Cosmological analysis of the DESI data to constrain general relativity and modified gravity models

Under the supervision of
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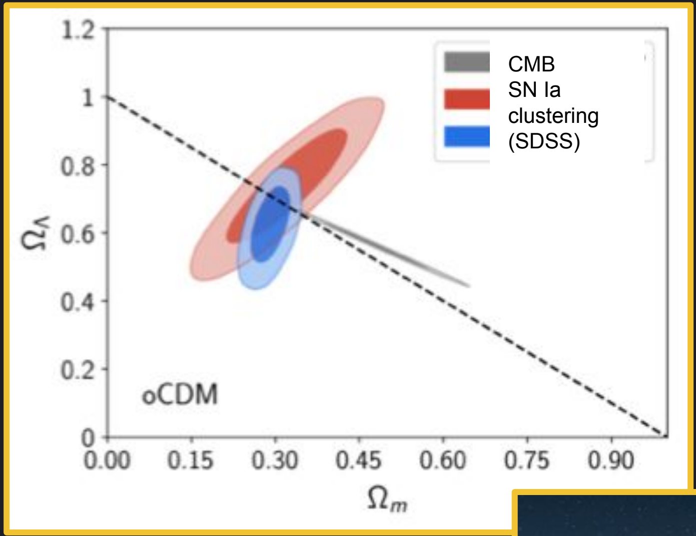
Dark Energy Spectroscopic Instrument



The goal

- constrain dark energy by measuring the expansion rate and test gravity using 3D maps of large-scale structures

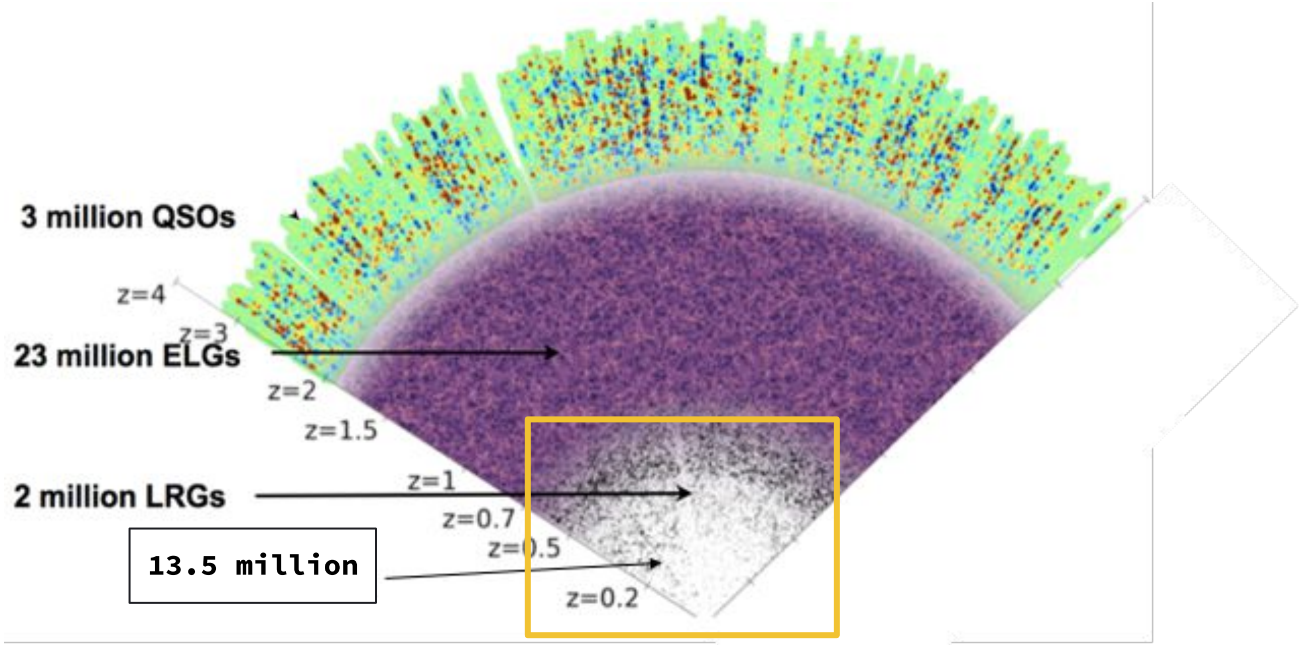
The instrument

- 4m Mayall telescope (USA)
- 5000 Fiber-fed spectrograph
- Footprint taking 36% of the sky
- 40 million spectra of galaxies
- A successor to the **BOSS/eBOSS**

Data taking now!

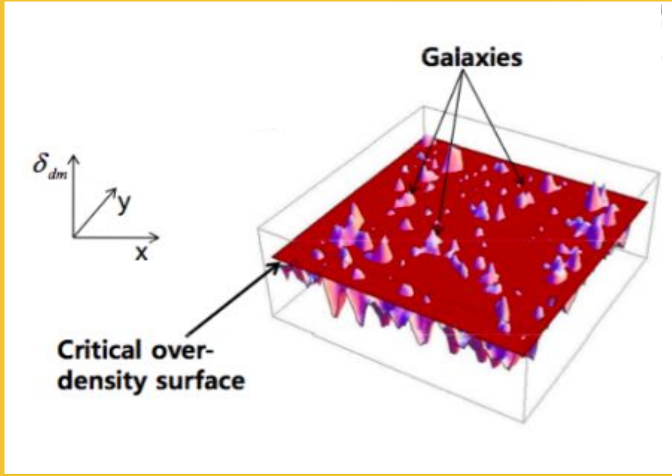
→ Scientific survey started on **May 17th, 2021.**

Bright Galaxy Survey (BGS)



Bright Galaxy Survey (BGS)
Dense and highly complete sample of bright low-z galaxies (z<0.5)
Simulated data (UCHUU Lightcone) is used to imitate the BGS

Power Spectrum / Correlation function



Clustering statistics
Statistics describing the spatial distribution of galaxies

Density contrast (overdensity field):

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

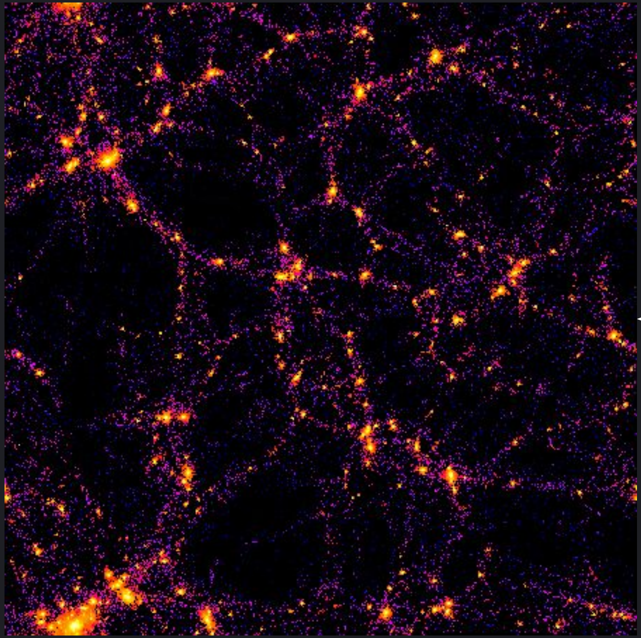
Two-point statistics:

$$\xi(r) = \langle \delta(\mathbf{x})\delta(\mathbf{x}') \rangle = \int \frac{d^3k}{(2\pi)^3} P(k) e^{i\mathbf{k}\cdot(\mathbf{x}-\mathbf{x}')}$$

$$\xi_l(s) = \frac{2l+1}{2} \sum_j \xi(s, \mu_j) P_l(\mu_j) d\mu$$

Theory and observations

What theories predict:
clustering of matter

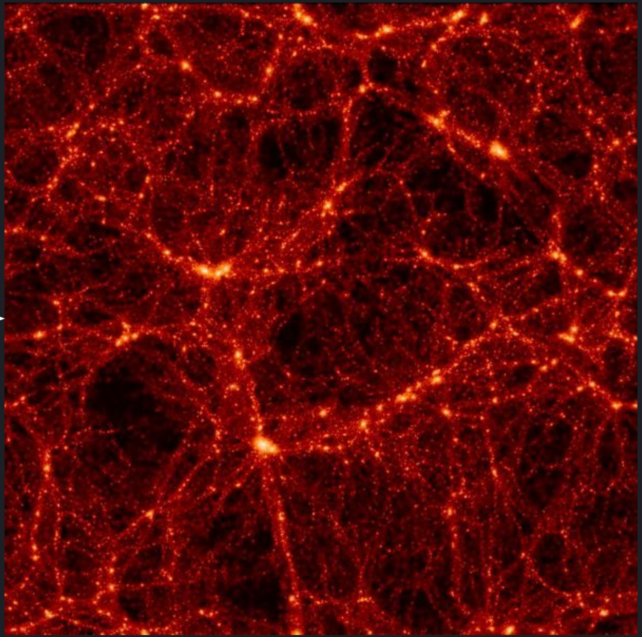


Cosmological model, e.g. expansion rate of the universe H(z)

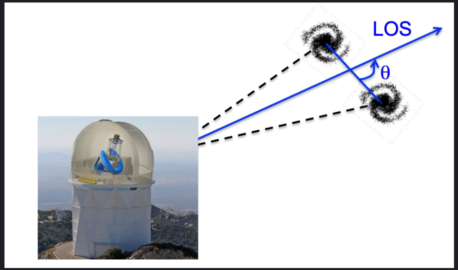
Growth rate of structure, f(z)

Galaxy bias, b(z)

What we actually observe:
clustering of galaxies



Bias and RSD



Growth rate

Directional cosine

$$\delta_g = (b + f\mu^2)\delta$$

This is only the linear theory. On practice, more accurate models have to be used.

What we actually observe

What theories predict

Galaxy density field (~15% of the matter)

Galaxy bias

Galaxies have peculiar velocities (redshift space distortions RSD)

Matter distribution (Dark + baryonic)

Testing the theory of gravity

Growth rate

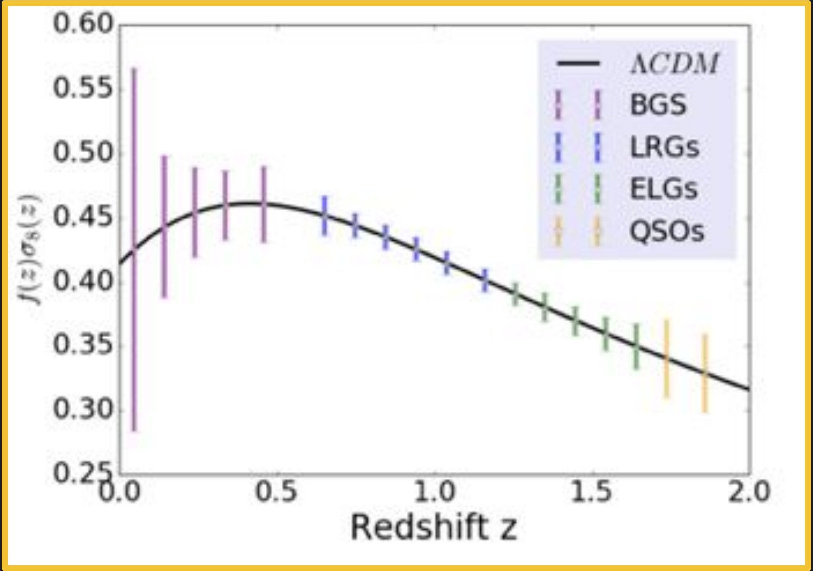
$$\delta(x,t) = A(x) D_a(t)$$

$$f = \frac{d\ln D}{d\ln a}$$

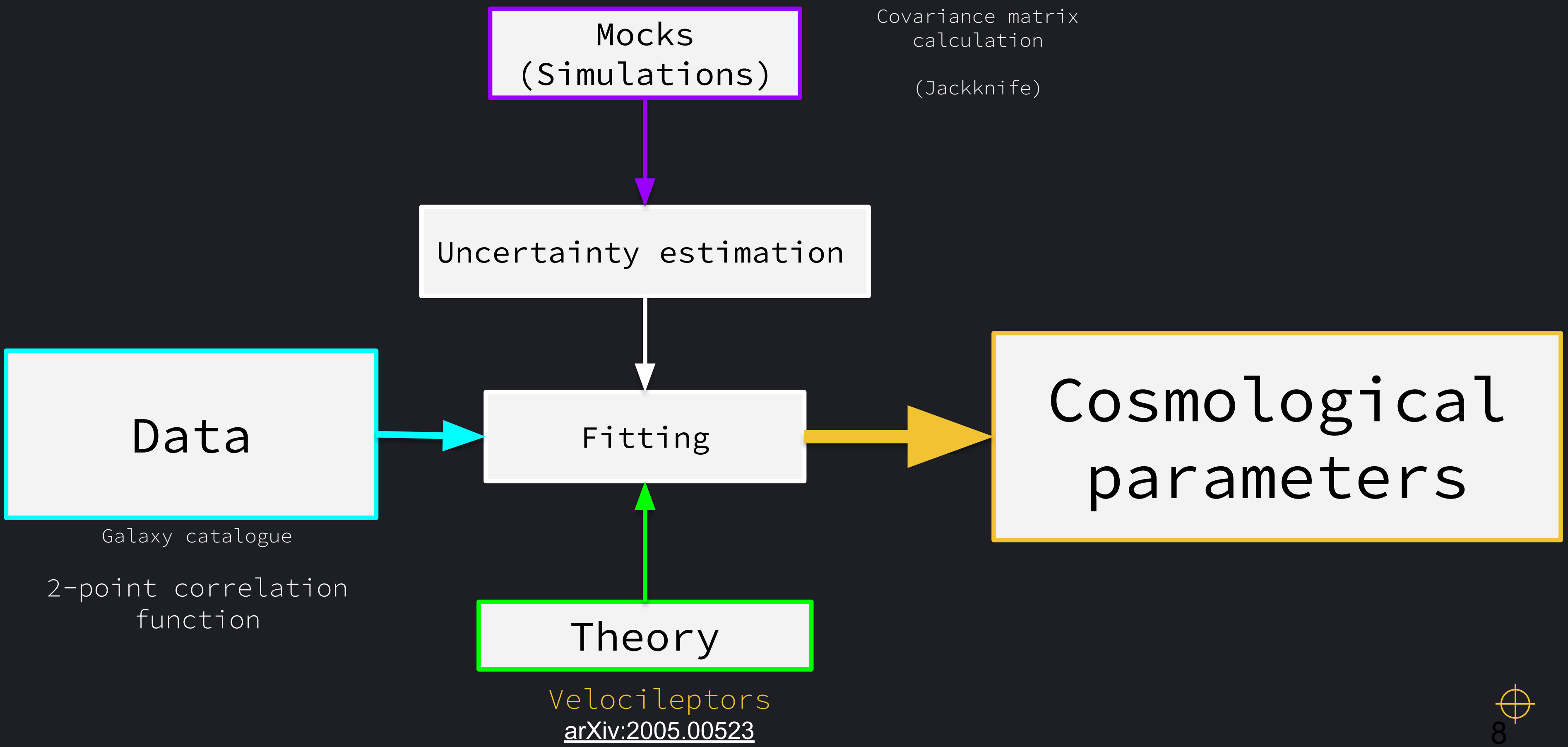
$$f \sim \Omega_m^{\frac{3(1-w_{DE})}{5-6w_{DE}}}$$

For ΛCDM: $w_{DE} = -1$

DESI Y5 forecasts

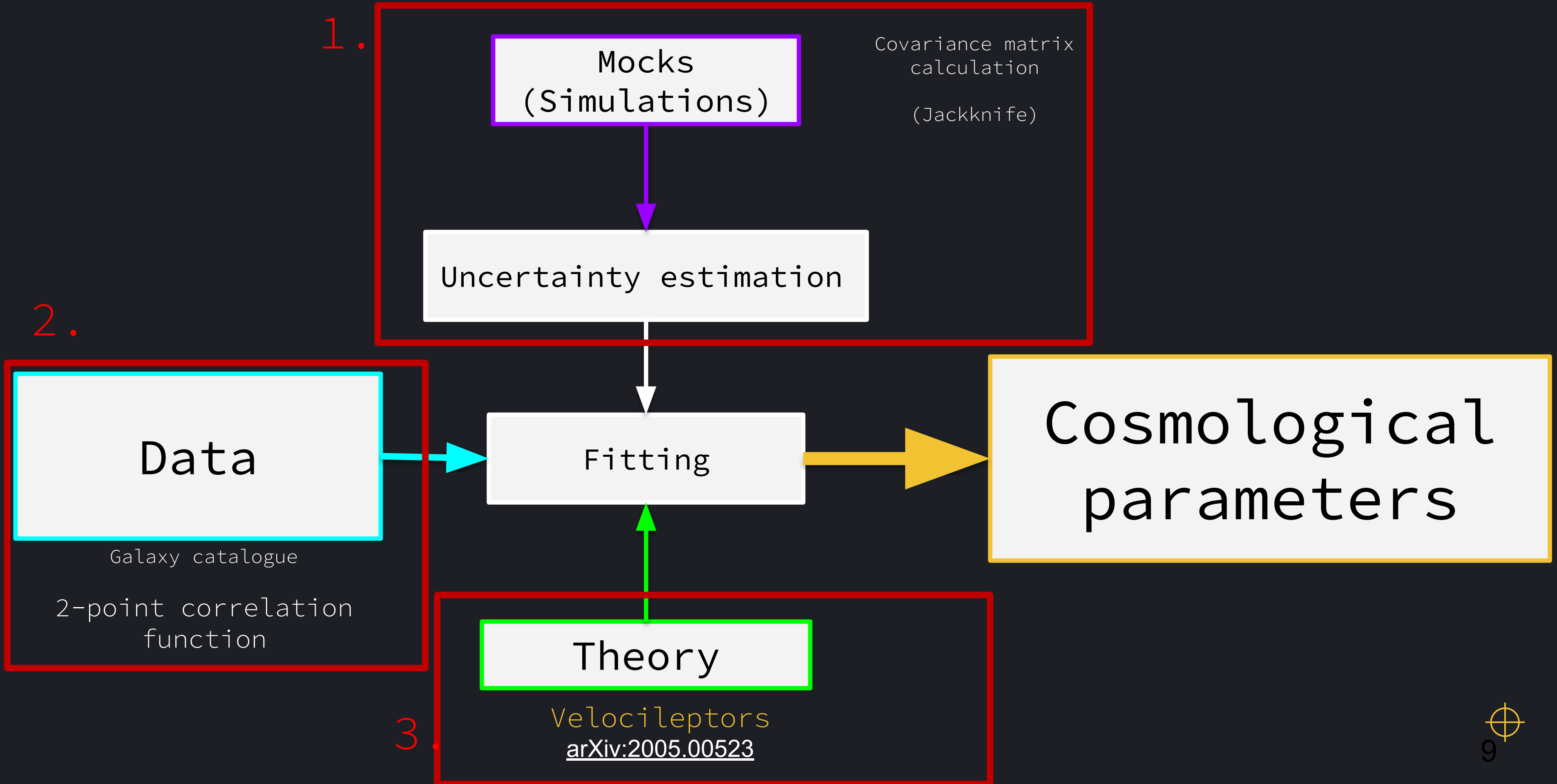


Analysis



Mocks (Simulations)
Covariance matrix calculation
(Jackknife)
Uncertainty estimation
Data
Fitting
Cosmological parameters
Galaxy catalogue
2-point correlation function
Theory
Velocileptors
arXiv:2005.00523

Analysis


1.
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1. Covariance

Standard approach: Creating thousands of mocks, compute the target statistics on them and estimate the covariance

A problem: The mocks for covariance matrix estimation are very expensive for certain datasets

How to solve?

1) Jackknife
   a) Biased
   b) Requires only one realization
   c) Very imprecise
   d) Has biases (large scales, number density)

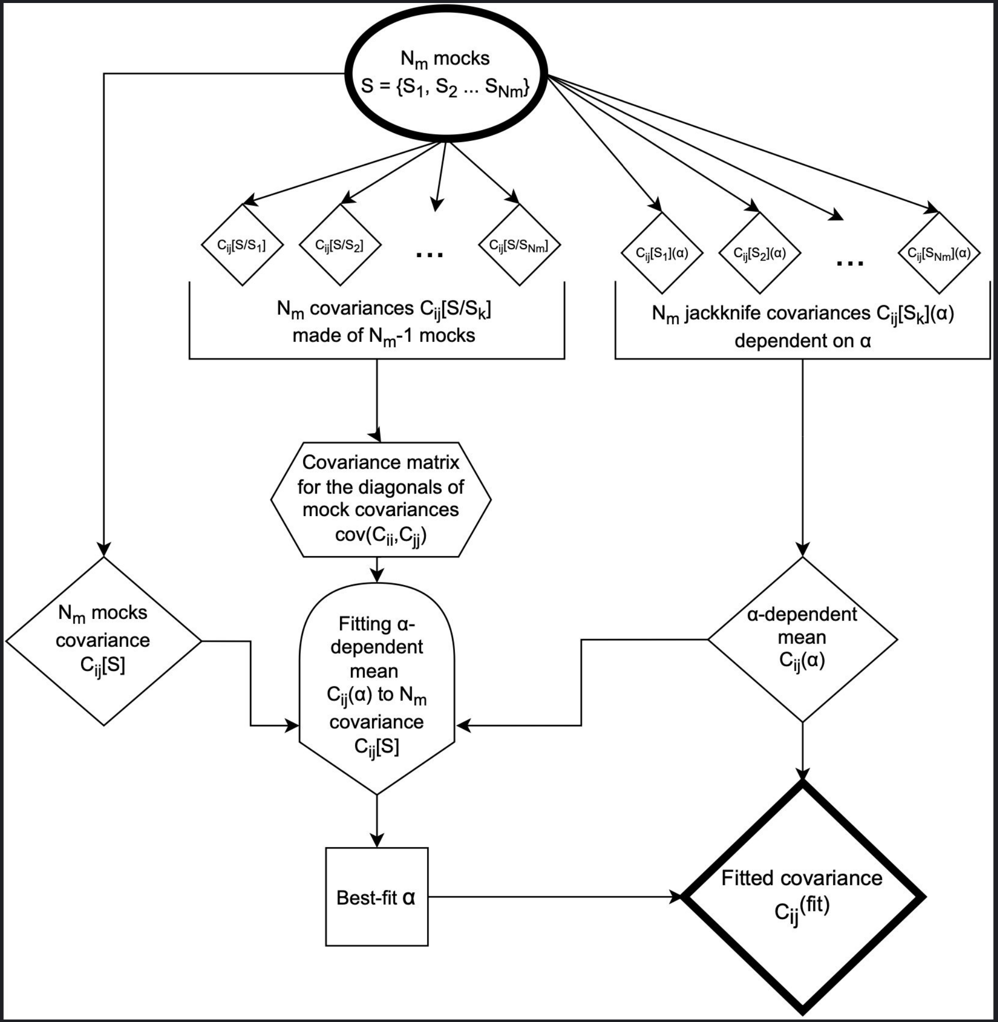
2) Analytic covariance
   a) Small scales unresolved

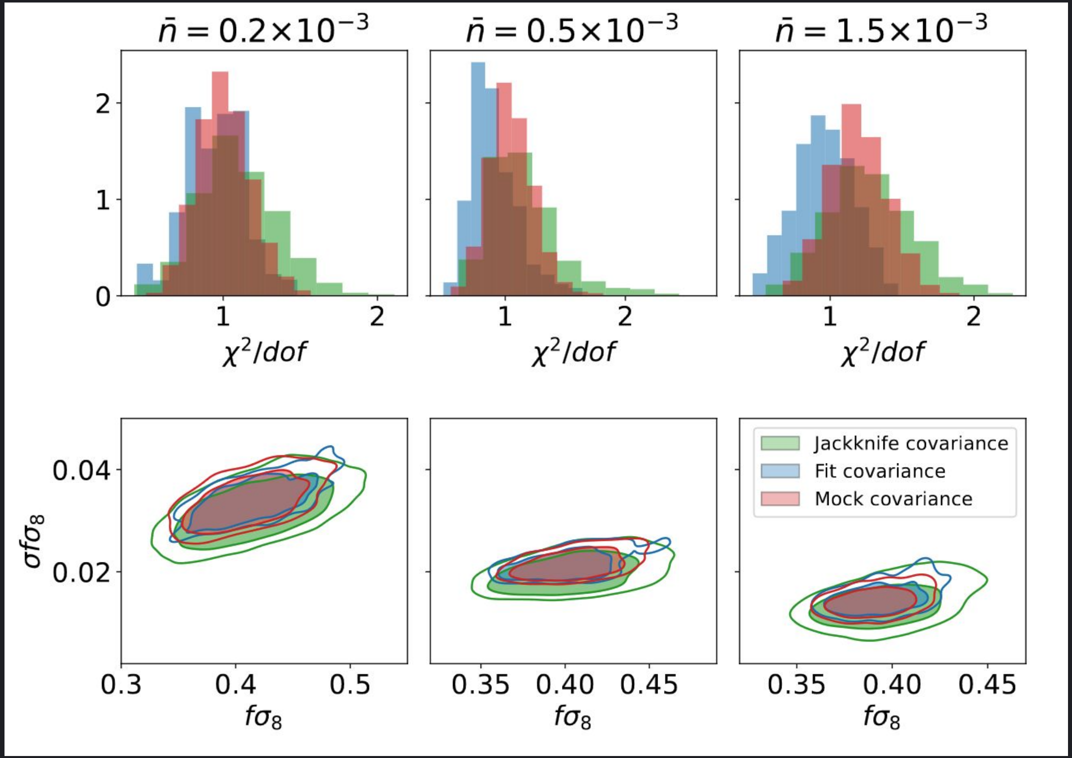
Fitted jackknife covariance (fit covariance)

N_m mocks = 50 (for example)

The same N_m mocks are used for jackknife covariance → **α** fitted on N_m mocks

The same N_m mocks are used to produce (N_m-1) covariances





Conventional method:
1500 mocks

Our method:
50 mocks

Similar performance

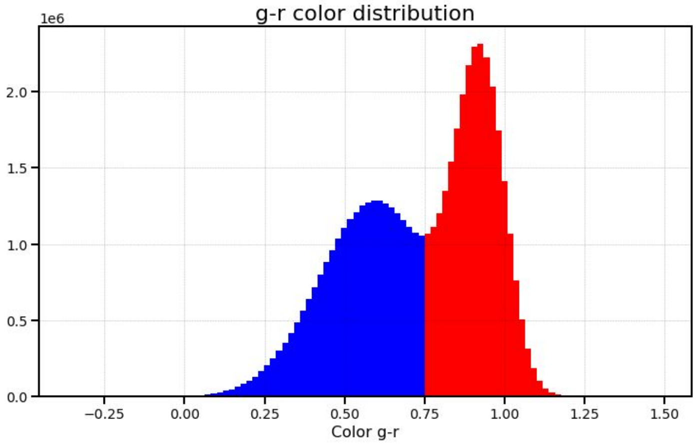
More information:
Trusov et al: arXiv:2306.16332

2. Multitracer analysis

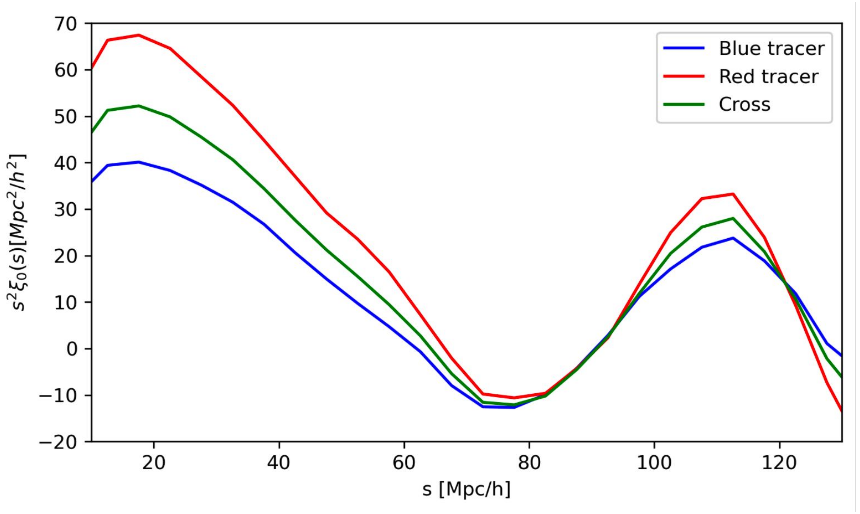
Cross-correlations of several samples allow to bypass cosmic variance for some of the parameters.

Bigger the difference between the samples (clustering properties, or bias) - the better.

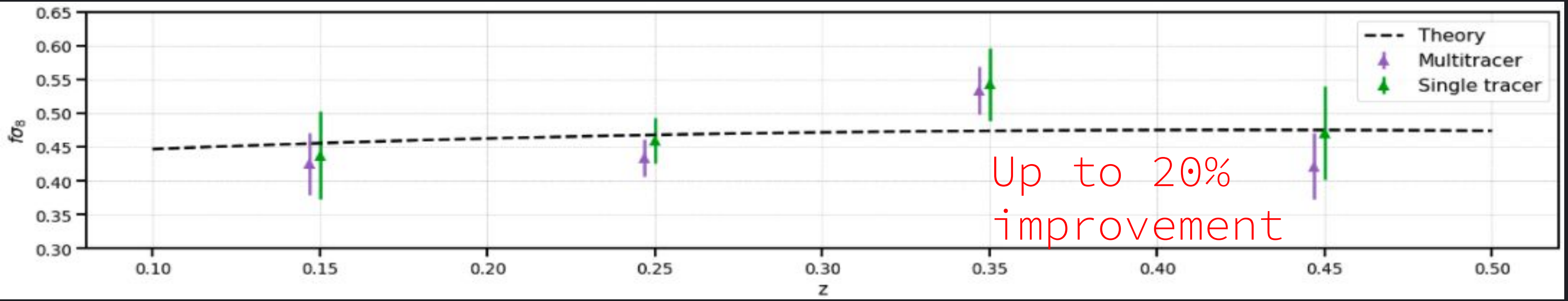
For BGS, split the sample between blue and red galaxies



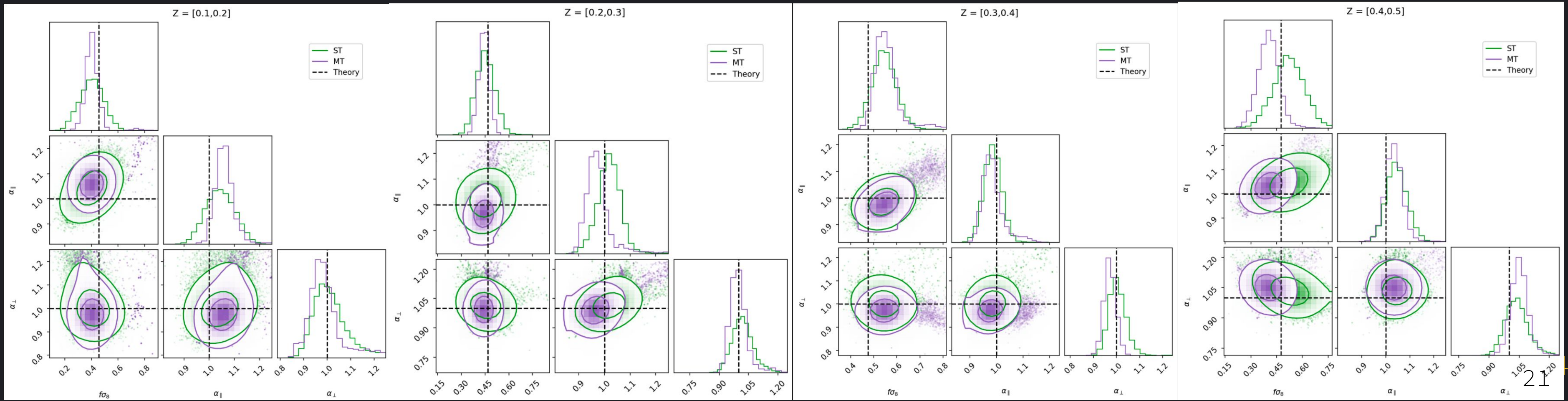
Clustering of red and blue galaxies
(monopole of the correlation function)



Likelihood minimization



Bayesian inference



3. LPT with ML techniques

Compressed analysis

Measured quantities:

Growth rate $f\sigma_8$
AP parameters (difference between fiducial and observed cosmologies)

Pros:
Very fast computationally

Cons:
Loss of information

Full modelling analysis

Measured quantities:

LCDM parameters (Ω_m, σ_8, h e.t.c.)

Pros:
No loss of information

Cons:
Extremely slow computationally (~1s per statistic analytically)

Motivation

1) Full modelling fits provide the maximum accuracy

2) Full modelling fits take a lot of time

3) Even longer for more complicated analysis (Multitracer, Density Split)

How to speed up?

Option 1: just emulate the multipoles with neural networks/interpolation

Option 2: Can we do something more general?

Velocileptors: Momentum Expansion

$$P_s^{\rm ME}(\mathbf{k}) = \left(P(k) + i(k\mu)v_{12,\hat{n}}(\mathbf{k}) - \frac{(k\mu)^2}{2}\sigma^2_{12,\hat{n}\hat{n}}(\mathbf{k})\right) + $$
$$+ \left(\alpha_0 + \alpha_2\mu^2 + \alpha_4\mu^4 + \dots\right) k^2 P_{\rm lin,Zel}(k) + R_h^3\left(1 + \sigma_v^2(k\mu)^2 + \dots\right)$$

$$P(k) = \int d^3\mathbf{q}\, e^{i\mathbf{k}\mathbf{q}} e^{-\frac{1}{2}k_ik_jA^{lin}_{ij}} \Big\{ 1 - \frac{1}{2}k_ik_jA^{\rm loop}ij + \frac{i}{6}k_ik_jk_kW_{ijk}$$
$$+ b_1\left(2ik_iU_i - k_ik_jA^{10}_{ij}\right) + b_1^2\left(\xi_{\rm lin} + ik_iU^{11}_i - k_ik_jU^{\rm lin}_iU^{\rm lin}_j\right) +$$
$$+ \frac{1}{2}b_2^2\xi^2_{\rm lin} + 2ib_1b_2\xi_{\rm lin}k_iU^{\rm lin}_i - b_2\left(k_ik_jU^{\rm lin}_iU^{\rm lin}_j + ik_iU^{20}_i\right) +$$
$$+ b_s\left(-k_ik_j\Upsilon_{ij} + 2ik_iV^{10}_i\right) + 2ib_1b_sk_iV^{12}_i + b_2b_s\chi + b_s^2\zeta +$$
$$+ 2ib_3k_iU_{b_3,i} + 2b_1b_3\theta + \alpha_P k^2 + \dots \Big\} + R_h^3$$

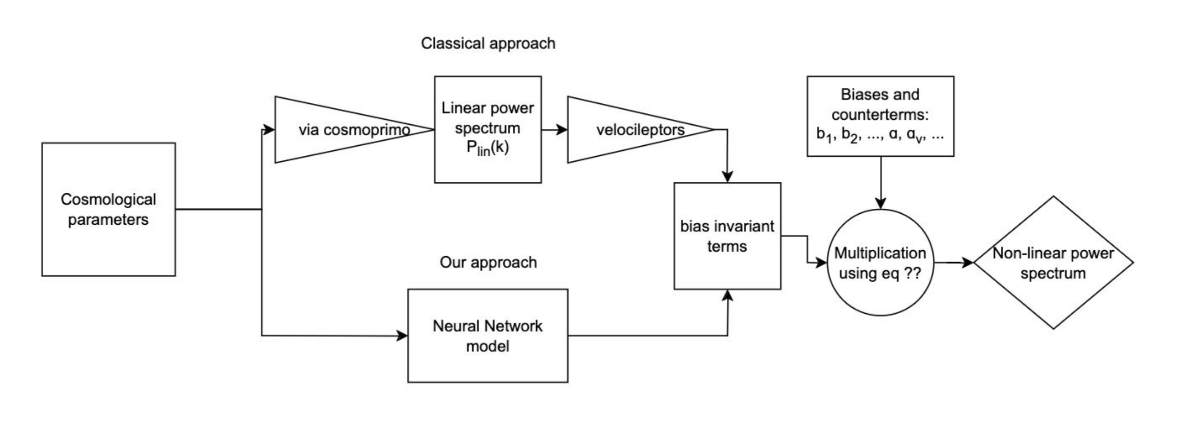
$$v_{12,i}(\mathbf{k}) = \int d^3\mathbf{q}\, e^{i\mathbf{k}\mathbf{q}} e^{-\frac{1}{2}k_ik_jA^{lin}_{ij}} \Big\{ ik_j\dot{A}_{ji} - \frac{1}{2}k_jk_k\dot{W}_{jki} +$$
$$+ 2b_1\left(\dot{U}_i - k_kU^{\rm lin}_k k_j\dot{A}^{\rm lin}_{ji} + k_j\dot{A}^{10}_{ji}\right) +$$
$$+ b_1^2\left(2ik_jU^{\rm lin}_j\dot{U}^{\rm lin}_i + i\xi_{\rm lin}k_j\dot{A}^{\rm lin}_{ji} + \dot{U}^{11}\right) +$$
$$+ b_2\left(\dot{U}^{20} + 2ik_jU^{\rm lin}_j\right) + 2b_1b_2\xi_{\rm lin}\dot{U}^{\rm lin}_i + 2b_s\left(\dot{V}^{10}_i + ik_j\dot{\Upsilon}_{ji}\right) +$$
$$+ 2b_1b_s\dot{V}^{12}_i + 2b_3U_{b_3,i} + \alpha_v k_i + \Big\} \dots + R_h^4\sigma_v$$

$$\sigma_{12,ij}(\mathbf{k}) = \int d^3\mathbf{q}\, e^{i\mathbf{k}\mathbf{q}} e^{-\frac{1}{2}k_ik_jA^{lin}_{ij}} \Big\{ \ddot{A}_{ij} + ik_n\ddot{W}_{nij} - k_nk_m\dot{A}^{\rm lin}_{ni}\dot{A}^{\rm lin}_{mj} +$$
$$+ b_1\left(2ik_nU^{\rm lin}_n\ddot{A}^{\rm lin}_{ij} + 2ik_n\left[\dot{A}^{\rm lin}_{ni}\dot{U}^{\rm lin}_j + \dot{A}^{\rm lin}_{nj}\dot{U}^{\rm lin}_i\right] + 2\ddot{A}^{10}_{ij}\right) +$$
$$+ b1^2\left(\xi_{\rm lin}\ddot{A}^{\rm lin}_{ij} + 2\dot{U}^{\rm lin}_i\dot{U}^{\rm lin}_j +\right) + 2b_s\ddot{\Upsilon}_{ij} +$$
$$+ \alpha_\sigma\delta_{ij} + \beta_\sigma\xi^2_{0,L}\left(\hat{q}_i\hat{q}_j - \frac{1}{3}\delta_{ij}\right) + \dots \Big\} + R_h^3s_v^2\delta_{ij} \quad (4)$$

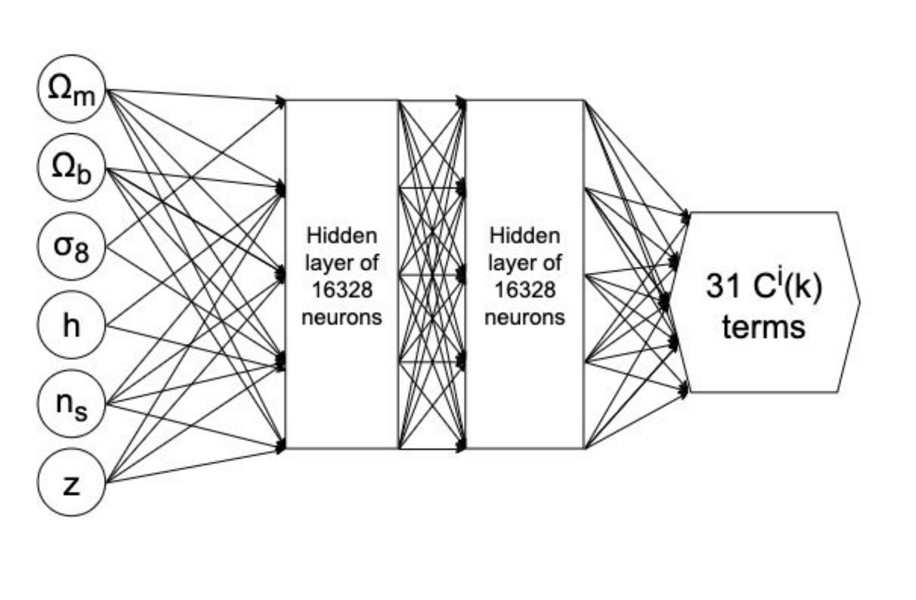
In total 31 terms which depend only on cosmology

$$\sigma_{ij} = \sigma_0(k)\delta_{ij} + \frac{3}{2}\sigma_2(k)\left(\hat{k}_i\hat{k}_j - \frac{1}{3}\delta_{ij}\right)$$

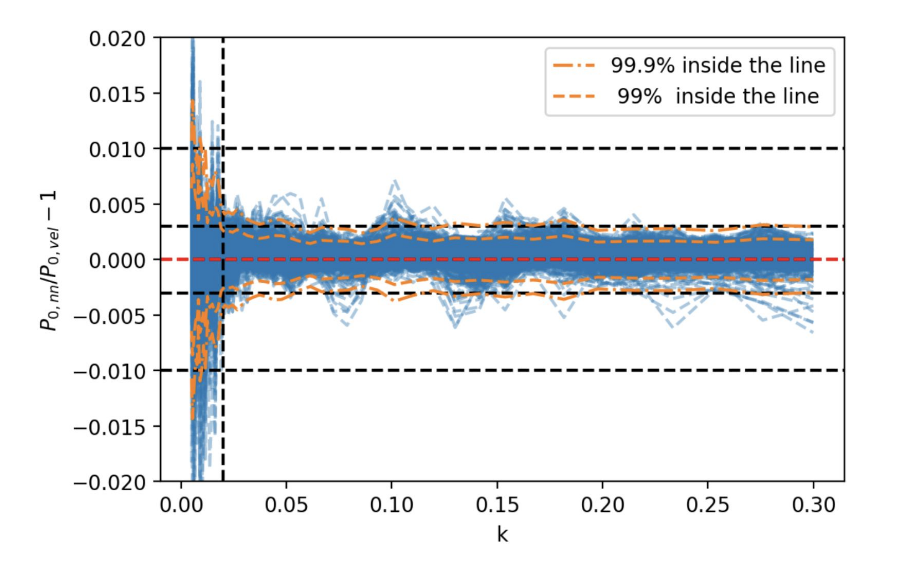
https://arxiv.org/pdf/2005.00523.pdf



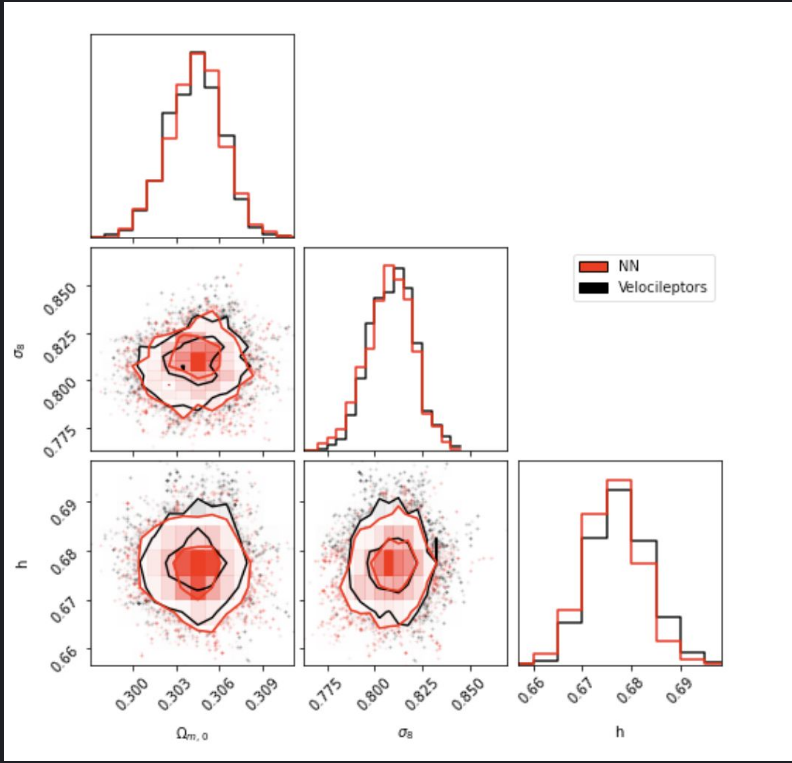
Classical approach
via cosmoprimo
Linear power spectrum $P_{lin}(k)$
velocileptors
Biases and counterterms: b_1, b_2, ..., α, α_v, ...
Cosmological parameters
bias invariant terms
Multiplication using eq ??
Non-linear power spectrum
Our approach
Neural Network model



Ω_m
Ω_b
σ_8
h
n_s
z
Hidden layer of 16328 neurons
Hidden layer of 16328 neurons
31 $C^i(k)$ terms

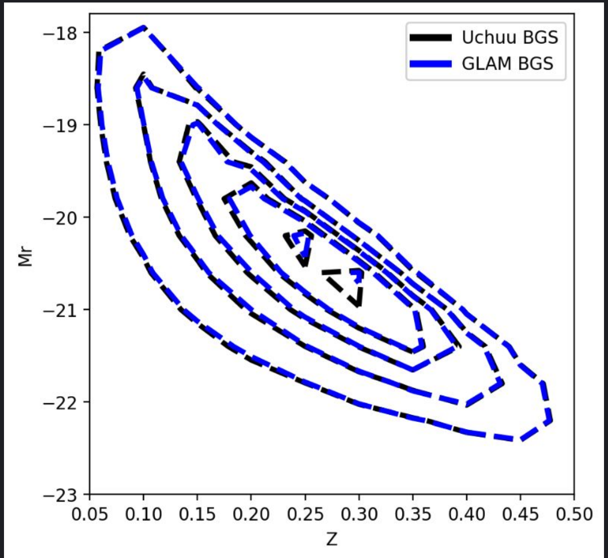


27 hours -> 5 minutes

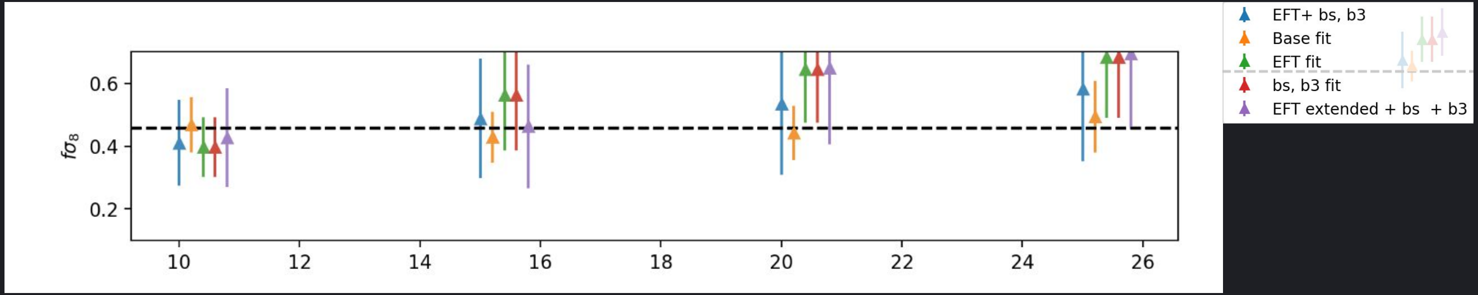


Other projects

- Production of the DESI-like GLAM mocks for BGS with inferred luminosities and colors



- Testing the theoretical systematics for BGS



Conclusions

- We have developed an approach which allows to circumvent the jackknife bias, and at the same time reduce the amount of mocks needed for the covariance matrix

- We have verified that multitracer analysis does indeed improve the precision up to 20%

- We have developed a NN-powered tool to speed up perturbation theory predictions, making computations faster by a factor of ~300, potentially allowing for previously too demanding analysis

Further plans

- Finish creation of the GLAM mocks
- Using the NN approach go further and use data from simulations and generalise to other theoretical frameworks

- Analyse DESI BGS Y1 data using the techniques developed (Full-modelling and multitracer analysis)

THANK YOU

It would be a pleasure to answer your questions!

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Main assumptions:

1) All covariance estimators try to estimate the same “true” covariance

2) The mock covariance is yielding the “true” unbiased covariance

3) We are focusing on the correlation function

Mohammad - Percival correction*

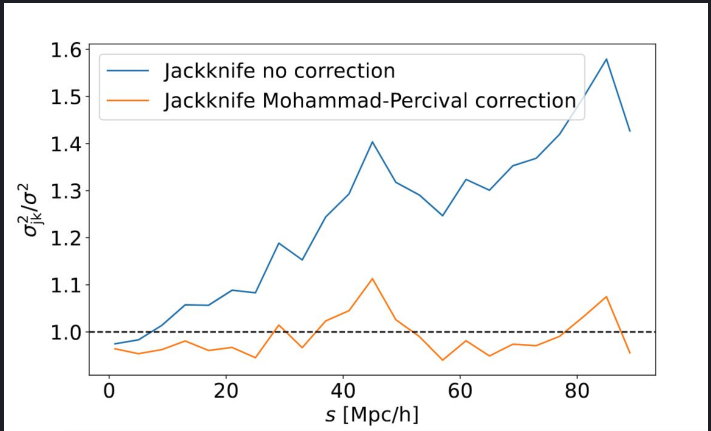
Consists in generalizing jackknife, and instead of deleting pair-counts, reweighting some of them by a fixed **α**

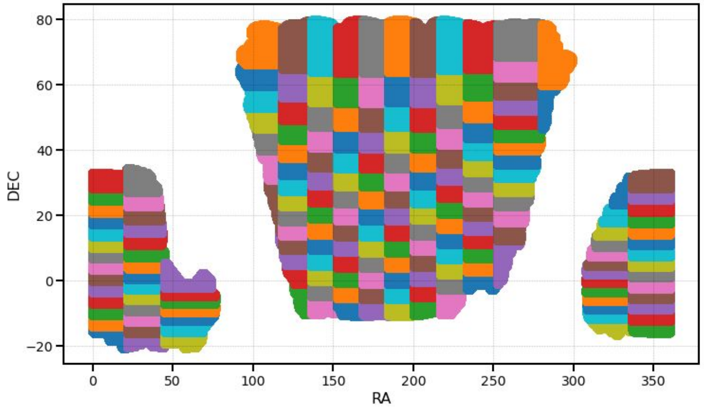
$AA_i = D_i D_i$ - pair-counts in the same region

$CC_i = \Sigma_{k \neq i} D_i D_k$ - pair-counts between the region and the rest of the survey

$DD_{total} = \Sigma_{k,i} D_i D_k$ - total paircounts of the survey

TT_i - total paircounts from the jackknife realization





Standard $TT_i = DD_{total} - AA_i - 2CC_i$

Mohammad and Percival: $TT_i = DD_{total} - AA_i - 2\alpha CC_i$

*Mohammad & Percival (2021) arXiv:2109.07071

$\bar{\theta}_{a,c}$ - normalized region counts estimator (a - auto, c - cross)

$TT_i = DD_{total} - AA_i - 2\alpha CC_i$

$$\theta_{a,i} = \frac{1}{n_{jk} - 1}(n_{jk}\overline{AA} - AA_i)$$

$$\theta_{c,i} = \frac{2}{n_{jk} - 2\alpha}(\frac{n_{jk}}{2}\overline{CC} - \alpha CC_i)$$

We will discuss this term later

$$Cov(TT_k, TT_k) = [Cov(CC, CC) + Cov(AA, AA) + 2Cov(AA, CC)]$$

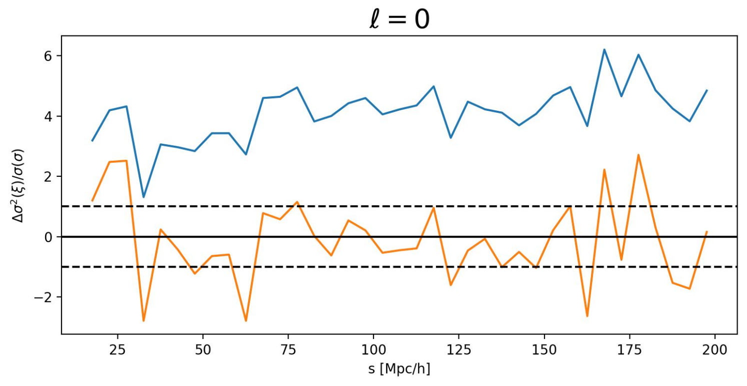
$$cov(AA, AA) = \frac{N_{jk} - 1}{N_j k} \sum_{k=1}^{N_{jk}} \left(\theta_{a,k} - \bar{\theta}_a\right)^2$$

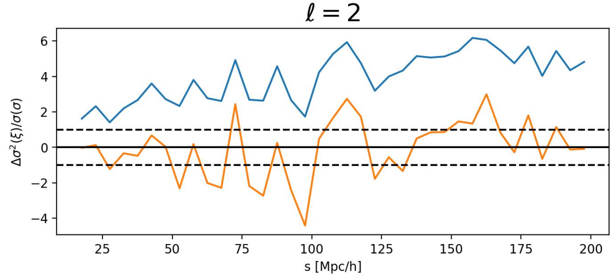
$$cov(CC, CC) = \frac{(N_{jk} - 2\alpha)^2}{2\alpha^2 N_{jk}(N_{jk} - 1)} \sum_{k=1}^{N_{jk}} \left(\theta_{c,k} - \bar{\theta}_c\right)^2$$

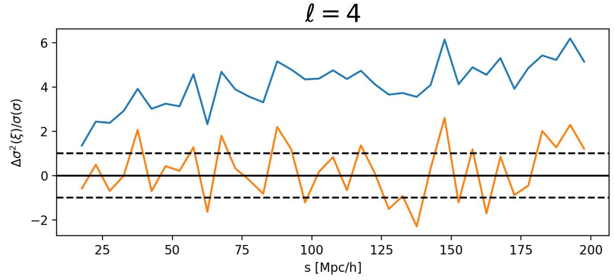
Fixed by $\alpha = \frac{N_{jk}}{2 + \sqrt{2}(N_{jk} - 1)}$

*More details in Mohammad & Percival (2021) arXiv:2109.07071

Random catalogues







no correction:

$$\alpha = 1$$

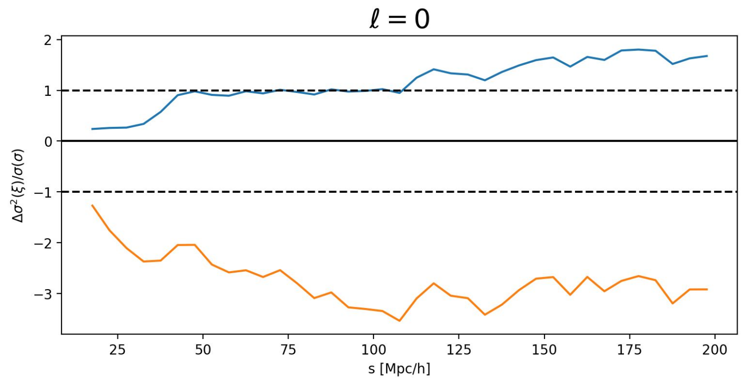
MP correction:

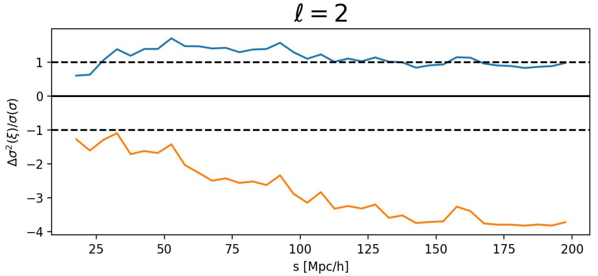
$$\alpha = \frac{n_{jk}}{\left(2 + \sqrt{2}(n_{jk} - 1)\right)}$$

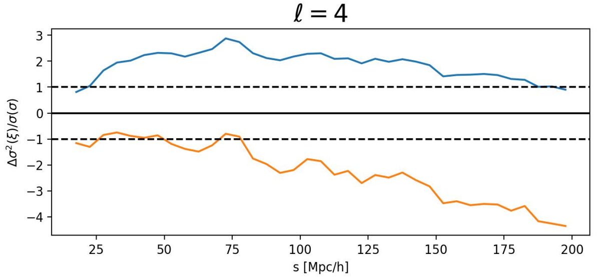
Bias measure:

$$\Delta\sigma(\xi_\ell)/\sigma(\sigma) = \frac{\sigma_{jk}(\xi_\ell) - \sigma_{mock}(\xi_\ell)}{\sigma[\sigma_{mock}(\xi_\ell))]}$$

BOSS DR12 mocks







Log-normal mocks

3 sets of **1500** mocks:

nbar: 2×10^{-4}, 5×10^{-4}, 15×10^{-4}

Box size: $(2\ \mathrm{Gpc}/h)^3$

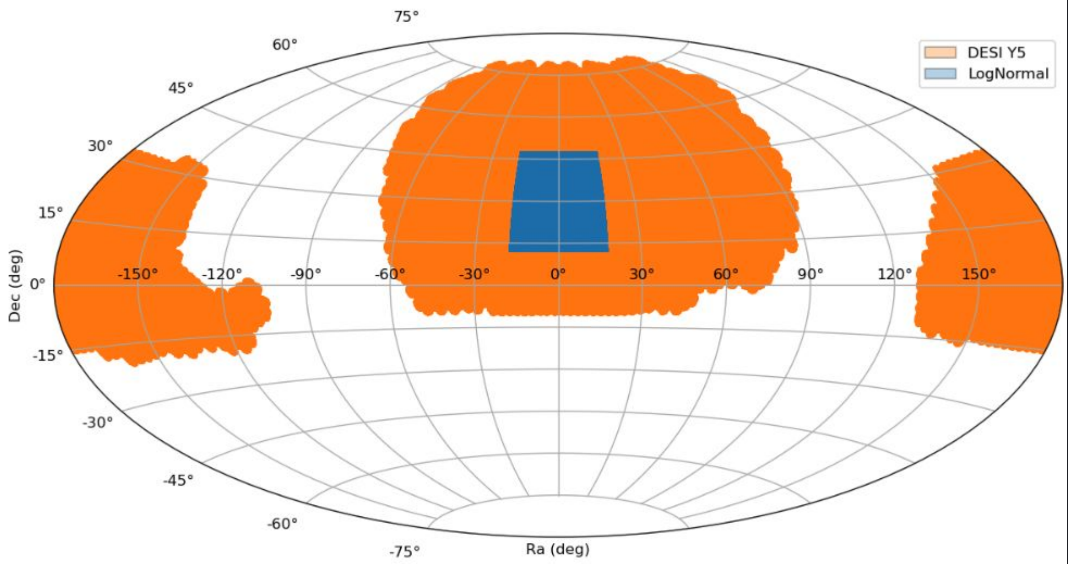
Grid size: $(512)^3$

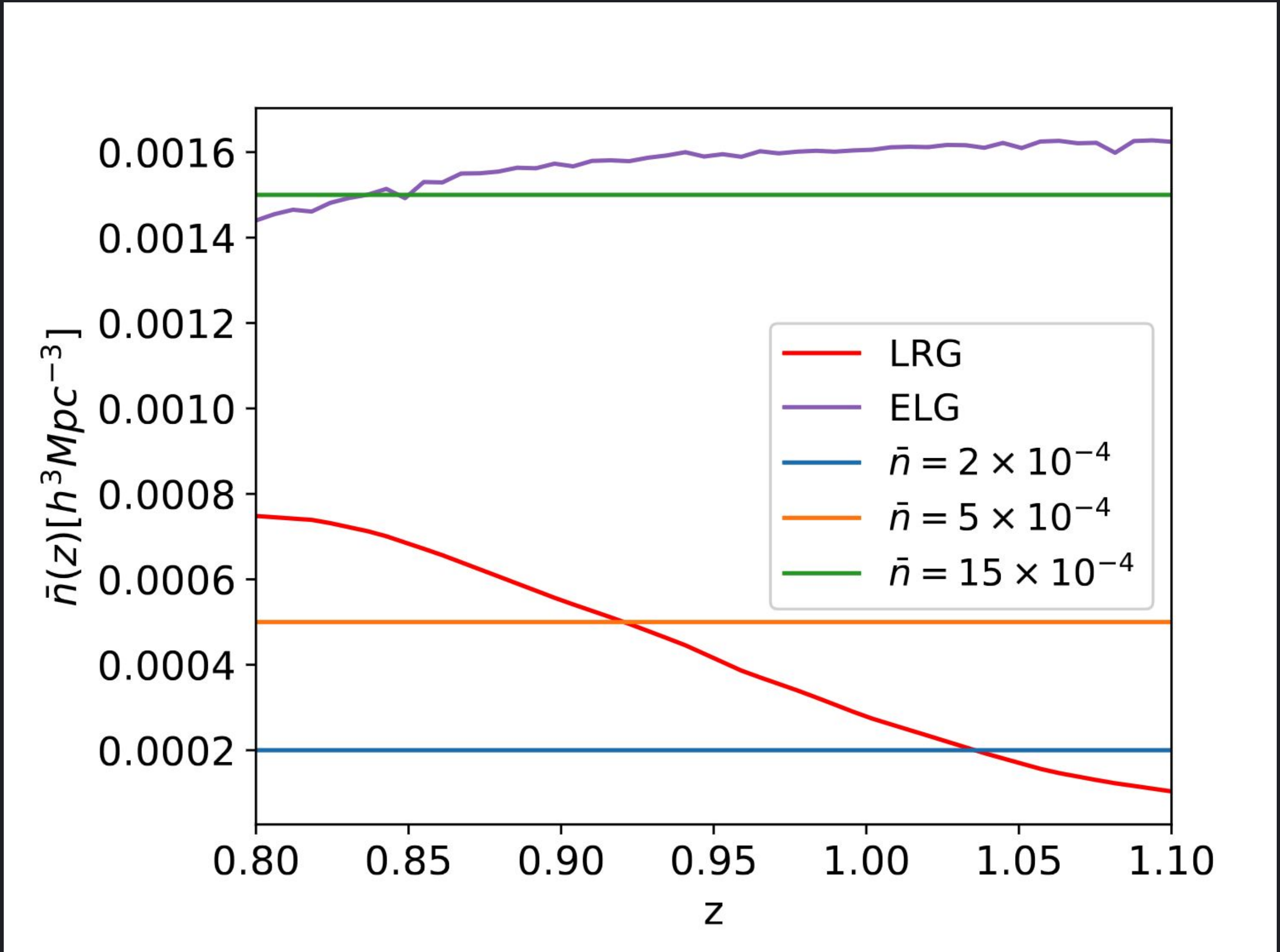
Initial redshift: $z=1$

Redshift range: $0.8 < z < 1.1$

1) Higher precision
2) Closer to DESI

Produced with **mockfactory**
(https://github.com/cosmodesi/mockfactory)





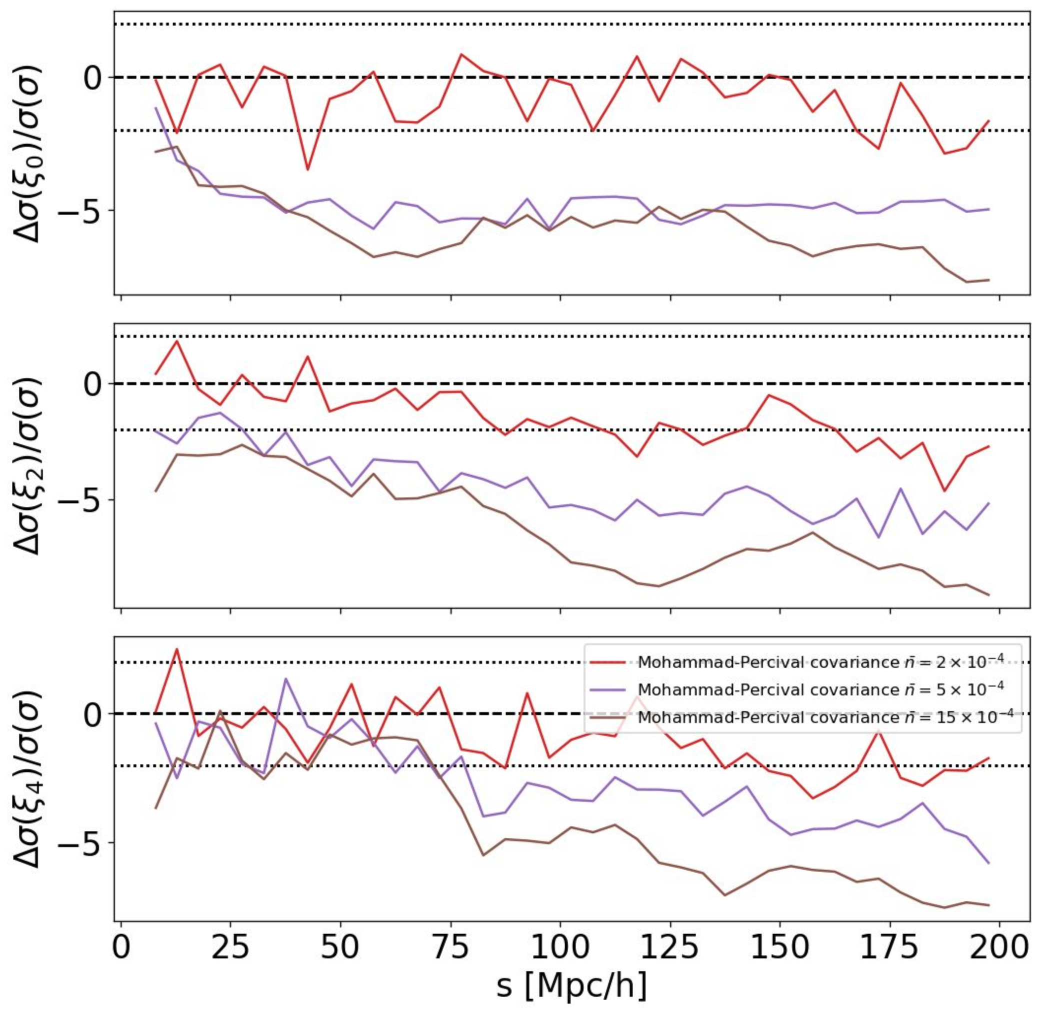
0.0016
0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
$\bar{n}(z)[h^3 Mpc^{-3}]$
0.80
0.85
0.90
0.95
1.00
1.05
1.10
z
LRG
ELG
$\bar{n} = 2 \times 10^{-4}$
$\bar{n} = 5 \times 10^{-4}$
$\bar{n} = 15 \times 10^{-4}$

Jackknife with Mohammad and Percival correction.

Bias measure:

$$\Delta\sigma(\xi_\ell)/\sigma(\sigma) = \frac{\sigma_{jk}(\xi_\ell) - \sigma_{mock}(\xi_\ell)}{\sigma[\sigma_{mock}(\xi_\ell))]}$$

uncertainty on mock covariance matrix computed using jackknife



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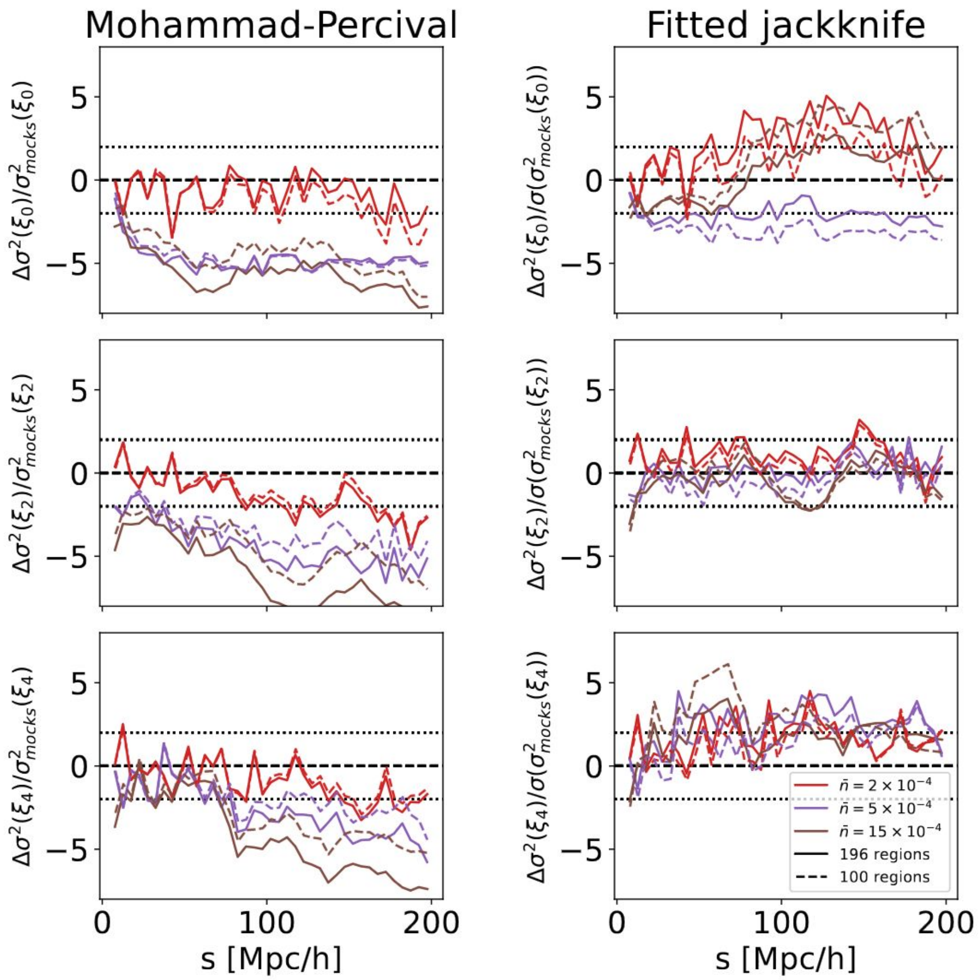
$$cov(CC, CC) = \frac{(N_{jk} - 2\alpha)^2}{2\alpha^2 N_{jk}(N_{jk} - 1)} \sum_{k=1}^{N_{jk}} \left(\theta_{c,k} - \bar{\theta}_c\right)^2$$

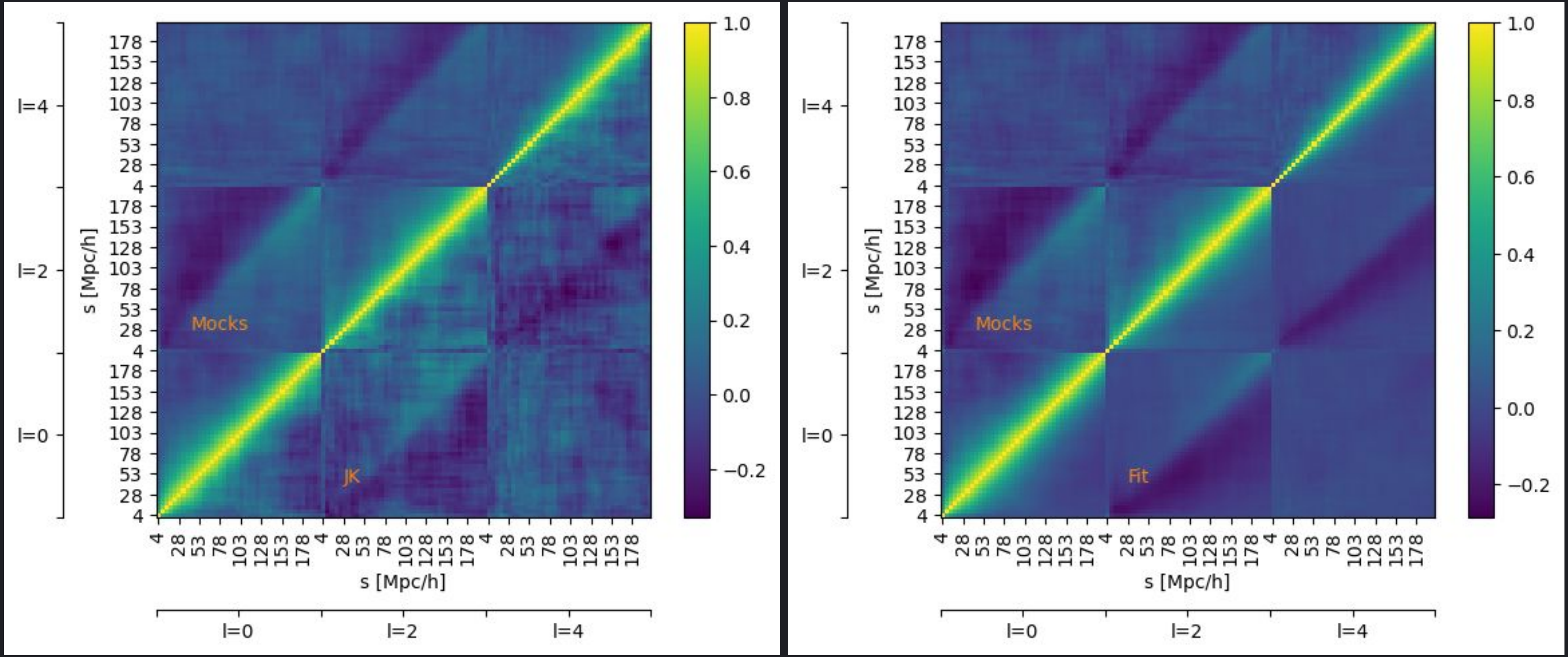
Fixed by $\alpha = \frac{N_{jk}}{2 + \sqrt{2}(N_{jk} - 1)}$

$$cov(CC, AA) = \frac{(N_{jk} - 1)(N_{jk} - \alpha)}{2\alpha N_{jk}} \sum_{k=1}^{N_{jk}} \left(\theta_{c,k} - \bar{\theta}_c\right)\left(\theta_{a,k} - \bar{\theta}_a\right)$$

left unfixed



Mohammad-Percival
Fitted jackknife
$\Delta\sigma^2(\xi_0)/\sigma^2_{mocks}(\xi_0)$
$\Delta\sigma^2(\xi_0)/\sigma(\sigma^2_{mocks}(\xi_0))$
$\Delta\sigma^2(\xi_2)/\sigma^2_{mocks}(\xi_2)$
$\Delta\sigma^2(\xi_2)/\sigma(\sigma^2_{mocks}(\xi_2))$
$\Delta\sigma^2(\xi_4)/\sigma^2_{mocks}(\xi_4)$
$\Delta\sigma^2(\xi_4)/\sigma(\sigma^2_{mocks}(\xi_4))$
s [Mpc/h]
s [Mpc/h]
$\bar{n} = 2 \times 10^{-4}$
$\bar{n} = 5 \times 10^{-4}$
$\bar{n} = 15 \times 10^{-4}$
196 regions
100 regions


Mocks
JK
Mocks
Fit
s [Mpc/h]
l=0
l=2
l=4

Cosmological parameter uncertainty

We have:

1500 lognormal mocks

We can obtain:

1500 independent jackknife covariances

30 independent x50 fit covariances

1 mock-based covariance

So we make 1500 fits:

Jackknife covariance: 50 mocks x 30 covs = 1500 fits

Fit covariance: 50 mocks x 30 covs = 1500 fits

Mock covariance: 1500 mocks x 1 cov = 1500 fits - covariance is produced from 1500 mocks

Fitting from 30 to 150 Mpc/h in bins of 5 Mpc/h

Iminuit used (for computational reasons)

Two main features to look at:

1) The value of the parameter estimated

2) The uncertainty on the parameter estimated

Results on cosmological fits

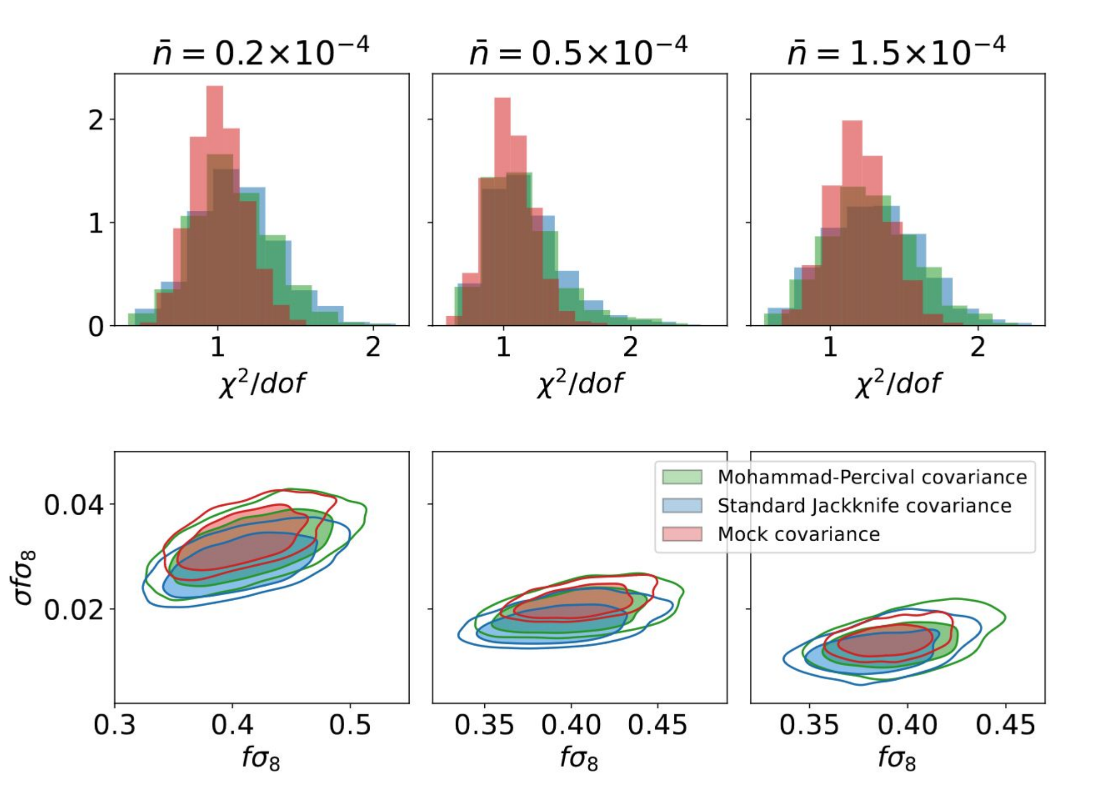
Setup:

1500 fits from each of the methods

MP covariance: 50 mocks x 30 covs = 1500 fits

Standard jackknife: 50 mocks x 30 covs = 1500 fits

Mock covariance: 1500 mocks x 1 cov = 1500 fits - covariance is produced from 1500 mocks



Results on cosmological fits

Setup:

1500 fits from each of the methods

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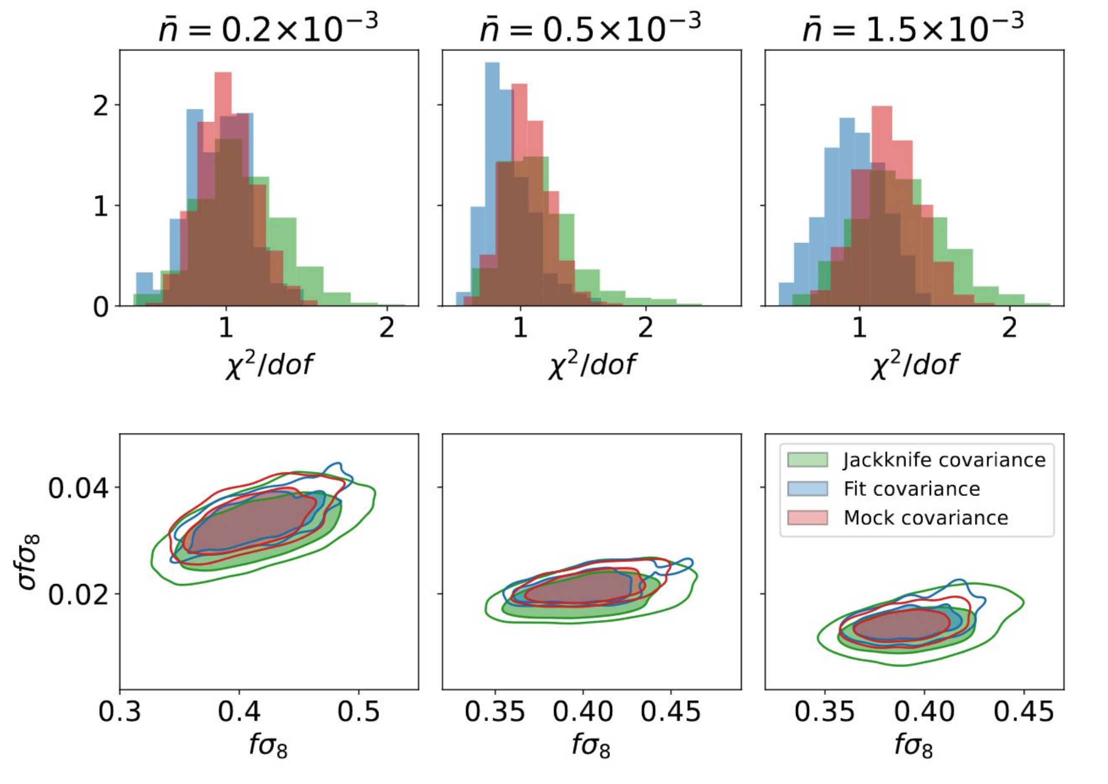
Fitting from 30 to 150 Mpc/h in bins of 5 Mpc/h



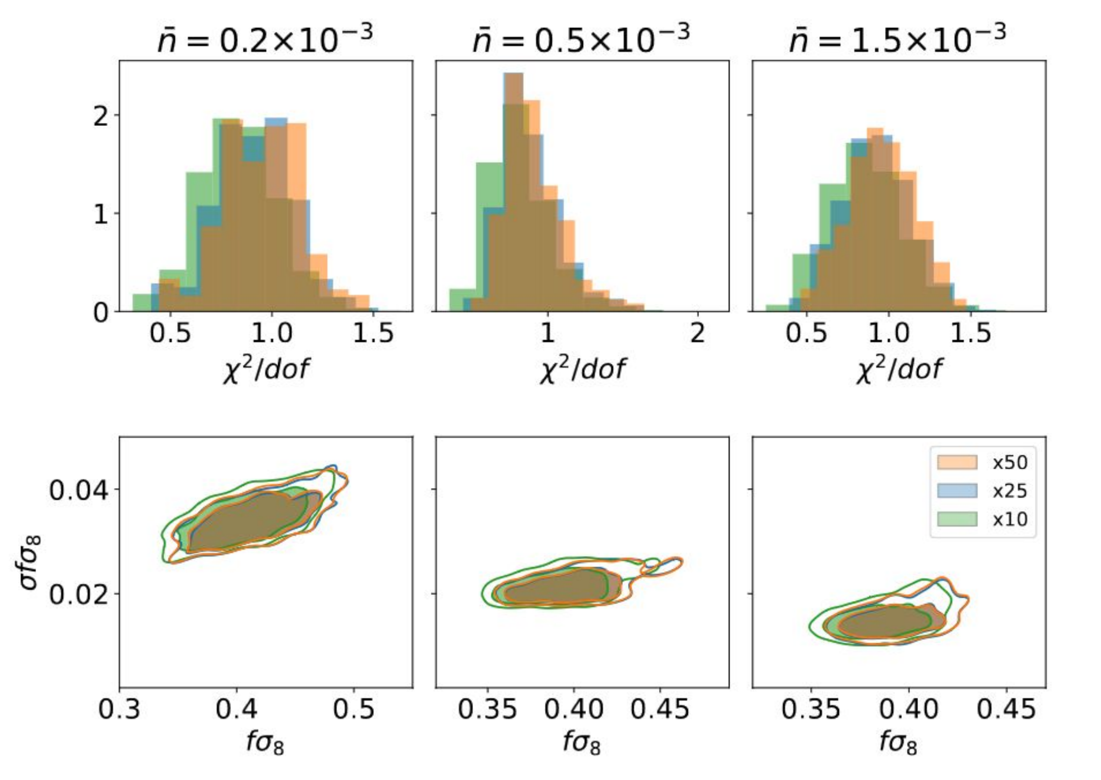
Conclusions: Fit covariance and Mock covariance perform in a very similar way, while Jackknife covariance gives twice bigger contours.

Results on cosmological fits

Setup:

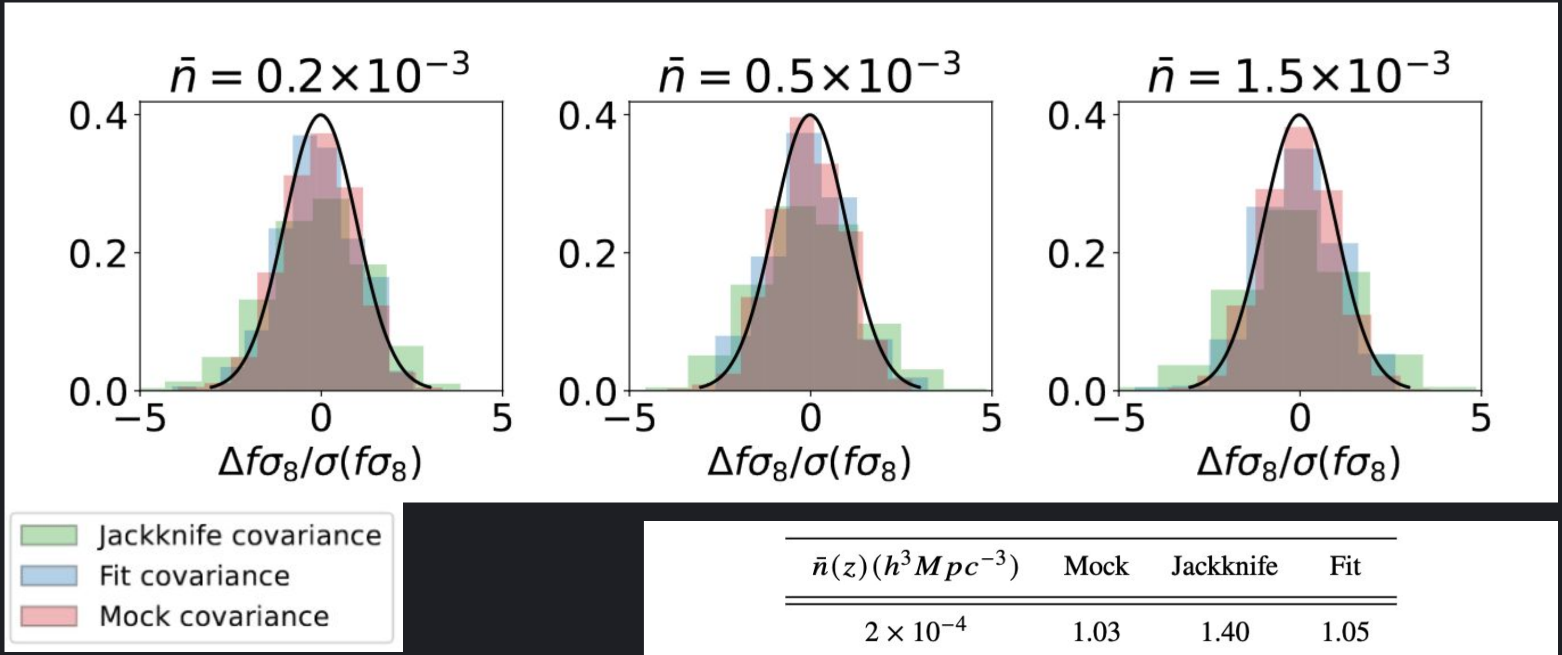
1500 fits from each of the methods

Fit covariance: 50 mocks x 30 covs = 1500 fits



Conclusions: Fit covariance x10 starts deviating from the x50, but x25 is still performing well

Pull distributions



$\bar{n}(z)(h^3Mpc^{-3})$	Mock	Jackknife	Fit
2×10^{-4}	1.03	1.40	1.05
5×10^{-4}	0.99	1.42	1.05
15×10^{-4}	1.00	1.56	1.08

standard deviation

EZ mocks (ELG, LRG)

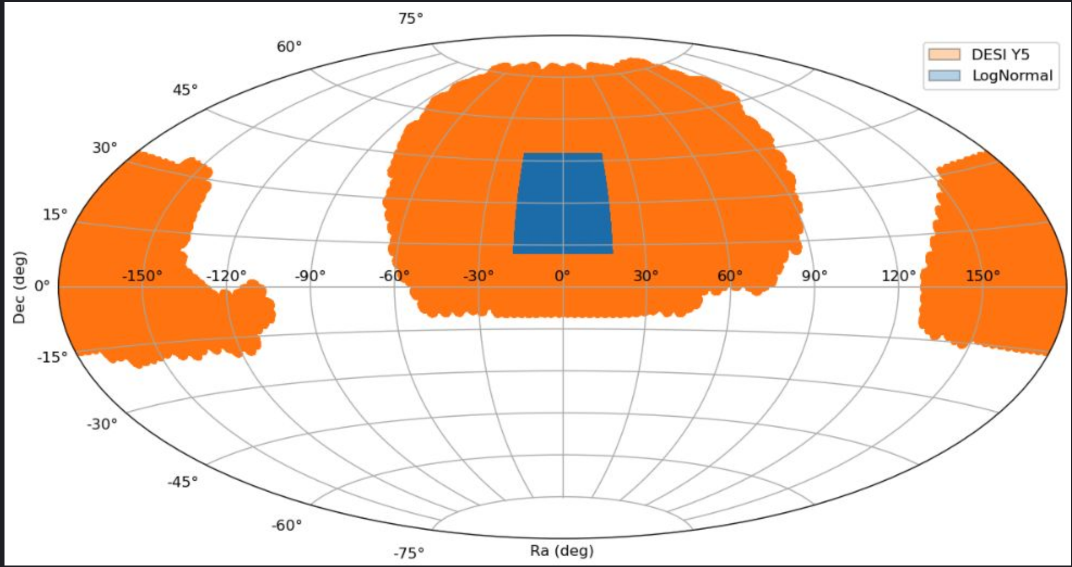
2 sets of **1000** EZ mocks:
LRG and ELG

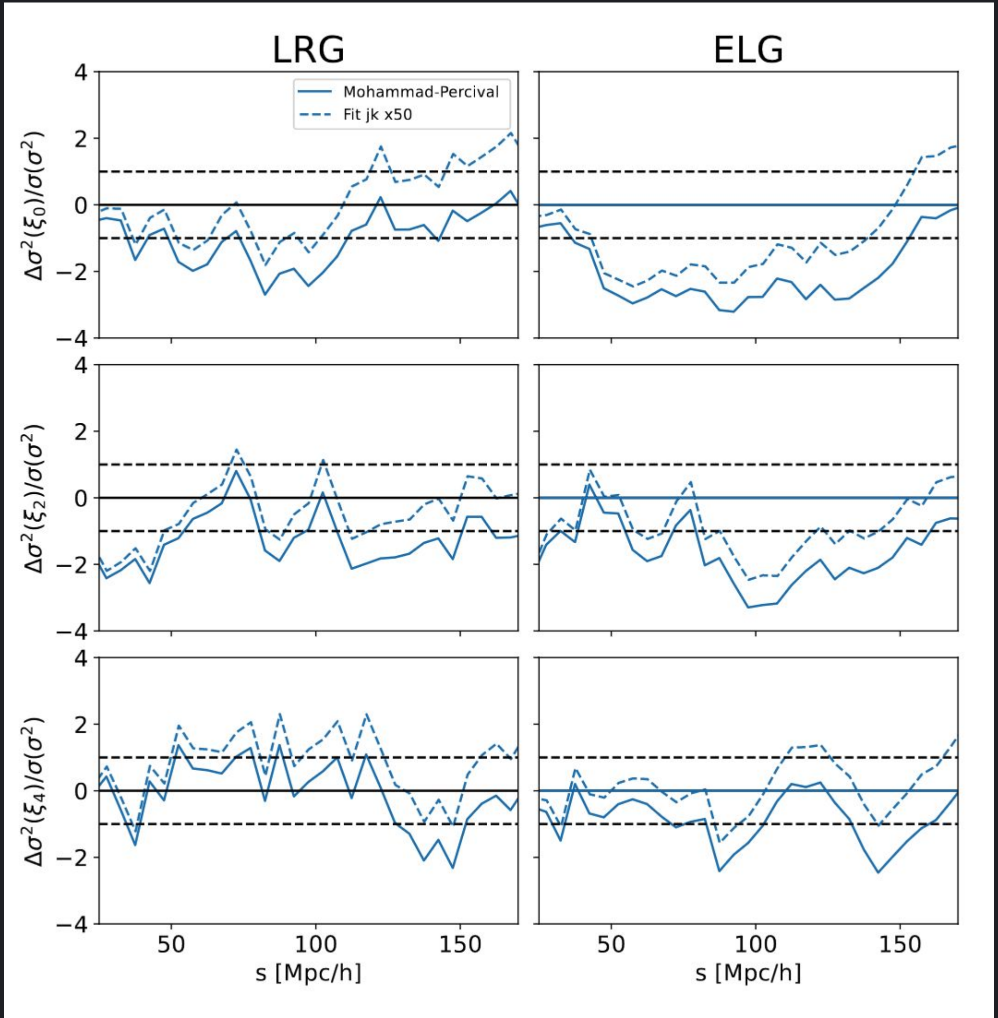
Box size: (6 Gpc/h)^3

Box redshift: 0.8/1.1 (LRG/ELG)
Redshift range: [0.8, 1.1]

DESI Y5 footprint

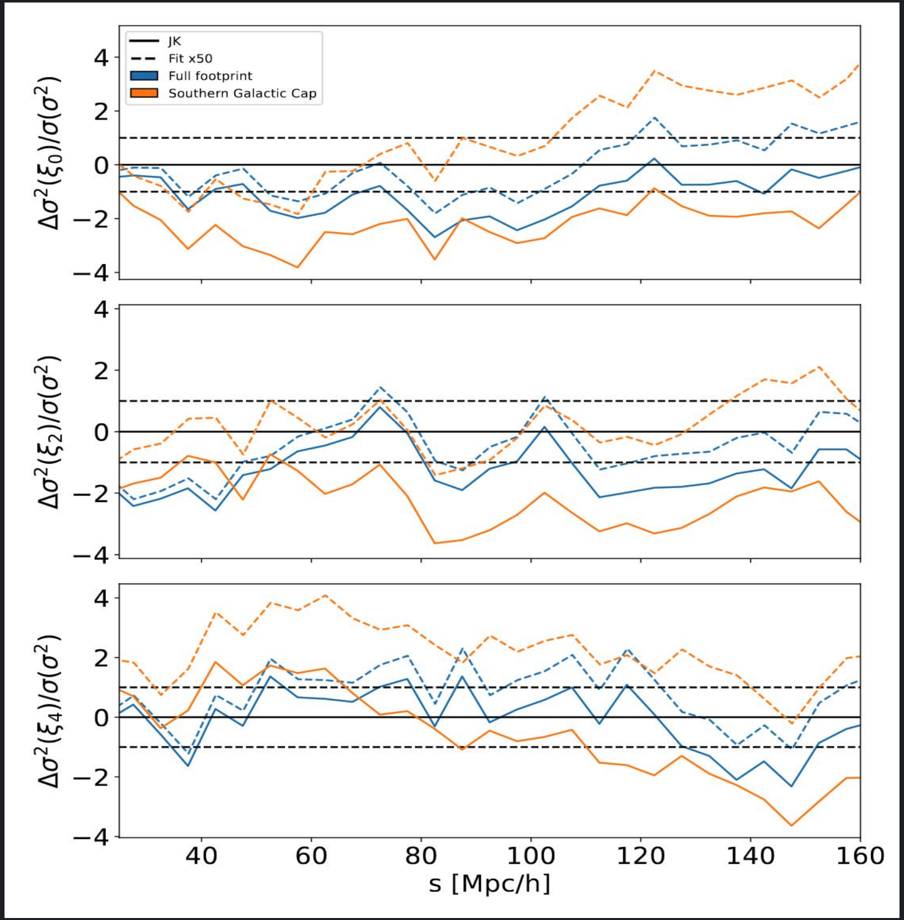
Credits to Cheng Zhao





LRG
ELG
Mohammad-Percival
Fit jk x50
$\Delta\sigma^2(\xi_0)/\sigma(\sigma^2)$
$\Delta\sigma^2(\xi_2)/\sigma(\sigma^2)$
$\Delta\sigma^2(\xi_4)/\sigma(\sigma^2)$
s [Mpc/h]
s [Mpc/h]

LRG only



JK
Fit x50
Full footprint
Southern Galactic Cap
$\Delta\sigma^2(\xi_0)/\sigma(\sigma^2)$
$\Delta\sigma^2(\xi_2)/\sigma(\sigma^2)$
$\Delta\sigma^2(\xi_4)/\sigma(\sigma^2)$
4
2
0
−2
−4
40
60
80
100
120
140
160
s [Mpc/h]

Results on cosmological fits

Setup:

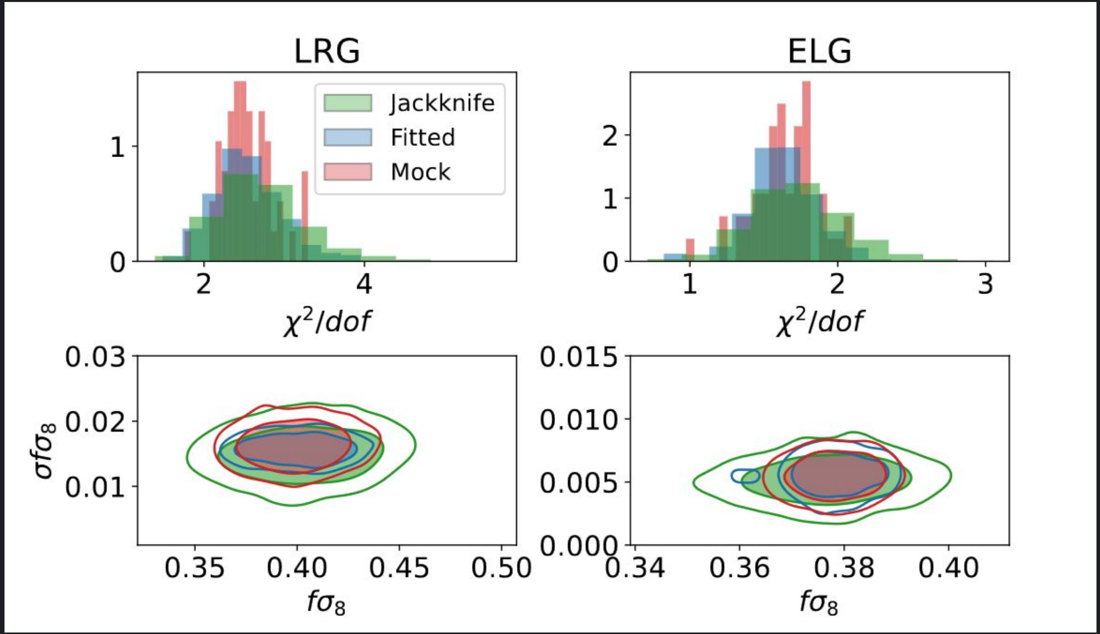
1000 fits from each of the methods

Jackknife covariance: 50 mocks x 20 covs = 1000 fits

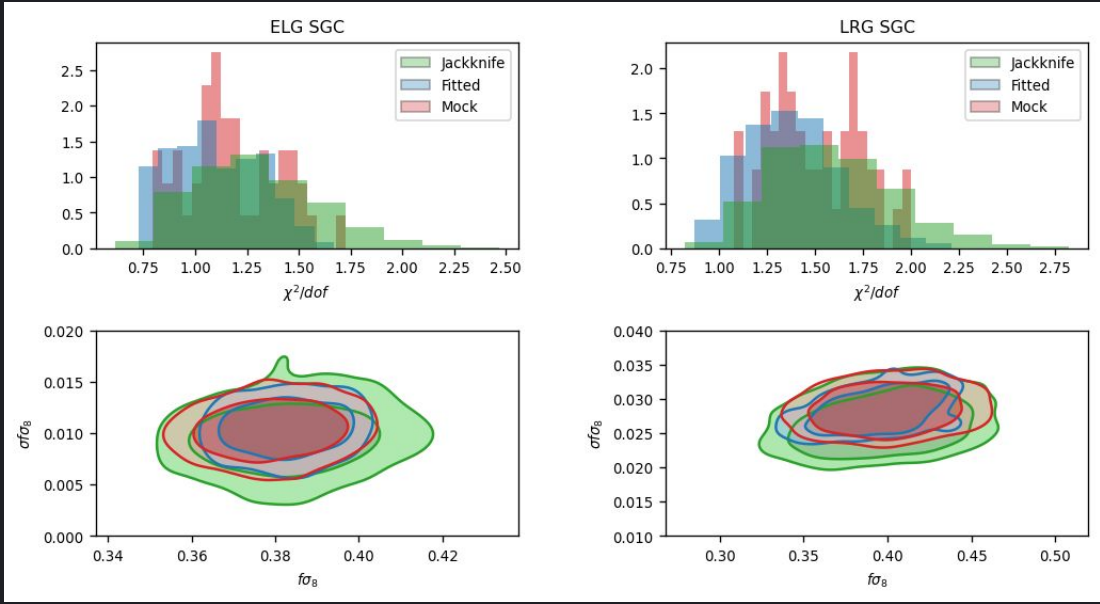
Fit covariance: 50 mocks x 20 covs = 1000 fits

Mock covariance: 1000 mocks x 1 cov = 1000 fits - covariance is produced from 1000 mocks

Fitting from 30 to 150 Mpc/h in bins of 5 Mpc/h



Results on cosmological fits



Setup:

1000 fits from each of the methods

Jackknife covariance: 50 mocks x 20 covs = 1000 fits

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Fitting from 30 to 150 Mpc/h in bins of 5 Mpc/h

Conclusions: Fit covariance and Mock covariance perform in a very similar way, while Jackknife covariance gives twice bigger contours.

Abacus Cutsky mocks using Y5 footprint

Z-bin	Effective redshift
0.1-0.2	0.16
0.2-0.3	0.25
0.3-0.4	0.35
0.4-0.5	0.43

Magnitude cut: r < 19.5

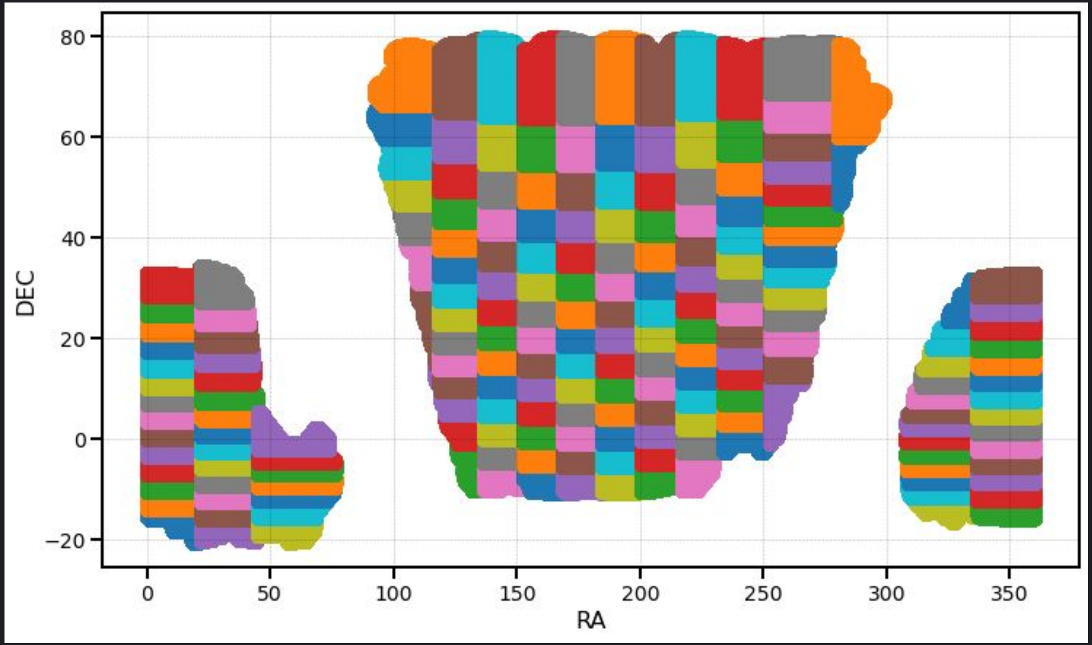
196 jackknife regions
Mohammad and Percival correction used
(arxiv.org:2109.07071)

Fitting from 32 Mpc/h to 144 Mpc/h in bins of 8 Mpc/h

Bayesian inference via MCMC

x20 randoms

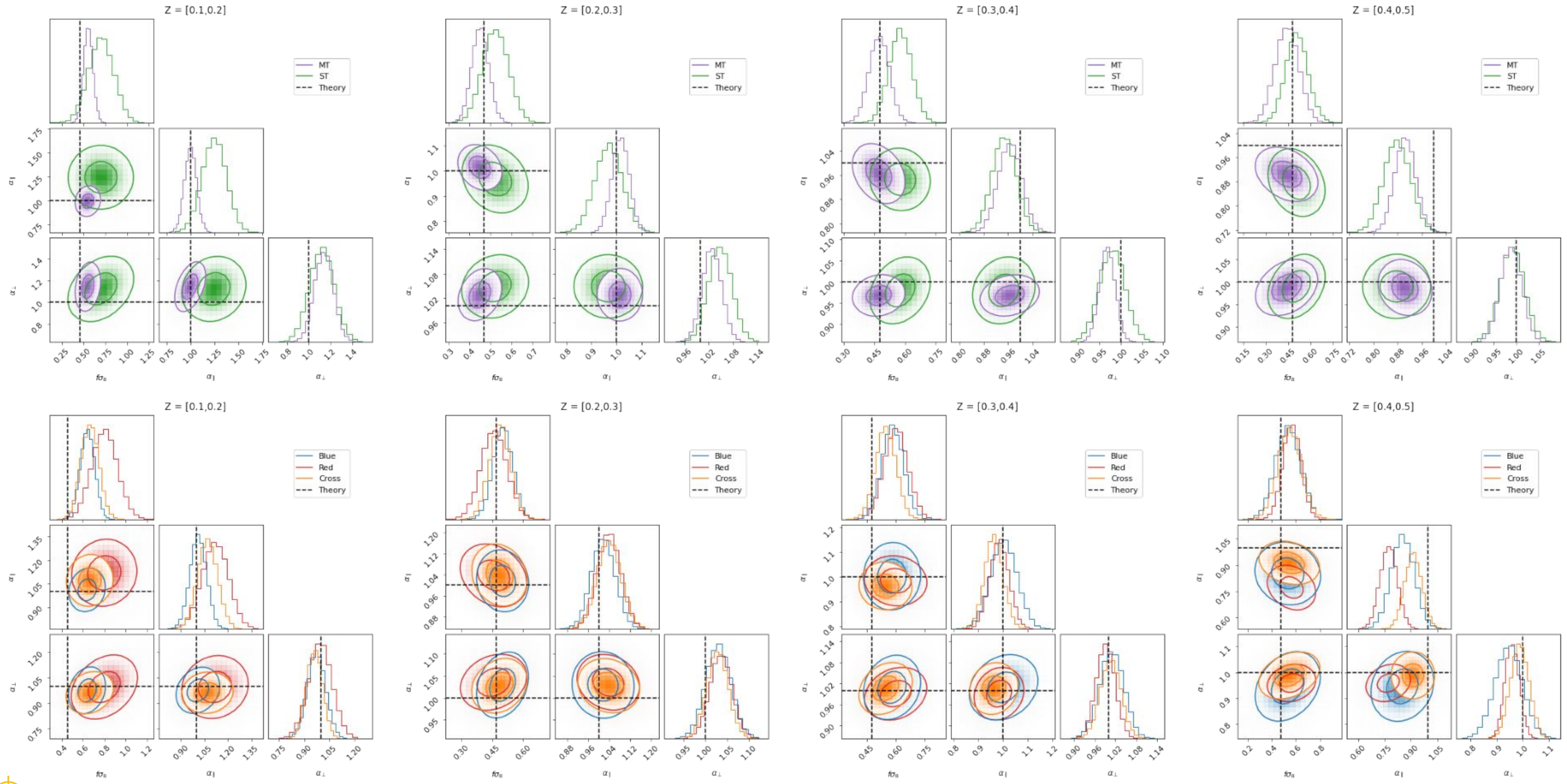
FirstGen mocks

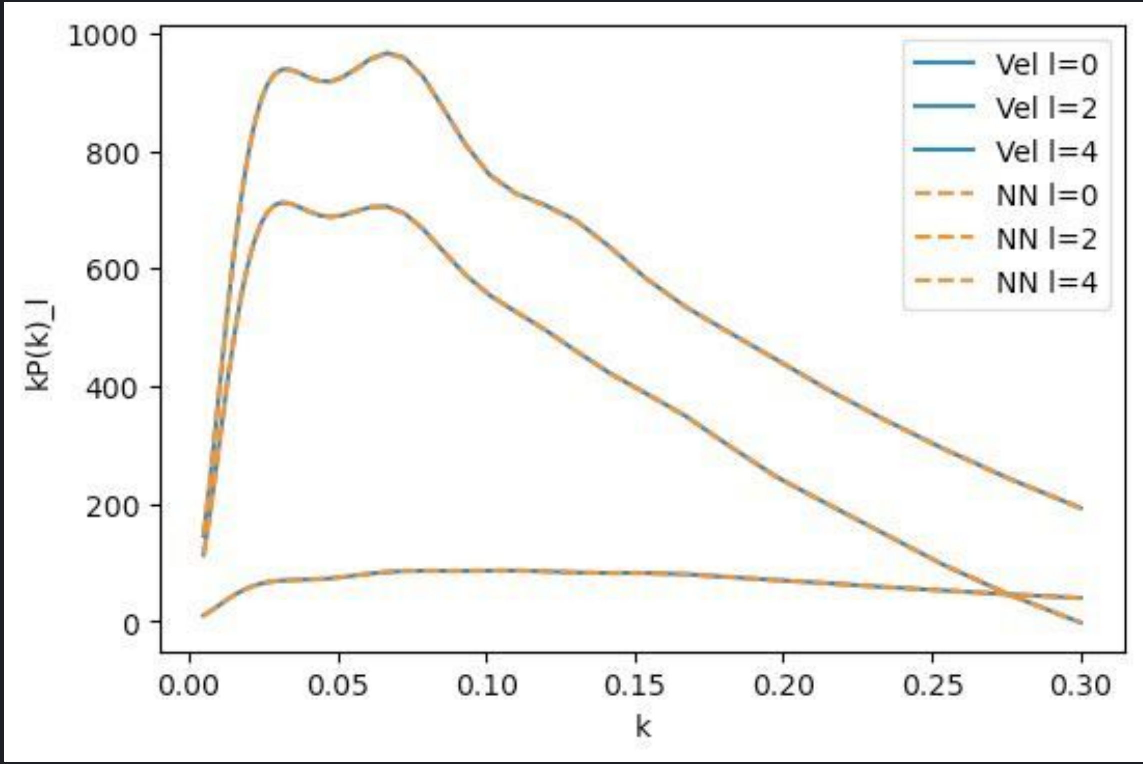


h = 0.674, sigma8 = 0.8159, Omega_m = 0.308

Planck 2018 cosmology

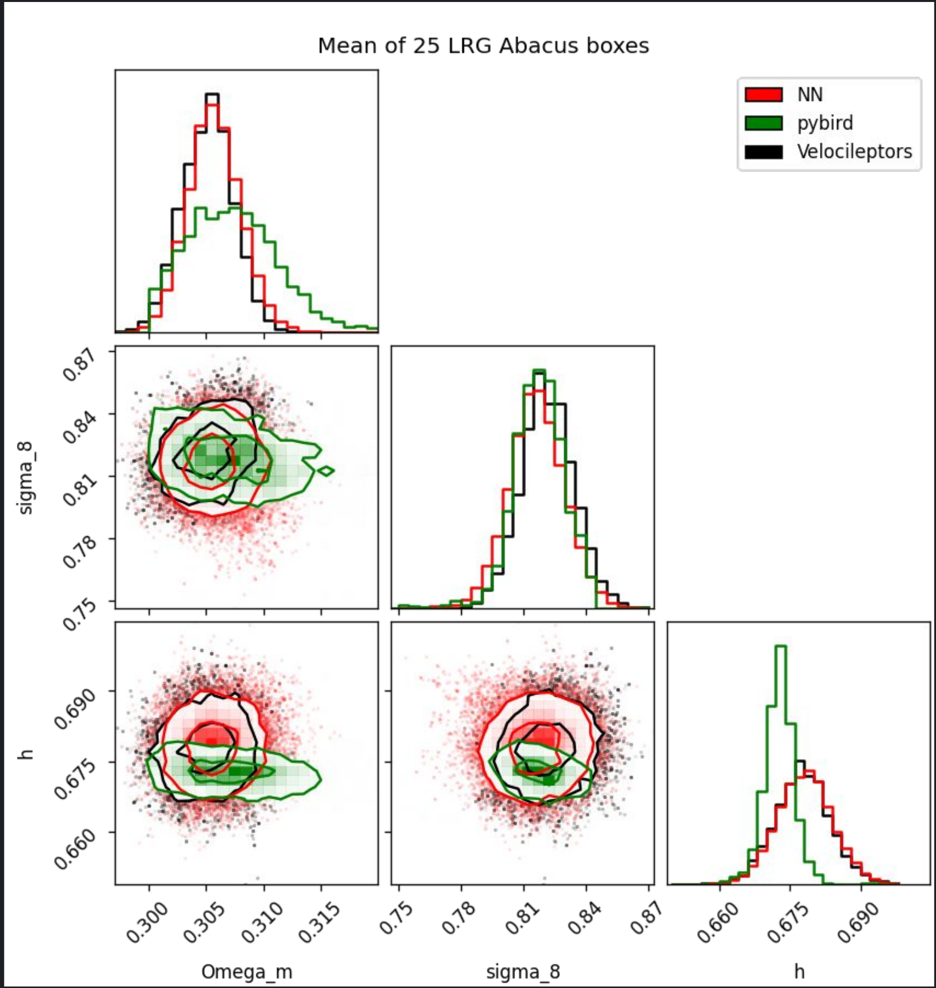
7 mocks 17 mocks 25 mocks 25 mocks





x320 times faster

Performance: huge gain in computational time for similar precision (see next slide)



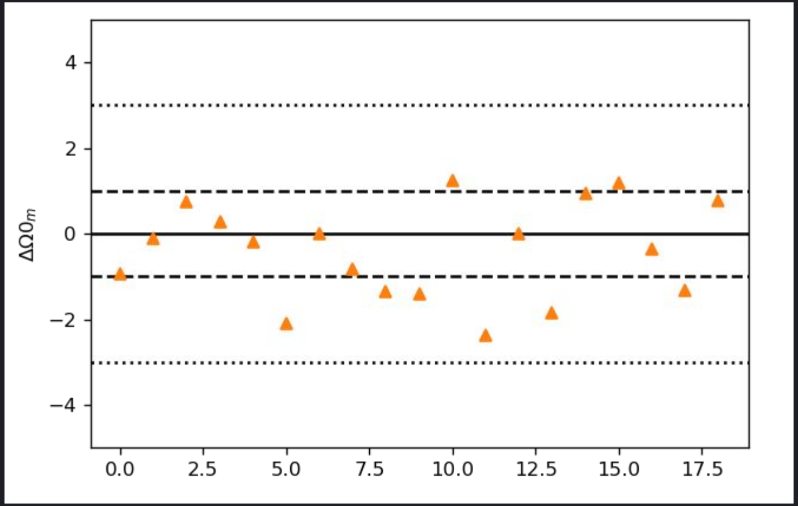
Fitting in s=[25,150]

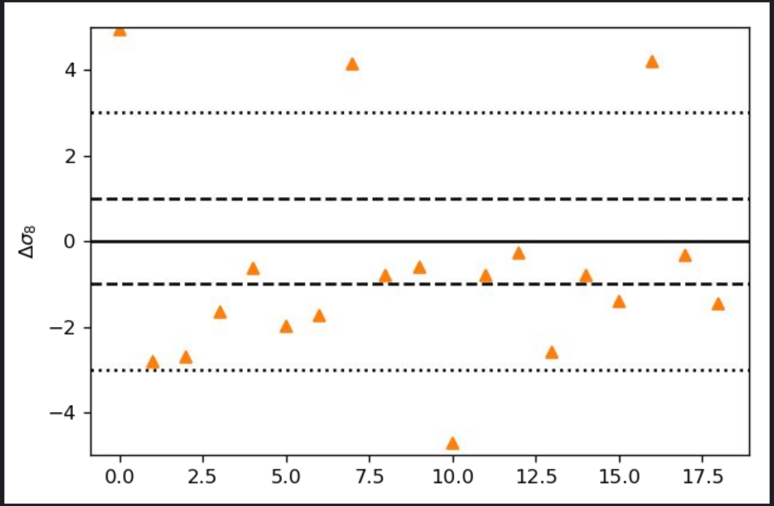
Omega0_m,sigma8,h

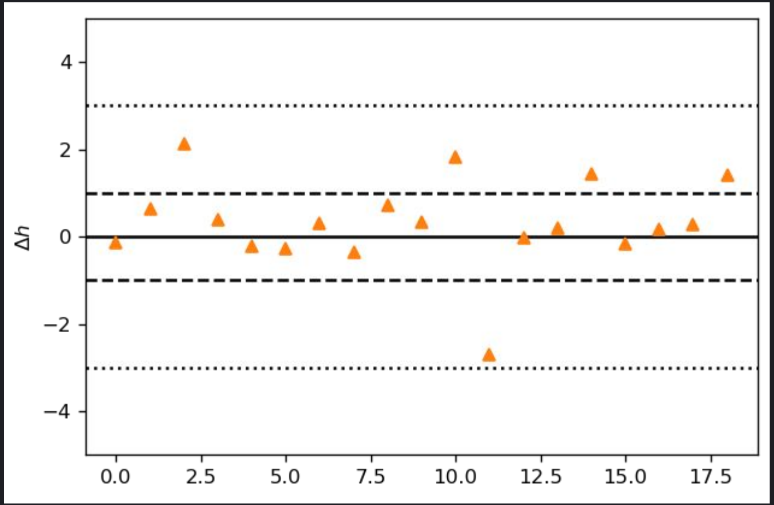
NN/Velocileptors:
b1,b2,alpha,alpha_v,c3,sv

Pybird:
b1,b2,alpha0,alpha1,alpha2,
alpha3,sv

N_s = 0.9625,
Omega0_b=0.049

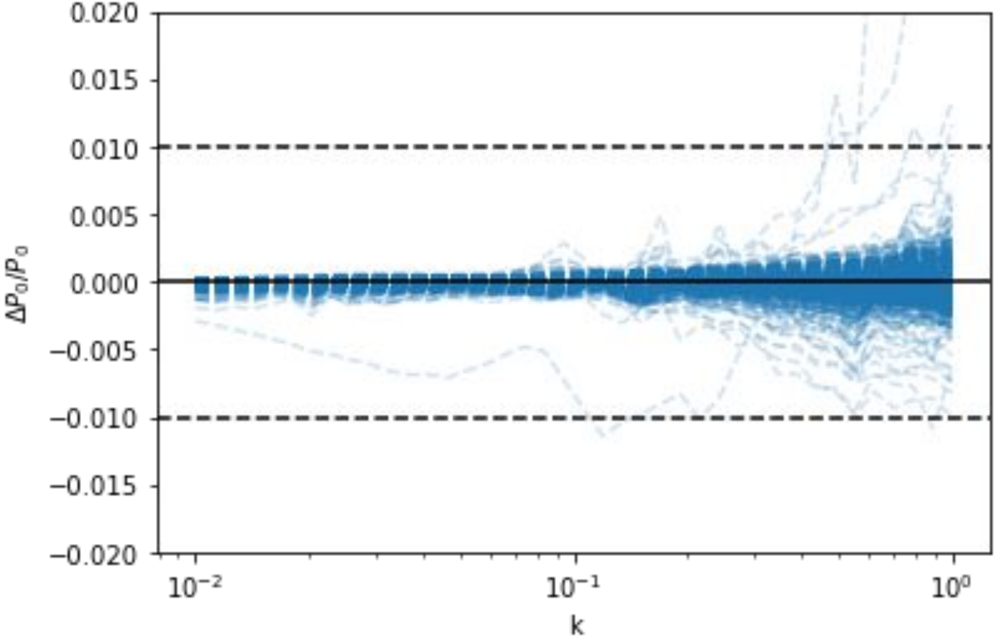






25 LRG Abacus boxes

LPT RSD tests to ensure the approach perspectives



Features of the GLAM-BGS lightcones:

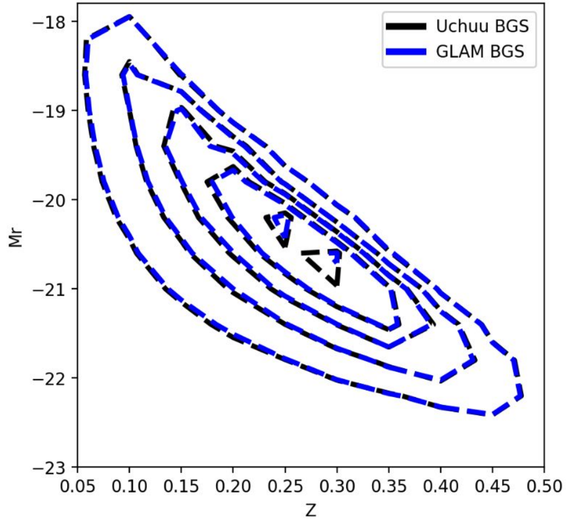
1) Based on GLAM E1

2) Clustering evolution is present

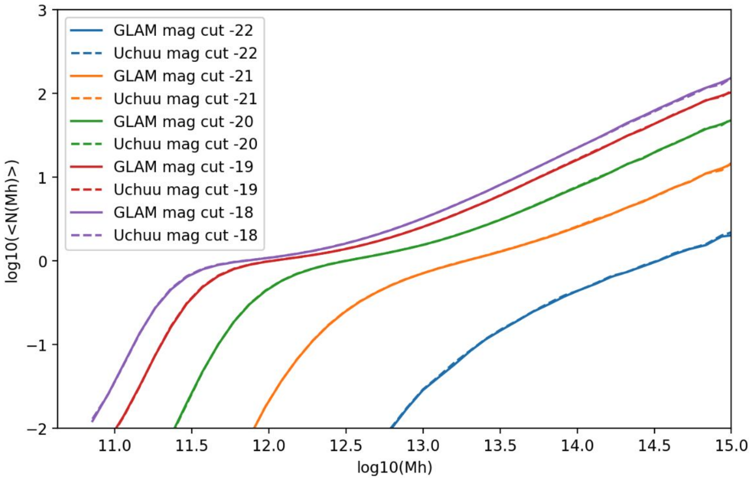
3) Color, absolute and apparent magnitudes, other properties are present

4) Lightcone represents BGS up to mag < 20.0

5) All the tests are done on the fullsky

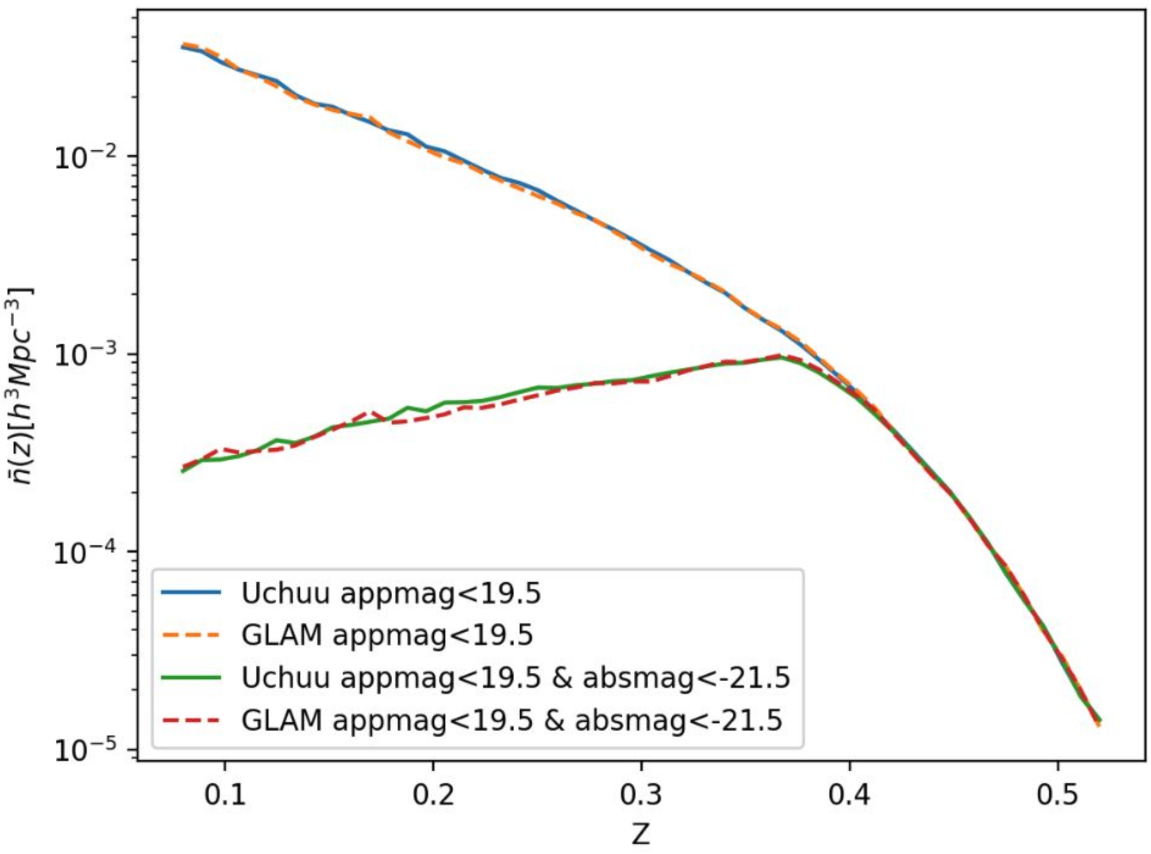


$^{0.1}M_r^h$ vs. z

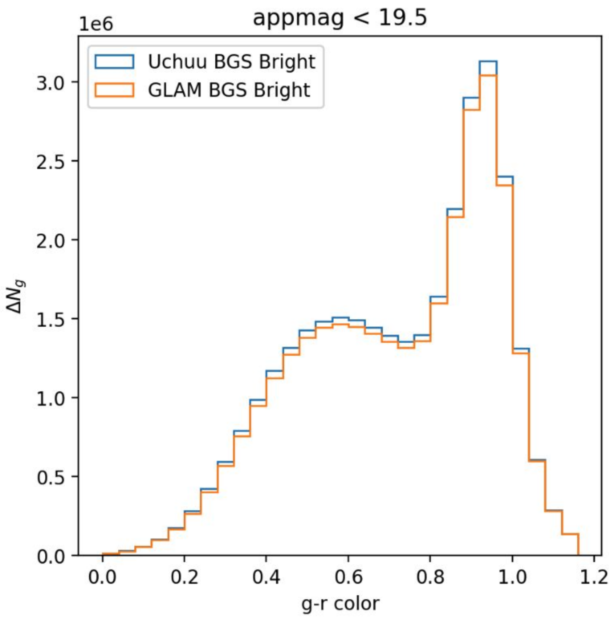


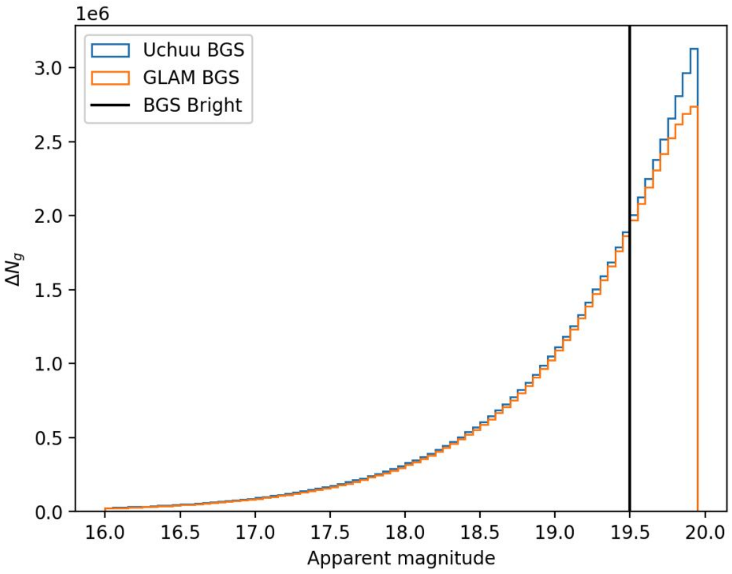
HOD

Number density



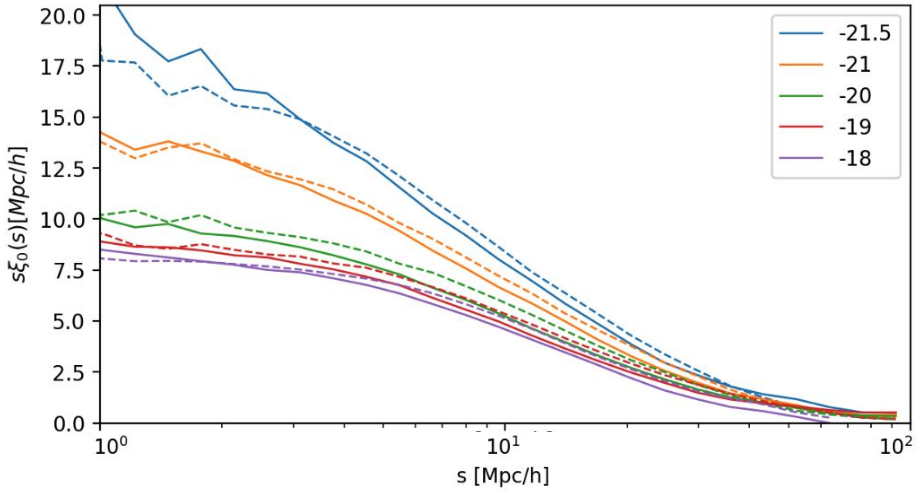
Apparent magnitudes and colors





Clustering

Monopole



Quadrupole