Perfecting Weak Lensing Measurements

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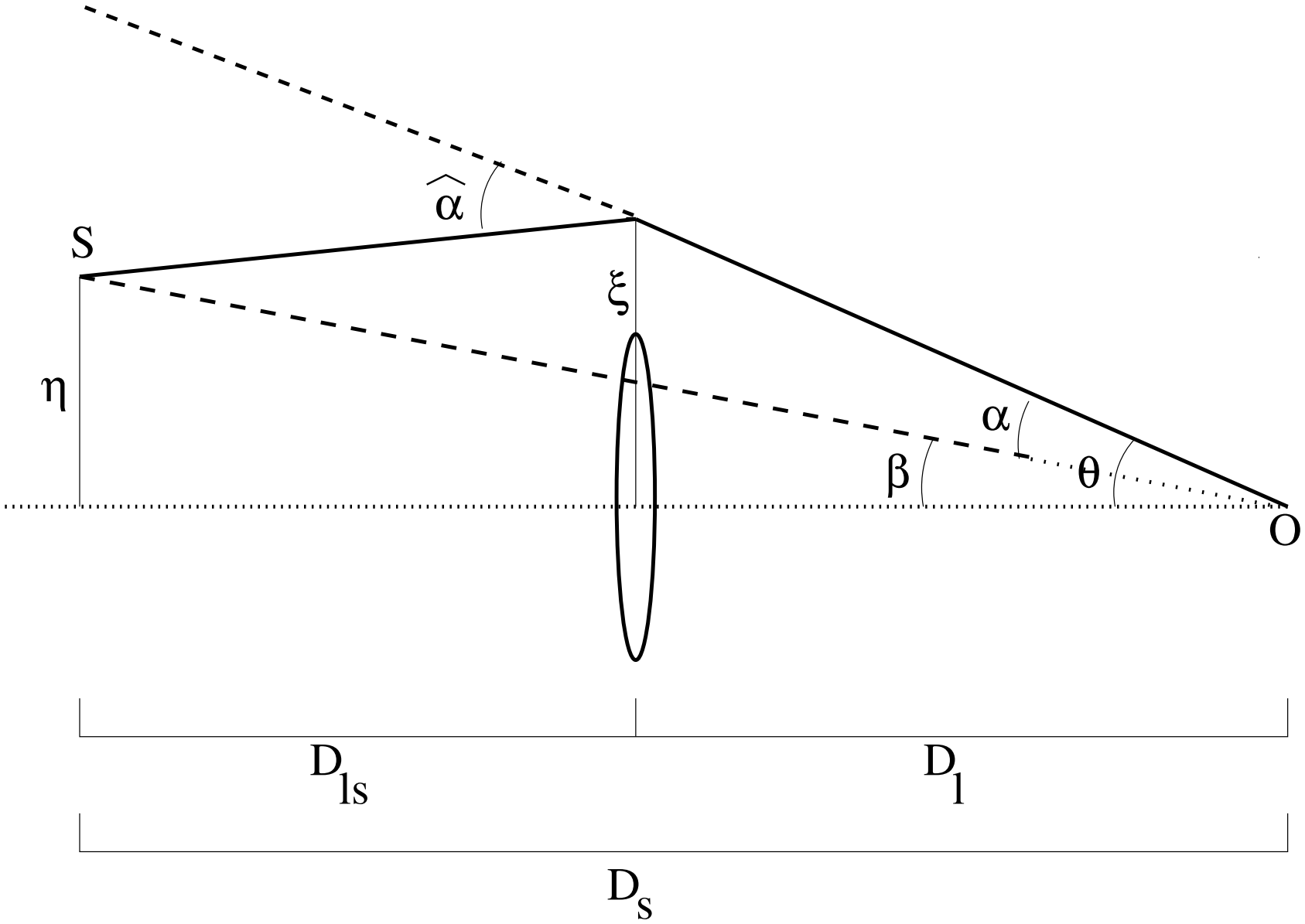
Outline

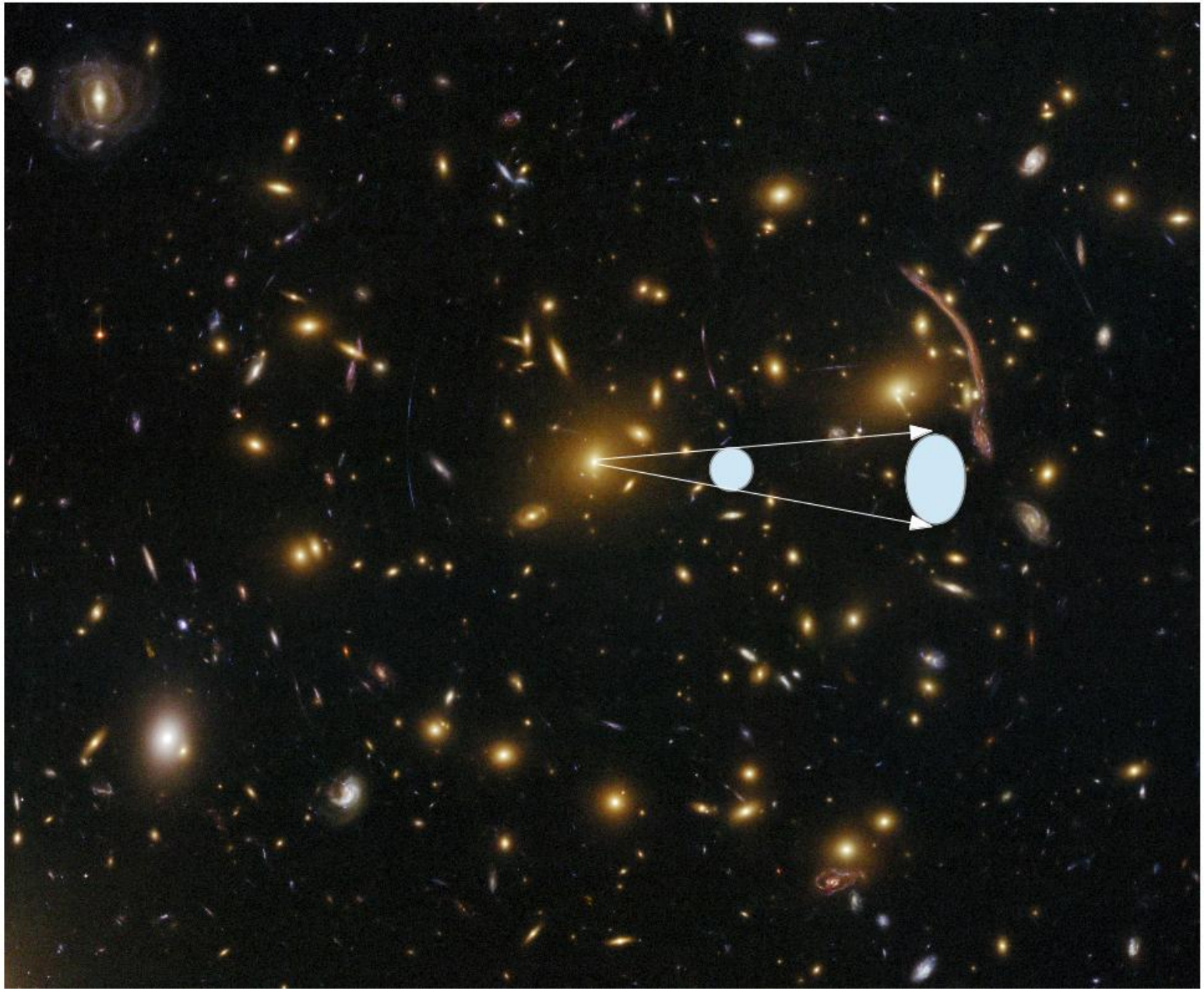
- Lensing and cosmology intro
- Example: Some preliminary cluster lensing results from the Sloan Digital Sky Survey
- Some steps towards perfecting these measurements
  - Photometric redshifts: use ensemble statistics
  - Unbiased shear estimation in the presence of noise: use ensemble statistics.
- Summary

Abell 370, HST

Lensing Geometry and Deflection



Shear Illustration



Tangential Shear

- Tangential Shear
- Depends on the projected mass density Σ.
- Depends on the distances to lens and source

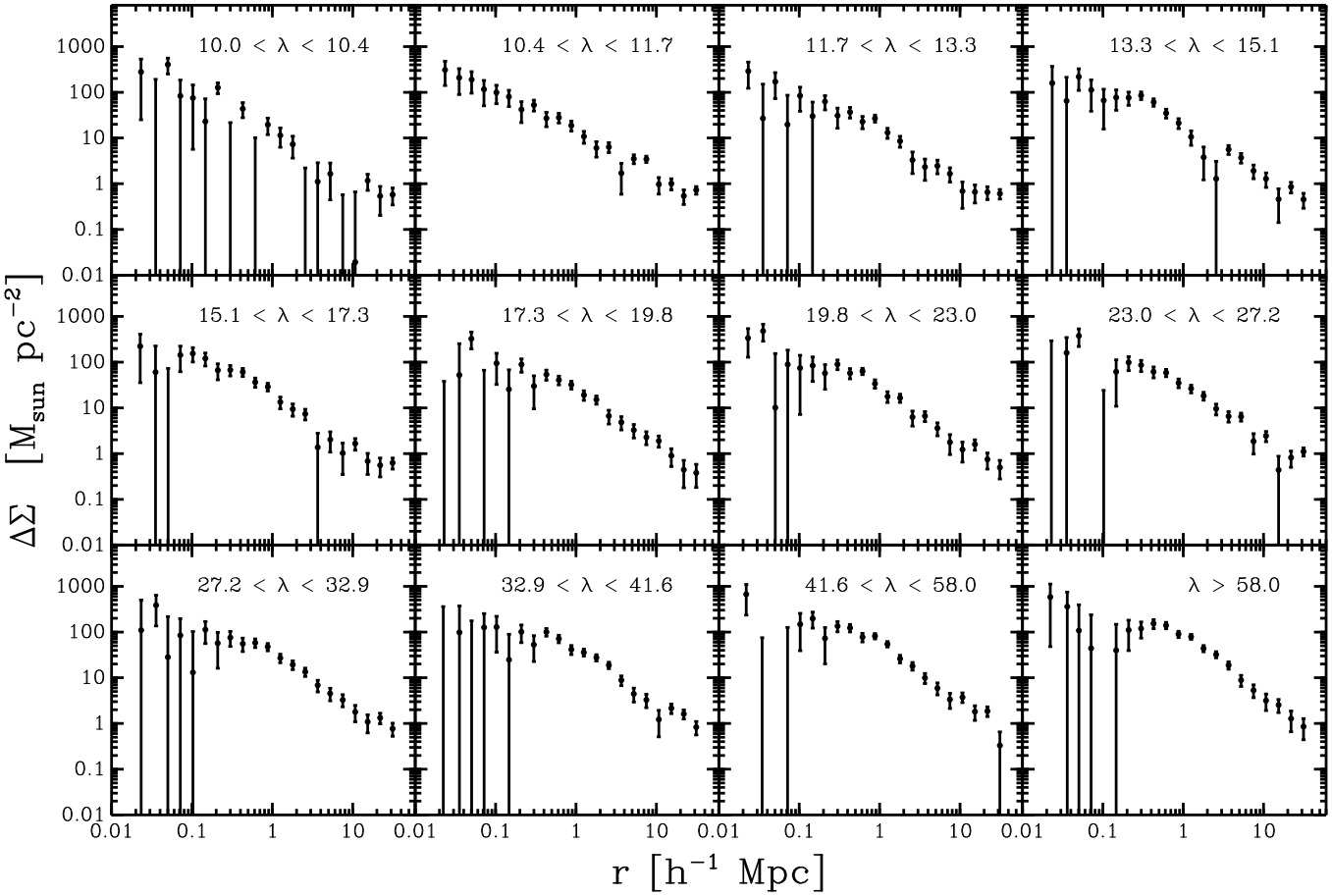
$$\begin{aligned}\langle\gamma_t\rangle &= \frac{\overline{\Sigma}(<R) - \overline{\Sigma}(R)}{\Sigma_{crit}} \\ &\equiv \frac{\Delta\Sigma}{\Sigma_{crit}} \\ \Sigma_{crit}^{-1} &\propto D_L \times \frac{D_{LS}}{D_S}\end{aligned}$$

Cosmology with Lensing

- Lensing depends on mass and geometry.
- If we know where everything is (lens and source) we can use lensing to measure mass.
  - This is especially useful for measuring the distribution of dark matter in the universe
  - The connection between galaxies and dark matter.
- If we know the mass, or control for it, we can measure geometry.
  - This is especially useful for measuring dark energy, which is driving the expansion of the universe.
  - If we know the redshifts to everything and the relative distance to things from lensing, we infer the redshift-distance relation and thus cosmological parameters, including dark energy.

Example: Ensemble Cluster Lensing with SDSS RedMapper

Preliminary measurement using SDSS DR8 imaging and the latest RedMapper cluster catalog from E. Rykoff.



Ensemble Cluster Lensing

- There is tons of S/N even in SDSS, with the Dark Energy Survey (DES) the signal will increase because the lenses are at higher redshift.
- DES images are deeper, 10 times more galaxies for shear measurement.
- Precision is great, but how do we know we got the right answer?

Did We Get the Right Answer?

- We might have used the wrong distances. We don't have redshifts for the background galaxies, only 5-filter photometry. Current and future surveys all have this same limitation.
- We might have measured the wrong shear. There are a lot of ways to get this wrong: atmosphere, instrument, noise, etc.

Photometric Redshifts

- Infer the redshift based on broad band photometry.
- Difficult because there are strong degeneracies: e.g. luminous blue objects at high redshift look like faint red objects at low redshift.
- Naive techniques have lots of scatter, significant bias, and a large outlier population. Worse when galaxy spectral features are near filter boundaries.
- Good progress in recent years with a huge variety of techniques. I will talk about one I am involved with (C. Cunha, M. Lima, also Huan Lin and Josh Frieman of FNAL).

Ensemble Photometric Redshifts

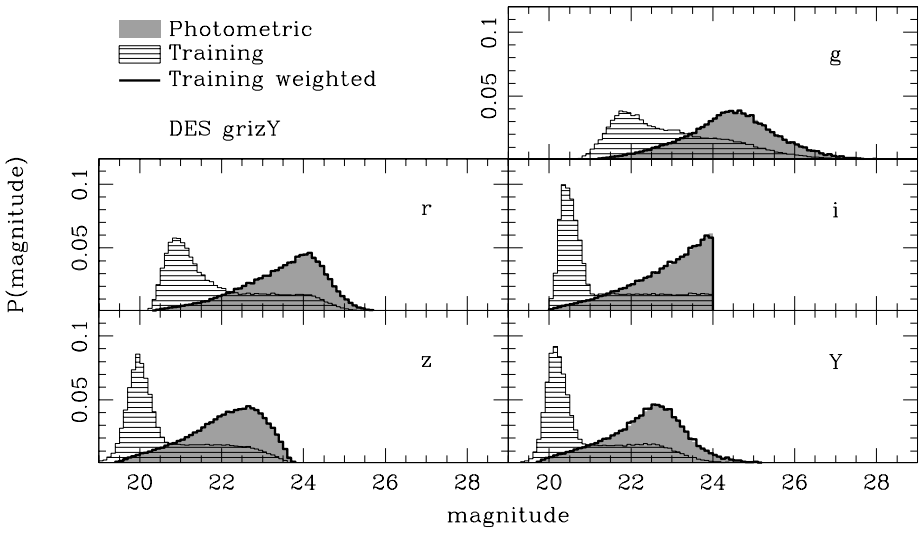
- Forget about estimating the redshift of a single galaxy from the light measured through a few broadband filters. It can't be done without strong prior information.
- Just try to estimate the overall redshift distribution $N(z)$.
- For much lensing work $N(z)$ is sufficient.
- Secondarily try to estimate the probability distribution for each galaxy $P(z)$. Mainly useful as a weight for studies such as ensemble cluster lensing.

ProbWTS: Probability Distributions from Weighted Training Sets.

- Hypothesis: If the distribution of all relevant observables are the same for two populations then so are the redshift distributions $N(z)$. This is true when there are no selection effects.
- What about when there are selection effects and only one sample has redshifts?
- Find a set of weights such that the distribution of observables for galaxies with redshifts matches the observables for a set of galaxies without redshifts. Then the weighted redshift histogram will also match, and that is an estimate of $N(z)$.
- Works for the part of observable space spanned by the training set.
- Degeneracies fully accounted for in the $N(z)$.
- Can break down if the two samples have very different selection in an unobserved property, but it turns out this is not the dominant error in practice (Cunha et al. 2012).

ProbWTS: Tests on DES Mocks

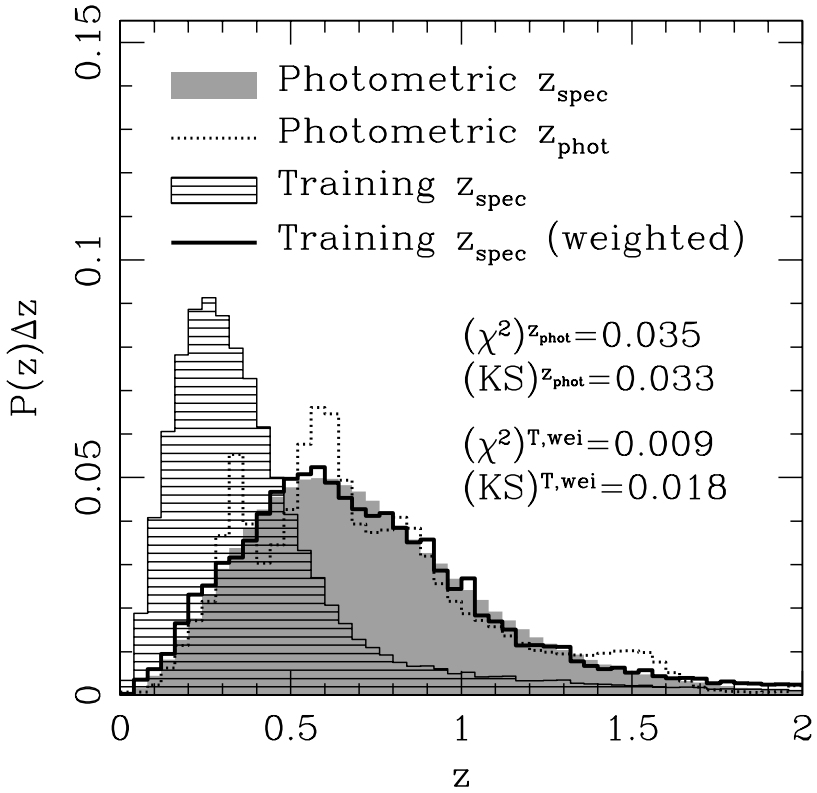
- DES Mock catalogs
- Very different magnitude distributions for spectroscopic training sample and photomety only sample.



Lima et al. 2008

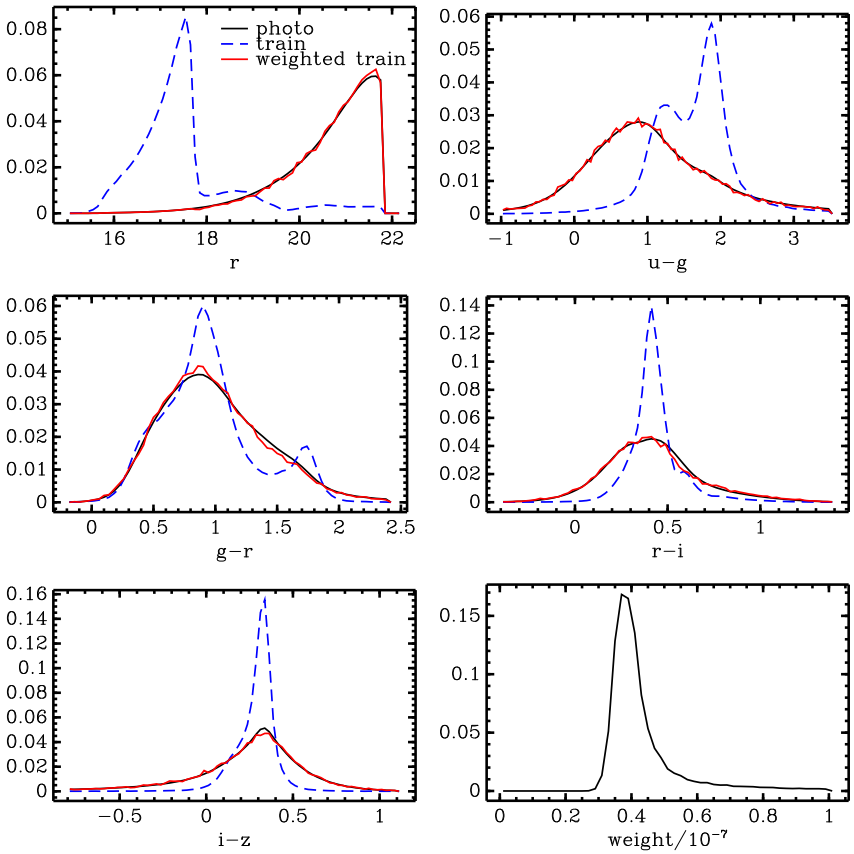
ProbWTS: Tests on DES Mocks

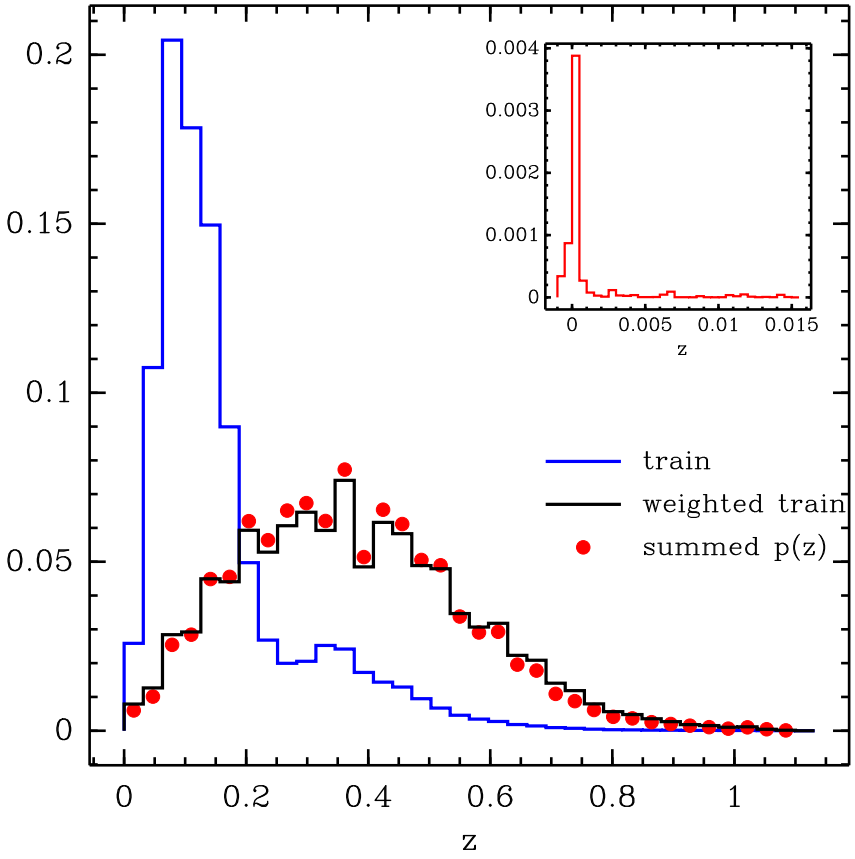
- Training set has very different magnitudes and redshift distribution.
- Good recovery of underlying $N(z)$.
- Uncertainties are dominated by sample variance (Cunha et al. 2012)



Lima et al. 2008

ProbWTS: Application to SDSS Data

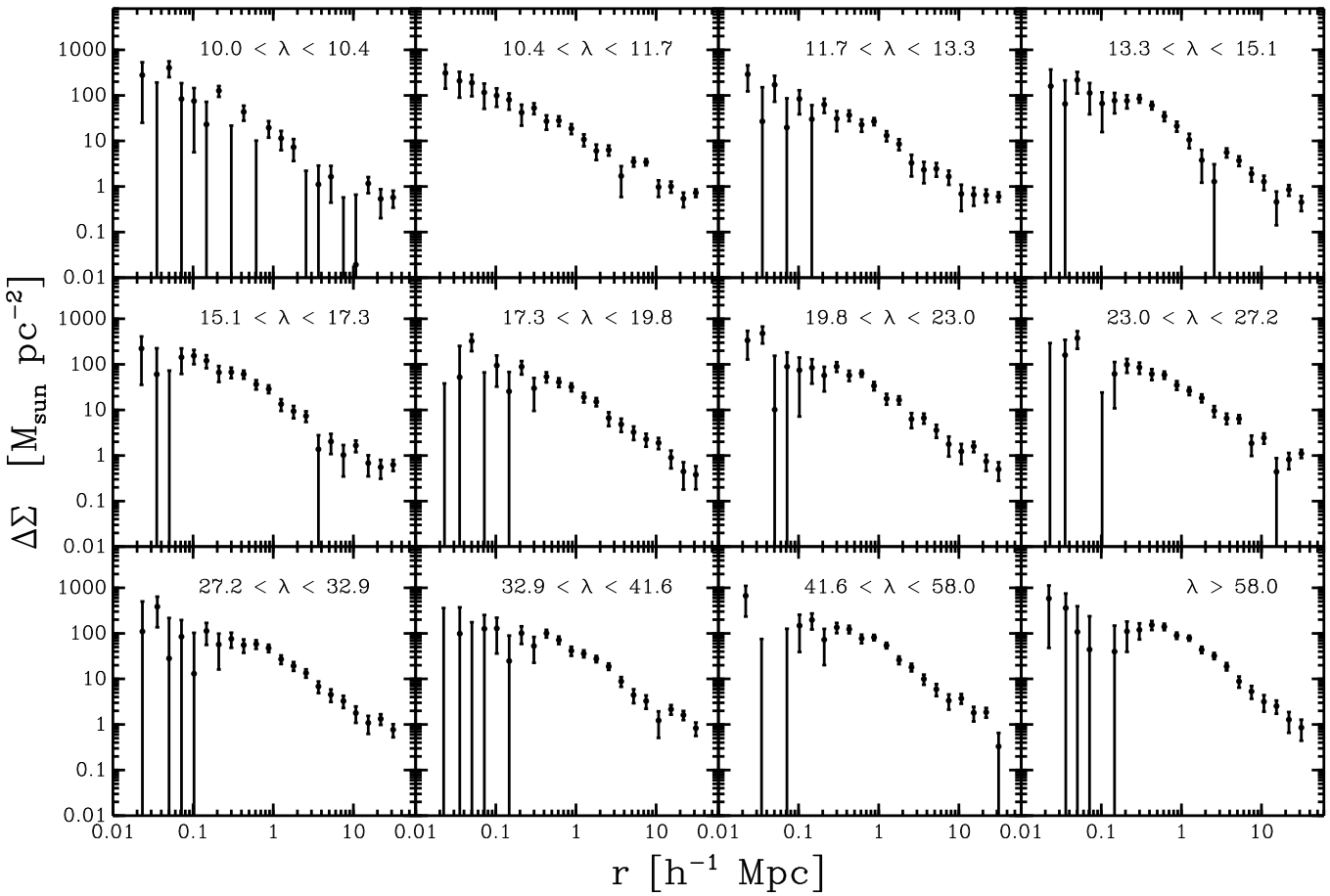




Sheldon et al. 2012

What Does This Mean for Lensing Measurements?

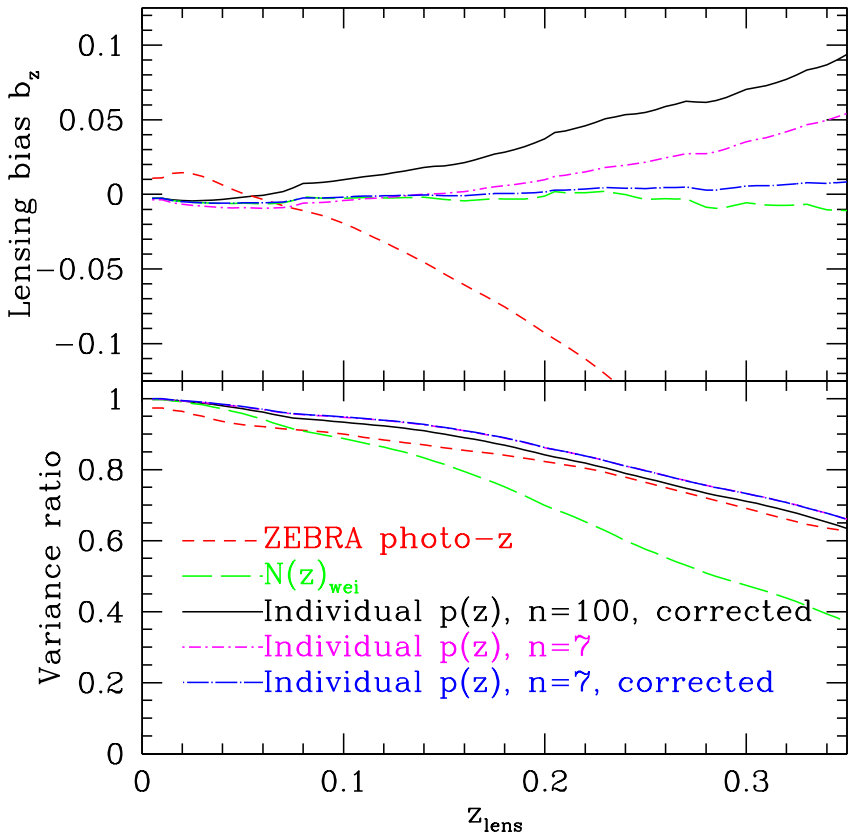
Systematic errors in $N(z)$ translate into a calibration error for the shear.



Preliminary

ProbWTS: Expected Lensing Bias

- Any systematic error in $N(z)$ translates to an error in distance and thus errors in the measured mass.
- Using a subset of the SDSS sample with redshifts in DEEP as validation shows `ProbWTS` works well for lenses in the redshift range of interest $[0.0, 0.3]$.
- For DES we need this to work for lens redshifts near unity. Calculations indicate it can work as long as we get less than a percent of redshifts in training sample wrong. (Cunha et al. 2012)
- Need deep spectroscopic datasets in widely separated fields.

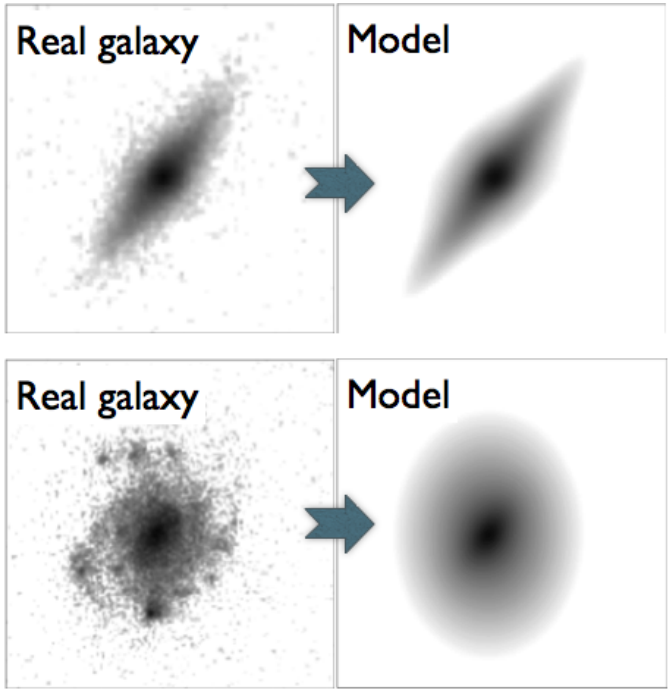


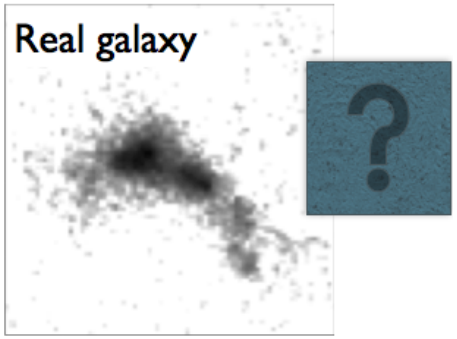
Sheldon et al. 2012

There is no absolute calibration source for shear.

Sources of error in shear measurement.

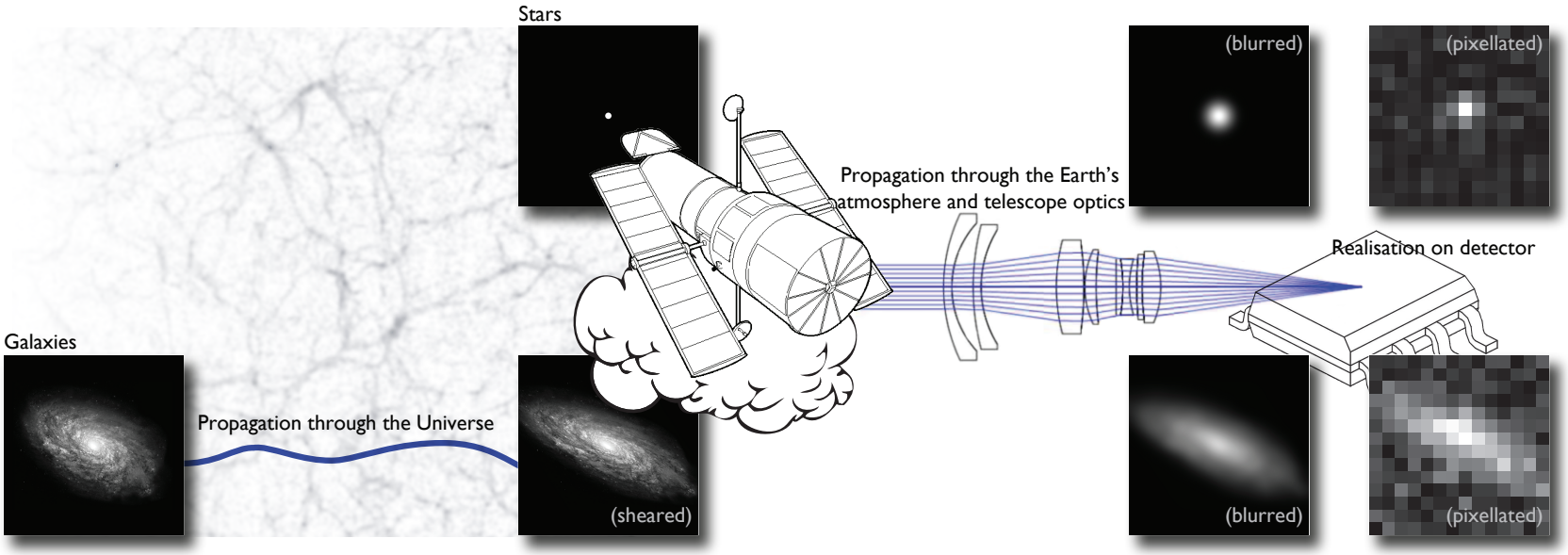
Wrong models.





Mandelbaum. et al. Great 3 Handbook

Sources of error in shear measurement

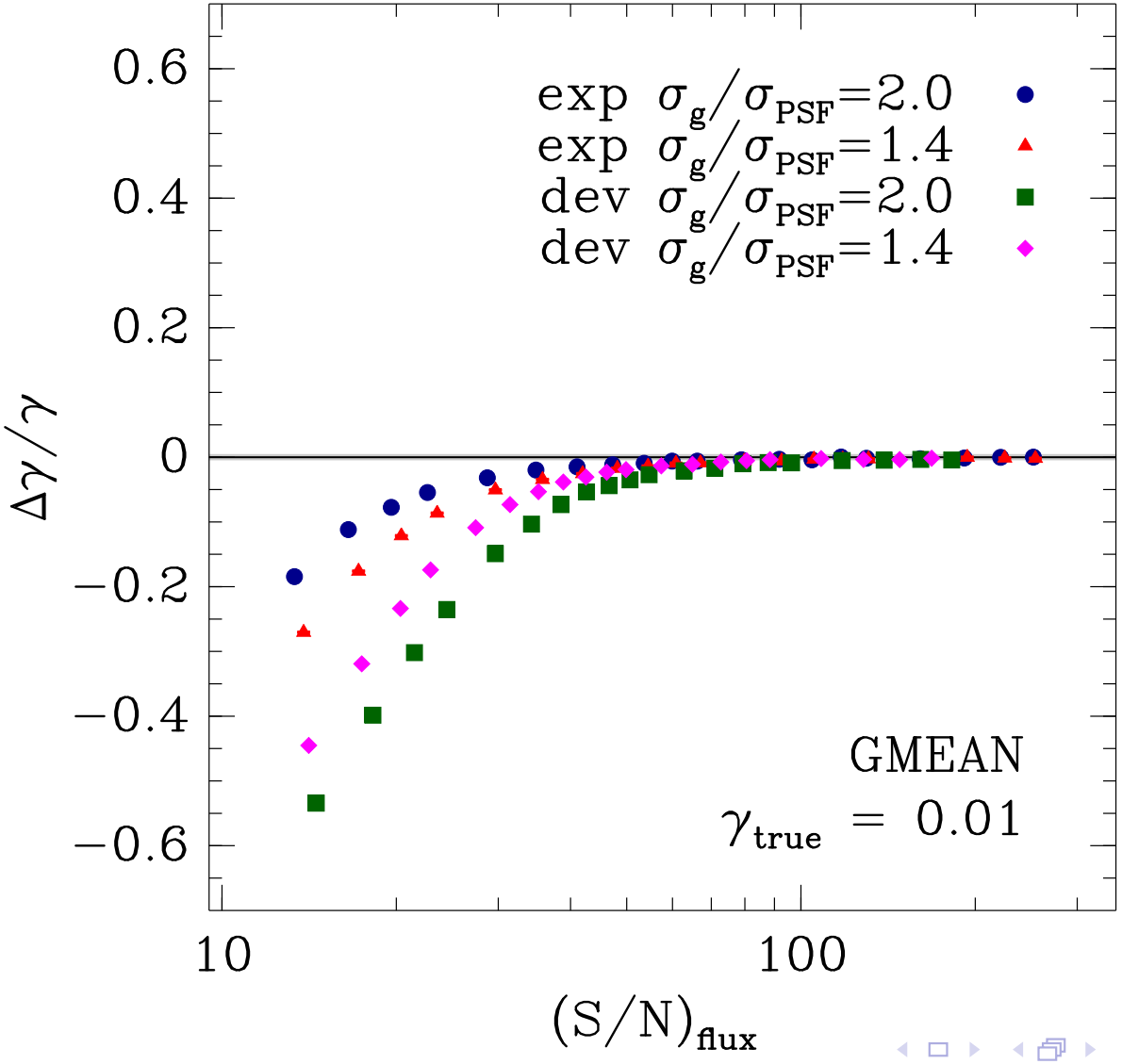


Mandelbaum. et al. Great 3 Handbook

Noise

- For low S/N galaxy images, techniques that measure shear from a galaxy ellipticity break down. This dominates the systematic error.
- Non-linear fitting in the presence of noise is biased, both the maximum likelihood and expectation value: using the mean shape won't work (Hirata, Refregier, etc). Results in a **calibration** error.
- Weighted moments can alleviate the problem somewhat, but there can still be of order 10% errors at $S/N = 10$.
- This is generally known in statistics, but not recognized for our particular problem until relatively recently. Badly aggravated by the PSF "deconvolution".

Extreme Example: Noise Bias using the Expectation Value



Ensemble Shear Measurement

- Bernstein & Armstrong 2014
- Forget about estimating a weak shear from a single galaxy image. It can't be done. Galaxies are elliptical and this noise dominates, so you have to average anyway.
- But we know true things that can help: the posterior distribution of the mean shear averaged from many galaxies must approach a Gaussian: central limit theorem.
- We also know the shear is weak.
- Assuming Gaussianity, weak shear, and knowledge of underlying distribution of shapes for the ensemble (the prior), one can derive an unbiased estimator for the mean shear of the ensemble.

Assume a small shear $\boldsymbol{g}$. The posterior probability for the shear estimated from many galaxies is

$$
\begin{aligned}
P(\boldsymbol{g}|\mathbf{D}) &= \frac{P(\boldsymbol{g})P(\mathbf{D}|\boldsymbol{g})}{P(\mathbf{D})} && (1)\\
&= P(\boldsymbol{g})\prod_i \frac{P(\mathbf{D}_i|\boldsymbol{g})}{P(\mathbf{D}_i)} && (2)\\
P(\mathbf{D}_i|\boldsymbol{g}) &\approx P_i + \boldsymbol{g}\cdot\boldsymbol{Q}_i + \frac{1}{2}\boldsymbol{g}\cdot\mathbf{R}_i\cdot\boldsymbol{g} && (3)\\
-\ln P(\boldsymbol{g}|\mathbf{D}) &\approx (\text{stuff}) - \boldsymbol{g}\cdot\sum_i \frac{\boldsymbol{Q}_i}{P_i} + \frac{1}{2}\boldsymbol{g}\cdot\left[\sum_i\left(\frac{\boldsymbol{Q}_i\boldsymbol{Q}_i^T}{P_i^2} - \frac{\mathbf{R}_i}{P_i}\right)\right]\cdot\boldsymbol{g} && (4)
\end{aligned}
$$

Note the $\boldsymbol{Q}$ and $\mathbf{R}$ involve first and second derivatives of the prior (the true shape distribution) with respect to shear. In practice the $\boldsymbol{Q}$ and $\mathbf{R}$ are averaged over the likelihood surface.

Then the shear can be solved for directly

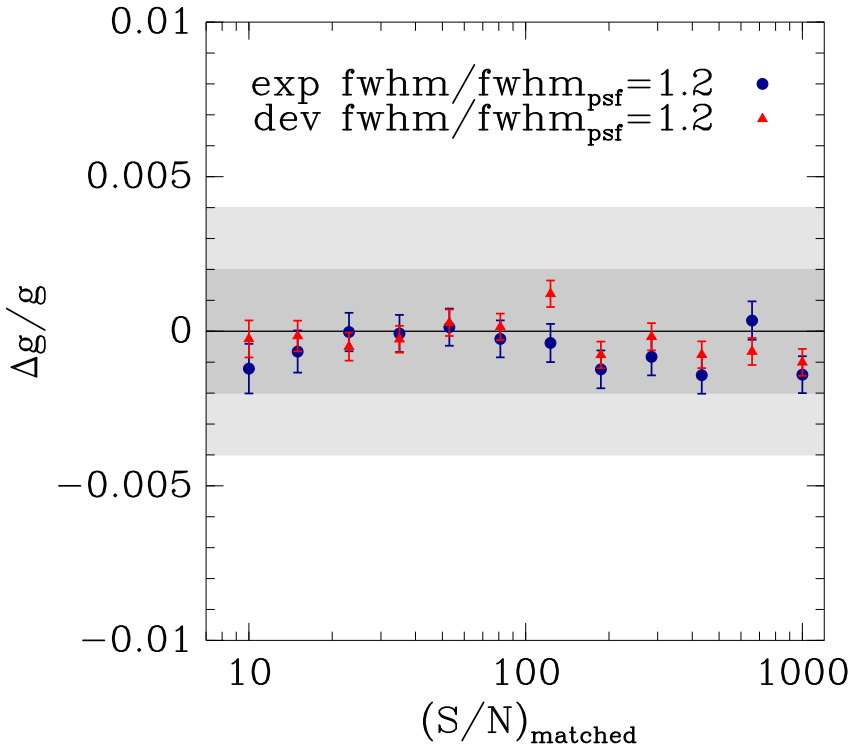
$$\begin{aligned} \mathbf{C}_g^{-1} &= \sum_i \left(\frac{\boldsymbol{Q}_i \boldsymbol{Q}_i^T}{P_i^2} - \frac{\mathbf{R}_i}{P_i} \right) \\ \bar{\boldsymbol{g}} &= \mathbf{C}_g \sum_i \frac{\boldsymbol{Q}_i}{P_i}. \end{aligned} \tag{5}$$

Bernstein & Armstrong

- Bernstein & Armstrong gave a simple demonstration but no implemenation to work with images.
- Computationally challenging to measure the full likelihood surface in a high dimensional space.
- Even the fastest existing codes took seconds to perform a few hundred likelihood evaluations. Tens of thousands are needed here.
- My solution is to make lots of approximations: use Gaussian mixtures for the galaxy models (Hogg and Lang 2013) and the PSF. Then the convolutions are fast and analytic. Use a fast approximate exponential function, etc.
- Can perform a likelihood evaluation in 100 microseconds, sample the full space in a few seconds.
- Just submitted to the arXiv over the weekend (Sheldon 2014)

Bayesian Shear Estimation: Test By Simulation

- Simulate galaxies with Sérsic index $n = 1$ for exponential radial profile (like spiral galaxies) and $n = 4$ for De Vaucouleurs' profile (like early type galaxies).
- PSF-convolved size just bigger than the PSF, similar to what you get from star-galaxy separation for faint noisy galaxies.
- In these controlled conditions, sufficiently unbiased for current surveys (light gray) and future surveys (dark gray).
- No other published method meets these requirements without some kind of post-correction based on simulations.



Sheldon 2014

Requirements derived from Huterer et al. 06

Bayesian Shear Estimation in Practice

- Need to know the distribution of galaxy shapes.
- Requires a second, deeper data set.
- Current best data set is the HST Cosmos fields, but they are a relatively small contiguous area. Dominated by sample variance.
- In DES we have deep supernova fields. Well separated and more area than Cosmos, but observing conditions are highly varied: bad seeing, non-photometric, bright sky etc.
- We need to explore if we can achieve what we want using those fields, or if a focused program is needed.

Summary

- Lensing can be used for studying the geometry of the universe and the distribution of dark matter.
- To meet our goals the requirements are stringent: 0.4% calibration on a 1% signal for current surveys, 0.2% for planned surveys.
- Calibration errors mainly due to incorrect distance estimation or incorrect shear estimation.
- Recent advances in distance estimation are approaching the requirements (`ProbWTS` among others) but much more study is needed.
- Recent advances in Bayesian shear estimation are now known to be accurate enough (Sheldon 2014 implementation of B&A 2014).
- For both distance calibrations and shear, need deep datasets in widely separated patches to establish the properties of the galaxy population.