echoIA Project Pitches

Pitches can have up to 3 slides with ca. 5mins of presentation time.
Please repeat the presenter name(s) on all slides.

Session 1 - Simulations focus (Monday, ~1620 UTC)

Dependence of IA on disk fraction

Yesukhei Jagvaral with Sukhdeep Singh and Rachel Mandelbaum
Status: almost complete

- Measuring morphological dependence of IA in IllustrisTNG
- Morphological samples were controlled for differences in mass
- **IA shows a decreasing trend with disc fraction (even when controlled for mass differences)**
- **IA of individual galaxy components (bulge vs disk) are determined by their dynamical state (rotation vs dispersion)**

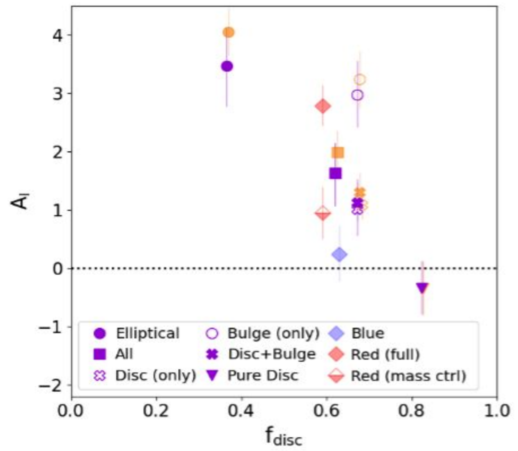
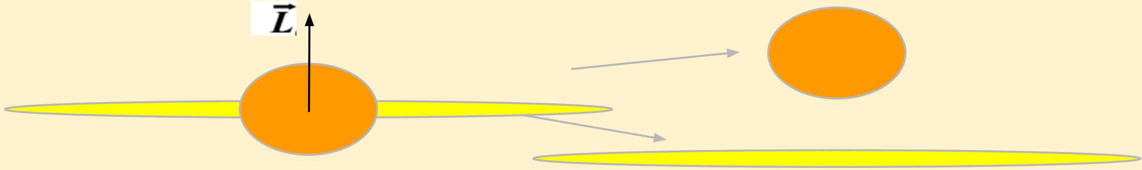


Figure 7. Dependence of the alignment strength parameter A_I on f_{disc}. The purple points are the main mass-controlled samples presented in the top row of Table 2. The orange points are the non-mass-controlled samples (i.e., the full samples from the simulation, shown in the second row of Table 2). In both cases, the alignment strength exhibits a decreasing trend with f_{disc}. The purple points are slightly below the orange points, indicating that there is some dependence on mass (with higher mass resulting in greater alignments), however the overall trend with f_{disc} is the same. Additionally we have plotted the color-split samples with the diamond-shaped points; for the *Red* sample, the half-filled diamond represents the mass-controlled sample and the full diamond represents the full sample.



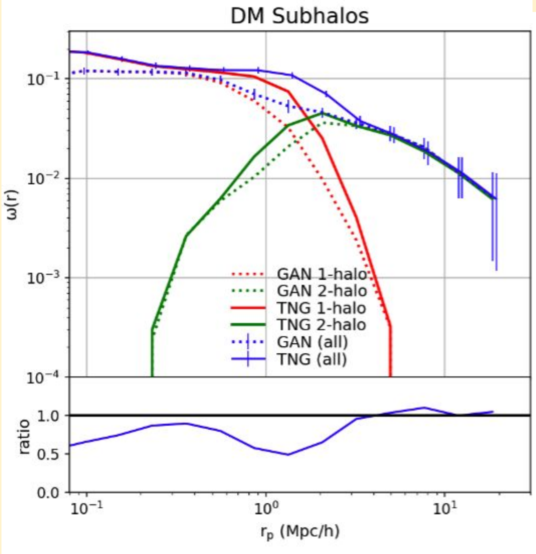
When 2-component galaxy is decomposed: Bulges show high IA consistent with Ellipticals

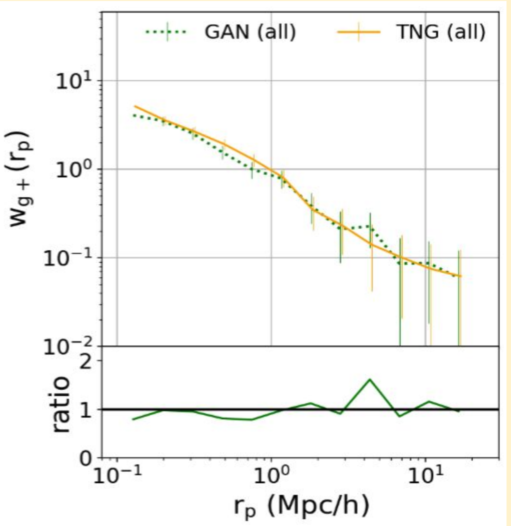
Learning IA with Graph Neural Networks

Yesukhei Jagvaral with Francois Lanusse, Sukhdeep Singh and Rachel Mandelbaum

Status: almost complete

- Learning IA with GANs from hydrosimulations using simple inputs like: tidal field, mass and a binary column of central vs satellite.
- **The Graph Neural Network was able to learn scalars such as shapes; the 3D orientation of the major axis and the 2D complex ellipticities.**
- The correlations ED and wg+ are shown in the right.
- **Also, the model captures dependence of IA on mass and central vs. satellite reasonably well.(not shown here)**





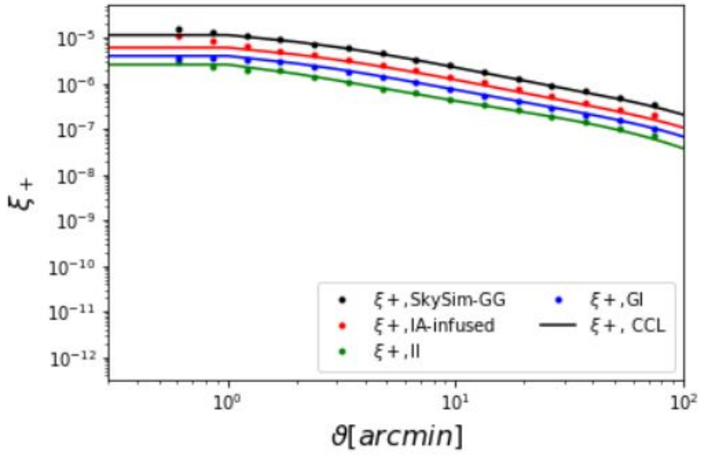
Future steps:

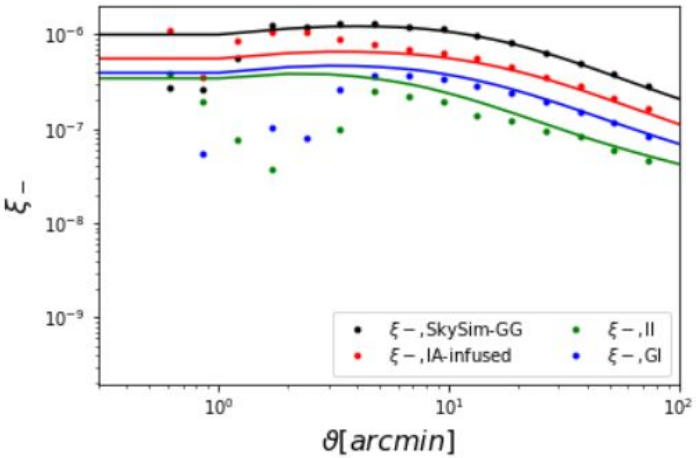
- Apply the Graph-GAN to large volume N-body simulation to create mock catalogs.
- Modeling of the full 3D orientation of the galaxy, for this need to properly implement SO(3) on a Neural Network.
- Possible applications is Simulation based Inference?

Intrinsic Alignment infusion in SkySim5000 mocks

(Leonel Medina-Varela, Denise Lanzieri, Mustapha Ishak, Joachim Harnois-Deraps, François Lanusse)

Infusion done by Joachim, theoretical predictions by Denise & Francois and TreeCorr measurements by Leonel & Mustapha. These plots are for NLA infusion:





Intrinsic Alignment infusion in SkySim5000 mocks

(Leonel Medina-Varela, Denise Lanzieri, Mustapha Ishak, Joachim Harnois-Deraps, François Lanusse)

Next:

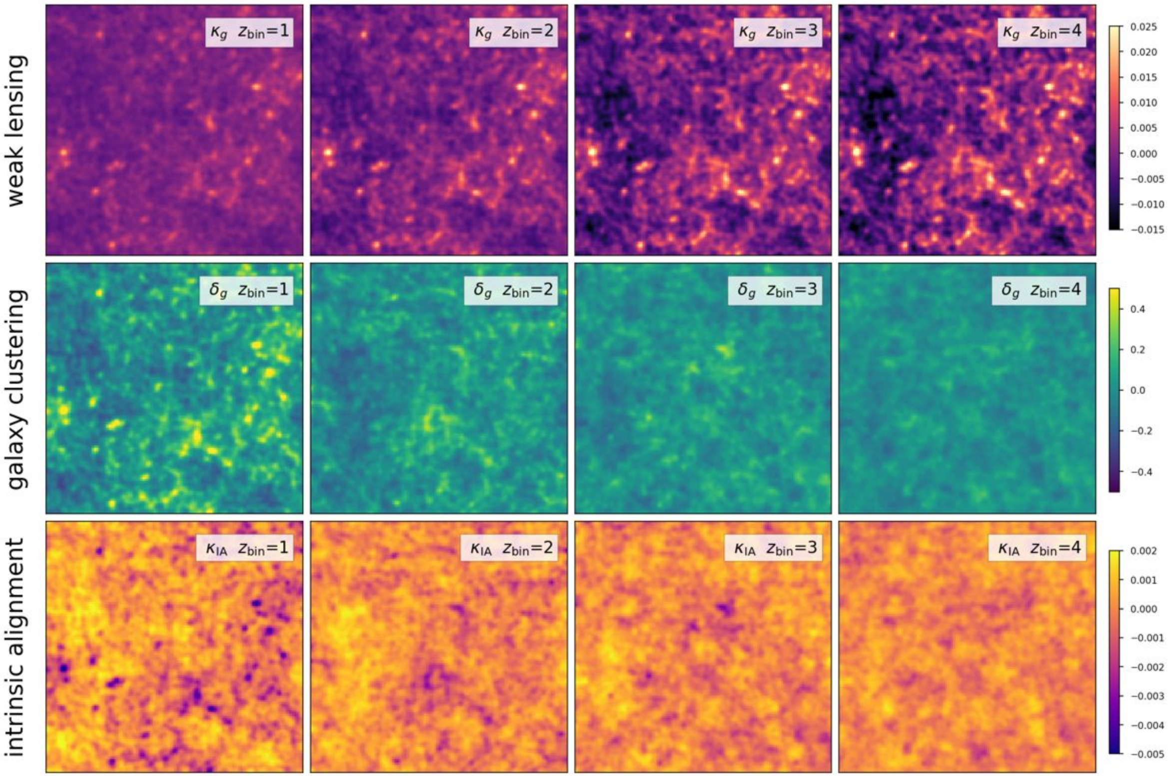
-Infuse more complexe IA models (redshift evolution, TATT…)

-Implement this in simulations with varying cosmologies (e.g. cosmoSLICS, MassiveNuS, f(R)...) and construct a simulation-based [cosmology + IA] inference pipeline.

-Apply to higher-order WL statistics

IA with AI: Intrinsic Alignments with Artificial Intelligence
Tomasz Kacprzak (ETHZ/SDSC)

- Create joint simulations of lensing, clustering, and IA
- Train neural networks to infer cosmology, galaxy field, and intrinsic alignment parameters jointly
- Pass on the lensing and clustering maps as channels
- Example maps from Kids450 redshift bins (right)



IA with AI: Intrinsic Alignments with Artificial Intelligence
Tomasz Kacprzak (ETHZ/SDSC)

- Current status: paper on "Combined LSS Probes with Deep Learning" in progress (co-author Janis Fluri, ETHZ)
- Implemented IA models: single component NLA with redshift evolution (2 parameters)
- Looking for collaborators for a more qualitative forecast for different IA models
- Massive simulation set CosmoGrid will be available soon (see Fluri et al. 2022, 2201.07771)

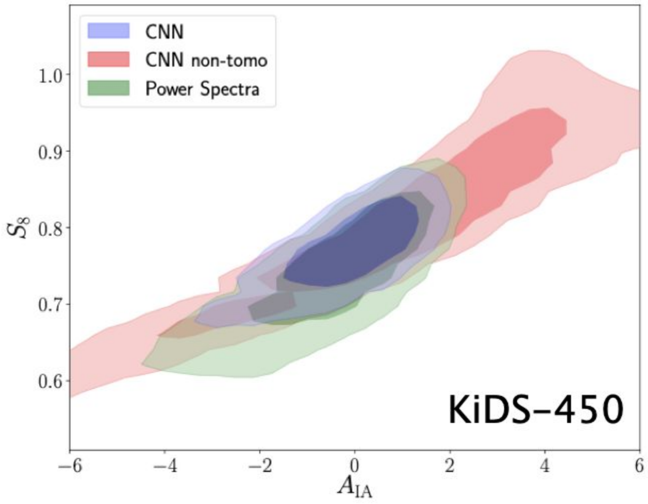


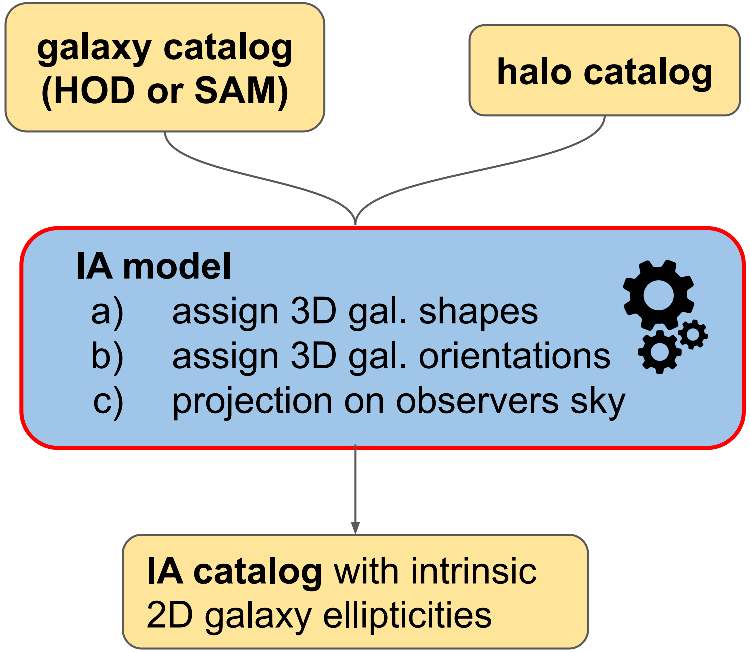
FIG. 13. The constraints on the intrinsic alignment amplitude $A_{\rm IA}$ and the degeneracy parameter S_8 for our fiducial analysis, a non-tomographic network analysis and our power spectrum analysis using our fiducial mock observation.

Fluri, TK, et al. 2019,1906.03156

Kai Hoffmann

modeling IA in cosmological simulations

Collaborators: L.Secco, J. Blazek, M. Crocce, P. Fosalba, P. Tallada, J.Carretero, J. Prat, S. Samuroff, B. Joachimi, A. Loreiro, E. Chisari, C. Laigle, J. Stadel



- model is calibrated using combined constraints from observations and hydrodynamic simulation
- IA model has been integrated in mock production pipeline at PIC datacenter in Barcelona
- IA model has been used to produce large IA mocks for Euclid and DES (based on the Euclid Flagship simulation and MICE respectively)

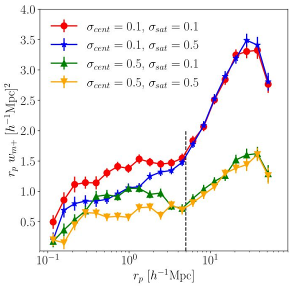
Kai Hoffmann

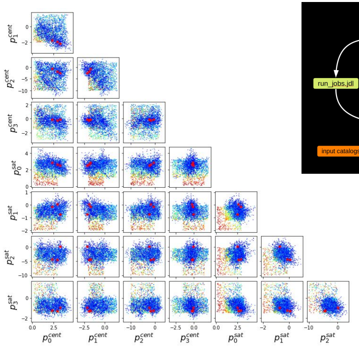
IA model calibration

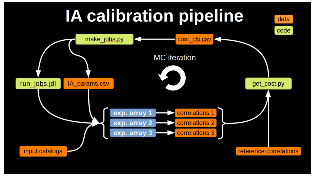
Euclid preliminary

Euclid Flagship 1 simulation against constraining data sets

exploring the parameter space of the galaxy-halo misalignment model

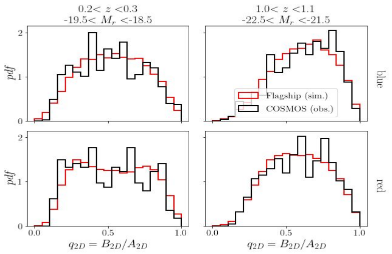






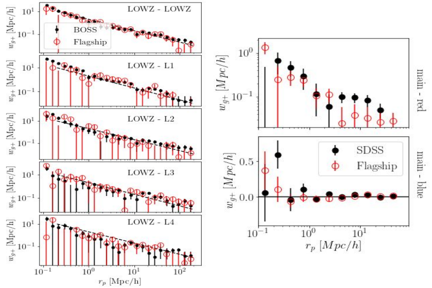
galaxy axis ratios:

- Flagship vs. COSMOS



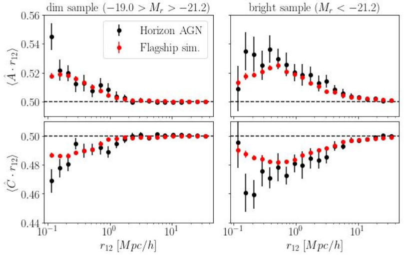
2-point IA stats:

- Flagship vs. LOWZ & SDSS



z<0.4

- Flagship vs. HAGN



z=1.0

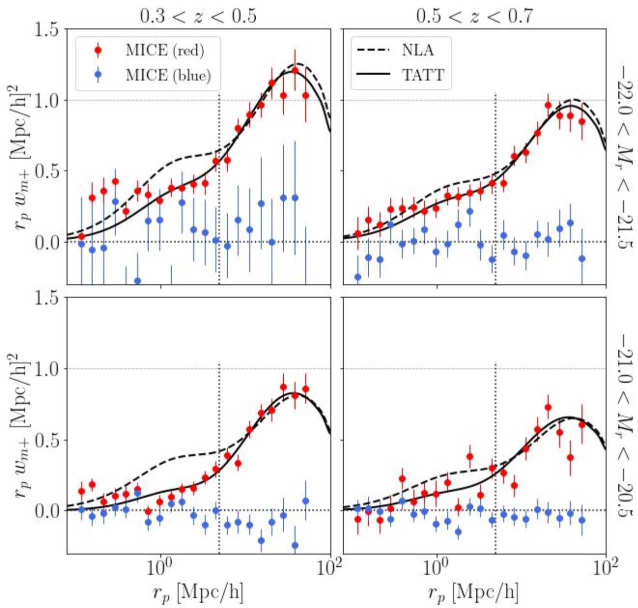
Hoffmann et al. in prep.

Kai Hoffmann

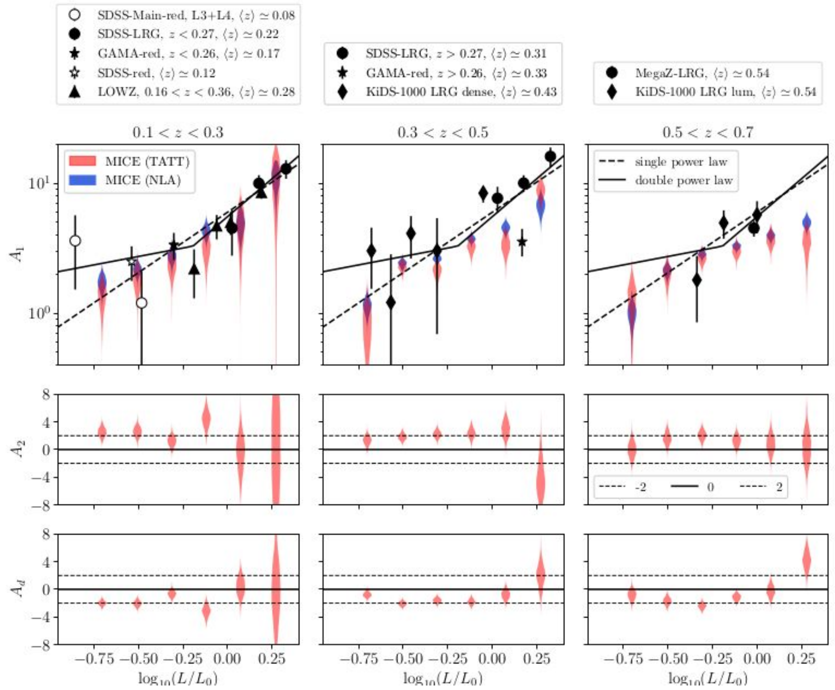
DES preliminary

2pt IA statistics in MICE

MICE vs. TATT and NLA



NLA and TATT parameters from red galaxies in MICE vs. different observations



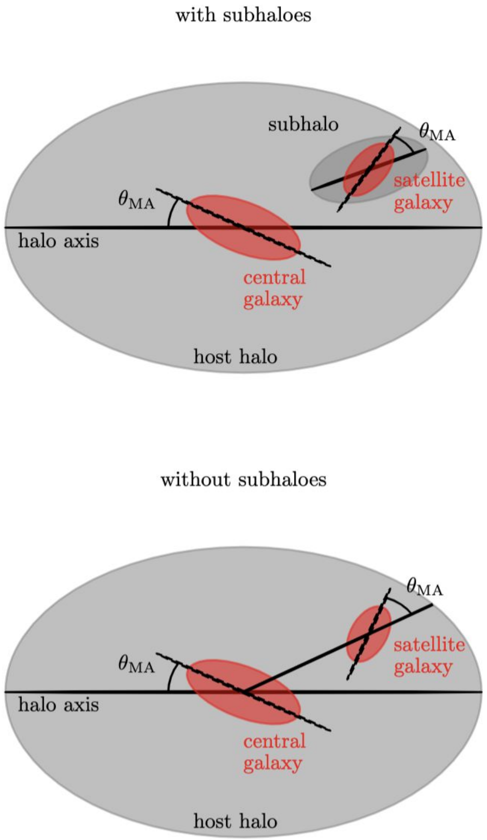
Hoffmann et al. in prep.

Nick Van Alfen

IA With Halo Method - Overview

Working with Jonathan Blazek, Danielle Leonard, Francois Lanusse, Andrew Hearin, and Duncan Campbell

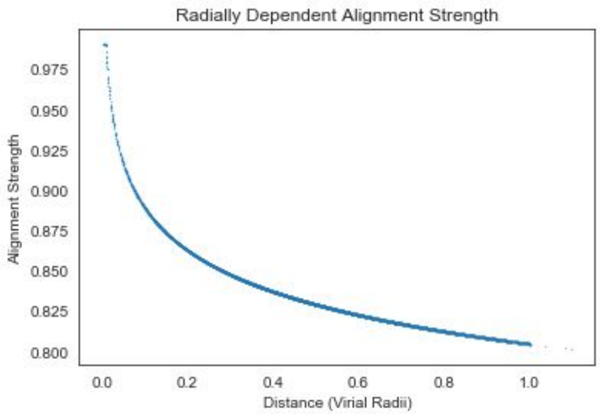
- Include orientation information as part of an HOD for galaxies
- Building on previous work by Duncan Campbell and others
- Validate model orientation against hydro sims like Illustris TNG
- Expand to include realistic shape information

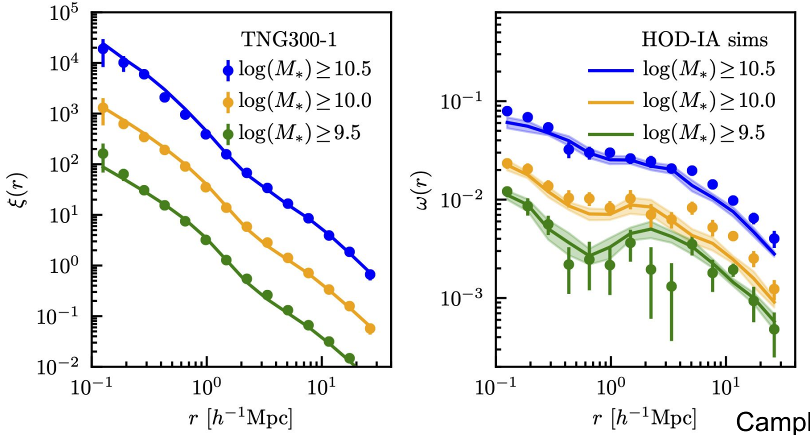


Nick Van Alfen

IA With Halo Method - Current Status

- We can assign galaxy alignments relative to subhalos, host halos, or the radial vector
- Developing a model for radially dependent alignment strength (left figure)
    - May help capture alignment information even if no halo information is available
    - Adds model flexibility
- In the future, we will compare the correlation functions from our HOD models to Illustris (right figure) and other hydro-sims





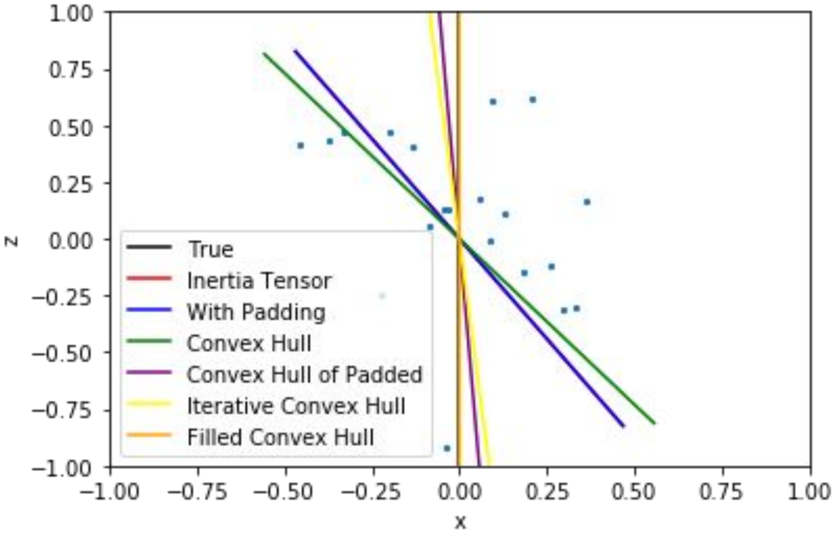
Campbell et al. in progress

Nick Van Alfen

IA With Halo Method - Related

A related project:

- Extracting a reliable axis from noisy stored particle data
- Some stored simulations have been downsampled to save space
- Can we extract a reliable axis for these halos?
- If so, we can apply the methods described earlier



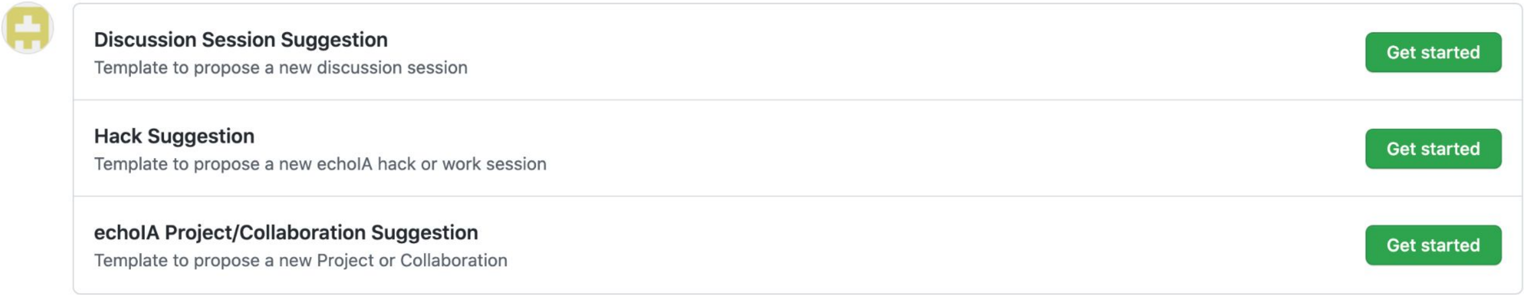
Session 2 - Modelling & methods focus (Tuesday, ~1330 UTC)

Housekeeping & Etiquette

- Please be respectful and abide by our code of conduct: https://echo-ia.github.io/FebKickoff
- If you have any concerns regarding conduct during the meeting, let the meeting points of contact know:
  - Rachel Mandelbaum (Mon-Tues): rmandelb@andrew.cmu.edu
  - Jonathan Blazek: j.blazek@northeastern.edu
  - Benjamin Joachimi: b.joachimi@ucl.ac.uk
- Please ensure you are muted when not speaking. Bandwidth and circumstances permitting, it would be lovely to see your video.
- Do join in the discussions and ask lots of questions. Contributions from junior participants especially encouraged.
  - Use the Raise Hand Zoom feature for any new question/discussion point
  - Use the Zoom chat
  - Write your question or comment into the live notes (anonymously if you prefer)
- Introductions and review talks will be recorded. Project pitches and discussions will not.
- We will be keeping notes during the pitches and discussions. Feel free to add to the notes as appropriate.

Discussions and Hacking on Wednesday

- We will use Github issues to keep track of topics for discussion and hack sessions. Click on the button on the website home page.
- Tag others and organize a plan.
- Join the echoIA github org!



Projected Intrinsic Alignment as an RSD Contaminant

Claire Lamman, Daniel Eisenstein | claire.lamman@cfa.harvard.edu

CENTER FOR ASTROPHYSICS HARVARD & SMITHSONIAN

DESI's fiber magnitude -based selection

↓

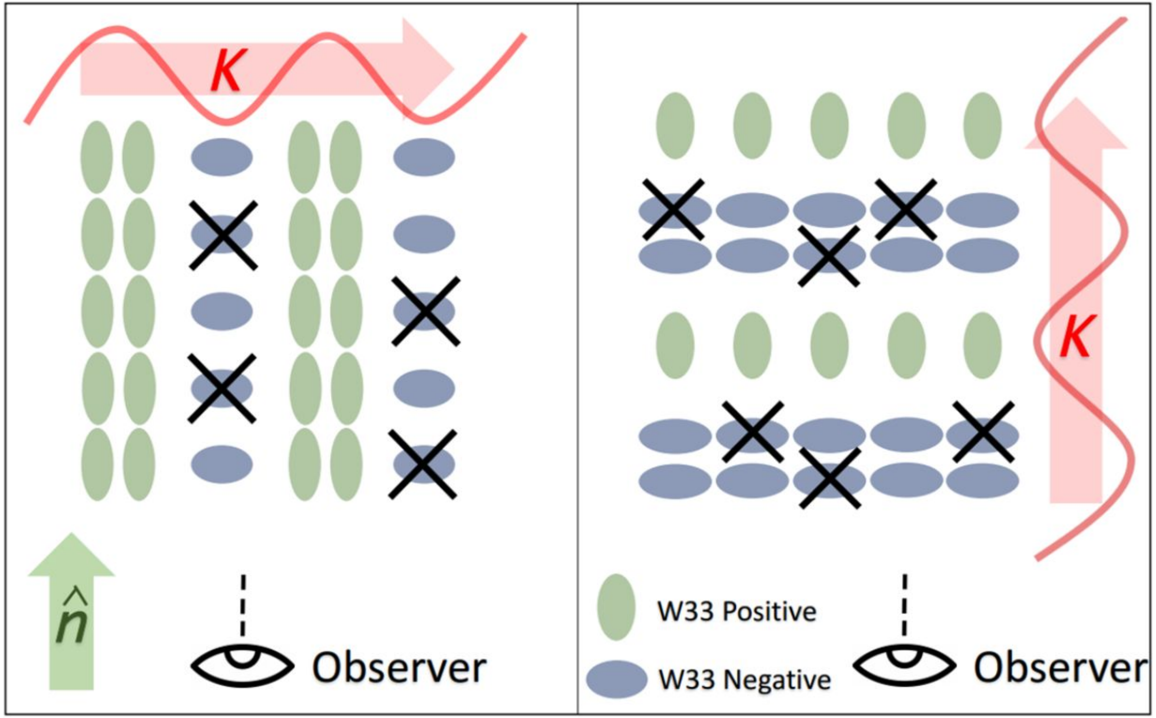
Bias to pole-on orientations

+

LRGs aligned with tidal field

↓

Systematic error in quadrupole



Martens et al. 2018

Projected Intrinsic Alignment as an RSD Contaminant

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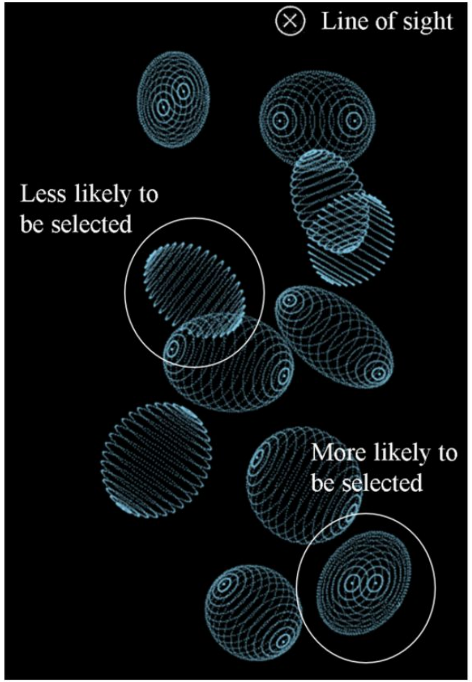
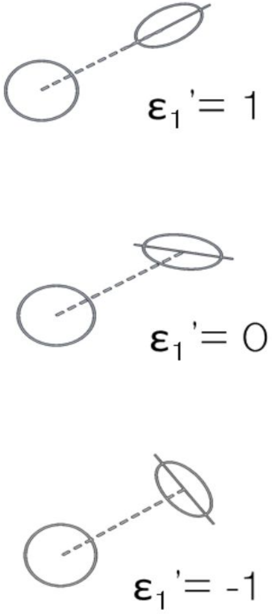
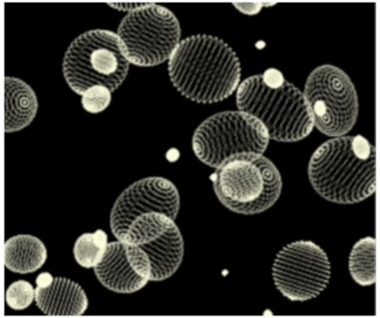


Estimate polarization of DESI LRGs along the line of sight



Measure 2D alignment of LRGs on sky

DESI Legacy Imaging Survey
Schlegel et al. 2021



AbacusSummit
Maksimova et al. 2021

Interpretation using AbacusSummit Mock

Projected Intrinsic Alignment as an RSD Contaminant

Claire Lamman, Daniel Eisenstein | claire.lamman@cfa.harvard.edu

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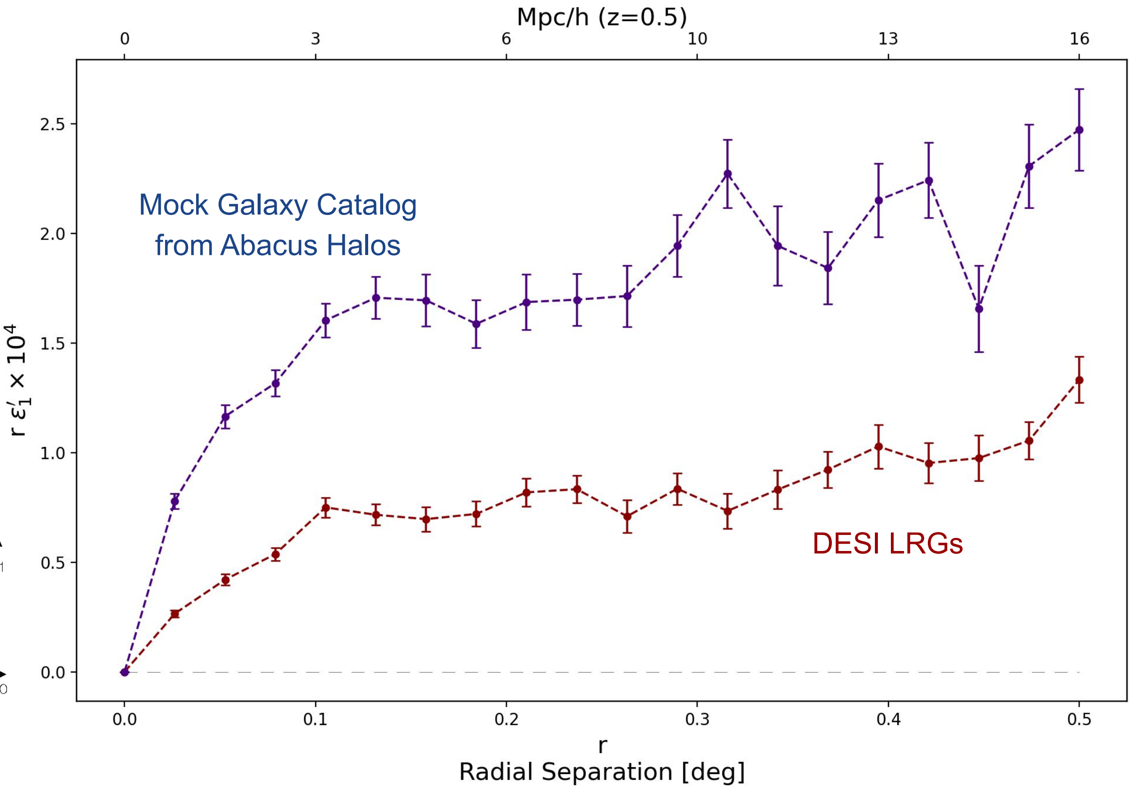
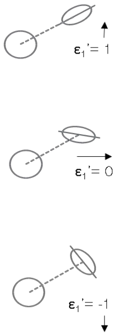




Projected Shape - Density Correlation

Galaxy ellipticities on the sky relative to a neighboring galaxy, as a function of projected separation between them

IA in Euclid

I. Tutusaus

Goal: forecast Euclid constraints for different IA models

Models considered so far:

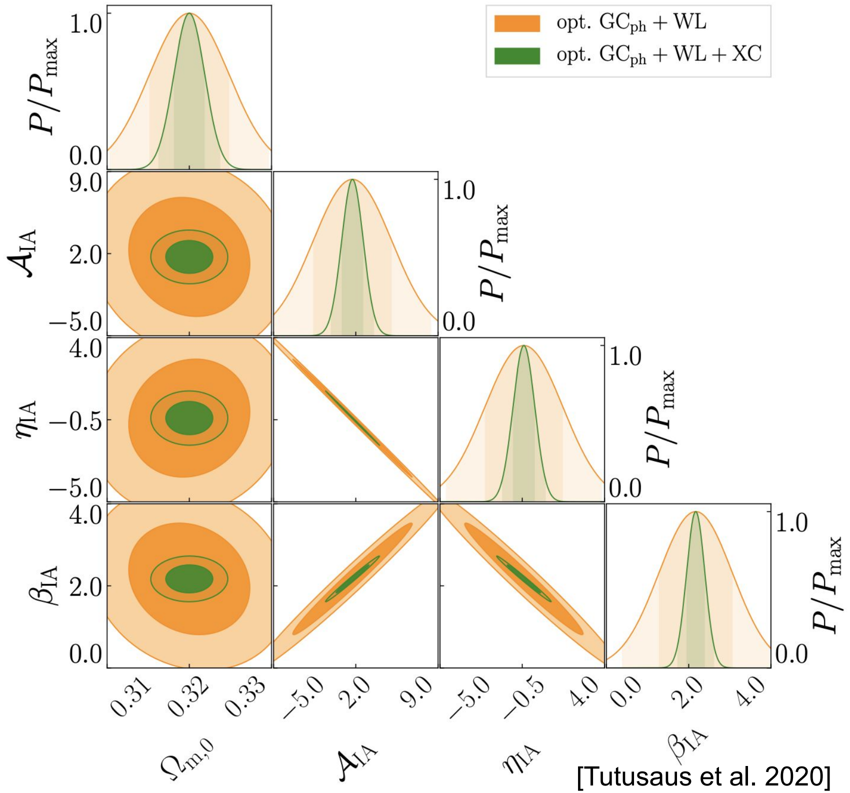
- eNLA (extended NLA) Fisher forecast – Euclid Collaboration: Blanchard et al. 2020 (1910.09273); Tutusaus et al. 2020 (2005.00055)

$$P_{\delta \mathrm{I}}(k,z) = -\mathcal{A}_{\mathrm{IA}} C_{\mathrm{IA}} \Omega_{\mathrm{m},0} \frac{\mathcal{F}_{\mathrm{IA}}(z)}{D(z)} P_{\delta\delta}(k,z),$$

$$P_{\mathrm{II}}(k,z) = \left[-\mathcal{A}_{\mathrm{IA}} C_{\mathrm{IA}} \Omega_{\mathrm{m},0} \frac{\mathcal{F}_{\mathrm{IA}}(z)}{D(z)} \right]^2 P_{\delta\delta}(k,z),$$

where the function $\mathcal{F}_{\mathrm{IA}}(z)$ reads

$$\mathcal{F}_{\mathrm{IA}}(z) = (1+z)^{\eta_{\mathrm{IA}}} [\langle L \rangle(z) / L_\star(z)]^{\beta_{\mathrm{IA}}} \ .$$



[Tutusaus et al. 2020]

IA in Euclid

I. Tutusaus

Goal: forecast Euclid constraints for different IA models

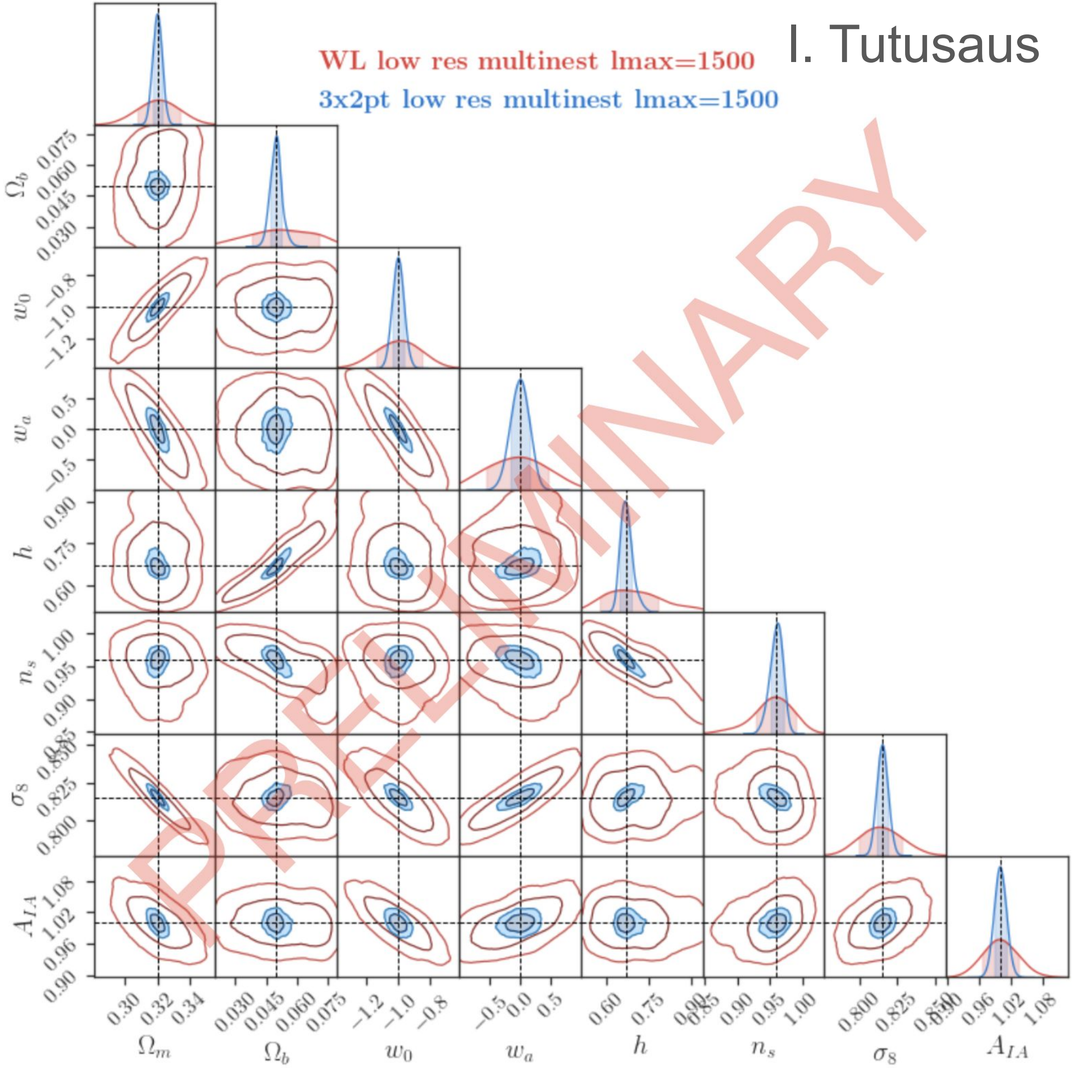
Models considered so far:

- NLA MCMC – multinest/polychord

Not prior dominated:

Om [0.1, 0.9]
Ob [0.02, 0.08]
w0 [-1.4, -0.6]
wa [-1.0, 1.0]
h [0.4, 0.94]
ns [0.5, 1.4]
sig8 [0.2, 1.14]
aIA [-5.0, 6.0]

Strong constraints on the IA parameter from WL alone



IA in Euclid

I. Tutusaus

Goal: forecast Euclid constraints for different IA models

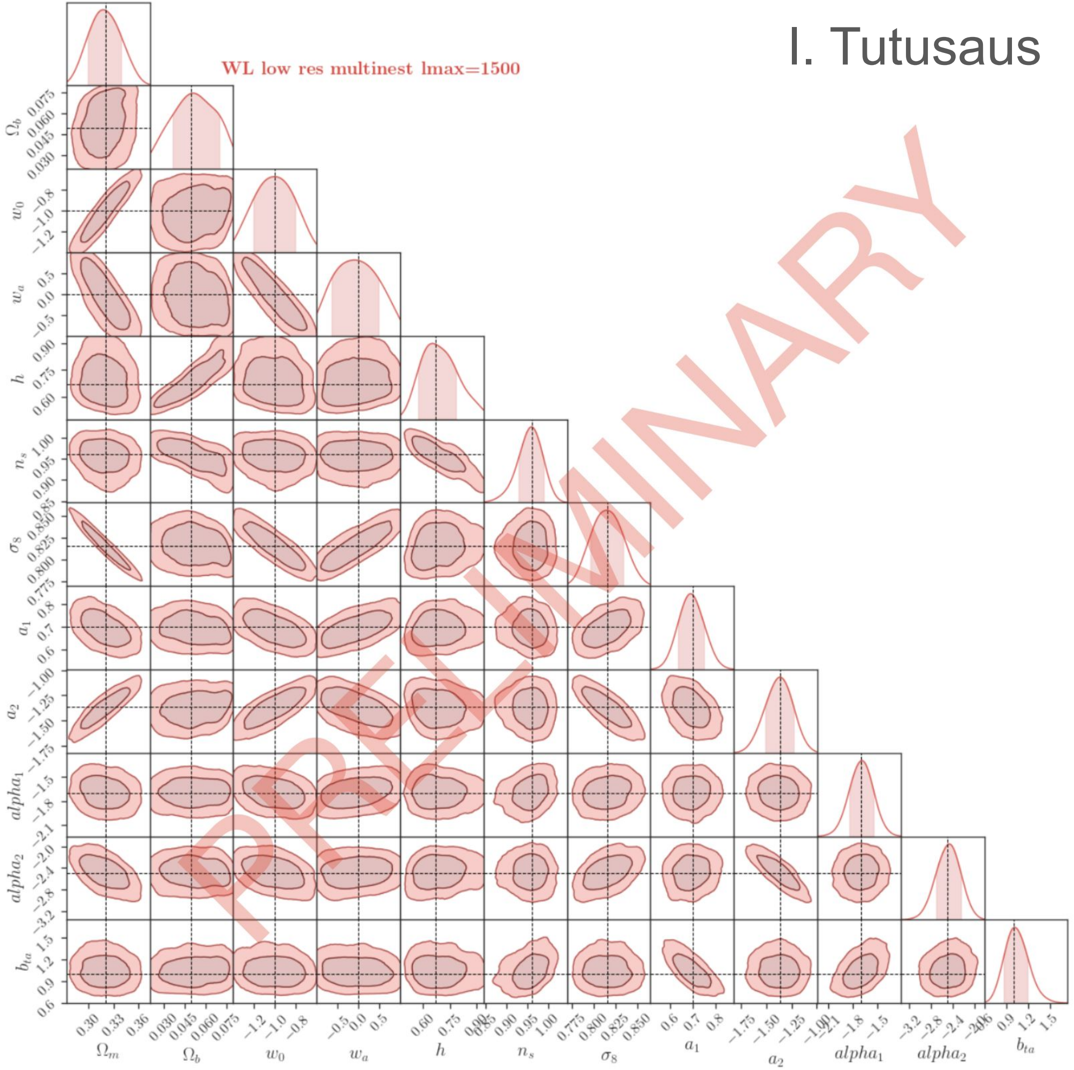
Models considered so far:

- TATT MCMC – multinest

Not prior dominated:

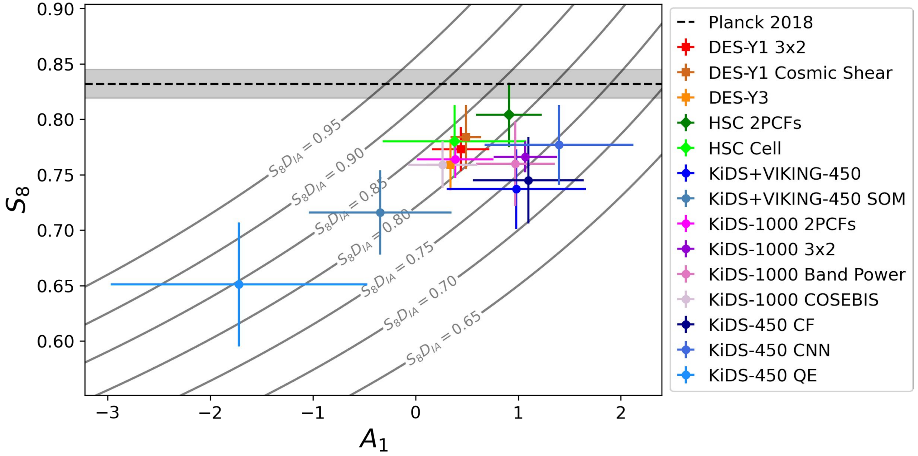
- Om [0.1, 0.9]
- Ob [0.02, 0.08]
- w0 [-1.4, -0.6]
- wa [-1.0, 1.0]
- h [0.4, 0.94]
- ns [0.5, 1.4]
- sig8 [0.2, 1.14]
- a1 [-5.0, 5.0]
- a2 [-5.0, 5.0]
- alpha1 [-5.0, 5.0]
- alpha2 [-5.0, 5.0]
- bta [0.0, 2.0]

Strong constraints on IA parameters from WL alone



Exploring the interplay between IA and redshift errors

Silvan Fischbacher, Tomasz Kacprzak, Jonathan Blazek, Alexandre Refregier

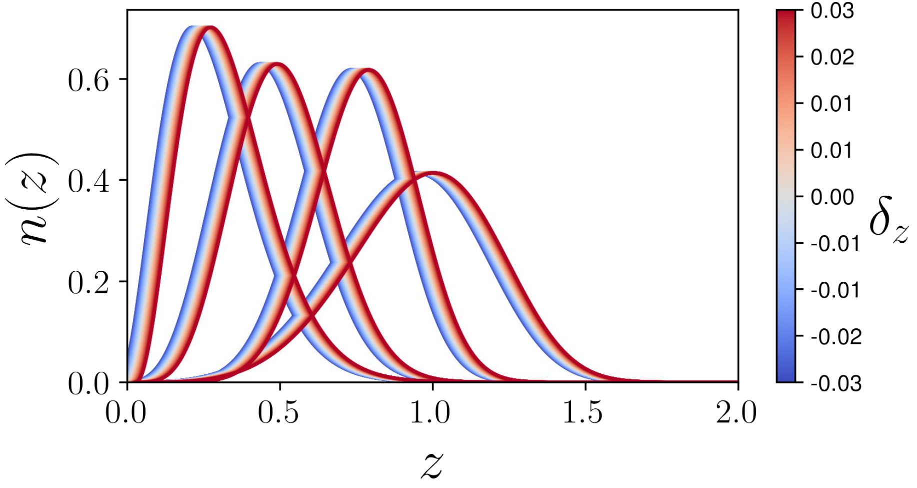


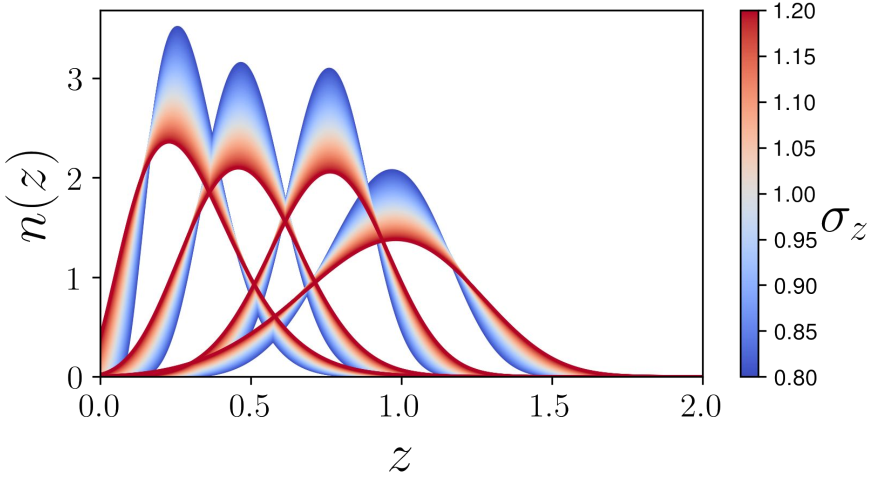
- Studying impact of systematic errors on cosmic shear constraints
- We developed ChaosHammer, a fast Cℓ emulator
- MCMC converges in a few seconds

Add systematic errors in mock observation → MCMC → Study impact on cosmological constraints

Parametrization of redshift bin errors

Silvan Fischbacher, Tomasz Kacprzak, Jonathan Blazek, Alexandre Refregier



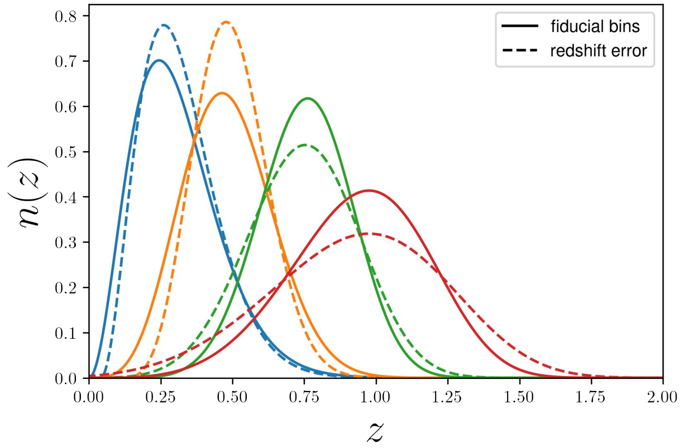


- Shifts of the mean
- Typically marginalized over in surveys

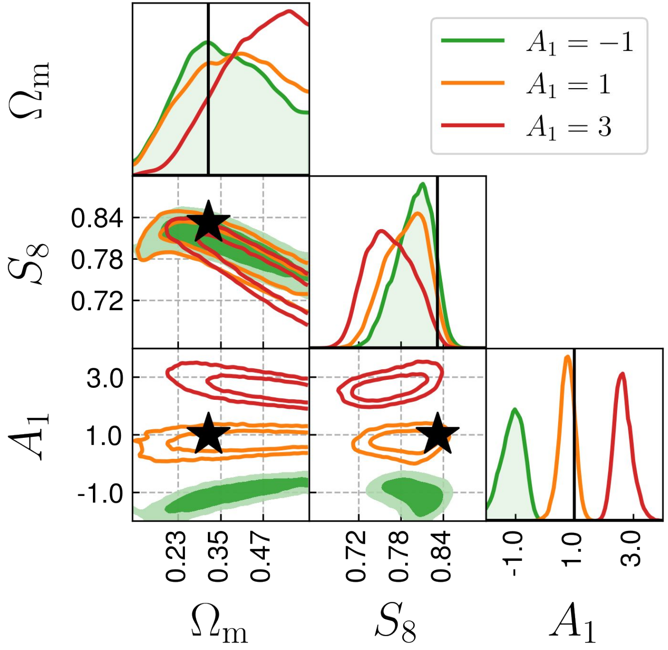
- Stretches of the width
- Typically not considered in surveys

Coupling between IA and z-errors

Silvan Fischbacher, Tomasz Kacprzak, Jonathan Blazek, Alexandre Refregier



MCMC



Different biases depending on underlying IA parameter

- Easily extendable to different systematics or parameters of interest
- Redshift calibration requirements for current and future surveys
- Quantification of prior volume effects
- Can redshift errors explain the S8 tension?

IA Self-Calibration mitigation method into DESC pipeline

Pitched by Mustapha: (Authors: Eske Pedersen, Leonel Medina-Varela, Emily Phillips-Longley, Mustapha Ishak, Joe Zuntz, Chihway Chang)

Part I: Led by Eske Pedersen: implementation of IA self-calibration modules into LSST-DESC TXPipe pipeline:

- Calculating new correlations with a selection function that takes into account the redshift dependencies
- **No IA model is assumed to extract IG signal**
- Calculation of other needed parts (e.g. eta, Q, scaling relations)
- Applied to DES Y1: IA extraction with high significance;
- Also in KIDS450 modest detection, Pedersen et al, Yao et al.
- LSST-DESC paper soon to go to internal review

$$C_{ij}^{IG}(\ell) \simeq \frac{W_{ij}\Delta_i}{b_i(\ell)} C_{ii}^{Ig}(\ell),$$

$$C_{ii}^{\gamma g} = C_{ii}^{Ig} + C_{ii}^{Gg},$$

$$C_{ii}^{\gamma g}|_S = C_{ii}^{Ig} + C_{ii}^{Gg}|_S,$$

$$Q_i(\ell) \equiv \frac{C_{ii}^{Gg}|_S(\ell)}{C_{ii}^{Gg}(\ell)}$$

$$C_{ii}^{Ig}(\ell) = \frac{C_{ii}^{\gamma g}|_S(\ell) - Q_i(\ell) C_{ii}^{\gamma g}(\ell)}{1 - Q_i(\ell)}.$$

IA Self-Calibration mitigation method into DESC pipeline

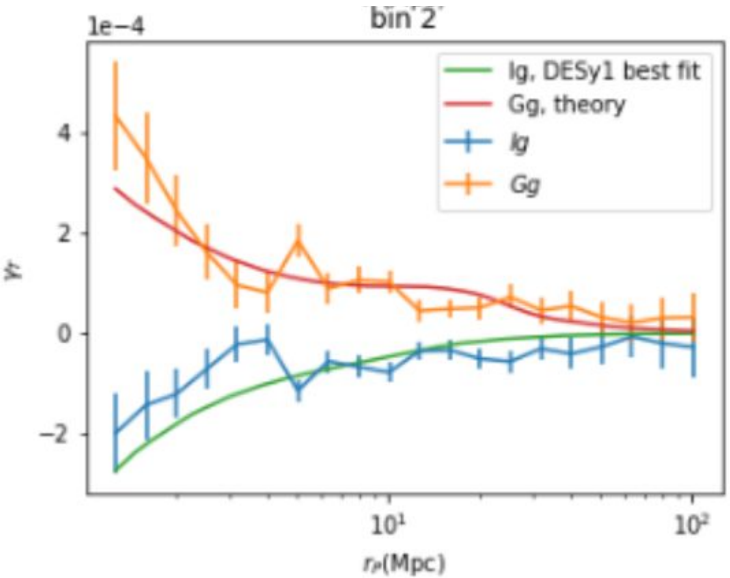
Pitched by Mustapha: (Authors: Leonel **M**edina-Varela, Alan **Z**ou , Mustapha **I**shak, Michael **T**roxel)

Part II: Led by **M**edina-Varela, **Z**ou: a more sophisticated implementation of IA self-calibration into analysis pipelines

Comparisons of codes ongoing

Application to mocks and data sets

Interested in Self-calibration method for other survey



Pedersen et al, 2021 TBS

NLA IA with PAUS data

Jacobo Asorey, Juan Mena, David S Cid (Ciemat, Madrid)

PAU Survey dataset properties

- Observations carried out on **40 narrow bands**
- Great **radial distance** determination suitable for IA analysis
- Galaxy sample already divided in **blue and red samples** H. Johnston et al. 2021
- Same starting point as *David Navarro* - W3 data presented in H. Johnston et al. 2021

Goals

- Calibrate NLA modeling to help Stage III & IV analysis (i.e. 3x2pt analysis)
- Perform the IA analysis considering
  - correlation functions in **real space** with **angular separations**
  - the DES inference tool: Cosmosis
- Check the advantages of using NLA modeling (**level of complexity**)

$$\bar{\gamma}_{ij}^{IA} = A_1 s_{ij} + A_{1\delta}\delta s_{ij} + A_2 \sum_k s_{ik} s_{kj} + \dots$$

NLA

TATT

$$A_1(z) = -\boxed{a_1}\bar{C}_1 \frac{\rho_{crit}\Omega_m}{D(z)}\left(\frac{1+z}{1+z_0}\right)^{\boxed{\eta_1}}$$

$$A_2(z) = 5\boxed{a_2}\bar{C}_1 \frac{\rho_{crit}\Omega_m}{D^2(z)}\left(\frac{1+z}{1+z_0}\right)^{\boxed{\eta_2}} \qquad A_{1\delta} = \boxed{b_{TA}} A_1$$

NLA IA with PAUS data

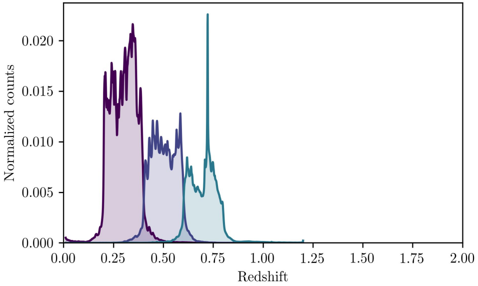
Jacobo Asorey, Juan Mena, David S Cid (Ciemat, Madrid)

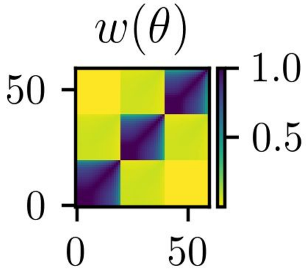
Preliminary results

- ❑ wtheta is computed using **treecorr** (Jacobo) and **nbodykit** (Juan) considering W3 field data (H. Johnston et al. 2021)
- ❑ a Cosmosis-ingestible dv is formatted using **twopoint** DES code

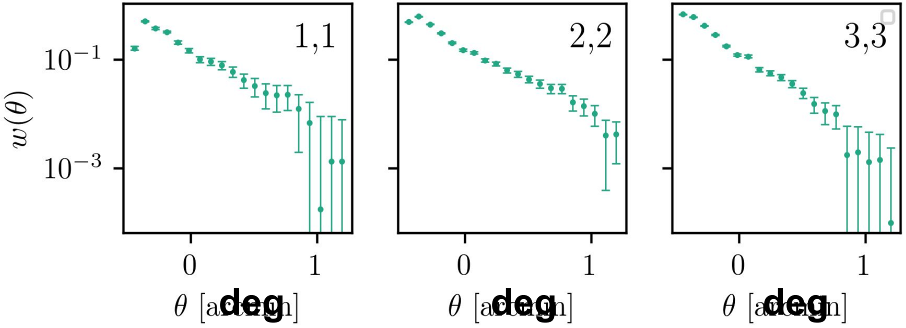
DV = dndz + ACFs + covariance matrix

- ❑ an analytical covariance matrix is computed using Cosmosis

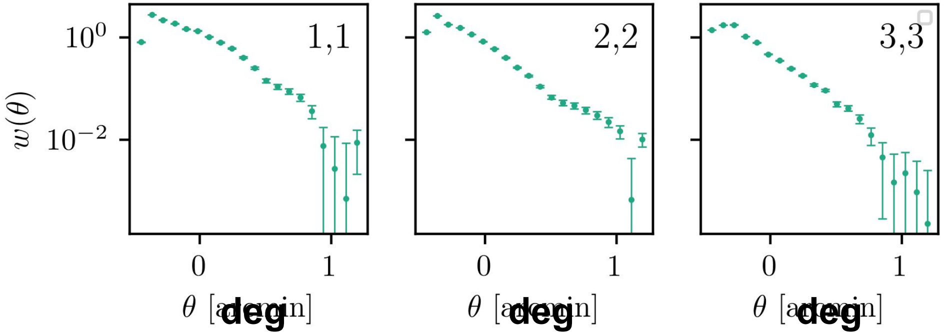




Blue galaxies



Red galaxies



NLA IA with PAUS data

Jacobo Asorey, Juan Mena, David S Cid (Ciemat, Madrid)

Next steps

- ❑ Compute gglensing correlation function
- ❑ Add dndz blue galaxies
- ❑ Add cross-correlations info
- ❑ Compute a more robust covariance matrix
- ❑ Start designing IA analysis pipeline
- ❑ **Comments/suggestions/advices ???**

Contact

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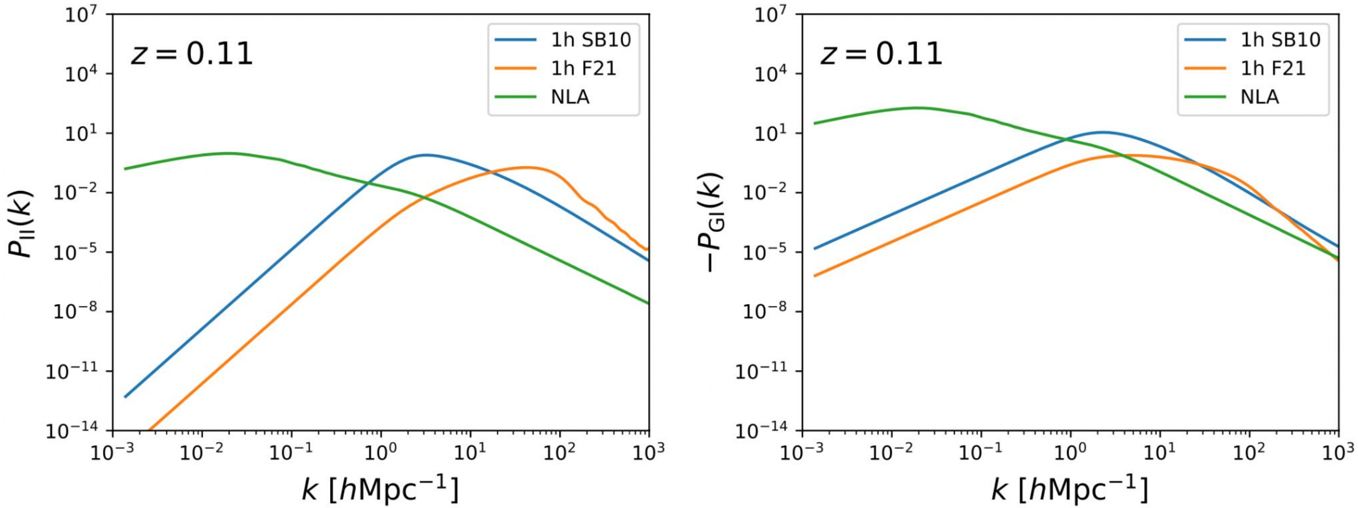
Juan Mena (juan.mena@ciemat.es)

Halo model for IA in CCL (Christos Georgiou)

- Implementation in CCL (based on Fortuna+2021) under development.
- Open source code, under IA_Halo_Model branch, planned to be included in master in the next couple of months.
- Not stopping there: EFT, firecrown likelihood + augur sampler.



Shared modeling tools - discussion (Jonathan Blazek)

Goal: We would like to analyze measurements using consistent implementation and modeling choices.

- Current status: public modules for NLA and TATT in the Core Cosmology Library (CCL) and CosmoSIS, (implemented with FAST-PT, so quite fast)
- Halo model (nearly ready) and EFT in progress in CCL.
- Coupling to nonlinear biasing (in progress, nearly complete)
- Choices for parameterization, normalization, etc?
- What will be most useful to the community?
- **Wednesday discussion for more technical details and planning**

Session 3 - Data focus (Tuesday, ~1500 UTC)

Intrinsic Alignments with PAUS data

David Navarro, Anna Wittje, Martin Crocce, Enrique Gaztañaga, Hendrik Hildebrandt

PAU Survey [pausurvey.org]:

- 40 narrow bands from 4500Å to 8500Å at 100Å intervals, combined with broad-band data
- Target photo-z accuracy of $\sigma_{68} < 0.01(1+z)$
- 5 different WL fields : 46 deg^2 in all the 40 NB.
- Targeted depth $i_{AB} < 23$ and ~ 1.5x10^6 galaxies
- Galaxy shapes from CFHTLS and KiDS
- Ideal for precise IA studies
- Data already taken and reduced

Area covered by the PAUS observed fields

	Area 40	Area 30	Area 20	Area 10
Cosmos	1.8	2.2	3.2	3.8
W1	11	11	13	15
W2	13	15	17.5	20
W3	20	21	22	26
W4	0.2	0.4	0.8	1.0
Total	46	49.6	56.5	65.8

Our starting point is H. Johnston et al. 2021: first measurements of the projected galaxy clustering and Intrinsic Alignments in the PAUS W3 field (null detection of IA for blue galaxies and radial alignments for red galaxies)

Intrinsic Alignments with PAUS data

David Navarro, Anna Wittje, Martin Crocce, Enrique Gaztañaga, Hendrik Hildebrandt

Photo-z computation:

- Generate new and improved catalogues of photo-z data in the CFHT Wide Fields (W1, W2 and W3), using a new method to calibrate and to obtain these photo-z.

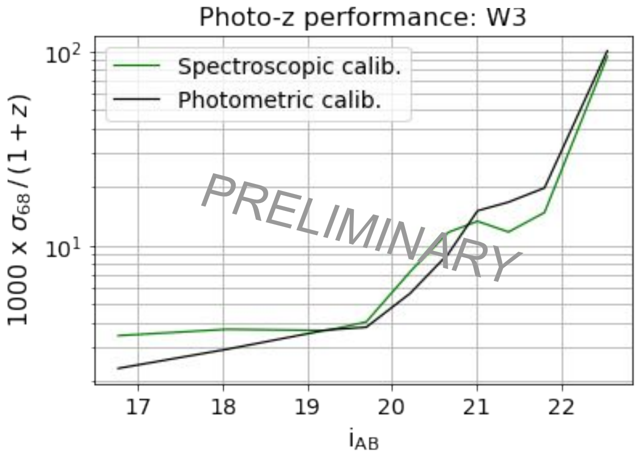
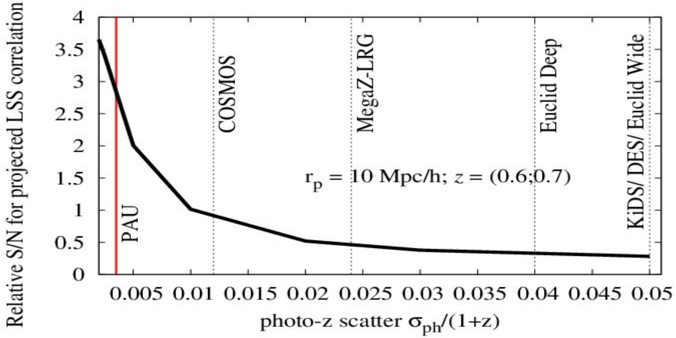


Photo-z requirements for IA:

- $\sigma_{68}/(1+z) < 0.01$ (<0.005 ideally)
- Catastrophic outliers: will restrict the subsample that can be used for IA
- Flux limited sample: easier to interpret



Intrinsic Alignments with PAUS data

David Navarro, Anna Wittje, Martin Crocce, Enrique Gaztañaga, Hendrik Hildebrandt

Projected position-shape correlations will be computed for the W1, W2 and W3 fields with a tree correlation code (TreeCorr).

$$\hat{\xi}_{g+}(r_p, \Pi) = \frac{S_+D - S_+R_D}{R_S R_D}\Big|_{r_p,\Pi} \qquad \hat{w}_{g+}(r_p) = \int_{-\Pi_{max}}^{\Pi max} \hat{\xi}_{g+,norm}(r_p, \Pi)d\Pi \quad \text{and} \quad \hat{w}_{gg}(r_p)$$

- The samples will be split by **color** (red/blue) and **redshift**.
- Results will be compared with dedicated simulations.

Improvements with respect to H. Johnston et al. 2021 :

(1) double the area to ~ 50 $\deg^2$ (2) improve the photo-z performance (3) reach fainter galaxies i_{AB} < 23.
(4) make new photo-z catalogues publicly available

Contact

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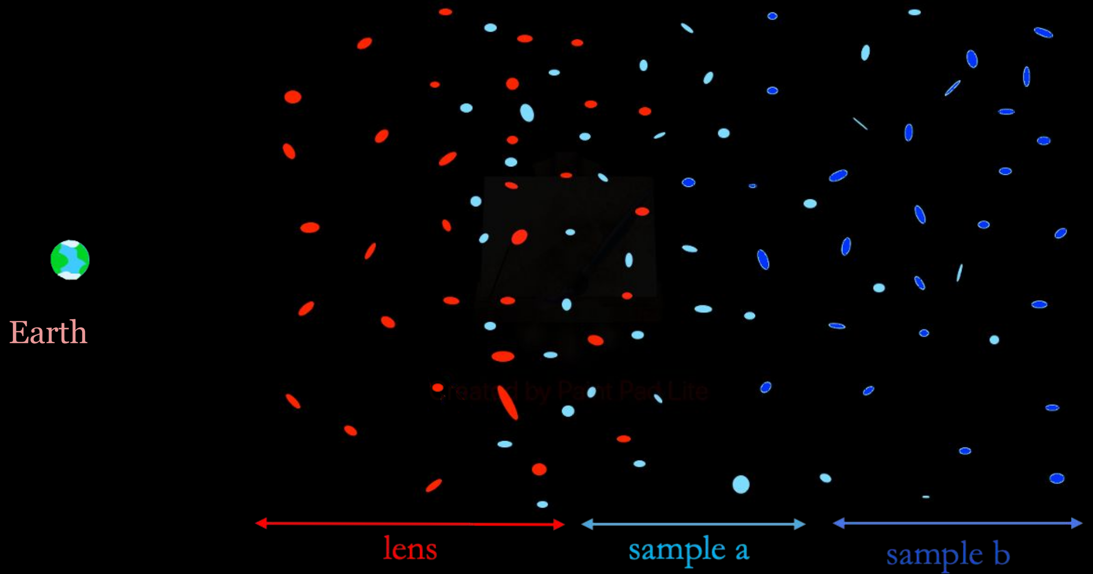
Separating Weak Gravitational Lensing and Galaxy Intrinsic Alignments in DES Y1 (Sara A. Safari)

In collaboration with Prof. Jonathan Blazek and Dr. Danielle Leonard.

Method

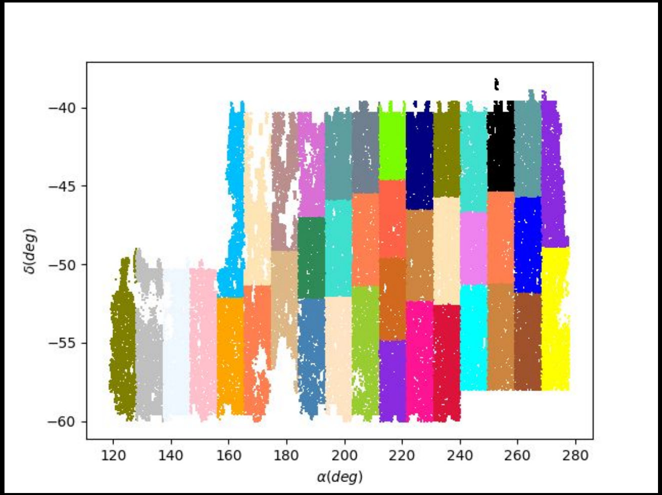
Blazek et al. 2012
Leonard & Mandelbaum 2018

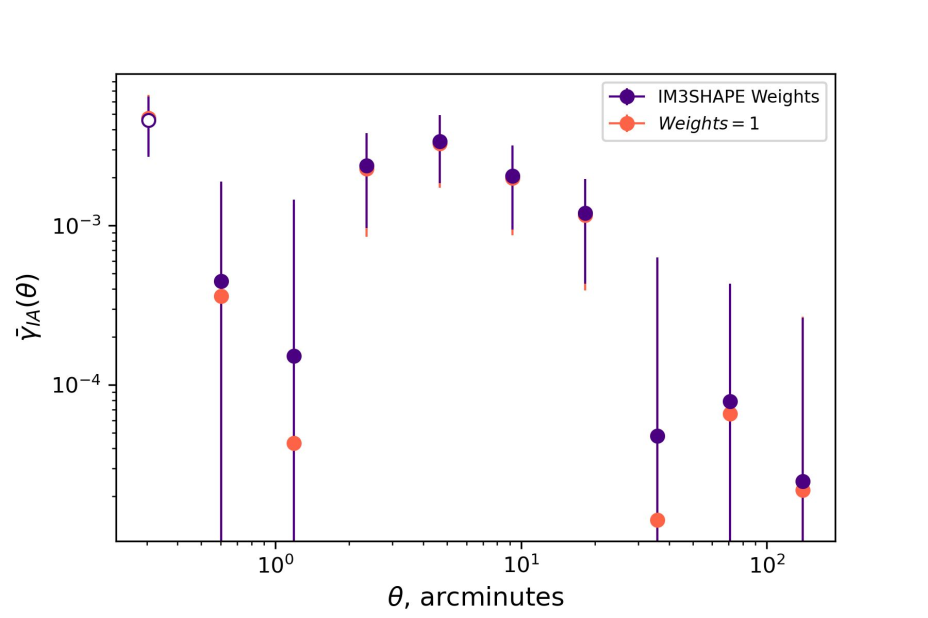


Separating Weak Gravitational Lensing and Galaxy Intrinsic Alignments in DES Y1 (Sara A. Safari)

In collaboration with Prof. Jonathan Blazek and Dr. Danielle Leonard.

Measured IA signal

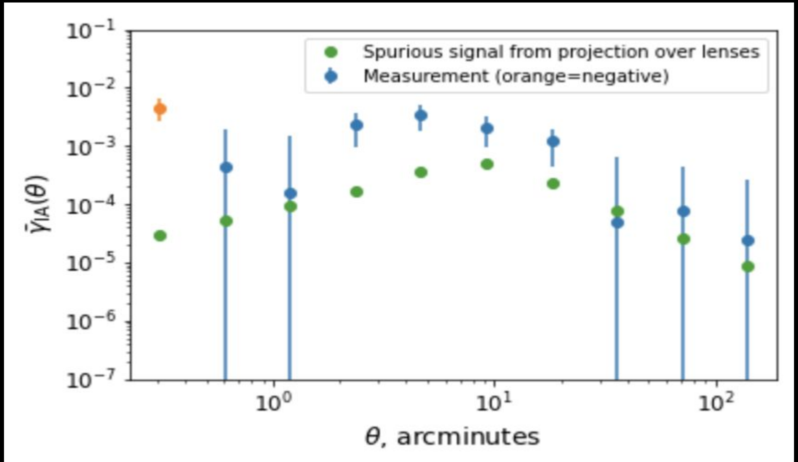


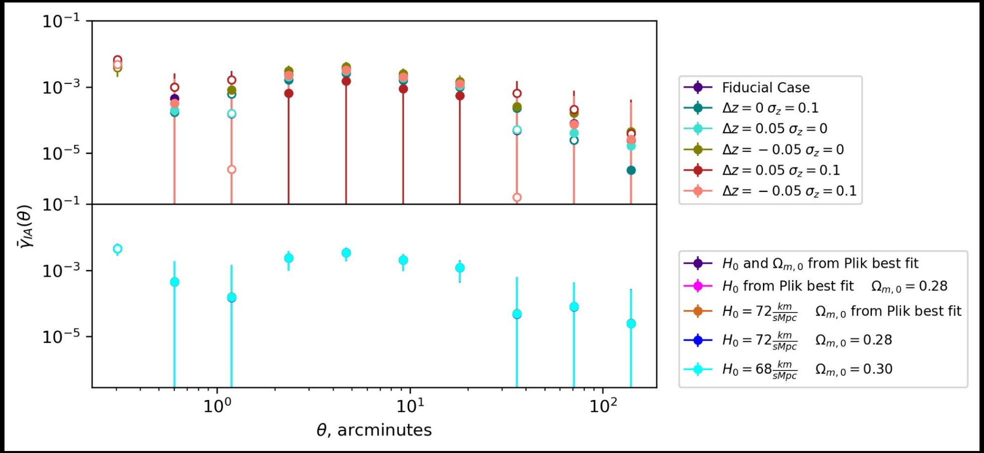


Separating Weak Gravitational Lensing and Galaxy Intrinsic Alignments in DES Y1 (Sara A. Safari)

In collaboration with Prof. Jonathan Blazek and Dr. Danielle Leonard.

Robustness checks

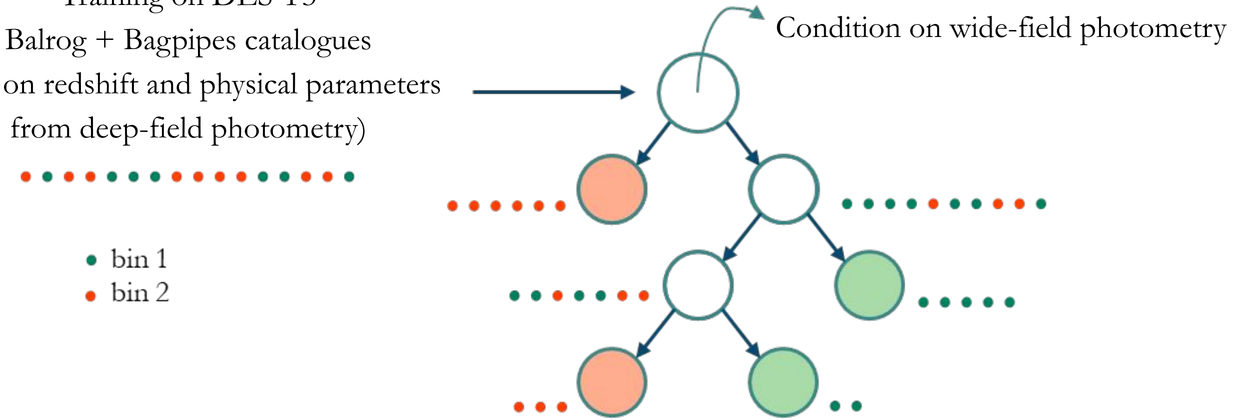




Measuring and modeling IA as function of physical galaxy parameters (Elisa Legnani with Alex Amon & Daniel Gruen)

Part 1: selecting subsamples of DES Y3 tomographic bins that differ by physical parameters with a decision tree

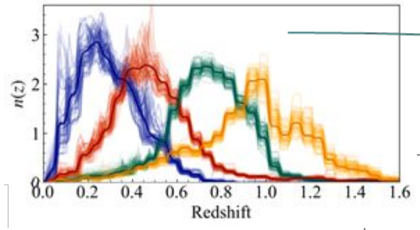
Training on DES Y3
Balrog + Bagpipes catalogues
(info on redshift and physical parameters
from deep-field photometry)

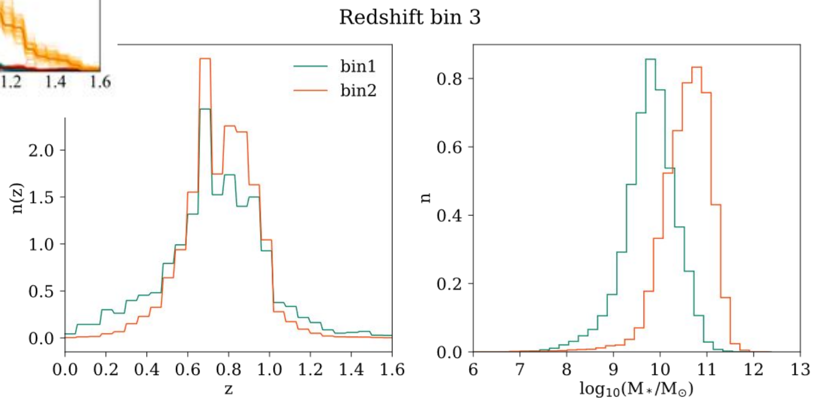


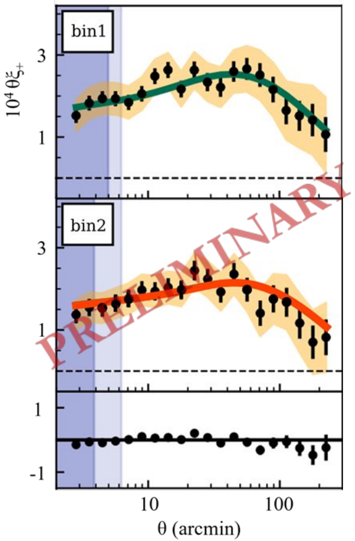
Measuring and modeling IA as function of physical galaxy parameters (Elisa Legnani with Alex Amon & Daniel Gruen)

Part 2: measuring lensing with subsamples that have distinct physical parameters but ~same redshift distribution: direct measurement of Delta IA!

For accurate results, requires re-calibration of shape measurement / redshifts for subsets



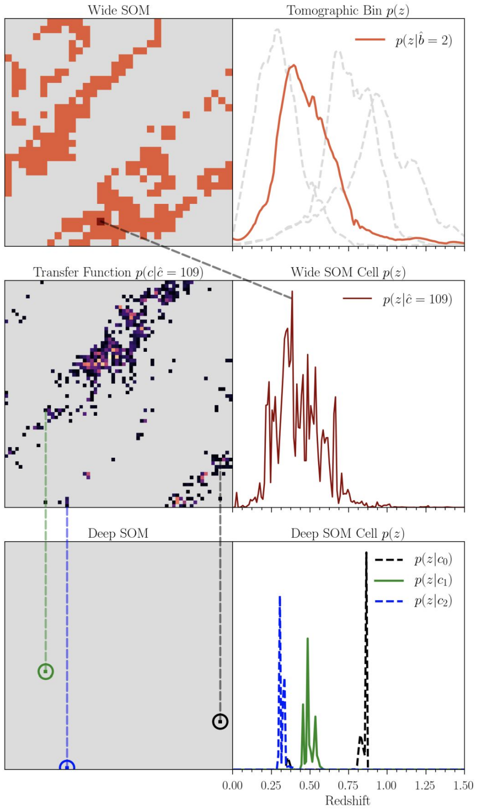




Measuring and modeling IA as function of physical galaxy parameters (Elisa Legnani with Alex Amon & Daniel Gruen)

Part 3: interpreting what we find!

Ultimate goal: a description of the galaxy population (SEDs, redshifts, luminosities, morphologies, IA, bias) forward-modeled into observables in photometric surveys. Steps towards that made in the deep-wide calibration of redshifts in DES Y3 [Figure from Myles, Alarcon, Amon+]



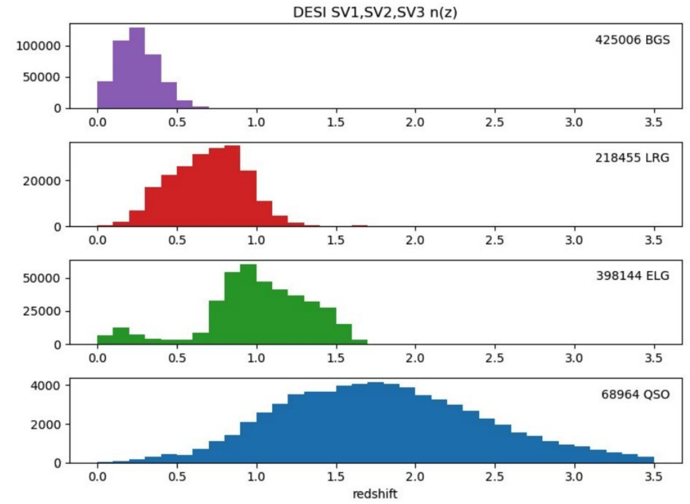
What's the right ansatz for IA model in this picture?

What's a simpler ansatz for modeling what we measure now, short of that?

Direct detection IA with DESI
(Alex Amon, Niall Jeffrey, Benjamin Joachimi, Mustapha Ishak, Leonel Medina)

- Planning to target the equatorial plane at full depth by end of Y1.

- Plan to use the combination of the DESI samples matched to public KiDS/DES/HSC following the methodology of Johnson et al.



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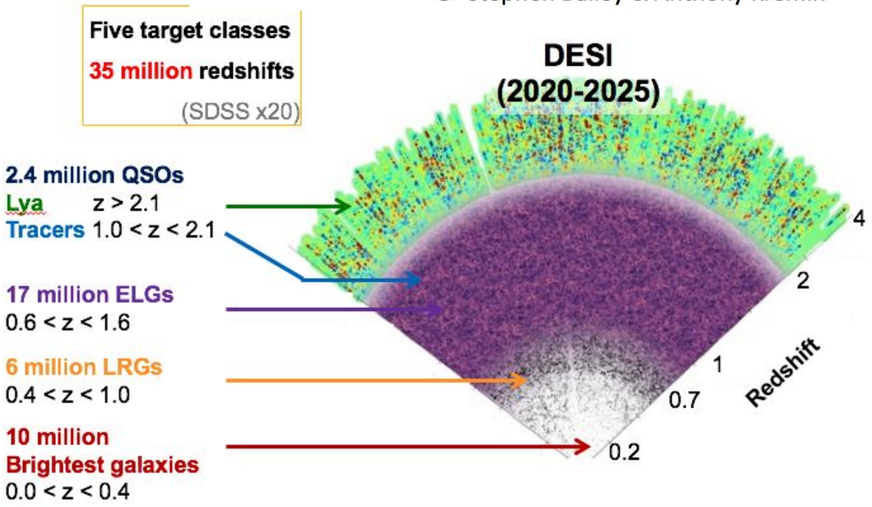
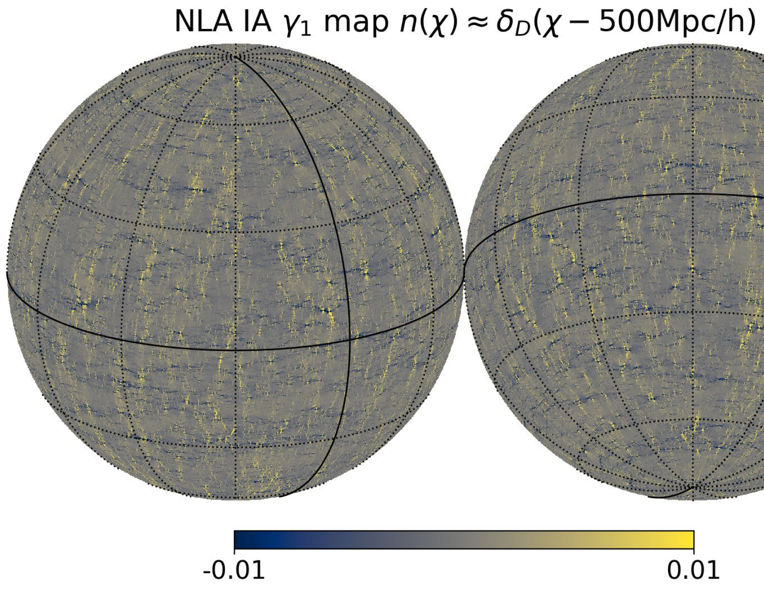
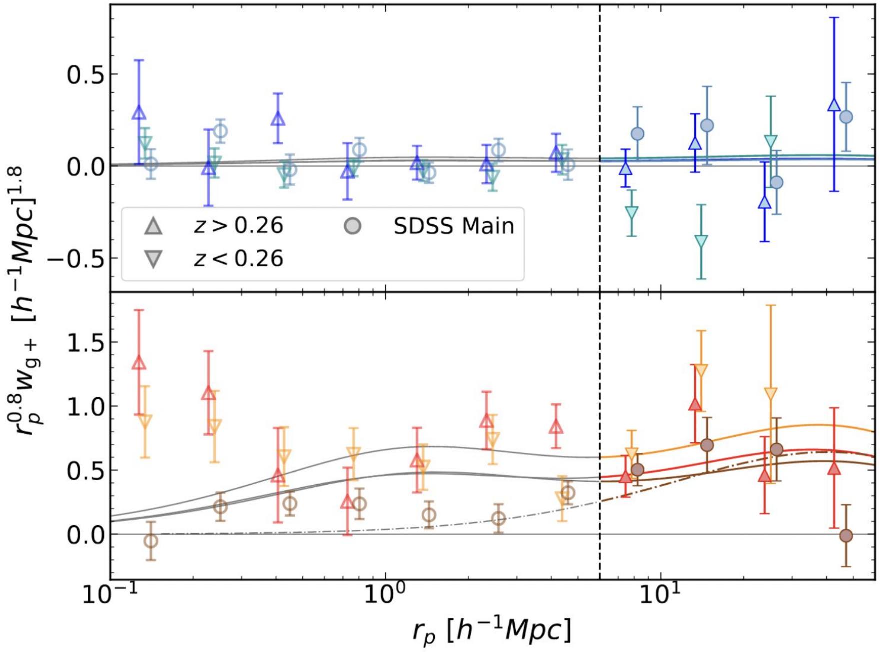


Direct detection IA with DESI

(Alex Amon, Niall Jeffrey, Benjamin Joachimi, Mustapha Ishak, Leonel Medina)

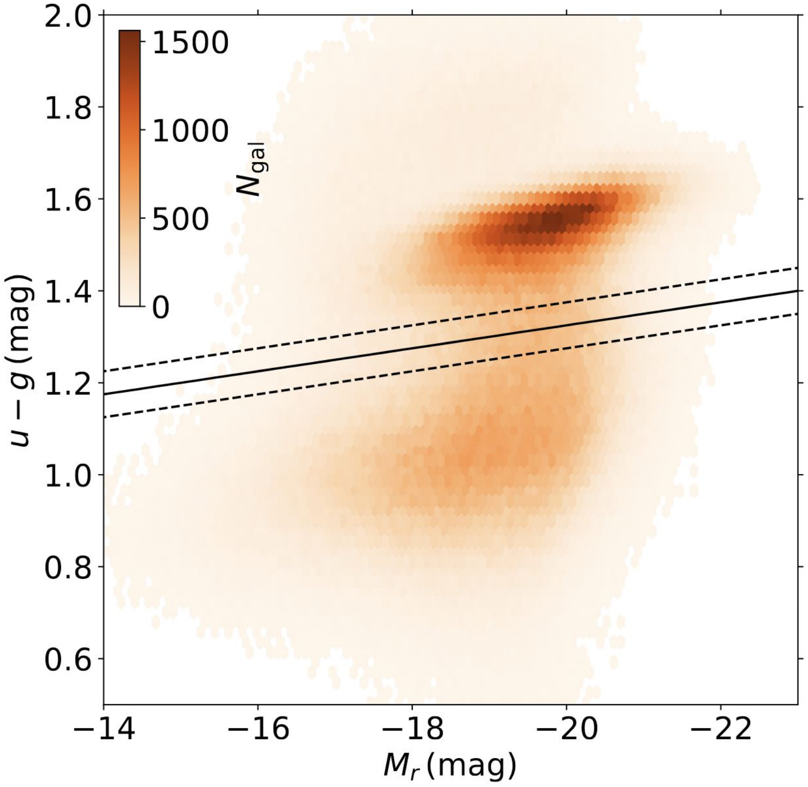




Following the methodology of Johnston et al. 1811.09598

IA on KiDS-1000 Bright Sample (Christos Georgiou)

- Photometric sample of m_r<19.8 galaxies, 0.1<z<0.5, redshifts trained on GAMA spectroscopy.
- 1 million galaxies
- Accuracy σ_z ~ 0.02 (1+z).
- If interesting; data products mostly ready for measurement.



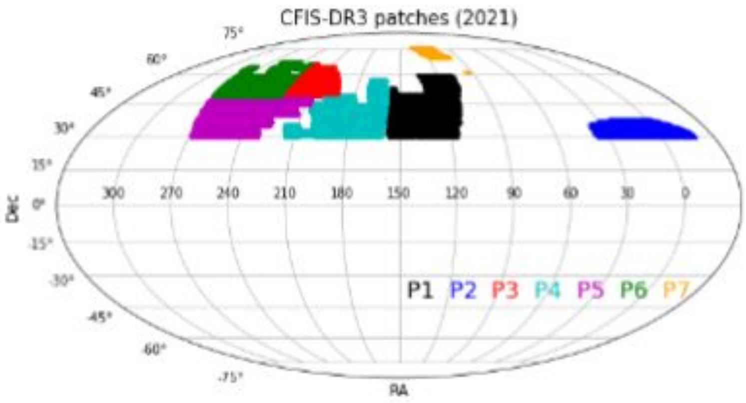
Bilicki et al. 2021

UNIONS/CFIS (Martin Kilbinger, François Lanusse)

UNIONS = Ultraviolet Near-Infrared Optical Northern Survey,
CFIS = Canada-France Imaging Survey

band	telescope	Consortium
u	CFHT	CFIS
g	Subaru	WHIGS
r	CFHT	CFIS
i	Pan-STARRS	UNIONS
z	Pan-STARRS, Subaru	UNIONS, WISHES

3,500 deg^2 *r*-band,
120 million WL galaxies, ~ 12 gal/amin^2



800 deg^2 *ugriz*, more coming soon

UNIONS/CFIS (Martin Kilbinger, François Lanusse)

Limiting *r*-band magnitude ~ 24.5
Median seeing = 0.65

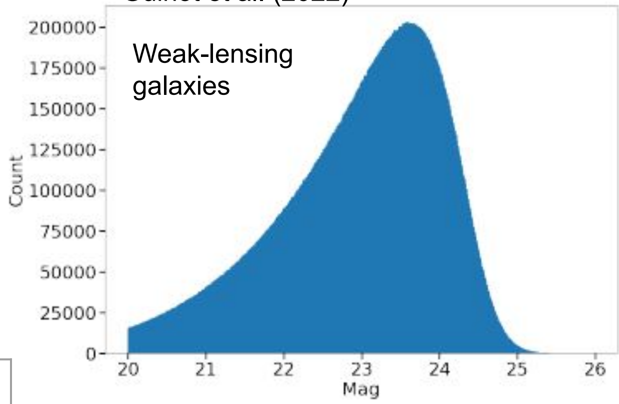
PSF to galaxy shape leakage < 0.02
Additive bias < 3 x 10^{-4}

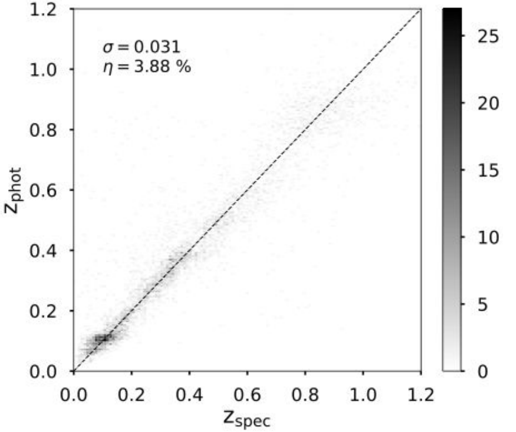
Photo-z's (prelim.)

UNIONS + DEEP3:
σ = 0.08, η=14%

UNIONS + SDSS:
σ = 0.03, η=4%

Guinot et al. (2022)





Overlap with deep spectroscopic surveys:

Survey	**Sample**	n_{gal} **[deg^{-2}]**	**redshift range**	A_{joint} **[deg^2]**
BOSS	LOWZ, CMASS	147	0.15 < z < 0.7	3000
eBOSS	LRG, ELG	50	0.6 < z < 1	3000
DESI	LRGs	285	0.4 < z < 1	4000
DESI	BGS	700	0.04 < z < 0.4	4000

Direct IA measurement with DES Y3 + eBOSS

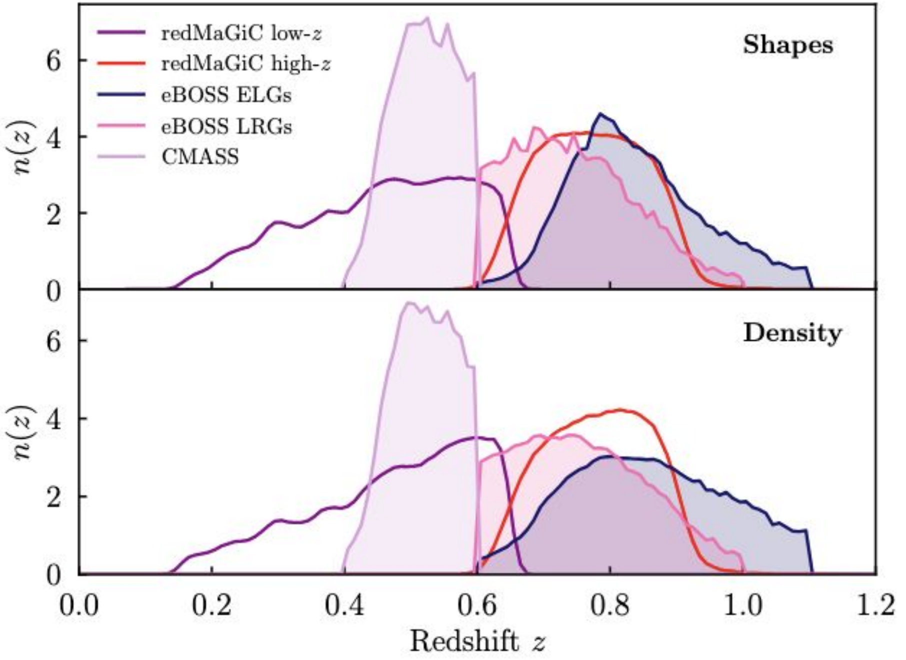
Simon Samuroff, Rachel Mandelbaum, Jonathan Blazek

Five samples:

- **eBOSS LRGs**
  - 600 sq. deg., $z \sim 0.75$
- **Y3 redMaGiC high-z**
  - 4143 sq. deg., $z \sim 0.8$
- **Y3 redMaGiC low-z**
  - 4143 sq. deg., $z \sim 0.45$
- **CMASS**
  - 600 sq. deg., $z \sim 0.5$
- eBOSS ELGs
  - 600 sq. deg., z~0.8

each of which are matched to DES Y3 for shapes.

For each sample, we measure the projected correlations wg+, w++ and wgg, as a fn. of r_p, and fit simultaneously

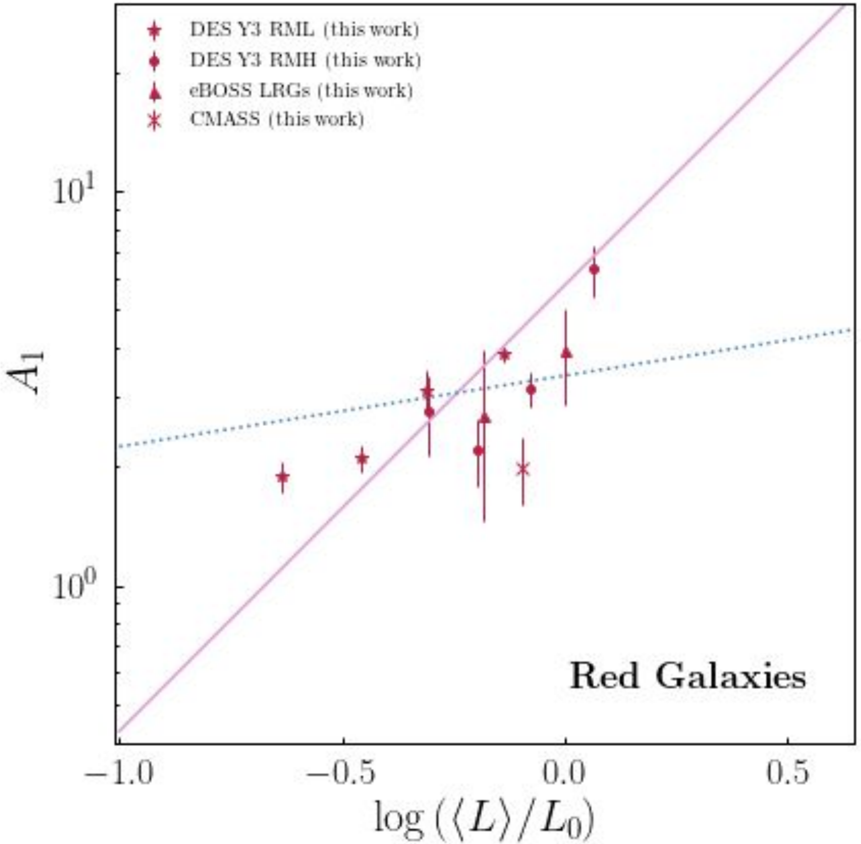


Direct IA measurement with DES Y3 + eBOSS

Simon Samuroff, Rachel Mandelbaum, Jonathan Blazek

- Model wg+ and w++ (and wgg) jointly using NLA on scales >6 Mpc/*h*
- We can then try to constrain IA strength as a fn. of galaxy properties such as luminosity (see right) and redshift
- redMaGiC low-*z* in particular is interesting, as it is a relatively large sample, reaching faint-ish luminosities

- The high S/N of our samples also provides good ground for IA model testing
→ Fit TATT + NLA on sequentially smaller scales, and use model comparison metrics to identify if/when TATT is preferred



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