Study on impacts of quantum noises on QGAN training

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Introduction

- **Artificial noises** are often injected in machine learning for a more robust, more stable and faster converging model.
- Current and near future quantum devices still have **considerable levels of noise**.
- Possibility to replace the artificial noise in classical ML with the intrinsic noise in quantum ML (QML).

Objectives

- Investigate the **impact of different errors** in the training of quantum Generative Adversarial Networks (qGAN) [1] for a simplified High-Energy Physics (HEP) use case.
- Provide a broad exploratory study to unfold the hidden impact of noise in QML.

Reduction in problem size

- We reduce the original calorimeter output size generated by Monte Carlo based *Geant4* simulations
- Use the longitudinal profile to estimate incoming particle $\rightarrow$ sum energy distribution along longitudinal direction
- Average over $10,000$ samples & bin into 2^n pixels for n qubit quantum generator $\rightarrow$ probability of getting state $|k\rangle$ = normalized energy at pixel k.
- Input dataset = scalars following the real energy distribution

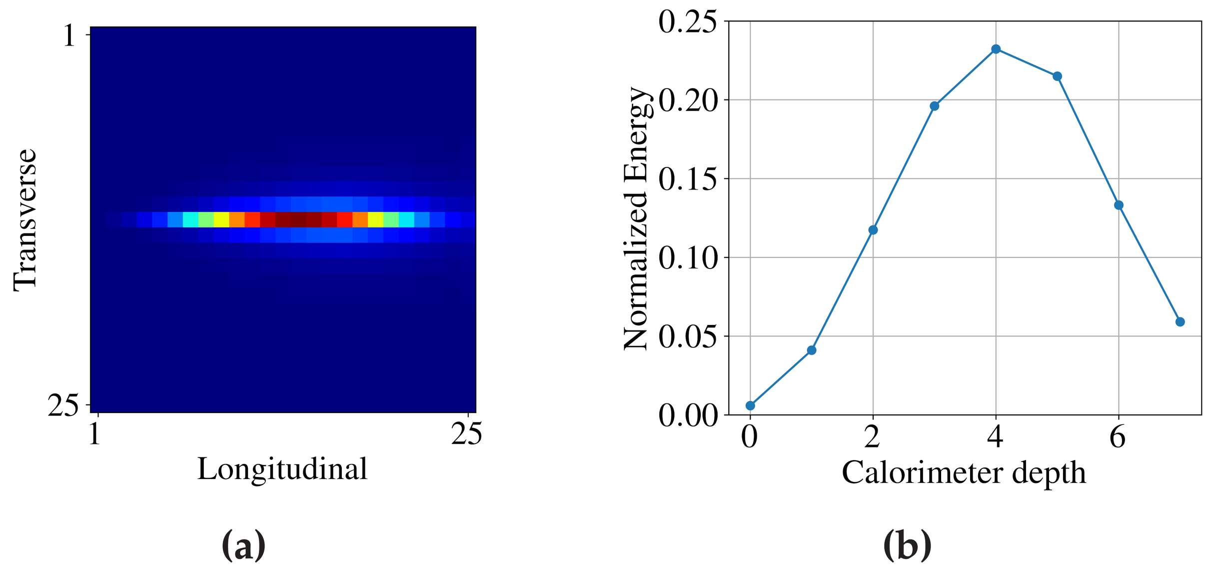


Figure 2: (a) Original calorimeter output generated by *Geant4*. (b) Reduced energy distribution used for our qGAN training.

References

[1] Christa Zoufal, Aurélien Lucchi, and Stefan Woerner. Quantum generative adversarial networks for learning and loading random distributions. *npj Quantum Information*, 5(1):103, Nov 2019.

Quantum GAN

- **Hybrid model** with a n-qubit quantum generator and a classical discriminator [1]

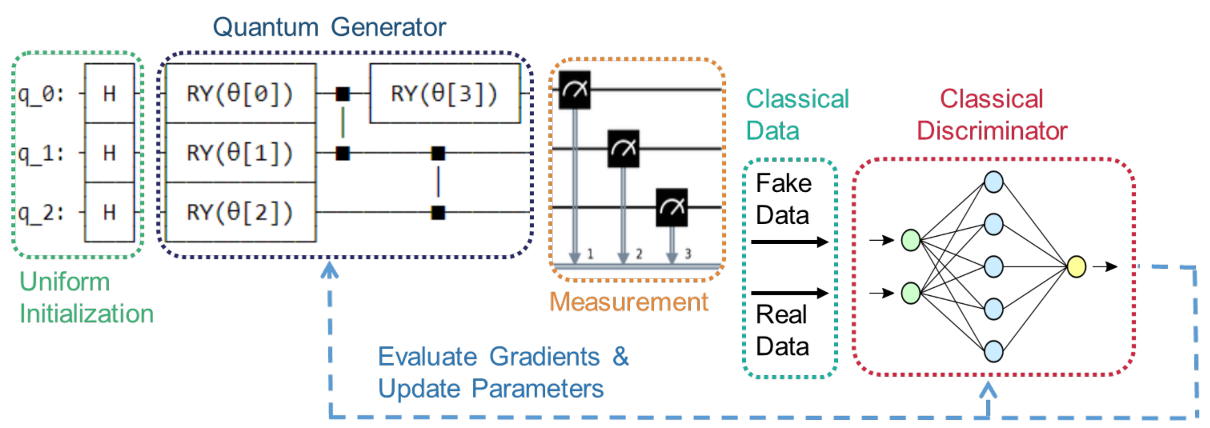
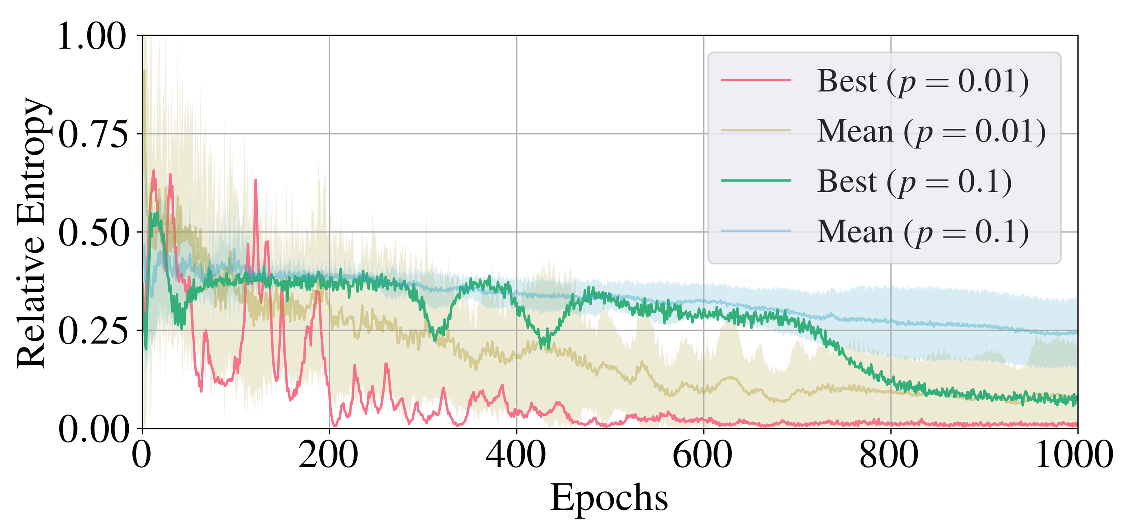


Figure 3: Schematic Diagram of qGAN.

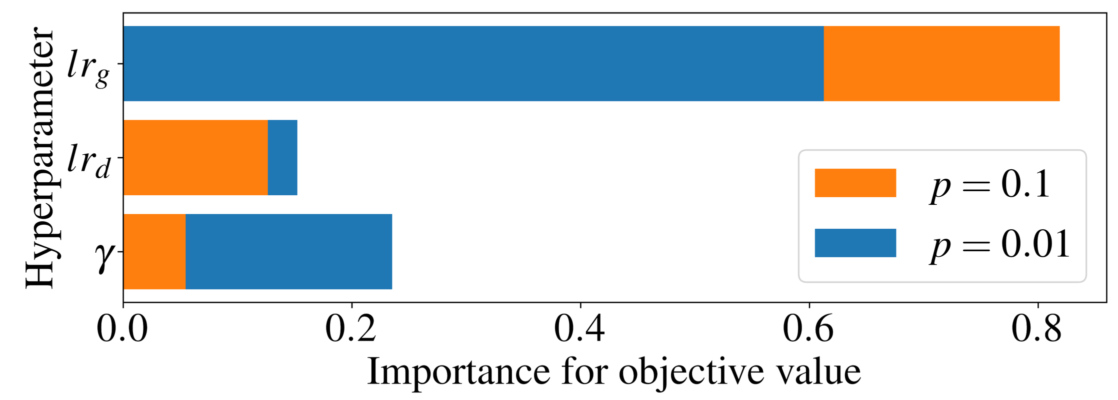
- Relative entropy (or *Kullback-Leibler (KL) divergence*) $D_{KL}(p\|q) = \sum_j p(j) \log \frac{p(j)}{q(j)}$ as accuracy metrics.

Hyperparameter scan

- We perform a scan on different **subsets of hyperparameters**: decay rate γ, generator lr_g, and discriminator learning rate lr_d.
- Test the qGAN training using a noise model **with readout error** in form of bit flips occurring independently for each qubit with a flip probability p.



(a) Progress in relative entropy



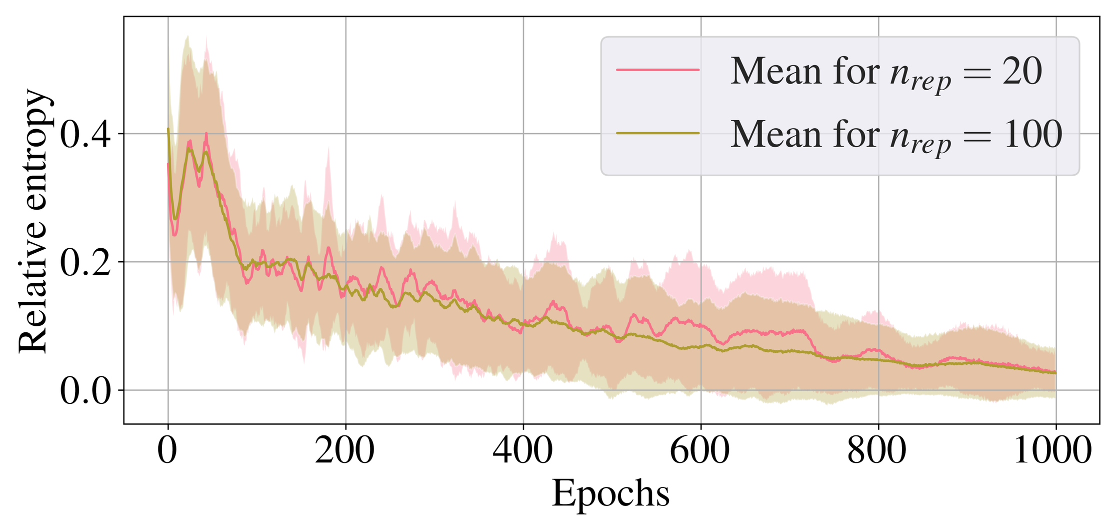
(b) Hyperparamter importance

Figure 5: Results of the scan on different hyperparameters for the readout error $p = 0.01$ and 0.1

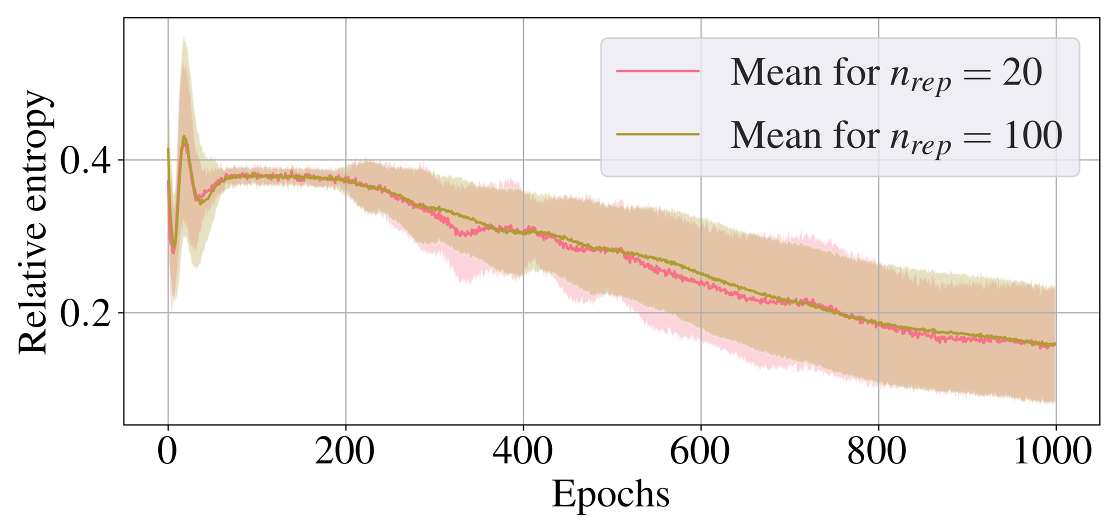
- Higher relative entropy for higher noise level, even with the optimal hyperparameters.
- Impact of generator learning rate becomes higher as the flip probability increases.

Instability of qGAN Training

- Repeat the qGAN training with the *qiskit* noise model with readout error only using the same hyperparameters and **investigate its statistical error**.



(a) $p = 0.01$



(b) $p = 0.1$

Figure 4: Progress in relative entropy averaged over $n_{rep} = 20$ and 100 runs for $p = 0.01$ and 0.1.

Flip probability p	$n_{rep} = 20$	$n_{rep} = 100$
0.01	0.026 ± 0.028	0.028 ± 0.040
0.05	0.029 ± 0.022	0.027 ± 0.020
0.1	0.153 ± 0.097	0.159 ± 0.077

Table 1: Relative entropy at the end of the training

- The model is stable on the "ensemble" of simulations, but unstable for the individual runs.
  $\rightarrow$ Fixed standard deviation despite increase in the number of simulations.

Discussion

- The **instability of the qGAN model** cannot be resolved even with large number of simulations.
  $\rightarrow$ Further study going on to find the origin of the instability.
- Small levels of quantum noise help to improve the performance of the model, while error mitigation is required for large noise.
- Effect of error mitigation in the full noise model and the real quantum hardware needs to be further studied.

Error Mitigation

- We compare the training results with and without **error mitigation method** implemented by *qiskit*.

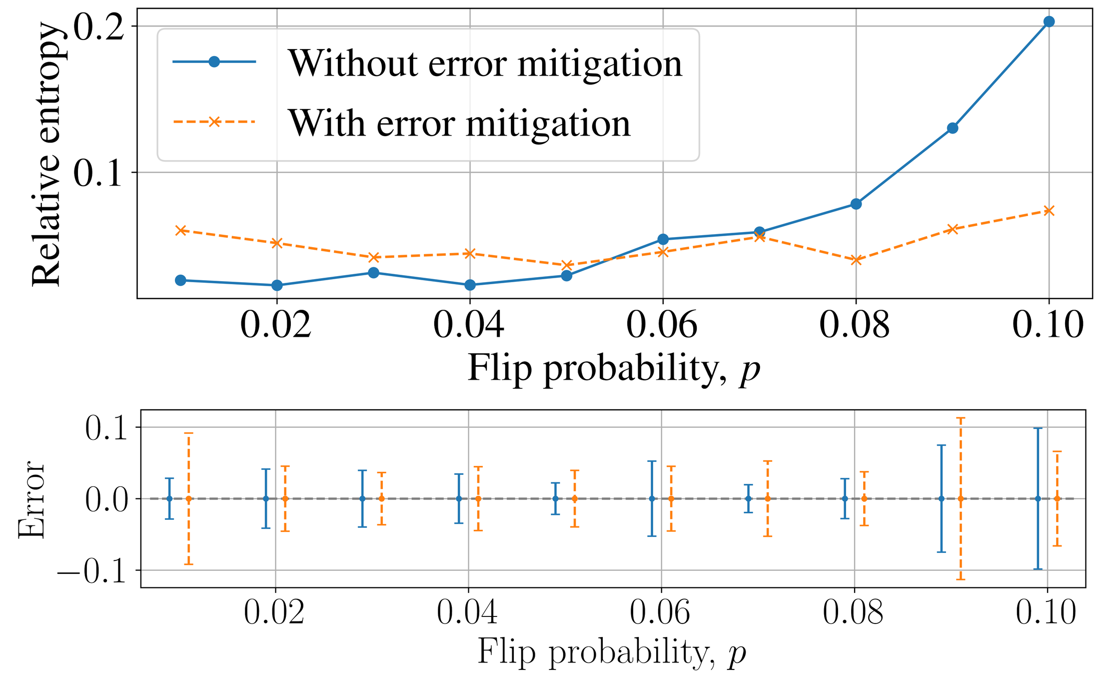


Figure 6: Mean (above) and standard deviation (below) of the final relative entropy, averaged over 20 simulations, with and without error mitigation w.r.t. the readout error.

- Low readout error ($p < 0.06$) helps the qGAN training, while error mitigation plays an important role for high readout error.
- Large standard deviation in the relative entropy which cannot be overcome with error mitigation.

Including CNOT error

- We run the training with a custom noise model consisting of 2.5% readout noise per qubit and 1.5% two qubit gate level noise (called CNOT error).
- We found new optimized hyperparameters to reduce the number of epochs to only 300 while reaching a good accuracy.

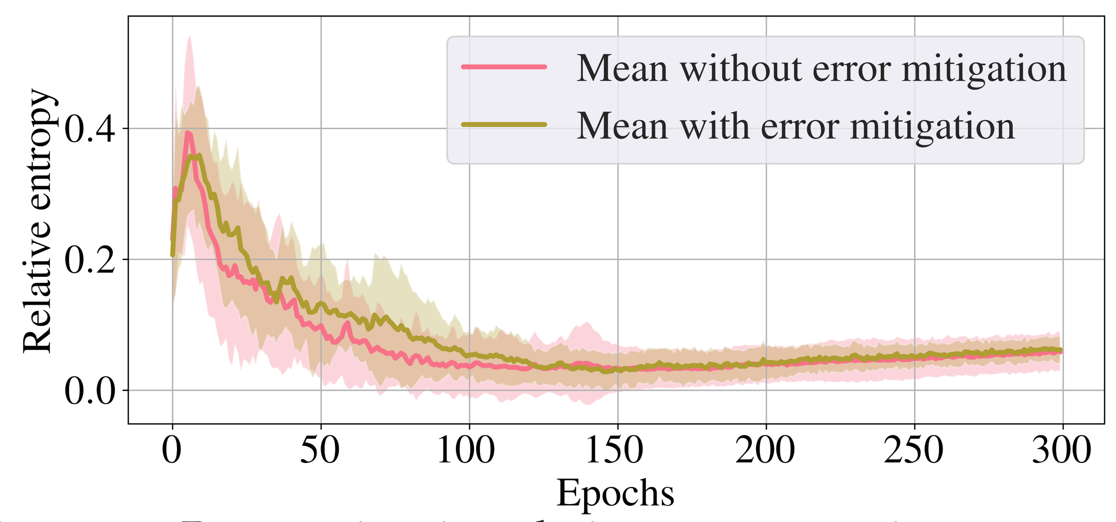


Figure 7: Progression in relative entropy using a custom noise model with and without error mitigation.

- For the chosen noise levels one cannot see any improvement when including error mitigation.

Ongoing Research

- Train the qGAN on real quantum hardware.
- Apply other error mitigation methods and compare the resulting outcomes.