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ProMage: fast galaxy magnitudes emulation combining SED forward-modelling and machine learning

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Abstract. We present ProMage, a feed-forward neural network that emulates the computation of observer- and rest-frame magnitudes from the SED generation package ProSpect. The network predicts magnitudes conditioned on input galaxy physical properties, including redshift, star formation history, gas and dust parameters. ProMage accelerates magnitude computation by a factor of 10^4 compared to ProSpect, while achieving per-mille relative accuracy for 99% of sources in the test set across the g, r, i, z, y Hyper Suprime-Cam bands. This acceleration is key to enabling fast inference of galaxy physical properties in next-generation Stage IV surveys and to generating large catalogue realisations in forward-modelling frameworks such as GalSBI-SPS.

Keywords. galaxies: stellar content, galaxies: fundamental parameters, methods: numerical, galaxies: statistics

1. Introduction

We are entering an era of unprecedented astronomical datasets with the advent of Stage IV galaxy surveys (Albrecht et al. 2006), such as Euclid (Euclid Collaboration et al. 2025), the Vera C. Rubin Observatory's Legacy Survey of Space and Time (hereafter, Rubin-LSST, Ivezić et al. 2019), DESI (DESI Collaboration et al. 2022), and 4MOST (de Jong et al. 2019). These surveys will measure positions, magnitudes, and shapes for billions of galaxies, and redshifts for tens of millions of them, enabling transformative advances in cosmology and galaxy evolution. However, the statistical power of these datasets makes systematic uncertainties the dominant limitation. For example, weak-lensing cosmology depends critically on accurate galaxy redshift distributions (Newman & Gruen 2022), motivating the use of forward-modelling approaches that generate realistic synthetic surveys constrained against real data to provide the required accuracy on the redshift distributions (Fischbacher et al. 2025; Tortorelli et al. 2025; Thorp et al. 2025). At the same time, the inference of galaxy physical properties for billions of galaxies demands orders-of-magnitude improvements in modelling efficiency.

Both forward-modelling and the inference of physical properties rely on spectral energy distribution (SED) generative codes, which connect galaxy physical properties to their observable stellar emission through stellar population synthesis (SPS; Conroy 2013).

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Table 1. Prior range for the network input parameters.

Parameter Name	Logarithmic	Prior range
z	No	$[0, 5]$
mSFR	Yes	$[-3, 4]$
mpeak	No	$[-(2 + t_{\rm lb}), 13.4 - t_{\rm lb}]$
mperiod	Yes	$[\log(0.3), 2]$
mskew	No	$[-0.5, 1]$
$Z_{\rm final}$	Yes	$[-4, -1.3]$
$\log U$	No	$[-4, -1]$
$\tau_{\rm birth}$	Yes	$[-2.5, 1.5]$
$\tau_{\rm screen}$	Yes	$[-2.5, 1]$
$\alpha_{\rm SF,birth}$	No	$[0, 4]$
$\alpha_{\rm SF,screen}$	No	$[0, 4]$

Codes such as FSPS (Conroy et al. 2009) and ProSpect (Robotham et al. 2020) provide physically consistent predictions, but their runtimes (tens of seconds for FSPS, tens of milliseconds for ProSpect) remain prohibitive for generating many synthetic survey realisations or running large-scale Monte Carlo Markov Chain (MCMC) inference of galaxy properties. Accelerating SPS predictions while preserving accuracy is therefore essential (see also Hearin et al. 2023; Alsing et al. 2020).

To address this, we introduce ProMage (**Pro**Spect **Mag**nitude **e**mulator), a feed-forward neural network that emulates galaxy magnitudes in observer and rest frames computed with ProSpect. Trained on physical inputs (redshift, star formation history, dust, gas parameters), ProMage predicts individual bands independently, simplifying extension to new filters and parameter spaces. It delivers a factor of $\sim 10^4$ speed-up in computation with respect to ProSpect, evaluating magnitudes for 10^5 sources in less than half a second, while maintaining per-mille accuracy across Hyper-Suprime Cam (HSC) g, r, i, z, y bands. This performance enables both efficient forward-modelling with GalSBI-SPS (Tortorelli et al. 2025) and scalable inference of galaxy properties for Stage IV surveys, including amortised simulation-based inference (Cranmer et al. 2020) and accelerated MCMC. ProMage is already implemented within GalSBI-SPS and will also be released as a standalone module for ProSpect.

2. Training sample

We train ProMage on observer- and rest-frame magnitudes generated with ProSpect in the g, r, i, z, y HSC bands. HSC is an ideal test case, given its depth and galaxy density, making it a precursor to Stage IV surveys. Tests conducted on different neural network architectures show that prediction accuracy improves, at fixed training set size, when networks are trained per band, consistent with results from Alsing et al. (2020); Thorp et al. (2025).

ProMage predicts total galaxy magnitudes conditioned on the physical inputs used by ProSpect, excluding AGN for now. Stellar emission is based on a custom single stellar population (SSP) created with ProGeny (Robotham & Bellstedt 2025; Bellstedt & Robotham 2025), using MIST isochrones (Dotter 2016), C3K spectra (Conroy et al. 2018), and a Chabrier (2003) IMF. Star-formation histories follow the truncated skewed Normal form of Robotham et al. (2020), parameterised by the peak SFR (mSFR), peak time (mpeak), width (mperiod), and skewness (mskew). Gas-phase metallicity histories are tied to stellar mass growth (Driver et al. 2013; Bellstedt et al. 2021), governed by the final metallicity $Z_{\rm final}$. Coupled with the ionisation parameter $\log U$, these control nebular emission through MAPPINGS-III tables (Levesque et al. 2010). Dust attenuation follows the two-phase model of Charlot & Fall (2000), with $\tau_{\rm screen}$

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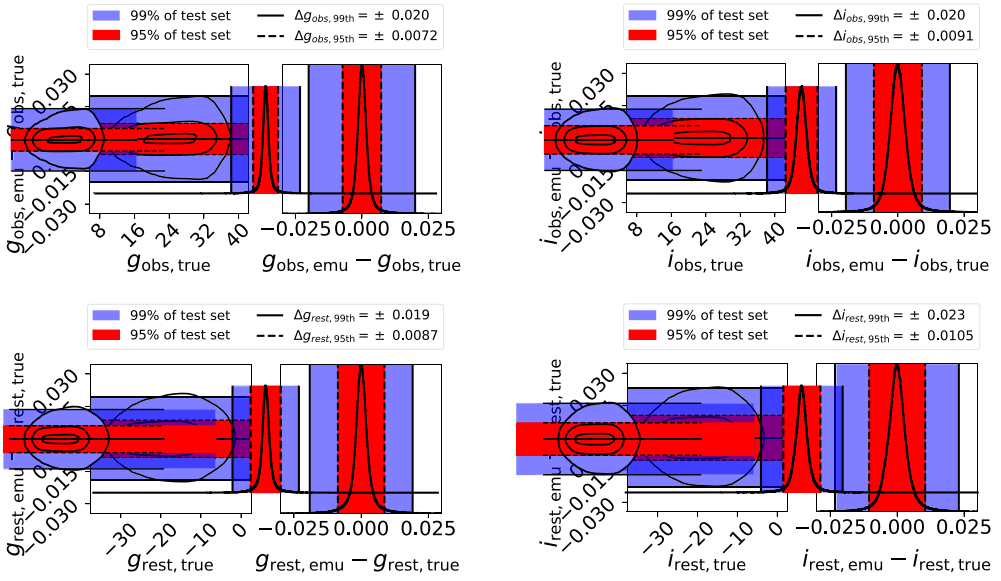


Figure 1. Figure showing the performance of ProMage in emulating galaxy magnitudes computed with ProSpect. The left panels refer to the g-band, while the right panels to the i-band, with upper and lower panels referring to observer ('obs') and rest-frame ('rest') magnitudes, respectively. We report both the histograms of the prediction accuracy and their distribution as function of the true input magnitude. Red and blue bands represent the ranges containing 95% and 99% of the samples, while the dashed and solid lines represent the 95th and 99th percentile values for each case. In all reported cases, 99% of the galaxies in the test set have an absolute difference with respect to the true input magnitude of $\Delta m < 0.02$. The prediction accuracy is even higher, $\Delta m < 0.01$, for 95% of galaxies. Similar performance occurs for the other HSC optical bands.

for stars older than 10 Myr and $\tau_{\rm birth}$ for younger stars. Dust emission is added using Dale et al. (2014) templates, parameterised by $\alpha_{\rm SF,screen}$ and $\alpha_{\rm SF,birth}$.

These ten physical parameters plus redshift z constitute the inputs to the network. We generate training data by sampling 10^7 galaxies in the redshift range $0 < z < 5$. with Latin hypercube sampling. ProSpect is then used to compute the true observer- and rest-frame magnitudes in the five HSC bands. Sampling ranges for the input quantities are listed in Table 1, with output magnitudes spanning a wide range in i-band observer-frame, $5 < i < 35$.

3. Network architecture and training phase

ProMage is implemented in PyTorch (Paszke et al. 2019) as a feed-forward neural network with five hidden dense layers of $[512, 256, 128, 64, 32]$ neurons. Inputs are 11-dimensional, scaled with a standard scaler, and mapped to a single magnitude output. The dataset is split into 80% training, 10% validation, and 10% testing. We also tested a Speculator-like architecture with four 128-neuron layers, but the deeper network achieved higher accuracy; an additional final 32-neuron layer is included to stabilise extreme predictions.

We adopt the activation function of Alsing et al. (2020), with γ and β initialised to 1 and 0.1, respectively, and optimised during training. The loss function is the mean squared error, evaluated on the original magnitudes values rather than the scaled ones. Training uses the Adam optimiser with batch size 64, a maximum of 200 epochs, and early stopping after 20 epochs without validation loss improvement. The learning rate starts at

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10^{-3} and is reduced adaptively with `ReduceLROnPlateau`. Separate networks are trained for each band (observer- and rest-frame). The network training phase is performed on the EL-9 cluster of the Leibniz Supercomputing Centre with a single Nvidia A100 GPU.

4. Results

We show in Fig. 1 results for the g and i observer- and rest-frame HSC bands, representative of the overall performance. The left panels display the prediction accuracies (difference between emulated and true magnitudes) for the observer and rest-frame g-band, while the right panels for the i-band. The results are based on a test set of 10^6 sources, evaluated in under three seconds on a Mac M1 CPU, corresponding to a 10^4 speed-up compared to ProSpect. The network achieves sub-percent relative accuracy for all sources and per-mille accuracy for 99% of them. Absolute errors are < 0.02 mag for 99% of galaxies and < 0.01 mag for 95% of them across all bands, in both observer and rest-frame. These values are below the typical photometric zero-point uncertainties of Stage III surveys (Wright et al. 2024), and comparable or lower than the expected photometric precision of Stage IV surveys, such as Rubin-LSST (Crenshaw et al. 2024). This demonstrates that the emulator is well suited both for galaxy property inference and for forward-modelling applications, where sensitivity to changes in SED model prescriptions depends critically on photometric accuracy (Tortorelli et al. 2024).

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