# Analytical 3x2pt Covariance

## this goes on every 2nd and 4th Friday of the month @ 15.00 CET

IST:NL leaders ~ 20 people participating, ~ 7 really active

Davide Sciotti & Marco Bonici et al.

### General thoughts

- the covariance will be computed from CLOE recipes but external to the code
- it will be computed once before the MCMC runs
- covariance setups need to be defined: window functions, masks, sky fractions, redshift distributions, non-linear reference models, scale-cuts or not scale-cuts, BNT transformation (K. Benabed, F. Bernardeau, M. Delaire, and action in IST:L) for the weak lensing part etc...

#### Photometric Catalogue(s)



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#### From the F2 simulations:

After testing different types and number of tomographic bins, the following selection has been chosen as fiducial for both lenses and sources:

- 13 tomographic bins

- equipopulated bins (same number density of galaxies per bin)

- minimum photo-z value: 0.2

- maximum photo-z value: 2.5

24.3 galaxies / arcmin<sup>2</sup>



#### Photometric Catalogue(s)

$$W^{\mathrm{A}}_i(z) = b^{\mathrm{A}}(z) rac{H(z)}{c} n^{\mathrm{A}}_i(z)$$
 Clustering

$$W_i^{\gamma}(z) = rac{3}{2} \left(rac{H_0}{c}
ight)^2 \Omega_{
m m}(1+z) \chi(z) \int_z^{z_{
m max}} {
m d}z' \, n_i^{
m ph}(z') \left[1 - rac{\chi(z)}{\chi(z')}
ight] \quad ext{Weak Lensing (+IA components))}$$

$$C^{AB}_{ij}(\ell)\simeq rac{c}{H_0}\int_{z_{
m min}}^{z_{
m max}}{
m d}zrac{W^A_i(z)W^B_j(z)}{E(z)\chi^2(z)}P_{\delta\delta}\left[k=rac{\ell+1/2}{r(z)},z
ight]$$

In the Limber approximation

#### Marco Bonici

#### **Baseline recipes for 3x2pt**



#### Why do we care about Super Sample Covariance?



Power spectrum : all scales probes react to  $\delta_{b}$   $\rightarrow$  more important when more modes

All probes react  $\rightarrow$  more important when more probes

Separate universe (e.g. Wagner et al. 2015) : can mimick  $\delta_{h}$  with a change of cosmology

Fabien Lacasa

#### **Current Status**

- **Gaussian**: <u>published package</u> for easy computation, saves a bit of ordering-related headaches

- SSC: three (and a half) codes available

- <u>PySSC</u>:

- Fast, good control over observables and responses
- Slowly varying response, may be inaccurate for WL?
- <u>PyCCL</u>:
  - Slower, less control over the observables (but still ok in general)
  - Dirac delta approximation for  $\sigma$  2 , suggested to be less accurate for GCph (Lacasa+19)
- <u>Spaceborne</u>:
  - Slowest
  - No approximation (except full-sky, as with the others)
  - Custom-built, full control over recipe, observables and responses
- <u>CosmoLike</u>:
  - Same recipe as PyCCL, excellent agreement found with input files of R. Upham
  - Runnable on a Docker image by Marco, least control over observables, tests ongoing
  - Already used in the literature

- **cNG**: ongoing tests with PyCCL

### SSC Covariance: $\sigma^2(z)$ <u>CosmoLike</u>, <u>PyCCL</u>

$$\operatorname{Cov}^{\mathrm{SSC}}\left(C_{AB}^{ij}(l_1), C_{CD}^{kl}(l_2)\right) = \int \mathrm{d}\chi \; \frac{q_A^i(\chi)q_B^j(\chi)q_C^k(\chi)q_D^l(\chi)}{\chi^4} \; \frac{\partial P_{AB}(l_1/\chi, z(\chi))}{\partial \delta_b} \frac{\partial P_{CD}(l_2/\chi, z(\chi))}{\partial \delta_b} \sigma_b(\Omega_{\mathrm{s}}; z(\chi)),$$

with  $\sigma_b(\Omega_s, z(\chi))$  the variance of the background mode over the survey window,

$$\sigma_b(\Omega_{\rm s};z) = \int \frac{d^2k_\perp}{(2\pi)^2} P_{\rm lin}(k_\perp,z) |\tilde{W}_{\rm s}(k_\perp,z)|^2 \approx \int \frac{d^2k_\perp}{(2\pi)^2} P_{\rm lin}(k_\perp,z) \left[\frac{2J_1(k_\perp\chi(z)\theta_{\rm s})}{k_\perp\chi(z)\theta_{\rm s}}\right]^2,$$

Krause & Eifler 2016 (assumes cylindrical window function)

with  $q_{a}^{i}$  the weight functions.

Approximation used by DES and KiDS analyses. (KiDS: different pipeline, not public)

- Single redshift integral: approximates  $\sigma^2(z)$  as a Dirac delta at  $z_1 = z_2$
- If no mask is passed as input, assumes the 3D window function  $W(\bar{x})$  to be much wider in the radial direction than in the transverse direction.
- Validity: expected OK for broad overlapping kernels (WL), but not for narrow independent kernels (GC) opposite as slowly varying approximation!

For cluster counts, <u>Lacasa+2018</u> showed it works well in auto-redshift but not in cross-redshift

#### SSC approximations : slowly varying response (<u>PySSC</u>)

If the response 
$$\frac{\partial o}{\partial \delta_b}$$
 varies slowly with redshift compared to  $\sigma^2(z_1, z_2)$   
 $\operatorname{Cov}_{SSC}\left[\mathcal{O}(i, \alpha), \mathcal{O}(j, \beta)\right] = \partial_{\delta_b}\mathcal{O}(i, \alpha) \ \partial_{\delta_b}\mathcal{O}(j, \beta) S_{\alpha, \beta}$   
 $= R(i, a) O(i, a) (definition of R)$   
 $\mathcal{O}(i, \alpha)$  cosmological probe: cluster counts, C<sub>1</sub> of WL / GCp / XC / CMBX,  
P(k) of GCs, high order statistic...  
 $R(i, \alpha)$  probe response: from theory, ansatz or SU simulations.  
Depends on probe, redshift (a), scale / other param (i).  
 $S_{\alpha, \beta}$  covariance matrix of the  $\delta_b$  of each redshift bin  
Can be computed with PySSC (Lacasa & Grain 2019)  
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 $S_{\alpha, \beta}$  covariance matrix of

Validity: expected OK for narrow independent kernels (GC), worse for broad overlapping kernels with low-z contribution (WL)

large survey areas (in general SSC does **not** scale as 1/fsky)

Sensitive to sky fraction / mask (Gouyou Beauchamps et al. 2022) - fsky rescaling works well for

#### Probe response

- SU probe response vs probe response from PyCCL (thanks to M. Bonici)
- Good overall agreement
- Next step: gauge the effect of the different recipes by plugging PyCCL responses into PySSC (spoiler alert: small impact on the final constraints)



### PySSC vs PyCCL: FM constraints, WL, GCph

- Same pipeline with SSC matrix from PySSC or PyCCL
- Good agreement found, except on the most impacted parameters for WL
- Difference between GS constraints wrt the *mean* shown in the plot
- Not the best metric for agreement between codes?
  - Direct comparison of the SSC covariance trickier, shows large discrepancies



### PySSC vs PyCCL: FM constraints, 3x2pt

- Good agreement, 10% max discrepancy
- PyCCL more pessimistic (than PySSC) for GCph, more optimistic for WL



#### Shear pseudo-Cl covariance

Importance of non-Gaussian terms:

 Mock parameter constraints including different contributions to covariance



**Robin Upham** 

### **MCMC** analyses

Improvement in constraints using non-linear modelling

#### 3x2pt photometric

- **Red** lines: Linear model and linear data vector, Gaussian diagonal covariance
- Green solid: Nonlinear model HMcode, with same model for data vector and covariance. DM-only.

SSC + Gaussian covariance.



### MCMC analyses

Impact of SSC on parameter constraints  $S_8 = 0.8421 \pm 0.0022$ ---- 3x2-mod HMC-data HMC-cov SSC 3x2-mod\_HMC-data\_HMC-cov\_Gauss 3x2pt photometric  $H_0 = 67.0 \pm 2.4$ data: HMCode 3x2-mod\_HMC-data\_HMC-cov SSC 3x2-mod HMC-data HMC-cov Gauss  $w = -0.996 \pm 0.047$  $\Omega_{\rm H} = 0.3202 \pm 0.0041$ model: HMCode Dm 0.32 -0.9 $\Omega_{h} = 0.0226^{+0.0025}_{-0.0031}$ covariance: HMCode  $\Omega_b h^2$ 0.03 ≥ -1.0 0.02 ₩ 0.961 ± 0.011 -1.1  $W_a = -0.02^{+0.17}_{-0.14}$ ° 0.96 58 + 0.8421 ± 0.0022 0.4 <sup>ა</sup> 0.84 w + 0.996 ± 0.047 Wa ≥ W = - 0.02+0.17 -0.4Na 1.719 ± 0.034 0.840 0.845 -1.1 -1.0 -0.9 0.0 Se Wa 144 AIA nA ± 0.409 ± 0.024 ALL -0.4 $5^{\text{d}cph} = 1.3587 \pm 0.0076$ 5 GCph 1.36 0.32 0.02 0.95 0.84 -1 Ò 1.7 -0.4 1.36 nIA becch FoM: 401 (with SSC), FoM: 1073 (just Gauss) AIA  $\Omega_h h^2$ W-

Blue dashed

SSC+Gaussian

Orange solid:

covariance

Gaussian

covariance.

lines:

#### Santiago Casas, Pedro Carrilho & Davide Sciotti

### Spaceborne SSC

- Possible test of σ<sup>2</sup> against latest version of PySSC, excellent agreement
- Responses from SU simulations, good match against PyCCL (extracted by Marco)
- Including magnification bias (for latest SPV3 forecasts) creates some issues with PySSC and PyCCL, work in progress to bring these up to speed



Davide Sciotti & Marco Bonici

### Spaceborne SSC: computing the integral

- Previous analysis: proof of concept with 2 \ell bins, integral feasible in Python
- Full matrix (32 \ell bins, 13 z bins) much more demanding:
  - Developed a Tensorflow version for GPU/TPU, good speed but memory still seems to be the bottleneck
  - Julia version by Marco, needs to be run on a cluster (10-ish hours for full matrix) V
  - Full control over recipe and approximations

67838032 Sep 19 04:43 cov\_SSC\_GGG\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 125984848 Sep 19 03:52 cov\_SSC\_GGL\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 67838032 Sep 19 02:21 cov\_SSC\_GGL\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 125984848 Sep 19 01:30 cov\_SSC\_GLG\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 233971792 Sep 18 23:55 cov\_SSC\_GLG\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 125984848 Sep 18 21:06 cov\_SSC\_GLL\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 67838032 Sep 18 19:31 cov\_SSC\_GLL\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 125984848 Sep 18 18:40 cov\_SSC\_LLG\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 67838032 Sep 18 18:40 cov\_SSC\_LLG\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy 67838032 Sep 18 17:09 cov\_SSC\_LLLL\_4D\_nbl32\_ellmax5000\_zbins13\_zsteps2899\_k1overMpc\_conventionPySSC.npy

#### Davide Sciotti & Marco Bonici

# **Results GCph**

- Low impact in general for GCph
- PyCCL approximation

   (\sigma^2 approximated as a
   Dirac Delta) seems to be
   good for GCph
- More accurate PyCCL GCph V
- Good match with Spaceborne V



### **Results WL**

- (previously seen) mismatch between PySSC and other codes for most affected parameters
- Good match between PyCCL and exact SSC V
- Found variability of results with varying precision parameter in PySSC
- Impact is now too small?



### **Results 3x2pt**

 Largest spread among the 3 codes: issues in the XC term?

	FoM degradation [%]
PySSC	49
PyCCL	41
Spaceborne	26



#### Next Steps and Future prospects

- Better understand PySSC WL mismatch and 3x2pt discrepancy
- Finish building independent PyCCL pipeline
- Finish implementing the cNG term
- Publish code on GitLab
- Migrate to PyCCL v3
- Improve integration routine in the Julia SSC integral (from trapz to simps), to reduce a bit number of steps
- Compare results against simulations!
- run MCMC with NL models in CLOE