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Observational cosmology with the
LSS





What i have been doing with my life.

- Clustering of galaxies.
- Semi-analytical model of halo occupation/galaxy-galaxy lensing.
- Intrinsic alignment of galaxies.

Cosmology

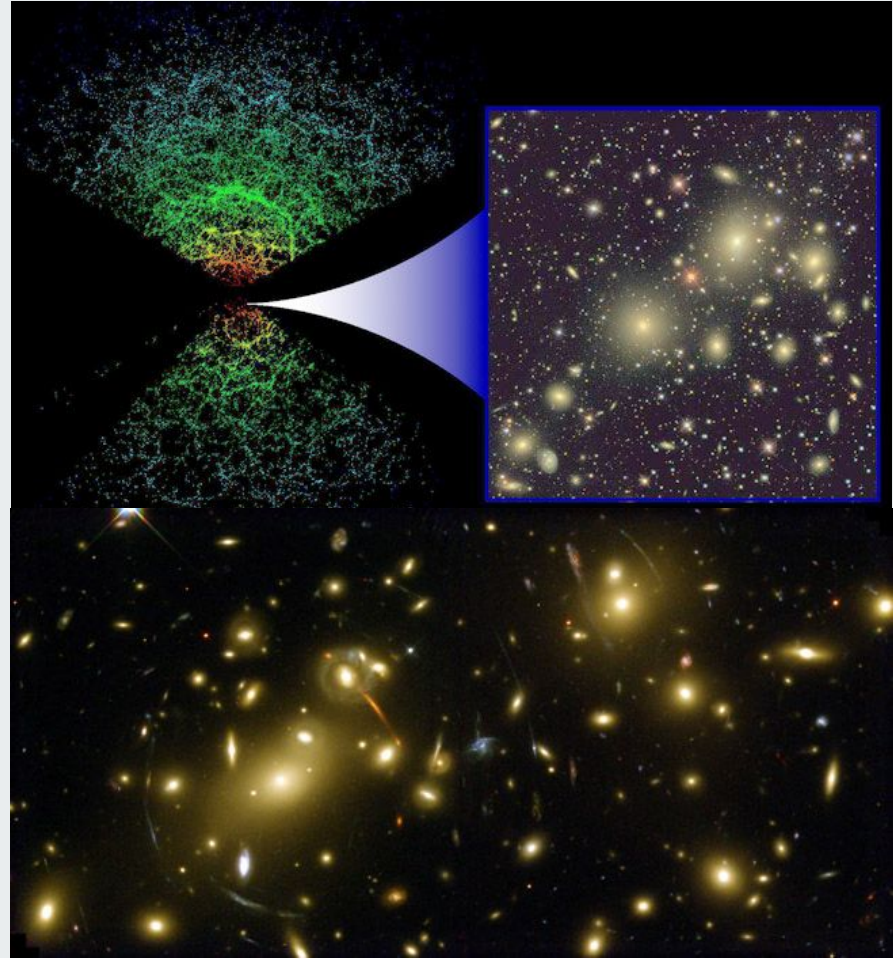
Study of the origin and evolution of the Univers.

Tracers of the density field :

- Galaxies
- Voids
- Clusters
-

Others cosmological probes :

- CMB
- Supernovae
- Lyman-alpha forest
-



Clustering of galaxies

Two observables : Redshift space distortions (RSD) and baryon acoustic oscillations (BAO).
 Constraints: growth rate of structure and distance ladder measurements

eBOSS DR16 luminous red galaxies 2PCF

[Bautista, Paviot, Vargas](#)
[Magaña et al. 2020](#)

$$\delta P = \bar{n}^2 \delta V_1 \delta V_2 (1 + \xi(r))$$

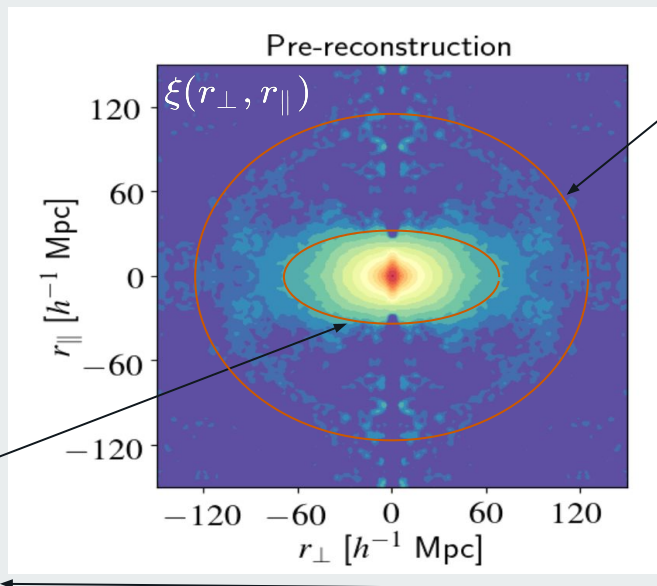
The Landy-Szalay (LS) estimator

$$\xi(s, \mu) = \frac{DD(s, \mu) - 2DR(s, \mu) + RR(s, \mu)}{RR(s, \mu)}$$

Anisotropies :
 Redshift
 space
 distortions

$$\mathbf{s} = \mathbf{r} + \frac{\mathbf{v} \cdot \mathbf{n}}{aH(a)} \quad \beta\delta = -\frac{1}{aH(a)} \nabla \cdot \mathbf{v}$$

$$z_{\text{eff}} = 0.70$$



Baryon acoustic
 oscillations

$$r_d = \int_{z_d}^{\infty} \frac{c_s(z)}{H(z)} dz$$

$$= 147.21 \pm 0.23 \text{ Mpc}$$

Line of sight separation



Statistics of the density field.

How can one describe the matter density field $\delta(\mathbf{r}) \equiv \frac{\rho(\mathbf{r}) - \bar{\rho}(\mathbf{r})}{\bar{\rho}(\mathbf{r})}$?

Useless to specify δ at every point space. Instead, describe the density field in term of some probability distribution function, totally defined by its moments:

$$\langle \delta_1^{\ell_1} \delta_2^{\ell_2} \dots \delta_n^{\ell_n} \rangle \equiv \int \delta_1^{\ell_1} \delta_2^{\ell_2} \dots \delta_n^{\ell_n} \mathcal{P}_x(\delta_1, \delta_2, \dots, \delta_n) d\delta_1 d\delta_2 \dots d\delta_n$$

First moment, $\langle \delta(\mathbf{r}) \rangle = 0$ following cosmological principle.

Second moment, $\xi(\mathbf{x}) \equiv \langle \delta(\mathbf{r}) \delta(\mathbf{r}') \rangle$ where $\mathbf{x} = |\mathbf{r} - \mathbf{r}'|$

$$\langle \delta_1 \rangle_c = \bullet$$

$$\langle \delta_1 \delta_2 \rangle_c = \bullet \text{---} \bullet$$

Fourier
transform

The power spectrum :

$$P(\mathbf{k}) = \int d\mathbf{r}^3 \exp(-i\mathbf{k} \cdot \mathbf{r}) \xi(\mathbf{r})$$

$$P(k) \equiv \langle |\delta_k|^2 \rangle,$$

ERGODICITY!

$$\langle \delta_1 \delta_2 \delta_3 \rangle_c = \text{triangle}$$

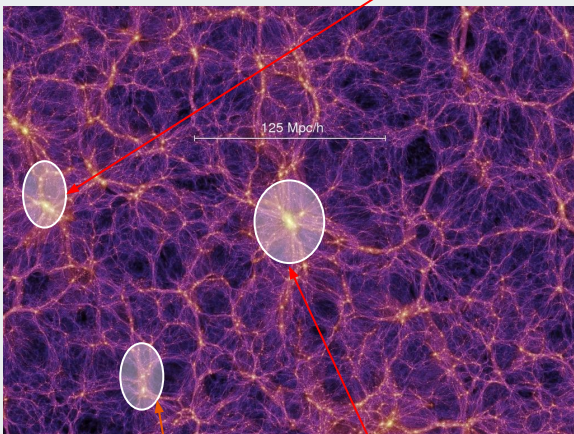
$$\langle \delta_1 \delta_2 \delta_3 \delta_4 \rangle_c = \text{quadrilateral}$$

Different moments of the density field.
[Bernardeau et al 2001](#)

Galaxies!

100-1000 galaxies

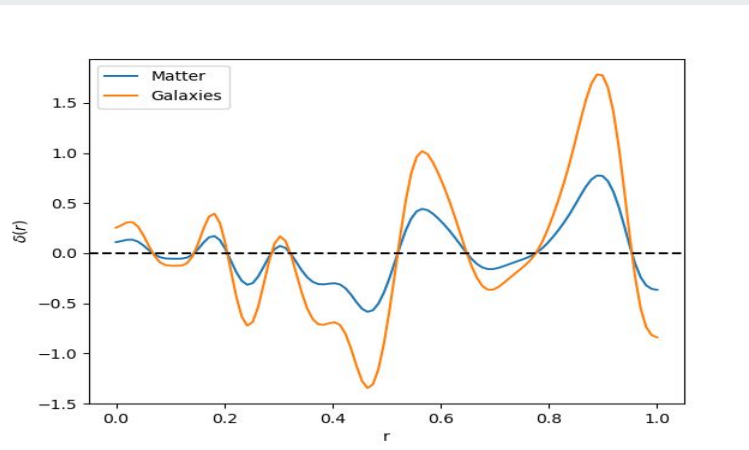
Galaxies are *biased* tracers of the underlying density field



[The Millenium simulation](#)

1 galaxy

10-100 galaxies



$$\delta_g(\mathbf{x}) = \mathcal{F}[\delta(\mathbf{x})] \text{ Linear:}$$

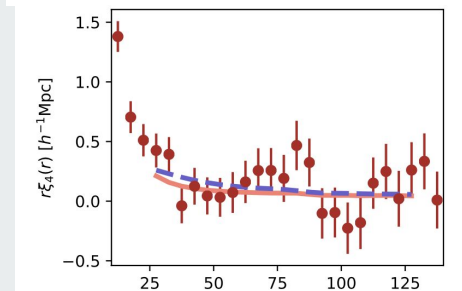
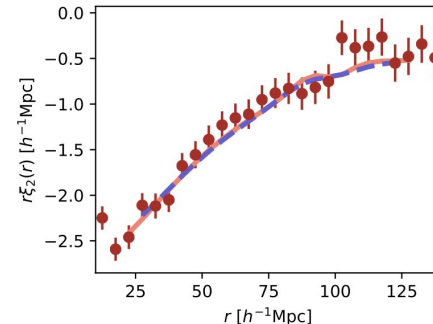
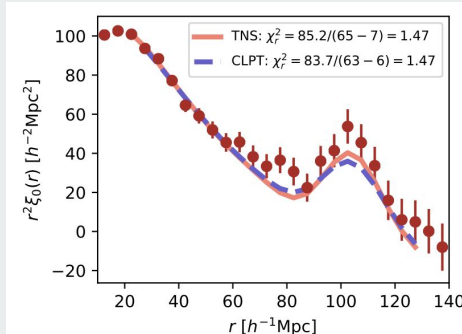
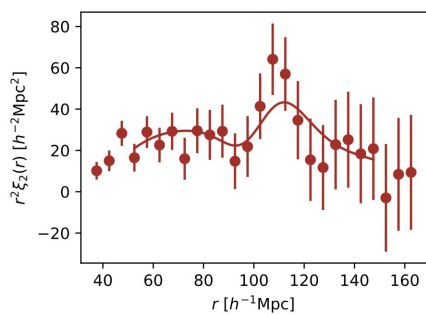
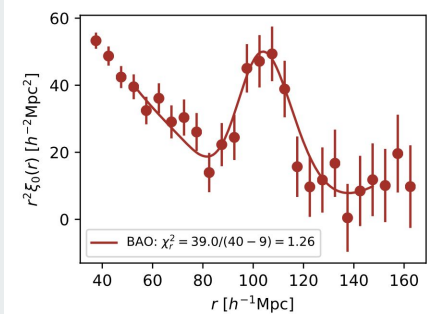
$$\delta_g = b\delta_m \quad P_g(k) = b^2 P_m(k) \quad \leftarrow \text{Perturbation theory}$$

$$P_g^s(k, \mu) = [b + f\mu^2]^2 P_m(k)$$

BAO measurement (Julian le S)

$$\xi^s(s, \mu) = \xi_0(s)L_0(\mu) + \xi_2(s)L_2(\mu) + \xi_4(s)L_4(\mu)$$

Monopole quadrupole hexadecapole

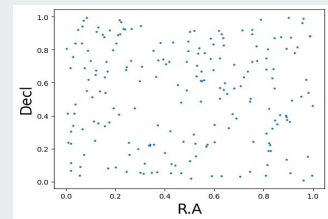
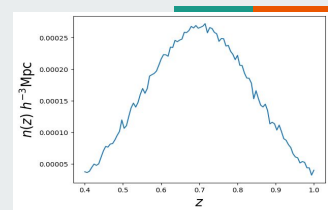


RSD measurements
(me and Mariana)

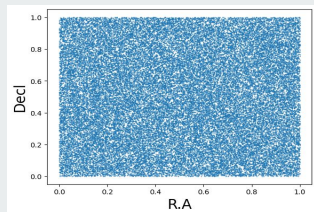
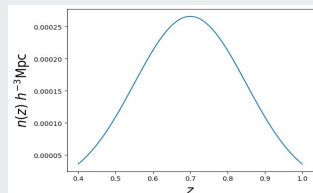
$$\mathbf{D}_{\text{BAO}, \xi_\ell} = \begin{pmatrix} D_M/r_d \\ D_H/r_d \end{pmatrix} = \begin{pmatrix} 17.86 \pm 0.33 \\ 19.34 \pm 0.54 \end{pmatrix}$$

$$\mathbf{D}_{\text{RSD}, \xi_\ell} = \begin{pmatrix} D_M/r_d \\ D_H/r_d \\ f\sigma_8 \end{pmatrix} = \begin{pmatrix} 17.42 \pm 0.40 \\ 20.46 \pm 0.70 \\ 0.460 \pm 0.050 \end{pmatrix}$$

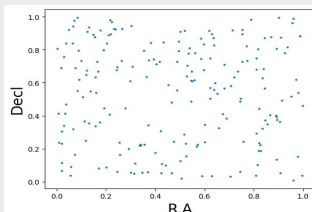
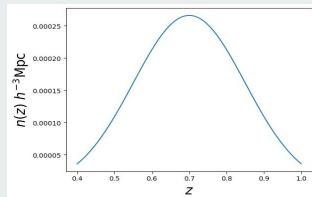
Angular modes free estimator (Paviot et al 2021)



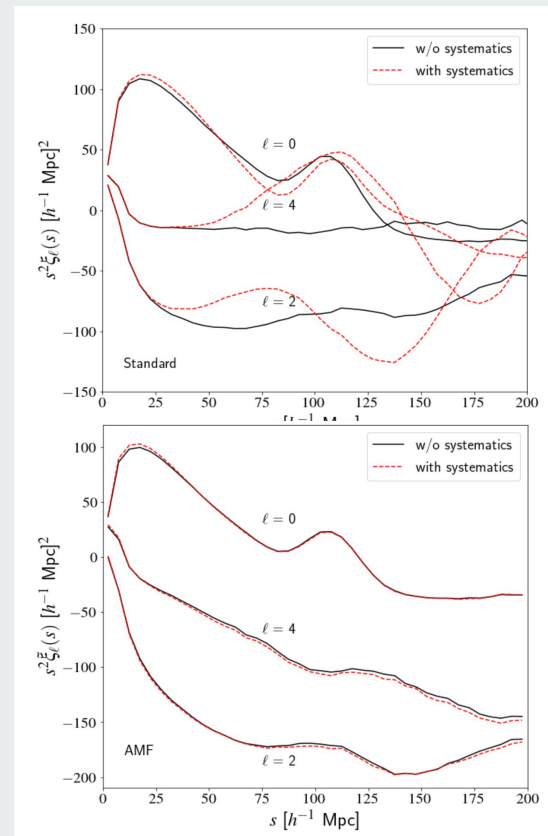
Data catalog



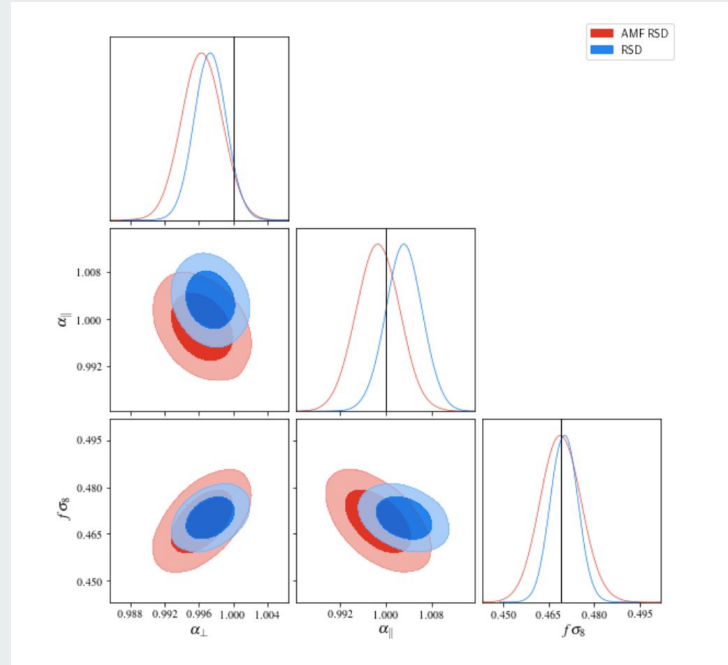
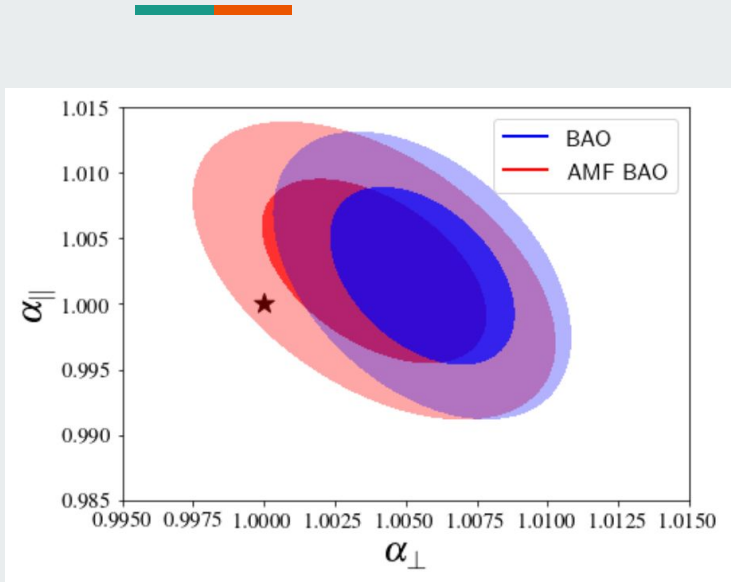
Random catalog R



Random catalog S



Angular modes free estimator



New estimator gives consistent constraint compared to the standard one !

Halo occupation model (HOD)

Populate dark matter haloes with galaxy given a semi-analytical model.

$$w_p(r_p) = 2 \int_0^{\pi_{max}} \xi(r_p, \pi) d\pi.$$

$$\langle N_g | M_h \rangle = \langle N_{cen} | M_h \rangle + \langle N_{sat} | M_h \rangle.$$

Red galaxies

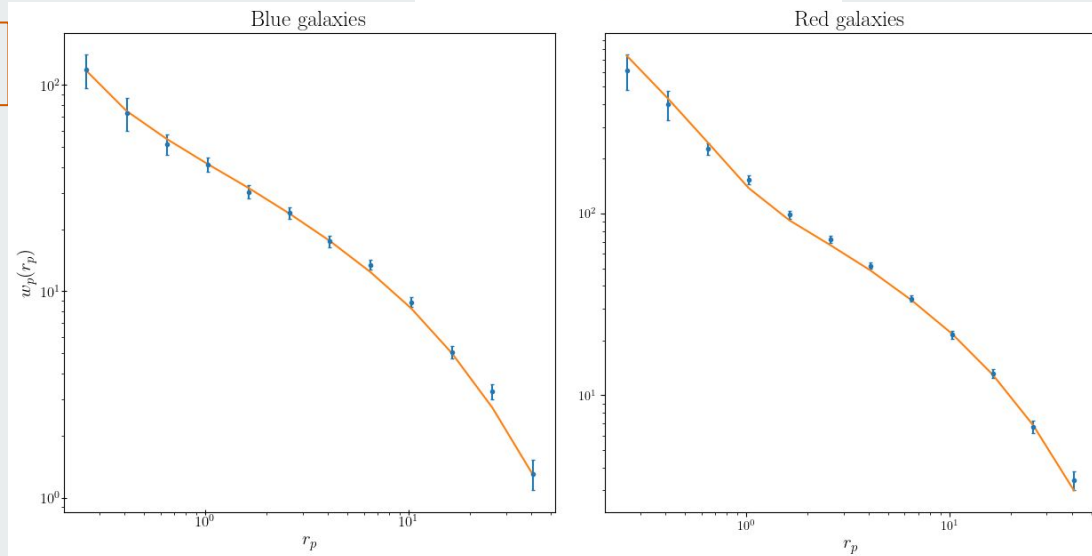
$$N_{cen}(M) = \frac{1}{2} \left[1 + \operatorname{erf} \left(\frac{\log M - \log M_{min}}{\sigma_{\log M}} \right) \right],$$

Blue galaxies

$$\langle N_{cent}(M) \rangle = \frac{A_c}{\sqrt{2\pi}\sigma_M} \cdot e^{-\frac{(\log_{10}(M) - \mu)^2}{2\sigma_M^2}}$$

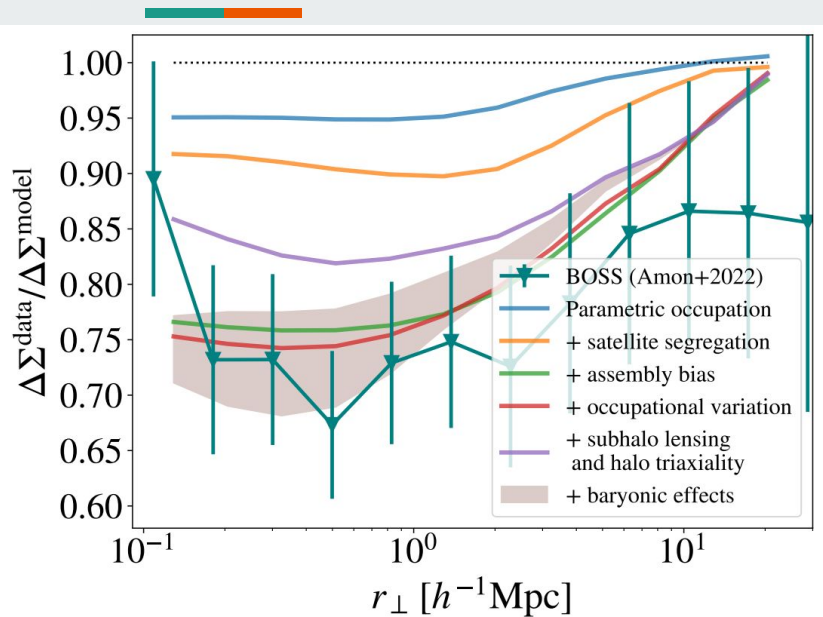
Satellites

$$\langle N_{sat}(M) \rangle = A_s \left(\frac{M - M_0}{M_1} \right)^\alpha$$



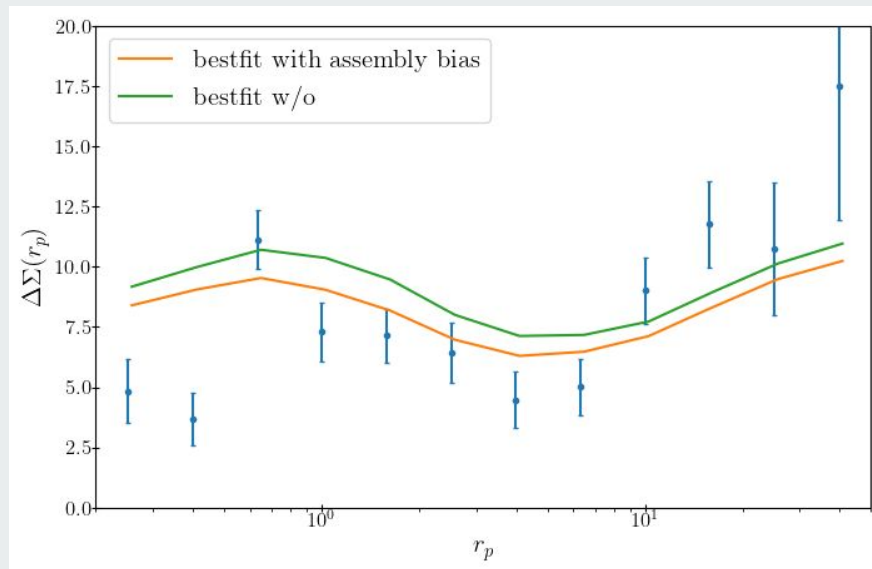
HOD Bestfit of eBOSS ELG and LRG on UCHUU simulations

Halo occupation model (HOD)



Chaves-Montero et al. 2023

HOD description fails to reproduce the lensing signal



UCHUU LRG HOD bestfit

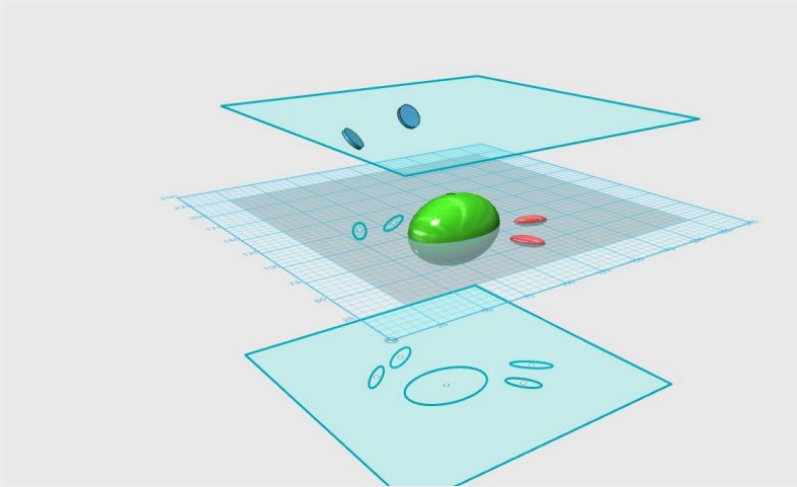
$$\log M_{\text{pseudo}} = \log M + A c_{\text{norm}} + B \delta_c + C \cdot \text{shape}$$

Goal : Combine fit of clustering (P_{gg}) and lensing (P_{gm}) to break degeneracy between f and σ_8 .

Constraint on galaxy intrinsic alignment (Euclid project)

3 main IA paper in EUCLID :

- Paper 0 : Hoffmann et al. : Semi-analytical of galaxy intrinsic alignments in EUCLID N-Body simulation.
- Paper I : Paviot et al. : Provides prior for cosmological 3x2pt forecast of EUCLID
- Paper II : Tutusaus et al. (Isaac le S): Will do 3x2pt analysis once my work is over !

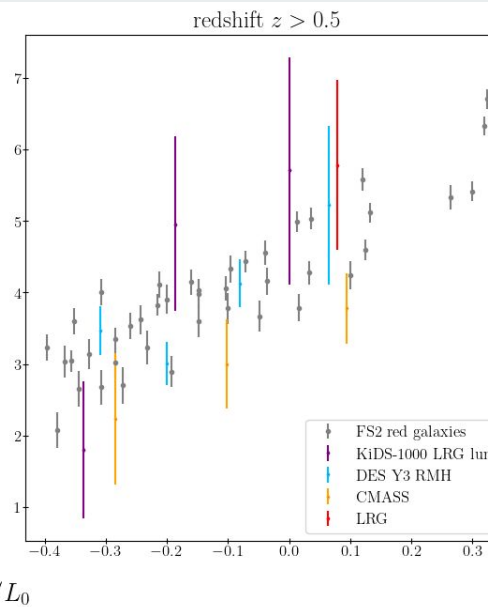
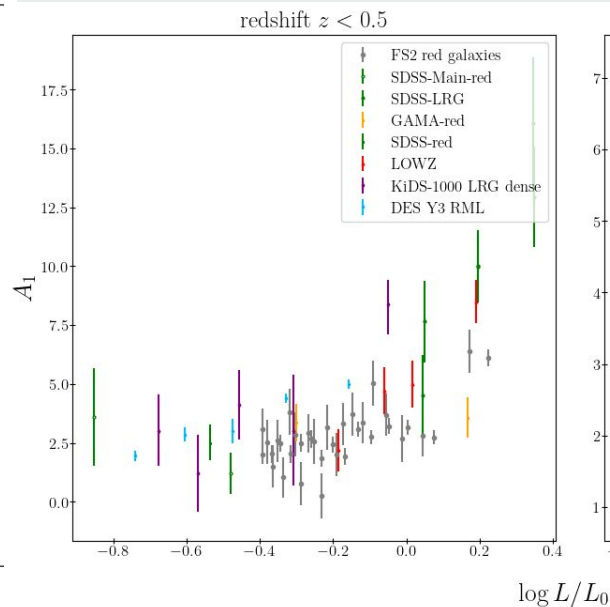
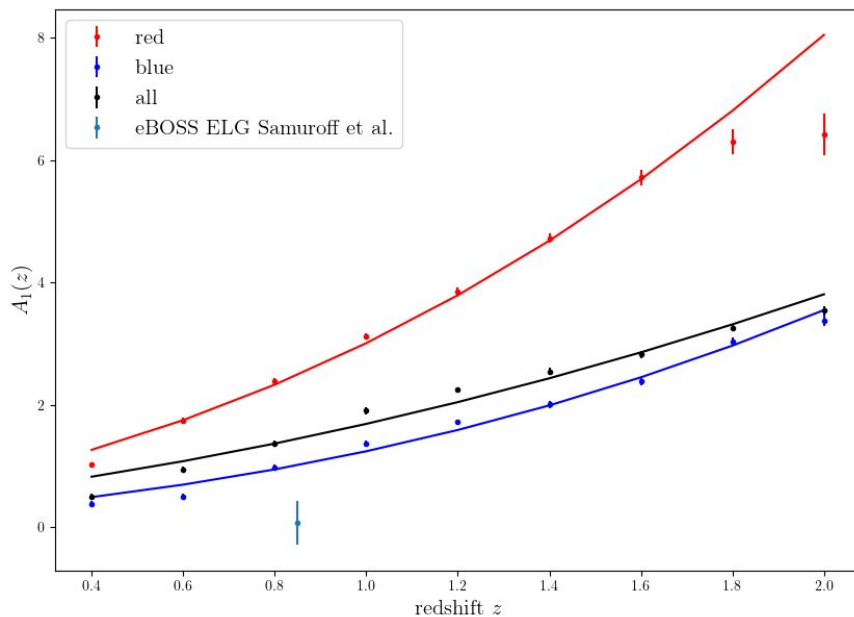


$$\langle \gamma \gamma \rangle = \langle \gamma^G \gamma^G + \gamma^G \gamma^I + \gamma^I \gamma^I \rangle = \xi_{GG} + \xi_{GI} + \xi_{II}.$$

$$\hat{\xi}_{g+} = \frac{S_+(D - R_D)}{R_S R_D}$$

IA constraint with FS2!

Calibration works OK for red galaxies, problem for blue galaxies!



Conclusion




I do a lot of stuff, but not a lot at the same time.
The future of cosmology looks very promising !

MERCI L'EQUIPE ! VIVE EUCLID !

APEROTIME BB





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Merci Coco pour ce montage 13 NRV!



Semi non-linear regime : TNS (Taruya et al. 2010) with non-linear bias (Assasi et al. 2017)

$$P_g^s(k, \mu) = D(k\mu\sigma_v) [P_{gg}(k) + 2\mu^2 f P_{g\theta} + \mu^4 f^2 P_{\theta\theta}(k) + C_A(k, \mu, f, b_1) + C_B(k, \mu, f, b_1)] \quad D(k\mu\sigma_v) = (1 + (k\mu\sigma_v)^2/2)^{-2}$$

$$P_{gg}(k) = b_1^2 P_{\delta\delta}(k) + b_2 b_1 I_{\delta^2}(k) + 2b_1 b_{g_2} I_{G_2}(k) + 2 \left(b_1 b_{g_2} + \frac{2}{5} b_1 b_{\Gamma_3} \right) F_{G_2}(k) + \frac{1}{4} b_2^2 I_{\delta^2\delta^2}(k) + b_{g_2}^2 I_{G_2 G_2}(k) + \frac{1}{2} b_2 b_{g_2} I_{\delta_2 G_2}(k)$$