Quantum Computing for Optimization and Sampling of Cosmological Functions

BAO, CMB, SNE IA, AND QUANTUM ALGORITHMS

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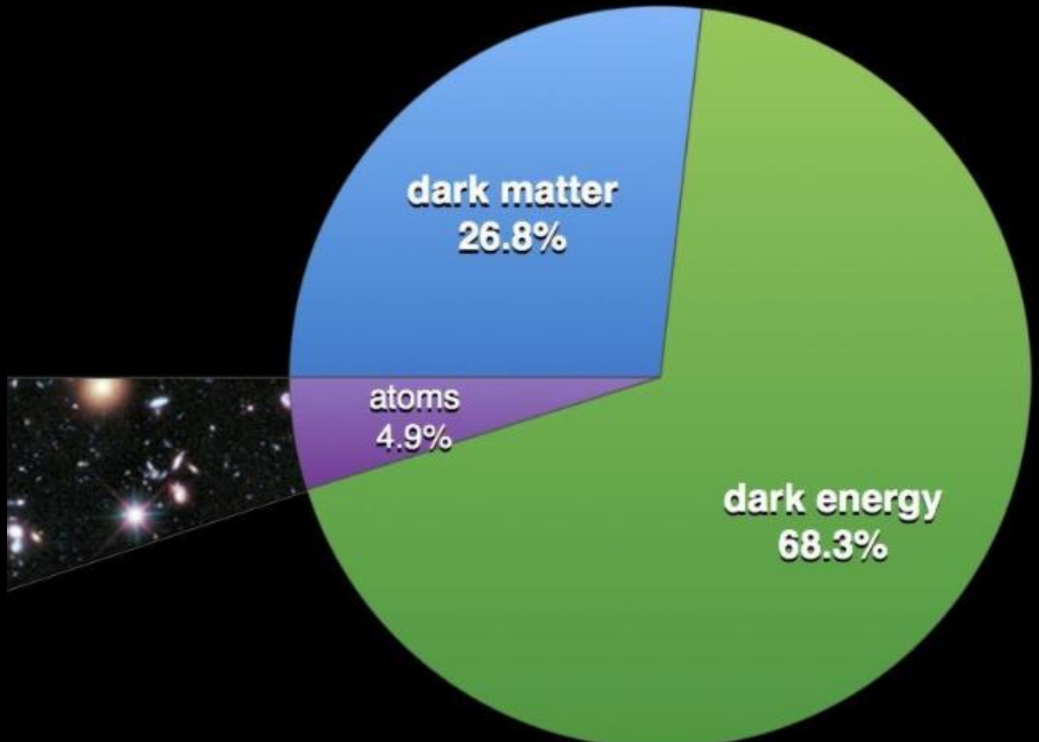
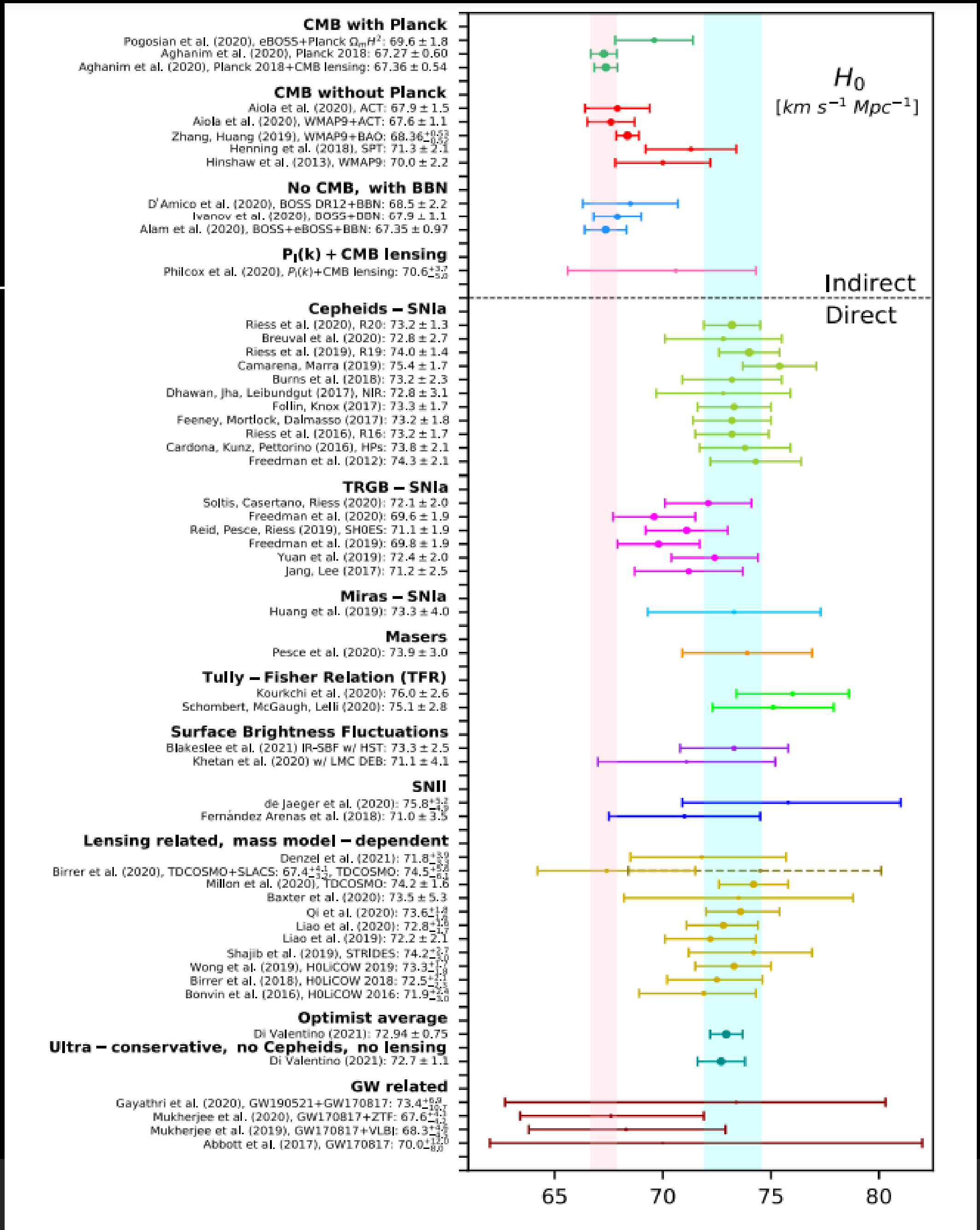
10/03/2026, Trieste

Investigating cosmological parameters.



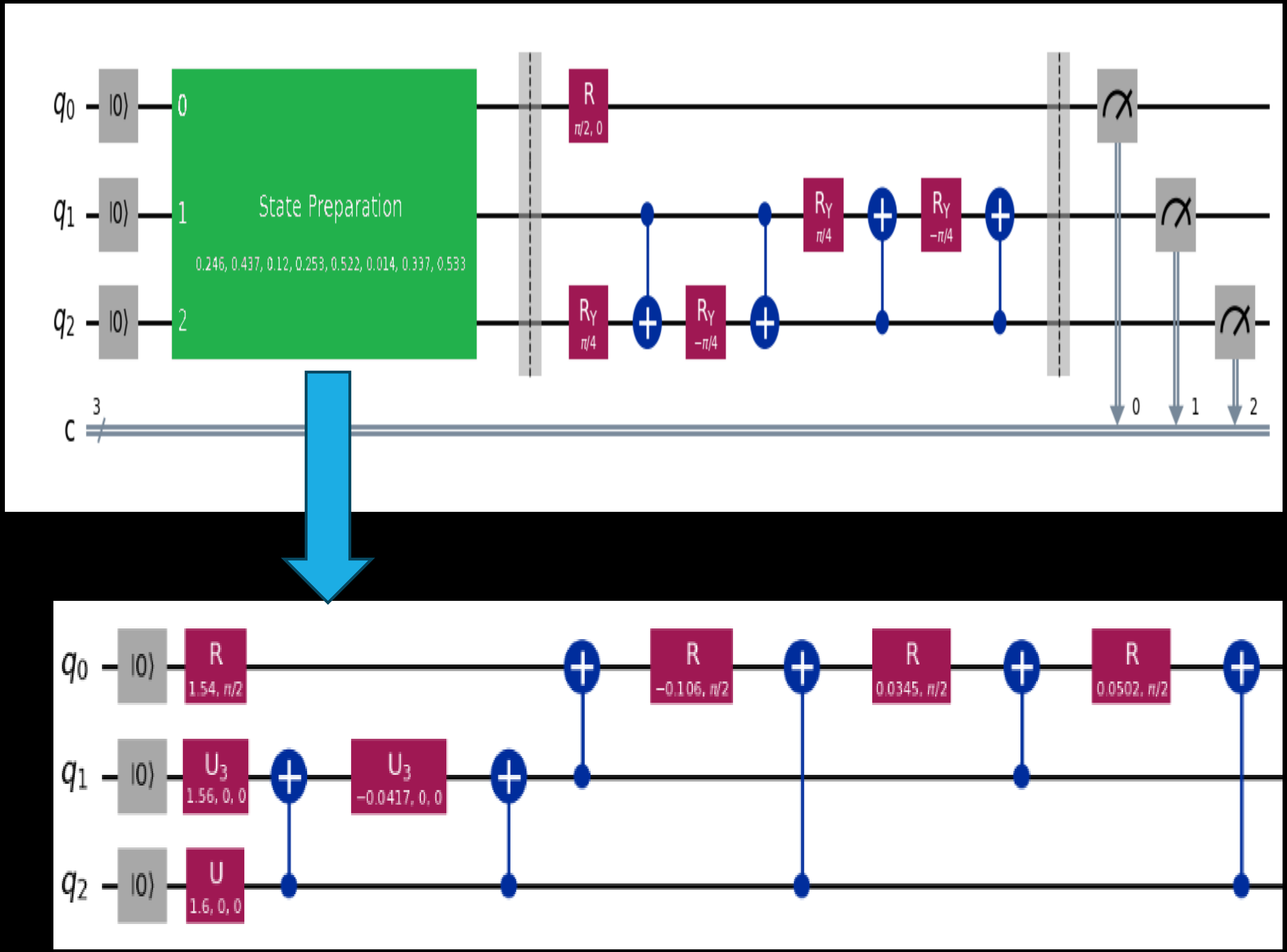


Quantum Genetic Algorithm: Workflow

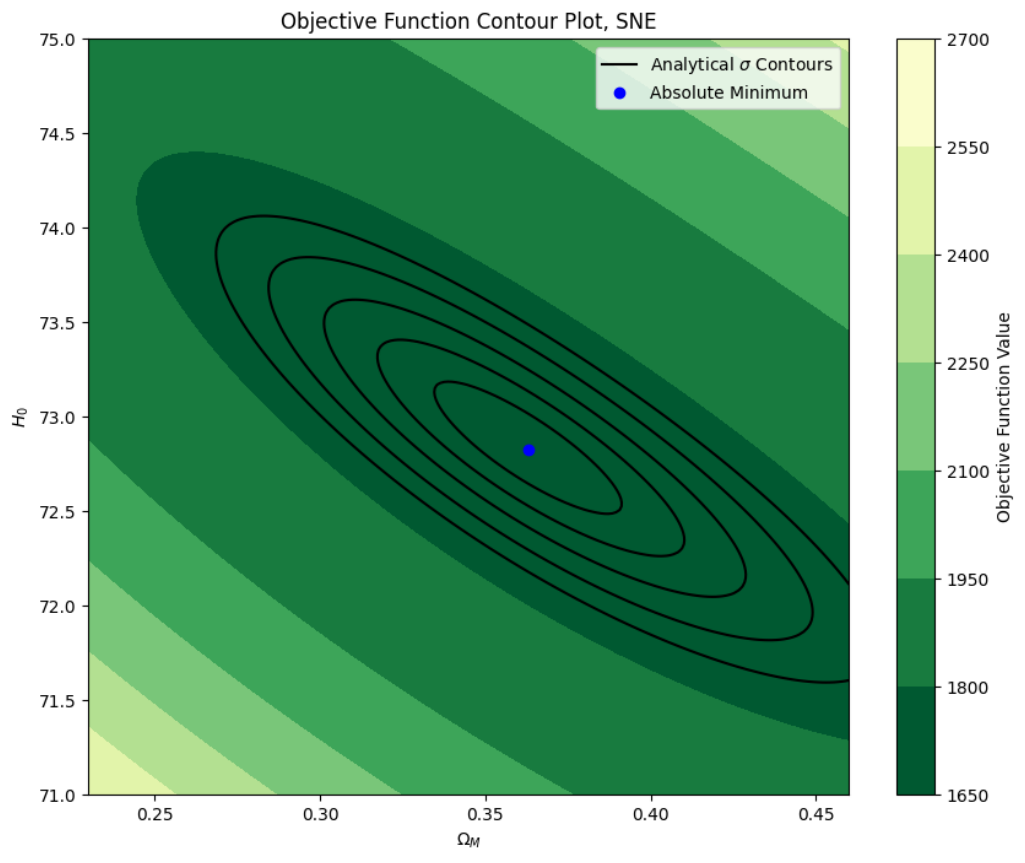
https://arxiv.org/abs/2602.15459

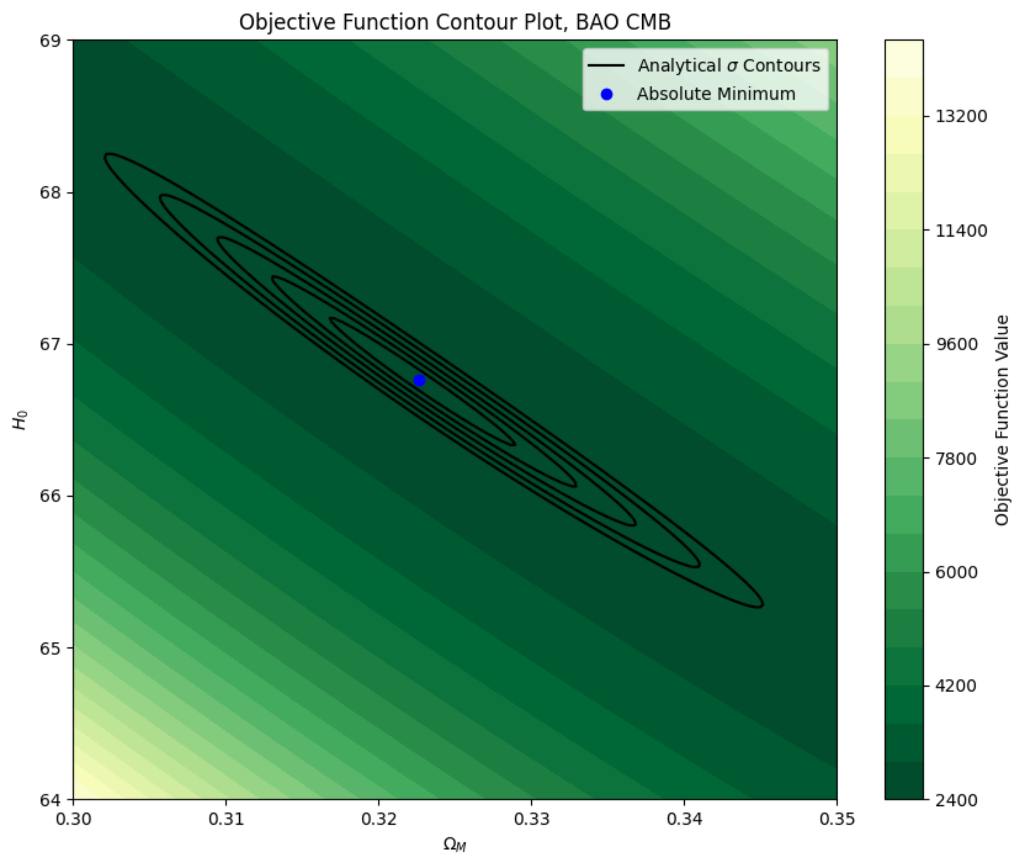
- Merit function Evaluation (Classical), evaluation of the chi-squared for the cosmological functions to find the minimization parameters
- Individual Selection and Repopulation (Classical, duplication of the selected individuals)
- 2 quantum circuits, one for the duplicated best data and the other for the rest of the population (random), while keeping the best individuals. Quantum Encoding
- Quantum Superposition (already implemented in the encoding)
- Quantum Crossover + Mutation
- Quantum Decoding

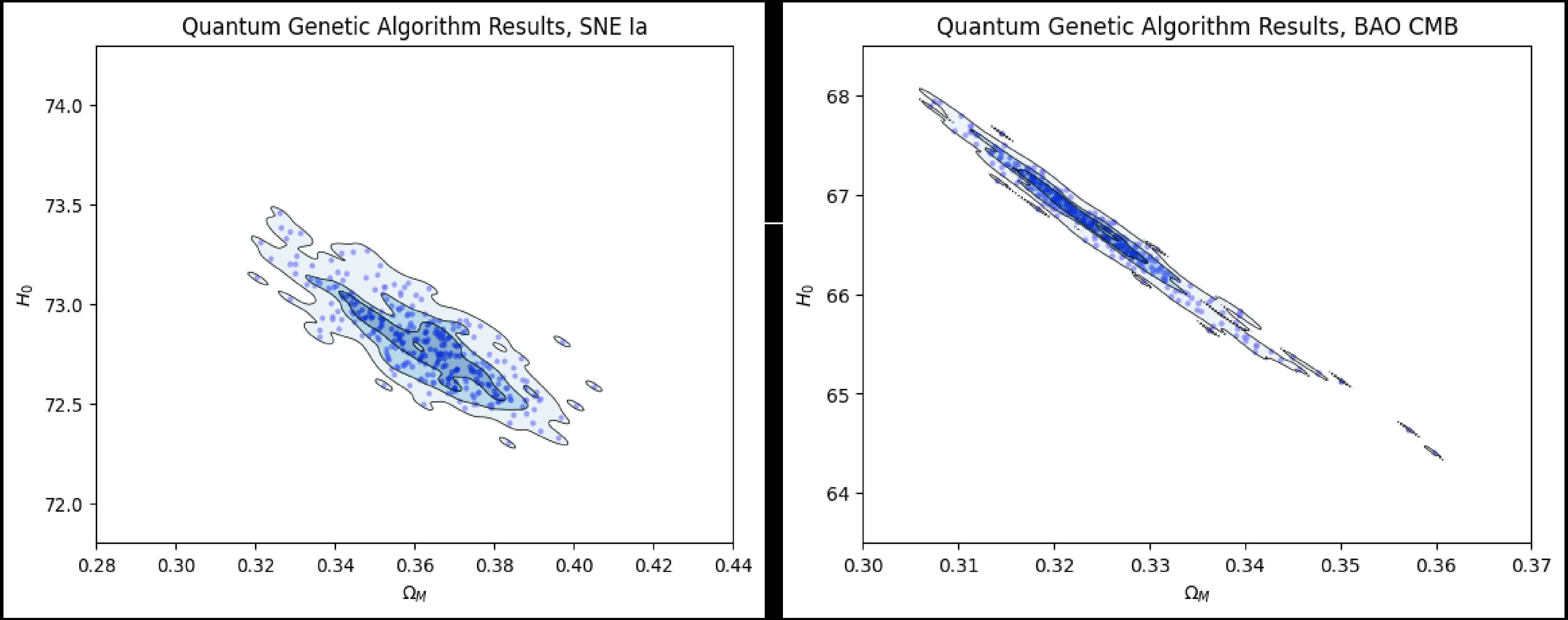
formulation for the quantum circuit for 3 qubits



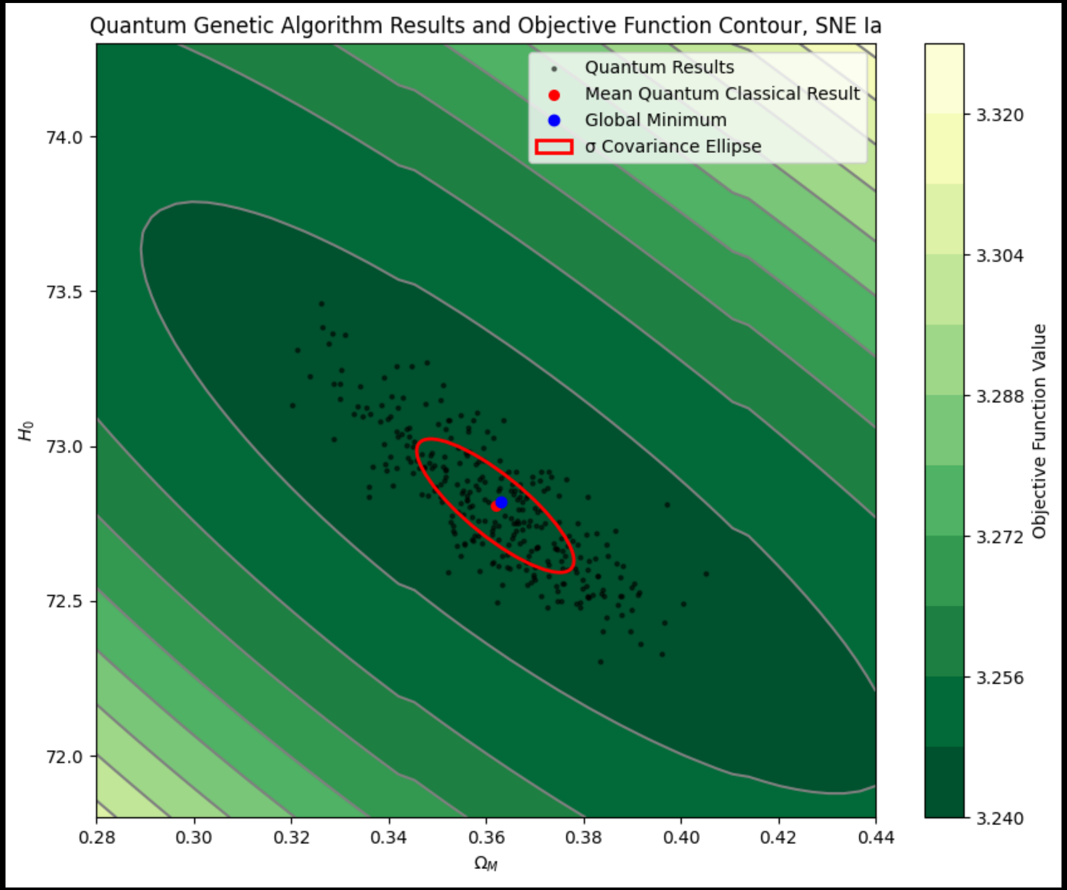
Contour Maps for the Cosmological Objective functions

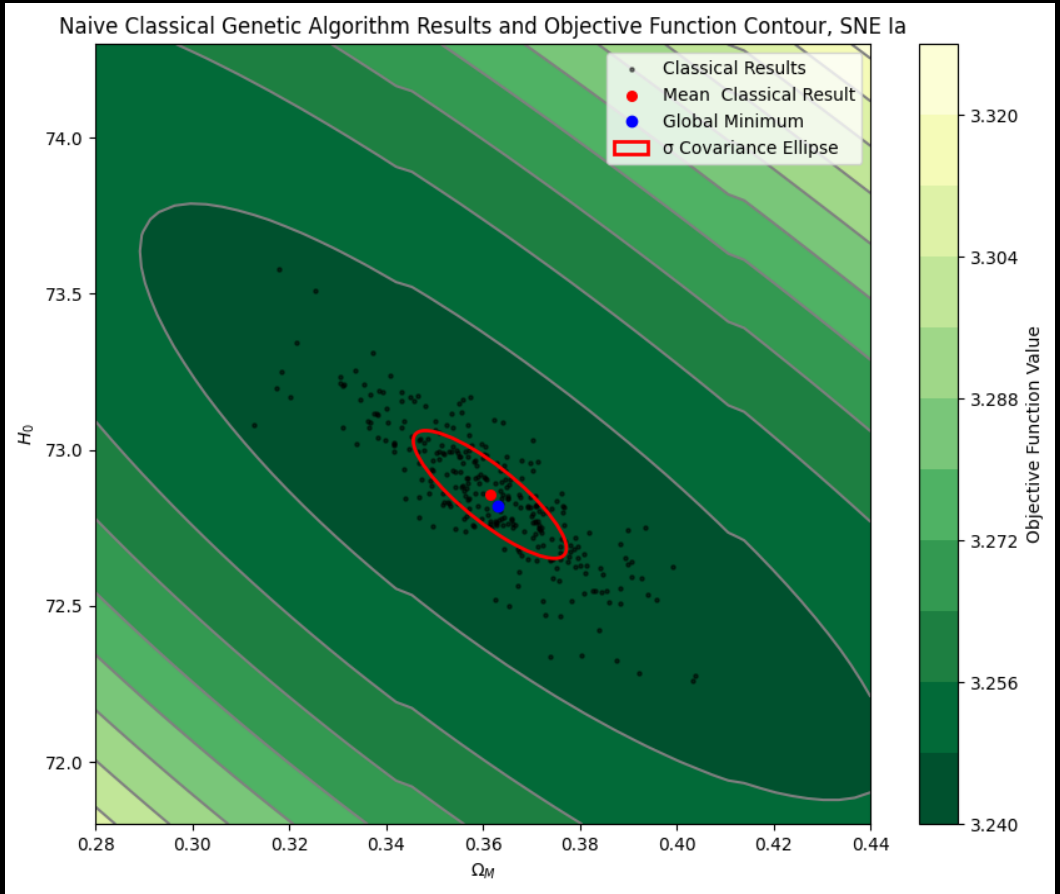






Results (SNe IA left, CMB+BAO right)

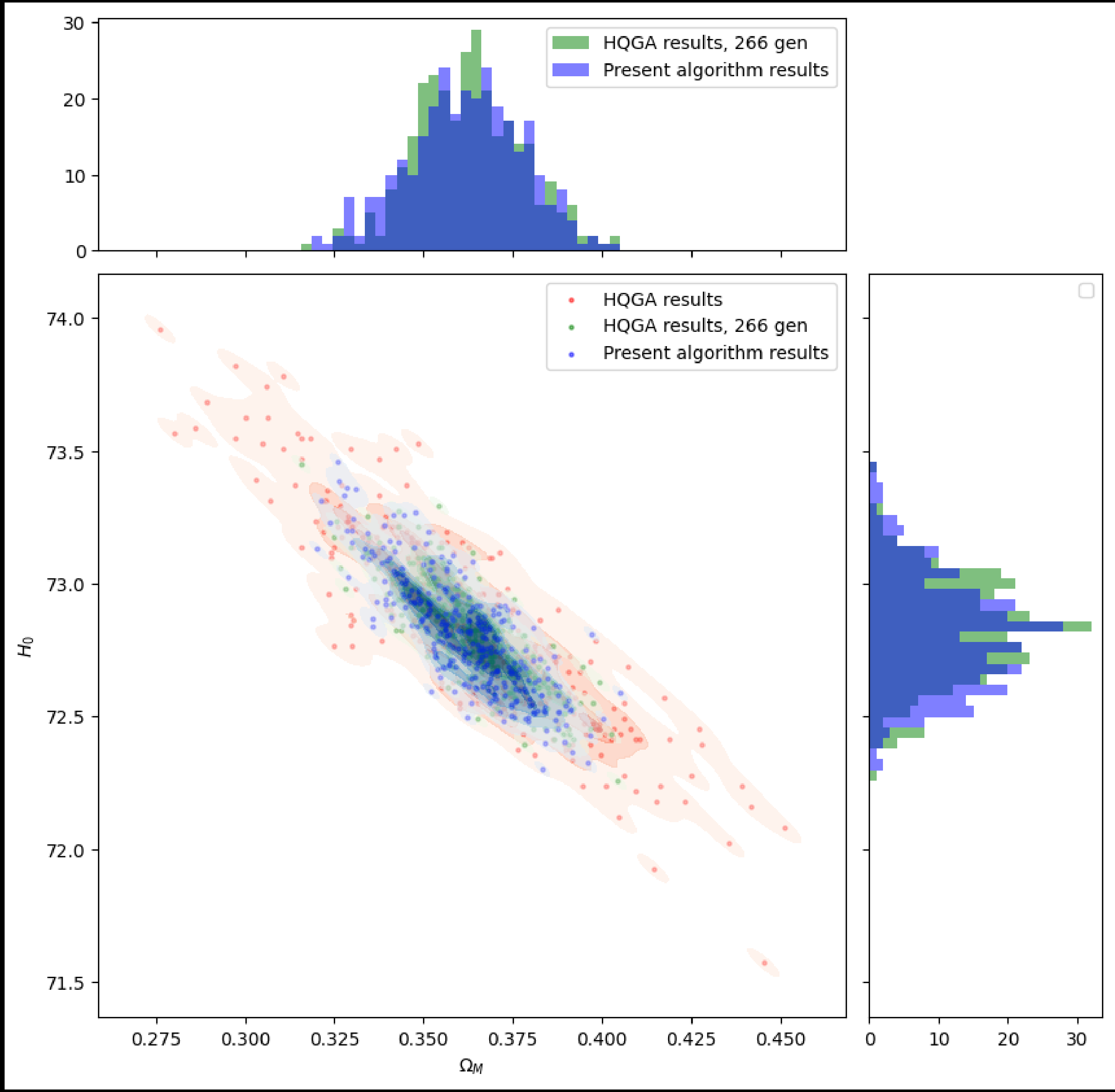




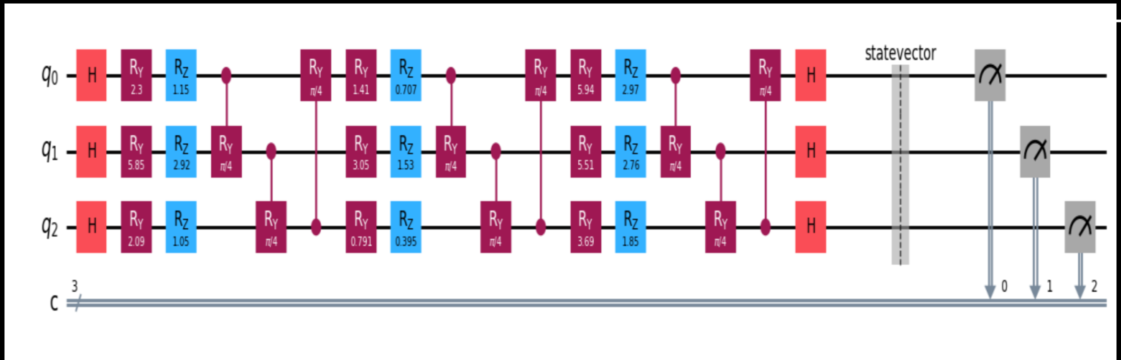
Comparison with classical algorithms (2)

Comparison with HQGA

Hybrid Quantum Genetic Algorithm (HQGA, Acampora et al. 2021) is a quantum genetic algorithm following a different philosophy from ours, but even so the results are comparable if the number of merit evaluation is similar.



The Quantum MCMC (Quantum Step, Classical Evaluation)



$$\mathbf{s} = \mathbf{i} \cdot \mathrm{Re}(\mathbf{v}) \cdot f(\mathrm{Im}(\mathbf{v})) \quad (7)$$

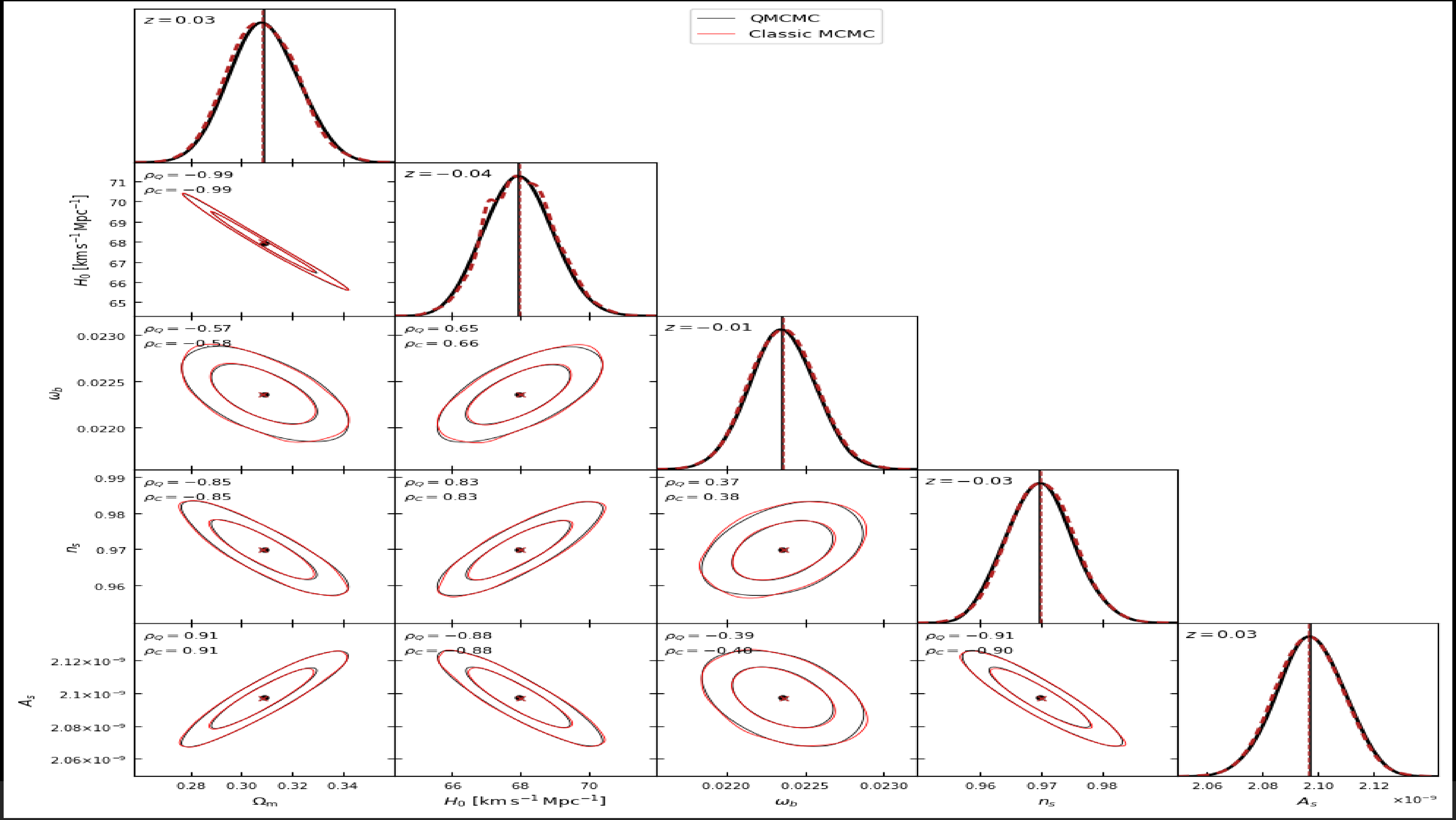
https://arxiv.org/abs/2509.09395

Algorithm 1 QMCMC Algorithm

Initialize:
- Number of dimensions d - Parameter bounds - Initial step size $\mathbf{i}$ - Initial point(s) for chains - Number of chains - Convergence criteria (τ, $R-1$) and frequency n - Prior (facultative) - Number of burn-in steps

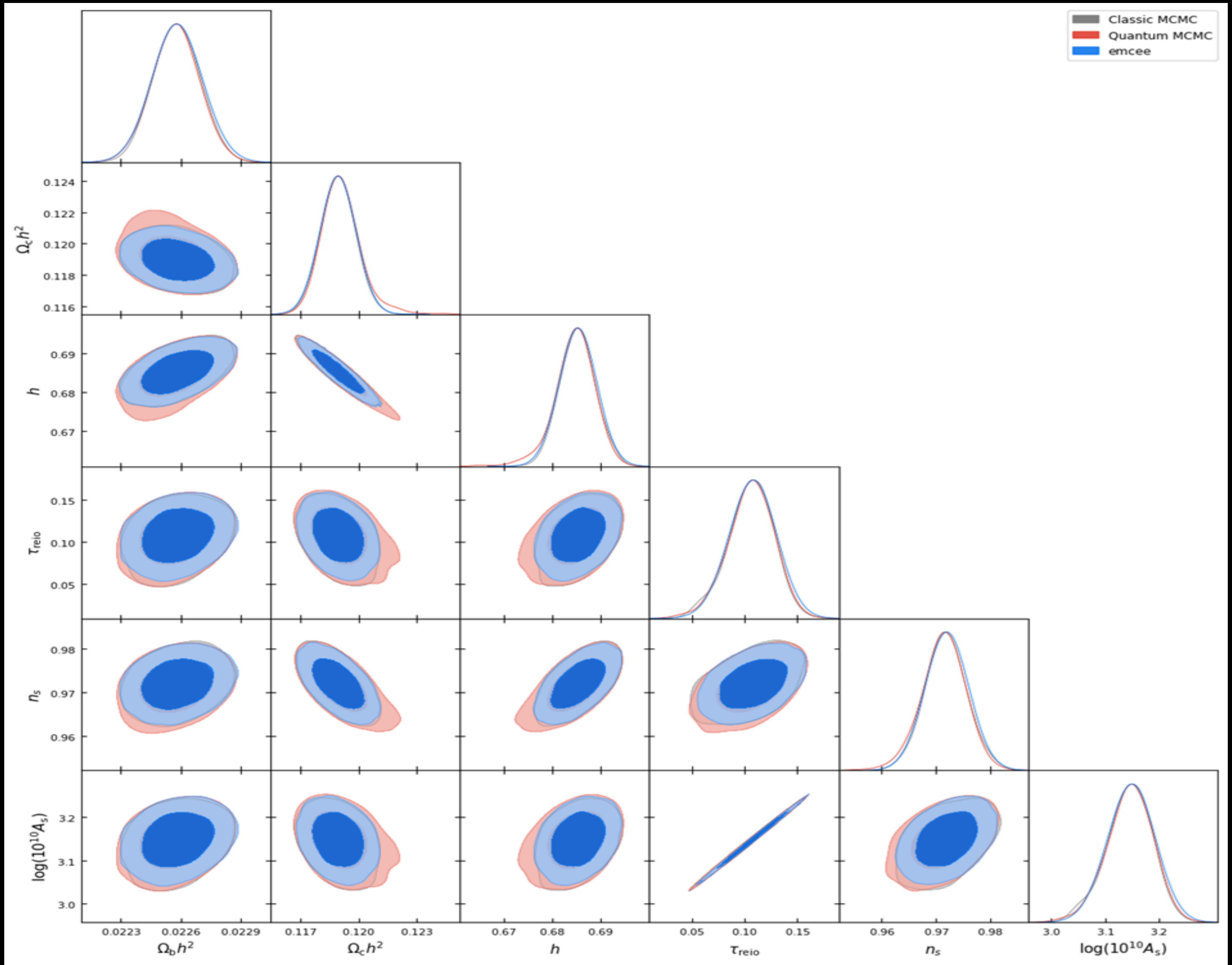
while convergence not reached **do**
    for each chain **do**
        Generate quantum statevector $\mathbf{v}$
        Compute shift as in Eq. 7.
        Propose new point using step $\mathbf{s}$
        Evaluate acceptance probability via Metropolis-Hastings, accept or reject accordingly
    end for
    if step $\mod n == 0$ **then**
        Compute convergence diagnostics:
        - Autocorrelation time τ
        - Gelman-Rubin $R-1$ statistic
    end if
end while
Save chains for posterior analysis (e.g., Bayesian contours)

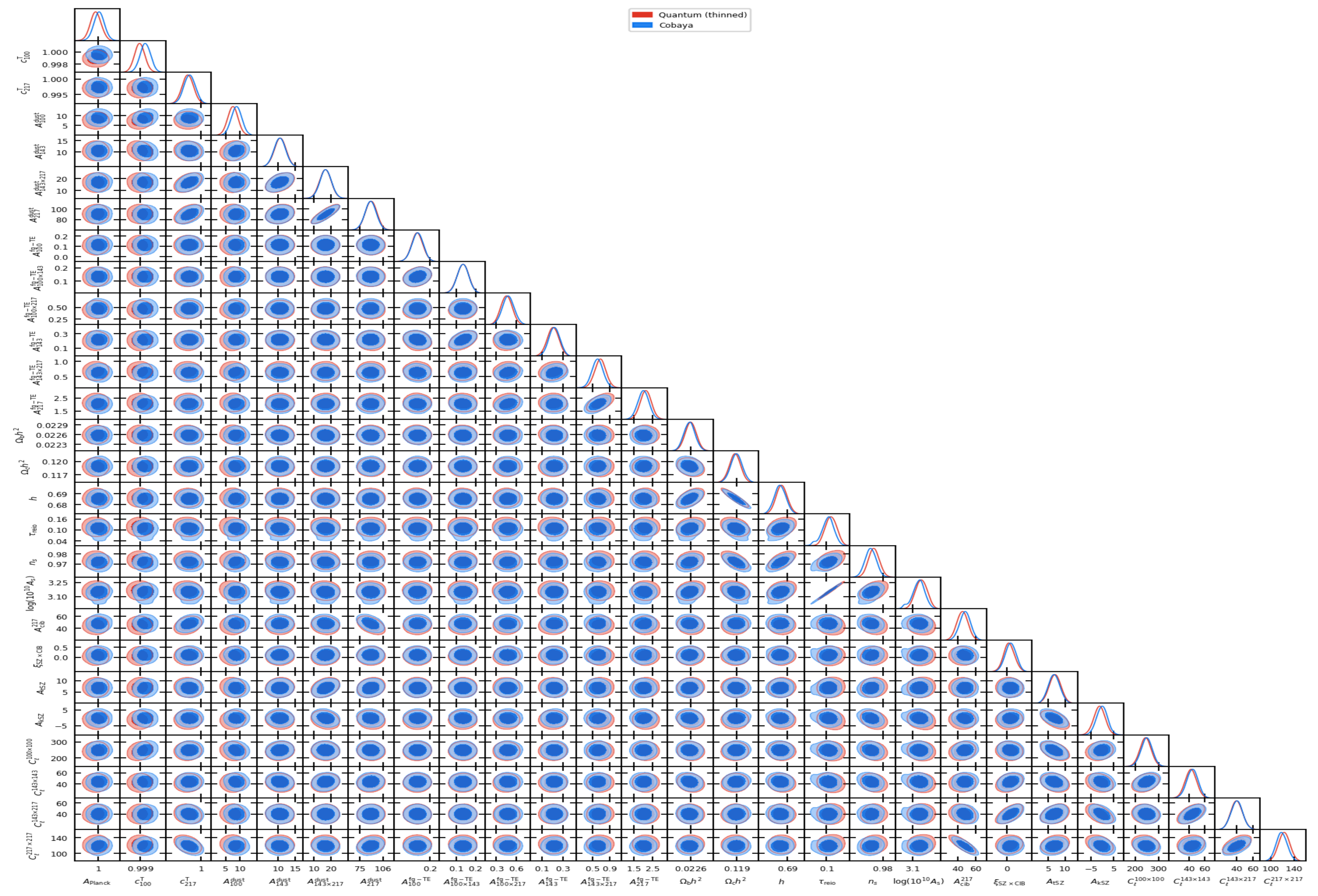
Results : CMB



QMCMC
Classic MCMC
$z = 0.03$
$z = -0.04$
$z = -0.01$
$z = -0.03$
$z = 0.03$
$\rho_Q = -0.99$
$\rho_C = -0.99$
$\rho_Q = -0.57$
$\rho_C = -0.58$
$\rho_Q = 0.65$
$\rho_C = 0.66$
$\rho_Q = -0.85$
$\rho_C = -0.85$
$\rho_Q = 0.83$
$\rho_C = 0.83$
$\rho_Q = 0.37$
$\rho_C = 0.38$
$\rho_Q = 0.91$
$\rho_C = 0.91$
$\rho_Q = -0.88$
$\rho_C = -0.88$
$\rho_Q = -0.39$
$\rho_C = -0.40$
$\rho_Q = -0.91$
$\rho_C = -0.90$
H_0 [km s^{-1} Mpc^{-1}]
ω_b
n_s
A_s
Ω_m
$\times 10^{-9}$

Results (2): CMB+SNe Ia+BAO, using the proper CMB likelihood





Results (3): CMB+SNe Ia+BAO, using the proper CMB likelihood, 27 Parameters

Conclusions

1) A hybrid QMCMC has been built to find Bayesian contours for cosmological functions, while a Quantum Genetic Algorithm has been built to minimize them.

2) These algorithms has been tested with different probes and functions, finding results which are consistent with classical computations.

3) Given that the likelihood evaluations remain classical, a speed up has to be found in the number of evaluations necessary to reach convergence.

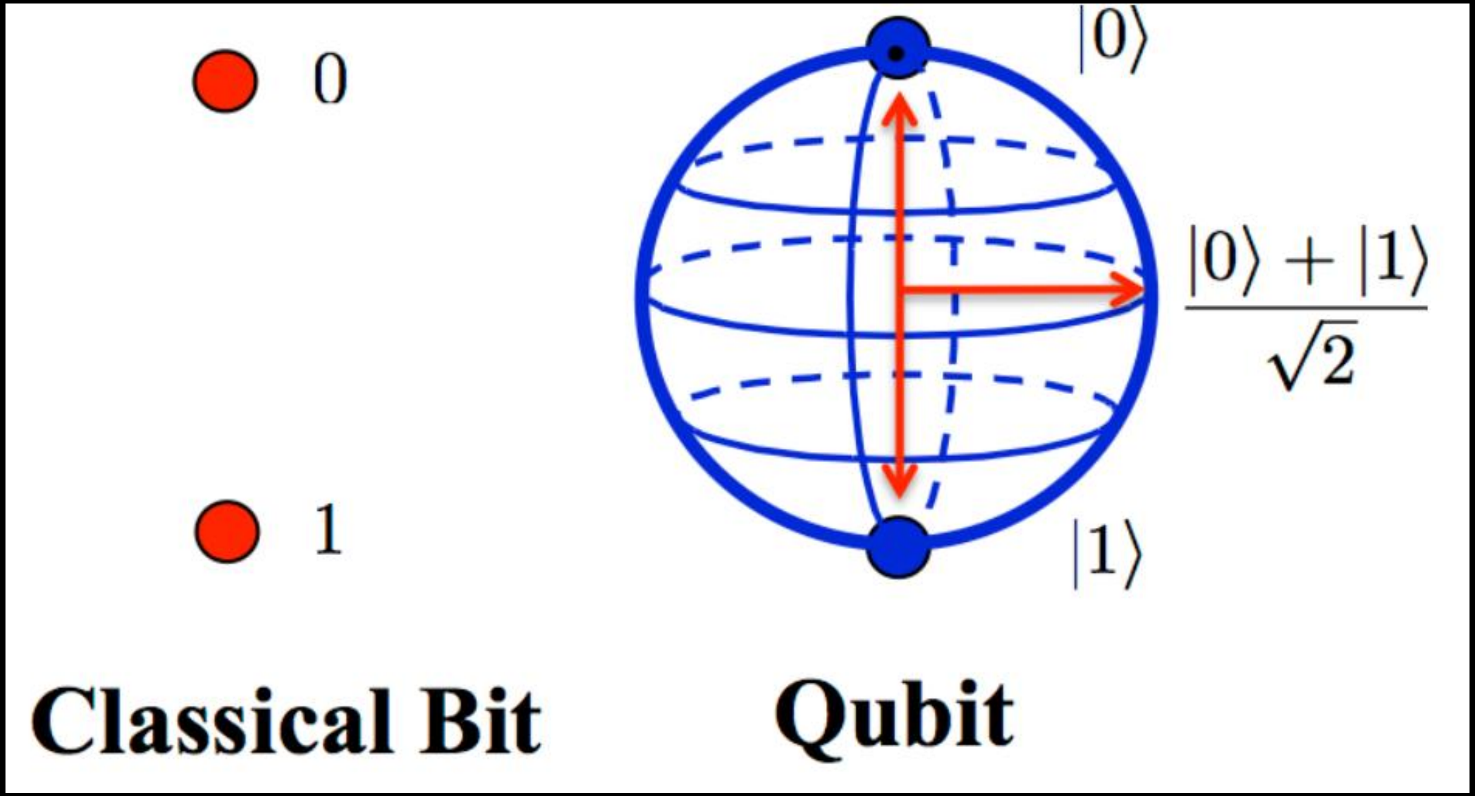
4) A possible outlook is to test these algorithms with combinations of different cosmological functions into a complex parameter space.

Back-up Slides.

The Qubit

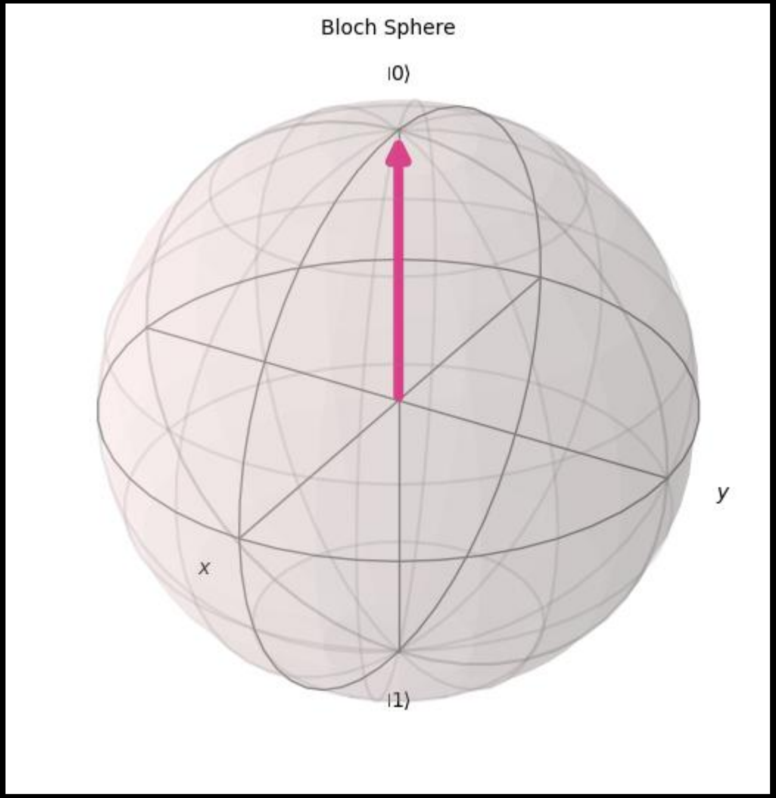
The Fundamental Concepts used to build the Qubit:

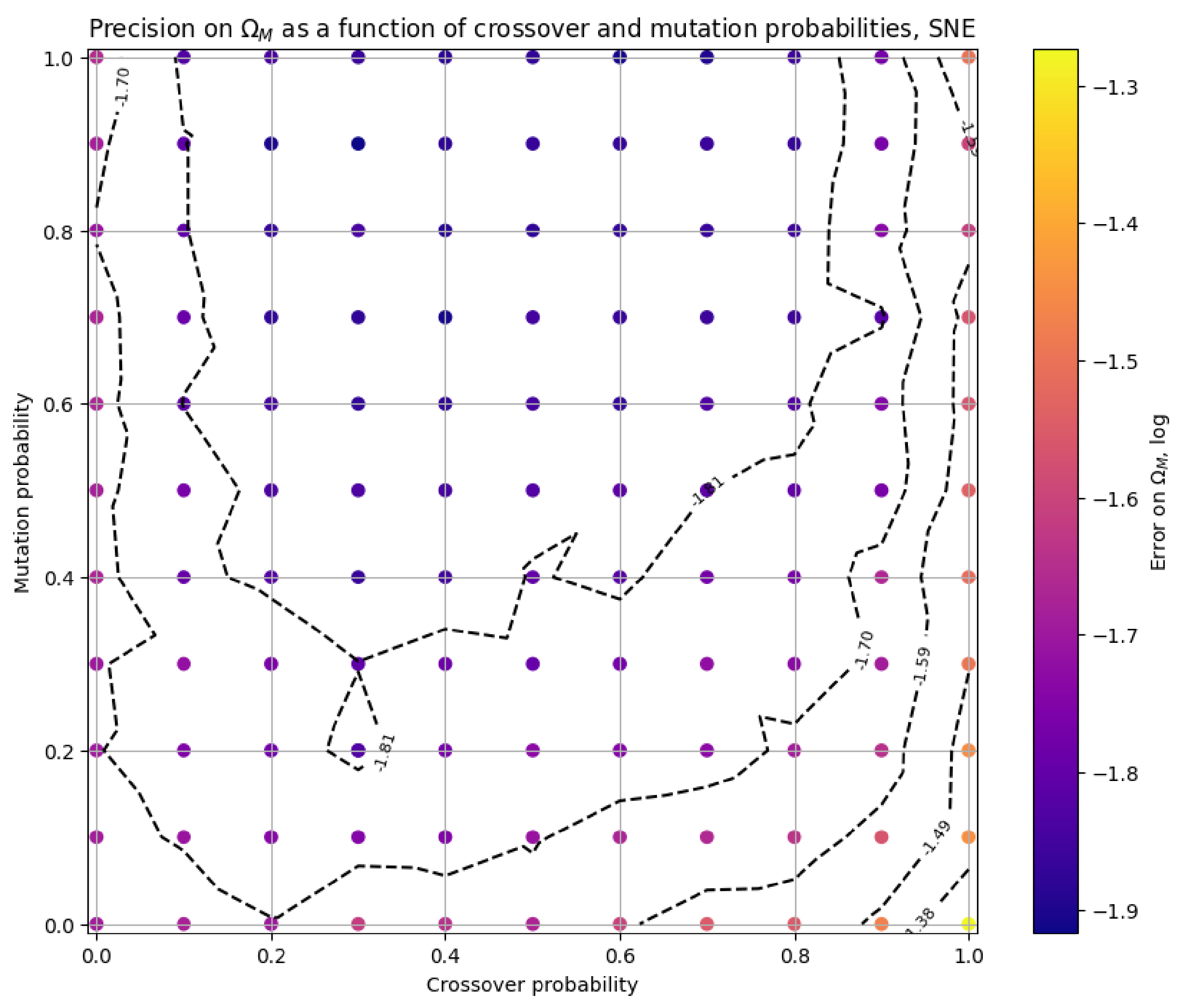
1) Entanglement.
2) Superposition.

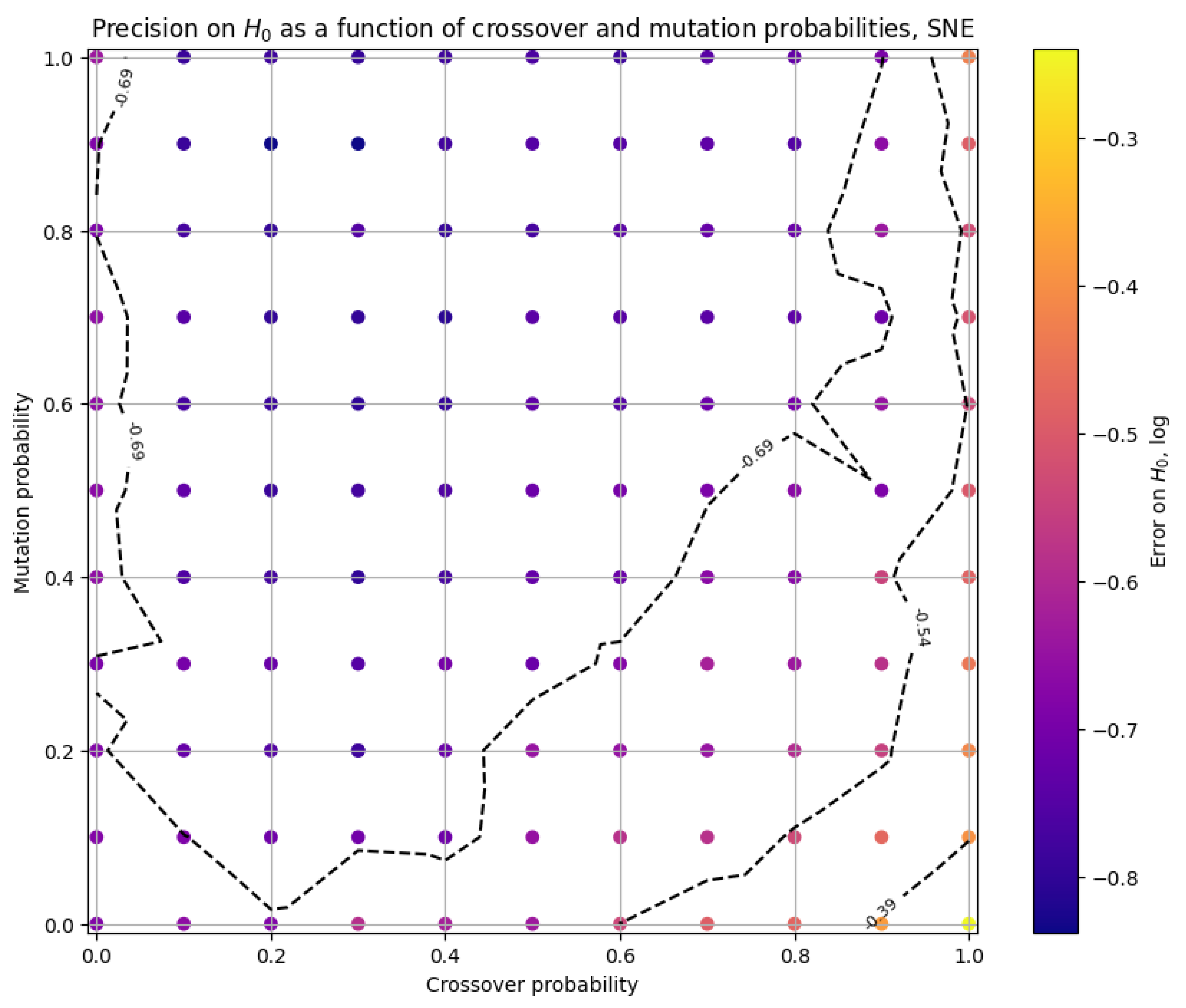


What is Quantum Computing?

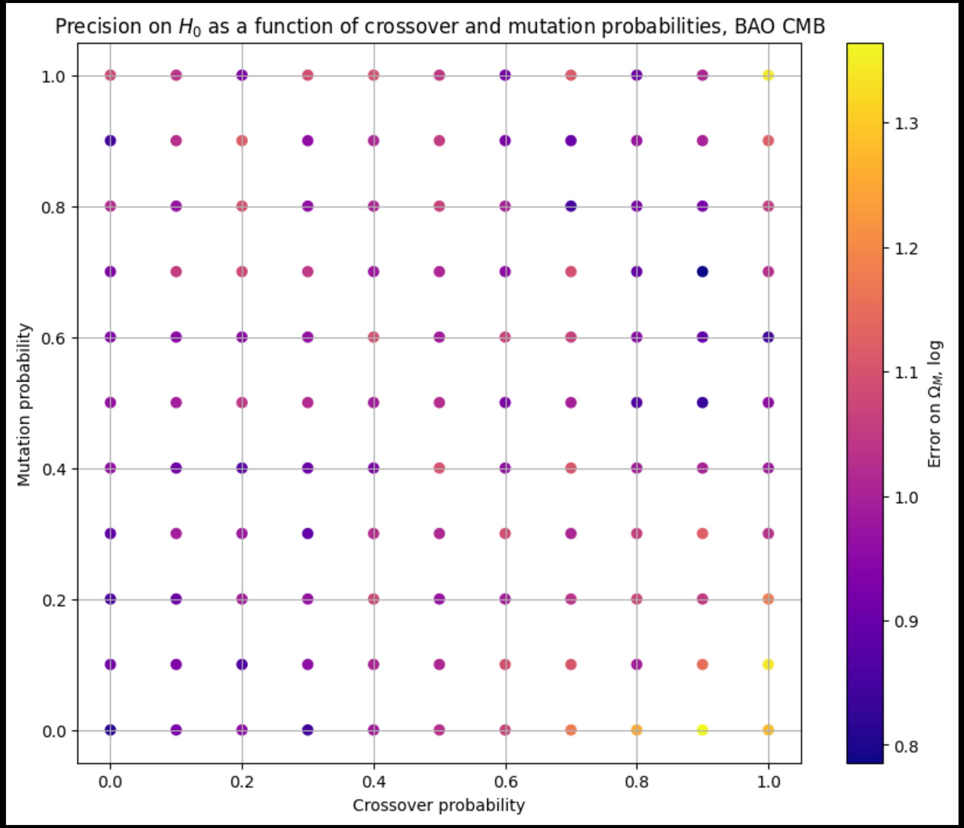
1) Quantum Computing Is a novel Scientific Discipline which uses concepts of Quantum Mechanincs and Computer Science.
2) The fundamental information unit is the Qubit, that can exist as a superposition of states as long as it is not classically measured.
3) Quantum Algorithms leverage these objects to perform opertations using properties of Quantum Mechanics, looking for advantages on the classical counterparts.
4) Quantum Computers have to be built with the idea of being able to manifest these operations and manipulate Qubits.

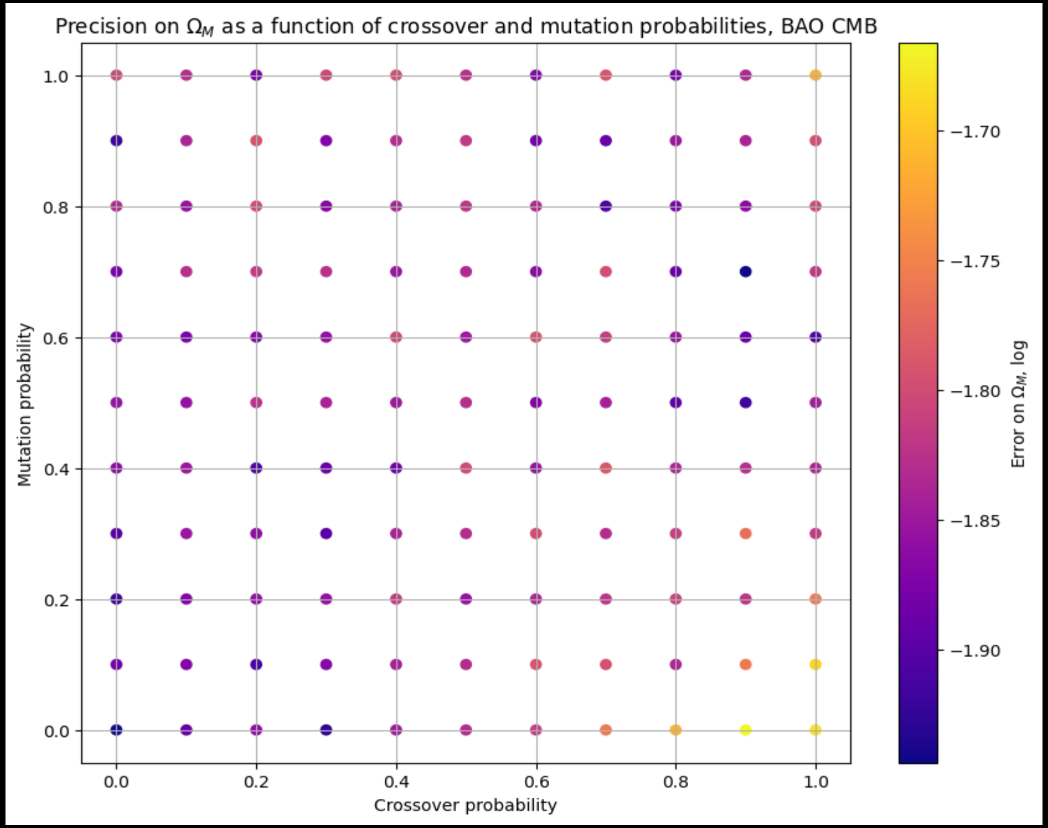






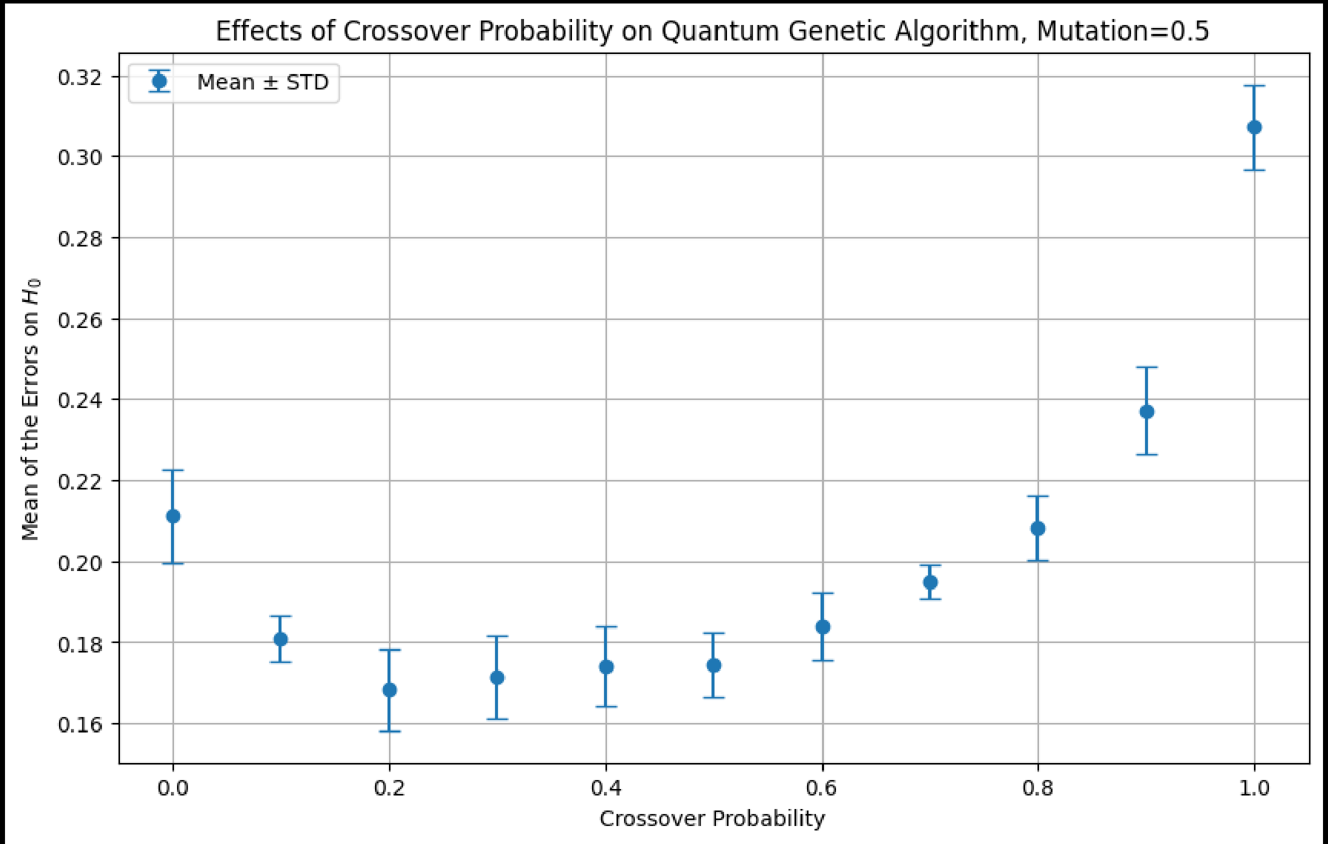
Testing the crossover and mutation effects for the SNe results



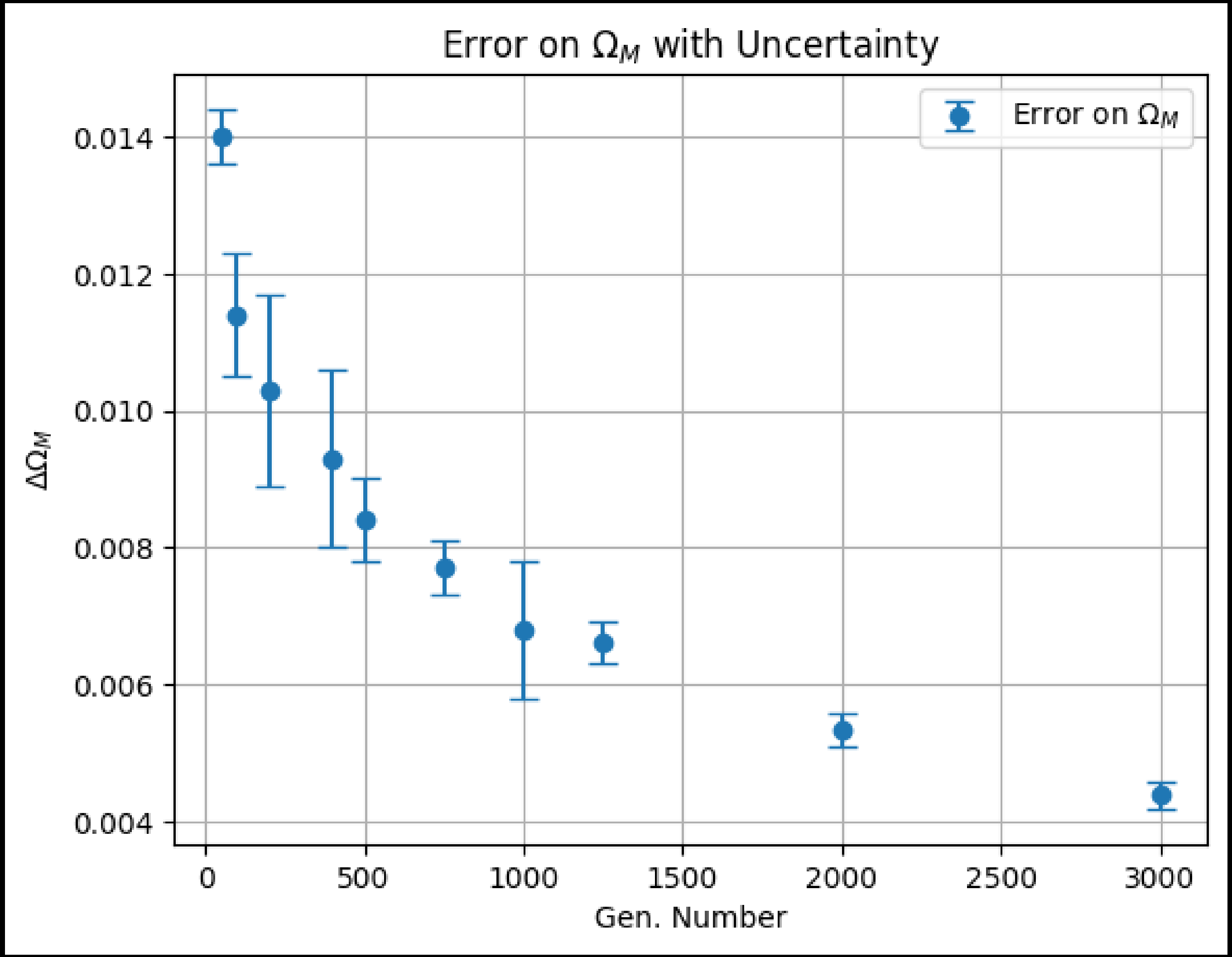


Testing the crossover and mutation effects for the CMB+BAO results

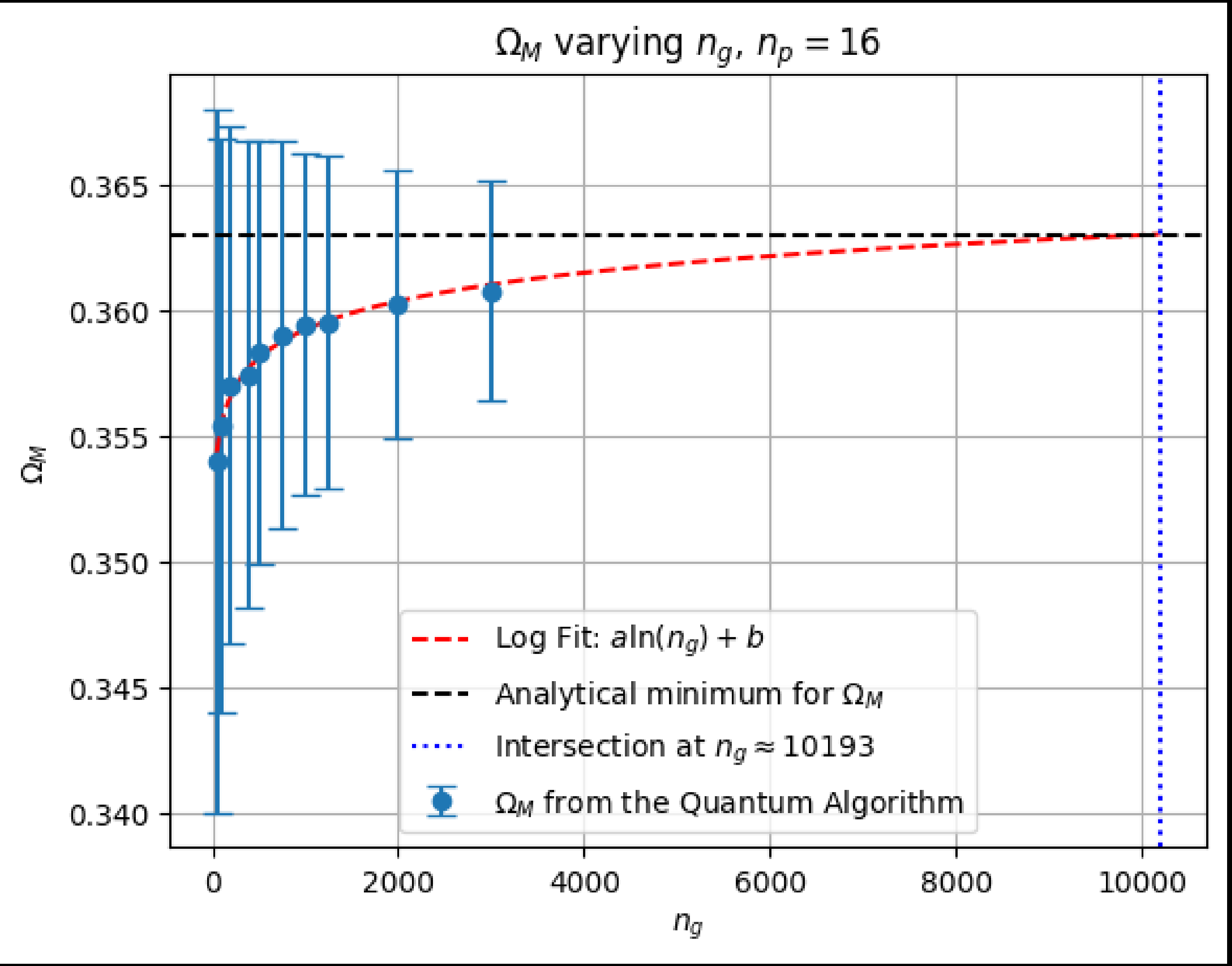
Studying the stability of the Algorithm, SNe Ia, error on H0

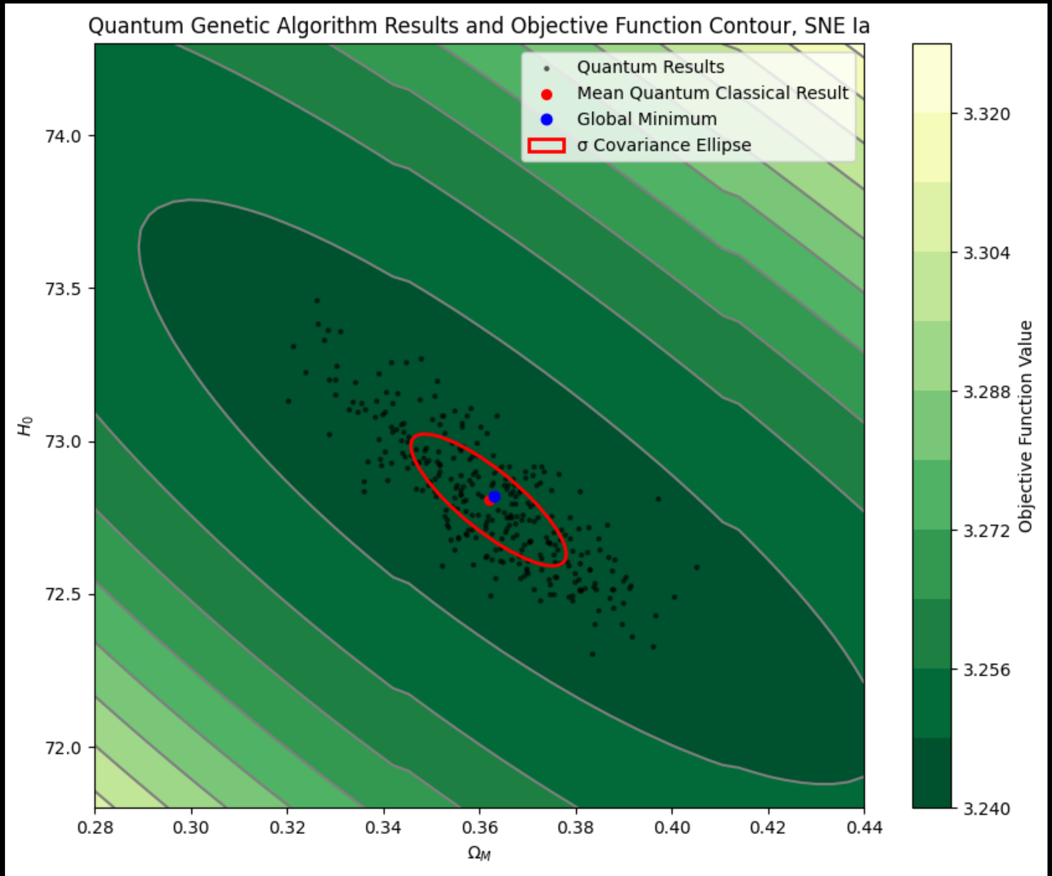


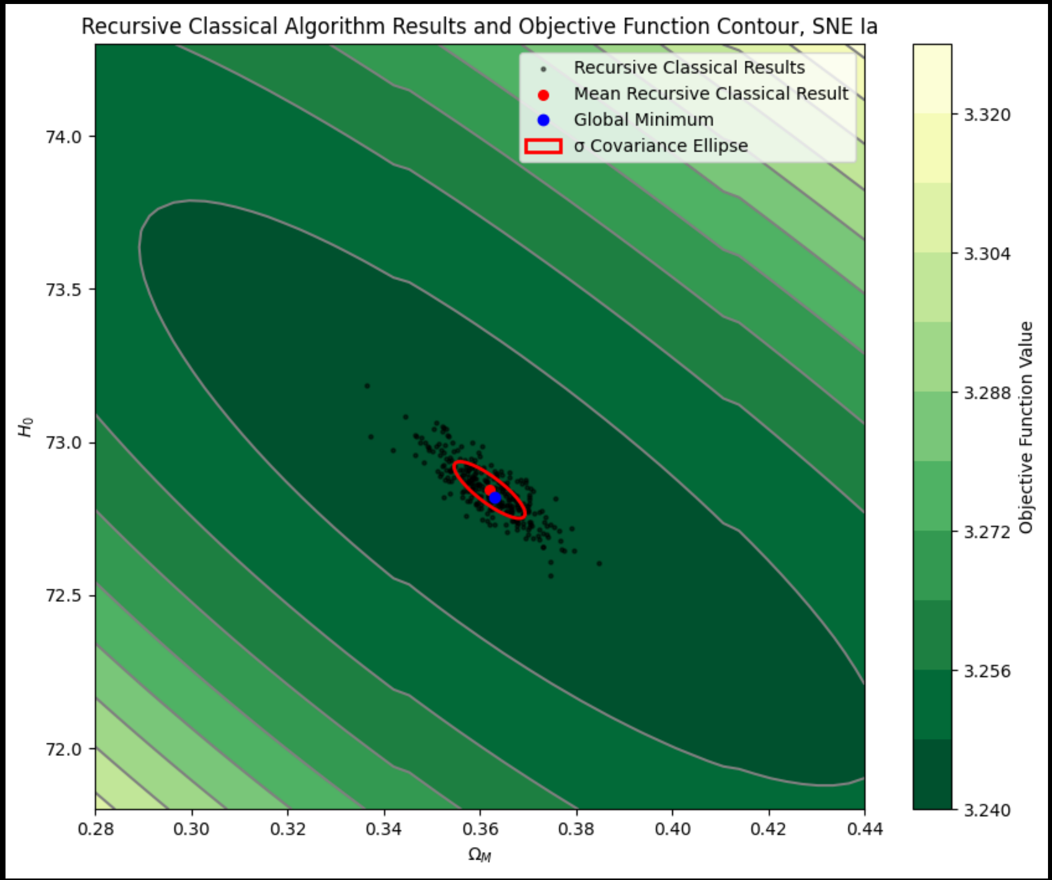
Precision and number of generations, SNE



Mean value and number of generations, SNE, with 16 individuals







Comparison with classical algorithms (1)

Markov Chain Monte Carlo (MCMC)

N different chains, accepting or rejecting steps according to the Metropolis-Hastings Criterion

$$\alpha(\theta \to \theta') = \min\left(1, \frac{\pi(\theta')}{\pi(\theta)}\right)$$

This quantity is confronted with a random number between 0 and 1. If it is bigger, the step is accepted, otherwise, is rejected. The run reaches convergence according to different criteria, among which the Gelman Rubin R or the autocorrelation time of the chains. Once the convergence is reached, one gets the posteriori distributions.

How does the algorithm scale?

Number of qubits $= \lceil \log_2 d \rceil$.

Depth $= 2 + n_l(2 + \log_2 d)$.

Time scales linearly with the number of chains used for the run, depends on how strict are the convergence criteria.

All the Qubits are connected one to the other.

Using the full Planck Likelihood varying all the nuisance parameters, only 5 Qubits are necessary for our algorithm.

Results, SNe Ia