Estimating Photometric Redshifts with Convolutional Neural Networks and Galaxy Images: A Case Study of Resolving Biases in Deep Learning Classifiers

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Cosmological redshift

- **Shift to longer wavelengths**

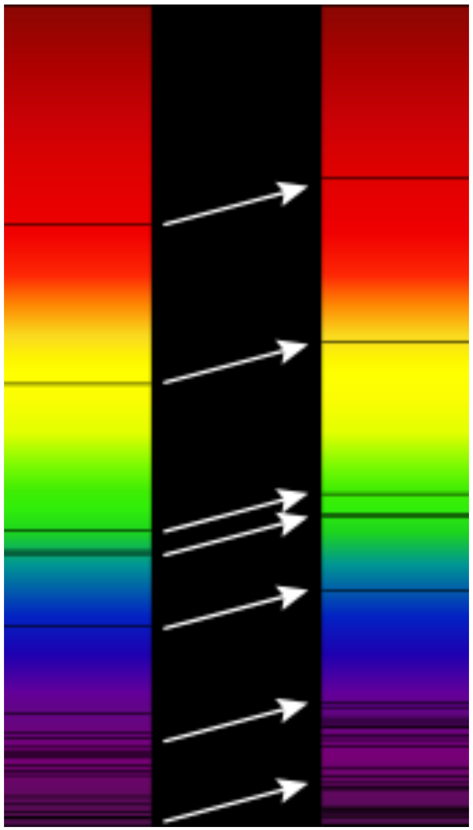


Image from: https://en.wikipedia.org/wiki/Redshift

- **Cosmological applications**

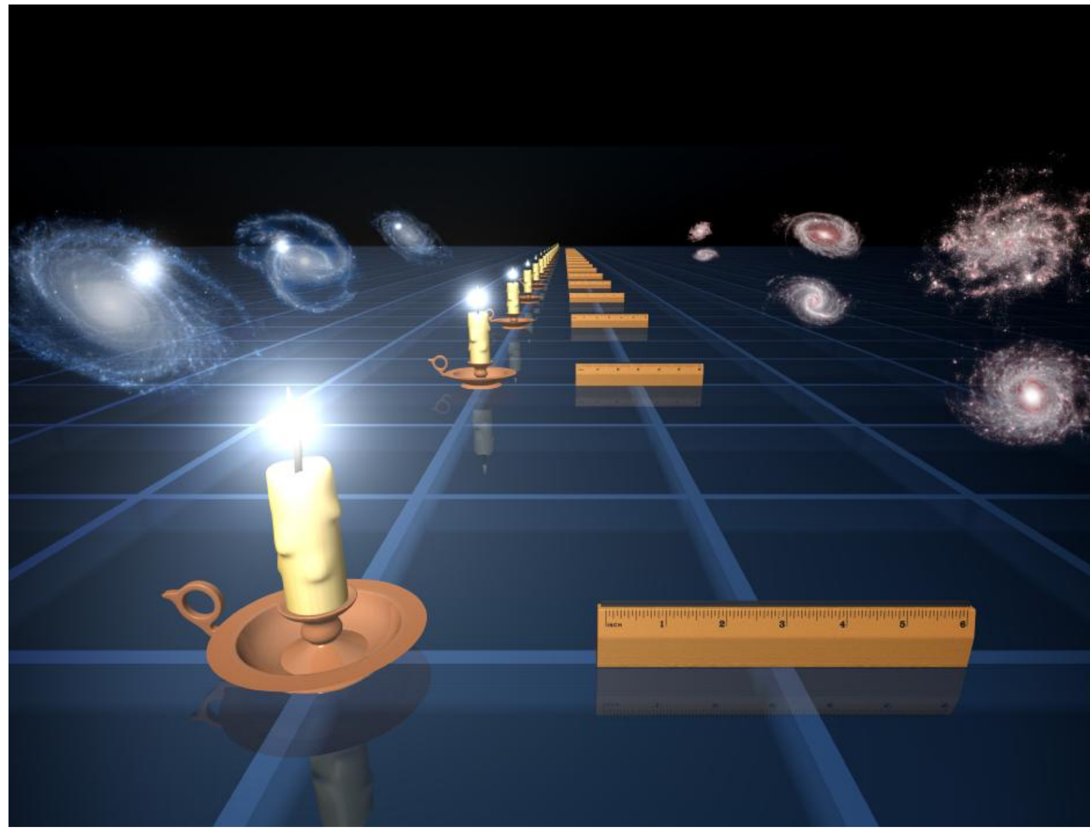


Image from: https://www.nasa.gov/mission_pages/galex/pia14095.html

‣ Spectroscopic redshift (spec z) v.s. Photometric redshift (photo z)

- **Spec z from spectroscopy**

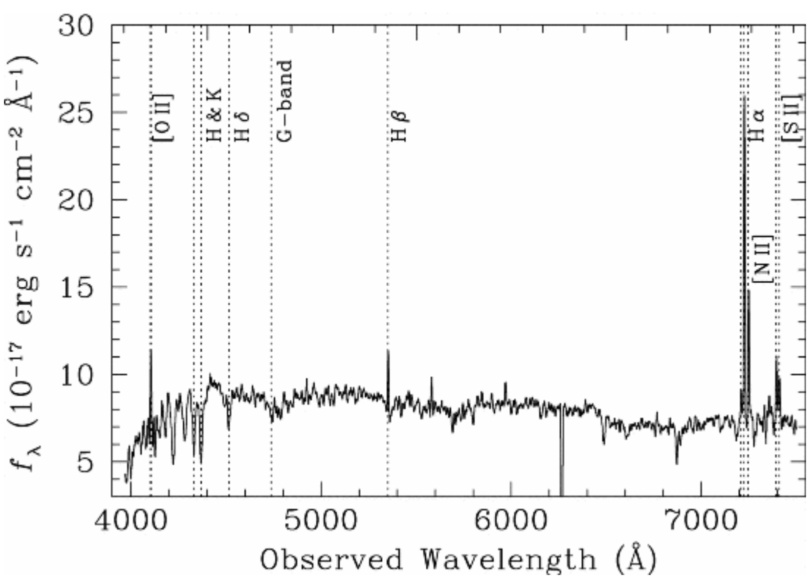


Image from: http://spiff.rit.edu/classes/phys301/lectures/doppler/doppler.html

- **Photo z from broad-band photometry**

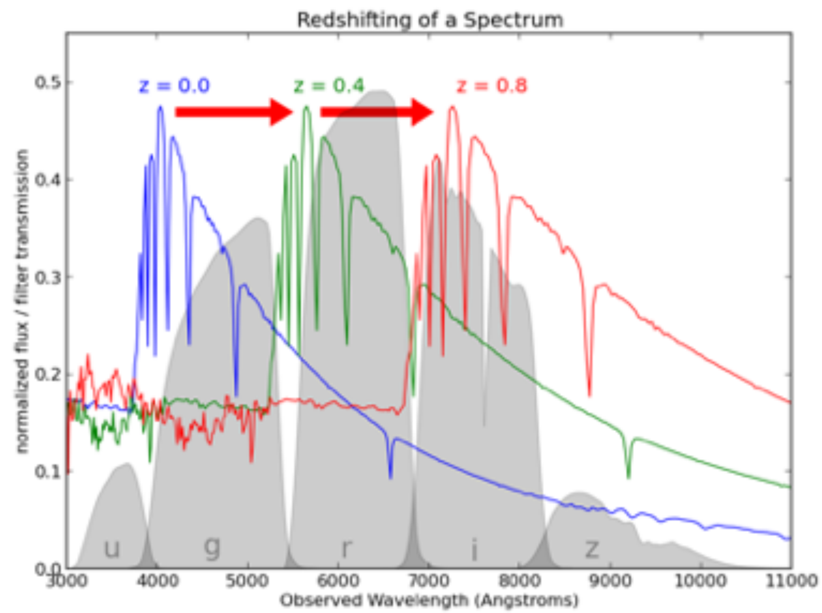
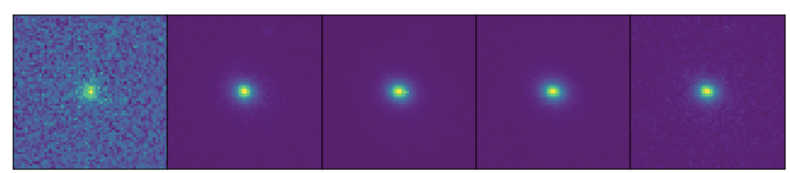


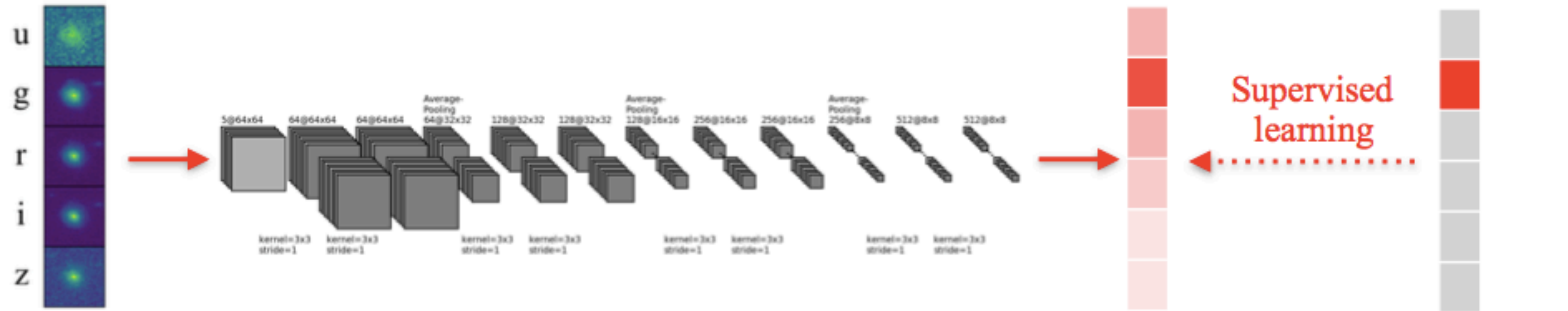
Image from: https://ogrisel.github.io/scikit-learn.org/sklearn-tutorial/tutorial/astronomy/regression.html

- **Photo z from images**

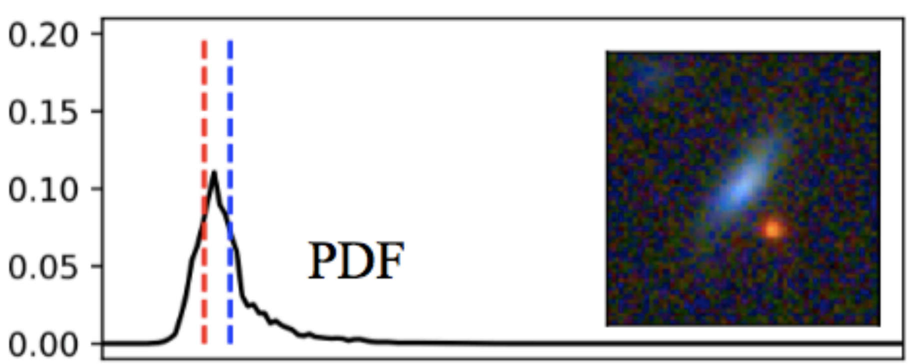


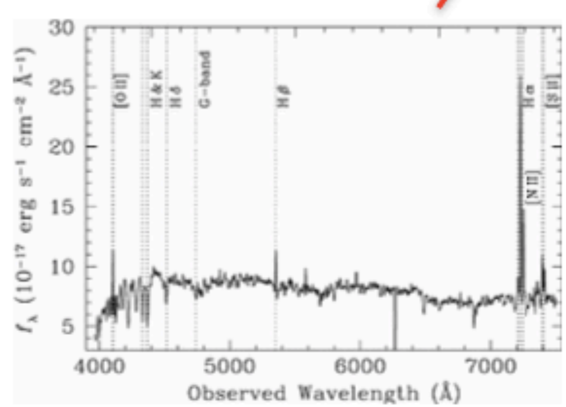
u g r i z

- **Photometric redshift (photo z) estimation as a classification problem supervised by spectroscopic redshift (spec z)**



Input image Network PDF output Label (spec-z)





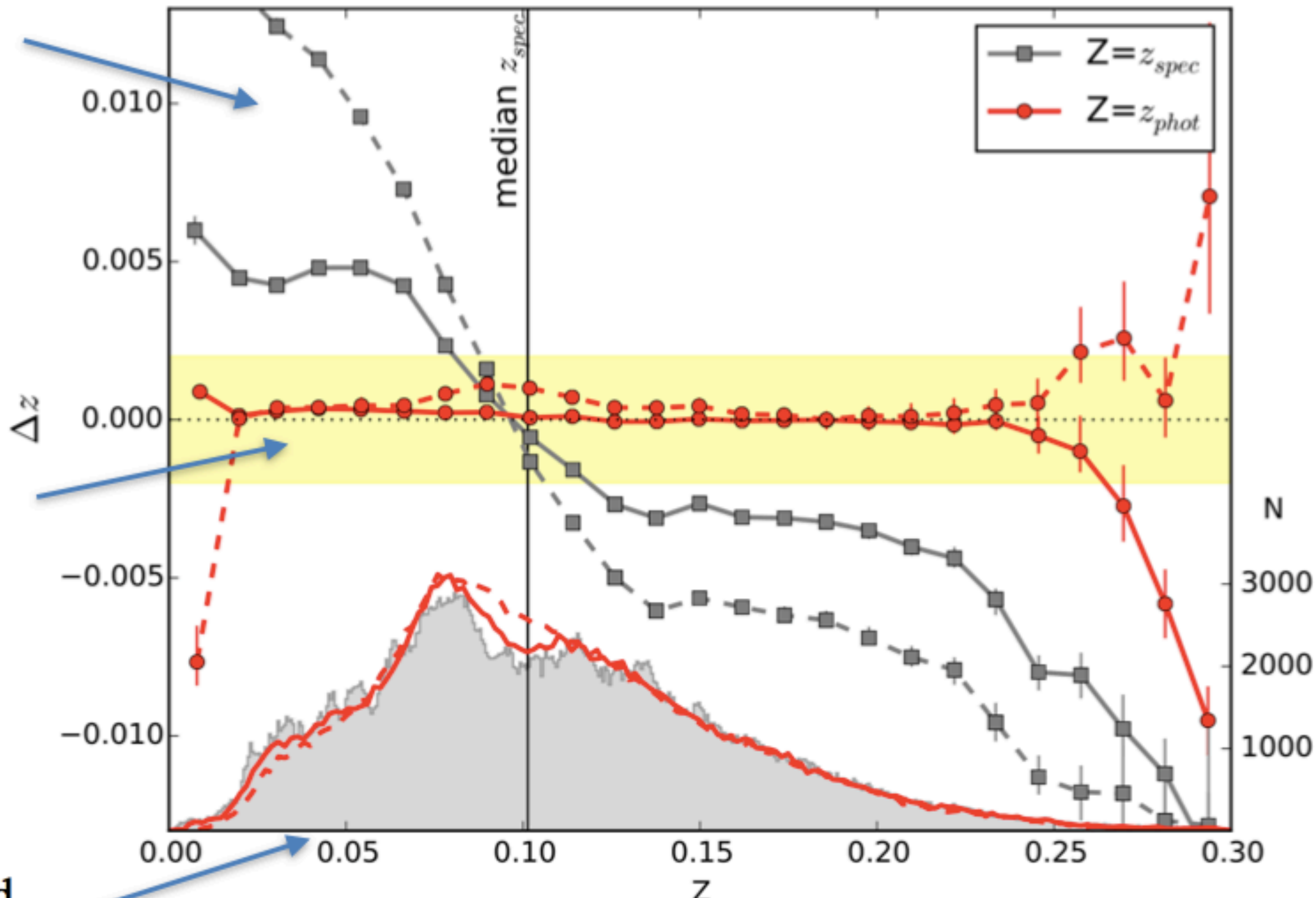
Spectroscopy

Bias 1: residual as a function of redshift (spec z / photo z)

Residual = (z_photo - z_spec) / (1 + z_spec)

w.r.t spec z (biased)

w.r.t photo z

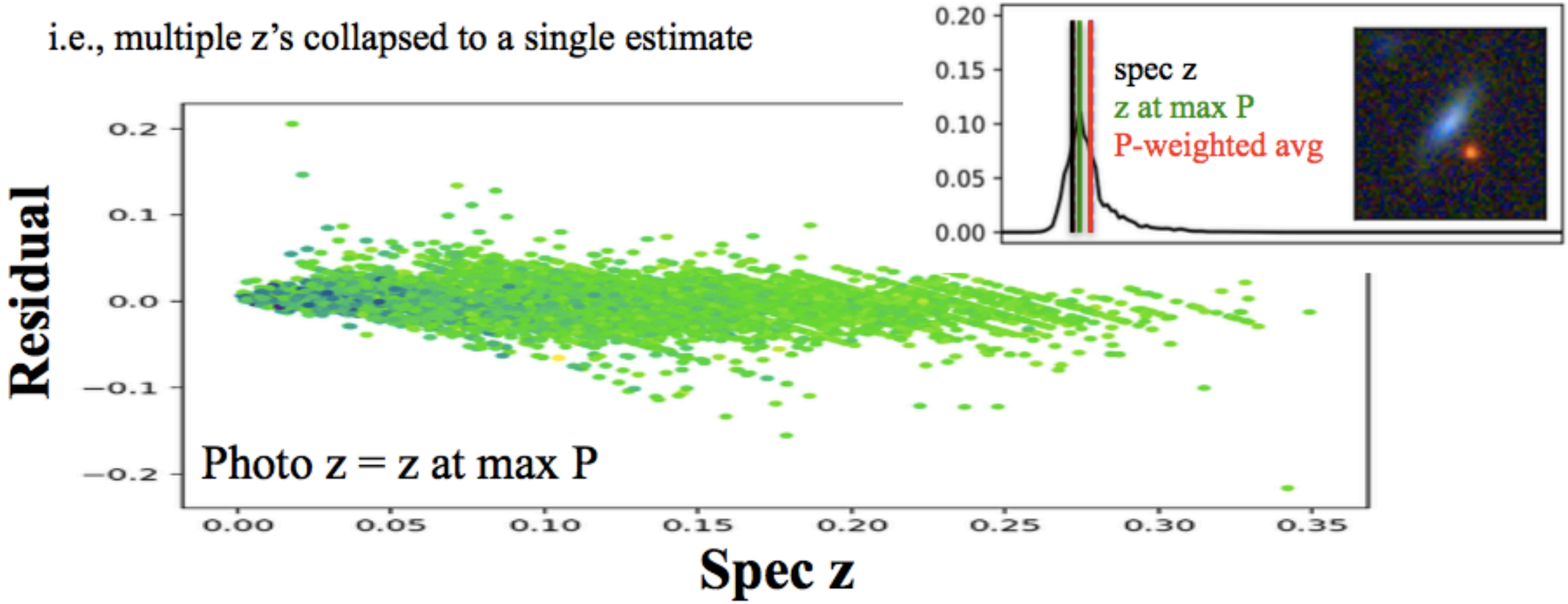


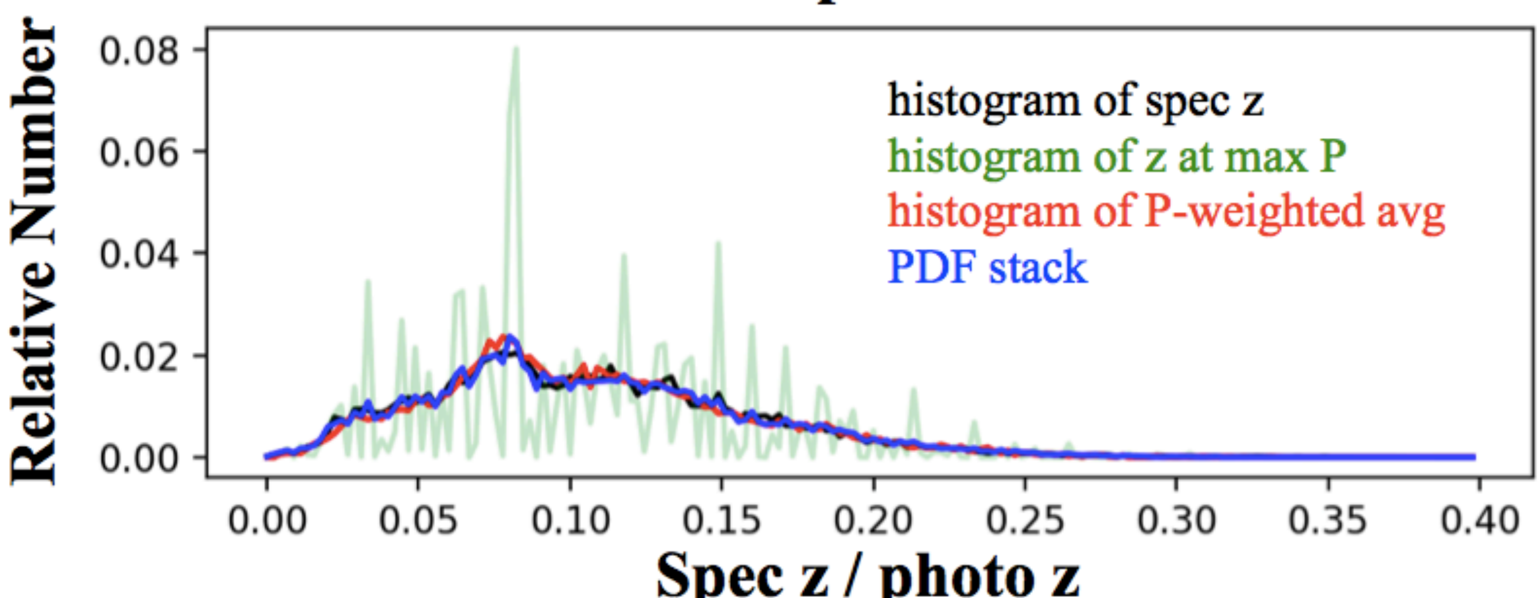
unbalanced distribution

SDSS z<0.4
(Pasquet et al. 2019)

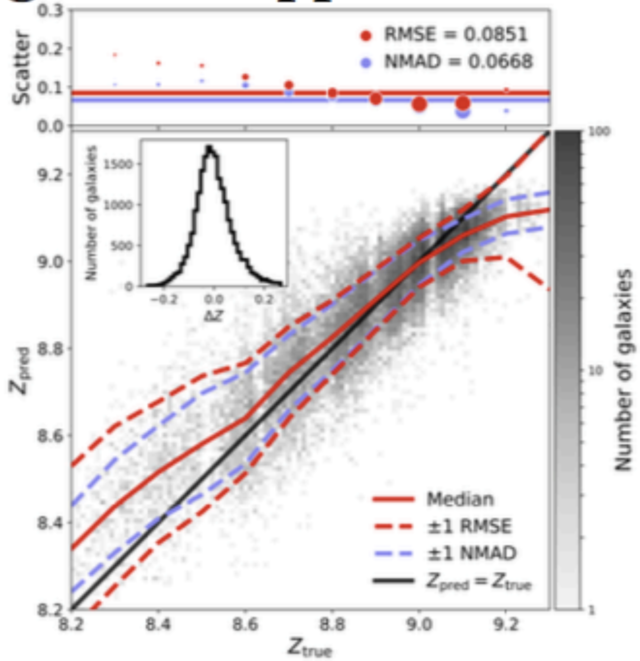
Bias 2: mode collapse

i.e., multiple z's collapsed to a single estimate

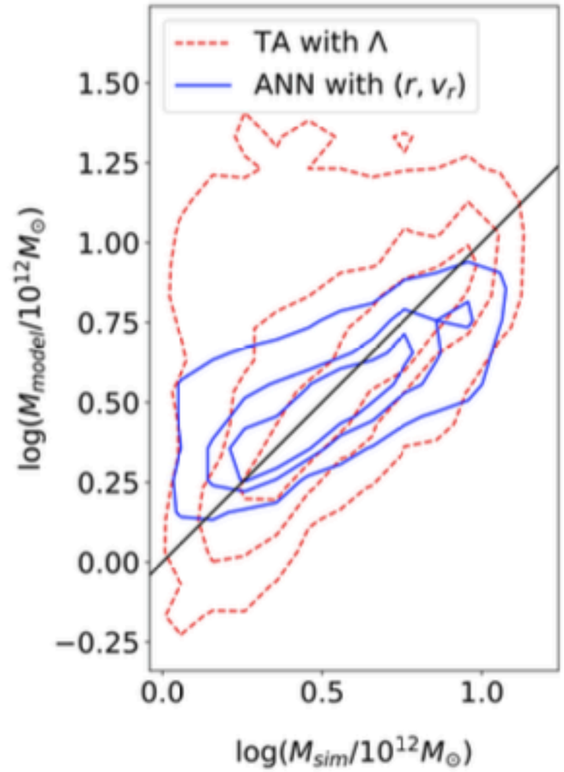




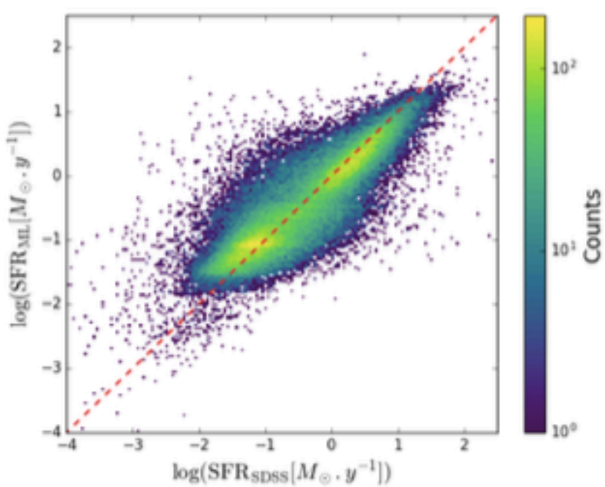
Biases exist in various classification & regression applications



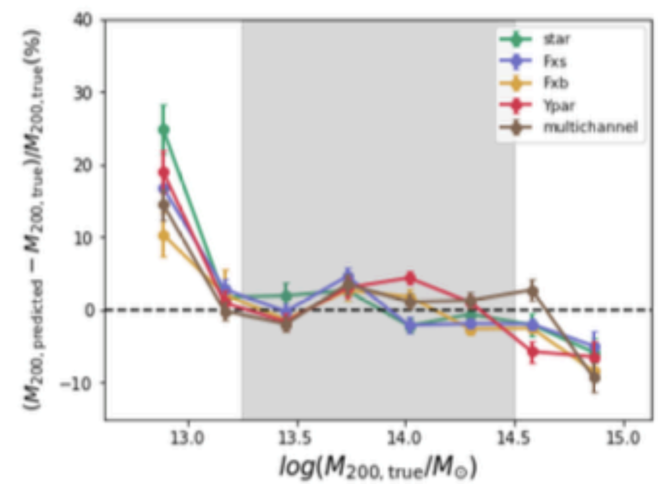
Metallicity (Wu et al. 2019)



Mass of the Local Group (McLeod et al. 2017)



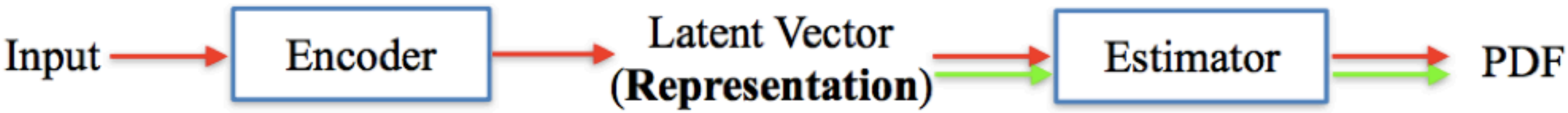
Star Formation Rate (Bonjean et al. 2019)



Cluster Mass (Yan et al. 2020)

Split the learning of representation and classification.

Representation Learning (all data) Classification (a balanced subset)



Over-confidence / imbalance / non-uniformity within data **(may not be due to overfit)**

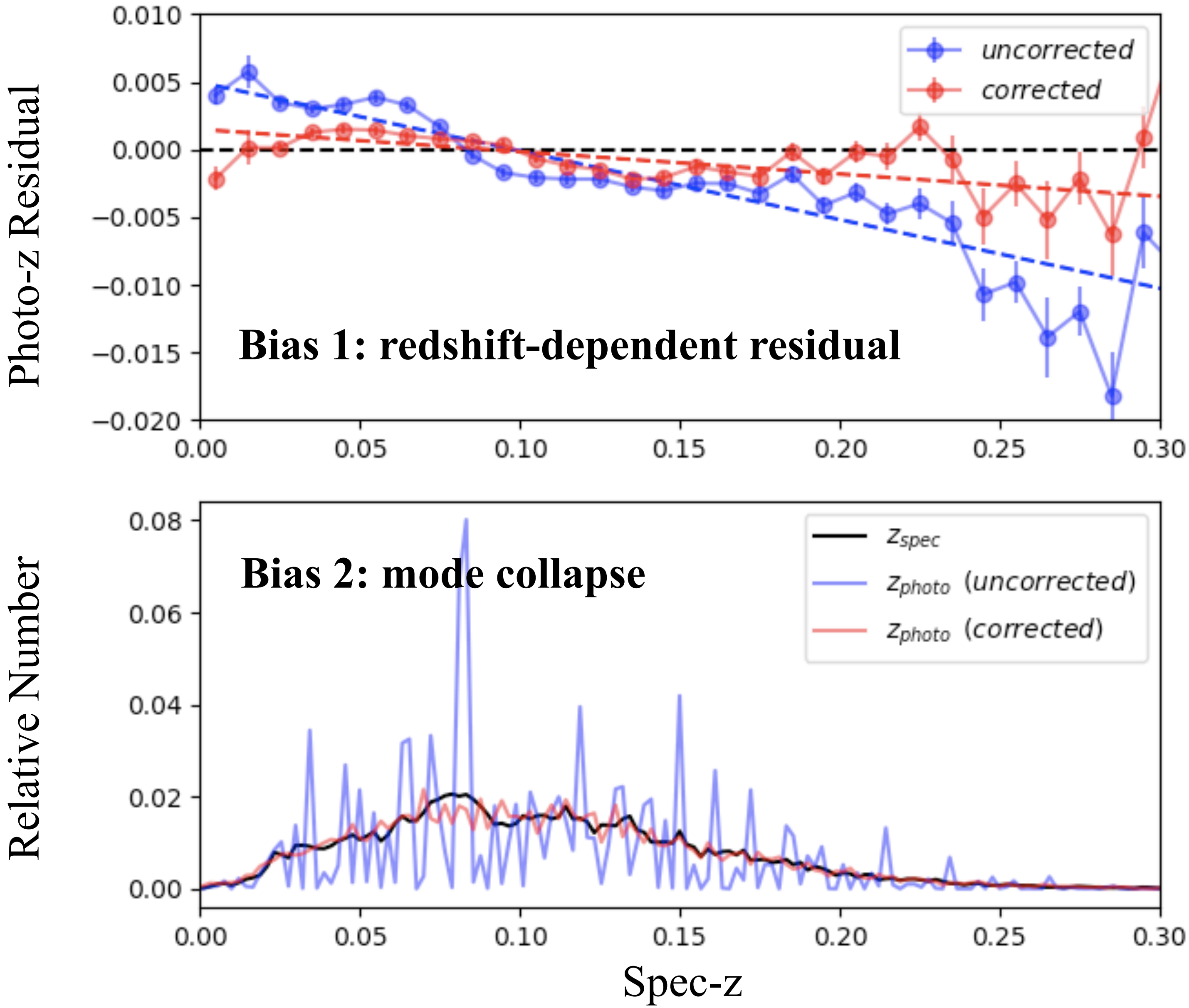
$$\hat{p}(z_{photo}\,|\,D) \sim \int q(z_{photo}\,|\,z_{spec}, D)\, p(z_{spec}\,|\,D)\, dz_{spec}$$

$$p(z_{spec}\,|\,D) \sim \int \tilde{q}(z_{spec}\,|\,z_{photo}, D)\, \hat{p}(z_{photo}\,|\,D)\, dz_{photo}$$

Dispersion / softening of over-confidence or any other adjustment

Bias	Cause	Correction
Distribution-induced residual	Unbalanced number density	Use near-flat distribution
Boundary-induced residual	Boundary effect	Shift labels
Mode collapse	Local over-confidence	Use soft labels

Biases are reduced by applying our correction method.



SDSS z<0.3

Conclusion

- Two forms of biases.

- Redshift-dependent residuals
  (distribution-induced & boundary-induced)
- mode collapse

- Key 1: split the learning of representation and classification.

- The representation potentially contains all required information
  (though biased).
- Fine-tune the classification part for resolving biases or other needs.

- Key 2: biases are reduced via balancing the training data.

- Balance the number density of the training data.
- Adjust the target output (= shift & soften labels).

- Prospect

- May be combined with other photo-z methods.
- May be generalized to regression problems and used in other applications.

Acknowledgement

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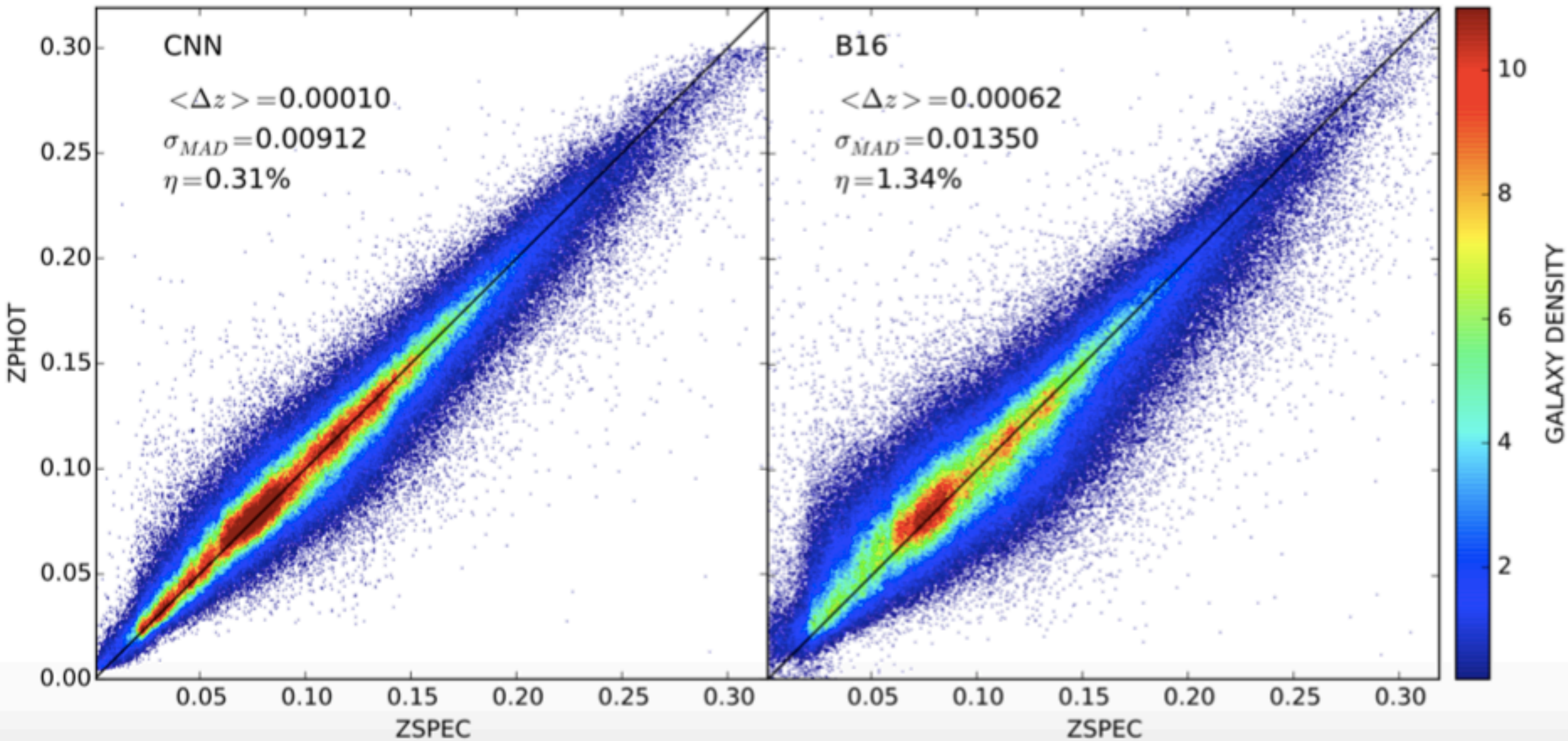
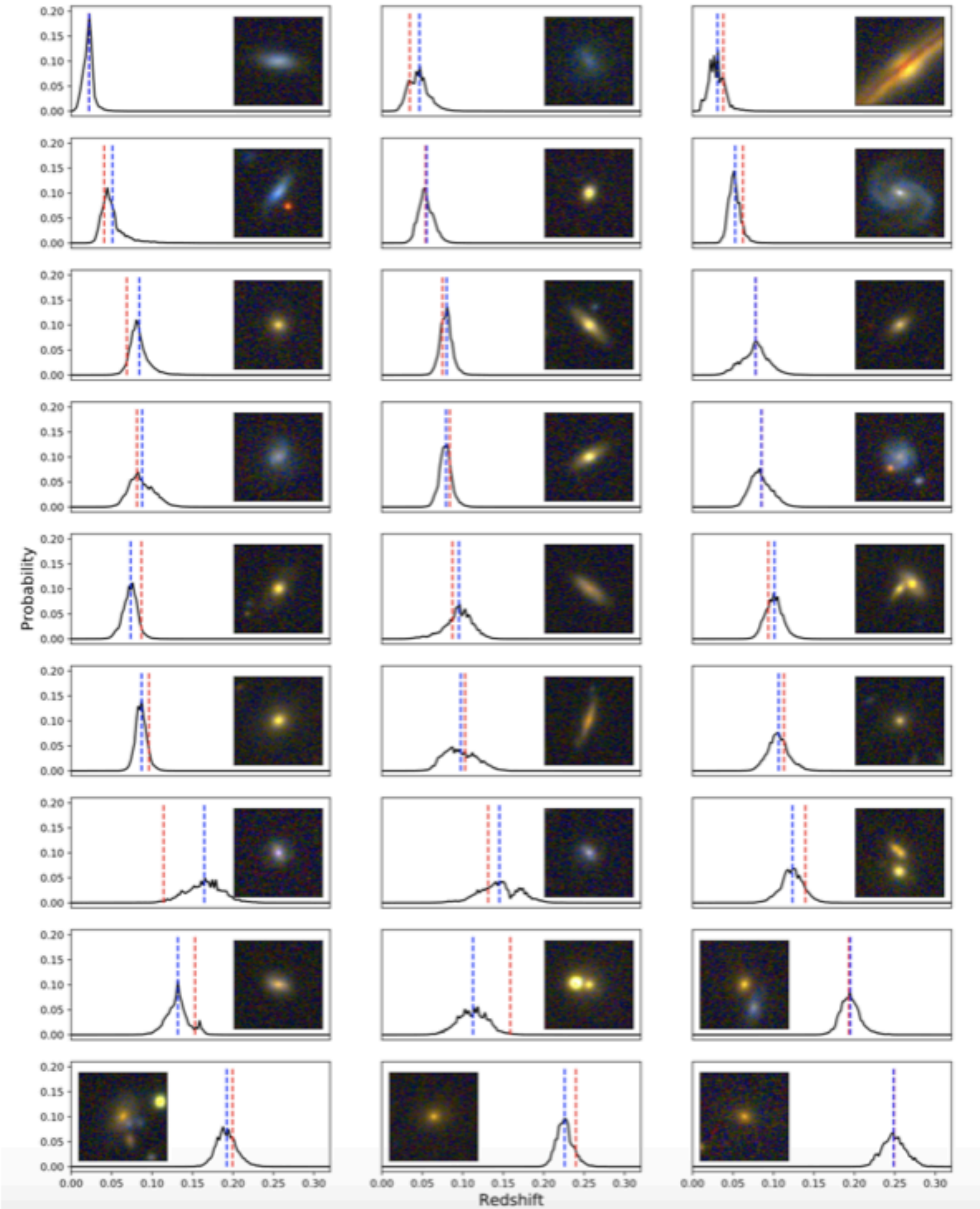
Back-up slides

Photometric redshift estimation



(Pasquet et al. 2019)



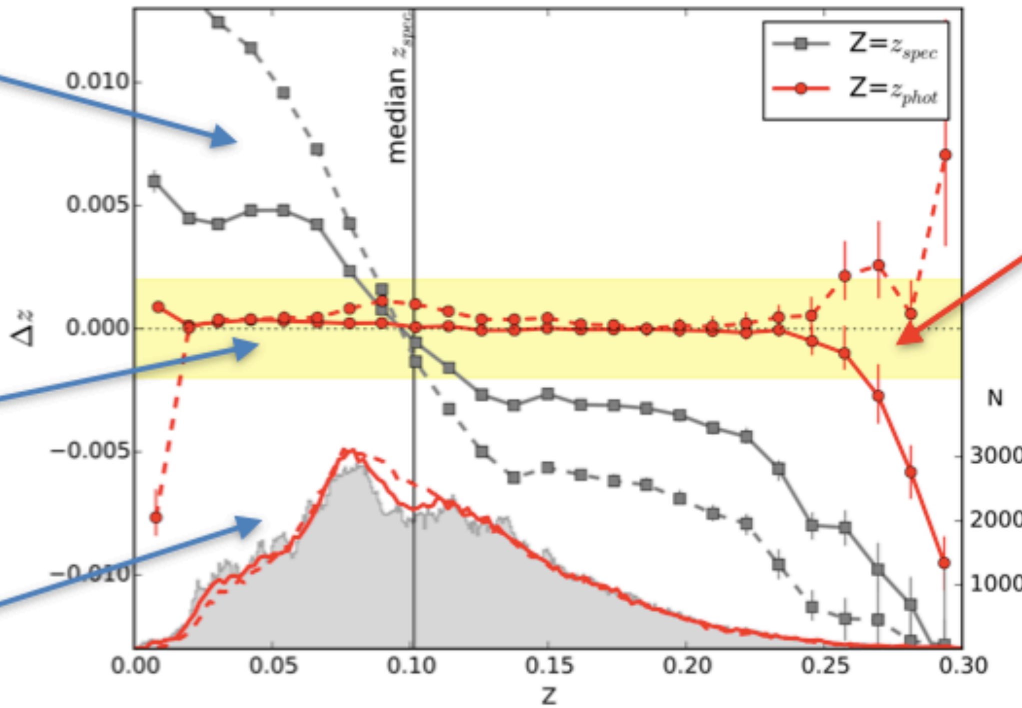
(Pasquet et al. 2019)

Bias 1: residual as a function of redshift (spec z / photo z)

w.r.t spec z

w.r.t photo z

unbalanced distribution



1. Coincident to be flat?
2. What if using a different test set?

SDSS z<0.4
(Pasquet et al. 2019)

	Training (if unbalanced)	Test (if != training)
w.r.t spec z	biased	biased
w.r.t photo z	may be unbiased	biased

Two perspectives (dilemma: not compatible unless perfect)

- **Individual bias (w.r.t spec z):** bias of a single estimate entered at a spec z (e.g., applied to SN host galaxies).
- **Bulk bias (w.r.t photo z):** bias of the average of estimates in a photo-z bin (e.g., applied to weak lensing).

$$\langle \Sigma_{\mathrm{cr}} \rangle \propto \int_{z_{\mathrm{Lens}}}^{\infty} \mathrm{d}z\, p(z) \left(\frac{D_{\mathrm{d}}(z_{\mathrm{Lens}}) D_{\mathrm{ds}}(z_{\mathrm{Lens}}, z)}{D_{\mathrm{s}}(z)} \right)$$

Correction procedure

- Correct the individual bias (w.r.t spec z) with our method.
- Correct the bulk bias (w.r.t photo z) with further calibration if needed.

➡ Correct residuals w.r.t spec z

- Our method with neural networks

Assumption: the training set and the test set at each (z, r) cell are produced from the same sampling regardless of the number density.

➡ Correct residuals w.r.t photo z

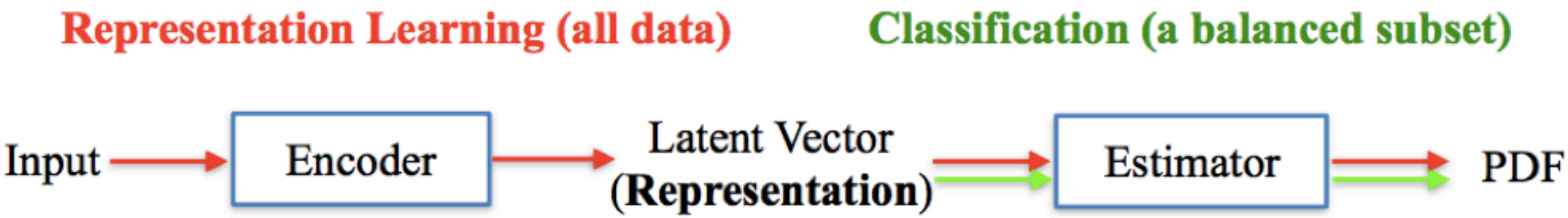
1. First correct residuals w.r.t spec z
2. Estimate the sample distribution of spec z for the test set $\hat{p}^{spec}_{test}(z\,|\,r)$

Either: $\hat{p}^{spec}_{test}(z\,|\,r) = p^{spec}_{training}(z\,|\,r)$

Or:

- Estimate errors (per magnitude) using the training set $\sigma = \sqrt{\frac{1}{N-1}\sum_n (z_n^{photo} - z_n^{spec})^2}$
- Deconvolve errors from $p^{photo}_{test}(z\,|\,r)$

3. Re-sample from the training set according to $\hat{p}^{spec}_{test}(z\,|\,r)$
4. For each photo z, correct the residual for the test set according to the residual estimated on the re-sampled training set



Our method

➡ Prune out interactions among different magnitudes
➡ Regularize

- Factorize PDFs into multiple magnitude slices
- Train with all data

$$\sum_r p(r\,|\,\theta)p(z\,|\,r,\theta)$$

➡ Correct distribution-induced residuals
➡ Correct differences among subsamples

- Factorize PDFs into multiple magnitude slices
- Fine-tune Estimator with a balanced subset

➡ Correct boundary-induced residuals
➡ Correct mode collapse

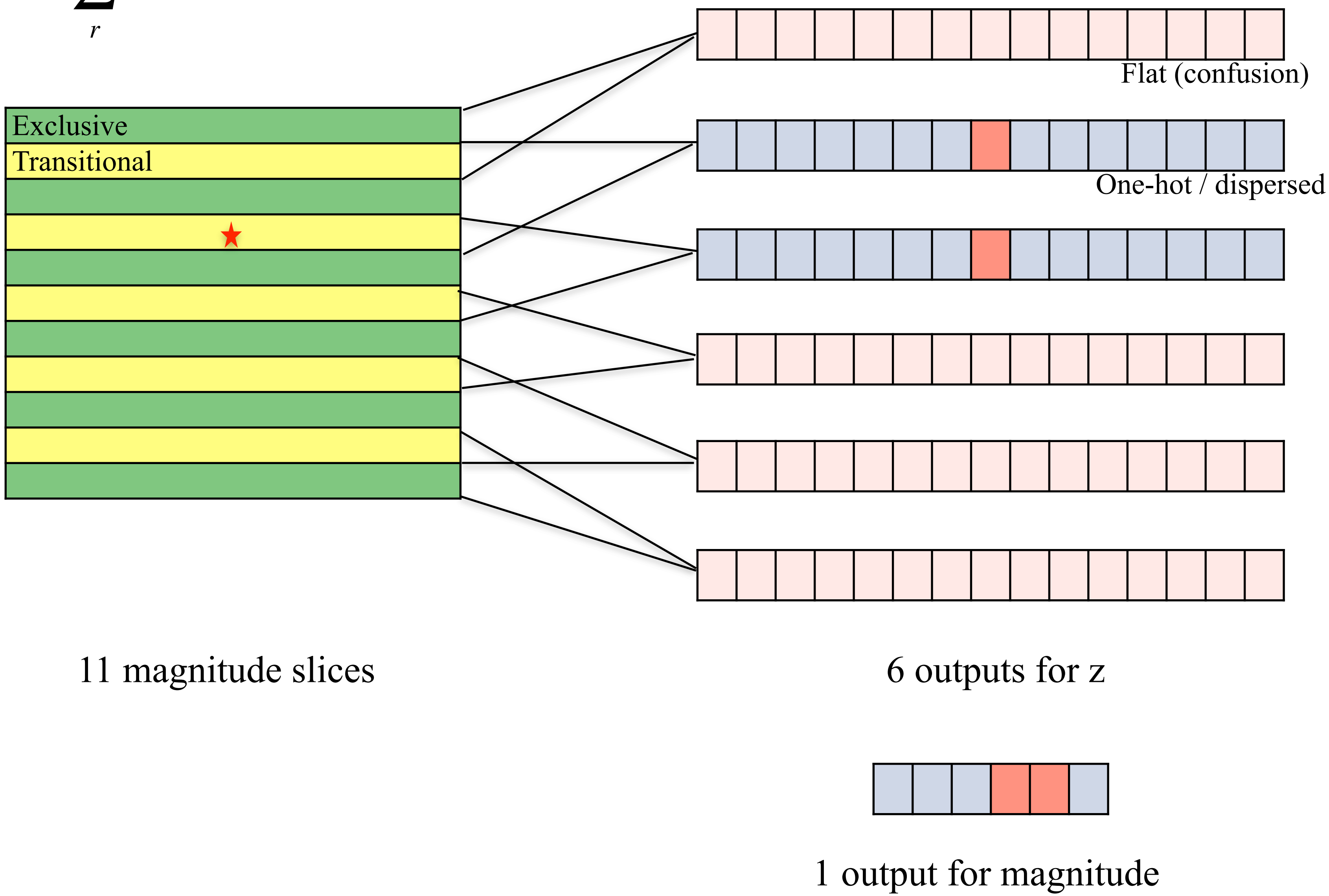
- Factorize PDFs into multiple magnitude slices
- Extend z range
- Use soft labels
- Shift labels
- Re-train Estimator with a balanced subset

Baseline

- Train with all data

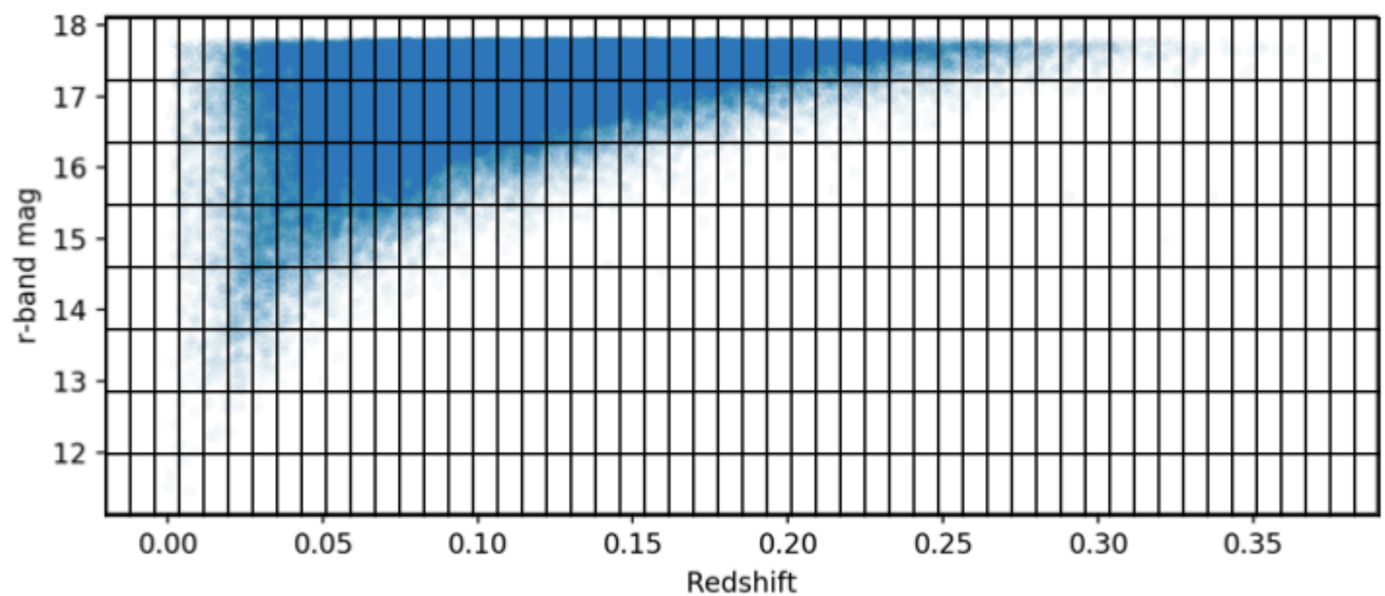
Factorization w.r.t r-band magnitude with multiple outputs

$$\sum_r p(r|\theta)p(z|r,\theta)$$



Correction of distribution-induced residual: construct a balanced (near-flat) distribution

- Divide the whole training set into two-dimensional (z, r) subregions.
- Balanced set: randomly select N events in each subregion (N <= Nth).

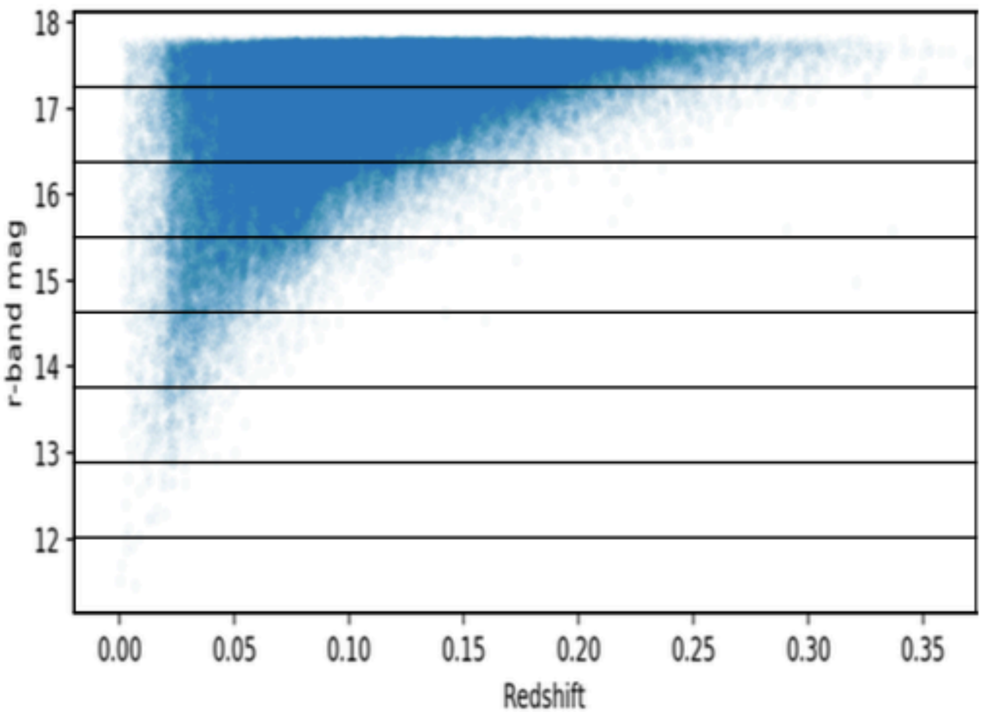


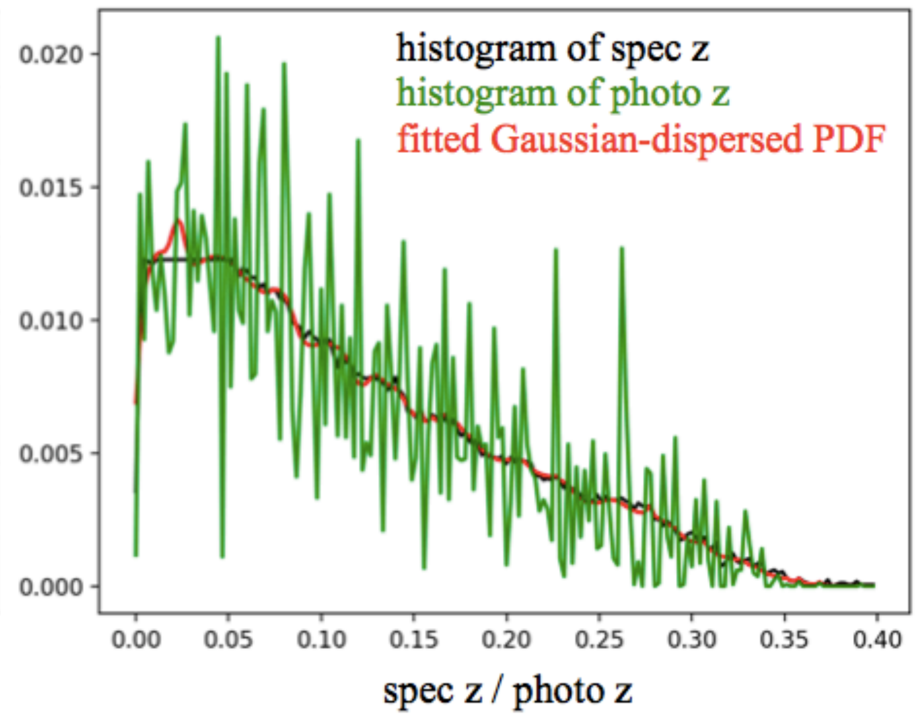
Correction of mode collapse: introduce dispersion to labels

- Model $\tilde{q}(z \mid z^*, D)$ as Gaussians. $\int \tilde{q}(z \mid z^*, D)\, \delta(z^* \mid D)\, dz^*$
- Fit with the histogram of spec z and the histogram of photo z (pre-estimated).

$$\min_{\sigma_1}\{ \int - p^{spec}(z) \log(p^{photo}(z) * N(0,\sigma_1)) dz \}$$

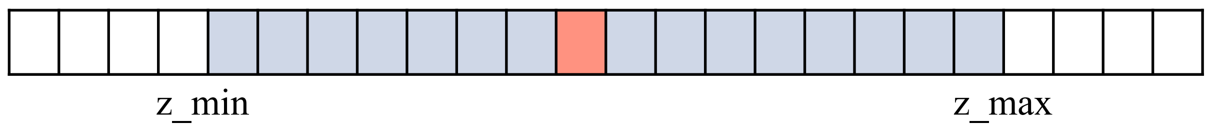
Assumption: same labelling dispersion along z for a given r.



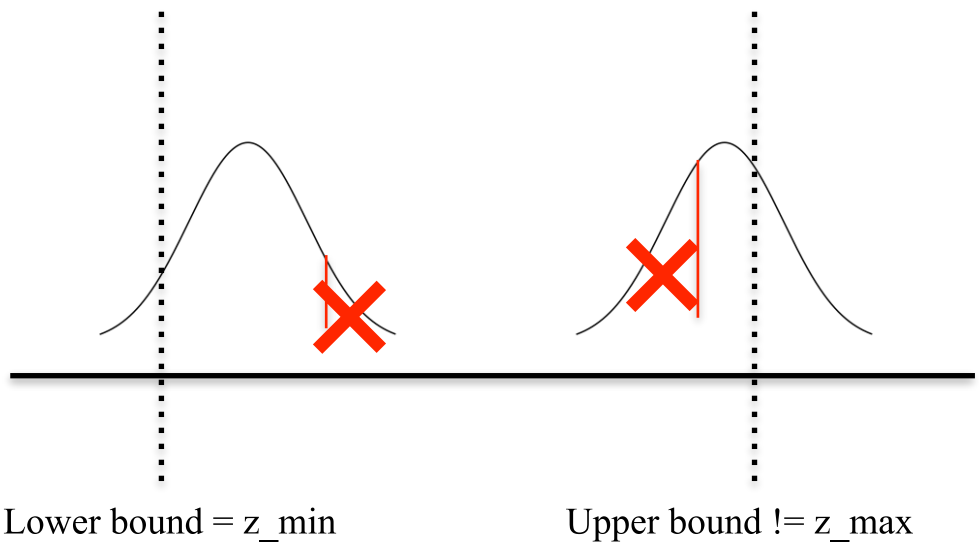


Correction of boundary-induced residuals

- Extend the range.



- (Re-)allocate the label at the center-of-mass of the truncated Gaussian $N(z_n^{spec}, \sigma_2)$.



$$\sigma_2 = \sqrt{\frac{1}{N}\sum_n (z_n^{photo} - z_n^{spec})^2}$$