

The Spitzer Extragalactic Representative Volume Survey - measuring photometric redshifts for ~ 4 million galaxies - challenges and ways forward

Janine Pforr

Scientific Support Office, Directorate of Science and Robotic Exploration,
European Space Research and Technology Centre, (ESA/ESTEC), Keplerlaan 1,
2201 AZ Noordwijk, The Netherlands
email: janine.pforr@esa.int, Research Fellow

Abstract. We highlight the challenges as well as lessons learnt in the derivation of the photometric redshifts for ~ 4 million galaxies at $0 < z \lesssim 6$ contained in the Spitzer Extragalactic Representative Volume Survey (SERVS) and summarise the photometric redshift results recently published in Pforr *et al.* (2019). The inhomogeneous nature of the ancillary photometry for SERVS presents a similar situation to the one future, large, extragalactic surveys with e.g. LSST and JWST will face. We employ template SED-fitting to determine photometric redshifts. Our comparison of photometric redshifts to $\sim 75,000$ public, spectroscopic redshifts results in an average σ_{NMAD} of ~ 0.038 and outlier fraction of 3.7% for sources with the best photometric coverage. We find that photometric redshifts are determined most robustly when filter bands are numerous and cover a wide wavelength range. We highlight some possible improvements for the photometric redshifts in SERVS in the future.

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1. The Spitzer Extragalactic Representative Volume Survey

Galaxy evolution studies have been driven by large galaxy surveys in the last decades. By now, some extragalactic fields are prime observation targets due to the large amount of existing ancillary data spanning a wide wavelength range. Particularly, for the robust derivation of photometric redshifts and other stellar population galaxy parameters such as age and stellar mass via spectral energy distribution (SED) fitting, a multi-wavelength approach is crucial. However, new facilities and technologies produce increasingly large data sets to process and analyse, providing a significant challenge for current tools and methods. One example large survey is the Spitzer Extragalactic Representative Volume Survey (SERVS; PI: M. Lacy; Mauduit *et al.* 2012) which covers five popular extragalactic fields in the 3.6 and 4.5 μm bands of the Spitzer Space Telescope Infrared Array Camera (IRAC, Fazio *et al.* 2004) carried out during the warm phase of the Spitzer Space Telescope mission. With a total of 18 deg^2 distributed over the Chandra Deep Field South (CDFS), ELAIS-South 1 (ES1), ELAIS-North 1 (EN1), Lockman Hole (LH) and XMM-LSS (XMM) fields SERVS is able to overcome cosmic variance. In this work we make use of the SERVS DR2 and data fusion containing photometry from the UV, optical, near- and mid-IR compiled by Vaccari (2015) (<http://www.mattivaccari.net/df>) and carry out a comparison between photometric and spectroscopic redshifts for sources detected in both IRAC bands down to the coverage-weighted signal to noise $\text{CSNR} = 3$

in both bands. Details about the survey and data fusion can be found in [Mauduit *et al.* \(2012\)](#) and [Vaccari \(2015\)](#), respectively.

2. The SERVS photometric redshifts

We determine the SERVS photometric redshifts via template spectral energy distribution (SED) fitting using the HYPERZ code package ([Bolzonella *et al.* 2000](#)). Depending on the specific SERVS field, we are able to use a maximum of 12 filter bands for the SED fitting ranging from the observed-frame UV to the IR. In order to match the various magnitude measurements and point spread function (PSF) differences between ancillary surveys and SERVS, we use apertures in each band as close to 1.9" (the SERVS flux measurement aperture we adopt) as possible.

The fitting is then carried out using model template spectra. These template spectra are based on the [Maraston \(2005\)](#) stellar population models for a [Salpeter \(1955\)](#) initial mass function and 221 age steps, and have exponentially declining star formation histories (SFHs), so called τ -models with e-folding times of $\tau=0.1, 0.3, 1.0$ and 2.0 Gyr. Our setup contains each τ -model in four metallicity flavours, i.e. $1/5, 1/2, 1,$ and 2 solar metallicity. We restrict the age of the model in the fitting to 0.1 Gyr as minimum and the age of the Universe at the probed redshift as the maximum. We further use a [Calzetti *et al.* 2000](#) dust reddening law with values of $A_V=0$ to 3 in steps of 0.2 . Each template is then redshifted from 0 to 6 in steps of 0.01 . The reduced χ^2 , χ_r^2 , is calculated for each template for each object. The template with the lowest χ_r^2 is deemed the best fit for that object and provides its photometric redshift. This template setup was chosen according to the findings of [Pforr *et al.* \(2013\)](#) who found this setup to provide a good compromise between CPU runtime and photometric redshift accuracy as determined with the help of simulated galaxies from a galaxy formation model.

In order to evaluate the photometric redshifts for SERVS, we compare the photometric with ~ 75000 publicly available spectroscopic redshifts and compute the normalised median absolute deviation $\sigma_{\text{NMAD}} = 1.48 \times \text{median}[\frac{|\Delta z - \text{median}(\Delta z)|}{(1+z_{\text{spec}})}]$ ([Huber 1981](#); [Hoaglin *et al.* 1983](#)) with $\Delta z = z_{\text{spec}} - z_{\text{phot}}$, and the percentage of catastrophic outliers (outlier fraction η) defined as $|\Delta z| > 0.15 \times (1 + z_{\text{spec}})$. Both quantities are commonly used to evaluate the photometric redshift success (e.g., [Brammer *et al.* 2009](#); [Dahlen *et al.* 2013](#)).

We investigate the dependency of σ_{NMAD} and outlier fraction η as a function of number of photometric filter bands in the fitting, for each SERVS fields, for each spectroscopic redshift source catalogue in the XMM field, and for SERVS as a whole, and as a function of i-band magnitude for each SERVS field. We find that overall, the photometric redshifts are determined best (smallest σ_{NMAD} and η) when the wavelength coverage is large, i.e. more filter bands are used in the fitting. We find a $\sigma_{\text{NMAD}} = 0.038$ and an outlier fraction $\eta < 4\%$ for sources with the largest number of filter bands. We also find that photometric redshifts are determined best for the brightest objects. The majority of SERVS sources lie at $z < 1.5$. Details about the method and the dependency of the photometric redshift accuracy can be found in [Pforr *et al.* \(2019\)](#).

3. Challenges for the SERVS photometric redshifts

The determination of photometric redshifts for SERVS faces several, non-trivial challenges. The first challenge is presented by the inhomogeneity of the ancillary data set. SERVS itself covers a much larger area than most of the optical and near-IR surveys available in the SERVS fields. Unsurprisingly, the deepest data is only available in very small areas such as portions of the CDFS field. On the other hand, much shallower data exists for almost each of the fields yet often only in a few filter bands. While we select

ancillary data in order to strike the best compromise between survey depth and area, differences between the surveys still arise. Differences are, e.g., the different PSF sizes between the optical, near-IR and Spitzer surveys which hamper source matching and deblending across different surveys, and different types of magnitude measurements such as AUTO vs corrected and uncorrected aperture magnitudes.

Another challenge arises from the spectroscopic surveys used to evaluate the reliability and robustness of the photometric redshifts. While there are plenty of spectroscopic redshifts available from a variety of surveys, they inherit their own selection function, often dictated by brightness limits. Consequently, often only the brightest objects with the best photometric wavelength coverage also have spectroscopic redshifts creating a potential bias for fainter, or more distant objects. Additionally, depending on the spectral resolution, the spectroscopic redshifts have different accuracies.

Finally, the number of sources to process provides a significant computing challenge in terms of CPU hours and disk storage space, a situation only expected to worsen with the advancement of new and larger facilities.

4. Possible improvements for the SERVS photometric redshifts

Given the challenges highlighted in Section 3 several methods could be used to improve future iterations of the SERVS photo-z and those of up-coming surveys. We highlight the following three examples.

Data homogenisation: In order to homogenise the data, recent surveys, e.g. CANDELS, have taken the approach of using so-called forced photometry for the creation of their multi-wavelength photometry which is subsequently used for the SED-fitting (Guo *et al.* 2013; Galametz *et al.* 2013). The goal of this technique is to improve the accuracy of the multi-band photometry for catalogues containing surveys with disparate angular resolutions. An example of an application of this type of technique to a large database is given in Lang (2016) which employed *The Tractor* image modelling code. *The Tractor* uses information on source positions, brightnesses, and shape parameters to model the source surface brightness profile at high resolution. This high resolution model is then convolved with the PSF of the other bands in the database with lower resolutions, thus ensuring accurate source cross-matching between bands, improved sensitivity to inherently faint sources, and deblending of sources in the lower resolution bands. For SERVS galaxies, this method gains fluxes for some bands that did not have an entry in the publicly available catalogues before (i.e. non-detections) and deals with blending issues in the IRAC photometry as shown by Nyland *et al.* (2017) for 1 deg² in the SERVS XMM field. Specifically, Nyland *et al.* (2017) were able to double the number of sources for which the maximum number of filter bands is available for the fitting which in turn greatly increases the number of accurate photometric redshifts compared to the position-matched catalogues. Additionally, in Nyland *et al.* (2017) the number of high-redshift sources (i.e. $z > 4$) increased due to the better photometry. However, for a survey of the size of SERVS the forced photometry approach results in a significant amount of reprocessing of ancillary data and presents a considerable computational challenge. Nevertheless, an effort to derive forced photometry for all SERVS sources is currently underway.

Computing-related issues: One major challenge for large surveys, existing and up-coming, relates to computing in terms of CPU runtime of any data analysis codes, and data storage of raw, reduced, and processed data. However, CPU runtime can be improved for example by parallelising and optimising existing codes. Alternatively, GPU processing offers new ways of fast computing. Data processing can then be carried out on large supercomputers to use many CPUs or GPUs simultaneously. Particularly for large surveys, standard data processing pipelines could be considered to offer easier access to processed and value-added data for large numbers of users.

Optimisation of the SED-fitting: Finally, the SED-fitting could be optimised itself, for example by using different sets of templates for specific objects such as AGN. Additionally, deeper photometric data could be used where it exists even if only for a comparatively small number of sources instead of the compromise we made by using shallower data that covers most of the fields. Finally, new fitting approaches such as those using neural networks, MCMC based codes and machine learning techniques could be employed (see, e.g., [Acquaviva et al. 2011](#)).

5. Summary

We provide a brief overview of the SERVS survey and the photometric redshifts ([Pforr et al. 2019](#)), highlighting the challenges of large data sets and inhomogeneous ancillary data in the photometric redshift determination. We further discuss improvements that can be made for SERVS and future, large surveys, such as data homogenisation via forced photometry, improvements in computing, and optimisation of the SED-fitting.

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Discussion

DAVID ROSARIO: Can you comment on the relative merits and performance of a model-based photo-z approach versus a pure template-based approach (often used for AGN, but also used for galaxies in XMM-XXL for instance)?

JANINE PFORR: Pure template based approaches have produced very good photo-z results in the past, particularly for AGN (see [Salvato et al. 2009](#)). Important for photo-z derivation is that the SED shapes in the sample are adequately covered by the templates. However, care has to be taken not to include too many options in order to avoid degeneracies which can result in catastrophic outliers. This might be easier to achieve with a pure template based approach. Overall, the last years have seen many excellent photo-z estimates using both approaches.

VÉRONIQUE BUAT: You mentioned that your data are similar (come from?) the data fusion results of the HELP project. Did you compare photo-z measures to those produced by HELP ([Duncan et al. 2018](#) for the method) in the same fields?

JANINE PFORR: Mattia Vaccari created the data fusion for SERVS and for the HELP project, so similar approaches were used for both. I have not yet compared the SERVS photo-z to other photo-z estimates for the same objects from other photo-z efforts, since the focus of the [Pforr et al. \(2019\)](#) paper was the comparison to spectroscopic redshifts and our overall photo-z robustness. We can certainly compare the different photo-z estimates in the future to learn about differences, similarities, and odd sources.

DENIS BURGARELLA: We see bumps in the redshift distribution at, for instance $z = 3$, $z = 5$. Are they real?

JANINE PFORR: Any structures in the high- z photo-z distribution need further investigation for several reasons. 1) Shown are only objects with more than 5 (8) filter bands available in the fitting, which biases the distribution particularly at high z where sources are more likely to be detected in fewer bands. I showed how this could be improved with forced photometry. 2) At high- z SERVS is only sensitive to the brightest and most massive galaxies. 3) We have very few z_{spec} available to test our photo-z at high redshift.