Applications of weak-lensing mass maps in cosmology

Austin Peel (奧斯汀)

Outline

1. Introduction to mass mapping
2. Inversion techniques
3. Peak statistics in cosmology
4. Distinguishing cosmological models
5. Summary

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Gravitational lensing

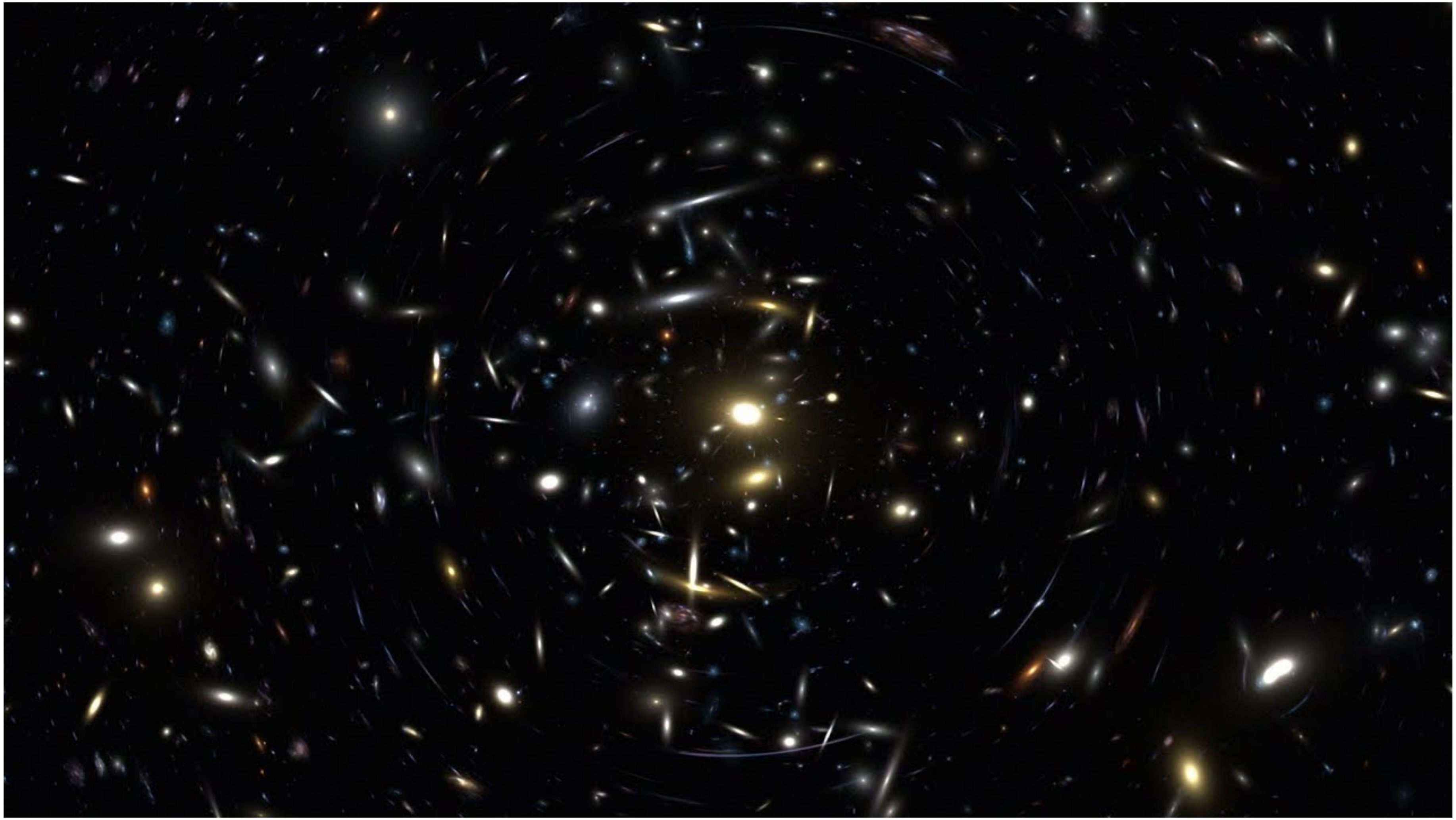


Image credit : NASA

Gravitational lensing

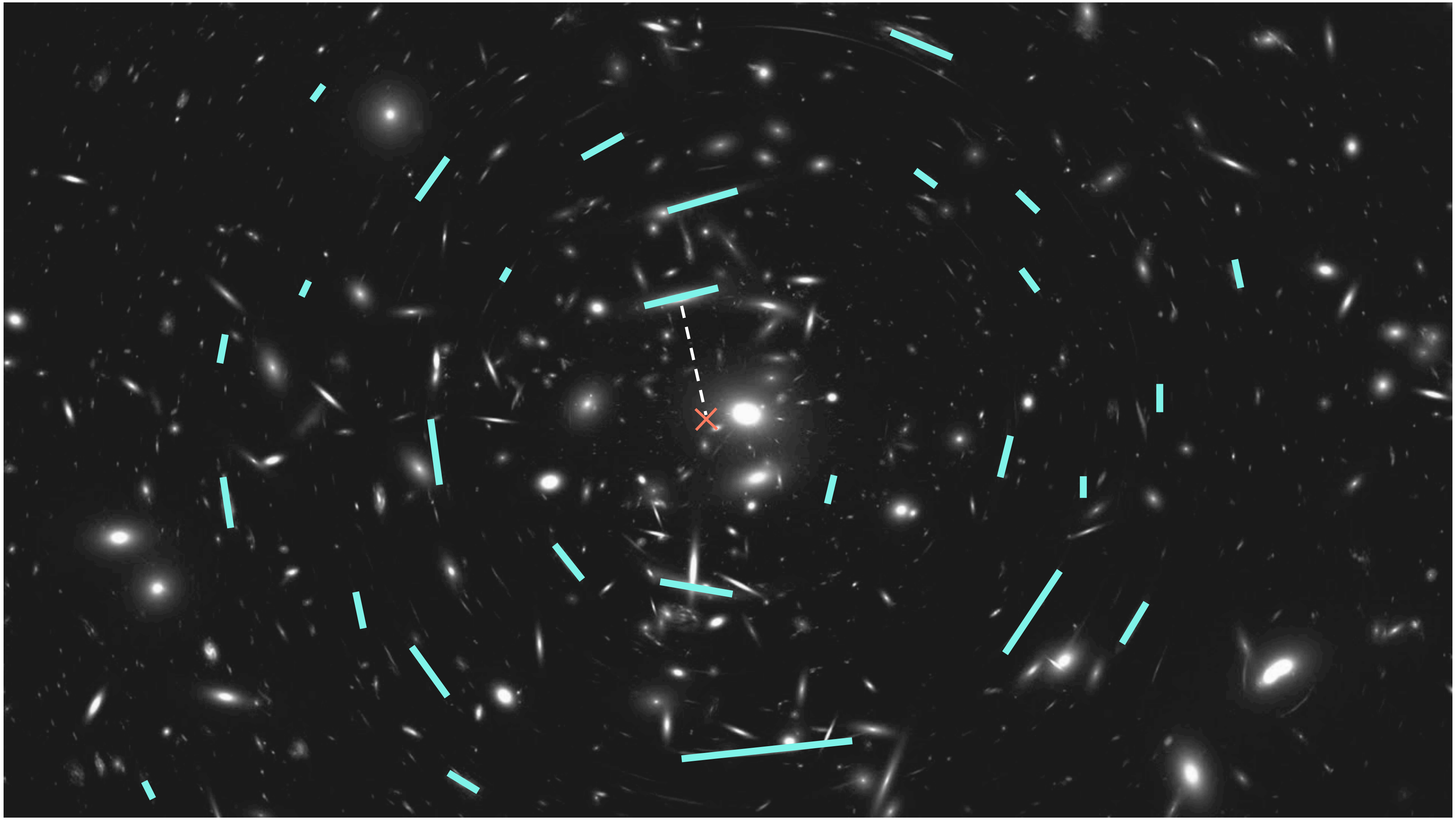


Image credit : NASA

Gravitational lensing

Image credit : NASA

Mass mapping

Main idea

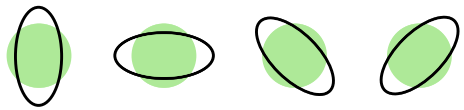
Reconstruct the projected mass density in a region of sky using measurements of slight galaxy shape distortions (weak lensing)

Applications

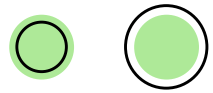
- probe matter distribution of the universe
- constrain cosmological parameters
- study substructure in galaxy clusters
- measure group and cluster masses
- distinguish among competing cosmological models

Mass mapping

galaxy shape catalog

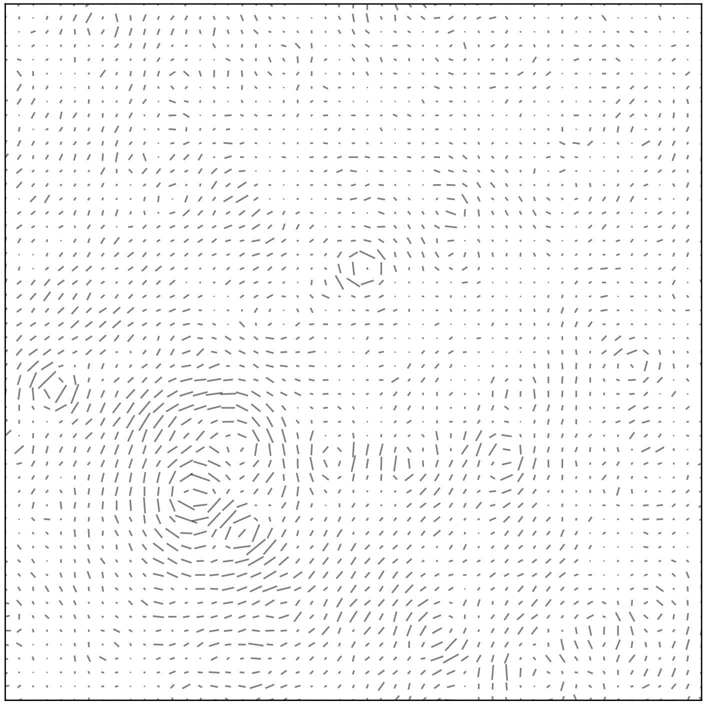


$$\gamma = \gamma_1 + i\gamma_2$$

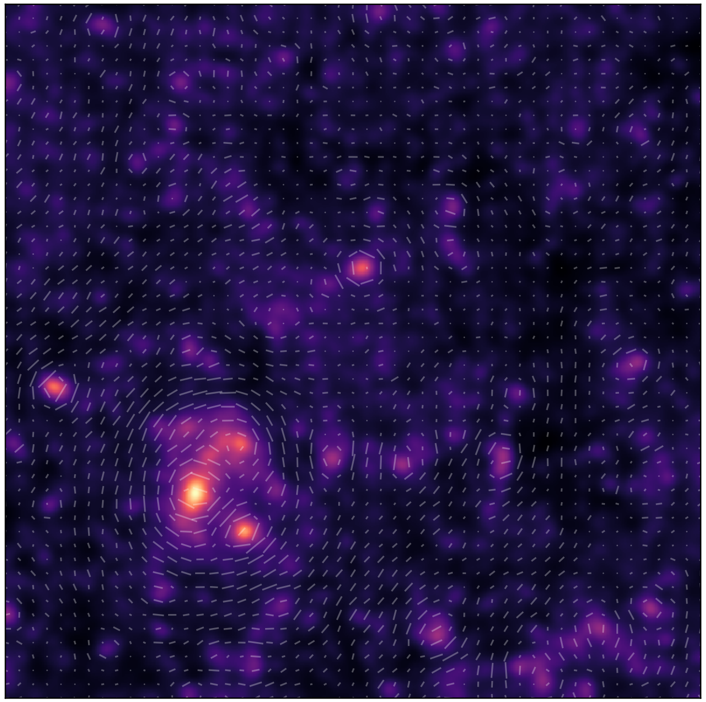


$$\kappa$$

shear $\gamma(\vec{\theta})$



convergence $\kappa(\vec{\theta})$



Outline

Shear inversion

Shear and convergence are derivable from a lensing potential $\psi(\boldsymbol{\theta})$

$$\gamma_1 = \frac{1}{2}\left(\partial_1^2 - \partial_2^2\right)\psi \qquad \gamma_2 = \partial_1\partial_2\psi \qquad \kappa = \frac{1}{2}\left(\partial_1^2 + \partial_2^2\right)\psi$$

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Kaiser & Squires (1993)

$$\kappa(\boldsymbol{\theta}) - \kappa_0 = \frac{1}{\pi}\int_{\mathcal{R}^2} \mathrm{d}^2\theta'\,\mathcal{D}^*(\boldsymbol{\theta}-\boldsymbol{\theta}')\,\gamma(\boldsymbol{\theta}')$$

$$\mathcal{D}(\boldsymbol{\theta}) = \frac{\theta_2^2 - \theta_1^2 - 2\mathrm{i}\theta_1\theta_2}{|\boldsymbol{\theta}|^4}$$

easy in Fourier space

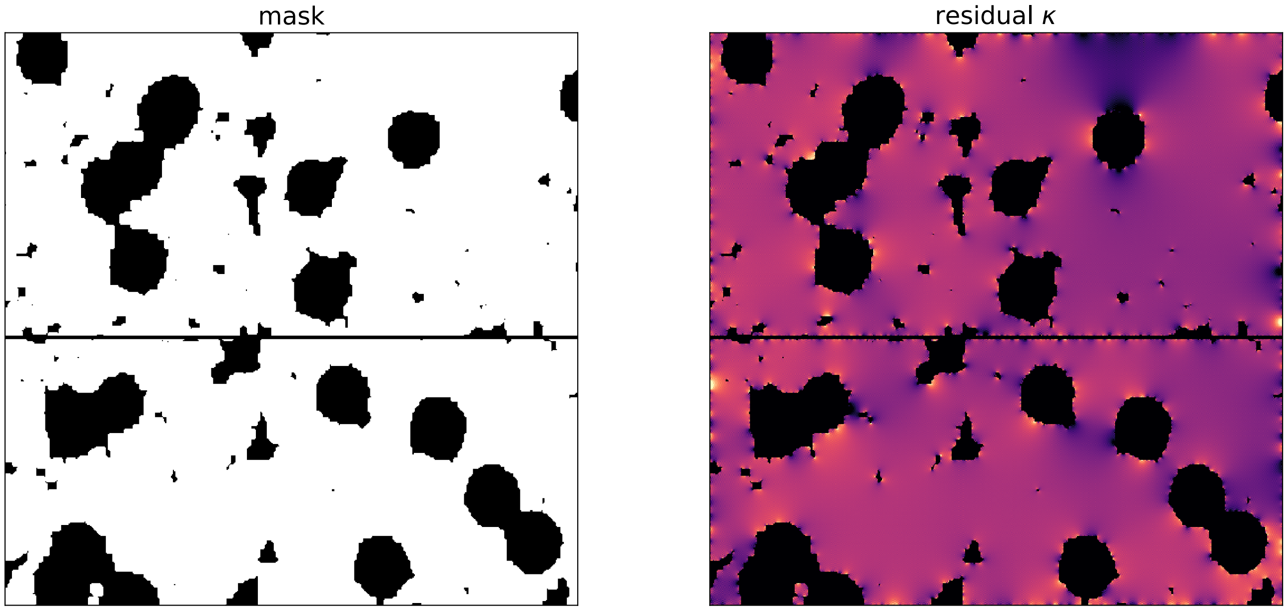
$$\hat{\kappa}(\boldsymbol{\ell}) = \hat{\mathcal{D}}^*(\boldsymbol{\ell})\,\hat{\gamma}(\boldsymbol{\ell}) \qquad (\boldsymbol{\ell} \neq 0)$$

$$\hat{\mathcal{D}}(\boldsymbol{\ell}) = \frac{\ell_1^2 - \ell_2^2 + 2\mathrm{i}\ell_1\ell_2}{|\boldsymbol{\ell}|^2}$$

regularize shear values
to a grid and use FFTs !

Practical difficulties

- Shear measurements are discrete and irregularly sampled
- We don't actually measure shear but the reduced shear $g = \gamma/(1-\kappa)$
- Integration over a subset of $\mathbb{R}^2$ leads to border problems
- Data masks induce reconstruction errors
- Noisy data need filtering



(A few) alternatives / improvements

Direct

Seitz & Schneider '95

- Iterative scheme to address reduced shear nonlinearity

Seitz & Schneider '01

- Finite-field algorithm avoids integration over entire real plane

Curved Sky

- Spin-2 spherical harmonics on the sphere

Inverse

Entropy-regularized ML

- Maximum likelihood fit of a general lens model with entropic regularization

Lenstool [Jullo+ 2007]

- Mass-follows-light parametric modeling of galaxy clusters

GLIMPSE [Lanusse+ 2016]

- High-resolution mapping with multi-scale wavelet sparsity prior

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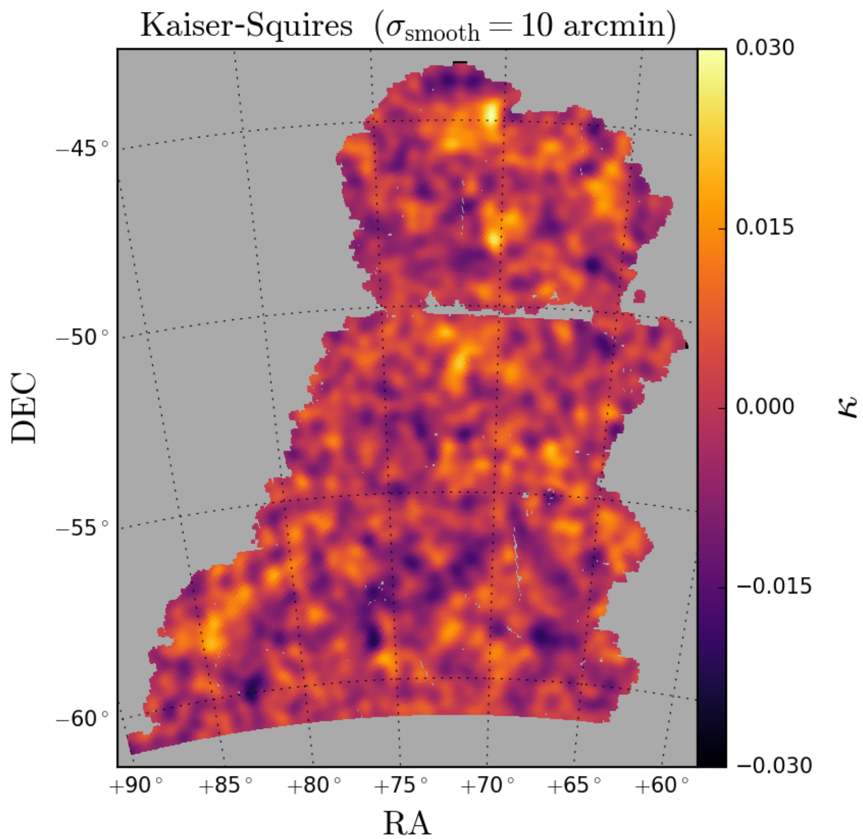
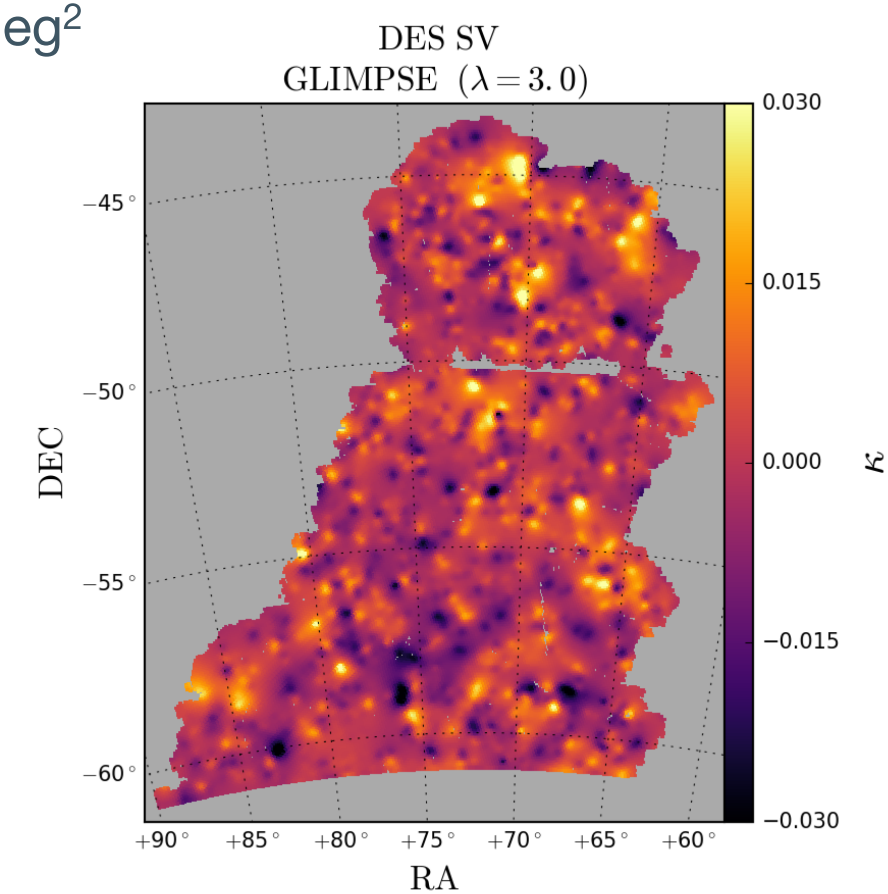
Glimpse2D on public DES SV data

139 deg^2

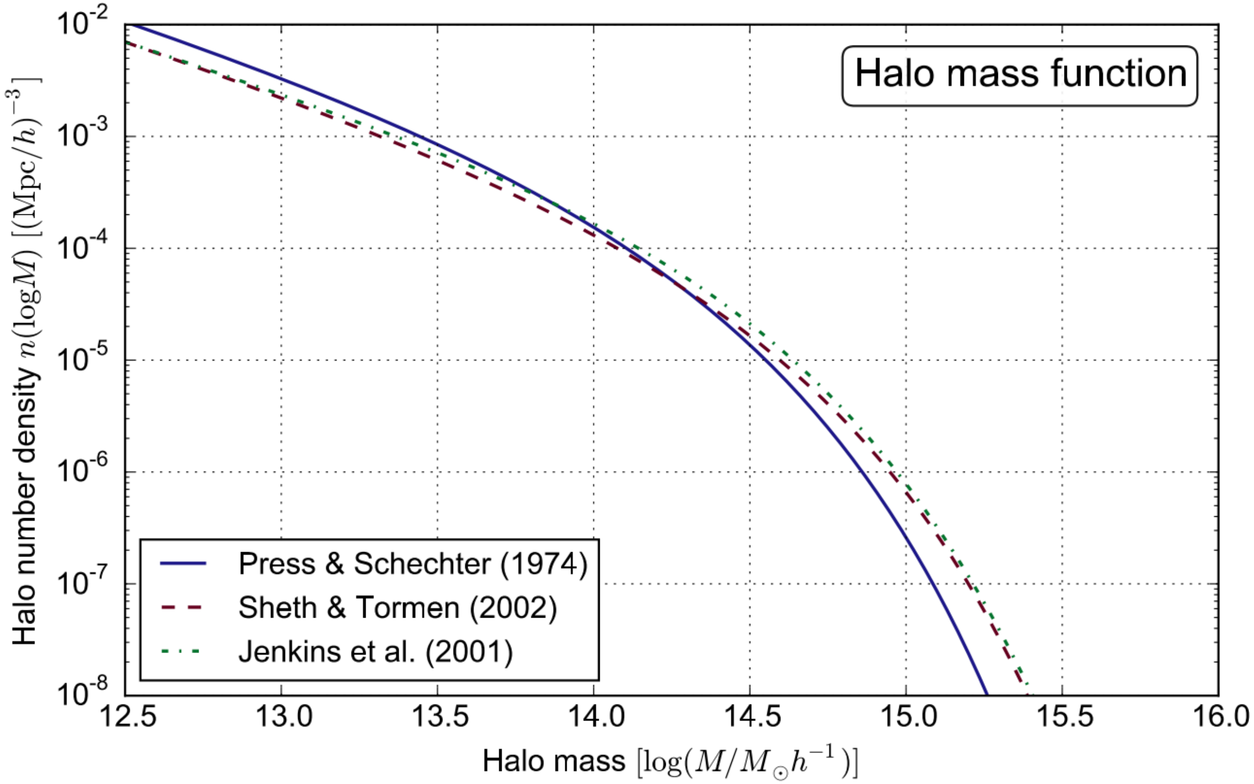




[N. Jeffrey et al. 2017, MNRAS 479, 2871]

Outline

Cosmology from peak counts

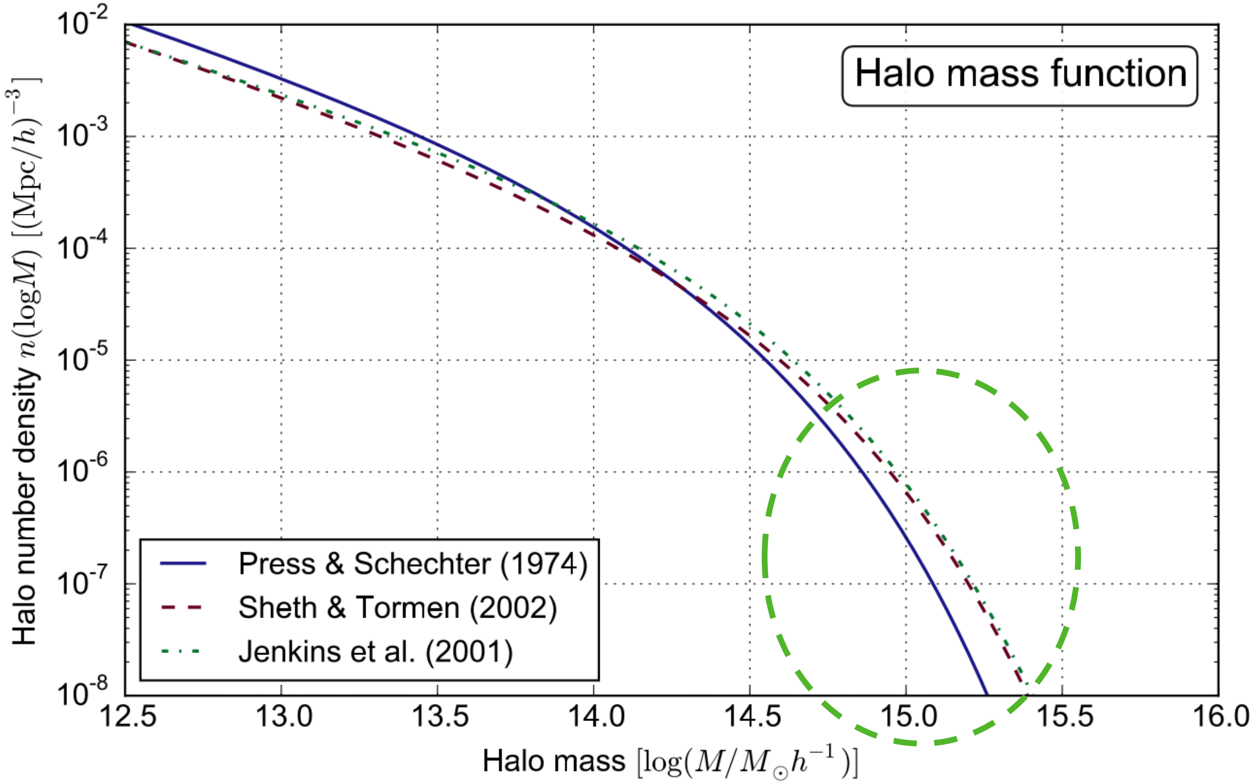


Peaks probe non-Gaussian information encoded by the nonlinear structure formation, which is a sensitive probe of cosmology

Complementary parameter constraints to shear 2-point correlation functions

Ω_m : amount of matter σ_8 : clustering amplitude

Cosmology from peak counts



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Ω_m : amount of matter

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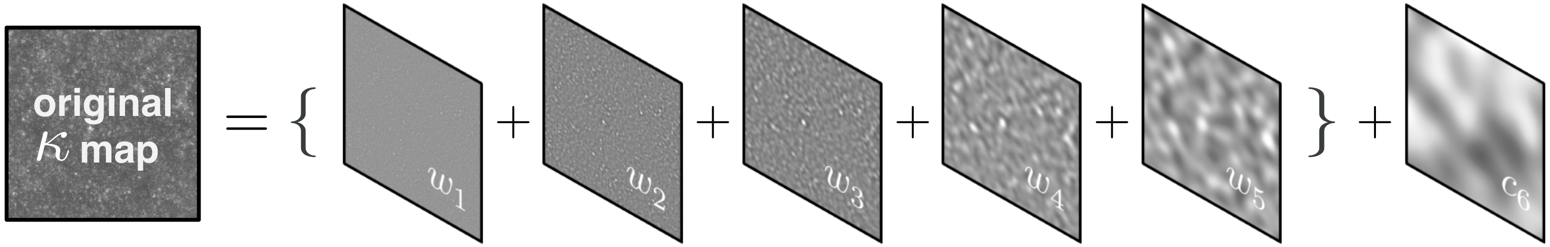
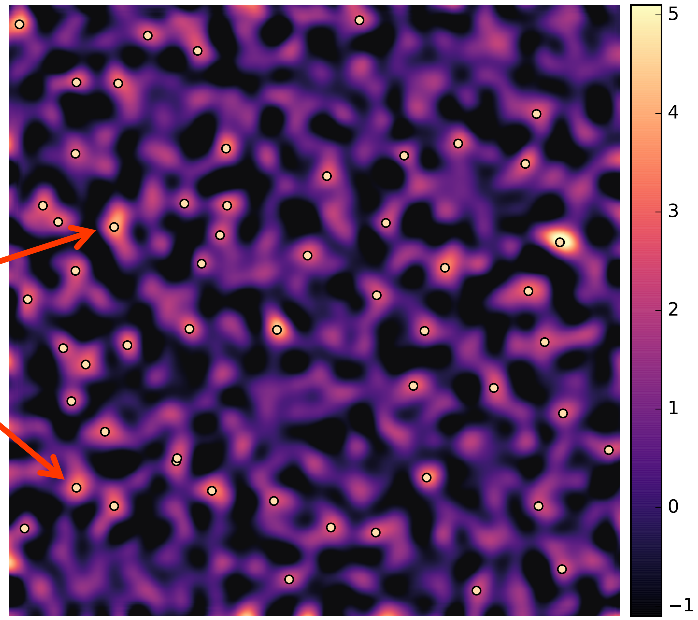
Peak detection

starlet transform

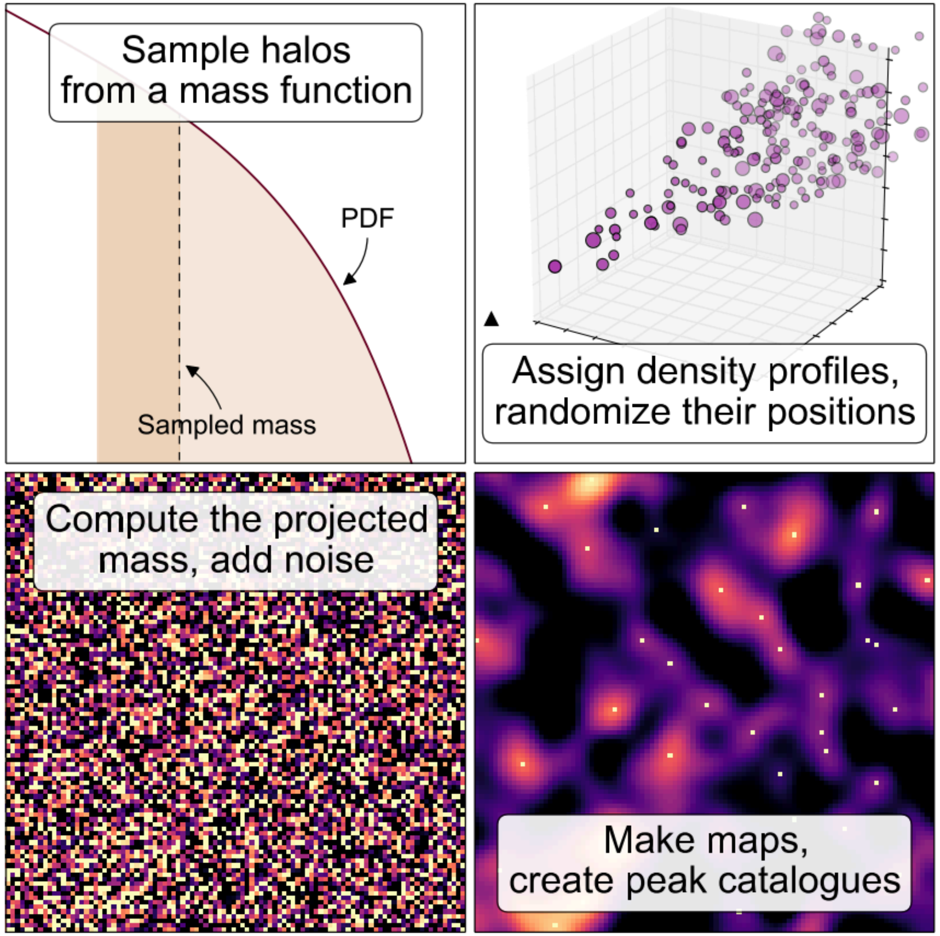


local maxima



[data vector of peak counts sorted by amplitude and scale]

Peak prediction model



Counts of **A**mplified **M**ass **E**levations from **L**ensing with **U**ltrafast **S**imulation

https://github.com/Linc-tw/camelus

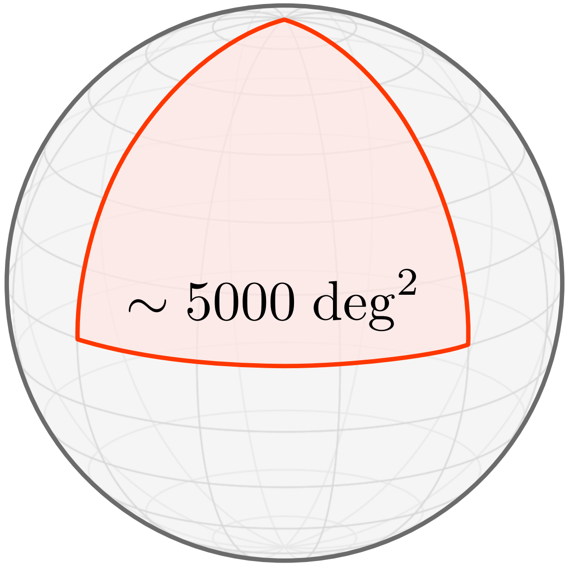
[C.-A. Lin & M. Kilbinger 2015, A&A 576, A24]
[C.-A. Lin & M. Kilbinger 2015, A&A **583**, A70]
[C.-A. Lin, M. Kilbinger, & S. Pires 2016, A&A 593, A88]

Assumptions

1. Diffuse / unbound matter does not contribute to peaks
2. Spatial correlation of halos does not impact peak counts

Testing CAMELUS on simulations

Extracted 186 patches
of $5 \times 5\ \mathrm{deg}^2$

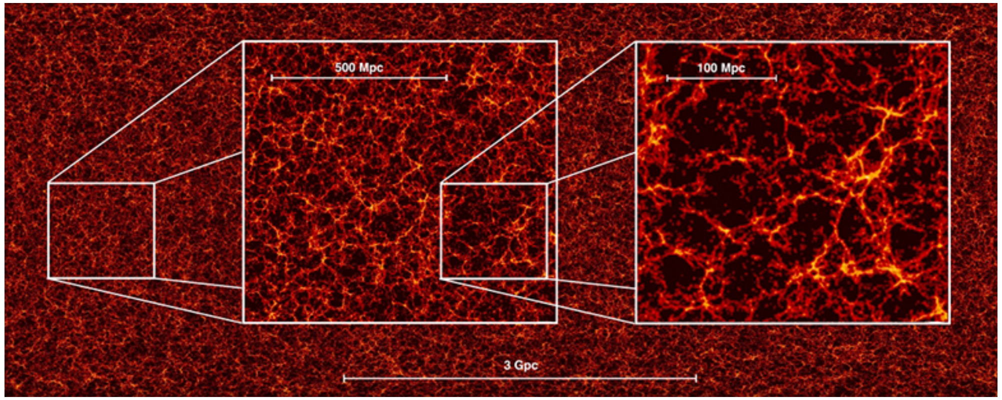


$0^\circ < \mathrm{RA} < 90^\circ$
$0^\circ < \mathrm{Dec} < 90^\circ$
$z < 1.4$

CAMELUS parameter settings

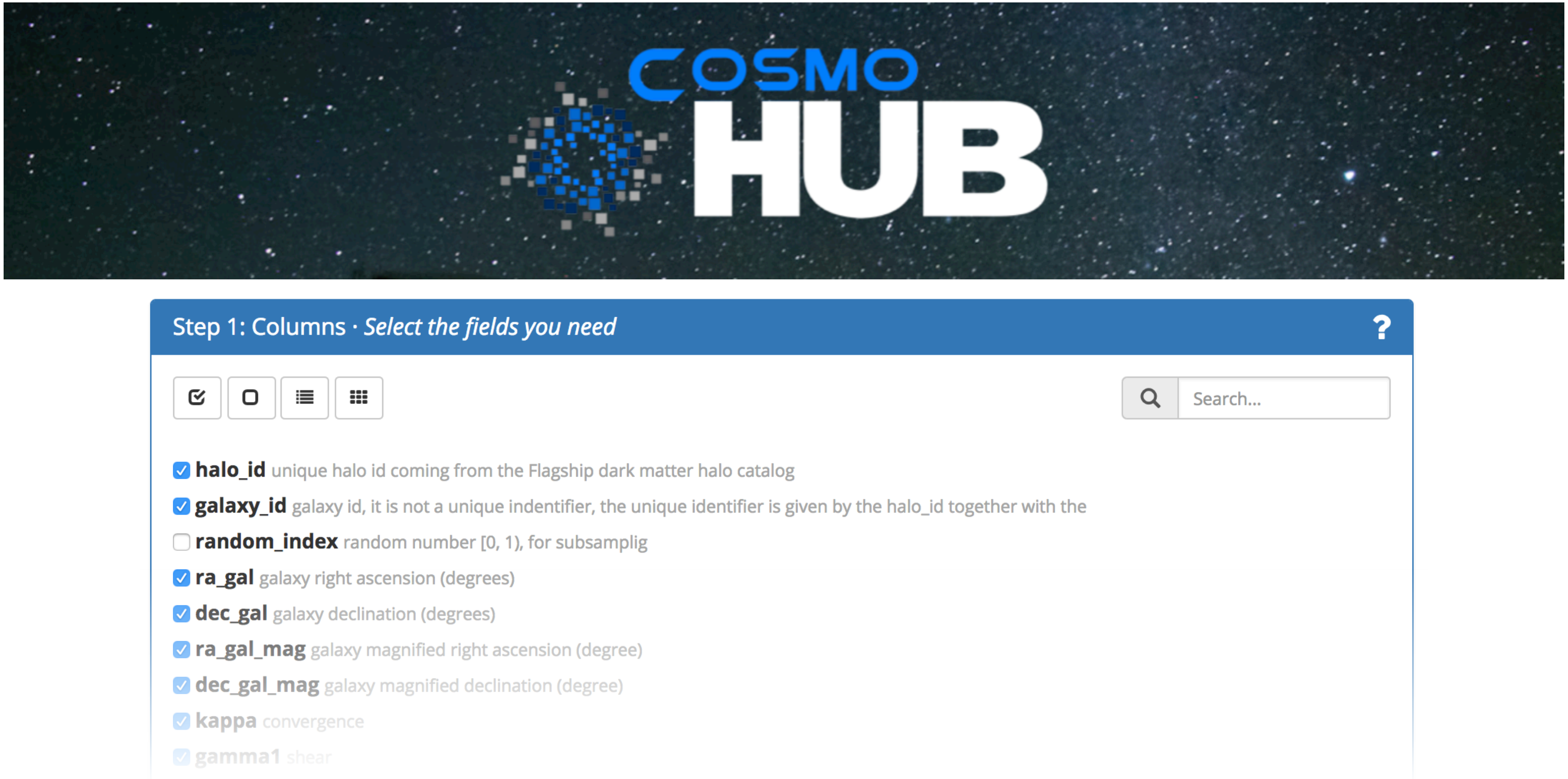
Description	Symbol	Value
Dimensionless Hubble param.	h_{100}	0.70
Baryon density	Ω_b	0.044
Spectral index	n_s	0.95
DE linear EOS param.	w_1	0.0
NFW inner slope	α	1.0
M–c relation param.	c_0	9.0
M–c relation param.	β	0.13
Galaxy density $[\mathrm{arcmin}^{-2}]$	n_gal	27
Source ellipticity st. dev.	σ_ϵ	0.43

MICE

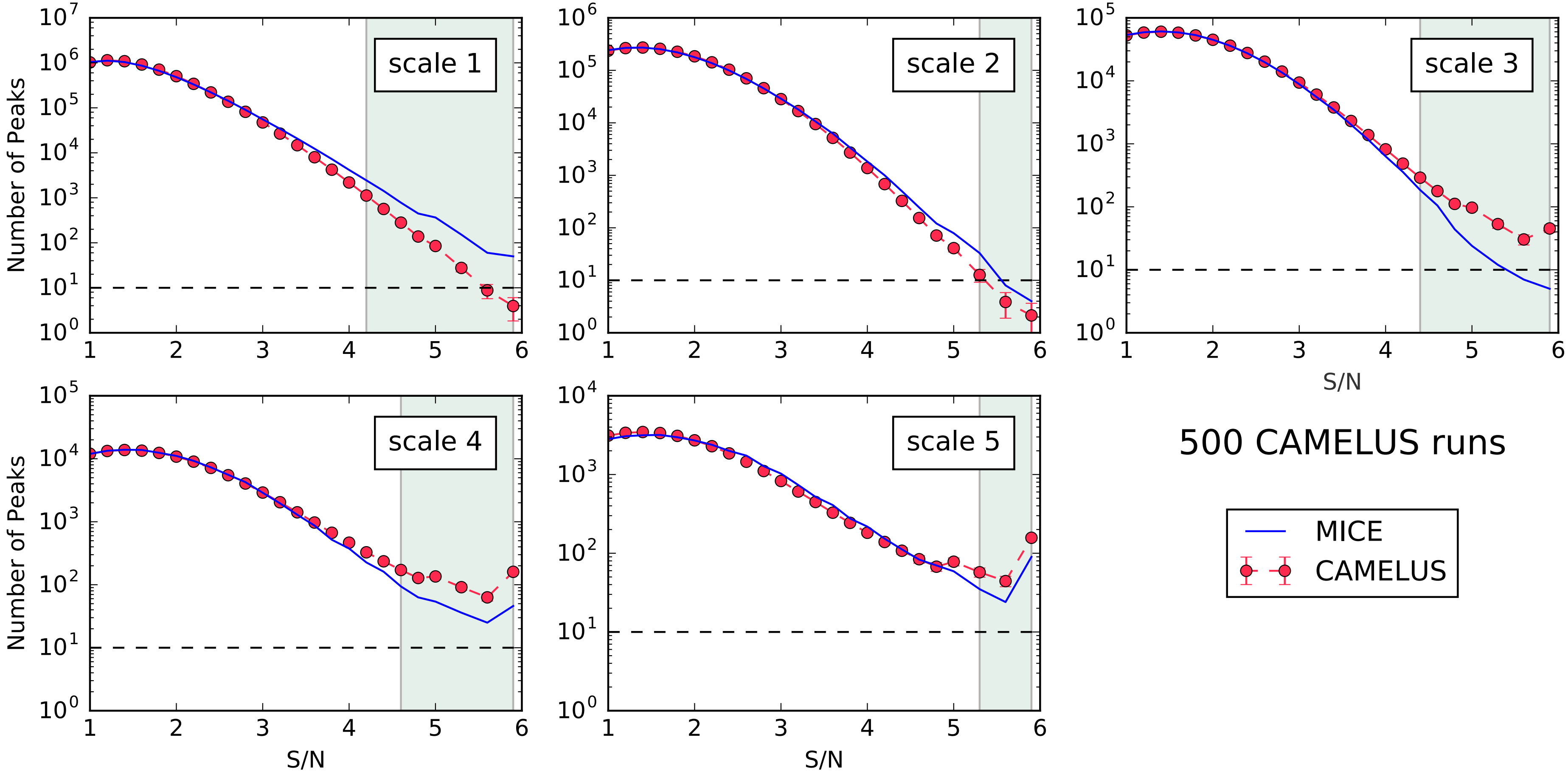


MICEv2 Euclid-like galaxy mock

https://cosmohub.pic.es/

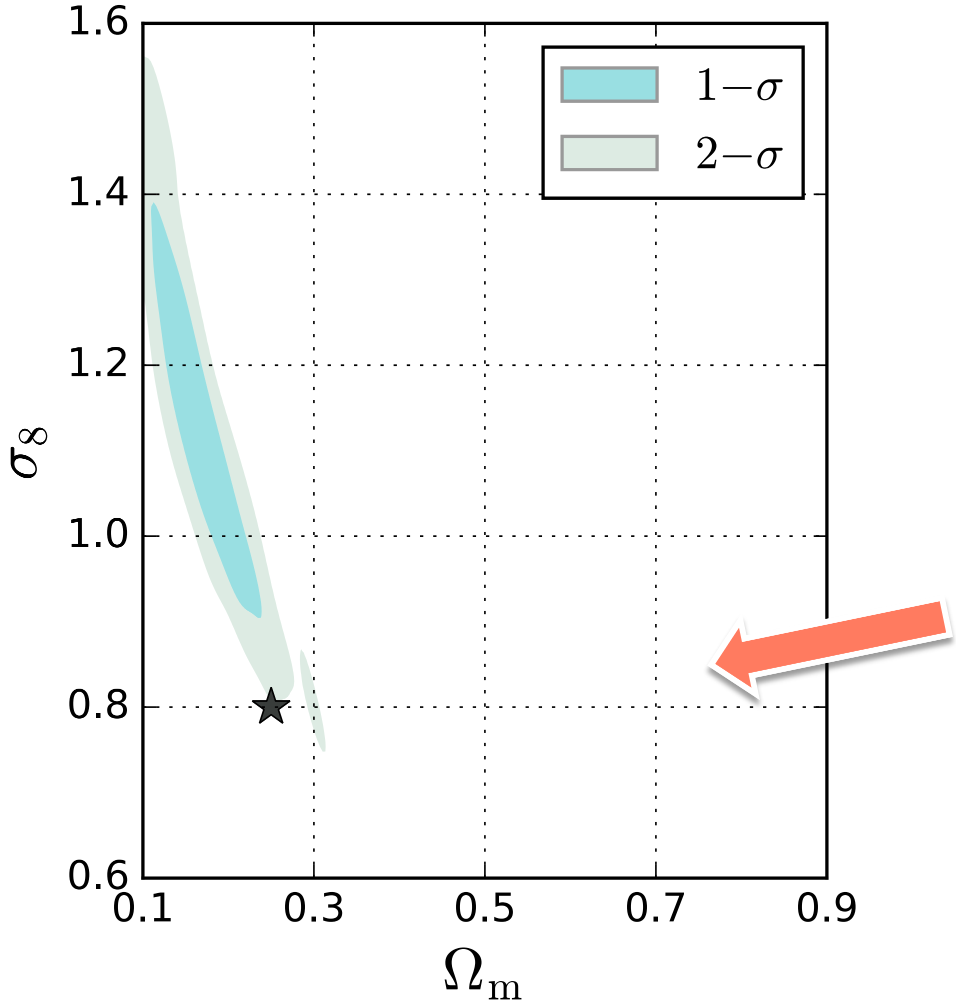


CAMELUS vs MICEv2



[A. Peel, C.-A. Lin, F. Lanusse et al. 2017, A&A **599**, A79]

Results : Parameter constraints with ABC

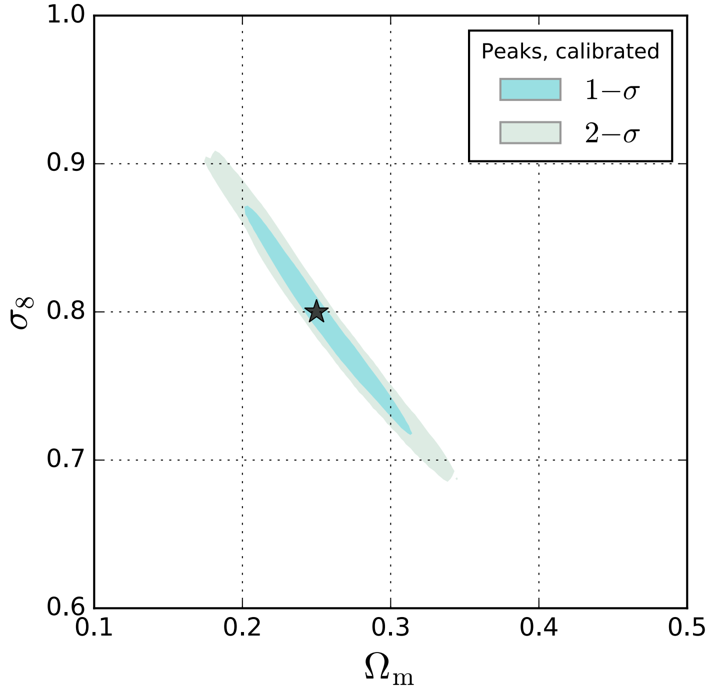


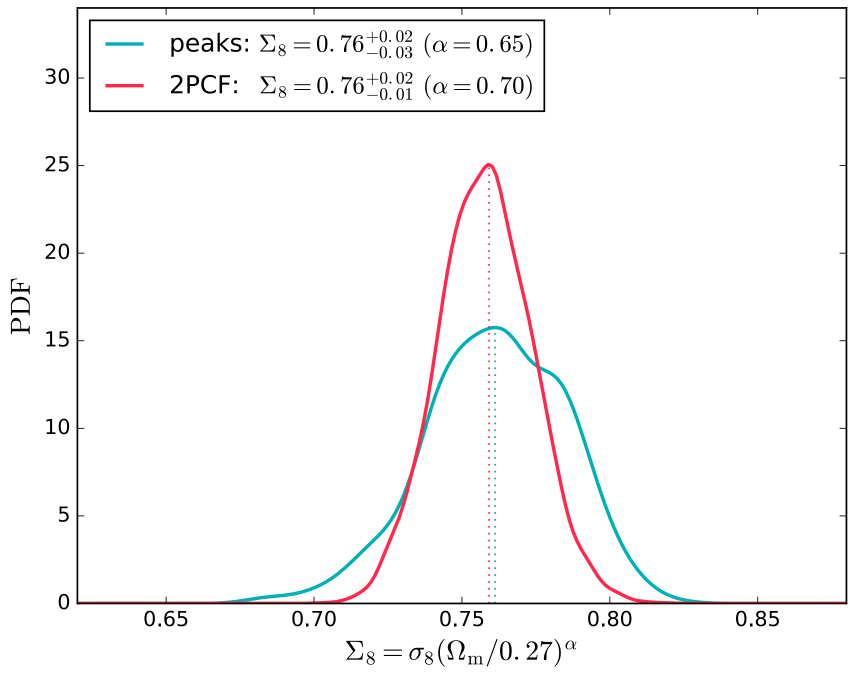
(Approximate Bayesian Computation)

Appears to have missed the mark…

[A. Peel, C.-A. Lin, F. Lanusse et al. 2017, A&A **599**, A79]

Results : Parameter constraints with ABC





Take-home message

Before CAMELUS can be applied to real data of this size, its systematics need to be carefully studied and corrected for : (1) lack of halo clustering, (2) modeling of halo concentration, and (3) possible limitations of NFW (spherical) profiles.

[A. Peel, C.-A. Lin, F. Lanusse et al. 2017, A&A **599**, A79]

Outline

Motivation

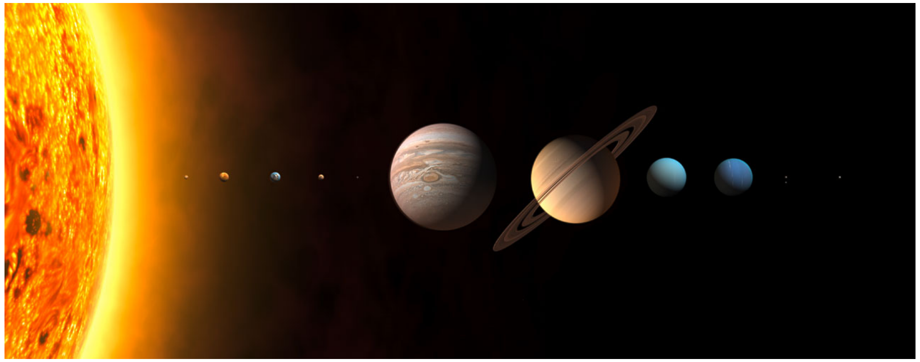
Dark energy is still a (big) problem.

If a **non-standard gravity** universe is masquerading as ΛCDM, can we find out using **weak lensing** ?

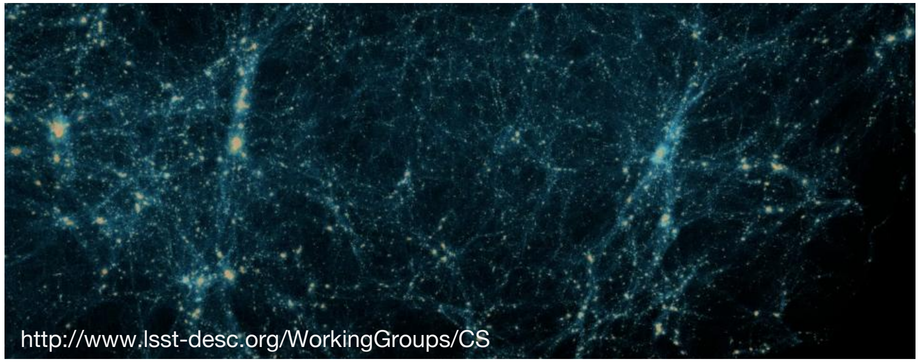
Reference

A. Peel et al., in press A&A (2018) [arXiv:1805.05146]

(✔) GR works very well here



many orders of magnitude



(?) we aren't sure about here

A good MG model should…

Change the fundamental gravitational interaction only on **large scales** (screening mechanism)

Result in a cosmology **close to ΛCDM** in the high-redshift regime (CMB constraints)

Provide late-time cosmic **acceleration**

Ricci scalar

Standard gravity (Einstein, 1915)

$$S = \frac{1}{16\pi G} \int \mathrm{d}^4x \sqrt{-g}\, R + S_m$$

One way to modify gravity

$$S = \frac{1}{16\pi G} \int \mathrm{d}^4x \sqrt{-g}\, [R + f(R)] + S_m$$

Hu-Sawicki model (2007)

$$f(R) \equiv -m^2 \frac{c_1 (R/m^2)^n}{c_2 (R/m^2)^n + 1} \qquad (n > 0)$$

Choose c_1 / c_2 to give a desired background (ΛCDM) evolution.

⇨ 2 parameters :

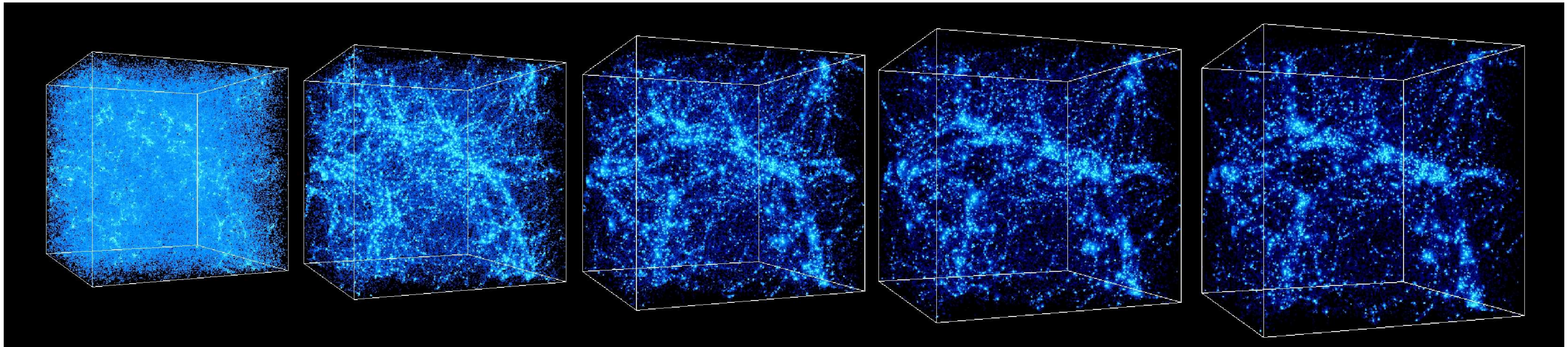
$$f_{R0} \equiv \frac{\mathrm{d}f}{\mathrm{d}R}(z = 0) \qquad n = 1$$

DUSTGRAIN-*pathfinder* simulations

C. Giocoli et al. 2018 [arXiv:1806.04681]

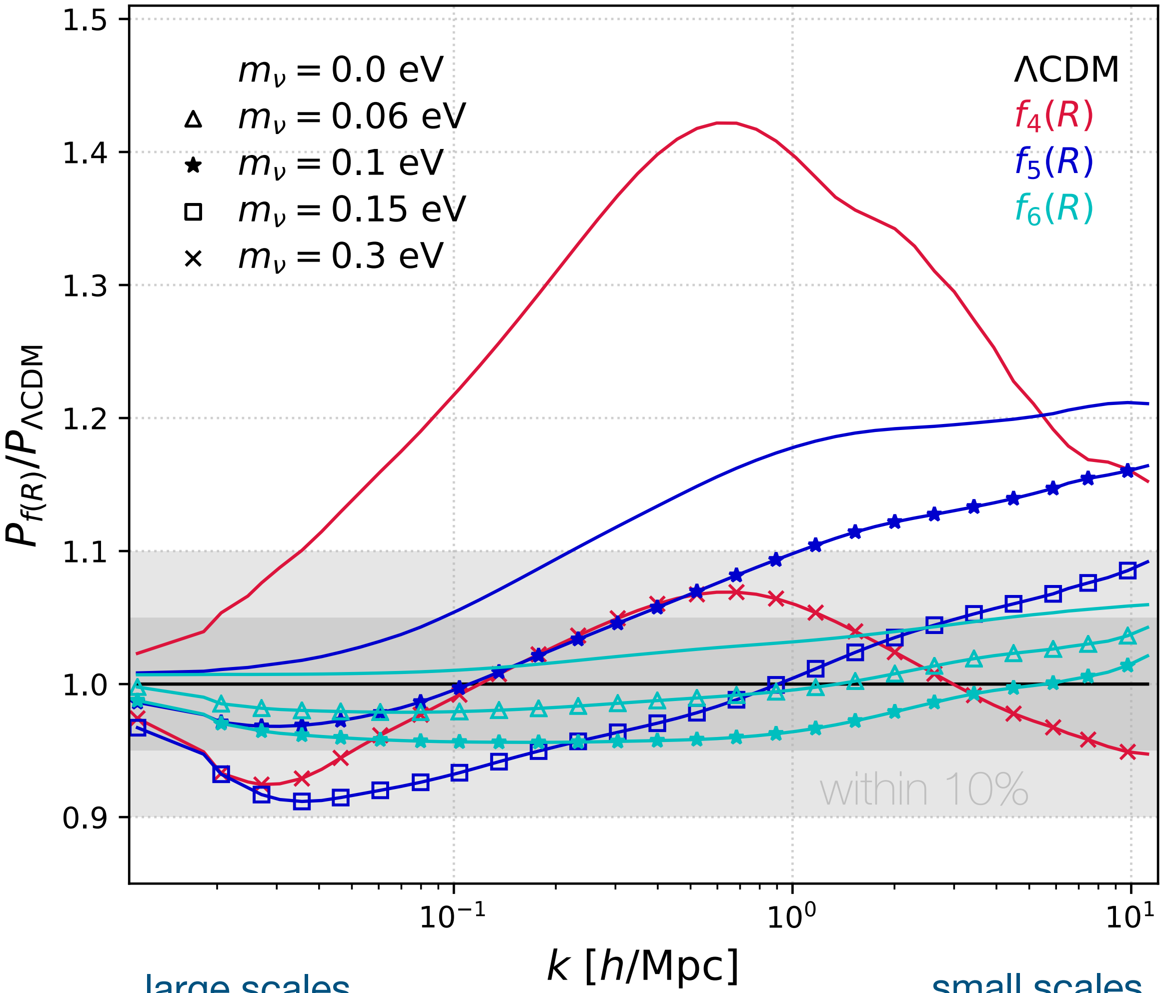
Sample joint parameter space of $f(R)$ gravity and massive neutrino cosmologies

Performed with MG-Gadget code that implements the extra fifth-force and screening



NOT DUSTGRAIN snapshots—for illustration only (http://cosmicweb.uchicago.edu/filaments.html)

Simulation Name	Gravity type	f_{R0}	m_ν [eV]	$\Omega_{\rm CDM}$	Ω_ν	$m^p_{\rm CDM}$ [M$_\odot$/h]	m^p_ν [M$_\odot$/h]
ΛCDM	GR	–	0	0.31345	0	8.1×10^{10}	0
fR4	$f(R)$	-1×10^{-4}	0	0.31345	0	8.1×10^{10}	0
fR5	$f(R)$	-1×10^{-5}	0	0.31345	0	8.1×10^{10}	0
fR6	$f(R)$	-1×10^{-6}	0	0.31345	0	8.1×10^{10}	0
fR4-0.3eV	$f(R)$	-1×10^{-4}	0.3	0.30630	0.00715	7.92×10^{10}	1.85×10^{9}
fR5-0.15eV	$f(R)$	-1×10^{-5}	0.15	0.30987	0.00358	8.01×10^{10}	9.25×10^{8}
fR5-0.1eV	$f(R)$	-1×10^{-5}	0.1	0.31107	0.00238	8.04×10^{10}	6.16×10^{8}
fR6-0.1eV	$f(R)$	-1×10^{-6}	0.1	0.31107	0.00238	8.04×10^{10}	6.16×10^{8}
fR6-0.06eV	$f(R)$	-1×10^{-6}	0.06	0.31202	0.00143	8.07×10^{10}	3.7×10^{8}



large scales (linear)

small scales (nonlinear)

matter power spectra (relative to LCDM)

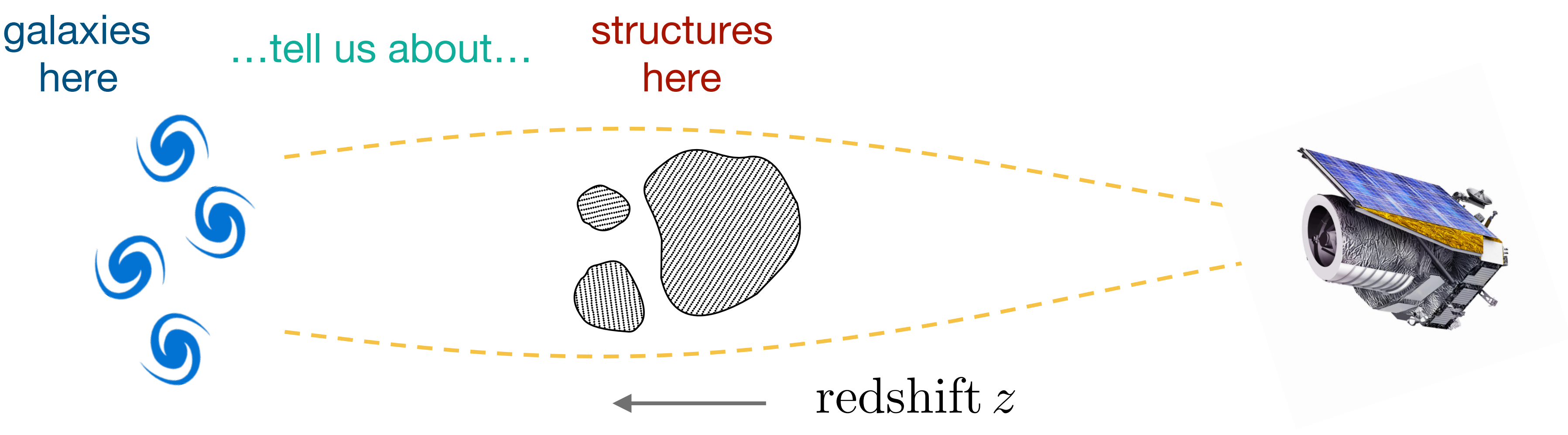
$f_4(R)$ farther from LCDM

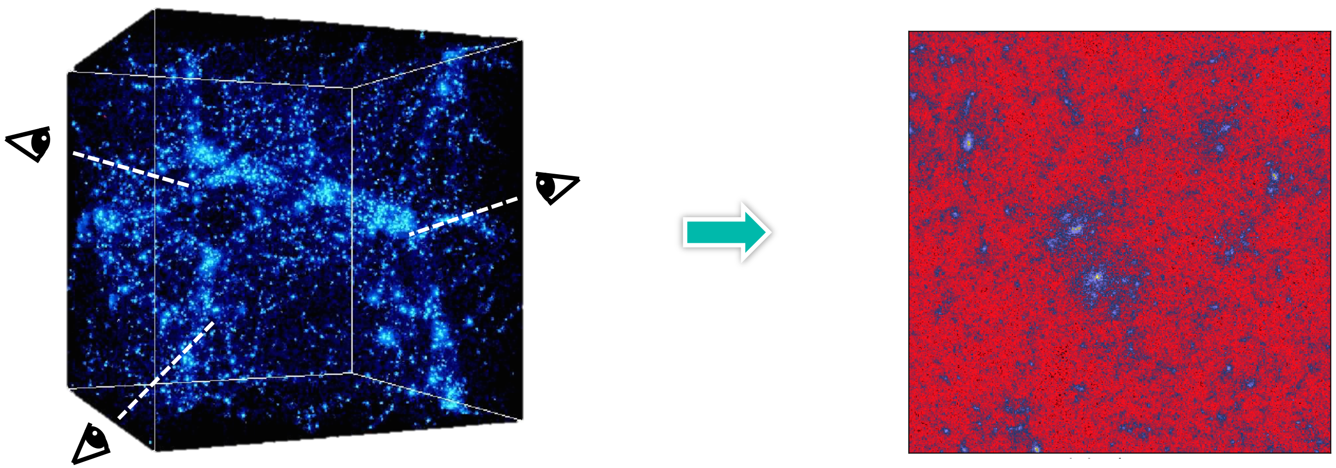
$f_5(R)$ intermediate

$f_6(R)$ closer to LCDM

neutrinos suppress the growth of structure

Weak gravitational lensing





$\times\ 256$ per redshift,
per model

WL convergence map $\kappa(\boldsymbol{\theta})$

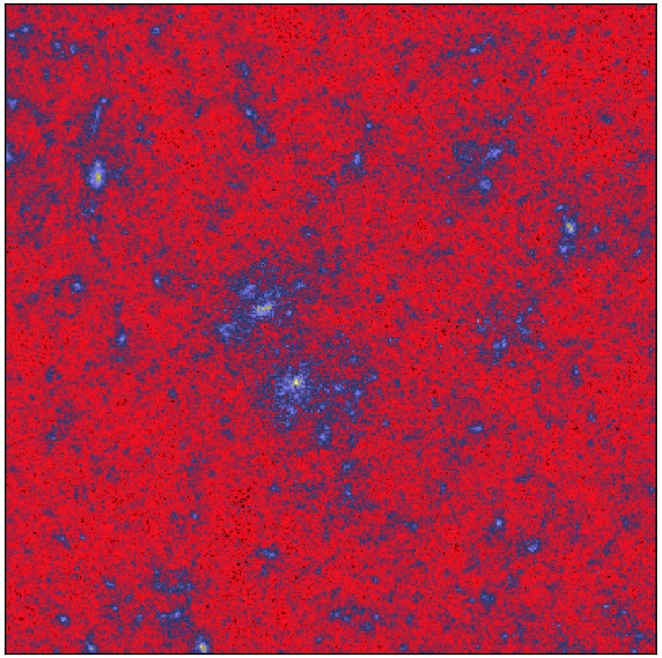
aperture mass :

$$M_{\mathrm{ap}}(\boldsymbol{\theta};\vartheta) = \int \mathrm{d}^2\theta' \, U_\vartheta(|\boldsymbol{\theta}' - \boldsymbol{\theta}|) \, \kappa(\boldsymbol{\theta}')$$

isotropic filter function

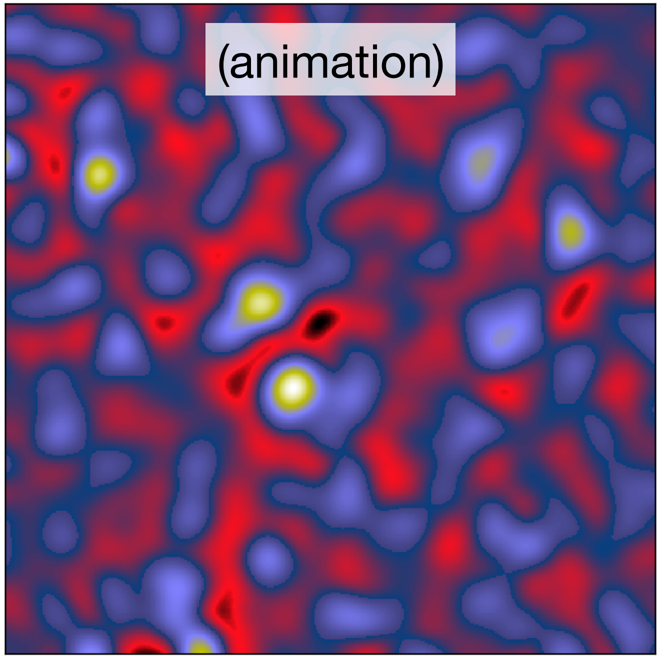
mass map

implemented as a **wavelet** transform (starlet)



original κ map

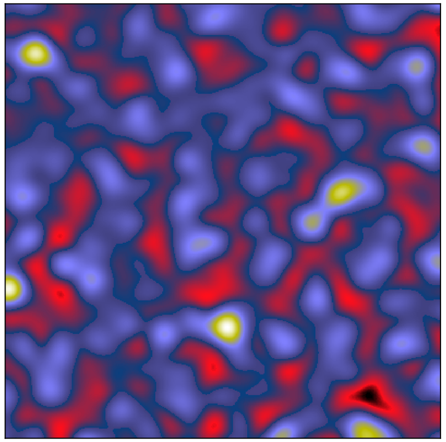
$$= \sum$$



aperture size $\vartheta_5 = 4.69$ arcmin

aperture mass map

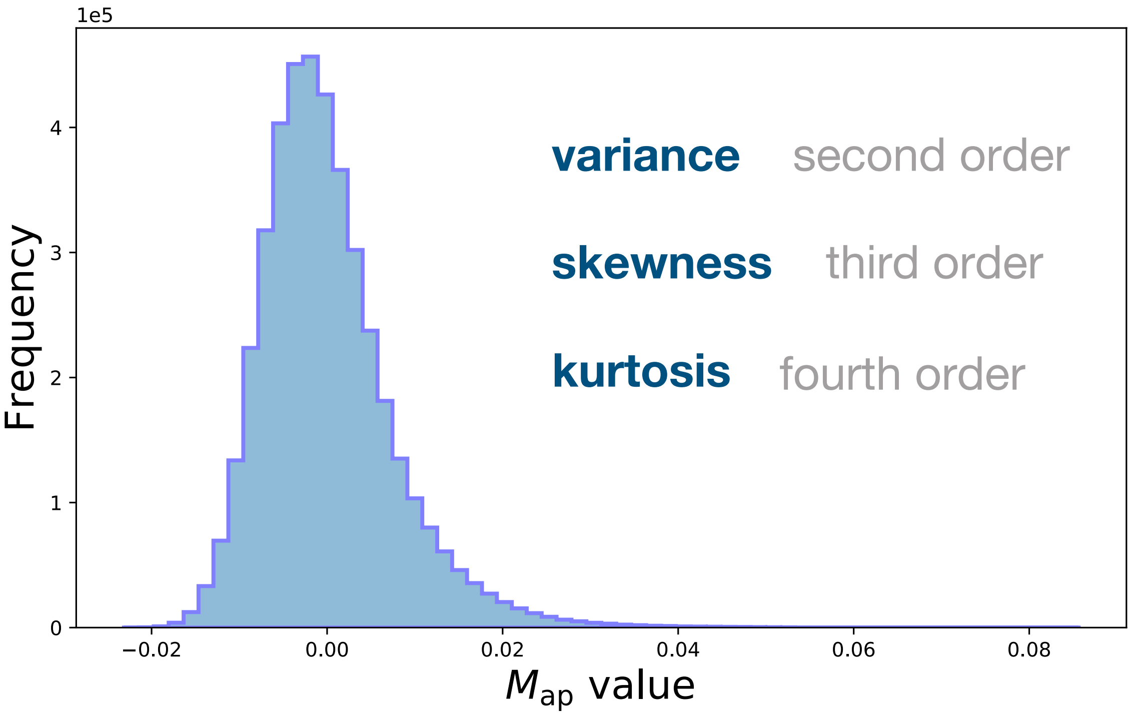
$$M_{\rm ap}(\text{model}, \vartheta_j, z_s) =$$

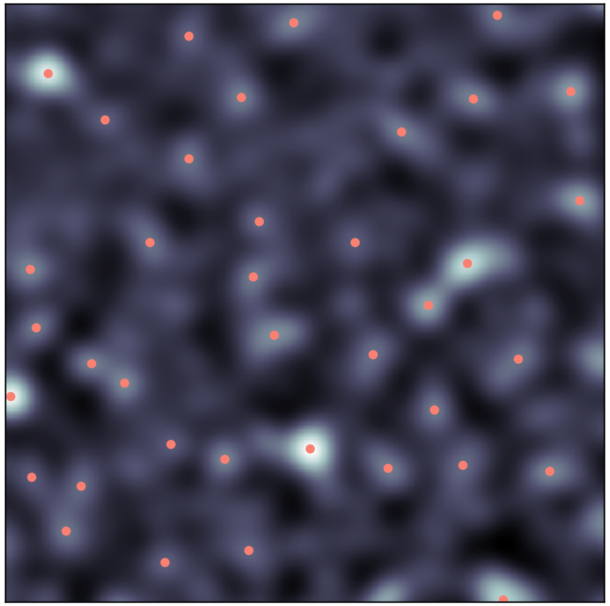


$5 \times 5 \ \text{deg}^2$

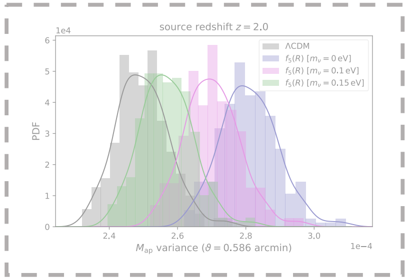
400×400 shown, but

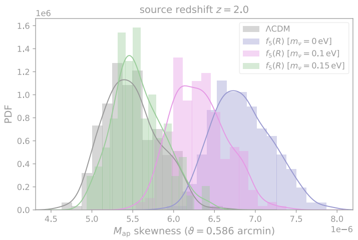
2048×2048 in practice

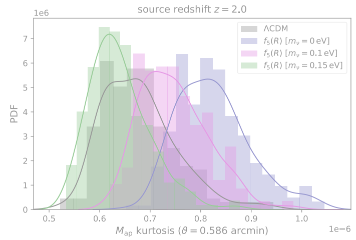


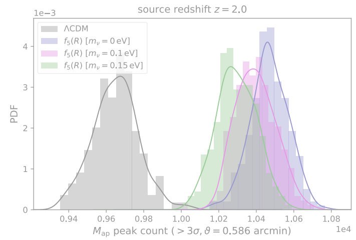


peak count

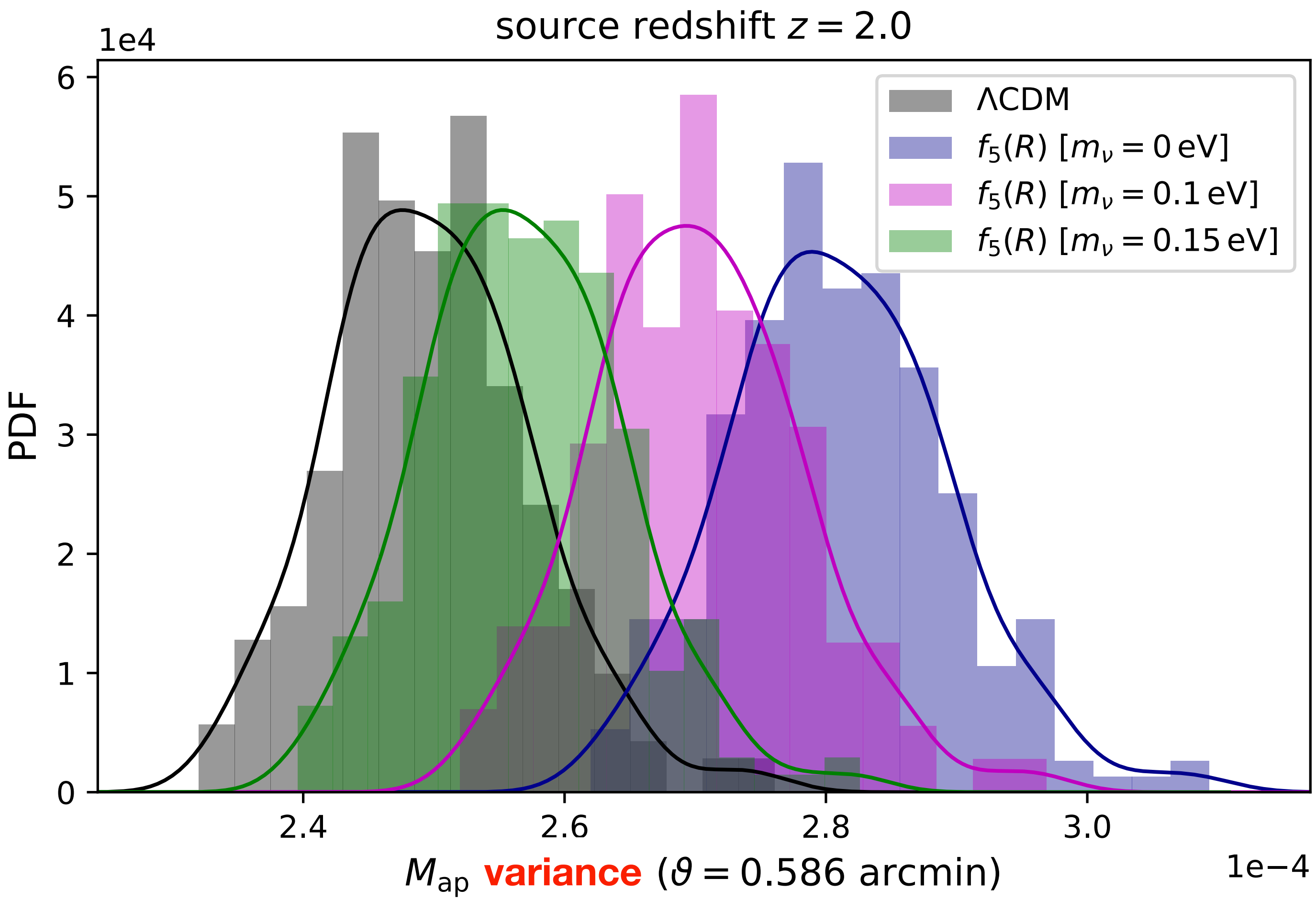


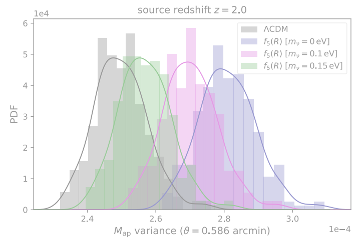
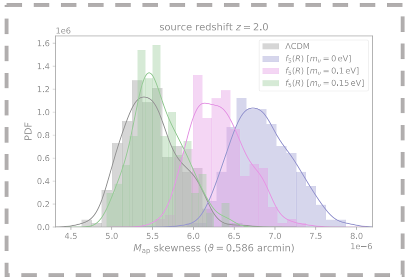
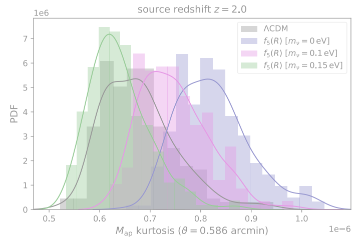
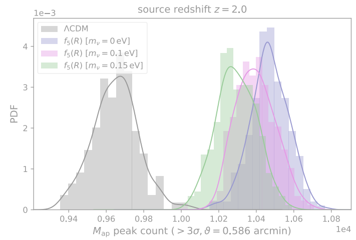






Distributions of observables



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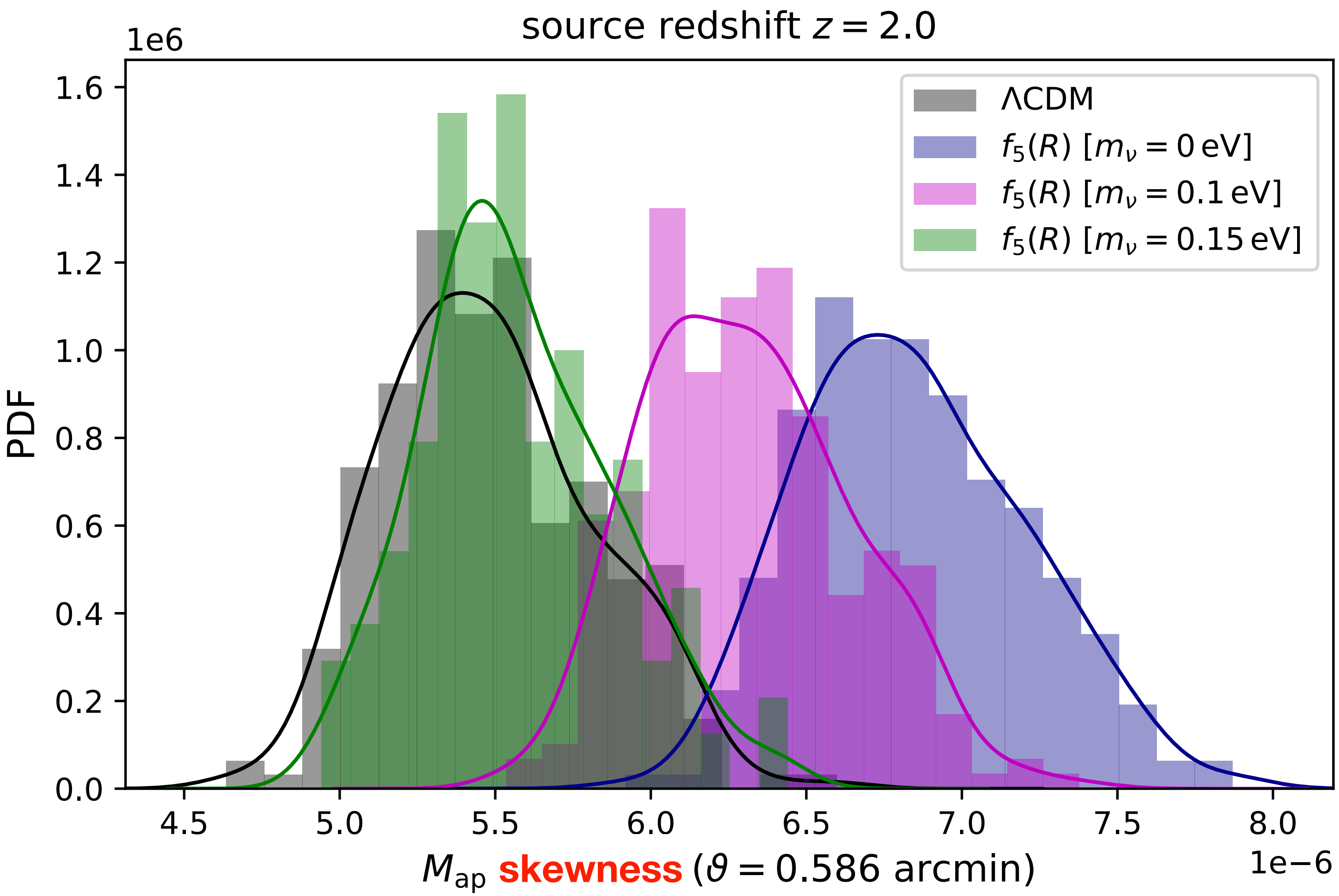
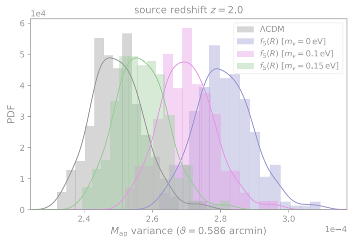
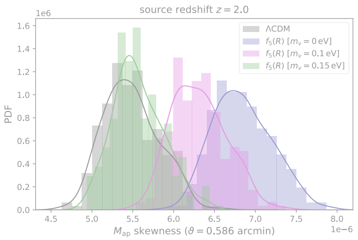
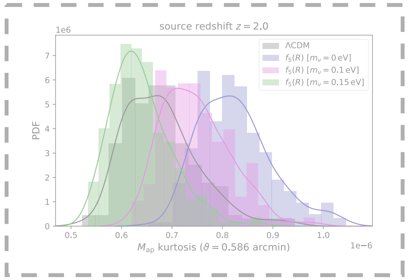
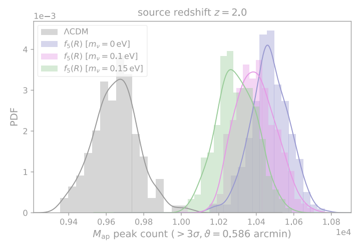


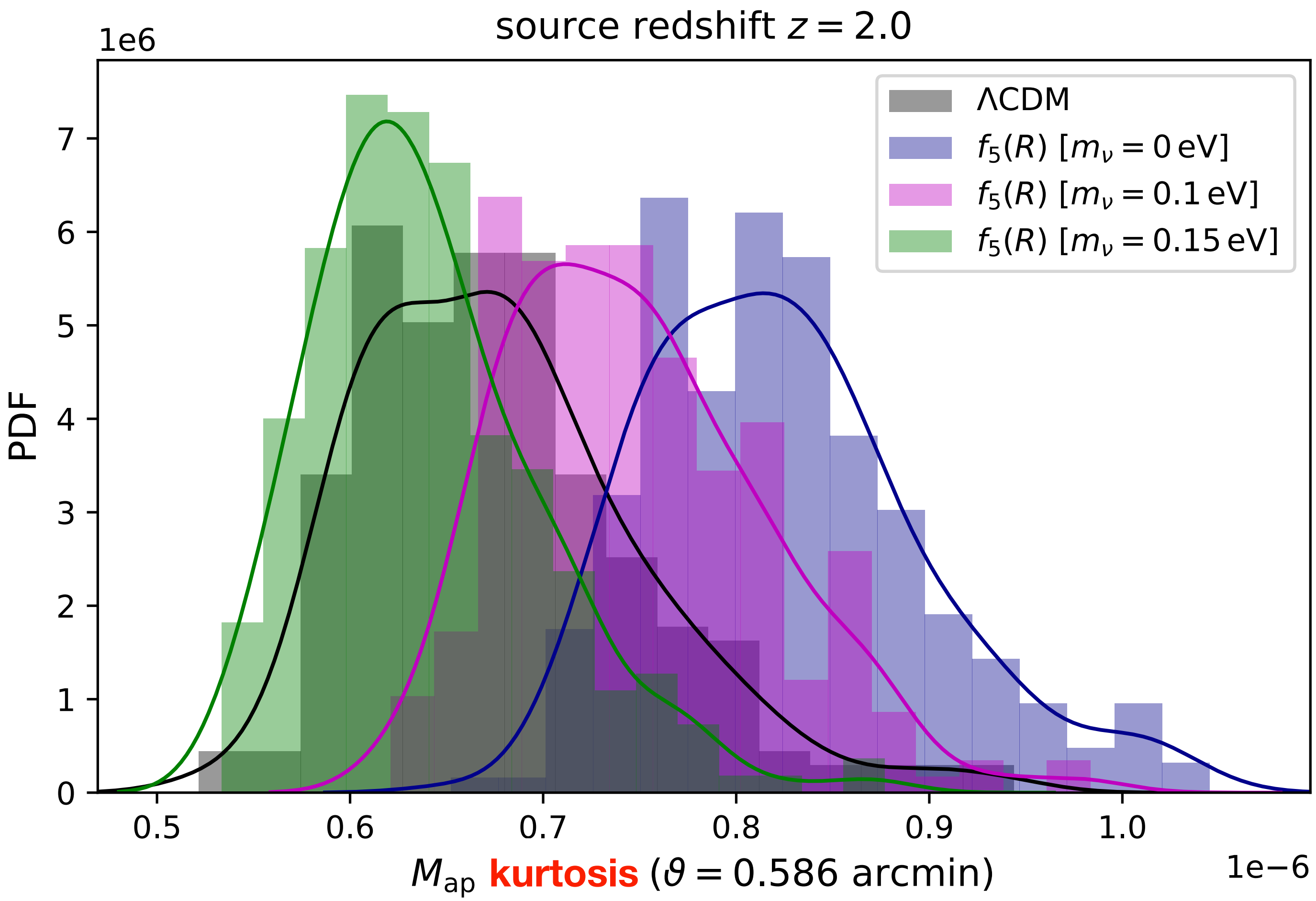


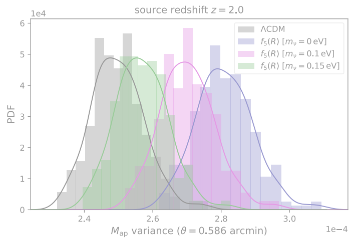


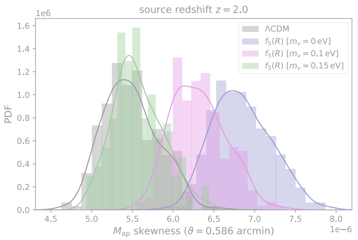


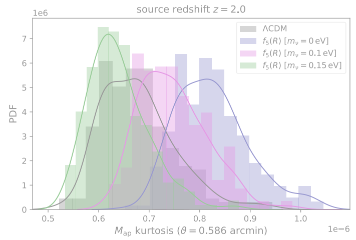


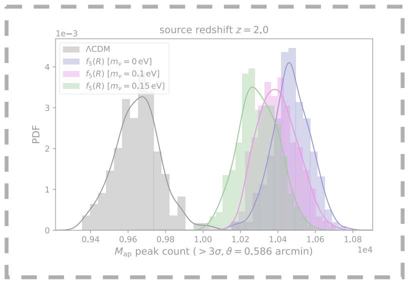
Distributions of observables



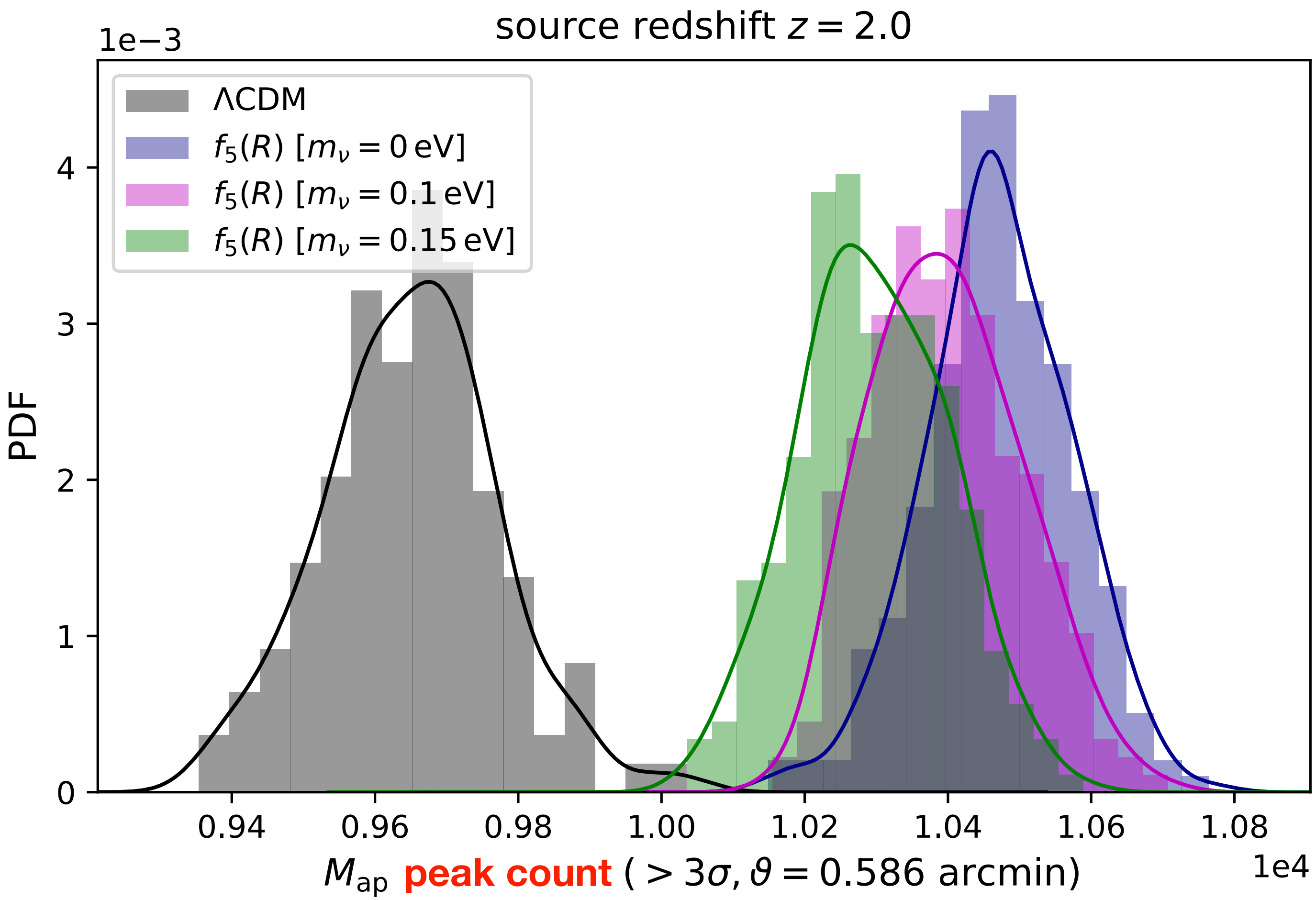






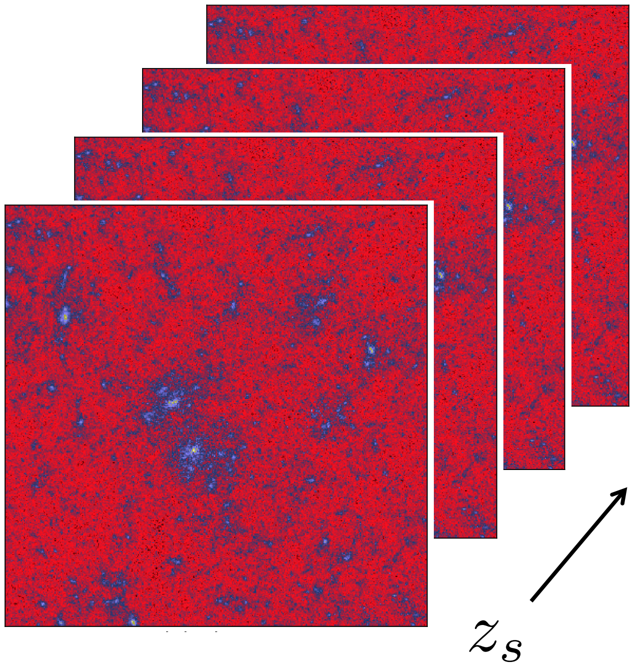


Distributions of observables

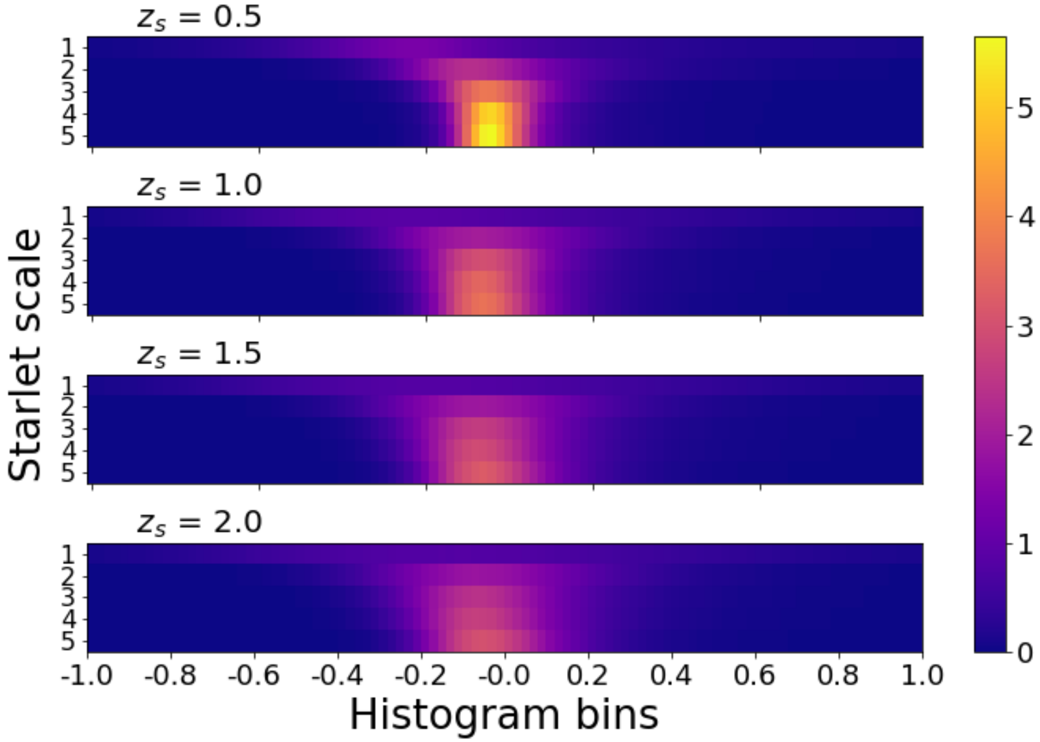


An alternative approach: machine learning

[A. Peel, F. Lalande, et al., submitted PRL (2018)]



New data representation



Convolutional neural network

Prediction

$\sigma_{\text{noise}} = 0$ (Truth ↓)	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	1.00	0.00	0.00	0.00
$f_5(R)$ $M_\nu = 0$ eV	0.00	0.88	0.12	0.00
$f_5(R)$ $M_\nu = 0.1$ eV	0.00	0.13	0.83	0.04
$f_5(R)$ $M_\nu = 0.15$ eV	0.00	0.00	0.04	0.96

Peak statistics (best case)

Prediction

$\sigma_{\text{noise}} = 0$ (Truth ↓)	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	1.00	0.00	0.00	0.00
$f_5(R)$ $M_\nu = 0$ eV	0.00	0.49	0.42	0.09
$f_5(R)$ $M_\nu = 0.1$ eV	0.00	0.34	0.44	0.22
$f_5(R)$ $M_\nu = 0.15$ eV	0.00	0.09	0.25	0.66

Convolutional neural network

Prediction (columns) / Truth (rows)

$\sigma_{\rm noise} = 0$	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	1.00	0.00	0.00	0.00
$f_5(R)$ $M_\nu = 0$ eV	0.00	0.88	0.12	0.00
$f_5(R)$ $M_\nu = 0.1$ eV	0.00	0.13	0.83	0.04
$f_5(R)$ $M_\nu = 0.15$ eV	0.00	0.00	0.04	0.96

$\sigma_{\rm noise} = 0.35$	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	0.80	0.00	0.04	0.15
$f_5(R)$ $M_\nu = 0$ eV	0.00	0.78	0.21	0.01
$f_5(R)$ $M_\nu = 0.1$ eV	0.03	0.28	0.53	0.16
$f_5(R)$ $M_\nu = 0.15$ eV	0.18	0.01	0.19	0.61

$\sigma_{\rm noise} = 0.7$	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	0.46	0.03	0.23	0.28
$f_5(R)$ $M_\nu = 0$ eV	0.02	0.70	0.25	0.03
$f_5(R)$ $M_\nu = 0.1$ eV	0.13	0.31	0.41	0.15
$f_5(R)$ $M_\nu = 0.15$ eV	0.38	0.05	0.23	0.34

Peak statistics (best case)

Prediction (columns) / Truth (rows)

$\sigma_{\rm noise} = 0$	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	1.00	0.00	0.00	0.00
$f_5(R)$ $M_\nu = 0$ eV	0.00	0.49	0.42	0.09
$f_5(R)$ $M_\nu = 0.1$ eV	0.00	0.34	0.44	0.22
$f_5(R)$ $M_\nu = 0.15$ eV	0.00	0.09	0.25	0.66

$\sigma_{\rm noise} = 0.35$	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	0.30	0.11	0.30	0.29
$f_5(R)$ $M_\nu = 0$ eV	0.11	0.38	0.37	0.14
$f_5(R)$ $M_\nu = 0.1$ eV	0.19	0.28	0.33	0.21
$f_5(R)$ $M_\nu = 0.15$ eV	0.29	0.14	0.29	0.28

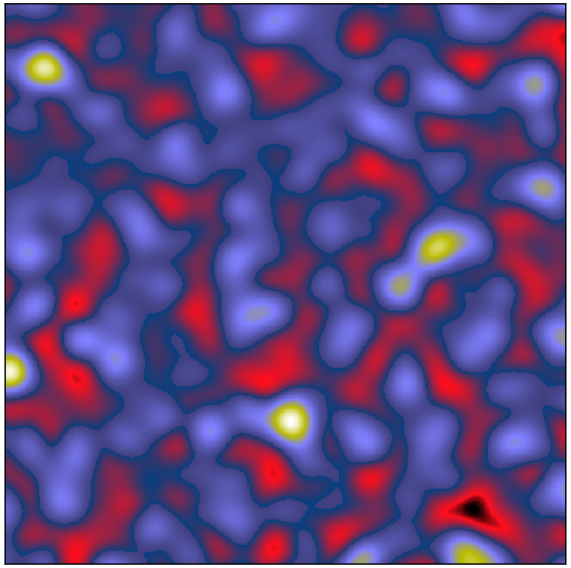
$\sigma_{\rm noise} = 0.7$	ΛCDM	$f_5(R)$ $M_\nu = 0$ eV	$f_5(R)$ $M_\nu = 0.1$ eV	$f_5(R)$ $M_\nu = 0.15$ eV
ΛCDM	0.25	0.25	0.25	0.25
$f_5(R)$ $M_\nu = 0$ eV	0.25	0.25	0.25	0.25
$f_5(R)$ $M_\nu = 0.1$ eV	0.25	0.25	0.25	0.25
$f_5(R)$ $M_\nu = 0.15$ eV	0.25	0.25	0.25	0.25

Outline

1. Introduction to mass mapping
2. Inversion techniques
3. Peak statistics in cosmology
4. Distinguishing cosmological models
5. **Summary**

To sum up

- **Mass maps** are indeed useful for cosmology
- Various **shear inversion** (mapping) techniques are available
- Peaks access **non-Gaussian information** that can be used to constrain cosmological models
- Modified gravity + neutrinos can mimic ΛCDM but **peak statistics** and (better yet) **machine learning** can break degeneracies



To sum up

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謝謝大家！