In collaboration with: N. Martinet & M. Gatti

Explicit vs. Implicit Likelihood Inference for Weak Lensing Cosmic Shear

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non-Gaussian Universe

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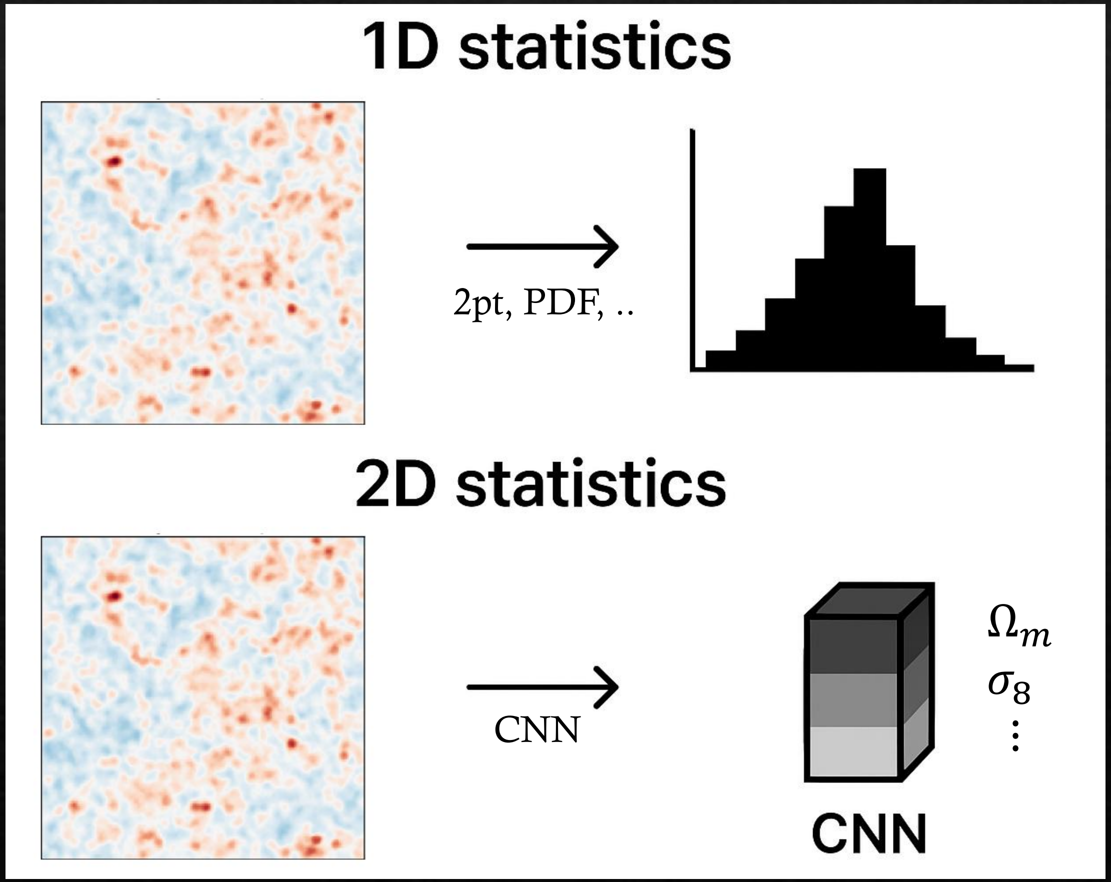
We want to compare 1D vs. 2D statistics

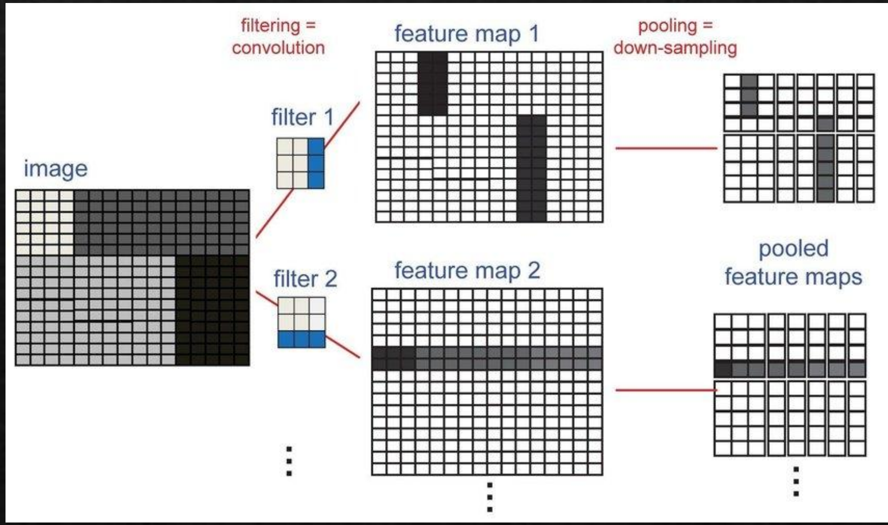
- 1D-statistics:
  1. image into a single-dimensional summary (global pixel properties),
  2. compression is less informative,
  3. High number of data vector entries.

- 2D-statistics:
  1. includes spatial correlations between pixels (global pixel properties + patterns),
  2. compression is more informative,
  3. Number of entries matches probed parameters.

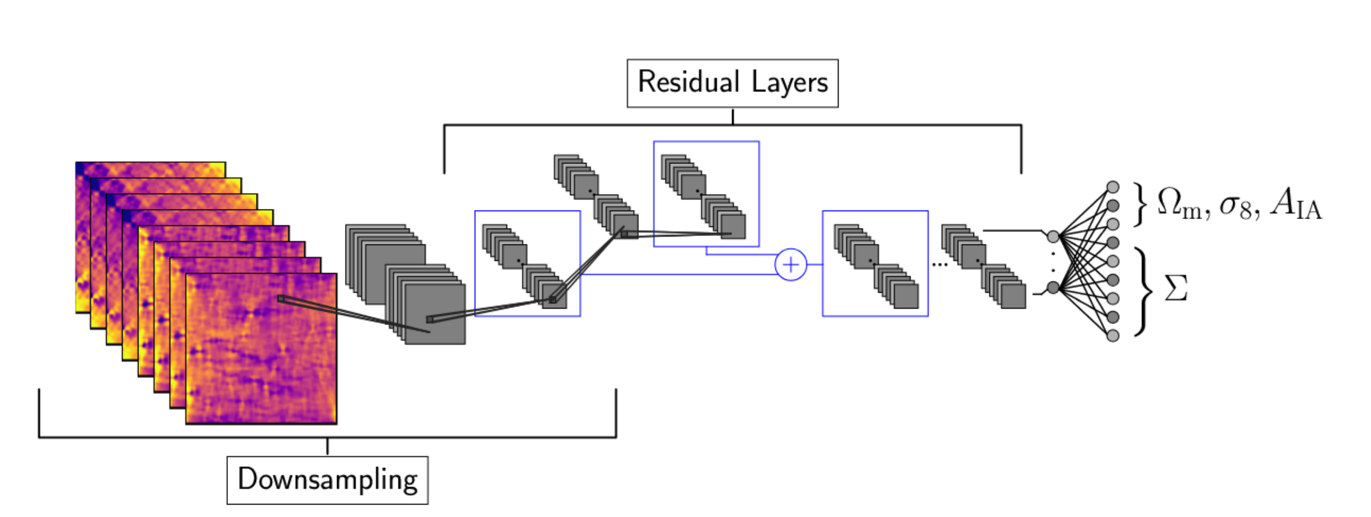


Understanding CNNs

How a CNN extracts features from a map



How a CNN maps WL images into cosmological parameters



Fluri et al. (2019)

1. A small filter (kernel) slides over the map → feature map.
2. Each filter detects a different pattern (edge, blob, peak, filament).
3. Pooling reduces spatial size while keeping the strongest features.
4. Pooled feature maps → flattened 1D vector → dense layers → outputs (e.g., cosmological parameters).

We want to compare two likelihood approaches: ELI & LFI

- Explicit Likelihood inference (ELI) requires:
    1. Data covariance matrix,
    2. Explicit Likelihood model

- Implicit Likelihood inference (LFI) requires:
    1. NO Data covariance matrix,
    2. NO Explicit Likelihood model
    3. Comprehensive training sample

Gaussian Likelihood

$$\mathcal{L}(\theta) = \frac{1}{\sqrt{(2\pi)^N \det \mathbf{C}}} \exp\left[-\frac{1}{2} (\mathbf{d} - \mathbf{m}(\theta))^{\mathrm{T}} \mathbf{C}^{-1} (\mathbf{d} - \mathbf{m}(\theta)) \right]$$

$$P(\theta \mid d) = \frac{\mathcal{L}(\theta)\, P(\theta)}{P(d)}$$

Learned (approx.) Likelihood

$$\mathcal{L}(\theta) = P(d \mid \theta) \approx q_\phi(d \mid \theta)$$

$$q_\phi(d \mid \theta) \approx \mathrm{NeuralDensityEstimator}\left(\{(\theta_i, d_i^{\mathrm{sim}})\}_{i=1}^{N_{\mathrm{sim}}} \right)$$

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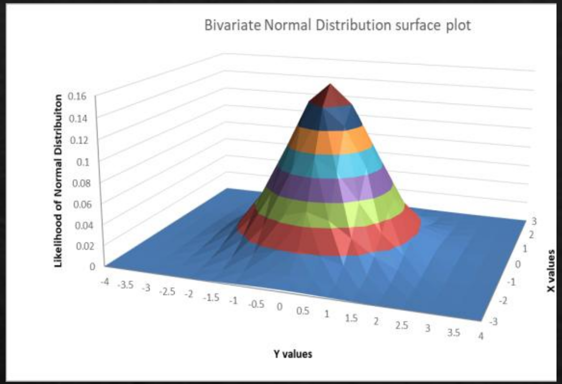
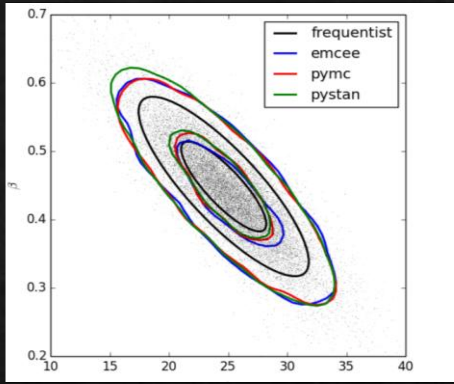
We want to compare two likelihood approaches: ELI & LFI



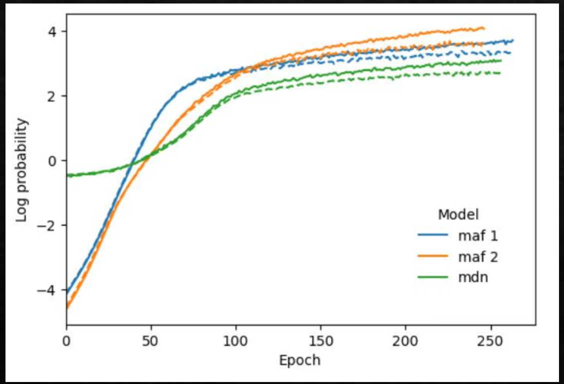
Multivariate Gaussian Likelihood



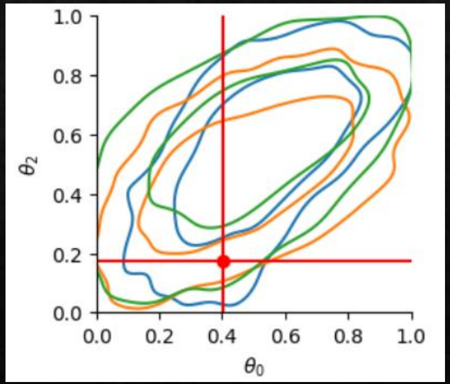
Gaussian Posterior
(Jake VanderPlas 2014)

ELI →

Theory / Numerical predictions + Theory / Numerical covariance
↓
Gaussian / Non-Gaussian likelihood
↓
MCMC
↓
Parameter inference



Neural Density Estimators
(LtU-ILI package)



Learned Posterior
(LtU-ILI package)

LFI →

Theory / Numerical predictions for N cosmological nodes
↓
Compression into lower-dimensional space
↓
NDE training (80% of N) + validation (10% of N) + test (10% of N)
↓
Learned posterior
↓
MCMC (optional)
↓
Parameter inference

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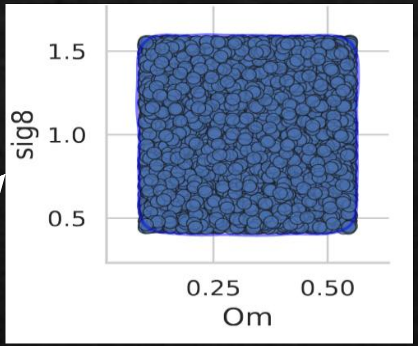
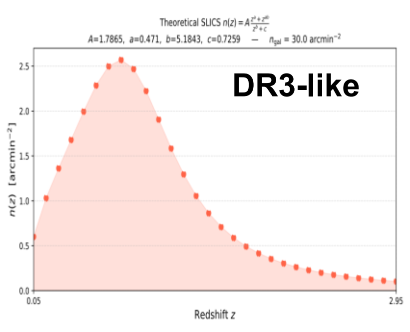
We use GLASS as our simulator

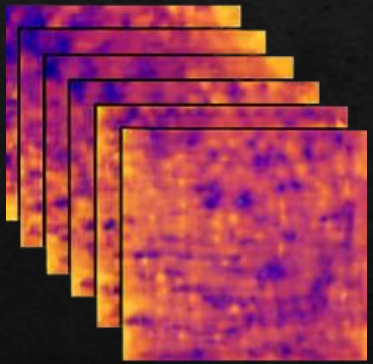
N. Tessore et al. (2023)



Parameter piors & n(z)



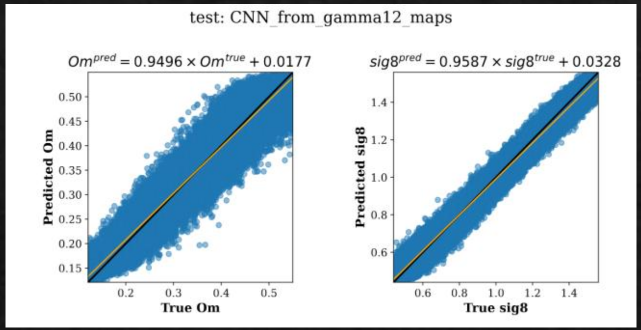
(<u>Gaussian</u>) WL-maps



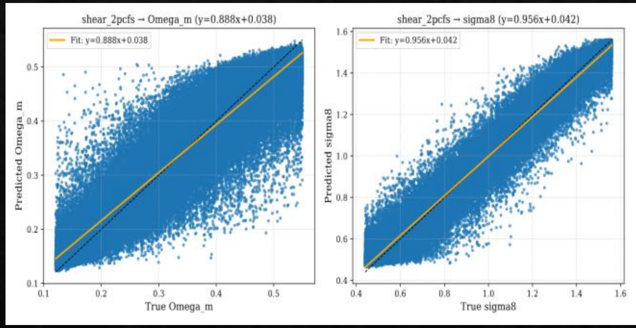
MOPED

NN

CNN from shears maps



NN-compressed shear-2PCFs



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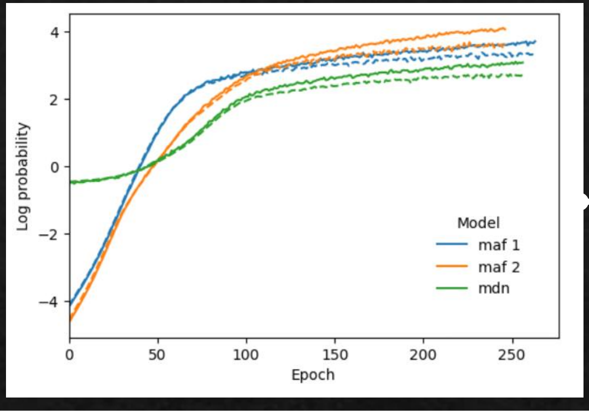
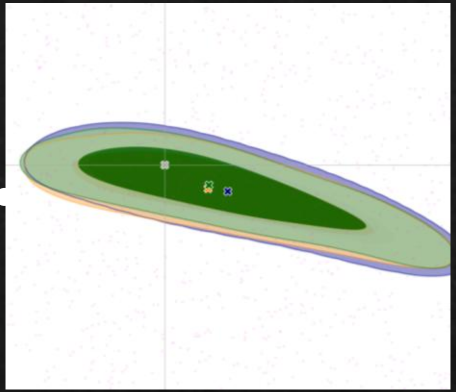
We perform multiple LFI calibration tests

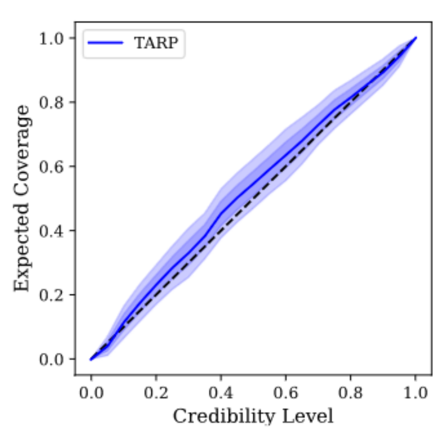
NDEs trained for multiple intial conditions



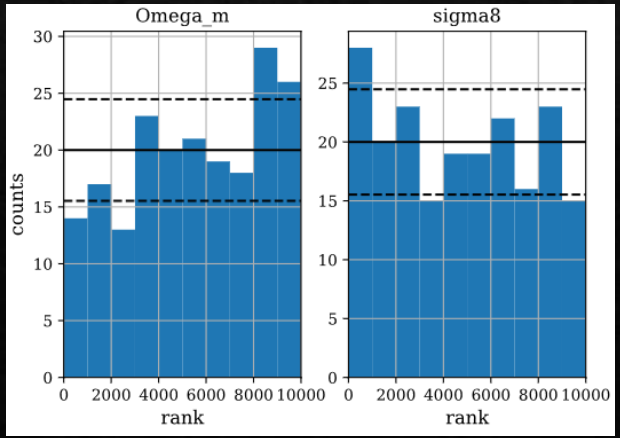
Reconstructed Posterior



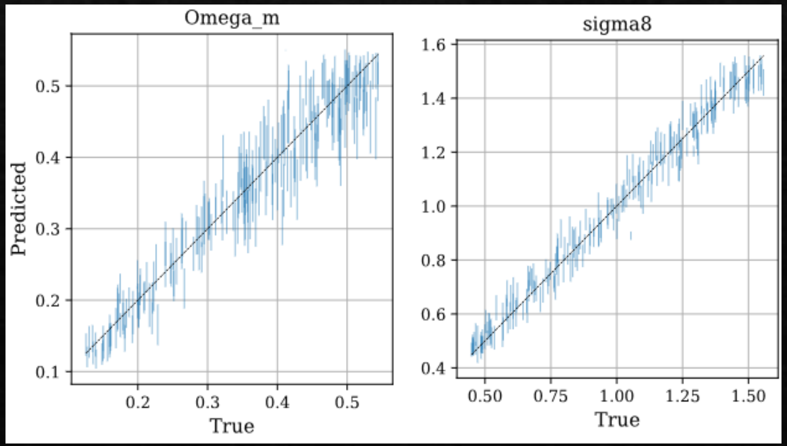
TARP: is each posterior confidence level calibrated?



PIT: is the full posterior coverage calibrated?



Predictive test: do we recover the true parameters?



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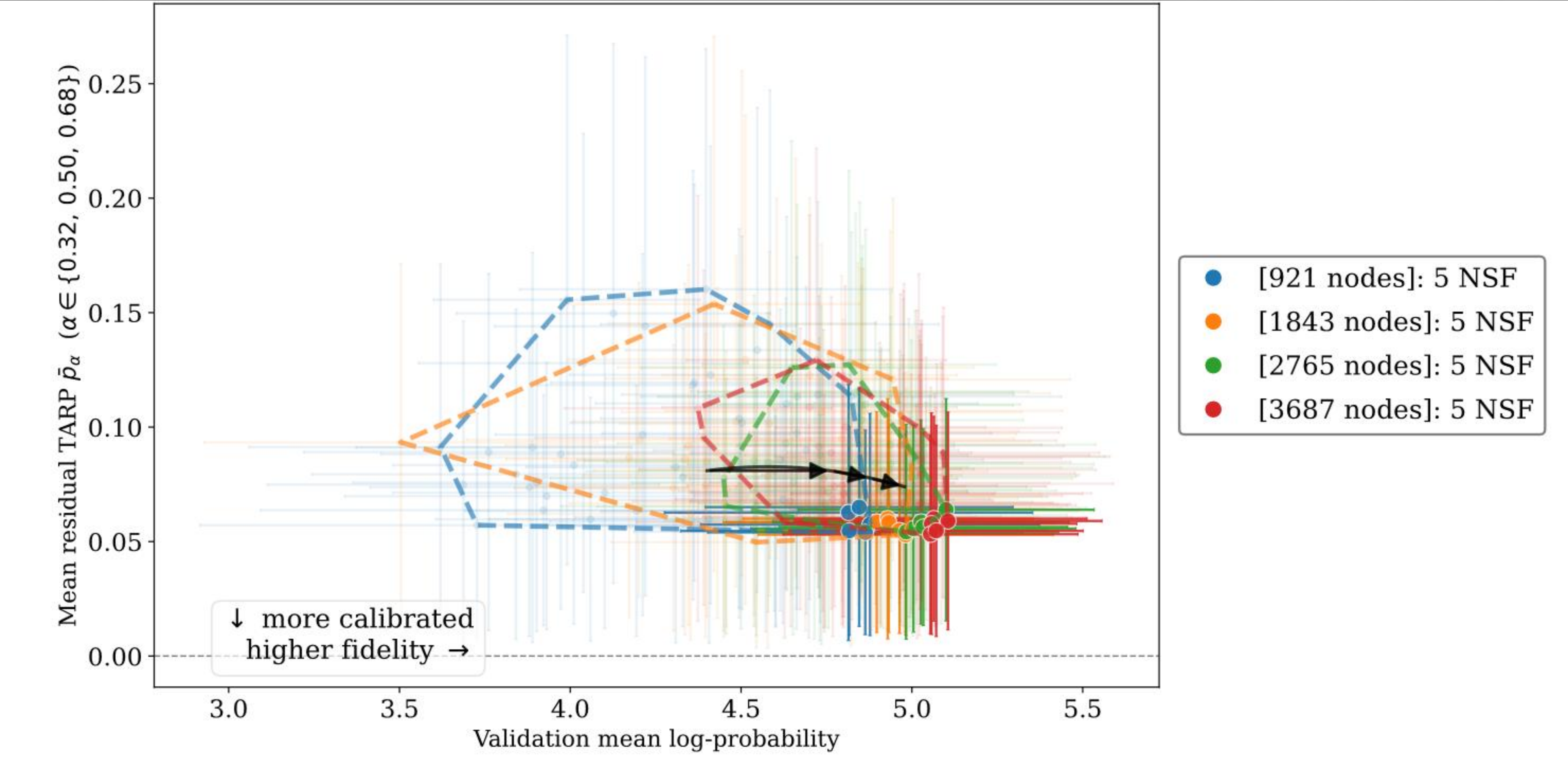
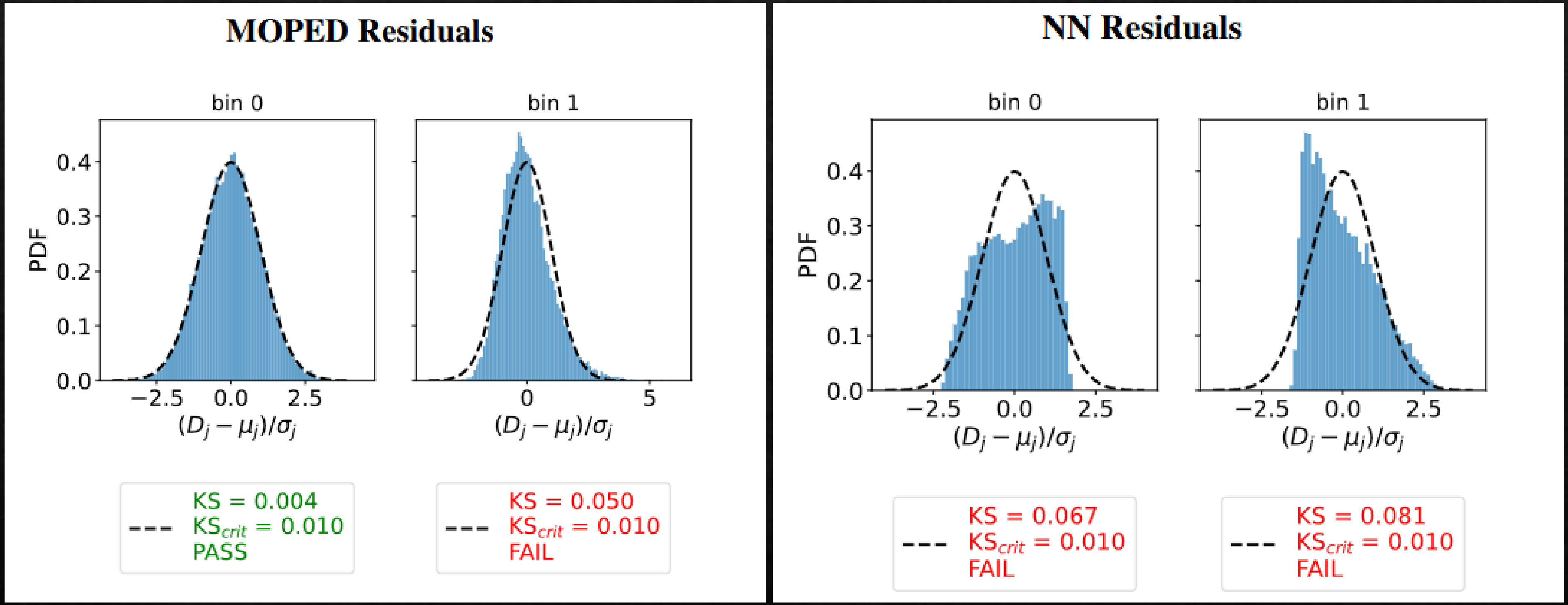
We investigate optimal NDEs for LFI via a grid-search approach



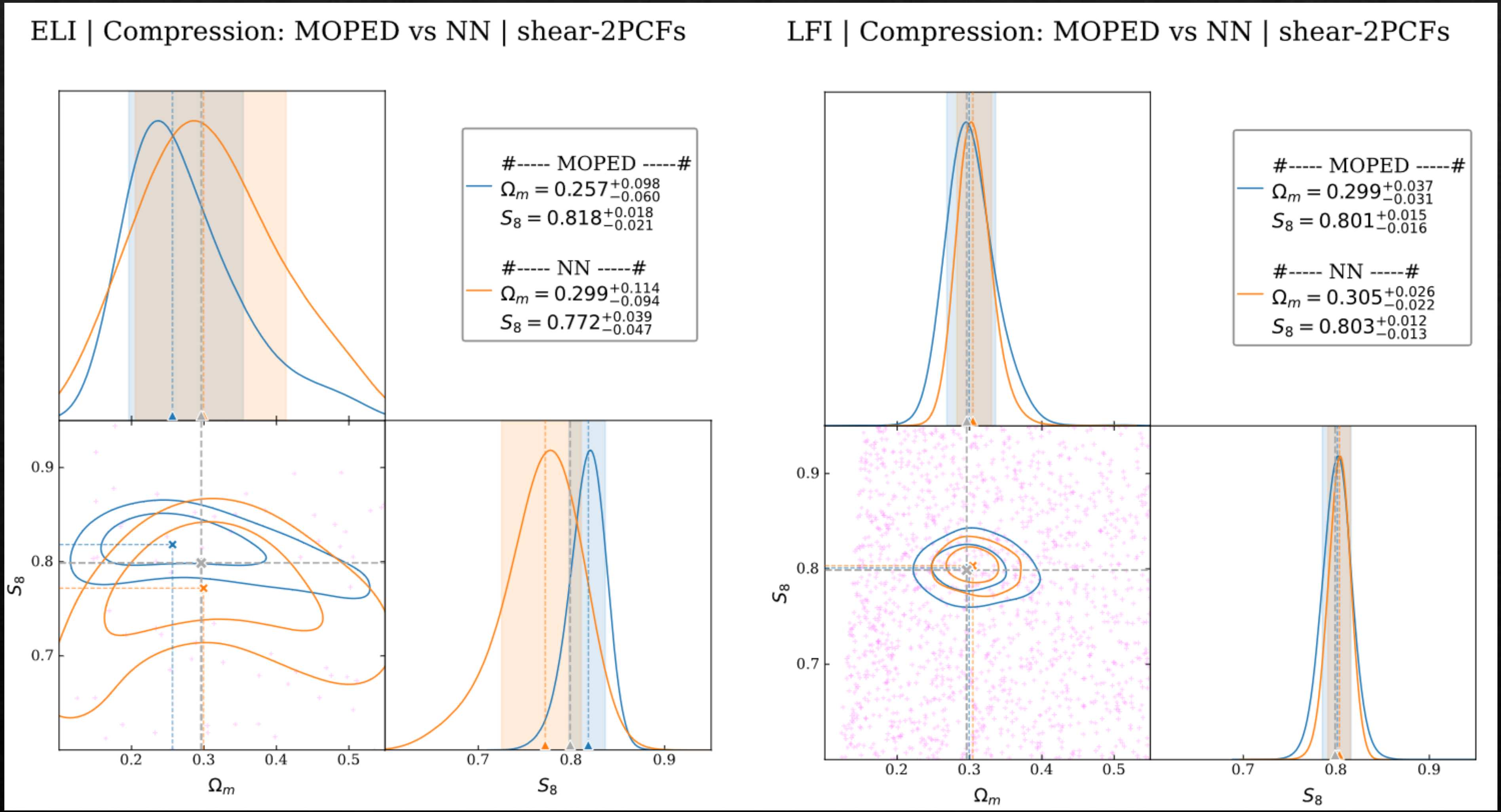
- MDN, MAF & NSF with hyper-parameters exploration
- Completely automated and versatile
- Stacking NDEs not needed for high training nodes
- Higher the training nodes, lower the differences

We quantify the presence of non-Gaussianity in the likelihood



- MOPED is mildly gaussian (second bin skewed)
- NN shows strong non-Gaussianity

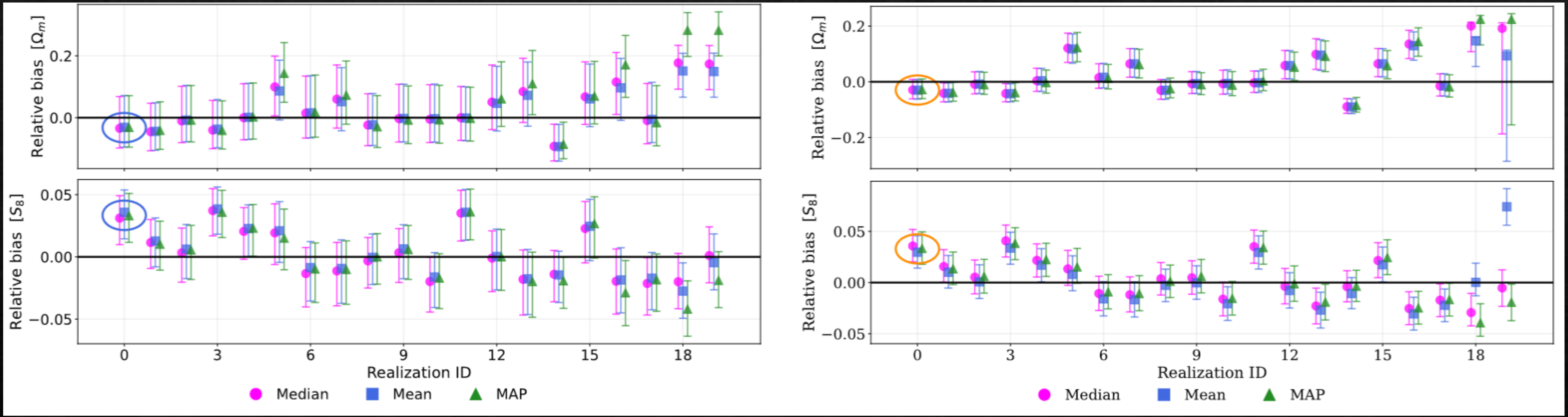
We test two different compression schemes: MOPED & NN



- NN breaks Gaussian Likelihood approximation
- Compression methods matters for ELI
- LFI preserves more information

We investigate noise and cosmic variance impact on posteriors

ELI ***MOPED Shear-2PCFs*** LFI



Consistent trend: the noise shifts the ELI & LFI posteriors in the same direction

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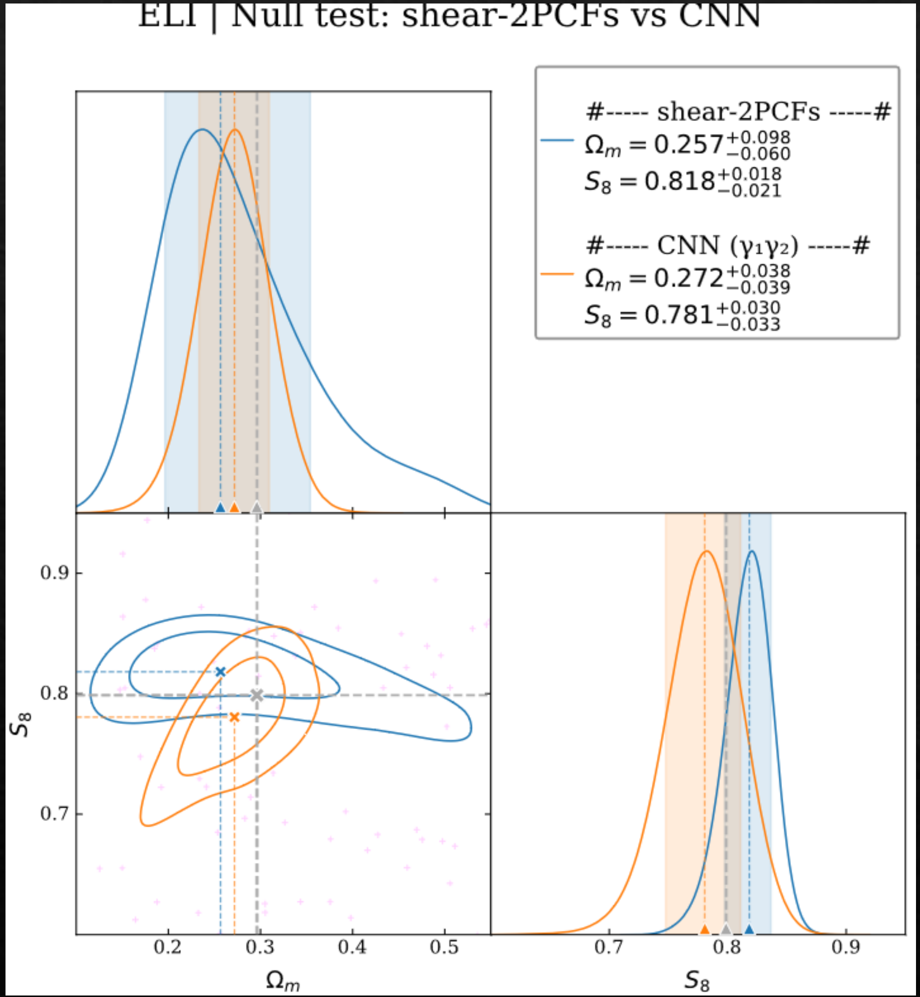
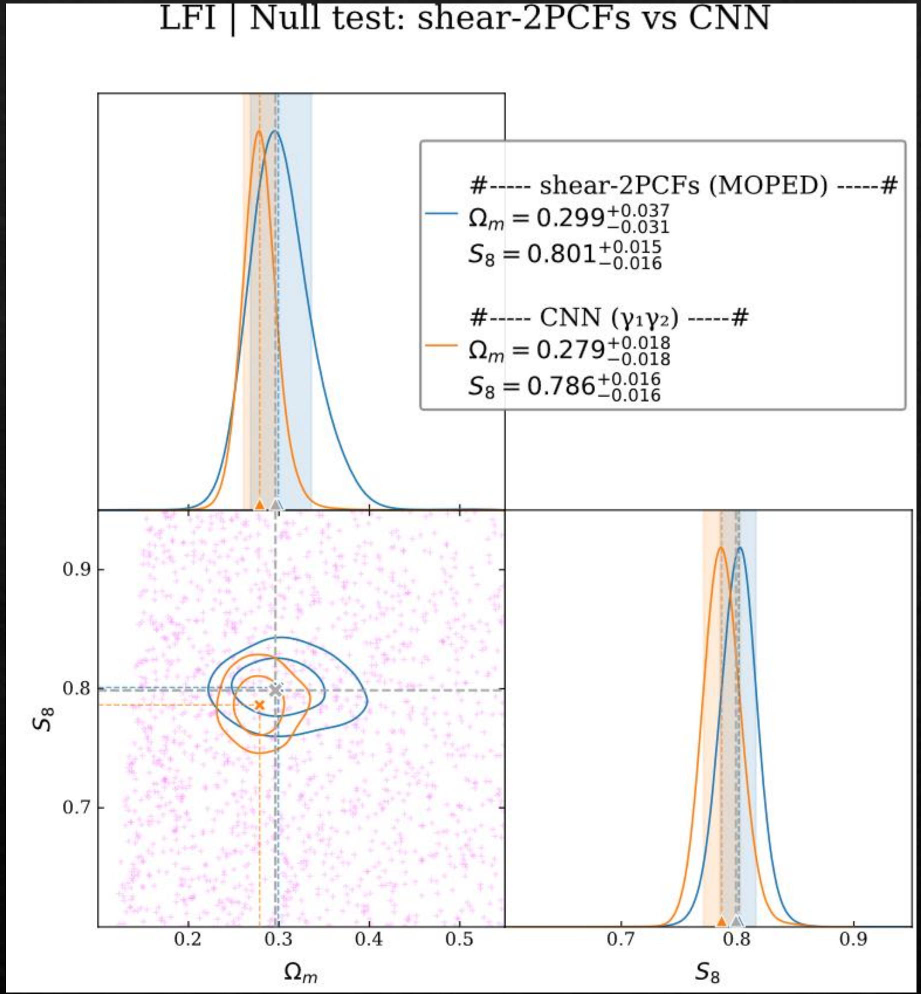
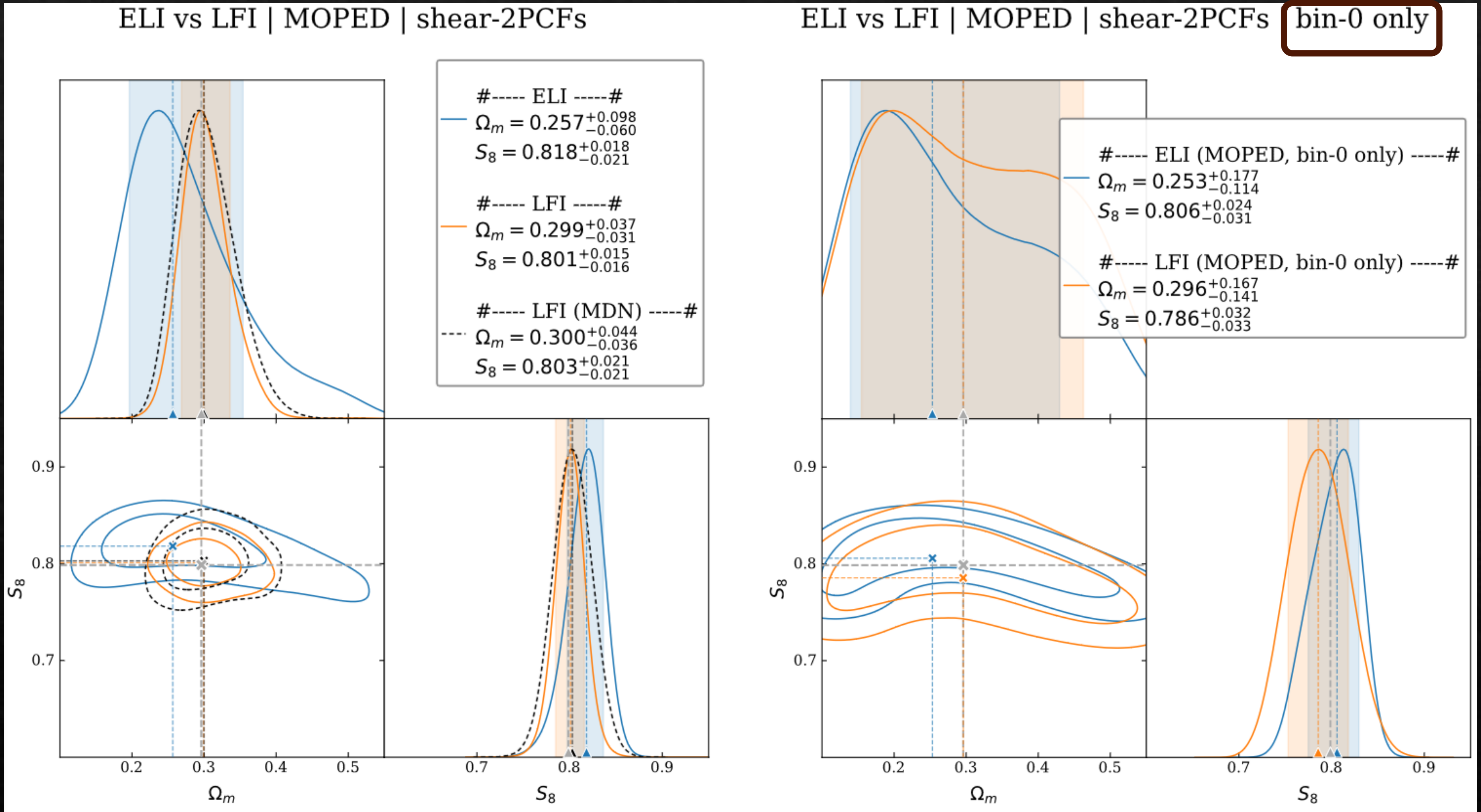
We compare shear-2PCFs and CNN (null test)





- ELI:
  - impact of MOPED compression and CNN-covariance
- LFI:
  - Consistent S8 constraints
  - CNN better constrains Ω_m

We quantify agreement of ELI & LFI posteriors



- ELI matches LFI when:
  - Retained bins are Gaussian
  - Emulation is accurate

Conclusions & Perspectives & Questions

- ELI and LFI give consistent results when the Gaussian likelihood holds and emulation is accurate
- Non-Gaussianity and emulation in the compressed summaries can limit ELI approach
- The impact of noise on the posterior is consistent in ELI & LFI
- Impact of non-Gaussian information needs to be addressed when comparing ELI vs. LFI
- Higher dimensionality of parameter space and systematics should be investigated
- Are the LFI calibration metrics comprehensive?
- Can we increase robustness from synergies between ELI & LFI?

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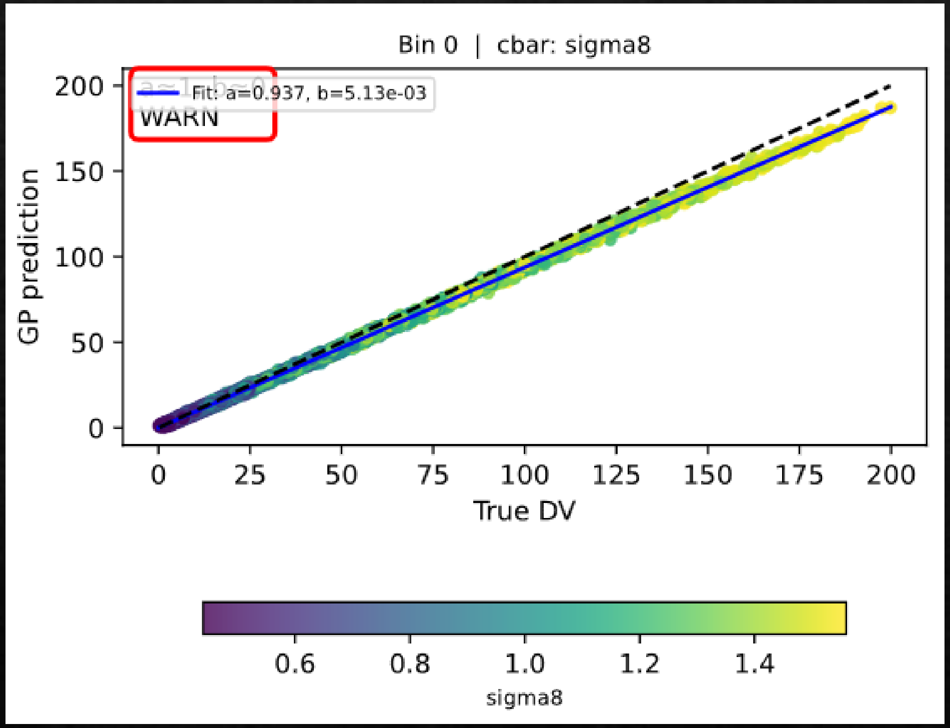
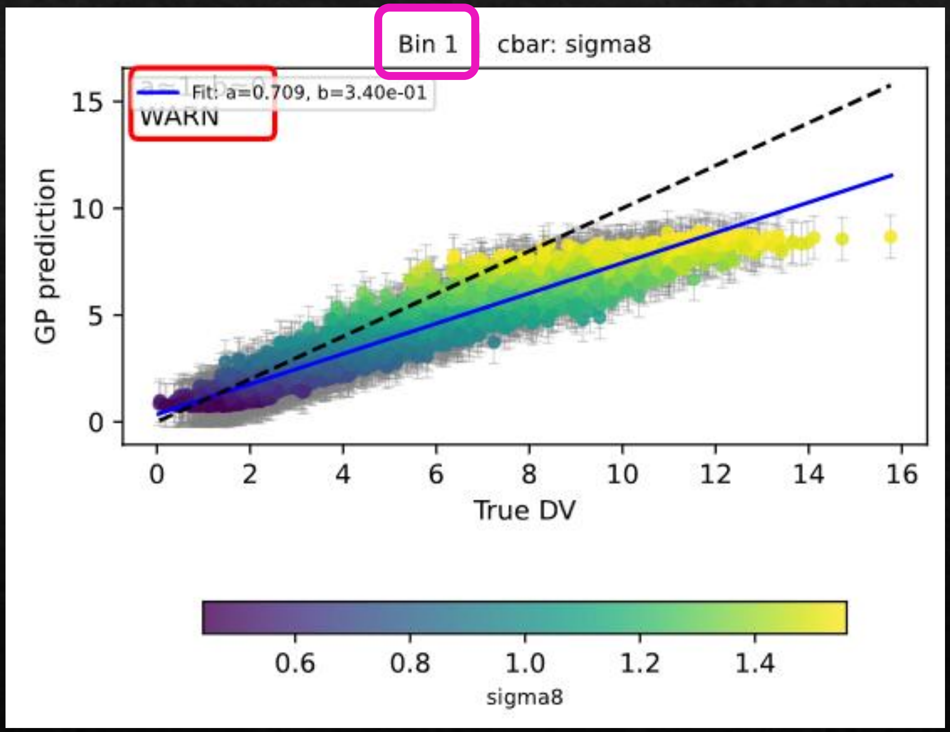
Supporting Slides

We check emulator accuracy on each compressed bin

MOPED Shear-2PCFs





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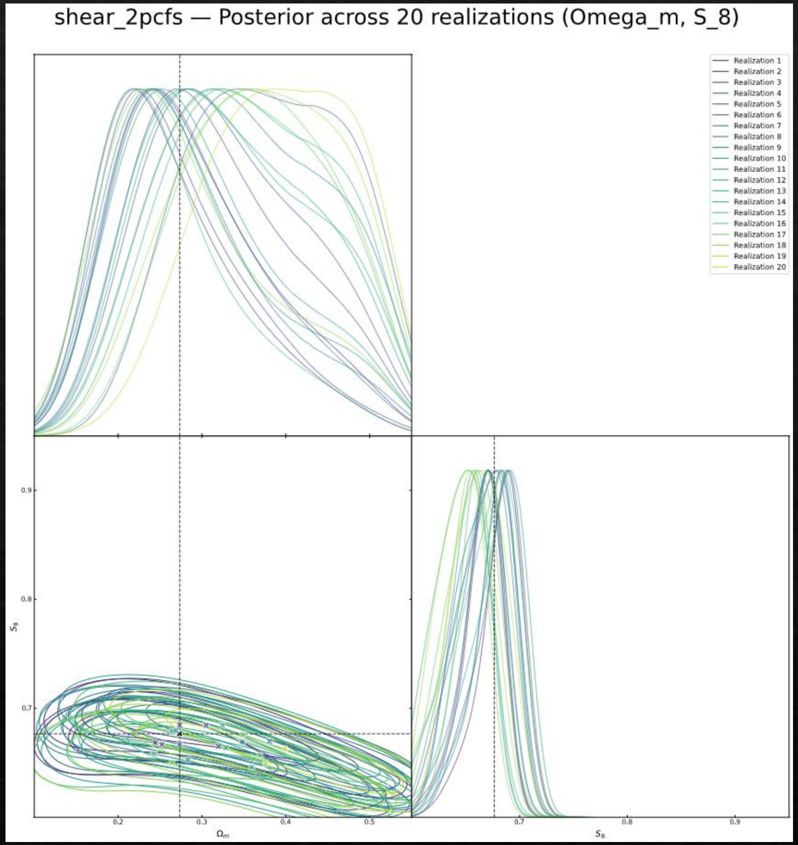
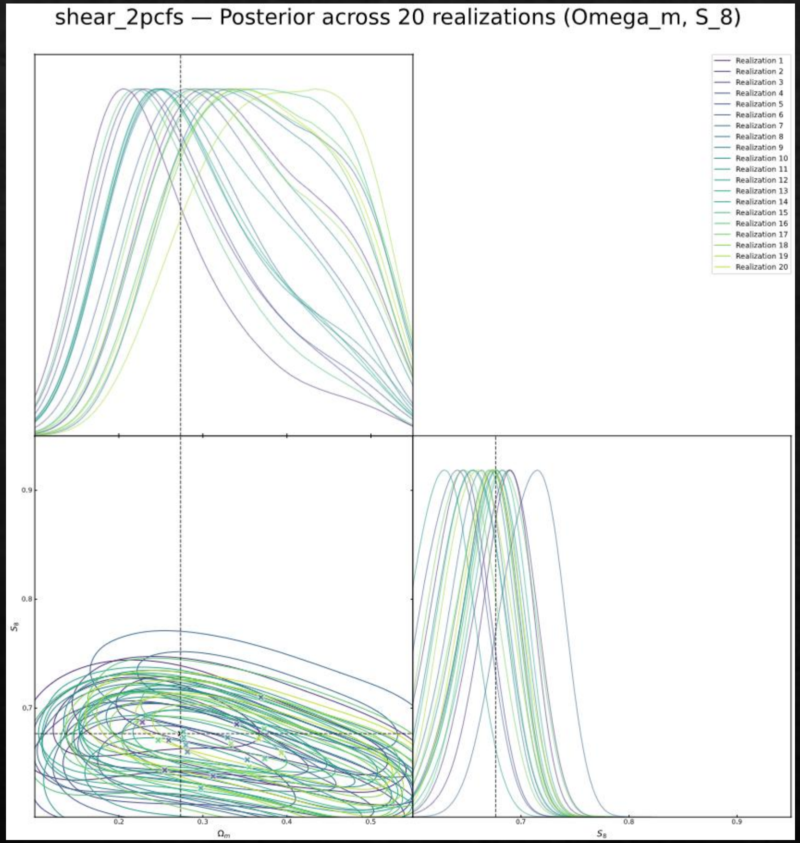
We investigate noise and cosmic variance impact on posteriors

ELI: Shear-2PCFs MOPED - NOISY



ELI: Shear-2PCFs MOPED - TRUE



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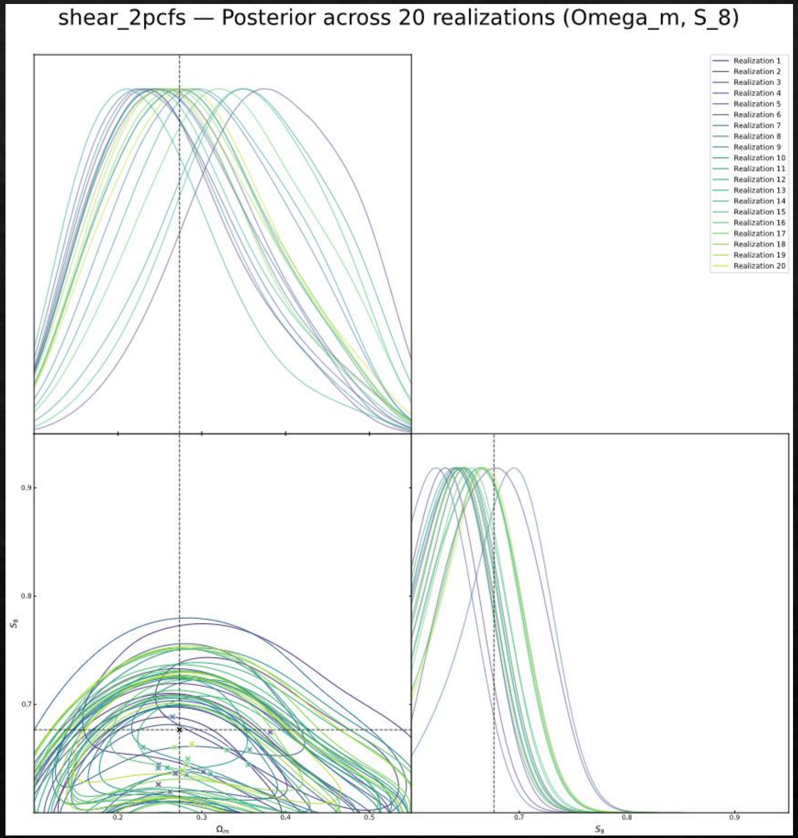
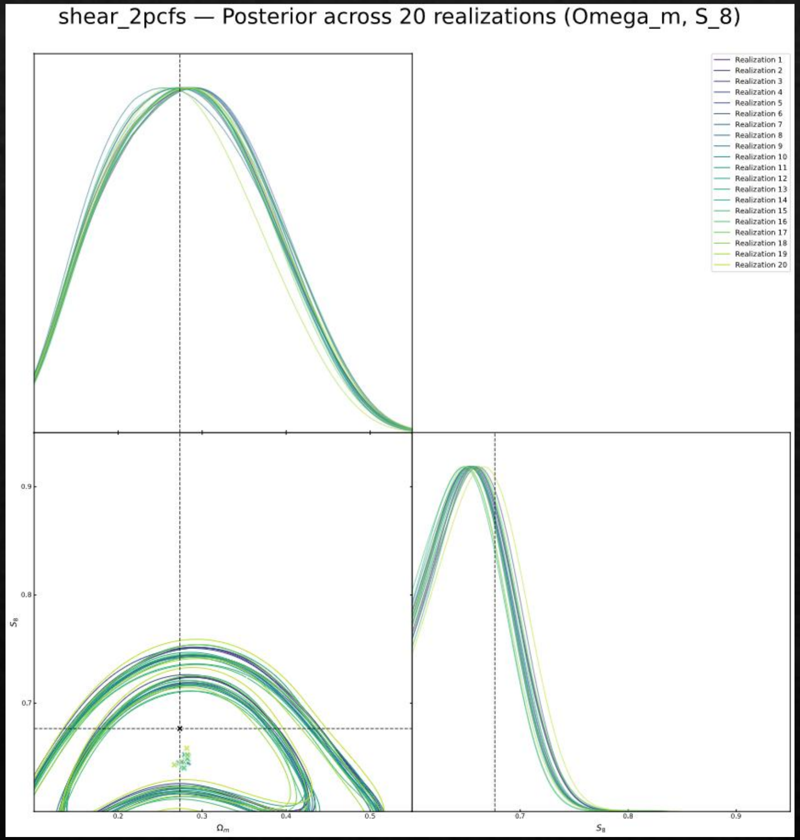
ELI: Shear-2PCFs NN - NOISY



ELI: Shear-2PCFs NN - TRUE



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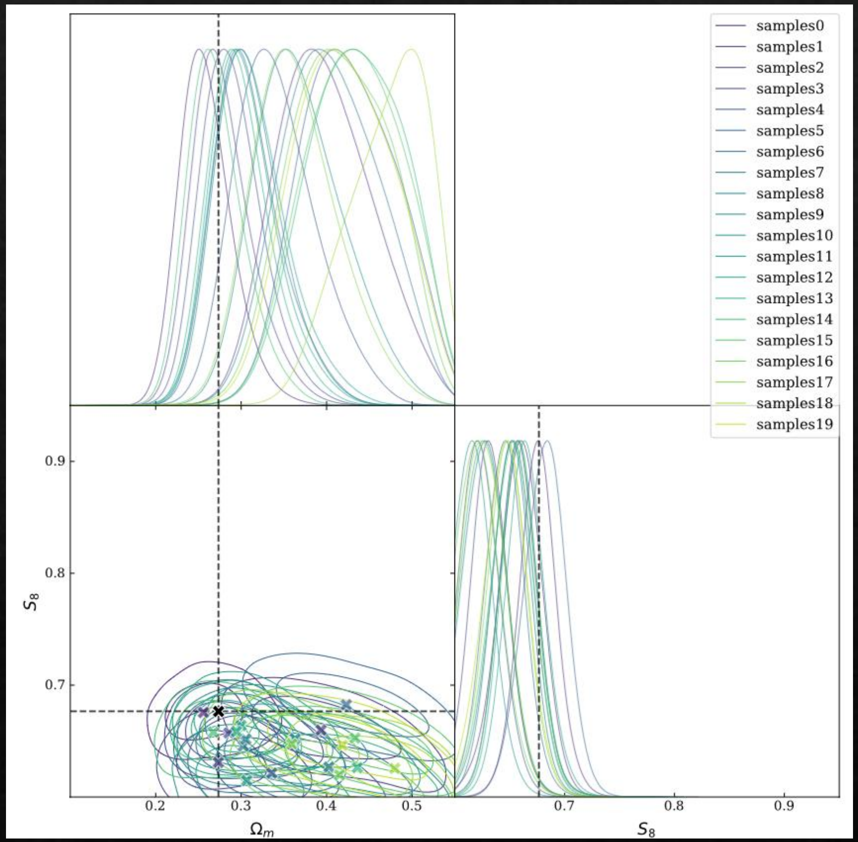
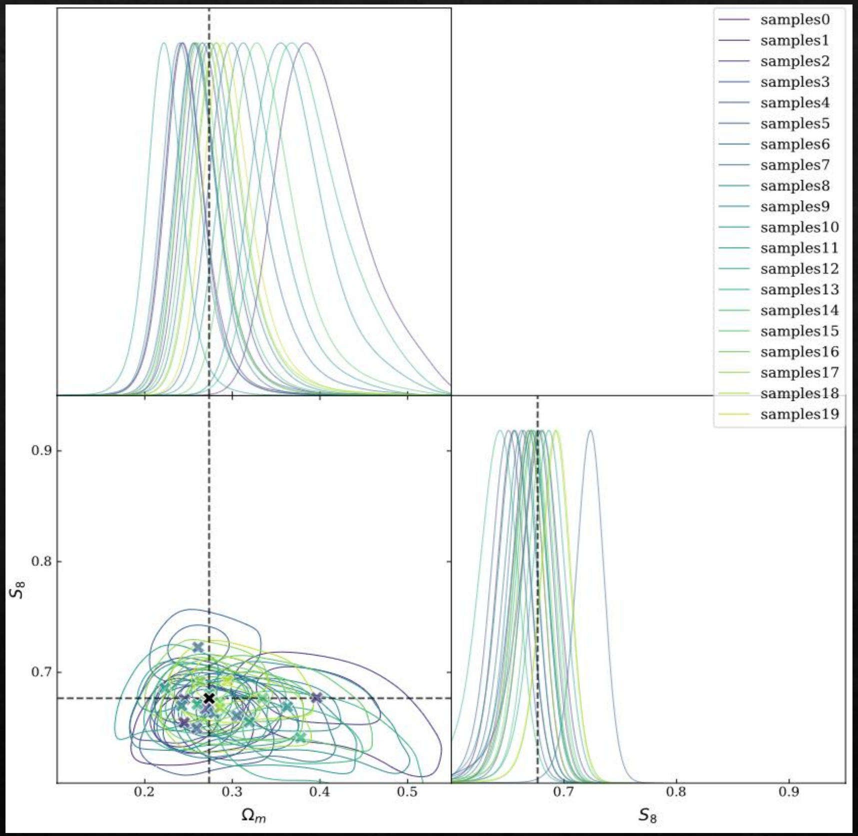
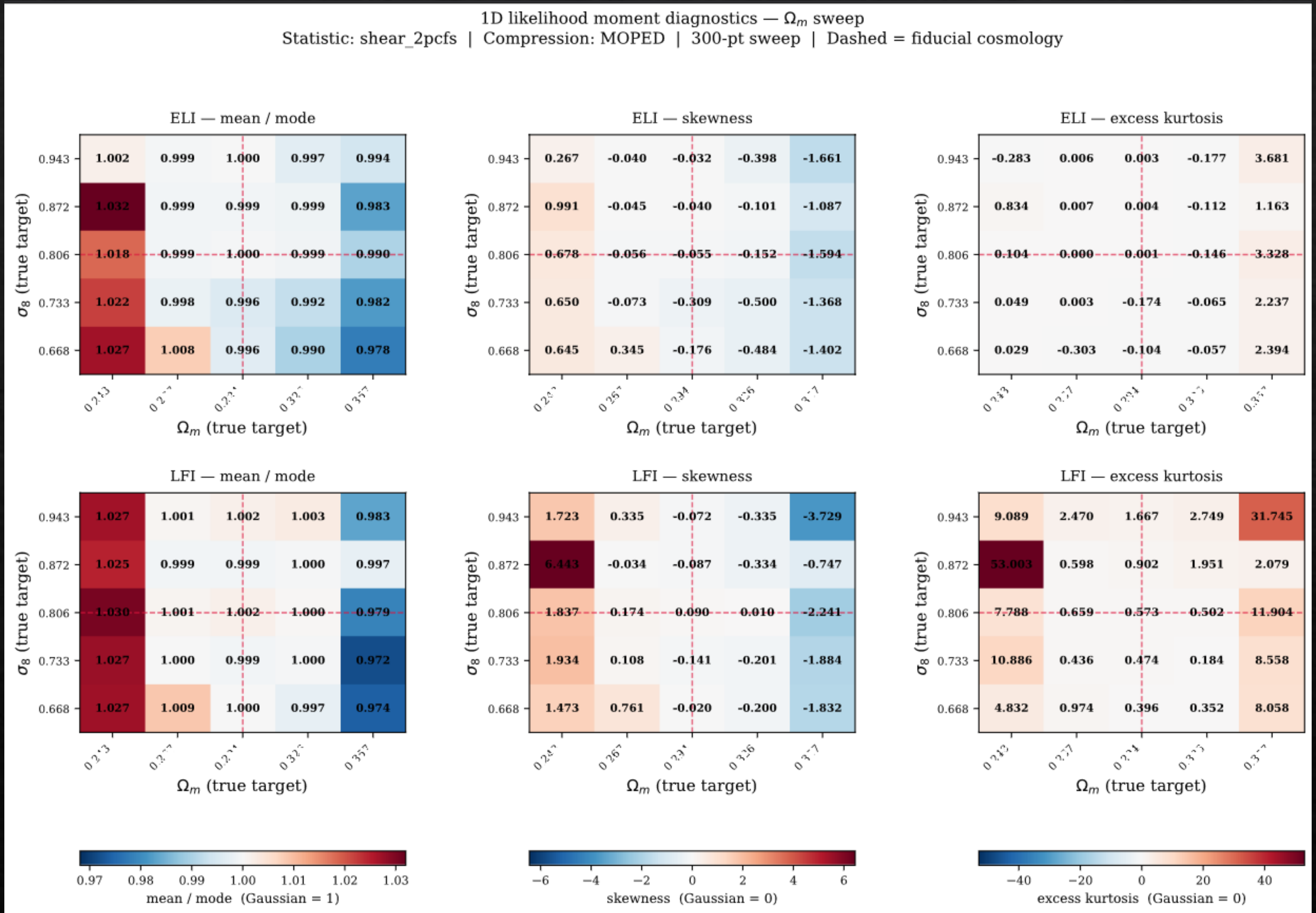
LFI: Shear-2PCFs **MOPED** - NOISY



LFI: Shear-2PCFs **NN** - NOISY



We check non-Gaussianity of the likelihood



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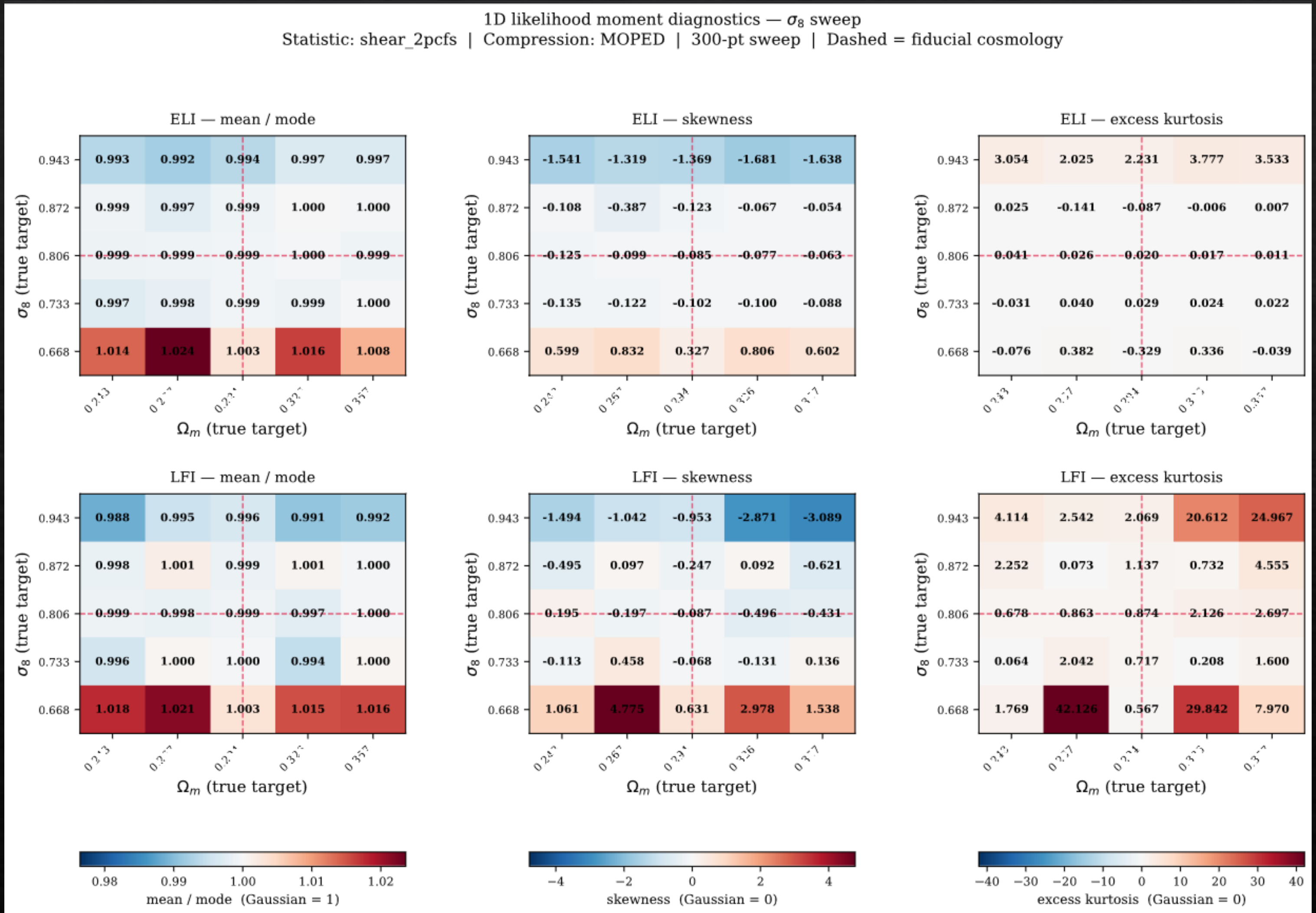
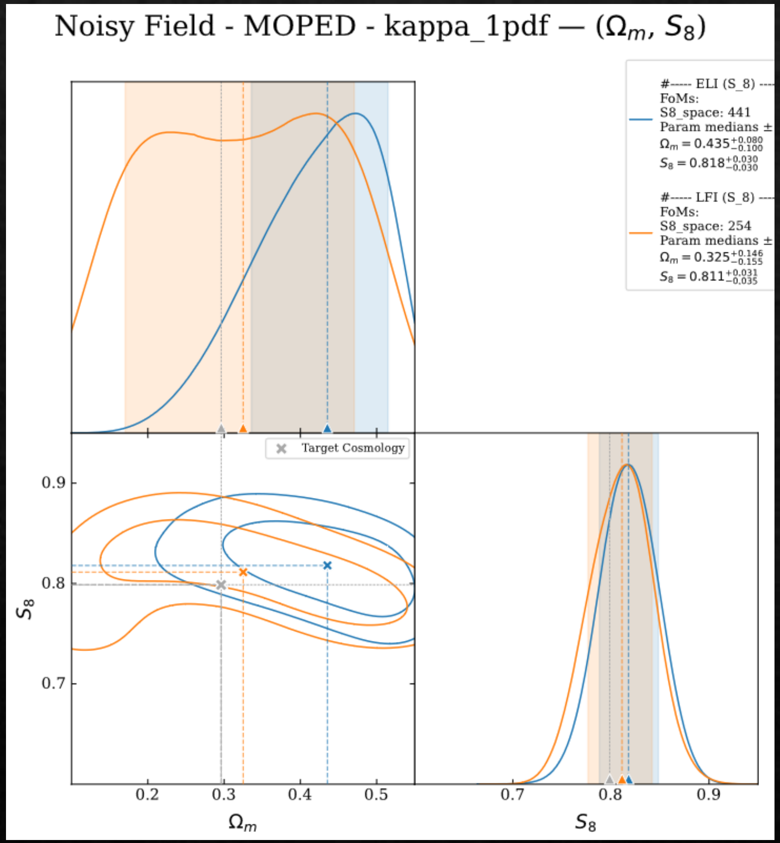
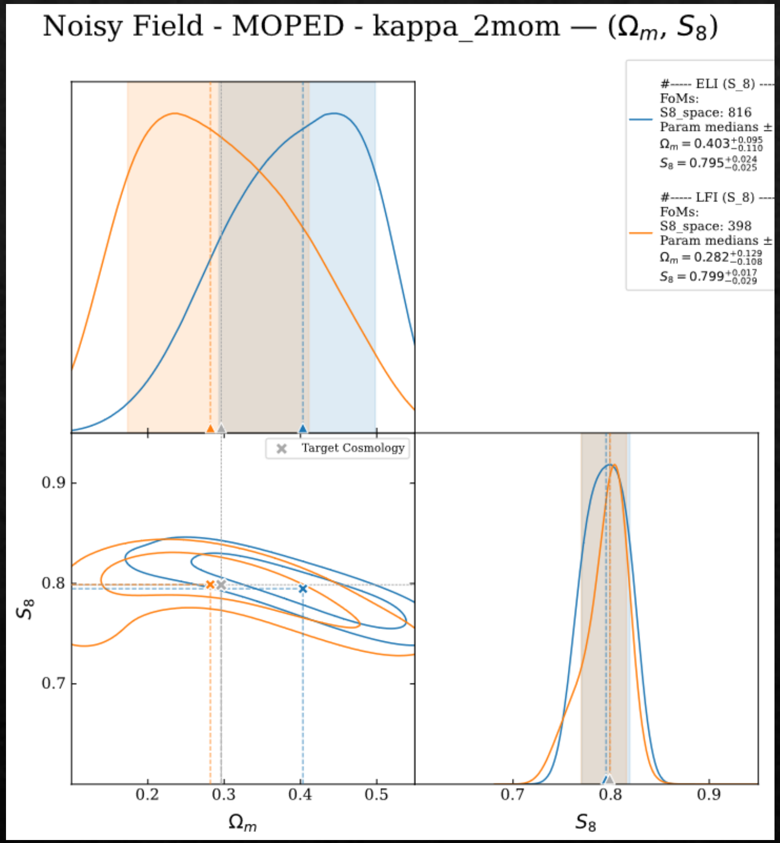
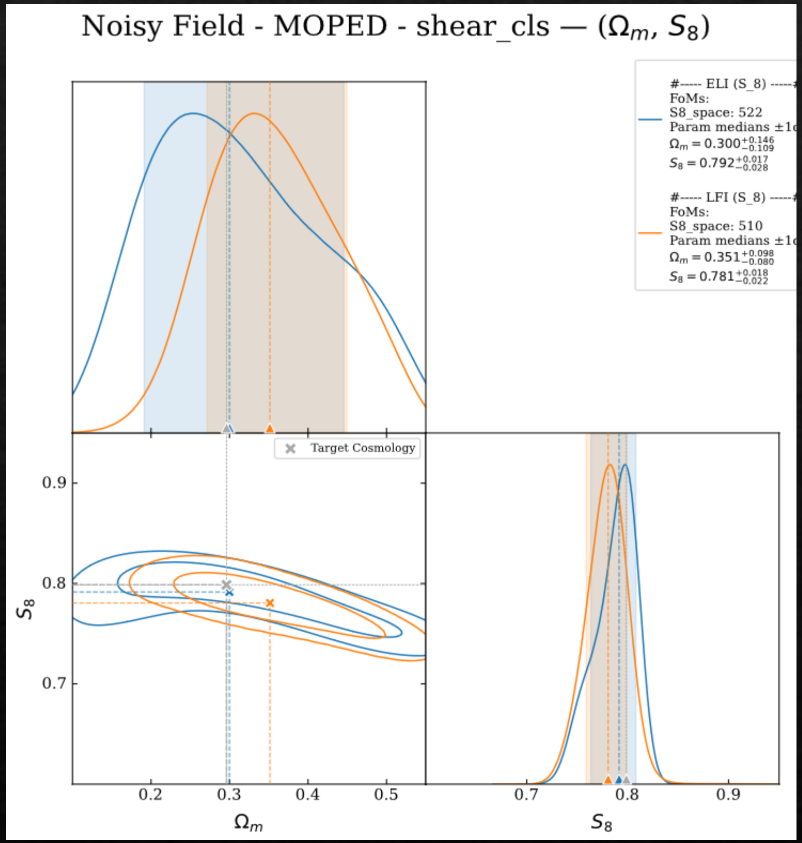
We check non-Gaussianity of the likelihood



We compare ELI vs. LFI posteriors for other statistics







We compare ELI vs. Cramer-Rao limit