Computational Challenges in Cosmological Parameter Estimation

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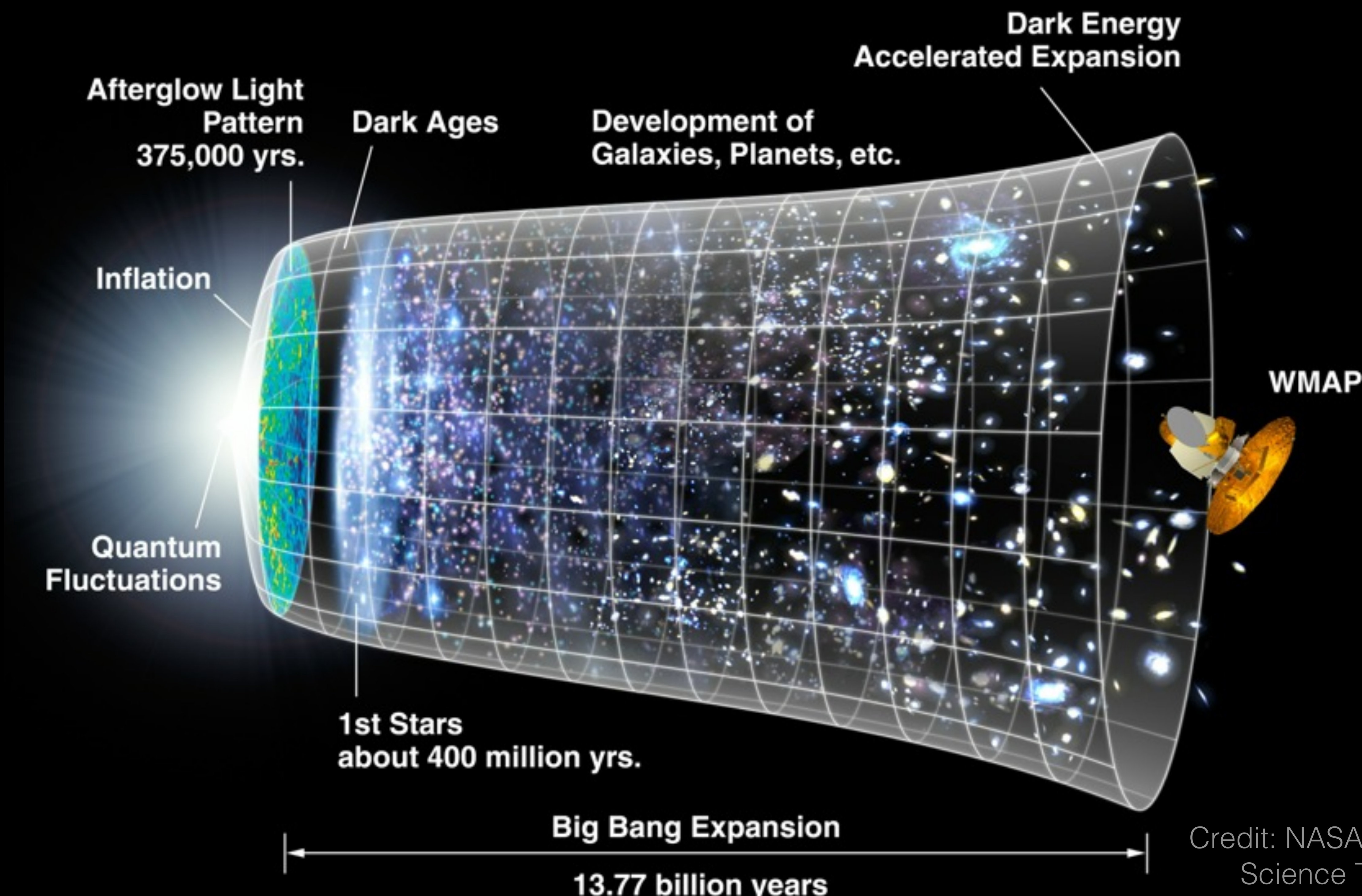
Joint work with Adam Amara, Alexandre Refregier, and André Csillaghy.
(In collaboration with University of Applied Sciences Northwestern Switzerland)

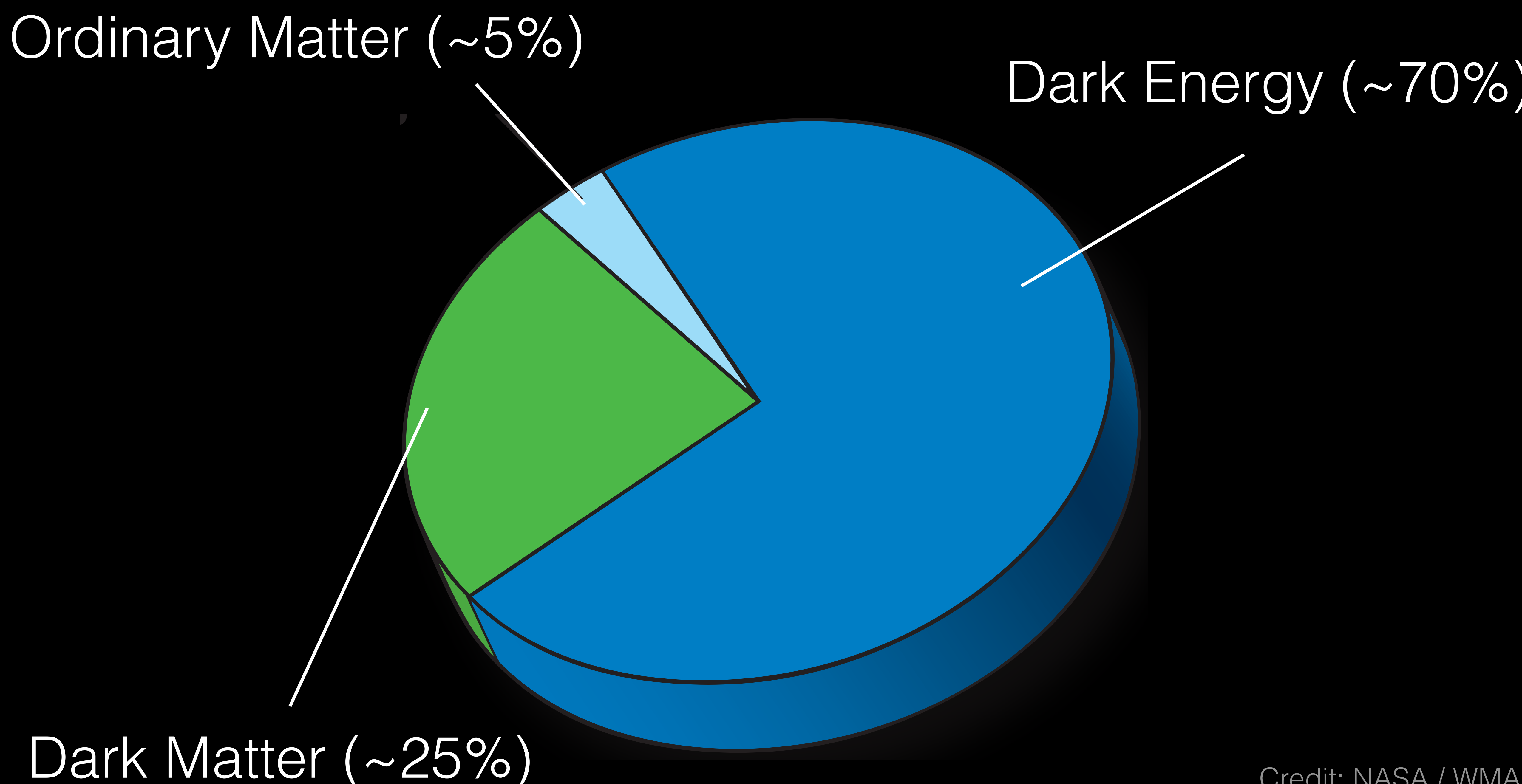
21.02.2014

Cosmology



Credit: NASA / WMAP
Science Team

Dark Components



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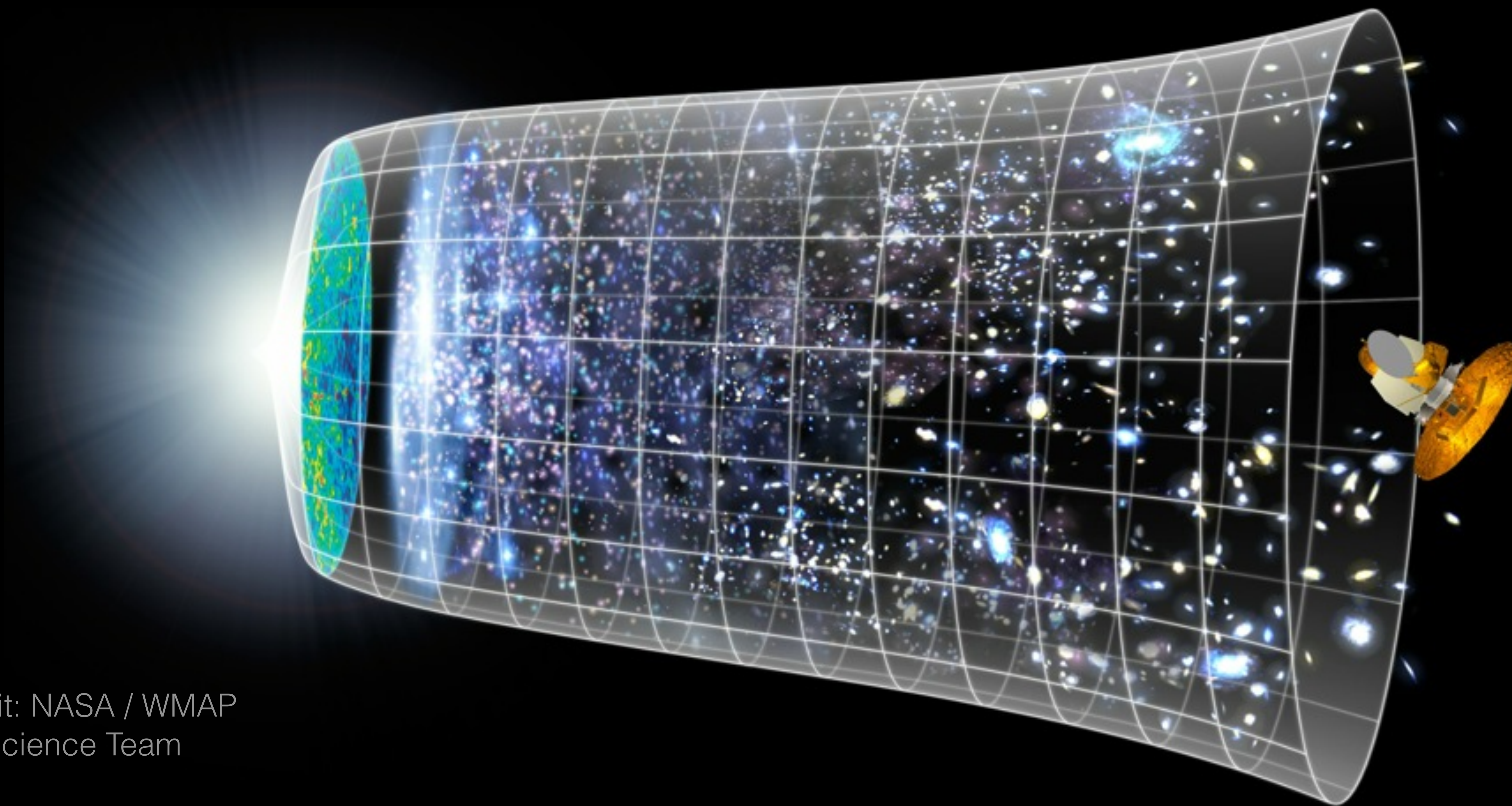
Computational Cosmology



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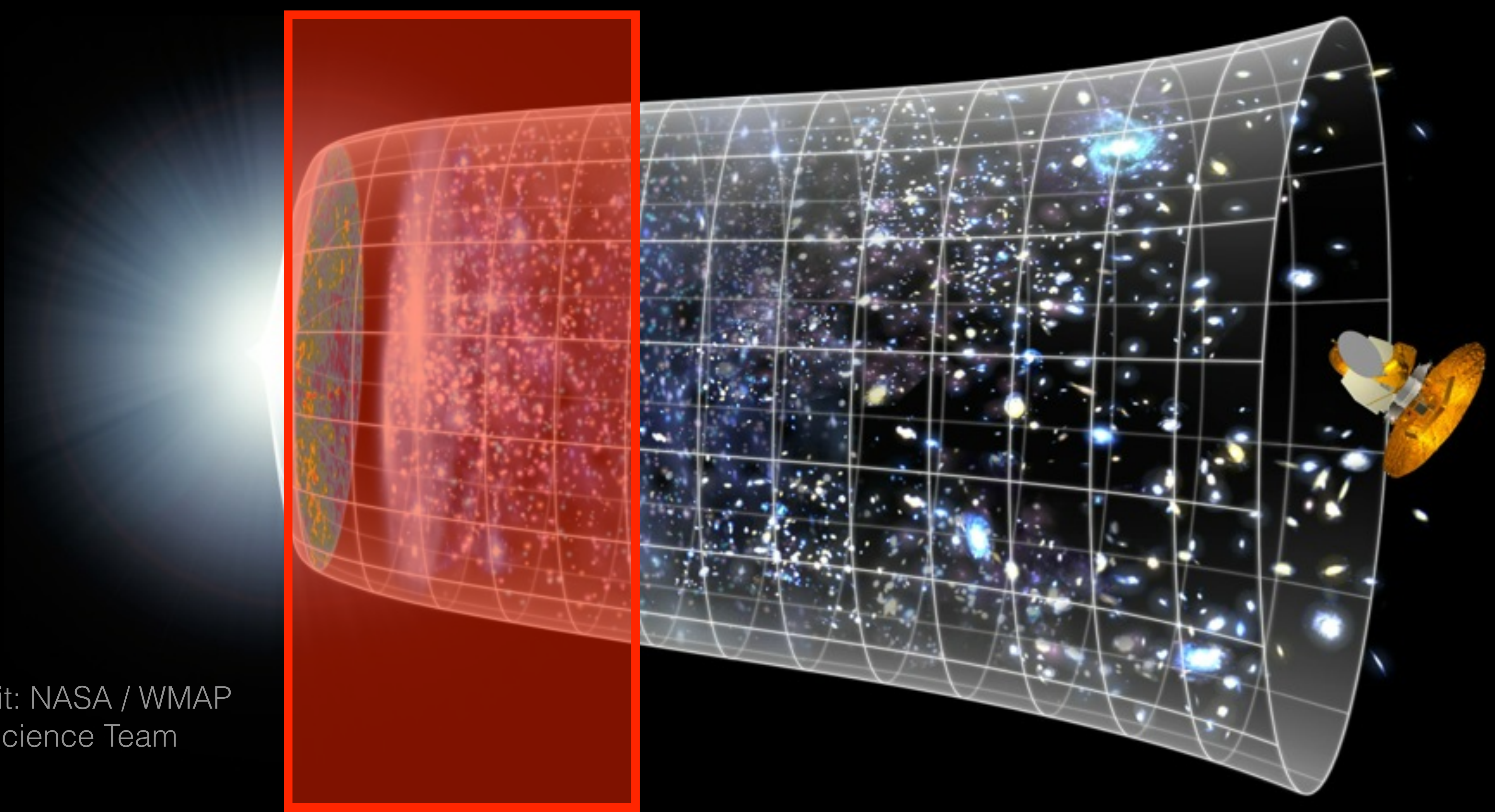
Computational Cosmology



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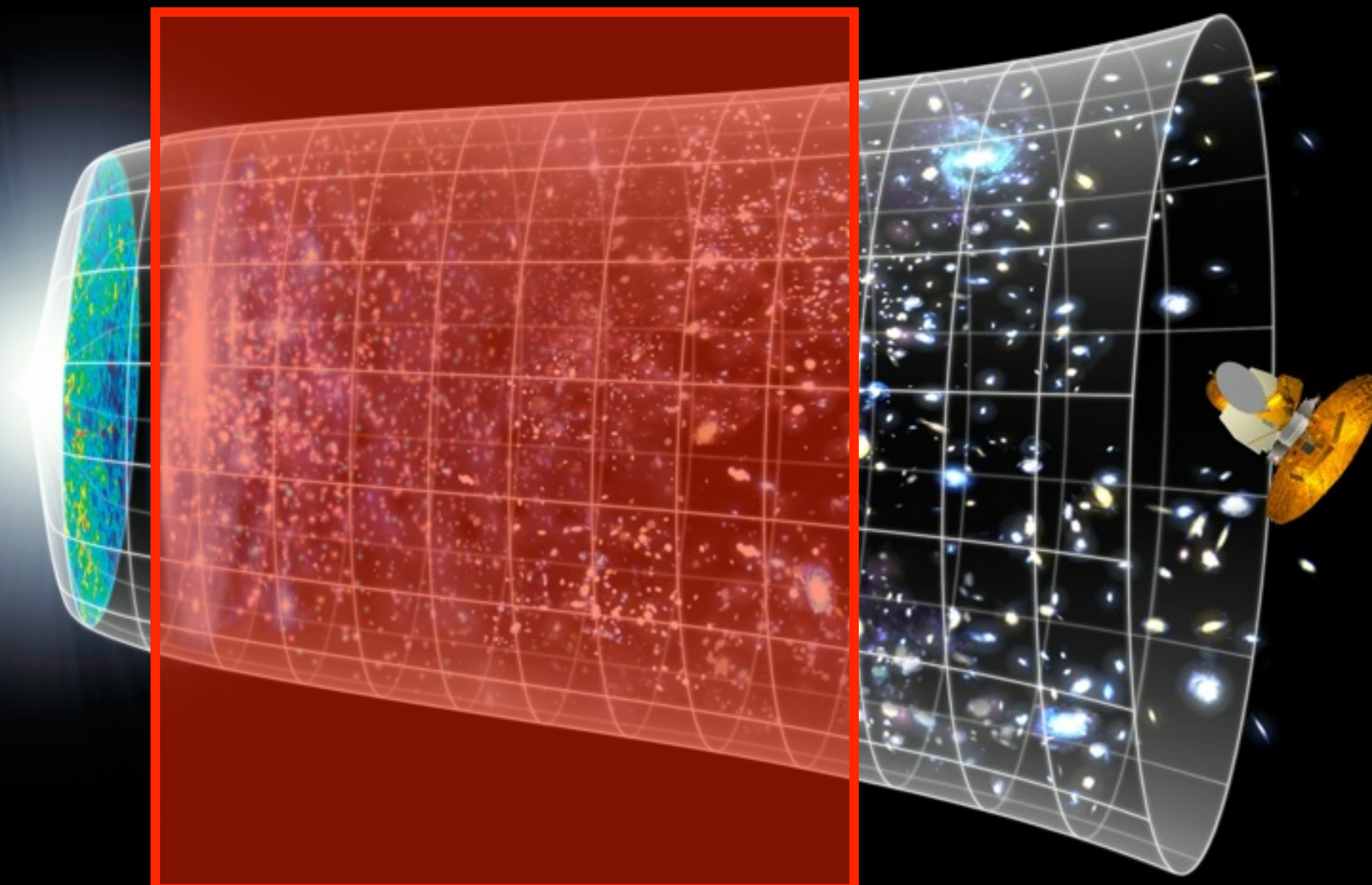
Linear perturbation theory:
Solving Boltzmann equations numerically

Computational Cosmology



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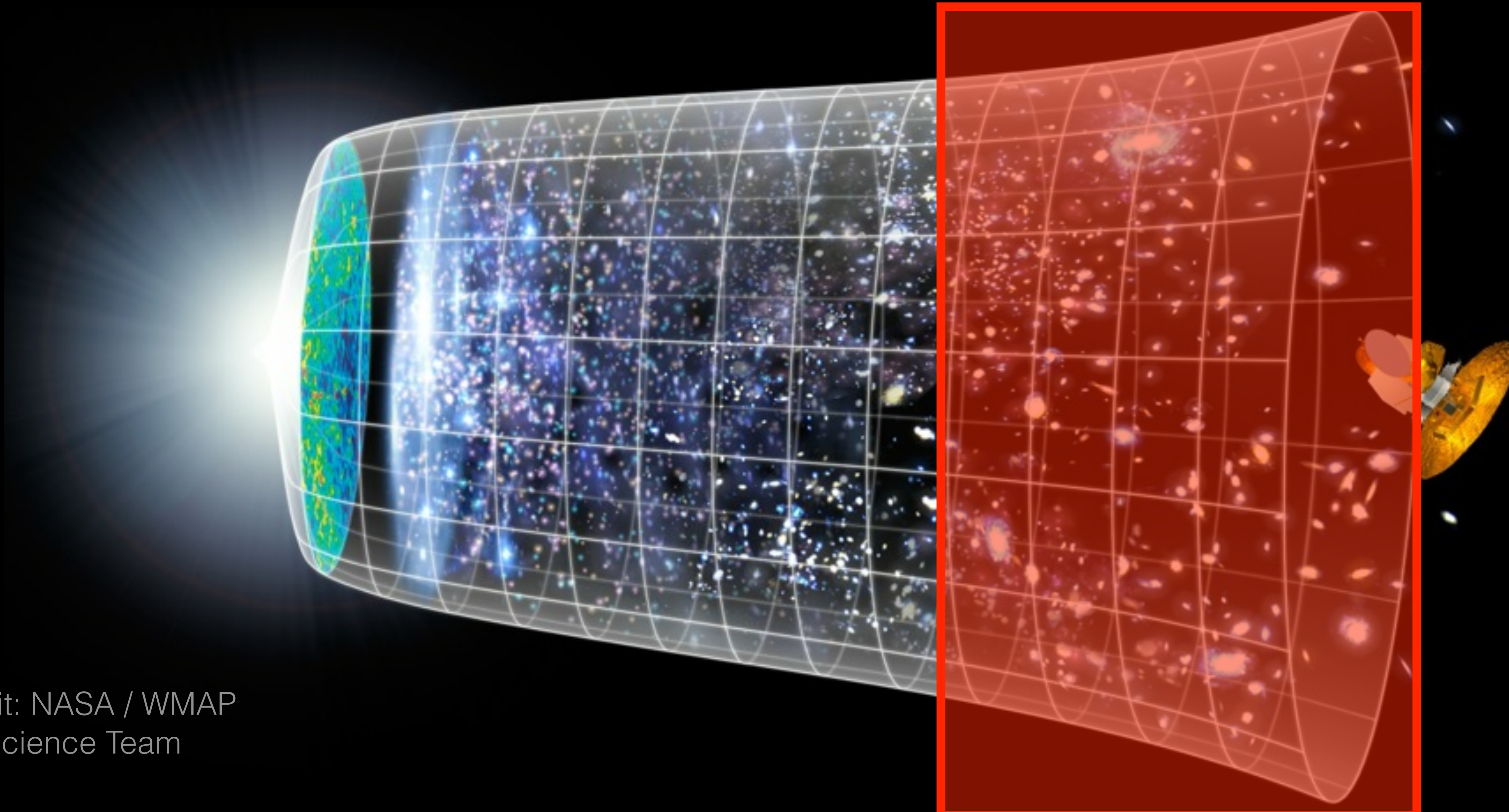
Large scale structure formation:
N-body simulations of dark matter dynamics

Computational Cosmology



Credit: NASA / WMAP Science Team

Galaxy formation:
Hydrodynamic simulations

Data Analysis

- Processing and analysis of large datasets
- Forward modelling
    - Astronomical foregrounds
    - Instrument effects
- Statistical inference

Incomplete History of Cosmic Microwave Background (CMB) Surveys

COBE
(1989)

→

BOOMERanG
(1997)

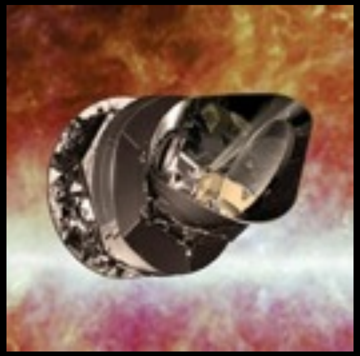
→

WMAP
(2001)

→

SPT
(2006)

→



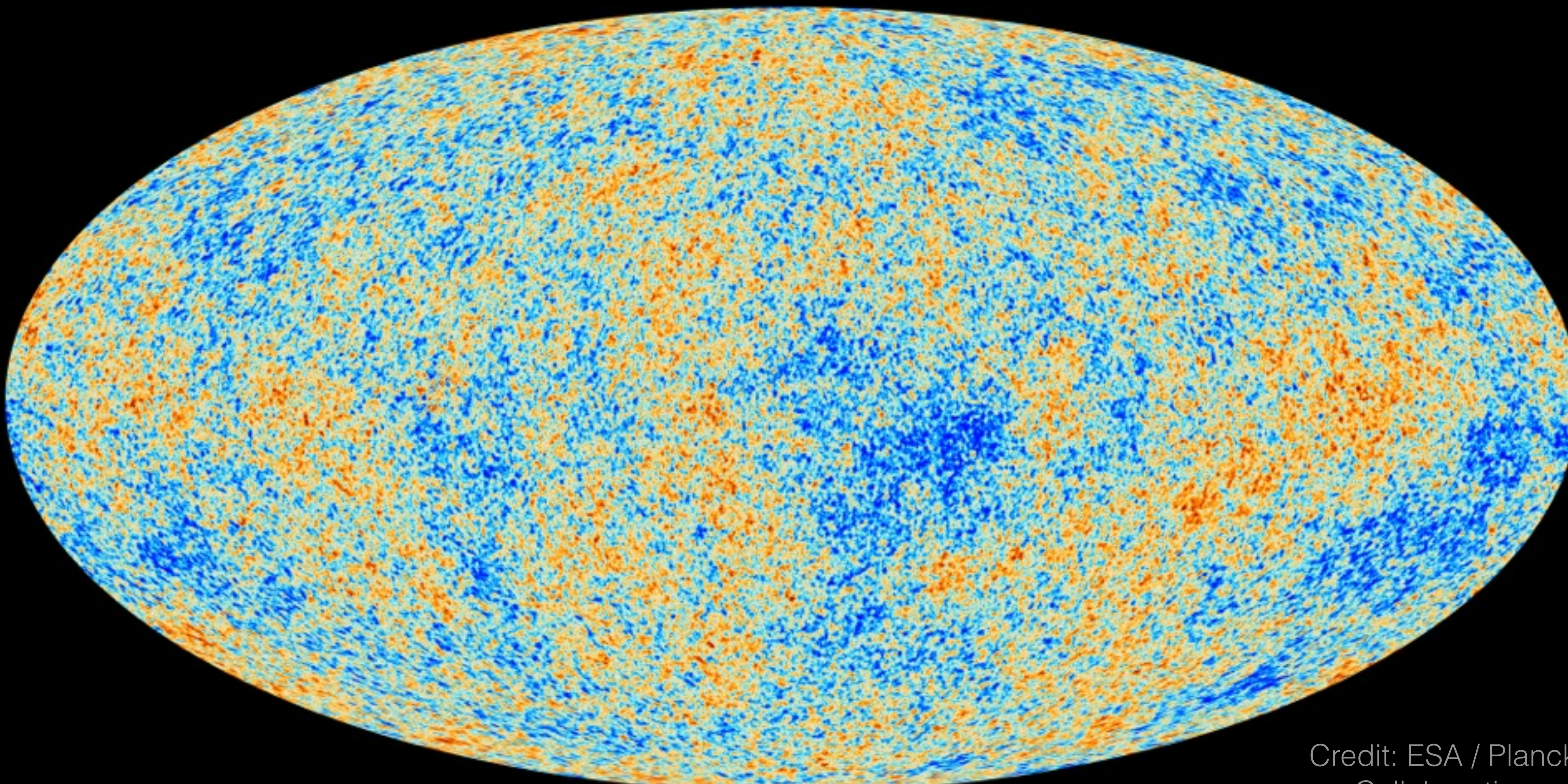
Planck
(2009)

→

PolarBear
Spider
…

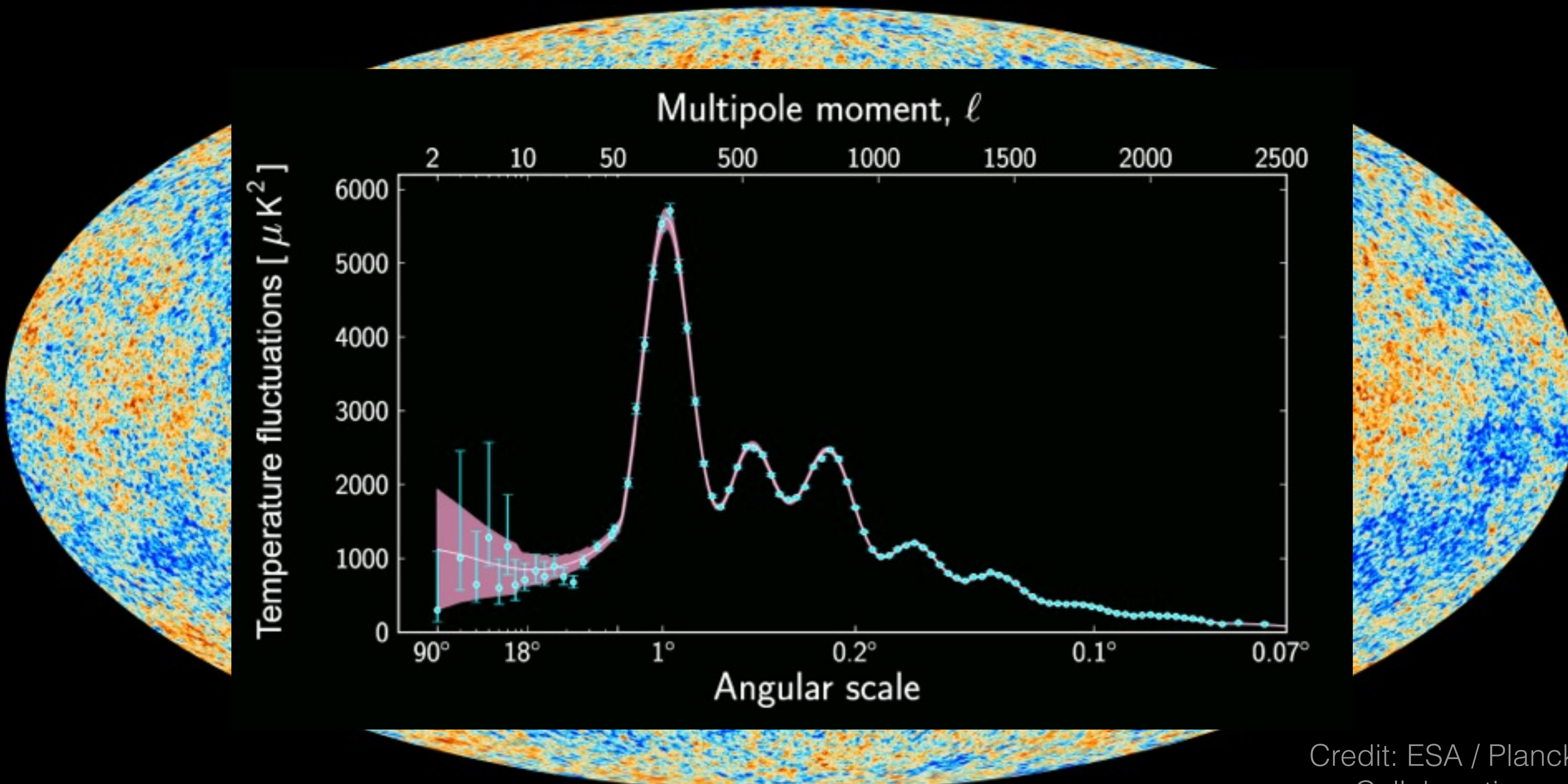
Future

Map of the CMB



Credit: ESA / Planck Collaboration

Map of the CMB



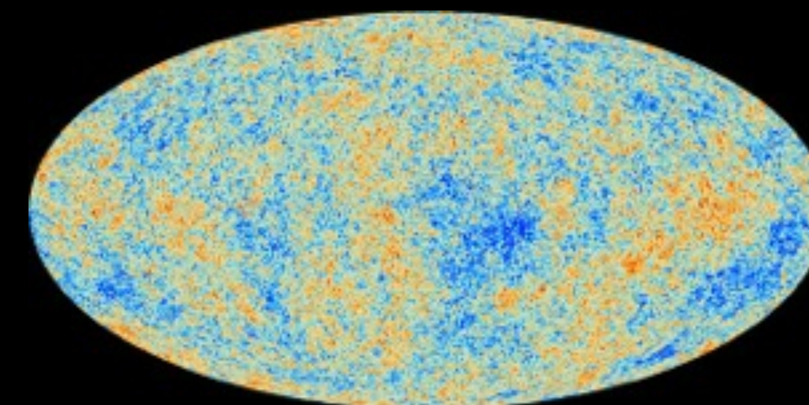
Credit: ESA / Planck Collaboration

Parameter Estimation

A_s

$\Omega_b h^2$ H_0 $\Omega_c h^2$

n_s τ



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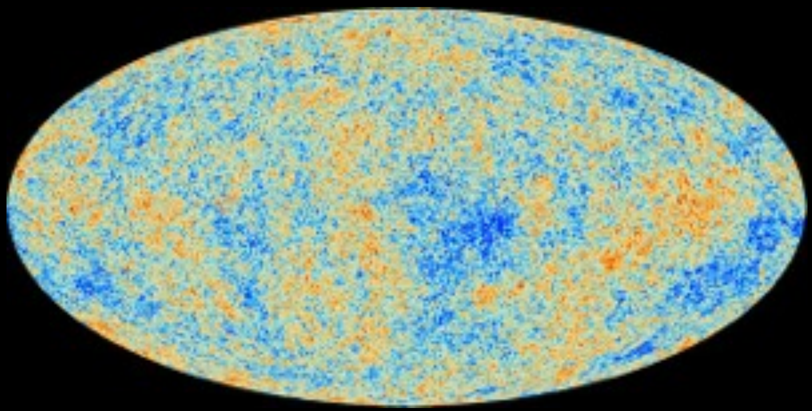

↓ Predictions from Theory

↓ Data and Errors

Credit: ESA / Planck Collaboration

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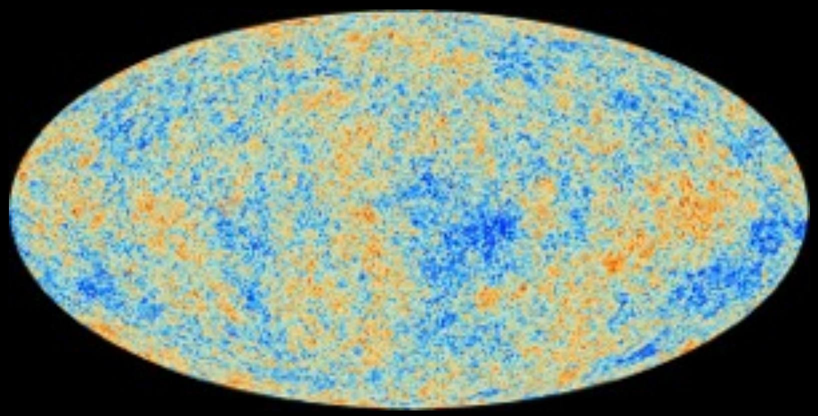

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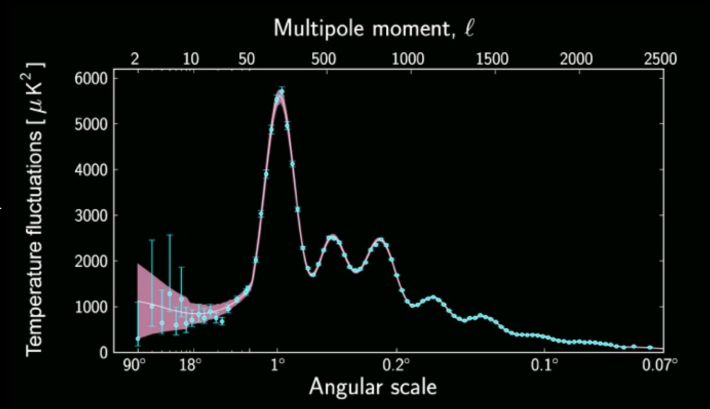

Data and Errors

Credit: ESA / Planck Collaboration

Parameter Estimation

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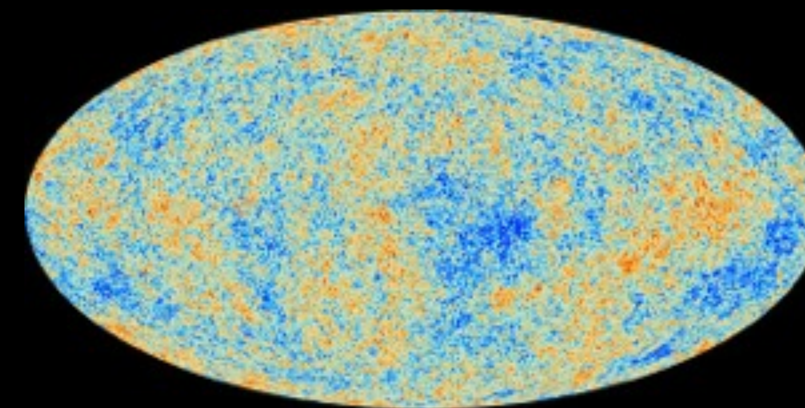

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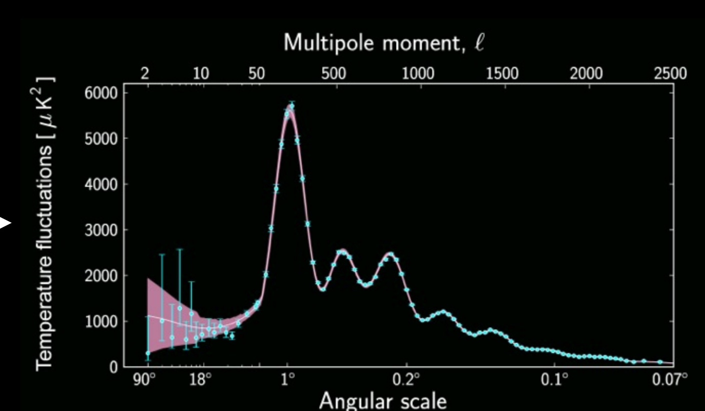

Data and Errors

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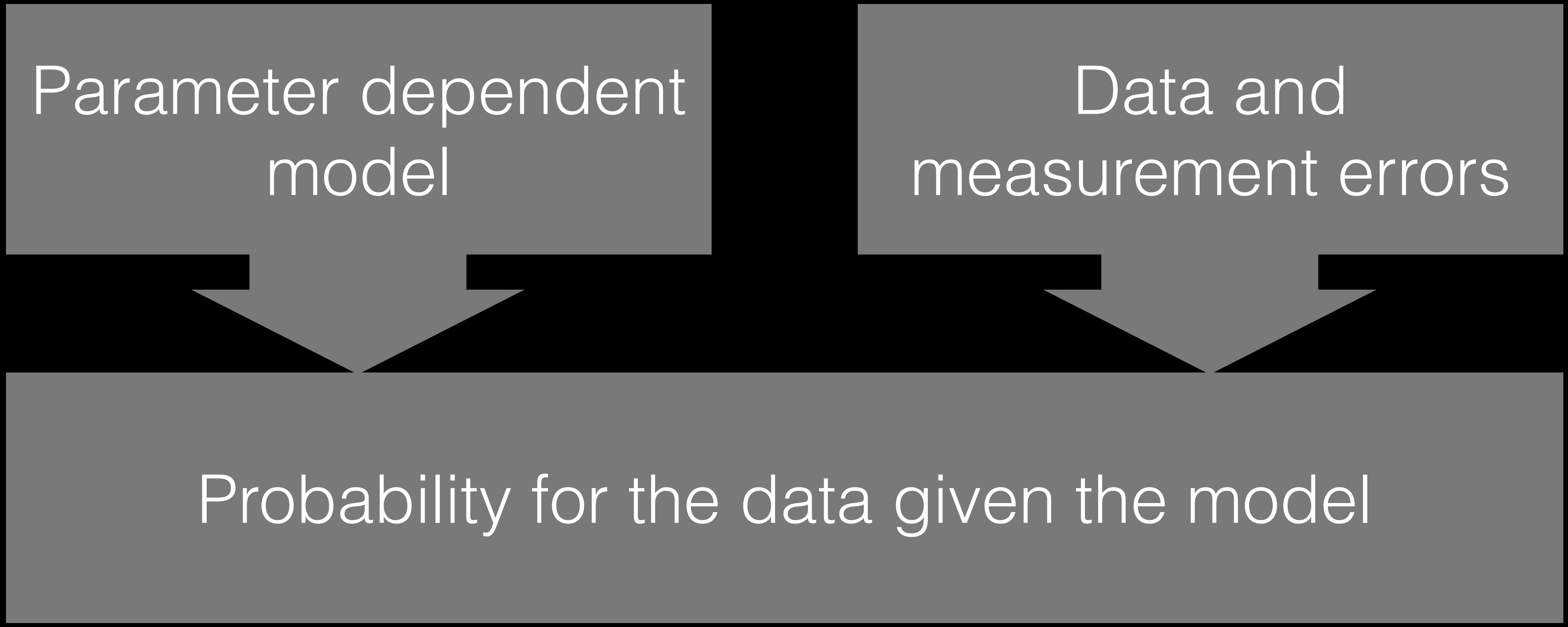
Likelihood


Parameter dependent model
Data and measurement errors
Probability for the data given the model

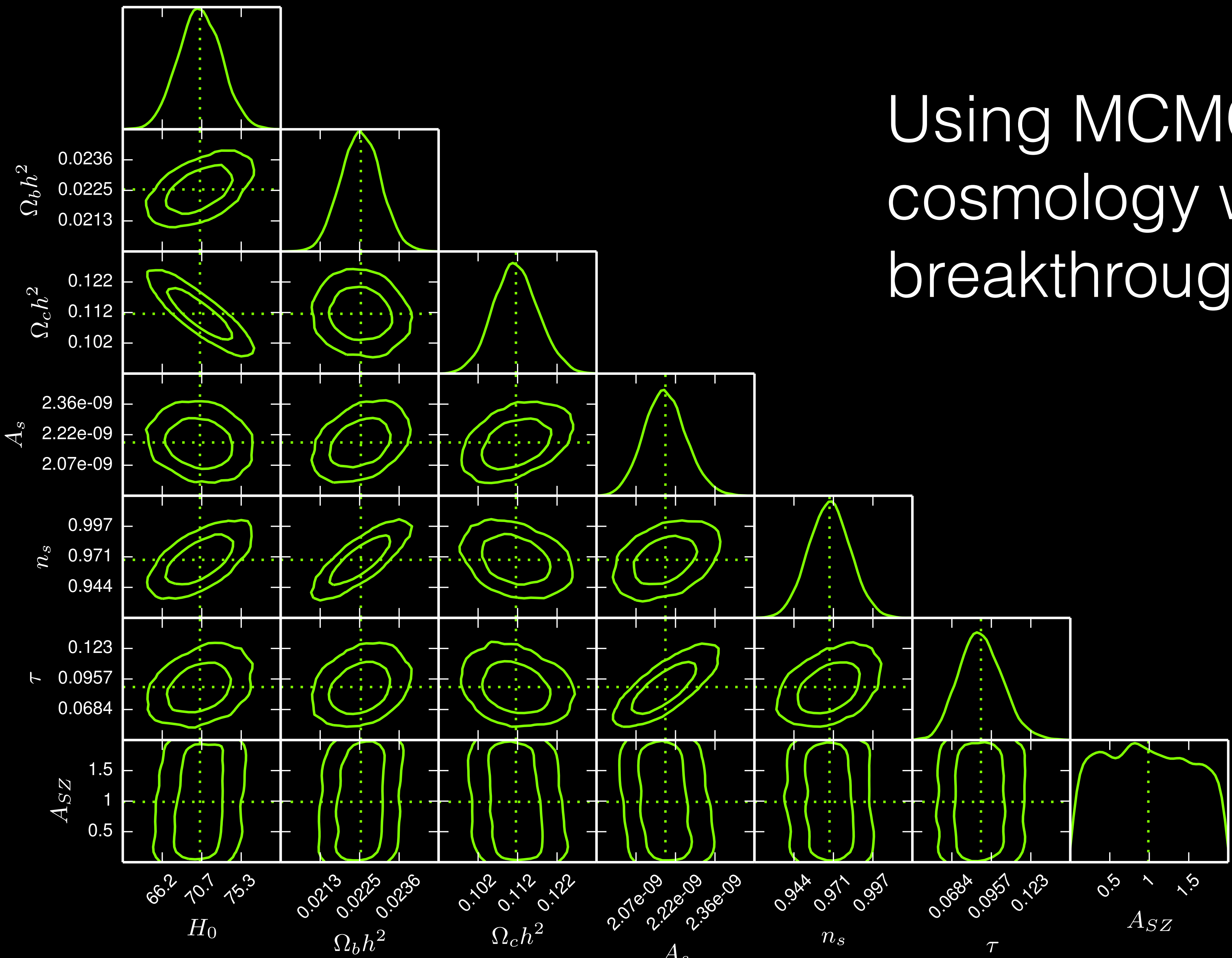
Bayesian Inference

$$p_{new}(\Theta) = \frac{\overbrace{p(D_{new}|\Theta)}^{\text{Likelihood}}\,\overbrace{p(\Theta)}^{\text{Prior}}}{\int d\Theta\, p(D_{new}|\Theta)p(\Theta)}$$

Bayesian Inference in Cosmology

- Parameter space is greater or equal to six
- Model predictions have to be evaluated numerically
- The likelihood is computationally intensive

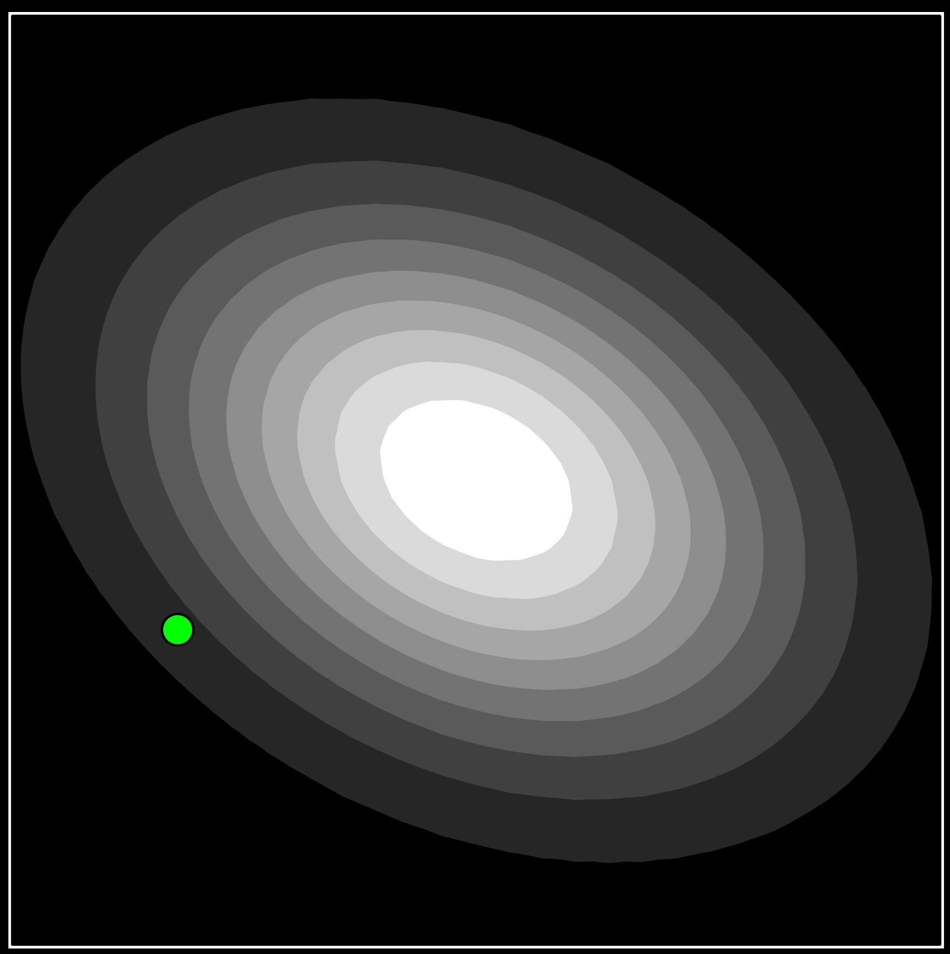
MCMC in Cosmology



Using MCMC in cosmology was a major breakthrough in 2001

Metropolis-Hasting

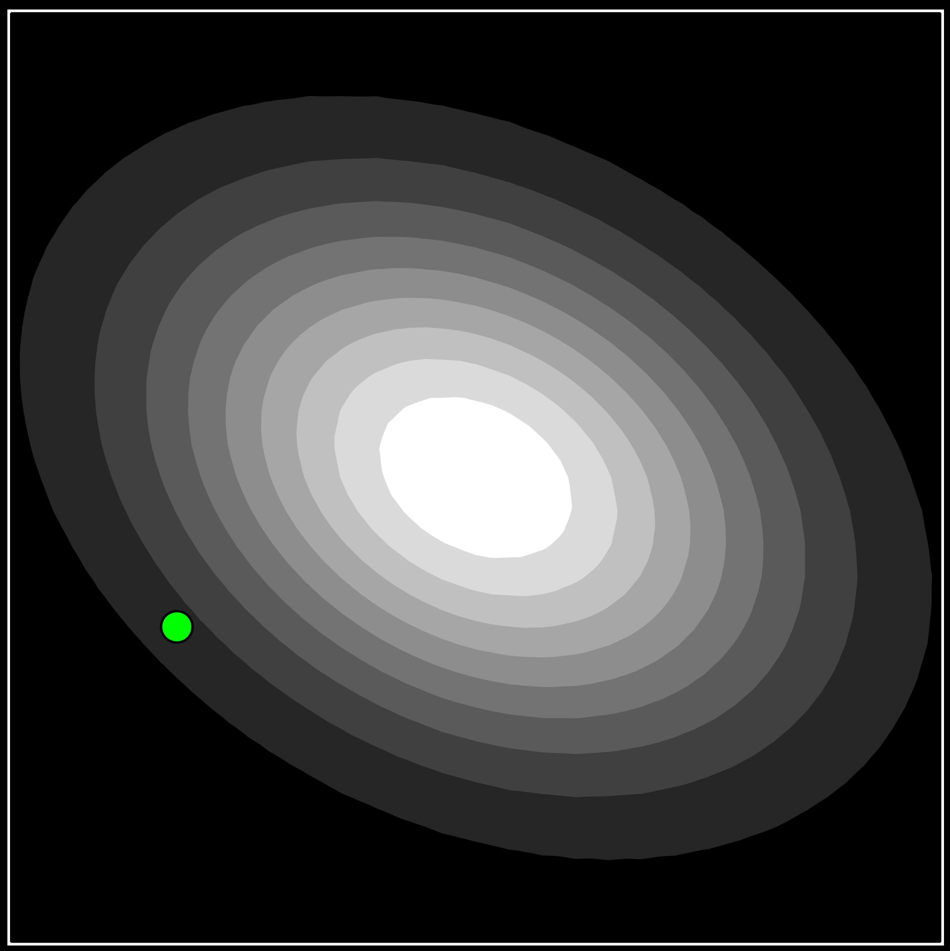
Metropolis+ 1953
Hastings 1970



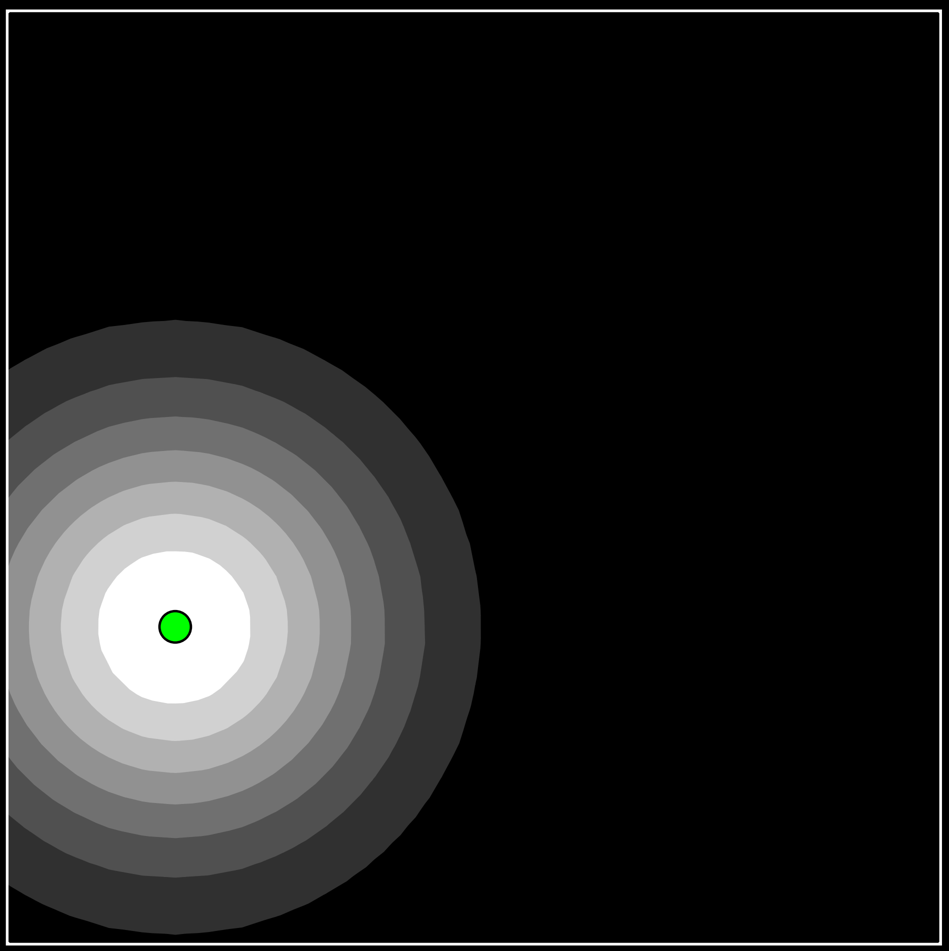
target distribution $P(\theta)$

Metropolis-Hasting

Metropolis+ 1953
Hastings 1970



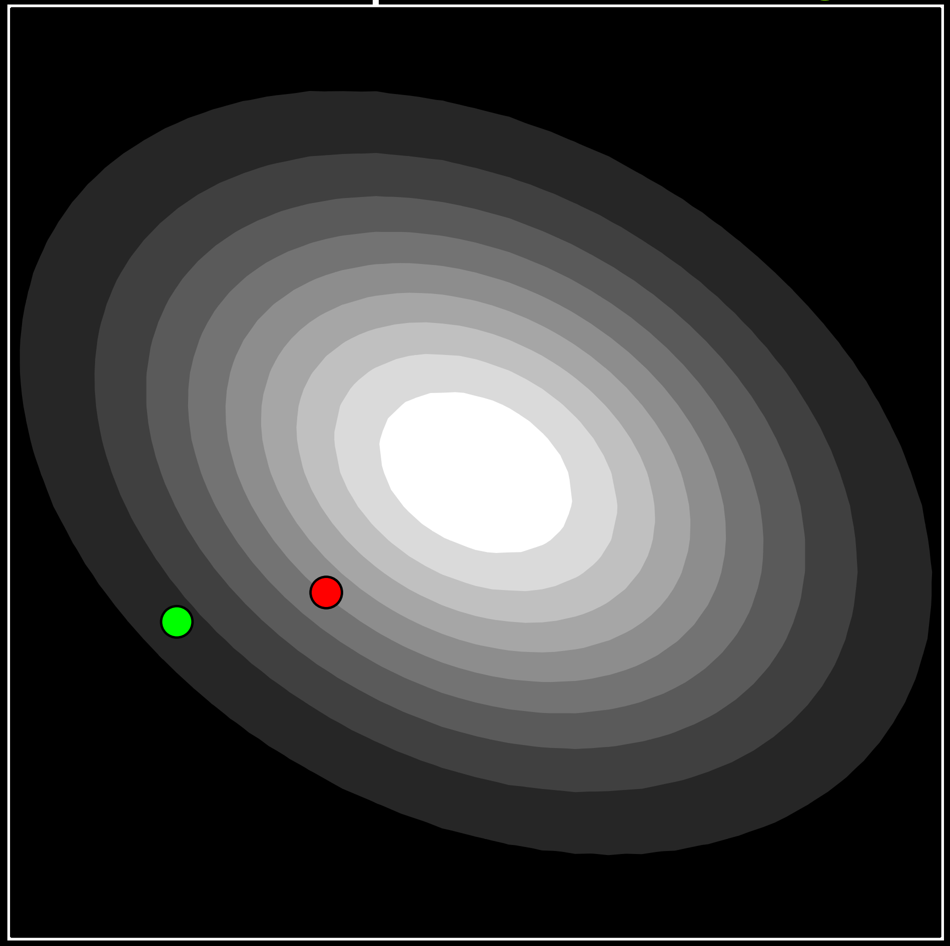
target distribution P(θ)



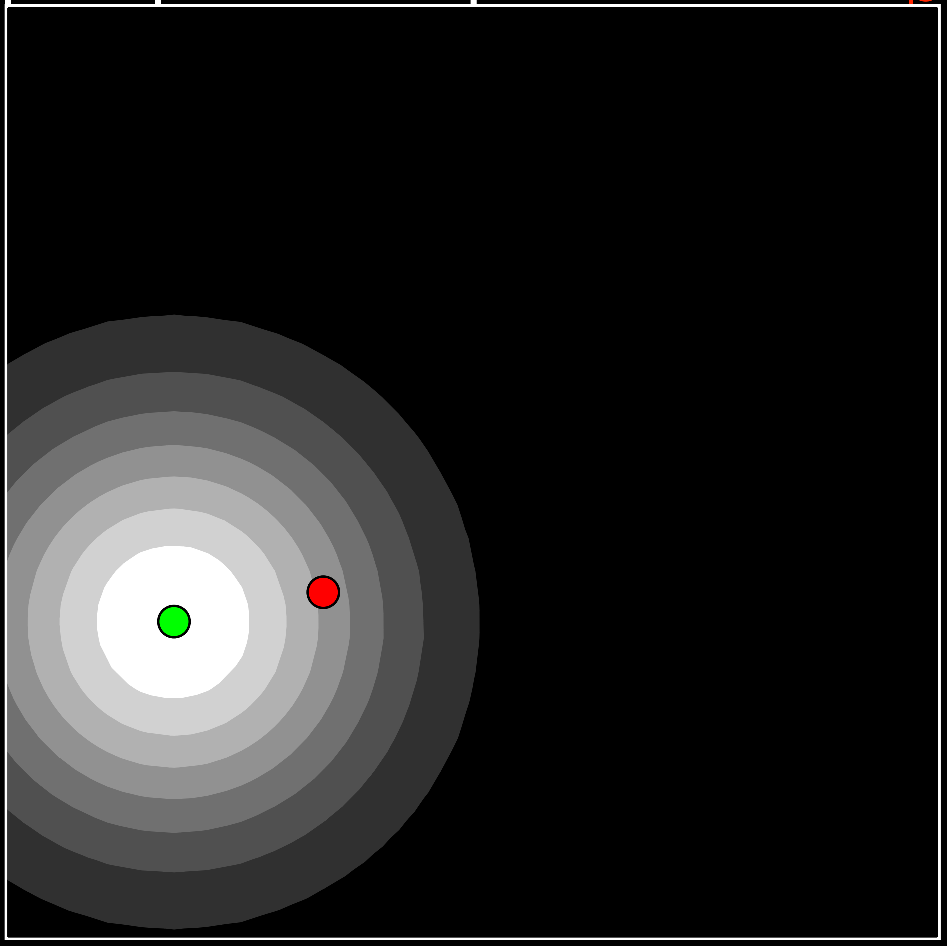
proposal distribution Q(θ)

Metropolis-Hasting

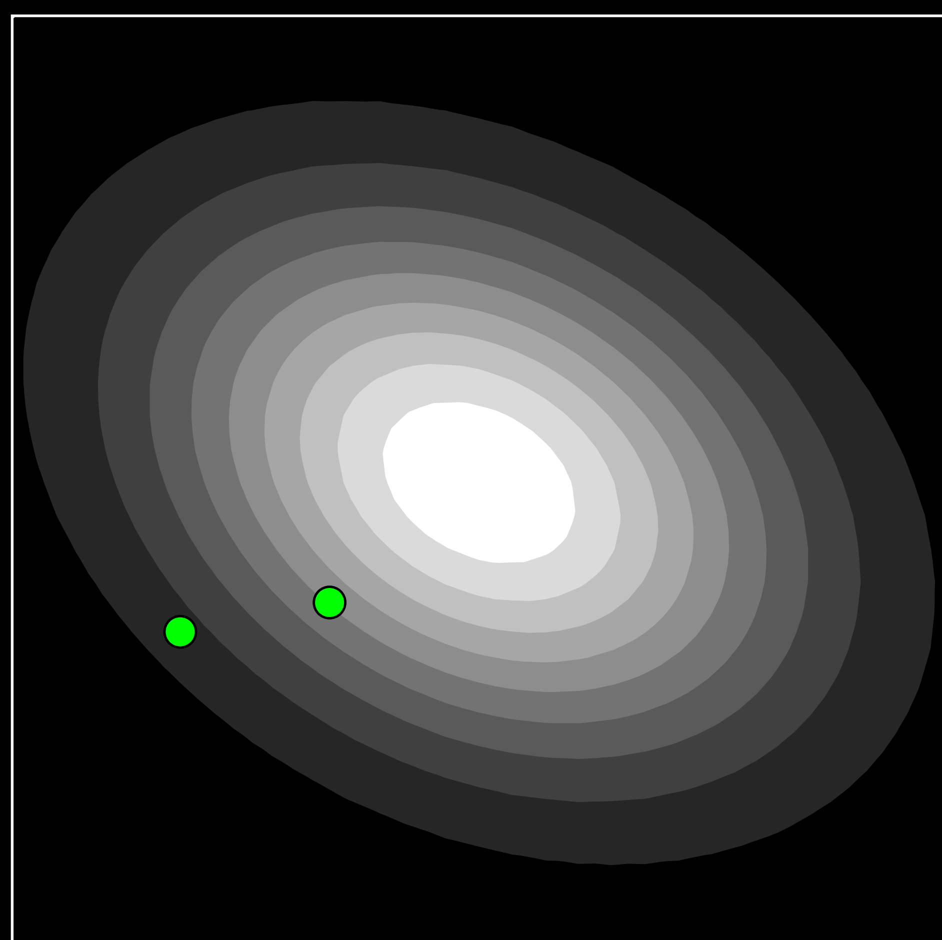
initial position θ_0



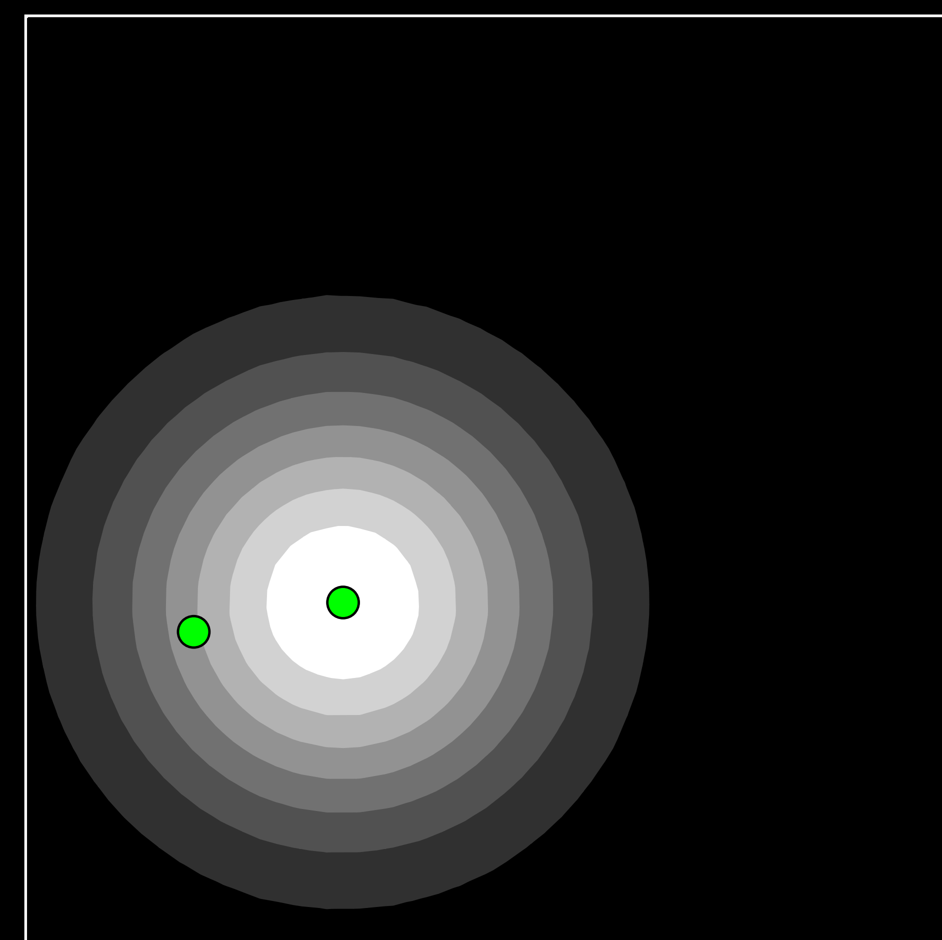
proposed position θ_p



Metropolis-Hasting

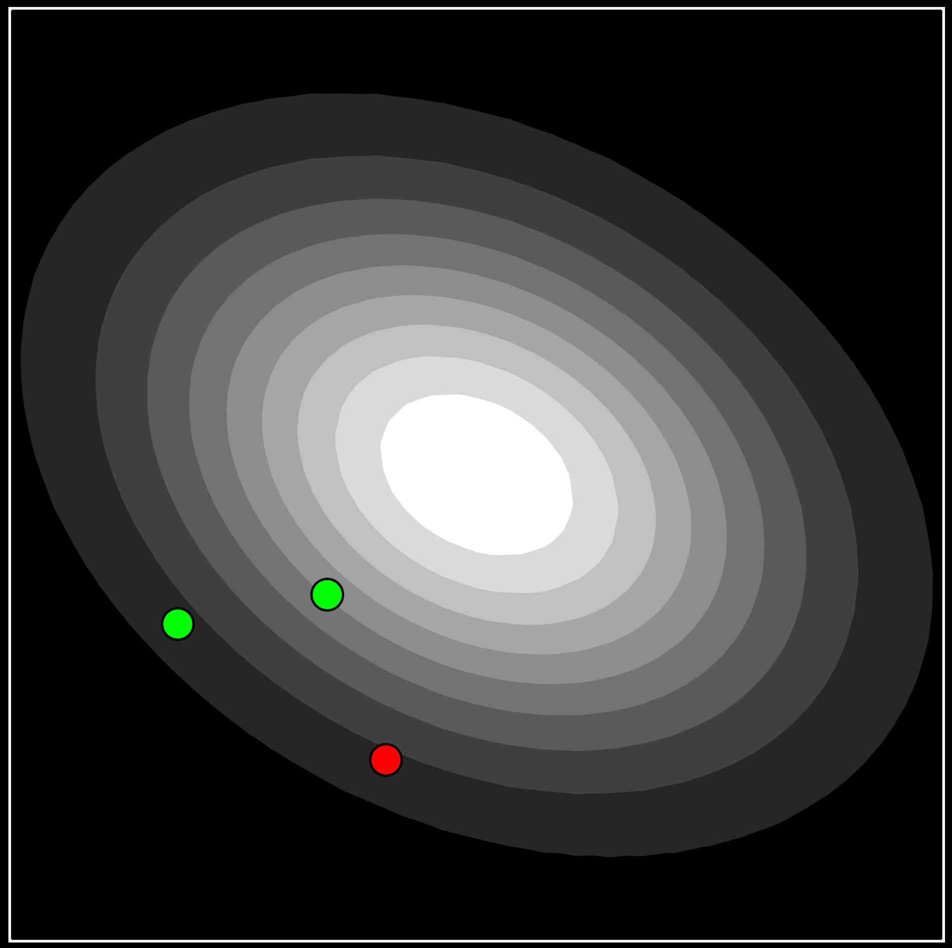


target distribution $P(\theta)$

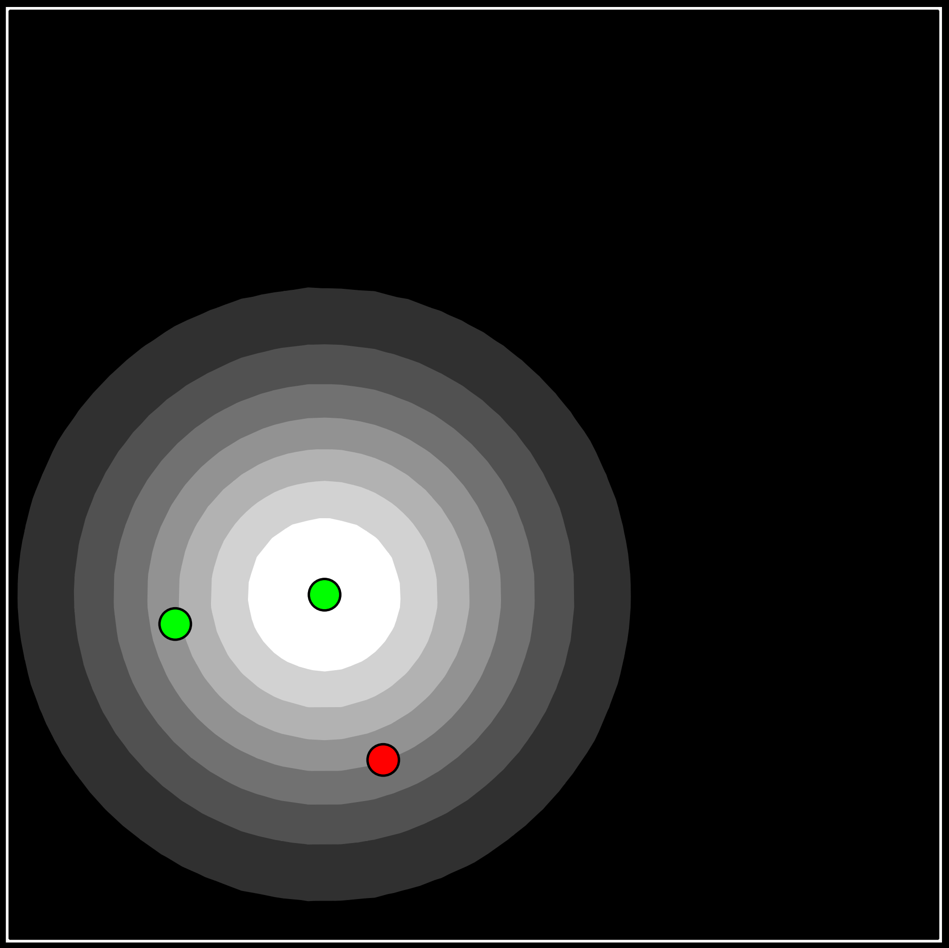


proposal distribution $Q(\theta)$

Metropolis-Hasting

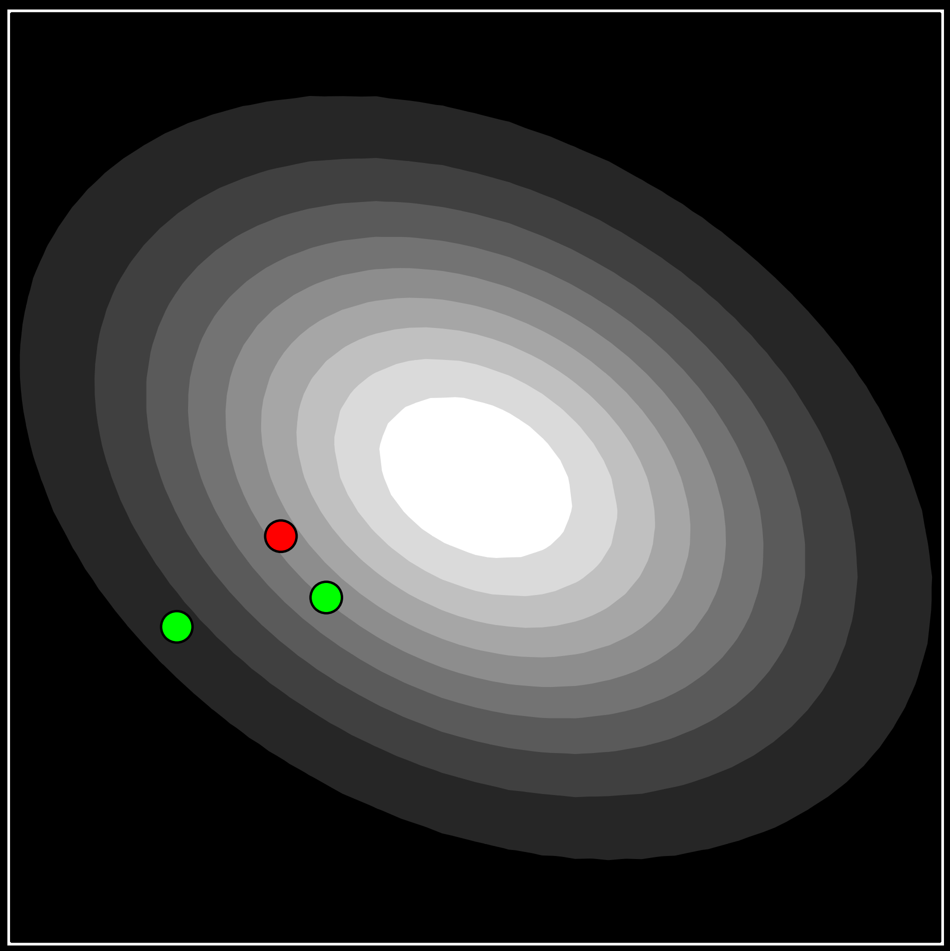


target distribution P(θ)



proposal distribution Q(θ)

Metropolis-Hasting



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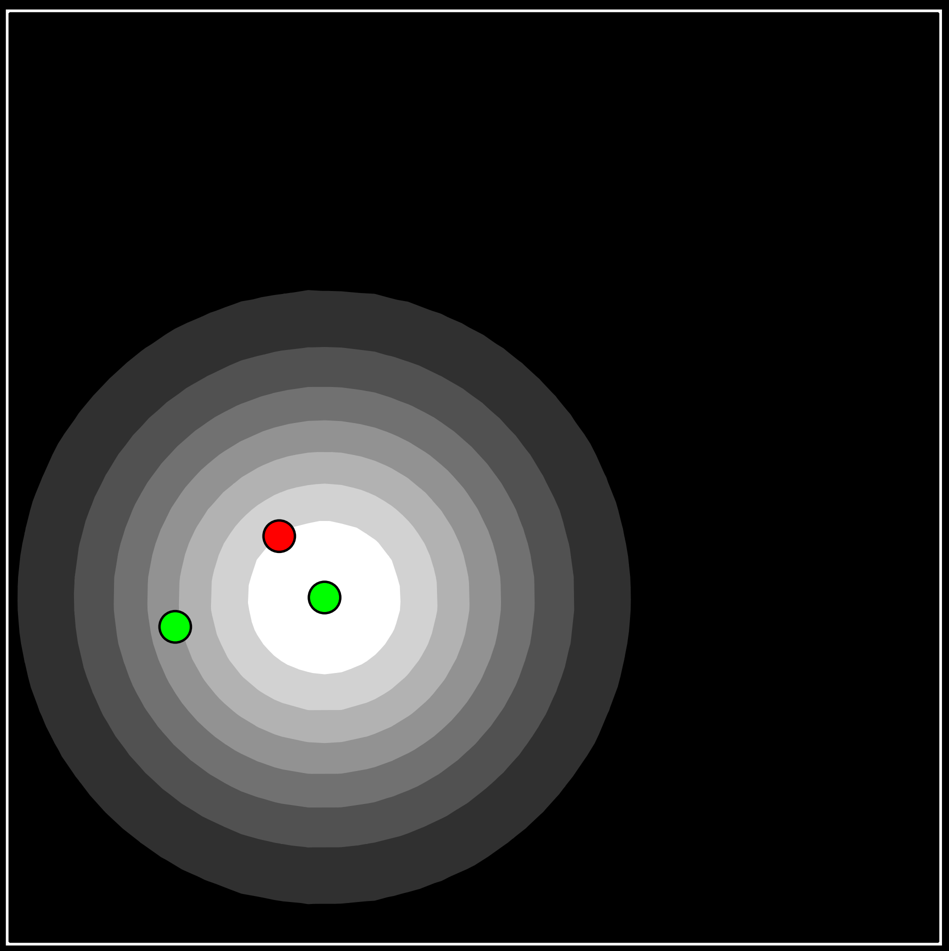

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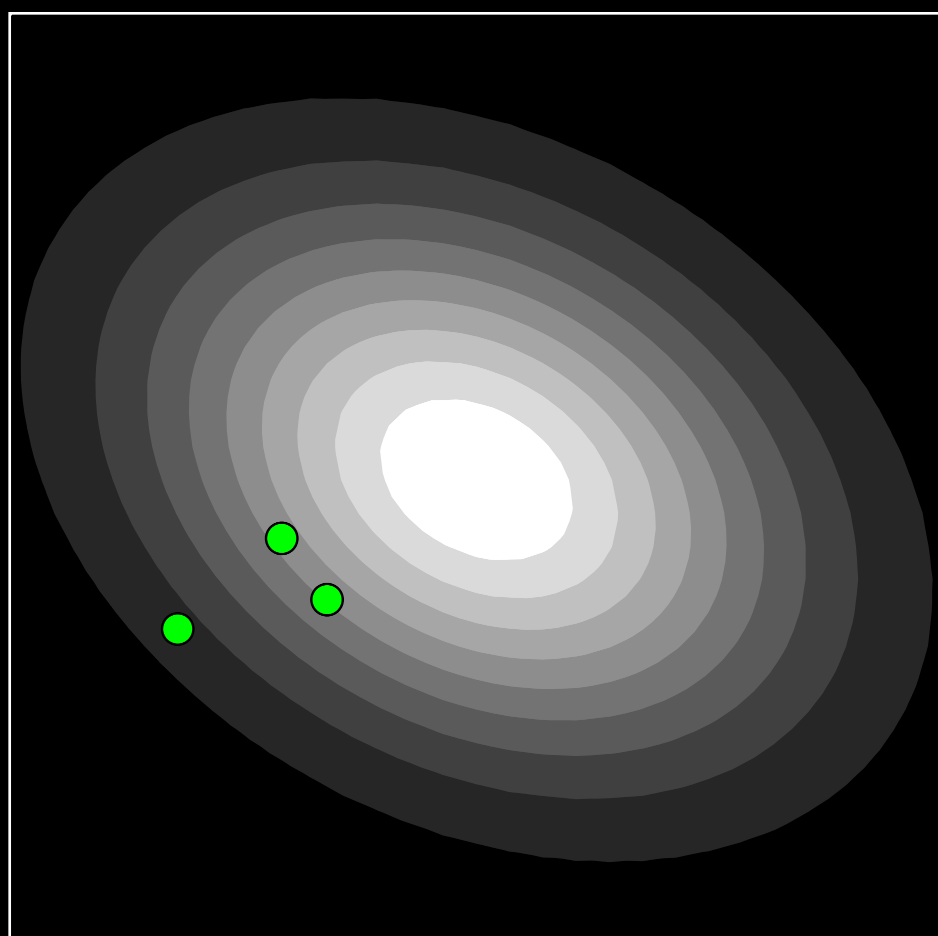

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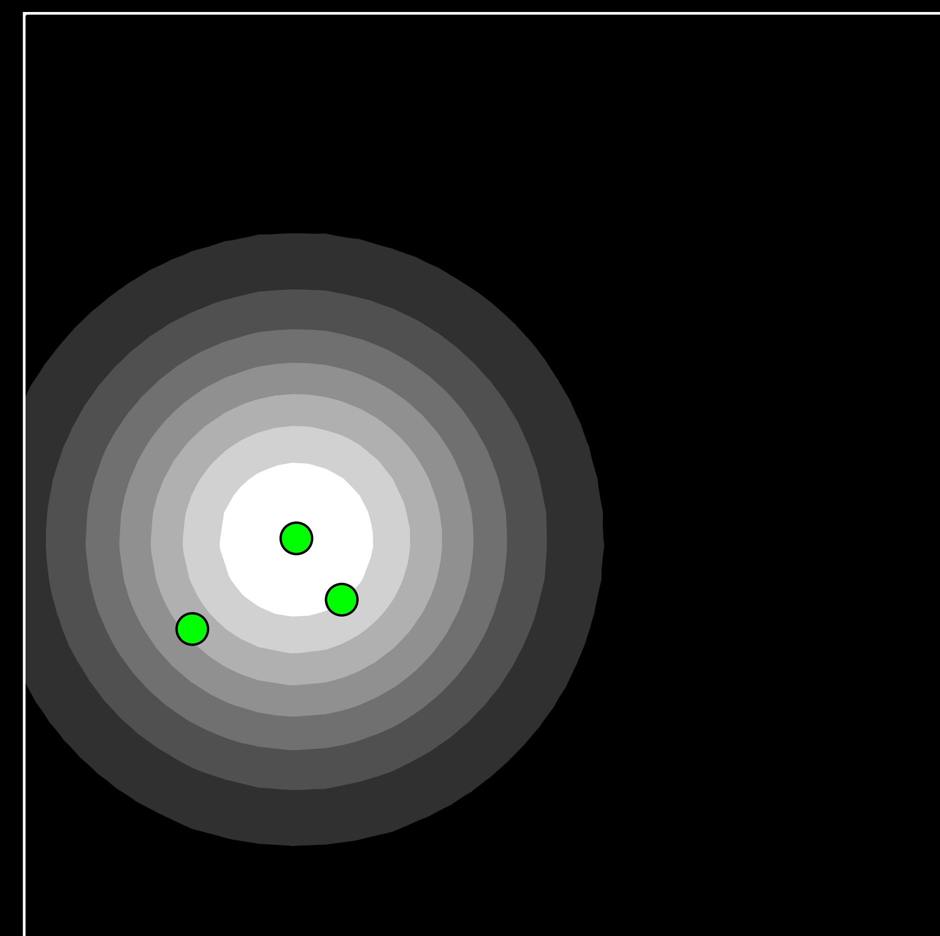

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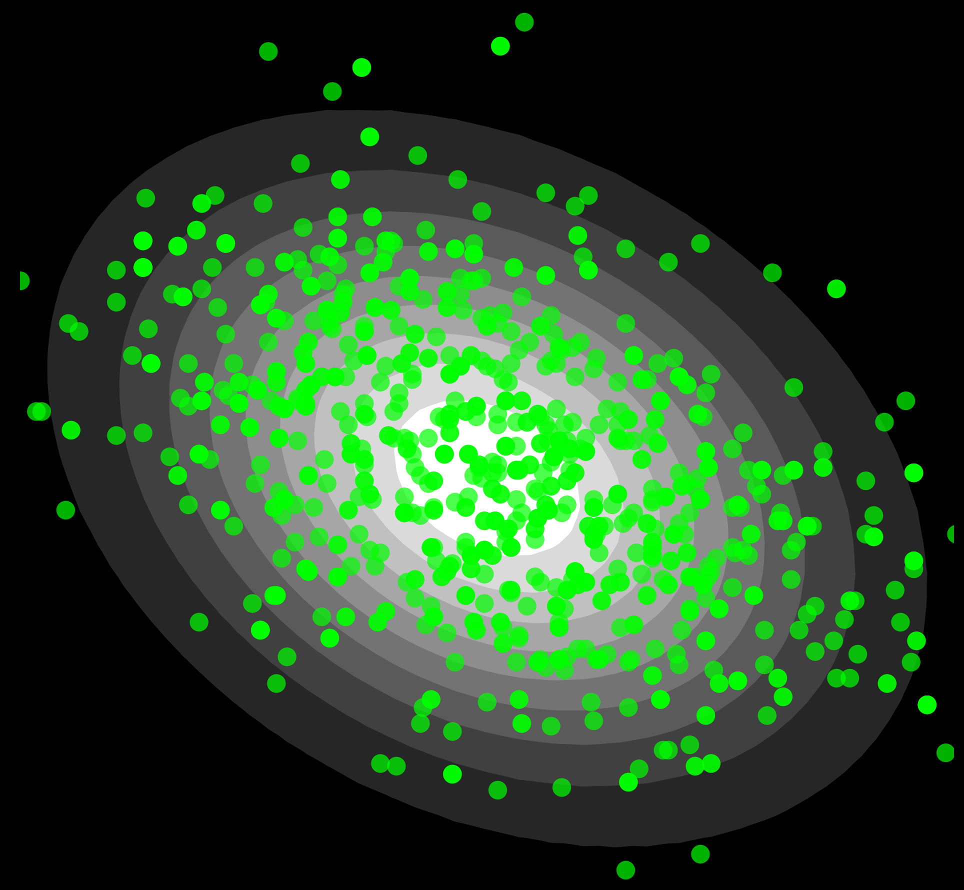


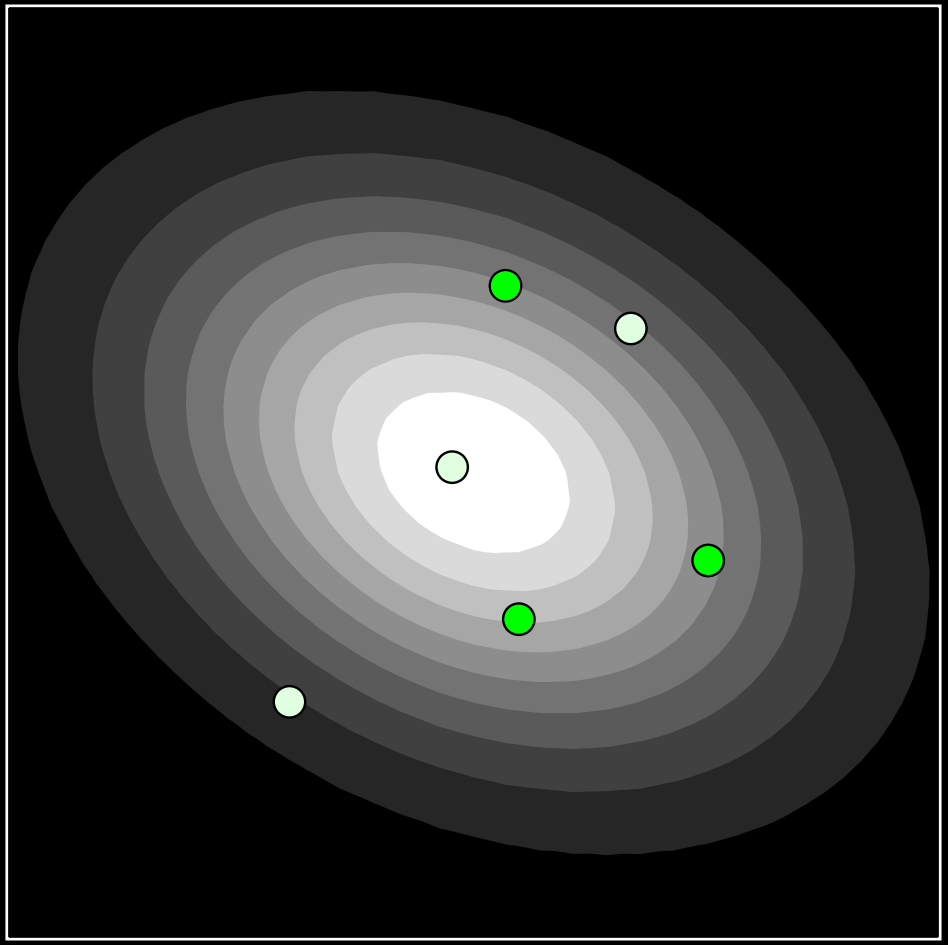
after 1,000 iterations

MCMC in Cosmology

- Estimation of cosmological parameters with MCMC is time consuming
- Multiple runs of the same likelihood
  - Learn about different models and configurations

emcee

Foreman-Mackey+ 2012
Goodman+ 2010



initial positions $\theta_0^1, \cdots, \theta_0^m$

emcee

Foreman-Mackey+
2012
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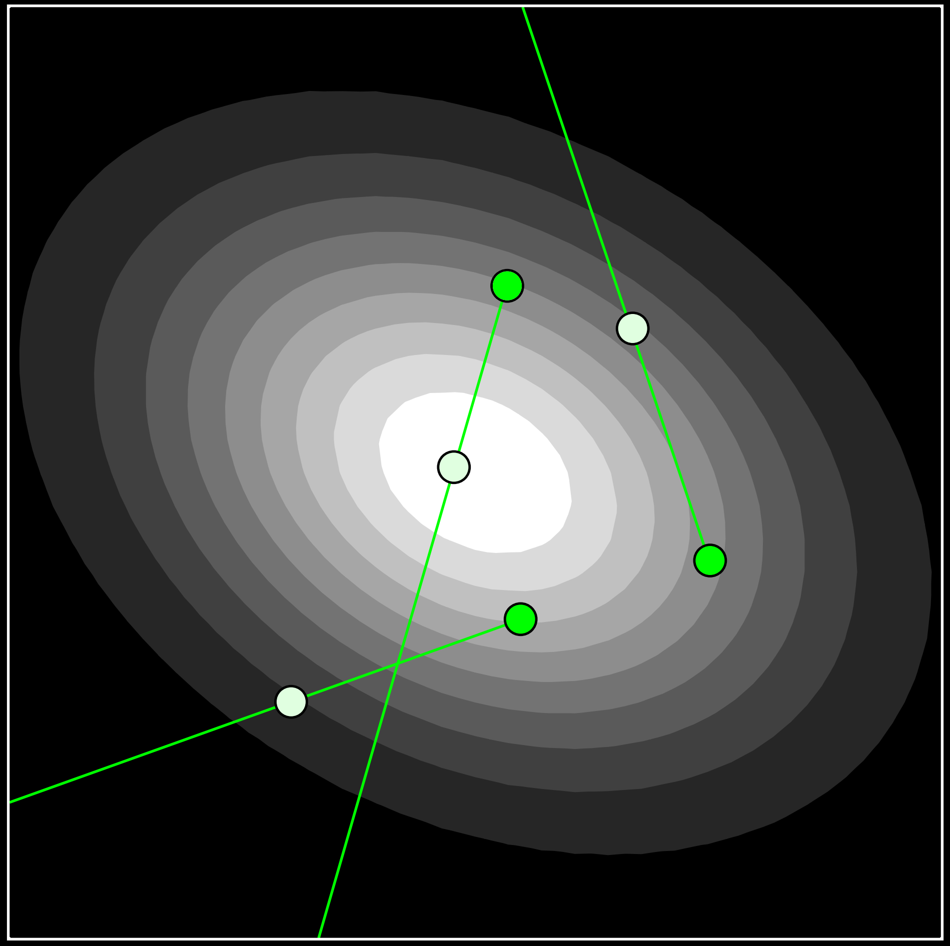
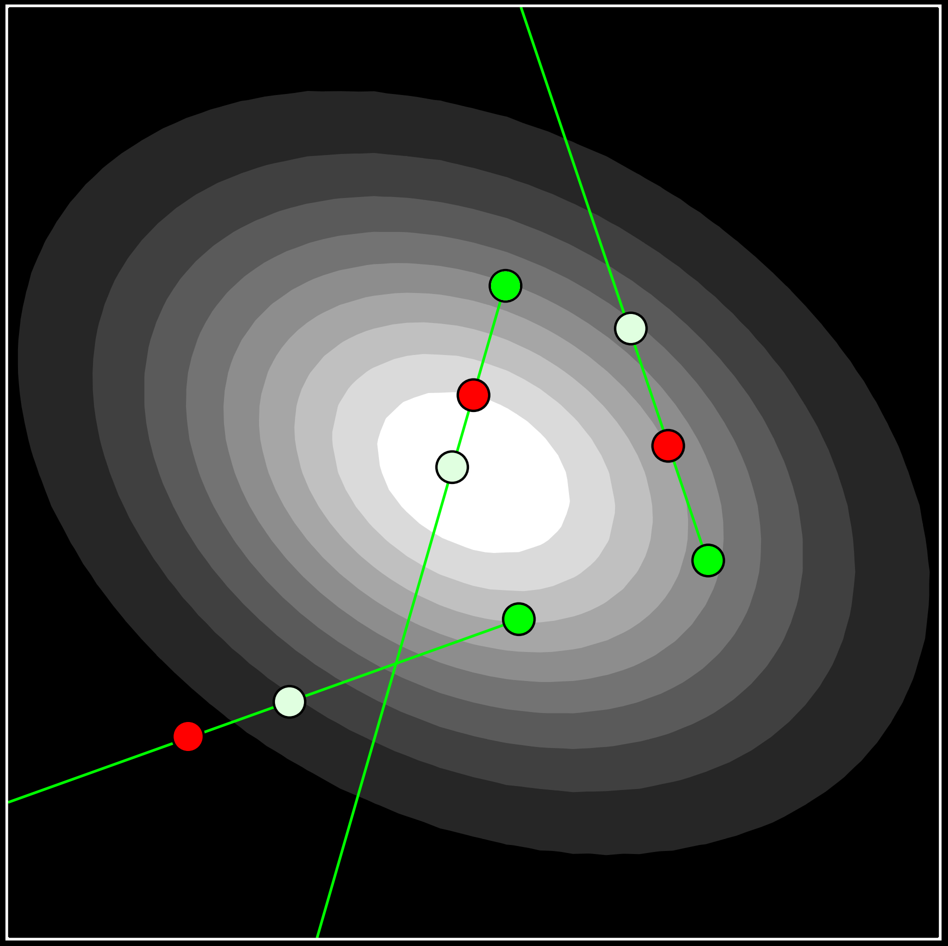


pick a partner at random

emcee

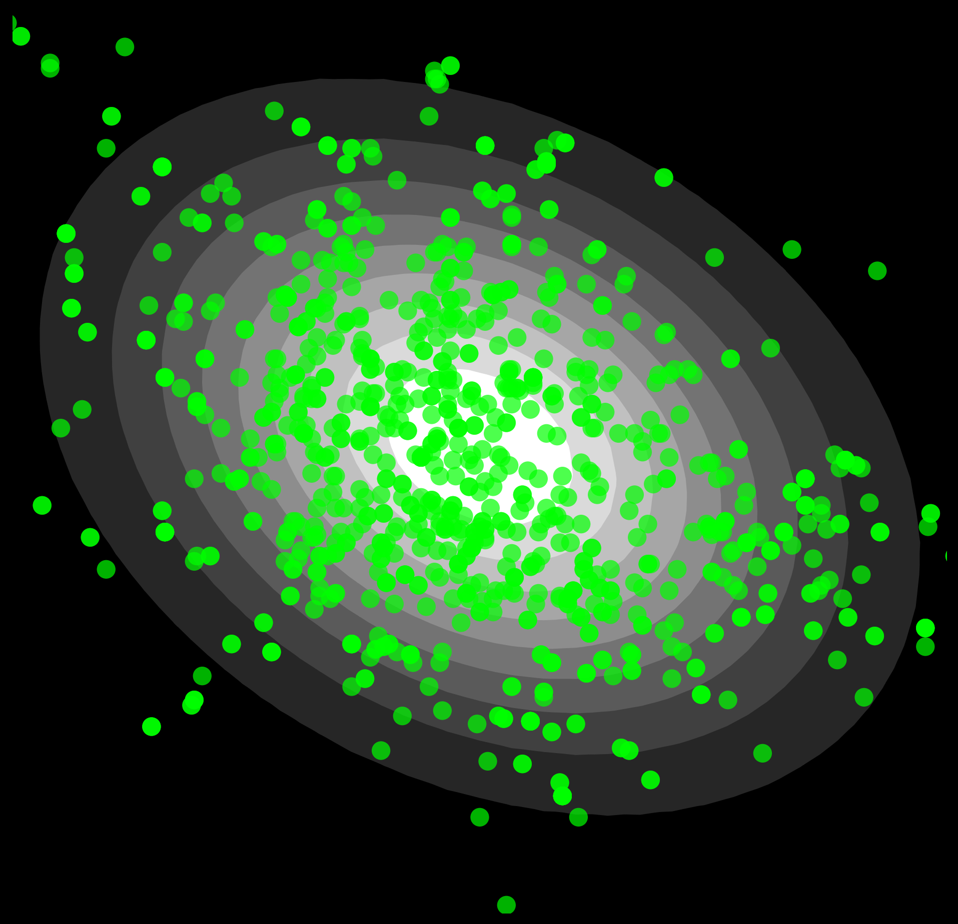
Foreman-Mackey+
2012
Goodman+ 2010



propose positions on connecting rays

emcee

Foreman-Mackey+ 2012
Goodman+ 2010

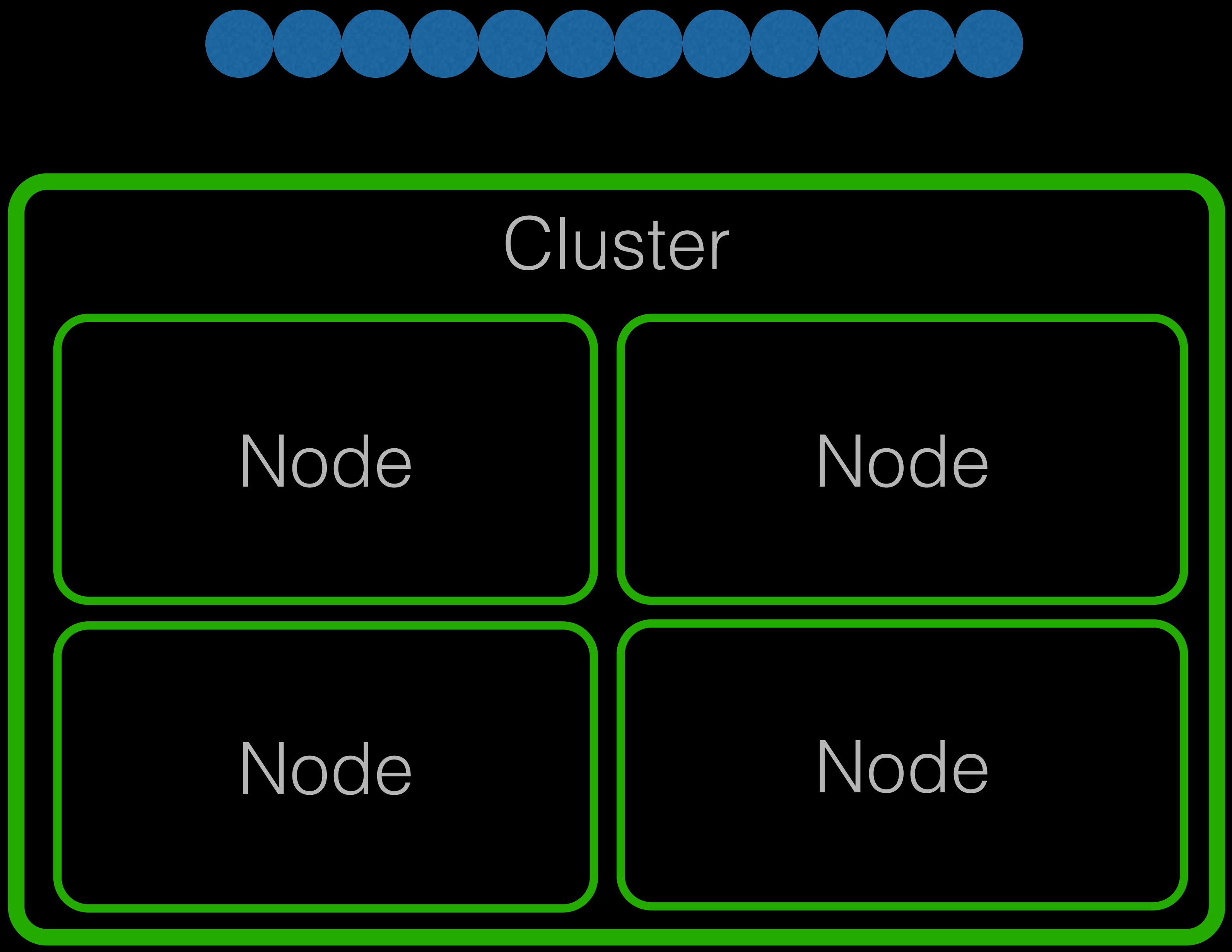


after 1,000 iterations

CosmoHammer

- Python framework for parallelised MCMC sampling with emcee
  - Flexible architecture to sample various models and data sets
- Distributes the workload over multiple nodes in a compute cluster
  - Built on MPI and Python multiprocessing

CosmoHammer



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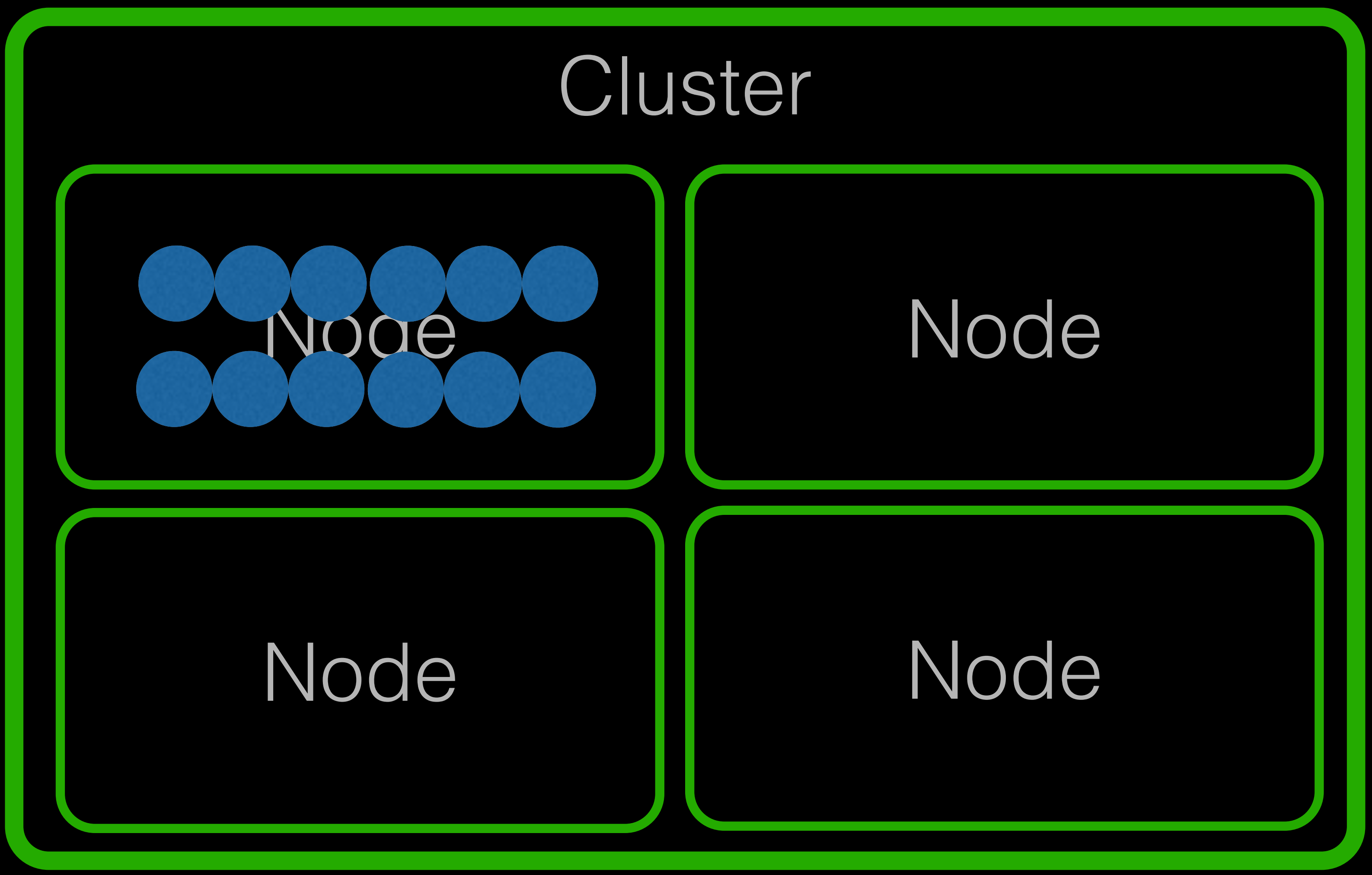

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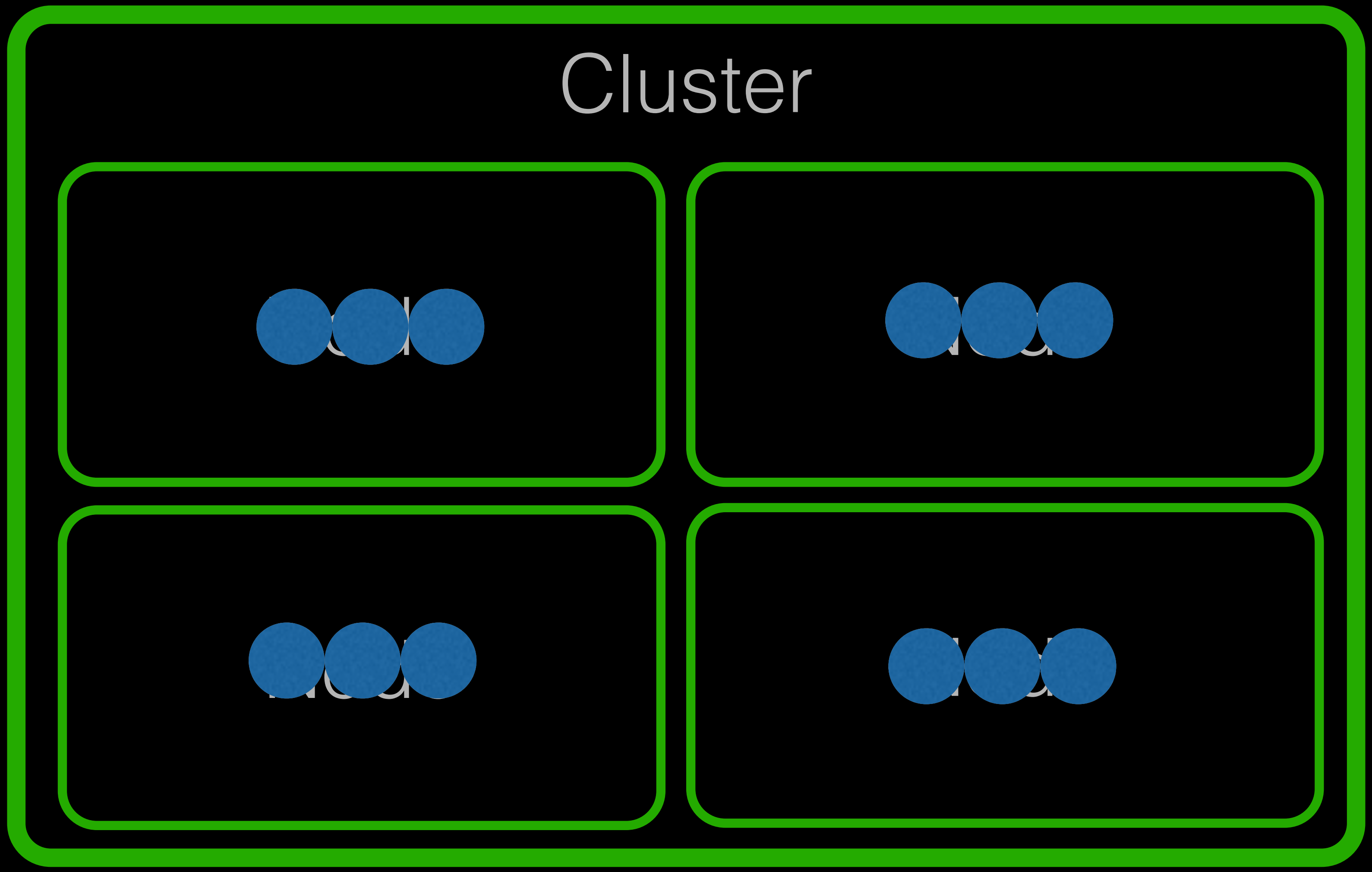

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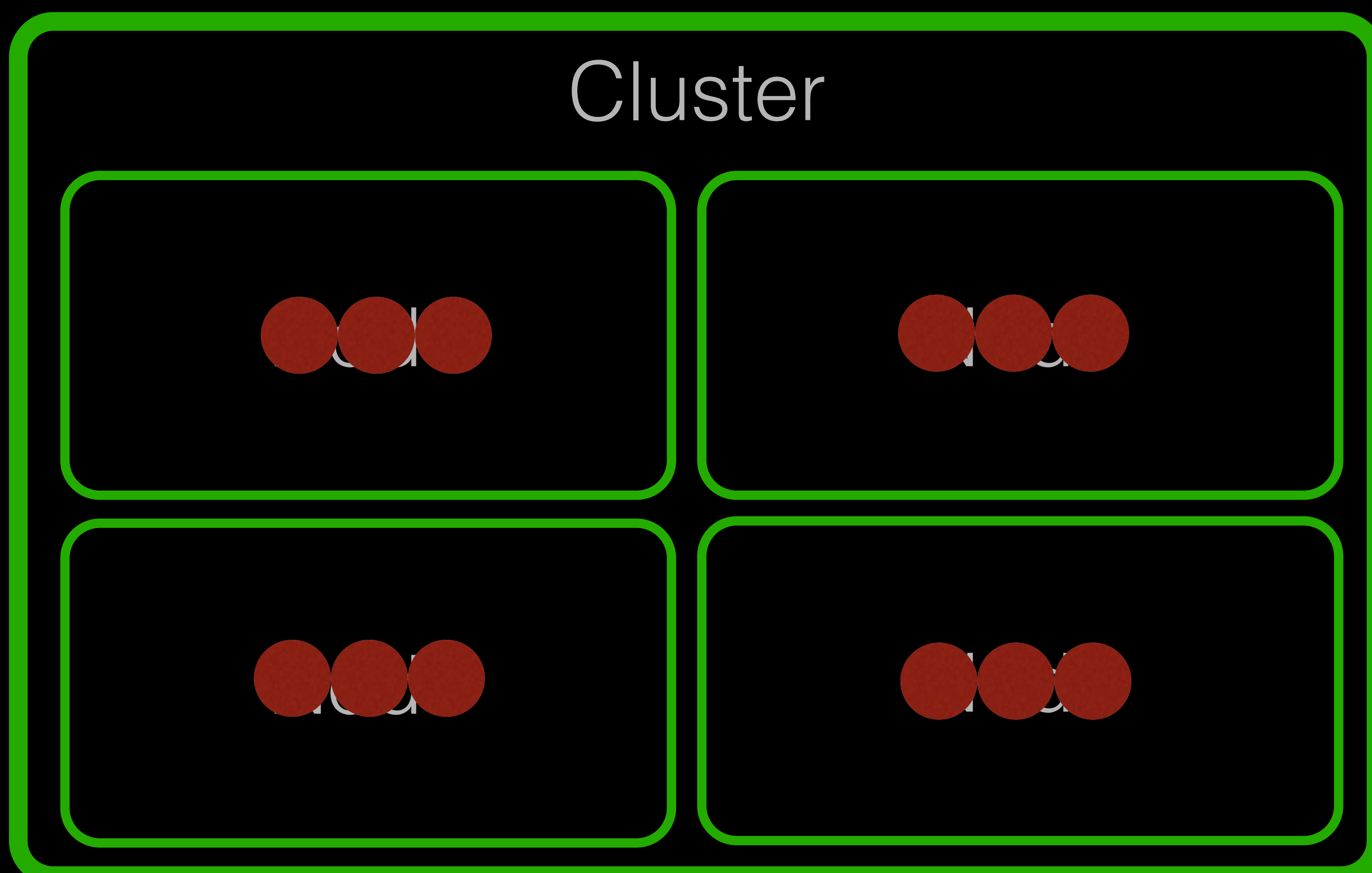

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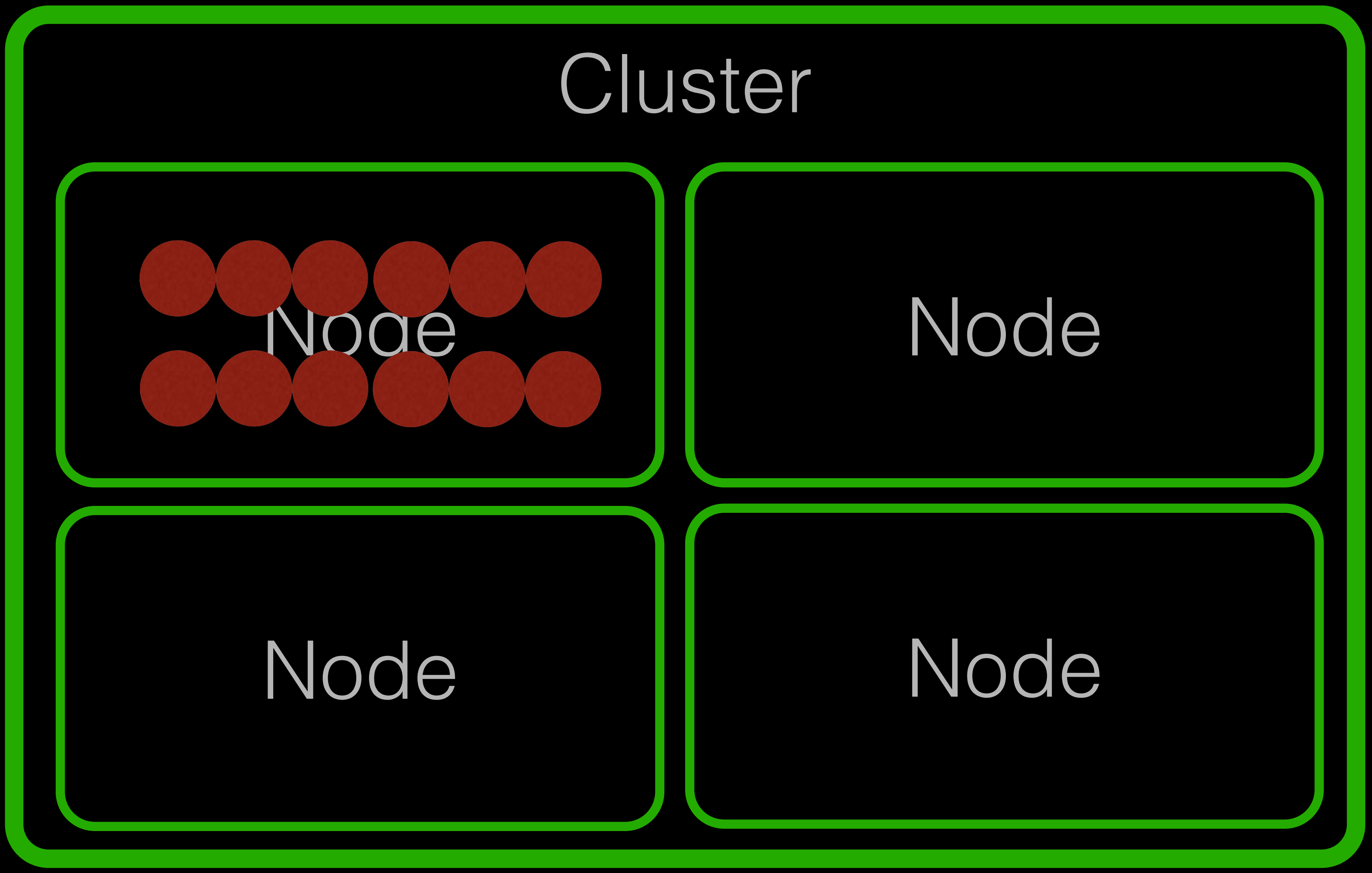

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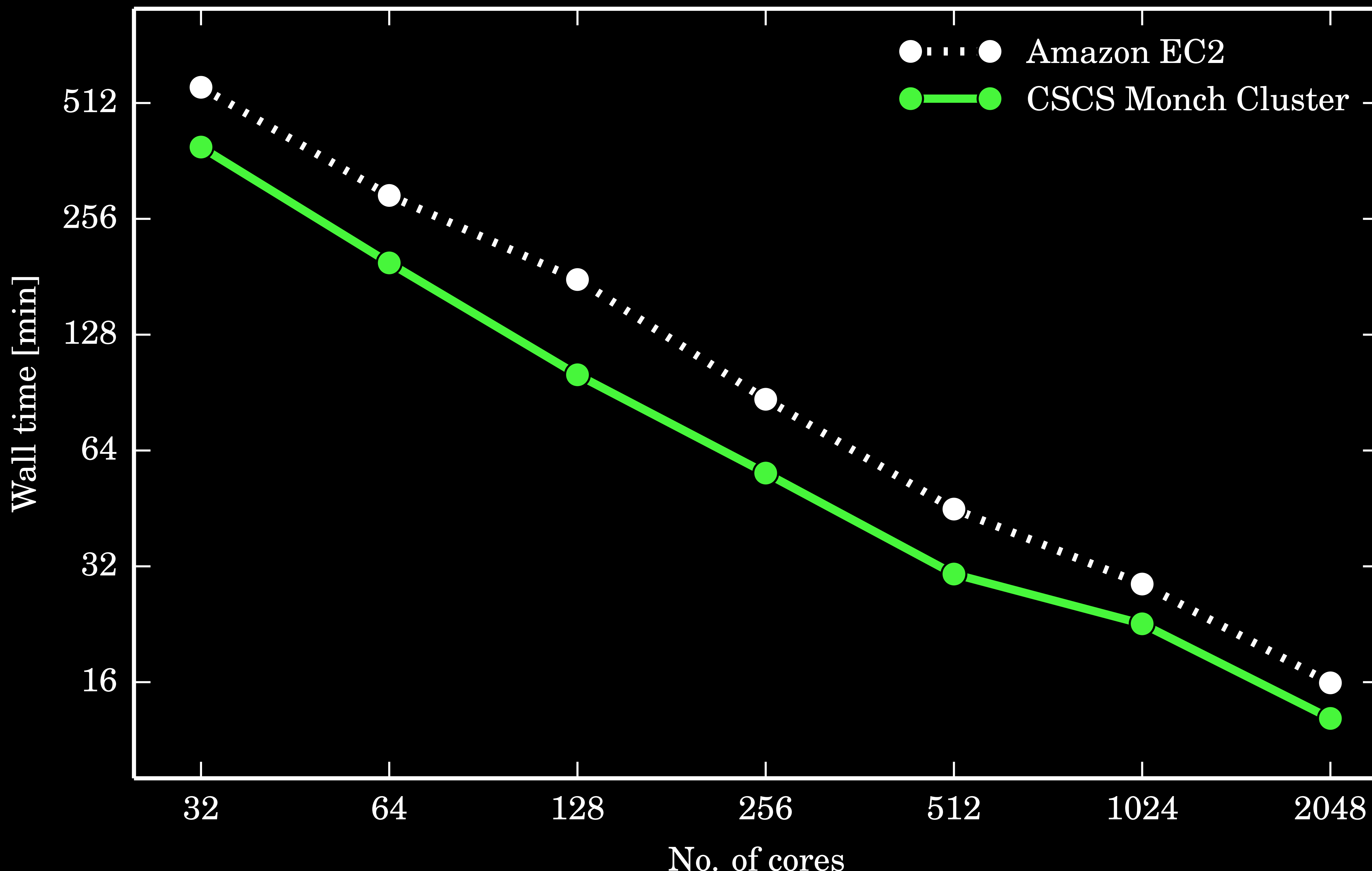
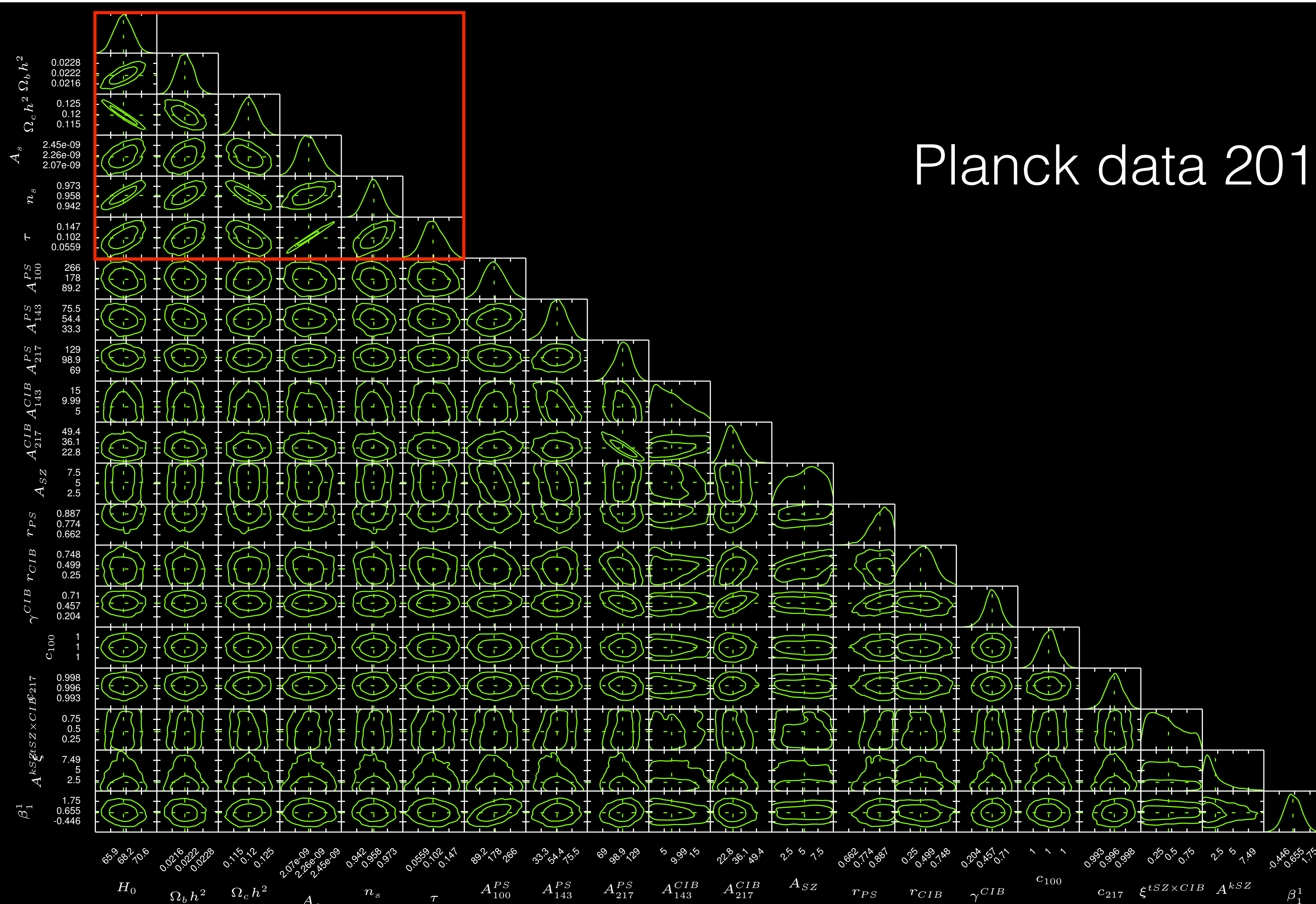


Current challenges



Planck data 2013

Current challenges

- Fast sampling in high dimensions
- Diagnostics & Convergence criteria
- Handling of systematic effects

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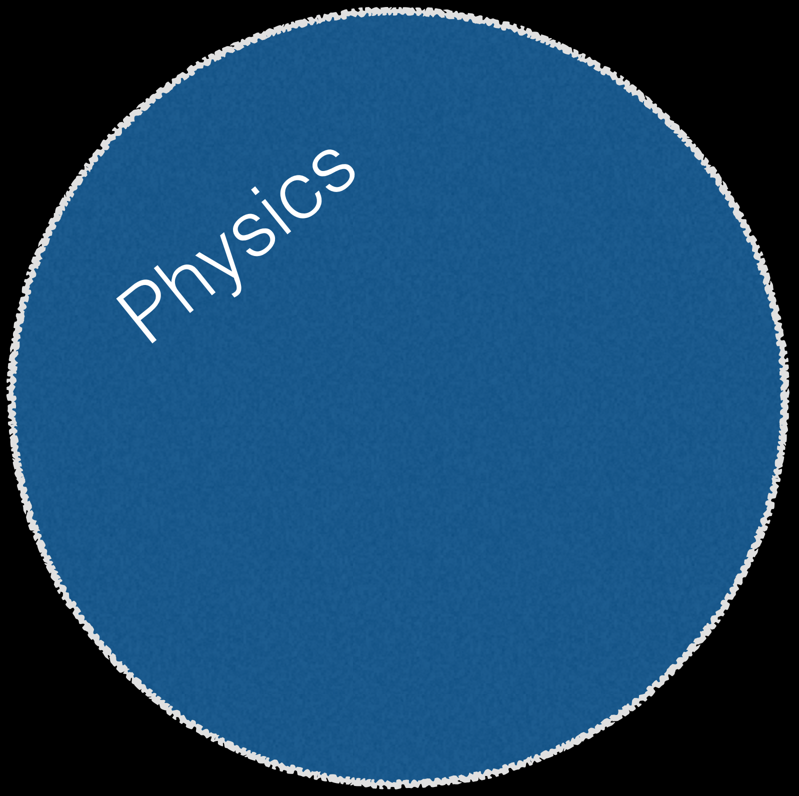

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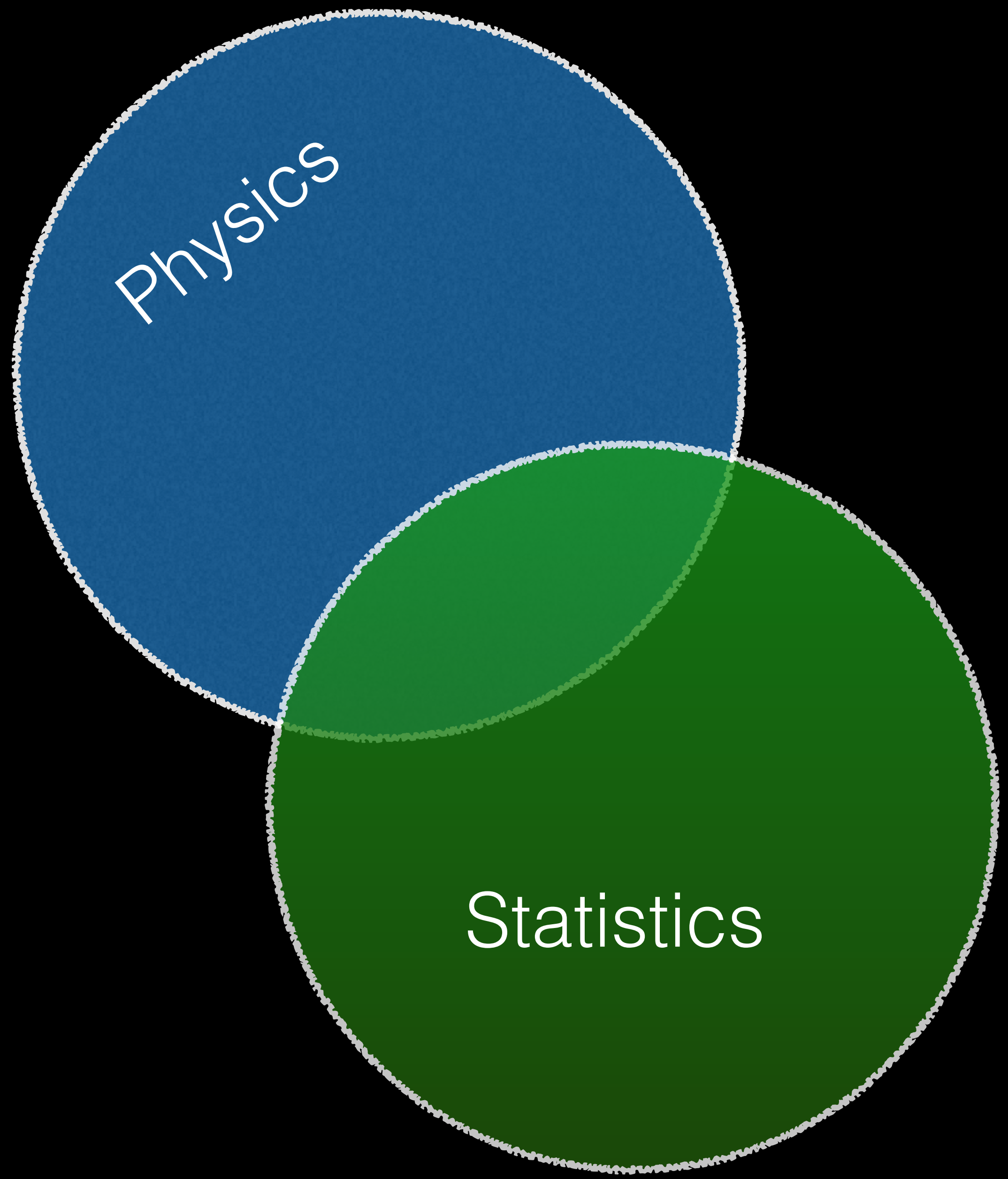

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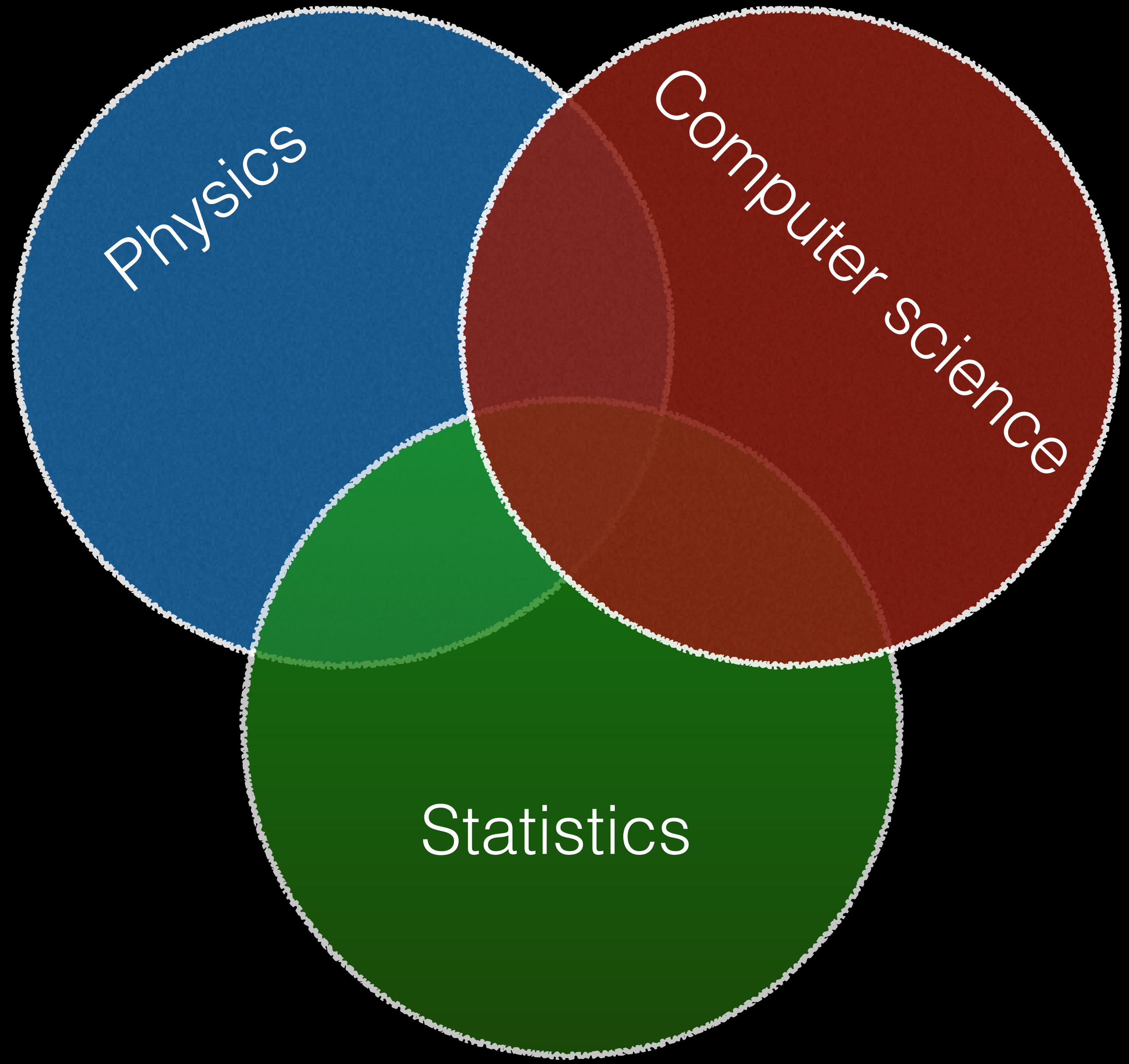

CosmoHammer References

- Akeret J., Seehars S., Amara A., Refregier A., and Csillaghy A. (2013). Astronomy and Computing, Volume 2, Pages 27-39
  - http://dx.doi.org/10.1016/j.ascom.2013.06.003
- Available at http://www.astro.ethz.ch/refregier/research/Software/cosmohammer