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DESI Speculator: Stellar Population Synthesis emulator for PROVA-BGS

K. J. Kwon[1,2] and ChangHoon Hahn[3]

[1]Department of Astronomy, University of California, Berkeley, CA 94720-3411, USA
[2]Department of Physics, University of California, Berkeley, CA 94720-3411, USA
[3]Department of Astrophysical Sciences, Princeton University, 4 Ivy Ln, Princeton, NJ 08544, USA

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ABSTRACT

We train a neural net emulation model for stellar population synthesis, Speculator (Alsing et al. 2020) to predict DESI galaxy spectra and photometry. . We confirm that DESI Speculator reproduces the same SEDs generated by FSPS given a set of galaxy properties with percent level accuracy. We further demonstrate that DESI Speculator can be used to construct PRObabilistic-VAlue Added Bright Galaxy Survey (PROVA-BGS) from upcoming BGS surveys.

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validation

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1. INTRODUCTION

1.1. *SPS Models*

1.1.1. Fsps

Stellar population synthesis (SPS) technique parameterizes the spectral energy distributions of galaxies in terms of their stellar and dust properties; the properties of galaxies can be estimated by evaluating SPS with their SEDs, and vice versa. However, galaxy evolution extensively pertains to complicatedly interweaved factors that we do not have clear understanding on, and investigation by Conroy et al. (2009) and Conroy & Gunn (2010) demonstrated that neglecting such factors can lead to systematic errors in derived properties of galaxies. Thus, providing and propagating adequate uncertainties of SPS parameters are critical components in SPS evaluation. Flexible Stellar Population Synthesis (Fsps) developed by Conroy et al. (2009) and Conroy & Gunn (2010) is one of the publicly available SPS models that is capable of flexibly propagating uncertainties.

Table 1. Fsps model parameters

Parameters	Description	Priors
τ		$\mathcal{U}(0.1, 10)$
Z_{metal}		$\mathcal{U}(-3, 1)$
dust_1	Dust parameter describing the attenuation of young stellar light	$\mathcal{U}(0, 4)$
dust_2	Dust parameter describing the attenuation of old stellar light	$\mathcal{U}(0, 4)$
$\mathrm{dust}_{\mathrm{index}}$		$\mathcal{U}(-2.2, 0.4)$
$\log M^*$	log Total mass in $M_\odot$	$\mathcal{U}(8, 13)$

kgb0255@berkeley.edu

Motivated by the capability of Fsps in uncertainty propagation, we utilize `python-fsps`[1] (Foreman-Mackey et al. 2014), the python implementation of Fsps, to evaluate SPS and obtain SEDs. The model parameters that were used are given in Table 1. Foreman-Mackey et al. (2013)

1.1.2. Speculator

Speculator by Alsing et al. (2020), is a neural net framework that emulates Fsps. It computes the galaxy SEDs by predicting the basis coefficients of the basis functions, which are obtained by performing PCA decomposition on SPS parameters. The star formation and chemical enrichment histories are represented as linear combinations of pre-determined basis functions. The basis functions are functions of lookback time and were obtained by applying a non-negative matrix factorization to the set of simulated star formation and chemical enrichment histories. As Speculator targets to emulate Fsps, Speculator takes the same SPS model parameters, but with the star formation and chemical enrichment histories parameters decomposed into basis functions. Compared to Fsps, Speculator is 10^4-10^5 faster in generating predicted SEDs and possibly gains

2. SPECULATOR TRAINING

To construct the training data set for Desi Speculator, we first sample large amount of training parameters from the priors listed in Table 2. For Complex dust model training, we include two additional dust parameters as well as the parameters used in Simple dust model training. We generated 5 million combinations of training parameters, which we fed in Fsps to obtain 5 million galaxy spectral energy distributions. Each SED is shifted and scaled for normalization. To initiate the training, we bin SEDs into three wavelength ranges: $2300\text{Å} \leq \lambda < 4500\text{Å}$, $4500\text{Å} \leq \lambda < 6500\text{Å}, 6500\text{Å} \leq \lambda < 11030\text{Å}$. Each binned SED is decomposed with N_{pca} principal component basis vectors, where N_{pca} varies between the wavelength bins. We empirically find that $N_{pca} = 50, 50, 30$ is optimal. The details about the validation are given in Section 3.

Table 2. The training parameters for DESI Speculator

Parameters	Description	Priors
β_1^{SFH}, β_2^{SFH}, β_3^{SFH}, β_4^{SFH}	Star formation history basis function coefficients	$\mathcal{U}(0, 1)$
γ_1^{ZH}, γ_2^{ZH}	Metallicty enrichment history basis function coefficients	$\mathcal{U}(6.5\text{e}{-3}, 7.5\text{e}{-3}$
dust_1	Dust parameter describing the attenuation of young stellar light	$\mathcal{U}(0, 3.5)$
dust_2	Dust parameter describing the attenuation of old stellar light	$\mathcal{U}(0, 4)$
$\text{dust}_{\text{index}}$		$\mathcal{U}(-2.5, 0.5)$
$\log M^*$	log Total mass in $M_\odot$	$\mathcal{U}(8.6, 13.8)$

3. SPECULATOR VALIDATION

3.1. *Methodology*

For validation,we generate another set of parameters theattest. We run these paramteers through FSPS to generate SEDs. We again decompose the SEDs into PCA coefficients. Then validate PCA coefficients and SED. Some plots here. (Fractional error, cumulative error).

4. SPECULATOR SIMULATION

4.1. *SED Generation*

Simulate galaxy properties using l-gal library from igal 0-96. Run jobs to infer galaxy properties (MCMC). Do this with both speculator and fsps.

4.2. *Comparison with* FSPS

Similar plots as DESI UG Research Forum, but with FSPS $\hat{\theta}$, not True θ. Explain quantitatively about accuracies.

[1] https://github.com/dfm/python-fsps

5. CONCLUSION

DESI SPECULATOR achieves $< 1\%$ accuracy. Can be used for PROVA-BGS because it's much faster and sufficiently accurate.

6. ACKNOWLEDGEMENT

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