

# Optimal intrinsic alignment estimators in the presence of redshift space distortions

Claire Lamman ,<sup>1\*</sup> Jonathan Blazek,<sup>2</sup> Daniel J. Eisenstein<sup>1</sup>

<sup>1</sup>Center for Astrophysics | Harvard & Smithsonian, 60 Garden Street, Cambridge, MA 02138, USA

<sup>2</sup>*Department of Physics, Northeastern University, Boston, MA, 02115, USA*



## SUMMARY

**MARY** Received YYY; in original form ZZZ

## ABSTRACT

*We have ideas for improving measurements you've probably never heard of. This paper was written for the tens of people who have. Although not particularly glamorous, technical papers like these can end up being some of the most useful to other scientists. This annotation gives a glimpse at the types of problems we need to think about for developing new methods.*

**TL;DR: When measuring how much galaxies point at each other, you should care more about galaxies that are close together. Except if they're too close, then you should care about ones a bit further away.**

**Key words:** methods: data analysis — Statistical cosmology; observations: large-scale structure of Universe

## 1 INTRODUCTION

# WHY BOTHER?

**s the cosmic web of dark matter grows, the shapes and orientations of galaxies tend to align with it. They point at each other (but really they're pointing at big invisible clumps of matter which tend to form lots of galaxies).** Joachimi et al. (2015); Troxel &

Ishak (2015) for reviews and Lamman et al. (2024a) for a guide to IA estimators and formalisms. Spectroscopic surveys, combined with imaging data, provide the best direct measurements of IA, including the Sloan Digital Sky Survey (SDSS) (Singh et al. 2021) and first year of data from the Dark Energy Spectroscopic Instrument (DESI) (Siegel et al. 2022). However, common conventions for measuring IA were largely developed with lensing in mind (Mandelbaum et al. 2006). The advent of large spectroscopic surveys like DESI, with their potential to yield insights on IA for both upcoming surveys and direct application, makes it time to revisit IA estimates.

Lyman-alpha emitters are commonly measured as projected statistics. The projected sample of galaxies are measured relative to the underlying matter density, as traced by galaxies, and the correlations are averaged over a range of scales.

**This is a real pain for people who care about weak lensing: a way to measure dark matter by the tiny little ways that its gravity messes with the light of galaxies. Most of the methods we use to measure galaxy alignments come from trying to solve this problem.**

A disadvantage of using these 3D estimators is that it is redshift-space-distortions (RSD). In redshift space galaxies' peculiar velocities create a “smearing” along the LOS below separations of about  $3 h^{-1} \text{Mpc}$  (Jackson 1972), known as the fingers-of-god effect (FOG). At larger scales, infall into overdense regions produces a LOS “dashedness” (Kaiser 1987), known as the Kaiser effect. This means the IA signal does not follow a perfect  $\mu$  relation in redshift space, and 3D IA correlations must successfully model these effects.

Here we present a set of alternative estimators that combine the advantages of both classic and 3D measurements: a  $\Omega_{\text{max}}$  which varies with the redshift,  $\Omega_{\text{max}}(z)$ , and a  $\Omega_{\text{max}}$  which is constant. These estimators are based on the same principle as the  $\Omega_{\text{max}}$  estimator, but they take into account the shape projection and RSD. They have the potential to provide similar information about the matter distribution and the expansion history of the universe.

\* E-mail: claire.lamman@cfa.harvard.edu

Variable	Description	Equation
$s_{\parallel}$	separation along the LOS in real space	$s_{\parallel} = r \cos \theta$
$\theta$	angle with respect to the LOS, $0 < \theta < \pi$	$\theta$
$\mu$	characterizes $\theta$ , $\mu = \cos \theta$	$\mu$

Measurements of galaxy alignment are tricky because we can only see the projected shape of galaxies. >>

Because of this, people often measure projected shapes relative to projected separation (distance between galaxies on the sky), a 2D measurement. But this throws out useful information, so some people have been working on measuring projected shapes relative to the full 3D separation between galaxies. But this comes with its own challenges...  
 Here we come up with a method that tries to get the best of both worlds.

## 2 IA ESTIMATORS EXISTING METHODS

IA is quantified through a class of correlations involving galaxy positions and intrinsic shapes. Here we will exclusively focus on the intrinsic shape - density correlation, which describes the correlation between the projected shapes of galaxies and underlying density, which is typically traced by galaxy position. Variables are summarized in Table 1 and marked in Figure 1. We use  $r_{\perp}$  to describe transverse distance relative to a central tracer,  $r_{\parallel}$  to describe LOS distance in redshift space, and  $\mu$  the angle relative to the LOS.

### 2.1.1 Relative Ellipticity

$\mathcal{E}_+(r)$  is the average projected ellipticity relative to a neighbor galaxy as a function of separation  $r$  (Lamman et al. 2023). It can be thought of as average intrinsic shear,  $\epsilon_+$ . This is averaged over  $N$  shape-tracer pairs. For a shape catalog  $S$  and tracer catalog  $D$ ,

$$\mathcal{E}_+(r) = \frac{1}{N} \sum_{i \in S, j \in D} \epsilon_{+D}(r) \quad (1)$$

I. The average amount that galaxies tends to point towards its neighbors.

$DD$  and  $S+D$  are pair and weighted pair counts binned in  $r$ . This can also be averaged over bins of  $r_p$  and/or  $s_{\parallel}$  to obtain completely projected correlations. The relative ellipticity used to weight the counts in  $S+D$  is quantified as  $|\epsilon| \cos(2\phi)$ .  $\phi$  is the on-sky angle between the galaxy orientation and separation vector to a tracer galaxy and  $|\epsilon|$  is the absolute value of the shape's projected complex ellipticity. We define this in terms of the galaxy's projected axis ratio,  $q$ , as  $(1-q)/(1+q)$ , but some other works use  $(1-q^2)/(1+q^2)$ . Our results for optimal estimators do not depend on this choice.

$\mathcal{E}_+$  is the estimator we use to determine weights and compare  $\Pi_{\max}$

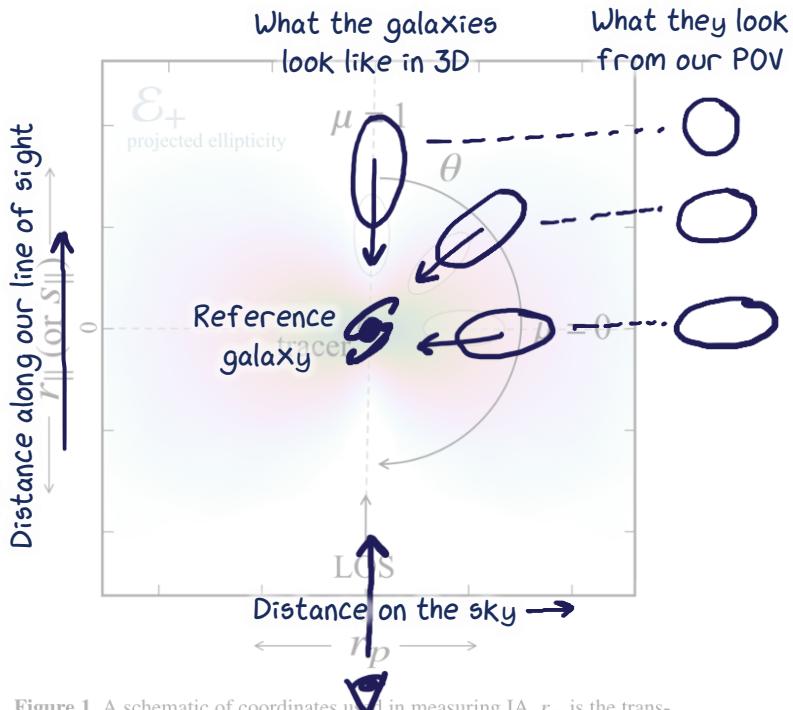
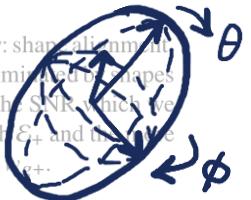


Figure 1. A schematic of coordinates used in measuring IA.  $r_p$  is the transverse distance relative to a central tracer,  $r_{\parallel}$  is the distance along the LOS in real space, and  $s_{\parallel}$  is the distance in redshift space. The background shading corresponds to the strength of measured tidal alignment; the extent to which a galaxy is at the position of the angular IA relative to a tracer. This is further generalized to the case of two galaxies too. Because we observe projected shapes, the measured alignment will be strongest along  $r_p$  and approaches 0 as  $r_p$  is small ( $r_p$  and ellipticity measurements scale from here to 100 $h$  Mpc in  $r_p$  and  $r_{\parallel}$ ). So you get a weird angular dependence if you try to measure this in 3D.

This diagram explains the setup: If you have a galaxy in the center, galaxies around it will tend to point at it. But we only observe the shapes of galaxies on the sky! to methods as it is related to the most relevant quantity: shape alignment independent of clustering. Assuming IA noise is dominated by shapes and not clustering (as is almost always the case), the SNR which we use to compare estimators will be the same for both  $\mathcal{E}_+$  and the more commonly used projected IA correlation function  $\xi_{g+}$ .



### 2.1.2 IA correlation function

The IA correlation function incorporates the 2-point galaxy clustering correlation function,  $\xi(r)$  and uses random catalogs for the shape and tracer samples,  $R_S$  and  $R_D$  (Mandelbaum et al. 2006). It is given as:

$$\xi_{g+} = \frac{S+D - S+R_D}{R_S R_D} \approx \frac{S+D}{R_S R_D} \quad (2)$$

This is a generalized form of the Landy-Szalay estimator Landy & Szalay (1993). The key difference compared to  $\mathcal{E}_+$  is that  $\xi_{g+}$  is not averaged on a per-pair basis. They are related as

$$\xi_{g+}(r) = \frac{DD - S+D}{DD} \xi(r) = (1 + \xi(r)) \mathcal{E}_+(r) \quad (3)$$

Especially for the case of clustering along the LOS to obtain the IA projected correlation function (e.g. Blazek et al. (2015)):

$$w_{g+}(r_p) = \int_{-\Pi_{\max}}^{\Pi_{\max}} dr_{\parallel} \xi_{g+}(r_p, s_{\parallel}) \approx (2\Pi_{\max} + w_p(r_p)) \mathcal{E}_+(r_p). \quad (4)$$

Here,  $w_p$  is the 2-point projected clustering correlation function integrated along the same  $\Pi_{\max}$  bounds. This can generally be related to the  $\mathcal{E}_+$  estimator through  $(2\Pi_{\max} + w_p(r_p))$ , but differences in binning pairs along the LOS can propagate as  $O(0.1)$  amplitude shifts.  $w_{g+}$  is the most common convention for direct IA measurements, and  $\Pi_{\max}$  is typically  $60 - 100 h^{-1}$  Mpc. While this estimator may be suitable for photometric surveys where there is a large LOS uncertainty, it is known to lose valuable LOS information when measuring

### 3. A fancy way to measure alignments IA in redshift space.

#### in 3D, taking into account the weird

##### 2.1.3 IA Measurements

Higher-order moments in each of the IA estimators allow us to reclaim LOS information lost in projected statistics. Unlike galaxy clustering, the tidal alignment of galaxies is much stronger when  $r_p > r_{\parallel}$  due to the geometry of projected shapes. This effect follows a  $1 - \mu^2$  dependence, as demonstrated in Figure 3, and is a result of projecting a 3D quadratic form onto a 2D plane. The projected shape orientation is not just a direct projection of the original axes, but a transformation of the entire ellipsoid surface, which involves a  $\sin^2(\theta) = 1 - \mu^2$  term. Singh et al. (2024) proposes a “weighted quadrupole”, which gives higher weight to shape-tracer pairs when  $\mu$  is small. The signal is measured as a function of  $r$ , made by summing over bins of  $\mu$  and weighting by  $1 - \mu^2 \propto L^{2,2}$ :

$$\tilde{\xi}_{g+,2}(r) = \xi(r) \frac{\sum_{i \in \mu} (1 - \mu_i^2) \mathcal{E}_+(r, \mu_i)}{\sum_i^n (1 - \mu_i^2)} \quad (5)$$

Singh et al. (2024) also removes all signal with  $r_p < 5h^{-1}$  Mpc to avoid noise from FOG at low separations and the difficulty of modeling IA in the nonlinear regime. From Equation 18 of that work, the “wedged” quadrupole for  $\xi_{g+}$  is:

## PROPOSED METHODS

$$\xi_{g+}(r) = \frac{1}{48} \int d\mu_r \Theta(r_p) L^{2,2}(\mu_r) \xi_{g+}(r, \mu_r) \quad (6)$$

Here,  $L^{2,2}$  are the ~~new methods that we propose.~~ ~~#3 considers the shape~~ ~~projection, but there's an addition problem that we want to consider.~~ ~~Redshift-Space Distortions (RSD)!~~ ~~the expectation of that signal, but the scale-dependence of alignment will have a marginal impact on the determined weights, weights are normalized in each  $r_p$  bin and the LOS-dependence in each  $r_p$  bin is dominated by shape projection and RSD. Therefore we can also derive weights~~ ~~from the Abacus halo catalogs (Section 3), which can be generalized to any elliptical galaxy population. Note that in real space, the derived weights will recover the  $1 - \mu^2$  dependence along the  $r_{\parallel}$  direction. We determine  $\mathcal{E}_+$  in 2D bins, shown in Figure 2, then fit a Gaussian to the  $s_{\parallel}$ -dependent signal to obtain weights for each  $r_p$  bin. The measurements and fits are shown in Figure 4. The Gaussian widths are plotted in Figure 5 and can be found in Table 2. There is a linear relation that follows  $\sigma = 3 + (2/5)r_p$ , with  $R_p = 0.5$  as the projected separation of  $r_p = 2h^{-1}$  Mpc. We explored fitting the curves with multiple  $1, 2, 3$  Gaussians but found no significant improvement in the fit.~~

## 2.2 Proposed estimators

In the presence of redshift-space distortions, there are two additional factors we seek to take into account: the Kaiser effect, which occurs near positive  $s_{\parallel}$  and negative  $s_{\parallel}$ , and the geometric effect, which occurs in the regime below  $r_p < 5h^{-1}$  Mpc. The Kaiser effect has a minimal impact on the IA signal, while the geometric effect is dominant in redshift space and not density (Kaiser 1987; Slepcev et al. 2014). Although modeling is challenging in the FOG regime, most information can be recovered in the  $r_p > 5h^{-1}$  Mpc regime. Figures 2 and 3 illustrate how the angular dependence of tidal alignment is affected by RSD using Abacus halos. The mathematical relation  $1 - \mu^2$  is replicated by tidal alignment in real space, but breaks down, especially at small separations, in redshift space. Here, close pairs of galaxies with strong alignments are smeared along the LOS. At very large  $r$ , the expected  $1 - \mu^2$  dependence is recovered. ~~If you've seen my other paper summaries, you might notice that my very first one was about how galaxy alignment can bias RSD. Now I'm looking at how RSD can bias alignments!~~

Here we explore two new ways to handle LOS information in each

bin of  $r_p$ : a LOS weighting and a variable  $\Pi_{\max}$ . Both seek to mitigate the impact of RSD, preserve LOS information, minimize modeling challenges, and improve SNR of direct detections. Both also result in a familiar projected correlation function, similar to  $w_{g+}$ , and can be modeled similarly (Section 4).

### 2.2.1 LOS weighting

A weighted  $\Pi_{\max}$ , or  $\tilde{\Pi}$ , functionally replaces the “top hat” of a set  $\Pi_{\max}$  cut with a Gaussian. This Gaussian assigns a LOS weight to each shape-tracer pair within a given  $r_p$  bin based on the signal dependence on shape projection and RSD. The result is a projected correlation function where each  $r_p$  bin contains a unique LOS weighting.

We define optimal weighting as one that maximizes the SNR of the final measurement and assume all noise comes from shape and shot noise. For a given  $r_p$  bin, the quantity of interest is the SNR of the signal. This can be characterized by the alignment amplitude, or model re-scaling:  $\mathcal{E} = \beta \mathcal{E}_{\text{model}}$ . The total signal summed over all pairs is proportional to  $\mathcal{E}(1 + \xi)$  and the noise is proportional to  $\sqrt{1 + \xi}$ . The  $\chi^2$  value for pairs in a given  $r_p$  bin is summed over their transverse separations  $s_{\parallel}$  as

$$\chi_{r_p}^2 = \frac{[\sum_{j \in s_{\parallel}} \mathcal{E}(1 + \xi) - \sum_{j \in s_{\parallel}} \beta \mathcal{E}_{\text{model}}(1 + \xi)]^2}{\sum_{j \in s_{\parallel}} (1 + \xi)}. \quad (7)$$

$\mathcal{E}$  and  $\xi$  are both functions of  $r_p$  and the  $j$  bin in  $r_p$ . To minimize this, we obtain weights  $W$  which are proportional to the expected signal in redshift space  $\mathcal{E}_+(r_p, s_{\parallel})$ . For a given  $r_p$ , the signal is a weighted sum across each pair, where the  $s_{\parallel}$ -dependent weight is determined individually for each  $r_p$  bin:

$$\tilde{\xi}_{g+}(r_p) = \frac{\sum_{j \in s_{\parallel}} W(r_p, j) \mathcal{E}_+(r_p, j)}{\sum_{j \in s_{\parallel}} W(r_p, j)}. \quad (8)$$

~~The new methods that we propose. #3 considers the shape projection, but there's an addition problem that we want to consider. Redshift-Space Distortions (RSD)!~~ ~~the expectation of that signal, but the scale-dependence of alignment will have a marginal impact on the determined weights, weights are normalized in each  $r_p$  bin and the LOS-dependence in each  $r_p$  bin is dominated by shape projection and RSD. Therefore we can also derive weights from the Abacus halo catalogs (Section 3), which can be generalized to any elliptical galaxy population. Note that in real space, the derived weights will recover the  $1 - \mu^2$  dependence along the  $r_{\parallel}$  direction. We determine  $\mathcal{E}_+$  in 2D bins, shown in Figure 2, then fit a Gaussian to the  $s_{\parallel}$ -dependent signal to obtain weights for each  $r_p$  bin. The measurements and fits are shown in Figure 4. The Gaussian widths are plotted in Figure 5 and can be found in Table 2. There is a linear relation that follows  $\sigma = 3 + (2/5)r_p$ , with  $R_p = 0.5$  as the projected separation of  $r_p = 2h^{-1}$  Mpc. We explored fitting the curves with multiple  $1, 2, 3$  Gaussians but found no significant improvement in the fit.~~

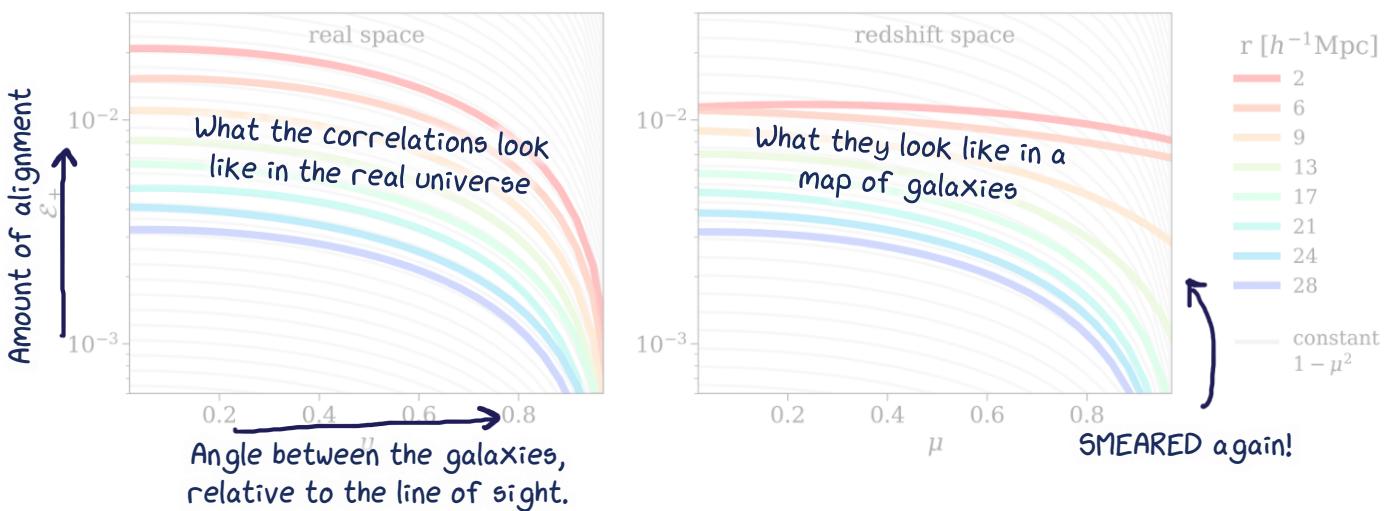
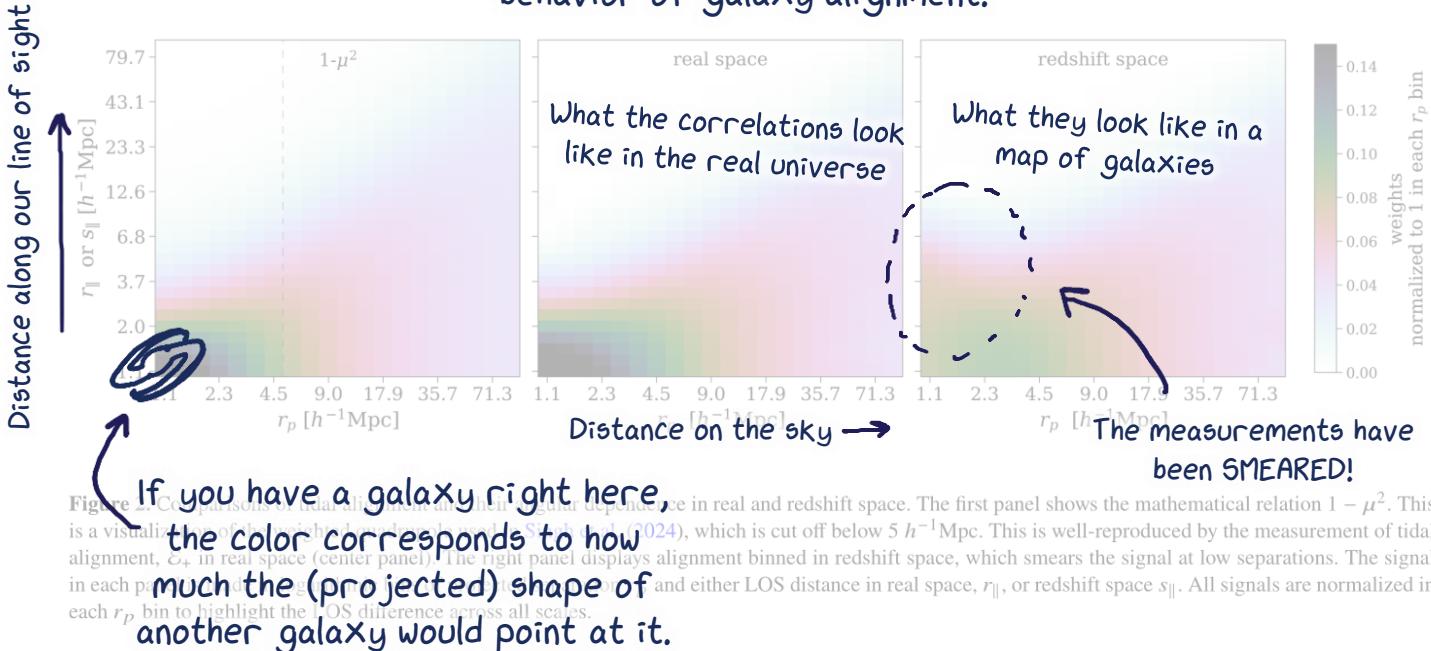
### 2.2.2 Optimal $\Pi_{\max}$ without RSD

## Galaxy map RSD causes the structure to looked more squished

In cases where a traditional projected statistic is preferred, we recommend varying the  $\Pi_{\max}$  for each  $r_p$  bin. A version of this variable  $\Pi_{\max}$  cut was used in Lamman et al. (2024b), and can be measured and modeled with most existing IA infrastructure. We use the weights above to produce  $\Pi_{\max}$  recommendations for given separation bins

~~If you've seen my other paper summaries, you might notice that my very first one was about how galaxy alignment can bias RSD. Now I'm looking at how RSD can bias alignments!~~ ~~For a given  $r_p$  bin, the  $\Pi_{\max}$  for a given separation  $s_{\parallel}$  is the~~

These plots attempt to visualize how RSD affects the 3D behavior of galaxy alignment.



These problems only really show up if you try to do 3D measurements. So do you stick to 2D or try to model RSD and get the full information from 3D?

$$\text{SNR}_{\Pi} = \frac{(2s_{\parallel} + \xi(s_{\parallel}))\mathcal{E}_+}{\sqrt{2\Pi_{\max} + w_p}}. \quad (9)$$

The peak of this function, the  $\Pi_{\max}$  choice to maximize signal-to-shot noise for IA measurements, is shown in Figure 5 and Table 2. This approximately follows the empirical relation  $\Pi_{\max,\text{optimal}} = 8 + (2/3)\mu^2$ . Here is our idea: keep making measurements as a function of distance on the sky (2D) but incorporate more 3D information by giving extra weight to pairs of galaxies that are close along the line of sight.

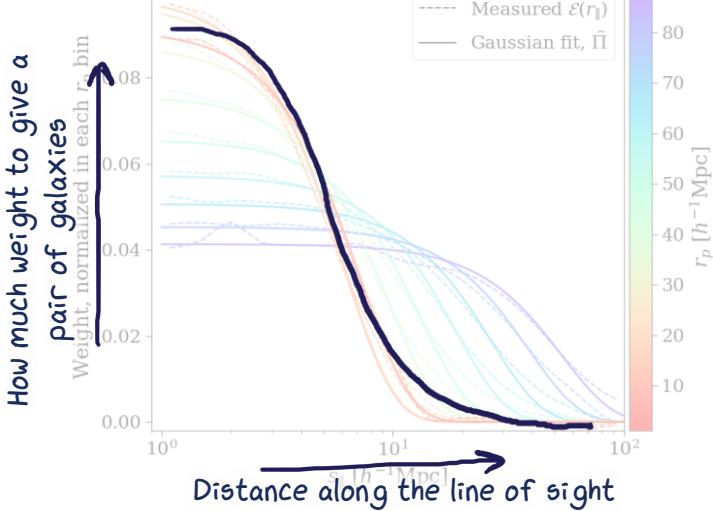
## COMPARING ESTIMATORS

### 3.1 Halo catalog

We evaluate the above estimators using samples from the ABACUSSUMMIT N-body simulations (Liu et al. 2021; Garrison et al. 2021). These large N-body simulations allow us to test many iterations of survey-like samples and precisely compare SNR across methods. We do not expect these simulations to accurately model the alignment of galaxies, which have weaker tidal alignment than halos and depend upon baryon dynamics, even at large scales. However, the relative performance of the estimators is independent of the true IA amplitudes, assuming they have similar scale dependence. We use the same set of samples as in Section 2.1, with  $\mu_p$  bins and the  $s_{\parallel}$  dependence of the signal in each bin is dominated by shot noise. ABACUSSUMMIT base simulations, generated at  $z = 0.8$ . Each contains  $6912^3$  particles in a



We propose giving more weight to galaxies that are close along the line of sight...



**Figure 4.** A selection of the LOS weights as a function of  $s_{\parallel}$  in each  $r_p$  bin. The dashed lines are measured  $\mathcal{E}_+$  and the solid are their Gaussian fits. At smaller projected separations, shown in blue, higher weight is given to close pairs. At very small separations, below  $3 \text{ } h^{-1} \text{Mpc}$ , the functions slightly widen to account for FOG. This general widening of the functions at large separations is a result of the angular dependence of projected shapes, as displayed in Figure 2. The Gaussian widths are plotted in Figure 5.

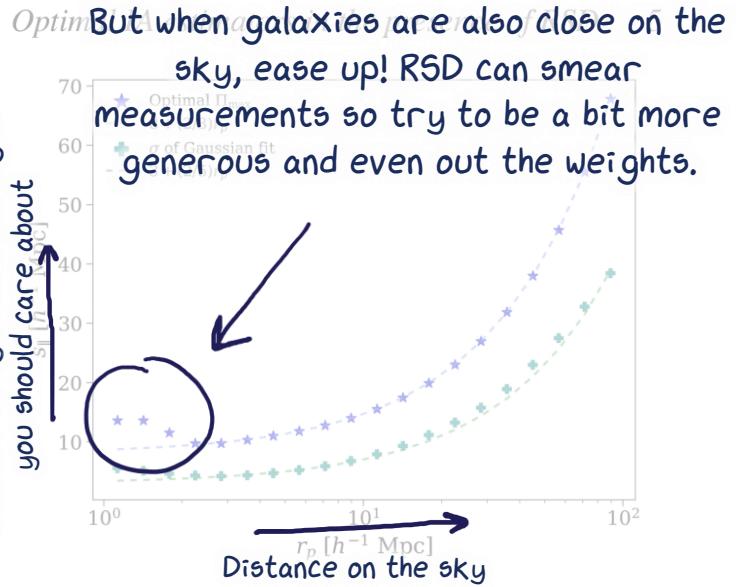
$r_p, \text{min}$	$r_p, \text{max}$	$\sigma$	Optimal $\Pi_{\text{max}}$
$[h^{-1} \text{Mpc}]$			
1.0	1.3	5.5	13.6
1.3	1.6	5.1	13.6
1.6	2.0	4.6	11.5
2.0	2.5	4.3	9.7
2.5	3.2	4.2	9.8
3.2	4.0	4.4	10.3
4.0	5.0	4.7	11.0
5.0	6.3	5.2	11.8
6.3	7.9	5.9	12.8
7.9	10.0	6.8	14.0
10.0	12.6	7.9	15.5
12.6	15.8	9.3	17.5
15.8	20.0	11.1	19.9
20.0	25.1	13.3	23.0
25.1	31.6	15.8	26.9
31.6	39.8	18.9	31.9
39.8	50.1	23.0	38.0
50.1	63.1	27.5	45.7
63.1	79.4	32.8	55.5
79.4	100.0	38.4	67.8

**Table 2.** The points plotted in Figure 5, showing recommendations for summing galaxy alignments along the LOS.  $\sigma$  is the standard deviation of  $s_{\parallel}$ -based Gaussian weights for logarithmic bins in  $r_p$ . When a traditional  $\Pi_{\text{max}}$  is preferred, the last column provides optimal values in these bins.

We're so close to figuring out the question

Gpc cubic box, which have been used to identify halos with the passive find (Huchra et al. 2021). We select the largest ones, resulting in average of about 10,000 particles per halo. Each of our simulations contains 2.5 million halos, with a comoving density of  $3.3 \times 10^{-4} h^3 \text{Mpc}^{-3}$ . This is designed to approximately match the density in DESI's Luminous Red Galaxy sample. We

I am shamelessly stealing a cartoon about simulated universes from another annotation because I am defending in two weeks and why did I commit to doing this for every paper in my phd ....



**Figure 5.** A guide for how to treat the LOS direction in projected IA measurements. Generally, a larger  $\Pi_{\text{max}}$  choice is recommended for tidal alignment at larger projected separations following  $3 + (2/3)r_p$ . Below  $3-4 \text{ } h^{-1} \text{Mpc}$ , a slightly larger  $\Pi_{\text{max}}$ 's recommended as RSD smears the signal along the LOS. A Gaussian fit further improves the signal. Widths of these Gaussians are shown as teal plus signs and based on the expected tidal alignment in a given  $r_p$  bin (Figure 2). These follow  $3 + (2/5)r_p$ .

create a light cone by placing an observer  $2590 \text{ } h^{-1} \text{Mpc}$  away from the center of each box along one axis (corresponding to comoving distance at  $z=0.8$ ), and determine a redshift without RSD and one with RSD.

## TESTING THE NEW METHODS

### 3.2 Alignment Measurements

To produce the weights displayed in Figures 2 - 4, we find pairs of galaxies and their relative separation of  $|r_{\parallel}| < 100 h^{-1} \text{ Mpc}$  and transverse separation of  $|r_{\perp}| < 100 h^{-1} \text{ Mpc}$  in real comoving space. Now time to put our galaxies where our mouths are and see just how well these new methods compare to traditional ones...  
transverse to the LOS  $r_{\perp}$  and along the LOS in both real and redshift space,  $r_{\parallel}$  and  $s_{\parallel}$ . The LOS is defined for each pair as the vector between the observer and pair center. We also obtain the projected ellipticity of each halo along its unique LOS, following (Lamman et al. 2023).

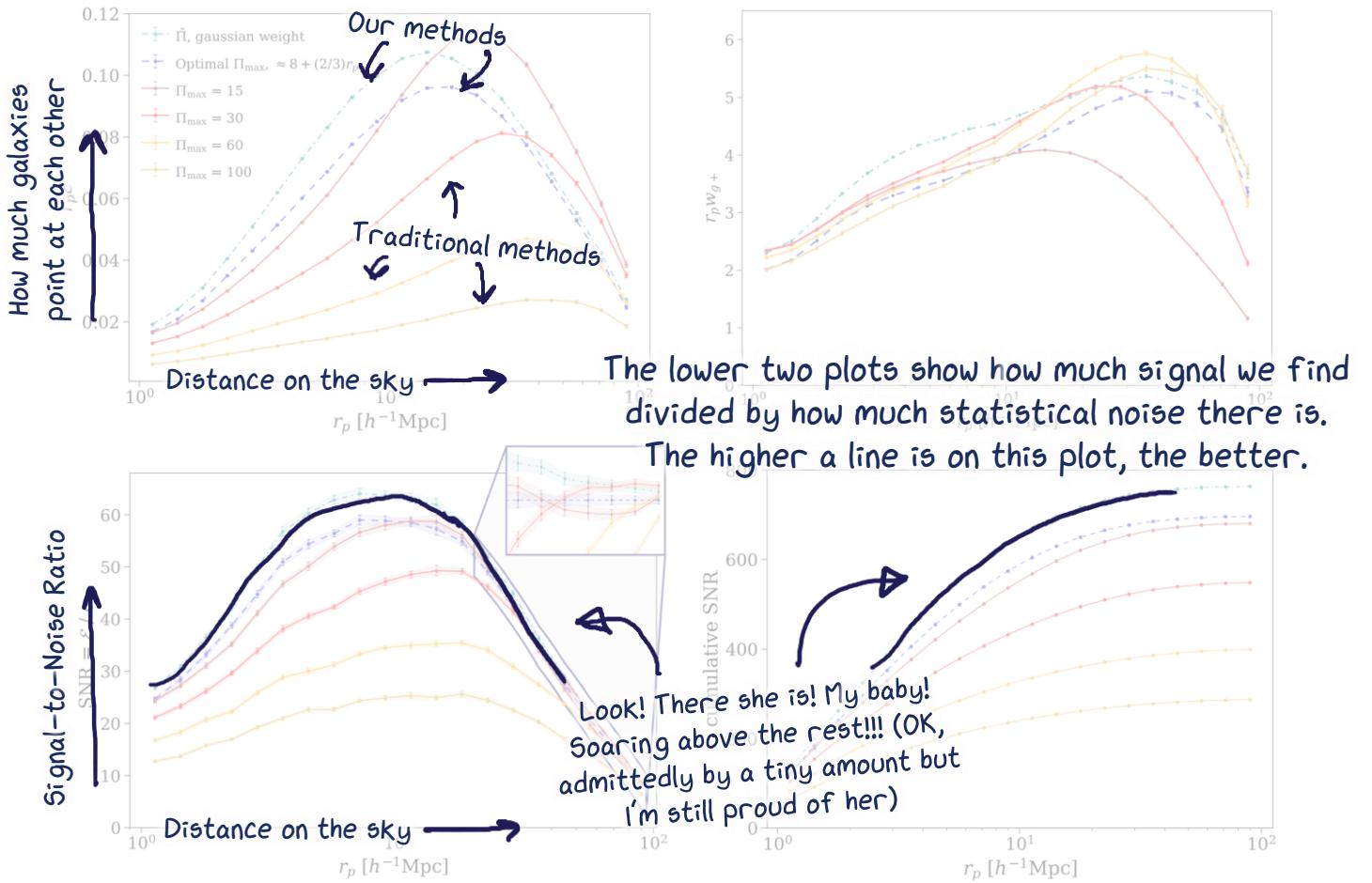
For comparing alignment estimators, we trim the ABACUS catalogs to a uniform survey geometry using RA and DEC within  $\pm 10 \text{ deg}$  and redshifts  $0.58 < z < 0.95$ . Within these mock catalogs, we measure  $\mathcal{E}_+(r_p)$  in each simulation using the  $\tilde{\Pi}$  weights described in Section 2.2.1, the variable  $\Pi_{\text{max}}$  described in Section 2.2.2, and a selection of tidal ellipsoids. The error is estimated in each simulation to be the standard deviation of the  $\mathcal{E}_+(r_p)$  values in independent  $100 \text{ } h^{-1} \text{Mpc}$  bins. This results in 25 determinations of SNR for each simulation. We then use these to calculate the average SNRs to evaluate the performance of each estimator in each  $r_p$  bin. The results are unchanged when using bootstrap error estimation from these regions.

Code for these measurements and the associated modeling is publicly available in the repository [github.com/cmlamman/spec-IA](https://github.com/cmlamman/spec-IA).

### 3.3 Results

The measurements of  $\mathcal{E}_+$  made with each  $\Pi_{\text{max}}$  choice, the corresponding plot for  $w_{g+}$ , and their average SNR are shown in Figure 6. The LOS weighting  $\tilde{\Pi}$  has a 2.3 times improvement over a flat  $\Pi_{\text{max}} = 100 h^{-1} \text{ Mpc}$ , followed closely by using the optimal

The top two plots show measurements made with several different methods



**Figure 6.** Comparison between different LOS treatments for  $\mathcal{E}_+$  and  $w_{g+}$ , estimated as  $(2\Pi_{\max} + w_p(r_p))\mathcal{E}_+(r_p)$ . The measurements made with various  $\Pi_{\max}$  choices and averaged over 25 ABACUS SUMMIT simulations are shown in the top two panels. Since the errors are dominated by shape noise, the SNR is the same for the two estimators. The bottom left panel shows the SNR of each measurement, and the bottom right shows the cumulative SNR as  $r_p$  increases. The SNR was estimated independently in each simulation and then averaged for this plot. As expected, the SNR is highest for the gaussian weights across all scales, followed by the optimal  $\Pi_{\max}$ . Among the single  $\Pi_{\max}$  choices, generally smaller  $\Pi_{\max}$  perform better, at least at scales below  $30 h^{-1} \text{Mpc}$ . The insert shows a closer look at where the estimators' SNR cross, although many become statistically indistinguishable at the largest scales.

$\Pi_{\max}$  in each  $r_p$  bin. As expected, smaller LOS distances tend to be more advantageous

$\Pi_{\max} = 15 h^{-1} \text{Mpc}$  performs significantly better than the common choice of  $\Pi_{\max} = 100 h^{-1} \text{Mpc}$ . Since tidal alignment concentrates most of the signal along the line of sight, it is more preferred compared to when measuring standard 2-point clustering. Above  $r_p = 12 h^{-1} \text{Mpc}$ , several estimators perform similarly as the signal has less variation in  $r_{\parallel}$  at very large  $r_p$ . All SNR curves on this plot peak around  $7 - 11 h^{-1} \text{Mpc}$ , a scale which depends on our choice of logarithmic binning.

respective  $\Pi_{\max}$  values. For the  $\tilde{\Pi}$  approach with Gaussian weights, the  $\Pi_{\max}$  value is set to  $15 h^{-1} \text{Mpc}$  for the results shown below.

The strength of intrinsic alignment is quantified by the alignment amplitude  $A_{IA}$ , which describes the response of galaxy shapes to the tensor  $T_{ij}$  is defined as:

$$T_{ij} = \partial_i \partial_j \phi - \frac{1}{3} \delta^K_{ij} \nabla^2 \phi \quad (10)$$

where  $\phi$  is the gravitational potential and  $\delta^K_{ij}$  is the Kronecker delta. In Fourier space, this becomes

$$T_{ij}(\vec{k}) = \int \frac{d^3 k}{(2\pi)^3} \left( \frac{k_i k_j - \frac{1}{3} \delta^K_{ij} k^2}{k^2} \right) \tilde{\delta}_m(\vec{k}) e^{i\vec{k} \cdot \vec{r}}, \quad (11)$$

## MODELING THE NEW METHODS

### 4 MODELING VARIABLE $\Pi_{\max}$

Now the mathy part -> explaining how people can build this measurement into their theoretical models. This is the vegetables that even an observer like I must take for a healthy science paper...

$$\epsilon = \tau [T_{xx} - T_{yy} + 2iT_{xy}] \equiv \tau \mathbf{T}_{\mathcal{E}}, \quad (12)$$



**CONCLUSION****5 CONCLUSION**

The advent of large spectroscopic surveys has led to a revolution in how to efficiently handle LOS information when measuring intrinsic alignments. Although 3D estimators can achieve higher SNR than projected correlations, they come with increased complexity effects, more complex modeling requirements, and are more difficult to directly relate to shear measurements. We present an alternative set of projected correlation functions that better capture LOS information. These result in similar SNR improvements compared to classic estimators, though at a weighted quadrupole, but with the benefits of a projected statistic.

Our main results demonstrate that, at minimum, direct IA detections should adopt smaller  $\Pi_{\max}$  values than the conventional 60–100  $h^{-1}$  Mpc scale. Among the choices with projected separation provides further improvement, approximately fulfilling  $\Pi_{\max} = 3 + (2/5)r_p h^{-1}$  Mpc. The most optimal approach utilizes our LOS weighting choice, which shows 2.2 times improvement in SNR over flat  $\Pi_{\max} = 100 h^{-1}$  Mpc cuts. The performance differences between alignments (a handful of researchers),

tions of  $12 h^{-1}$  Mpc. While modeling remains challenging at small separations, considerable information resides there. Our modified  $\Pi_{\max}$  approach can help extract IA correlations which are relatively independent of RSD effects.

It is worth emphasizing that our recommendations for optimal LOS treatment are effectively independent of features within the signal itself. An ideal, but perhaps ineffectual, approach would be to measure IA with basic weights and then re-iterate with new weights based on these measurements. However, the choices for optimal  $\Pi$  and weights are dominated by the projection of shapes and LOS. They are also independent of various convenient choices for correlation functions (such as  $\mathcal{E}$  vs  $w_{g+}$ ), shape definitions, and object type (galaxies vs halos vs ensembles of galaxies). Although we focus on shape-density correlations in this work, similar principles apply to shape-shape correlations such as  $w_{++}$ , with the same RSD model combined with a  $(1 - \mu^2)^2$  dependence.

Maximizing the precision of IA measurements directly improves constraints on the alignment amplitude. By more efficiently handling LOS information, these estimators will enhance the cosmological information extracted from large spectroscopic surveys, benefiting both weak lensing analyses and the exploration of direct cosmological applications of IA.

**ACKNOWLEDGEMENTS**

This material is based upon work supported by the U.S. Department of Energy under grants DE-SC0015718 and DE-SC0024787, NASA under ROSES grants NAG-1-1281 and NAG-1-1300, the National Science Foundation Support Participation program grant 80NSSC24K0083, the U.S. National Science Foundation under award AST-2206563, and the Simons Foundation.

**DATA AVAILABILITY**

ABACUSSUMMIT data products are publicly available at [abacushbody.org](https://abacusbody.org) (Maksimova et al. 2021).

**REFERENCES**

- Kulkarni T., Tasse C., Chisari N. E., 2025, The Bispectrum of Intrinsic Alignments: Theory, Modeling and Forecasts for BICEP3, [arXiv:2504.10009](https://arxiv.org/abs/2504.10009)
- Bilicki M., Wan L., Slepnev V., 2017, *Journal of Cosmology and Astroparticle Physics*, 2015, 015
- Brown M. L., Taylor A. N., Hambly N. C., Dye S., 2002, *Monthly Notices of the Royal Astronomical Society*, 333, 501
- Chisari N. E., Dvorkin C., 2013, *Journal of Cosmology and Astroparticle Physics*, 12, 029
- Dark Energy Survey and Kilo-Degree Survey Collaboration et al., 2023, *The Open Journal of Astrophysics*, 6, 36
- Garrison L. H., Eisenstein D. J., Ferrer D., Maksimova N. A., Pinto P. A., 2021, *Monthly Notices of the Royal Astronomical Society*, 508, 575
- Hadzhiyska B., Eisenstein D., Bose S., Garrison L. H., Maksimova N., 2021, *Monthly Notices of the Royal Astronomical Society*, 509, 501
- Hirata C. M., et al., 2004, *Monthly Notices of the Royal Astronomical Society*, 353, 529
- Jackson J. C., 1972, *Monthly Notices of the Royal Astronomical Society*, 156, 1P
- Joachimi B., et al., 2015, *Space Science Reviews*, 193, 1
- Kaiser N., 1987, *Monthly Notices of the Royal Astronomical Society*, 227, 1
- Kirk D., et al., 2015, *Space Science Reviews*, 193, 139
- Kurita T., Takada M., Nagai T., Takahashi R., Osato K., Kobayashi Y., 2021, *Monthly Notices of the Royal Astronomical Society*, 501, 833
- Laguna P., et al., 2023, *Monthly Notices of the Royal Astronomical Society*, 522, 27
- Lamman C., Hirata L., Shi J., Šarčević N. N., Pyne S., Legnani E., Ferreira P., 2024a, *The Open Journal of Astrophysics*, 7
- Lamman C., Hirata L., Šarčević N. N., Pyne S., Legnani E., Ferreira P., 2024b, *Monthly Notices of the Royal Astronomical Society*, 534, 3540
- Maksimova N. A., 2012, *Physical Journal*, 412, 64
- Maksimova N. A., Garrison L. H., Eisenstein D. J., Hadzhiyska B., Bose S., Satterthwaite T. P., 2021, *Monthly Notices of the Royal Astronomical Society*, 508, 4017
- Mandelbaum R., Hirata C. M., Ishak M., Sjak J., Brinkmann J., 2006, *Monthly Notices of the Royal Astronomical Society*, 37, 611
- Pyne S., Tenneti A., Joachimi B., 2022, *Monthly Notices of the Royal Astronomical Society*, 516, 290
- Schmitz D. M., Hirata C. M., Blazek J., Krause E., 2018, *Journal of Cosmology and Astroparticle Physics*, 2018, 040
- Scoccimarro R., 2004, *Physical Review D*, 70, 083007
- Singh S., Mandelbaum R., More S., 2014, *Monthly Notices of the Royal Astronomical Society*, 450, 221
- Singh S., Mandelbaum R., More S., 2015, *Monthly Notices of the Royal Astronomical Society*, 530, 3515
- We come up with a completely new method (based on lots of other people's ideas) that ANNIHILATES (works slightly better then) the other measurement methods.

This paper has been typeset from a *TeX/LaTeX* file prepared by the author.

Thank you for reading! Check out [ClaireLamman.com](http://ClaireLamman.com) for other accessible annotations made by myself and others!  
- Claire

I made this in power point using the XKCD font:  
<https://github.com/ipython/xkcd-font>

