UNIVERSITÀ DEGLI STUDI FIRENZE

Analyzing LatentQGAN

A Hybrid Quantum-Classical GAN with Autoencoders

Vieloszynski, et al. *LatentQGAN: A Hybrid QGAN with Classical Convolutional Autoencoder*, 2024.

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Introduction

- **generative models** aim to learn the underlying data distribution and generate new, realistic samples

- **applications** include image synthesis, natural language processing, anomaly detection, and data augmentation

- **GANs** (Generative Adversarial Networks) use adversarial training between a generator and a discriminator to create high-quality synthetic data

- despite their success, **GANs face challenges** like unstable training, mode collapse, and high computational costs

Classical GANs

Background Concepts

- two adversarial models: a generator (*G*) synthesizes data, and a discriminator (*D*) distinguishes real from generated samples

- training as a **min-max optimization problem**, where both models iteratively improve by competing against each other

$$\min_G \max_D \mathcal{L}(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}\left[\log(1 - D\big(G(z)\big)\right]$$

- training **convergence to a theoretical equilibrium** when the generator produces samples indistinguishable from real data, but in practice this is rarely achieved

- **training GANs is highly unstable** due to factors like discriminator dominance, mode collapse, and weak gradient signals for *G*

- **techniques to stabilize training** include label smoothing, avoiding zero-gradient operations, modifying loss functions, and using different optimizers for *D* and *G*

QuantumML based Approaches

Background Concepts

- approaches based on quantum mechanics, a theory that describes the behavior of particles
- **quantum machine learning** (**QML**) may offer significant advantages over classical approaches by leveraging the principles of quantum physics
- uses **qubits**, leveraging quantum mechanics' principles to perform computations beyond classical capabilities
- **superposition**: qubits can exist in multiple states simultaneously, enabling parallel processing and representiation of complex data distributions with few qubits
- **entanglement**: creates strong correlations between qubits, allowing non-classical interactions
- measurement causes **quantum states collapse** into classical values, making repeated sampling necessary for reliable results

QuantumML based Approaches

Background Concepts

- quantum computation enables **encoding of high-dimensional data** and fast **sampling from probability distributions**, crucial for QML

- quantum circuits are built with **quantum gates** to manipulate qubits

- challenges include **qubit decoherence**, **gate errors**, and **connectivity constraints**, limiting scalability and reliability of quantum hardware

- **quantum error correction** techniques use redundancy to mitigate errors

- the studied model, **LatentQGAN**, addresses these challenges by designing shallow quantum circuits to minimize the impact of hardware limitations

Similar Methods

Related Works

- GANs typically introduce **autoencoders** to compress data into a lower-dimensional latent space: an encoder extracts features, and a decoder reconstructs the original input

- classical **LatentGAN** integrates autoencoders into GANs, training the generator on latent representations instead of high-dimensional data, improving efficiency and reducing overfitting

- **Q-PatchGAN** is a hybrid quantum-classical model, using a quantum generator composed of multiple sub-circuits to generate image patches, but struggles with scalability and mode collapse

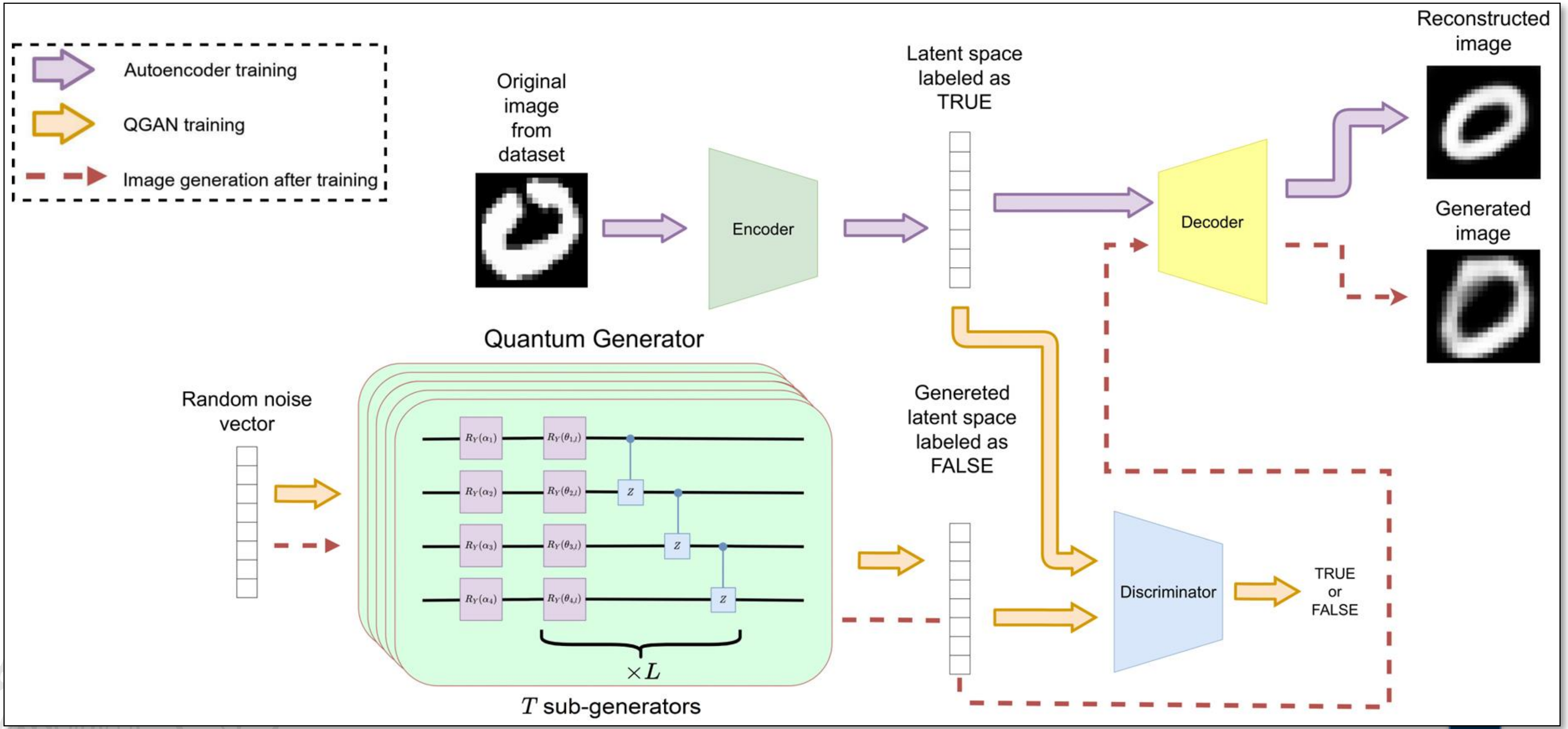
- **MosaiQ** incorporates PCA for dimensionality reduction, allowing a quantum generator to operate in a lower-dimensional space while a classical discriminator evaluates both real and generated data

LatentQGAN

LatentQGAN Architecture

combines an autoencoder and hybrid q-GAN

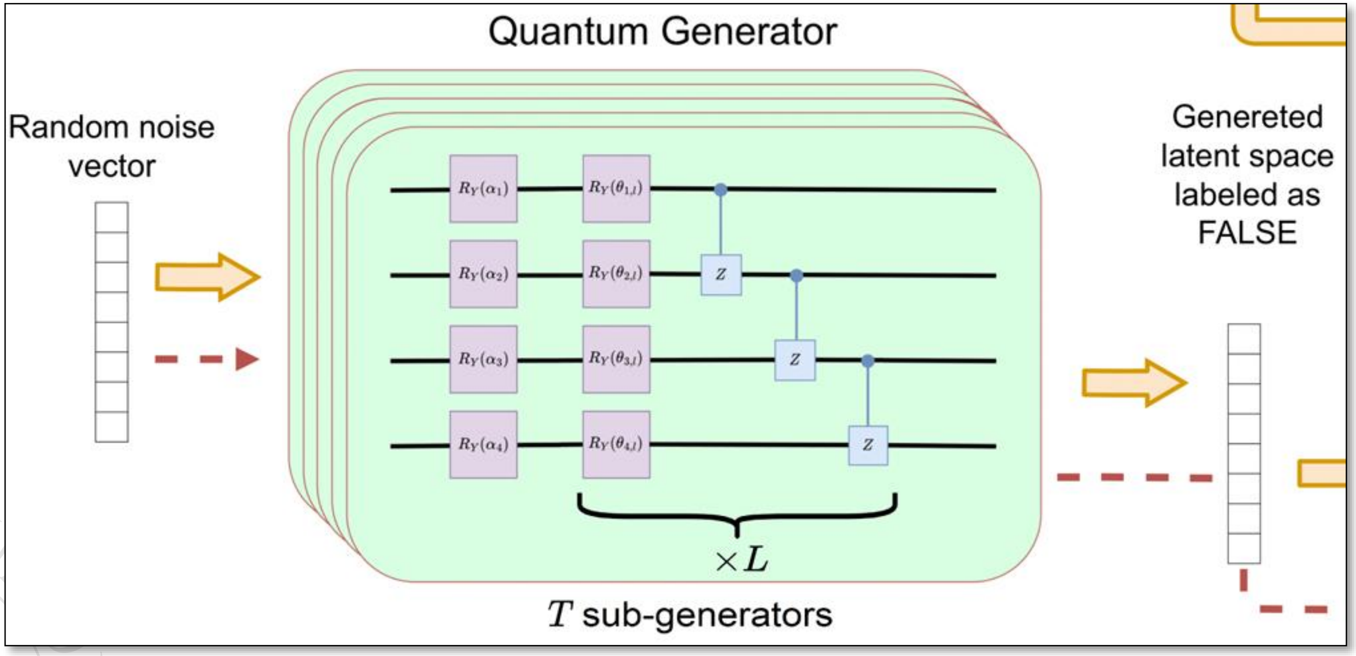
- **autoencoder** maps pixel-space with compressed latent-space
- **q-GAN** generates new latent samples



Q-GAN

LatentQGAN Architecture

- generator based on **Q-PatchGAN**: multiple identical quantum sub-circuits, each generating a portion of the latent representation
- generator applies **rotation gates** R_Y to encode input noise and **parameterized layers** with $R_Y(\theta)$ rotations and *controlled-Z* gates
- θ parameters optimized during training



Q-GAN

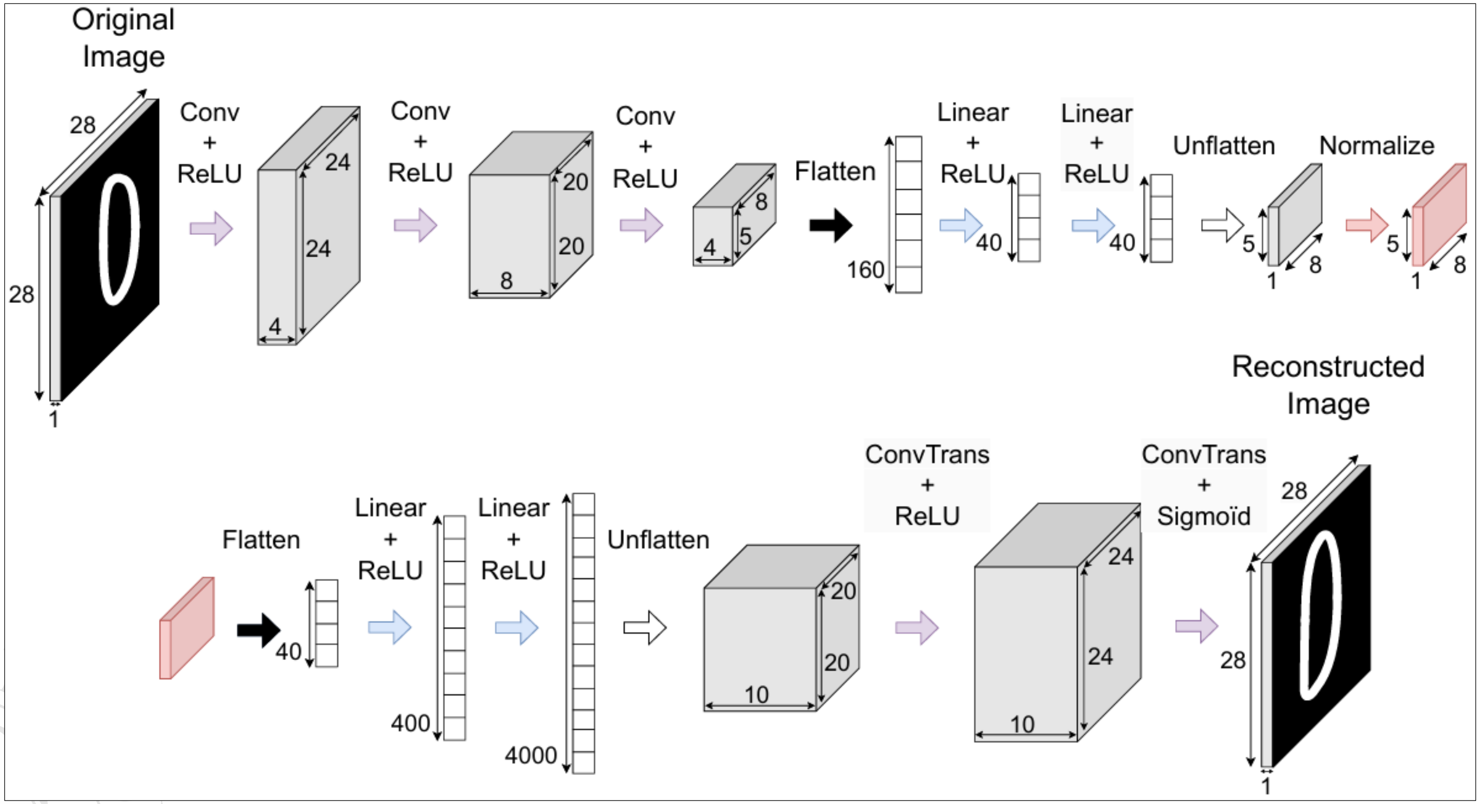
LatentQGAN Architecture

- **post-selection** in generator introduces non-linearity by keeping only results of measurement where *ancilla* qubit is $|0\rangle$
- final **normalization** step to ensures output represents a valid probability distribution
- **classical discriminator** as a set of fully-connected linear layers, evaluates latent representation of real and fake data
- new images generated with q-generator forward pass, and latent result mapped to pixel-space with decoder
- generator gradients computed with analytical method of **parameter-shift rule**, leveraging macroscopic parameter shifts (*numerical differentiation* and *automatic differentiation* are impractical for quantum circuits)

Autoencoder

LatentQGAN Architecture

- **CNN-based encoder** and **decoder**, extracts latent representation and reconstructs input images
- encoder applies per-line **normalization**, to be compatible with generator output



Experiment Settings

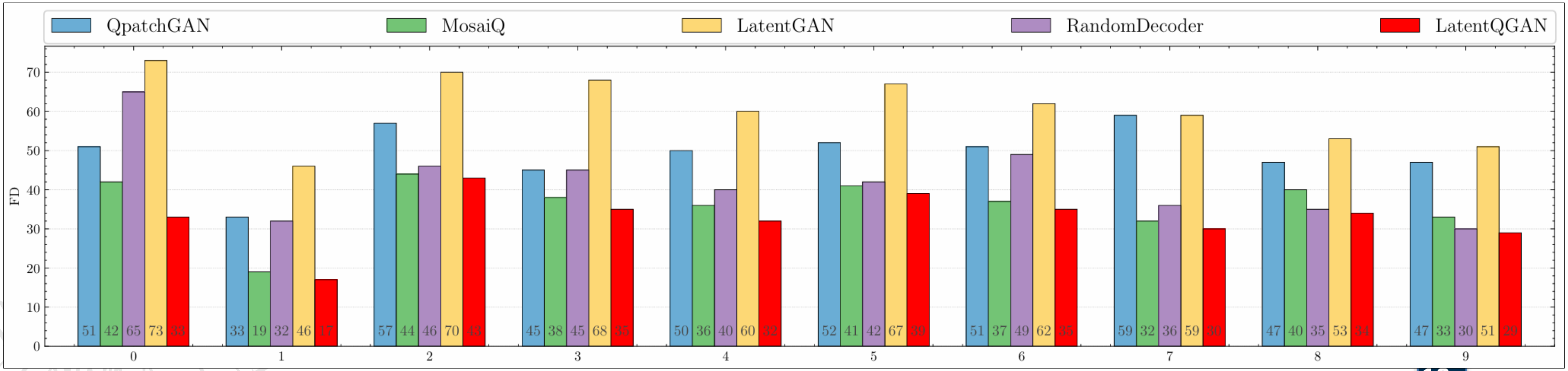
Tests

- tests on **simulators and real quantum computers**, 2048-shot experiments
- **MNIST dataset**: 28×28 grey-scale handwritten digits
- **autoencoder** compresses images into a (5×8) latent space
- **q-generator** with 5 sub-circuits, 4 qubits each, and 140 trainable parameters
- **autoencoder trained first**, minimizing *MSE* as reconstruction loss
- q-GAN trained using the *SGD* optimizer and *BCE* loss
- evaluation with **Fréchet Inception Distance** (FID): high-level full-reference metric, compares distributions of generated and real images
- LatentQGAN compared to both quantum (*QPatchGAN* and *MosaiQ*) and classical methods (*LatentGAN* and *RandomDecoder*)

Results

Tests

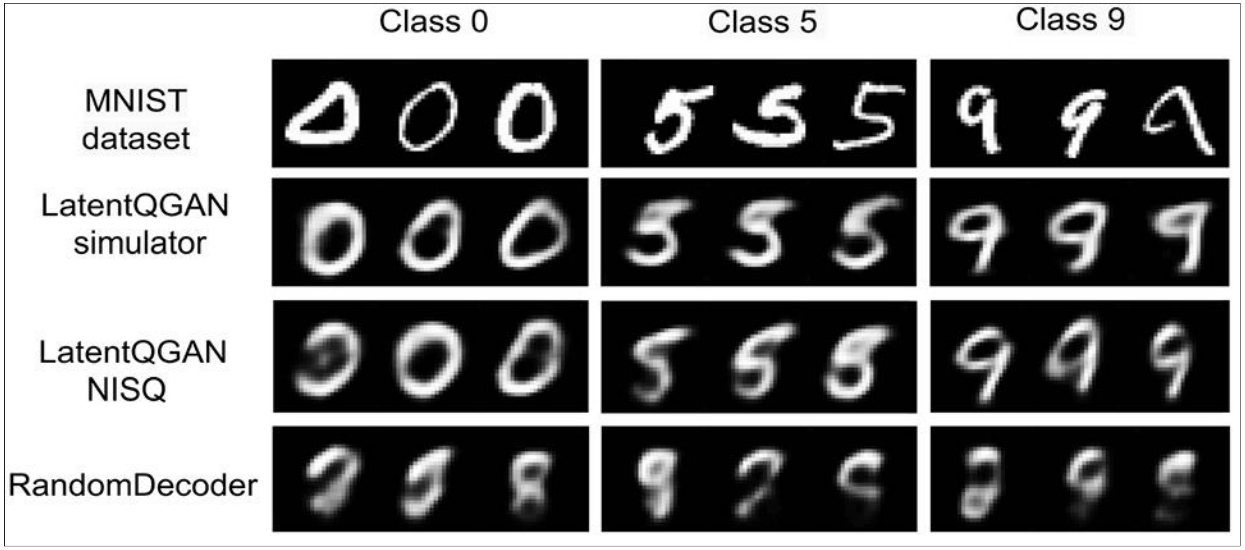
- LatentQGAN achieves best FID between 350 and 700 iterations
- it outperforms quantum methods like *QPatchGAN* and *MosaiQ*
- other QGAN models perform well in simulations but are impractical on current *NISQ* devices as they require significantly more parameters and iterations
- **LatentQGAN outperforms classical LatentGAN** with same number of parameters, emphasizing the advantages of the quantum generator



Results

Tests

- autoencoder is crucial but **the generator ensures meaningful latent space representations:** *RandomDecoder* fails without it
- results on real quantum hardware show **slightly lower FID due to noise**, but generated images remain visually recognizable



	Class 0	*Class 5*	*Class 9*
Quantum simulator	33	39	29
Quantum computer	38	43	34

Conclusions

LatentQGAN

- hybrid quantum-classical GAN: classical discriminator, quantum generator
- autoencoder to project to and from lower-dimensional space
- uses shallow quantum-circuits to allow efficient use of NISQ devices

Limitations

- **quantum noise and hardware limitations** could limit deployment beyond small-scale tests
- **scalability to larger datasets** (more complex, high-resolution) uncertain, especially given quantum hardware limitations

Future work

- explore extending LatentQGAN to a **full quantum implementation**
- application to other tasks, like **time-series data processing** and **anomaly detection**

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