Title: Large Scale Bayesian Inference in Cosmology

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Abstract: Already the last decade has witnessed unprecedented progress in the collection of cosmological data. Presently proposed and designed future cosmological probes and surveys permit us to anticipate the upcoming avalanche of cosmological information during the next decades.
The increase of valuable observations needs to be accompanied with the development of efficient and accurate information processing technology in order to analyse and interpret this data. In particular, cosmography projects, aiming at studying the origin and inhomogeneous evolution of
the Universe, involve high dimensional inference methods. For example, 3d cosmological density and velocity field inference requires to explore on the order of 10^7 or more parameters. Consequently, such projects critically rely on state-of-the-art information processing techniques
and, nevertheless, are often on the verge of numerical feasibility with present day computational resources. For this reason, in this talk I will address the problem of high dimensional Bayesian inference from cosmological data sets, subject to a variety of statistical and systematic uncertainties. In particular, I will focus on the discussion of selected Markov Chain Monte Carlo techniques, permitting to efficiently solve inference problems with on the order of 10^7 parameters. Furthermore, these methods will be exemplified in various cosmological applications, raging from 3d non-linear density and photometric redshift inference to 4d physical state inference. These techniques permit us to exploit cosmologically relevant information from
observations to unprecedented detail and hence will significantly contribute to the era of precision cosmology.

Large Scale Bayesian Inference in Cosmology

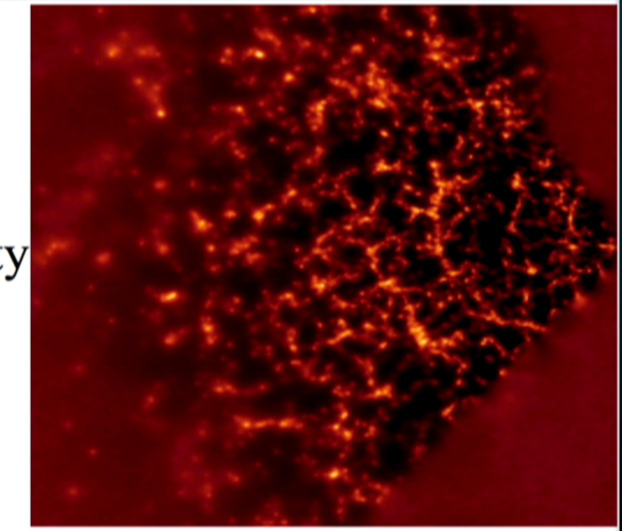
Jens Jasche,

Benjamin Wandelt, Emilio Romano Diaz

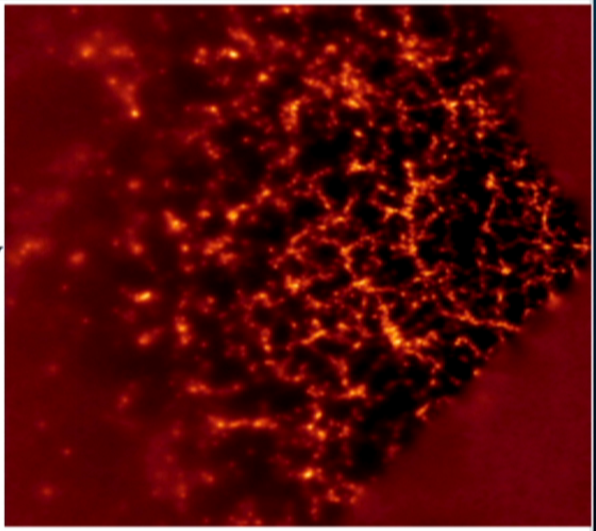
Waterloo, 11 April 2013

Introduction

- Cosmography
  - 3D density and velocity fields
  - Power-spectra, bi-spectra
  - Dark Energy, Dark Matter, Gravity
  - Cosmological parameters



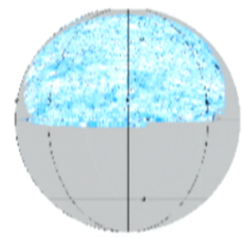
Introduction



- Cosmography
  - 3D density and velocity fields
  - Power-spectra, bi-spectra
  - Dark Energy, Dark Matter, Gravity
  - Cosmological parameters
- Large Scale Bayesian inference
  - High dimensional (~ 10^7 parameters)
  - State-of-the-art technology
  - On the verge of numerical feasibility

Introduction

- Why do we need Bayesian inference?
  - Inference of signals = ill-posed problem
    - Noise
    - Incomplete observations



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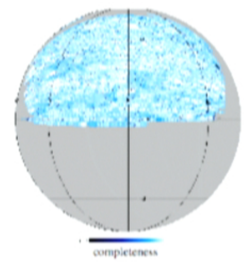

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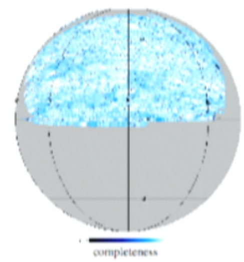

→ No unique recovery possible!!!

Introduction

"**What are the possible signals compatible with observations?**"

- Object of interest: Signal posterior distribution

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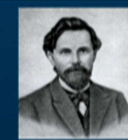
- We can do science!
  - Model comparison
  - Parameter studies
  - Report statistical summaries
  - Non-linear, Non-Gaussian error propagation

Markov Chain Monte Carlo



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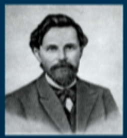

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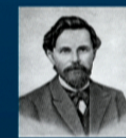

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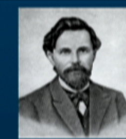

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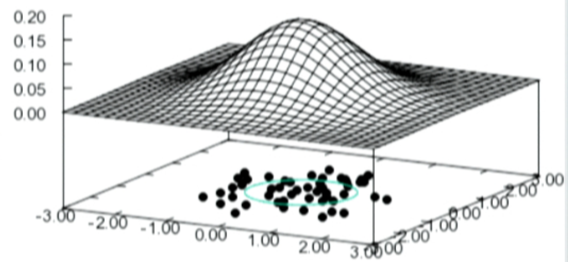
- Numerical approximation
  - Dim > 4 ➡ MCMC

$$\mathcal{P}(s|d) \rightarrow \mathcal{P}_N(s|d) = \frac{1}{N}\sum_{i=1}^{N}\delta^D(s - s_i)$$



  - Metropolis-Hastings

Hamiltonian sampling

- Parameter space exploration via Hamiltonian sampling

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  - interpret log-posterior as potential

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  - introduce Gaussian auxiliary "momentum" variable

$$H = \sum_i \sum_j \frac{1}{2} p_i M_{ij}^{-1} p_j + \psi(x)$$

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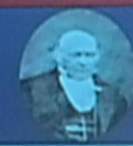
$$H = \sum_i \sum_j \frac{1}{2} p_i \, M_{ij}^{-1} \, p_j + \psi(x)$$

  - resultant joint posterior distribution of x and p

$$e^{-H} = \mathcal{P}(\{x_i\}) \, e^{-\frac{1}{2} \sum_i \sum_j p_i \, M_{ij}^{-1} \, p_j}$$

    - ➢ separable in x and p

Hamiltonian sampling



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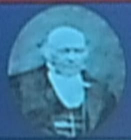
    - separable in x and p
    - marginalization over p yields again $\mathcal{P}(x)$

Hamiltonian sampling



- IDEA: Use Hamiltonian dynamics to explore e^{-H}

Hamiltonian sampling

- IDEA: Use Hamiltonian dynamics to explore e^{-H}
  - solve Hamiltonian system to obtain new sample

$$\{x^i, p^i\} \Rightarrow \boxed{\begin{aligned} \frac{dx_i}{dt} &= \frac{\partial H}{\partial p_i} \\ \frac{dp_i}{dt} &= \frac{\partial H}{\partial x_i} = -\frac{\partial \psi(x)}{\partial x_i} \end{aligned}} \Rightarrow \{x^{i+1}, p^{i+1}\}$$

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- Hamiltonian dynamics conserve the Hamiltonian H
  - ➢ Metropolis acceptance probability is unity

$$\mathcal{P}_A = min\left[1, exp(-(H(\{x_i'\}, \{p_i'\}) - H(\{x_i\}, \{p_i\}))\right]$$

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Hamiltonian sampling

- Example: Wiener posterior = multivariate normal distribution

$$\Psi = \frac{1}{2}\sum_{ij} x_i S^{-1}_{ij} x_j + \frac{1}{2}\sum_{ij}(x_i - d_i) N^{-1}_{ij}(x_j - d_j)$$

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$$\begin{aligned}\frac{\partial \Psi}{\partial x_m} &= \sum_j \left[S_{mj}^{-1} + N_{mj}^{-1}\right] x_j - \sum_{ij} N_{mj}^{-1} d_j \\ &= \sum_j A_{mj} x_j - B_m\end{aligned}$$

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$$\frac{\mathrm{dx_m}}{\mathrm{dt}} = \sum_j M^{-1}_{mj} p_j$$

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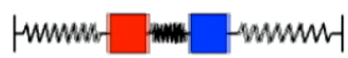
EOM:

coupled harmonic oscillator



Hamiltonian sampling

- How to set the Mass matrix?
  - Large number of tunable parameter
  - Determines efficiency of sampler

$$\frac{d^2 x_i}{dt^2} = -\sum_l M_{il}^{-1} \sum_j A_{lj} x_j + \sum_l M_{il}^{-1} B_l$$

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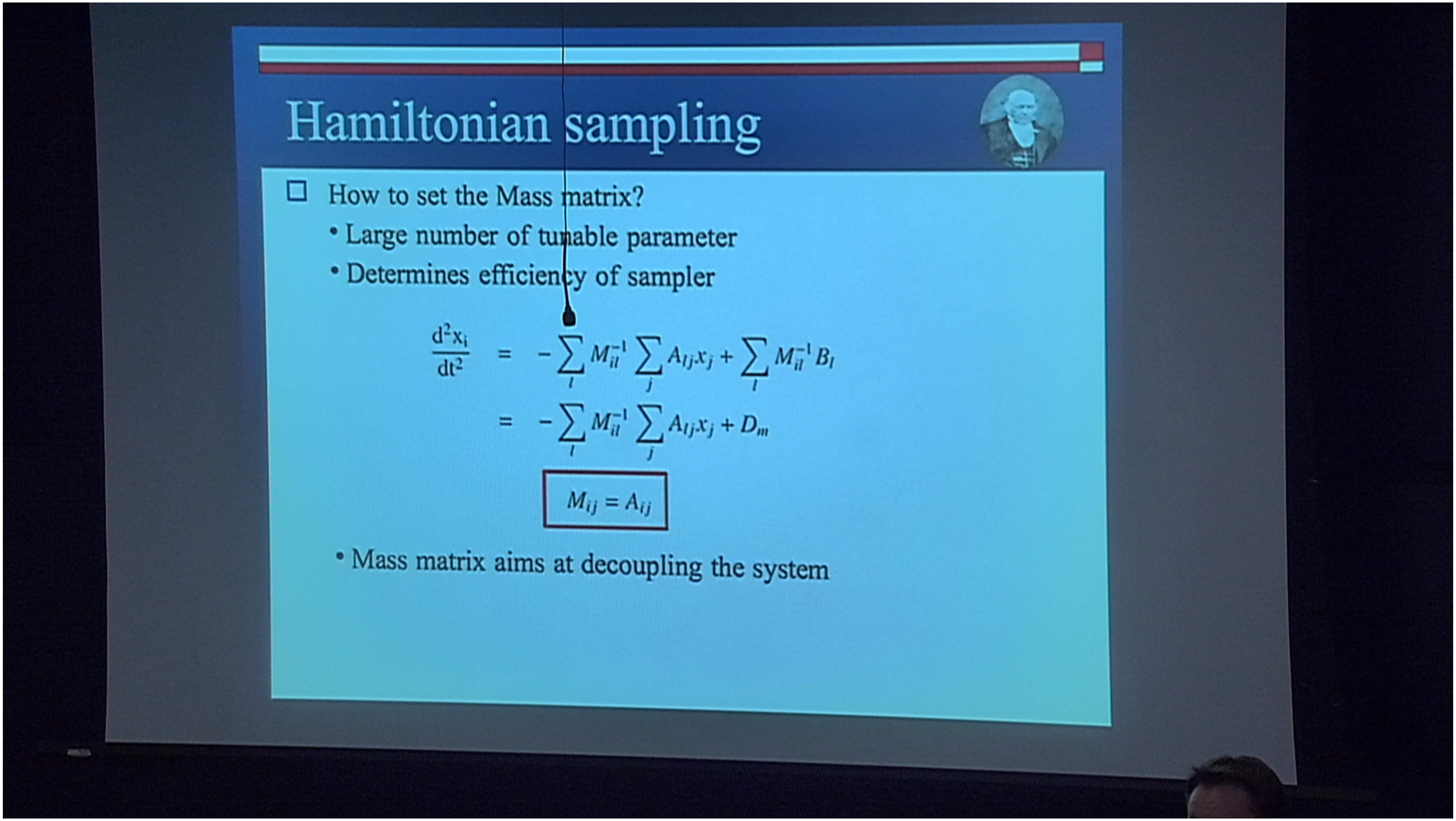
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$M_{ij} = A_{ij}$
• Mass matrix aims at decoupling the system

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$$
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  - In practice: use diagonal approximation
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  - Non-Gaussian case: Taylor expand to find Mass matrix

HMC in action

- Inference of non-linear density fields in cosmology
  - Non-linear density field
    - Log-normal prior

      See e.g. Coles & Jones (1991), Kayo et al. (2001)

Jasche, Kitaura (2010)

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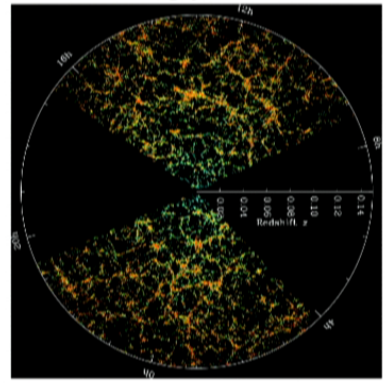

Credit: M. Blanton and the Sloan Digital Sky Survey

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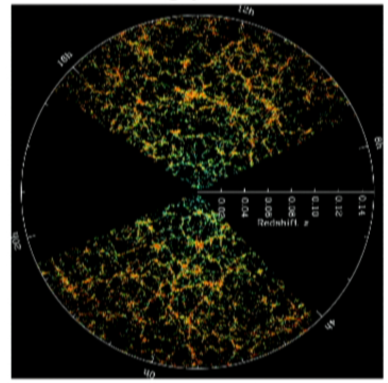

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Problem: Non-Gaussian sampling in high dimensions

➡ **HADES** (HAmiltonian Density Estimation and Sampling)

Jasche, Kitaura (2010)

LSS inference with the SDSS

- Application of HADES to SDSS DR7
  - cubic, equidistant box with sidelength 750 Mpc
  - ~ 3 Mpc grid resolution
  - ~ 10^7 volume elements / parameters

Jasche, Kitaura, Li, Enßlin (2010)

LSS inference with the SDSS

- Application of HADES to SDSS DR7
  - cubic, equidistant box with sidelength 750 Mpc
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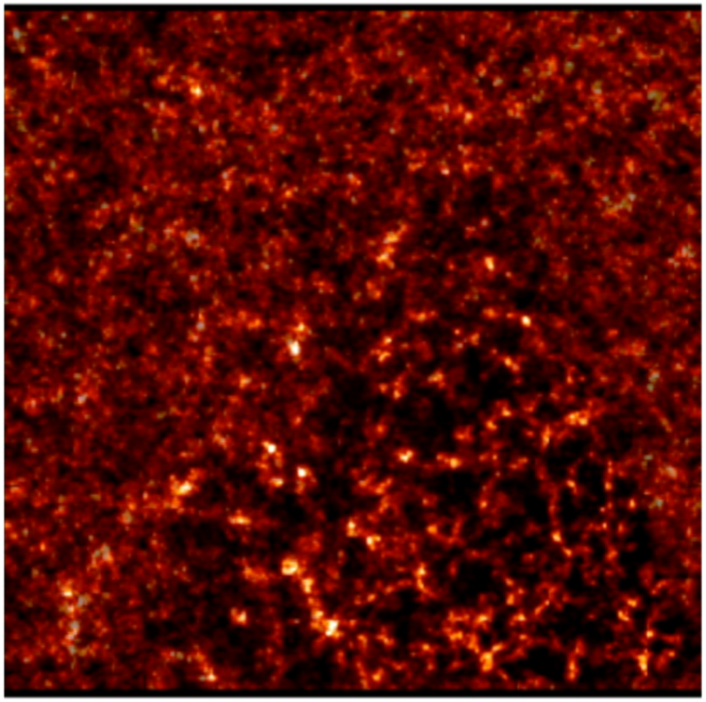
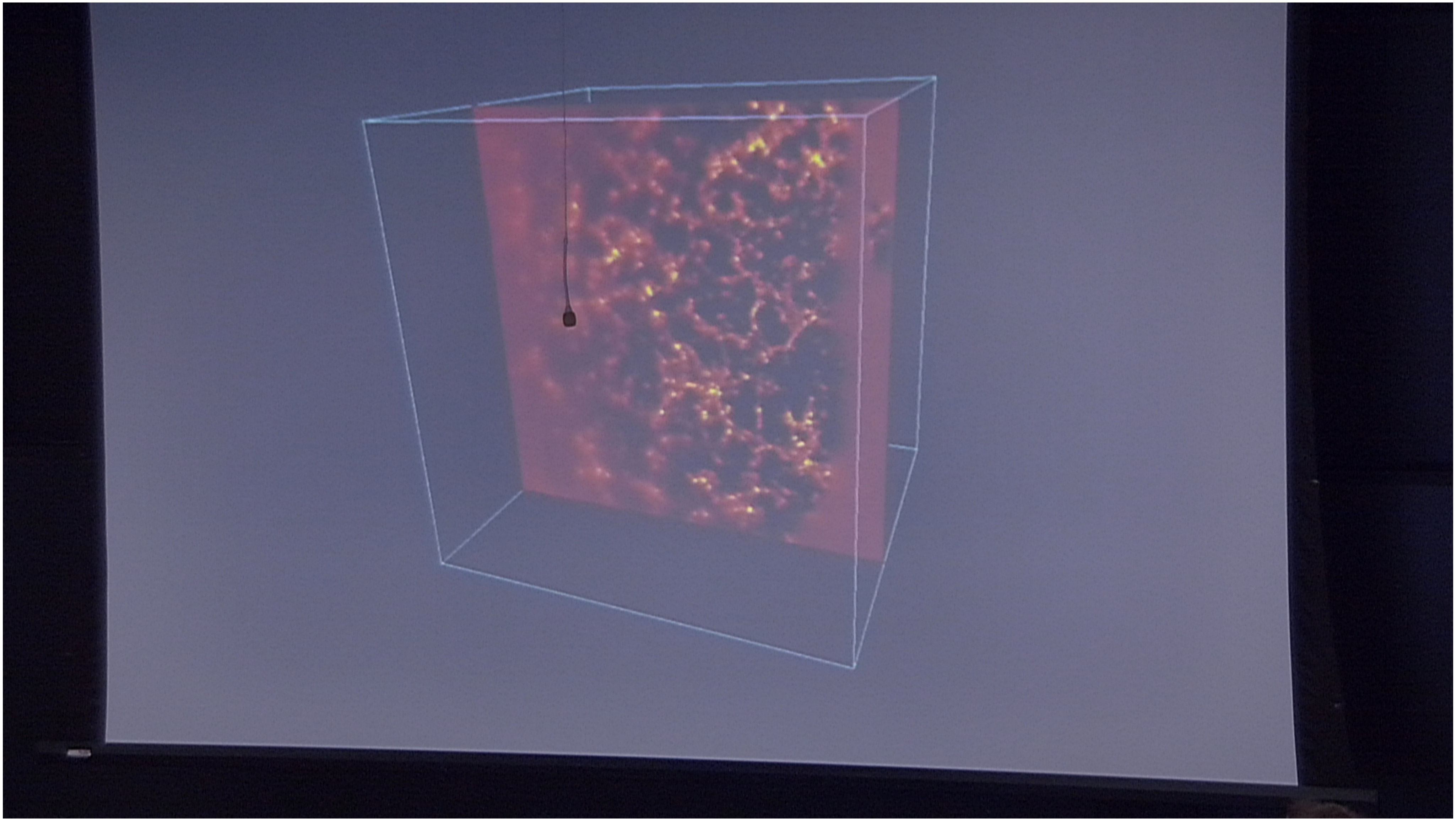
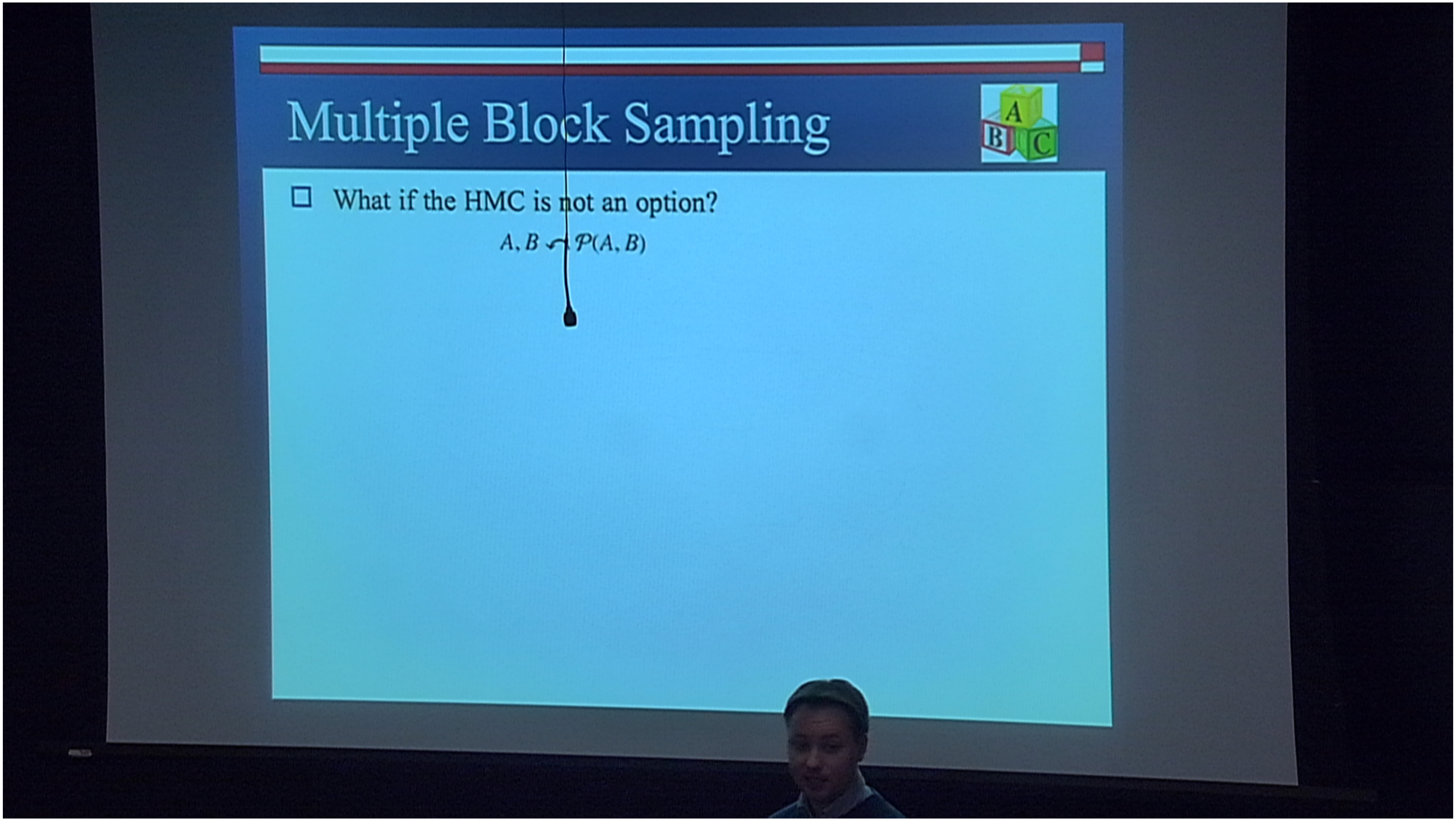
- Goal: provide a representation of the SDSS density posterior
  - to provide 3D cosmographic descriptions
  - to quantify uncertainties of the density distribution

Jasche, Kitaura, Li, Enßlin (2010)

LSS inference with the SDSS






Multiple Block Sampling
A B C
What if the HMC is not an option?
$A, B \curvearrowleft \mathcal{P}(A, B)$

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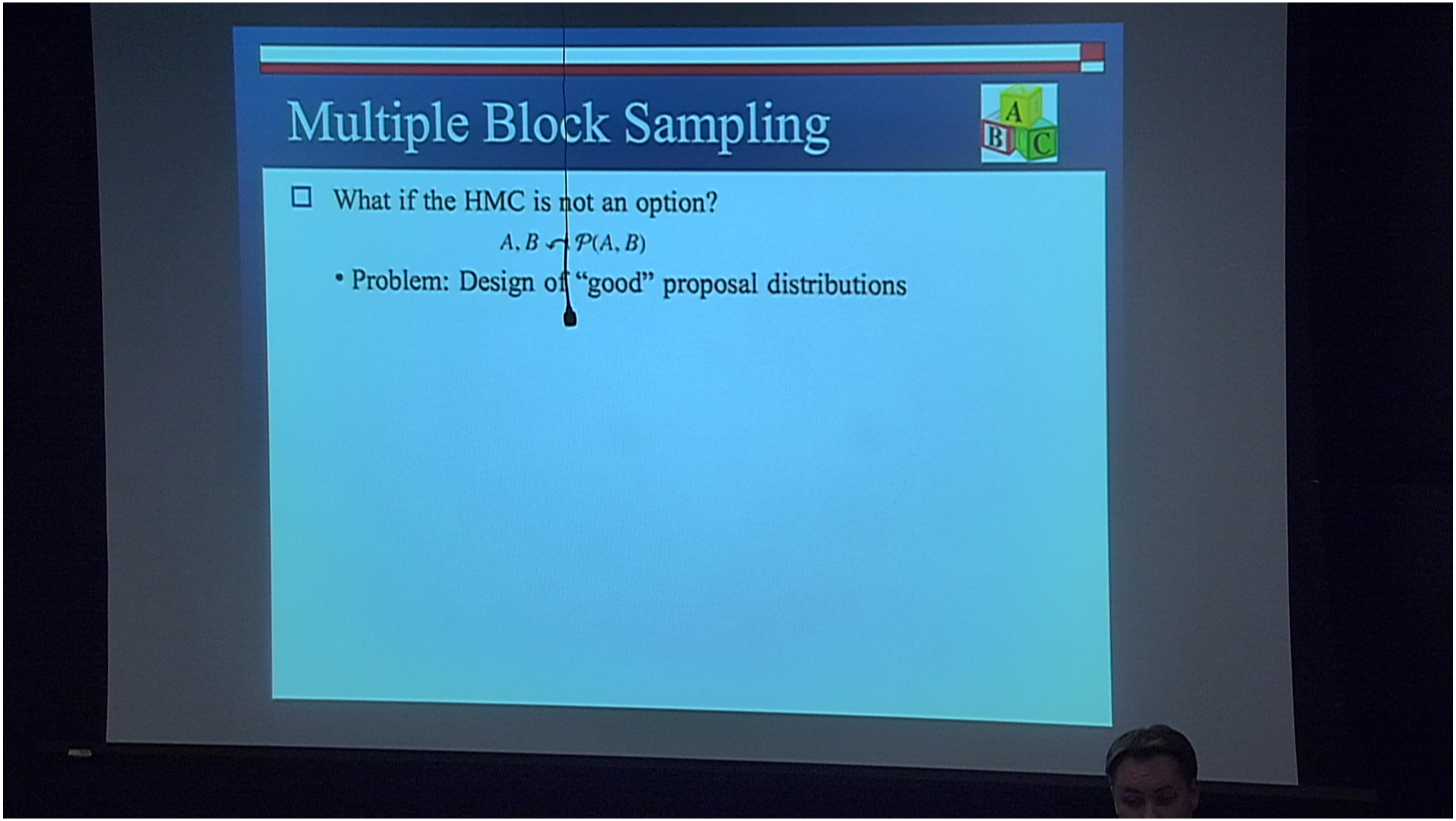
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Serial processing only!

  - simplifies design of conditional proposal distributions
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  - Requires serial processing

Multiple Block Sampling

- Can we "boost" block sampling?

$$\mathcal{P}(A, B) = \int \mathrm{d}C\, \mathcal{P}(A, B, C)$$

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Input: DVI - 1920x1080p@60Hz
Output: SDI - 1920x1080i@60Hz

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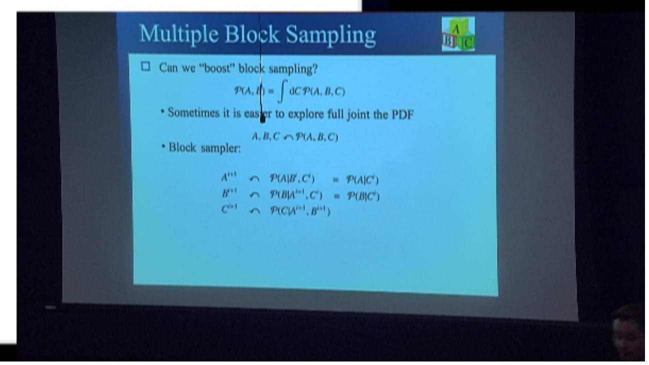

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process in parallel!

  - Permits efficient sampling for numerical expensive posteriors

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  - millions of galaxies (~10^7 - 10^8)

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$$\{z_p\}, \delta \curvearrowleft \mathcal{P}(\delta, \{z_p\}|d)$$

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$$\vdots$$

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$$\vdots$$

$$z_N^{i+1} \curvearrowleft \mathcal{P}(z_N|\delta^i, d)$$

$$\delta^{i+1} \curvearrowleft \mathcal{P}(\delta|\{z_p\}^{i+1}, d)$$

Process in parallel!

Photometric redshift sampling

- Photometric surveys
  - millions of galaxies (~10^7 - 10^8)
  - low redshift accuracy (~ 100 Mpc along LOS)
  - → Infer accurate redshifts: $\{z_p\} \curvearrowleft \mathcal{P}(\{z_p\}|d)$
  - Rather sample from joint distribution:

$$\{z_p\}, \delta \curvearrowleft \mathcal{P}(\delta, \{z_p\}|d)$$

  - Block sampler:

$$z_1^{i+1} \curvearrowleft \mathcal{P}(z_1|\delta^i, d)$$

$$\vdots$$

$$z_N^{i+1} \curvearrowleft \mathcal{P}(z_N|\delta^i, d)$$

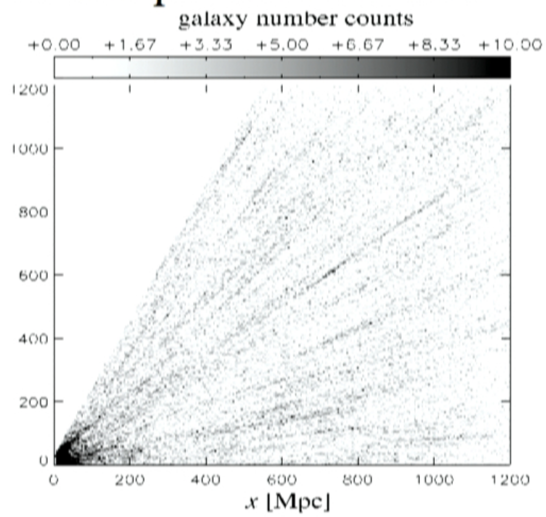
Process in parallel!

$$\delta^{i+1} \curvearrowleft \mathcal{P}(\delta|\{z_p\}^{i+1}, d)$$

HMC sampler!

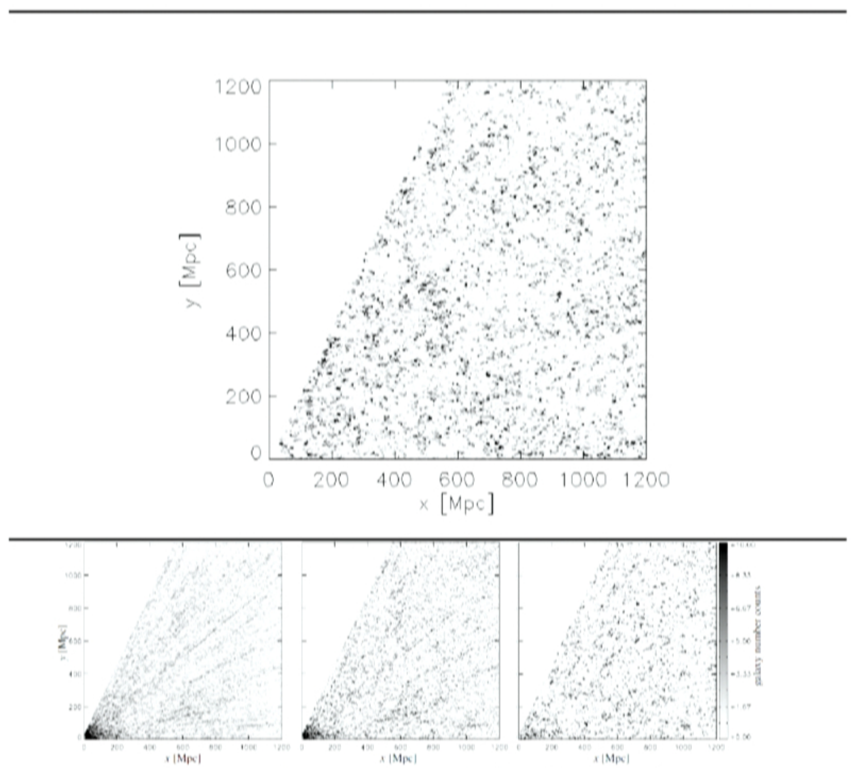
Photometric redshift sampling

- Application to artificial photometric data



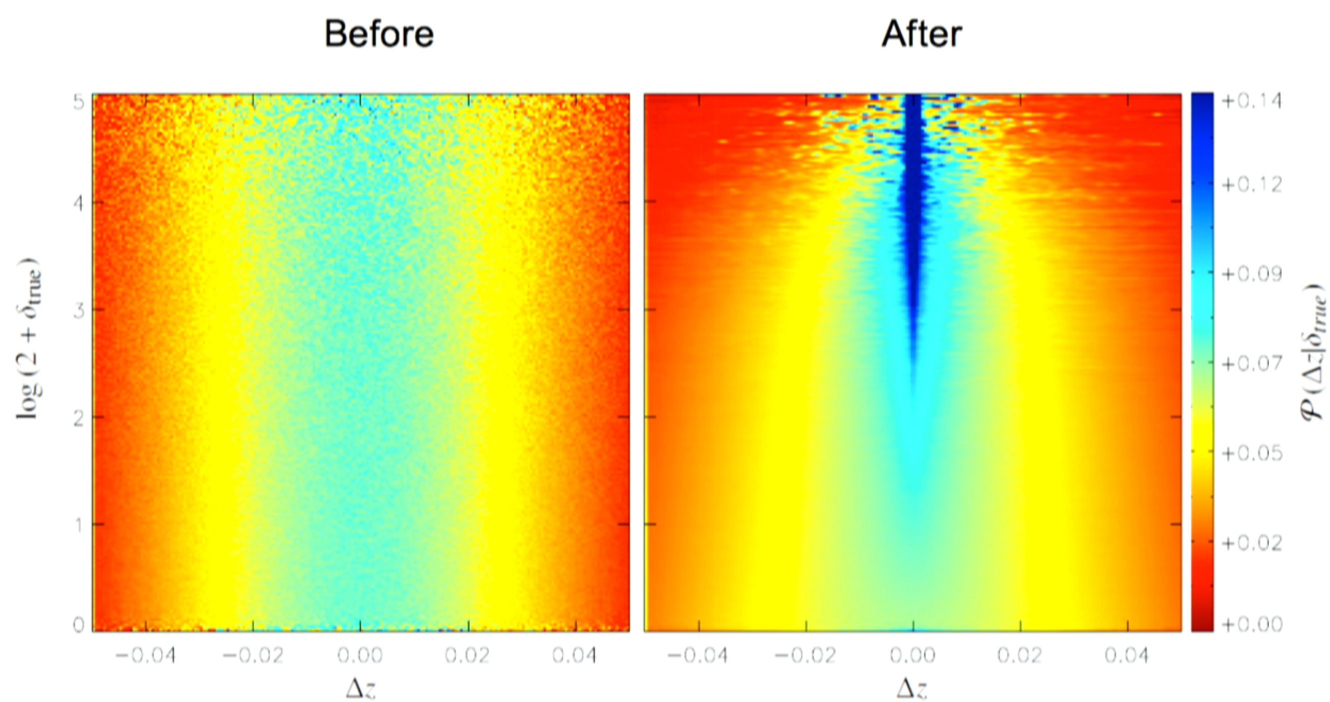
- ~ Noise, Systematics, Position uncertainty (~100 Mpc)
- ~ 10^7 density amplitudes /parameters
- ~ 2x10^7 radial galaxy positions / parameters

Photometric redshift sampling



Jasche, Wandelt (2012)

Deviation from the truth

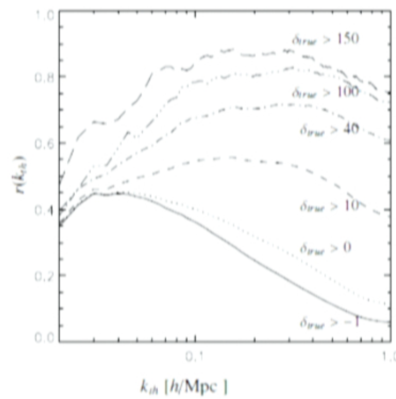


Jasche, Wandelt (2012)

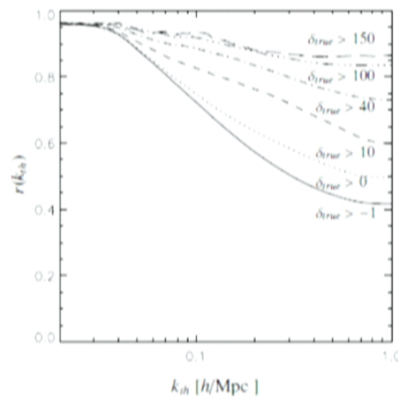
Deviation from the truth

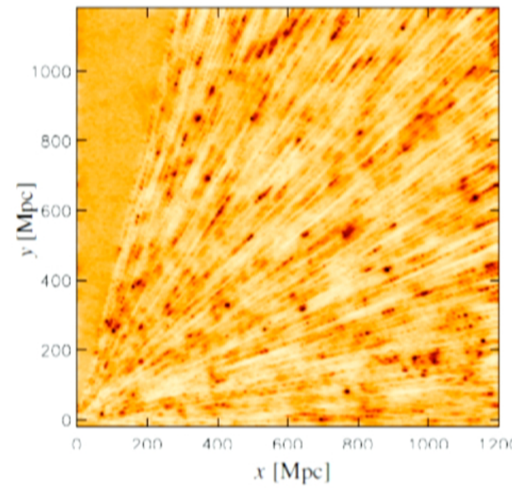
$$r(k_{th}) = \frac{\left\langle \delta_{true}^{k_{th}} \, \langle \delta \rangle^{k_{th}} \right\rangle}{\sqrt{\left\langle \left(\delta_{true}^{k_{th}} \right)^2 \right\rangle} \, \sqrt{\left\langle \left(\langle \delta \rangle^{k_{th}} \right)^2 \right\rangle}}$$

Raw data



Density estimate

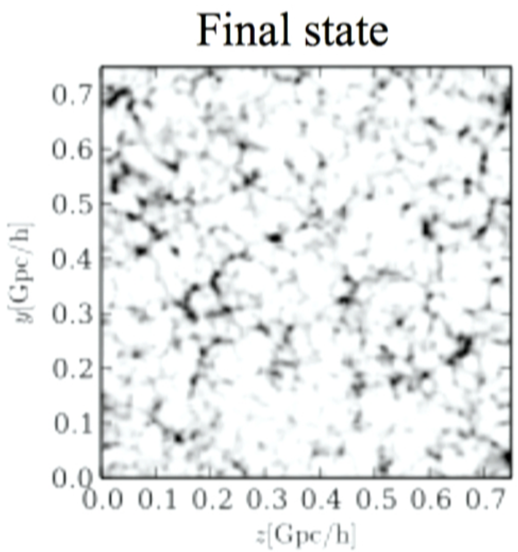




Jasche, Wandelt (2012)

4D physical inference

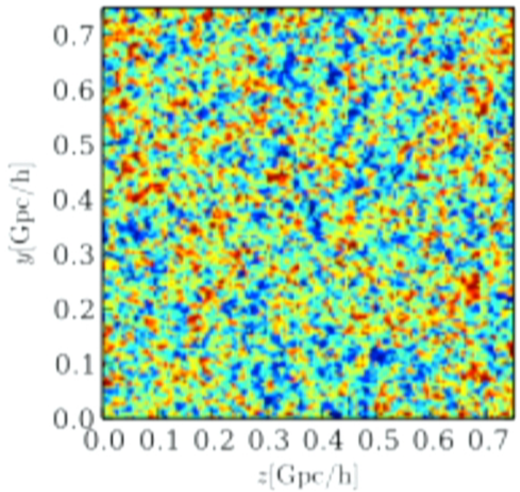
- Physical motivation
  - Complex final state



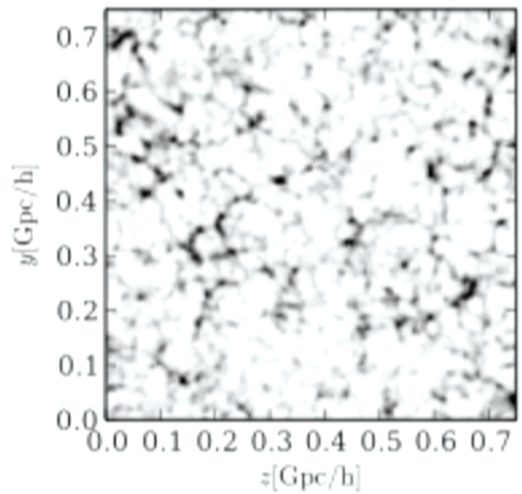
4D physical inference

- Physical motivation
  - Complex final state
  - Simple initial state

Initial state



Final state



4D physical inference

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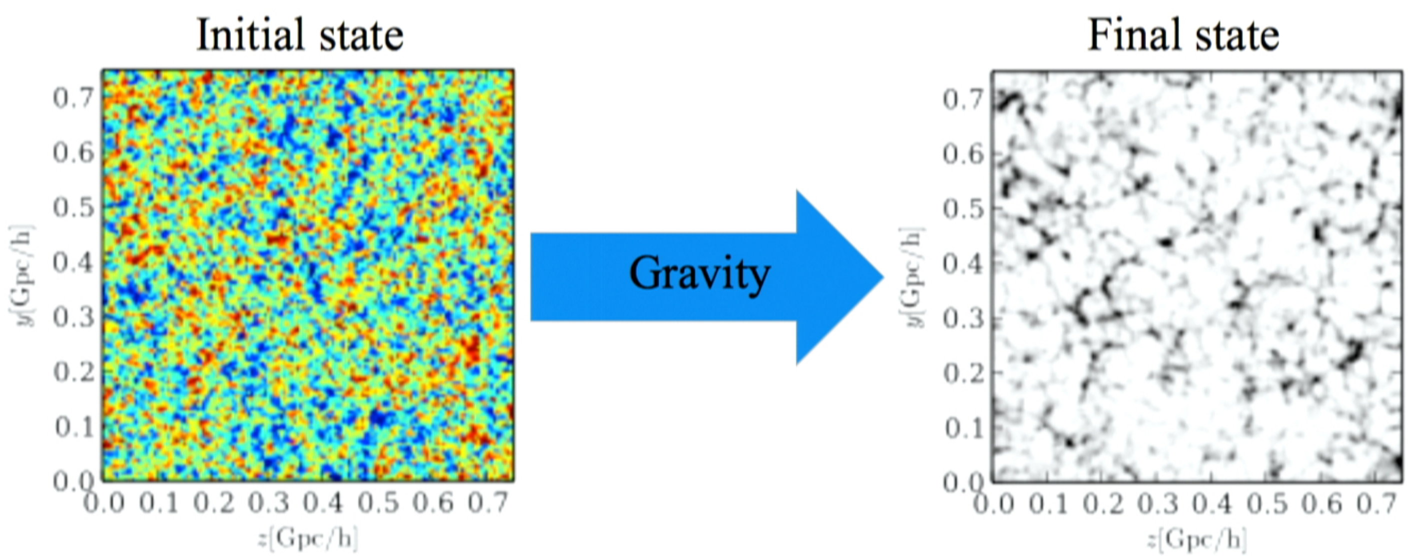
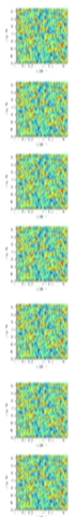
  - Complex final state
  - Simple initial state



4D physical inference

- The ideal scenario:
  - We need a **very very very** large computer!



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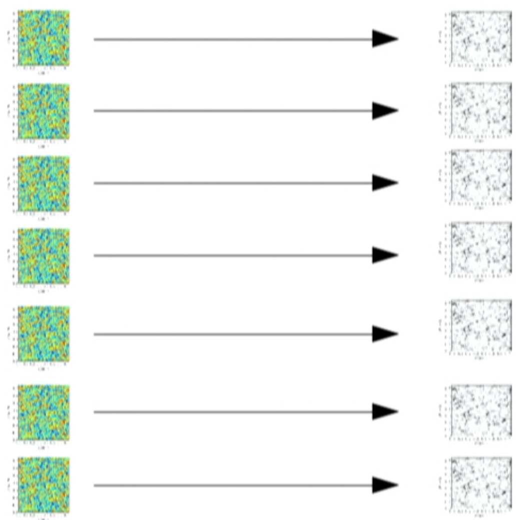

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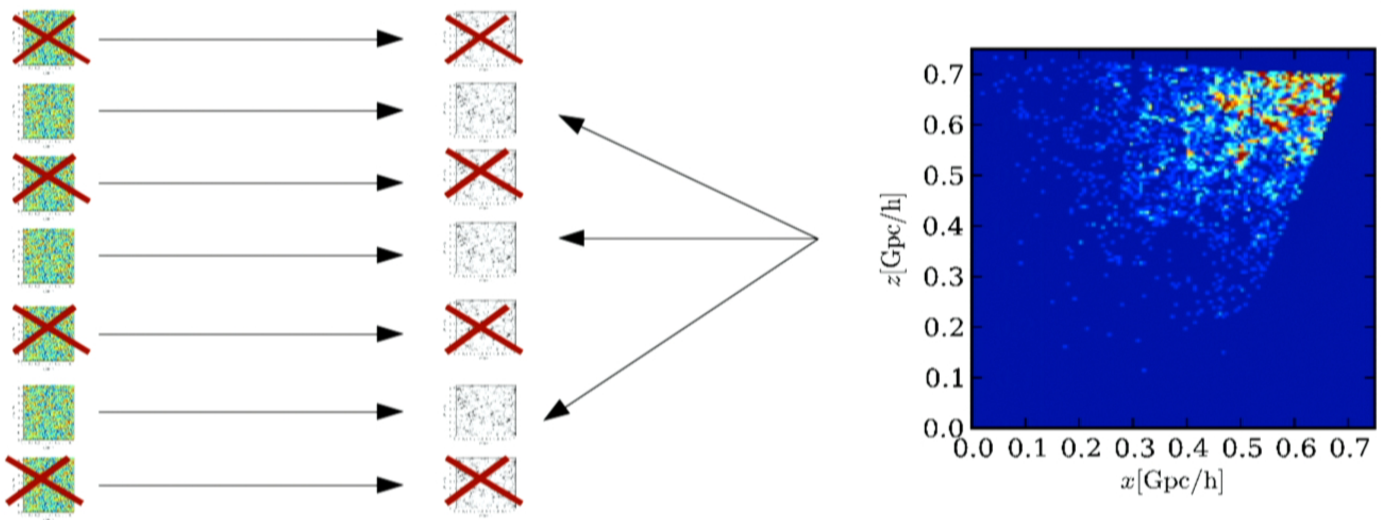
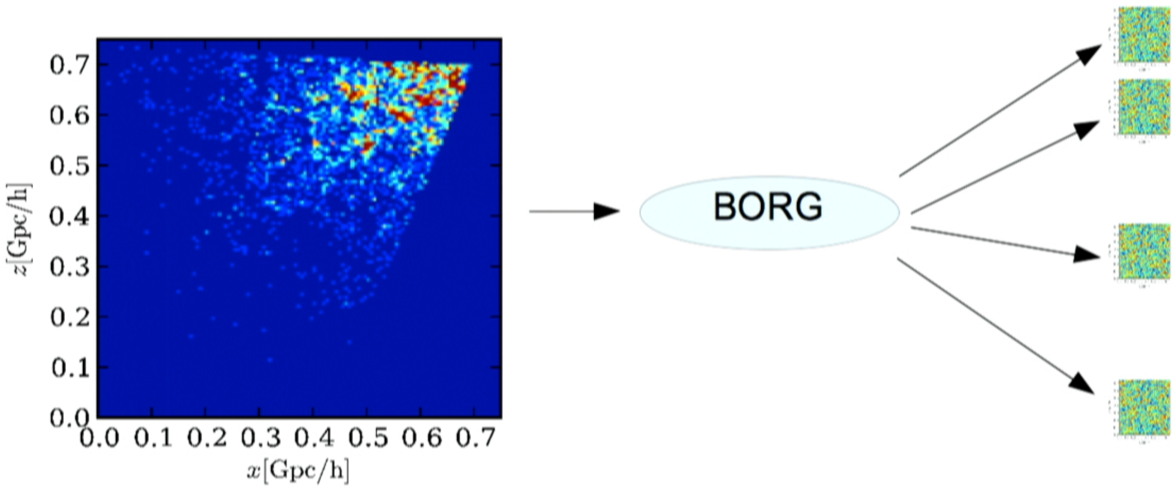


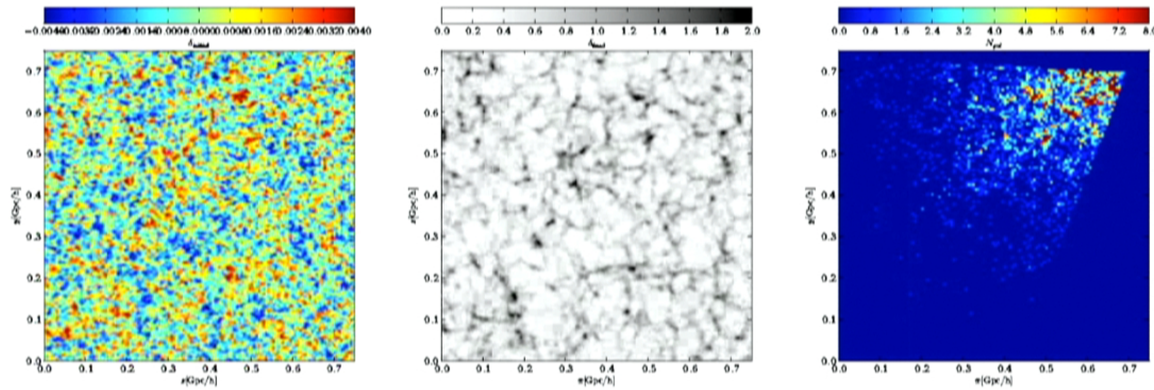
4D physical inference

- BORG (Bayesian Origin Reconstruction from Galaxies)
  - HMC
  - Second order Lagrangian perturbation theory

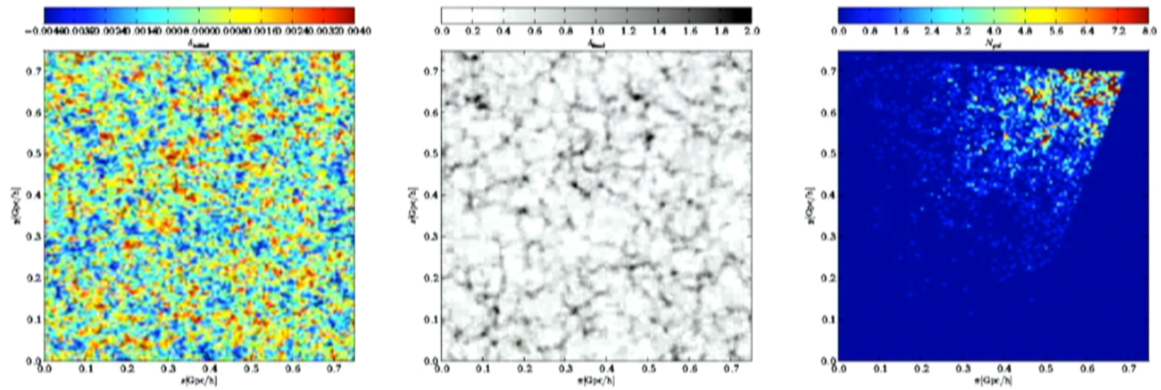


Jasche, Wandelt (2012)

4D physical inference



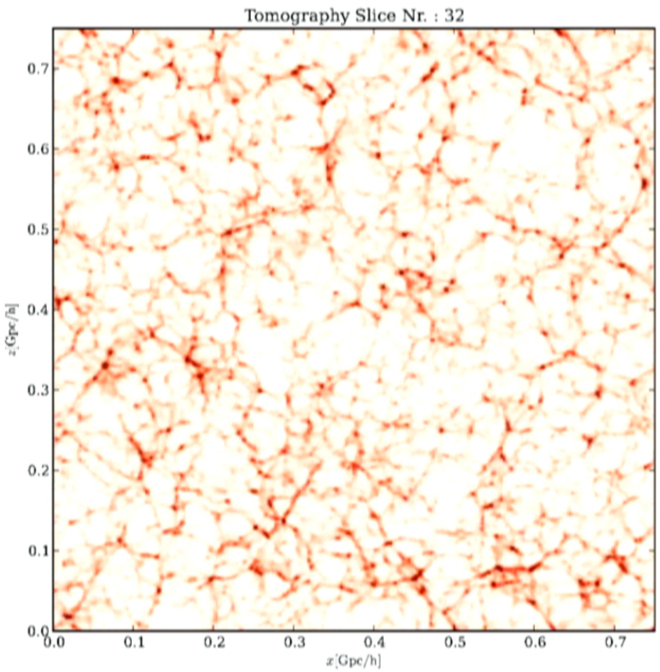
4D physical inference



- Cosmological applications:
  - Higher order statistics ➡ primordial non-Gaussianity
  - 4D dynamic states ➡ Dark Energy, ISW, kSZ
  - Physically joint analysis of data at different cosmic Epochs

Constrained simulations

- Constrained simulation of the Sloan Volume (Preliminary work)

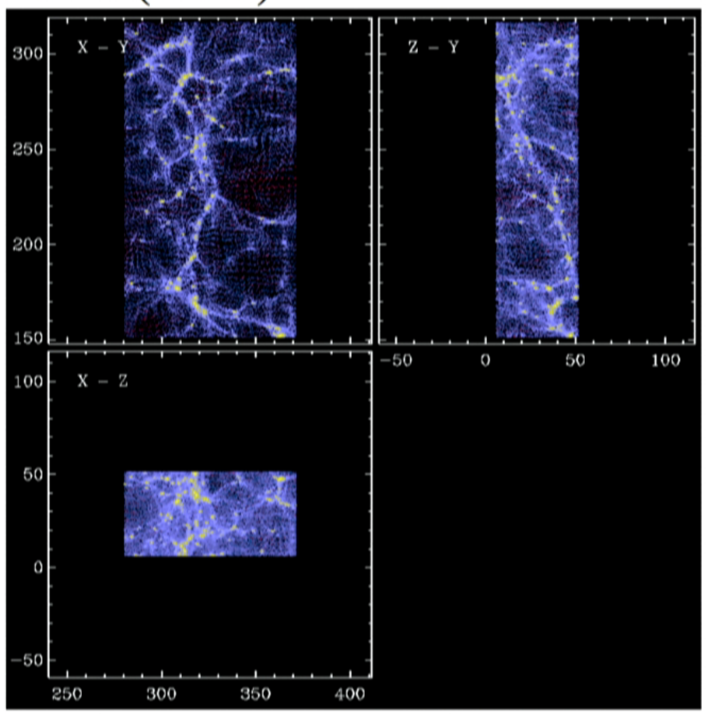


Simulation by Emilio Romano Diaz

Resimulating the SGW

Preliminary Work

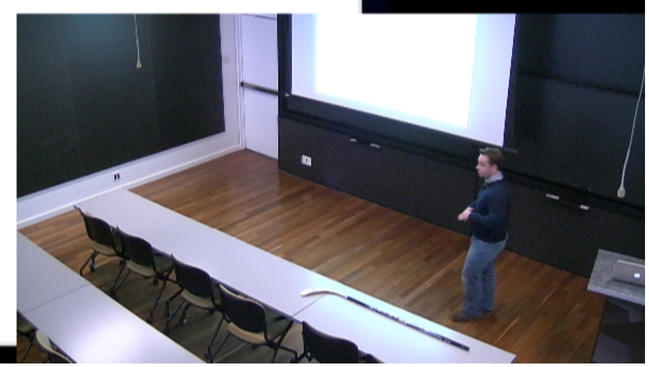
- Sloan Great Wall (SGW)



Simulation by Emilio Romano Diaz

Summary & Conclusion

- Large scale Bayesian inference
  - Inference in high dimensions from incomplete observations
    - Noise, systematic effects, survey geometry, selection effects, biases
  - Need to quantify uncertainties → **explore posterior distribution**
    - Markov Chain Monte Carlo methods
    - Hamiltonian sampling (exploit symmetries, decouple system)
    - Multiple block sampling (break down into subproblems)
- 3 high dimensional examples (>10^7 parameter)
  - Nonlinear density inference
  - Photometric redshift and density inference
  - 4D physical inference



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