Precise Quantum Angle Generator Designed for Noisy Quantum Devices

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Roadmap

Quantum Computing

QAG Model

Model Evaluation

Conclusions
Future developments

Quantum Computing

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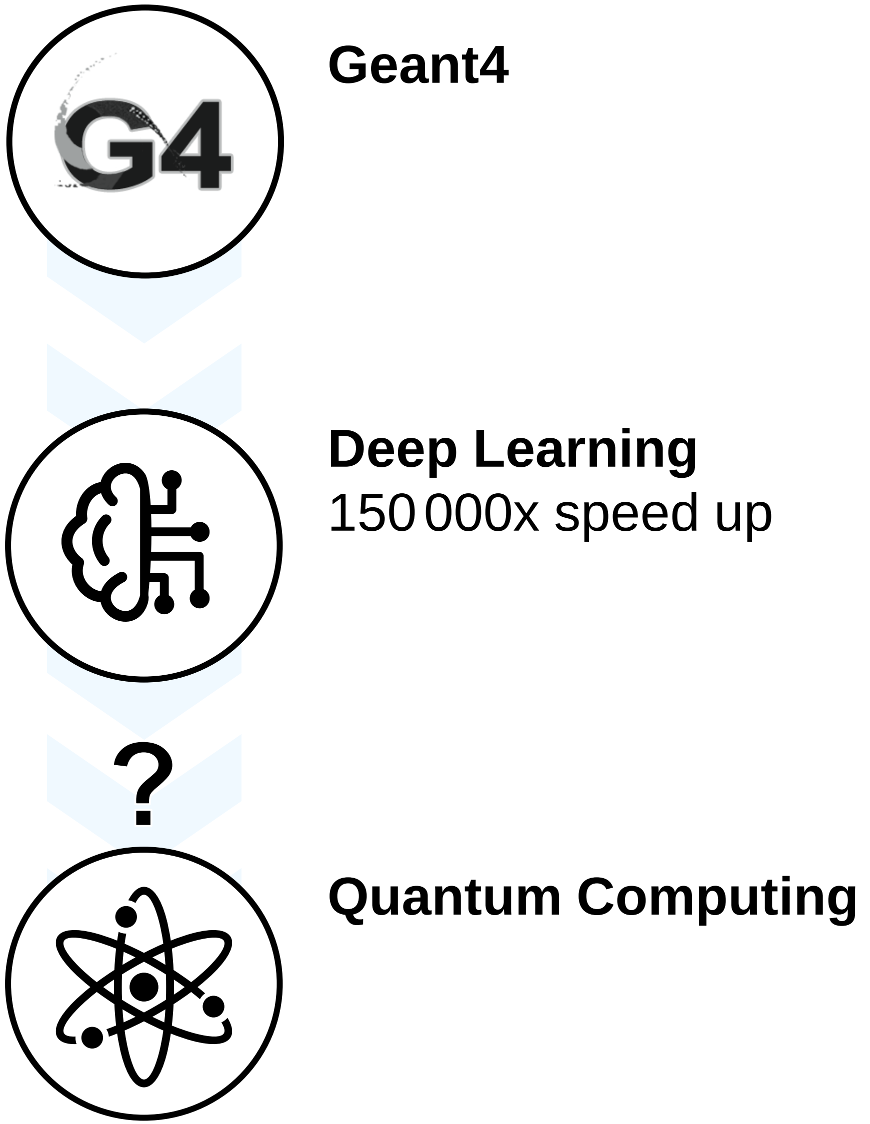
Quantum Computing

Introduction

- **Use case**: Particle Physics Calorimeter Simulations
  - Calorimeter detectors responsible for measuring particle energies in physics
  - Current Geant4 Monte Carlo simulations are computationally demanding

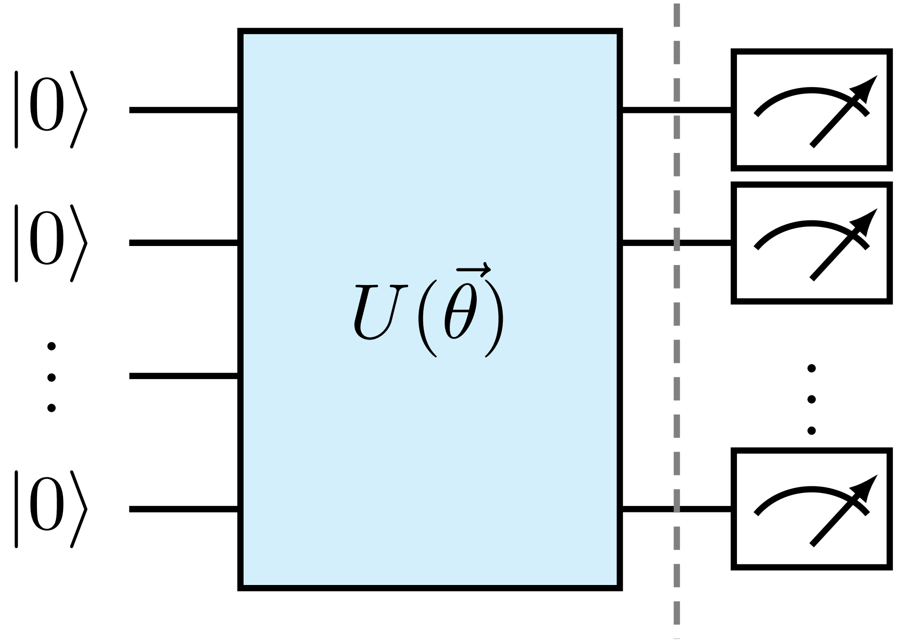
    → Searching for alternatives

- Previously: **Geant4 Monte Carlo Simulations**
- Now: **Deep Learning**
  - → Developed a Deep Learning model for calorimeter simulations which requires fewer computing resources (DLGAN)
- Next: Try **Quantum Computing**



Quantum Computing

What is Quantum Computing



$$|\psi\rangle = U(\vec{\theta})|0\rangle^{\otimes N}$$

Initial state

Evolved state

Quantum Computing **allows for the accurate evolution of a quantum state** $|0\rangle^{\otimes N}$ into another $|\psi\rangle$

✓ High-dimensional search space

- Fewer parameters needed
- Faster learning

QAG Model

Quantum Computing

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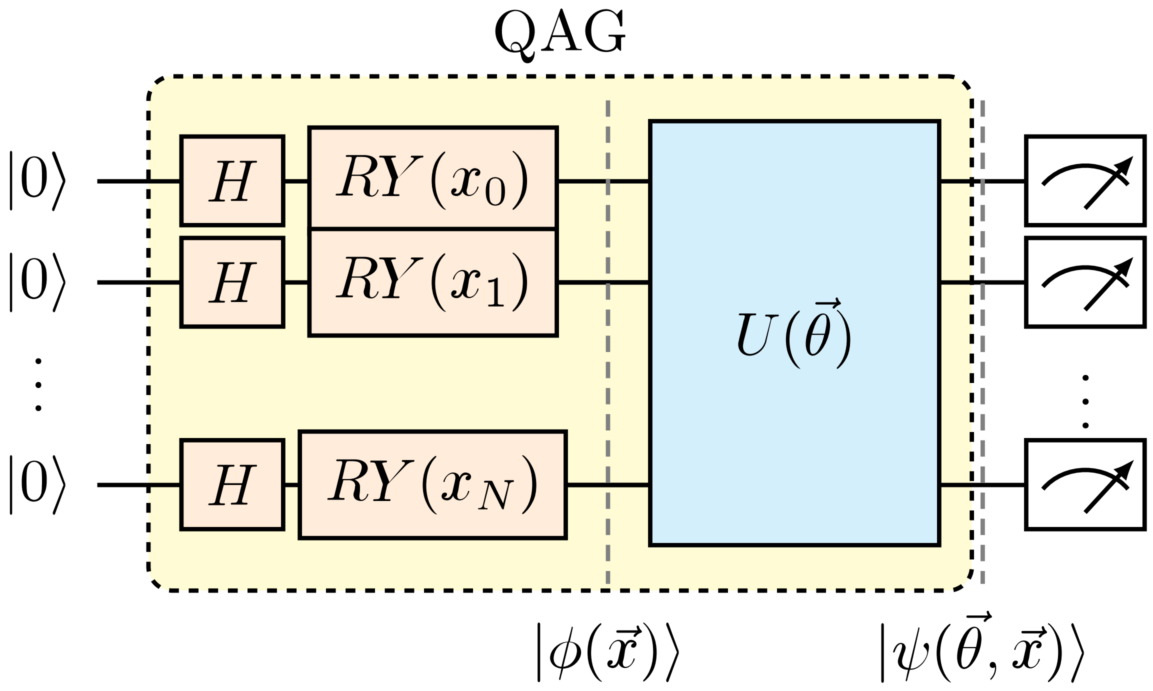
QAG Model

Introduction

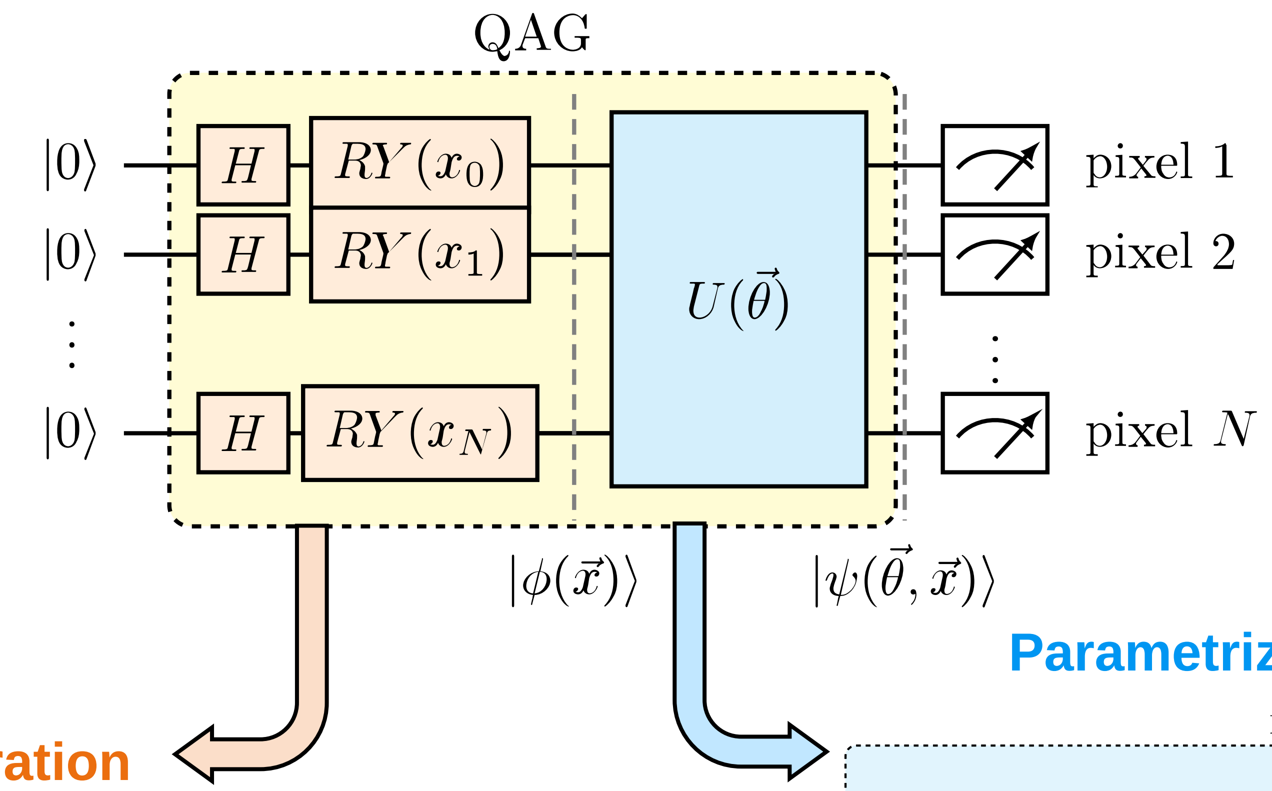
- In this study: A new quantum generative model: **Quantum Angle Generator** (QAG)
- Why a new model?
  - Current quantum models do not satisfy our requirements
    - QGAN: Training is resource inefficient and unstable
    - QCBM: Do not scale well in qubits and gates



QAG Model

Model Schema

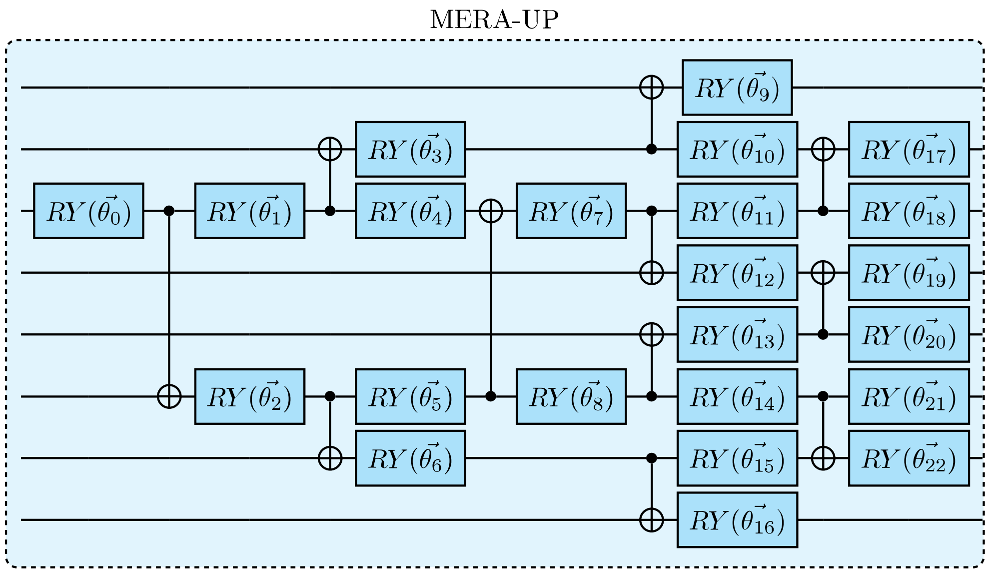
- The generation of N pixels requires N qubits



Quantum state preparation

- Implement superposition (Hadamard Gate H)
- Implement random noise (RY Gate)

Parametrized unitary U



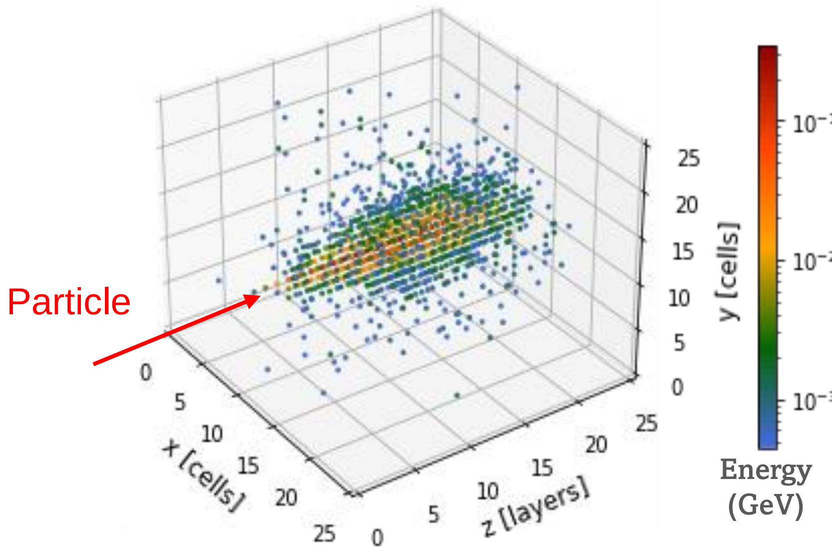
QAG Model

Downsampling

✗ "Quantum Advantage" not yet reached

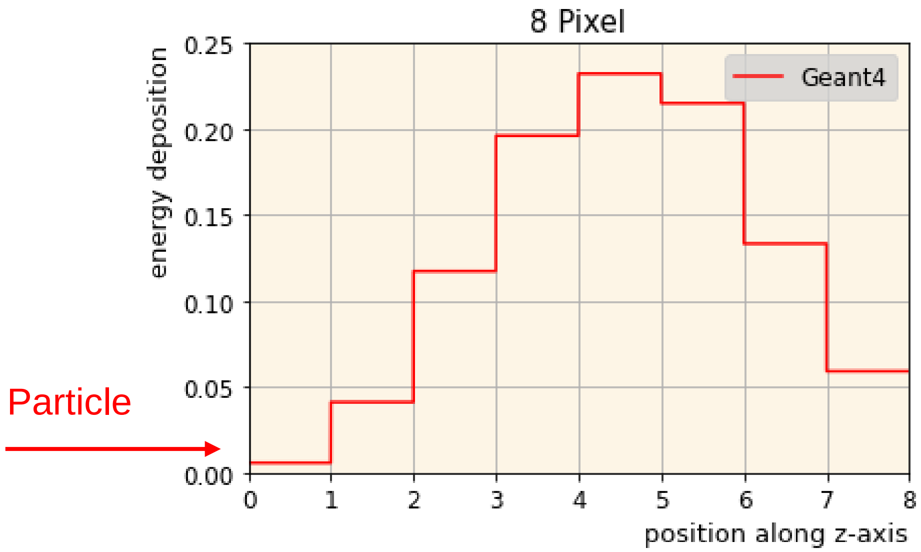
- Only initial investigations with simplified models
- Understand advantages and challenges

(25 x 25 x 25)



Downsampling

(1 x 1 x 8)



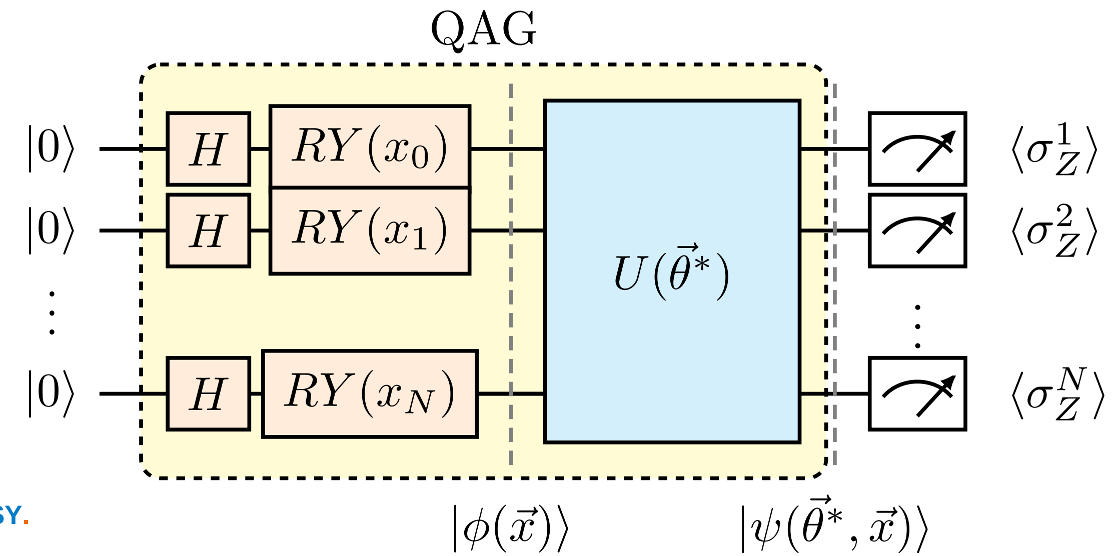
QAG Model

Generation process

Once the optimal parameters $\vec{\theta}^*$ are found through the training process

1. Generate a random vector $\vec{x}$ for the RY gates
2. Repeat nb_{shots} times:
   1. Measure the qubits ({0,1})

$$\langle \sigma_Z \rangle = 2 * \frac{\#|0\rangle}{nb_{shots}} - 1$$



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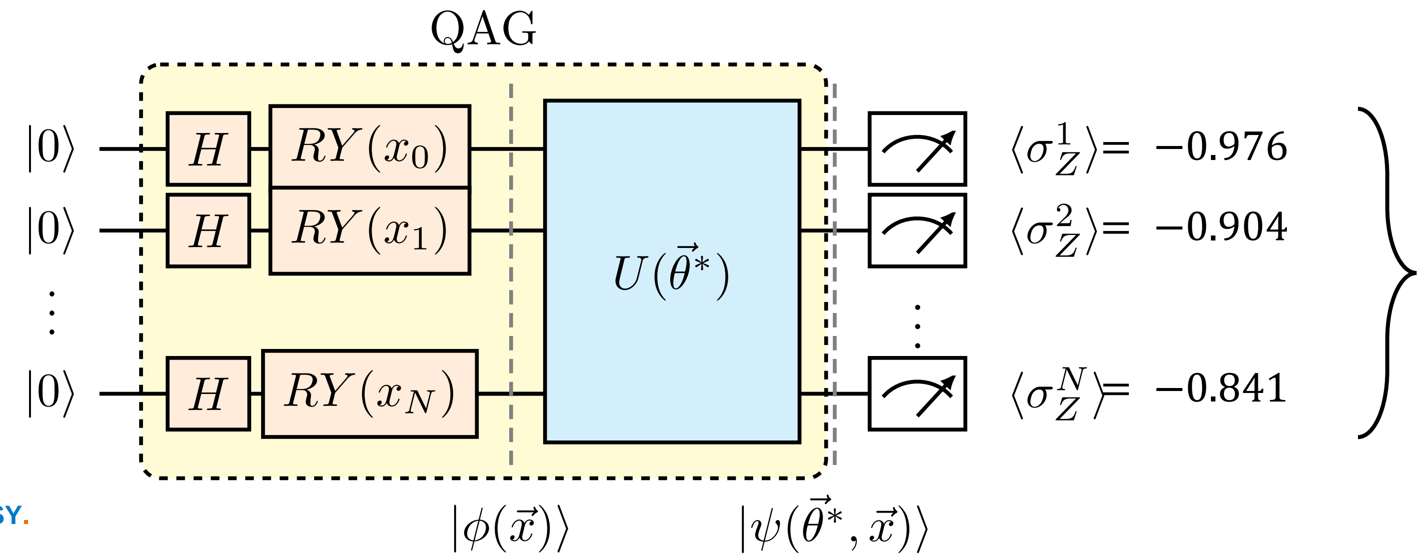
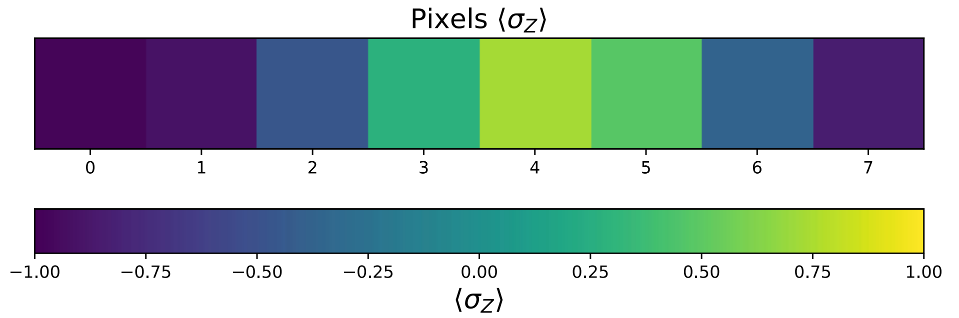




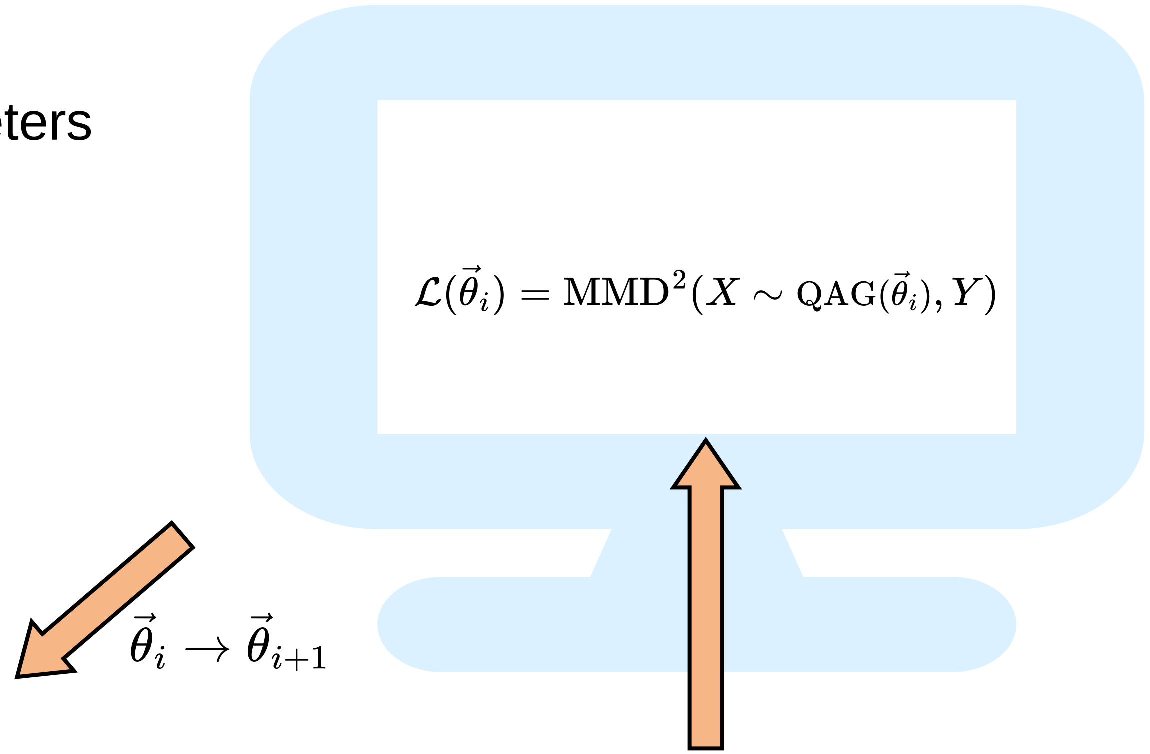
QAG Model

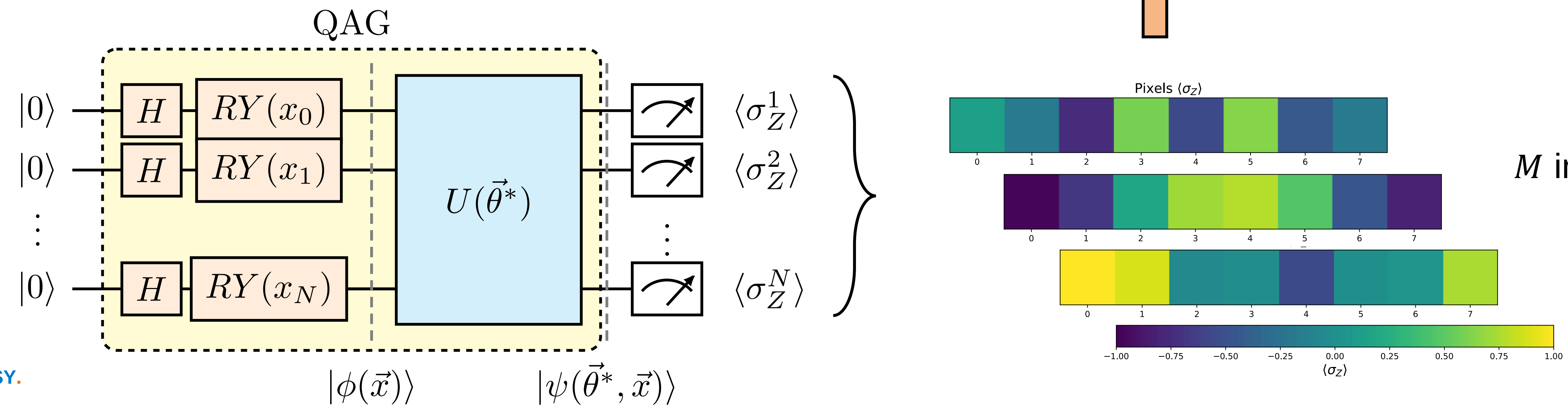
Training process

Choose a random initial set of parameters $\vec{\theta}_0$:

For each epoch i:

1. Generate M images
2. Evaluate the loss
3. Update the parameters $\theta_i \to \theta_{i+1}$ (Gradient descent, SPSA)





M images

Model Evaluation

Quantum Computing

QAG Model

Model Evaluation

Conclusions
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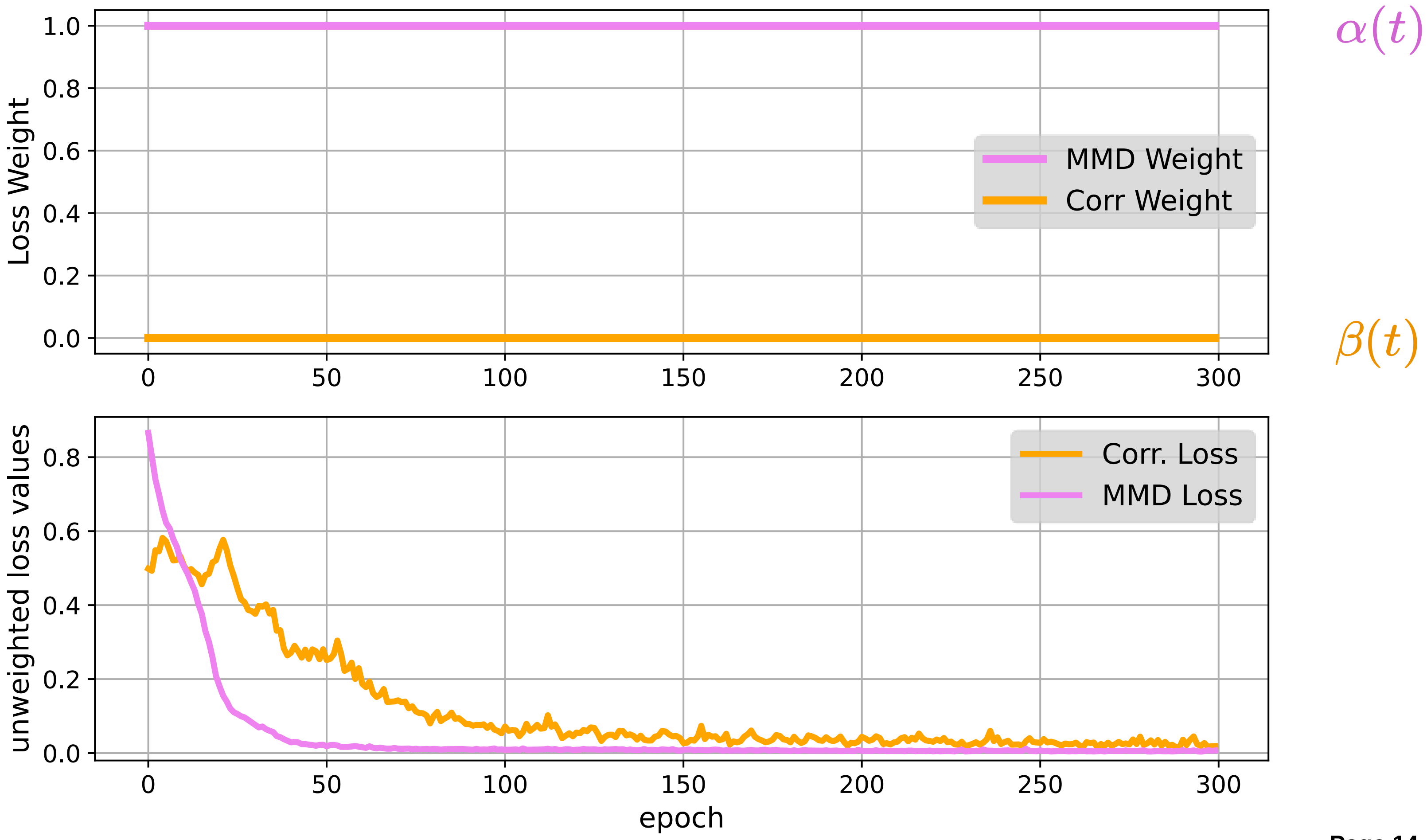
Model Evaluation: Example Run

Training

$$\mathcal{L}(\vartheta, Y, t) = \alpha(t) \cdot \mathrm{MMD}^2(\vartheta, Y) + \beta(t) \cdot \mathrm{Corr}(\vartheta, Y)$$

- ✓ Stable, smooth and fast convergence
- ✓ MMD loss is sufficient to learn the correlation between the features (pixels in the detector)



Model Evaluation: Example Run

Training

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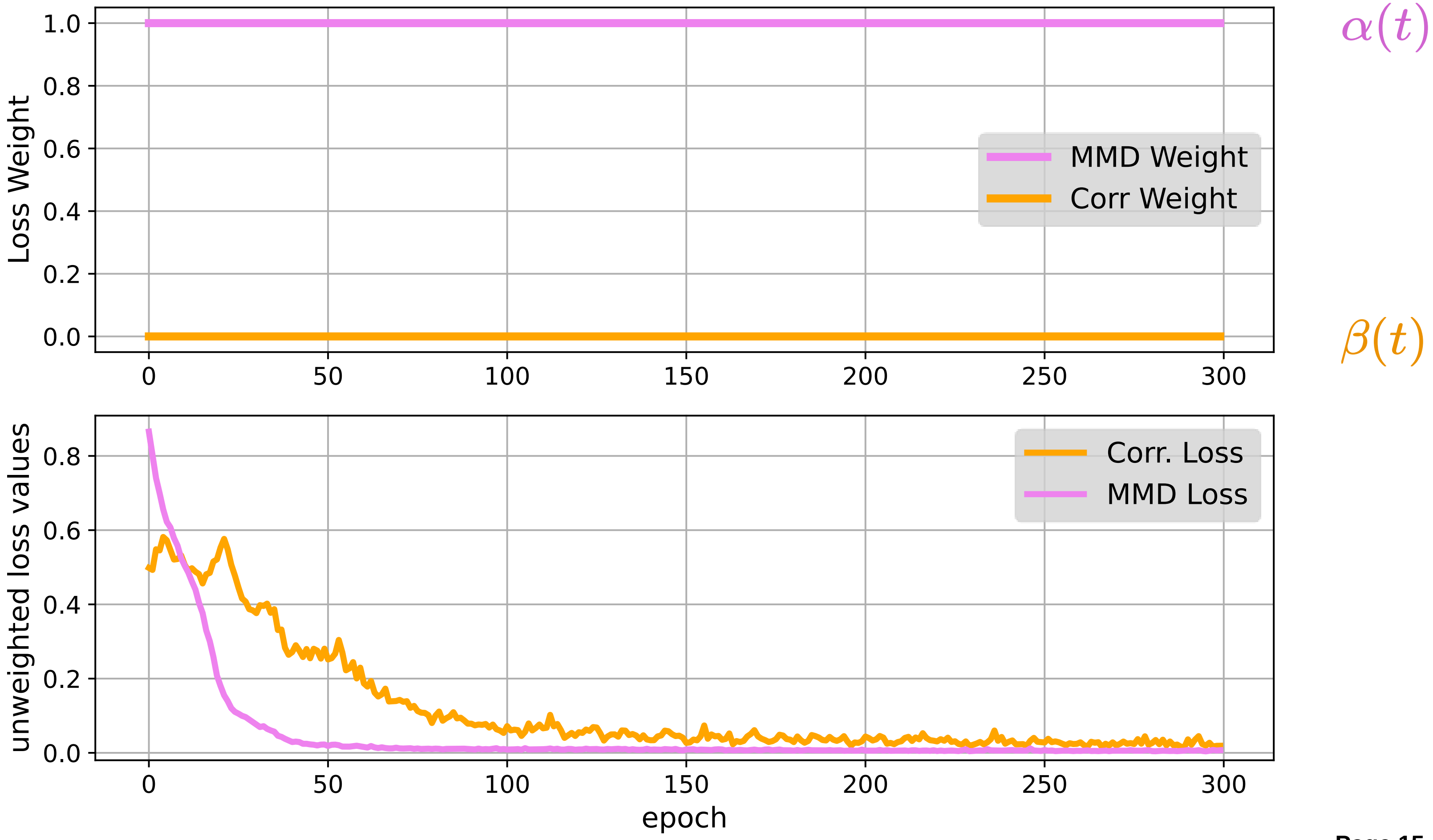
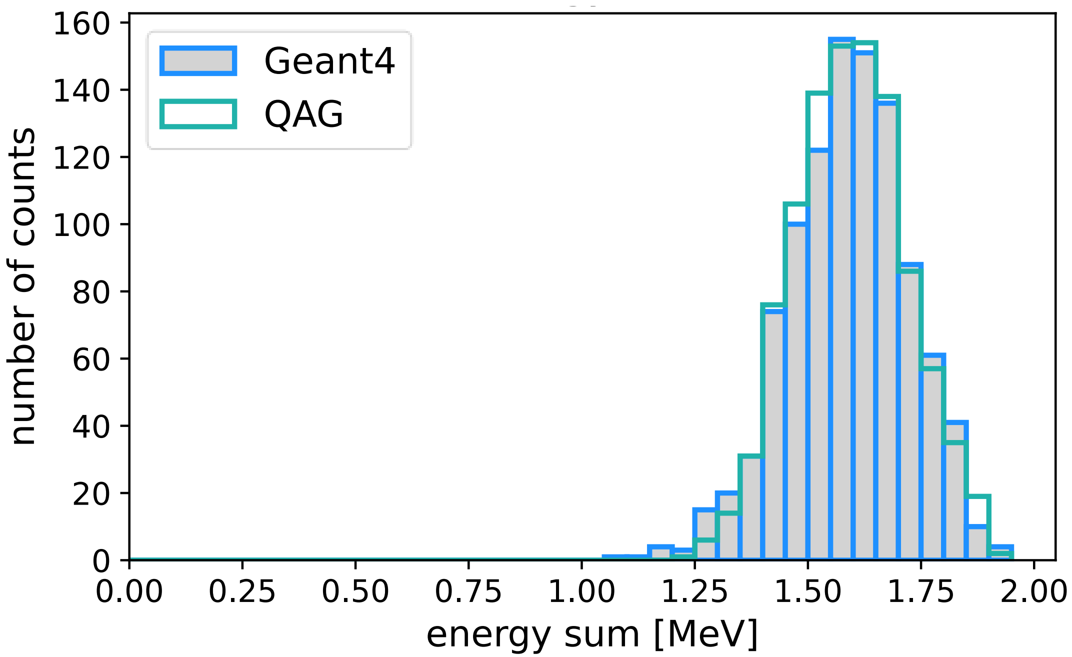


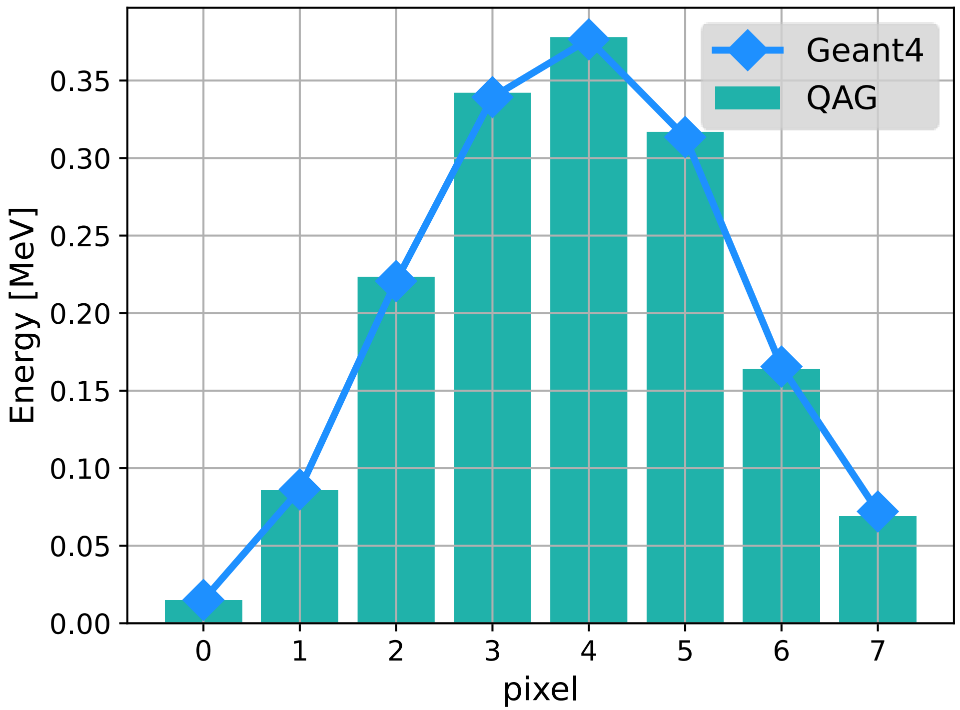
Model Evaluation: Example Run

Events generated

Total energy distributions of true (Geant4) and generated events



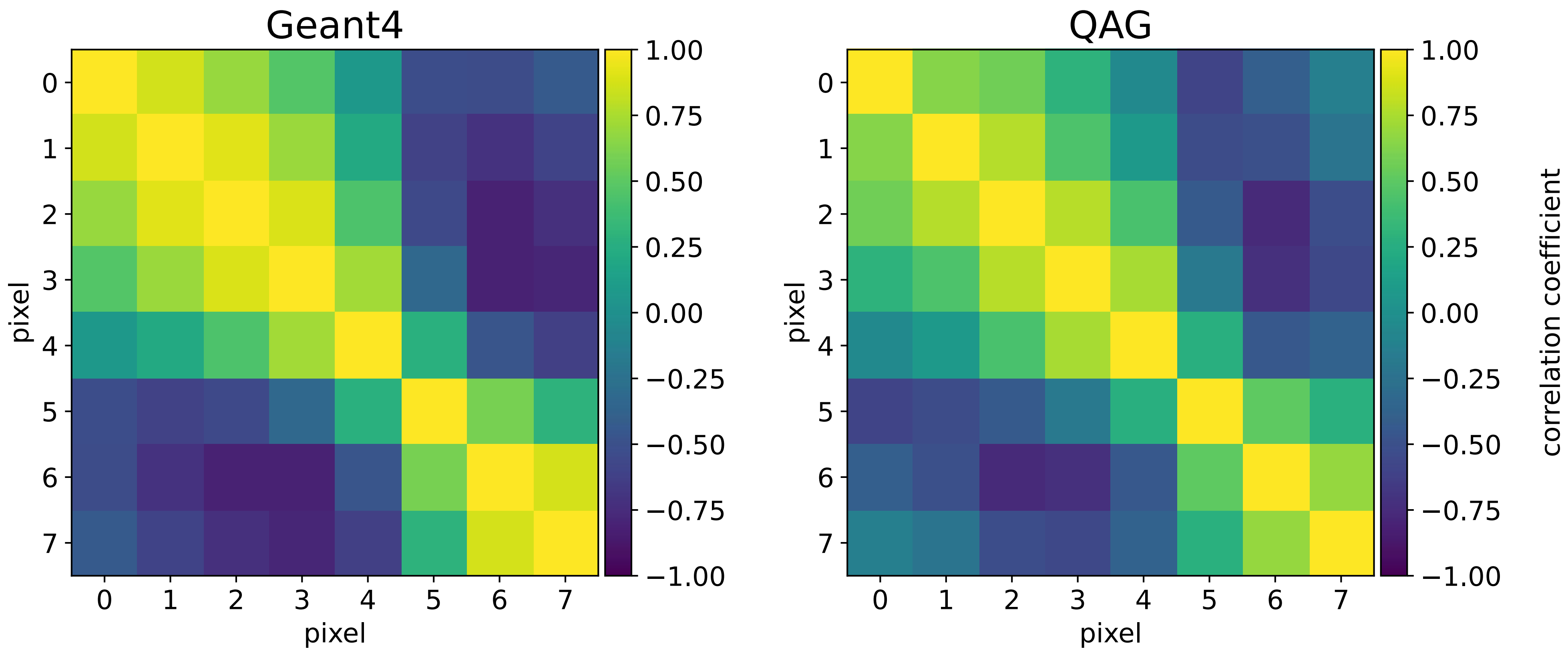
Average measured energy for each pixel



✓ Good accuracy in both total energies and average pixel-wise energies

Model Evaluation: Example Run

Correlations



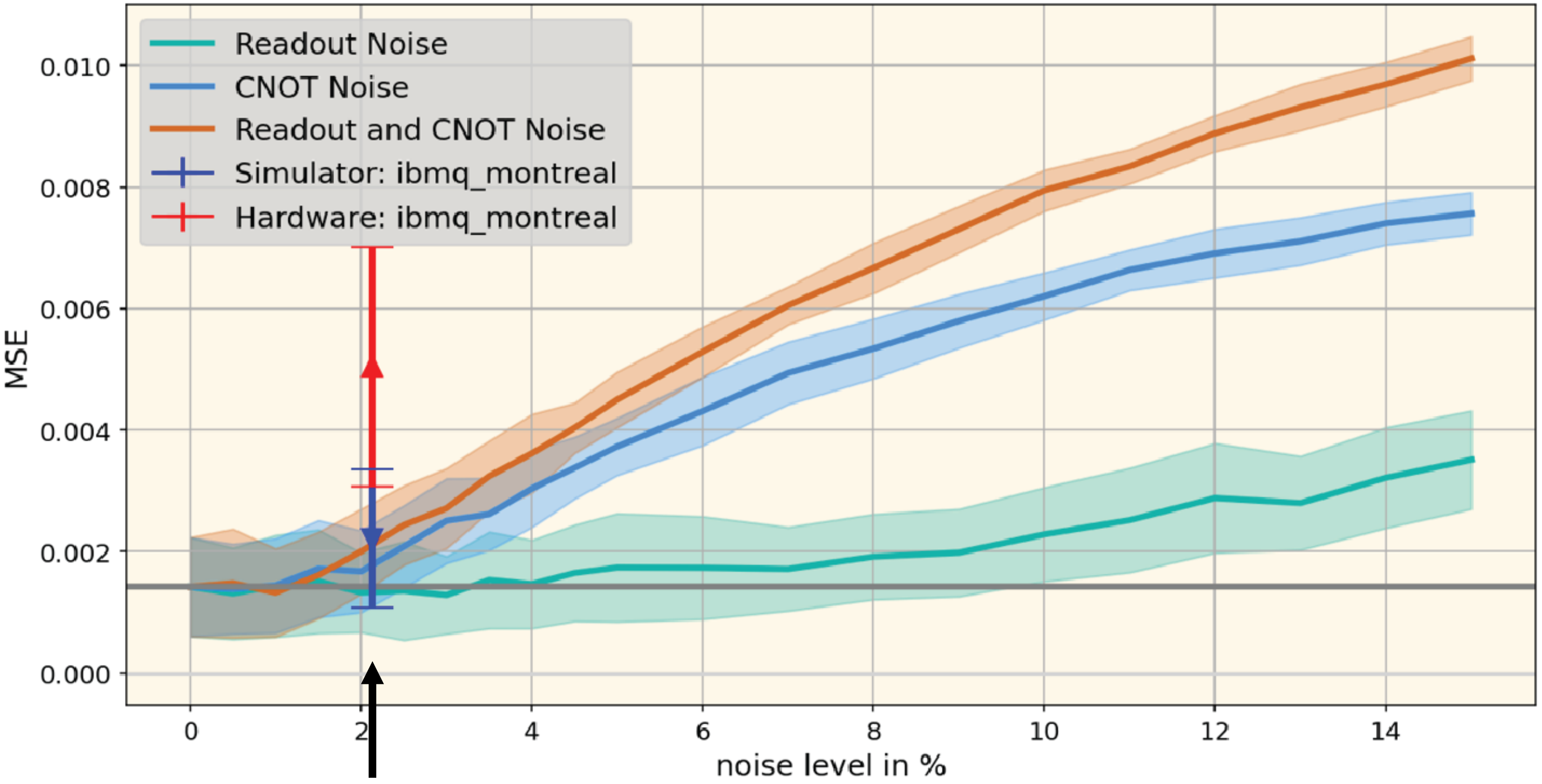
✓ Model is able to reproduce correlations and anti-correlations in the shower

Model Evaluation: Noise Study

Models trained without noise

- Models trained without noise
- Inference made with noise, 20 images generated

⚠️ Less accuracy in Hardware due to the presence of swap gates in the transpiled circuit



Present usual noise level $\lesssim 2\%$

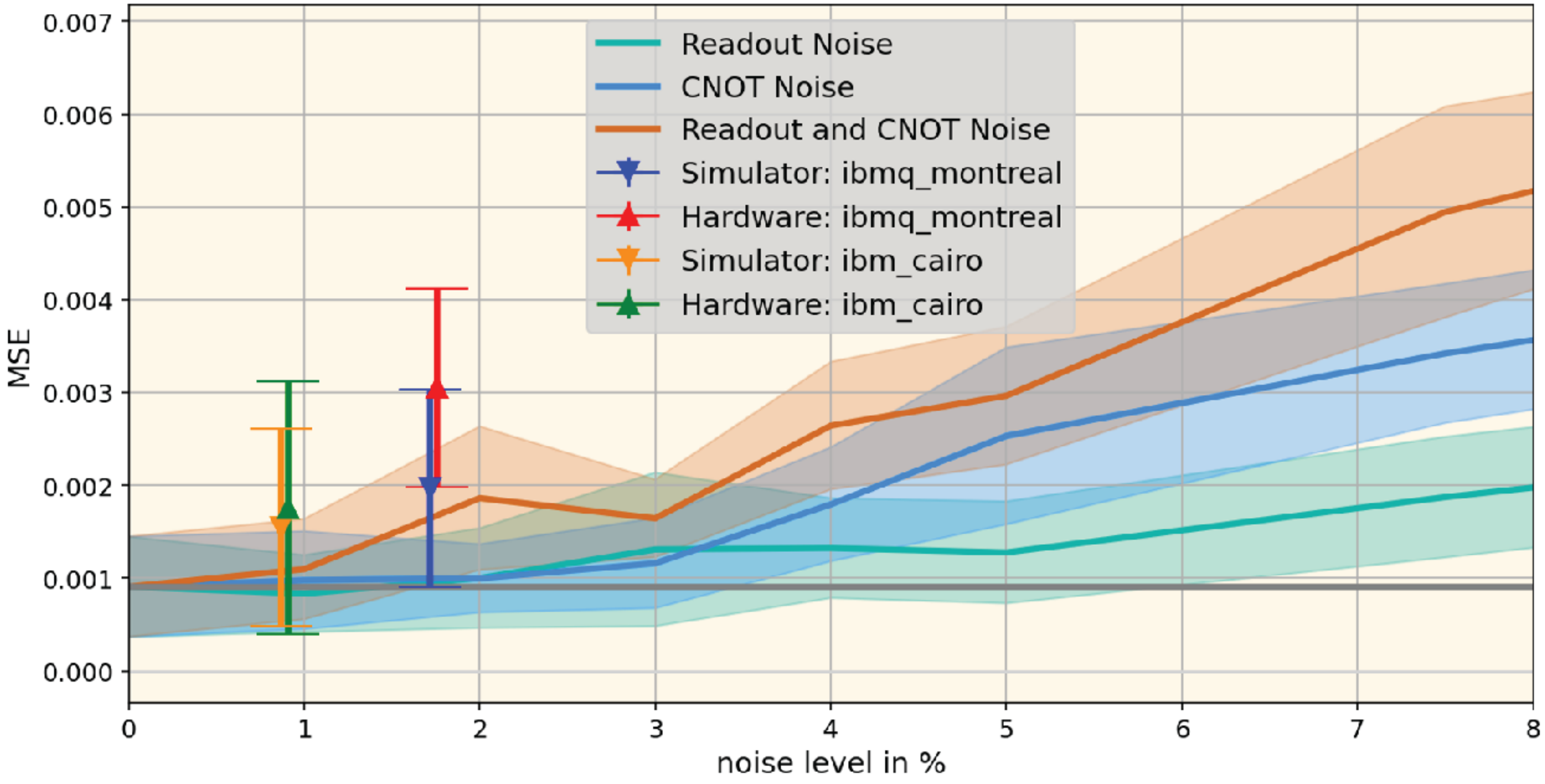
Model Evaluation: Noise Study

Models trained in noisy instances

To be noted:
Different scale in x and y

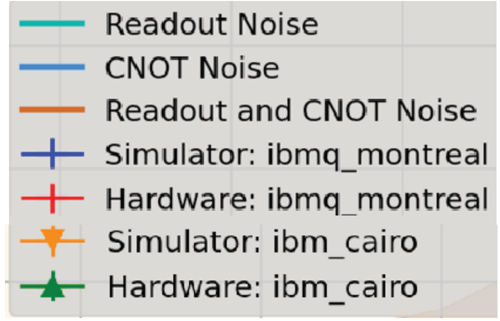
- Models trained with noise
- Inference made with noise, 20 images generated

✓ Improved accuracy: the QAG model is able to adapt its parameters to the noisy hardware to improve its precision

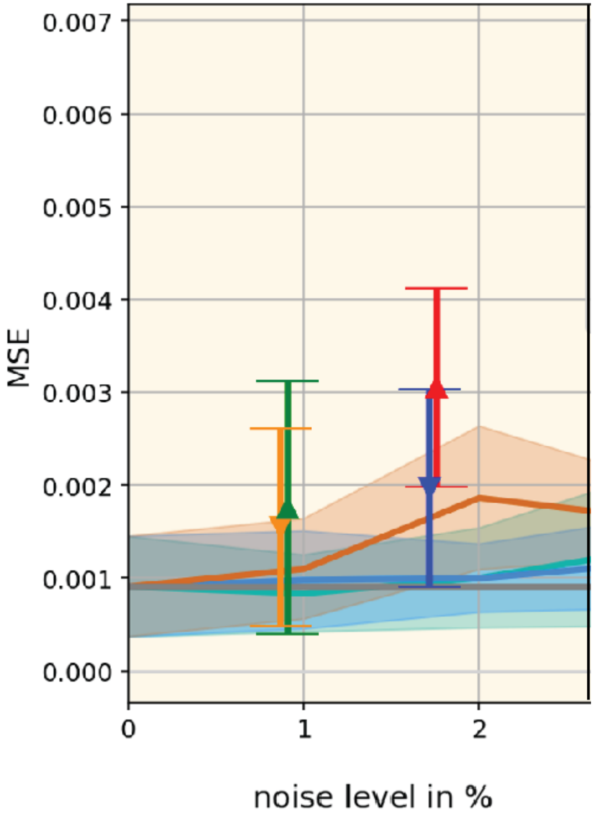


Model Evaluation: Noise Study

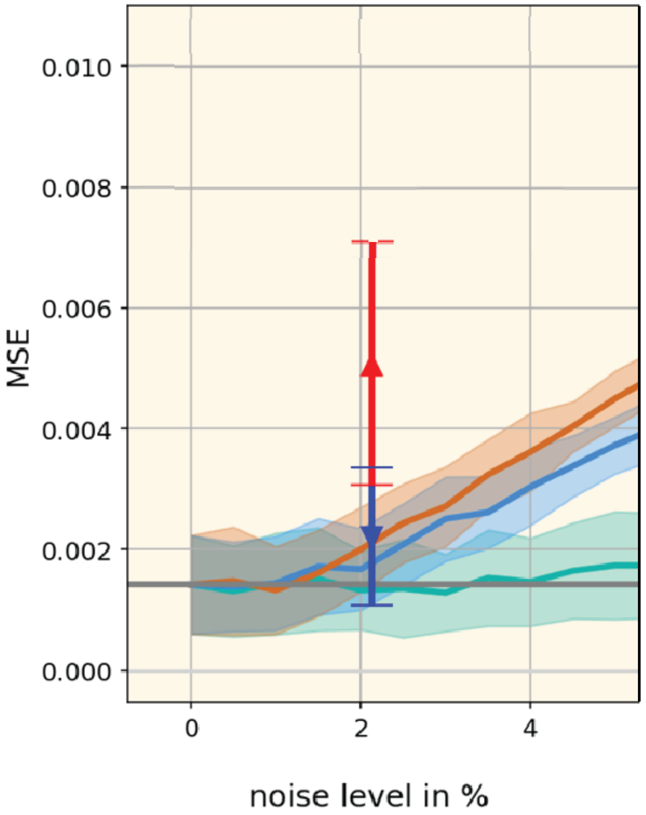
✓ **When trained directly on the noisy instance** the QAG model is able to adapt its parameters to the noisy hardware to improve its precision



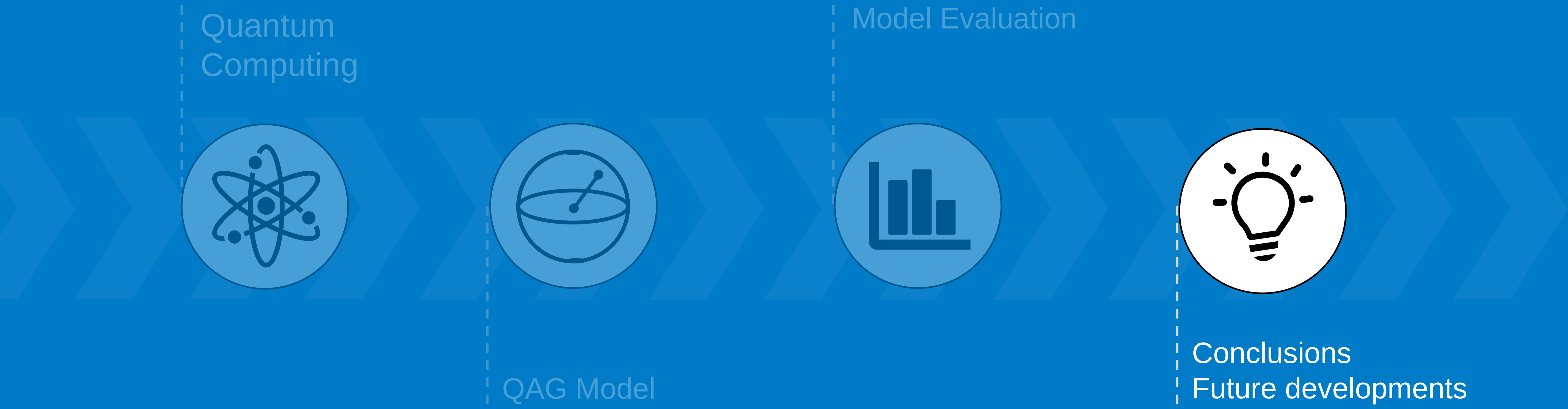
Models trained in
noisy instances



Models trained in
noiseless simulators



Conclusions

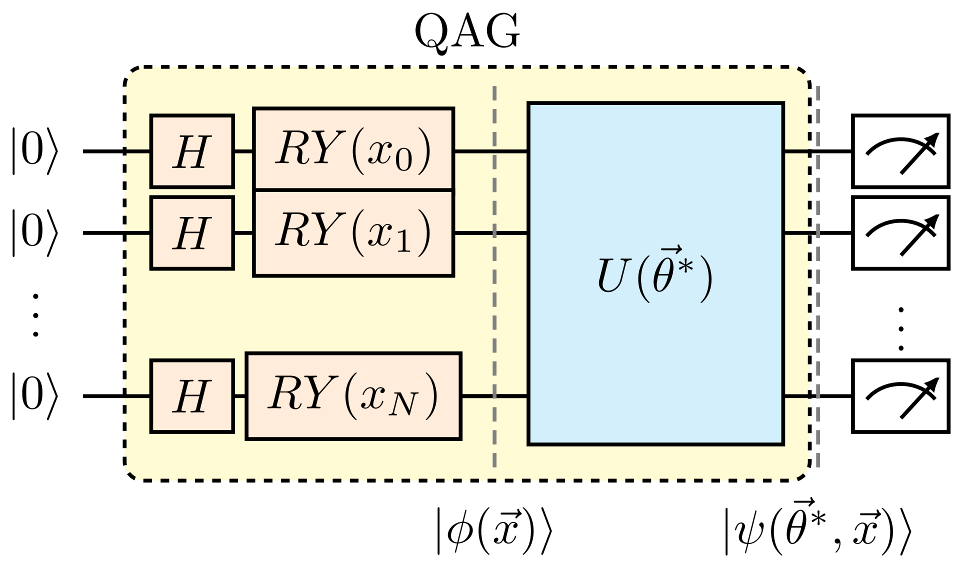


Conclusions

Summary

QAG: a quantum generative model

- ✓ Good scaling of gates and qubits
- ✓ Stable, smooth and fast training convergence
- ✓ Good inference accuracy
- ✓ Can easily adapt to current NISQ Devices



Future developments

- More in-depth hyperparameter study
- Overcome limit 1 qubit $\leftrightarrow$ 1 pixel

References

Main Paper:

1. Rehm, F., Vallecorsa, S., Borras, K., Krücker, D., Grossi, M., & Varo, V. (2023). **Precise image generation on current noisy quantum computing devices**. *Quantum Science and Technology, 9(1), 015009.*

PhD Thesis:

2. Rehm, F. (2023). **Deep learning and quantum generative models for high energy physics calorimeter simulations.** (Doctoral dissertation, RWTH Aachen University, RWTH Aachen U.).

Thank You!

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github.com/SaverioMonaco/QAG (Private)

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Backup slides

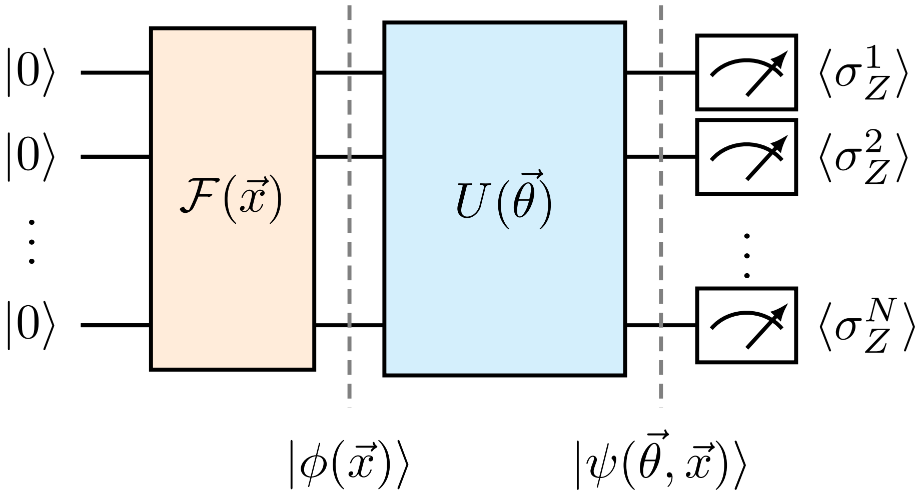
Backup: QAG Model

Types of generative models

QAG

QCBM

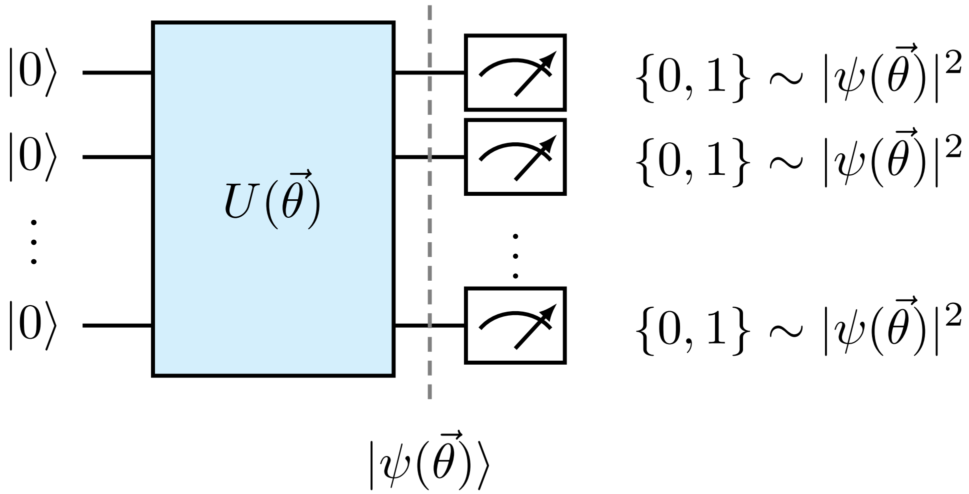
Continuous



- Source of entropy given by $\vec{\boldsymbol{x}}$

✓ Fewer qubits needed
✗ Multiple measurement needed

Discrete



- Source of entropy given by the **measurement process**

✗ More qubits needed
✓ Single measurement

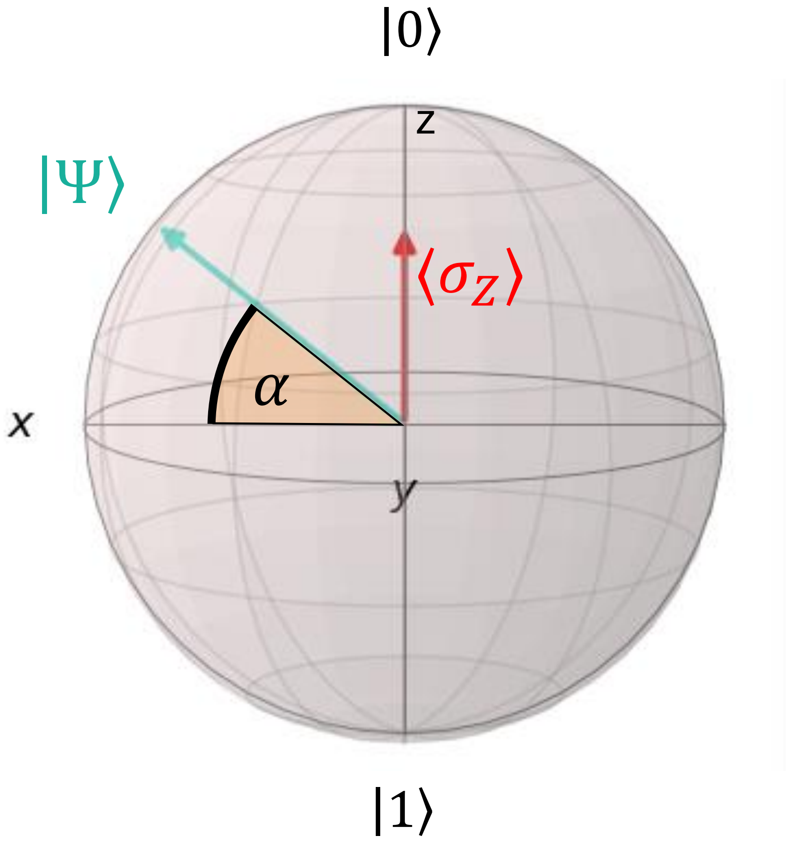
Backup: Encoding / Decoding

Angle – Expectation value - Energy

$$\langle \sigma_Z \rangle = 2 * \frac{\#|0\rangle}{nb_{shots}} - 1$$

$$\alpha = \sin^{-1}(\langle \sigma_Z \rangle)$$

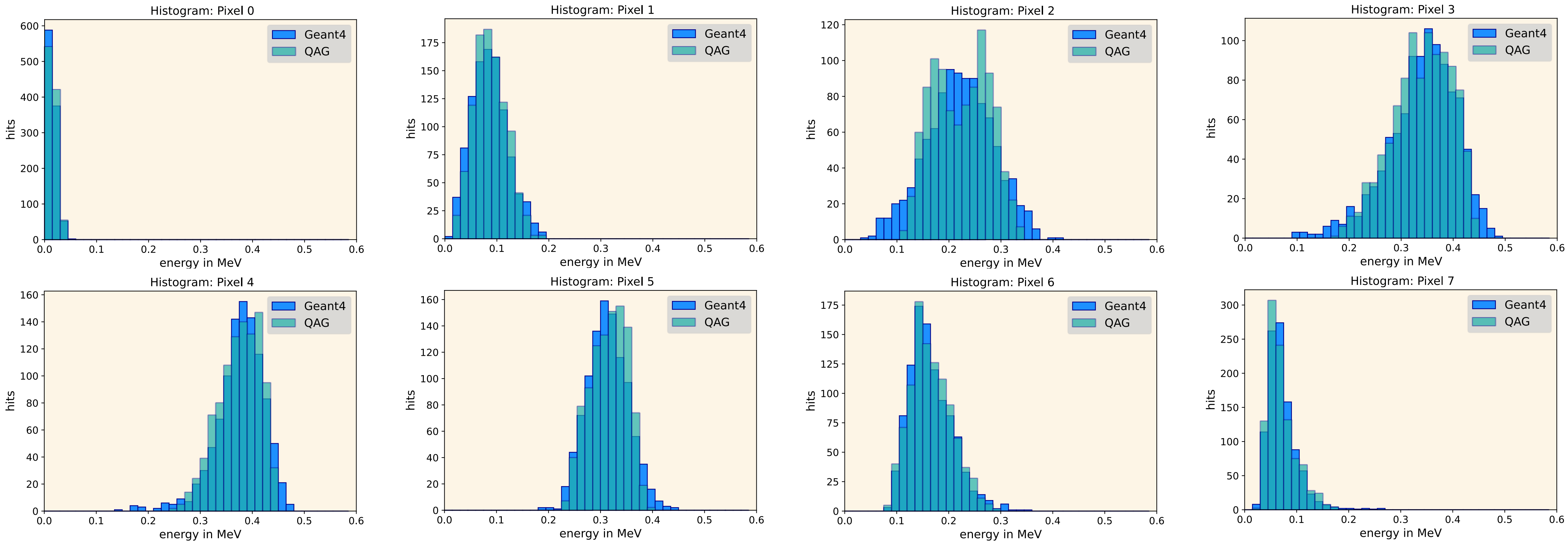
$$E = \left(\frac{E_{max}}{2 \cdot \theta_{max}}\right) \cdot (\theta + \theta_{max})$$



Backup: Example Run

Hyperparameters

- circuit block : mera_up
- depth : 2
- lr : 0.03
- n_images : 100
- sigmas : $[0.1, 1, 10]$



Backup: Loss Functions

Loss terms

$$\mathrm{MMD}^2 = E_{X\sim P}\left[k(X,X)\right] + E_{Y\sim Q}\left[k(Y,Y)\right] - 2E_{X\sim P, Y\sim Q}\left[k(X,Y)\right]$$

$$\mathrm{Corr} = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(R_{ij}^{X\sim \mathrm{QAG}(\vec{\theta})} - R_{ij}^{Y}\right)^2$$

where $R_{ij} = \frac{C_{ij}}{\sqrt{C_{ii}C_{jj}}}$

Losses

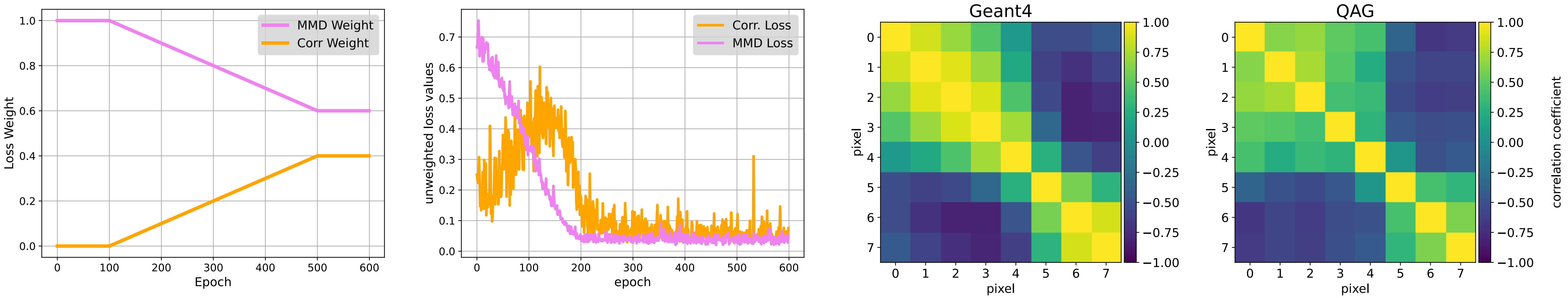
- $L(\vartheta, Y, t) = \mathrm{MMD}^2(\theta, Y) + \sout{\mathrm{Corr}(\theta, Y)}$
- $L(\vartheta, Y, t) = \alpha(t)\cdot\mathrm{MMD}^2(\theta, Y) + \beta(t)\cdot\mathrm{Corr}(\theta, Y)$

Backup: Loss Functions

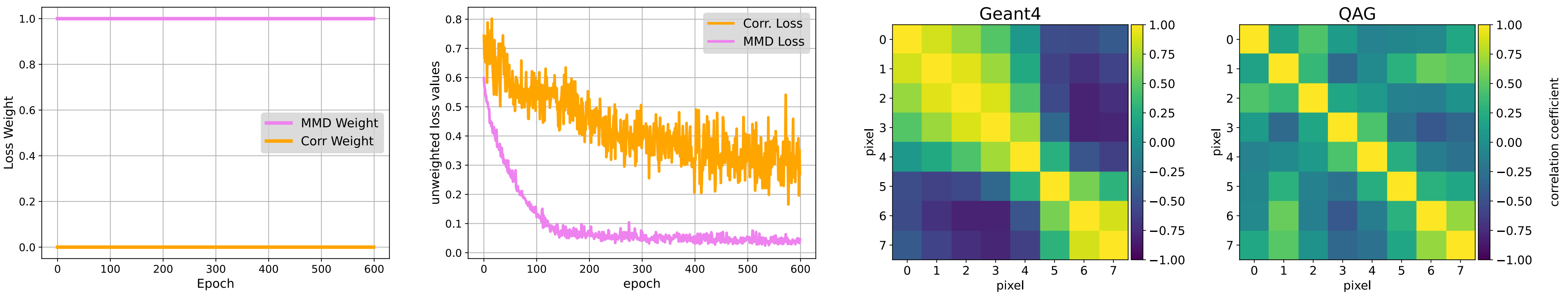
Simple setup

$$\text{depth} = 1$$
$$\text{n\_images} = 30$$

Loss : MMD + Corr



Loss : MMD

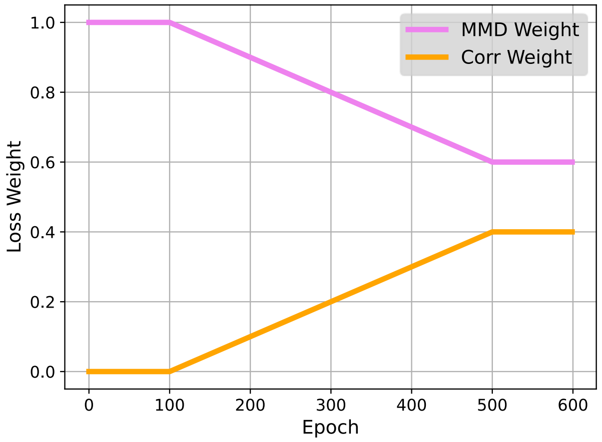


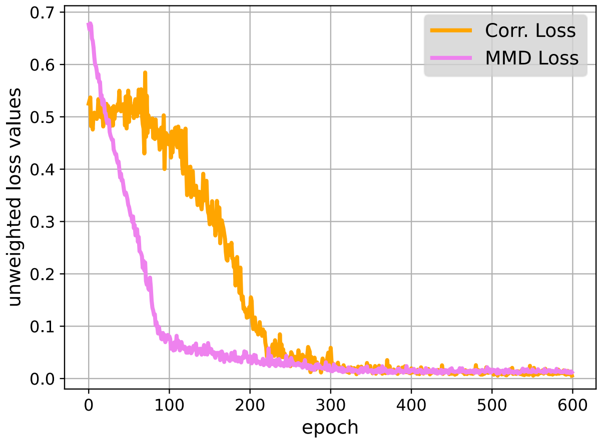
Backup: Loss Functions

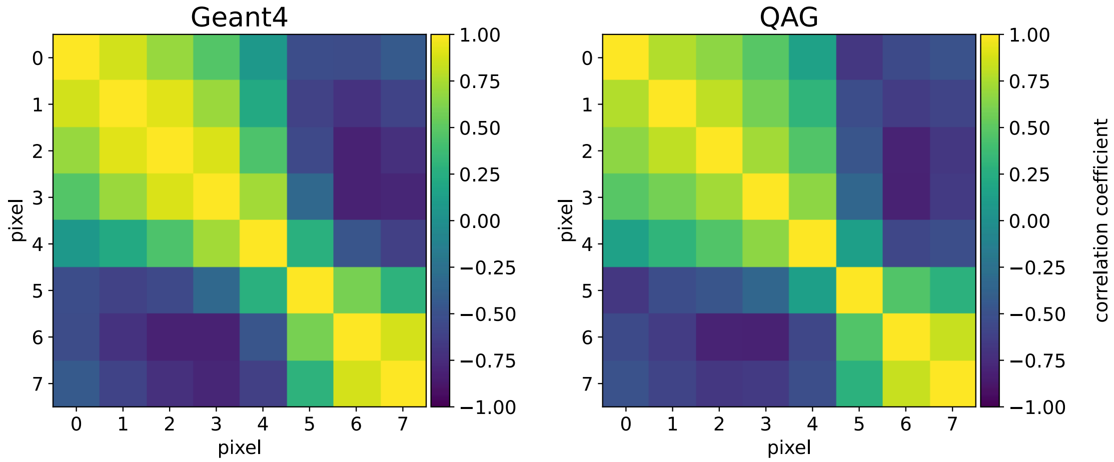
Complex setup

$$\begin{aligned} \text{depth} &= 2 \\ \text{n\_images} &= 200 \end{aligned}$$

Loss : MMD + Corr







Loss : MMD