The Non-Gaussian Likelihood of WL Correlation Functions

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*This work is currently under the internal review of the LSST DESC collaboration.

Likelihood analysis

Likelihood function

- Bayes' rule:

$$P(\vec{\pi} \mid \vec{\xi}) = \frac{\boxed{P(\vec{\xi} \mid \vec{\pi})} P(\vec{\pi})}{N}$$

- Gaussian Likelihood function:

$$P(\vec{\xi} \mid \vec{\pi}) = A \cdot e^{-\frac{1}{2}(\vec{\xi}-\vec{\xi_\pi})^T C^{-1} (\vec{\xi}-\vec{\xi_\pi})}$$

- Assumptions in standard likelihood analysis:
  Gaussian likelihood assumption

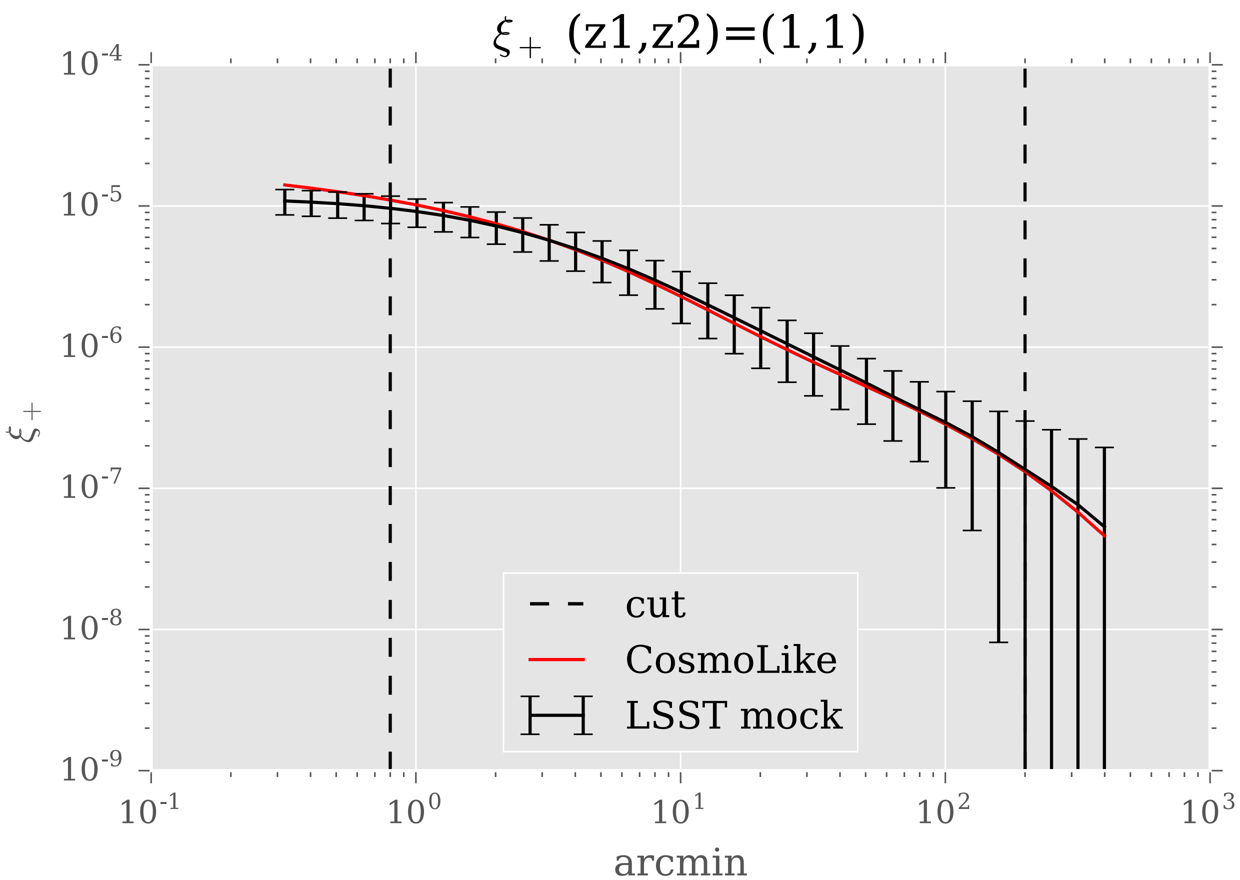
Simulations

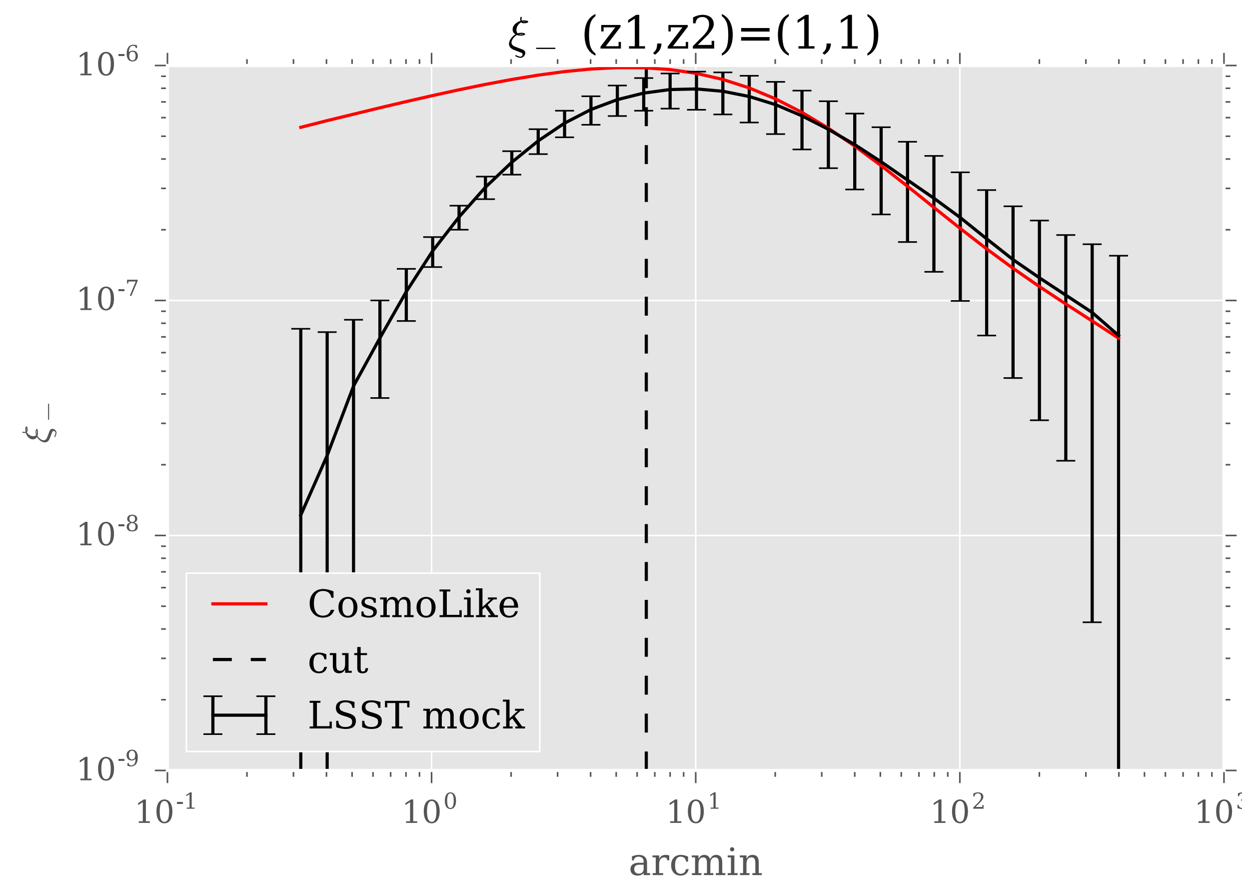
- Scinet LIght Cone Simulations (SLICS)

Covered in Joachim's talk yesterday

- 932 lines-of-sight realizations of 100 deg^2
- N-body simulation: 1536^3 particles in a box size of 505 $\mathrm{Mpc\ h^{-1}}$
- Reproduce redshift distribution of LSST (10 tomographic redshift bins with $n_{\mathrm{gal}} = 2.6\ \mathrm{gal/arcmin^2}$ in each bin).
- Intrinsic shape $\sigma_{\mathrm{e}} = 0.29$ (shape noise can be switched off)

Harnois-Déraps J., van Waerbeke L., 2015, MNRAS, 450, 2857





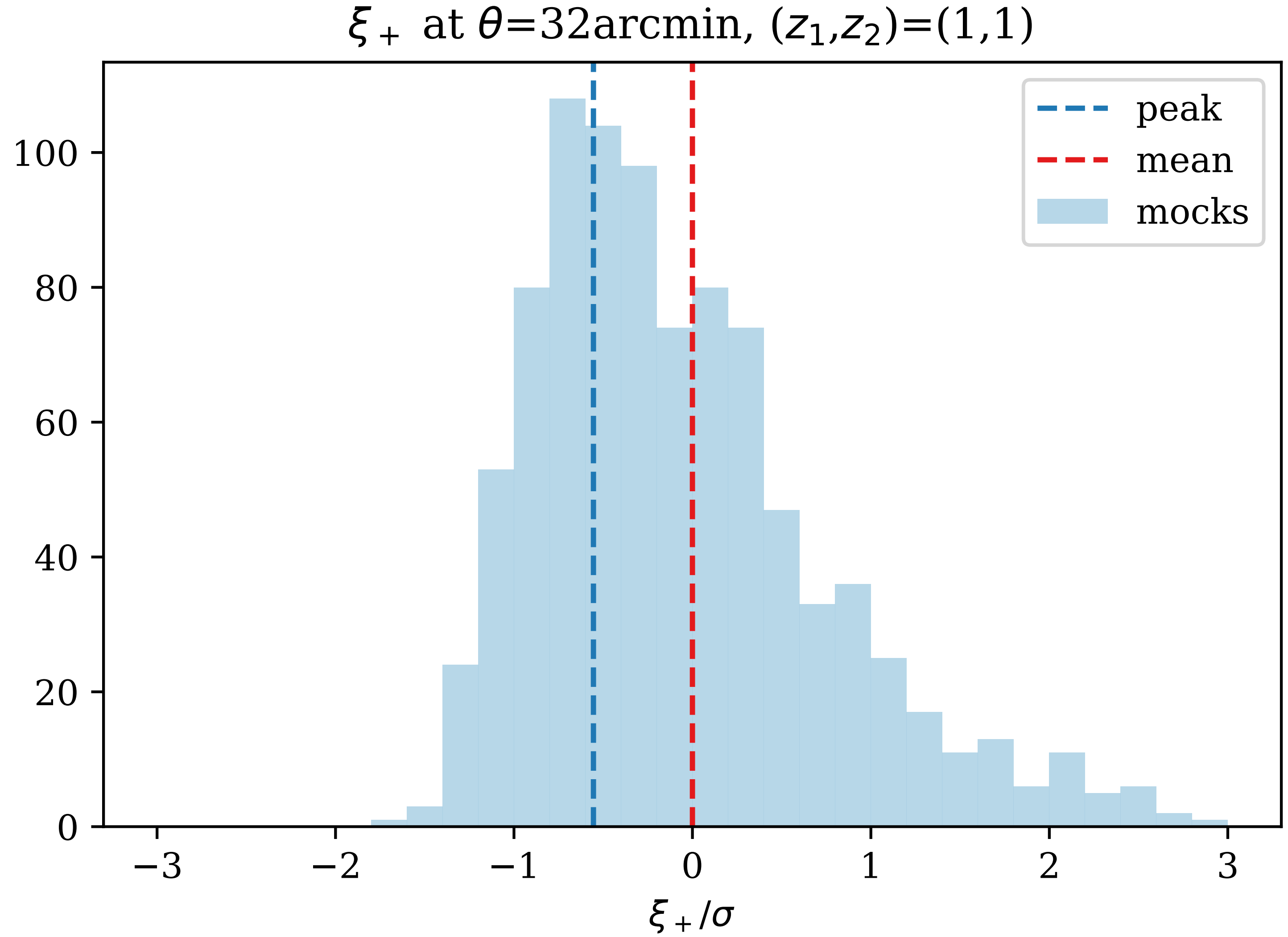
- To avoid biases due to the mismatch between the mocks and the theory, we rescale the mock ξ data vector with compensating ratios: $\xi_{\rm theory}/\langle\xi_{\rm mocks}\rangle$

Theory curves from CosmoLike:

Krause, E. and Eifler, T., MNRAS 2017 stx1261

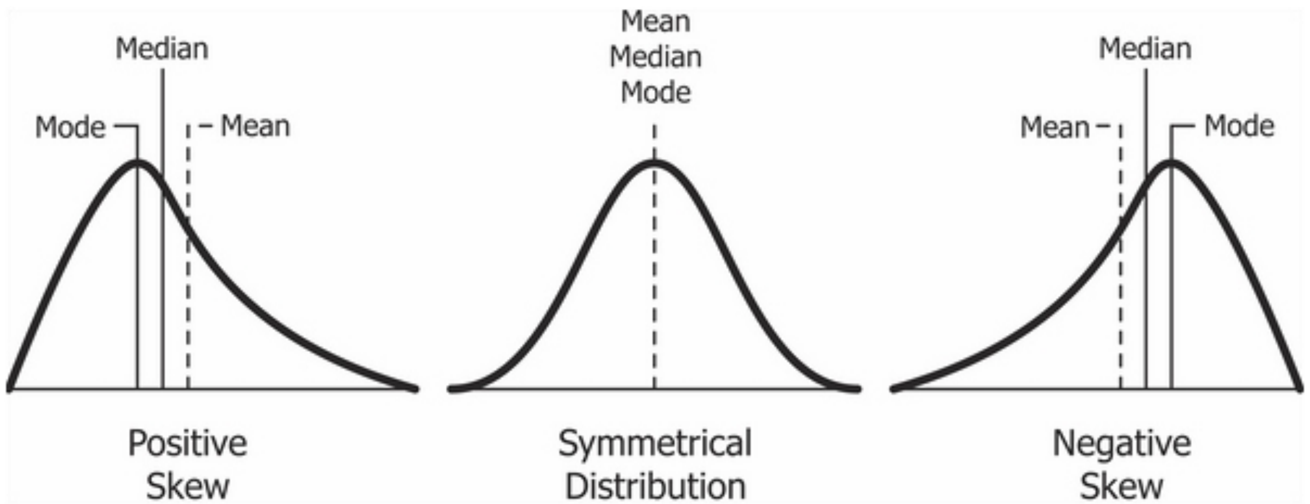
1-D likelihood distributions

- 1-D histograms



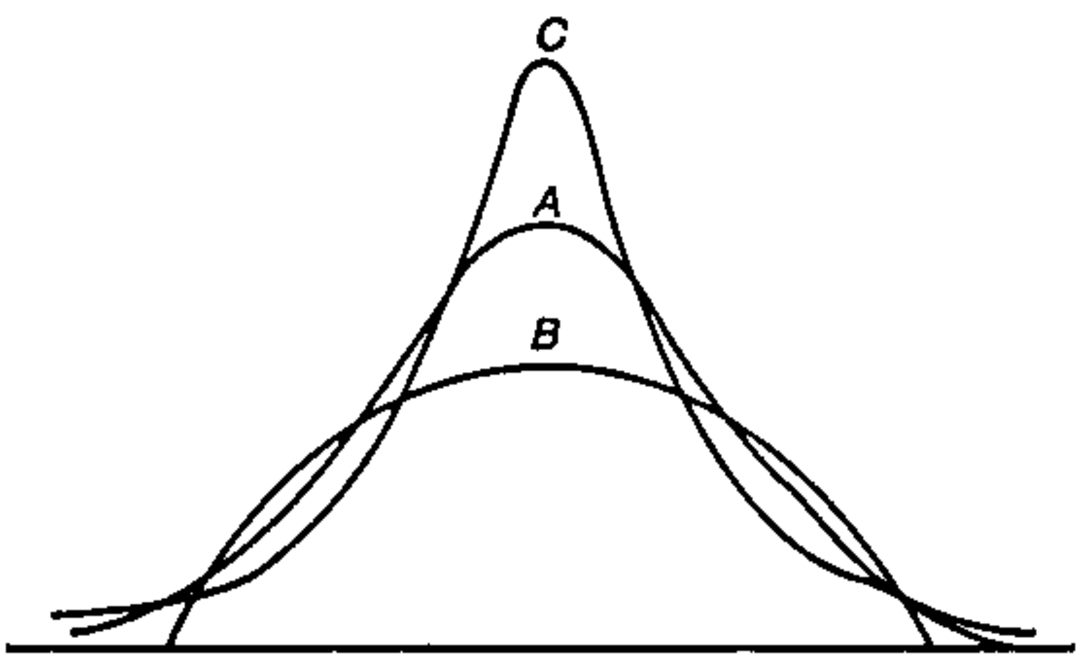
Skewness (asymmetry)

$$\mathrm{Skew}[X] = \frac{\langle (X-\mu)^3 \rangle}{\sigma^3}$$



Kurtosis (tails, outliers)

$$\mathrm{Kurt}[X] = \frac{\langle (X-\mu)^4 \rangle}{\sigma^4} - 3$$



- The plots show the statistically significant non-zero skewness and kurtosis in marginal likelihoods of ξ.

  Note that these marginal 1D likelihoods of $\xi_\pm$ values do not fully represent the level of non-Gaussianity in the multivariate observable space.

- Data with vs. without shape noise

- The results of selected tomographic bins show the redshift evolution of skewness and kurtosis. Non-Gaussian features decrease as redshift increase.

PCA and MV non-Gaussian likelihood

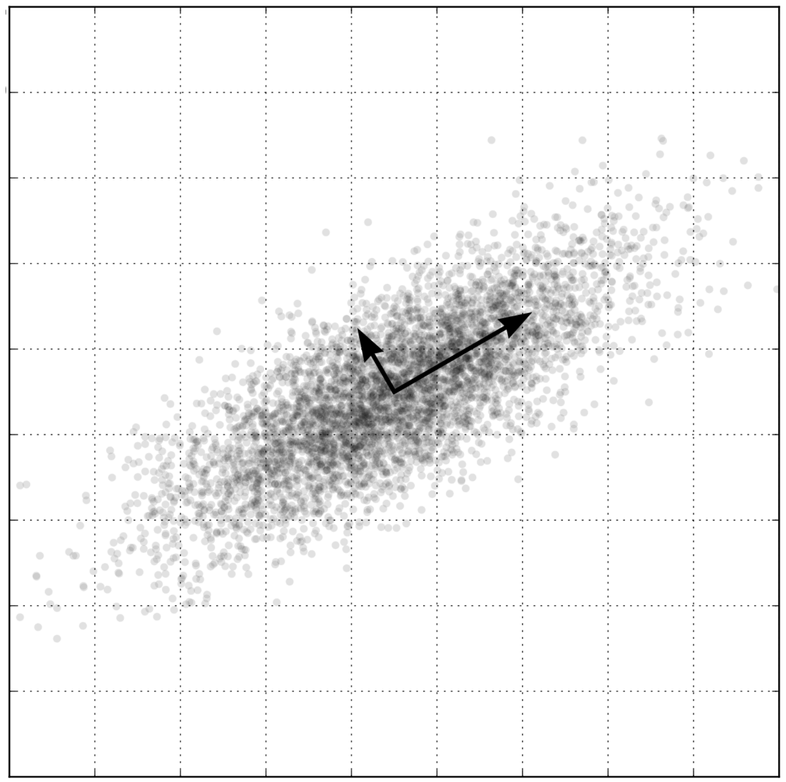
- Difficulty:
  High Dimensionality of the data vectors ~ 770
  Number of LOS ~ 932

- PCA is a transformation that transforms data points into linearly uncorrelated coordinates.

- Apply Principal Component Analysis (PCA) to approximate the joint distribution as multiple 1-d distributions.

- Model the 1-d distribution with parametric models: **Gaussian, Edgeworth**

- non-parametric multivariate models: kNN, spectral series



Conclusions

- We found strong non-Gaussianity in marginal distributions of ξ.
- We build non-Gaussian multivariate likelihood distributions via PCA. But we do not detect a difference between a Gaussian model and more complicated models.
- We do not detect strong biases in Ω_m and s_8 in the Maximum Likelihood Fitting method or MCMC chains.
- Sims:100 deg^2 / LSST: 18k deg^2

  Since the mean-mode difference scales with the survey area as $(\tilde{\xi} - \overline{\xi})/\sigma \propto f_{\rm sky}{}^{-1/2}$, the biases would be even smaller for LSST.
- Our results suggest that neglecting the non-Gaussianity of the likelihood for shear-shear correlations is not a significant source of bias for ongoing surveys or even future ones such as LSST.