



# PART 1 – THE COSMIC BALLET

**spinning in the web**

---

**Punyakoti Ganeshaiyah Veena**

with Rien van de Weygaert , Elmo Tempel, Marius Cautun



# PART 2 - Unmasking the Universe with neural nets

arXiv: 2212.06439

*with Robert Lilow and Adi Nusser  
Technion, Haifa, Israel.*



# IN PART - 1

Explore the interplay between the **cosmic web and halo/ galaxy properties.**

## Spin and shape

1. **P. Ganeshaiyah Veena**, M. Cautun, R. van de Weygaert, E. Tempel, B.J.T Jones, S. Reider, C.S. Frenk; MNRAS, Volume 481, **2018**.
2. **P. Ganeshaiyah Veena**, M. Cautun, E. Tempel, R. van de Weygaert, C.S. Frenk; MNRAS, Volume 487, **2019**.
3. **P. Ganeshaiyah Veena**, M. Cautun, R. van de Weygaert, E. Tempel, C. S. Frenk; MNRAS, **2021**.

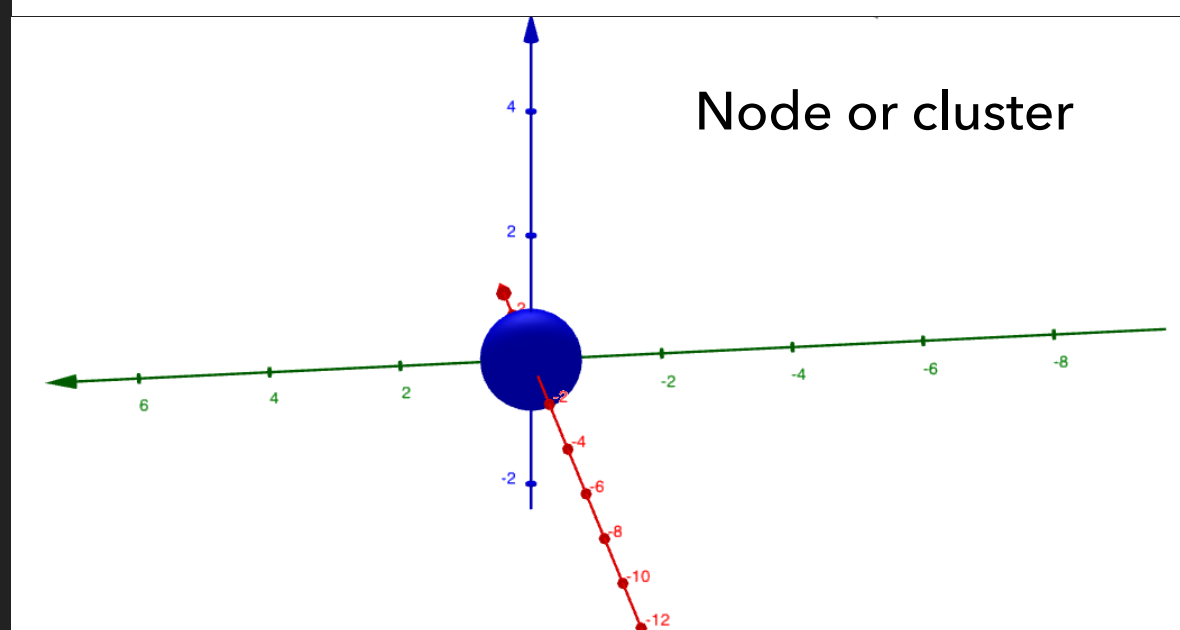
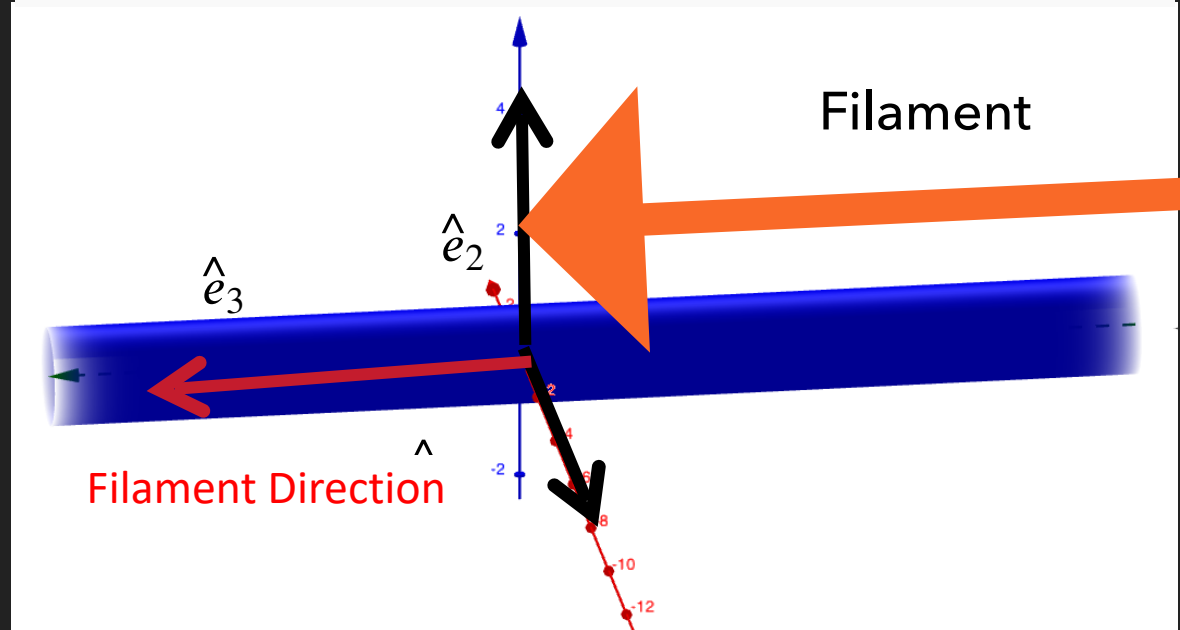
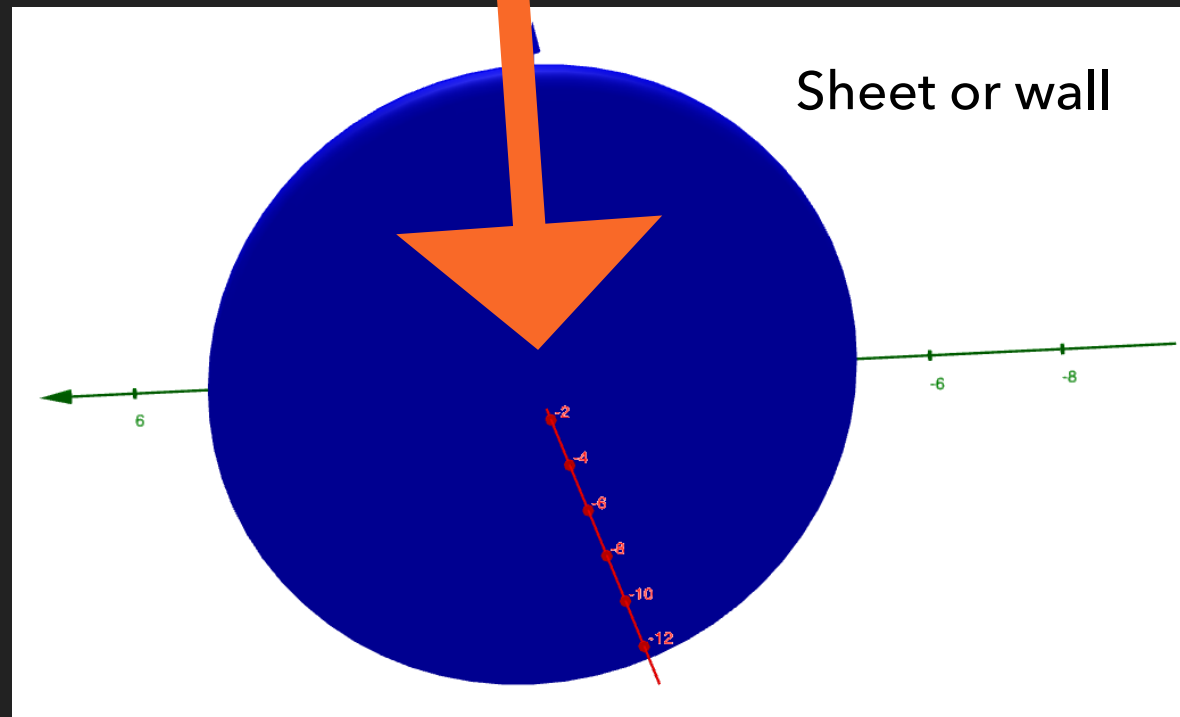
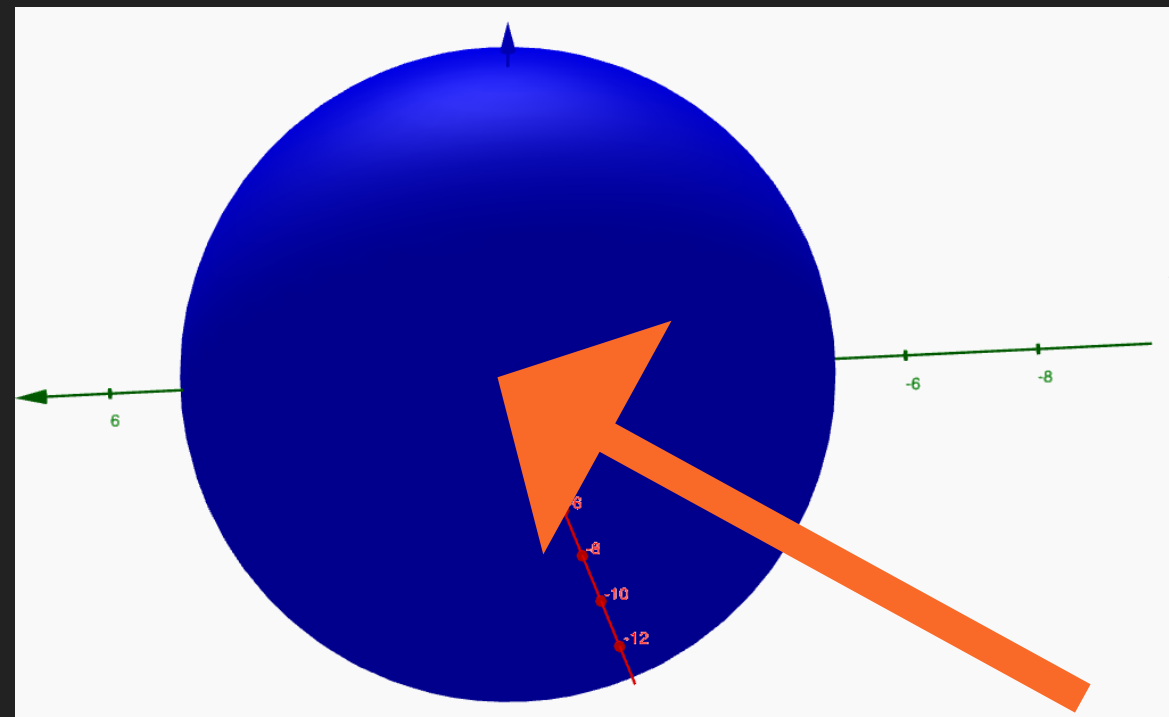


# TIDAL FIELDS AND COSMIC WEB – ANISOTROPIC COLLAPSE

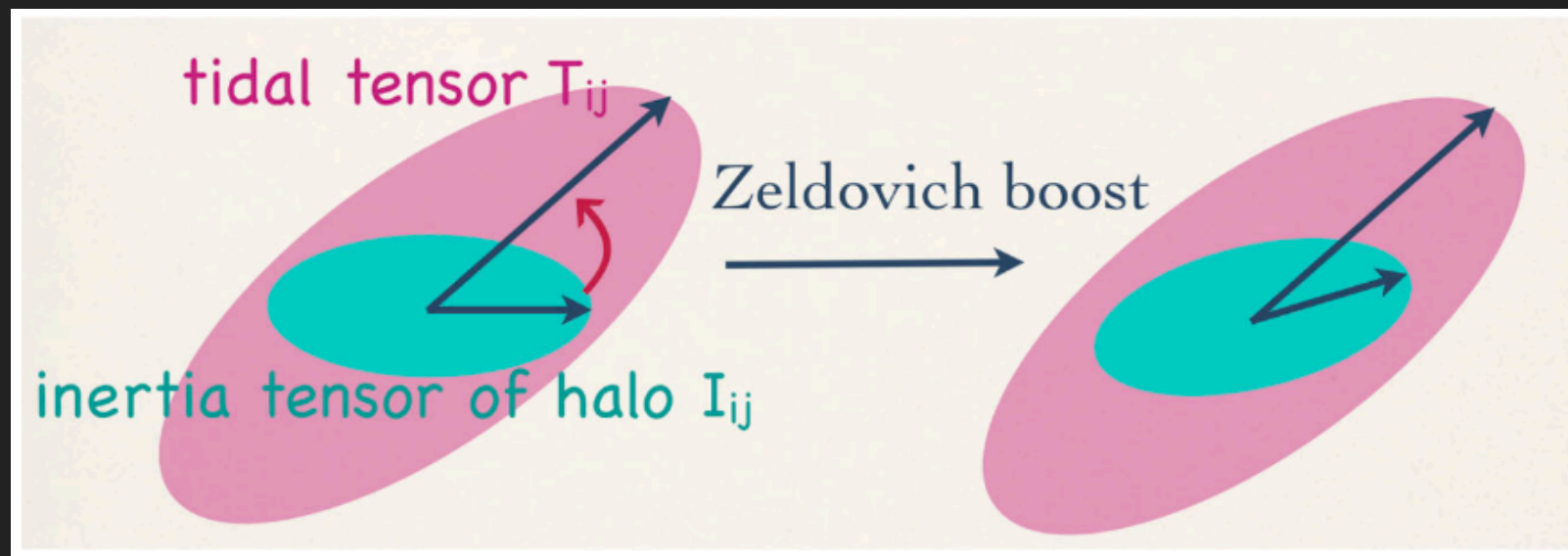
$$\Psi_{ij} = \frac{\partial^2 \Psi}{\partial q_i \partial q_j} \quad \Psi(q) = -\frac{2}{3\Omega_0 H_0^2} \Phi_0$$

$$\lambda_1 \geq \lambda_2 \geq \lambda_3$$

Cluster	Filament	Wall	Void
$\lambda_1 > 0$	$\lambda_1 > 0$	$\lambda_1 > 0$	$\lambda_1 < 0$
$\lambda_2 > 0$	$\lambda_2 > 0$	$\lambda_2 < 0$	$\lambda_2 < 0$
$\lambda_3 > 0$	$\lambda_3 < 0$	$\lambda_3 < 0$	$\lambda_3 < 0$







Codis et al 2015

$$J_i(t) = a^2 \dot{D}(t) \epsilon_{ijk} T_{jl} I_{lk}$$

$$T_{jl} = \frac{\partial^2 \phi(\mathbf{q})}{\partial q_j \partial q_l} \quad I_{lk} = \int_{V_L} d^3 \mathbf{q} \rho(q) q_l q_k$$

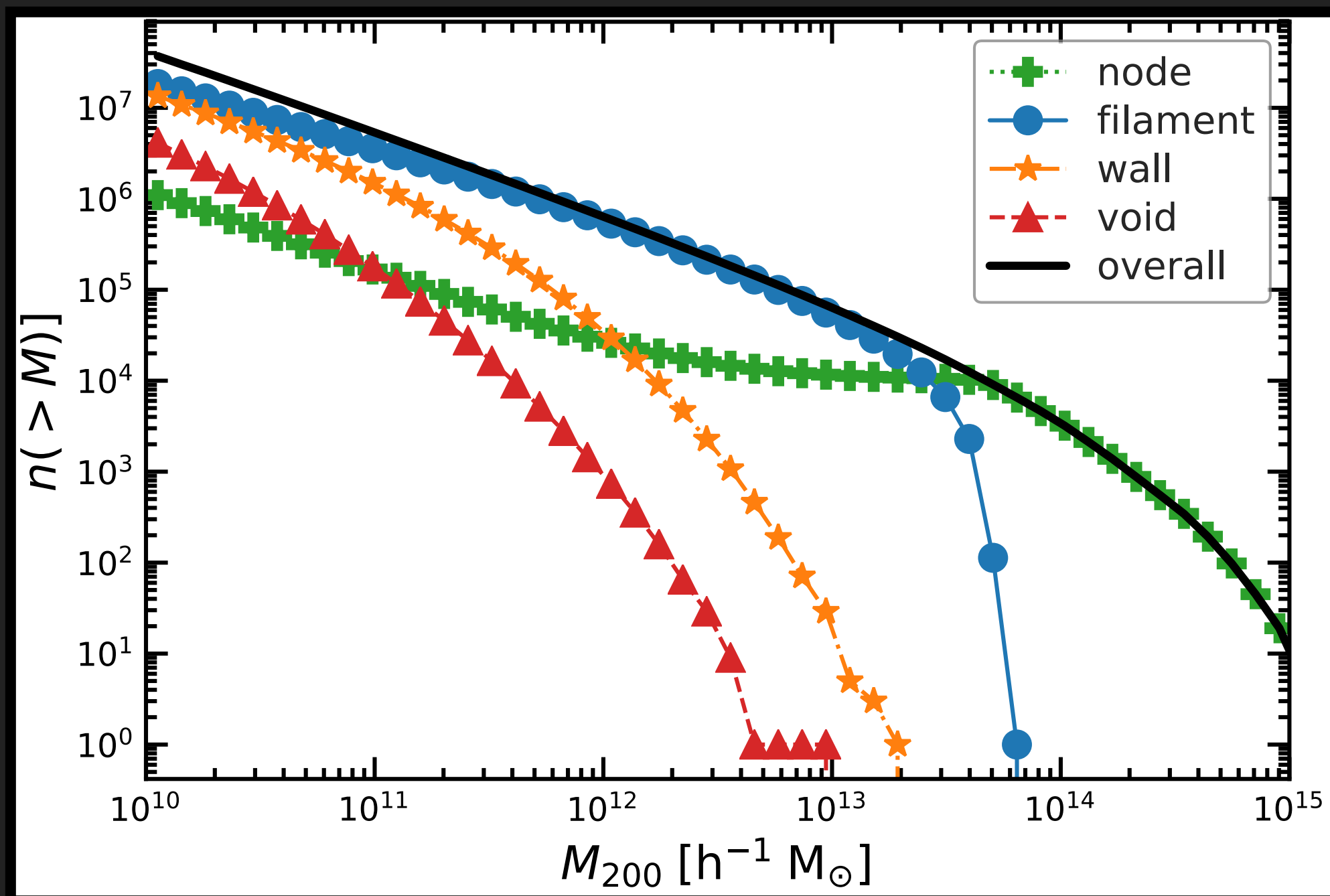
Angular momentum grows linearly until turn-around.



1. Does the cosmic web environment influence **halo spin magnitude and orientation**? How are spins aligned with the underlying geometry of the cosmic web?
2. How do the halo/galaxy spin alignments depend on the **filament properties**?
3. How do spin-alignments **evolve with time**?
4. **Halo-galaxy connection**: How does galaxy alignment compare to its halo spin alignment? How does it relate to galaxy **morphology**?



# PLANCK-MILLENNIUM SIMULATION - MASS FUNCTION



P. Ganeshaiah Veena et al 2018

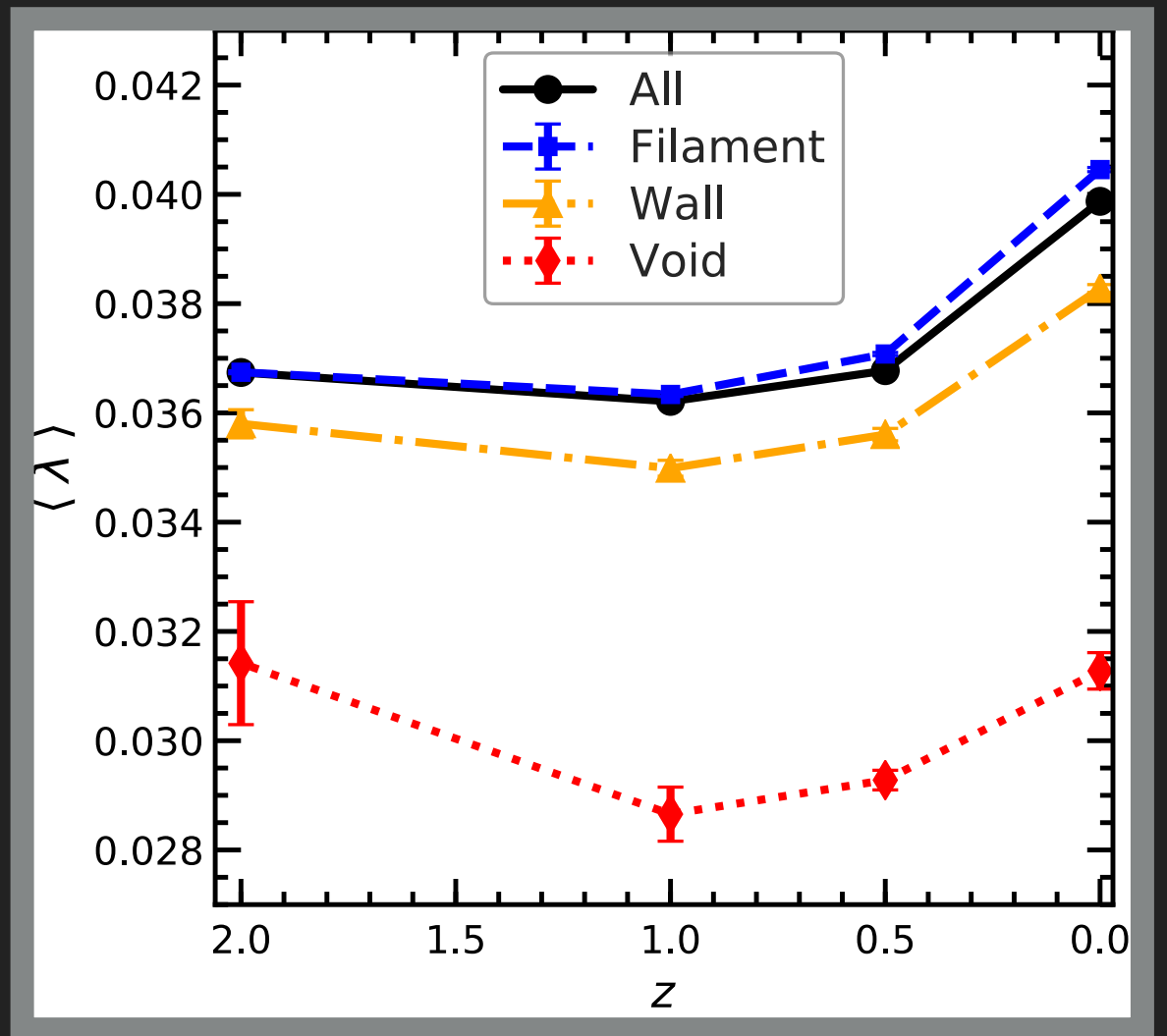
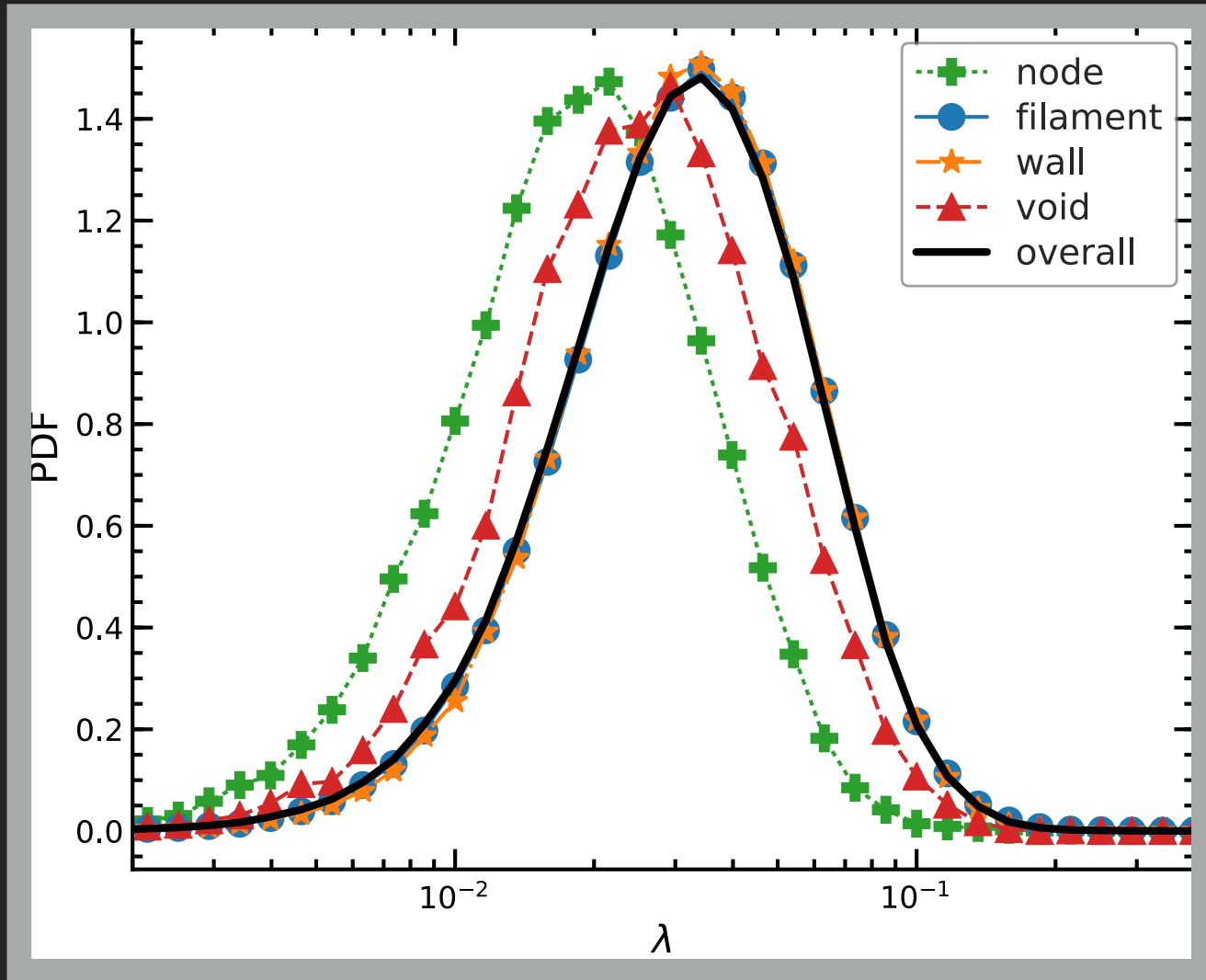
**~36 million haloes at  
z=0**

**~2.8 million haloes  
chosen for this study**



# PLANCK-MILLENNIUM SIMULATION – SPIN PARAMETER

PGV et al 2018



PGVa et al 2021

$$\lambda = \frac{J}{\sqrt{2MVR}}$$

$\lambda = 0 \longrightarrow$  dispersion supported

$\lambda = 1 \longrightarrow$  rotation supported



## NEXUS +

## NEXUS VELOCITY SHEAR

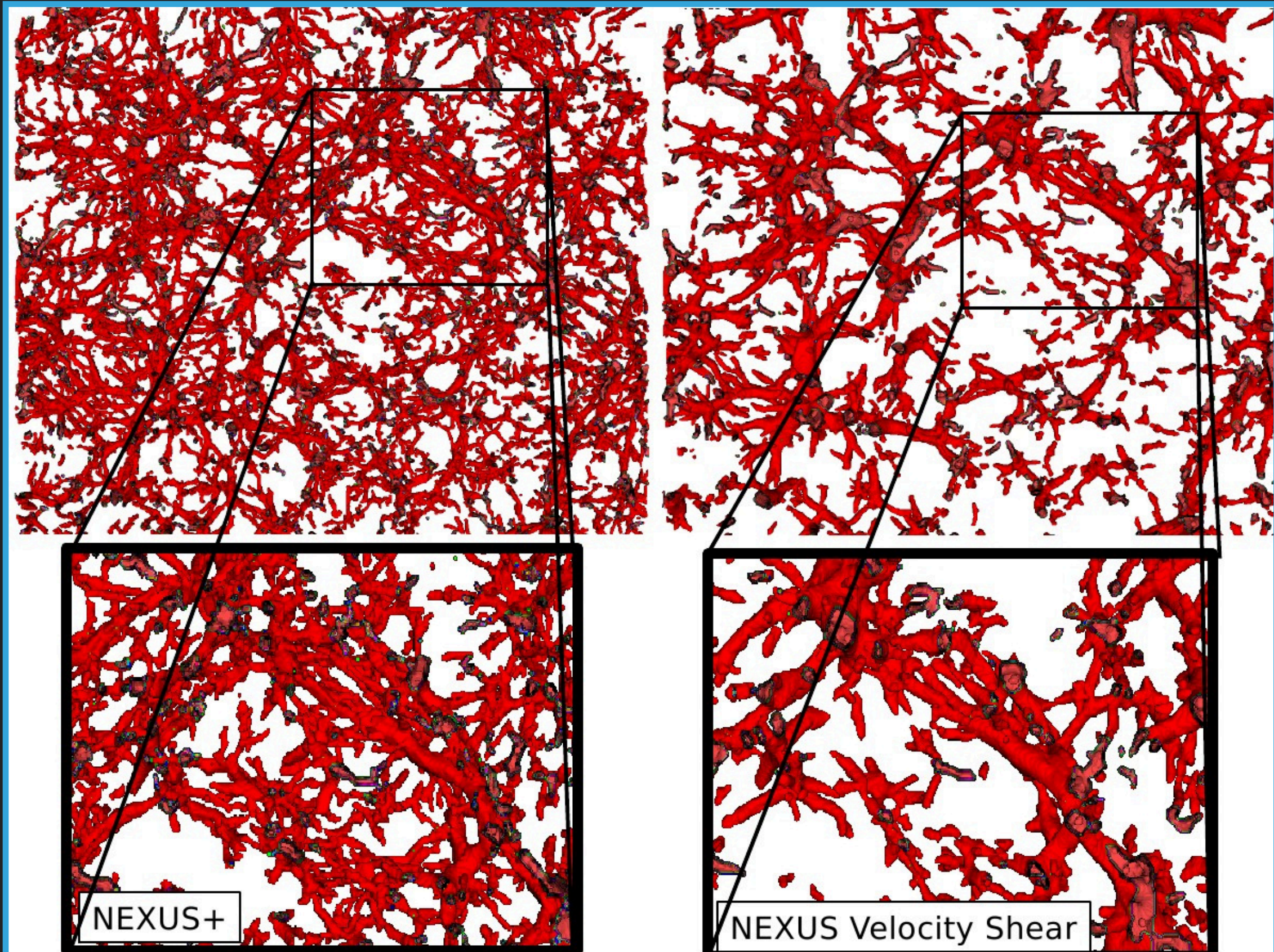
- ▶ Input tracer field - density field
- ▶ Geometry of matter distribution
- ▶ Velocity shear
- ▶ Dynamical signature

Morphology: eigenvalue conditions

Multiscale detection

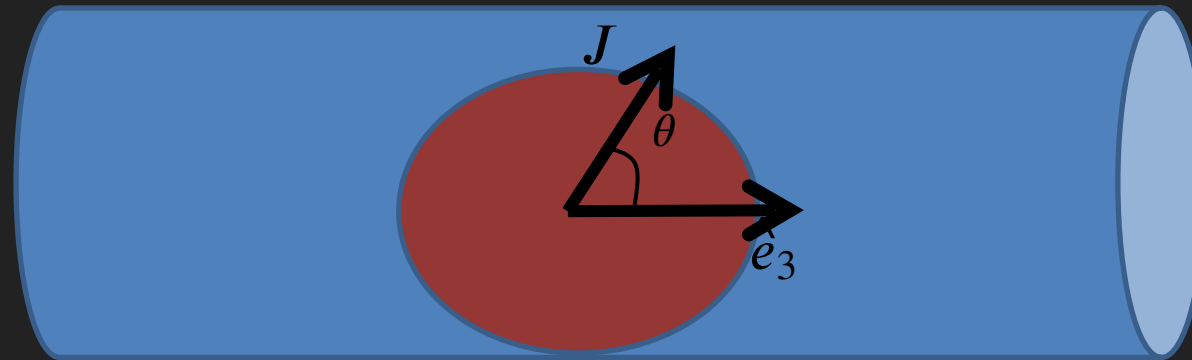
Spine of filament or last collapse:  $\hat{e}_3$





P. Ganeshaiah Veena et al 2018





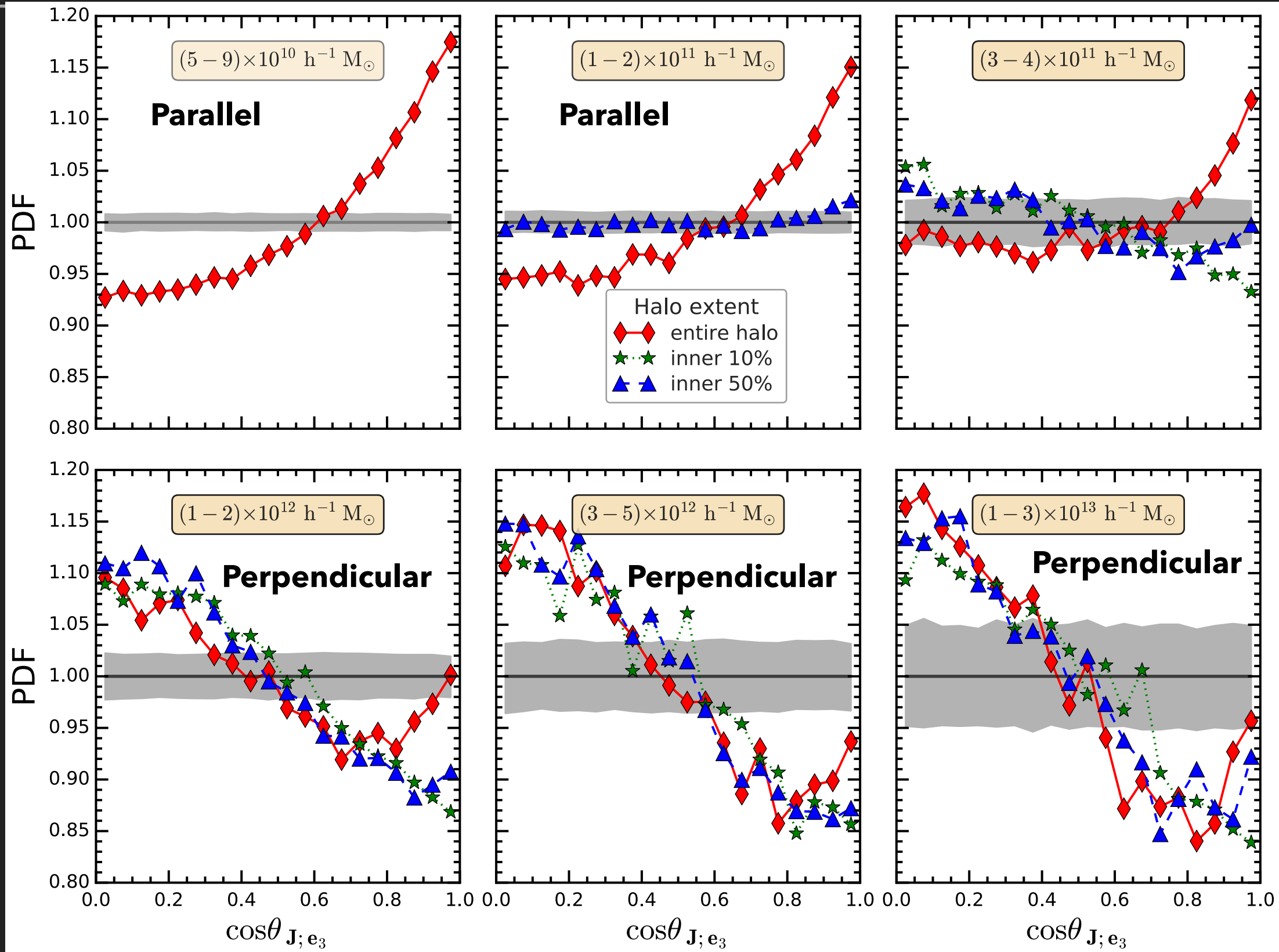
$$\cos \theta_{\mathbf{J}, \mathbf{e}_3} = \left| \frac{\mathbf{J} \cdot \mathbf{e}_3}{|\mathbf{J}| |\mathbf{e}_3|} \right|$$

$$\cos(\theta) = 1 \quad \longrightarrow \text{Parallel}$$

$$\cos(\theta) = 0.5 \quad \longrightarrow \text{No preferential alignment}$$

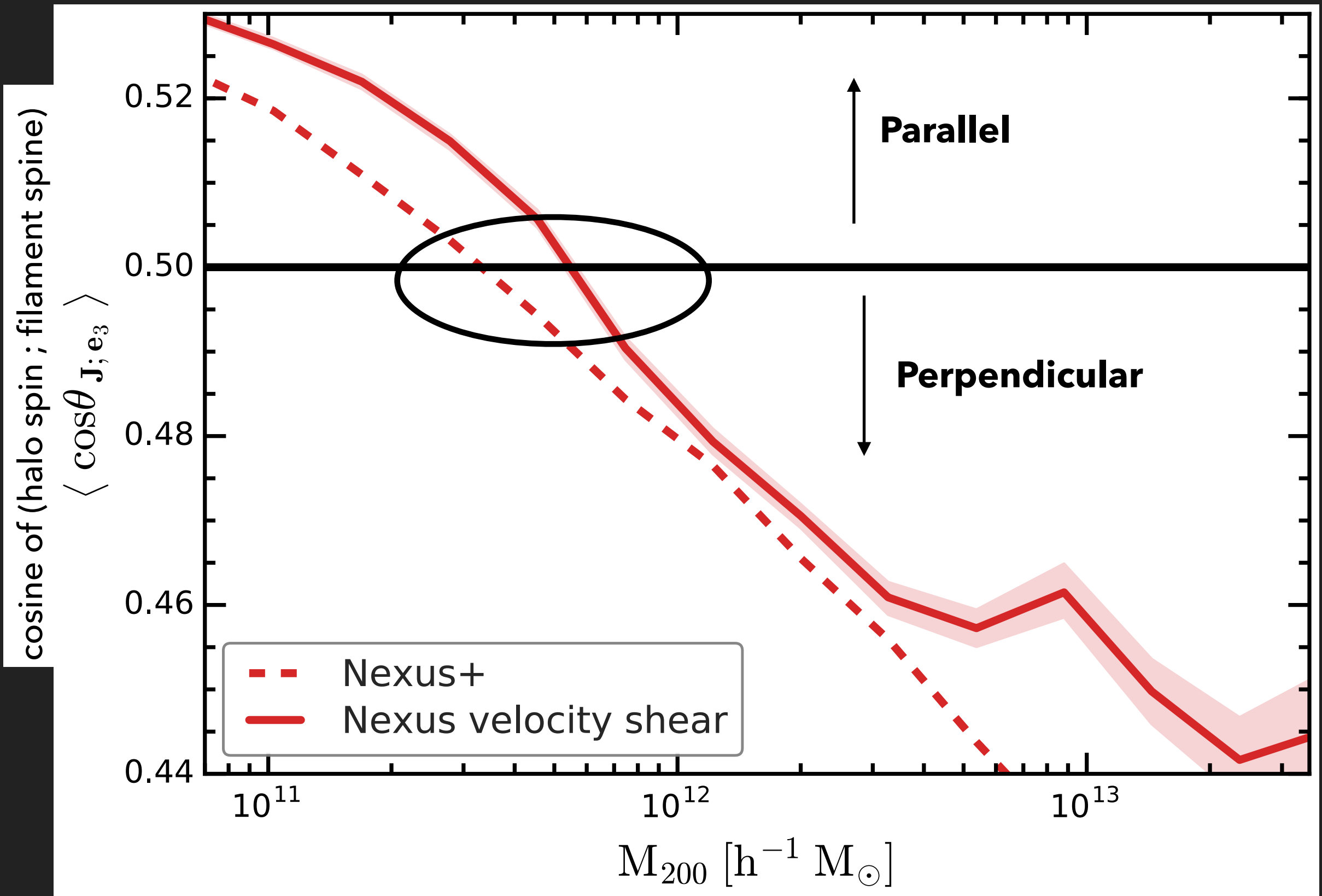
$$\cos(\theta) = 0 \quad \longrightarrow \text{Perpendicular}$$





P. Ganeshaiah Veena et al 2018

# NEXUS + VELOCITY SHEAR





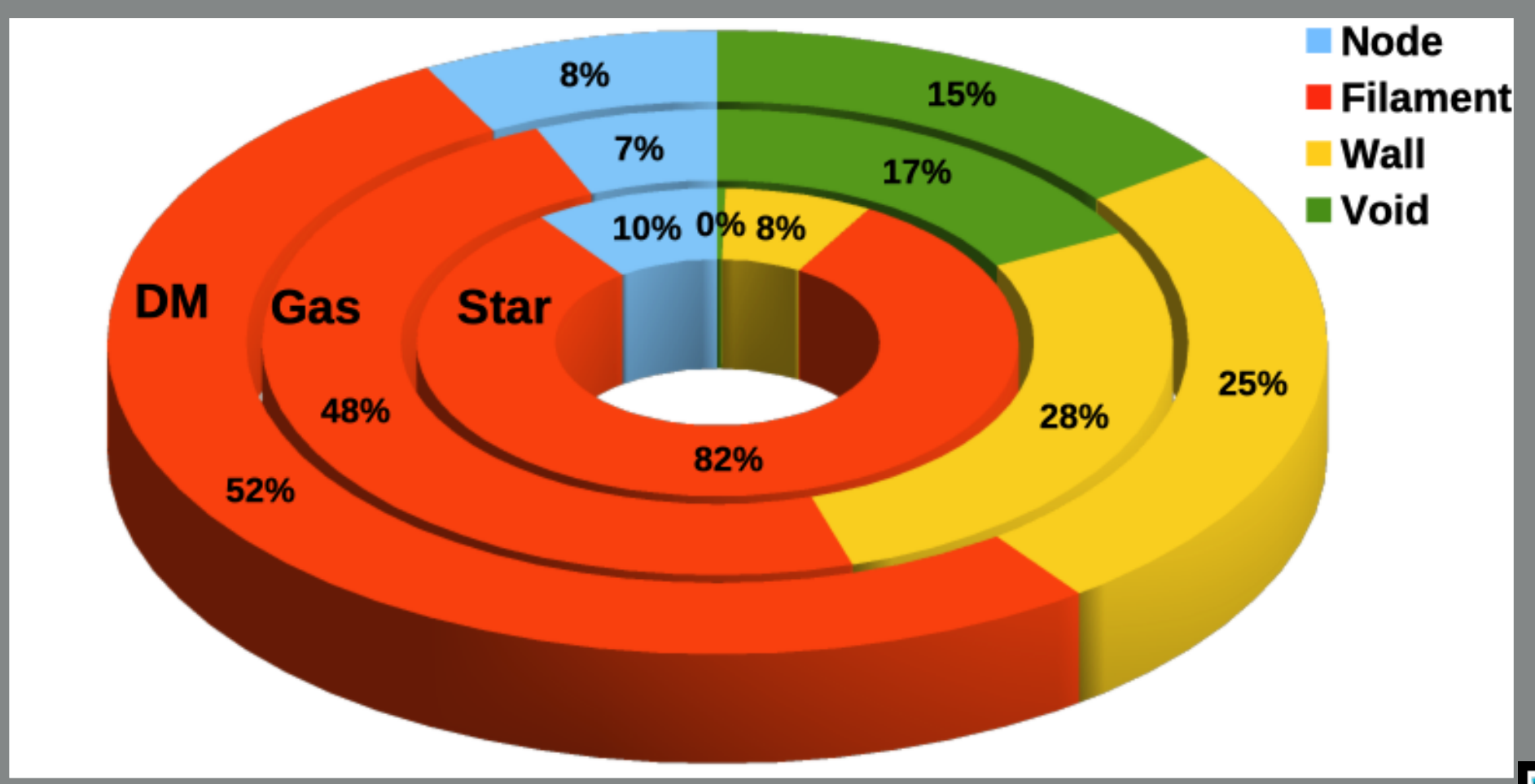
# TRANSITION MASS AND WEB FINDERS

Table 1: Halo spin alignments in simulations

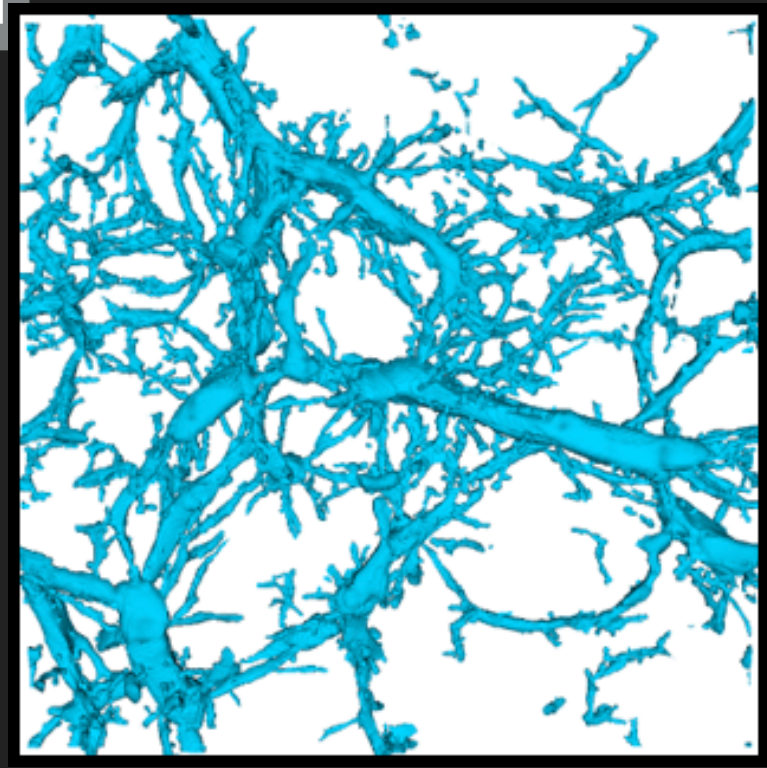
Work by	Simulation box length [ $h^{-1}$ Mpc]	Cosmic web detection	Transition mass ( $\times 10^{12} h^{-1} M_{\odot}$ )
Aragón-Calvo et al. (2007b)	150	MMF	$\sim 1$
Hahn et al. (2007a)	180	tidal tensor	–
Codis et al. (2012)	2000	DISPERSE	$\sim 3.5$
Libeskind et al. (2012)	64	velocity shear tensor	–
Trowland et al. (2013)	300	density Hessian	$\sim 1.2$
Forero-Romero et al. (2014)	250	T-Web	1
		V-Web	2
Aragon-Calvo & Yang (2014)	32	MMF-2	
Wang & Kang (2018b)	200	tidal tensor	0.5 - 1.4
Ganeshaiyah Veena et al. (2018)	542	NEXUS+	0.3
		NEXUS_VEL_SHEAR	0.5
Lee (2019)	400	tidal tensor	–

Table from: PGV thesis, table 1, page number 34

# MASS FRACTION IN THE UNIVERSE – EAGLE SIMULATION



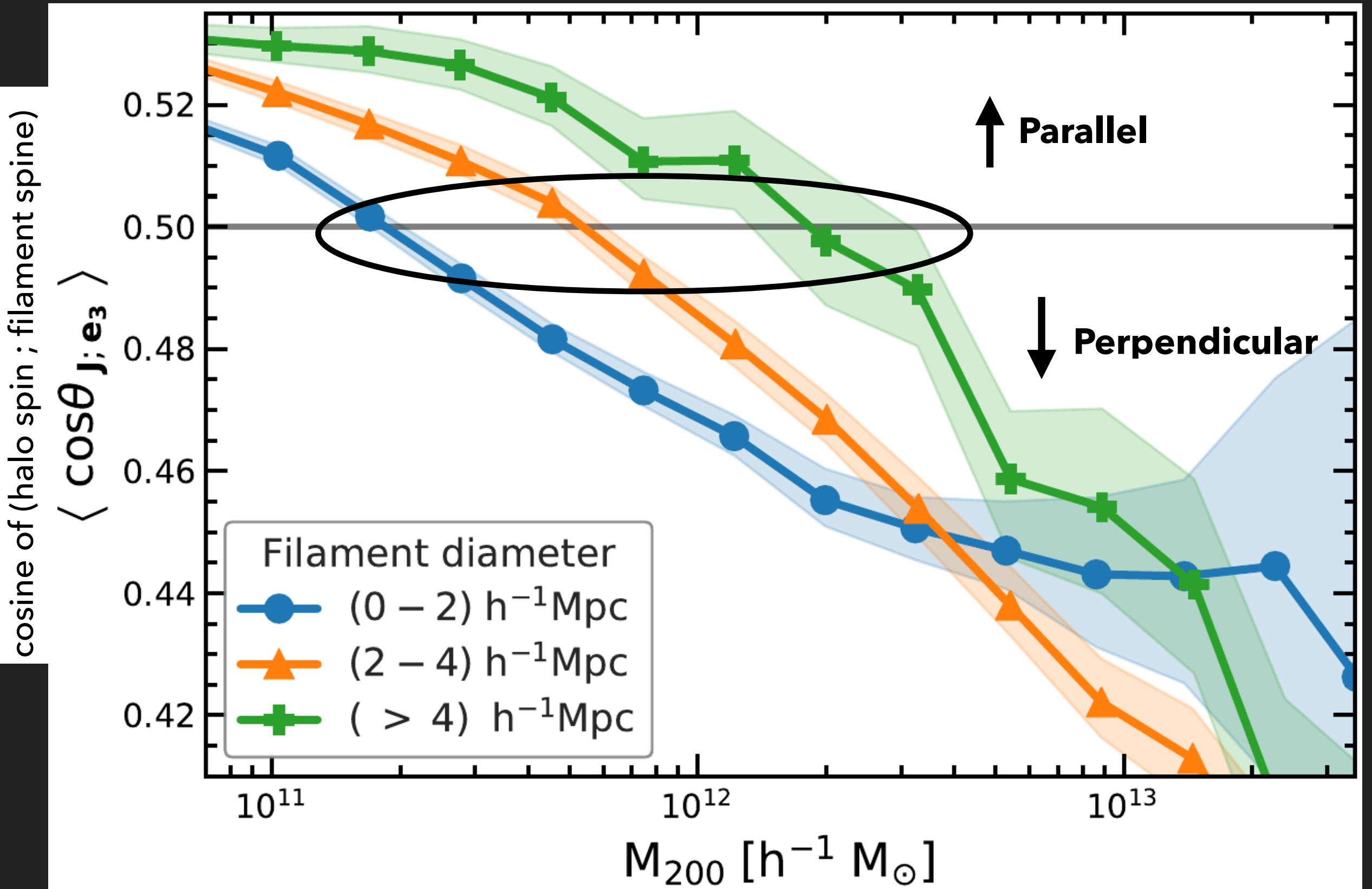
P. Ganeshiah Veena, M. Cautun, E. Tempel, R. van de Weijgaert and C. Frenk, 2020.

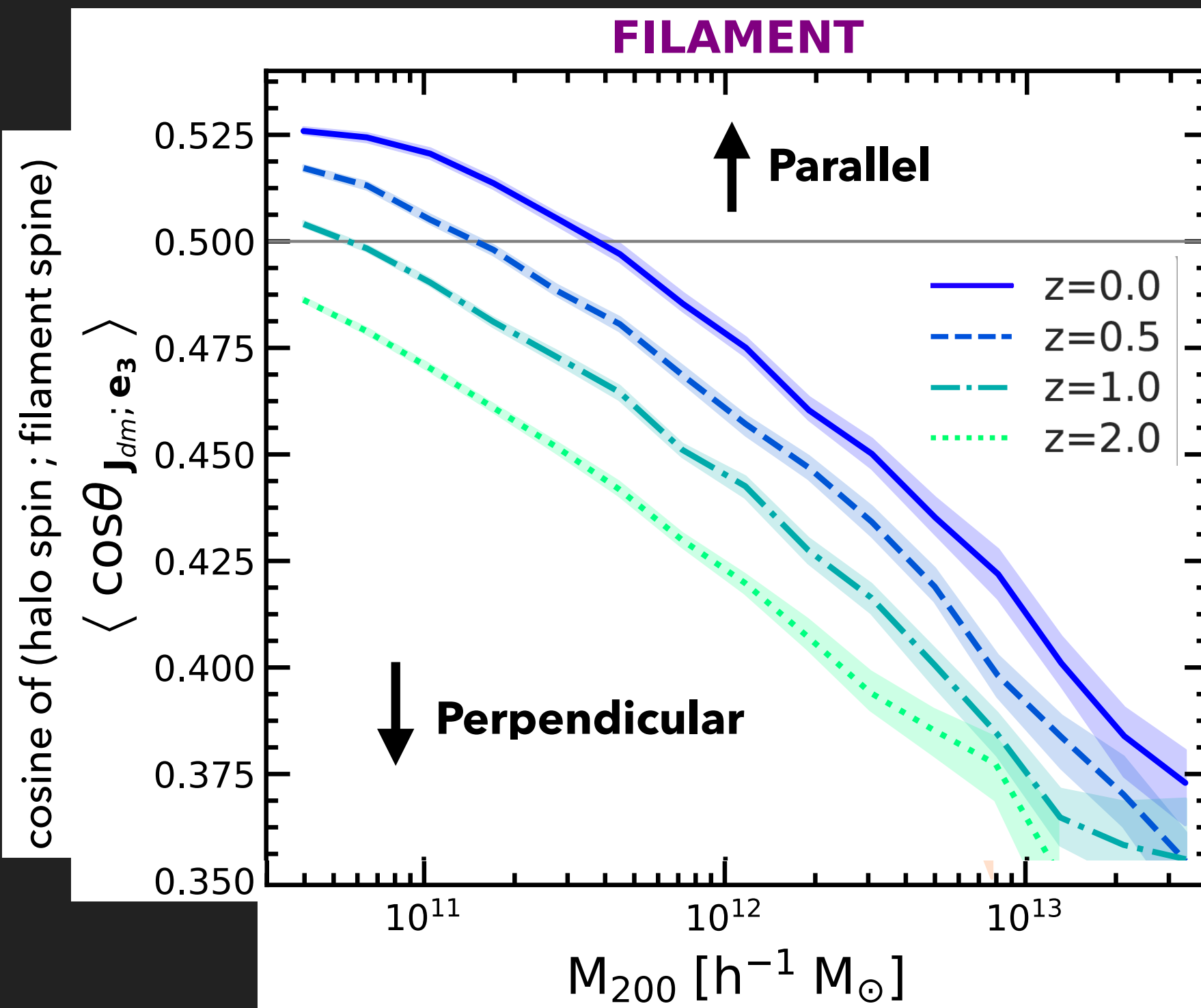


Nexus+ filaments, from Cautun et al 2014.

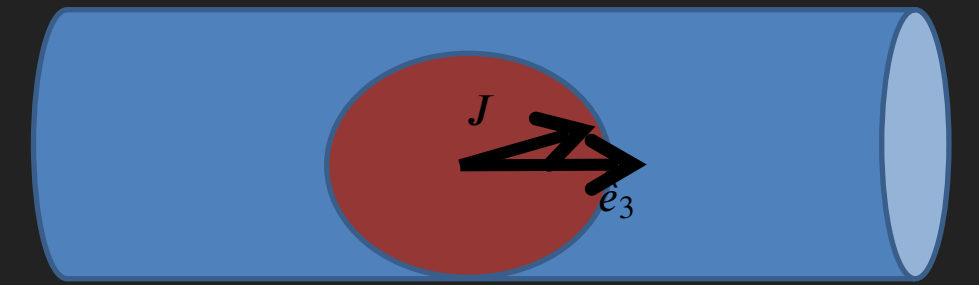
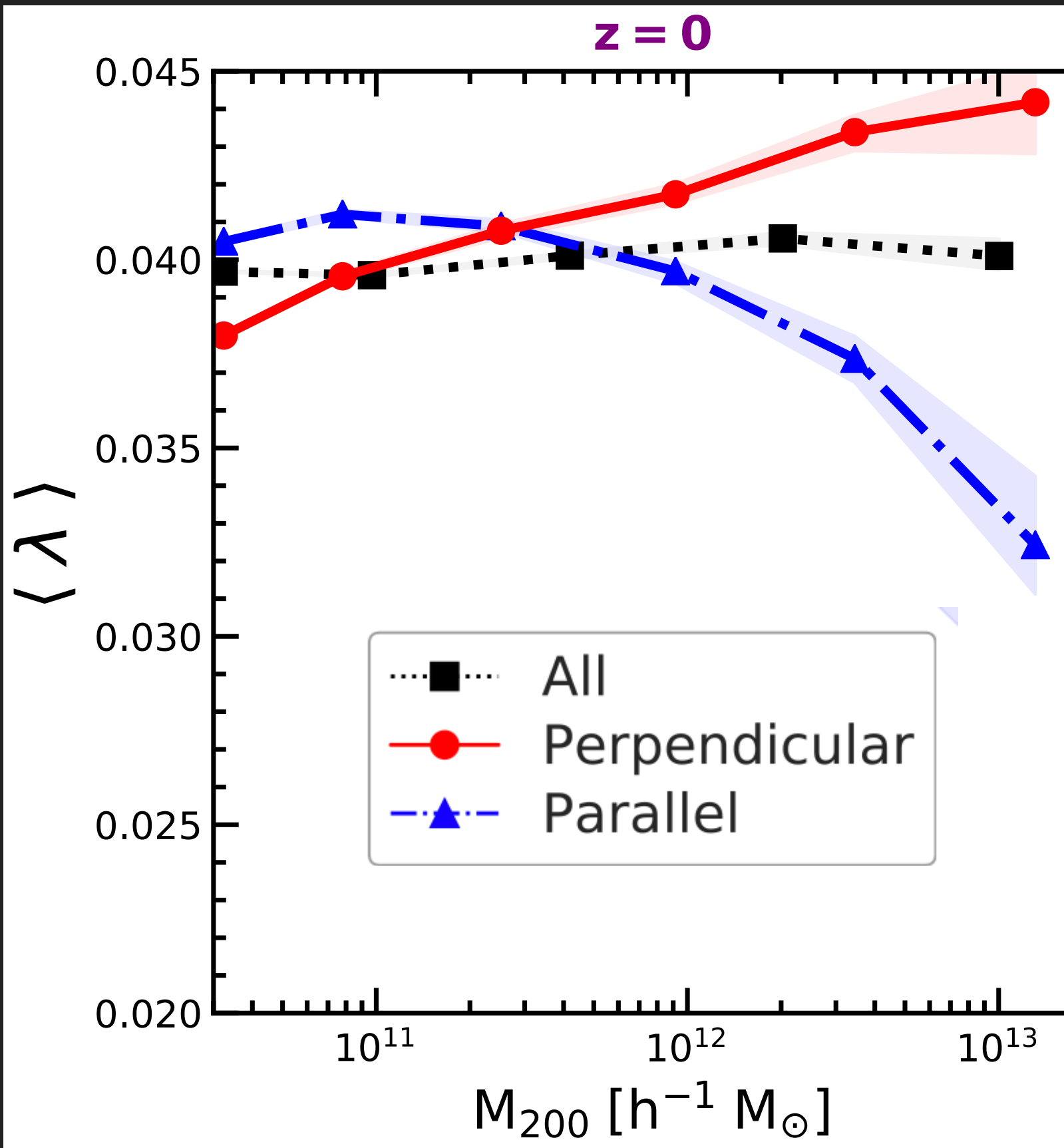


# FILAMENT THICKNESS



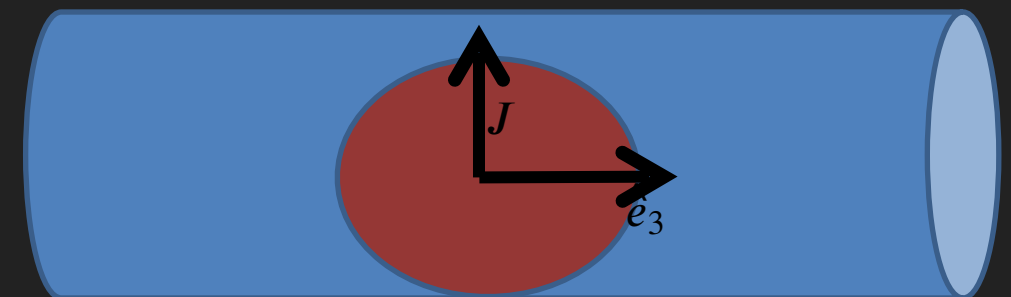


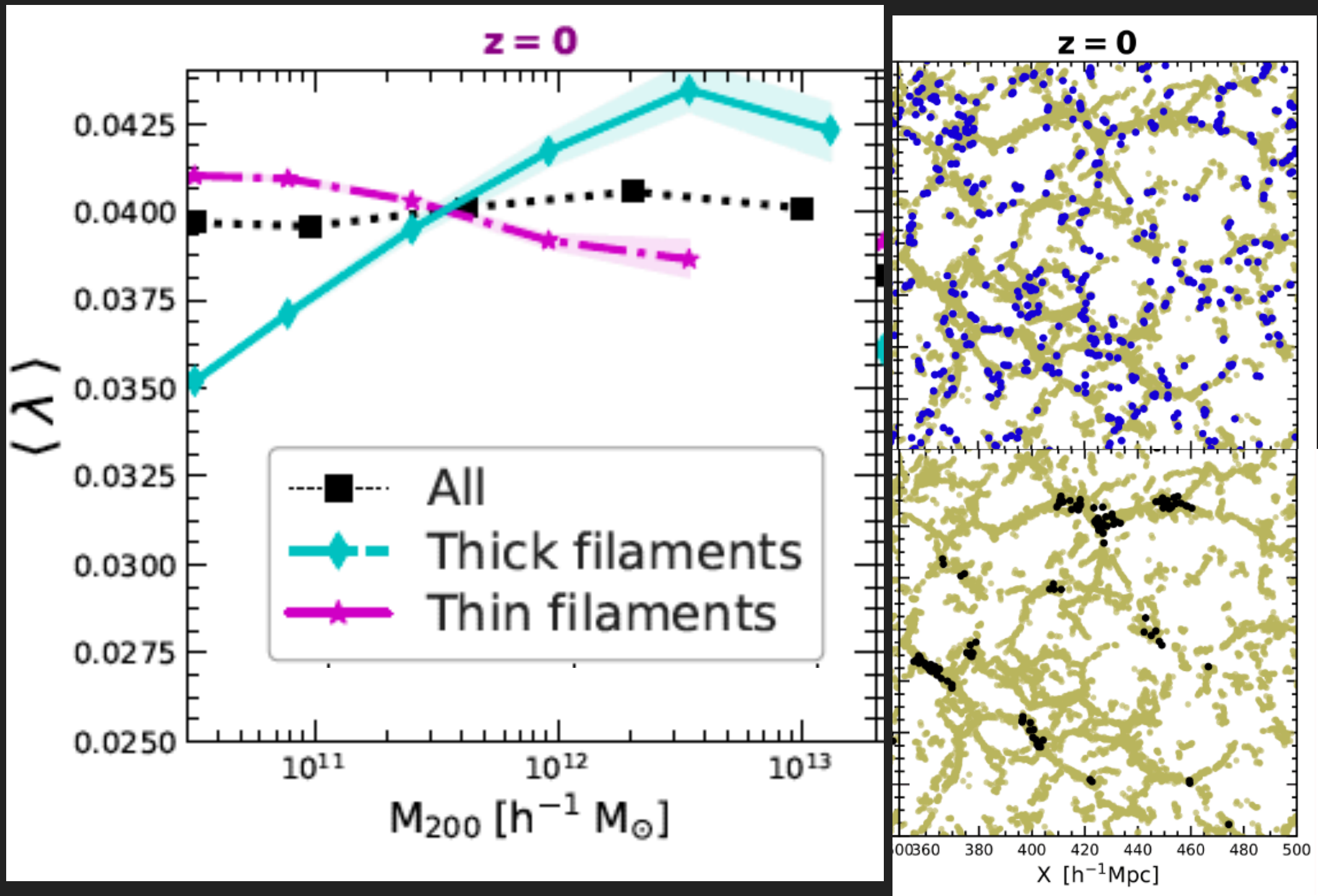




$\cos(\theta) \geq 0.8 \quad \longrightarrow \text{Parallel to fila.}$   
 $\theta \leq 36^\circ$

$\cos(\theta) \leq 0.2 \quad \longrightarrow \text{Perpendicular}$   
 $\theta \geq 80^\circ$

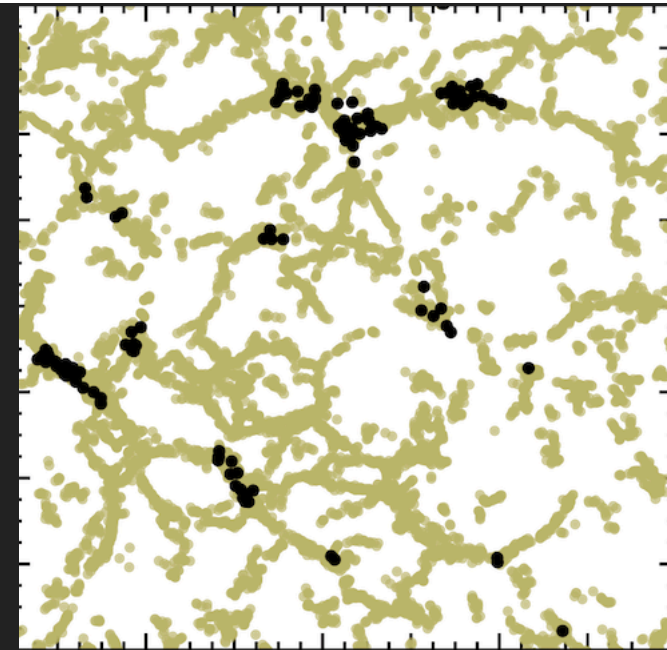
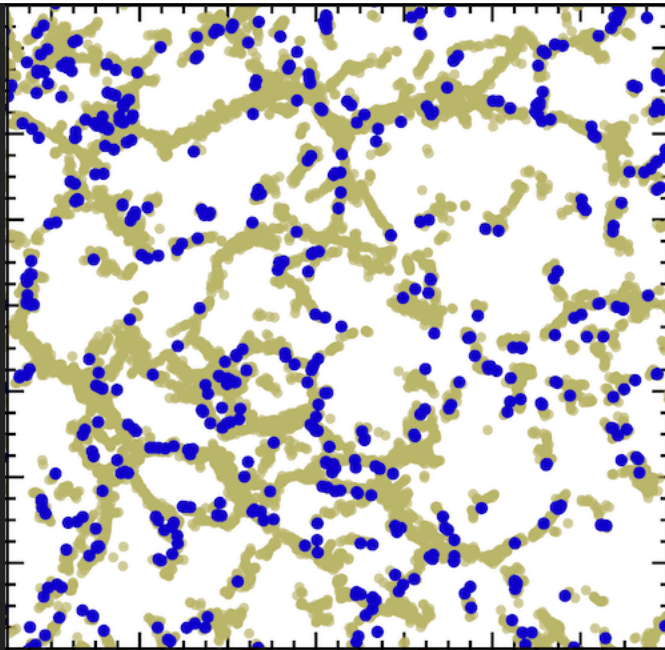
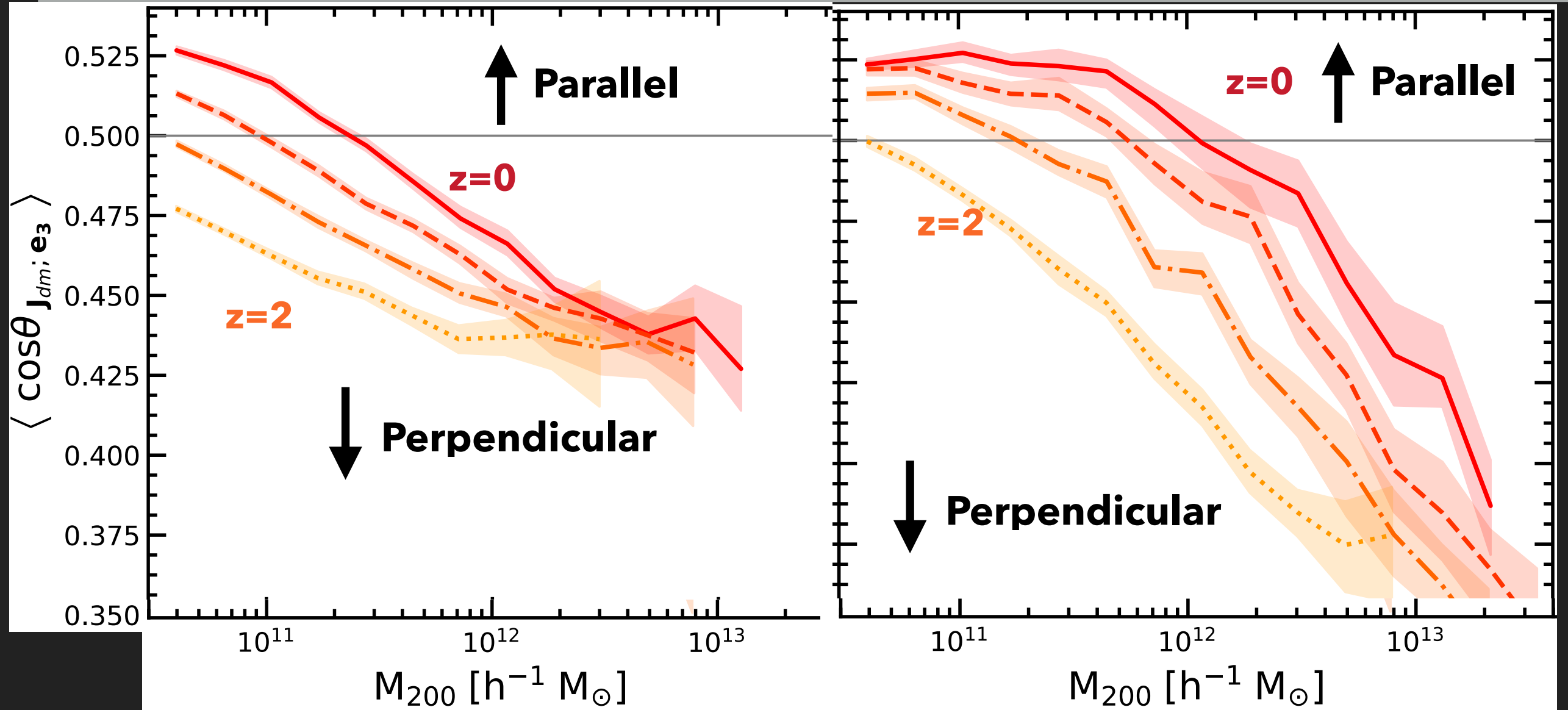


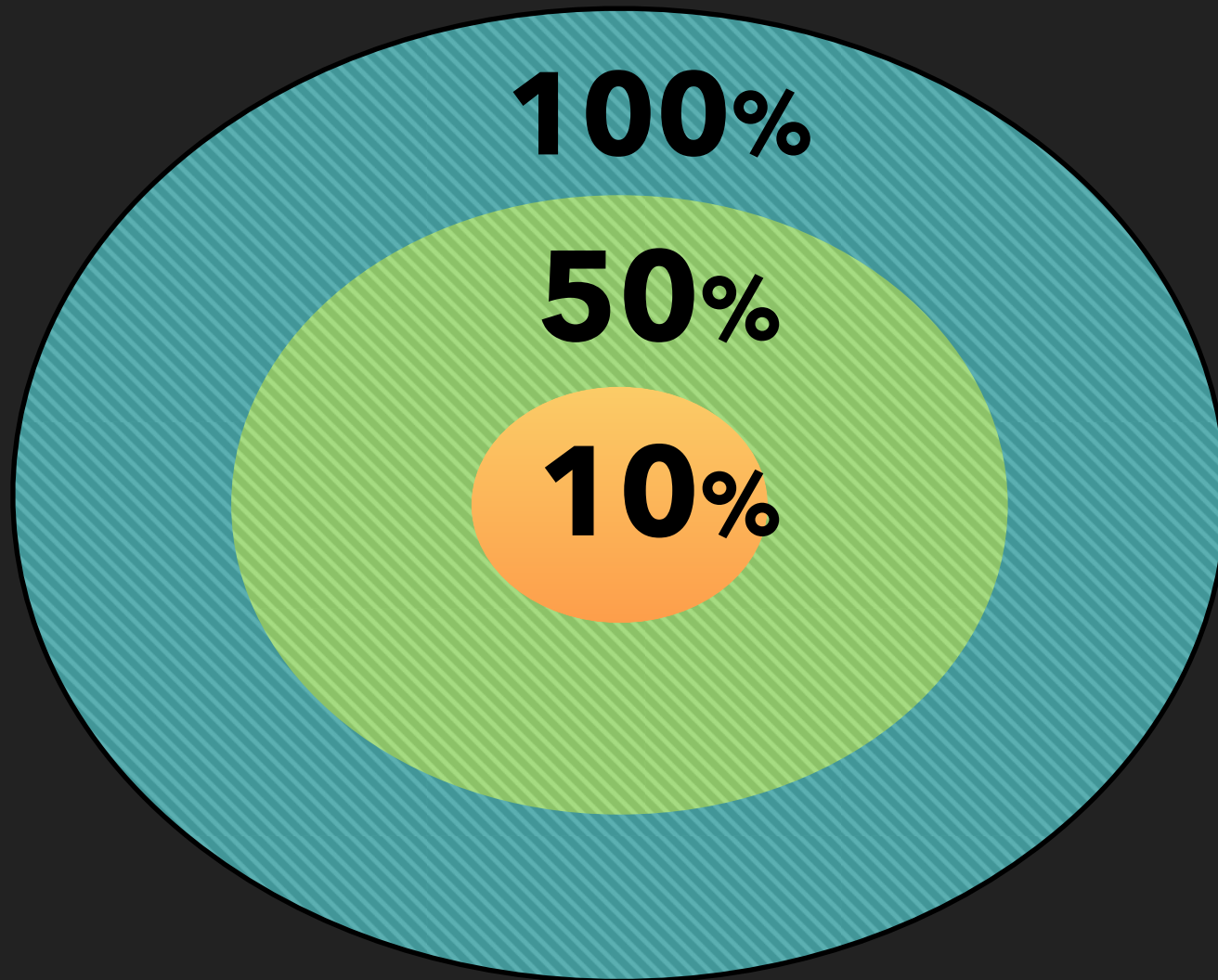




# THIN FILAMENTS

# THICK FILAMENTS



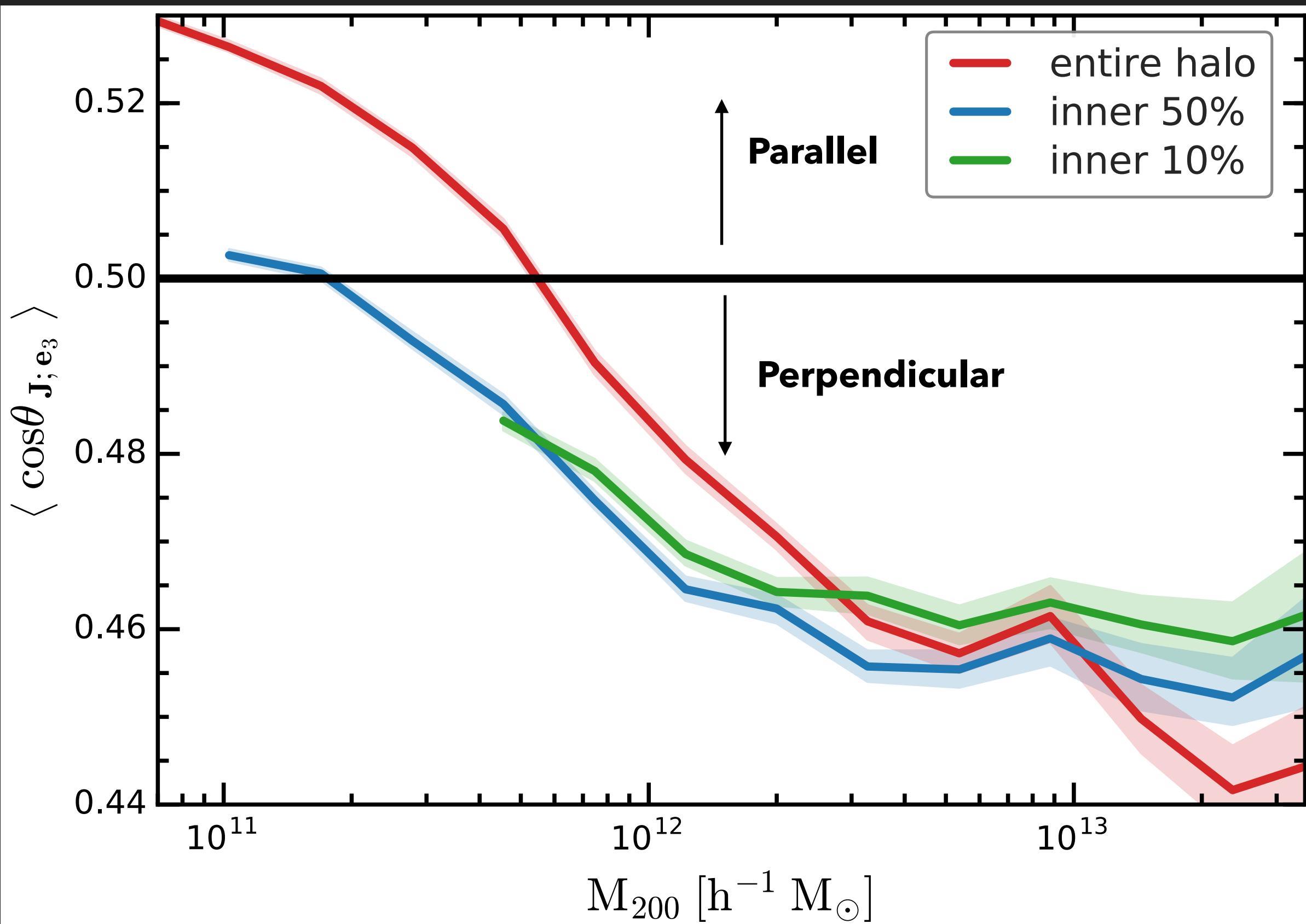


$$\mathbf{J} = \sum_{k=1}^N m_k (\mathbf{r}_k \times \mathbf{v}_k)$$

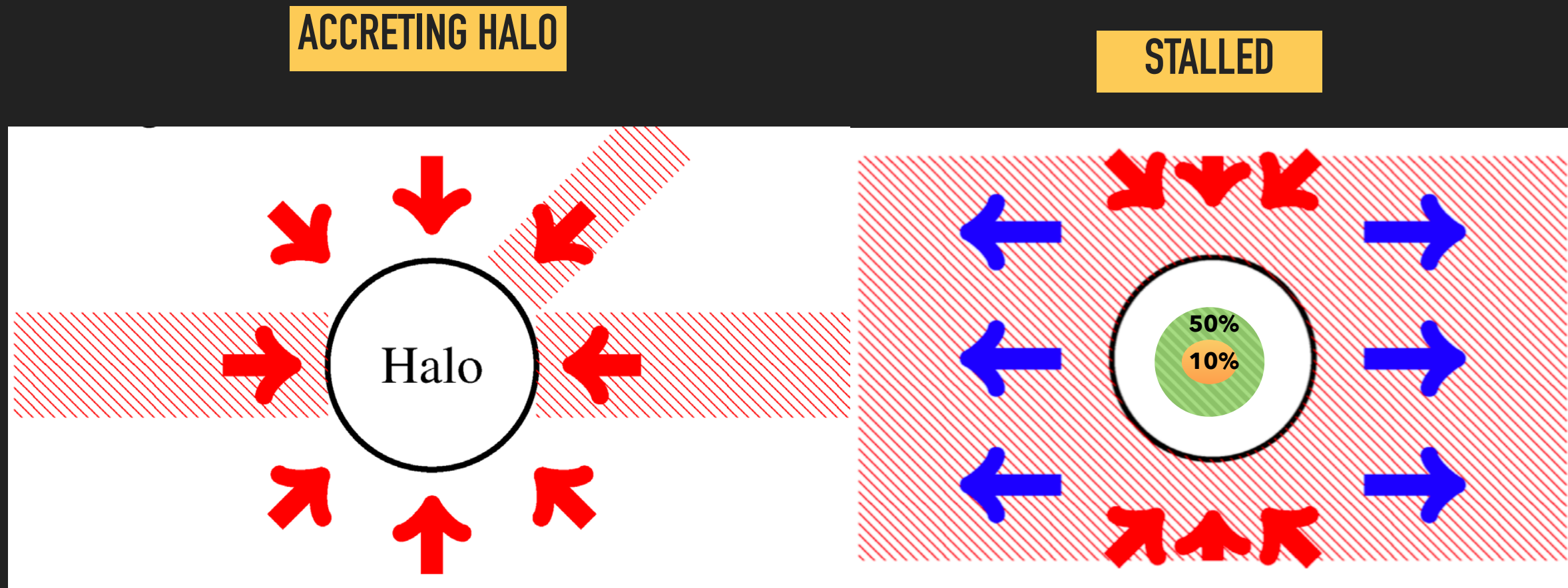
$$\cos \theta_{\mathbf{J}, \mathbf{e}_3} = \left| \frac{\mathbf{J} \cdot \mathbf{e}_3}{|\mathbf{J}| |\mathbf{e}_3|} \right|$$



## INNER HALO FRACTIONS



## POSSIBLE CAUSE:

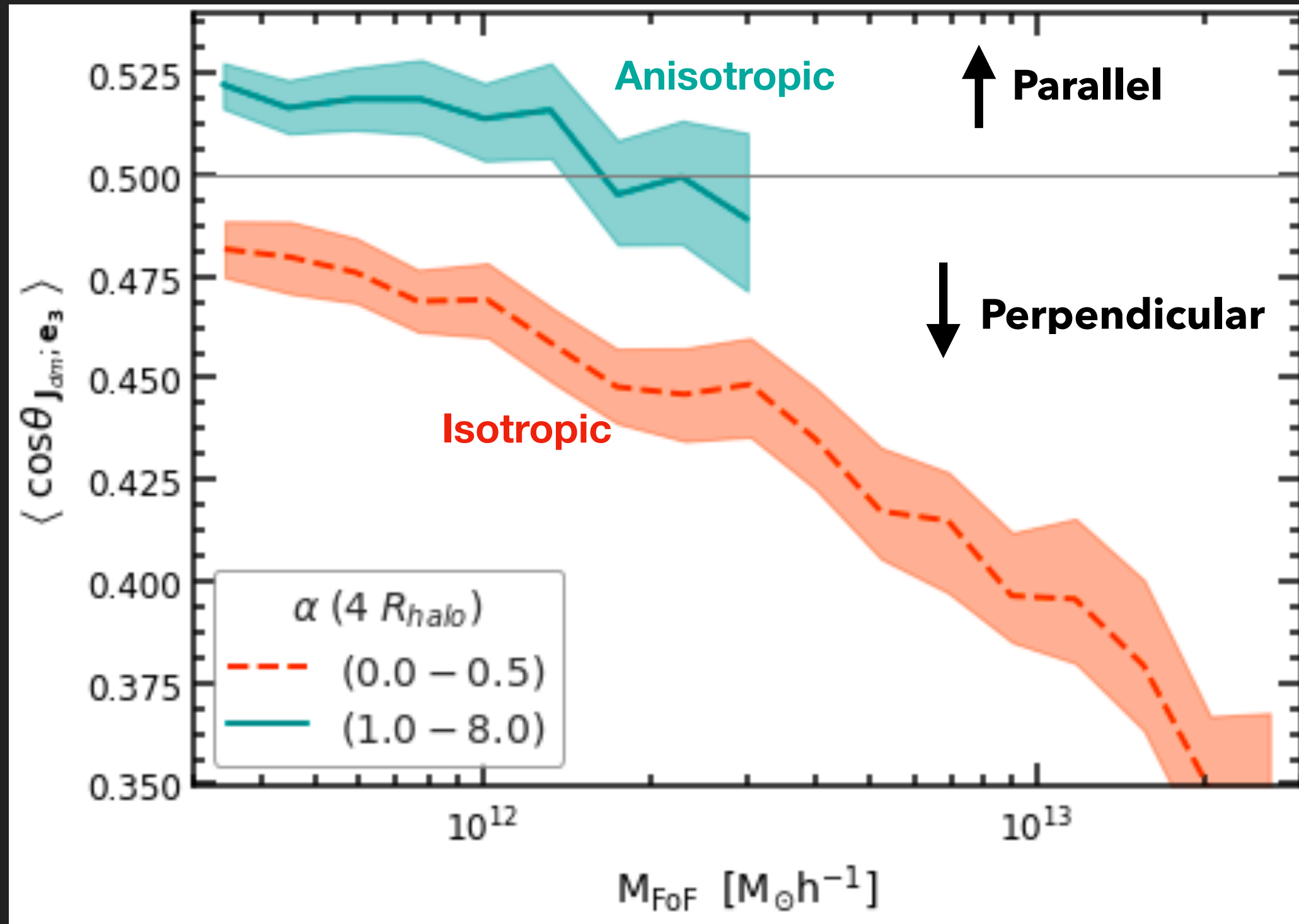


- ▶ Thin filaments
- ▶ Accretion - perpendicular spin
- ▶ Isotropic

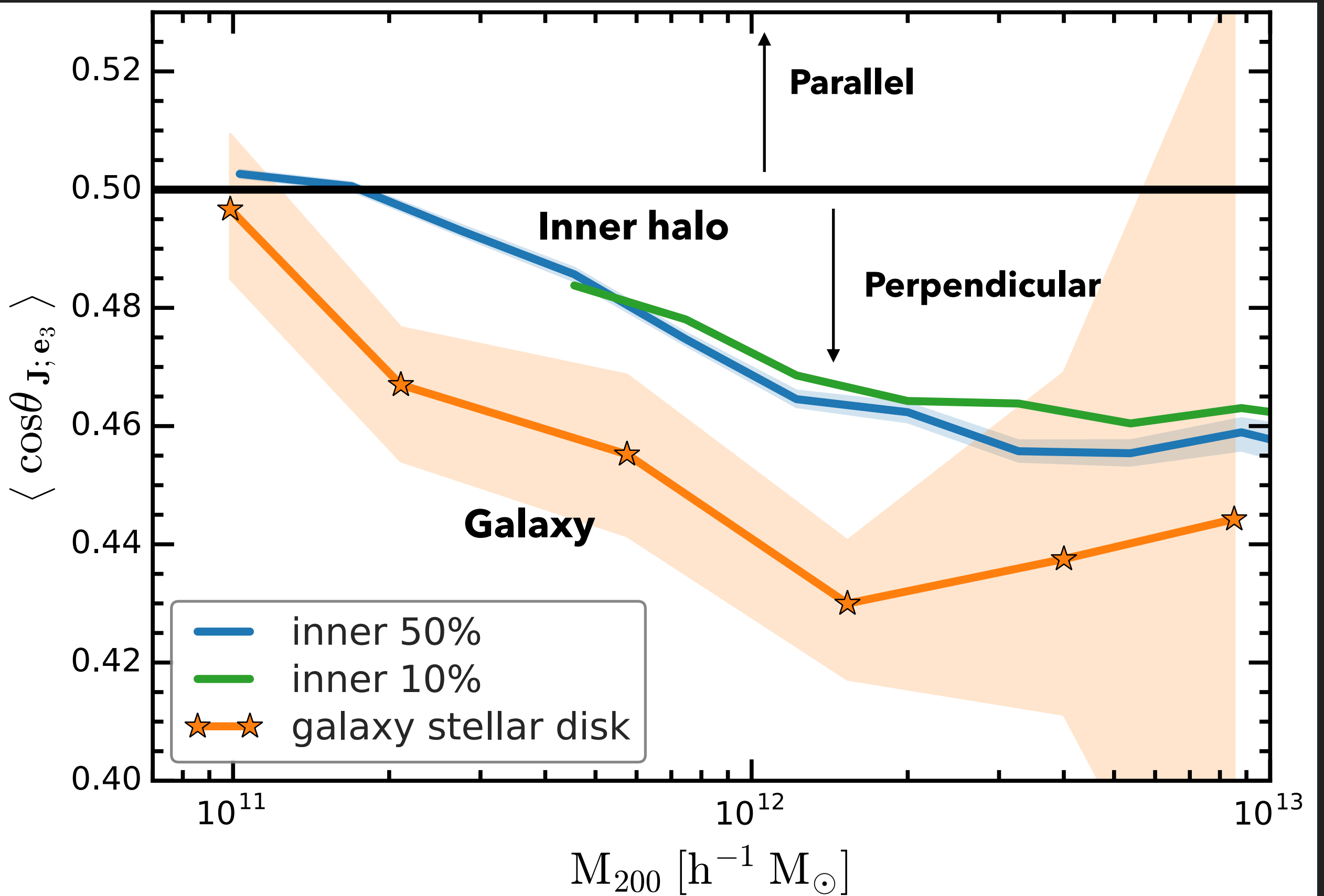
- ▶ Thick filament
- ▶ Accretion - parallel spin
- ▶ Anisotropic



# Tidal anisotropy - preliminary results

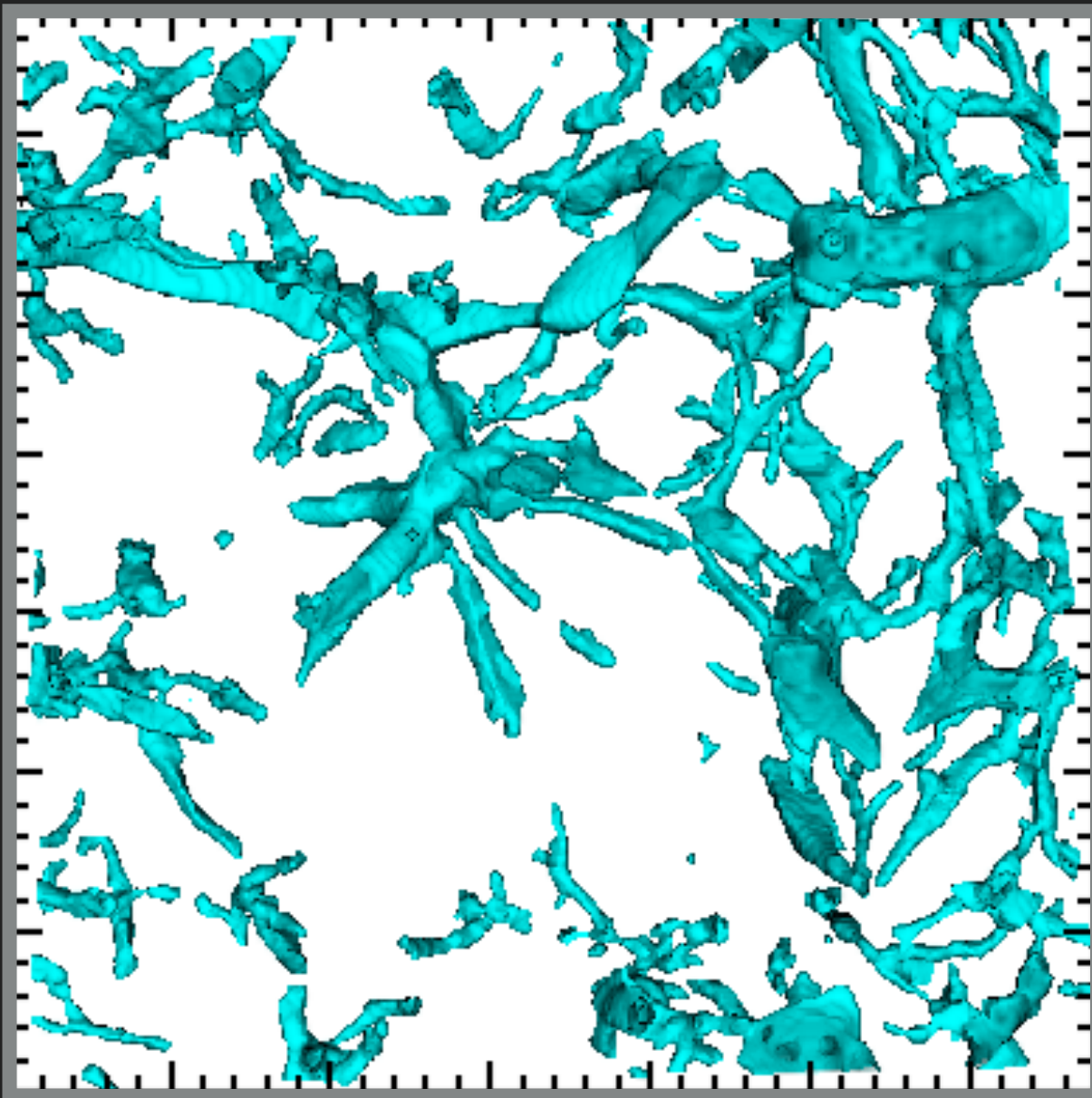


Thanks to Pablo Lopez for sharing the data and Aseem Paranjape for the discussion.

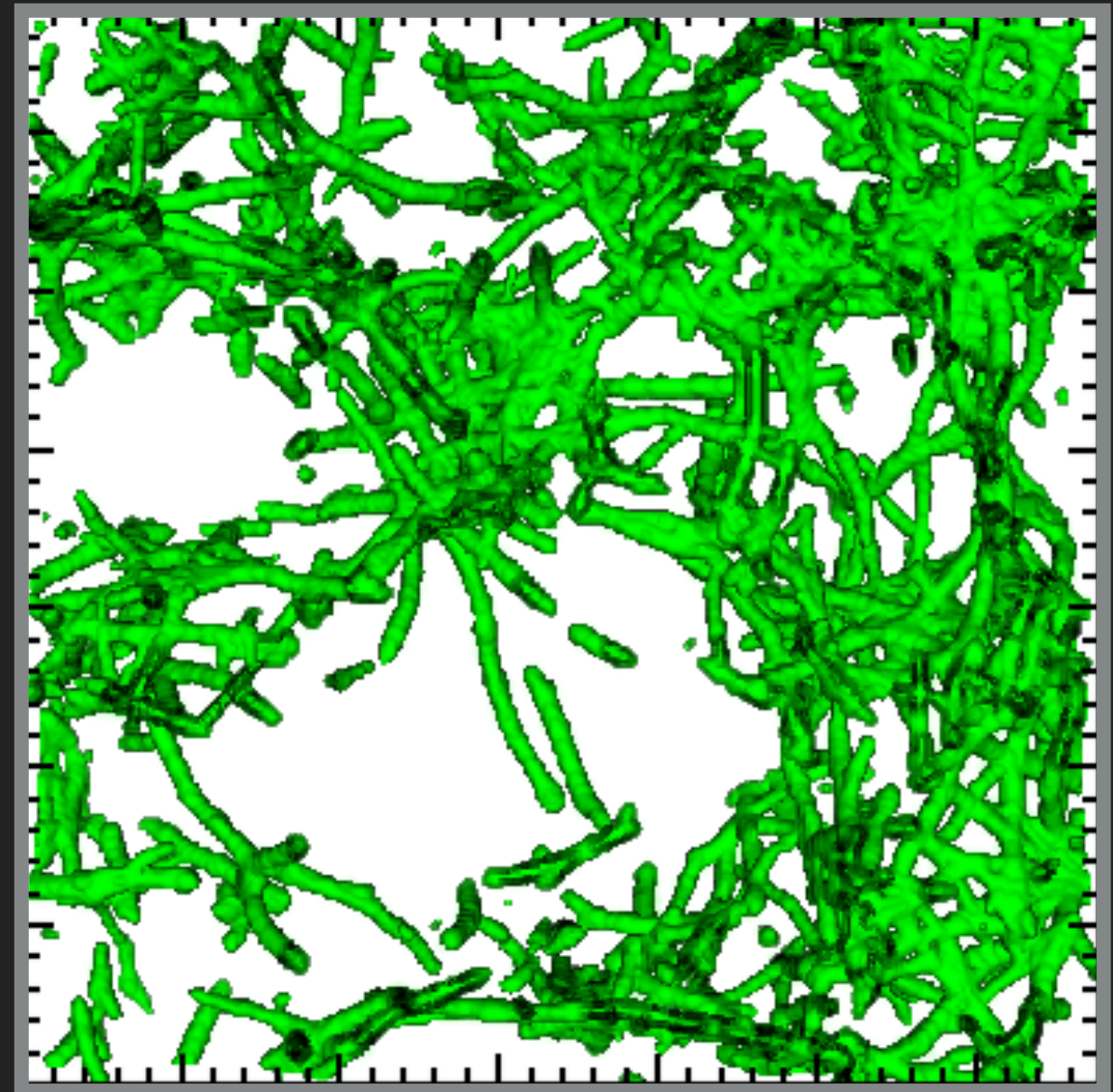




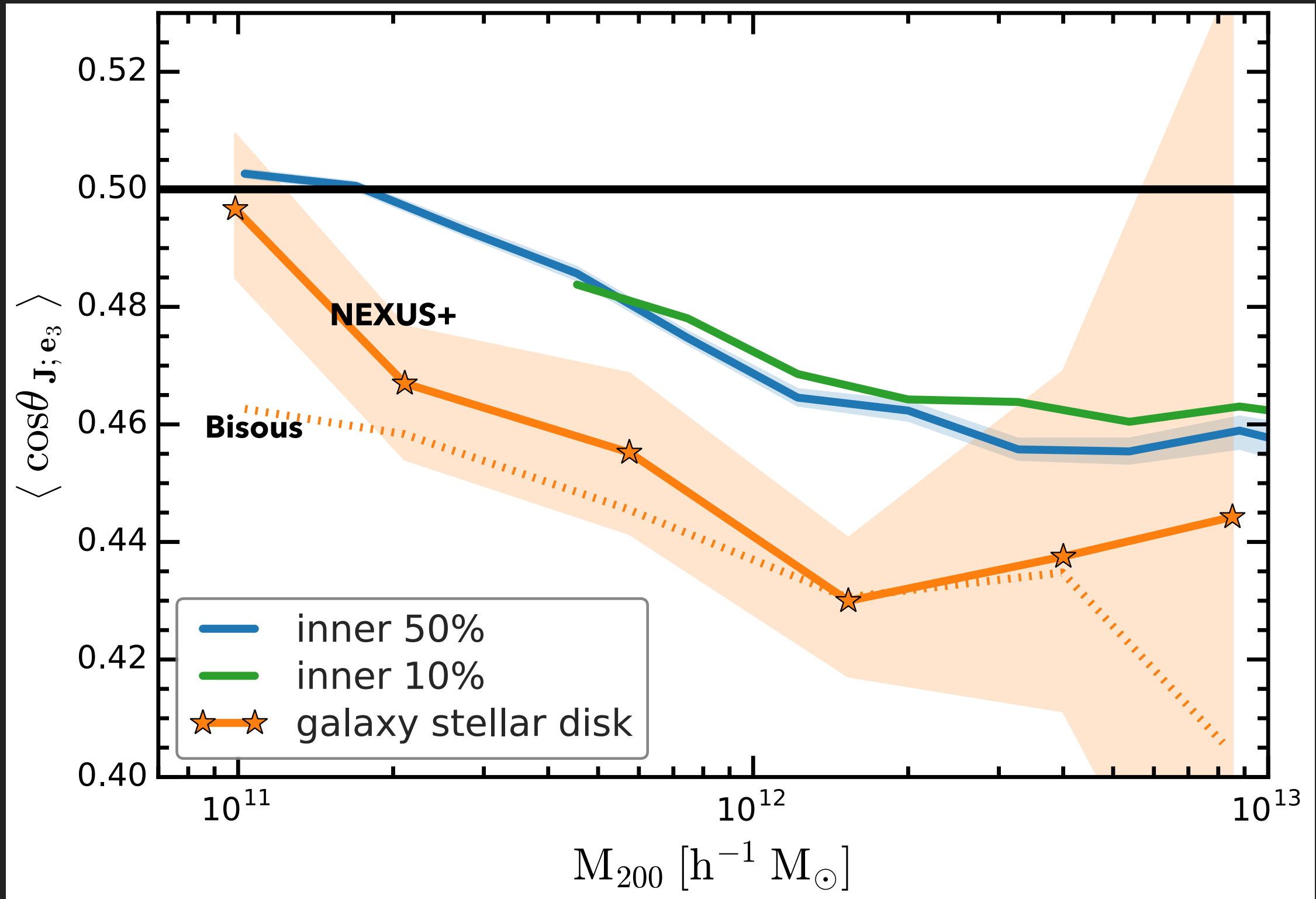
## NEXUS + FILAMENTS



## BISOUS FILAMENTS



P. Ganeshiah Veena et al 2019



- ▶ **Cosmic web** environment influences **halo/galaxy spin magnitude and orientation**.
- ▶ **Definition of filament** or filament detection method is crucial when dealing with weak signals.
- ▶ **Transition mass** is influenced by several factors such as host filament properties, cosmic time and anisotropy of the web environment.
- ▶ **Galaxies** are more perpendicular to filaments than their host haloes and their spin alignments depends on their **mass and morphology**.
- ▶ Host **haloes of parallel and perpendicular galaxies** show different degree of alignments with their galaxies.



# PART 2 - Unmasking the Universe with neural nets

arXiv: 2212.06439



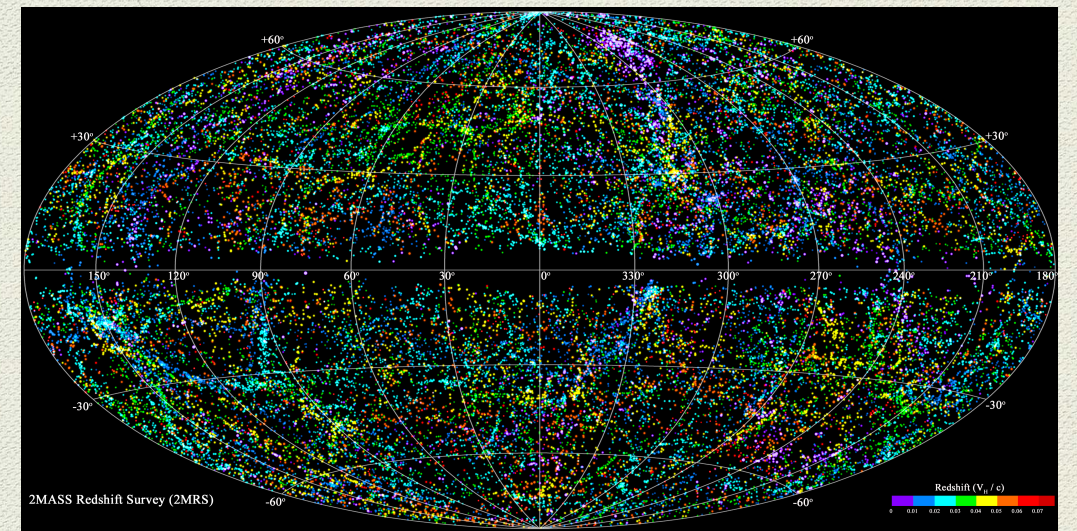
***Punyakoti Ganeshaiah Veena***  
*with Robert Lilow and Adi Nusser*  
*Technion, Haifa, Israel.*



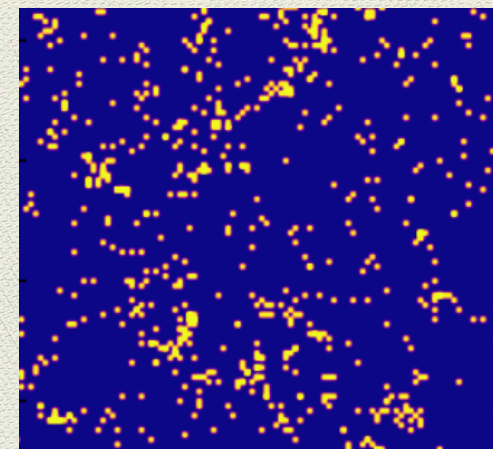
# Mapping the Universe

- ◆ 3D positions of galaxies - trace the underlying dark matter distribution.
- ◆ Infer the matter density and 3D flows - constraints on the cosmological parameters.

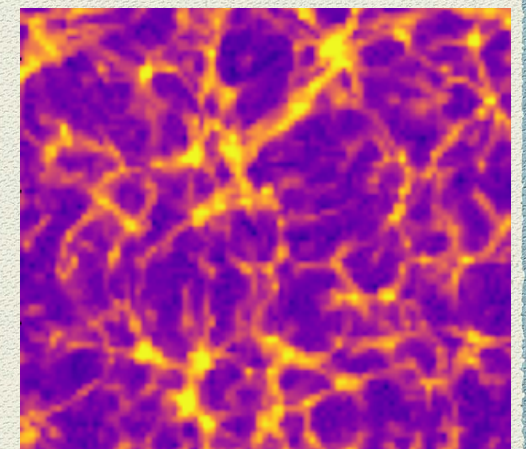
$$\text{◆ } -\frac{1}{H} \vec{\nabla}_r \cdot \vec{v}_{lin} = f \sigma_8 \delta \quad f \approx \Omega_m^{0.55}$$



2MRS



galaxy distribution

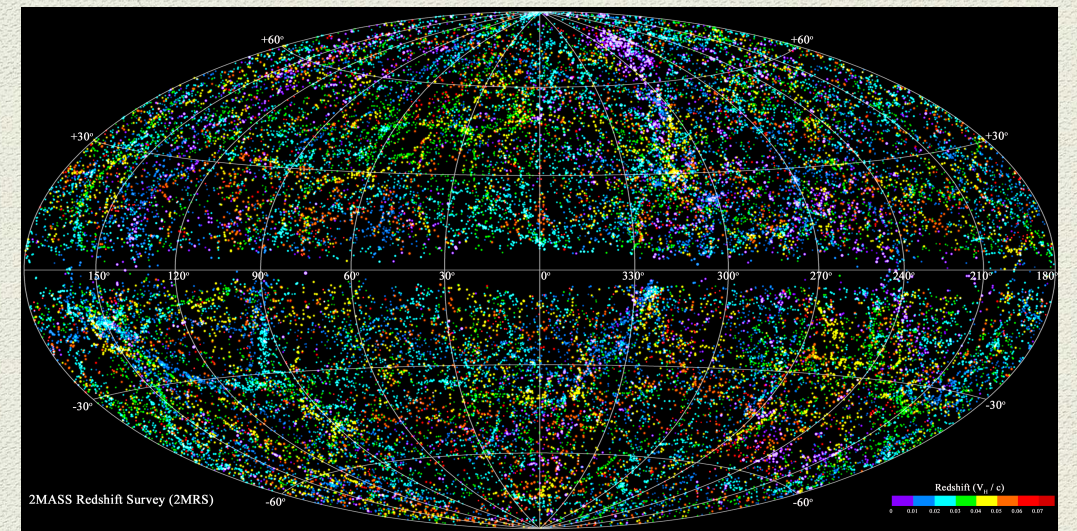


underlying density field



# Noisy, missing and incomplete data

- ◆ Discrete sampling.
- ◆ Redshift space distortions - structures are elongated along the line-of-sight.
- ◆ Gaps in the data - eg. galaxies in the ZoA are obscured by star, dust and gas.
- ◆ In optical wavelengths, this covers almost 20% of the sky.





# Other methods used so far for reconstructing LSS?

- ◆ **Wiener filter** - linear reconstruction - e.g. *Zaroubi et al 1994, Lilow et al 2021*
- ◆ **Other reconstruction methods** - e. g. *Bertschinger & Dekel 1989; Yahil et al. 1991; Nusser & Davis 1994; Fisher et al. 1995; Bistolas & Hoffman 1998; Zaroubi et al. 1999; Kitaura et al. 2010; Jasche et al. 2010; Courtois et al. 2011; Kitaura 2013; Jasche & Wandelt 2013; Wang et al. 2013; Carrick et al. 2015; Lavaux 2016; Jasche & Lavaux 2019; Graziani et al. 2019; Kitaura et al. 2020; Zhu et al. 2020*

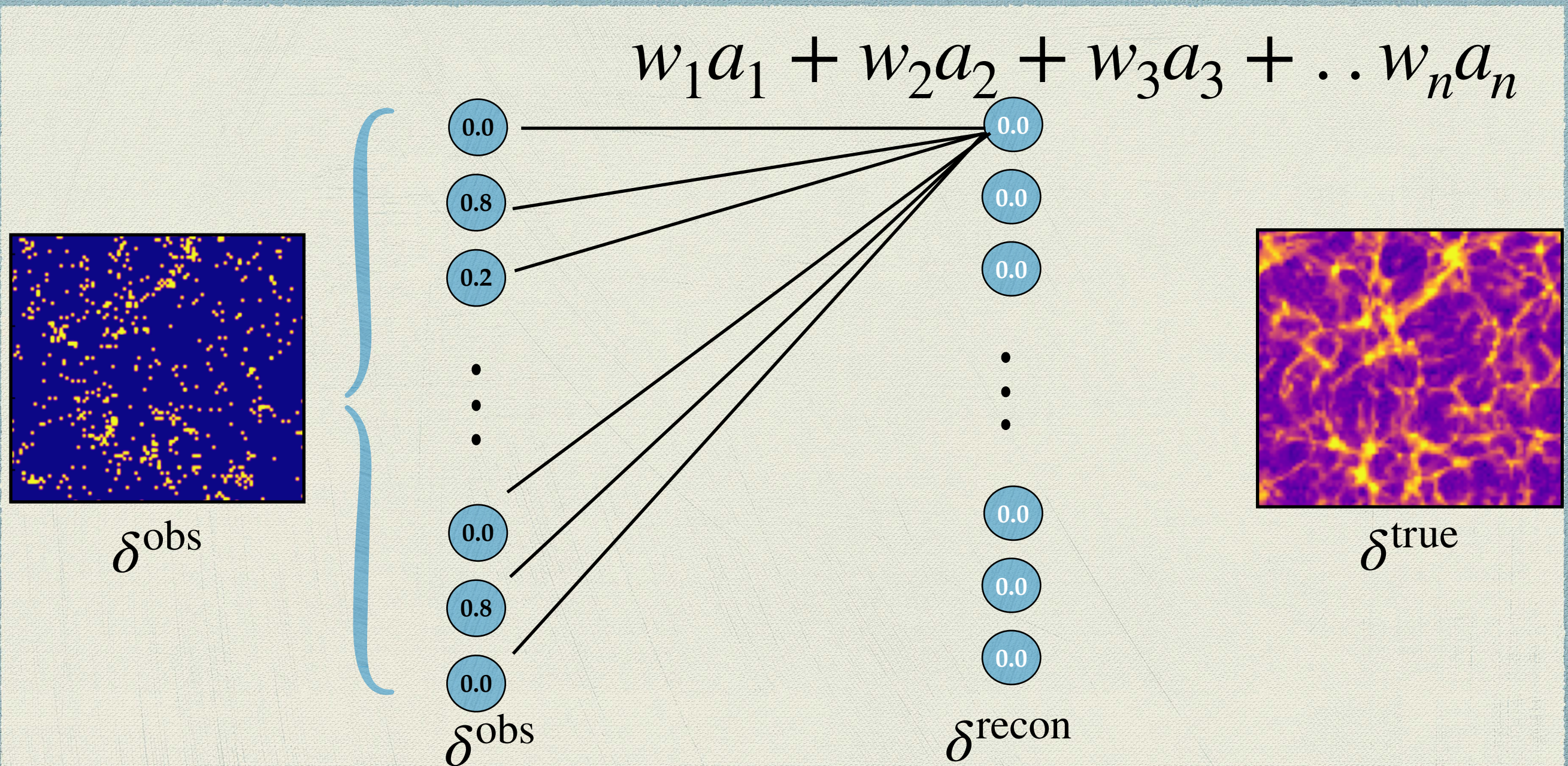


# What did we do in this paper?

- ◆ Reconstruct **underlying density and velocity fields** from galaxy distributions using neural networks.
- ◆ In the process, demystify machine learning:
  - ◆ understand the black-box
  - ◆ can we recreate what the machine does using known statistical techniques?
- ◆ What are the **advantages and caveats** of using neural nets over the traditional techniques for such reconstructions? And why so?
- ◆ Can we recover Wiener Filter from neural network methods?



# A simple network (3Blue1Brown - youtube channel)

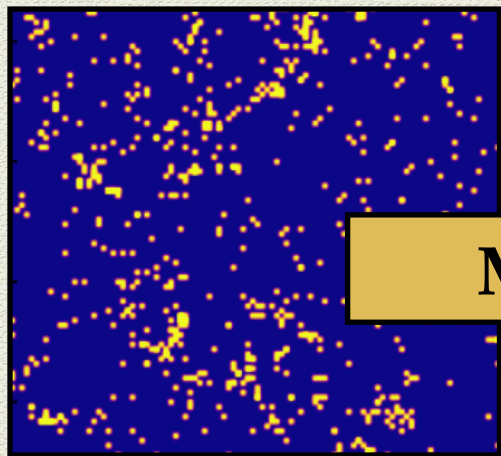


$$\text{MSE}(\hat{\delta}) = \frac{1}{N} \sum_{j=1}^N \left( \delta_j^{recon} - \delta_j^{true} \right)^2$$

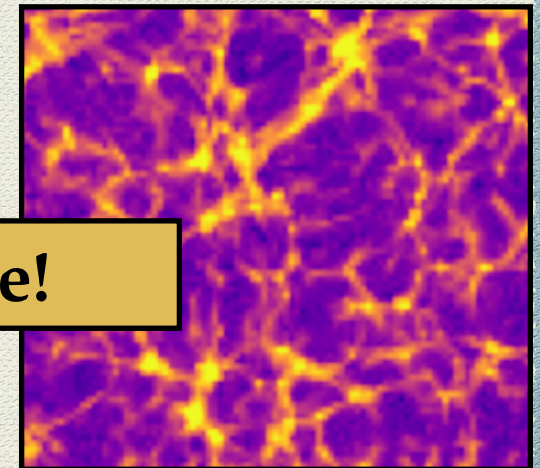


Non-linear network + MSE loss = Mean posterior estimate

$$L^{\text{MSE}}(\hat{\mathbf{T}}[\lambda]) = \frac{1}{MN} \sum_{\alpha=1}^M \sum_{j=1}^N (T_j^\alpha - \hat{T}_j[\lambda](\mathbf{I}^\alpha))^2$$



Input field :  $I_j$



Target field :  $T_i$

Minimising MSE gives the mean posterior estimate!

$$\hat{\mathbf{T}}_i^{\text{MSE}}(\mathbf{I}) = \sum_T P(\mathbf{T} | \mathbf{I}) T_i = \langle T_i | \mathbf{I} \rangle,$$



# Wiener filtering for galaxy distributions

[Zaroubi et al 1994]

- ◆ Observed density field  $\longrightarrow$  True density field
- ◆ Assume a prior for the true fields
- ◆ Reconstructed field is a linear combination of the observed field. 
$$\hat{T}_i^{WF(I)} = \sum_j w_{ij}^{WF} I_j + b_i^{WF},$$
- ◆ Minimum variance estimator: minimise MSE.
- ◆ 
$$T^{WF} = \langle TI \rangle \langle II \rangle^{-1} I$$



# Wiener filtering for galaxy distributions

[Zaroubi et al 1994]

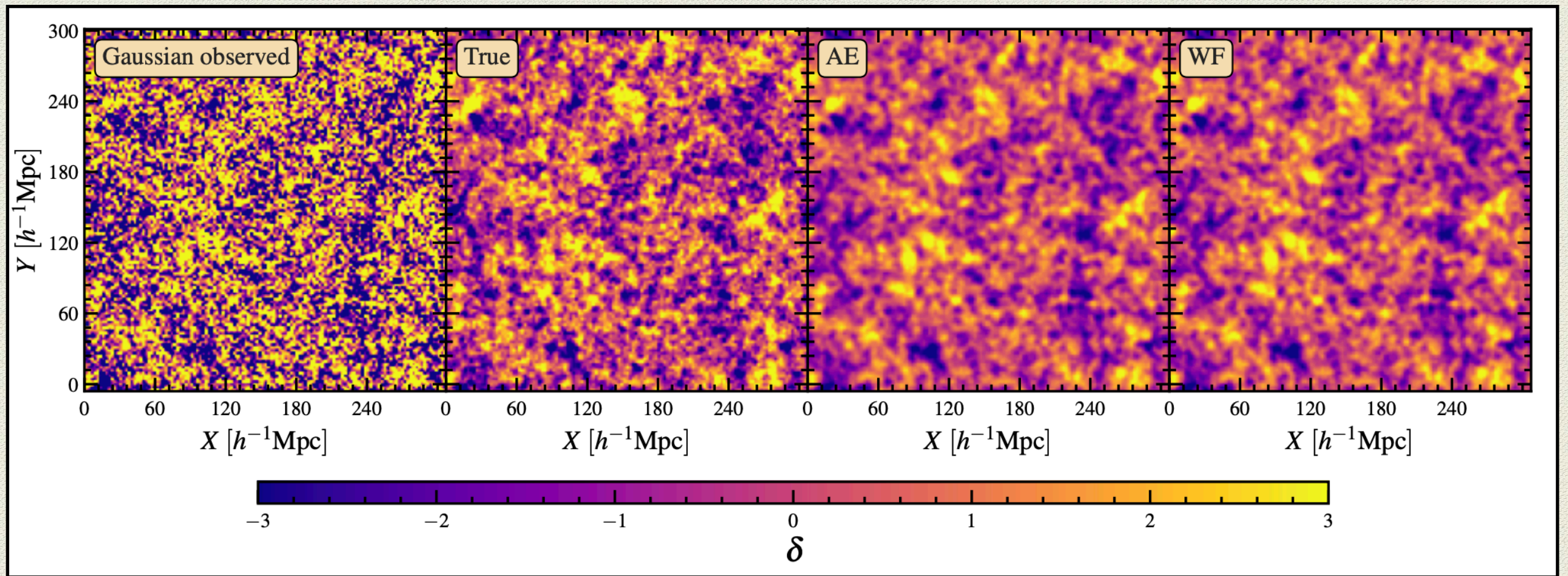
1. A **neural network** with an input and output layer and **linear activation** is equivalent to a **WF**.
2. When the field is **Gaussian**, WF and NN estimates should both be the mean posterior estimates.

Minimum variance estimator. Minimum MSE.

$$T^{WF} = \langle TI \rangle \langle II \rangle^{-1} I$$



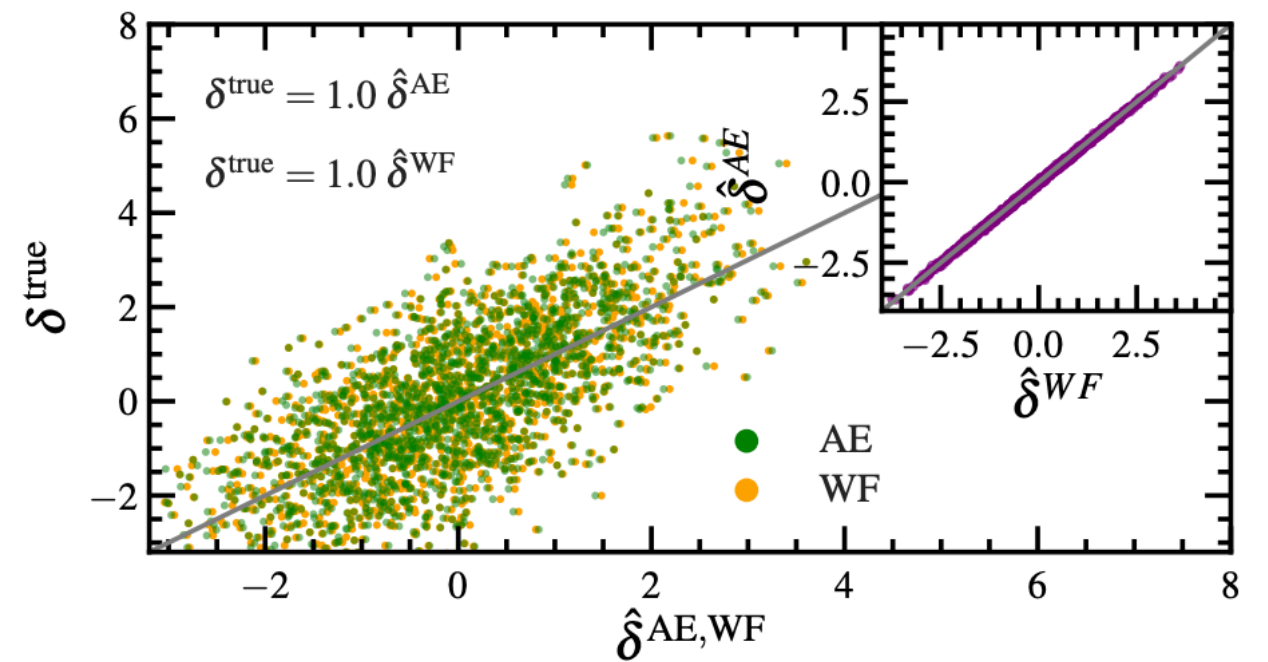
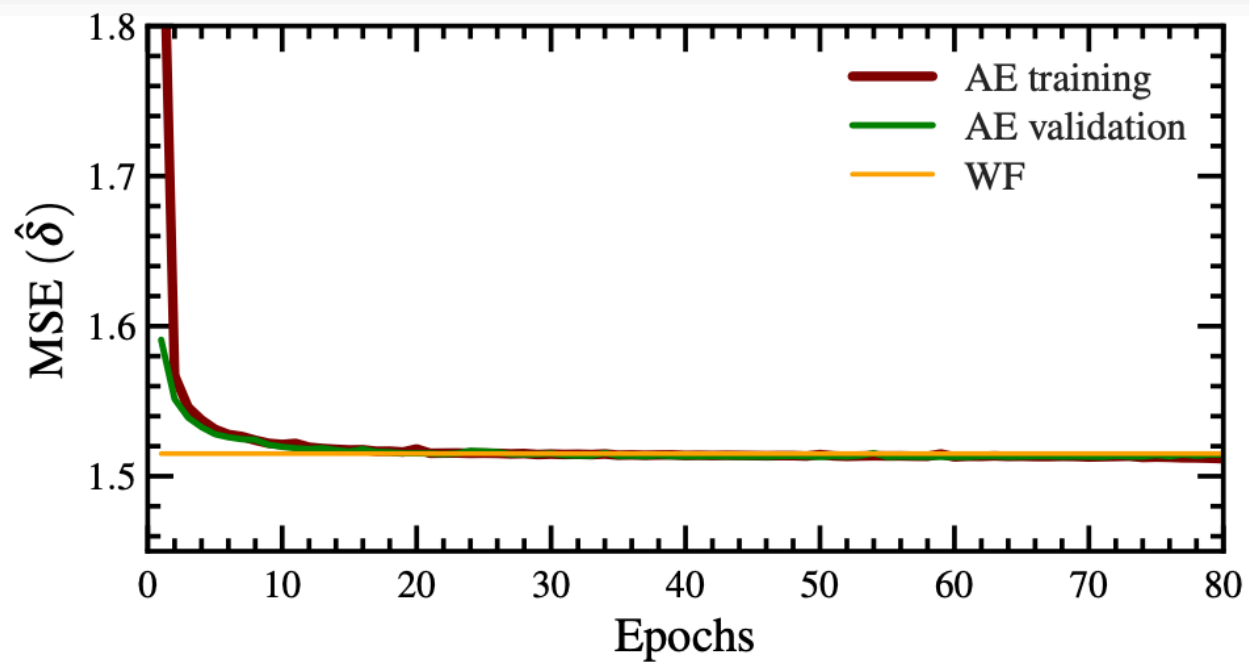
# Gaussian fields



**WF and AE are minimum variance solutions and give the same result for Gaussian fields.**

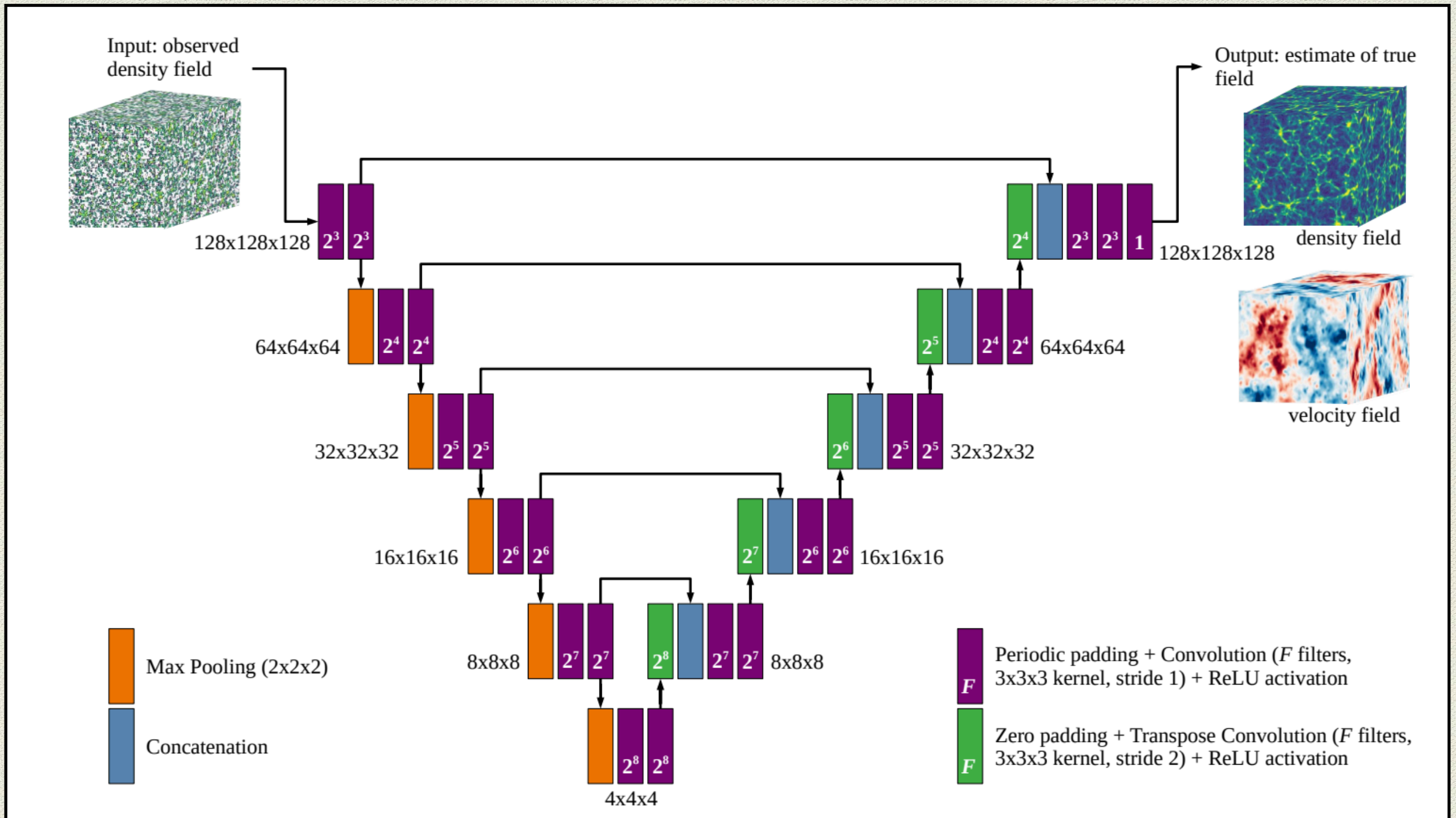


# Gaussian fields



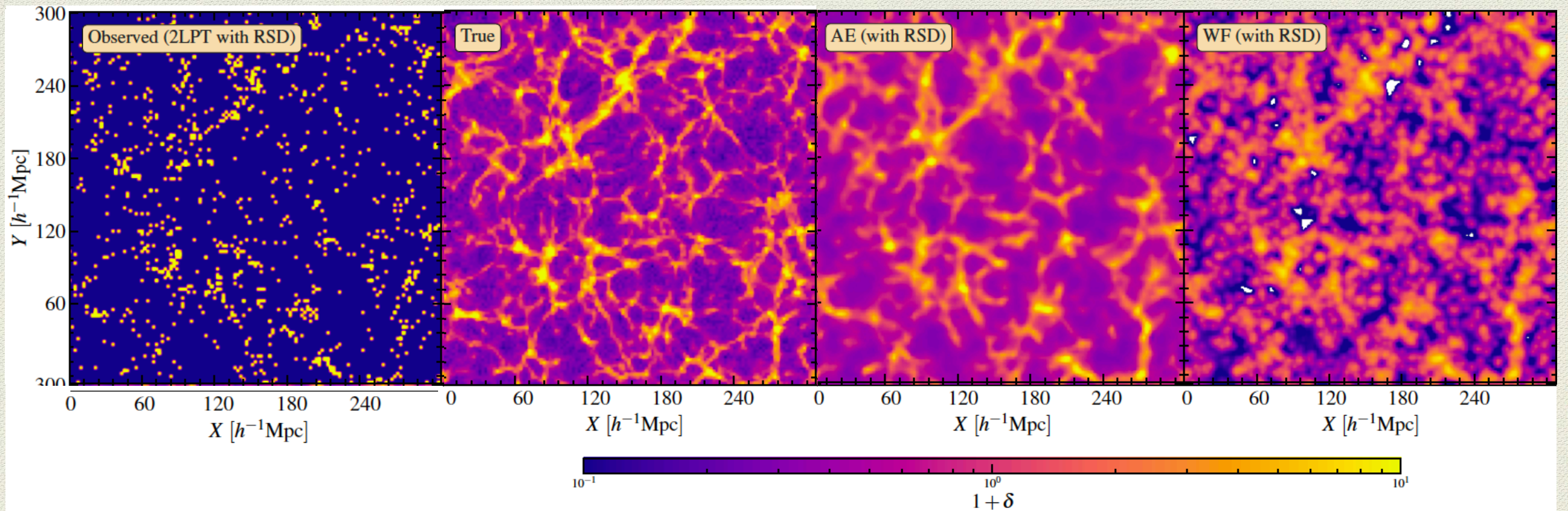


# For 3D data, use convolutions: Autoencoder

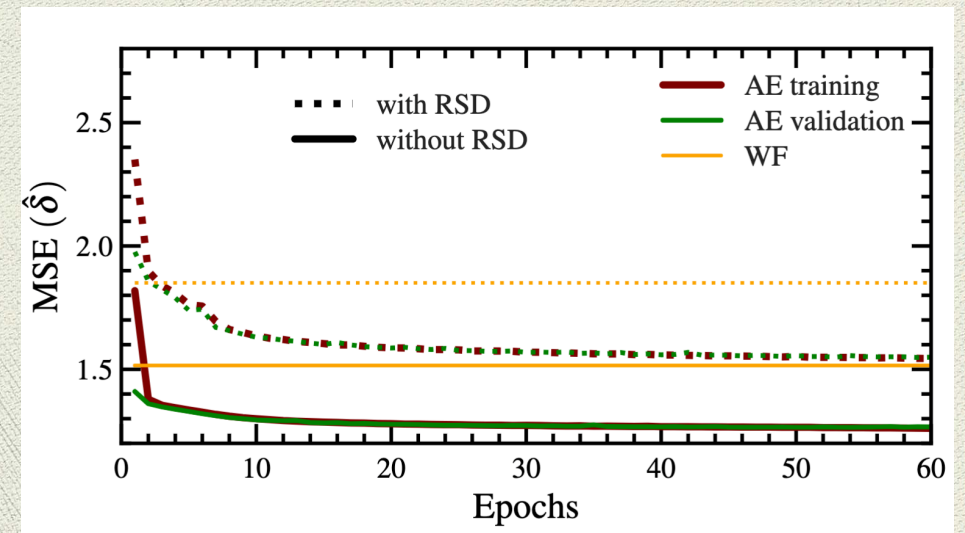




# Density field reconstructions.

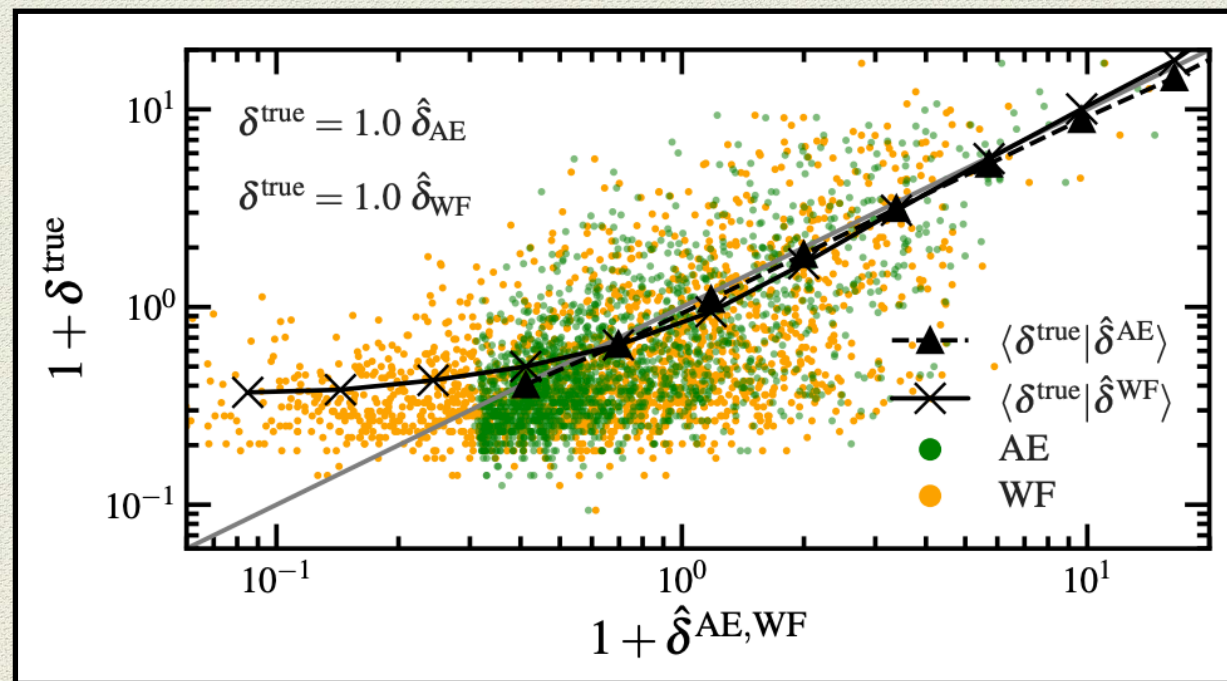


$$\delta(x) = \frac{\rho(x) - \bar{\rho}}{\bar{\rho}}$$

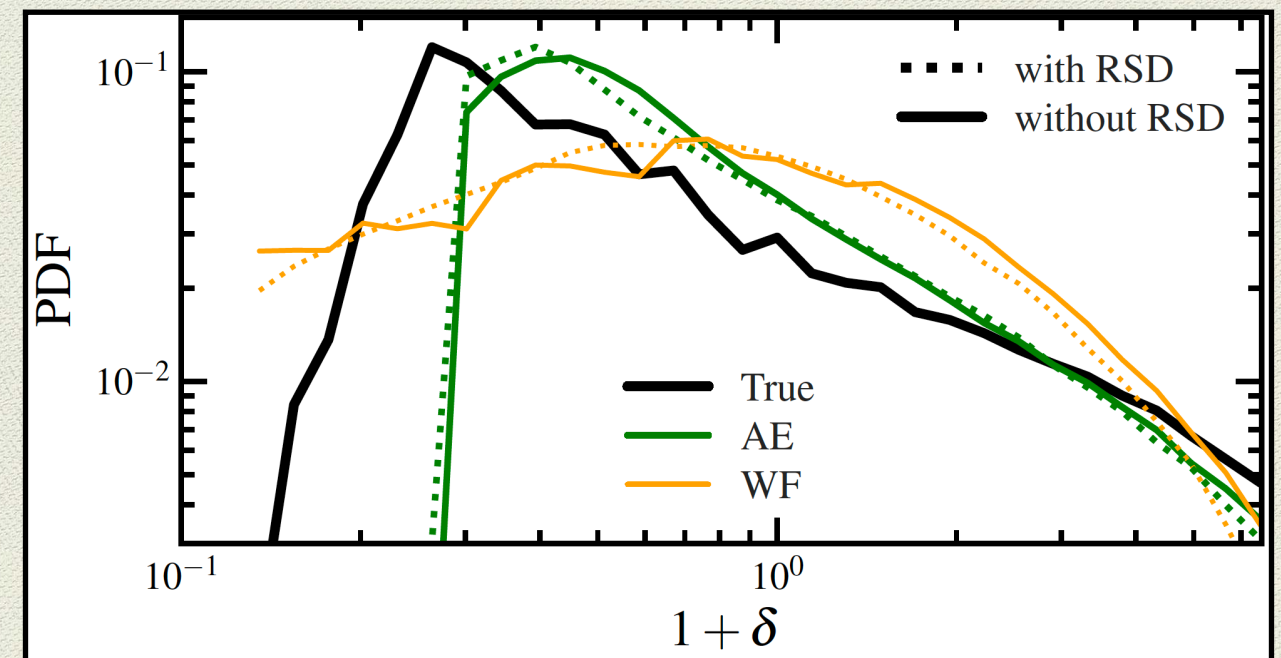




# Density field reconstructions.



- ◆ Floor - is a result of the choice of our loss function and Poisson sampling.
- ◆ Towards the tails, NN is better.

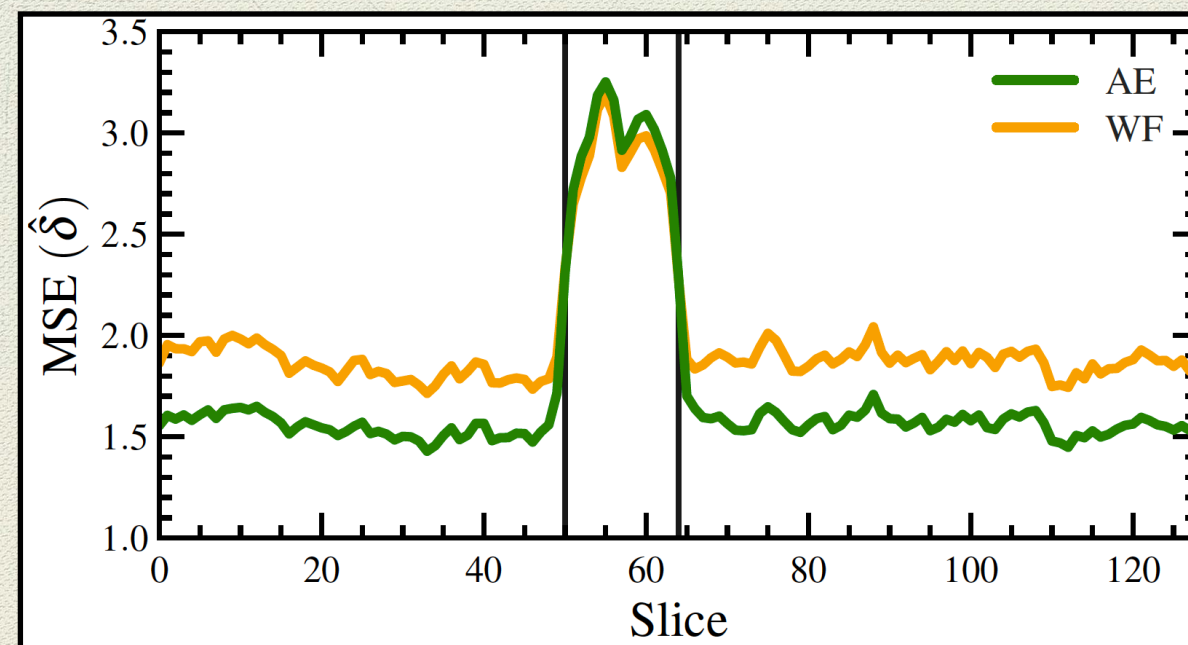
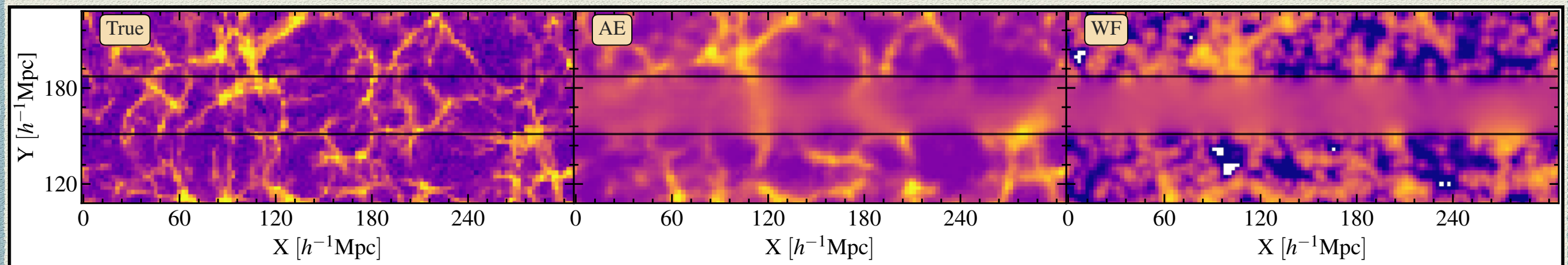






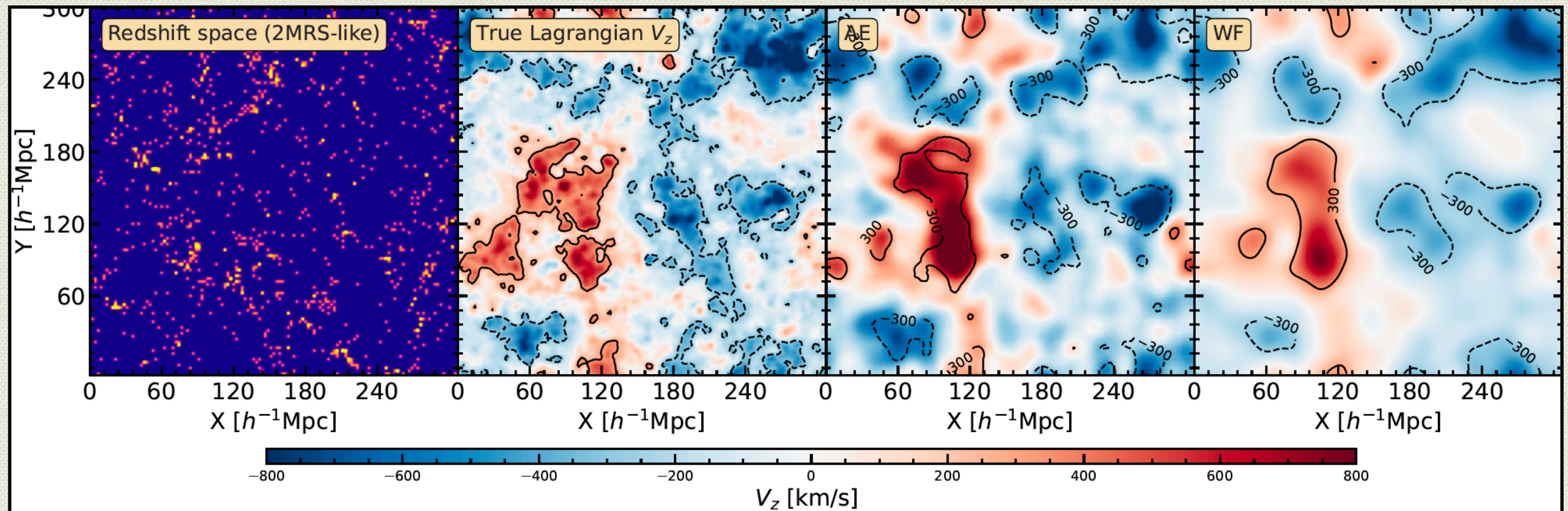


# Density field reconstructions - with gap



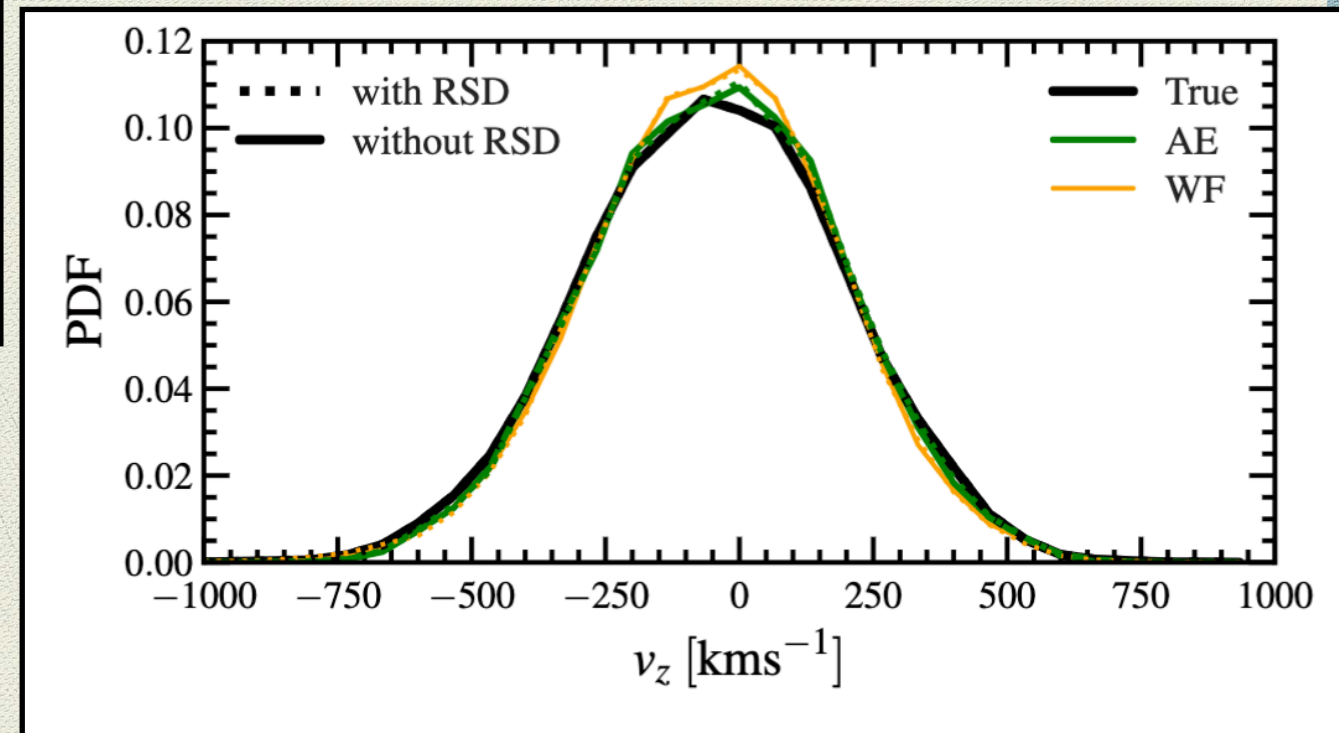
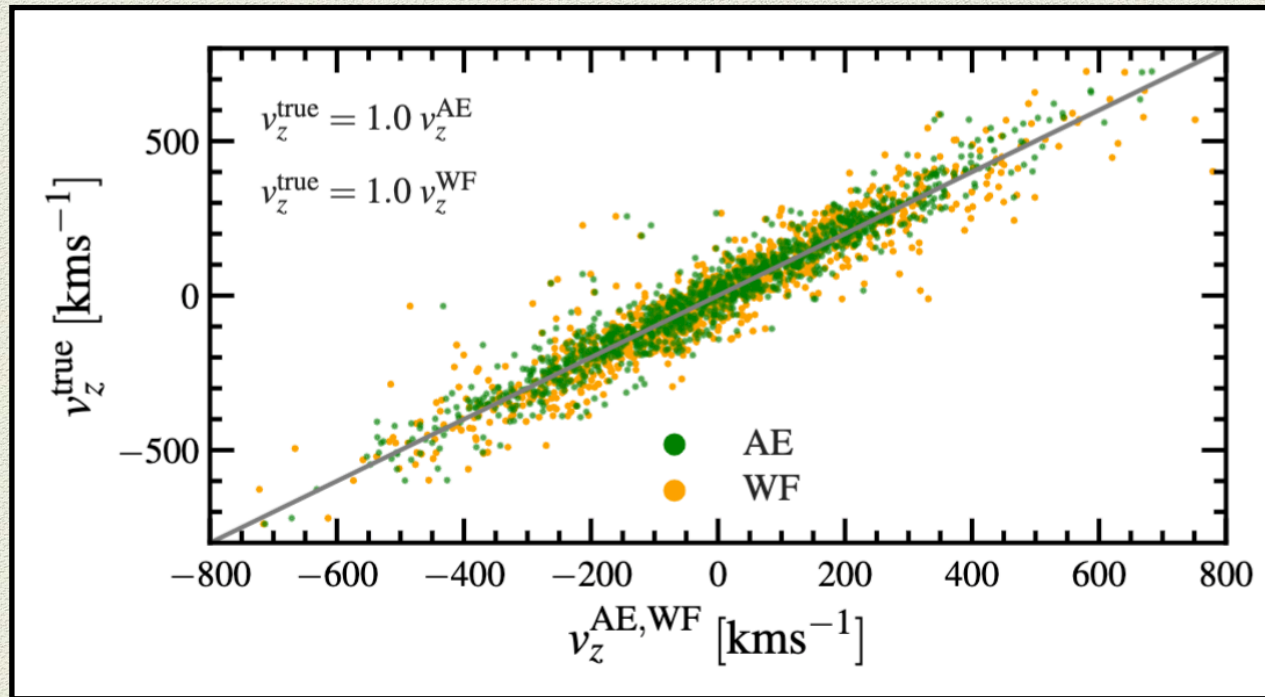


# Velocity field reconstructions.



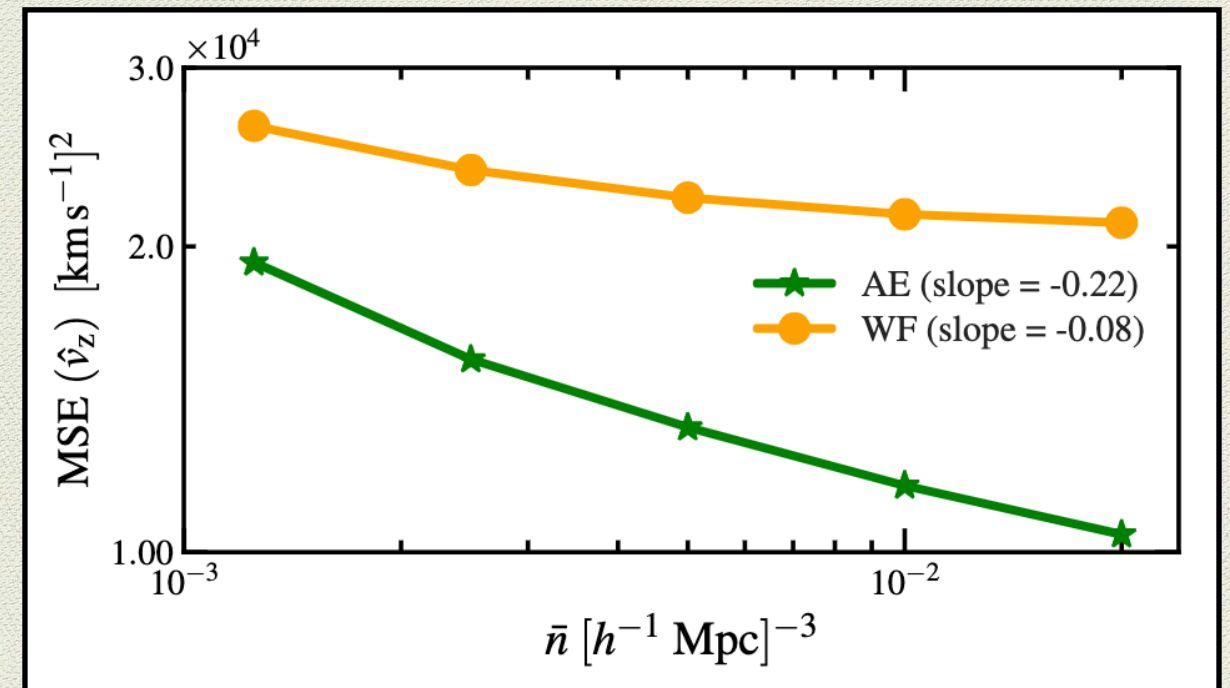
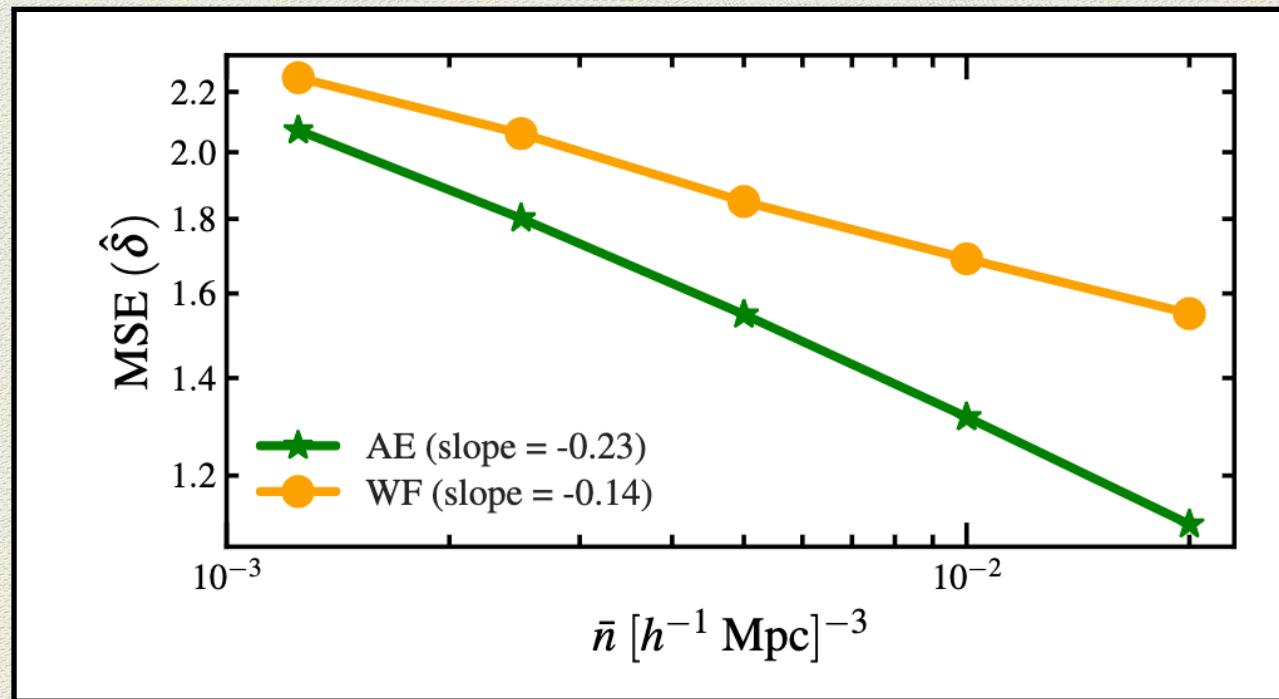


# Velocity field reconstructions.





# Reconstruction for different galaxy number densities





Thank you!