# Photo-z challenges for 2-pt cosmology* at LSST depths

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for LSST DESC PZ and DES redshift-wg

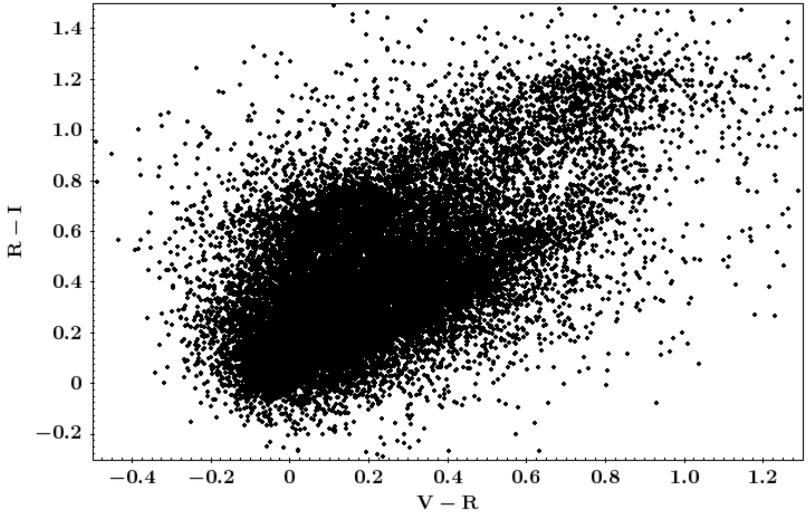
* and the vast majority of other extragalaxic science with LSST

Statistical challenges for LSS in the era of LSST, Oxford, 20 Apr 2018

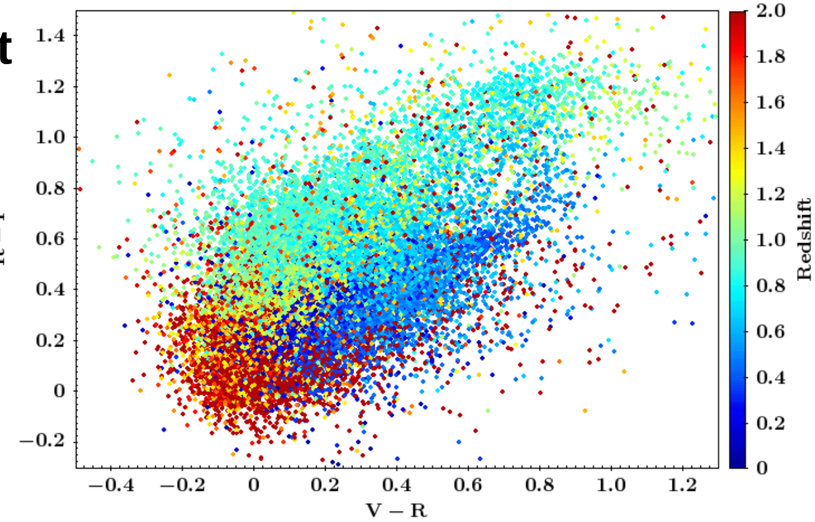
# Photo-z wishlist in the LSST era

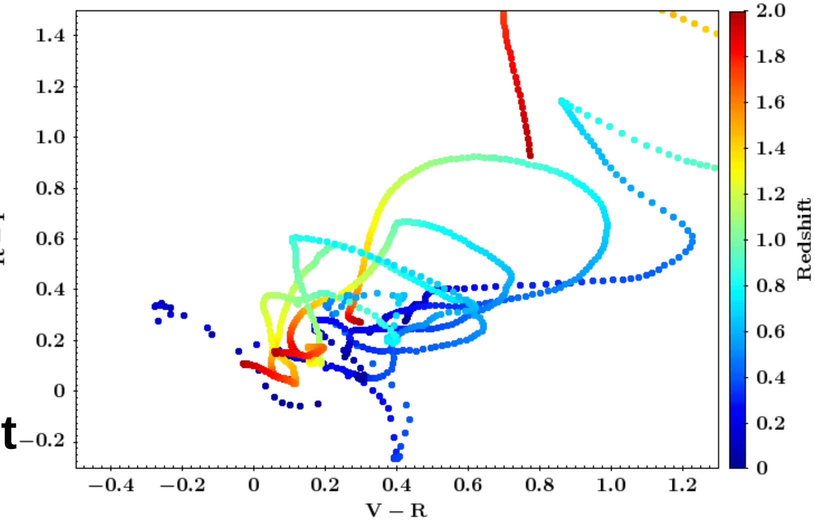
- Accurate (unbiased) galaxy redshift probability distribution functions (PDF).
- Precise (i.e. narrow) PDFs (tomography is only useful if bins are distinct).
- Accurate, precise point redshifts (for tomographic bin assignment), or an equivalent method.
- Galaxy types (early vs late types – for I.A., SN hosts, improved redshift priors from galaxy evolution).
- **Accurate ensemble redshift distributions, n(z).**

# Traditional photo-z in a nutshell




Training set

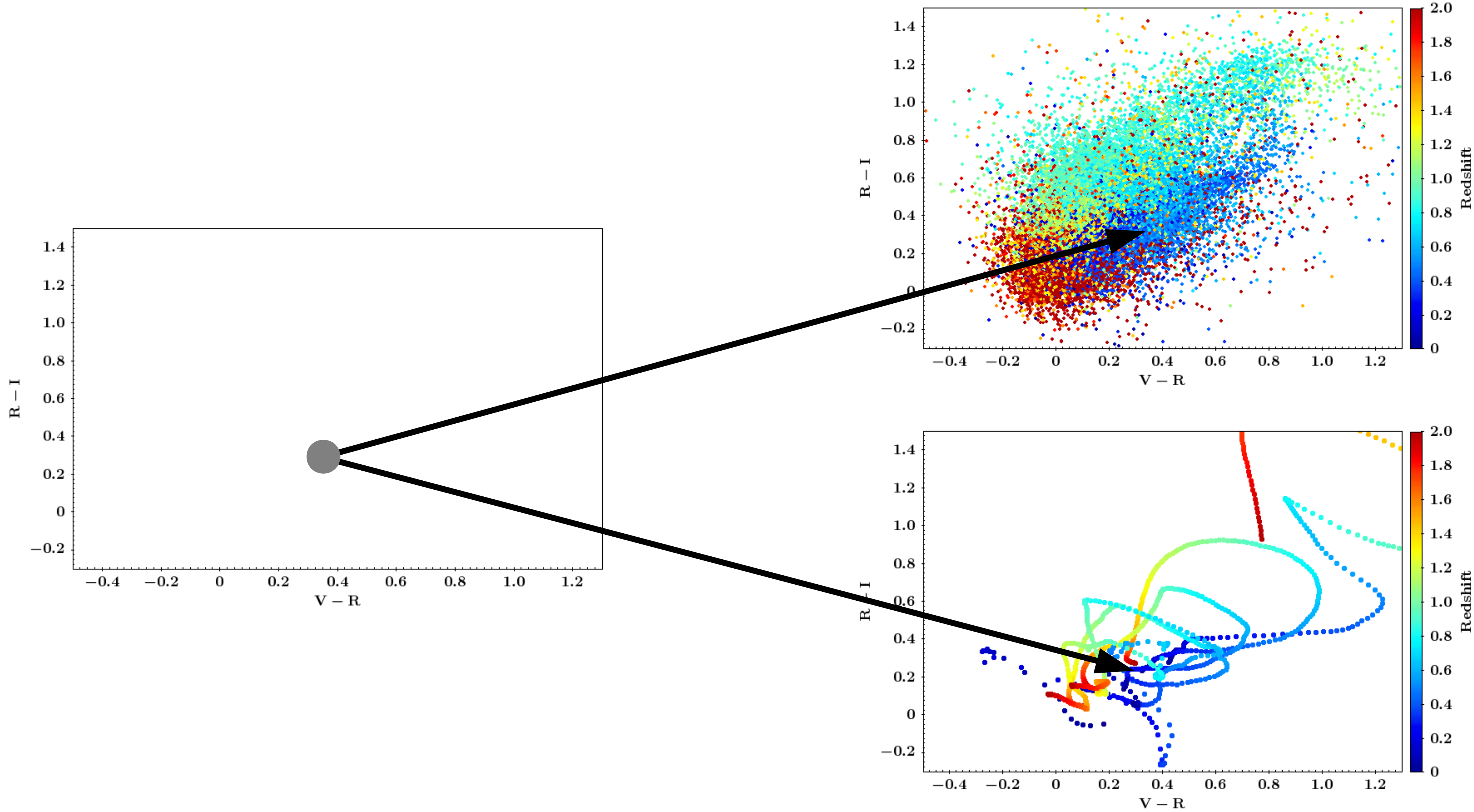



Template set

Data: COSMOS, Laigle et al., 2016
Templ.: Coleman et al., 1980

# Traditional photo-z in a nutshell

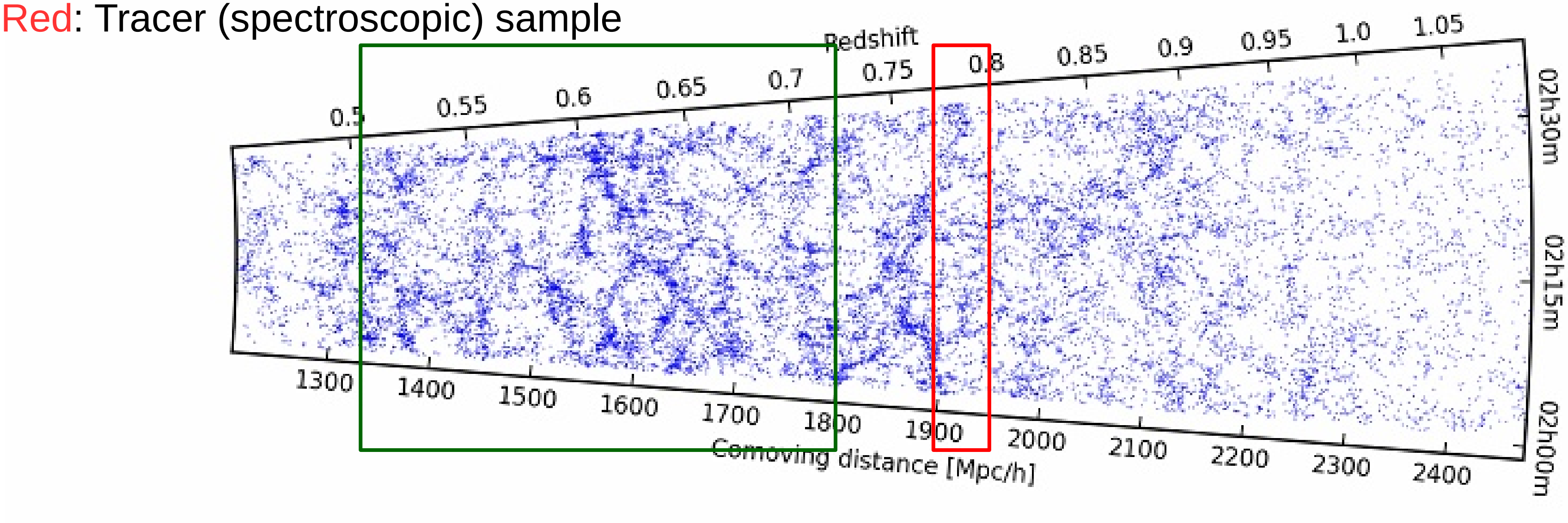



Data: COSMOS, Laigle et al., 2016
Templ.: Coleman et al., 1980

# Clustering photo-z (WZ)

Green: target photometric redshift sample
Red: Tracer (spectroscopic) sample

Galaxy density: Guzzo et al., 2013




Positions of galaxies on the sky at different redshifts are uncorrelated → zero signal.

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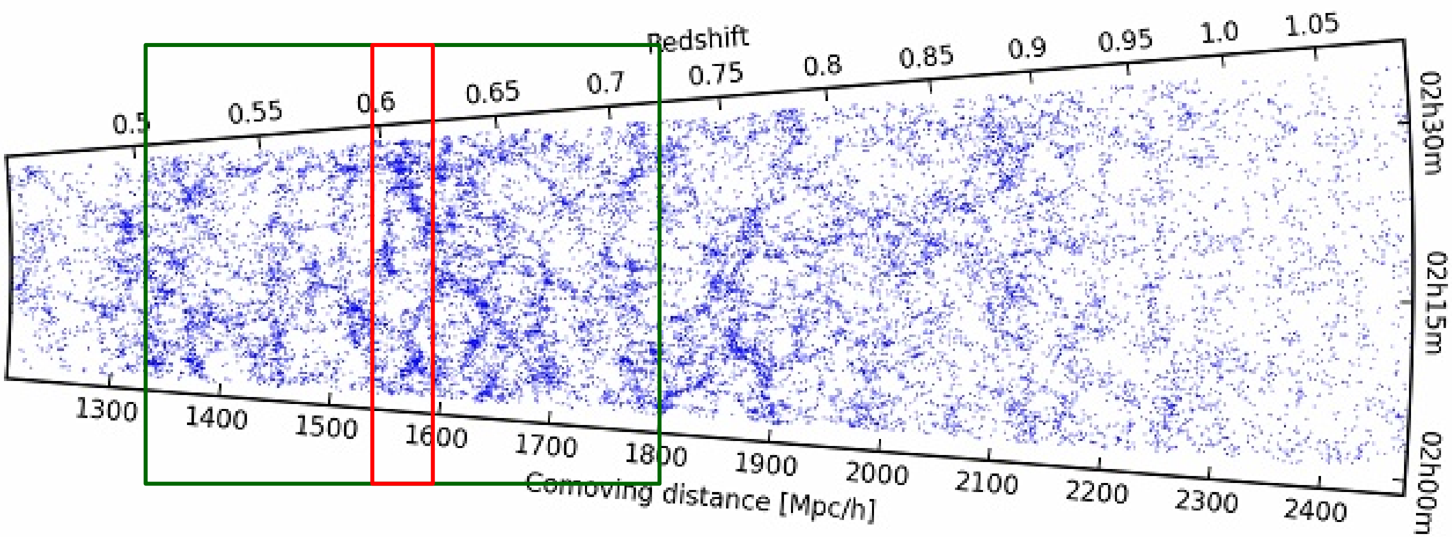
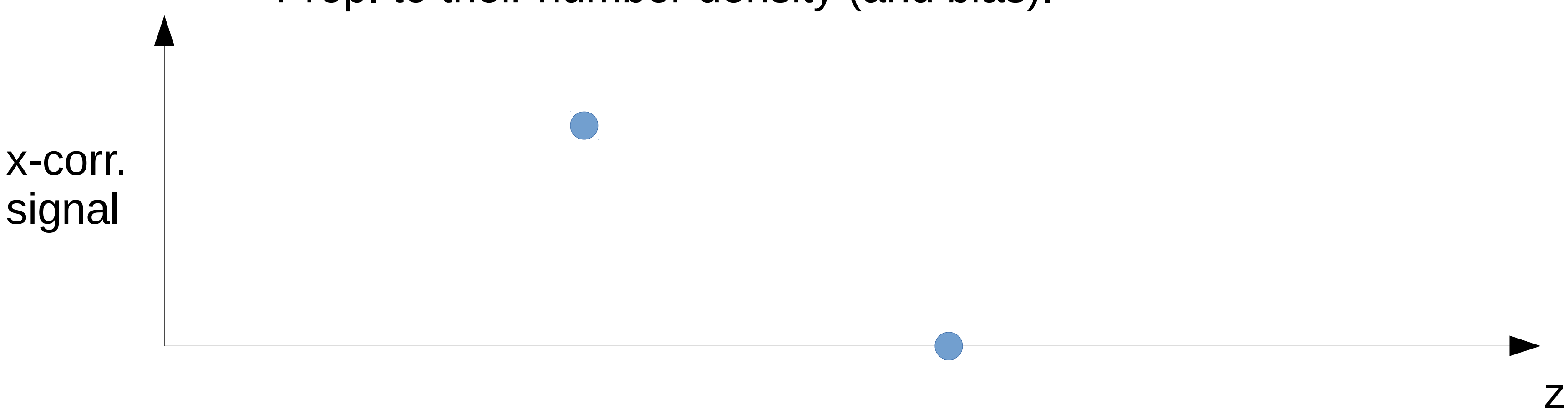
Galaxy density: Guzzo et al., 2013




Galaxies that trace the same underlying density distribution are correlated on the sky.
→ Prop. to their number density (and bias).



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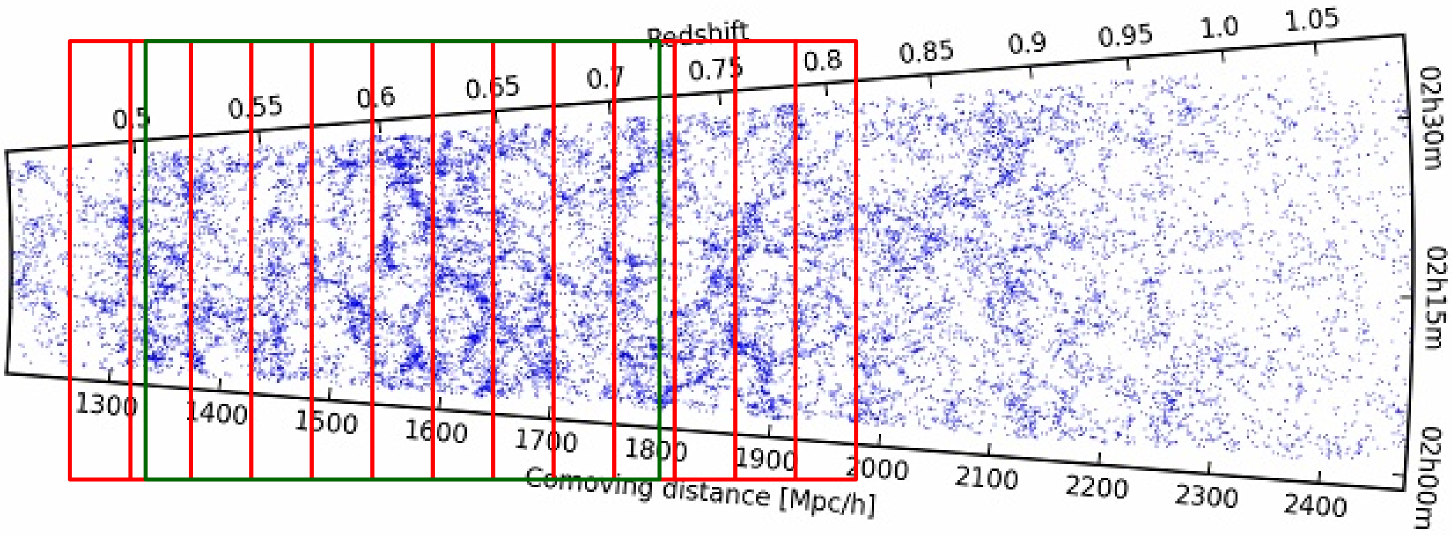
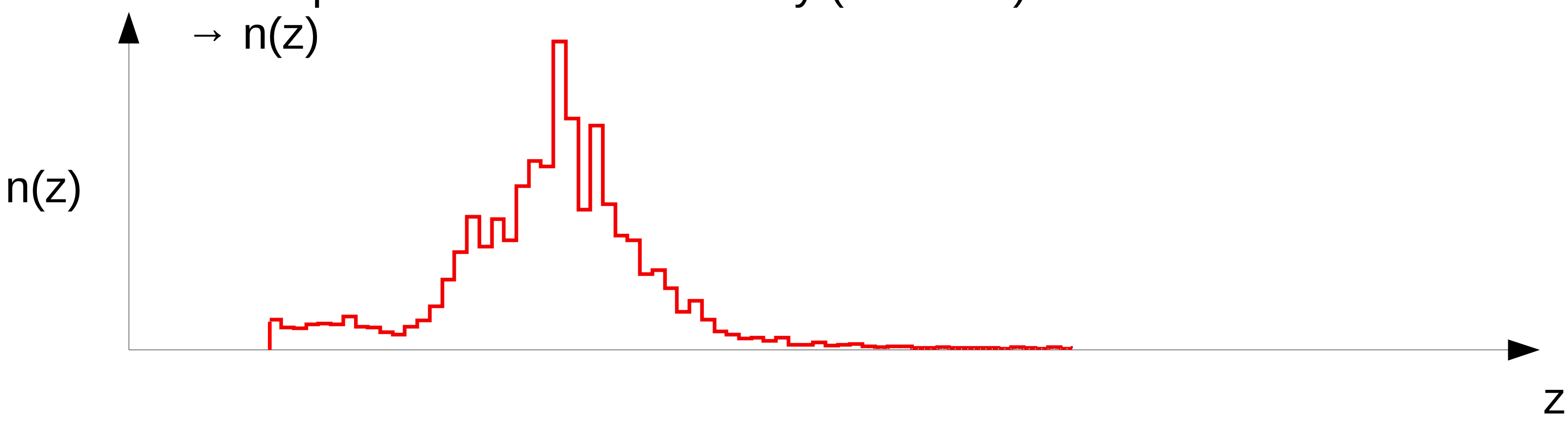



Galaxies that trace the same underlying density distribution are correlated on the sky.

→ Prop. to their number density (and bias).

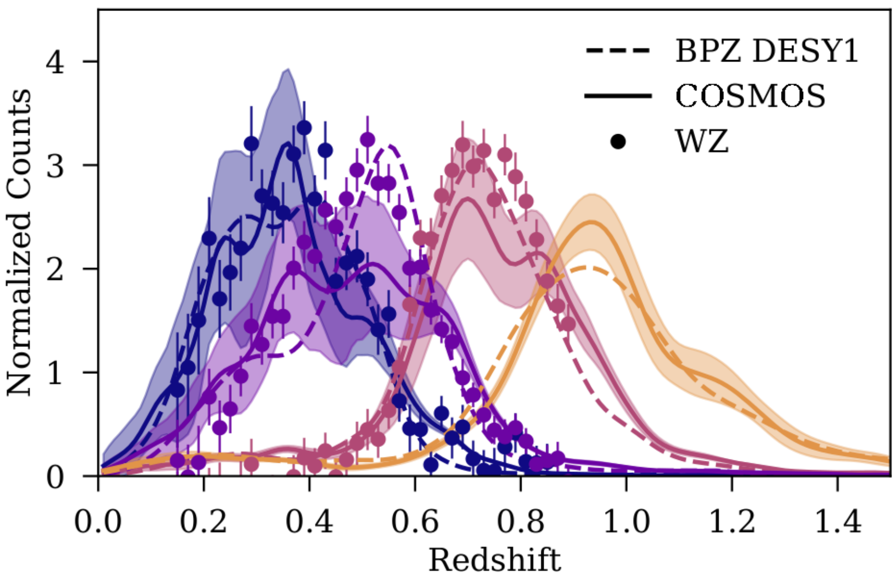
→ n(z)



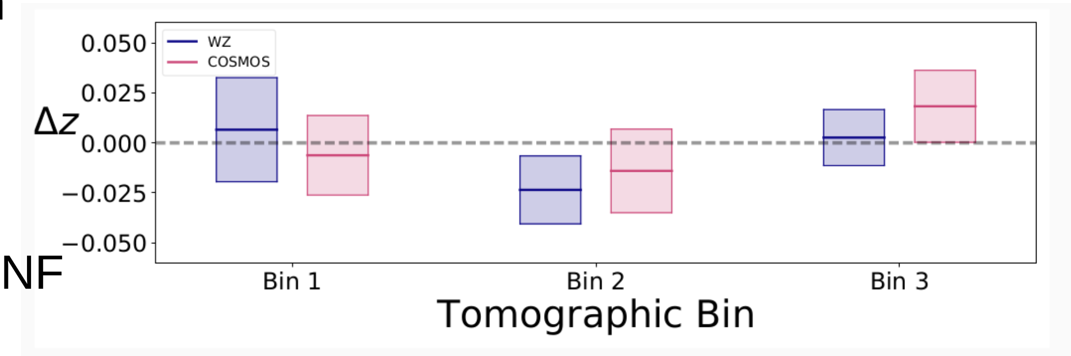
# State-of-the-Art: DES Y1

- Object-by-object p(z) from BPZ, with customised templates, prior.
- Tomo bin assignment by BPZ mean z.
- Stacked p(z) used as estimator of n(z).
- Compared against resampled COSMOS photo-z (Laigle et al. 2016) and clustering redshifts, with redMaGiC as tracer. (Davis et al., subm.; Gatti, Vielzeuf et al., in press; Cawthon et al., subm.; Rozo et al., 2016)
- Systematics parameterised as per-bin shift in mean of n(z).
- Validation consistent with Δz = 0.
- Also performed for training method, DNF (de Vicente et al., 2016).

Hoyle et al., in press



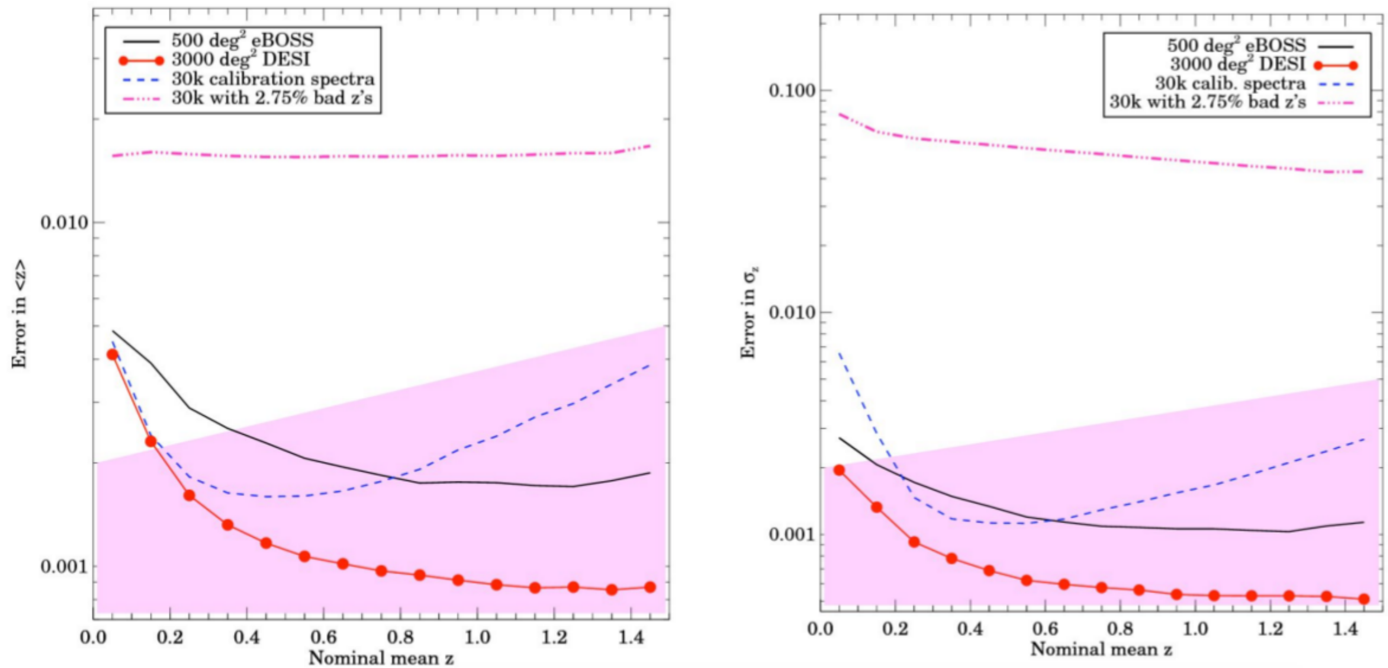

Davis et al., subm.



# The ideal training set, LSST era

**Newman et al. (2013):**

- To measure w to 1% accuracy, we need to know the mean of any given tomo bin to 0.2%, in (1 + z).
- Implies a training sample of ~30,000 objects, sparsely sampled over the sky and representative of the target sample.
- Accuracy in clustering redshifts achieved via planned DESI surveys (subject to treatment of systematics), at least over the peak of expected n(z).



# Results from LSST DESC DC1

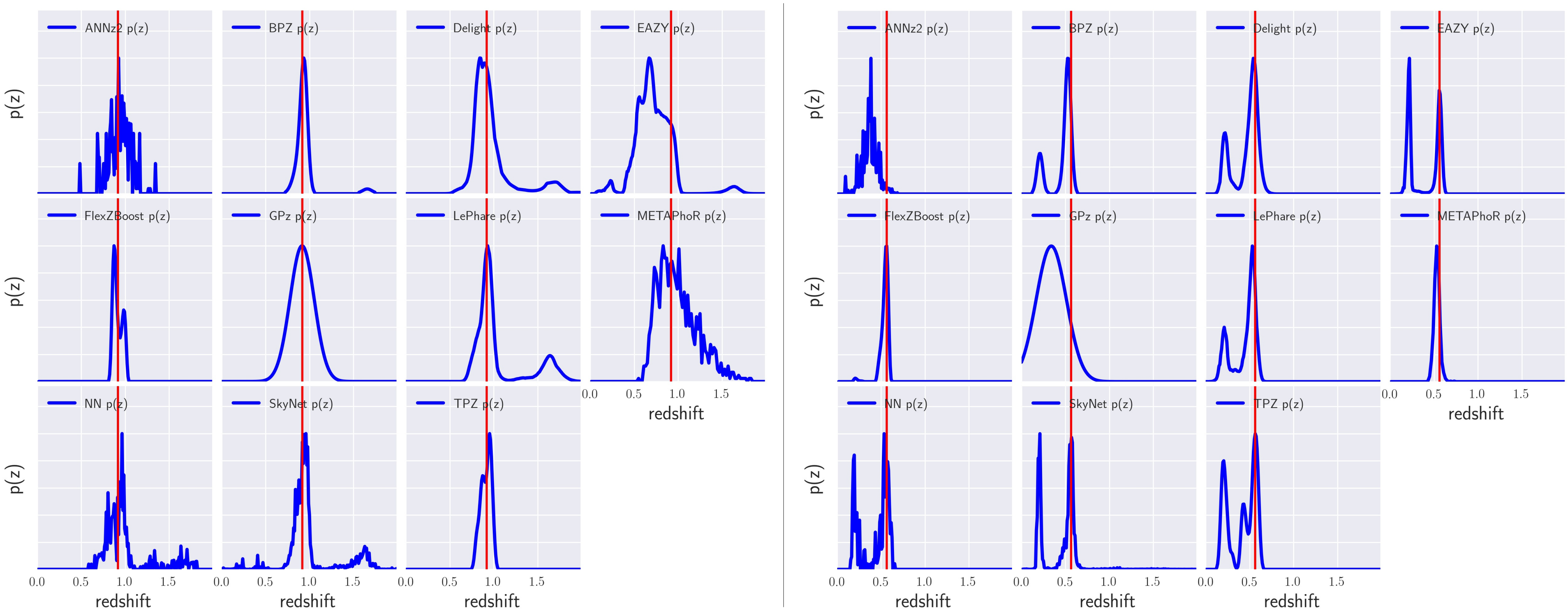
**Data Challenge 1:**

- Perfect set-up over 8 sq. deg..
- Same templates used to generate photometry used in codes.
- Training sample complete and representative to full depth (~44,000 objects).
- No stars.
- No AGN contribution.
- $0 < z < 2$.

Aim to understand the impact of method on the interim redshift posterior by removing errors associated with training, templates, prior.

# Results from LSST DESC DC1

- Considerable diversity in results, even with a perfect set-up.

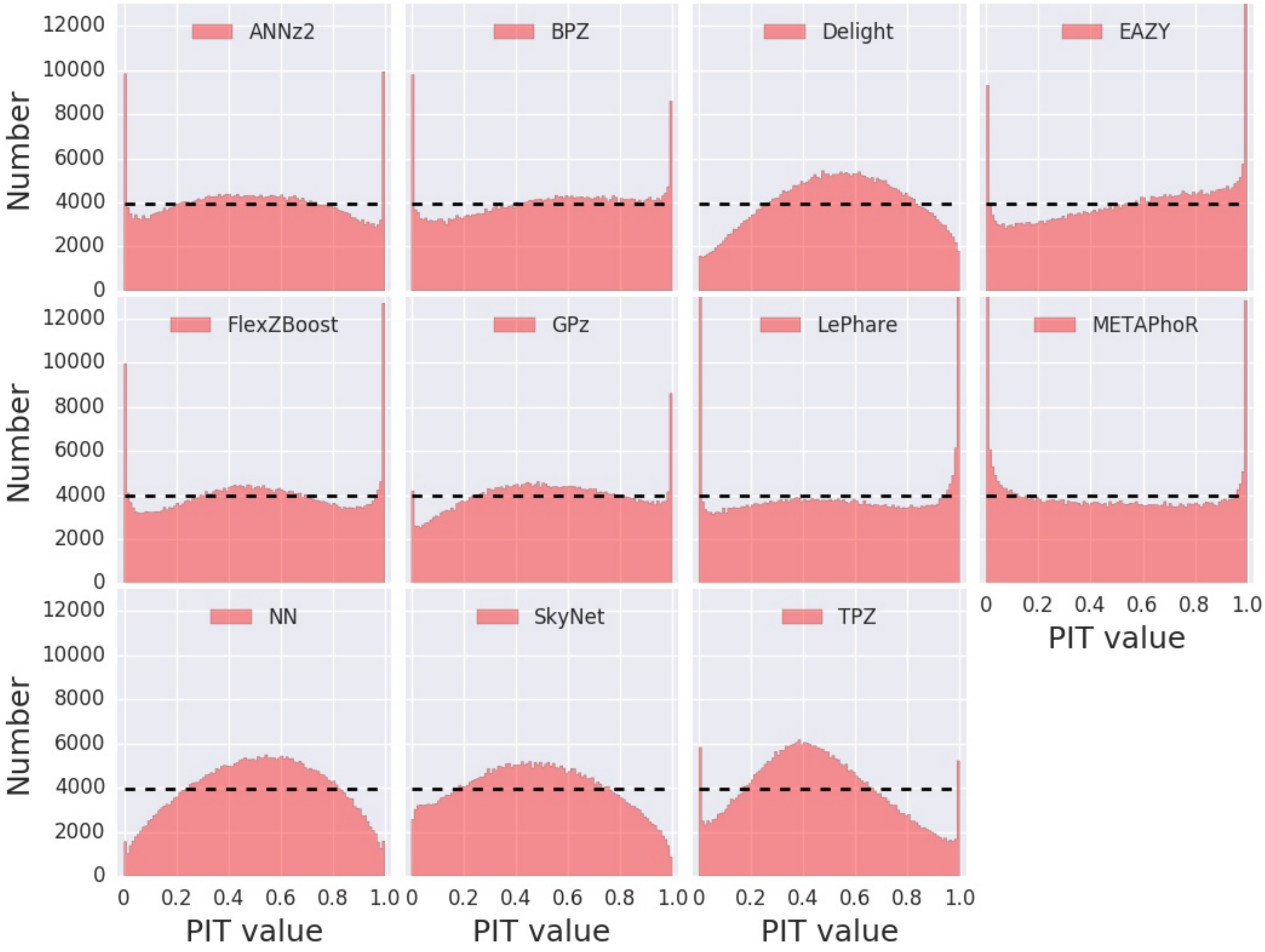



Schmidt et al., in prep.

# Results from LSST DESC DC1

$$\mathrm{PIT} = \int_{-\infty}^{z_{\mathrm{true}}} p(z)\, dz\,.$$

Perfect would be a flat histogram.




Schmidt et al., in prep.

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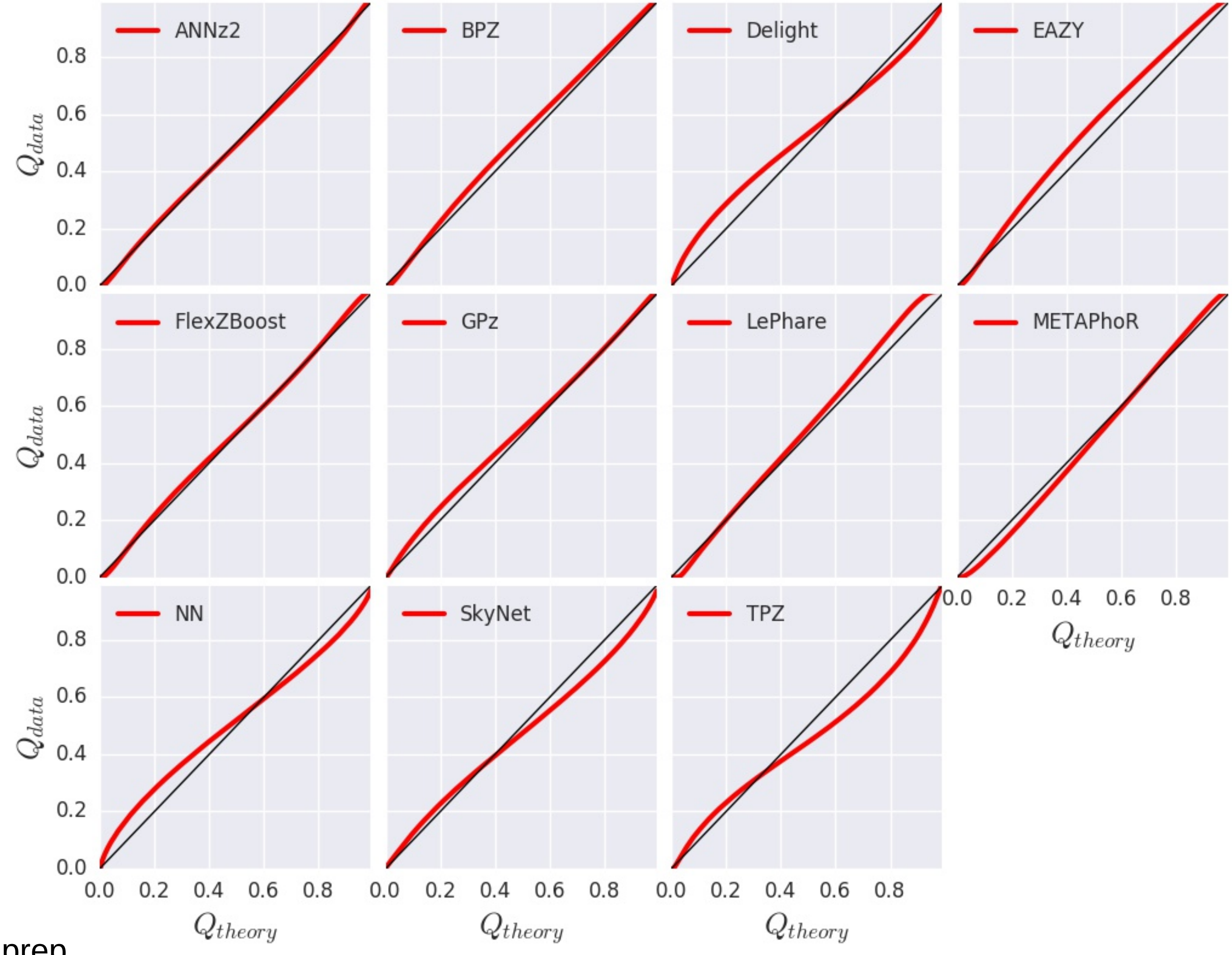


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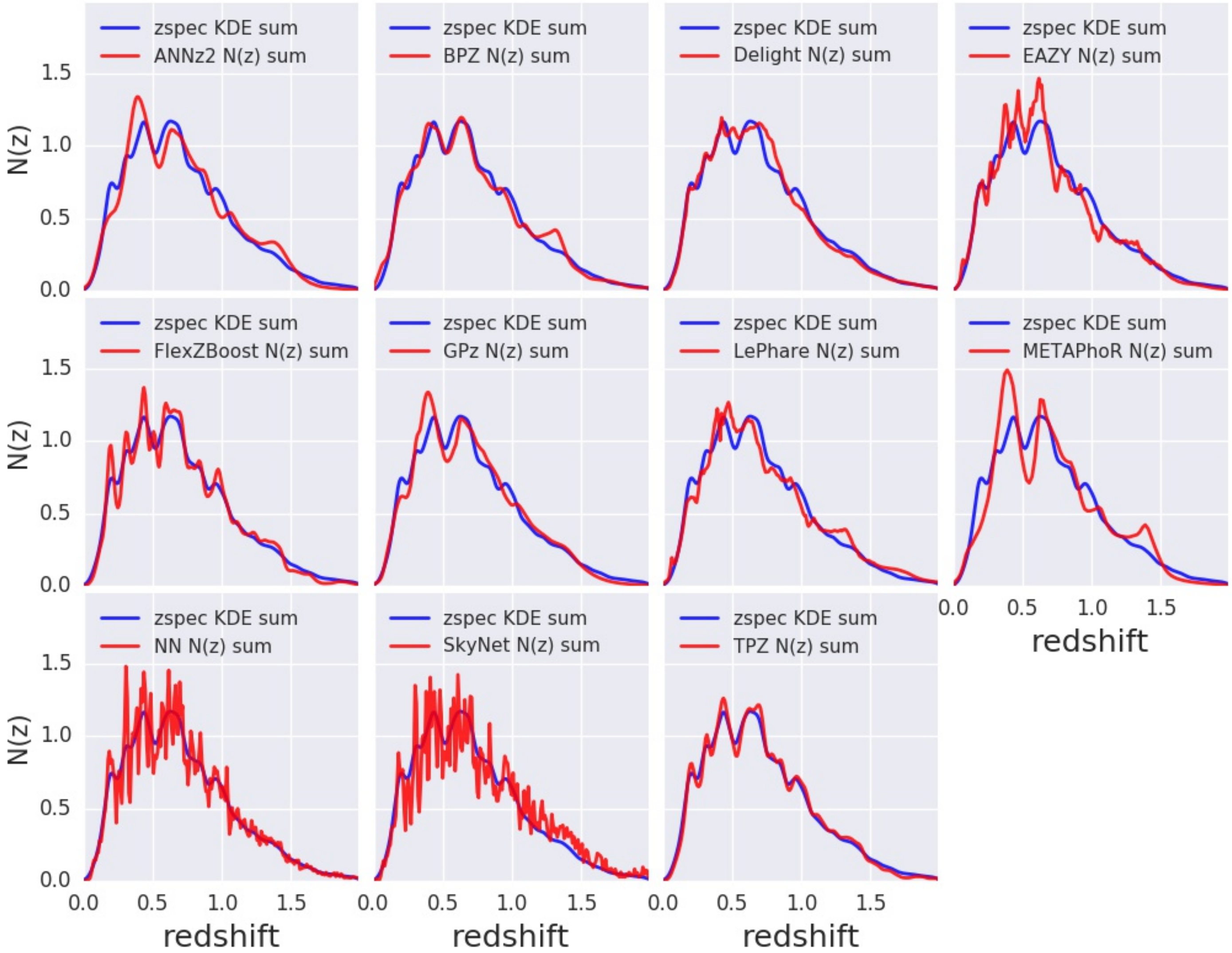
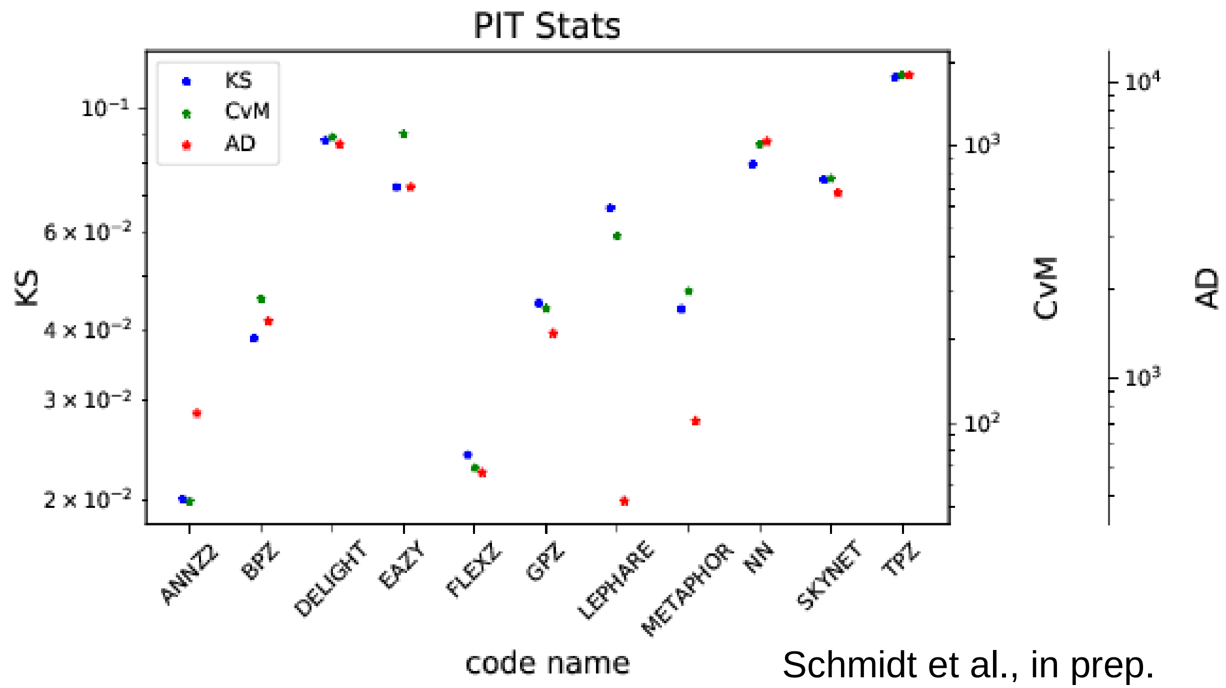



Schmidt et al., in prep.

# Results from LSST DESC DC1

PIT histogram versus perfect performance

- Series of stats. on the PIT hist. and n(z) recovery.
- How these translate to biases in cosmo params, still W.I.P.



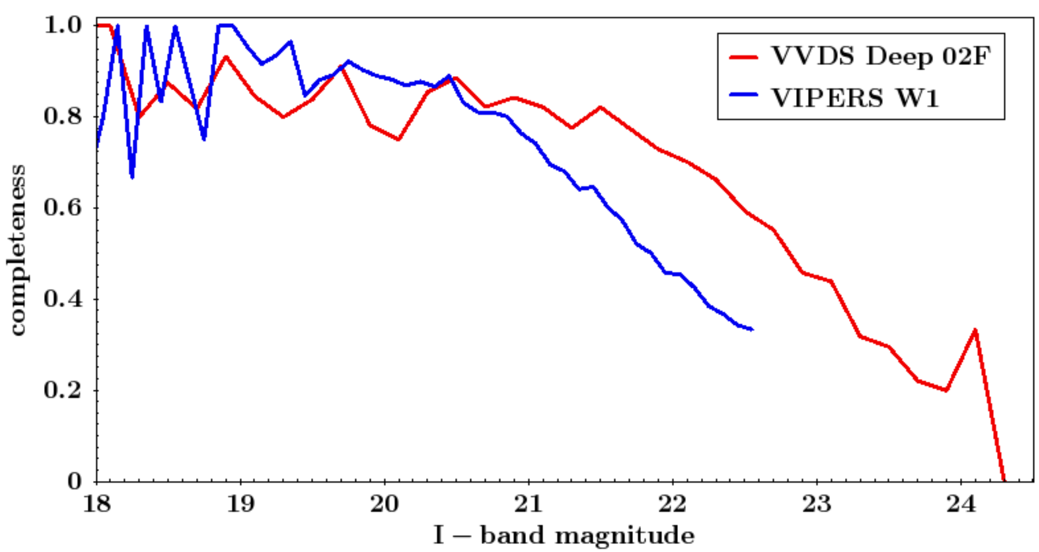

Schmidt et al., in prep.

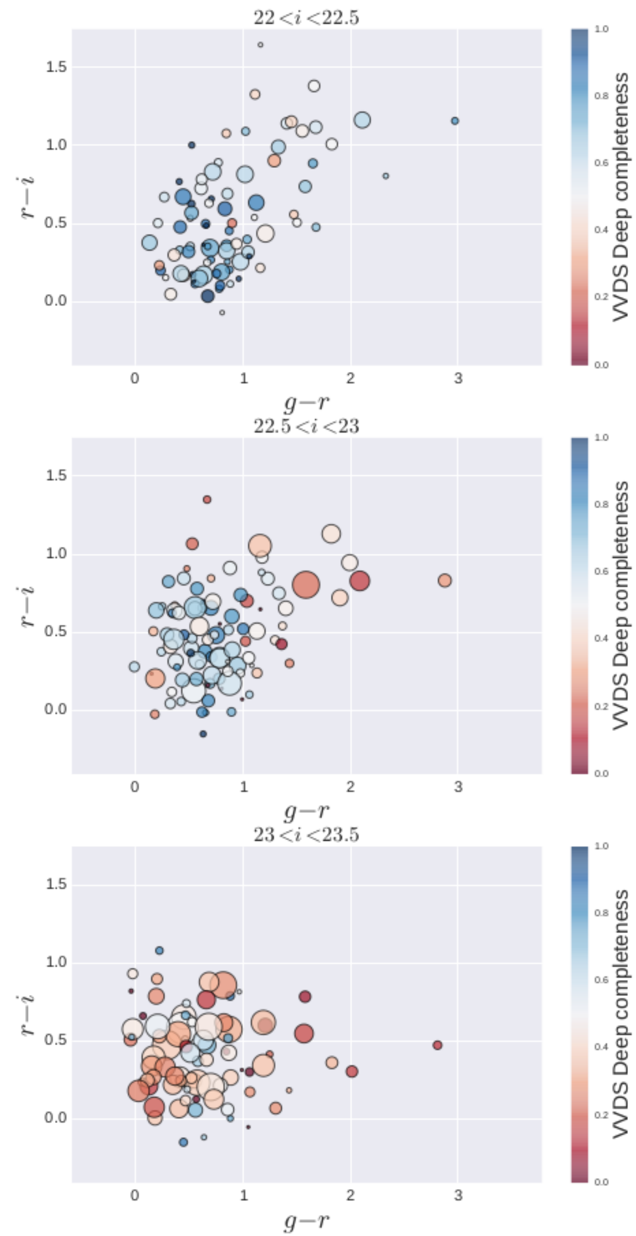
KS = Kolmogorov-Smirnoff
CvM = Cramer von Mises
AD = Anderson Darling

# But now the real problems start...

## Spectroscopic incompleteness:

- Spectroscopic datasets are not remotely complete even at DES depths.
- Unless addressed, this will propegate to n(z) and result in biases.
- Sometimes addressed by upweighting successful redshifts by the local (in col-mag space) incompleteness (e.g. Lima et al. 2008).

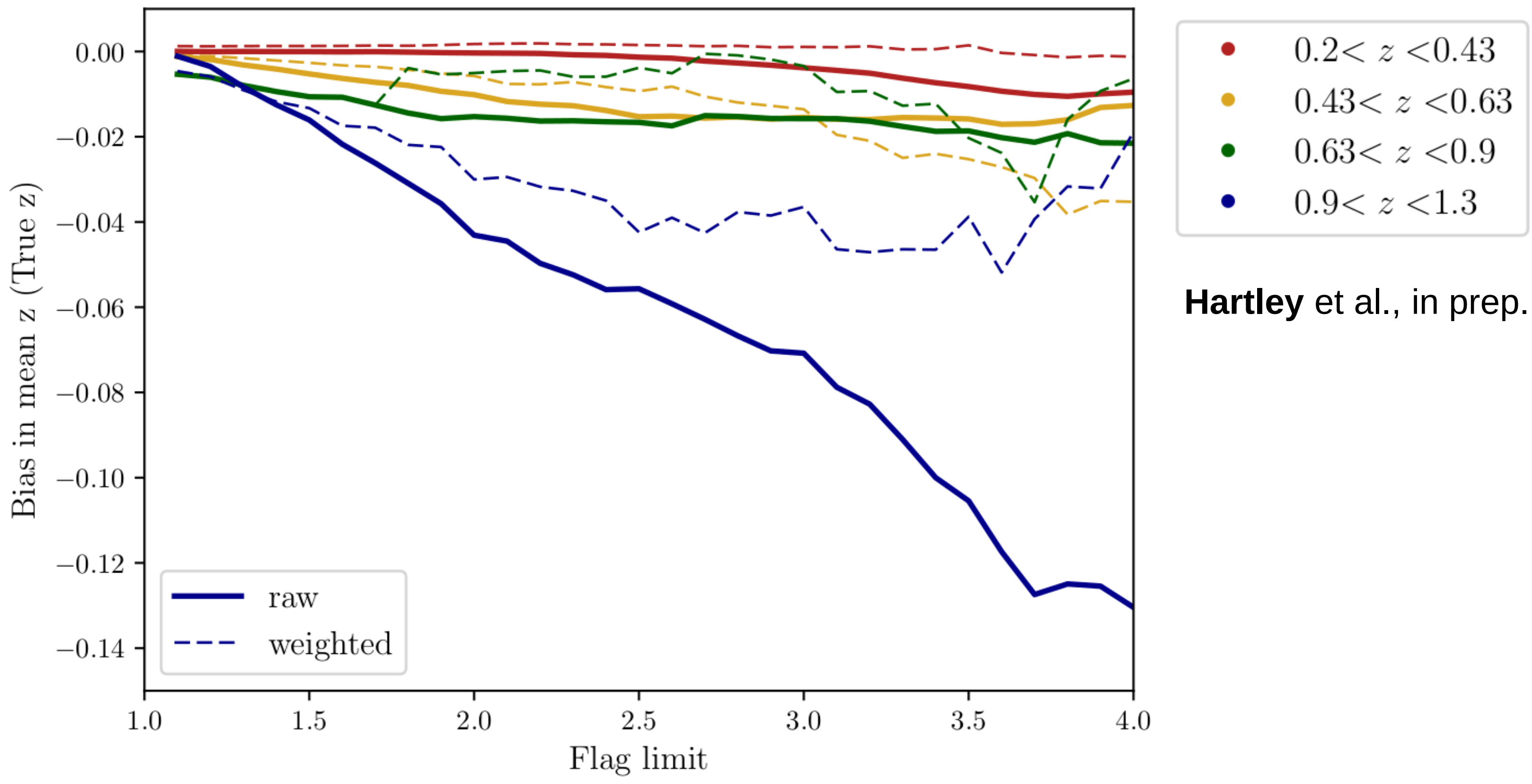



Bonnett, Troxel, **Hartley** et al., 2016

# But now the real problems start...

- Incompleteness in spectroscopic samples is typically systematic in redshift, not random.
- Even at fixed colour!
- Simply upweighting populations with poor completeness results does not remove biases.
- **Complete** samples are required, at I ~ 25. (This is essentially impossible)
- Large effort in LSST DESC to simulate, understand and try to mitigate these problems.

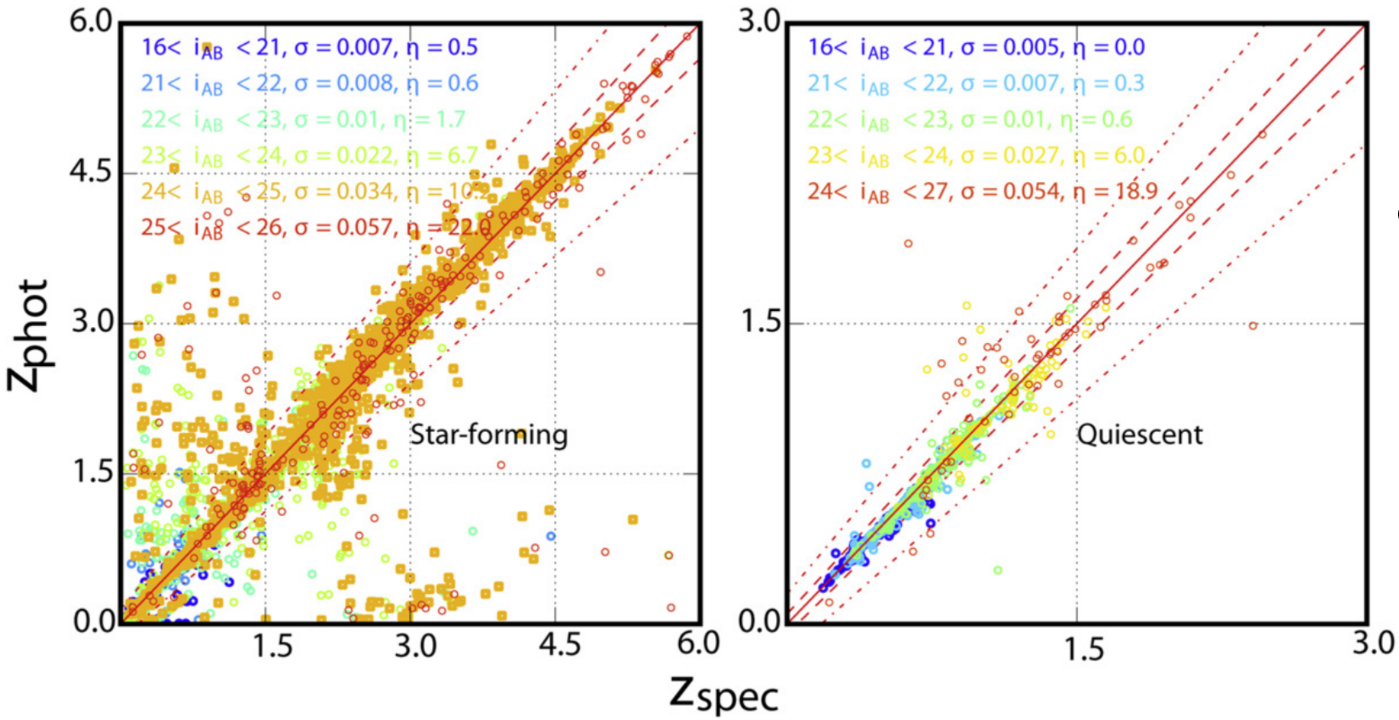



**Hartley** et al., in prep.

# But now the real problems start...

## Degeneracies:

- Even with 30 photometric bands, COSMOS photo-z have 10% outliers at 24<i<25.
- Expect this to be much worse with LSST (+ Euclid / WFIRST).
- Degeneracy between z~3 and z~0.5.
- Redshift prior needs to be exceptional to get n(z) correct!

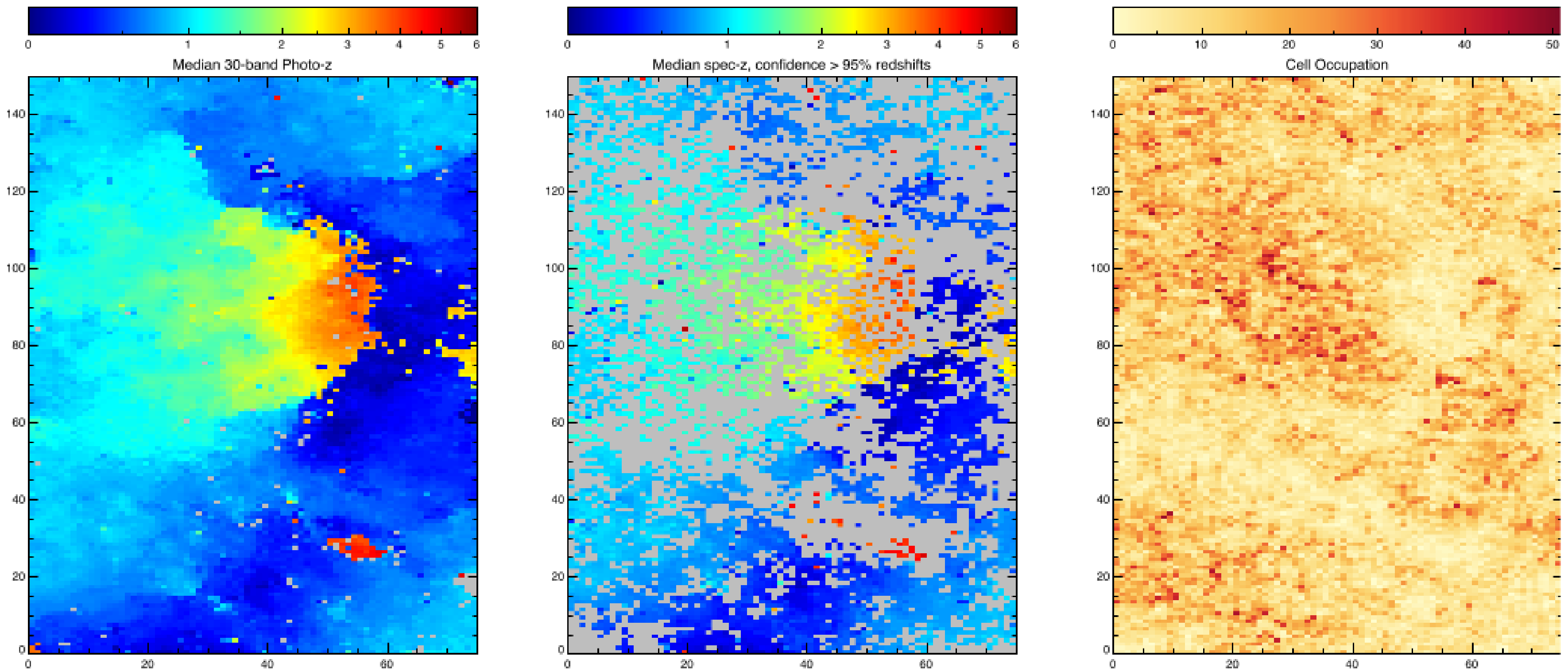



Laigle et al., 2016

# Self-organising maps: a possible solution?

LSST DESC
Dark Energy Science Collaboration

- 2D representation of higher dimensional colour-mag space.
- Neighbouring cells have similar SEDs.
- Allows us to identify important galaxy populations that need spec follow up (C3R2), have degenerate solutions, poor completeness etc..
- Convenient sample selection that doesn't depend on final photo-z run (though it's not deterministic).
- **Sample selection become critically important** – high S/N photometry, consistency across survey footprint required.




Masters et al., 2015

# Outlook

- Obtaining the ideal spec. training sample for ML methods seems a very remote possibility.
- Synthetic model template sets are probably not accurate enough at present (binarity, non-MW stellar populations).
- Emprical templates typically only appropriate at z~0, difficult to get correct evolution to high-z (though see Hoyle et al., subm. and **Boris Leistedt**'s talk).
- Prior, $P(z, T \mid m)$, will need to be very accurate.
- Clustering redshifts inherit most of the systematics relevant to $w(\theta)$ data vector.
- Need coverage over the whole redshift range, $0 < z < \sim 4$.
- Method, and many systematics in WZ are cosmology sensitive: bias, magnification etc..
- Joint cosmology, n(z) inference may be unavoidable (e.g. McLeod et al., 2017; Herbel et al., 2017; Hoyle et al., in press).

# Open questions in a joint solution

- What is the most appropriate / sensible way to parameterise redshift distributions?
  - Needs to be flexible enough, but with minimal number of parameters.

- How do we use information from traditional photo-z methods (and elsewhere) to inform priors on these params?

- Can we handle the covariance with, e.g., the shear, g-g lensing, $w(\theta)$ data vector?
  (**A:** Yes, if we have to...)