Universality of halos shape as a strong cosmological probe

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Journées du LUTH

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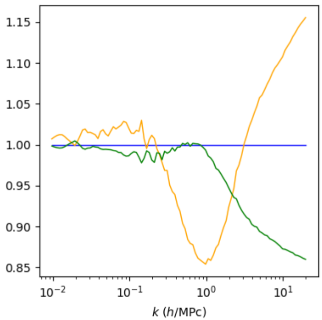
on the right, $\frac{P}{P^{lin}} / \frac{P_{\Lambda CDM}}{P^{lin}_{\Lambda CDM}}$
Behaviors and critical k_c depend on the cosmology.



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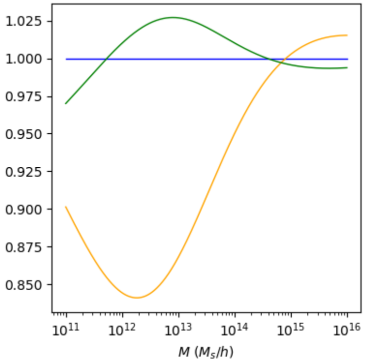

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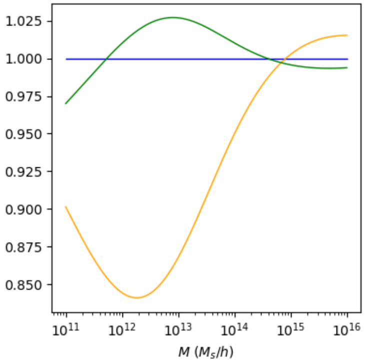

$<< 10^{15} M_s$

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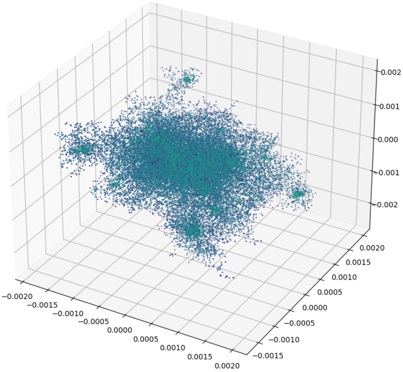

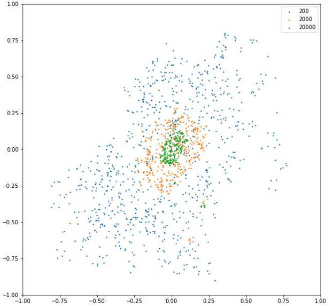

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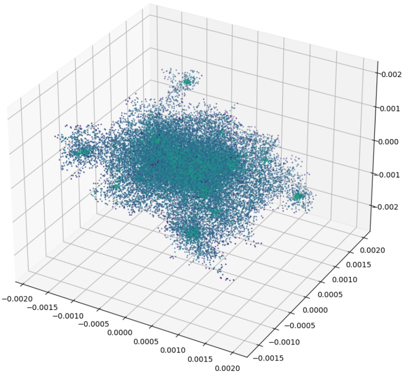

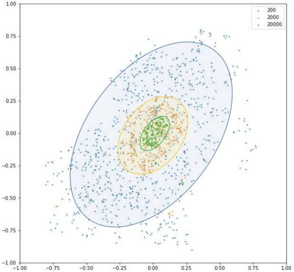

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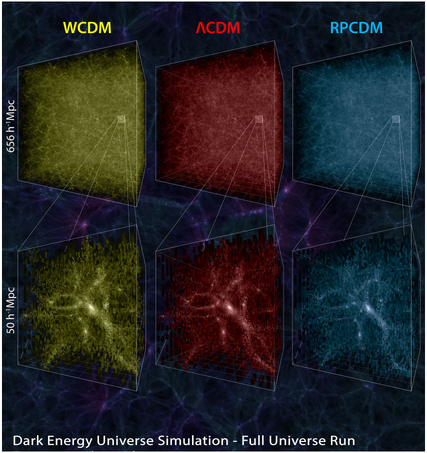

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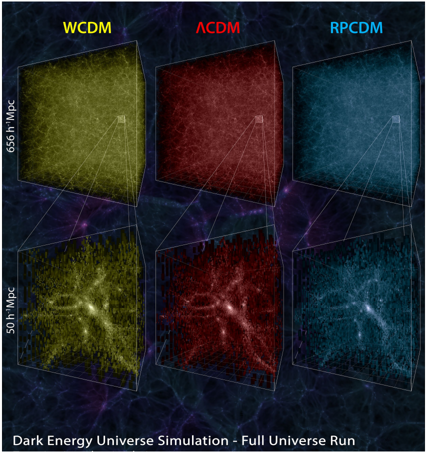

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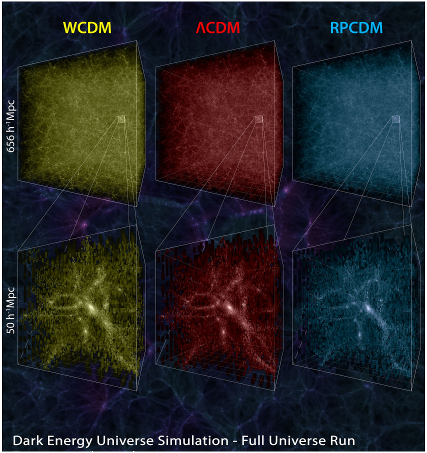

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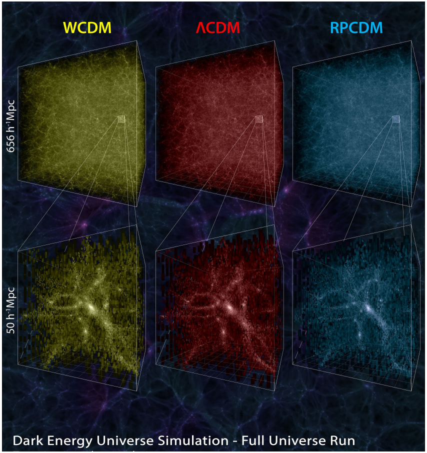

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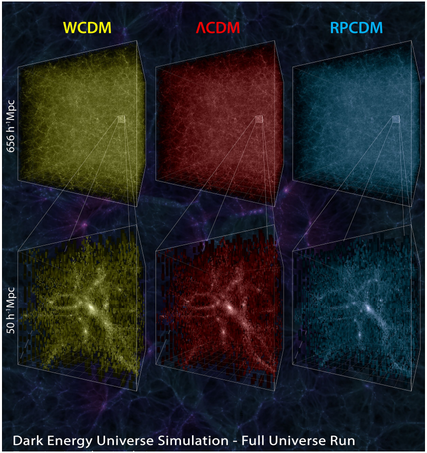

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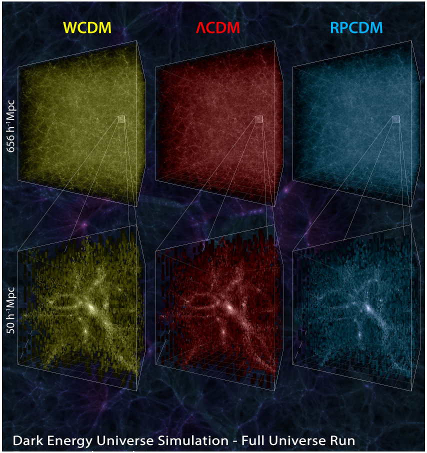

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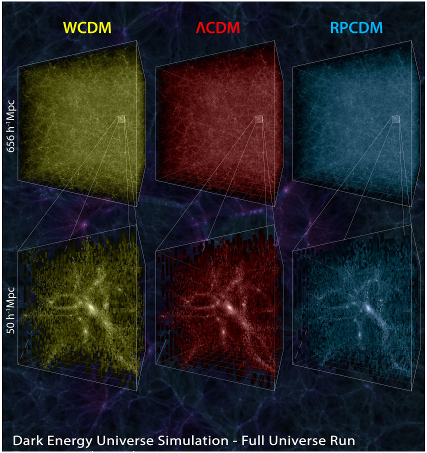

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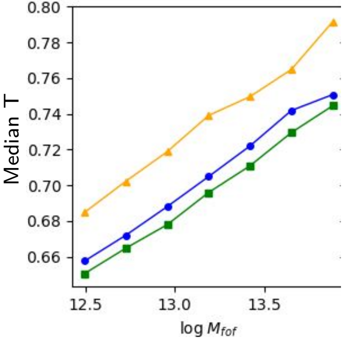
T-M median scatter plot:



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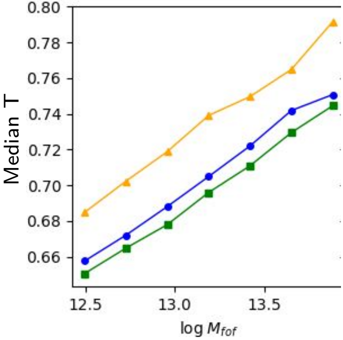

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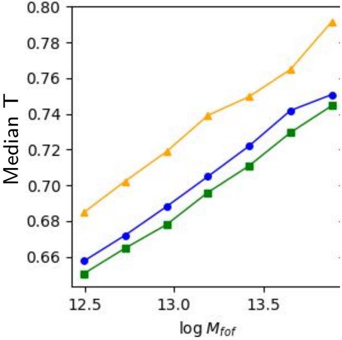

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To understand this cosmological dependence, the best way is to absorb it , ie to find a cosmological dependent function $f_c(M)$ s.t $T - f_c(M)$ is cosmologically independent.

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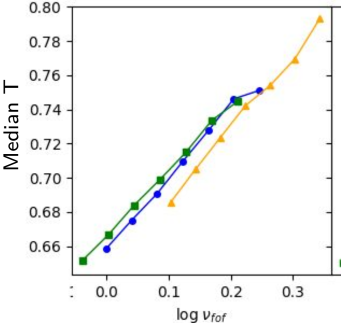

Surprisingly, the curves are closer in (ν, T) space than in (M, T) space.

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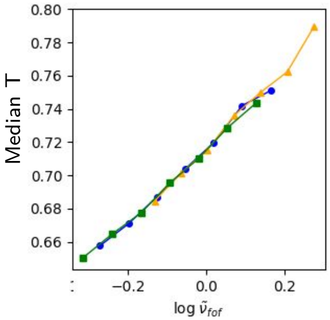

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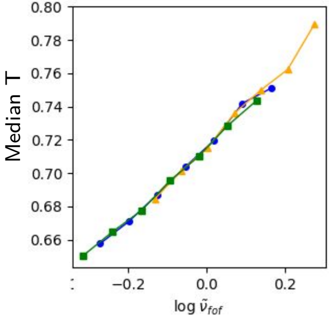

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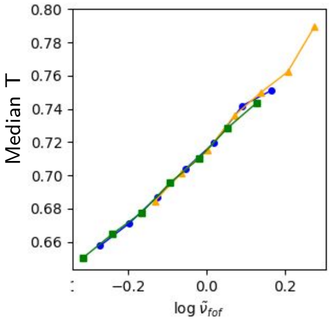

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In other words, we have showed that all the cosmological content of clusters' shape is embedded in the (non linear) power spectrum

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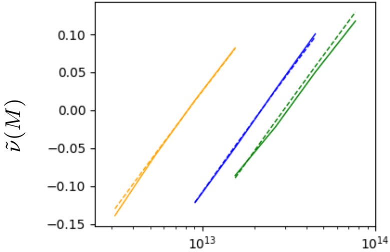
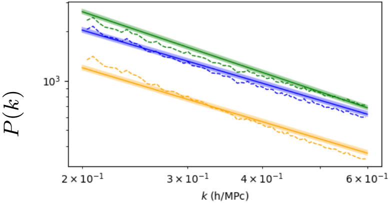
In terms of cosmological parameters, shape curves are not very sensitive to Ω_m but highly depend on (the non linear) σ_8. Complete computations are in [**Alimi Koskas 2022**]





Getting all together

Now we have in hand all the tools to build a brand new procedure to measure the non-linear power spectrum:

1. Measure the (M, T) curve in our universe.
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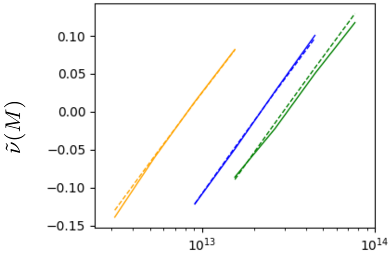
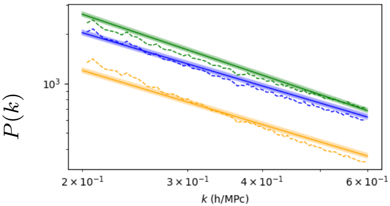


Model	ΛCDM	$RPCDM$	$wCDM$
Exact σ_8	0.8	0.7	0.9
Estimated $\overline{\sigma_8}$	0.8	0.6	0.9



Model	ΛCDM	$RPCDM$	$wCDM$
Exact $\tilde{\sigma}_8$	0.9	0.8	1
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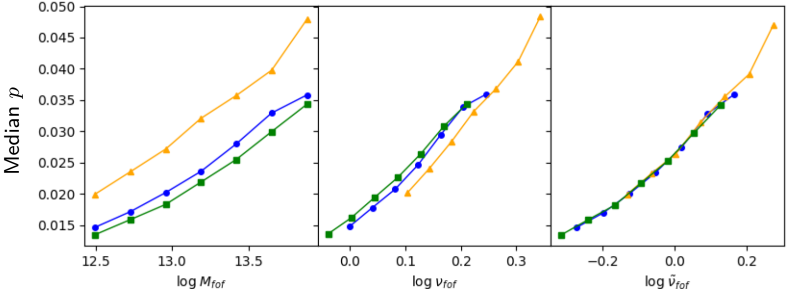
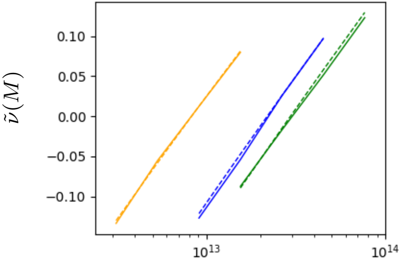
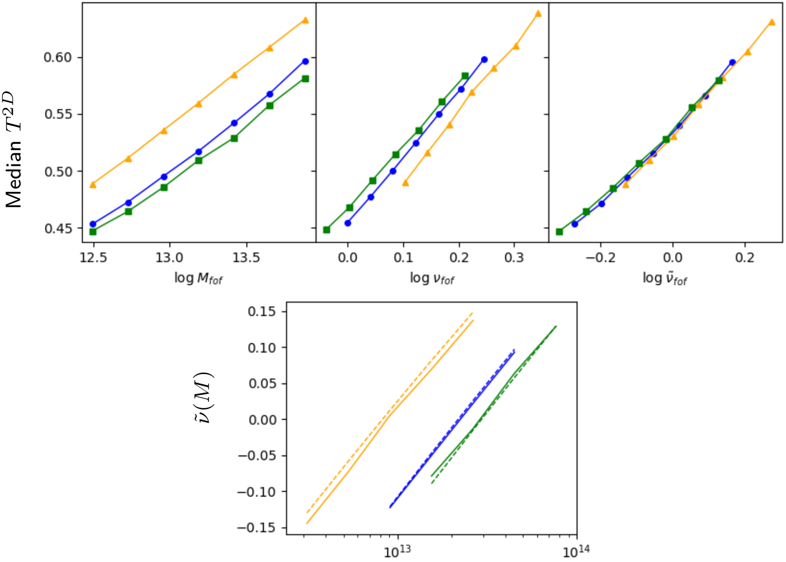
Results for other geometrical quantities (p)





What about 2D ?



Conclusion and perspectives

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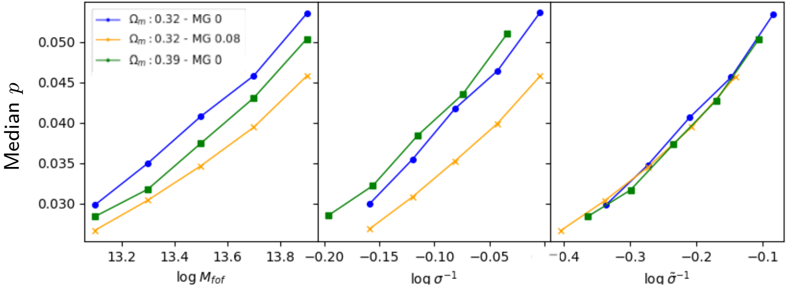
- It works because, from a statistical point of view, halos shape indeed carries cosmological information: one can read in halos shape the non linear PS (which is highly cosmology-impregnated)
- Also the equivalence between 2pt corr. in real and Fourier spaces seems to be a Fundamental Geometric Rule : it is independent on the DE model (above) but it is also independent on the $f(R)$ parameters [Simulations of Inigo and Yann]



Universality of halos shape as a strong cosmological probe

Rémy Koskas
Doctoral advisor: Jean Michel Alimi

LUTH l'Observatoire de Paris | PSL

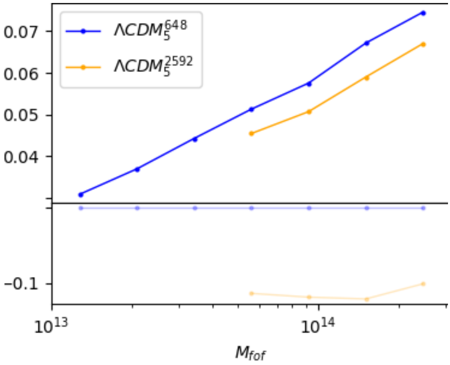
Laboratoire Univers et THéories

Journées du LUTH

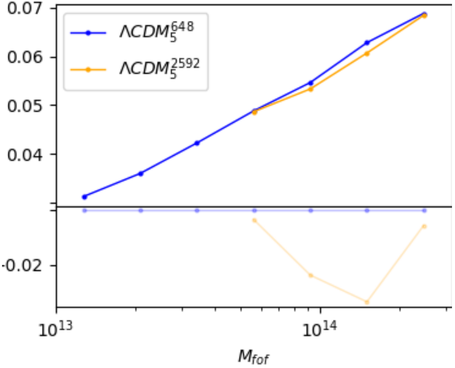
December 7, 2022

Resolution Effects

Example for prolatness:



From inertia tensor without treatment



From inertia tensor after substructures removal

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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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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)