Review of "Stellar Population Inference with Prospector"

Vikrant Gupta
Second-Year (BS–MS), IISER Pune

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Overview and Motivation

Understanding how galaxies form their stars over cosmic time is a central problem in galaxy evolution. Observationally, this information is encoded in the integrated light of galaxies across different wavelengths, commonly referred to as the spectral energy distribution (SED). Extracting physical quantities such as stellar mass, star formation history (SFH), metallicity, and dust content from observed SEDs is a challenging inverse problem due to strong degeneracies between parameters and the limited information content of the data.

This paper presents *Prospector*, a Bayesian SED-fitting framework designed to address these challenges in a flexible and physically motivated way. Rather than focusing on a single modeling choice, the authors emphasize how assumptions about star formation histories, dust, nebular emission, and priors influence the inferred physical properties of galaxies. A major motivation of the work is to move beyond overly restrictive SFH parameterizations and to properly quantify uncertainties using full posterior probability distributions.

While the title highlights non-parametric SFHs, the paper as a whole aims to demonstrate Prospector as a general inference engine capable of handling diverse data types, complex models, and realistic uncertainties.

The Prospector Framework

Prospector is built as a modular Bayesian inference tool that generates model galaxy SEDs on the fly and compares them to observational data. At its core, Prospector uses the FSPS (Flexible Stellar Population Synthesis) library to model stellar emission, along with physically motivated prescriptions for dust attenuation, dust emission, nebular emission, and AGN contributions.

The key idea is forward modeling: given a set of physical parameters, Prospector predicts what a galaxy should look like in photometry and/or spectroscopy. These predictions are then compared to the observed data through a likelihood function. Bayesian sampling methods are used to explore the posterior probability distribution of the parameters, allowing uncertainties and degeneracies to be quantified rather than hidden behind a single best-fit solution.

An important feature of Prospector is its ability to simultaneously fit different kinds of data, such as broadband photometry and spectra, while accounting for calibration uncertainties. This makes it particularly suitable for modern multi-wavelength datasets.

Inference from Mock Photometry and Spectroscopy

The authors first demonstrate Prospector's behavior using mock datasets, where the true input parameters are known. In Section 3.1, mock photometry is generated from a simple parametric SFH model and then re-fit using Prospector. This exercise highlights well-known degeneracies, such as those between stellar age, star formation timescale, dust attenuation, and metallicity.

A key lesson from these tests is that even when the model used for inference matches the model used to generate the data, posterior distributions can be broad and asymmetric. The maximum a posteriori values do not always coincide with the true input parameters, emphasizing the importance of interpreting full posterior distributions rather than relying on point estimates.

The authors then show how adding spectroscopy provides complementary information. Continuum-normalized spectra constrain parameters like metallicity and velocity dispersion, while broadband photometry carries most of the information about dust attenuation and stellar mass. Jointly fitting photometry and spectroscopy leads to significantly tighter and more reliable constraints, demonstrating the advantage of combining multiple data sources within a single Bayesian framework.

Parametric vs Non-Parametric Star Formation Histories

A central demonstration of the paper is the comparison between parametric and non-parametric SFH models. Parametric models assume a specific functional form for the SFH, such as an exponentially declining or delayed exponential model. While computationally convenient, these impose strong priors that may not reflect the true complexity of galaxy formation.

To address this, Prospector supports non-parametric SFHs, where star formation is described in discrete time bins and the star formation rate in each bin is inferred. To avoid unphysical solutions, the authors adopt a continuity prior that favors smooth variations in star formation unless the data strongly indicate otherwise.

Using mock spectra generated from galaxies in the Illustris simulation, the authors show that non-parametric SFHs are better able to recover both recent and older star formation episodes. In contrast, parametric models tend to over-constrain the SFH and underestimate uncertainties, particularly at early times. This section demonstrates how model flexibility affects inferred quantities such as stellar mass and mass-weighted age.

Importantly, the authors emphasize that non-parametric models do not eliminate priors; instead, they make the influence of priors more explicit and controllable.

Complex Models and the Role of Data

The paper further explores how Prospector performs when fitting complex, high-dimensional models that include detailed dust physics, nebular emission, and AGN components. By progressively increasing the number of photometric bands used in the fit, the authors show how additional data move posterior distributions away from the prior and toward the true values.

This exercise illustrates a key strength of Bayesian inference: even limited data can provide meaningful constraints when combined with informative priors, while richer datasets allow those priors to be overridden by the data. It also highlights why grid-based fitting approaches struggle with complex models, as the parameter space becomes prohibitively large.

Demonstrations with Real Data

The authors apply Prospector to several real datasets, including Milky Way globular clusters, the high-redshift galaxy GNz-11, and a post-starburst galaxy from SDSS. These examples demonstrate Prospector's versatility across very different astrophysical regimes.

For globular clusters, Prospector recovers metallicities and reddening values consistent with literature measurements, while also illustrating known limitations in age inference due to unmodeled stellar populations such as blue horizontal branch stars. The GNz-11 example shows that Prospector can infer accurate photometric redshifts at very high redshift when physical modeling and Bayesian inference are combined. The SDSS post-starburst galaxy highlights the importance of flexible SFHs and nebular emission modeling when fitting spectra.

Key Conclusions

The main conclusions of this paper are:

- Assumptions about star formation histories act as strong priors and significantly affect inferred galaxy properties.
- Bayesian inference with full posterior sampling provides a more honest representation of uncertainties and degeneracies than best-fit approaches.
- Joint fitting of photometry and spectroscopy yields stronger and more reliable constraints than either data type alone.
- Non-parametric SFHs offer greater flexibility and more realistic uncertainty estimates, though they remain prior-dependent.
- Prospector is a powerful and extensible framework capable of modeling complex galaxy physics across a wide range of datasets.

Personal Assessment

As a second-year undergraduate, this paper was valuable in clarifying how physical assumptions and statistical methods shape our interpretation of galaxy data. Rather than presenting a single "best" model, the authors emphasize understanding uncertainty, degeneracy, and the role of priors. This perspective is especially instructive for students, as it highlights that astrophysical inference is not just about fitting data, but about carefully reasoning from incomplete information.

Overall, the paper successfully establishes Prospector as a flexible and physically grounded tool for galaxy SED fitting, while also providing practical insight into the strengths and limitations of different modeling choices.