A cooperative approach among methods for photometric redshifts estimation

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Cavuoti et al. 2016, Accepted by MNRAS

Always in history mankind has been divided:

Romans vs Barbarians

Coffee Vs Tea

Republicans vs Democrats

Gryffindor vs Slytherin

Batman vs Superman

Star Wars vs Star Trek

Godzilla vs King Kong

Cowboys vs Indians

windows vs mac vs linux

Always in history mankind has been divided:

Rom

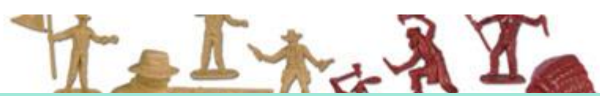
ats

And of course the most bloody war in history:

Machine Learning vs SED fitting for photometric redshift

Batman vs Superman

Star Wars vs Star Trek



**"We must, indeed, all hang together,
or assuredly we shall all hang separately."**
— Benjamin Franklin, July 1776

Outline

In this work we perform a comparison between five different photo-z techniques applied to the same KiDS dataset:

1. **MLPQNA** (Multi Layer Perceptron with Quasi Newton Algorithm);
2. **RF** (Random Forest);
3. **LEMON** (LEvenberg-Marquardt Optimization Network);
4. **Le Phare** SED template fitting;
5. **BPZ** (Bayesian Photometric Redshift model).

Then we propose a combination of different methods that provides an improvement in the accuracy of the final estimates.

The Data (KiDS DR2) pre-processing

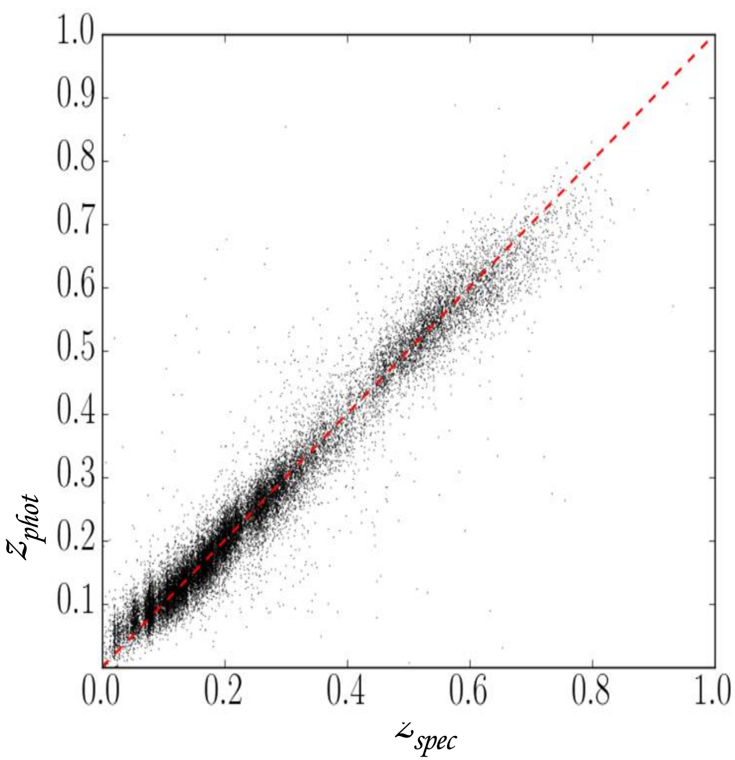
We used the KiDS DR2 (*de Jong et al. 2015*)**, photometry with SDSS and GAMA spectra as KB**

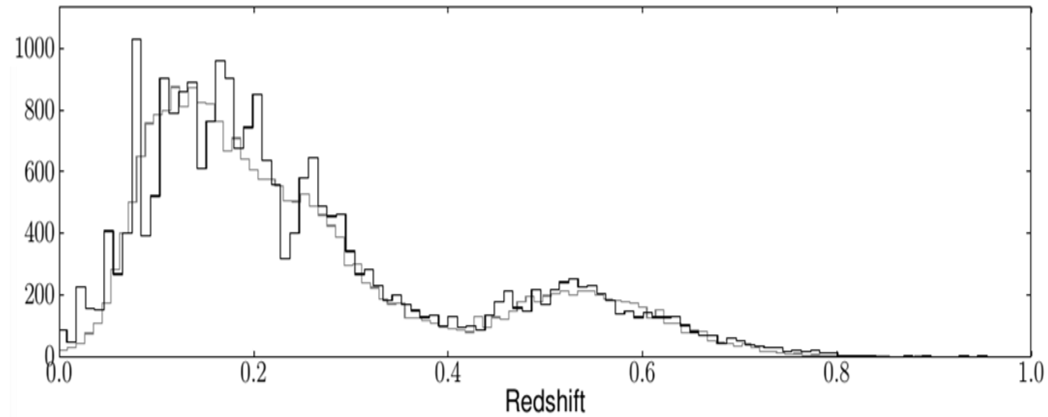
- excluded objects with low photometric quality (i.e. with flux error higher than one magnitude);
- removed all objects having at least one missing band (or labeled as Not-a-Number or NaN);
- selected objects with IMA FLAGS equal to zero in the g, r and i bands (i.e. sources that have been flagged because located in proximity of saturated pixels, star haloes, image border or reflections, or within noisy areas). The u band is not considered since the masked regions relative to this waveband are less extended than in the other three KiDS bands.

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

Related work (KiDS Collaboration)

In a recent paper (*Cavuoti et al. 2015*) we provided a catalogue of photometric redshifts for about 1 million KiDS galaxies, using MLPQNA.





2. Redshift distribution of objects included in the blind test set, spectroscopic (black line) and photometric (gray line).

$\|bias\|$	σ	NMAD	Outliers % $\|\Delta z\| > 0.15$	Outliers % $\|\Delta z\| > 2\sigma$
0.0011	0.0303	0.0212	0.38	3.13

and in these days we are producing the photo-z catalogue for the KiDS DR3 release (*De Jong et al. in prep.*)

Robustness Experiments

- EX_{clean} : fully corrected photometry
- EX_{ext} : corrected by extinction but with a residual offset
- EX_{off} : without the offset but not corrected by extinction
- EX_{no} : not corrected by extinction and with a residual offset

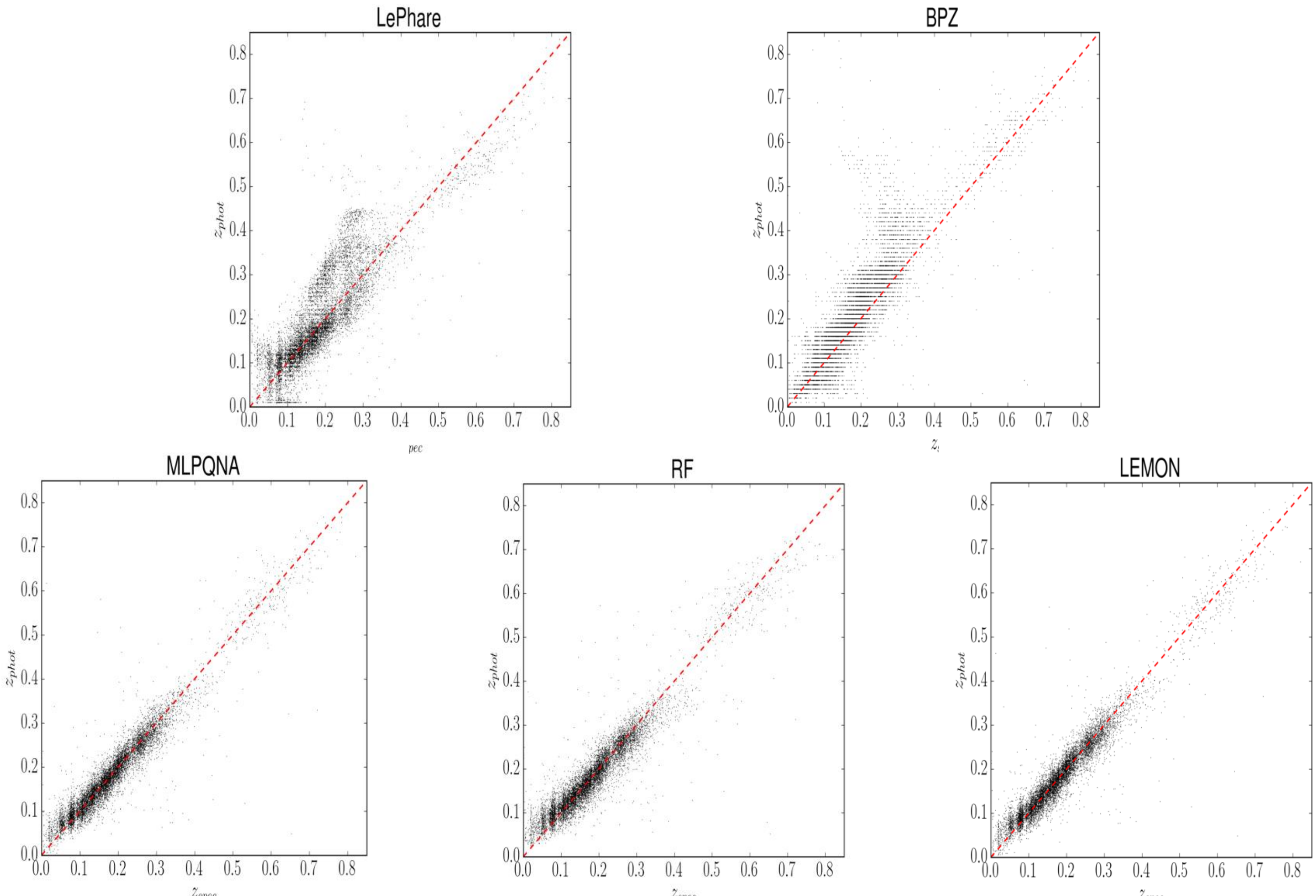
Highlights

- SED fitting methods less accurate than ML models;
- Residual offset has a not negligible impact on ML methods also;
- ML methods robust to reddening;
- Le Phare more robust than BPZ to reddening;
- The lower impact of offset and reddening on estimators σ_{68} and NMAD is justified by their lower dependence from outliers;

- **More in general, the most relevant affecting factors are residual offset and outliers**

EXP	MLPQNA	LEMON	RF	Le Phare	BPZ
			bias		
EX_{clean}	0.0007	0.0006	0.0010	0.0121	0.0289
EX_{ext}	0.0009	0.0009	0.0012	0.0183	0.0393
EX_{off}	0.0006	0.0007	0.0010	0.0158	0.0405
EX_{no}	0.0009	0.0010	0.0012	0.0225	0.0496
			σ		
EX_{clean}	0.026	0.026	0.029	0.065	0.127
EX_{ext}	0.028	0.028	0.030	0.079	0.218
EX_{off}	0.026	0.026	0.029	0.066	0.142
EX_{no}	0.028	0.028	0.030	0.079	0.222
			σ_{68}		
EX_{clean}	0.018	0.018	0.021	0.041	0.039
EX_{ext}	0.021	0.020	0.023	0.048	0.039
EX_{off}	0.018	0.019	0.021	0.041	0.045
EX_{no}	0.021	0.020	0.023	0.049	0.043
			NMAD		
EX_{clean}	0.018	0.018	0.021	0.038	0.031
EX_{ext}	0.020	0.020	0.022	0.044	0.034
EX_{off}	0.018	0.018	0.021	0.037	0.033
EX_{no}	0.020	0.020	0.022	0.044	0.034
			% Outliers		
EX_{clean}	0.31	0.30	0.40	0.89	2.18
EX_{ext}	0.34	0.35	0.42	2.51	3.83
EX_{off}	0.31	0.29	0.39	1.12	3.21
EX_{no}	0.33	0.36	0.36	2.63	4.37

First Results (EX_{clean} experiment type)



Spectral-type classification

based on Le Phare without bounding the fitting with any kind of redshift

The evident performance variation for different morphological types, induced us to explore the possibility to combine the methods, by exploiting Le Phare spectral-type classification to specialize ML methods to predict photo-z's for objects belonging to a single spectral class.

Recap of EX_{clean} experiment type

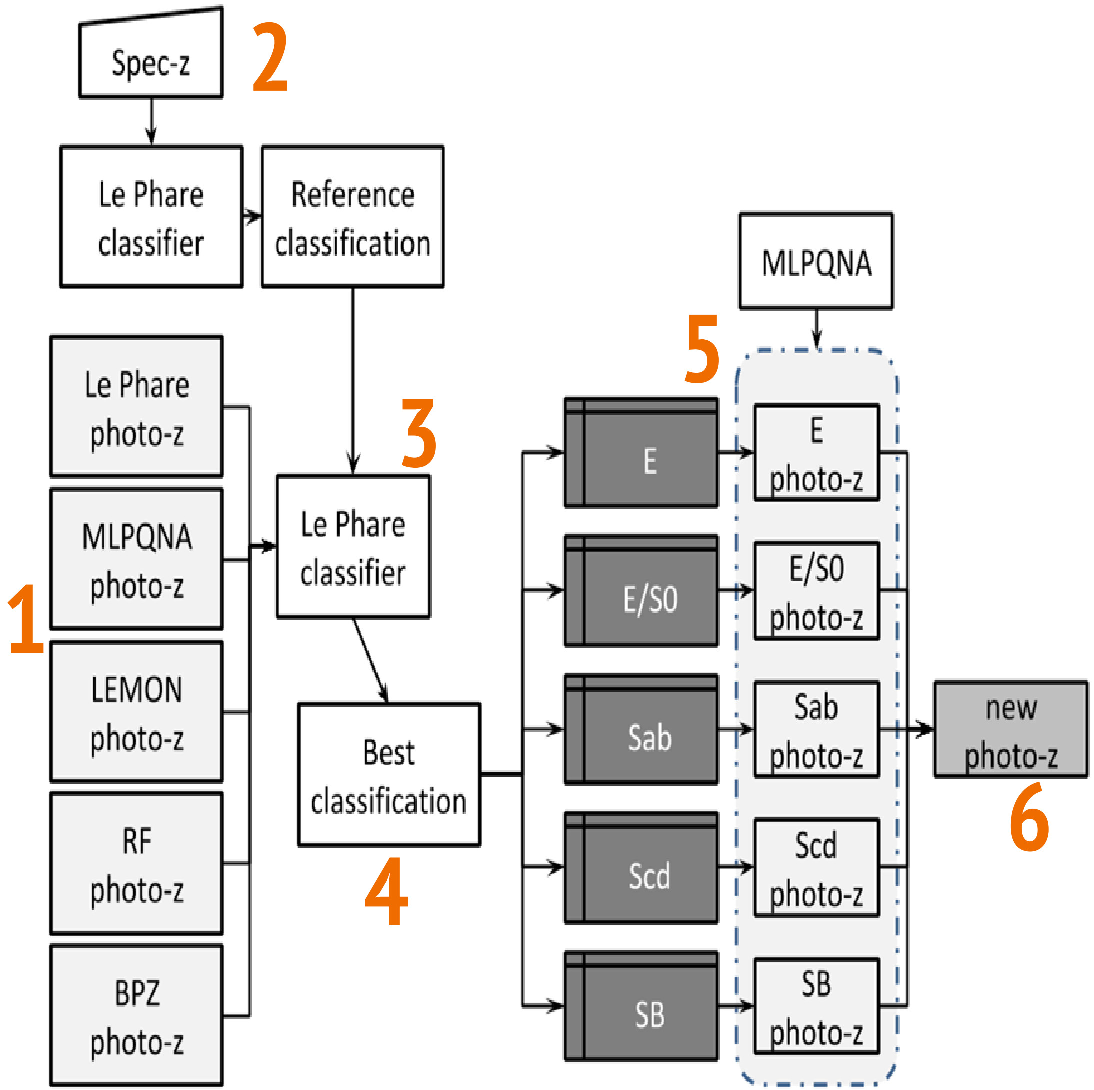
EXP	MLPQNA	LEMON	RF	Le Phare	BPZ
bias					
EX_{clean}	0.0007	0.0006	0.0010	0.0121	0.0289
σ					
EX_{clean}	0.026	0.026	0.029	0.065	0.127
σ_{68}					
EX_{clean}	0.018	0.018	0.021	0.041	0.039
NMAD					
EX_{clean}	0.018	0.018	0.021	0.038	0.031
% Outliers					
EX_{clean}	0.31	0.30	0.40	0.89	2.18

	MLPQNA	LEMON	RF	Le Phare	BPZ
class *E* - 2169 objects					
bias	-0.0007	-0.0004	0.0019	-0.0641	-0.0297
σ	0.022	0.022	0.024	0.045	0.041
σ_{68}	0.016	0.016	0.017	0.086	0.042
NMAD	0.015	0.015	0.016	0.036	0.027
out.(%)	0.18	0.23	0.28	0.60	0.65
class *E/S0* - 1542 objects					
bias	0.0001	-0.0002	-0.0035	0.0124	-0.0381
σ	0.020	0.019	0.020	0.029	0.097
σ_{68}	0.014	0.014	0.016	0.0267	0.040
NMAD	0.014	0.014	0.015	0.020	0.024
out.(%)	0.26	0.19	0.2596	0.19	3.11
class *Sab* - 1339 objects					
bias	0.0007	0.0005	-0.0030	0.0073	-0.0560
σ	0.024	0.023	0.026	0.036	0.186
σ_{68}	0.019	0.020	0.023	0.030	0.050
NMAD	0.019	0.020	0.022	0.029	0.034
out.(%)	0.07	0.08	0.15	0.60	5.23

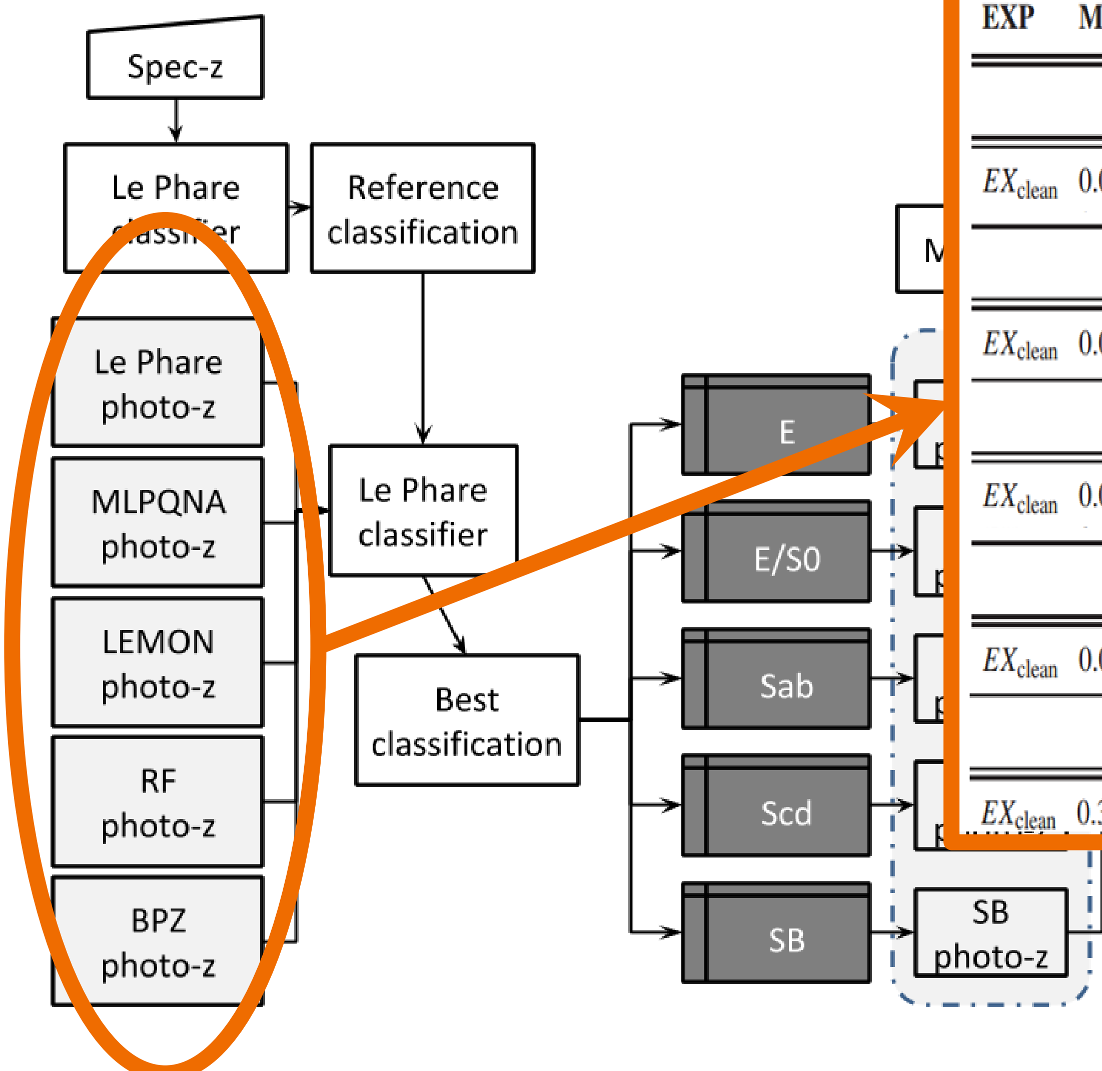
	MLPQNA	LEMON	RF	Le Phare	BPZ
class *Scd* - 3799 objects					
bias	-0.0013	-0.0011	-0.0013	0.0022	-0.0244
σ	0.026	0.026	0.031	0.051	0.112
σ_{68}	0.020	0.019	0.023	0.028	0.036
NMAD	0.019	0.019	0.023	0.027	0.031
out.(%)	0.32	0.34	0.47	0.92	1.61
class *SB* - 1218 objects					
bias	-0.0015	-0.0012	0.0003	-0.0163	0.0005
σ	0.038	0.036	0.040	0.121	0.196
σ_{68}	0.024	0.023	0.031	0.043	0.033
NMAD	0.023	0.023	0.031	0.041	0.030
out.(%)	0.82	0.66	0.82	2.55	2.13

Concept Idea - cooperation between SED fitting and ML

1. Derive traditional photo-z's with all methods;
2. Use Le Phare bounded with spec-z's to obtain a reference classification;
3. Use Le Phare bounded with photo-z's to perform a series of classifications;
4. Identify the best classification using as ground truth the reference classification (step 2);
5. Perform a photo-z regression by training MLPQNA on separated subsets specific for each class;
6. Recombine the output.



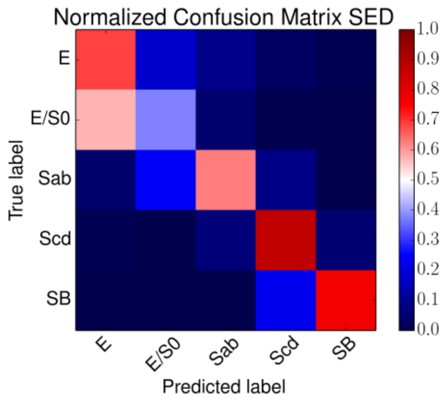
Step 1 - Usual Redshifts

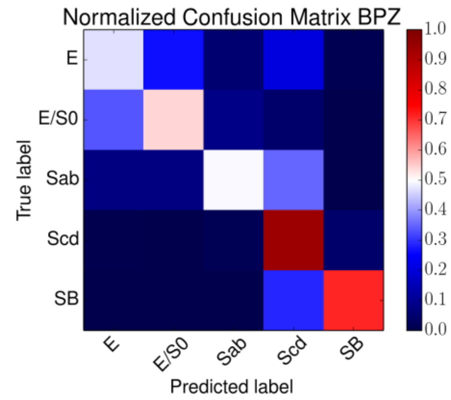


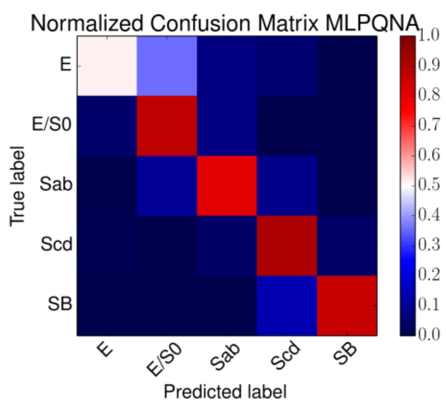
EXP	MLPQNA	LEMON	RF	Le Phare	BPZ
bias					
EX_{clean}	0.0007	0.0006	0.0010	0.0121	0.0289
σ					
EX_{clean}	0.026	0.026	0.029	0.065	0.127
σ_{68}					
EX_{clean}	0.018	0.018	0.021	0.041	0.039
NMAD					
EX_{clean}	0.018	0.018	0.021	0.038	0.031
% Outliers					
EX_{clean}	0.31	0.30	0.40	0.89	2.18

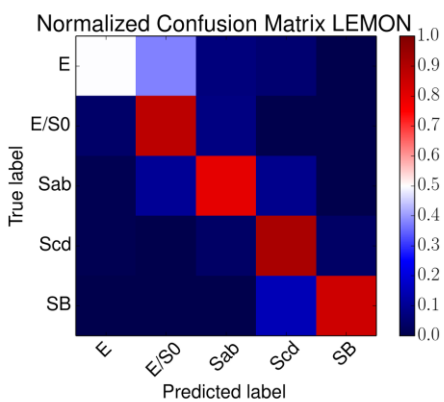
Step 2 and 3 - Le Phare Classification (bounded by photo-z's)

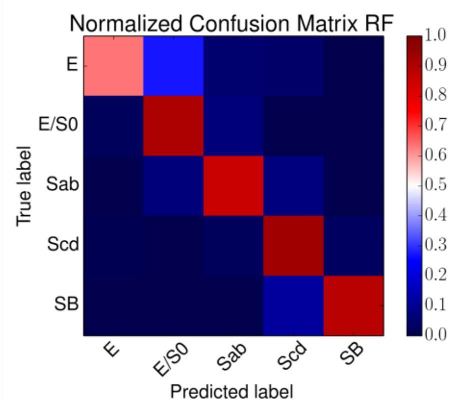
Confusion Matrices











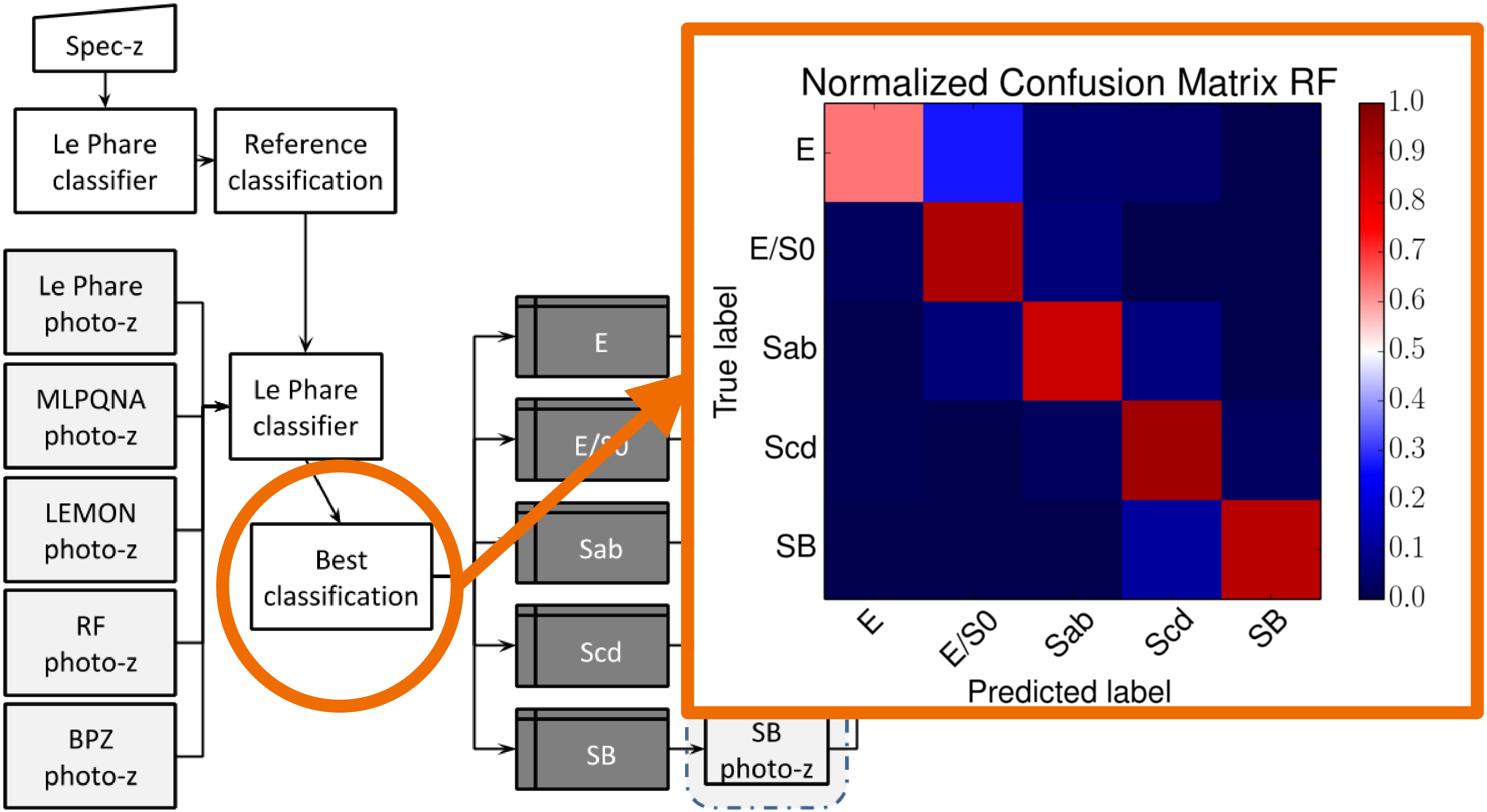
Scd and SB classes are always well classified

E/S0 and Sab are classified better by ML redshifts

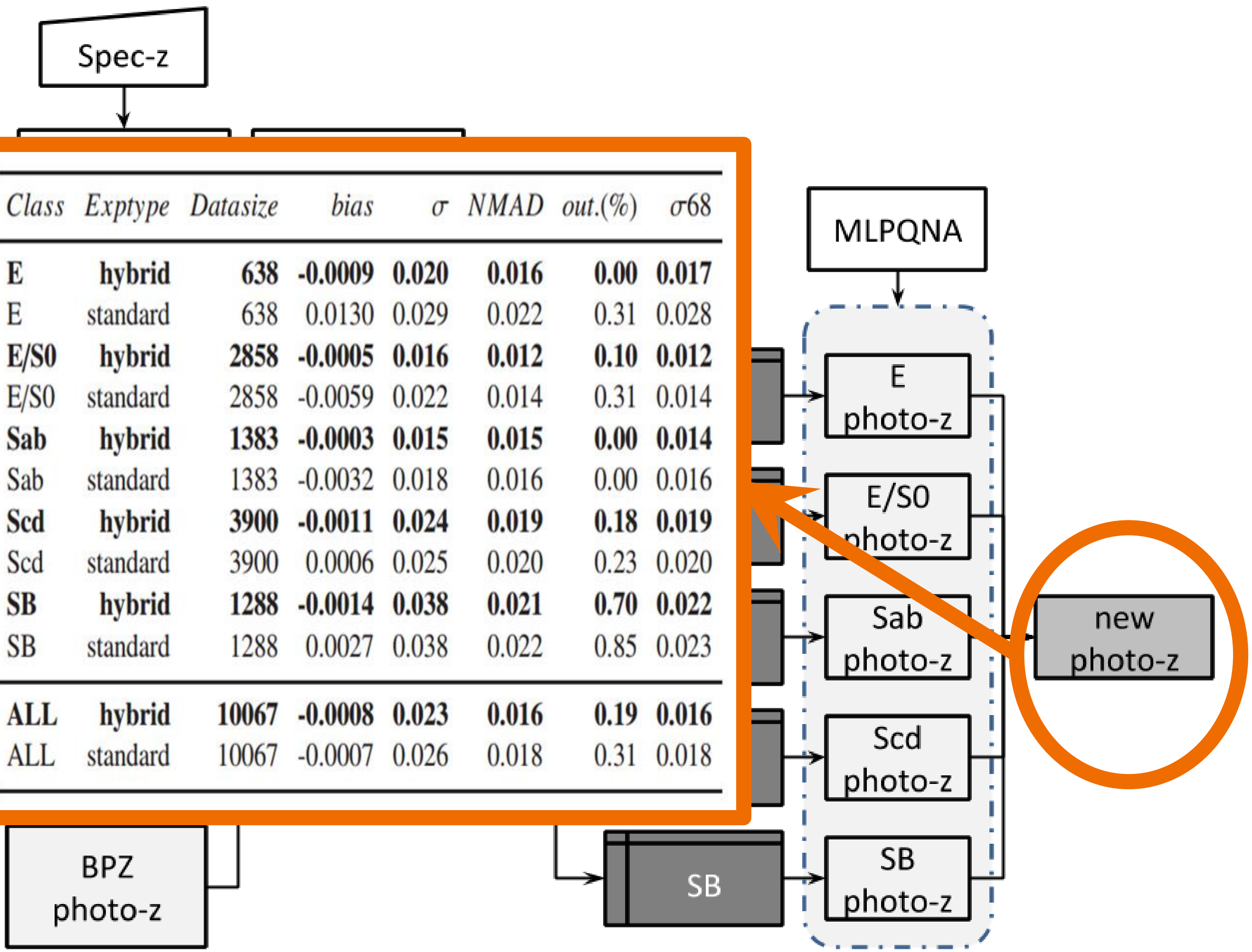
E type is classified better by Le Phare and RF redshifts

Therefore, RF redshifts are the best candidate (for such purpose)

Step 4 - Find the best Classification



Step 5 and 6 - Improved Redshifts by recombination



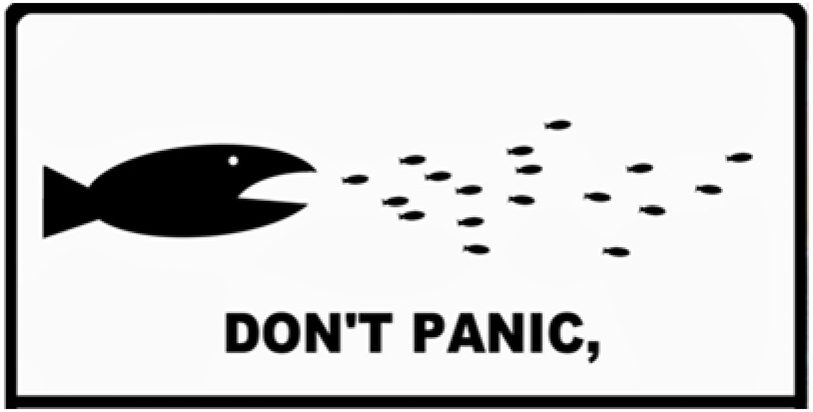
Class	*Exptype*	*Datasize*	*bias*	σ	*NMAD*	*out.(%)*	$\sigma 68$
E	**hybrid**	**638**	**-0.0009**	**0.020**	**0.016**	**0.00**	**0.017**
E	standard	638	0.0130	0.029	0.022	0.31	0.028
E/S0	**hybrid**	**2858**	**-0.0005**	**0.016**	**0.012**	**0.10**	**0.012**
E/S0	standard	2858	-0.0059	0.022	0.014	0.31	0.014
Sab	**hybrid**	**1383**	**-0.0003**	**0.015**	**0.015**	**0.00**	**0.014**
Sab	standard	1383	-0.0032	0.018	0.016	0.00	0.016
Scd	**hybrid**	**3900**	**-0.0011**	**0.024**	**0.019**	**0.18**	**0.019**
Scd	standard	3900	0.0006	0.025	0.020	0.23	0.020
SB	**hybrid**	**1288**	**-0.0014**	**0.038**	**0.021**	**0.70**	**0.022**
SB	standard	1288	0.0027	0.038	0.022	0.85	0.023
ALL	**hybrid**	**10067**	**-0.0008**	**0.023**	**0.016**	**0.19**	**0.016**
ALL	standard	10067	-0.0007	0.026	0.018	0.31	0.018

Conclusions

The proposed workflow, involving different methodologies by mixing for the first time in a single collaborative framework SED fitting and machine learning models, is able to improve the photo-z prediction accuracy by ~10%.

The performance are strongly depending on the class definition; therefore on the SED models selected and on the SED fitting setup.

When a proper classification is provided, the photo-z’s produced by ML methods would benefit.



GIVE

PEACE A

CHANCE