Modeling the Spectral Energy Distributions of High-Redshift Galaxies in the Era of JWST

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Why do we model the spectral energy distribution (SED) of galaxies?

Typically, we want to measure some relevant physical quantity (e.g., redshift, stellar population properties, nebular properties, dust properties, etc.).

Some of the Most Common SED Modeling Codes

- *BAGPIPES*
  - https://bagpipes.readthedocs.io/en/latest/
  - https://github.com/ACCarnall/bagpipes
  - https://ui.adsabs.harvard.edu/abs/2018MNRAS.480.4379C/abstract
- *BEAGLE*
  - http://www.jacopochevallard.org/beagle/
  - https://github.com/jacopo-chevallard/PyP-BEAGLE
  - https://ui.adsabs.harvard.edu/abs/2016MNRAS.462.1415C/abstract
- *Prospector*
  - https://github.com/bd-j/prospector
  - https://prospect.readthedocs.io/en/latest/
  - https://ui.adsabs.harvard.edu/abs/2021ApJS..254...22J/abstract

Summary of BAGPIPES

- Sampling the posteriors
  - Nested sampling with MultiNest
- Stellar population synthesis
  - 2016 version of the Bruzual & Charlot (2003) models
- Available star formation histories
  - Parametric
    - Constant
    - Exponential decay
    - Delayed-exponential decay
    - Double power law
    - Log-normal
  - Non-parametric
    - Variable age bins (from Iyer et al. 2019)
    - Fixed age bins (from Leja et al. 2019 and Johnson et al. 2021)
- Available dust attenuation laws
  - Models from Calzetti et al. (2000)
  - Models from Cardelli et al. (1989)
  - Models from Charlot & Fall (2000)
  - Models from Salim et al. (2018)
- Dust emission
  - Models from Draine & Li (2007)
- Nebular emission
  - CLOUDY implementation via Byler et al. (2017)

Summary of Prospector

- Sampling the posteriors
  - Ensemble sampling with emcee
  - Nested sampling with dynesty
- Stellar population synthesis
  - FSPS (Conroy et al. 2009; Conroy & Gunn 2010)
- Available star formation histories
  - Parametric
    - Constant
    - Exponential decay
    - Delayed-exponential decay
  - Non-parametric
    - Variable age bins (from Leja et al. 2019)
    - Fixed age bins (from Leja et al. 2019 and Johnson et al. 2021)
- Available dust attenuation laws
  - Models from Calzetti et al. (2000)
  - Models from Cardelli et al. (1989)
  - Models from Charlot & Fall (2000)
  - Models from Kriek & Conroy (2013)
  - Models from Reddy et al. (2015)
- Dust emission
  - Models from Draine & Li (2007)
  - THEMIS models from Jones et al. (2013, 2017)
- Nebular emission
  - CLOUDY implementation via Byler et al. (2017)

Important Caveats

- These most common SED modeling codes (particularly Prospector) were designed to extract the most information (particularly galaxy properties) from high signal-to-noise photometry and/or spectroscopy.
    - ***However, these codes are commonly applied with the help of spectroscopic redshifts or strong photometric redshift priors from external codes.***

- External codes which do a good (and quick) job at estimating photometric redshifts typically use SED templates (e.g., EAzY), where the colors of these templates are frequently degenerate with redshift.
    - ***To mitigate this problem, some codes add on a magnitude-dependent redshift prior, but very few codes have adopted a full Bayesian approach in doing this.***

- These most common SED modeling codes (particularly Prospector) adopt a full Bayesian approach to self-consistently model the stellar, nebular, and dust properties using advanced sampling techniques.
    - ***However, these are not optimized for modeling SEDs when the redshift is completely unknown.***

JWST has signaled a new era in exploring high-redshift galaxies.

Current and upcoming observing programs will detect galaxies at $z > 10$.

Finding these high-redshift galaxies relies on accurately measuring photometric redshifts from $z = 0$ to $z = 20$, while measuring their stellar population properties.

The Astrophysical Journal Letters, 944:L58 (9pp), 2023 February 20 https://doi.org/10.3847/2041-8213/acba99

Inferring More from Less: Prospector as a Photometric Redshift Engine in the Era of JWST

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Received 2022 November 28; revised 2023 February 8; accepted 2023 February 9; published 2023 February 23

Abstract

The advent of the James Webb Space Telescope (JWST) signals a new era in exploring galaxies in the high-z universe. Current and upcoming JWST imaging will potentially detect galaxies at $z \sim 20$, creating a new urgency in the quest to infer accurate photometric redshifts (photo-z) for individual galaxies from their spectral energy distributions, as well as masses, ages, and star formation rates. Here we illustrate the utility of informed priors encoding previous observations of galaxies across cosmic time in achieving these goals. We construct three joint priors encoding empirical constraints of redshifts, masses, and star formation histories in the galaxy population within the `Prospector` Bayesian inference framework. In contrast with uniform priors, our model breaks an age–mass–redshift degeneracy, and thus reduces the mean bias error in masses from 0.3 to 0.1 dex, and in ages from 0.6 to 0.2 dex in tests done on mock JWST observations. Notably, our model recovers redshifts at least as accurately as the state-of-the-art photo-z code `EAzY` in deep JWST fields, but with two advantages: tailoring a model based on a particular survey is rendered mostly unnecessary given well-motivated priors; obtaining joint posteriors describing stellar, active galactic nuclei, gas, and dust contributions becomes possible. We can now confidently use the joint distribution to propagate full non-Gaussian redshift uncertainties into inferred properties of the galaxy population. This model, "`Prospector`-β," is intended for fitting galaxy photometry where the redshift is unknown, and will be instrumental in ensuring the maximum science return from forthcoming photometric surveys with JWST. The code is made publicly available online as a part of `Prospector` [9].

Unified Astronomy Thesaurus concepts: Bayesian statistics (1900); Computational astronomy (293); Galaxy evolution (594); Galaxy formation (595); Redshift surveys (1378); Spectrophotometry (1556); Spectral energy distribution (2129)

https://ui.adsabs.harvard.edu/abs/2023ApJ...944L..58W/abstract

Summary of Prospector-Beta

“We present a new model, Prospector-β, optimized to recover photometric redshifts in deep JWST fields, while taking full advantage of the capability of Prospector to produce a high-dimensional SED-model and obtain joint constraints on all inferred physical parameters. This means that the full probability distribution can be used to propagate full non-Gaussian redshift uncertainties into inferred properties of the galaxy population. Doing so will significantly enhance our confidence in the inferred properties, and will thus maximize the information returned from JWST. We devise three new priors: a mass function prior, a galaxy number density prior, and a dynamic nonparametric SFH prior that reflects the consistent observational finding that massive galaxies form much earlier than low-mass galaxies. Our SFH prior also respects the observed cosmic star formation rate density by encouraging rising histories early in the universe, and falling histories late in the universe. Moreover, we identify and characterize an age–mass–redshift degeneracy that contaminates the results of standard uniform priors. We show that our model is able to break this degeneracy, while recovering redshifts at least as accurately as EAzY in JWST surveys.”

The main takeaways:

- **Prospector-β is a new physical model with observationally motivated priors, allowing for self-consistent inference of photometric redshifts and stellar population properties.**
- **Introducing a neural net emulator for the FSPS calls significantly reduces the convergence time of Prospector-β fits.**

The Astrophysical Journal, 954:132 (21pp), 2023 September 10 https://doi.org/10.3847/1538-4357/ace720

As Simple as Possible but No Simpler: Optimizing the Performance of Neural Net Emulators for Galaxy SED Fitting

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Received 2022 December 22; revised 2023 June 15; accepted 2023 July 11; published 2023 August 29

Abstract

Artificial neural network emulators have been demonstrated to be a very computationally efficient method to rapidly generate galaxy spectral energy distributions, for parameter inference or otherwise. Using a highly flexible and fast mathematical structure, they can learn the nontrivial relationship between input galaxy parameters and output observables. However, they do so imperfectly, and small errors in flux prediction can yield large differences in recovered parameters. In this work, we investigate the relationship between an emulator's execution time, uncertainties, correlated errors, and ability to recover accurate posteriors. We show that emulators can recover consistent results to traditional fits, with a precision of 25%–40% in posterior medians for stellar mass, stellar metallicity, star formation rate, and stellar age. We find that emulation uncertainties scale with an emulator's width N as $\propto N^{-1}$, while execution time scales as $\propto N^2$, resulting in an inherent tradeoff between execution time and emulation uncertainties. We also find that emulators with uncertainties smaller than observational uncertainties are able to recover accurate posteriors for most parameters without a significant increase in catastrophic outliers. Furthermore, we demonstrate that small architectures can produce flux residuals that have significant correlations, which can create dangerous systematic errors in colors. Finally, we show that the distributions chosen for generating training sets can have a large effect on an emulator's ability to accurately fit rare objects. Selecting the optimal architecture and training set for an emulator will minimize the computational requirements for fitting near-future large-scale galaxy surveys. We release our emulators on GitHub (http://github.com/elijahmathews/MathewsEtAl2023).

Unified Astronomy Thesaurus concepts: Computational methods (1965); Astronomy software (1855); Galaxies (573)

https://ui.adsabs.harvard.edu/abs/2023ApJ...954..132M/abstract

Summary of Everything

1. ***BAGPIPES***
    a. The worst flexibility in modeling assumptions
    b. Fast (~5-10 minutes for parametric SFHs, ~1-2 hours for non-parametric SFHs)
    c. However, I worry about convergence issues because of the fast run times, particularly when the redshift is allowed to be a free parameter with no prior, but I think this is the best for quick and dirty self-consistent fits to the properties of the stars, nebular gas, and dust...
2. ***BEAGLE***
    a. Decent flexibility in modeling assumptions
    b. Slow (~30-60 minutes for parametric SFHs, ~2-4 hours for non-parametric SFHs)
    c. However, this code is proprietary and the least documented of the three, but I think represents a good middle ground between the capabilities of BAGPIPES and Prospector...
3. ***Prospector***
    a. The best flexibility in modeling assumptions
    b. Very slow (~1-2 hours for parametric SFHs, ~8-16 hours for non-parametric SFHs)
    c. However, while this code is very slow, it makes up for it in terms of convergence and the derived physical quantities, and I think this is the best for slow but accurate self-consistent fits...
4. ***Prospector-Beta***
    a. Unknown flexibility in modeling assumptions
    b. Very fast (I don't think this allows parametric SFHs, ~3-30 minutes for non-parametric SFHs)
    c. However, while this code is very fast, there are three assumed priors that encode observational constraints on redshifts, stellar masses, and SFHs; still, I think this is the best for quick but accurate self-consistent fits...
        i. The impact of these priors has not been well explored though...

****** This is all assuming you are fitting z > 2 galaxies with 10-15 bands of photometry. ******