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ICSC
Centro Nazionale di Ricerca in HPC, Big Data and Quantum Computing

Benchmarking of Quantum Convolutional Neural Networks in the Astrophysical Signal Detection: Focus on Transient Gamma-Ray Bursts

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The Goal: Exploring possible application of Quantum Computation and Quantum machine Learning in Astrophysics and Cosmology

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A QUICK OVERVIEW OF THE WORK

1

GRB SIGNAL (SIMULATED OR FROM THE OBSERVATION)

2

ENCODING THE CLASSICAL DATA INTO QUANTUM STATE

3

FIND THE BEST ARCHITECTURE (FINETUNING THE HYPERPARAMETRS)

4

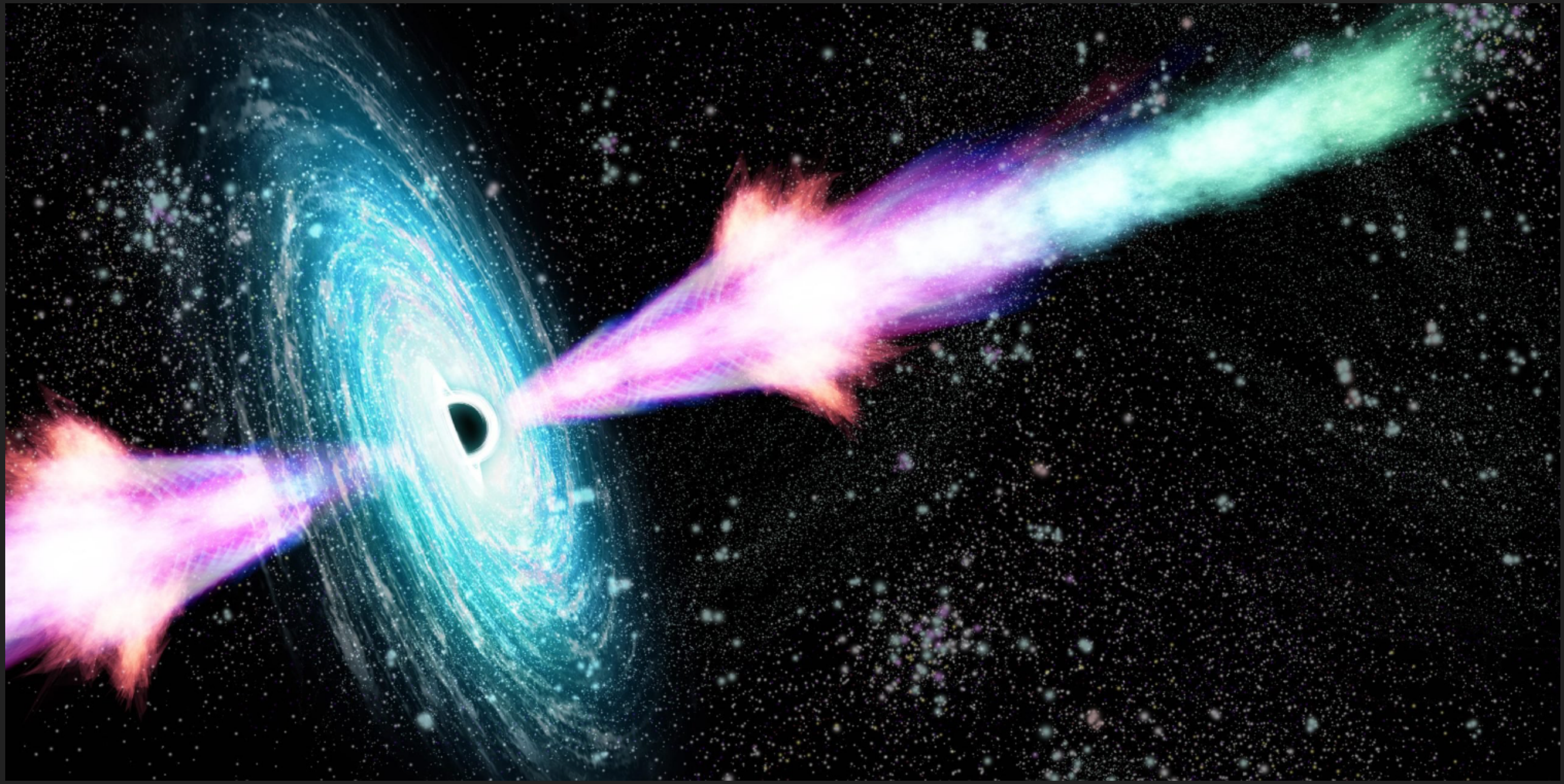
TRAINING THE QUANTUM NEURAL NETWORK

5

TEST THE RESULT (DECODE THE QUANTUM DATA INTO CLASSIC IN CASE), REPEAT THE STEPS

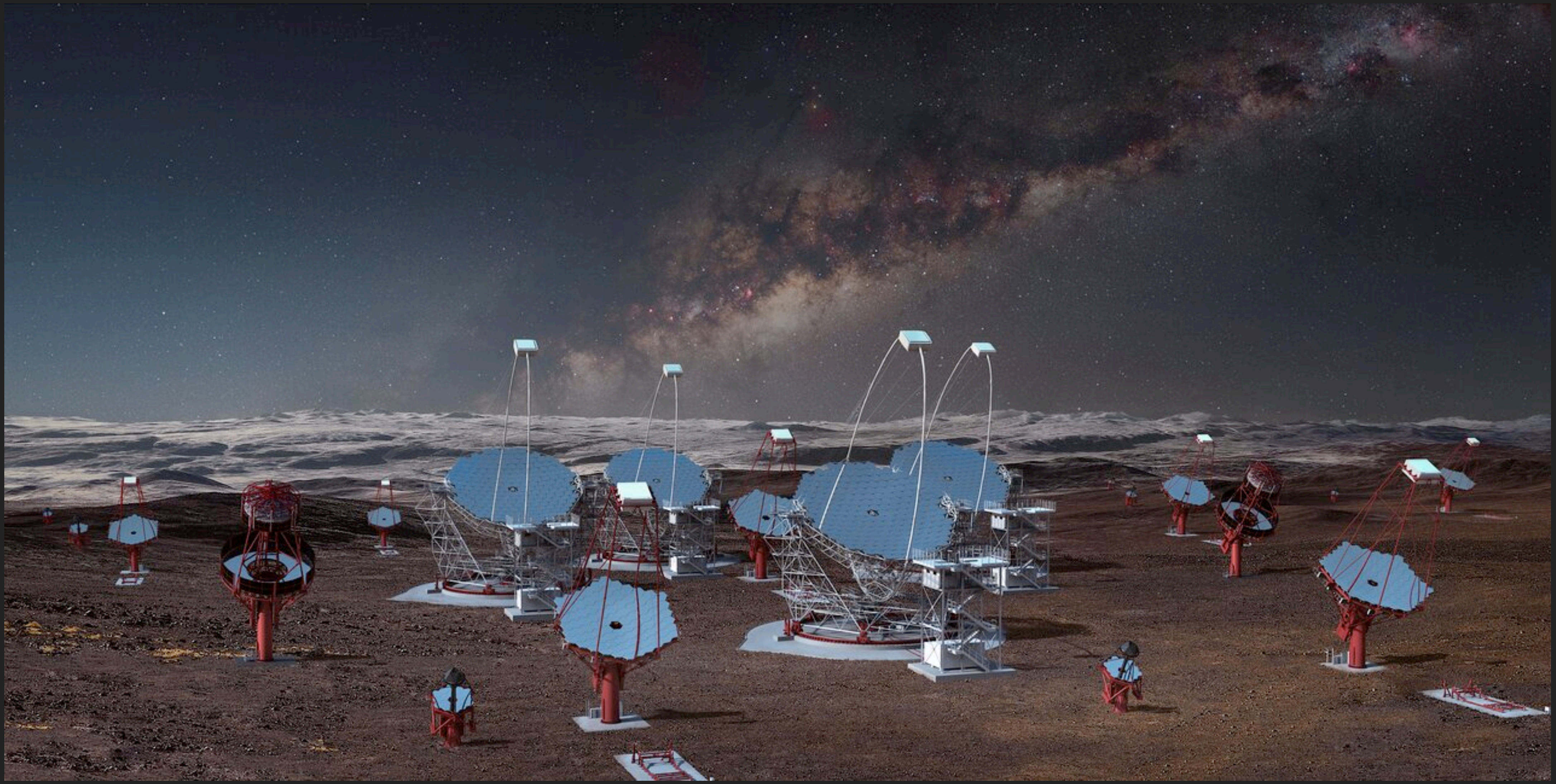
GAMMA RAY BURSTS

- Gamma-ray bursts (GRBs) are extremely energetic explosions that occur in distant galaxies, emitting intense bursts of gamma rays, the most energetic form of light.
- They are typically classified into two types: short-duration GRBs, lasting less than 2 seconds, likely caused by the merger of neutron stars, and long-duration GRBs, lasting over 2 seconds, usually associated with the collapse of massive stars into black holes.
- GRBs are among the brightest and most powerful events in the universe, often followed by an afterglow that can be observed in other wavelengths like X-rays, visible light, and radio waves.



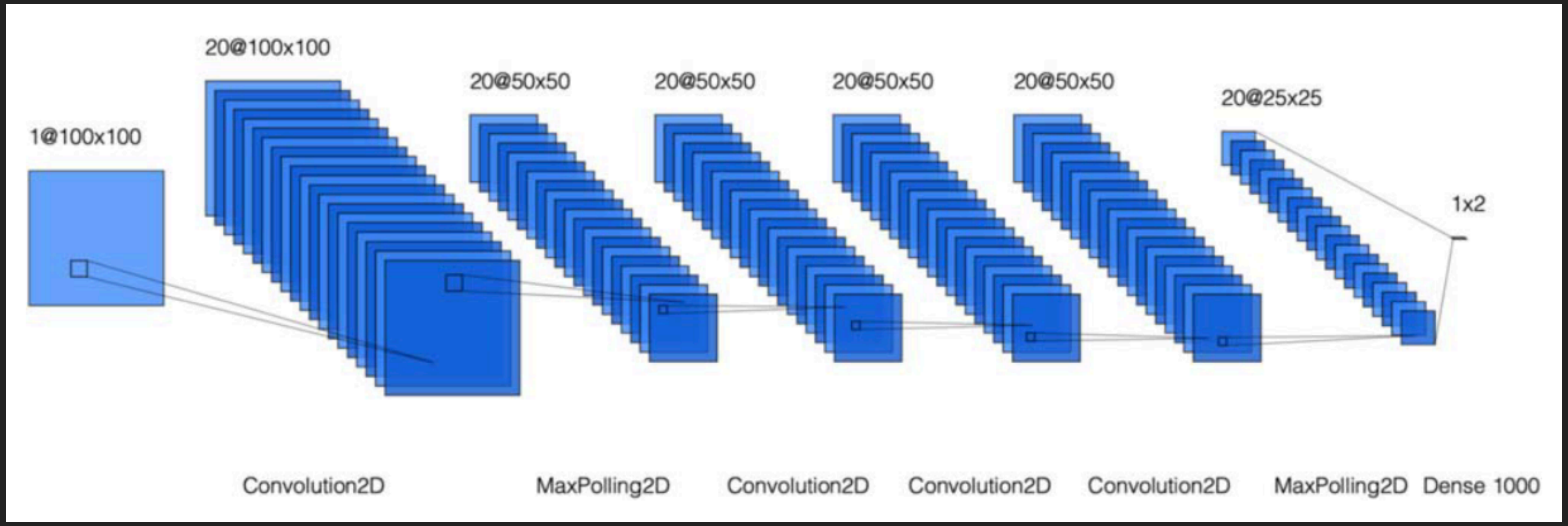
CHERENKOV TELESCOPES ARRAY (CTA)

- The **Cherenkov Telescope Array Observatory (CTAO)** will be the world's most powerful ground-based observatory for very high-energy **gamma-ray astronomy**. The facility will be equipped with **real-time analysis** software that automatically generates science alerts and analyzes ongoing observational data in real-time.



PROJECT'S MOTIVATION

- The need of automation and real-time analysis for GRB data
- There are classical model (Convolutional Neural Network), but heavy architecture with many parameters
- Comparison of QNN with classical NN and Increasing the performance, in terms of time and complexity of the model



N. Parmiggiani, et al. A Deep Learning Method for AGILE-GRID Gamma-Ray Burst Detection.
The Astrophysical Journal, Volume 914, Number 1, 2021.

SETTING THE STAGE FOR QUANTUM MACHINE LEARNING

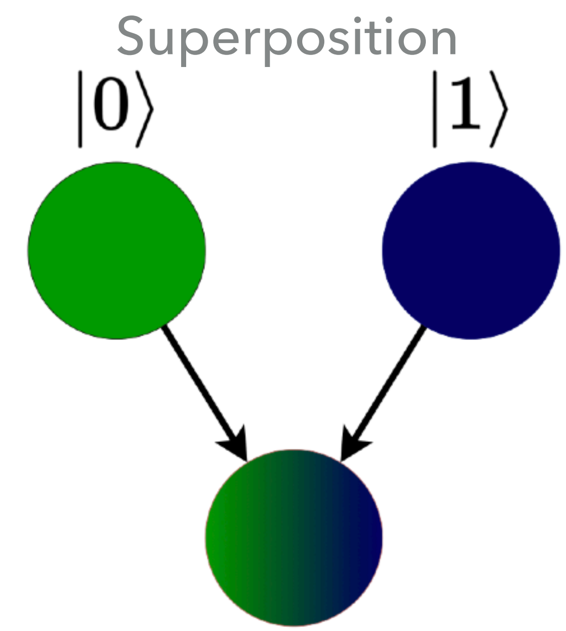
- **Qubit** : The unit of information for QC

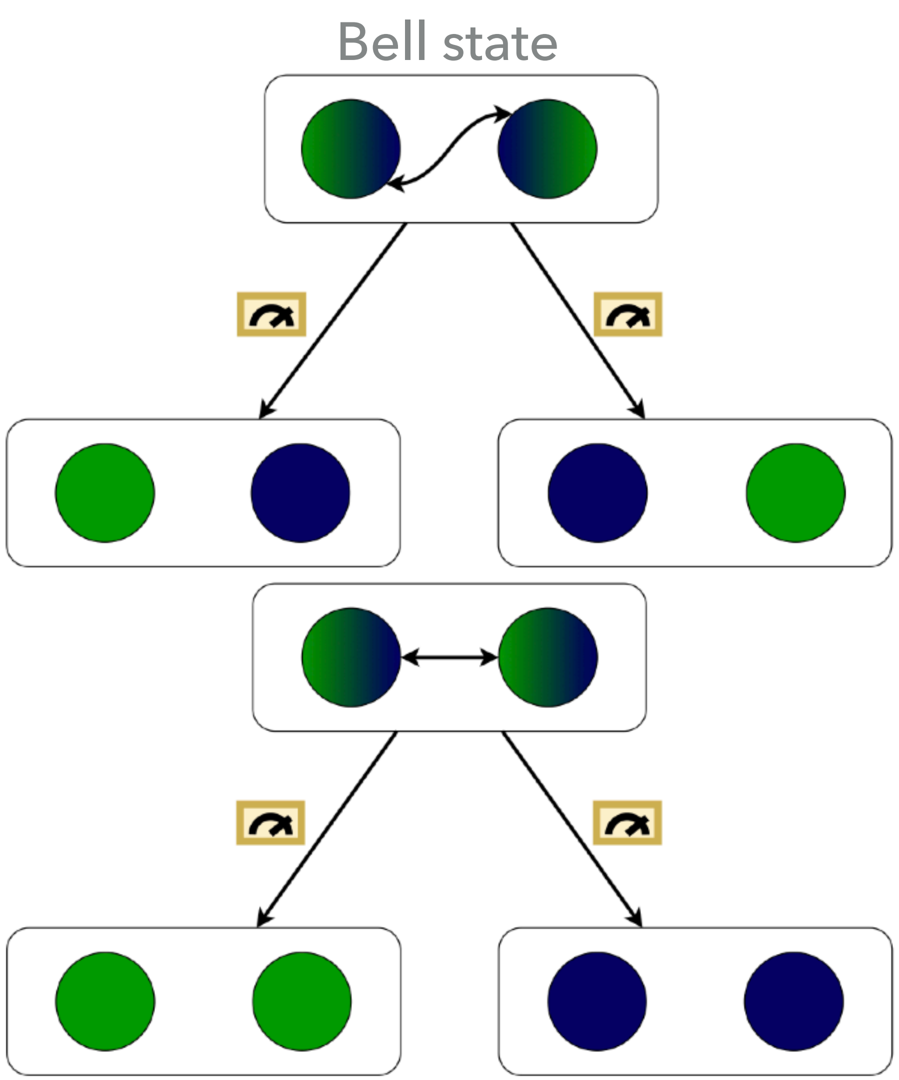
$$|\psi\rangle = \begin{pmatrix} c_0 \\ c_1 \end{pmatrix} = c_0 |0\rangle + c_1 |1\rangle$$

- **Measurement**: an operation that alters the system and is a non-deterministic process (unlike classical computation).

- The basis of Quantum computing:
  Superposition: the state with no-null probability of being in both the state $|0\rangle$ and $|1\rangle$.
  Entangelment: the correlation of two qubits.

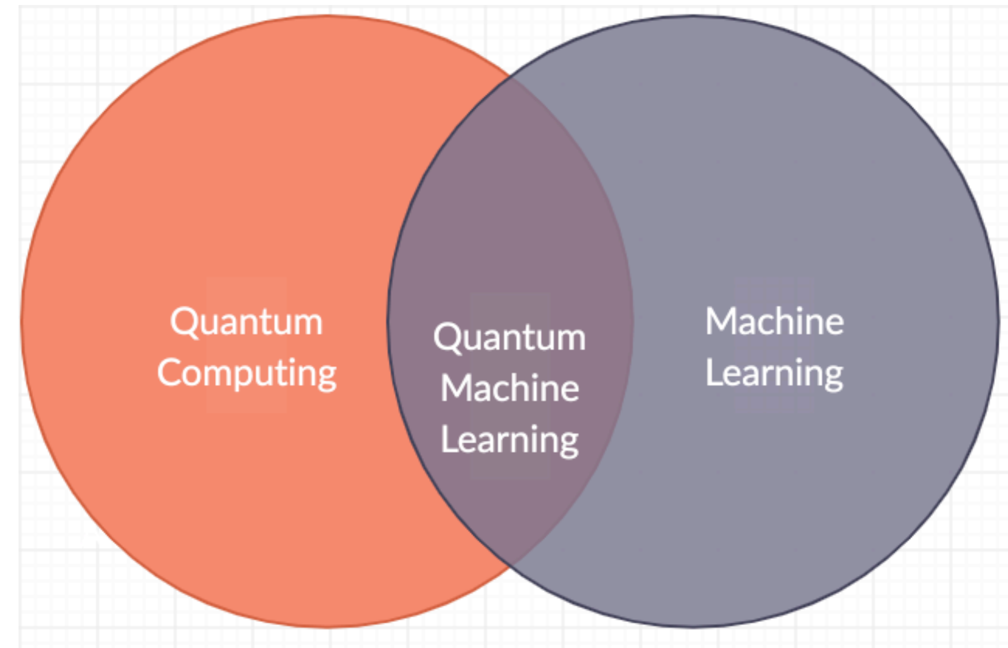
- **Quantum gate**: transformations (matrices) which can be used to manipulate the qubits. They should have these properties: Linearity, Unitarity and Reversibility

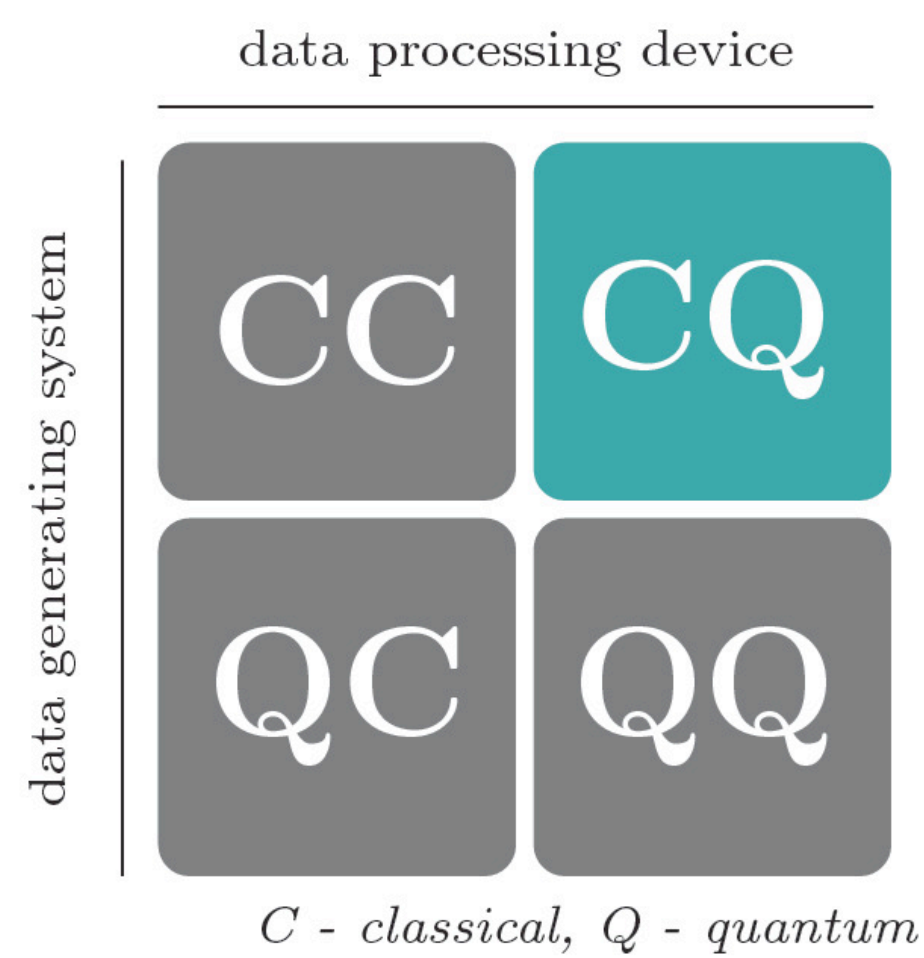




QUANTUM MACHINE LEARNING (QML)

- Combines concepts from **quantum computing** and **machine learning** to develop algorithms capable of exploiting quantum phenomena to enhance learning tasks.
- Quantum computing uses **qubits**, which unlike classical bits, can be in **superposition** states of 0 and 1 simultaneously. This allows to perform multiple computations simultaneously, potentially leading to **exponential speedups** for certain problems.
- QML faces **challenges** like fault-tolerant hardware, efficient algorithms, and integrating quantum with classical systems.



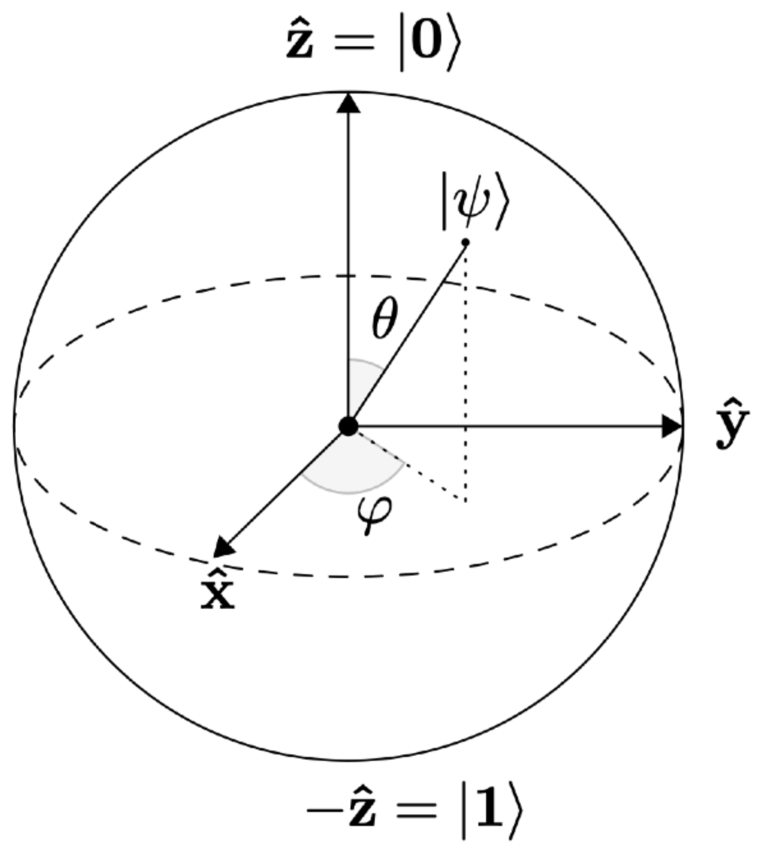


DATA ENCODING METHODS

For encoding (embedding), we take a classical data point, *x*, and encode it by applying a set of gate parameters in the quantum circuit.

There are different types of encoding the data:

- Basic encoding
- **Angle encoding**
- **Amplitude encoding**
- **Data Reuploading**
- QuAM (Quantum Associated Memory)
- QRAM (Quantum Random Access Memory)
- …

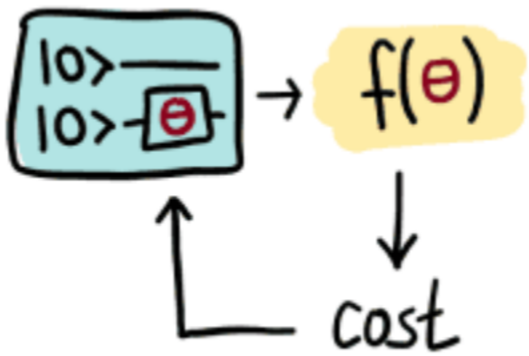


PARAMETRISED QUANTUM CIRCUIT (PQC)

Parameterized quantum circuits (PQC) bridge quantum and classical computing: the quantum computer estimates a quantity, while the classical computer optimizes the parameters. This process iterates, continually refining the quantum state.

They consist of three ingredients:

- Preparation of a fixed **initial state** (e.g., the vacuum state or the zero state).
- A quantum circuit $U(\theta)$, parameterized by a set of free parameters θ
- **Measurement** of an observable $\hat{B}$ at the output.

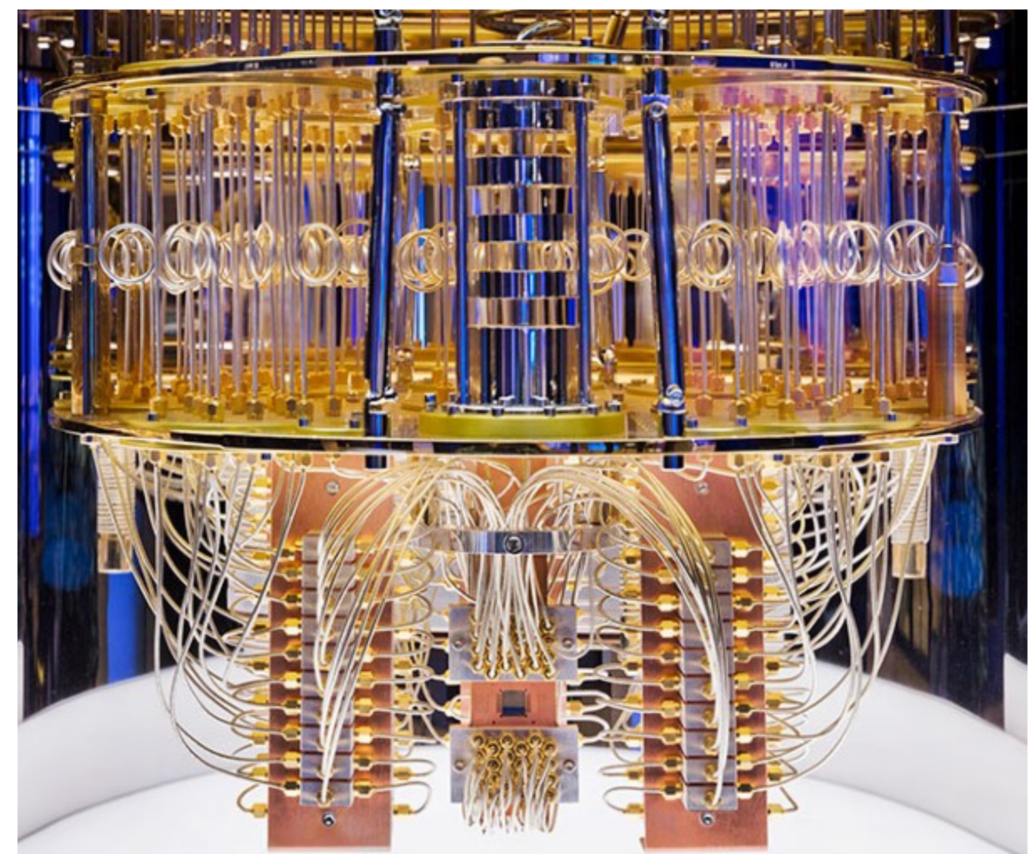


$$f(\theta) = \langle 0|U^\dagger(\theta)\hat{B}U(\theta)|0\rangle$$

trained by a classical optimization algorithm, by querying to the quantum device.

WHICH PLATFORM TO USE

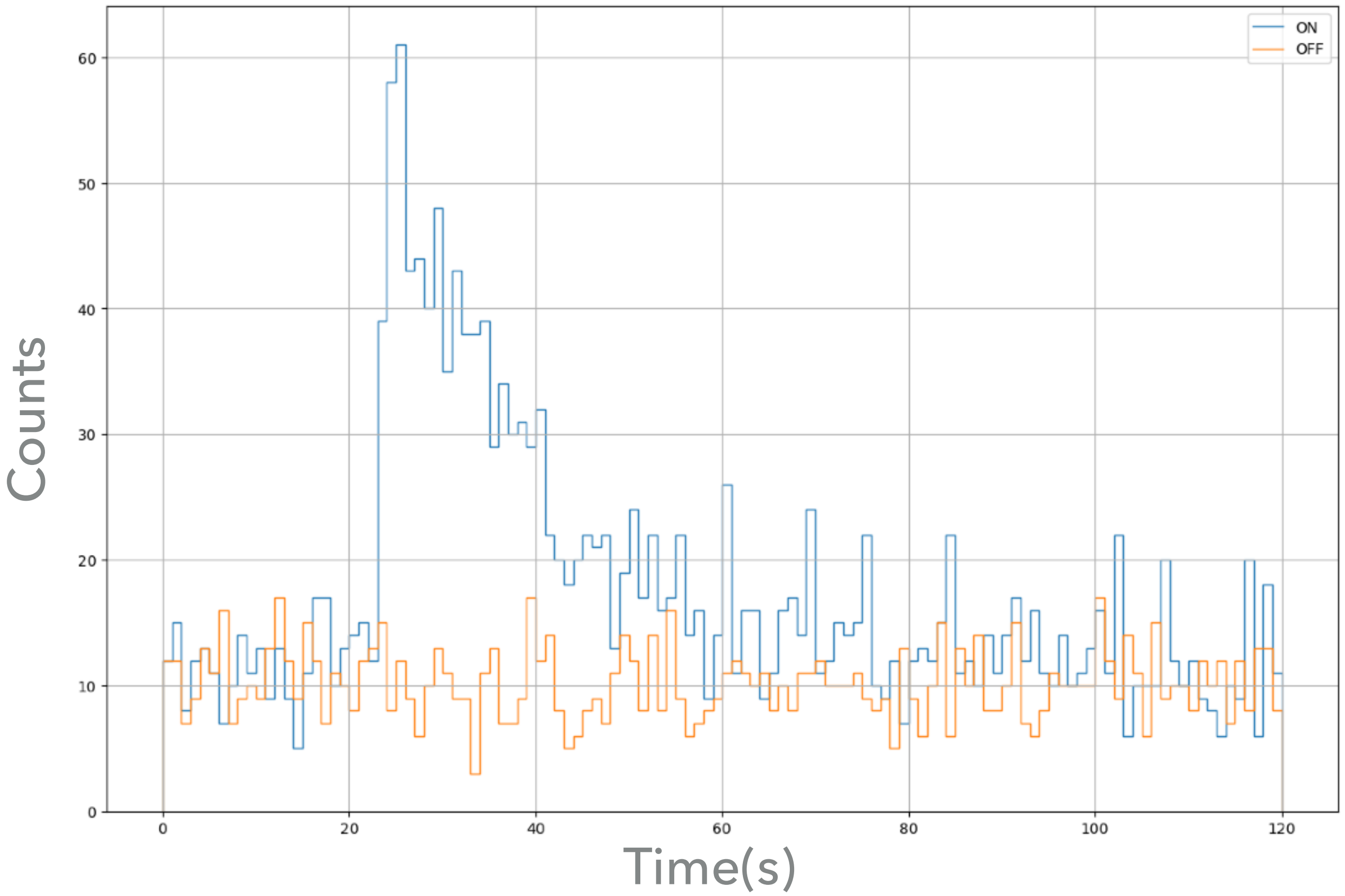
- Qiskit is an open-source quantum computing software development framework created by IBM
- Provides a way to interact with quantum computers through a high-level programming language
- Offers a comprehensive set of tools and libraries, including simulators for testing quantum algorithms, access to real quantum hardware, and a variety of algorithms and techniques for quantum information processing.
- IBM offers access to Superconducting qubit devices



https://qiskit.org/
https://quantum-computing.ibm.com/

DATASET

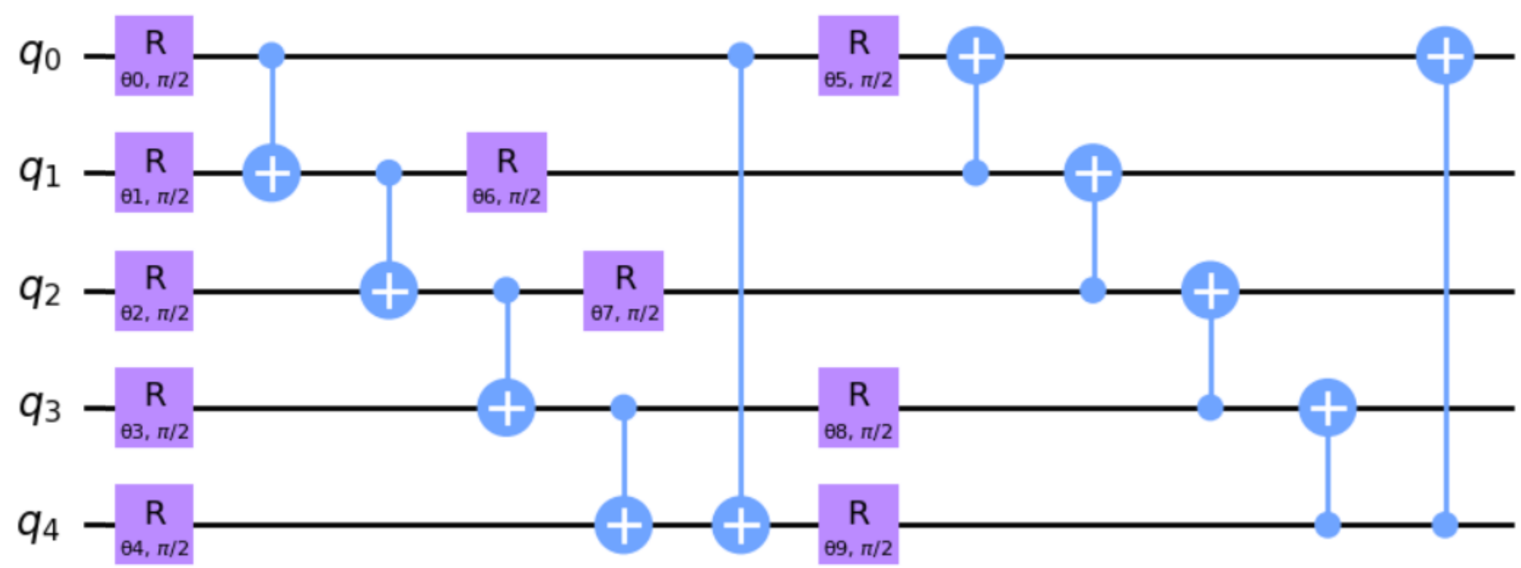
- Simulated Dataset are composed by two classes: **GRB Signal** and **background noise**, leading to a binary classification problem
- Light Curve as time series**:** 450 GRBs and background noise as training set, 150 for the test set.
- The x-axis represents the time window with a certain Binnig.
- The y-axis represents the count rate of photons detected by ACS over time. The presence of high and structured spikes can be used to detect GRBs.

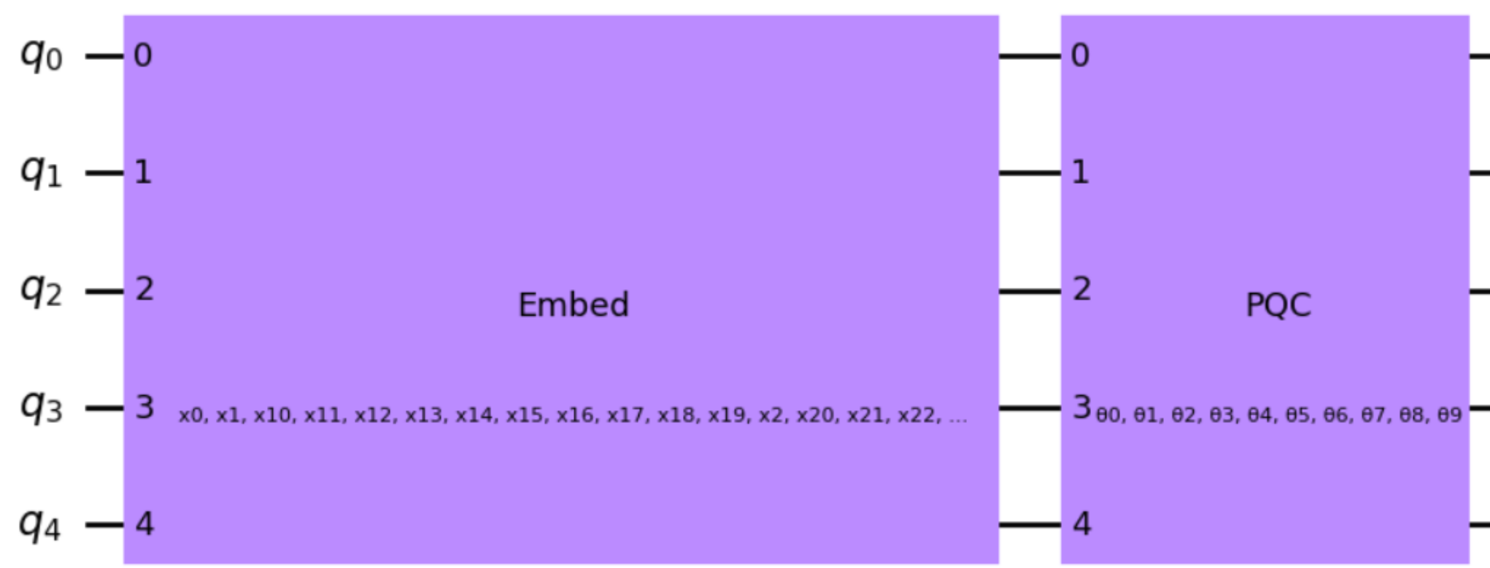


IMPLEMENTED ARCHITECTURE

- Parametrised Quantum Circuit in Qiskit has been used
- Using Angle Encoding and data Reuploading methods for Data Encoding
- COBYLA optimizer
- Binary cross entropy as loss function

Feature map





BENCHMARKING PARAMETERS

Parameters related QCNN architecture and its performance in the case of binary classification:

- Number of Qubits
- Number of data reuploading layers
- Data encoding type
- Training dataset size
- Training Epochs

Variable Physical Parameters related to the signal and background noise to check the performance of the Model:

- LC length
- Binning
- Offset for the event
- Model of the GRB
- Normalization factor of the GRB
- Decay time scale (in case of exponential)

RESULTS

- Model performance in case of 450 light curves training set and 150 for the test set
- By increasing the number of Qubits the accuracy increases but with the price of increasing of training time
- Decreasing the number of Qubits less than a threshold causes model doesn't get the substructure of the data
- Classical CNN is a simple network composed of 2 Conv1D and a pooling layer

NN model	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set	Time
Classical CNN	-	56	99.7%	97.35%	21s
Fully Quantum	6	12	**90.3%**	**87.7%**	89s
Fully Quantum	12	24	**99.38%**	**97.5%**	713s
Fully Quantum	4	8	Doesn't learn	**-**	-

F.Farsian et al, 2024 in prep

RESULTS

- Model performance in case of only 20 light curves for training set and 180 for the test set
- The model reaches very high accuracy after a short time
- The classical CNN cannot detect the GRB signal due to few training data
- The other parameters are fixed, the best value is chosen:
  Binnig= 50s (LC length= 24), Normalization= [0.1, 1], Offset fixed= randomly changing in range of [50, 1150]s, Model of GRB= ExpDecayTemporalModel

NN model	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set	Time
Classical CNN	-	56	55%	52.22%	91s
Fully Quantum	6	24	**95%**	**98.33%**	**23s**

F.Farsian et al, 2024 in prep

PERVIOUS WORK OF OUR GROUP

Quantum Convolutional Neural Networks for the detection of Gamma-Ray Bursts in the AGILE space mission data

A. Rizzo,[1] N. Parmiggiani,[2], A. Bulgarelli [2], A. Macaluso[3], V. Fioretti[2], L. Castaldini[2], A. Di Piano[4,2], G. Panebianco[5,2], C. Pittori[6,7], M. Tavani[8], C. Sartori[9], C. Burigana[10], V. Cardone[6], F. Farsian[11], M. Meneghetti[2], G. Murante[12], R. Scaramella[6], F. Schillirò[11], V. Testa[6] and T. Trombetti[10]

Abstract. Quantum computing represents a cutting-edge frontier in artificial intelligence. It makes use of hybrid quantum-classical computation which tries to leverage quantum mechanic principles that allow us to use a different approach to deep learning classification problems. The work presented here falls within the context of the AGILE space mission, launched in 2007 by the Italian Space Agency. We implement different Quantum Convolutional Neural Networks (QCNN) that analyze data acquired by the instruments onboard AGILE to detect Gamma-Ray Bursts from sky maps or light curves. We use several frameworks such as TensorFlow-Quantum, Qiskit and PennyLane to simulate a quantum computer. We achieved an accuracy of 95.1% on sky maps with QCNNs, while the classical counterpart achieved 98.8% on the same data, using however hundreds of thousands more parameters.

arXiv:2404.14133 , proceedings of the ADASS XXXIII (2023) conference

CONCLUSION

- **One of the first implemented** Quantum Convolutional Neural Network (QCNN) to analyze astrophysical data, specifically **to detect the GRB signal**.
- More than 50 types of architecture and different data encoding has been tested
- The performance of QCNN in terms of **accuracy** is equal or better than the classical CNN in a specific case.
- **Reduction in parameters of the model** underlines the efficiency and power of QML algorithms.
- **Generalization power** of QML in case of very few training dataset and its advantage respect to classical ML. In this case we have **only 20 light curves** as the training set
- In this study we reach **Quantum Advantage** in terms of **sample complexity.**


THANKS FOR YOUR
ATTENTION

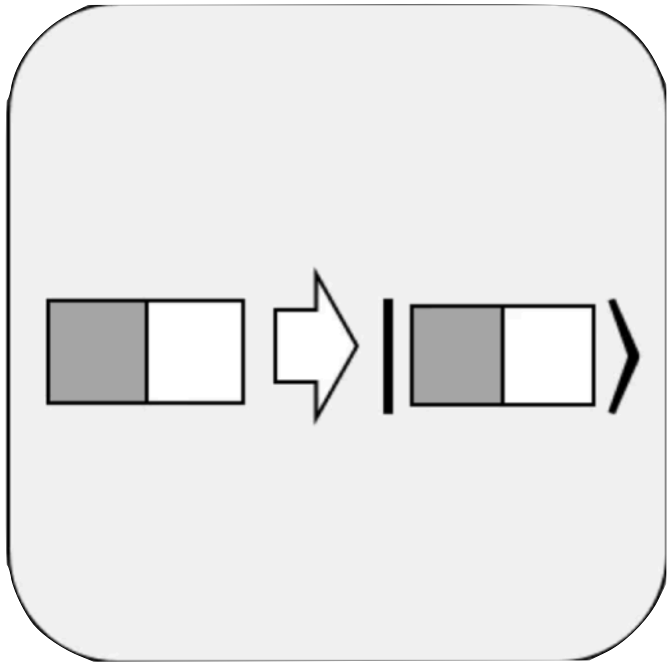
BACKUP SLIDES

POTENTIAL OF QML AND QC IN ASTROPHYSICS AND COSMOLOGY

- Algorithm optimization (Quantum Monte Carlo, Quantum Particle Swarm Optimization) for parameter estimation
- Cosmological numerical simulations (quantum algorithms to solve better equations such Vlasov-Poisson to Schrodinger-Poisson)
- Data Analysis and Pattern Recognition (using Quantum Convolutional Neural Network, quantum Variational AutoEncoder)
- Optimizing gravitational wave detection (by improving the sensitivity of detectors and reducing noise)
- …

BASIC ENCODING

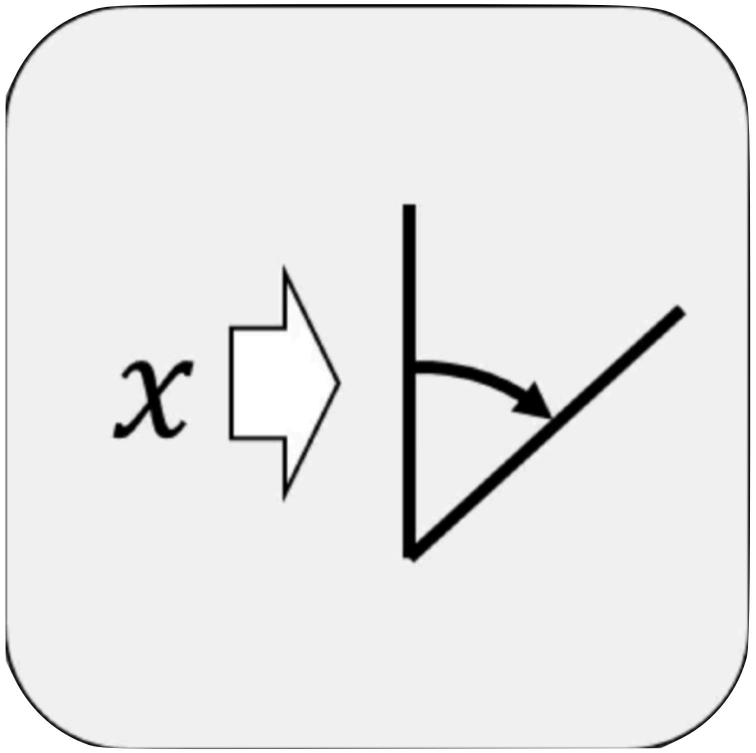
- This encoding represents real numbers as binary numbers and then transforms them into a quantum state on a computational basis.
- Is not efficient in terms of the required number of qubits but is good for arithmetic operation.



Input Data			Pre-processing to convert to Binary form		Basis encoded state	
Input Sample	Feature x1	Feature x2	Binary(x1)	Binary(x2)	Basis encoded Quantum state	Amplitude vector
X^1	5	6	101	110	$\vert 101110\rangle$	$\frac{1}{\sqrt{2}}\vert 101110\rangle$
X^2	4	1	100	001	$\vert 100001\rangle$	$\frac{1}{\sqrt{2}}\vert 100001\rangle$

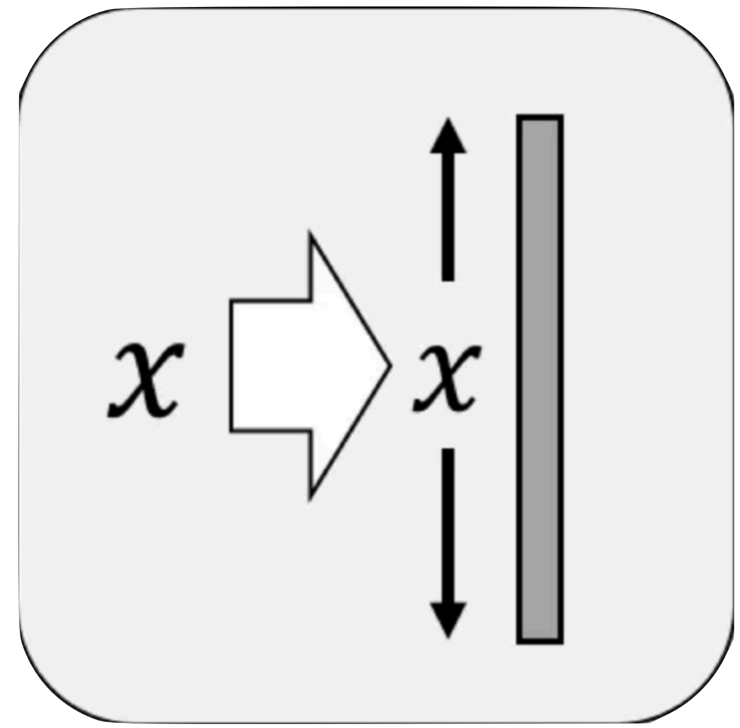
ANGLE ENCODING

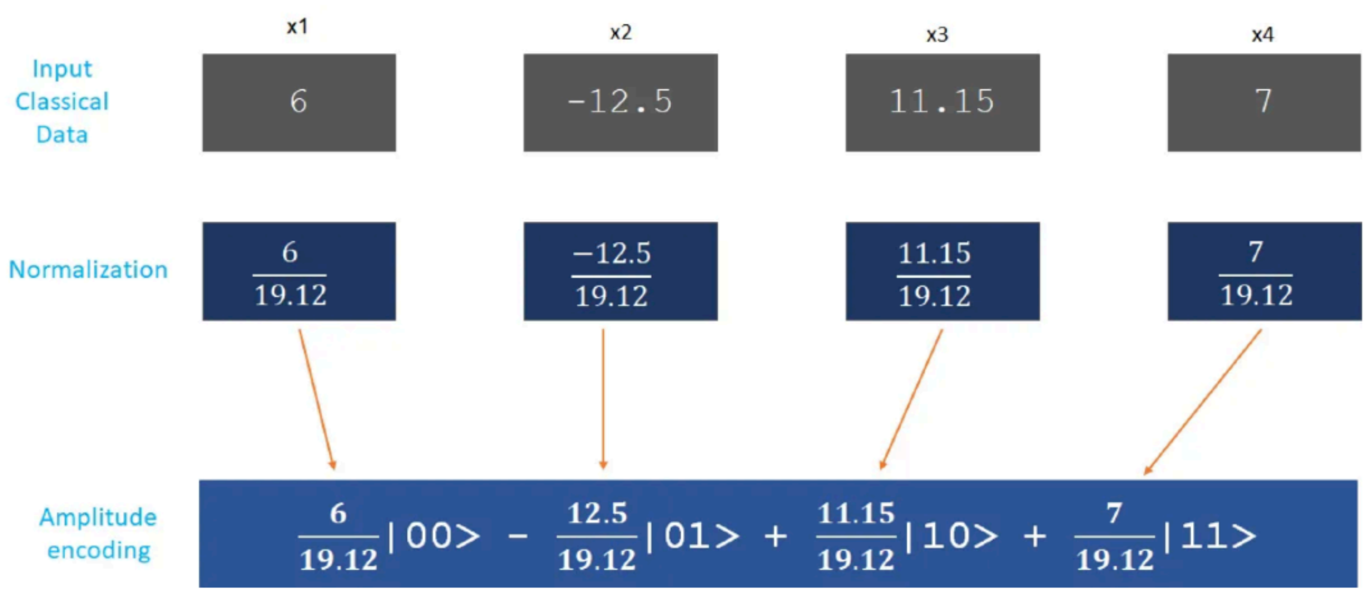
- The n classical features are encoded into the rotation angle of the n qubit.
- It requires **n qubits** to represent n-dimensional data but is cheaper to prepare in complexity: it requires one rotation on each qubit.



AMPLITUDE ENCODING

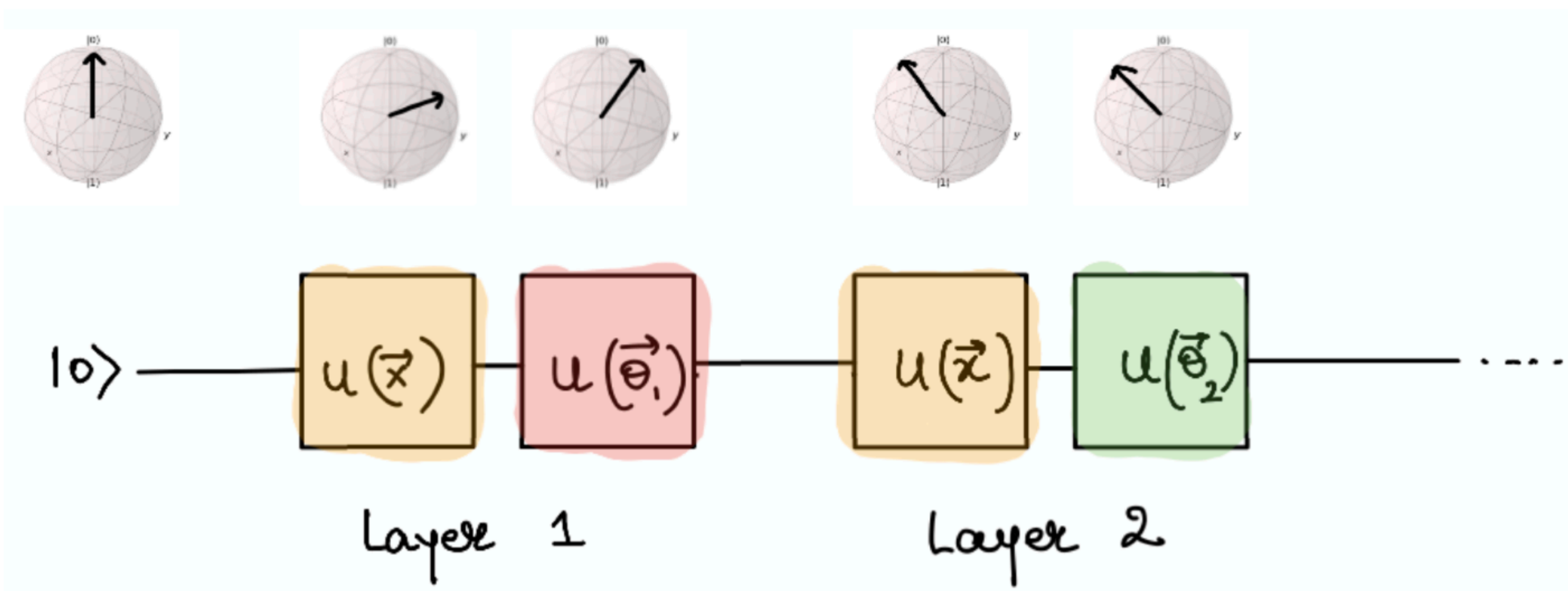
- The data is encoded into the amplitudes of a quantum state.
- This encoding requires **log2 (n) qubits** to represent an n-dimensional data point.





DATA REUPLOADING

- Data re-uploading addresses the limitations imposed by the no-cloning theorem.
- It adds extra layers or repetitions of quantum gates within a variational quantum circuit, enabling more complex transformations of the quantum state.
- This method enhances the circuit's expressiveness, improving its ability to capture intricate patterns in data for machine learning tasks.



AGILE SPACE MISSION

- AGILE is a space mission launched from the Italian Space Agency (ASI) in 2007 to study X-ray and gamma-ray phenomena through data acquired by different instruments onboard the satellite.
- The **AntiCoincidence System** (ACS) is part of the **Gamma-Ray Imaging Detector** (GRID). It is composed of five panels and it can detect photons. Each ACS panel count rate constitutes a time series.
- The **AGILE-GRID** RTA pipeline generates count maps, exposure maps and upper limit maps.