UNIVERSITÉ
DE GENÈVE

FACULTÉ DES SCIENCES
Département d'astronomie

Euclid consortium

Euclid photo-z Challenge

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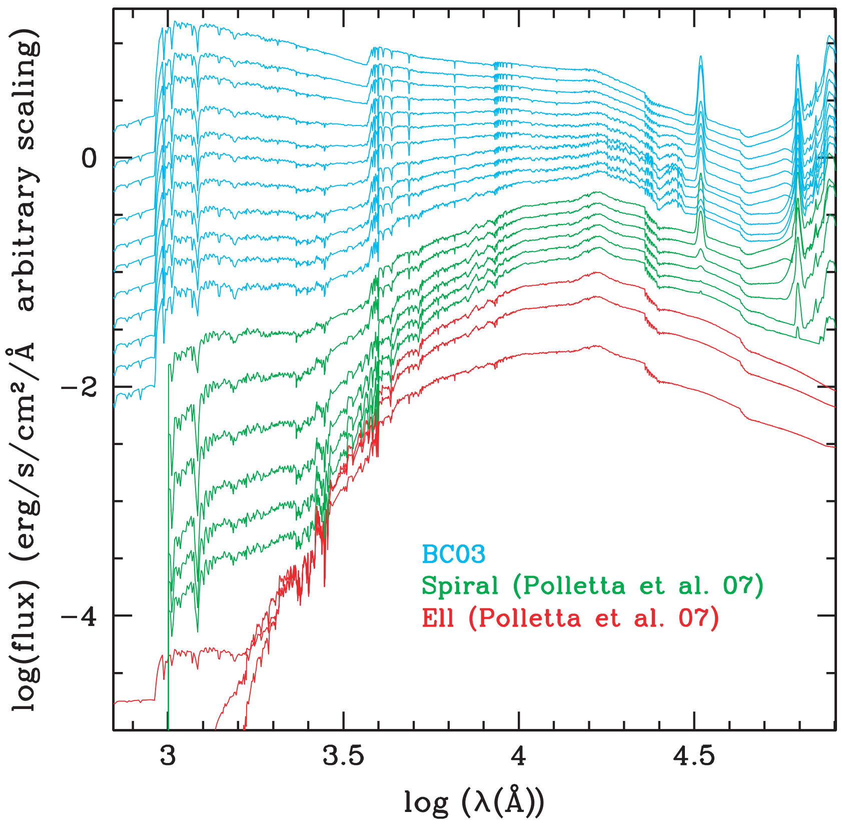
Swiss Euclid days 04-02-2020

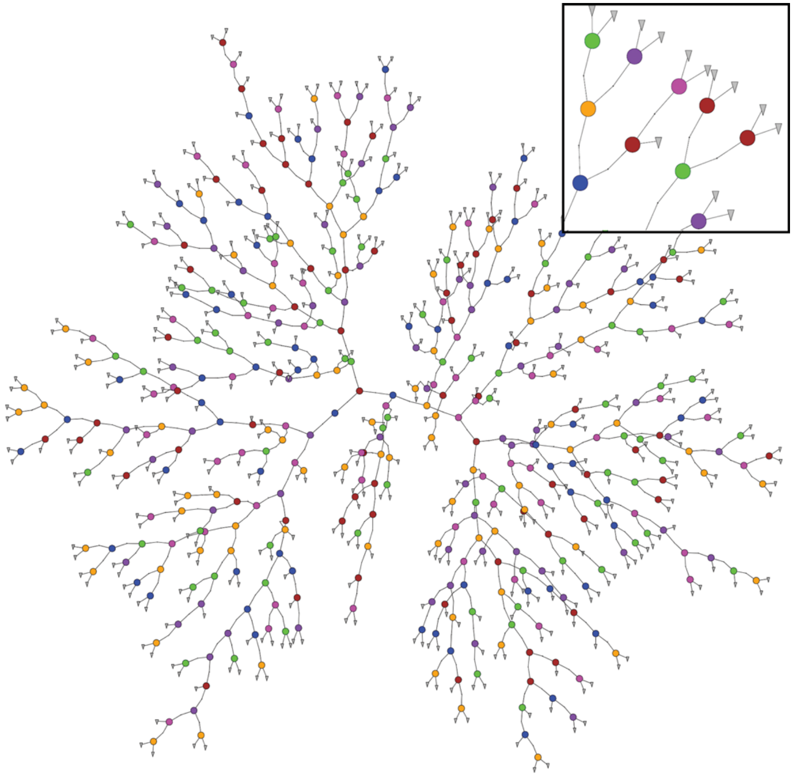
Photometric redshift

Template Fitting



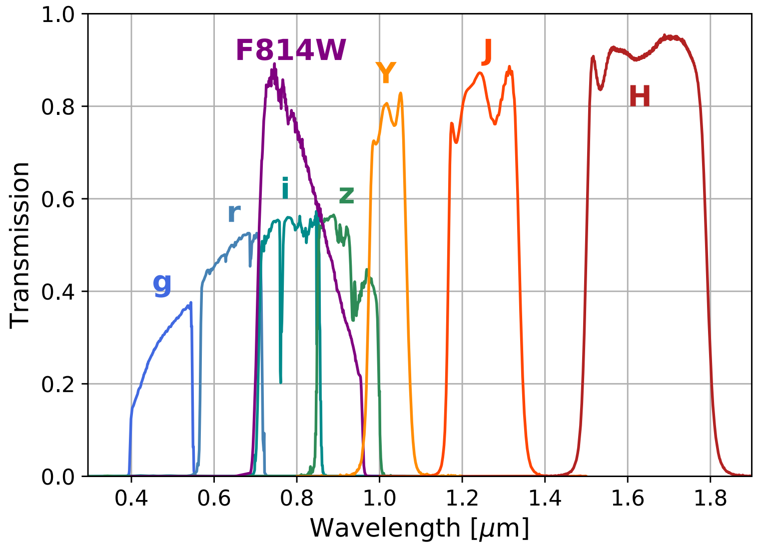
Ilbert+2009

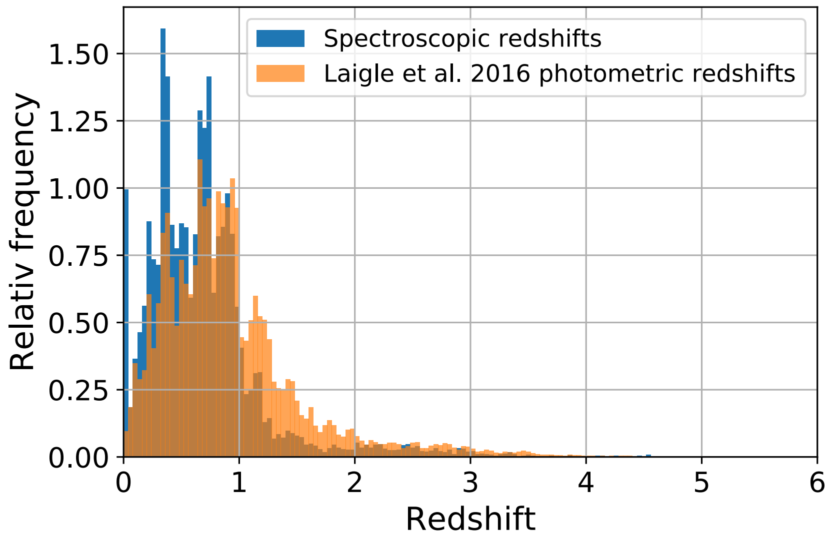
Machine Learning



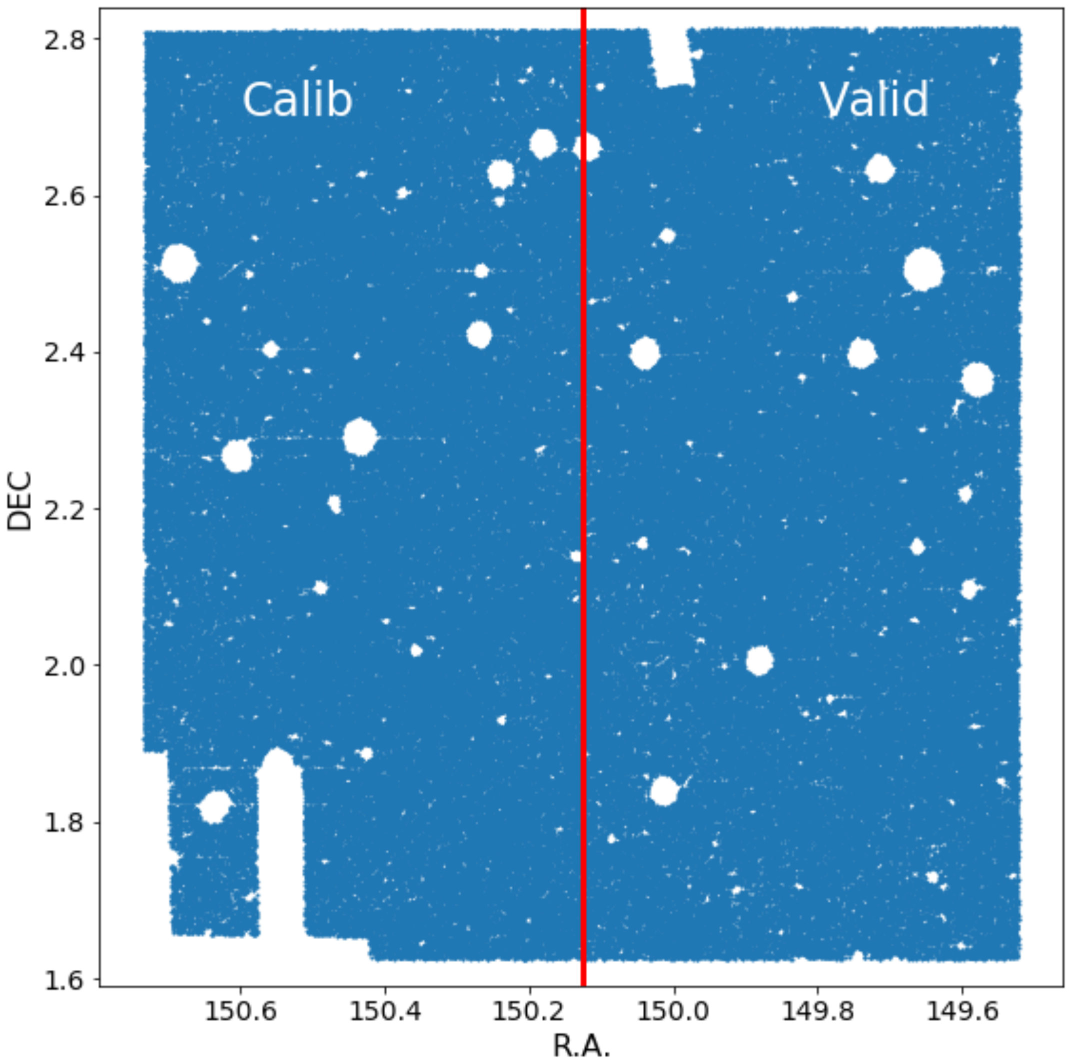
Carrasco Kind & Brunner 2013

The challenge





COSMOS



Challenge contestants

Template Fitting

- Phosphoros
- Lephare
- CPZ
- EAzY

Machine Learning

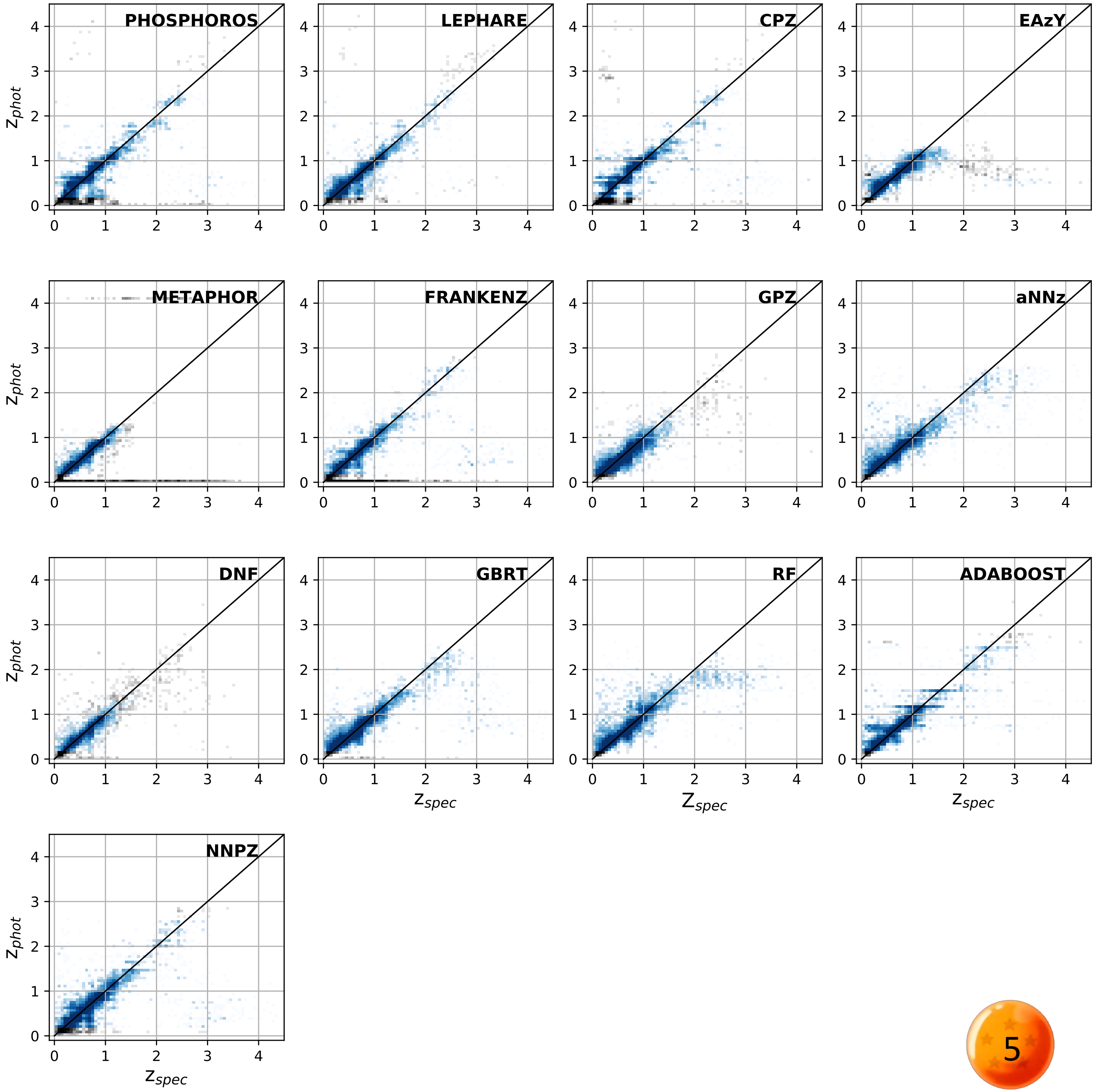
- Frankenz
- Metaphor
- GPZ
- DNF
- aNNz
- GBRT
- RF
- Adaboost
- NNPZ

Provided results per source :

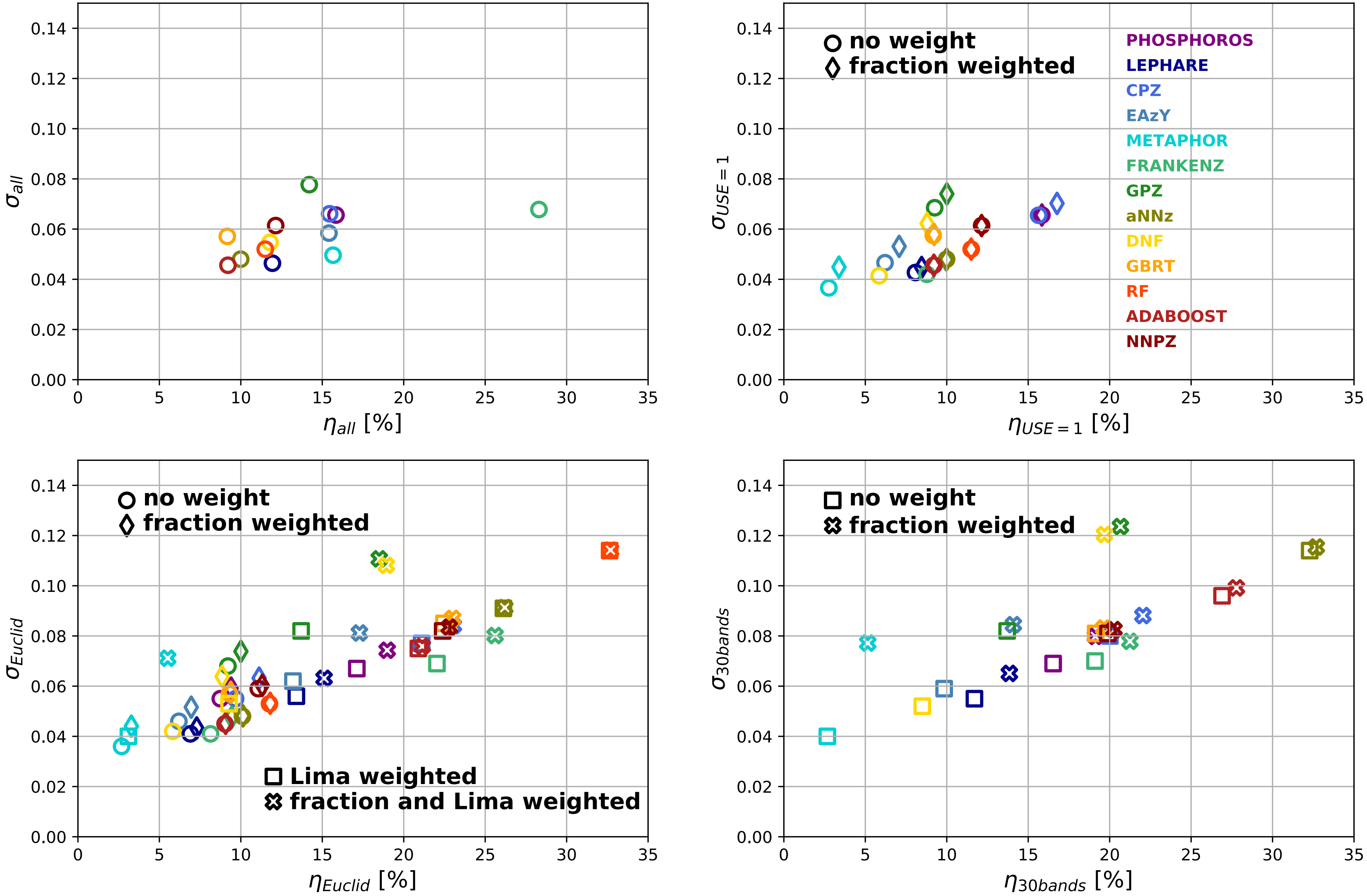
- A redshift point estimate
- A PDZ
- A USE flag

Results

- Euclid selection :
  - Photo-z 0.2<z<2.6
  - Shear Flag =1
  - USE = 1
- Metrics :
  - σ_{NMAD}
  - Outlier rate



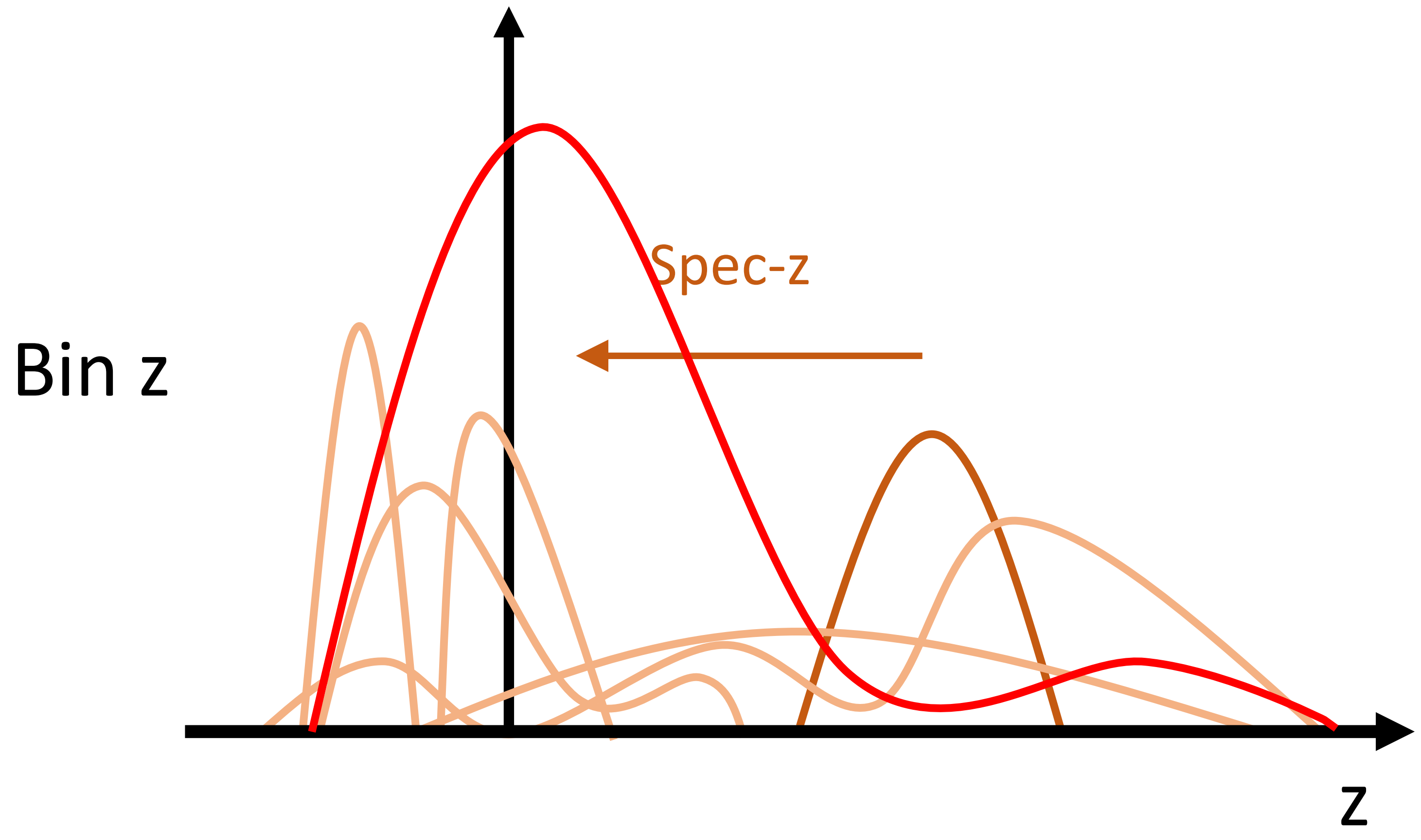
Point estimate statistics



$$wht_{fraction} = \sqrt{\frac{n_{good,i}}{n_{true,i}}}$$

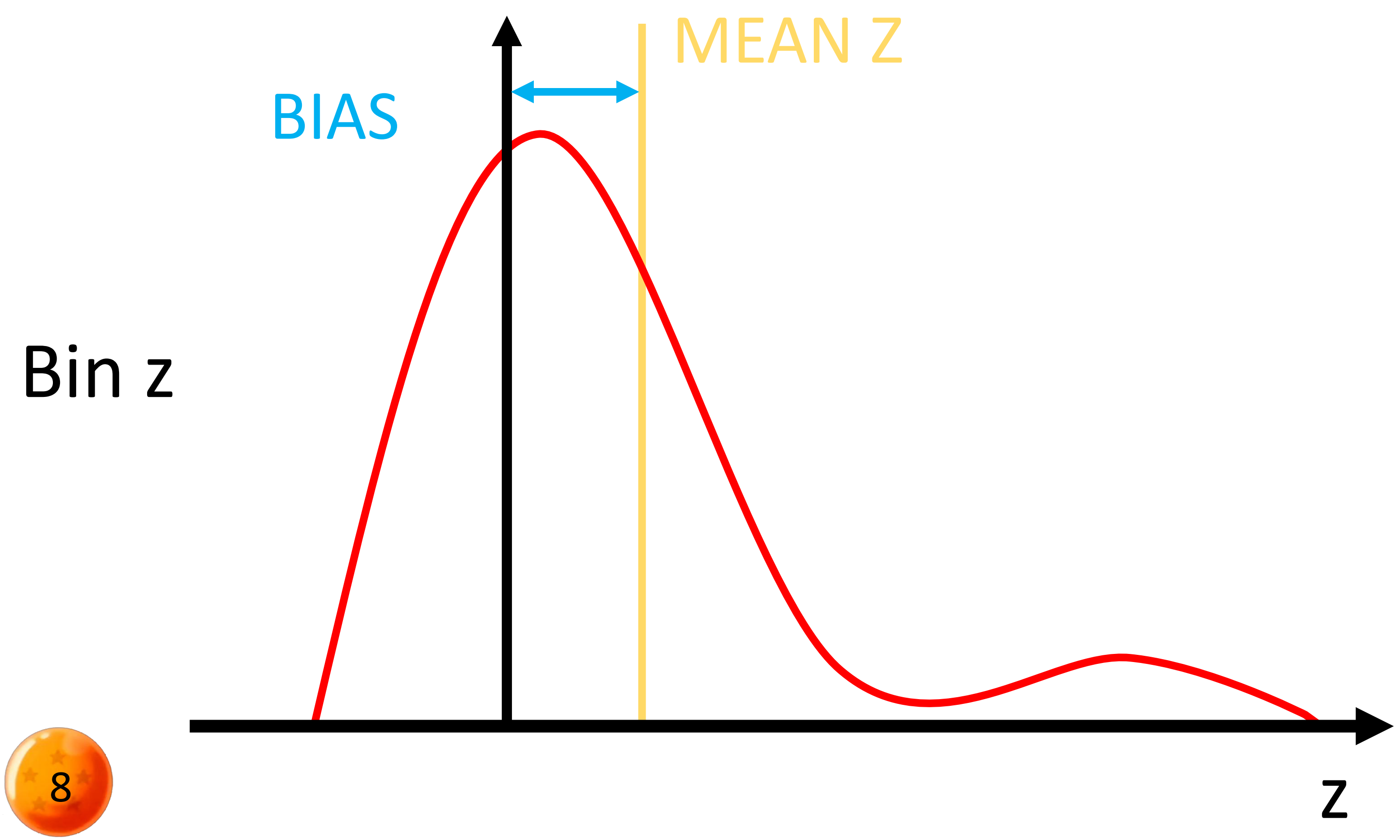
$$wht_{Lima,s} \propto \frac{1}{d_{neighbor,phot,s}}$$

PDF metrics



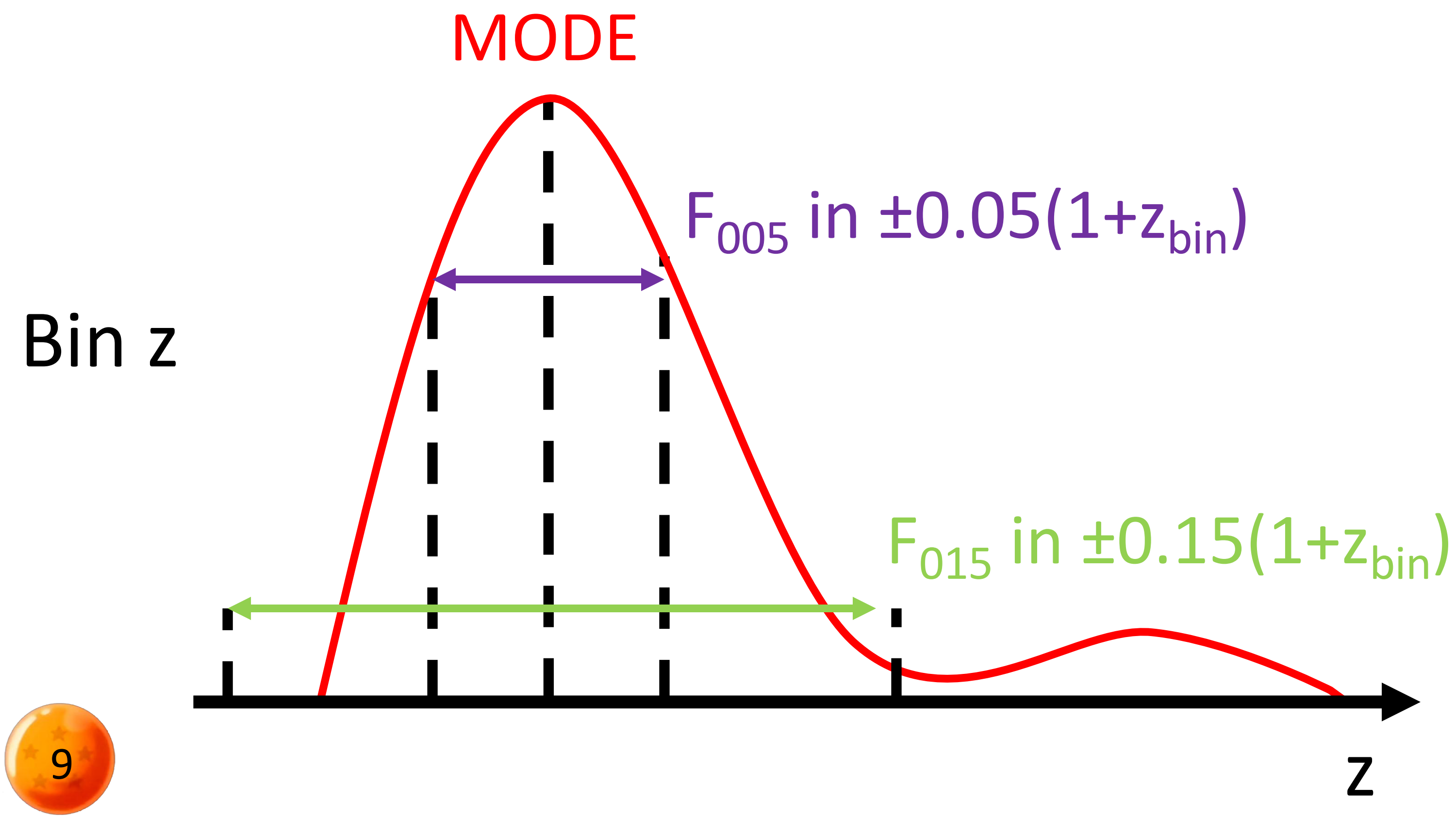
- Sources assigned to tomographic bin with point estimates
- PDF shifted with spec-z
- All PDFs stacked in a bin

PDF metrics



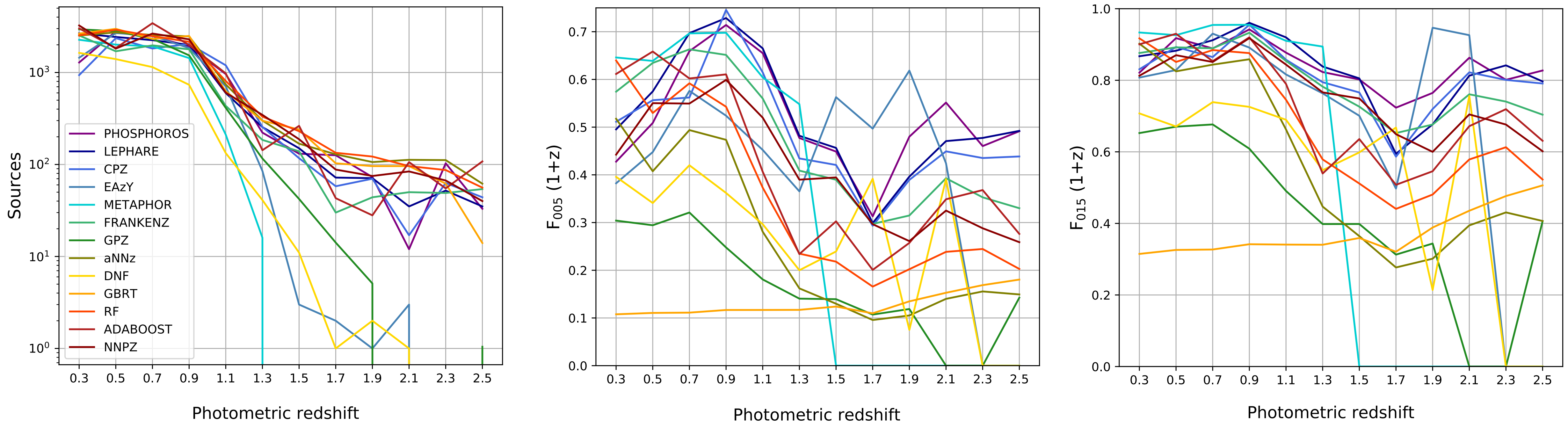
- Sources assigned to tomographic bin with point estimates
- PDF shifted with spec-z
- All PDFs stacked in a bin
- Bias : difference between stacked PDZ mean and 0

PDF metrics



- F_{005} : fraction of the stacked PDF in 0.05(1+z) around the mode → scatter
- F_{015} : fraction of the stacked PDF in 0.15(1+z) around its mode → outlier fraction

Fraction plots

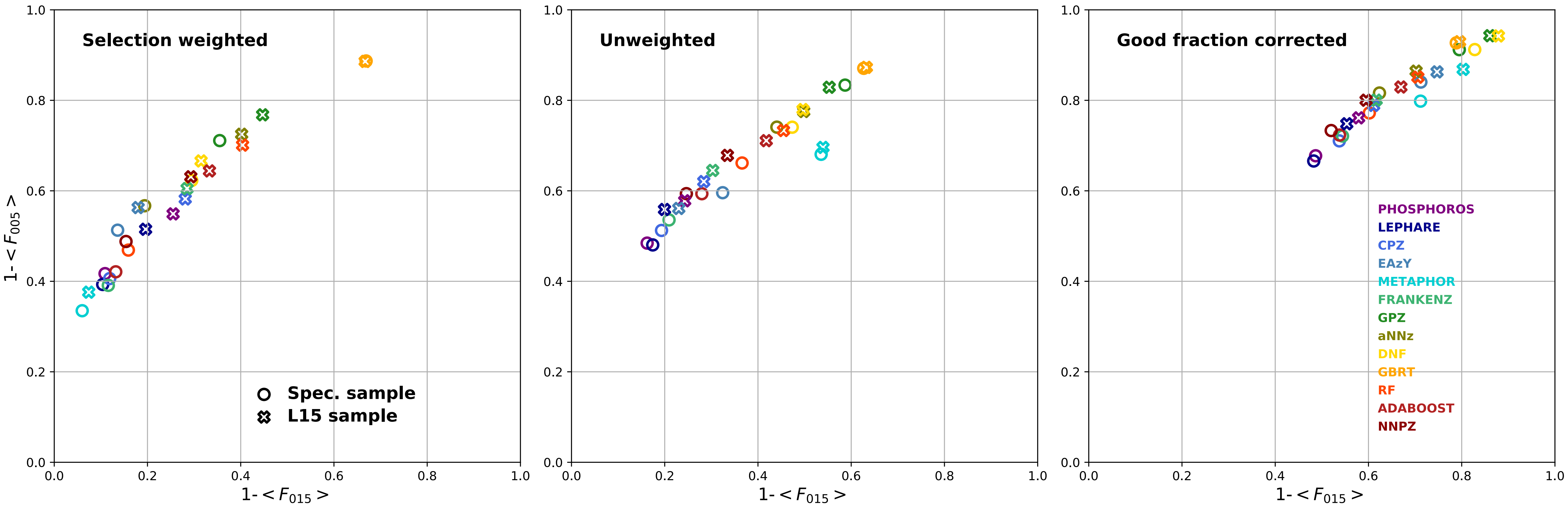


Possible improvements

- TF methods struggle at low z → templates do not disentangle the information in the photometry :
  - New templates
  - New priors

- Machine-learnings are struggling to provide sensible PDZ
- Most of machine-learning fail at high z or for the full photometric sample → training sample not representative of the full photometric sample :
  - A good training sample require a complete coverage in redshift of the color-magnitude space (e.g. C3R2)

Photo-z precision not enough

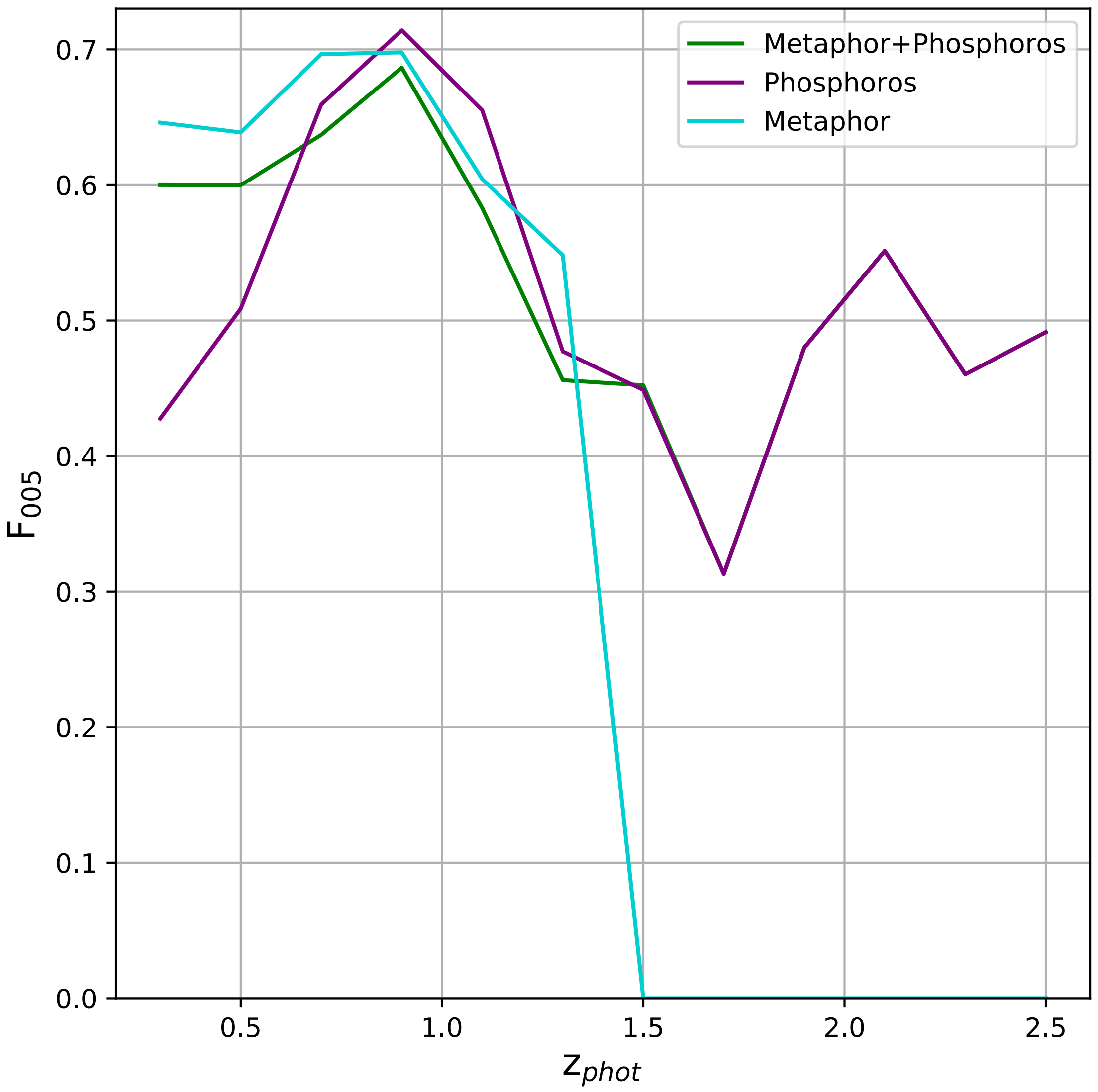


$$\langle F_{0XX} \rangle = \sum_i^{bins} F_{0XX,i} \cdot \frac{n_i}{n_{sel}}$$

$$\langle F_{0XX} \rangle = \sum_i^{bins} F_{0XX,i} \cdot \frac{1}{12}$$

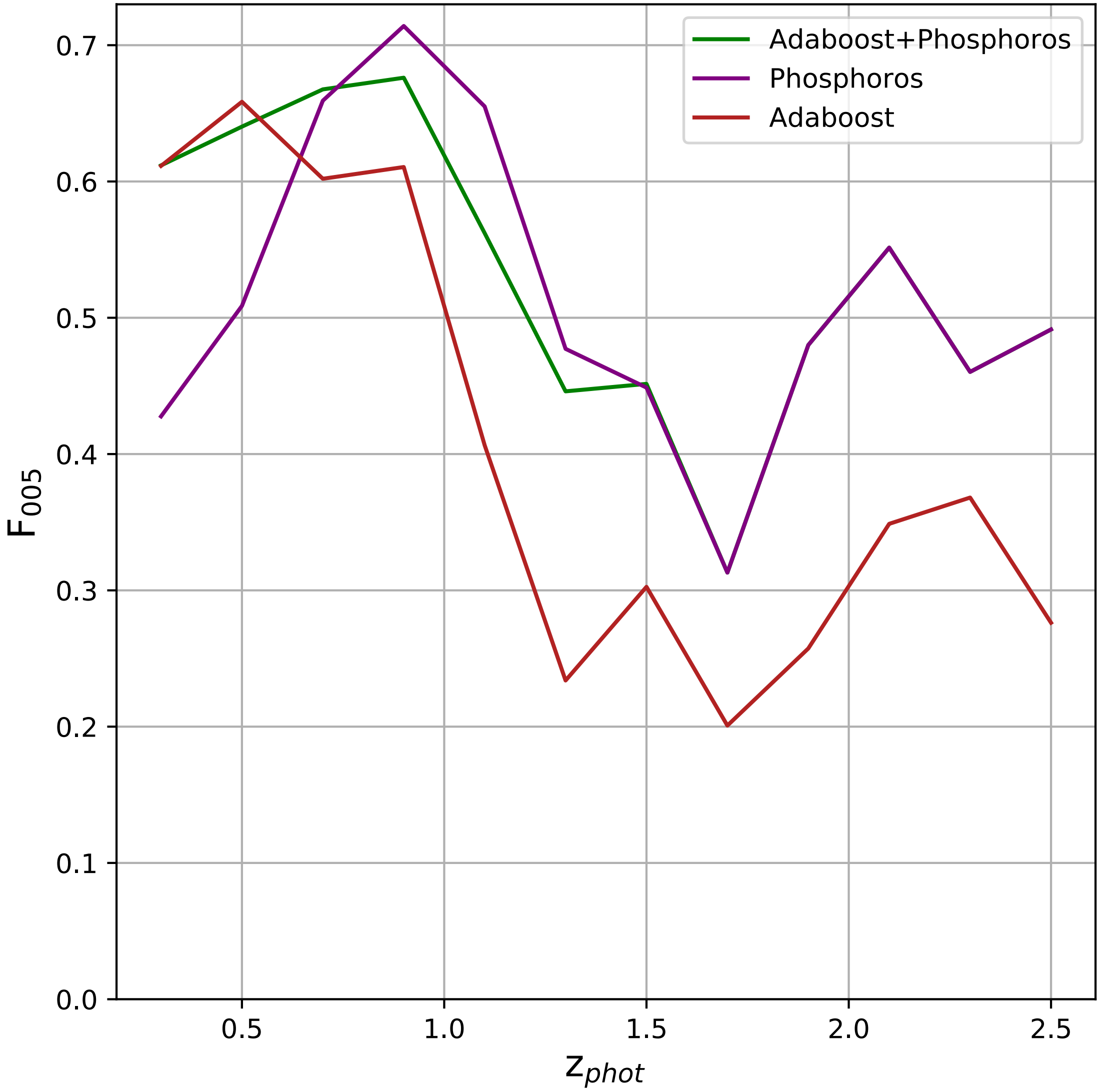
$$\langle F_{0XX} \rangle = \sum_i^{bins} F_{0XX,i} \sqrt{\frac{n_{good,i}}{n_{true,i}}}.$$

Combining methods



	<F005>corr	<F015>corr
Metaphor	0.202	0.288
Phosphoros	0.322	0.513
Combination	0.344	0.537

Combining methods



	<F005>corr	<F015>corr
Adaboost	0.277	0.462
Phosphoros	0.322	0.513
Combination	0.346	0.536

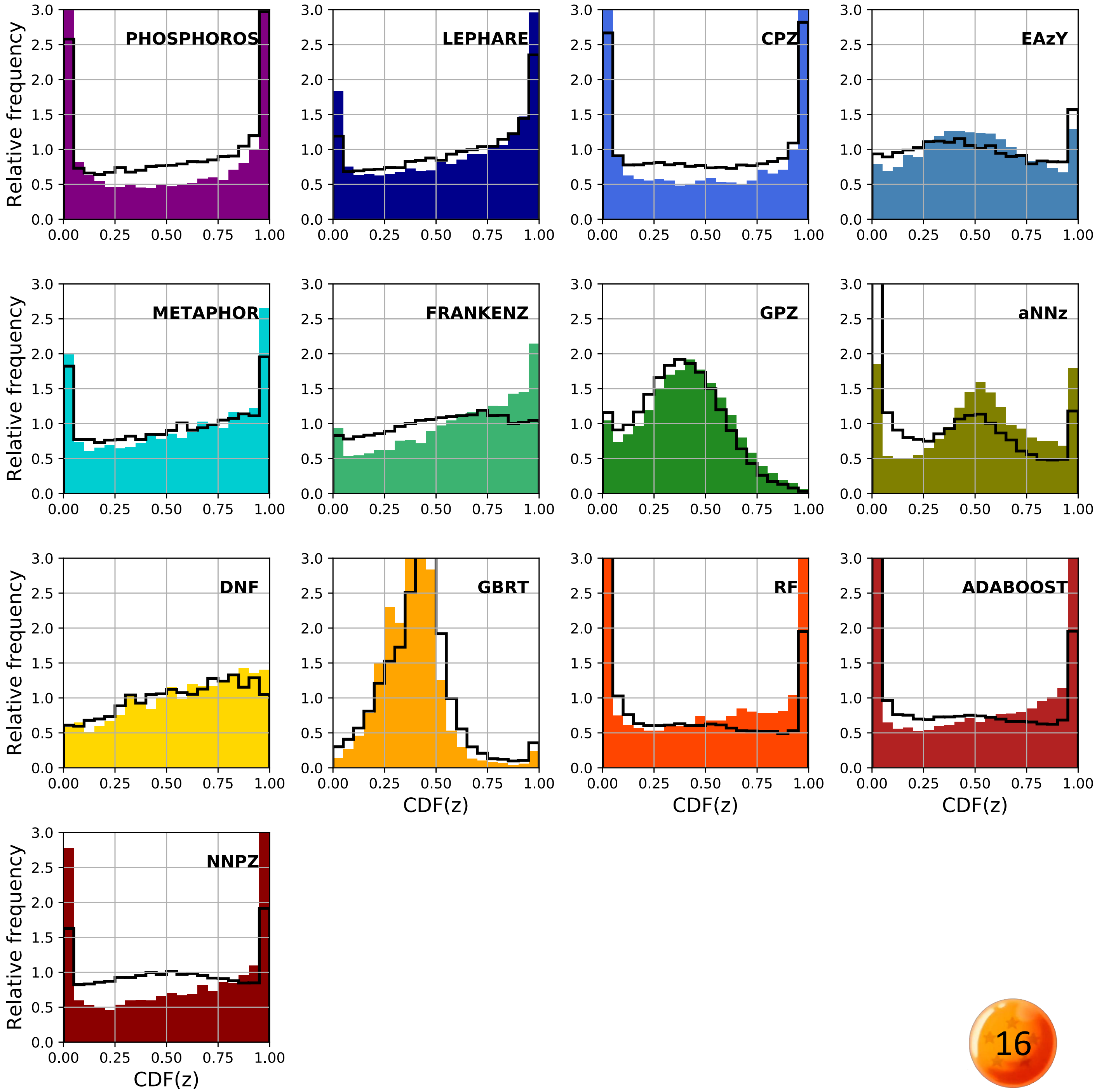
Conclusions

- A test of the relative performance of photo-z methods
- To improve the results :
  - Machine-learning needs more training
  - Template-fitting need better templates and prior
- Precision of photo-z is not enough, completeness is also important → a metric must take this in account to properly compare the code results
- Fusion of machine-learning and template-fitting results could be a solution to get the best answer
- Further tests can be lead on actual cosmological survey (e.g. HSC-SSP)

PIT

Probability Integral Transform

$$CDF_i(z_i) = \int_0^{z_i} PDF_i(z)dz$$



CRPS

Continuous Ranked Probability Score

$$CRPS_i = \int_{-\infty}^{z_I} CDF_i(z)^2 dz + \int_{z_i}^{+\infty} (CDF_i(z) - 1)^2 dz$$

	mean_{sp}	median_{sp}	mean_{L15}	median_{L15}
Phosphoros	0.099	0.051	0.173	0.083
Lephare	0.071	0.037	0.102	0.056
CPZ	0.103	0.049	0.194	0.091
EAzY	0.078	0.040	0.102	0.048
Metaphor	0.046	0.031	0.048	0.034
Frankenz	0.084	0.036	0.148	0.072
GPZ	0.113	0.075	0.151	0.113
aNNz	0.103	0.047	0.257	0.124
DNF	0.101	0.070	0.104	0.072
GBRT	0.196	0.157	0.229	0.165
RF	0.112	0.049	0.309	0.119
Adaboost	0.088	0.043	0.222	0.090
NNPZ	0.107	0.055	0.157	0.081