Universality of halos shape as a strong cosmological probe

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Laboratoire Univers et THéories

Action Dark Energy

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Halo Collapse

ΛCDM: concordance model with 6 parameters ans $w = -1$. Other dynamical realistic DE models (quintessence $w > -1$, phantom $w < -1$ ...) exist that are compatible with CMB/SNIa. We will use here the $2 \cdot 10^{12} - 10^{14} M_s$ halos of Dark Energy universe Simulations

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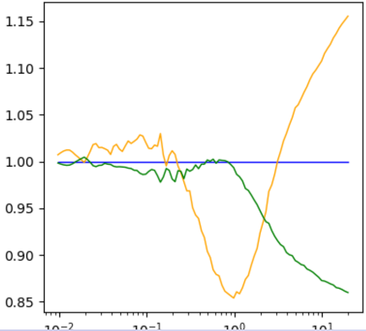
on the right, $\frac{P}{P^{lin}} / \frac{P_{\Lambda CDM}}{P^{lin}_{\Lambda CDM}}$

Behaviors and critical k_c depend on the cosmology.



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RMS of Linear fluctuations

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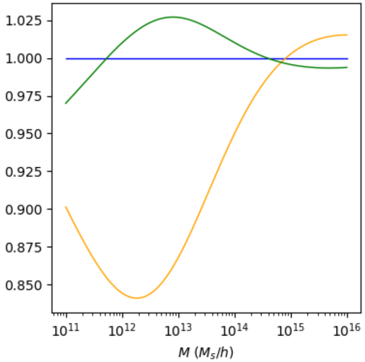

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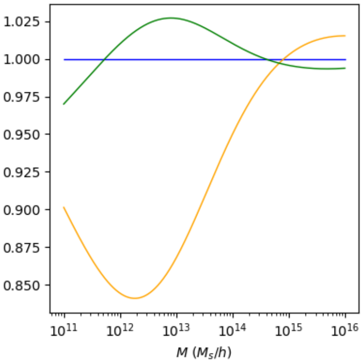

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Halos are essentially triaxial. [Doroshkevich 1973; Sheth, Mo, and Tormen 2001; Rossi 2012; Jing and Suto 2002; Bailin and Steinmetz 2005; Kasun and Evrard 2005; Allgood 2005; Allgood et al. 2006; Vera-Ciro et al. 2011; Limousin et al. 2013]

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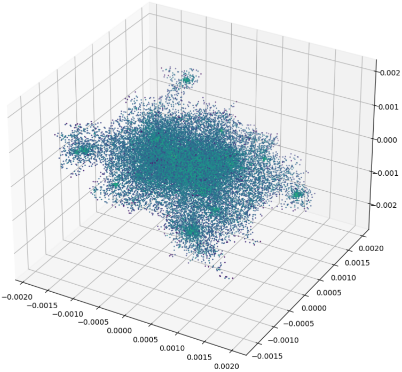

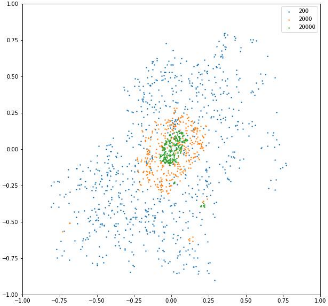

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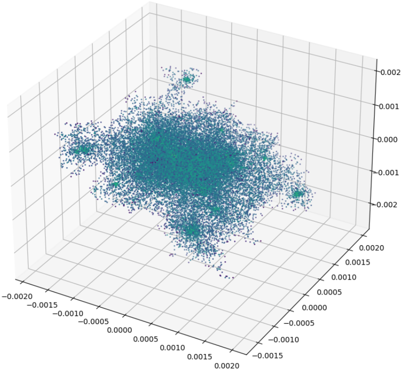
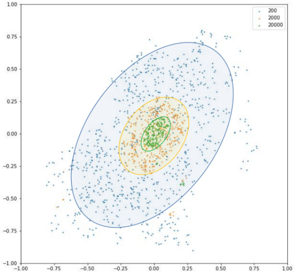
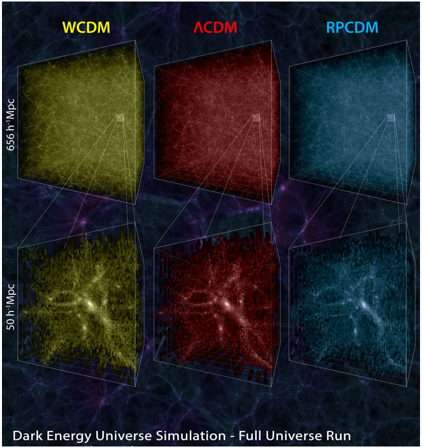




Previously (SF2A 2021)



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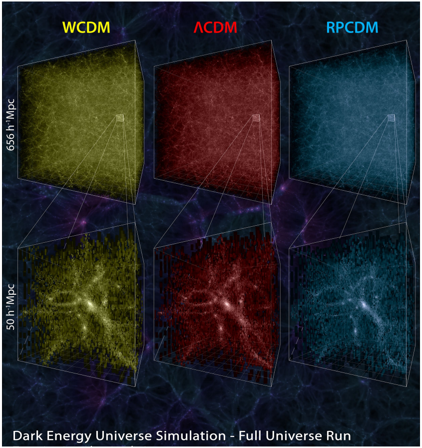

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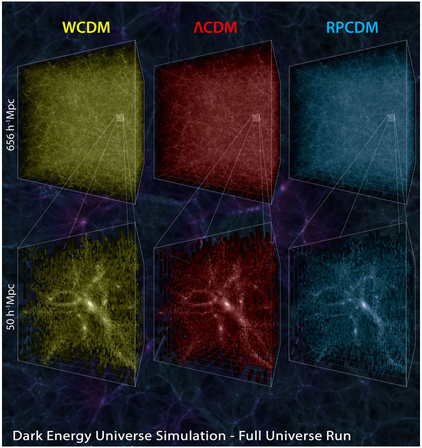

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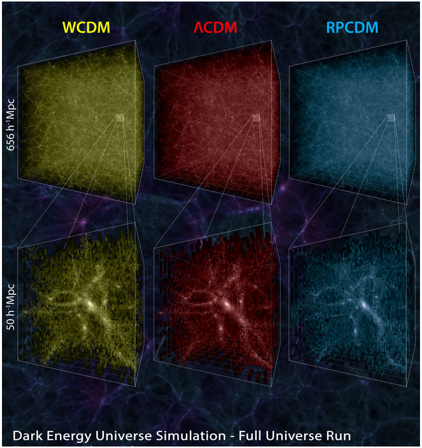

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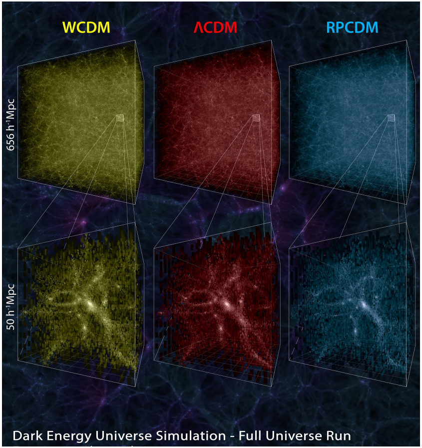

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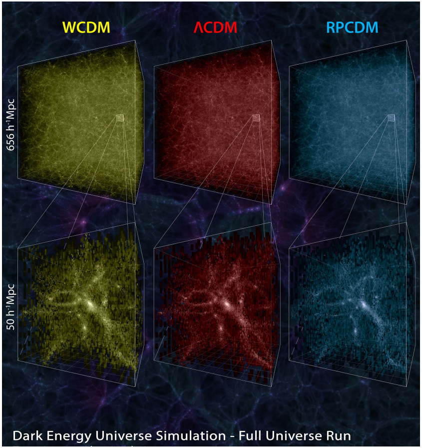

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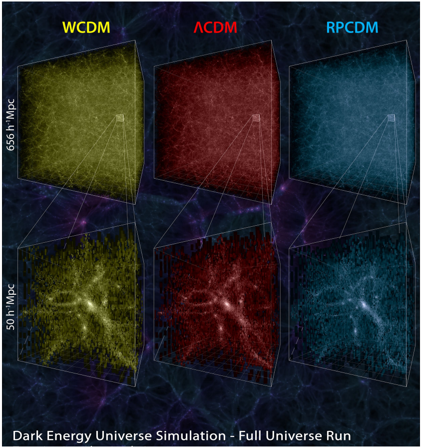

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It's working. But why ?

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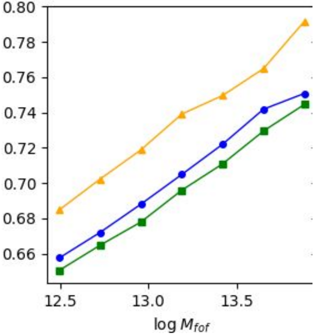
T-M median scatter plot:



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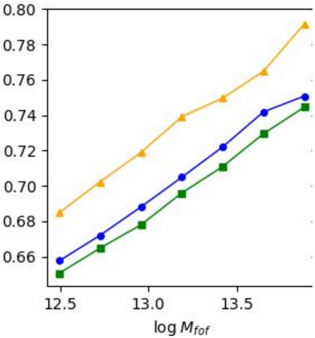

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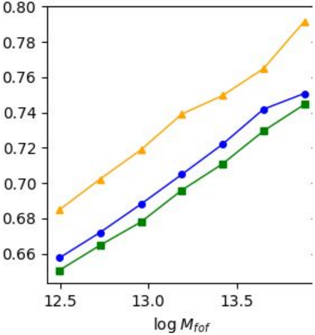

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To understand this cosmological dependence, the best way is to absorb it , ie to find a cosmological dependent function $f_c(M)$ s.t $T - f_c(M)$ is cosmologically independent.

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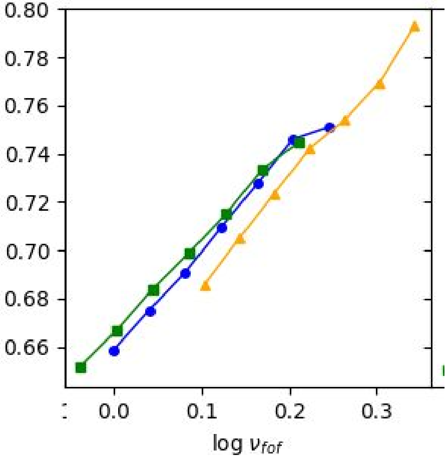
where W is a Gaussian window function and the peak height [BBKS] is $\nu = \delta_c/\sigma$. The critical density δ_c is a very slowly varying function of Ω_m



Surprisingly, the curves are closer in (ν, T) space than in (M, T) space.

Toward Universality (II)

But we can go much further: let us introduce the non-linear rms (using the NL power spectrum) :

$$\tilde{\sigma}^2 \left(M = \frac{4}{3}\pi R^3 \Omega_m \rho_c \right) = \frac{1}{2\pi^2} \int_{\mathbb{R}_+} k^2 P(k) W^2 \left(kR \right) \mathrm{d}k$$

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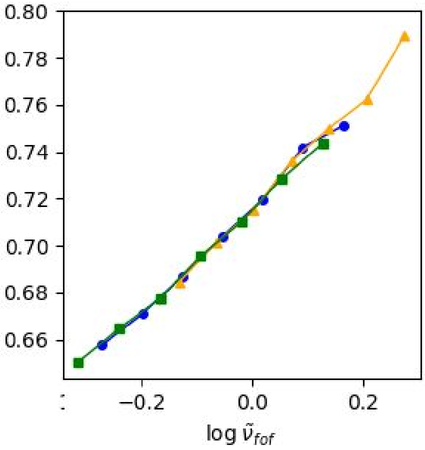
This result holds not only for the median curves (we plot here) but for the whole of the T distribution (except the most extreme values).



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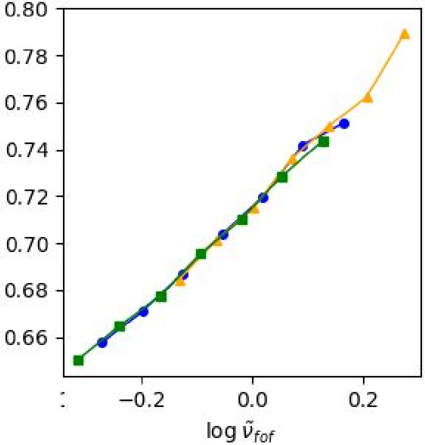

In other words, we have showed that all the cosmological content of clusters' shape is embedded in the (non linear) power spectrum

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1. Measure the (M, T) curve in our universe.
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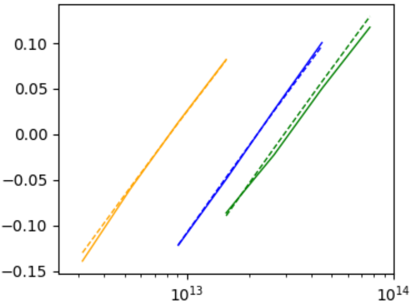
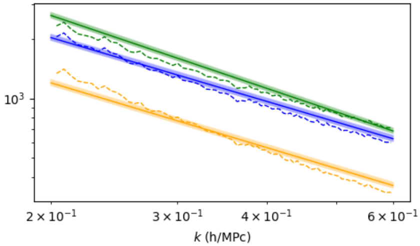
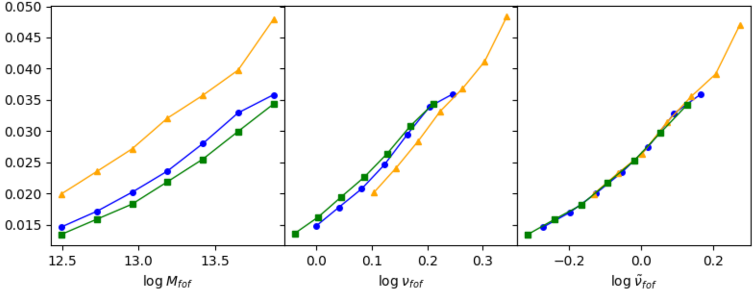
3. $P(k)$ is finally directly inferred from $\tilde{\nu}(M)$

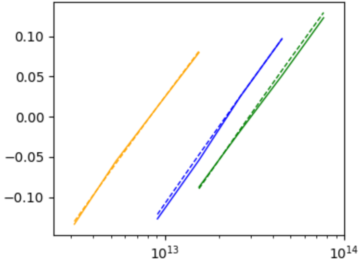
In terms of cosmological parameters, shape curves are not very sensitive to Ω_m but highly depend on (the non linear) σ_8. Complete computations are in [Alimi Koskas 2022]



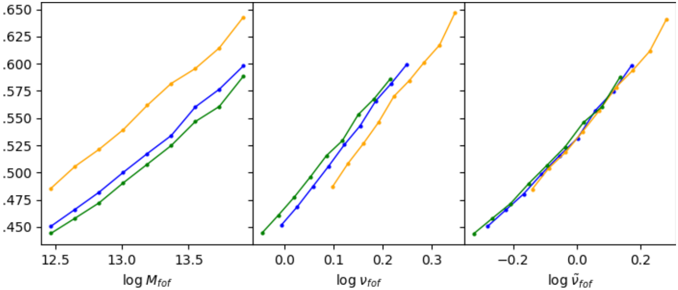


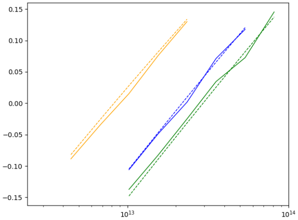
Results for other geometrical quantities (p)





What about 2D ?





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- It works because, from a statistical point of view, halos shape indeed carries cosmological information: one can read in halos shape the non linear PS (which is highly cosmologically impregnated)

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LUTH l'Observatoire de Paris | PSL

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  4. We try to determine which properties are important to achieve the recognition - those are the "cosmologically impregnated" attributes. this is a physical output

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"The ‘Clever Hans’ effect occurs when the learned model produces correct predictions based on the ‘wrong’ features. This effect [...] goes undetected by standard validation techniques has been frequently observed [...] where the training algorithm leverages spurious correlations in the data." **[Kauffman et al 2020]**

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This is a typical Clever Hans : the data embody clues w.r.t. the target variables of purely arithmetical nature, which are thus not reproducible out of this set of simulations - on real observations, for example. This kind of effects should be carefully hunted if we want to obtain physically reliable results.

ML Results

- About 74$\%$ for two models (Λ, RP)
- Resistant to "attacks"
- Output probabilities are calibrated [so that each "prediction" is assorted with a meaningfull uncertainty]
- Almost no biais from total mass (in the studied range)