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

Benchmarking Quantum Convolutional Neural Networks for Signal Classification in Simulated Gamma-Ray Burst Detection

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AI in Astronomy Workshop

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INAF BRANCH OF ICSC SPOKE 10

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

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The Application of Quantum Fourier Transform in Cosmic Microwave Background Data Analysis

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DIFFERENT WORKS OF OUR GROUP

Comparing Quantum Machine Learning Approaches in Astrophysics

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***Abstract*—Machine Learning (ML) serves as a general-purpose, highly adaptable, and versatile framework for investigating complex systems across domains. However, the resulting computational resource demands, in terms of the number of parameters and the volume of data required to train ML models, can be high, often prohibitive. This is the case in astrophysics, where multimedia space data streams usually have to be analyzed. In this context, quantum computing emerges as a compelling and promising alternative, offering the potential to address these challenges in a feasible way. Specifically, a four-step quantum machine learning (QML) workflow is proposed encompassing data encoding, quantum circuit design, model training and evaluation. Then, focusing on the data encoding step, different techniques and models are investigated within a case study centered on the Gamma-Ray Bursts (GRB) signal detection in the astrophysics domain. The results thus obtained demonstrate the effectiveness of QML in astrophysics, highlighting the critical role of data encoding, which significantly affects the QML model performance.**

***Index Terms*—Data Encoding, Kernel Methods, Quantum Fingerprinting, Data Reuploading, Gamma-Ray Bursts.**

traditional statistical methods struggle to handle. Modern astronomical surveys generate extensive and complex data streams, necessitating automated classification, anomaly detection, and predictive modeling. ML techniques have been widely adopted in tasks such as galaxy classification, transient detection, and cosmological parameter estimation, demonstrating significant improvements in accuracy and efficiency [1], [2]. While ML has proven effective, astrophysical data present additional challenges beyond sheer volume. ML, indeed, well-suits astrophysical research due to the confluence of several factors: i) astrophysical datasets are characterized by their high dimensionality and volume, often exceeding the capacity of traditional statistical methods; ii) astrophysical phenomena are frequently governed by intricate physical processes that generate complex, non-Gaussian statistical distributions; iii) the inherent noise and incompleteness of astronomical observations, arising from instrumental limitations and observational constraints, require robust data imputation, filtering and

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DIFFERENT WORKS OF OUR GROUP

From Vlasov-Poisson to Schrödinger-Poisson: dark matter simulation with a quantum variational time evolution algorithm

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(Dated: January 29, 2024)

Cosmological simulations describing the evolution of density perturbations of a self-gravitating collisionless Dark Matter (DM) fluid in an expanding background, provide a powerful tool to follow the formation of cosmic structures over wide dynamic ranges. The most widely adopted approach, based on the N-body discretization of the collisionless Vlasov-Poisson (VP) equations, is hampered by an unfavourable scaling when simulating the wide range of scales needed to cover at the same time the formation of single galaxies and of the largest cosmic structures. On the other hand, the dynamics described by the VP equations is limited by the rapid increase of the number of resolution elements (grid points and/or particles) which is required to simulate an ever growing range of scales. Recent studies showed an interesting mapping of the 6-dimensional+1 ($6D+1$) VP problem into a more amenable $3D+1$ non-linear Schrödinger-Poisson (SP) problem for simulating the evolution of DM perturbations. This opens up the possibility of improving the scaling of time propagation simulations using quantum computing. In this paper, we introduce a quantum algorithm for simulating the Schrödinger-Poisson (SP) equation by adapting a variational real-time evolution

arXiv:2307.06032 , Published in Physical Review Research, March 2024

DIFFERENT WORKS OF OUR GROUP

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

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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 , Published in proceedings of the ADASS XXXIII (2023) conference

DIFFERENT WORKS OF OUR GROUP

A Quantum Genetic Algorithm for Cosmological Parameters Estimation

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Abstract

An Amplitude-Encoded Quantum Genetic Algorithm (AEQGA) has been developed to minimize χ^2 functions of different cosmological probes (Supernovae Type Ia, Baryon Acoustic Oscillations, Cosmic Microwave Background Radiation), to find the best-fit value for two cosmological parameters, namely the Hubble Constant and the density matter content of the Universe today. Our main aim is to pave the way to testing the adoption of quantum optimization in the inference of the cosmological parameters that describe the universe evolution. AEQGA computes the merit function classically, and then uses a quantum circuit to entangle the population and perform crossover and mutation operations. The results show consistency with the isocontours of the objective functions. We then tested the general behavior of AEQGA as a function of its hyperparameters and compared it with a second quantum genetic algorithm found in the literature as well as with classical algorithms, finding consistent results.

Submitted to Astronomy & Computing

DIFFERENT WORKS OF OUR GROUP

Quantum Markov Chain Monte Carlo for Cosmological Functions

***Abstract*—We here present an implementation of Quantum Computing for a Markov Chain Monte Carlo method with an application to cosmological functions, to derive posterior probabilities of given likelihoods and chi-squared of cosmological probes such as Supernovae Type Ia and the Cosmic Microwave Background radiation. The algorithm proposes new steps in the parameter space via a quantum circuit whose resulting statevector provides the components of the shift vector. The proposed point is accepted or rejected via the Metropolis-Hastings acceptance method evaluated classically. The advantage of taking the steps via our quantum approach is in the fact that the step size and direction changes in a way independent of the evolution of the chain, thus ideally avoiding the presence of local minima. Gaussian and Uniform priors have also been defined. This algorithm has been tested for both a test function and two cosmological ones with real data. The results are consistent with analyses performed with classical methods. The final goal is to generalize this algorithm to many dimensions, thus testing its application to complex cosmological computations, looking for a possible quantum advantage for a very relevant problem for the cosmological community.**

***Index Terms*—I.4.1.c Quantization, G.3.e Markov processes, G.1.2.g Minimax approximation and algorithms.**

review of quantum algorithms presented in the literature, see [12], [13].

Among the different scientific fields in which interesting applications of QC could be found, astrophysics and cosmology are the ones we focus on. Indeed, we live in an epoch of astronomical data richness, for which vast, high-quality data catalogs are at the disposal of the astronomical community, and strategies for efficiently searching and analyzing these datasets are becoming mandatory [14], [15]. Examples of missions and instruments that have given us such remarkable datasets are Gaia [16], the Sloan Digital Sky Survey (SDSS, [17]), and the Very Large Telescope (VLT, [18]). These will be accompanied by the data provided by novel instruments like Euclid [19]–[21], and the Vera C. Rubin Observatory [22]. Efficient and fast analyses have been performed with novel strategies like machine learning models [23]–[26] as well as the redesign of algorithms to employ high-performance computing (HPC) hardware as efficiently as possible. The idea is to understand if QC can be used in this context as well, finding possible applications in which it can bring advantages to classical

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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

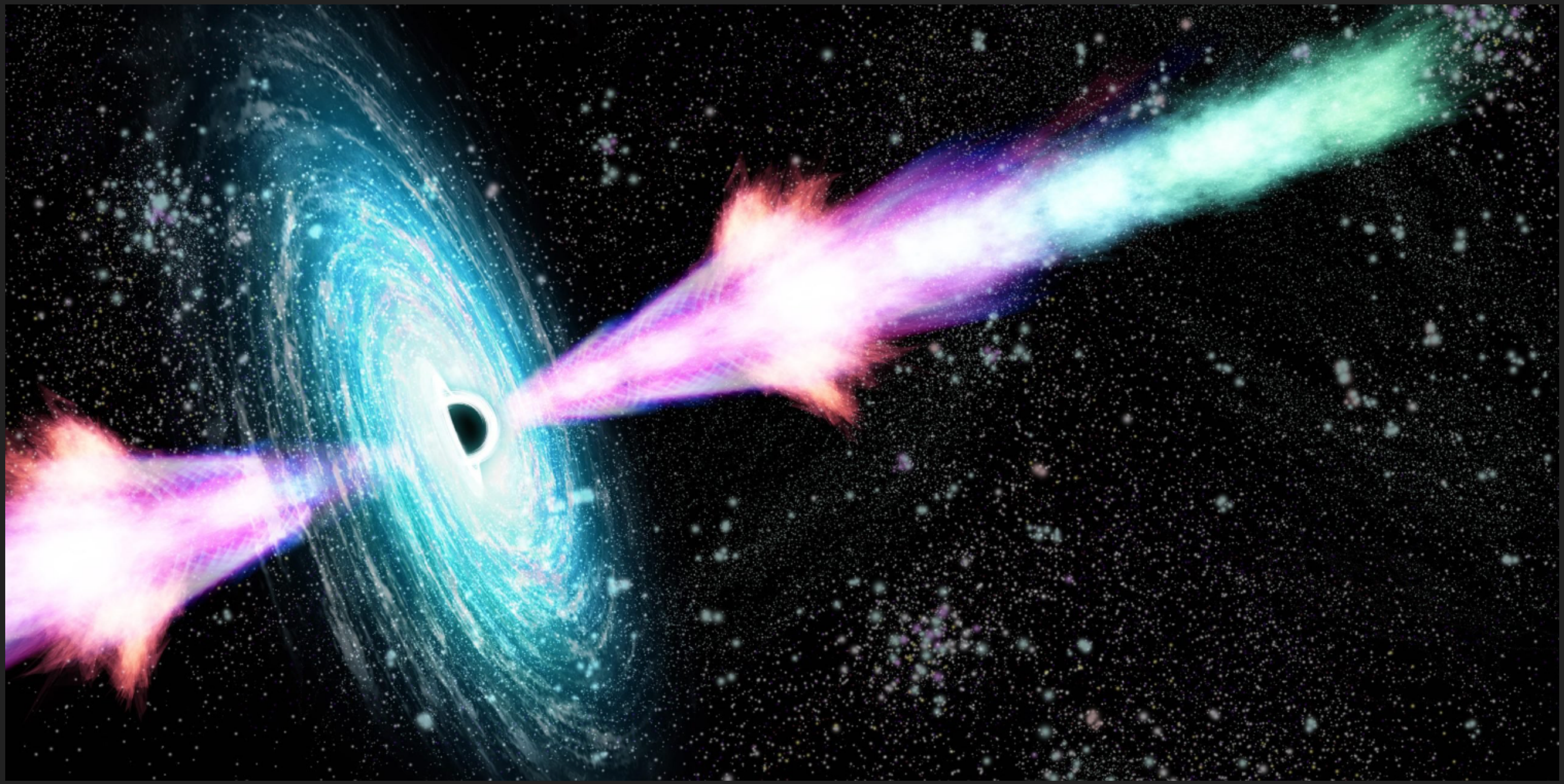
TRAINING THE QUANTUM NEURAL NETWORK

5

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

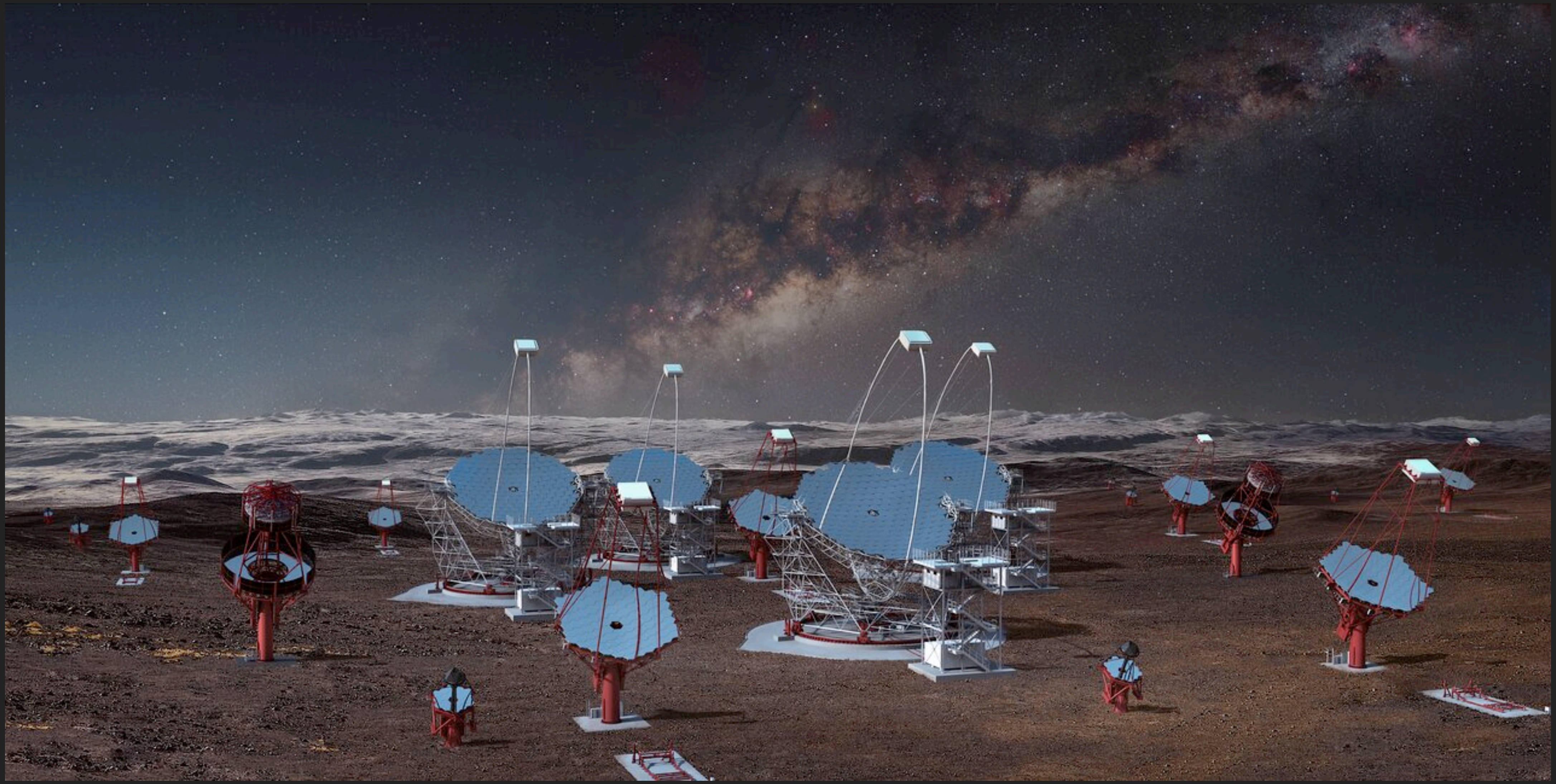
GAMMA RAY BURSTS

- 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.



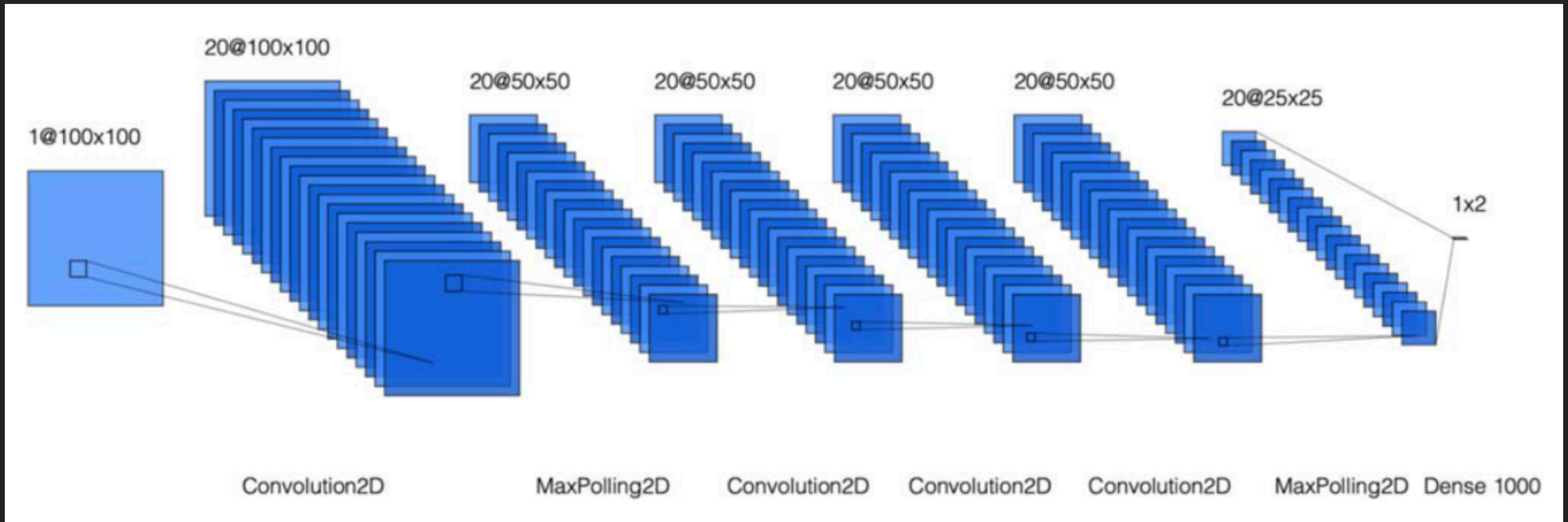
CHERENKOV TELESCOPES ARRAY OBSERVATORY (CTAO)

- 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 Quantum Neural Network 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

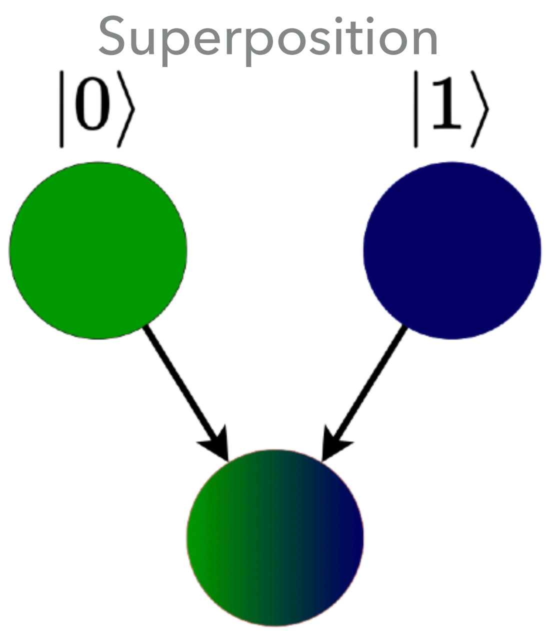
- **Qubit** : The unit of information for QC

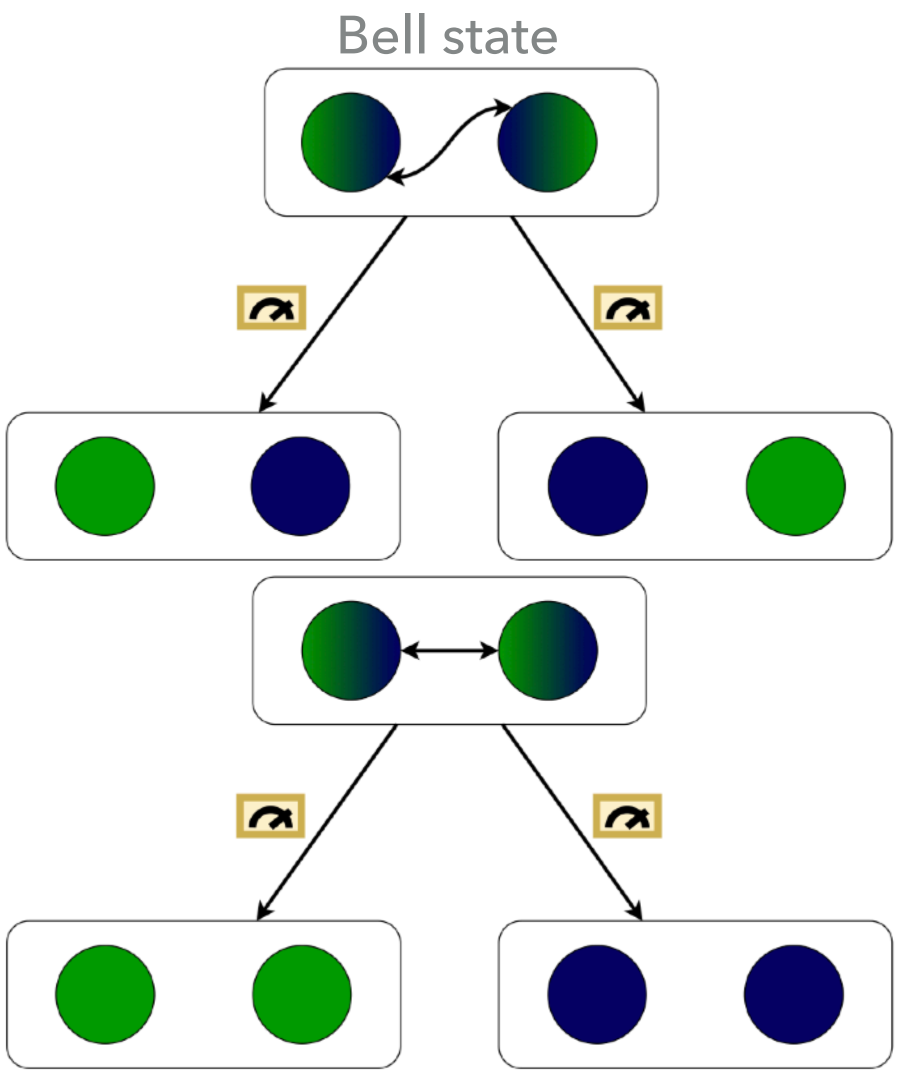
$$|\psi\rangle = \begin{pmatrix} c_0 \\ c_1 \end{pmatrix} = c_0 |0\rangle + c_1 |1\rangle$$

- **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.

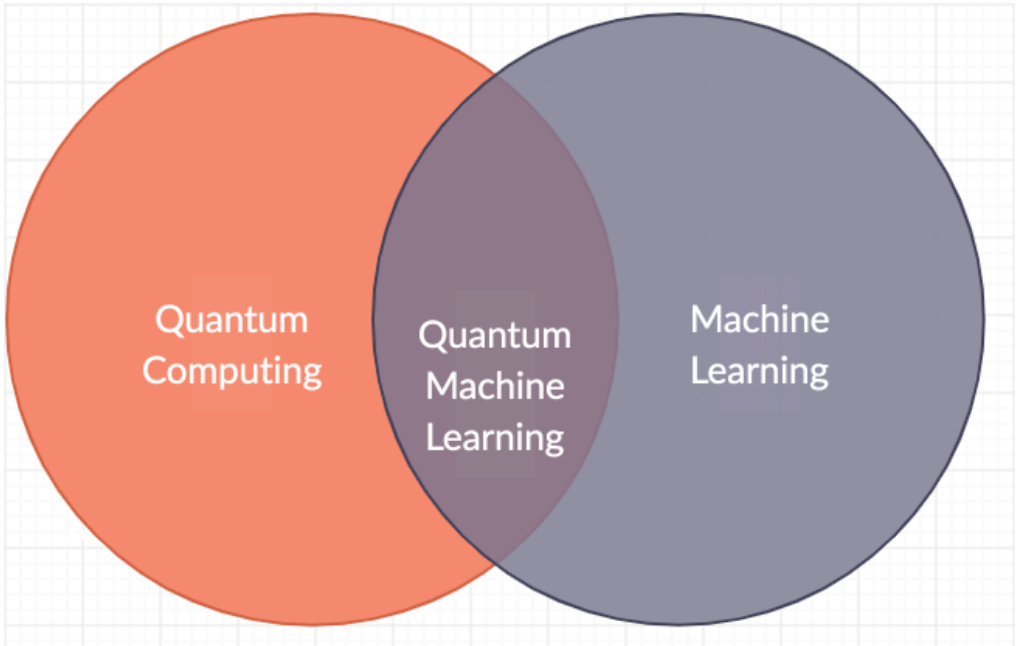
- **Quantum gate**: transformations (matrices) which can be used to manipulate the qubits. They should have these properties: Linearity, Unitarity and Reversibility

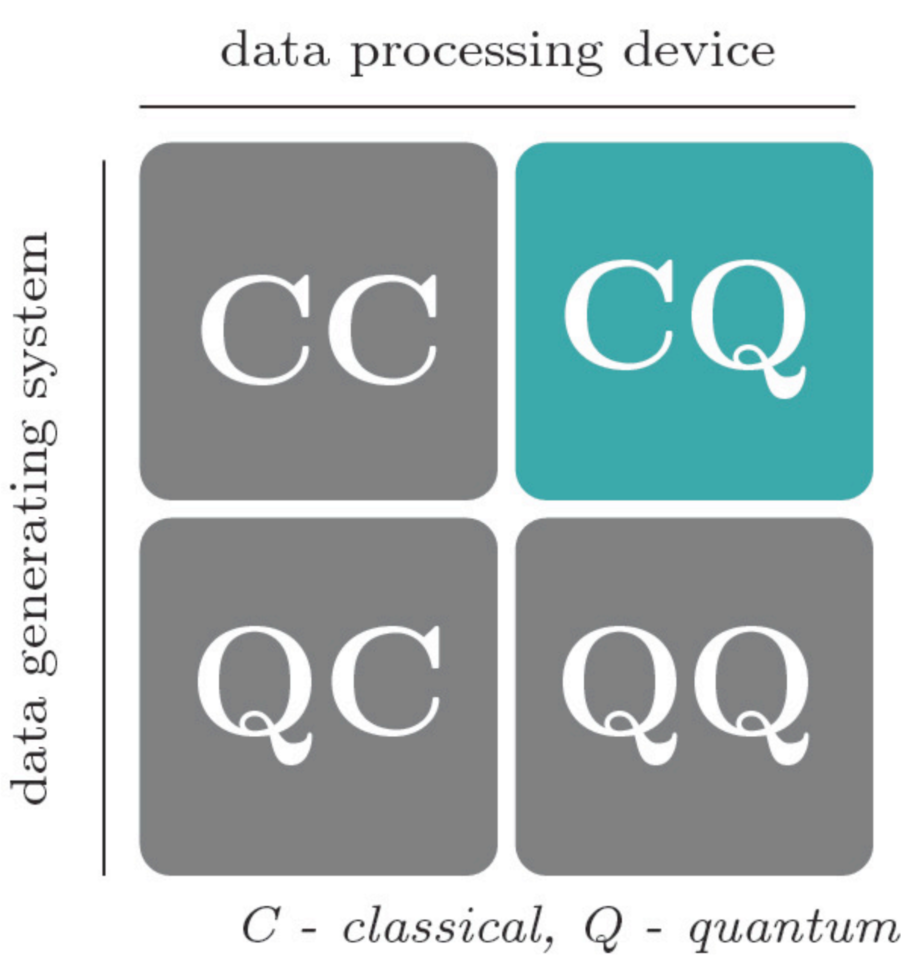




QUANTUM MACHINE LEARNING (QML)

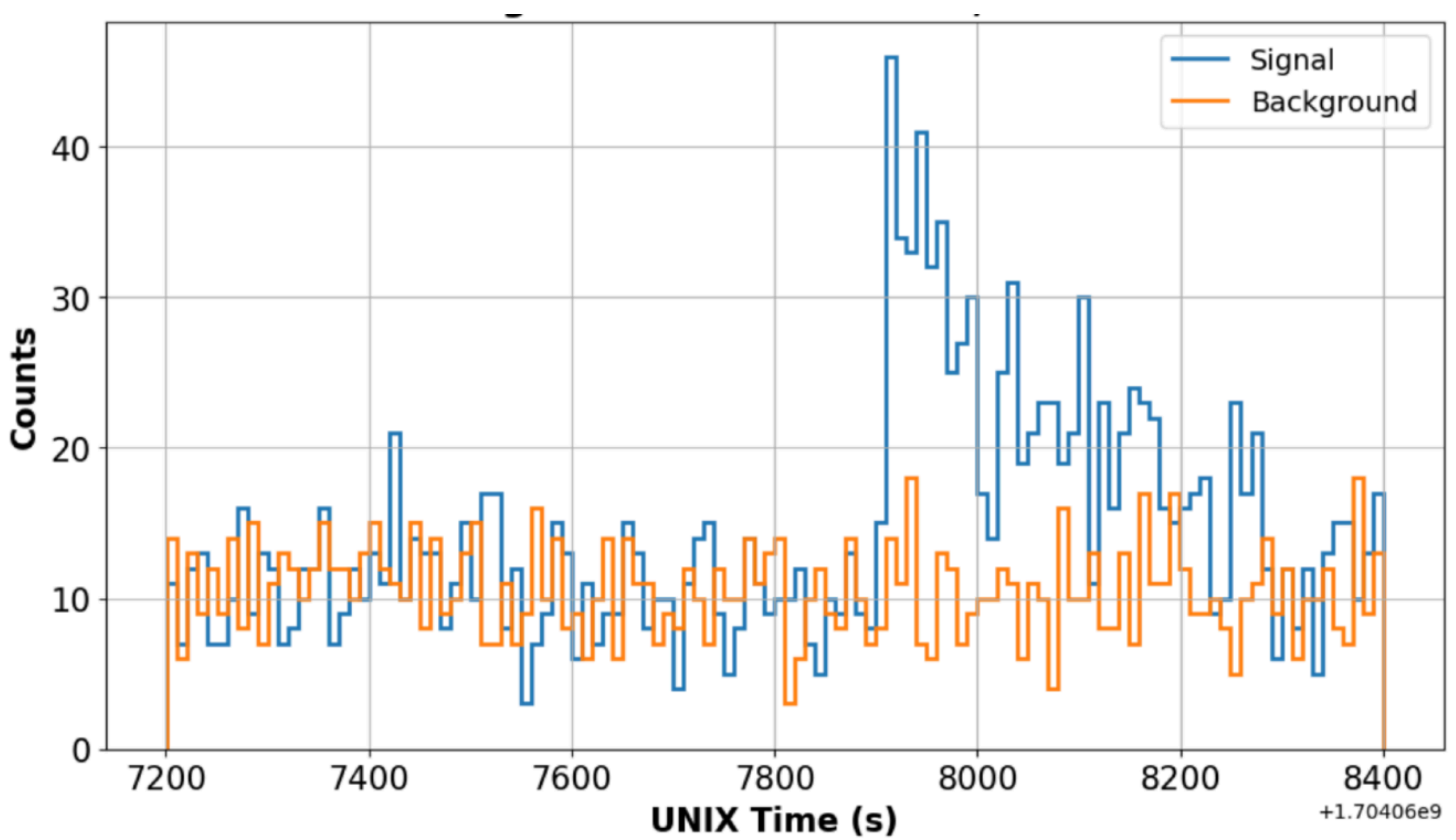
- Combines concepts from **quantum computing** and **machine learning** to develop algorithms capable of exploiting quantum phenomena to enhance learning tasks.
- Quantum computing uses **qubits**, which unlike classical bits, can be in **superposition** states of 0 and 1 simultaneously. This allows 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.





DATASET

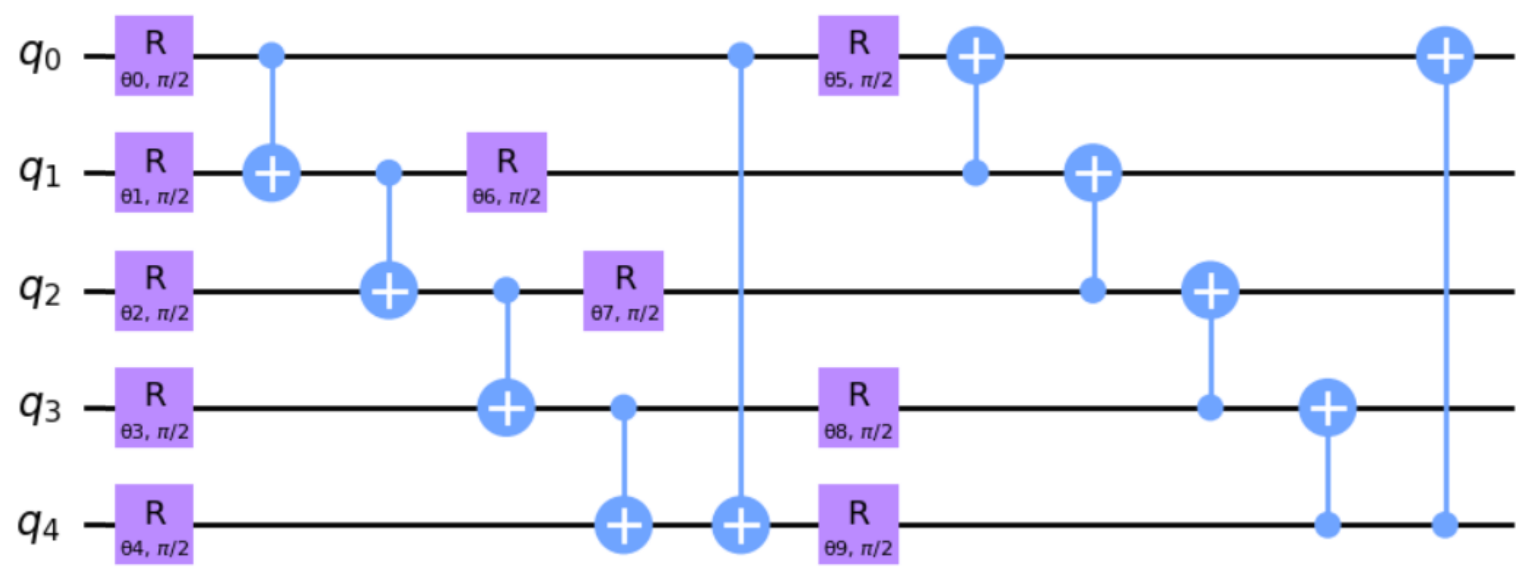
- Simulated Dataset are composed by two classes: **GRB Signal** and **background noise**, leading to a binary classification problem
- Light Curve as time series**:** 440 GRBs and background noise as training set, 160 for the test set.
- The x-axis represents the time window with a certain Binnig.
- 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.

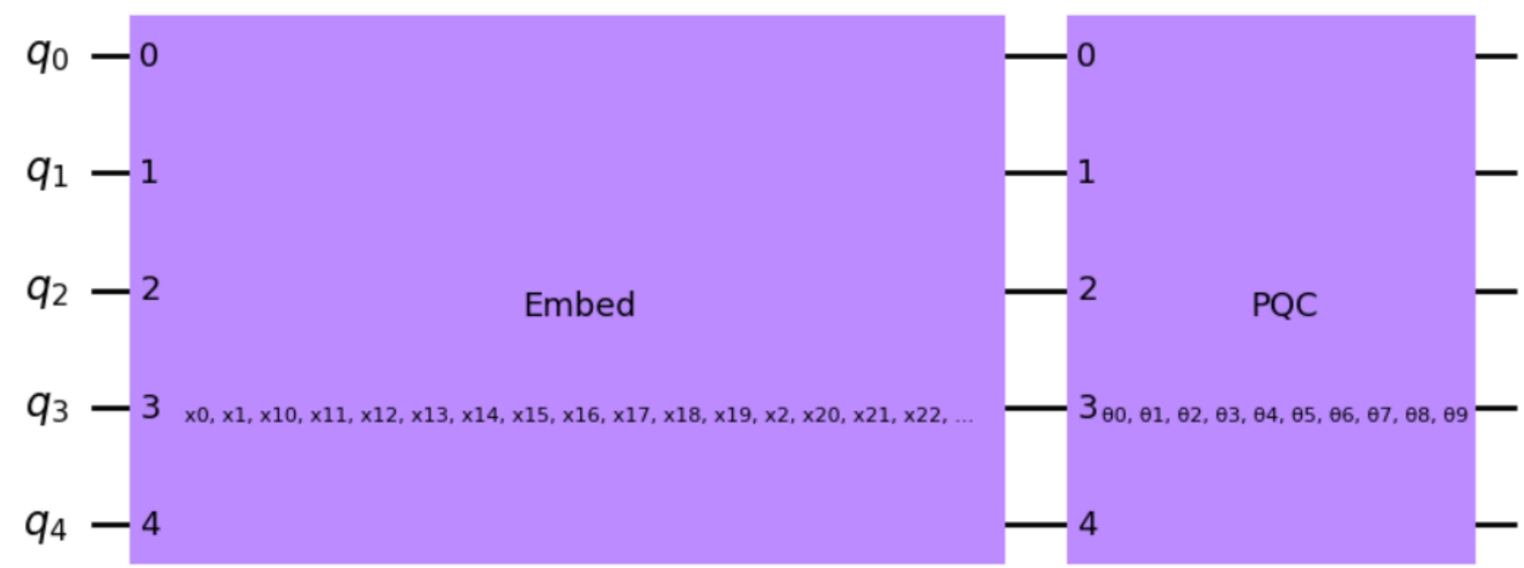


IMPLEMENTED ARCHITECTURE

- Parametrised Quantum Circuit in Qiskit has been used
- Using Angle Encoding and data Reuploading methods for Data Encoding
- COBYLA optimize
- 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 440 light curves training set and 160 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
Quantum NN	4	8	Doesn't learn	**-**	-
Quantum NN	6	12	**90.3%**	**87.7%**	89s
Quantum NN	12	24	**99.38%**	**97.5%**	713s

F.Farsian et al, 2025

RESULTS

- Comparison of amplitude encoding and the data re-uploading method
- The **accuracy dropped** when using **amplitude encoding**, indicating its limitations in this context.
- **Advantage of Data Re-Uploading**: The data re-uploading method enhances the **expressiveness of the variational quantum circuit** by embedding input data at multiple stages, enabling more complex transformations.
- **Improved Representational Power**: This method is particularly well-suited for **high-dimensional or complex data**, making it valuable for QML applications.

Data Encoding	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set
Amplitude Encoding	7	14	76.56%	66.67%
Data Reuploading	7	63	**91.13%**	**88.12%**

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RESULTS

- **Test on Sample complexity**—the ability to perform tasks with fewer labeled training samples.
- **Quantum Generalization Advantage**: Quantum algorithms are theoretically expected to generalize better than classical models by leveraging superposition and entanglement to process information more efficiently.
- **Evaluation with Limited Data**: The performance was tested under **data-scarce conditions** (only 20 training sample) to explore its potential advantage in generalization
- **Astrophysical Significance**: This result highlights the **practical advantage** of QCNNs in astrophysics, where labeled data is often scarce due to the rarity of observed phenomena.

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

F.Farsian et al, 2025

RESULTS

- **Evaluation on Real Data**: The QCNN was tested on real observational data from the AGILE satellite, consisting of 43 GRB samples and 101 background samples, introducing a class imbalance.
- The dataset was split into training (70%), test (20%), and validation (10%) sets. Details on its preparation can be found in previous work [Rizzo et al. 2024].
- **Performance Comparison**:

NN model	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set
Classical CNN	-	56	96.55%	93.91%
Quantum NN	7	14	**91.17%**	**90.72%**

F.Farsian et al, 2025

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

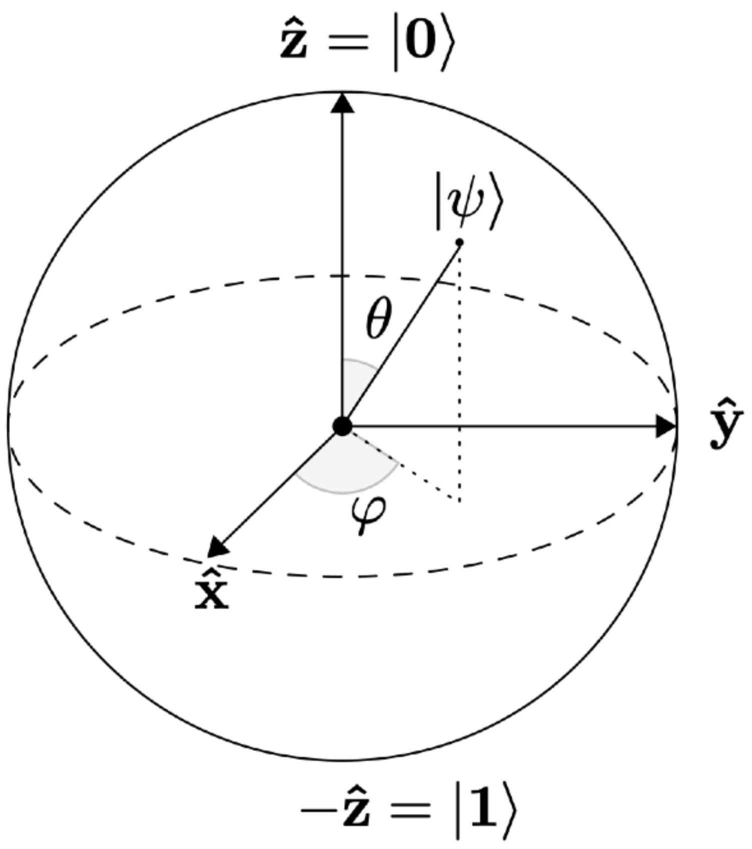
BACKUP SLIDES

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)
- …

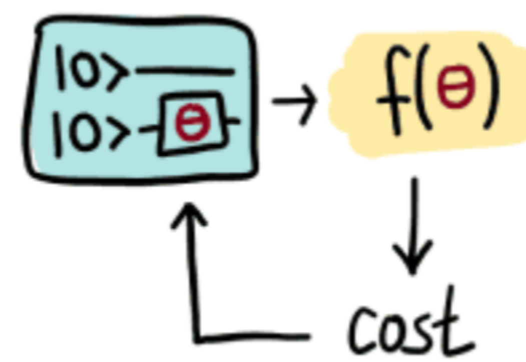


PARAMETRISED QUANTUM CIRCUIT (PQC)

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.



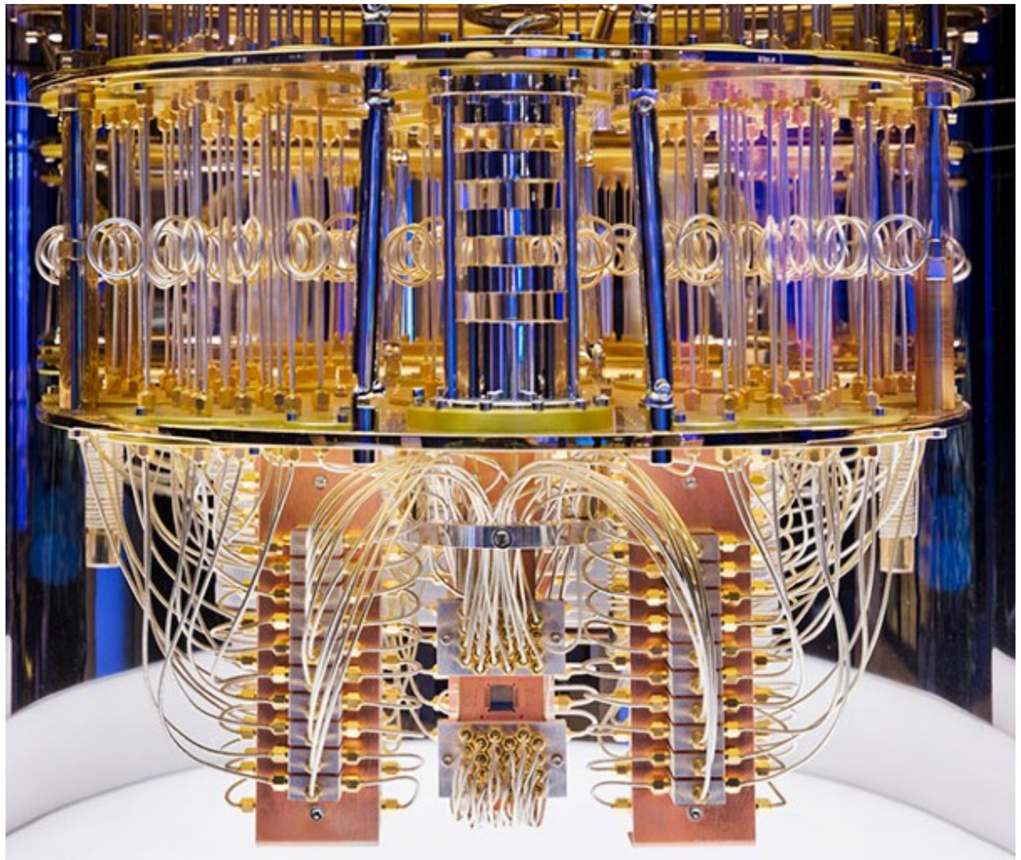
$$f(\theta) = \langle 0|U^\dagger(\theta)\hat{B}U(\theta)|0\rangle$$

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

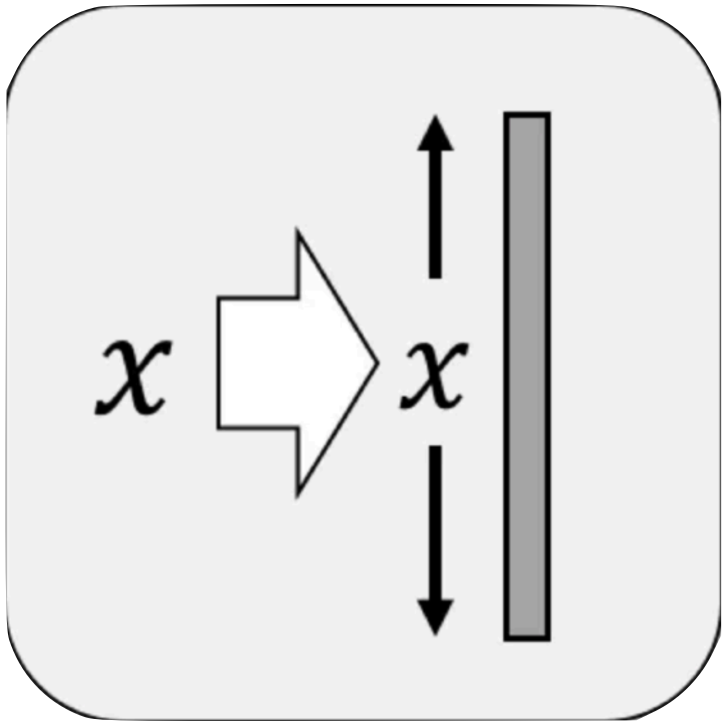
Qiskit

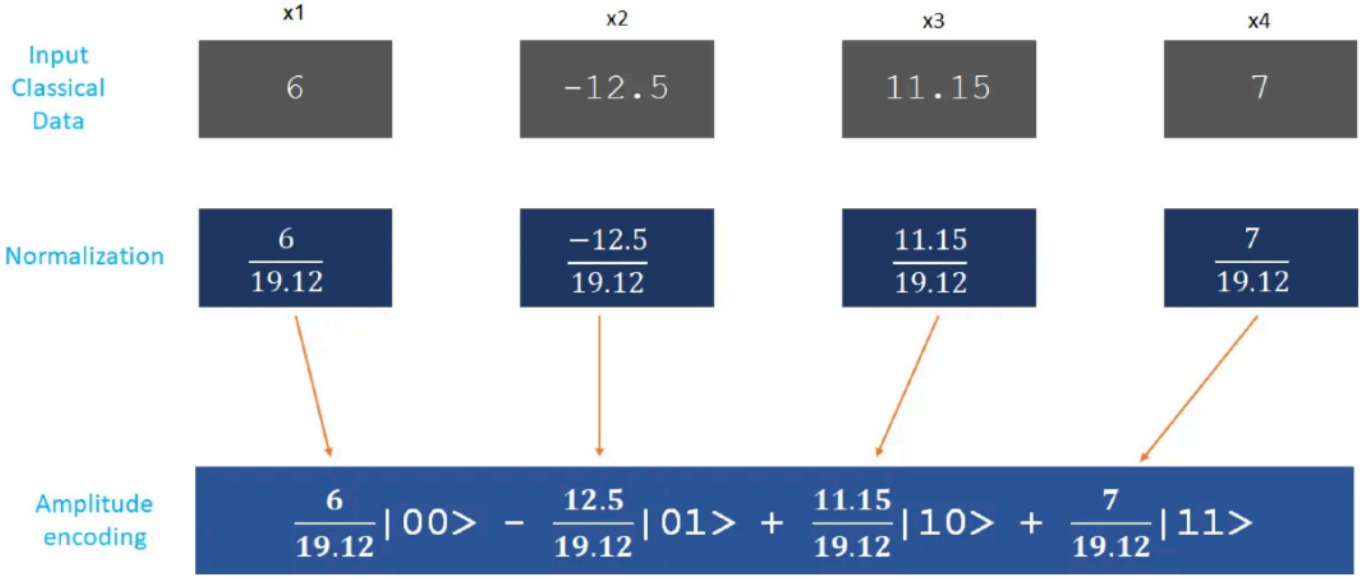


https://qiskit.org/
https://quantum-computing.ibm.com/

AMPLITUDE ENCODING

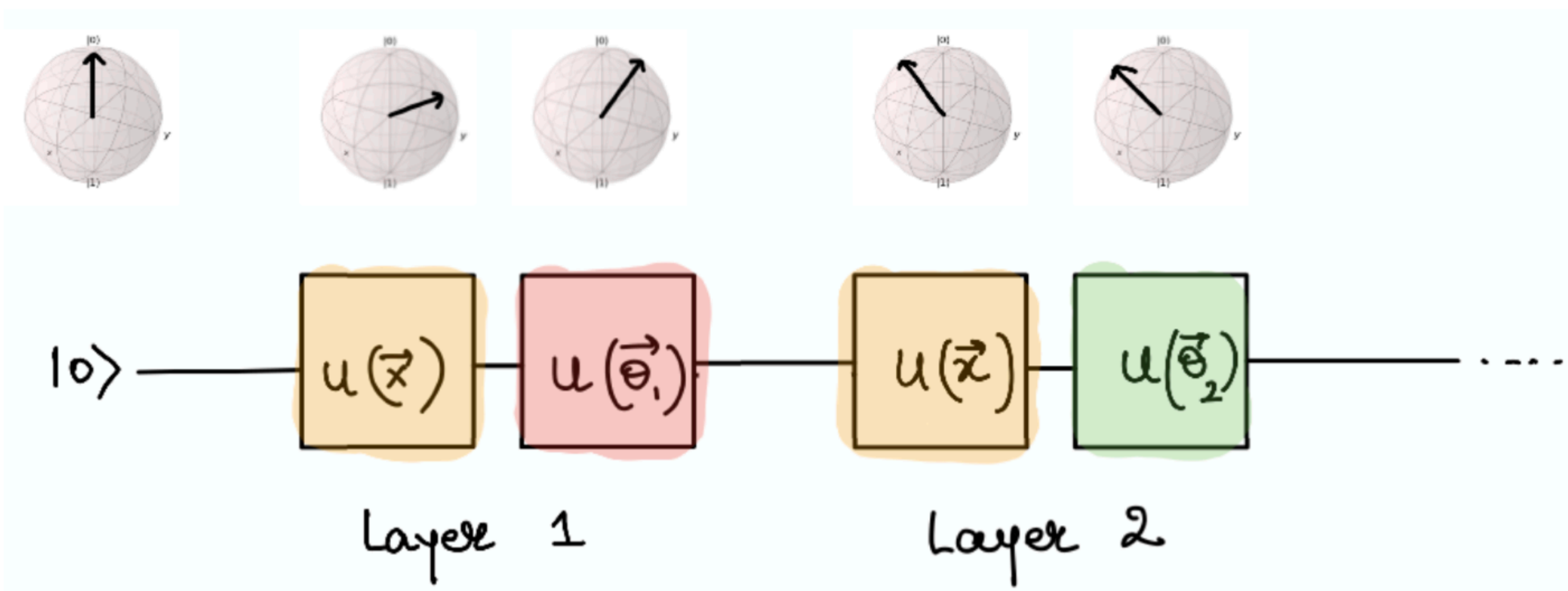
- The data is encoded into the amplitudes of a quantum state.
- This encoding requires **log2 (n) qubits** to represent an n-dimensional data point.





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.