Title: Going Beyond the Galaxy Power Spectrum: an Analysis of BOSS Data with Wavelet Scattering Transforms

Speakers: Georgios Valogiannis

Series: Cosmology & Gravitation

Date: January 17, 2023 - 11:00 AM

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Abstract: Optimal extraction of the non-Gaussian information encoded in the Large-Scale Structure (LSS) of the universe lies at the forefront of modern precision cosmology. In this talk, I will discuss recent efforts to achieve this task using the Wavelet Scattering Transform (WST), which subjects an input field to a layer of non-linear transformations that are sensitive to non-Gaussianity in spatial density distributions through a generated set of WST coefficients. In order to assess its applicability in the context of LSS surveys, I will present the first WST application to actual galaxy observations, through a WST re-analysis of the BOSS DR12 CMASS dataset. After laying out the procedure on how to capture all necessary layers of realism for an application on data obtained from a spectroscopic survey, I will show results for the marginalized posterior probability distributions of 5 cosmological parameters obtained from a WST likelihood analysis of the CMASS data. The WST is found to deliver a substantial improvement in the values of the predicted 1? errors compared to the regular galaxy power spectrum, both in the case of flat and uninformative priors and also when a Big Bang Nucleosynthesis prior is applied to the value of ?_b. Finally, I will discuss ongoing follow-up work towards applying this estimator to the next generation of spectroscopic observations to be obtained by the DESI and Euclid surveys.

Zoom link: https://pitp.zoom.us/j/96291506998?pwd=TVVFYnNIQ1F0cktna000cUp3SU1kQT09

Going Beyond the Galaxy Power Spectrum: an Analysis of BOSS data with Wavelet Scattering Transforms

Georgios Valogiannis
Harvard University

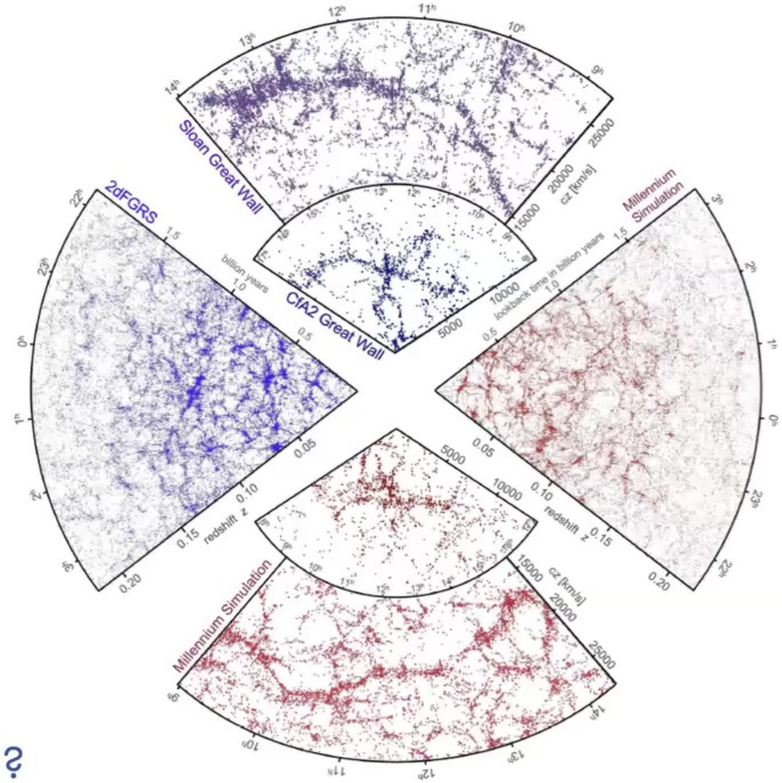
Cosmology Seminar
Perimeter Institute for Theoretical Physics
Tuesday, January 17, 2023

Background from
Millennium Simulation, 2005

Based on prior work
arXiv: 2204.13717 & 2108.07821
in collaboration with **Cora Dvorkin**
& ongoing also with **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 Scientific 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??

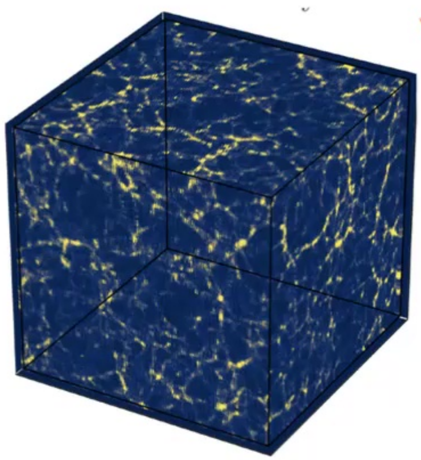


V. Springel et al. (2006)

The quest for an ideal estimator

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

Power Spectrum



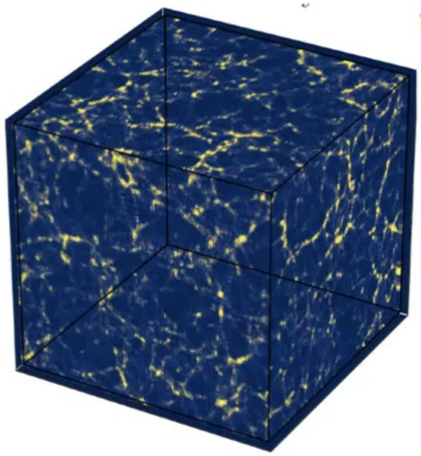
Physical Information

F. Villaescusa-
Navaro et al. (2019)

The quest for an ideal estimator

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

Power Spectrum (Incomplete)



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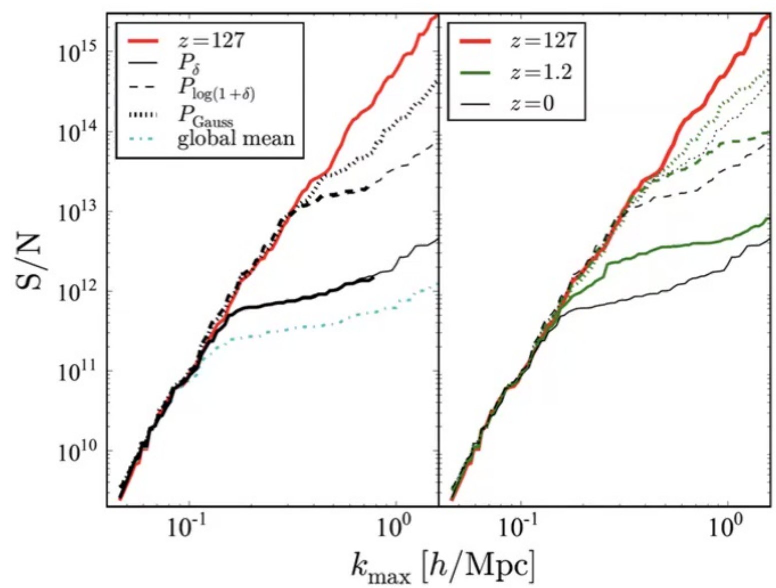

M. Neyrinck et al. (2009)

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

The quest for an ideal estimator

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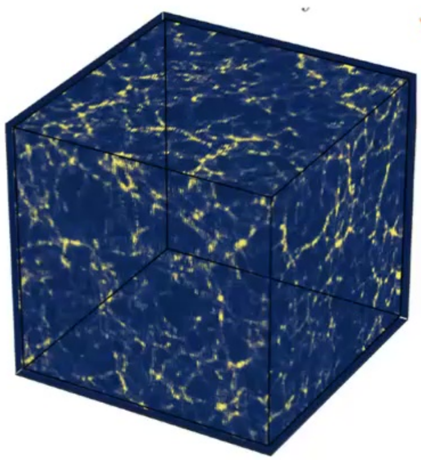


F. Villaescusa-Navaro et al. (2019)

Power spectrum + Higher order statistics

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

Physical Information

Convolutional Neural Networks (CNNs)
(Training, interpretability)

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

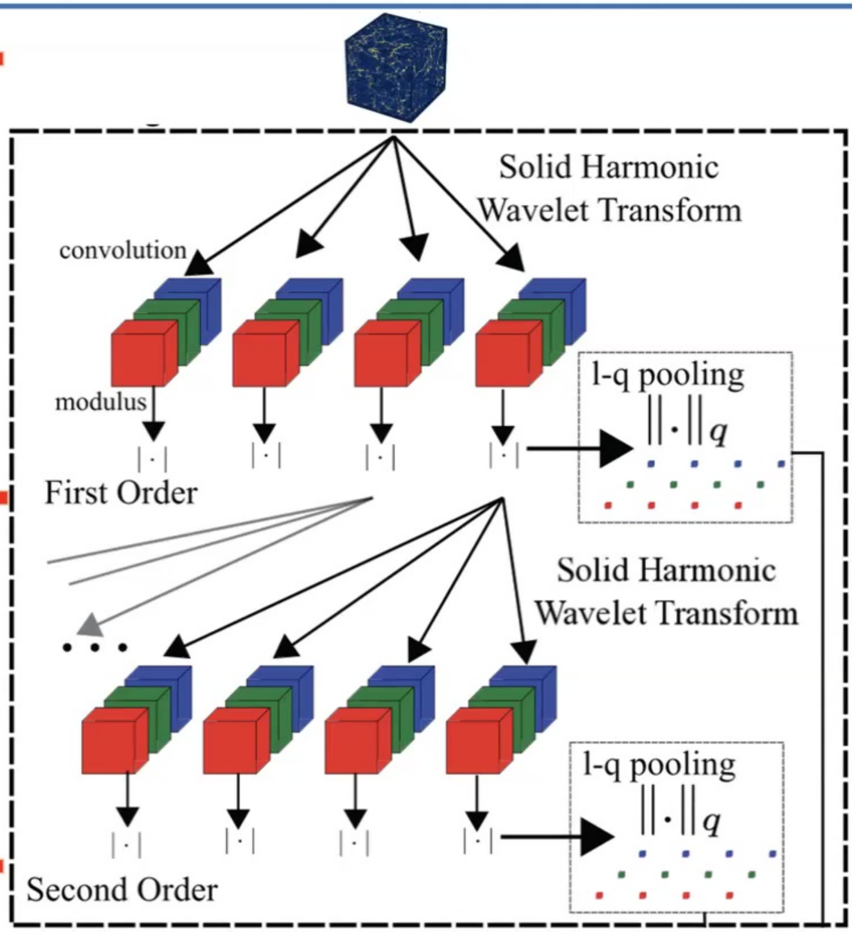
Input field

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

$$S_0 = \langle |I_0| \rangle$$

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

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



The Wavelet Scattering Transform (WST)

Physical interpretation of WST coefficients

- $S_0 = \langle |I_0| \rangle$: Mean field
- $S_1^{j_1,l_1} = \langle \left| I_0 \star \psi^{j_1,l_1} \right| \rangle$: ~ P(k). In fact, P(k) ⟹ $\langle |I \star e^{-ikx}|^2 \rangle$
- $S_2^{j_1,l_1,j_2,l_2} = \langle \left| |I_0 \star \psi^{j_1,l_1}| \star \psi^{j_2,l_2} \right| \rangle$: *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)

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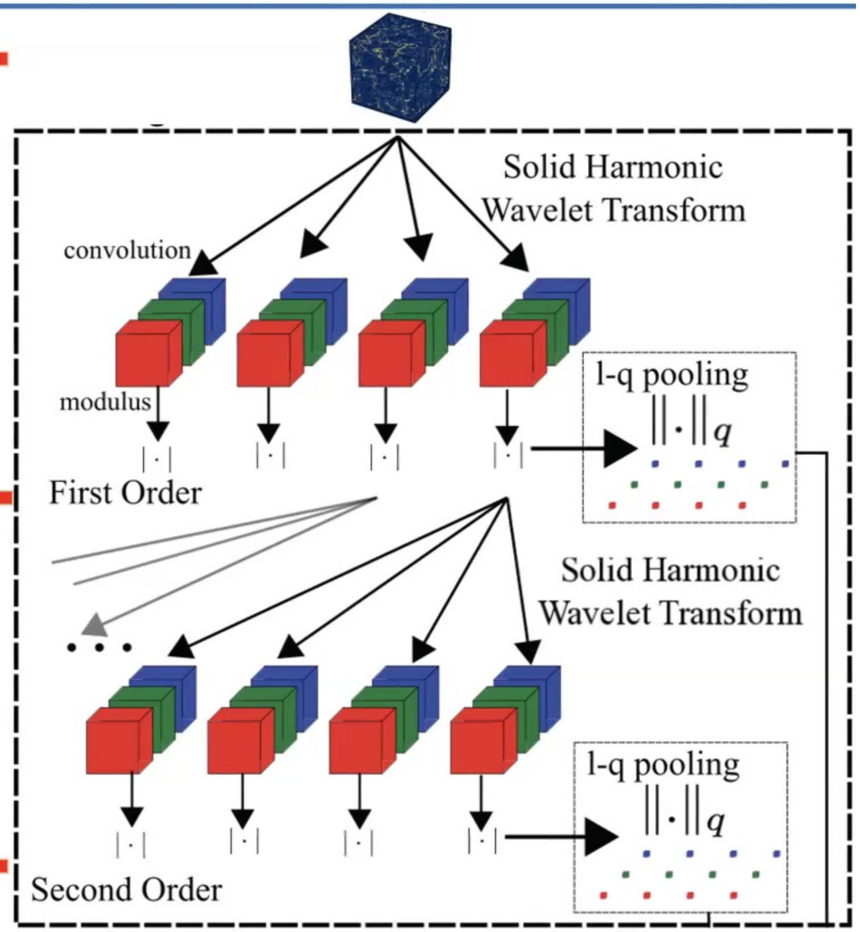
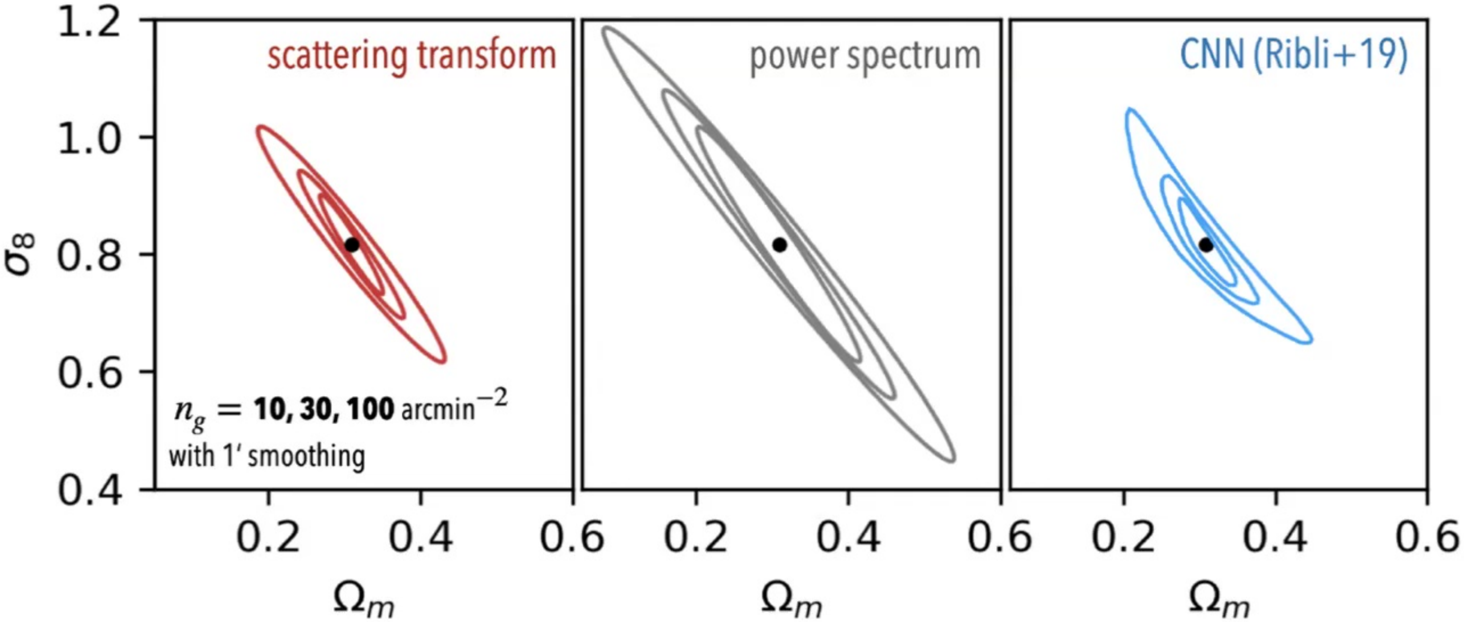


WST application on weak lensing

- Fisher information obtained from 2D simulated WL shear maps
- Performance on par with a state-of-the-art CNN!

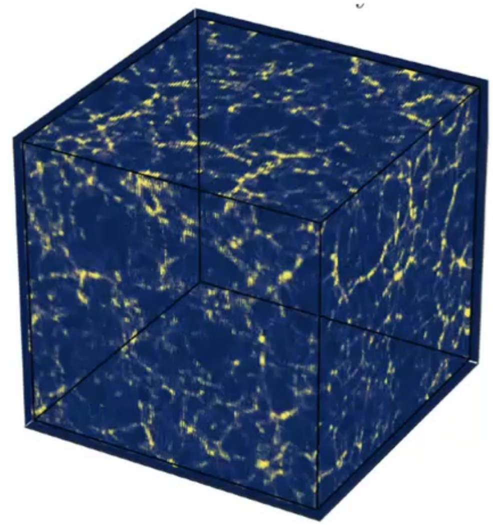


Cheng et al. (2020)

First WST application on 3D LSS

- **First** WST application on 3D matter density field! **(Valogiannis & Dvorkin, 2022a)**

$$I(\vec{x}) \equiv \delta_m(\vec{x}) = \frac{\rho_m(\vec{x})}{\bar{\rho}_m} - 1.0$$, resolution $N_{grid} = 256^3$



- Evaluated from the *Quijote* simulations (F. Villaescusa-Navaro et al., 2019)
- Fiducial cosmology

$$\Omega_\mathrm{m} = 0.3175,\ \Omega_\mathrm{b} = 0.049,\ h = 0.6711$$

$$n_s = 0.9624,\ \sigma_8 = 0.834,\ M_\nu = 0.0\,\mathrm{eV},\ \text{and}\ w = -1$$

Box L=1.0 Gpc/h

- In presence of massive neutrinos, trace both:
- $\delta_m = \delta_{CDM} + \delta_b + \delta_\nu$ Total ‘m’ field
- $\delta_{cb} = \delta_{CDM} + \delta_b$ ‘cb’ field

Fisher forecast

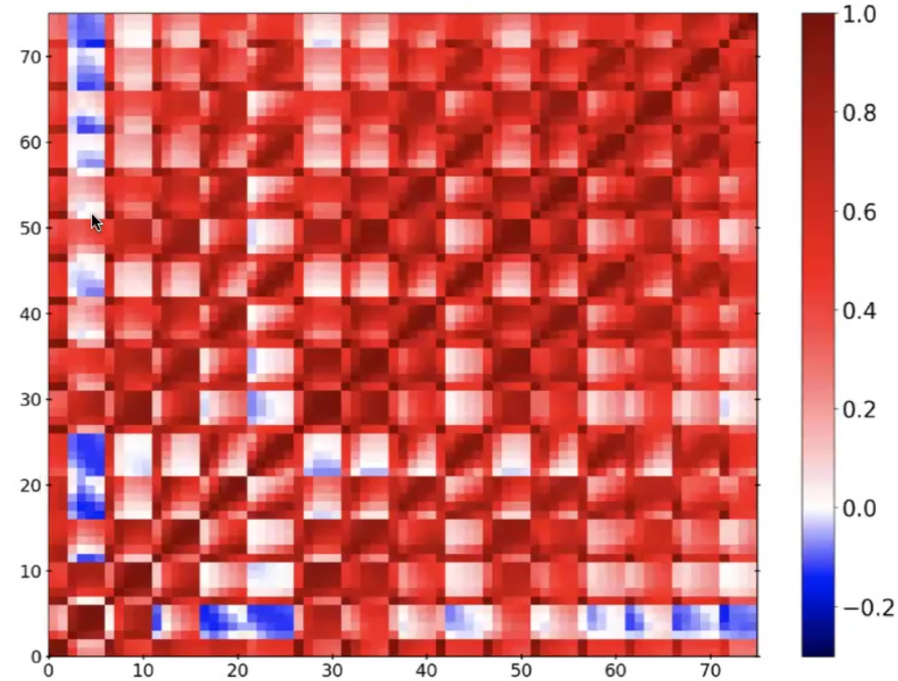
Fisher forecasting
- 15,000 realizations for fiducial cosmology
- 7,000 for linear derivatives in parameters

$$F_{\alpha\beta} = \frac{\partial O_i}{\partial \theta_\alpha} C_{ij}^{-1} \frac{\partial O_j^T}{\partial \theta_\beta}$$

- Marginalized $\sigma_\alpha = \sqrt{(F^{-1})_{\alpha\alpha}}$

for $\boxed{\theta_\alpha = \{\Omega_m, \Omega_b, H_0, n_s, \sigma_8, M_\nu\}}$, z=0

Comparing 3 observables O_i:
- Power spectrum **P(k)**
- Marked power spectrum **M(k)**
- $S_0 + S_1 + S_2 = 76$ **WST** coefficients
  Using J=5 scales and L=5 orientations



WST coefficients - correlation matrix
Valogiannis & Dvorkin 2022a

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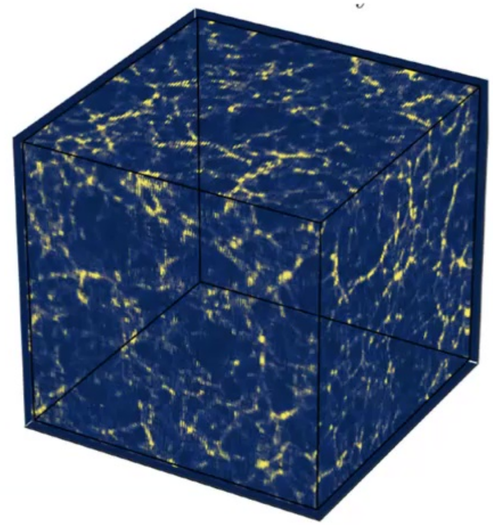

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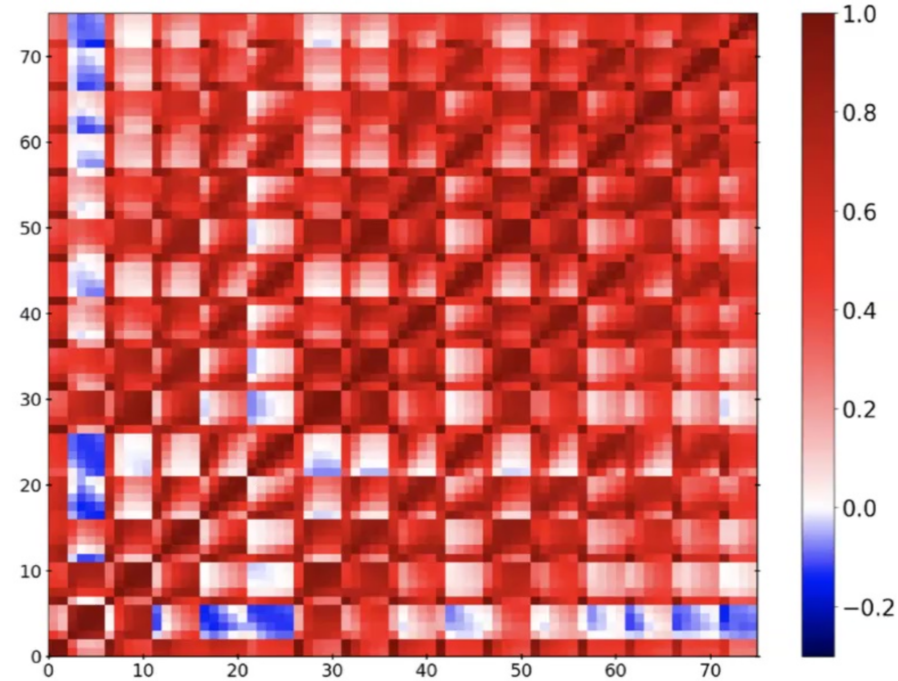


WST coefficients - correlation matrix
Valogiannis & Dvorkin 2022a

Marked Power Spectrum

- Marked correlation function generalizes 2-point function

$$\mathcal{M}(r) = \frac{1}{n(r)\bar{m}^2} \sum_{ij} \delta_D(|\mathbf{x}_i - \mathbf{x}_j| - r) m_i m_j = \frac{1 + W(r)}{1 + \xi(r)}$$

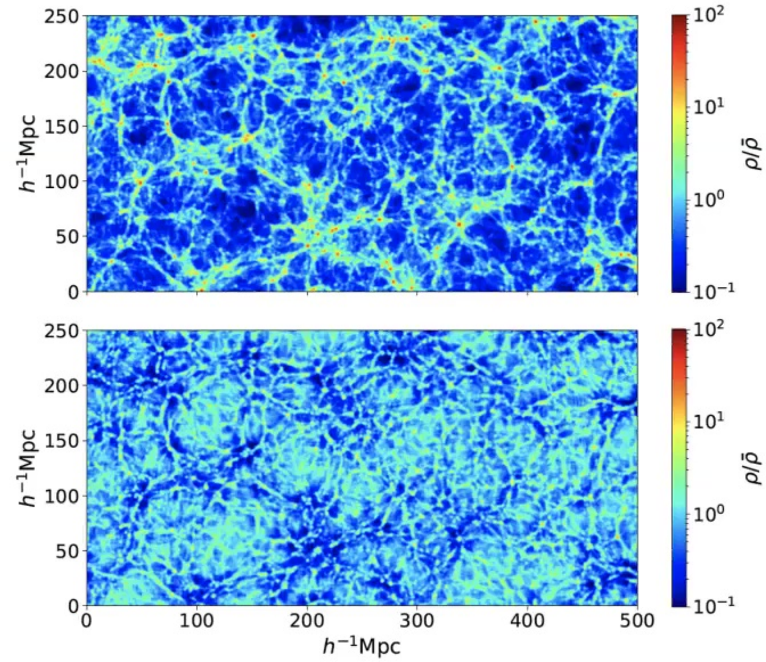
- Each galaxy weighted by mark 'm'
- Inverse density weighted mark (highlights voids)

$$m\left[\mathbf{x}, R, \delta_s, p\right] = \left(\frac{1 + \delta_s}{1 + \delta_s + \delta_R(\mathbf{x})}\right)^p$$

- Can constrain modified gravity (M. White 2016, **Valogiannis & Bean 2018**, Alam et al., 2021)
- Can constrain neutrino mass (Massara et al, PRL 2020)
- Contains info beyond 2-point function (Philxcox et al., 2020)

$\delta(x)$

$m(x)$



Massara et al 2020

The Wavelet Scattering Transform (WST)

- 3-dimensional WST implementation with 'solid harmonic' wavelets (Eickenberg et al. (2018))

$$S_0 = \langle |I(\vec{x})|^q \rangle,$$

$$S_1(j_1, l_1) = \left\langle \left(\sum_{m=-l_1}^{m=l_1} |I(\vec{x}) * \psi^m_{j_1,l_1}(\vec{x})|^2 \right)^{\frac{q}{2}} \right\rangle,$$

$$S_2(j_2, j_1, l_1) = \left\langle \left(\sum_{m=1}^{m=l_1} |U_1(j_1, l_1)(\vec{x}) * \psi^m_{j_2,l_1}(\vec{x})|^2 \right)^{\frac{q}{2}} \right\rangle$$

$$U_1(j_1, l_1)(\mathbf{x}) = \left(\sum_{m=-l_1}^{m=l_1} |I(\mathbf{x}) * \psi^m_{j_1,l_1}(\mathbf{x})|^2 \right)^{\frac{1}{2}}$$

$$\psi^m_l(\mathbf{x}) = \frac{1}{(2\pi)^{3/2}} e^{-|\mathbf{x}|^2/2\sigma^2} |\mathbf{x}|^l Y^m_l \left(\frac{\mathbf{x}}{|\mathbf{x}|} \right)$$

Gaussian envelope — Solid Harmonics

- Dilated by dyadic scales 2^{j_1}

$$\psi^m_{j_1,l_1}(\mathbf{x}) = 2^{-3j_1} \psi^{m_1}_{l_1}(2^{-j_1}\mathbf{x})$$

- Wavelets in the literature
  - Bump steerable wavelets (Eickenberg et al, 2022, Allys et al, 2020)
  - Morlet wavelets (Cheng et al. 2020b, Cheng & Menard 2021a)

- Implemented in KYMATIO package (Andreux et al. 2019)

WST sensitivity to neutrino mass

- Raising modulus to powers q<1 emphasizes on cosmic voids
- Very sensitive to neutrino mass!

$$S_0 = \langle |I(\vec{x})|^{q} \rangle,$$

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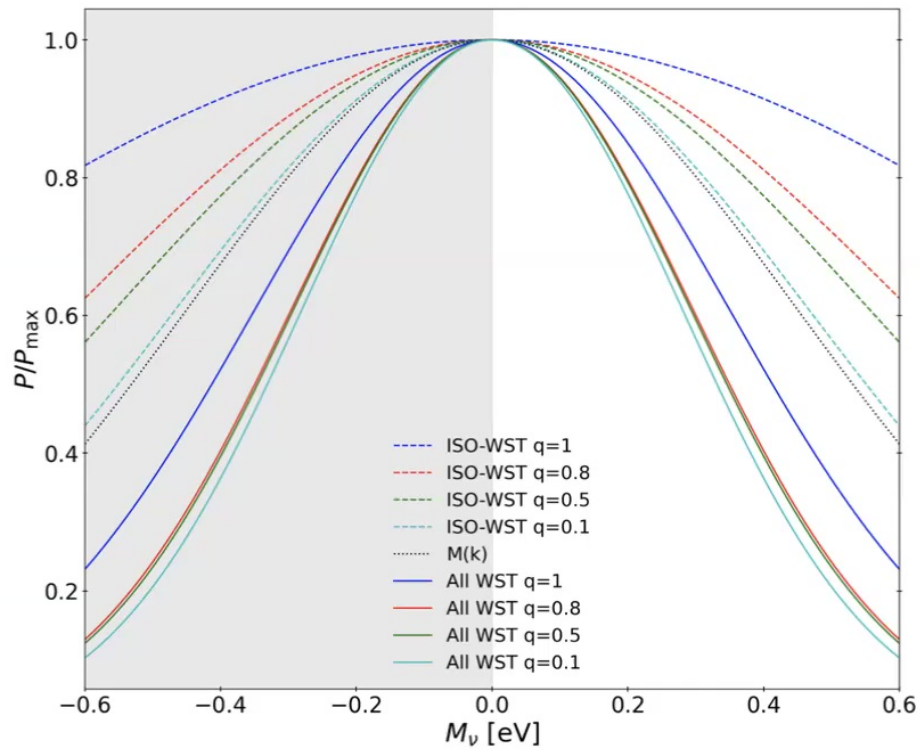
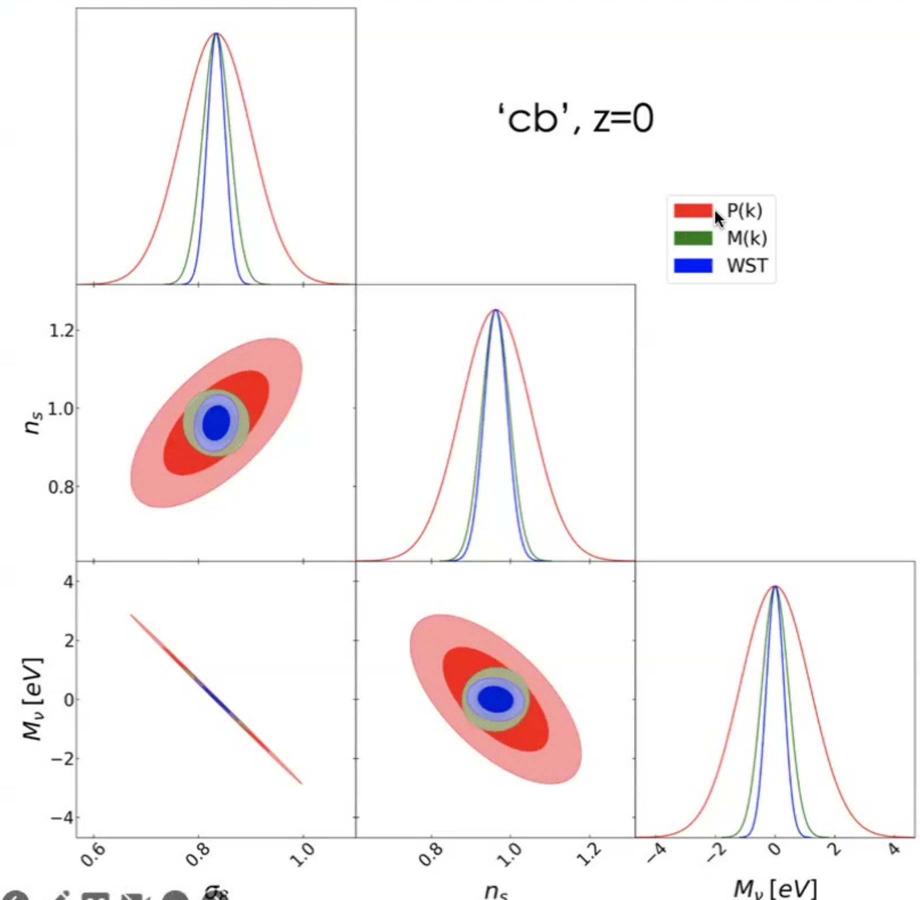
- q=0.8 found to be optimal



Valogiannis & Dvorkin 2022a

Great improvement over P(k)!



- WST delivers ***significant*** improvement in the 1-σ errors for *all* parameters!
- ~1.2-4x **tighter** errors than from 'cb' P(k)!
- Constrains on neutrino mass:
  - ~4x **tighter** than 'cb' P(k)!
  - ~1.6x **tighter** than 'cb' M(k)!
- ~3x100x **tighter** errors than from 'm' P(k)

Matter type	'm'			'cb'		
Statistic	$P(k)$	$M(k)$	WST	$P(k)$	$M(k)$	WST
$\sigma(\Omega_m)$	0.076	0.013	0.014	0.040	0.016	0.016
$\sigma(\Omega_b)$	0.033	0.010	0.012	0.015	0.009	0.012
$\sigma(\sigma_8)$	0.01	0.002	0.001	0.067	0.026	0.017
$\sigma(n_s)$	0.39	0.044	0.031	0.088	0.035	0.029
$\sigma(H_0)$ [km/s/Mpc]	40.62	9.50	10.34	14.42	8.28	10.32
$\sigma(M_\nu)$ [eV]	0.72	0.016	**0.008**	1.17	0.45	**0.29**

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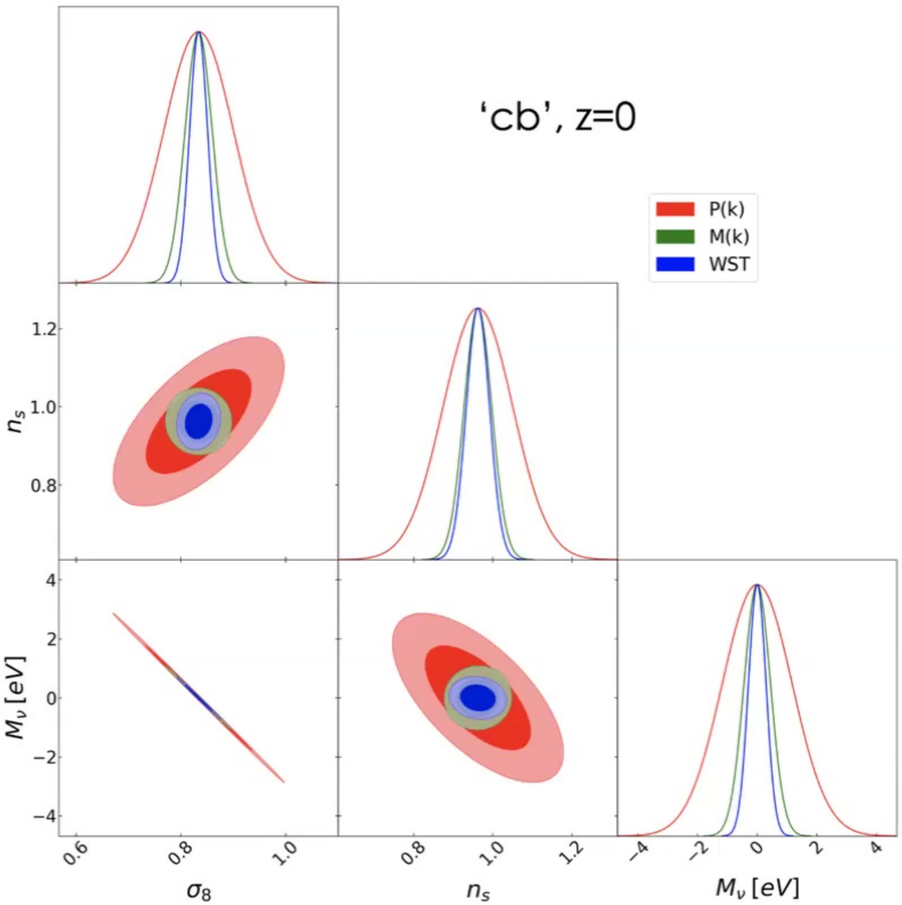
Great improvement over P(k)!



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Valogiannis & Dvorkin 2022a

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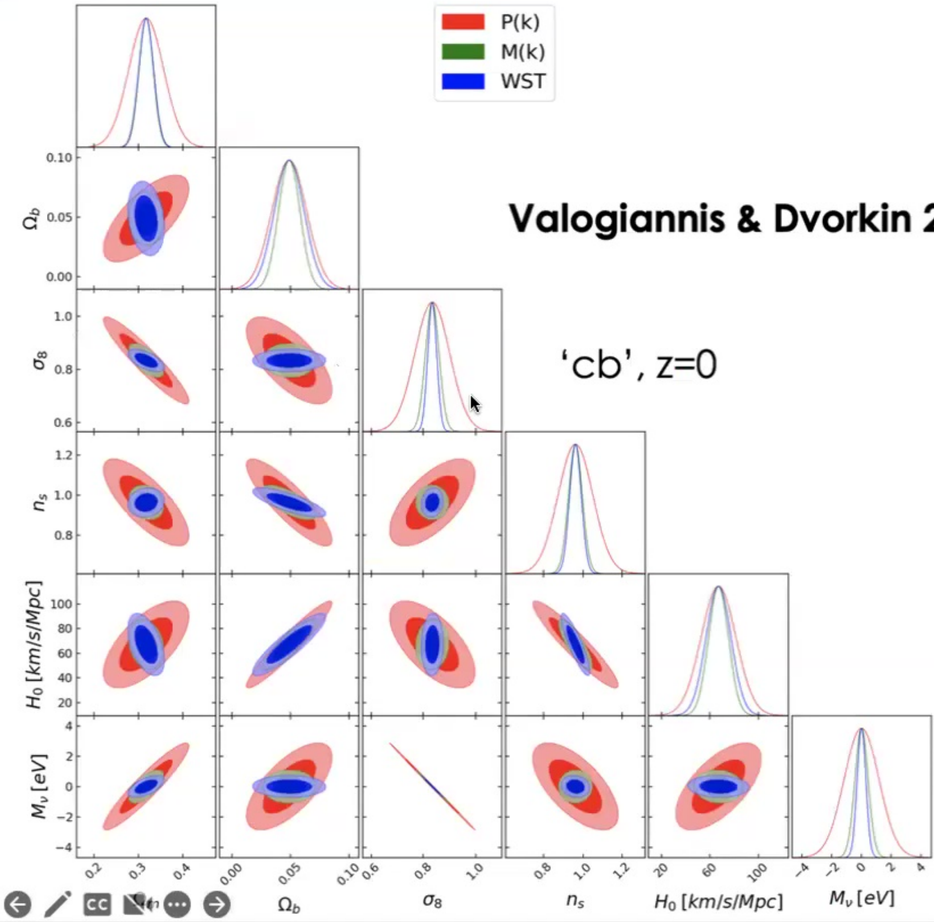
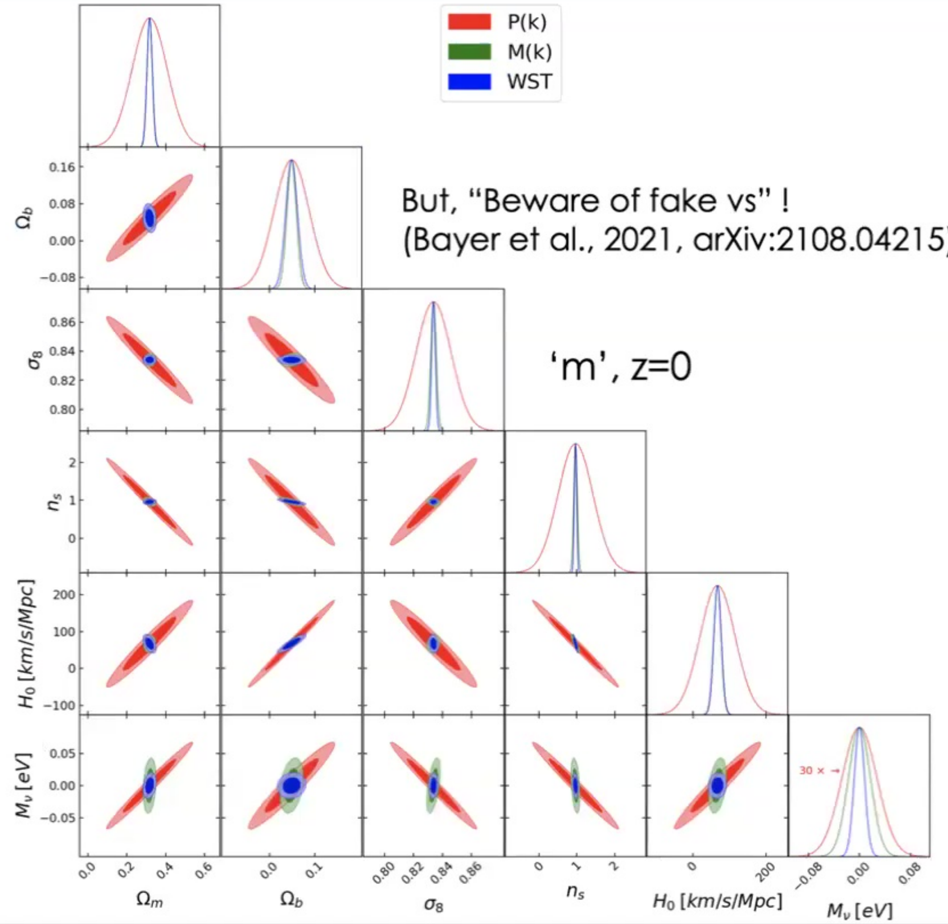


Valogiannis & Dvorkin 2022a

'cb', z=0



But, "Beware of fake νs" !
(Bayer et al., 2021, arXiv:2108.04215)

'm', z=0

Physical explanation of results

Why does the WST work so well??

WST key physical properties

- Successive WST layers pick up information >2-point function ✅
  - Known to encode additional information (eg. Hahn et al. 2020 & 2021)

+

- Choice of q<1 highlights cosmic voids (under-densities) ✅
  - Sensitive cosmological probe (eg. Massara et al, 2020)

↓

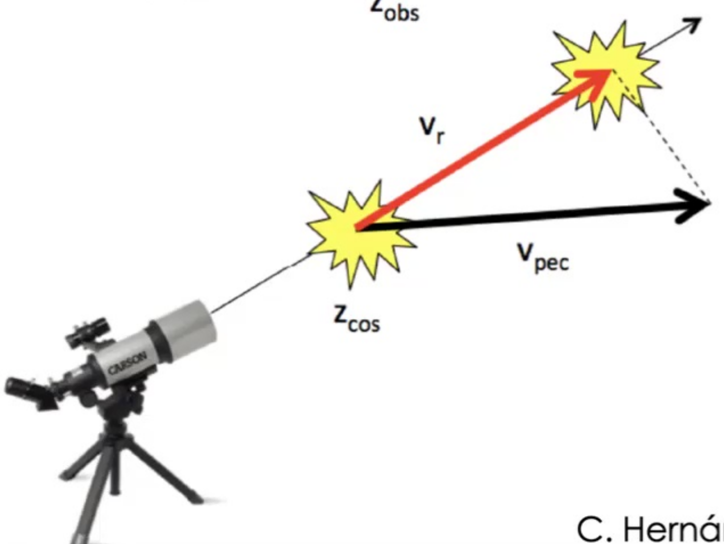
Enhanced cosmological information

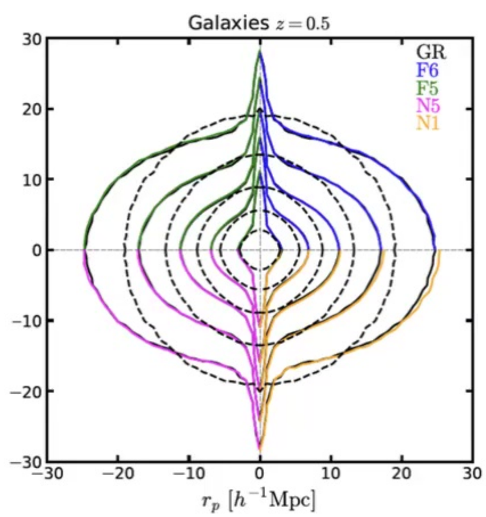
- Parallels to marked M(k) (Massara et al, 2020)

Realistic galaxy survey data

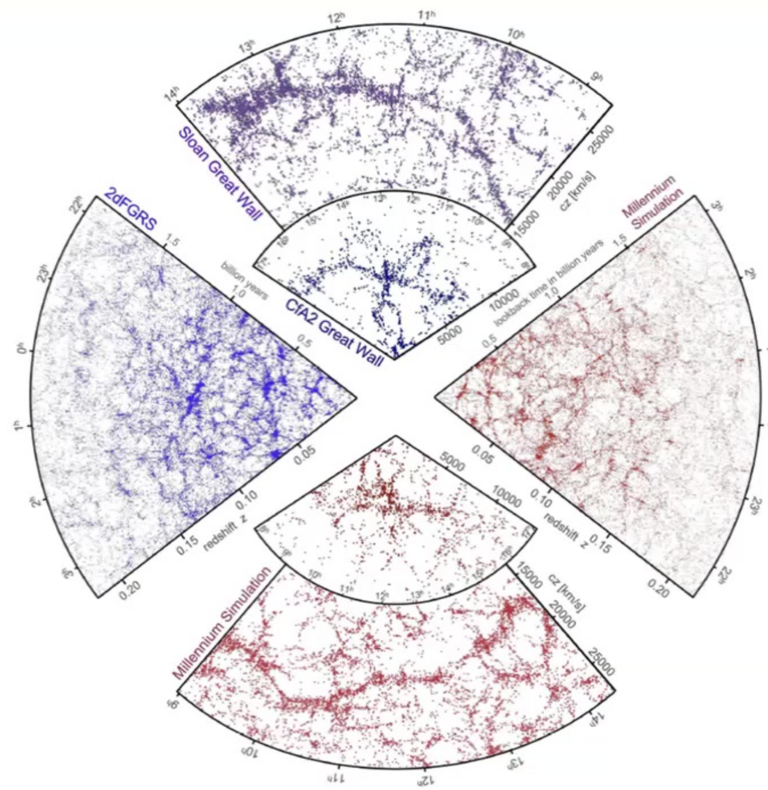
However

- 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<0.60
  - Northern + Southern Galactic Cap
- For survey data, fundamental quantity of interest is the *FKP field* (Feldman, Kaiser, Peacock et al., 1994) :

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

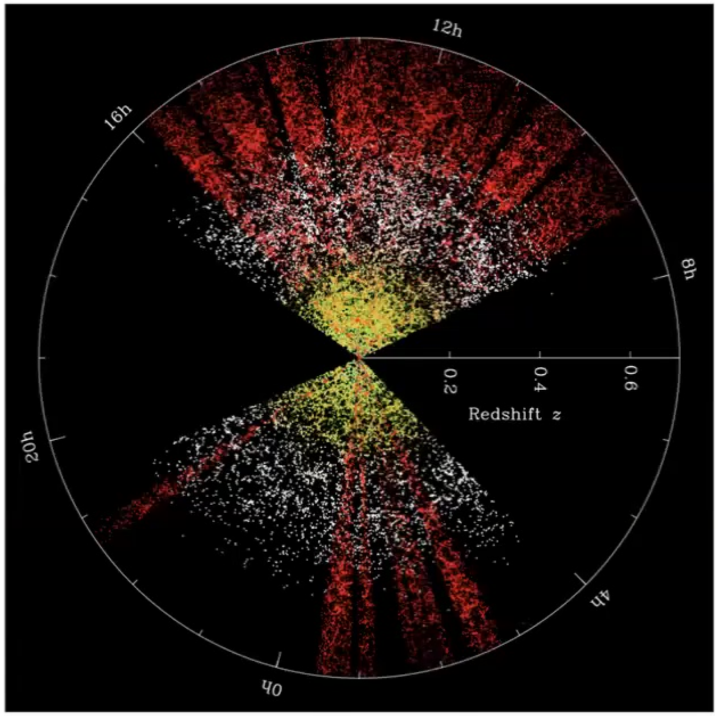
Galaxies Randoms

- 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 $N_{grid} = 282^3$ and $L_{Box} = 2820\ Mpc/h$



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, $N_{grid} = 200^3$

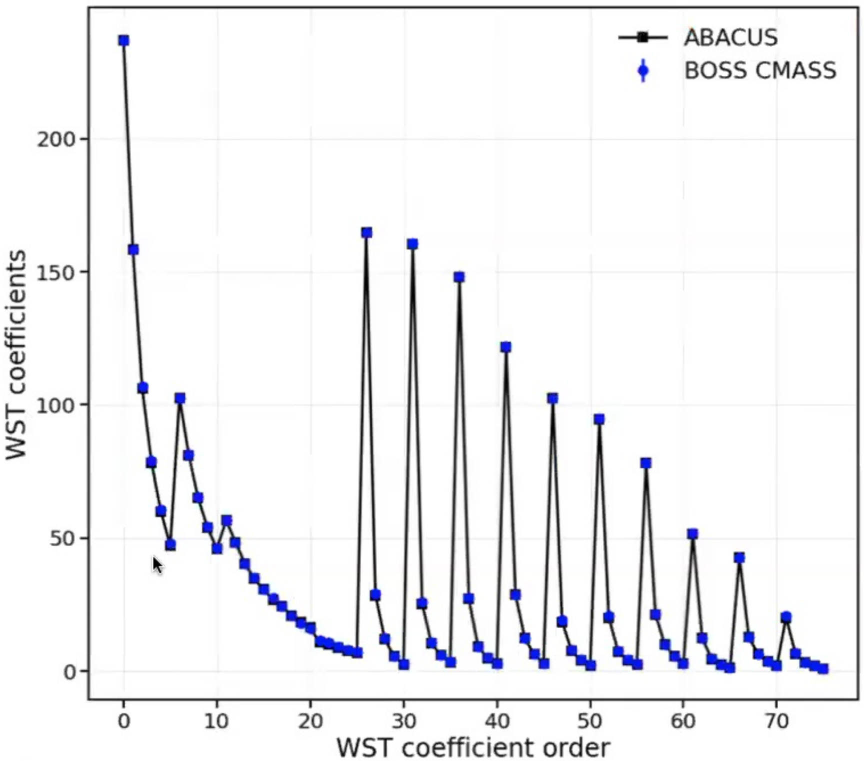
- Fiducial cosmology from Planck 2018 $\{\omega_b, \omega_c, n_s, \sigma_8\} = \{0.02237, 0.120, 0.9649, 0.8114\}$
- + Fixed angular size of sound horizon at last scattering. $100\theta_\star = 1.041533$
- + 7 HOD model paramerers (vanilla HOD + velocity bias)

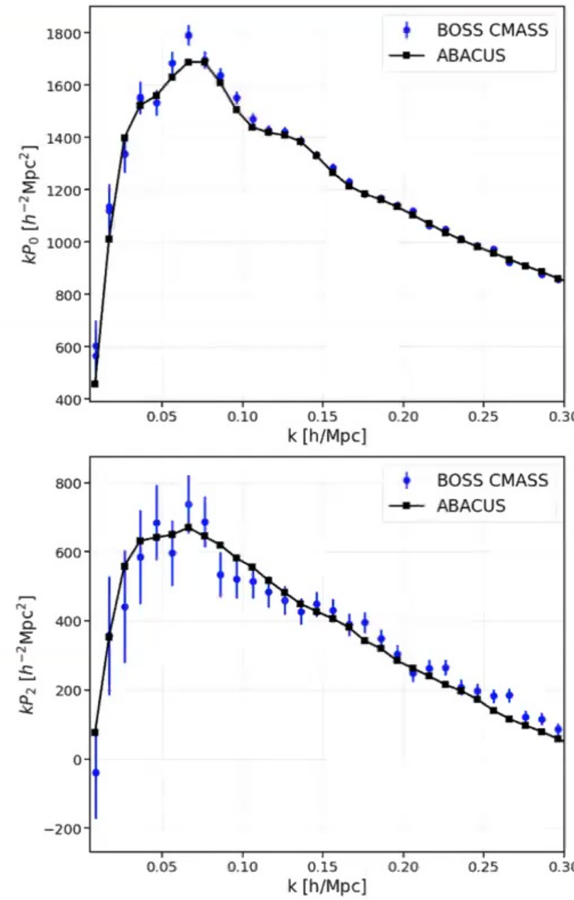
$$\{\alpha, \alpha_{\mathrm{c}}, \alpha_{\mathrm{s}}, \kappa, \log M_1, \log M_{\mathrm{cut}}, \sigma\} = \{0.9022, 0.2499, 1.1807, 0.3288, 14.313, 12.8881, 0.02084\}$$

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

Likelihood analysis

- Fiducial cosmology predictions





Valogiannis & Dvorkin 2022b

Likelihood analysis

- Theory model

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

- To model WST (and P(k)) cosmological dependence, we use the *approximation:*

$$\mathbf{X}_t(\theta) = \mathbf{X}_t(\theta_{\mathrm{fid}}) + (\theta - \theta_{\mathrm{fid}})\nabla_\theta \mathbf{X}$$

Prediction for fiducial cosmology

Constructed from 'Linear derivative grid' of cosmologies

ω_b	ω_c	n_s	σ_8
0.02237	0.1200	0.9649	0.8114
0.02282	0.1200	0.9649	0.8114
0.02193	0.1200	0.9649	0.8114
0.02237	0.1240	0.9649	0.8114
0.02237	0.1161	0.9649	0.8114
0.02237	0.1200	1.0249	0.8114
0.02237	0.1200	0.9049	0.8114
0.02237	0.1200	0.9649	0.8698
0.02237	0.1200	0.9649	0.7532

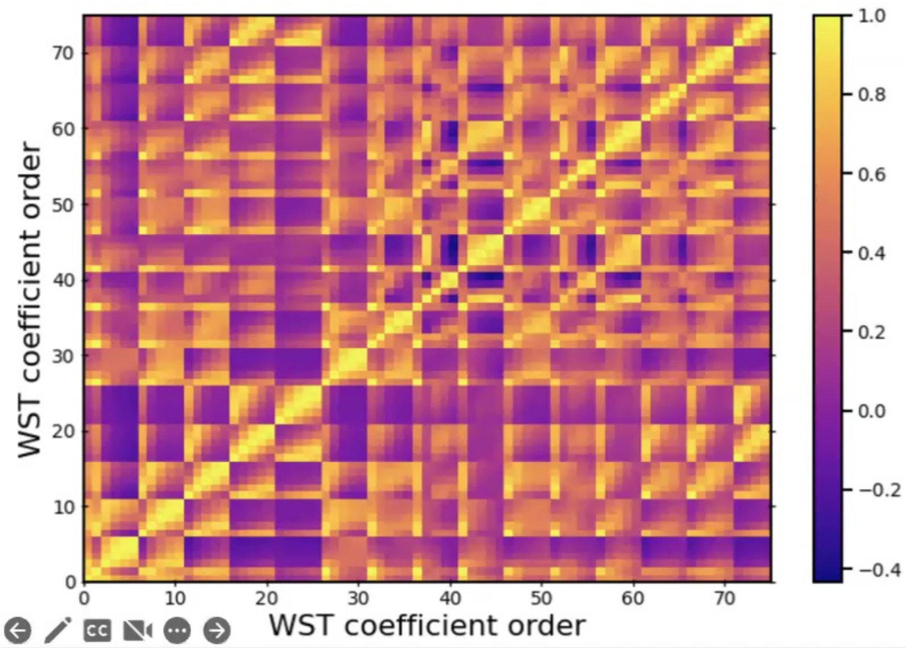
- + Additional derivative steps in the 7 HOD parameters

Valogiannis & Dvorkin 2022b

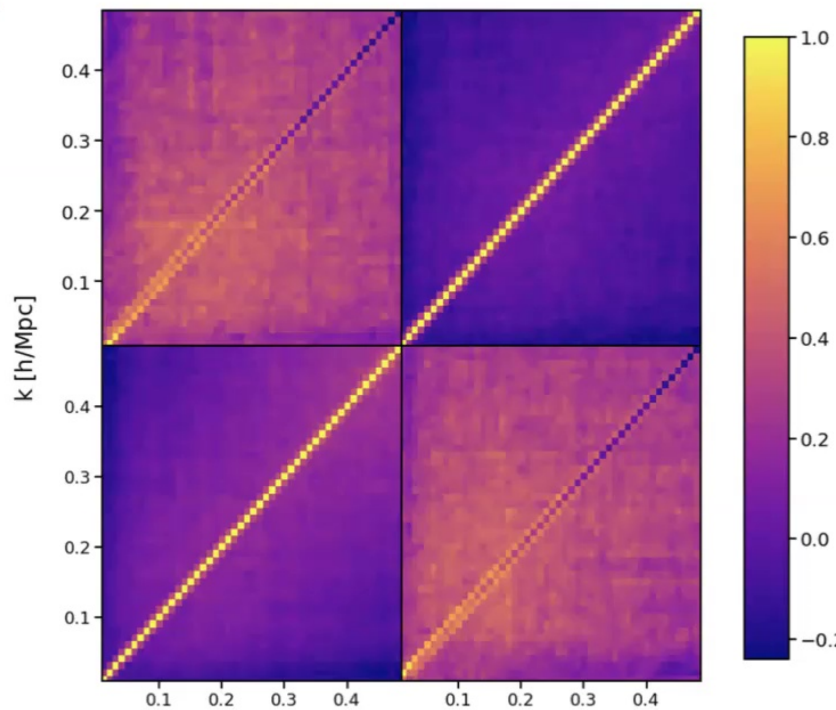
Likelihood analysis

- Covariance matrix obtained from N=2048 *PATCHY* mocks (S. A. Rodriguez-Torres et al., 2016)

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

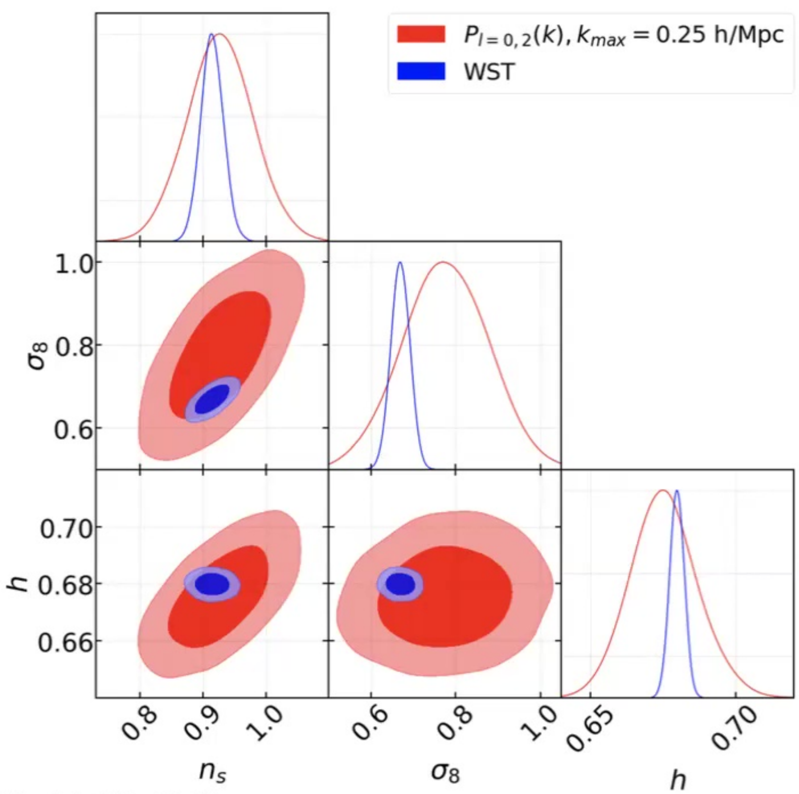


Valogiannis & Dvorkin 2022b



Likelihood analysis

- Likelihood analysis using a BBN prior on ω_b $\omega_b = 0.02268 \pm 0.00038$



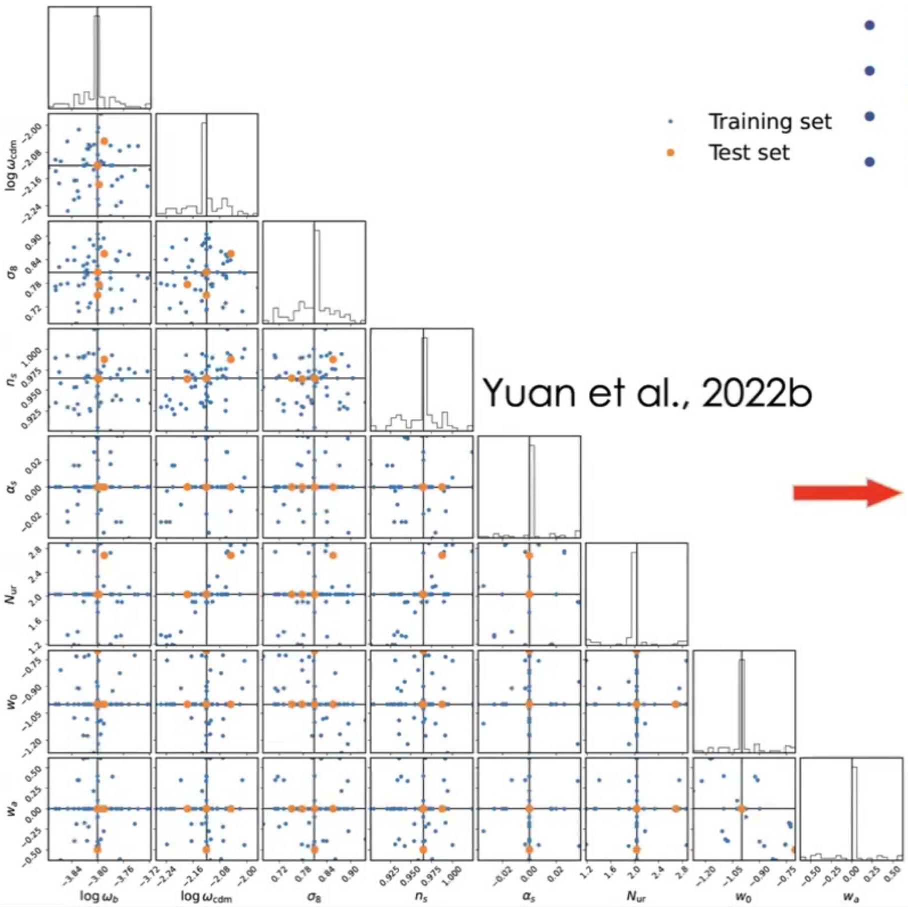
	BBN prior on ω_b		unrestricted priors	
	P(k)	WST	P(k)	WST
ω_b	$0.02268^{+0.00036}_{-0.00036}$	$0.02225^{+0.00034}_{-0.00034}$	$0.0217^{+0.0043}_{-0.0043}$	$0.0184^{+0.0011}_{-0.0011}$
ω_c	$0.1225^{+0.0037}_{-0.0037}$	$0.120^{+0.00041}_{-0.00041}$	$0.1217^{+0.0058}_{-0.0058}$	$0.1154^{+0.0012}_{-0.0012}$
n_s	$0.927^{+0.063}_{-0.063}$	$0.914^{+0.018}_{-0.018}$	$0.921^{+0.057}_{-0.049}$	$0.931^{+0.018}_{-0.018}$
σ_8	$0.77^{+0.13}_{-0.13}$	$0.67^{+0.023}_{-0.023}$	$0.762^{+0.11}_{-0.094}$	$0.691^{+0.023}_{-0.023}$
h	$0.675^{+0.014}_{-0.014}$	$0.68^{+0.0025}_{-0.0025}$	$0.668^{+0.024}_{-0.024}$	$0.653^{+0.0074}_{-0.0074}$

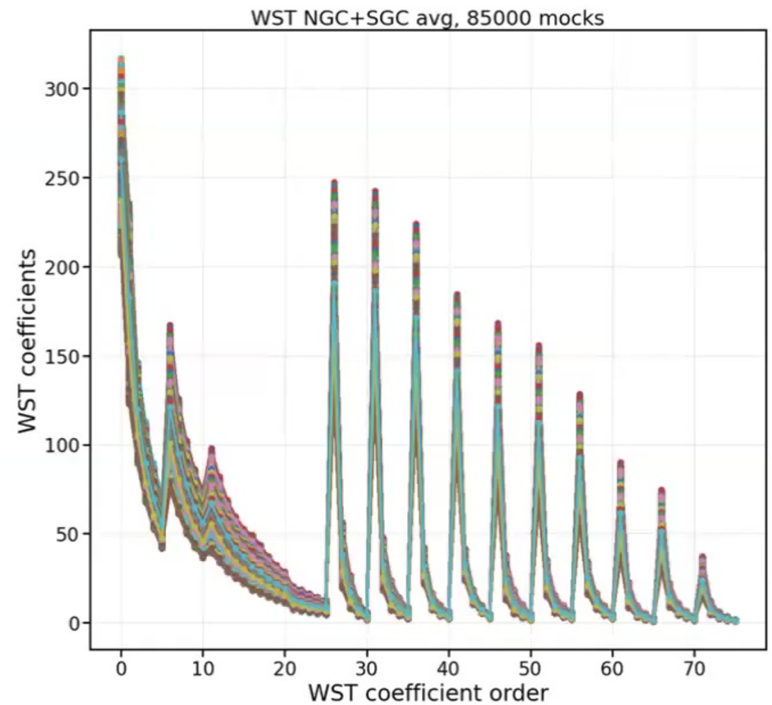
- Parameter mean values from WST & P(k) always consistent with each other within 1σ (of the P(k))
- Much **tighter** errors from WST compared to P(k)!

Valogiannis & Dvorkin 2022b

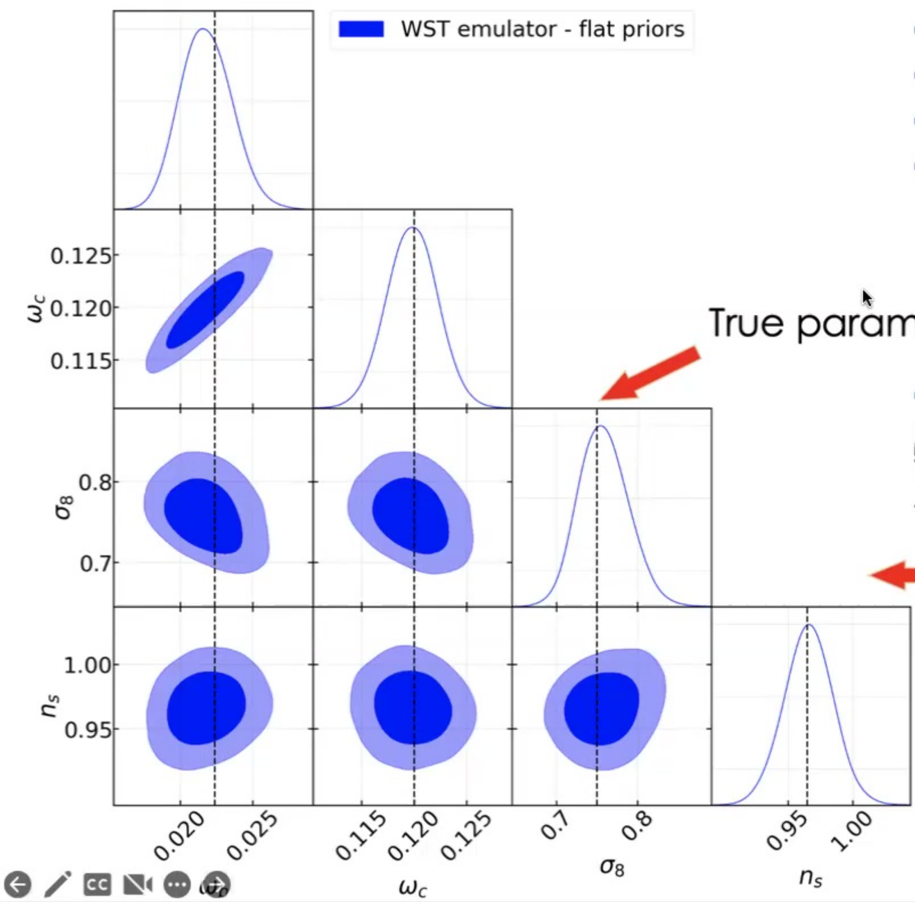
WST emulator (in progress)

- Construct *full emulator* of WST's cosmological dependence
- Data vector of 76 coefficients up to 2nd order, for J=L=5
- Trained from 85x1000 = 85,000 Abacus Summit mocks!
- Neural net-based





Hold-out tests on Abacus 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

- For parameters $\{\omega_b, \omega_c, \sigma_8, n_s\}$, WST gives (with flat priors):

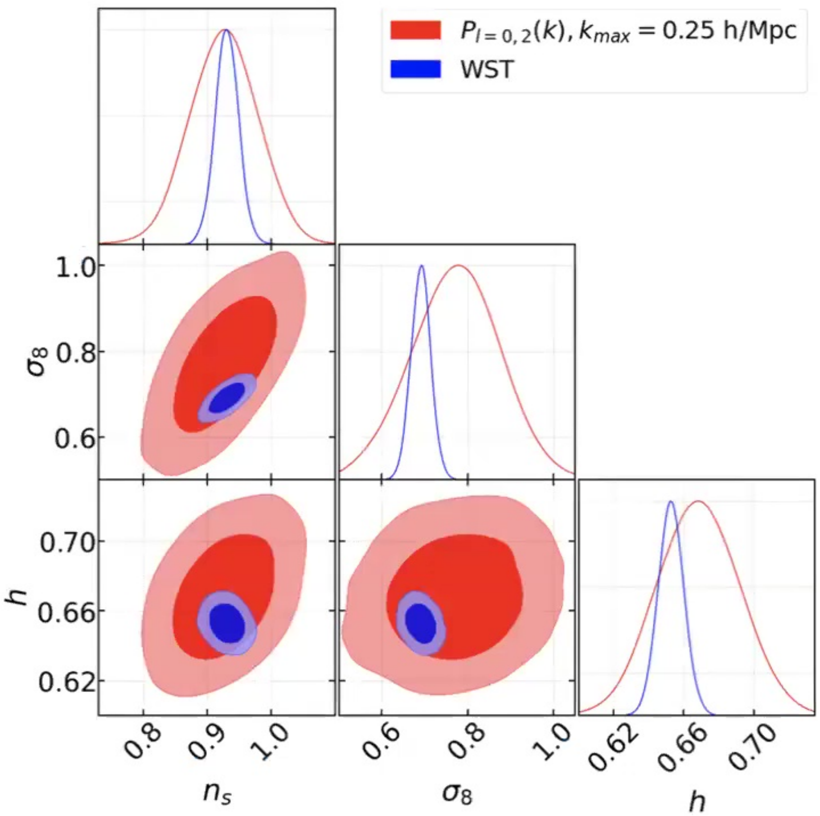
Mean values: 0.0223, 0.1194, 0.8159 , 0.9667
1-σ errors: 0.00178, 0.00242, 0.0308, 0.0192

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

Valogiannis et al., in prep

Likelihood analysis

- Likelihood analysis using flat unrestricted priors



	BBN prior on ω_b		unrestricted priors	
	P(k)	WST	P(k)	WST
ω_b	$0.02268^{+0.00036}_{-0.00036}$	$0.02225^{+0.00034}_{-0.00034}$	$0.0217^{+0.0043}_{-0.0043}$	$0.0184^{+0.0011}_{-0.0011}$
ω_c	$0.1225^{+0.0037}_{-0.0037}$	$0.120^{+0.00041}_{-0.00041}$	$0.1217^{+0.0058}_{-0.0058}$	$0.1154^{+0.0012}_{-0.0012}$
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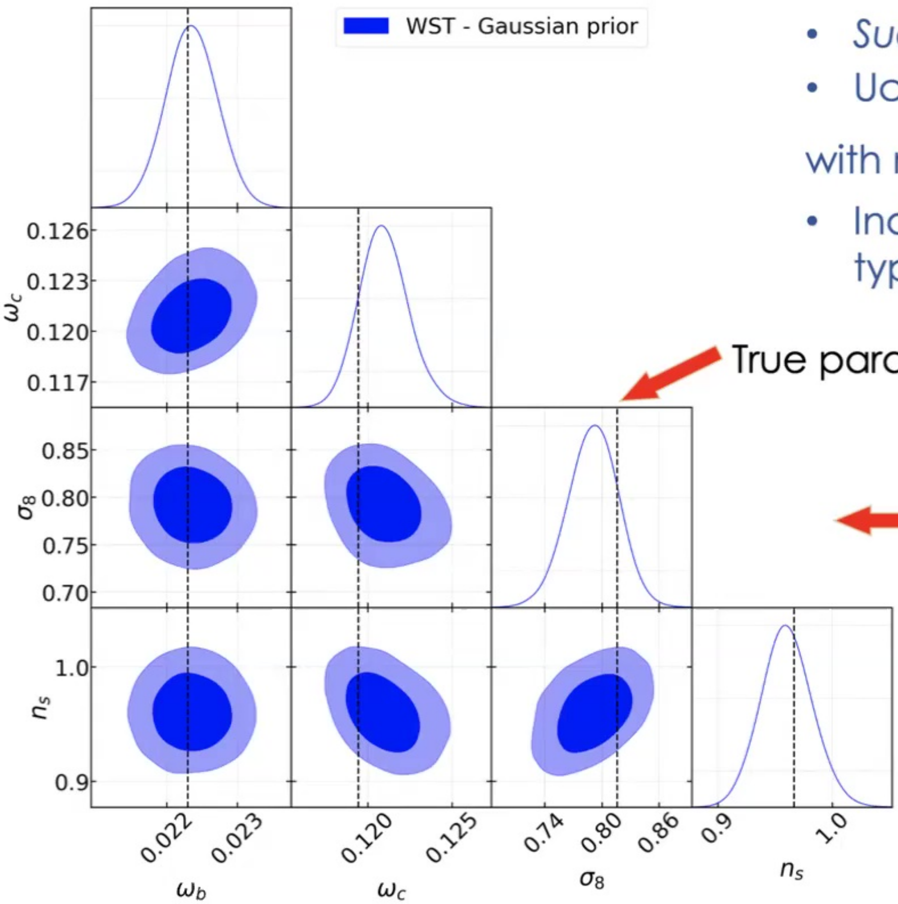
- Parameter mean values from WST & P(k) always consistent with each other within 1σ (of the P(k))
- Much **tighter** errors from WST compared to P(k)!

Valogiannis & Dvorkin 2022b

Hold-out tests on Uchuu mock



- *Successful* parameter recovery in non-HOD mock!!
- Uchuu mock (T._Ishiyama et al., 2021), 2.0 $\frac{Gpc}{h}$ side box

with number density $n_g = 3x10^{-4} \frac{h^3}{Mpc^3}$. Thanks to **Jeremy Tinker**!

- Indicates robustness against different galaxy mock type/model, and also phase!

True parameter values

Example of successful parameter recovery from Uchuu test mock using abundance matching

Valogiannis et al., in prep

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 & Dvorkin , arXiv: 2204.13717, Phys. Rev. D 105, 103534, 2022)**
  - Worked with BOSS CMASS galaxy sample at $0.46<z<0.60$
  - **Great** improvement in the 1σ errors over traditional galaxy P(k) multipoles
- Ongoing & future improvements (in progress)
  - Construct full emulator for WST coefficients ✓
  - Pass mock tests ✓
  - Re-analyze BOSS CMASS (**Valogiannis et al., in prep.)**
  - More accurately capture lightcone, fiber collision/systematic effects in galaxy mocks (Eg. see Yuan et al. 2022c), Simulation-based inference, etc
  - Blinded mock challenges
- Future applications
  - Application to DESI (& Euclid) spectroscopic observations
  - Constrain neutrino mass (Eg. as in **Valogiannis & Dvorkin, arXiv: 2108.07821, Phys. Rev. D 105, 103534, 2022)**
  - Constrain fundamental physics (theories of gravity, primordial non-Guassianity etc)
  - Weak lensing & cross-correlations (with future applications to Rubin LSST & Euclid observations)