Breaking degeneracies in modified gravity cosmologies with WL

Austin Peel

Outline

1. Modified gravity simulations
2. Aperture mass statistics
3. Distinguishing cosmological models
4. A machine learning approach
5. Summary

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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** ?

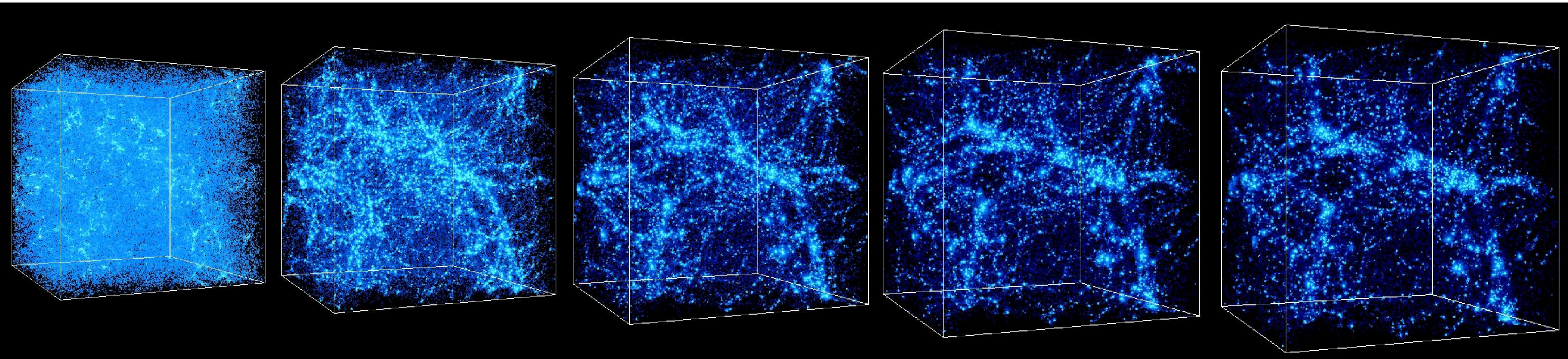
Reference

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

DUSTGRAIN-*pathfinder* simulations C. Giocoli et al. 2018 [arXiv:1806.04681]

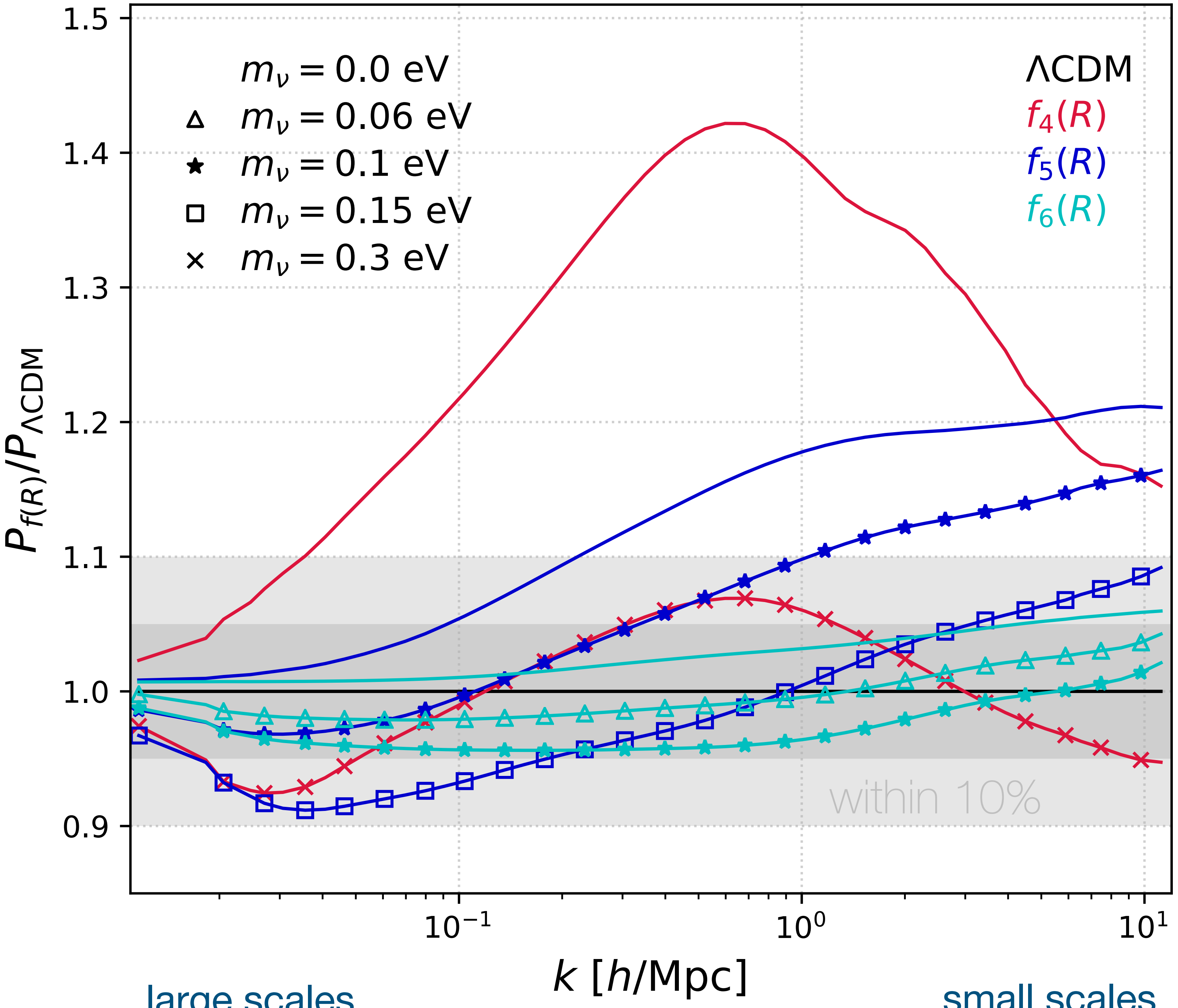
Sample joint parameter space of $f(R)$ gravity and massive neutrino cosmologies

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)

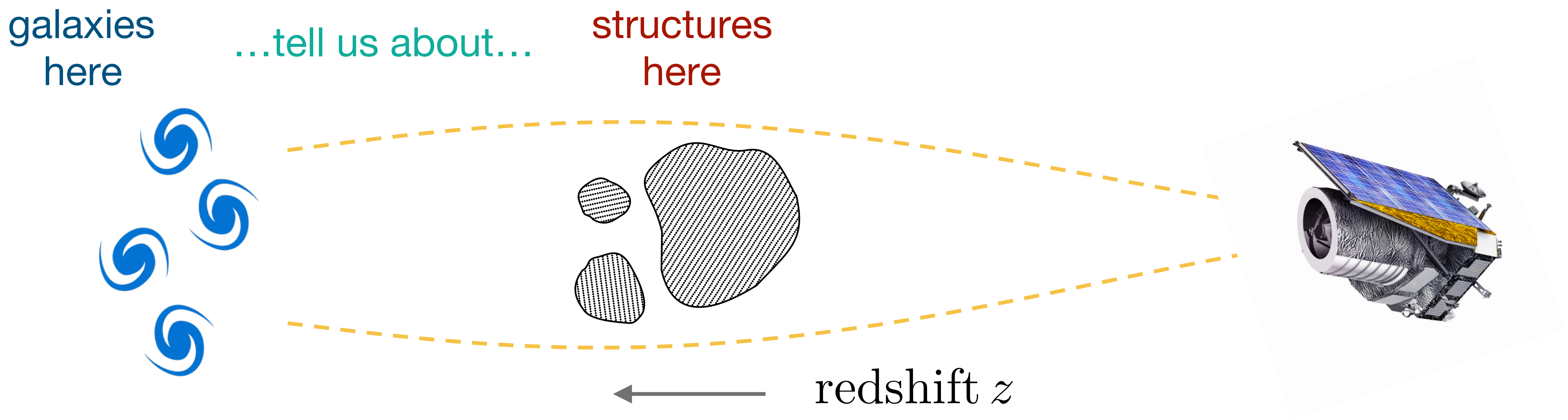
$f_4(R)$ farther from LCDM

$f_5(R)$ intermediate

$f_6(R)$ closer to LCDM

neutrinos suppress the growth of structure

Weak lensing maps from ray tracing

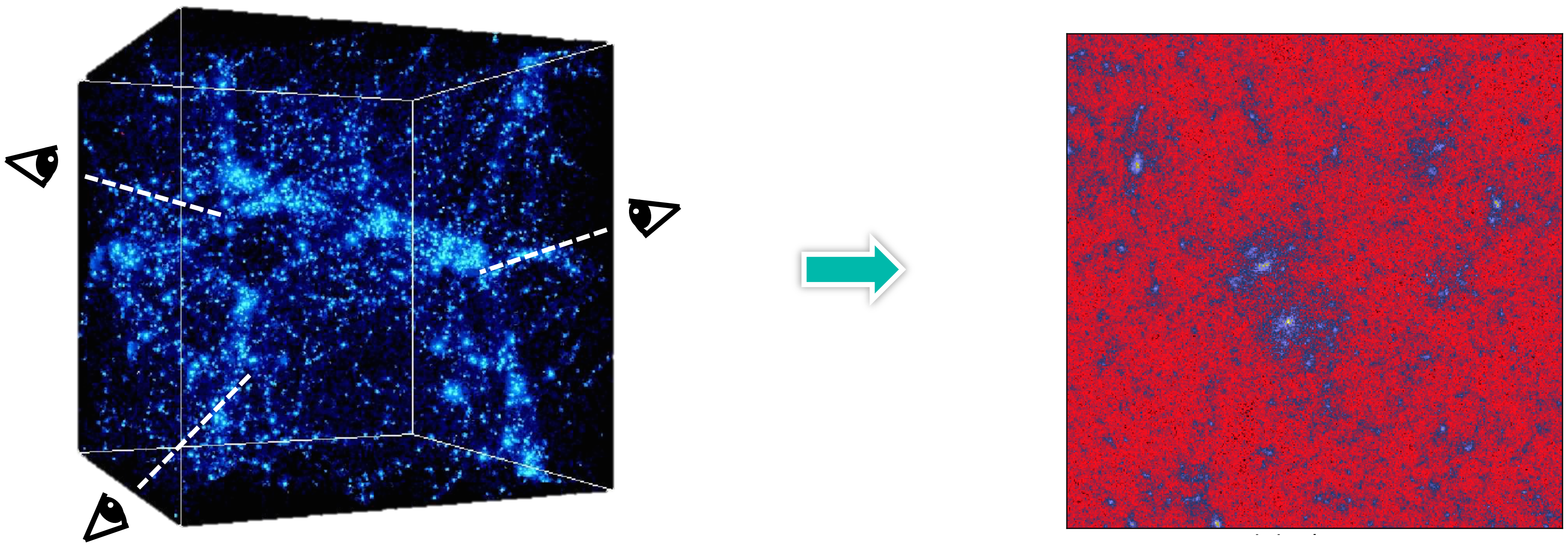


galaxies here

…tell us about…

structures here

redshift z



$\times\ 256$ per redshift, per model

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

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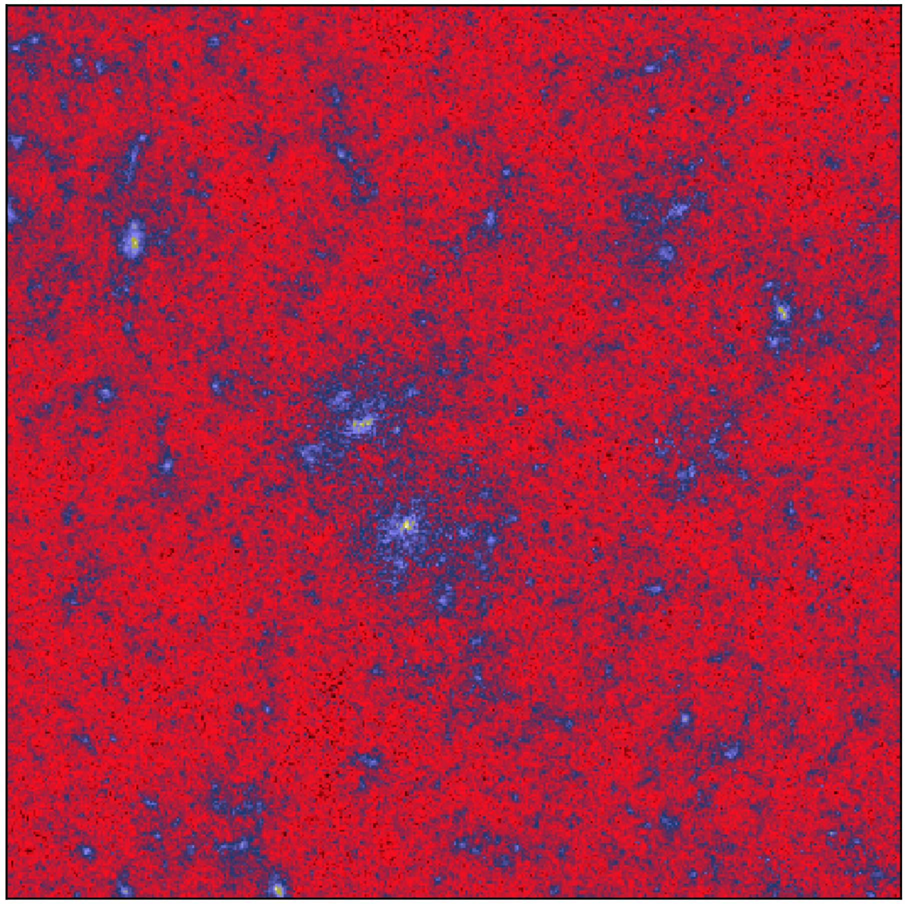
isotropic filter function

aperture mass :

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

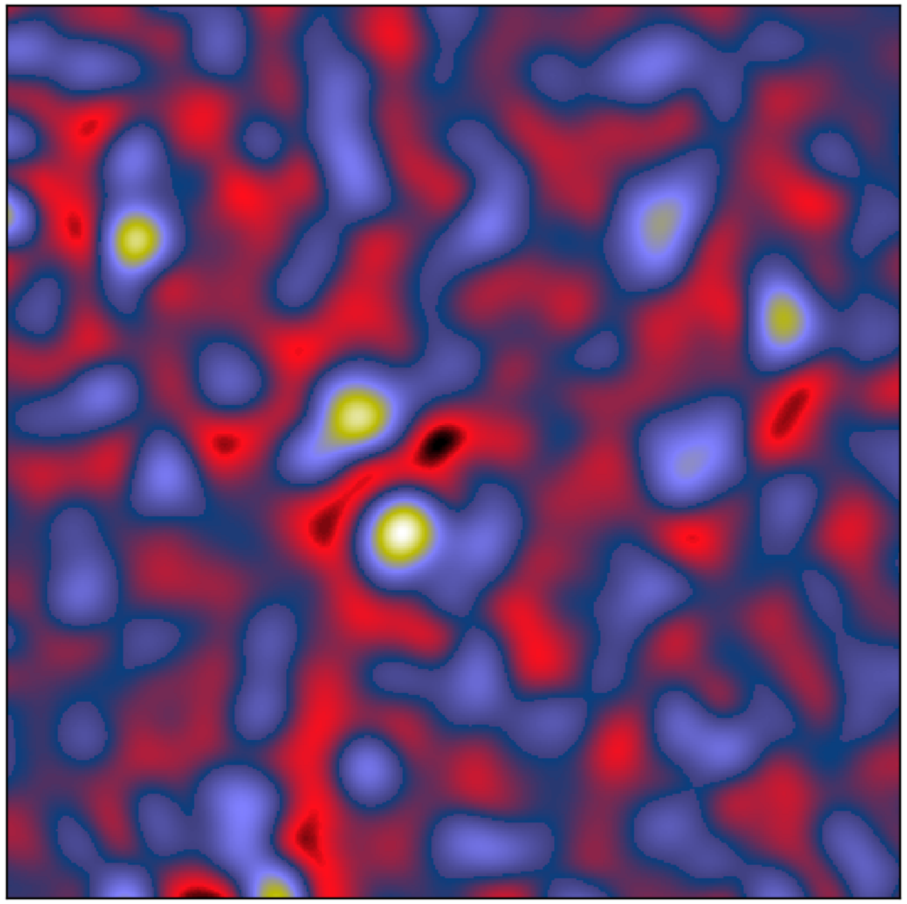
mass map

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



original κ map

$$= \sum$$

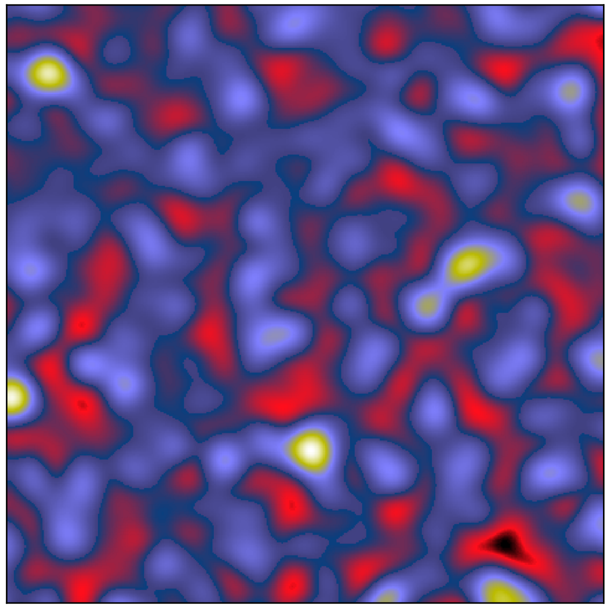


aperture size $\vartheta_5 = 4.69$ arcmin

Breaking Degeneracies in MG with WL

aperture mass map

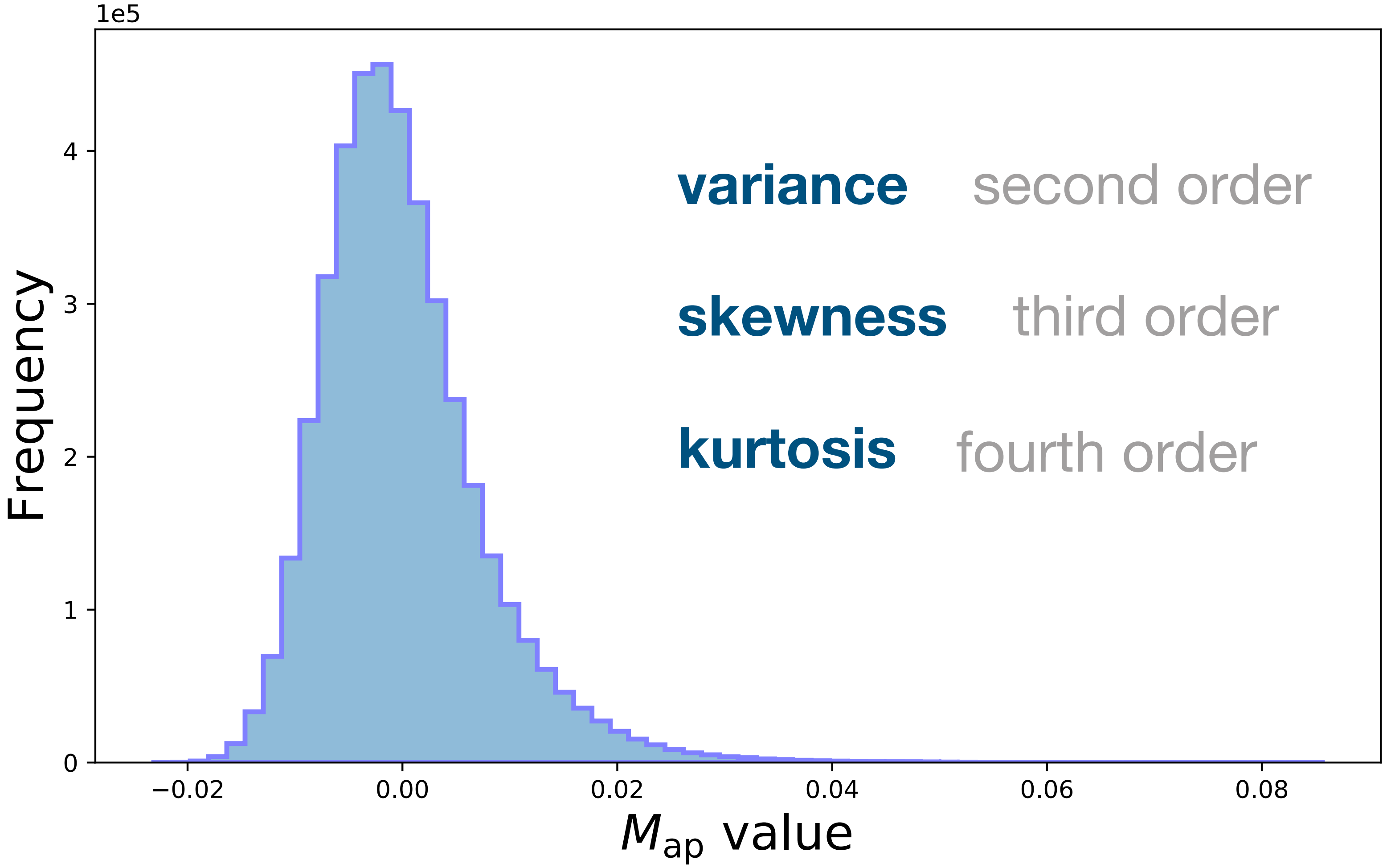
$$M_{\mathrm{ap}}(\mathrm{model}, \vartheta_j, z_s) =$$



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

400×400 shown, but

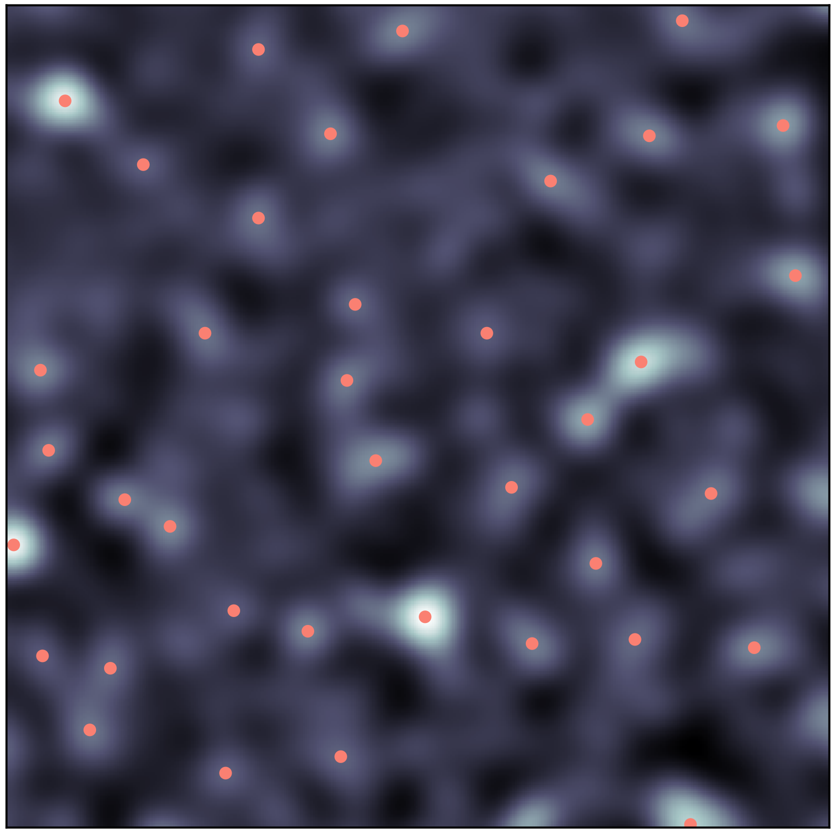
2048×2048 in practice



variance second order

skewness third order

kurtosis fourth order



peak count

Outline

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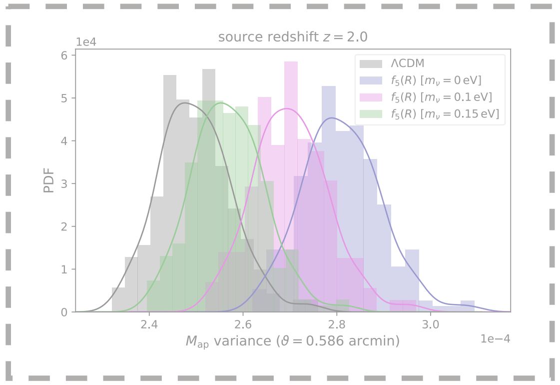
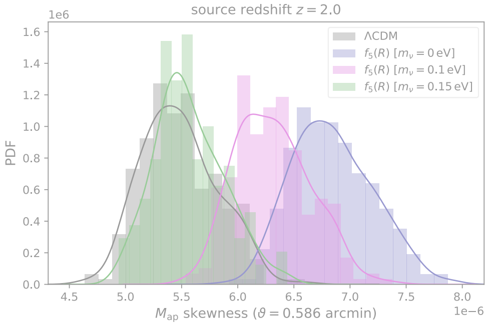
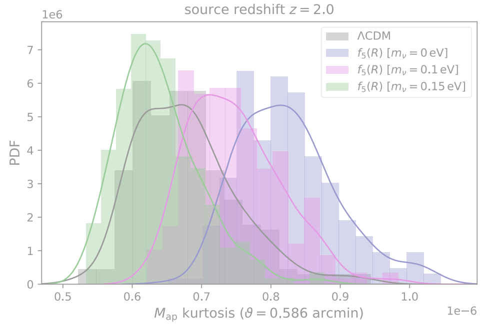
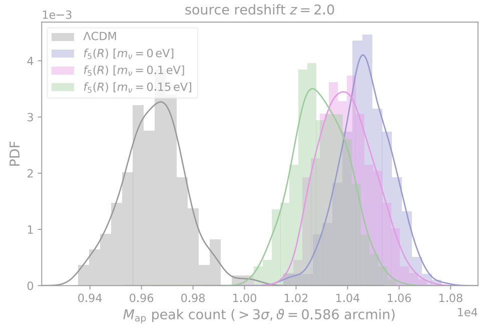
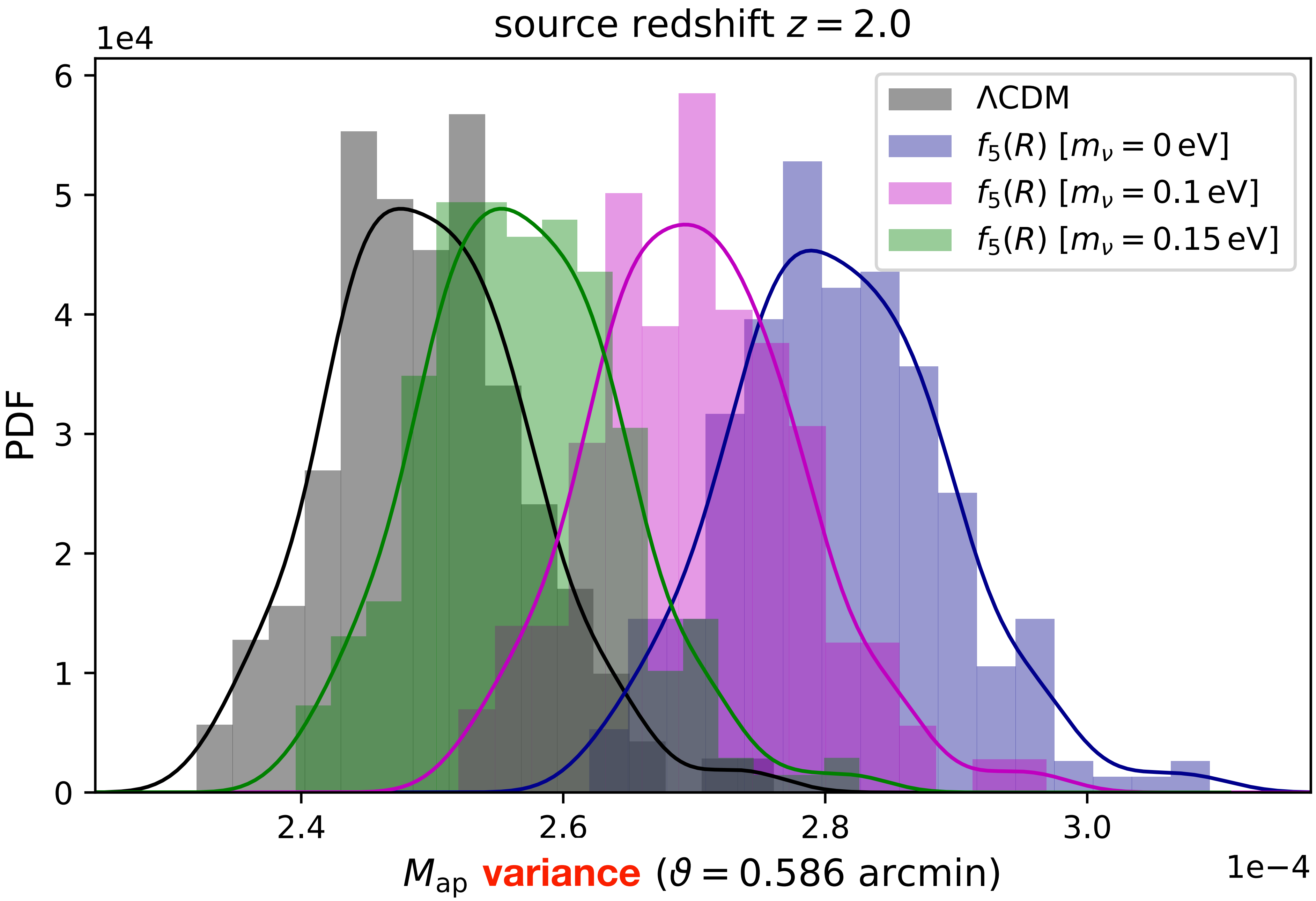








distributions of observables



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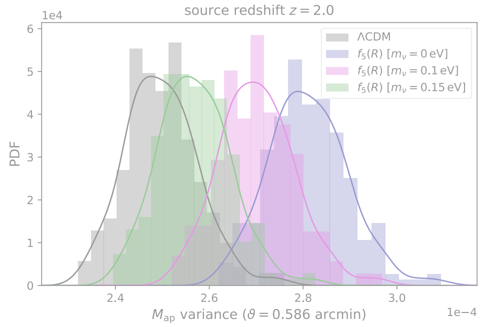

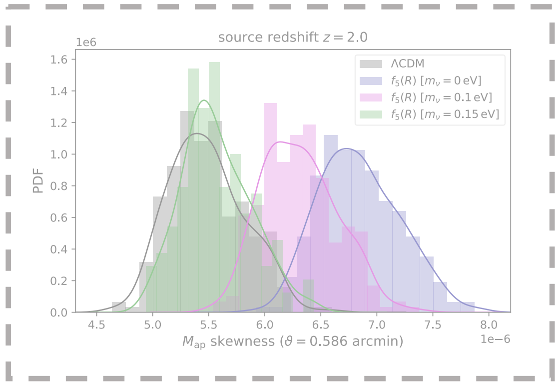

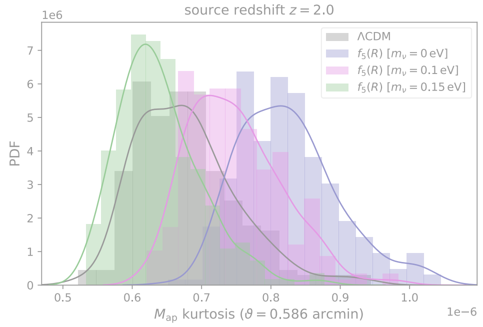

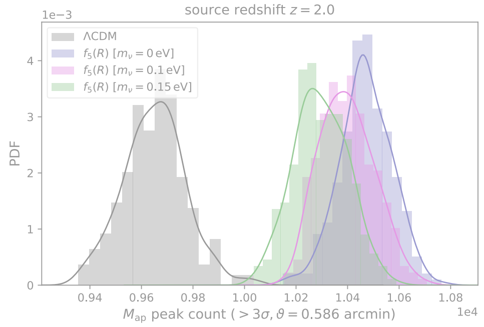

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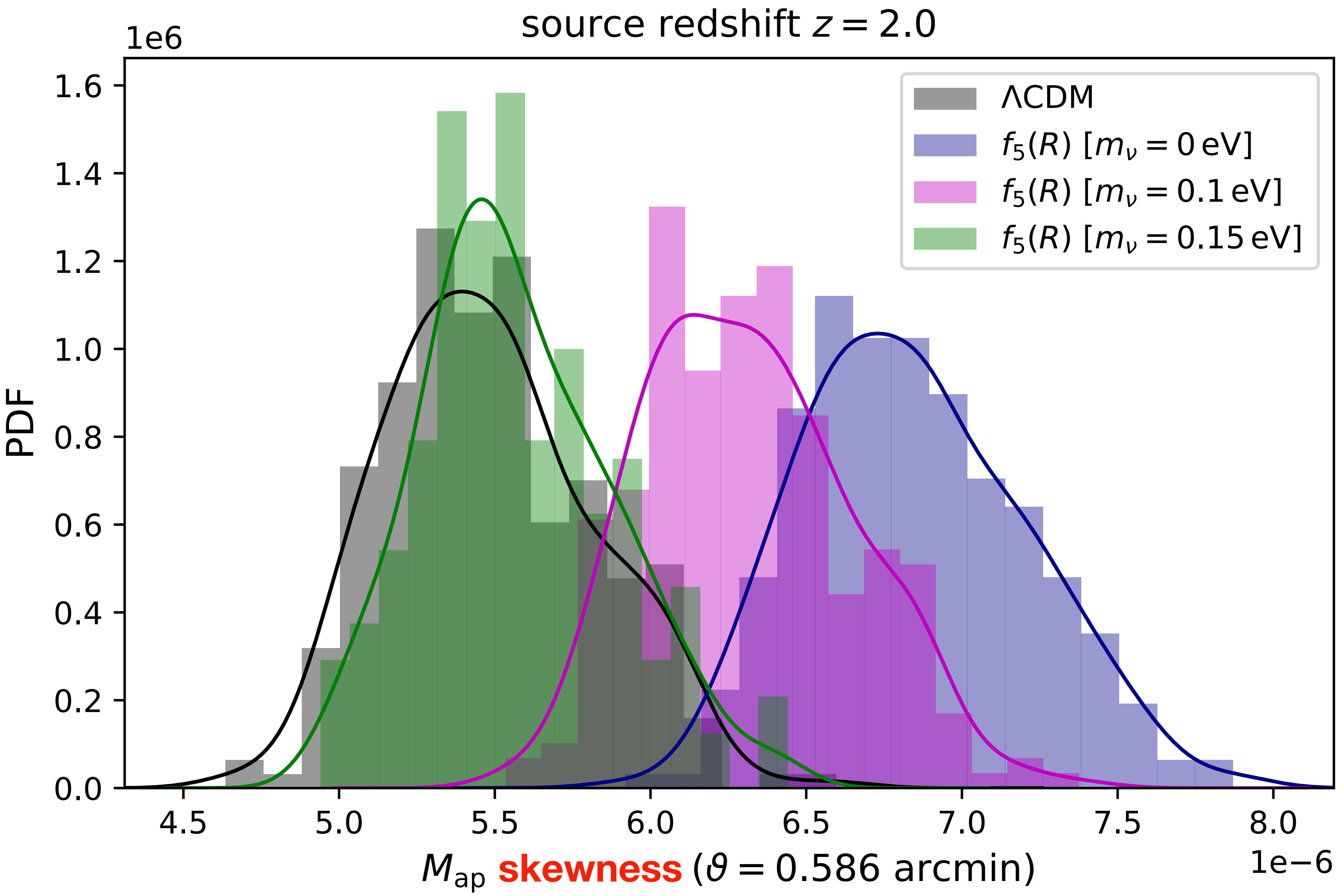

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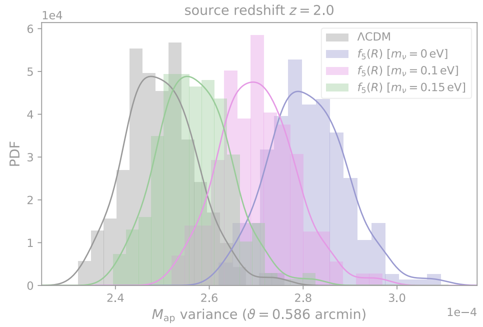
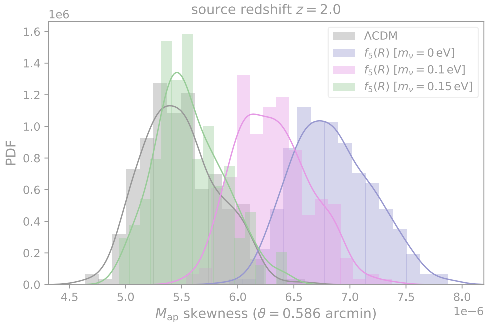
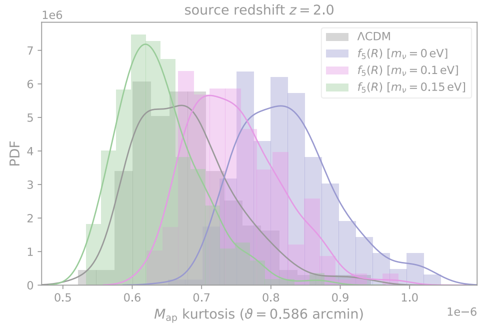
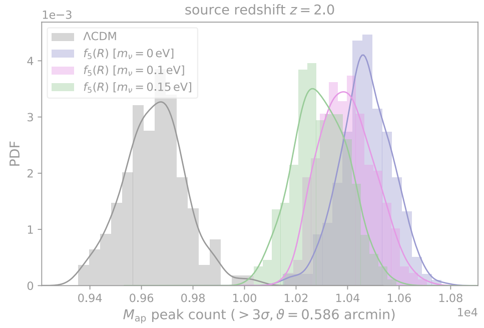
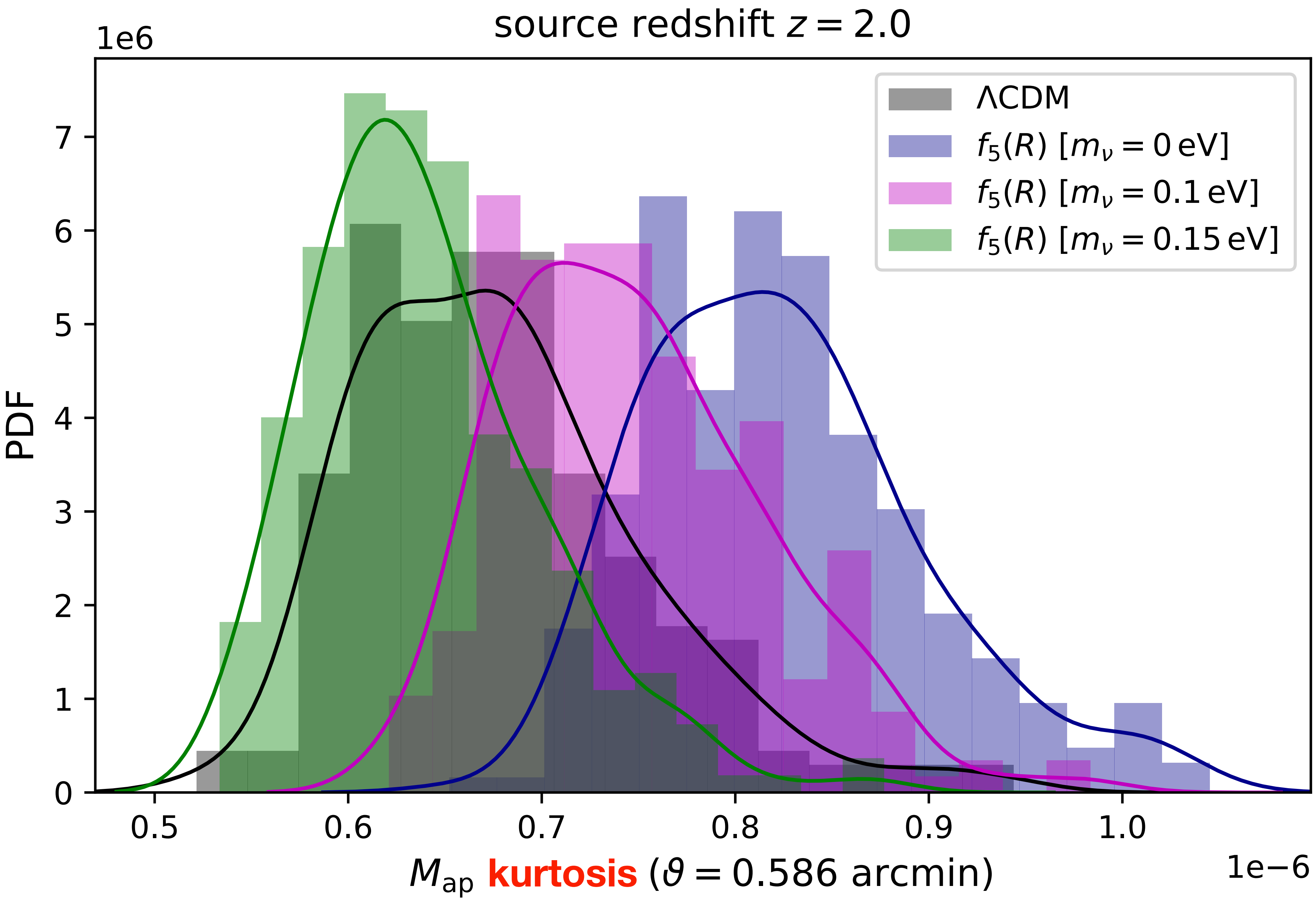








distributions of observables



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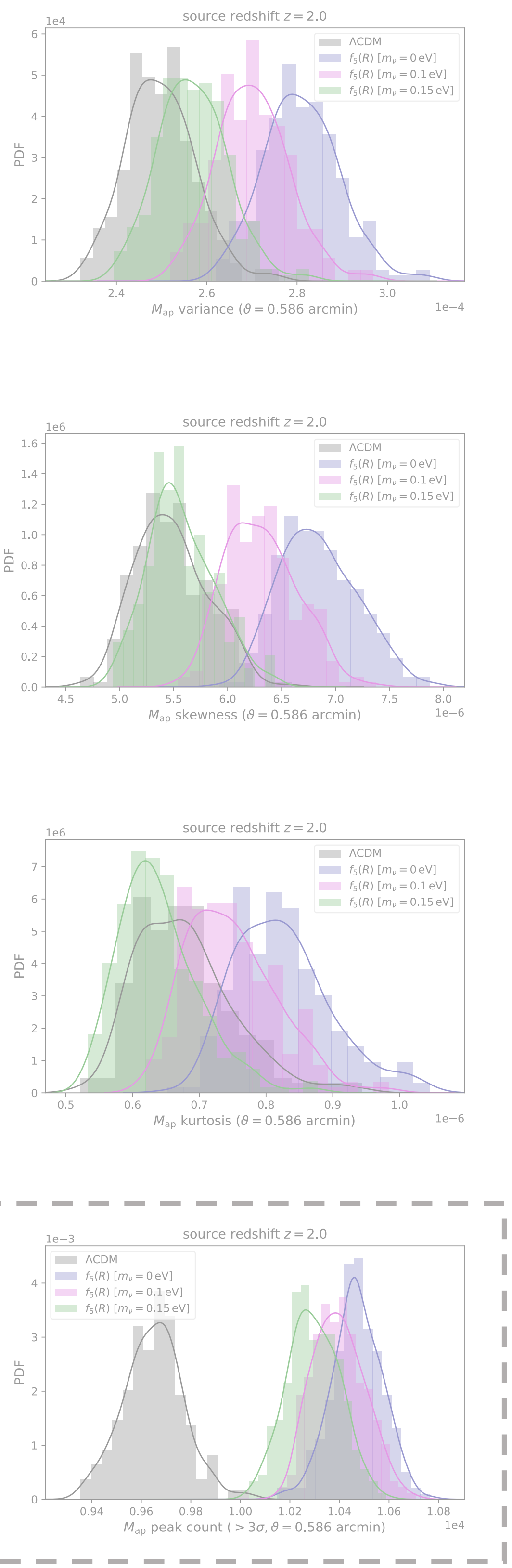
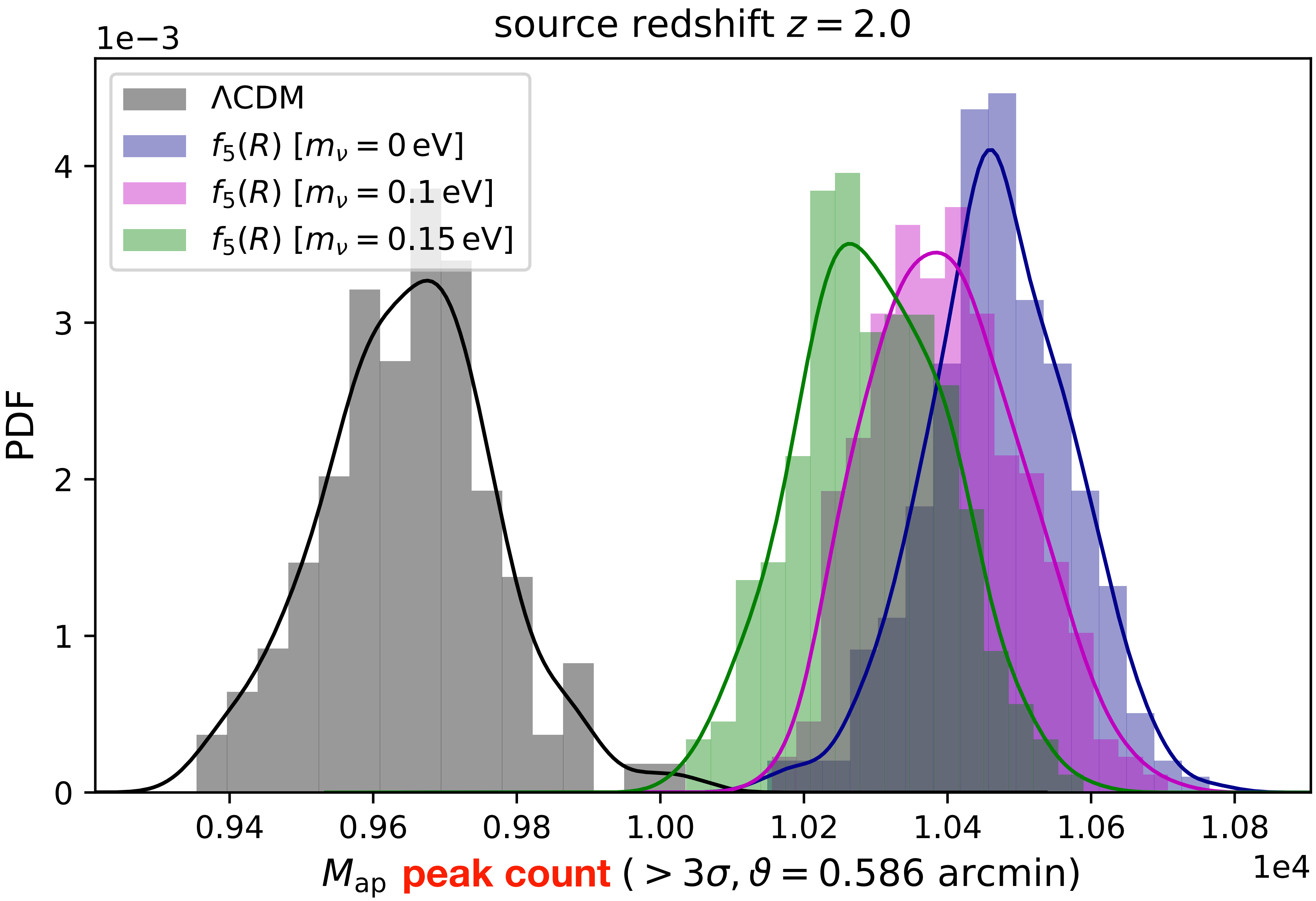


distributions of observables



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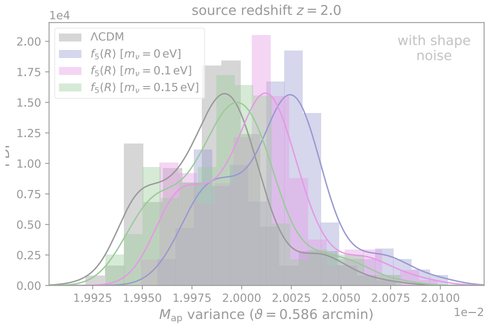
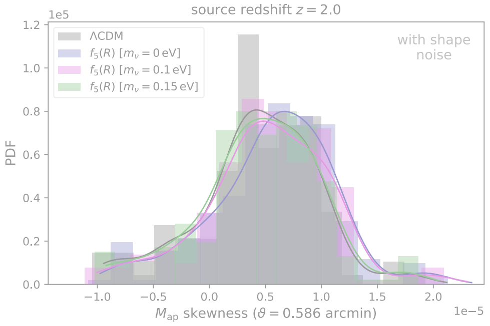
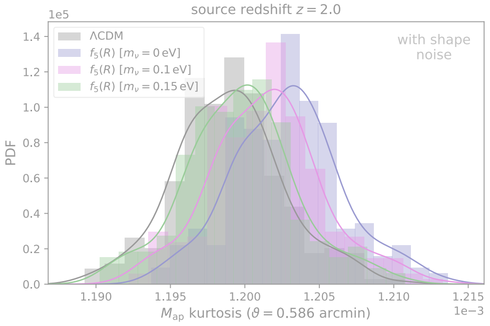
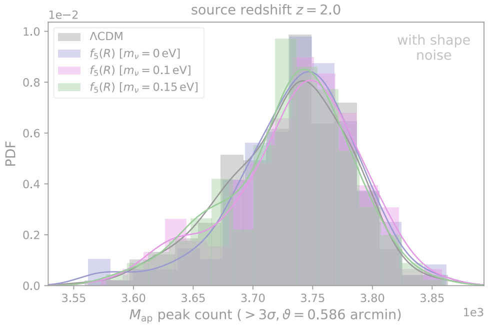
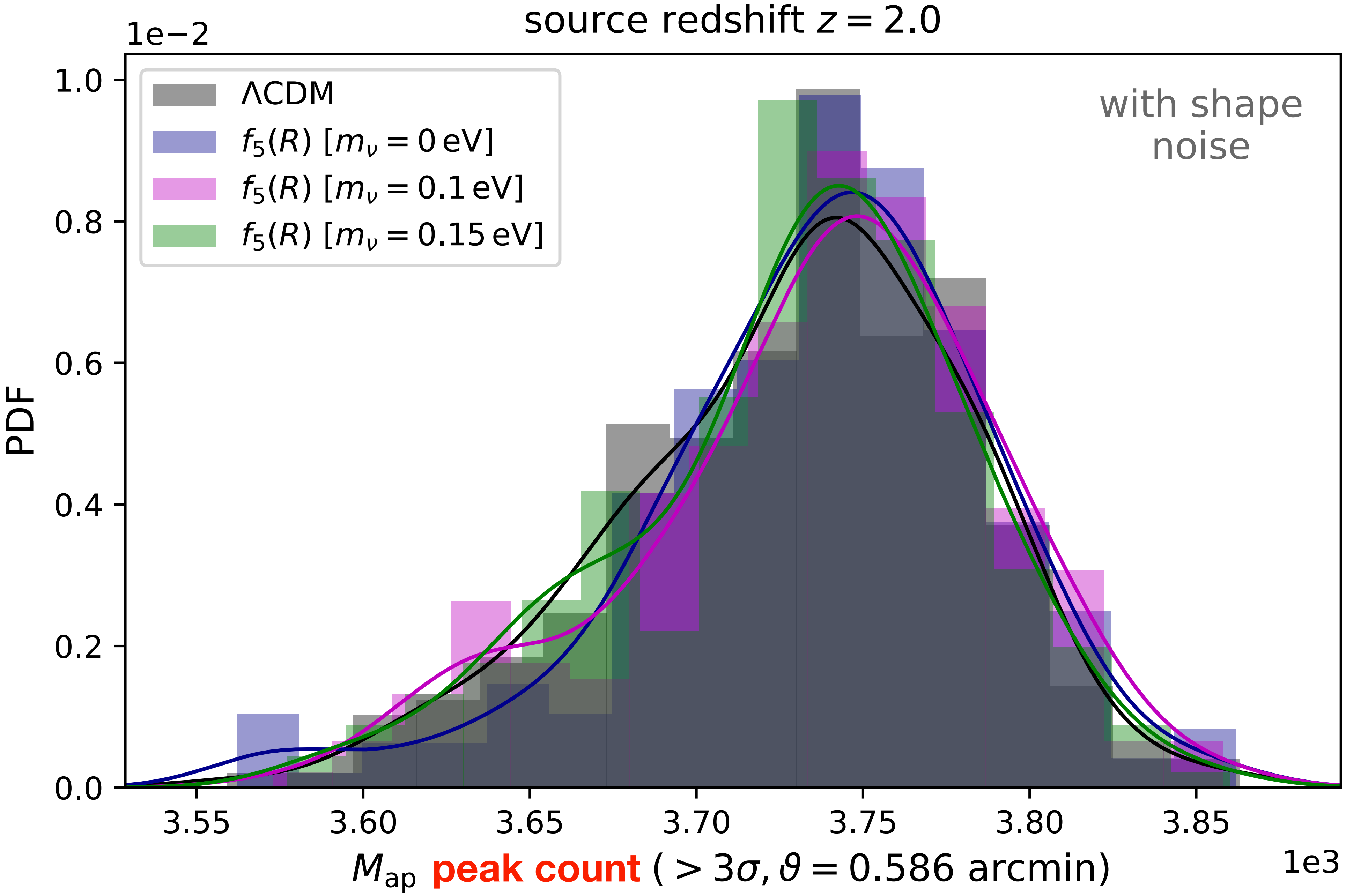








noisy distributions of observables



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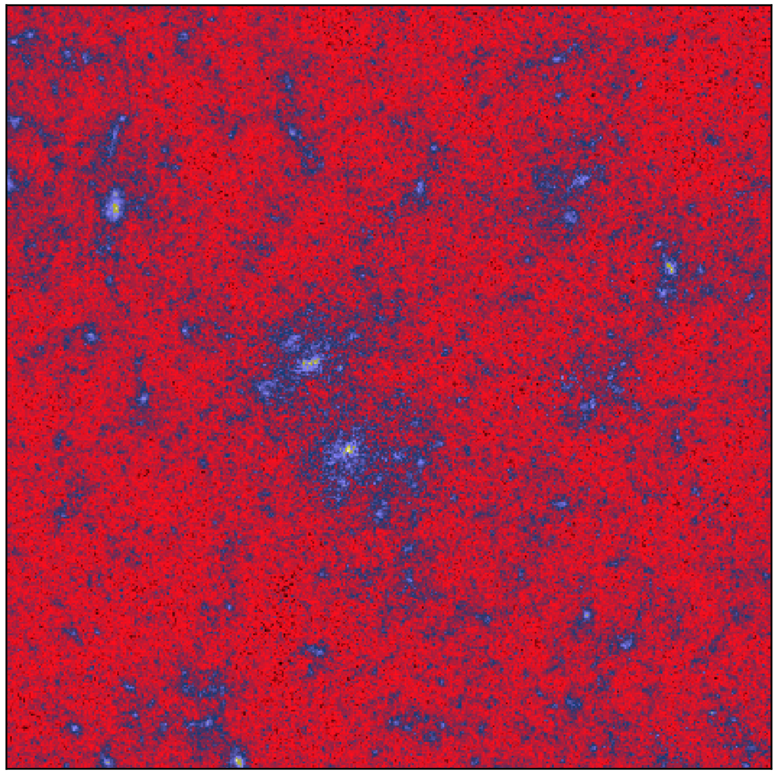
Can a neural network do better ?

Let’s recall the data



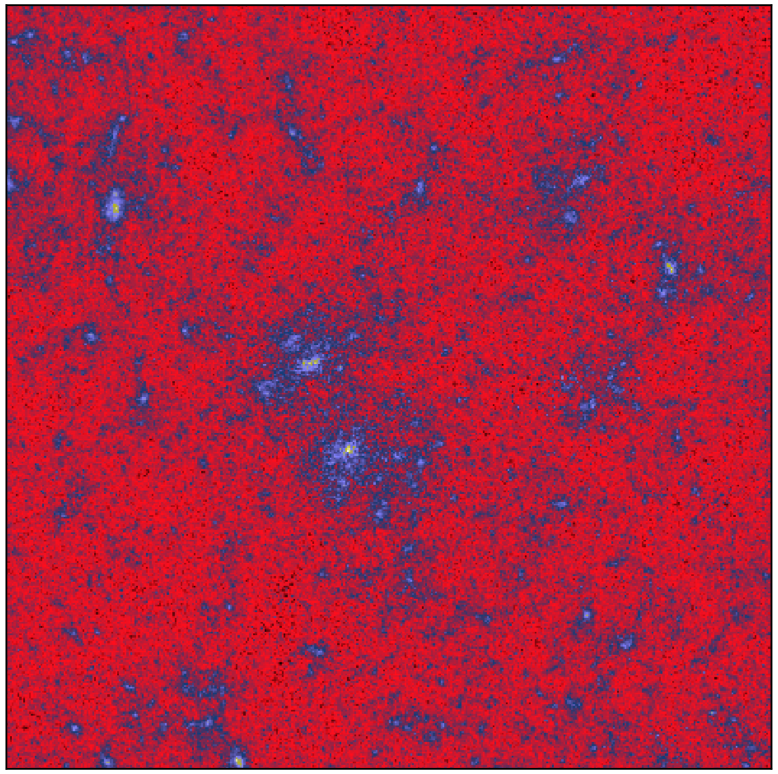
4,194,304 pixels
per map

x (256 maps per model)
x (4 source redshifts)
x (4 cosmological models)

=

Can a neural network do better ?

Let's recall the data

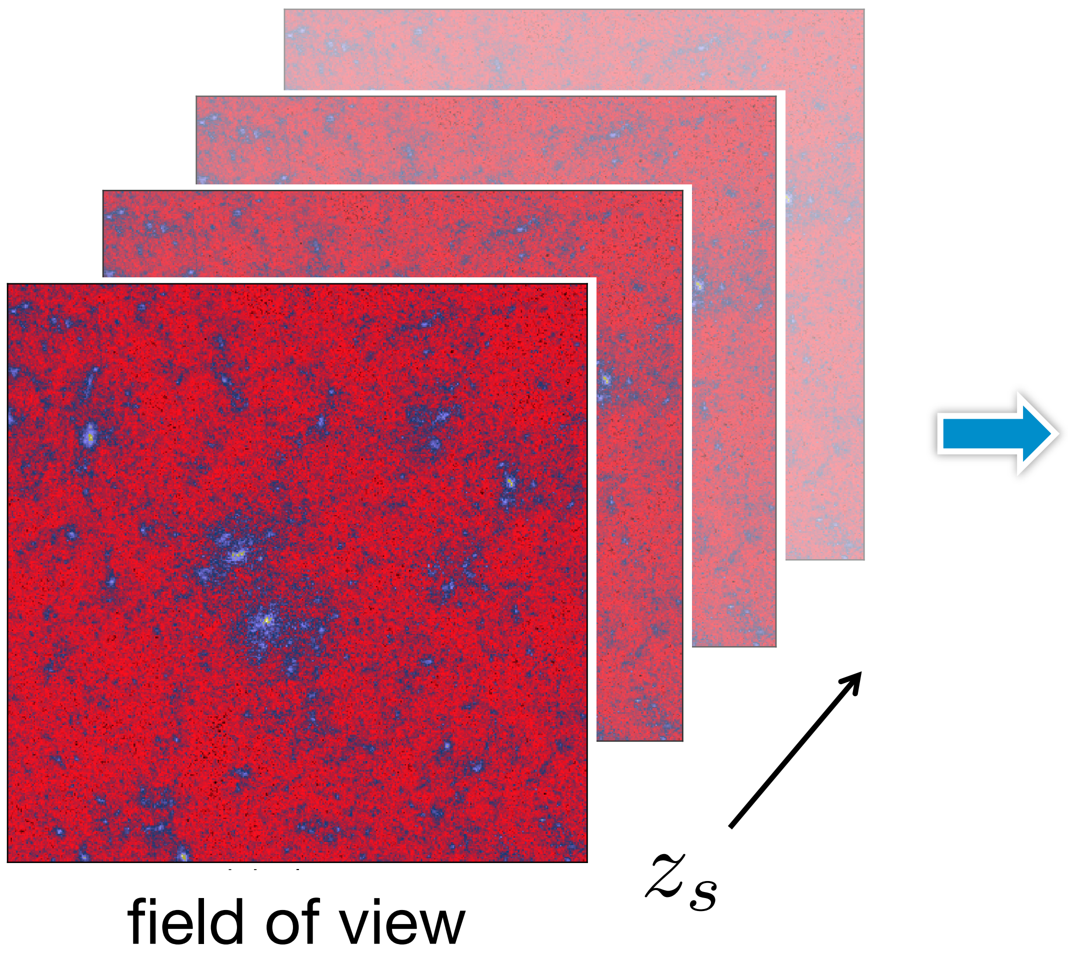


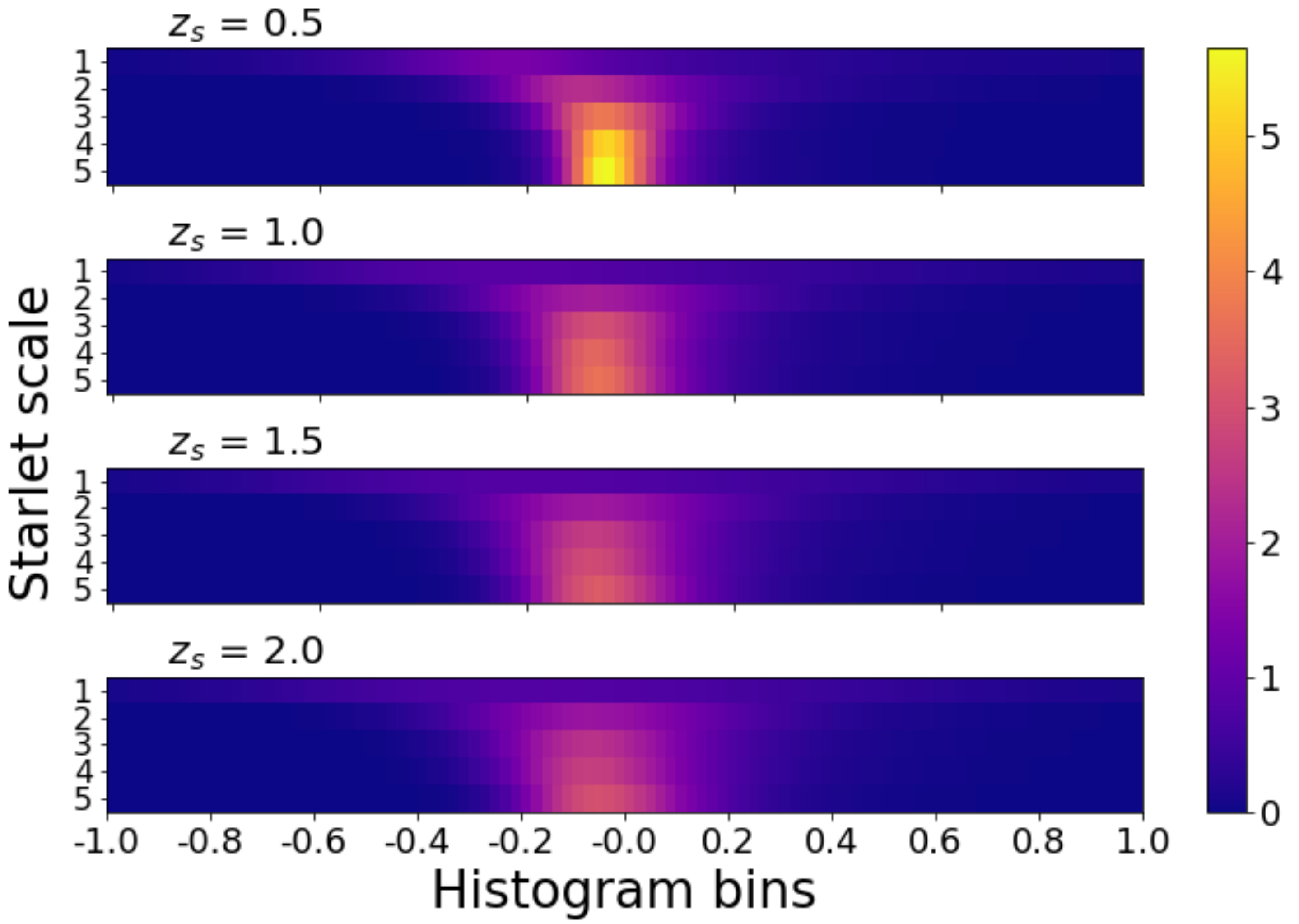
4,194,304 pixels
per map

x (256 maps per model)
x (4 source redshifts)
x (4 cosmological models)

= a computational challenge

A new data representation

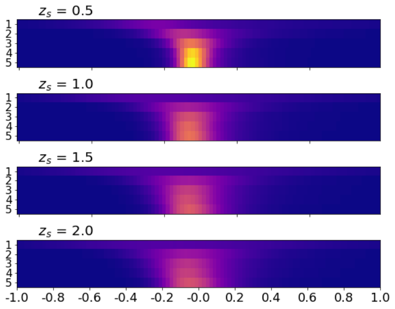




[A. Peel, F. Lalande, et al., submitted PRL (2018)]

Network architecture

Convolutional neural network (CNN) classification problem



input data

75% train
25% test

Layer type	Output shape	# params
Input layer	$1 \times 4 \times 5 \times 100$	0
Conv 3D $[2 \times 3 \times 10]$	$8 \times 4 \times 5 \times 100$	448
Conv 3D $[2 \times 3 \times 10]$	$8 \times 4 \times 5 \times 100$	3848
Max pooling $[1 \times 1 \times 5]$	$8 \times 4 \times 5 \times 20$	0
Conv 3D $[2 \times 3 \times 10]$	$8 \times 4 \times 5 \times 20$	3848
Max pooling $[1 \times 1 \times 2]$	$8 \times 4 \times 5 \times 10$	0
Dropout [0.3]	$8 \times 4 \times 5 \times 10$	0
Flatten	1600	0
Fully connected	32	51232
Fully connected	16	528
Fully connected	4	68

$\longrightarrow$ ΛCDM

? $f_5(R)$

$\longrightarrow$ $M_\nu = 0$ eV

$\longrightarrow$ $M_\nu = 0.1$ eV

$\longrightarrow$ $M_\nu = 0.15$ eV

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

Breaking Degeneracies in MG with WL

noise level ▨ ☐ ☐ zero

Convolutional neural network

Prediction

Truth

$\sigma_{\text{noise}} = 0$	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

Peak statistics (best case)

Prediction

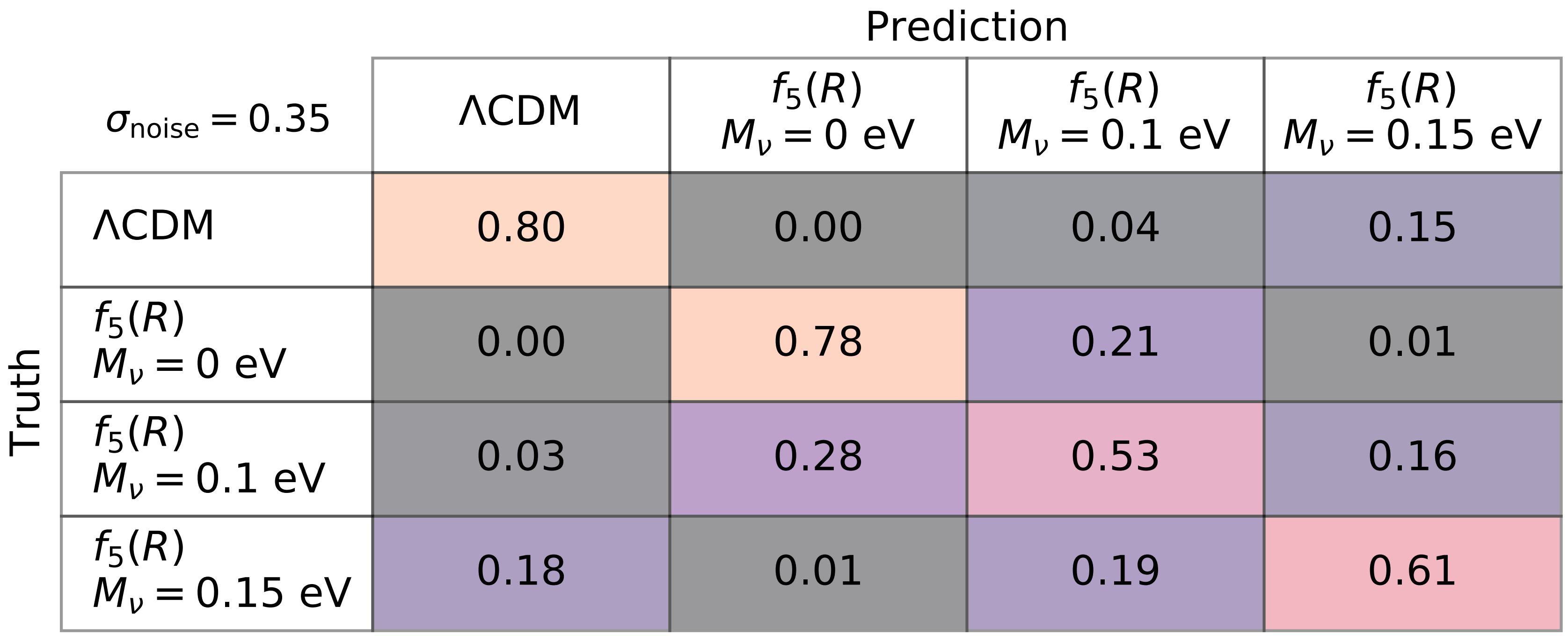
Truth

$\sigma_{\text{noise}} = 0$	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	0.33	0.45	0.22
$f_5(R)$ $M_\nu = 0.15$ eV	0.00	0.09	0.25	0.66

Breaking Degeneracies in MG with WL

noise level ☐▨☐ optimistic

Convolutional neural network

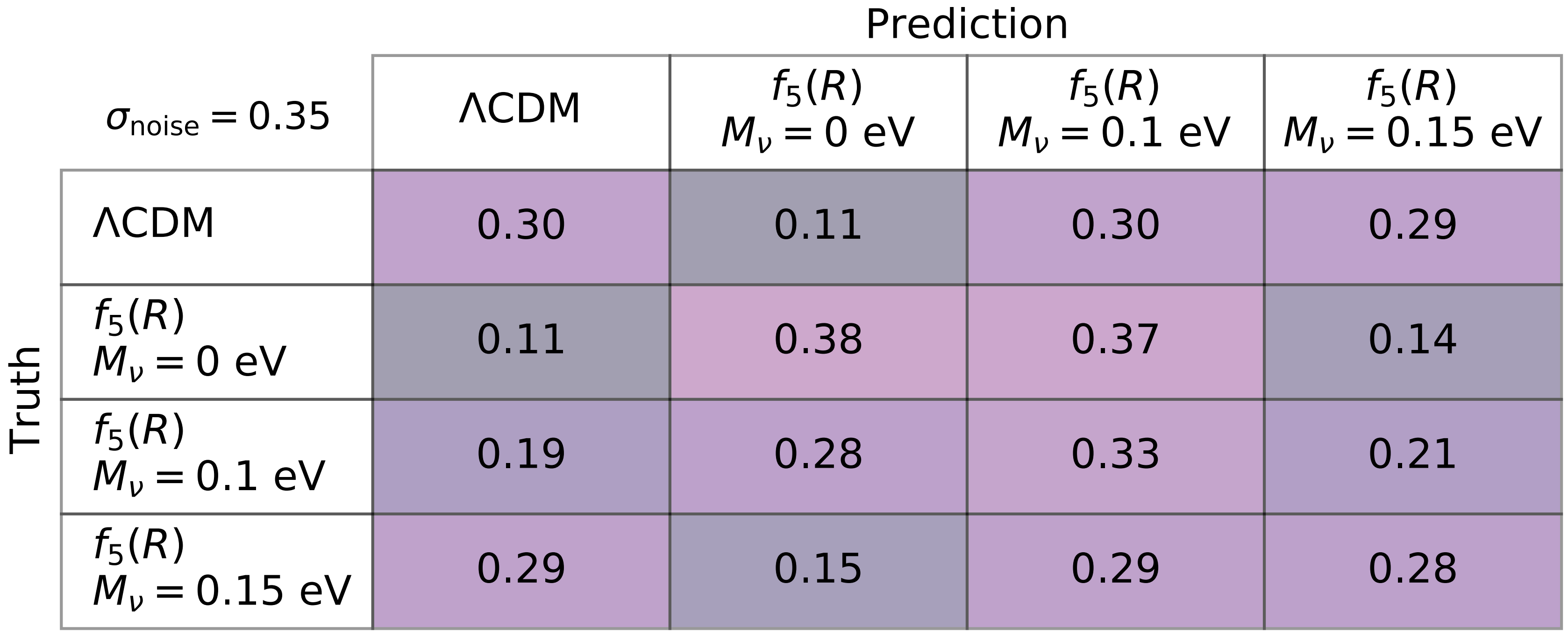


Prediction

Truth

$\sigma_{\text{noise}} = 0.35$	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

Peak statistics (best case)



Prediction

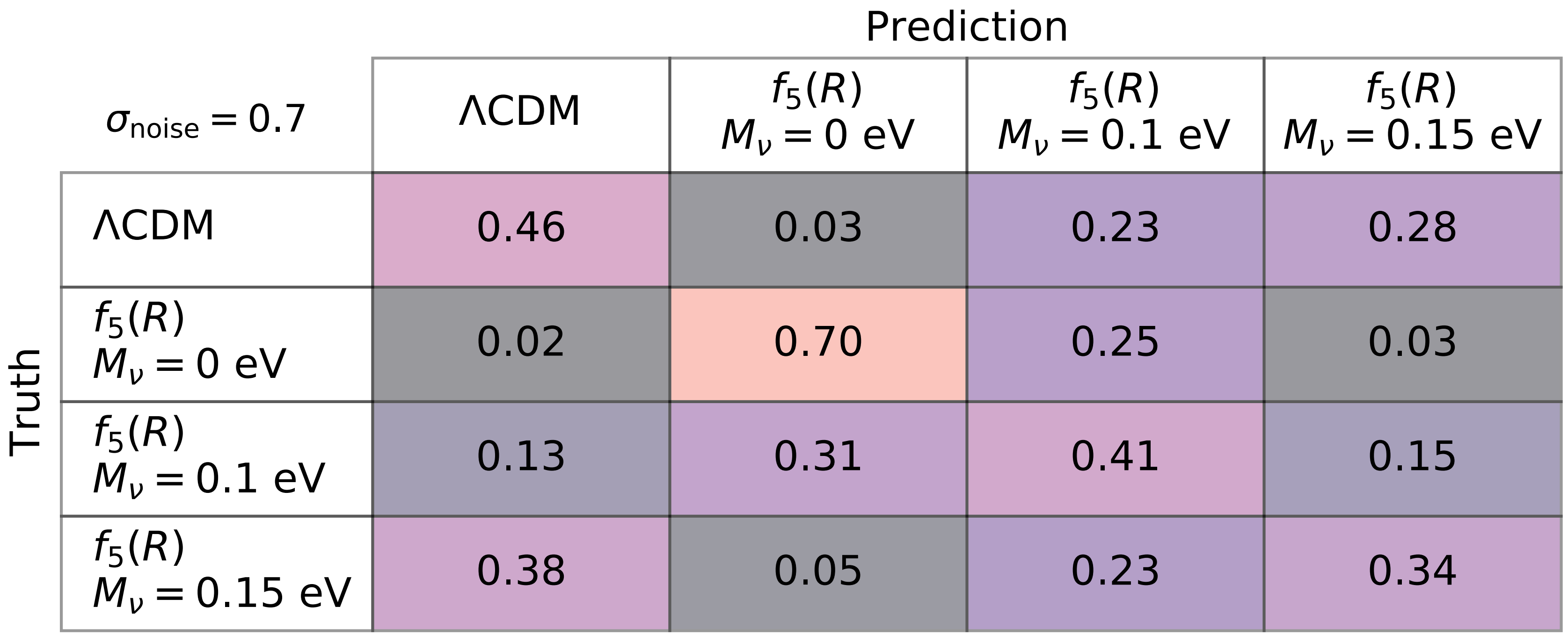
Truth

$\sigma_{\text{noise}} = 0.35$	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	0.15	0.29	0.28

Breaking Degeneracies in MG with WL

noise level ☐☐▨ pessimistic

Convolutional neural network

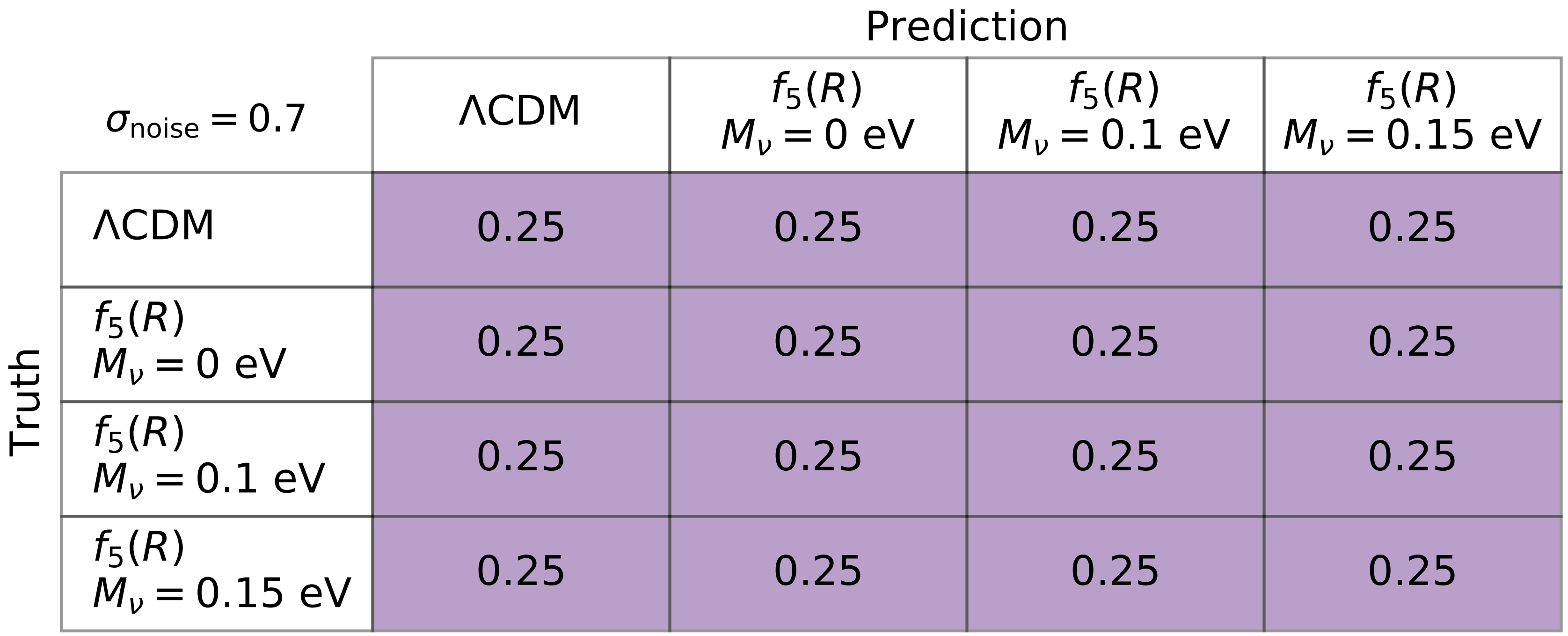


Prediction

Truth

$\sigma_{\text{noise}} = 0.7$	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

Truth

$\sigma_{\text{noise}} = 0.7$	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

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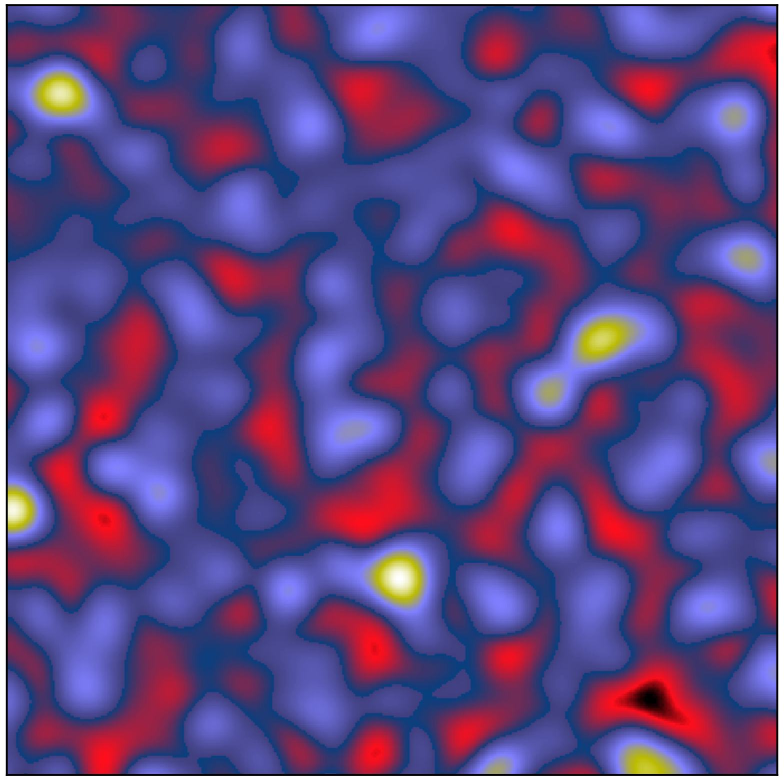
To sum up

- MG + neutrinos can **mimic ΛCDM** at the background and linear level
- Weak-lensing observations accessing **non-Gaussian information** can be used to break degeneracies
- In particular, **peak counts** generally outperform higher (than second) order moments of the aperture mass
- **Machine learning** can do even better, especially in the presence of noise



To sum up

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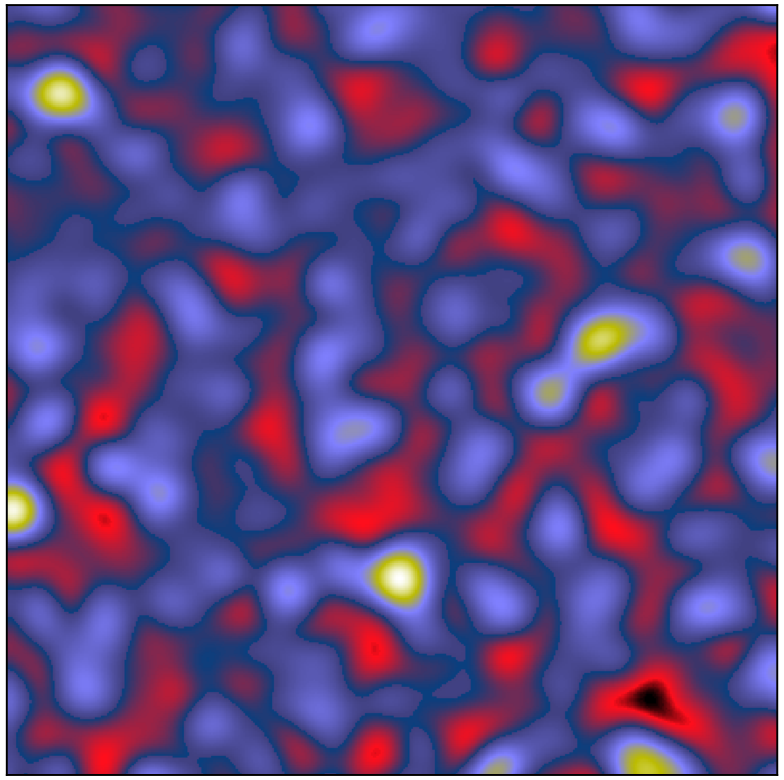

Thank you !