Virtual universes vs. the real thing

Andreea Font, Juliana Kwan, Ian McCarthy, Jaime Salcido
(on behalf of the Computational Galaxy Formation group)

Astrophysics Research Institute,
Liverpool JMU

Outline

- Cosmological simulations (“virtual universes”) - Ian
- The EAGLE database & visualisation - Jaime
- The Milky Way & Gaia - Andreea
- Parameter inference & MCMC - Juliana

Virtual universes

Ian McCarthy
(with thanks to Rob Crain)

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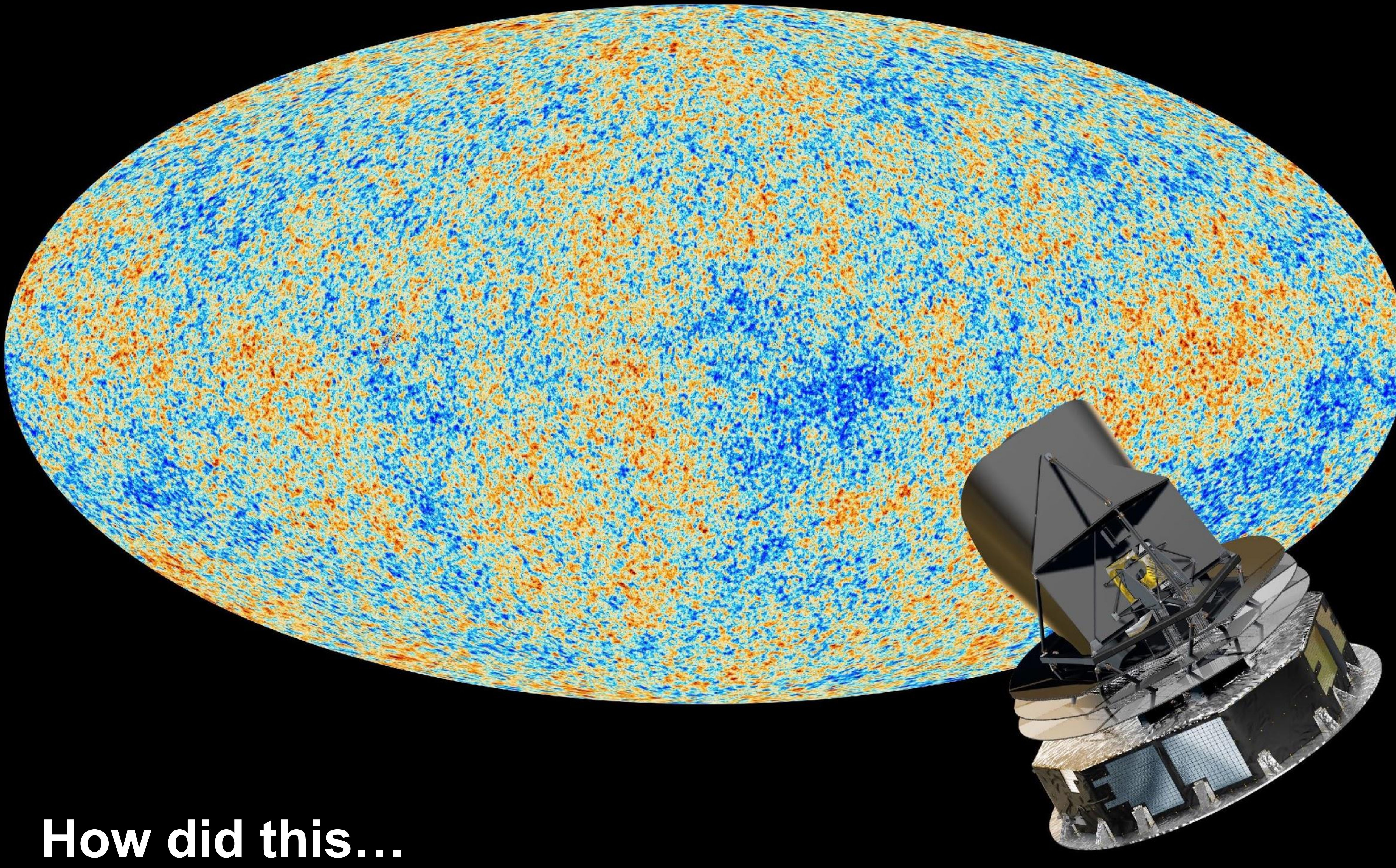
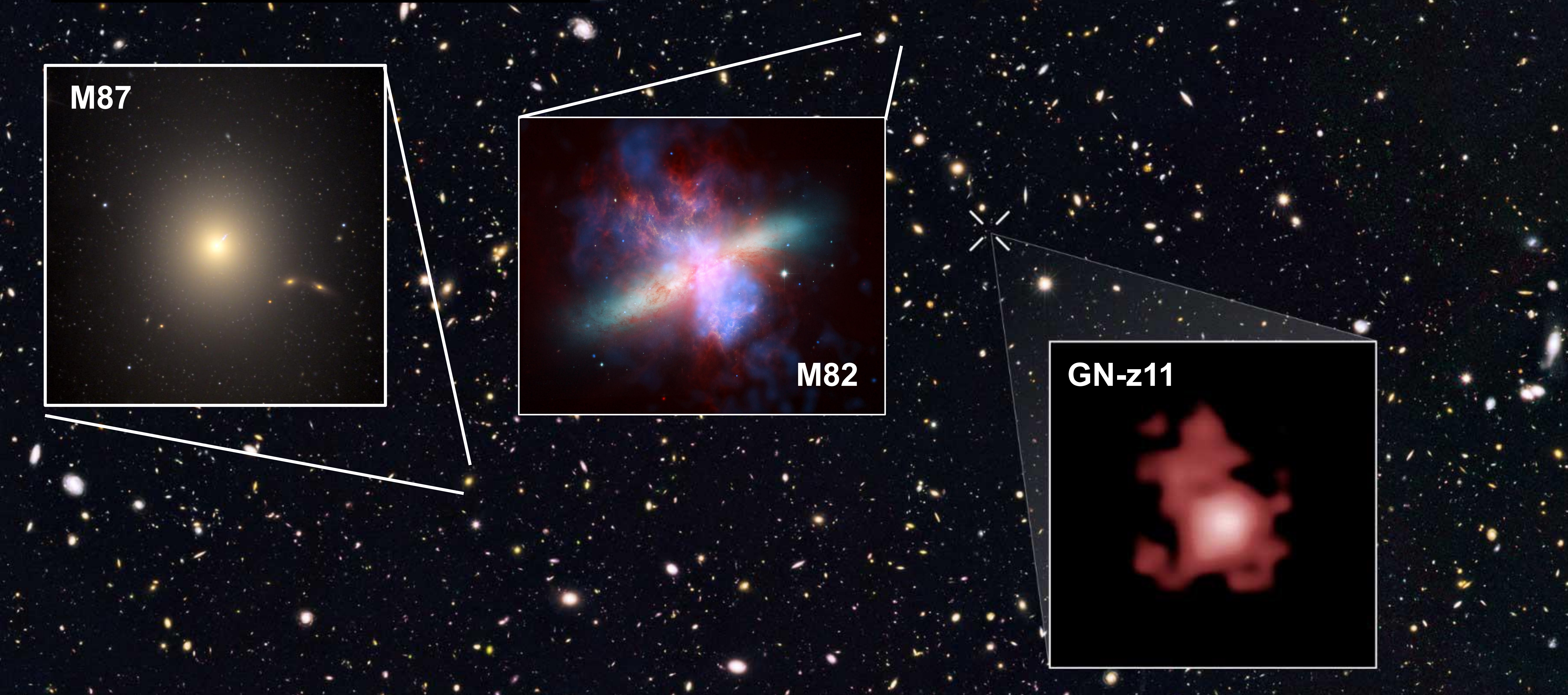
14 billion years ago, the Universe looked like this.



How did this…

…evolve into this?

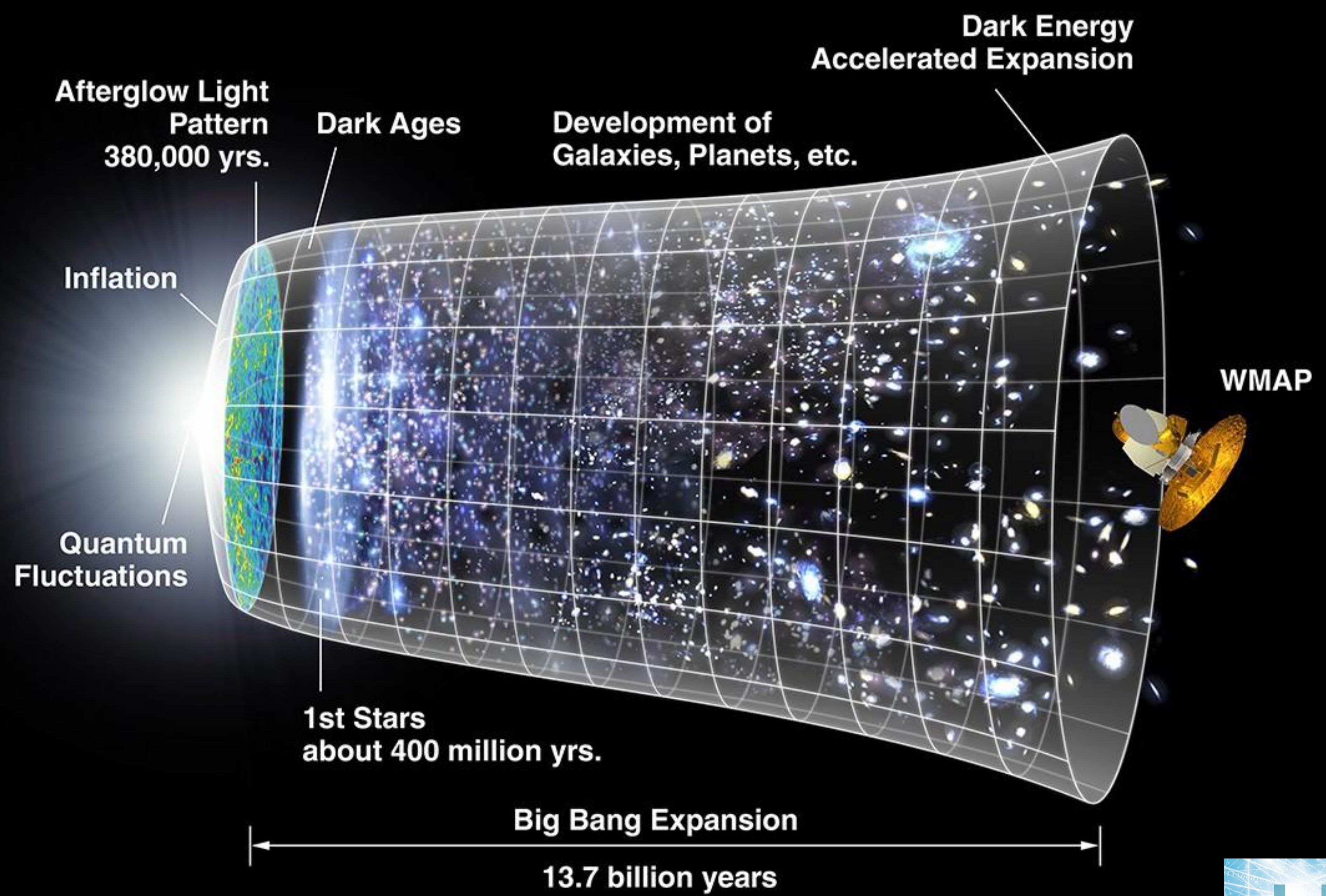


The formation & evolution of the galaxy population:

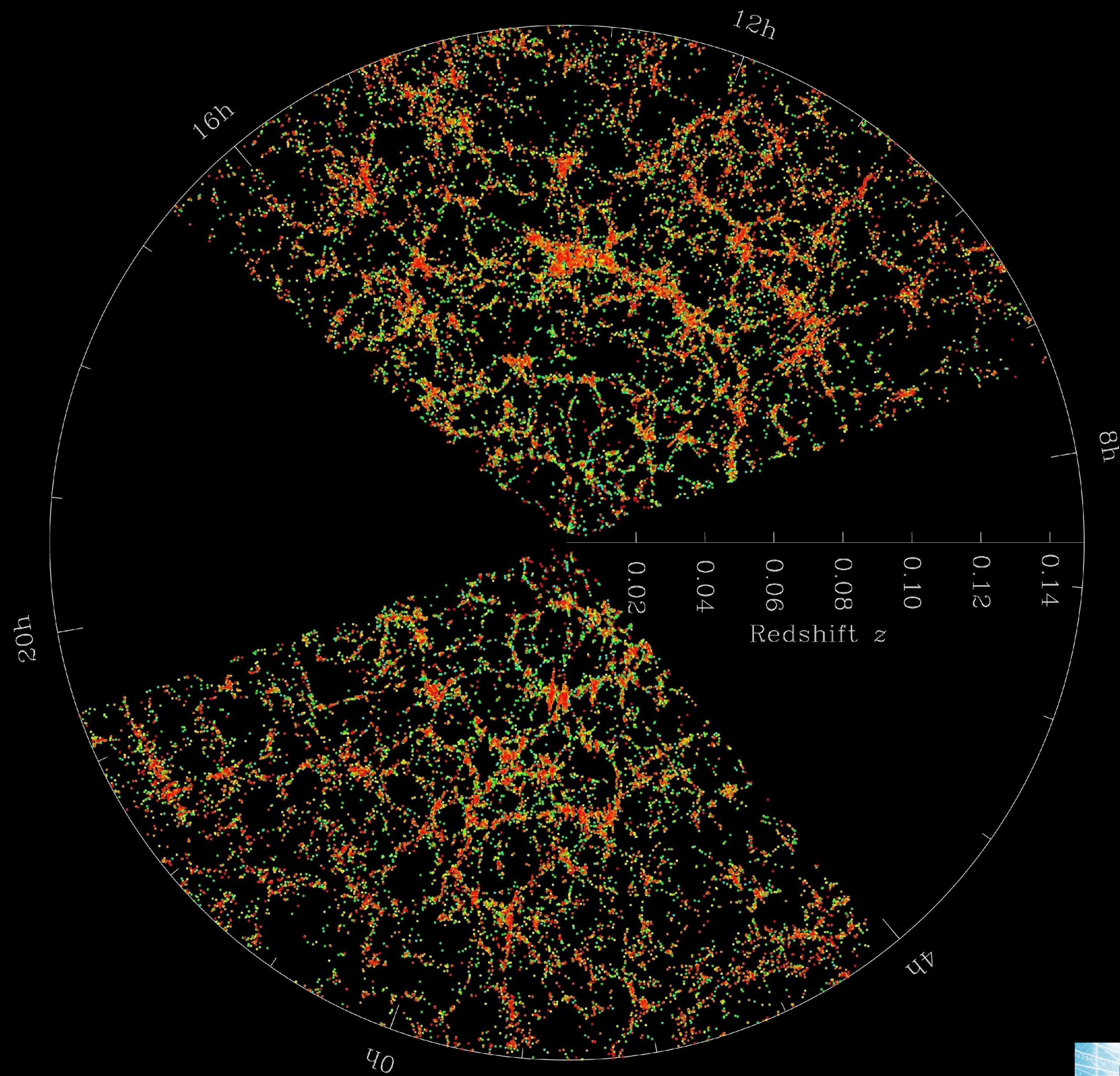
- How do dark matter, gas, stars and black holes assemble into galaxies?
- How do galaxies populate the cosmic large scale structure?
- How are galaxies influenced by physical processes & their environments?

Interfacing astrophysics with cosmology

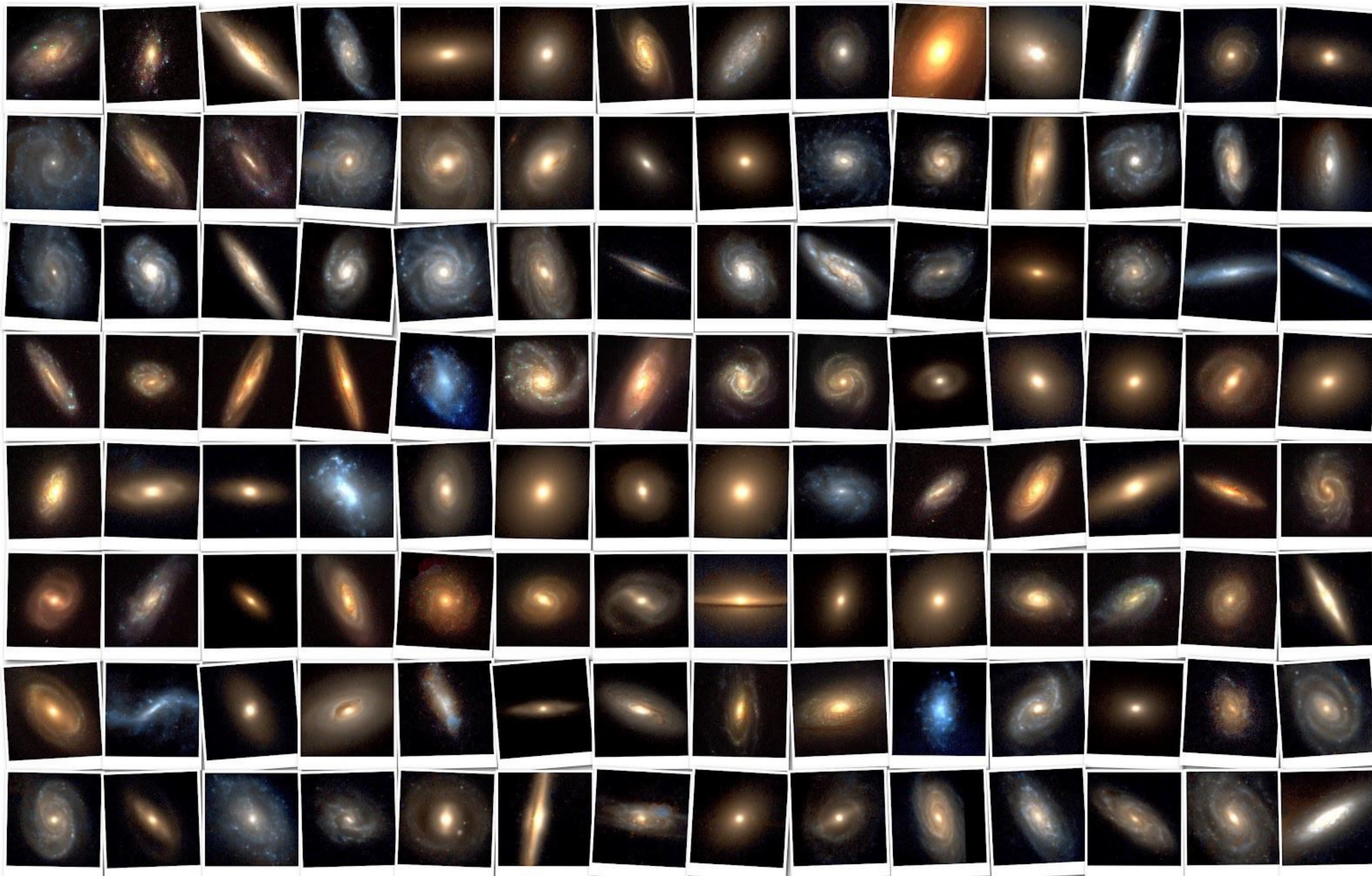
- Can we constrain the identify of dark matter via structural tests?
- Can we establish the influence of exotic ingredients on cosmic structures?
- What are the consequences of galaxy formation for observational tests?



Key question: why this distribution of galaxies?

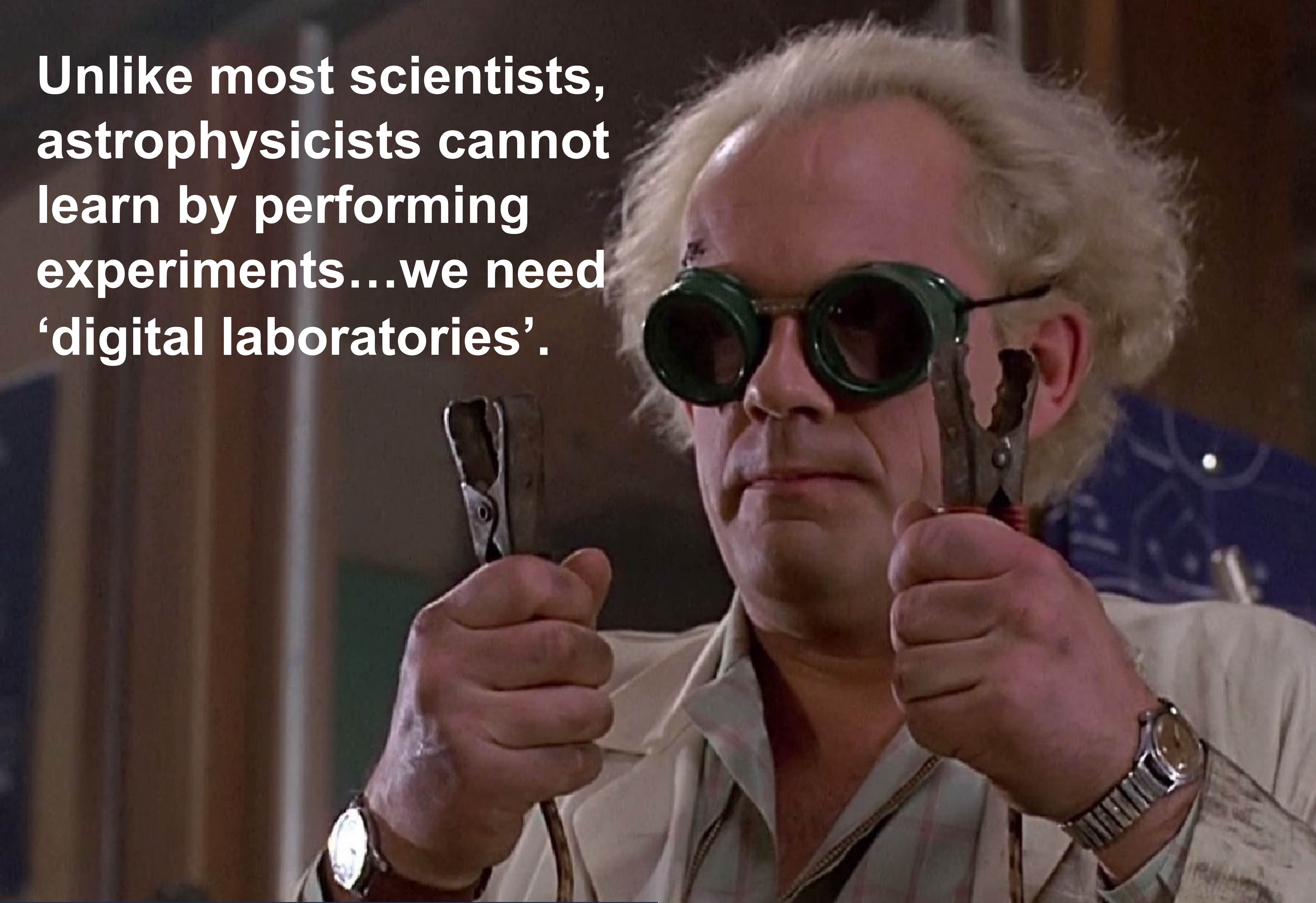


Key question: why this diversity of galaxies?



Key question: what drives these apparent environmental effects?

Unlike most scientists, astrophysicicists cannot learn by performing experiments…we need ‘digital laboratories’.

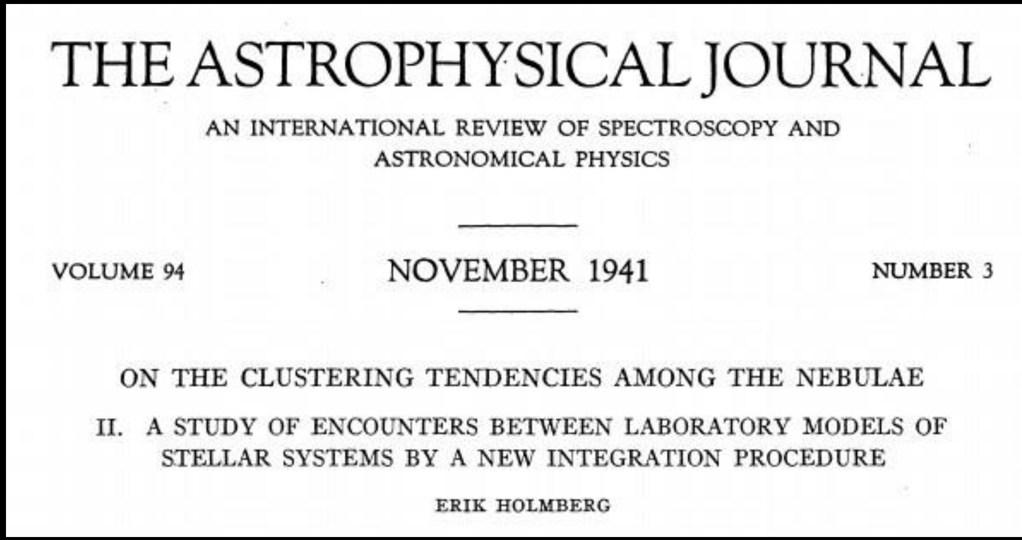


First attempt with analogue computers: Holmberg (1941)

Simulate 2 galaxies each with
37 “stars”, so 74 stars.

Each interacts with 73 others; total #
of interactions per step = 73*74 = 5402

No fun with pencil and paper:
use lightbulbs and light meters.



THE ASTROPHYSICAL JOURNAL

AN INTERNATIONAL REVIEW OF SPECTROSCOPY AND
ASTRONOMICAL PHYSICS

VOLUME 94 NOVEMBER 1941 NUMBER 3

ON THE CLUSTERING TENDENCIES AMONG THE NEBULAE

II. A STUDY OF ENCOUNTERS BETWEEN LABORATORY MODELS OF
STELLAR SYSTEMS BY A NEW INTEGRATION PROCEDURE

ERIK HOLMBERG

Feed initial conditions into a computer

(The Universe shortly after Big Bang is remarkably well understood)

↓

Program the computer with descriptions of the key astrophysical processes

(These are understood in vastly differing degrees)

↓

Evolve the initial conditions for 14 billion years, from the Big Bang to the present day

(Requires lots of calculations, i.e. a big computer)

↓

Compare with observational data (or make predictions)

(Occasionally we show the observers got it wrong!)

The ultimate calculation?

- **Length scales**
  - Event horizon of galactic black hole: ~ 100 Earth orbits: 10^{13} m
  - Size of observable Universe: ~ 10^{10} light years: 10^{28} m

  15 orders of magnitude

- **Mass scales**
  - Mass of star clusters: ~ 10^4 solar masses 10^{34} kg
  - Mass within obs. Universe: ~ 10^{21} solar masses 10^{51} kg

  17 orders of magnitude

- **Time scales**
  - Variability of galactic black hole: ~ few days 10^5 s
  - Age of the Universe: ~14 billion years 10^{17} s

  12 orders of magnitude

This would require a computer with 10^{12} processors and 10^9 TB of memory.
It would need 100 million times the current global electricity consumption. It would run for 10 million years (at least)!

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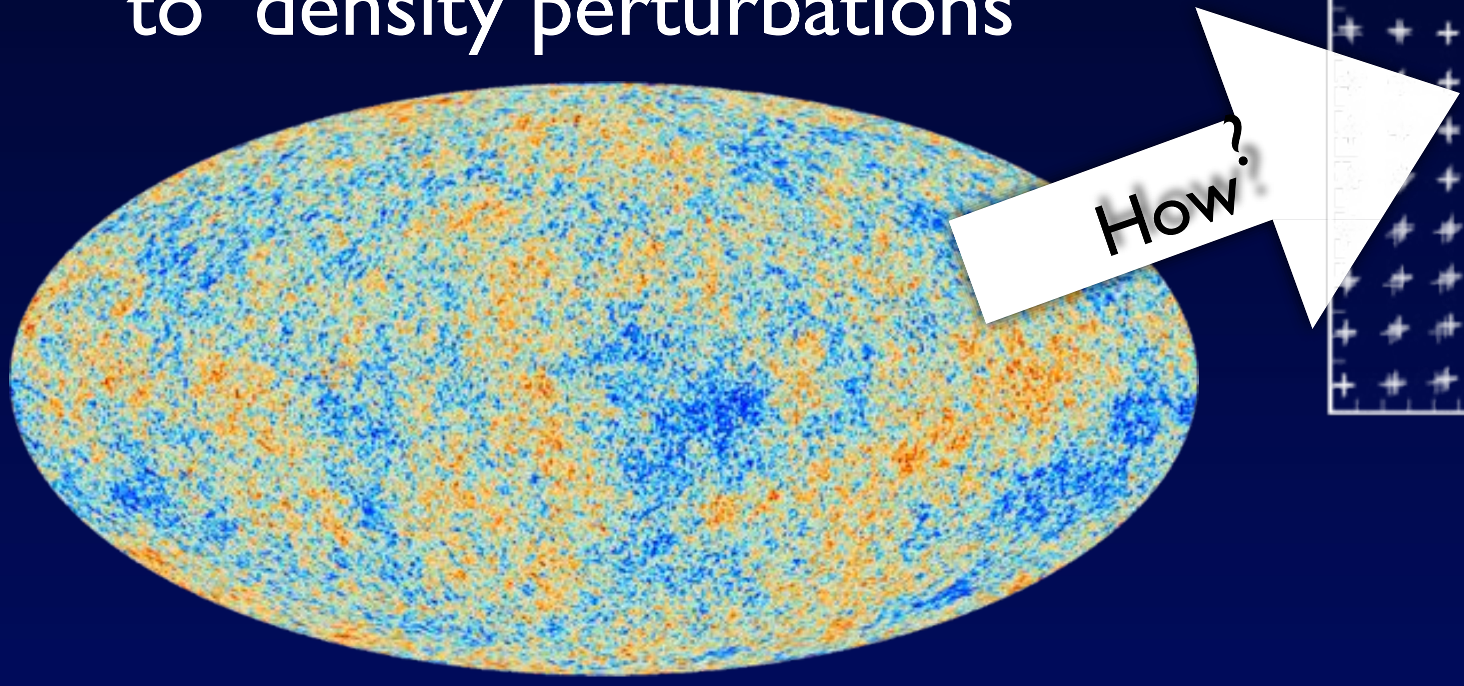
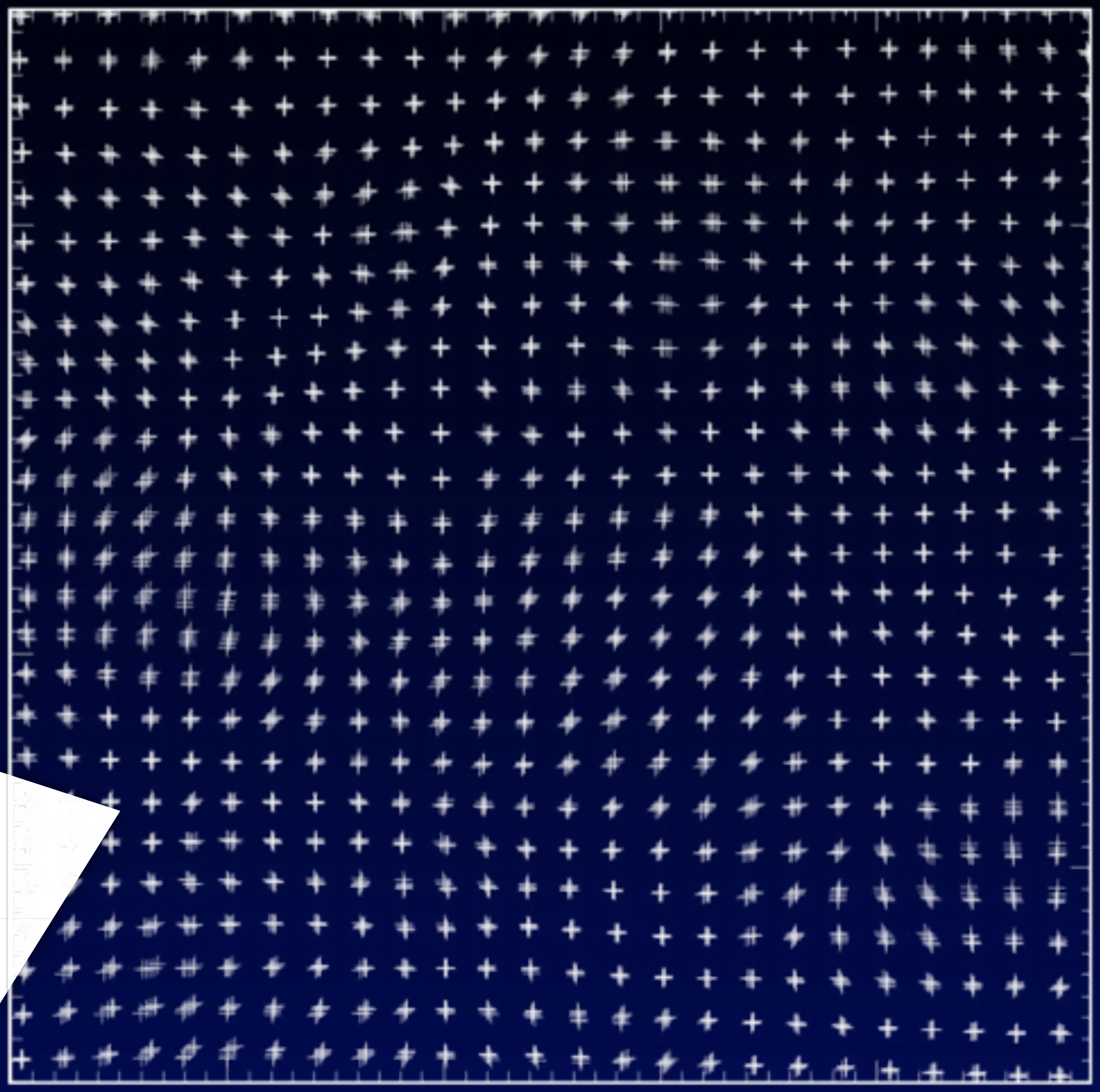
Perturbations

- Universe shows small density fluctuations already at high z (see CMB)
- Convert CMB fluctuations to density perturbations

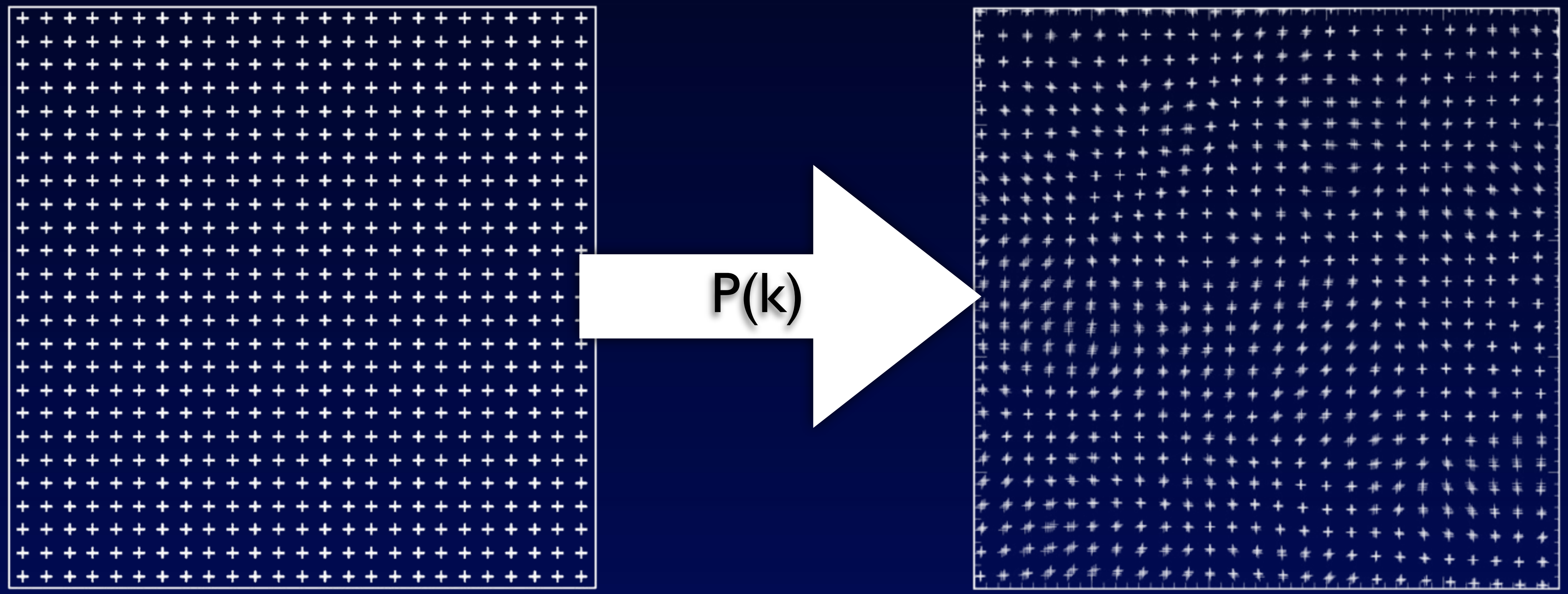




perturbed density field

The power spectrum

- Use the power spectrum to describe the density fluctuations
- From inflation: $P_i(k) = Ak^n$
- Temporal evolution (in the linear regime): $P(k, t) = P_0(k)D^2(t)$



Power spectrum tells us "how far" to displace particles from their starting positions.

Fluctuations were a Gaussian random field - direction of perturbation is random.

Limitations of this method

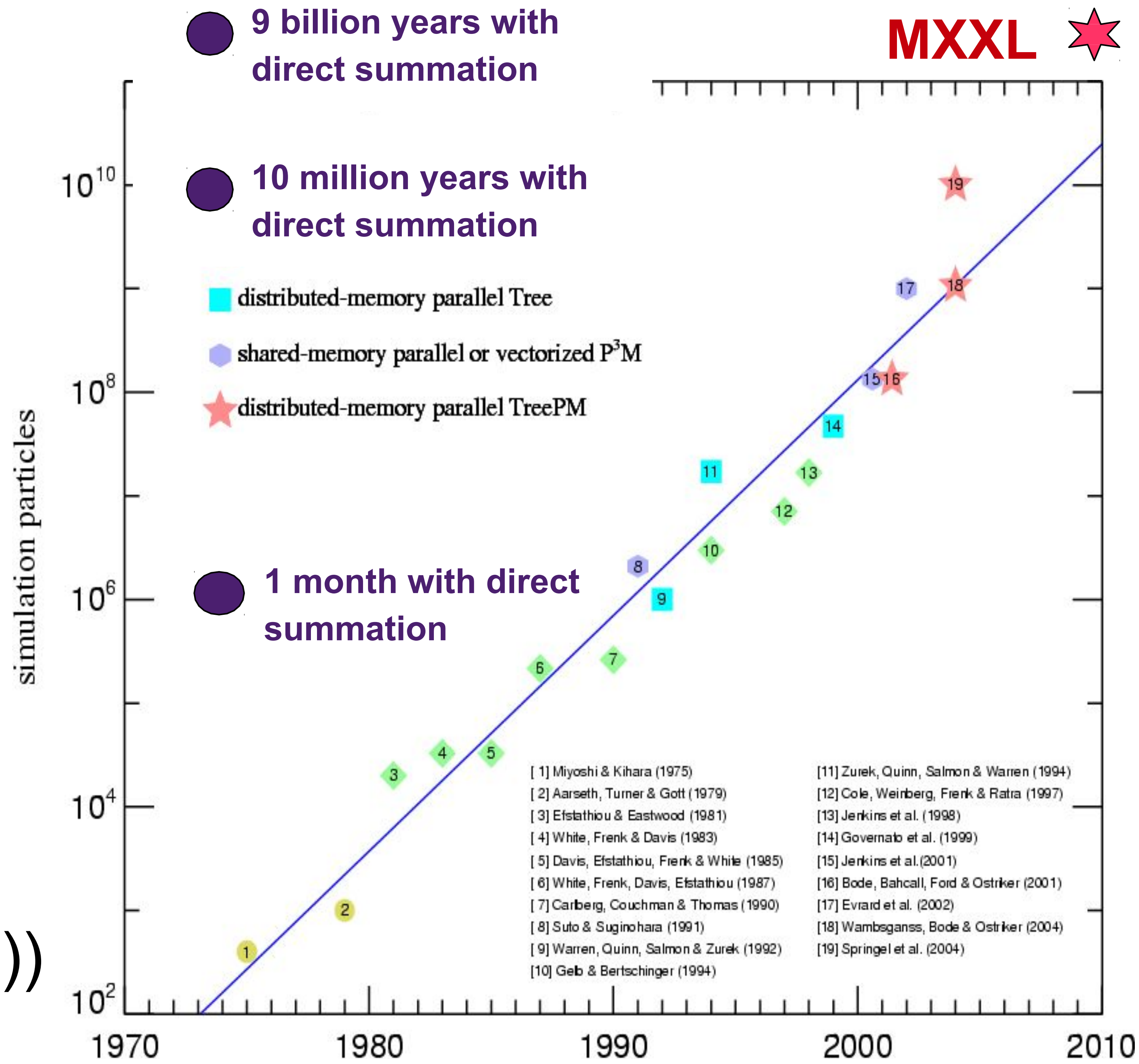
- There are a number of parameters that have to be chosen:
  - Box size B
  - Number of particles N
  - Starting redshift z_i
- In practice there are several constraints on these:
  - Minimal modes that are included: $2B/\sqrt[3]{N}$
  - Largest mode has to stay linear: $B \geq 2\pi/k_{nl} \sim 20 Mpc$
  - Starting redshift (typically $40 < z_i < 80$):

    Too late: shell crossing not taken into account

    Too early: numerical noise is integrated

Size of cosmological simulations over time

- computers double speed every 18 months (Moore's law)
- particle number in simulations doubles every 16-17 months
- only possible with algorithms that scale close to ~N (or N log(N))



The particle-mesh (PM) method

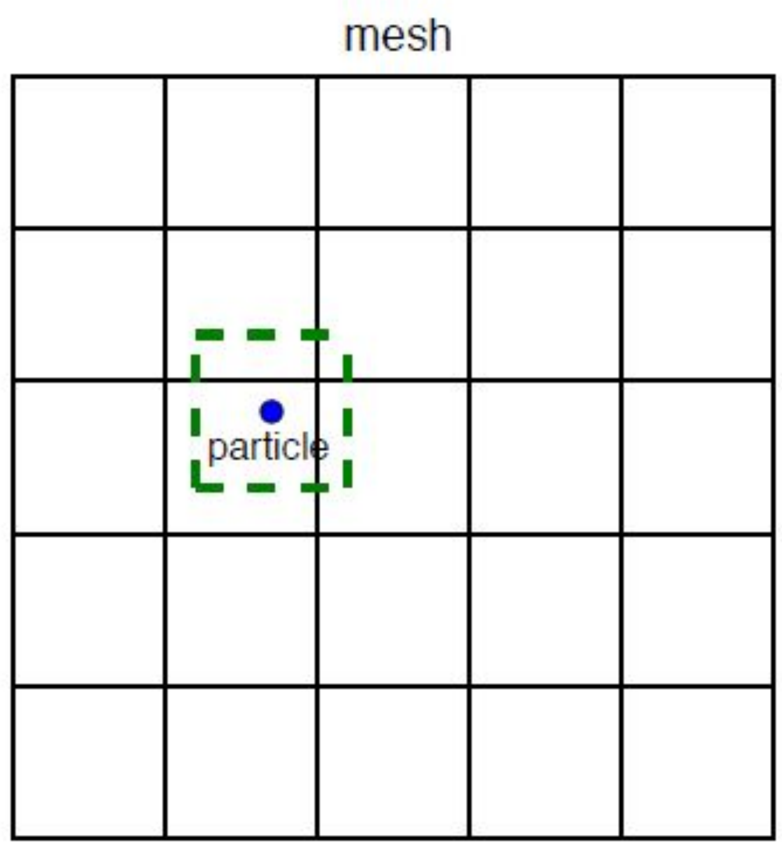
Poissonʼs equation: potential due to a “charge” e.g. mass

- particle-mesh method
  - Poissonʼs equation in real space:
  - Poissonʼs equation in Fourier space:
  - assign particle mass to grid (e.g. CIC)
  - compute Fourier transform of density contrast (FFT ~ N log N)
  - convert to Fourier transform of potential
  - transform the potential back to real space
  - compute gradient by finite differencing of the potential

average comoving matter density $\bar{\rho}_c$

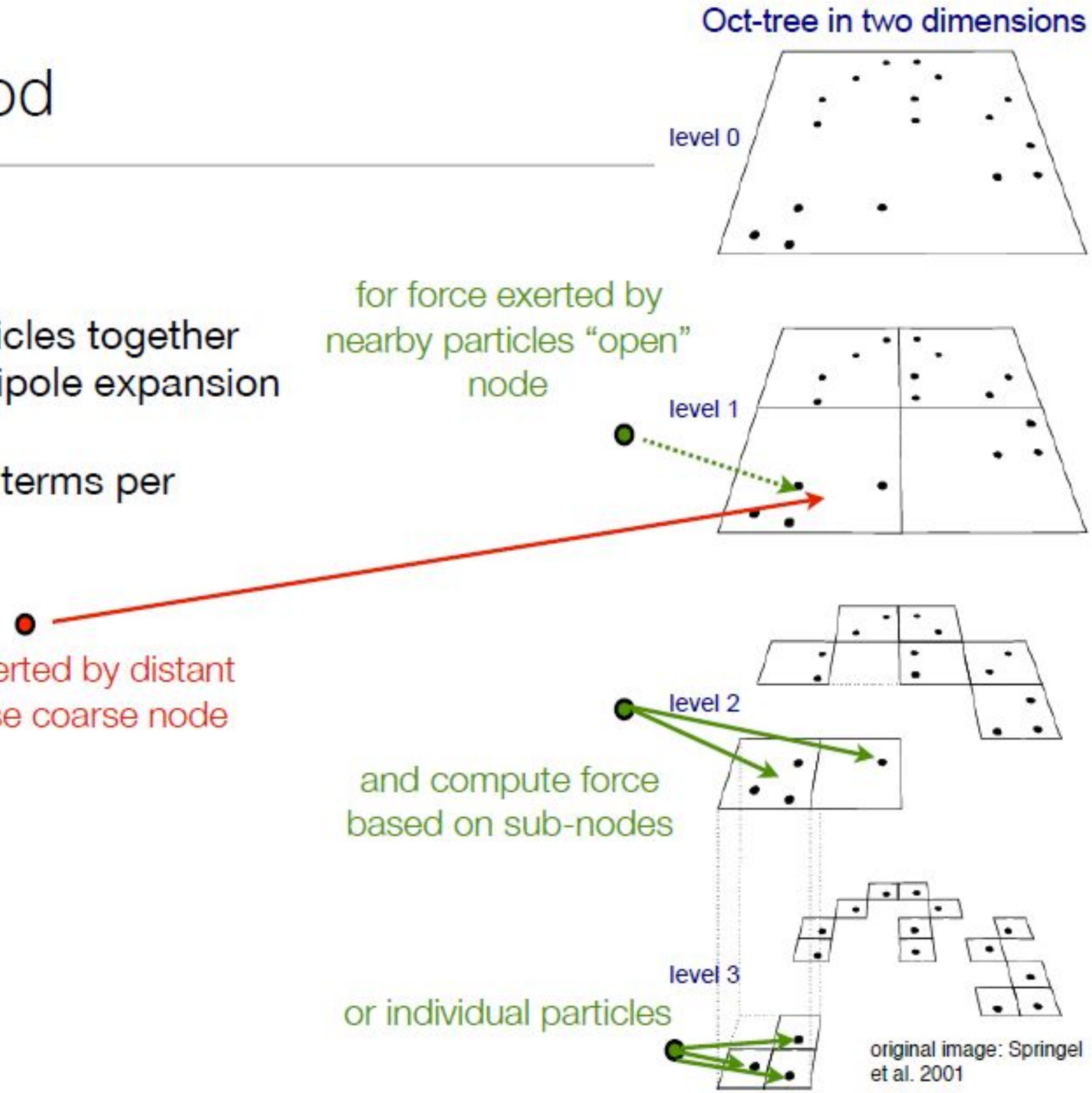
$$\vec{\nabla}^2 \delta\phi = 4\pi G \bar{\rho}_c \delta a^{-1}$$

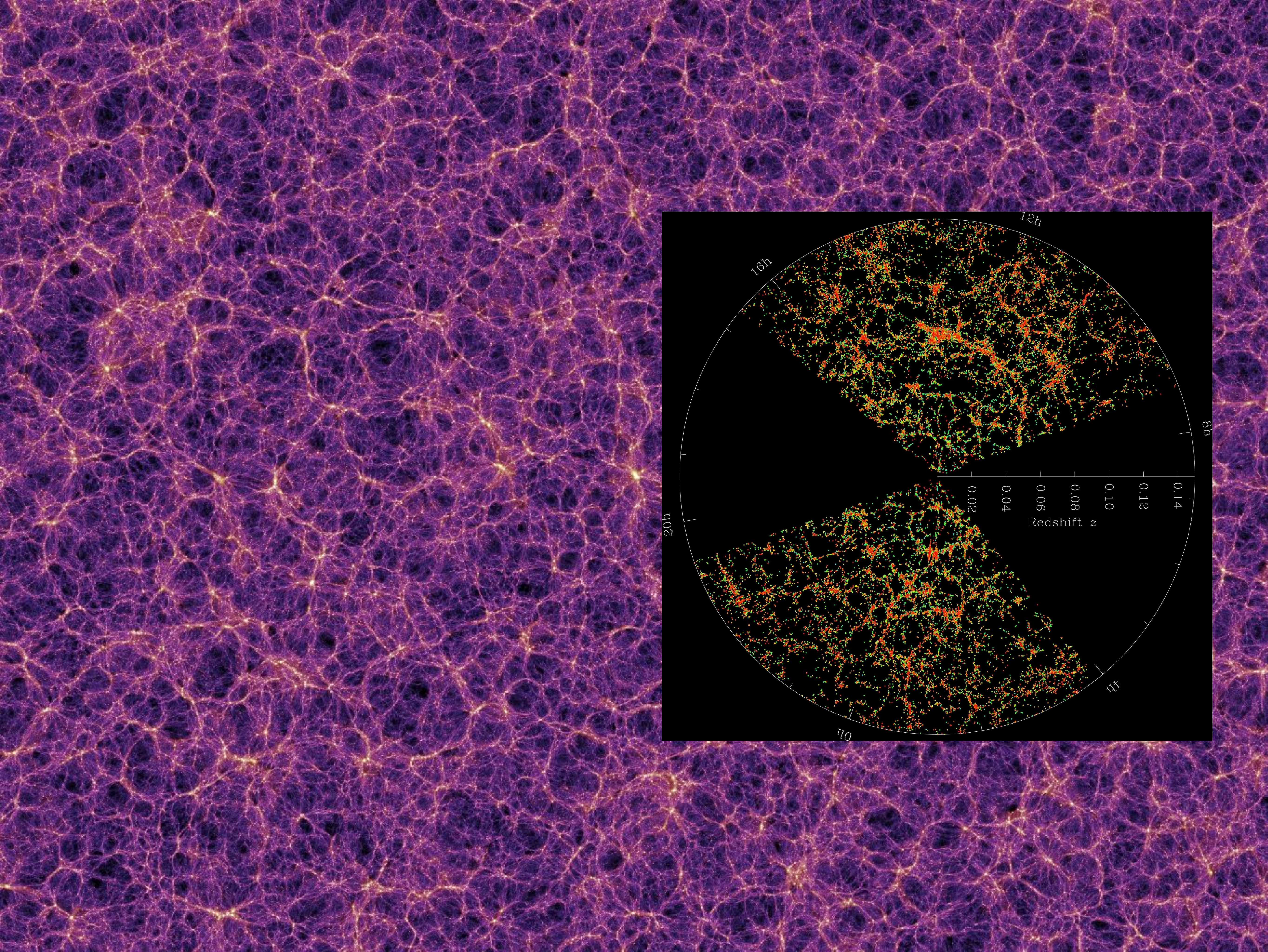
$$-k^2 \delta\phi_{\vec{k}} = \frac{4\pi G \bar{\rho}_c \delta_{\vec{k}}}{a}$$



The tree method

- tree algorithm:
  - group distant particles together and use their multipole expansion
  - only ~log(N) force terms per particle

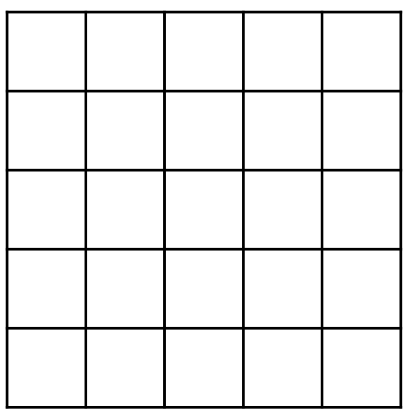



12h
16h
8h
20h
4h
0h
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Redshift z

Eulerian vs Lagrangian methods

Eulerian methods

discretize space
(finite-volume scheme)



use a grid fixed in space

moving-mesh

discretize space
(finite-volume scheme)

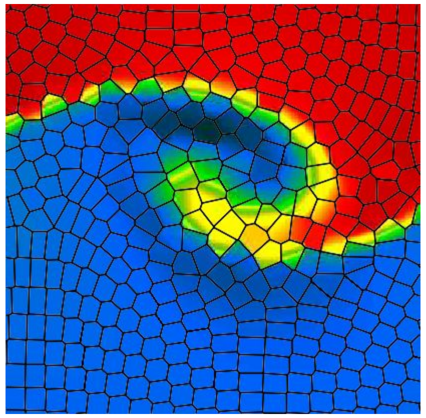
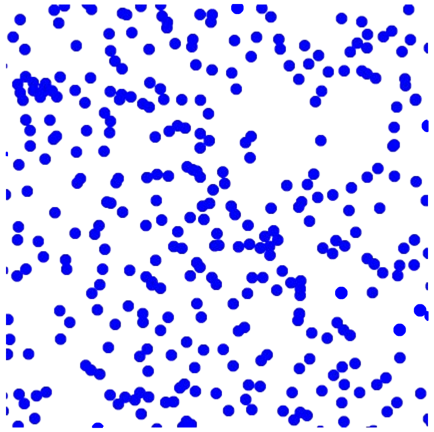


image credit: V. Springel

uses an unstructured mesh moving with the flow

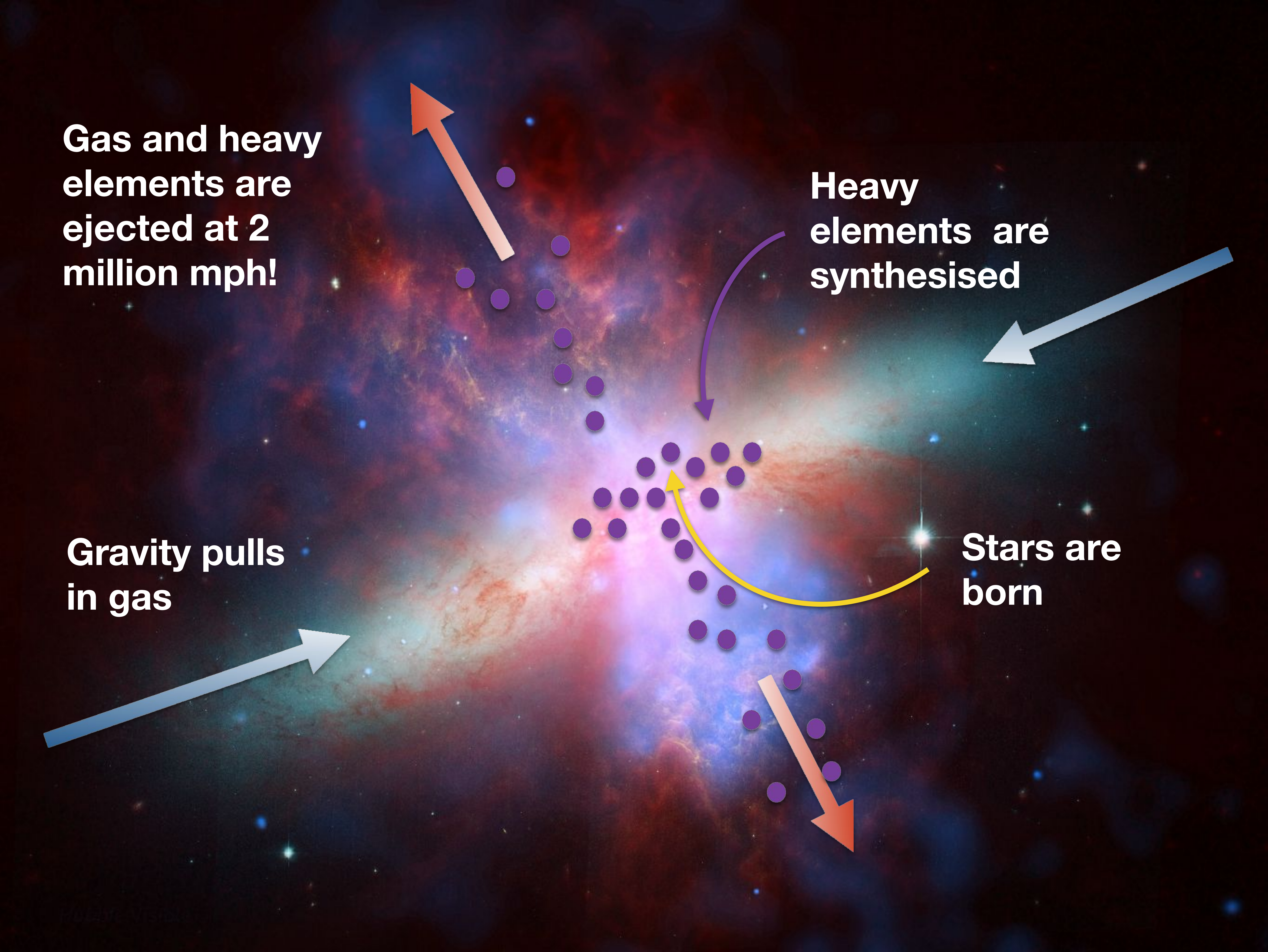
Lagrangian methods

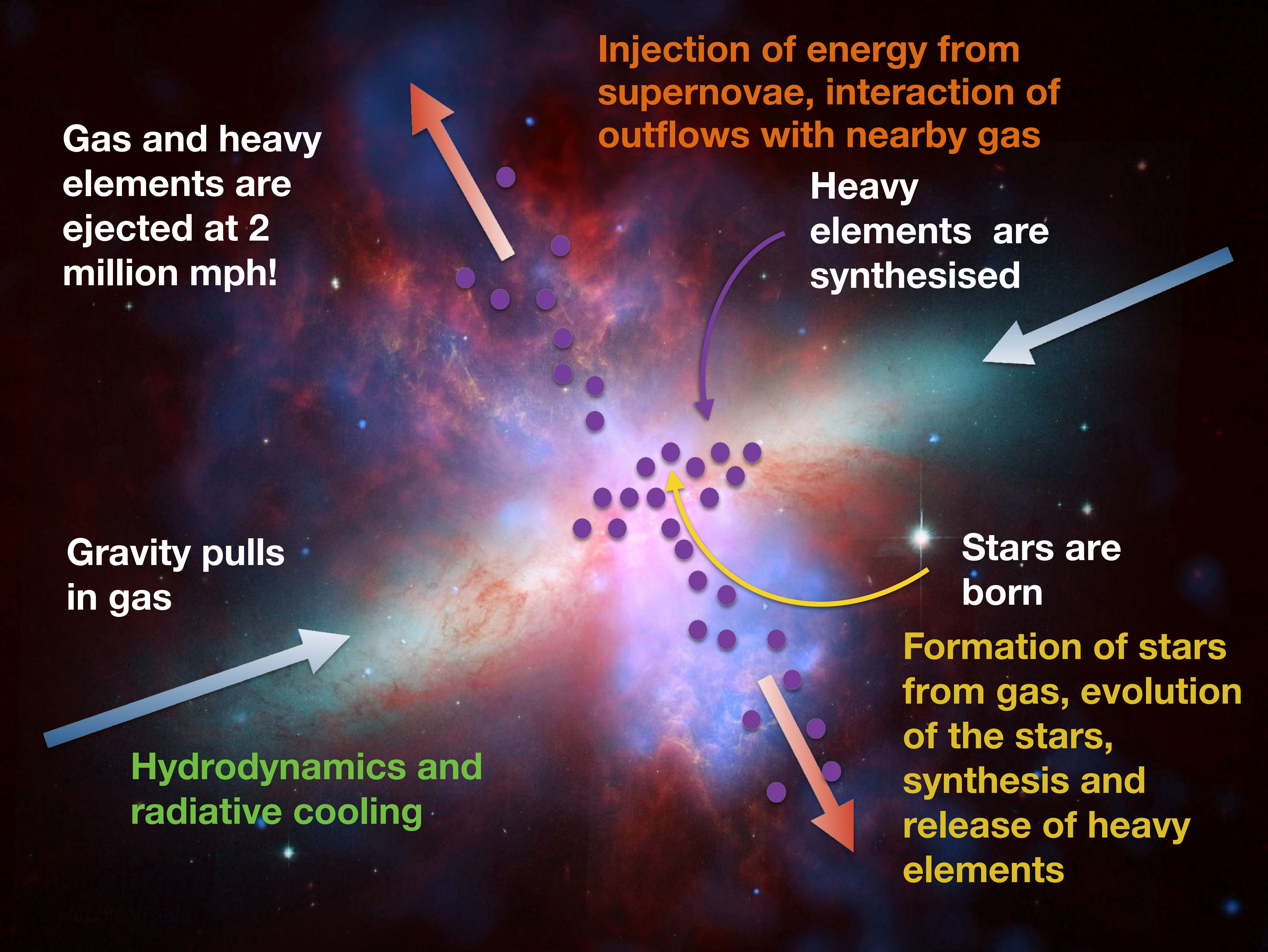
discretize mass



use particles for the gas (like in n-body) which move with the flow

What other ingredients are necessary?


Gas and heavy elements are ejected at 2 million mph!
Heavy elements are synthesised
Gravity pulls in gas
Stars are born


Injection of energy from supernovae, interaction of outflows with nearby gas
Gas and heavy elements are ejected at 2 million mph!
Heavy elements are synthesised
Gravity pulls in gas
Stars are born
Formation of stars from gas, evolution of the stars, synthesis and release of heavy elements
Hydrodynamics and radiative cooling

What other ingredients are necessary?

Gravity (all components)
Hydrodynamics for compressible fluid

Everything else…is below our resolution limit!

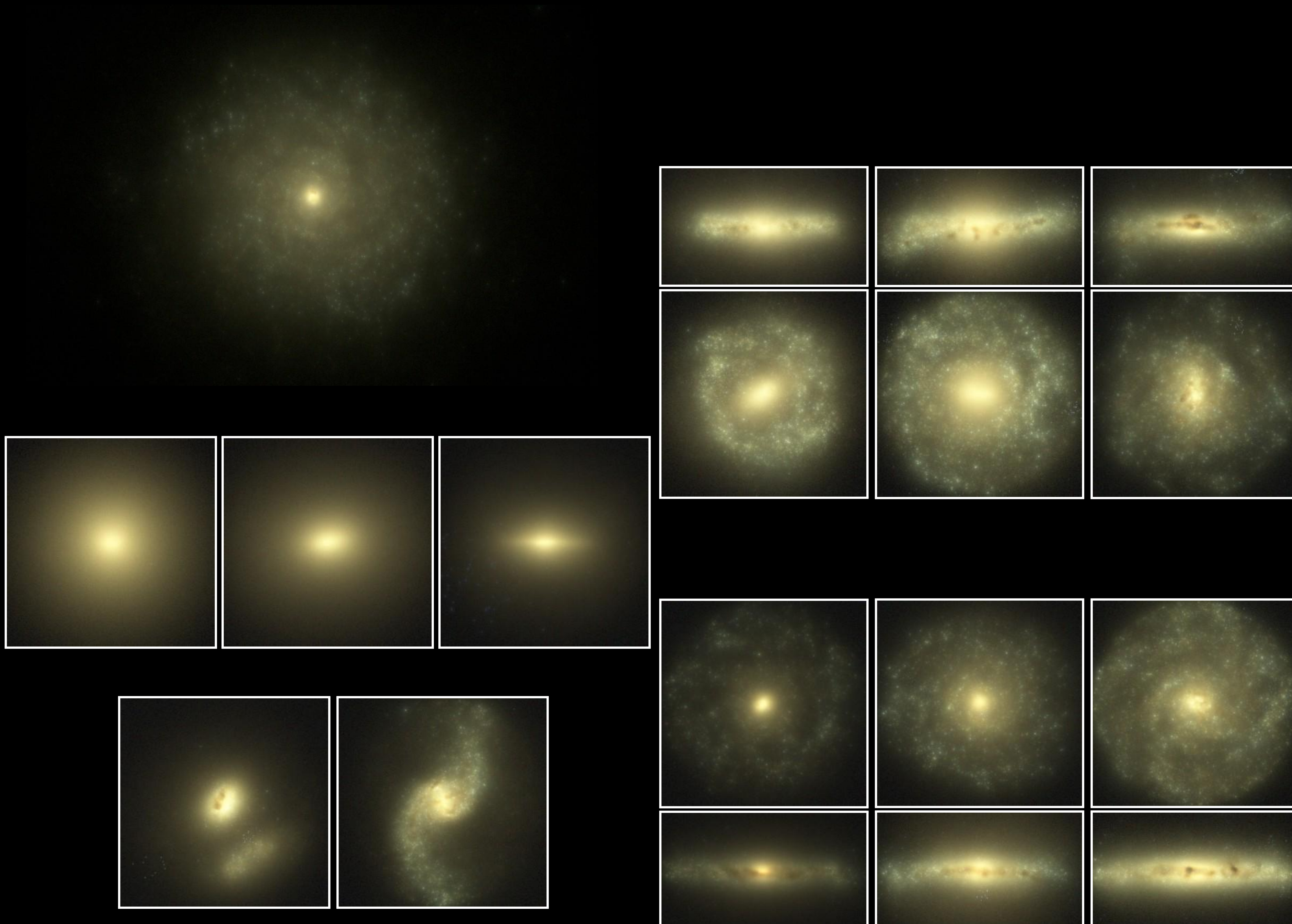
Radiative cooling & heating of gas

Star formation

Stellar evolution & nucleosynthesis Black hole formation and growth Feedback from stars and black holes

Intimately coupled in a non-linear fashion!


EAGLE
Evolution and Assembly of GaLaxies and their Environments
Universiteit Leiden
Durham University
LIVERPOOL JOHN MOORES UNIVERSITY



Summary

HPC central to building an understanding of how the early Universe evolved into that we observe today.

Confrontation of dark matter simulations with observed galaxy distribution is major evidence for a CDM-dominated Universe.

Realism of simulations including complex “gastrophysics” has broadly corroborated galaxy formation theory in CDM cosmogony.

Challenge used to be “can we reproduce what we see?”. But now, sims are the premier tool with which to interpret observations. Simulations give us access to components (and epochs!) that we cannot easily observe.

Still huge amount of “known unknowns” to tackle! Much of the gastrophysics is implemented phenomenologically: we want to understand the physics of the messy stuff in detail!

Questions?

Eagle database & PySPHviewer

Jaime Salcido

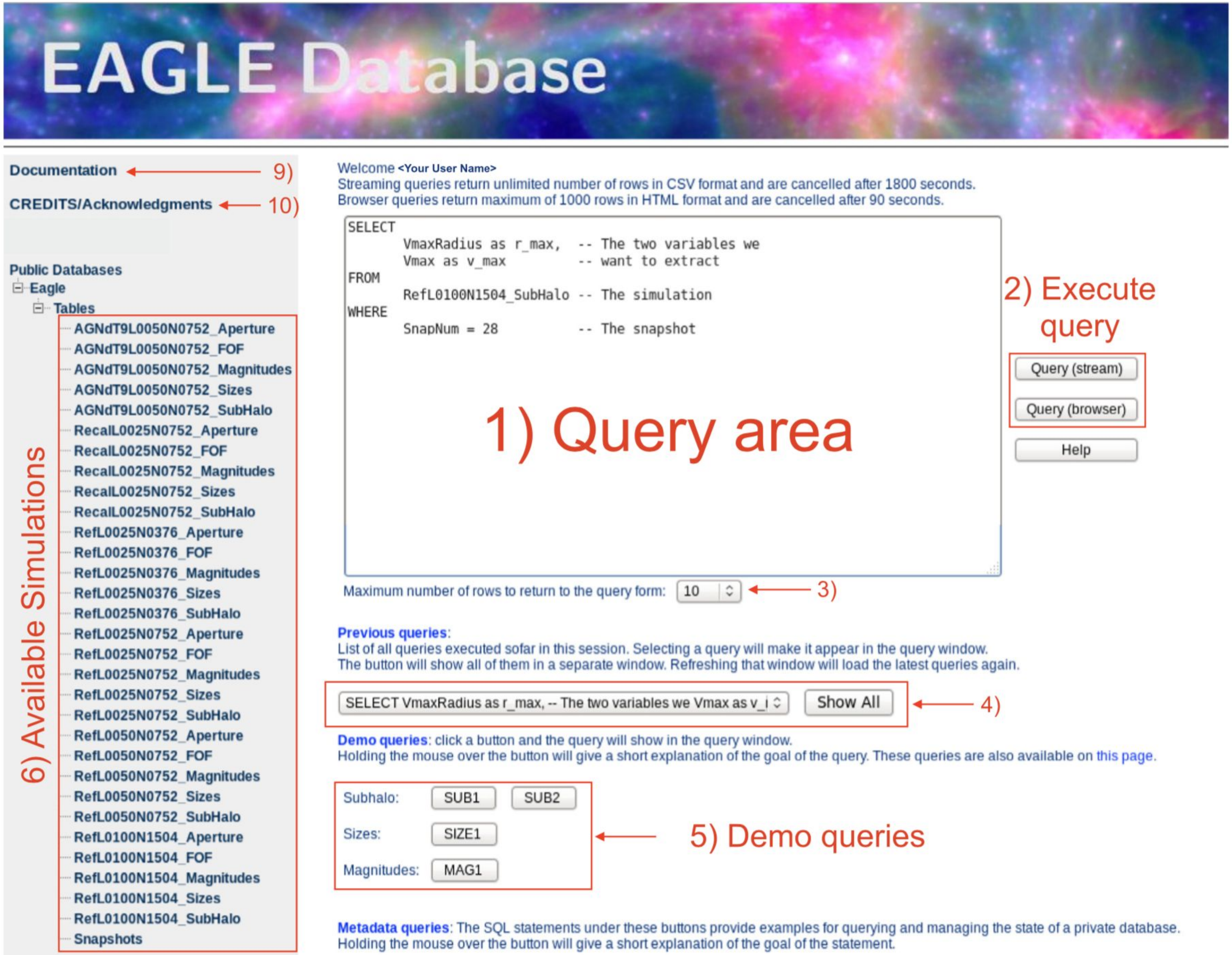
The EAGLE public database contains galaxy properties (such as masses, star formation rates, luminosites and metallicities), merger histories and images for more than 1,000,000 simulated galaxies extracted from multiple simulations of various box sizes, numerical resolutions and physical models.

You can access the database in the following link:

http://icc.dur.ac.uk/Eagle/database.php

Useful information about the simulations and available datasets can be found in the data release paper:

https://arxiv.org/abs/1510.01320



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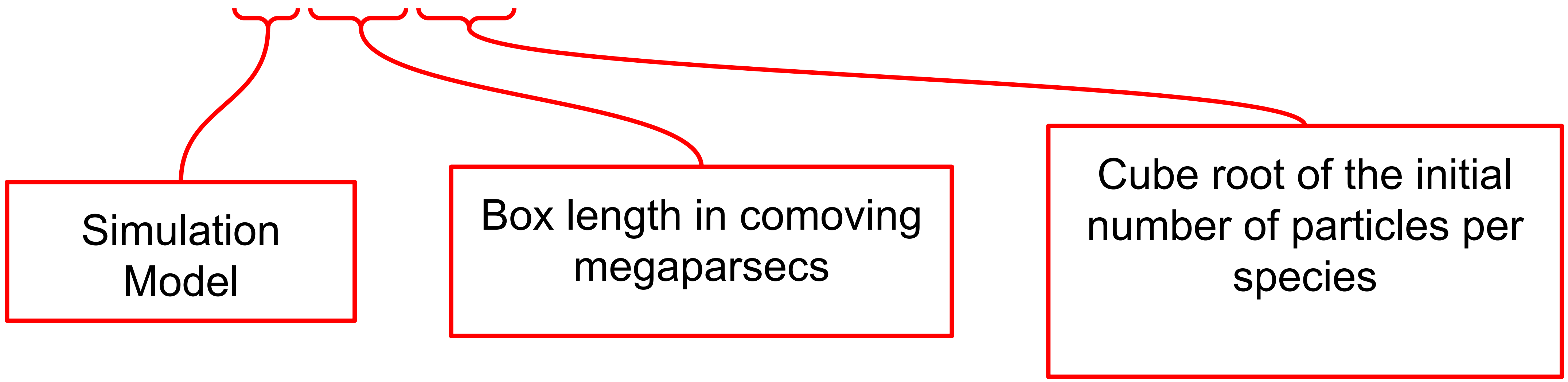
Available datasets:

- Simulations:
  - Ref L0025N376



- Datasets:
  - **Subhalo** - Main galaxy properties
  - **FOF** - Halo properties
  - **Sizes** - Galaxy sizes
  - **Aperture** - Galaxy properties in 3D apertures
  - **Magnitudes** - Galaxy photometry in the GAMA bands
  - **Particle data**

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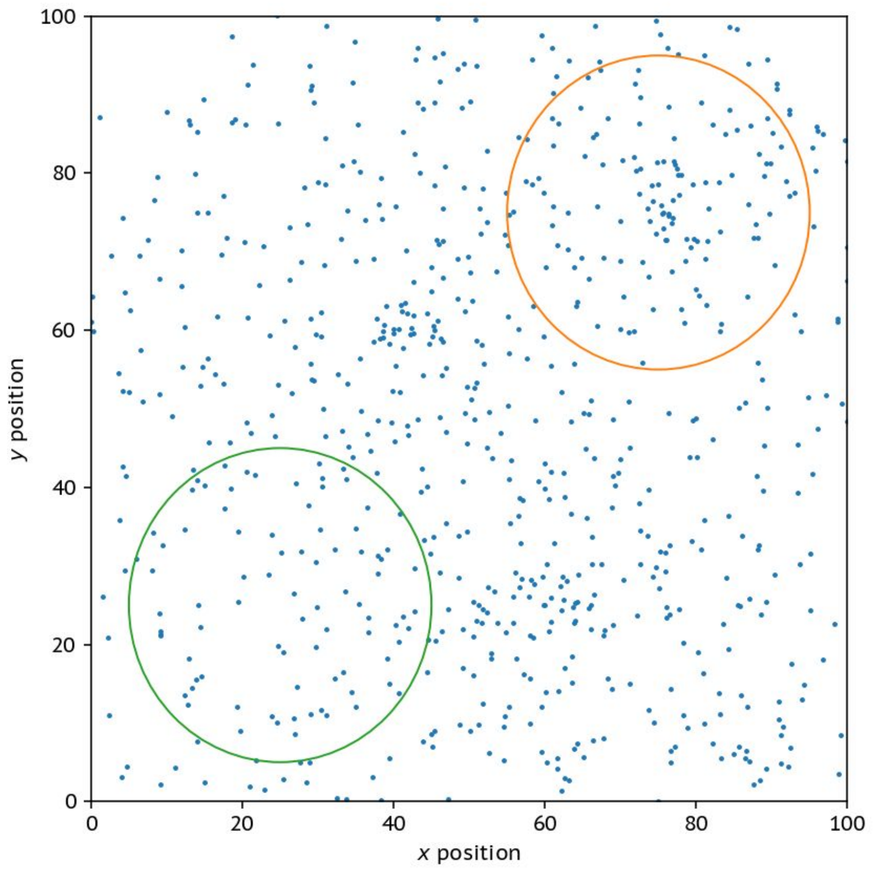
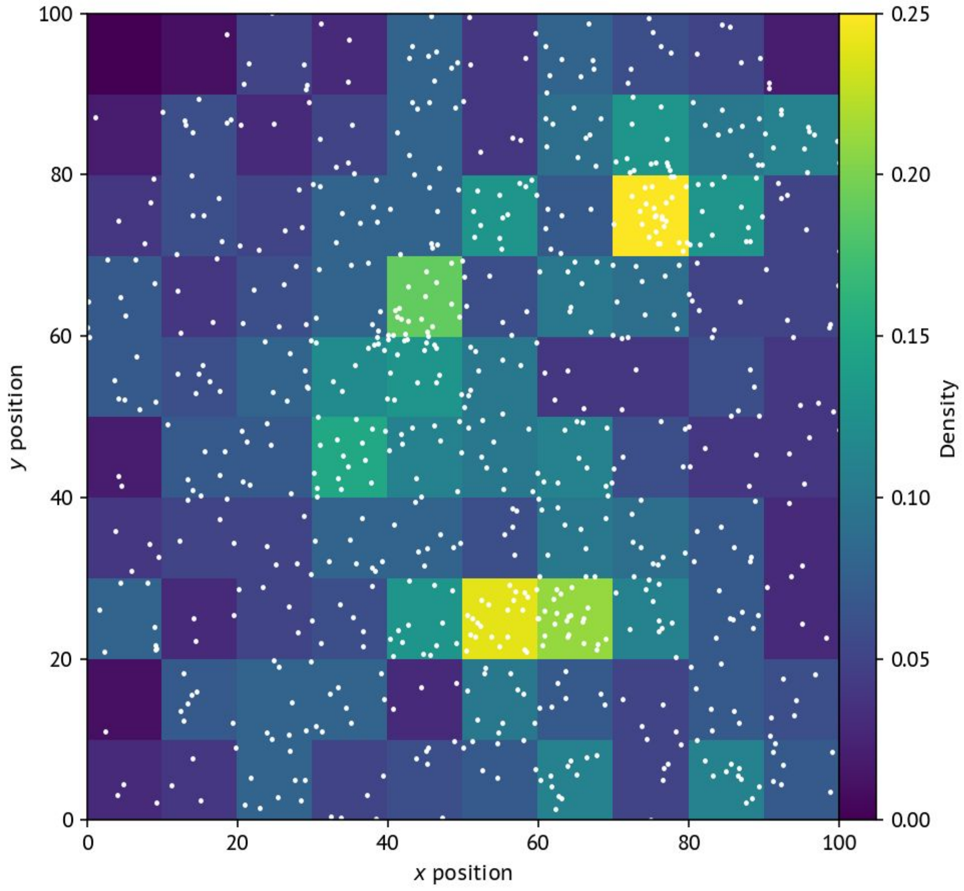
Example - 1

Visualisation - What is a smooth density field?

The problem:



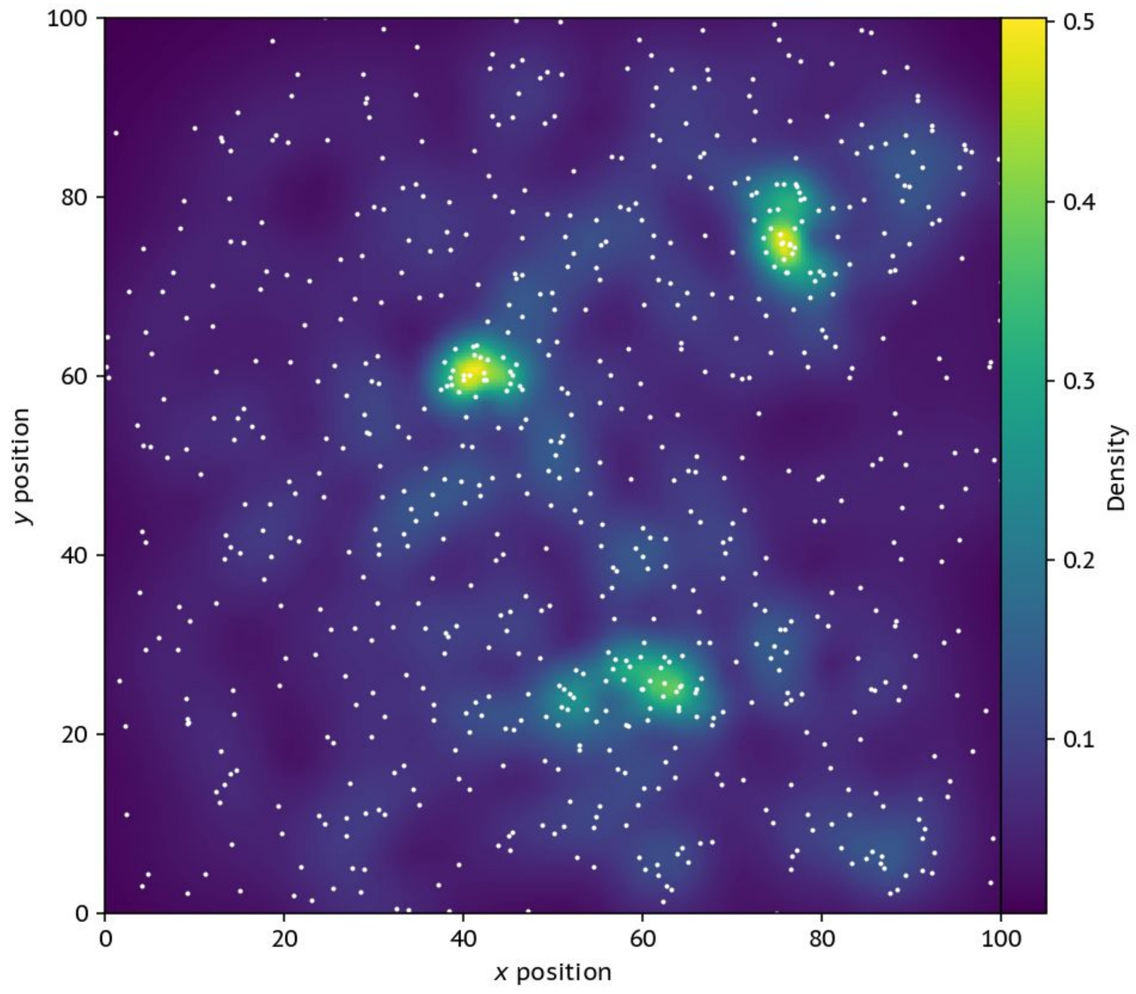
Solution 1: Build a grid

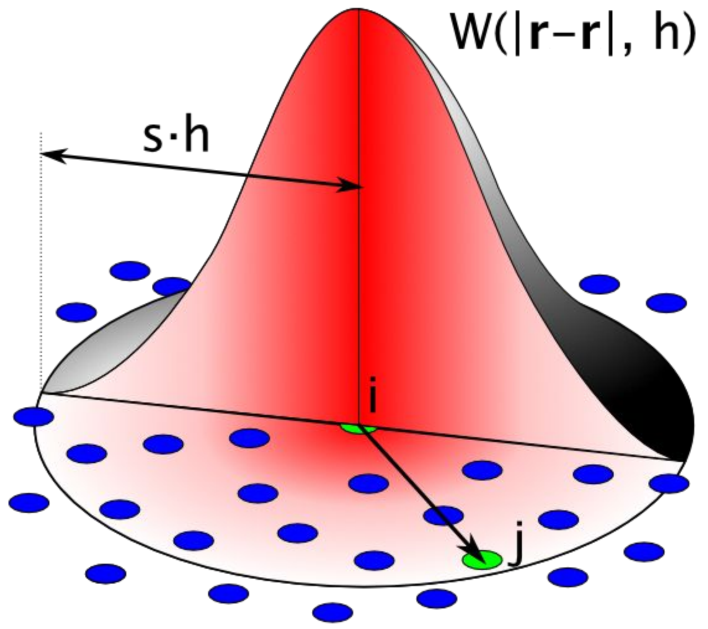


Example taken from: https://community.dur.ac.uk/joshua.borrow/blog/posts/density_from_particles/

Visualisation - What is a smooth density field?

Solution 2: Use a smoothed density estimate





Source: Wikipedia

The density at each point calculated using a kernel keeping the number of (weighted-)particles in each cell constant.
This kernel ensures that particles that are further away matter less to the density estimate.

Py-SPHViewer

Under the SPH (Smoothed-particle hydrodynamics) approximation, the projected density field at any pixel is the contribution of all particles within the “projected” kernel.

$$\rho(x) = \sum_j m_j W(|x - x_j|, h_j)$$

$$\Sigma(x, y) = \int \rho(x, y, z')dz' = \sum_j m_j \int W(|x - x_j|, h_j)dz'$$

$$\Sigma(x, y) = \sum_j m_j \tilde{W}(R_j, h_j)$$

You can download Py-SPHViewer here:

https://github.com/alejandrobll/py-sphviewer

Example - 2

Some additional examples using SPH visualisation:

- https://www.youtube.com/watch?v=S7WCR39brw0
- https://www.youtube.com/watch?v=2Fp_VK-xuKE

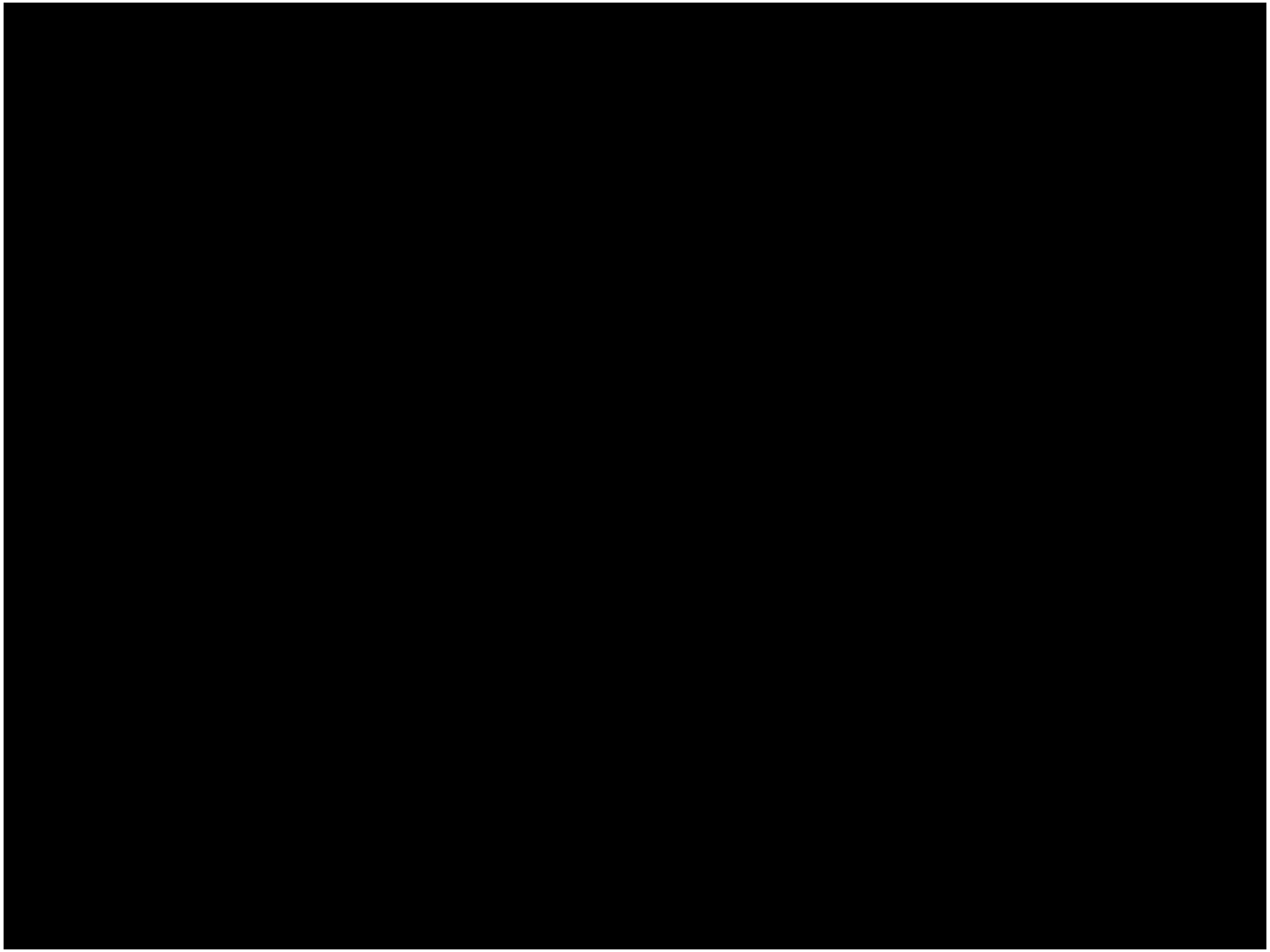
Questions?

Milky Way and Gaia

Andreea Font

How did the Milky Way form?

STARS



GAS

ARTEMIS simulations

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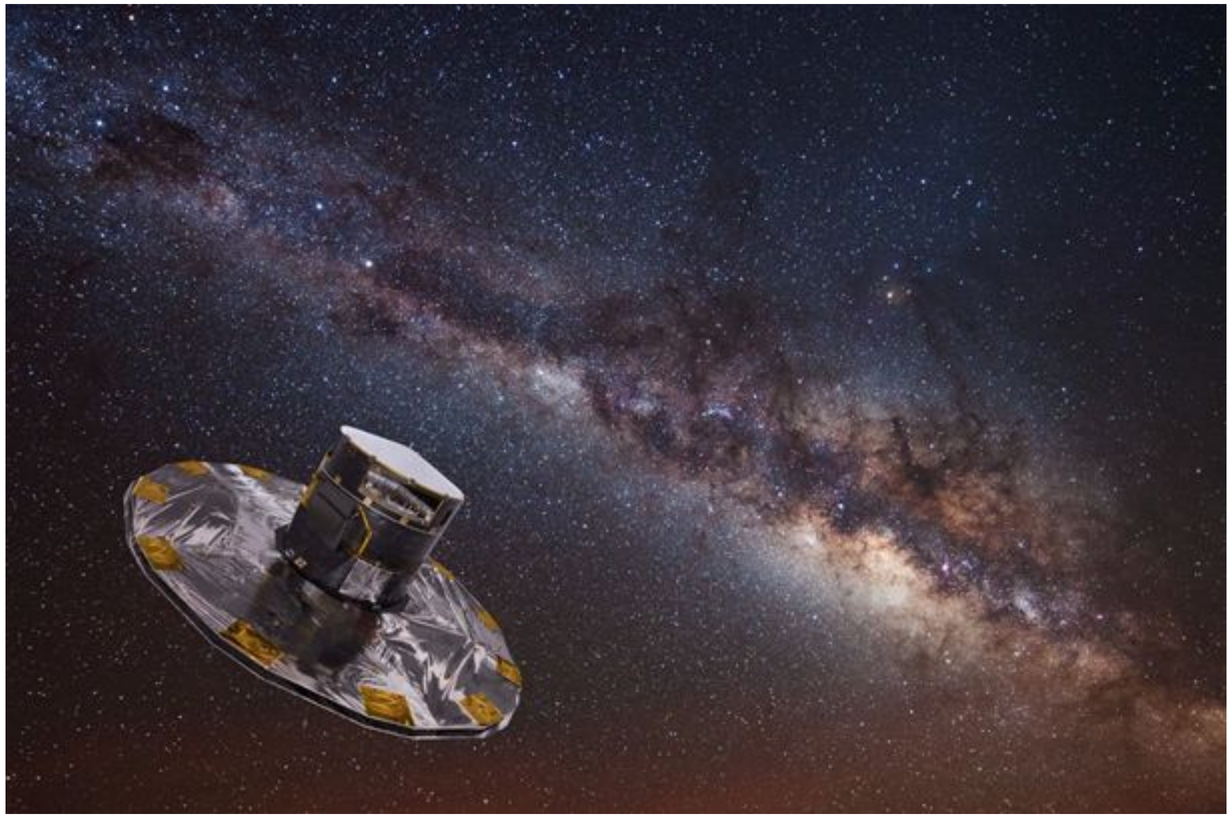
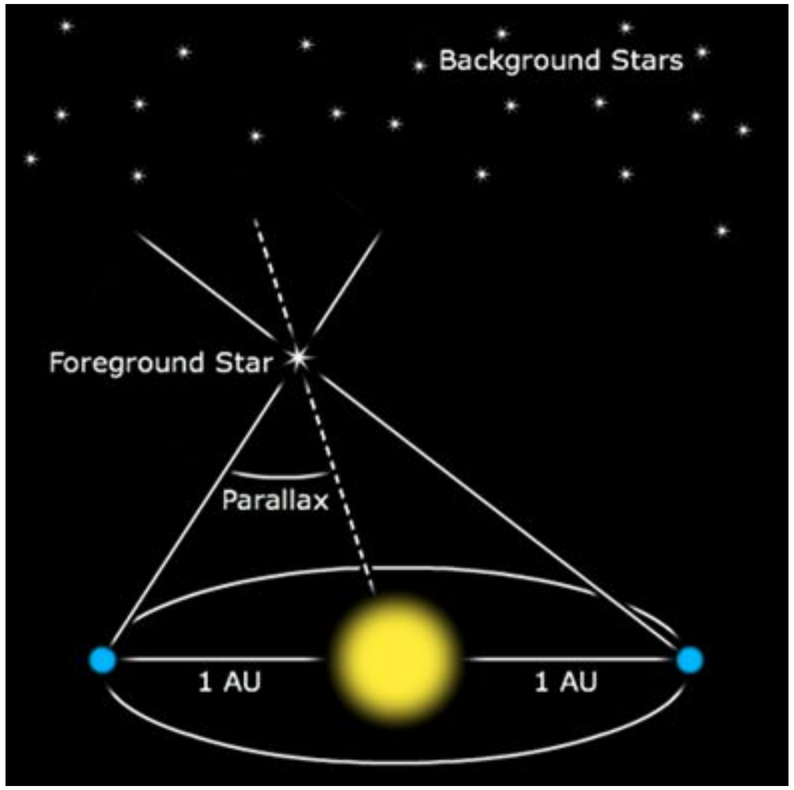




- Gaia can infer distances by measuring **parallax**
- Gaia DR2 contains parallaxes for **1.3 billion stars** with errors as small as 50 micro-arcseconds, equivalent to seeing a human hair from a distance of 500 km.
- Gaia is also taking precise measurements of the **brightness** (down to mag G=20), **colours** and **proper motions** of ~ 1 billion stars.

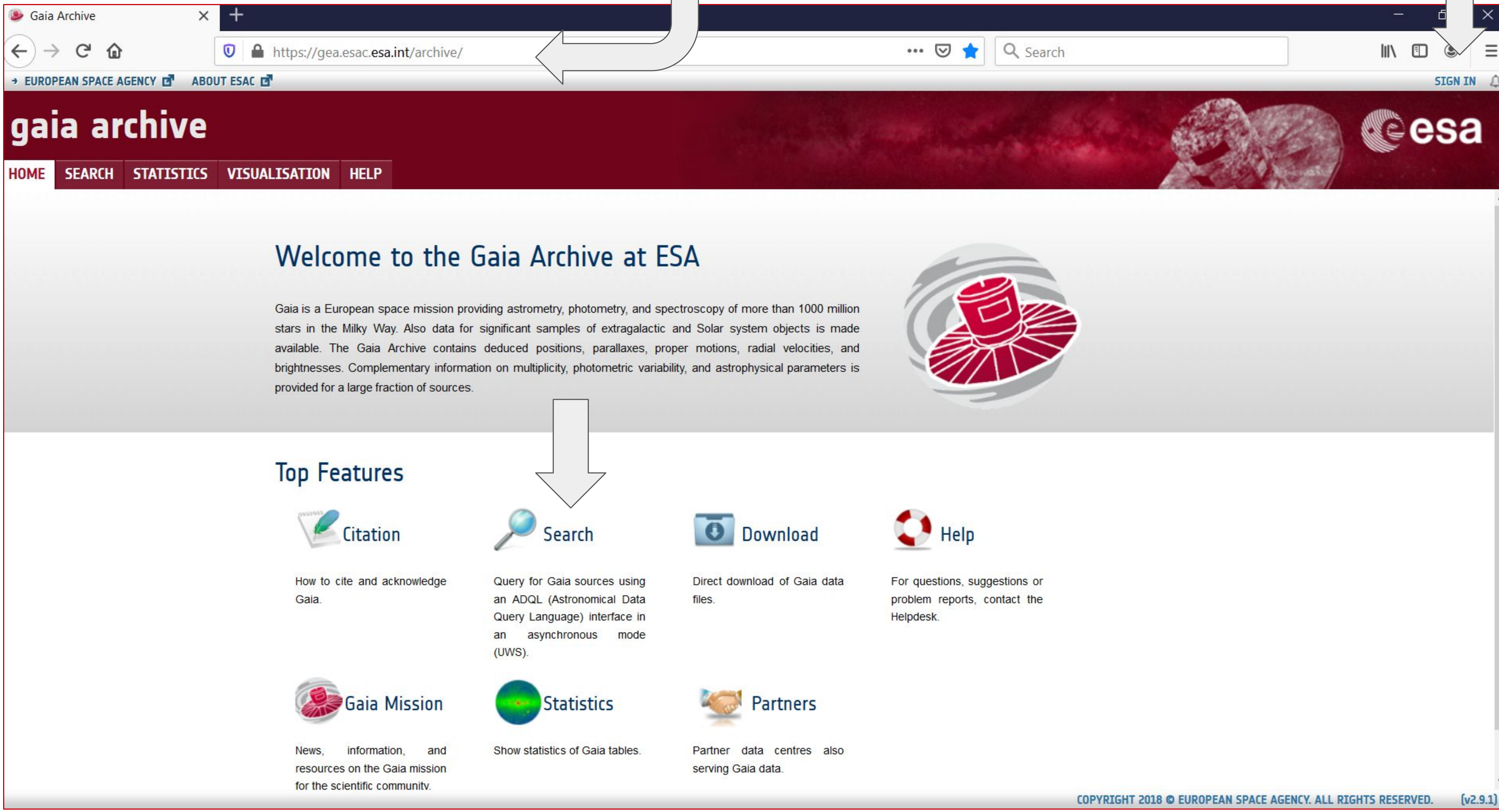
360° view of Gaia's sky

https://www.youtube.com/watch?v=8cXURHmtf3I

360º Parallax and proper motion on the sky
https://www.youtube.com/watch?v=KyQdK56Qee0

Gaia Archive:
https://gea.esac.esa.int/archive/

Login (optional)



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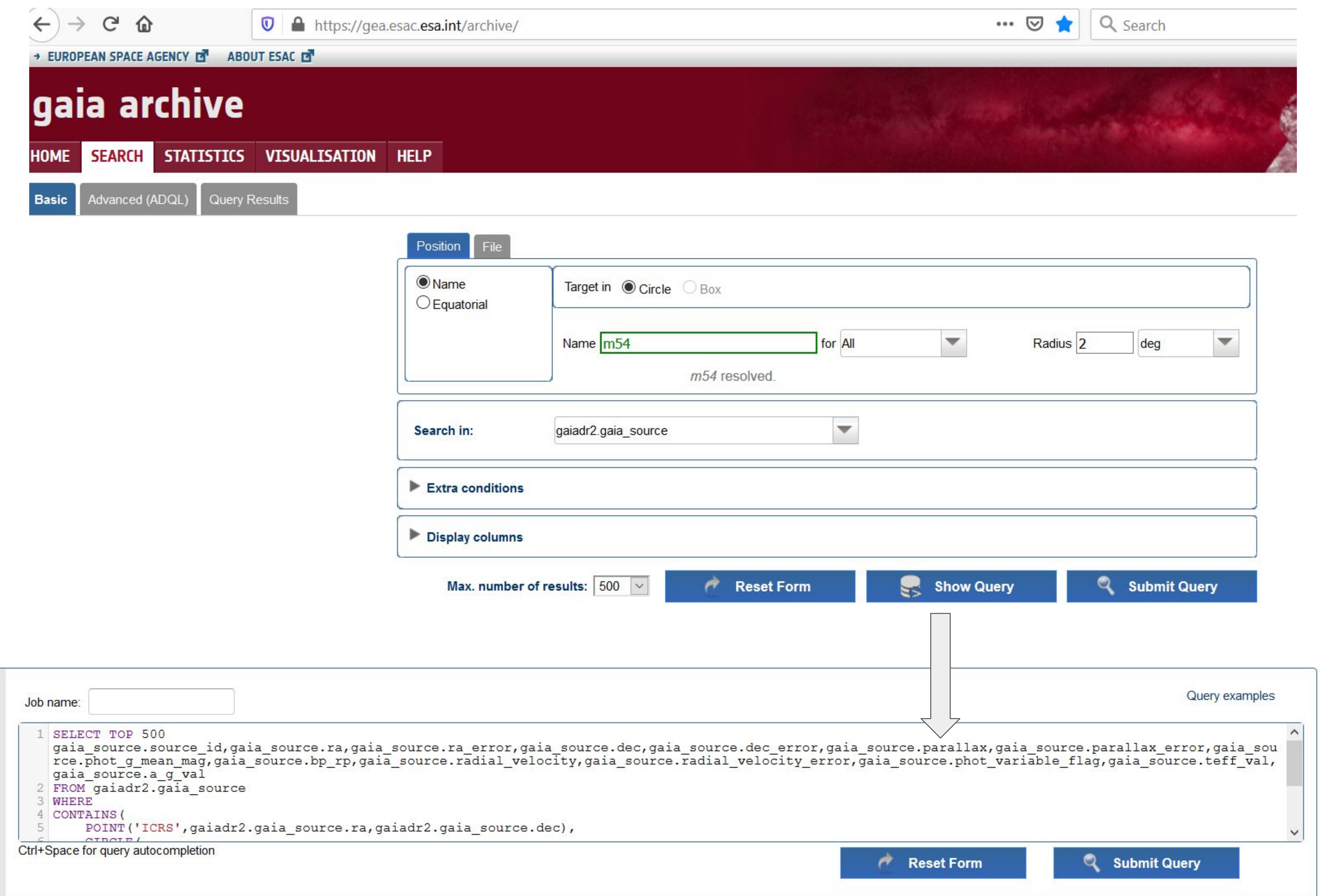
https://gea.esac.esa.int/archive/
Search
EUROPEAN SPACE AGENCY
ABOUT ESAC
gaia archive
HOME
SEARCH
STATISTICS
VISUALISATION
HELP
Basic
Advanced (ADQL)
Query Results
Position
File
Name
Equatorial
Target in
Circle
Box
Name
m54
for
All
Radius
2
deg
m54 resolved.
Search in:
gaiadr2.gaia_source
Extra conditions
Display columns
Max. number of results:
500
Reset Form
Show Query
Submit Query
Job name:
Query examples
SELECT TOP 500
gaia_source.source_id,gaia_source.ra,gaia_source.ra_error,gaia_source.dec,gaia_source.dec_error,gaia_source.parallax,gaia_source.parallax_error,gaia_source.phot_g_mean_mag,gaia_source.bp_rp,gaia_source.radial_velocity,gaia_source.radial_velocity_error,gaia_source.phot_variable_flag,gaia_source.teff_val,gaia_source.a_g_val
FROM gaiadr2.gaia_source
WHERE
CONTAINS(
POINT('ICRS',gaiadr2.gaia_source.ra,gaiadr2.gaia_source.dec),
Ctrl+Space for query autocompletion
Reset Form
Submit Query

Astronomical Data Query Language (ADQL)

- an **SQL** `dialect` developed for astronomy by the Virtual Observatory.

Example 1:

Retrieve the source identifier (‘source_id’), right ascension (‘RA’), declination (‘DEC’), and parallax (‘parallax’) for all sources in *Gaia DR2* that have parallaxes in the range 15–50 mas as well as G-band magnitudes (‘photo_g_mean_mag’) in the range 9–9.5 mag.

Syntax:

SELECT source_id, ra, dec, parallax
FROM gaiadr2.gaia_source
WHERE parallax between 15 **AND** 50 **AND** phot_g_mean_mag >= 9 **AND** phot_g_mean_mag <= 9.5

More on **SQL**:
https://www.sqlcourse.com/

ADQL Cookbook:
https://www.gaia.ac.uk/data/gaia-data-release-1/adql-cookbook

More technical document on ADQL:
https://www.ivoa.net/documents/REC/ADQL/ADQL-20081030.pdf

Gaia archive tutorials:
https://gea.esac.esa.int/archive-help/

Gaia DR2 Model (what parameters? units):
https://gea.esac.esa.int/archive/documentation/GDR2/Gaia_archive/chap_datamodel/

The result of the query can be downloaded in various formats:

- VOTable; CSV; FITS; JSON

Basic | Advanced (ADQL) | **Query Results**

1602442464549O ✖

source_id	ra (deg)	ra_error (mas)	dec (deg)	dec_error (mas)	parallax (mas)	parallax_error (mas)	phot_g_mean_mag (mag)	bp_rp (mag)	radial_velocity (km.s**-1)
567304539159590528	1.943847263933078	2.2183004778840067	83.12859840421683	2.756514142970163	3.000000020417362	3.475613783408368	20.939615	0.5976505	
3414837379320591872	80.02290762770141	1.9465328828698256	22.88710089519733	1.4243181489062613	3.0000000596066667	2.2737769575597175	20.760464	1.3391247	
5822151567899459968	239.0472862601741	0.955014342022537	-66.98889682574703	0.8227704830378849	3.000000065216071	1.5035975446501049	20.914507	1.7310066	
4167250675314428416	259.5514160201236	1.1641967677427485	-9.912790188719985	0.9086419255686005	3.0000001313622646	1.2489709348257345	20.667692	1.3010616	
141500278843232768	42.95468605883477	1.4715598278428972	37.20253861954247	1.1856796327153942	3.000000152252159	1.7110310689387886	20.696165	2.5031128	
2039147637754335488	288.9754089690946	0.12496466266918414	29.475322703391143	0.14187644941915395	3.0000001579249047	0.1655308649585397	16.90919	1.9975939	
1619244074077007616	226.35541022706713	0.9312738033931112	62.00466670054089	0.9908709390600131	3.0000002483662227	0.781459394239726	20.544878	1.5413342	
6254938822251371648	233.46202255275068	0.664707727662377	-19.34378285293941	0.5168971496988178	3.000000260012579	0.6809436523811101	19.646704	2.7502308	
5836729850822906240	185.1059865652506	0.24444911409000072	-77.35478669798637	0.22117033795155253	3.0000002769076595	0.27423828129253003	19.256058	3.1434574	
6038615548788017024	242.60299072044393	1.1012034920836296	-29.559970816174804	0.4631838379259978	3.0000003262728345	1.2284870904687217	20.519066	1.5972118	
4623106199028573568	88.19212843767284	0.653731725808769	-80.12776382114767	0.7922502370482454	3.0000003647225246	0.7197339206976358	20.423838	2.1796303	
4268279610528053760	288.293430501706	0.8948793024185012	3.3943705024953252	0.8872743050785302	3.000000373509193	0.6252419963135777	19.723185	1.6490498	
5990805897006793216	244.25372844199248	0.8809506644628131	-44.33483749717577	0.5302076879306866	3.0000004429439953	0.9009132517389731	19.997984	2.8739681	
4127732784311532544	256.9437022904397	1.4167252289152663	-20.83203845590637	1.1499734099674228	3.0000005275129786	1.7797986741500376	20.628622	1.3486176	
5933653729259316864	247.6997330473052	0.08721423579163519	-53.193412492148944	0.06554892875593755	3.0000006028003705	0.09870426143643522	17.190062	2.2877522	
3301620289051645952	59.26762490803188	0.036848956380880225	9.025956428245957	0.02064047241124432	3.0000006149079264	0.04247739914147331	11.725768	0.87062454	
6097862762908102656	213.41959512739965	1.042407430994955	-42.14846414905339	0.9146906229945896	3.000000630580003	1.3755530115362051	20.021347	1.8532658	

1-20 of 2,000

Gaia DR2 Data Model | Show query in ADQL form | CSV | Download results

Download your data

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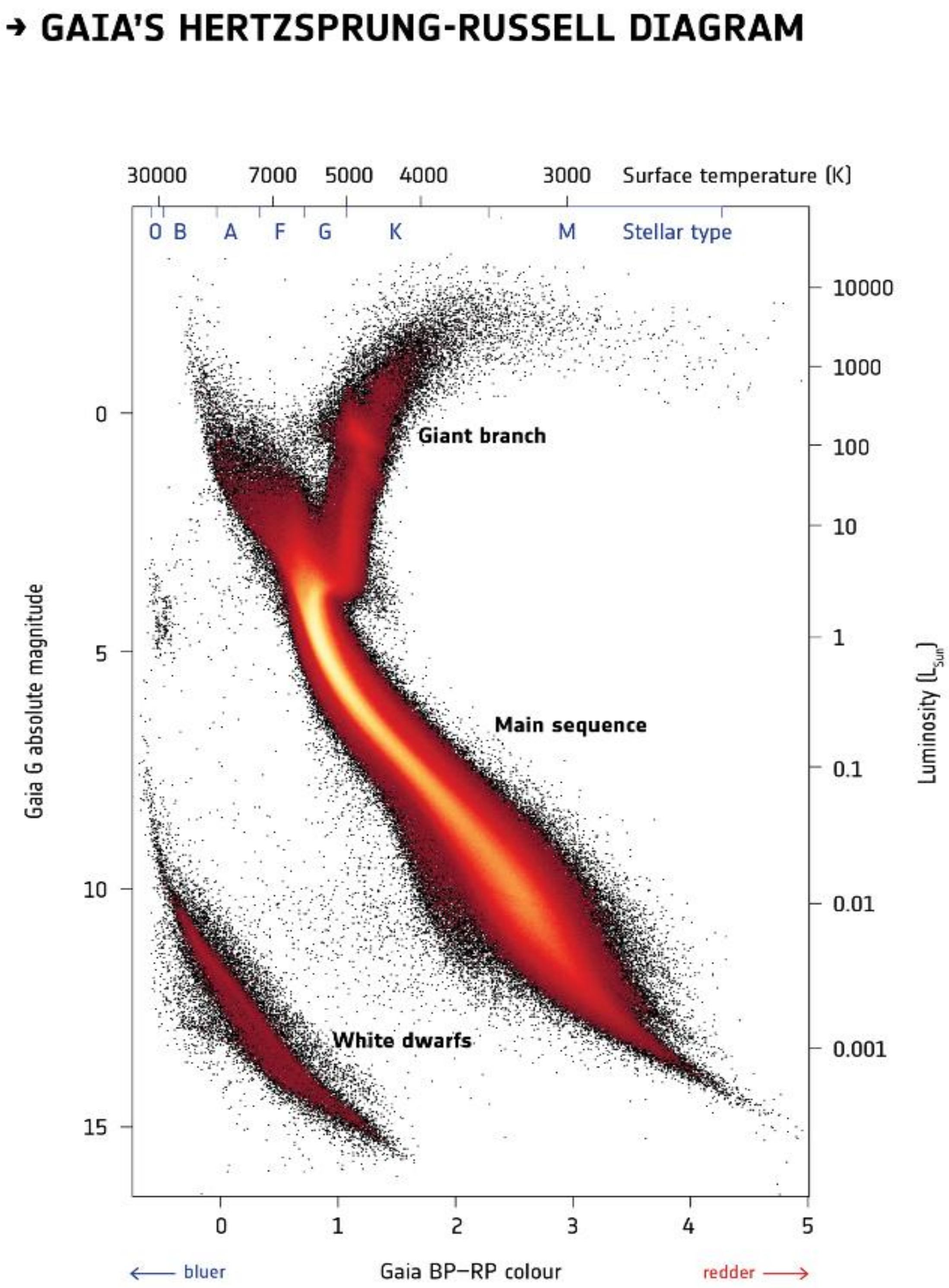
Hertzsprung - Russell diagram with Gaia
https://www.youtube.com/watch?v=jutw-lOwriw



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Example 2:

Select for top 10000 stars the G-band magnitudes and BP-RP colours.

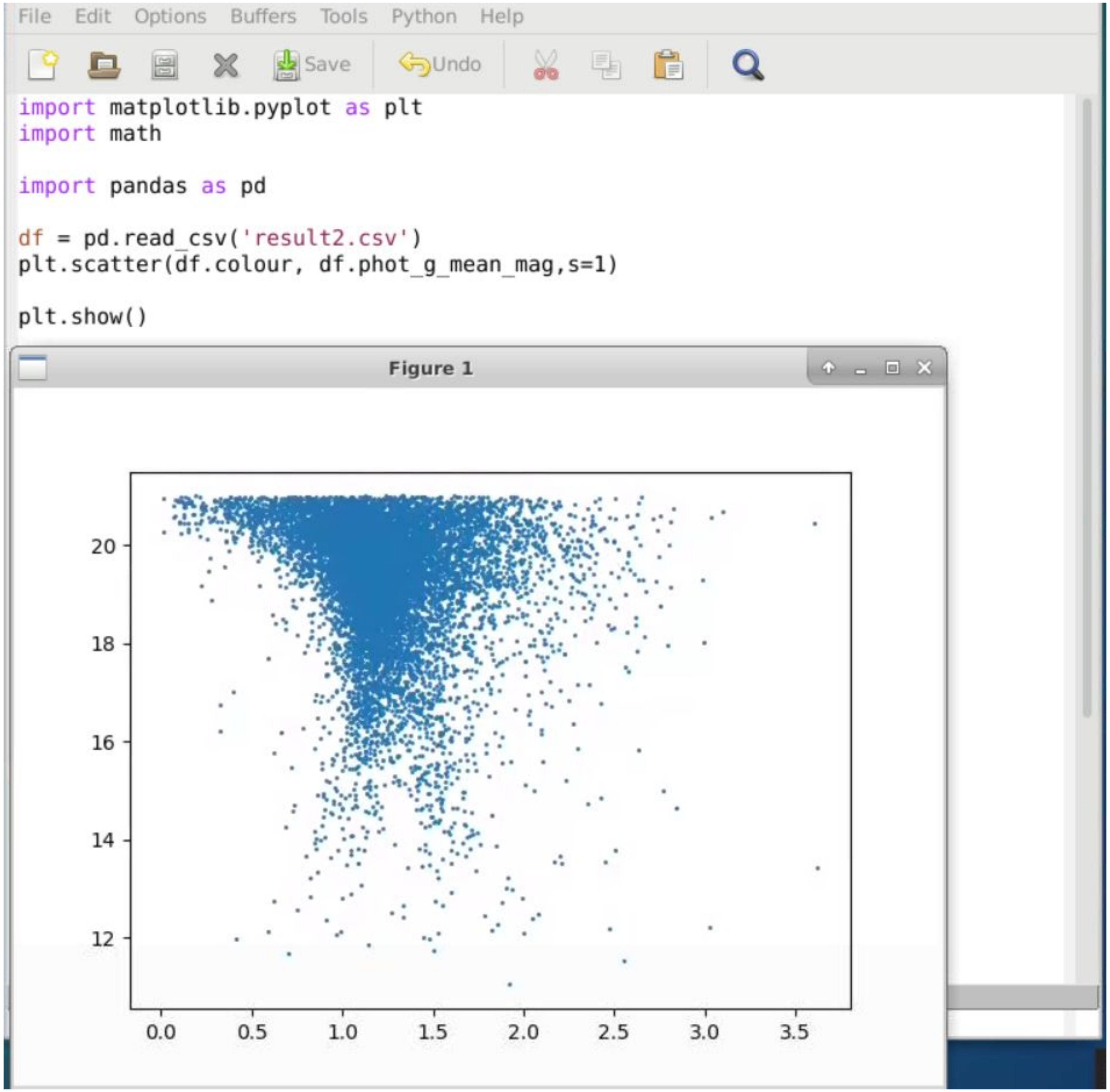
where BP and RP are ‘blue’ and ‘red’ pass bands specific to Gaia.

ADQL query:

```
SELECT TOP 10000 source_id, phot_g_mean_mag, (phot_bp_mean_mag-phot_rp_mean_mag) as colour
FROM gaiadr2.gaia_source
WHERE (phot_bp_mean_mag-phot_rp_mean_mag) > 0
```

With the result saved in a file, one can plot a colour - magnitude diagram.

Here is an example of Python code for data in csv format :



Example 3:

Select top 10000 stars in the ‘Solar neighborhood’, i.e. a spherical region of radius of 300 parsec (1 pc = 3.26 lyr),

or, equivalently, with parallax > 3

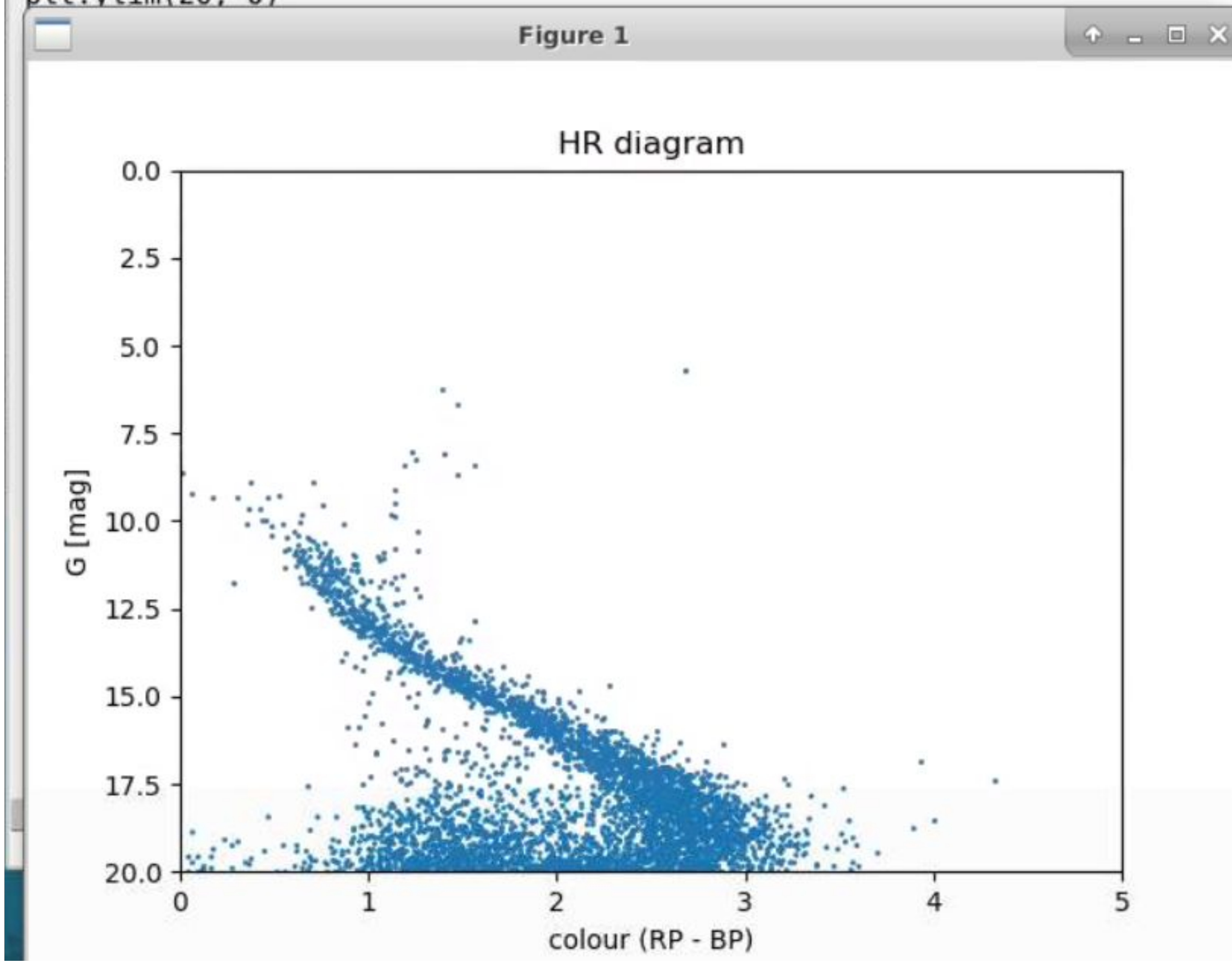
ADQL query
(note: here I’ve limited the search only to 10000 objects. The real region contains millions of stars; to get them all, omit ‘TOP’; the query will take longer)

```
SELECT TOP 10000
gaia_source.source_id,gaia_source.ra,gaia_source.ra_error,gaia_source.dec,gaia_source.dec_error,gaia_source.parallax,gaia_source.parallax_error,gaia_source.phot_g_mean_mag,gaia_source.bp_rp,gaia_source.radial_velocity,gaia_source.radial_velocity_error,gaia_source.phot_variable_flag,gaia_source.teff_val,gaia_source.a_g_val
FROM gaiadr2.gaia_source
WHERE(parallax > 3)
```

.. and the colour - magnitude diagram from this query:

```
import matplotlib.pyplot as plt
import math
import pandas as pd

df = pd.read_csv('result-SN.csv')
plt.scatter(df.bp_rp,df.phot_g_mean_mag,s=1)
plt.title('HR diagram')
plt.xlabel('colour (RP - BP)')
plt.ylabel('G [mag]')
plt.xlim(0, 5)
plt.ylim(20, 0)
```



Major discovery: *"Gaia Enceladus"*

- ***an ancient merger of the Milky Way with another galaxy the size of the LMC***

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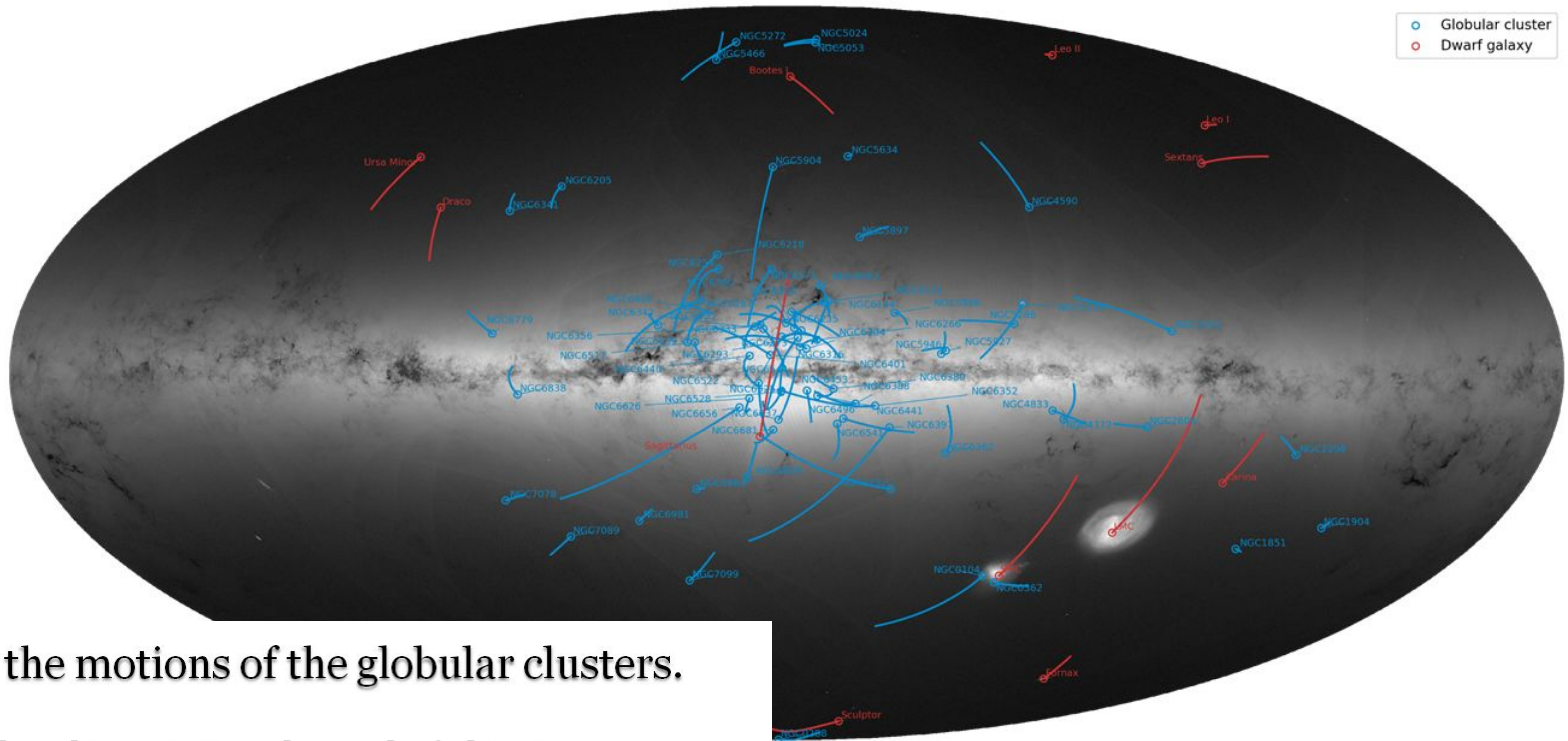
Gaia has made **a more precise measurement of the total mass of the Milky Way**

~1.5 trillion Solar masses (including dark matter)



from the motions of the globular clusters.

(mass is related to rotational speed of objects:
the faster they rotate, the more underlying mass)

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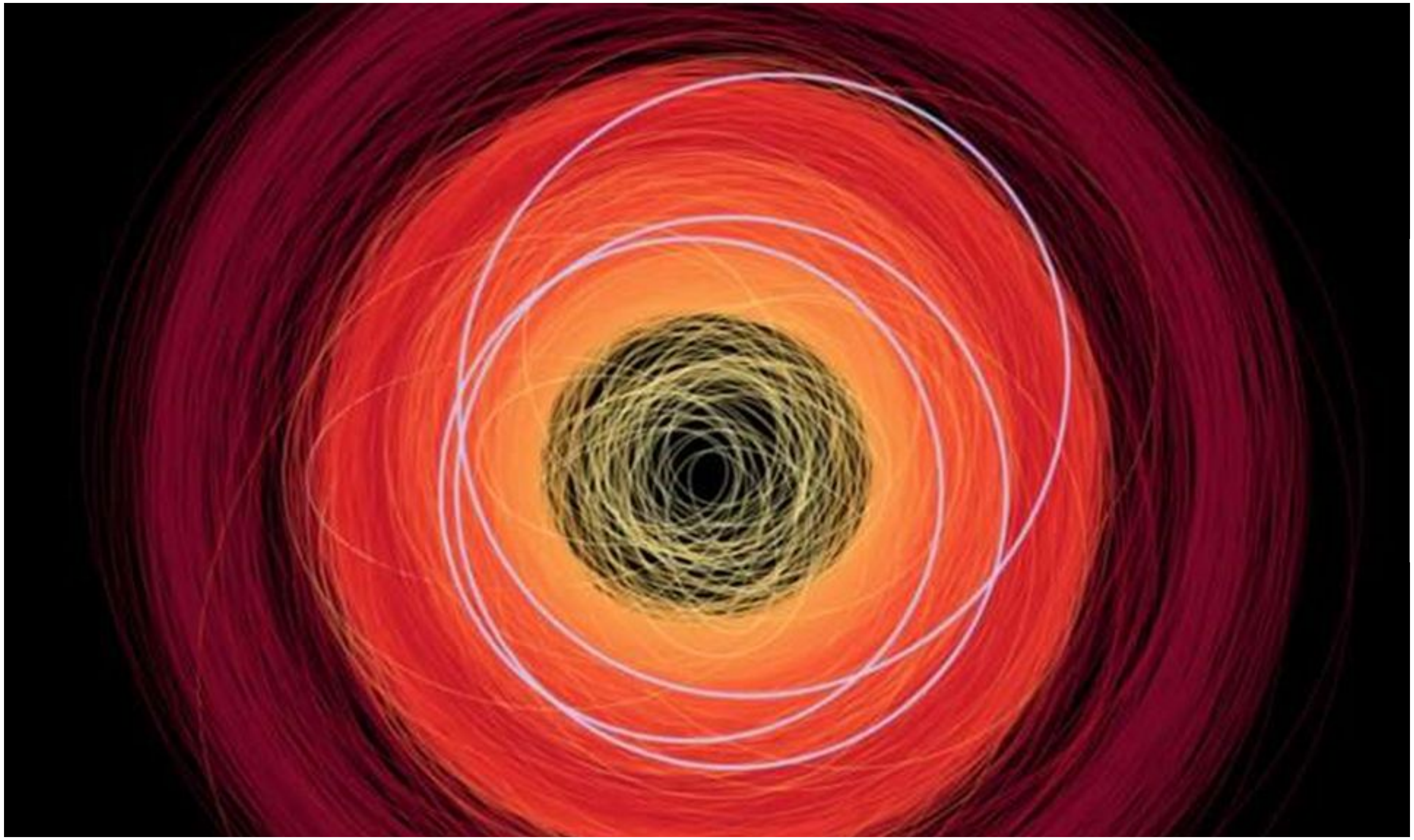
Orbits of ~14,000 known asteroids with Gaia



Grey shows asteroids discovered by Gaia.

Asteroids shown in bright red and orange hues are **main-belt asteroids**, located between the orbits of Mars and Jupiter.
Trojan asteroids, found around the orbit of Jupiter, are shown in dark red.
In yellow are the orbits of several tens of **near-Earth asteroids** (<1.3 AU).

Next Gaia release (Gaia DR3) : 3 Dec 2020

(mission will continue until 2022 and maybe beyond)

It is estimated that in the next few years Gaia will discover:

- ✓ hundreds of thousands of asteroids and comets within our Solar System
- ✓ seven thousand planets beyond our Solar System (exoplanets)
- ✓ tens of thousands of 'failed' stars, called brown dwarfs
- ✓ twenty thousand exploding stars, called supernovae
- ✓ hundreds of thousands of distant active galaxies, called quasars.

Gaia will also give us:

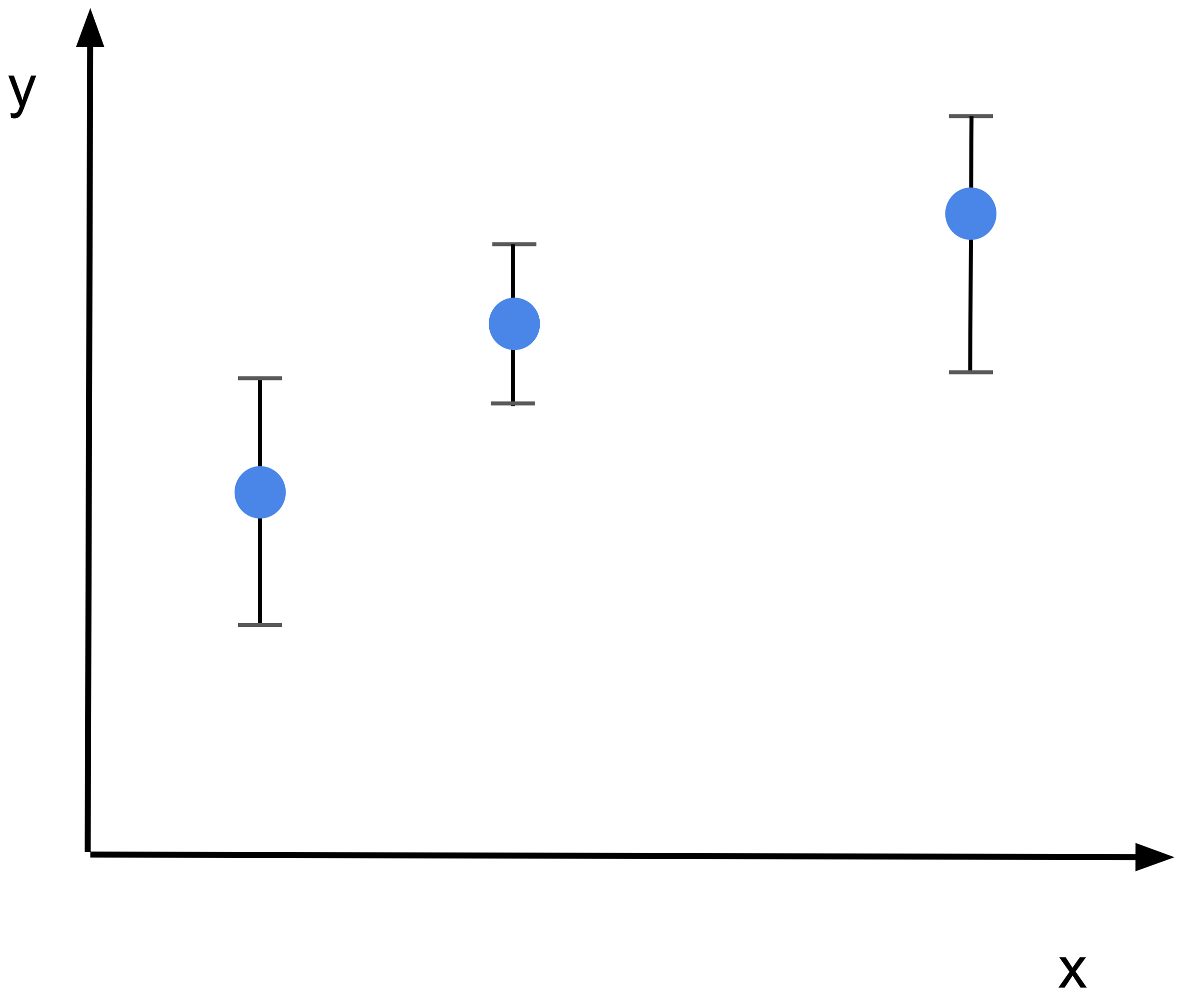
- ✓ a refined measurement of the cosmic distance scale
- ✓ new tests of general relativity

Questions?

Parameter Inference & MCMC

Juliana Kwan

Suppose you needed to fit a straight line to some data...



My model is: y = mx + b

$$\chi^2 = \sum_i \frac{[y_i - \tilde{y}(x_i|m,b)]^2}{\sigma_i^2}$$

Work out the best fitting values of m, b by minimising χ^2.

Need to solve $\partial\chi^2/\partial\alpha_i = 0, \alpha_i = (m, b)$

The Bayesian approach:

$$P(H|D) = \frac{P(H)P(D|H)}{P(D)}$$

Bayes' Theorem

P(H|D) is the probability of the hypothesis given the data (**posterior**; this is what we want)

P(D|H) is the probability of the data given the hypothesis (**likelihood**)

P(H) is the **prior** hypothesis

P(D) is the probability distribution of the data (important for model comparison)

Bayesian parameter estimation involves calculating the likelihood, P(D|H):

$$\mathcal{L} \propto \exp\left[-\frac{1}{2}\sum_i (y_i - \tilde{y}(x_i)) C_{ij}^{-1} (y_j - \tilde{y}(x_j))\right]$$

You'll notice that:

$$\log \mathcal{L} \propto -\frac{1}{2}\chi^2$$

This is true for Gaussian distributions only!

We must also choose a prior on the parameters, m, b, e.g:

$$\pi(m) = (m_{\max} - m_{\min})^{-1} \qquad \pi(b) = \frac{1}{\sigma\sqrt{2\pi}}\exp[-\frac{1}{2}(\frac{b-\mu}{\sigma})^2] \qquad \pi(b) = 1/b$$

This represents any external knowledge that we already have about the system, e.g. a weighted coin.

Now that we have the likelihood and prior, how should we calculate the posterior?

Markov Chain Monte Carlo Analyses

In real world applications, we often have many parameters, which makes evaluating the posterior expensive.

Fortunately there are numerical methods to deal with this.

The Metropolis-Hastings algorithm:

1. Choose a starting point, x_0, calculate $L(x_0)$ (close to what you think the parameters should be)
2. Take a step to x_1 by calculating $L(x_1)$
3. If $L(x_1) \geq L(x_0)$, then keep x_1 by adding it to the chain
4. If $L(x_1) < L(x_0)$, generate a random number, $r \sim U(0,1)$
   a. If $r \geq L(x_1)/L(x_0)$, keep x_1 by adding it to the chain
   b. If $r < L(x_1)/L(x_0)$, discard x_1 (add x_0 to the chain)
5. Repeat steps 2 - 4 until convergence is reached.

Markov Chain Monte Carlo Analysis

At the end of the process, you will have a chain (list of parameter values) that represents the combination of the likelihood and the prior. The density of points in the chain is the posterior.

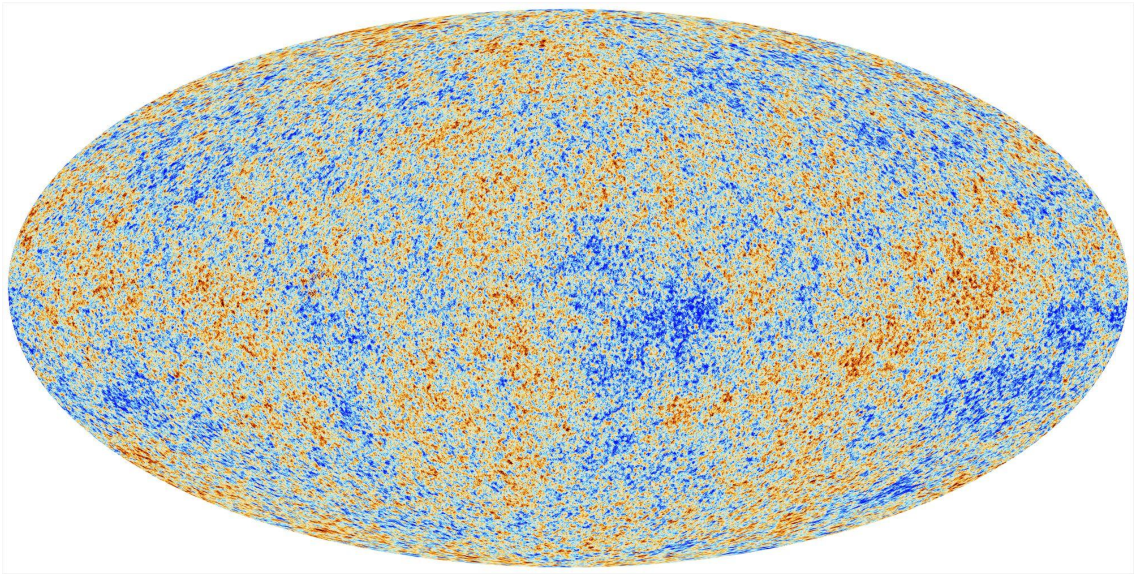
Some caveats:

- You must check for convergence. MCMC gives the correct posterior in the limit of infinite samples.
- Be careful in your choice of step size - too small and the chain will get stuck around the peaks of the posterior, too large and the chain can 'step over' the peaks.
- Multimodal posteriors require special treatment; see nested sampling

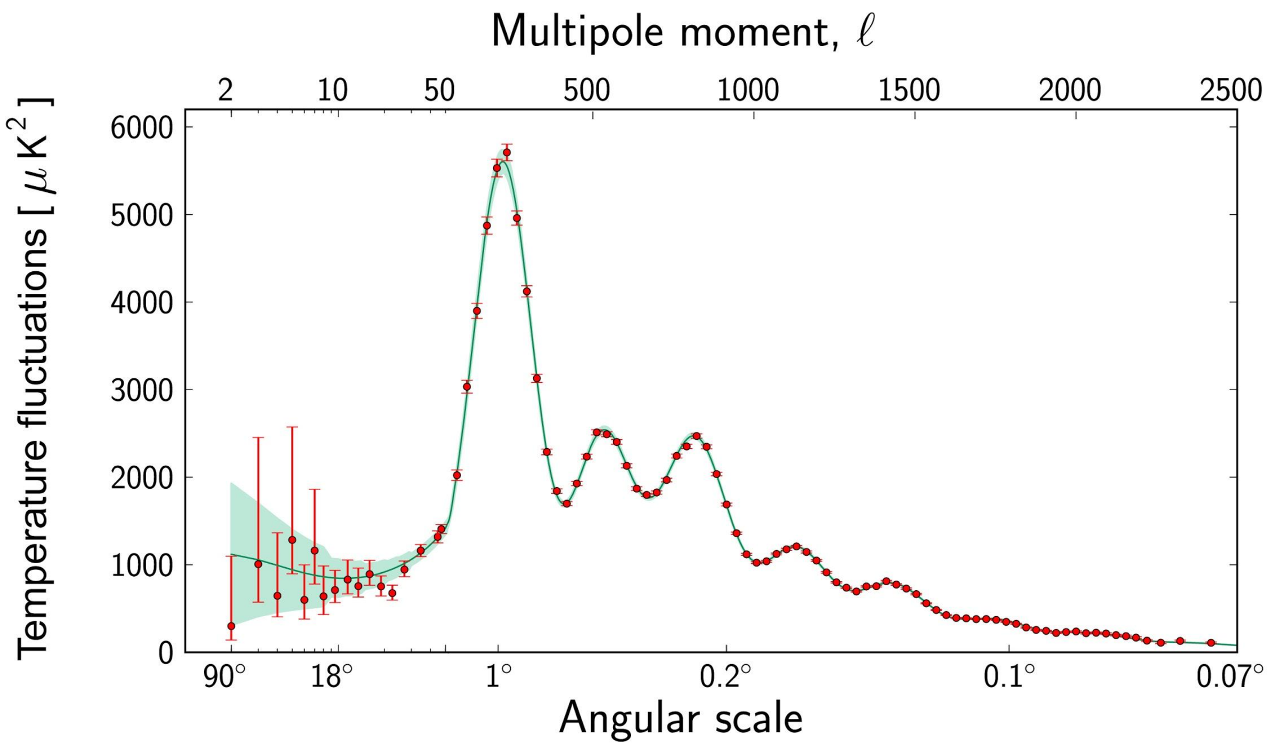
Helpful packages for parameter inference:

- CosmoMC and GetDist
  - https://cosmologist.info/cosmomc/
- CosmoSIS
  - https://bitbucket.org/joezuntz/cosmosis/wiki/Home
- emcee
  - https://emcee.readthedocs.io/en/stable/
- dynesty
  - https://github.com/joshspeagle/dynesty
- anesthetic
  - https://anesthetic.readthedocs.io/en/latest/

Example: Planck 2018 likelihood



Map of temperature fluctuations in the early universe



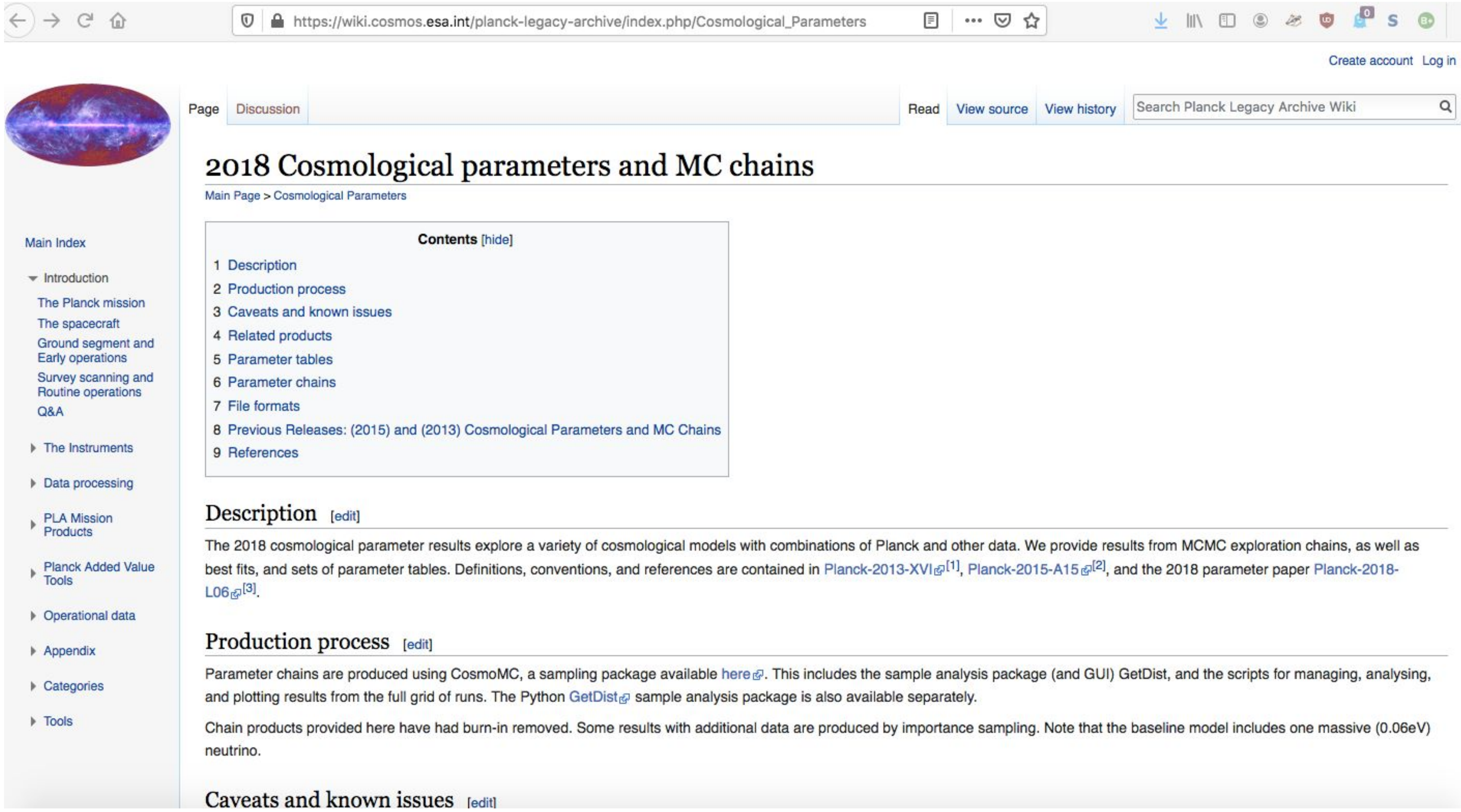
Spectrum of fluctuations as a function of angular size

Question: What model parameters best fit the observed fluctuations?

Example: Planck 2018 likelihood

Download the chains:

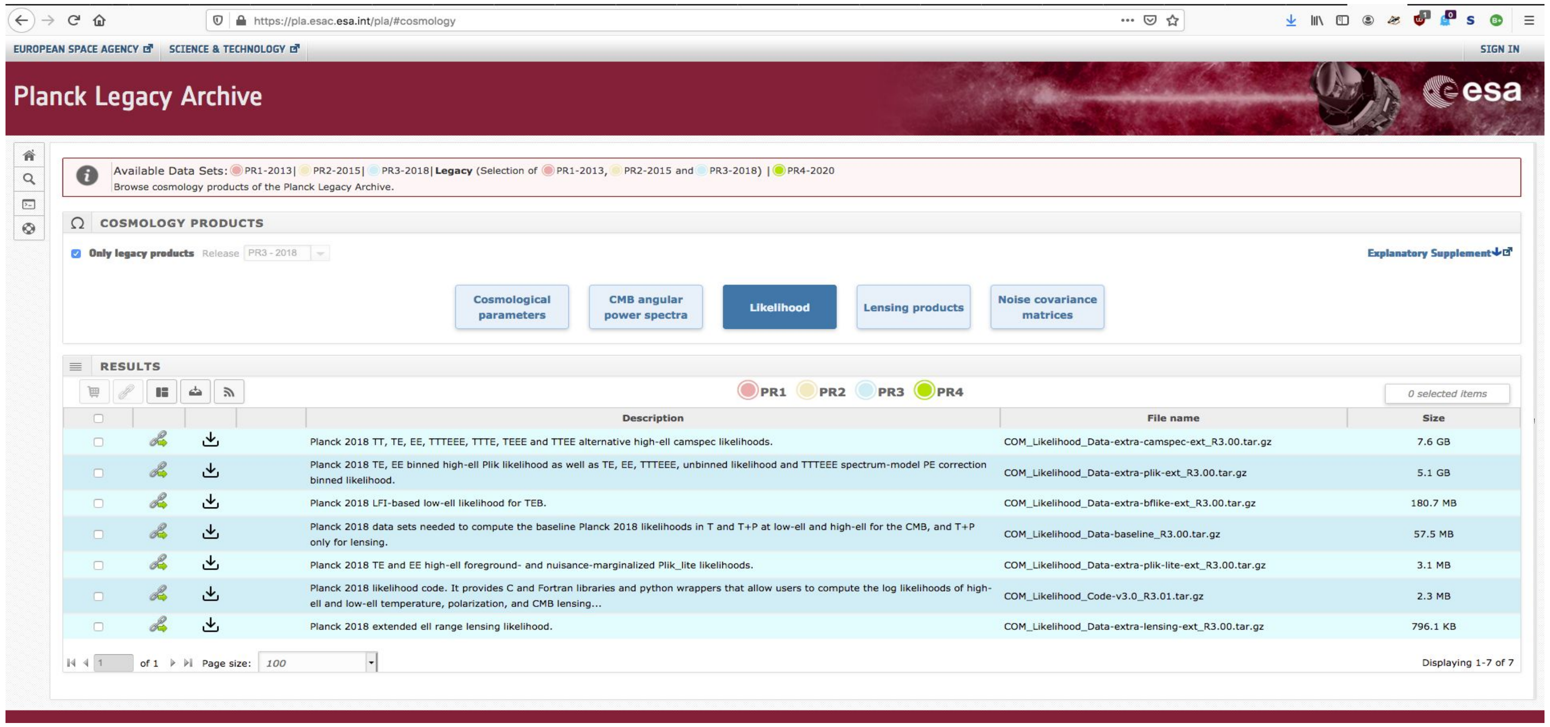
https://wiki.cosmos.esa.int/planckpla/index.php/Cosmological_Parameters

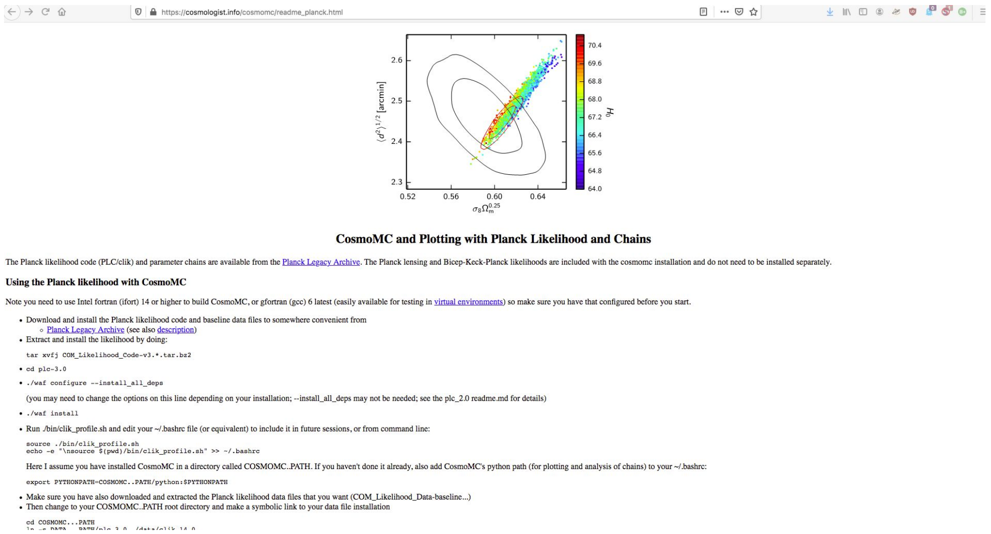


If you want to run them for yourself (long!):

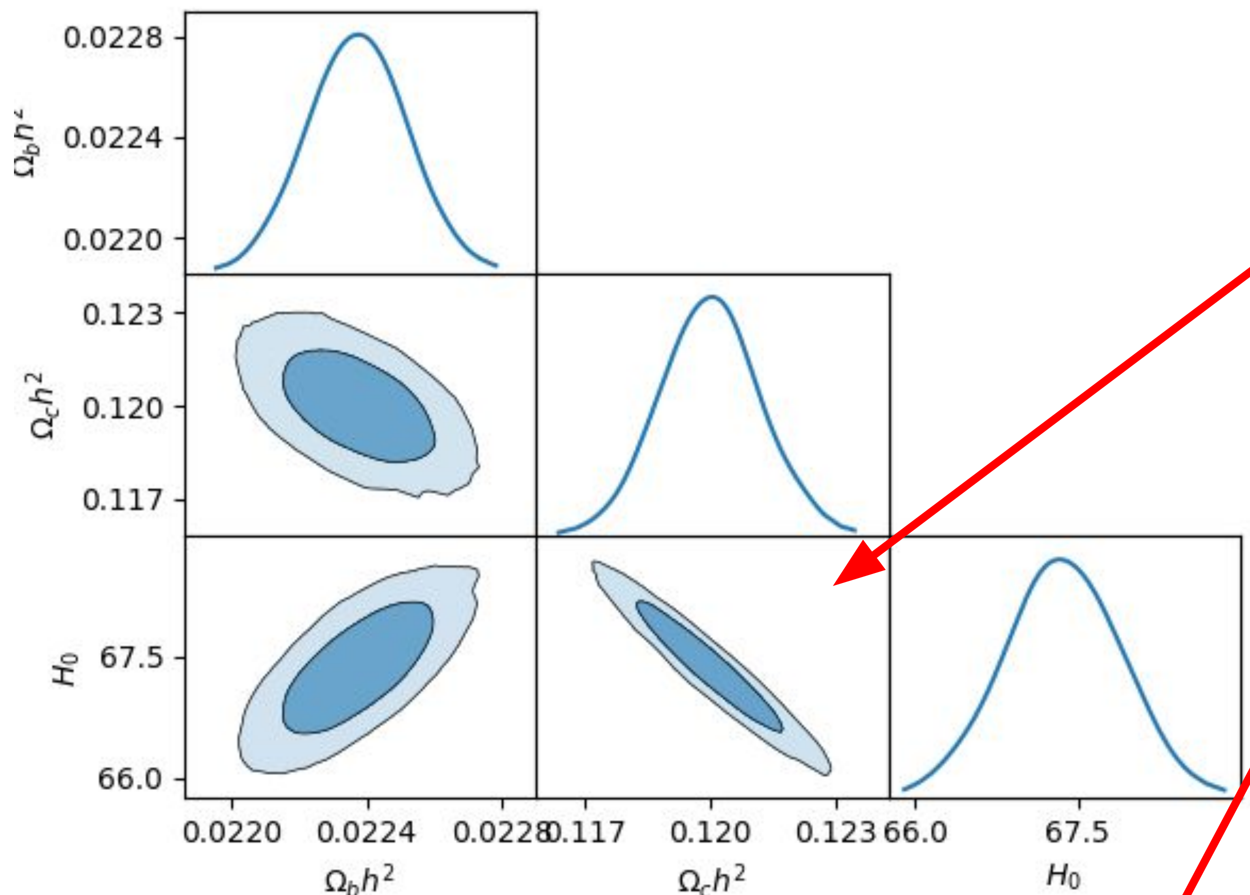
Download likelihood code: https://pla.esac.esa.int/pla/#cosmology

Install into CosmoMC: https://cosmologist.info/cosmomc/readme_planck.html





pip install anesthetic (use flag --user if no root access)



2D marginalized posterior distributions

1D marginalized posterior distributions

```
import matplotlib.pyplot as plt
from anesthetic import MCMCSamples
mcmc_root =
'plikHM_TTTEEE_lowl_lowE_lensing/base_plikHM_TTTEEE_lowl_lowE_lensing'
mcmc=MCMCSamples(root=mcmc_root)
mcmc.plot_2d(['omegabh2','omegach2','H0'], types={'lower':'kde','diagonal':'kde'})
```

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Why does this work?

The file directory contains

- .paramnames file

    This lists the names of the parameters and their latex labels

- .ranges file

    This lists the min, max values of each parameter. Can be ‘none’

If using CosmoMC, these files are automatically generated.

Some useful commands...

- mcmc.mean()
- mcmc.median()
- mcmc.std()
- mcmc.describe(): prints mean, std dev, confidence levels for each parameter, max/min values
- mcmc.info(): prints names of each column, data type, no. of entries.

Bayesian statistics is a very powerful tool for analysing large datasets.

Two functions:

- Parameter inference: given a certain model, what are the best fitting parameters to the observed data?
- Model selection: which model is better able to fit the data?

There are many publically available packages to help you!

Questions? Email: j.kwan@ljmu.ac.uk or message via Slack

Questions?