Cosmology with Spectroscopic Surveys

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The simplified plan

Why clustering for cosmology ?

From photons to spectra

From spectra to clustering

From clustering to cosmology

Why clustering for cosmology ?

Which fundamental questions in Physics we would like to answer?

Why clustering for cosmology ?

Dark energy

Alternate theories of gravity

Inflation

Neutrino masses

Dark matter

Clustering informs us about all these questions

Dark energy Alternate theories of gravity Inflation Neutrino masses





Equation of state of dark energy





 Dark energy
 Alternate theories of gravity
 Inflation
 Neutrino masses

 Perturbations to GR

 0.5
 0.5



Dark energy

Alternate theories of gravity

Inflation

Neutrino masses

Non-Gaussianities



Mueller et al. 2022



eBOSS Collaboration 2021

Palanque-Delabrouille et al 2020

Why clustering for cosmology ?

Dark energy

Alternate theories of gravity

Inflation

Neutrino masses

Dark matter

Clustering informs us about all these questions



 $\gamma_n \rightarrow \begin{pmatrix} \theta_i, \phi_i, z_i \end{pmatrix} \\ \begin{pmatrix} \theta_i, \phi_i, z_i, \{f_j\} \end{pmatrix}$

From photons to spectra

Obtain redshifts for galaxies and quasars + Measure fluxes in the Lyman- α forests of quasars



Obtain **redshifts** for **galaxies and quasars** + Measure **fluxes** in the **Lyman-α forests** of quasars

From photons to spectra



 $\gamma_{n} \rightarrow \begin{pmatrix} \theta_{i}, \phi_{i}, z_{i} \end{pmatrix} \rightarrow \begin{pmatrix} \delta_{g}(\vec{x}) \\ \delta_{g}(\vec{x}) \end{pmatrix} \rightarrow \langle \delta \delta' \rangle$ $\begin{pmatrix} \theta_{i}, \phi_{i}, z_{i}, \{f_{j}\} \end{pmatrix} \rightarrow \begin{pmatrix} \delta \delta' \end{pmatrix}$

From photons to spectra

Obtain **redshifts** for **galaxies and quasars** +Measure **fluxes** in the Lyman- α forests of quasars

From spectra to clustering

Compute contrast of galaxy, quasar densities or Lyman- α fluxes +Compute 2-point statistics





From photons to spectra

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From photons to spectra

Obtain redshifts for galaxies and quasars Measure **fluxes** in the Lyman- α forests of quasars

From spectra to clustering

Compute contrast of galaxy, quasar densities or Lyman- α fluxes +Compute 2-point statistics Fit models for BAO, RSD (observables)

From clustering to cosmology

Fit for dark energy or alternative gravity models

+





Obtain **redshifts** for **galaxies and quasars** From photons to spectra Measure **fluxes** in the Lyman- α forests of quasars

From spectra to clustering

Compute contrast of galaxy, quasar densities or Lyman- α fluxes +Compute 2-point statistics

From clustering to cosmology

Fit models for BAO, RSD (observables) +

Fit for dark energy or alternative gravity models

Each step is equally important for cosmology

From photons to spectra and redshifts

A small portion of our sky as seen by Legacy Survey

https://www.legacysurvey.org/viewer

A small portion of our sky as seen by Legacy Survey spectra by Sloan Digital Sky Survey









https://www.legacysurvey.org/viewer



QSO z=1.166 (Zwarn=0x5)

GALAXY z=0.317

Photometry





Photometry









Photometry









Photometry







Longueur d'onde observée [1 Ångstrom = 10⁻¹⁰ mètre]



Photometry

Spectroscopy

Main differences ?

Implications for cosmology ?

Discuss !

Photometry

- angular information $\rightarrow (\theta_i, \phi_i)$
- integrated fluxes over few bands
- rough spectral information
- higher signal-to-noise
- many more detected objects
- no prior selection required
- ... ?

- 1D flux information $\rightarrow f_j$
- precise radial information $\rightarrow z_i$
- higher spectral resolution
- lower signal-to-noise
- requires long exposure times
- requires prior selection of targets (if not slitless)
- fewer objects measured
- ?

Photometry

Spectroscopy

- angular information $\rightarrow (\theta_i, \phi_i)$
- integrated fluxes over few bands
- rough spectral information
- higher signal-to-noise
- many more detected objects
- no prior selection required
- ... ?



Less selection effects (SNIa) Great for galaxy shapes (WL) Cluster characterisation and counts

Better redshifts for clustering (BAO, RSD) Better physical characterisation of galaxies/stars

- 1D flux information $\rightarrow f_j$ - precise radial information $\rightarrow z_i$

- higher spectral resolution
- lower signal-to-noise
- requires long exposure times
- requires prior selection of targets (if not slitless)
- fewer objects measured
- ?



How to make a spectroscopic survey?

boldface for the slit-less case

How to make a spectroscopic survey?

boldface for the slit-less case

- 1 make a photometric survey
- 2 decide the sky coverage for spectroscopy
- 3 select targets using magnitudes and colors
- 4 define observing strategy for spectroscopy
- 5 test and validate
 - a instruments
 - **b** data reduction pipeline
 - c target selection
- 6 measure redshifts
- 7 analyse data
- 8 publish results
- 9 ...
- 10 profit !

From photons to spectra

2 - Sky coverage

BOSS and eBOSS surveys



BOSS overview - <u>Dawson et al. 2013</u> eBOSS overview - <u>Dawson et al. 2016</u> Plot from <u>Zhao et al. 2021</u>

From photons to spectra

2 - Sky coverage

Euclid Wide Survey



Euclid Preparation I - Euclid Collaboration 2022
2 - Sky coverage

Euclid Wide Survey



Euclid Preparation I - Euclid Collaboration 2022

The sky coverage defines the selection/window function of the survey Important for clustering !

4 - Observing strategy







Ecliptic longitude [deg]



Scanning strategy depends on :

- time of the year, time of the day
- moon brightness
- weather
- location of telescope
- etc...

From photons to spectra

4 - Observing strategy

eBOSS tiling

Scanning strategy depends on :

- time of the year, time of the day
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- location of telescope
- etc...

Strategy directly impacts cosmological constraints

eBOSS tiling

4 - Observing strategy

5b - Spectroscopic data reduction

5b - Spectroscopic data reduction

Raw image

5b - Spectroscopic data reduction

Multi-object fiber based case (SDSS or DESI-like)

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Objects

Wavelength

5b - Spectroscopic data reduction

Multi-object fiber based case (SDSS or DESI-like)

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Objects

Wavelength

Slitless case (Euclid-like)

Raw image

5b - Spectroscopic data reduction

Multi-object fiber based case (SDSS or DESI-like)

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Objects

Wavelength

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5b - Spectroscopic data reduction

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Slitless case (Euclid-like)

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Objects

Wavelength

Slitless case (Euclid-like)

Raw image

Estimate **sky** counts and remove it from object spectra

5b - Spectroscopic data reduction

Multi-object fiber based case (SDSS or DESI-like)

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Objects

Wavelength Slitless case (Euclid-like)

Raw image **Extraction** of counts from CCD Clean cosmic rays Estimate sky counts and remove it from object spectra Calibrate wavelengths solution using arc lamps

5b - Spectroscopic data reduction

Multi-object fiber based case (SDSS or DESI-like)

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Objects

Wavelength Slitless case (Euclid-like)

Raw image **Extraction** of counts from CCD Clean cosmic rays Estimate sky counts and remove it from object spectra Calibrate wavelengths solution using arc lamps Convert counts into physical flux using standard stars

5b - Spectroscopic data reduction

Multi-object fiber based case (SDSS or DESI-like)

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Objects

Wavelength Slitless case (Euclid-like)

5b - Spectroscopic data reduction

Raw image

Multi-object fiber based case (SDSS or DESI-like)

6 - Measuring redshifts

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Visual inspection

Fitting templates (empirical or physical)

Machine learning

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

Machine learning

Pros

Cons

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

Machine learning

Pros

Identification of peculiar objects Identification of problems in spectra Robust when double checked Required to start a survey

Cons

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

Machine learning

Pros

Identification of peculiar objects Identification of problems in spectra Robust when double checked Required to start a survey

Cons

Slow

Small number of objects Prone to human error or biases Hard to define uncertainties

6 - Measuring redshifts

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Visual inspection

Fitting templates (empirical or physical)

Machine learning

Physical templates : galaxy models from stellar populations

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

Machine learning

Physical templates : galaxy models from stellar populations

6 - Measuring redshifts

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Shift templates and minimise χ^2 versus redshift

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

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Shift templates and minimise χ^2 versus redshift

BOSS fitter - <u>Bolton et al. 2012</u> eBOSS and DESI fitters - <u>redrock</u>

Machine learning

Pros

Fast and automated Deterministic Quantifiable uncertainties Good on low S/N spectra

BOSS fitter - <u>Bolton et al. 2012</u> eBOSS and DESI fitters - <u>redrock</u>

BOSS fitter - Bolton et al. 2012 eBOSS and DESI fitters - redrock Machine learning

Fast and automated Deterministic Quantifiable uncertainties Good on low S/N spectra

Results depend on templates Fails on peculiar objects

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

Machine learning

Useful for quasars : no physical model !

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

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Useful for quasars : no physical model !

Pros

Fast and automated Better than templates for quasars

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

Machine learning

Useful for quasars : no physical model !

Pros

Fast and automated Better than templates for quasars

Requires careful training "Black-box" Uncertainties not well defined Fails on peculiar objects

6 - Measuring redshifts

Visual inspection

Fitting templates (empirical or physical)

Machine learning

All three methods have been used in eBOSS, are being used in DESI, and will most likely be used in Euclid and other surveys From photons to spectra and redshifts

Summary

Type of instrument and survey

Choice of sky coverage, target type and scan strategy

Quality of spectroscopic data reduction

Quality of spectral classification and redshift measurement

All directly impact cosmological constraints

From spectra to clustering

From spectra to clustering



From spectra to clustering

 $\begin{pmatrix} \theta_i, \phi_i, z_i \end{pmatrix}$ $\delta_{g}(x)$ $\delta_{Ly\alpha}(\vec{x})$ How to convert a list of (θ_i, ϕ_i, z_i) to $\delta_g(\vec{x})$? Case of galaxies and quasars How to convert a list of $(\theta_i, \phi_i, z_i, \{f_j\})$ to $\delta_{Ly\alpha}(\vec{x})$? Case of Lyman- α forests How to compute 2-pt statistics $\langle \delta(\vec{x}) \delta(\vec{x}') \rangle$ from $\delta(\vec{x})$? How to compute covariance/error-matrix for $\langle \delta(\vec{x}) \delta(\vec{x}') \rangle$? BAO and RSD **BAO** and Neutrino masses

Case of galaxies and quasars



Case of galaxies and quasars

 $\delta_g(\vec{x})$ (θ_i, ϕ_i, z_i) $\delta_g(\vec{x}) = \frac{n_g(\vec{x})}{\bar{n}_g} - 1$ Galaxy overdensity field:

Case of galaxies and quasars

$$\begin{pmatrix} \theta_i, \phi_i, z_i \end{pmatrix} \longrightarrow \delta_g(\vec{x}) \longrightarrow \langle \delta \delta' \rangle$$

Galaxy overdensity field:
$$\delta_g(\vec{x}) = \frac{n_g(\vec{x})}{\bar{n}_g} - 1$$

How to compute $n_g(\vec{x})$?

How to compute $\bar{n}_g \equiv \langle n(\vec{x}) \rangle$?

Case of galaxies and quasars

$$(\theta_i, \phi_i, z_i)$$

 $\rightarrow \delta_g(\vec{x})$ $\delta \tilde{\delta}_g(\vec{x}) = \frac{n_g(\vec{x})}{\bar{n}_g} - 1$

Galaxy overdensity field:

How to compute
$$n_g(\vec{x})$$
 ?

We only want cosmological fluctuations !

 $\delta\delta'$

How to compute $\bar{n}_g \equiv \langle n(\vec{x}) \rangle$?

Case of galaxies and quasars

$$(\theta_i, \phi_i, z_i)$$

 $z_i) =$

 $\delta_g(\vec{x}) \quad \downarrow \quad \langle \delta \delta' \rangle$

Galaxy overdensity field:

$$\delta_g(\vec{x}) = \frac{n_g(\vec{x})}{\bar{n}_g} - 1$$

How to compute $n_g(\vec{x})$?

We only want cosmological fluctuations !

How to compute $\bar{n}_g \equiv \langle n(\vec{x}) \rangle$?







The sky area is described by a random (unclustered) set of points



Not all targets receive a fiber = fiber completeness





declination J2000 (degrees)





declination J2000 (degrees)

<u>Ross, JB, et al. 2020</u>





Spurious non-cosmological fluctuations







Correction method 1: Simultaneous linear fit of trends



Correction method 2 : Machine learning



Correction method 2 : Machine learning



Rezaie et al. 2020







Correction method 2 : Machine learning

Correction method 3 : Simulate photometry





Obiwan - Kong et al. 2020



Correction method 2 : Machine learning

Correction method 3 : Simulate photometry

Correction method 4 : Mode projection/nulling





Correction method 2 : Machine learning

Correction method 3 : Simulate photometry

Correction method 4 : Mode projection/nulling









Missing pairs of galaxies due to physical size of optical fibers !





Missing pairs of galaxies due to physical size of optical fibers !











1 + 1 + 1



Assumes missing galaxy is physically close angularly (ok) and radially (strong assumption!)







Correction method 2 : model "collisioned" clustering <u>Hahn et al. 2017</u>

$$\frac{1+\xi^{\text{coll}}(\vec{r})}{1+\xi^{\text{true}}(\vec{r})} \equiv 1-f_s W_{\text{coll}}(\vec{r}) \quad \text{and Fourier Transform to obtain model for } P^{\text{coll}}(\vec{k})$$



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Correction method 3 : use pairwise weighting

Bianchi & Percival 2017



Each galaxy pair has a weight $w_{ij} \neq w_i w_j$ defined as the inverse probability of it being observed



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Requires running tiling algorithm several times to compute probabilities

Currently used in DESI



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Requires running tiling algorithm several times to compute probabilities

Currently used in DESI

Is Euclid affected by "collisions" ? How to correct for them ?



Some spectra have low S/N and do not yield a confident redshift





Some spectra have low S/N and do not yield a confident redshift





Some spectra have low S/N and do not yield a confident redshift


Some spectra have low S/N and do not yield a confident redshift





Some spectra have low S/N and do not yield a confident redshift





How to convert a list of (θ_i, ϕ_i, z_i) to $\delta_g(\vec{x})$?

Case of galaxies and quasars



Redshift distribution $\bar{n}(z)$



How to convert a list of (θ_i, ϕ_i, z_i) to $\delta_g(\vec{x})$?

Case of galaxies and quasars



Redshift distribution $\bar{n}(z)$



Optimal weights for clustering: FKP weights <u>Feldman, Kaiser & Peacock 1994</u> $w_{\text{FKP,i}} = \frac{1}{1 + \bar{n}(z_i)P(k_0)}$

 $P(k_0)$ is power spectrum at some scale of interest (usually $k_0 \sim 0.02 \ h {
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Case of galaxies and quasars



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Galaxies are weighted by $w_{photo}w_{coll}w_{no-z}w_{FKP}$ Randoms are weighted by $w_{mask}w_{comp}w_{FKP}$



From spectra to clustering



Case of galaxies and quasars

 $(\theta_i, \phi_i, z_i) \rightarrow \delta_g(\vec{x}) \rightarrow \langle \delta \delta' \rangle$

How to compute 2-pt statistics $\langle \delta(\vec{x})\delta(\vec{x}') \rangle$ from $\delta(\vec{x})$? Case of galaxies and quasars

Configuration space

Correlation function

$$\xi(\vec{r}) \equiv \left\langle \delta_g(\vec{x}) \delta_g(\vec{x} + \vec{r}) \right\rangle$$

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Fourier space

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Power spectrum

$$(2\pi)^{3}\delta_{\rm D}^{3}(\vec{k}-\vec{k}')P(\vec{k}) \equiv \left\langle \tilde{\delta}_{g}^{*}(\vec{k})\delta_{g}(\vec{k}')\right\rangle$$

Case of galaxies and quasars

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Case of galaxies and quasars

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To observer

Case of galaxies and quasars

Configuration space

-ourier space

Correlation function

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To observer

and sim

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Correlation function

$$\xi(\vec{r}) \equiv \left\langle \delta_g(\vec{x}) \delta_g(\vec{x} + \vec{r}) \right\rangle$$

Estimator Landy & Szalay 1993

$$\hat{\xi}(\vec{r}_A) = \frac{DD(\vec{r}_A) - 2DR(\vec{r}_A)}{RR(\vec{r}_A)} + 1$$

Power spectrum

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120 60 $r_{\parallel} \; [h^{-1} \; \mathsf{Mpc}]$ 0 -60 -120120 -6060 -1200 $r_{\perp} [h^{-1} \text{ Mpc}]$ <u>JB et al. 2020</u>

eBOSS LRG

Case of galaxies and quasars

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$$\hat{\xi}(\vec{r}_A) = \frac{DD(\vec{r}_A) - 2DR(\vec{r}_A)}{RR(\vec{r}_A)} + 1$$

Compute multipolos

$$\hat{\xi}_{\ell}(r) = (2\ell + 1) \sum_{i} \xi(r, \mu_i) L_{\ell}(\mu_i) d\mu$$

where $\mu_i = \frac{r_{\parallel}}{r}$ and $L_{\ell} \equiv$ Legendre polynomials

eBOSS LRG



Case of galaxies and quasars

Configuration space

Correlation function

$$\xi(\vec{r}) \equiv \left\langle \delta_g(\vec{x}) \delta_g(\vec{x} + \vec{r}) \right\rangle$$

Estimator Landy & Szalay 1993

$$\hat{\xi}(\vec{r}_A) = \frac{DD(\vec{r}_A) - 2DR(\vec{r}_A)}{RR(\vec{r}_A)} + 1$$

Compute multipoles

$$\hat{\xi}_{\ell}(r) = (2\ell + 1) \sum_{i} \xi(r, \mu_{i}) L_{\ell}(\mu_{i}) d\mu$$
where $\mu_{i} = \frac{r_{\parallel}}{r}$ and $L_{\ell} \equiv$ Legendre polynomials

How to compute 2-pt statistics $\langle \delta(\vec{x}) \delta(\vec{x}') \rangle$ from $\delta(\vec{x})$?

Case of galaxies and quasars

Configuration space

eBOSS LRG

Correlation function

$$\xi(\vec{r}) \equiv \left\langle \delta_g(\vec{x}) \delta_g(\vec{x} + \vec{r}) \right\rangle$$

Estimator <u>Landy & Szalay 1993</u>

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Fourier space

Power spectrum

$$(2\pi)^{3}\delta_{\rm D}^{3}(\vec{k}-\vec{k}')P(\vec{k}) \equiv \left\langle \tilde{\delta}_{g}^{*}(\vec{k})\delta_{g}(\vec{k}')\right\rangle$$

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↓To observer

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How to compute 2-pt statistics $\langle \delta(\vec{x})\delta(\vec{x}') \rangle$ from $\delta(\vec{x})$? Case of **galaxies and quasars**

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Case of galaxies and quasars



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Codes

<u>pycorr</u> by de Mattia et al. based on <u>Corrfunc</u> <u>pypower</u> by de Mattia et al. based on nbodykit

<u>nbodykit</u> by Nick Hand & Yu Feng

... and many others!

Reconstruction for BAO

Removing bulk motions (~ 10 Mpc) that smear BAO peak



Evolved field



Padmanabhan et al. 2012


Removing bulk motions (~ 10 Mpc) that smear BAO peak

Initial field



Evolved field



<u>Padmanabhan et al. 2012</u>



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Evolved field



Reconstructed field



Padmanabhan et al. 2012

Code: <u>pyrecon</u>

Removing bulk motions (~ 10 Mpc) that smear BAO peak



Evolved field

Padmanabhan et al. 2012

Before reconstruction



After reconstruction



Cosmology with Spectroscopic Surveys

Julián Bautista Aix Marseille Université - CPPM









Summary until now

Main questions in cosmology

How to make a spectroscopic survey : getting redshifts

Defining the survey window function for galaxies $\delta_{q}(\vec{x})$

Two-point statistics : correlation function and power spectra



How to compute covariance/error-matrix for $\xi_{\ell}(r_i)$ or $P_{\ell}(k_i)$?

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Likelihood

$$\mathscr{L} = \frac{1}{(2\pi)^n \det(C)^{1/2}} \exp\left(-\frac{1}{2}[\vec{d} - \vec{m}(\vec{p})]^T C^{-1}[\vec{d} - \vec{m}(\vec{p})]\right)$$

Data vector

 $\vec{d} = \begin{bmatrix} \xi_0 \\ \xi_1 \\ \dots \\ \xi_n \end{bmatrix}$

Model \overrightarrow{m} Parameters \overrightarrow{p} Covariance matrix

 $C_{ij} = \langle \xi_i \xi_j \rangle$ $C_{ij} = \langle P_i P_j \rangle$

How to compute covariance/error-matrix for $\xi_{\ell}(r_i)$ or $P_{\ell}(k_i)$?



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Analytical	Data based Bootstrap/Jacknife	Monte-Carlo Mocks
$C \propto \langle \delta \delta \delta \delta \rangle$ $C \rightarrow C(\vec{p})$ Systematics?	More subsamples, less volume Noisier	CPU expensive Realistic clustering?
<u>Grieb et al 2016</u>	Mohammad & Percival 2022	

How to compute covariance/error-matrix for $\langle \delta(\vec{x})\delta(\vec{x}')\rangle$? Case of galaxies and quasars

Mocks = approximate simulations of clustering, realistic observational properties

Covariance matrix is given by "scatter" over 1000 measurements of $\xi_{\ell}(r), P_{\ell}(k)$

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eBOSS EZmocks

<u>Zhao et al. 2020</u>

- Zel'dovich approximations to rapidly construct density field
- 1000 realisations of the survey
- includes redshift evolution
- includes observational effects
- includes cross-correlations
 between tracers

How to compute covariance/error-matrix for $\langle \delta(\vec{x}) \delta(\vec{x}') \rangle$?





eBOSS EZmocks Zhao et al. 2020

Points = data Shaded area = mocks

Covariance matrix is given by "scatter" over 1000 measurements of $\xi_{\ell}(r), P_{\ell}(k)$



Covariance matrix is given by "scatter" over 1000 measurements of $\xi_{\ell}(r), P_{\ell}(k)$

What next

Baryon acoustic oscillations (BAO) Redshift-space distortions (RSD) Models and simulations Non-Gaussianities $f_{\rm NL}$

Converting quasar spectra to $\delta_{Ly\alpha}(\vec{x})$ Clustering measurements BAO analysis Neutrino masses Simulations

 $\gamma_n \rightarrow \begin{pmatrix} \theta_i, \phi_i, z_i \end{pmatrix} \rightarrow \delta_g(x) \\ \begin{pmatrix} \theta_i, \phi_i, z_i, \{f_j\} \end{pmatrix} \rightarrow \delta_{Ly\alpha}(\vec{x}) \rightarrow \langle \delta \delta' \rangle \rightarrow \langle \delta \delta' \rangle$

Cosmic microwave background (CMB) z ~ 1100 or t ~ 380 000 years

Type-la Supernovae (SNIa)	Baryon Acoustic Oscillations (BAO)
as standard candles	as standard ruler
0 < z < 1.5	0.1 < z < 2.5
5 Gy < t < 13.8 Gy	3 Gy < t < 13 Gy

 $F = \frac{L_{\text{candle}}}{4\pi D_r^2(z)}$

 $\Delta \theta = \frac{r_{\text{ruler}}}{D_{M(z)}}$

 $\Delta z = \frac{r_{\rm ruler}}{D_H(z)}$



 $F = \frac{L_{\text{candle}}}{4\pi D_I^2(z)}$



 $\Delta z = \frac{r_{\text{ruler}}}{D_H(z)}$















Well described by GR + Boltzmann



Link to code

Well described by GR + Boltzmann



Link to code

Well described by GR + Boltzmann



Well described by GR + Boltzmann





How to extract the BAO scale ?



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A cosmological model is needed to convert redshifts into comoving distances

$$z_i \to \chi(z_i)$$

$$\chi(z) = c \int_0^z \frac{dz'}{H(z)} \approx \frac{c}{H_0} \int_0^z \frac{dz'}{\sqrt{\Omega_m (1+z')^3 + \Omega_\Lambda}}$$
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BAO would appear different in radial and transverse directions

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Run Boltzmann solver, CAMB or CLASS, to obtain $P_m^{\text{lin}}(k)$ with BAO peak at r_{drag}

Need to choose a "template" cosmology

e.g.,
$$\Omega_m = 0.31$$
, $\Omega_k = 0$, $h = 0.67$

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104

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k [h/Mpc]

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If $\Omega_i^{\text{template}} \neq \Omega_i^{\text{true}}$, an extra scaling is need :

r [Mpc/h]

r_{drag}

template

*r*_{drag}

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1+2) If we measure BAO radial and transverse :

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In practice

Linear redshift-space distortions: $P(\vec{k}) = (b + f\mu_k^2)^2 P_m^{\text{lin}}(k)$ where $\mu_k = k_{\parallel}/k$

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Empirical smoothing of BAO peak (non-linearities):

$$O(k) \exp\left(-\frac{k^2 \Sigma_{\rm NL}^2(\mu_k)}{2}\right)$$
$$\Sigma_{\rm NL}(\mu_k) = \Sigma_{\parallel}^2 \mu_k^2 + \Sigma_{\perp}^2(1 - \mu_k^2)$$





 $\Sigma_{\parallel} = 7 \ h^{-1}$ Mpc, $\Sigma_{\perp} = 5 \ h^{-1}$ Mpc

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Modelling of reconstruction and removal of RSD: $f\mu_k^2 \rightarrow f\mu^2 \left(1 - e^{-k^2 \Sigma_r^2/2}\right)$

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$$f\mu_k^2 \to f\mu^2 \left(1 - e^{-k^2 \Sigma_r^2/2}\right)$$

Power-laws to marginalise shape information :

 $+\sum_{\ell,i=0}a_{\ell,i}k^i$

In practice

Linear redshift-space distortions: $P(\vec{k}) = (b + f\mu_k^2)^2 P_m^{\text{lin}}(k)$ where $\mu_k = k_{\parallel}/k$

Separate BAO peak from smooth part: $O(k) = P(k)/P_{nopeak}(k) - 1$

Empirical smoothing of BAO peak (non-linearities):

Modelling of reconstruction and removal of RSD:

$$\Sigma_{\rm NL}(\mu_k) = \Sigma_{\parallel}^2 \mu_k^2 + \Sigma_{\perp}^2 (1 - \mu_k^2)$$

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Power-laws to marginalise shape information :

$$+\sum_{\ell,i=0}a_{\ell,i}k^i$$

Scaling of separations: $k_{\parallel} = k_{\parallel}^{\text{fid}} / \alpha_{\parallel}$ $k_{\perp} = k_{\perp}^{\text{fid}} / \alpha_{\perp}$ $r_{\parallel} = \alpha_{\parallel} r_{\parallel}^{\text{fid}}$ $r_{\perp} = \alpha_{\perp} r_{\perp}^{\text{fid}}$





Results of BAO fits

eBOSS LRG reconstructed



Results of BAO fits

eBOSS LRG reconstructed



Results of BAO fits

eBOSS LRG reconstructed



These constraints will be used to fit cosmological models

SDSS BAO Distance Ladder



Redshift-space distortions (RSD)

We measure redshifts : peculiar velocities affect our distance inferences

Redshift-space distortions (RSD)

We measure redshifts : peculiar velocities affect our distance inferences



Real space

Redshift space

Redshift-space distortions (RSD)

We measure redshifts : peculiar velocities affect our distance inferences



Observed redshift is : $(1 + z_{obs}) = (1 + z_{cosmo})(1 + z_v)$

Real space

Redshift space
We measure redshifts : peculiar velocities affect our distance inferences



Velocities on large separations

Linear RSD

Non-linear RSD *Fingers-of-God*



From Dodelson & Schmidt 2020



From Dodelson & Schmidt 2020









Impact on correlation function $\xi(\vec{r}) = \langle \delta(\vec{x})\delta(\vec{x}+\vec{r}) \rangle$



Simulation by Kuruvilla & Porciani 2018

Impact on correlation function $\xi(\vec{r}) = \langle \delta(\vec{x})\delta(\vec{x}+\vec{r}) \rangle$

Linear RSD Kaiser 1987















Impact on correlation function $\xi(\vec{r}) = \langle \delta(\vec{x})\delta(\vec{x}+\vec{r}) \rangle$

Linear RSD Kaiser 1987 Easy to model with linear continuity equation: $\nabla \cdot \vec{v}(\vec{x}, a) = -a^2 H(a) \frac{d\delta(\vec{x}, a)}{da}$ $\nabla \cdot \vec{v}(\vec{x}, a) = -aH(a)f(a)\delta(\vec{x}, a)$ FΤ $i\vec{k}\cdot\vec{v}(\vec{k},a) = -aH(a)f(a)\delta(\vec{k},a)$ Growth-rate of structures f(a)

Positions in redshift-space :

$$\vec{s} = \vec{x} + \frac{\vec{v}(\vec{x}, a) \cdot \hat{x}}{aH(a)}$$



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Mass conservation + plane-parallel :

$$\delta_{\text{RSD}}(\vec{k}, a) = \left[1 + f(a)\mu_k^2\right]\delta(\vec{k}, a)$$



Impact on correlation function $\xi(\vec{r}) = \langle \delta(\vec{x})\delta(\vec{x}+\vec{r}) \rangle$

Linear RSD Kaiser 1987 Easy to model with linear continuity equation: $\nabla \cdot \vec{v}(\vec{x}, a) = -a^2 H(a) \frac{d\delta(\vec{x}, a)}{da}$ $\nabla \cdot \vec{v}(\vec{x}, a) = -aH(a)f(a)\delta(\vec{x}, a)$ $\int FT$ $i\vec{k} \cdot \vec{v}(\vec{k}, a) = -aH(a)f(a)\delta(\vec{k}, a)$ Growth-rate of structures f(a)

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Linear RSD model is basis for more advanced theoretical models

What about $\sigma_{\!8}\,?$

What about σ_8 ?

Variance of top-hat smoothed linear matter density field on scales of 8 Mpc/h

$$\sigma_8^2(z) \equiv \frac{1}{2\pi^2} \int_0^\infty dk \ k^2 P_m^{\rm lin}(k, z) W_8^2(k)$$

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$$P_{s}(\vec{k}) = \left[\sigma_{8}(z) + f(z)\sigma_{8}(z)\mu_{k}^{2}\right]^{2}\tilde{P}^{\text{lin}}(k, z)$$

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$$\sigma_8^2(z) \equiv \frac{1}{2\pi^2} \int_0^\infty dk \ k^2 P_m^{\rm lin}(k, z) W_8^2(k)$$

Used to define amplitude of power spectrum instead of A_s (primordial amplitude)

$$P_{s}(\vec{k}) = \left[1 + f(z)\mu_{k}^{2}\right]^{2} P^{\text{lin}}(k, z)$$

$$P_{s}(\vec{k}) = \left[1 + f(z)\mu_{k}^{2}\right]^{2} \sigma_{8}^{2}(z)\tilde{P}^{\text{lin}}(k, z)$$

$$P_{s}(\vec{k}) = \left[\sigma_{8}(z) + f(z)\sigma_{8}(z)\mu_{k}^{2}\right]^{2}\tilde{P}^{\text{lin}}(k, z)$$

Anisotropic clustering is proportional to $f(z)\sigma_8(z)$

Going beyond linear theory, few examples

Going beyond linear theory, few examples

TNS (Taruya, Nishimishi & Saito 2010) + non-linear bias

 $P_{g}^{s}(k,\mu) = D(k\mu\sigma_{v}) \Big[P_{gg}(k) + 2\mu^{2} f P_{g\theta} + \mu^{4} f^{2} P_{\theta\theta}(k) \\ + C_{A}(k,\mu,f,b_{1}) + C_{B}(k,\mu,f,b_{1}) \Big],$

Going beyond linear theory, few examples

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$$+C_A(k, \mu, f, b_1) + C_B(k, \mu, f, b_1)],$$

Comoving Lagrangian Perturbation Theory + Gaussian streaming <u>Carlson et al. 2013, Reid & White 2011</u>

$$\begin{split} 1 + \xi_{\rm X}(r_{\perp}, r_{\parallel}) &= \int \frac{1}{\sqrt{2\pi} \left[\sigma_{12}^2(r) + \sigma_{\rm FoG}^2 \right]} [1 + \xi_{\rm X}(r)] \\ &\times \exp\left\{ - \frac{[r_{\parallel} - y - \mu v_{12}(r)]^2}{2 \left[\sigma_{12}^2(r) + \sigma_{\rm FoG}^2 \right]} \right\} \mathrm{d}y, \end{split}$$

Going beyond linear theory, few examples

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- effective field theory: small scale sourced counterterm to regularize loop integrals (pybird, CLASS-PT, velocileptors...) (k < 0.3 h Mpc⁻¹)
- **hybrid PT/HOD models**, e.g. Hand et al. 2017 ($k < 0.4 h \text{ Mpc}^{-1}$)





Approaches:

- n-body simulations
- hybrid : emulators, machine learning
- theoretical formulations

Realism



Speed



Approaches:

- n-body simulations
- hybrid : emulators, machine learning
- theoretical formulations





Reviews on this topic

Large-scale structure of the Universe and cosmological perturbation theory <u>Bernardeau, Colombi, Gaztanaga, Scoccimarro 2002</u>

> Large-scale galaxy bias Desjacques, Jeong & Schmidt 2018

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Any theoretical model is validated with n-body simulations

In practice

We fit simultaneously for $(f\sigma_8, \alpha_{\parallel}, \alpha_{\perp})$ + bias and FoG terms

No power-laws, we want the *full-shape* information !

No reconstruction !



In practice

We fit simultaneously for ($f\sigma_8, \alpha_{\parallel}, \alpha_{\perp}$) + bias and FoG terms

No power-laws, we want the *full-shape* information !

No reconstruction !



Measurements from SDSS II, III and IV



Used in constraining cosmological models

In a nutshell

	BAO	RSD
Goal	Standard ruler distances	Growth rate of structures
Information source	BAO peak position only	Full anisotropic shape of $\langle\delta\delta' angle$
Reconstruction	Yes	No
Parameters	$\left(\frac{D_H(z)}{r_{\rm drag}}, \frac{D_M(z)}{r_{\rm drag}}\right)_{\rm peak}$	$f(z)\sigma_8(z)$ and $\left(\frac{D_H(z)}{r_{\rm drag}}, \frac{D_M(z)}{r_{\rm drag}}\right)_{\rm shape}$
Model dependant	Less	More

In a nutshell

Galaxy survey $\delta_g(\vec{x})$

In a nutshell


In a nutshell



In a nutshell



In a nutshell



$$\begin{split} \xi_{\ell}(r) \\ D_{\xi} &= \{\alpha_{\parallel}, \alpha_{\perp}, f\sigma_8\} \\ C_{\xi} &= 3 \times 3 \text{ covariance} \end{split}$$

$$\begin{split} P_{\ell}(r) \\ D_P &= \{\alpha_{\parallel}, \alpha_{\perp}, f\sigma_8\} \\ C_P &= 3 \ge 3 \text{ covariance} \end{split}$$









- assumes Gaussian input posteriors
- yields Gaussian posteriors
- needs adjusting on $C_{\xi,P}$ for particular data realisation
- trickier to include systematic uncertainties

Obtaining consensus results

Application to eBOSS LRG sample



Obtaining consensus results

Application to eBOSS LRG sample



BAO results are really consistent between Fourier and Config

Alternative : joint fit of Fourier+Config

Dumerchat & JB 2022

- concatenate Fourier and Config data-vectors
- fit for same $\{\tilde{\alpha}_{\parallel}, \tilde{\alpha}_{\perp}\}$ on both, different nuisance parameters



Alternative : joint fit of Fourier+Config

Dumerchat & JB 2022

- concatenate Fourier and Config data-vectors
- fit for same $\{\tilde{\alpha}_{\parallel}, \tilde{\alpha}_{\perp}\}$ on both, different nuisance parameters



Pros:

- does not assume Gaussian posteriors
- simpler, no adjustments
- same model, just FFT'ed

Cons:

- larger covariance matrix

Alternative : joint fit of Fourier+Config

Dumerchat & JB 2022

Correlation matrix from 1000 mocks





Joint fit is well-behaved, less biased statistically, with correct uncertainties



How to obtain consensus between BAO and RSD ?

Chen, Vlah & White 2022

Gil-Marín 2022

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Fitting directly cosmological parameters with LPT predictions

How to obtain consensus between BAO and RSD ?

Chen, Vlah & White 2022

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Using very large-scale clustering of **quasars**

 $f_{\rm NL} = 0$ corresponds to Gaussian initial conditions after inflation

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Using very large-scale clustering of **quasars**

 $f_{\rm NL} = 0$ corresponds to Gaussian initial conditions after inflation



Large scales are the most prone to systematic effects : window, photometry, etc...

Using very large-scale clustering of **quasars**



No detection of departures from Gaussian initial conditions

Comparison between probes



Comparison between probes



Forecast for future (DESI Collaboration 2016a)
$$\begin{split} &\sigma(f_{\rm NL}^{\rm local}) < 5.0 \text{ (DESI)} \\ &\sigma(f_{\rm NL}^{\rm local}) < 2.5 \text{ (DESI + Planck)} \end{split}$$

How to convert a list of $(\theta_i, \phi_i, z_i, \{f_j\})$ to $\delta_{Ly\alpha}(\vec{x})$? Case of Lyman- α forests $(\theta_i, \phi_i, z_i, \{f_j\}) \rightarrow \delta_{Ly\alpha}(\vec{x}) \rightarrow \langle \delta \delta' \rangle$

How to convert a list of $(\theta_i, \phi_i, z_i, \{f_j\})$ to $\delta_{Ly\alpha}(\vec{x})$?

Case of Lyman- α forests

 $\left(\theta_{i},\phi_{i},z_{i},\{f_{j}\}\right) \rightarrow \delta_{\mathrm{Ly}\alpha}(\vec{x})$ $\langle \delta \delta' \rangle$

What is a Lyman-alpha forest ?



https://www.youtube.com/watch?v=6Bn7Ka0Tjjw

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What is a Lyman-alpha forest ?



https://www.youtube.com/watch?v=6Bn7Ka0Tjjw

A survey of Lyman-alpha forests can map the neutral hydrogen fluctuations $\delta_{Ly\alpha}(\vec{x})$



A Lyman-alpha forest

A high signal-to-noise ratio quasar spectrum from eBOSS



From fluxes $\{f_j\}$ to $\delta_{Ly\alpha}(\vec{x})$



$$F(\lambda) = \frac{f(\lambda)}{C(\lambda)} = e^{-\tau(\lambda)}$$














We want
$$\delta_F(\lambda) = \frac{F(\lambda)}{\langle F \rangle(\lambda)} - 1$$

Just like for galaxies



We want
$$\delta_F(\lambda) = \frac{F(\lambda)}{\langle F \rangle(\lambda)} - 1$$

Just like for galaxies

$$\delta_g(\vec{x}) = \frac{n_g(\vec{x})}{\bar{n}_g} - 1$$



 $F(\lambda)$ We want

Just like for galaxies

$$\delta_F(\lambda) = \frac{\Gamma(\lambda)}{\langle F \rangle(\lambda)} - 1$$

$$\delta_g(\vec{x}) = \frac{n_g(\vec{x})}{\bar{n}_g} - 1$$

Methods to obtain $C(\lambda)$

- Use measurements of $\langle F \rangle(\lambda)$ from highresolution spectra (Lee et al. 2012) or from stacks (Kamble et al. 2020)
- Build **PCA** templates for $C(\lambda_{rest})$ from low-z • high-res spectra (Suzuki et al. 2006)
- Use a flux P.D.F. from mocks (Busca et al. 2013)
- Give up and do the simplest thing for now (du Mas des Bourboux et al. 2020)

$$\hat{\delta}_F(\lambda) = \frac{f(\lambda)}{(a_q + b_q \lambda)\bar{C}(\lambda_{\text{rest}})} - 1$$

where $C(\lambda_{rest})$ is a universal function

Weights of $\delta_{Ly\alpha}(\vec{x})$

$$\hat{\delta}_F(\lambda) = \frac{f(\lambda)}{(a_q + b_q \log \lambda)\bar{C}(\lambda_{\text{rest}})} - 1 \qquad w = 1/\sigma_{\delta_F}^2$$

Total variance of $\hat{\delta}_F$













Lyman- α or **metal absorption (Si, C, N, etc)**?



Lyman- α or **metal absorption (Si, C, N, etc)**?

 $z_{\text{line}} = \lambda_{\text{obs}} / \lambda_{\text{SiIII}} - 1$ $z_{\text{line}} = 5300 \text{ Å} / 1207 \text{ Å} - 1$ $z_{\text{line}} = 3.39$



Lyman- α or **metal absorption (Si, C, N, etc)**?

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Ly β or metal absorption is indistinguishable from Ly α !







"Intensity map" : no need for randoms!

Tracers :

- Ly α (in Ly α forest)
- QSOs
- Lylpha (in Lyeta forest)
- Ly β (in Ly β forest)
- metals (CIV, SiIV, MgII...)



Tracers :

- Ly α (in Ly α forest)
- QSOs
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$$\hat{\xi}(A) = \frac{\sum_{(i,j)\in A} w_i w_j \delta_i \delta_j}{\sum_{(i,j)\in A} w_i w_j}$$



"Intensity map" : no need for randoms!

Auto and cross-correlations

Ly α (in Ly α forest) x Ly α (in Ly α forest) Ly α (in Ly α forest) x QSOs Ly α (in Ly β forest) x Ly α (in Ly α forest) Ly α (in Ly β forest) x QSOs Others do not add much

$\begin{array}{l} \textbf{Correlation functions}\\ \textbf{Auto-correlation of } \textbf{Ly}\alpha \text{ (in the } \textbf{Ly}\alpha \text{ forest)}\\ \boldsymbol{\xi}(\vec{r}_A) = \langle \delta_{\textbf{Ly}\alpha} \delta_{\textbf{Ly}\alpha} \rangle \end{array}$



eBOSS Lyα-forests <u>du Mas des Bourboux et al. 2020</u>

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eBOSS Lyα-forests <u>du Mas des Bourboux et al. 2020</u>

Auto-correlation of Ly α (in the Ly α forest)

$$\xi(\vec{r}_A) = \langle \delta_{\mathrm{Ly}\alpha} \delta_{\mathrm{Ly}\alpha} \rangle$$



Not-so-transverse wedge

Transverse wedge

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Transverse wedge

eBOSS Lyα-forests <u>du Mas des Bourboux et al. 2020</u>

Cross-correlation of Ly α (in the Ly α forest) and QSOs

 $\xi(\vec{r}_A) = \langle \delta_{\rm Ly\alpha} \delta_{\rm QSO} \rangle$



Cross-correlation of Lylpha (in the Lylpha forest) and QSOs

 $\xi(\vec{r}_A) = \langle \delta_{\rm Ly\alpha} \delta_{\rm QSO} \rangle$



Cross-correlation of Lylpha (in the Lylpha forest) and QSOs

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Have you noticed the **sign flip** compared to the auto-correlation ?

$$C_{AB} = \langle \xi_A \xi_B \rangle - \langle \xi_A \rangle \langle \xi_B \rangle$$

Subsamples or 4-pt with Wick Theorem





Smoothing required for a positive definite matrix (since N_{samples} < N_{bins}) !

 $C_{AB} = \langle \xi_A \xi_B \rangle - \langle \xi_A \rangle \langle \xi_B \rangle$ Subsamples or 4-pt with Wick Theorem $\langle \delta \delta \delta \delta \rangle \approx \sum \langle \delta \delta \rangle \langle \delta \delta \rangle$ Covariance matrix
Case of Lyman- α forests $C_{AB} = \langle \xi_A \xi_B \rangle - \langle \xi_A \rangle \langle \xi_B \rangle$ Subsamplesor4-pt with Wick Theorem $\langle \delta\delta\delta\delta \rangle \approx \sum \langle \delta\delta \rangle \langle \delta\delta \rangle$

Configurations for auto correlation



Covariance matrixCase of Lyman- α forests $C_{AB} = \langle \xi_A \xi_B \rangle - \langle \xi_A \rangle \langle \xi_B \rangle$ Subsamplesor4-pt with Wick Theorem $\langle \delta\delta\delta\delta\rangle \approx \sum \langle \delta\delta \rangle \langle \delta\delta \rangle$



Why not use mocks, like in galaxy clustering ?

- Hard to reproduce signal in data + noise properties
- Costly to produce hundreds of realisations

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But we can **test our methods** using mocks self-consistently

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We can combine BAO constraints assuming they are independent



Covariance between $\langle \delta_{Ly\alpha} \delta_{QSO} \rangle$ and $\langle \delta_{Ly\alpha} \delta_{Ly\alpha} \rangle$ is less than 2% !

We can combine BAO constraints assuming they are independent

Contaminants and systematic effects Case of Lyman- α forests



Damped Lyman-alpha A optically thick patch of gas



Damped Lyman-alpha A optically thick patch of gas



Strong absorption in the forest is **masked** when fitting continuum
Distortions

By fitting continuum using fluxes $\{f_i\}$ in a given forest we introduce correlations between all $\delta_{Ly\alpha,j}$ of that forest!



Distortions

... creating an artificial distortion of the correlation function



<u>JB et al. 2017</u>

How to extract the BAO scale ?

Case of Lyman- α forests

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Separate BAO peak from smooth part: $O(k) = P(k)/P_{nopeak}(k) - 1$

Empirical smoothing of BAO peak (non-linearities):

$$O(k)\exp\left(-\frac{k^2 \Sigma_{\rm NL}^2(\mu_k)}{2}\right)$$
$$\Sigma_{\rm NL}(\mu_k) = \Sigma_{\parallel}^2 \mu_k^2 + \Sigma_{\perp}^2(1-\mu_k^2)$$

Modelling of reconstruction and removal of RSD: $f\mu_k^2 \rightarrow f\mu^2 \left(1 - e^{-k^2 \Sigma_r^2/2}\right)$

Power-laws to marginalise shape information :

$$+\sum_{\ell,i=0}a_{\ell,i}k^{i}$$

Scaling of separations:

$$\begin{aligned} k_{\parallel} &= k_{\parallel}^{\text{fid}} / \alpha_{\parallel} & k_{\perp} &= k_{\perp}^{\text{fid}} / \alpha_{\perp} \\ r_{\parallel} &= \alpha_{\parallel} r_{\parallel}^{\text{fid}} & r_{\perp} &= \alpha_{\perp} r_{\perp}^{\text{fid}} \end{aligned}$$

Similar than for model for galaxies

Modelling the correlations Case of Lyman- α forests

 $\hat{P}(k) = b_i b_j (1 + \beta_i \mu_k^2) (1 + \beta_j \mu_k^2) P_{\text{QL}}(k) F_{\text{NL}}(k) G(k)$

Modelling the correlations Case of Lyman- α forests

$$\hat{P}(\boldsymbol{k}) = b_i b_j (1 + \beta_i \mu_k^2) (1 + \beta_j \mu_k^2) P_{\text{QL}}(\boldsymbol{k}) F_{\text{NL}}(\boldsymbol{k}) G(\boldsymbol{k})$$
linear bias
linear RSD
Both account for
damping tails from DLAs

Modelling the correlations Case of Lyman- α forests



Modelling the correlations Case of Lyman- α forests



Case of Lyman- α forests



Case of Lyman- α forests



Case of Lyman- α forests



Template auto:
$$\xi^{t} = \xi^{Ly\alpha \times Ly\alpha} + \sum_{m} \xi^{Ly\alpha \times m} + \sum_{m_{1},m_{2}} \xi^{m_{1} \times m_{2}} + \xi^{sky}$$
Template cross:
$$\xi^{t} = \xi^{Ly\alpha \times QSO} + \sum_{m} \xi^{QSO \times m} + \xi^{TP}$$

Case of Lyman- α forests



Template auto:
$$\xi^{t} = \xi^{Ly\alpha \times Ly\alpha} + \sum_{m} \xi^{Ly\alpha \times m} + \sum_{m_{1},m_{2}} \xi^{m_{1} \times m_{2}} + \xi^{sky}$$
Template cross:
$$\xi^{t} = \xi^{Ly\alpha \times QSO} + \sum_{m} \xi^{QSO \times m} + \xi^{TP}$$

Case of Lyman- α forests



Template auto:
$$\xi^{t} = \xi^{Ly\alpha \times Ly\alpha} + \sum_{m} \xi^{Ly\alpha \times m} + \sum_{m_{1},m_{2}} \xi^{m_{1} \times m_{2}} + \xi^{sky},$$

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Case of Lyman- α forests





Case of Lyman- α forests





Modelling the correlations Case of Lyman- α forests

Contamination by metals

Contamination by sky residuals

Modelling the correlations Case of Lyman- α forests

Contamination by metals

Contamination by sky residuals

Linear transformation between true correlation and shifted/confused correlation



119.3

126.0

-56

+111

Si ∏b

Si IIc

Modelling the correlations Case of Lyman- α forests

Contamination by metals

Contamination by sky residuals

Linear transformation between true correlation and shifted/confused correlation



Metal Line	λ_m (nm)	r_{\parallel} (h^{-1} Mpc)
Si III	120.7	-21
Si IIa	119.0	-64
Si IIb	119.3	-56
Si IIc	126.0	+111



Constraints on BAO peak position

Case of Lyman- α forests



Good agreement with prediction by Planck flat LCDM

Constraints on BAO peak position

Case of Lyman- α forests



Robust against many analysis choices (at this precision)









Neutrino masses with $Ly\alpha$ forests

Impact on linear matter power-spectrum <u>Palanque-Delabrouille et al. 2014</u>



Current limits from ground oscillation experiments $\sum m_{\nu} < 0.06 \text{ eV}$

Instead of 3D correlations....



in Configuration space...



in Configuration space...

in Fourier space!

BOSS+eBOSS data: 43k forests <u>Chabanier et al. 2019</u>

Start from fluctuations

 $\hat{\delta}_F(\lambda) = \frac{f(\lambda)}{(a_q + b_q \log \lambda)\bar{C}(\lambda_{\text{rest}})} - 1$

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Start from fluctuations

$$\hat{\delta}_F(\lambda) = \frac{f(\lambda)}{(a_q + b_q \log \lambda)\bar{C}(\lambda_{\text{rest}})} - 1$$

Compute raw power-spectrum along line-of-sights $P_{raw}(k) = \langle |\tilde{\delta}_F(k)|^2 \rangle$

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Removing contaminations from uncorrelated metals

 $P_{raw}(k) = [P_{Ly\alpha}(k) + P_{correlated}(k) + P_{uncorrelated}(k)] \cdot W^{2}(k) + P_{noise}(k)$

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Removing contaminations from uncorrelated metals

 $P_{raw}(k) = [P_{Ly\alpha}(k) + P_{correlated}(k)] + P_{uncorrelated}(k)] \cdot W^{2}(k) + P_{noise}(k)$ Final result

BOSS+eBOSS data: 43k forests <u>Chabanier et al. 2019</u>



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Modelling the 1D power spectrum of Ly α forests

Suite of hydrodynamical n-body simulations Borde et al. 2014, <u>Rossi et al. 2014</u>, <u>Chabanier et al. 2019</u>

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Cosmology grid

Parameter	Value	
$\sigma_8(z=0)$	0.83	± 0.05
n _s	0.96	± 0.05
$H_0 [{\rm km}~{\rm s}^{-1}~{\rm Mpc}^{-1}]$	67.5	± 5.0
$\Omega_{ m m}$	0.31	± 0.05
$\Omega_{ m b}$	0.044	
Ω_{Λ}	0.69	
$T_0(z = 3)[K]$	15 000	± 7000
$\gamma(z=3)$	1.3	±0.3
Starting redshift	30	

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G-astrosphysics

Adiabatic cooling Ultraviolet background ionization heating Compton and recombination cooling Feedback from star formation and AGNs Particle based neutrino implementation
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Massive neutrinos

$$M_{\nu} = 0.1, 0.2, 0.3, 0.4, \text{ and } 0.8 \text{ eV}$$

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Model is interpolation/emulation of simulation results

Gas



Dark Matter

(1)

Neutrinos



Gas



Dark Matter



Neutrinos



Rossi et al. 2014

Constraints on neutrino mass from 1D power spectrum of Ly α forests



	In a nutshell Case of Lyman- α forests	
	3D	1D
Goal	BAO at high-redshift	Small-scale clustering
Space	Configuration	Fourier
Parameters	$\left(\frac{D_{H}(z)}{r_{\rm drag}}, \frac{D_{M}(z)}{r_{\rm drag}}\right)_{\rm peak}$	$M_{\nu}, A_s, n_s, \Omega_m h^2$
Model type	Analytical	Emulators from hydro-sims

From clustering to cosmology



From clustering to cosmology

eBOSS Collab 2021

CMB

From clustering to cosmology

eBOSS Collab 2021



RSD

From clustering to cosmology

eBOSS Collab 2021



What does it measure ?

$$\Delta \theta(z) = \frac{r_{\text{ruler}}}{D_M(z)}$$

$$\Delta z(z) = \frac{r_{\text{ruler}}}{D_H(z)}$$

$$\Delta \theta(z) = \frac{r_{\text{ruler}} H_0}{c \int_0^z dz' \left[\Omega_m (1+z')^3 + \Omega_{\text{DE}}(z') \right]^{-1/2}}$$

$$\Delta z(z) = \frac{r_{\text{ruler}} H_0}{c [\Omega_m (1+z')^3 + \Omega_{\text{DE}}(z')]^{-1/2}}$$



What does it measure ?





What does it measure ?



BBN measures $\Omega_b h^2$, constraining $r_{\rm ruler}$



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Distance Ladder measures H₀



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BBN measures $\Omega_b h^2$, constraining $r_{\rm ruler}$

Distance Ladder measures H₀

CMB measures both (in a flat ΛCDM model!)

Still, we can constrain dark-energy without knowledge of r_{ruler}

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Baryon Acoustic Oscillations (BAO)

What does it measure ?



What does it measure ?



BAO as powerful as SNIa, and independently showing acceleration !

What does it measure ?



BAO as powerful as SNIa, and independently showing acceleration !

Redshift-space distortions (RSD) + Weak gravitational lensing (WL)

Scalar metric perturbations in the conformal Newtonian gauge :

$$ds^{2} = a^{2}(\tau)[(1+2\Psi)d\tau^{2} - (1-2\Phi)\delta_{ij}dx_{i}dx_{j}]$$

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 $k^2\Psi = -4\pi Ga^2(1+\mu(a))\rho\delta,$

where $\mu(a) = \Sigma(a) = 0$ in GR

 $k^2(\Psi + \Phi) = -8\pi Ga^2(1 + \Sigma(a))\rho\delta$

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Choosing :

$$egin{aligned} \mu(z) &= \mu_0 rac{\Omega_\Lambda(z)}{\Omega_\Lambda}, \ \Sigma(z) &= \Sigma_0 rac{\Omega_\Lambda(z)}{\Omega_\Lambda} \end{aligned}$$

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A hint of the future of observations

Future cosmological constraints

Expansion rate with BAO

Growth-rate of structures with RSD and peculiar velocities



Future cosmological constraints

Expansion rate with BAO

Growth-rate of structures with RSD and peculiar velocities



We hope we can learn more about cosmology !

