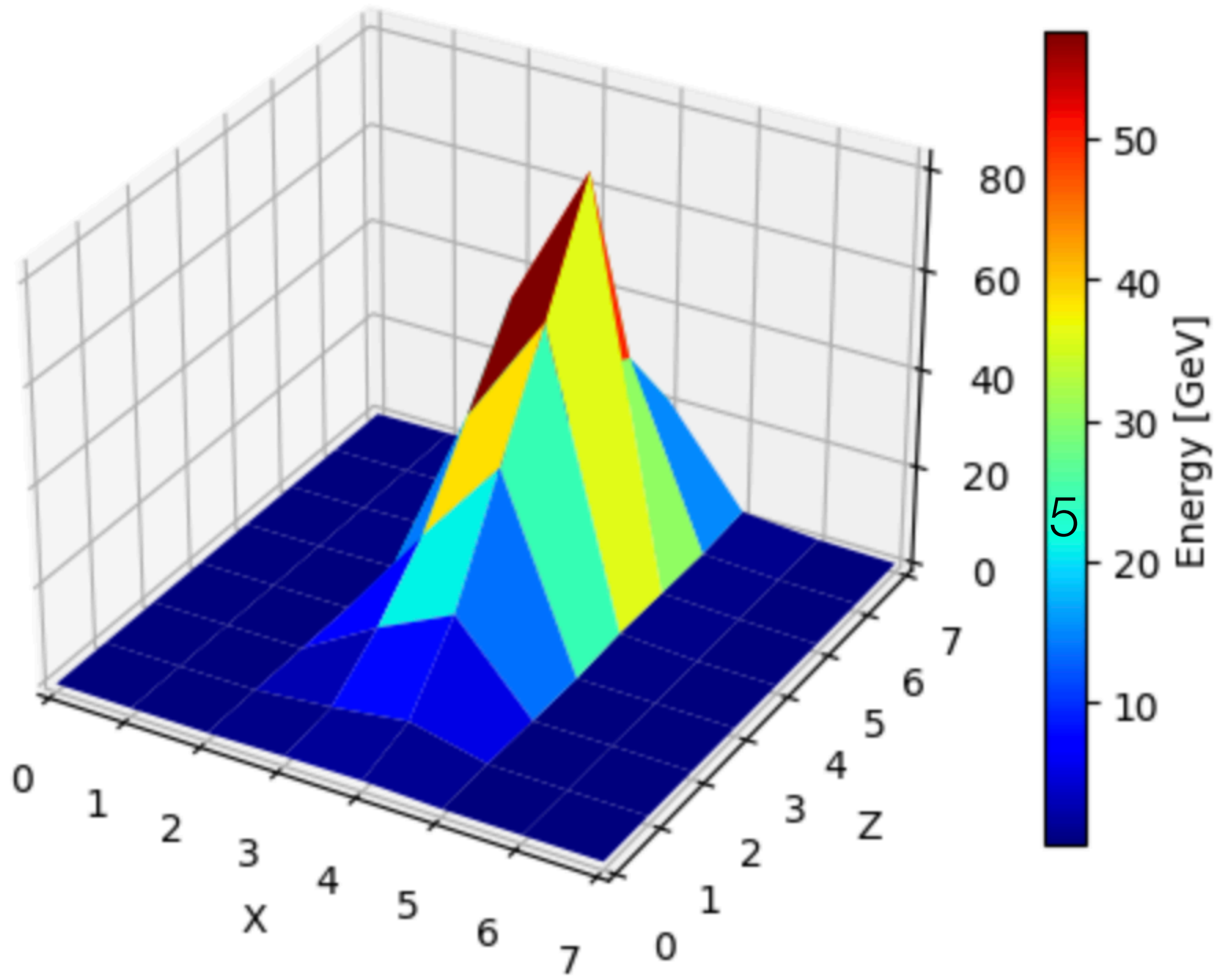
$51 \times 51 \times 25$



8



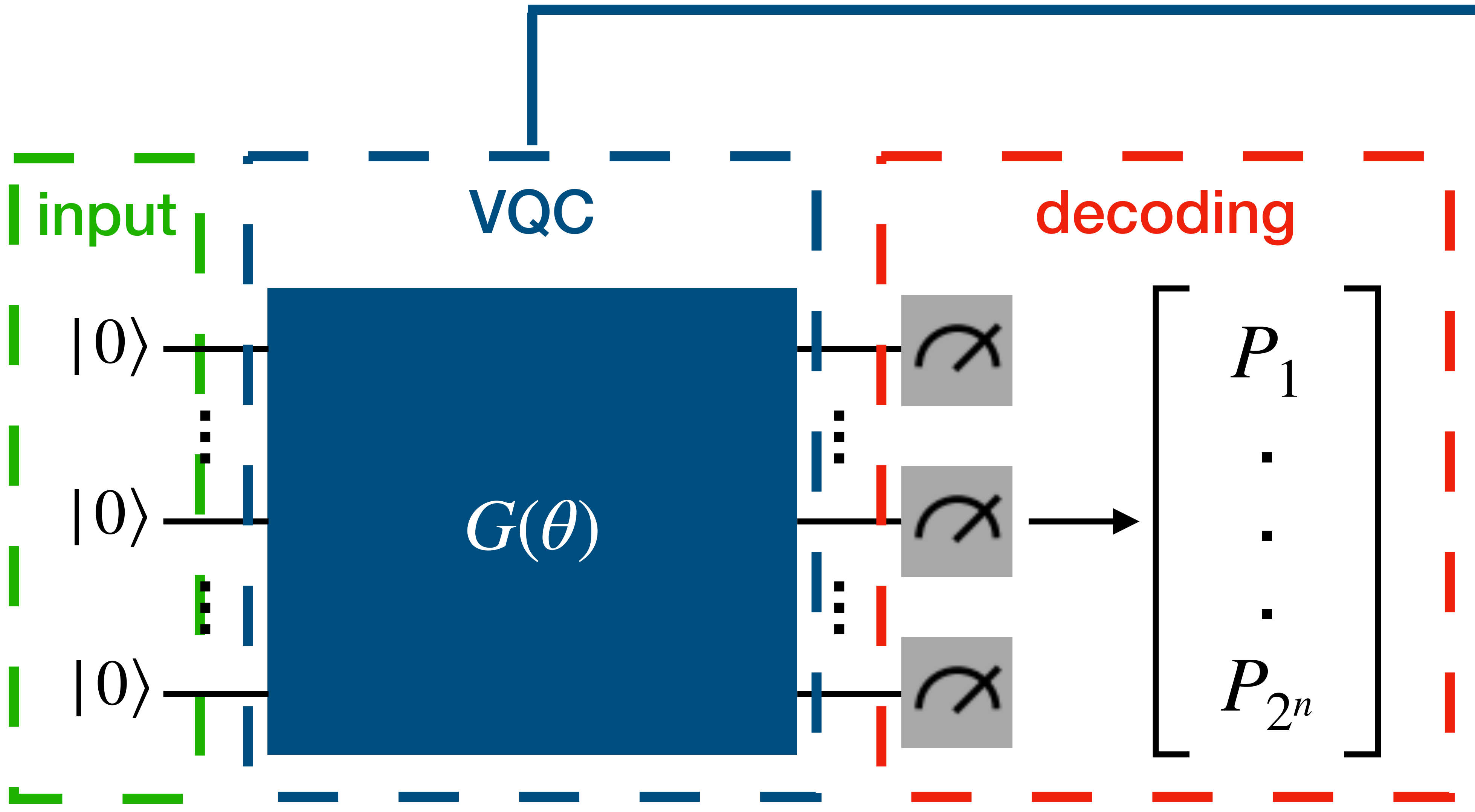
8×8

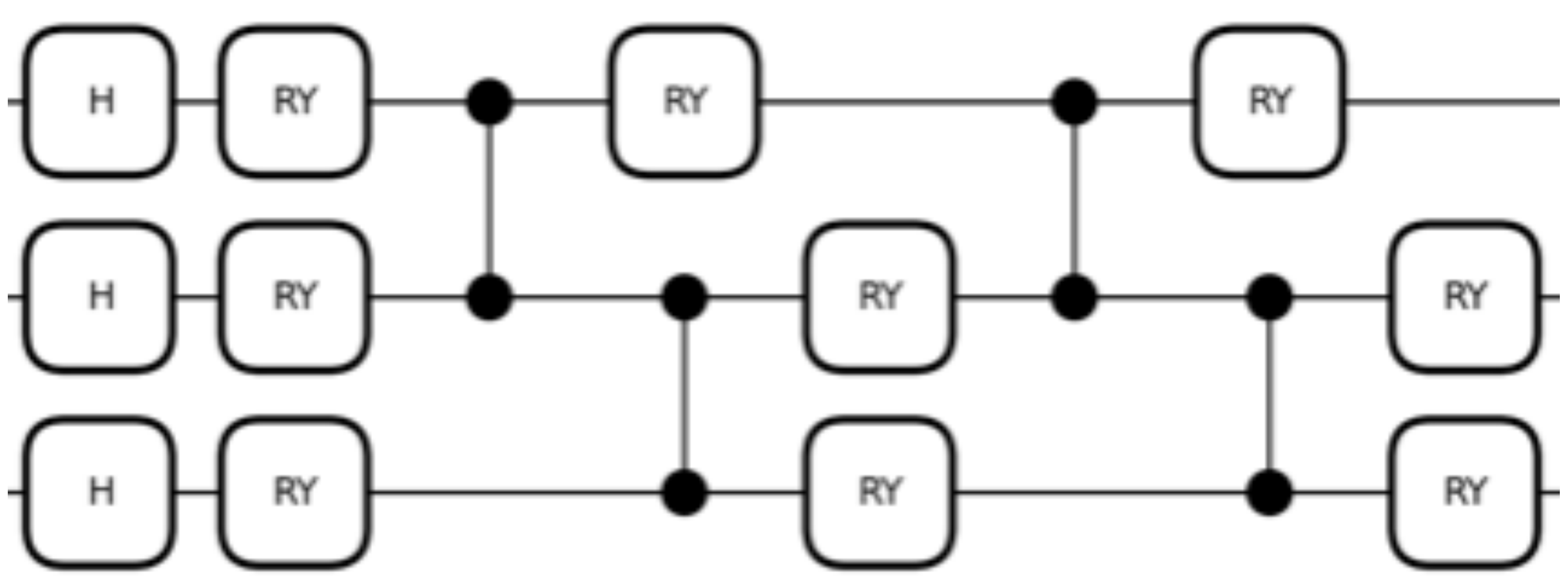


Average Shower Image (PDF)

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

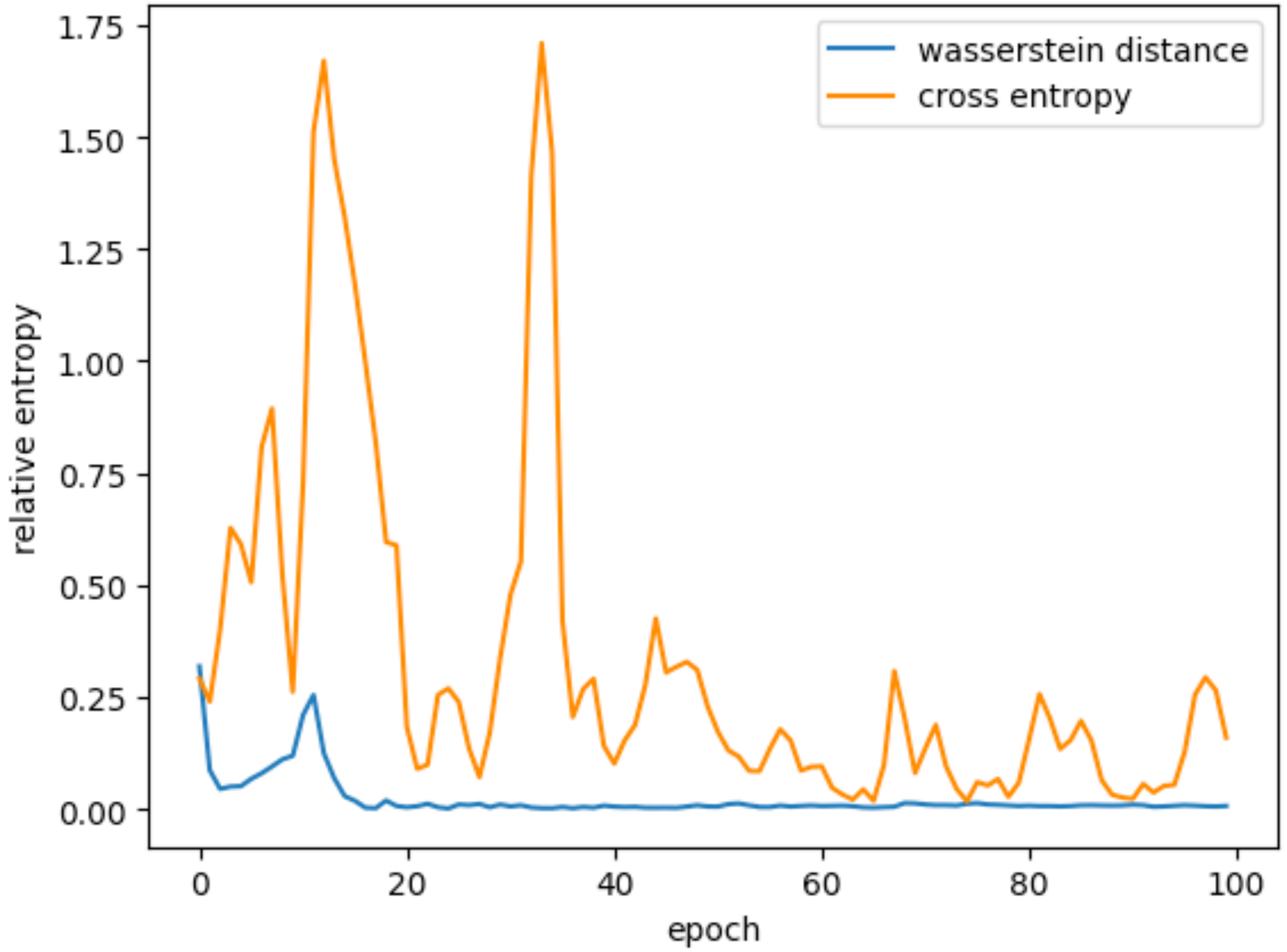




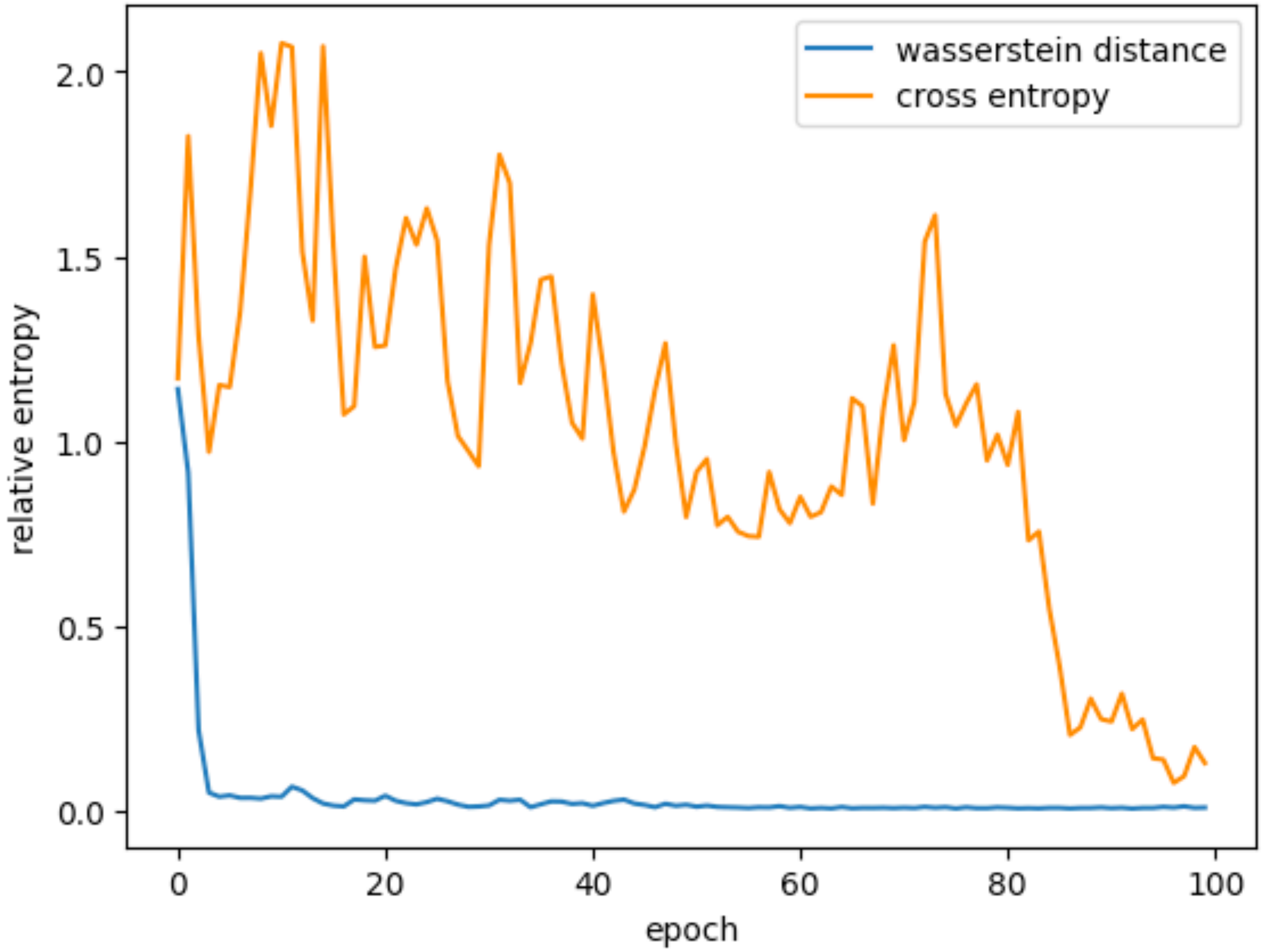
Training: Cross Entropy vs Wasserstein Loss

- Training with Wasserstein distance is more stable than cross-entropy loss
- Hyper-parameter optimization could help when using cross-entropy loss
  - time-consuming …
  - training fluctuates for the data with 64 pixels

8 pixels

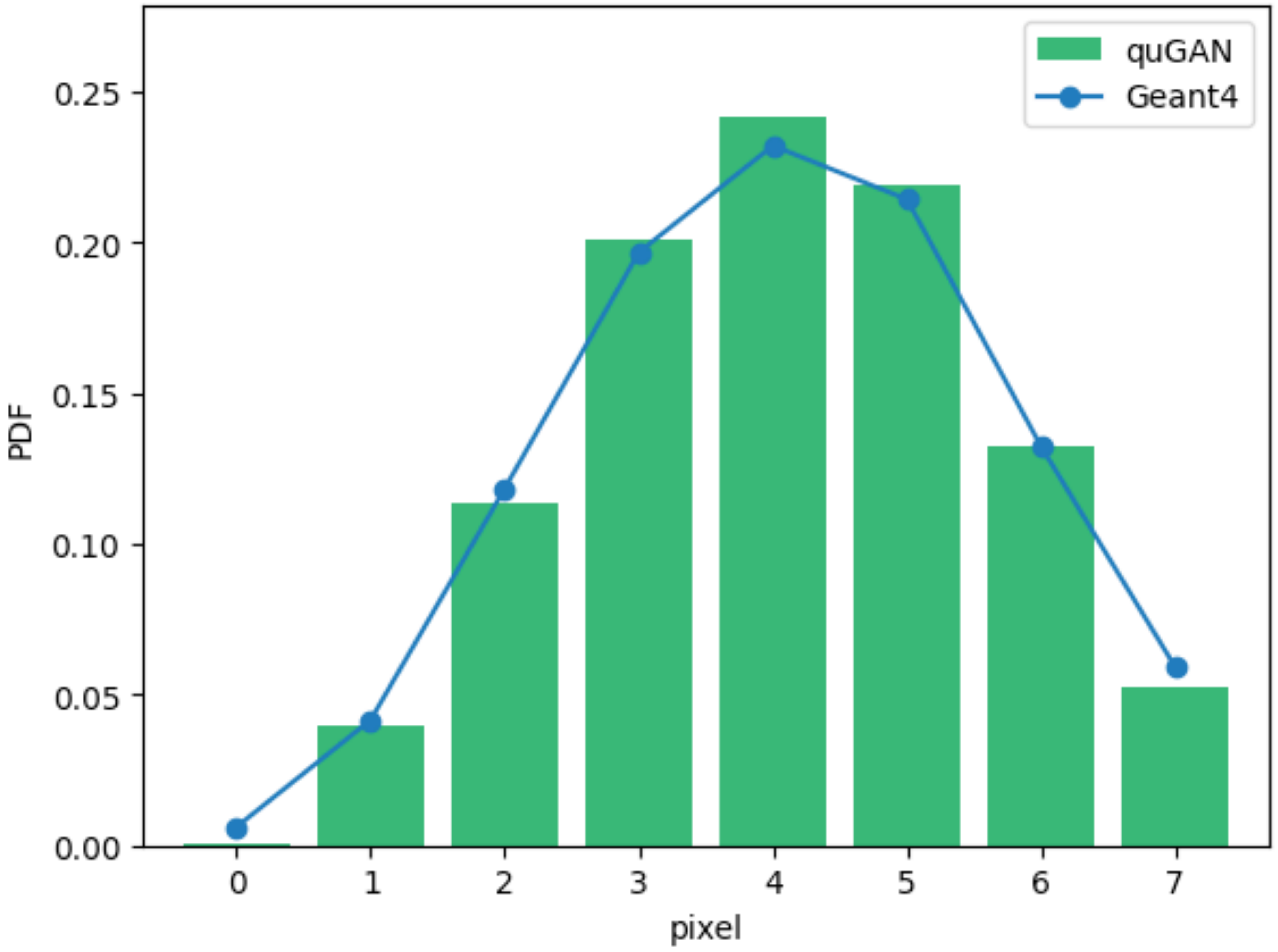


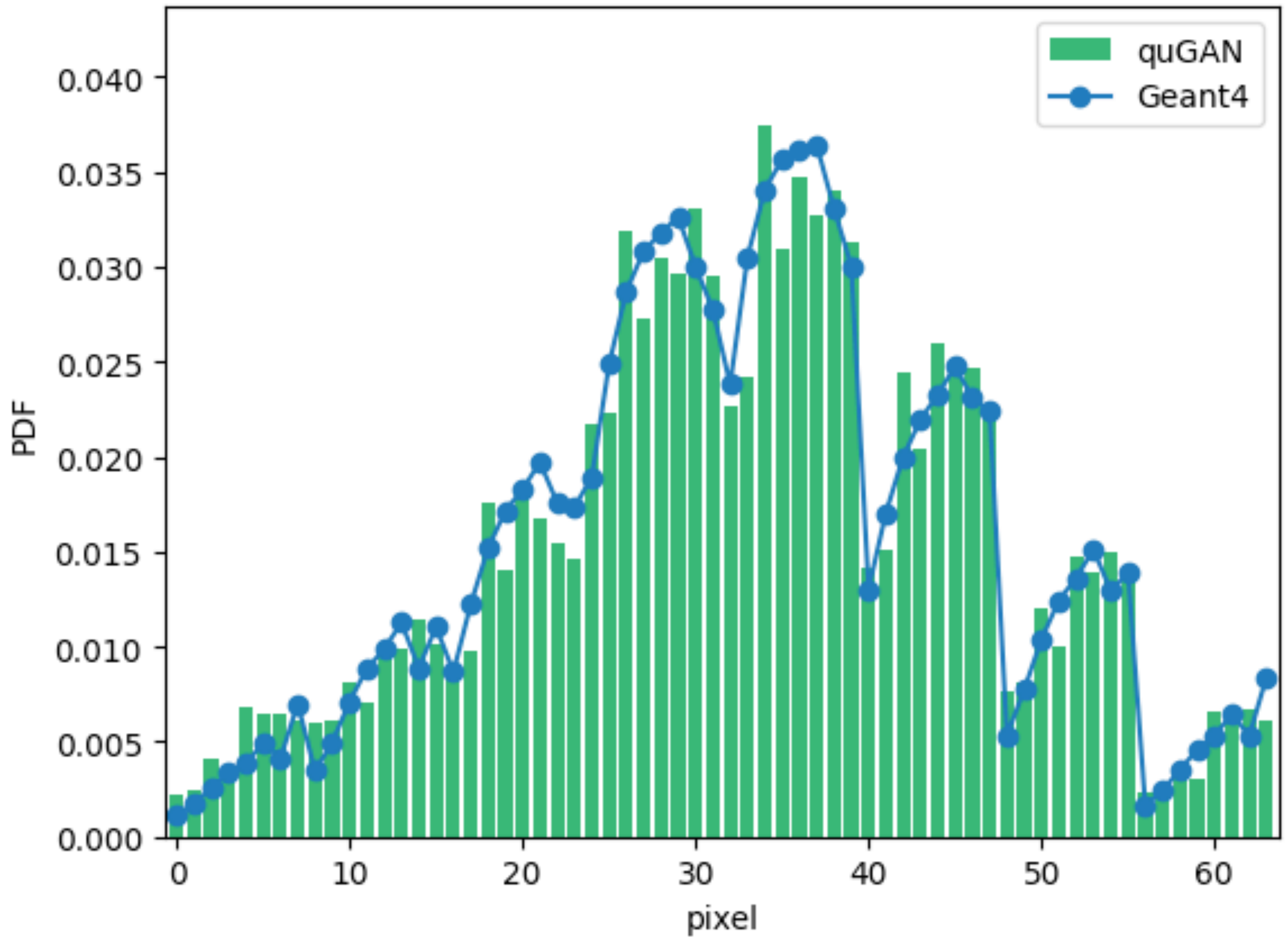
64 pixels



Performance (Ideal Simulator)

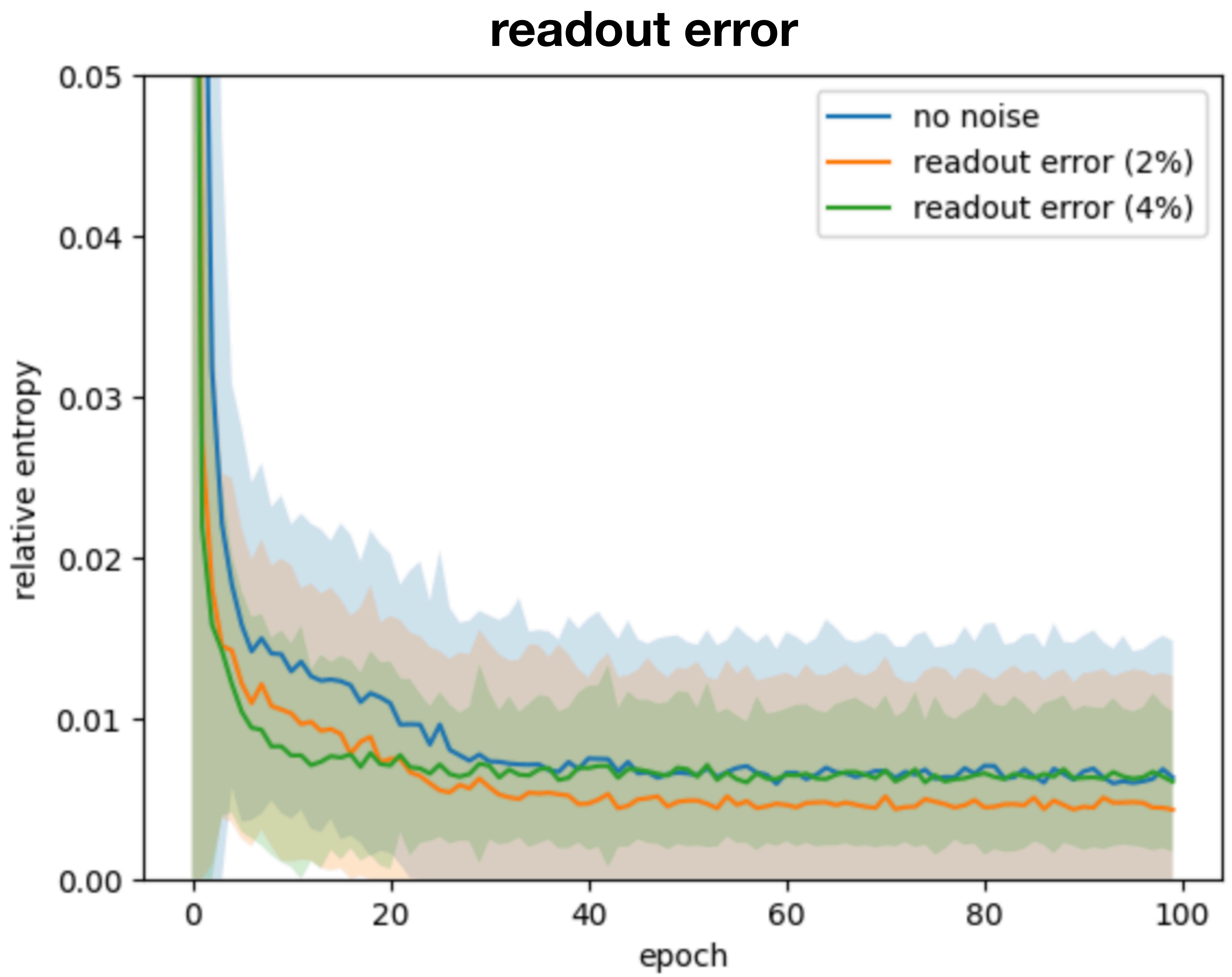
- Generated data are consistent with Geant4.

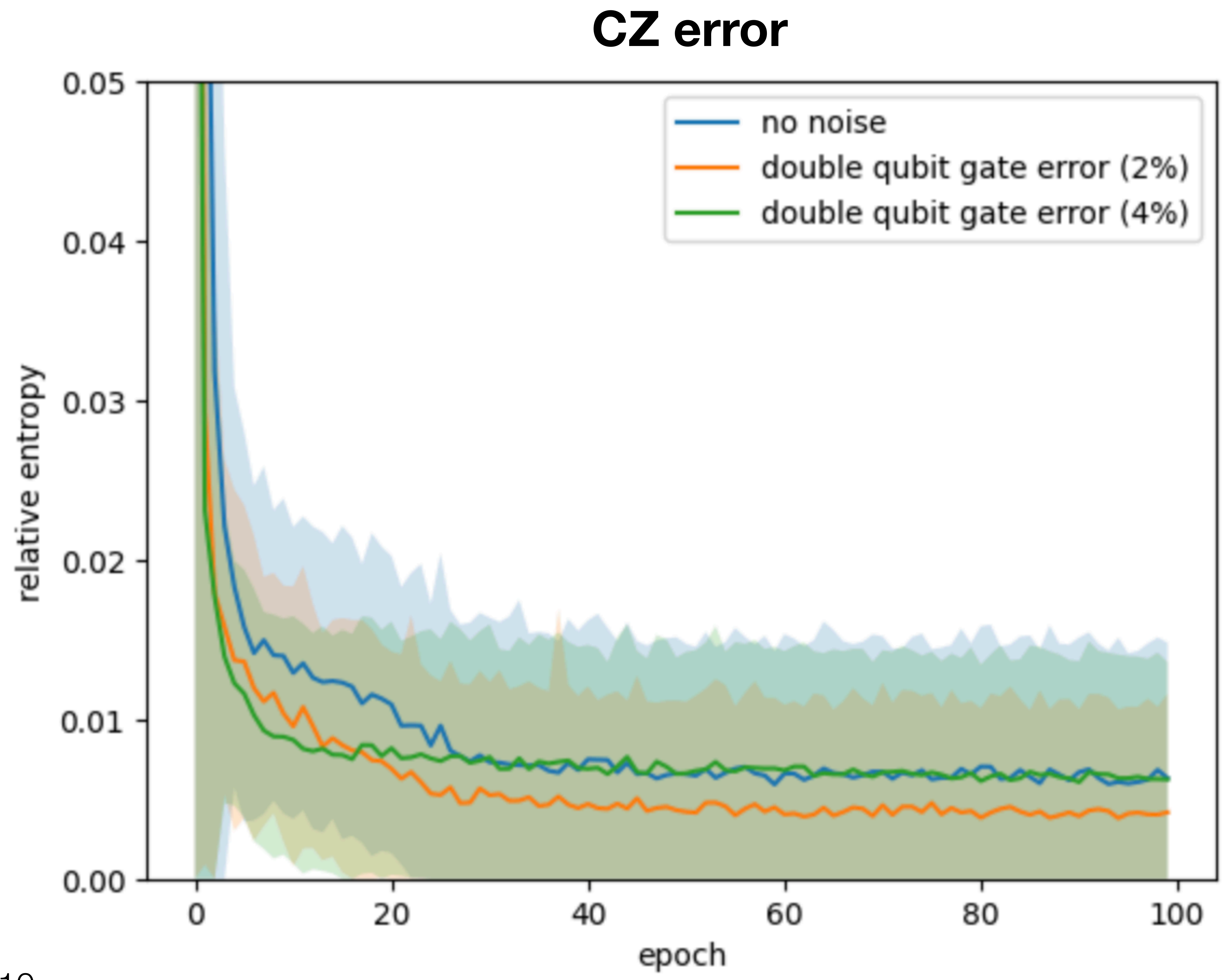




Impact of Noise: Training (8 pixels)

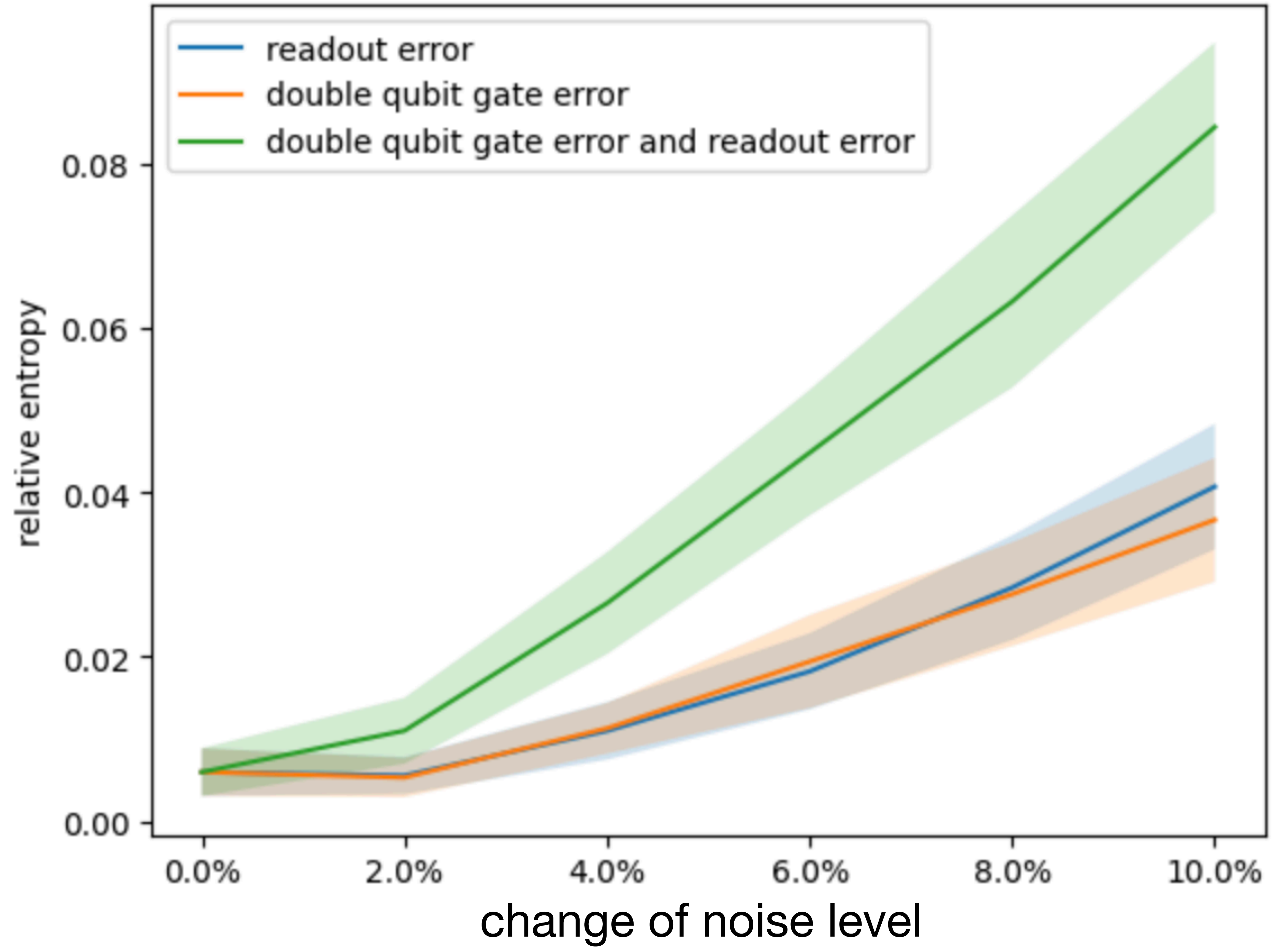
- Consider the impact of readout error and double qubit gate (CZ) error
  - line: mean value
  - band: fluctuation due to the initialization
  - noise (<2%) could improve the training

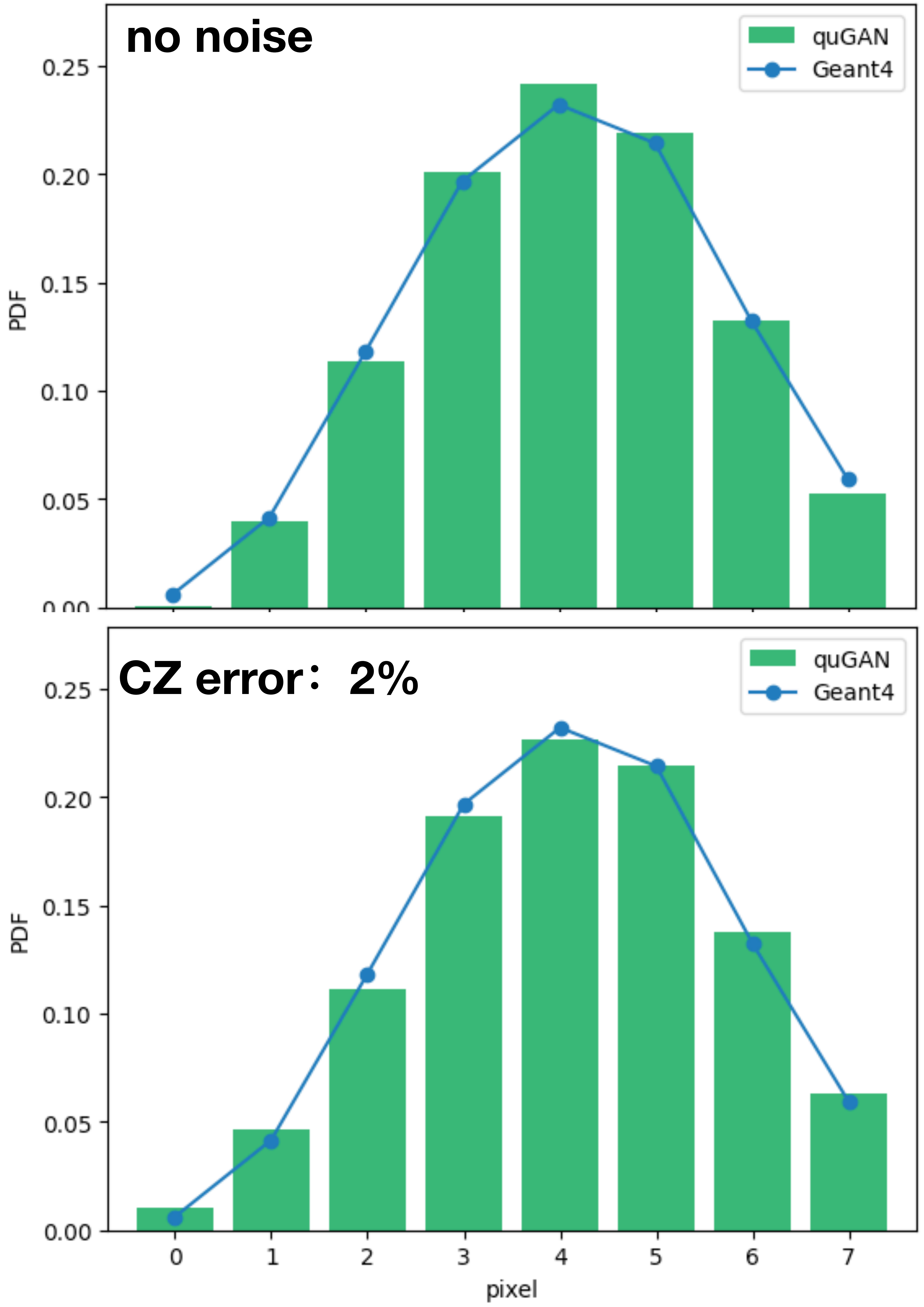




Impact of Noise: Inference (8 pixels)

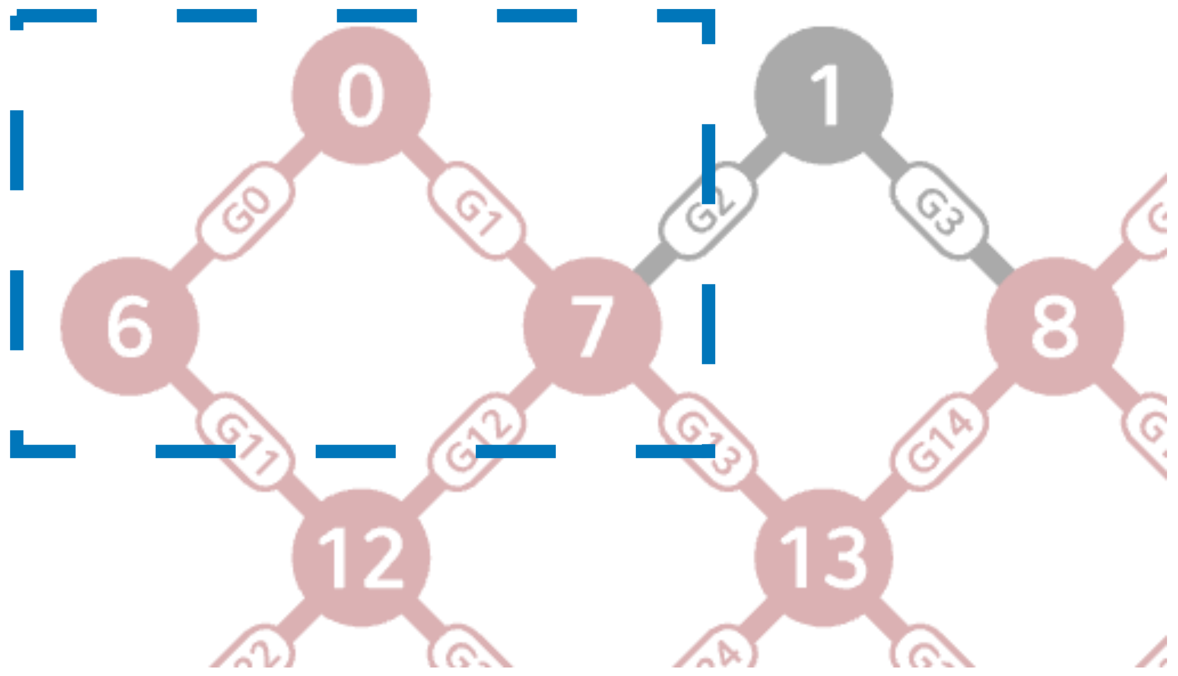
- Noise level at the inference stage may change
  - stable performance when the change is small



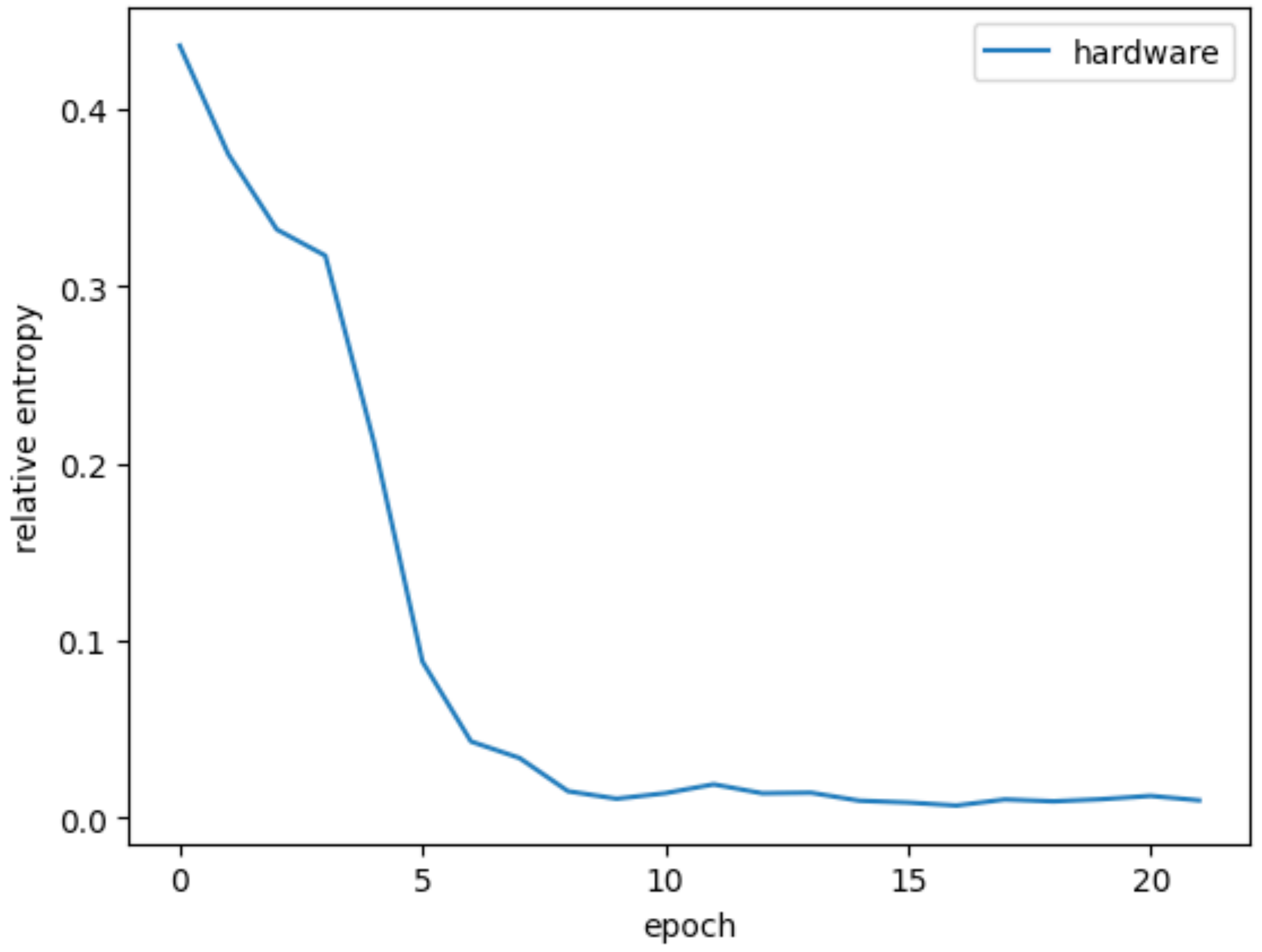


Results on the Hardware (8 pixels)

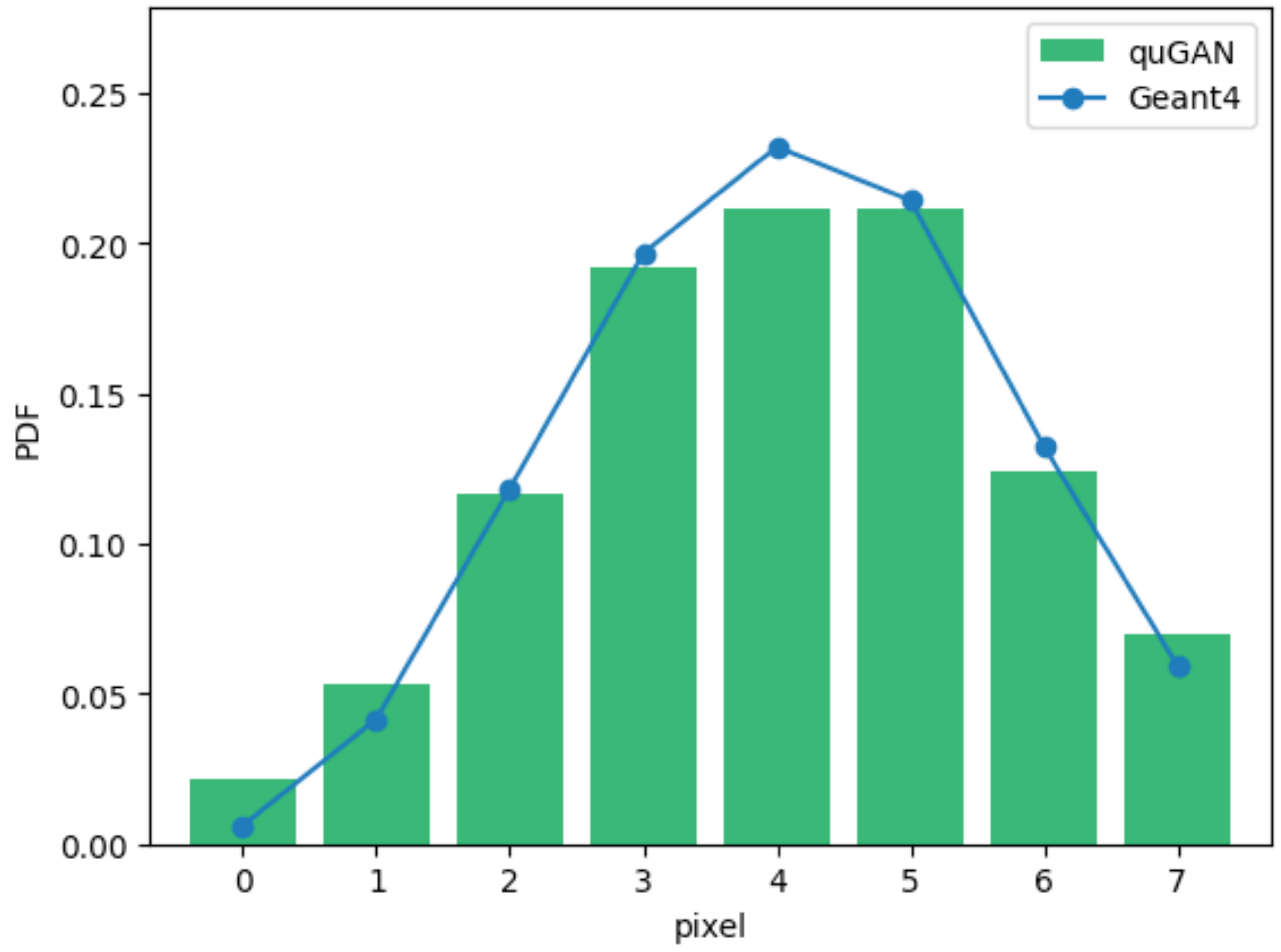
- Test the model on the hardware (Xiaohong: 骁鸿)
  - CZ error: 2%
  - readout error: 2%



training process



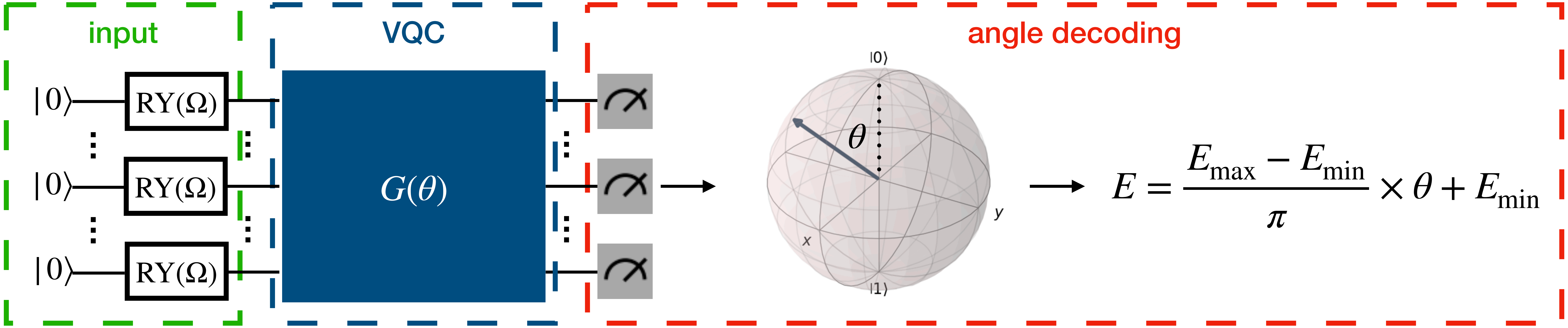
performance



Pixel-wise Energy Distribution

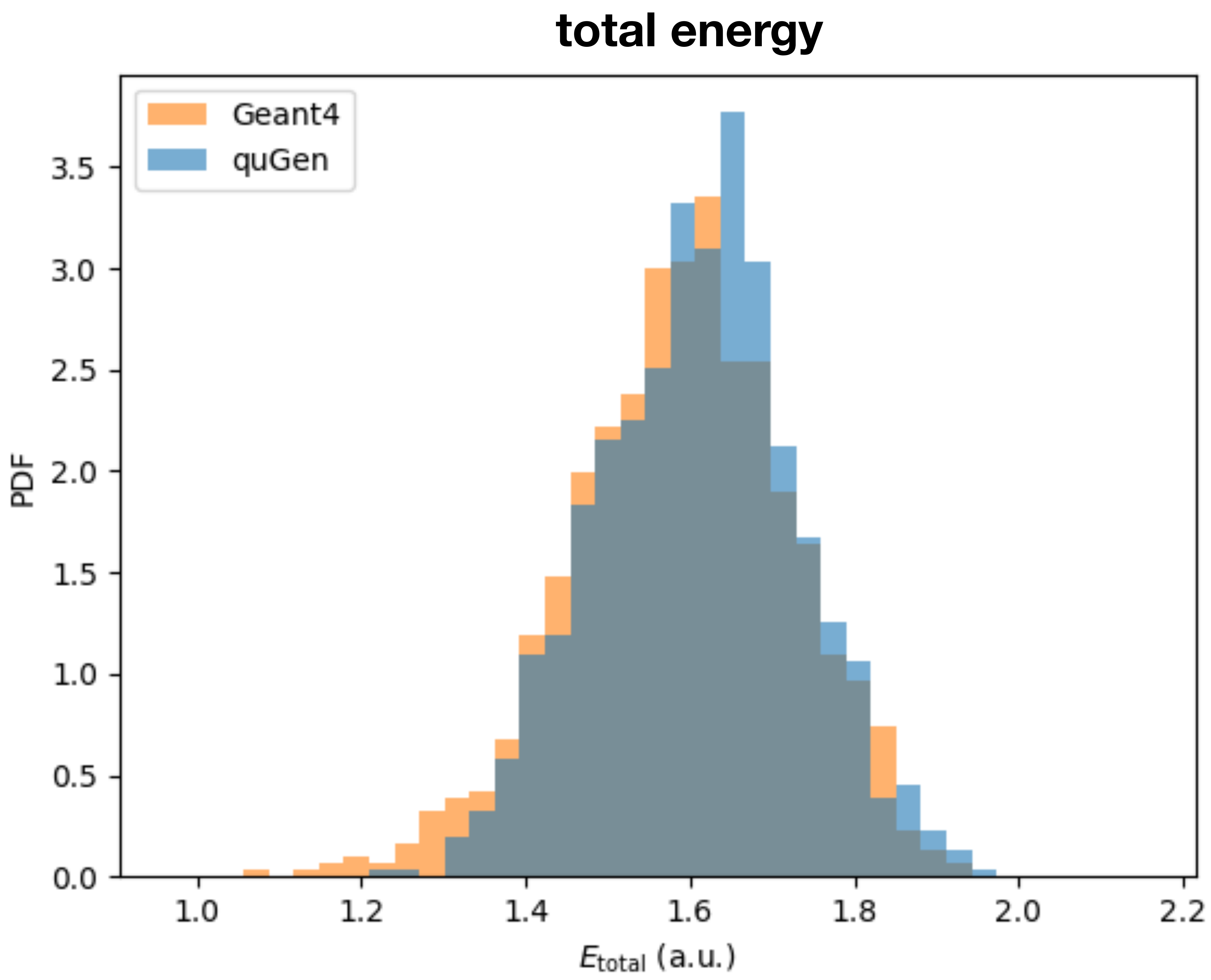
Generator Model

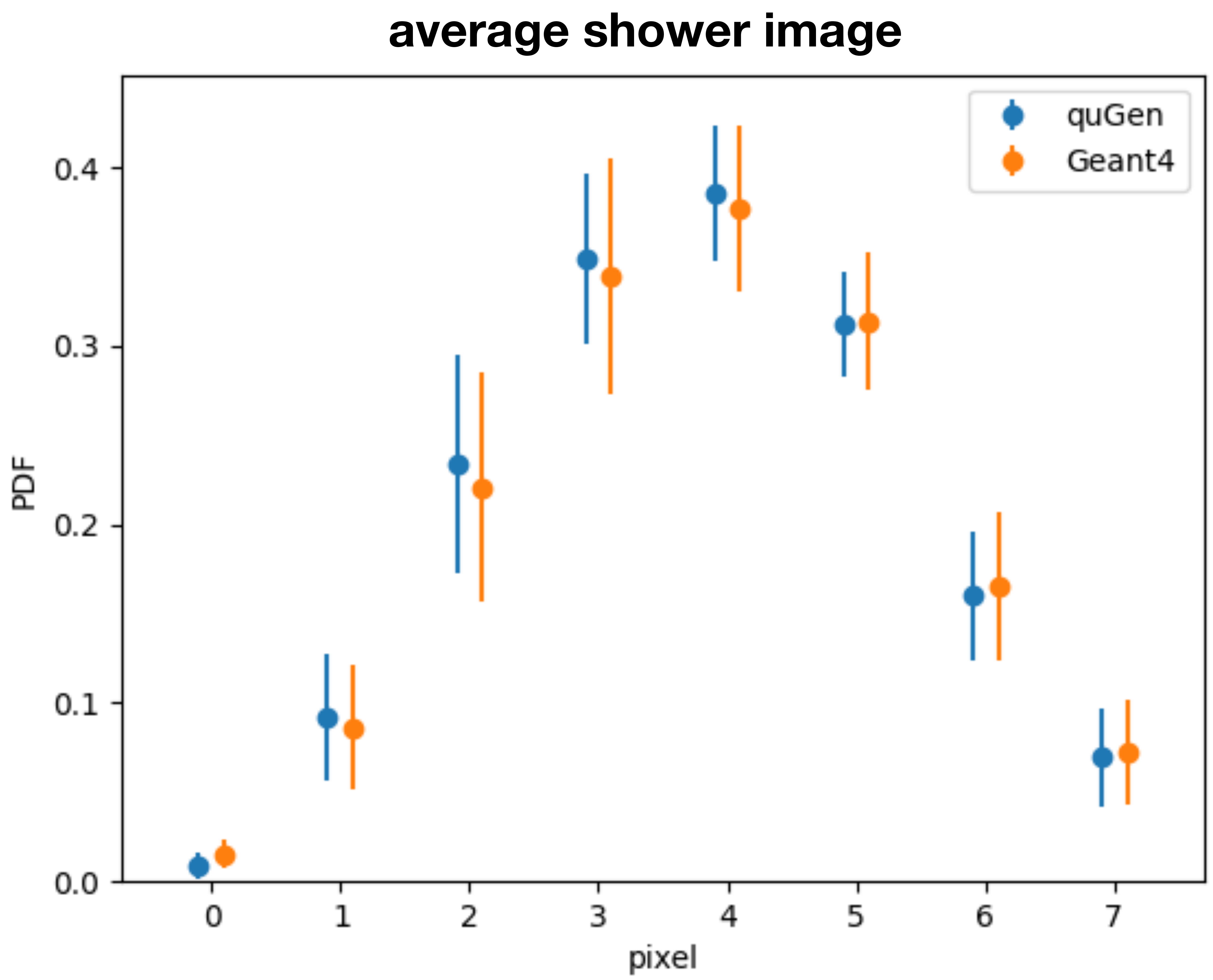
- Input states: $R_Y(\Omega)\,|\,0\rangle^{\otimes n}$
- Variational quantum circuits: $G(\theta)R_Y(\Omega)\,|\,0\rangle^{\otimes n} \rightarrow |\,\psi\rangle$
- Angle decoding: n qubits → n angles
  - 8 pixels: 8 qubits



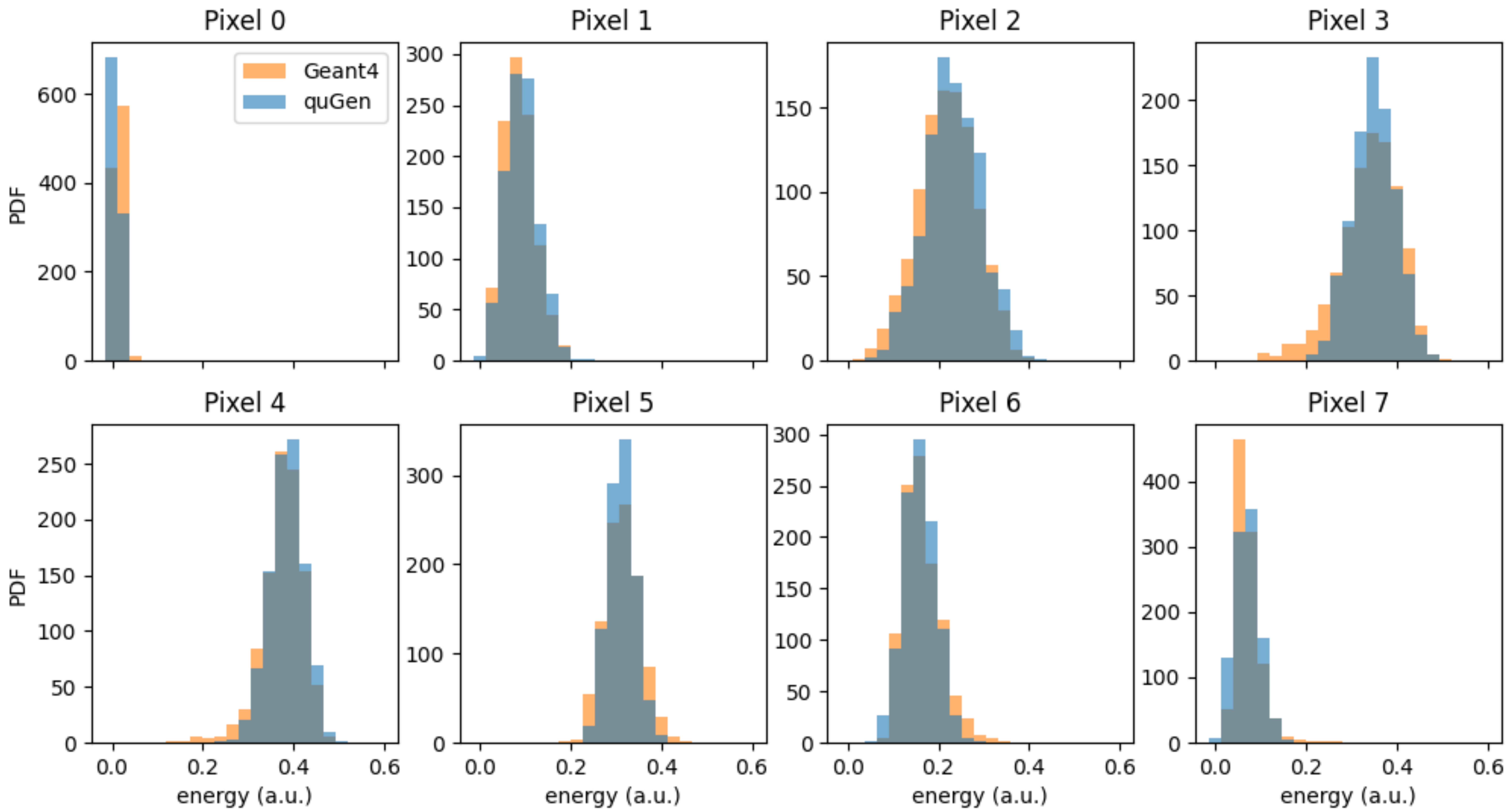
Overall Performance (Ideal Simulator)

- Consistent distribution between the generated data and Geant4





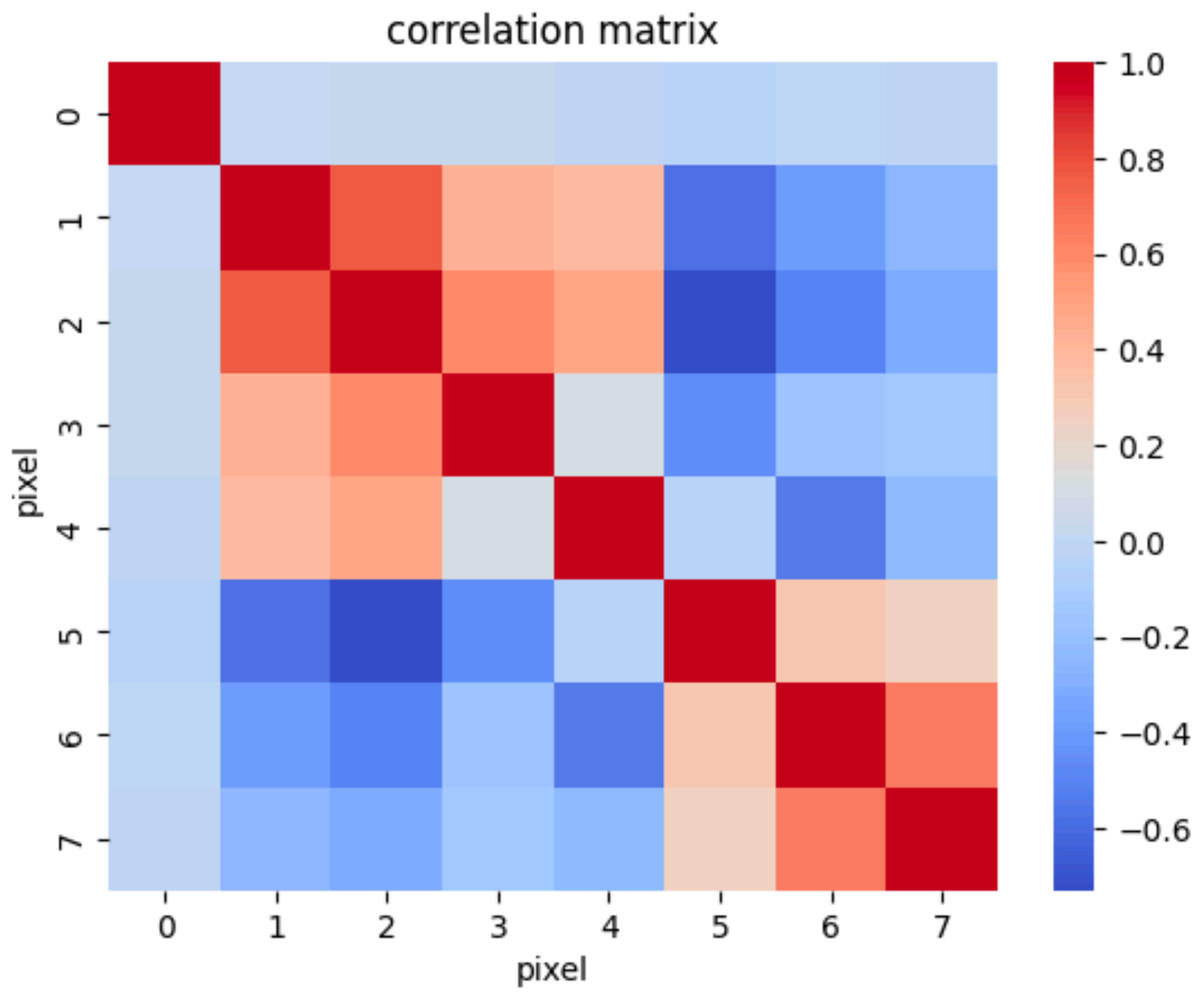
Pixel-wise Energy Distribution (Ideal Simulator)



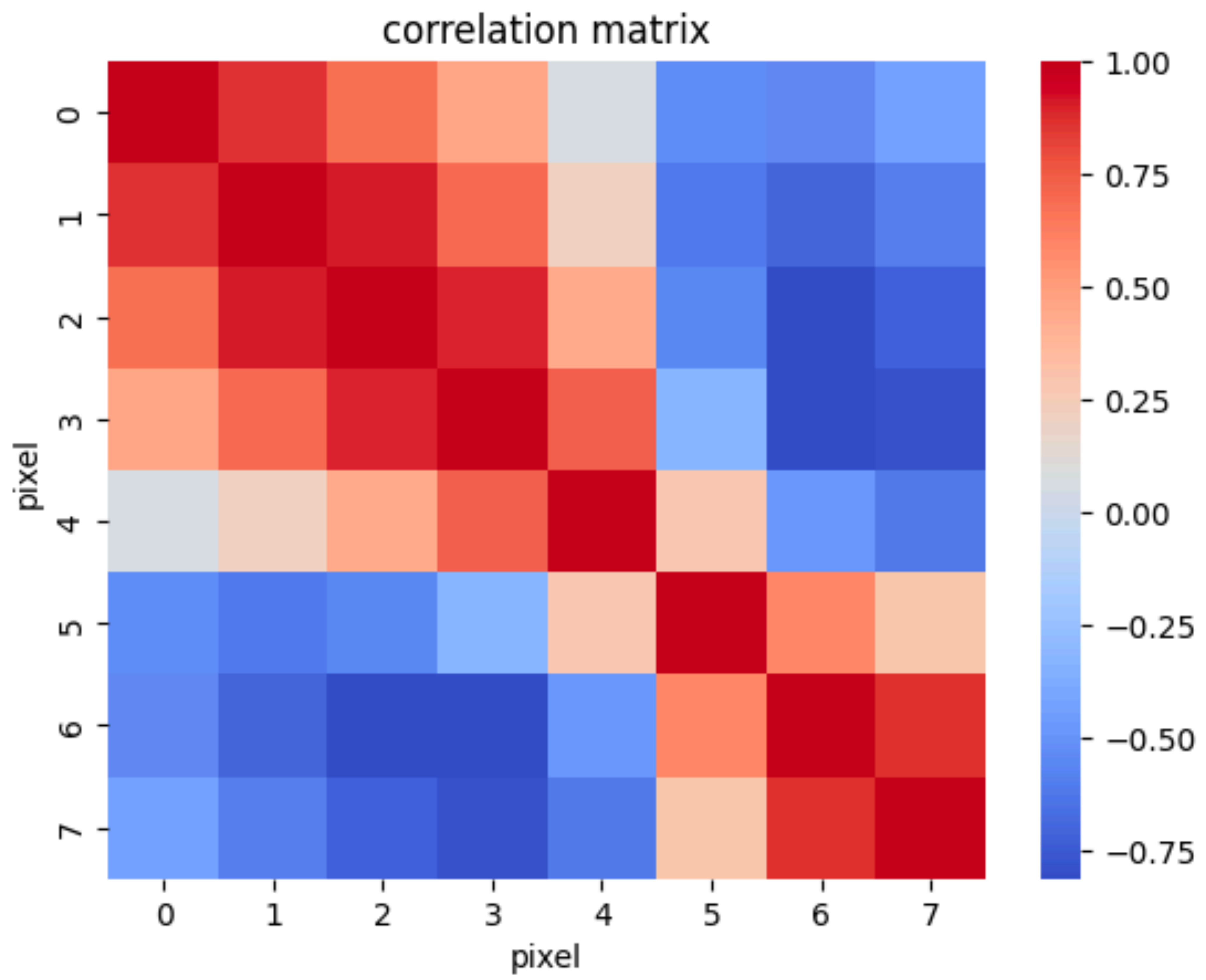
Correlation Matrix (Ideal Simulator)

- Correlation coefficients in generated data is less than those in Geant4
  - need further investigations

generated data



Geant4



Summary

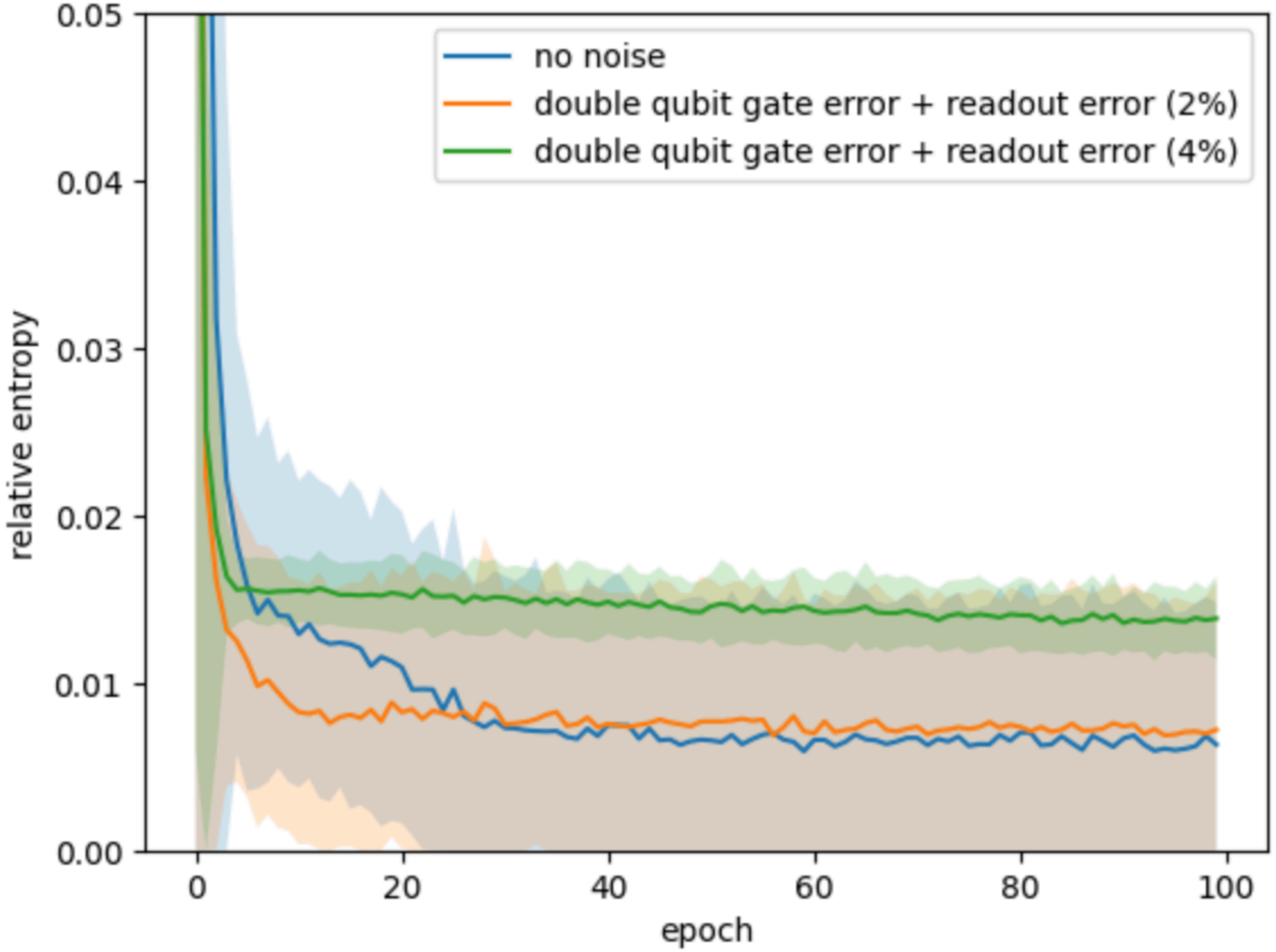
Average shower image

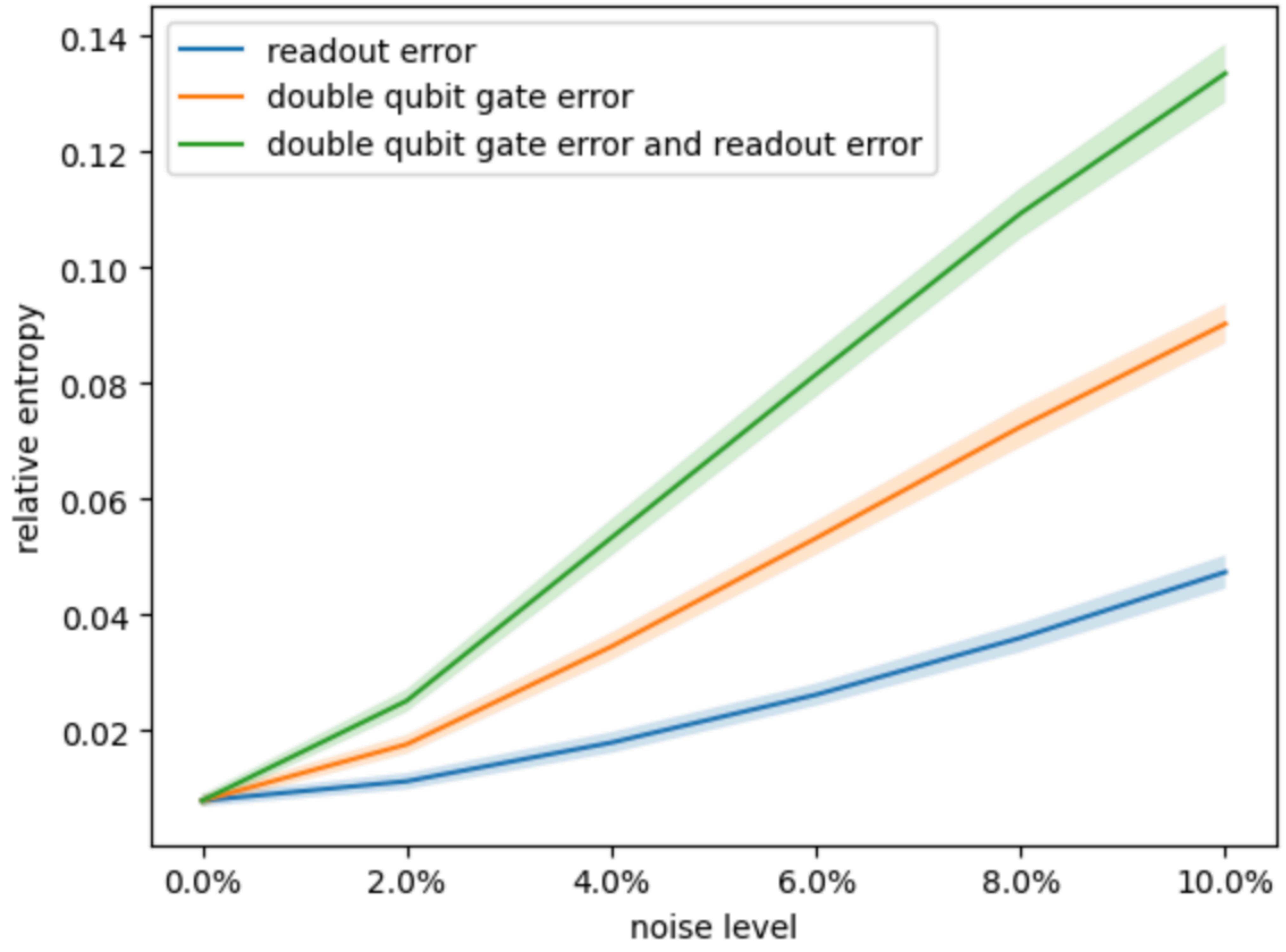
- Quantum GAN could generate images consistent with Geant4
- Training with noise (<2%) improves the performance
- The model inference is stable against noise (<2%)
- Successfully running the model on the hardware (Xiaohong)

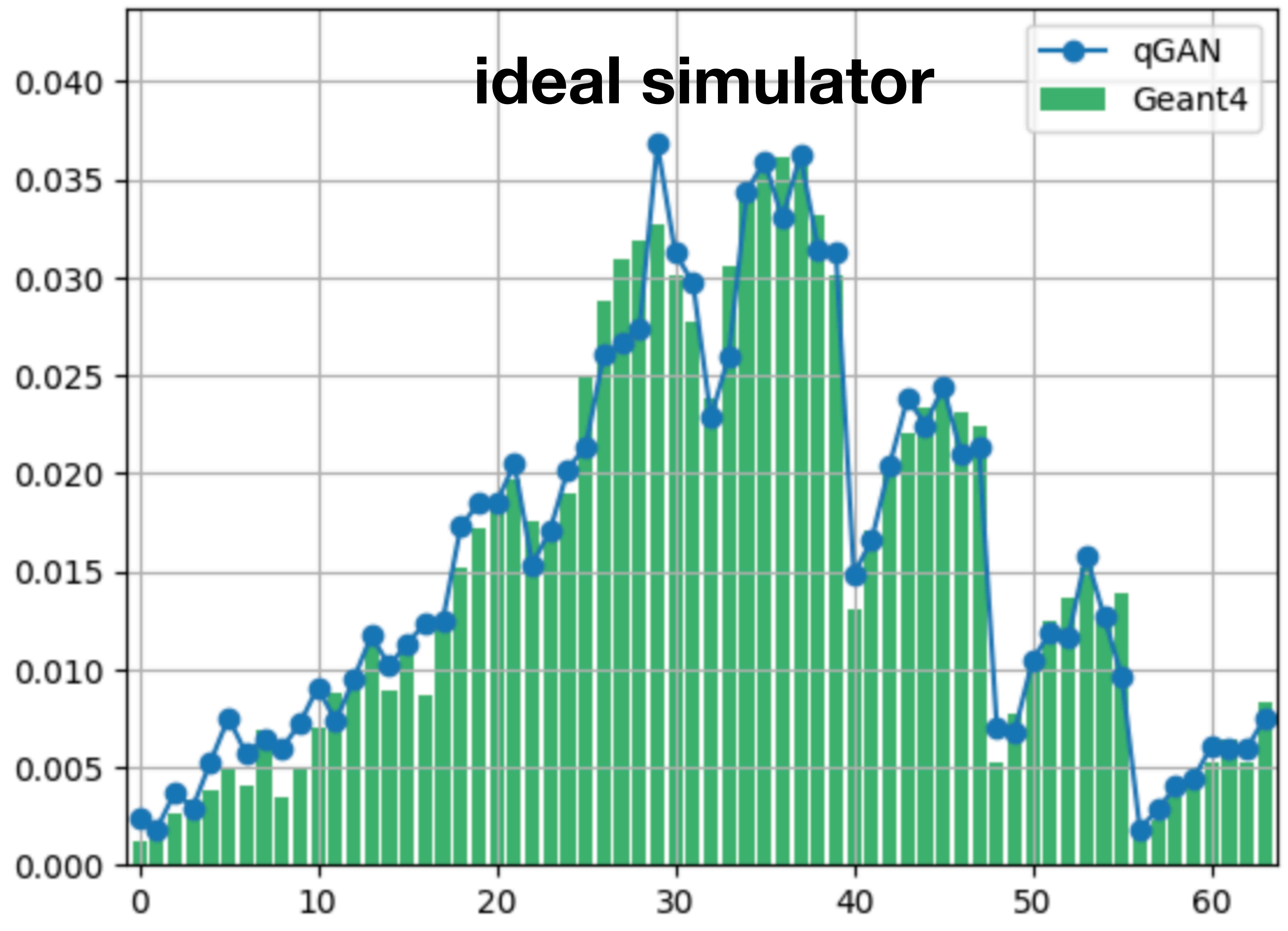
Pixel-wise energy distribution:

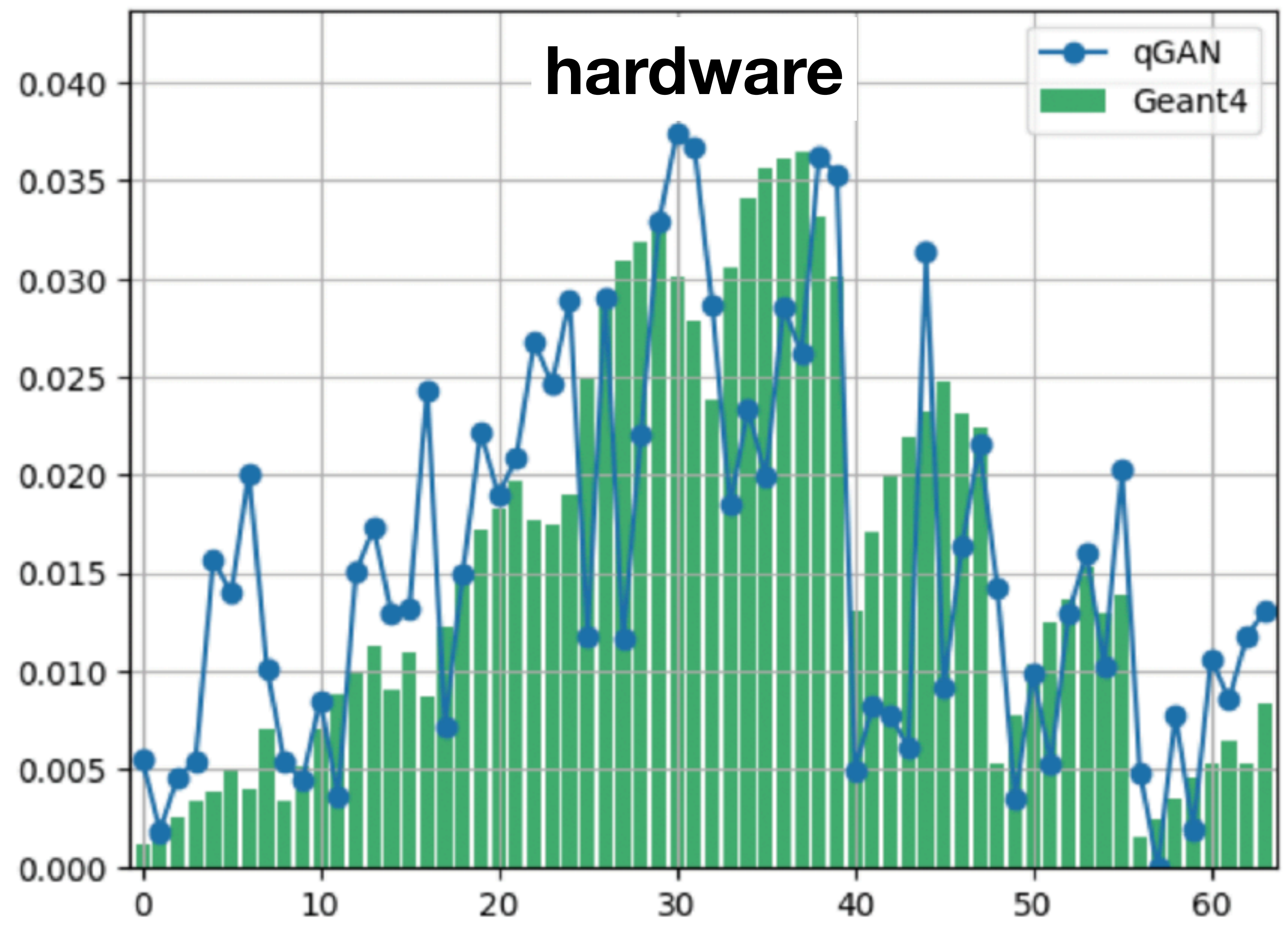
- In general, the generated data is consistent with Geant4
- The correlation matrix needs further investigations

backup


no noise
double qubit gate error + readout error (2%)
double qubit gate error + readout error (4%)
relative entropy
epoch
0.00
0.01
0.02
0.03
0.04
0.05
0
20
40
60
80
100


readout error
double qubit gate error
double qubit gate error and readout error
0.14
0.12
0.10
0.08
0.06
0.04
0.02
relative entropy
0.0%
2.0%
4.0%
6.0%
8.0%
10.0%
noise level


ideal simulator
qGAN
Geant4
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
10
20
30
40
50
60


hardware
qGAN
Geant4
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
10
20
30
40
50
60