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Quantum Generative Modeling for Calorimeter Simulations in Noisy Quantum Devices

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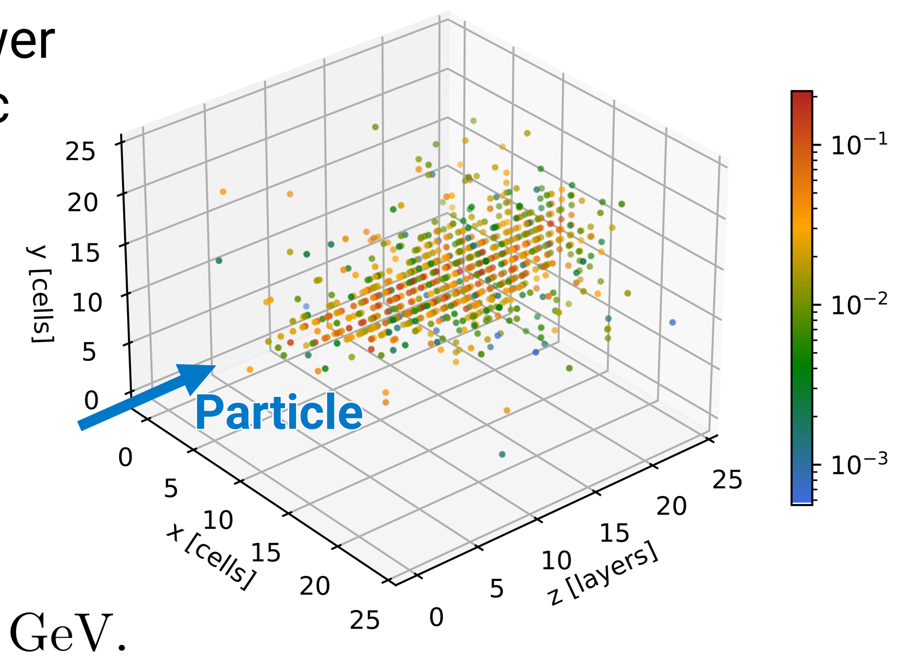
Motivation & challenges

- **Use case**: simulation of shower images from electromagnetic calorimeters in particle physics with Quantum Machine Learning.
- **Dataset**: training and test datasets both consisting of condensed 1D images recorded by particles within the energy range of $[225, 275]$ GeV.



Why Quantum?

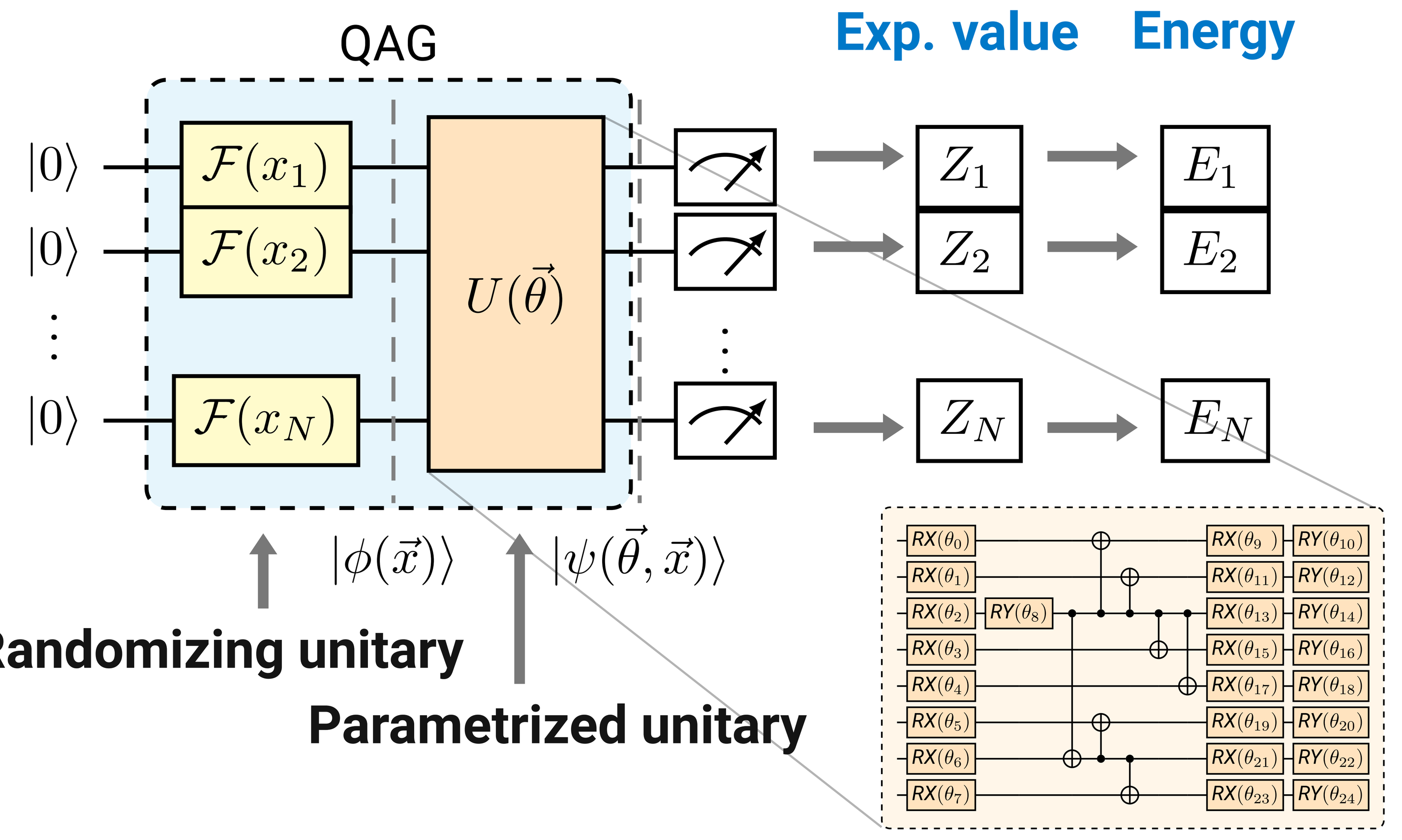
- Generation is **inherently probabilistic**, which can be represented by wavefunctions.
- Hilbert space is able to capture complexity easier.

Challenges in QC

- Presence of noise in NISQ devices.
- Gradient-free optimizations.
- Size of the `I/O` capabilities.
- Limited hardware availability.

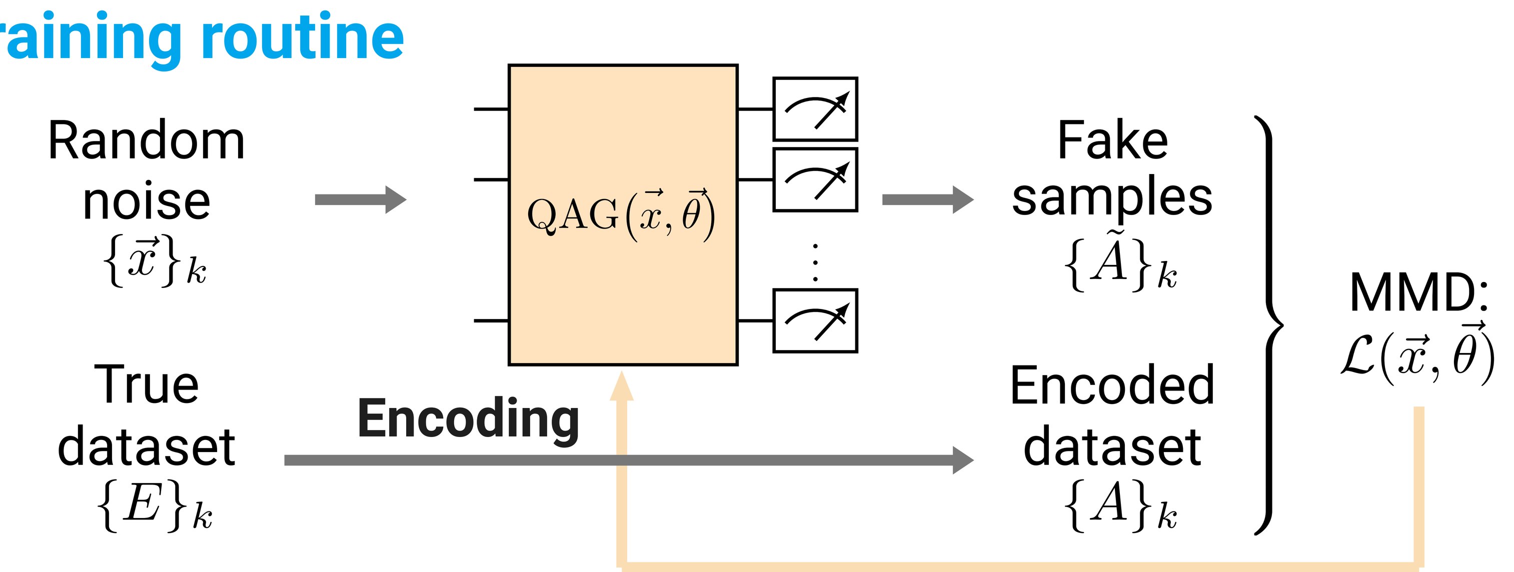
Quantum Angle Generator

- **Model**: quantum generative model that employs angle encoding.
  - **Encoding**: classical images into a quantum state, by encoding pixel energies into rotational angles of qubits.
  - **Decoding**: translate repeated measurements of quantum states into energies.

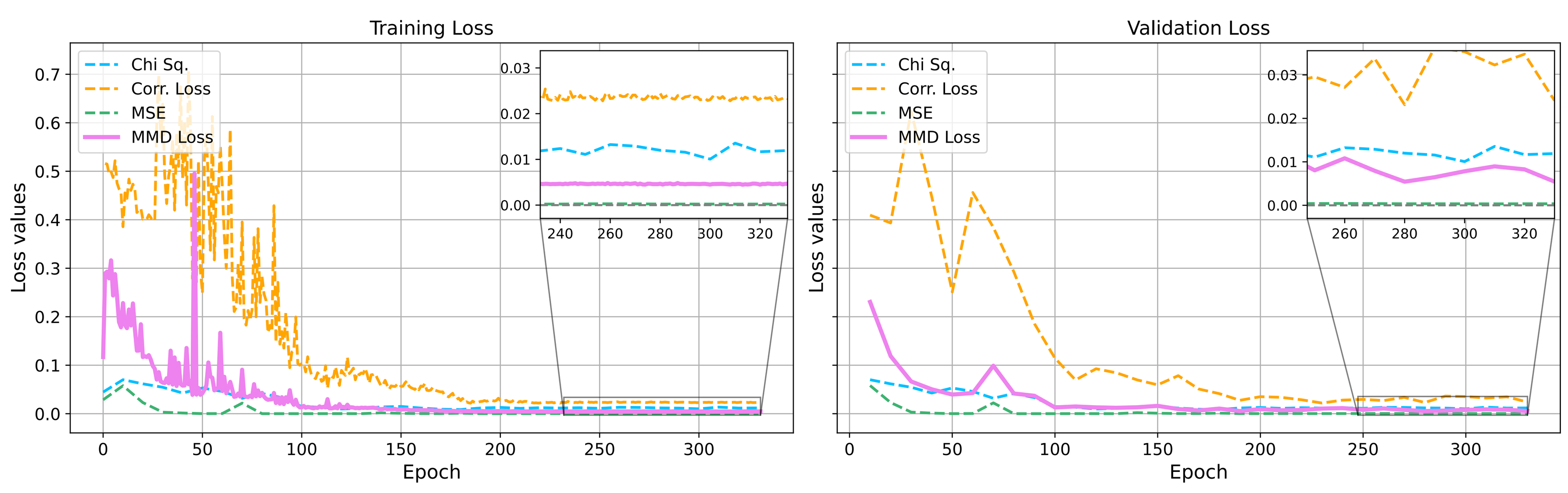


Training evaluation

Training routine



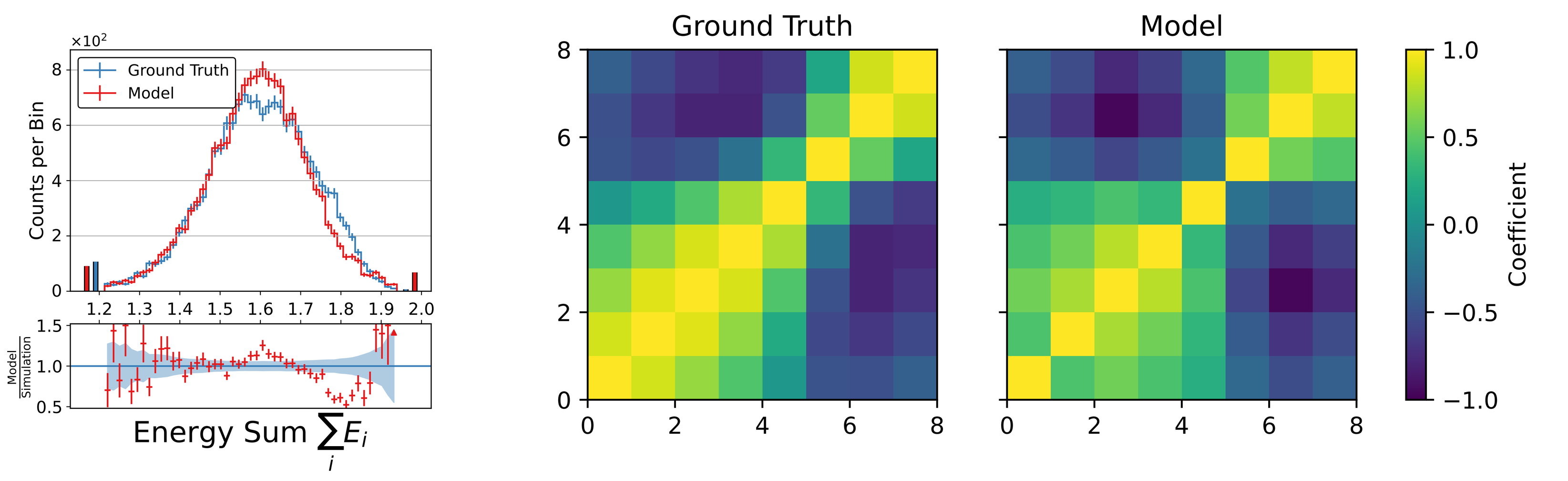
Loss function (optimizer: COBYLA | loss: MMD)



★ MMD loss alone is able to effectively learn **correlations between pixels**.

Inference evaluation

Energy sum / Pixel correlations

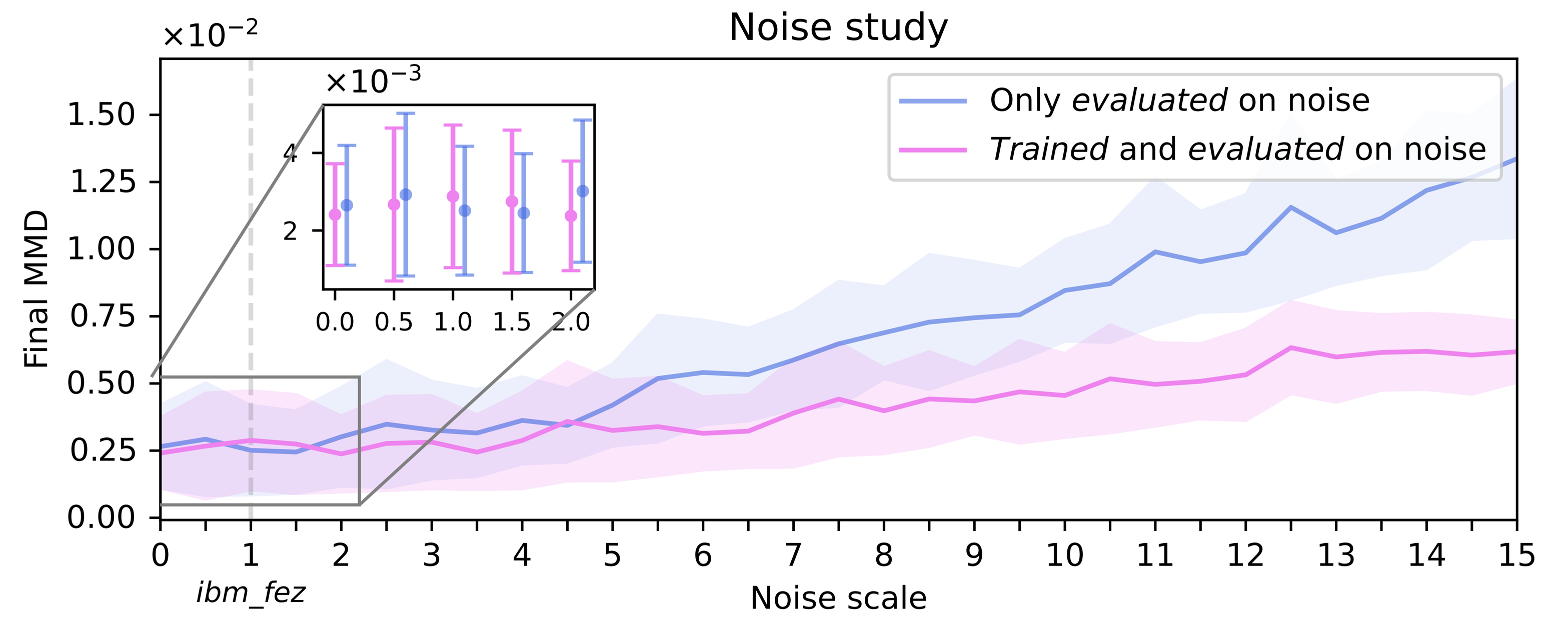


★ The model successfully captures pixel correlations and accurately reproduces the expected energy distributions.

Noise study

Two types of models trained at different noise scales:

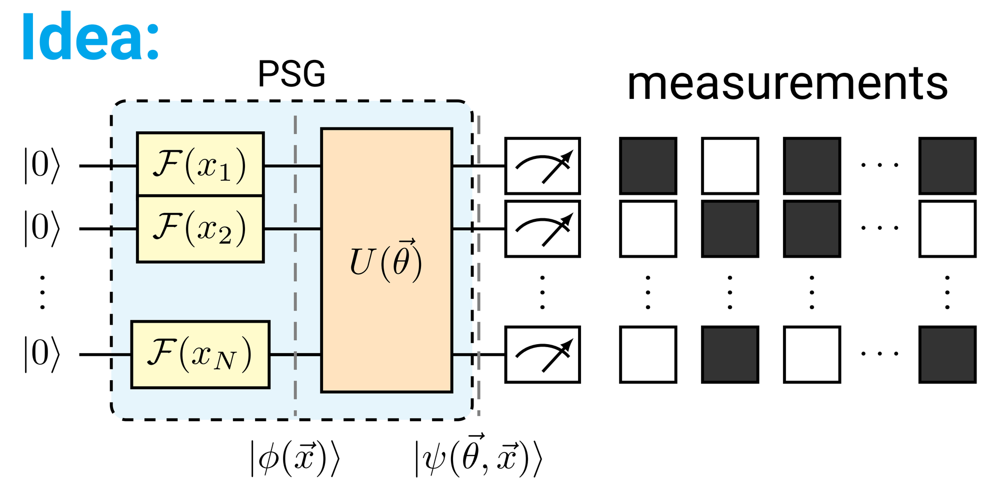
- trained on noiseless simulator, evaluated on noisy instance
- trained and evaluated on noisy instance



★ The model is capable of **adapting to the underlying noise**. **Current noise levels on real QPUs do not impact performance.**

Scaling up

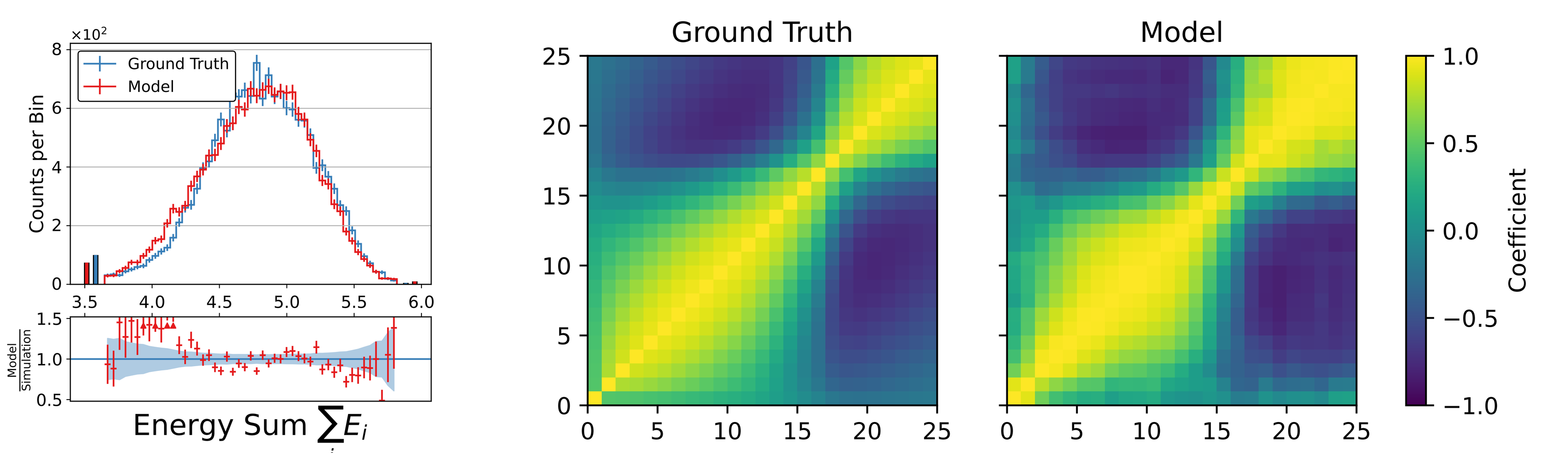
Idea:



Observables:
Weight 1:
$Z_1, Z_2, \ldots Z_N$ (QAG)
Weight 2:
$Z_1 Z_2, Z_1 Z_3,$ …

Output: linear combination of observables per pixel $\sum_j c_{ij} O_j$

Showcase: Run on IQM architecture Deneb:



✔ **Advantages**
- Enables a larger output space
- Provides faster training

✖ **Disadvantages**
- Training is more complex
- Qubit-to-pixel mapping lost

References

[1] F. Rehm: *Deep learning and quantum generative models for high energy physics calorimeter simulations*, RWTH Aachen University, PhD Dissertation (2023)

[2] F. Rehm, S. Vallecorsa, K. Borras, D. Krücker, M. Grossi, V. Varo: *Precise Image Generation on Current Noisy Quantum Computing Devices*, Quantum Science and Technology (2023)

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