Quantum GAN for fast calorimeter simulation

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IHEP

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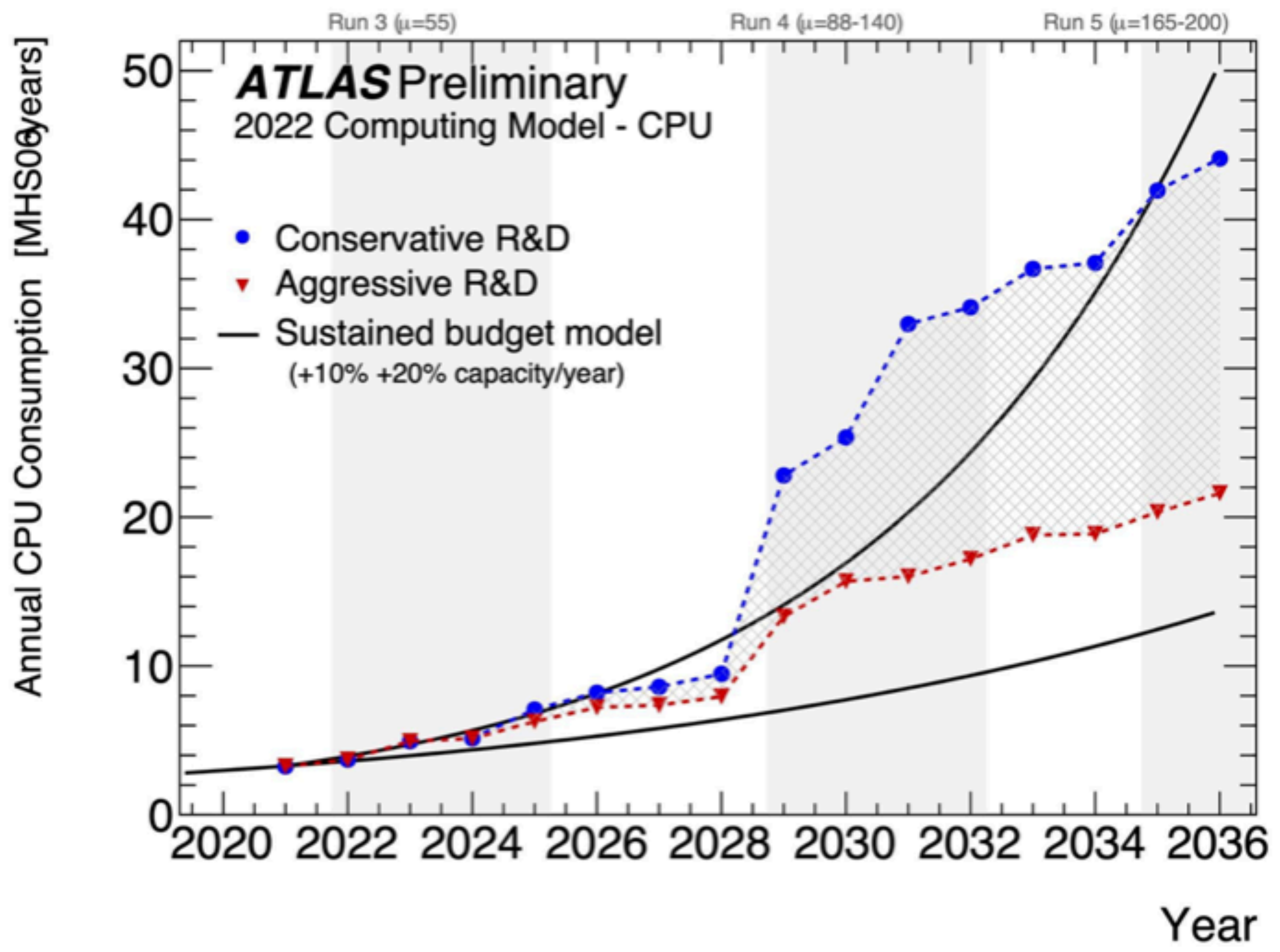
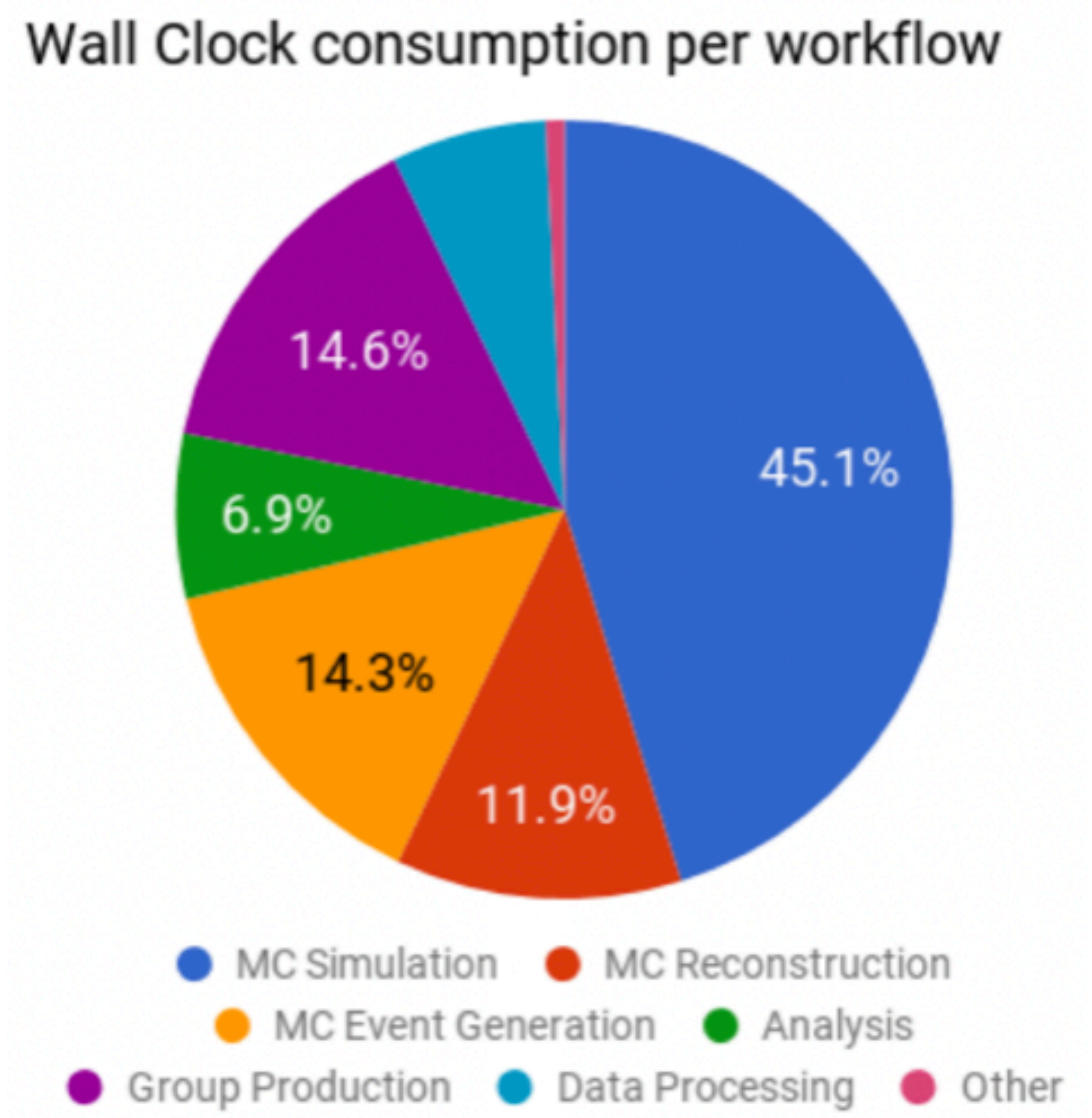
Why we need fast calorimeter simulation ?

- 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

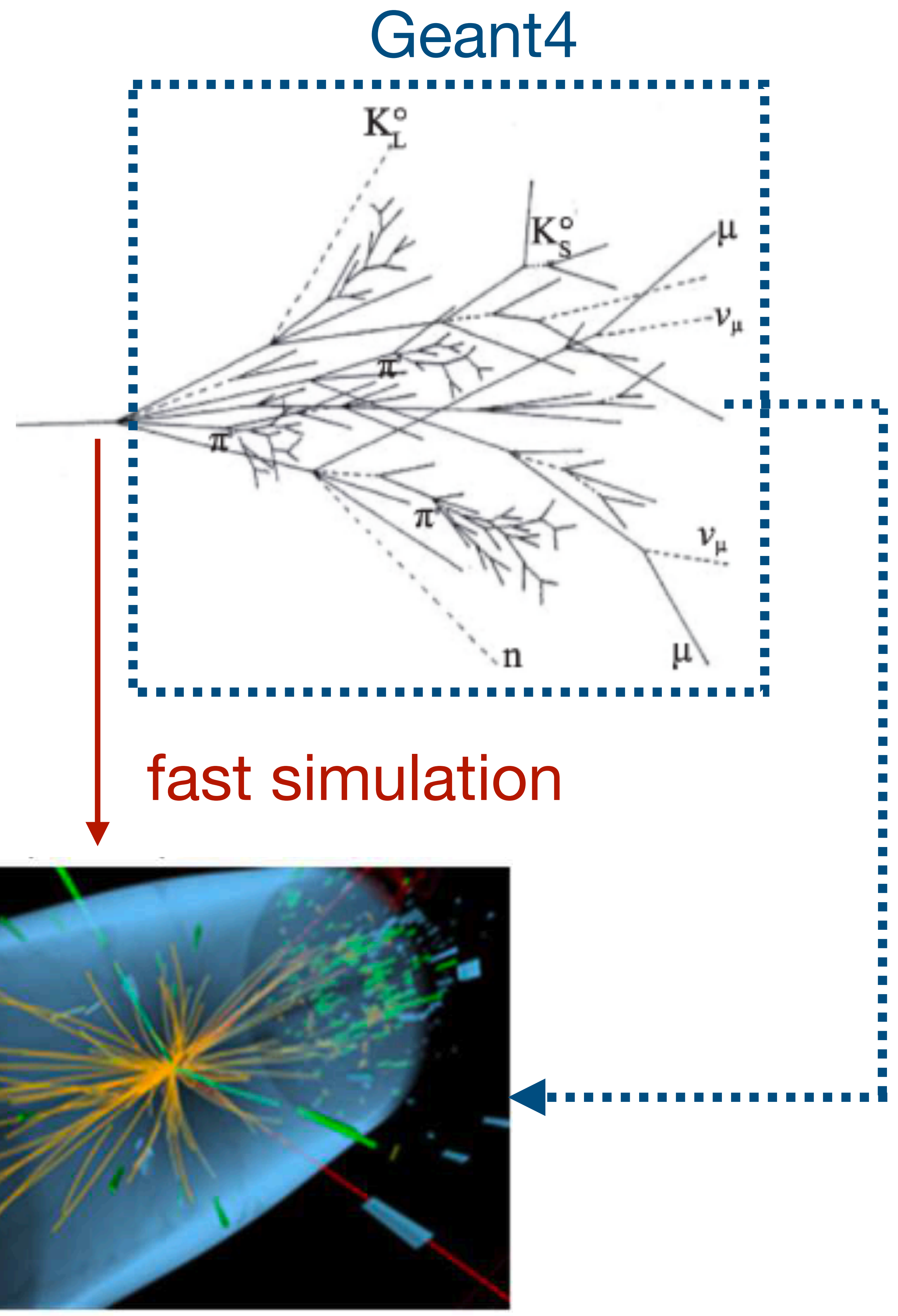


ATLAS 2017 number

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

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



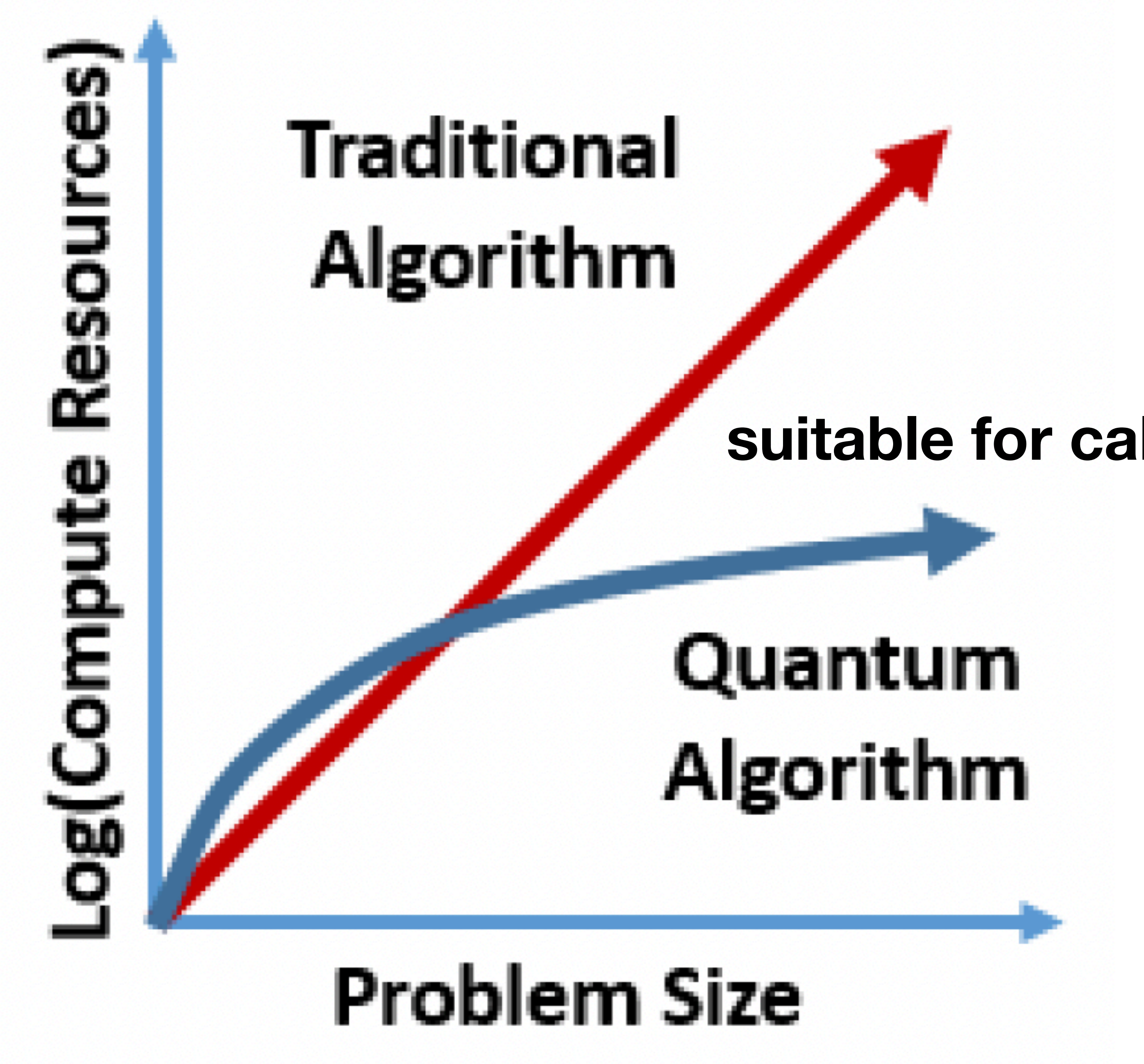
QC is an alternative to classical computing

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

Quantum computing

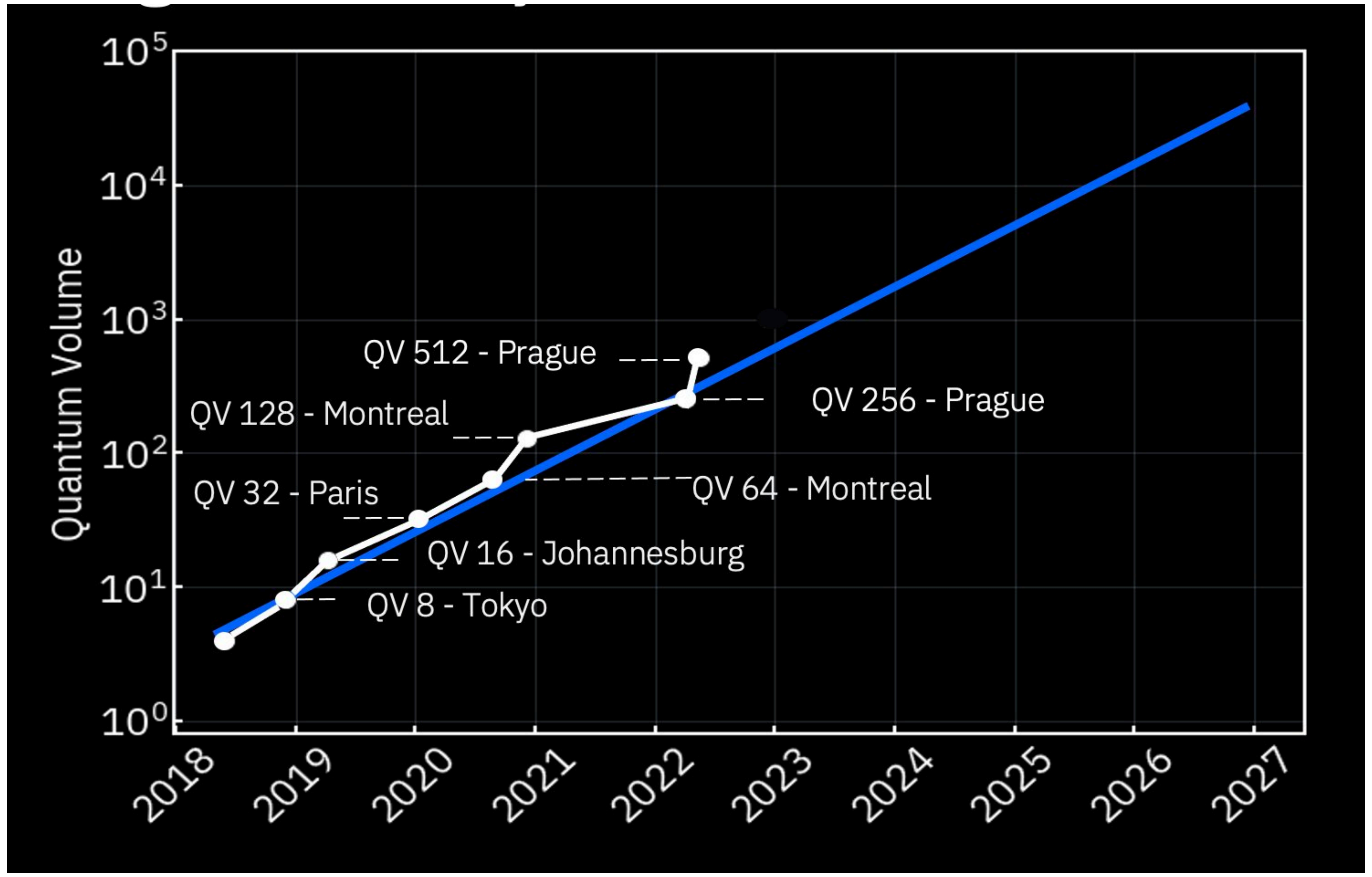
Image source

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



suitable for calorimeter simulation

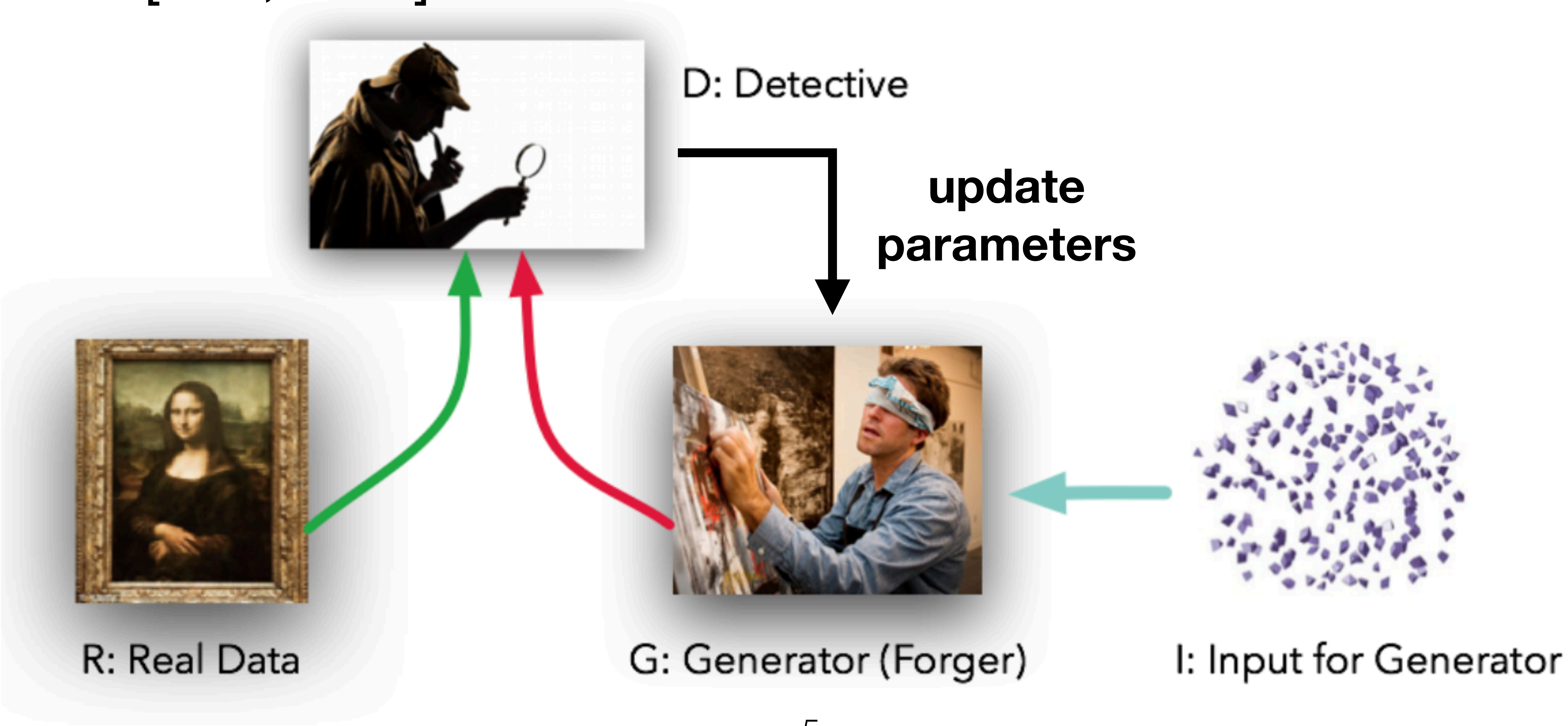
IBM



Quantum GAN

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

- NISQ
  - noisy and unstable qubit
  - number of qubits: [~10, $\sim 10^2$]



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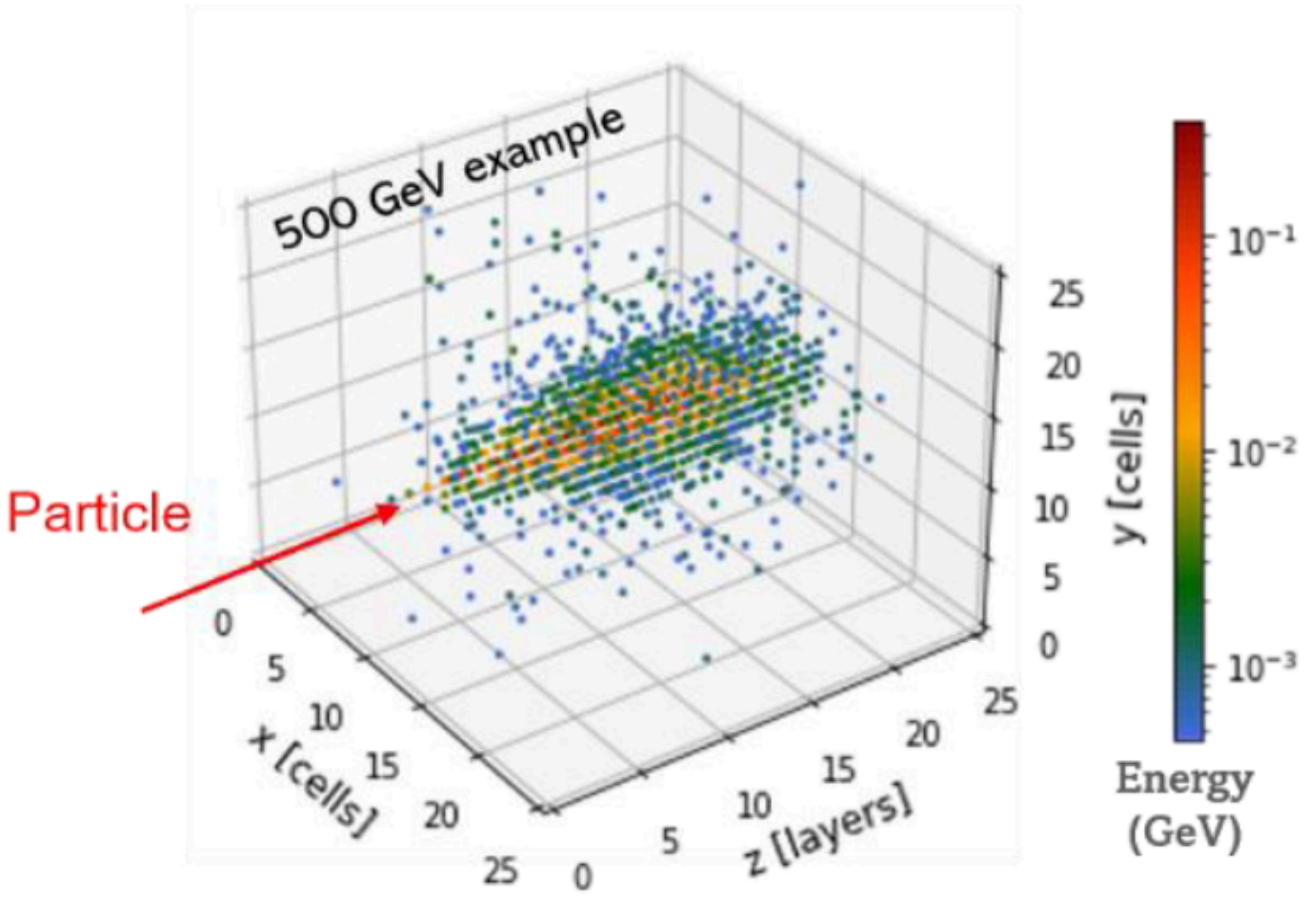
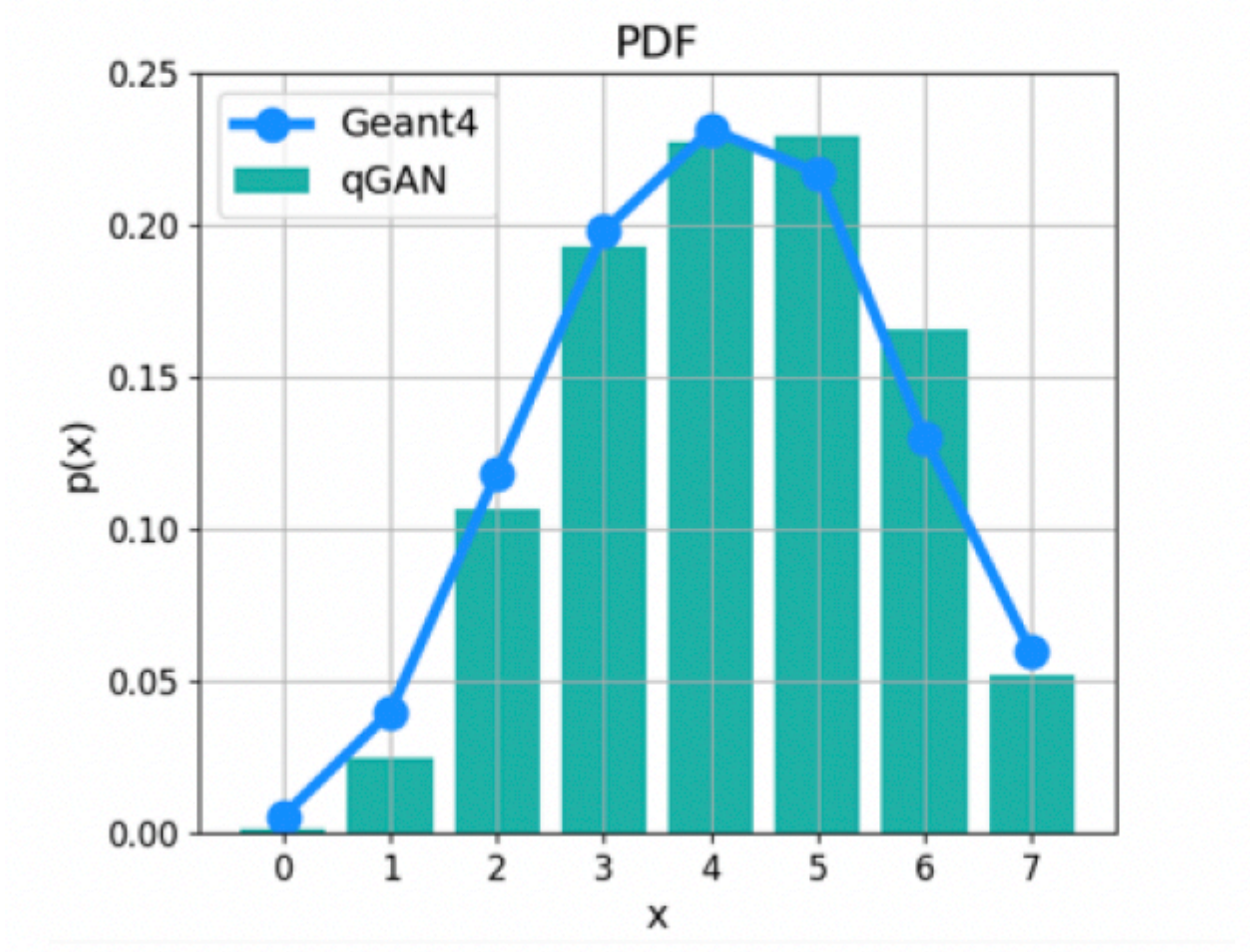
Current status

- 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



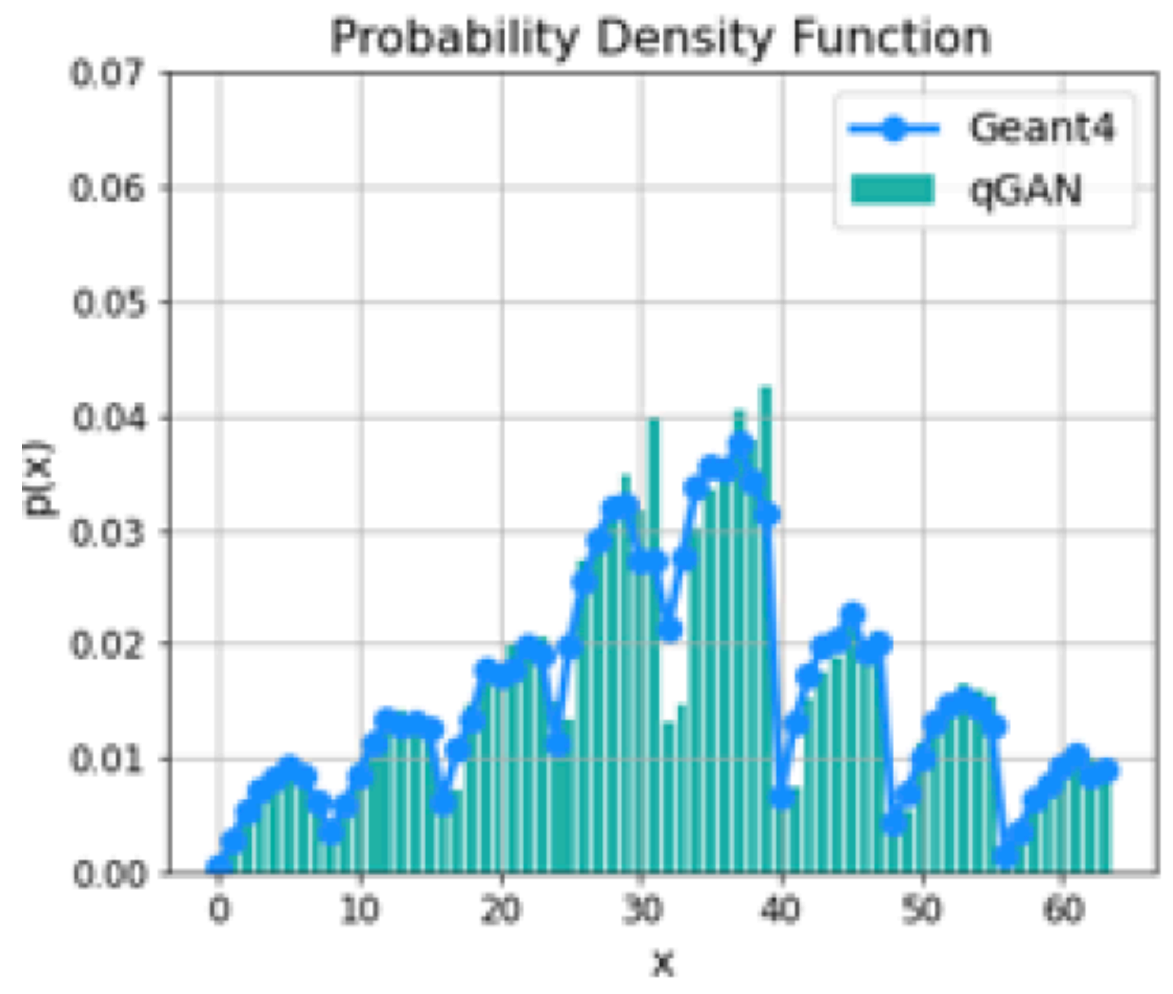
1D： 8 pixels

3 qubits ($2^3 = 8$)



2D： 8x8 pixels

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



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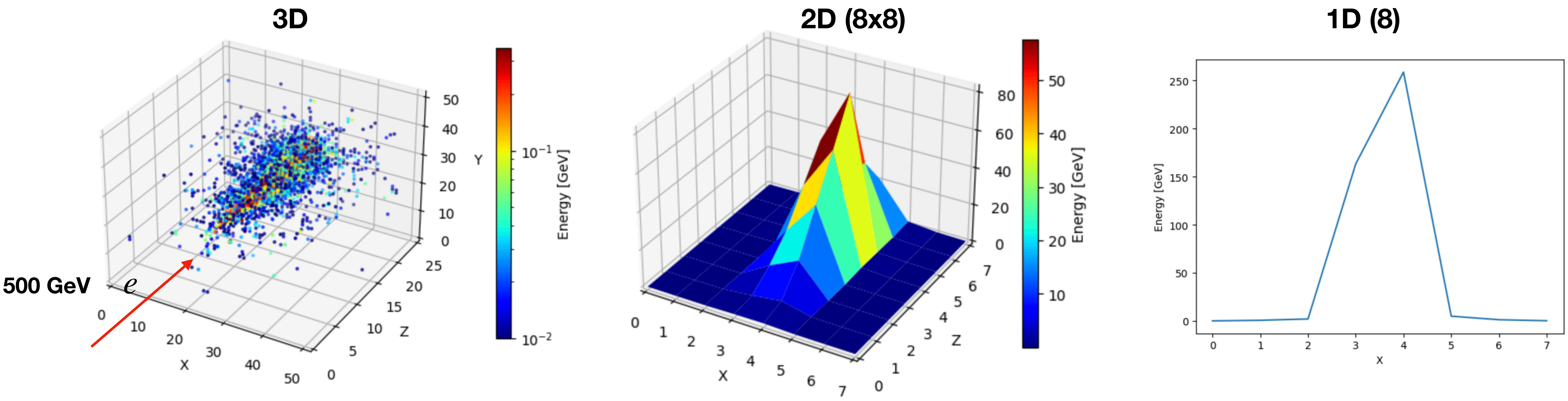
Research strategy

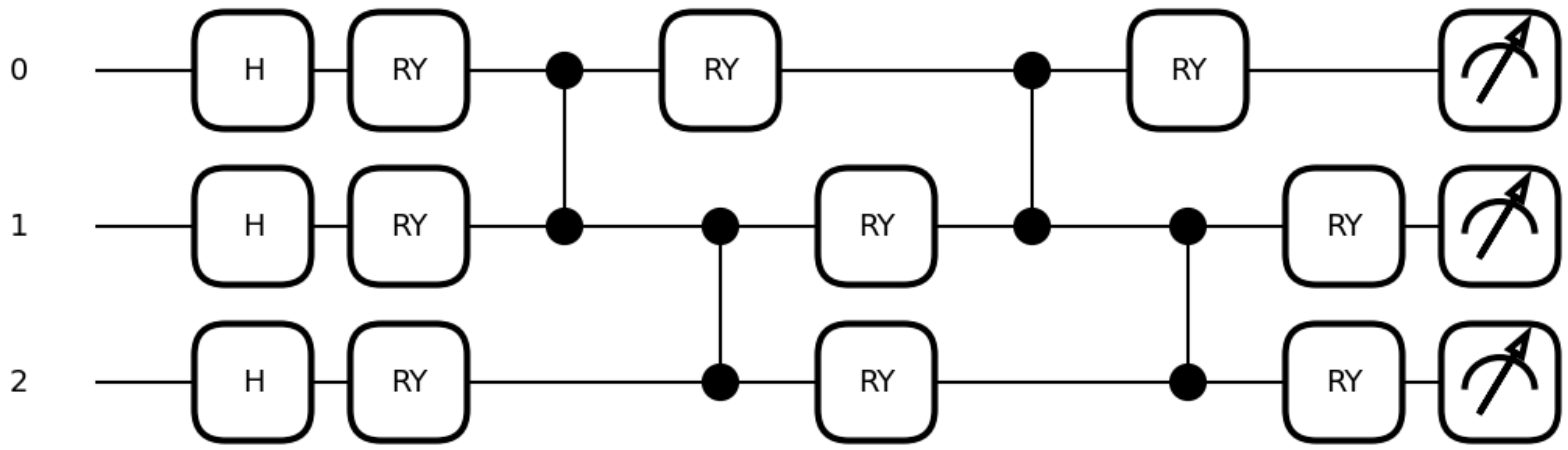
- Collaboration: IHEP & DESY

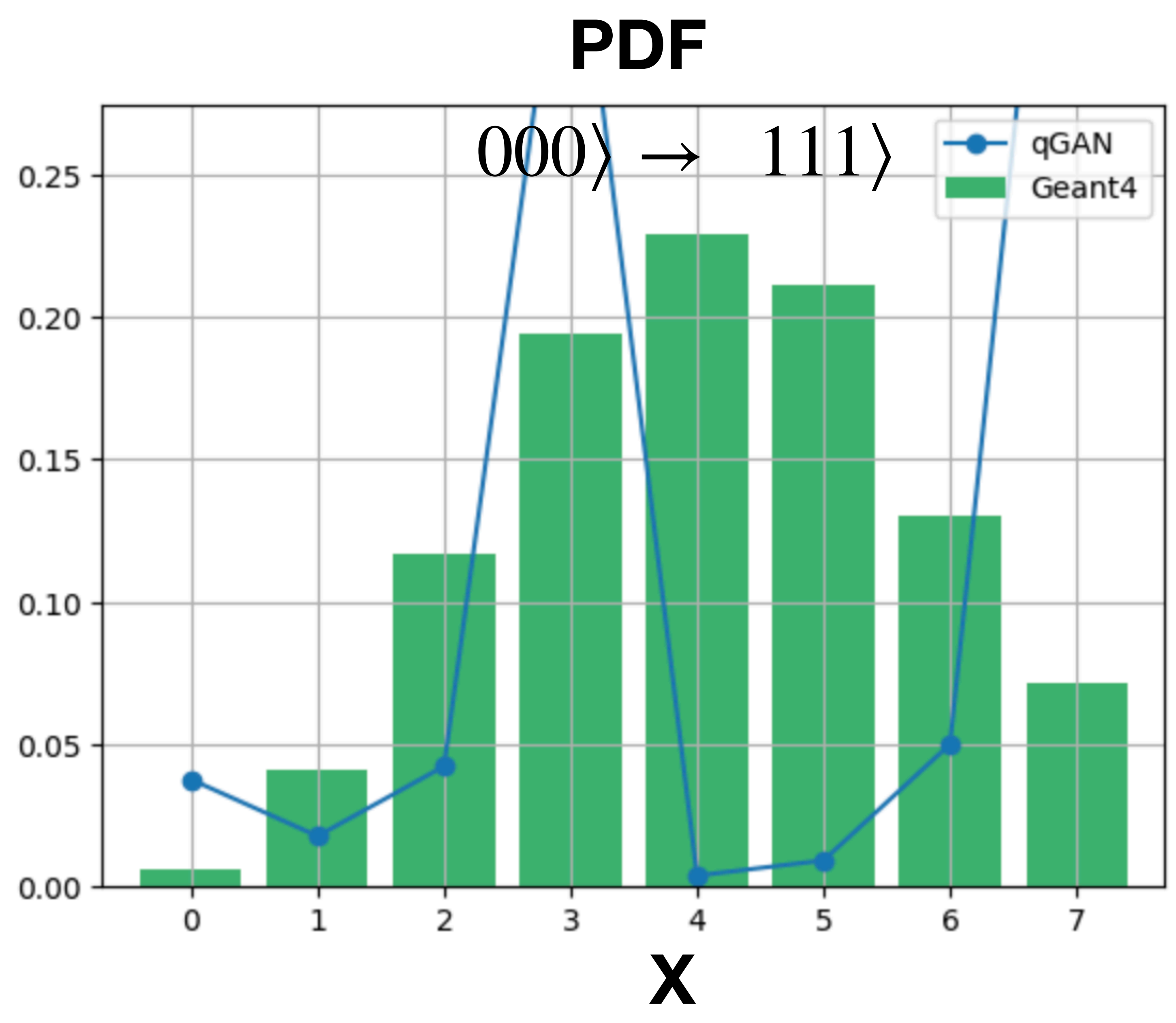
- CLIC open data
  - target: average shower shape (done) → event fluctuation (ongoing)
  - dataset: down sampling, 1D (8 pixels) → 2D (pixels) --→ 3D
  - backend: ideal simulator→ noisy simulator → quantum computing cloud



1D quantum generator model

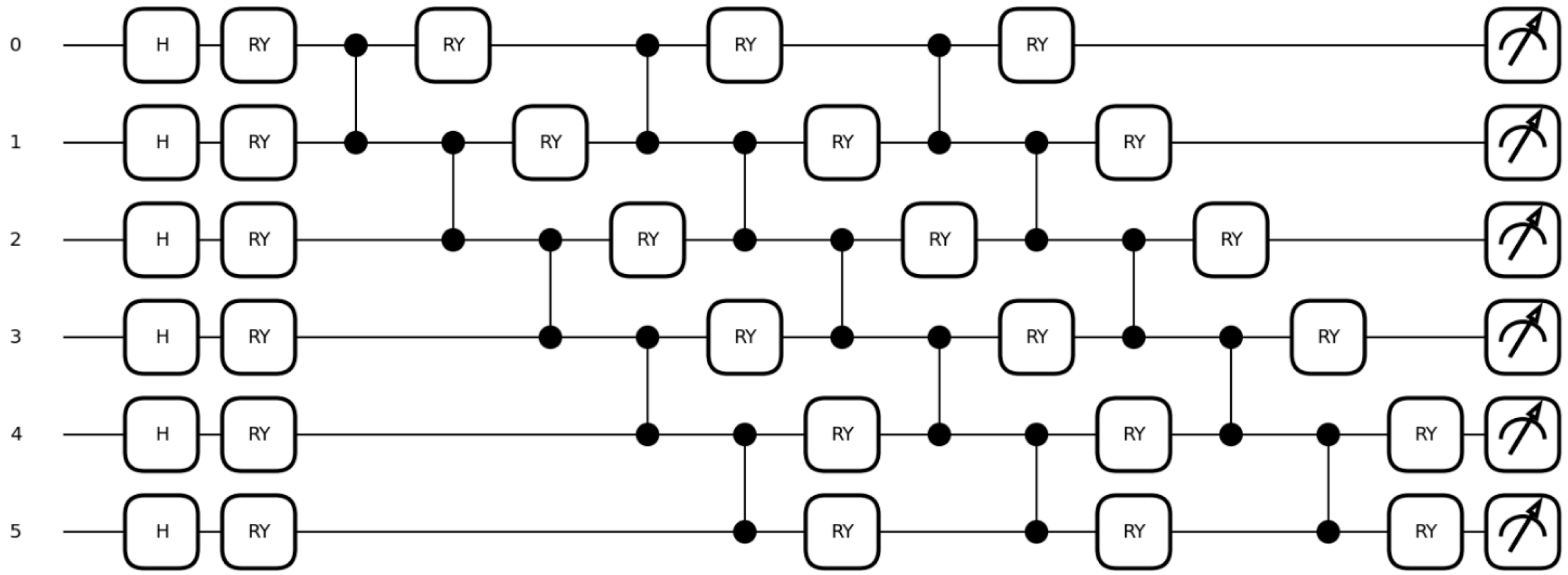
- Generator model consists of H, RY, and CZ
  - H： $0\rangle \rightarrow$ $0\rangle$ and $1\rangle$
  - RY： trainable parameters
  - CZ： entanglement
- Frequency of the 8 states -> energy deposition of the 8 pixels
  - one of the eight states each shot: $000\rangle$, $001\rangle$, $010\rangle$, $011\rangle$,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





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



1D performance（ideal simulator）

- Training GAN is difficult：vanishing gradient, mode collapse, **instability**

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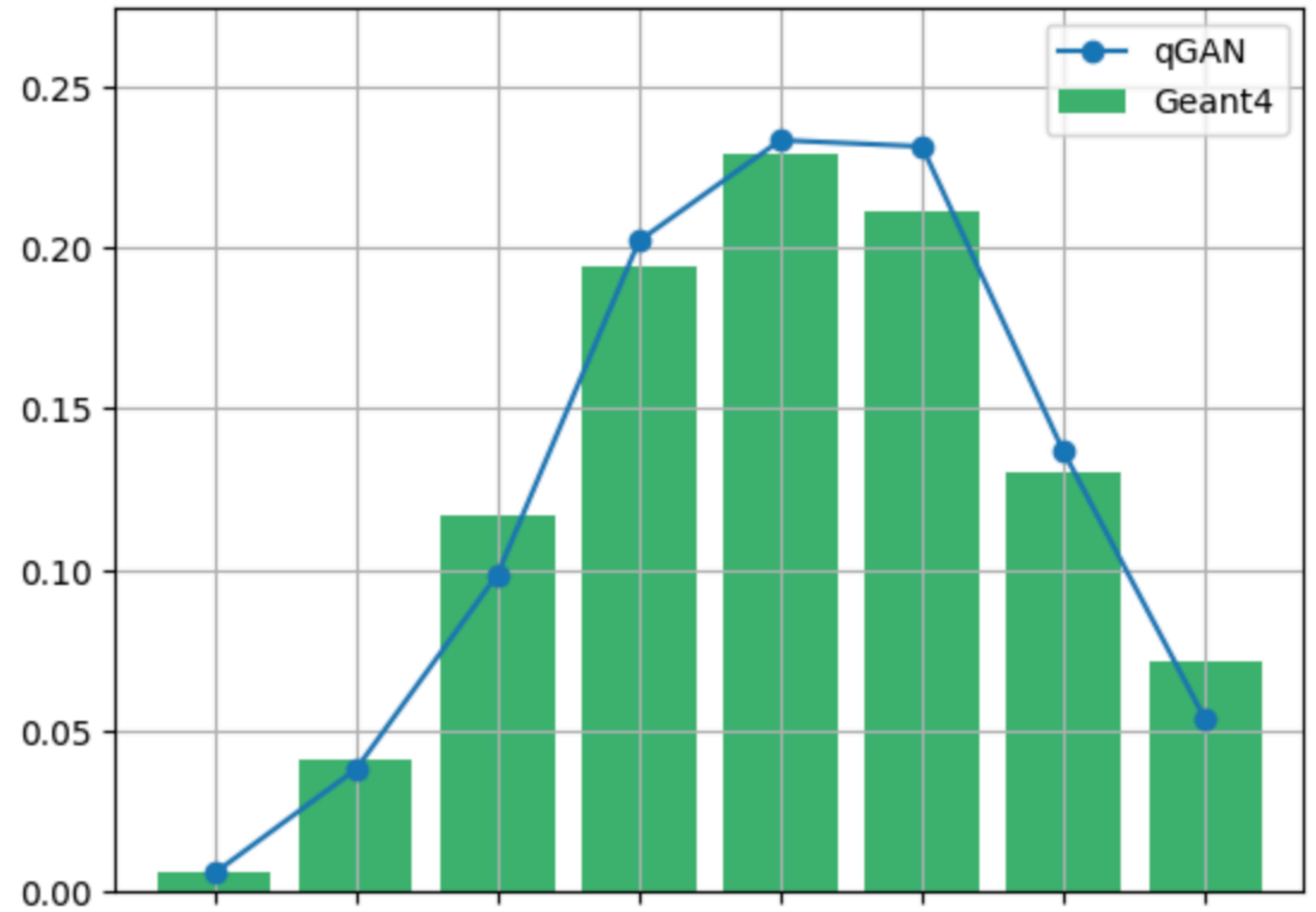
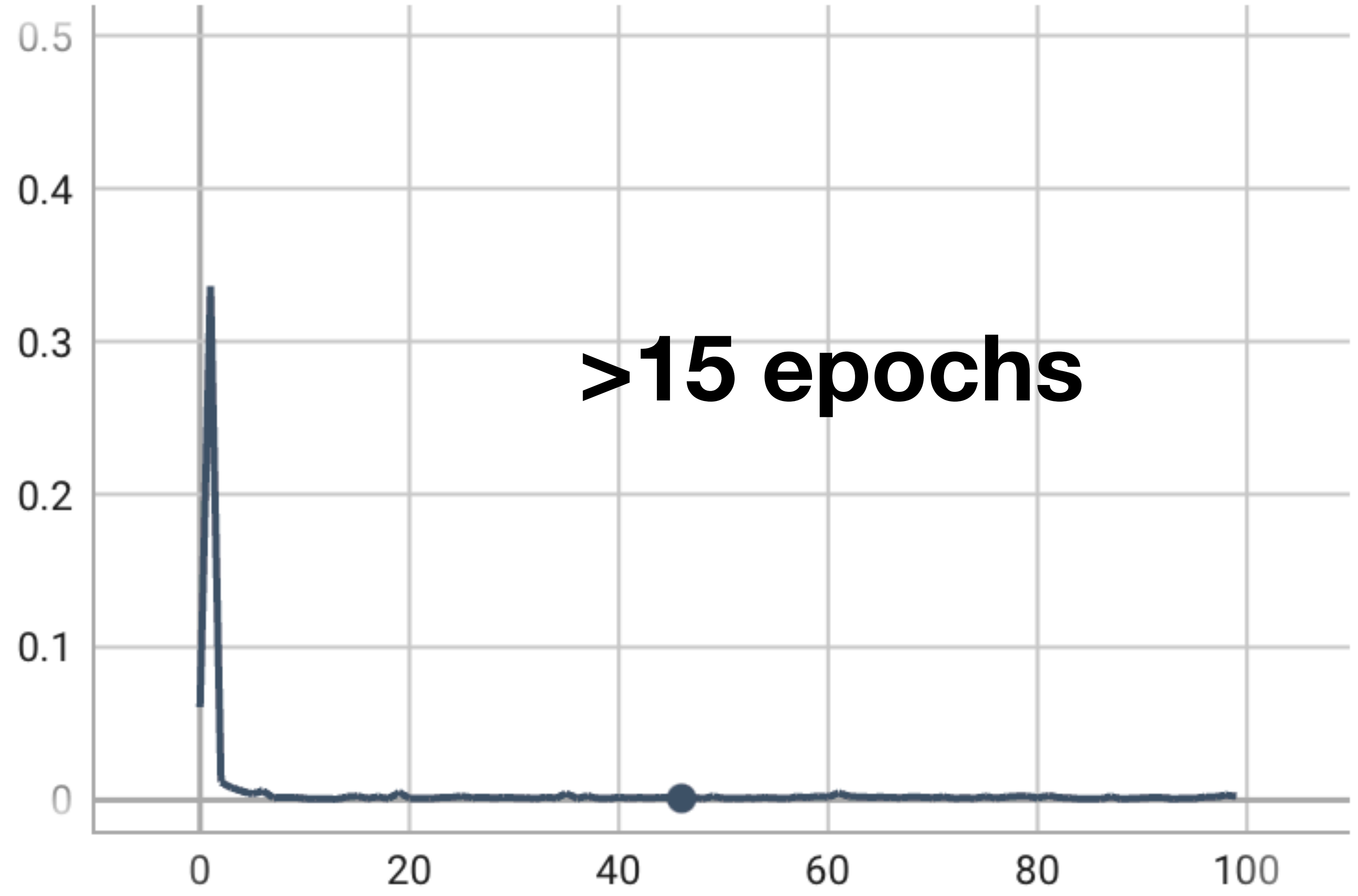
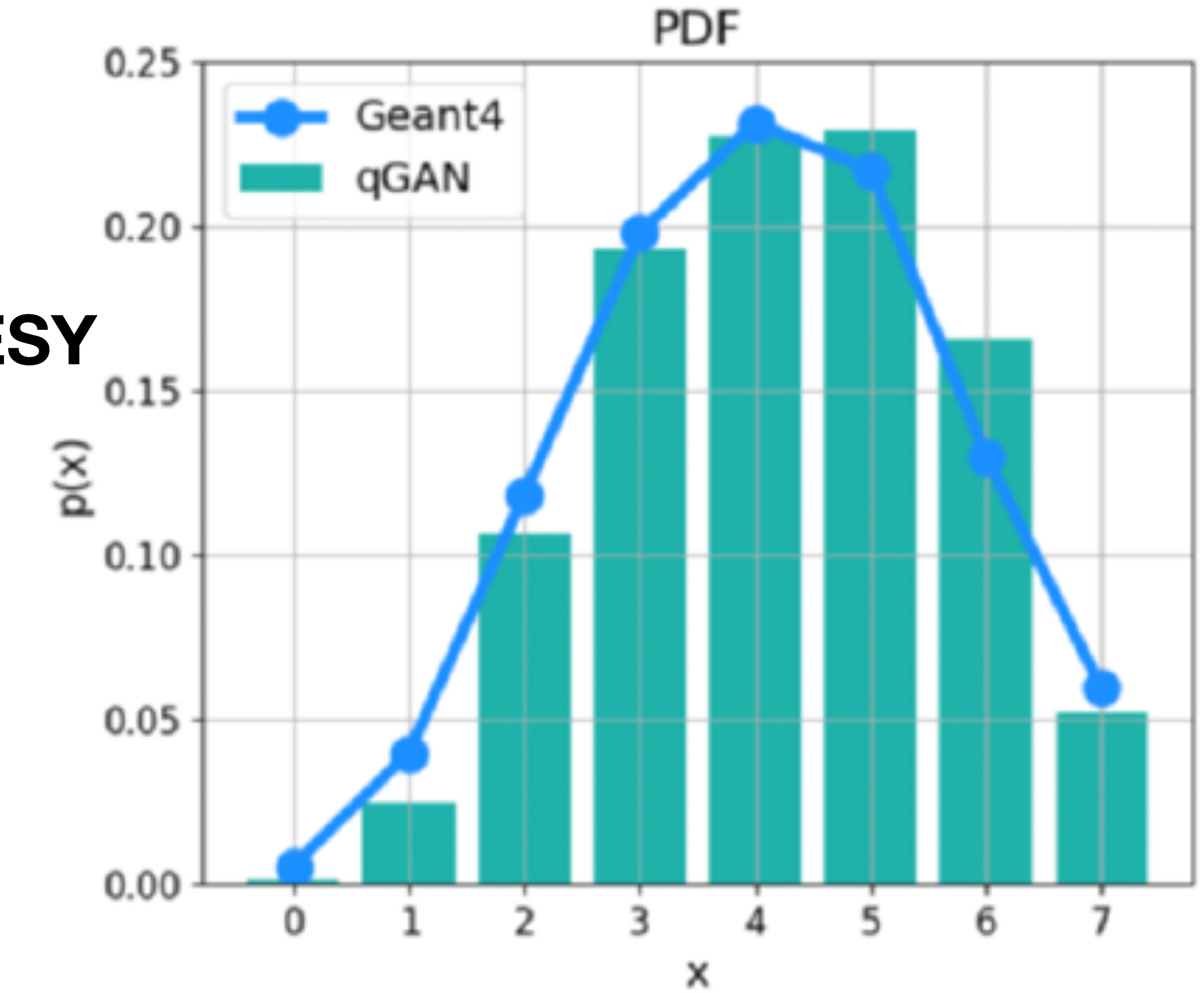
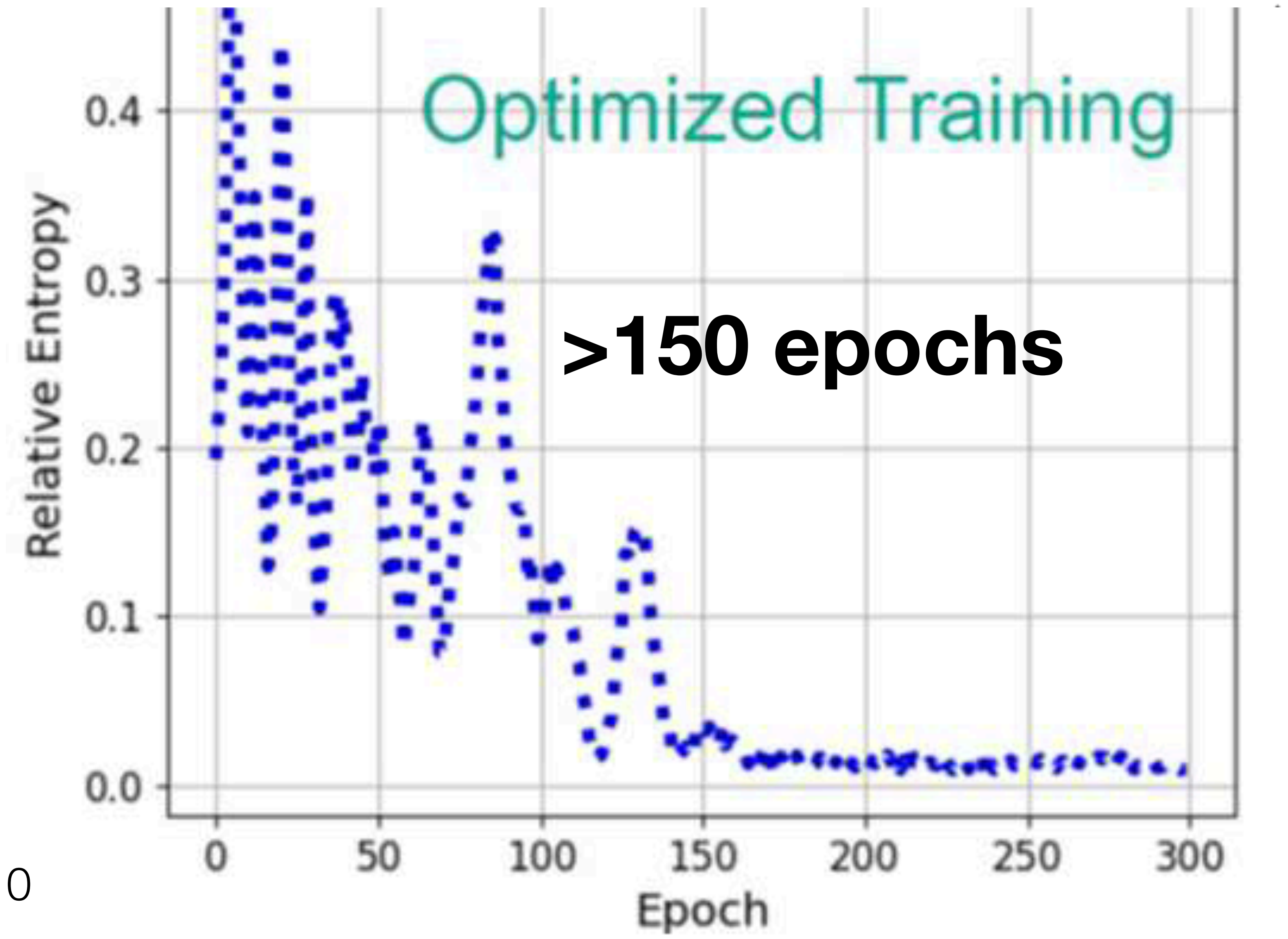




CERN & DESY





2D performance（ideal simulator）

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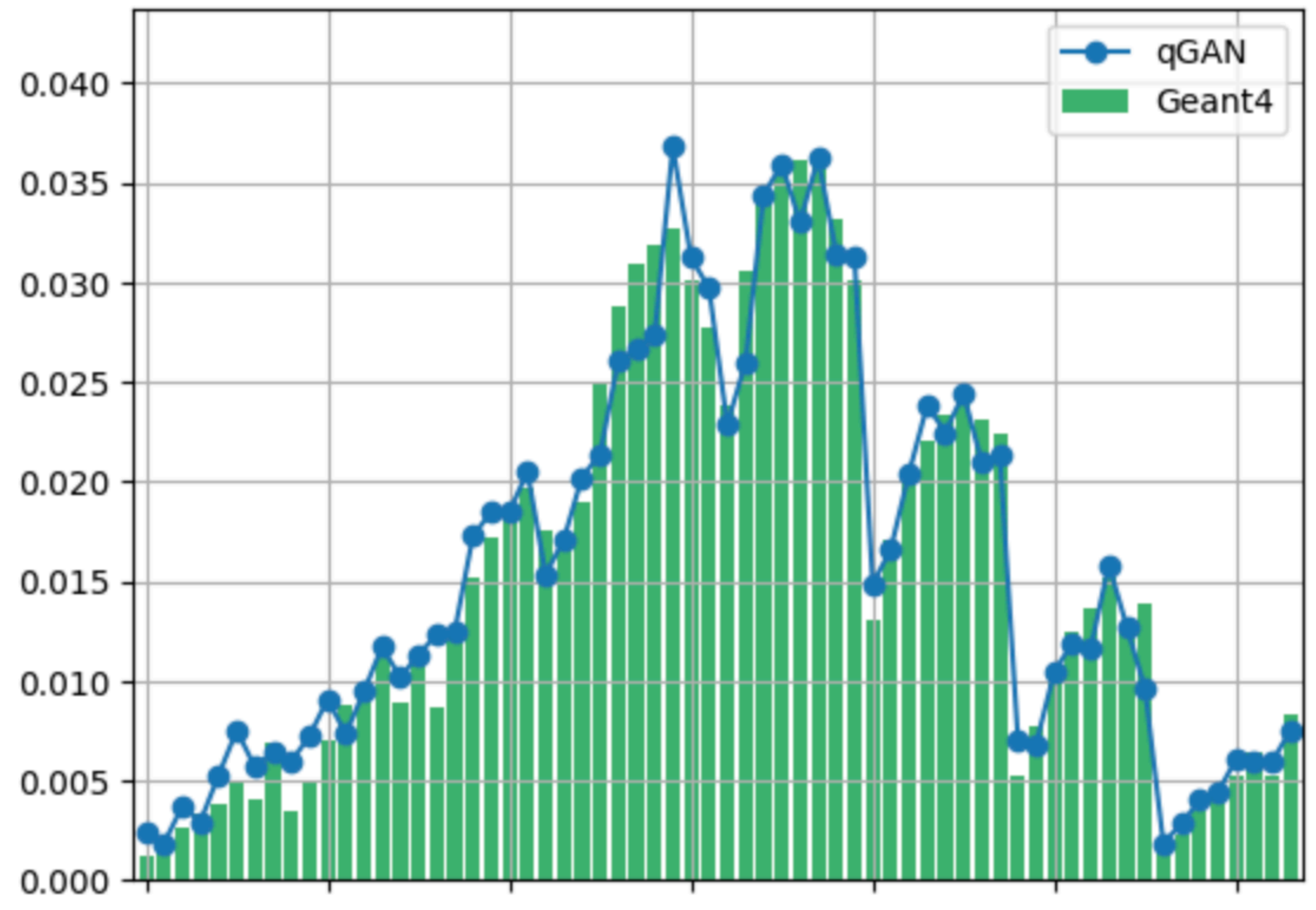
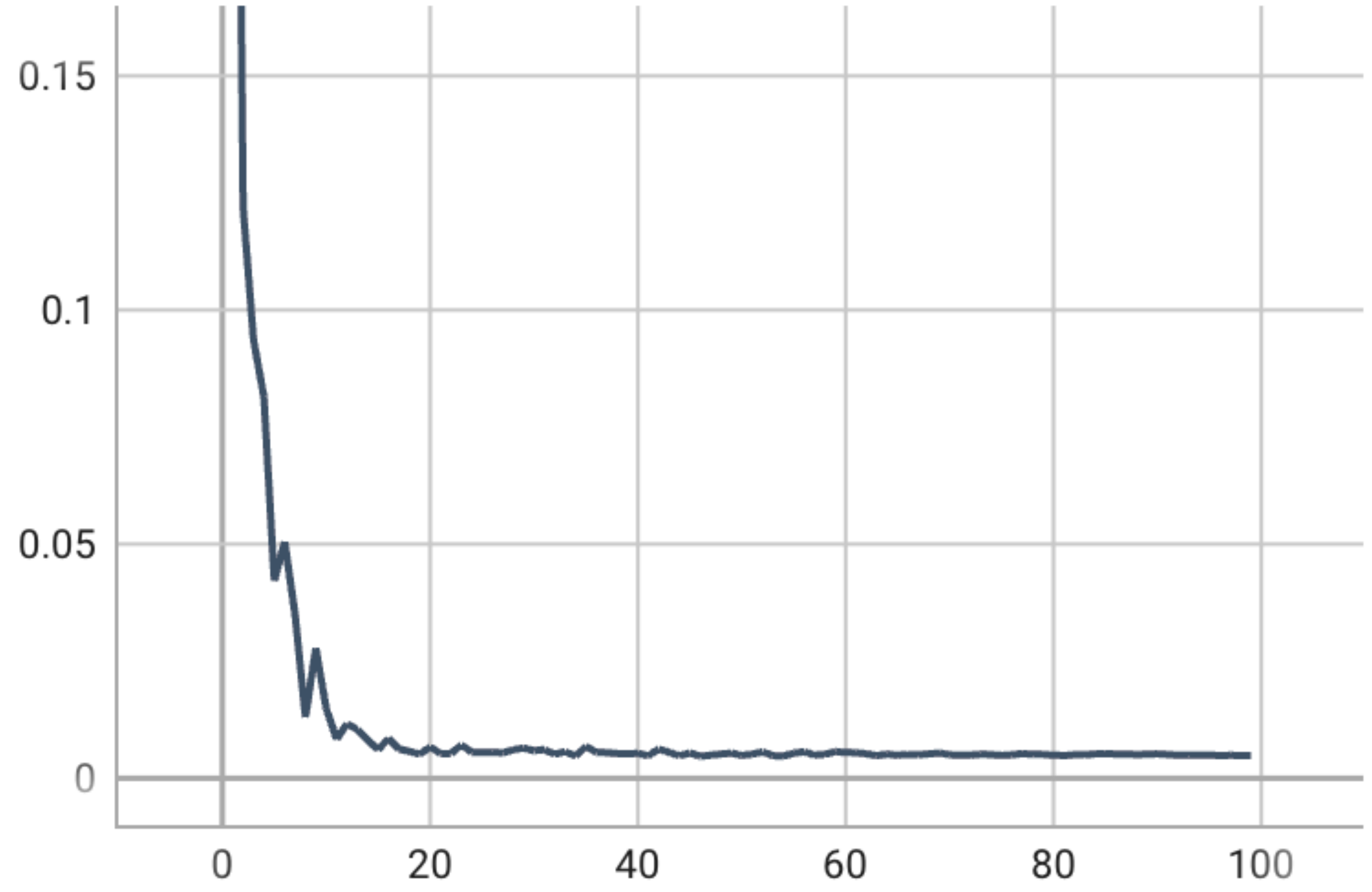
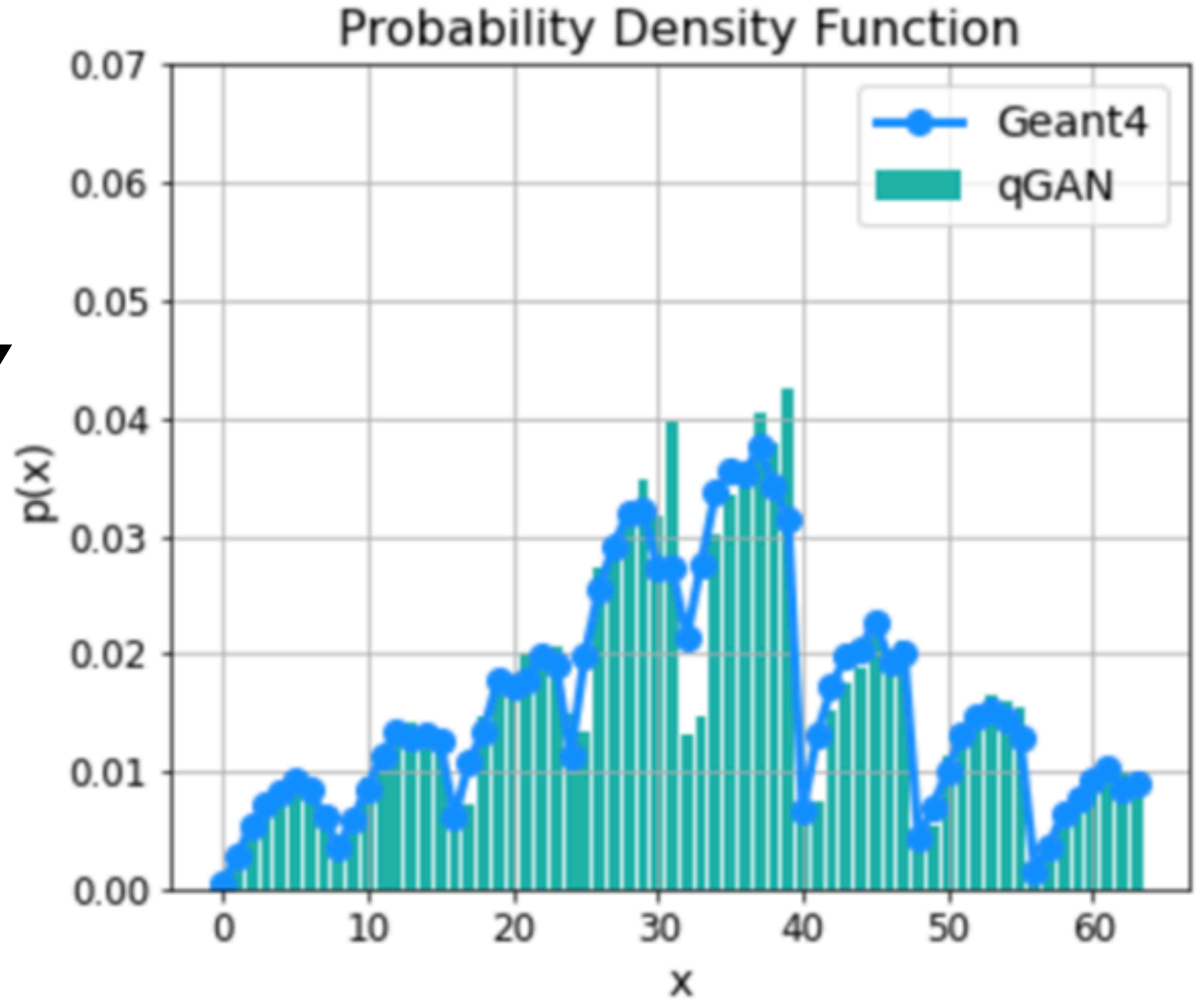
IHEP

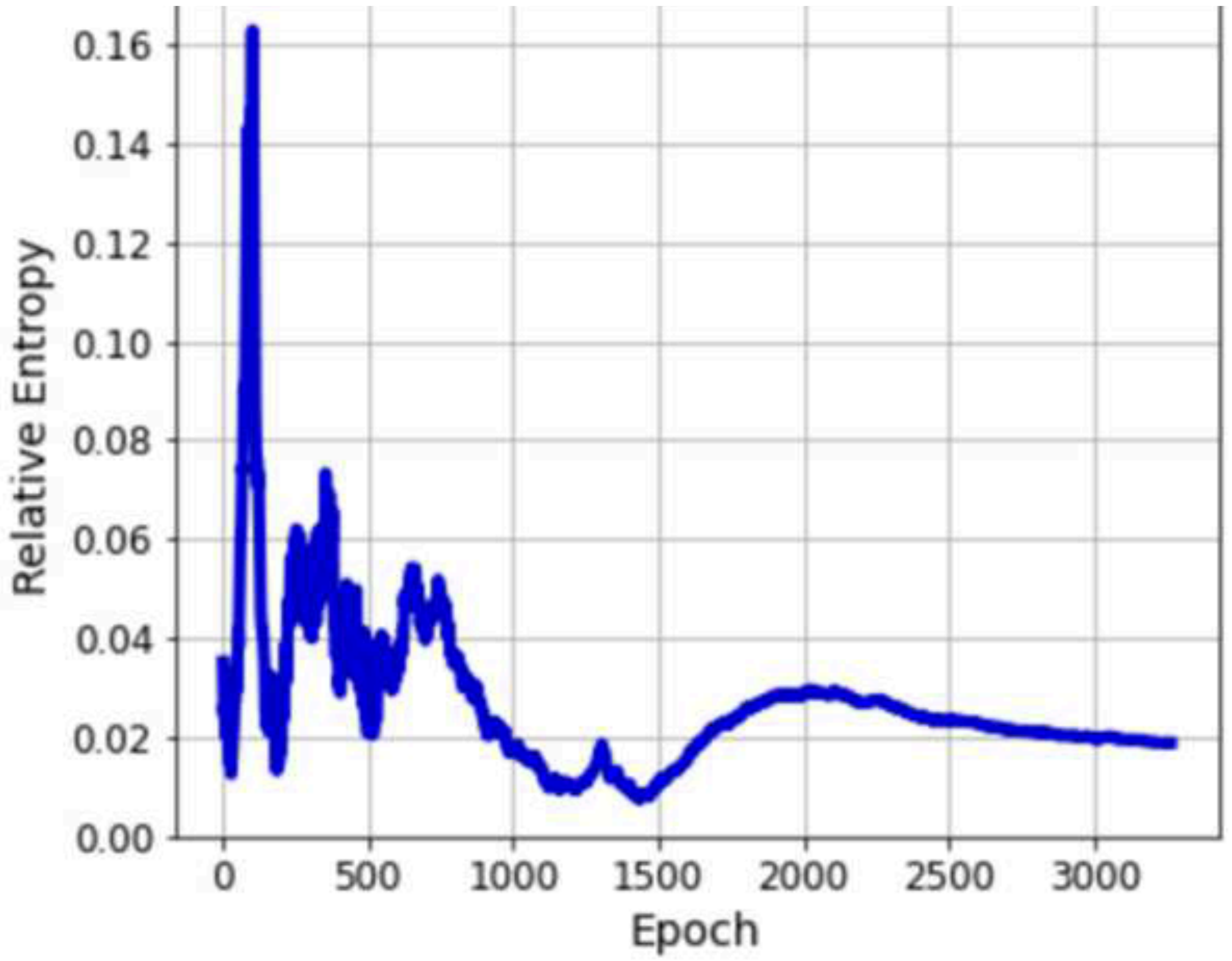




training time< 2h

CERN & DESY



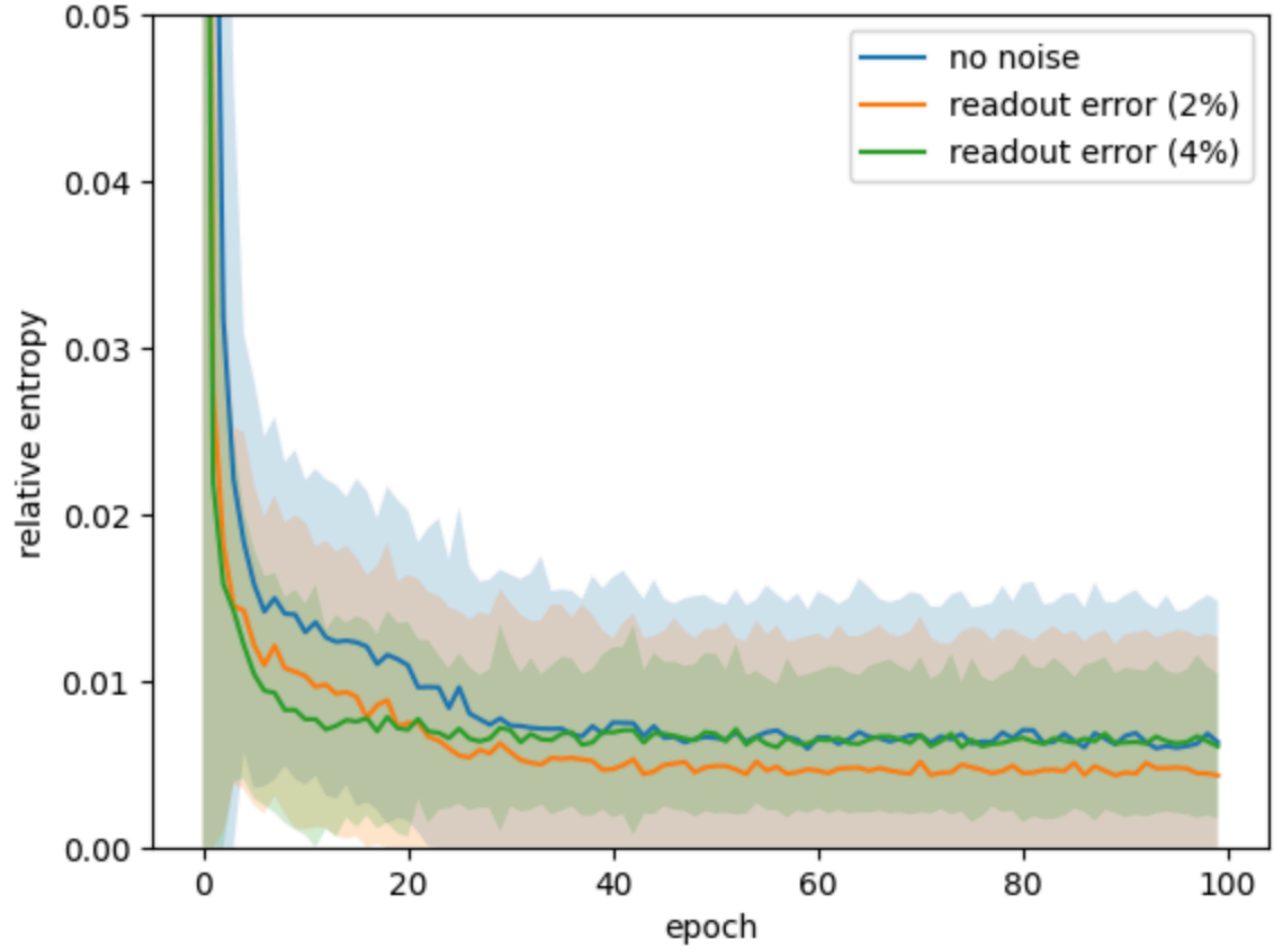


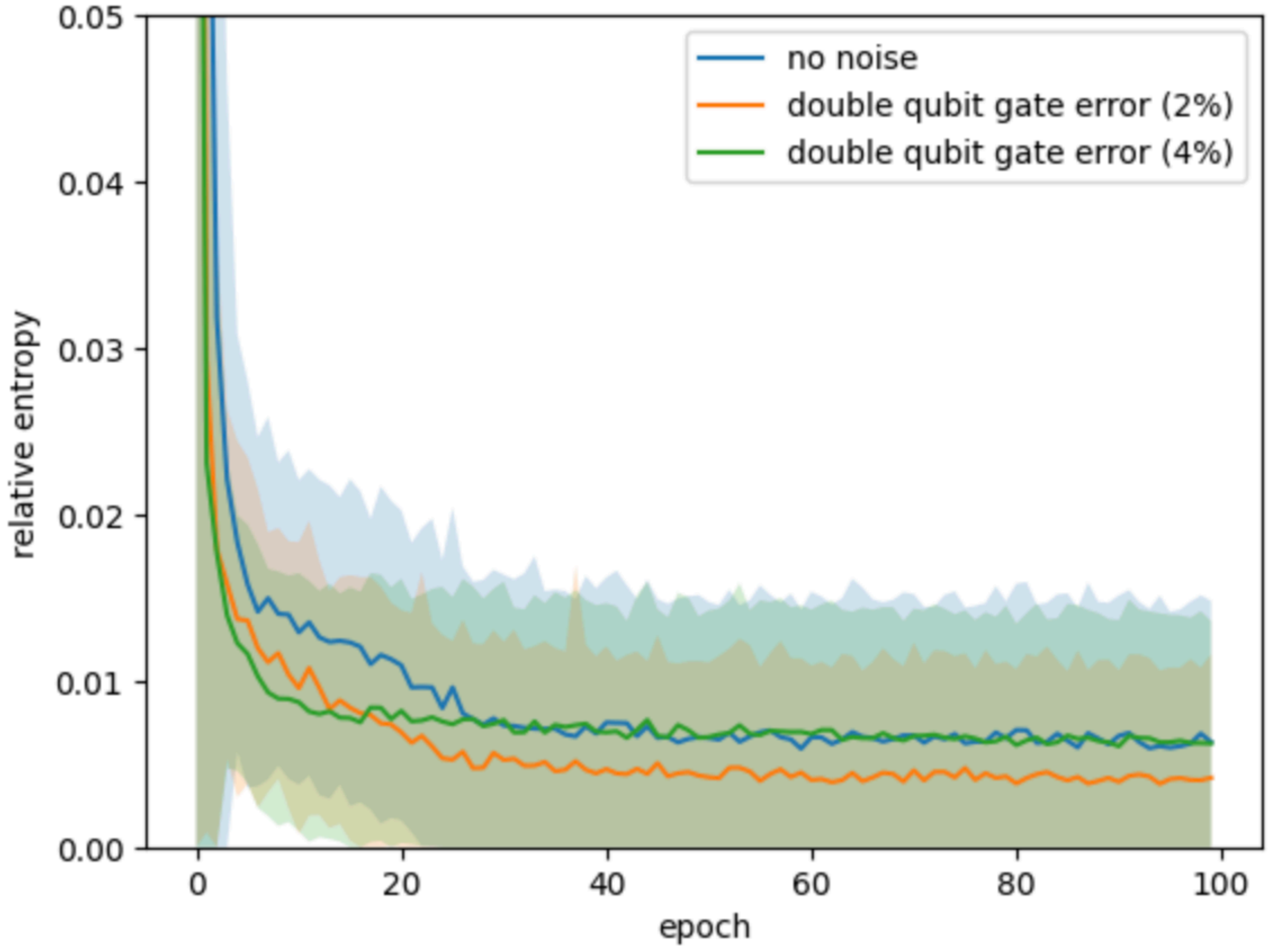
instability

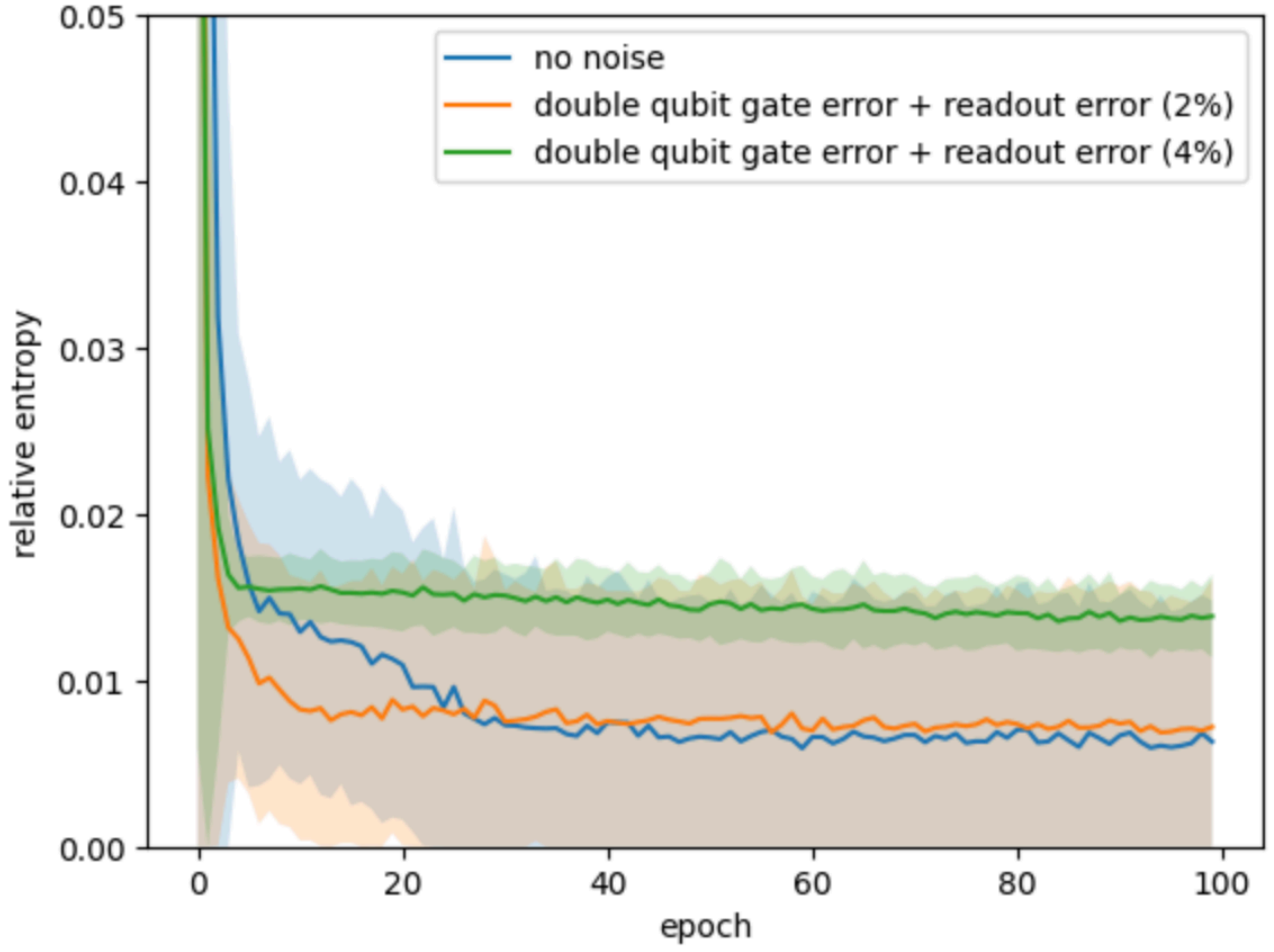
training time > 5d

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)





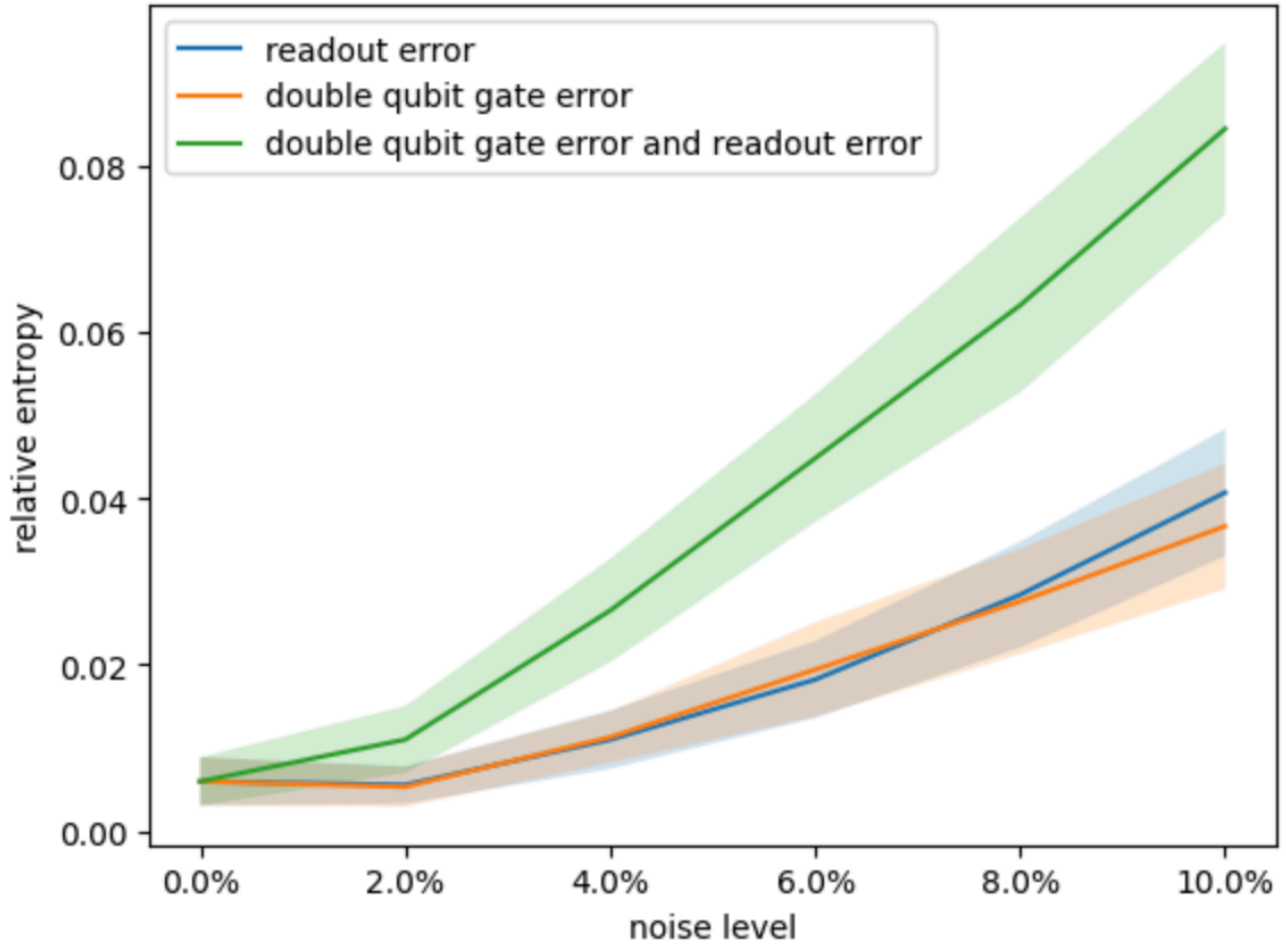


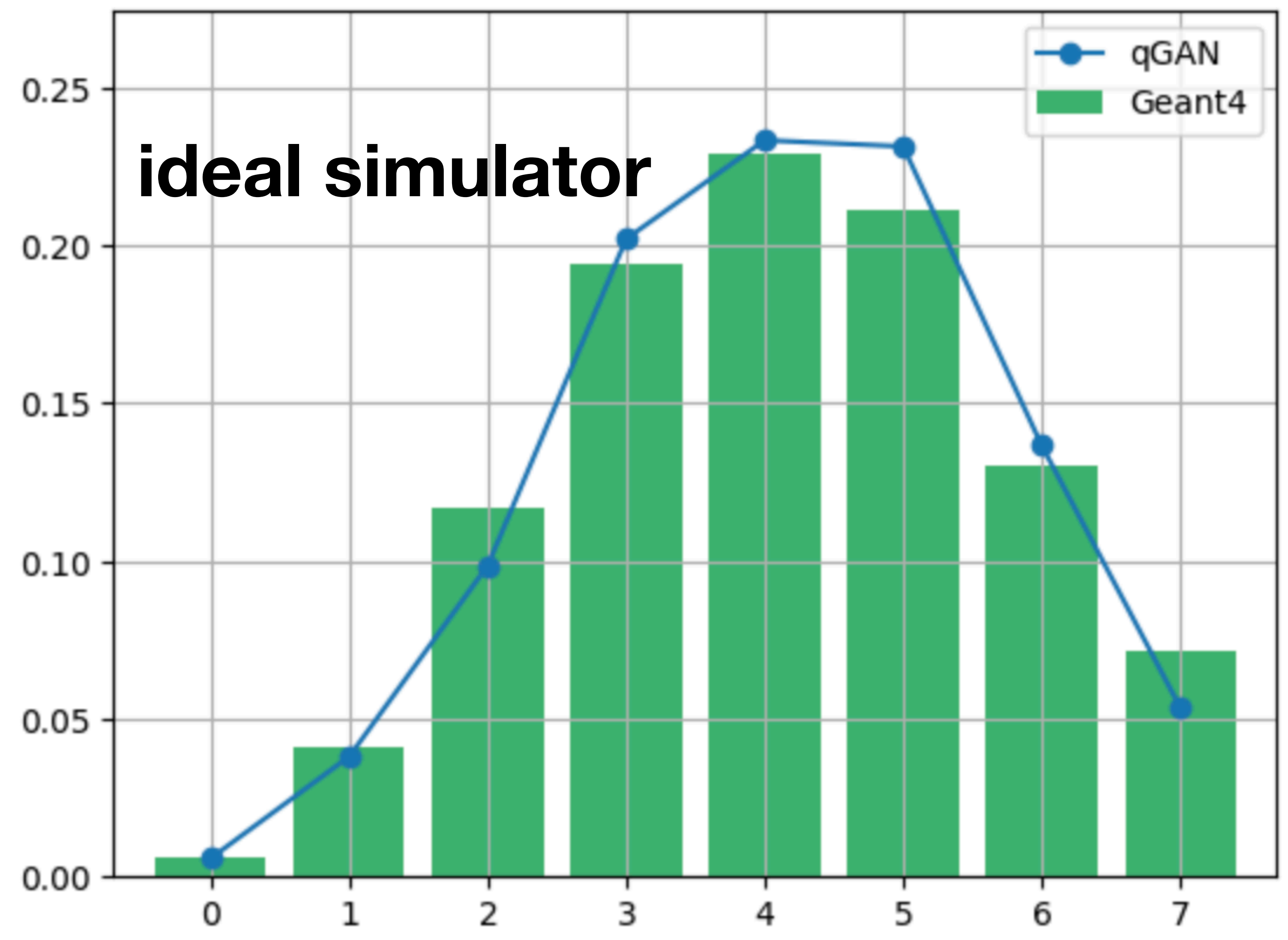
Low level noise (< 2%) could improve the performance

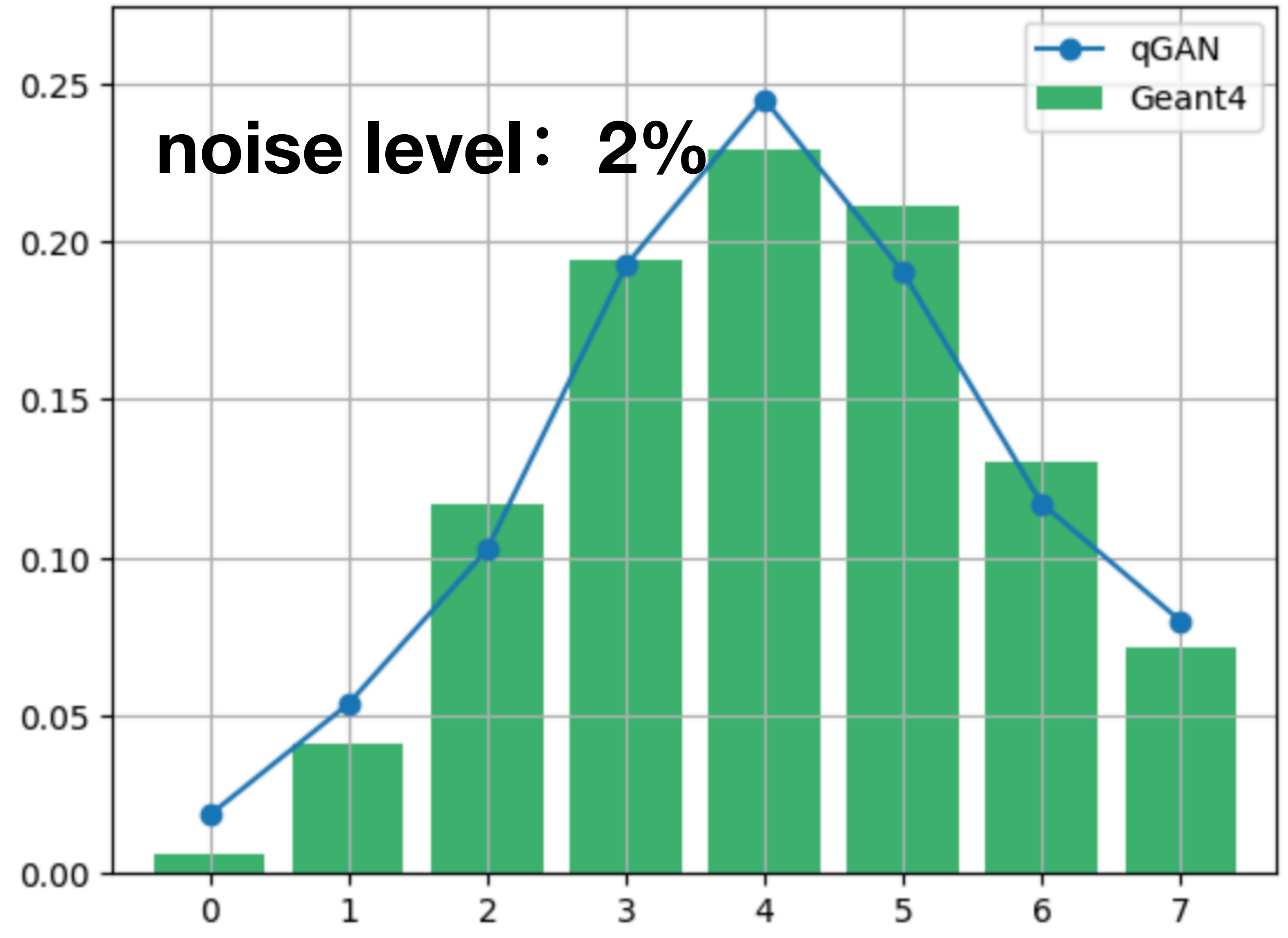
1D: Impact of the noise on the model inference

- 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

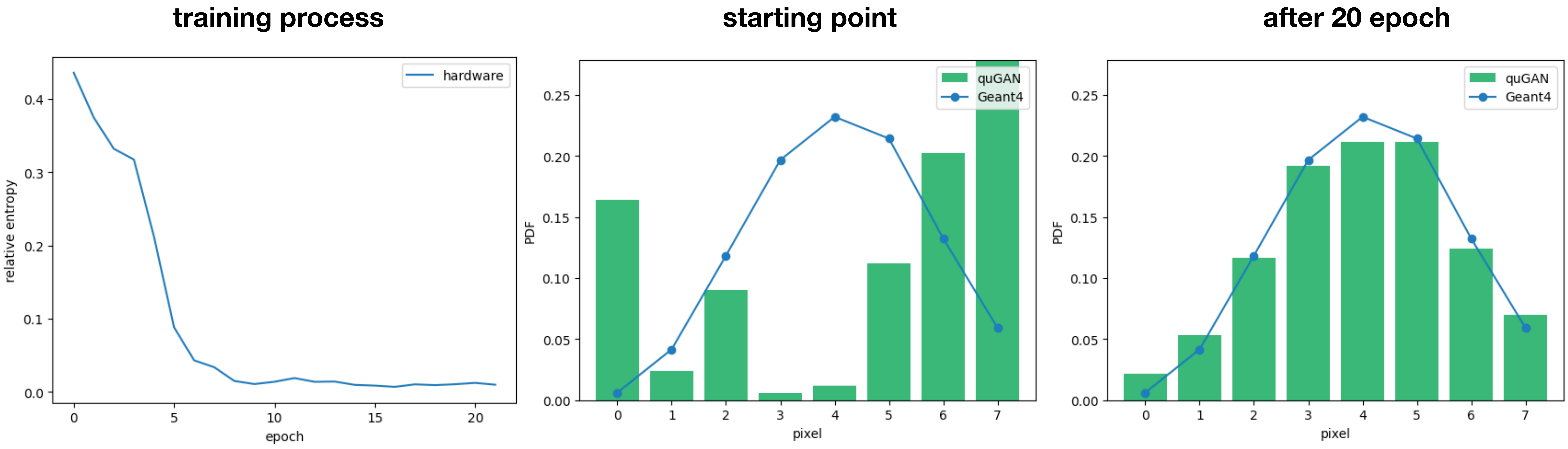






1D performance（hardware）

- Access the hardware via the quantum computing cloud
  - performance looks good and consistent with the noisy simulation
  - training speed on the hardware (simulator) 0.5h/epoch (5s/epoch)



Summary and Plan

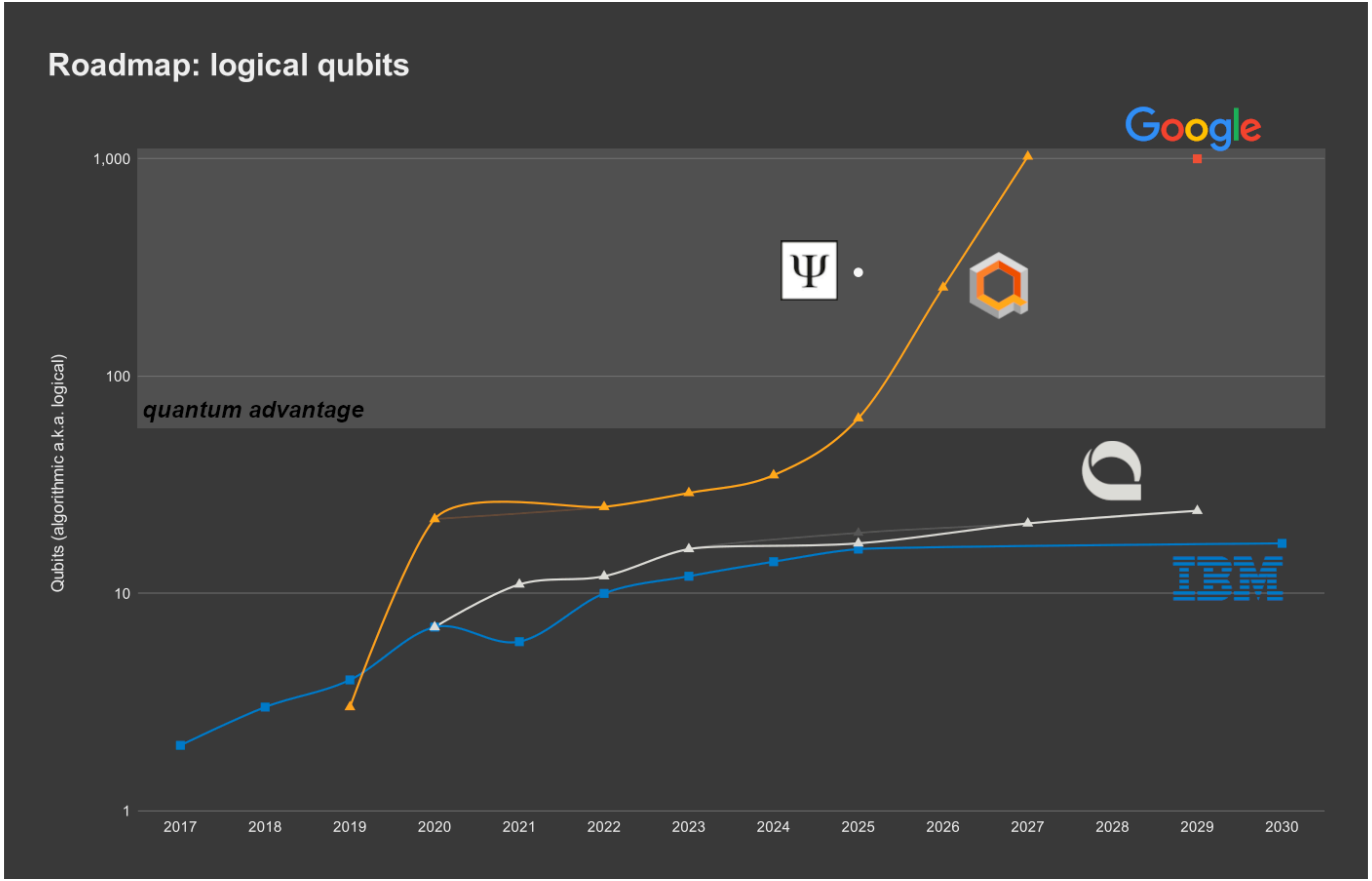
- Successfully generate 1D and 2D average shape energy distribution on the ideal simulator, noisy simulator, and hardware
  - 1D: 3 qubits -> 8 pixels
  - 2D: 6 qubits -> 64 pixels

- 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 on the hardware is time-consuming
    - try simplified optimizers, e.g. SPSA
    - hybrid classical and quantum computing

Thank you!

backup

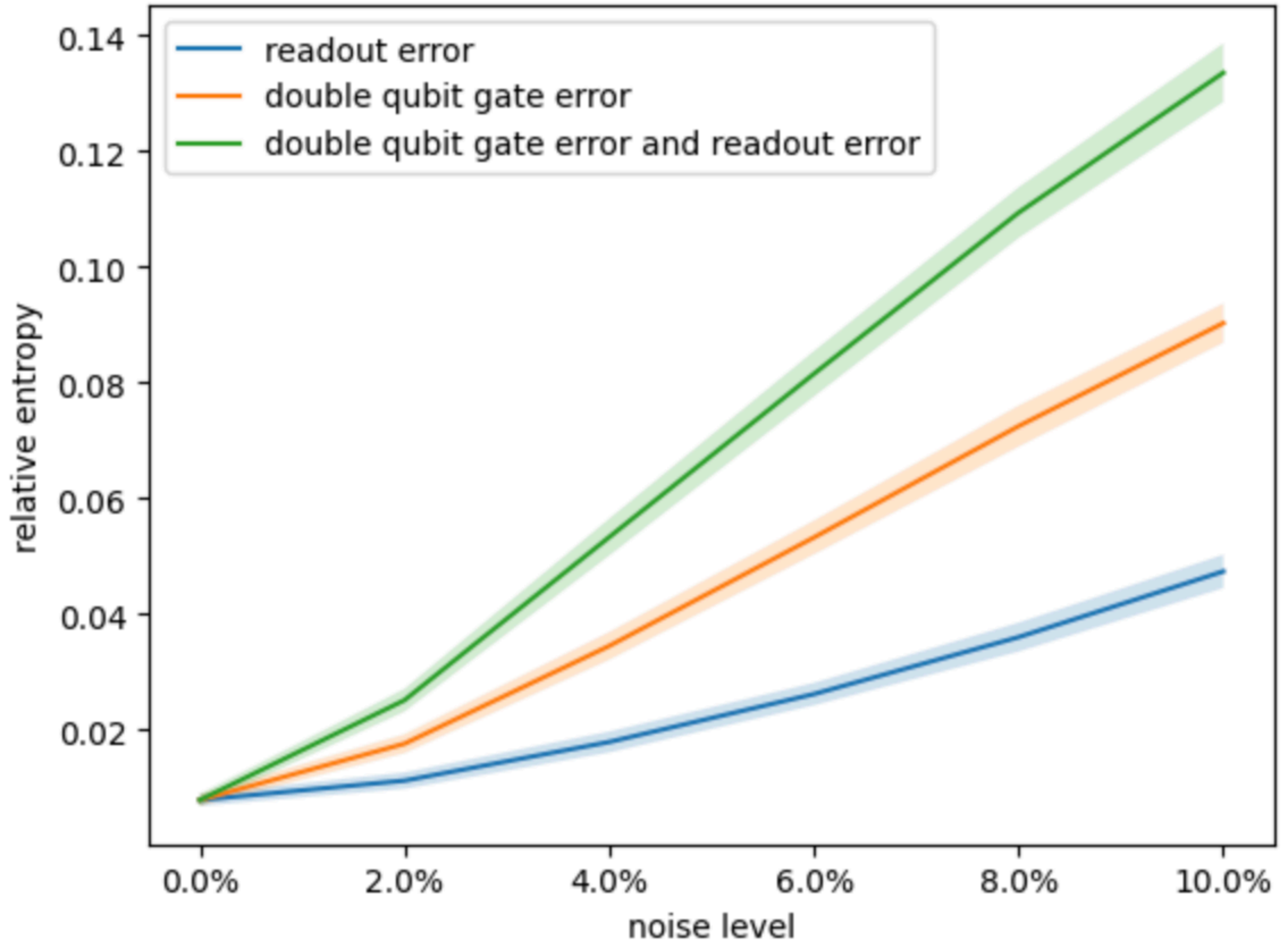


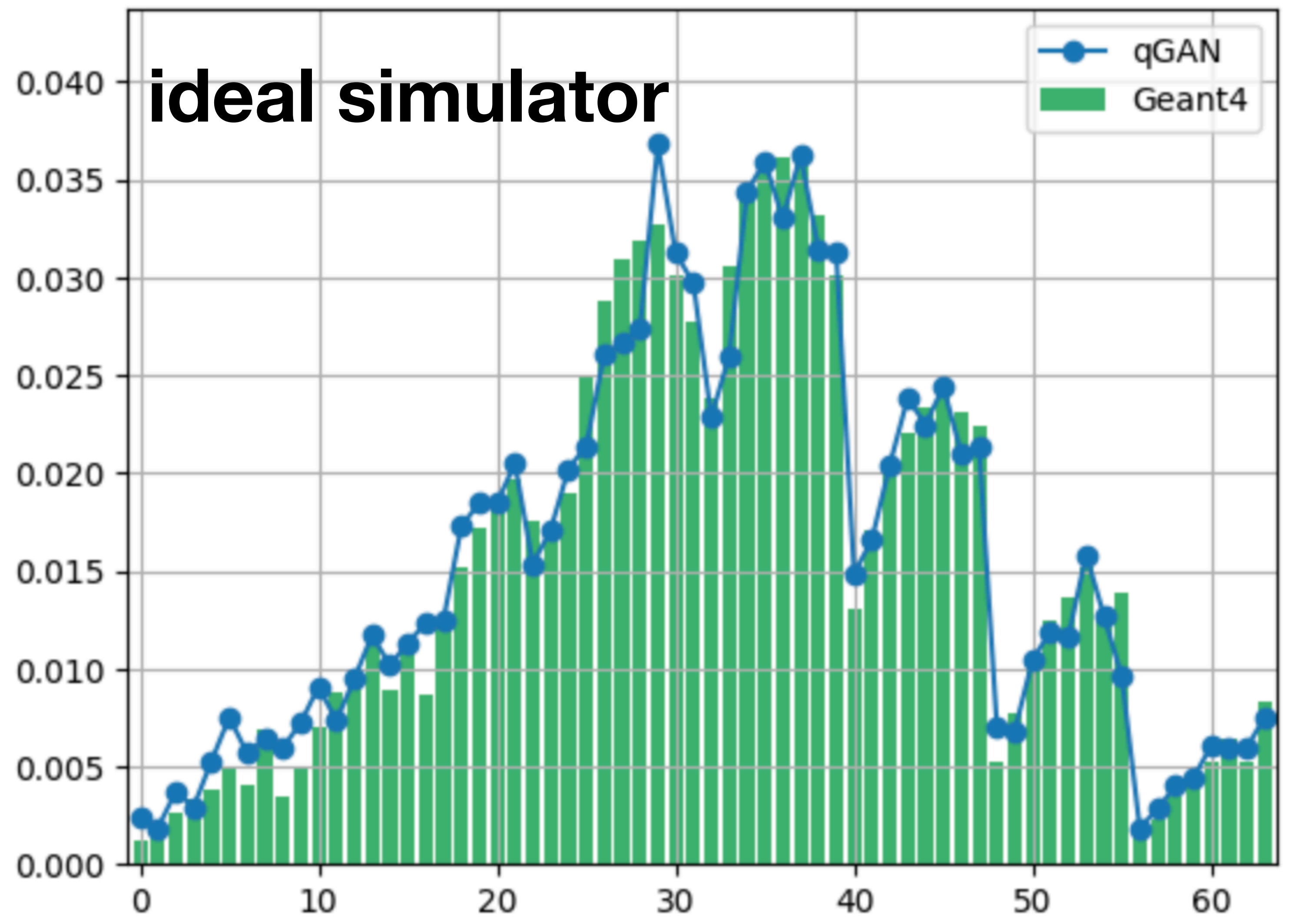
Roadmap: logical qubits
Google
IBM
quantum advantage
Qubits (algorithmic a.k.a. logical)
1,000
100
10
1
2017
2018
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030

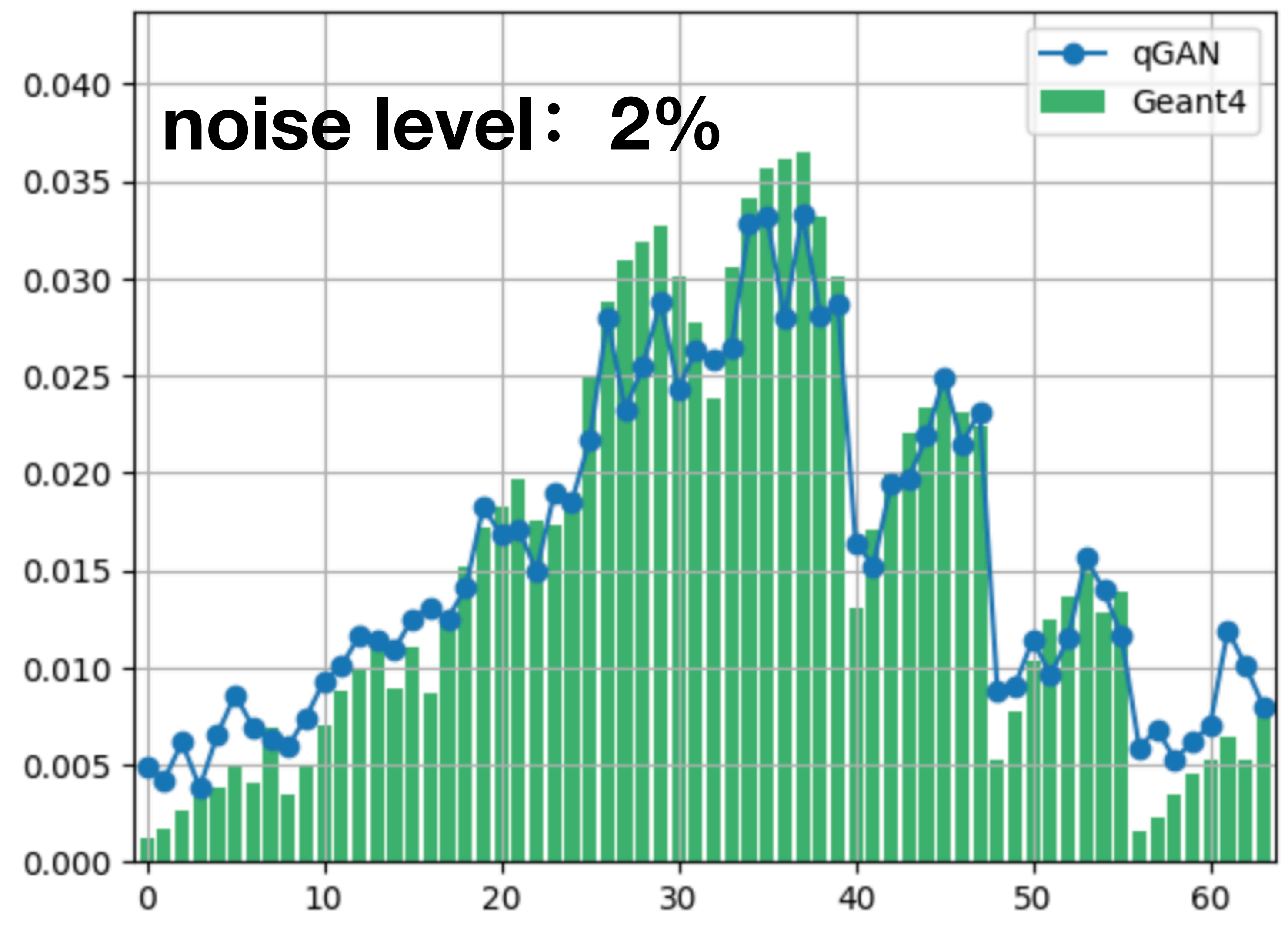
2D: Impact of the noise on the model inference

- 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

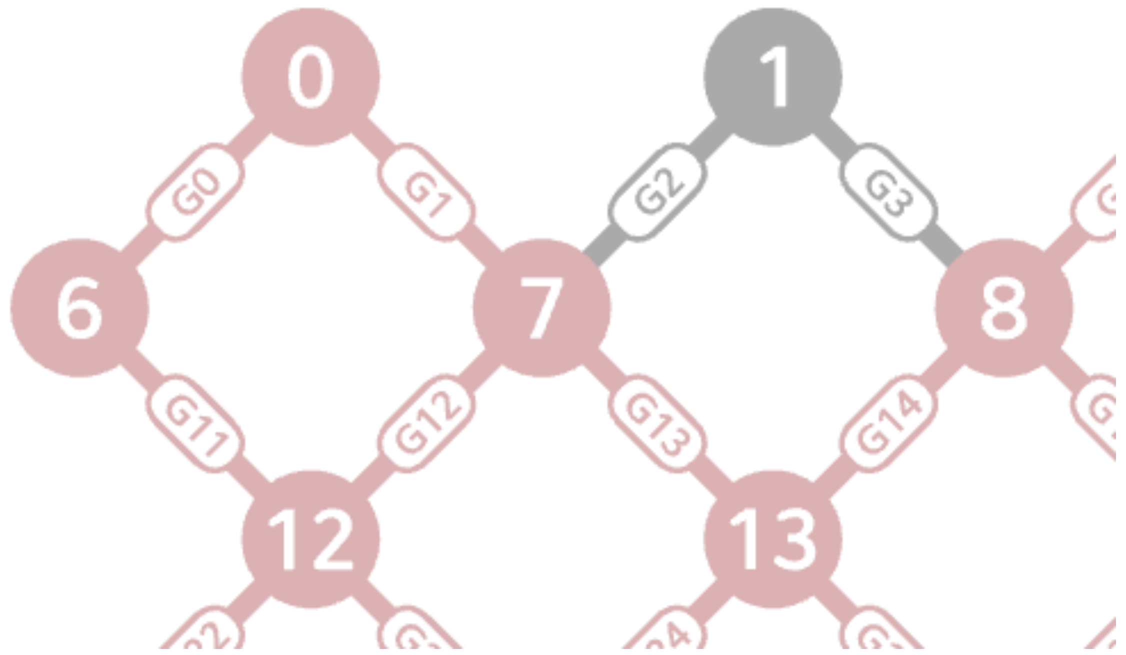


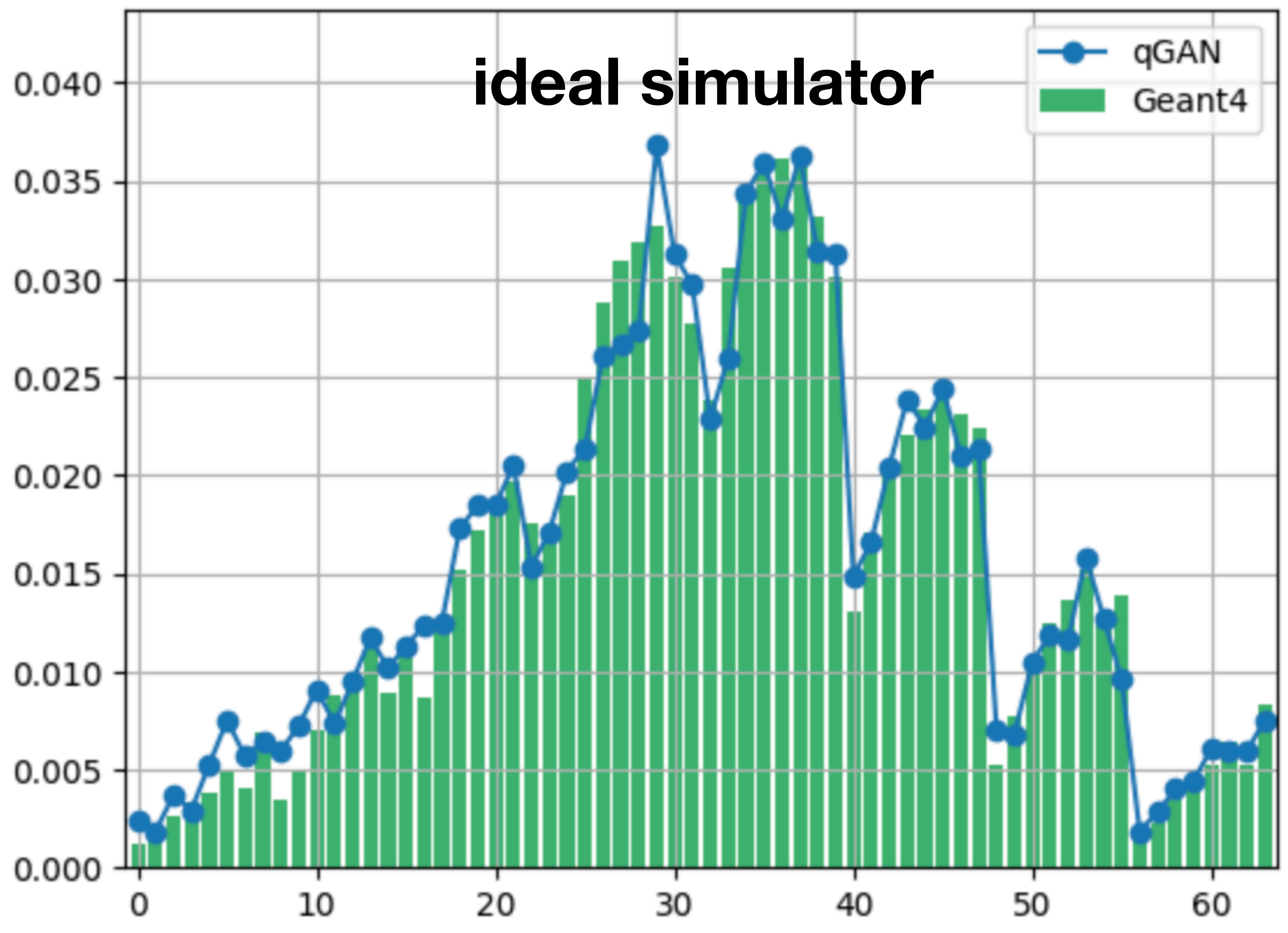


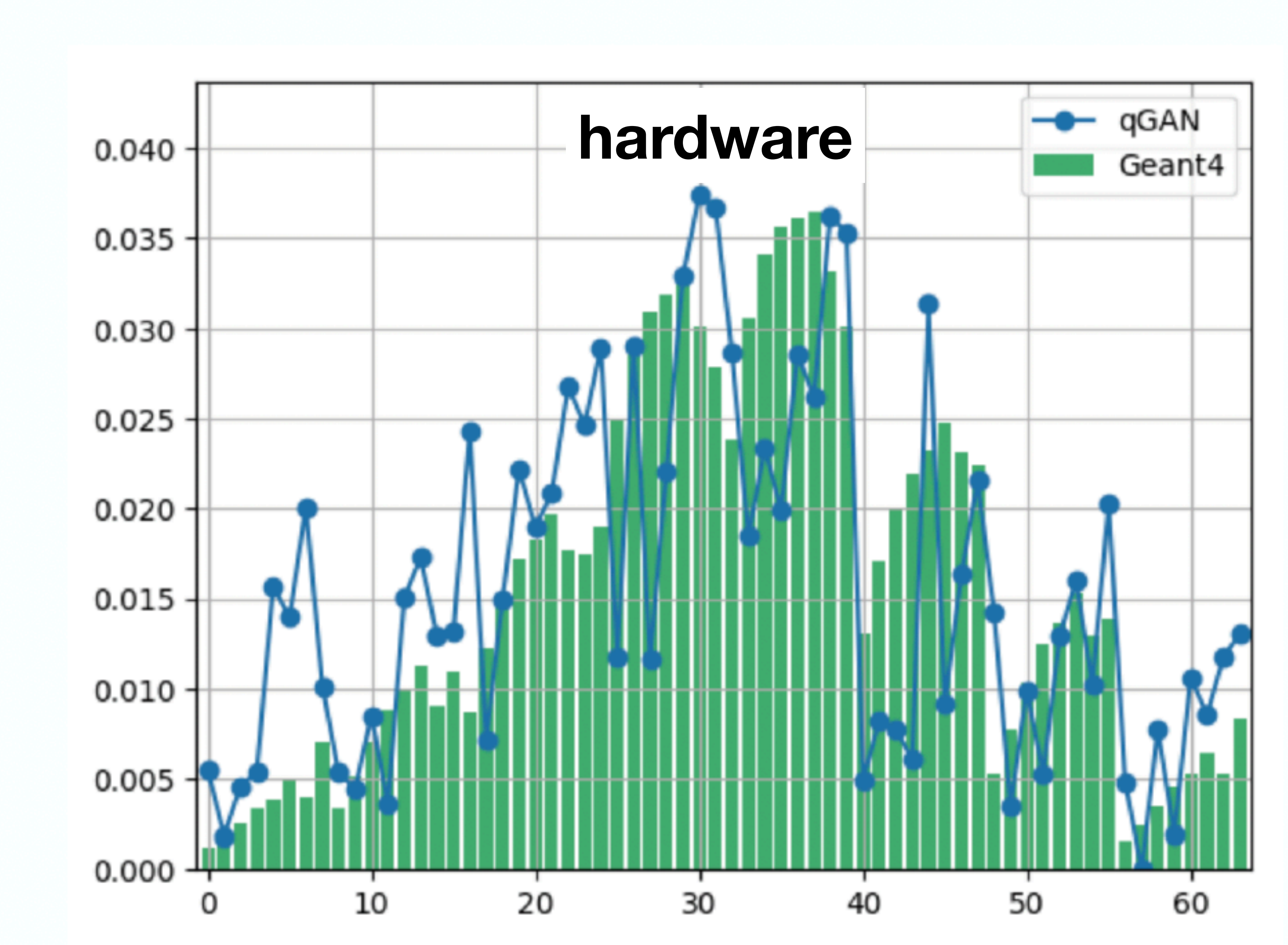


2D performance（quantum computing cloud）

- 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







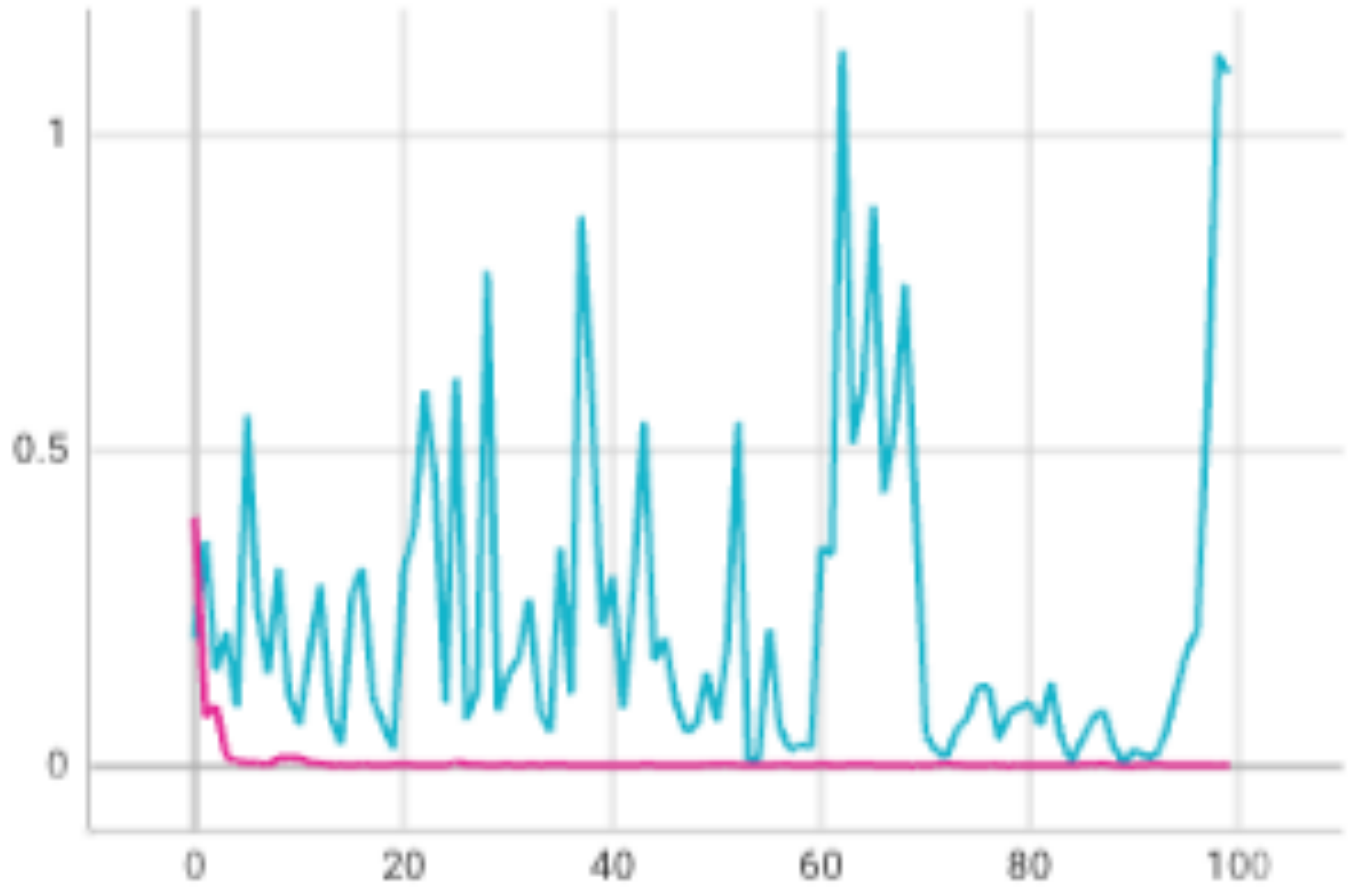
Loss

1D

DESY: Cross-entropy
IHEP: W distance with GP

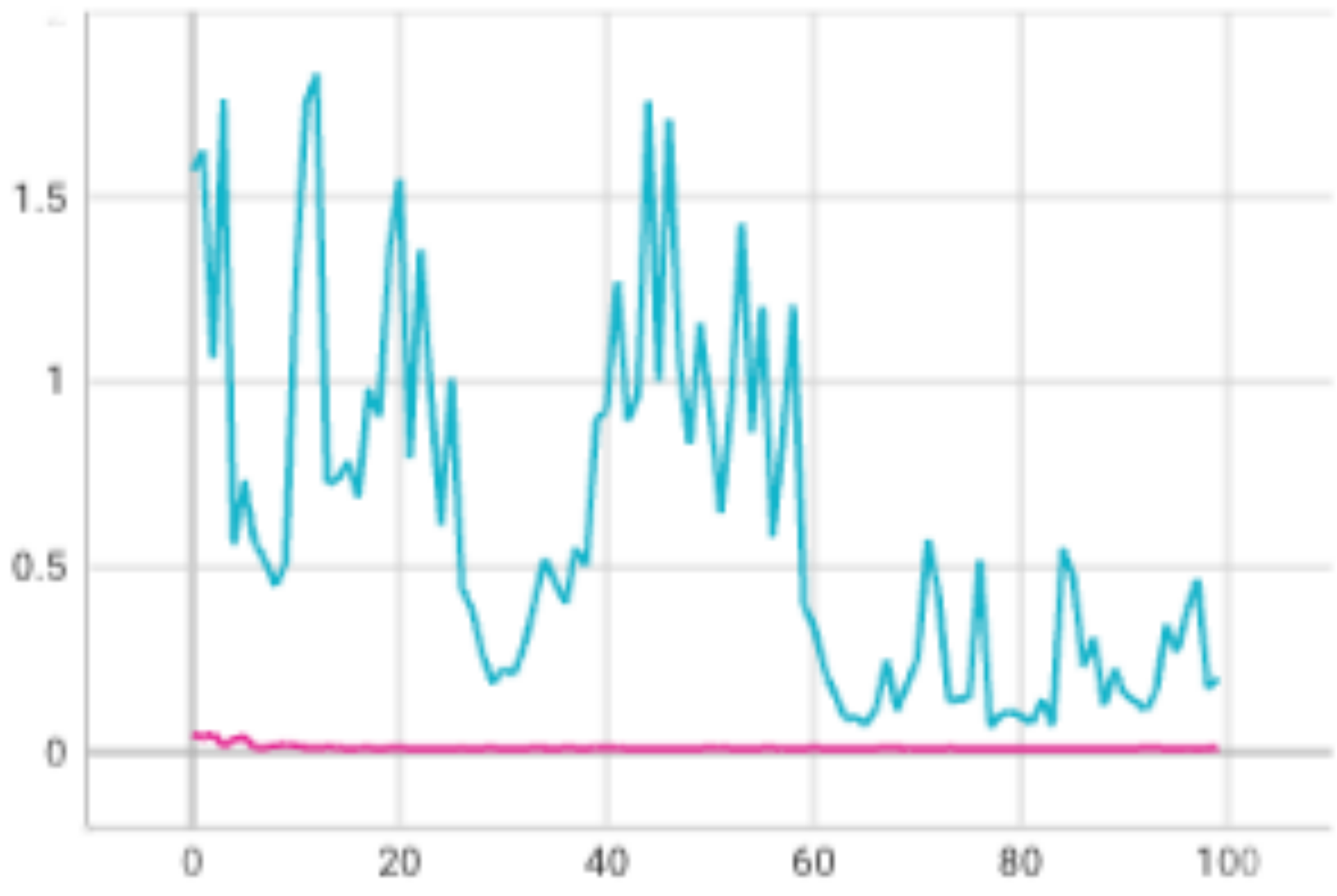
2D

relative entropy



epoch

relative entropy



epoch

On Stabilizing Generative Adversarial Training with Noise