Quantum GAN for fast calorimeter simulation

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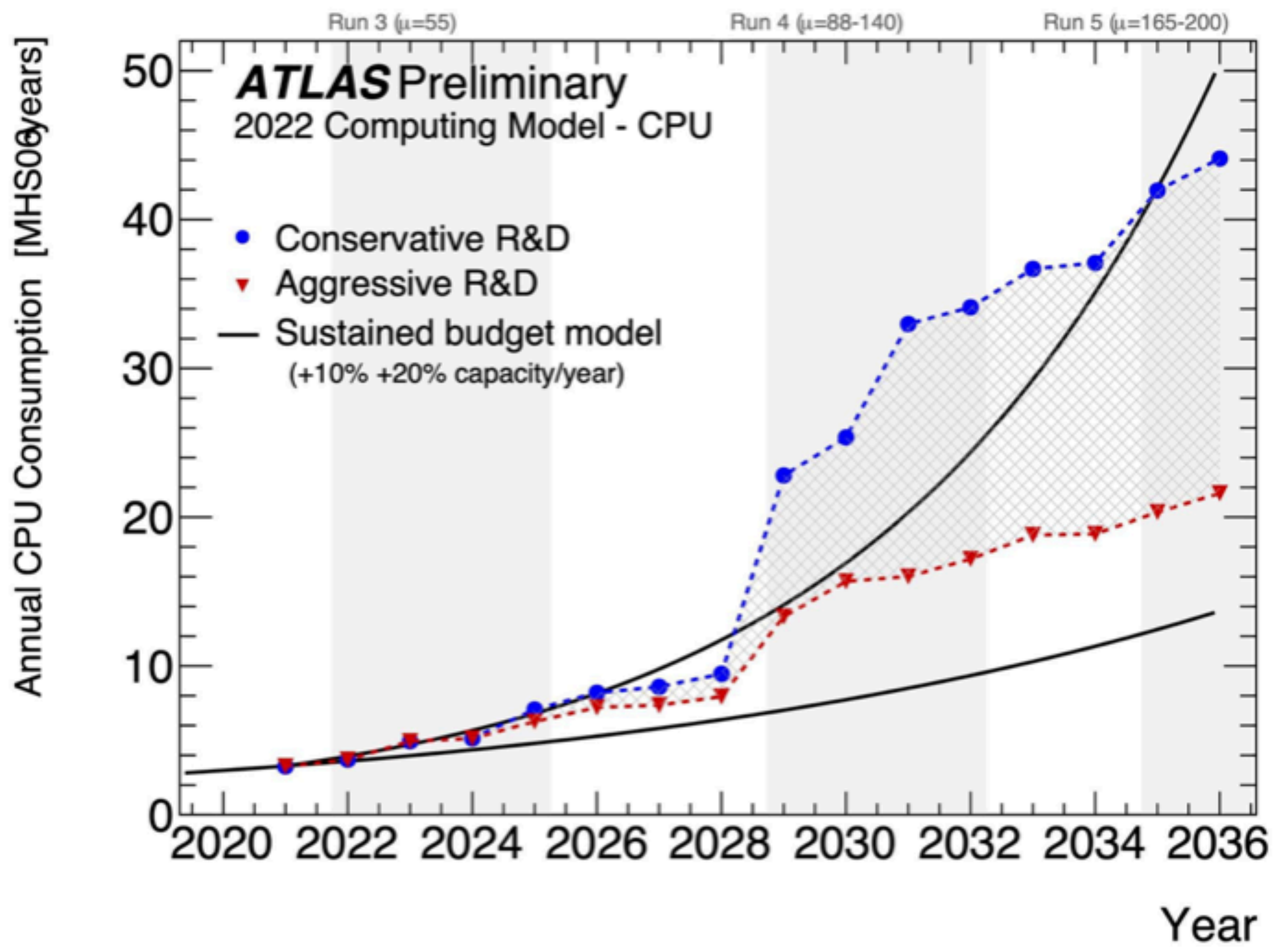
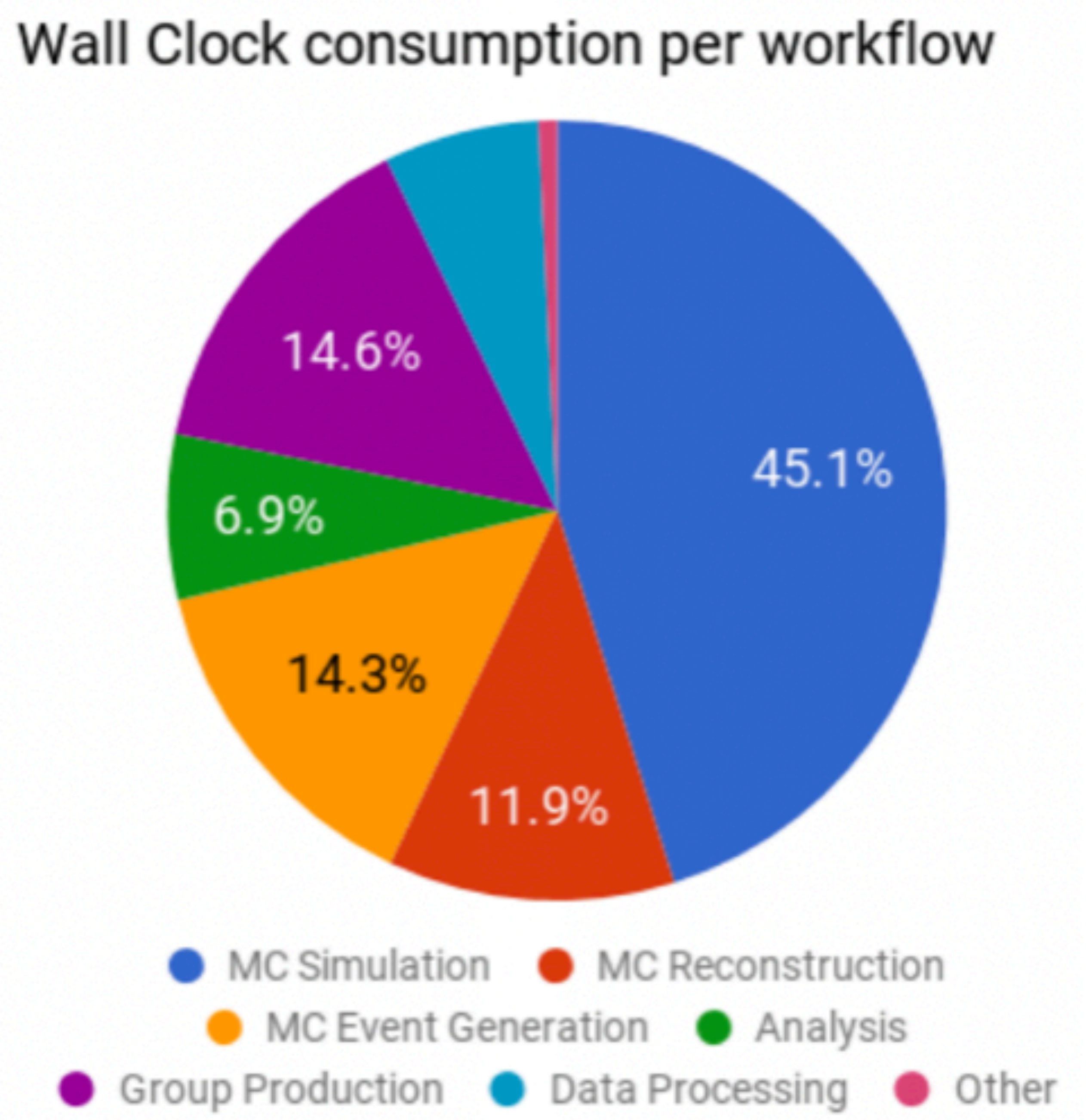
Why we need fast calorimeter simulation ?

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



ATLAS Software and Computing HL-LHC Roadmap

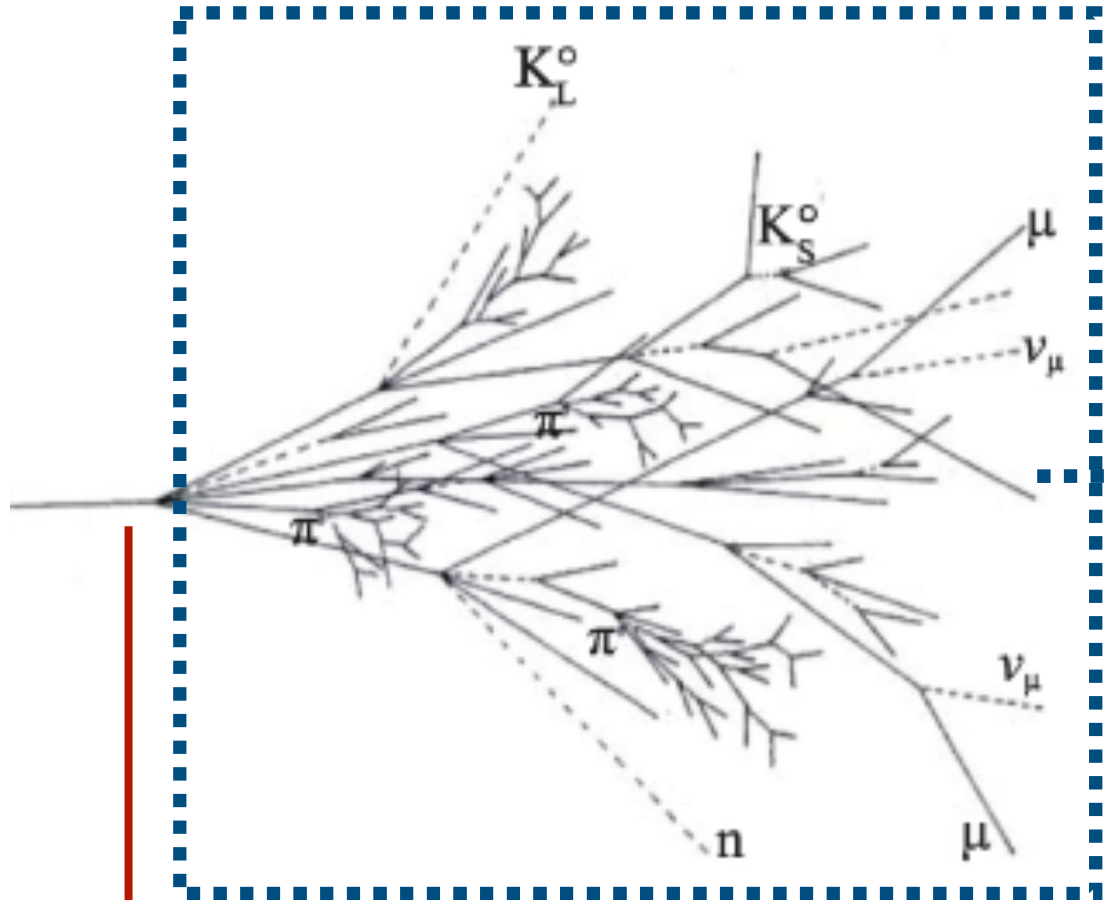


ATLAS 2017 number

Fast calorimeter simulation

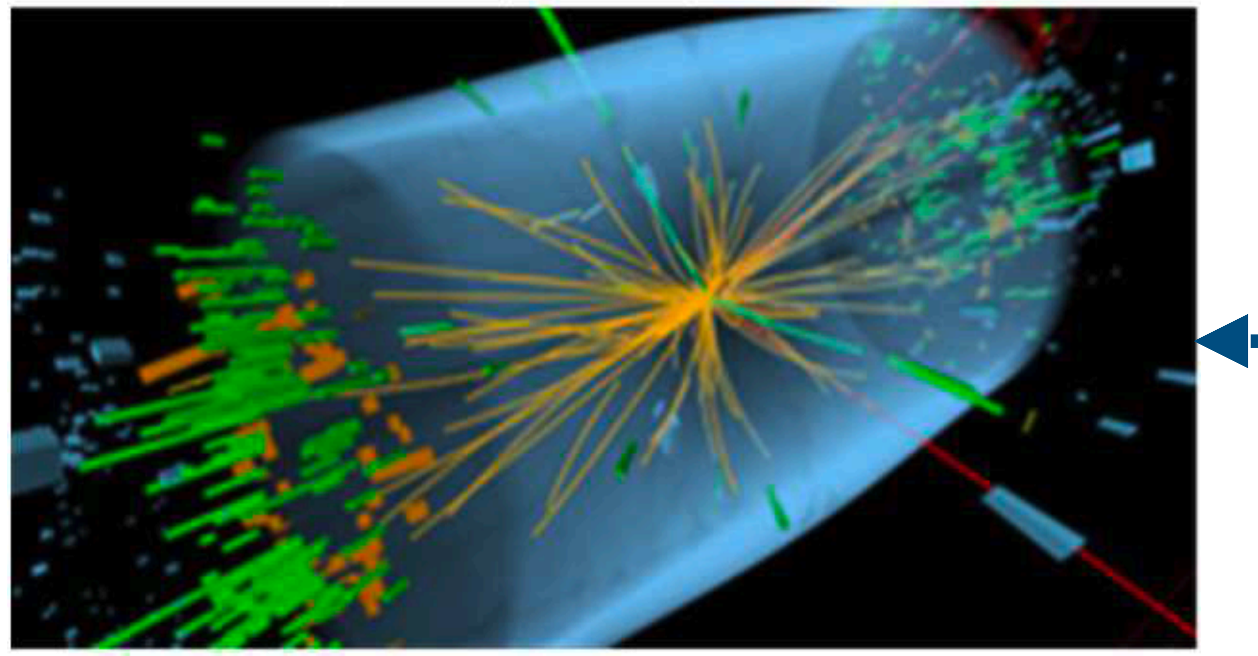
- Geant4: incoming particle -> physics process in the detector-> energy deposition
  - accurate results, but time-consuming
  - complex geometry
  - number of secondary particles grows quickly

Geant4



- fast simulation: incoming particle -> energy deposition)
  - parameterization
  - **GAN (ATLAS：张瑞的报告)**
  - ……

fast simulation



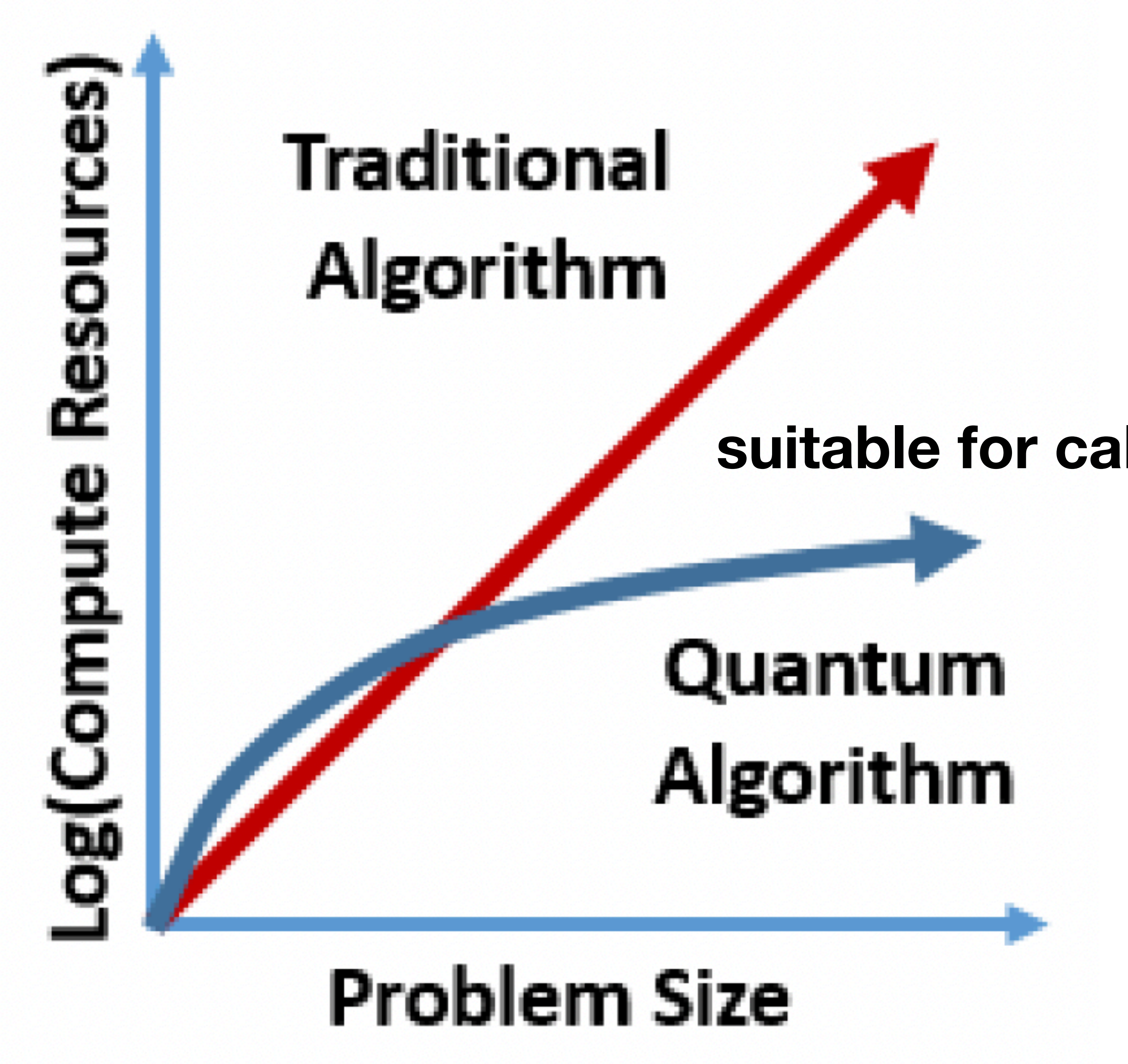
QC is an alternative of classical computing

QC + GAN: the potential to out-perform classical GAN

Quantum computing

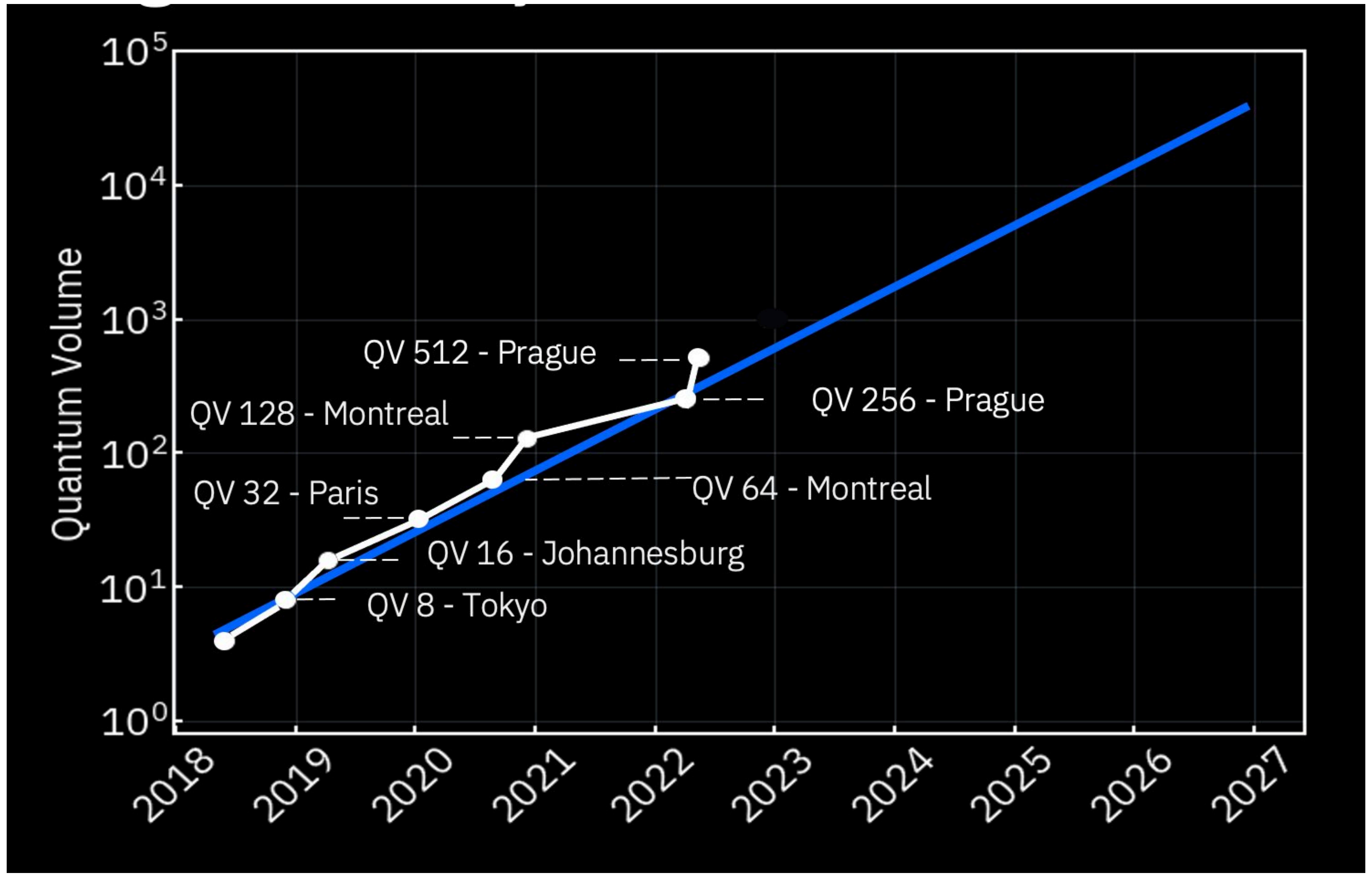
Image source

- Quantum computing: superposition, entanglement
  - N bits, could represent 2^N results， contain the information of one result
  - N qubits, could represent 2^N results， contain the information of all the results



suitable for calorimeter simulation

IBM

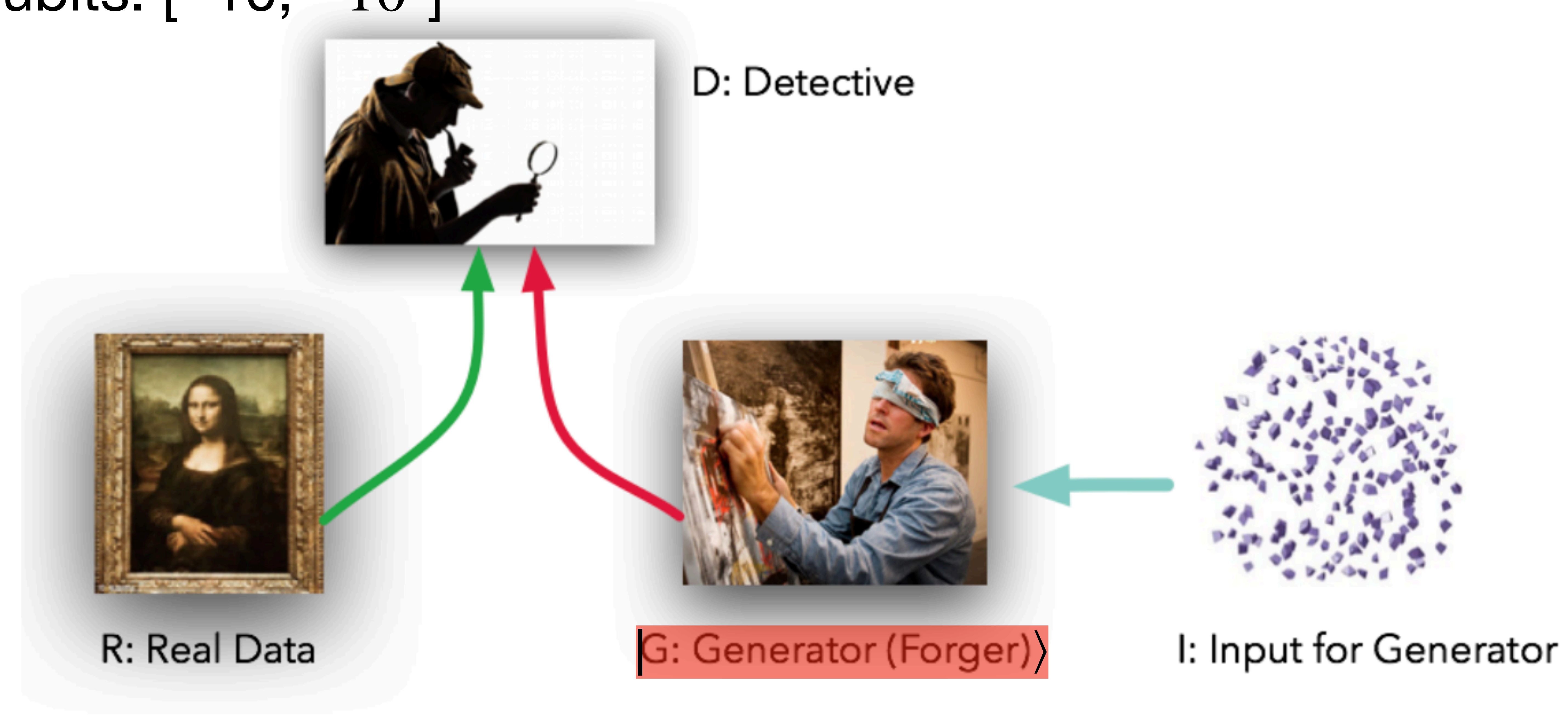


Quantum GAN

- Two kinds of quantum GAN
  - quantum generator + classical discriminator
  - quantum generator + quantum discriminator

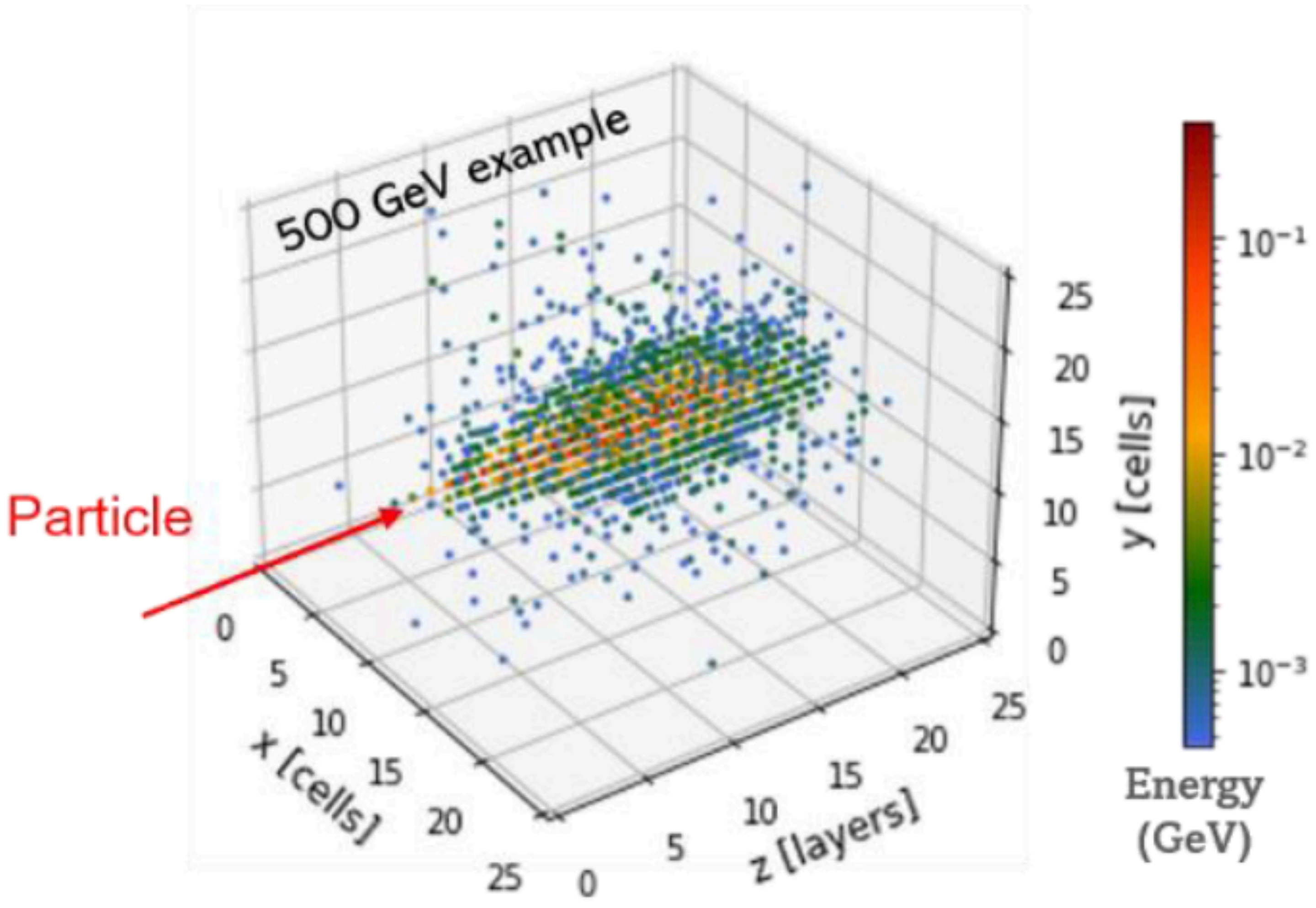
- NISC
  - noisy and unstable qubit
  - number of qubits: [~10, ~10^2]

image source



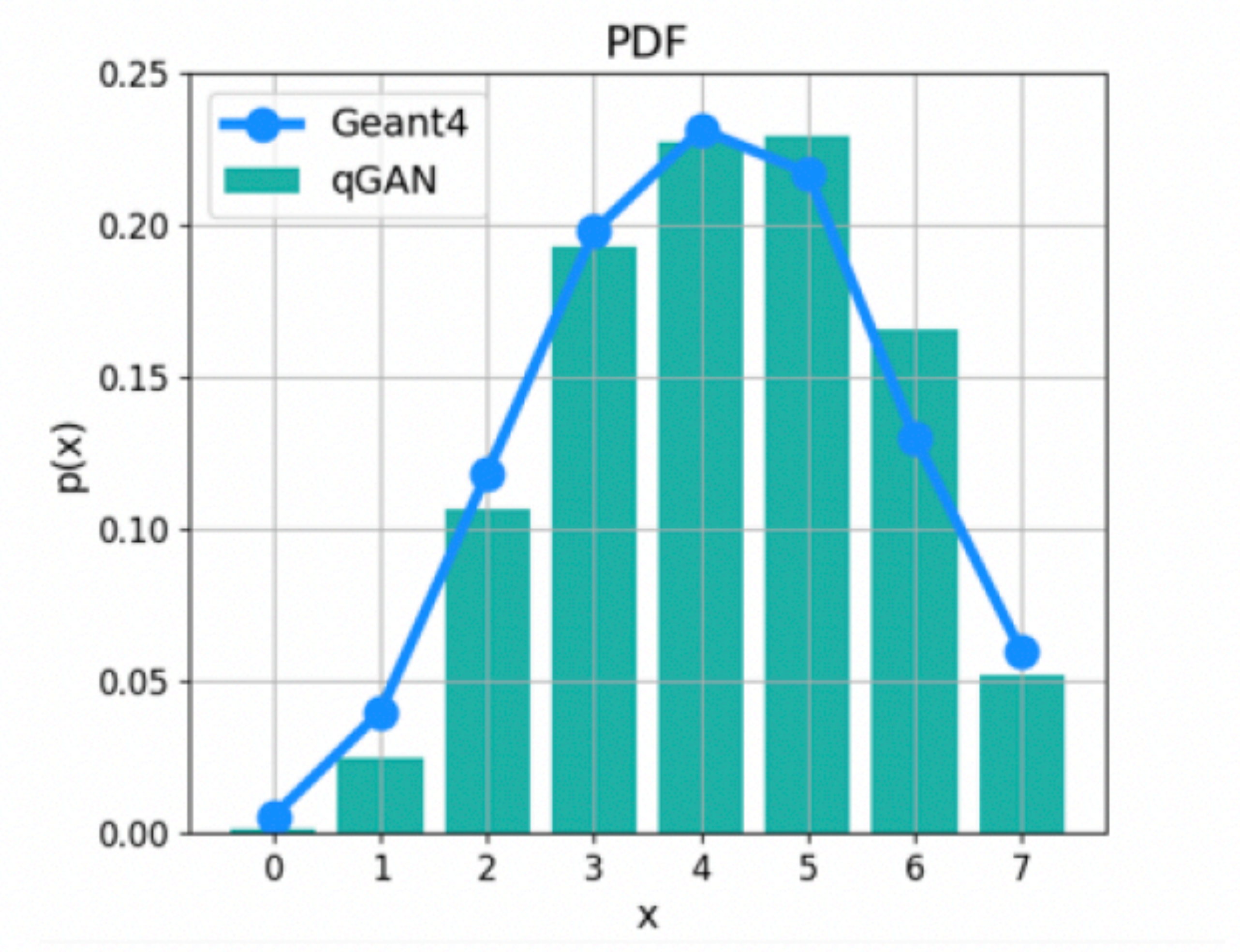
Current status

- CERN QTI started to investigate quantum GAN about 3 years ago(link) (CERN & DESY)
  - research strategy： 1D → 2D → 3D
  - current states： 1D and 2D fast calorimeter simulation on the simulator
    simplified 1D fast calorimeter simulation on the hardware



1D： 8 pixels

3 pixels ($2^3 = 8$)



2D： 8x8 pixels

6 qubits ($2^6 = 8 \times 8$)

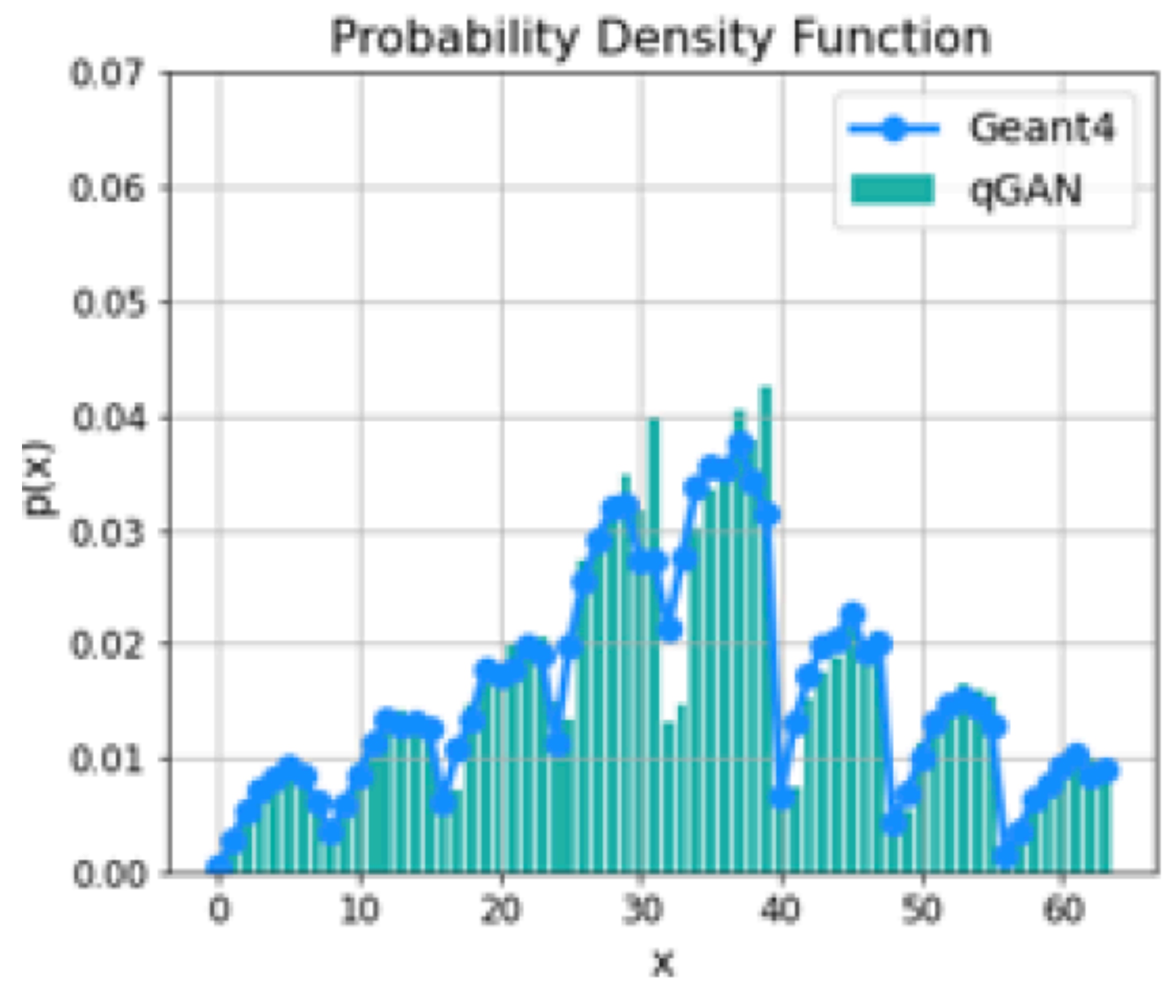
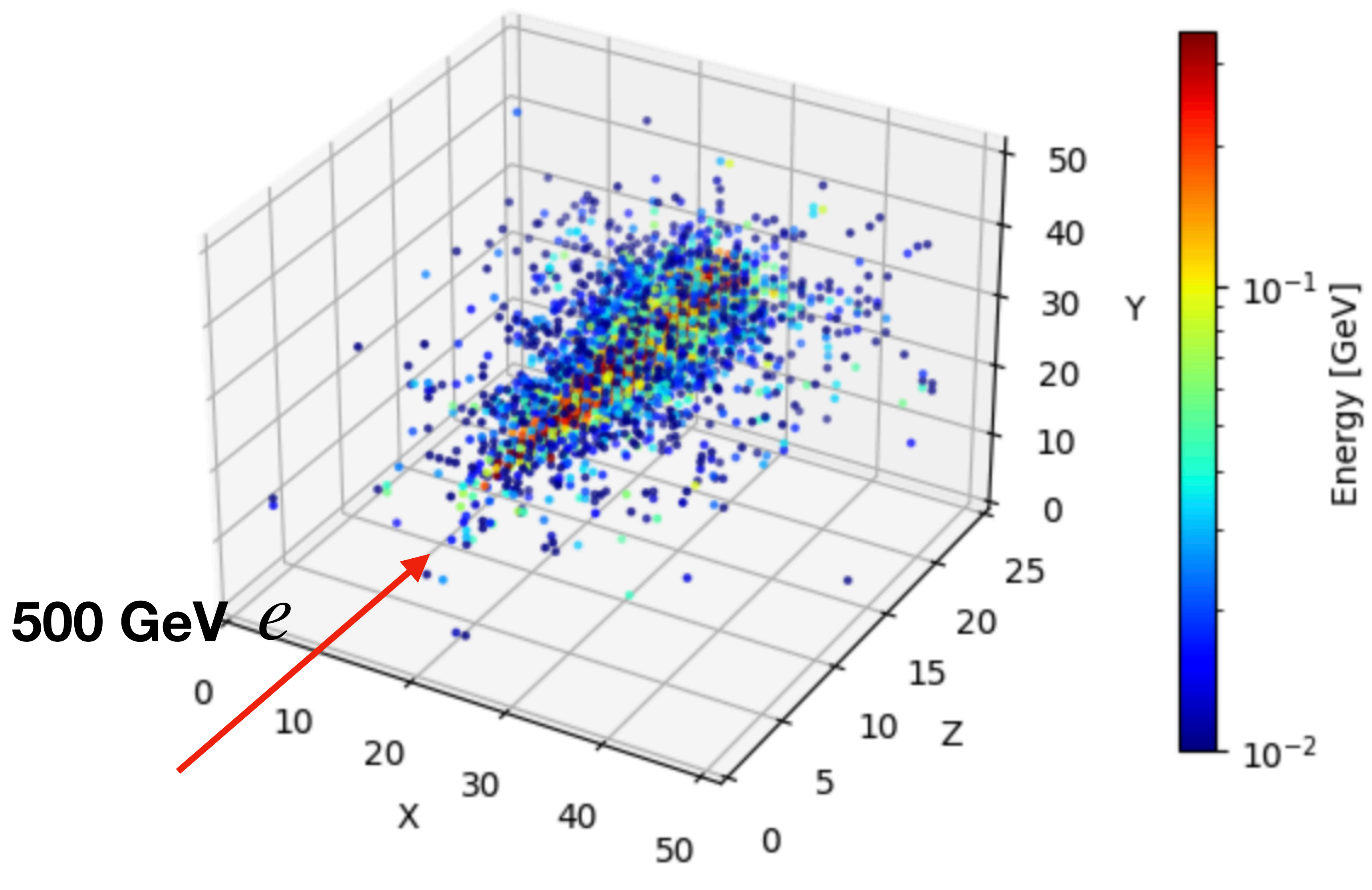


image source

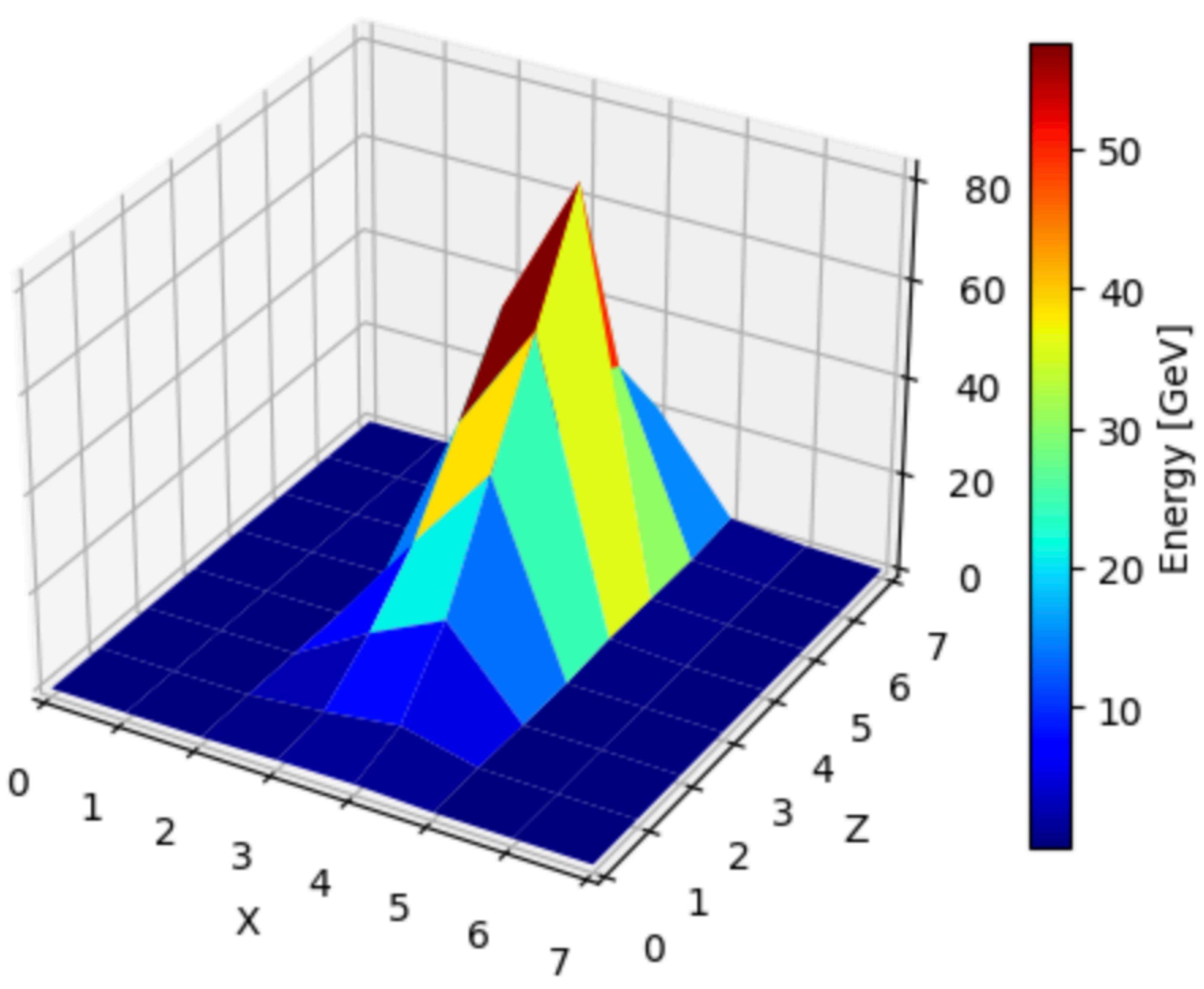
Research strategy

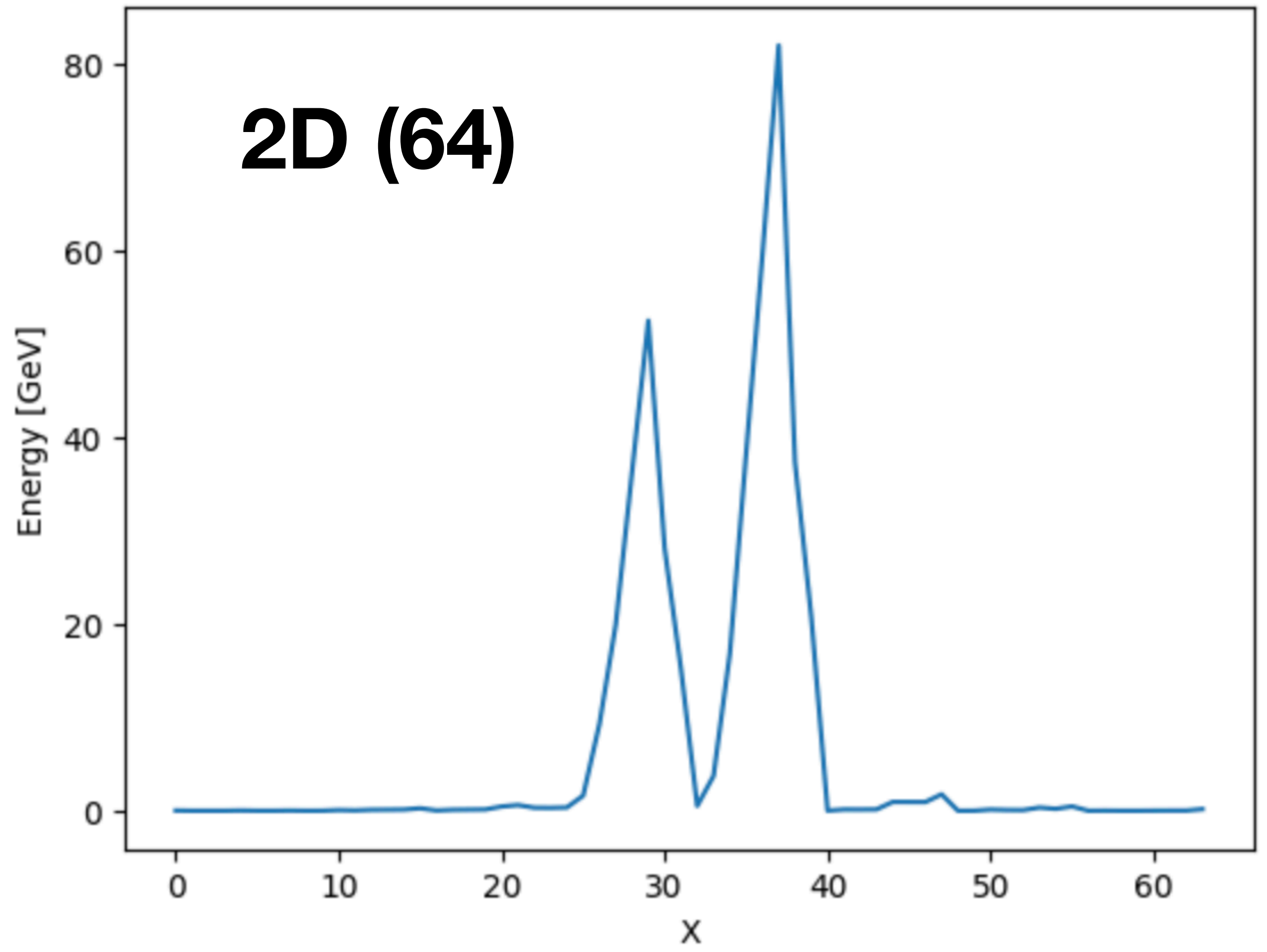
- Open data of CLIC detector（Hideki: collaborate with DESY）
  - 3D : 51 x 51 x 25 （65000 pixels）
  - downsampling (1D → 2D → 3D）
  - Ideal simulator→ noisy simulator → quantum computing cloud （梁福田老师的报告）

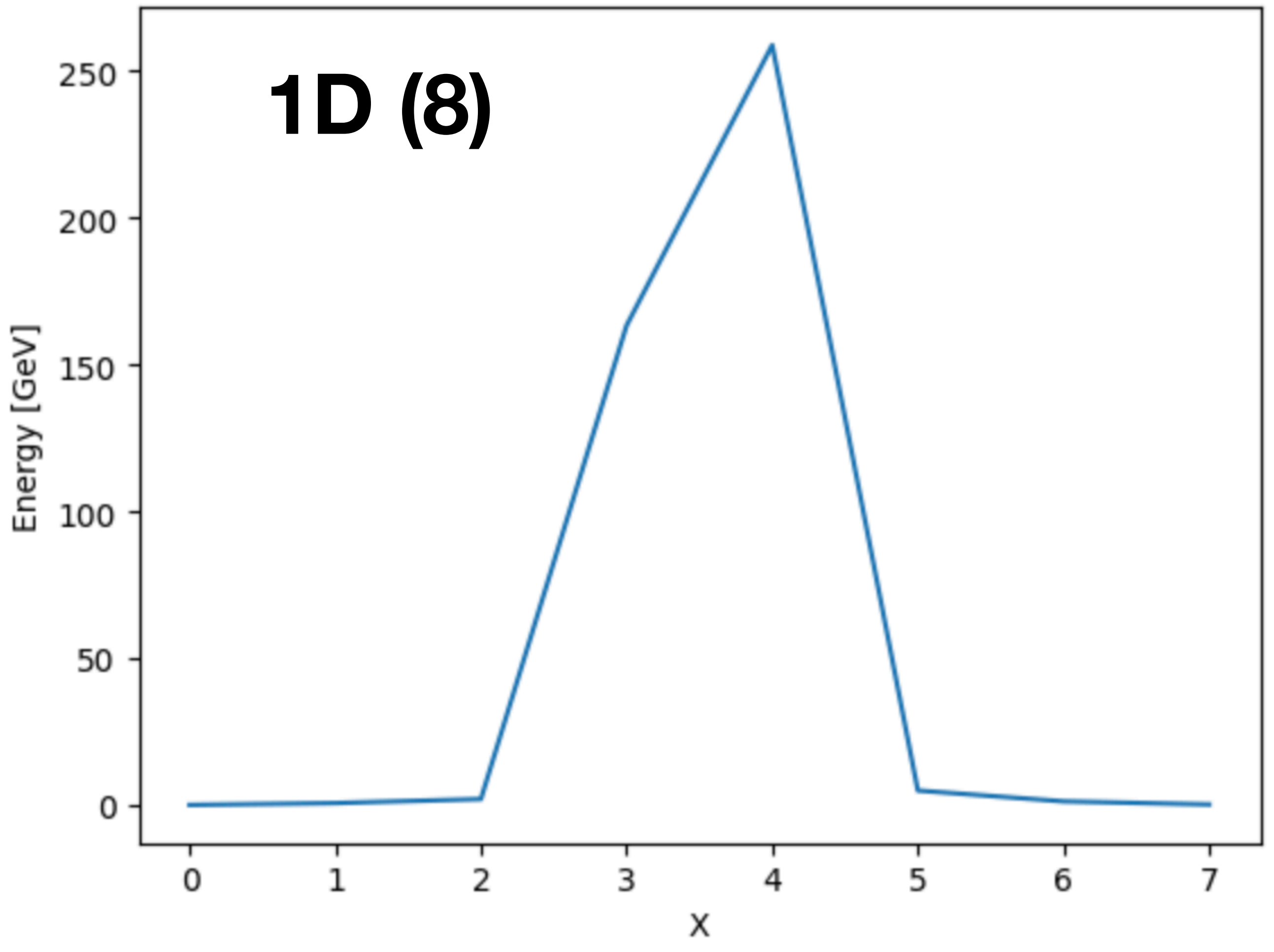
3D



2D (8x8)

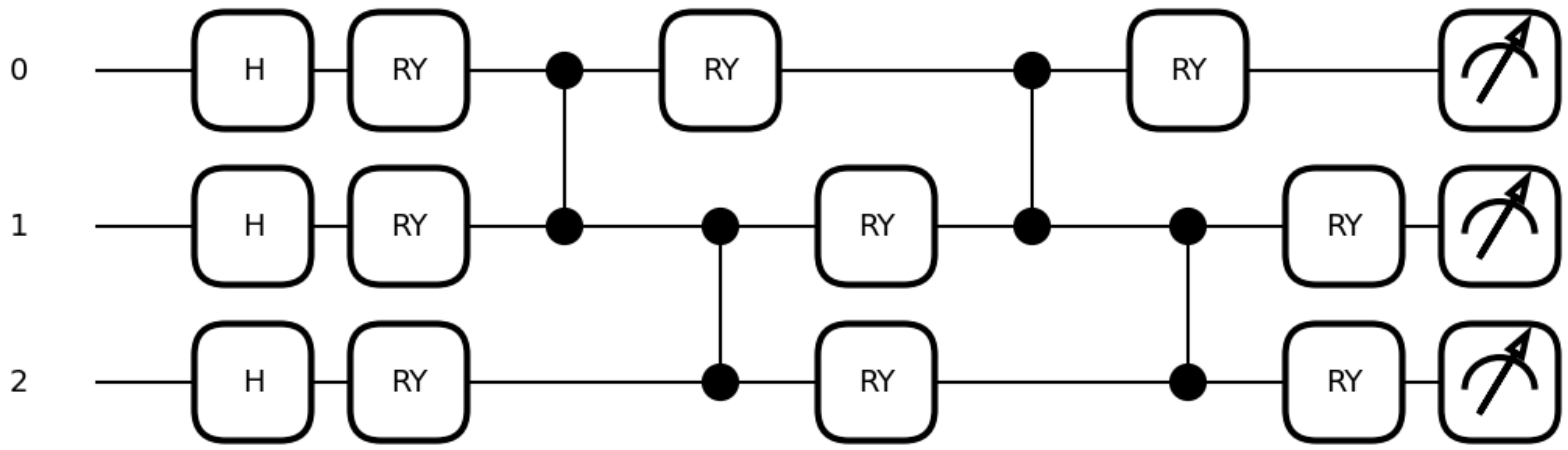


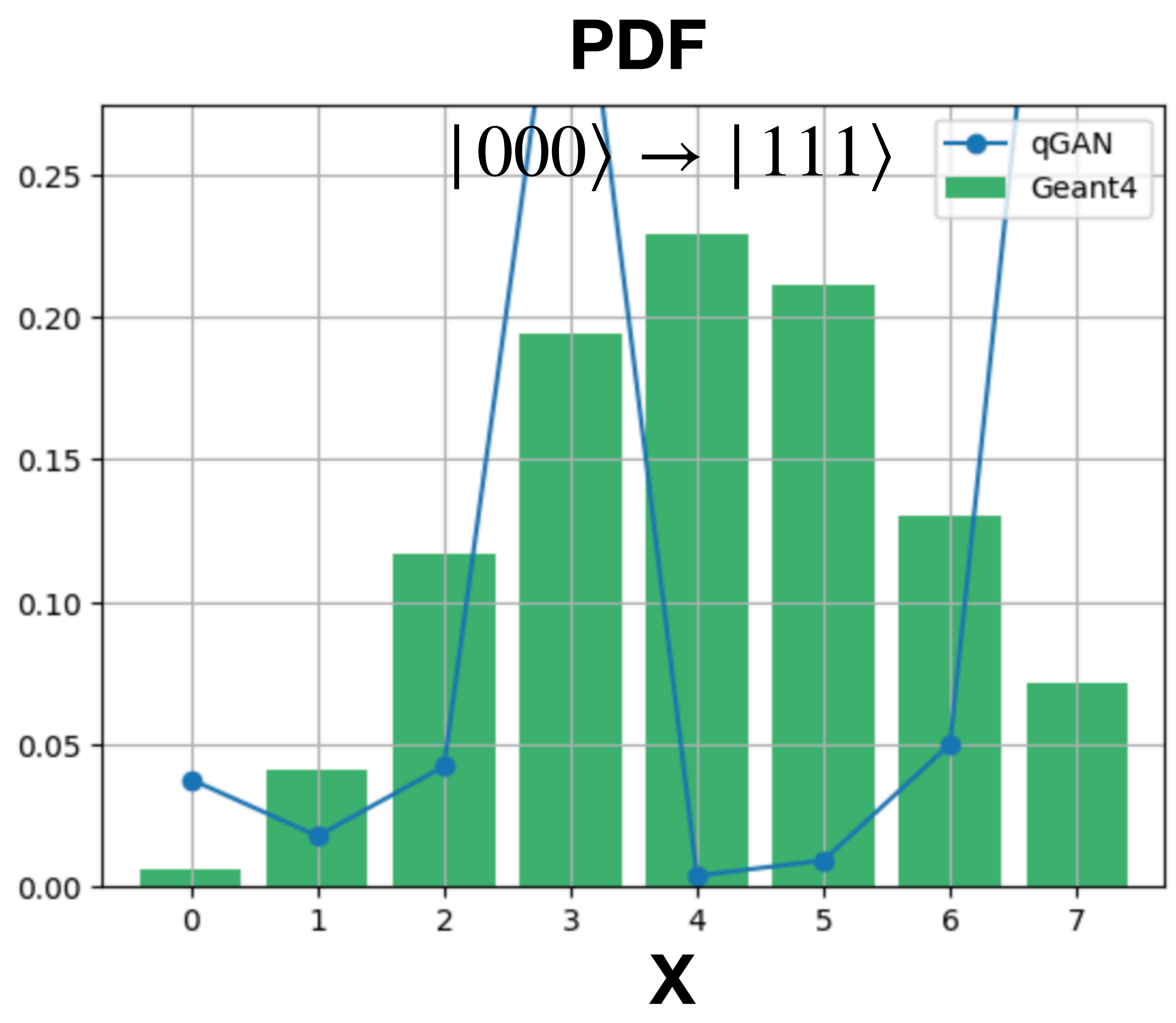




1D quantum generator model

- Generator model consists of H, RY, and CZ
  - H： $|0\rangle \rightarrow |0\rangle$ and $|1\rangle$
  - RY： trainable parameters
  - CZ： entanglement
- Frequency of the 8 states -> energy deposition of the 8 pixels
  - one of the eight states each shot: $|000\rangle, |001\rangle, |010\rangle, |011\rangle, |100\rangle, |101\rangle, |110\rangle, |111\rangle$
  - obtain the frequency of the 8 states with multiple shots





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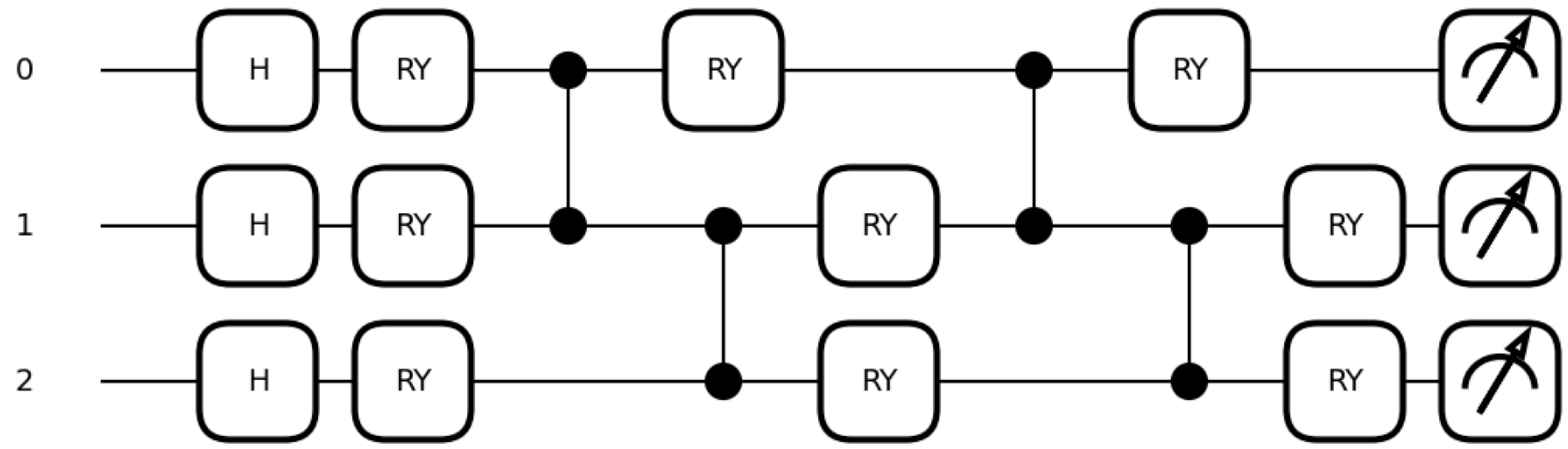
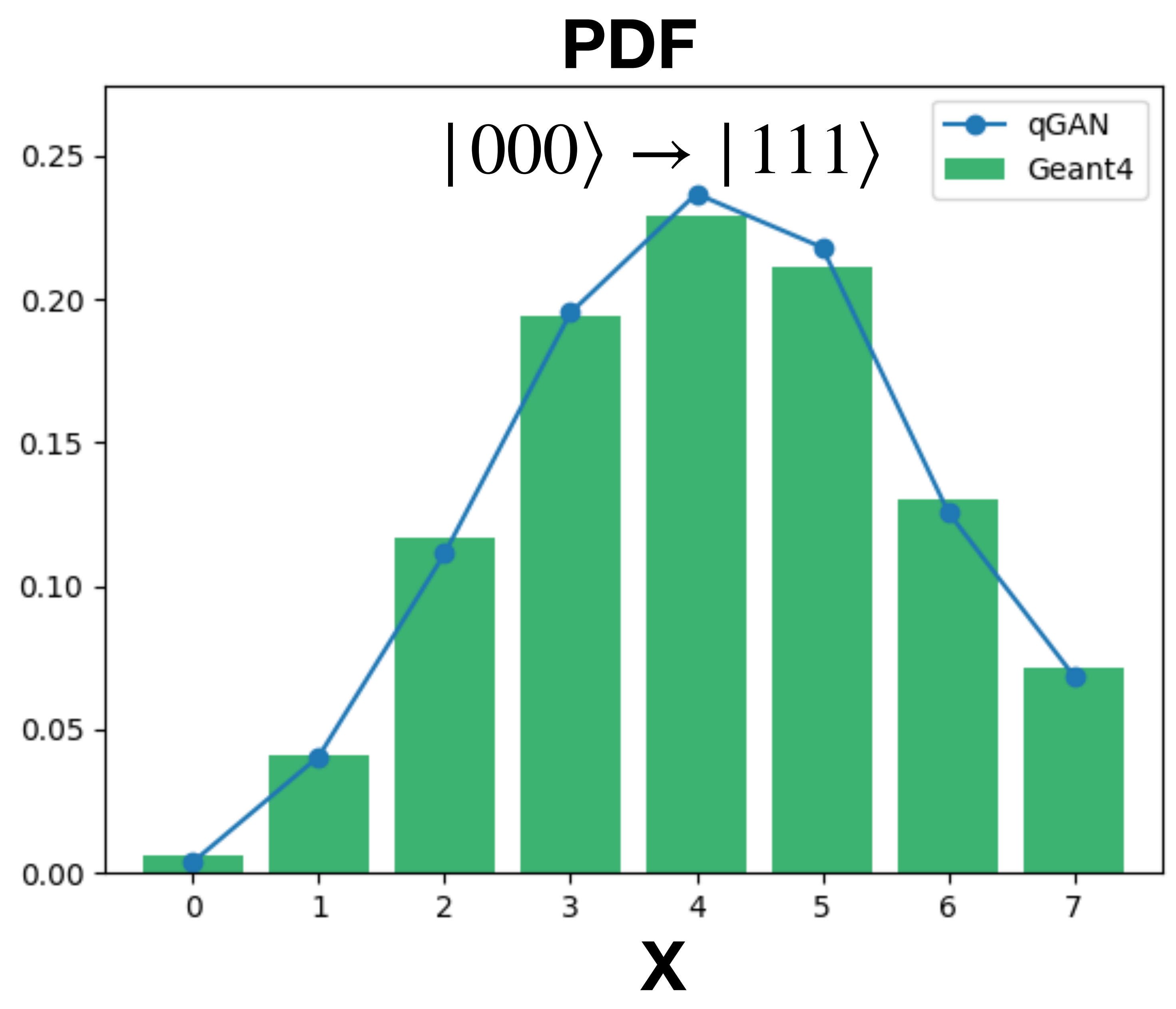
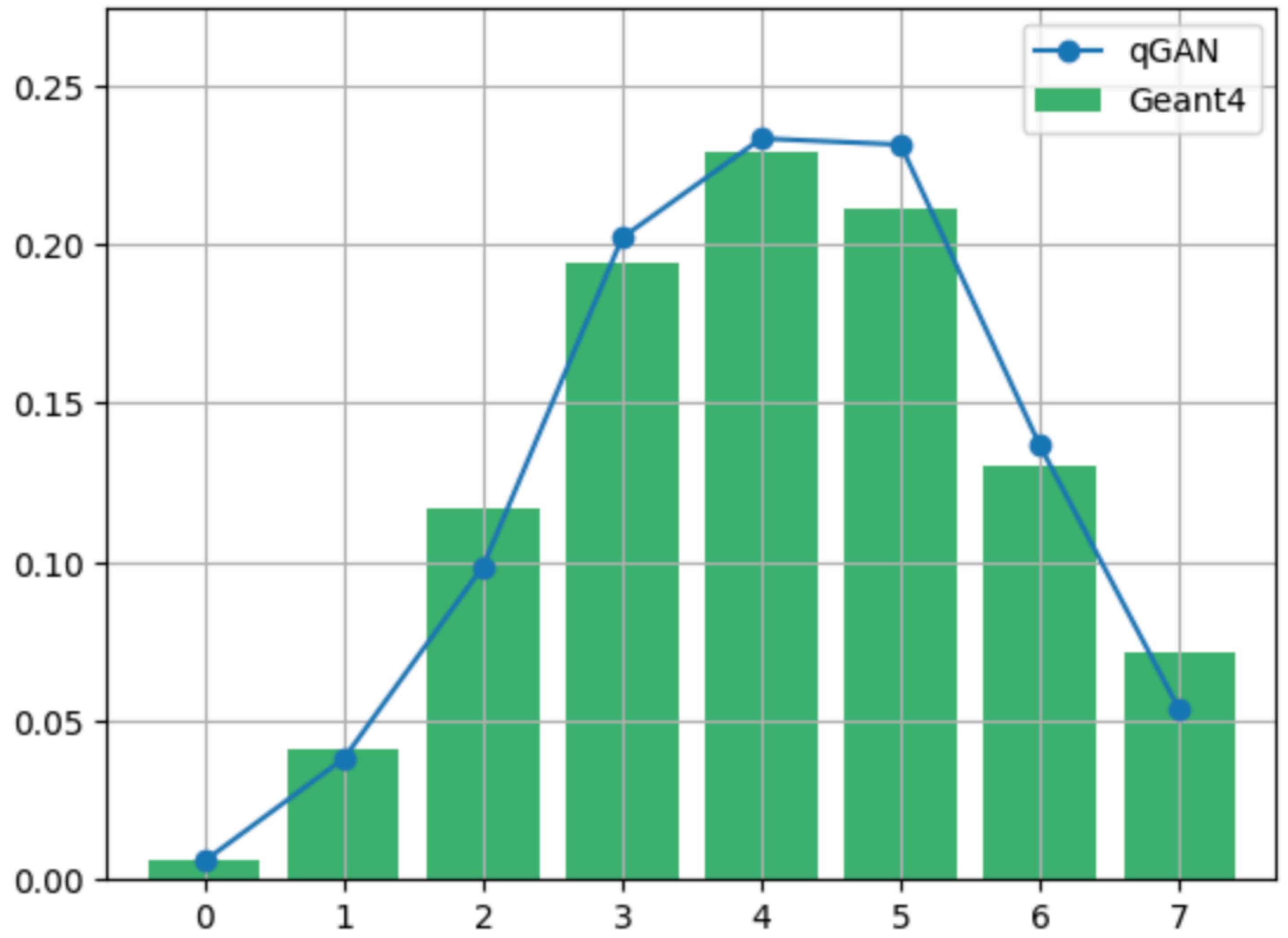
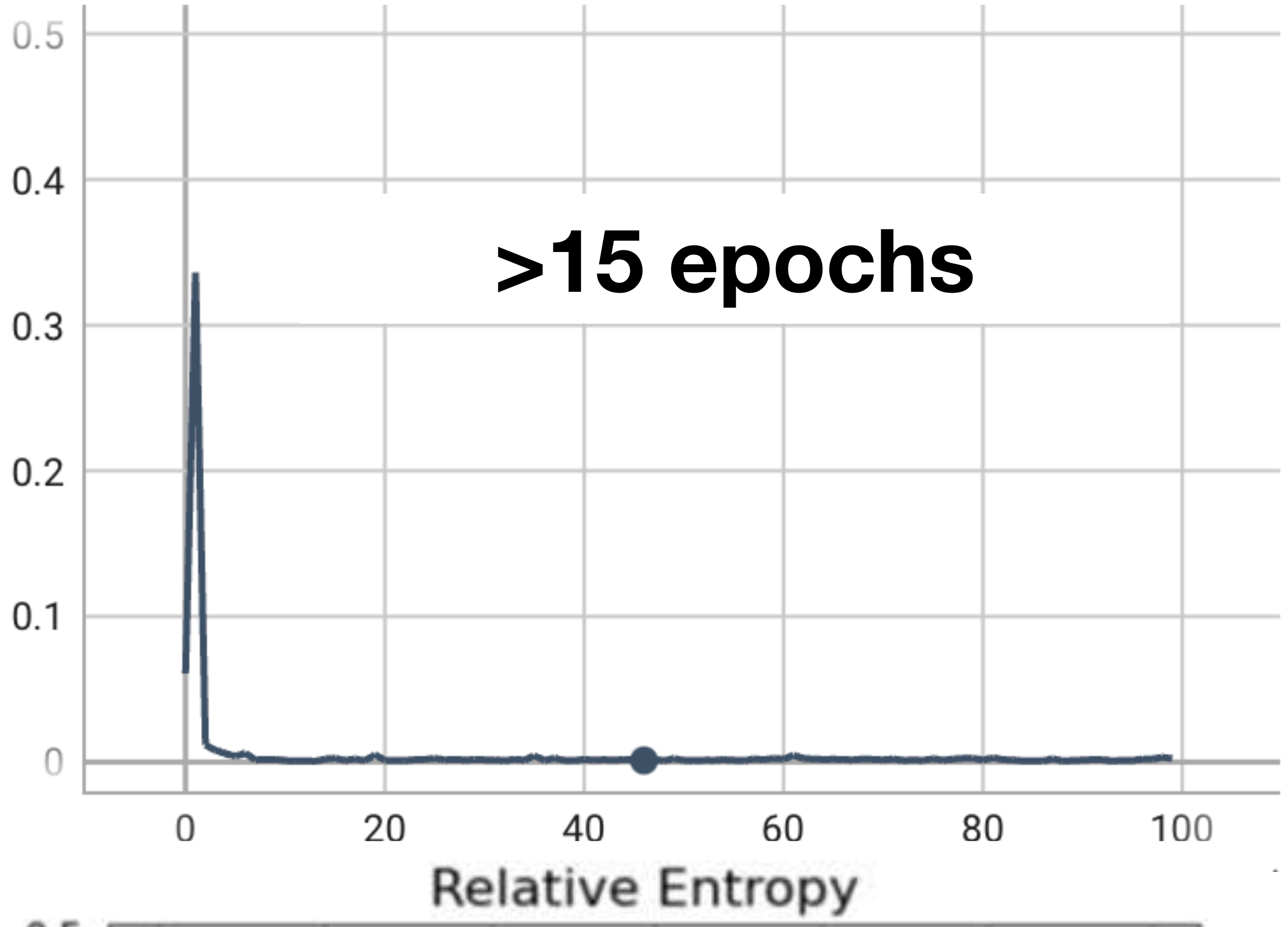




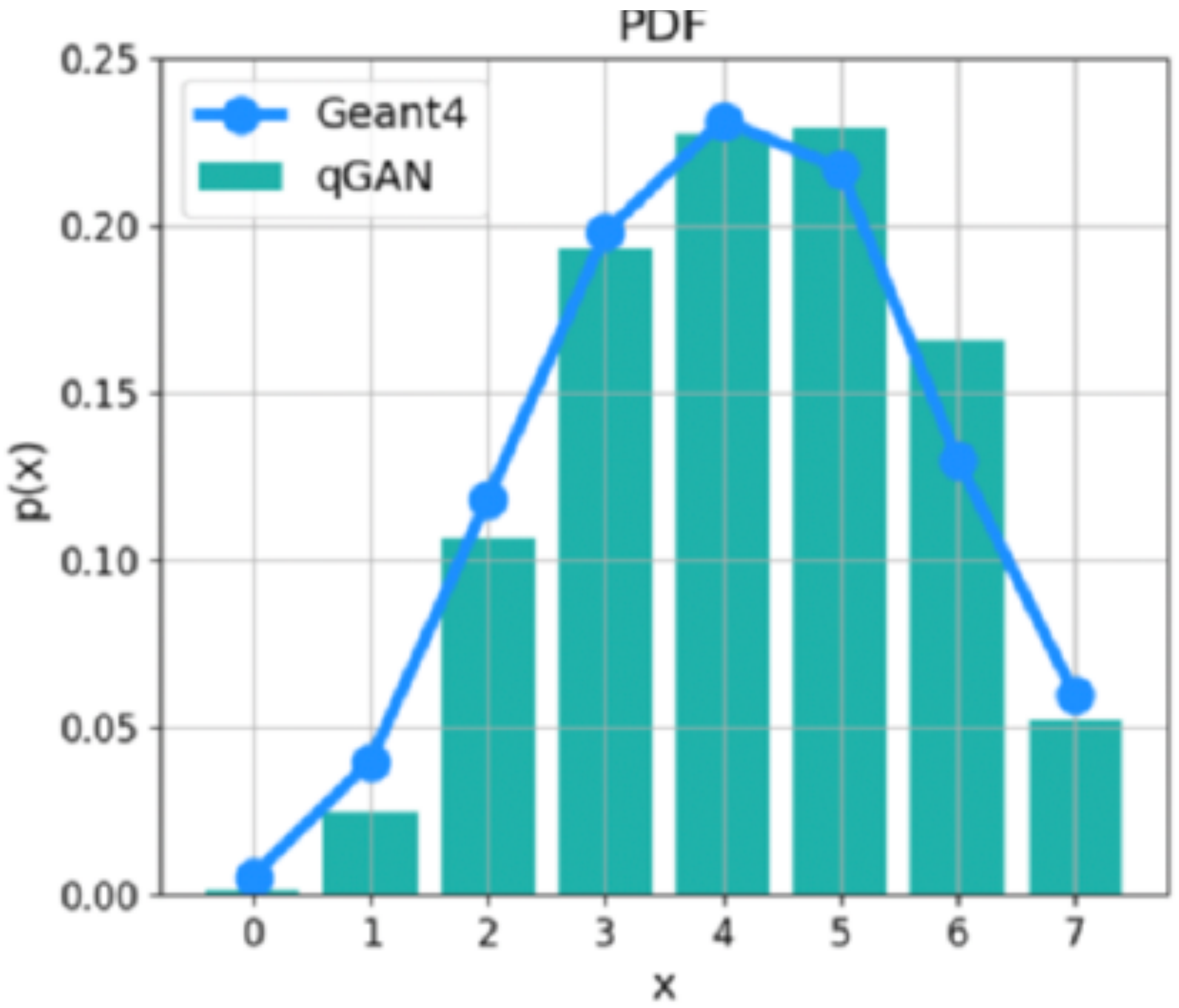
1D performance（ideal simulator）

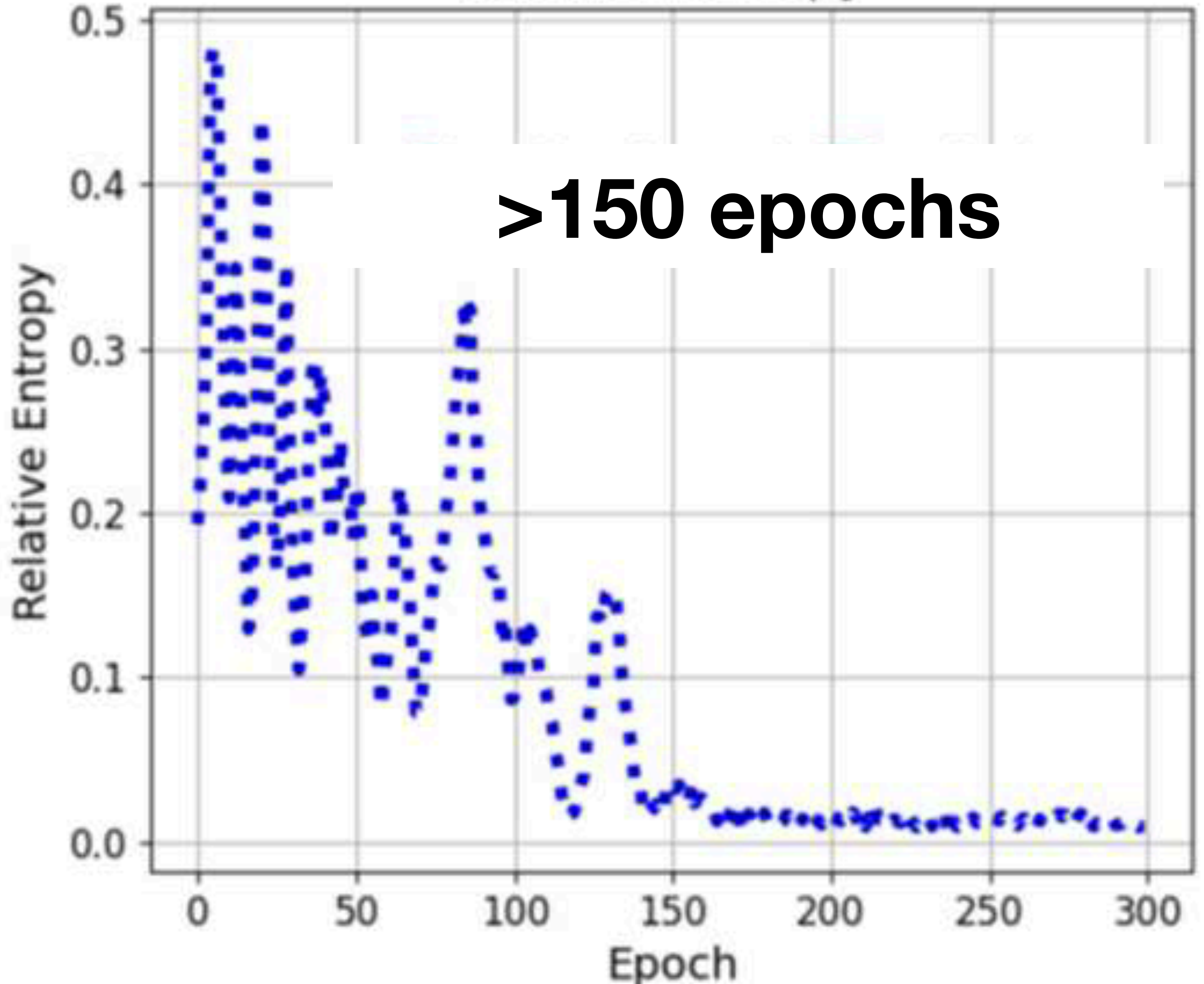
IHEP





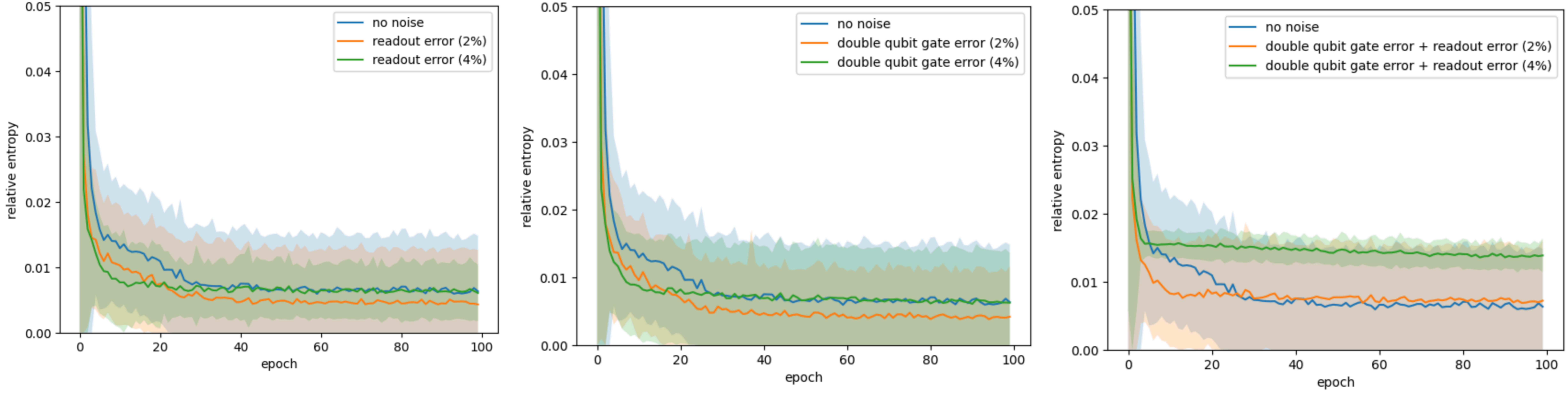
CERN & DESY





1D: Impact of the noise on the training

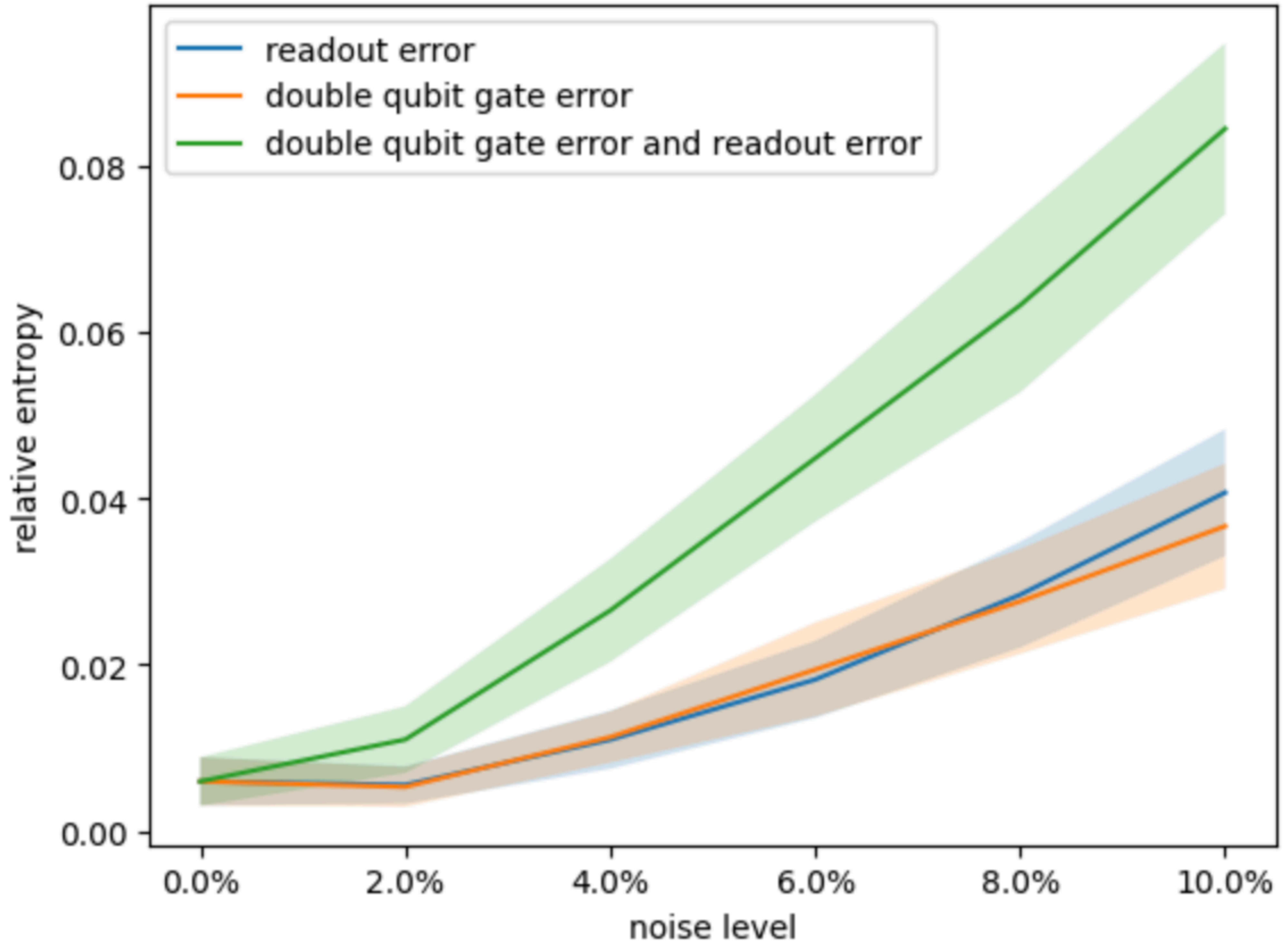
- Simplified noise model: consider the double qubit gate error and readout error
  - same noise level for all qubits (hardware: noise level depends on the qubit)
  - symmetrical readout error (hardware: $|0\rangle$ fidelity differs from $|1\rangle$ fidelity)
  - noise level does not change (hardware: noise level changes)

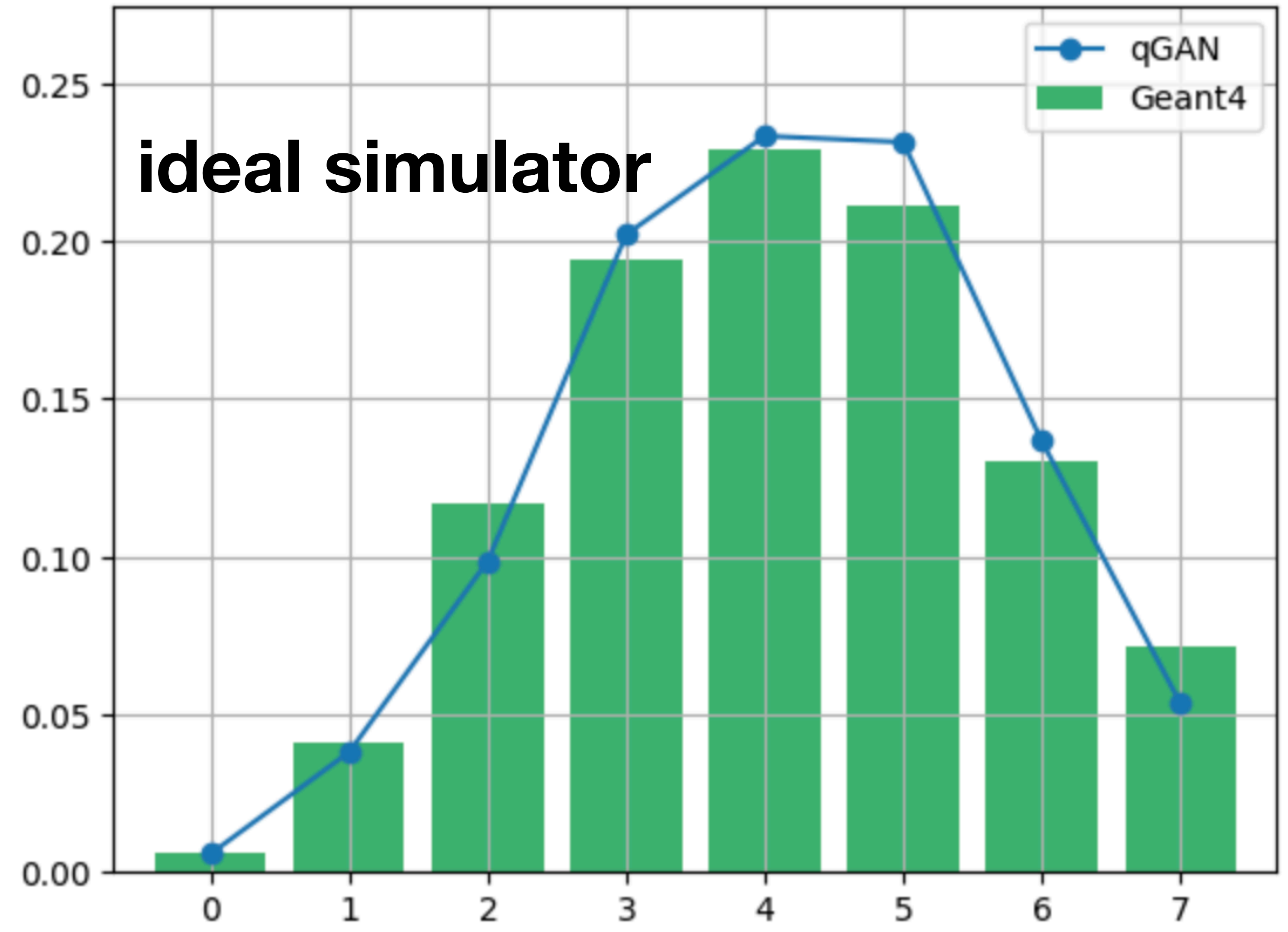


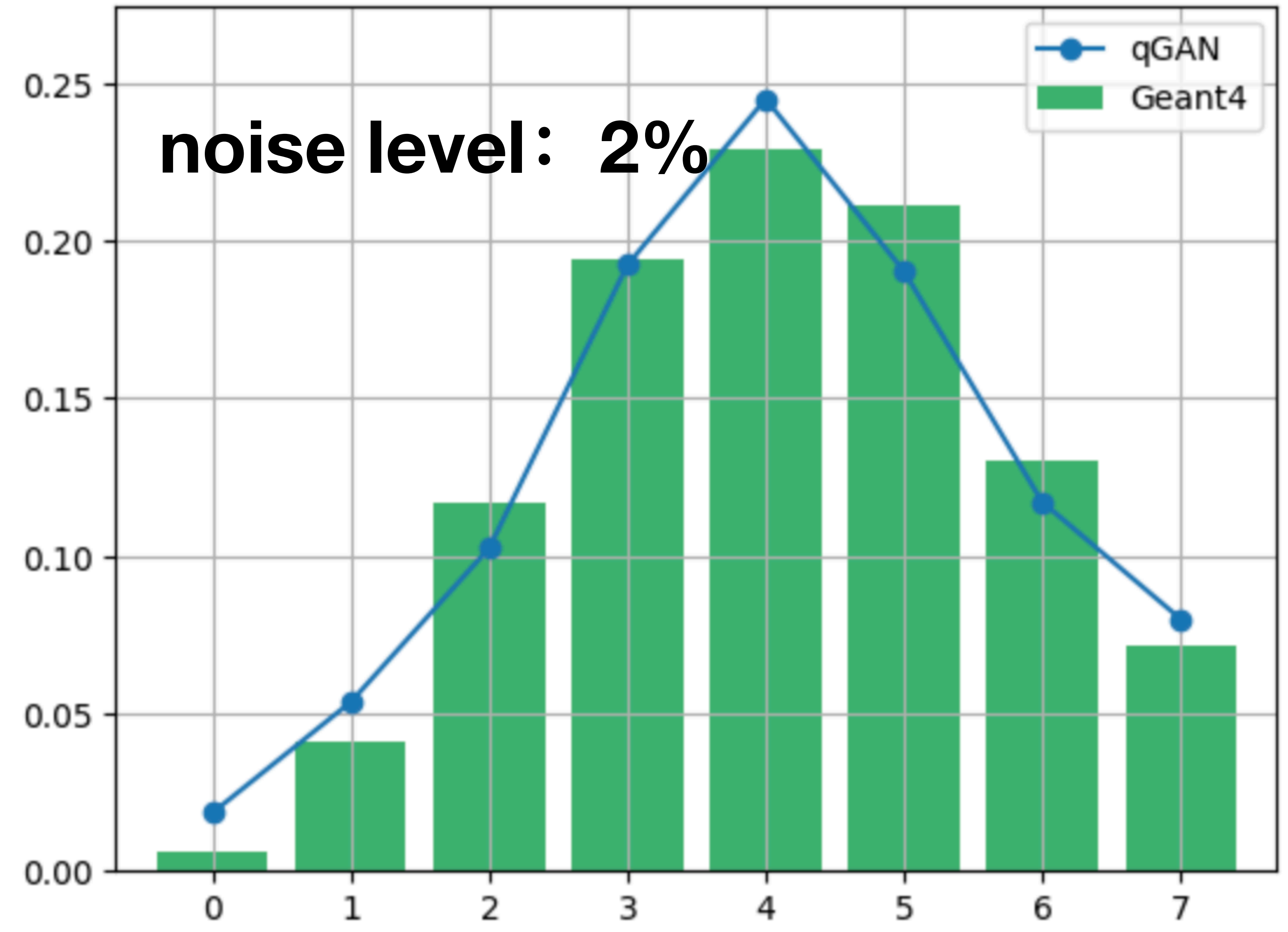
1D: Impact of the noise on the model inference

- 1D generator model is simple
  - impact of the double qubit gate error is comparable with the readout error
  - performance almost not affected with 2% noise level

parameters obtained by training on the ideal simulator

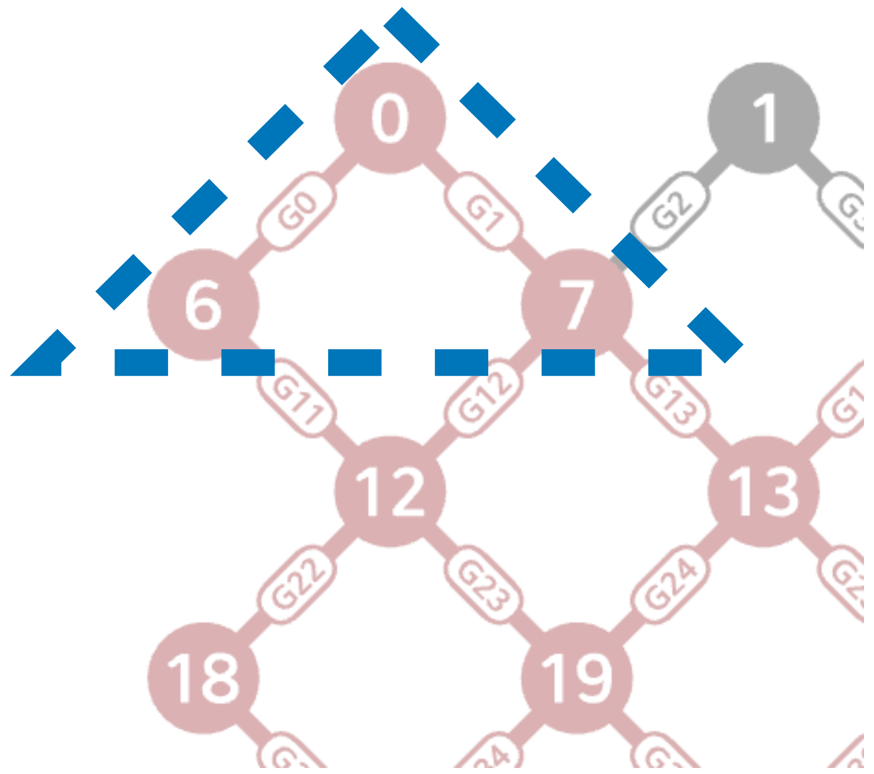




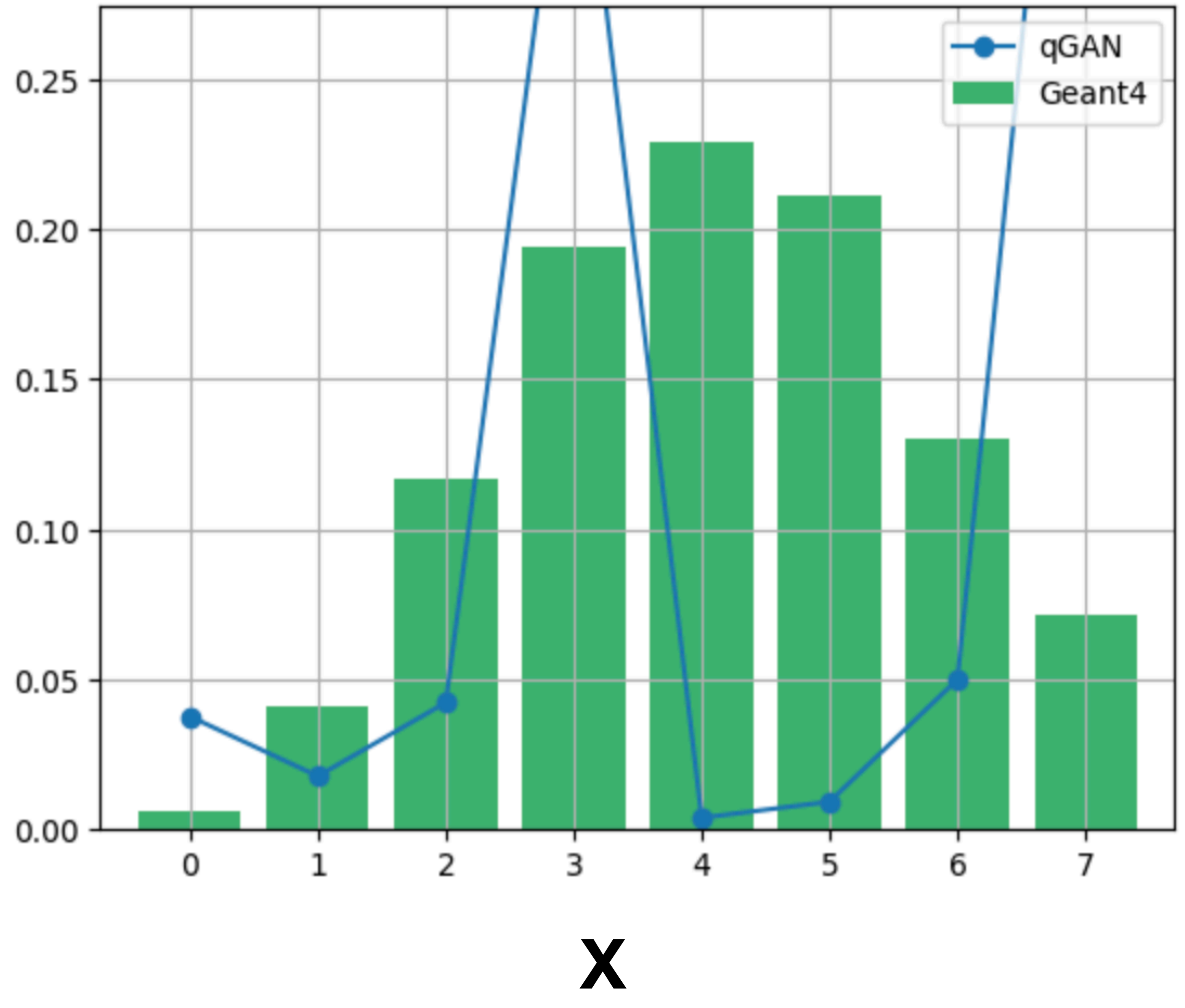


1D performance（quantum computing cloud）

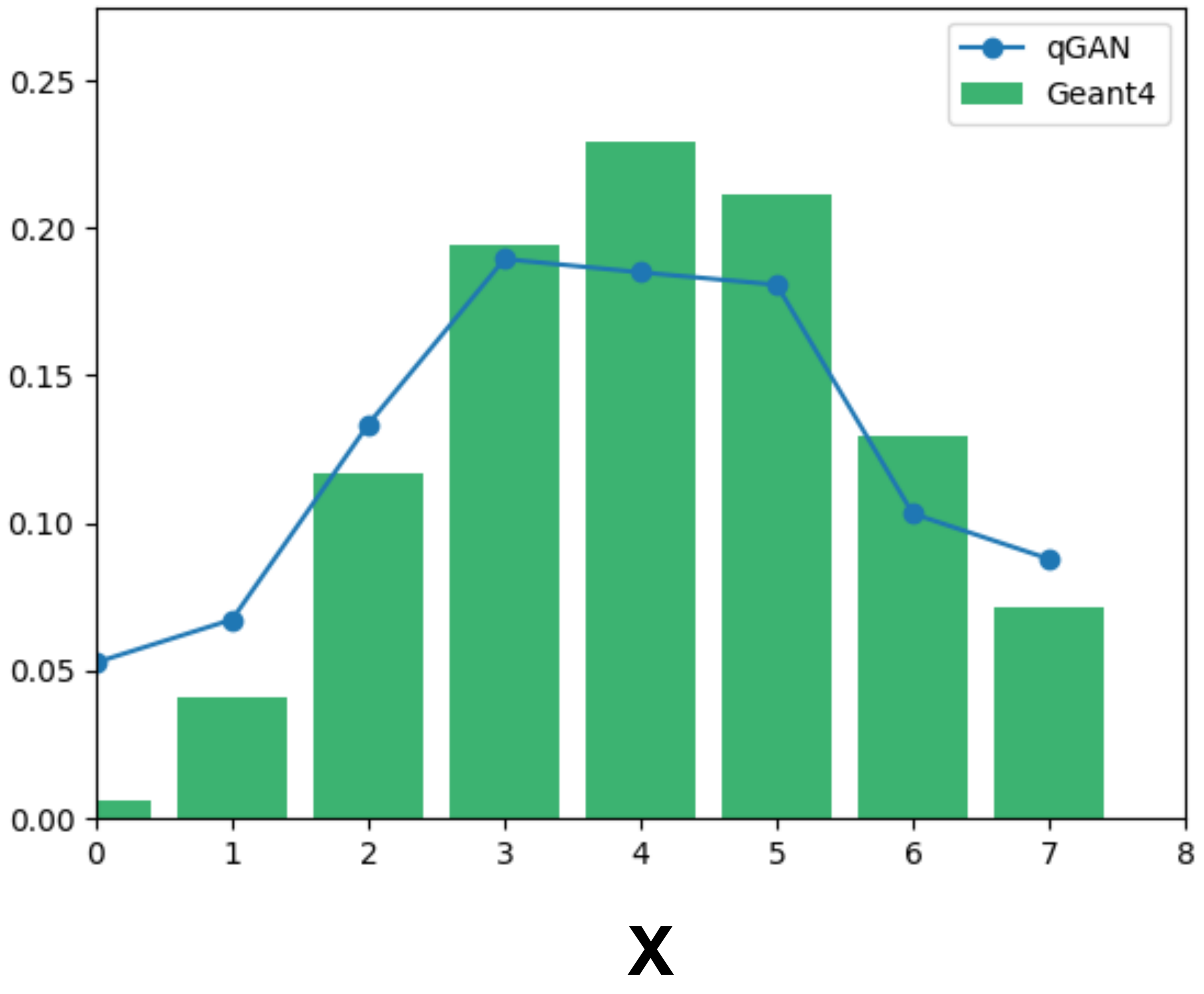
- Test the training procedure on the hardware
  - could basically generate the PDF after training of 1 epoch
  - training is time-consuming (1 day/epoch)
  - could use the parameters from the ideal simulator



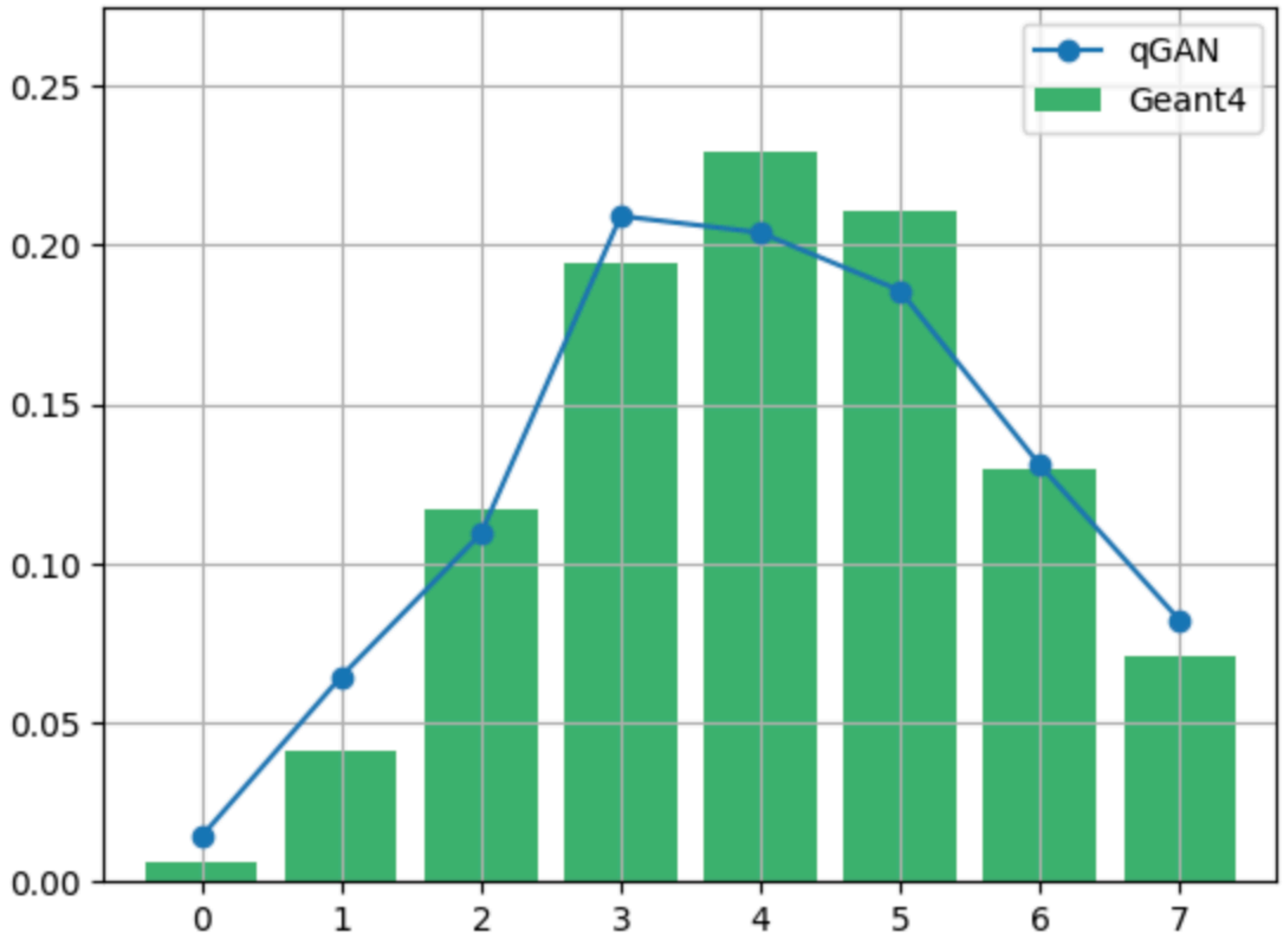
starting point



after 1 epoch training on the hardware

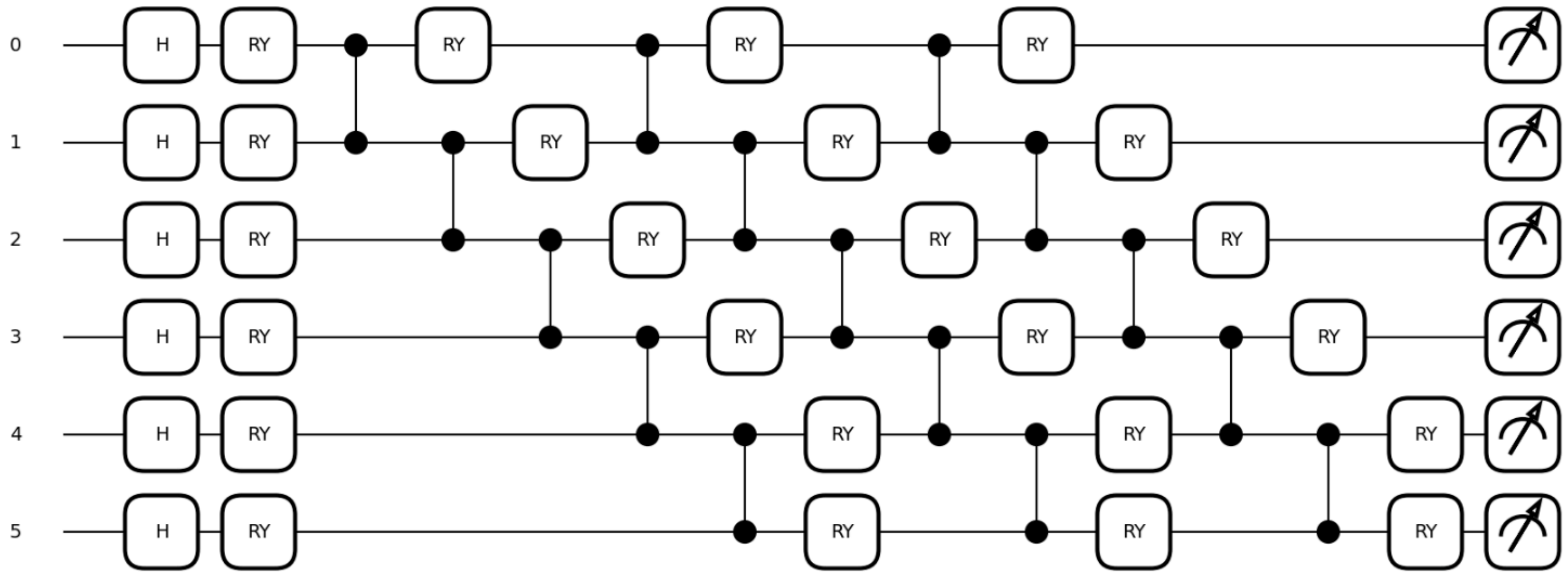


use the parameters from ideal simulator



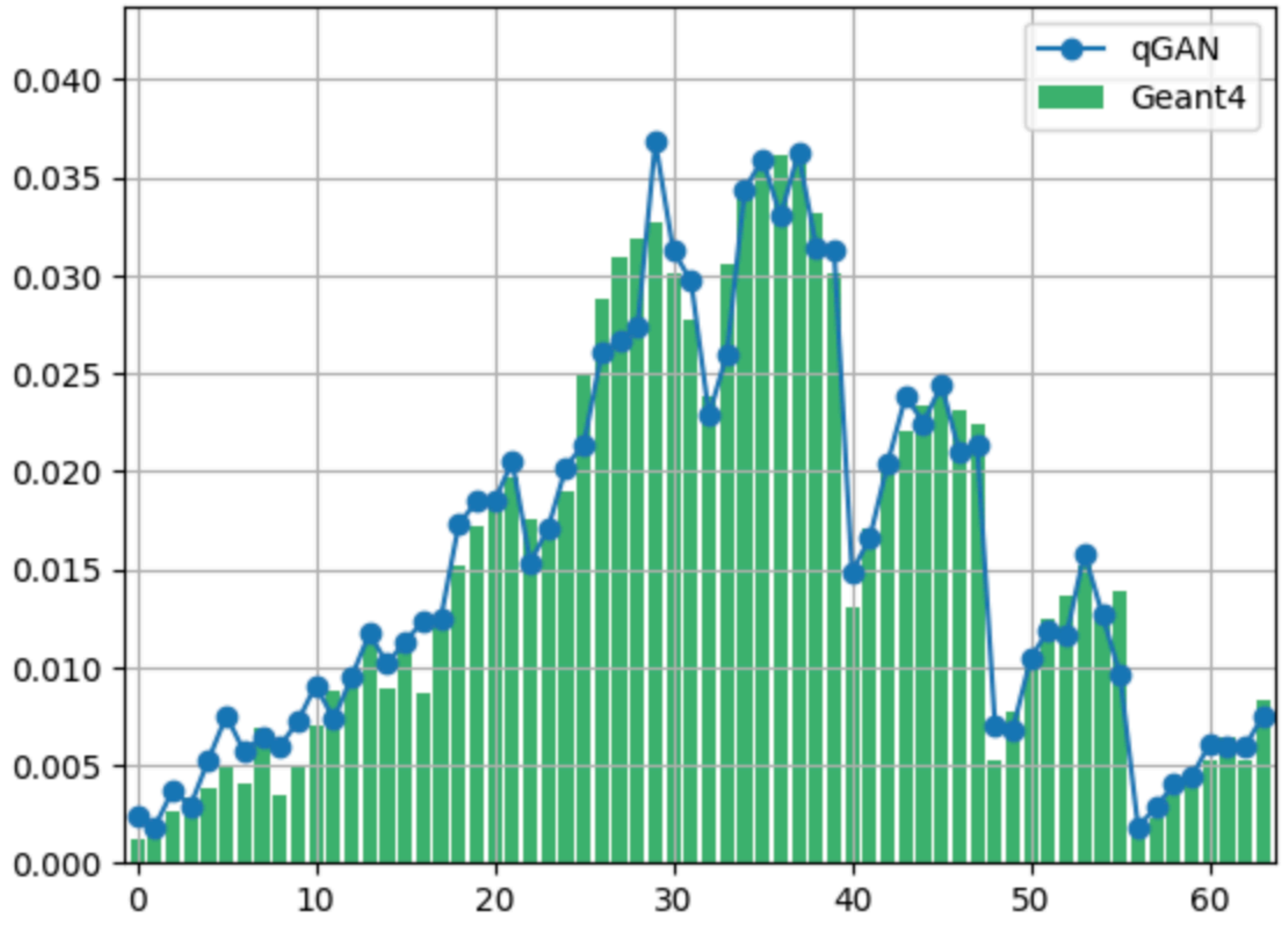
2D quantum generator model

- 2D model is similar to the 1D case
  - 3 qubits（8 pixels） → 6 qubits（64 pixels）
  - 2 layers of RY + CZ → 3 layers of RY + CZ

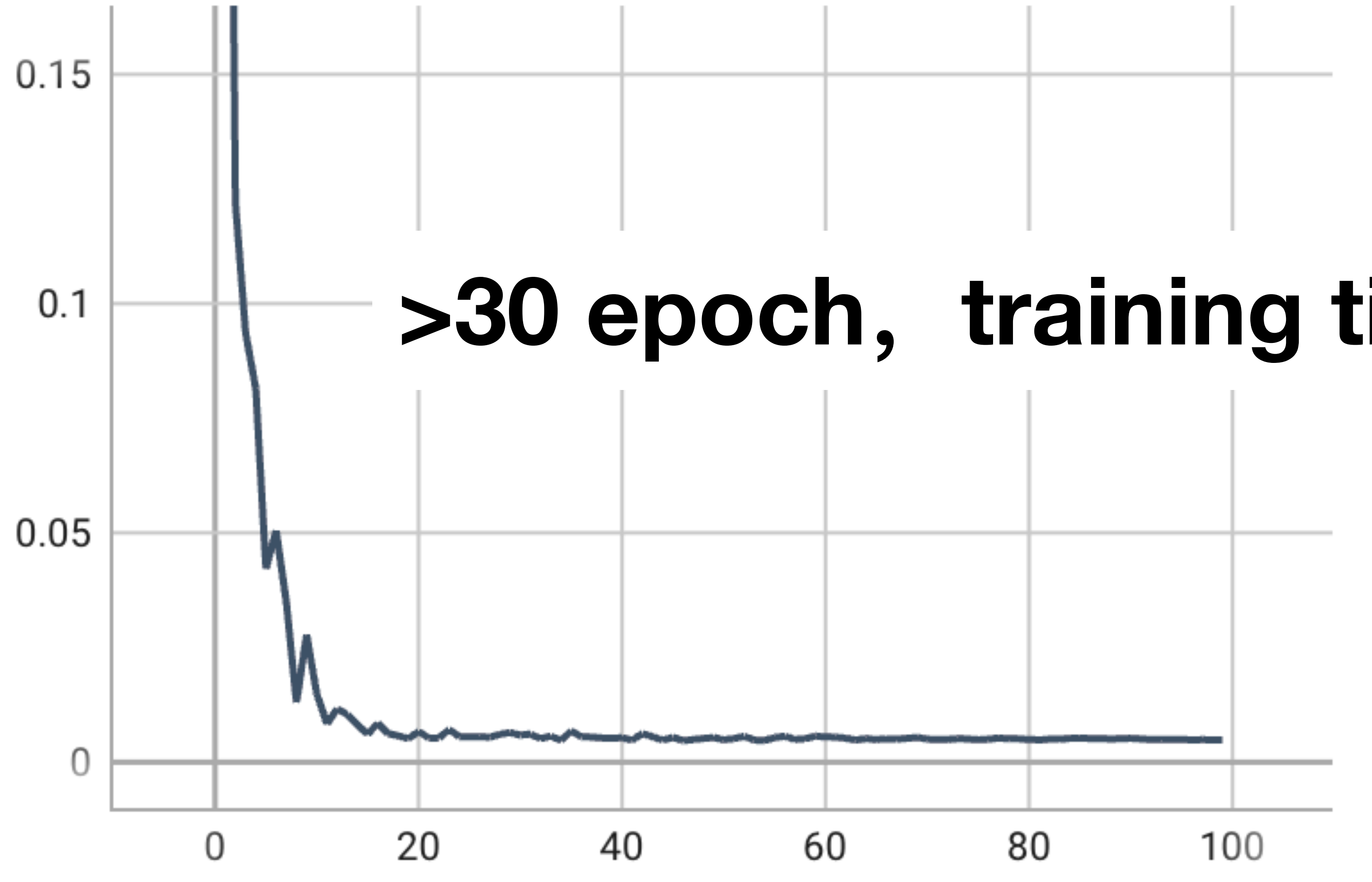


2D performance（ideal simulator）

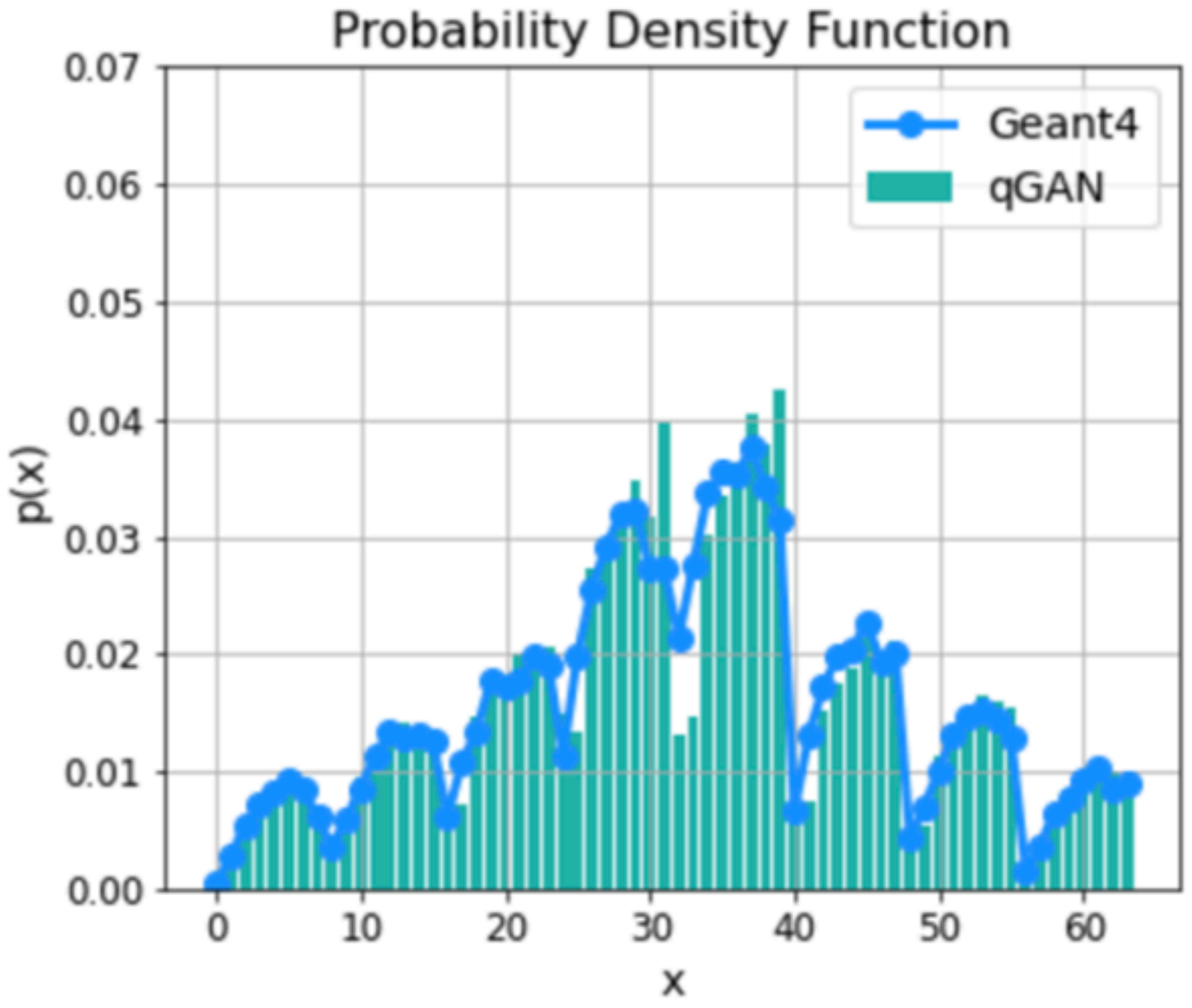
IHEP



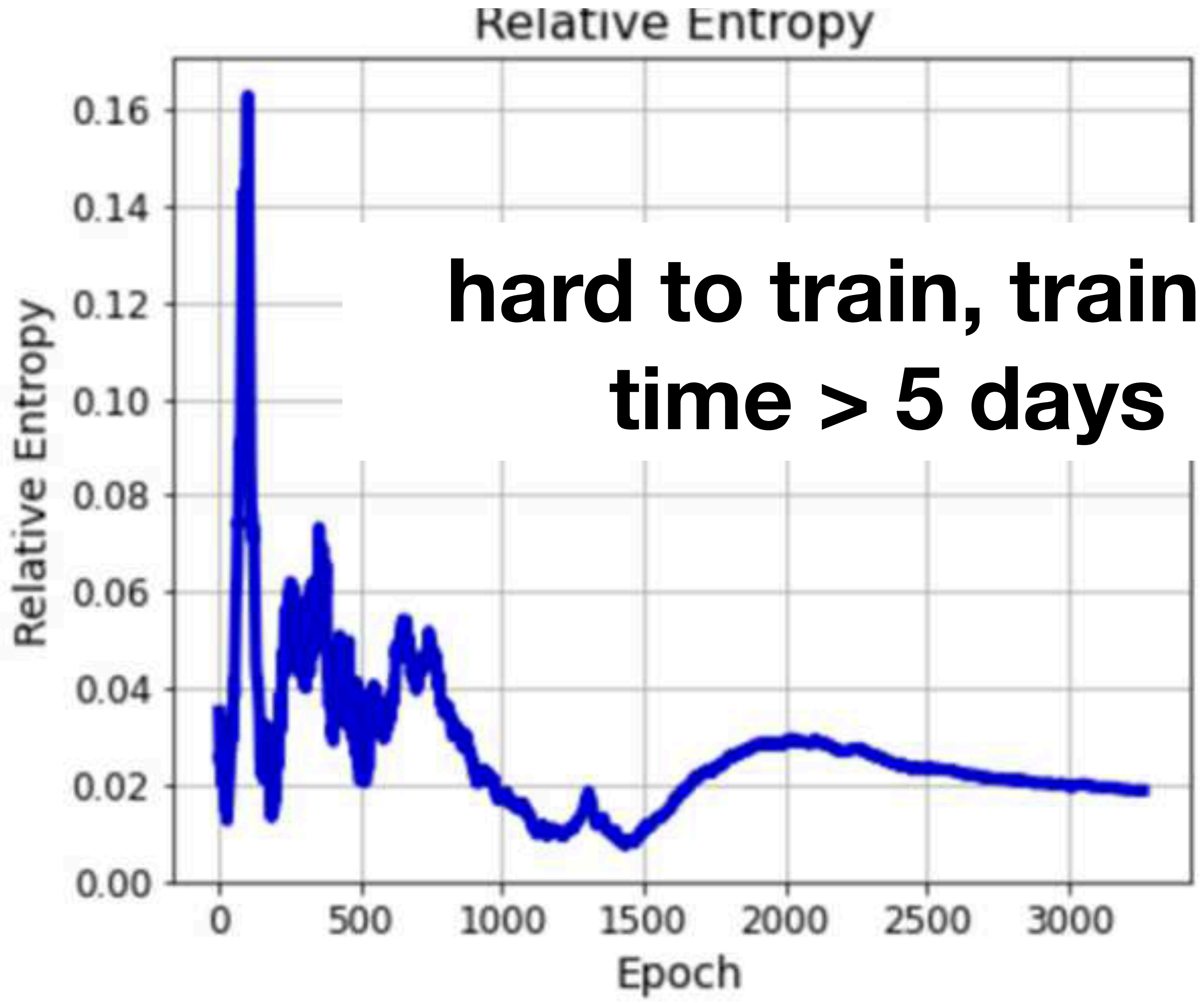
>30 epoch，training time<2h



CERN & DESY



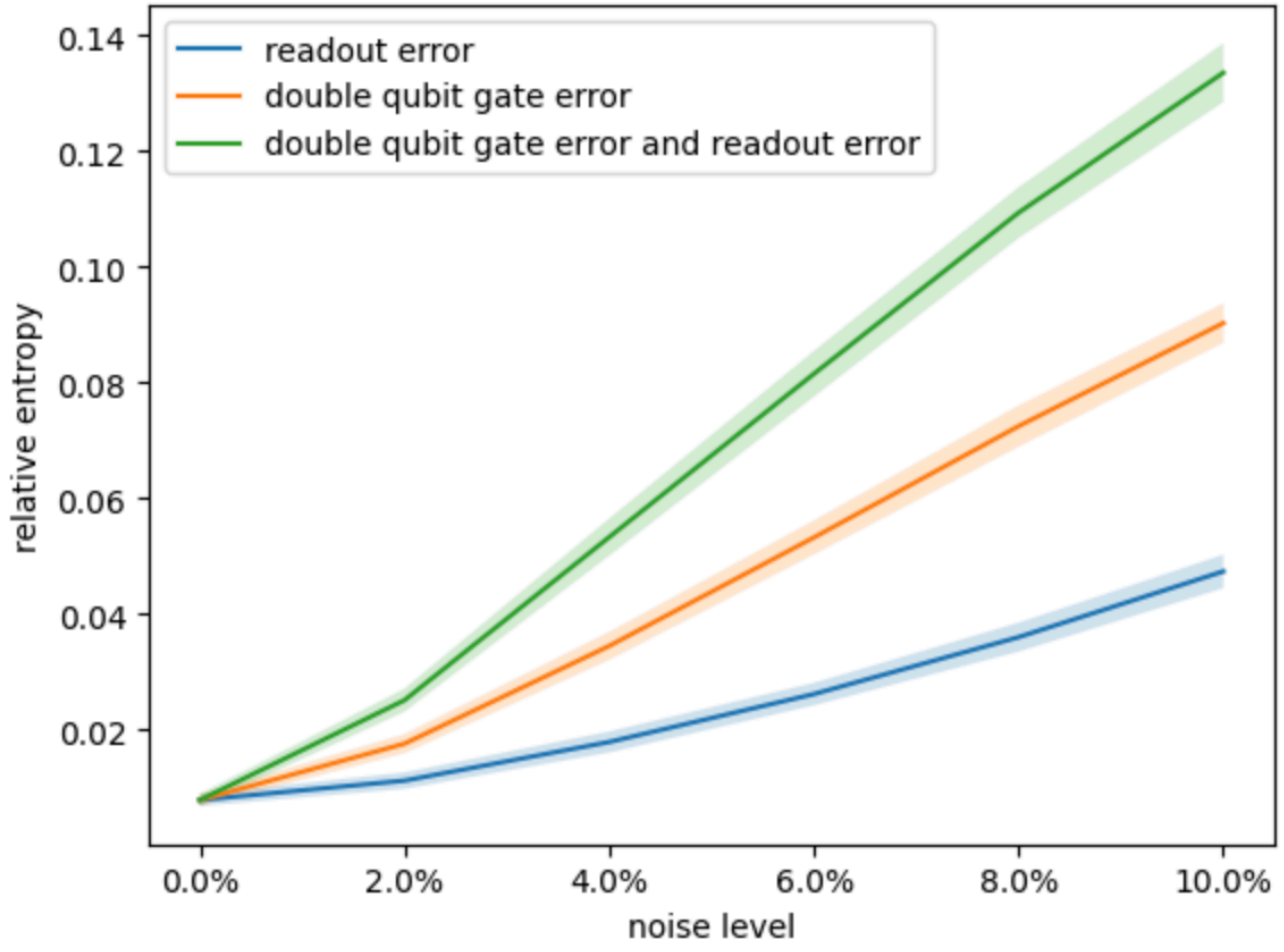
hard to train, training time > 5 days

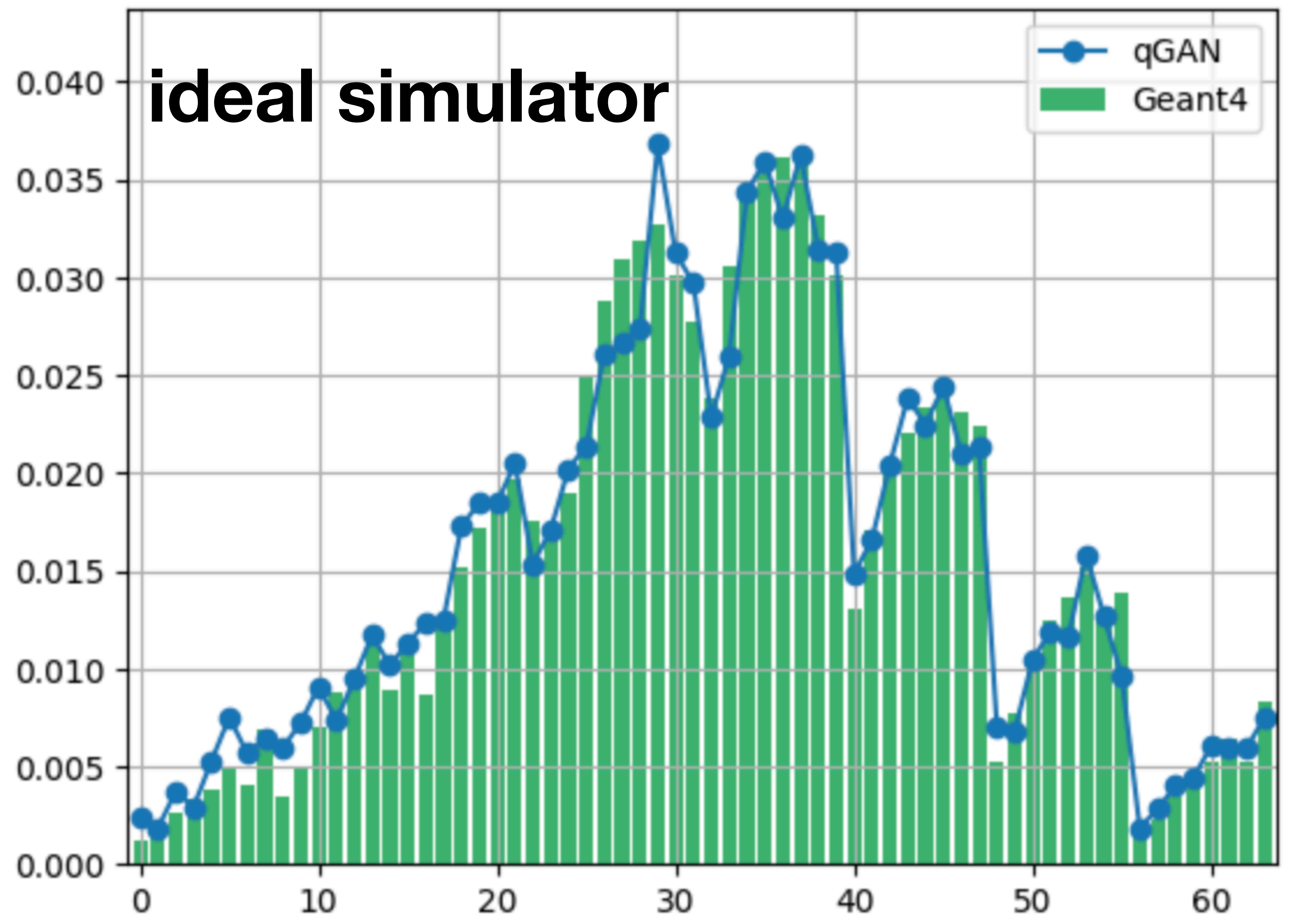


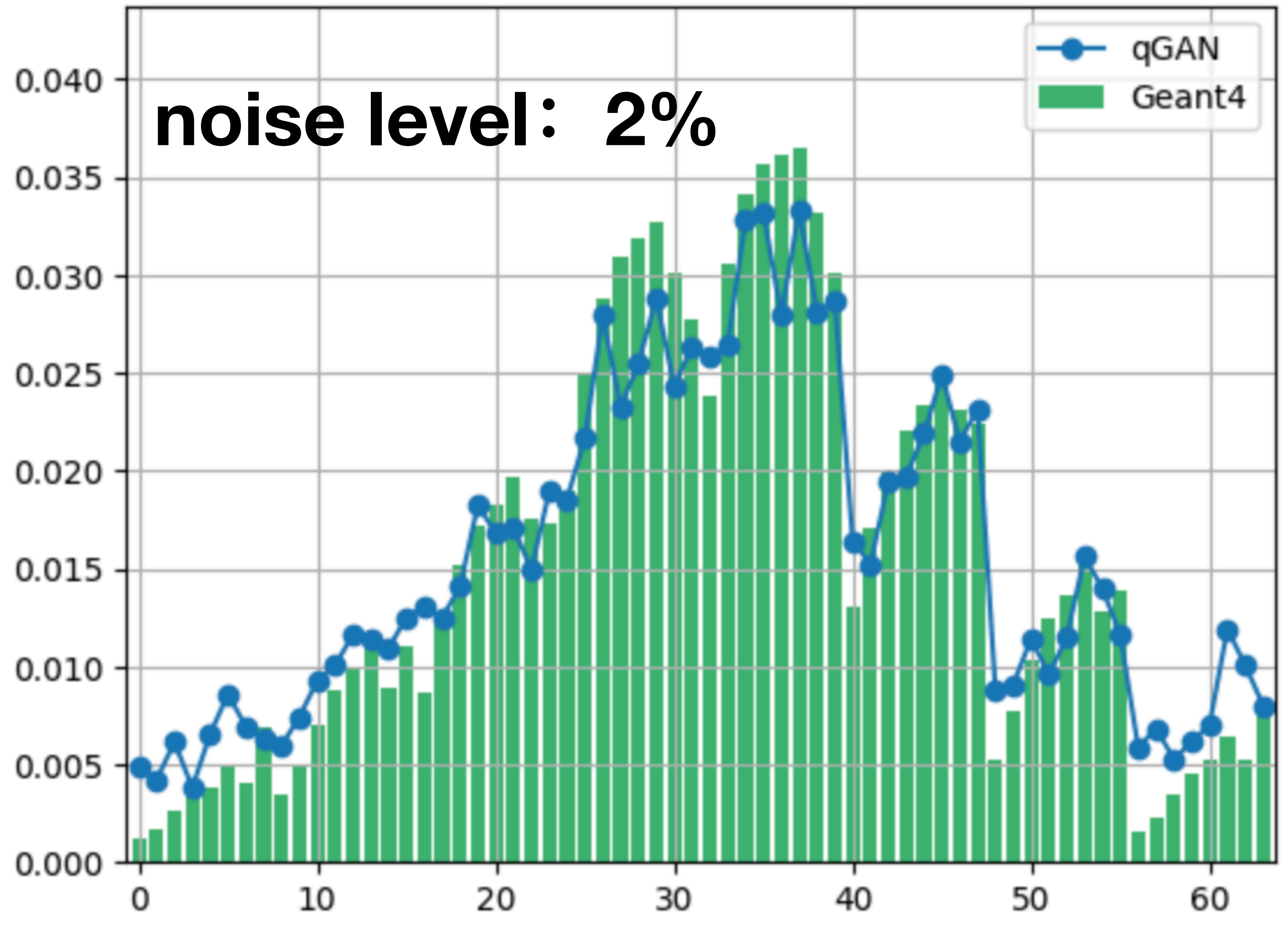
2D: Impact of the noise on the model inference

- 2D model is more complicated
  - impact of double qubit gate error is large
  - visible performance decrease with a 2% noise level

parameters obtained by training on the ideal simulator

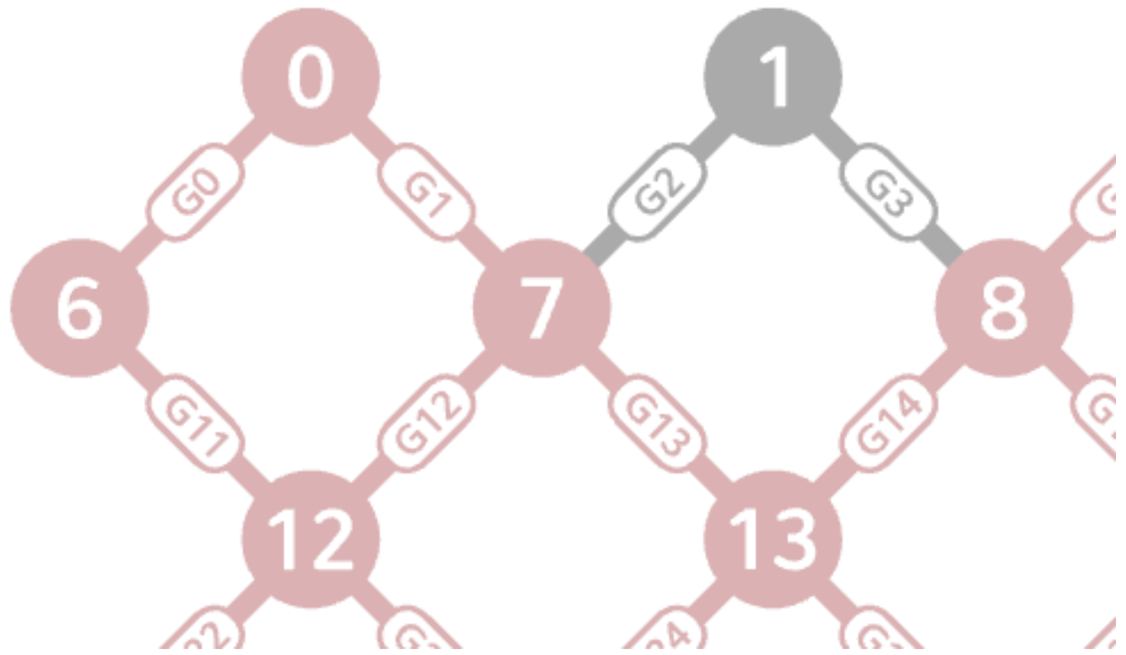


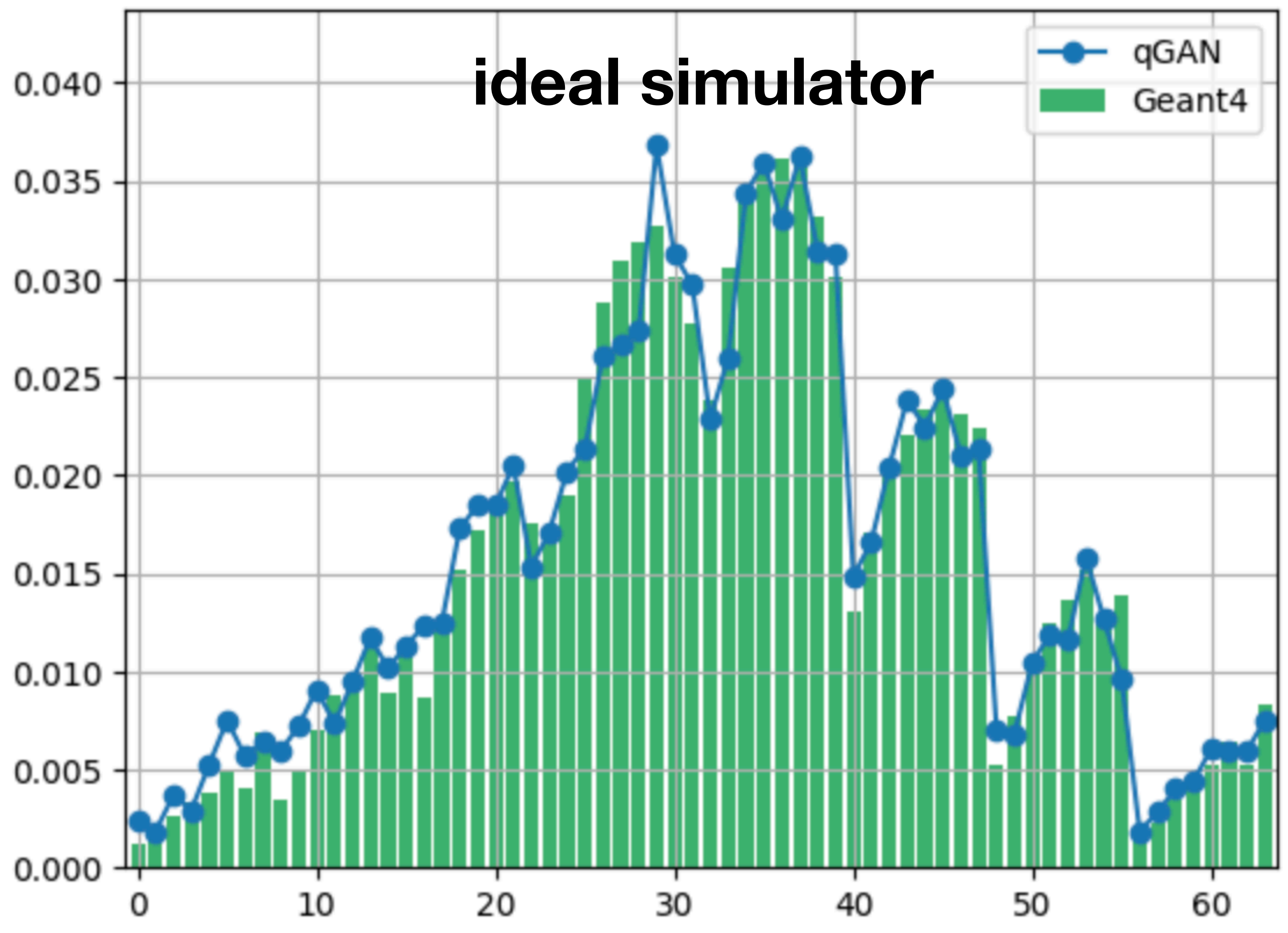


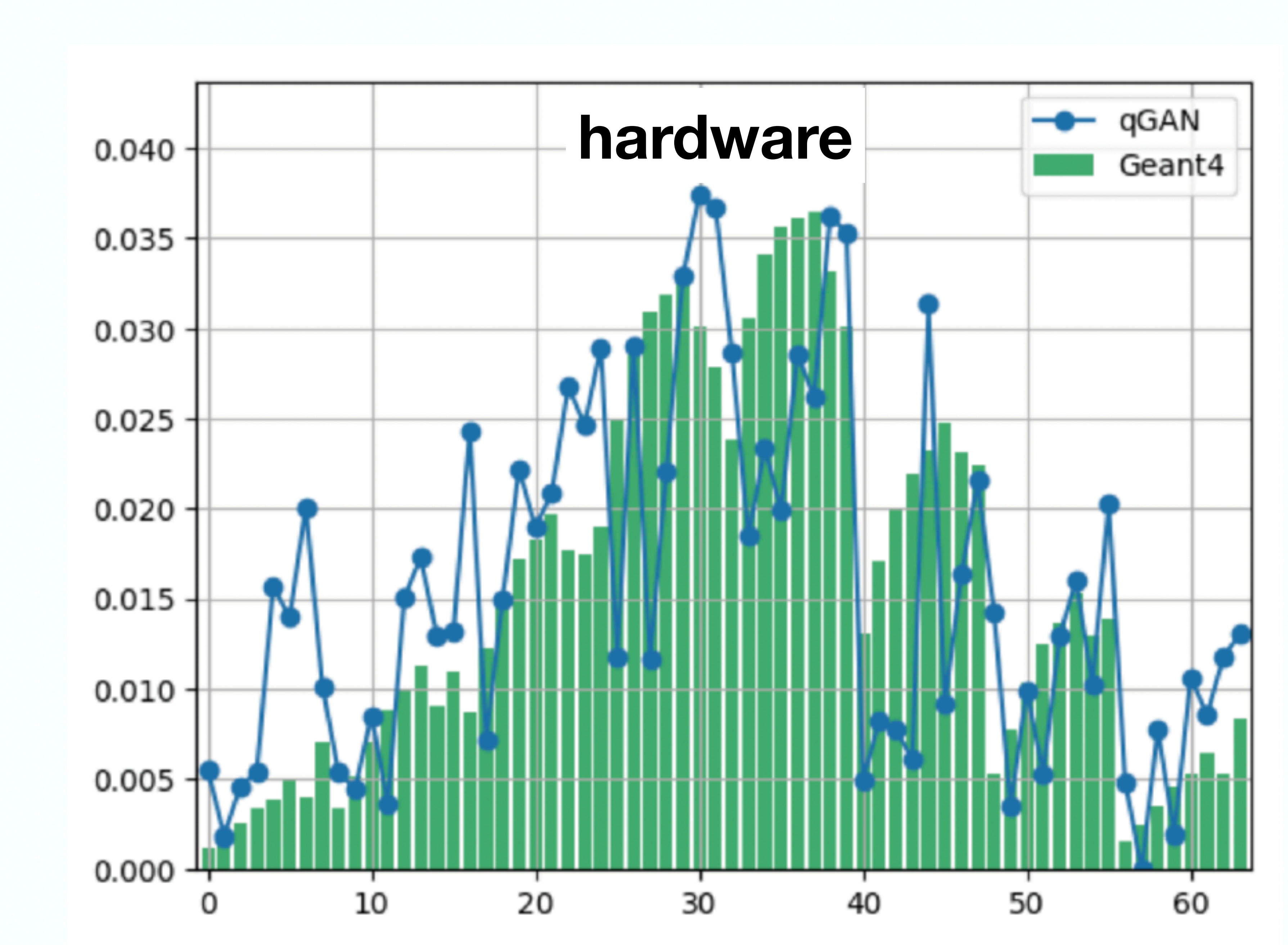


2D performance（quantum computing cloud）

- Run test on the real hardware with the parameters trained on the ideal simulator
  - could generate the PDF in general
  - suffers from the hardware noise







Summary and Plan

- Successfully generate 1D and 2D average shape energy distribution on the ideal simulator, noisy simulator, and hardware
  - 1D: 3 qubits -> 8 pixels
  - 2D: 6 qubits -> 64 pixels
- Compared to DESY’s result, the training is more stable and faster
  - training time for 2D data： 5d -> 2h
- Future plan
  - current model could only generate the average PDF→ try other models
  - training time on the hardware is too long → batch jobs
  - quantum generator + classical discriminator → quantum generation + quantum discriminator