INAF
ISTITUTO NAZIONALE DI ASTROFISICA
OSSERVATORIO ASTROFISICO DI CATANIA

USC-C

QUANTUM COMPUTING AND QUANTUM MACHINE LEARNING IN ASTROPHYSICAL DATA ANALYSIS

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

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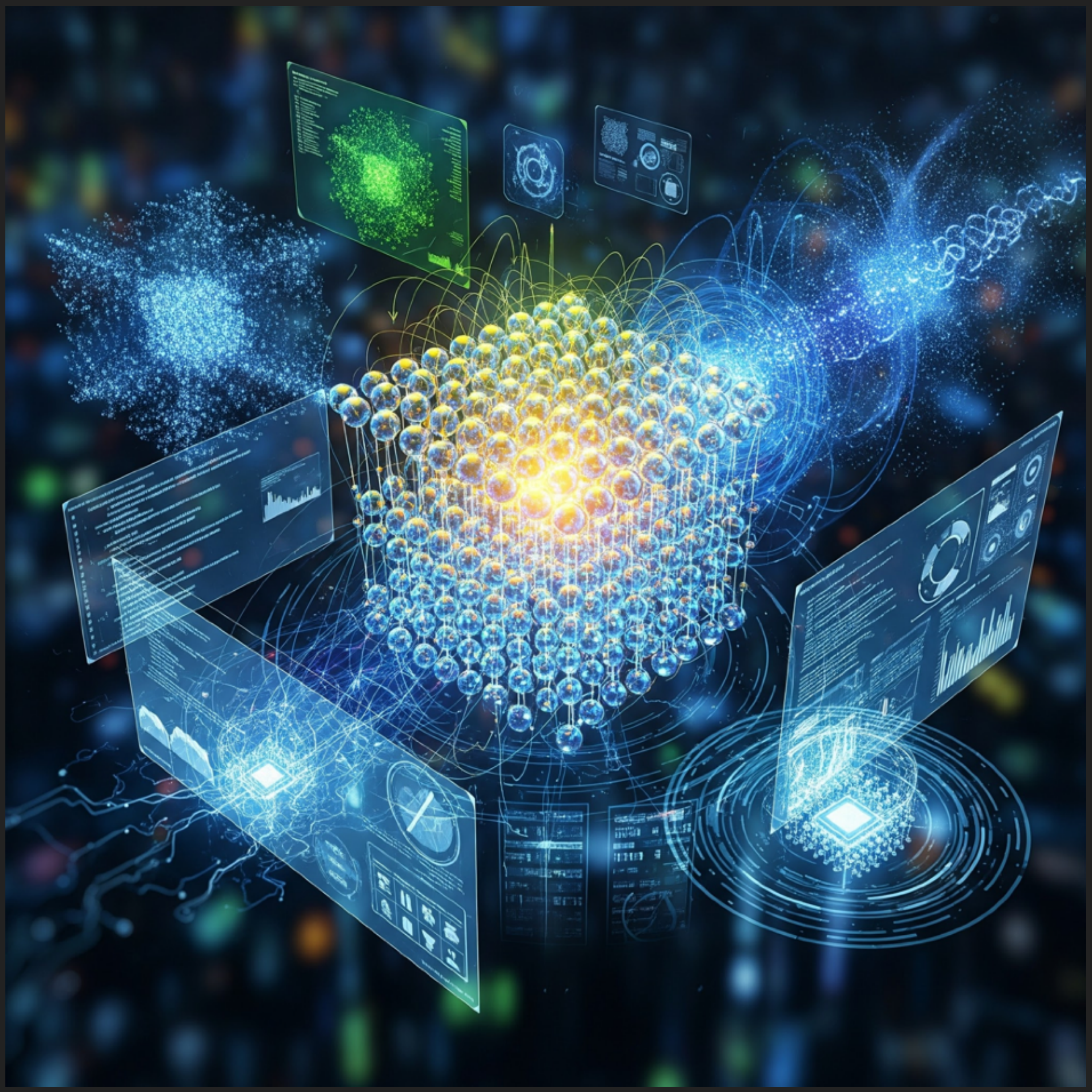
APPLICATION OF QC & QML IN ASTROPHYSICS AND COSMOLOGY

- "**Exploring the potential of Quantum Graph Neural Networks in analysing large scale structure of Universe**", F.Farsian et al. 2026, published in Astronomy and Computing journal.
- "**A Quantum Genetic Algorithm for Cosmological Parameters Estimation**", G. Sarracino et al., including F.Farsian, 2026, published in Astronomy & Computing journal.
- "**Benchmarking Quantum Convolutional Neural Networks for Signal Classification in Simulated Gamma-Ray Burst Detection**", F.Farsian et al., published in IEEE PPDP 2025, arXiv:2501.17041.
- "**The Application of Quantum Fourier Transform in Cosmic Microwave Background Data Analysis**", F.Farsian et al., published in IEEE QSW 2025, arXiv:2505.15855.
- "**Comparing Quantum Machine Learning Approaches in Astrophysical Signal Detection**", M. Ziiatdinov, F.Farsian et al., published in IEEE QSW 2025, arXiv:2507.19505.
- "**Quantum Markov Chain Monte Carlo for Cosmological Functions**", G. Sarracino et al., including F.Farsian, 2025, published in IEEE International Conference on Quantum Artificial Intelligence 2025, arXiv:2509.09395.
- "**Comparing Classical and Quantum Deep Learning Techniques for Anomaly Detection of GRBs**", A. Rizzo et al. including F.Farsian, 2026, published in Astronomy and Computing journal.
- "**Numerical limits in the integration of Vlasov-Poisson equation for Cold Dark Matter**", L. Cappelli et al., including F.Farsian, 2025, arXiv:2503.22842.

WHY QUANTUM MACHINE LEARNING?

- Classical ML struggles with some classes of high-dimensional data
- Quantum systems naturally represent **2^n-dimensional vectors** with n qubits
- QML explores whether **quantum feature spaces** can capture patterns difficult for classical models
- Hybrid quantum–classical methods are promising for the **NISQ era**
- QML is not about replacing ML, but about finding tasks where quantum circuits offer expressive power



SETTING THE STAGE FOR QUANTUM MACHINE LEARNING

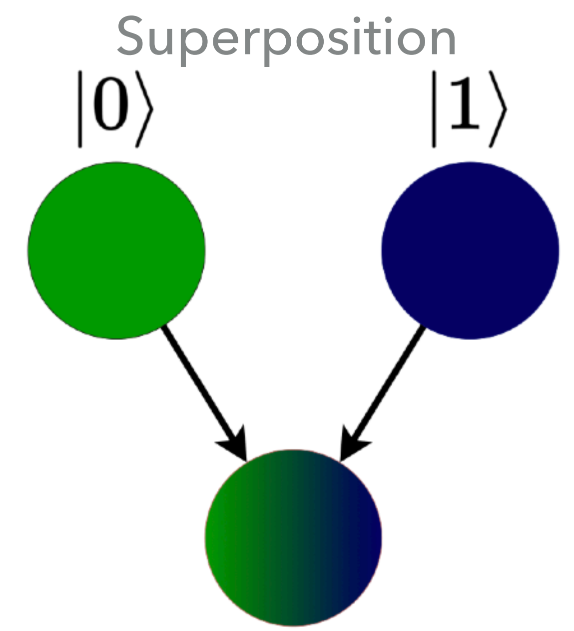
- **Qubit** : The unit of information for QC

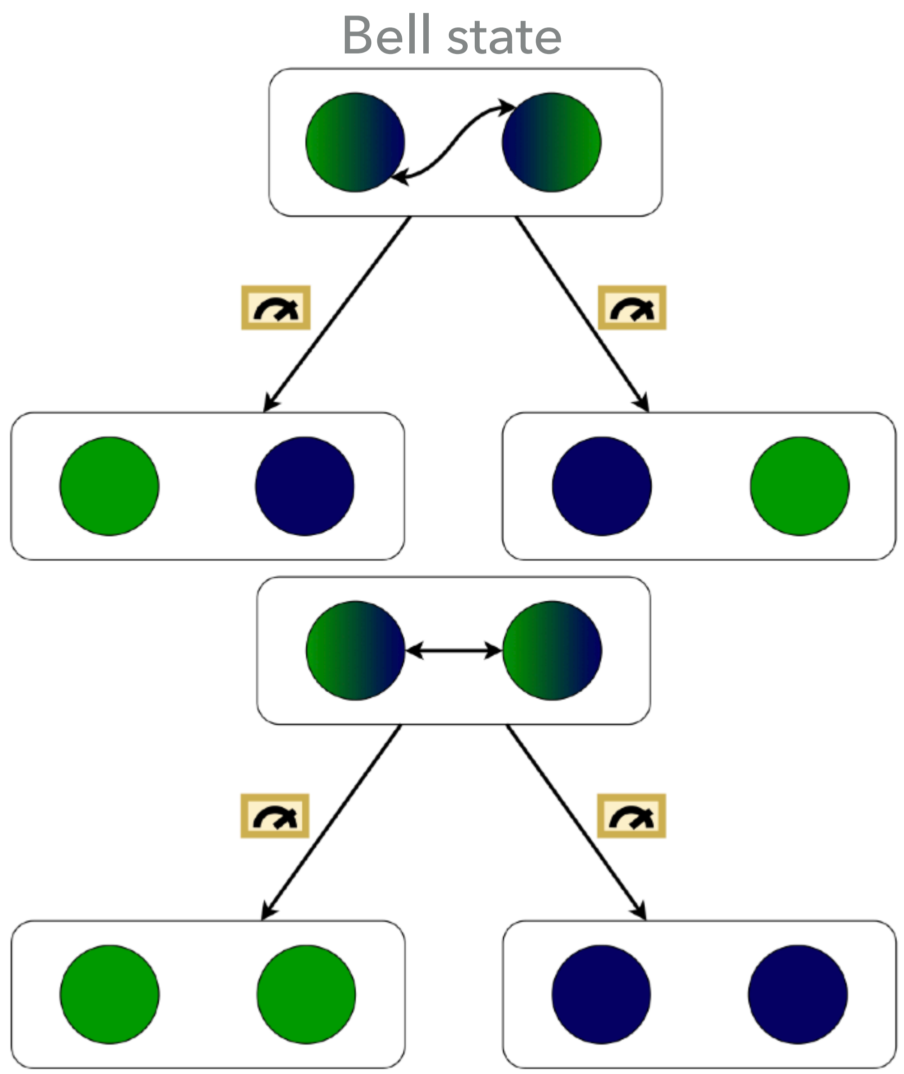
$$|\psi\rangle = \begin{pmatrix} c_0 \\ c_1 \end{pmatrix} = c_0 |0\rangle + c_1 |1\rangle$$

- **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

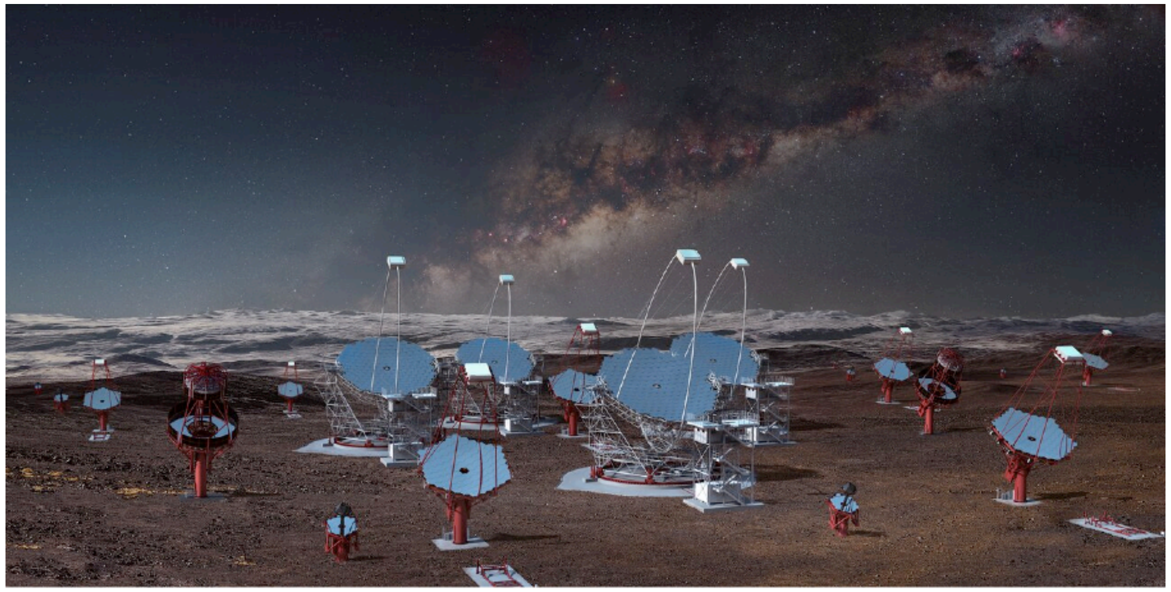




Detection of Gamma-Ray Burst signal through Quantum Neural Network

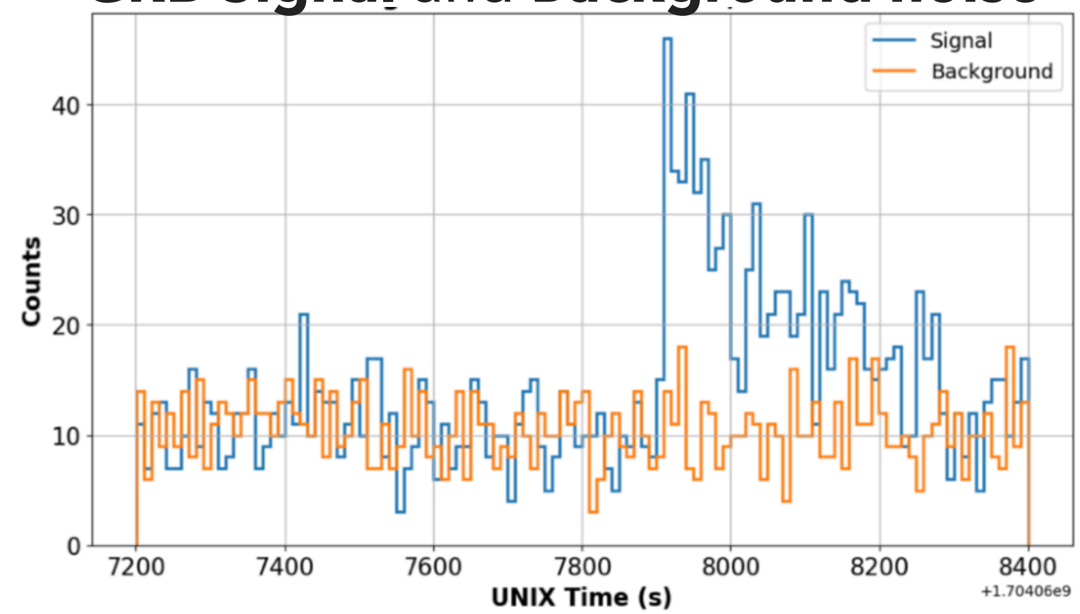
PROBLEM AND EXPERIMENT SETUP

Cherenkov Telescope Array Observatory

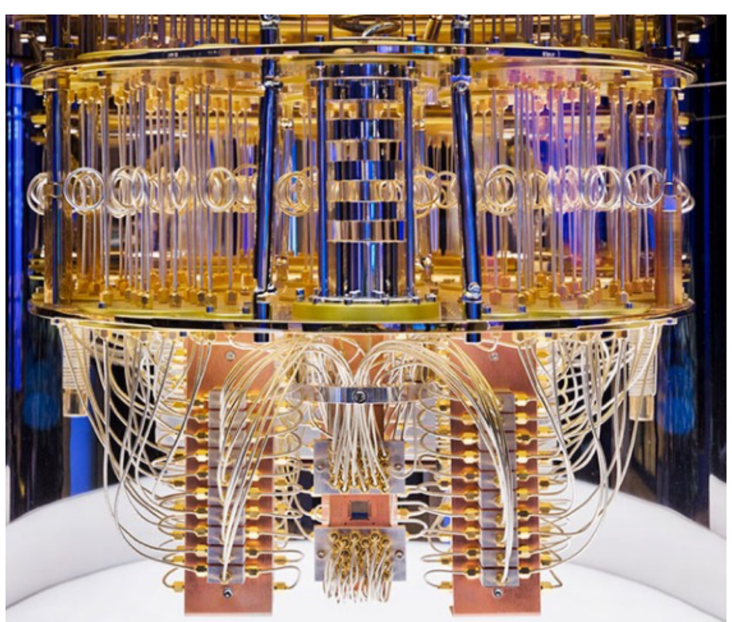


Simulated Dataset:

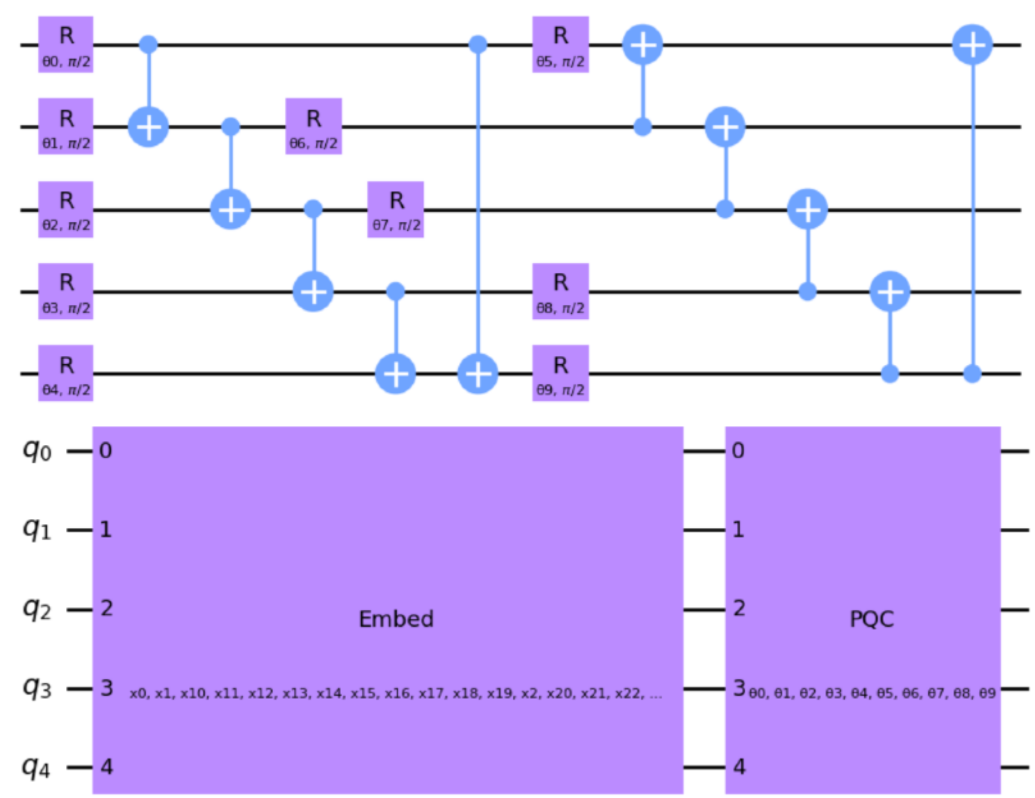
GRB Signal and B**ackground noise**



Qiskit



Parametrised Quantum Circuit in Qiskit



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RESULTS

Test on Quantum Neural Network performance and number of Qubits

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

Test on Sample complexity and Quantum Generalization Advantage

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**

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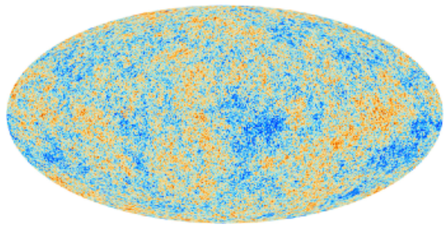
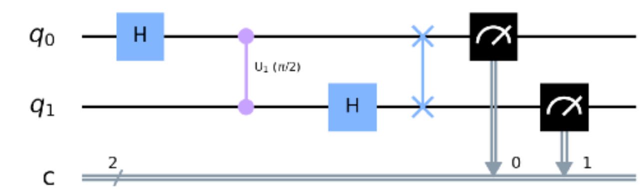
Application of Quantum Fourier Transform in CMB Data Analysis

STEPS DOWN TO CHECK THE QFT PERFORMANCE





1

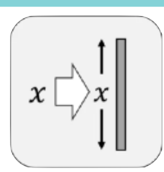
CMB Map Generation: Used *CAMB* to compute power spectra and *healpy* to generate maps.

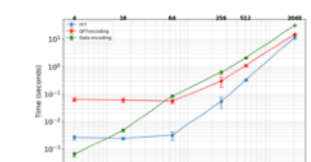
2

Classical vs. Quantum Decomposition: Applied FFT and QFT in *map2alm* for spherical harmonic analysis.

3

QFT Implementation: Used *Qiskit* for state preparation, QFT execution, and measurement.





4

Data Encoding: Adopted amplitude encoding for efficient quantum data representation.

5

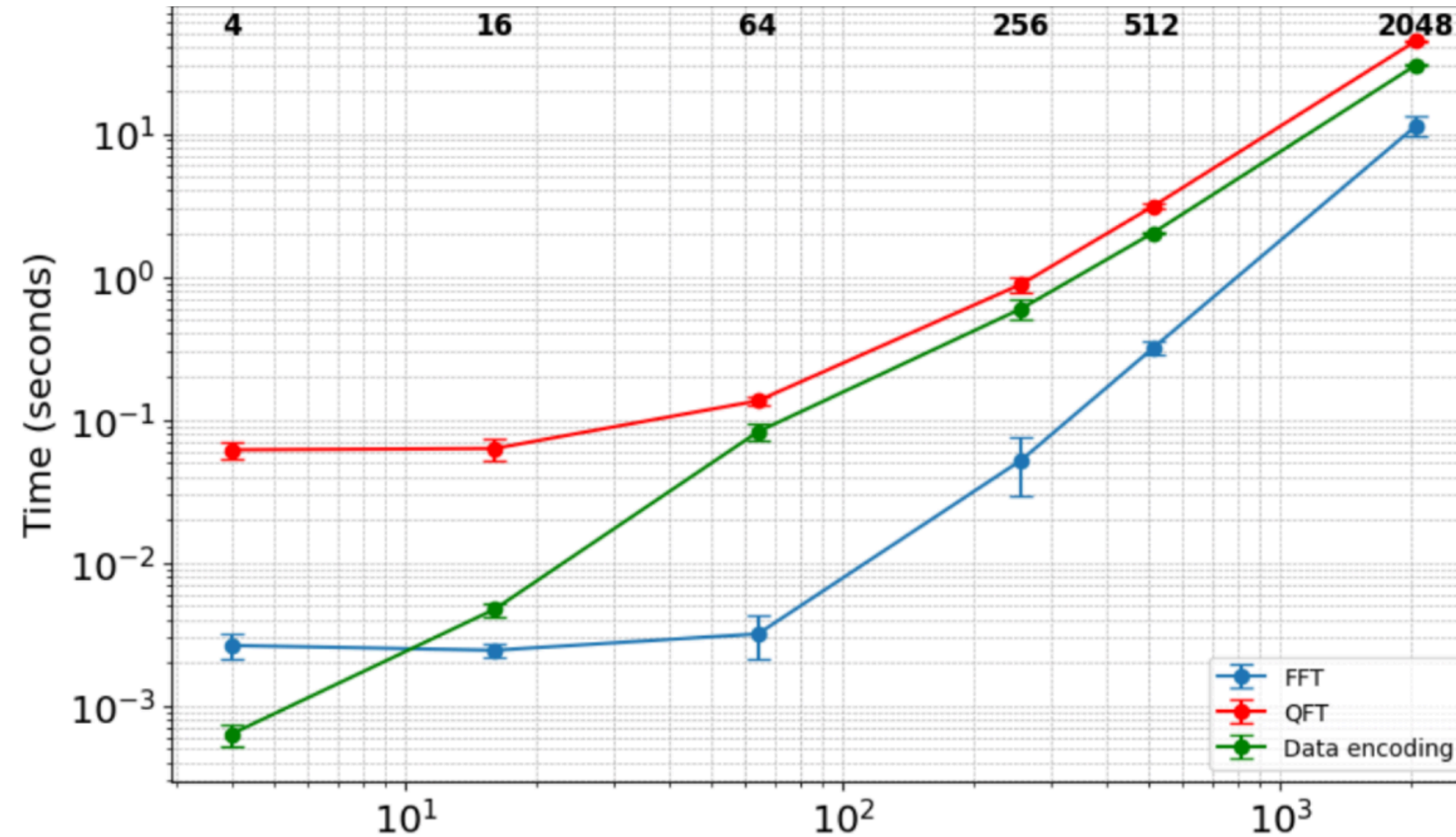
Padding Strategy: Used periodic padding to match quantum circuit constraints.

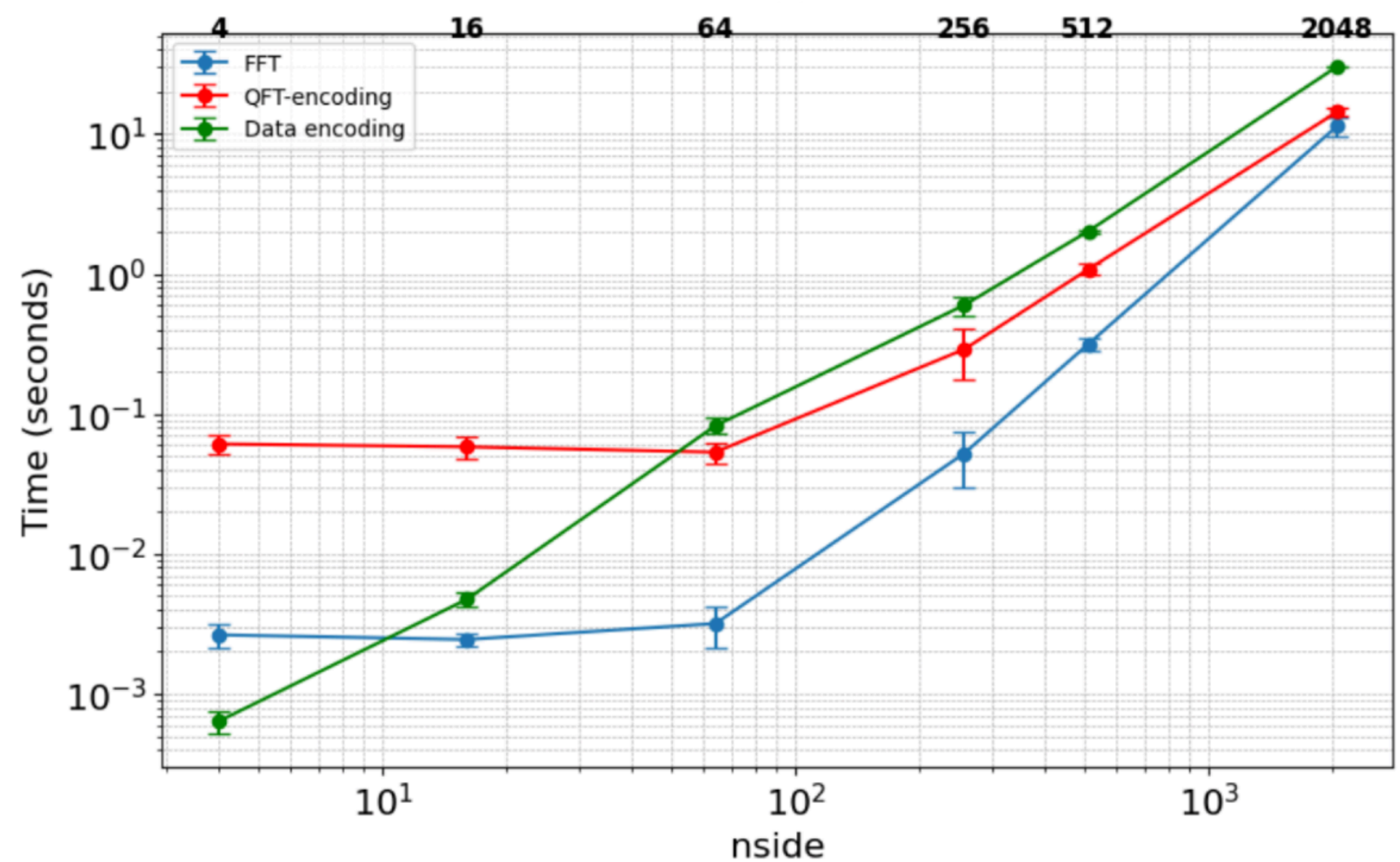
6

Performance Benchmarking: Compared QFT execution time with classical FFT.

TESTS

- The FFT consistently outperforms the QFT across all tested nside values, with significantly lower computational times.
- The primary slowdown in the quantum approach comes from data encoding, which dominates execution time as nside increases.
- The QFT itself is not the limiting factor; rather, the inefficiencies of amplitude encoding introduce significant computational overhead.





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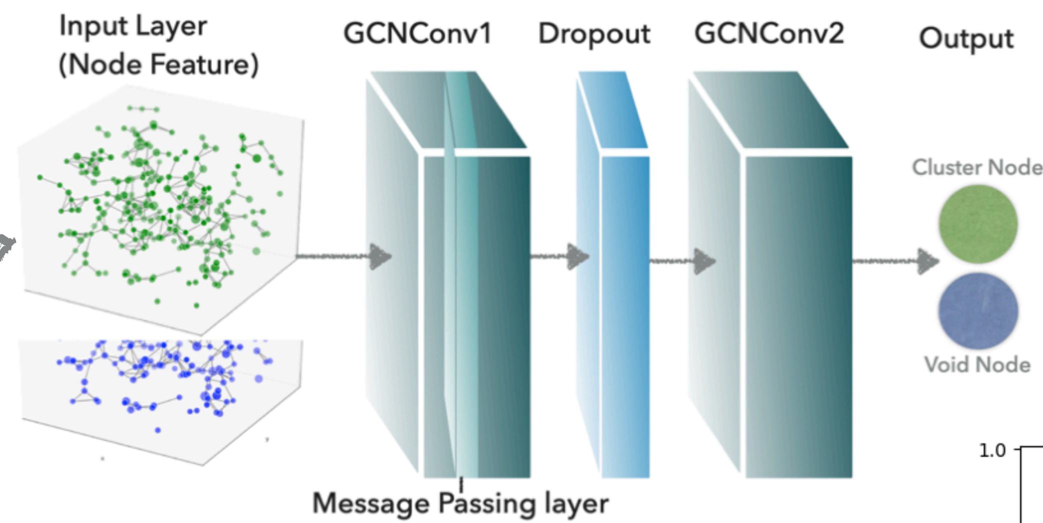
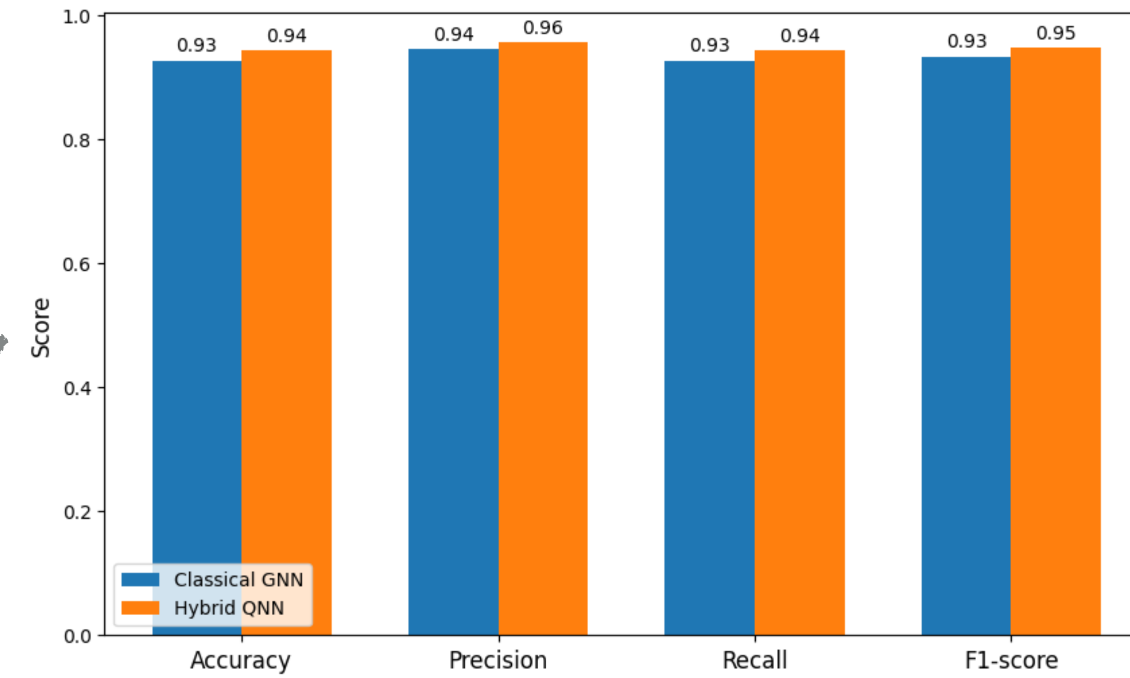
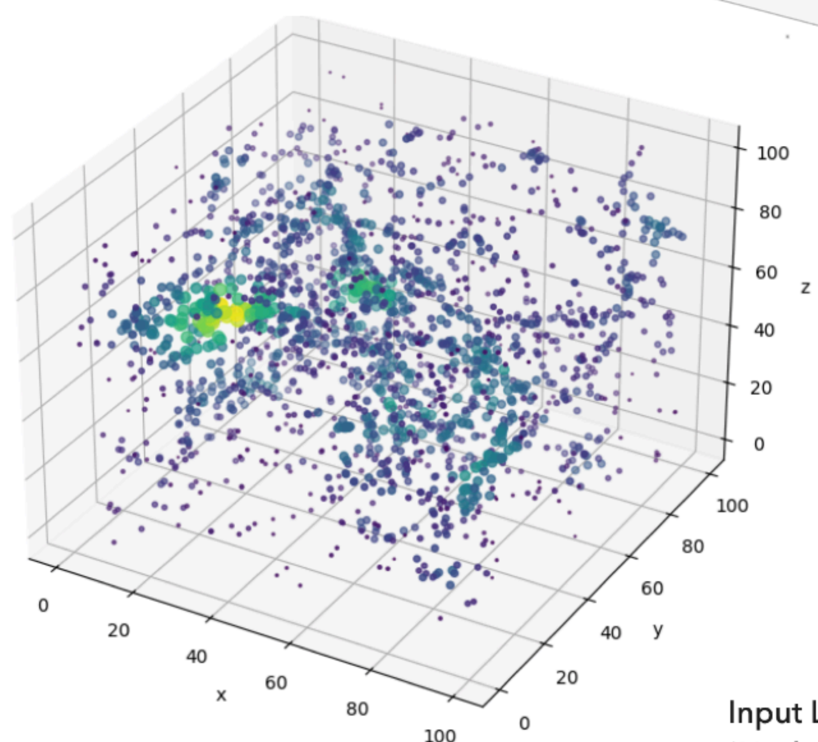
Application of Quantum Graph Neural Network in Large Scale Structure



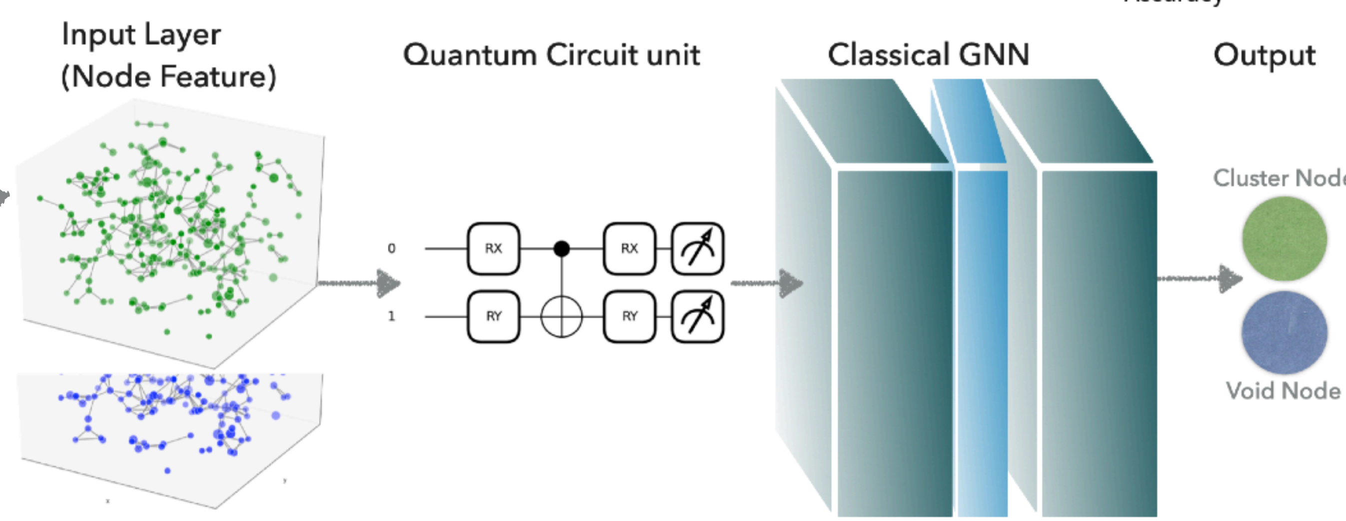
Classical GNN

Analysis:
Comparison of two classical and hybrid quantum GNN in classification of halos





Data:
dark matter halo catalogue as graphs



Hybrid GNN with a Parametrized Quantum Circuit layer

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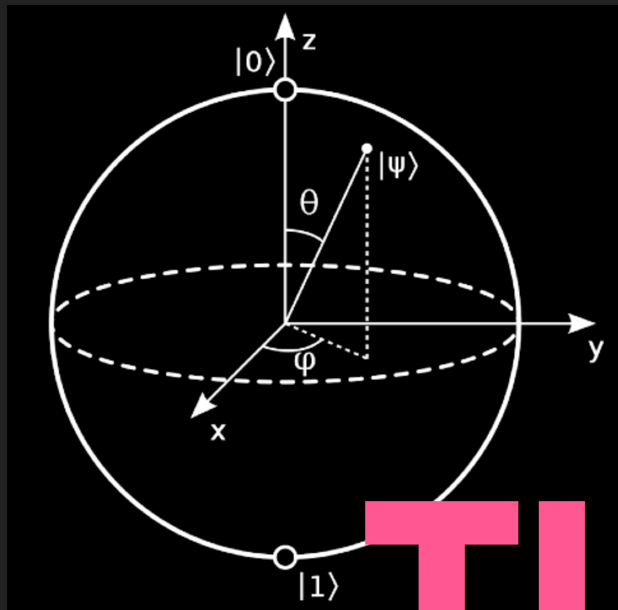
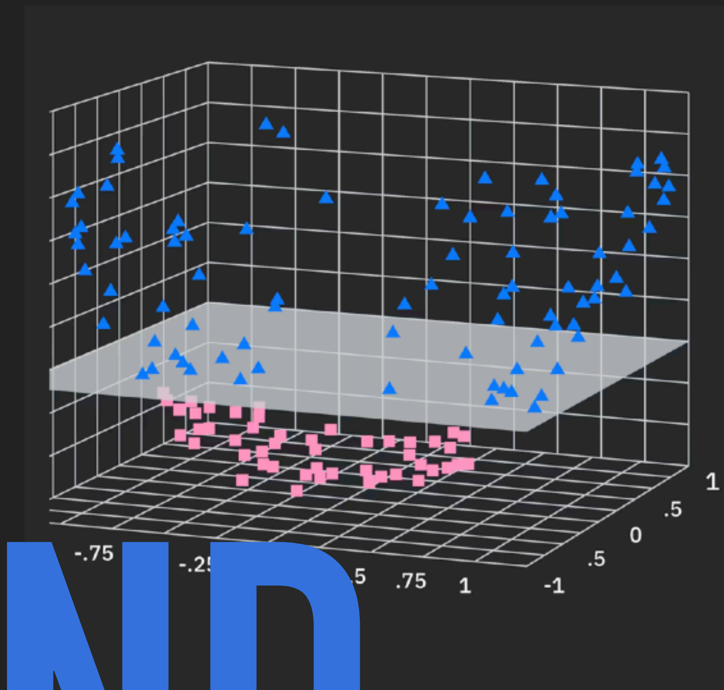
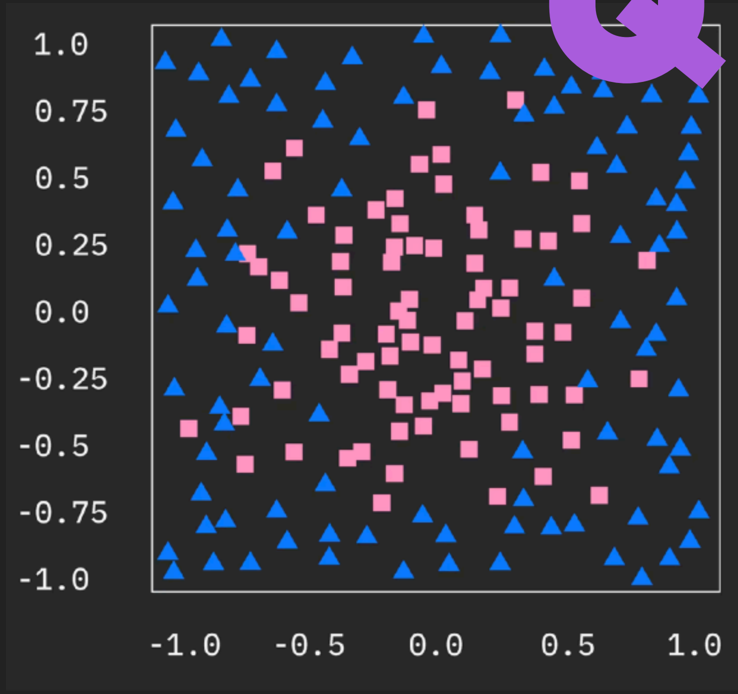
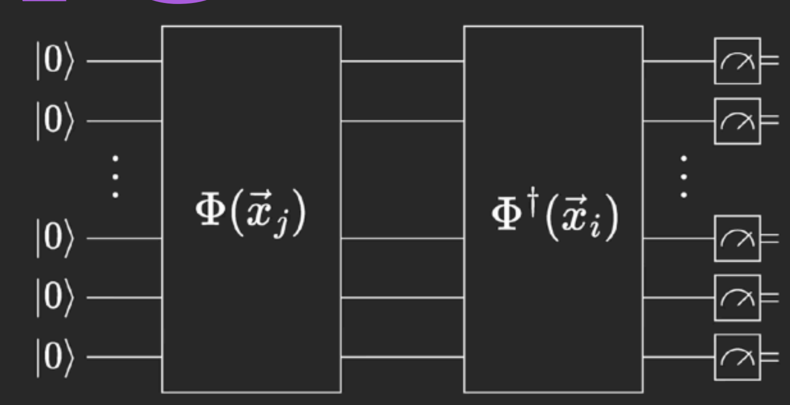




THANKS AND QUESTIONS





$$P_{|0\rangle} = |\langle 0|\Phi^\dagger(\vec{x}_i)\Phi(\vec{x}_j)|0\rangle|^2$$

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