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

Su Yeon Chang[1,2], Sofia Vallecorsa[1], Elias F. Combarro[3], Federico Carminati [1]

[1]CERN , Geneva, Switzerland. [2]EPFL, Lausanne, Switzerland. [3]University of Oviedo, Oviedo, Spain

su.yeon.chang@cern.ch Sofia.Vallecorsa@cern.ch
efernandezca@uniovi.es Federico.Carminati@cern.ch

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

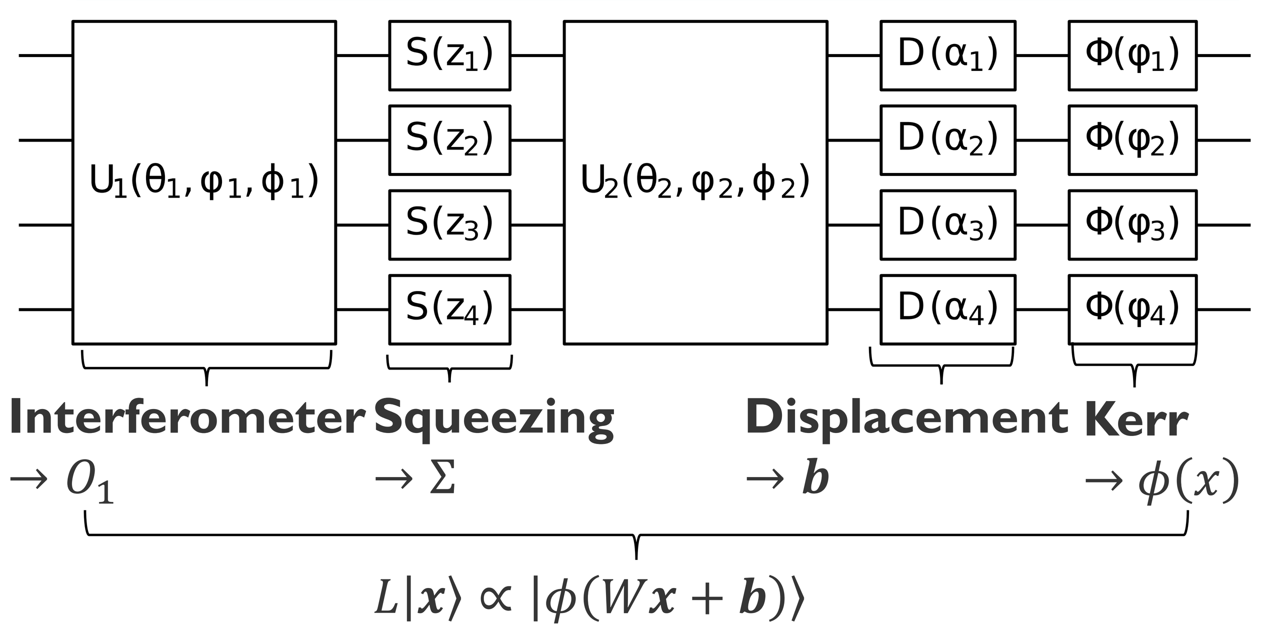
CV QUANTUM COMPUTING

- 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



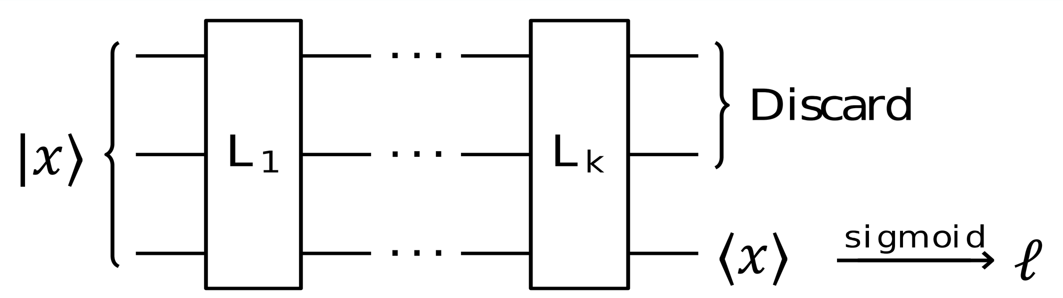
- **CV neural network** (CVNN) [2] performs the transformation equivalent to a fully connected layer : $\boldsymbol{x} \to \phi(W\boldsymbol{x} + \boldsymbol{b})$

  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, Σ = diagonal matrix

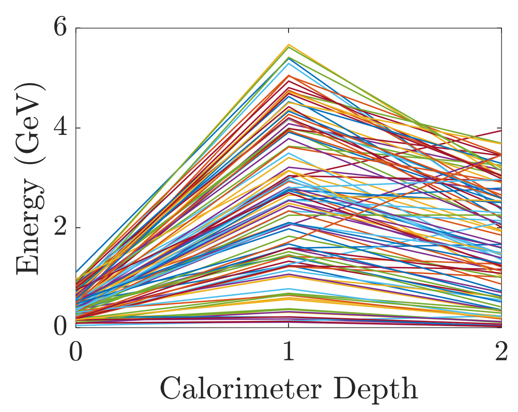
CV CLASSIFIER



- 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

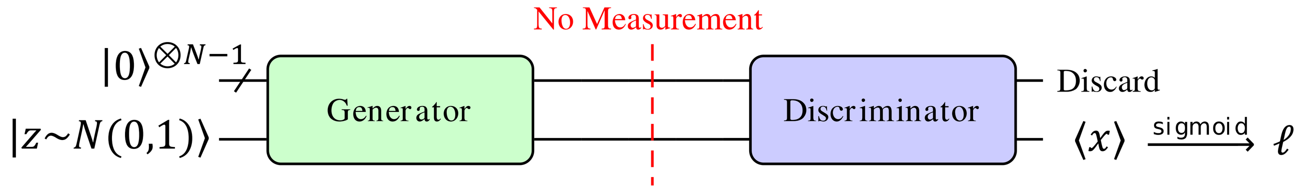
- Propose two qGAN models
- Quantum CVNN generator with one qumode initialized by noise $z \sim N(0,1)$ (latent space =1)

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

1) Fully Quantum

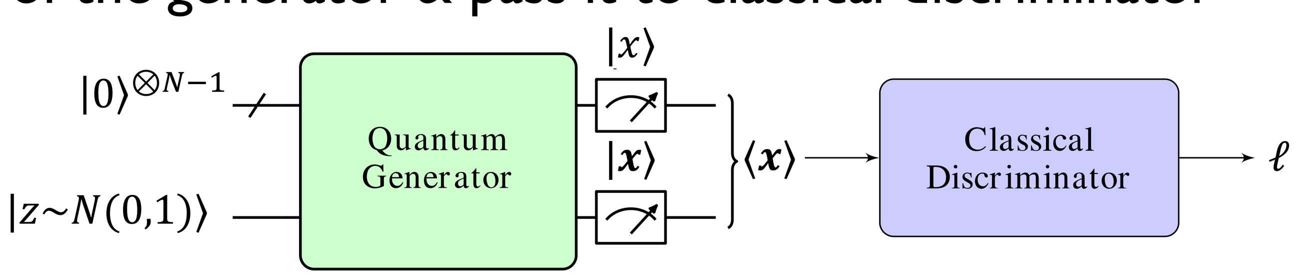
→ Quantum generator (depth d_g) directly connected to quantum discriminator (depth d_d)

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



2) Hybrid

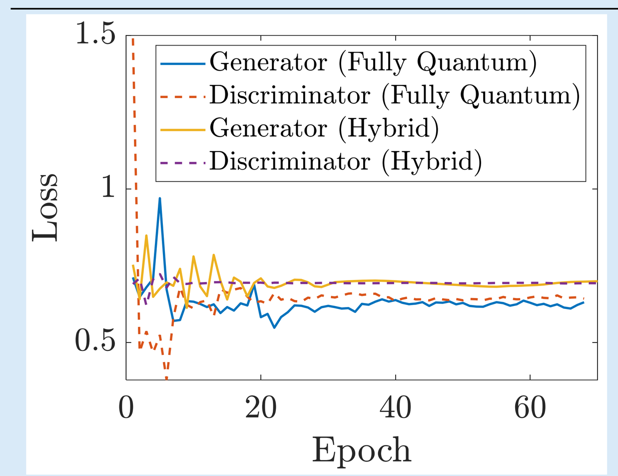
→ Construct a fake image by measuring the position expectation values $\langle \boldsymbol{x} \rangle$ of all N qumodes at the end of the generator & pass it to classical discriminator



RESULTS

Fully Quantum& Hybrid (d_g = 5)

Loss



Mean Image

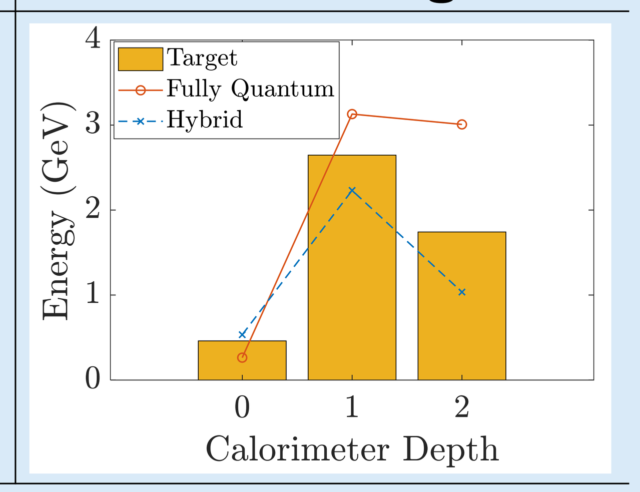
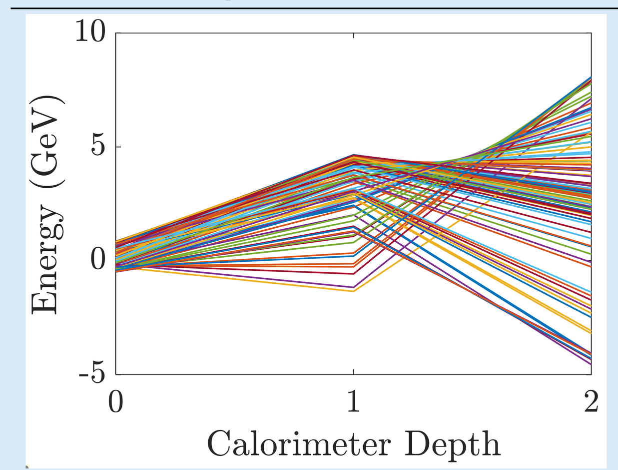
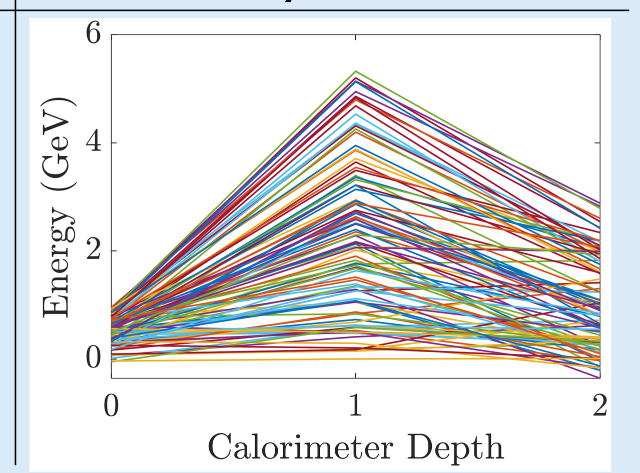


Image samples

Fully Quantum

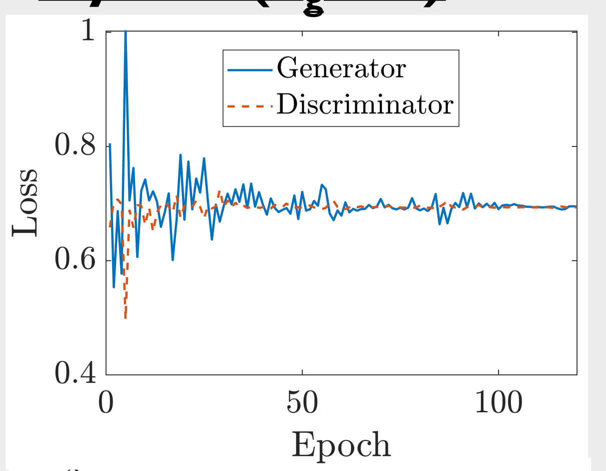


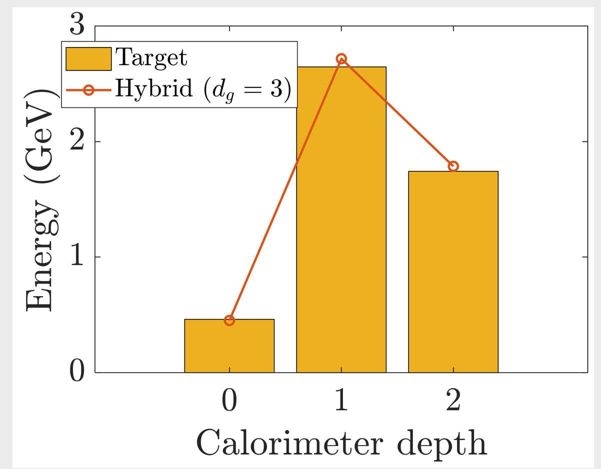
Hybrid

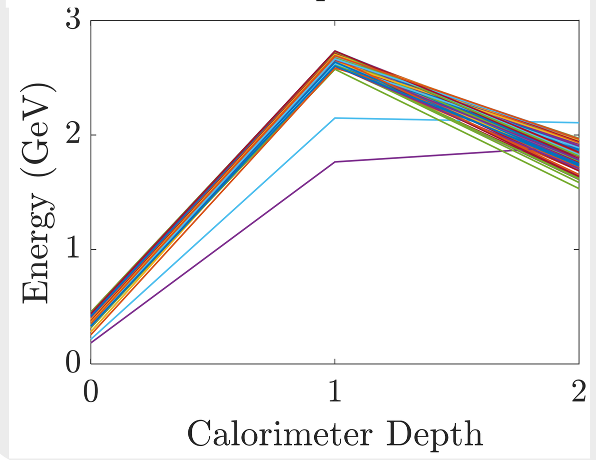


- Losses converge, but mean images are slightly off
- Some unphysical values (negative energy)
- Hybrid model reproduces image shape despite difference in energy levels

Hybrid (d_g = 3)







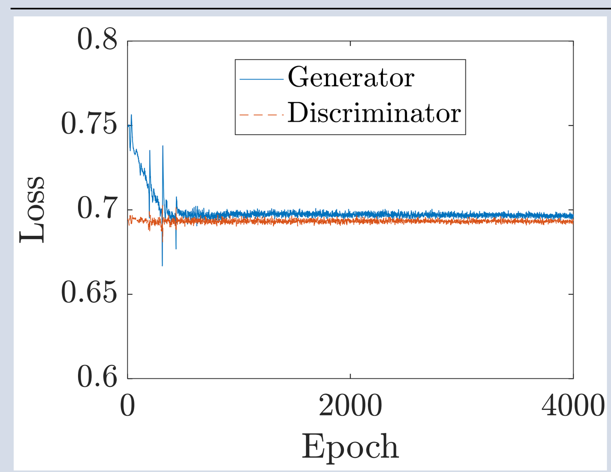
- Convergence in losses & mean image
- Low variety in samples

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

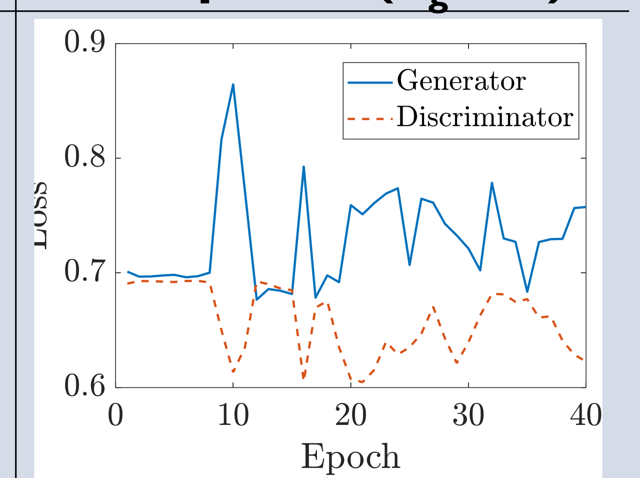
Increase Latent Space Dimension

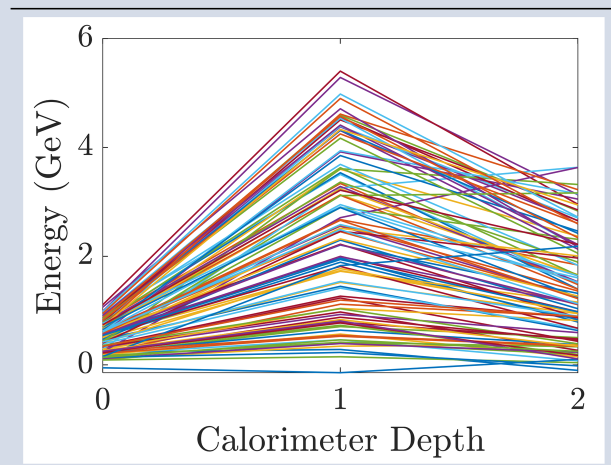
- Compare qGAN (latent space size =3) to classical GAN
- Same discriminator in both cases

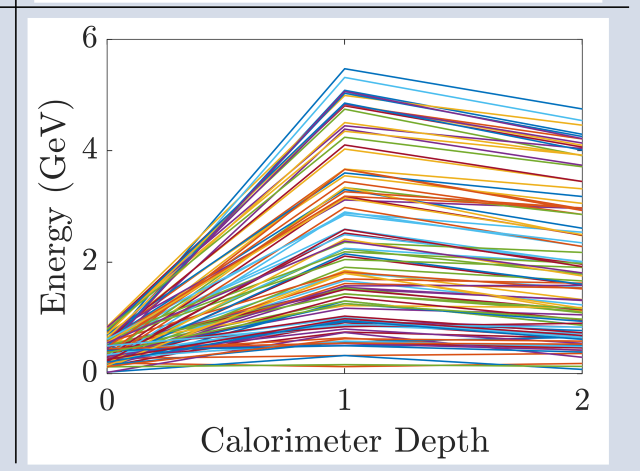
Classical

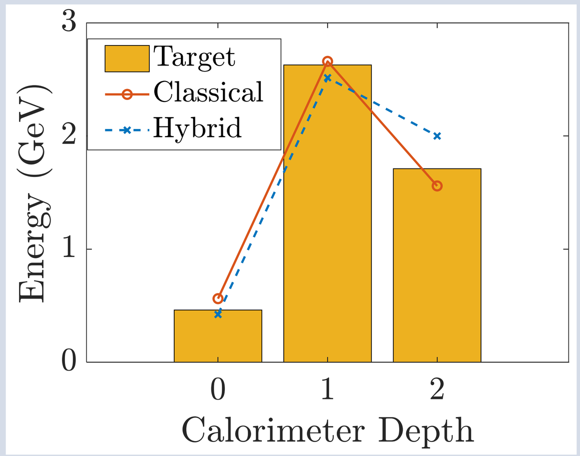


CV qGAN (d_g = 8)









- (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.