Precise Cosmological Constraints from BOSS (& DESI) Galaxy Clustering using the Wavelet Scattering Transform

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New Strategies for Extracting Cosmology from Galaxy Surveys - 2nd edition
Tuesday, July 7, 2024

Background from Millennium Simulation, 2005

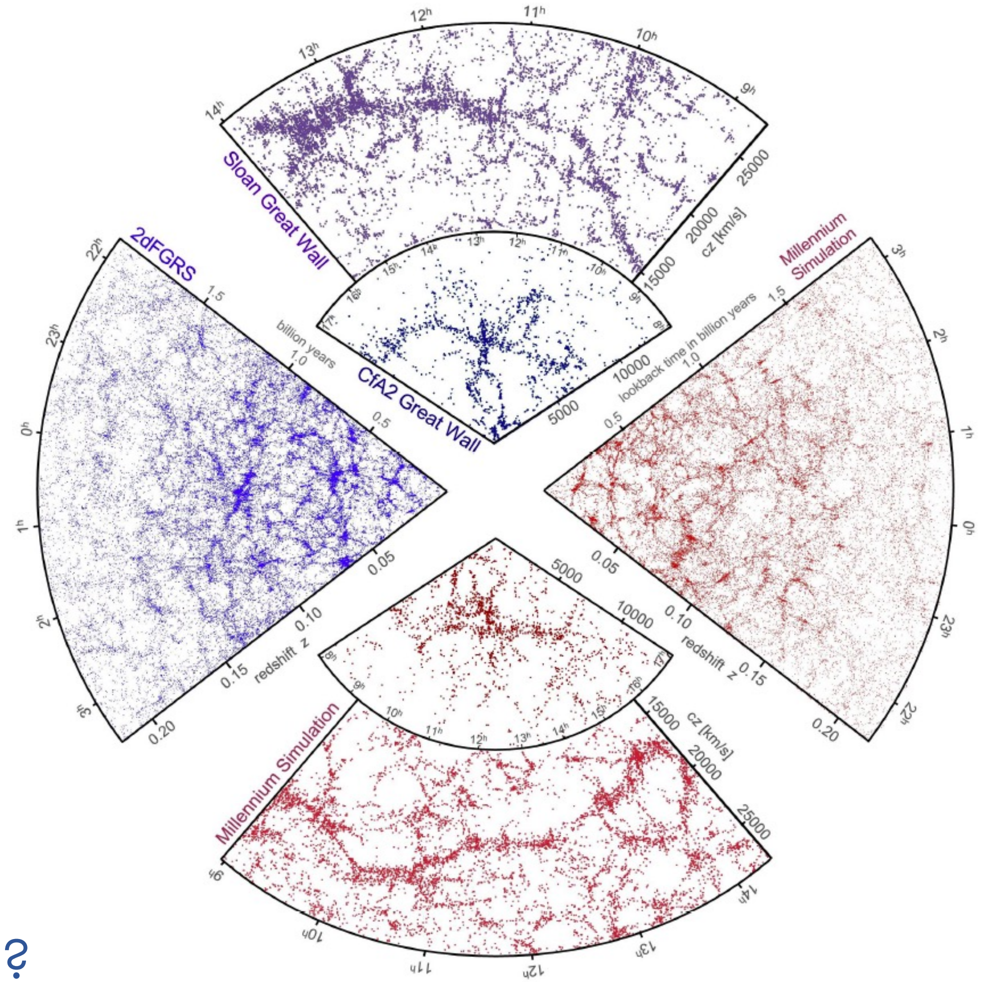
Based partly on
arXiv: 2310.16116, 2204.13717 & 2108.07821
in collaboration with **Cora Dvorkin & Sandy Yuan**

Challenges in the era of precision cosmology

- Large-Scale Structure (LSS) of the universe a powerful probe of *fundamental physics*
  - Dark energy
  - Dark matter
  - Massive neutrinos
  - Gravity

- Will soon be mapped precisely by:
  - Dark Energy Spectroscopic Instrument (DESI)
  - V. Rubin Observatory LSST
  - Euclid
  - Nancy Grace Roman Space Telescope
  - SPHEREx
  - + Synergies with CMB

- How do we *optimally* extract information from the LSS??



V. Springel et al. (2006)

The quest for an ideal estimator

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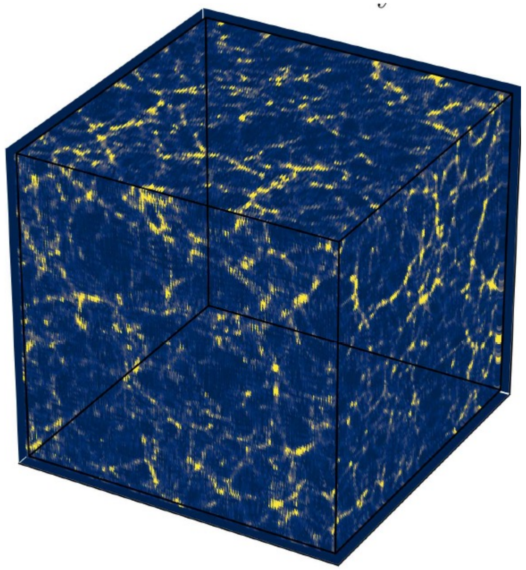
- Attempts to describe the information encoded in the 3D cosmic density field



F. Villaescusa-Navaro et al. (2019)

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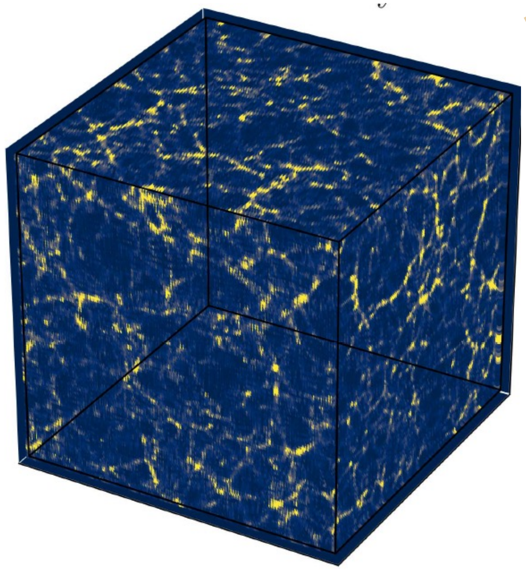
2-point correlation function/Power Spectrum



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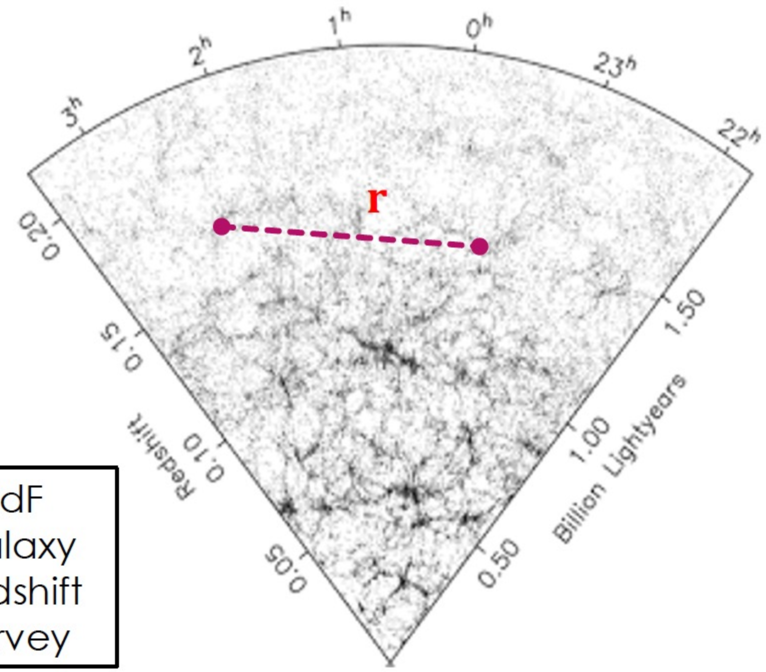

2dF Galaxy Redshift Survey

O. Philcox et al. (2021)

Physical Information

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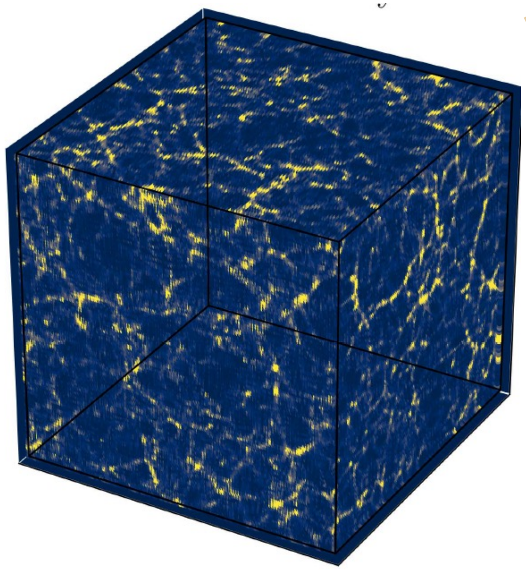
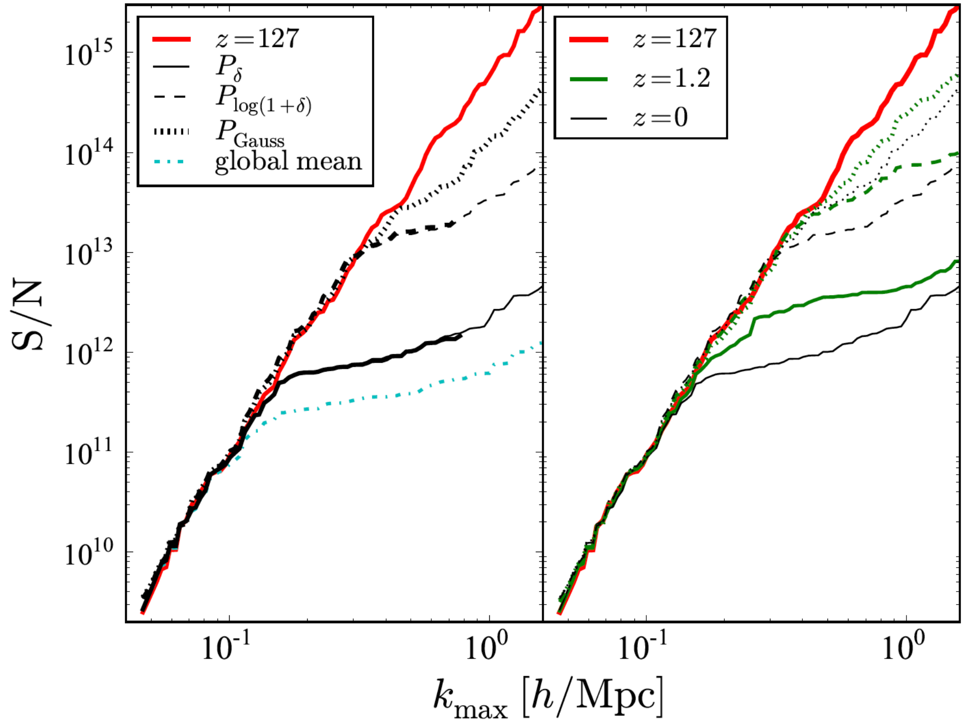


F. Villaescusa-Navaro et al. (2019)

2-point correlation function/Power Spectrum (incomplete)



M. Neyrinck et al. (2009)

Power Spectrum information saturates in nonlinear regime. Inadequate!
(Carron 2011,2012)

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The quest for an ideal estimator

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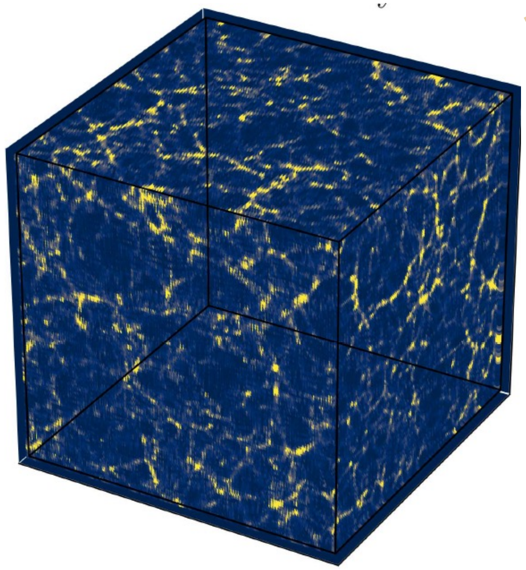
Power spectrum + Higher order statistics (expensive, incomplete?)



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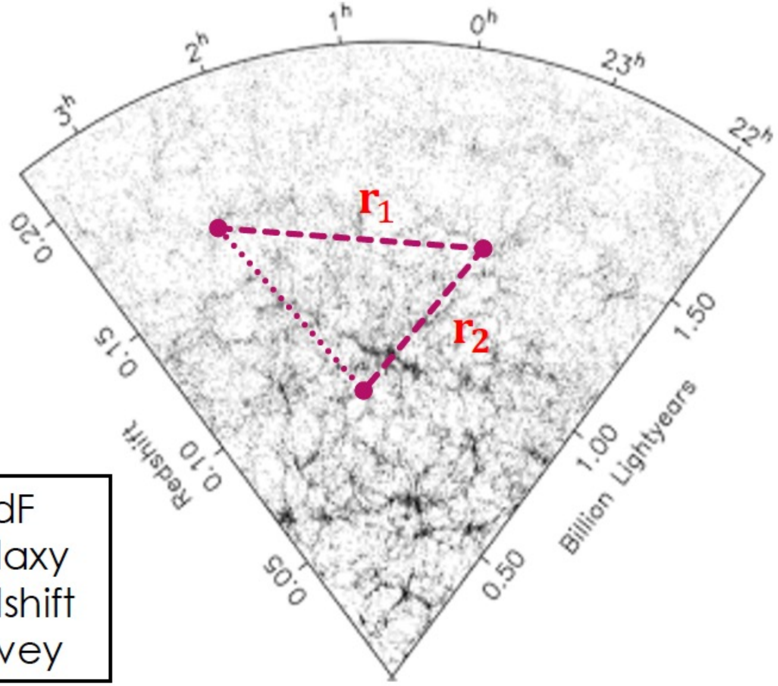
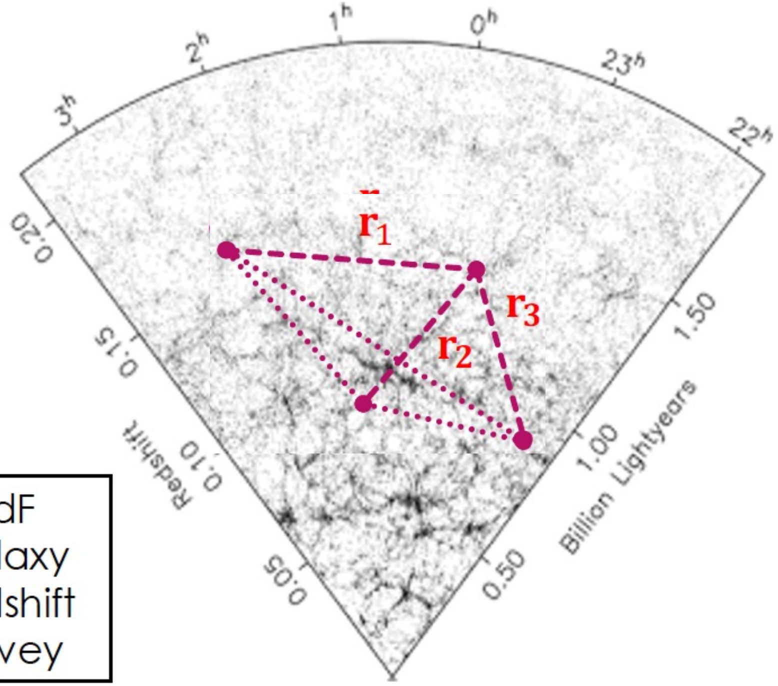
3-point function



2dF Galaxy Redshift Survey

4-point function



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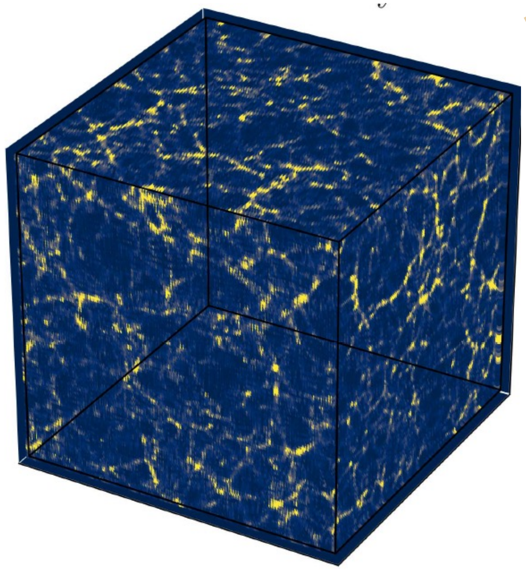

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Power spectrum + Higher order statistics

Marked power spectrum, log. transform, skew spectrum
Nearest neighbor distributions, density split, voids, etc

Physical Information

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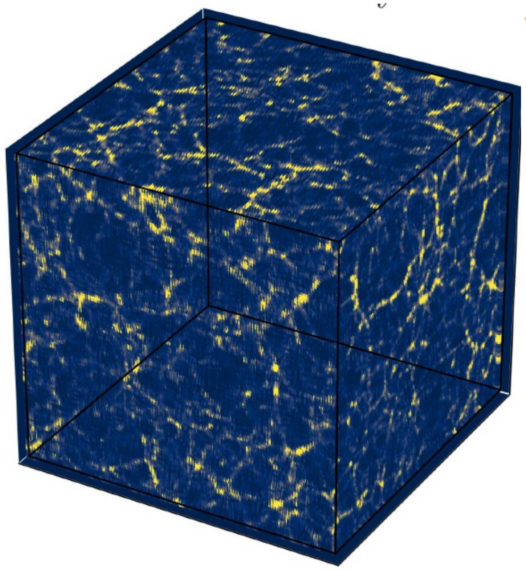

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Physical Information

Artificial Intelligence (e.g. CNNs)
(Training, interpretability)

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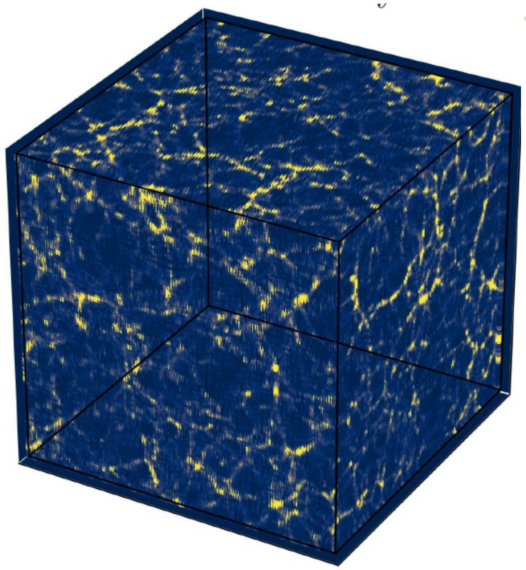
The quest for an ideal estimator

- Attempts to describe the information encoded in the 3D cosmic density field



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Wavelet Scattering Transform (WST)
S. Mallat (2012)

Physical Information

Artificial Intelligence (e.g. CNNs)

The Wavelet Scattering Transform (WST)

"Scattering Network" image by G. Exarchakis (2018)

Convolution

Modulus

WST: $\langle \left| I_0 \star \psi^{j_1,l_1} \right| \rangle$ → Averaging

Input field

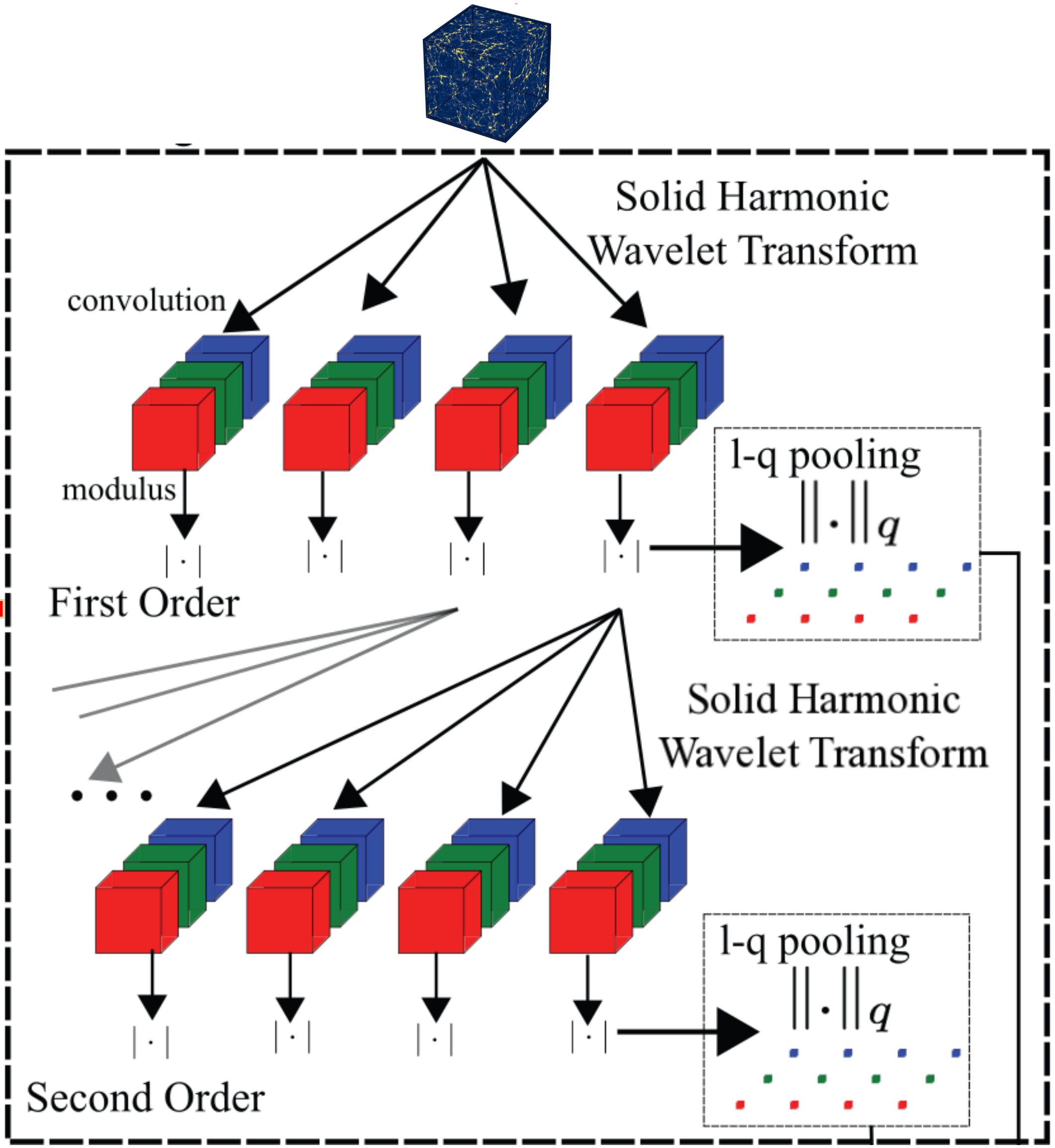
Family of Wavelets

- Dilated by 2^{j_1} - J scales
- Rotated by l_1 - L orientations

$$\boxed{S_0 = \langle |I_0| \rangle}$$

$$\boxed{S_1^{j_1,l_1} \equiv \langle I_1^{j_1,l_1} \rangle = \langle \left| I_0 \star \psi^{j_1,l_1} \right| \rangle}$$

$$\boxed{S_2^{j_1,l_1,j_2,l_2} \equiv \langle I_2^{j_1,l_1,j_2,l_2} \rangle = \langle \left| \left| I_0 \star \psi^{j_1,l_1} \right| \star \psi^{j_2,l_2} \right| \rangle}$$



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The Wavelet Scattering Transform (WST)

Physical interpretation of WST coefficients

- $S_0 = \langle |I_0| \rangle$: Mean field
- $S_1^{j_1,l_1} = \left\langle \left| I_0 \star \psi^{j_1,l_1} \right| \right\rangle$: ~ P(k). In fact, P(k) ⟹ $\langle |I \star e^{-ikx}|^2 \rangle$
- $S_2^{j_1,l_1,j_2,l_2} = \left\langle \left| \left| I_0 \star \psi^{j_1,l_1} \right| \star \psi^{j_2,l_2} \right| \right\rangle$: *Non-Gaussian* information (up to $2^2 = 4$pcf , for n=2)
- Basis $S_0 + S_1 + S_2$ reflects clustering properties of target field $I_0(x)$
- Retaining all *desirable* properties of regular P(k) ✅ Mallat (2012)

  +

- Compactness ✅ (Anden & Mallat, 2011,2014, Bruna & Mallat, 2013) & Robustness/Stability ✅ (Carron 2011,2012, Cheng & Menard 2021b)
- A CNN with fixed weights, but interpretable! (Bruna & Mallat 2013)
  - Performance on par with a CNN in WL applications! (Cheng et al. 2020b, Cheng & Menard 2021a)
- WST exceeds performance of traditional P(k) in 3D LSS studies **(Valogiannis & Dvorkin 2022a,b)**
  - Also overperforms marked P(k) (Massara et al., PRL 126, 011301 (2021))

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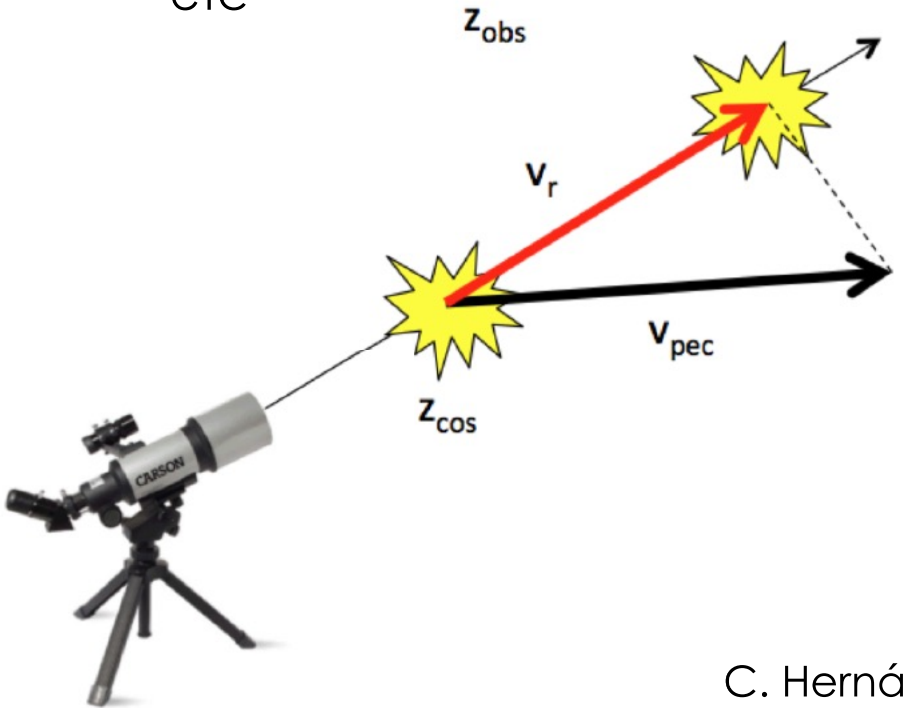
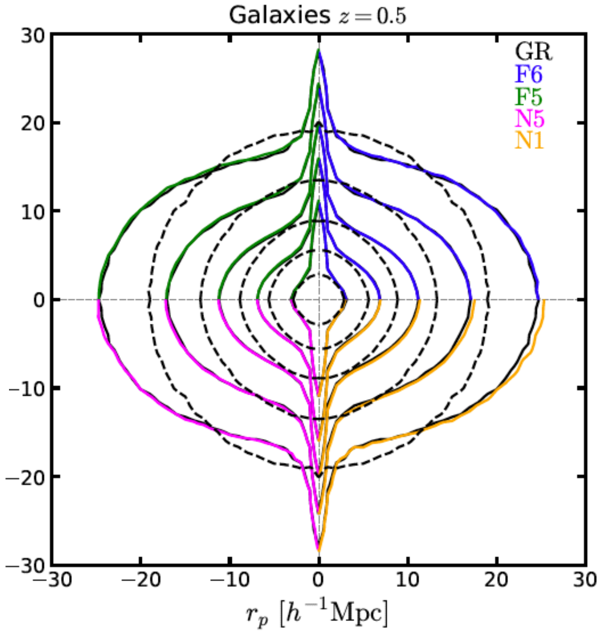
Realistic galaxy survey data

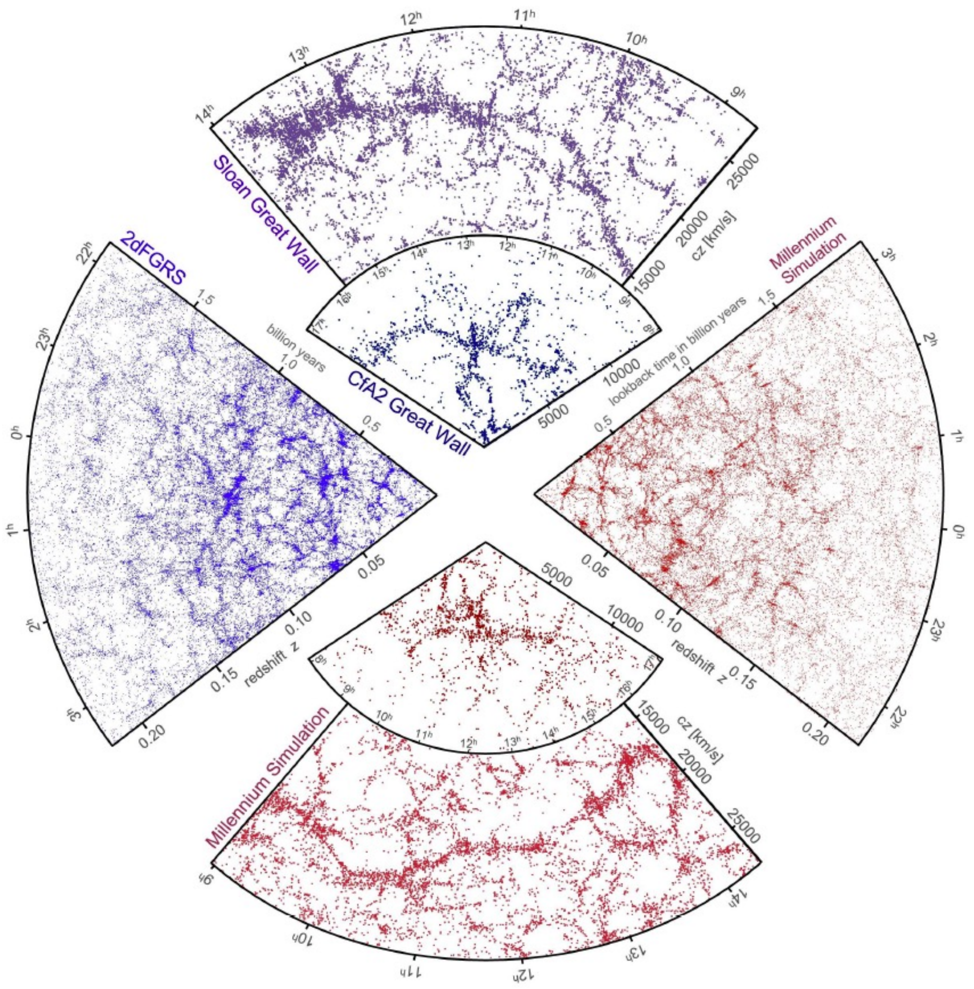
However

- LSS surveys observe *galaxies*:
  - Biased tracers of dark matter field
  - Redshift-Space Distortions (RSD)
  - Systematics (Geometry, fiber collisions, etc..)
  - Lightcone
  - etc





C. Hernández-Aguayo et al., 2018



V. Springel et al. (2006)

First WST application on BOSS

- **First** WST application on 3D *redshift-space galaxy* density field! (**Valogiannis & Dvorkin 2022b)**
  - Working with *BOSS CMASS DR12* sample at 0.46<z<0.57
  - Northern + Southern Galactic Cap
- For survey data, fundamental quantity of interest is the *FKP field* (Feldman, Kaiser, Peacock et al., 1994) :

$$F(\mathbf{r}) = \frac{w_{\rm FKP}(\mathbf{r})}{I_2^{1/2}}\left[w_c(\mathbf{r})n_g(\mathbf{r}) - \alpha_r n_s(\mathbf{r})\right]$$

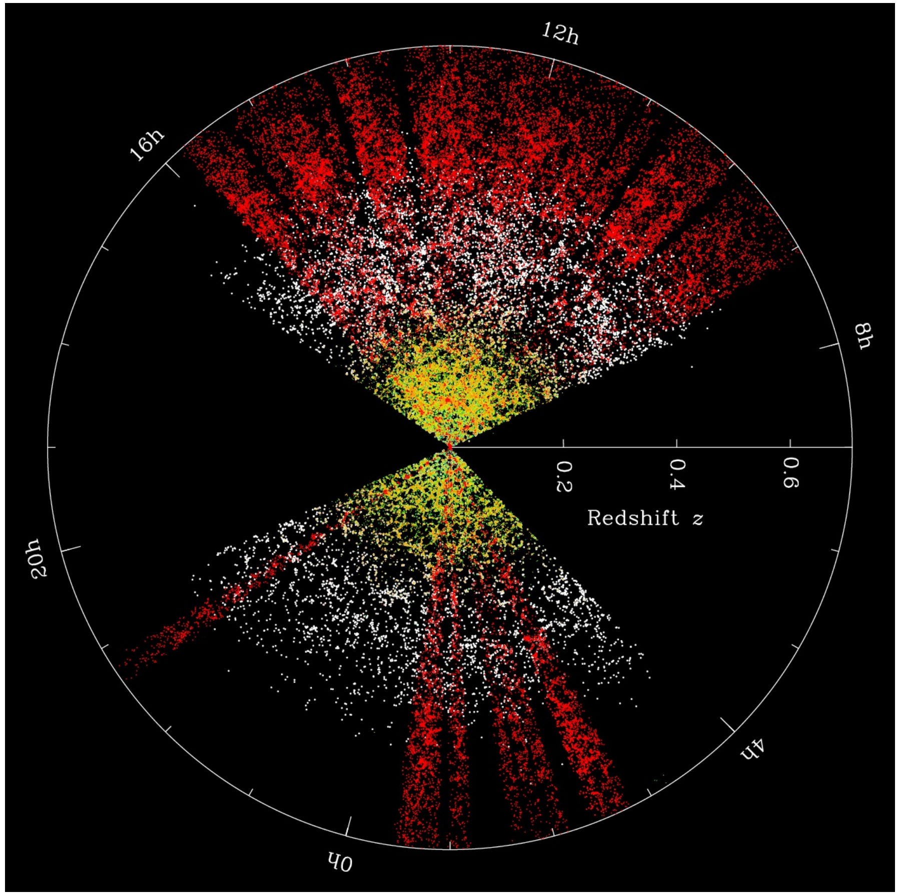
Galaxies Randoms

- Systematic + FKP weights

$$w_c(\mathbf{r}) = \left(w_{\rm rf}(\mathbf{r}) + w_{\rm fc}(\mathbf{r}) - 1.0\right) w_{\rm sys}(\mathbf{r})$$

$$w_{\rm FKP}(\mathbf{r}) = \left[1 + \bar{n}_g(\mathbf{r})P_0\right]^{-1}$$

- Serves as input into WST network
  - With $N_{grid} = 270^3$ and $L_{Box} = 2700\ Mpc/h$



SDSS https://blog.sdss.org/

Likelihood analysis

- We perform likelihood analysis, sampling from Gaussian likelihood

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1} \left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]$$

Likelihood analysis

- Data

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1}\left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]$$

- Use vector of WST coefficients as observable
- Extracted from BOSS CMASS FKP field, using

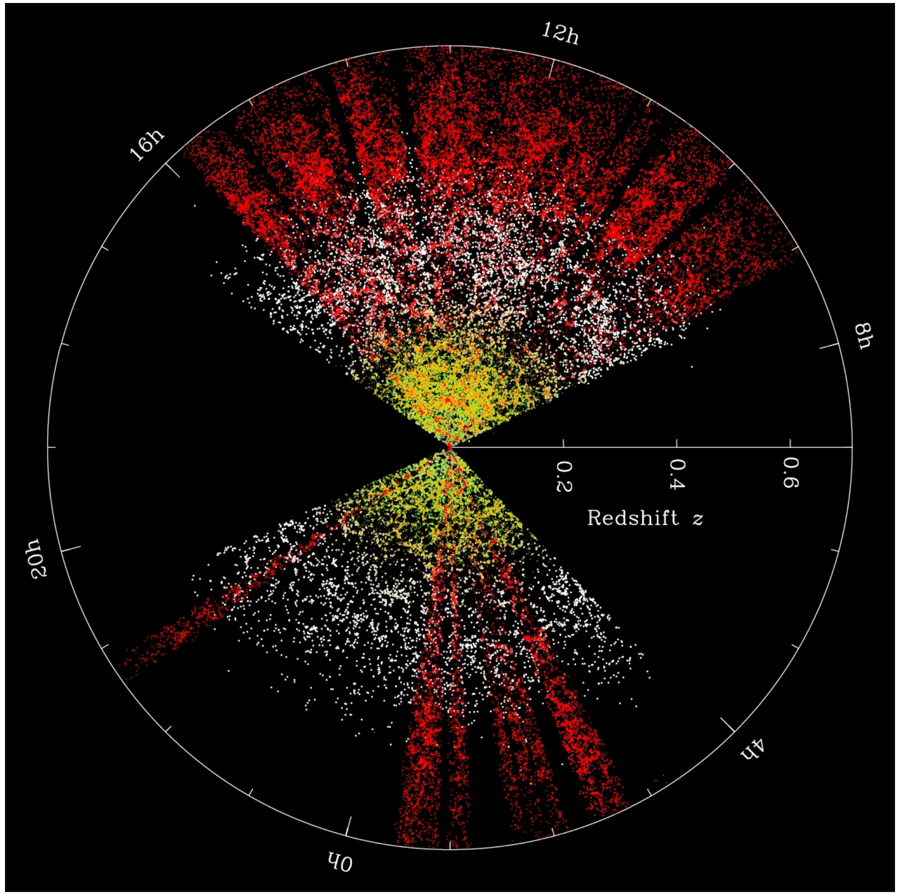
J=5 scales and L=5 orientations

- $\boldsymbol{S_0 + S_1 + S_2 = 76}$ WST coefficients

- Also, use galaxy 2-point correlation function multipoles

$\boldsymbol{\xi_{l=0,2}(r)}$ **($\boldsymbol{r_{min} = 8}$ Mpc/h)**

as benchmark



SDSS https://blog.sdss.org/

Likelihood analysis

- Theory model

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1}\left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]$$

- Capture cosmological dependence using

Abacus Summit simulations (Maksimova et al. 2021, Garrison et al. 2019&2021)

HOD tuned to BOSS CMASS at 0.46<z<0.60 with AbacusHOD (**Yuan et al. 2021**)

Box L=2000 Mpc/h, $N_{grid} = 200^3$

- Fiducial cosmology from Planck 2018 $\{\omega_b, \omega_c, n_s, \sigma_8\} = \{0.02237, 0.120, 0.9649, 0.8114\}$
- + Fixed angular size of sound horizon at last scattering. $100\theta_\star = 1.041533$
- + 7 HOD model paramerers (vanilla HOD + velocity bias)

$$\{\alpha, \alpha_c, \alpha_s, \kappa, \log M_1, \log M_{\mathrm{cut}}, \sigma\} = \{0.9022, 0.2499, 1.1807, 0.3288, 14.313, 12.8881, 0.02084\}$$

- We cut Abacus cubic boxes into actual CMASS geometry
  - Using 'make survey' (White et al., 2013)

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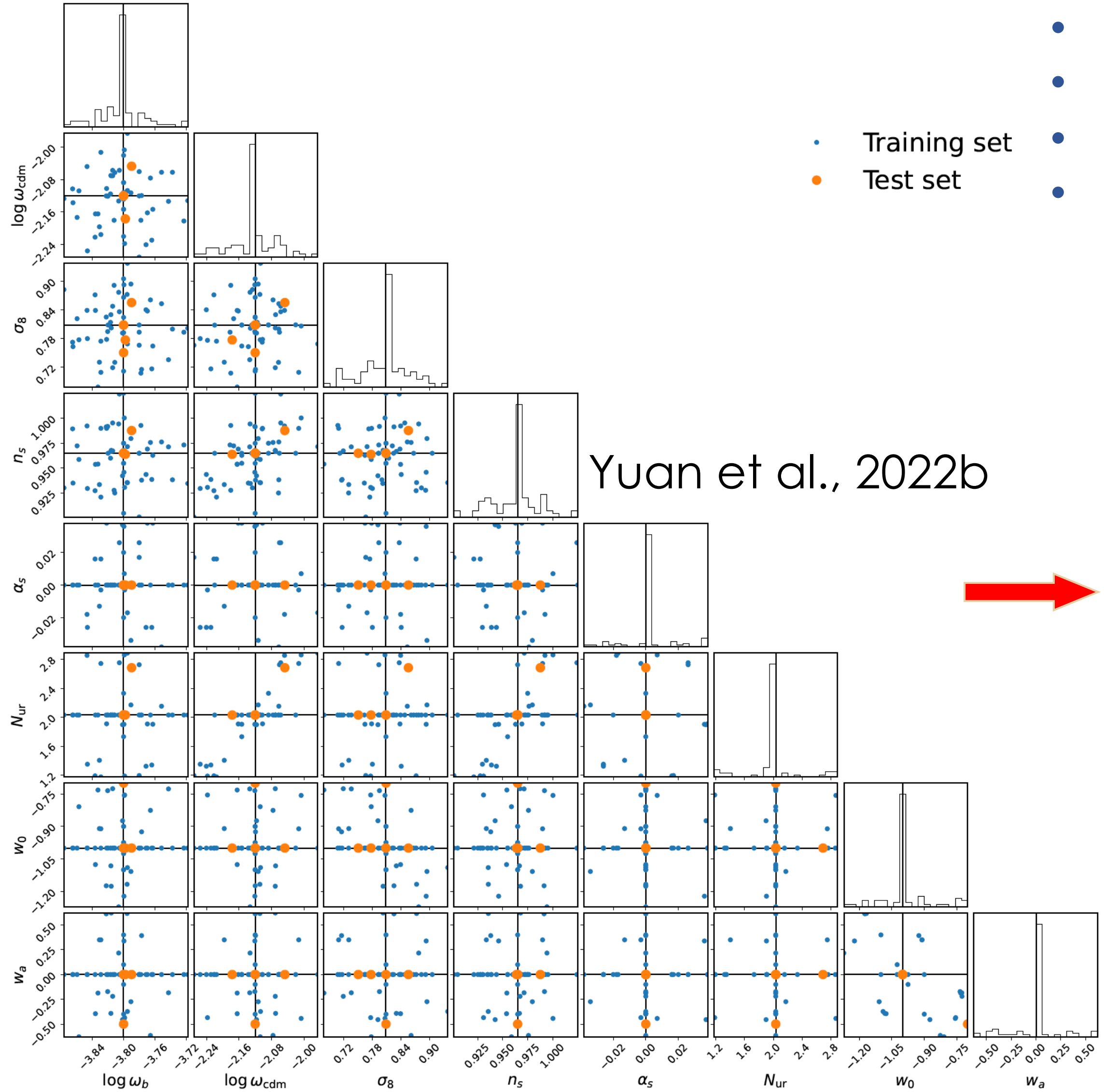
WST emulator

- Construct *full emulator* of WST's cosmological dependence
- Data vector of 76 coefficients up to 2nd order, for J=L=5
- Trained from 151,474 Abacus Summit galaxy mocks!
- 8 cosmo + 7 HOD = 15d space, neural net-based



Yuan et al., 2022b

	Parameter	Bounds
ΛCDM	ω_b	[0.0207, 0.0243]
	ω_c	[0.1032, 0.14]
	σ_8	[0.687, 0.938]
	n_s	[0.901, 1.025]
Extended	$a_{\rm run}$	[-0.038, 0.038]
	$N_{\rm eff}$	[2.1902, 3.9022]
	w_0	[-1.27, -0.70]
	w_a	[-0.628, 0.621]
HOD	$\log_{10} M_{\rm cut}$	[12.4, 13.3]
	$\log_{10} M_1$	[13.0, 15.0]
	σ	[0.001, 1.0]
	α	[0.5, 1.5]
	κ	[0.0, 8]
	α_c	[0.0, 0.8]
	α_s	[0.0, 1.5]

Valogiannis et al., 2023

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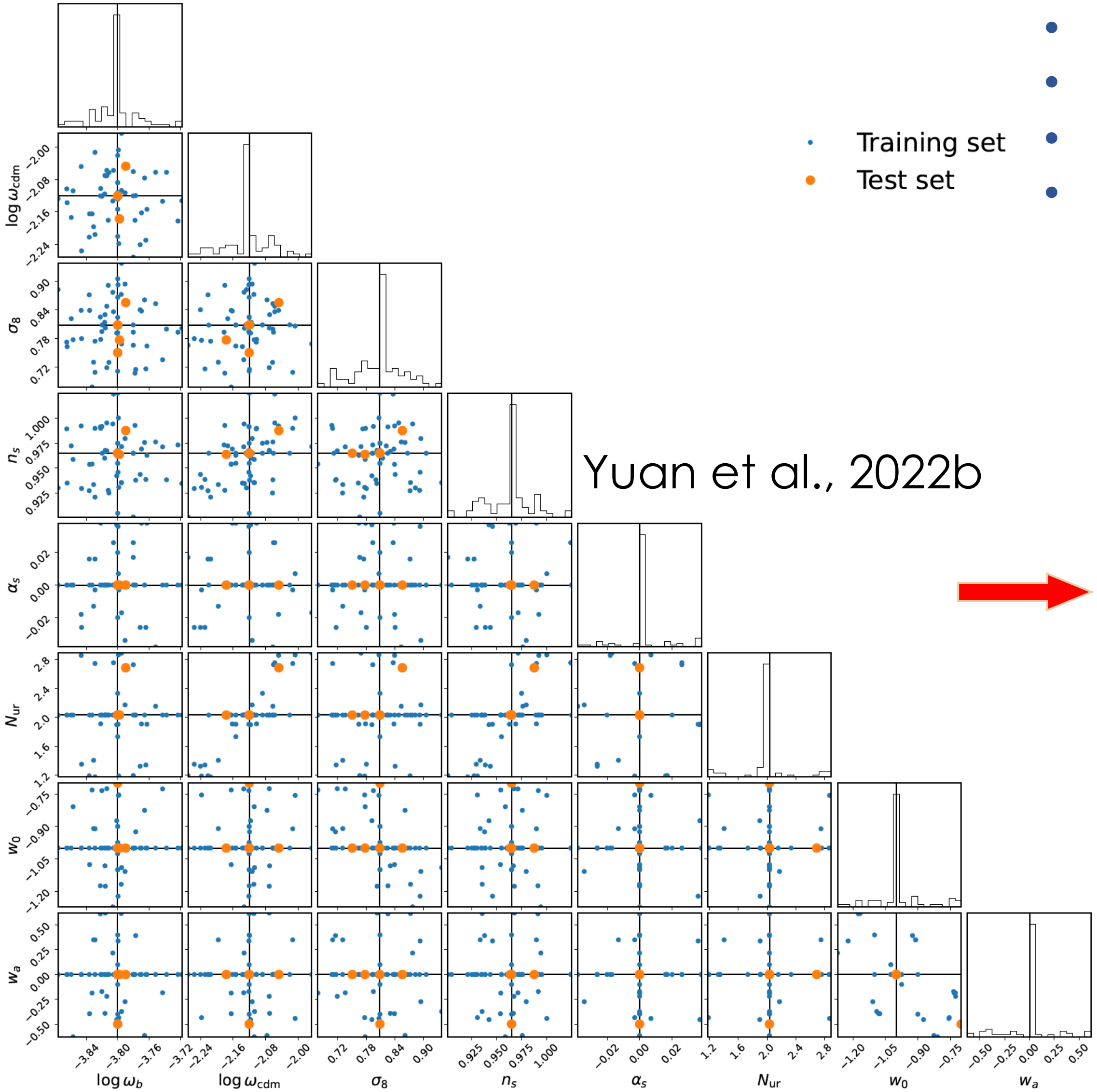
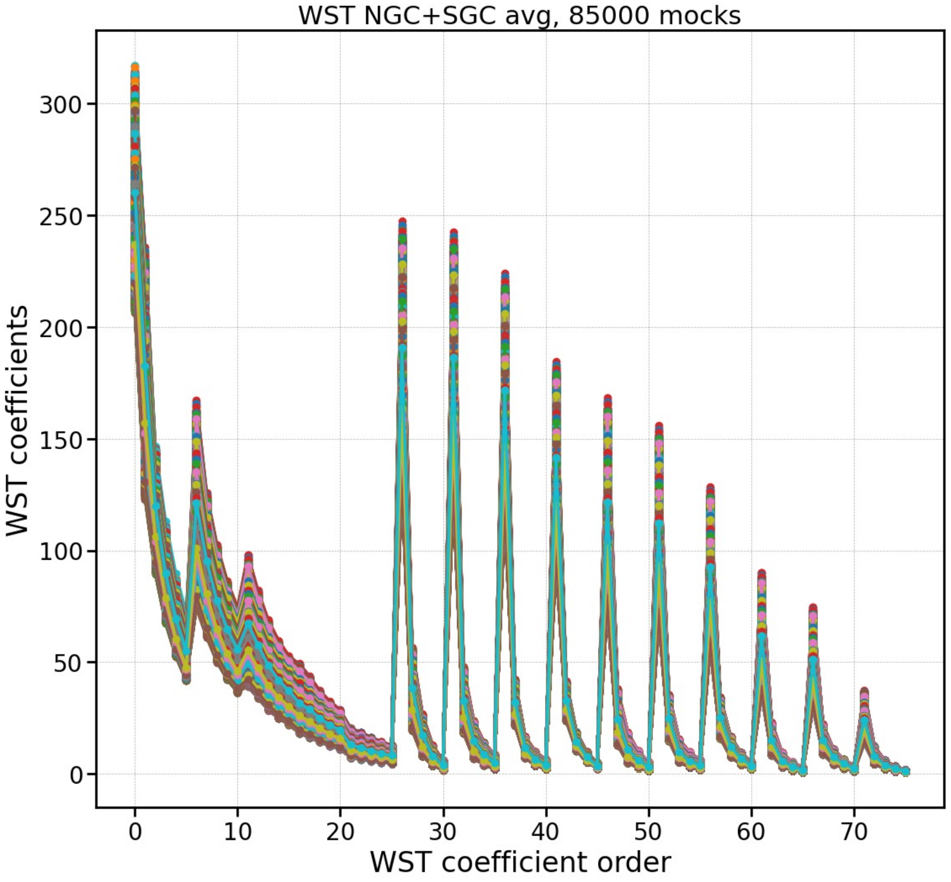


Yuan et al., 2022b



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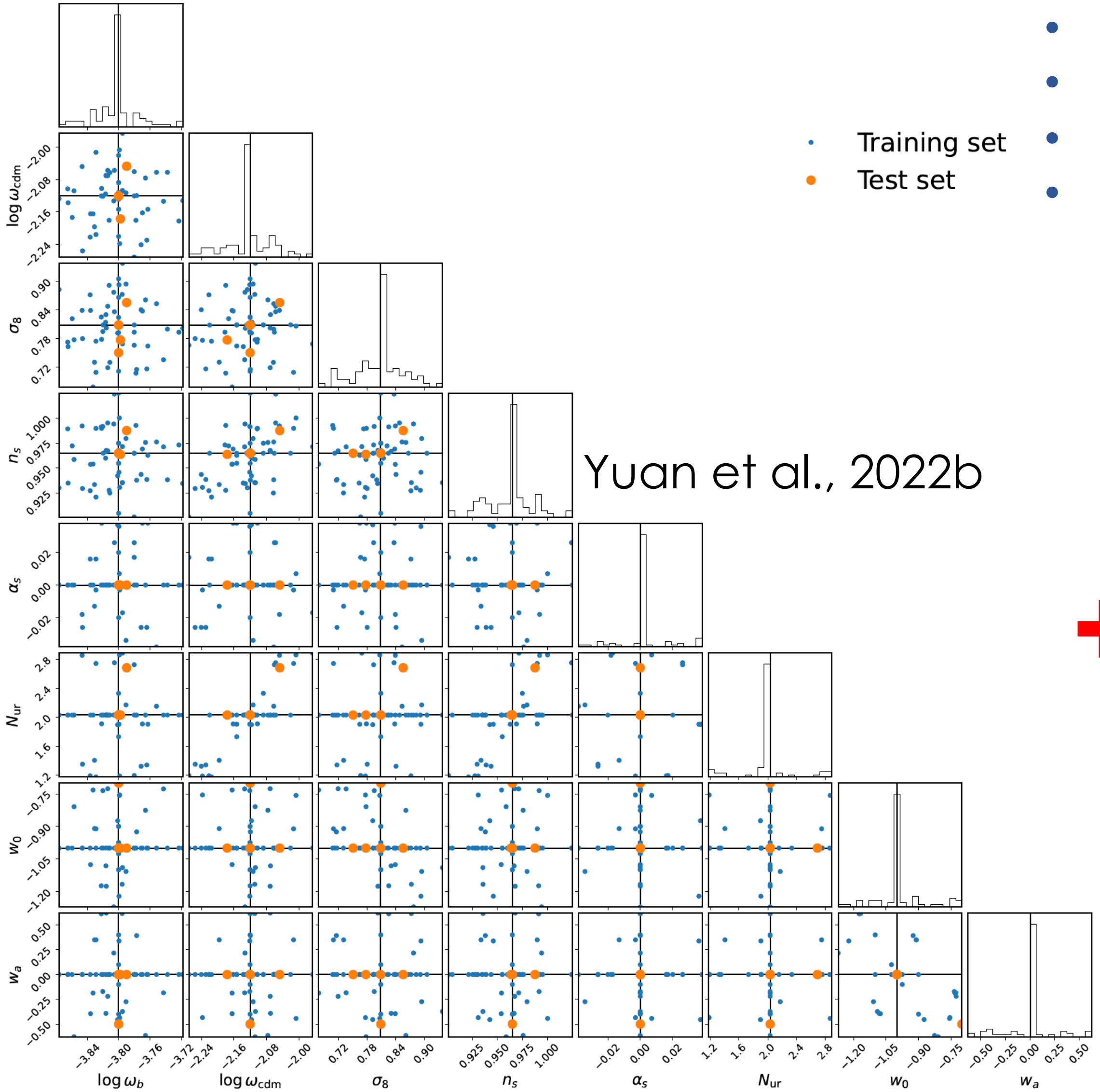

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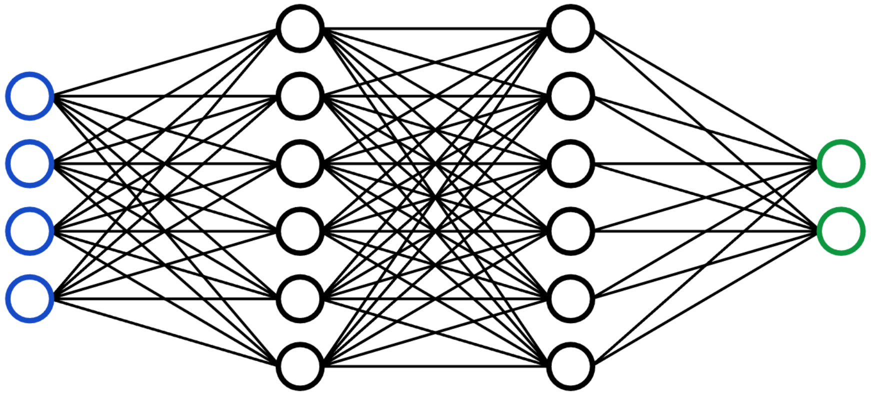

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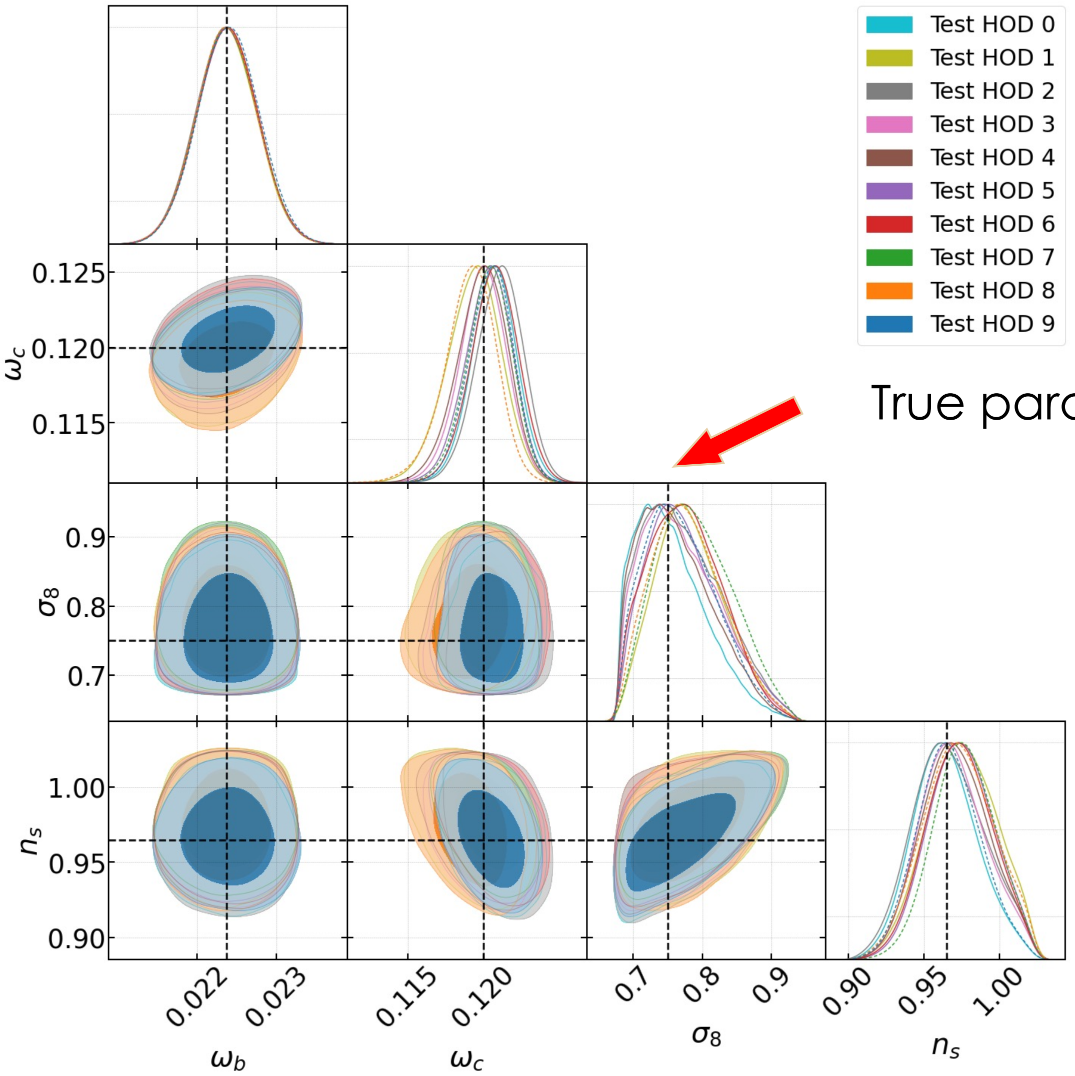
Hold-out tests on Abacus mocks



- Tests against out-sample test set of mocks
- *Successful* parameter recovery in all 40 hold-out tests!!
- Confirms tight 1-σ errors using full likelihood/MCMC!
- Marginalized over 7 HOD nuisance parameters
- In agreement with conclusions of (**Valogiannis** & Dvorkin, 2022b) !

True parameter values

Example of successful parameter recovery from a test mock with low σ_8

Valogiannis et al., 2023

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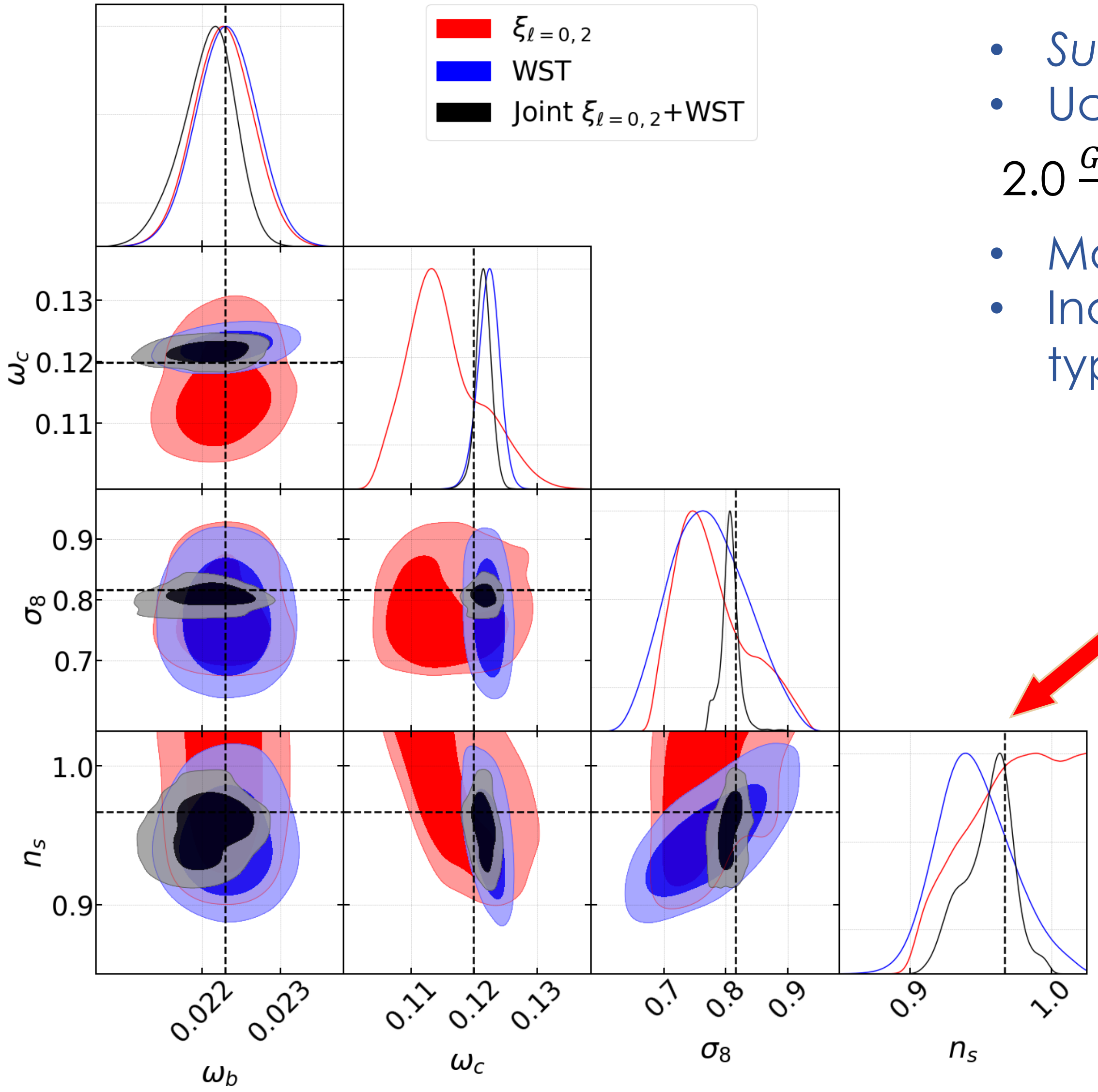
Hold-out tests on external Uchuu mock



- *Successful* parameter recovery in non-HOD mock!!
- Uchuu UniverseMachine mock (T._Ishiyama et al., 2021), $2.0\,\frac{Gpc}{h}$ side box with number density $n_g = 2.9x10^{-4}\,\frac{h^3}{Mpc^3}$.
- More realistic treatment than HOD
- Indicates robustness against different galaxy mock type/model, and also phase!

True parameter values

Evidence of successful parameter recovery from more realistic Uchuu-UM test mock

Valogiannis et al., 2023

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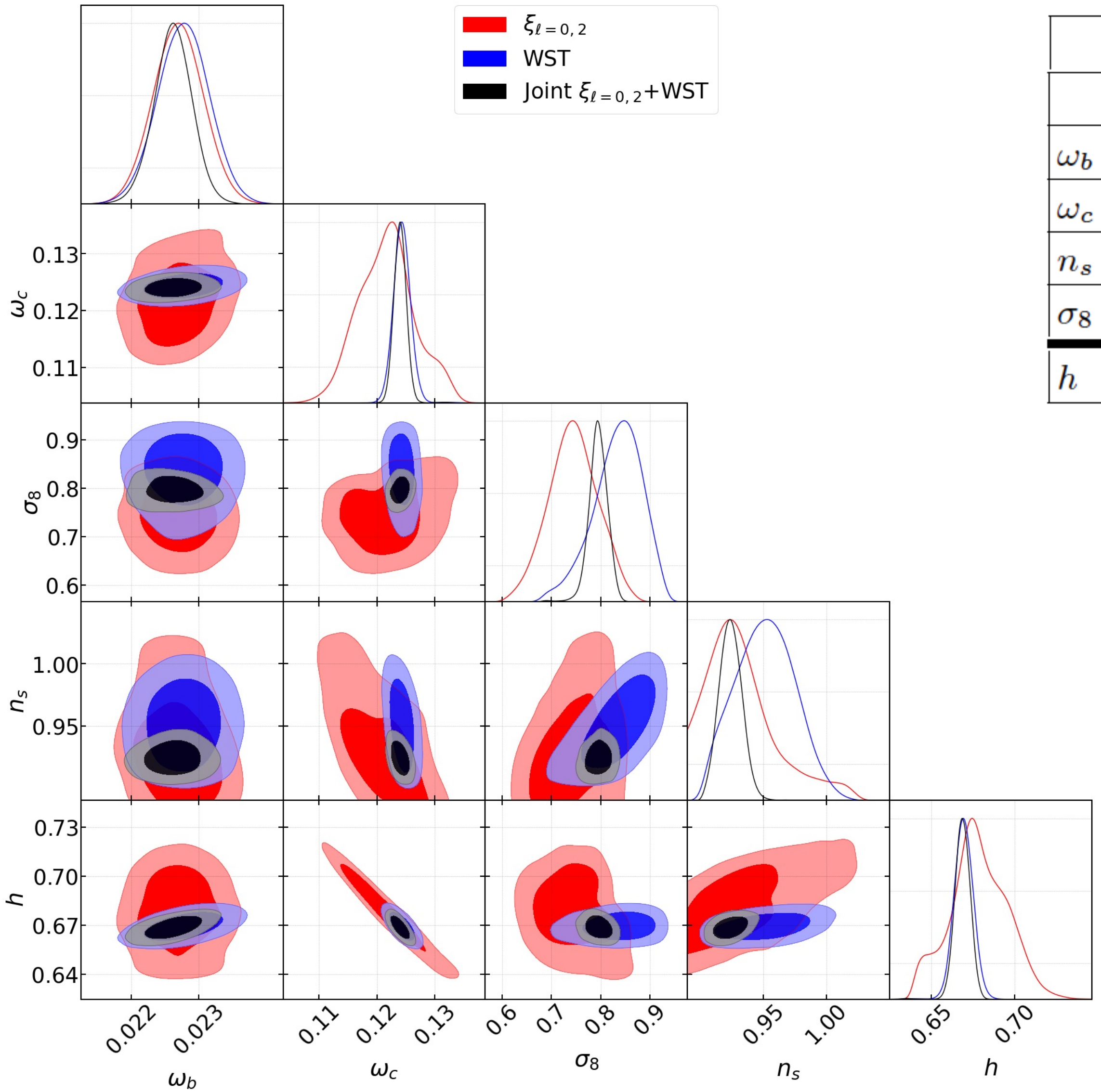
WST Constraints from BOSS CMASS data!



	2-point c.f.		WST		Joint 2-point c.f.+WST	
	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$
ω_b	0.02261	$0.02270^{+0.00037}_{-0.00037}$	0.02274	$0.02277^{+0.00038}_{-0.00038}$	0.0225	$0.02262^{+0.00029}_{-0.00029}$
ω_c	0.1201	$0.1222^{+0.0040}_{-0.0063}$	0.1239	$0.1244^{+0.0015}_{-0.0015}$	0.1238	$0.1241^{+0.0011}_{-0.0011}$
n_s	0.925	$0.922^{+0.037}_{-0.037}$	0.961	$0.951^{+0.023}_{-0.023}$	0.927	$0.924^{+0.01}_{-0.01}$
σ_8	0.742	$0.746^{+0.051}_{-0.051}$	0.860	$0.834^{+0.058}_{-0.039}$	0.793	$0.795^{+0.019}_{-0.019}$
h	0.677	$0.677^{+0.022}_{-0.015}$	0.67	$0.669^{+0.0059}_{-0.0059}$	0.668	$0.669^{+0.0049}_{-0.0049}$

- WST 1σ errors on ω_c & n_s 4.2x & 1.6x *tighter* than ξ(r)
- Joint WST+ξ(r) analysis *improves* 1σ errors by **2.5-6x** compared to ξ(r)-only!
- Joint WST+ξ(r) analysis *improves* 1σ errors by 1.4-2.5x compared to WST-only
- Competitive 0.9%, 2.3% & 1% determination of ω_c, σ_8 & n_s
- 0.7% determination of H_0, as a *derived* parameter from fixed θ_*

Valogiannis et al., 2023

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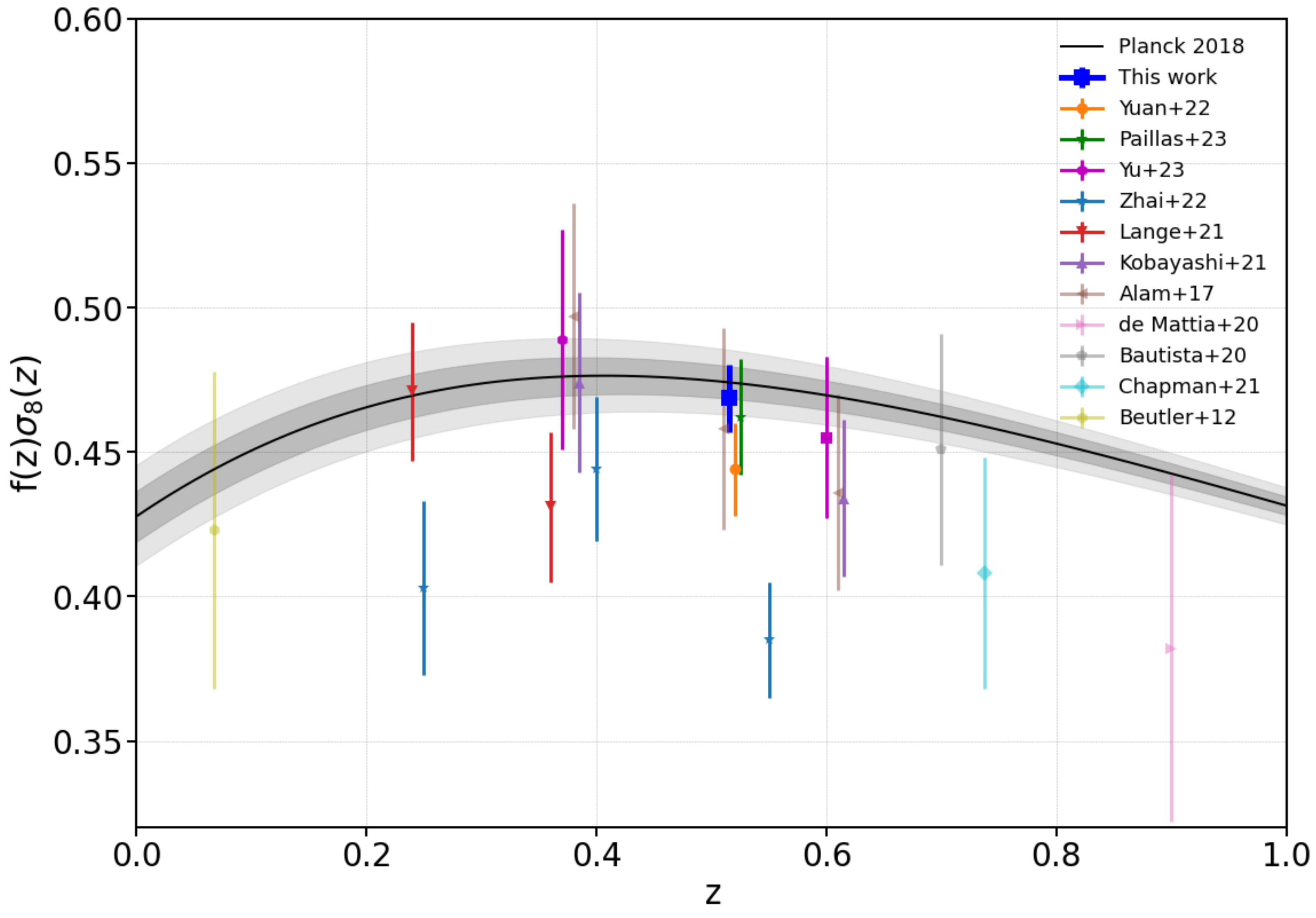
Competitive Constraints on Structure Growth!



- $\mathbf{f\sigma_8(z_{eff} = 0.515)}$**= 0.469** $\pm$ **0.012**
- 2.5% level of determination in agreement with *Planck 2018*
- In 1σ agreement with density-split analysis (Paillas et al., 2023)

- S_8 = **0.833** $\pm$ **0.023**, in almost perfect agreement with Planck 2018 $S_8 = 0.832 \pm 0.013$

Valogiannis et al., 2023

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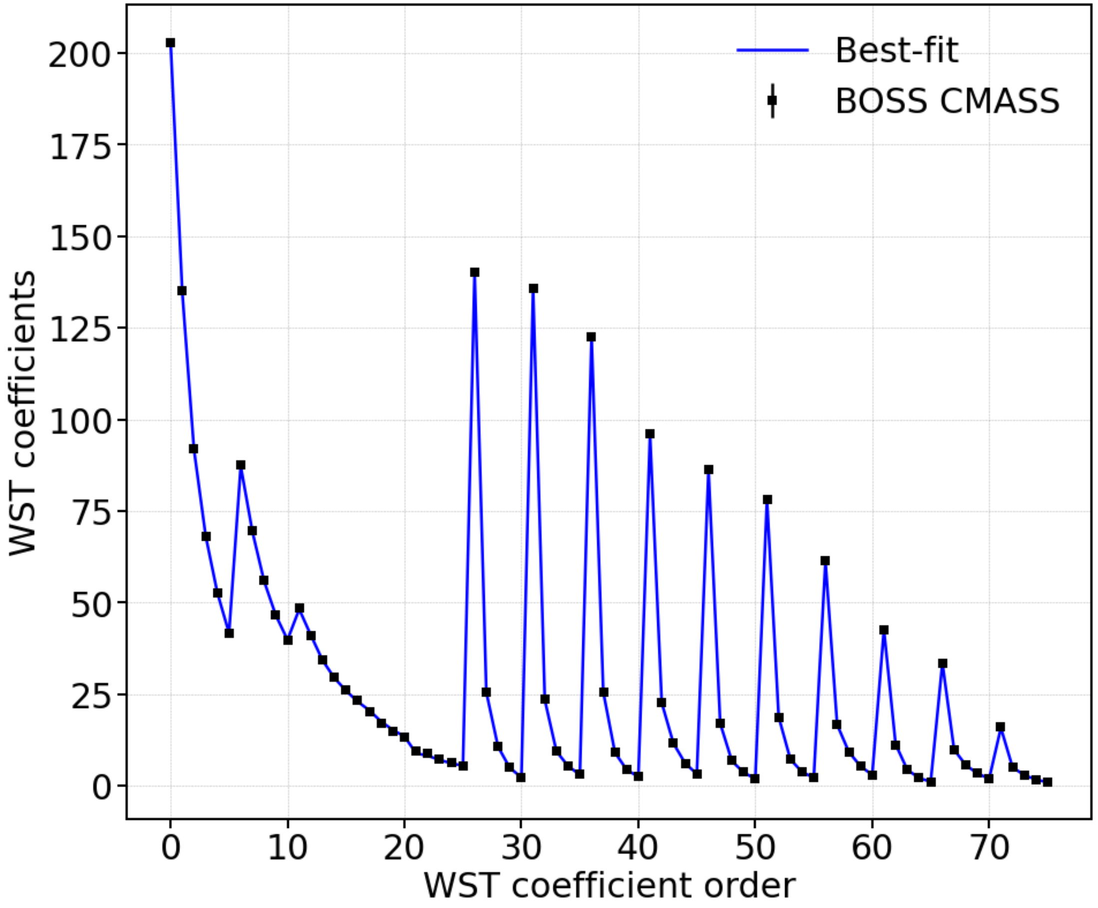
WST Constraints from BOSS CMASS data!



	2-point c.f.		WST		Joint 2-point c.f.+WST	
	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$
ω_b	0.02261	$0.02270^{+0.00037}_{-0.00037}$	0.02274	$0.02277^{+0.00038}_{-0.00038}$	0.0225	$0.02262^{+0.00029}_{-0.00029}$
ω_c	0.1201	$0.1222^{+0.0040}_{-0.0063}$	0.1239	$0.1244^{+0.0015}_{-0.0015}$	0.1238	$0.1241^{+0.0011}_{-0.0011}$
n_s	0.925	$0.922^{+0.037}_{-0.037}$	0.961	$0.951^{+0.023}_{-0.023}$	0.927	$0.924^{+0.01}_{-0.01}$
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h	0.677	$0.677^{+0.022}_{-0.015}$	0.67	$0.669^{+0.0059}_{-0.0059}$	0.668	$0.669^{+0.0049}_{-0.0049}$

Valogiannis et al., 2023

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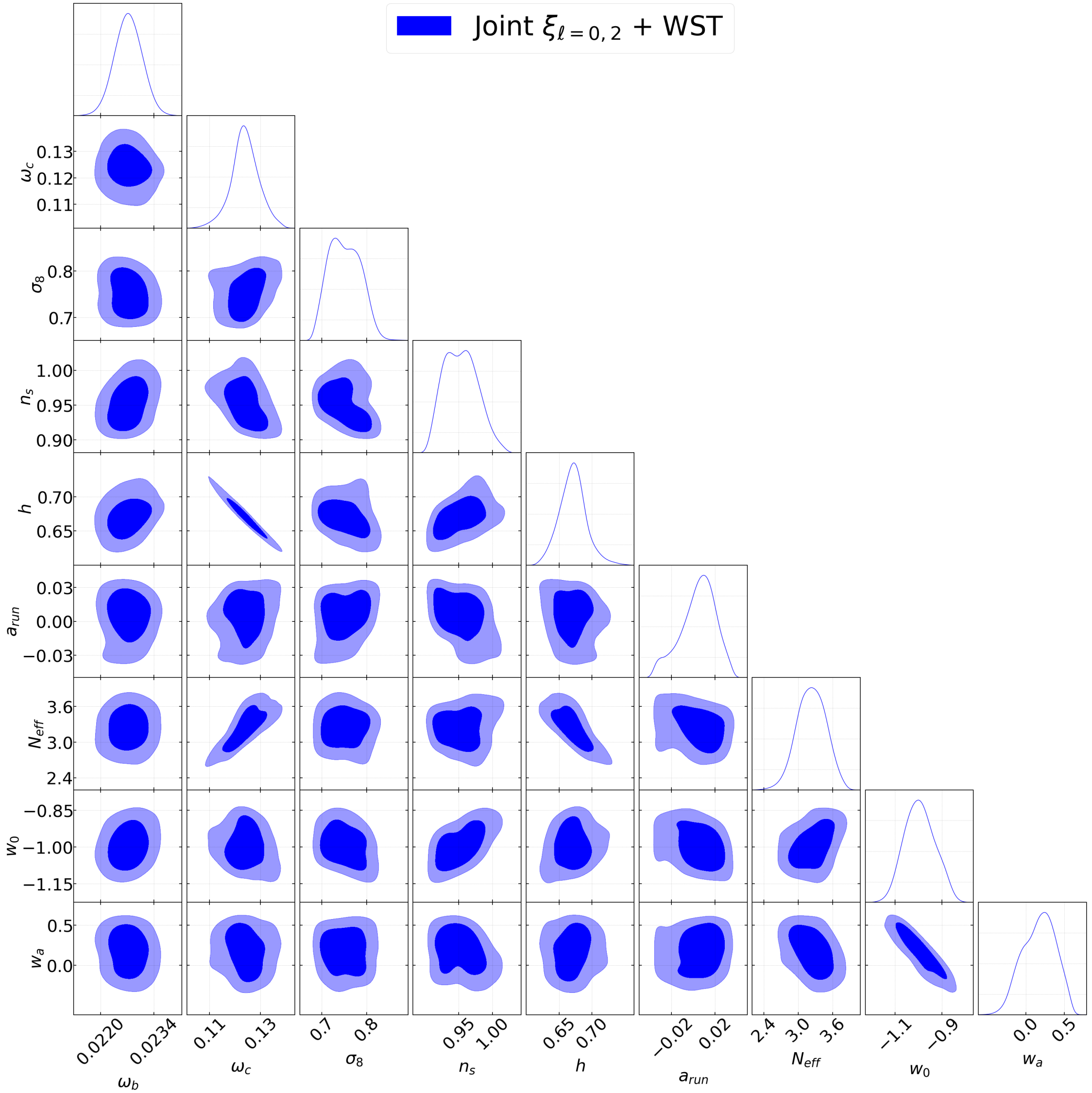
Constraints on ΛCDM extensions



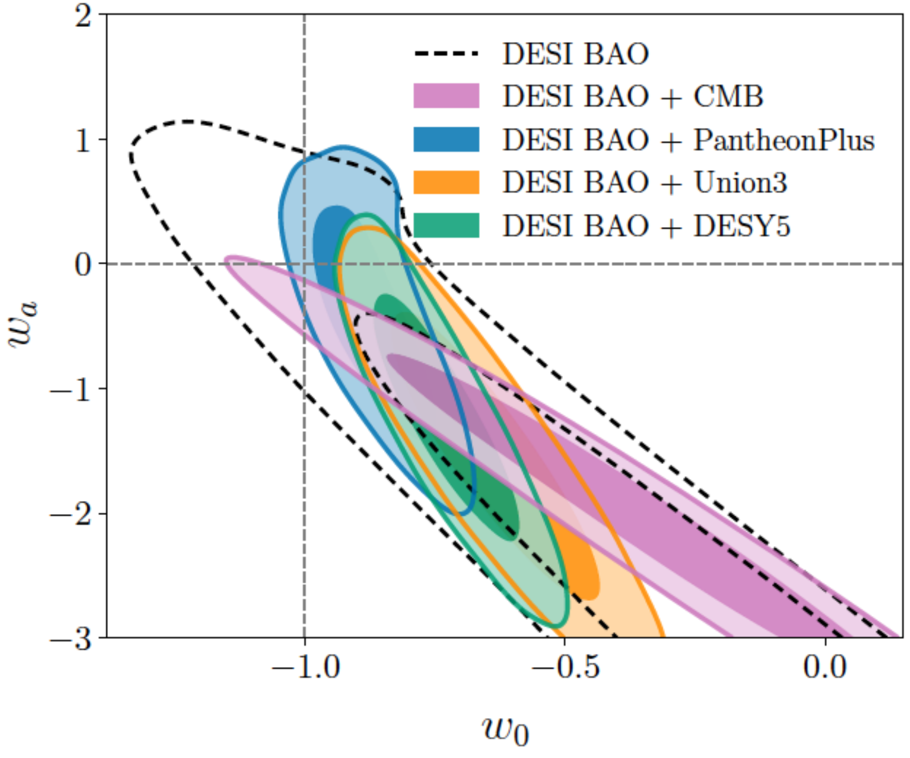
- Joint WST+ξ(r) analysis allows simultaneous constraints on 4 extensions to ΛCDM
- 1σ consistency with ΛCDM limits

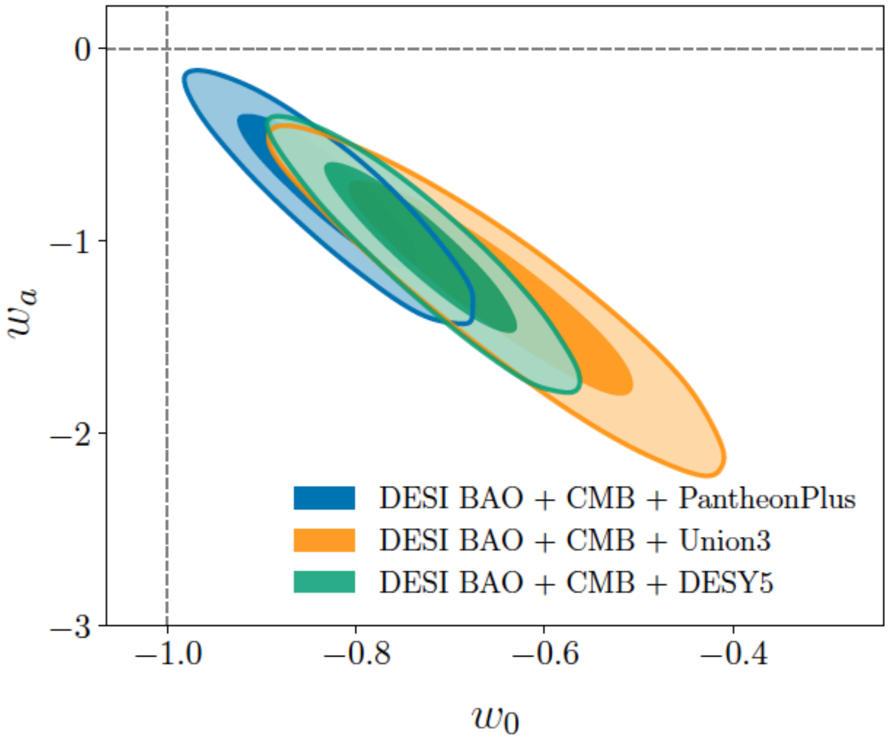
$$w_0 = -1, w_a = 0, a_{\rm run} = 0, N_{\rm eff} = 3.046$$

	Joint 2-point c.f.+WST	
	Best-fit	Mean±σ
ω_b	0.02280	$0.02273^{+0.00036}_{-0.00036}$
ω_c	0.1227	$0.1239^{+0.0056}_{-0.0056}$
σ_8	0.748	$0.751^{+0.034}_{-0.040}$
n_s	0.928	$0.953^{+0.022}_{-0.030}$
h	0.675	$0.671^{+0.021}_{-0.021}$
$a_{\rm run}$	0.002	$0.004^{+0.019}_{-0.012}$
$N_{\rm eff}$	3.048	$3.23^{+0.26}_{-0.26}$
w_0	−1.039	$-0.995^{+0.061}_{-0.073}$
w_a	0.29	$0.17^{+0.24}_{-0.21}$

Valogiannis et al., 2023

DESI Year 1 BAO analysis





See Hector's talk earlier today

arXiv:2404.03002

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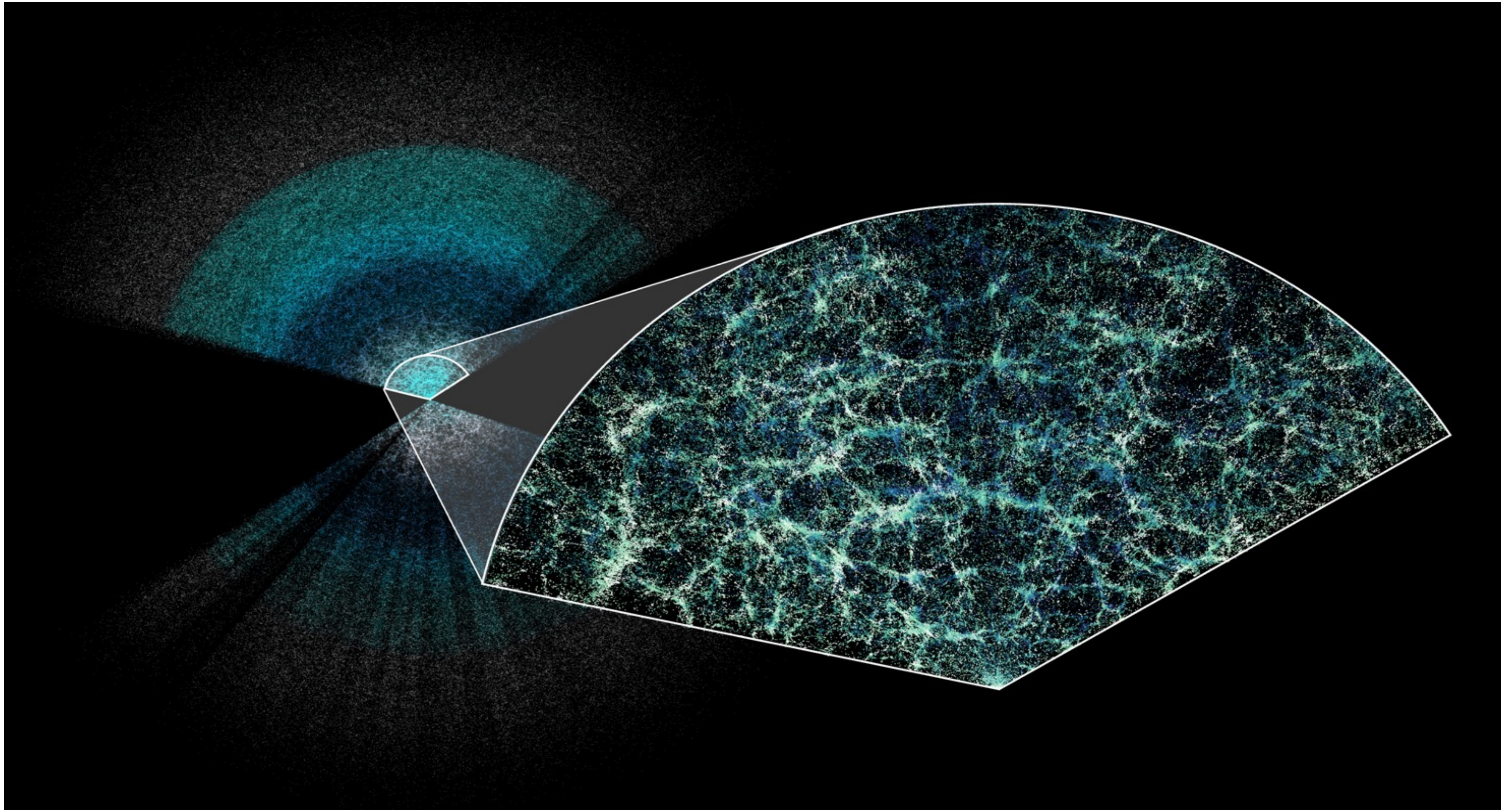
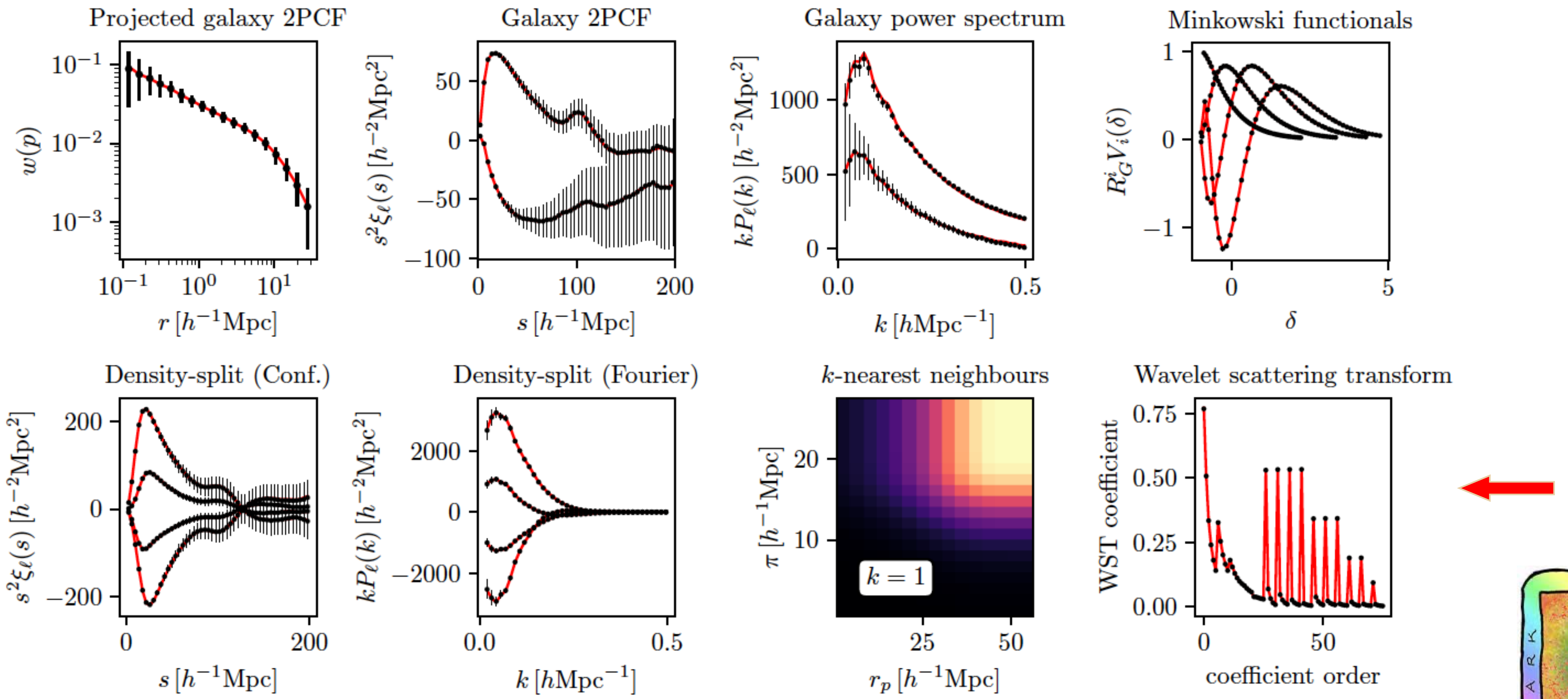
WST application to DESI Year 1 data!



Credit: Claire Lamman & Dark Energy Spectroscopic Instrument (DESI)

WST application to DESI Year 1 data!

Alternative Summary Statistics in DESI: Intense activity aiming to fully utilize the constraining power of DESI Y1 data and beyond



Plot credit: Enrique Paillas & Carolina Cuesta-Lazaro

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Conclusions

- Wavelet Scattering Transform: a novel statistic that efficiently extracts non-Gaussian information from physical fields. *Ideal* middle ground between CNN and traditional estimators
- *First* WST application to actual spectroscopic data **(Valogiannis et al., arXiv: 2310.16116, Phys. Rev. D 109, 103503, 2024, Valogiannis & Dvorkin , arXiv: 2204.13717, Phys. Rev. D 105, 103534, 2022)**
  - Worked with BOSS CMASS galaxy sample at $0.46<z<0.57$
  - **Substantial** improvement in the 1σ errors over traditional galaxy $\xi(r)$ multipoles
- Ongoing & future improvements (in progress)
  - Can more accurately capture lightcone evolution, fiber collision/systematic effects in galaxy mocks (See talks by Rongpu, Tanveer and discussion section later today!)
  - Design wavelets tailored for cosmological/RSD applications (public package under construction!)
  - Blind mock challenges (see talks this week by Gillian, Elisabeth)
- Future applications
  - Application to DESI (& Euclid)
  - Constrain neutrino mass (Eg. as in **Valogiannis & Dvorkin, arXiv: 2108.07821, Phys. Rev. D 105, 103534, 2022**)
  - Constrain fundamental physics (theories of gravity (in prep),primordial non-Gaussianity, parity violation)
  - Weak lensing & cross-correlations (HSC, DES, future applications to Rubin LSST & Euclid)
  - Recent applications also to Lyman-a, 21cm cosmology, axion string-induced effects

Thank you!