



METAPHOR

Machine-learning Estimation Tool for Accurate Photometric Redshifts

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A reliable PDF should be able to:

- 1) evaluate photometric error distributions;
- 2) assess the correlation between spectroscopic and photometric errors;
- 3) disentangle photometric uncertainties from those intrinsic to the method itself.

Source PDFs contain more information than simple redshift estimates. PDF's are able to improve the accuracy of cosmological measurements (Mandelbaum et al. 2008-2015).

Many PDF methods for ML have been developed over the past years, mostly based on:

- Supervised methods (ANN, RF, MLP, used both as regressors and classifiers)
- Unsupervised methods (SOMs, random atlas)

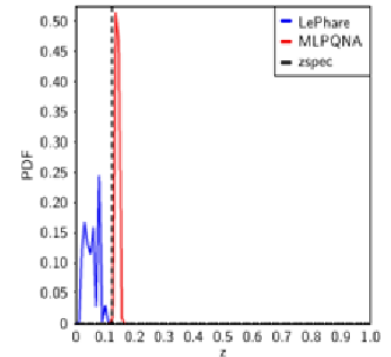
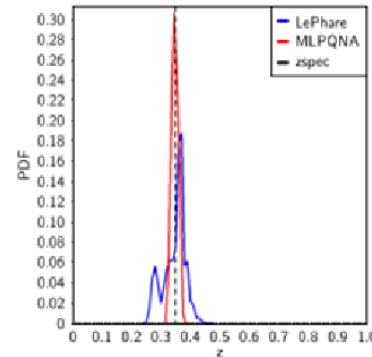
Rau et al. 2015, MNRAS, 452

Carrasco & Brunner 2013, MNRAS, 442

Bonnet 2013, MNRAS, 449

Sadeh et al. 2015, arXiv:1507.00490

Speagle et al. 2015, arXiv:1510.08073

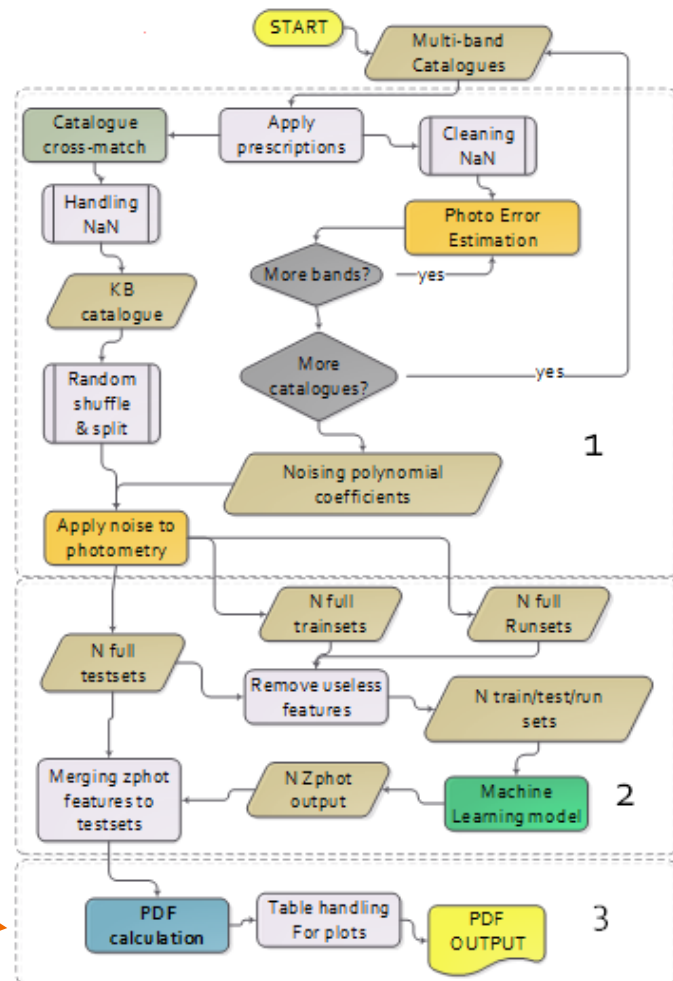


METAPHOR workflow

Data pre-processing:
KB preparation +
Photometry perturbation

Photo-z Prediction:
train/test phase by
means of any arbitrary
ML model (in our case
the multi-threading
MLPQNA)

**Probability Density
Function Estimation**





MLP+ (QNA)/(LEMON)



METAPhoR embeds a multi-thread version of MLPQNA, made by a Python wrapper, to improve training computational performance

The model architecture is a standard 4-layers Multi Layer Perceptron trained by:

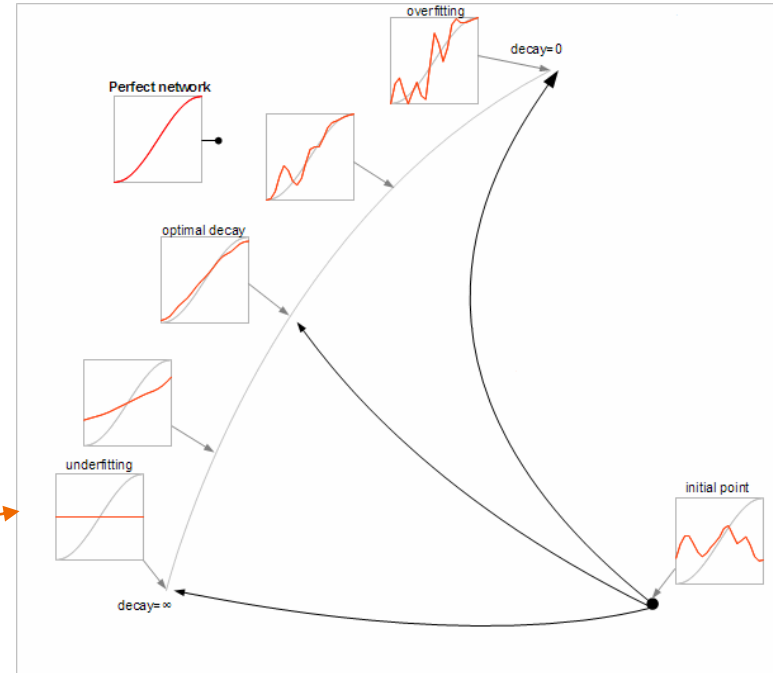
QNA rule, based on the L-BFGS algorithm (limited memory BFGS), implementing the Quasi-Newton algorithm

One command-line parameter may switch to the use of an alternative learning rule, called **LEMON** (Levenberg-Marquardt Optimization Network)

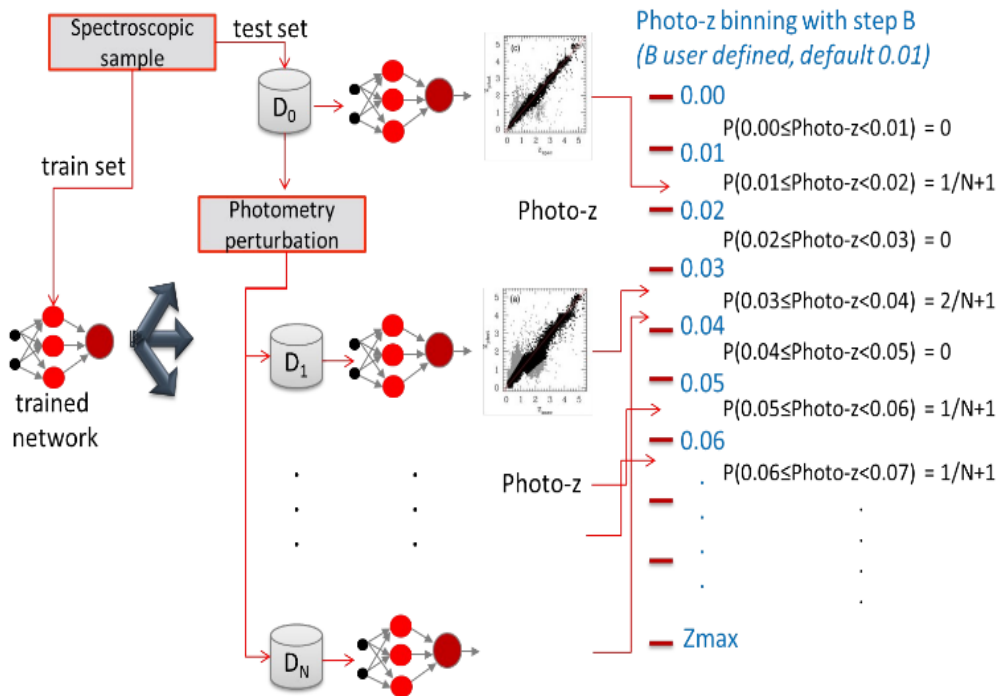
Regression error: Least Square error + Tikhonov regularization

$$E = \sum_{i=1}^{N_{patterns}} \frac{(y_i - t_i)^2}{2} + \frac{\|W\|^2 \lambda}{2}$$

decay →



PDF estimation algorithm scheme



1. INPUT: the KB (train + test sets), the photo-z binning step B (by default 0.01) and the zspec Region of Interest (RoI) $[Z_{\min}, Z_{\max}]$ (a typical use case is $[0, 1]$);

2. Produce N photometric perturbations, thus obtaining N additional test sets;

3. Perform 1 training (or N + 1 trainings) and N + 1 tests;

$$\text{PDF}(\text{photo-z}) = \frac{P(Z_i \leq \text{photo-z} < Z_{i+B})}{C_{B,i}/N+1}_{[Z_{\min}, Z_{\max}]};$$

4. Derive: number of photo-z bins $(Z_{\max} - Z_{\min})/B$; N+1 photo-z estimations; the number of photo-z $C_{B,i} \in [Z_i, Z_{i+B}]$;

The photometry perturbation procedure

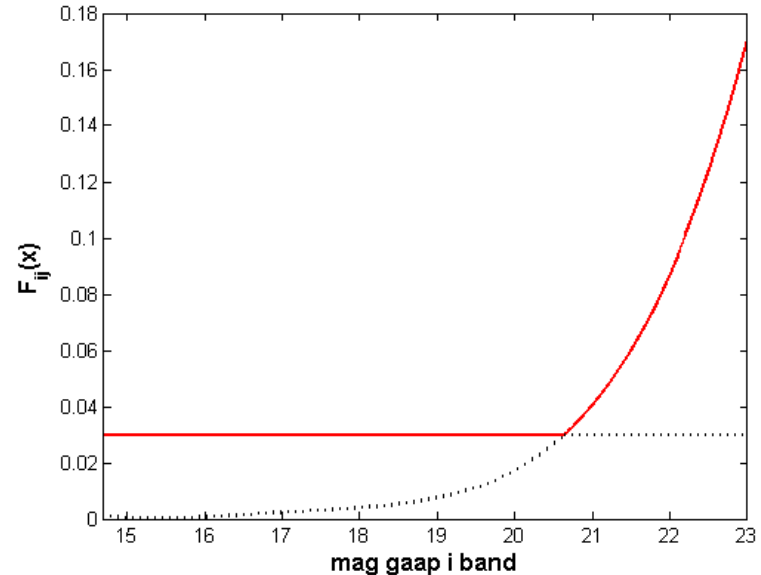
At the very base of the capability to determine a PDF in ML there is a photometry perturbation law

$$m_{ij} = m_{ij} + \alpha_i F_{ij} * \text{gaussRandom}(\mu=0, \sigma=1)$$

- α_i is a multiplicative constant defined by the user;
- $F_{ij}(x)$ is the weighting associated to each specific band used to weight the Gaussian noise contribution to magnitude values;
- $\text{gaussRandom}(\mu=0, \sigma=1)$ is the random value from the normal standard;
- In particular $\alpha_i F_{ij}$ is the term used to generate the set of perturbed replicates of the blind test set.

Generally, we can identify and test different types of weighting coefficients:

- **constant weight (flat);**
- **individual magnitude errors (indiv.);**
- **polynomial fitting (poly.);**
- **bimodal function (bimod.).**



$\alpha_i = 0.9$; $thresh = 0.03$; $N_{pert} = 1000$ for all the bands

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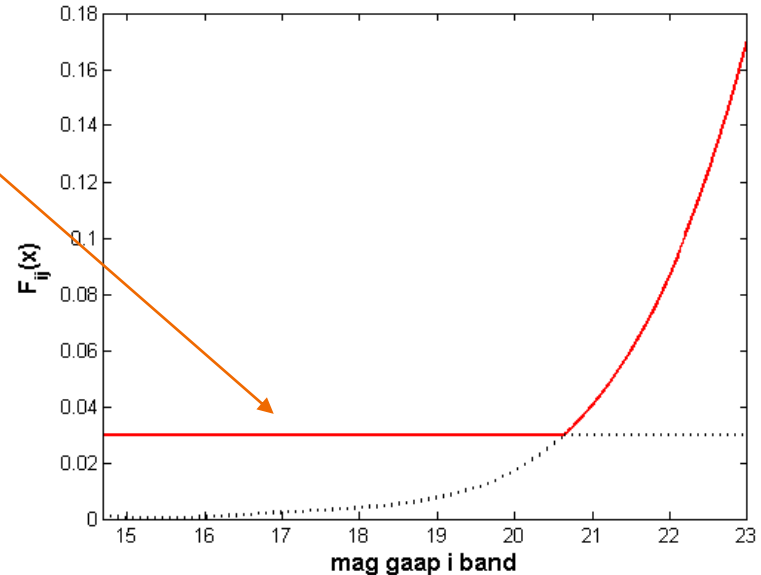
$$m_{ij} = m_{ij} + \alpha_i F_{ij} * \text{gaussRandom}(\mu=0, \sigma=1)$$

- α_i is a magnitude
- $F_{ij}(x)$ is used to magnitude
- gaussRandom the normal
- In particular set of parameters

F_{ij} has been chosen as a bimodal function, i.e. with a constant value representing a threshold under which the polynomial function is considered too low to provide a significant noise contribution to the perturbation

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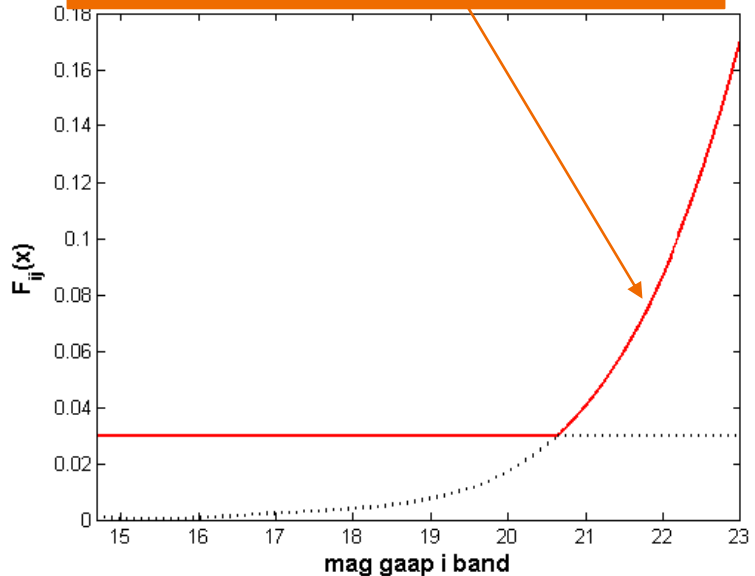
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(*individ.*);
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In the fainter region F_{ij} follows the derived photometric uncertainties



METAPHOR statistics output

Statistics provided for $\Delta z = (z_{\text{spec}} - z_{\text{phot}}) / (1 + z_{\text{spec}})$ on the blind test set:

bias, standard deviation, NMAD, σ_{68} (*radius of the region including 68% of residuals close to 0*), $\eta_{0.15}$ (*fraction of outliers with $|\Delta z| > 0.15$*), skewness (asymmetry);

for the cumulative PDF performance, three estimators on the stacked residuals of the PDFs:


$f_{0.05}$: percentage of residuals within 0.05;

$f_{0.15}$: percentage of residuals within 0.15;

$\langle \Delta z \rangle$: weighted average of all residuals of stacked PDFs.

METAPHOR for KiDS DR3

For the training, we used a KB prepared as follows:

- 214 tiles of KiDS cross-matched with SDSS DR9 and GAMA DR2;  **#120,047 objects** before the mag distribution tails cuts and NaN removal
- Parameter Space: a total of **12 magnitudes**, in four bands *ugri* (4",6" apertures + GAaP), and **9 derived** natural colours, for a total of **21 features**;
- Two experiments performed with two KBs :
 - *i)* $0.01 \leq z_{\text{spec}} \leq 1$;
 - *ii)* $0.01 \leq z_{\text{spec}} \leq 3.5$

| Band | lower cut limit | upper cut limit |
|---------------|-----------------|-----------------|
| MAG_APER_20_U | 16.8 | 28.5 |
| MAG_APER_30_U | 16.8 | 28.1 |
| MAG_GAAP_U | 16.8 | 28.8 |
| MAG_APER_20_G | 16.2 | 24.4 |
| MAG_APER_30_G | 15.8 | 24.6 |
| MAG_GAAP_G | 16.0 | 24.5 |
| MAG_APER_20_R | 15.3 | 23.2 |
| MAG_APER_30_R | 15.0 | 23.3 |
| MAG_GAAP_R | 15.1 | 23.3 |
| MAG_APER_20_I | 14.9 | 22.8 |
| MAG_APER_30_I | 14.6 | 23.0 |
| MAG_GAAP_I | 14.8 | 23.0 |

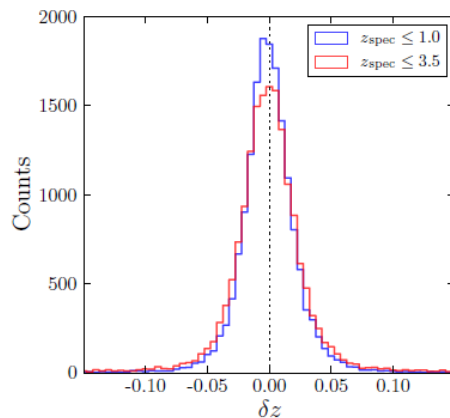
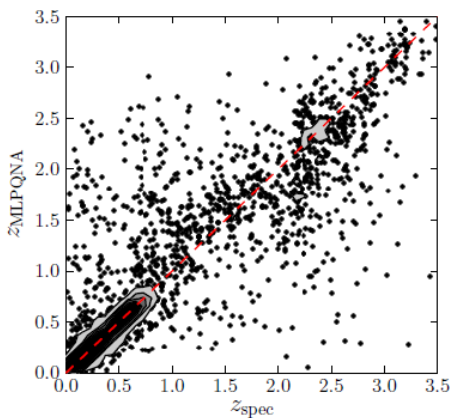
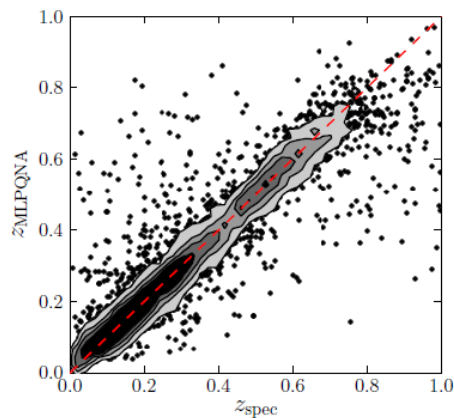
The final KBs consisted in:

- i)* 66,731 train and 16,742 test samples;
- ii)* 70,688 train and 17,559 test samples.

METAPHOR for KiDS DR3: Results

Statistics *i)* $0.01 \leq z_{\text{spec}} \leq 1$ *ii)* $0.01 \leq z_{\text{spec}} \leq 3.5$

| | | |
|-----------------|--------|--------|
| δz | 0.0014 | 0.0063 |
| σ | 0.035 | 0.101 |
| <i>NMAD</i> | 0.018 | 0.022 |
| <i>outliers</i> | 0.93% | 3.4% |



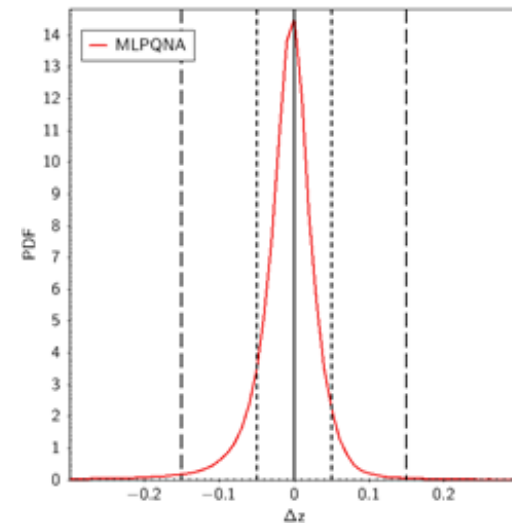
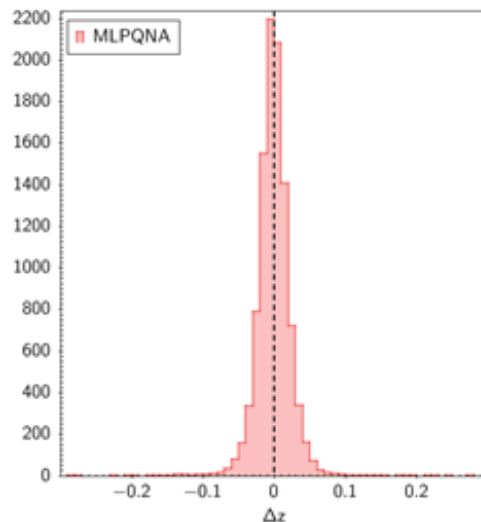
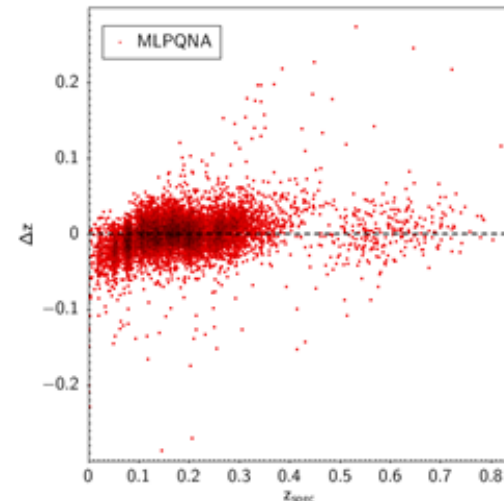
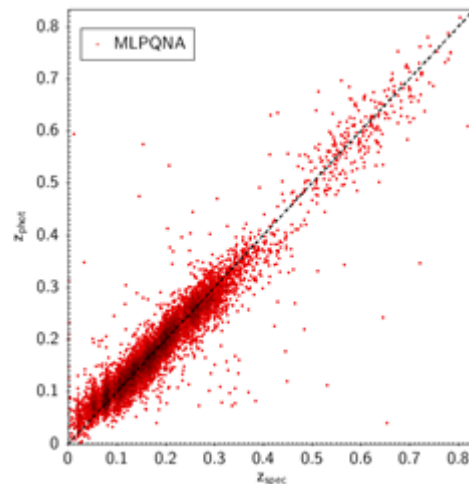
KiDS DR2 results with METAPHOR

| Estimator | MLPQNA |
|---------------|---------|
| mean | -0.0007 |
| sigma | 0.026 |
| sigma68 | 0.018 |
| NMAD | 0.018 |
| outliers>0.15 | 0.31% |

| Estimator | MLPQNA |
|----------------------------|---------|
| $f_{0.05}$ | 81.3% |
| $f_{0.15}$ | 98.4% |
| $\langle \Delta z \rangle$ | -0.0084 |

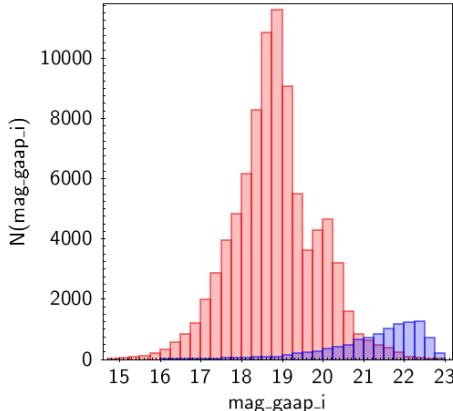
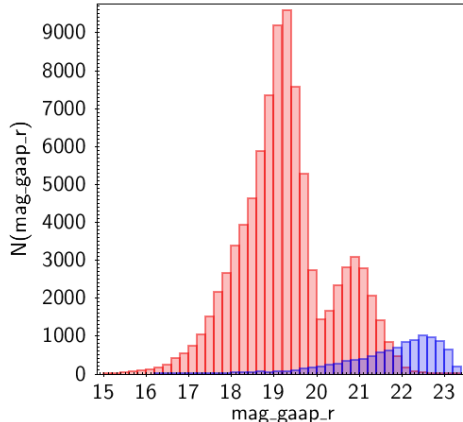
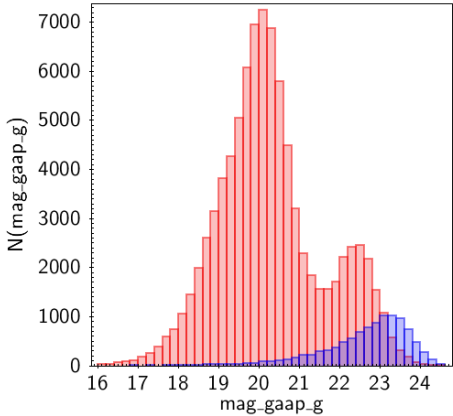
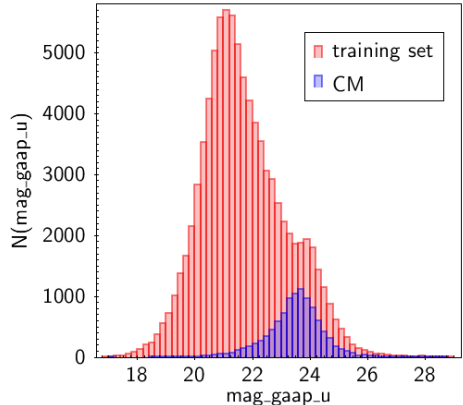
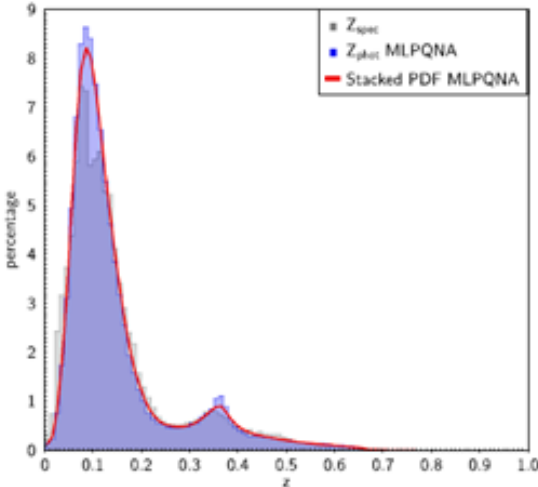
KB consisted of 15,180 training and 10,067 blind test objects

Cavuoti et al. 2015, MNRAS, 452



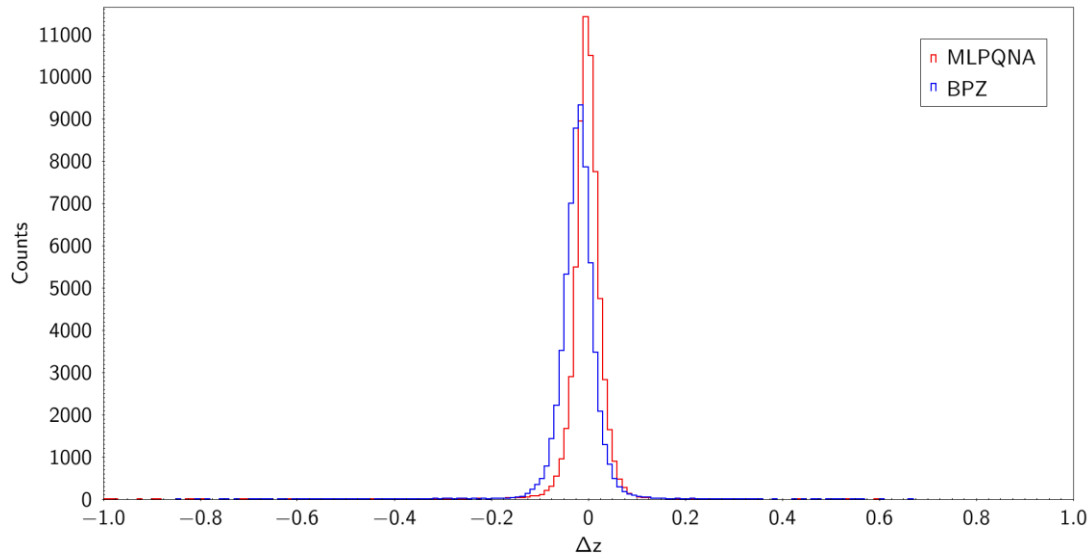
Ongoing analysis on KiDS DR3

- Comparison of the overall photo-z statistics and of the stacked PDF performance of METAPHOR with respect to BPZ in the COSMOS and GAMA spectroscopic fields
- Further comparison among methods (*Bilicki et al, 2017, in prep.*)



CM is the cross-match between zCosmosBright and KiDS DR3 training set (SDSS + GAMA)

Ongoing analysis on KiDS DR3: preliminary results



On the stacked PDFs

| KiDS CM GAMA | MLPQNA |
|----------------------------|--------|
| $f_{0.05}$ | 63.2% |
| $f_{0.15}$ | 96.6% |
| $\langle \Delta z \rangle$ | -0,027 |

Residuals distribution for the cross-match KiDS DR3-GAMA, comparison between MLPQNA and BPZ

Conclusions

- **General applicability** : METAPHOR can be applied with any arbitrary empirical photo-z estimation model. It is able to take into account photometric errors due to both measurements and **method** itself;
- **Perspectives:** Besides the ongoing comparison between METAPHOR and BPZ KiDS DR3 PDFs, METAPHOR is going to be used for cosmology through weak lensing;
- Under preliminary testing in Euclid PHZ pipeline;
- Available for other surveys on request.