Simulation-based inference with the integrated 3PCF

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DPG

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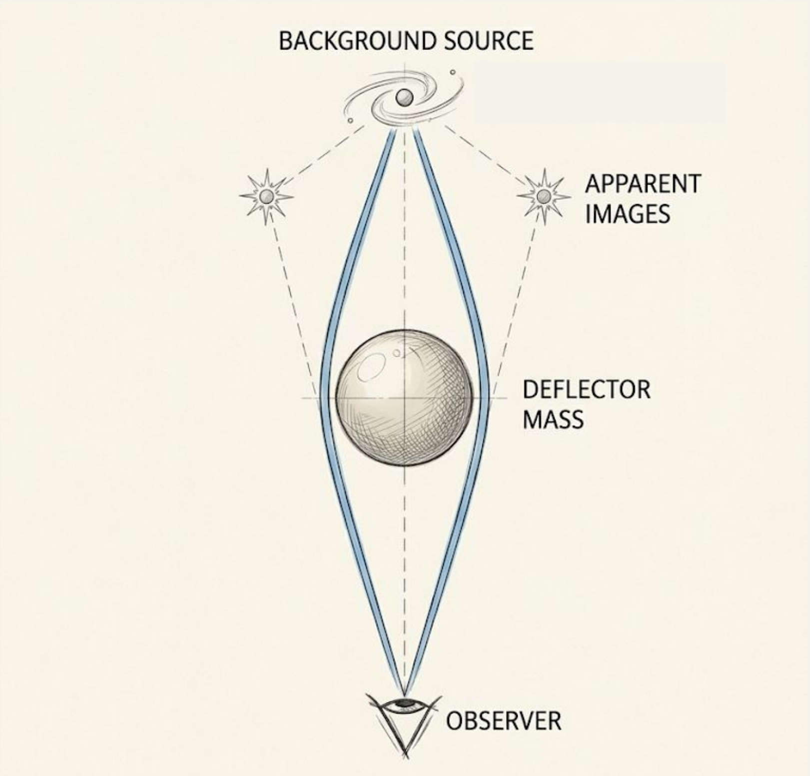
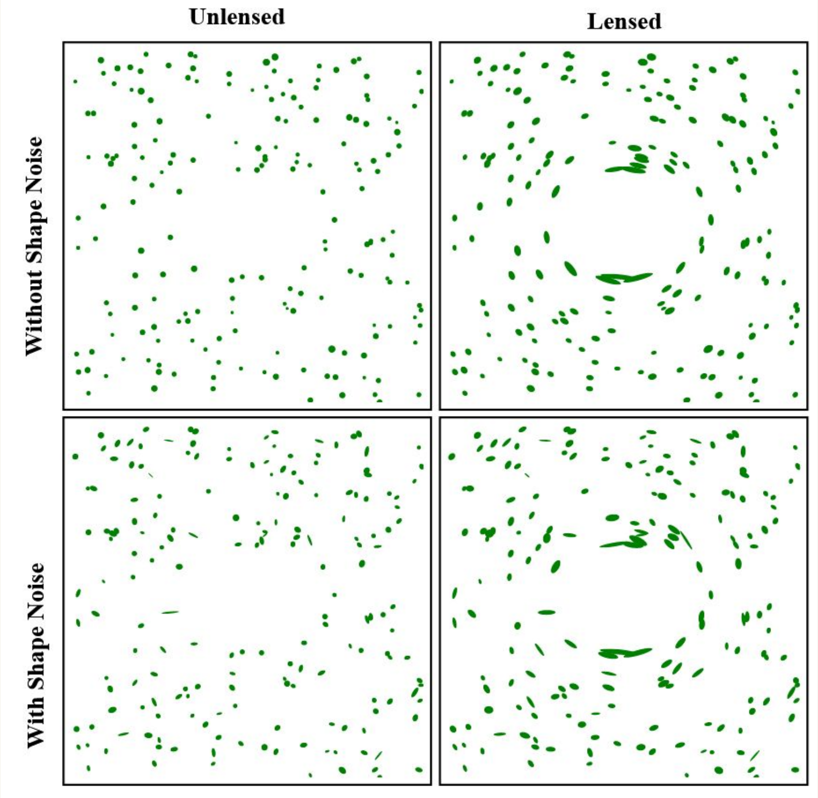
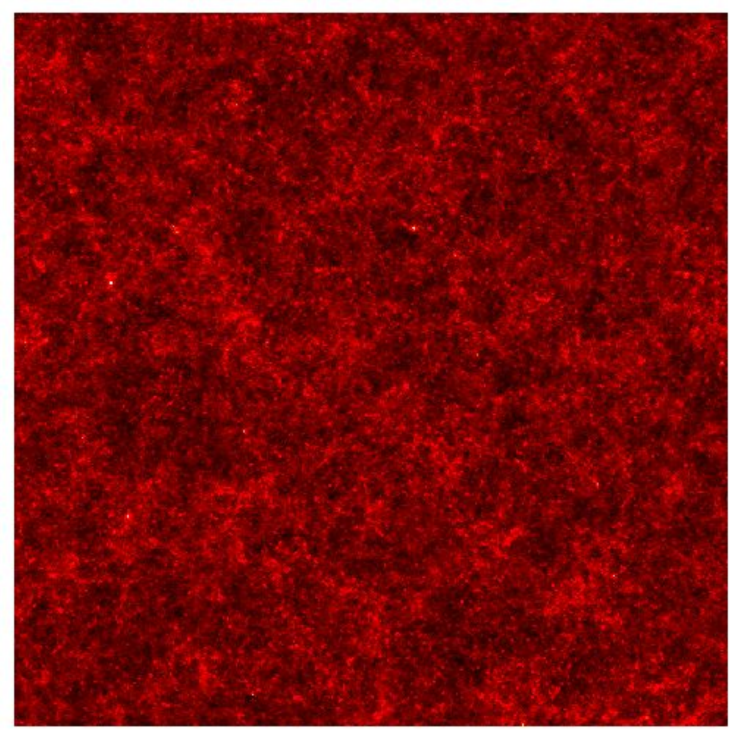
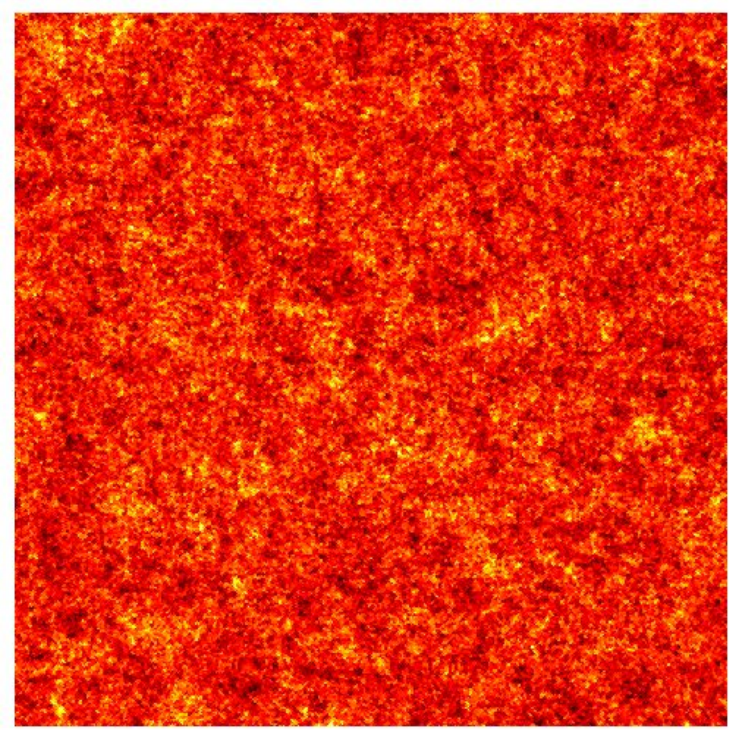
Cosmic Shear Traces the Universe





The Non-Gaussian Field





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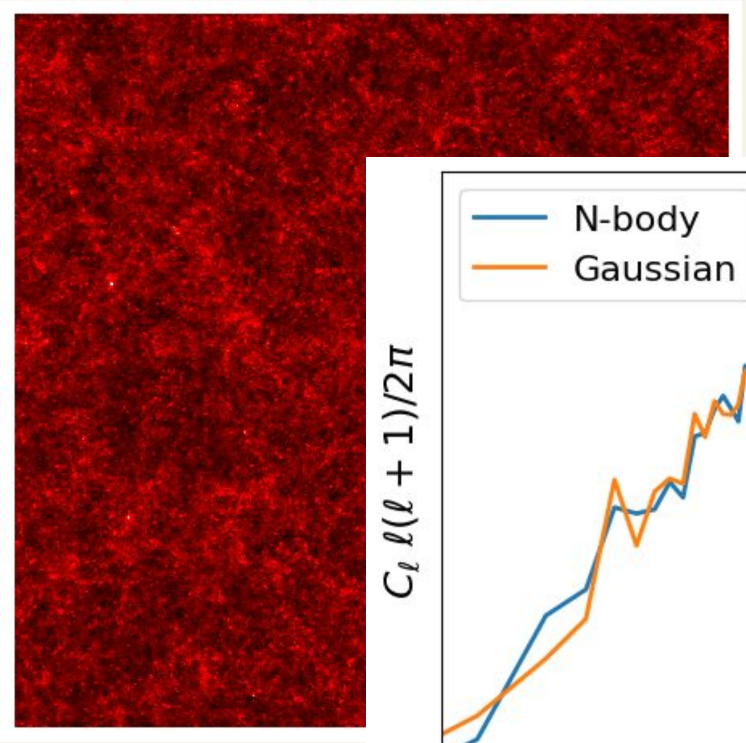
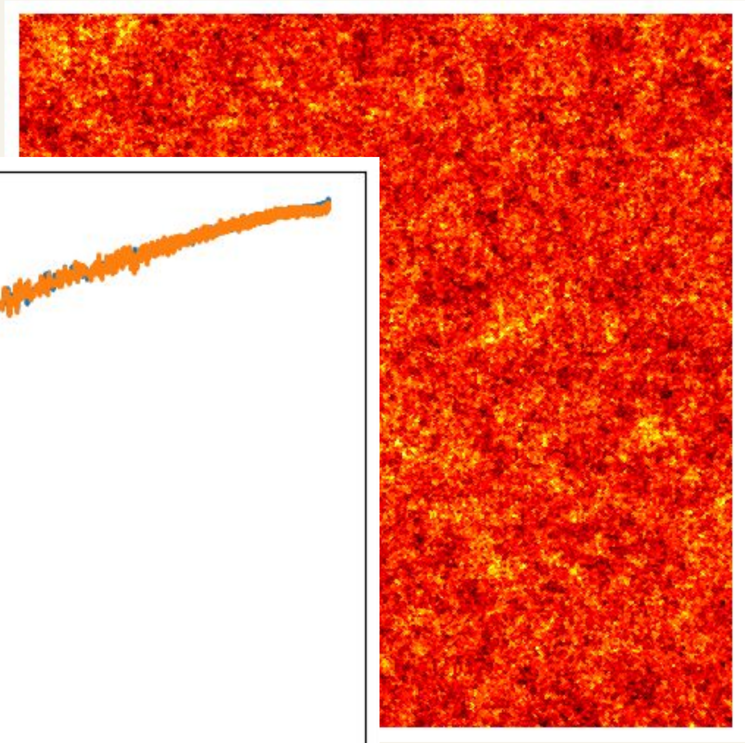
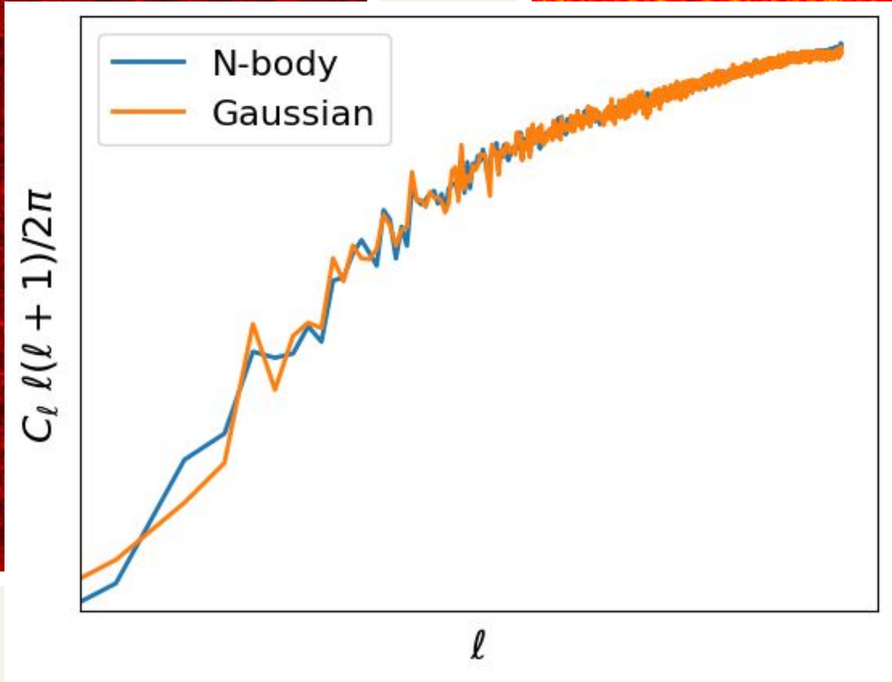
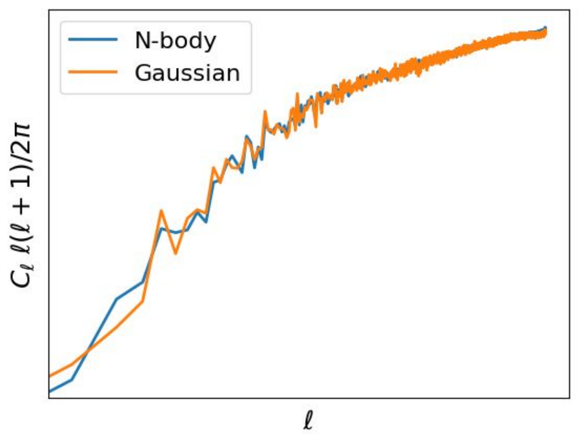


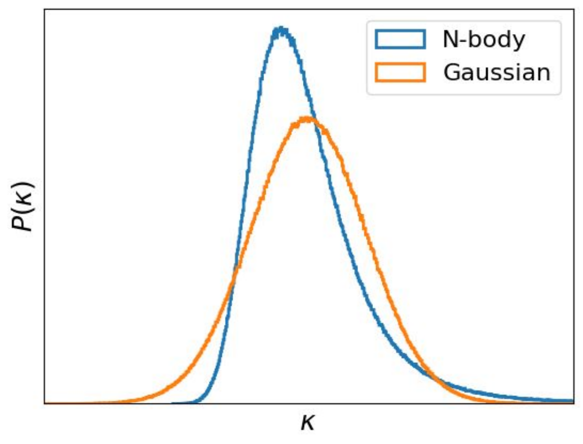




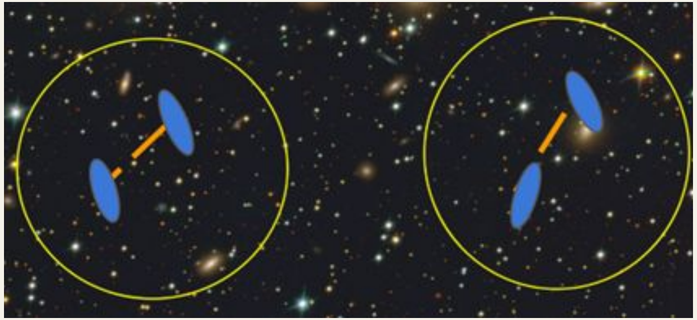
Higher Order Statistics

Statistic	Information Captured	Computational Cost	Analytical Model
2PCF	Gaussian	Low	Yes
Field Level	Full	Very High	No
3PCF	Bispectrum	High	Yes (expensive)
i3PCF	Squeezed Bispectrum	Low	Yes





The Integrated 3 Point Correlation Function



From Halder et al. 23

⇒ Correlates local 2PCFs with Aperture Mass

$$\zeta_{\pm} = \langle M_A \xi_{\pm} \rangle$$

The Integrated 3 Point Correlation Function

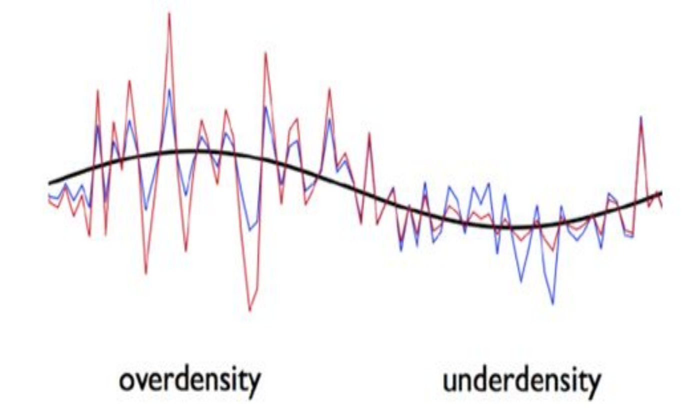


Image credit:
E. Komatsu

⇒ Correlates local 2PCFs with Aperture Mass

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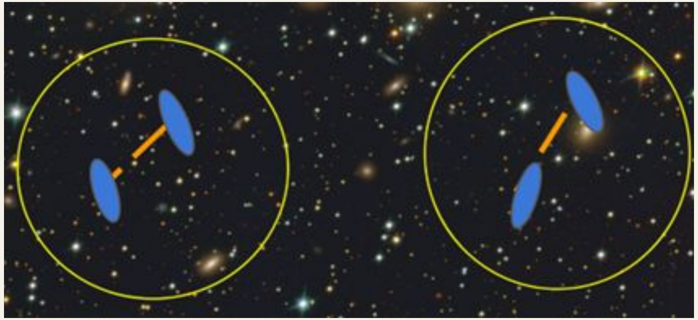
The Integrated 3 Point Correlation Function



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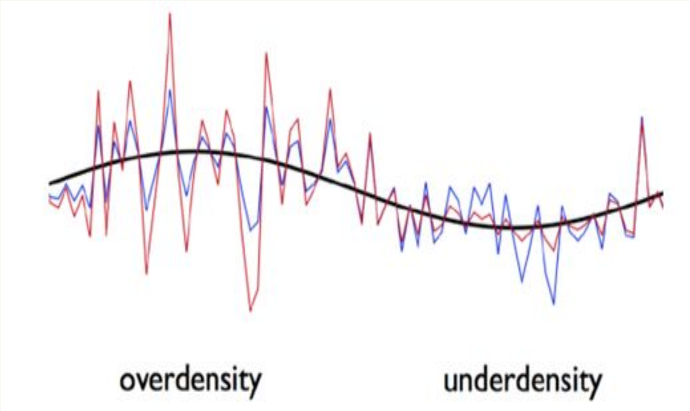
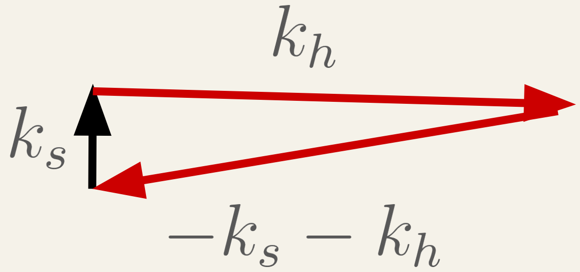


Image credit: E. Komatsu



Squeezed Bispectrum

Why not Likelihood Based Inference?

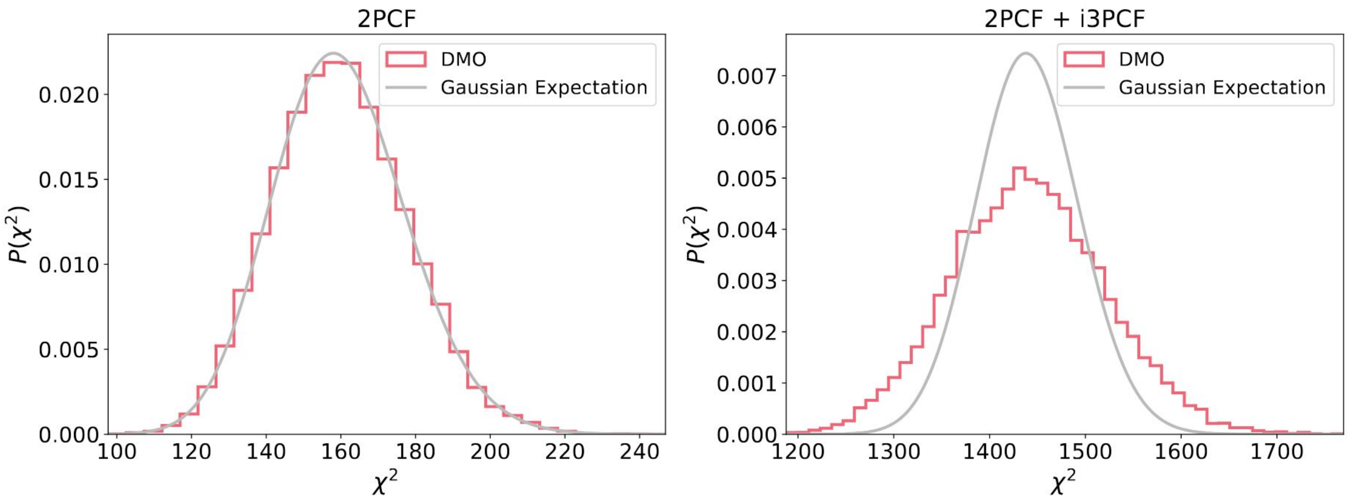
Correction	Reference	Percentage of sample variance		
		$\ell = 10$	$\ell = 100$	$\ell = 1000$
Source-lens clustering	Yu et al. (2015)	N/A	6.0	57.2
Reduced shear + magnification bias	Deshpande et al. (2020a)	0.4	1.8	15.3
Post-Limber reduced shear	Deshpande & Kitching (2020)	0.2	0.6	1.9
Non-linear ellipticity-shear relation	Krause & Hirata (2010)	0.2	0.6	1.9
Limber + fla[illegible]	Kitching et al. (2017)	9.8	3.0	1.0
Local Univ[illegible]	Hall (2020)	7.8	24.2	N/A
Higher-ord[illegible]	[illegible] & Hirata (2010)	$O(\phi^4)$	$O(\phi^4)$	$O(\phi^4)$
Time delay[illegible]	[illegible]	$O(\phi^4)$	$O(\phi^4)$	$O(\phi^4)$
Deflection[illegible]	[illegible]	[illegible]	$O(\phi^4)$	$O(\phi^4)$
Born app[illegible]	[illegible]	[illegible]	[illegible]	$O(\phi^4)$
Lensing [illegible]	[illegible]	[illegible]	[illegible]	$O(\phi^4)$
Second-order [illegible]	[illegible]	[illegible]	[illegible]	<0.01
Temporal-Born approximation	[illegible]	[illegible]	[illegible]	<0.01
Finite-beam corrections	[illegible]	[illegible]	[illegible]	<0.01
Doppler-shift	Deshpande [illegible]	[illegible]	[illegible]	<0.01
Unequal-time correlators	Kitching & Heavens (201[illegible])	[illegible]	[illegible]	<0.01
Sachs-Wolfe effect	Cuesta-Lazaro et al. (2018)	[illegible]	[illegible]	<0.01
Integrated Sachs-Wolfe effect	Cuesta-Lazaro et al. (2018)	<0.01	[illegible]	<0.01
Flexion correction	Schneider & Er (2008)	N/A	N/A	N/A
Flat-geometry assumption	Taylor et al. (2018b)	–2.0	–6.0	–19.1
Source obscuration	Hartlap et al. (2011)	–2.0	–6.0	–19.1
Spatially-varying survey depth	Heydenreich et al. (2020)	–5.9	–18.1	–57.2

Too many effects for analytical modelling!

Euclid Collaboration et al. 2024

⇒ Stage IV Surveys much more sensitive to systematic effects

Why not Likelihood Based Inference?

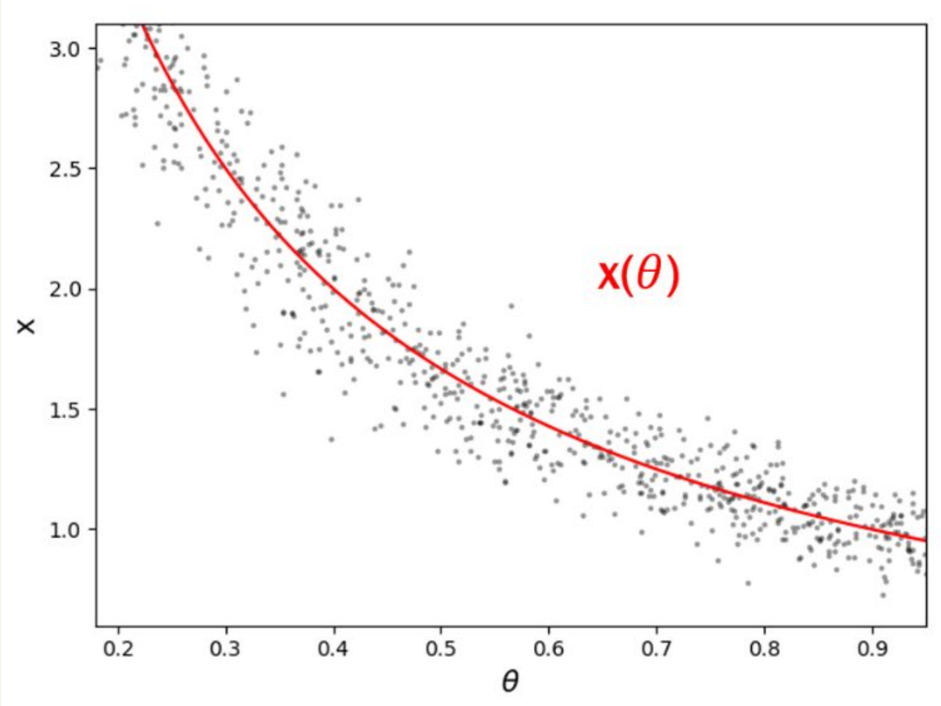


(a) 2PCF

(b) 2PCF + i3PCF (all filters)

⇒ Gaussian likelihood assumption breaks down for many HOS

Simulation Based Inference



1D Example:
Observable/Data: *x*
Parameter: θ

Traditionally:

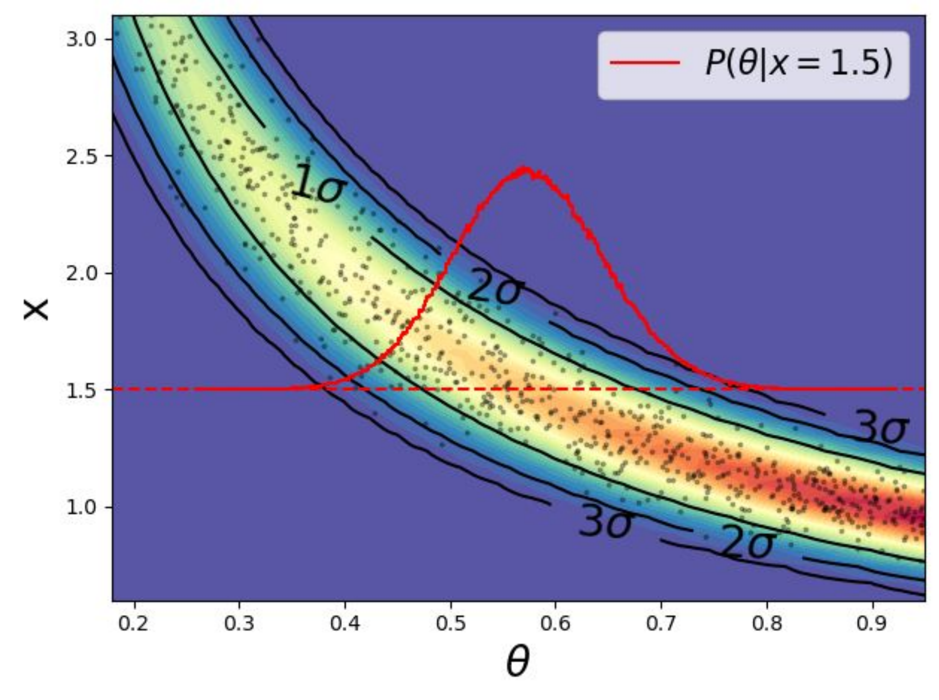
- ➔ Analytical model describing mean
- ➔ Gaussian likelihood
- ➔ Scatter estimated from simulations (covariance)

Simulation Based Inference

1D Example:
Observable/Data: x
Parameter: θ

SBI:

➔ Jointly learn model & scatter
➔ Likelihood flexible
➔ Quick evaluation



Normalizing Flows

Parametrize distribution as bijective transformation of some base

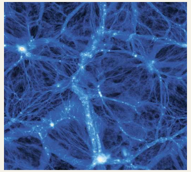
Training process:

1. Apply inverse transformation to target
2. Calculate difference to Gaussian

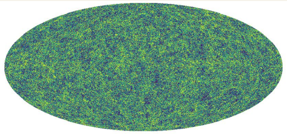
Likelihood can be quickly evaluated

$\Rightarrow$ Very efficient for MCMC sampling

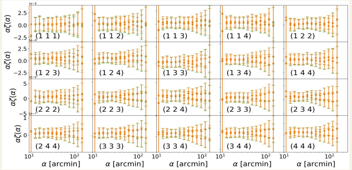
The SBi3PCF Framework



N-Body Simulations

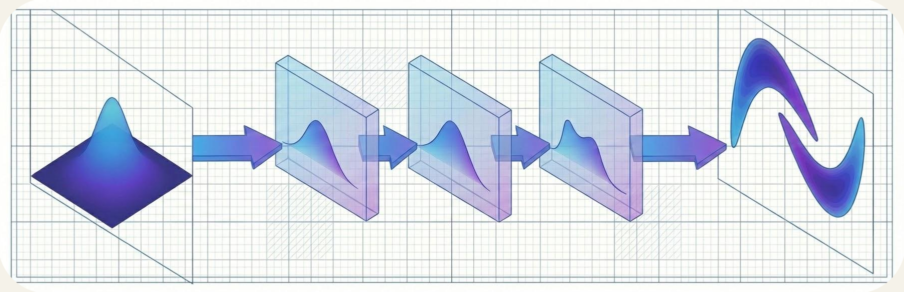


Weak Lensing Maps

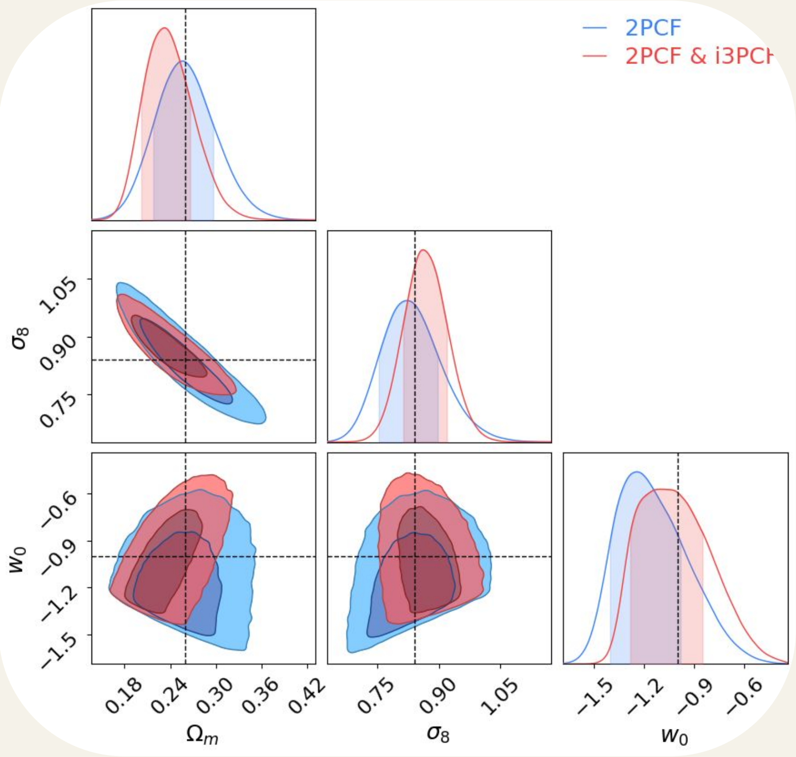


Summary Statistics

Forward Model



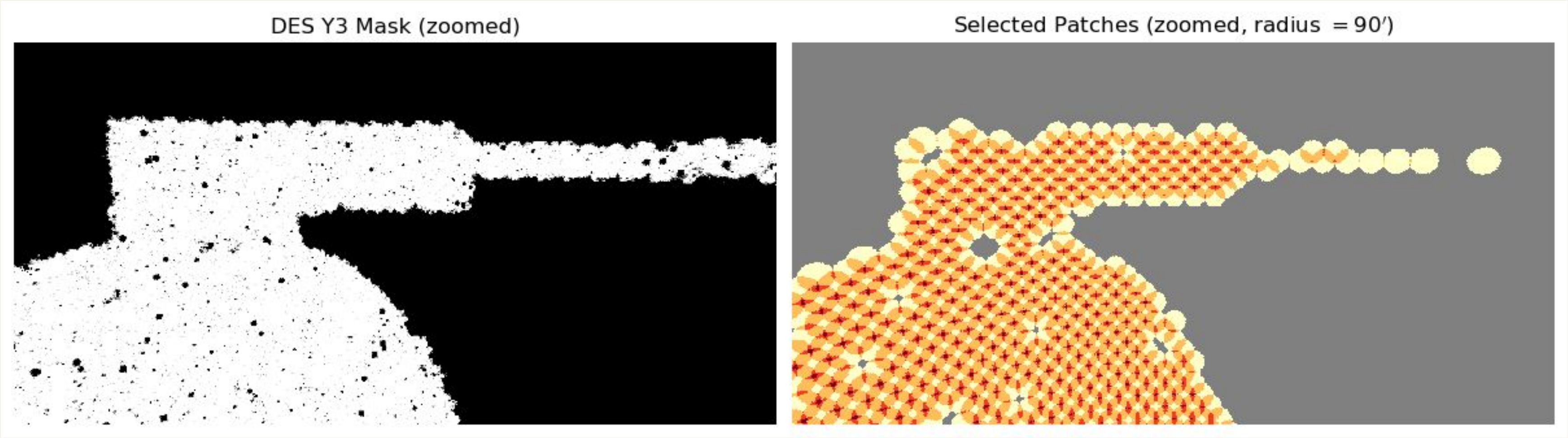
Normalizing Flow



CosmoFuse

Precompute pairs for local 2PCFs

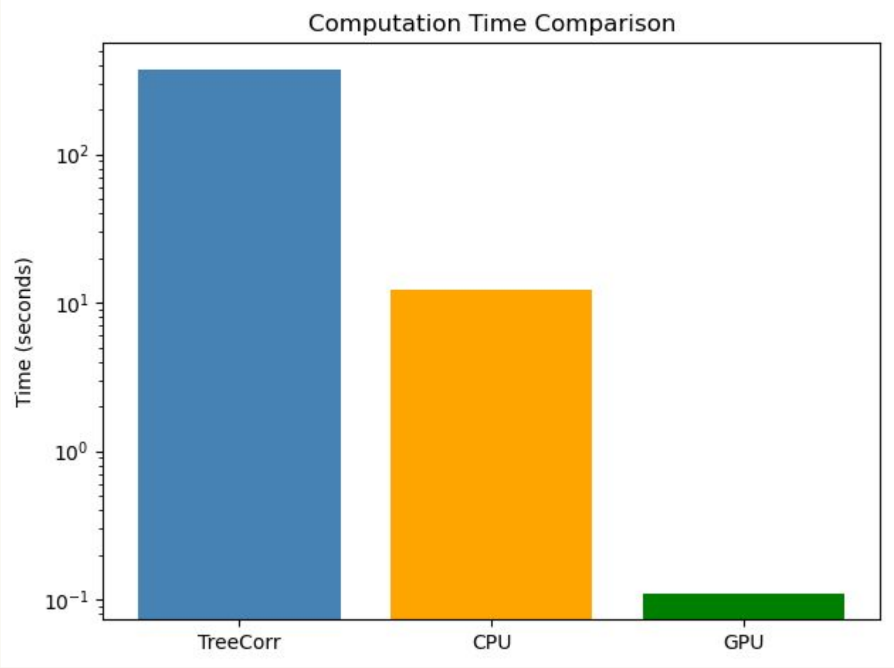
⇒ Correlation function measurement reduced to matrix multiplication



CosmoFuse

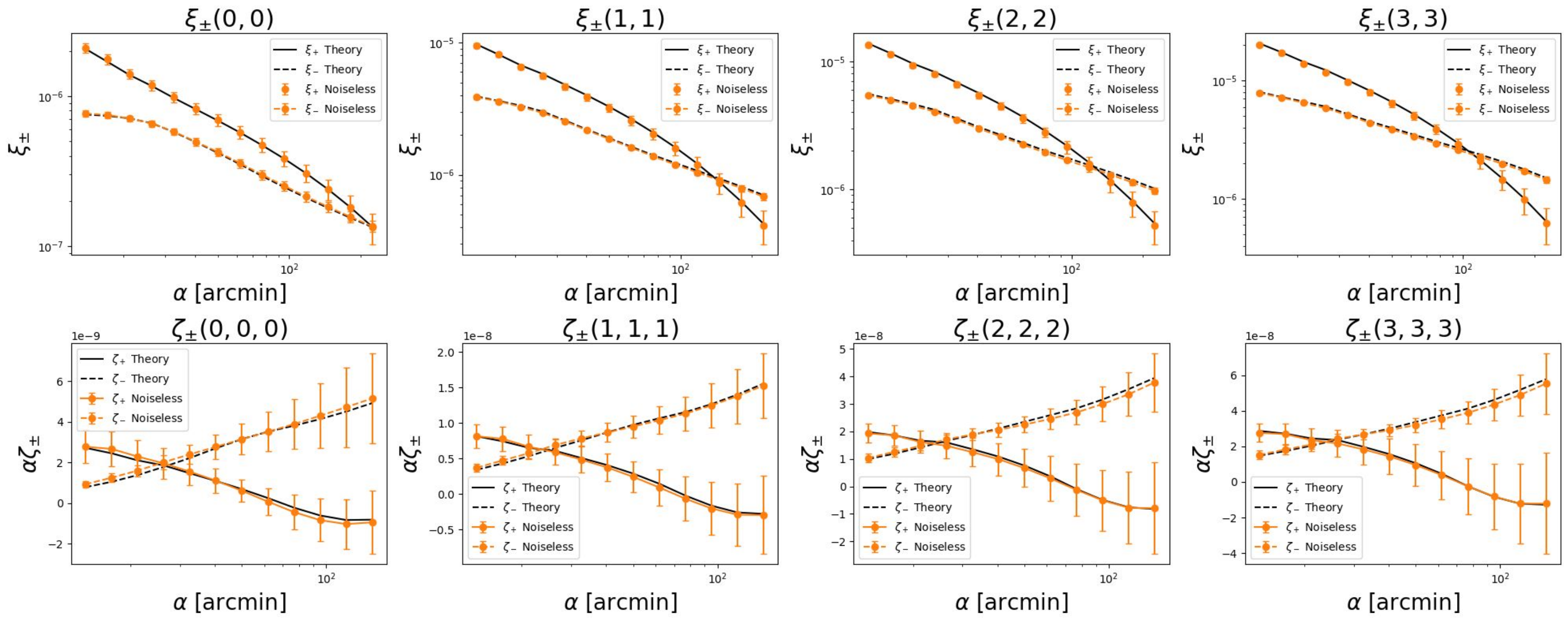
Move onto GPUs for maximum efficiency gains:

Method	Time Needed
TreeCorr	6 minutes
CosmoFuse (CPU)	12 seconds
CosmoFuse (GPU)	110 milliseconds



NSIDE 512, 1000 90' patches, 4 tomographic bins
Full WL, GGL & GC tomographic analysis
On 160 CPU cores and 1x A100 80GB GPU

Validation

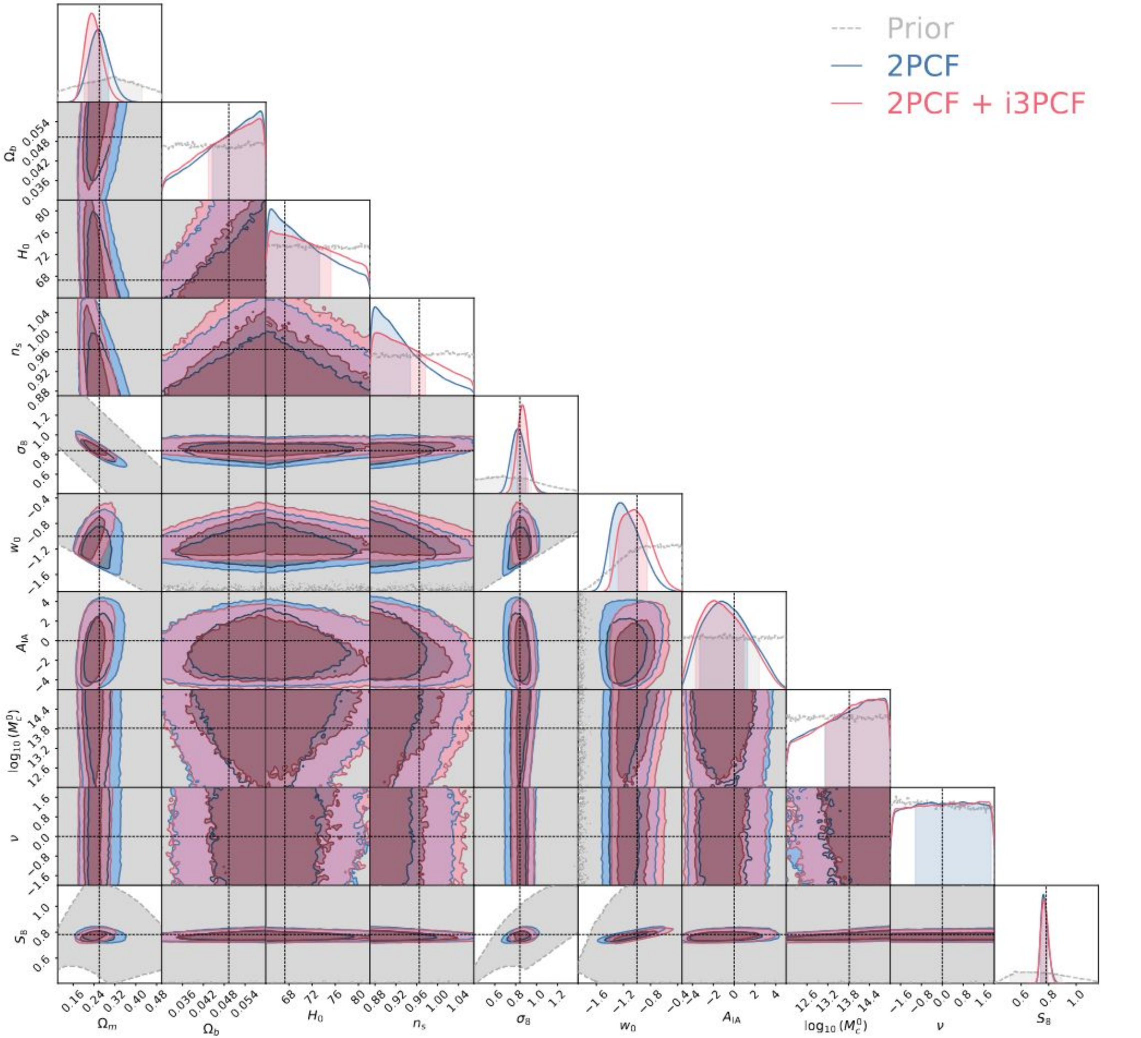


⇒ Excellent agreements of forward model with analytical

Fiducial Constraints

⇒ Chain for prior probability in grey

⇒ Most parameters unconstrained

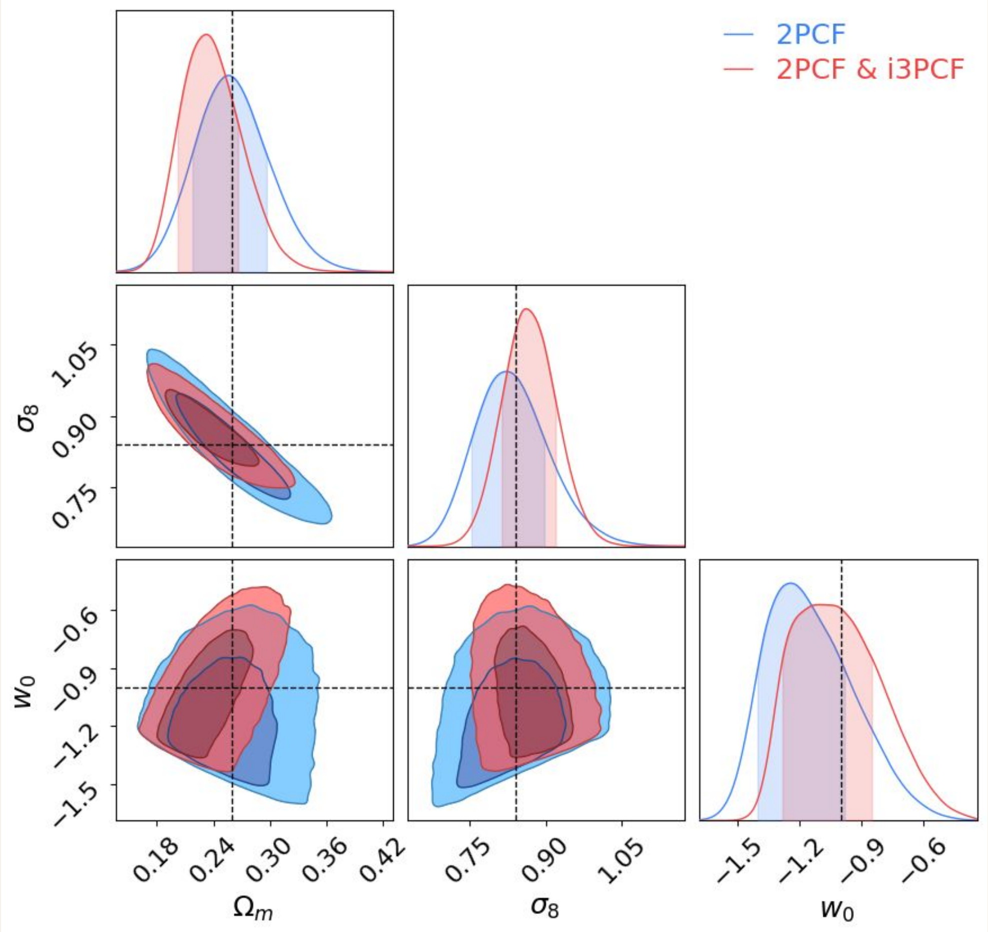


Fiducial Constraints

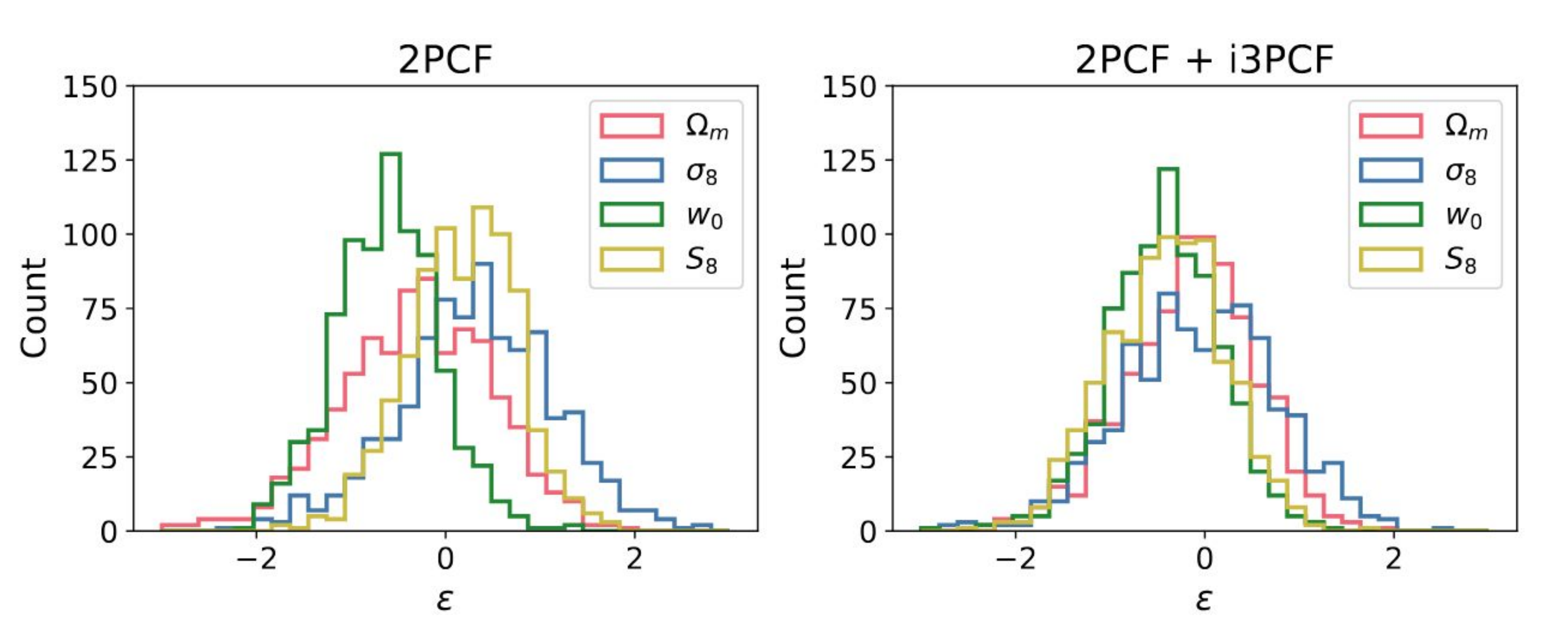
⇒ Chain for prior probability in grey

⇒ Most parameters unconstrained

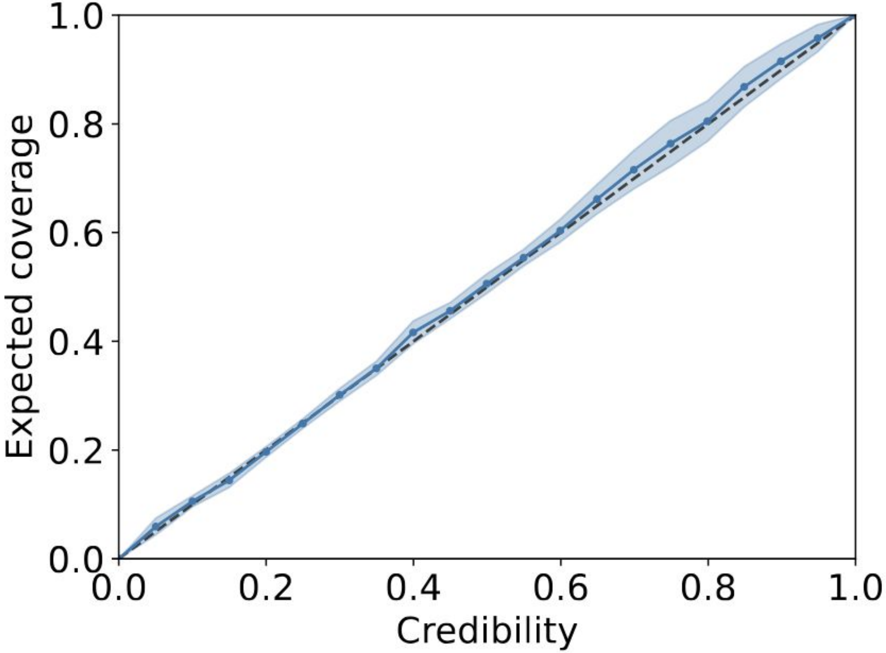
⇒ True parameters recovered!



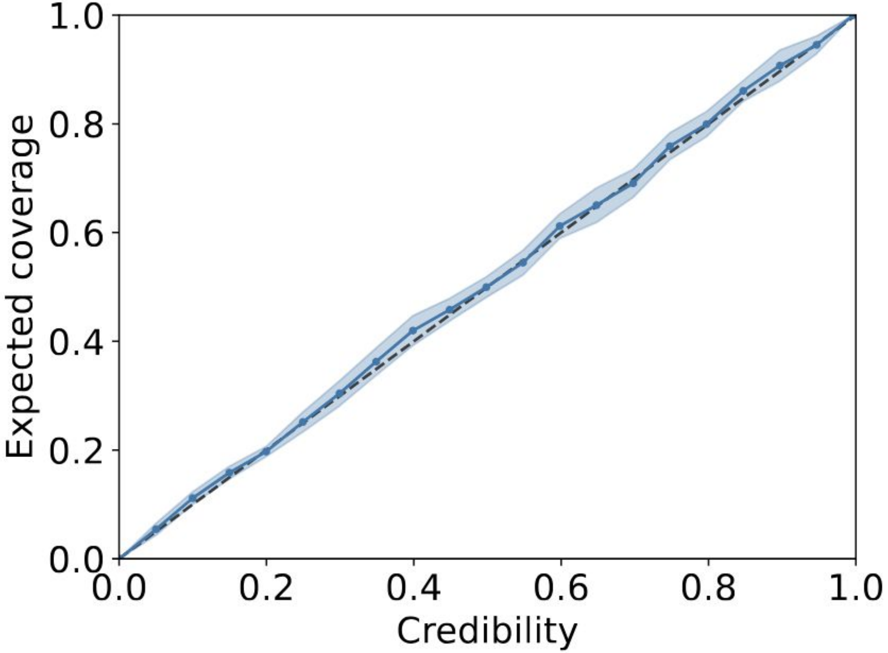
Posterior Bias



Coverage Test (Tarp)

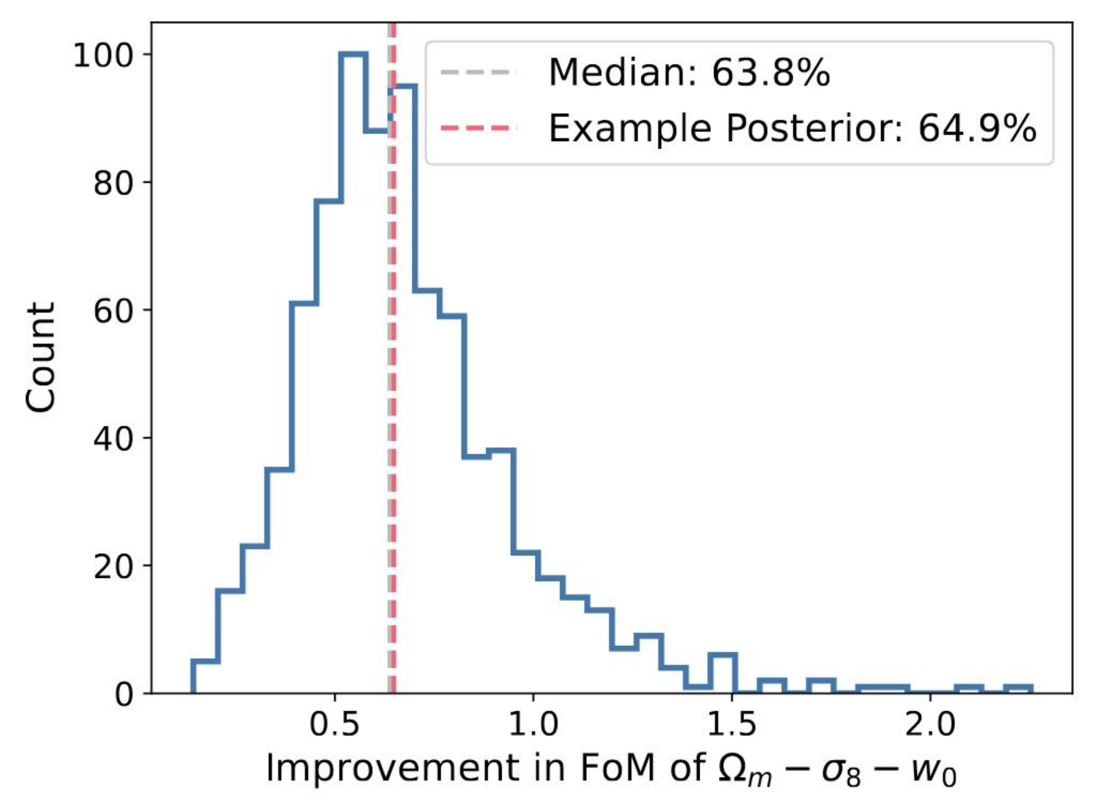


(a) Coverage using 2PCF data vector.



(b) Coverage using 2PCF + i3PCF data vector.

Improvements



Summary and Outlook

- ➔ The i3PCF efficiently captures non-Gaussian information
- ➔ Our forward model agrees with analytical predictions
- ➔ We can robustly infer cosmological parameters

Future:

- ➔ Apply this to DES Y3 source catalogue
- ➔ Include more HOS (e.g. 1-pt PDF)
- ➔ Extend to galaxy clustering and galaxy-galaxy lensing