Update on photometric redshifts for galaxies with machine learning techniques

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Introduction

From groups of galaxies up to the Large-Scale Structure, the distance to extragalactic objects are of great interest for several studies. The current and future surveys will observe millions of galaxies over a large area in the sky and this poses a challenge for spectroscopic measurements, requiring a different approach to estimate distances using not the spectra, but the photometry. In this work we developed a deep-learning model that uses photometric and morphologic data from S-PLUS, GALEX, 2MASS, and unWISE, together with spectroscopic redshifts from several studies, to predict photometric redshifts for galaxies in S-PLUS.

Data

In the most recent version of the code, the spectroscopic sample was updated and more objects were included. In total the sample contains 512607 objects (galaxies, quasars and stars), of which 262521 galaxies remain after the following pre-processing selection:

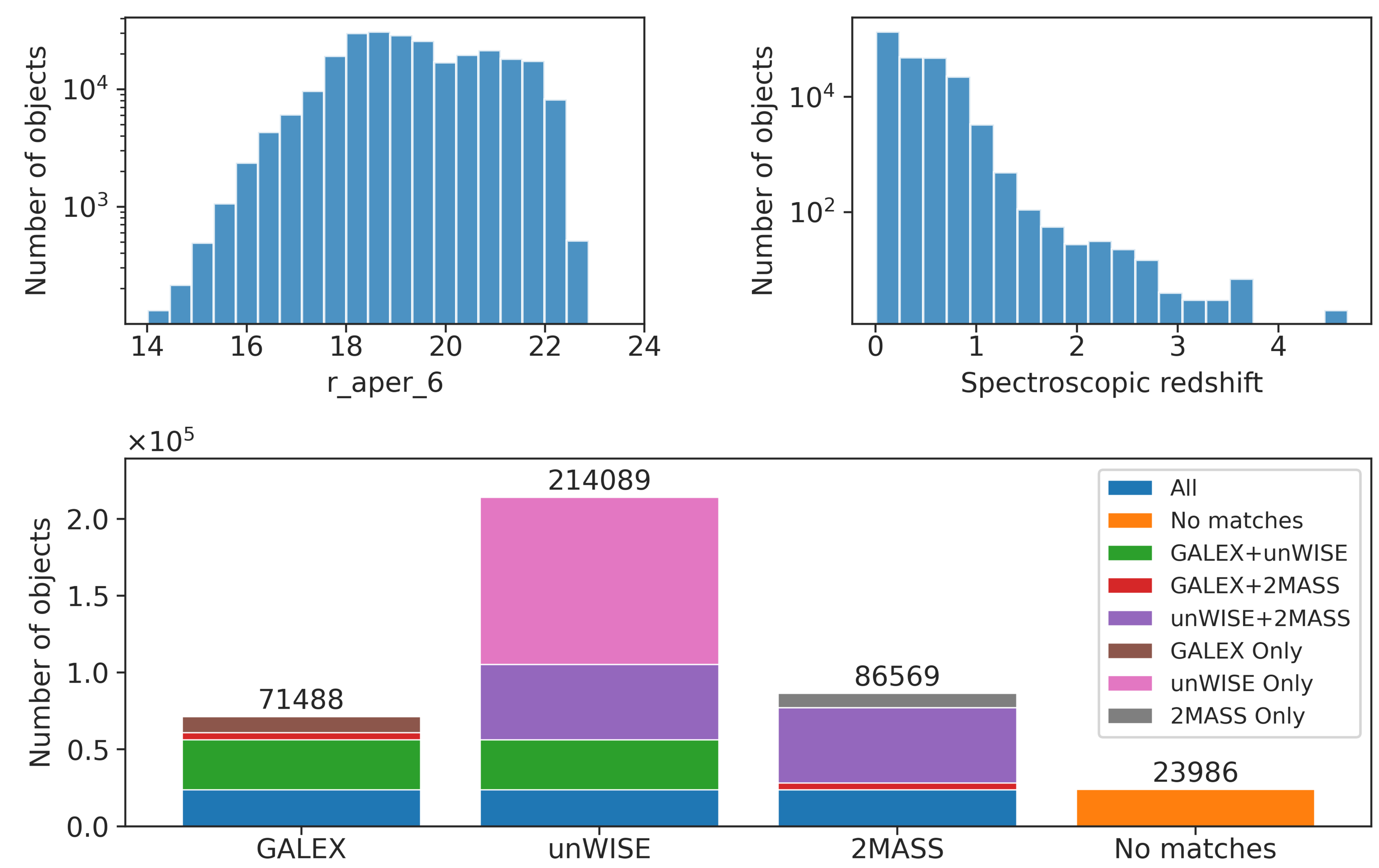
$$\begin{aligned}
&\texttt{r_aper_6} && \geq 14\\
&\texttt{e_r_aper_6} && \leq 0.5\\
&\texttt{nDet_aper_6} && \geq 1\\
&\texttt{z} && \geq 0.002\\
&\texttt{z_err} && \leq 0.002\\
&\texttt{class_spec} && \neq STAR \texttt{ or } \neq QSO
\end{aligned}$$

All these objects are crossmatched with GALEX, 2MASS, and unWISE to complement the photometric information of S-PLUS.

The spectroscopic redshifts were obtained from a compilation of surveys including SDSS, 2dFGRS, 2dFLens, 6dFGS, zCosmos, 2MRS, and others.

The plots on the left show the distribution of magnitudes in the r_aper_6 band, of spectroscopic redshifts, and the distribution of matches per photometric survey.

Compared to the previous version, the new pre-processing step does not limit the r_aper_6 magnitude, but does limit the error on this band.



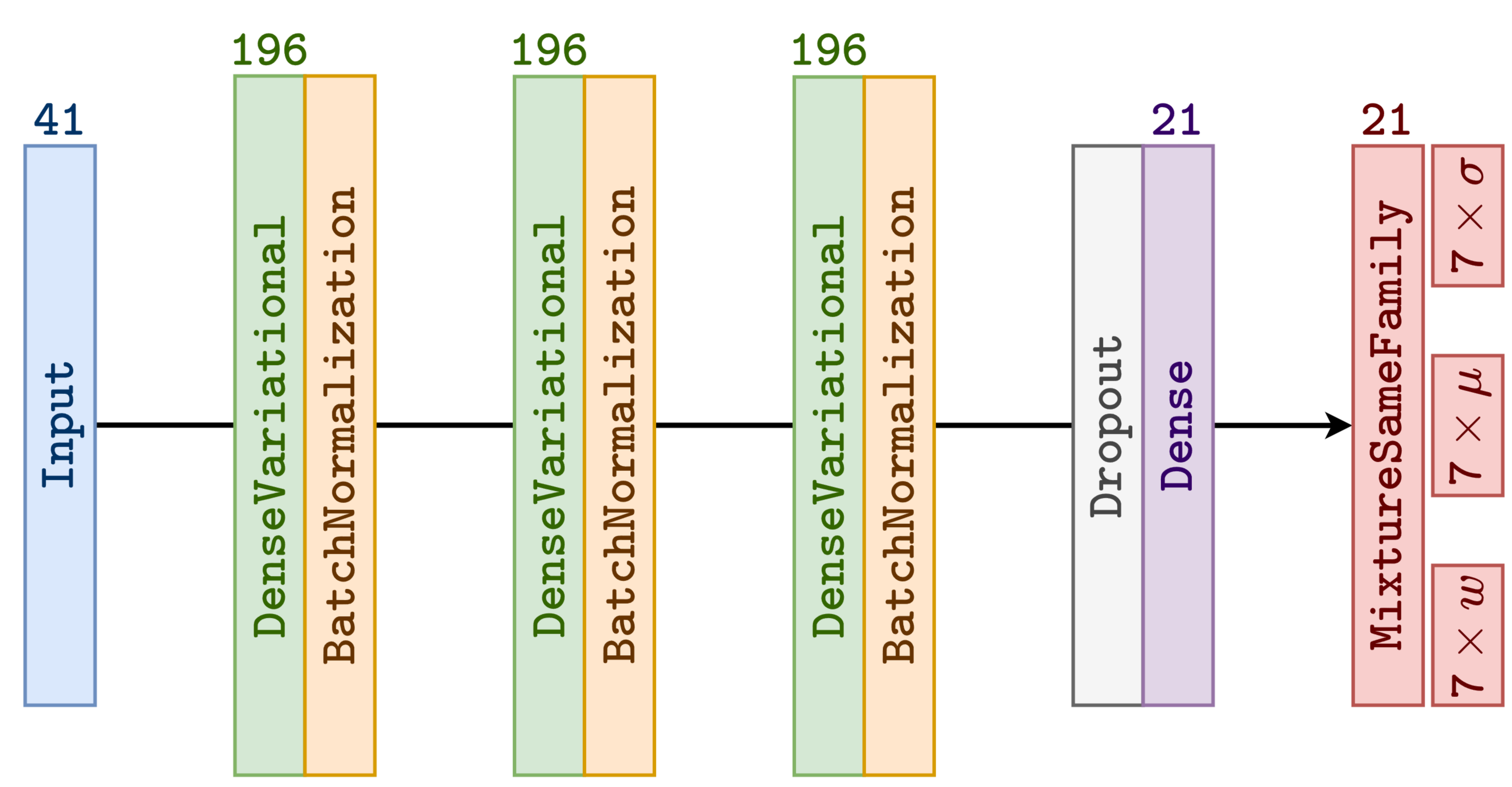
Methodology

The pre-processed sample is split into 90% for training and 10% for testing. Given the size of our sample these numbers allow a good training while also maintaining a reasonable amount of objects to analyse the results.

The data is then fed to a Bayesian Mixture Density Network. The configuration we use is a combination of a Bayesian Neural Network and a Mixture Density Network. This architecture provides a greater generalization capacity and can easily generate well-calibrated probability distribution functions (PDFs).

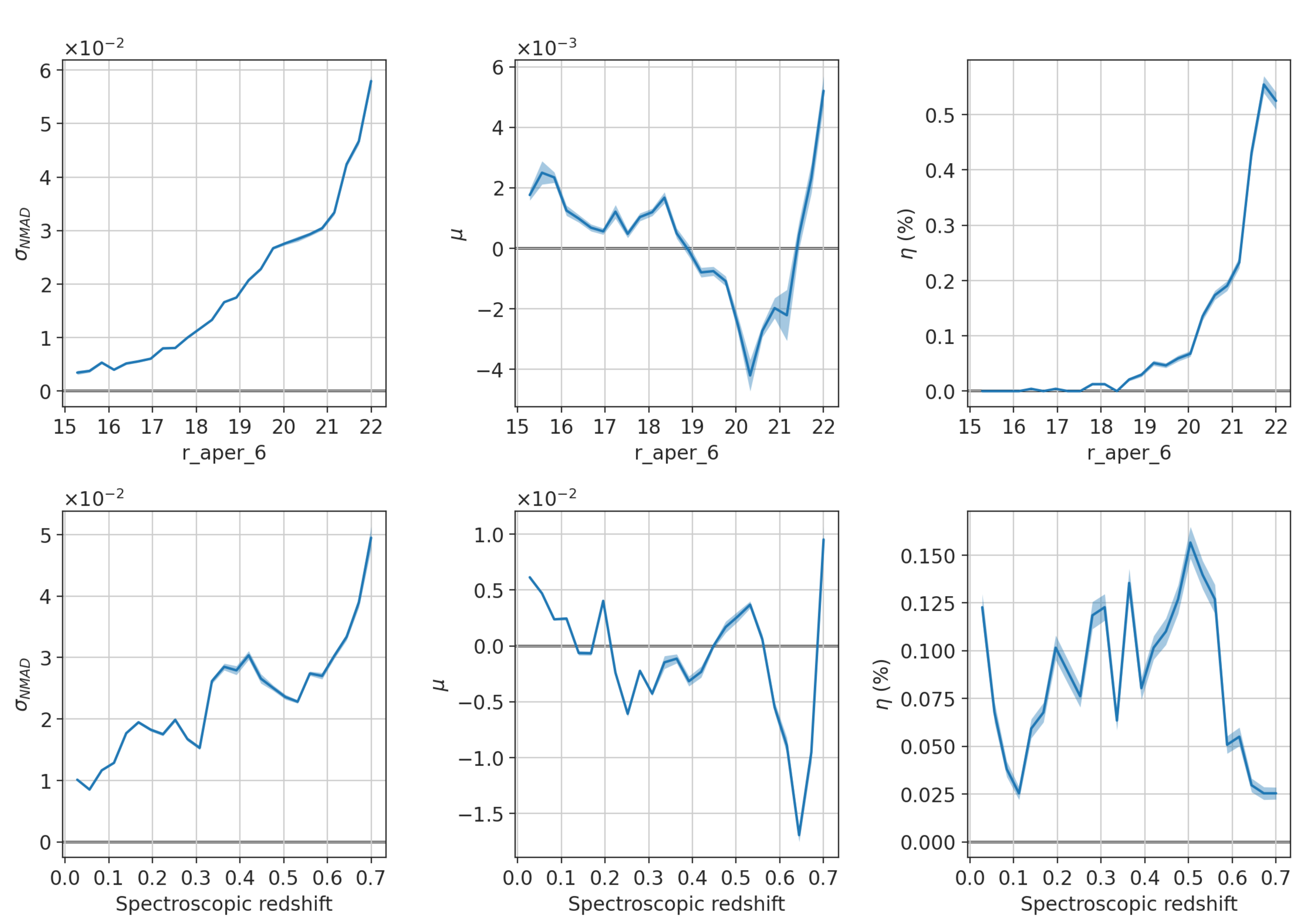
The PDFs generated are a combination of seven Gaussian functions. This number was chosen due to better results during testing.

Compared to the previous version, this architecture has a different number of input features, one additional `Dropout` layer and the PDF is generated from a different number of distributions (7 from 20)



Results

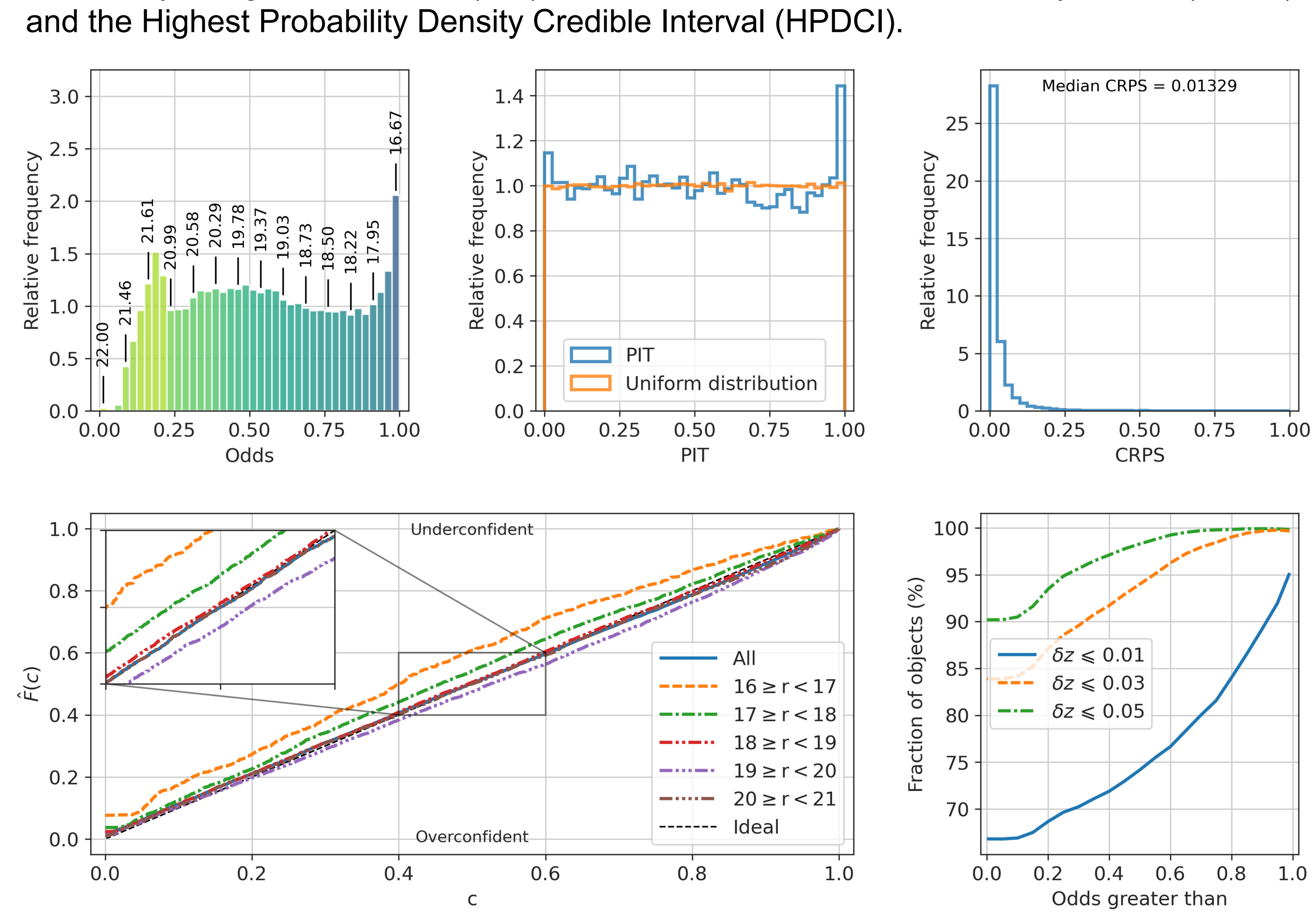
The single point results (SPE) are evaluated using the Normalized Mean Absolute Deviation (σ_{NMAD}), the normalized bias (μ), and the outlier fraction (η).



The results show a high accuracy, low bias and low outlier fraction for galaxies with r_aper_6 between 15 and 21.5 and/or spectroscopic redshift below 0.6. Since the training sample contains a low amount of low-z objects, the photometric redshifts are not reliable for objects with z_{spec} < 0.008.

Compared to the previous version, this architecture can estimate redshifts for fainter objects (up to r_aper_6 ~ 22, from 21.3) with a high precision, low bias and low outlier fraction.

The probability distribution function results are evaluated using the Odds values, the Probability Integral Transform (PIT), the Continuous Ranked Probability Score (CRPS), and the Highest Probability Density Credible Interval (HPDCI).



The metrics shown above indicate that the method is capable of generating well-calibrated PDFs, able to reliably represent the uncertainties in the predictions. The PDFs are narrower for brighter objects (lower uncertainty) and broader for fainter objects (higher uncertainty).

Compared to the previous version, this model generates PDFs with better calibration.

More details can be found at **http://tiny.cc/SPLUSPhotoz** or **arxiv.org/abs/2110.13901**.

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