

Stellar Population Photometric Synthesis with AI of S-PLUS galaxies

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Abstract. We trained a Neural Network that can obtain selected STARLIGHT parameters directly from S-PLUS photometry. The training set consisted of over 55 thousand galaxies with their stellar population parameters obtained from a STARLIGHT application by [Cid Fernandes *et al.* \(2005\)](#). These galaxies were crossmatched with the S-PLUS iDR 3 database, thus, recovering the photometry for the 12 band filters for 55803 objects. We also considered the spectroscopic redshift for each object which was obtained from the SDSS. Finally, we trained a fully connected Neural Network with the 12-band photometry + redshift as features, and targeted some of the STARLIGHT parameters, such as stellar mass and mean stellar age. The model performed very well for some parameters, for example, the stellar mass, with an error of 0.23 dex. In the future, we aim to apply the model to all S-PLUS galaxies, obtaining never-before-seen photometric synthesis for most objects in the catalogue.

Keywords. galaxies, stellar populations, machine learning

1. Introduction

As astronomical surveys get more complex, the amount of data produced increases year after year. This has created a need for robust statistical tools that can operate on massive amounts of data and reliably find relationships between data parameters without dealing with each object separately.

The knowledge of intrinsic parameters of galaxies, such as stellar mass and mean stellar age, is a necessary part of understanding how a galaxy operates. Such parameters can be obtained through spectral energy distribution (SED) fitting. Although this process yields significant results, obtaining the spectrum in the first place can be a difficult task. Photometric surveys tackle this observational problem by providing the photometry of each object in several bands. While the spectrum has more information, the photometry of galaxies can be measured much easily in photometric surveys like the Southern Photometric Local Universe Survey (S-PLUS, [Mendes de Oliveira *et al.* 2019](#)). In this work, we aim to create a tool that can predict stellar population parameters directly from S-PLUS photometry using machine learning techniques.

2. Methodology and Results

To create this machine learning tool, we have used supervised learning. We needed large amounts of robust data, both for the inputs (photometry) and the outputs (stellar population parameters). This model is intended to be applied to S-PLUS data, thus the photometry was gathered directly from the S-PLUS iDR3. The redshift plays a significant role in determining such parameters, so we also collected the Sloan Digital Sky Survey (SDSS)-IV ([Blanton *et al.* 2017](#)) spectroscopic redshift for each object from the

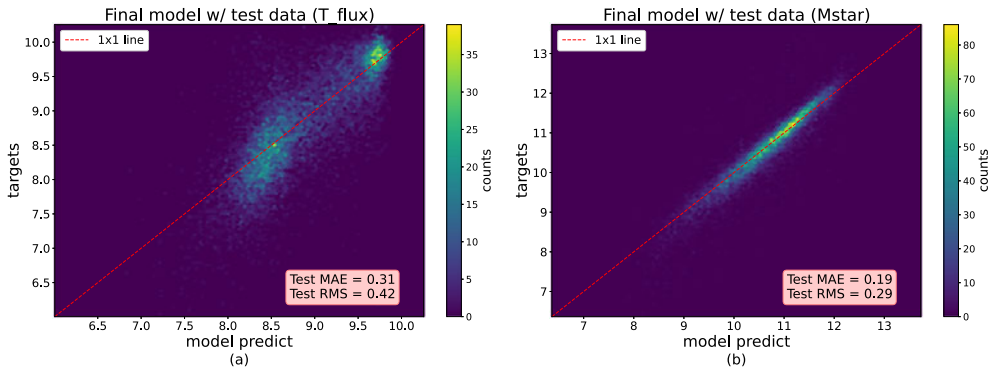


Figure 1. Prediction plots for: (a) mean star age weighted by flux; (b) stellar mass. The MAE and RMS of the test set is depicted, as well as the 1 x 1 line.

extended Baryon Oscillation Spectroscopic Survey (eBOSS, Dawson *et al.* 2016). We used the stellar population parameters from a STARLIGHT (Cid Fernandes *et al.* 2005) application to the SDSS. We decided to use 11 different parameters that could be interesting for astronomers, including age, metallicity, stellar mass, and others. After crossmatching all databases, we ended up with data for 55803 objects. Each object is detected in the 12 S-PLUS photometric bands, is matched with an SDSS spectroscopic redshift, and is associated with STARLIGHT fits to the 11 target parameters.

Our objective was to solve a regression problem. While we can use many different models, we eventually found from testing that a Neural Network had the best performance. We chose a fully-connected feed-forward architecture for this network with just two hidden layers. The input layer had 13 nodes (12 magnitudes + 1 redshift), and the output had a single node (one parameter). We used the Keras framework (Keras *et al.* 2015) and evaluated the performance of each network using the Mean Average Error (MAE) and Root Mean Square Error (RMS).

Out of the 11 parameters we predicted, 8 of them presented satisfying results with an adequate MAE and RMS by comparing it to a baseline zero rule prediction algorithm. The 8 parameters are: visible absorption, velocity dispersion, mean star age weighted by flux and by mass, metallicity weighted by flux and by mass, stellar mass and stellar star formation rate. The results for age and stellar mass are depicted in Figure 1.

3. Conclusions

In this work, we created a machine learning tool that can reliably predict eight stellar population parameters directly from S-PLUS photometry. Better network performance can still be achieved, but we are now interested in applying each network to the whole S-PLUS database using photometric redshifts.

In the following months, we will achieve new, never-before-seen parameters for thousands of galaxies in the S-PLUS catalogue and study the properties of the galaxy population as described by these parameters. The method used here can be generalized to other photometric surveys, such as J-PAS, J-PLUS, and others.

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