

# Neutrino Cosmology

## Weighing the Ghost Particle with the Universe



**Elena Giusarma**

**Center for Computational Astrophysics**

**Assistant Professor at Michigan Tech University, from August**

**Beyond 2019**

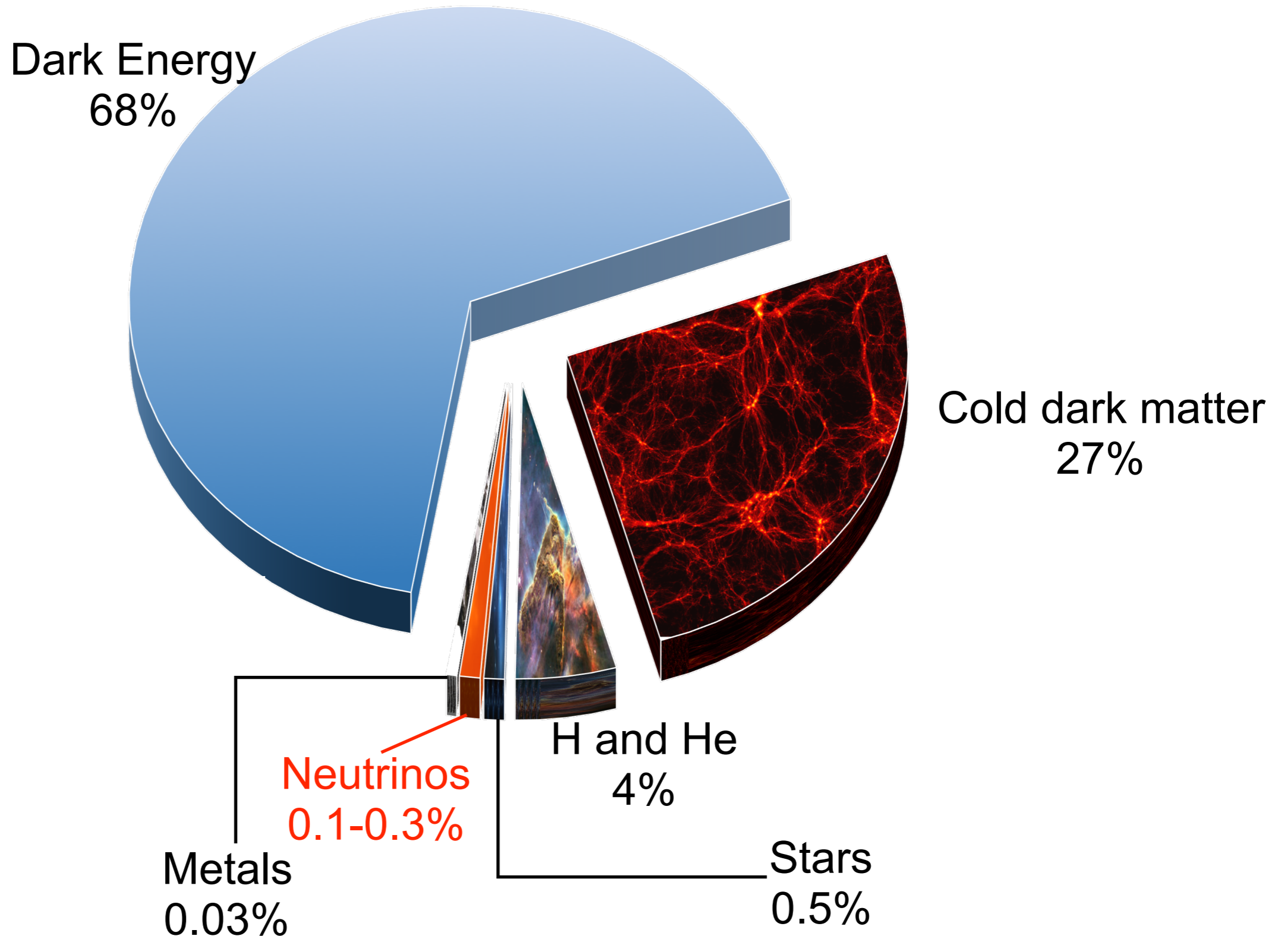
**University of Warsaw**

# Outline

- Cosmic Neutrinos
- Effects on cosmological observations
- Constraints on neutrino masses
- Machine Learning application



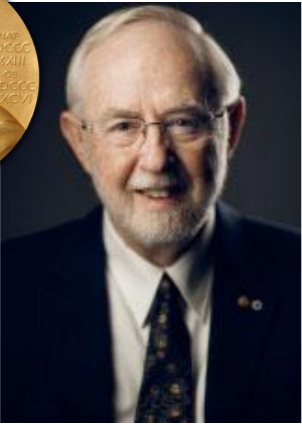
# What is the Universe composed of?



# Neutrino: the invisible particle

$\nu_e$   $\nu_\mu$   $\nu_\tau$  **Massless particles** in the Standard Model

# Neutrino: the invisible particle $\nu_e$ $\nu_\mu$ $\nu_\tau$

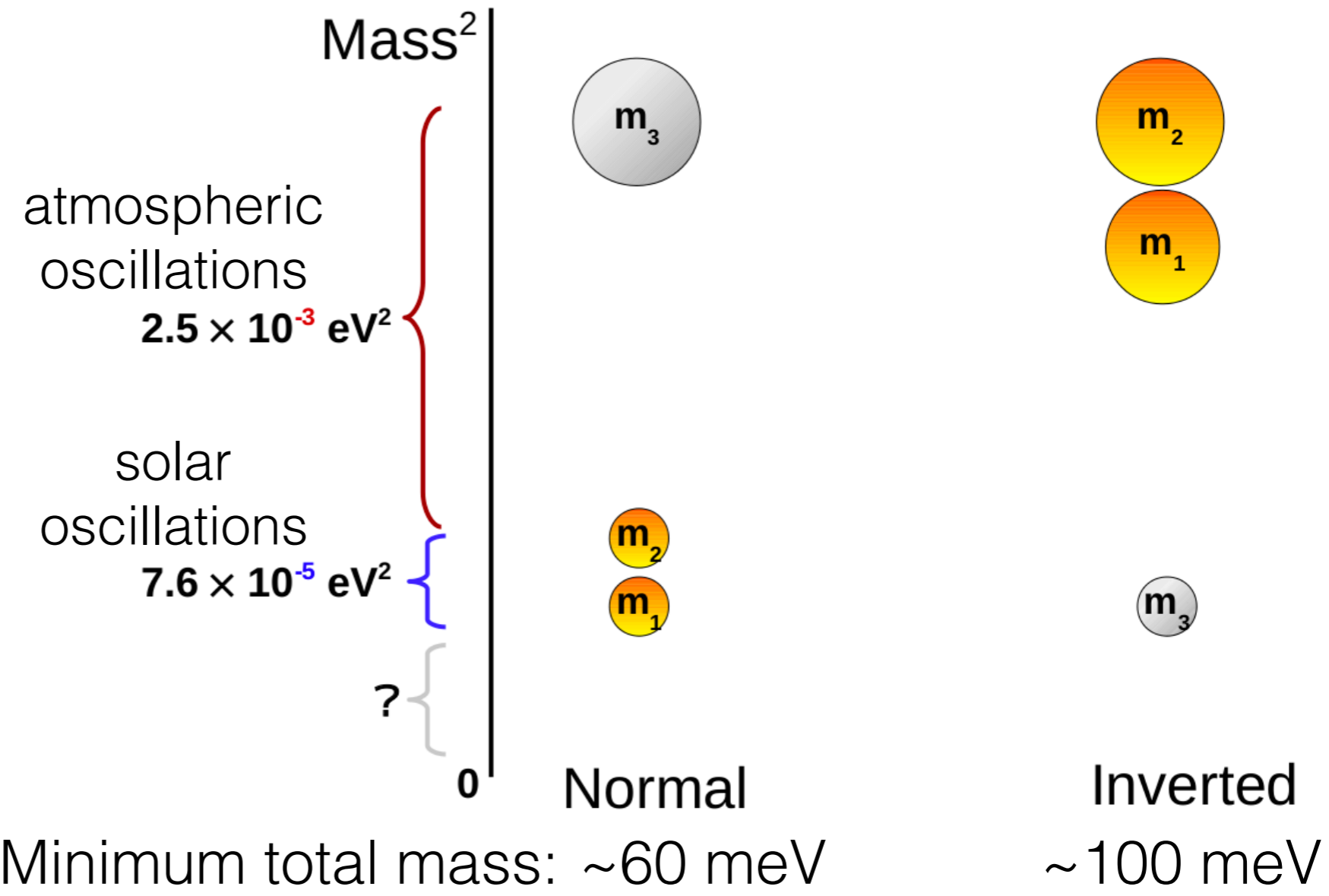


T. Kajita

A. B. McDonald

## Neutrinos are massive particle

### Neutrino Mass Hierarchy

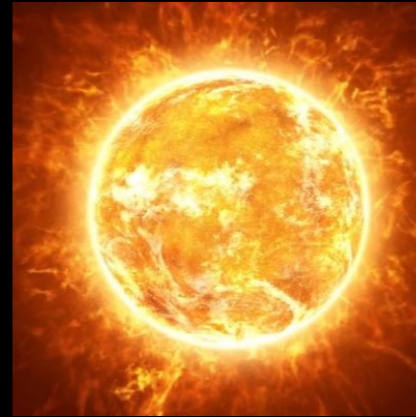


# Where do neutrinos come from?

✓ Nuclear Reactors



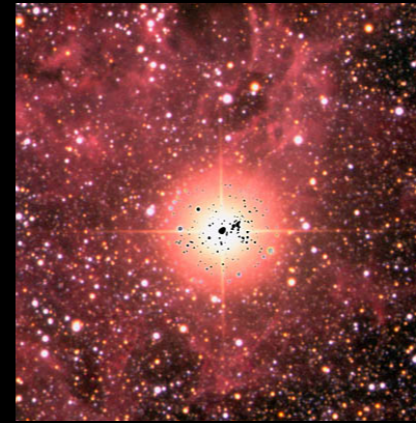
✓ Sun



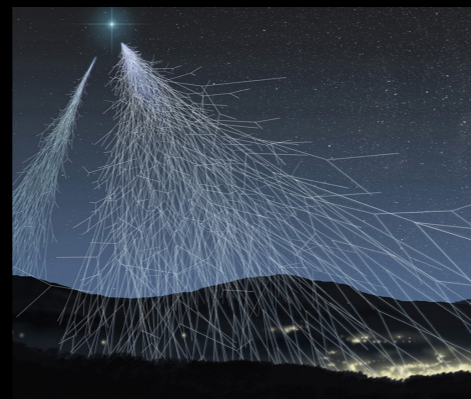
✓ Particle Accelerators



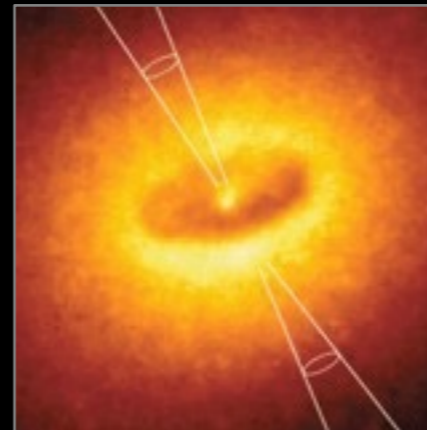
✓ Supernovae  
(Stellar Collapse)  
**SN 1987A**



✓ Earth Atmosphere  
(Cosmic Rays)



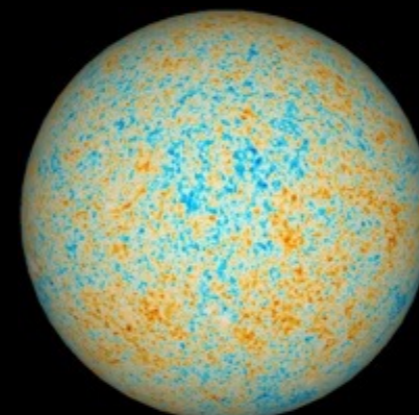
✓ Accelerators in  
astrophysical  
sources



✓ Earth Crust  
(Natural Radioactivity)



✓ Early Universe  
**Indirect Evidence**





# Why Study Neutrinos?

They are the only **direct evidence for Beyond Standard Model physics!**



# Why Study Neutrinos?

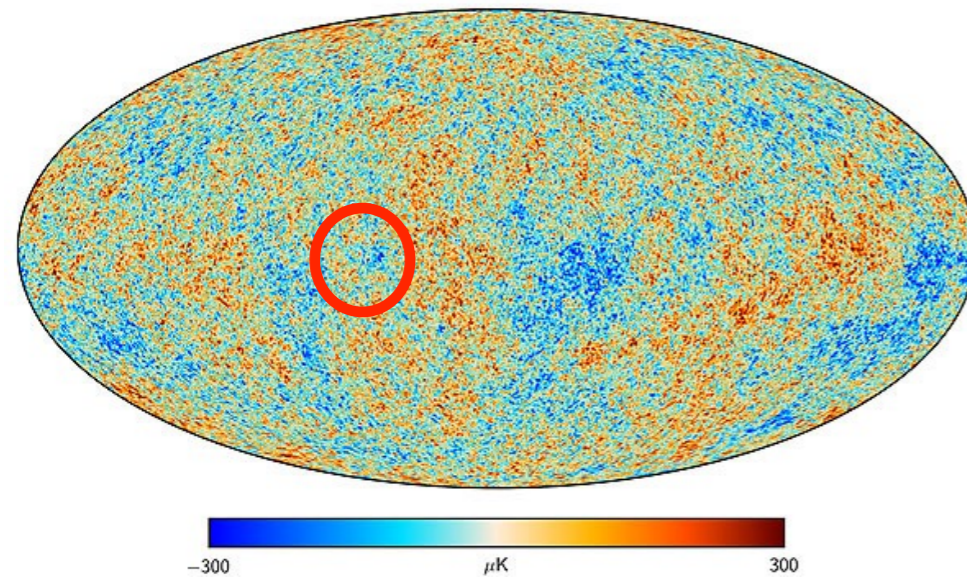
They are the only **direct evidence for Beyond Standard Model physics!**

## Cosmology

- \* They provide information on the **evolution of the Universe.**
- \* They are the **second most abundant particles** in the Universe.
- \* They are the the first and only known **form of dark matter** until now.
- \* They leave key **signatures on different cosmological probes.**
- \* Through precise cosmological measurements, we can **derive constraints on the sum of neutrino masses.**

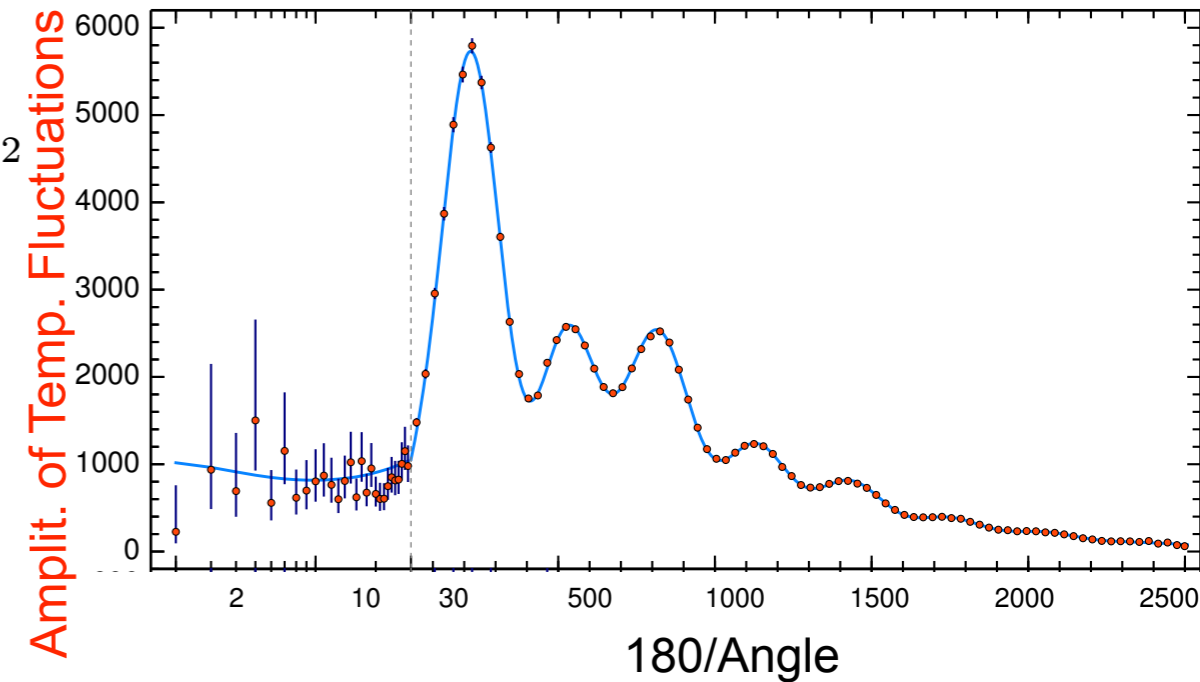
# CMB and LSS: Summary Statistics

## CMB Temperature

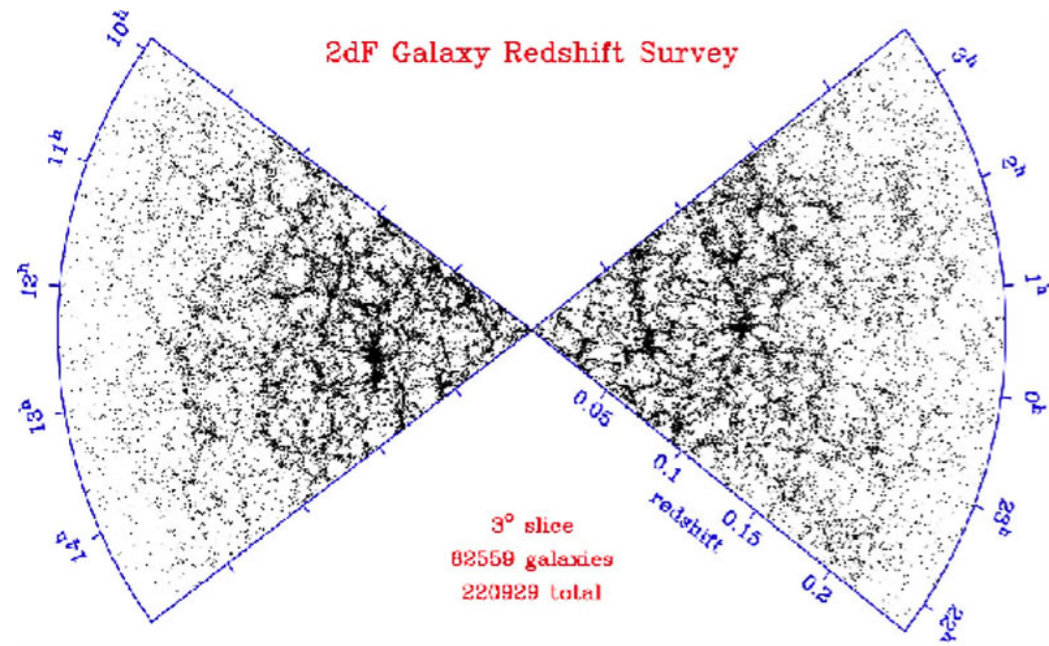


$$C_l = \frac{1}{2l + 1} \sum_{m=-l}^l |a_{lm}|^2$$

## Power Spectrum



## Large-Scale Structure (LSS)

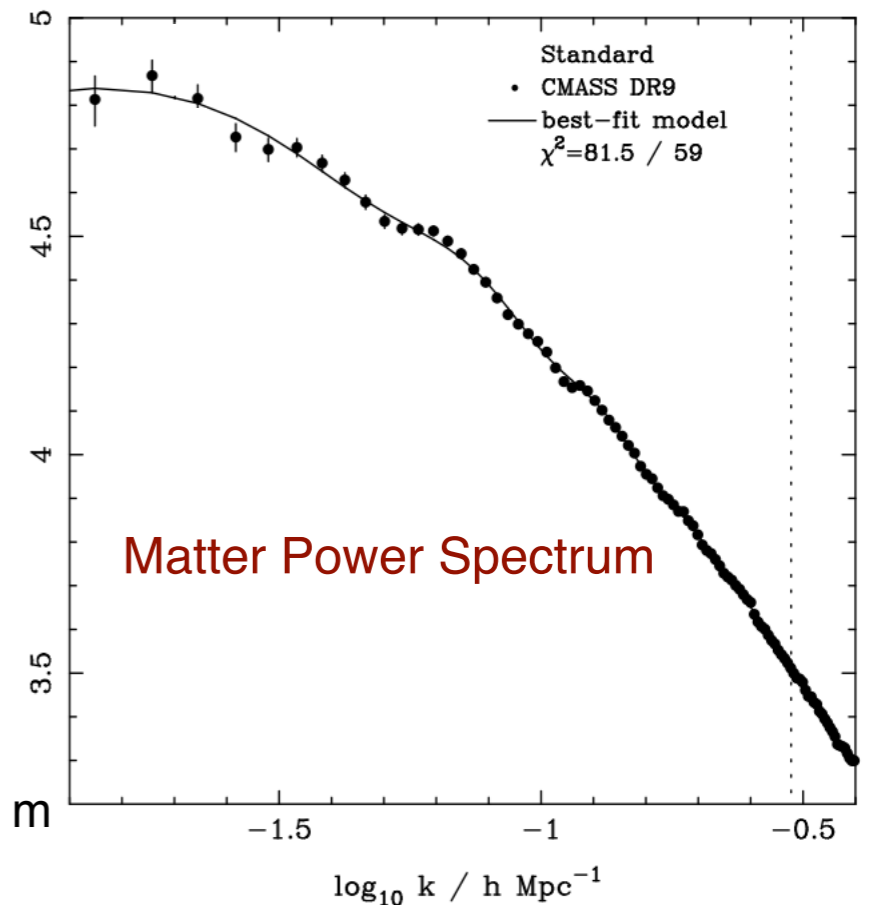


$$P(k) = \langle \delta(\mathbf{k})\delta(\mathbf{k}) \rangle$$

Variance

Matter Power Spectrum

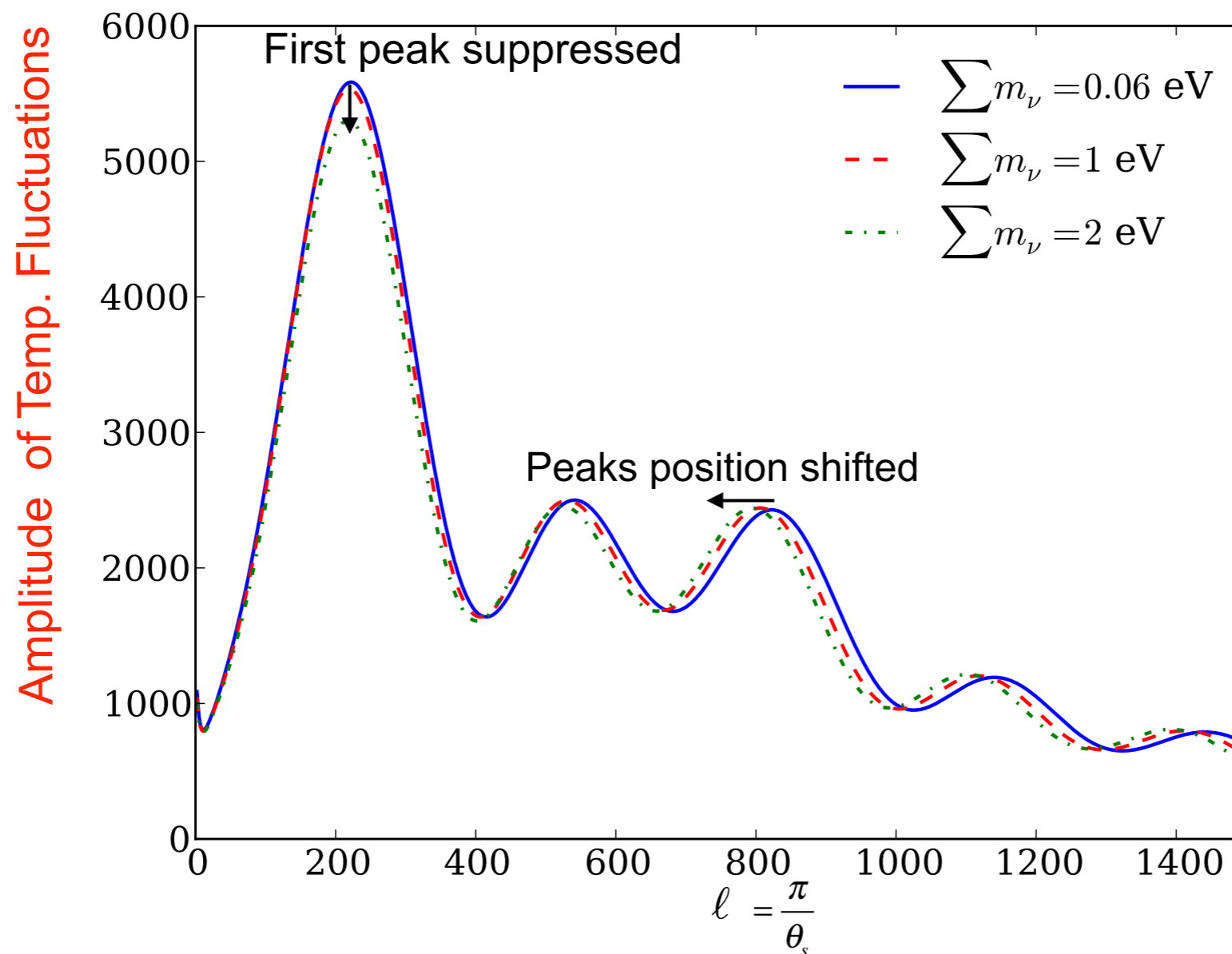
1 Mpc =  $3.1 \times 10^{22}$  m  
h = 0.67



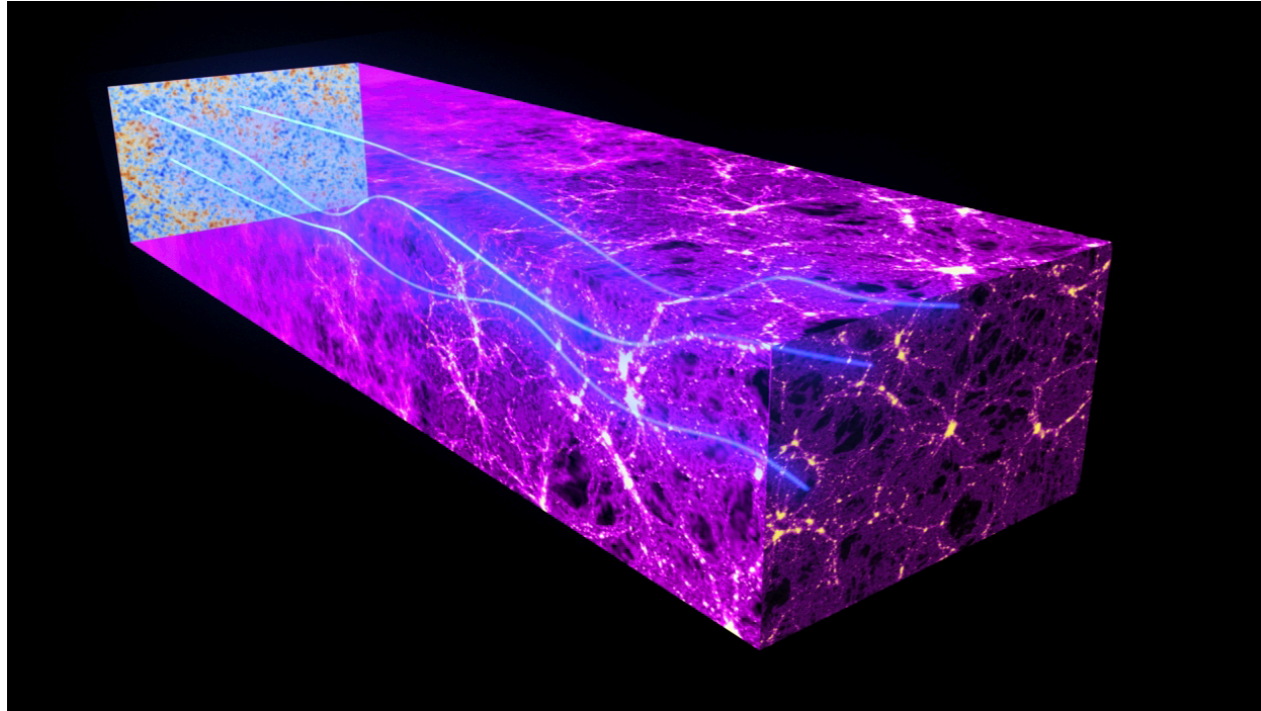
# Neutrino mass effect on CMB

Neutrinos alter background and perturbation evolution:

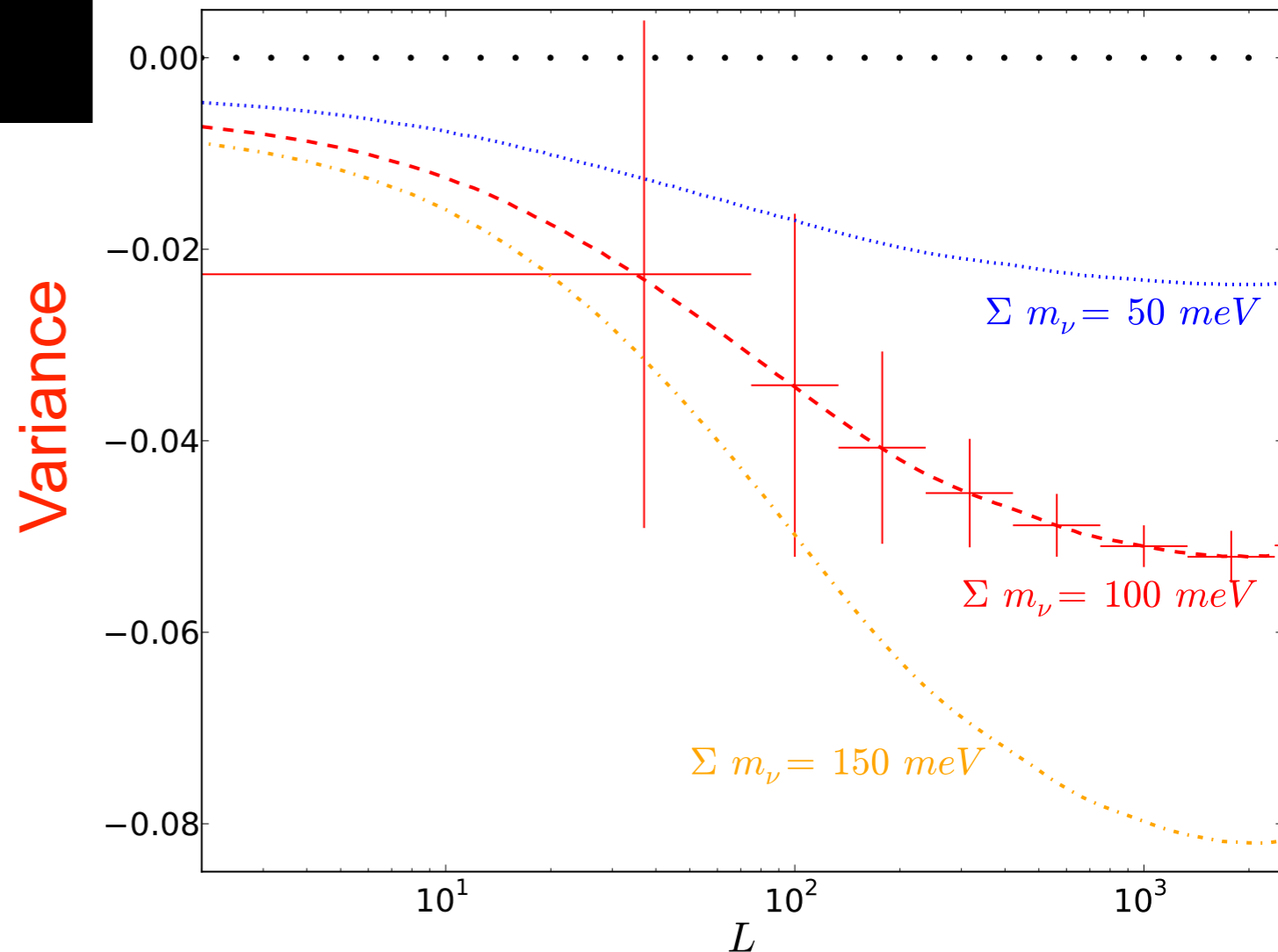
- **Background:** matter-radiation equality delayed and angular diameter distance changed (compensated by acting on other parameters, e.g  $H_0$ )
- **Perturbations:** early-ISW at intermediate scales and damping of small scales perturbations



# Neutrino mass effect on CMB



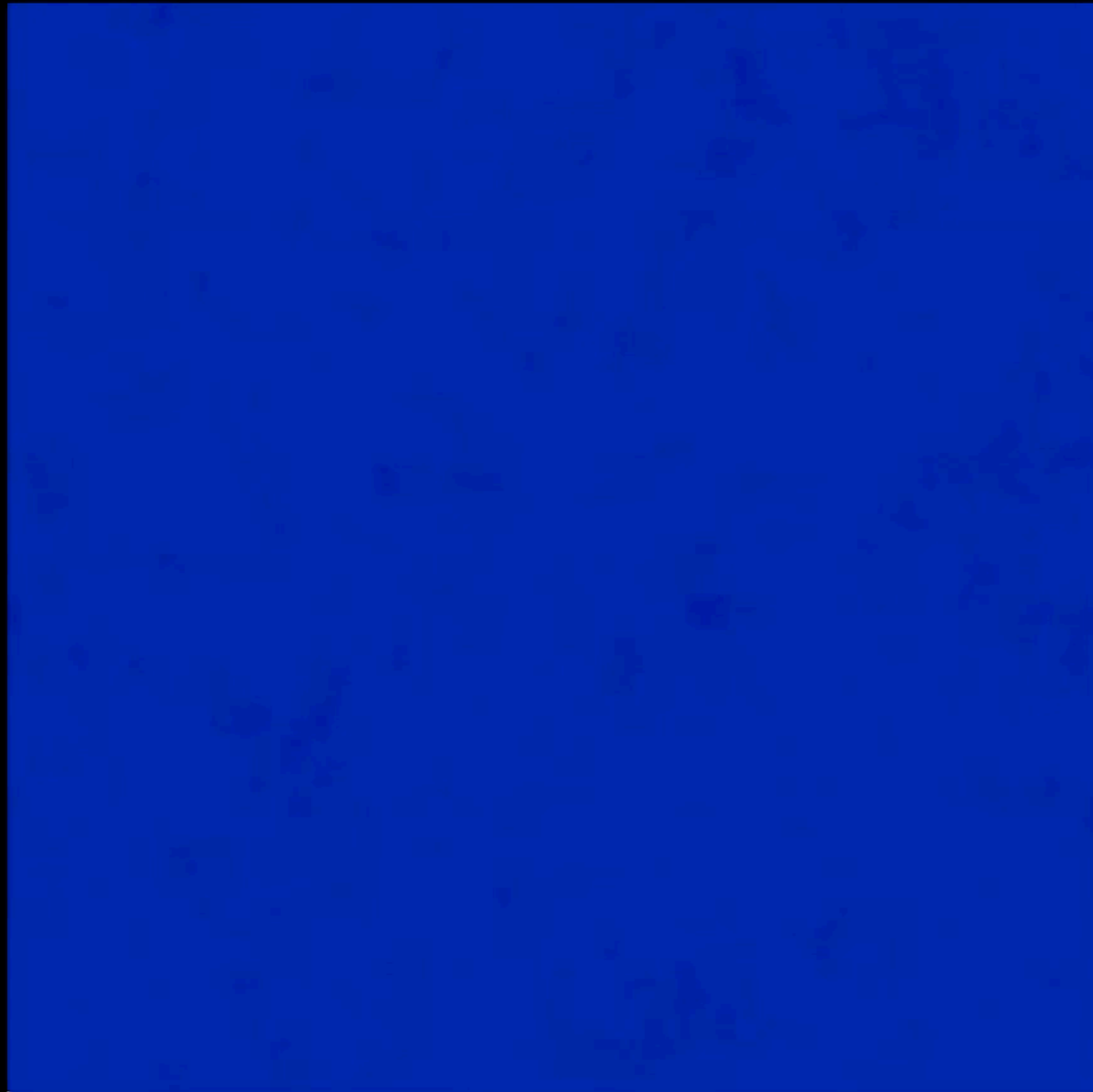
## CMB Lensing



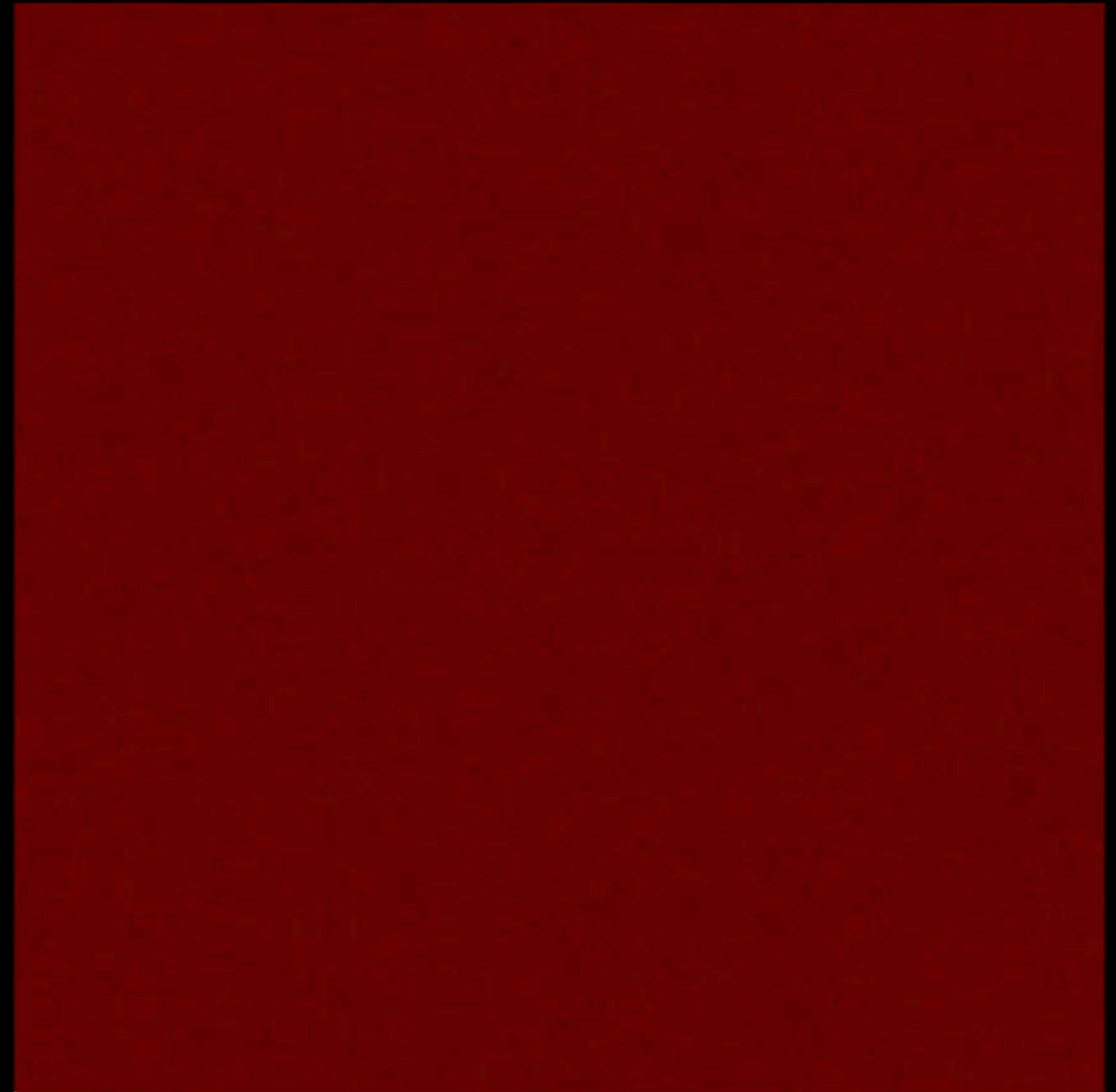
Abazajian et al., Astropart. Phys., 2015

# Neutrino clustering

Dark Matter



Neutrino



$a=0.02$

<https://franciscovillaescusa.github.io/neutrinos.html>

Credit: Francisco Villaescusa-Navarro

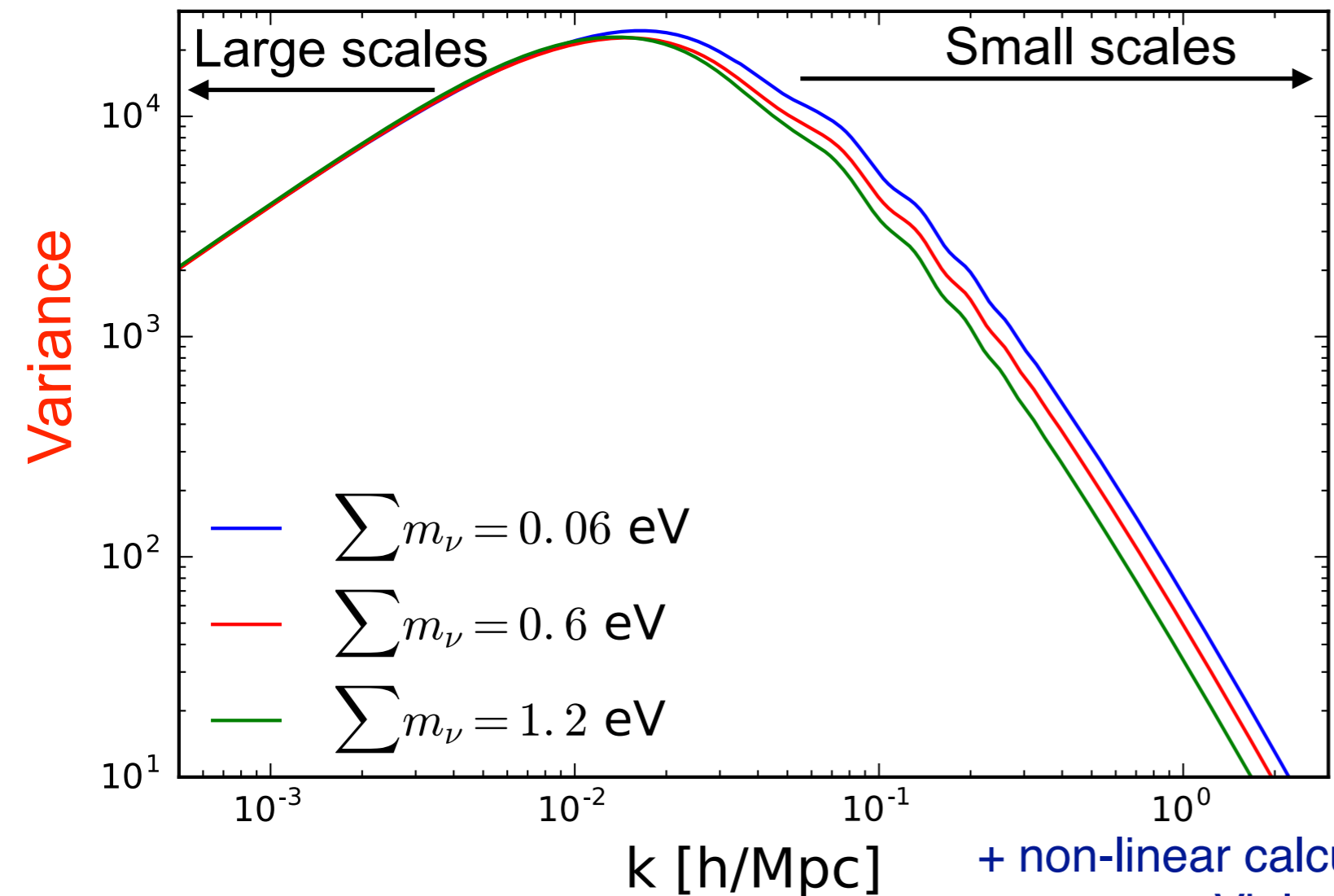


# Neutrino mass effect on LSS

The small-scale matter power spectrum,  $k > k_{\text{fs}}$ , is reduced in presence of massive neutrinos:

- On larger scales  $\nu$ s cluster in the same way as cold dark matter
- Free-streaming  $\nu$ s do not cluster
- The growth rate of CDM and baryon fluctuations is reduced

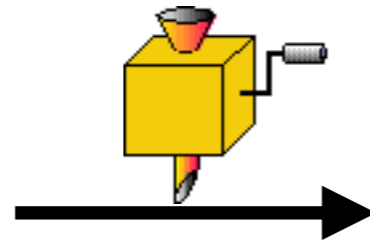
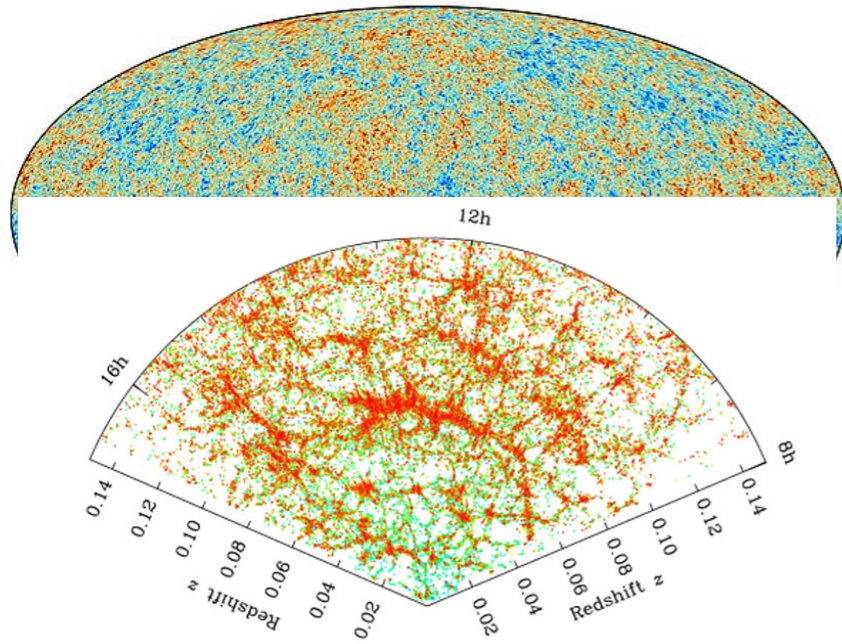
$$k_{\text{fs}} \simeq 0.018 \Omega_m^{1/2} \left( \frac{M_\nu}{1\text{eV}} \right)^{1/2} h \text{ Mpc}^{-1}$$



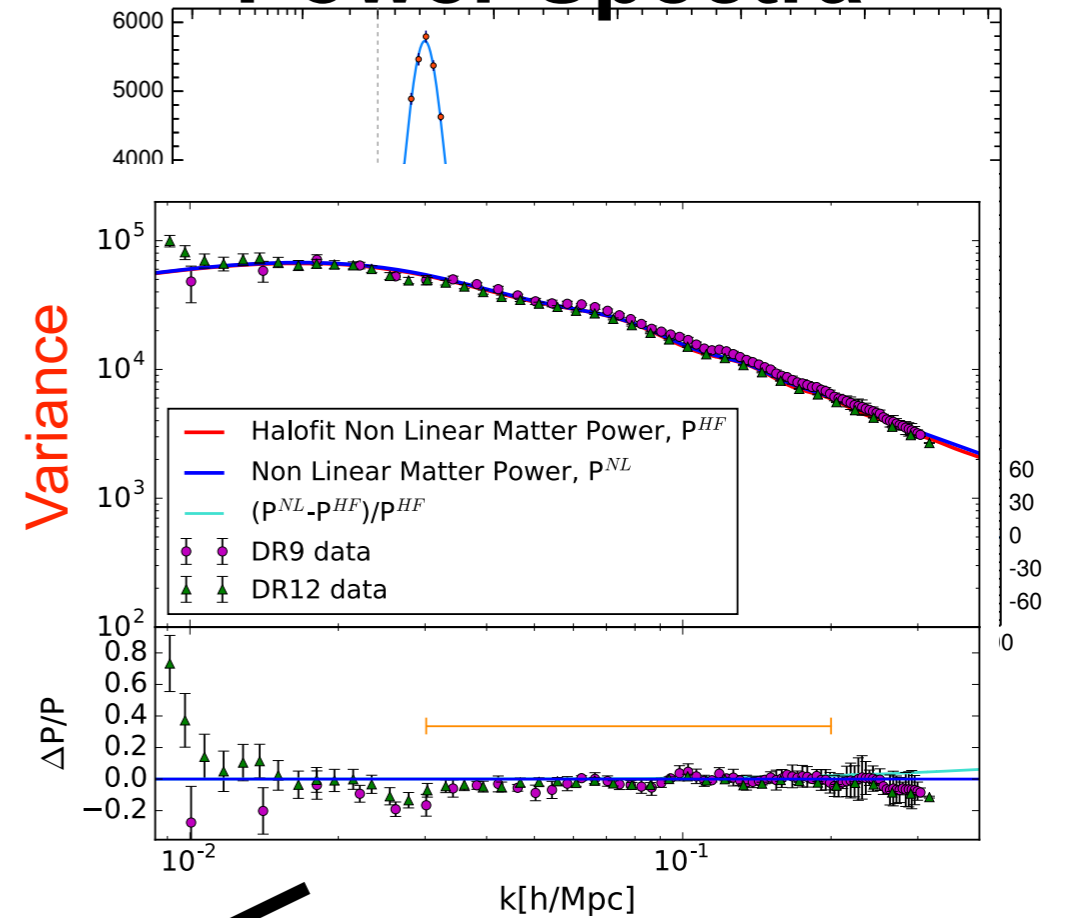
+ non-linear calculations: additional suppression at large  $k$   
see e.g. Viel et al. 2010, Villaescusa-Navarro et al. 2013

# Cosmological parameter estimation

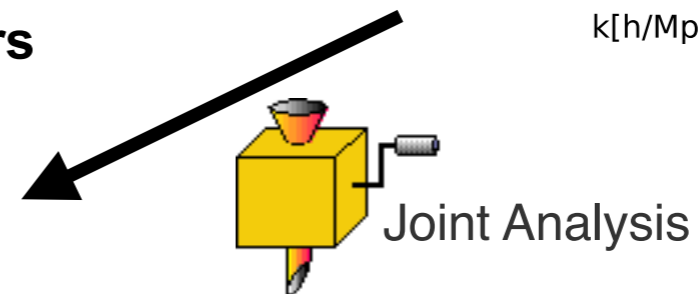
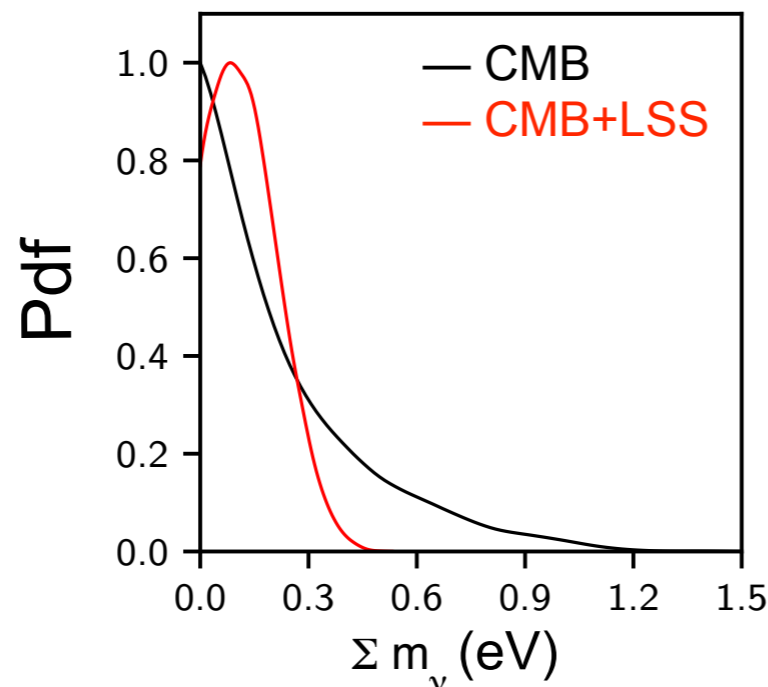
## Sky Maps



## Power Spectra



## Cosmological parameters



- Apply Bayesian parameter Inference to derive the posterior pdf using MCMC.
- Compute the bounds on each model parameter from the marginalized probability distribution for such parameter.

# CURRENT COSMOLOGICAL BOUNDS ON NEUTRINO MASSES

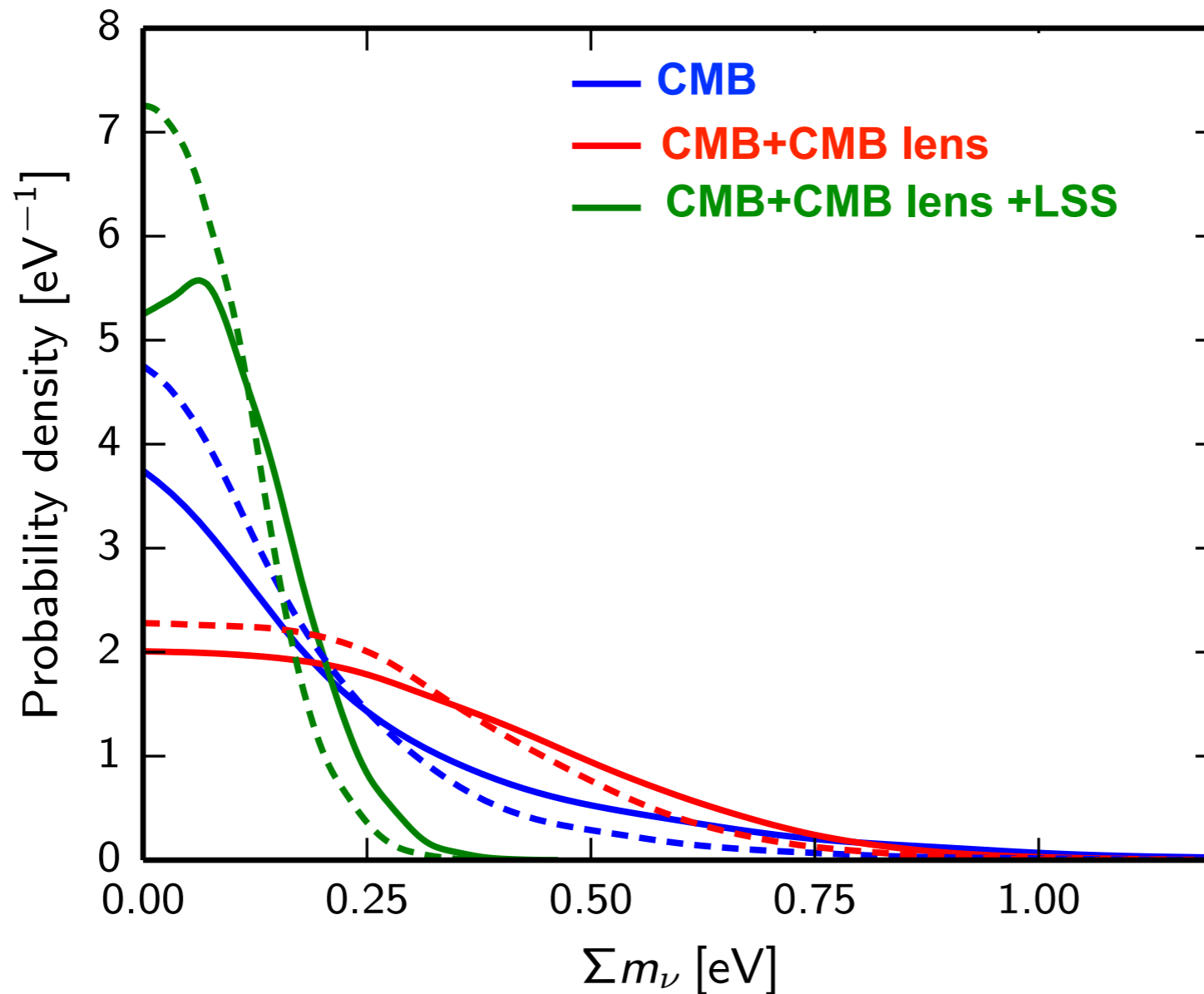
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# $\Sigma m_\nu$ limits from cosmology

6 standard cosmological parameters + neutrino masses

The bounds on neutrino properties depend on

✓ The combination of **cosmological data** used



Planck collaboration (including **Elena Giusarma**), 2015

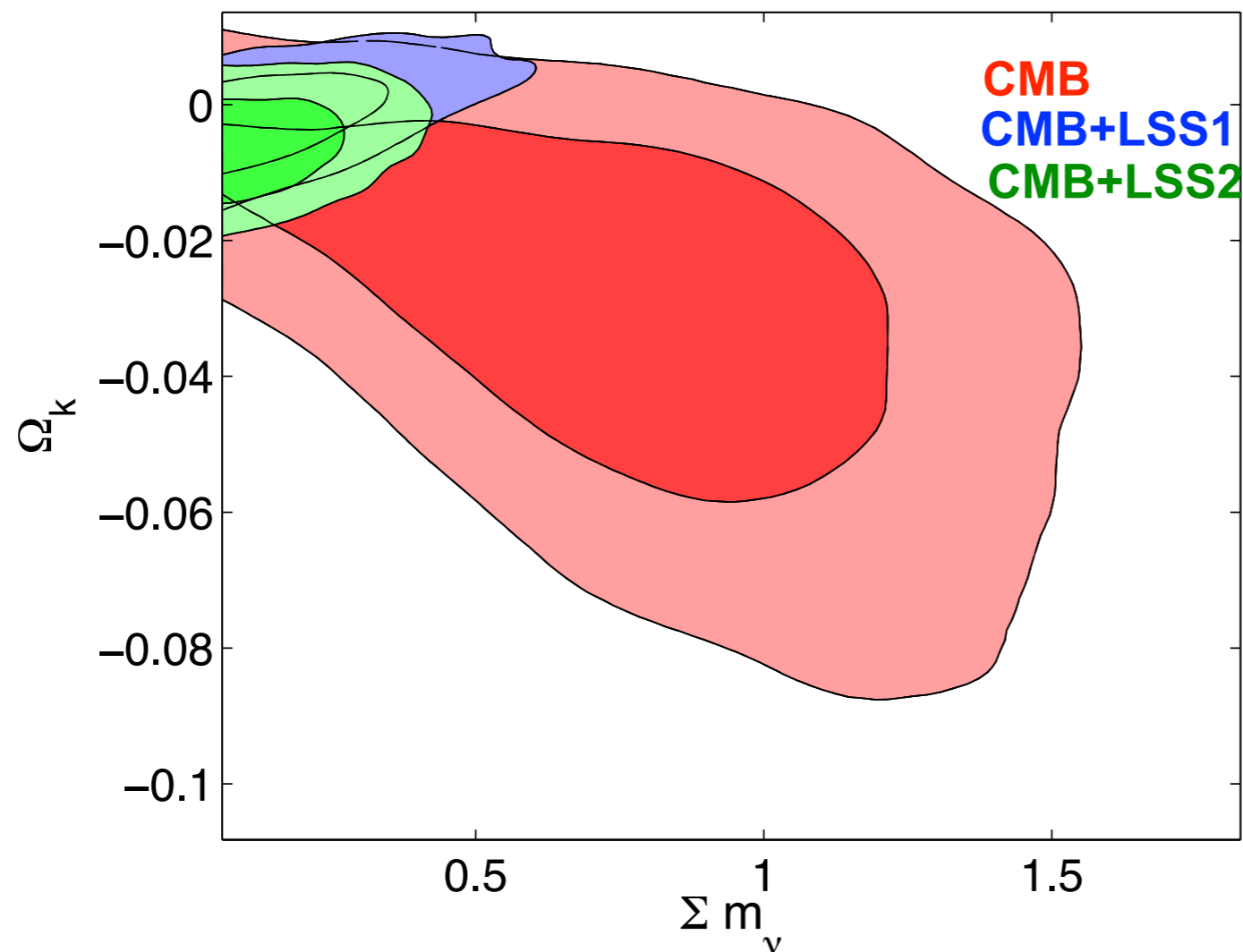
# $\Sigma m_\nu$ limits from cosmology

6 standard cosmological parameters + neutrino masses + geometry of the universe

The bounds on neutrino properties depend on

✓ The combination of **cosmological data** used

✓ The assumed **cosmological model** (problem of parameter degeneracies )

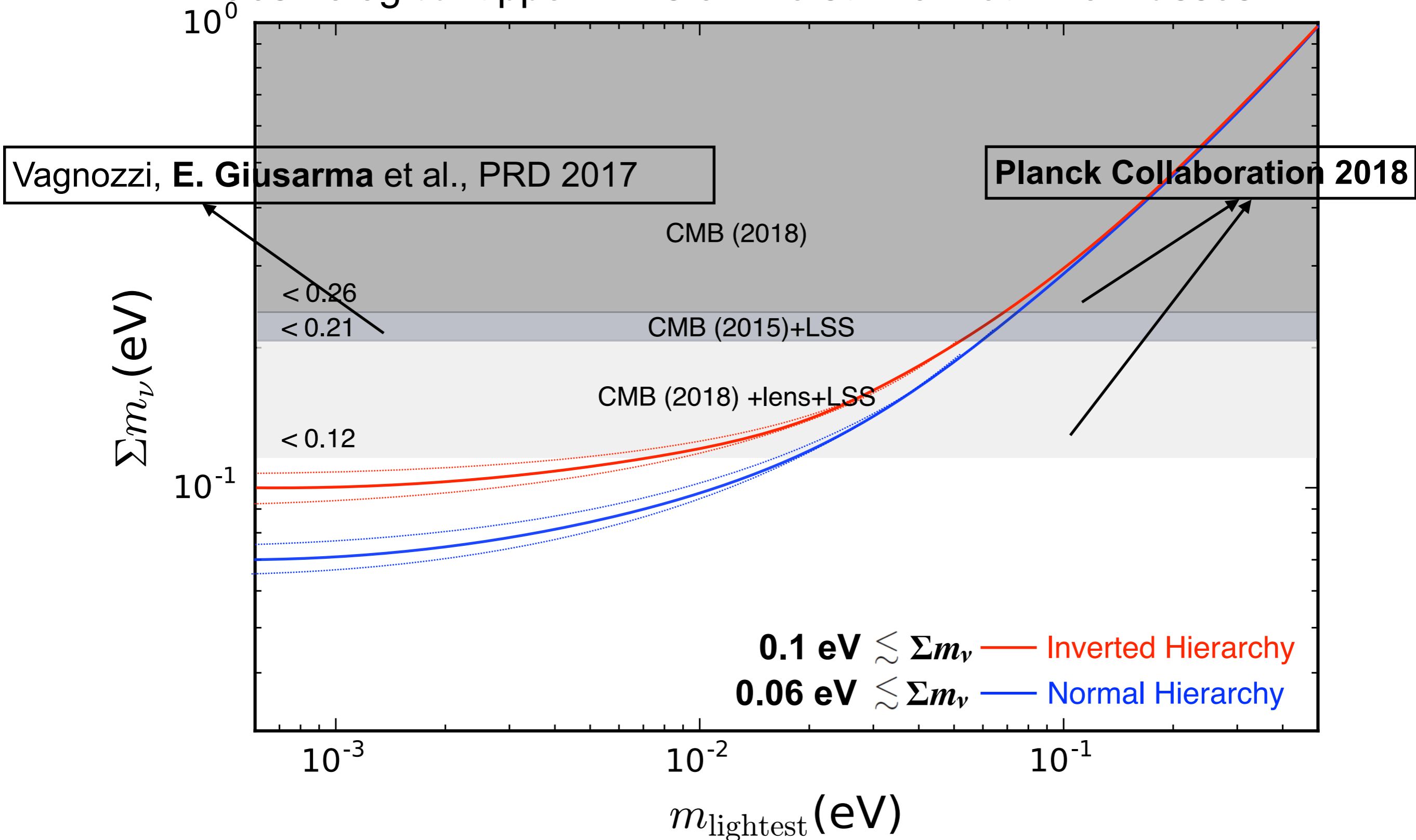


Elena Giusarma et al., PRD 2013



# 2019 state $\Sigma m_\nu$ from cosmology

Cosmological upper limits on the sum of neutrino masses



# How to improve $\Sigma m_\nu$ limits?

**We need to improve the use of  $P(k,z)$ !**

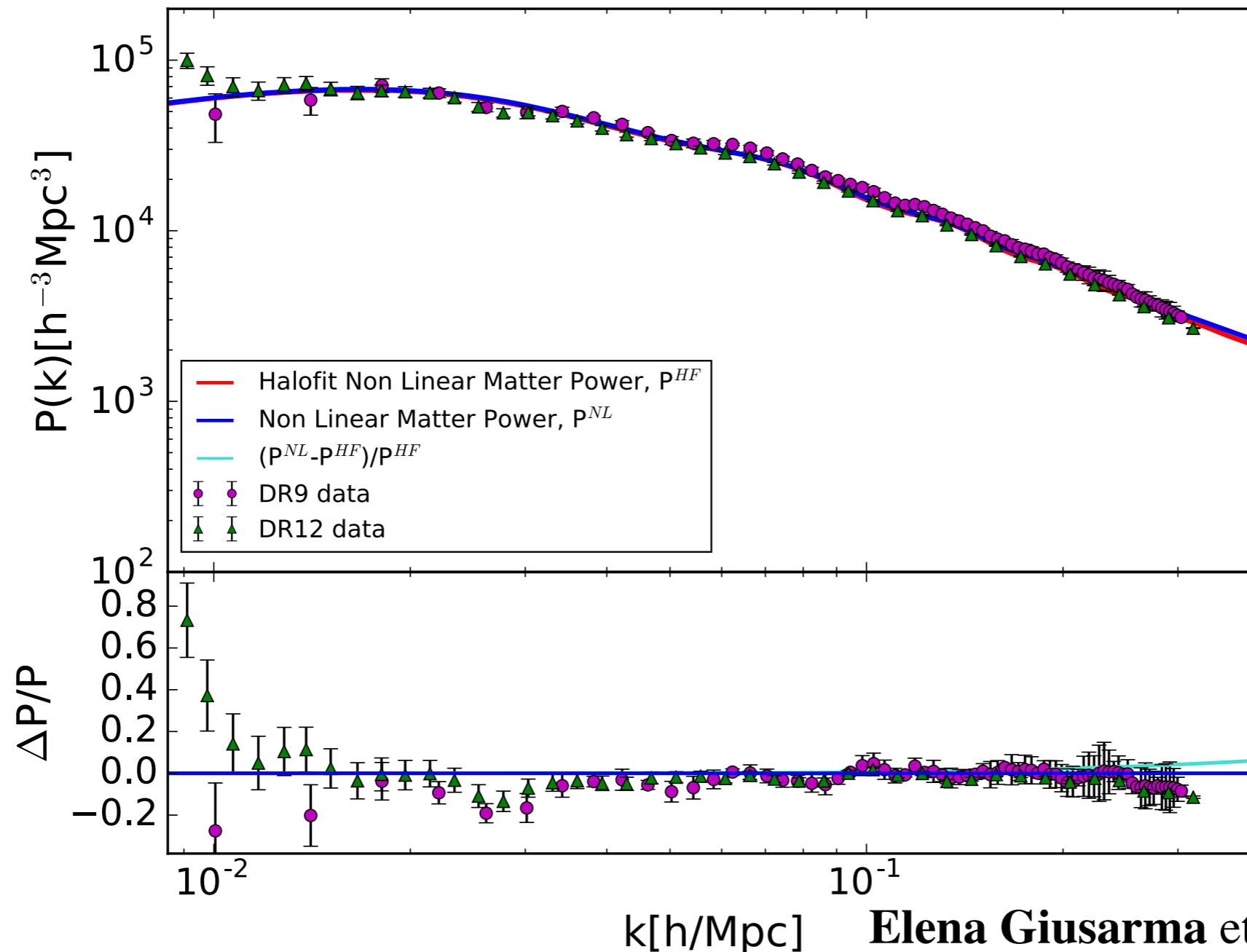
Galaxy power spectrum:

$$P_g(k, z) \approx b^2 P(k, z)$$

What we measure

Galaxy Bias

What we want to measure



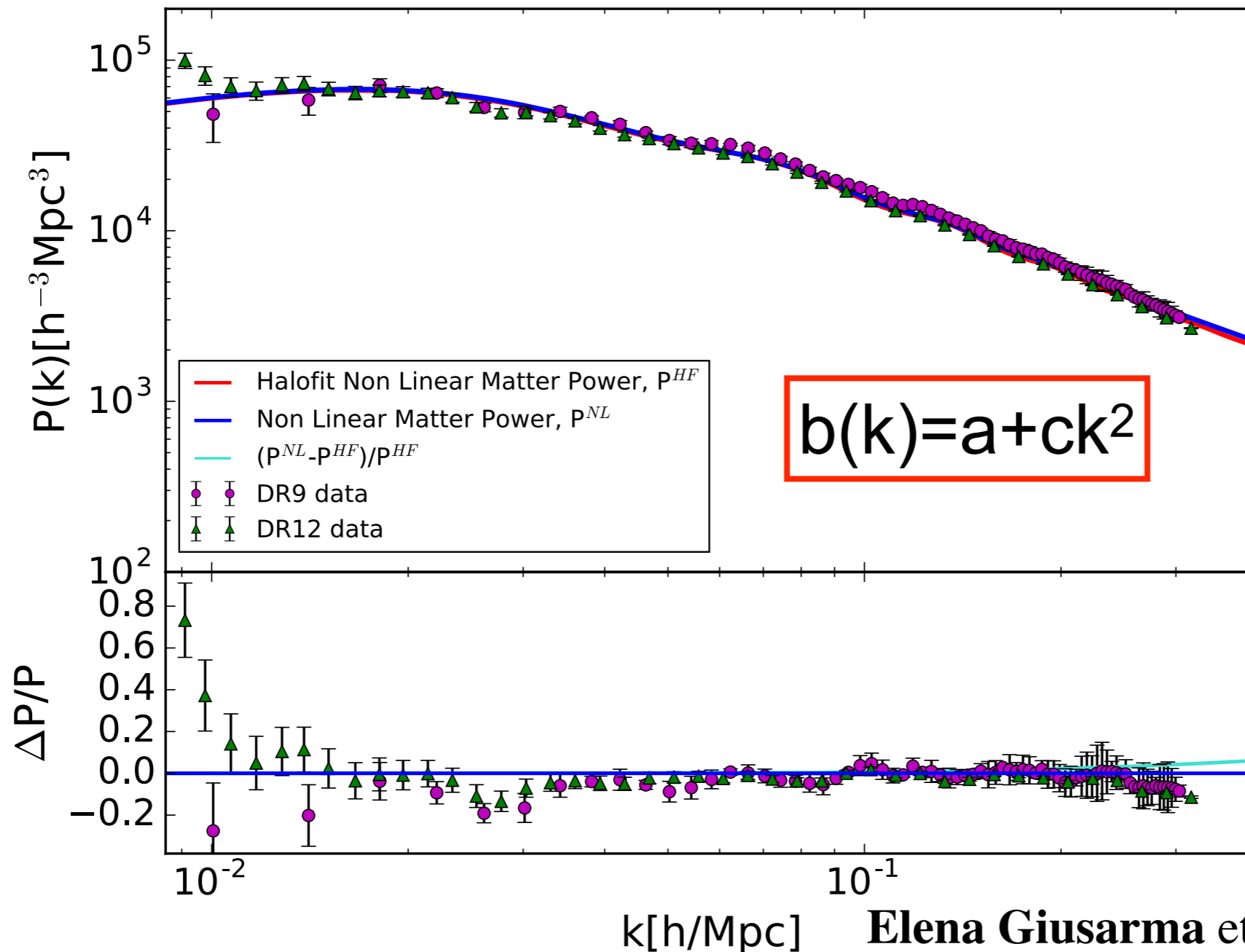
Elena Giusarma et al., PRD 2016

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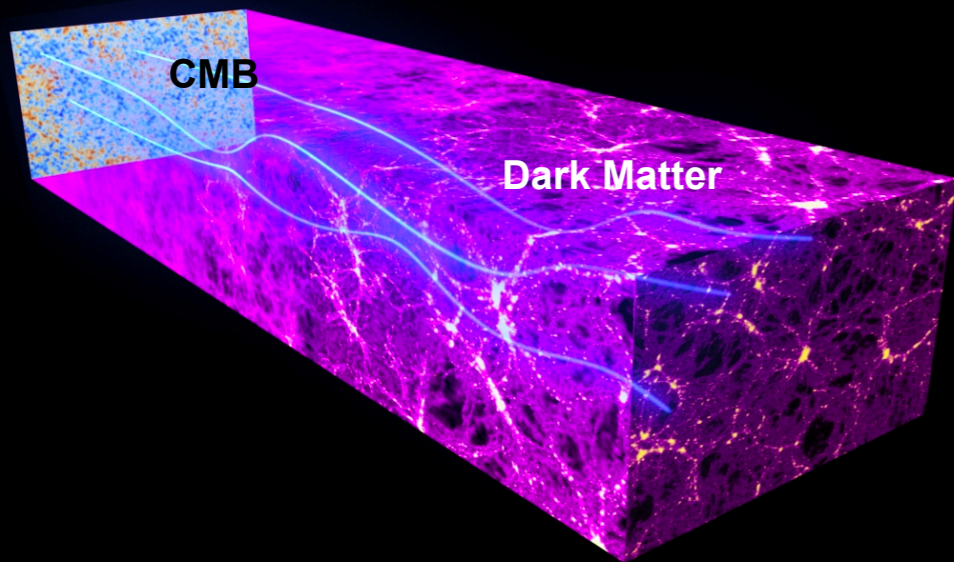
$$P_g(k, z) \approx b^2(k)P(k, z)$$



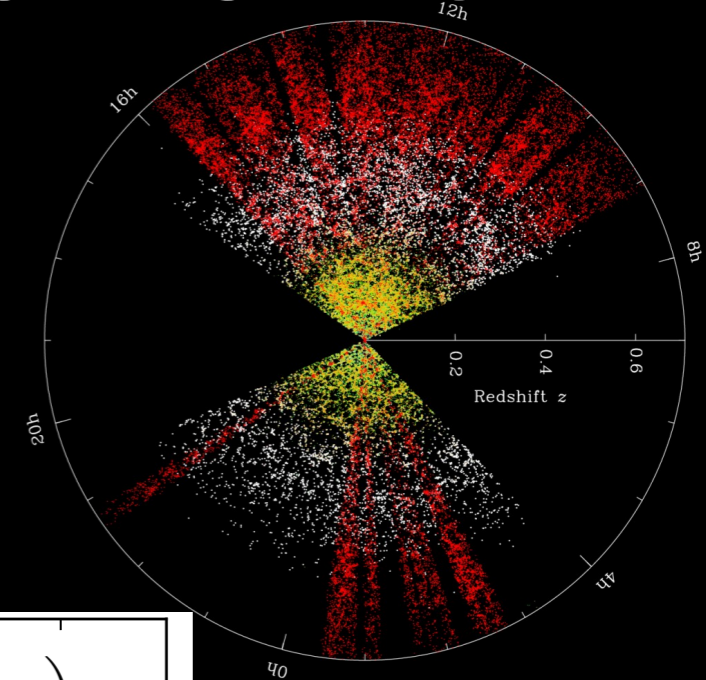
Elena Giusarma et al., PRD 2016

# CMB lensing-galaxy cross-correlations

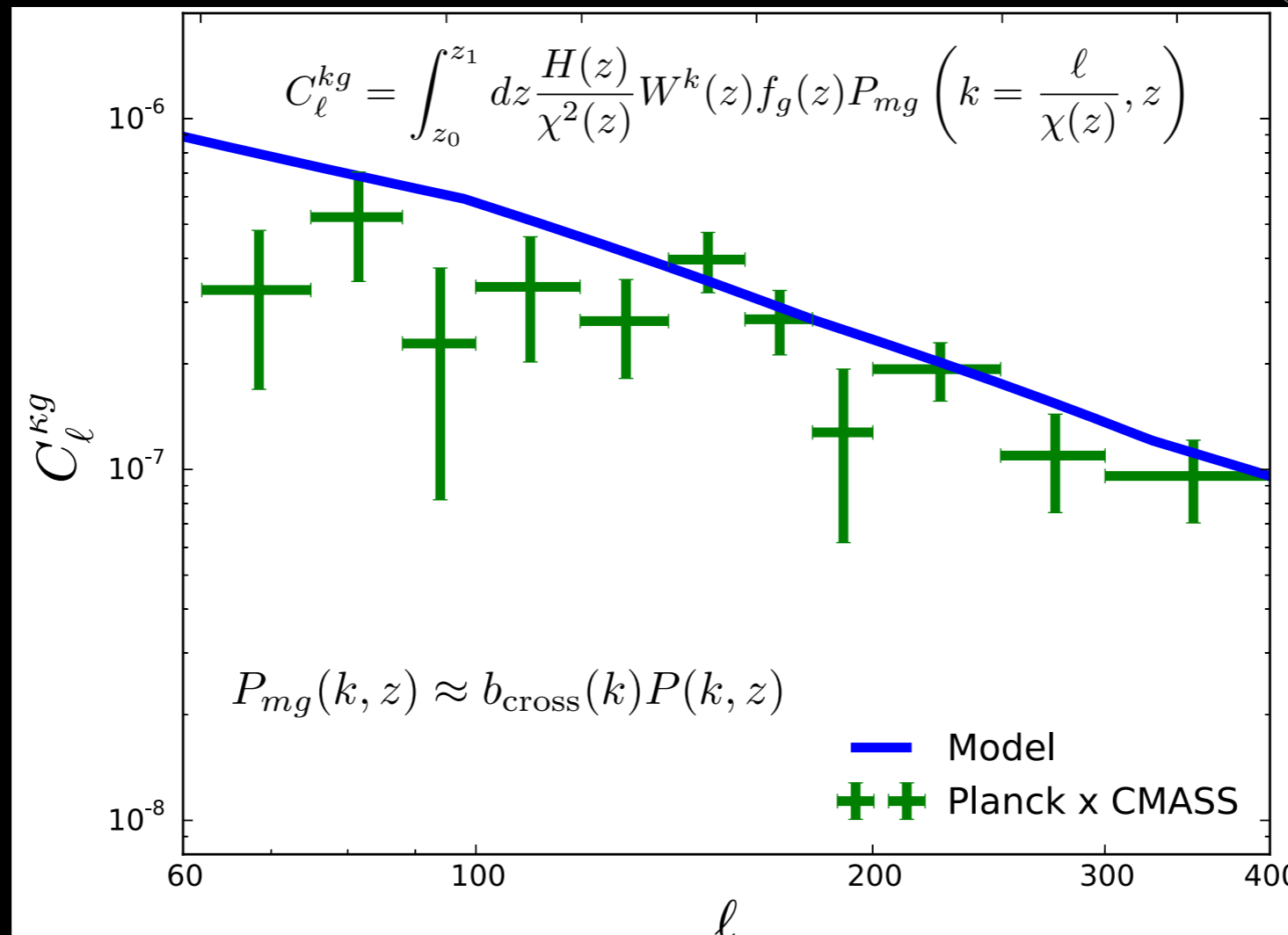
Planck CMB Lensing



BOSS high-z galaxy survey

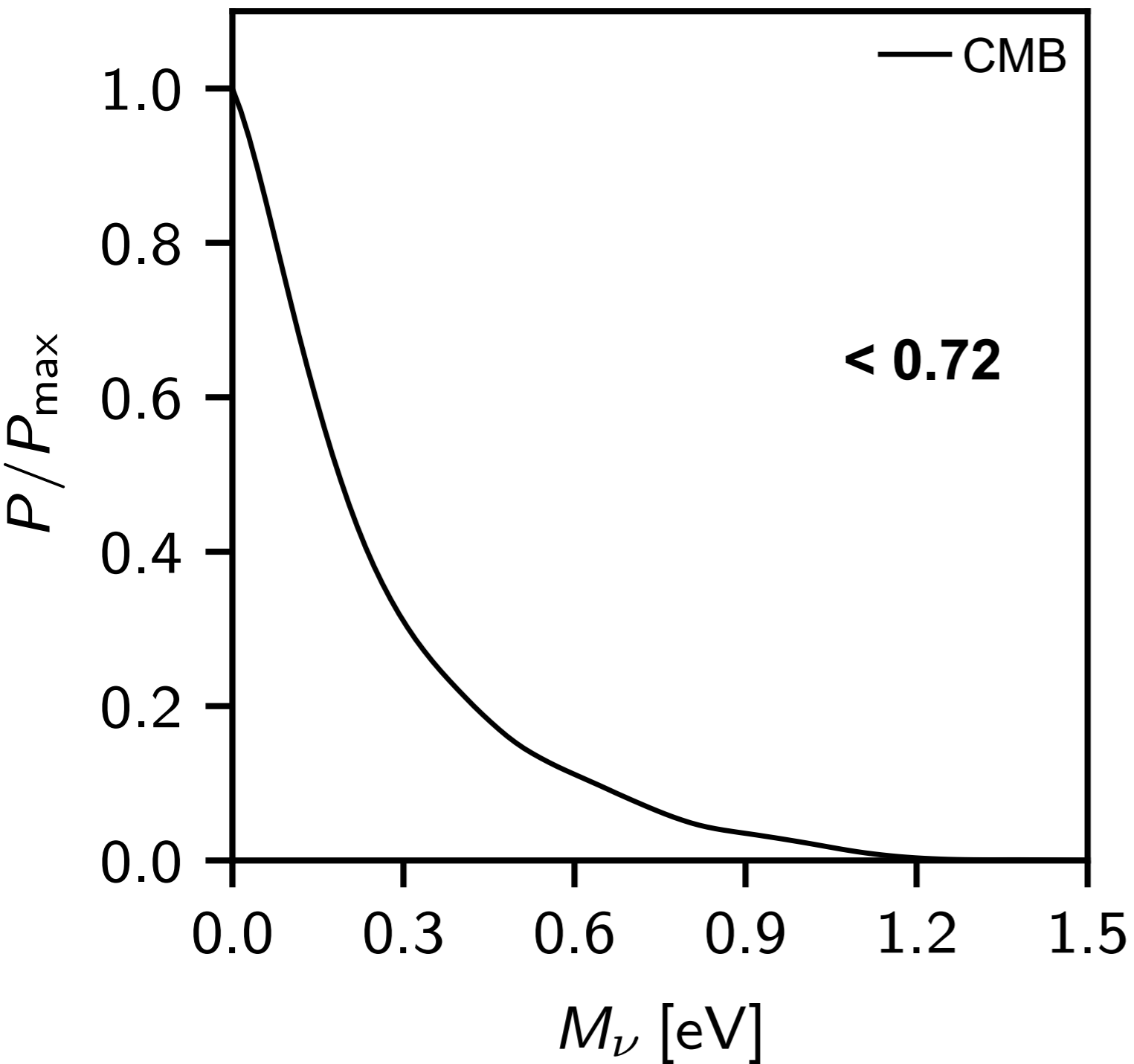


X



# First application on real data

**95% C.L. neutrino mass constraints (eV):**

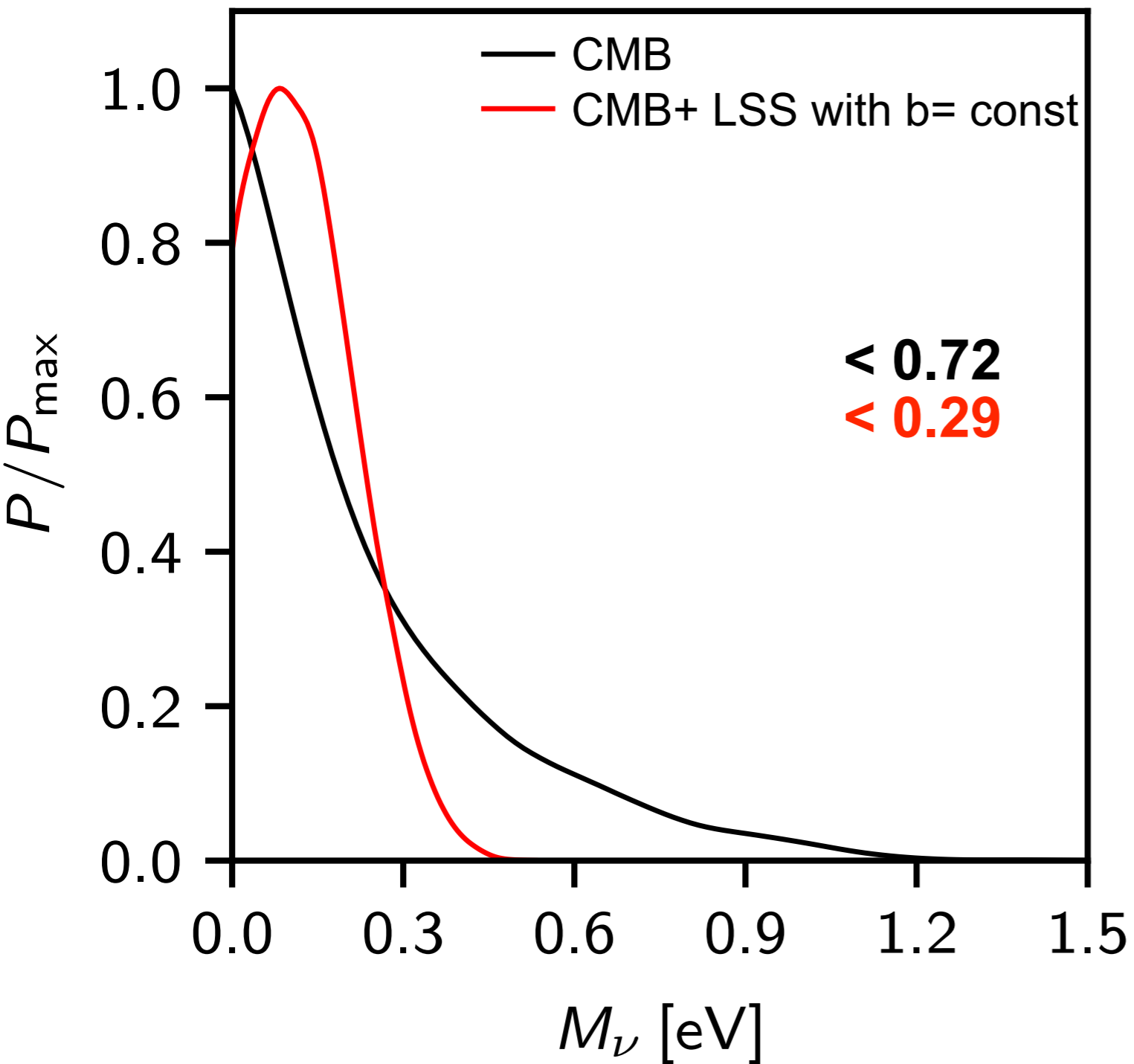


Elena Giusarma et al., PRD 2018



# First application on real data

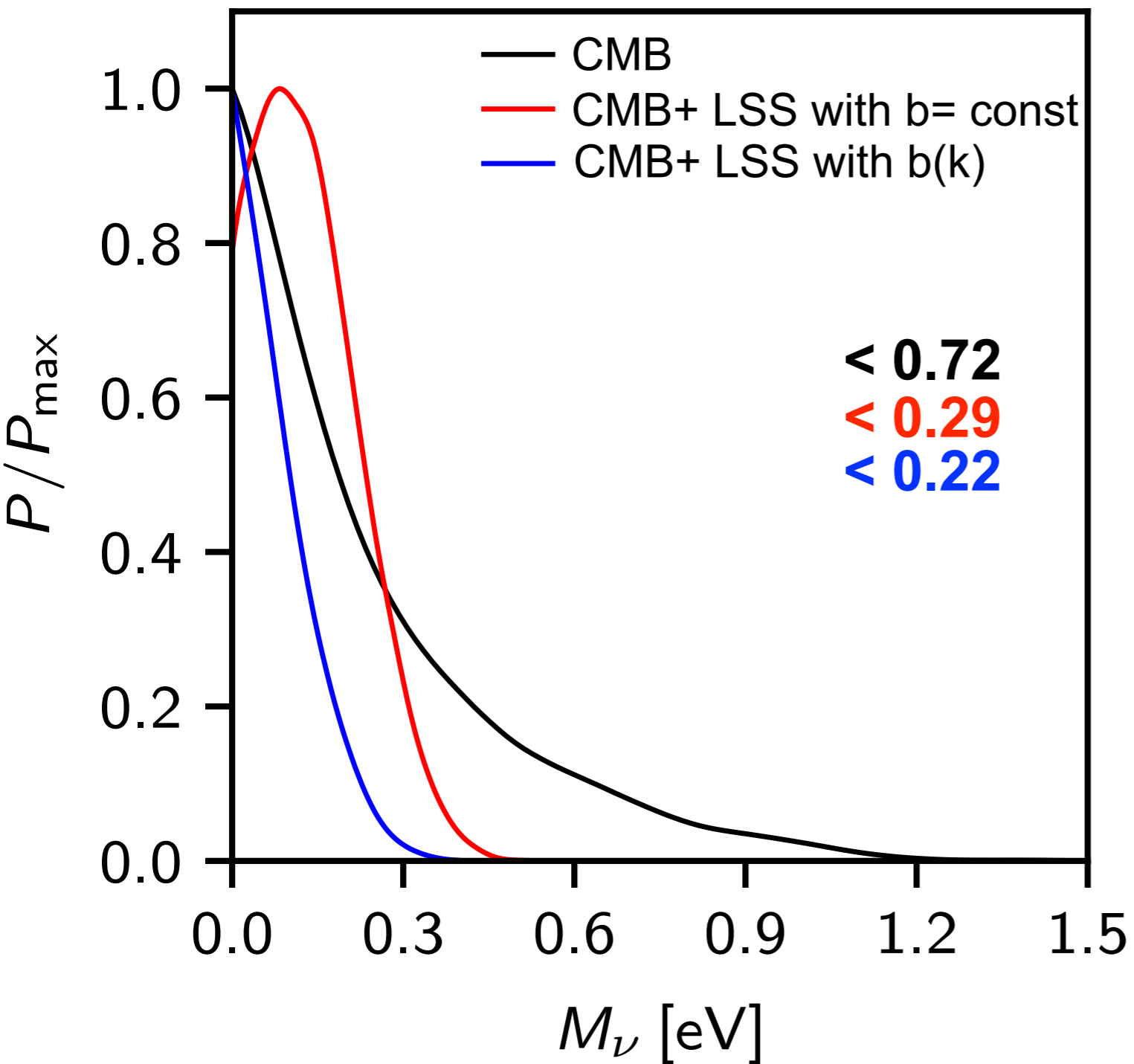
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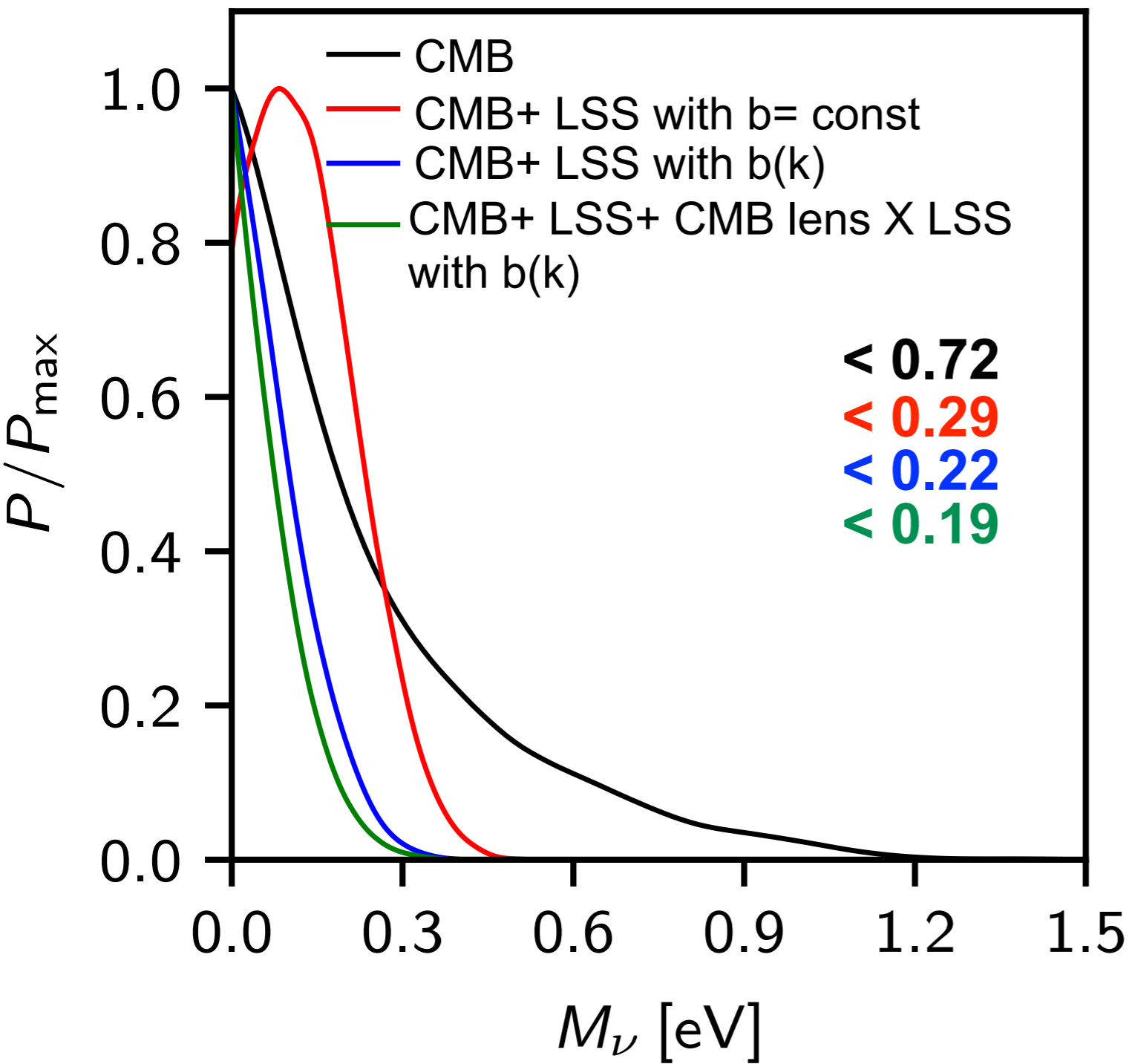


$$b(k) = a + ck^2$$

Elena Giusarma et al., PRD 2018

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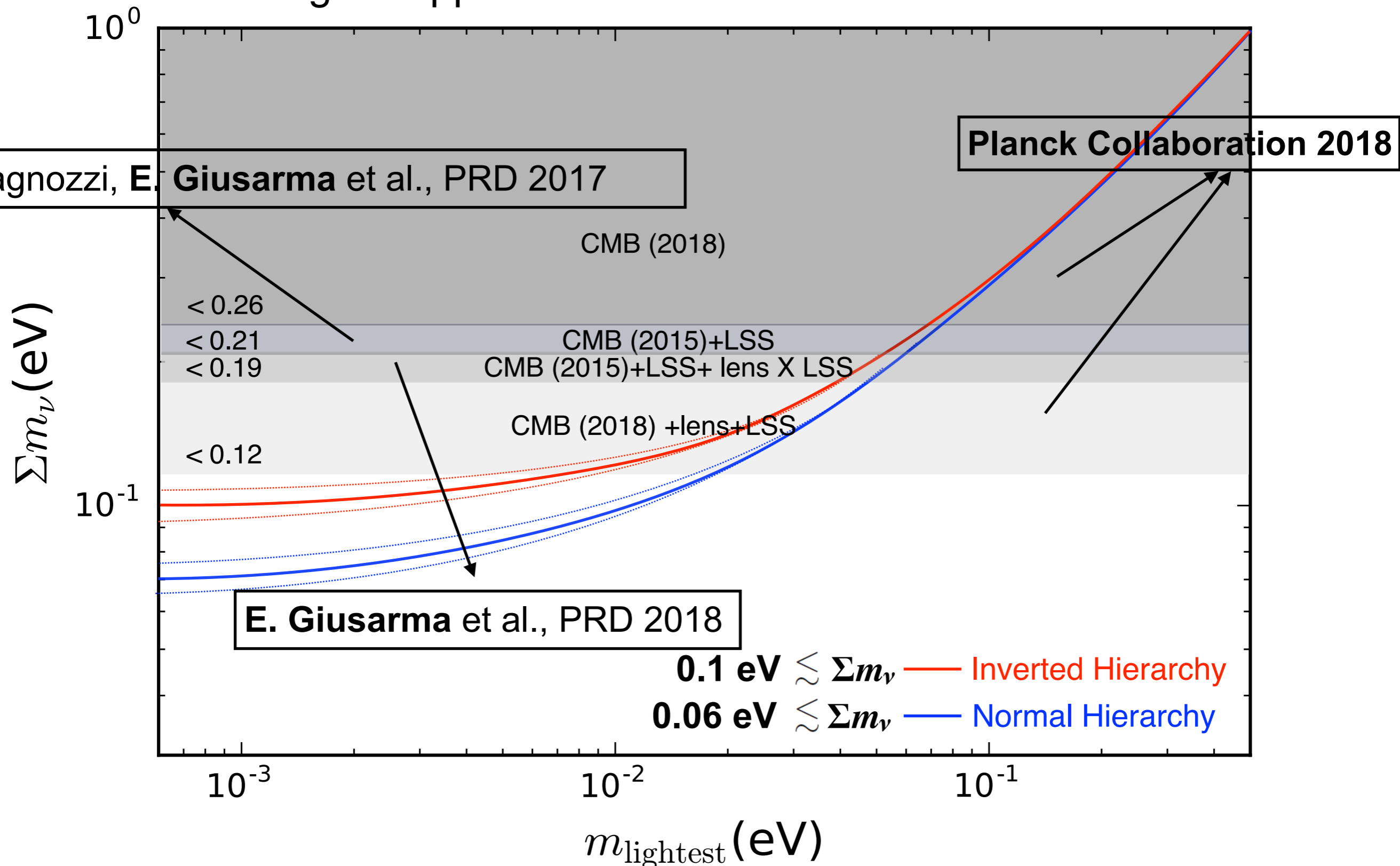


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# 2019 state $\Sigma m_\nu$ from cosmology

Cosmological upper limits on the sum of neutrino masses



# The role of N-body simulations in Cosmology

- ◆ Theoretical tool for calculations in the non-linear regime (important on small scales).
- ◆ Connect the cosmological initial conditions (simple problem) with the universe today (complex problem).

## Simulations are essential for:

### 1. Make prediction of theory:

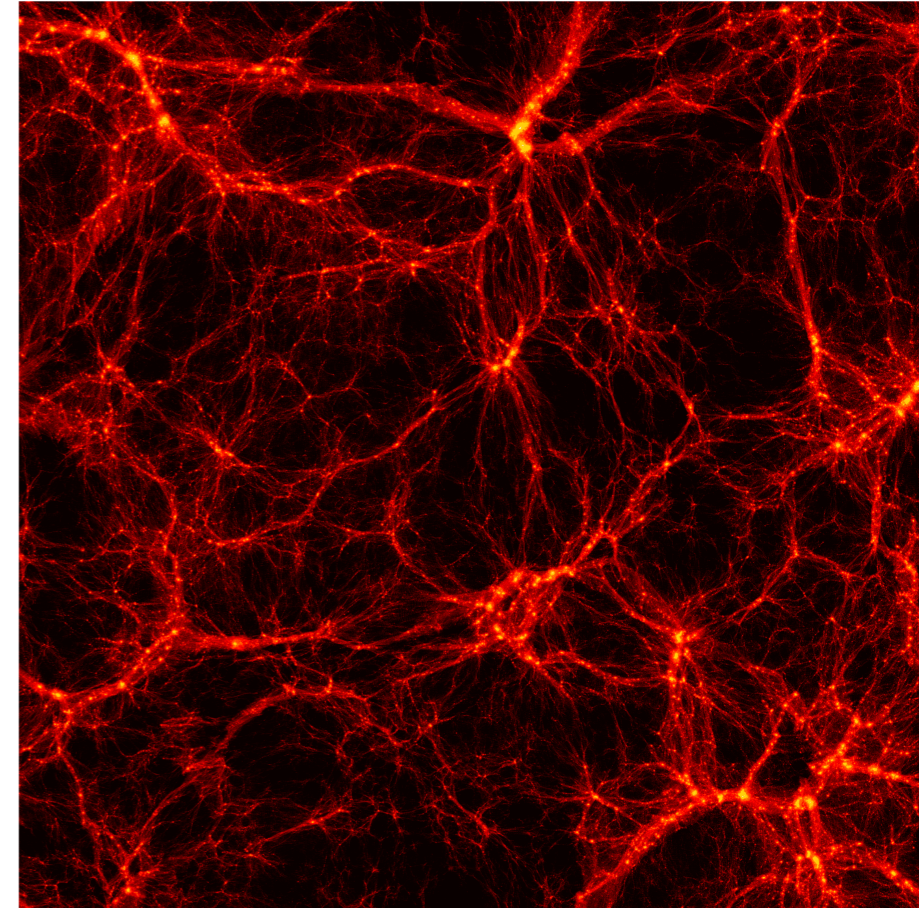
- Internal structure of Halos
- Galaxy formation models
- Baryonic acoustic oscillations in the matter distribution
- Neutrino clustering
- .....

### 2. Generate mock data

### 3. Compute the Covariance Matrix

### 4. Data Analysis

### 5. Optimization of observational strategies

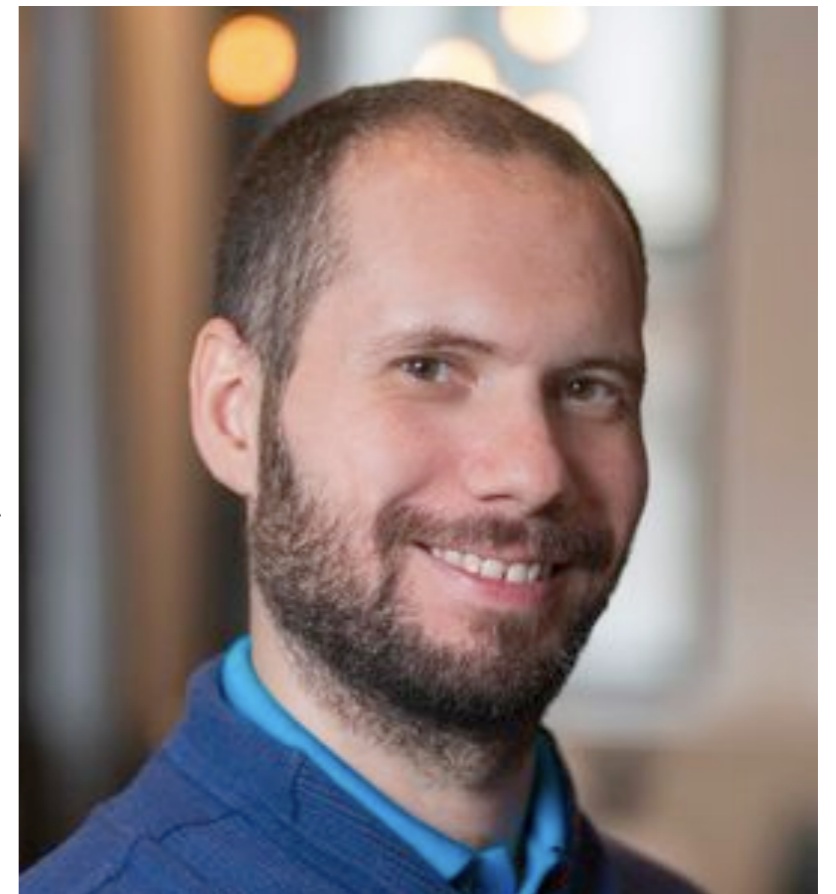


Villaescusa-Navarro SIMS

# The Quijote simulations

- A set of 34500 N-body simulations
- 1000 Mpc/h
- $512^3$  DM particles (+  $512^3$   $\nu$  particles)
- $z = \{0, 0.5, 1, 2, 3\}$
- Latin hypercube with 4000 simulations in the  $\{\Omega_m, \Omega_b, h, n_s, \sigma_8\}$  hyperplane
- More than 5 trillion particles at a single redshift
- 750 Tb, 18M cpu hours
- **Publicly available** at <https://github.com/franciscovillaescusa/Quijote-simulations>

Villaescusa-Navarro  
Flatiron Institute CCA





# Neutrino Simulations

We run 100 N-body simulations in a box of 1000 Mpc/h

$\Sigma m_\nu = 0.06 \text{ eV}$   $\longrightarrow$   $\sim 10^4$  CPU hours  
(8 years)

$\Sigma m_\nu = 0.0 \text{ eV}$

$\Sigma m_\nu = 0.1 \text{ eV}$   $\longrightarrow$   $\sim 10^6$  CPU hours

$\Sigma m_\nu = 0.15 \text{ eV}$

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**$\sim 10^6$  CPU hours**

$\Sigma m_\nu = 0.15 \text{ eV}$

*Can we use Machine Learning to  
predict fast cosmological  
simulations?*

# Deep learning: Convolutional Neural Network (CNN)

## Deep learning

- Part of machine learning methods based on artificial neural networks.
- Breakthroughs in processing images, videos, speeches and audio
- Composition of non-linear transformation of the data.
- Goal: Learn useful representations, features, directly from data.

# Deep learning: Convolutional Neural Network (CNN)

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## Simple single layer Neural Network

- Consists of a linear combination of input through a nonlinear function:  
$$z = Wx + b$$
$$a = f(z)$$

# Deep learning: Convolutional Neural Network (CNN)

## Deep learning

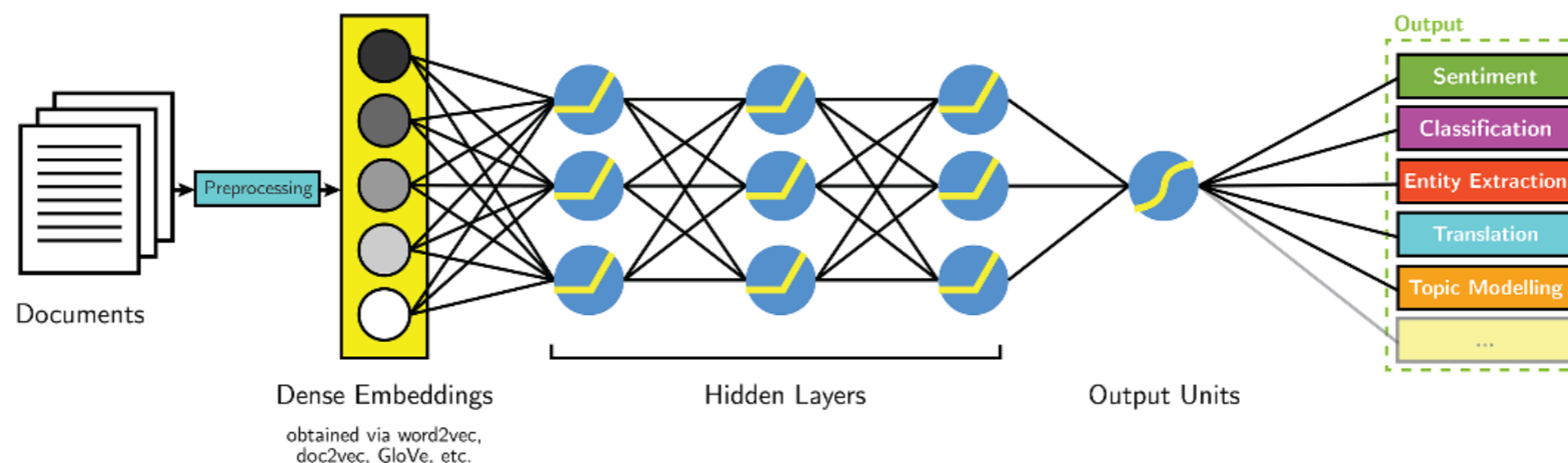
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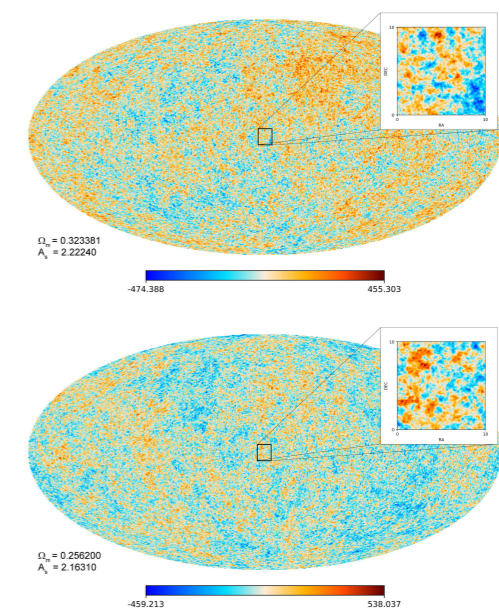
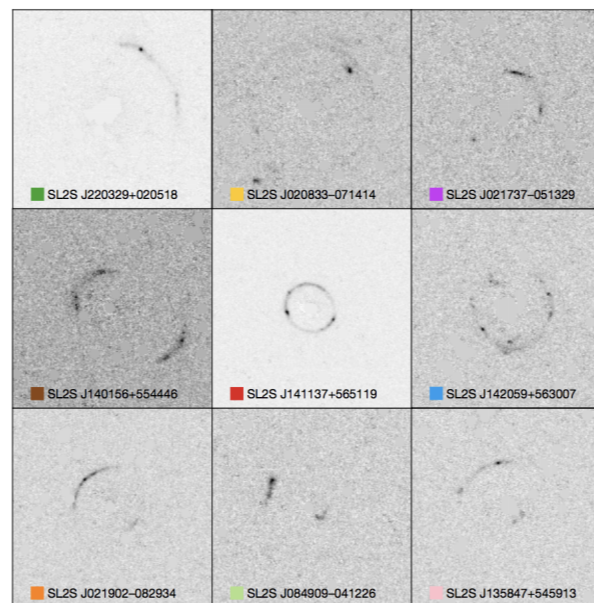
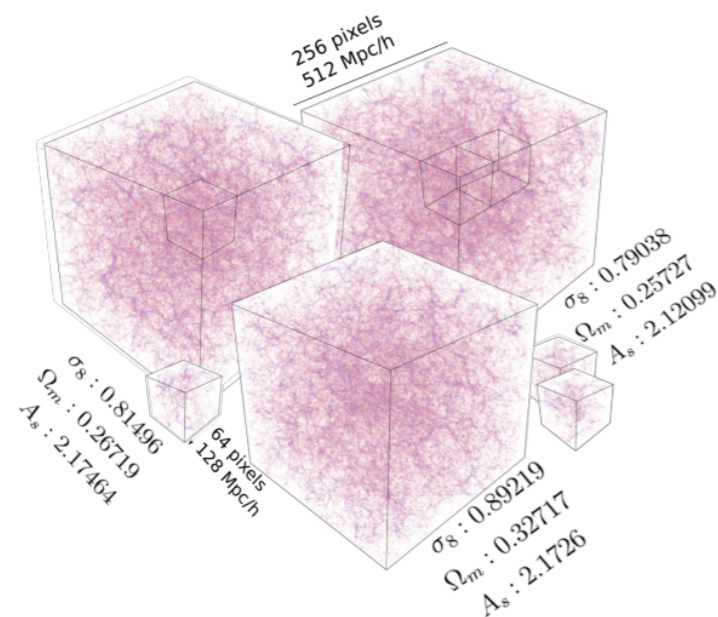
## CNN

- Neural Network with a convolution operation instead of matrix multiplication in at least one of the layers



# Deep learning: Convolutional Neural Network (CNN)

## Deep learning application



Large Scale Structure  
*S.Ravanbakhsh et al. (2016)*

Gravitational lensing  
*Y.D.Hezaveh et al. (2017)*

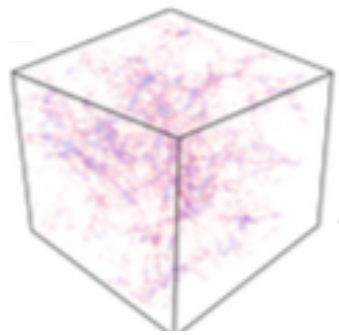
CMB  
*S.He et al. (2018)*



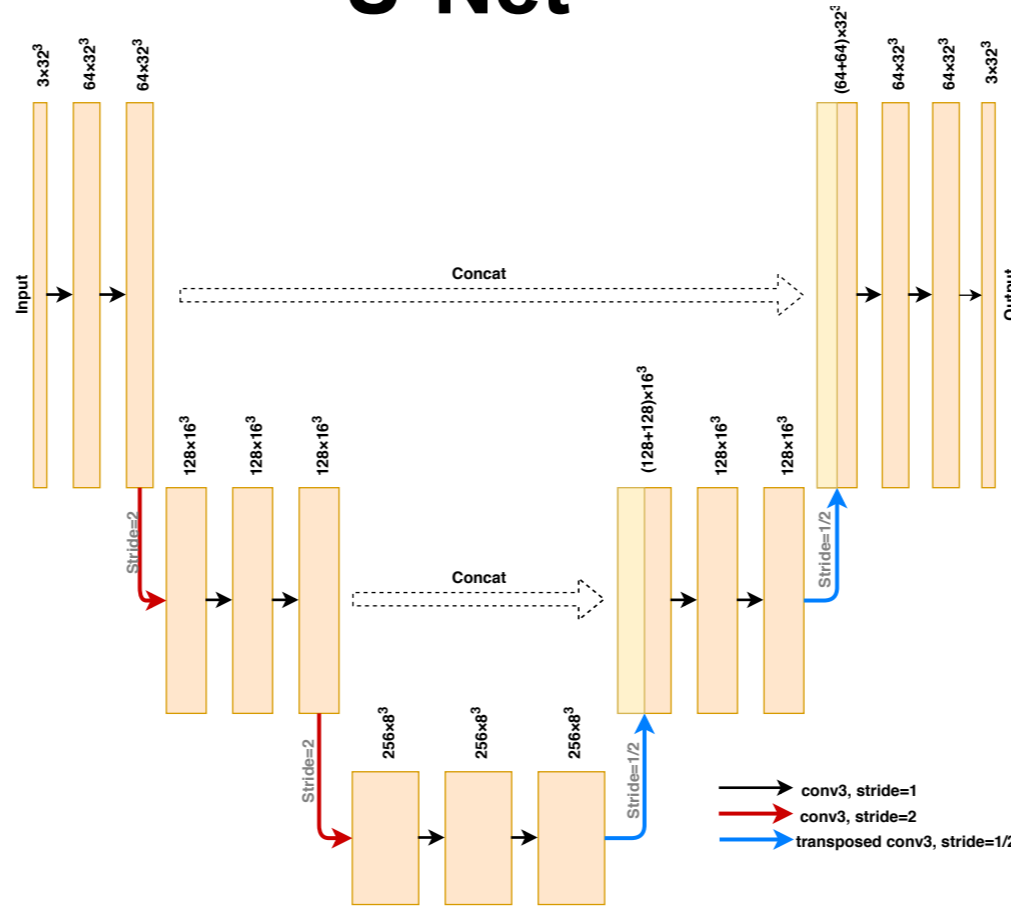
# Predicting massive neutrino simulations

Deep learning: Convolutional neural network

## Input

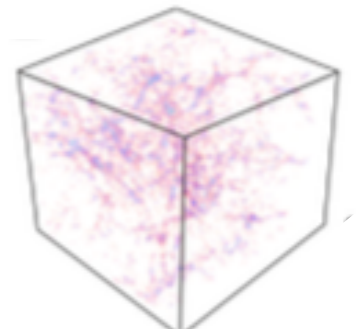


## U-Net



Credit: Siyu He

## Prediction



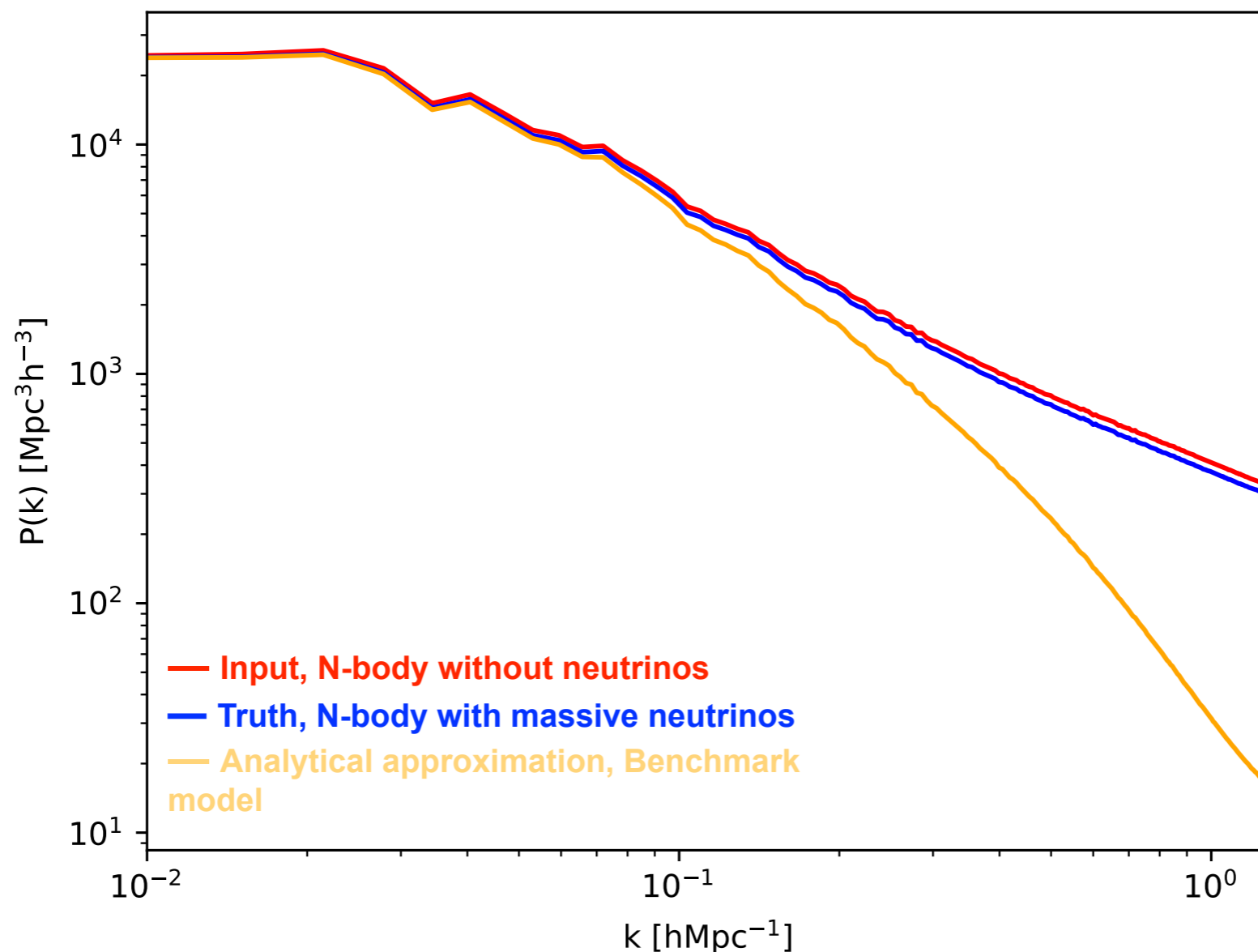
N-body simulations  
with massless  
neutrinos:  $\Sigma m_\nu = 0.0 \text{ eV}$

N-body  
simulations with  
massive neutrinos:  
 $\Sigma m_\nu = 0.15 \text{ eV}$

Preliminary results: **E. Giusarma**, He, Reyes, Villaescusa-Navarro, Ho

# Predicting massive neutrino simulations

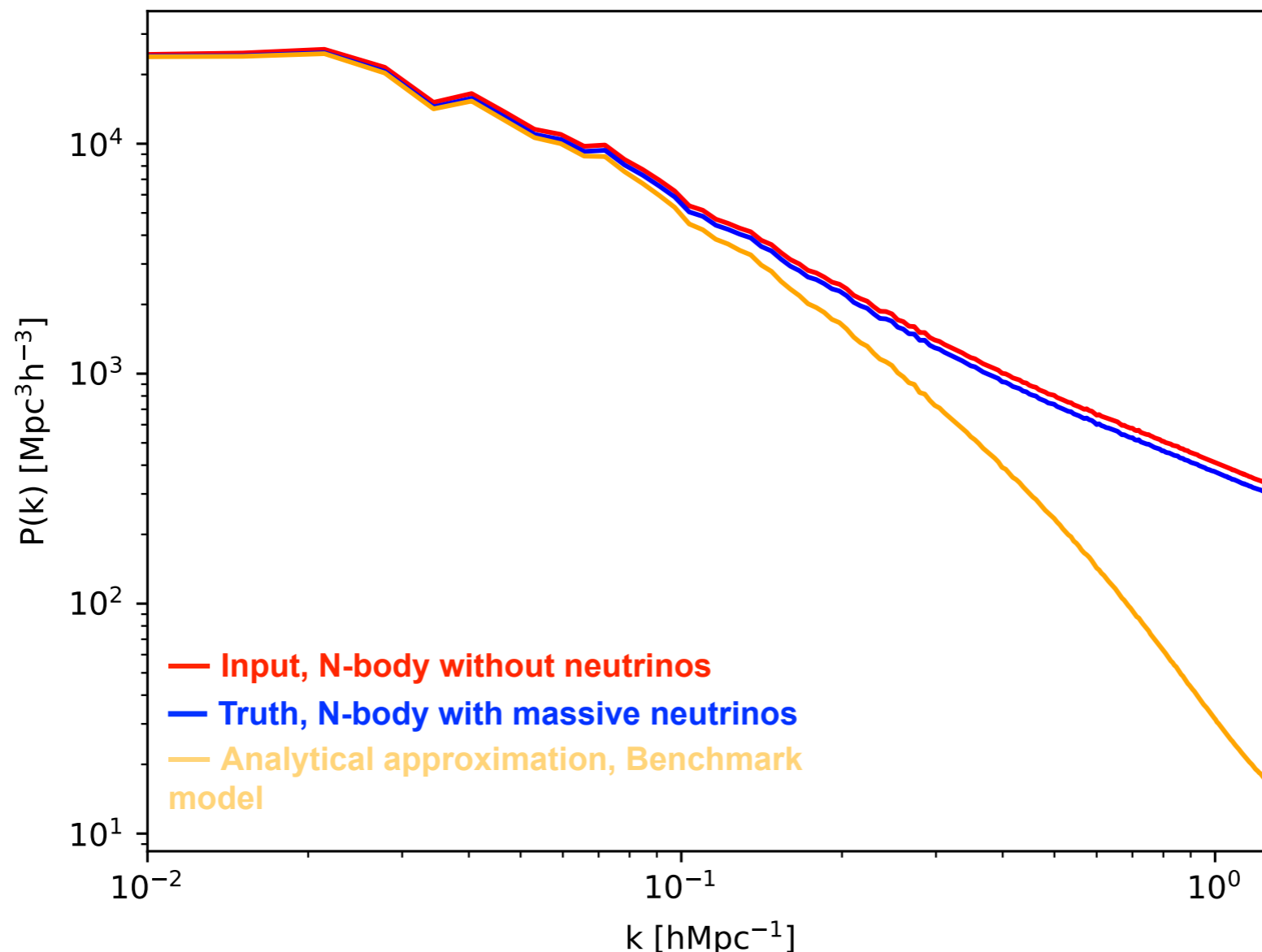
- ✓ 100 N-body simulations without neutrinos as input and 100 N-body simulations with massive neutrinos as target ( $\Sigma m_\nu = 0.15 \text{eV}$ ).
- ✓ Each simulation consists of 130 million particles in a volume of 1,000 Mpc/h on each side.



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- ✓ Each simulation consists of 130 million particles in a volume of 1,000 Mpc/h on each side.
- ✓ Each simulation is separated into 4,000 sub-cubes of size 33,000 voxels corresponding to regions of size around 62.5 Mpc/h.



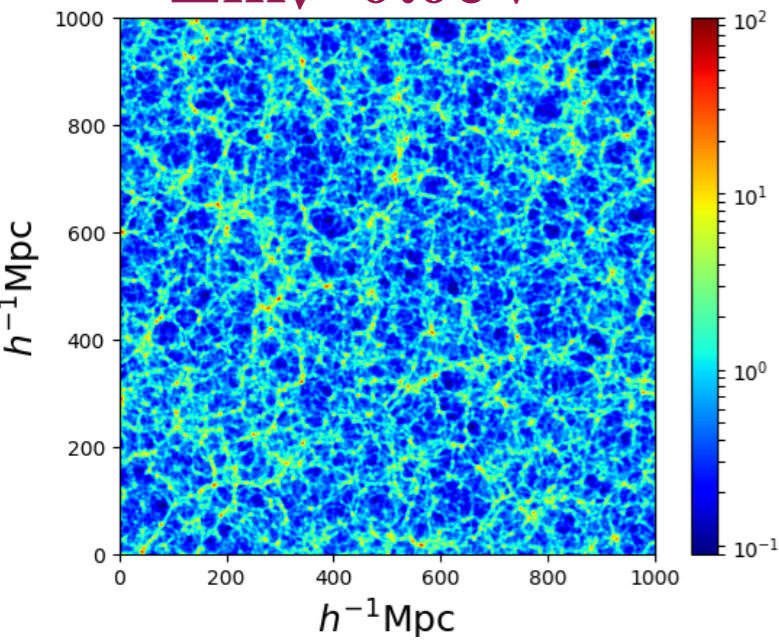
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# Predicting massive neutrino simulations

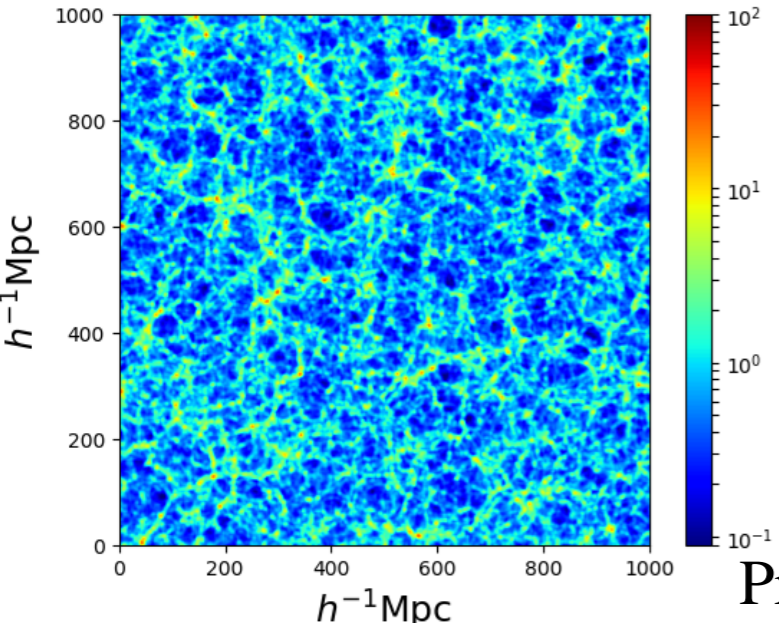
Deep learning: Convolutional neural network

## Training

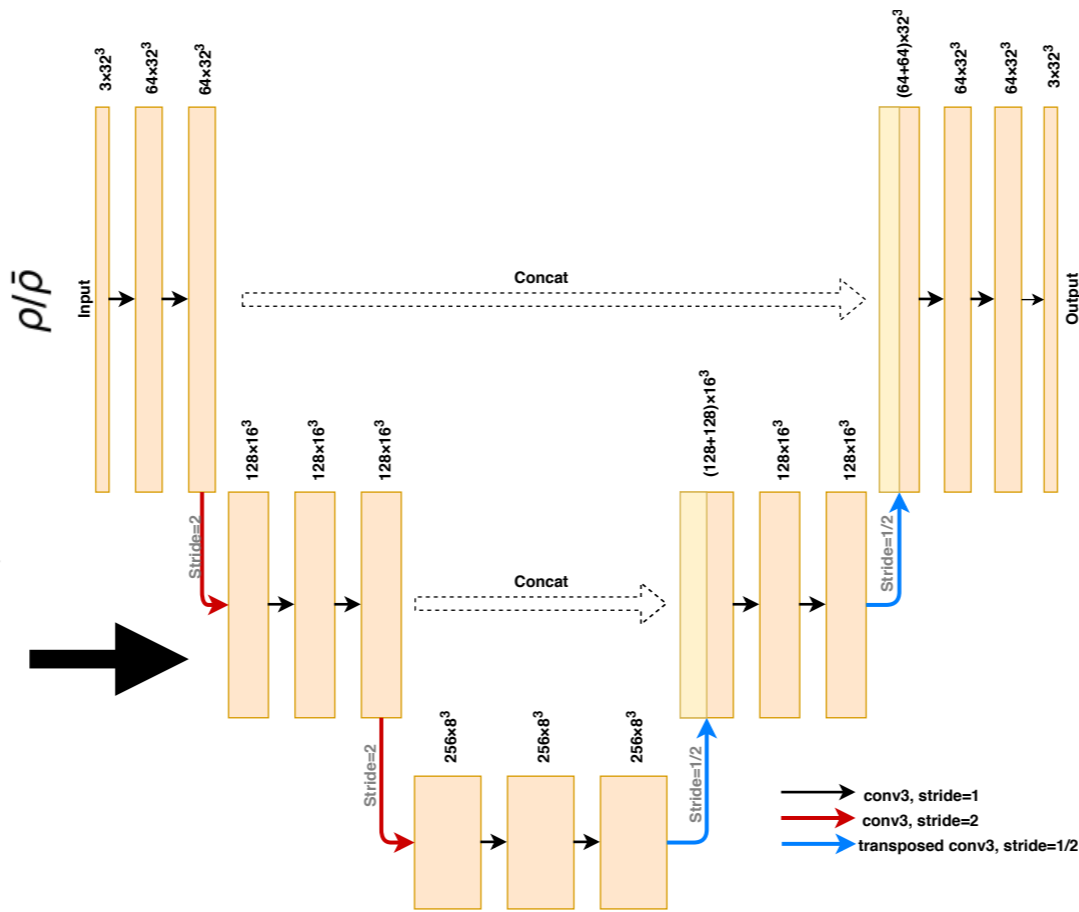
$\Sigma m_\nu = 0.0 \text{ eV}$



$\Sigma m_\nu = 0.15 \text{ eV}$



## U-Net



Credit: Siyu He

## Prediction

Preliminary results: Elena Giusarma, He, Reyes, Villaescusa-Navarro, Ho

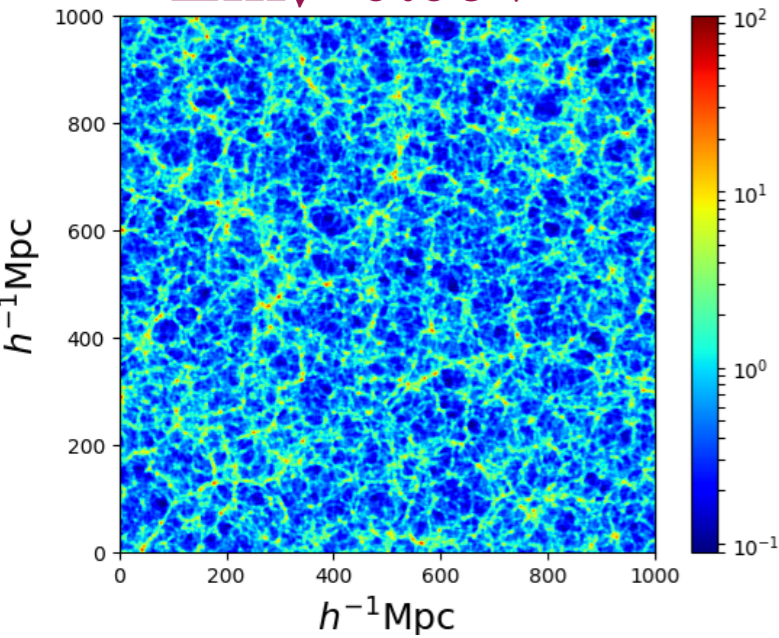


# Predicting massive neutrino simulations

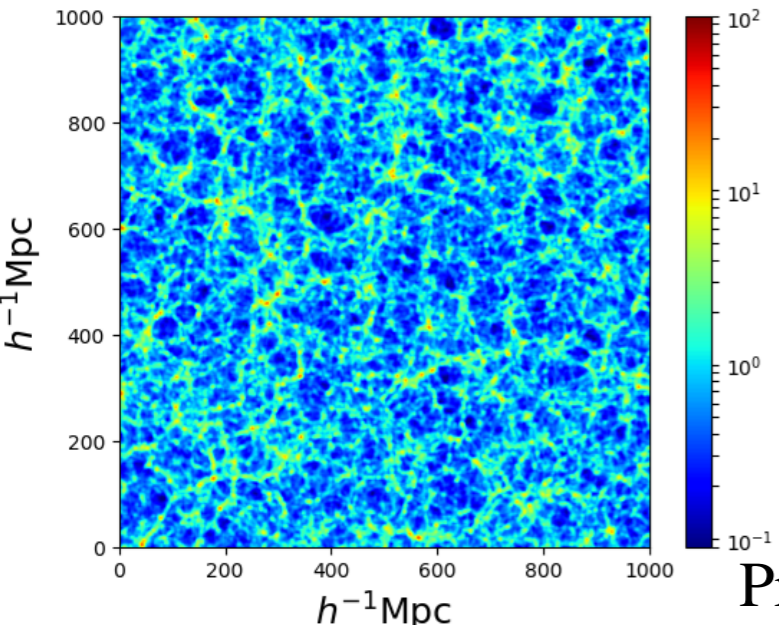
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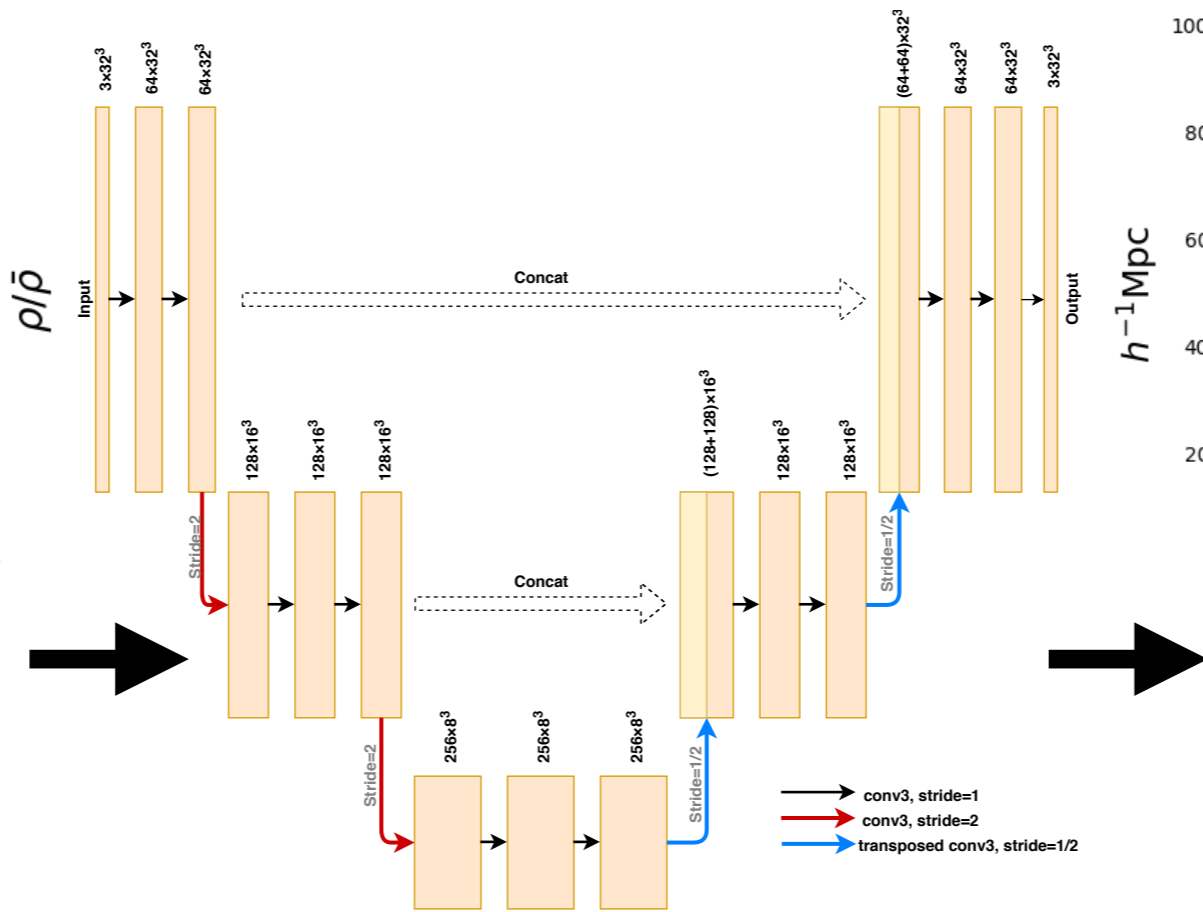
$\Sigma m_\nu = 0.0\text{eV}$



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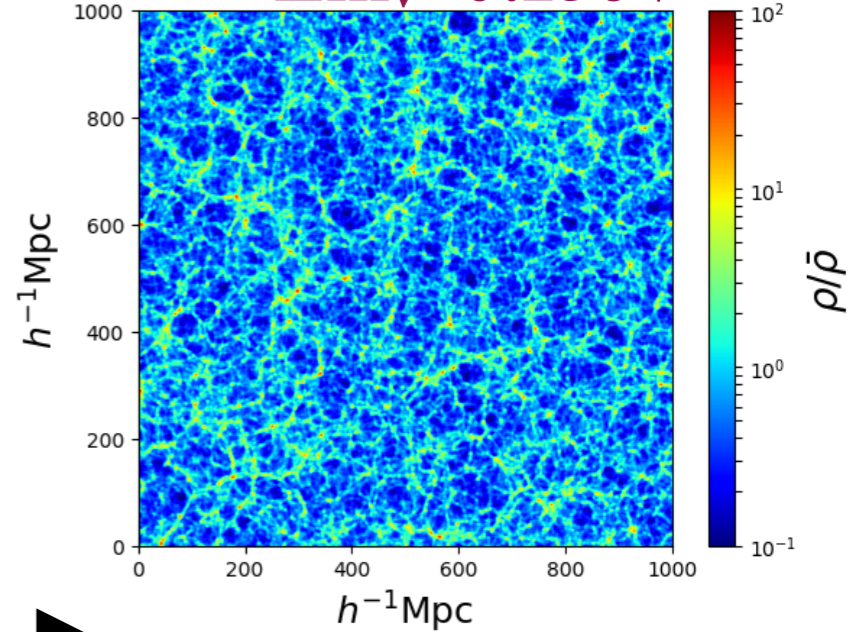
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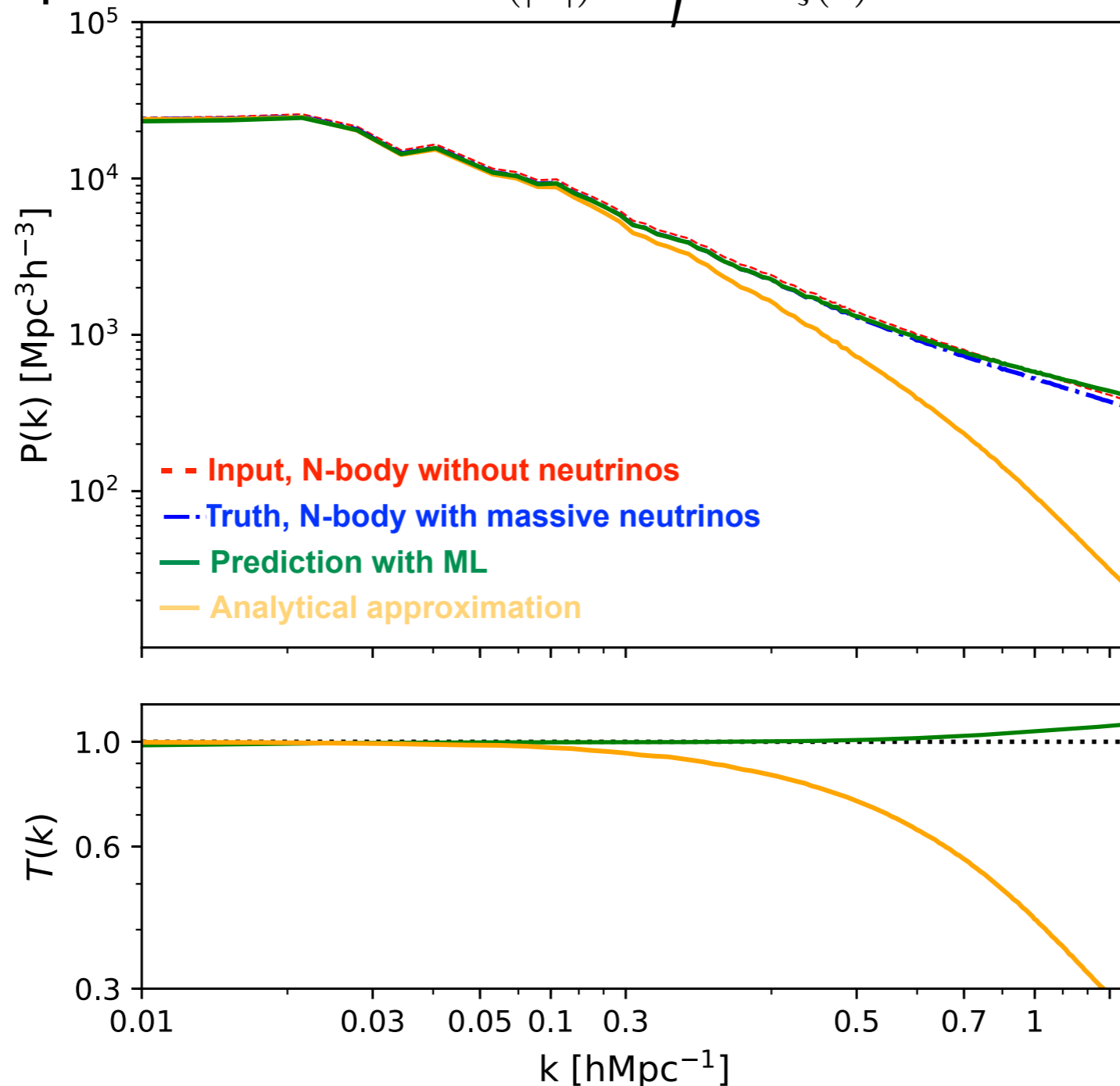


Preliminary results: Elena Giusarma, He, Reyes, Villaescusa-Navarro, Ho

# Results: Summary statistics

Two-point correlation function:  $\xi(|\mathbf{r}|) = \langle \delta_A(\mathbf{r}') \delta_B(\mathbf{r}' + \mathbf{r}) \rangle$

Power spectrum:  $P(|\mathbf{k}|) = \int d^3\mathbf{r} \xi(\mathbf{r}) e^{i\mathbf{k}\cdot\mathbf{r}}$



Average Power Spectrum of 10 simulations

Transfer Function:

$$T(k) = \sqrt{\frac{P_{\text{pred}}(k)}{P_{\text{true}}(k)}}$$

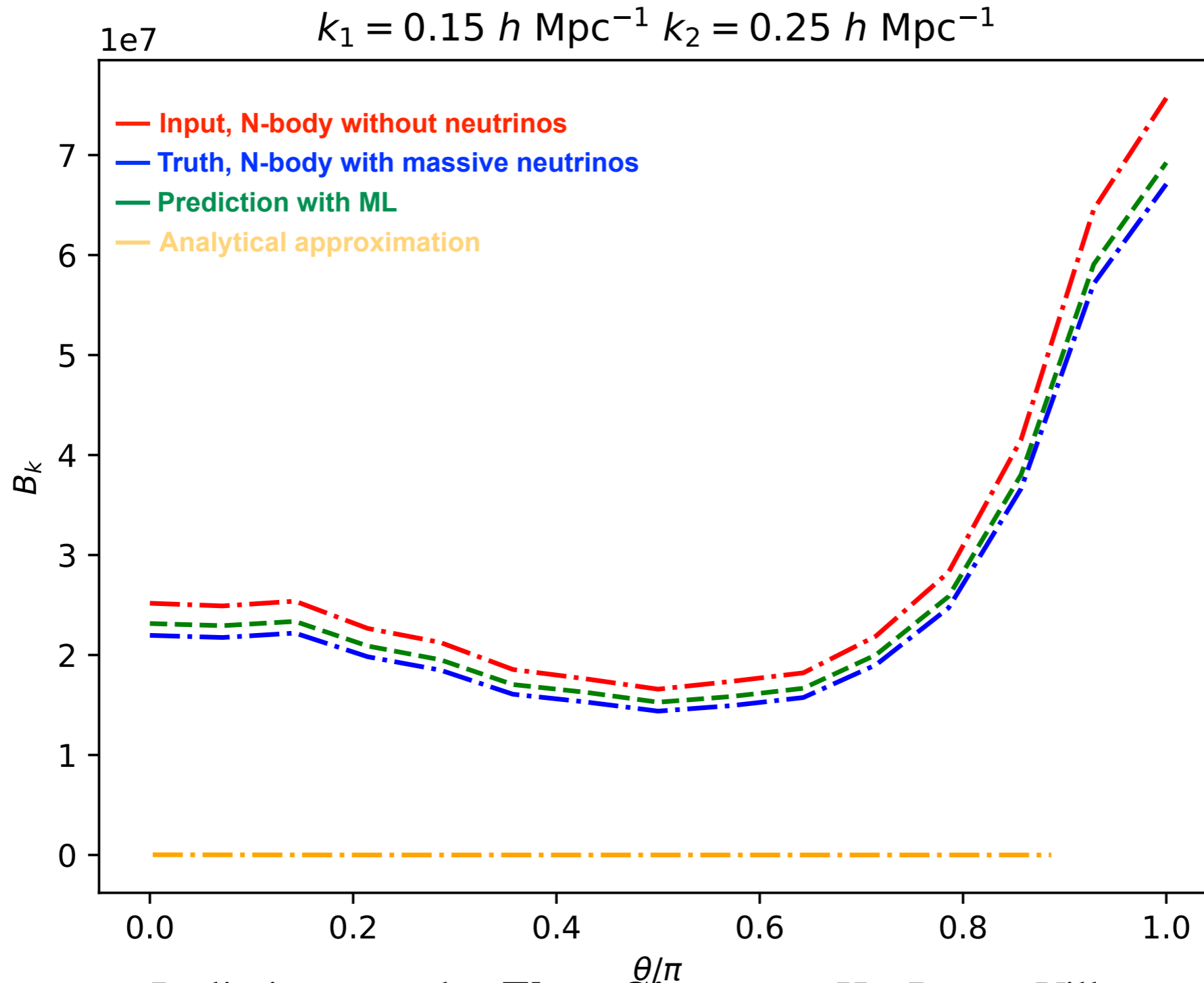
Preliminary results: **Elena Giusarma**, He, Reyes, Villaescusa-Navarro, Ho



# Results: Bispectrum

Looking at non-gaussian information

3-point correlation function:  $B(k_1, k_2, k_3)\delta(\mathbf{k}_{123}) = \langle \delta_{\mathbf{k}_1} \delta_{\mathbf{k}_2} \delta_{\mathbf{k}_3} \rangle$



Preliminary results: **Elena Giusarma**, He, Reyes, Villaescusa-Navarro, Ho

# Questions and Challenges

- It seems like the model is predicting quite well, and quite fast.
- Why does it work?
- How can we interpret the model learnt in ML?
- Do we understand where the information is coming from?
- Can we deduce what are the important features to predict cosmological simulations correctly?
- Can we understand the physics underpinning?

# ML to predict faster standard and non standard cosmological simulation

- Neutrino simulations within a mass range.
- Modified gravity simulations.
- N-body simulations with generic non-Gaussian initial conditions.
- Hydrodynamical simulations .....

## **in order to**

- Study the impact of non-standard parameters on standard cosmological simulations.
- Understand the physics underpinning.
- Deduce the important features to predict cosmological simulations correctly.
- Make prediction of theories.

# Summary

- Cosmological data can be used to constrain neutrino properties, in particular the absolute scales of neutrino masses.
- Neutrino masses leave key signatures in cosmological observables.
- Cosmology provides tightest constraints on sum of  $\nu$  masses,  $\Sigma m_\nu \lesssim 0.12 - 0.15$  eV (assuming  $\Lambda$ CDM).
- It is time to start worrying about scale-dependent galaxy bias when using galaxy clustering measurement.
- ML potential tool to solve major problems in cosmology.

Thank you!

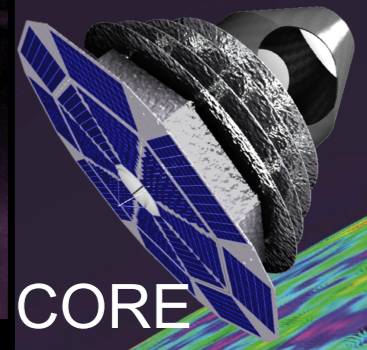
# Backup Slides



# Cosmology in 2020

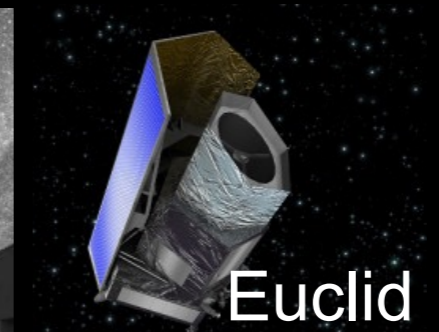
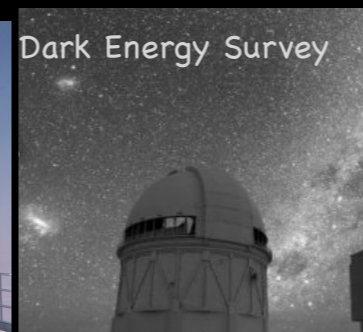
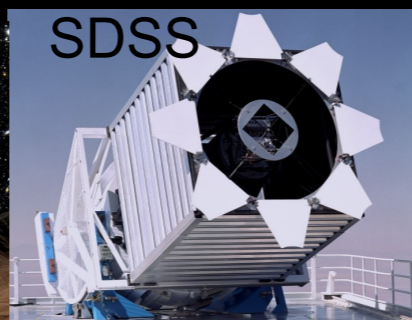
## CMB experiments

- Ground based: CMB S4, SO
- Satellites: LiteBIRD, CORE.



## Large-scale structure surveys

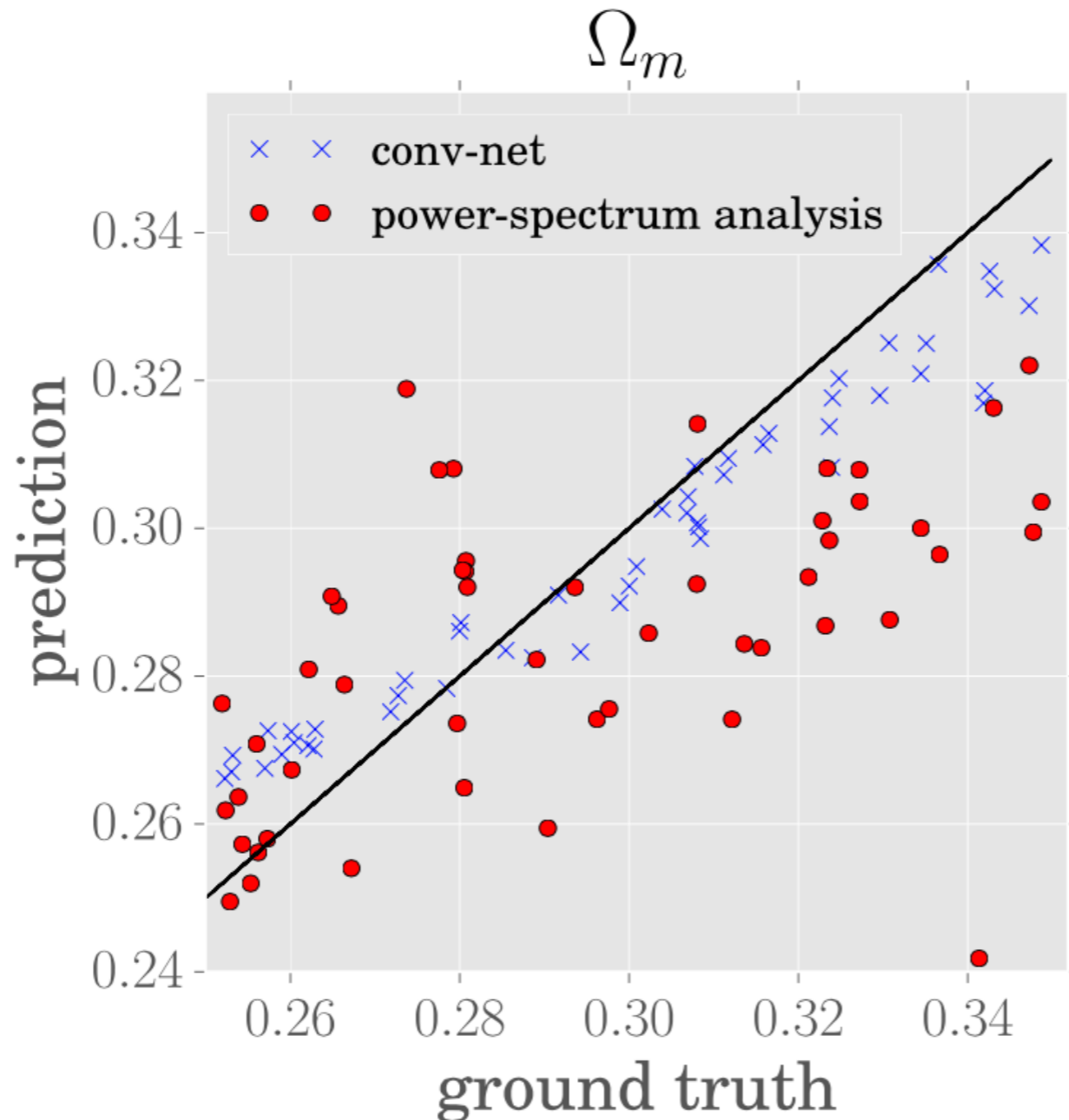
- SDSS: 3 million of objects, 3-D map of the Universe
- DESI: 10 million of galaxies, a 3-D map of the Universe
- DES: 100 million of galaxies, 3-D map of the Universe
- LSST: 20 billion galaxies, 3-D map of the Universe
- Euclid: space mission
- SKA: black holes and pulsar
- WFIRST: space mission



# ML to extract more information from the cosmological survey

Integrate traditional statistical methods with modern ML models.

Predict cosmological parameters directly from the distribution of matter



Can we use such models to estimate the parameters of our own Universe?

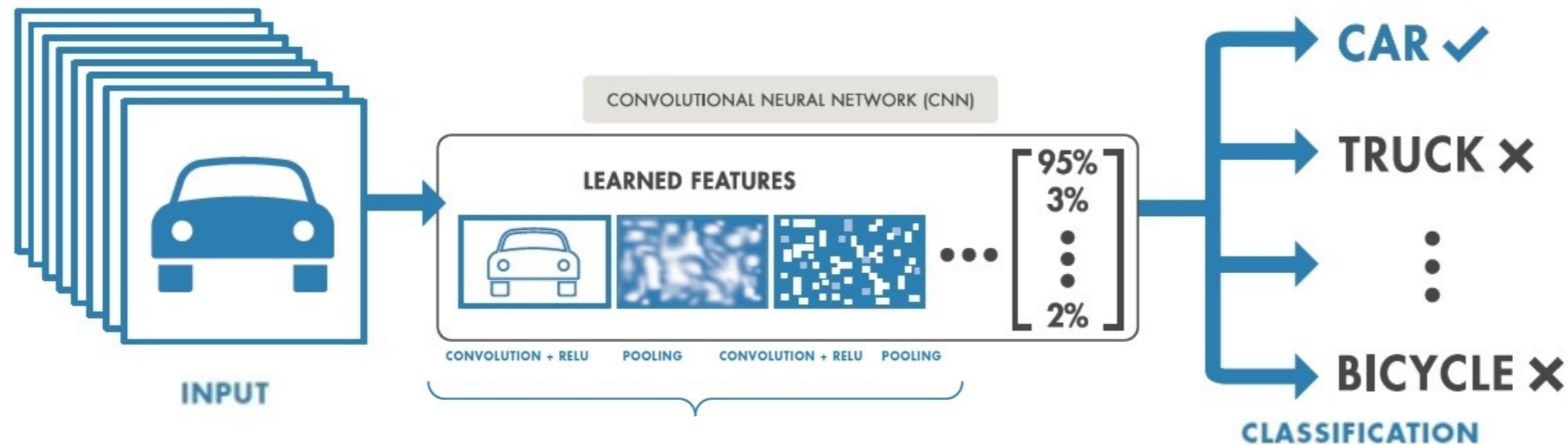
Ravanbakhsh, Oliver, Price, Ho, Schendier & Póczos ICML 2016



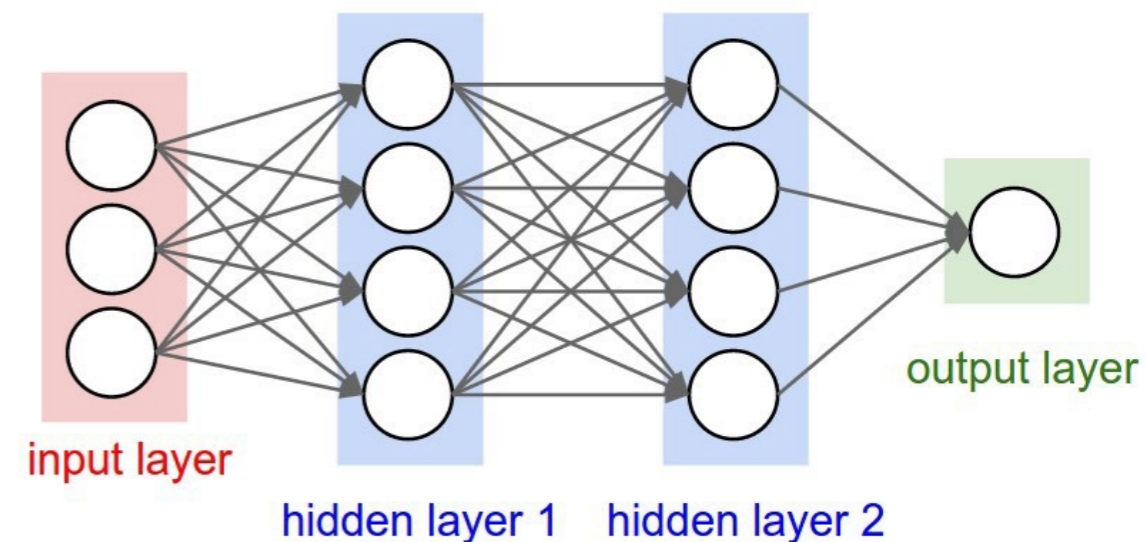
# Deep learning: Convolutional Neural Network (CNN)

## Why convolutional?

Convolution is a process where the network tries to label the input signal by referring to what it has learned in the past.



- **CNN** consists of an **input** and an **output** layer, as well as **multiple hidden layers**.
- The hidden layers consist of convolutional layers, RELU layer i.e. activation function, pooling layers, fully connected layers and normalization layers.



# Degeneracies

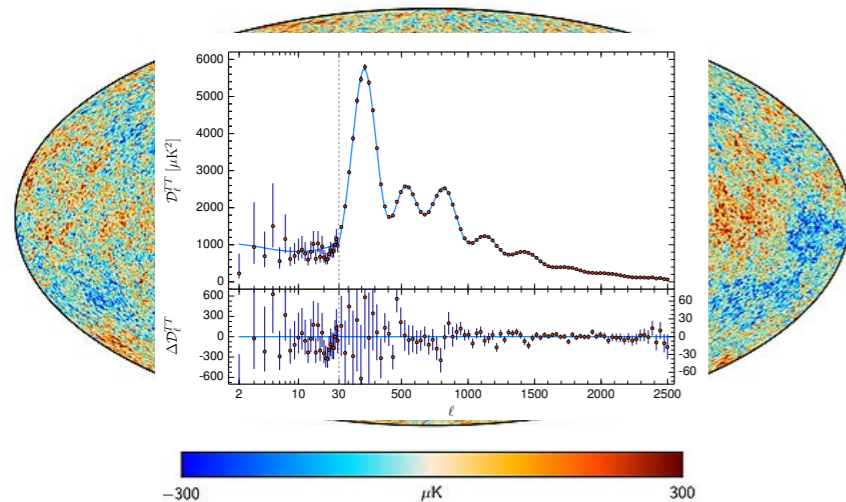
- Definition: When two (or more) variables are **correlated**, it is conventional to say that they are **degenerate** with the other parameter(s).



- This is both “good” and “bad”. The “bad” part is that the parameters are allowed to take any value along the degeneracy direction. The “good” news is that, if A and B are degenerate, even if there is no experiment that can constrain parameter A, you can improve limits on the allowed values of A indirectly, by designing an experiment that can constrain parameter B.
- Note that this is **not an intrinsic property of the parameters themselves**, but of their posterior distributions: we will see that two parameters might be degenerate in one experiment (CMB) but not in other experiment (CMB+BAO)

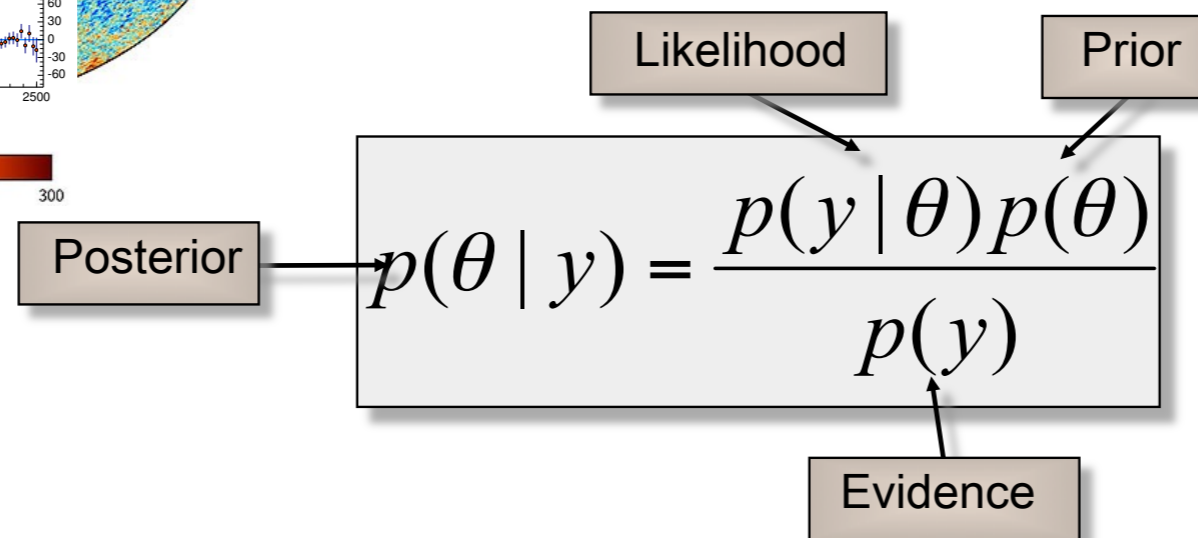
# Cosmological parameter estimation

**Data  $y$**



**Model  $\theta$**

$$\theta = \{\Omega_c, \Omega_b, \tau, n_s, A_s, H_0, \Sigma m_\nu, \dots\}$$



The measurements in cosmological datasets are translated to likelihoods. The total likelihood, assuming the measurements of the experiments are not correlated (usually the case), is the product of individual likelihoods.

$$\mathcal{L} \propto \exp(-\chi^2/2)$$

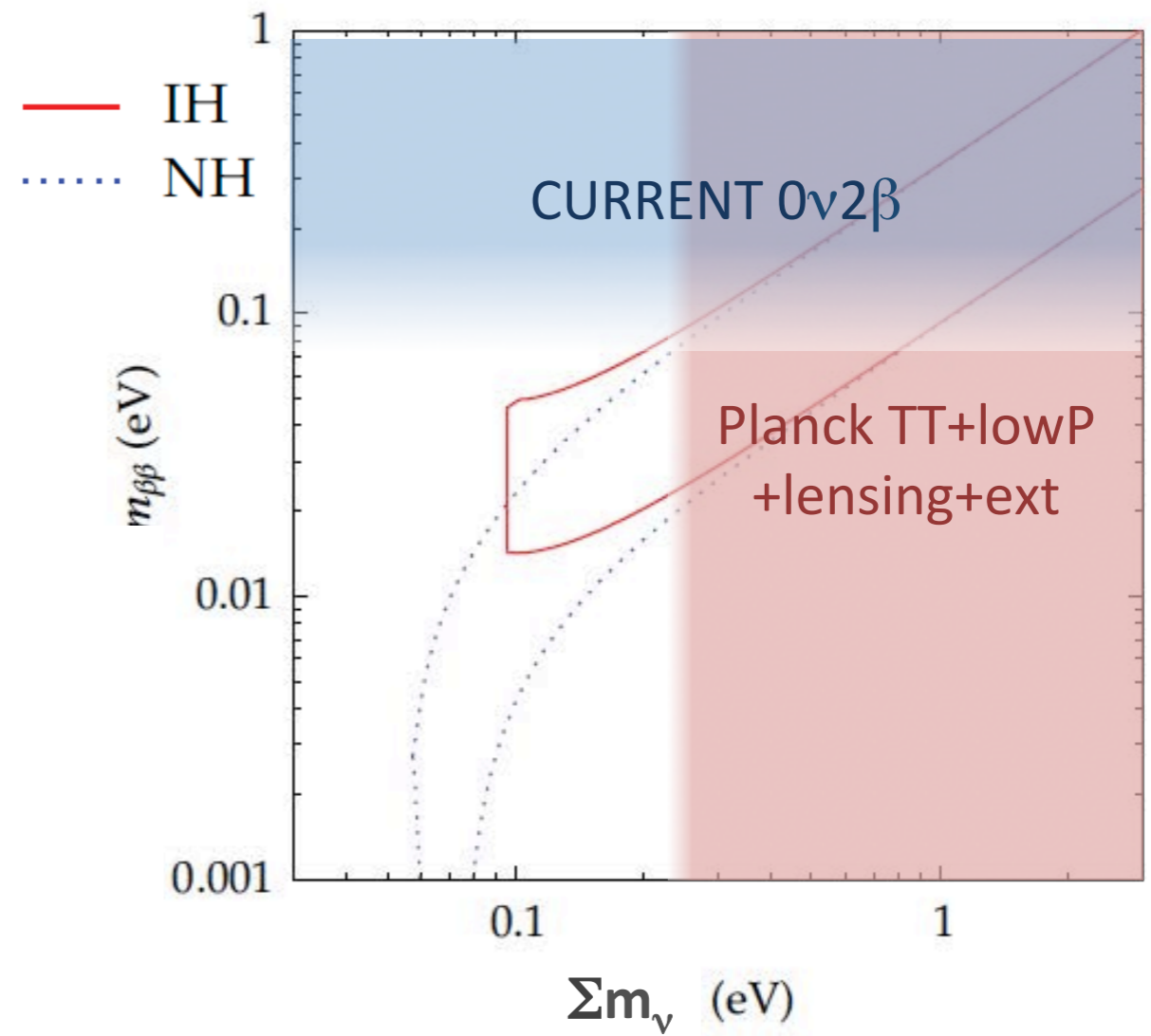
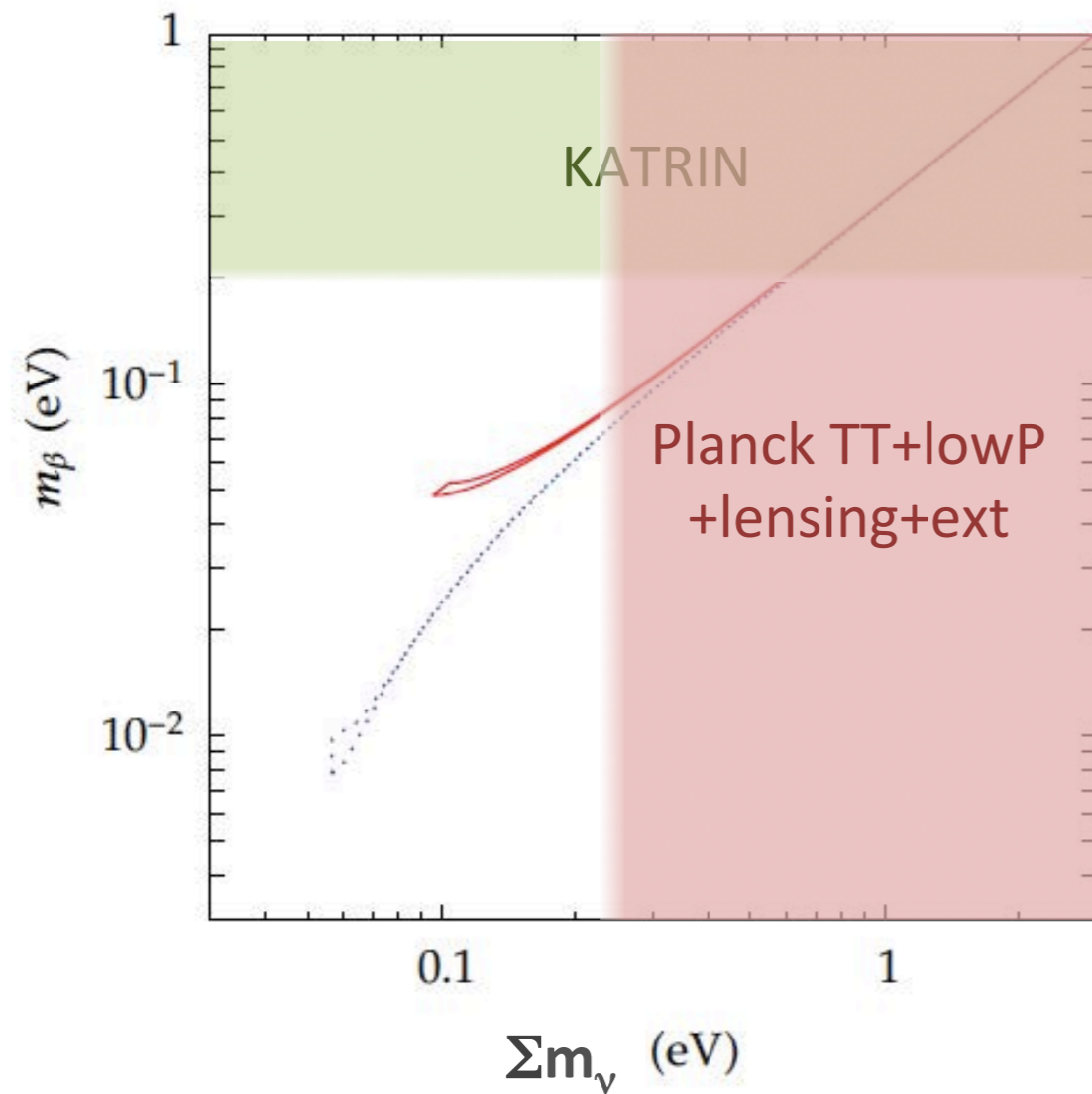
$$\chi^2 = (\mathbf{D}-\mathbf{T})^t \mathbf{C}^{-1} (\mathbf{D}-\mathbf{T})$$

$\mathbf{D}$  = vector of data measurements

$\mathbf{C}$  = covariance matrix

$\mathbf{T}$  = theory vector generated at each MCMC step

# Tritium $\beta$ decay, $0\nu 2\beta$ and Cosmology





# Future sensitivities on neutrino masses

Probe	Potential sensitivity (short term)	Potential sensitivity (long term)
CMB	0.4-0.6	0.4
CMB with lensing	0.1-0.15	0.04
CMB + Galaxy Distribution	0.2	0.05-0.1
CMB + Lensing of Galaxies	0.1	0.03-0.04
CMB + Lyman- $\alpha$	0.1-0.2	Unknown
CMB + Galaxy Clusters	-	0.05
CMB + 21 cm	-	0.0003-0.1

**Table 1.** Future probes of neutrino mass, as well as their projected sensitivity to neutrino mass. Sensitivity in the short term means achievable in approximately 5-7 years, while long term means 7-15 years.

Hannestad, Progr. Part. Nucl. Phys. 65 (2010) 185

# New approach

Cross-Correlation between CMB lensing and galaxy over-density:

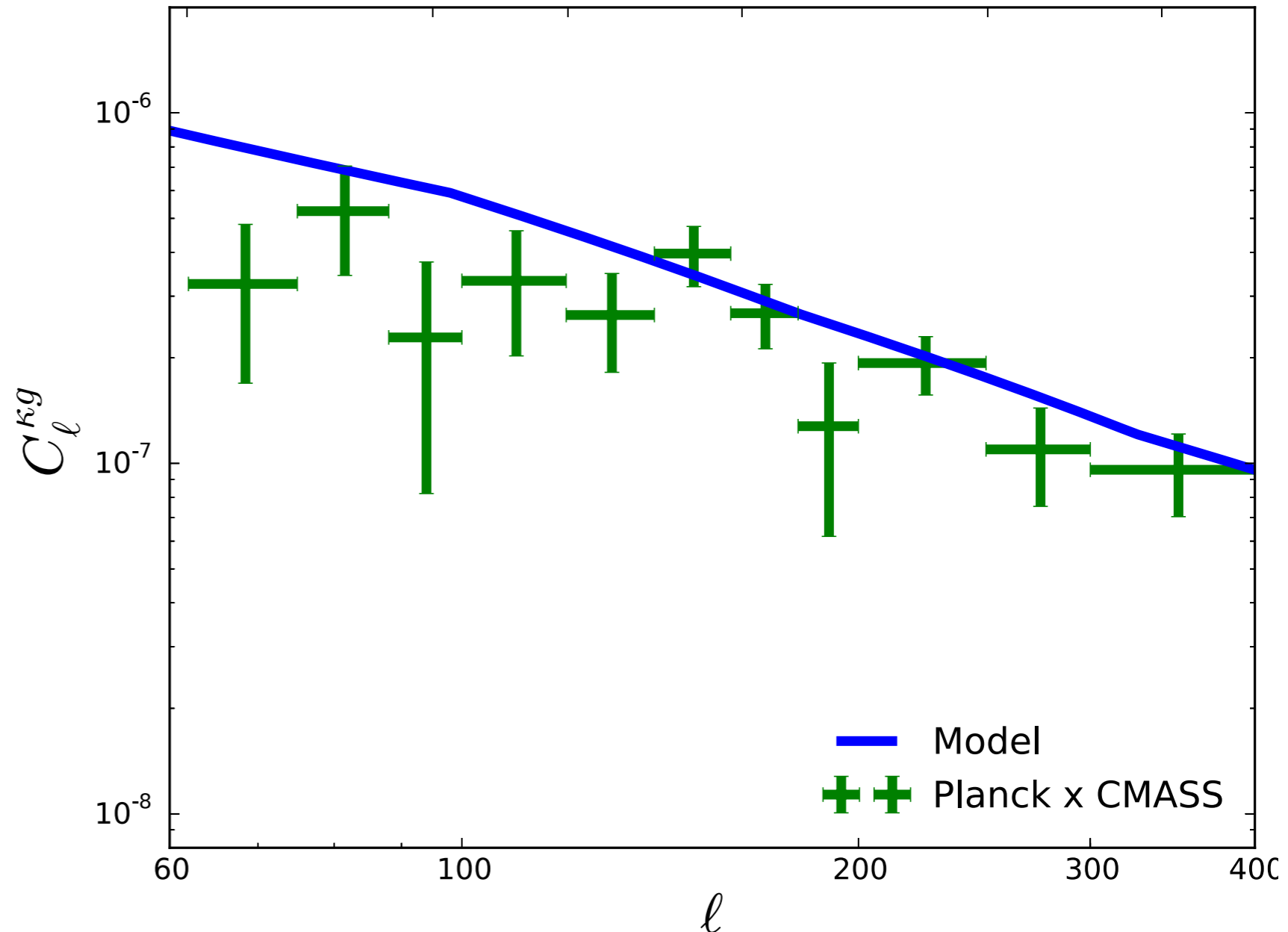
$$C_{\ell}^{kg} = \int_{z_0}^{z_1} dz \frac{H(z)}{\chi^2(z)} W^k(z) f_g(z) P_{mg} \left( k = \frac{\ell}{\chi(z)}, z \right)$$

$$W^k(z) = \frac{3\Omega_{m,0}}{2c} \frac{H_0^2}{H(z)} (1+z)\chi(z) \frac{\chi_{CMB} - \chi(z)}{\chi_{CMB}} \quad \text{Kernel for CMB lensing converge}$$

$$P_{mg}(k, z) = b_{\text{cross}}(k) P_{mm}(k, z) \quad \text{Matter-galaxy 3D cross- power spectrum}$$

# Lensing-Galaxy Angular Power Spectra

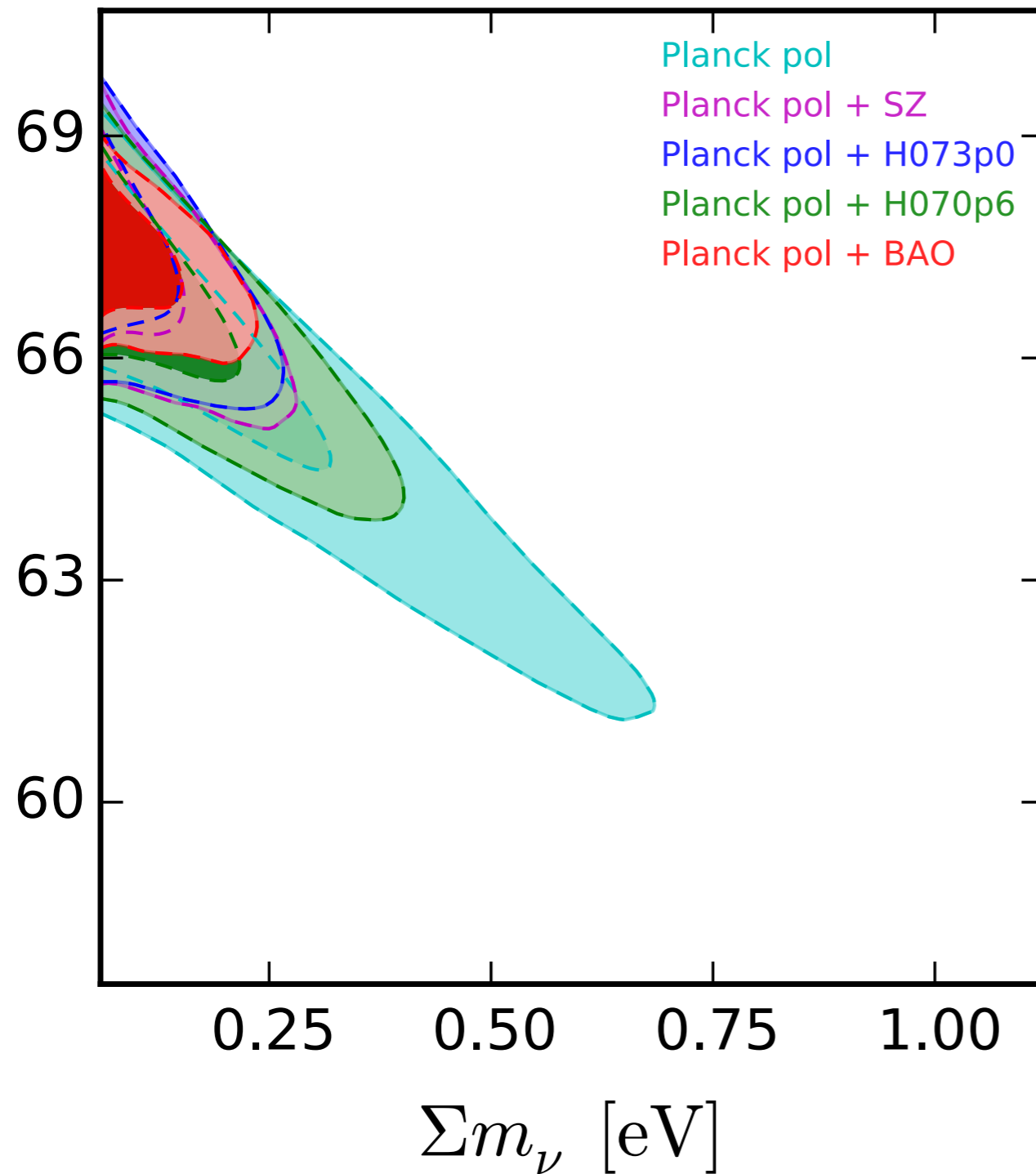
- Deviation from prediction, particularly at large scales
- Deficit seen in other Planck lensing analyses.
- Deficit also seen in DES-SPT lensing analysis.



Pullen et al. MNRAS 2015

# $H_0$

68% and 95% CL allowed regions in the  $(\Sigma m_\nu, H_0)$  plane.



$H_0$ : distance to the last scattering surface changes

$$\chi = c \int_0^{z_{\text{dec}}} \frac{dz}{\sqrt{\omega_r(1+z)^4 + \omega_m(1+z)^3 + (1 - \frac{\omega_m}{h^2})}}$$

# What is the advantage of $b(k)$ ?

We can recover the information on the matter power spectrum at non-linear scales and obtain better constraints on the cosmological parameters which are affected by scale-dependent bias of the tracers.

We can apply this method to future surveys of galaxies

