

The Dark Energy Survey

Year 6: 3×2 pt analysis



*William d'Assignies (IFAE, PhD, redshift team)
on behalf of the Dark Energy Survey Collaboration*



*Presentation using material from M.
Crocce, G. Bernstein, C. Chang*



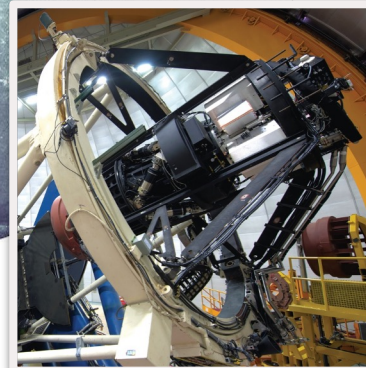
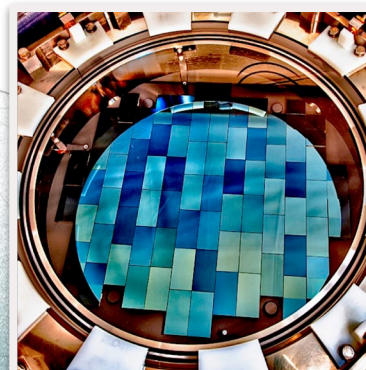
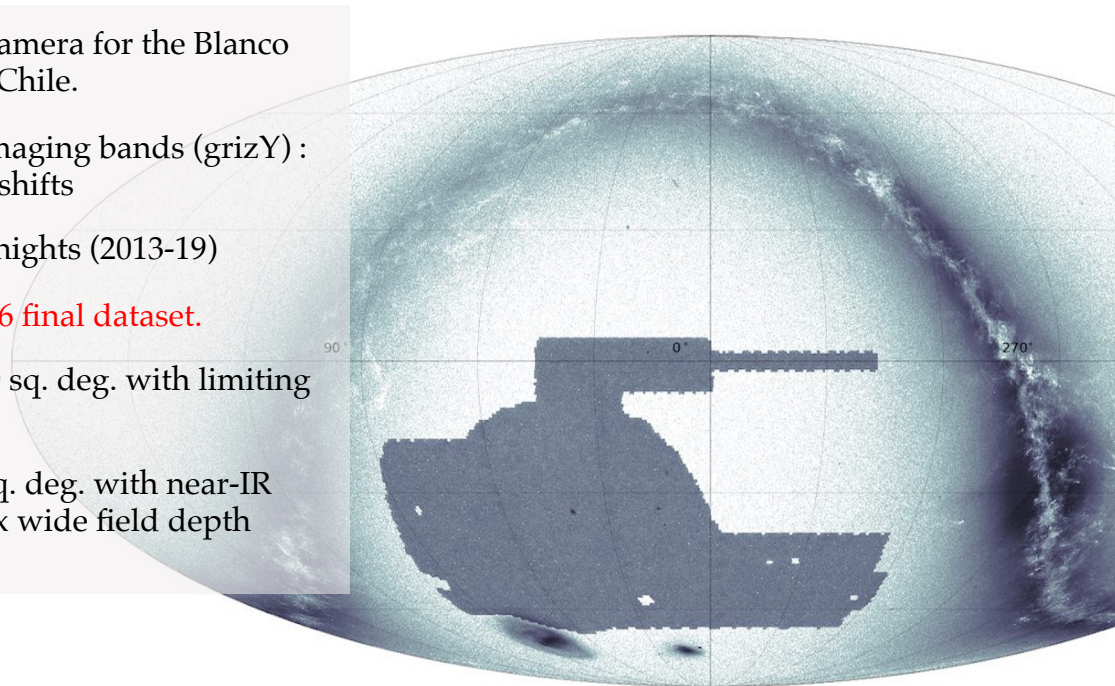
- Intro
 - DES in few numbers
 - 3x2pt analysis
 - 3x2pt results of DES Y3
- DES Y6 :
 - Samples
 - Redshift calibration
 - Modelling
- What's next ?
 - Y6 FOM vs Y3
 - Higher orders analysis

- Intro
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The Dark Energy Survey (DES)



- 570 Megapixel camera for the Blanco 4m telescope in Chile.
- Observed in 5 imaging bands (grizY) : photometric redshifts
- Full survey 758 nights (2013-19)
- **This talk DES Y6 final dataset.**
- **Wide field:** 5000 sq. deg. with limiting depth $i \lesssim 24$
- **Deep field:** 30 sq. deg. with near-IR YJHK bands, 10x wide field depth



- **Weak lensing** (distance, structure growth) shapes of up to **200 millions galaxies**
- **Baryonic acoustic oscillations** (distance) **16 millions red galaxies** to $0.6 < z < 1.2$
- **Galaxy clusters** (distance, structure growth) **~ 20,000 RedMapper clusters** ($z \sim 0.7$) synergies with WL, SZ, Xray
- **Type Ia supernovae** (distance) 30 sq. deg. SN fields : **1650 SNIa** up to $z \sim 1.13$

Robust combination of probes

- shared photometry / footprint
- shared analysis of systematics
- shared galaxy redshift estimates
- consistent blinding strategy

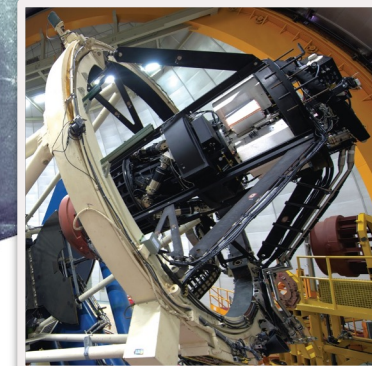
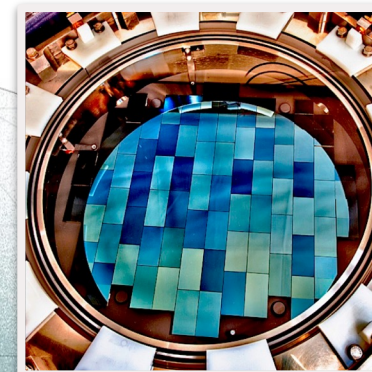
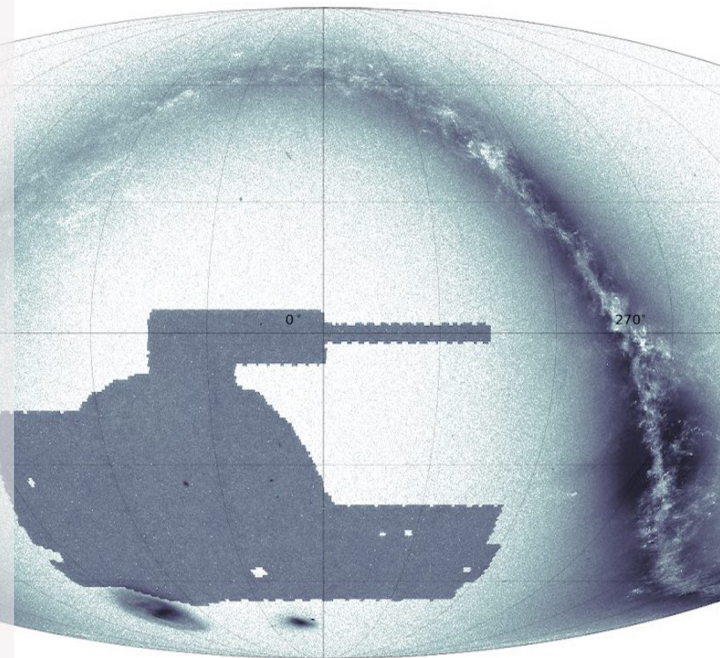
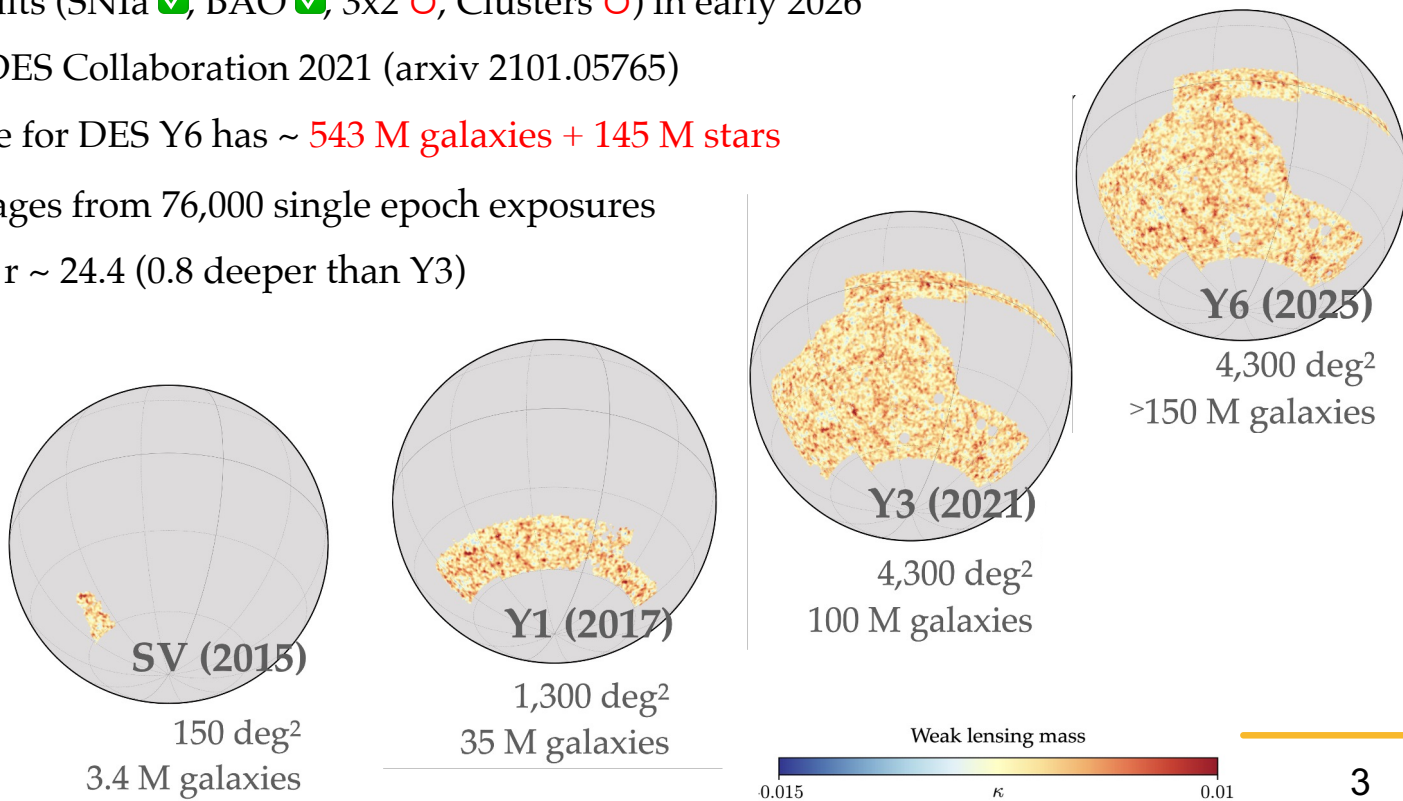


Image Credit: CosmoHub, Port d'Informació Científica (PIC)

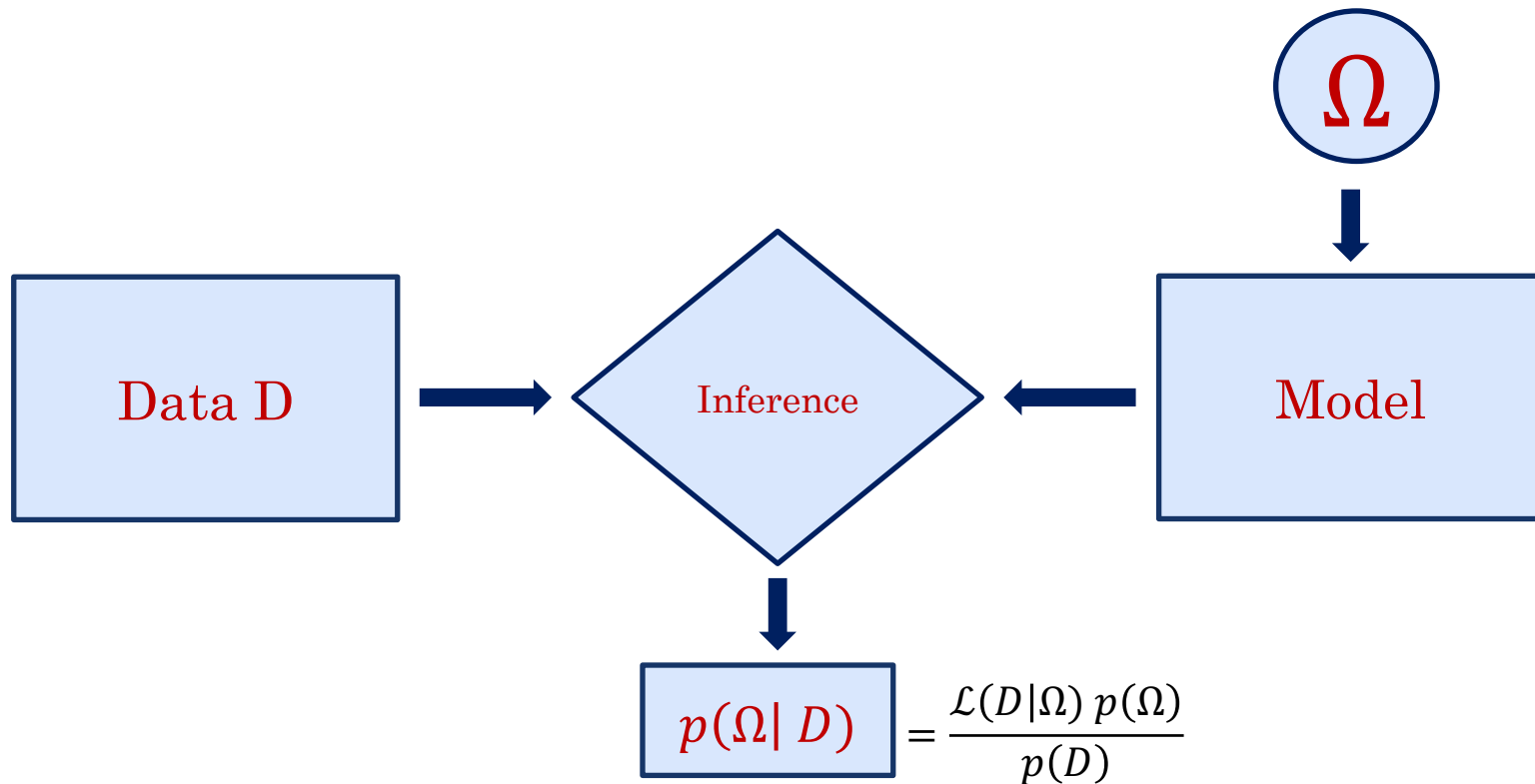
- DESY1 (1300 deg²/2017) to DESY3 (4300 deg²/2020) to DESY6 (4300 deg²/2025)
- DES Y6 science results (SNIa ✓, BAO ✓, 3x2 ⤴, Clusters ⤴) in early 2026
- DR2 final dataset, DES Collaboration 2021 (arxiv 2101.05765)
- DR2 Gold Catalogue for DES Y6 has ~ 543 M galaxies + 145 M stars
- 10,000 co-added images from 76,000 single epoch exposures
- (co-added) lim mag r ~ 24.4 (0.8 deeper than Y3)
- 5000 deg²



- Intro
 - DES in few numbers
 - 3x2pt analysis
 - 3x2pt results of DES Y3

Cosmological inference

$$\Omega = \{\Omega_m, \Omega_b, \Omega_\Lambda, \sigma_8, h, n_s, \sum m_\nu, \dots\}$$



Cosmological inference



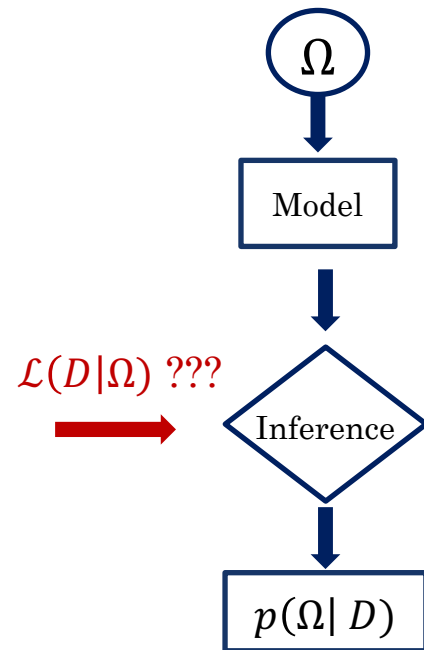
Data D:

Wide: $\sim 80,000$ exposures $\times$ 0.5 Gpix

Deep: $\sim 10,000$ exposures $\times$ 0.5 Gpix

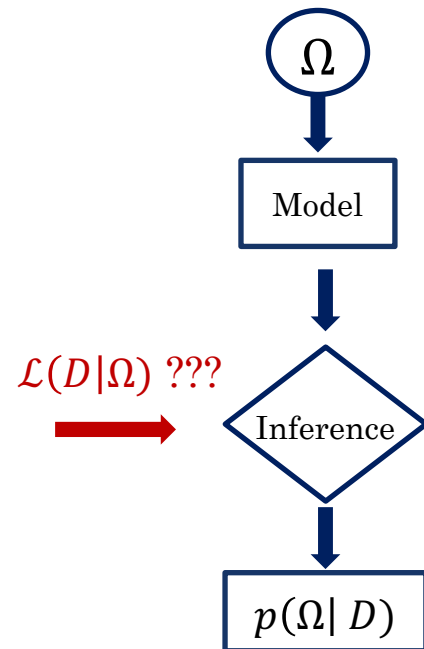
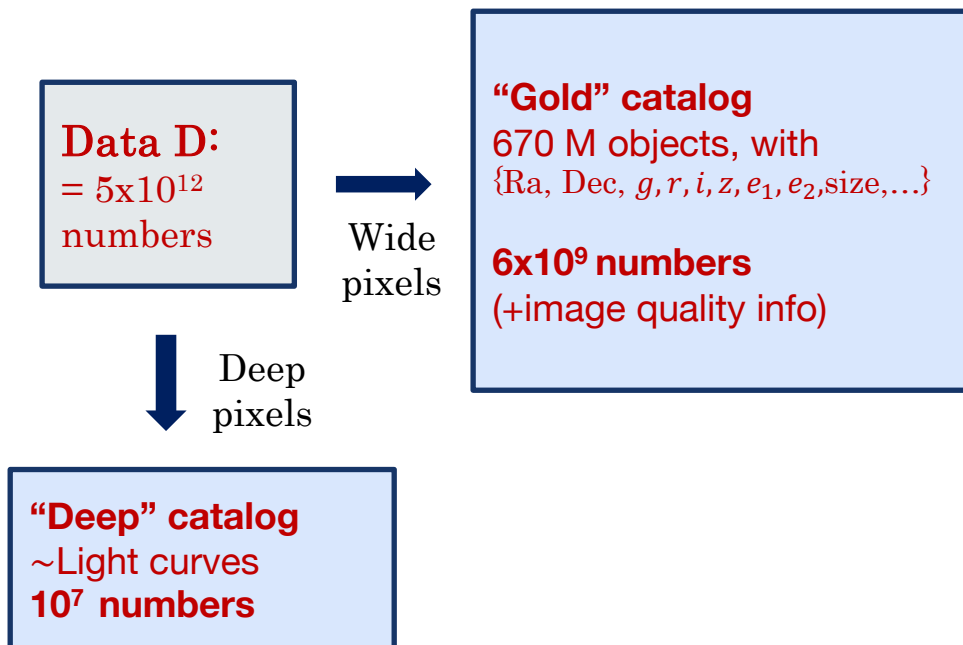
$= 5 \times 10^{12}$ numbers

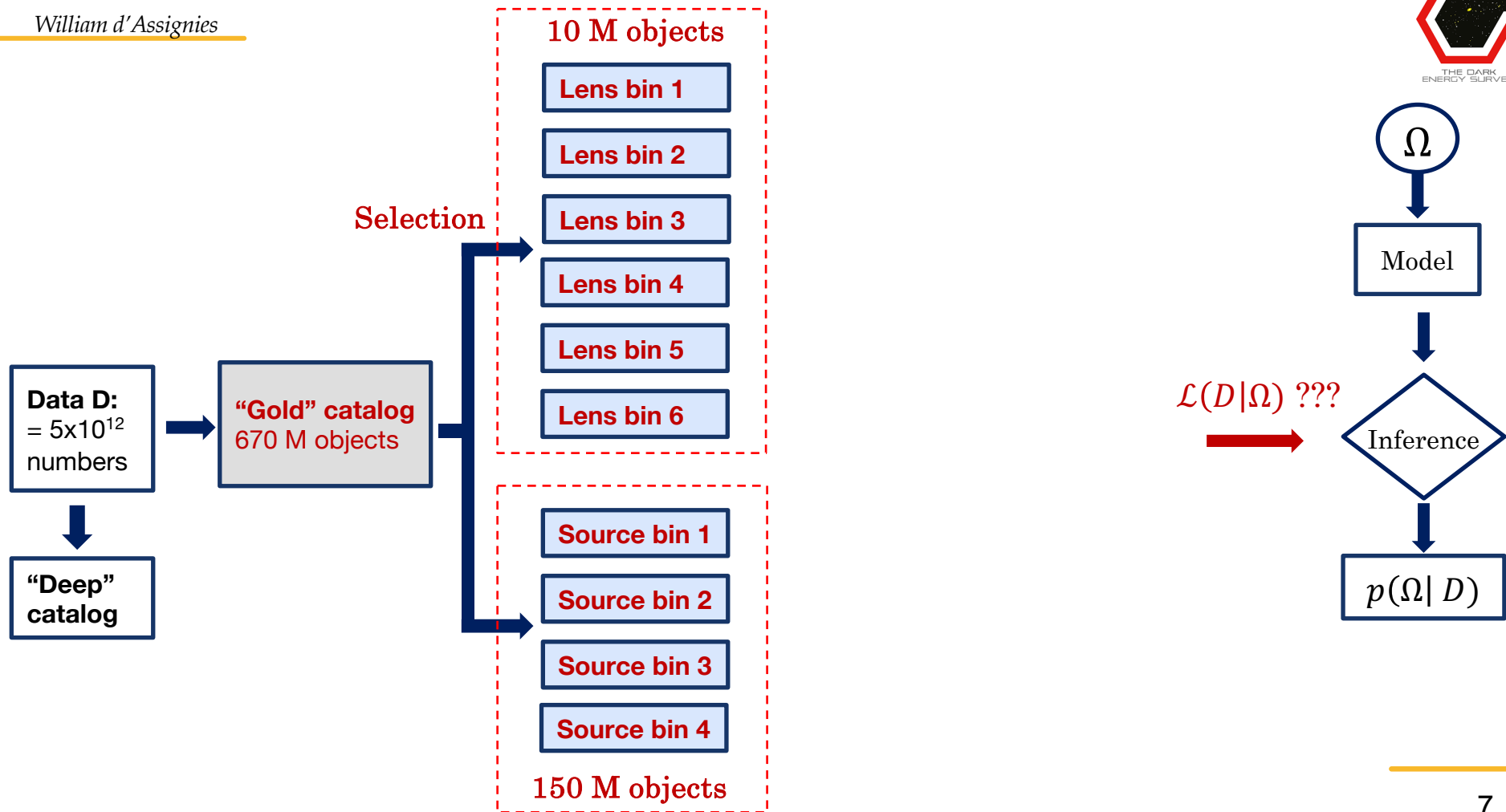
*Glossing over the many steps
in converting raw CCD outputs
into estimates of true sky
intensity in each pixel!*

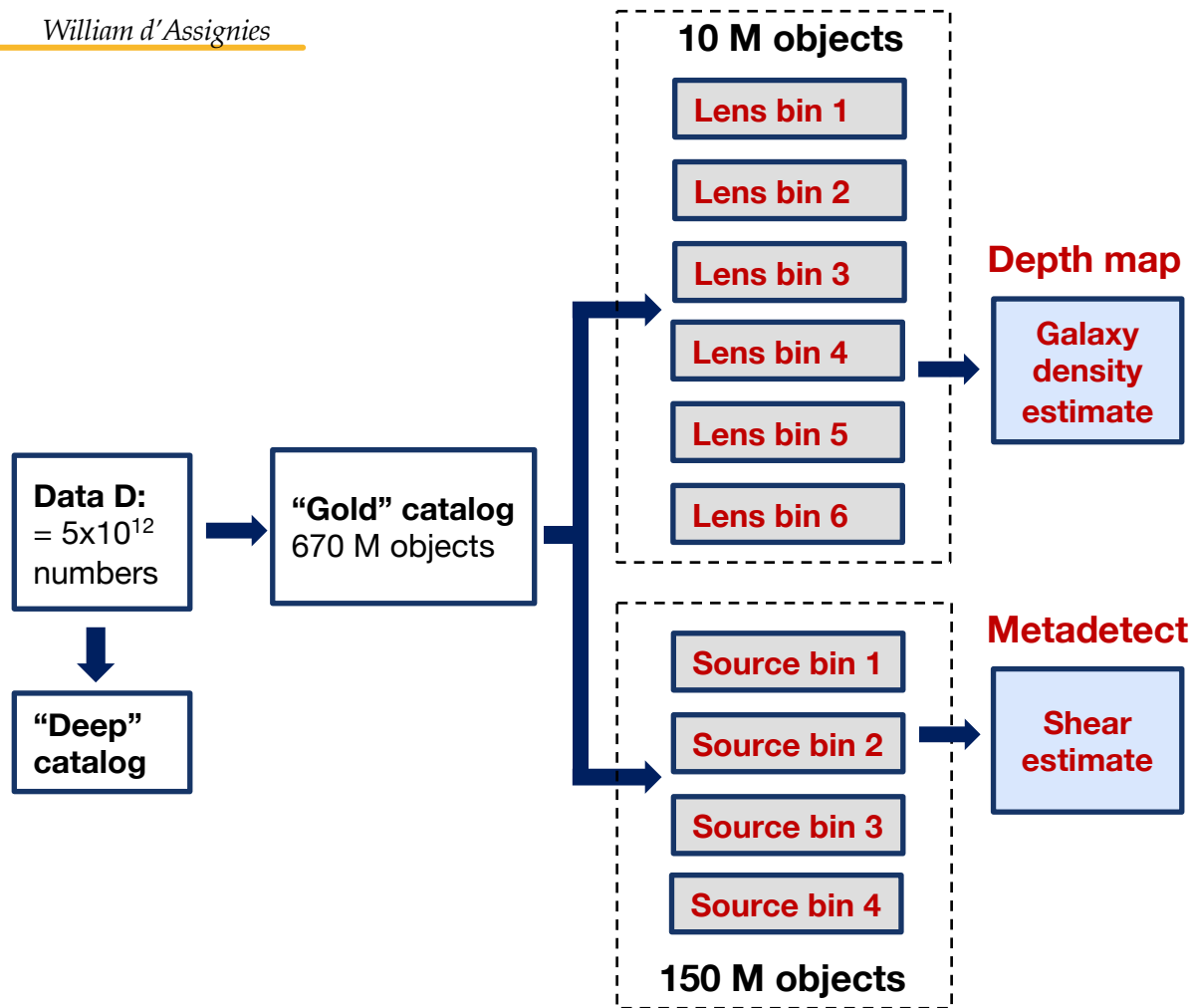


Cosmological inference

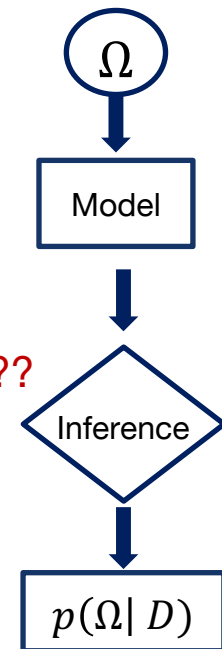
Glossing over more complex steps of object identification, splitting, photometry, shape/size measurement, with complex selection functions.

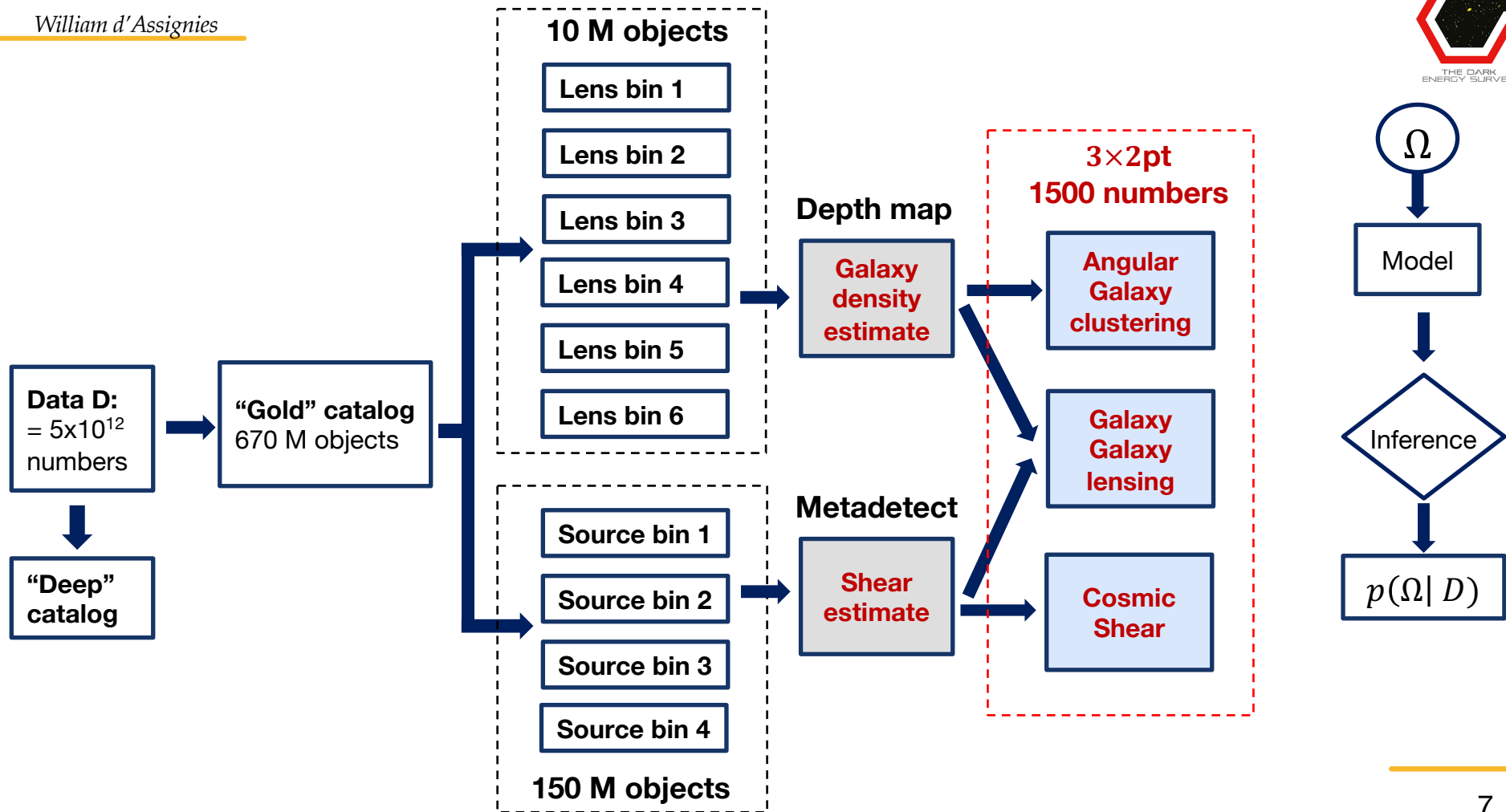


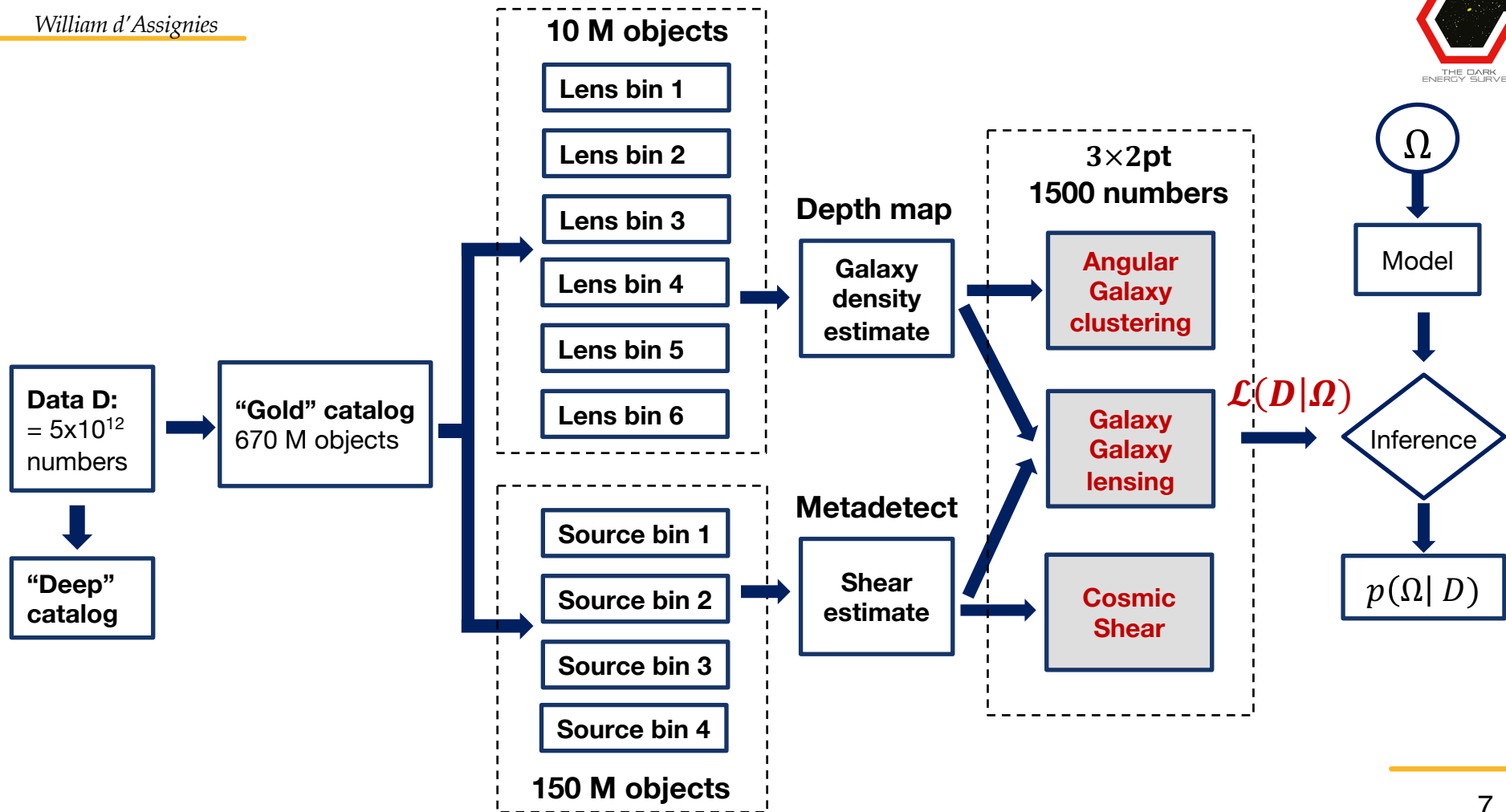




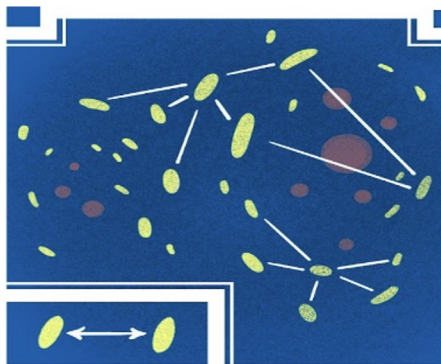
$$\mathcal{L}(D|\Omega) ???$$







3x2 Cosmology

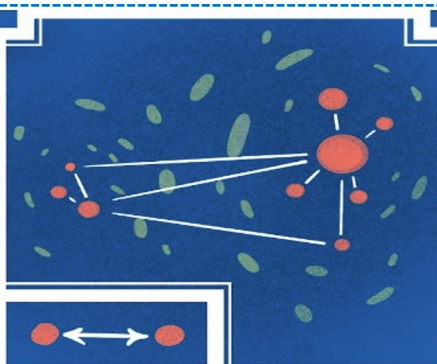


cosmic shear
correlation in the shapes of
(source) galaxies

$$\xi_{\pm} = \langle e_t(\theta') e_t(\theta' + \theta) \rangle - \langle e_x(\theta') e_x(\theta' + \theta) \rangle$$

$$\propto \sigma_8^2$$

1x2pt

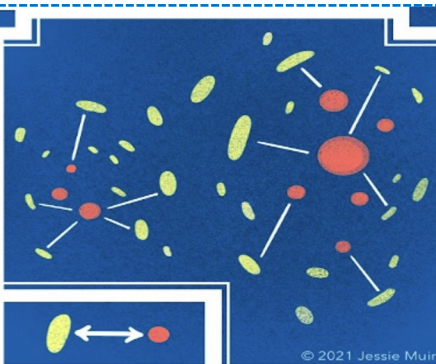


galaxy clustering
correlation in the positions
of (lens) galaxies

$$w(\theta) = \langle \delta(\theta') \delta(\theta' + \theta) \rangle$$

$$\propto b^2 \sigma_8^2$$

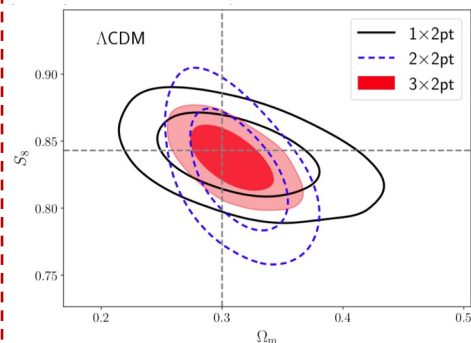
2x2pt



galaxy galaxy lensing
correlation between
positions of the lenses and
shapes of the sources

$$\gamma_t(\theta) = \langle \delta(\theta') e_t(\theta' + \theta) \rangle$$

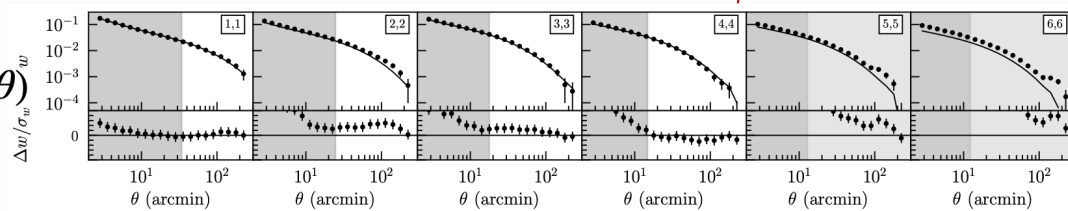
$$\propto b \sigma_8^2$$



3x2pt

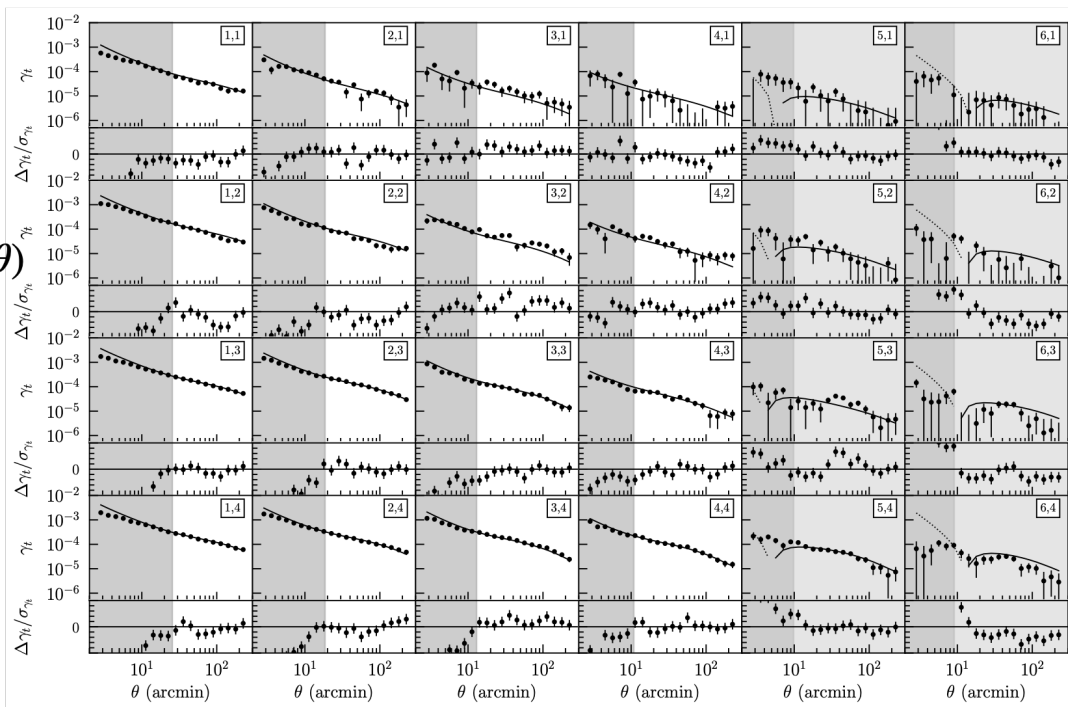
Galaxy clustering

Y3 $w(\theta)$



Galaxy-galaxy lensing

Y3 $\gamma_t(\theta)$

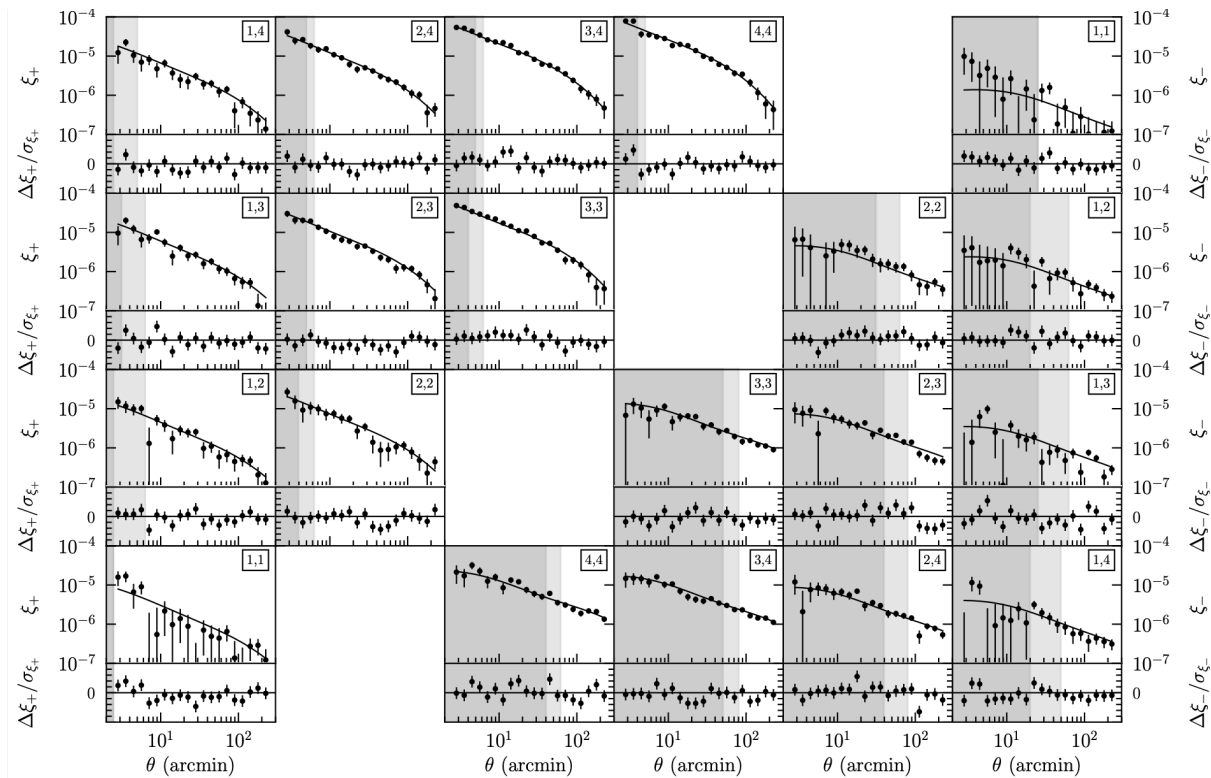


Y3 $\xi_{-}(\theta)$

Scale cuts, removing data

Y3 $\xi_{+}(\theta)$

Cosmic Shear



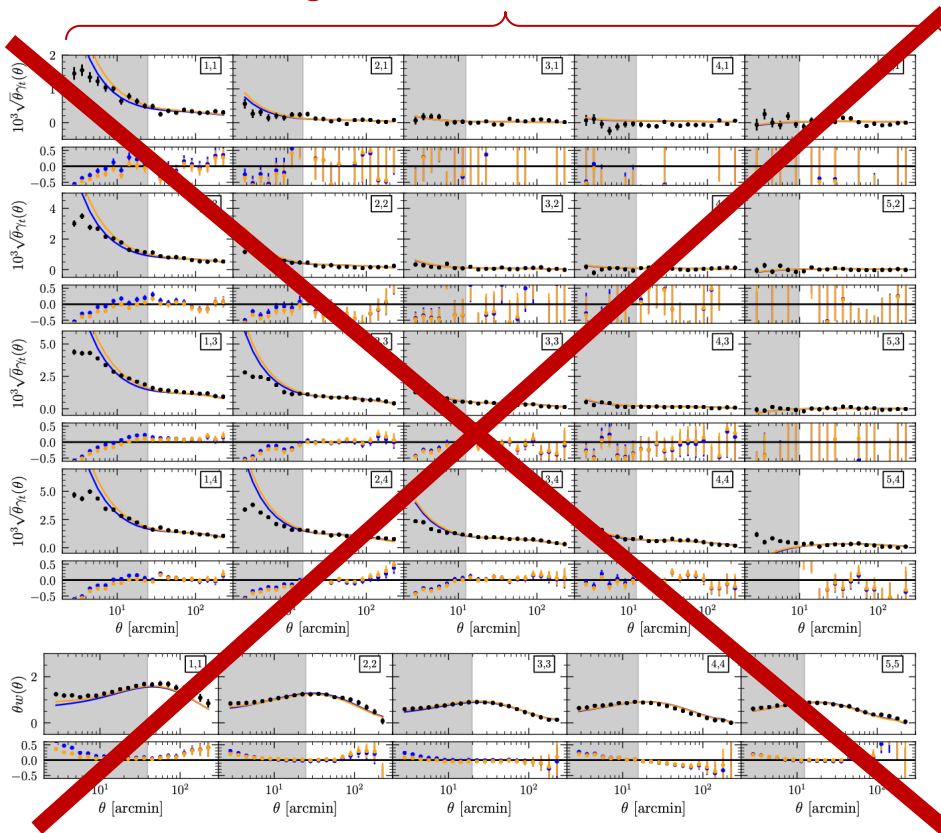
Scale cuts, removing data

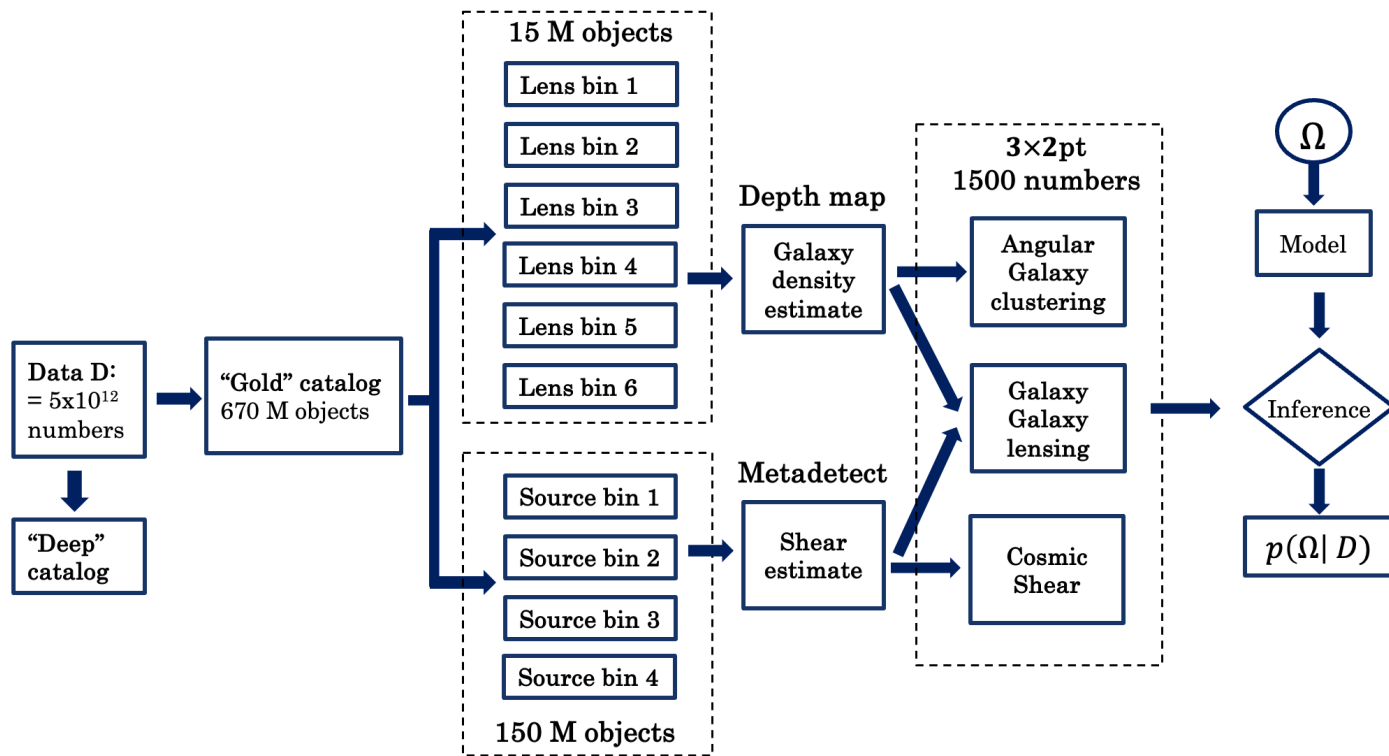
Y3 Redmagic curse

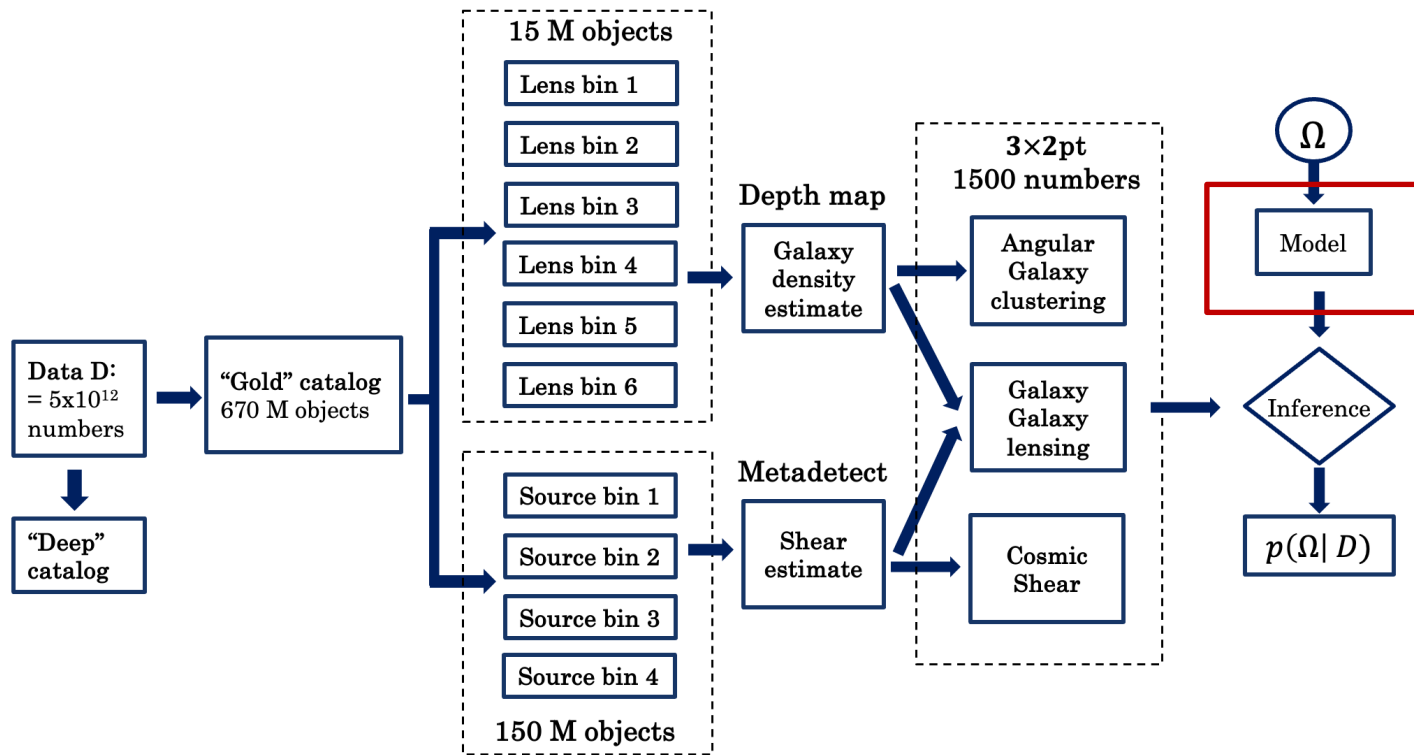
Removing all the data for 5 bins

Galaxy clustering

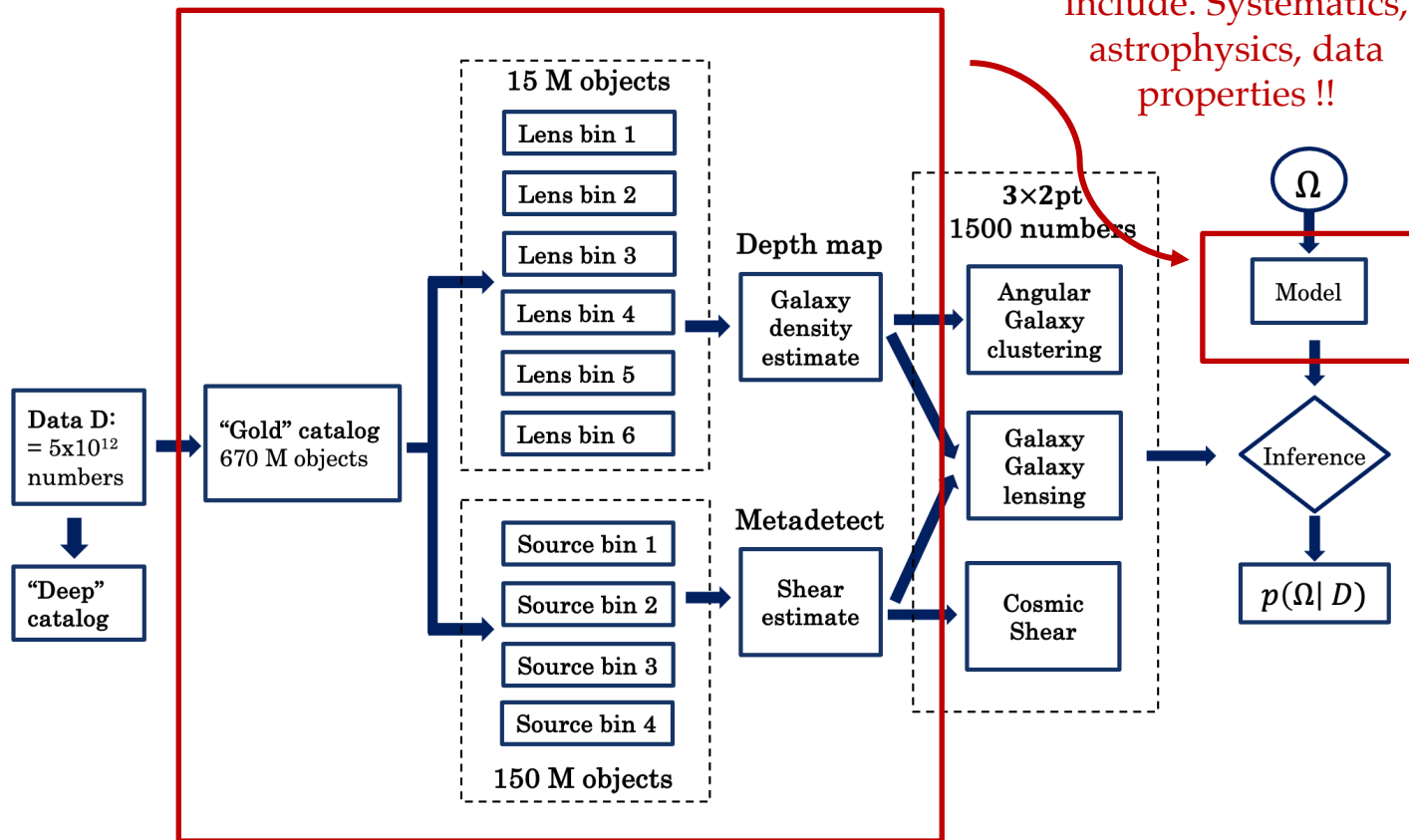
Galaxy-galaxy
lensing







We need a model
for the data $\bar{D}$ and
 $\text{cov}(\bar{D})$

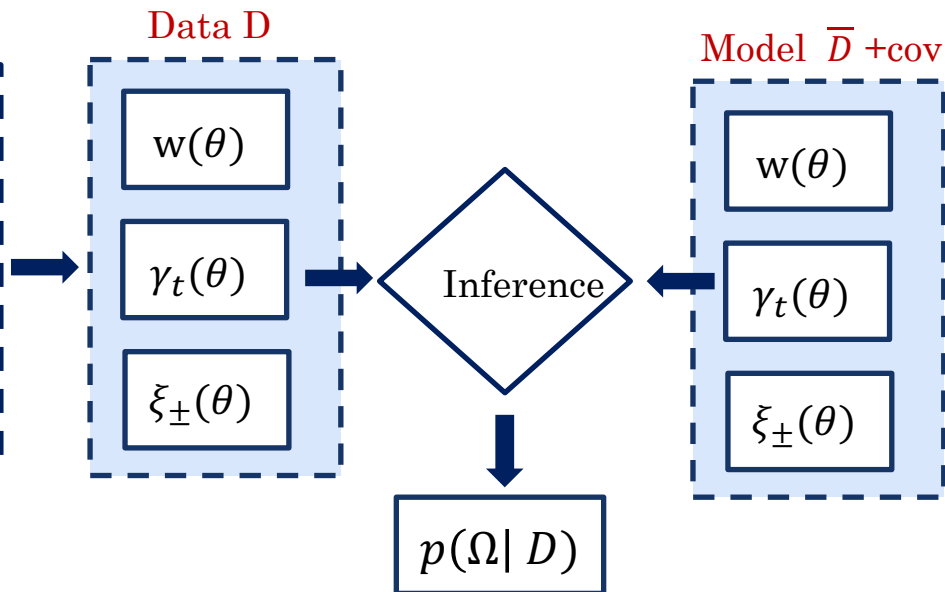
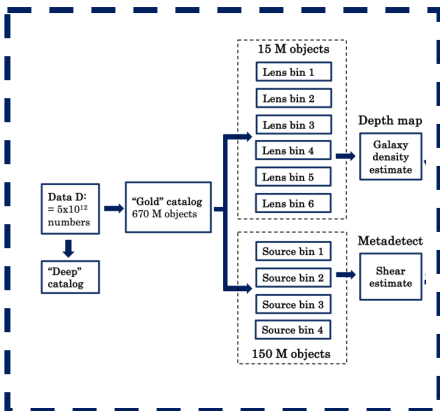


Selection steps have to be include. Systematics, astrophysics, data properties !!

We need a model for the data $\bar{D}$ and $\text{cov}(\bar{D})$

3x2pt inference

$$\Omega = \{\Omega_m, \Omega_b, \Omega_\Lambda, \sigma_8, h, n_s, \Sigma m_v, \dots\}$$

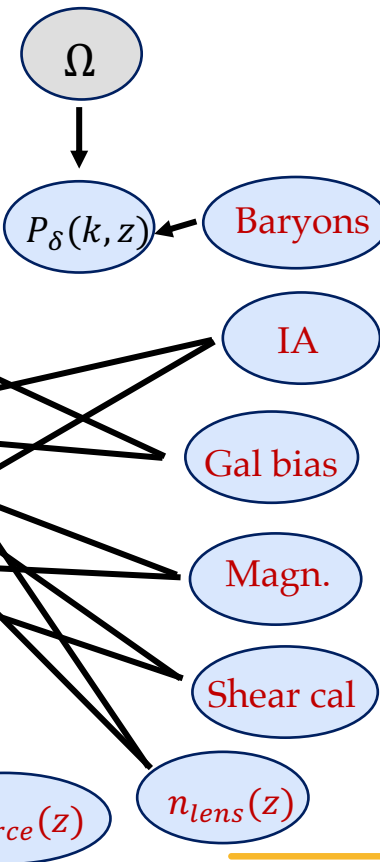
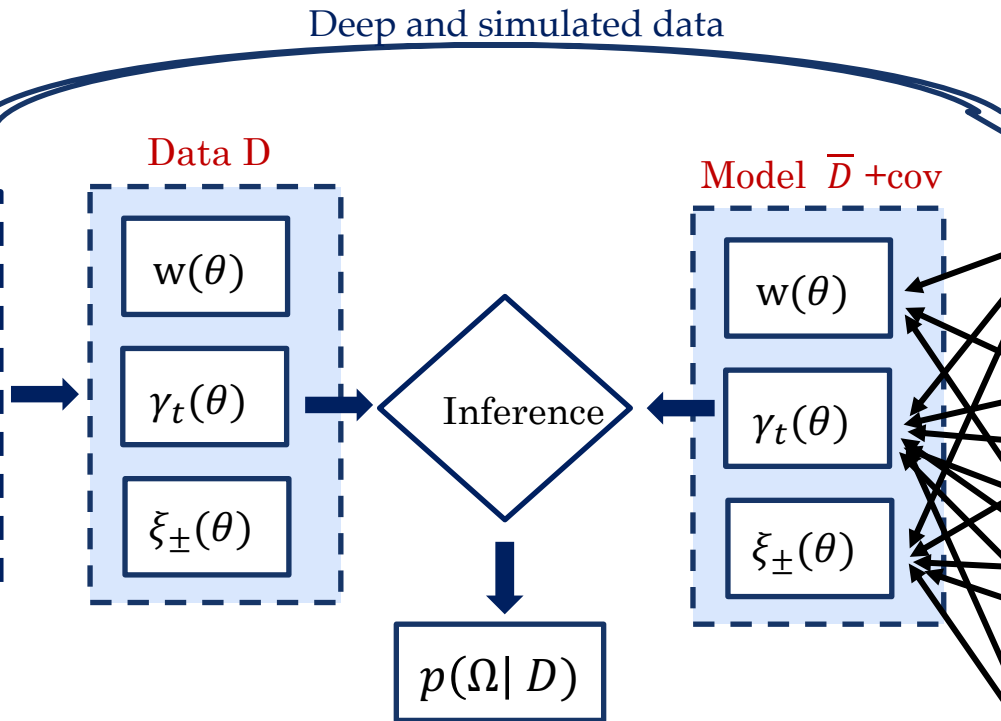
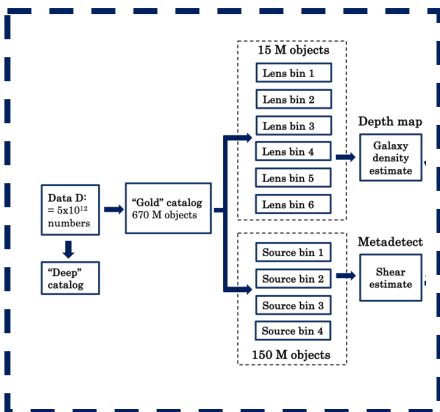

 Ω
Images $\rightarrow$ Catalogues

3x2pt inference

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Deep and simulated data

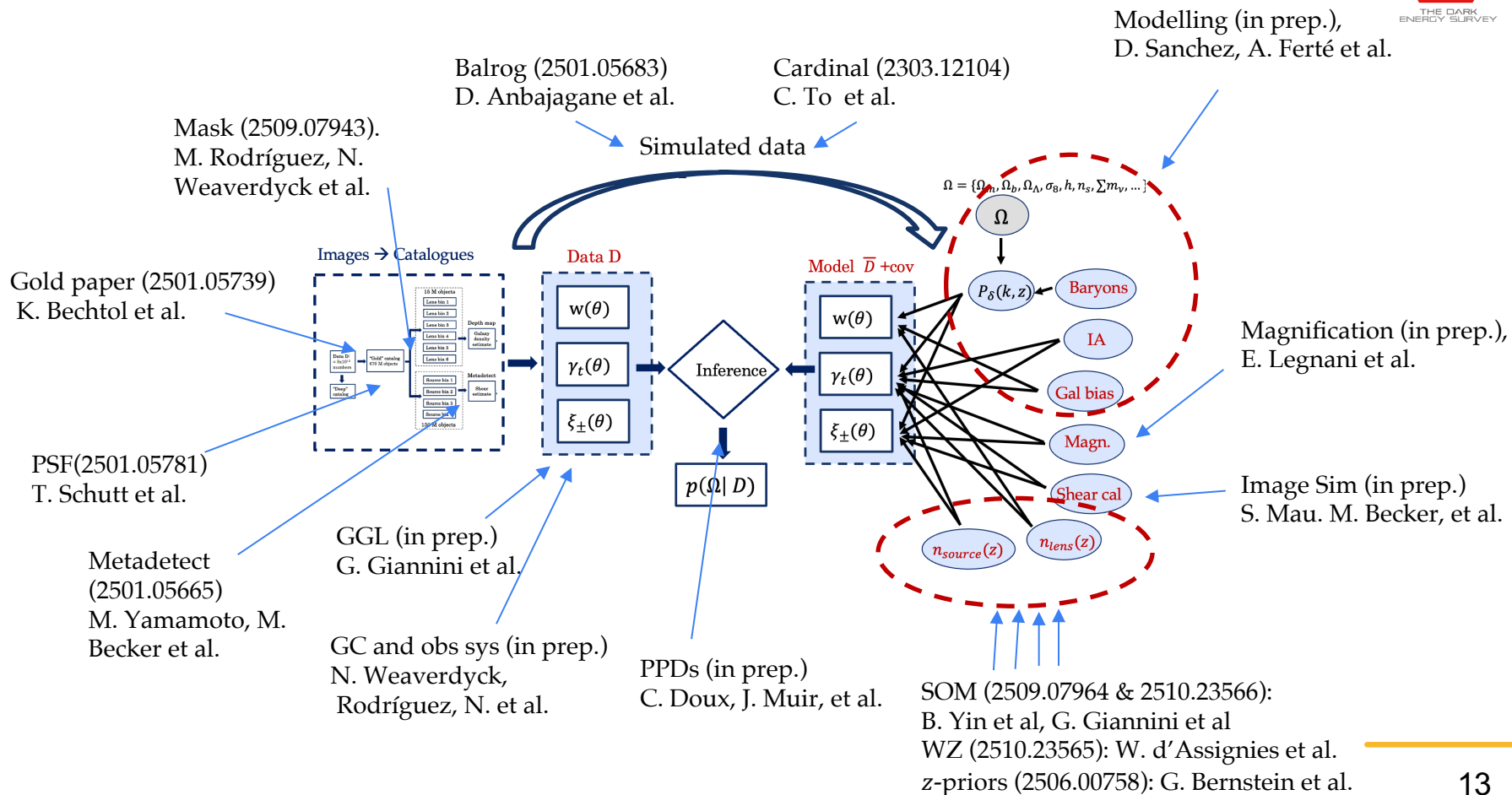
Images $\rightarrow$ Catalogues



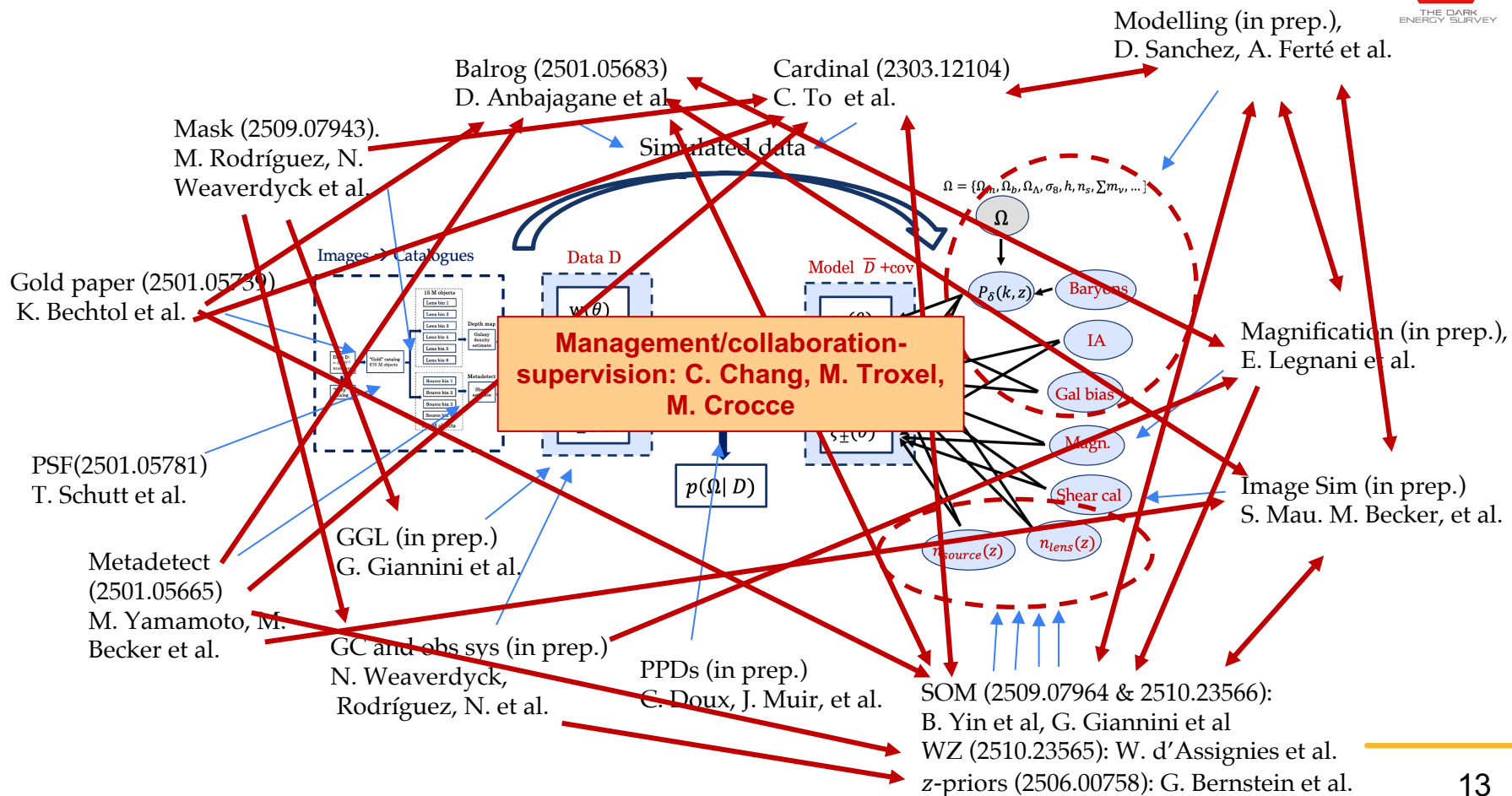
$$\mathcal{L}(D|\Omega) = \mathcal{N}(D|\bar{D}, \text{Cov})$$

Bonus questions: -is the distribution normal ?
-Does the cov depends on Ω & sys parameters

3x2pt 'pre-unblinding' papers



3x2pt 'pre-unblinding' papers



DES Y3 3x2pt results

DES Collab(2021)arxiv 2105.13549

$$S_8 = 0.776^{+0.017}_{-0.017} \quad (0.776)$$

$$\text{In } \Lambda\text{CDM: } \Omega_m = 0.339^{+0.032}_{-0.031} \quad (0.372)$$

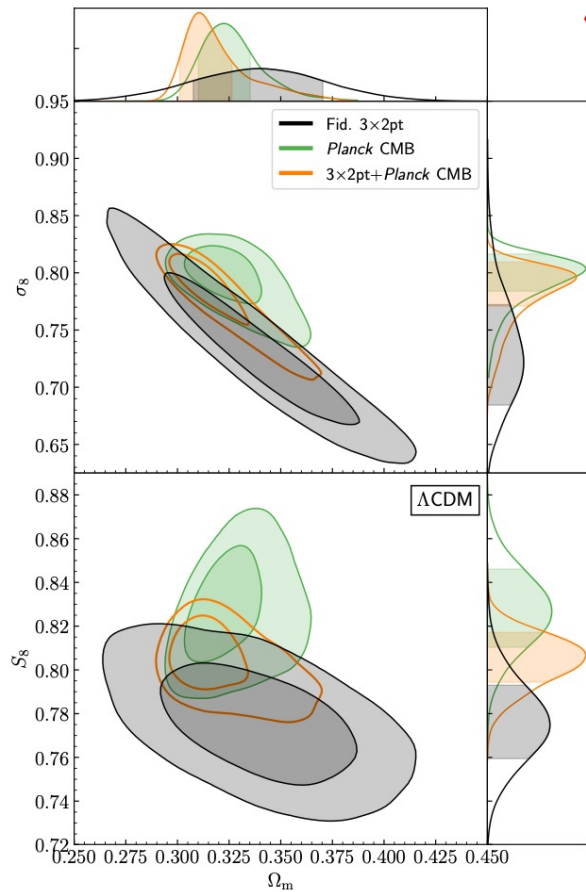
$$\sigma_8 = 0.733^{+0.039}_{-0.049} \quad (0.696)$$

$$\text{In } w\text{CDM: } \Omega_m = 0.352^{+0.035}_{-0.041} \quad (0.339)$$

$$w = -0.98^{+0.32}_{-0.20} \quad (-1.03)$$

DESY3 3x2 in agreement with Planck $< 2\sigma$

Still competitive (e.g. same S_8 constraint as KiDS Legacy arxiv 2503.19441 shear-only)



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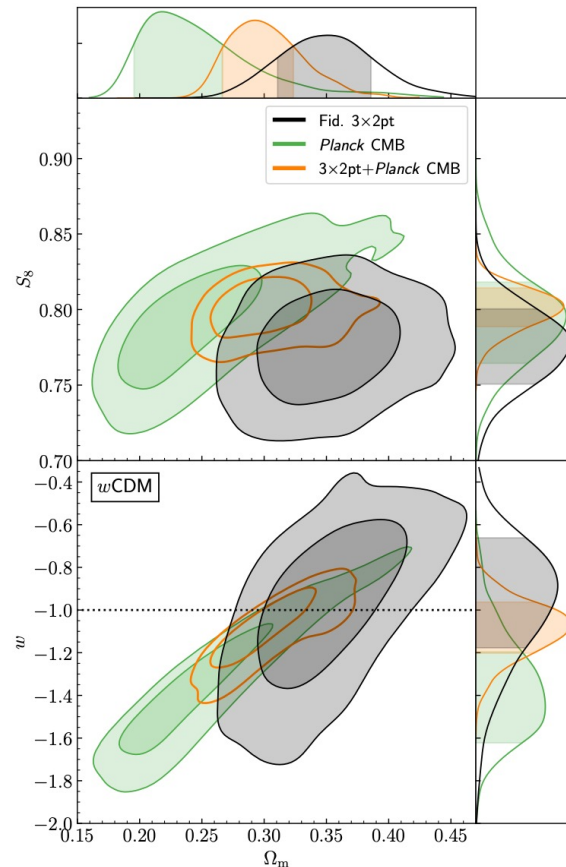
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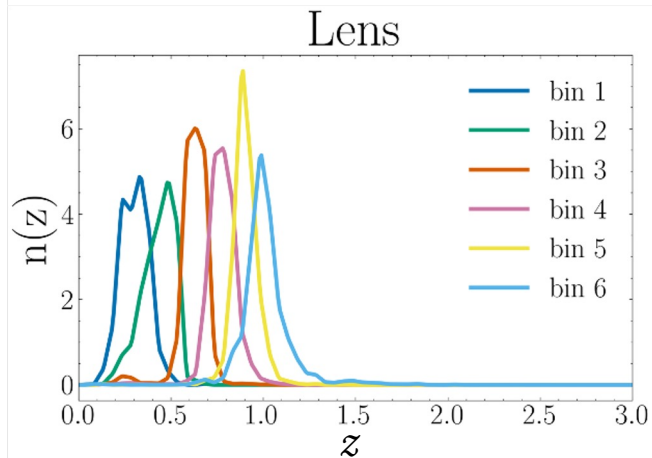
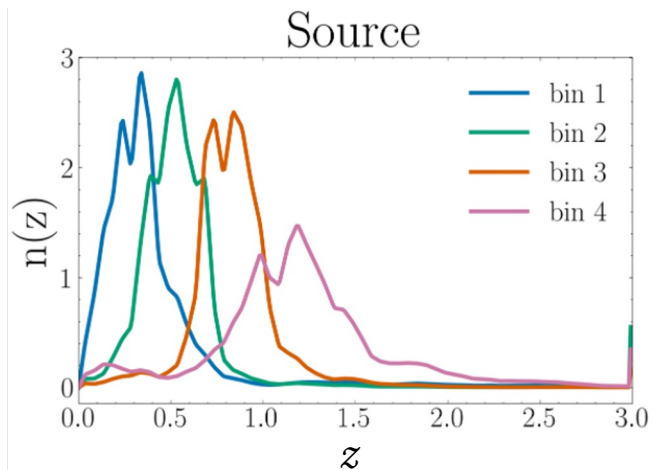
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 - Samples and their properties
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Samples



source sample = Metadetection (Yamamoto, Becker et al.)

- ~ 150 million galaxies
- $n_{\text{eff}} = 8 \text{ gals / arcmin}^2$ and $\sigma_e = 0.272$
- Reduced shear bias (e.g. in blended objects).
- **50% more sources than Y3.**

lens sample = MagLim ++ (Weaverdyck, Rodriguez et al.)

- 10 million galaxies with mag cut : $i < 4 z_{\text{photo}} + 18$
- Selected by optimizing the w CDM constraints by balancing density and photo-z.

→ **Both selections are being used in Stage IV**

lens sample 2 = broad redmax^2

Twice more galaxies, a bit worse photo-z than Y3

source sample 2 = BFD [bayesian fourier domain

200 million shapes a bit worse shape noise than metadetect

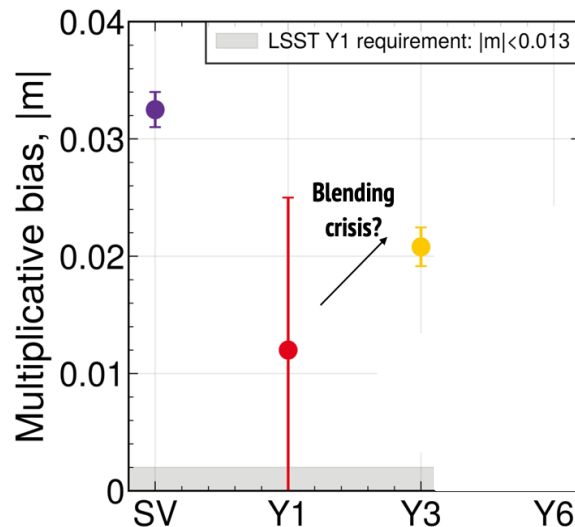
[BFD → Bernstein and Armstrong 2014]

- We have access to apparent ellipticities, but we are interested in the shear.

$$\mathbf{e} = \mathbf{e}|_{\gamma=0} + \left. \frac{\partial \mathbf{e}}{\partial \gamma} \right|_{\gamma=0} \gamma + \dots$$

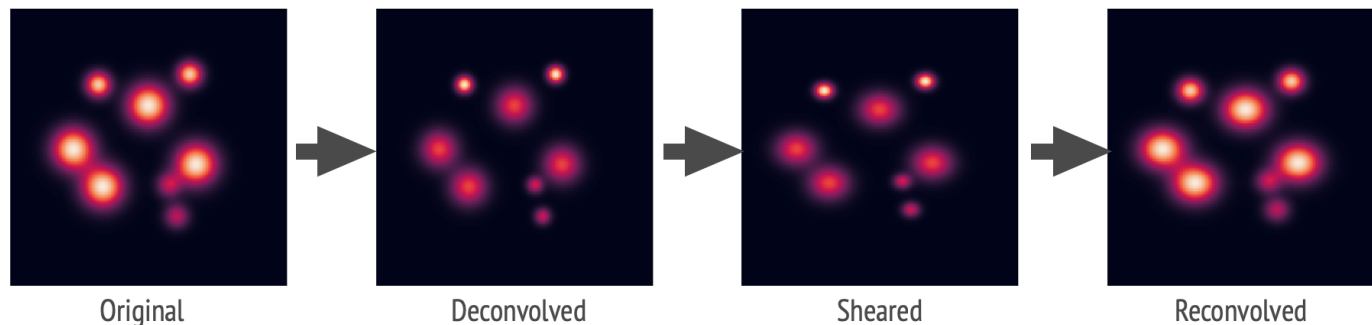
Shear response

$$\mathbf{R} \equiv \left. \frac{\partial \mathbf{e}}{\partial \gamma} \right|_{\gamma=0} = \begin{pmatrix} \partial e_1 / \partial \gamma_1 & \partial e_2 / \partial \gamma_1 \\ \partial e_1 / \partial \gamma_2 & \partial e_2 / \partial \gamma_2 \end{pmatrix}$$



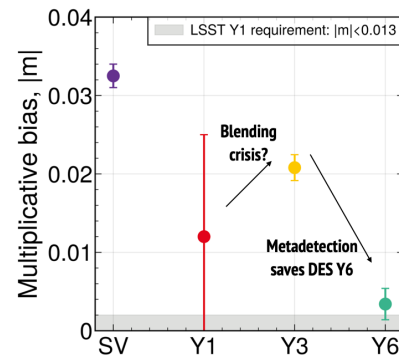
- We want an unbiased shear estimate.
- Shear biases c and m should be close to 0 : $\gamma_{obs} = (1 + m)\gamma_{true} + c$

Metadetect: A technic to self-calibrate raw galaxy shape measurements that contain noise bias, model bias, and selection bias by artificially process the image and calculating the shear response R



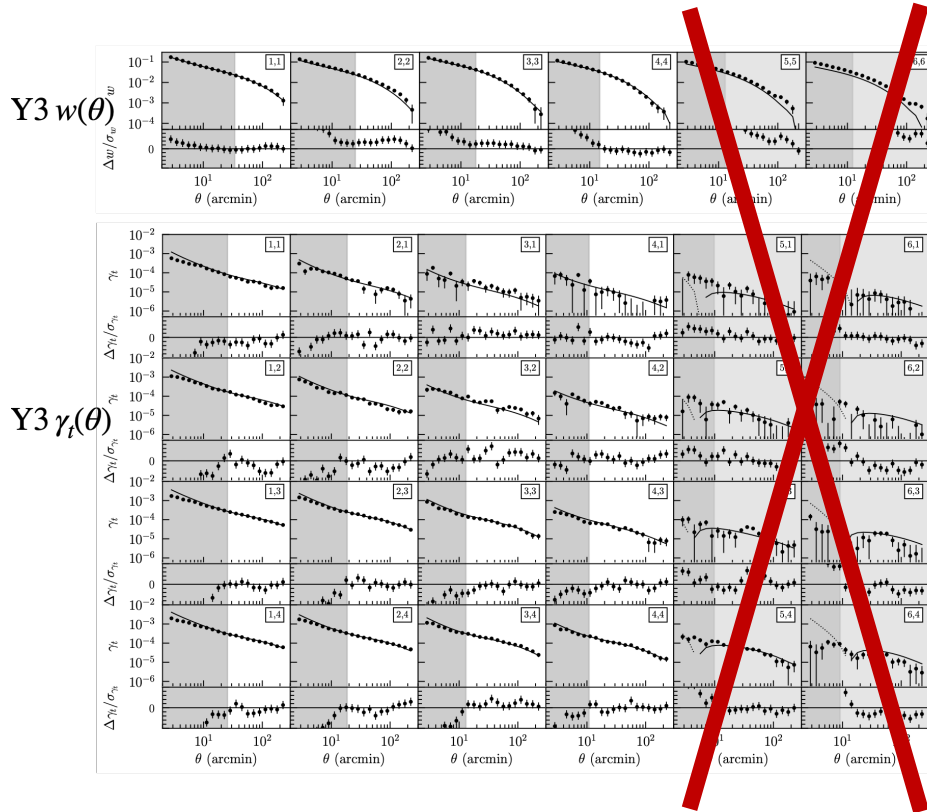
Improvements :

- Addition of chromatic PSF allows us to use g-band flux for photo-z, and reduce shear bias. (*T. Schutt et al.*)
- Improvement to Metadetect improves multiplicative shear bias
- Multiplicative bias from im-sim + accounting for the impact on $n(z)$ s (*S. Mau et al., in prep.*)



Maglim++

- In Y3, we had to remove 2 bins from the analysis because of systematics contamination, internal inconsistencies



Maglim++

- (i) mag-lim sample, 10 M galaxies into 6 (photo-z) bins:
- Improve purity and reduce systematics wrt Y3 Maglim

$$i < 4 \times z_{\text{DNF}} + 18, \quad i > 17.5$$

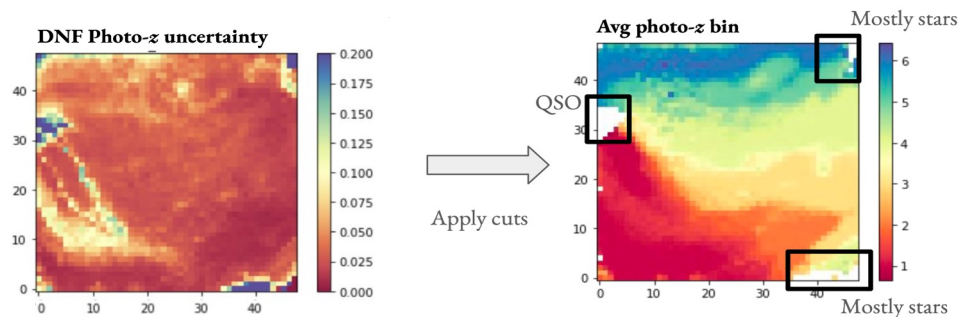
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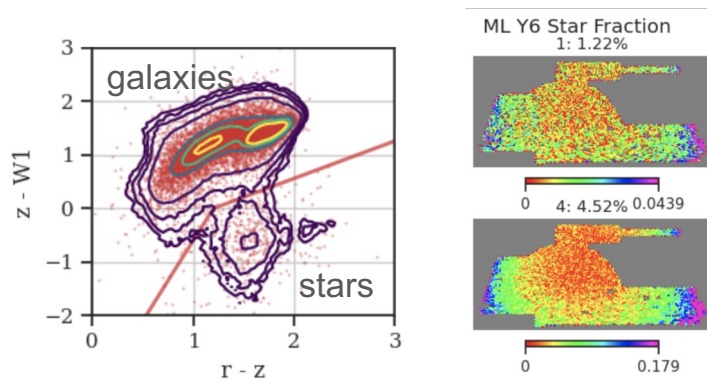
Photo-z quality cuts

- Use SOM to group galaxies, identify and remove colors with *bad photo-zs*



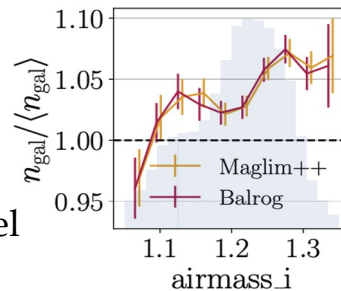
Improved star-galaxy separation

- (Bin) optimized cuts in the $(r - z, z - W_1)$ color space to isolate and remove stars
- Uses W_1 , a NIR magnitude (unWISE catalog)



- **BALROG** (*D. Anbajagane et al. 2501.05683*)

- Synthetic source injection of sources (from deep fields) into pixel-level wide field images
- 146 million injections spanning the entire 5000 deg² DES footprint !
- Generate co-added images, detection catalogues, metadetector catalogues, maglim, etc
- Critical to map deep-to-wide survey, lens magnification, star/gal separation, systematics



- **IMAGE SIMS** (*S. Mau et al.*)

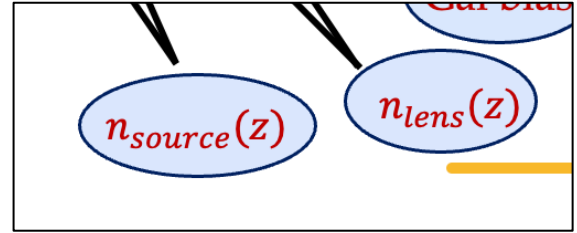
- Injecting galaxy stamps in DES configuration images with known shear, 1/10th of survey
- Apply the same shear measurements and image co-addition (+mask) as real data
- Calibrate multiplicative shear bias and effective redshifts distributions (e.g. in the presence of blending)

- **CARDINAL** (*Chun-Hao To et al, arxiv 2303.12104*)

- N-body simulation + Update SHAM catalogue to $i < 27$. Characterize bias and clustering

- DES Y6 :
 - Samples
 - **Redshift calibration**
 - Modelling

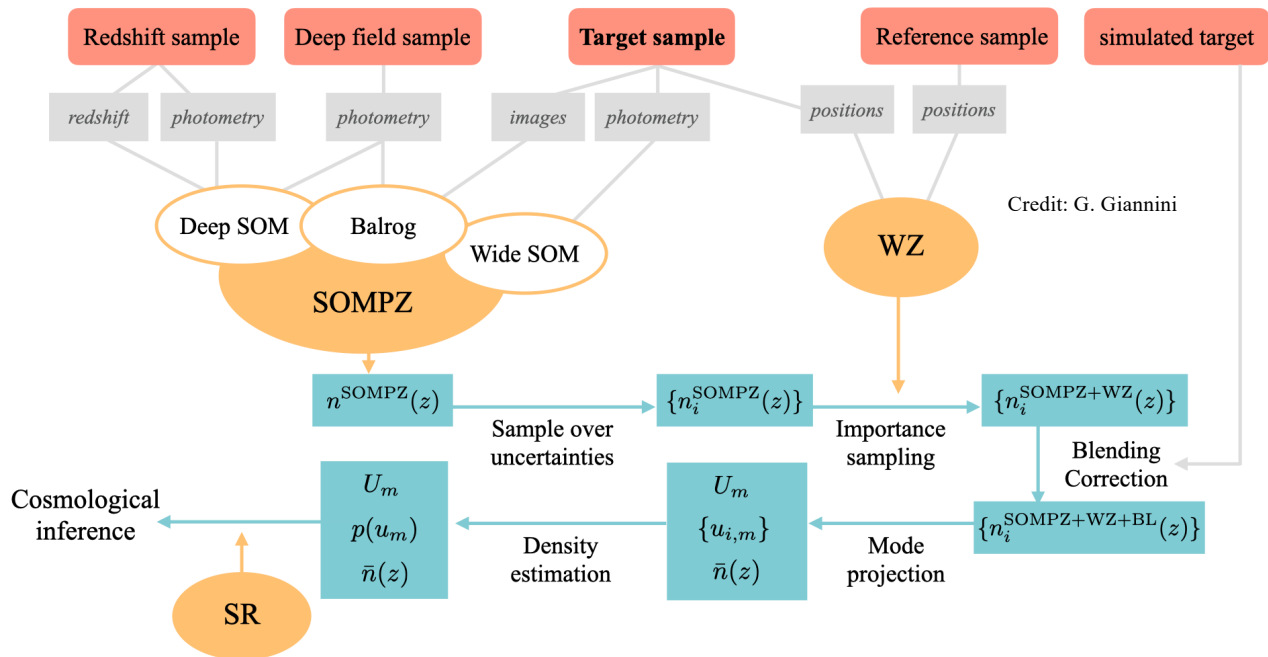
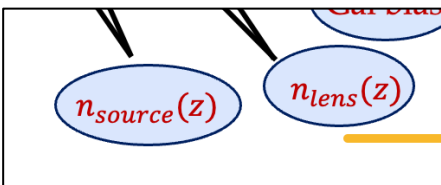
*Do you remember
these guys ?*



DES redshift calibration pipeline:



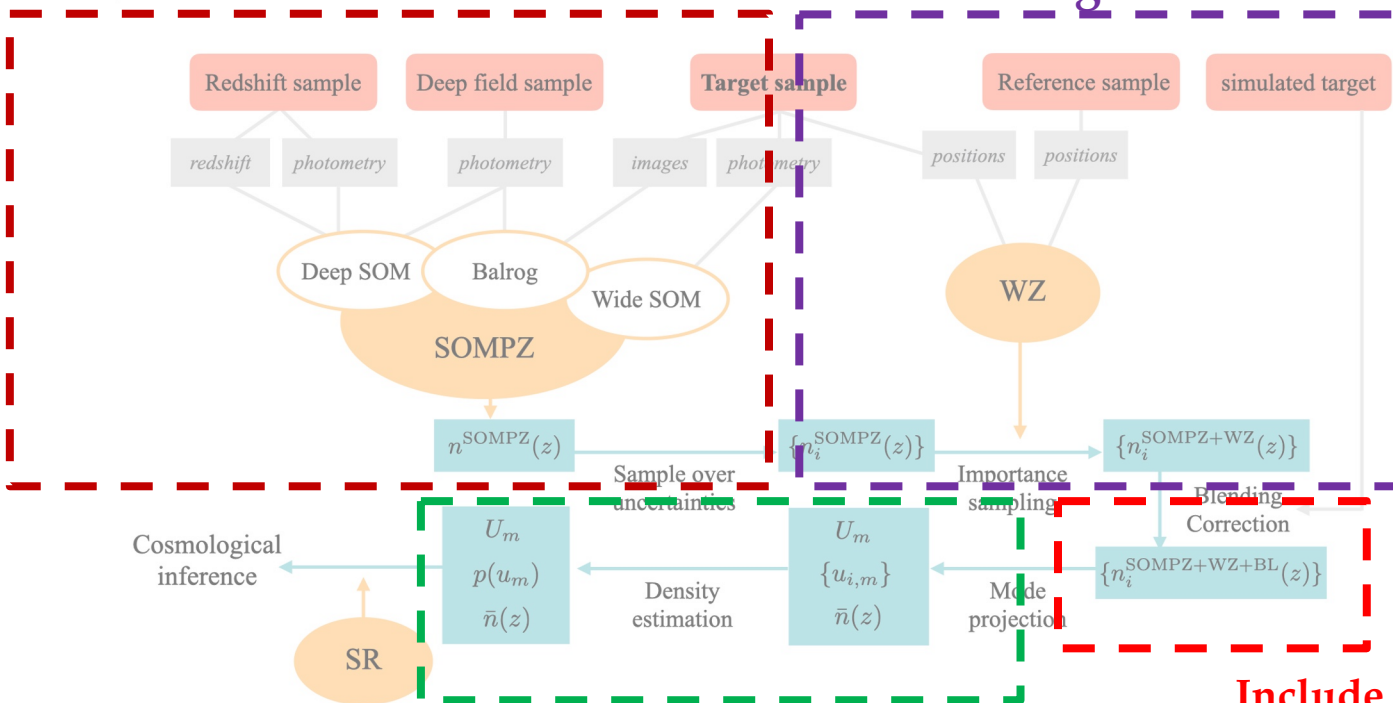
Do you remember
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DES redshift calibration pipeline:

Self-Organised-Maps, photometry

Adding WZ: clustering



Credit: G. Giannini

Include effect of
blending on redshift

Parametrisation of
uncertainties for the inference

Self-Organised-Maps



(Yin et al. Giannini, Alarcon et al.)

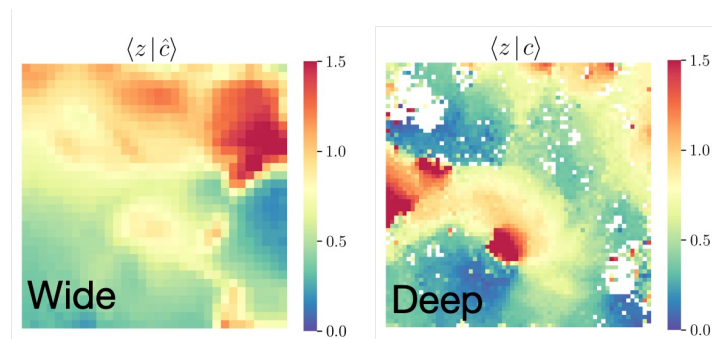
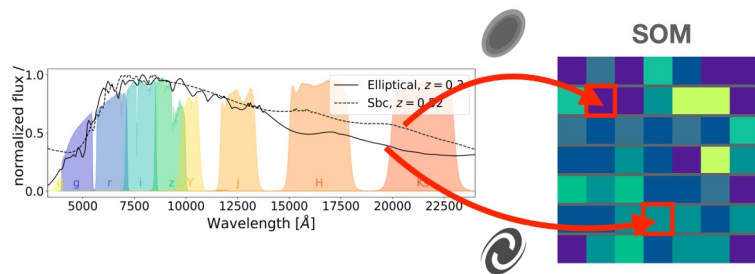
- Wide-survey galaxies live in the *griz* space (we call it $\hat{c}$).
- A tomographic bin b is a region of $\hat{c}$ space.
- We want to know their distribution $p(z | b)$
- Key concept: introduce latent *ugrizJHK* space c , the deep som, then:

Redshift distribution of a bin

Redshift info on the deep

How deep would look like in the wide

$$p(z|b) = \sum_{c, \hat{c}} \underbrace{p(z|c, \hat{c})}_{\text{Redshift}} \underbrace{p(c|\hat{c})}_{\text{Deep-Balrog}} \underbrace{p(\hat{c}|b)}_{\text{Wide}}.$$



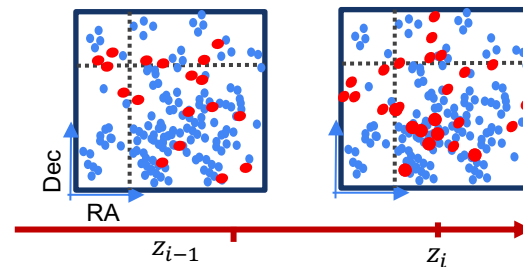
@B. Yin

Clustering redshifts (Wz or Cz)



(d'Assignies, Bernstein et al.)

- A **photometric galaxy sample** is spread over a large redshift range
- Idea : Correlate it with **many spectroscopic samples** at different z , compare random expectation



Cross-correlation spec-photo

What we want

Photo galaxy bias

What we know

Magnification

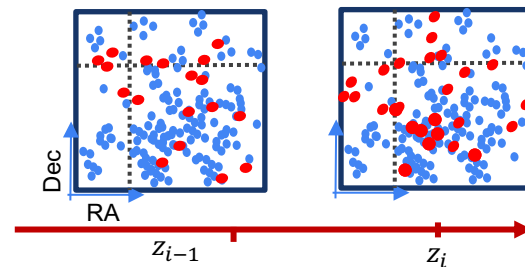
$$w_{\text{sp}}(\theta) = \int dz n_s(z) n_p(z) b_p(z) b_s(z) w_m(z, \theta) + w_{\text{sp}}^\mu(\theta)$$

Clustering redshifts (Wz or Cz)



(d'Assignies, Bernstein et al.)

- A **photometric galaxy sample** is spread over a large redshift range
- Idea : Correlate it with **many spectroscopic samples** at different $-z$, compare random expectation



Cross-correlation spec-photo

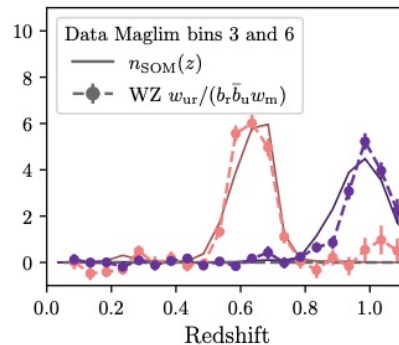
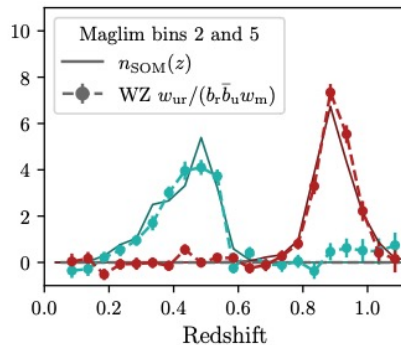
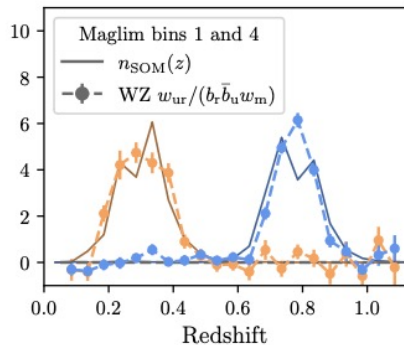
What we want

Photo galaxy bias

What we know

Magnification

$$w_{\text{sp}}(\theta) = \int dz n_s(z) \underbrace{n_p(z)}_{\text{What we want}} b_p(z) b_s(z) w_m(z, \theta) + w_{\text{sp}}^\mu(\theta)$$



Combining WZ with SOM



(d'Assignies, Bernstein et al.)

Proba of a proposed $\mathbf{n}(z)$ s given our photometry and clustering z

Proba clustering- z given $\mathbf{n}(z)$ s (previous slide)

Proba of $\mathbf{n}(z)$ s given our photometry (3sDir)

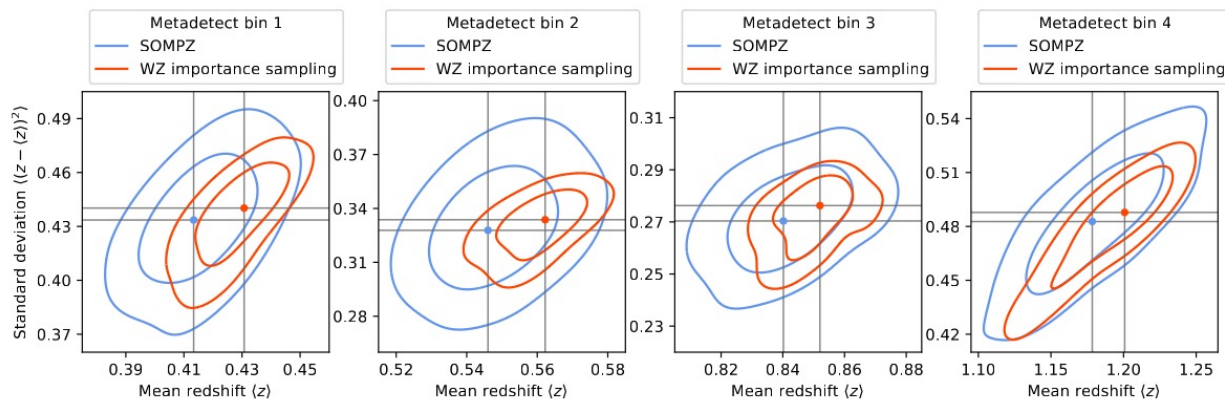
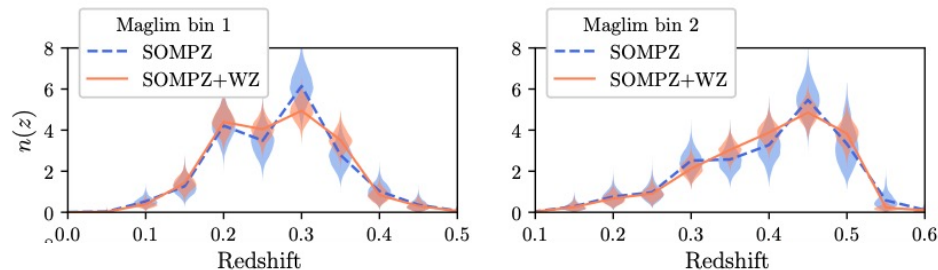
$$p(\mathbf{n}|\mathbf{PZ}, \mathbf{WZ}) \propto p(\mathbf{WZ}|\mathbf{n}) p(\mathbf{n}|\mathbf{PZ})$$

- Both probability on the right, analytical models, with explicit systematics marginalisation
- We start from 100M $\mathbf{n}(z)$ s candidates from 3sDir, all equi-prob.
- We select 1000 of them, with proba $p(\mathbf{WZ}|\mathbf{n})$
- The resulting sample $\sim p(\mathbf{n}|\mathbf{PZ}, \mathbf{WZ})$

Combining WZ with SOM

(*d'Assignies, Bernstein et al.*)

- The procedure ‘produces’ a smoothing of the $n(z)$ (Right for lenses)
- It reduces uncertainties on the mean- z and std- z (bottom)



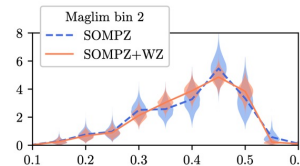
- DES Y6 :
 - Samples
 - Redshift calibration
 - **Modelling**

Redshift uncertainty : modes vs shift and stretch

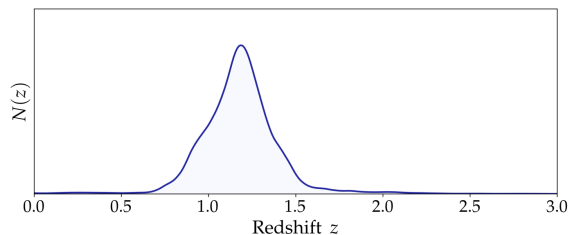
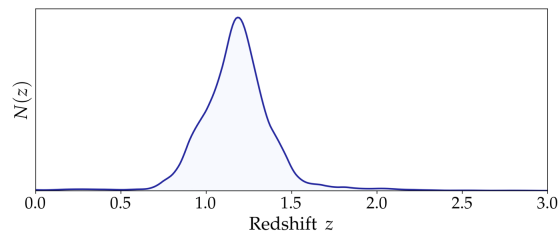


(Bernstein, d'Assignies, Troxel et al.)

- Y3: **shift and stretch** → Y6: **redshift modes (PCA)**
- MCMC: sample mode coefficients u_i :

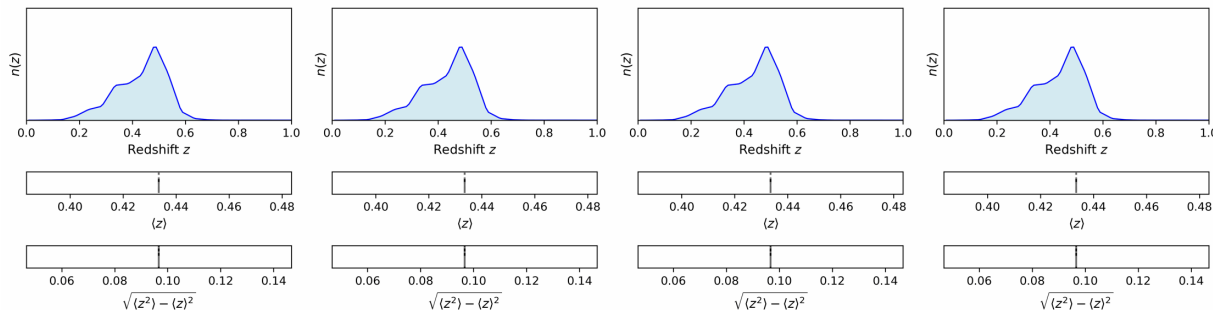


$$\hat{n}(z, \delta z, s) = \frac{1}{s} n_0 \left(\frac{z - \delta z}{s} \right)$$



$$\hat{n}(z) = n_0(z) + \sum_i u_i \cdot U_i(z)$$

First 4 modes of one lens bin



Redshift uncertainty : modes

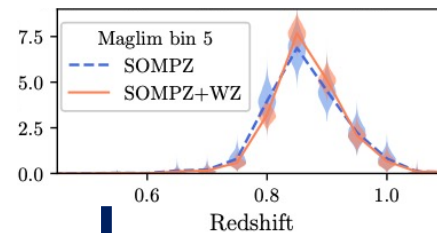


(Bernstein, d'Assignies, Troxel et al.)

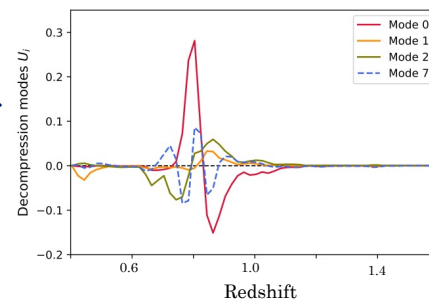
- Idea: Use Principal Component Analysis to extract a set of redshift modes $U_i(z)$
- MCMC: sample mode coefficients u_i :

$$\hat{n}(z) = n_0(z) + \sum_i u_i \cdot U_i(z)$$

- We don't capture all the variations of the $n(z)$, only the variations which have an impact on *cosmology observables* $\hat{c}$ (1x2 or 3x2 or whatever).



'PCA'



$$\langle \chi^2 \rangle = \frac{1}{N_\alpha} \sum_\alpha [\hat{c}(\mathbf{q}, \mathbf{n}_\alpha) - \hat{c}(\mathbf{q}, \hat{\mathbf{n}}_\alpha)]^T C_c^{-1} [\hat{c}(\mathbf{q}, \mathbf{n}_\alpha) - \hat{c}(\mathbf{q}, \hat{\mathbf{n}}_\alpha)]$$

Quantity to minimize

Sum over realisations

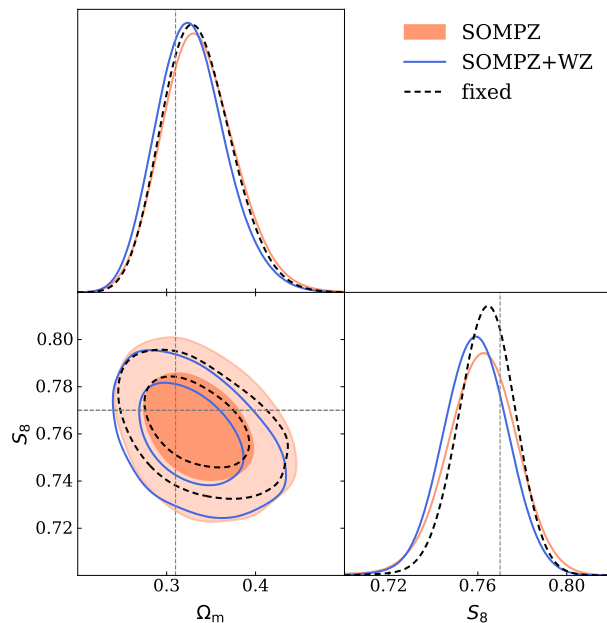
Calibration realisation

Observables (1x2, 3x2pt)

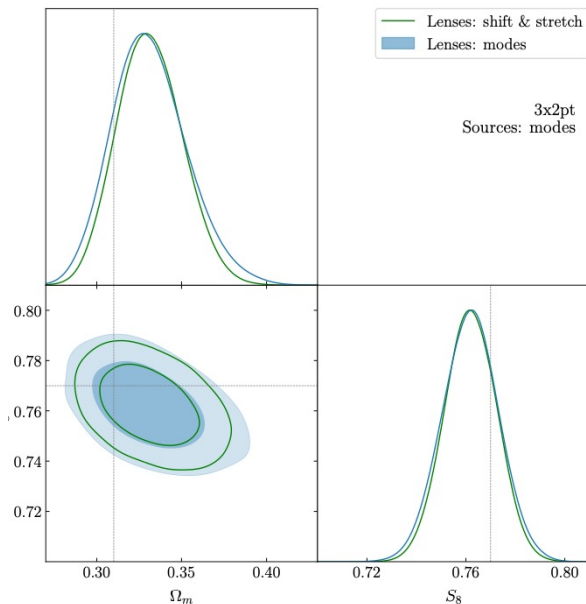
Mode model of the realisation

Observables covariance

Cosmic Shear (1x2), simulated DV



GGL, GC (3x2), simulated DV



4 takeaways:

Left:

- Improvement 10% level adding WZ (1x2 and 3x2)
- Very good consistency between SOM and WZ
- Still losing some constraining power (10-15% for 1x2 and 3x2)

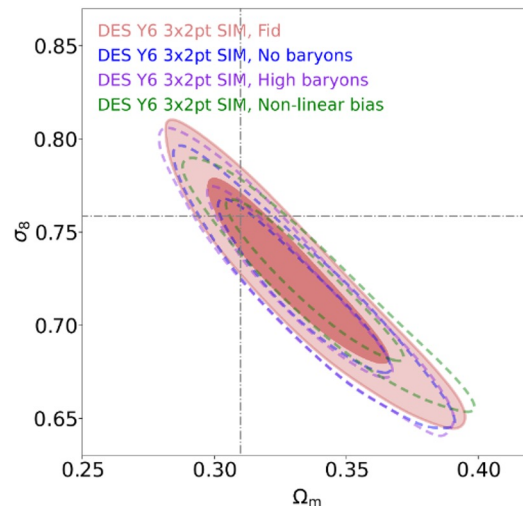
Right:

- Shifts&stretch on 3x2 underestimates uncertainty (1x2 it overestimates)

(D. Sanchez, A. Fertè, J. Blazek, S. Samuroff et al)

Analysis choices changes wrt Y3 :

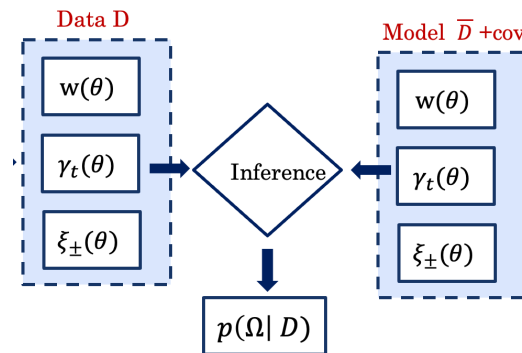
- HMCode 2020 for **nonlinear DM $P(k)$** (+baryons)
- **Linear and Nonlinear bias** are baseline now $\rightarrow$ helps pushing to smaller scales
- Inclusion of fixed **baryon feedback** signal with $\log(T_{\text{agn}}) = 7.7$
- **Intrinsic alignment**
 - TATT 4 parameters for 3x2 and 2x2 (bta=1)
 - NLA and TATT for 1x2
- We use more complex models or simulations to set scale cuts
 - Scale-cuts defined such that biases in front of nonlinear bias and baryons are $< 0.5 \sigma$ in 2D posterior $S_8 - \Omega_m$
 - Min scales: $8.7'$ for $\gamma_t(\theta)$, $13''$ for $w(\theta)$, and $3'$ for ξ_+



Inference and unblinding



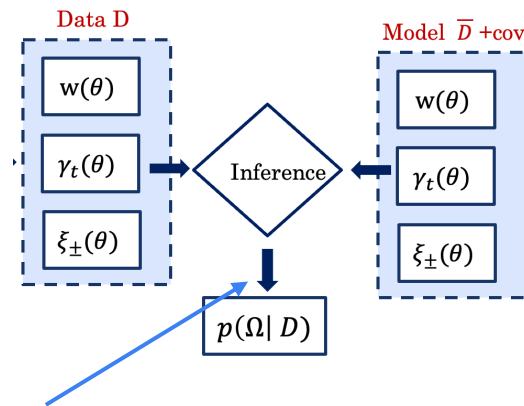
- CosmoSIS and nautilus algorithm sampling over **50+ parameters**
- Params = Cosmology (6/7) + Galaxy bias (6) + Intrinsic alignments (4) + Lens Magnification (6) + shear calibration (4) + Redshift Modes (18 lenses + 7 sources)
- **Computing cost:** 5k-40k CPU-hours per chain *OR* ~ 1 day in 256 cores
→ 100's of chains (few M CPU hrs) !!!



Inference and unblinding



- CosmoSIS and nautilus algorithm sampling over **50+ parameters**
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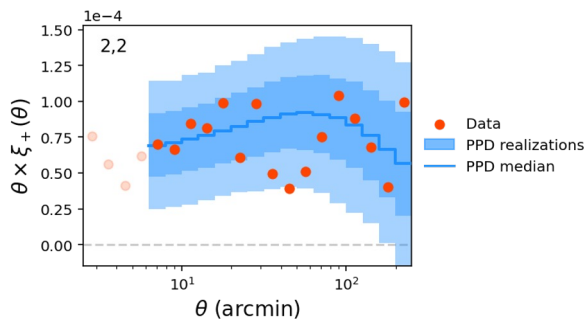
We use Posterior Predictive Distributions (PPDs) to assess goodness of fit and internal consistency

Generate a trial Cov, run first MCMC chain, blindly update Covariance

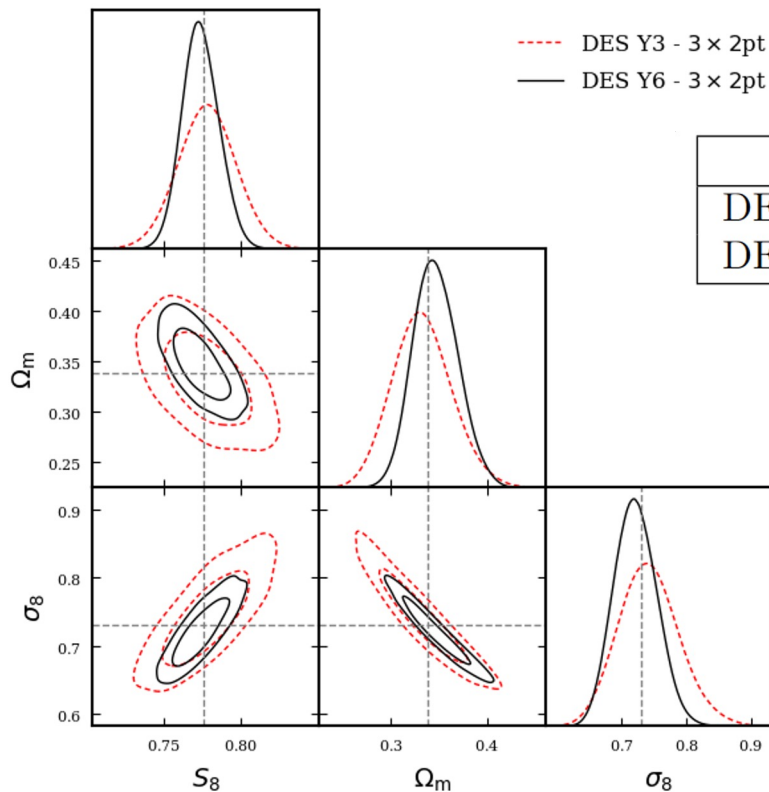
2. Run a set of MCMC chains and check

- Compute p-value of 3x2, 2x2, 1x2 and check posterior of calibrate nuisance
- Compute PPD(1x2 | 2x2), PPD(wt | cs+gt), PPD(gt | cs+wt)

3. Unblind if all consistent



- Intro
 - DES in few numbers
 - 3x2pt analysis
 - 3x2pt results of DES Y3
- DES Y6 :
 - Samples
 - Redshift calibration
 - Modelling
 - FOM (blinded)
- What's next ?
 - Y6 FOM vs Y3
 - Higher orders analysis

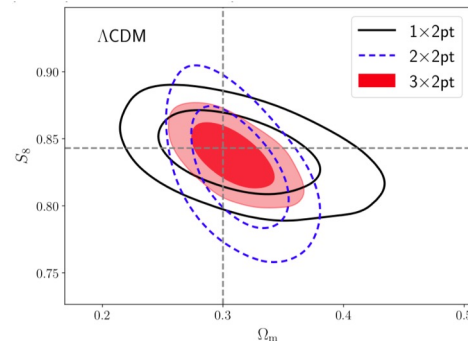


Case	FoM $_{\Omega_m, \sigma_8}$	Relative Difference (%)
DES Y3 - $3 \times 2\text{pt}$	2011.20	-
DES Y6 - $3 \times 2\text{pt}$	4942.84	145.77%

The Y3 results here correspond to the published DES Y3 results (4 lens bins, linear galaxy bias, non-optimised LCDM scale-cuts, no shear ratios). More than a factor of 2 from Y3 to Y6

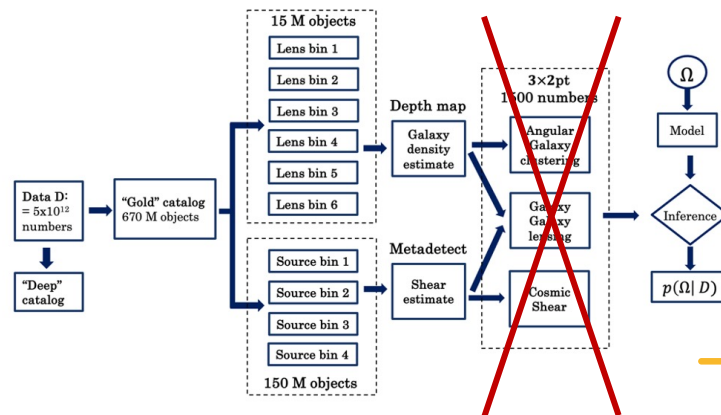
Fiducial cosmology papers (early 2026):

- 3x2pt and combined probes (BAO, SN, clusters, cmb, ...)
- 3x2pt ext-models (w_0w_a CDM, gravity, ...)
- 1x2pt (CS)
- 2x2pt (GC+GGL)



Higher orders statistics

- Use non-gaussian info
- SBI, peaks, etc..
- Later !!



Summary



DES as a collaboration – over 420 publications (cosmology and legacy science). Massive imaging dataset (optical and near IR). **Trained a very large group of scientists, developed methodology usable for Stage IV surveys**

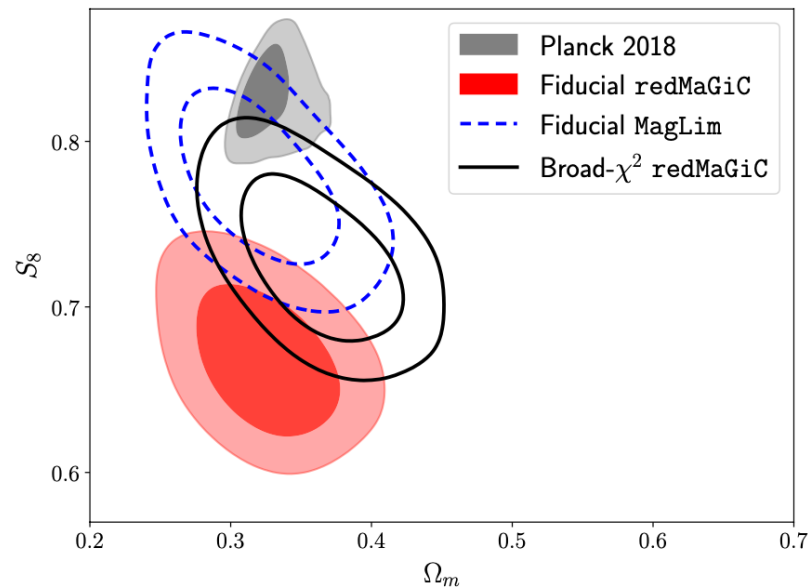
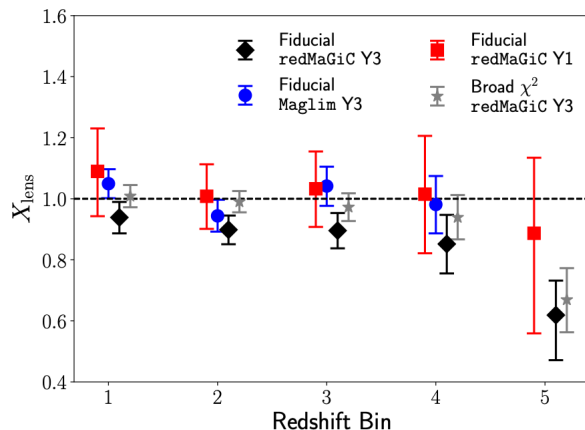
- DES BAO - arxiv 2402.10696, DES SNIa - arxiv 2401.02929, cosmology from 1500 SNIa (soon re-analysis)
- **3x2pt is hard!**
- **DES Y6 3x2 cosmology - to appear in early 2026** (IR next week!)
- Higher orders and additional work
- **Data, catalogues, calibrations will be public soon**, as well as chains. Best data sets for a couple more years, **use them !!!**



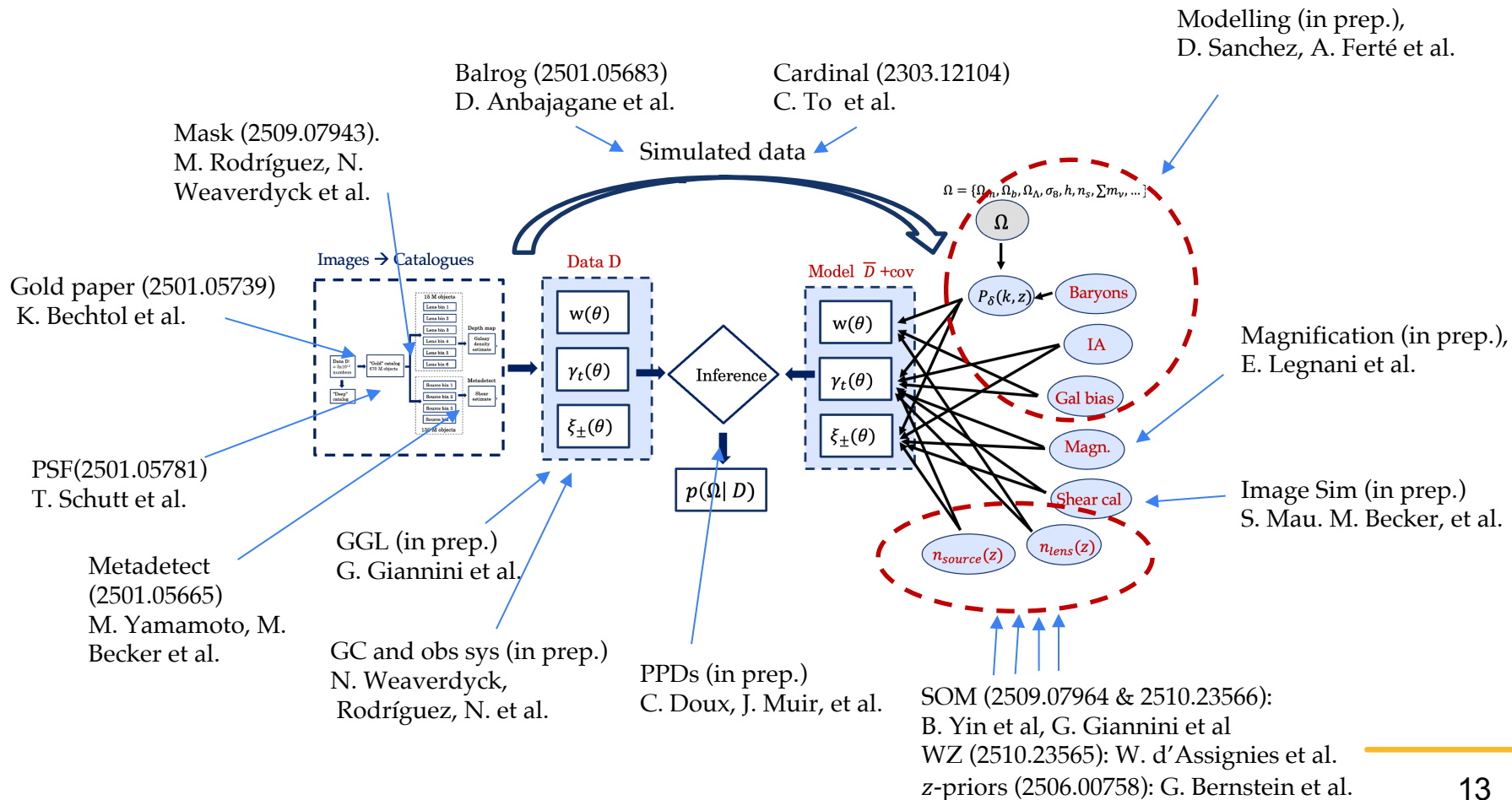
(On my side, first overview talk, happy to take any feedback, also looking for postdocs!)

Y3 Redmagic curse

- Inconsistent with Maglim: same physics, same volume...
- Inconsistent 3x2pt and 2x2pt, visible on galaxy bias:
- $X_{lens} = b_{3 \times 2} / b_{2 \times 2}$, not consistent with 1...
- Had to change sample after unblinding, still ?, reason why PPDs in Y6



3x2pt 'pre-unblinding' papers



Mitigation of large-scale observational systematics

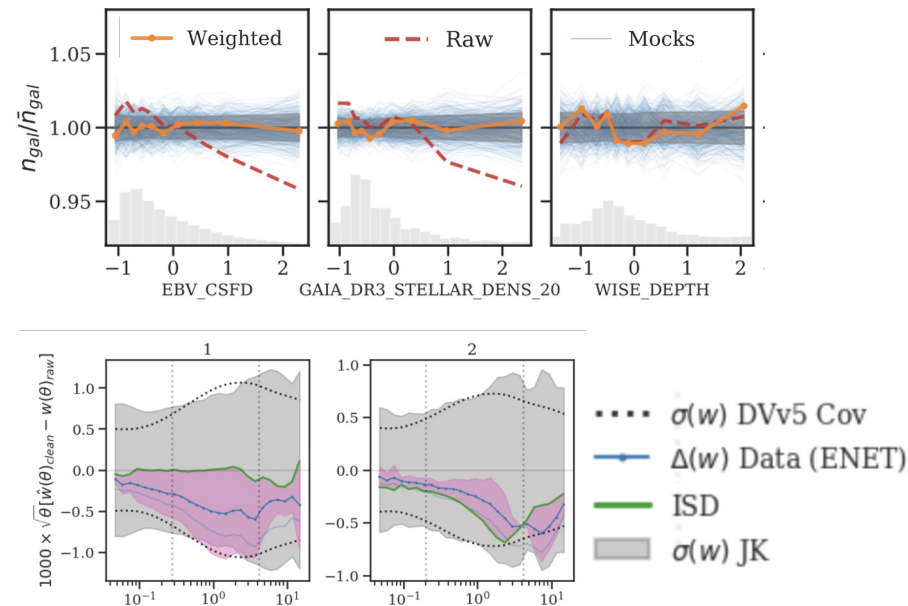
(Weaverdyck, Rodriguez Monroy et al)

Correlation of survey properties and astrophysical maps are unphysical

We check for correlation with ~ 20 maps:
seeing, airmass, depth, stellar density, dust, sky brightness

Iterative Decontamination (IDS) Significance of 1D correlations estimated with mock catalogues, we iterative apply weights the galaxies to remove the trends, starting from the most significant

Neural Net (ENet) Multilinear combination of all SP maps, very fast, allows non-linear relations



Complementary Methods - Cross-validation - We analytically marginalize over the difference.

Combining WZ with SOM.

Likelihood of clust-z data given a proposed $n(z)$ s
 Clust-z data and Cov
 Model for Clust-z data, including n , magn, sys

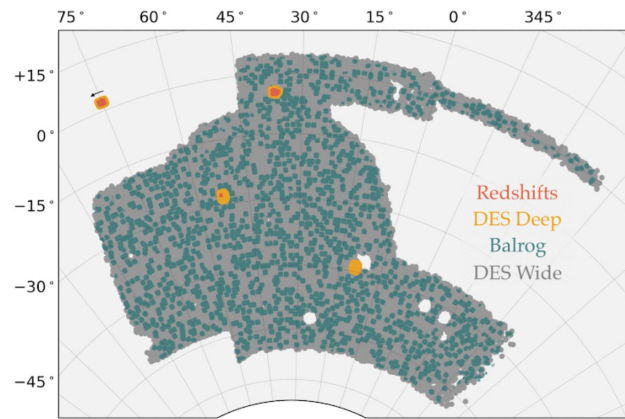
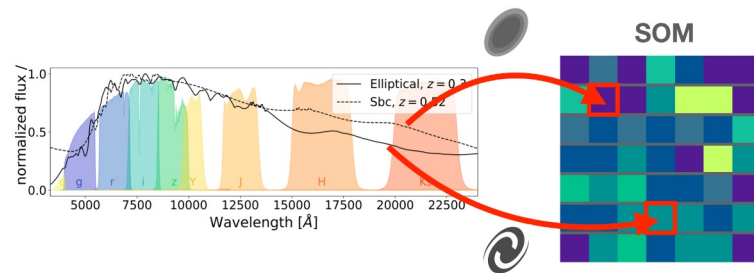
$$\begin{aligned}
 p(\mathbf{w}|\mathbf{n}) \propto & \int d\mathbf{q} \exp \left[-(\mathbf{w} - \hat{\mathbf{w}})^T C_w^{-1} (\mathbf{w} - \hat{\mathbf{w}}) / 2 \right] \leftarrow \hat{\mathbf{w}} \text{ is linear in } \mathbf{q}, \text{ this is Gaussian in } \mathbf{q} \\
 & \times \exp \left[-\left(\alpha_r - \alpha_r^{(0)} \right)^2 / 2\sigma^2(\alpha_r) \right] \prod_u \exp \left[-\left(\alpha_u - \alpha_u^{(0)} \right)^2 / 2\sigma^2(\alpha_u) \right] \prod_{u,k} \exp \left[-s_{uk}^2 / 2\sigma^2(s_{uk}) \right] \\
 & \underbrace{\hspace{10em}}_{\text{Magnification spec-sample Gaussian priors}} \quad \underbrace{\hspace{10em}}_{\text{Magnification photo-sample Gaussian priors}} \quad \underbrace{\hspace{10em}}_{\text{WZ systematic coefficients Gaussian priors}}
 \end{aligned}$$

- Everything is Gaussian !
- Integral reduces to the product of one exponential and one determinant !

Self-Organised-Maps

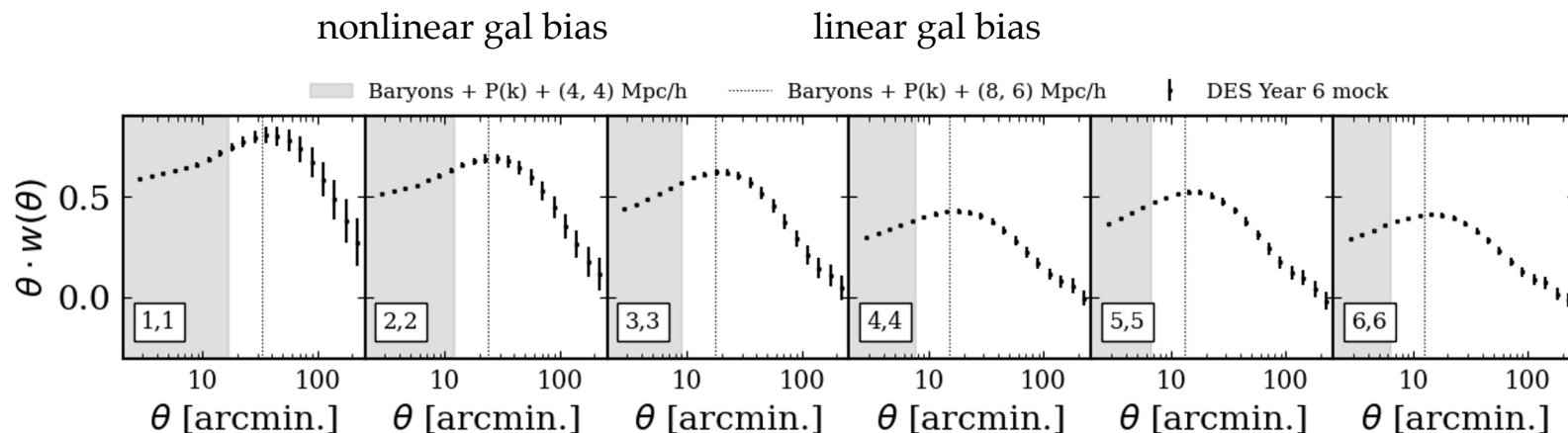


- **Self Organising Map (SOMs)** are used to classify galaxies multi-band fluxes in phenotypes ‘cells’—> c
- 4 small but **Deep Fields** with 8 bands coverage (*ugrizJHKs*) at 25.4
- Galaxies from wide and deep fields are grouped into two SOMs
- The two SOMs are mapped through a transfer function using **BALROG**
- Photo-*z*’s in the deep fields are validated through a high precision redshift sample



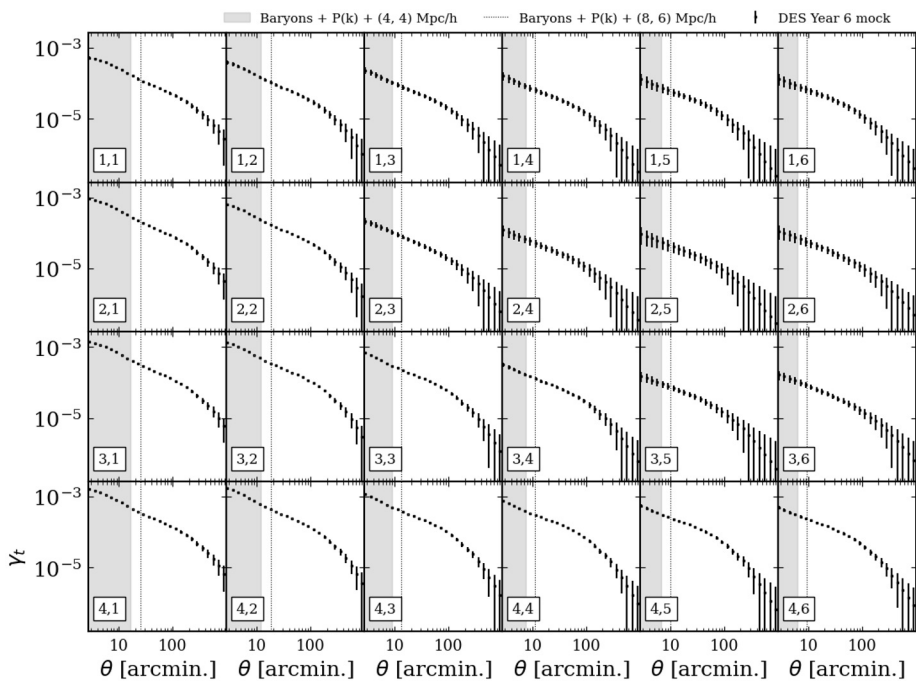
Credit C. Sánchez

What to expect from DES Y6 ?

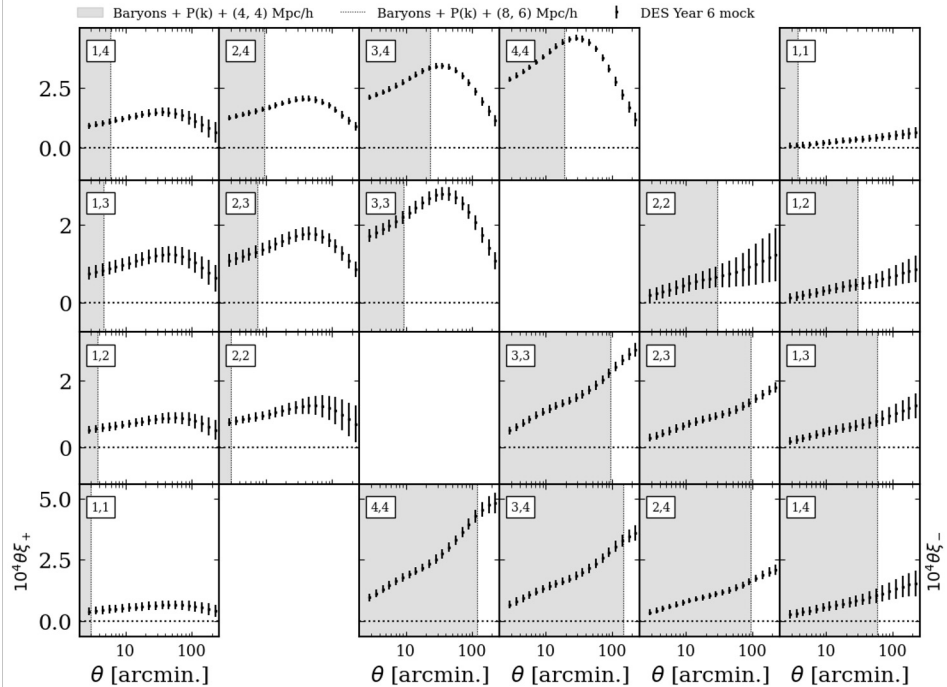


Analysis	Scale cuts	ξ_+	ξ_-	γ_t	$w(\theta)$	Total	SNR
Cosmic shear NLA	$\Delta\chi^2 = 3.5$	178	89	-	-	267	37.52
Cosmic shear TATT-4	$\Delta\chi^2 = 5$	183	99	-	-	282	39.76
2×2 pt Λ CDM Linear scales	(9, 6) Mpc/h	-	-	312	66	378	114.71
3×2 pt w/Λ CDM Linear scales	(9, 6) Mpc/h + $\Delta\chi^2 = 5$	183	99	312	66	660	115.85
2×2 pt Λ CDM Non-linear scales	(4, 4) Mpc/h	0	0	348	87	435	171.58
3×2 pt Λ CDM Non-linear scales	(4, 4) Mpc/h + $\Delta\chi^2 = 5$	183	99	348	87	717	172.2

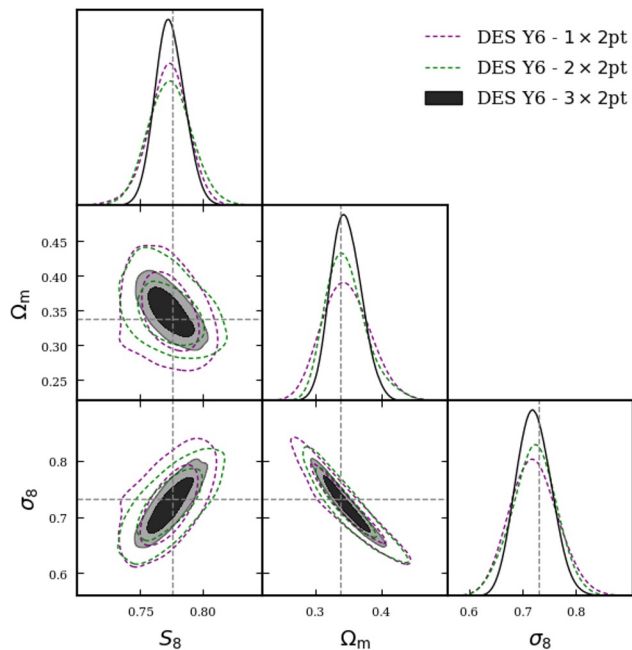
Galaxy galaxy lensing



Cosmic Shear



The sustained gain of 1x2 + 2x2 :



Case	FoM $_{\Omega_m, \sigma_8}$	Relative Difference (%)
DES Y6 - $1 \times 2\text{pt}$	1812.45	-
DES Y6 - $2 \times 2\text{pt}$	2019.41	11.42%
DES Y6 - $3 \times 2\text{pt}$	4942.84	172.72%

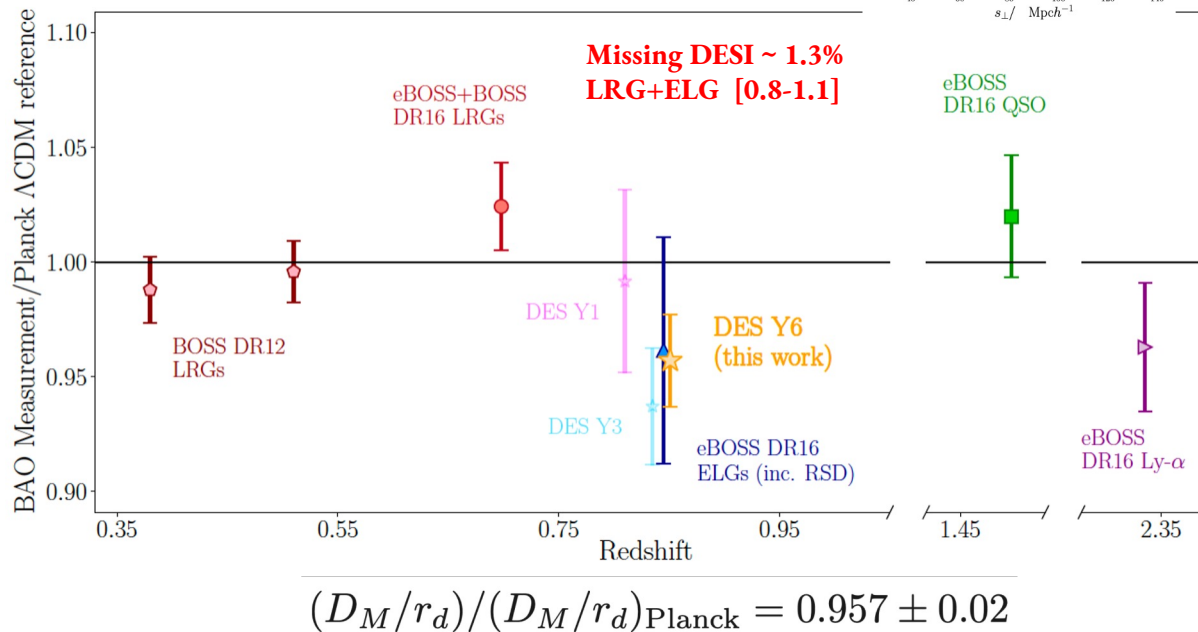
- More than a **factor of 2 increase** in FoM in LCDM from combining three 2pt combination (as in Y3)
- **3x2 is very robust to systematics** in general

ΛCDM	S_8	Ω_m	σ_8	FoM $_{\sigma_8, \Omega_m}$
DES Data Y3				
$3 \times 2\text{pt}$	$0.776^{+0.017}_{-0.017}$ (0.776)	$0.339^{+0.032}_{-0.031}$ (0.372)	$0.733^{+0.039}_{-0.049}$ (0.696)	2068
$\gamma_t + w(\theta)$	$0.778^{+0.031}_{-0.037}$ (0.809)	$0.320^{+0.034}_{-0.041}$ (0.306)	$0.758^{+0.063}_{-0.074}$ (0.801)	927
$\xi_{\pm}$	$0.759^{+0.025}_{-0.023}$ (0.755)	$0.290^{+0.039}_{-0.063}$ (0.293)	$0.783^{+0.073}_{-0.092}$ (0.763)	740

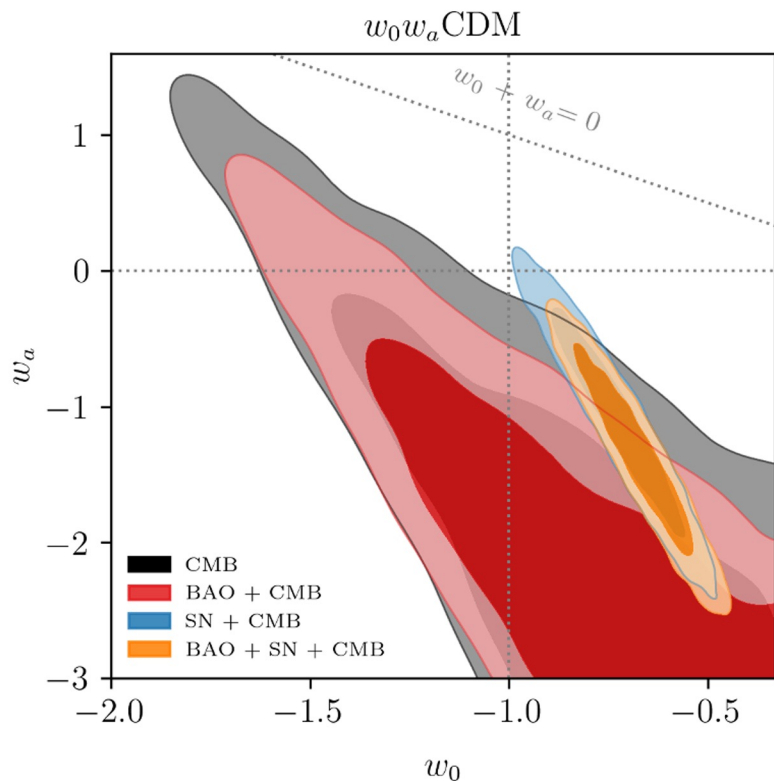
DES beyond 3x2 : BAO at $z \sim 0.85$

A 2.1% measurement of the angular Baryonic Acoustic Oscillation scale at $z_{\text{eff}}=0.85$ from the DES final dataset (submitted in **Feb 2024**, arxiv 2402.10696)

- 16 M galaxies in $0.6 < z < 1.2$
- 2.1σ below Planck (4.3%)
- 3.5σ significance of the BAO peak
- Most precise BAO measurement from a photometric survey
- Competitive with spectroscopic surveys
- Angular BAO at the closure of Stage-III surveys



Y5 DES SNIa + DESY6 BAO + CMB



Cosmology from DES Y6 BAO and DES Y5 SN represent the culmination of what the final DES can tell us about the expansion of the Universe via geometric probes.

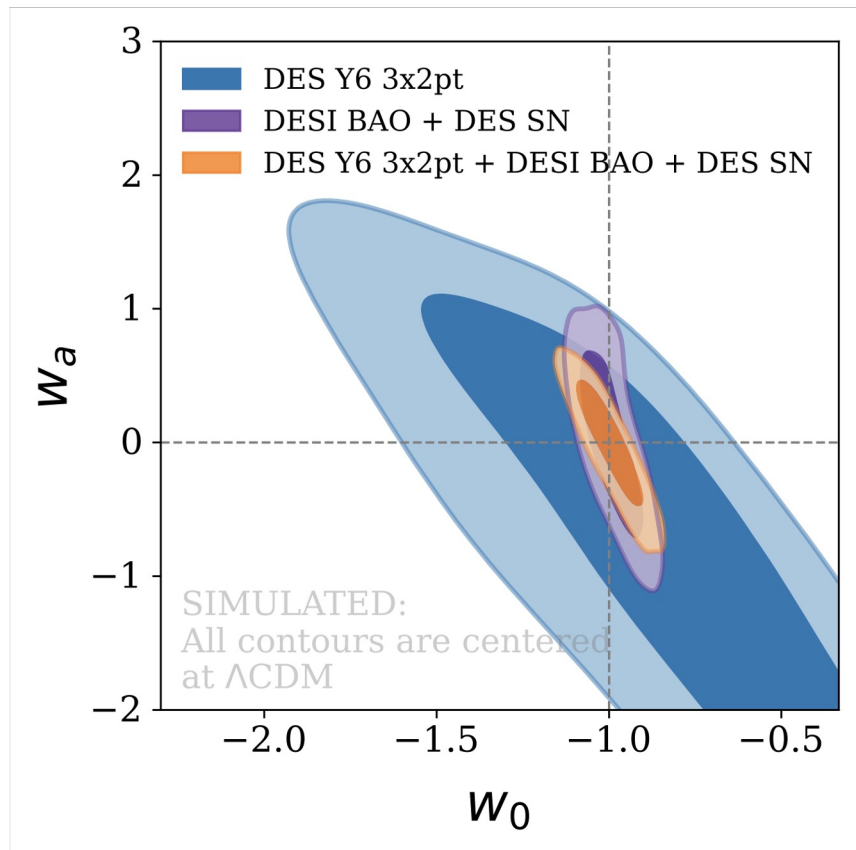
DES Collaboration 2025, **March**, arXiv:2503.06712

In Λ CDM BAO tends to pull towards lower Ω_m , SNIa towards higher Ω_m , with some $\sim 2\text{-}3\sigma$ tensions between data combinations (assuming minimal neutrino mass).

Dynamic dark energy $w_0 w_a \text{CDM}$ shows $\sim 3.2 \sigma$ discrepancy with Λ CDM (similar, but a bit lower, than using DESI Y1 BAO).

See also *Notari et al* arXiv:2411.11685

Evolving dark energy from low- z probes



- DES 3x2pt

$$w_0 > -1.64 \text{ (95\% bound)}$$

$$w_a = -0.5^{+1.3}_{-1.1}$$

- DESI DR2 BAO + DES Y5 SN

$$w_0 = -0.994^{+0.053}_{-0.062}$$

$$w_a = 0.01 \pm 0.46$$

- DES 3x2pt + DESI DR2 BAO + DES Y5 SN

$$w_0 = -0.996 \pm 0.064$$

$$w_a = -0.02^{+0.35}_{-0.28}$$

3x2 helps in constraining
mainly w_a

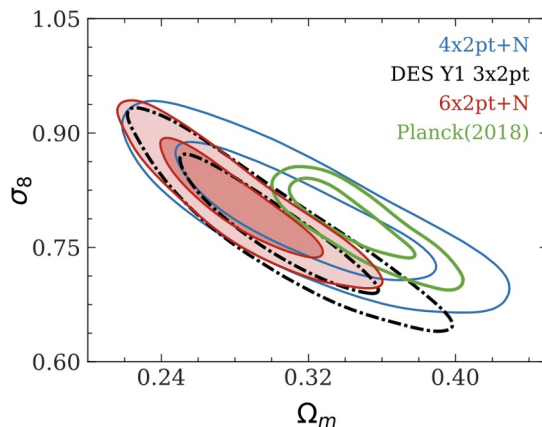
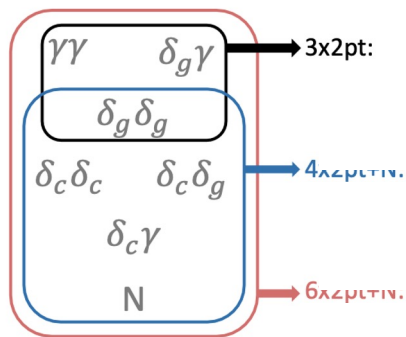
DES beyond 3x2 : Combination with Clusters

[1] To, Krause et al arxiv 2002.11124

[2] Costanzi 2020 arxiv 2010.13800

Largest virialized objects in the Universe, sensitive probe of structure growth - requires “mass-observable” relation between observed mass proxy (richness) and halo mass. One can use stacked WL profiles (selection biases at low richness, see [1]), or SPT + WL (limited to high richness and overlap area, see [2])

4x2pt+N: same sample, **mass calibration from large-scale clustering** – marginalized over wide range of selection bias (C. To et al 2020, 2010.01138)



1. From **DESY1** consistent cosmology with 3x2.
2. Possible to combine because of “large-scale covariance”
3. Limited gain (1500 clusters) and conservative scale cuts

18,000 Y3 RedMaPPer clusters ($\lambda > 20$ and $z < 0.65$) combined with Y6 3x2 – 25% gain in FoM($\Omega_m\sigma_8$)

The Dark Energy Survey Year 6: 3×2 pt analysis



*William d'Assignies (IFAE, PhD in the redshift team)
on behalf of the Dark Energy Survey Collaboration*

*Presentation using material from M.
Crocce, G. Bernstein, C. Chang*



@J. Muir