Bayesian analyses of galaxy surveys

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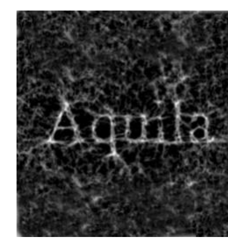
and the Aquila Consortium
www.aquila-consortium.org



November 11th, 2019

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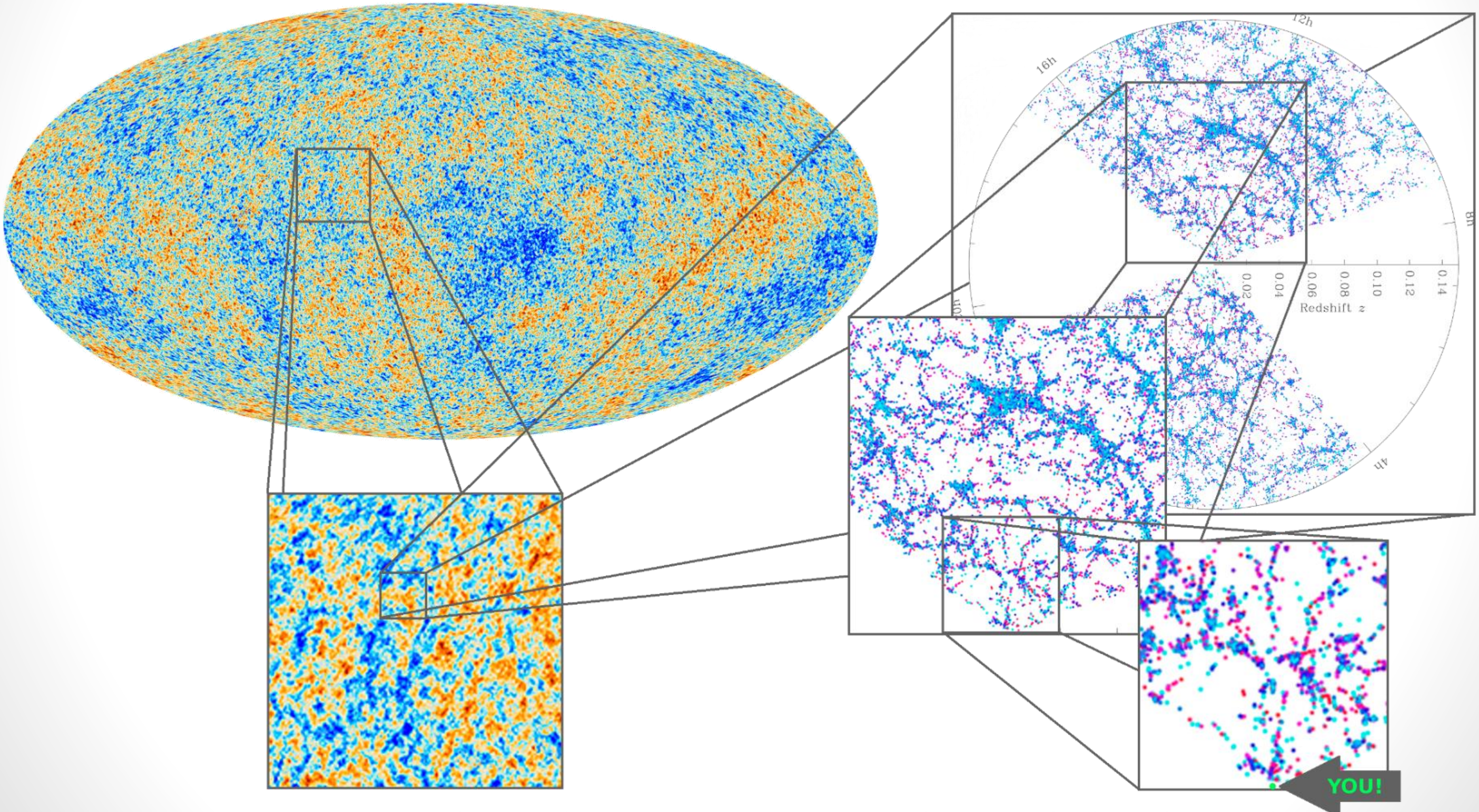
The big picture: the Universe is highly structured

You are here. Make the best of it…



Planck collaboration (2013-2015)

M. Blanton and the Sloan Digital Sky Survey (2010-2013)

What we want to know from the large-scale structure

The LSS is a vast source of knowledge:

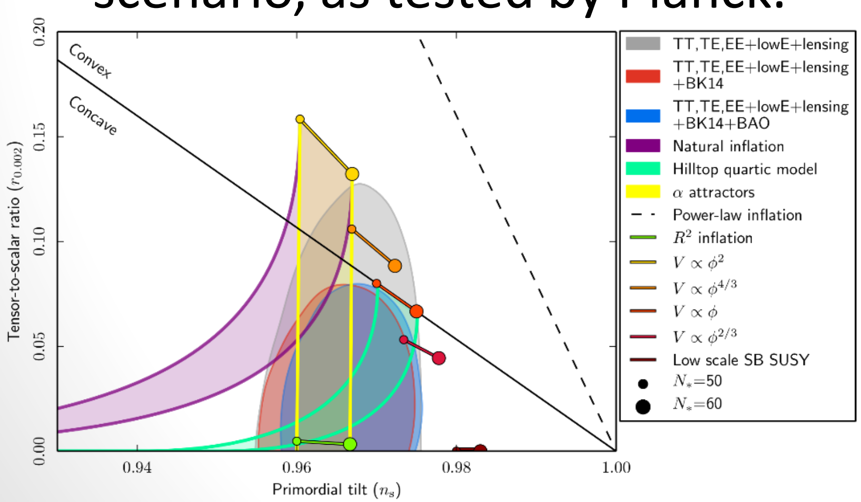
- Cosmology:
  - ΛCDM: cosmological parameters and tests against alternatives,
  - Physical nature of the dark components,
  - Neutrinos: number and masses,
  - Geometry of the Universe,
  - Tests of General Relativity,
  - Initial conditions and link to high energy physics
- Astrophysics: galaxy formation and evolution as a function of their environment
  - Galaxy properties (colours, chemical composition, shapes),
  - Intrinsic alignments, intrinsic size-magnitude correlations

We have theoretical and computer models…

- **Initial conditions:**
  a Gaussian random field

$$\mathcal{P}(\delta^{\mathrm{i}}|S) = \frac{1}{\sqrt{|2\pi S|}} \exp\left(-\frac{1}{2}\sum_{x,x'} \delta^{\mathrm{i}}_x S^{-1}_{xx'} \delta^{\mathrm{i}}_{x'}\right)$$

Everything seems consistent with the simplest inflationary scenario, as tested by Planck.

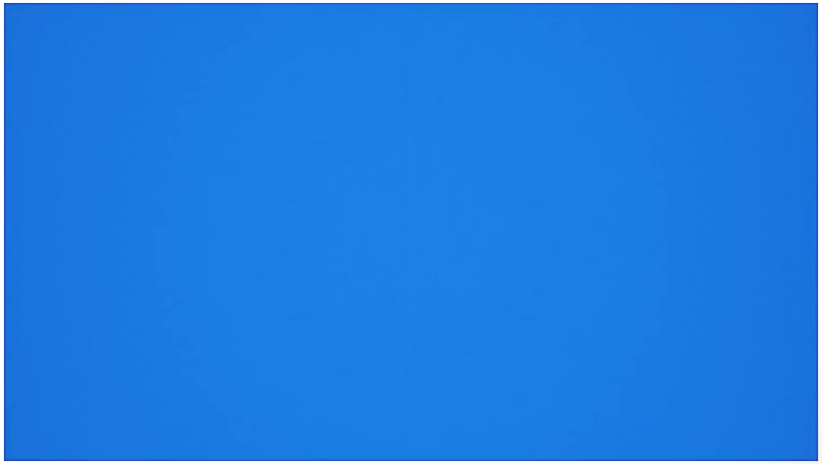


Planck 2018 X, 1807.06211

- **Structure formation:**
  numerical solution of the Vlasov-Poisson system for dark matter dynamics

$$\frac{\partial f}{\partial \tau} + \frac{\mathbf{p}}{ma} \cdot \nabla f - ma \nabla \Phi \cdot \frac{\partial f}{\partial \mathbf{p}} = 0$$

$$\Delta \Phi = 4\pi \mathrm{G} a^2 \bar{\rho} \delta$$



Y. Dubois & S. Colombi (IAP)

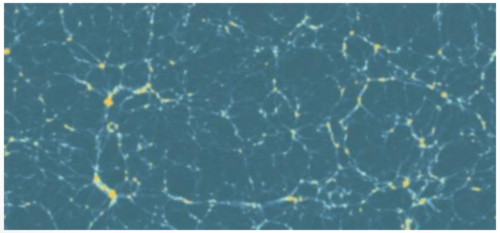
… how do we test these models against survey data?

J. Cham – PhD comics

Redshift range	Volume (Gpc^3)	k_{max} $(\mathrm{Mpc}/h)^{-1}$	N_{modes}
0-1	50	0.15	10^7
1-2	140	0.5	$5\mathrm{x}10^8$
2-3	160	1.3	10^{10}

M. Zaldarriaga

- Precise tests require many modes.
- In 3D galaxy surveys, the number of modes usable scales as k_{max}^3 .



- The challenge: non-linear evolution at small scales and late times.
- The strategy:
  - Pushing down the smallest scale usable for cosmological analysis
  - Using a numerical model linking initial and final conditions

In other words: go beyond the linear and static analysis of the LSS.

Why Bayesian inference?

- Inference of signals = ill-posed problem
  - Incomplete observations: finite resolution, survey geometry, selection effects
  - Noise, biases, systematic effects
  - Cosmic variance

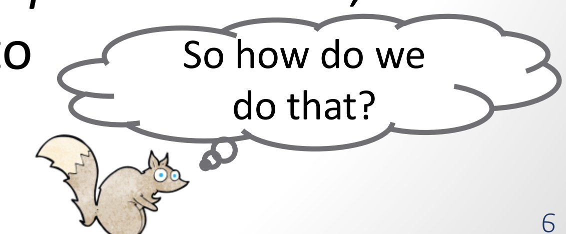
No unique recovery is possible!

"What is the formation history of the Universe?"

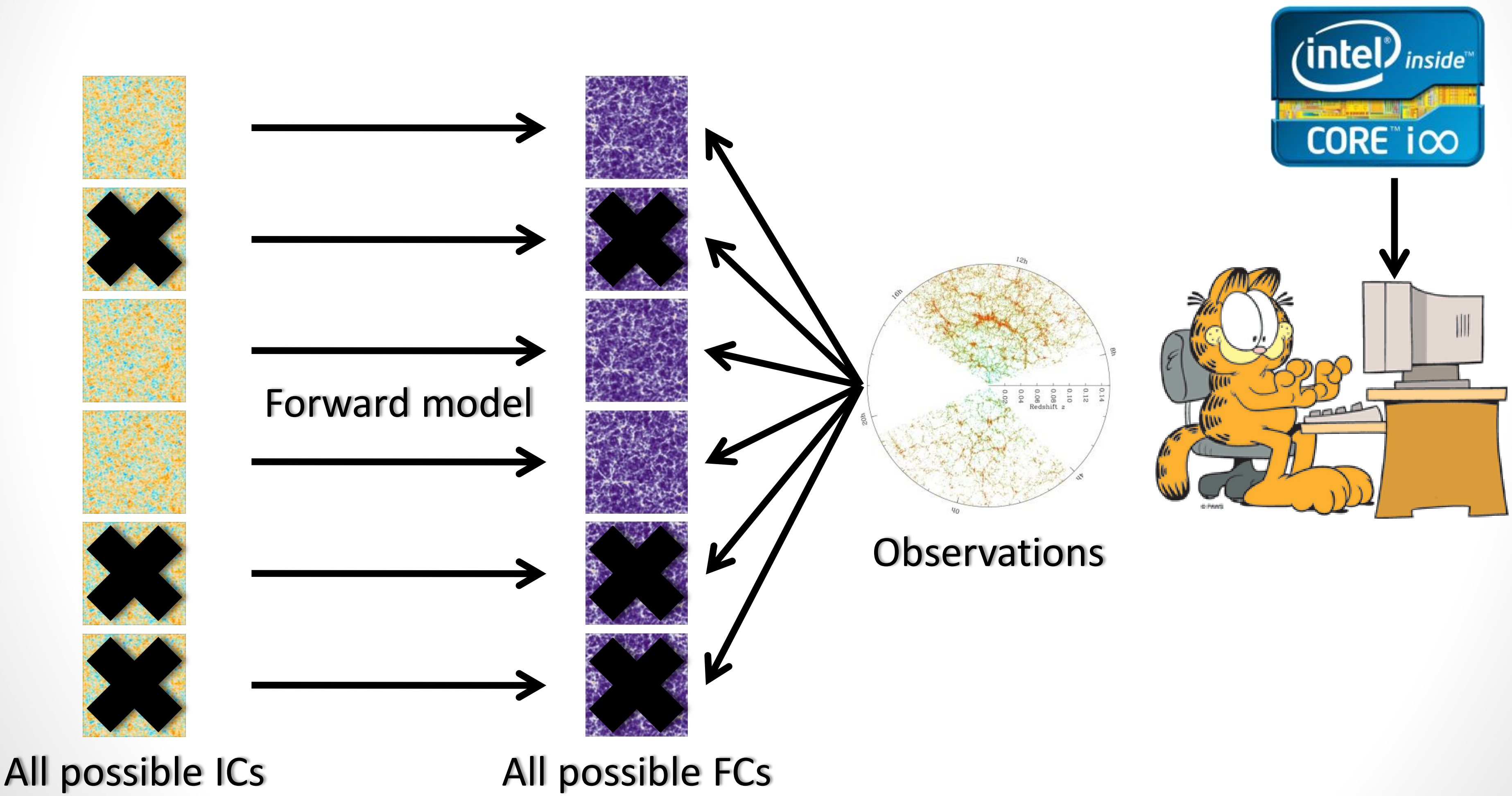
"What is the probability distribution of possible formation histories (signals) compatible with the observations?"

Bayes' theorem: $$\mathcal{P}(s|d)\mathcal{P}(d) = \mathcal{P}(d|s)\mathcal{P}(s)$$

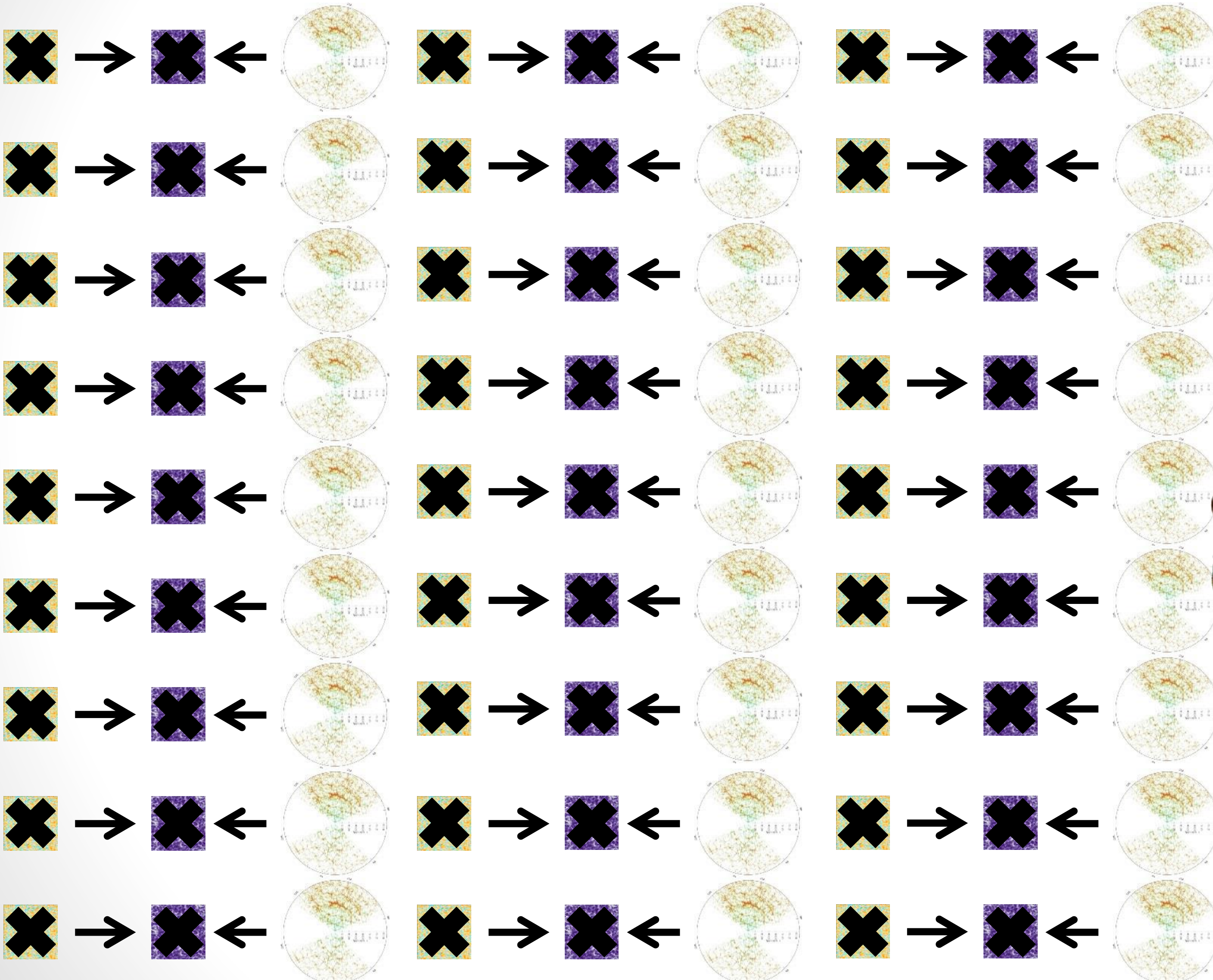
- Cox-Jaynes theorem: Any system to manipulate *"plausibilities"*, consistent with Cox's desiderata, is isomorphic to (Bayesian) probability theory



Bayesian forward modelling: the ideal scenario



Bayesian forward modelling: the challenge



The (true) likelihood lives in

$d \approx 10^7$!

Likelihood-based solution: BORG

Bayesian Origin Reconstruction from Galaxies

Likelihood-based solution:
Exact statistical analysis
Approximate data model

Data assimilation

?

Hamiltonian (Hybrid) Monte Carlo

- Use classical mechanics to solve statistical problems!
  - The potential: $\psi(\mathbf{x}) \equiv -\ln p(\mathbf{x})$
  - The Hamiltonian: $H(\mathbf{x},\mathbf{p}) \equiv \frac{1}{2}\mathbf{p}^{\intercal}\mathbf{M}^{-1}\mathbf{p} + \psi(\mathbf{x})$

$$(\mathbf{x},\mathbf{p}) \Rightarrow \left\{ \begin{aligned} \frac{\mathrm{d}\mathbf{x}}{\mathrm{d}t} &= \frac{\partial H}{\partial \mathbf{p}} = \mathbf{M}^{-1}\mathbf{p} \\ \frac{\mathrm{d}\mathbf{p}}{\mathrm{d}t} &= -\frac{\partial H}{\partial \mathbf{x}} = -\frac{\mathrm{d}\psi(\mathbf{x})}{\mathrm{d}\mathbf{x}} \end{aligned} \right\} \Rightarrow (\mathbf{x}',\mathbf{p}')$$

gradients of the pdf

$$a(\mathbf{x}',\mathbf{x}) = \mathrm{e}^{-(H'-H)} = 1 \Leftarrow$$

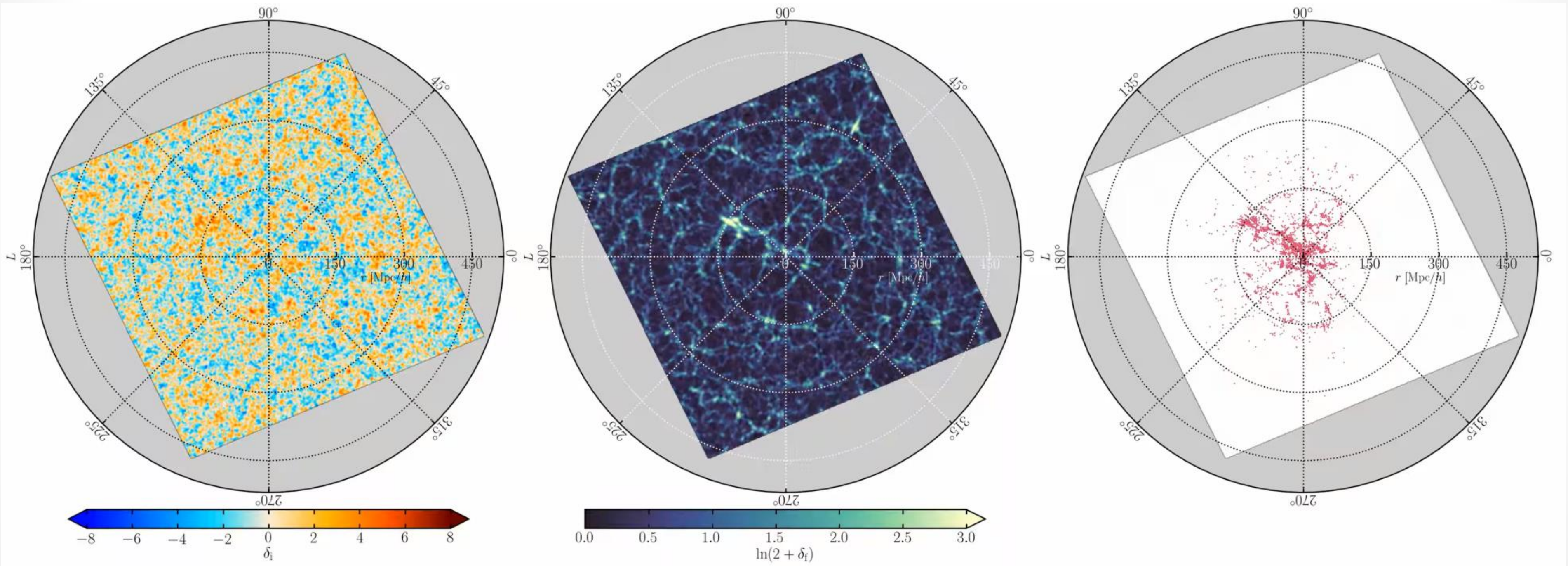
acceptance ratio unity

- HMC beats the curse of dimensionality by:
  - Exploiting gradients
  - Using conservation of the Hamiltonian

Duane et al. 1987, Phys. Lett. B 195, 2

BORG at work: Bayesian chrono-cosmography

Initial conditions **Final conditions** **Observations**

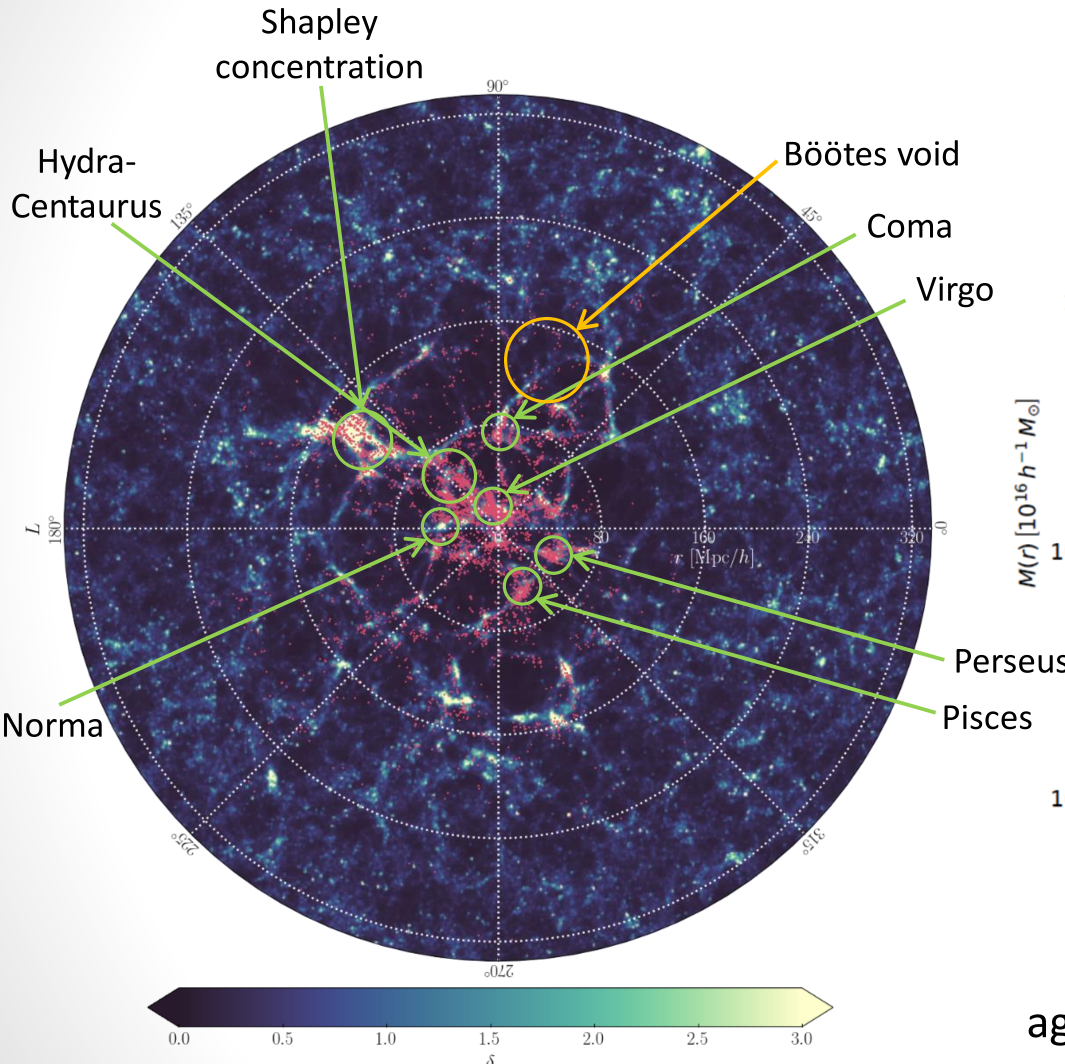


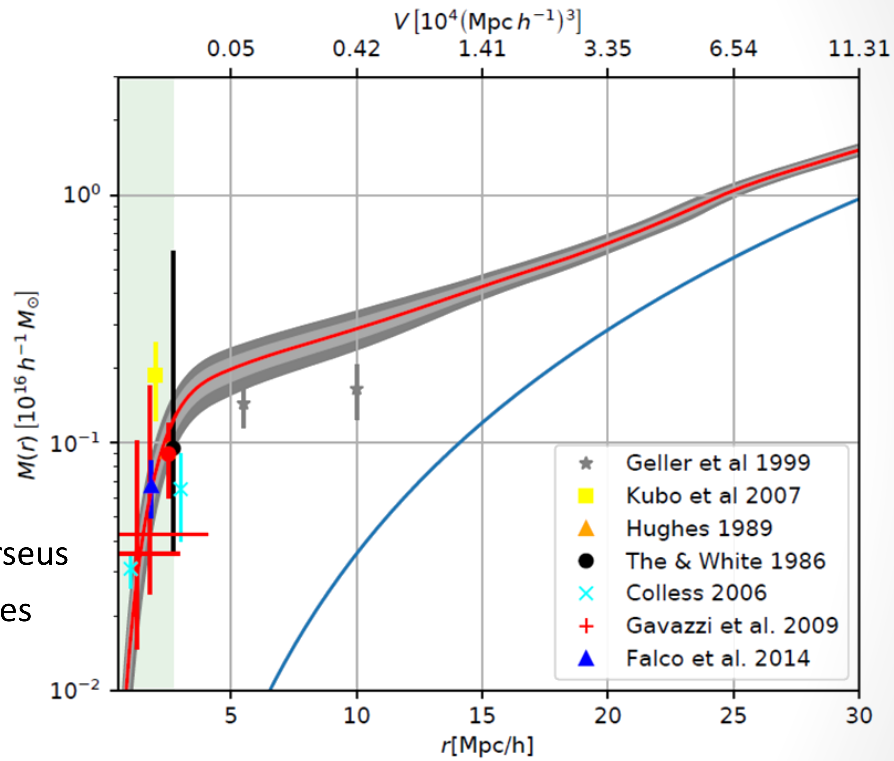
Supergalactic plane

67,224 galaxies, ≈ 17 million parameters, 5 TB of primary data products, 10,000 samples, ≈ 500,000 forward and adjoint gradient data model evaluations, 1.5 million CPU-hours

Jasche & Lavaux 2019, 1806.11117 – FL, Lavaux & Jasche, in prep.

BORGPM density field: full non-linear dynamics



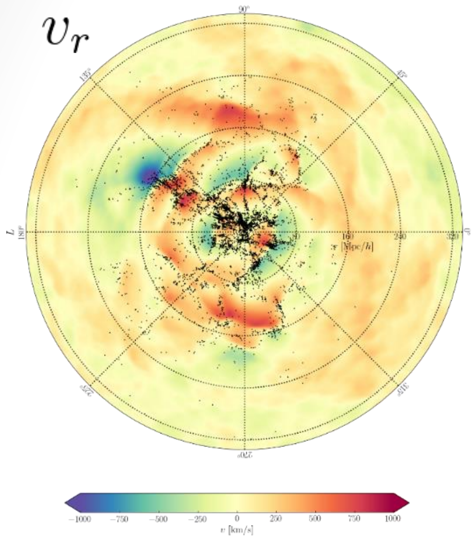


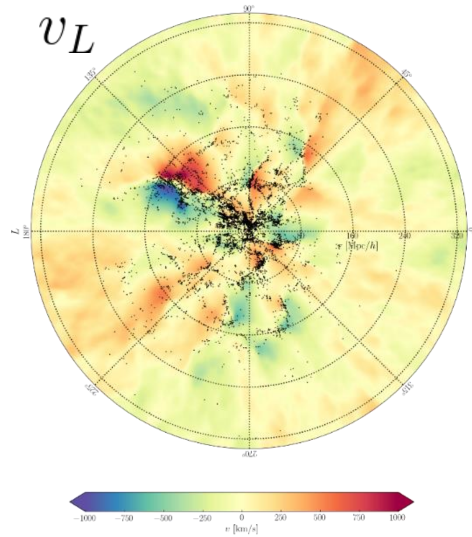
Mass profile of the Coma cluster, in agreement with gravitational lensing and X-ray observations down to a few Mpc.

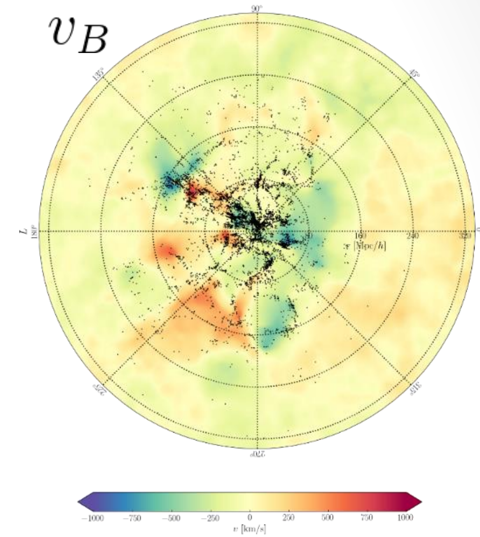
Jasche & Lavaux 2019, 1806.11117 – FL, Lavaux & Jasche, in prep.

Velocity field in the supergalactic plane

with James Prideaux-Ghee (PhD student) & Alan Heavens

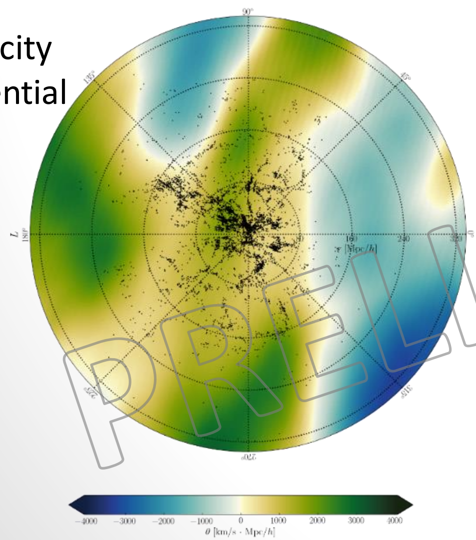




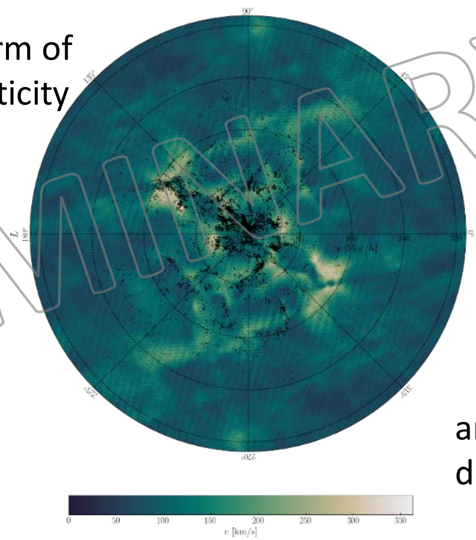


The gravitational infall of known structures can be observed.

Velocity potential



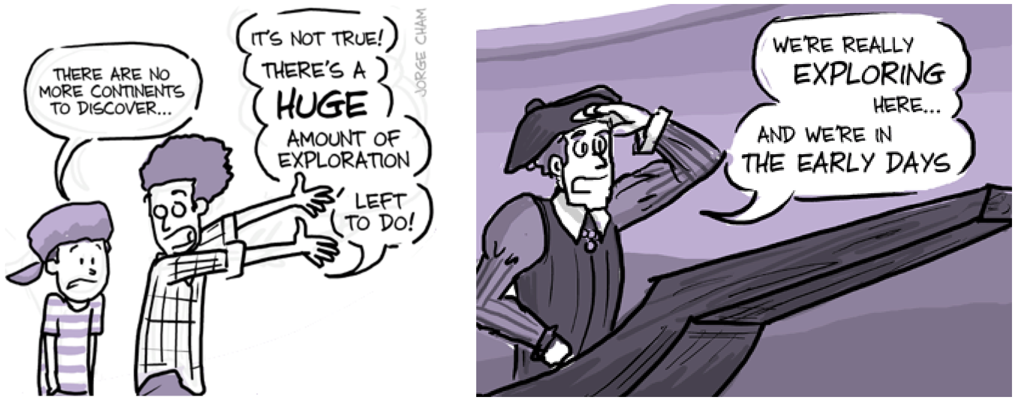
Norm of vorticity



and velocity dispersion…

In earlier work (Leclercq, Jasche, Lavaux, Wandelt & Percival 2017, 1601.00093), vorticity was a postdiction. Thanks to BORGPM (full non-linear dynamics), we have now actual measurements - with uncertainties.

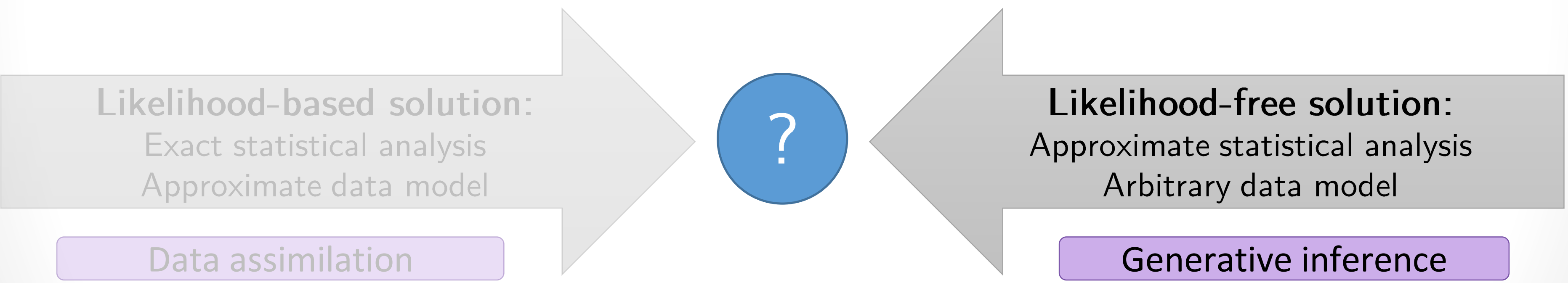
Mapping the Universe: epilogue?



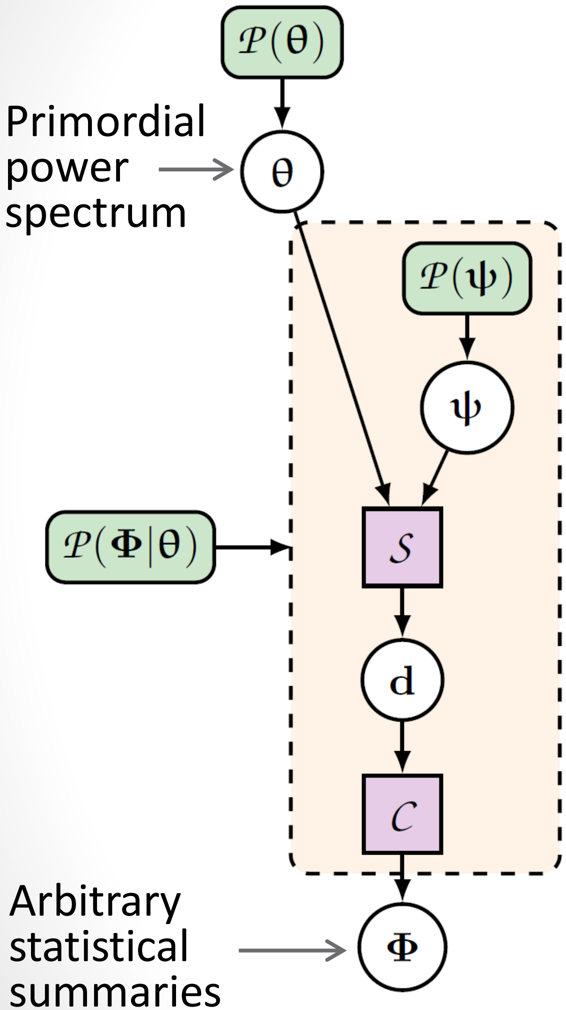
J. Cham – PhD comics

Likelihood-free solution: SELFI

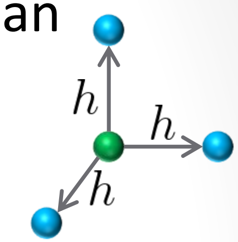
Simulator Expansion for Likelihood-Free Inference



SELFI: Method



- Gaussian prior + Gaussian effective likelihood
- Linearisation of the black-box around an expansion point + finite differences:



$$\hat{\Phi}_\theta \approx \mathbf{f}_0 + \nabla \mathbf{f}_0 \cdot (\theta - \theta_0)$$

➡ The posterior is Gaussian and analogous to a Wiener filter:

expansion point

observed summaries

$$\gamma \equiv \theta_0 + \Gamma \, (\nabla \mathbf{f}_0)^\intercal \, \mathbf{C}_0^{-1} (\Phi_\mathrm{O} - \mathbf{f}_0)$$

$$\Gamma \equiv \left[(\nabla \mathbf{f}_0)^\intercal \, \mathbf{C}_0^{-1} \nabla \mathbf{f}_0 + \mathbf{S}^{-1} \right]^{-1}$$

prior covariance

covariance of summaries

gradient of the black-box

$\mathbf{f}_0$, $\mathbf{C}_0$ and $\nabla \mathbf{f}_0$ can be evaluated through simulations only.
The number of required simulations is fixed *a priori*.

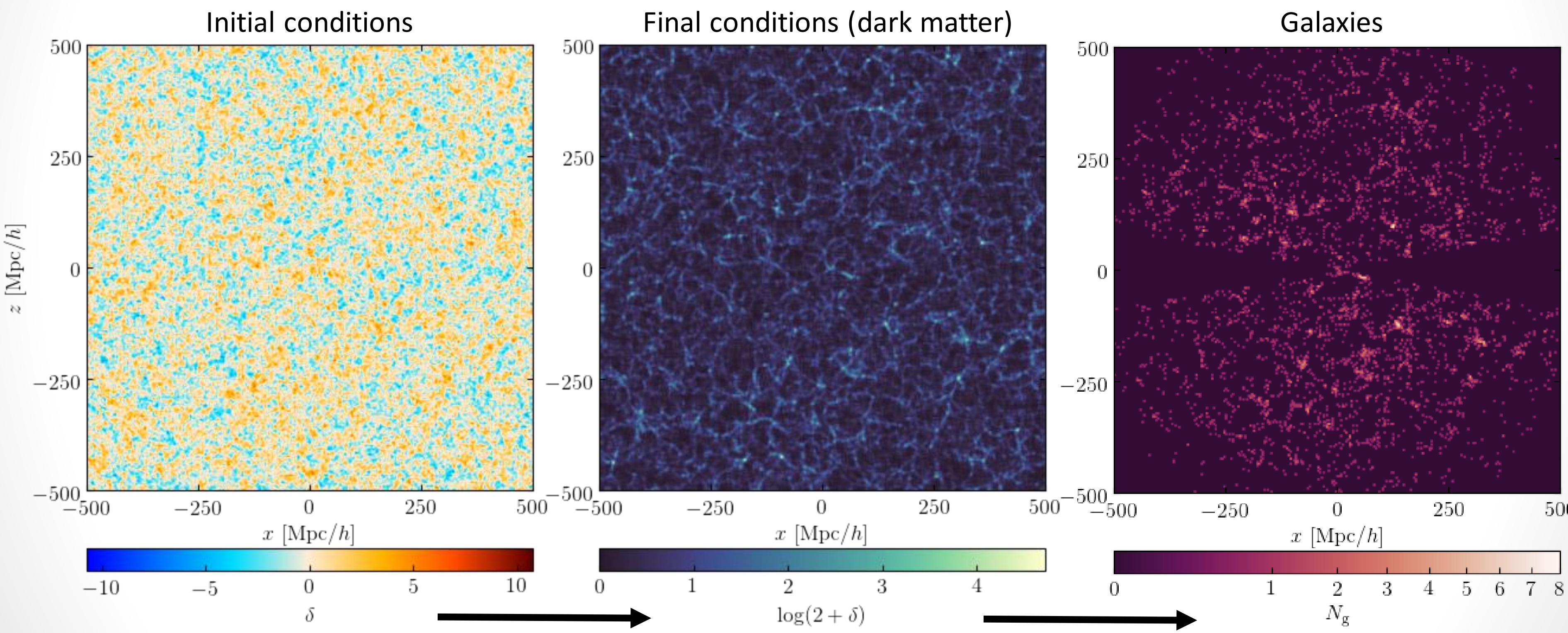
FL, Enzi, Jasche & Heavens 2019, 1902.10149

A black-box: Simbelmynë

I’m happy to explain the name later today…

Publicly available code:

https://bitbucket.org/florent-leclercq/simbelmyne/

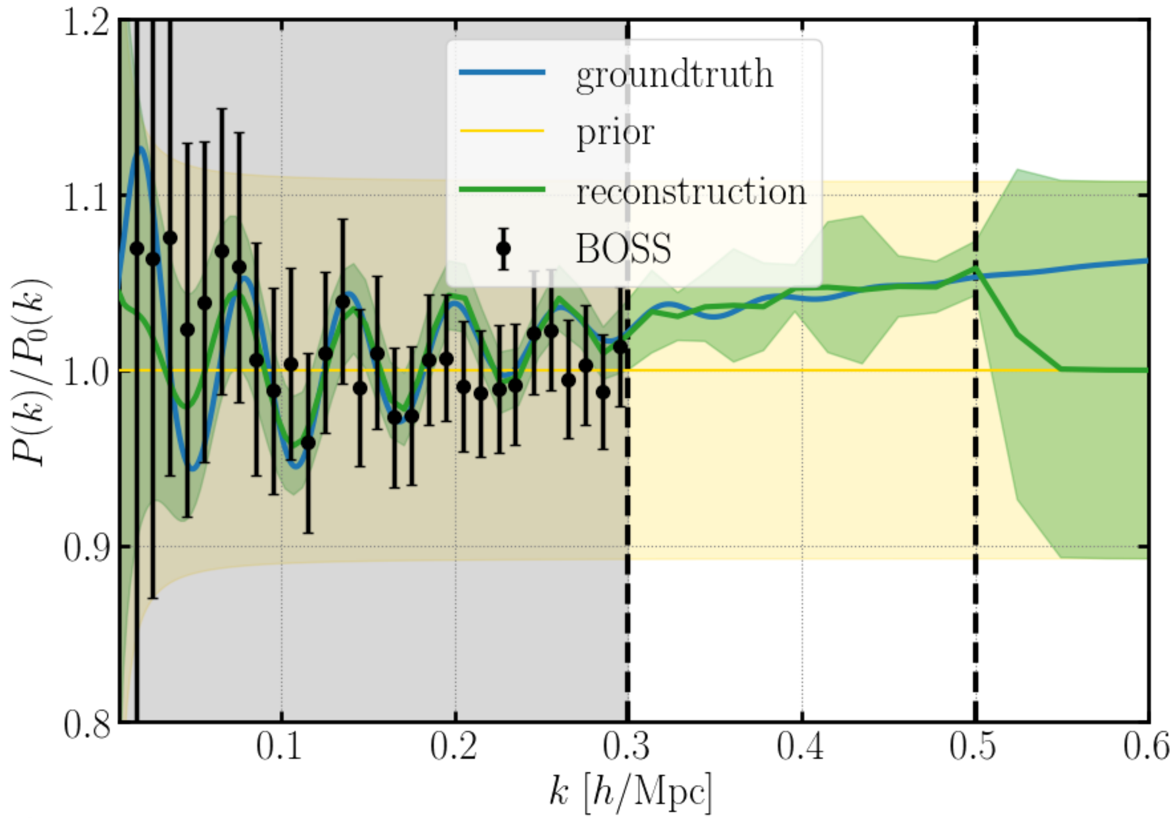


Dark matter simulation with COLA

Tassev, Zaldarriaga & Eisenstein 2013, 1301.0322

Survey simulation: Redshift-space distortions, galaxy bias, selection effects, survey geometry, instrumental noise

SELFI + Simbelmynë: Proof-of-concept



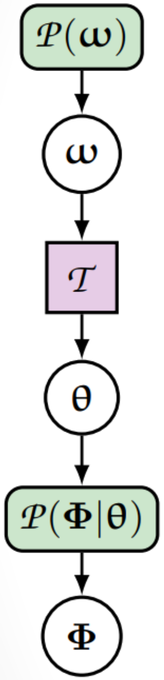
100 parameters are simultaneously inferred from a black-box data model

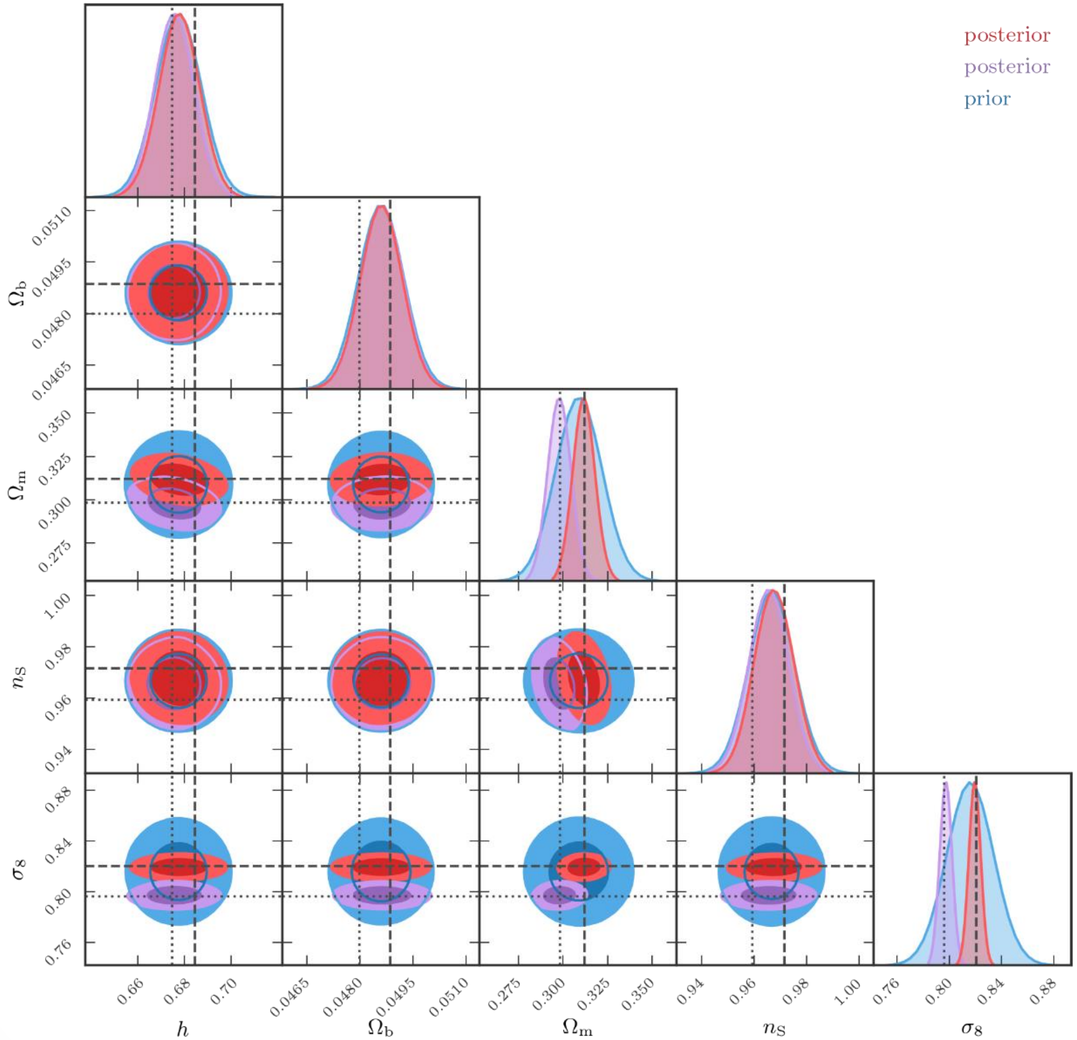
$N_{\mathrm{modes}} \propto k^3$: **5** times more modes are used in the analysis

1 (Gpc/h)^3 only! Much more potential for Euclid data…

FL, Enzi, Jasche & Heavens 2019, 1902.10149

SELFI + Simbelmynë: Proof-of-concept

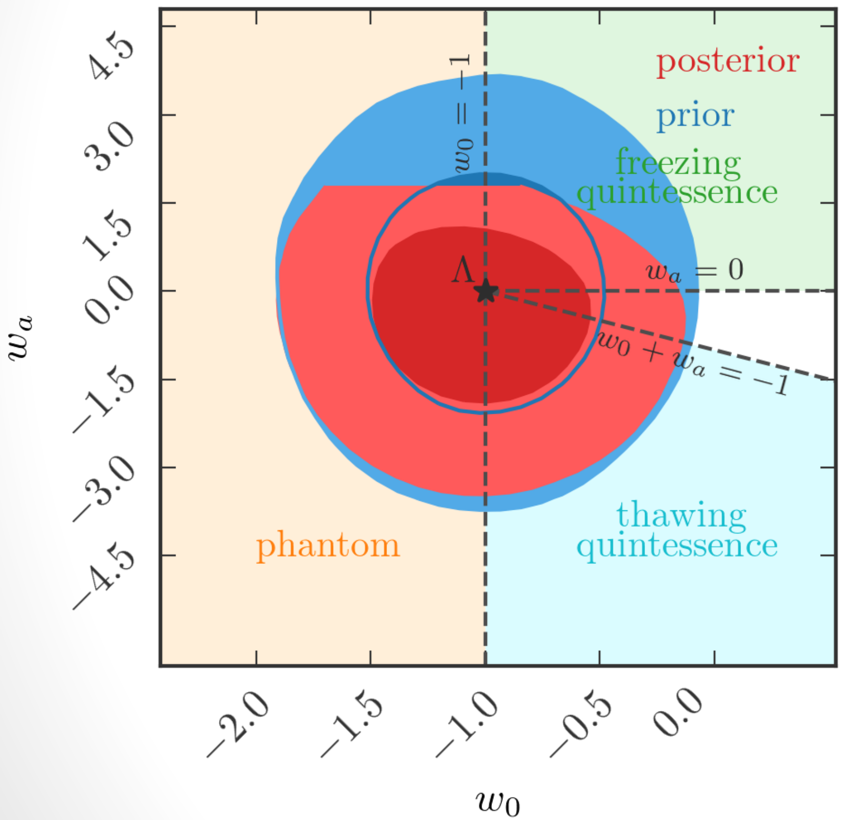


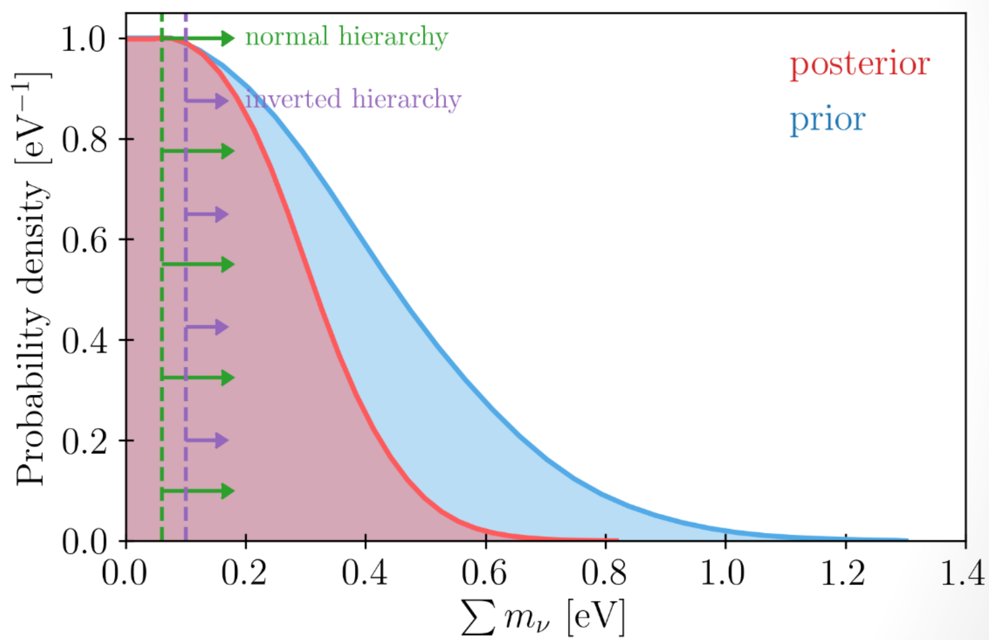


- Robust inference of cosmological parameters can be easily performed *a posteriori* once the linearised data model is learnt

FL, Enzi, Jasche & Heavens 2019, 1902.10149

Dark energy and neutrino masses with SELFI



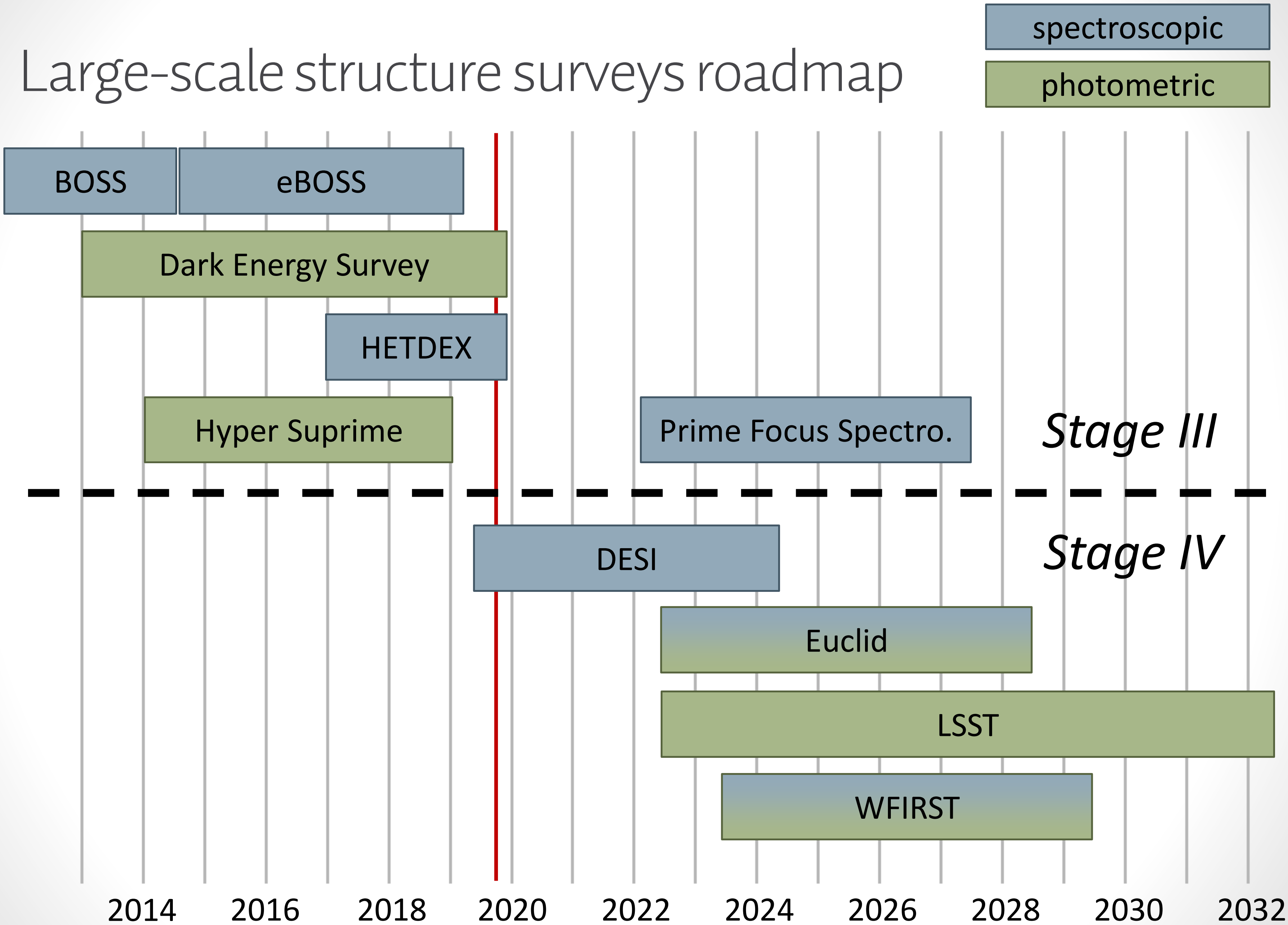


pyselfi is publicly available at https://github.com/florent-leclercq/pyselfi/

The Future: Opportunities & Challenges

DESI, Euclid, LSST, WFIRST, and more…

Large-scale structure surveys roadmap



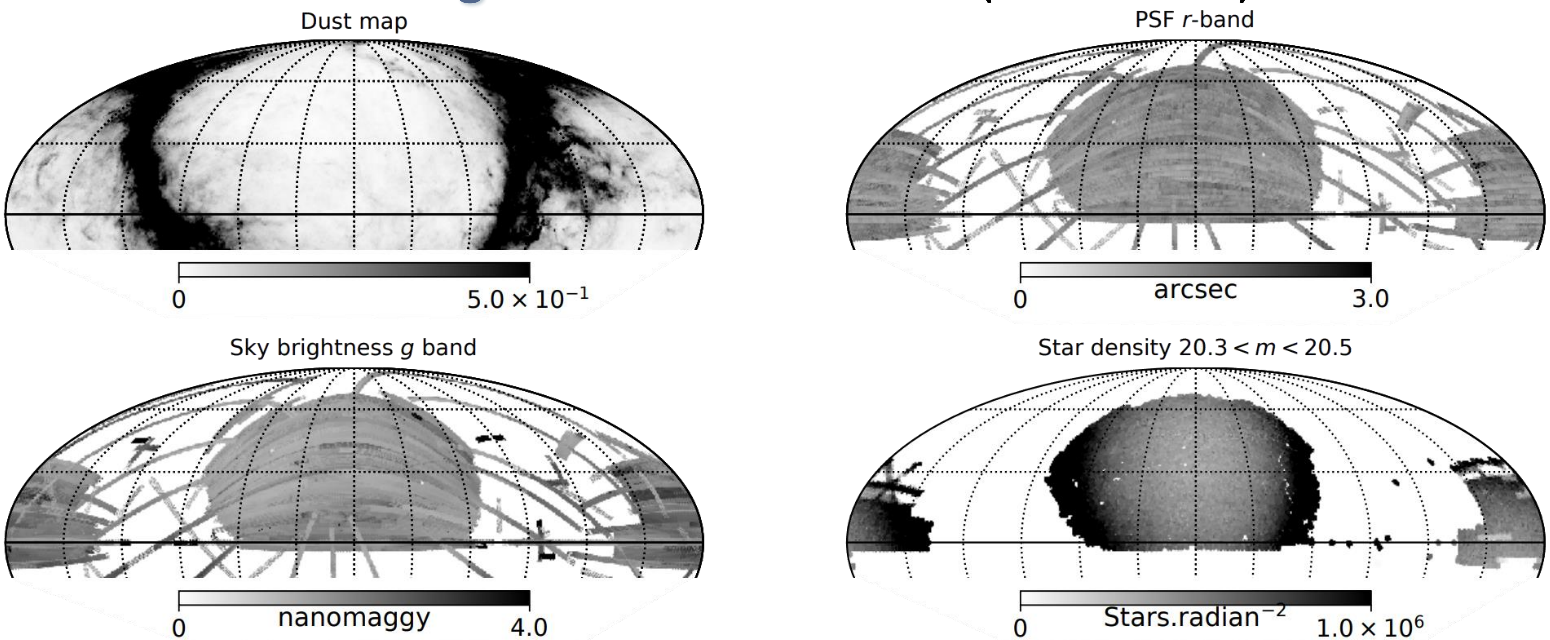
Data-intensive scientific discovery from galaxy surveys

- Next-generation surveys will be dominated by systematics
- 80% of the total signal will come from non-linear structures
- Challenging data analysis questions and/or hints for new physics will first show up as tensions between measurements

- Can data analysts keep pace?

Accounting for known and unknown systematics

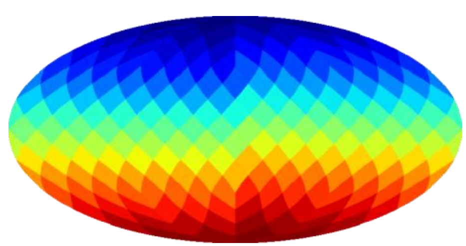
- Some known foreground contaminants (11 in total)

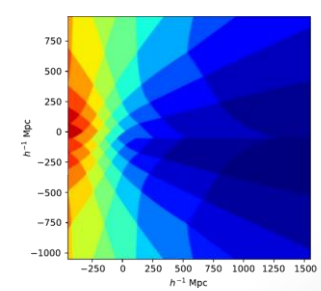


Forward model introduced by Jasche & Lavaux 2017, 1706.08971

- A procedure to marginalise over unknown foreground contaminations Robust likelihood introduced by Porqueres, Ramanah, Jasche & Lavaux 2018, 1812.05113

Map of patches on the sky…



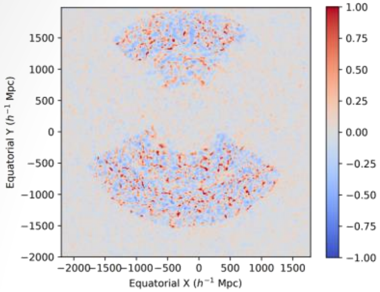


… extruded in 3D

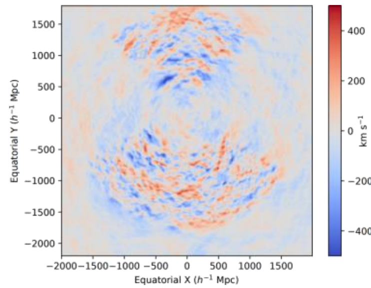
Lavaux, Jasche & FL 2019, 1909.06396

Application to SDSS-III/BOSS (LOWZ+CMASS)

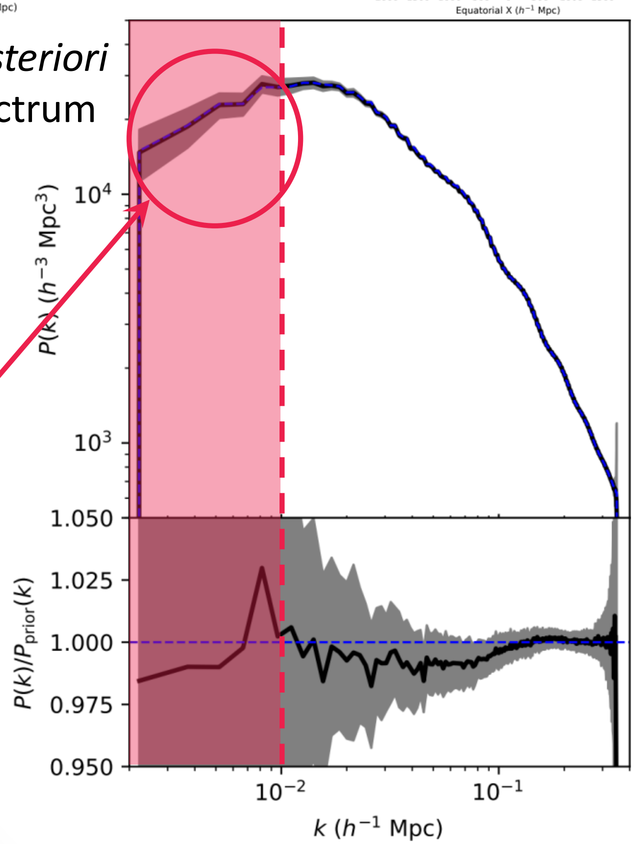
Density field



Velocity field



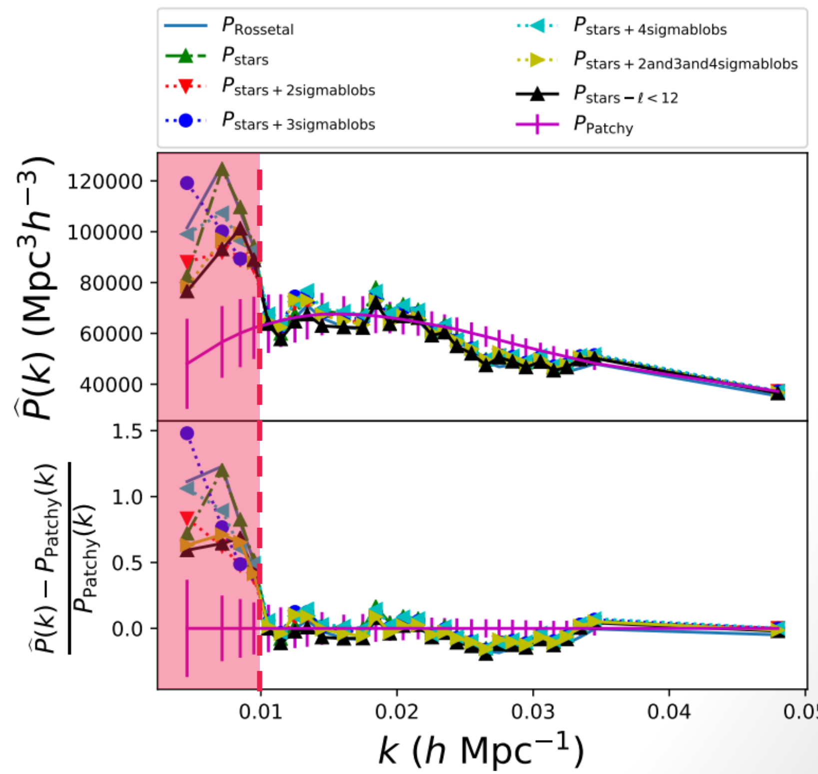
BORG *a posteriori* power spectrum



No apparent contamination, even well beyond the turn-over

Lavaux, Jasche & FL 2019, 1909.06396

State-of-the-art with backward-modelling technique (mode subtraction)

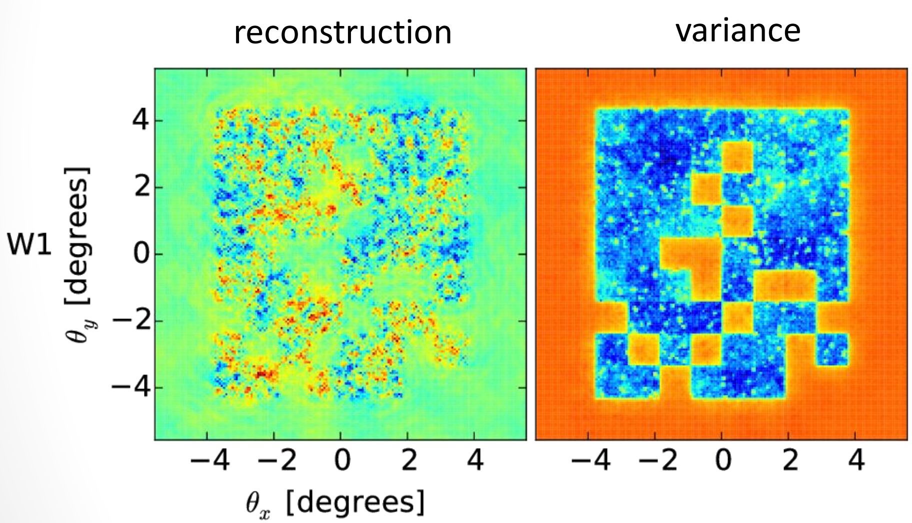


Kalus, Percival *et al.* 2018, 1806.02789

The Imperial weak lensing inference framework

with George Kyriacou (PhD student), Arrykrishna Mootoovaloo (PhD student), Natàlia Porqueres, Alan Heavens & Andrew Jaffe

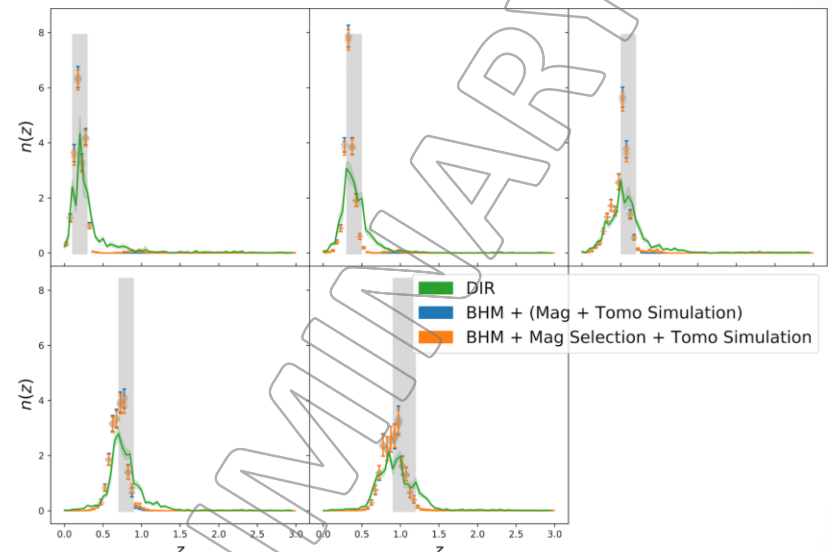
Joint inference of cosmic shear maps and power spectra/cosmology from CFHTLenS



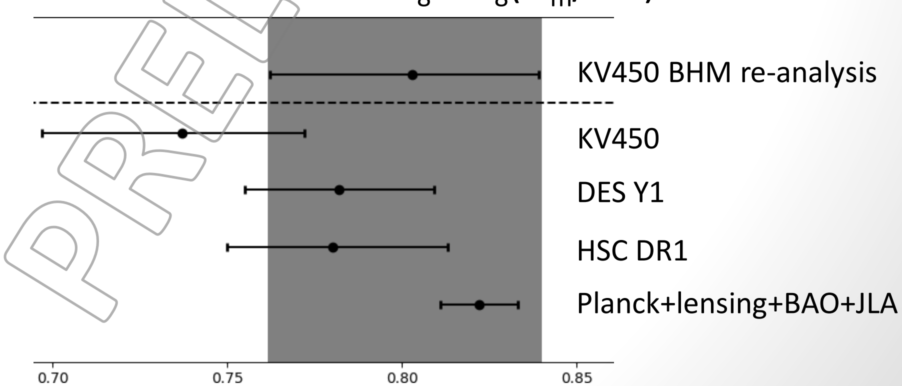
$$\sum m_\nu < 4.6 \text{ eV}(95\%)$$ from lensing data alone

Alsing, Heavens & Jaffe 2016, 1607.00008

Bayesian hierarchical inference of galaxy redshift distributions $n(z)$ with KV450



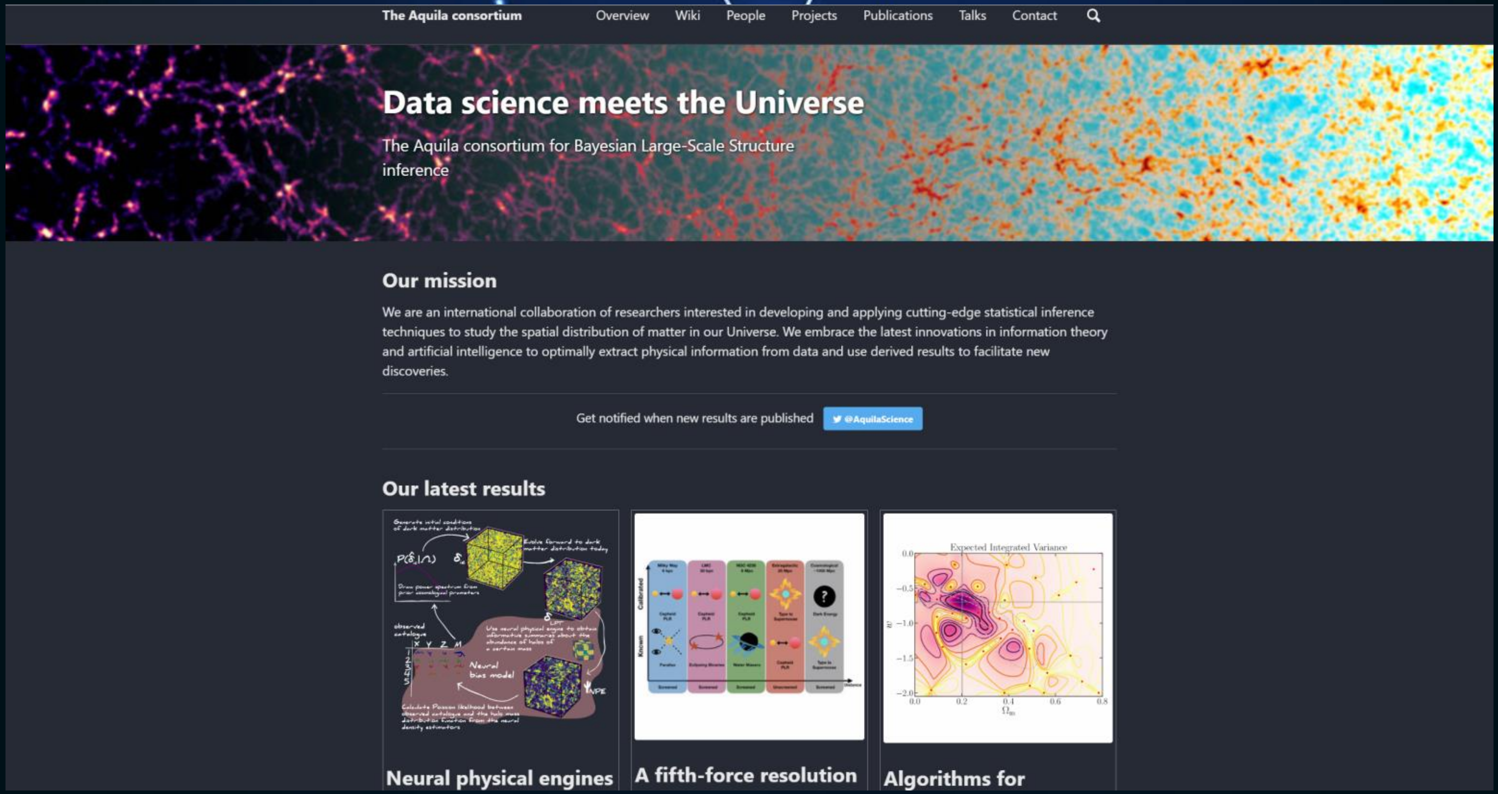
Results on $S_8 = \sigma_8(\Omega_m/0.3)^{0.5}$



Kyriacou *et al.* in prep.

The Aquila Consortium

- Created in 2016. Currently 22 members from the UK, France, Germany, Sweden, Denmark & Canada.
- Gathers people interested in developing the Bayesian pipelines and running analyses on cosmological data.



Visit us at www.aquila-consortium.org

Concluding thoughts

Likelihood-based solution:
Exact statistical analysis
Approximate data model

Data assimilation

?

Likelihood-free solution:
Approximate statistical analysis
Arbitrary data model

Generative inference

- Bayesian analyses of galaxy surveys with fully non-linear numerical models is not an impossible task!
- A likelihood-based solution (BORG): general purpose reconstruction of dark matter from galaxy clustering, providing new measurements and predictions
- A likelihood-free solution (SELFI): algorithm for targeted questions, allowing the use of simulators including all relevant physical and observational effects

Concluding thoughts

- The future: great science and challenges

Galaxy formation: bias model & likelihood
Large volume, photometric redshifts
Instruments modelling

DESI, Euclid, LSST, WFIRST

Bayesian large-scale structure analyses

Cosmological measurements:

- Cosmic expansion
- Power spectrum (and governing parameters)
- Gaussianity tests of the initial conditions
- Dark energy from the growth of structure

Predictive cosmology:

- Velocity field
- X-ray cluster emission
- Gravitational lensing
- CMB secondary effects
- Dark matter?