

INAF leads Spoke 3 coleads Spoke 2 member of Spoke 1 member of Spoke 10

INAF

OA—Trieste

OA-Bologna

I. Radioastronomy (BO)

OA-Roma

OA-Catania

STAFF — 33 Months

2 Full

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5 Researcher

WP 1

Numerical simulations Nbody - fluids 1 PhD **UniTS**

45% south

1 TD (2y) **OA Napoli**

WP 2

Multiparameter **Optimisation**

WP 3

Machine Learning catalogs features

1 TD (2y) **OA Catania**

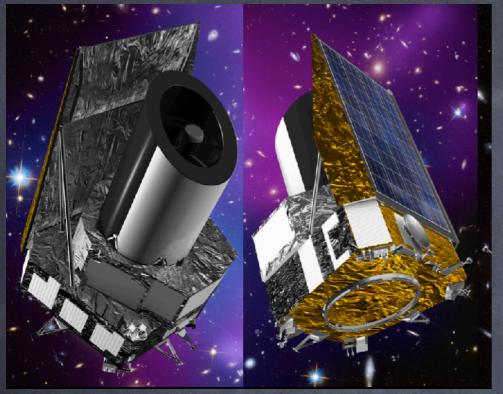
WP 4

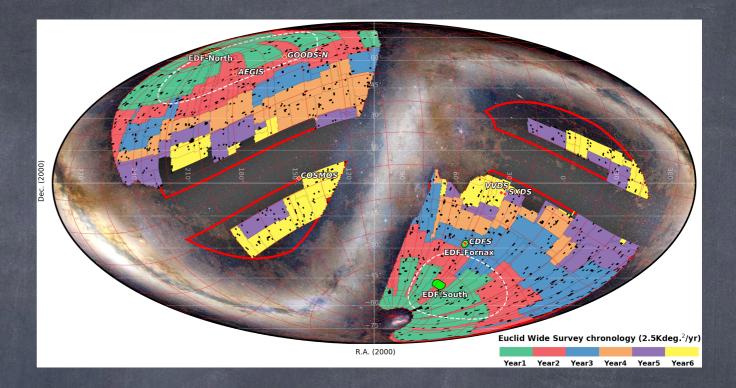
raw data level (radio, pixel) objects, components

1 TD (2y) **OA Catania**

alzignano – 15 October 2024

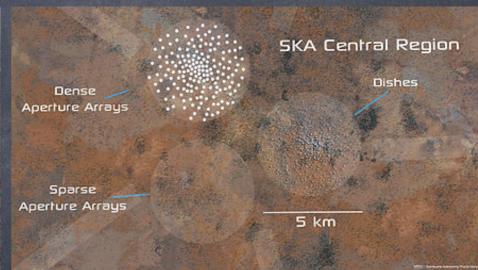
Plenty of HUGE data and problems. Examples: Euclid, SKA











Goals:

- find if some of actual methods/problems can benefit from QC (select some toy models; examine & discard; test most promising with emulators)
- think/investigate NEW ways of approaching old problems

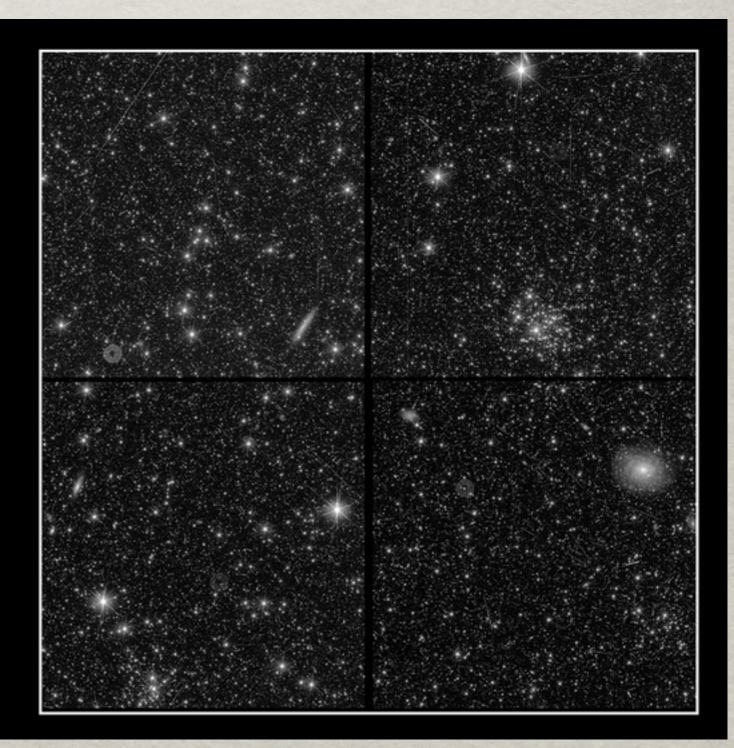


esa

Euclid Mission (Dark Energy, Dark Matter and billions of galaxies: satellite launched July 1st 2023

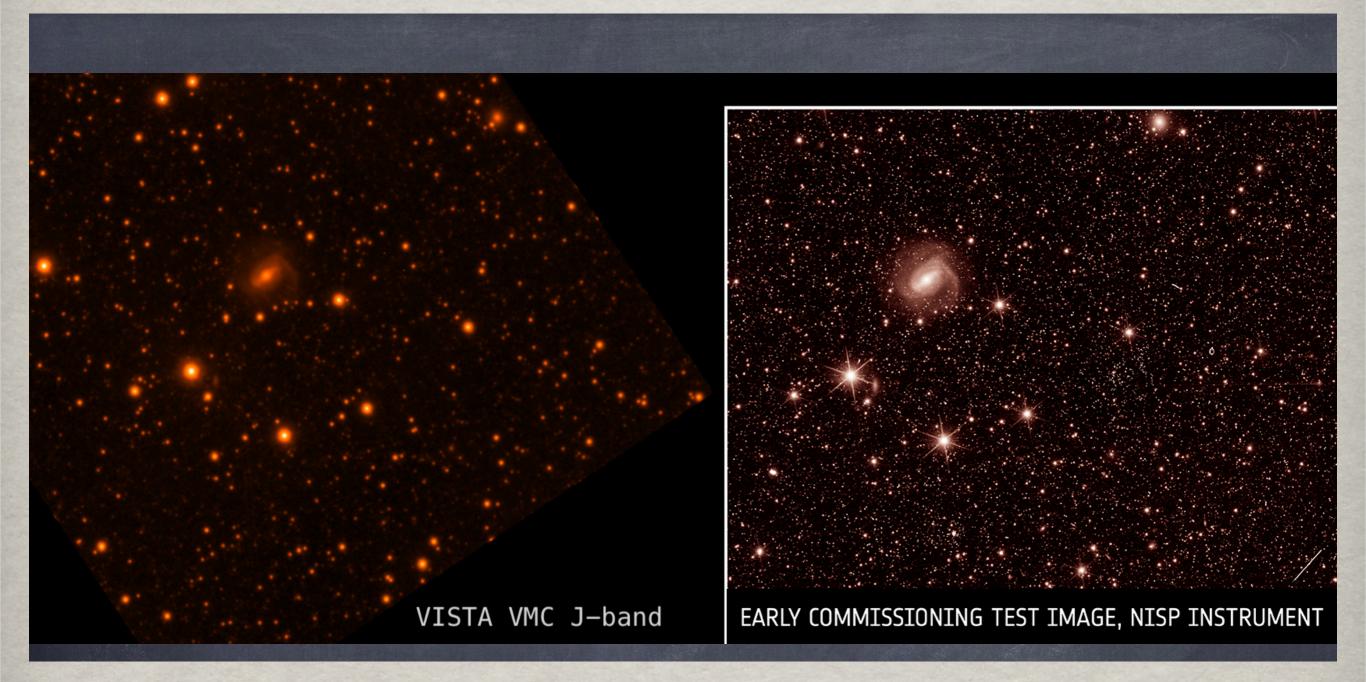
Cost ~1.5 G€, ~150 Science Institutes, ~1500 scientists

EARLY COMMISSIONING TEST IMAGE, VIS INSTRUMENT



Euclid Mission: wide survey started in 2024, end 2030





~ 1/3 of the sky at resolution 0.1"/pix ~ 6E6 large images from two instruments Several billions objects to study

Food for thought

Superposition

Probability

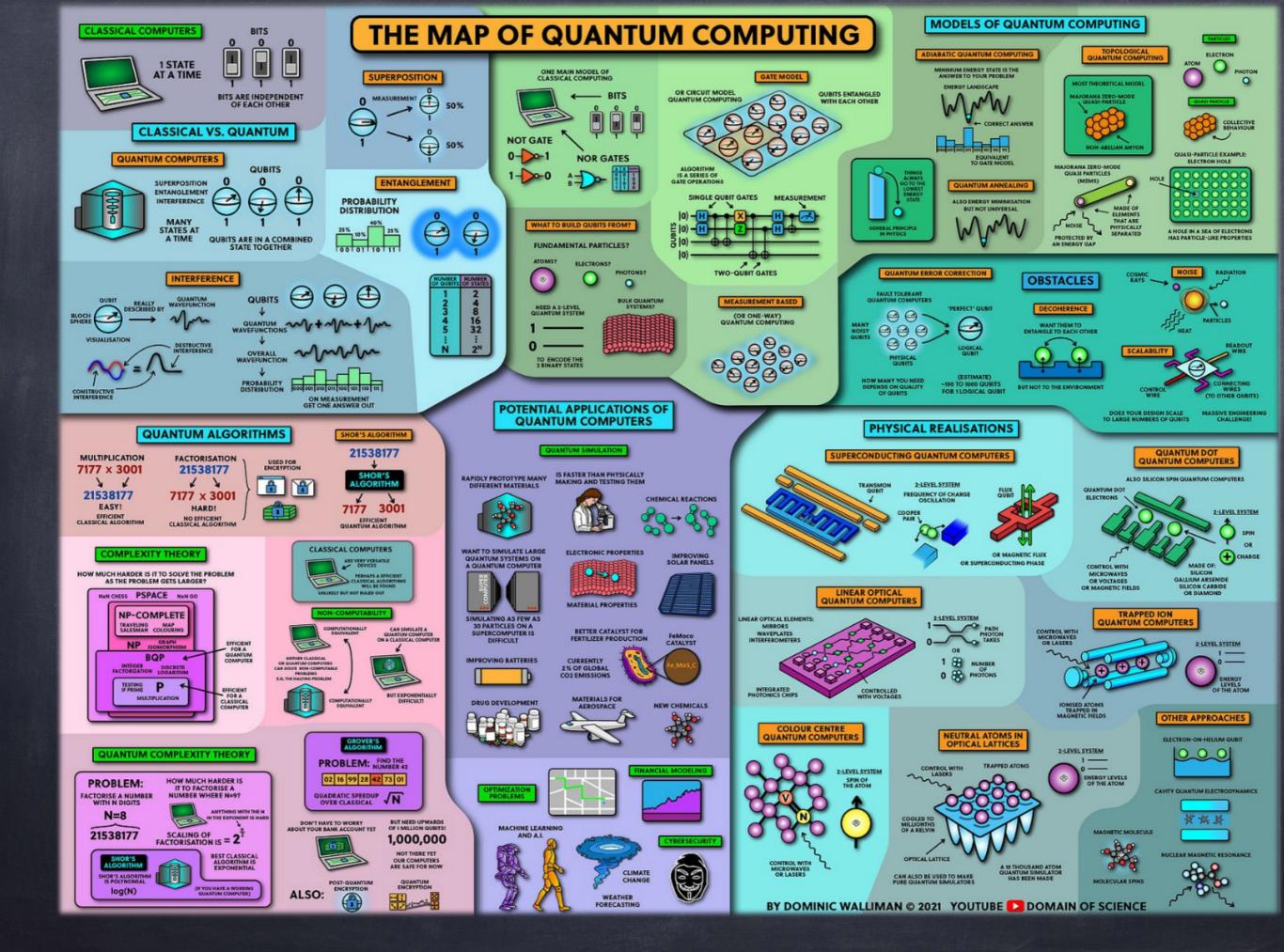
Quantum entanglement

Bell inequalities

Einstein-[Podolski]-Rosen

Hybrid algorithms

Non locality



Quantum computing is...

NOT a general purpose super duper computer

Undergoing FAST hardware evolution (but bottlenecks, errors)





In principle allows a QUANTUM LEAP in selected problems (optimisation, factorisation etc etc)

For the time being is FUN!

Cosmological numerical simulations (Schroedinger -Poisson & Vlasov-Poisson equation) with Quantum Computers

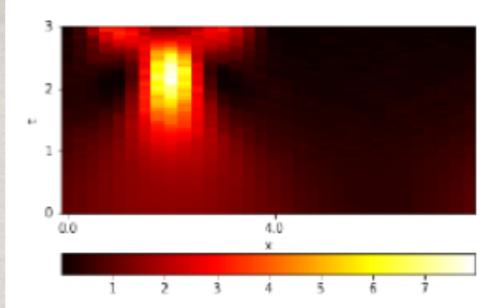
Schroedinger-Poisson:

$$\begin{split} i\hbar\frac{\partial\psi}{\partial t} &= -\frac{\hbar^2}{2m}\nabla^2\psi + mV\psi,\\ \rho &= |\psi|^2\\ \nabla^2V &= 4\pi G(\rho - \overline{\rho}), \end{split}$$

Nonlocal quantum pressure:

$$p_{Q} = -\left(\frac{\hbar}{2m}\right)^{2} \rho \nabla \otimes \nabla \ln \rho.$$

Becomes Euler-Poisson when m tends to infinity



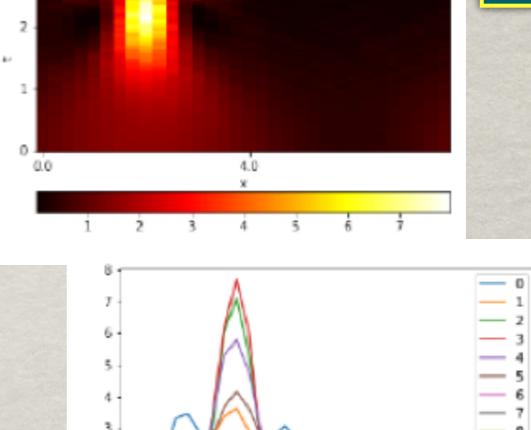


Figure 6.9: Exact potential simulation with a total number of ansatz parameters M = 60. $N_t = 2 \cdot 10^4$, $r_c = 10^{-7}$, No regularization.

1.55

6.2

4.65

- One dimensional
- Following an idea by Mocz & Szasz, 2021, ApJ, 910, 29
- Variational algorithm completely rewritten

Luca Cappelli won the PhD position at Trieste University IBM Zurich collaborates with the PhD project

Research lines for WP1

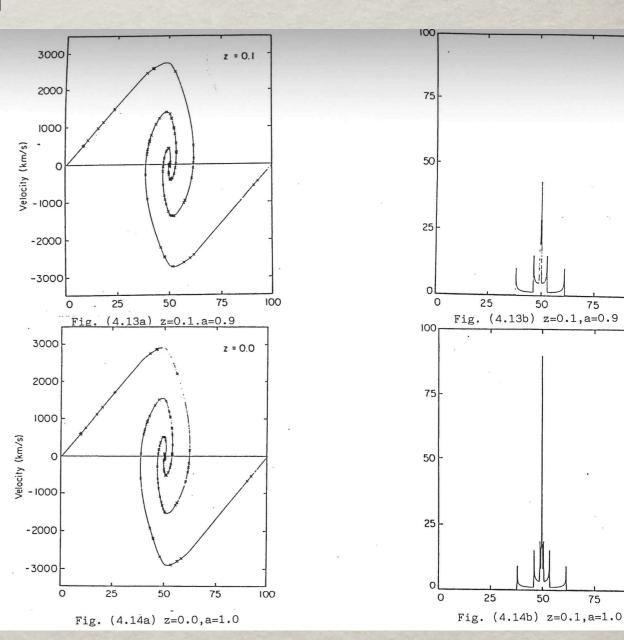


Quantum Technicality

- Study scaling properties of the QC algorithm
- Reduce circuit depth of the variational algorithm
- Implement the algorithm on a real quantum device
- Study the feasibility of 3D simulations
- Study the quantum advantage when m is large

Physics

- Application: fuzzy dark matter
- Comparison of Schroedinger-Poisson with Vlasov-Poisson when the field mass m varies
- Study the possibility to use SP as a proxy for VP, m acting as the softening in a Nbody simulation
- Study if a similar variational algorithm can be applied to hydrodynamics



One-dimensional VP simulation. Left panel: phase space, v vs x. Right panel: density vs x

WP1

Schroedinger vs **Vlasov - Poisson**

- Collisionless dark matter
- Vlasov Poisson equation
- hard to solve numerically
- N body simulations
- Schroedinger equation
- goes to VP for m to infinity

Vlasov-Poisson eq.

Distribution function

$$\begin{cases} f(\boldsymbol{x}, \boldsymbol{v}, t) \\ \rho = \int f(\boldsymbol{x}, \boldsymbol{v}, t) d\boldsymbol{v} \end{cases}$$

- Collisionless particles
- Self interacting potential

$$egin{align} & rac{\partial f}{\partial t} + oldsymbol{v} \cdot rac{\partial f}{\partial oldsymbol{x}} -
abla U \cdot rac{\partial f}{\partial oldsymbol{v}} = 0 \ &
abla^2 U = 4\pi G(
ho -
ho^*) \end{aligned}$$



Schrödinger-Poisson eq.

Quantum field

$$\begin{cases} \psi(\boldsymbol{x},t) \\ \rho \mapsto |\psi|^2 \end{cases}$$

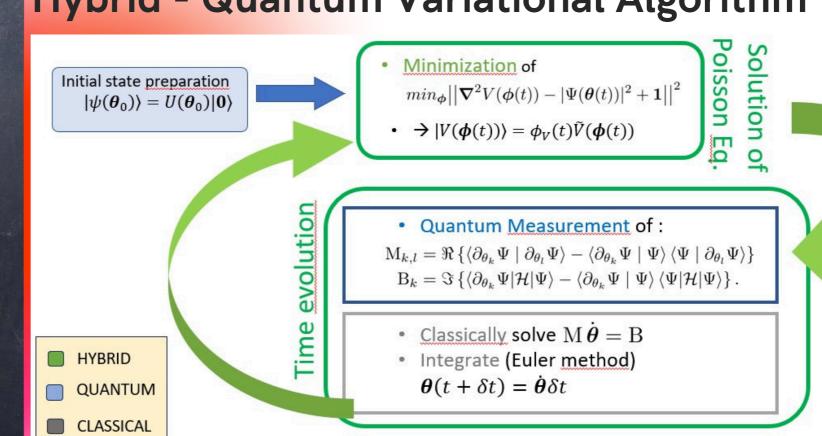
- Non-linear equation
- Efficient on quantum computers

$$\begin{vmatrix} \frac{\partial f}{\partial t} + \boldsymbol{v} \cdot \frac{\partial f}{\partial \boldsymbol{x}} - \nabla U \cdot \frac{\partial f}{\partial \boldsymbol{v}} = 0 \\ \nabla^2 U = 4\pi G(\rho - \rho^*) \end{vmatrix} \stackrel{\mathcal{M}^{-1}}{\underbrace{\int_{\hbar/m \to 0}^{-1} \left| \frac{\partial \psi}{\partial t} - \frac{\hbar}{2m} \nabla^2 \psi + \frac{m}{\hbar} V \psi} \right|}$$

VARIATIONAL ALGORITHM FOR SOLVING SCHROEDINGER EQUATION

CAPPELLI ET AL., 2024, PHYSICAL REVIEW RESEARCH, 6, 013282

Hybrid - Quantum Variational Algorithm



OPTIMISATION PROBLEMS



Combinatorial Optimisation Problems

s input models from a set S and m conditions defining a cost function to be minimised or maximised

examples:

- maximise a cosmological likelihood
- minimise the chisq of a lens model
- choose the specifics maximizing FoM

Quantum Approximation Optimization Algorithm

Quantum Annealing

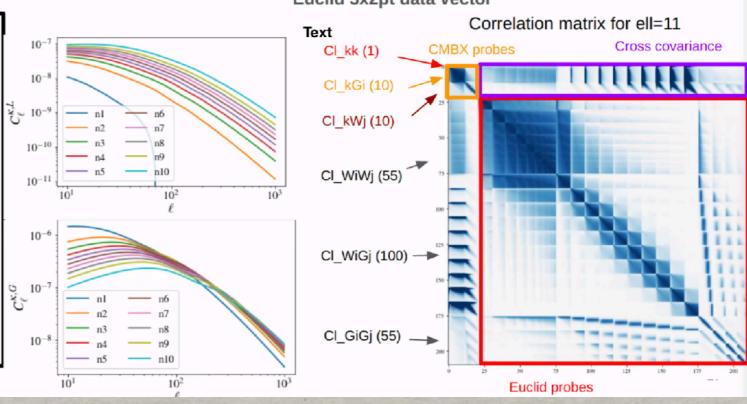
Quantum Evolutionary Algorithm

Joint analysis of Euclid photometric probes and CMB lensing



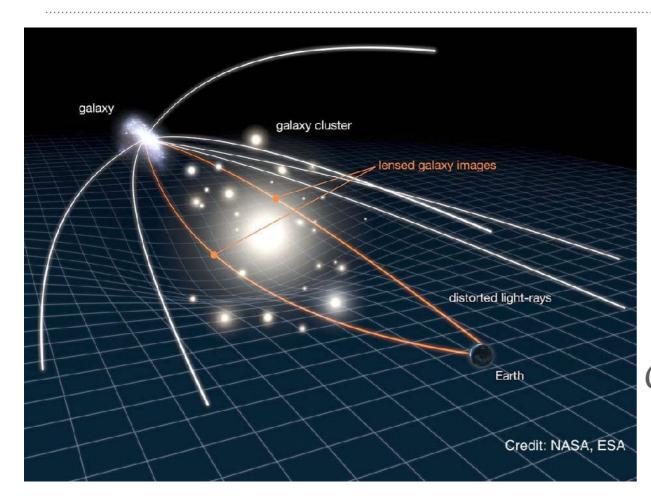
- 6x2 points data vector: CMB-L, Euclid WL and GC phot, cross correlations
- Interface with CLOE (mirror git)
- Limber and Gaussian likelihood (following IST:L)
- Code development progressing well
- Next step is to sample the joint likelihood with mock data

Baccigalupi, Lattanzi, La Casa Euclid CMBXC WP6





GRAVITATIONAL LENSING



 $\overrightarrow{\alpha}(\overrightarrow{\theta}) \propto \nabla \int \Phi(\overrightarrow{\theta}, z) dz$ Gravitational potential

Deflection angle

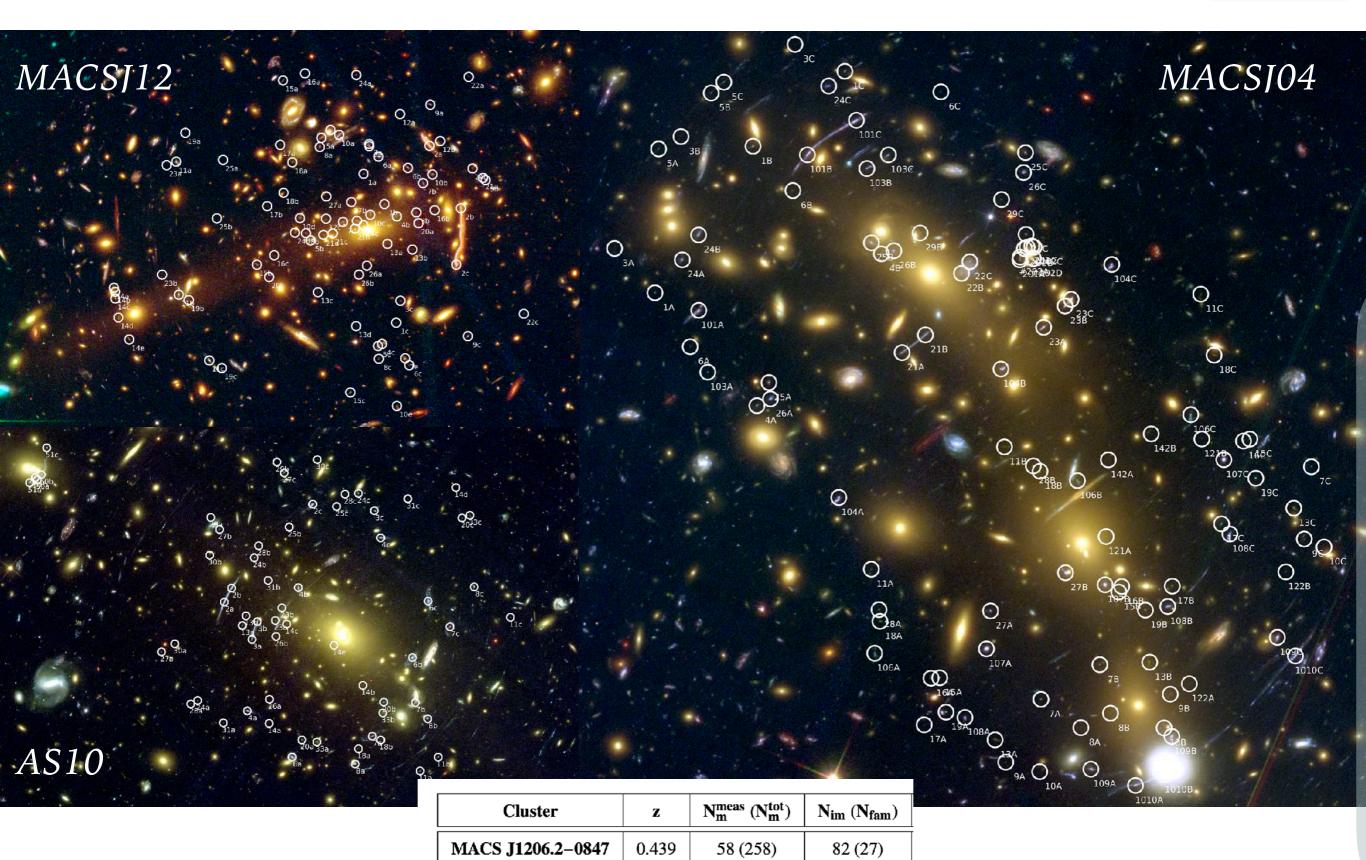
Gravitational lensing: mass-energy curving space time.

Consequences:

- Multiple images (strong lensing SL)
- Distortions:
 gravitational arcs
 (SL), induced
 ellipticities (WL)
- Magnifications

All these effects can be used to recover the mass distribution of the lens (dark matter, gas, stars)





0.396

0.348

49 (193)

37 (222)

102 (37)

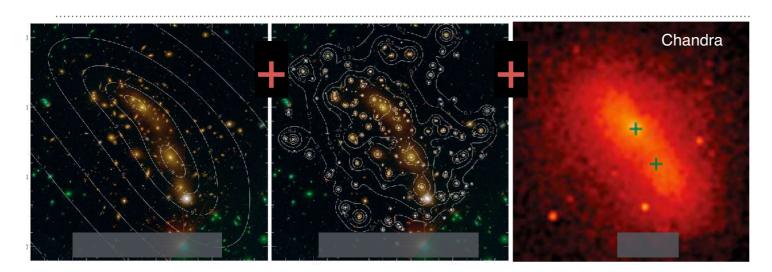
55 (20)

MACS J0416.1-0403

Abell S1063



EXAMPLE: SL MODEL OPTIMISATION



Total gravitational potential is the sum of each component:

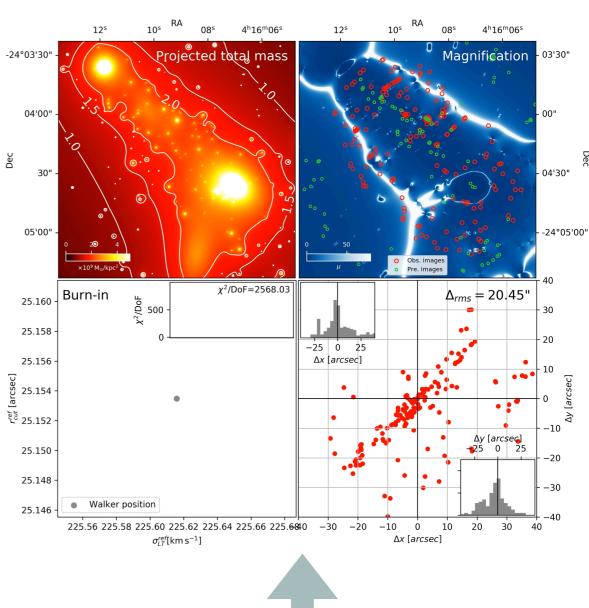
$$\phi_{tot}(\vec{\xi}) = \sum_{i=1}^{N_h} \phi_i^{halo}(\vec{\xi}_{halo}) + \sum_{k=1}^{N_{gal}} \phi_k^{gal}(\vec{\xi}_{gal}) + \phi_{shear}(\vec{\xi}_{shear}) + \phi_{gas}$$

Each mass component is parametrised:

Pseudo (non-singular) Isothermal Ellipsoids:
$$\rho_{PIEMD}(r) = \frac{\sigma_0}{2\pi G(1+r^2/r_{core}^2)}$$

Truncated-Isothermal Spheres:

$$\rho_{sub-halo}(r) = \frac{\rho_0}{(1 + r^2/r_{core}^2)(1 + r^2/r_{cut}^2)}$$



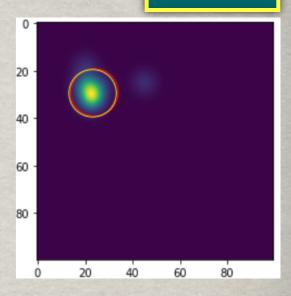


Model optimisation

GRB detection localization in AGILE/GRID data

- We developed a new method for detecting and localizing GRB in the AGILE/GRID sky maps as a reaction to external science alerts.
- The science alerts can have error regions with different sizes depending on the instruments that detected the transient event. For this reason, we trained this method to detect GRBs in the AGILE sky maps located in a radius of 20 degrees from the map center; this radius is larger than 99.5 % of the error region present in the GRBWeb catalog.
- The method comprises two Deep Learning models implemented with two Convolutional Neural Networks. The first model detects if the sky map contains a GRB, and the second model localizes the GRB in the sky maps filtered from the first model.
- We trained and tested the models using simulated sky maps and GRBs. The detection model achieves an accuracy of 95.7 %, and the localization model has a mean error lower than 0.8 degrees.

0 -20 -40 -60 -80 -



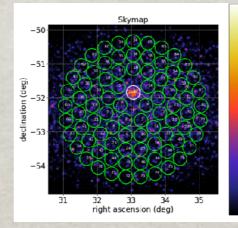
Anomaly detection for GRB search in light curves

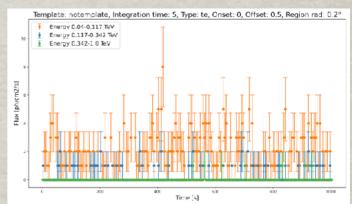
This method performs source detection with a statistical gaussian significance $\geq 5\sigma$.

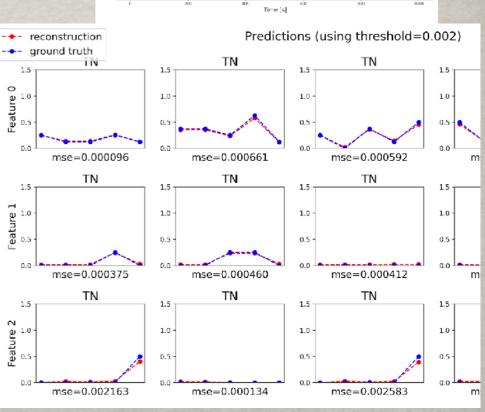
- No assumptions on the source position.
- ullet No assumptions on the source γ -rays emission / background models.

Details:

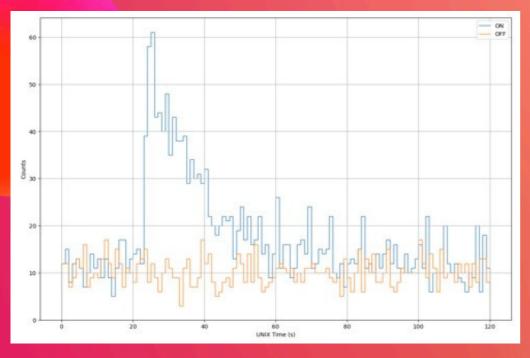
- •the input data is composed by multivariate time series.
- the chosen anomaly detection techniques is based on deep learning (CNN/RNN autoencoders).
- the AE is trained offline with normal samples only (semisupervised approach) and it learns to reconstruct the input, minimizing the reconstruction error.
- •Then, the AE is fed with online data:
 - the reconstruction error for anomalous time series will be higher;
 - () a threshold guides the classification.







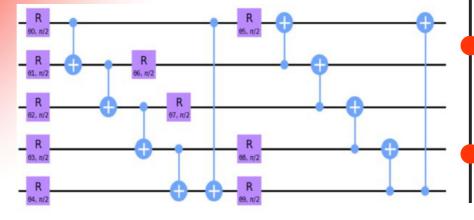
WP3 Quantum Convolutional Neural Network for GRB detection in CTA data



Classical Data

- GRB lightcurves vs noise
- 250 time series for training
- 150 time series for testing
- data mimicking CTA data
- see Farsian, F. et al. (in prep)

Quantum Convolutional Neural Network



QUANTUM CIRCUIT

parameterized in Qiskit

QUANTUM ENCODING

data reuploading method

OPTIMIZATION

performed using the COBYLA optimizer

LOSS FUNCTION

binary cross entropy

Results: 1st implementation (smaller number of parameters in QCNN)

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	99.38%	97.5%	62s

Results: 2nd implementation (only 20 light curves in the training sample)

NN model	Num of Qubits	Num of parameters	Accuracy on Train set	Accuracy on Test set	Time
Classical CNN	-	56	54%	52%	100s
Fully Quantum	6	24	99.7%	98.35%	23s

Quantum Autoencoders for GRB detection in AGILE

 $U3(\theta_1, \phi_2, \lambda_3)$

 $U3(\theta_{10},\phi_{11},\lambda_{12})$

 $U3(\theta_{13}, \phi_{14}, \lambda_1)$

(i) Convolutional circuit 9

Classical Algorithm

- classical convolutional autoencoder
- convolutional variational autoencoder
- encoders composed of 1D convolutions
- decoders composed of 1D transpose convolutions
- works on simulated data and ready to be tested on AGILE ones

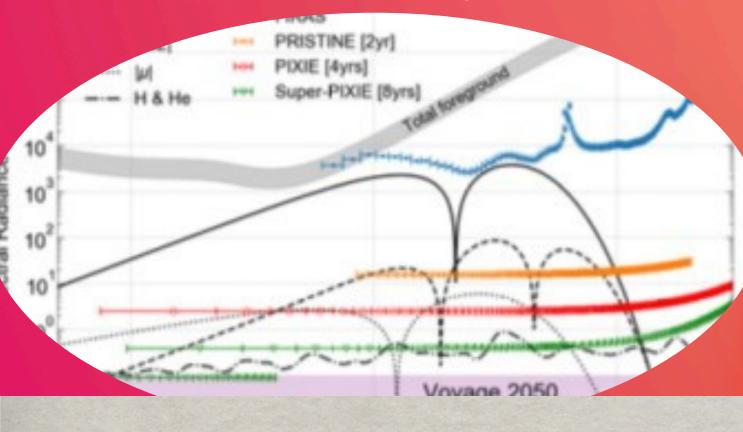
Quantum Algorithm

- quantum encoder + classical latent space + classical decoder
- quantum encoder + quantum latent space + classical decoder
- data reuploading and amplitude embedding as encoding techniques
- 8 qubits and 16 qubits
- interesting preliminary results but work still in progress (A. Rizzo, et al. in prep)

From 1E5 parameters —> 51 parameters!!

WP4 CMB components separation

- CMB maps as sum of different contributions
 - cosmological signal (anisotropy power spectrum)
 - galactic foregrounds (e.g., synchroton and thermal dust)
 - Cosmic Infrared Background)
 - extragalactic radio and far IR sources
- difficult to separate and time consuming



Research Plan

- different spectral features
- already available methods, e.g.
 - template fitting
 - internal linear combination
 - PCA decomposition
- develop quantum counterparts of classical methods

217 GHz .

• use Quantum Machine Learning techniques

WP2 Multiparameter Optimisation

COSMOLOGY

Constraining a small set of cosmological parameters in a sea of nuisance ones

STRONG LENSING

Constraining halo dark matter profile marginalising over single galaxies ones

SAMPLING

Reconstructing the posterior density in many dimensional spaces

Fitness Evaluation (Classical)

Individual Selection and repopulation (classical)

Quantum Encoding (with

superposition)

First tests

Quantum Genetic Algorithm

FINDING BEST FIT
COSMOLOGICAL
PARAMETERS FROM THE
FIT TO SNEIA, BAO AND

CMB DATA

Quantum Crossover + Mutation

> Quantum Deconding

FITNESS EVALUATION

quantify the agreement between model and data

QUANTUM ENCODING

encode model DNA through amplitude encoding

QUANTUM CROSSOVER AND MUTATION

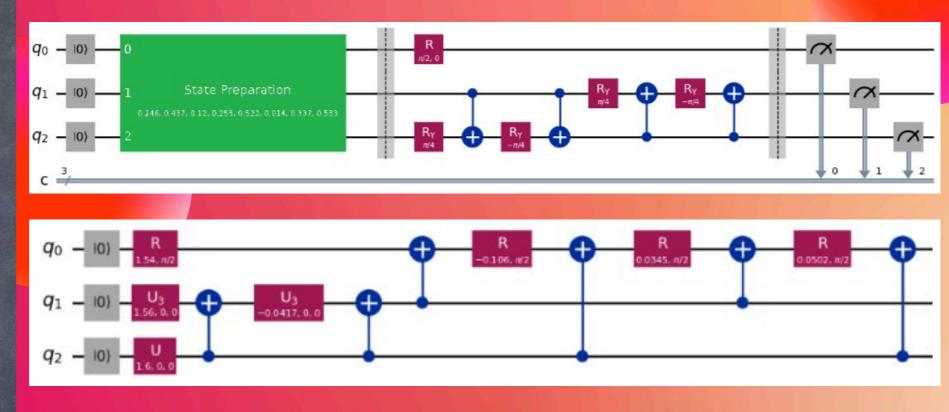
use quantum operations for genetic operations

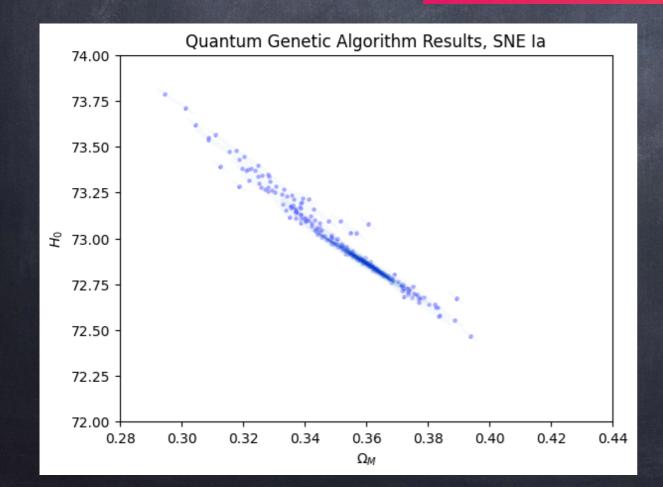
QUANTUM DECODING

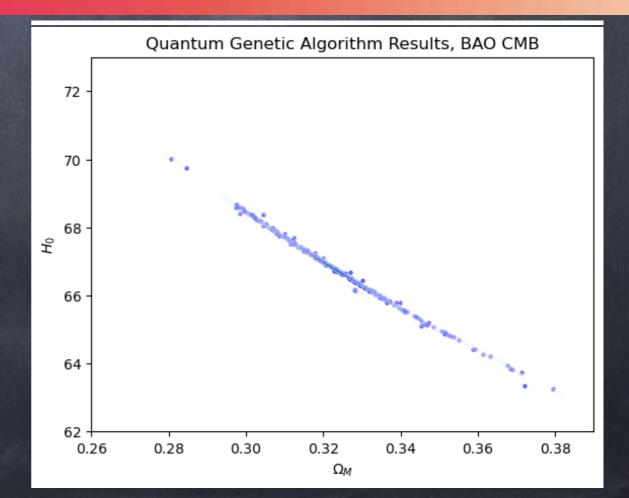
decoding back to classical algorithm and iterate

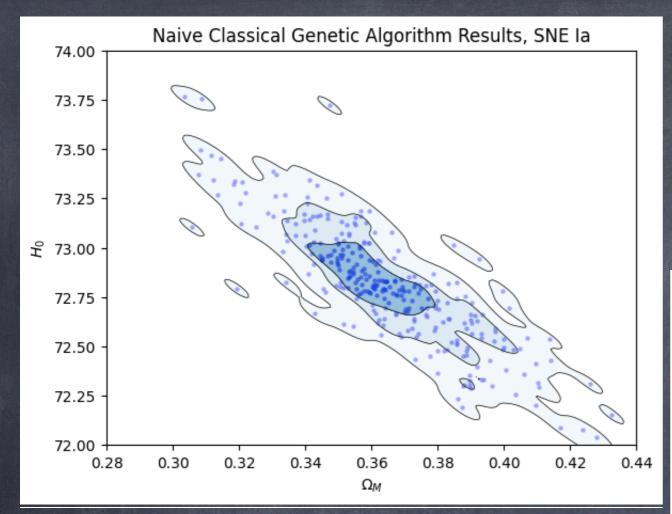
Find best Ω_0 and H_0 from SN and CMB

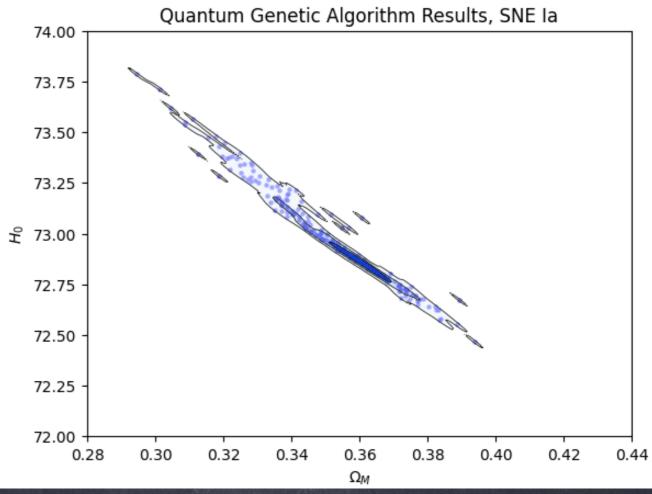
Quantum Genetic Algorithm Circuit











Quite encouraging!!

Stay tuned ...