H2020 Engage Conference:

Detector Simulation and Jet Clustering for HL-LHC with Quantum Computing

Saverio Monaco

June 19, 2025

Status of the PhD

Progress Overview

Status of the PhD

Overview

Supervisor: Kerstin Borras

Title: Development of Quantum Computing Models for Calorimeter Simulations and Jet-Clustering in Particle Physics

03/2024 - 03/2027 (?)

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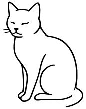

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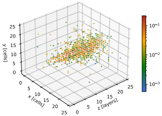
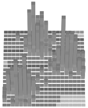
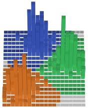
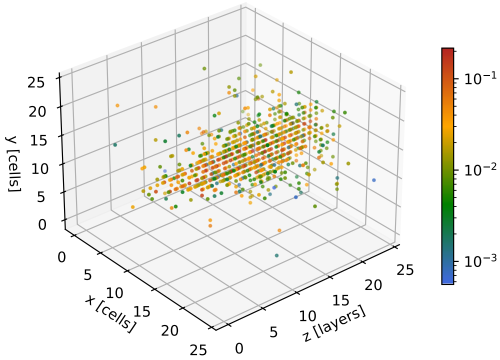






Motivation

A brief motivation for Quantum Models in High Energy Physics.



Tom’s Hardware article

IBM is building a large-scale quantum computer that 'would require the memory of more than a quindecillion of the world's most powerful supercomputers' to simulate

News By Mark Tyson published 3 days ago

That's 1,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000

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Taming the Quantum Hype

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$= 10^{48}$

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$= 10^{48}$

Comments (20)

Motivation

Taming the Quantum Hype

Representation of a quantum state

- A quantum state of n qubits is represented by a complex vector of 2^n amplitudes.
- On a classical machine, each amplitude (a complex number) needs:

  32 bytes for the real part + 32 bytes for the imaginary part = 64 bytes

- Hence to represent a state of n qubits, we need 2^n amplitudes, which amounts to $64 \cdot 2^n$ bytes

Motivation

Taming the Quantum Hype

IBM Starling (2029) - 200 (logical) qubits

- A quantum state of 200 qubits is represented by a complex vector of 2^{200} amplitudes.
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Motivation

Taming the Quantum Hype

IBM Starling (2029) - 200 (logical) qubits

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- Hence to represent a state of 200 qubits, we need 2^{200} amplitudes, which amounts to $64 \cdot 2^{200}$ bytes $\sim 10^{43}$ EB

El Captain (Current best supercomputer): $\sim 10^{-2}$ EB

$$\frac{\text{"Memory" IBM Starling}}{\text{"Memory" El Captain}} = \frac{10^{43}\text{ EB}}{10^{-2}\text{ EB}} = 10^{45}$$

Motivation

Quantum Computer Bottleneck

$$\underbrace{|0\rangle^{\otimes n}}_{\text{dummy state}} \rightarrow |\psi\rangle \rightarrow \{0,1\}^n$$

Motivation

Quantum Computer Bottleneck

$$|0\rangle^{\otimes n} \rightarrow \underbrace{|\psi\rangle}_{\substack{\text{wavefunction: impossible to describe classically} \\ \text{for large } n}} \rightarrow \{0,1\}^n$$

Motivation

Quantum Computer Bottleneck

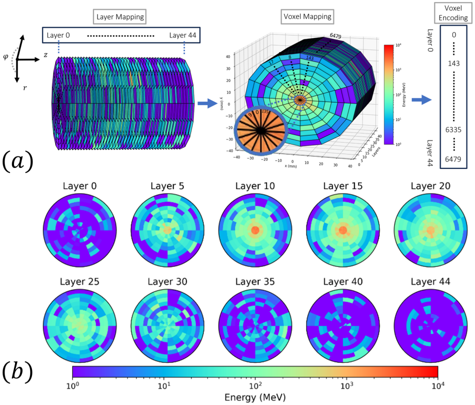
$$|0\rangle^{\otimes n} \rightarrow |\psi\rangle \rightarrow \underbrace{\{0,1\}^n}_{\substack{\text{output / measurement} \\ \text{bitstrings of } n \text{ qubits}}}$$

Measurement bottleneck

$$|\psi\rangle \rightarrow \{0,1\}^n$$

collapse of the wavefunction

Argument #1: Complexity of HEP datasets



[5] Toledo-Marin et al.

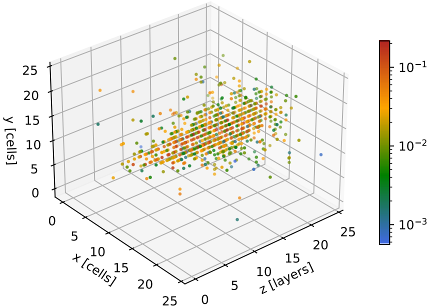
Potential Advantages:

- Variational models
  - Faster solution times
  - Improved generalization capabilities [2]
  - Reduced number of required parameters
- Standard Quantum Algorithms
  - Access to a family of different algorithms with different scalings:
    ex: Shor: Exponential $\rightarrow$ *Polynomial*

Motivation

Quantum Computing in HEP

Argument #2: HEP datasets are *quantum* (in a way)

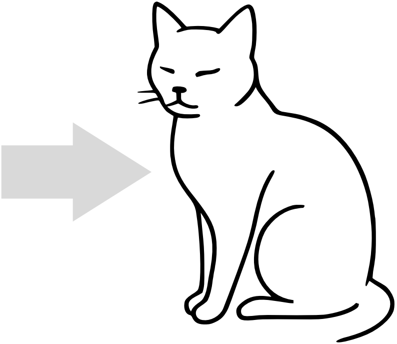


Example: Detector Dataset

A particle shower can be seen as the collapse of a complex wave-function which might be best described through a quantum state.

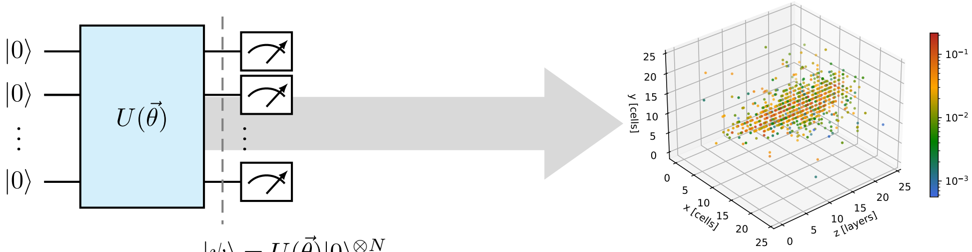
Detector Simulation

How to generate images from quantumness



Detector Simulation

Mapping of the generative task

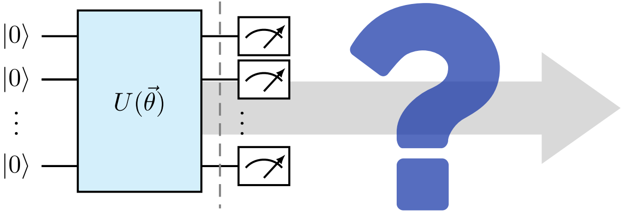


$$|\psi\rangle = U(\vec{\theta})|0\rangle^{\otimes N}$$

Detector Simulation

Mapping of the generative task

Not a trivial task!



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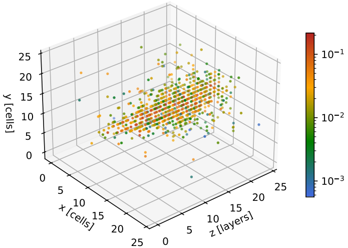
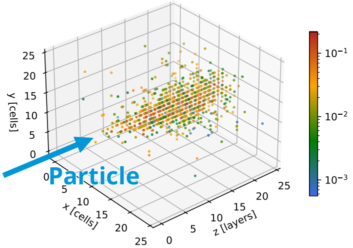


Detector Simulation

Downsampling

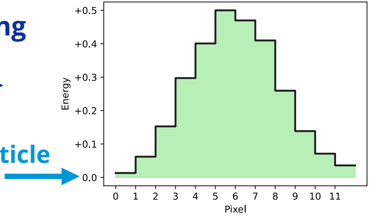
- Preliminary study using simplified models
- Understand advantages and challenges

$(25 \times 25 \times 51)$



Downsampling

$(1 \times 1 \times 12)$



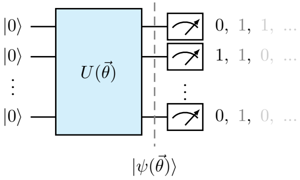
Detector Simulation

Types of Quantum Generative Models[4]

Detector Simulation

Types of Quantum Generative Models[4]

Discrete Architectures



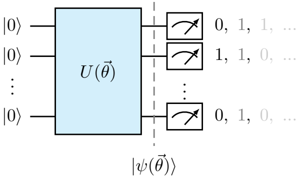
Output: Single measurement of the wavefunction

- ✓ Fast generations
- ✓ Always hard to simulate classically
- ✗ Sensitive to noise
- ✗ *Black and white* images

Detector Simulation

Types of Quantum Generative Models[4]

Discrete Architectures



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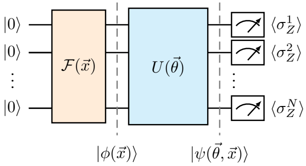
Continuous Architectures



Output: Multiple measurements of the wavefunction

- ✗ Slow generations
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Detector Simulation

Types of Quantum Generative Models[4]

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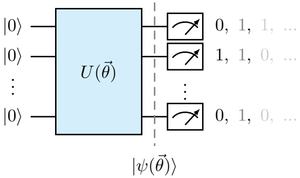

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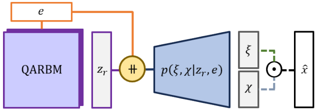
Hybrid Architectures



[5] Toledo-Marin et al.

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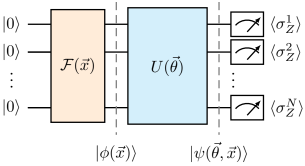

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Detector Simulation

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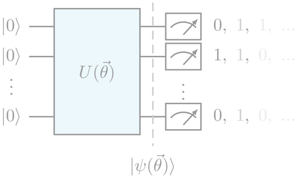

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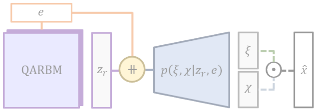

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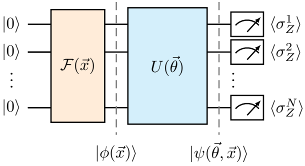

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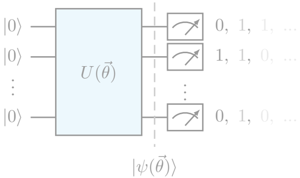

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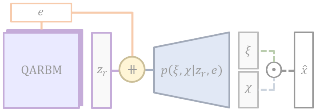

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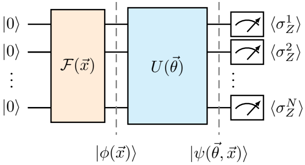

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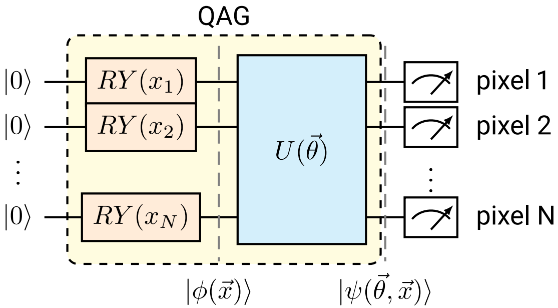
Calorimeter images ≡

Detector Simulation

Quantum Angle Generator

- Generation of N pixels requires N qubits



Detector Simulation

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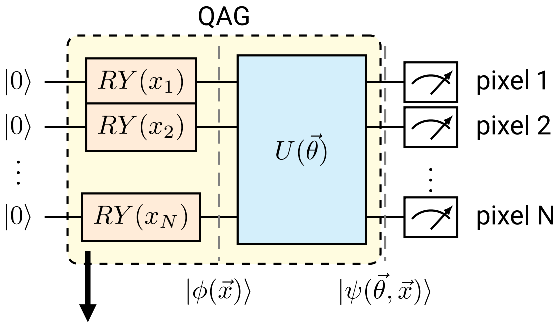

Quantum State Preparation

- Implement randomness using RY rotations

Detector Simulation

Quantum Angle Generator

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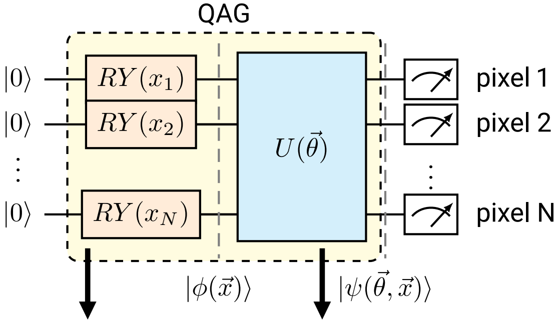

Quantum State Preparation

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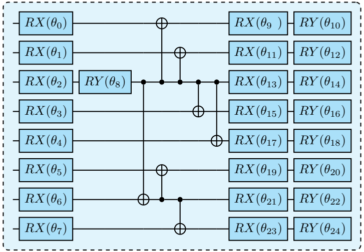
Parametrized Unitary $U(\vec{\theta})$



Detector Simulation

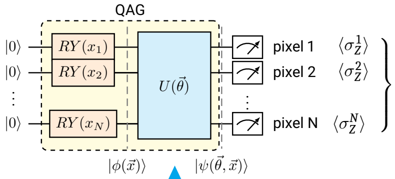
Quantum Angle Generator

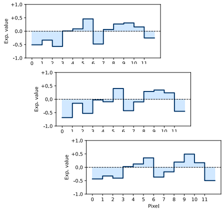
Choose a random initial set of parameters $\vec{\theta}_0$

For each epoch i

1. Generate M images
2. Evaluate the *MMD* loss
3. Update the parameters $\theta_i \to \theta_{i+1}$

M images (epoch 0)





$$\mathcal{L}(\theta_i) = \text{MMD}^2(\text{True Data}, \text{Gen. Data}(\theta_i))$$

$$\theta_i \to \theta_{i+1}$$

Detector Simulation

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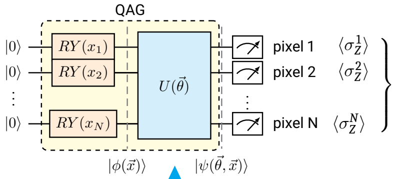
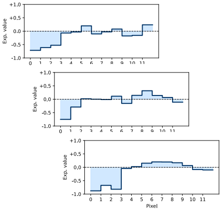
M images (epoch 20)





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Detector Simulation

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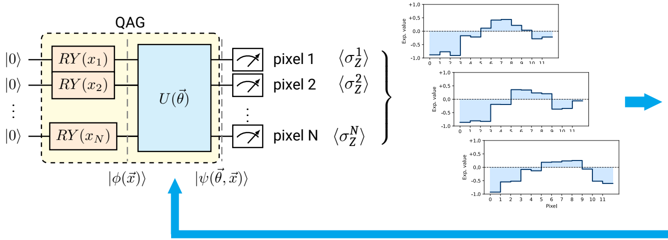
M images (epoch 40)



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Detector Simulation

Quantum Angle Generator

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For each epoch i

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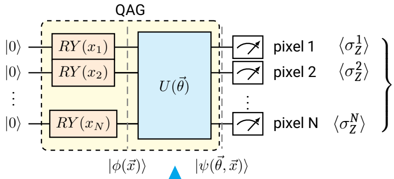
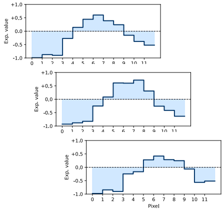
M images (epoch 60)





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Detector Simulation

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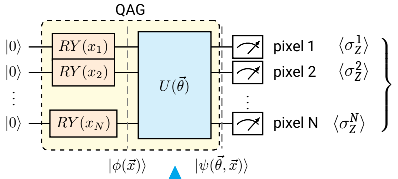
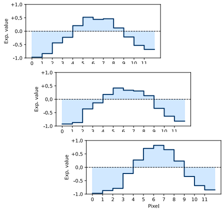


M images (epoch 80)



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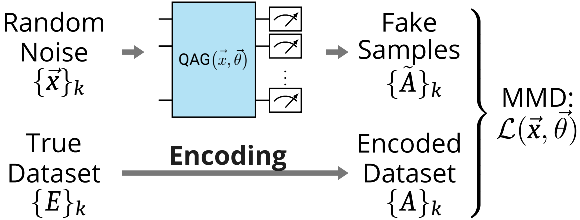
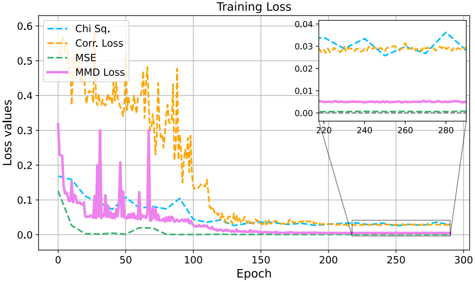
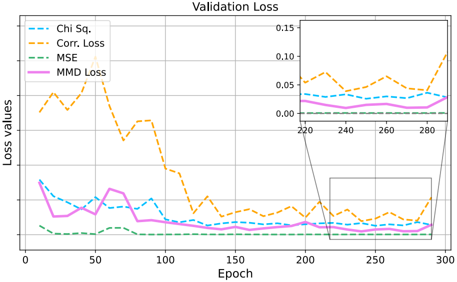
Detector Simulation

Training



✓ MMD sufficient to learn correlations between pixels





Detector Simulation

Quantum Angle Generator

Combined Energy distribution

Detector Simulation

Quantum Angle Generator

Energy sum

Energy average

Correlations

Detector Simulation

Quantum Angle Generator

Done:

- Implementation
  - Implementation in both *Pennylane* and *Qiskit*
  - GPU support
- In depth study of Hyperparameters:
  - Number of qubits
  - Ansatz (State Preparation + Trainable)
  - Loss function
  - Data preprocessing
  - Optimizer

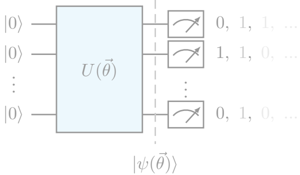
In progress:

- Study under different levels of simualted noise
- Deployment on IBM machines (superconductng)
- Deployment on IQM machines (superconducting)
- Deployment on eleQtron machines (ion-based)
- Comparison with classical counterpart

Detector Simulation

What's next

Discrete Architectures



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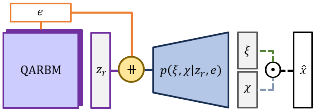
Hybrid Architectures



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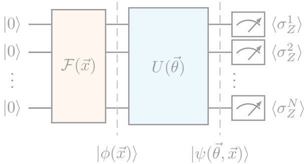

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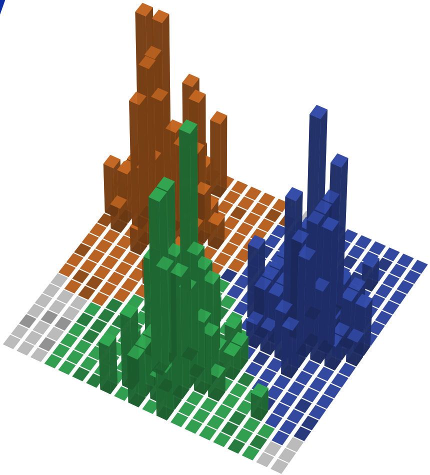
Jet Clustering

How to cluster quantumly



Jet Clustering

Overview

Classical algorithm (anti-k_T)

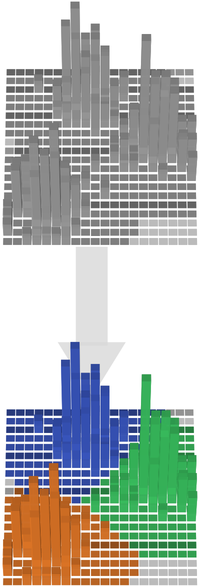
combines particles in order of decreasing transverse momentum, computing the pairwise distance measures between all particles ($\mathcal{O}(N^2)$)

Quantum algorithm[3]

Quantum subroutines

1. Computing distances between all particles
2. Seach for maxima in the unsorted list of resulting distances

(Theoretical exponential speed-up)



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Questions?

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