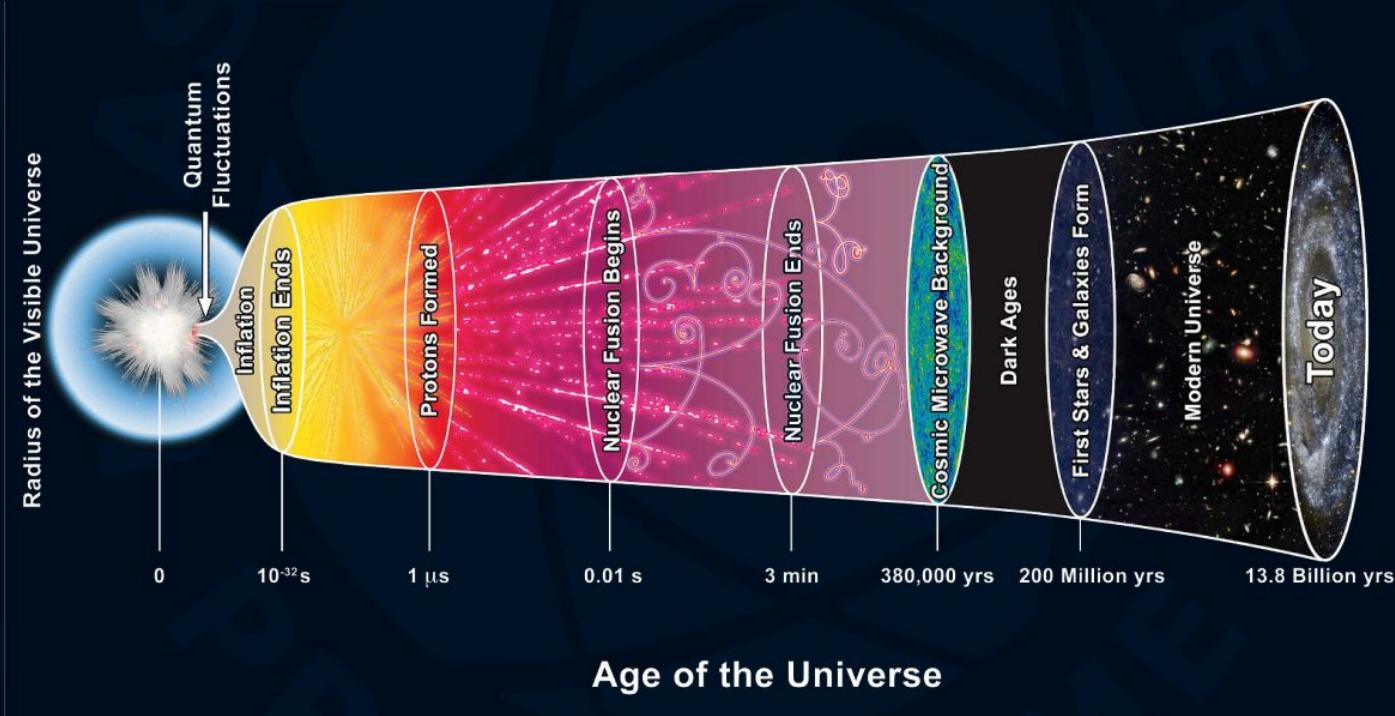


Cosmology Big Data

Rens Verkade

Cosmology in a nutshell

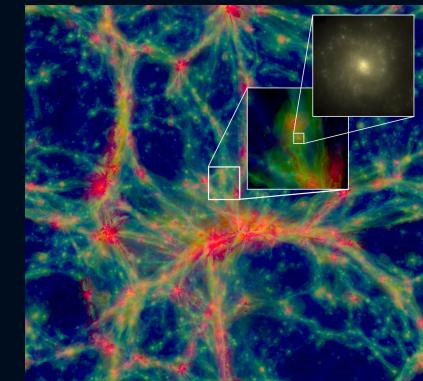


Age of the Universe

BICEP2/CERN/NASA

Cosmological model

- Current ‘standard’ Λ CDM model
- A universe with Cold Dark Matter and a cosmological constant Λ
- Cold Dark matter allows for bottom-up clustering
- The Cosmological constant plays an important role in the expansion of the universe



EAGLE simulation

Standard candles

- Type I A Supernovae
- White dwarf in a binary system
(usually with a red giant)



Nasa

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Nasa

Standard candles

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- White dwarf in a binary system
(usually with a red giant)
- Accretion until $M_{WD} \simeq 1.43M_\odot$
- The Chandrasekhar limit where $R_{WD} = 0$
- White dwarf contracts heavily and a runaway thermo-nuclear reaction produces the supernova

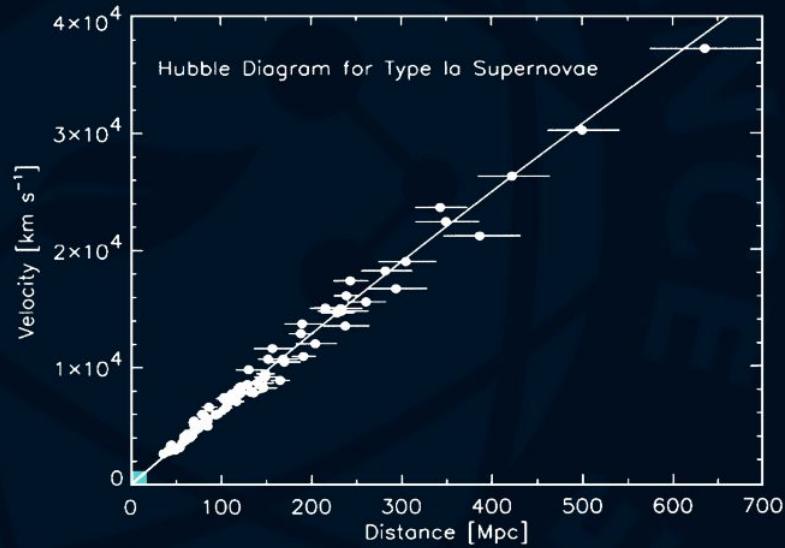


Nasa

An expanding universe

- Type Ia Supernovae have the same peak absolute magnitude
- Difference to observed magnitude gives distance
- Velocity from redshift of peak and spectral lines
- Hubble finds a linear relation!

$$v = H_0 d$$



E. Hubble, PNAS March, 1929, 15 (3) 168-174

Hubble parameter

- The Hubble rate parameterises the growth/shrinkage of the universe

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- Little h is an often used unitless version
- Depends on the cosmological contents

$$h \equiv \frac{H_0}{100 \text{ km/s/Mpc}}$$

$$H(z) = H_0 \sqrt{\Omega_\Lambda + \Omega_k(1+z)^2 + \Omega_m(1+z)^3 + \Omega_r(1+z)^4}$$

$$\Omega_i = \frac{\rho_i}{\rho_{crit}} \qquad \qquad \Omega_k = 1 - \Omega_m - \Omega_r - \Omega_\Lambda$$

Some statistical tools

- Probability of B, given A

$$P(B|A)$$

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- Our goal is how likely the values of some parameters θ are, given how well they reproduce the data D.
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- Prior

$$P(\theta)$$

- Evidence

$$P(D)$$

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- The statistic we are interested in depends on what you want to know
- Posterior tells you how likely your theory model is given the data $P(\theta|D)$
- In discoveries we are more interested in the likelihood $P(D|\theta)$
- Given your hypothesised model, probability of finding the data you have measured. Often we first predict and then measure. (Higgs!)

Bayes' Theorem in practice

- Let's say you get tested for some disease
- It's rare so 1 in 100 people with the symptoms actually have the disease

Example from Megan Bell
[https://tomrocksmaths.com/
2021/08/31/bayes-theorem-
and-disease-testing/](https://tomrocksmaths.com/2021/08/31/bayes-theorem-and-disease-testing/)

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- Not 1/100, we have additional info, the test

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	Have the disease	Don't have the disease
Test positive	99%	6%
Test negative	1%	94%

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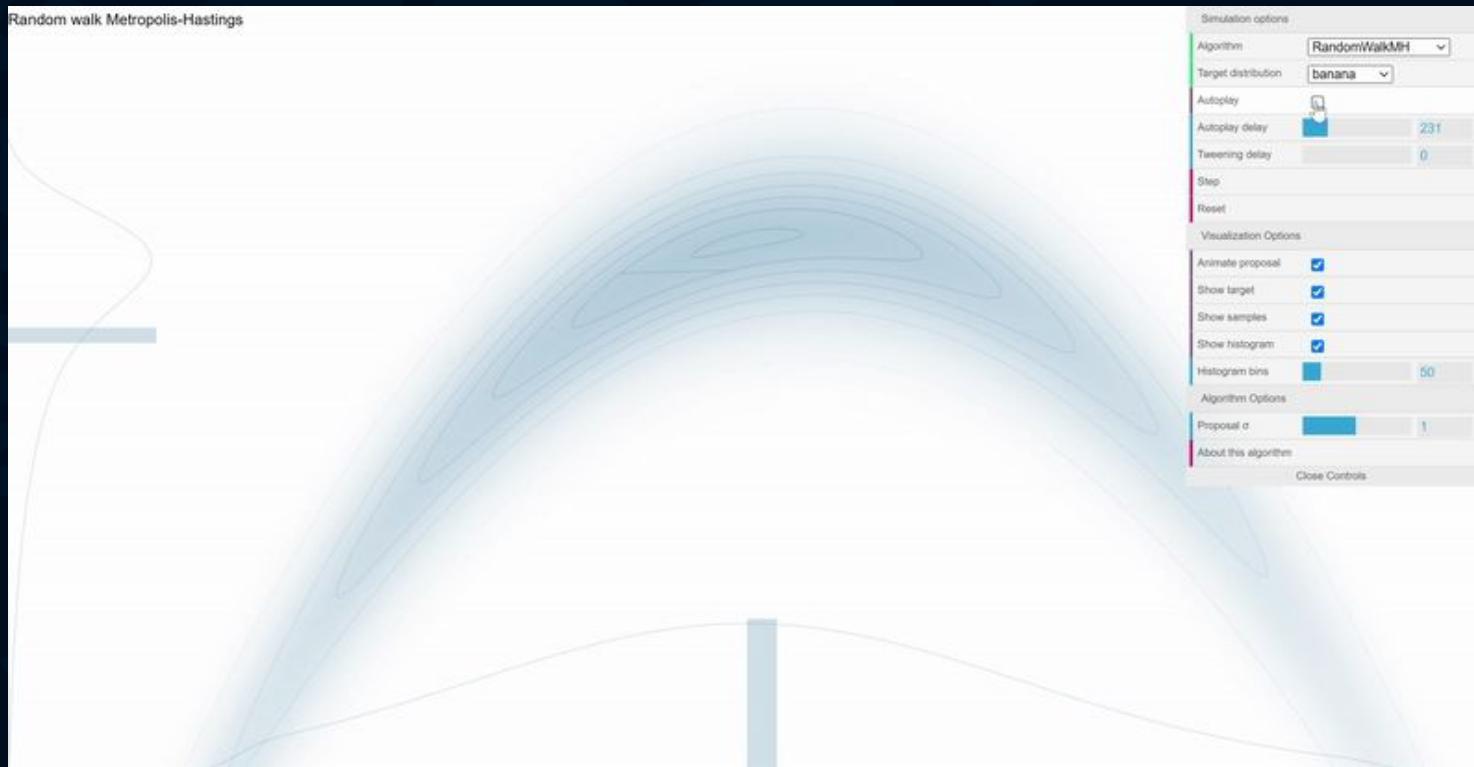
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$$P(\text{sick} \mid t = +) = \frac{0.99 \times 0.01}{0.99 \times 0.01 + 0.06 \times 0.99} = \frac{1}{7}$$

Monte Carlo Markov Chain (MCMC)

- MCMC is one way to sample the probability distribution $P(\theta|D)$
- The algorithm steps randomly and checks if the new Θ is better (χ^2 - test)
- If the step is better we keep the new location, if not try again

Monte Carlo Markov Chain (MCMC)



<https://chi-feng.github.io/mcmc-demo/>

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- Stop after n steps, or preferably after some convergence test is met

Hand-in

- Work on the cluster <https://jupyterhubroute-pra3024-2025.apps.dsri2.unimaas.nl/>
- Notebook is on Canvas and due DATE at 00:00
 - needs to be compiled (so output visible)
 - needs to be runnable (without extra installations)
 - Have comments AND Markdown (graded)
 - Use of sources is fine but give proper references otherwise it's plagiarism and you fail the exercise
 - Use of AI is allowed but understand the code so explain properly what you do in the markdown cells!
 - Check rubric on canvas to see how you are graded
- If questions arise email ON TIME
 - rens.verkade@maastrichtuniversity.nl
 - george.scriven@maastrichtuniversity.nl



PROGRAM

MASTERS

SCIENCE



MASTERS
PROGRAM

SCIENCE
EDUCATION

$$P(\text{have disease}|\text{positive test}) = \frac{P(\text{positive test}|\text{have disease})P(\text{have disease})}{P(\text{positive test})}$$

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