# Continuous-Variable Quantum Generative Adversarial Networks for High Energy Physics Detector simulation


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## MOTIVATION

- Monte Carlo simulation is time consuming
- Generative Adversarial Networks (GAN) can replace this approach with high fidelity
- Development of quantum computing leads to extension of GAN → Quantum GAN (qGAN)
- Best-known *qubits-based* qGAN model reproduces distributions over discrete variables [1]
- **AIM** : Develop qGAN to learn a distribution over continuous variables

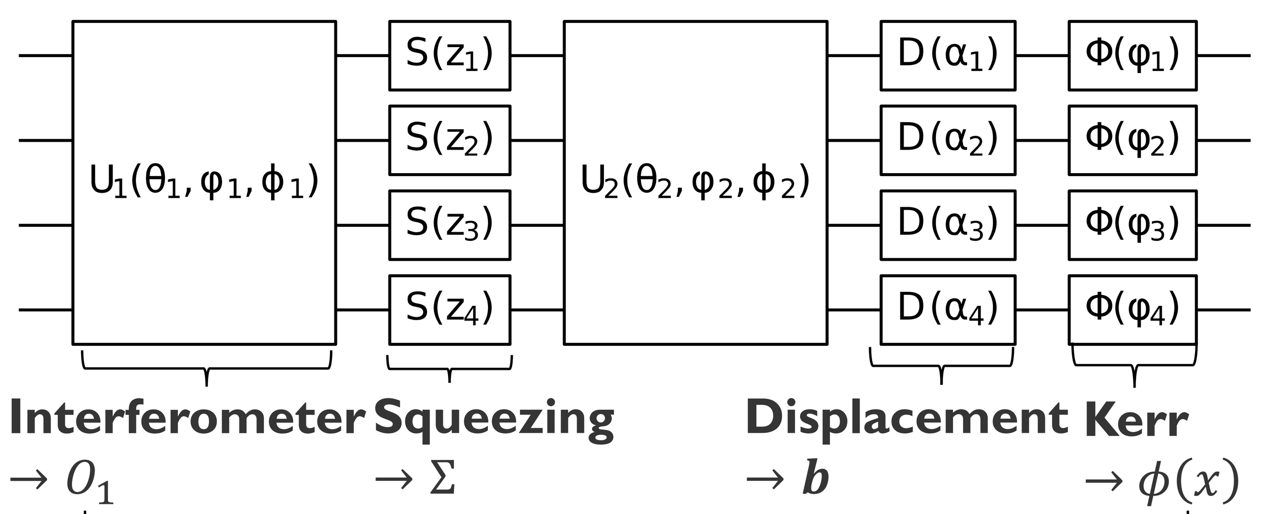
## CV QUANTUM COMPUTING

- Alternative approach (photonic quantum computing)
- Encode information in continuous physical observable (ex : Electromagnetic Field Strength)
- Fundamental information-carrying unit = **qumode**

→ Expressed as a superposition of position basis $|x\rangle$ or Fock basis $|n\rangle$

$$|\psi\rangle = \int dx\, \psi(x)|x\rangle dx = \sum_{n=0}^{\infty} \langle n|x\rangle |n\rangle$$

## CV NEURAL NETWORK




$$L|\boldsymbol{x}\rangle \propto |\phi(W\boldsymbol{x} + \boldsymbol{b})\rangle$$

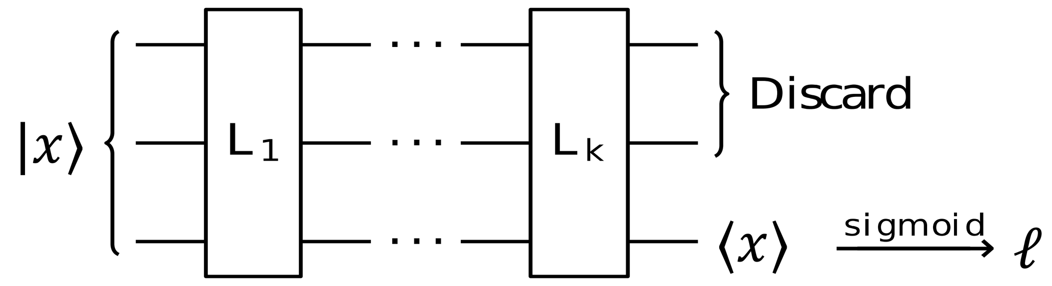
- **CV neural network** (CVNN) [2] performs the transformation equivalent to a fully connected layer : $\boldsymbol{x} \to \phi(W\boldsymbol{x} + \boldsymbol{b})$

  $W$= Weight matrix, $\boldsymbol{b}$ = bias,

  $\phi(x)$ = Non-linear activation Function
- Use singular value decomposition $W = O_2 \Sigma O_1$

  $O_1, O_2$ = orthogonal matrix, $\Sigma$ = diagonal matrix

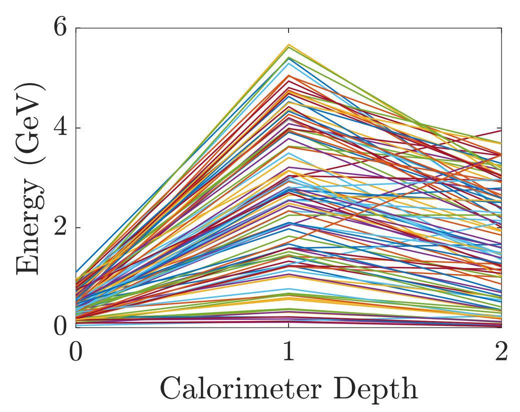
## CV CLASSIFIER




- CVNN-based classifier to discriminate real images from random fake images
- Input data = 1D energy distribution along calorimeter longitudinal direction (downsampled to 3 pixels)
- Encoded as a displaced state

$$|\boldsymbol{x}\rangle = \otimes_{i=1}^{N} |x_i\rangle = \otimes_{i=1}^{N} D_i(x_i)|0\rangle$$

→ Can correctly discriminate real and fake data




**Real Images (Reduced size)**

| Actual \ Predicted | Real | Fake |
|---|---|---|
| Real | 100% | 0% |
| Fake | 3.6% | 96.4% |

**Confusion matrix**

## CV QUANTUM GAN

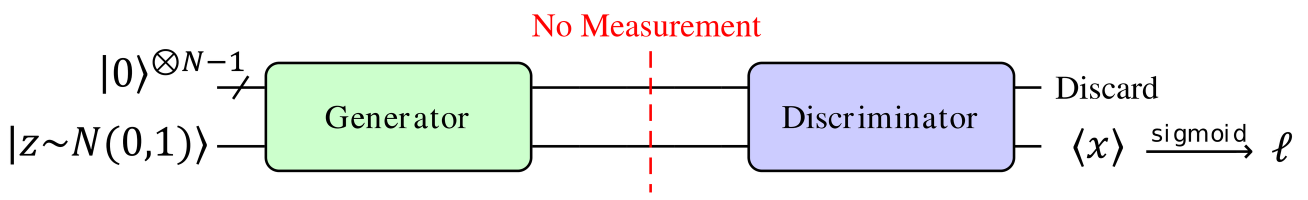
- Propose two qGAN models
- Quantum CVNN generator with one qumode initialized by noise $z \sim N(0,1)$ (latent space =1)

$$|initial\rangle = |z\rangle \otimes |0\rangle^{\otimes N-1} = D_0(z)|0\rangle \otimes |0\rangle^{\otimes N-1}$$

**1) Fully Quantum**

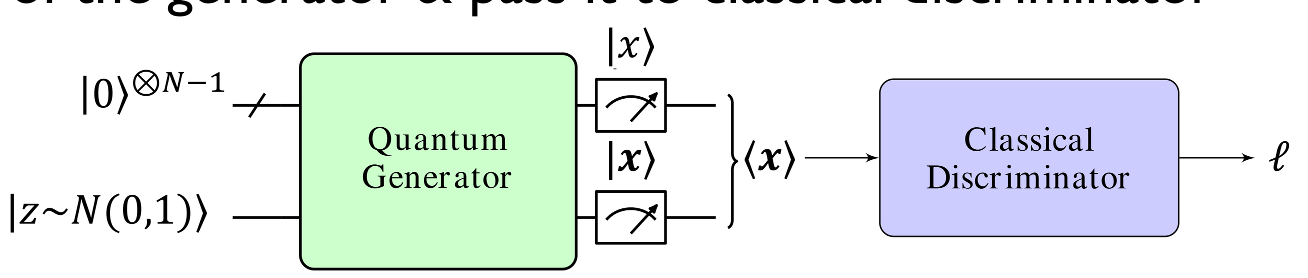
→ Quantum generator (depth $d_g$) directly connected to quantum discriminator (depth $d_d$)

→ Position expectation value $\langle x\rangle$ of qumode $N$ at the end of discriminator = Predicted label




**2) Hybrid**

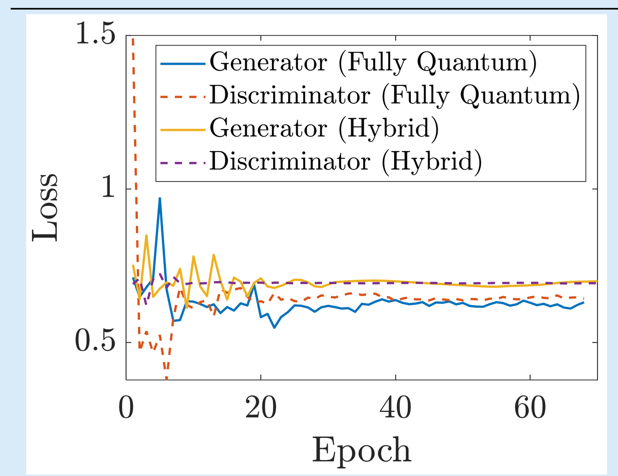
→ Construct a fake image by measuring the position expectation values $\langle \boldsymbol{x}\rangle$ of all $N$ qumodes at the end of the generator & pass it to classical discriminator




## RESULTS

### Fully Quantum& Hybrid ($d_g$ = 5)

**Loss**




**Mean Image**

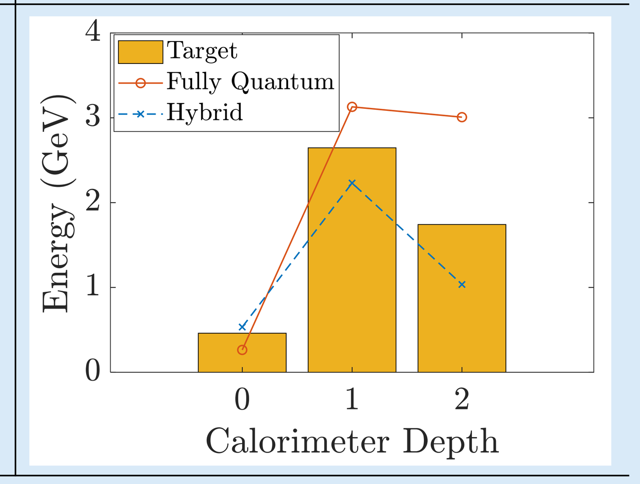
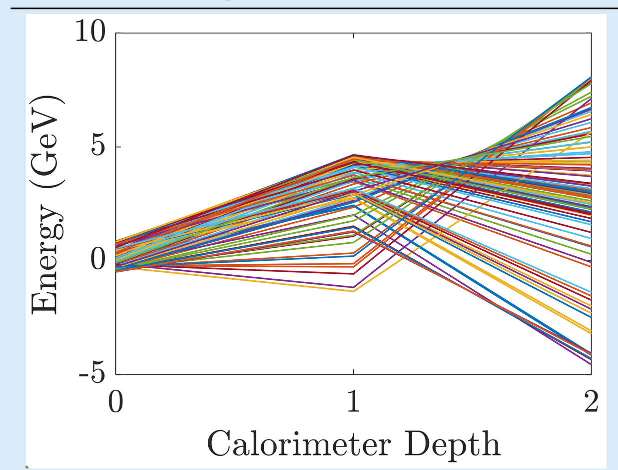
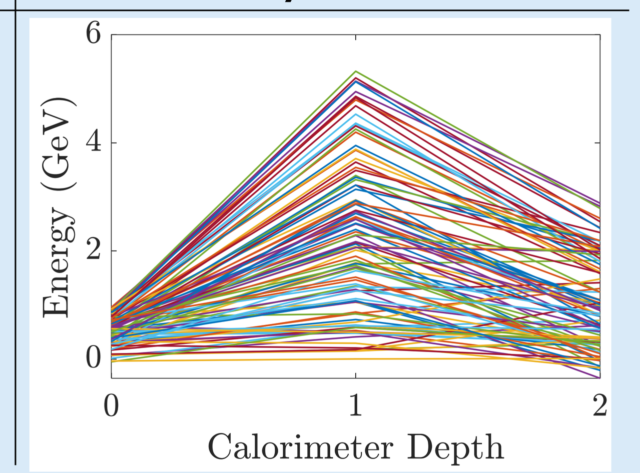



**Image samples**

Fully Quantum

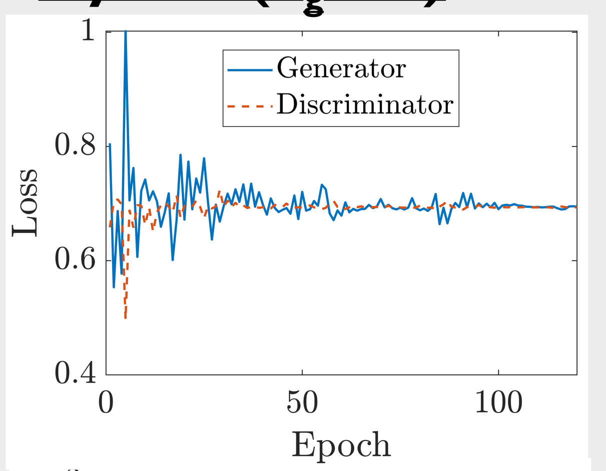


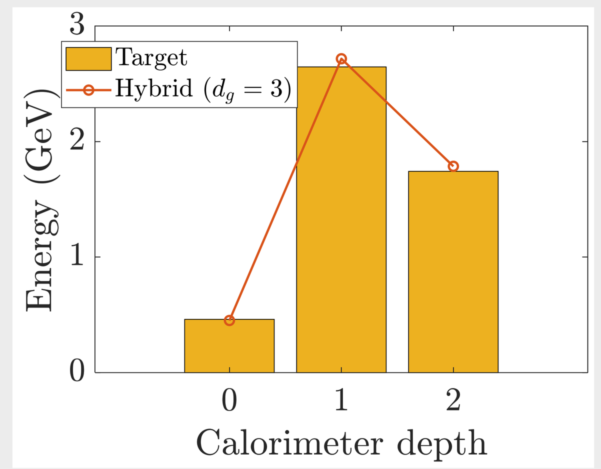

Hybrid

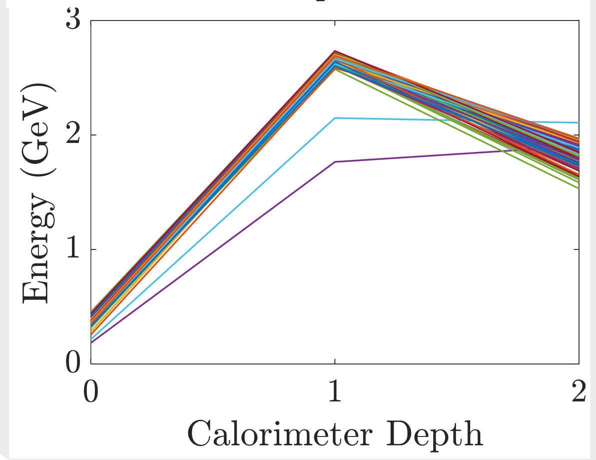



- Losses converge, but mean images are slightly off
- Some unphysical values (negative energy)
- Hybrid model reproduces image shape despite difference in energy levels

### Hybrid ($d_g$ = 3)



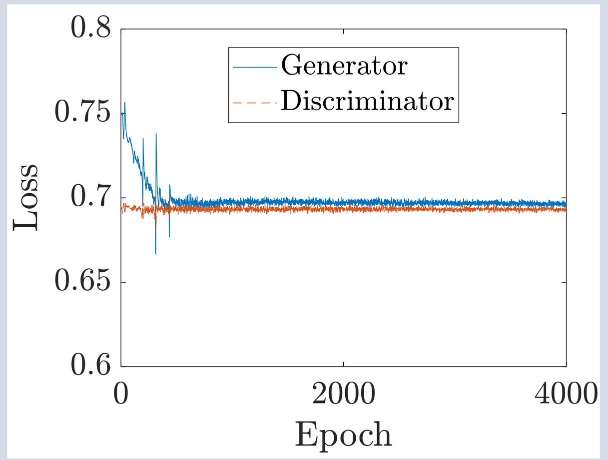

- Convergence in losses & mean image
- Low variety in samples

→ **Mode collapse** (common in classical GAN)

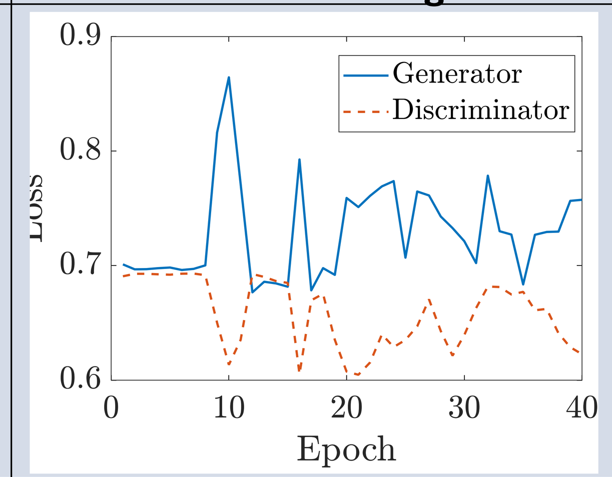
### Increase Latent Space Dimension

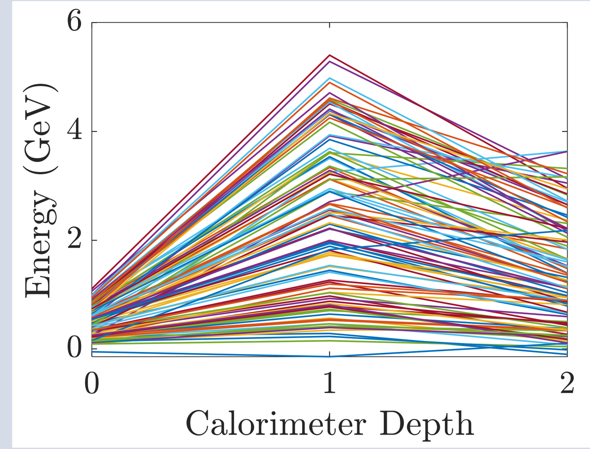
- Compare qGAN (latent space size =3) to classical GAN
- Same discriminator in both cases

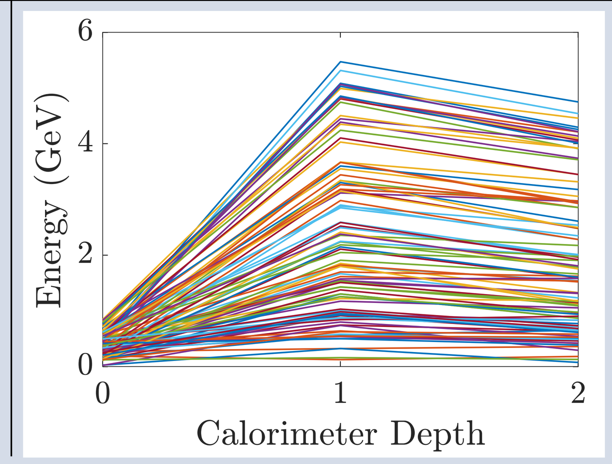
**Classical**

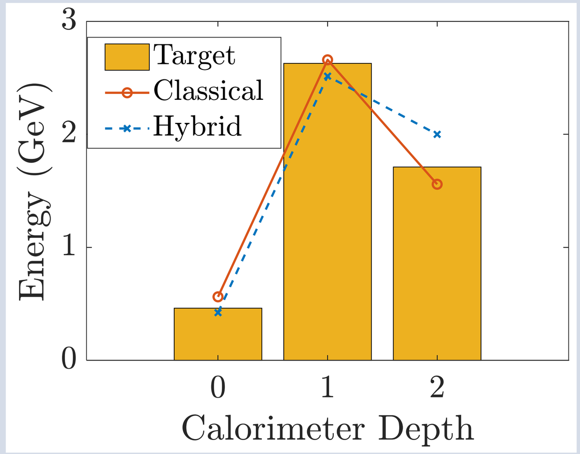



**CV qGAN ($d_g$ = 8)**




- (Quasi-)convergence in mean image & image samples
- No negative energy

- qGAN imitates performance of classical GAN
- 150x less parameters; 10x fewer epoch
- First hints at advantage in terms of computational complexity w.r.t the time to convergence
- Simulation time (120min/epoch) = limiting factor
- Further optimization: losses stabilization and missing modes (samples with a peak at x = 2)

## CONCLUSION

- Two new prototypes of CV qGAN
- Limited convergence and stability
- Aimed at understanding potential and limitations of quantum technology for Machine Learning
- Further optimization planned (ex : Speed up computations, Increase number of qumodes, Regularization techniques,…)

## REFERENCES


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

[2] N. Killoran, T. R. Bromley, J. M. Arrazola, M. Schuld, N, Quesada, and S. Lloyd. Continuous-variable quantum neural networks. *Phys. Rev. Research*, 1:033063, Oct 2019.