

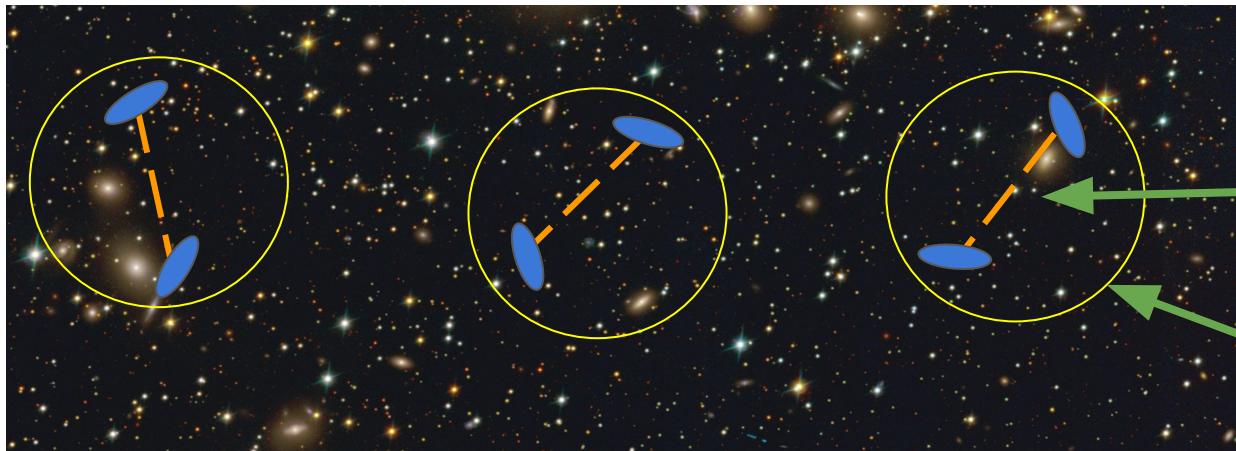
Cosmology from the integrated shear 3-point correlation function: simulated likelihood analyses with machine-learning emulators

Zhengyangguang (Laurence) Gong (USM)

with: Anik Halder, Alex Barreira, Stella Seitz and Oliver Friedrich
<https://arxiv.org/abs/2304.01187>

GCCL seminar
05.05.2023

Integrated shear 3-point correlation functions



$$\zeta_{\pm}(\theta) \equiv \langle M_{\text{ap}}(\boldsymbol{\theta}_C) \hat{\xi}_{\pm}(\theta; \boldsymbol{\theta}_C) \rangle$$

Position-dependent shear
2-pt correlation in top-hat
aperture

$$\hat{\xi}_{\pm}(\theta; \boldsymbol{\theta}_C)$$

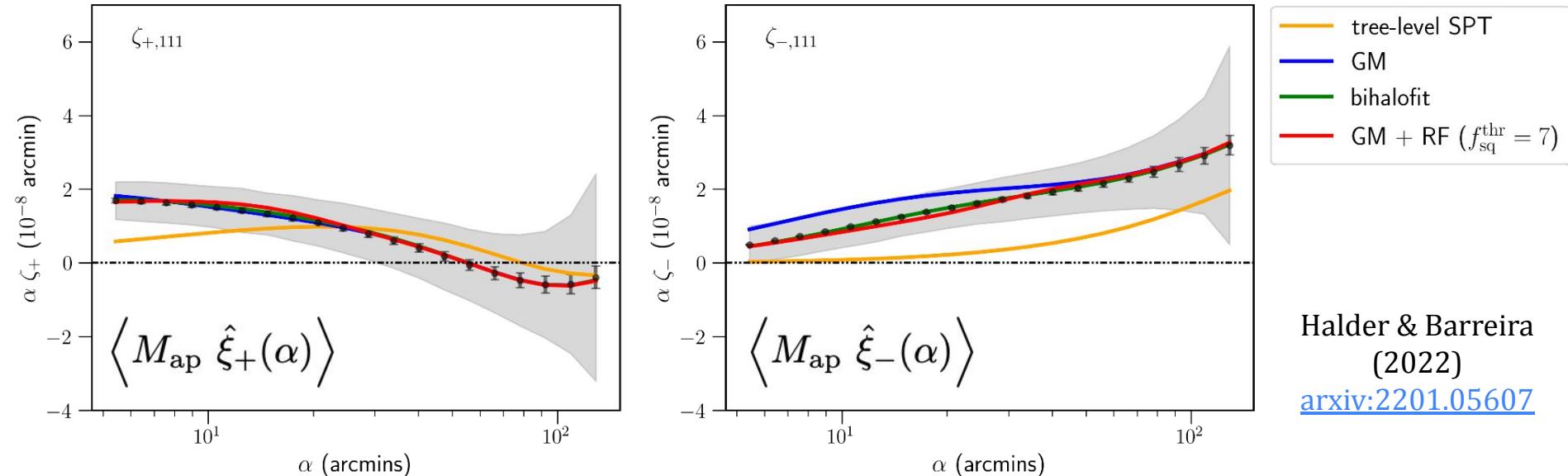
Aperture mass
 $M_{\text{ap}}(\boldsymbol{\theta}_C)$

Weighted tangential shear
inside the filter

- Directly observable higher-order statistic of the cosmic shear field
- Probes the line-of-sight projection of the 3D matter bispectrum

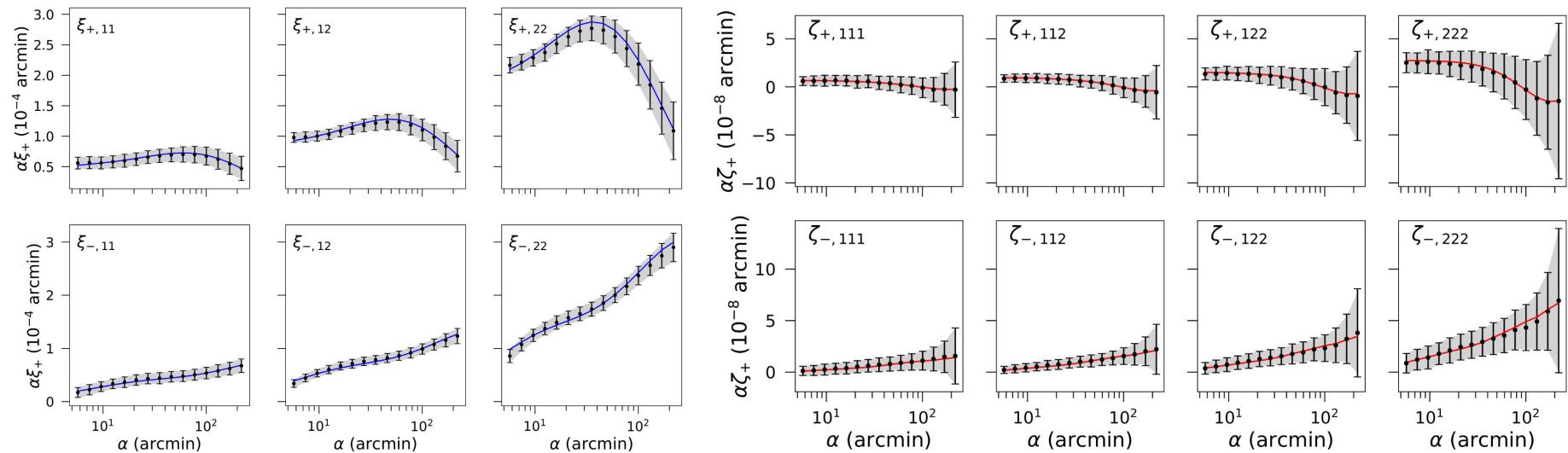
Halder et al. (2021)
[arxiv:2102.10177](https://arxiv.org/abs/2102.10177)

Theory prediction vs. N-body simulation



- **Response approach** (Barreira & Schmidt 2017) modelling of the integrated 3PCF (red curves → show good agreement to the T17 simulations)
- Encode baryonic feedback effects into integrated shear 3PCF

Theory prediction vs. N-body simulation



- Two DES Y3-like tomographic bins for both ξ^\pm and ζ^\pm (auto/cross-correlation)
- Theory prediction including response function approach to perturbation theory and baryonic feedback recipe in ζ^\pm
- Simulation data points from 540 DES Y3-like footprints in 2017 Takahashi full-sky simulation
[arXiv:1706.01472](https://arxiv.org/abs/1706.01472)

Emulation of integrated shear 3PCF and the modelling of systematic effects

Gong, Halder, Barreira, Seitz & Friedrich 2023 ([arxiv:2304.01187](https://arxiv.org/abs/2304.01187))

Modelling the integrated shear 3PCF

$$\zeta_{\pm}(\alpha) = \left\langle \hat{M}_{\text{ap}}(\boldsymbol{\theta}_C) \hat{\xi}_{\pm}(\alpha; \boldsymbol{\theta}_C) \right\rangle$$

$$= \frac{1}{A_{2\text{pt}}(\alpha)} \int \frac{d\ell}{2\pi} \ell \mathcal{B}_{\pm}(\ell) J_{0/4}(\ell\alpha)$$

$$\mathcal{B}_{\pm}(\ell) = \int d\chi \frac{q_{\kappa}^3(\chi)}{\chi^4} \int_{\ell_1} \int_{\ell_2} B_{\delta}^{3\text{D}} \left(\frac{\ell_1}{\chi}, \frac{\ell_2}{\chi}, \frac{-\ell_{12}}{\chi}; \chi \right) e^{2i(\phi_{\ell_2} \mp \phi_{-\ell_{12}})} U(\ell_1) W(\ell_2 + \ell) W(-\ell_{12} - \ell)$$

Line-of-sight
projection

3D matter
bispectrum

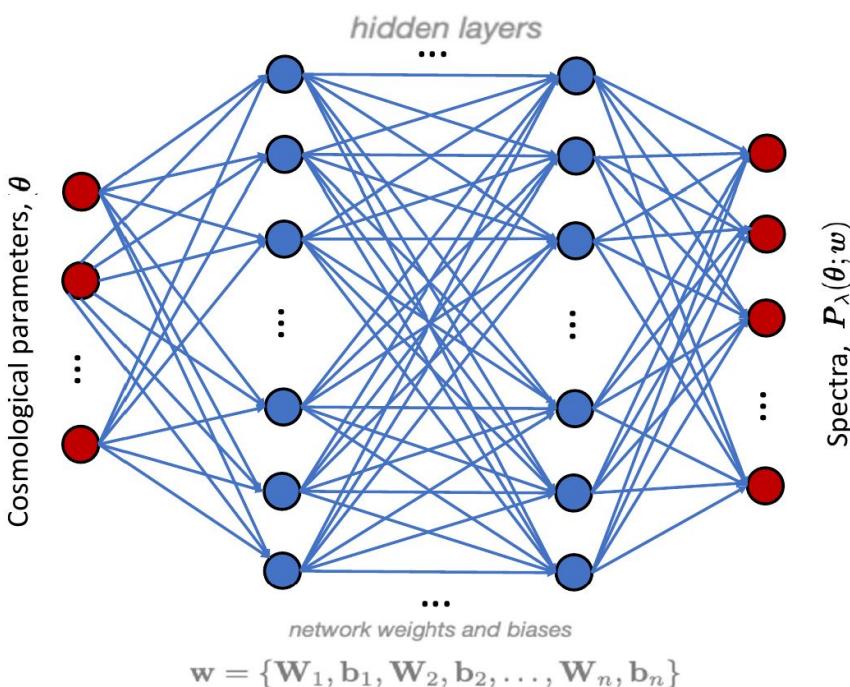
Compensated filter
Top-hat filter

Window functions

Emulation

- Emulate the 4-dimensional integration which is computationally expensive
- Leaving the line-of-sight projection out of emulation:
Preserving the flexibility in the systematic modelling

Emulate the integrated bispectrum using neural network (NN)



Mancini et al. (2021)
[arXiv:2106.03846](https://arxiv.org/abs/2106.03846)

- The emulator is constructed using the package containing a suite of fully connected NN: **Cosmopower**
- **Cosmopower**:
 - training feature: $\{\Omega_m, \ln(10^{10} A_s), w_0, c_{\min}, z\}$
 - training label: pre-computed spectra at 100 multipoles
 - training on GPU
- Each emulator is for a specific filter size:
 - 100000 training nodes (10% validation)
 - 1000 testing nodes

Data preparation and pre-processing

Prior range	
Cosmological parameters (emulated)	
Ω_m	$U [0.16, 0.45]$
$\ln(10^{10} A_s)$	$U [1.61, 4.20]$
w_0	$U [-3.33, -0.33]$
Baryonic feedback parameter (emulated)	
c_{\min}	$U [1.0, 5.5]$
Systematic parameters (not emulated)	
Δz_1	$\mathcal{N}(0.0, 0.023)$
Δz_2	$\mathcal{N}(0.0, 0.020)$
m_1	$\mathcal{N}(0.0261, 0.012)$
m_2	$\mathcal{N}(-0.061, 0.011)$
$A_{\text{IA},0}$	$U [-5.0, 5.0]$
α_{IA}	0 (fixed)

With the additional emulated parameter redshift z between 0.0 and 2.0

- Emulation prior:

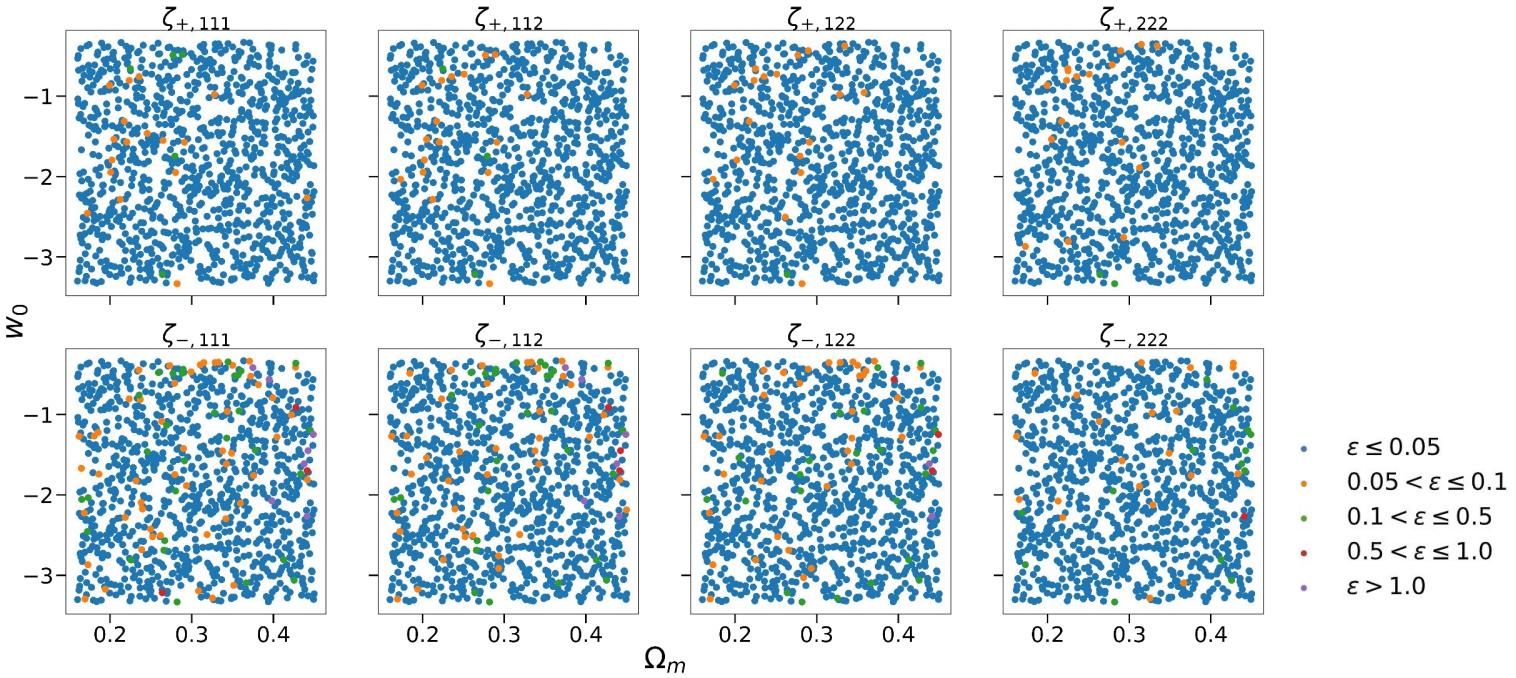
Too wide: 1. a waste of training data;
2. Labels can experience numerical instability or give unusual predictions that form prominent outliers

Too narrow: Parameter inference will be dominated by priors

- Scale primordial power spectrum amplitude logarithmically;
Scale the training labels: integrated bispectrum and matter power spectrum with $\log 10$

Emulation accuracy test

$$\epsilon \equiv \left| \frac{\chi^2_{\text{emu},i}}{\chi^2_{\text{test},i}} - 1 \right|$$



- All 8 non-redundant integrated shear 3PCF from 2 DES Y3-like tomographic bins
- Using chi2 fractional difference as the emulation accuracy metric: It describes how closely the emulators describe the log-likelihood surface w.r.t the theory model predictions

Including other weak lensing systematics

- **Photometric redshift uncertainty**

$$n_s^i(z) = \hat{n}_s^i(z + \Delta z^i)$$

- We do not include these components in the emulation so that the flexibility enables others to adopt different models

- **Multiplicative shear bias**

$$\xi_{\pm,ij}(\alpha) \rightarrow (1 + m_i)(1 + m_j)\xi_{\pm,ij}(\alpha) ,$$

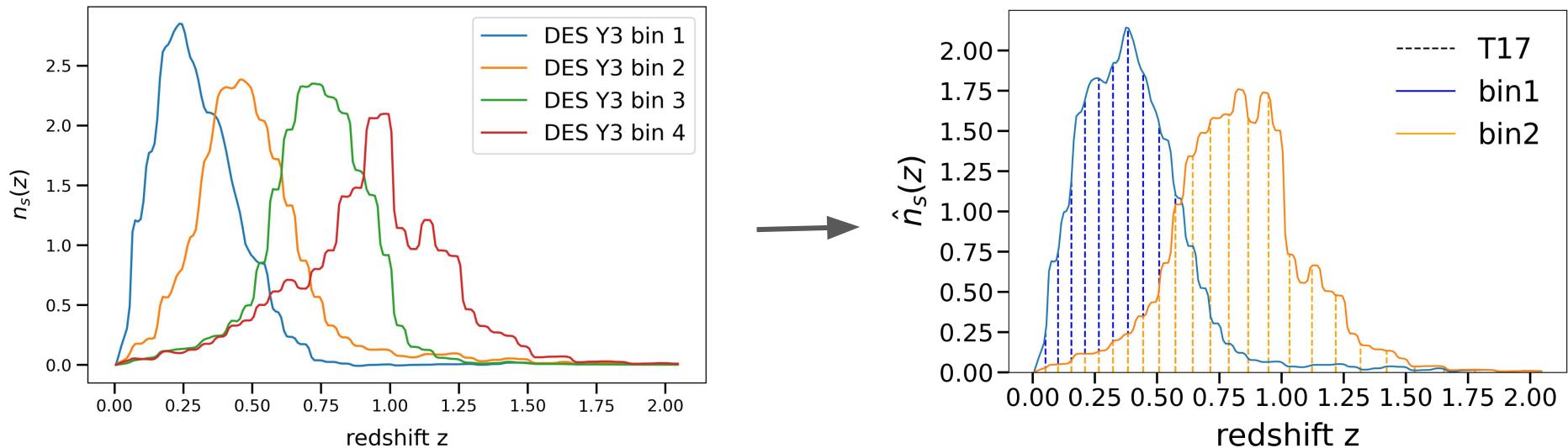
$$\zeta_{\pm,ijk}(\alpha) \rightarrow (1 + m_i)(1 + m_j)(1 + m_k)\zeta_{\pm,ijk}(\alpha)$$

- **Intrinsic alignment** (non-linear linear alignment (NLA) model)

$$q^i(\chi) \rightarrow q^i(\chi) + f_{\text{IA}}(z(\chi)) \frac{n_s^i(\chi)}{\bar{n}_s^i} \frac{dz}{d\chi} \quad f_{\text{IA}}(z) = -A_{\text{IA},0} \left(\frac{1+z}{1+z_0} \right)^{\alpha_{\text{IA}}} \frac{c_1 \rho_{\text{crit}} \Omega_{\text{m},0}}{D(z)}$$

Covariance estimation

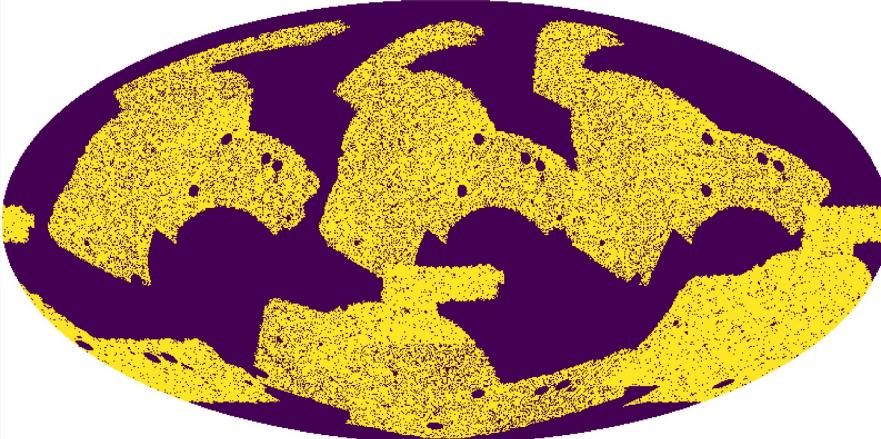
Covariance estimation I



- We merge 4 DES Y3 source redshift bins into 2 via a weighted summation
- Increase the signal-to-noise ratio of the integrated shear 3PCF

Covariance estimation II

5 rotated DES Y3-like footprints



- Superimpose the DES Y3 footprint onto the full sky simulation map and rotate it to five non-overlapping locations
- Add shape noise following the equation:

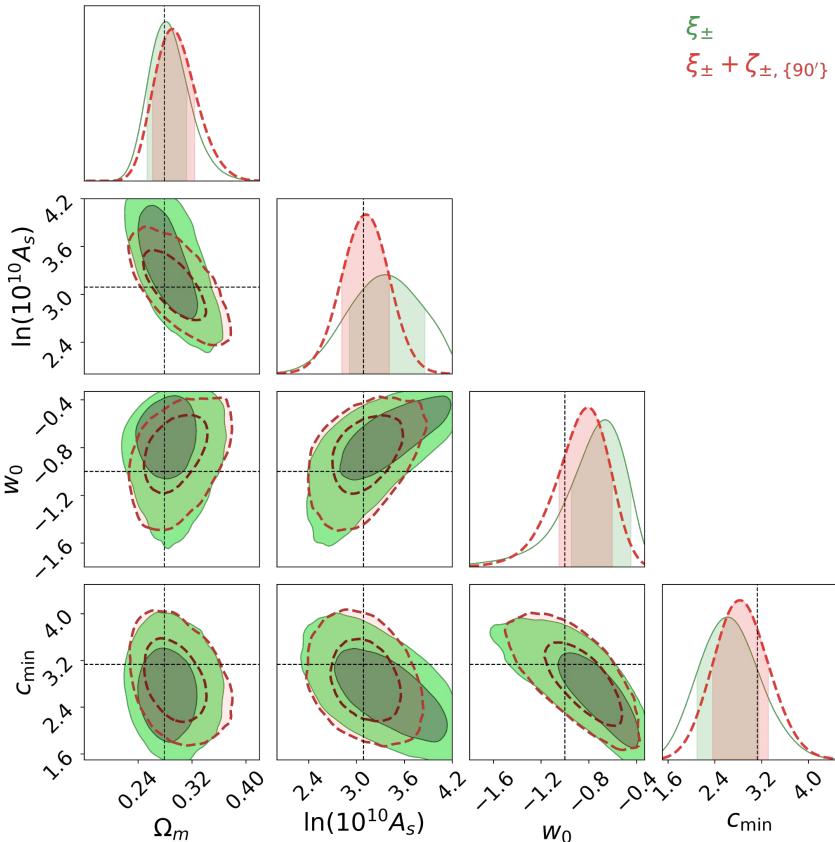
$$\gamma_{\text{pix}} = \gamma_{\text{noise}} + \gamma_{\text{sim}} = \frac{\sum_{j=1}^N \omega_j \gamma_{j,\text{DES}} \exp(i\phi_j)}{\sum_{j=1}^N \omega_j} + \gamma_{\text{sim}}$$

- Select mass apertures that have enough number of valid pixels
- Estimate data covariance from both N-body T17 simulation and FLASK log-normal maps

Results of simulated likelihood analyses

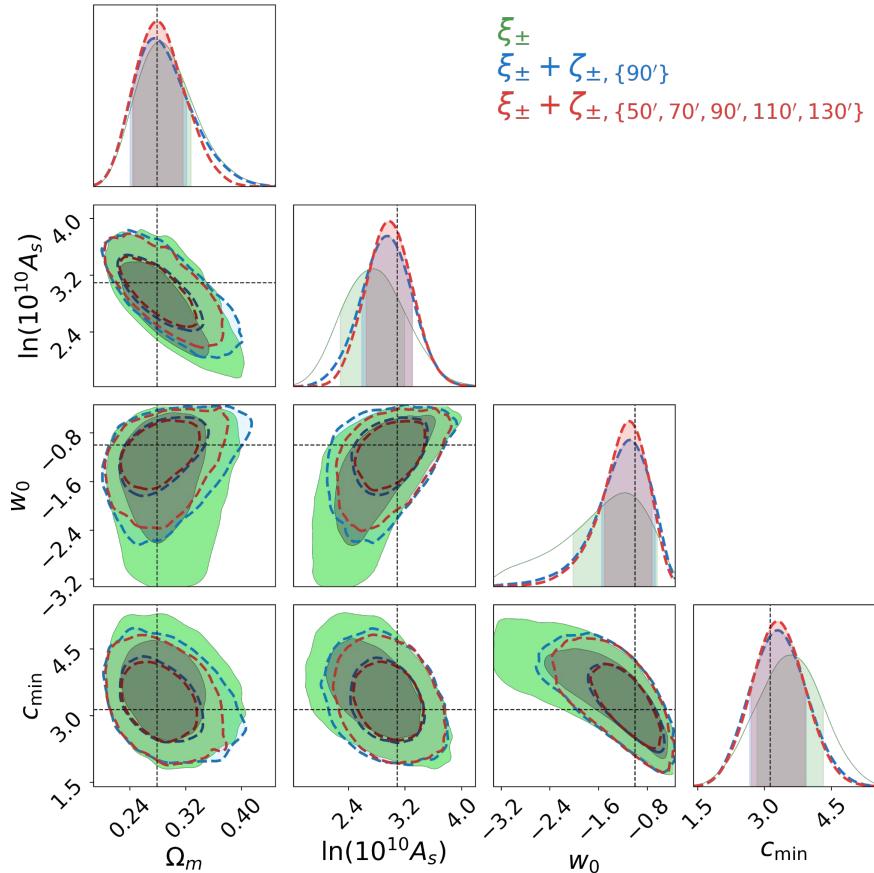
- Validation on the T17 cosmic shear maps
- The impact of the aperture size
- The impact of systematics and their modelling
- The impact of different covariance estimates

Validation on the T17 cosmic shear maps



- The data vector comes from the average over 540 DES Y3-like footprints on T17 shear maps (Takahashi et al (2017), [arXiv:1706.01472](https://arxiv.org/abs/1706.01472))
- The data covariance matrix is estimated from 1500 DES Y3-like footprints on FLASK log-normal shear maps
- The inferred parameter covariance is not biased from the fiducial T17 cosmological parameter values

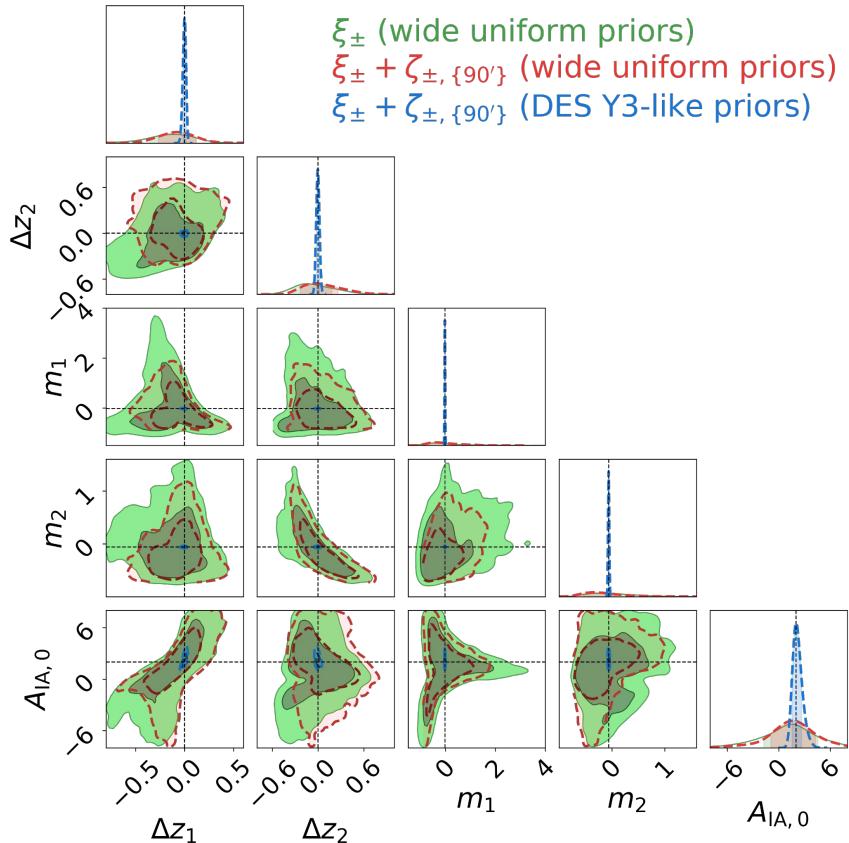
The impact of the aperture size



- We train 5 emulators for integrated shear 3PCF with different filter sizes: $\{50', 70', 90', 110', 130'\}$
- Marginalized over systematic parameters – photo-z, shear bias and intrinsic alignment (NLA) parameters

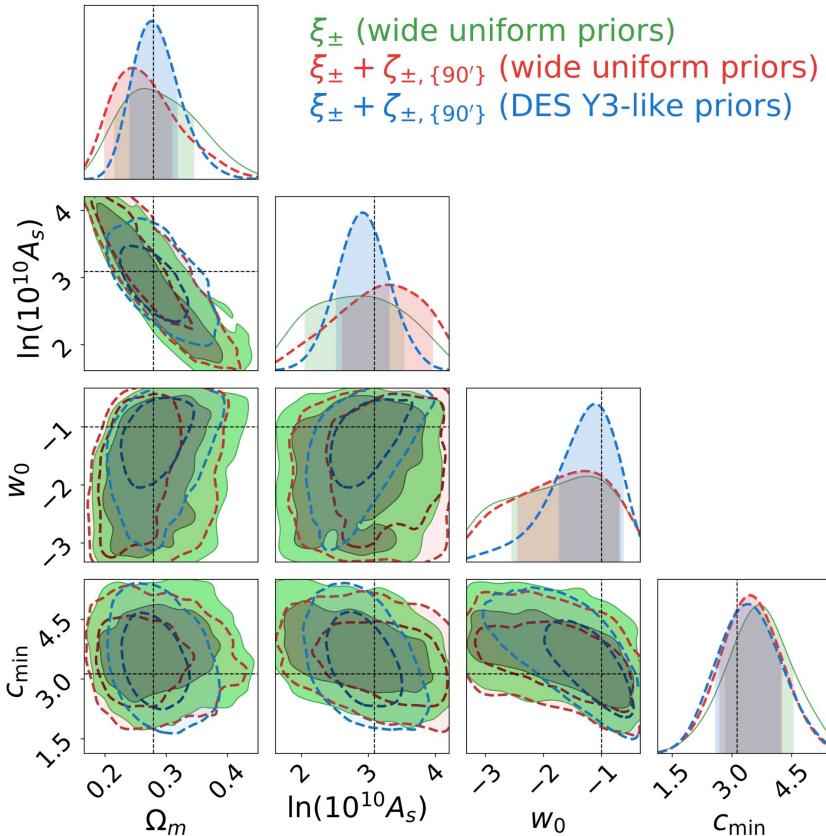
Aperture sizes (arcmin)	Ω_m	$\ln(10^{10} A_s)$	w_0	c_{\min}
50	1.2%	9.0%	18.1%	4.8%
70	1.2%	16.9%	31.9%	11.6%
90	3.7%	20.2%	38.4%	15.1%
110	1.2%	19.1%	34.1%	11.0%
130	1.2%	16.9%	32.6%	12.3%
$\{50, 70, 90\}$	2.5%	24.7%	39.1%	15.8%
$\{50, 90, 130\}$	3.7%	23.6%	41.3%	16.4%
$\{70, 90, 110\}$	6.2%	25.8%	39.1%	15.1%
$\{90, 110, 130\}$	8.6%	25.9%	42.8%	15.8%
$\{50, 70, 90, 110, 130\}$	12.4%	28.1%	44.9%	19.9%

The impact of systematics and their modelling



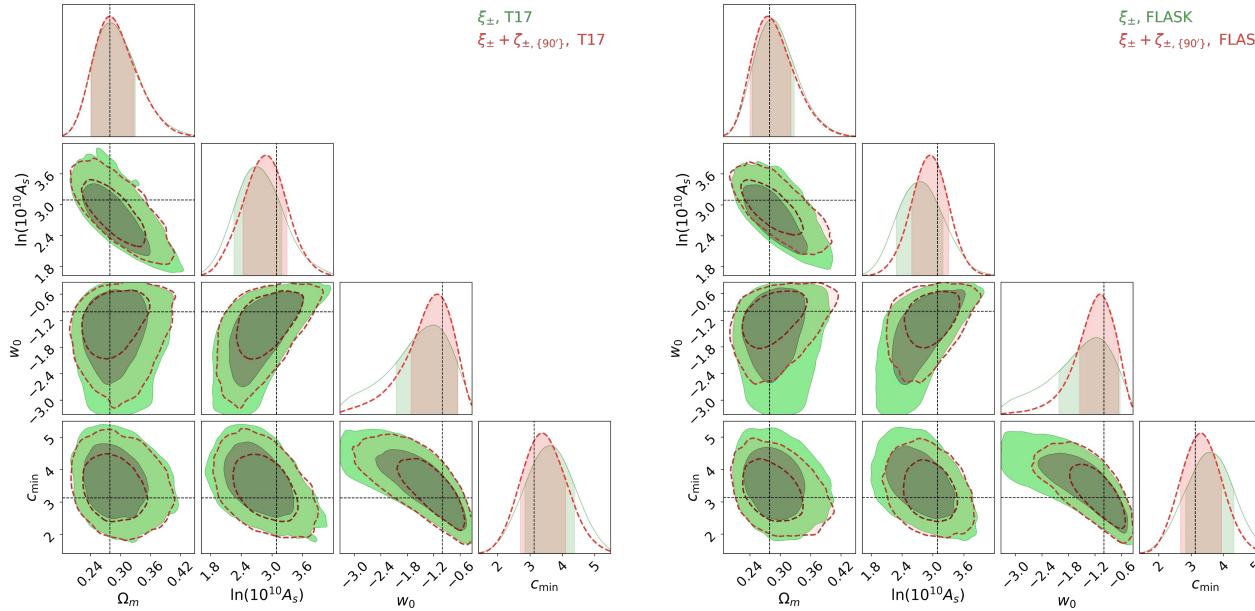
- Idea: 2-point and 3-point statistics depend differently on systematic parameters
→ **Self-calibration** of systematic parameters that can reduce the need for external calibration data
- Quantitatively it is **in contrast with** the results reported in the work Pyne & Joachimi (2021) [arXiv: 2010.00614](https://arxiv.org/abs/2010.00614) for an Euclid-like survey setups

The impact of systematics and their modelling



- Same wide priors on nuisance parameters; Cosmological parameter constraints by adding ζ_{\pm}
- Adding ζ_{\pm} to ξ_{\pm} does not prevent the degradation of parameter constraints as significantly as predicted in
[arXiv: 2010.00614](https://arxiv.org/abs/2010.00614)

The impact of different covariance estimates



- FLASK-based covariance may not be suitable to cosmological constraints using 3-point cosmic shear information
- Real-data analyses may require using more expensive N-body simulations, or calculating the covariance matrix analytically

Covariance type	Ω_m	$\ln(10^{10} A_s)$	w_0	c_{\min}
FLASK (lognormal)	3.7%	20.2%	38.4%	15.1%
T17 (<i>N</i> -body simulations)	3.5%	8.8%	26.1%	8.7%

Summary

- Our analysis pipeline is accurate and able to yield unbiased parameter constraints from our N -body simulation DES Y3-like data vectors.
- Aperture size 90 arcmin is what results in the largest information gain from ζ^\pm . The combination of several filter sizes can improve the constraints further but at the cost of dealing with a larger data vector and covariance matrix.
- We do not find significant improvements of systematic constraints in combined $\xi^\pm + \zeta^\pm$ analyses; i.e. the mitigation of systematic effects still requires prior calibration from external data
- Lognormal realizations might not provide reliable estimates of the ζ^\pm covariance matrix.
- The next step is to apply this higher-order statistic pipeline to **DES Y3 data** and extract cosmological information

Thank you!

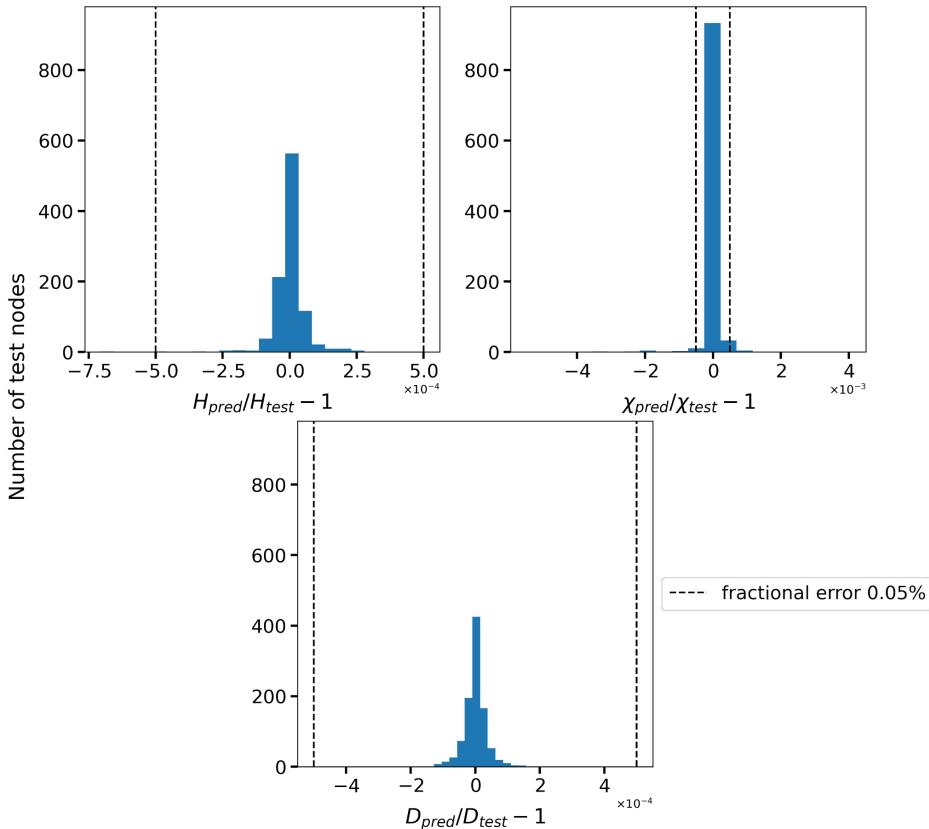
Additional slides

Responses in large-scale structures

- For details please refer to Barreira & Schmidt 2017 [arXiv: 1703.09212](#)
- Non-SPT method to compute higher-order correlation function in squeezed limit into nonlinear regime via nonlinear matter power spectrum and different orders of responses \mathcal{R}_n
- Squeezed limit configuration:
$$\langle \delta(\mathbf{k})\delta(\mathbf{k}')\delta(\mathbf{p}_1)\delta(\mathbf{p}_2)\cdots\delta(\mathbf{p}_n) \rangle_c, \quad \text{with} \quad p_i \ll k, k' \quad (i = 1, 2, \dots, n) \text{ and } p_{12..n} \ll k, k'$$
- Responses in 3-point correlation function [**(n+2)-point correlation function linked to nth order response**]

$$\lim_{p \rightarrow 0} \left(\begin{array}{c} \text{Diagram showing a horizontal line with arrows at both ends, labeled } k' \text{ and } k. \text{ A shaded circle at the origin is labeled } \mathcal{R}_1(k, \mu). \text{ An arrow labeled } P_L(p) \text{ points from the circle to a point above it, labeled } p. \text{ Another arrow labeled } (\mathbf{k} \leftrightarrow \mathbf{k}') \text{ points from the circle to the right.} \\ + (\mathbf{k} \leftrightarrow \mathbf{k}') \end{array} \right) = \mathcal{R}_1(k; \mu_{\mathbf{k}, \mathbf{p}}) P_m(k) P_L(p) (2\pi)^3 \delta_D(\mathbf{k} + \mathbf{k}' + \mathbf{p})$$

Including other weak lensing systematics



- The emulator is constructed using the package exploiting Gaussian Process: **GPflow** (de G. Matthews et al (2016) [arXiv:1610.08733](https://arxiv.org/abs/1610.08733))
- **GPflow**:
 - training feature: $\{\Omega_m, A_s, w_0, z\}$
 - training label: H, chi or D (growth factor)
 - training on GPU
- 10000 training nodes
- 1000 testing nodes

Intrinsic alignment modelling in power spectrum and bispectrum

- Illustratively the 2-point correlation of weak lensing shear:

$$\xi_{\pm, \text{obs}}^{ij} = \xi_{\pm, \text{GG}}^{ij} + \xi_{\pm, \text{GI}}^{ij} + \xi_{\pm, \text{IG}}^{ij} + \xi_{\pm, \text{II}}^{ij}$$

The relation between different power spectrum terms and the NLA kernel:

$$\propto f_{\text{IA}}^0 \text{ (GG)}, \propto f_{\text{IA}} \text{ (GI, IG)} \text{ and } \propto f_{\text{IA}}^2 \text{ (II)}$$

- Contributions to the integrated shear 3-point correlation function:

$$\zeta_{\pm, \text{obs}}^{ijk} = \zeta_{\pm, \text{GGG}}^{ijk} + \zeta_{\pm, \text{GGI}}^{ijk} + \zeta_{\pm, \text{GIG}}^{ijk} + \zeta_{\pm, \text{GII}}^{ijk} + \zeta_{\pm, \text{IGG}}^{ijk} + \zeta_{\pm, \text{IGI}}^{ijk} + \zeta_{\pm, \text{IIG}}^{ijk} + \zeta_{\pm, \text{III}}^{ijk}$$

The relation between different bispectrum terms and the NLA kernel:

$$\propto f_{\text{IA}}^0 \text{ (GGG)}, \propto f_{\text{IA}} \text{ (GGI, GIG, IGG)} \text{ and } \propto f_{\text{IA}}^2 \text{ (GII, IGI, IIG)} \text{ and } \propto f_{\text{IA}}^3 \text{ (III)}$$

Intrinsic alignment modelling in power spectrum and bispectrum

Pyne & Joachimi (2021) [arXiv: 2010.00614](https://arxiv.org/abs/2010.00614)

- $P_{\delta\delta_I}(k) = f_{IA} P_{NL}(k),$

$$P_{\delta_I\delta_I}(k) = f_{IA}^2 P_{NL}(k)$$

- $$\begin{aligned} B_{\delta\delta\delta_I}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) = & 2 \left[f_{IA}^2 F_2^{\text{eff}}(\mathbf{k}_1, \mathbf{k}_2) P_{NL}(k_1) P_{NL}(k_2) \right. \\ & + f_{IA} F_2^{\text{eff}}(\mathbf{k}_2, \mathbf{k}_3) P_{NL}(k_2) P_{NL}(k_3) \\ & \left. + f_{IA} F_2^{\text{eff}}(\mathbf{k}_3, \mathbf{k}_1) P_{NL}(k_3) P_{NL}(k_1) \right] \end{aligned}$$

$$\begin{aligned} B_{\delta\delta_I\delta_I}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) = & 2 \left[f_{IA}^3 F_2^{\text{eff}}(\mathbf{k}_1, \mathbf{k}_2) P_{NL}(k_1) P_{NL}(k_2) \right. \\ & + f_{IA}^2 F_2^{\text{eff}}(\mathbf{k}_2, \mathbf{k}_3) P_{NL}(k_2) P_{NL}(k_3) \\ & \left. + f_{IA}^3 F_2^{\text{eff}}(\mathbf{k}_3, \mathbf{k}_1) P_{NL}(k_3) P_{NL}(k_1) \right], \end{aligned}$$

$$B_{\delta_I\delta_I\delta_I}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) = f_{IA}^4 B_{\delta\delta\delta}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3).$$

Cosmic shear 2-point correlation functions



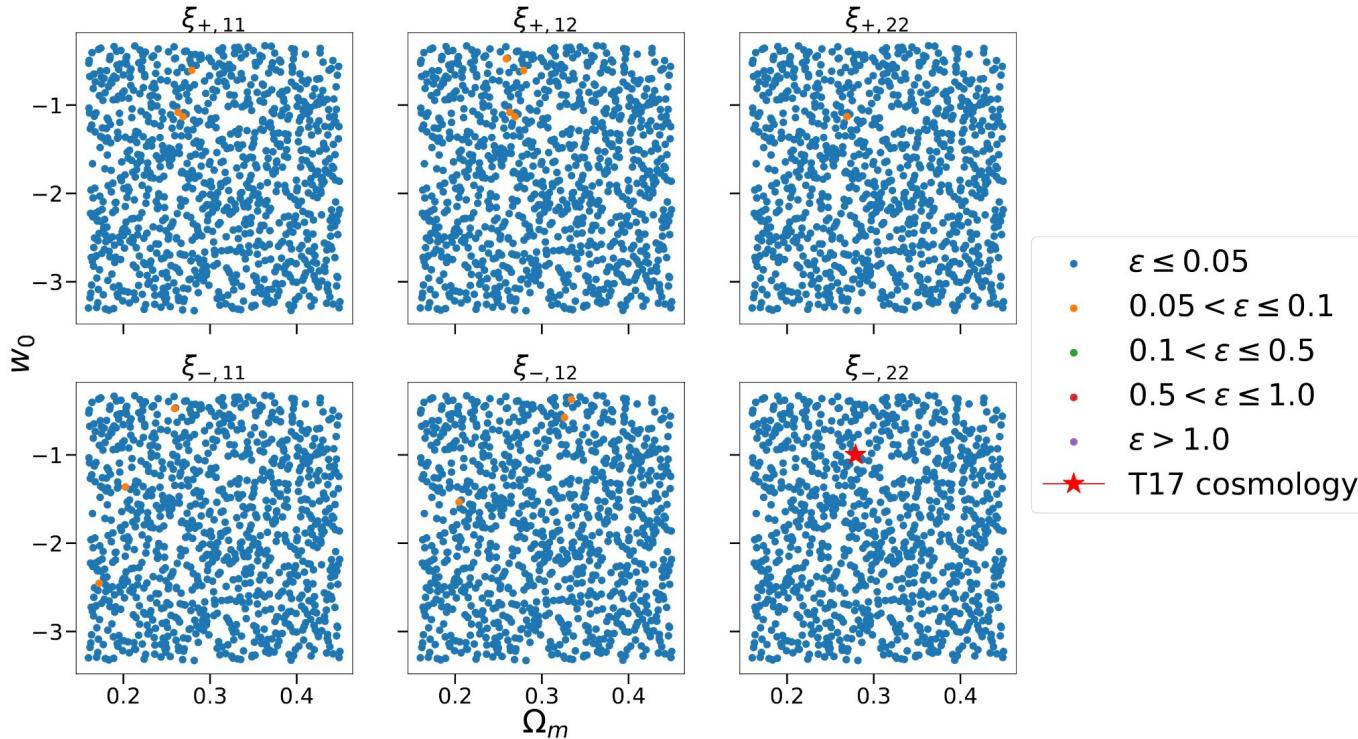
Background source
galaxy ellipticity

$$\hat{\xi}_{\pm}(\theta)$$

Shear 2-point correlation
functions

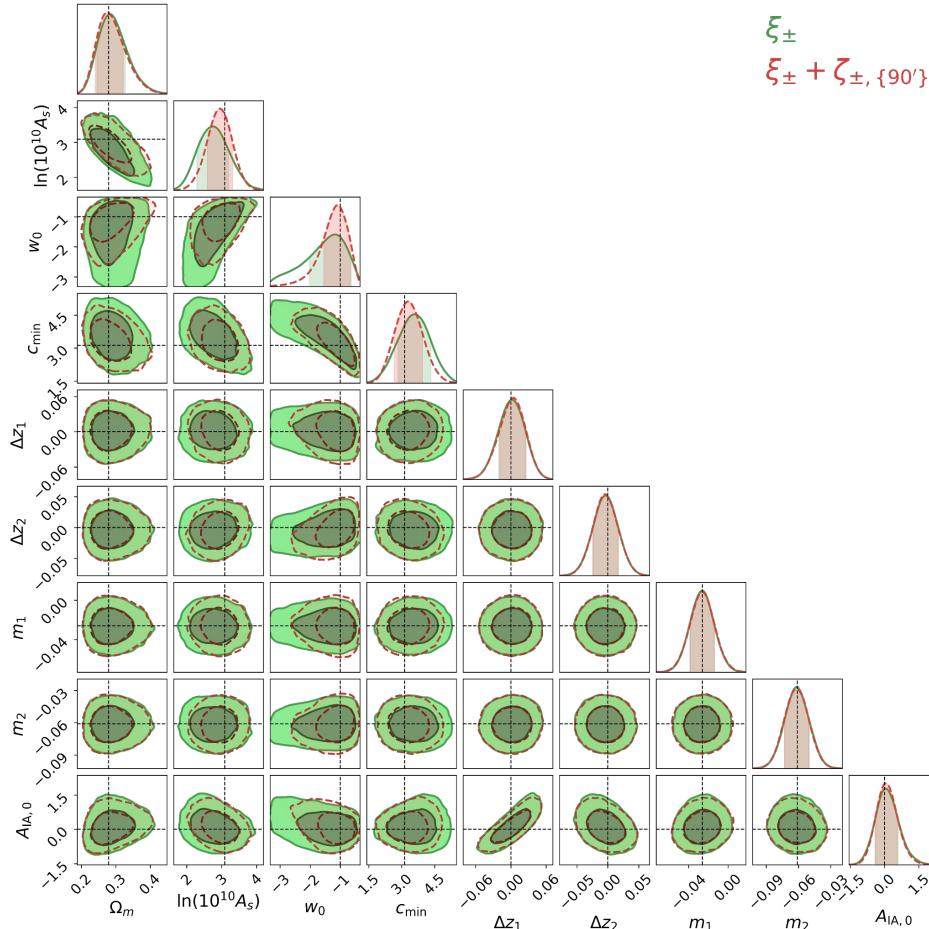
- Probes the line-of-sight projection of the 3D matter power spectrum
- But cosmic shear is a non-Gaussian field with information beyond 2-point correlations!

Emulation for shear 2PCF



- All 6 shear 2PCFs from 2 DES Y3 tomographic bins

Simulated DESY3 MCMCs with 2PCF and integrated 3PCF



- Green: shear 2PCF only
Red: shear 2PCF & integrated shear 3PCF (*for a single filter size*)
- MCMC on GPU: using emcee affine invariant sampler and sample **million points in ~ 1 hour**
- The inferred systematic parameter covariance is dominated by the corresponding DES Y3 gaussian priors

T17 vs. FLASK

