Running the Dual-PQC GAN on Noisy Simulators and Real Quantum Hardware

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Introduction

- In an earlier work [1], we introduced **dual-Parameterized Quantum Circuit (PQC) GAN**, which is an advanced prototype of quantum GAN
- Dual-PQC GAN was tested to imitate calorimeter outputs in High-Energy Physics (HEP) in the absence of noise, with statevector simulator
- However, noise due to the interaction with the environment is the major obstacle for the near-term quantum devices

Objectives

- Investigate the impact of hyperparameters in dual-PQC GAN training using noisy simulators
- Test the inference of the model using trained parameters on *superconducting* and *trapped-ion* quantum device

Reduction in problem size

- We reduce the original calorimeter output size (25x25x25 pixels) generated by Monte Carlo based *Geant4* simulation
- Longitudinal profile used to estimate incoming particle → Sum energy distribution along longitudinal direction
- To compare with generated images : **Classify the real images** into 4 sets via K-mean clustering & average over each class → 4 images $\tilde{\mathcal{I}}_j, j = 0, 1, 2, 3$

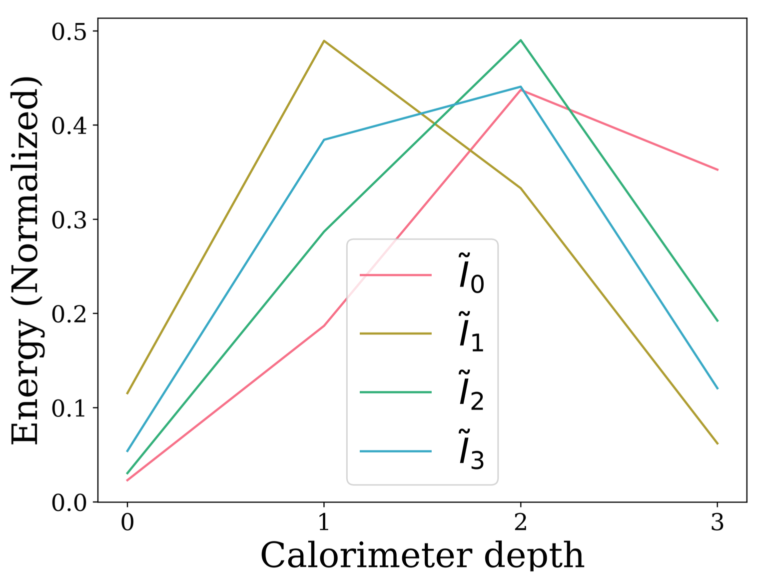


Figure 1: Mean image of 20,000 normalized real image samples, classified into 4 classes.

References

[1] Su Yeon Chang, Steven Herbert, Sofia Vallecorsa, Elías F. Combarro, and Ross Duncan. Dual-parameterized quantum circuit gan model in high energy physics. *EPJ Web of Conferences (CHEP 2021)*, 251:03050, 2021.

Dual-PQC GAN

- Training set of images with 2^n pixels
- **Two quantum generators** (PQCs in qiskit) & One classical discriminator (in PyTorch)
- **PQC1** : Reproduce a probability distribution $p(j)$ for $j = 0, ..., 2^{n_1} - 1$ images
  → Pass the measured computational basis state to PQC2 as an input
- **PQC2** : Measure n qubits among n_2 qubits & return a normalized image $\mathcal{I}_j$ for each input sate $|j\rangle$ by constructing the probability distribution over 2^n states, $|i\rangle \in \{|0\rangle, ..., |2^n - 1\rangle\}$
  → each state corresponds to one pixel in an image
- Both PQC with alternating layers of R_y rotations gates and CZ entanglement gates
- Ultimately, can generate 2^{n_1} images of size 2^n
- To solve unitarity constraint, require $\mathbf{n_2 = 2n}$
- For the following simulations, we use $n = n_1 = 2$, $n_2 = 4$, $d_1 = 2$, $d_2 = 5$

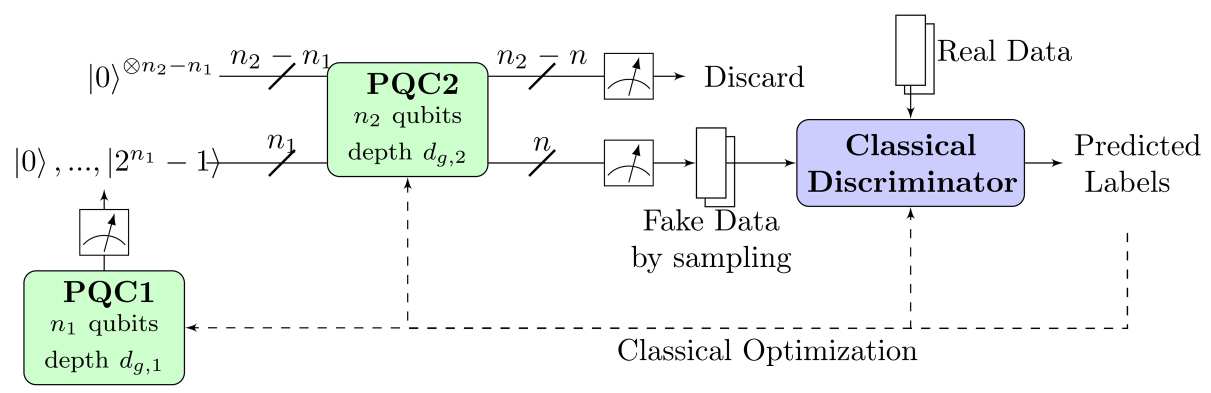


Figure 2: Schematic Diagram of dual-PQC GAN to reproduce images of 2^n pixels.

Metric

- We evaluate performance of the model using two different metrics :

1. **Relative entropy**, $D_{KL}(\mathcal{I}_{mean} \| \tilde{\mathcal{I}}_{mean})$, between the average of the real images, $\tilde{\mathcal{I}}_{mean}$ and the generated images $\mathcal{I}_{mean}$, with

$$D_{KL}(p\|q) = \sum_j p(j) \log \frac{p(j)}{q(j)} \quad (1)$$

2. ***Individual* relative entropy** : the mean of the minimum relative entropy for each of generated images with respect to the real images

$$D_{KL,ind} = \frac{1}{2^{n_1}} \sum_{i=0}^{2^{n_1}-1} \min_j D_{KL}(\tilde{\mathcal{I}}_j \| \mathcal{I}_i) \quad (2)$$

Hyperparameter Scan

- We perform **hyperparameter scan** in order to evaluate the impact of different hyperparameters depending on the noise level → decay rate and learning rate for PQC1, PQC2 and discriminator
- We use *qiskit* noise model with a two-qubit gate error, p
- We consistently get hyperparameters which lead the training to convergence for both $p = 0.02$ and $p = 0.04$, but with higher D_{KL} for the latter.

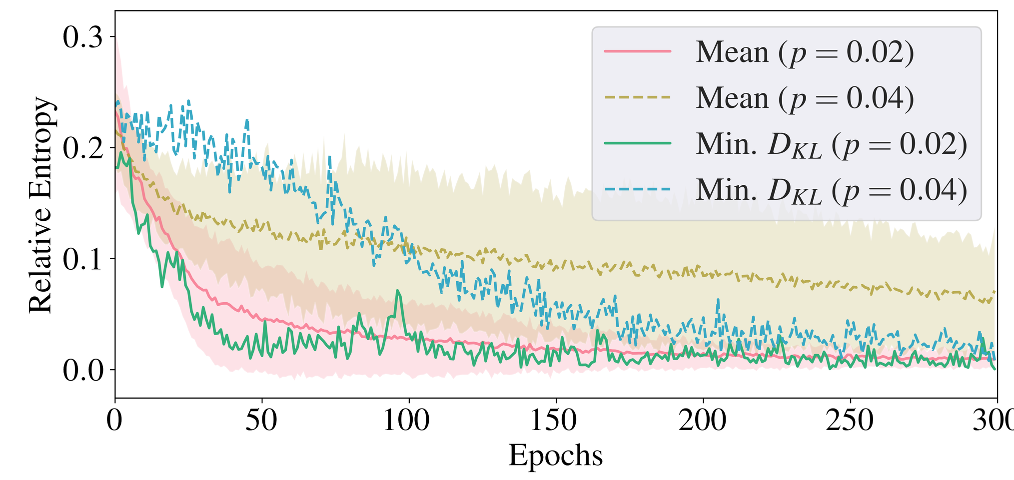
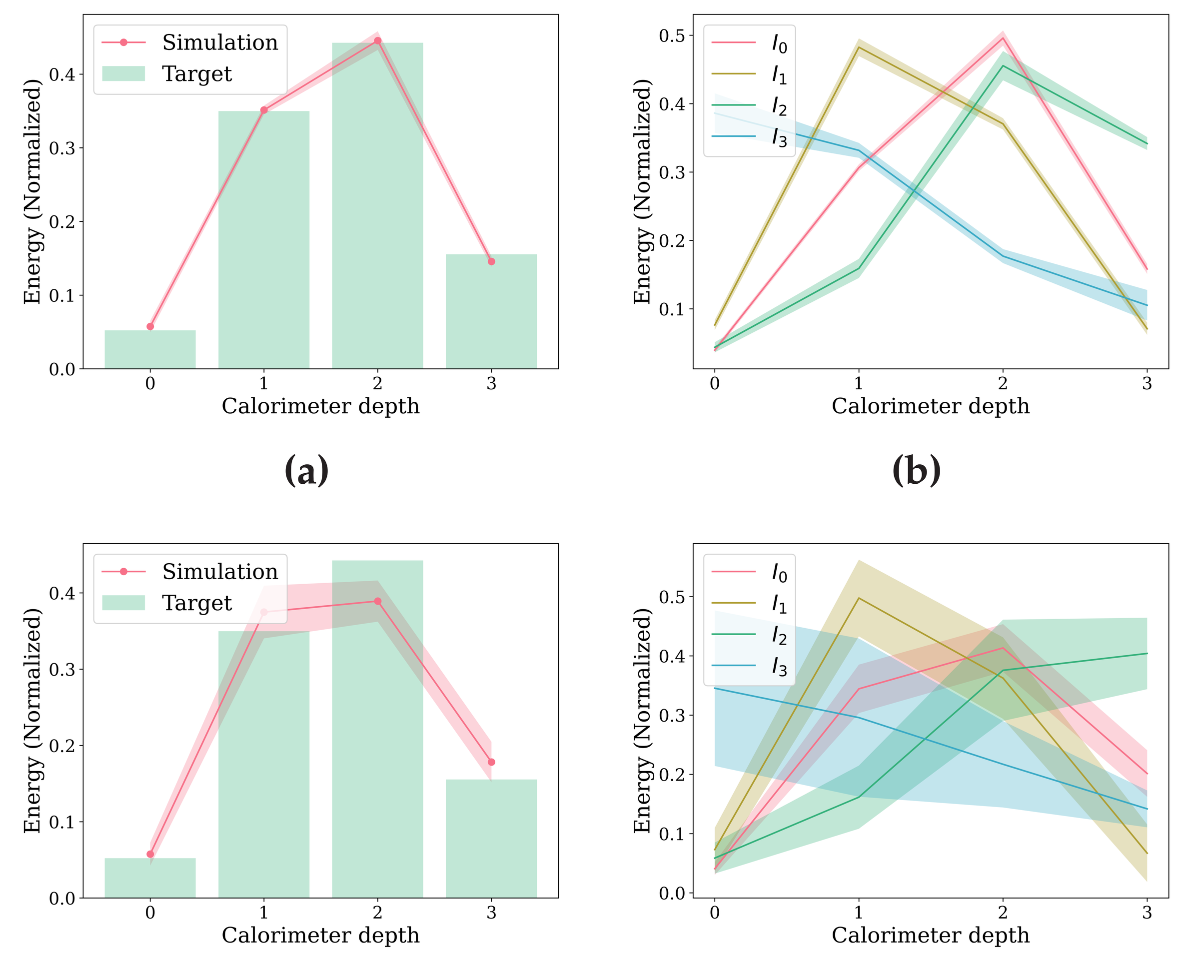


Figure 3: The relative entropy obtained from the hyperparameter scan with $p = 0.02$ and 0.04.

Inference

- Using the parameters pretrained on the noisy simulator, we test the **inference** of the model on the superconducting (IBMQ) and trapped-ion (IONQ) quantum hardware



(a) (b) (c) (d)

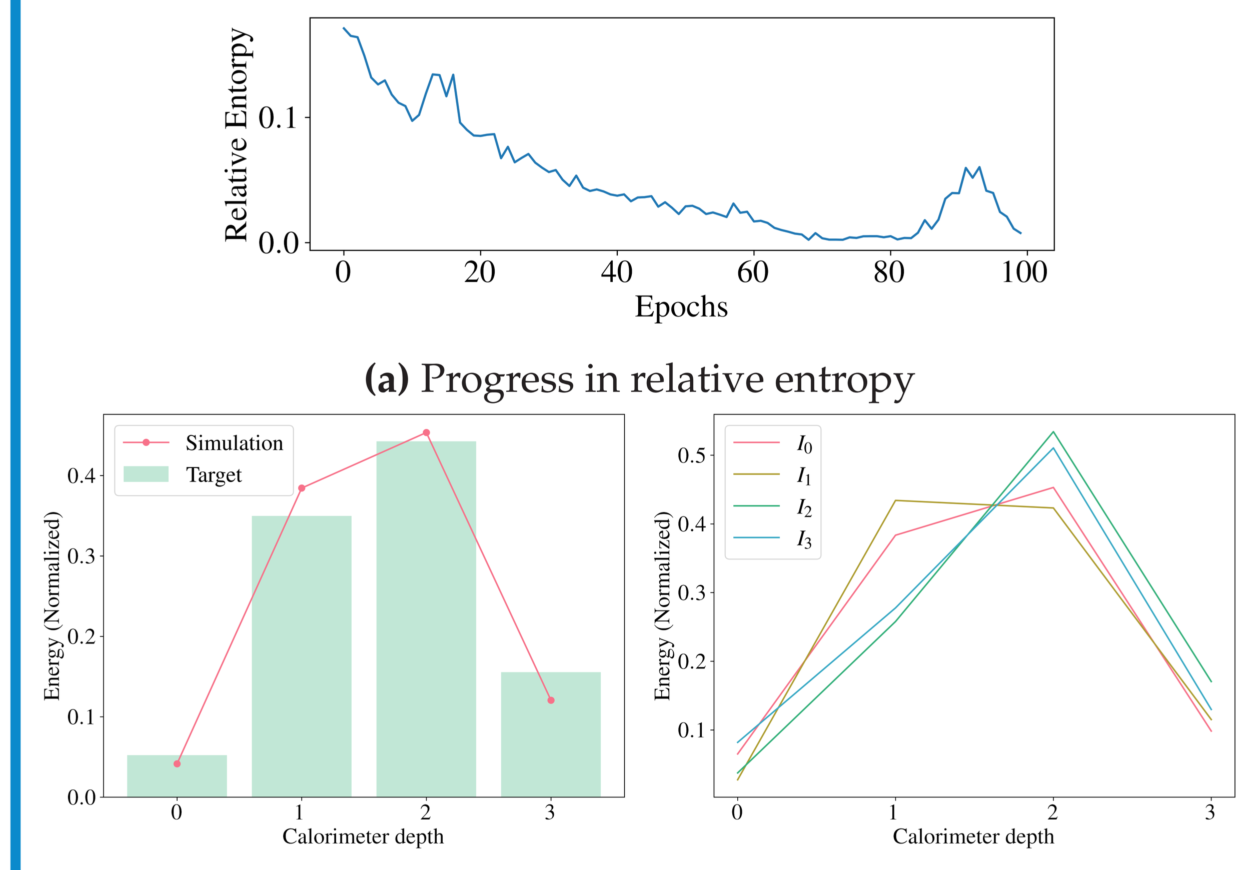
Figure 4: Mean (a,c) and individual images (b,d) obtained by inference test on ibmq_jakarta (a,b) and IONQ (c,d).

Device	Readout error CX error	$D_{KL}/D_{KL,ind}$ $(\times 10^{-2})$
ibmq_jakarta	0.028 $1.367 \cdot 10^{-2}$	0.14 ± 0.14 6.49 ± 0.54
ibm_lagos	0.01 $5.582 \cdot 10^{-3}$	0.26 ± 0.11 6.92 ± 0.71
ibmq_casablanca	0.026 $4.58 \cdot 10^{-2}$	4.03 ± 1.08 6.58 ± 0.81
IONQ	NULL $1.59 \cdot 10^{-2}$	1.24 ± 0.74 10.1 ± 5.6

Table 1: D_{KL} and $D_{KL,ind}$ (averaged over 20 runs) obtained from the inference test on different quantum hardware and their error rates.

Training on a real hardware

- Train the dual-PQC GAN model on the **real quantum hardware**, *ibmq_lagos*.



(a) Progress in relative entropy

(b) Mean image **(c)** Individual images

Figure 5: Results of dual-PQC GAN training on the real quantum hardware, *ibmq_lagos*.

Discussion

- For the inference test, we get stable results using IBMQ machines with low influence of noises, while more inspection would be required for IONQ.
- We were able to reach convergence in mean image on the real quantum hardware, but further simulations are required to get **more diversity in the individual images**.

Ongoing Research

- Improve the performance of dual-PQC GAN training on the real IBMQ machine
- Increase the problem size → number and size of images increasing exponentially with n_1 and n_2