Long-lived particle Anomaly detection with parameterized quantum circuits

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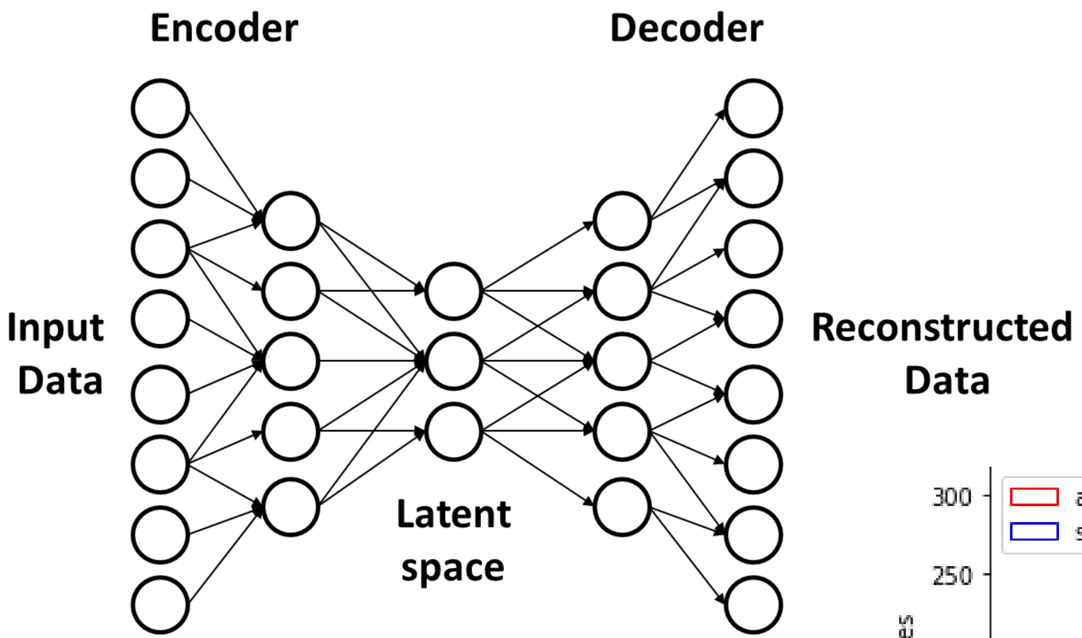
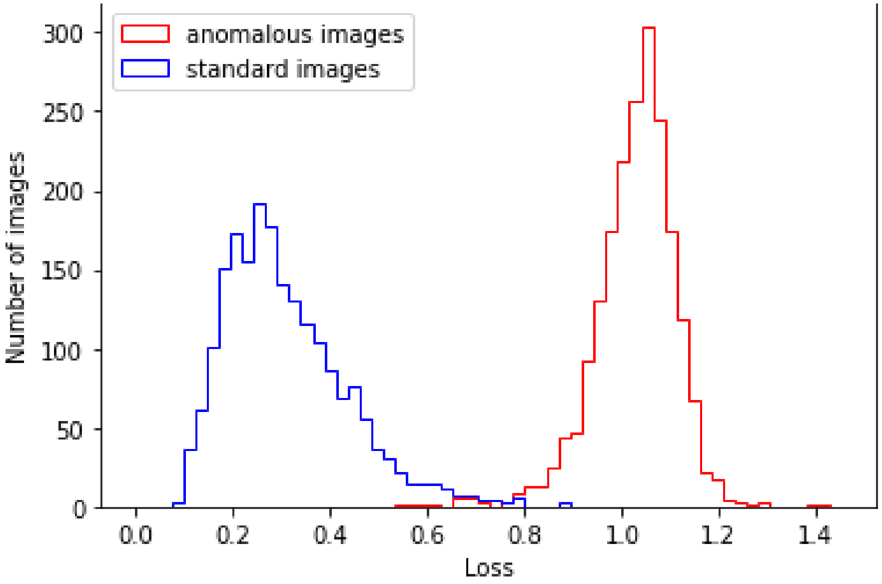
Anomaly detection

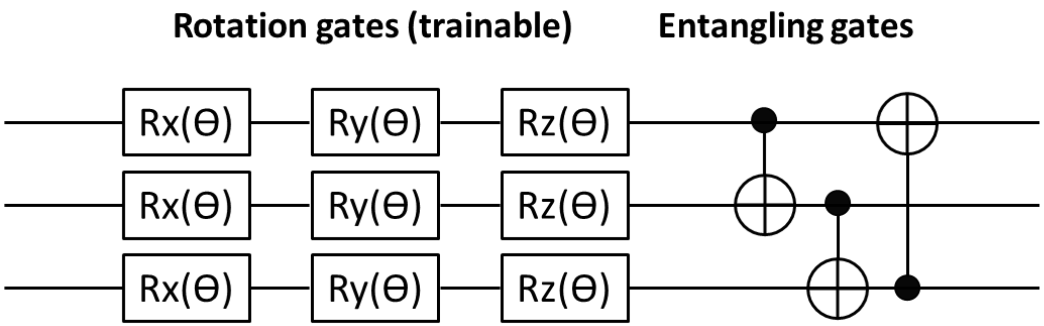


Autoencoder architecture (AE) implemented with an **artificial neural network**

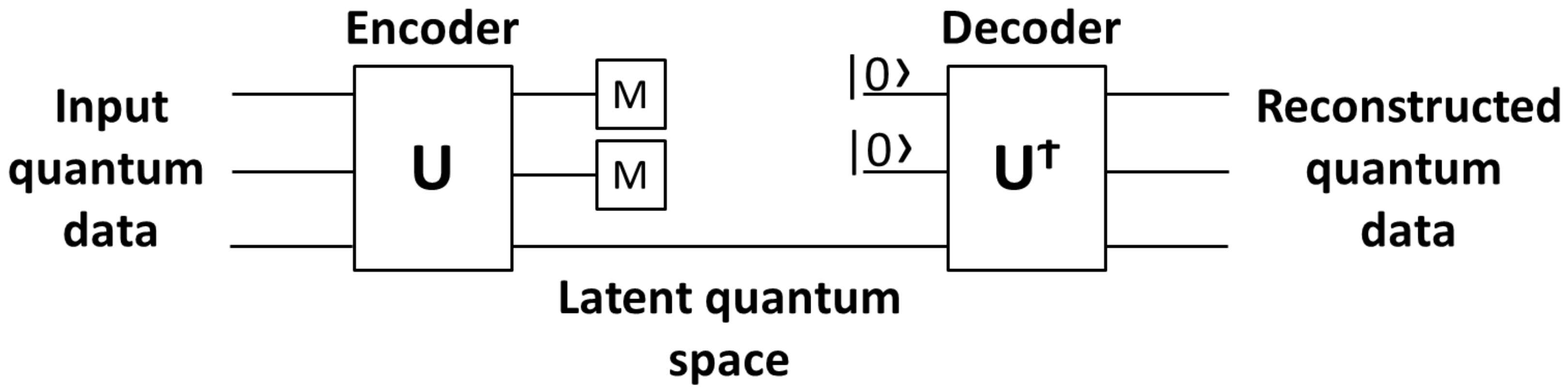
The **Loss** measures the difference between input and reconstructed data (MSE, MAE, Binary Crossentropy)



Parametrized quantum circuits



PQC usually composed of a repetition of **rotation gates** (trainable parameters) and **entangling gates** (C-NOT)



The encoder circuit implements a **unitary transformation** U(Θ), the decoder can be taken as the inverse of the encoder
The loss is the **measurement expectation value** of compressed qubits

Circuit model and data encoding

Circuit simulations implemented with **QIBO*** and training with **Tensorflow**

```
q0:     ─RX─RY─RZ─o──────────X─RX─RY─RZ─o──────────X─RX─RY─RZ─o──────────X─RX─RY─ ...
q1:     ─RX─RY─RZ─X─o────────|─RX─RY─RZ─X─o────────|─RX─RY─RZ─X─o────────|─RX─RY─ ...
q2:     ─RX─RY─RZ───X─o──────|─RX─RY─RZ───X─o──────|─RX─RY─RZ───X─o──────|─RX─RY─ ...
q3:     ─RX─RY─RZ─────X─o────|─RX─RY─RZ─────X─o────|─RX─RY─RZ─────X─o────|─RX─RY─ ...
q4:     ─RX─RY─RZ───────X─o──|─RX─RY─RZ───────X─o──|─RX─RY─RZ───────X─o──|─RX─RY─ ...
q5:     ─RX─RY─RZ─────────X─o─RX─RY─RZ─────────X─o─RX─RY─RZ─────────X─o─RX─RY─ ...
```

Classical data encoding with **amplitude encoding**
Example: vector (1,2,3,4) is mapped into state:

$$\frac{1}{\sqrt{30}}\left|00\right\rangle + \frac{2}{\sqrt{30}}\left|01\right\rangle + \frac{3}{\sqrt{30}}\left|10\right\rangle + \frac{4}{\sqrt{30}}\left|11\right\rangle$$

Exponential advantage?... Unfortunately not the case

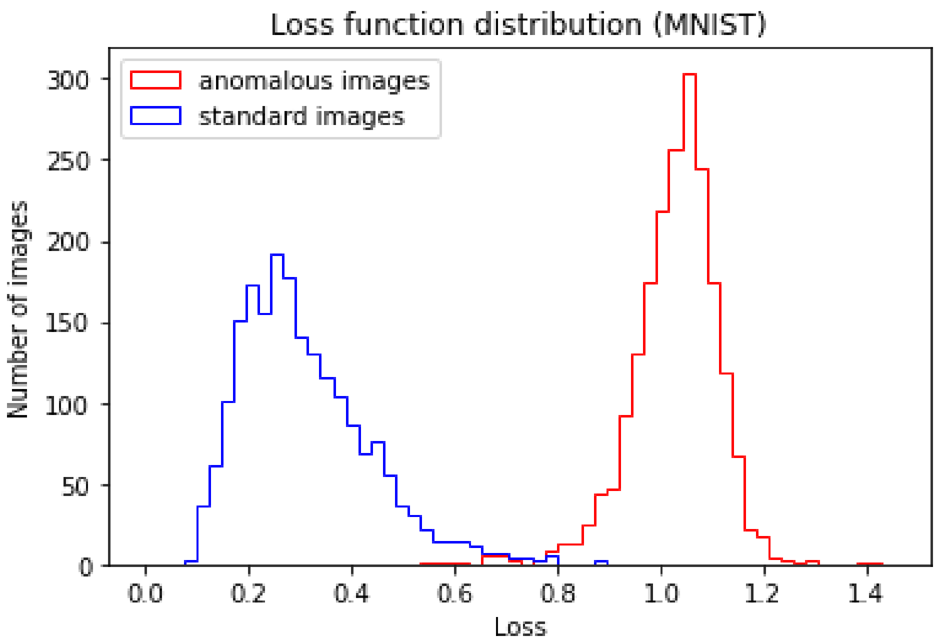
***** Qibo: a framework for quantum simulation with hardware acceleration. https://doi.org/10.1088/2058-9565/ac39f5. 351

Test methodology on a simple benchmark (MNIST)

```
q0:     -RX-RY-RZ-o----------X-RX-RY-RZ-o----------X-RX-RY-RZ-o----------X-RX-RY- ...
q1:     -RX-RY-RZ-X-o--------|-RX-RY-RZ-X-o--------|-RX-RY-RZ-X-o--------|-RX-RY- ...
q2:     -RX-RY-RZ---X-o------|-RX-RY-RZ---X-o------|-RX-RY-RZ---X-o------|-RX-RY- ...
q3:     -RX-RY-RZ-----X-o----|-RX-RY-RZ-----X-o----|-RX-RY-RZ-----X-o----|-RX-RY- ...
q4:     -RX-RY-RZ-------X-o--|-RX-RY-RZ-------X-o--|-RX-RY-RZ-------X-o--|-RX-RY- ...
q5:     -RX-RY-RZ---------X-o-RX-RY-RZ---------X-o-RX-RY-RZ---------X-o-RX-RY- ...

q0: ... RZ-o----------X-RX-RY-RZ-o----------X-RX-RY-RZ-o----------X-RX-RY-RZ-
q1: ... RZ-X-o--------|-RX-RY-RZ-X-o--------|-RX-RY-RZ-X-o--------|-RX-RY-RZ-
q2: ... RZ---X-o------|-RX-RY-RZ---X-o------|-RX-RY-RZ---X-o------|-RX-RY-RZ-
q3: ... RZ-----X-o----|-RX-RY-RZ-----X-o----|-RX-RY-RZ-----X-o----|----------
q4: ... RZ-------X-o--|-RX-RY-RZ-------X-o--|-RX-RY-RZ-------X-o--|----------
q5: ... RZ---------X-o-RX-RY-RZ---------X-o-RX-RY-RZ---------X-o------------
```

Best circuit:
6 layers
3 qubits compression
60 epochs
ADAM optimizer
Variable learning rate
(from 0.4 to 0.005)



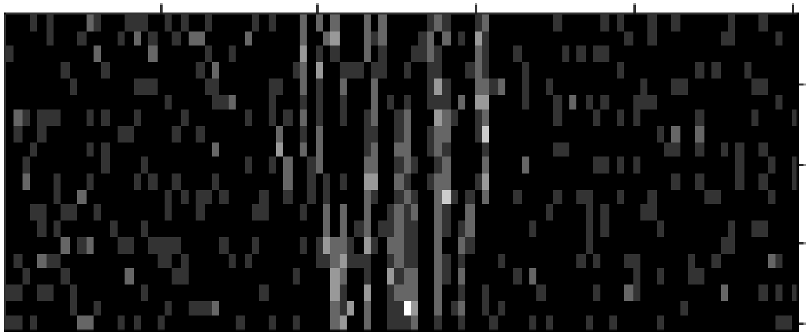
Handwritten digits of dimension 8x8 (6 qubits)
Standard images: Zeroes
Anomalous images: Ones

Training set: 5000 standard images
Test set: 5000 images for each class

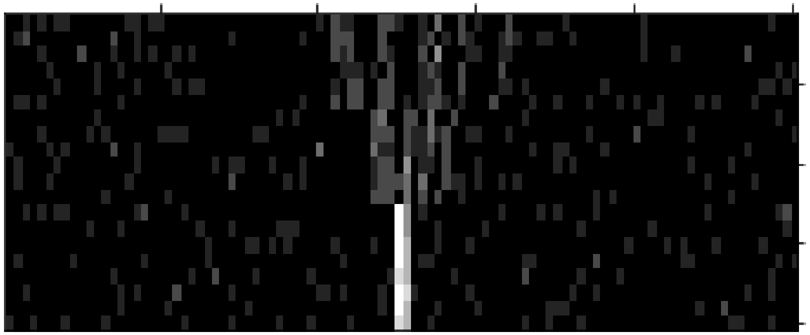
Similar results with classical AE

HEP use case

Example case: Identification of anomalous patterns in high level muon trigger system of ATLAS experiment. Standard and anomalous samples are respectively prompt and displaced decays of X->in multi-muons (from two to ten muons).
Hits produced by the muons reconstructed in toy simulation of ATLAS MDT chambers, (includes random hit background noise mimicking expected ATLAS phase-2 noise).
Samples in the form of images 100x20 pixels (2000 features mapped in 11 qubits)



Standard Images: radial decay lengths between 0.0 and 20.0 cm



Anomalous Images: radial decay lengths between 250.0 and 450.0 cm

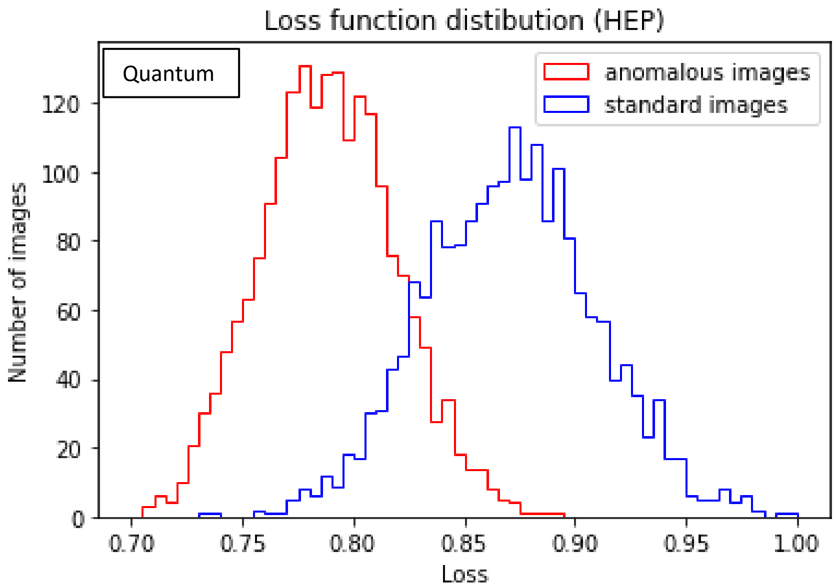
Quantum circuit characteristics:

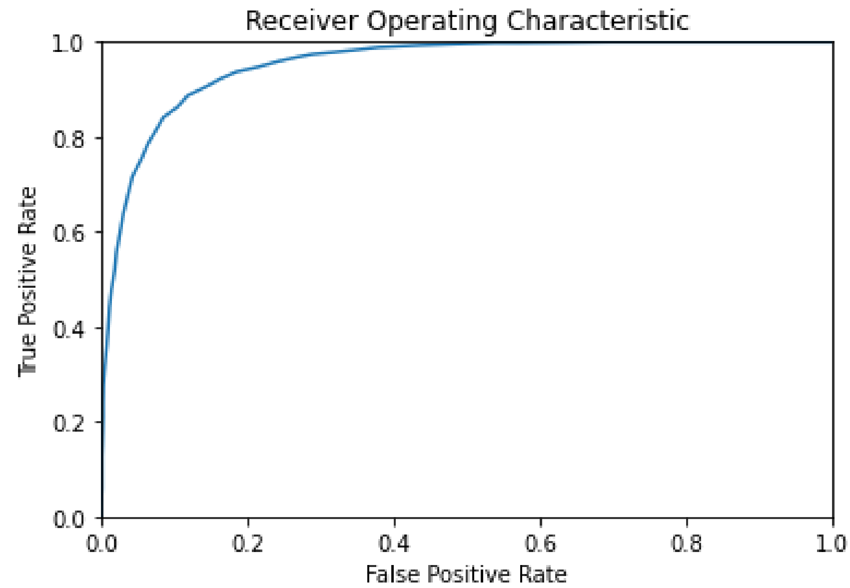
- 8 layers
- 3 qubits compression
- Same training process as MNIST

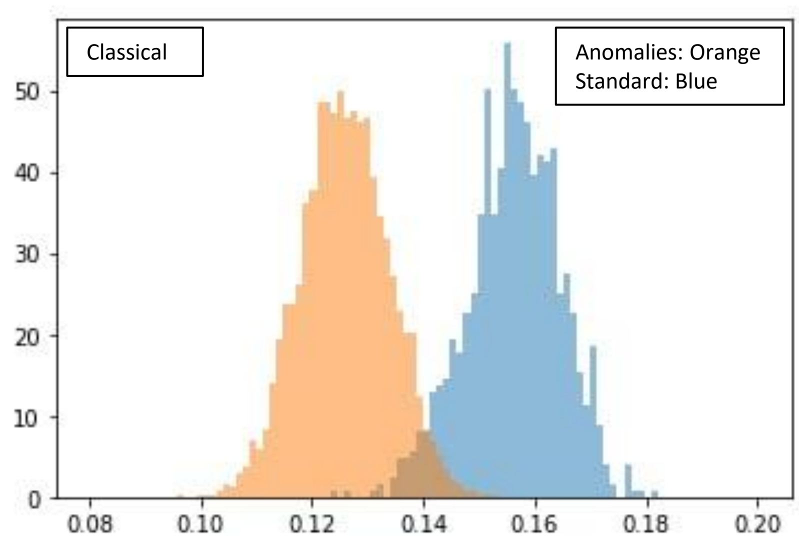
Dataset characteristics:

- Training: 5000 standard samples
- Testing: 5000 standard and 5000 anomalous samples

Simulation results







Comparison with **classical AE**:

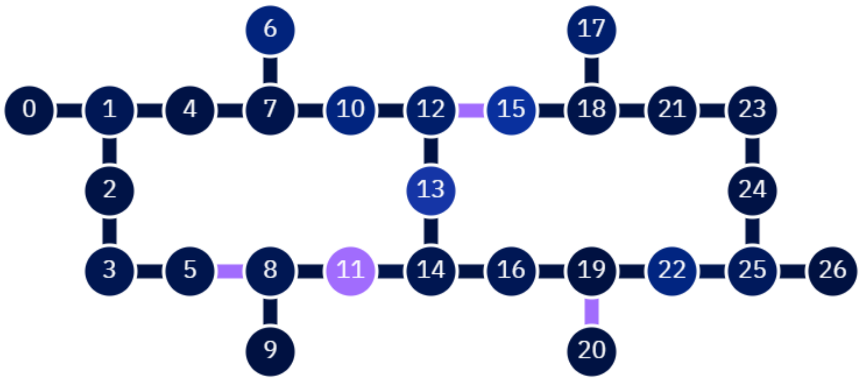
- CNN architecture
- 8x10^4 parameters
- Loss: binary crossentropy
- Optimizer: ADAM

Hardware adaptation

Two main problems:

Qubits connectivity: not every C-NOT is possible

Amplitude encoding: requires exponential number of gates



IBM_hanoi* qubits connectivity

Qubits connectivity:

- Proposed circuit does not match hardware connectivity
- Many SWAP gates required
- Every SWAP gate requires 3 C-NOT
- C-NOT high level of noise

Adopted solution: Remove last C-NOT gate of each layer so that circuit can be mapped to hardware without SWAP gates

* IBM Quantum. https://quantum-computing.ibm.com/services/resources?system=ibm hanoi, 2021

Approximated amplitude encoding

Initial state preparation requires deep circuit (number of C-NOT gates grows exponentially in number of qubits)

Adopted solution:

Train another PQC for an approximated amplitude encoding (AAE)

```
q0:   -RX-RY-RZ-o---------RX-RY-RZ-o---------RX-RY-RZ-o---------RX-RY-RZ-o---------RX-RY-RZ-
q1:   -RX-RY-RZ-X-o-------RX-RY-RZ-X-o-------RX-RY-RZ-X-o-------RX-RY-RZ-X-o-------RX-RY-RZ-
q2:   -RX-RY-RZ---X-o-----RX-RY-RZ---X-o-----RX-RY-RZ---X-o-----RX-RY-RZ---X-o-----RX-RY-RZ-
q3:   -RX-RY-RZ-----X-o---RX-RY-RZ-----X-o---RX-RY-RZ-----X-o---RX-RY-RZ-----X-o---RX-RY-RZ-
q4:   -RX-RY-RZ-------X-o-RX-RY-RZ-------X-o-RX-RY-RZ-------X-o-RX-RY-RZ-------X-o-RX-RY-RZ-
q5:   -RX-RY-RZ---------X-RX-RY-RZ---------X-RX-RY-RZ---------X-RX-RY-RZ---------X-RX-RY-RZ-
```

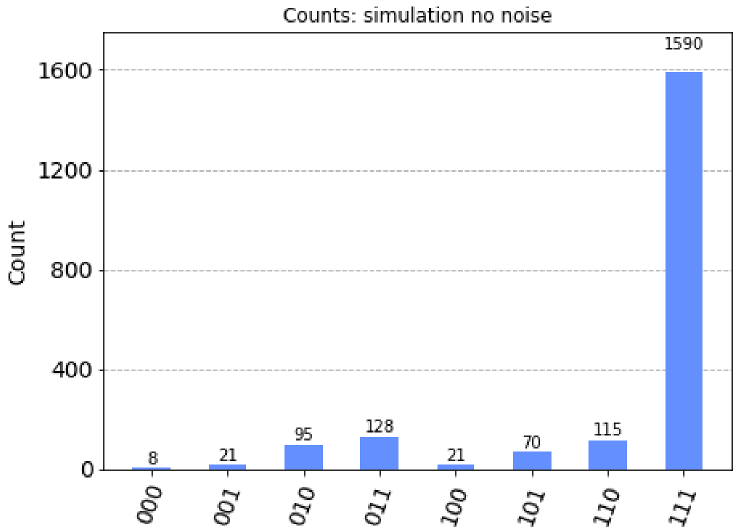
Circuit characteristics:

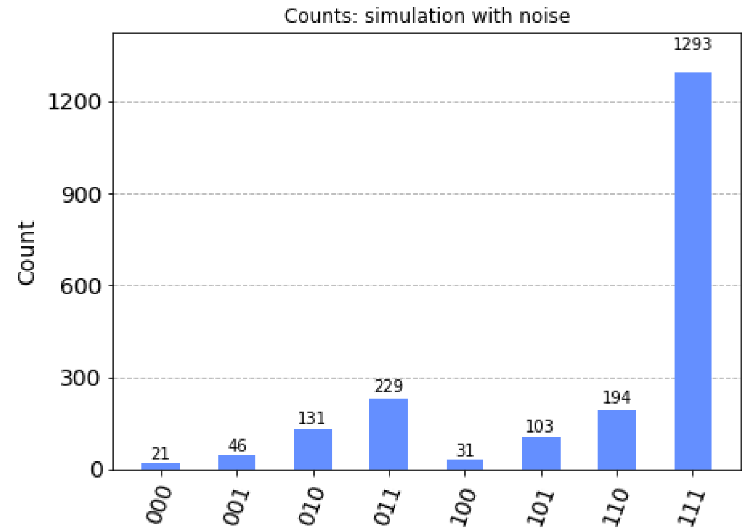
- 4 layers
- 5 C-not each layer (no SWAP)
- One different training each sample
- Loss: MSE (state fidelity)

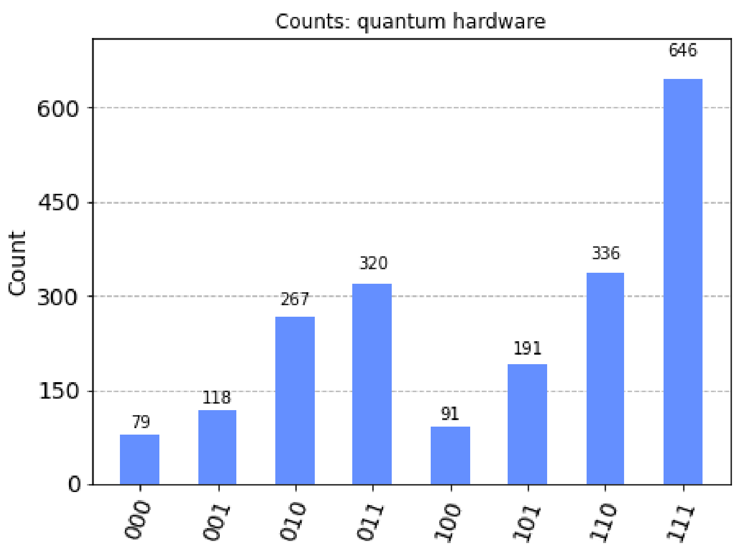
Samples characteristics:

- 200 standard and 200 anomalous (MNIST)
- Accepted loss under 0.1
- Anomalous data with average lower loss

Quantum hardware results (counts)







Circuit composed of 8 layers:

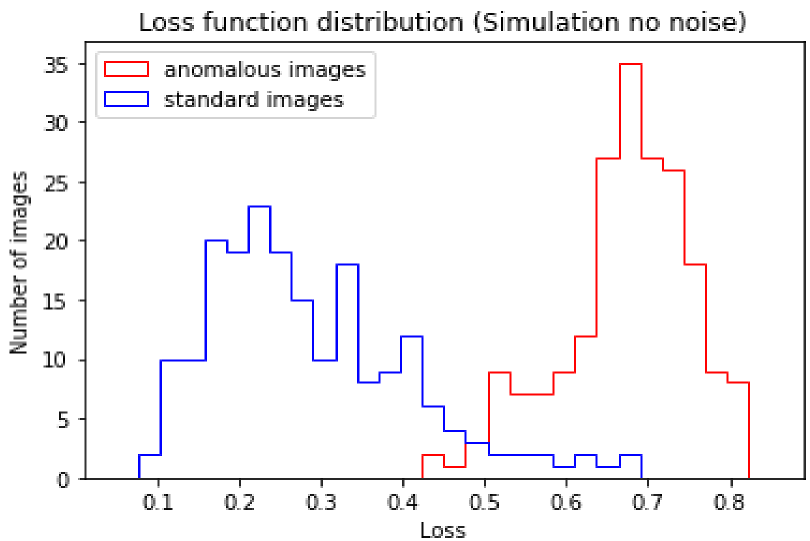
- 4 layers for AAE
- 4 layers for the encoder

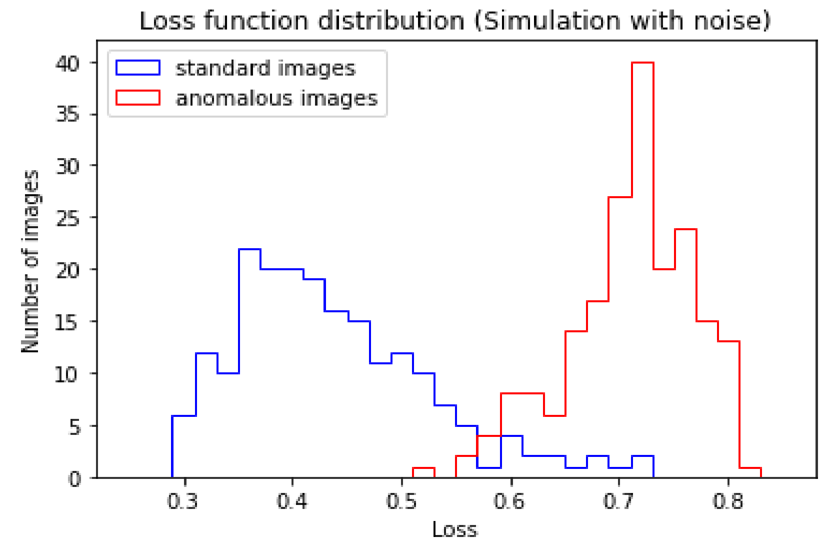
Only MNIST use case possible

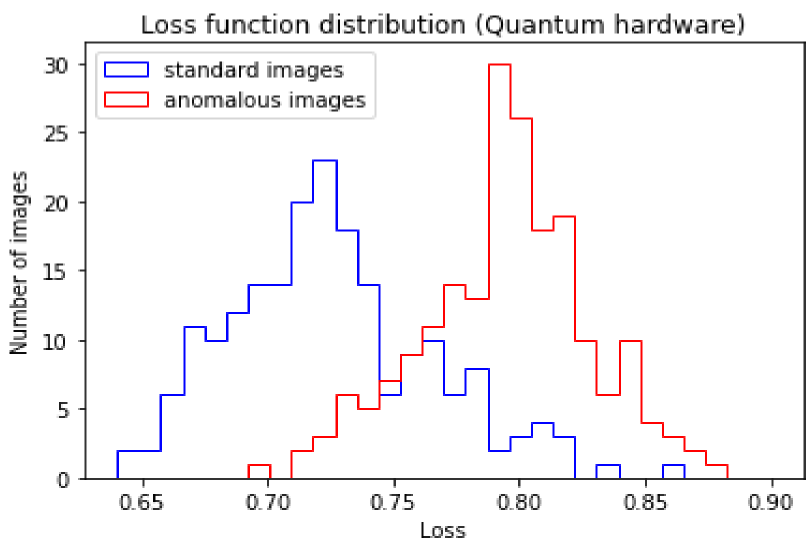
2048 shots for circuit

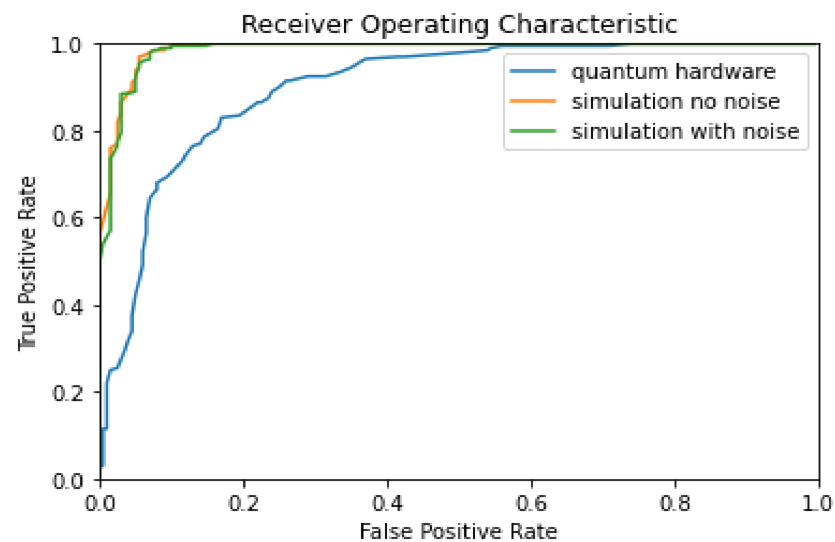
Realistic noise for simulation (Qiskit) taken from IBM_hanoi calibration (19/10/2022)

Quantum hardware results (anomaly detection performance)









Conclusions

- Growing number of quantum machine learning algorithms
- PQCs can be employed for anomaly detection (simulations)
- Amplitude encoding not yet possible on the available NISQ devices
- Hardware driven adaptation of algorithms required on current quantum devices with low connectivity
- Only simple tasks can be performed on NISQ devices
- So far no advantages apparent for quantum anomaly detection on classical data
- Possible advantages on quantum data?

Future work

- Further optimise PQCs and classical data encoding
- Study anomaly detection for Long Live Particles with tabular inputs based on high level classical observables (phase encoding)
- Study possible advantages using quantum data as input (for example from quantum sensors)

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Thank you for your attention!

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