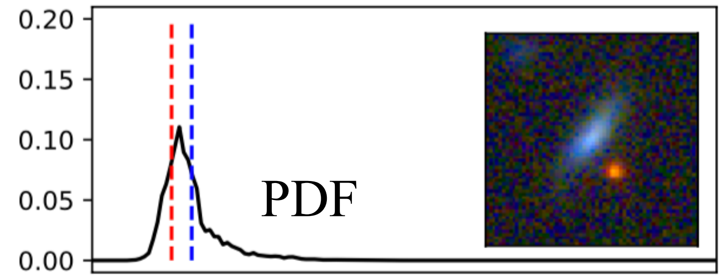
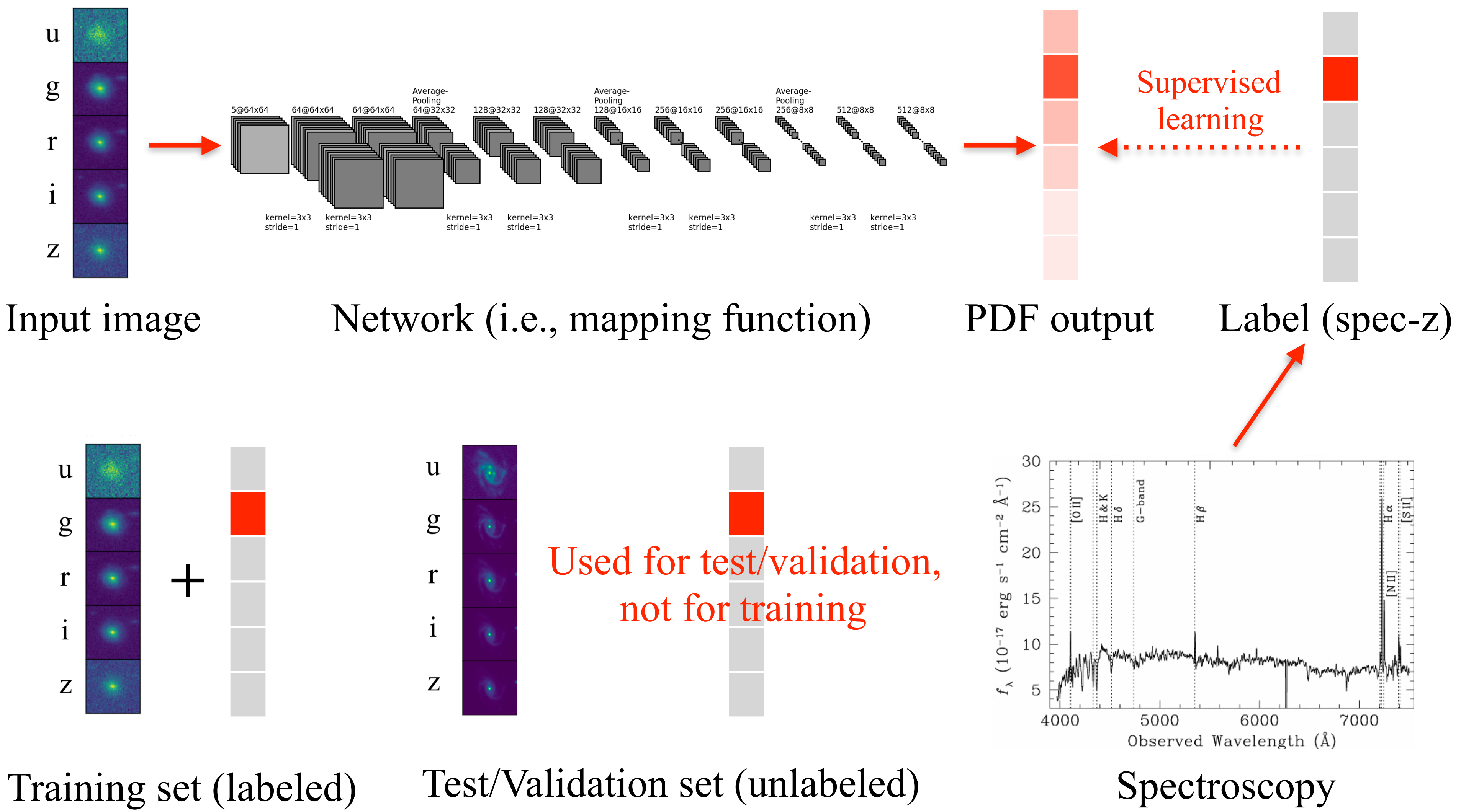
Correcting galaxy photometric redshift estimation biases using Deep Learning neural networks

Qiufan Lin

Centre de Physique des Particules de Marseille

Galaxy photometric redshift (photo-z) prediction using Deep Learning neural networks





Outline

- **Biases associated with neural networks (and other data-driven algorithms)**
  1. Residual as a function of redshift
  2. Mode collapse

- **Methods for correcting biases**
  1. Balance the training distribution
  2. Balance the training labels

- **Results**

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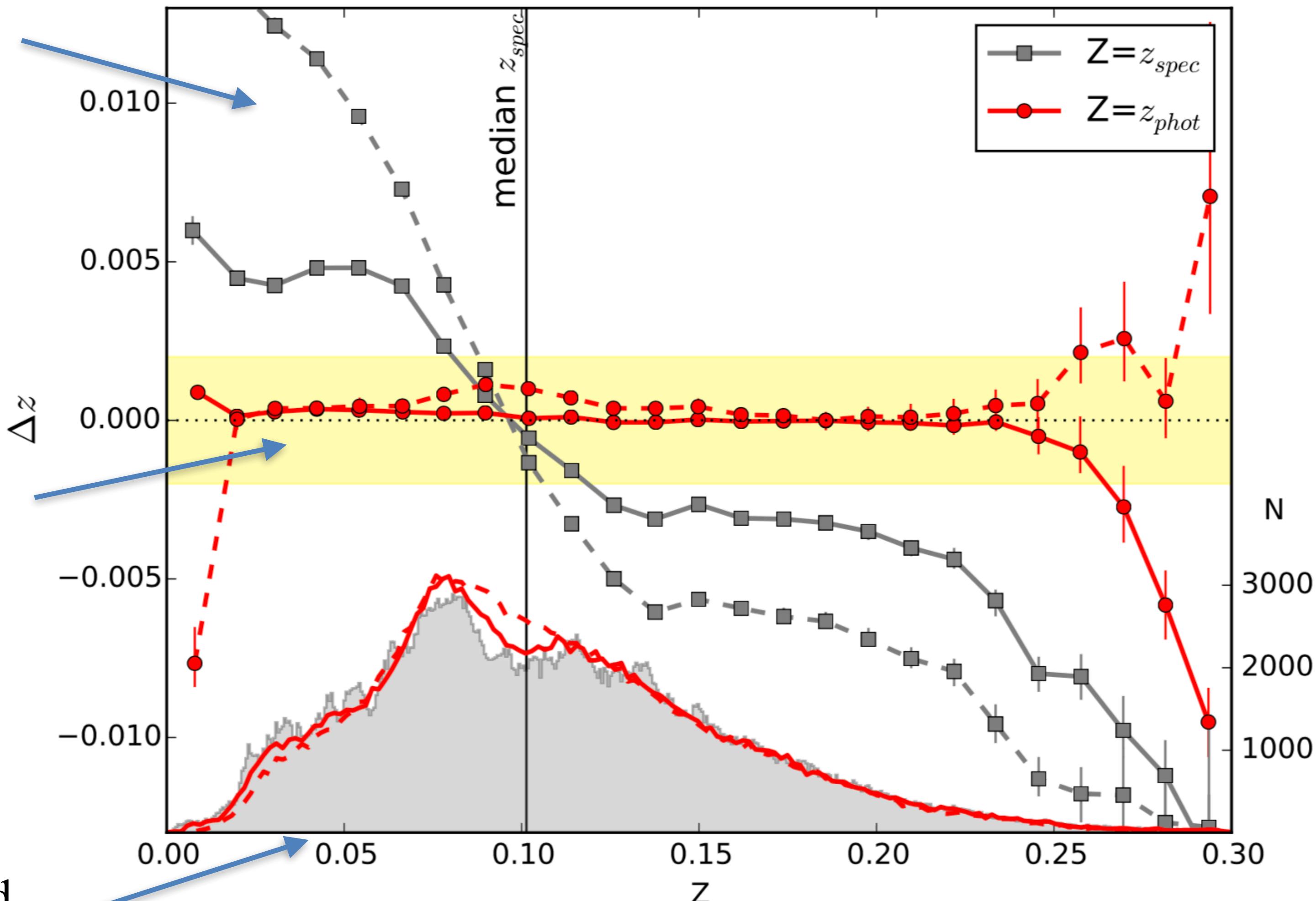
Bias 1: Residual as a function of redshift (spec z / photo z)

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

w.r.t spec z (biased)

w.r.t photo z

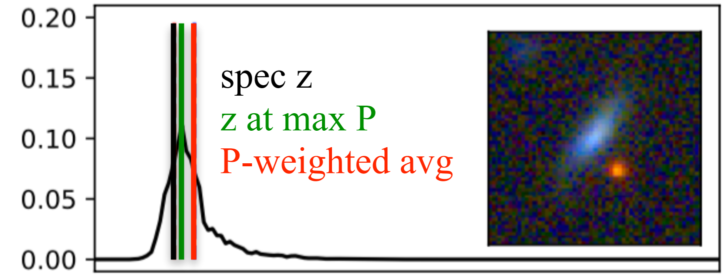
unbalanced distribution

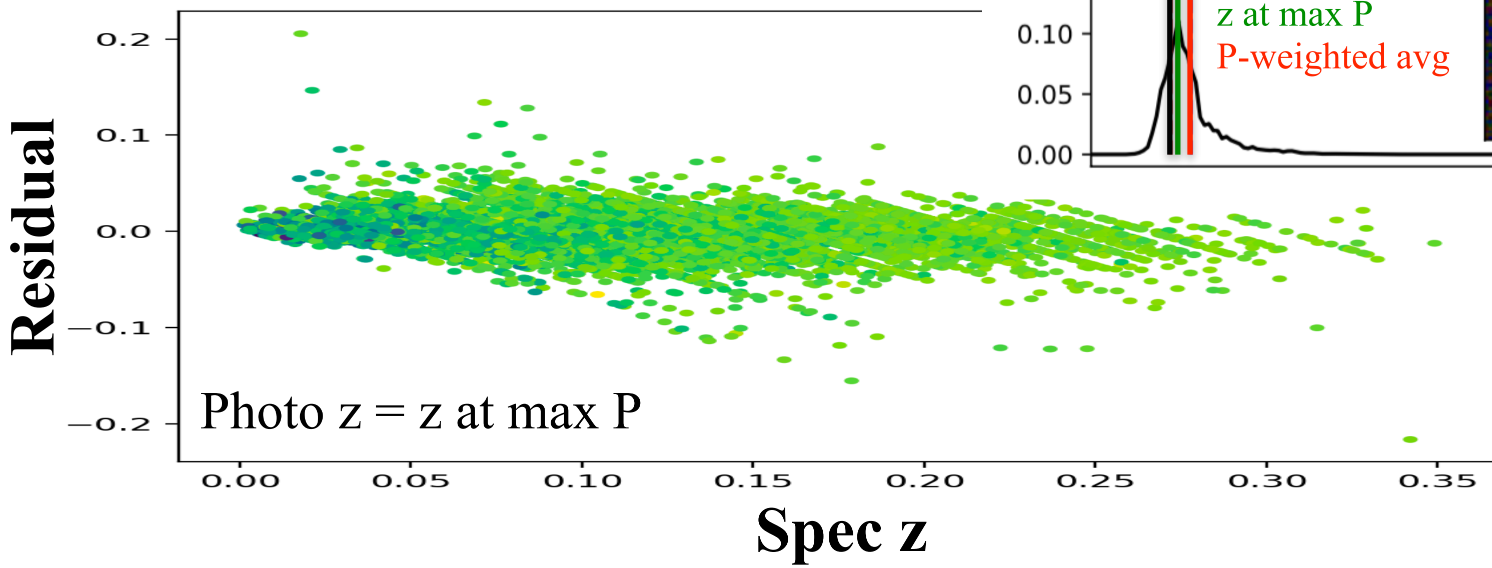


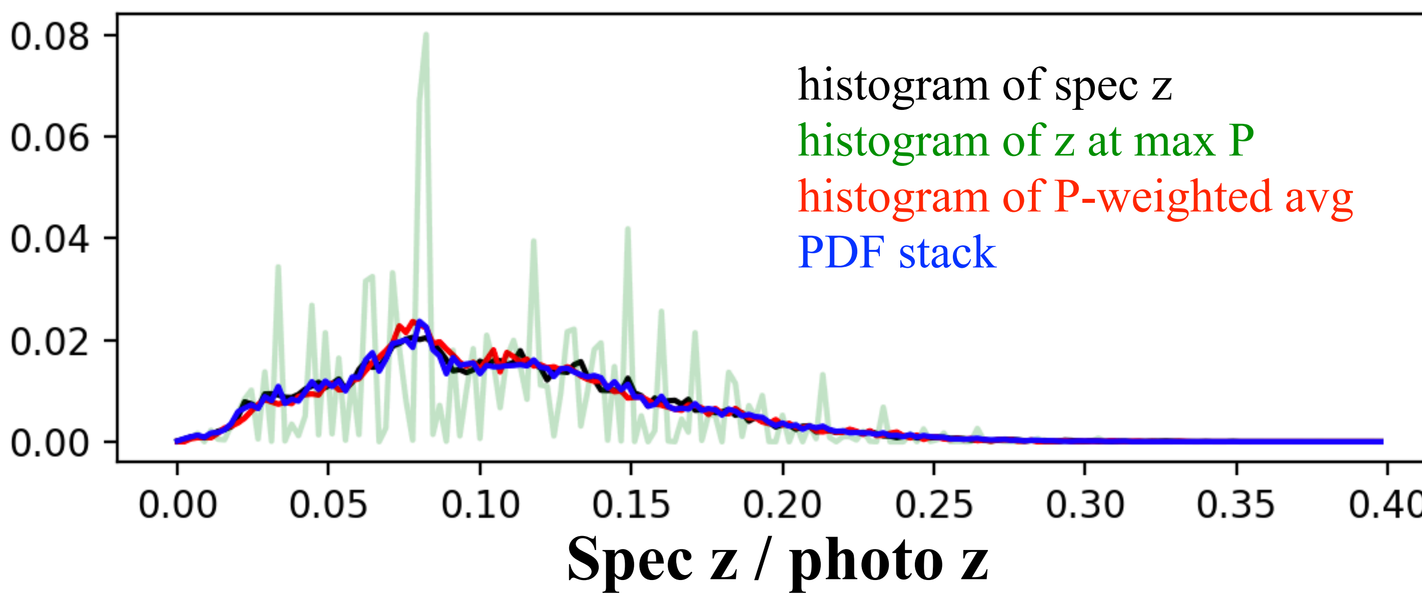
SDSS z<0.4
(Pasquet et al. 2018)

Bias 2: Mode collapse

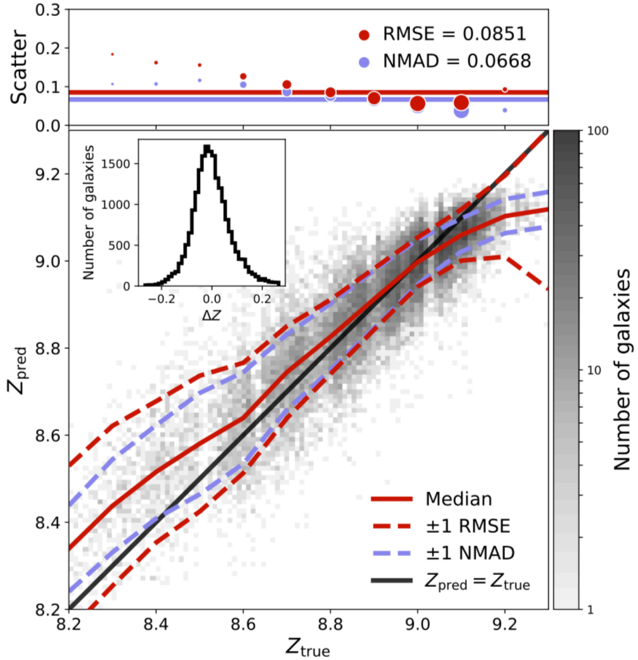
i.e., multiple z's collapsed to a single estimate



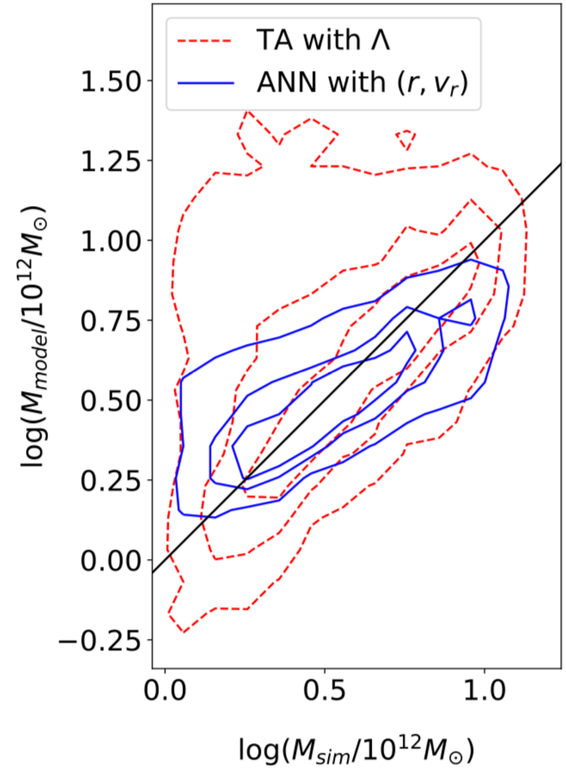




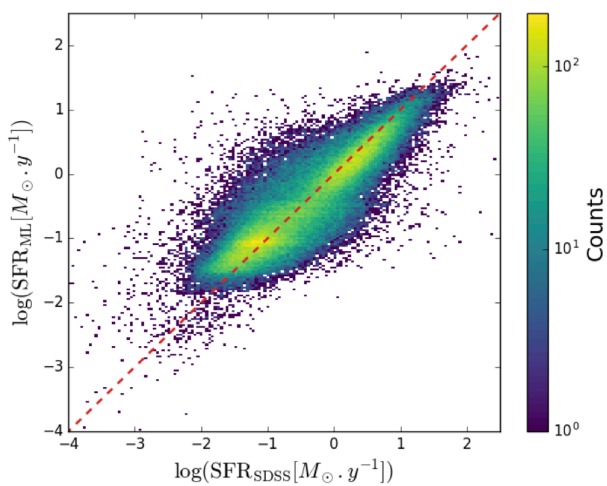
Biases exist in various classification & regression applications



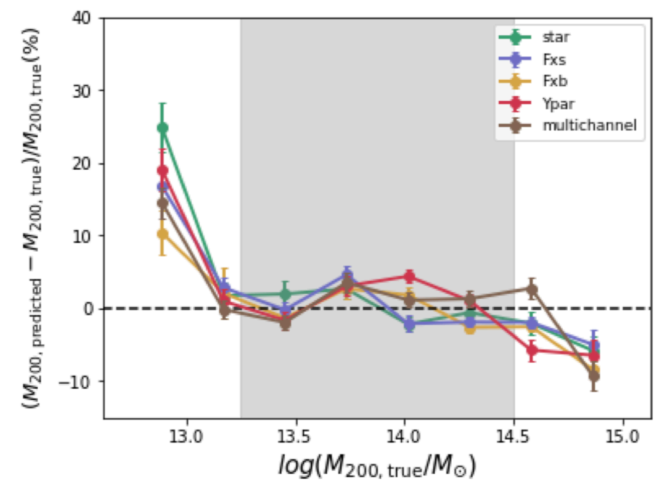
Metallicity (Wu et al. 2019)



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



Star Formation Rate (Bonjean et al. 2019)



Cluster Mass (Yan et al. 2020)

Statistical interpretation of photo-z estimation

Over-confidence / overfit on systematics, spurious correlations, etc.

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

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

Dispersion / softening

Cause: unbalanced data distribution (uneven number density)

Bias: z-dependent residual

Correction: use a near-flat (balanced) data distribution

Cause: $q(z_{photo} | z_{spec}, D)$ not uniform over data

Bias: mode collapse

Correction: introduce dispersion to labels

$$\int \tilde{q}(z | z^*, D)\, \delta(z^* | D)\, dz^*$$

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Separate the learning of representation and classification

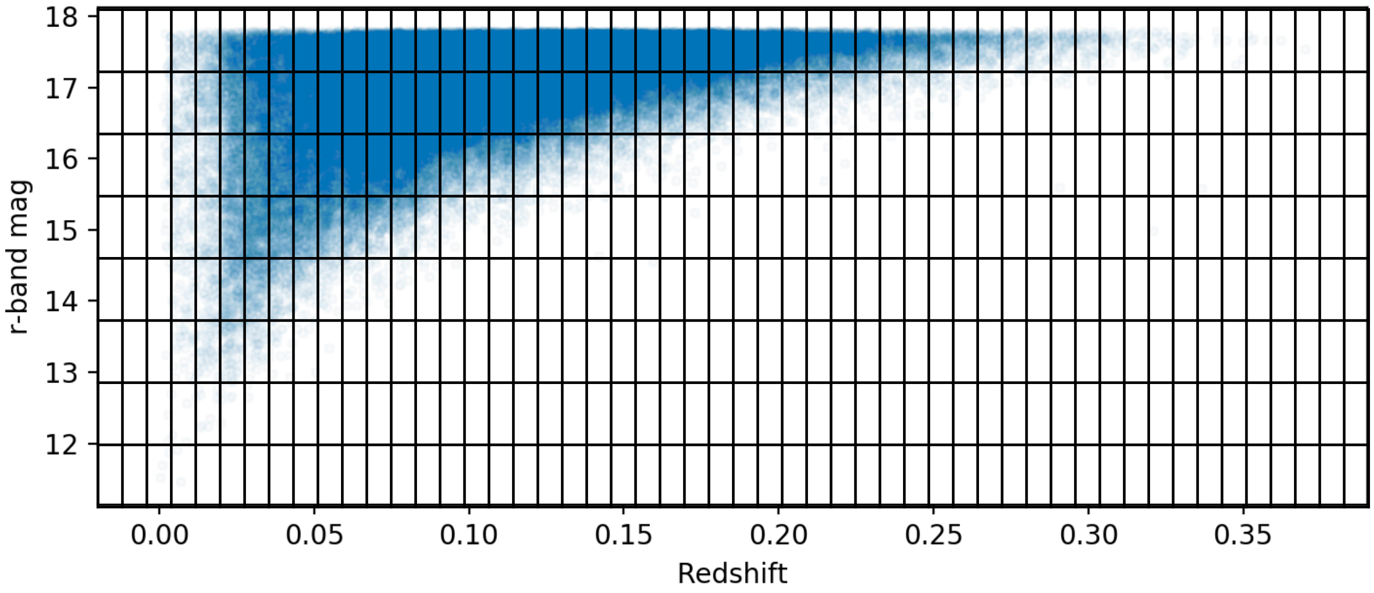
Original distribution (SDSS 393219) **Balanced distribution (SDSS 16301)**

(a) Representation Learning: Train the Encoder and the Classifier using all data.
(b) Classification: Freeze the Encoder. Train the Classifier using data from a balanced (near-flat) distribution and dispersed labels (may also combined with the technique of multiple outputs).

Bias	Correction
z-dependent residual	Balanced distribution
Mode collapse	Dispersed labels (& Multiple outputs)

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

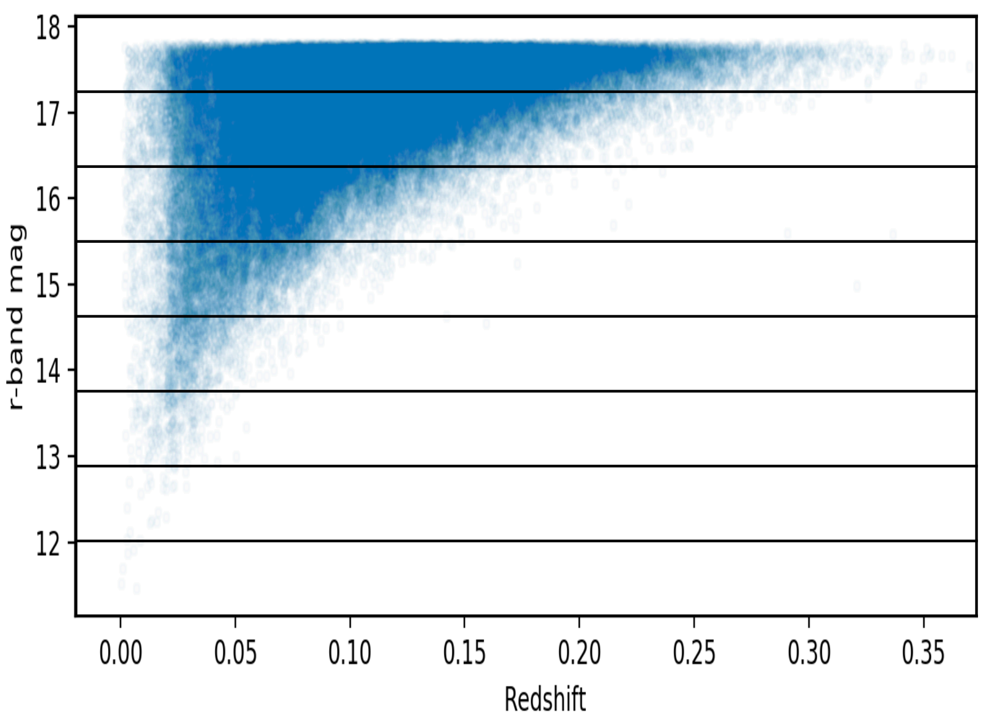
- Divide the whole training set into two-dimensional (z, r) subregions.
- Balanced set: randomly select N events in each subregion (N <= Nth).

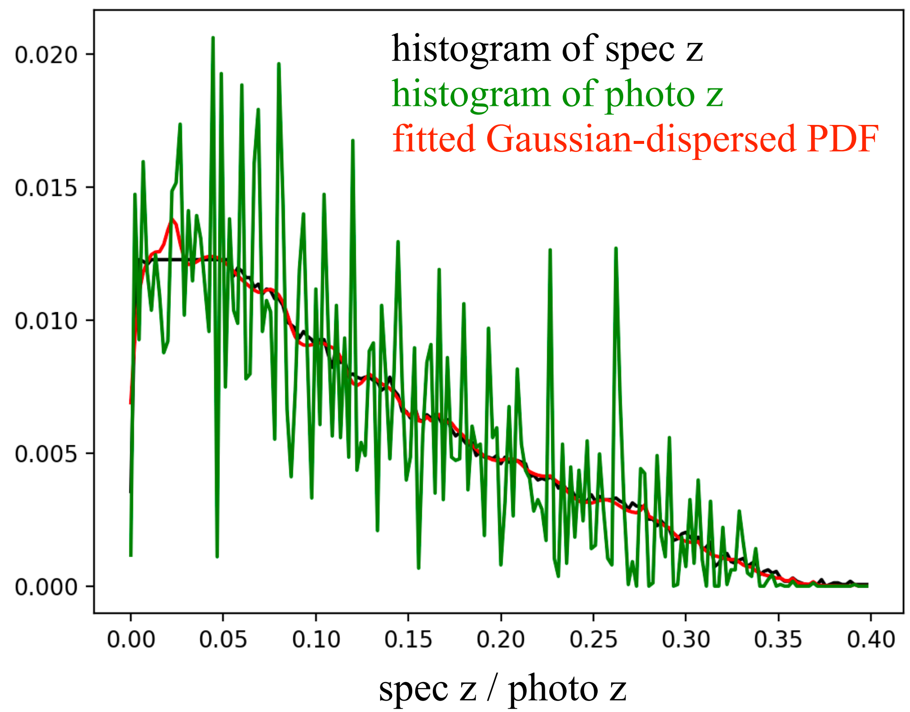


Correction of mode collapse: introduce dispersion to labels

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

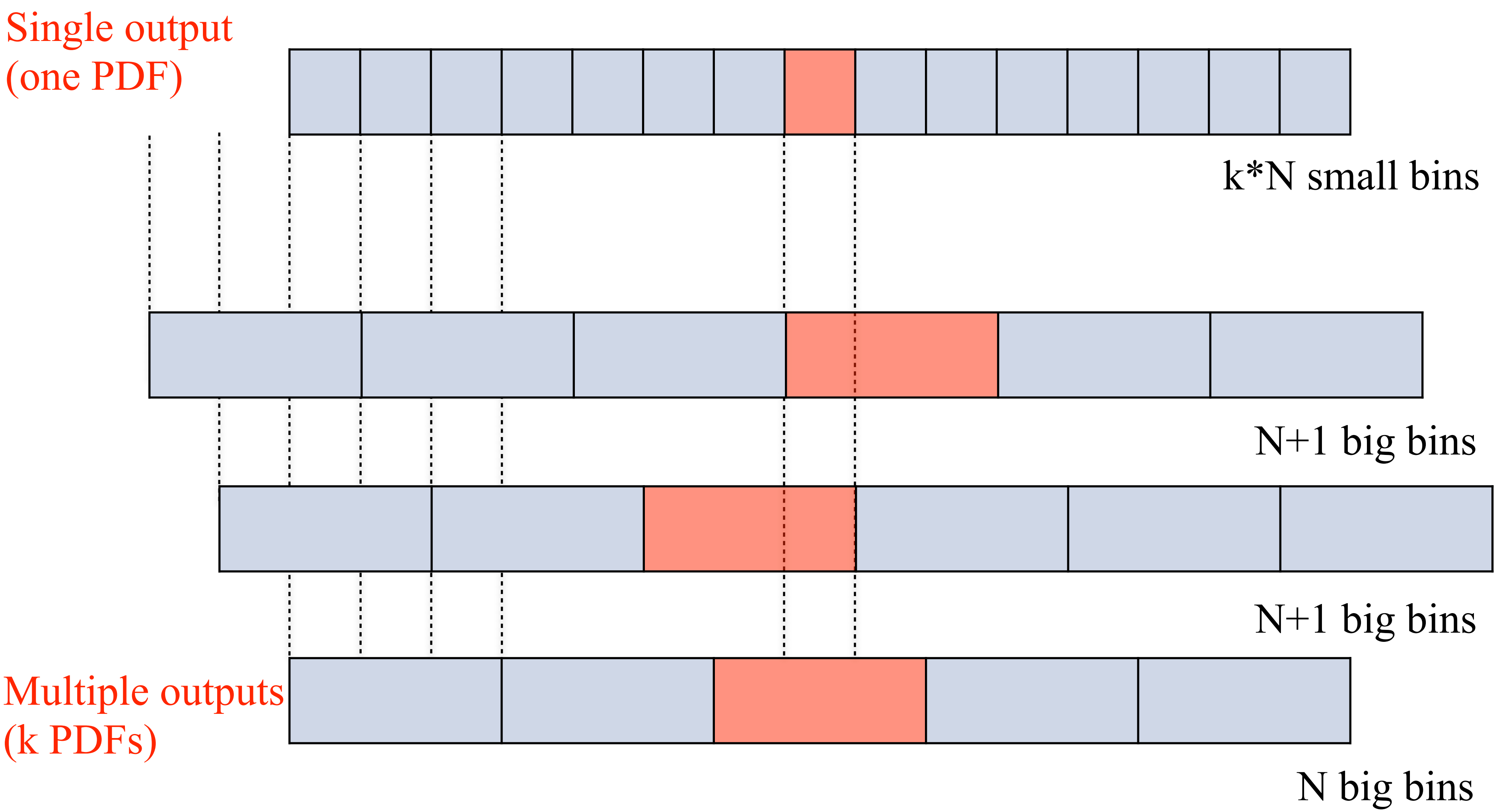
Approximation: same label dispersion along z for each r.





Account for binning correlation: multiple outputs

Train with multiple outputs, then convert to single output by weighted average.



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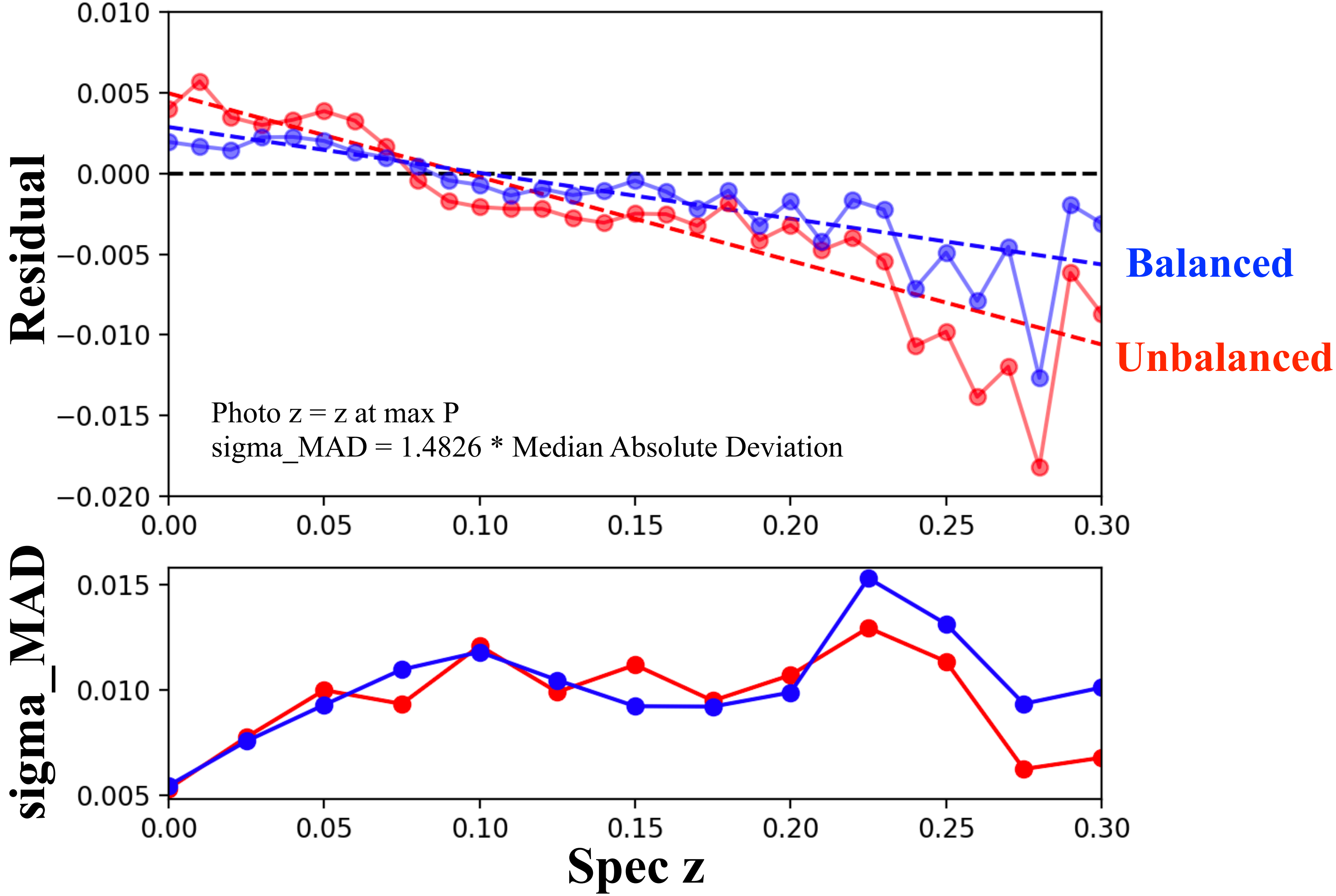
Redshift-dependent residual reduced by balancing the training distribution in number density



Mode collapse softened by label dispersion and multiple outputs

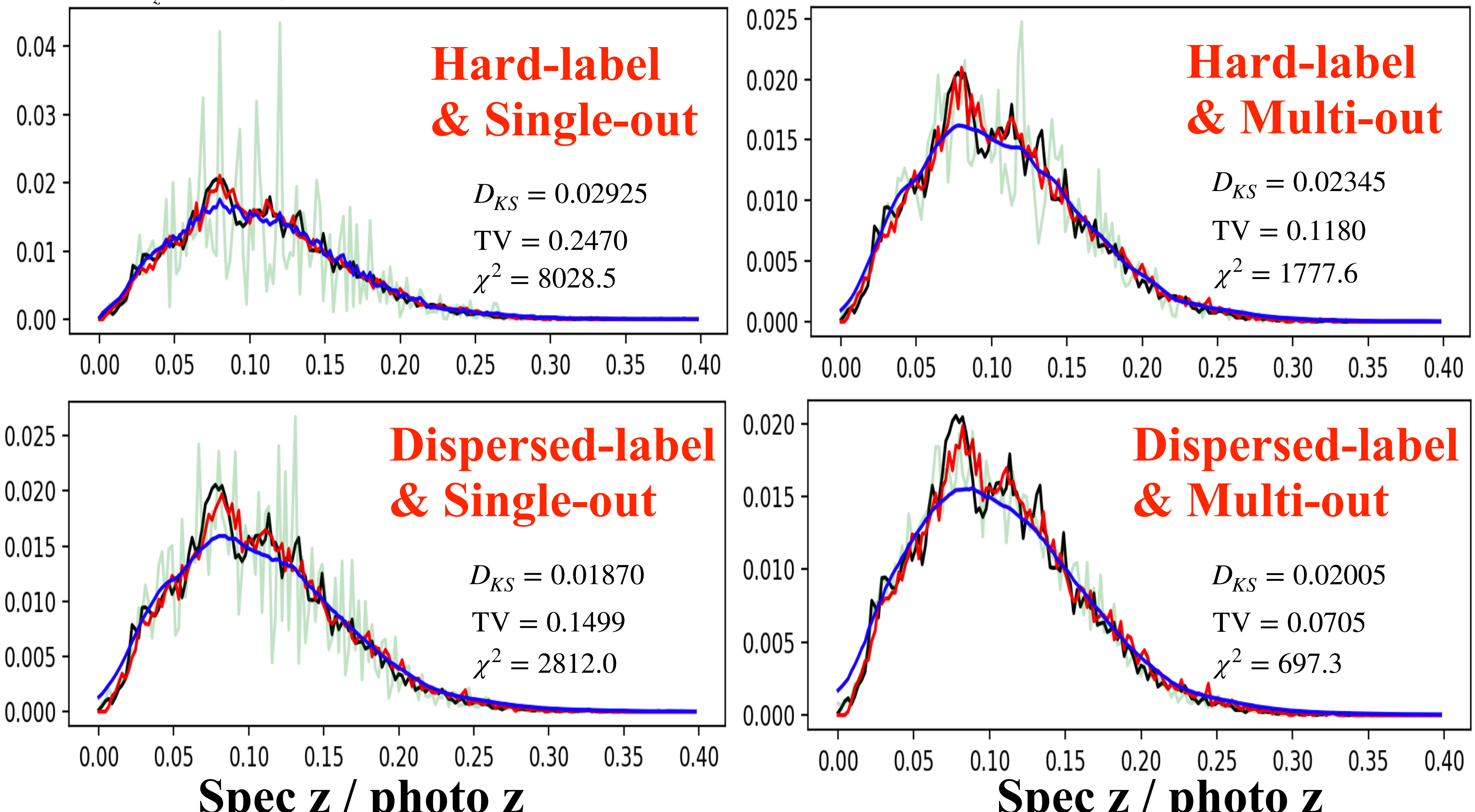
$$D_{KS} = \sup_z |CDF_{photo}(z) - CDF_{spec}(z)|$$

$$\text{Total Variation} = \frac{1}{2}\int_z |PDF_{photo}(z) - PDF_{spec}(z)|\,dz$$

$$\chi^2 = \sum_z \frac{[N_{photo}(z) - N_{spec}(z)]^2}{N_{spec}(z)}$$

Photo z = z at max P
in test: 19974

histogram of spec z
histogram of z at max P
histogram of P-weighted avg
PDF stack



Summary

- Two forms of biases with neural networks

- Redshift-dependent residual
- Mode collapse

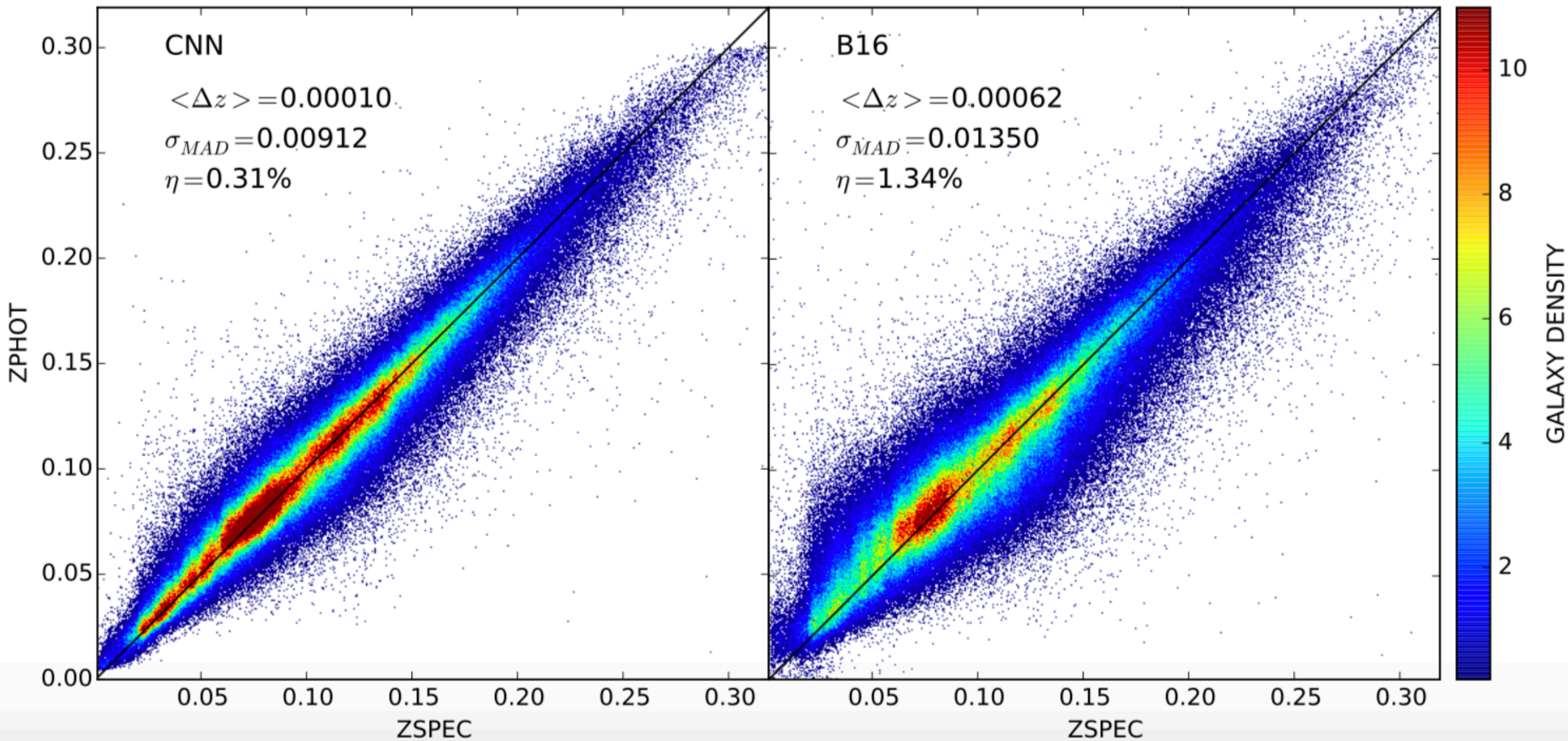
- Biases corrected via balancing training data

- Number density
- Labels

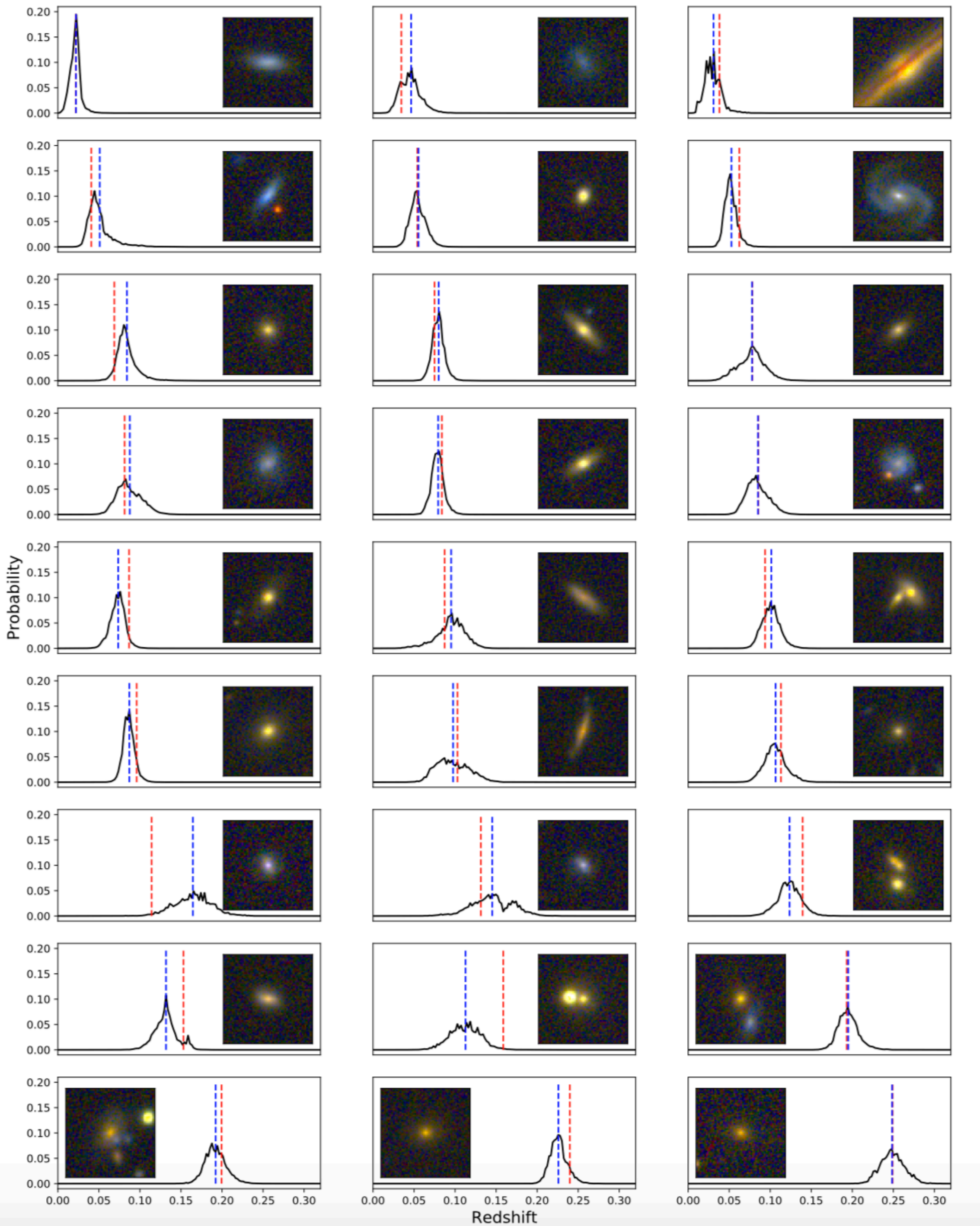
- Next stage: evaluate/use this method in real photo-z analyses as well as other applications

Back-up slides

Photometric redshift estimation



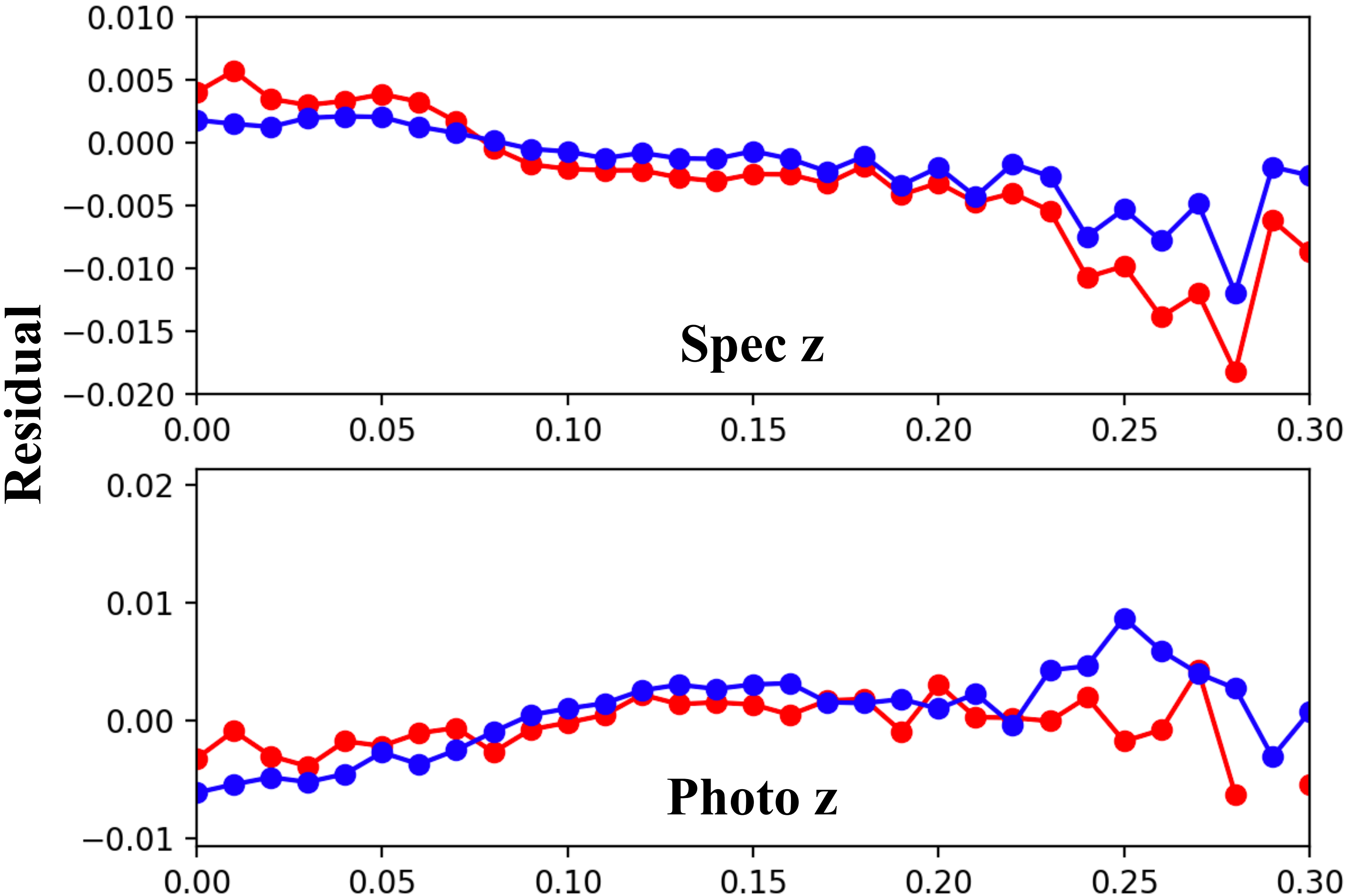
(Pasquet et al. 2018)



(Pasquet et al. 2018)

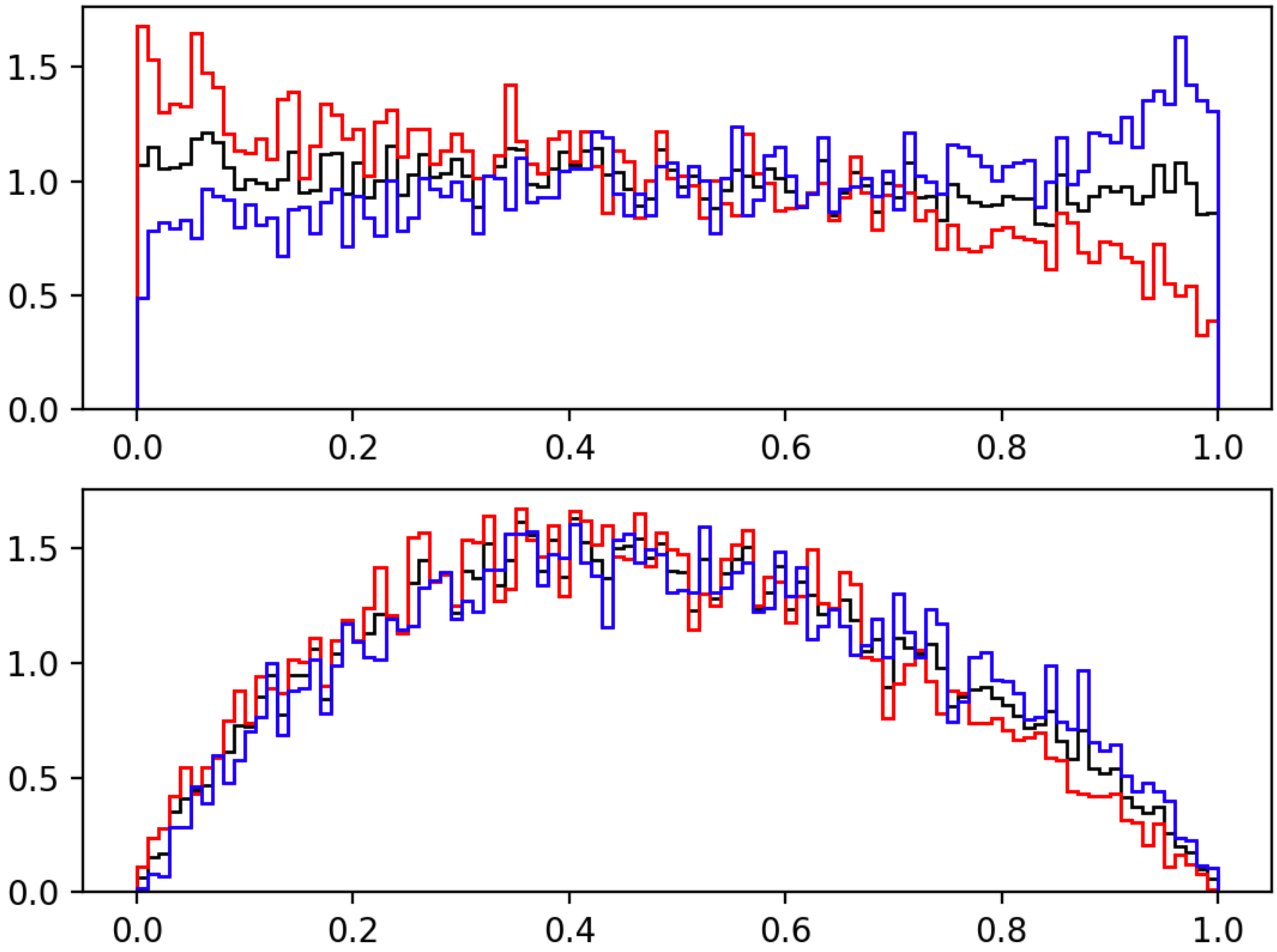
Bias correction by balancing both the number density and labels

Red: unbalanced
Blue: balanced
Photo z = z at max P



Probability Integral Transforms (original)

Black: all
Red: z < 0.1
Blue: z > 0.1



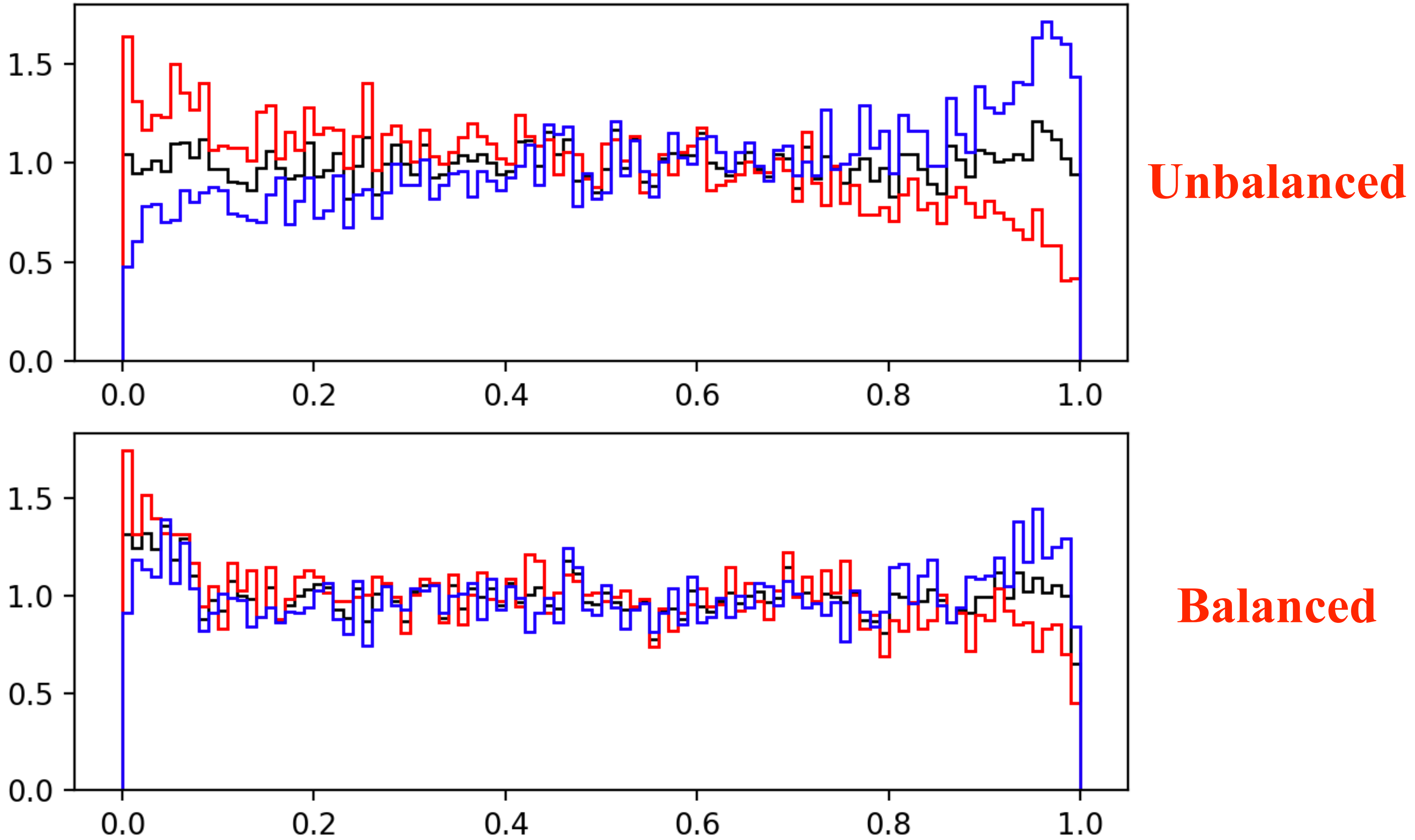
Unbalanced

Balanced

PIT (calibrated)

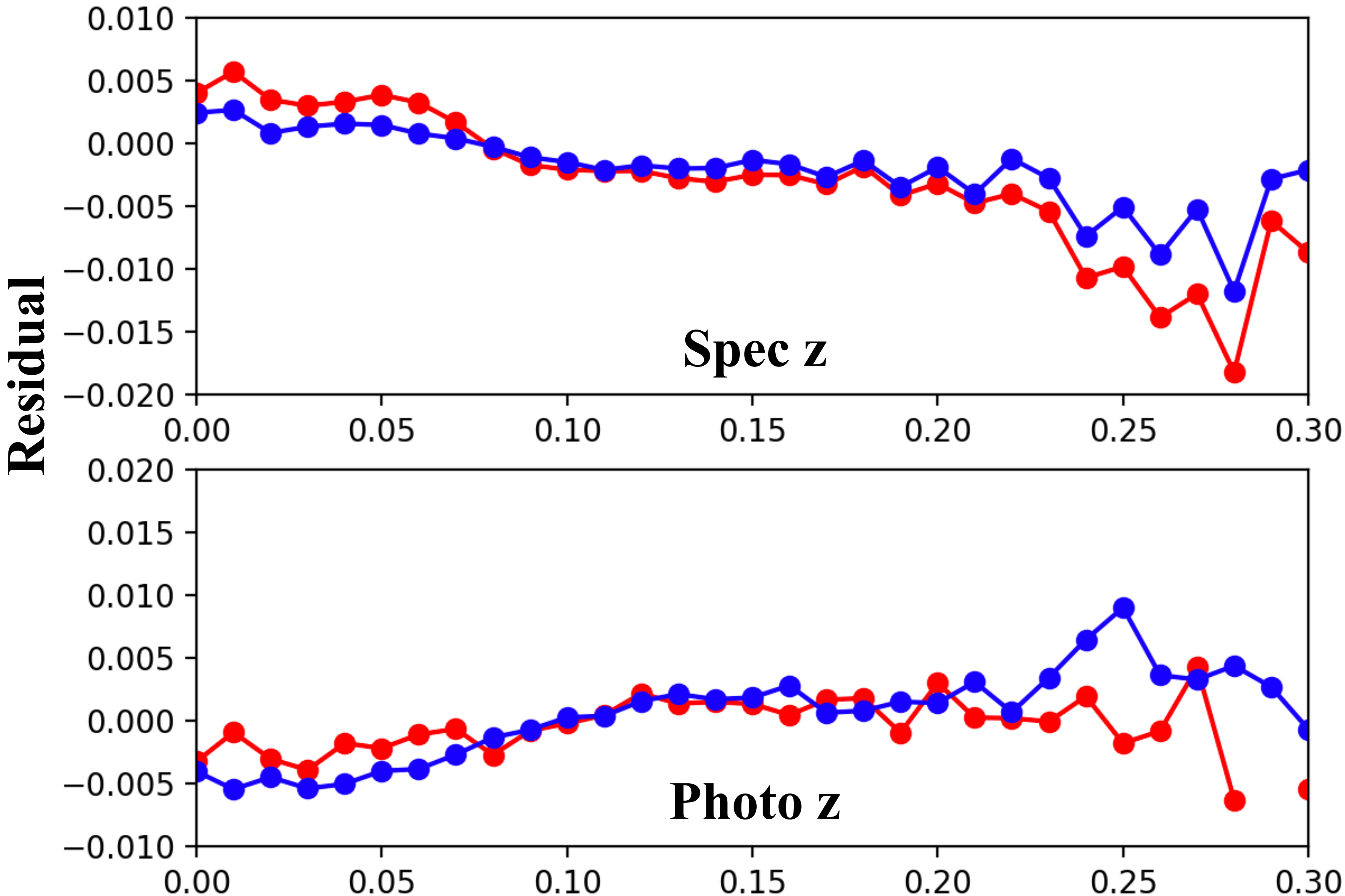
PIT calibration: 0910.5735

Black: all
Red: z < 0.1
Blue: z > 0.1



Bias correction by balancing both the number density and labels and calibrating PIT

Red: unbalanced
Blue: balanced
Photo z = z at max P



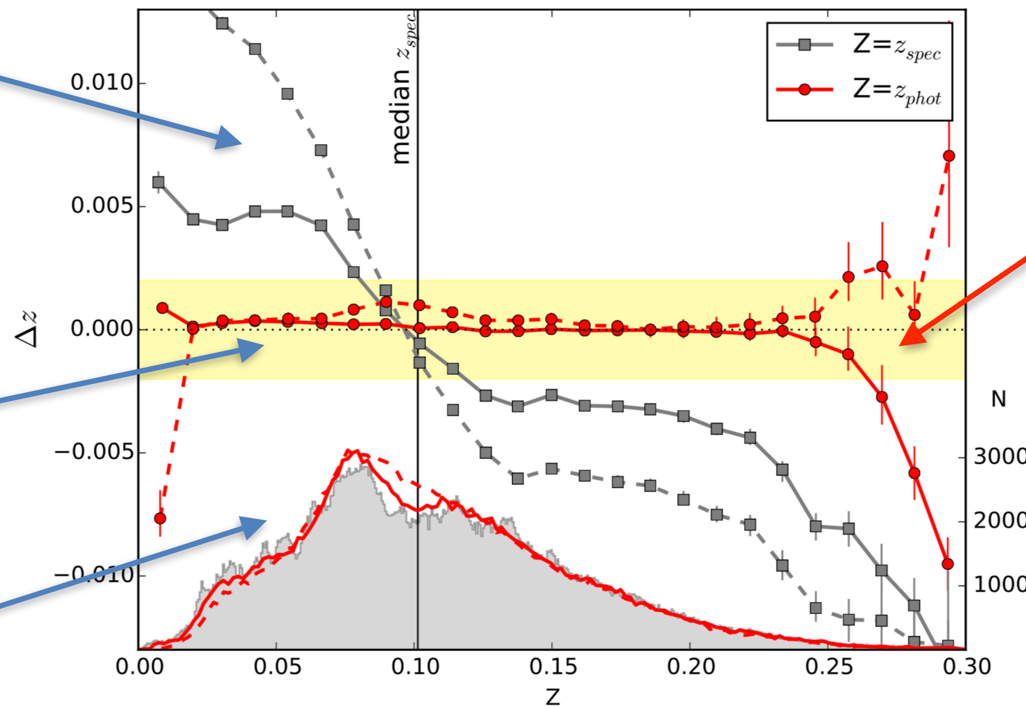
Bias 1: Residual as a function of redshift (spec z / photo z)

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

w.r.t spec z

w.r.t photo z

unbalanced distribution



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

SDSS z<0.4 (Pasquet et al. 2018)

	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 for a single galaxy (centered at z_spec); to be reduced for individual estimates (e.g. SN host galaxies)

- **Bulk bias (w.r.t photo z):** average bias at a photo-z bin (centered at z_photo); to be reduced for average estimates (e.g., surface density)

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

Correction Procedures

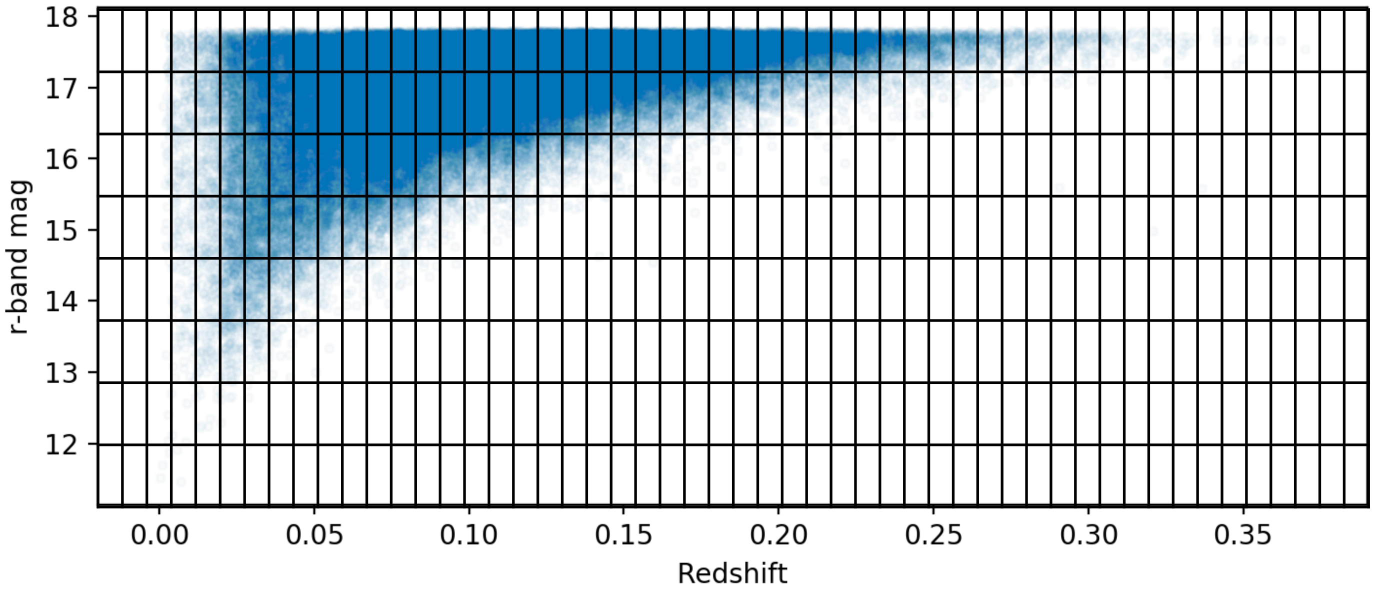
- Correct individual bias (w.r.t spec z) with a two-step training scheme using a balanced training distribution

- Correct bulk bias (w.r.t photo z) with further calibration if needed

Recalibration: correct bias w.r.t photo z

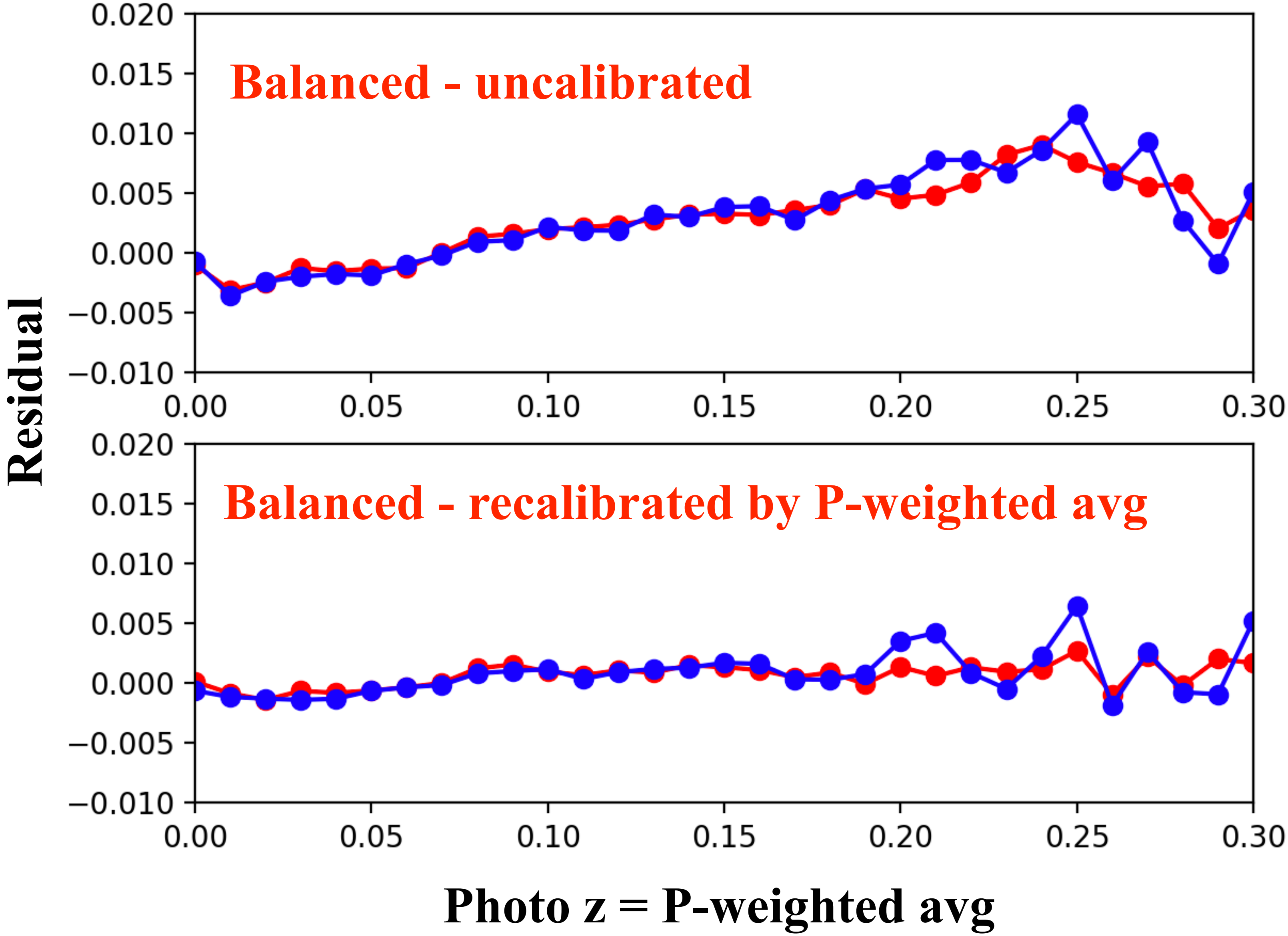
Method: all PDF_photo's at each (z, r) subregion shifted by -1*b_train*(1+z) so that (b_train_recalibrated = 0)

Assumption: same p(z|r) in each r row for different samples.



Reduced bias for photo z after balancing + recalibration

Red: training
Blue: test
Photo z = P-weighted avg



Reduced bias for photo z after balancing + recalibration

Red: training
Blue: test
Photo z = z at max P