Introduction to Quantum Computing
Semester Project Presentation

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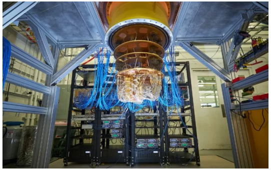

Conclusion

Introduction

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About this presentation

This presentation is a semester project for the course *Introduction to Quantum Computing* and aims to explain the ***Quantum Generative Adversarial Networks for learning and loading random distributions*** paper, a novel approach into using hybrid Quantum-Classical algorithms in order to avoid the data loading bottleneck and use the real quantum speedup. This paper was written by Christa Zoufal, Aurélien Lucchi and Stefan Woerner. In addition of the paper's presentation I will try to reproduce or if possible improve, some of their results and confirm the successfull results seen in the paper.

The Core Challenge: The Data Loading Bottleneck

Why do we need a new way to load data?

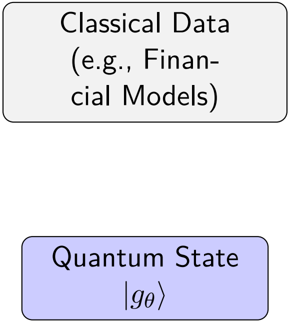

Figure: The problem of loading classical data into a quantum state.

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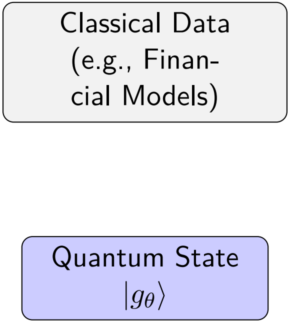

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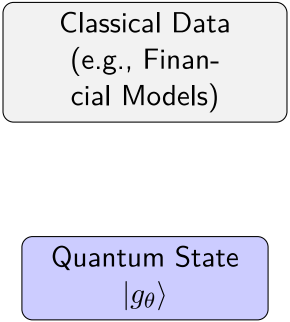

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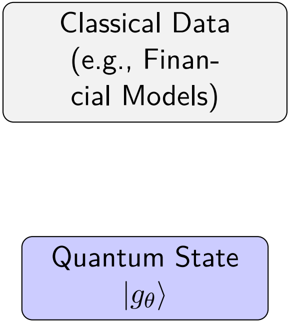

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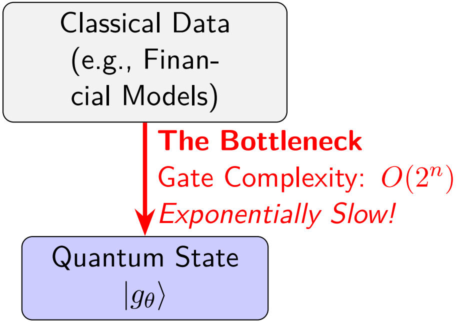

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Background: Generative Adversarial Networks (GANs)

The Adversarial Game: Generator VS Discriminator

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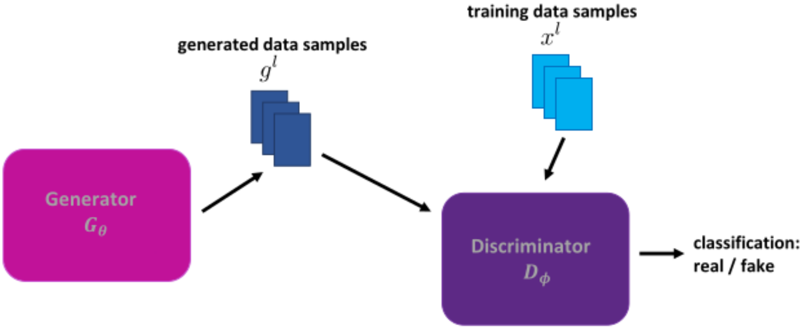
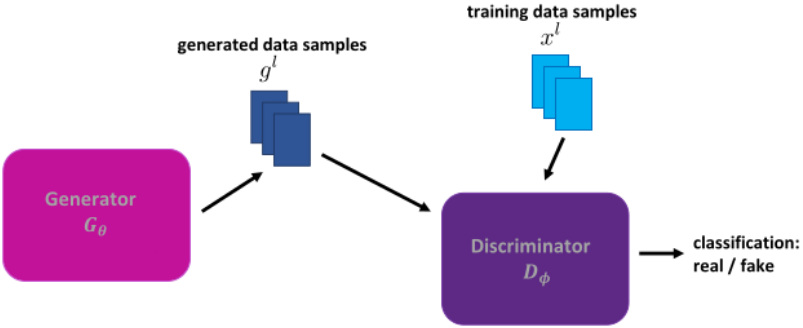


The Adversarial Game: Generator VS Discriminator



Key Idea: They are trained together. The Generator gets better at making realistic fakes, and the Discriminator gets better at spotting them. The goal is to train the Generator so well that it can fool the Discriminator.

Loss functions

In order to train the model effectivelly we need to define the loss functions.

1. Generator loss:
   - $L_G(\phi, \theta) = -\frac{1}{m} \sum_{l=1}^{m} [\log(D_\phi(G_\theta(z^l)))]$
2. Discriminator loss:
   - $L_D(D_\phi, G_\theta) = \frac{1}{m} \sum_{l=1}^{m} [\log D_\phi(x^l) + \log(1 - D_\phi(G_\theta(z^l)))]$

They are mathematicly related as expected and they are based on the classical binary-cross entropy methods.

The Proposed Solution: Quantum GAN (qGAN)

A Hybrid Quantum-Classical Approach

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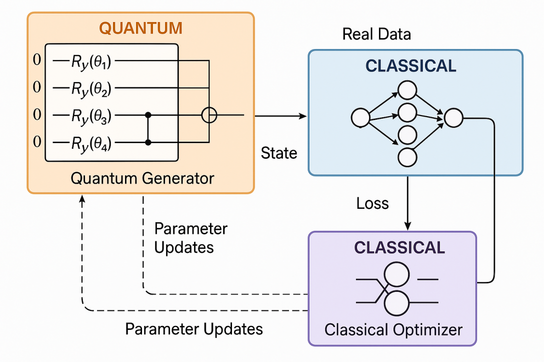

Figure: The qGAN training loop.

Parametrized Quantum Circuits (PQC)

Parametrized Quantum Circuits

Parametrized Quantum Circuits (PQC) are quantum circuits that consist of both fixed and parametrized gates. Fixed gates are typically multi-qubit entangling gates, such as C-NOT and C-Z. Parametrized gates are single-qubit rotation gates (R_Y and R_Z) and the operations of these gates depend on a set of adjustable classical parameters, θ, that define the rotation angles. They are often used inside Variatonal Quantum Circuits (VQAs) and form a Machine Learning model.

The Quantum Generator

Quantum circuit

Quantum circuit

Circuit parts

An initial $R_Y(\theta)$ rotation gate layer. Alternating k layers of:

- Rotation gates $R_Y(\theta)$, the trainable parameters.
- Entangling gates CZ, in order to create complex correlations.

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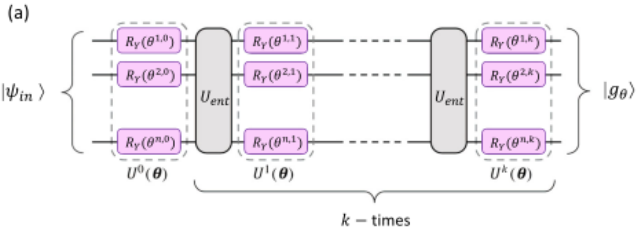

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Generator Creation

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The application of the above circuit onto the initial state, $|\psi_{in}\rangle = |0\rangle^{\otimes n}$ is:

$$|g_\theta\rangle = G_\theta|\psi_{in}\rangle = \prod_{p=1}^{k}\left(\otimes_{q=1}^{n}(R_Y(\theta^{q,p}))U_{ent}\right)\otimes_{q=1}^{n}(R_Y(\theta^{q,0}))|\psi_{in}\rangle$$

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$$G_\theta|0\rangle^{\otimes n} = \otimes_{i=1}^{n}\begin{bmatrix} a & b \\ c & d \end{bmatrix}\cdot\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \otimes_{i=1}^{n}\underbrace{\begin{bmatrix} a \\ c \end{bmatrix}}_{a|0\rangle + c|1\rangle}$$

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Hence,

$$G_\theta|0\rangle^{\otimes n} = \sum_{j=0}^{2^n - 1} [G_\theta]_{j,0} |j\rangle$$

where the elements $[G_\theta]_{j,0}$ are complex functions of all the parameters θ in the circuit.

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Key takeaway: The gate complexity of the circuit now is $O(poly(n))$. Sounds like a massive improvement right?

Classical Discriminator

Discriminator Creation

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- **Input Layer**: 8-dimensional, receives the flattened output from the quantum generator.
- **Hidden Layers**: 2 fully connected layers with the nonlinear activation function LeakyReLU, to capture complex patterns.
- **Output Layer**: A single neuron using sigmoid activation function, to express the output in probability terms.

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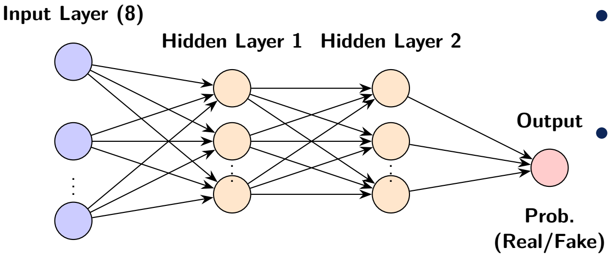

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Dataset and Preperation

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From each of the above mentioned distributions, 20,000 samples were generated and then truncated to the range $[0, 7]$, so we can have a natural mapping between training data and generator states.

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For the first two ways the circuit parameters are set by a uniform distribution on $[-0.1, 0.1]$

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In the context of training a model to learn a random distribution, the Kolmogorov-Smirnov (KS) statistic as well as the relative entropy represent suitable measures to evaluate the training performance.

Application in Finance: Pricing a European Call Option

A Real-World Use Case

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Remember

The qGAN can be used to efficiently load a probability distribution into a quantum computer.

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According to the Black-Scholes model, the spot price at maturity S_T is assumed to follow a Log-Normal distribution like the ones created before, so the qGAN can be trained to learn this distribution successfully, after a carefull initialization though, with normal and uniform distributions to constitute the best options based on the previous experiments.

A Note

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In more realistic and complex cases, where the spot price follows a more generic stochastic process or where the payoff function has a more complicated structure, options are usually evaluated with Monte Carlo simulations.

Quantum Advantage with QAE

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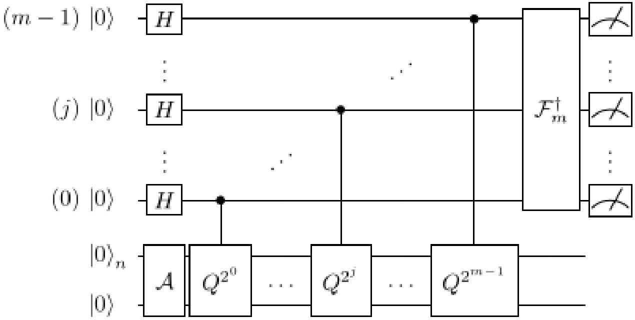

Figure: QAE circuit

Circuit Analysis

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2. Unitary operator A, acts on the initial state plus one ancilla qubit. This gives us

$$A|0\rangle^{\otimes(n+1)} = \sqrt{1-\alpha}|\psi_0\rangle^{\otimes n}|0\rangle + \sqrt{\alpha}|\psi_1\rangle^{\otimes n}|1\rangle$$

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3. The following unitary operator, Q, is called Grover operator. This operator is used because its eigenvalues are directly related to amplitude: $\lambda_{1,2} = \exp^{\pm 2i\theta_\alpha}$, where $\alpha = \sin^2(\theta_\alpha)$. The m additional evaluation qubits in the algorithm are required to control the applications of $Q = -AS_0A^\dagger S_{\psi_0}$, where $S_0 = I^{\otimes(n+1)} - 2|0\rangle\langle 0|^{\otimes(n+1)}$ and $S_{\psi_0} = I^{\otimes(n+1)} - 2|\psi_0\rangle\langle\psi_0| \otimes |0\rangle\langle 0|$

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4. Finally, an Inverse Quantum Fourier Transform (IQFT) is applied to the evaluation register, to transform the phase information into a computational basis state and the measurements.

Problem Solved: European Option Price

Estimation Process

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Now, qGAN model was trained on real quantum hardware (IBM Q Boeblingen) with 20 qubits, using a batch size of 2000 samples and a circuit with the architecture mentioned above with 1 layer depth for 200 training steps (epochs).

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Figure: Payoff function European Call option. Probability distribution of the spot price at maturity S_T and the corresponding payoff function for a European Call option.

Estimation Comparisson

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More specifically, they integrated the distribution loading quantum channel into a quantum algorithm based on QAE, using m $= 8$ evaluation qubits, i.e., $2^8 = 256$ quantum samples and into a Monte Carlo simulation, working with 1024 random samples. Estimations of $\mathbb{E}[\max\{ST - K, 0\}]$ are:

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Method	Distribution	Samples	CI
1. Analytic (Exact)	$X \sim$ Log-N(1, 1)	-	-
2. Monte Carlo (Quantum HW)	$\lvert g_\theta \rangle$	1024	± 0.0848
3. QAE (Simulated)	$\lvert g_\theta \rangle$	256	± 0.0710

Table: Comparisson of option price estimation methods, their samples and their confidence intervals.

Estimation Comparisson

At this point it is worth noting that the estimates and CIs of Monte Carlo and QAE evaluation are not subject to the same level of noise effects. Monte Carlo simulation solely run on actual quantum hardware, while QAE on a quantum simulator. In order to run QAE on a quantum computer, further improvements are required, e.g., longer coherence times and higher gate fidelities.

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Reproducing the Results

Validating the Paper's Findings

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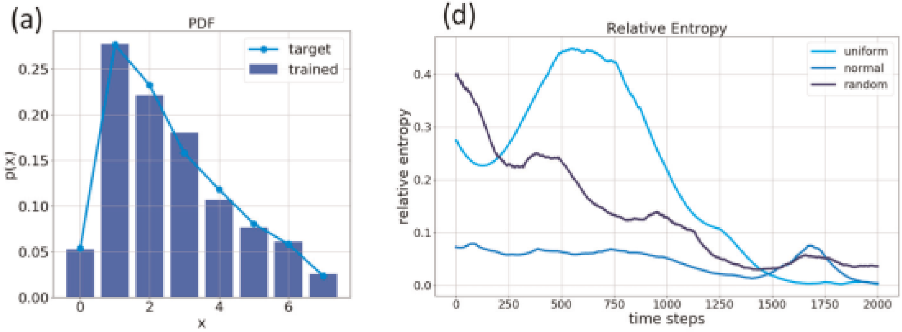

Figure: Comparisson of the real and the generated distribution, with the generator initialized with a uniform distribution (left) and relative entropy of the generator (right).

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Solutions

1. Use seperate loss functions. Generator computes and sums up the loss, on a probability distribution $\sum_{i=0}^{7} L_{G_i}$, where L_{G_i} the generator loss value for each discrete value.

Challenges Faced

The main challenges were on how to process and manage the dataset effectivelly. This was needed because the IN/OUT values for Discriminator were 8/1 and for Generator 8/8.

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2. Use one-hot encoding for batches, to ensure dimension compatibility between the two models and effective classical processing.

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These two changes should lead us into later convergence of the loss functions but, slightly better results regarding the relative entropy and KS statistic, based on empirical knowledge from previous runs.

The Results

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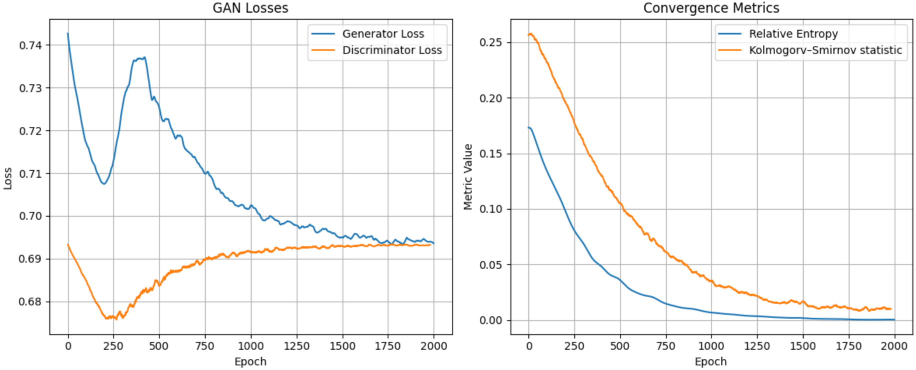
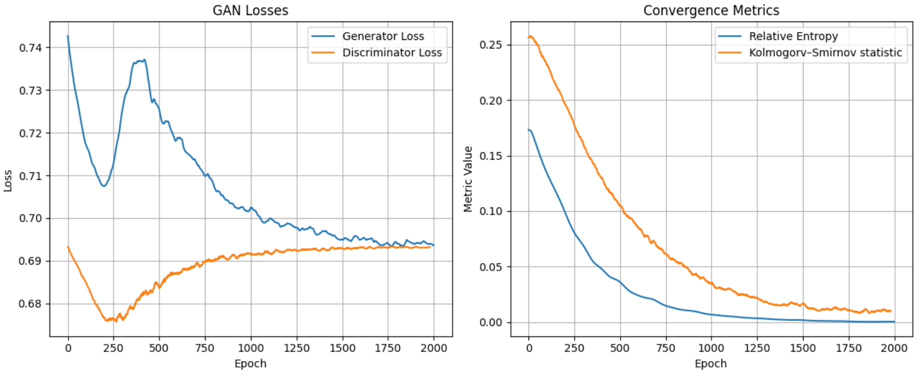


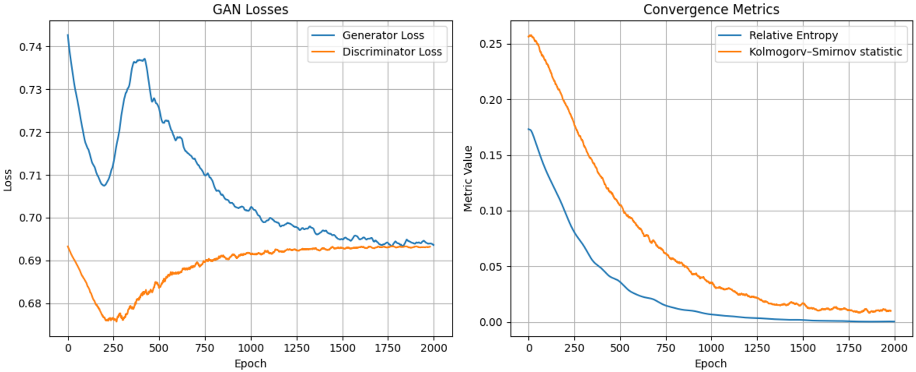
Figure: Training loss functions (left) and convergence metrics (right)

The Results



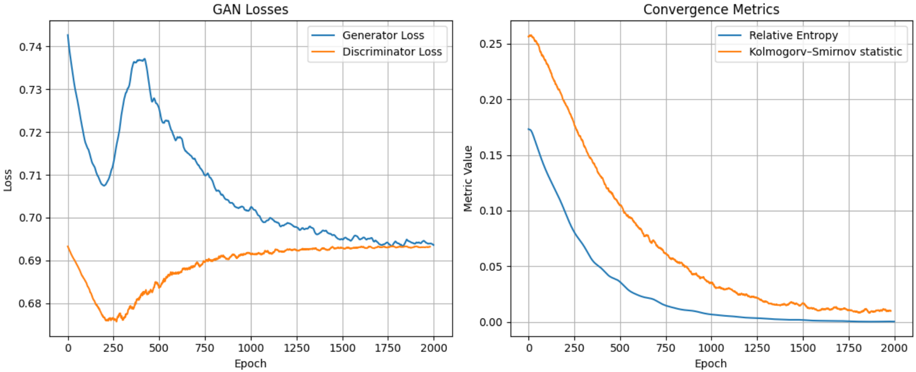
Confidence level of KS statistic was set to 95% from paper authors. Here 99.19% was achieved.

The Results



Relative entropy reaches 0.0004, when the training is finished.

The Results



Loss functions converge later during the training process.

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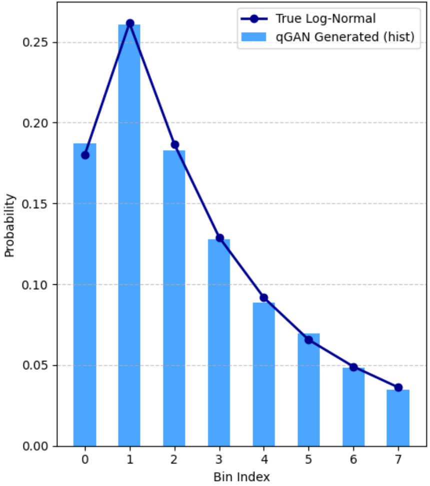


Figure: True Log-Normal versus qGAN generated

Comparisson (1/4)

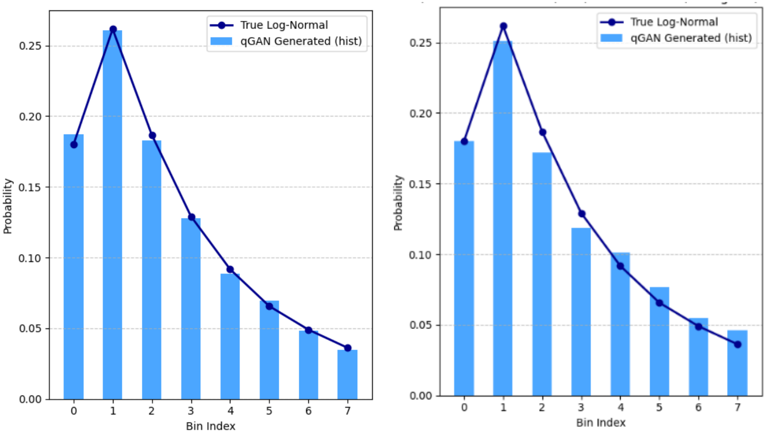


Figure: My setup results (left) in comparisson with paper's setup results (right)

Comparisson (2/4)

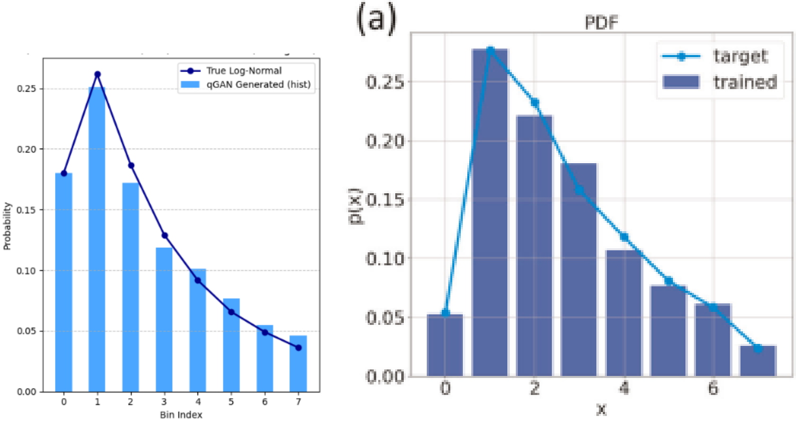
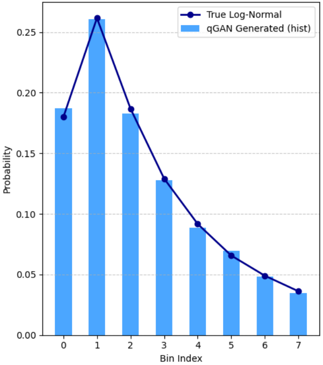


Figure: **Paper's setup**: My results (left) in comparisson with paper's results (right)

Comparisson (3/4)



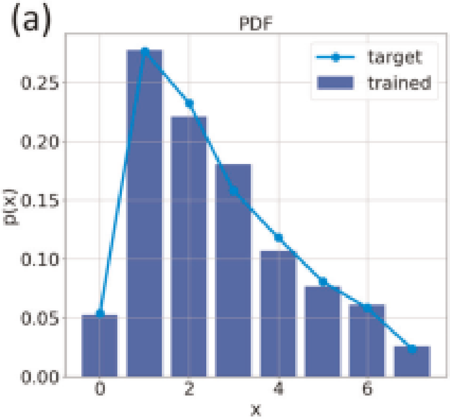


Figure: My results (left) in comparisson with paper's results (right)

Comparisson (4/4)

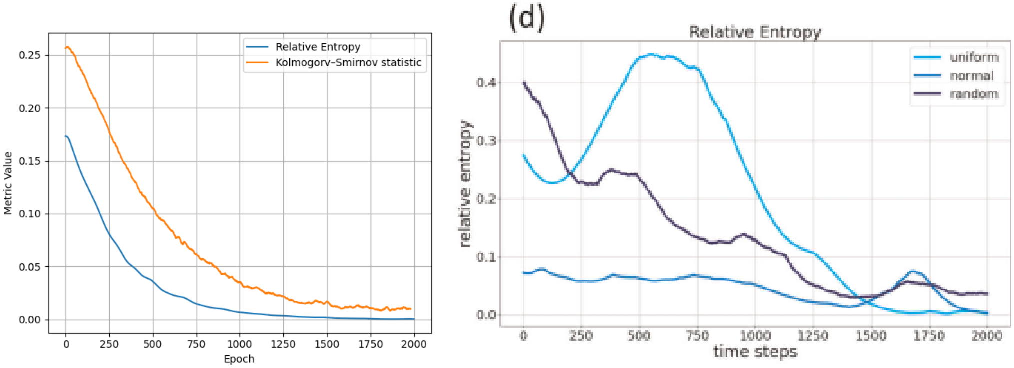


Figure: My results (left) in comparisson with paper's results (right)

Discussion & Key Takeaways

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- qGANs are really powerfull! Imaging having the huge quantum advantage and in the same time being able to generate such realistic data, that can in a way predicting the future.

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- The "hybrid" aspect is critical. Success depends just as much on classical machine learning techniques (like data representation and loss functions) as it does on the quantum circuit design.
- **Limitation**: Training is very sensitive to hyperparameters, requiring careful and many times empirical fine-tuning.

Conclusion & Future Work

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Ideas:

- Scaling the model to more qubits and more complex distributions.
- Running those experiments on real quantum hardware to study the effects of noise.
- Intergrating this loading technique into other quantum algorithms.

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Thank you!

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