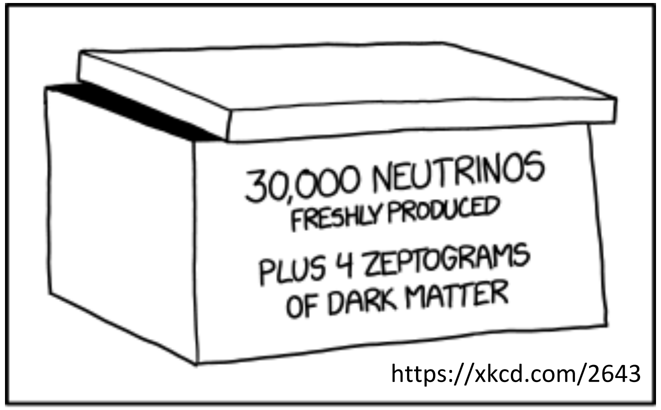
Towards an Optimal Cosmological Detection *of* Neutrino Mass *with* Joint Analyses *and* Field-Level Inference

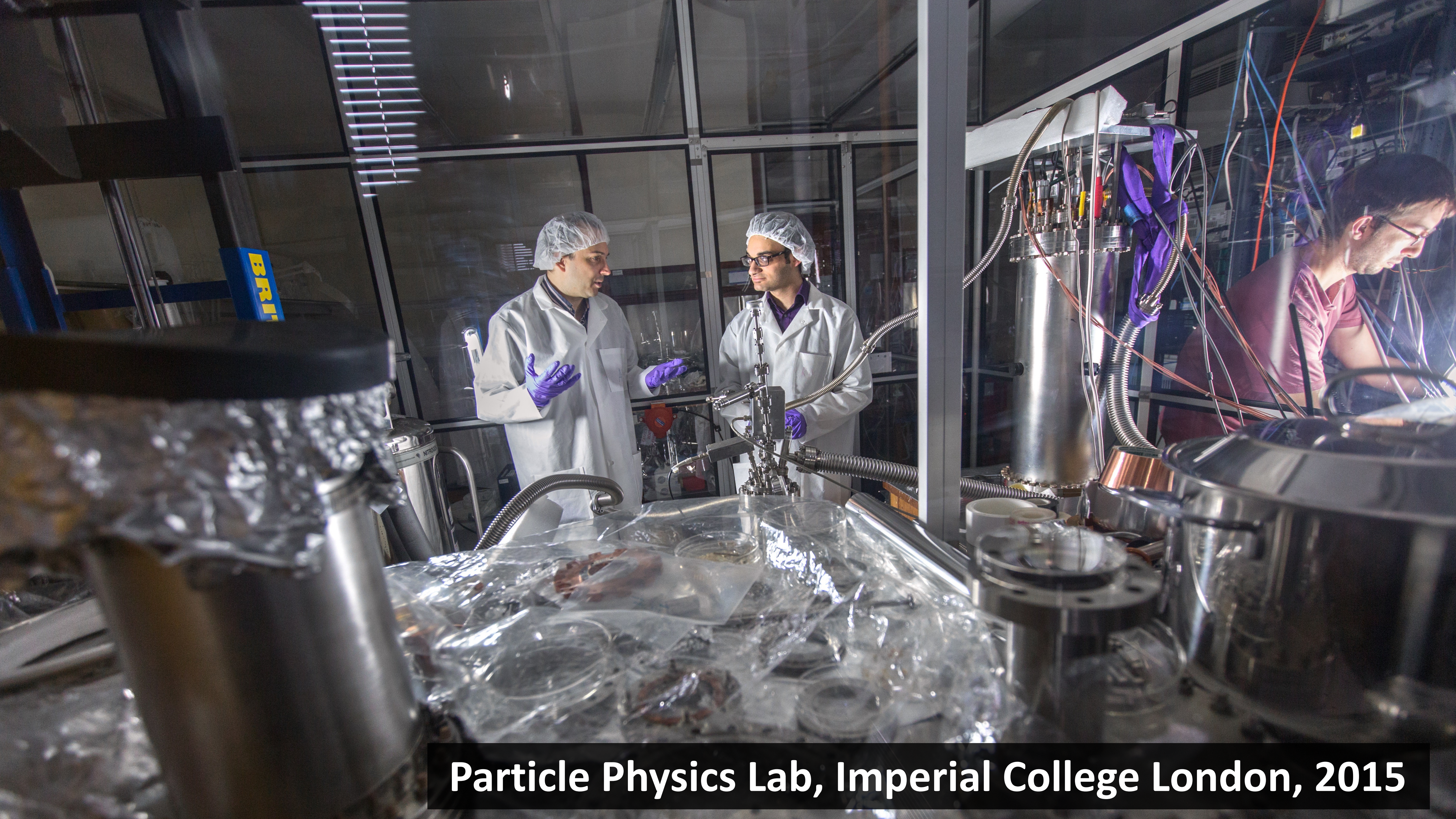
Adrian Bayer

Princeton University / Simons Foundation

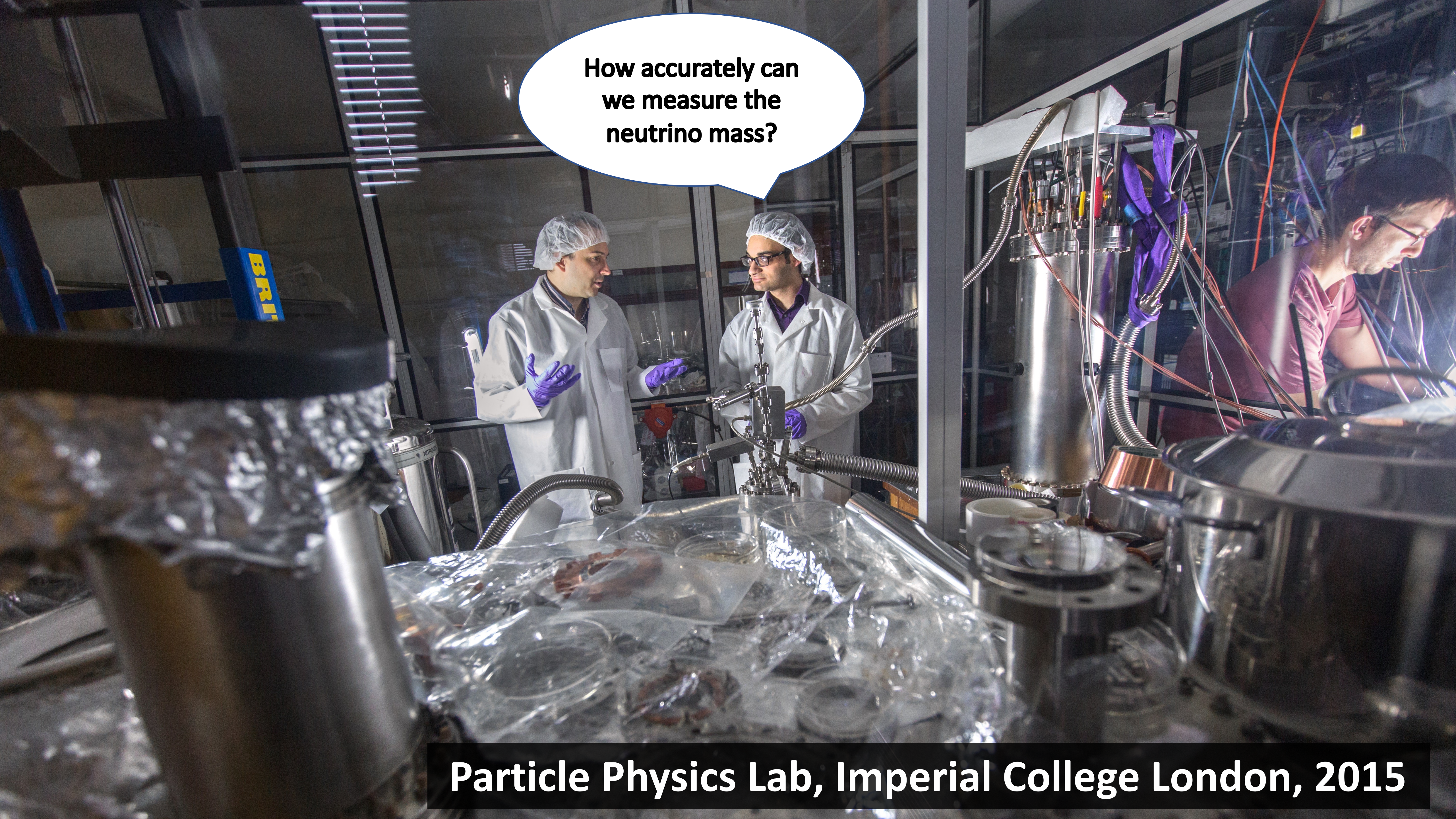
COSMO21
Chania, Greece
22 May 2024



COSMOLOGISTS ARE EASY TO SHOP FOR BECAUSE YOU CAN JUST GET THEM A BOX.



Particle Physics Lab, Imperial College London, 2015



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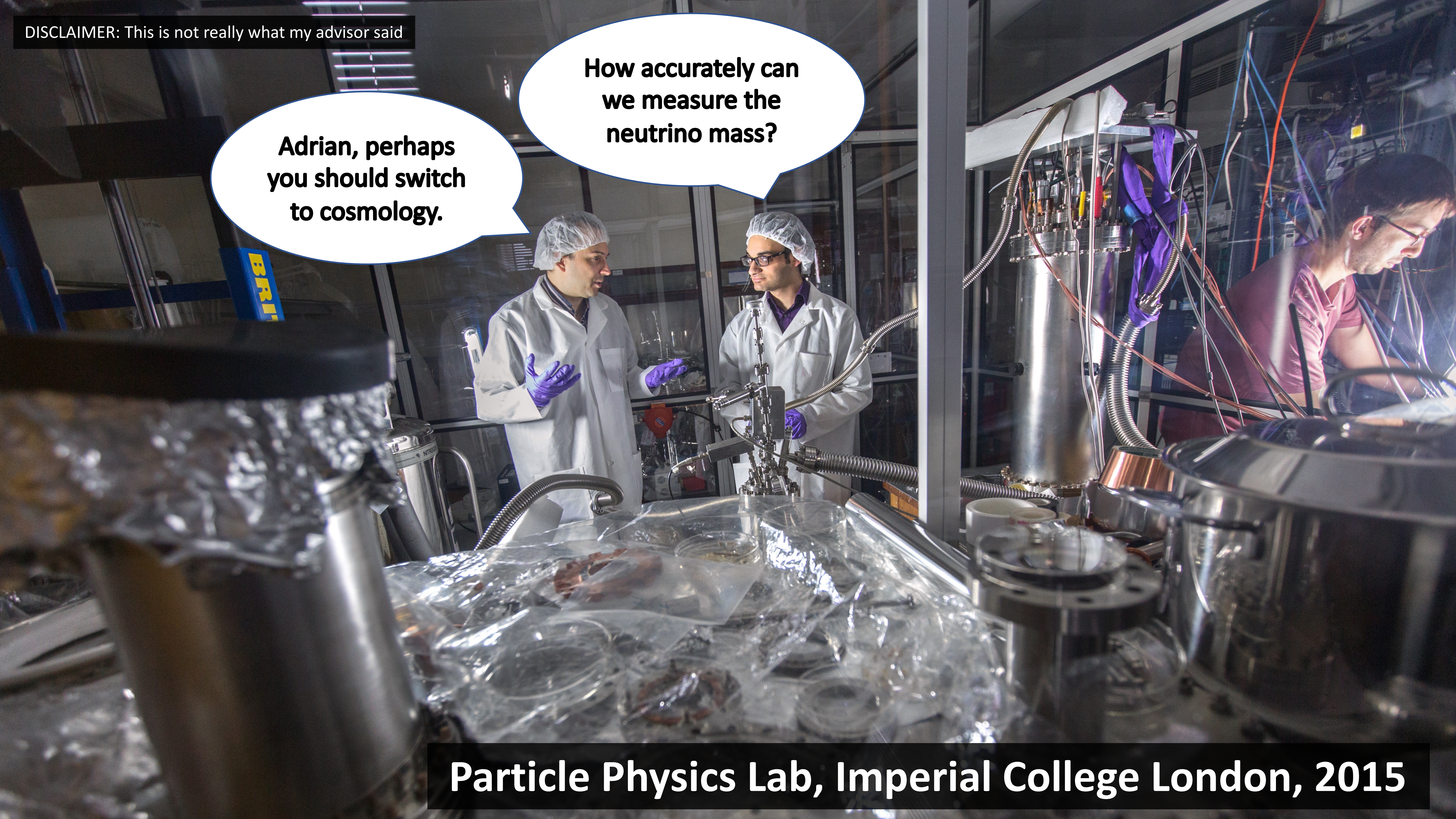
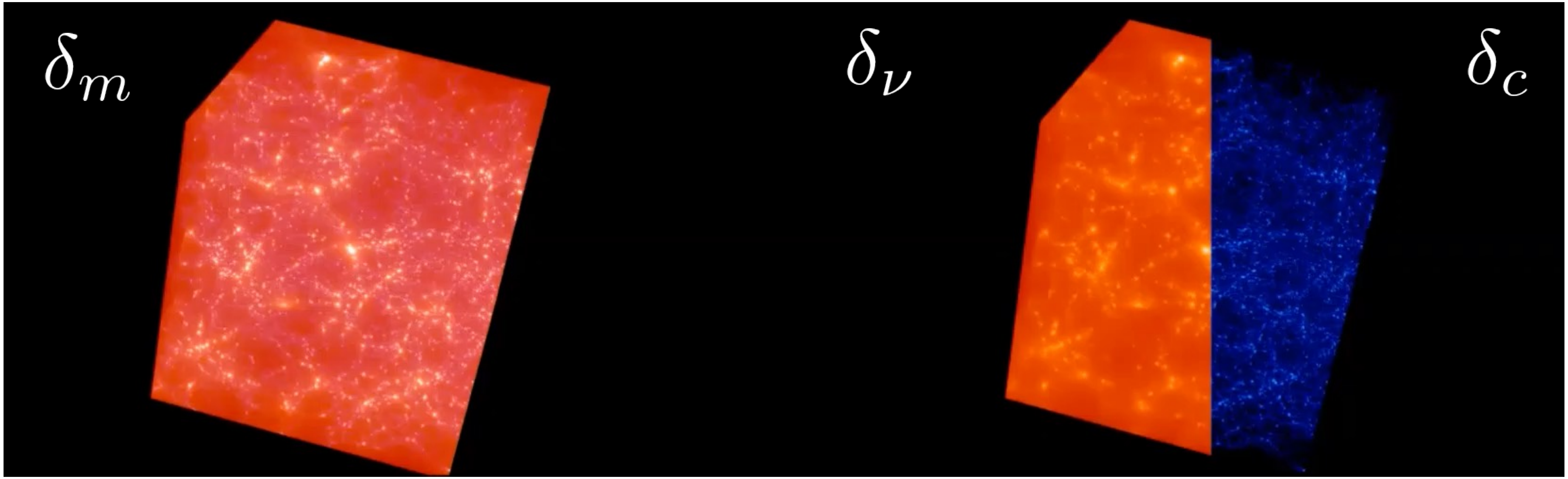

DISCLAIMER: This is not really what my advisor said
Adrian, perhaps you should switch to cosmology.
How accurately can we measure the neutrino mass?
Particle Physics Lab, Imperial College London, 2015

Cosmological simulations of massive neutrinos

$$\delta_m = (1 - f_\nu)\delta_c + f_\nu \delta_\nu$$



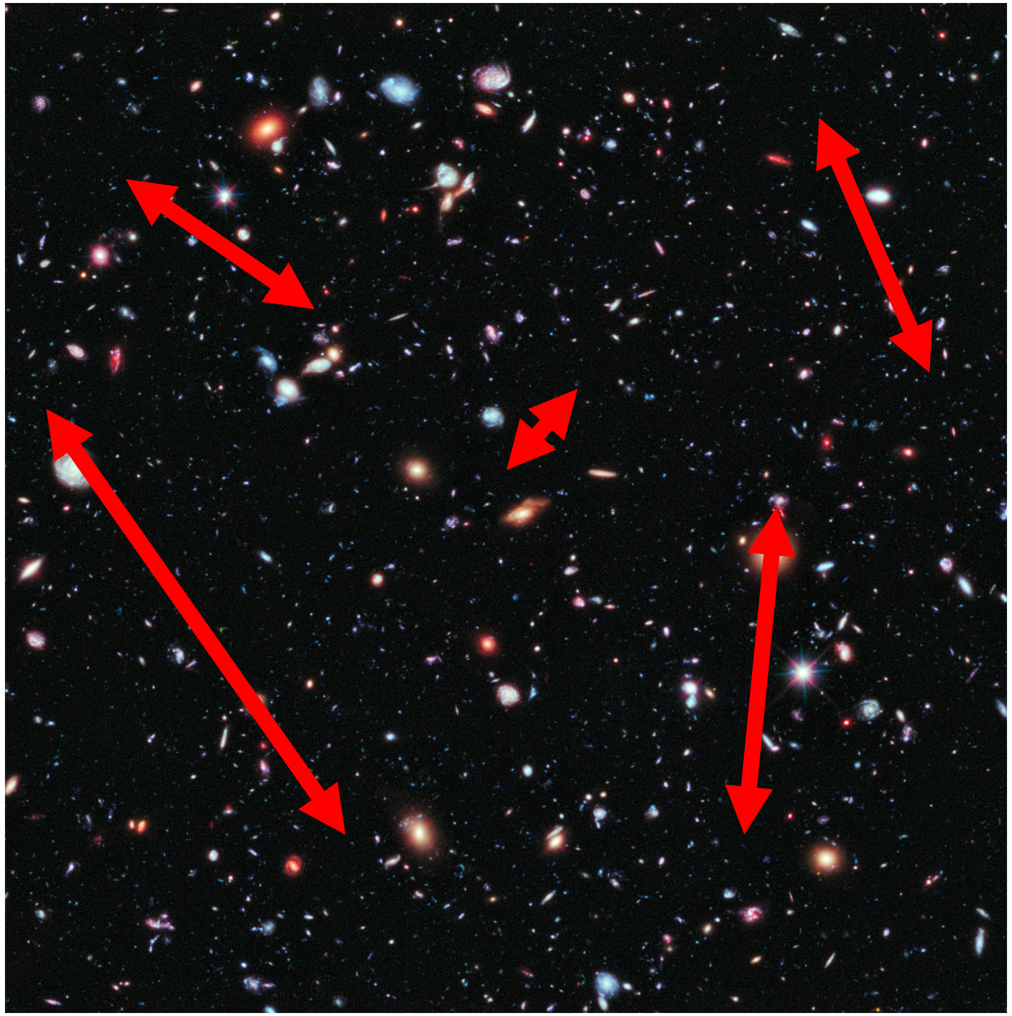
Animation Credit: Francisco Villaescusa-Navarro

Many methods to simulate massive neutrinos with different pros/cons:
Linear response approach: Ali-Haïmoud & Bird (2012), Hybrid approach: Bird, et al. (2019), FastPM: Bayer, Banerjee, Feng (2021), …

$$\delta_m = (1 - f_\nu)\delta_c + f_\nu \delta_\nu$$

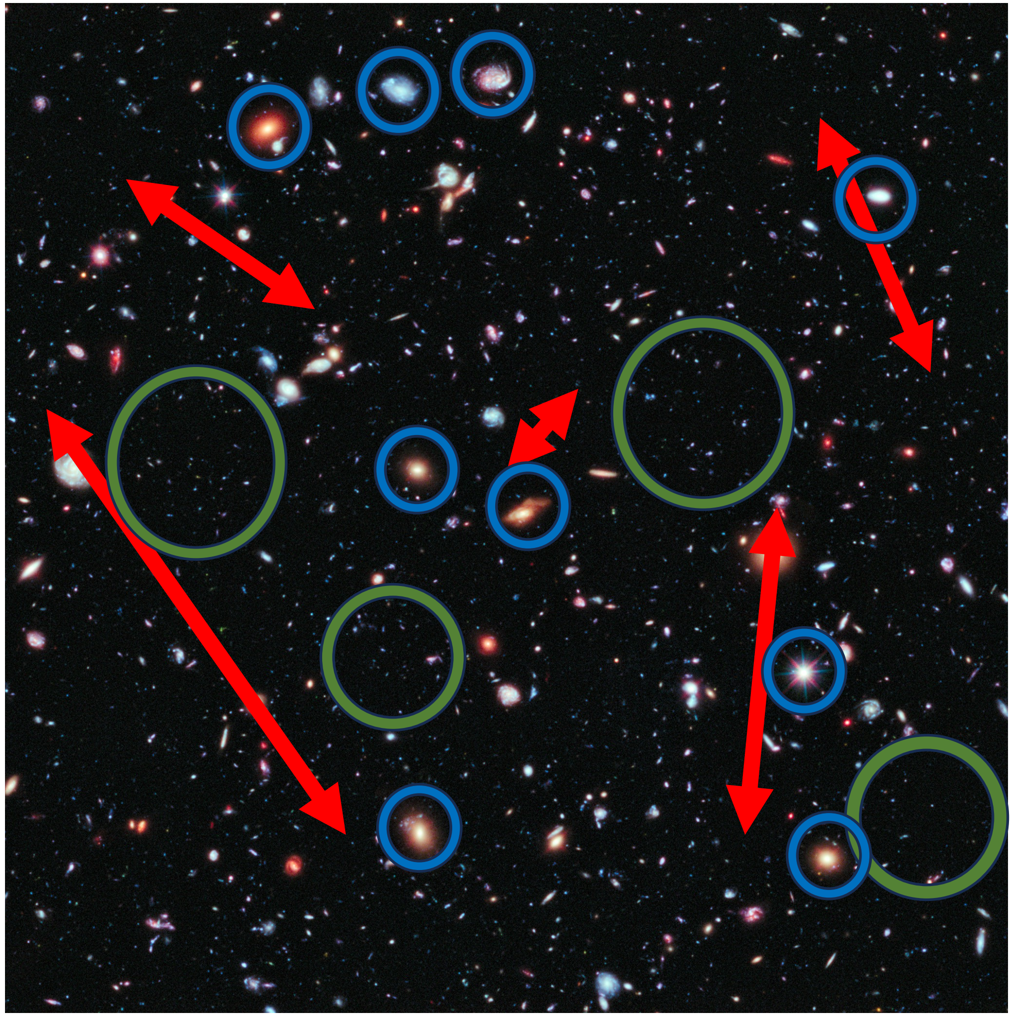
Traditional cosmology uses 2-pt information

but this is no longer optimal as we probe smaller scales



Higher-order statistics

can provide information beyond the 2-pt



Halo Mass Function

2-pt correlation

Void Size Function

Bayer+2021

Higher-order statistics

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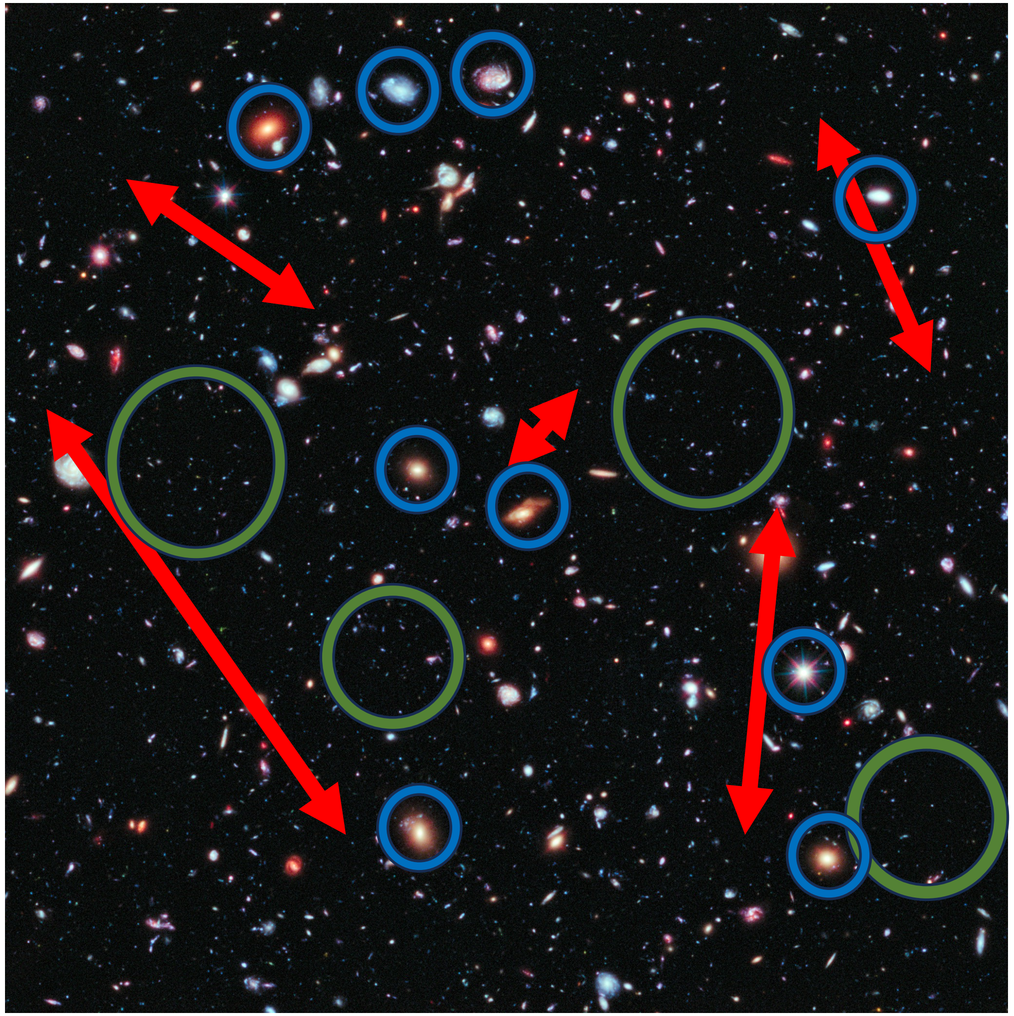

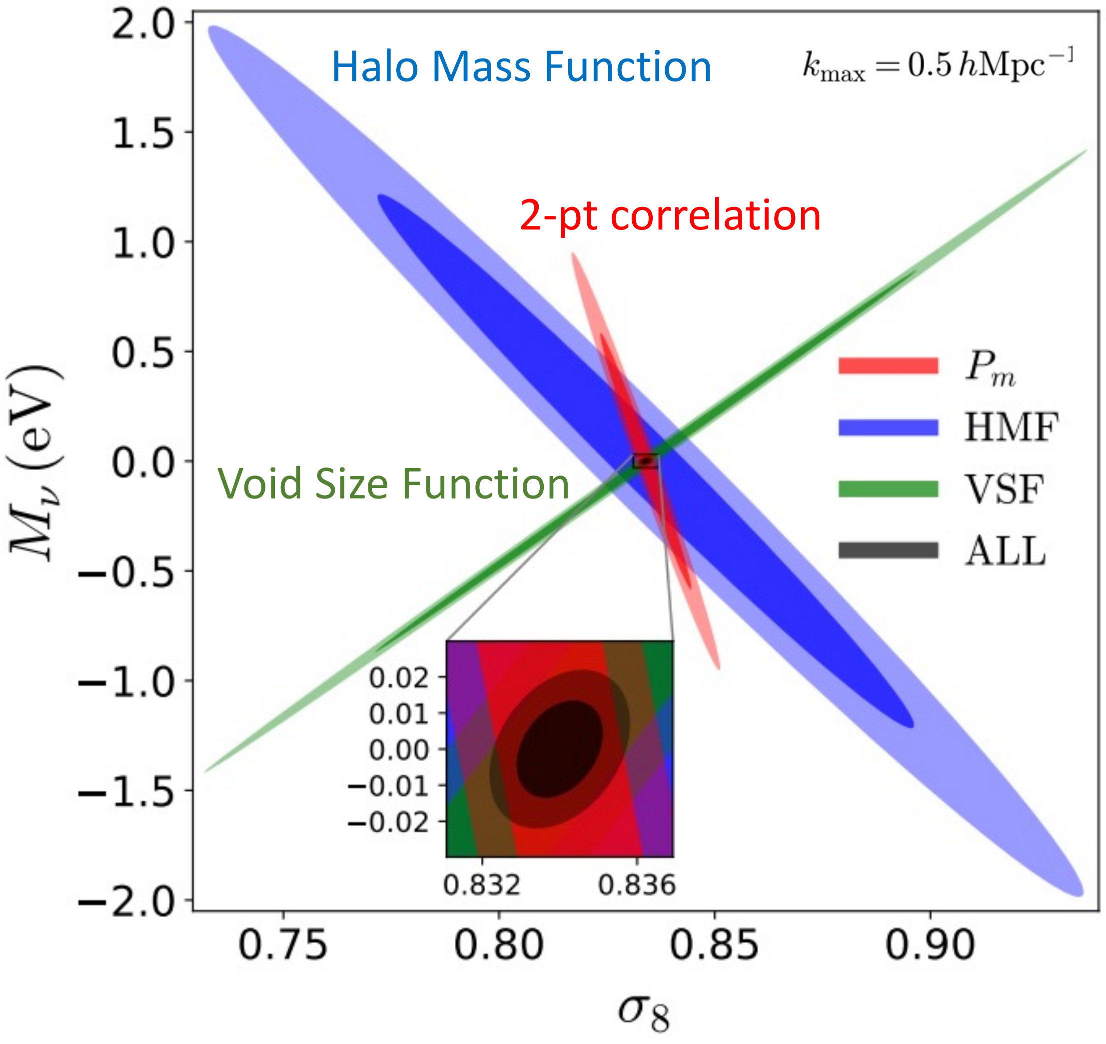

Bayer+2021

Many proposals for higher-order statistics

- Lensing bispectrum (Coulton+2018)
- Lensing Minkowski functionals (Marques+2018)
- Lensing peak counts (Li+2018, Ajani+2020)
- Lensing probability density function (Liu+2020)
- Matter probability density function (Uhlemann+2020)
- Redshift-space bispectrum (Hahn+2020)
- Marked power spectrum (Massara+2021)
- Wavelets (Cheng+2021, Valogiannis+2021)
- Voids (Bayer+2021, Kreisch+2021)
- …

Constraining neutrino mass with weak lensing Minkowski Functionals

Gabriela A. Marques,[a,1] Jia Liu,[b] José Manuel Zorrilla Matilla,[c] Zoltán Haiman,[c] Armando Bernui[a] and Camila P. Novaes[a]

Constraining neutrino mass with tomographic weak lensing one-point probability distribution function and power spectrum

Jia Liu* and Mathew S. Madhavacheril

Fisher for complements: Extracting cosmology and neutrino mass from the counts-in-cells PDF

Cora Uhlemann[1,2], Oliver Friedrich[3,4], Francisco Villaescusa-Navarro[5,6], Arka Banerjee[7,8,9], Sandrine Codis[10]

Constraining M_ν with the Bispectrum I: Breaking Parameter Degeneracies

ChangHoon Hahn[a,b] Francisco Villaescusa-Navarro[c,d] Emanuele Castorina[a,b] Roman Scoccimarro[e]

DETECTING NEUTRINO MASS BY COMBINING MATTER CLUSTERING, HALOS, AND VOIDS

Adrian E. Bayer[1,2,*], Francisco Villaescusa-Navarro[3,4,†], Elena Massara[5,4], Jia Liu[1,2,6], David N. Spergel[3,4], Licia Verde[7,8], Benjamin D. Wandelt[9,10,4], Matteo Viel[11,12,13,14], Shirley Ho[4,3,15]

The GIGANTES dataset: precision cosmology from voids in the machine learning era

Christina D. Kreisch[1], Alice Pisani[1], Francisco Villaescusa-Navarro[1], David N. Spergel[1,2], Benjamin D. Wandelt[2,3,4], Nico Hamaus[5], and Adrian E. Bayer[6,7]

Constraining neutrino masses with weak-lensing multiscale peak counts

Virginia Ajani,[1,*] Austin Peel,[2] Valeria Pettorino,[1] Jean-Luc Starck,[1] Zack Li,[3] and Jia Liu[4,3]

Constraining Neutrino Mass with the Tomographic Weak Lensing Bispectrum

William R. Coulton

Using the Marked Power Spectrum to Detect the Signature of Neutrinos in Large-Scale Structure

Elena Massara,[1,2,*] Francisco Villaescusa-Navarro,[3,2] Shirley Ho,[2,3,4] Neal Dalal,[5] and David N. Spergel[2,3]

Constraining neutrino mass with tomographic weak lensing peak counts

Zack Li* and Jia Liu

Many proposals for higher-order stat…

- Lensing bispectrum (Coulton+2018)
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- Lensing probability density fun…
- Matter probability den…
- Redshift-space …
- Marke…
- …2021)
- …2021)

Where is the information coming from?
Can we find it in real data?

Constraining neutrino mass … one-point probability distri…

Jia L…

…nals

…atilla,[c] … Novaes[a]

…raining M_ν with the Bispectrum … Breaking Parameter Degeneracies

ChangHoon Hahn[a,b] Francisco Villaescusa-Navarro[c,d] Emanuele Castorina[a,b] Roman Scoccimarro[e]

…mology and neutrino mass

…s[10], Francisco Villaescusa-Navarro[5,6],

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What do surveys measure?

$$\delta_m = (1 - f_\nu)\delta_c + f_\nu \delta_\nu$$

Bayer, Banerjee, Seljak (2022)

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Bayer, Banerjee, Seljak (2022)

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- Halos/Galaxies:

$$\delta_h = b\delta_c$$

Bayer, Banerjee, Seljak (2022)

What do surveys measure?

$$\cancel{\delta_m} = (1 - f_\nu)\cancel{\delta_c} + f_\nu \cancel{\delta_\nu}$$

- Halos/Galaxies:

$$\delta_h = b\delta_c$$

- Lensing:

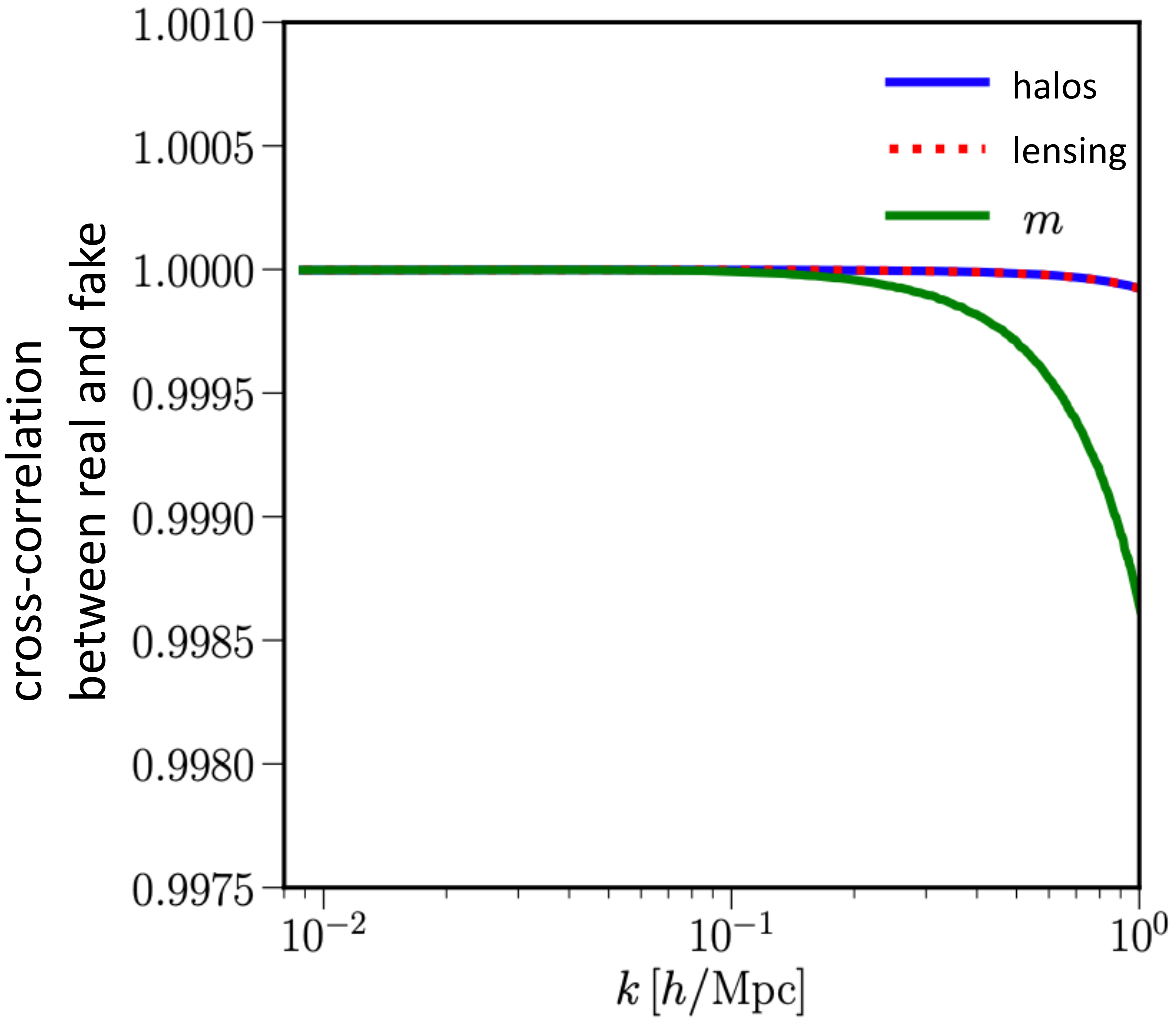
$$\kappa(\chi_*, \hat{\boldsymbol{n}}) = \frac{3H_0^2\Omega_m}{2c^2} \int_0^{\chi_*} d\chi \, \frac{\chi}{a(\chi)} \left(1 - \frac{\chi}{\chi_*}\right) \delta_m(\chi\hat{\boldsymbol{n}})$$

Bayer, Banerjee, Seljak (2022)

Fake νs?

- Run two N-body simulations using **matched linear physics**:
  1. with massive neutrinos (**real**)
  2. without massive neutrinos (**fake**)

- Nonlinear effects of massive neutrinos at a **single redshift** can be **faked by CDM** for halos and lensing



Bayer, Banerjee, Seljak (2022)

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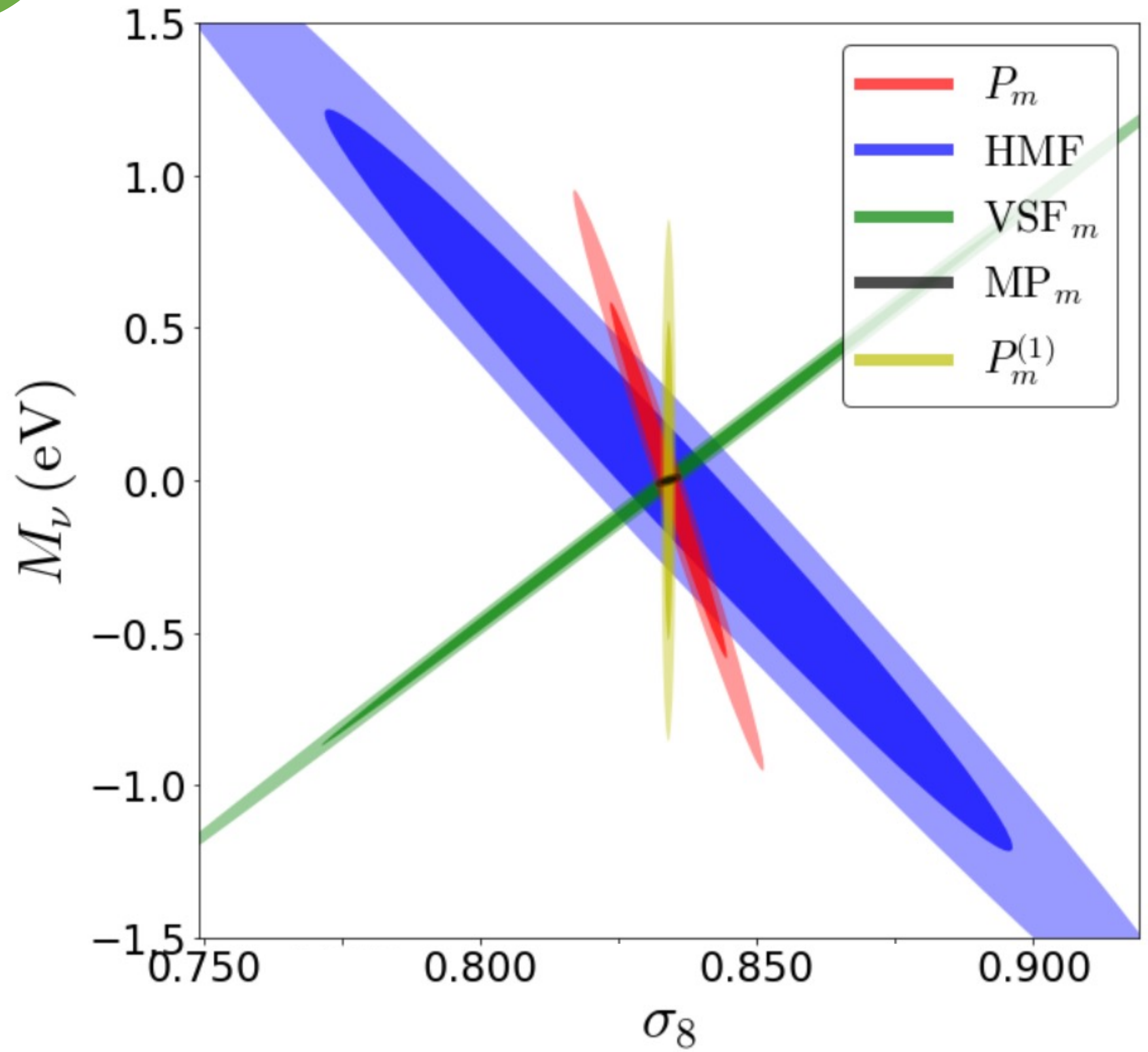

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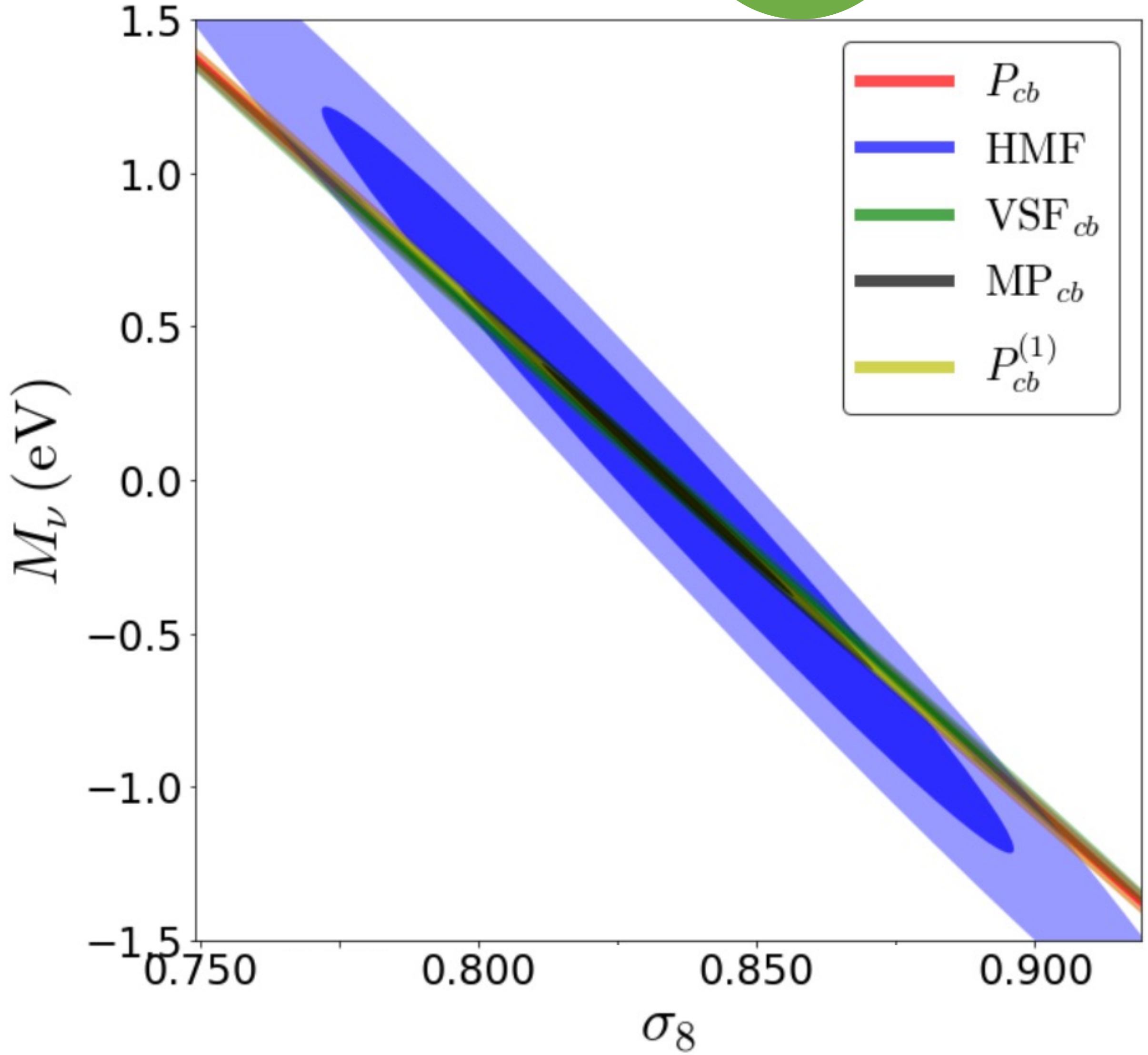

How to maximize the ν information?

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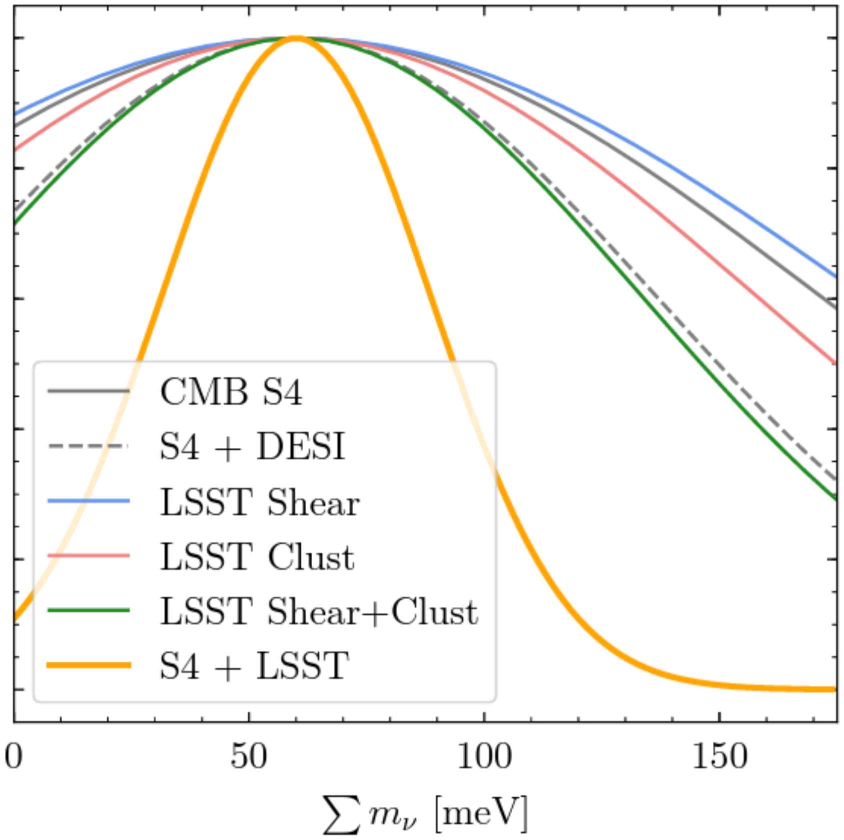
1. Jointly analyze **multiple redshifts** and **multiple tracers** to break degeneracies
   e.g. CMB x LSS



Mishra-Sharma+2018

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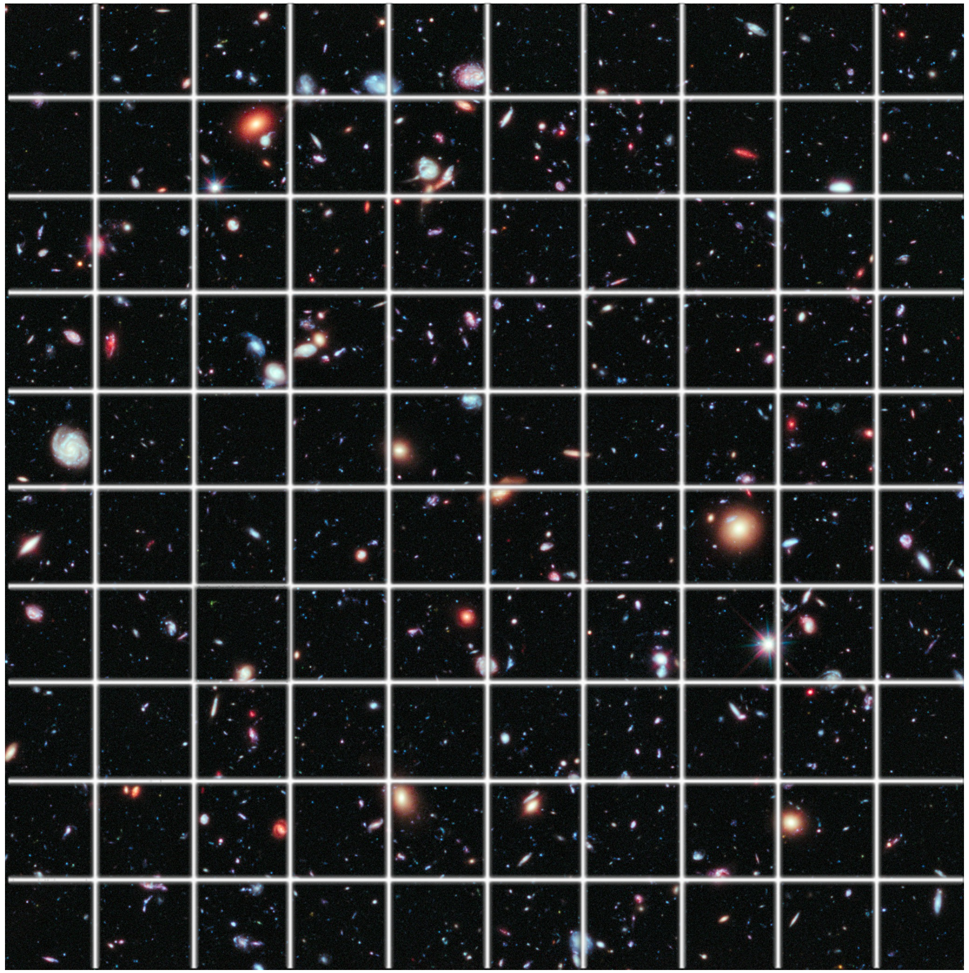
2. Develop **statistical methods** to optimally extract information
   e.g. field-level inference



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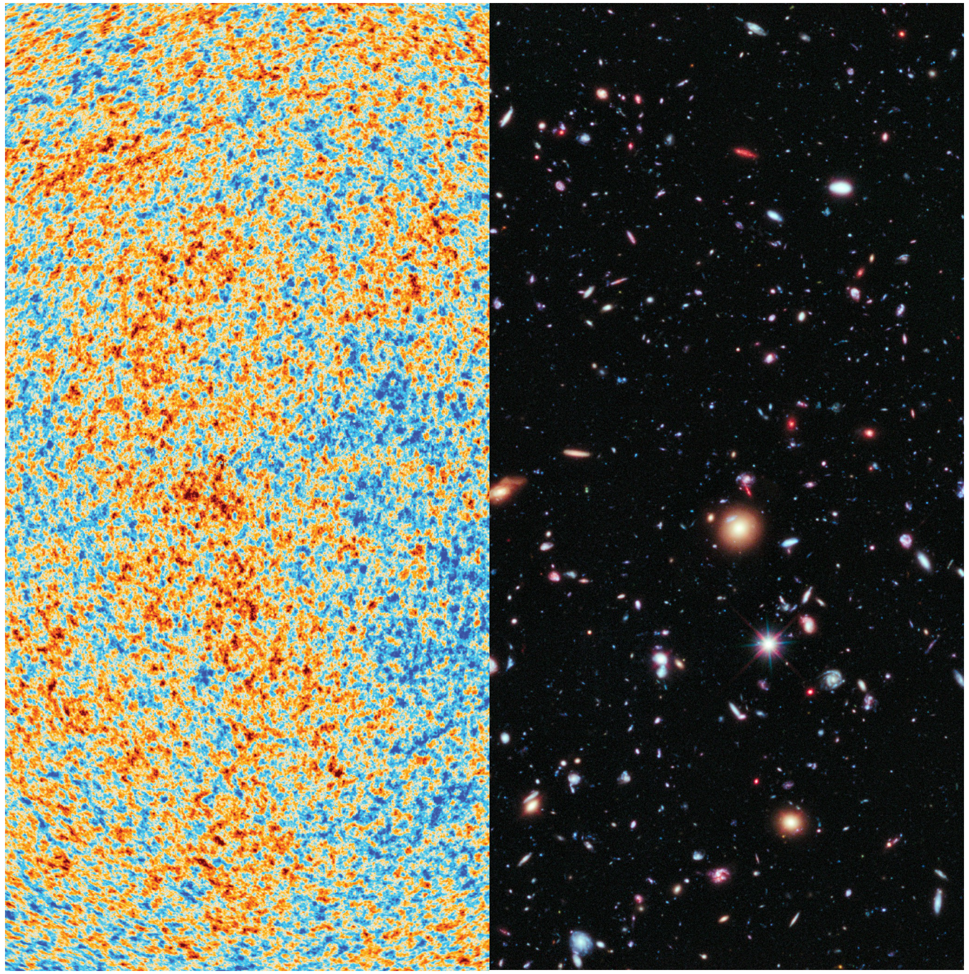

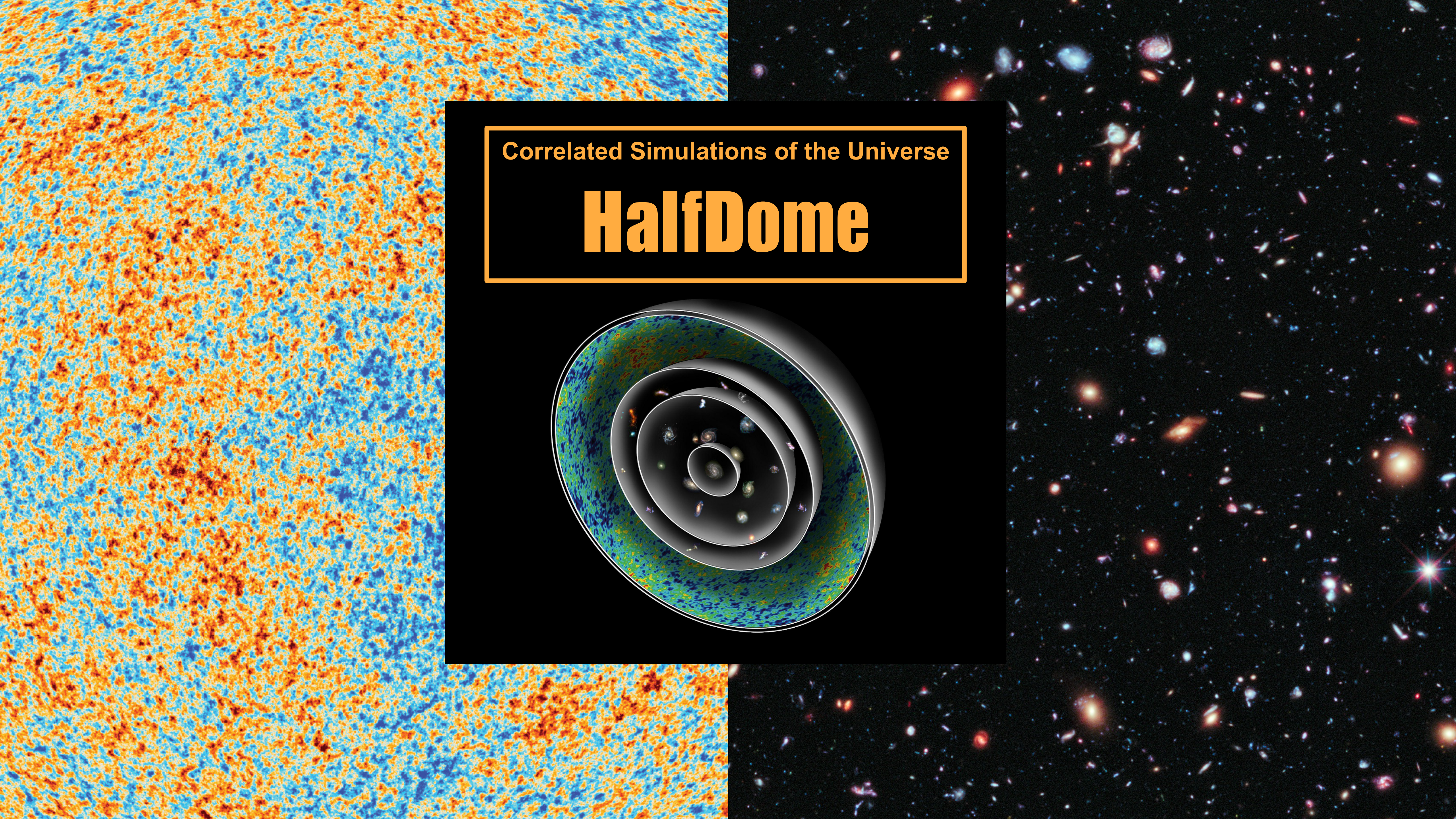
Correlated Simulations of the Universe
HalfDome

Simulation Comparison

	Sehgal+2010	**Websky** Stein+2020 Li+2022	**Agora** Omori 2022	**Stage IV requirements***
Box Size $N_{particles}$	1 Gpc/h 1024^3	7.7 Gpc 6144^3	1 Gpc/h 3840^3	a few Gpc/h
Min. M_{halo}	10^{13} $M_\odot$	1.2×10^{13} $M_\odot$	1.5×10^{9} $M_\odot$/h	10^{12} $M_\odot$/h
LSS observables	None	None	κ, clusters, LIM, +more to come	κ, galaxies,clusters
Number of realizations	1	1	1	10–100

* Inputs from SO, CMB-S4, LSST, DESI, PFS, SPHEREx, Roman collaborators

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LSS observables	None	None	κ, clusters, LIM, +more to come	κ, galaxies,clusters	κ, galaxies, clusters, +more
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The Team

Adrian Bayer

Princeton/CCA

Jia Liu

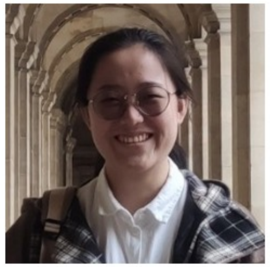
Kavli IPMU

Zack Li

UC Berkeley/LBL

Joe DeRose

UC Berkeley/LBL



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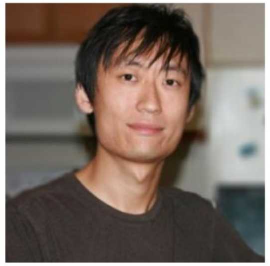
U Tokyo

Linda Blot

Kavli IPMU

Marcelo Alvarez

LBL



Yu Feng

Google

Junjie Xia

Kavli IPMU

Alex Laguë

U Penn

Will Coulton

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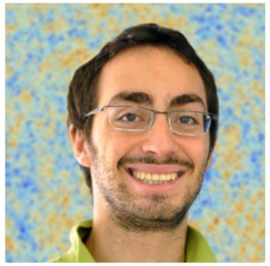


Giuseppe Puglisi

U Catania

Hideki Tanimura

Kavli IPMU

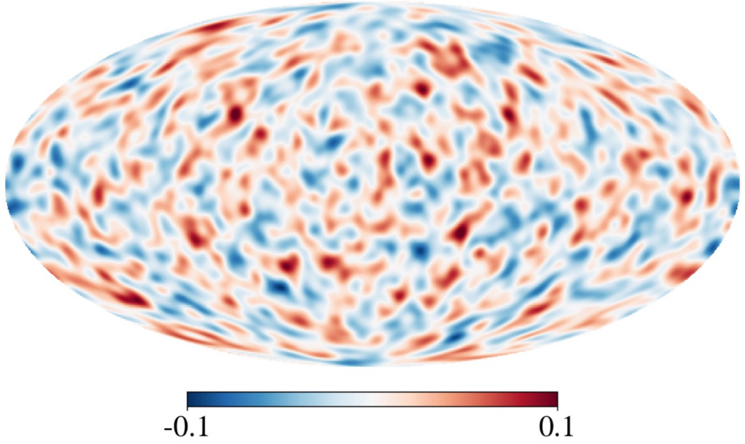
Mathew Madhavacheril

U Penn

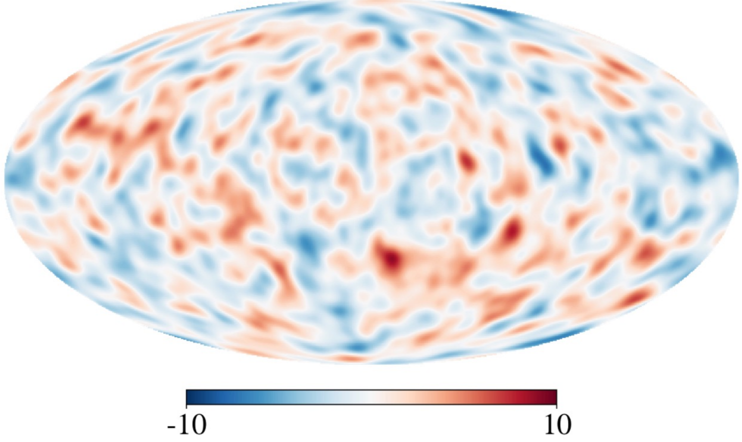
Preliminary Maps

stay tuned for more!

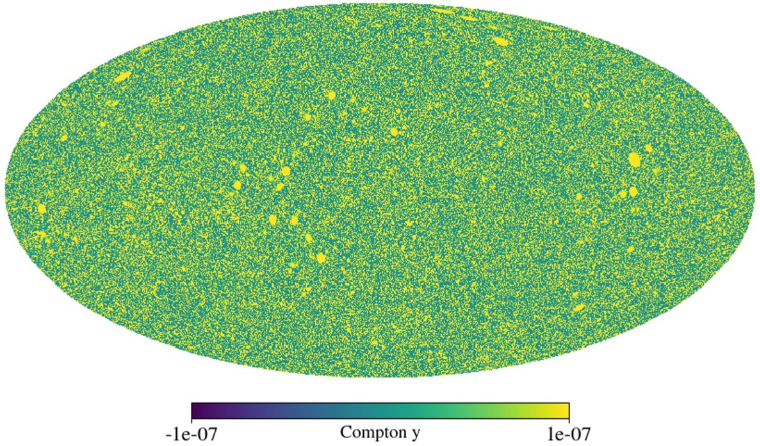
Matter Density



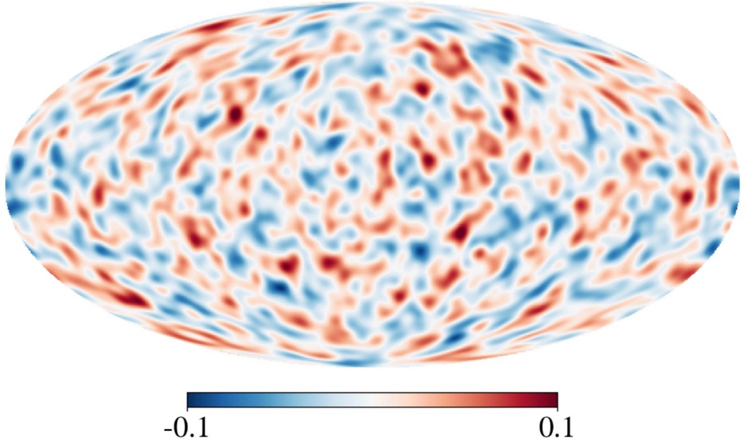
Velocity Sheet



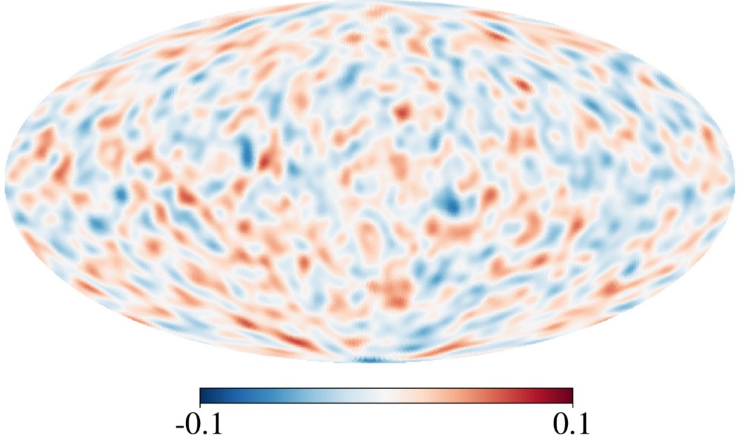
tSZ



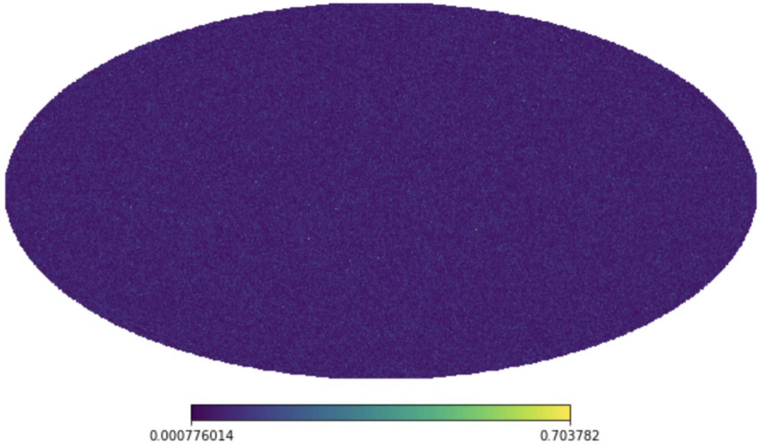
Mass Sheet



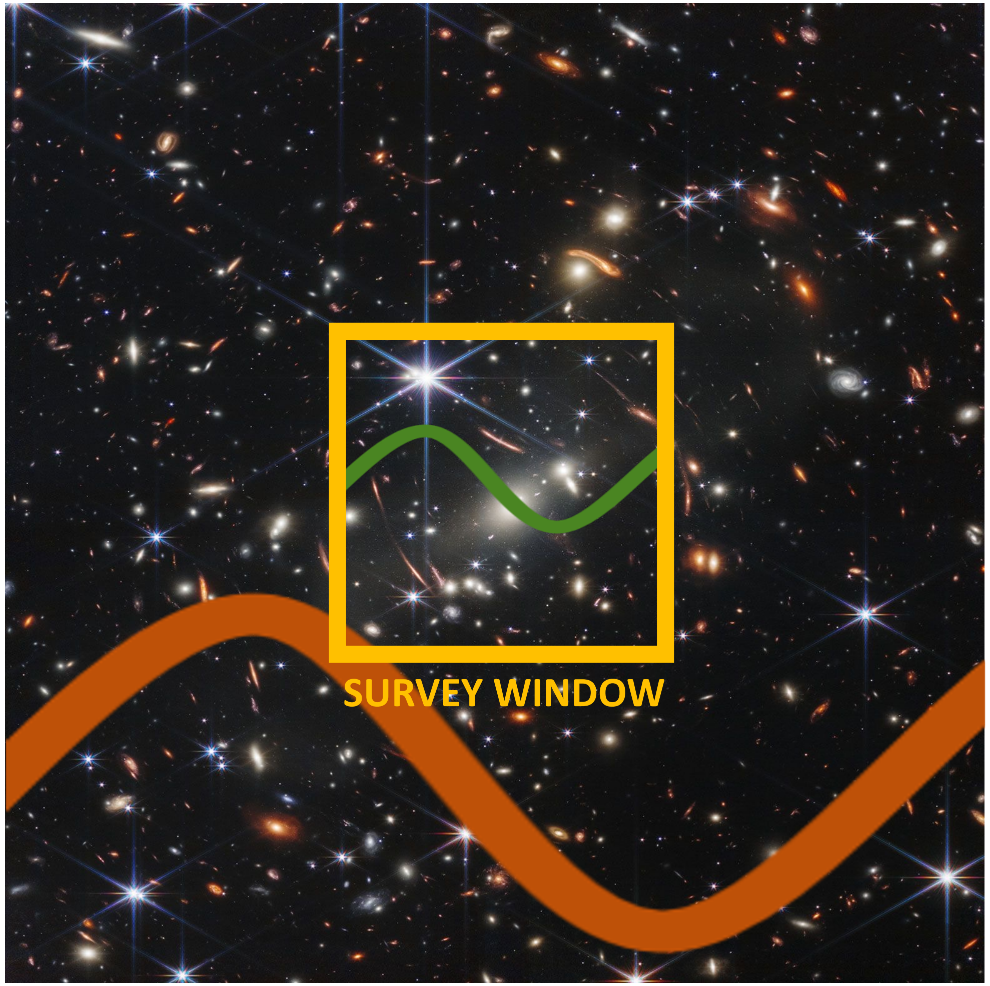
Halo Density



z_s=3 lensing map



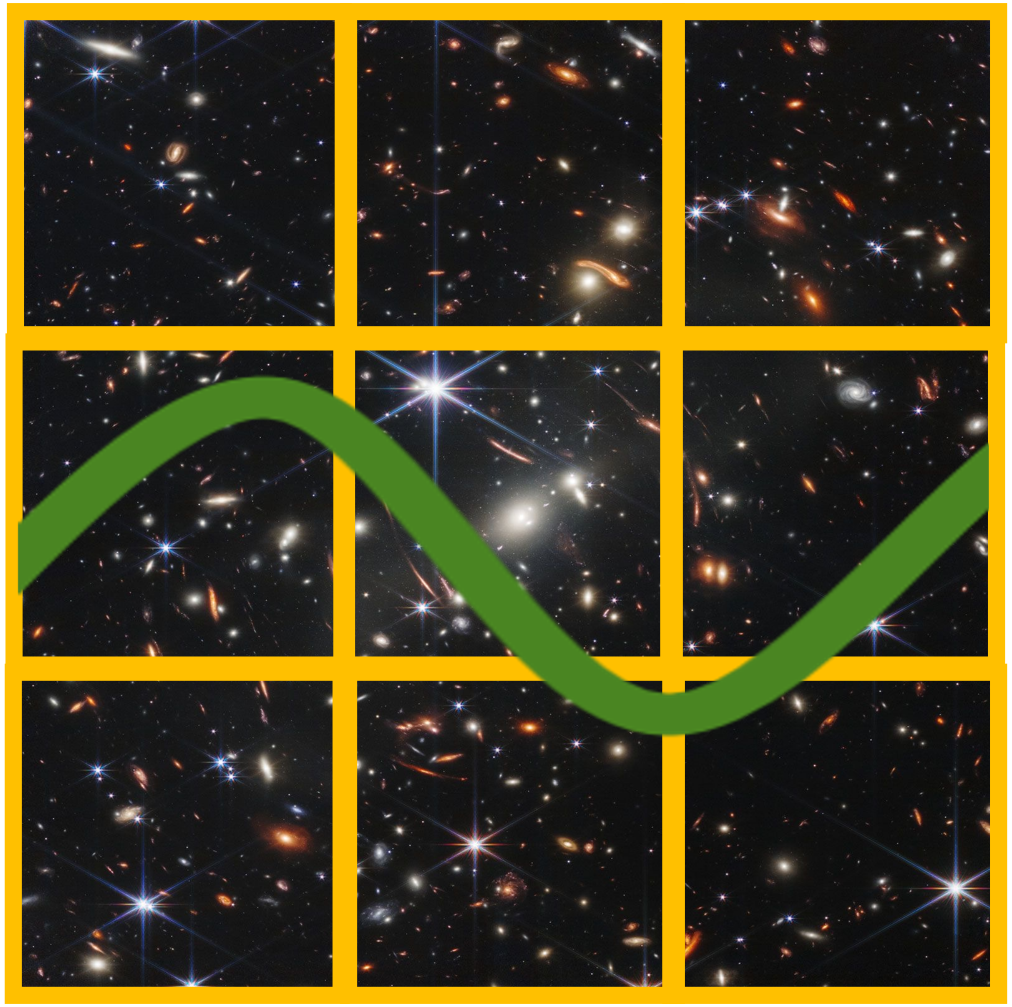
Super-sample covariance



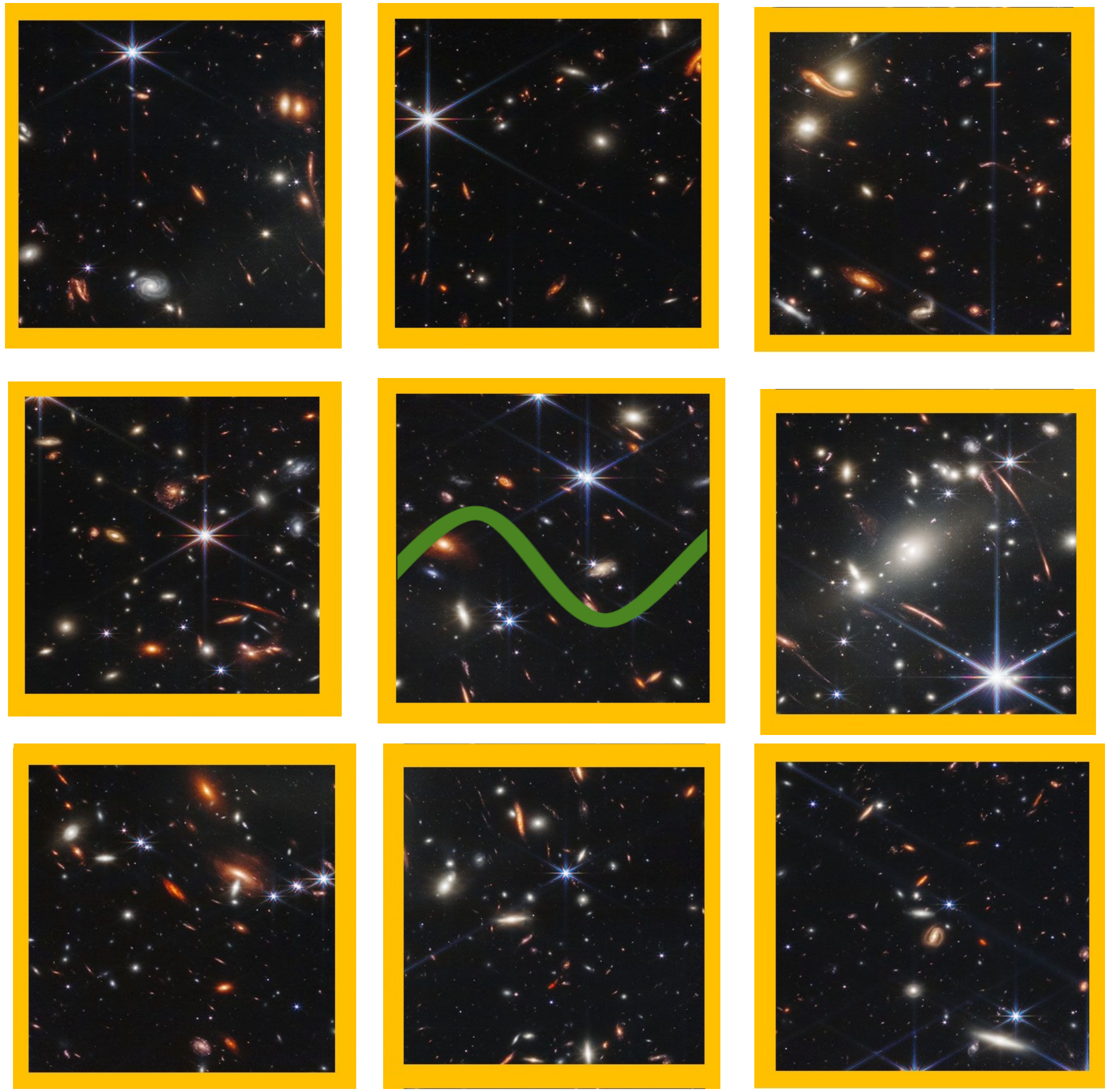
Takada+2013, Li+2014

Compare

sub-boxes



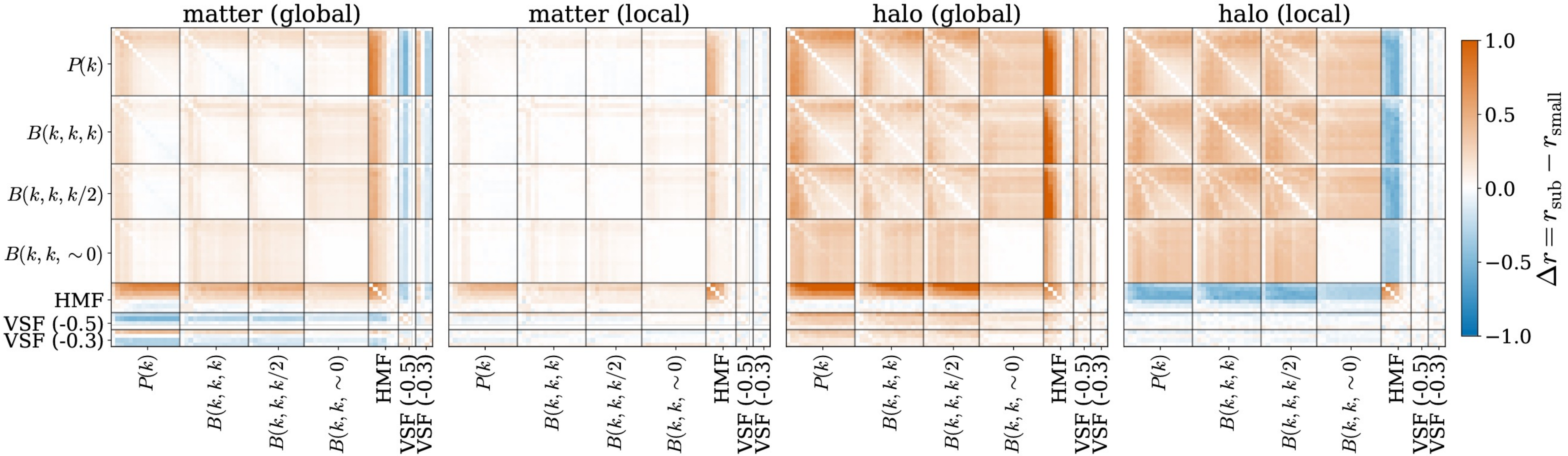
small boxes



Bayer, Liu + (2023)

Cross-correlations

sub-box size 625 Mpc/*h*

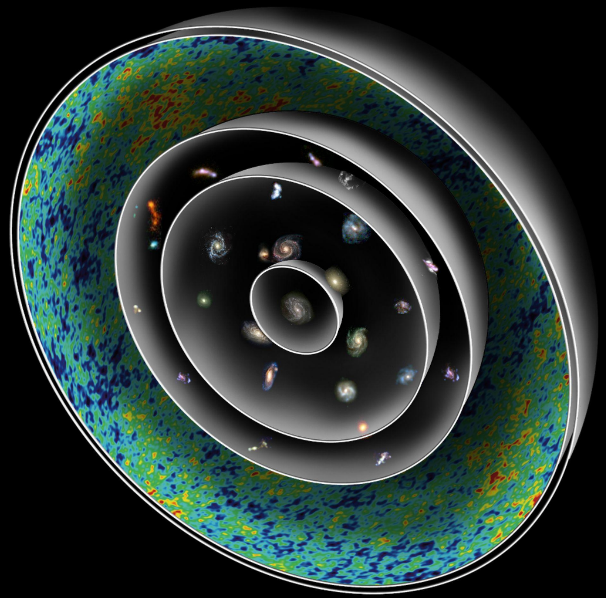


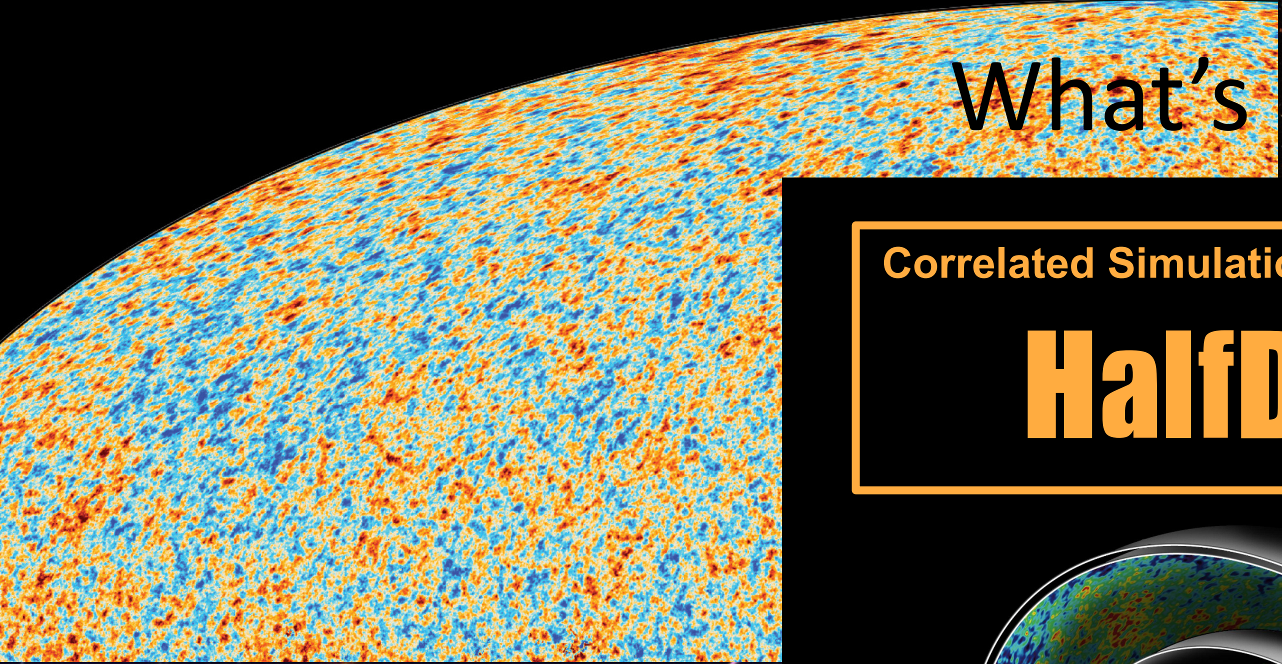
Bayer, Liu + (2023)

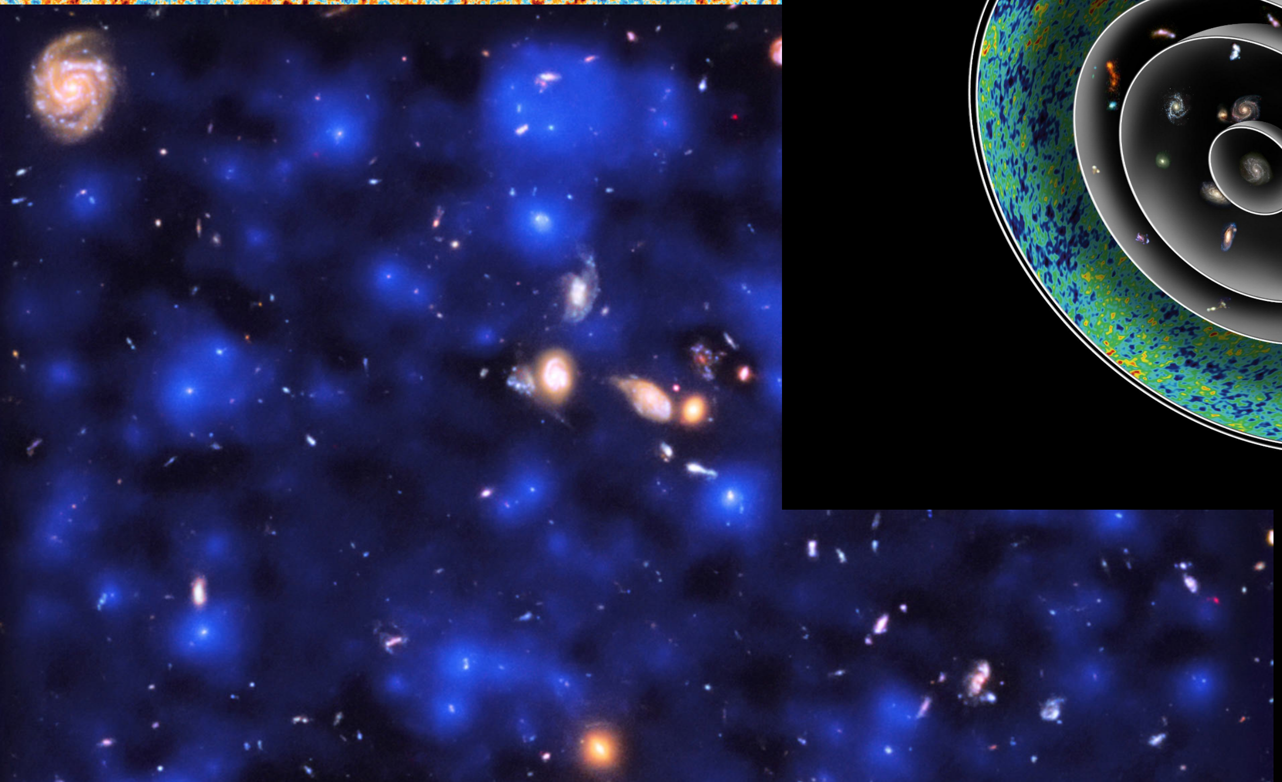
What's next?

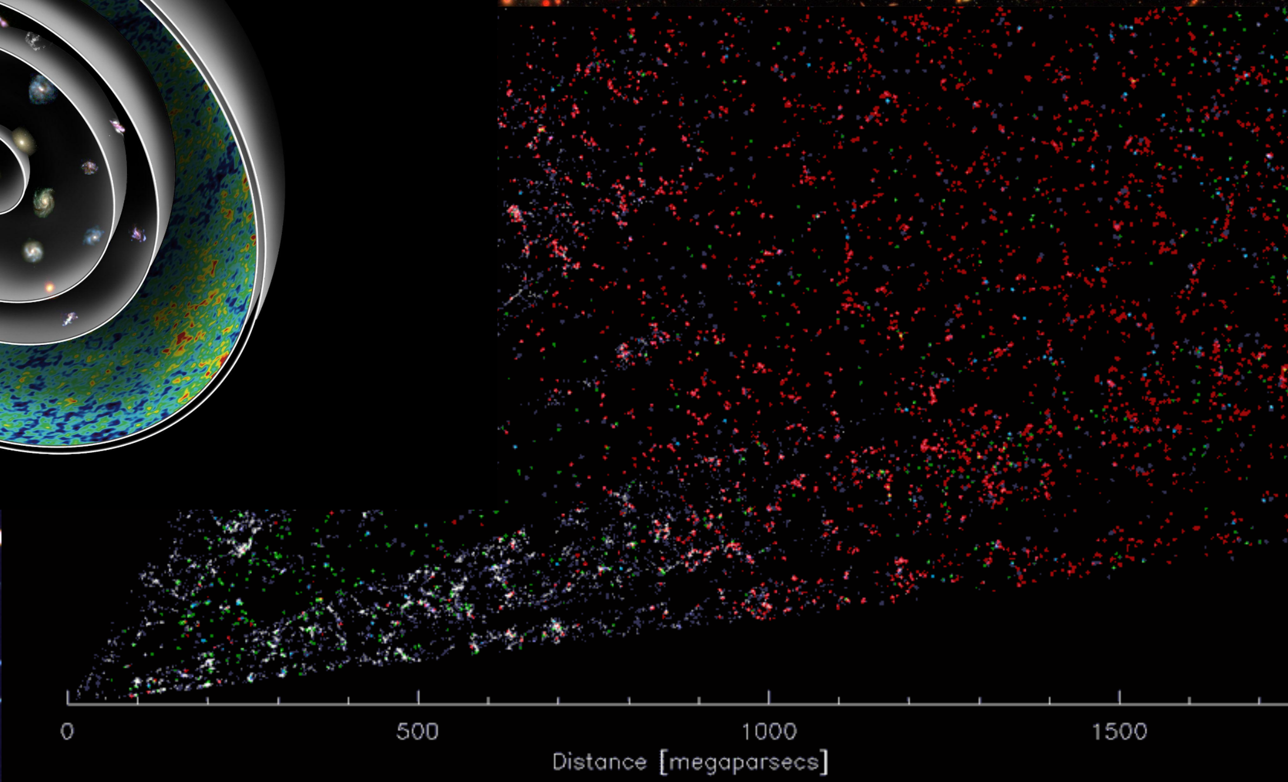
Correlated Simulations of the Universe

HalfDome



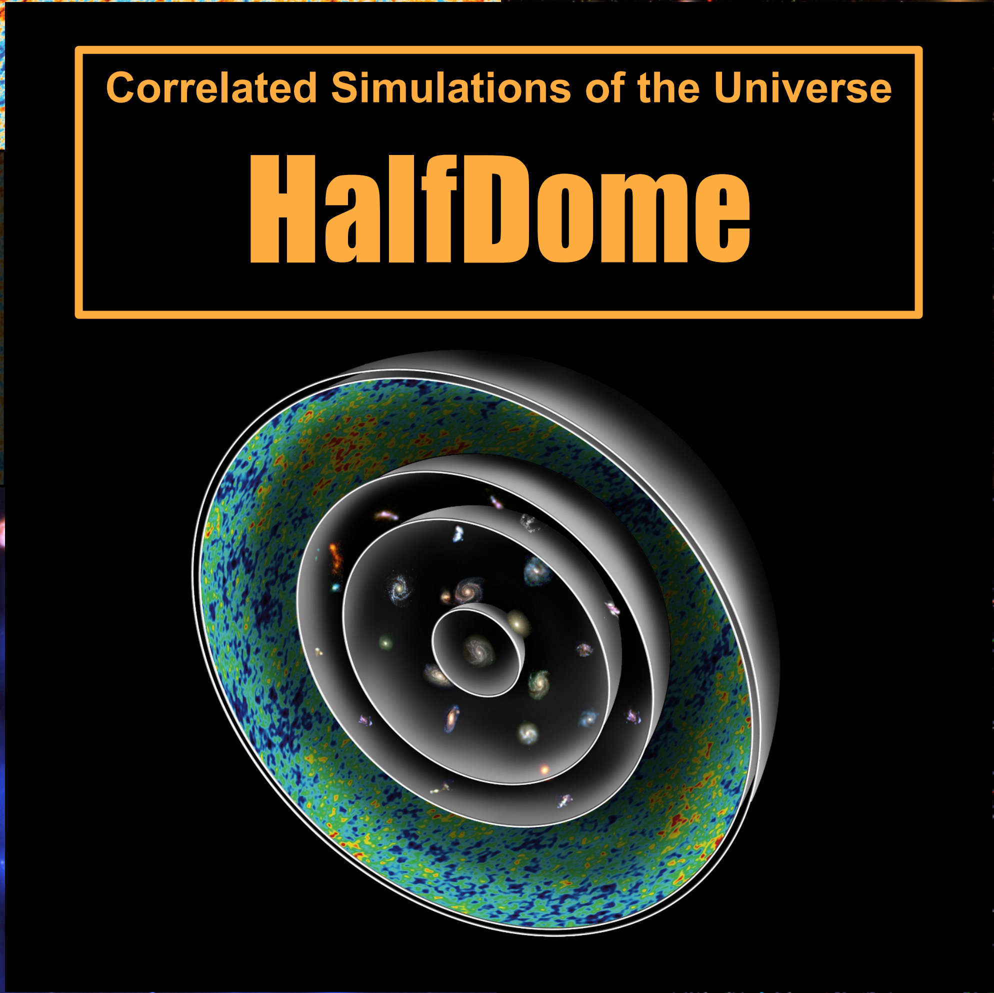


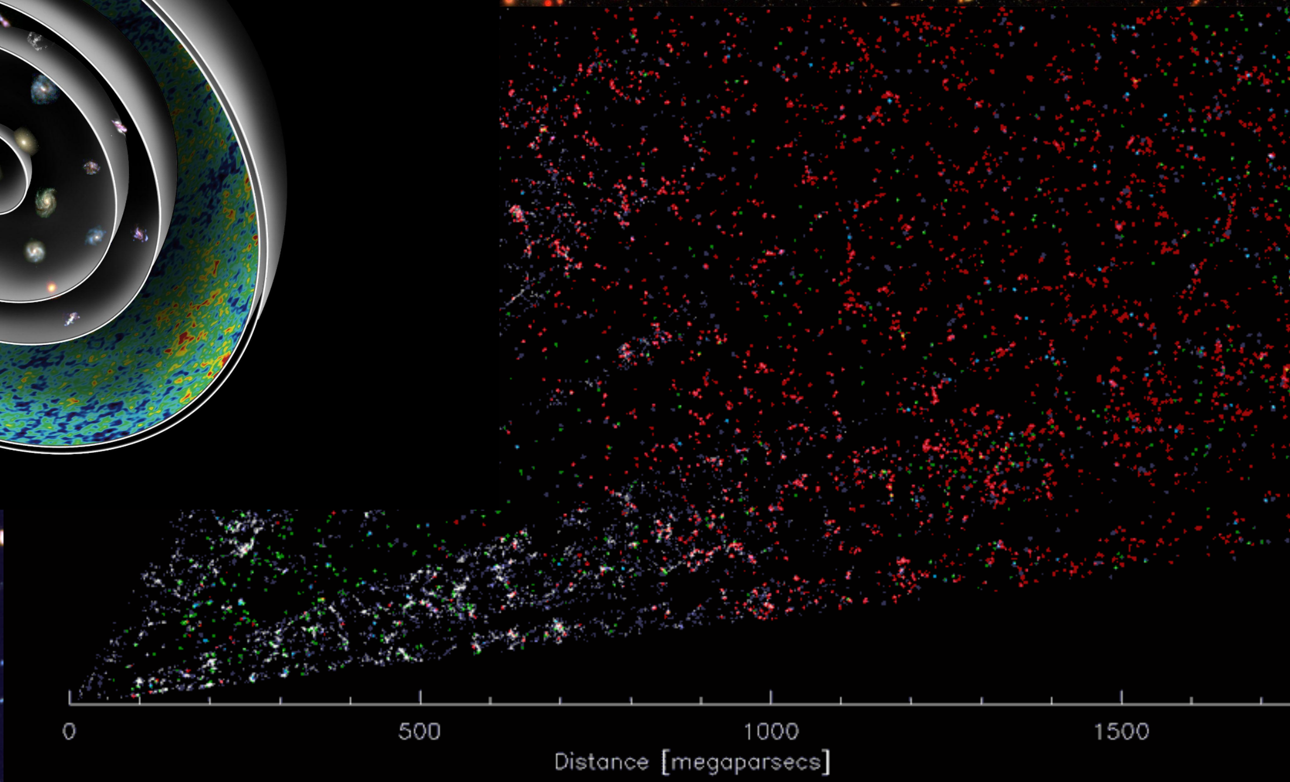




What's next?

1. Complete production
of tSZ, kSZ, CIB, radio, lensing, galaxy data by summer 2024





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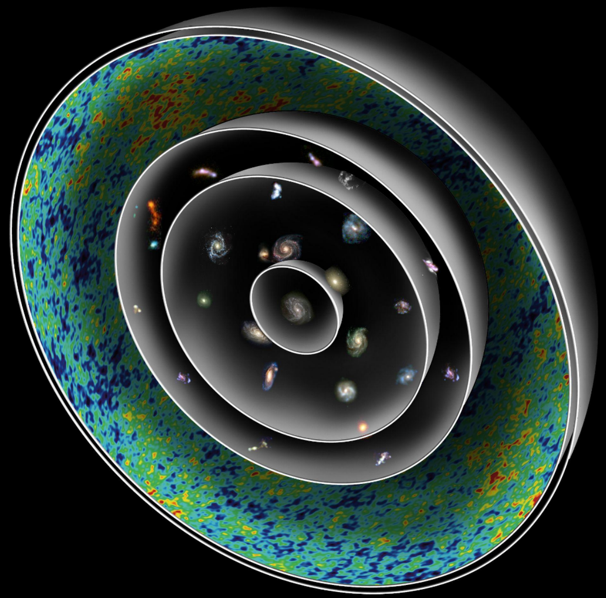

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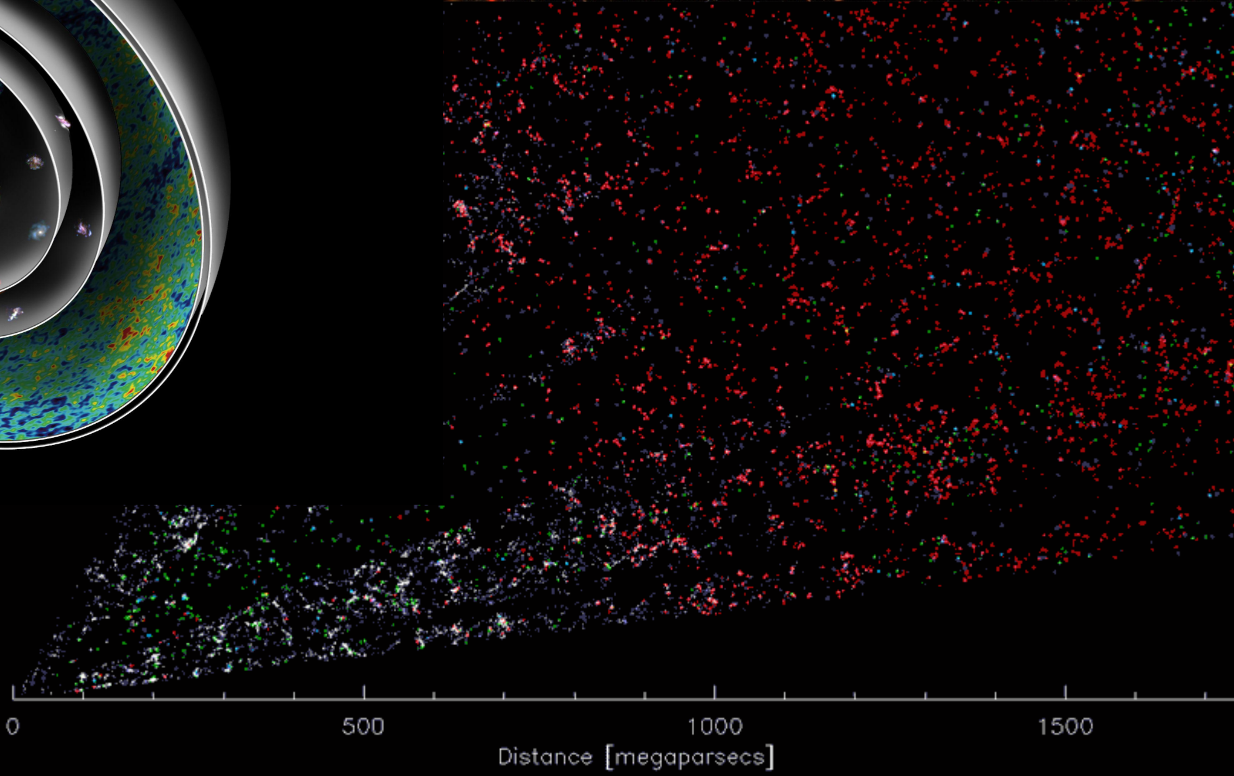
2. More simulations
wCDM + neutrinos
Full N-body



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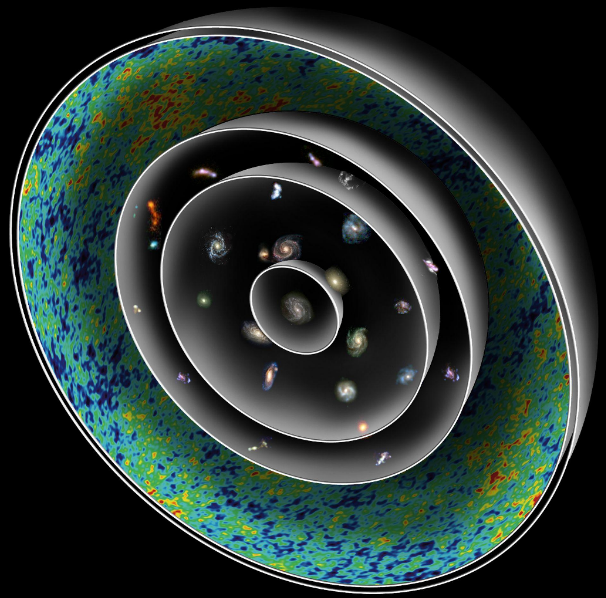

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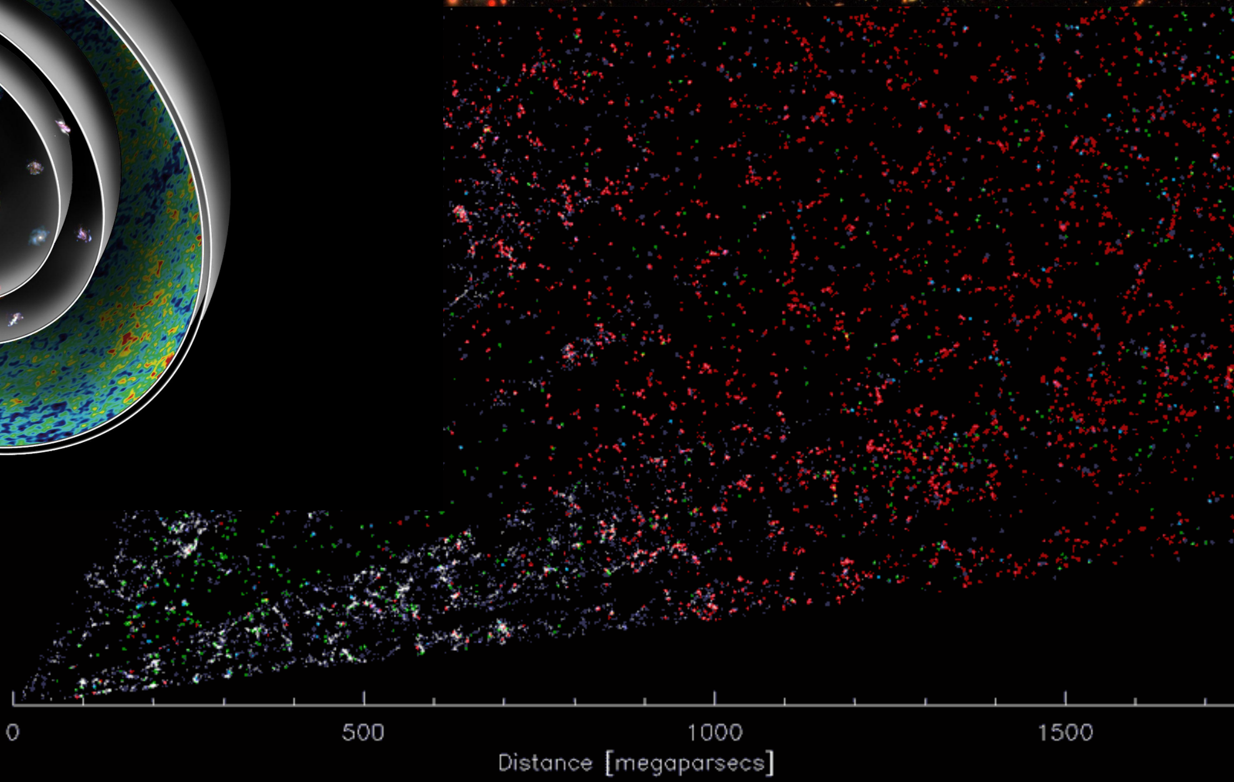
Super-resolution
Field-level inference



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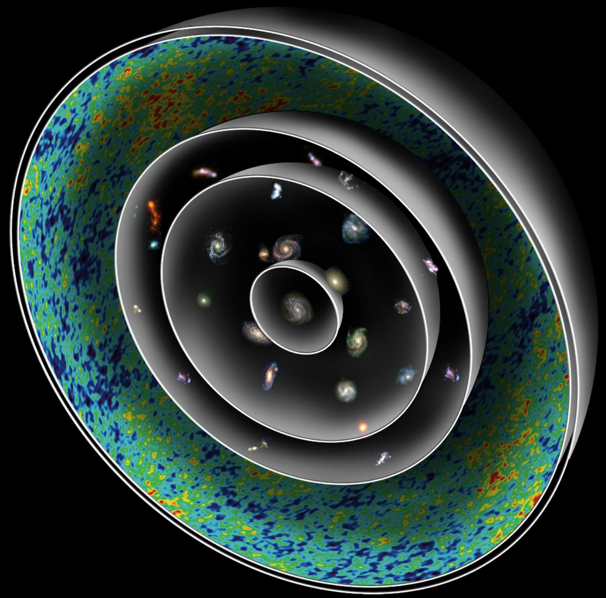

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Super-resolution
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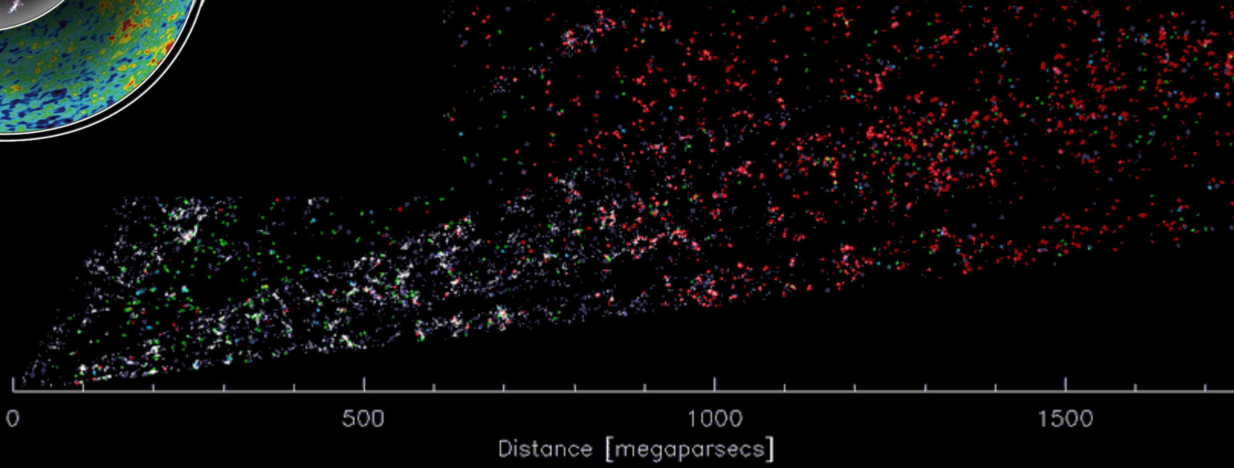
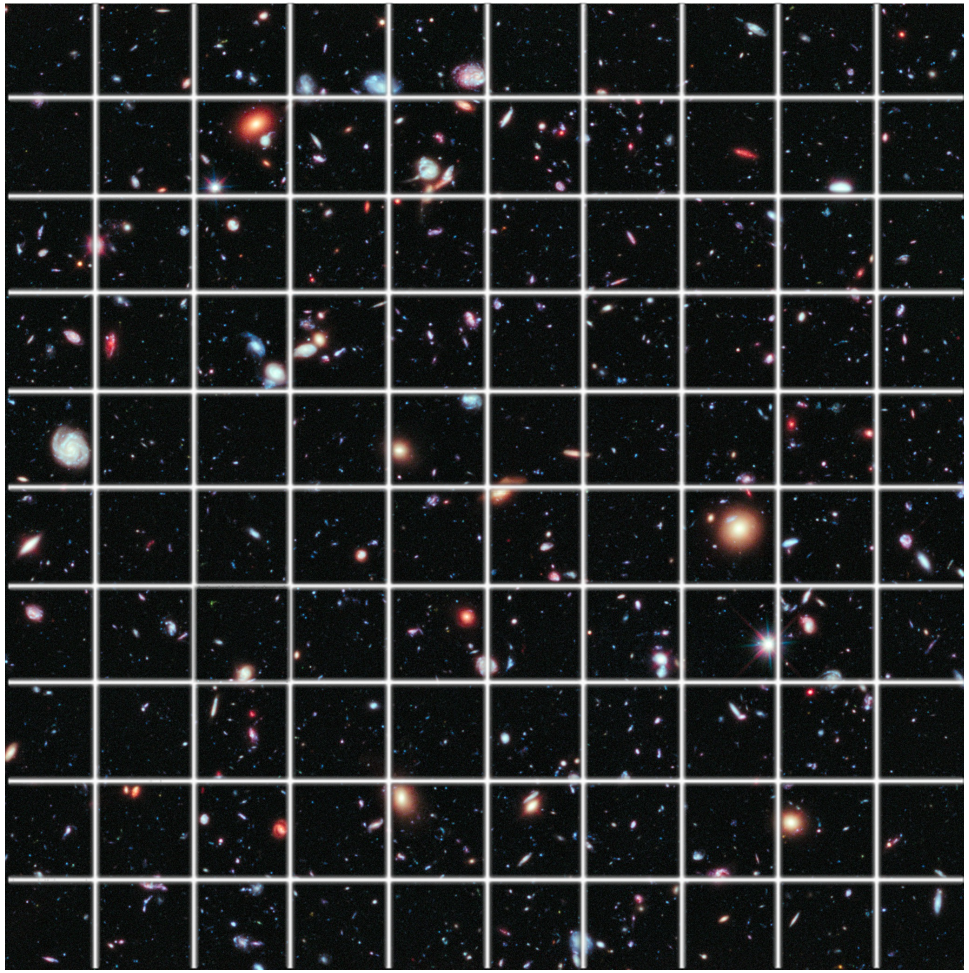
Listen to you!
Interested in other science?
Let us know!



How to maximize the ν information?

1. Jointly analyze **multiple redshifts** and **multiple tracers** to break degeneracies
   e.g. CMB x LSS

2. Develop **statistical methods** to optimally extract information
   e.g. field-level inference



Field-Level Inference *with* Microcanonical Langevin Monte Carlo

Field-Level Inference

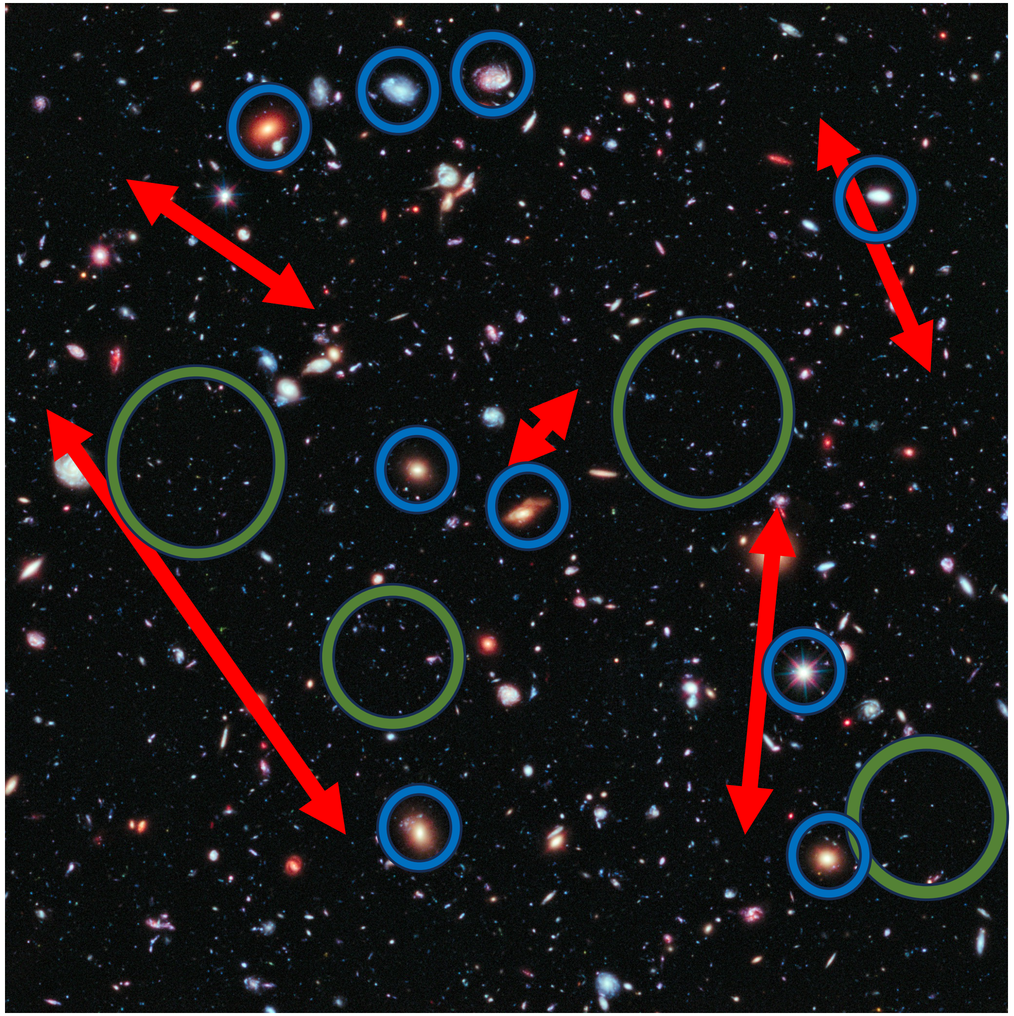
with

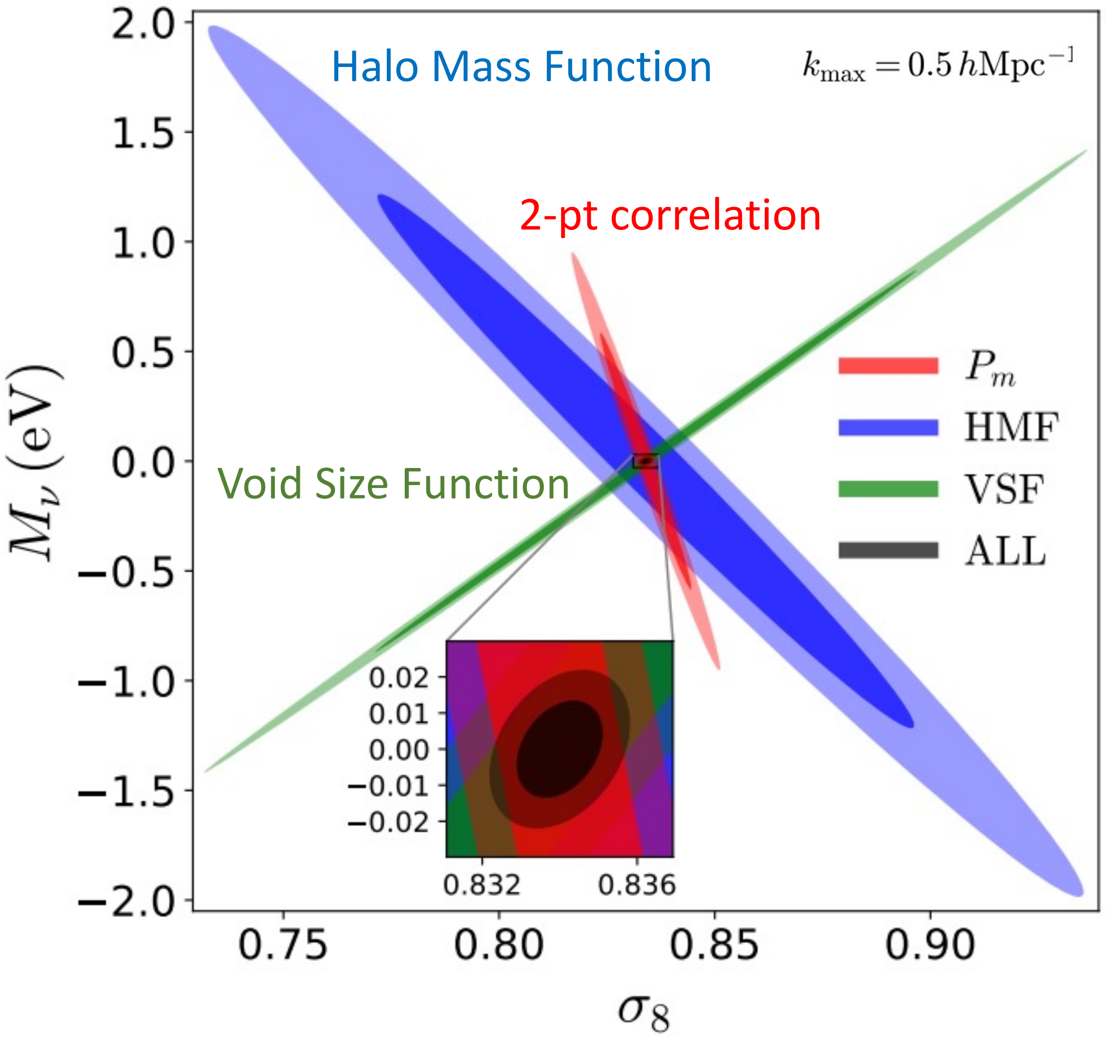
Microcanonical

Langevin Monte Carlo

Higher-order statistics

can provide information beyond the 2-pt

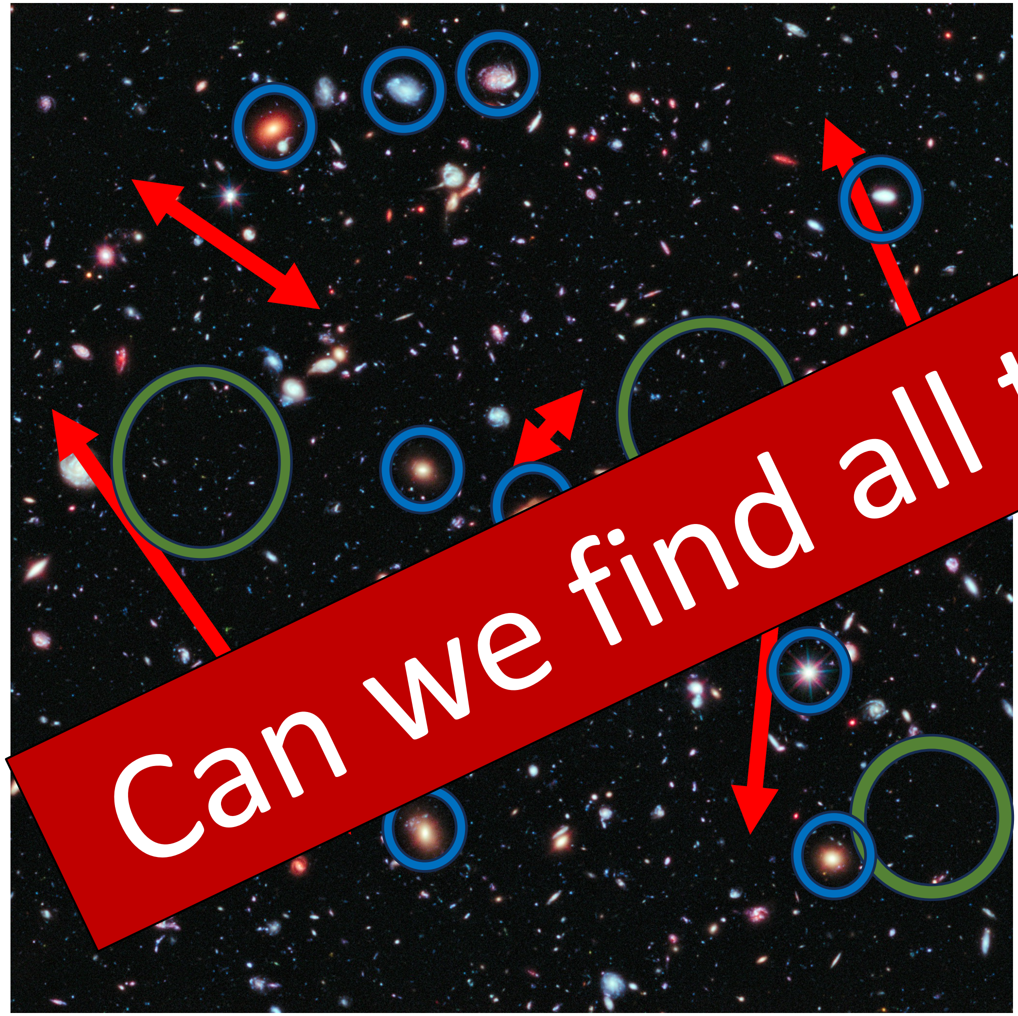


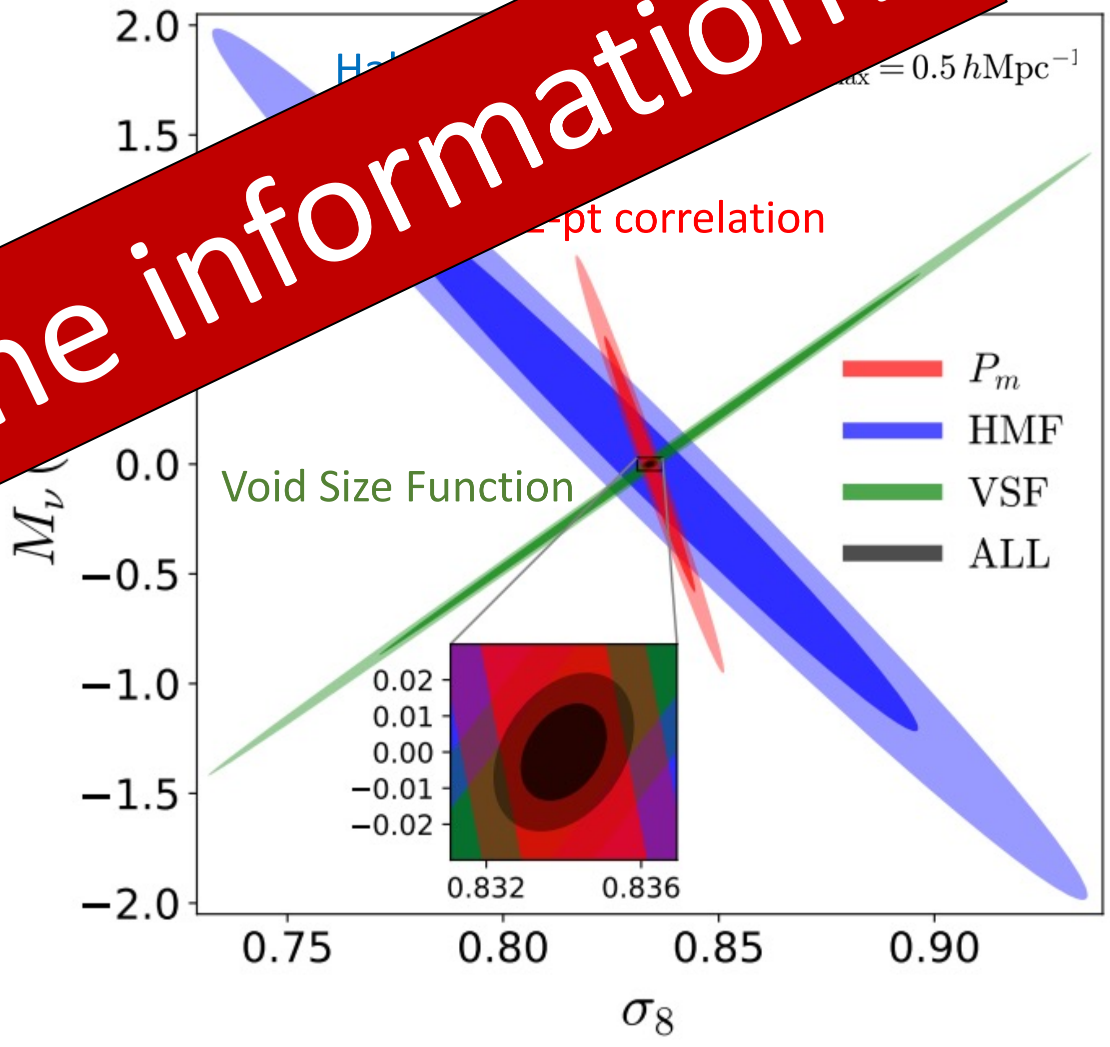


Bayer+2021

Higher-order statistics

can provide information beyond the 2-pt



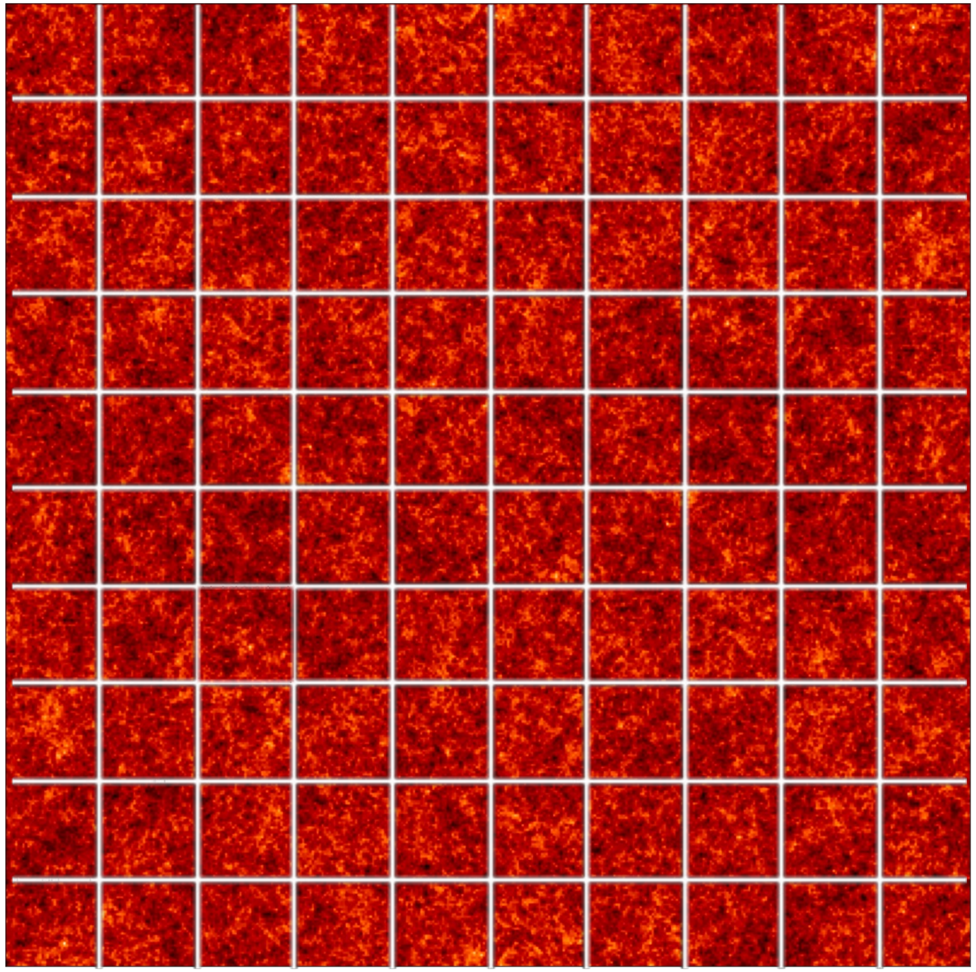


Can we find all the information?

Bayer+2021

Forward modeling

INITIAL $\boldsymbol{s}$



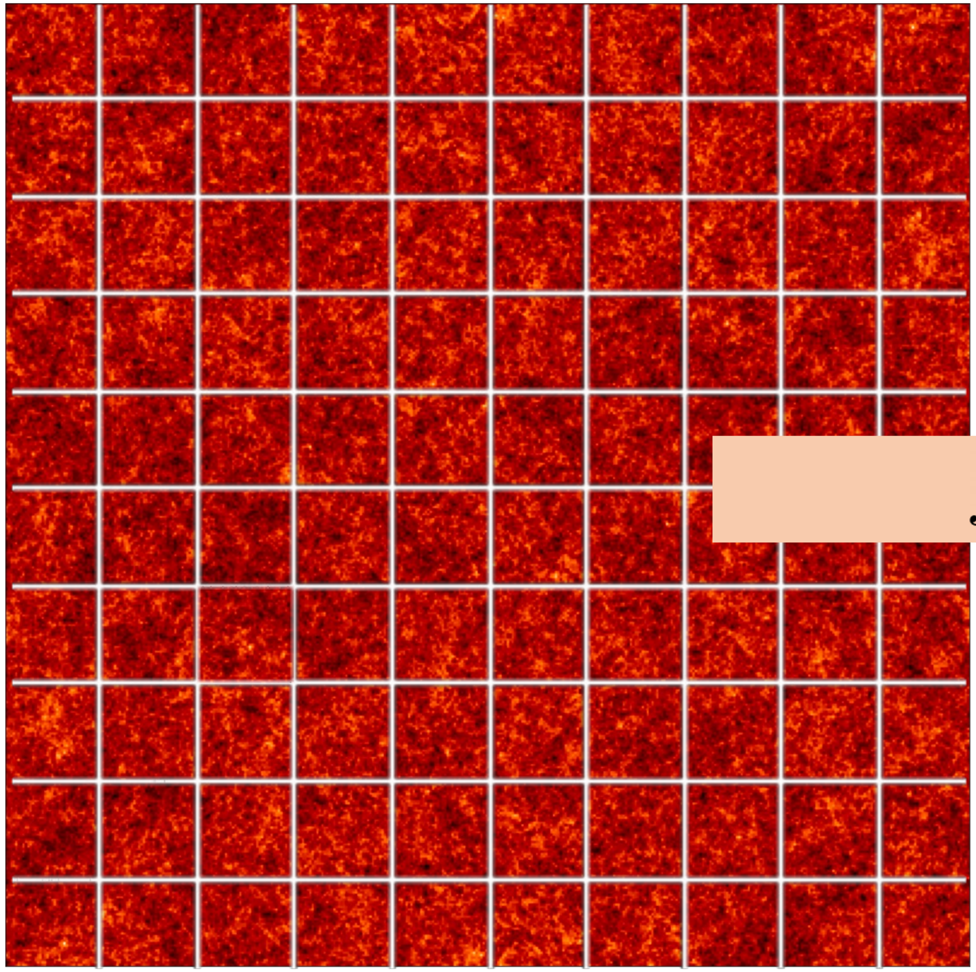
Kitaura & Ensslin (2007), Jasche & Wandelt (2012), Jasche & Lavaux (2017), Seljak et al. (2017), Schmidt et al. (2020), …

Forward modeling

INITIAL

s

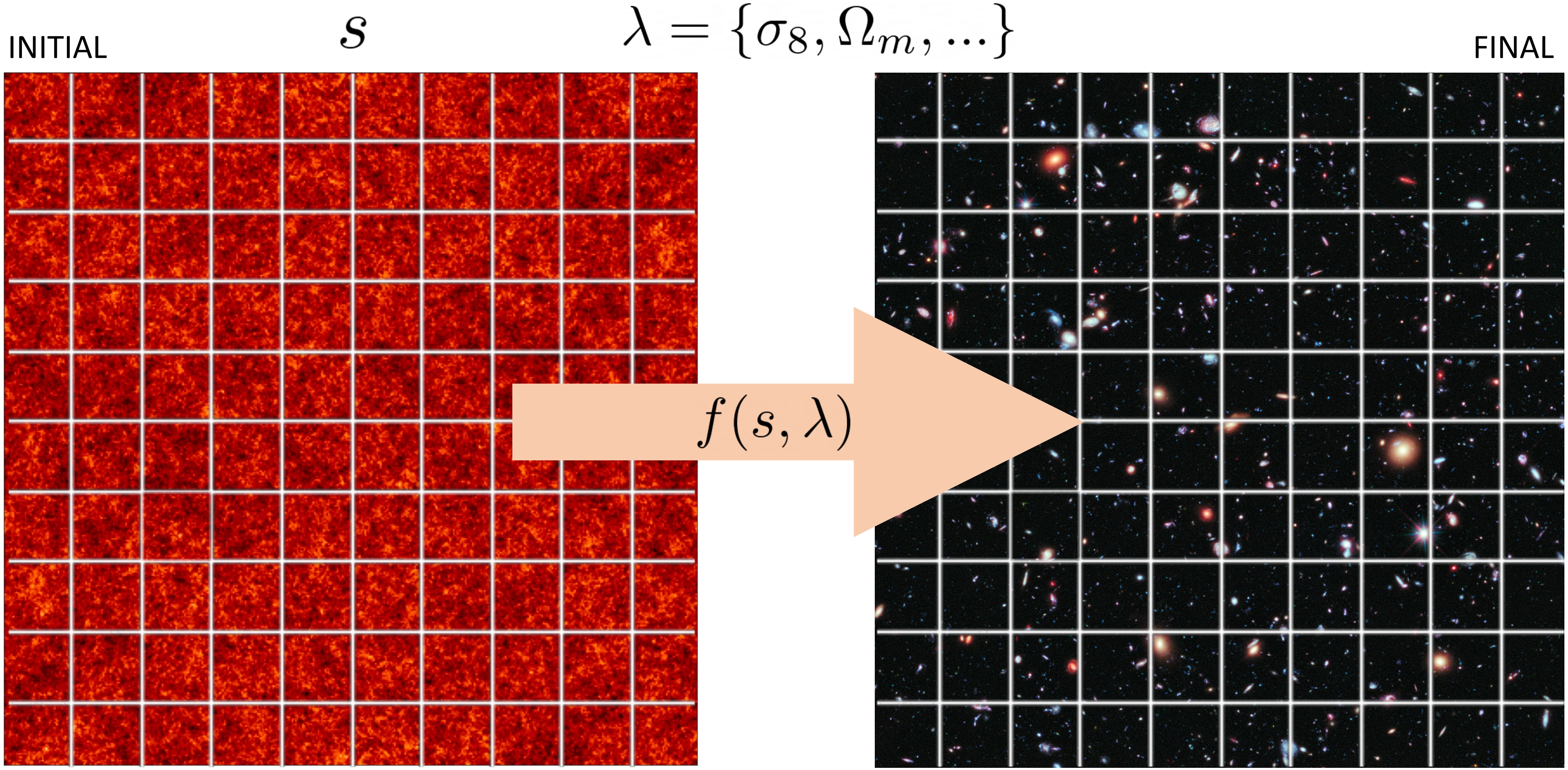
$\lambda = \{\sigma_8, \Omega_m, ...\}$



$f(s, \lambda)$

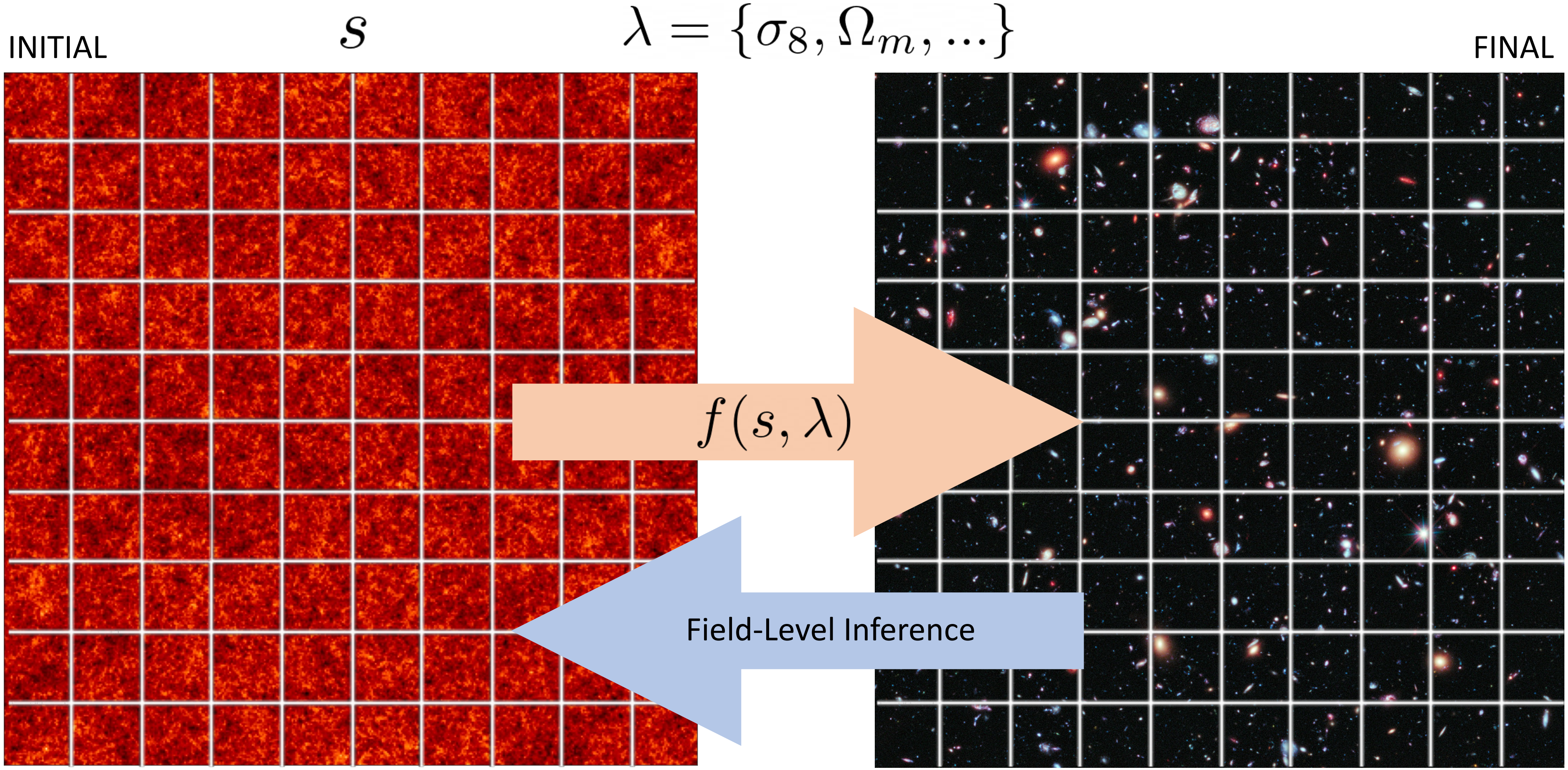
Kitaura & Ensslin (2007), Jasche & Wandelt (2012), Jasche & Lavaux (2017), Seljak et al. (2017), Schmidt et al. (2020), ...

Forward modeling



Kitaura & Ensslin (2007), Jasche & Wandelt (2012), Jasche & Lavaux (2017), Seljak et al. (2017), Schmidt et al. (2020), …

Forward modeling



Kitaura & Ensslin (2007), Jasche & Wandelt (2012), Jasche & Lavaux (2017), Seljak et al. (2017), Schmidt et al. (2020), …

Field-Level Inference

Given field data d and forward model f infer

initial modes s and cosmological parameters λ

$$-2\log P(s,\lambda|d) = \sum_{\vec{k}} \left[\frac{|d - f(s,\lambda)|^2}{N} + \frac{|s|^2}{\mathcal{P}(\lambda)} \right]_{\vec{k}}$$

posterior likelihood prior

Field-Level Inference

Given field data d and forward model f infer

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posterior likelihood prior

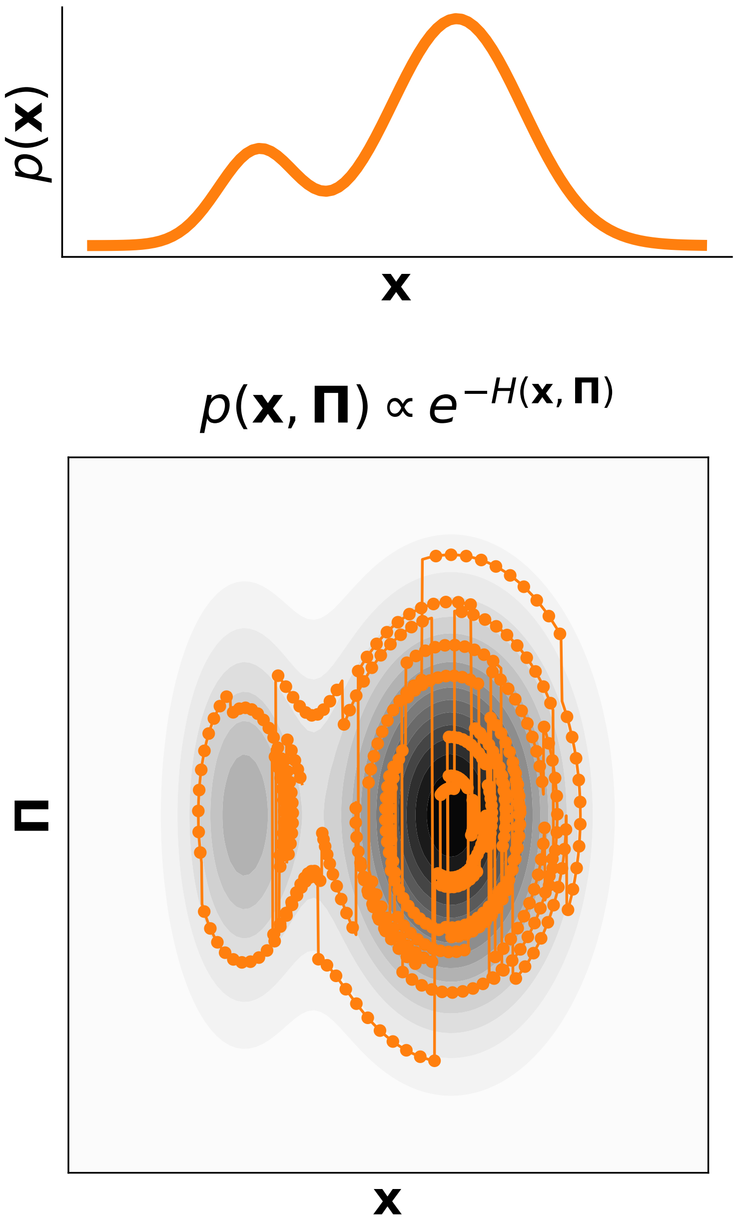
CHALLENGE: Multimillion dimensional parameter space!

Field-Level Inference

with

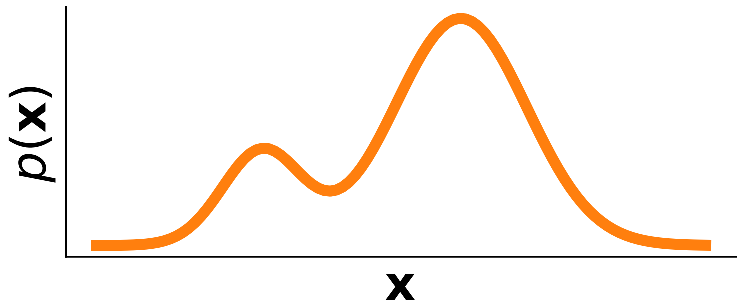
Microcanonical Langevin Monte Carlo

Canonical HMC

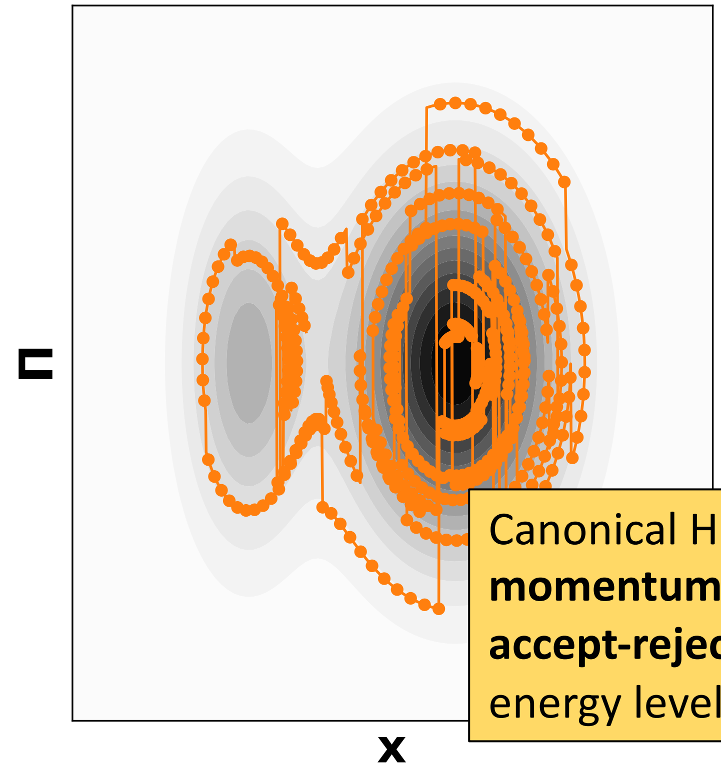


Robnik+2022

Canonical HMC



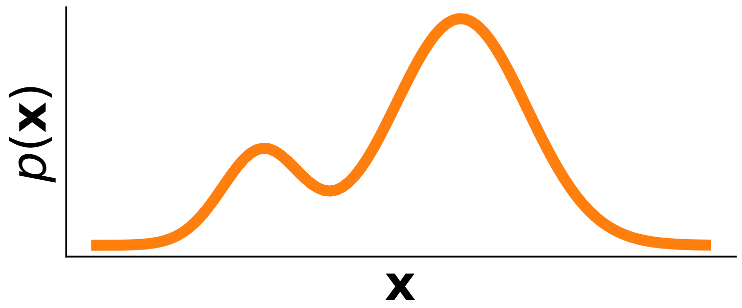
$$p(\mathbf{x}, \mathbf{\Pi}) \propto e^{-H(\mathbf{x}, \mathbf{\Pi})}$$



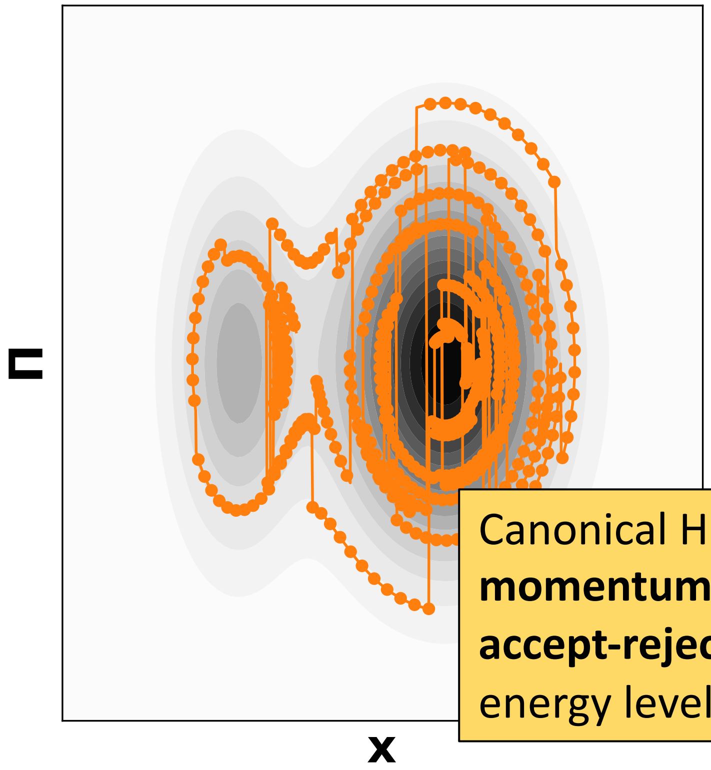
Canonical HMC requires **momentum resampling** and **accept-reject step** to change energy levels and converge

Robnik+2022

Canonical HMC

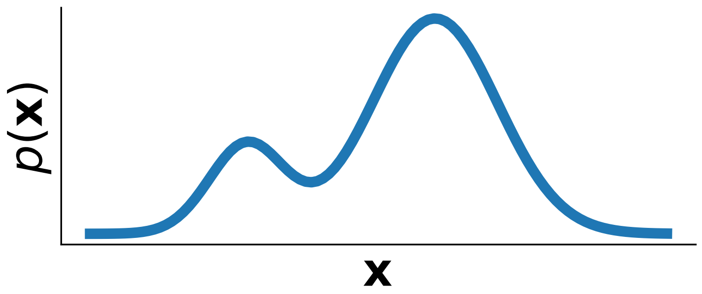


$$p(\mathbf{x}, \boldsymbol{\Pi}) \propto e^{-H(\mathbf{x}, \boldsymbol{\Pi})}$$

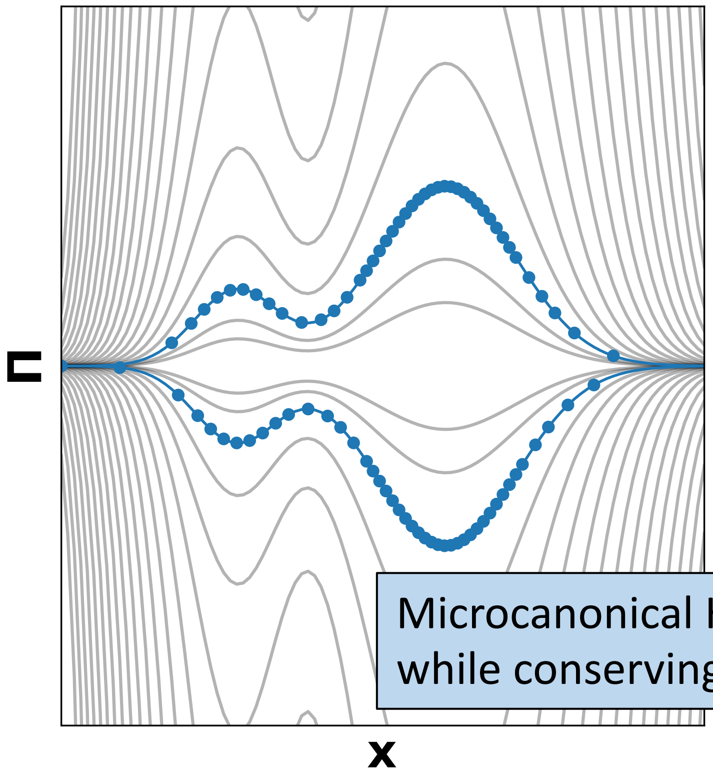


Canonical HMC requires **momentum resampling** and **accept-reject step** to change energy levels and converge

Microcanonical HMC



$$p(\mathbf{x}, \boldsymbol{\Pi}) \propto \delta(H(\mathbf{x}, \boldsymbol{\Pi}) - E)$$



Microcanonical HMC converges while conserving energy

Robnik+2022

Microcanonical Hamiltonian Monte Carlo

$$dz = u\,dt$$

$$du = -\boxed{(d-1)^{-1}(1 - uu^T)}\nabla \mathcal{L}(z)$$

MCHMC

Robnik+2022

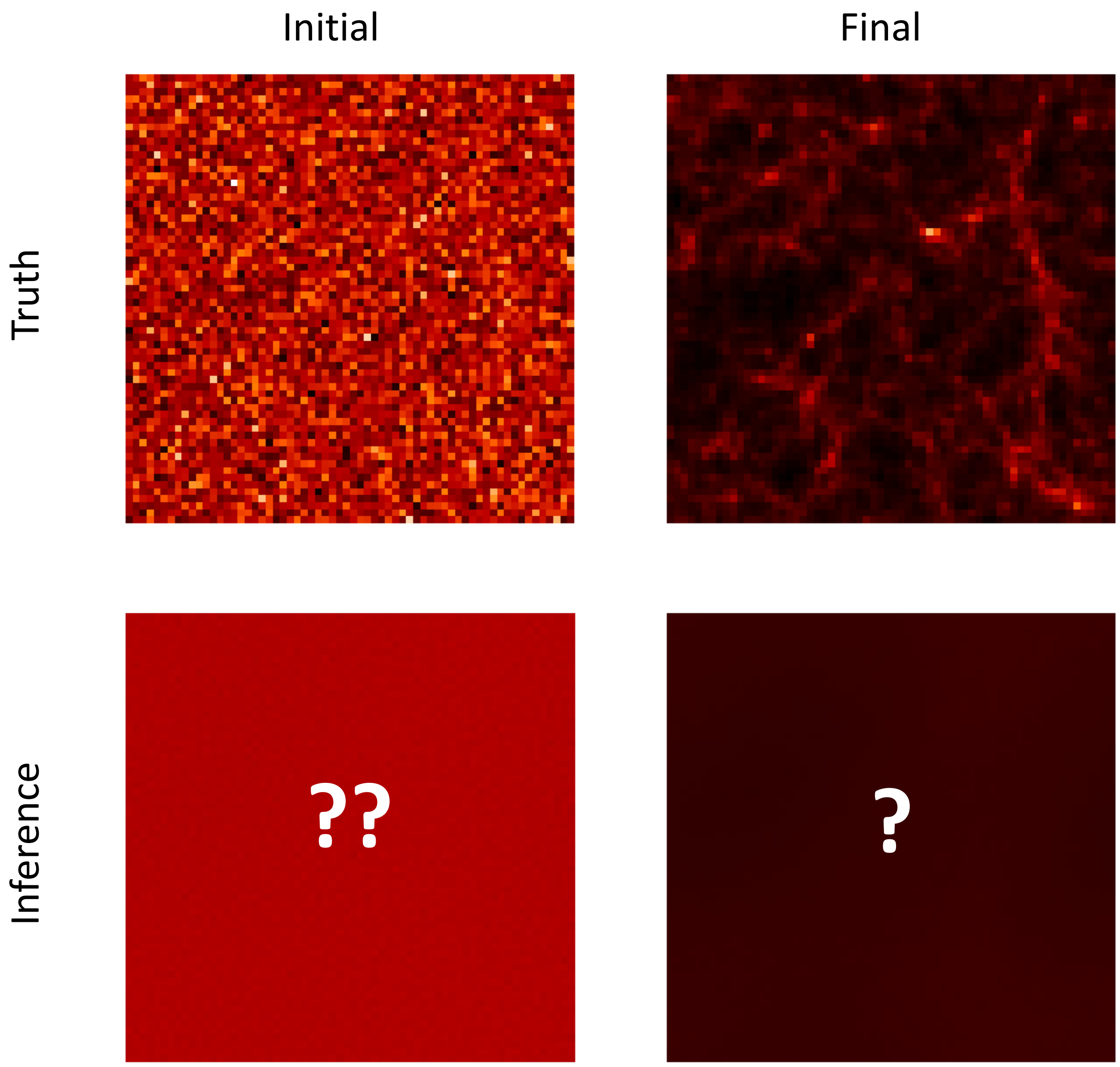
Microcanonical Langevin Monte Carlo

$$dz = u\,dt$$
$$du = -\underbrace{(d-1)^{-1}(1-uu^T)}_{\text{MCHMC}}[\nabla\mathcal{L}(z)\underbrace{+\eta\,dW}_{\text{MCLMC}}]$$

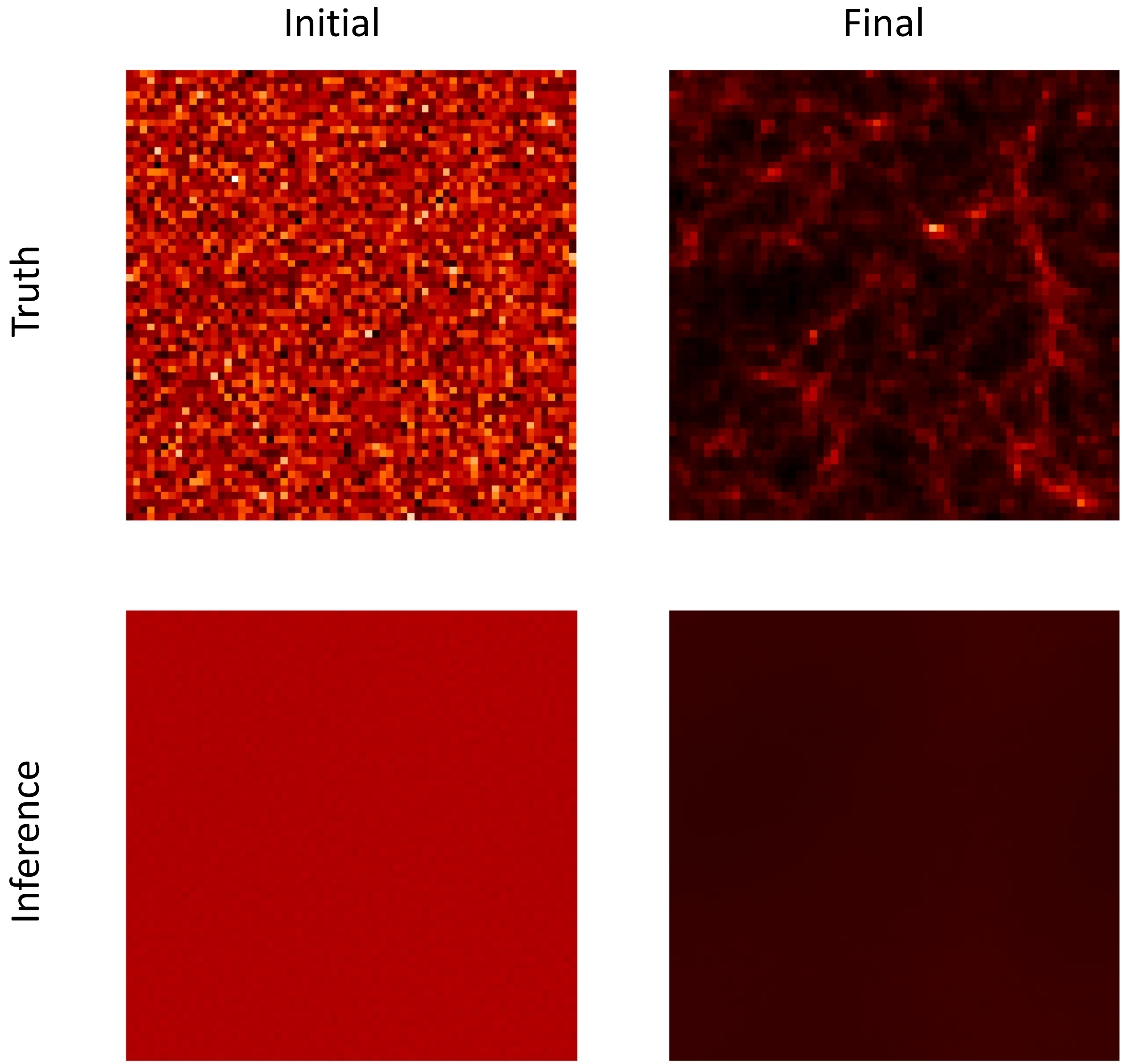
Improve ergodicity by including Langevin-like stochastic term

Robnik+2022

Field-Level Inference *with* Microcanonical Langevin Monte Carlo



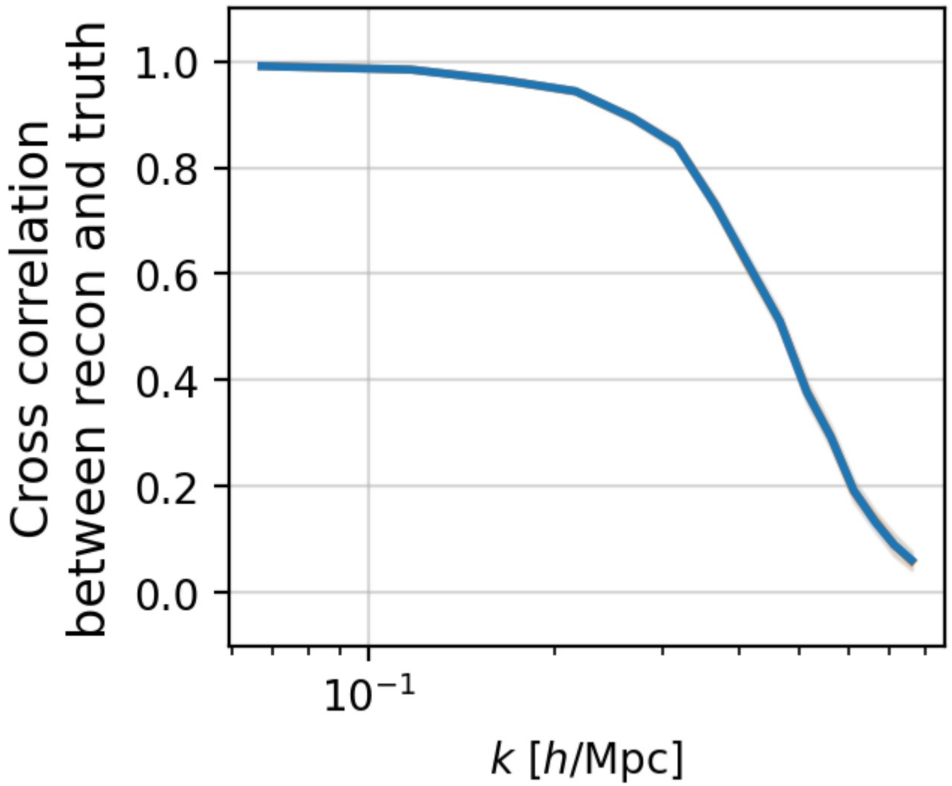
Bayer, Seljak, Modi (2023)

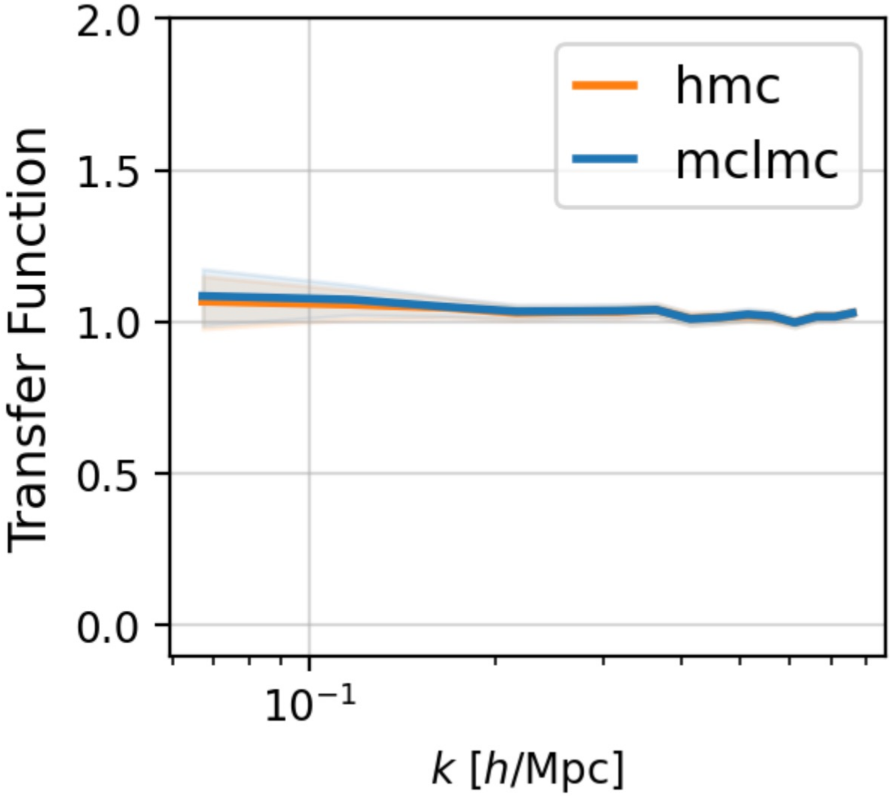


Bayer, Seljak, Modi (2023)

Samples of Initial Modes

d = $32^3 + 2 = 32{,}770$

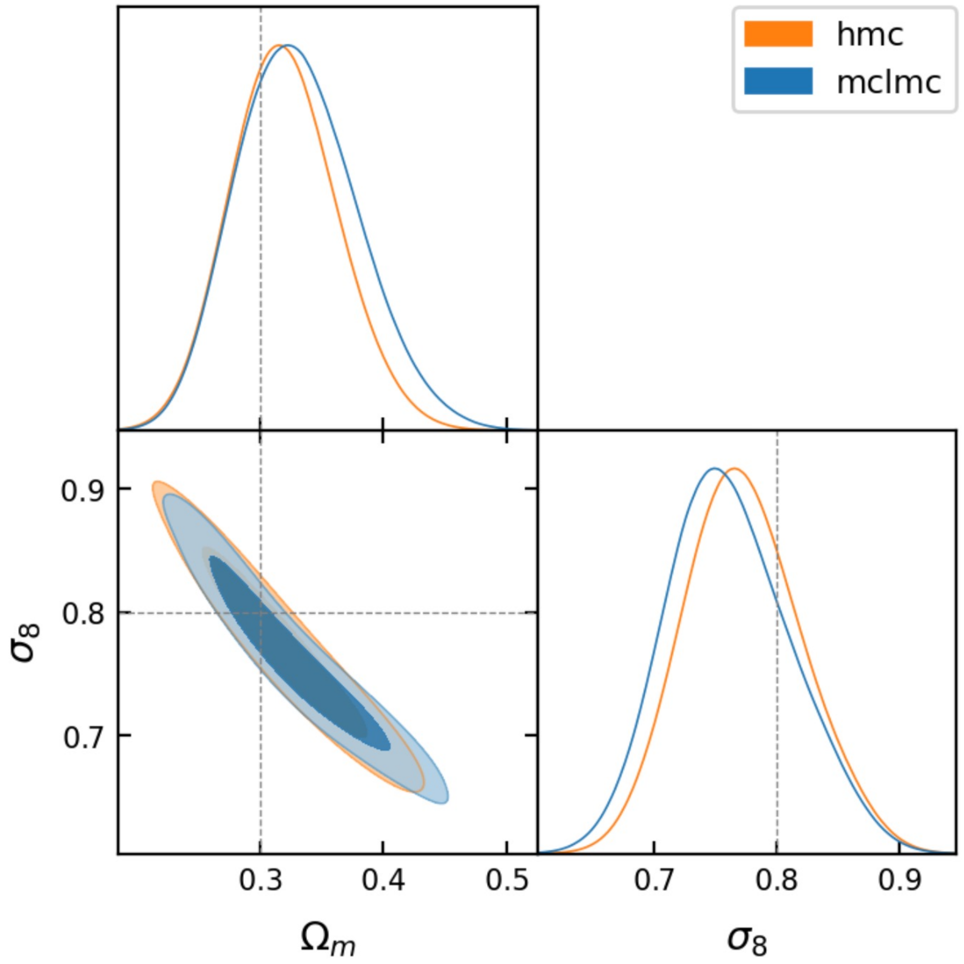




Bayer, Seljak, Modi (2023)

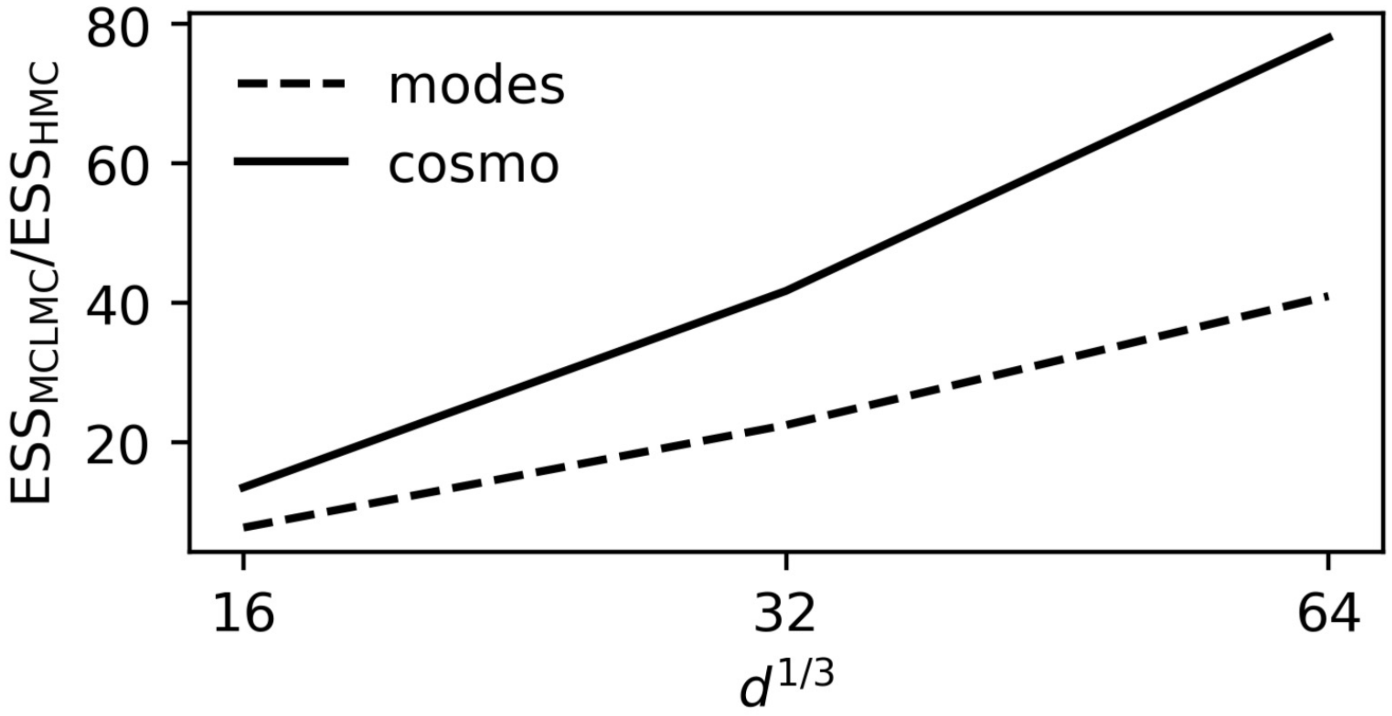
Samples of Cosmological Parameters

$d = 32^3 + 2 = 32{,}770$



Bayer, Seljak, Modi (2023)

Efficiency improves with dimensionality!



Bayer, Seljak, Modi (2023)

Summary

Neutrino mass from cosmology

Simulation: Bayer, Banerjee, Feng [2007.13394]

Fisher Analysis: Bayer, Villaescusa-Navarro, et al. [2102.05049]

Fake vs: Bayer, Banerjee, Seljak [2108.04215]

Void Shape: Bayer, Liu, et al. [2405.12302 , **today!**]

The HalfDome Simulations [in prep]

Super-Sample Covariance: Bayer, Liu, et al. [2210.15647]

Field-level inference

Microcanonical MC: Bayer, Seljak, Modi [2307.09504]

Joint Densities + Velocities: Bayer, Modi, Ferraro [2210.15649]

Thank you! http://adrianbayer.github.io

No Time ☹

Look-elsewhere effect

Theory: Bayer, Seljak [2007.13821]

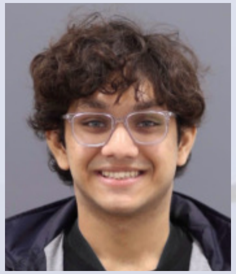
Theory: Bayer, Seljak, Robnik [2108.06333]

BBH: Robnik, Bayer, Charisi, et al. [in prep]

What are CNNs learning?

Golshan, Bayer, Böhm [in prep]

Lahiry, Bayer, Villaescusa-Navarro [in prep]



Arnab Lahiry
Graduate Student
(FORTH)