

Cosmic Shear Covariances for DES SV and internal Covariance Estimation

Oliver Friedrich, Stella Seitz, USM

Cosmic Shear Basics

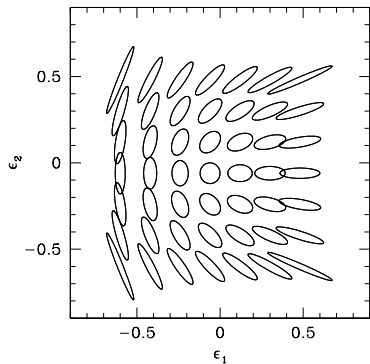
Becker et al. 2015

Friedrich et al. 2015



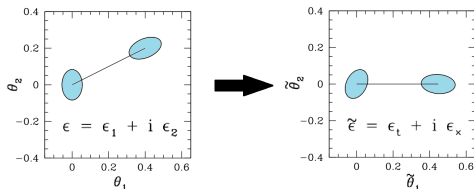
DARK ENERGY
SURVEY

Cosmic Shear in a Nutshell



⇐ Characterize ellipticities by complex number:

$$\begin{aligned}\epsilon &= \epsilon_1 + i\epsilon_2 \\ &= \epsilon \cdot e^{2i\phi}\end{aligned}$$



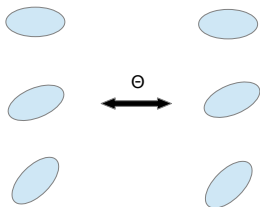
⇐ For each galaxy pair define tangential and cross component ϵ_t and ϵ_x .

Cosmic Shear in a Nutshell

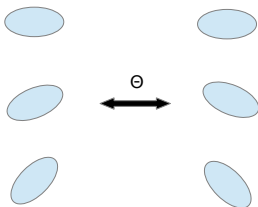
- The Cosmic Shear 2-pt. functions $\xi_{\pm}(\theta)$ can be measured by:

$$\hat{\xi}_{\pm}(\theta) = \frac{\sum_{ij} (\epsilon_{i,t} \epsilon_{j,t} \pm \epsilon_{i,\times} \epsilon_{j,\times})}{N_{\text{pair}}(\theta)} .$$

- largest contributions to $\xi_{+}(\theta)$ from parallel alignment of galaxy shapes:



- largest contributions to $\xi_{-}(\theta)$ from galaxies aligned mirror symmetric to their connection line:



Covariance Matrices for Cosmic Shear

- measure the data vector $\hat{\xi} = [\hat{\xi}_{\pm}(\theta_1), \dots, \hat{\xi}_{\pm}(\theta_d)]$.

Covariance Matrices for Cosmic Shear

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- Assuming a Gaussian likelihood one needs to know the *covariance matrix*,

$$C(\theta_1, \theta_2) = \langle [\hat{\xi}(\theta_1) - \xi(\theta_1)] \cdot [\hat{\xi}(\theta_2) - \xi(\theta_2)] \rangle ,$$

to constrain cosmological models.

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- Ways to get the covariance matrix:
 - > Modelling
 - > Estimating from simulations
 - > Estimating from data

Covariances from Becker et al. 2015

Cosmic Shear Measurements with DES Science Verification Data

- > M. R. Becker, M. A. Troxel, N. MacCrann, E. Krause, T. F. Eifler, O. Friedrich, A. Nicola + DES Collaboration
- > [arxiv:1507.05598](https://arxiv.org/abs/1507.05598)

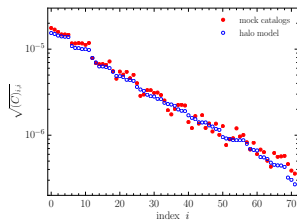
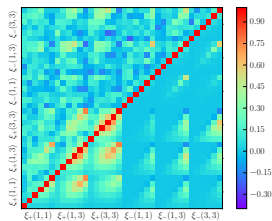


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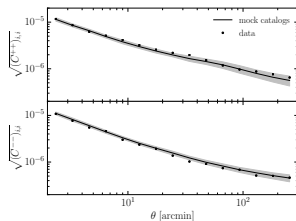
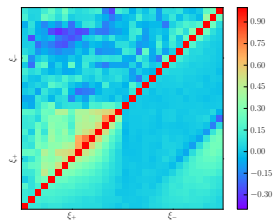


Covariances from Becker et al. 2015

tomographic covariance from halo-model and mock catalogs:



jackknife covariance from data and mock catalogs:



Covariances from Becker et al. 2015

- Modelling:

- > halo-model covariance from CosmoLIKE (Eifler et al. 2014b, Krause et al. 2015):
including Gaussian contributions, convergence trispectrum and finite volume effects

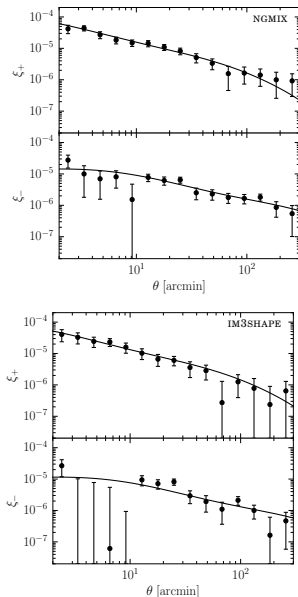
- Simulations:

- > 7×3 N-body light cones patched together along line of sight
- > box size = $1050h^{-1}Mpc$, $2600h^{-1}Mpc$, $4000h^{-1}Mpc$ resp.
- > particles = 1400^3 , 2048^3 , 2048^3 resp.

- Jackknife:

- > Jackknife estimation as in Friedrich et al. 2015.
- > computed for both data and mocks to check for field-to-field systematics

Covariances from Becker et al. 2015



Conclusions:

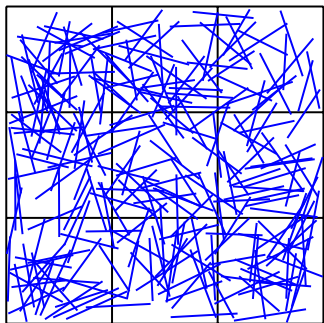
- Covariance from mocks and halo-model give consistent constraints on $\sigma_8(\Omega_m/0.3)^{0.5}$.
- Our mock catalogs have the same size as the data, i.e. no area rescaling.
- Ready to do science! See also DES Collaboration (2015) for first DES cosmic shear cosmology results!

Friedrich et al. 2015, Performance of internal Covariance Estimators for Cosmic Shear Correlation Functions

- > O. Friedrich, S. Seitz, T. F. Eifler, D. Gruen
- > use **log-normal simulations** of the convergence field to test covariance estimation from the data
- > Hilbert et al. (2011) approximate the covariance matrix in case of log-normal convergence as

$$C_{\pm\pm}^{ss}(\theta_1, \theta_2) = \text{Gaussian Covariance} + \frac{8\pi}{\kappa_0^2 A} \xi_{\pm}(\theta_1) \xi_{\pm}(\theta_2) \int_0^{\theta_A} d\theta \theta \xi_{\kappa}(\theta) .$$

Internal Covariance Estimation



Measure $\hat{\xi}^\alpha$ in sub-patches
 $\alpha = 1, \dots, N_S$.

Main idea:

- measure covariance of sub-patches
- (hope to) rescale it to the total survey area:

$$\hat{\xi} \approx \frac{1}{N_S} \sum_{\alpha} \hat{\xi}^{\alpha}$$

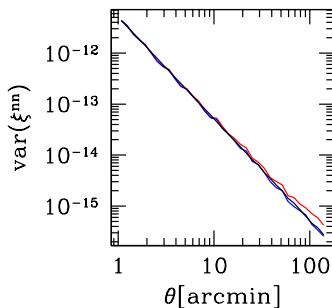
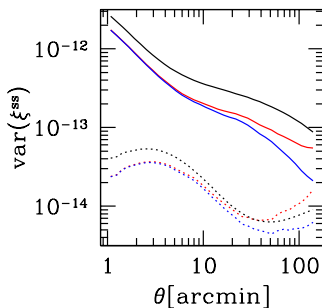
$$C_{\text{tot}} \approx \frac{1}{N_S} \cdot C_S$$

- other methods: jackknife, bootstrap (almost identical, especially on small scales)

Problems in internal Covariance Estimation

- What about galaxy pairs that cross between subregions?
- Subregions are correlated!
- How many subregions are needed to get stable covariance estimates?

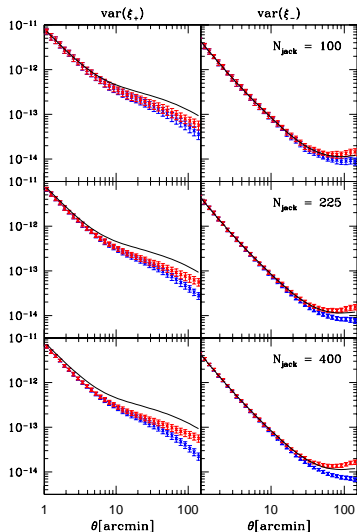
Finite Area Effect



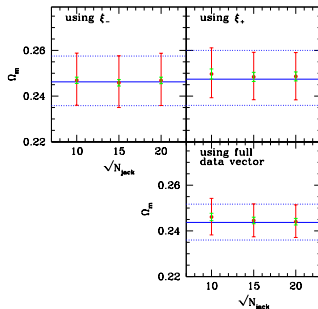
- Example: survey of 5000 deg^2 , 400 sub-regions
- C is NOT proportional to $1/A$! Recall:

$$C_{\pm\pm}^{ss}(\theta_1, \theta_2) = \text{Gaussian Covariance} + \frac{8\pi}{\kappa_0^2 A} \xi_{\pm}(\theta_1) \xi_{\pm}(\theta_2) \int_0^{\theta_A} d\theta \theta \xi_{\kappa}(\theta) .$$

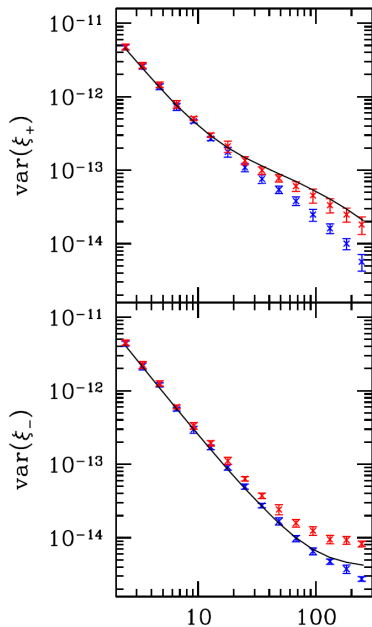
Cosmological Parameters from Jackknife?



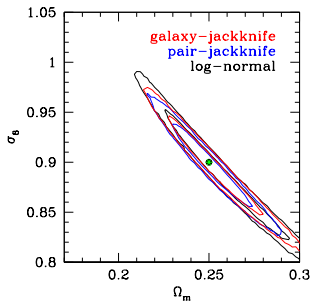
- marginalisation over σ_8 , fixing other parameters
- inversion of the covariance estimate using Hartlap-Kaufmann factor



Forecast for DES Y5



- measuring ξ_{\pm} from $2'$ to $300'$
- compute likelihood in $\Omega_m - \sigma_8$ plane using CosmoLIKE (Eifler et. al 2014)



(10 of these plots in the paper)

Conclusions

- reconstruct $\gtrsim 80\%$ of the likelihood contours in 2D, $\gtrsim 90\%$ in 1D
- basic limitations: systematic under estimation of the uncertainties
- code will be public within 2 weeks, i.e. when paper is on arxiv.

