

Cosmology with Only the Photometry of Galaxies

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Abstract

We present the first cosmological constraints from only the observed photometry of galaxies. (?) recently demonstrated that a galaxy’s internal physical properties contain a significant amount of cosmological information. These physical properties, however, cannot be directly measured from observations. In this work, we present how we can go beyond theoretical demonstrations to infer cosmological constraints from actual galaxy observables (*e.g.* optical photometry) using neural density estimation and the CAMELS suite of hydrodynamical simulations. We find that the cosmological information in the photometry of a single galaxy is limited. However, we can combine the constraining power of photometry from many galaxies using hierarchical population inference and place significant cosmological constraints. With the observed photometry of $\sim 15,000$ NASA-Sloan Atlas galaxies, we constrain $\Omega_m = 0.290^{+0.077}_{-0.088}$ and $\sigma_8 = 0.793^{+0.098}_{-0.092}$.

1. Introduction

2. Data

2.1. NASA-Sloan Atlas

For our observations, we use galaxy photometry from the NASA-Sloan Atlas¹ (hereafter NSA). The NSA provides photometry of $z < 0.05$ galaxies observed by the Sloan Digital Sky Survey Data Release 8 (SDSS; Aihara et al., 2011) with improved background subtraction (Blanton et al., 2011). In particular, we use optical g , r , i , z band absolute magnitudes derived using KCORRECT (Blanton & Roweis, 2007), assuming a (Chabrier, 2003) initial mass function. In Fig. 1, we present the $(g - r) - M_r$ color-magnitude distribution of $\sim 120,000$ NSA galaxies (black), which

reveals the modes that correspond to blue star-forming and red quiescent galaxies.

Among the full NSA sample, we focus on luminous galaxies with $-18 > M_r > -22$. We exclude galaxies brighter than $M_r > -22$ since our simulated galaxy sample does not include a large number of the most luminous galaxies. In addition, we only select galaxies with precisely measured photometry: magnitude uncertainties below $\sigma_g, \sigma_r, \sigma_i < 0.022$ and $\sigma_z < 0.04$. Lastly, we impose the color cuts to exclude galaxies within the central 68 percentile of the $g - r$, $g - i$, $g - z$, $r - i$, $r - z$, $i - z$ color distributions. The color cuts remove NSA galaxies that potentially have observational artifacts or problematic photometry. They also ensure that the NSA galaxies are within the photometric distribution (*i.e.* support) of the simulated galaxies used in this work. We mark the 95th percentile contour of our NSA subsample in Fig. 1 (black dot-dashed). In total, we use 14,736 NSA galaxies.

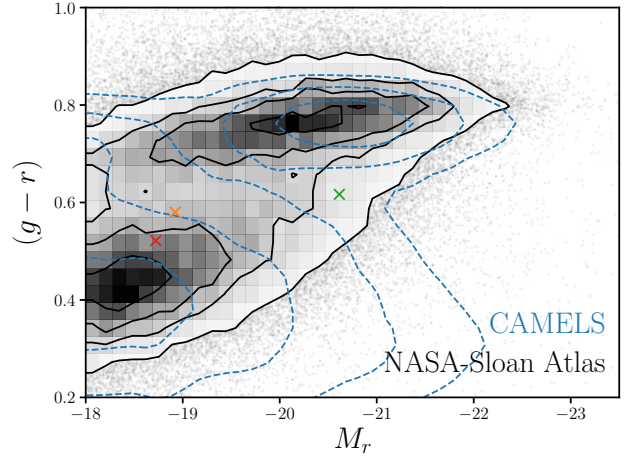


Figure 1. Color-magnitude distribution, $(g - r) - M_r$, of observed galaxies from the NSA (black) and simulated galaxies from CAMELS-TNG (blue). The distribution reveals the bimodality distribution of blue star-forming and red quiescent galaxies. Overall, the distributions of NSA and CAMELS-TNG galaxies are in good agreement. The distribution for CAMELS-TNG is significantly broader since its simulated galaxies are generated using a wide range of cosmological and baryonic feedback parameters.

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¹<http://www.nsatlas.org/>

2.2. Forward Model: CAMELS

In this work, we also use simulated galaxies from the Cosmology and Astrophysics with Machine Learning Simulations (Villaescusa-Navarro et al., 2021; 2022, CAMELS;), a suite of hydrodynamical simulations constructed over a wide range of cosmological and hydrodynamical parameters. In particular, we use the 1,000 hydrodynamical simulations (CAMELS-TNG) constructed using the subgrid physics model of the state-of-the-art IllustrisTNG (?). The simulations are generated with different cosmological parameters, $\Omega = \{\Omega_m, \sigma_8\}$, and baryonic feedback parameters, $\mathcal{B} = \{A_{\text{SN1}}, A_{\text{SN2}}, A_{\text{AGN1}}, A_{\text{AGN2}}\}$, arranged in a latin hypercube. A_{SN1} and A_{SN2} represent the normalization factors for the galactic wind flux and speed; A_{AGN1} and A_{AGN2} represent the normalization factors for the energy output and specific energy of AGN feedback. All the cosmological parameter besides Ω_m and σ_8 are fixed: $\Omega_b = 0.049$, $h = 0.6711$, $n_s = 0.9624$, $\sum m_\nu = 0.0\text{eV}$, and $w = -1$.

In all 1,000 CAMELS-TNG simulations, there are $\sim 700,000$ galaxies with more than 20 star particles. The galaxies, however, are not evenly distributed across the simulations and have a significant dependence on the CAMELS parameters. For instance, simulations constructed at higher Ω_m values have more galaxies. Since the goal of this work is to conduct cosmological inference on a per galaxy basis, we must correct for this implicit prior on the CAMELS parameters. We do this by randomly selecting 100 galaxies from each simulation. This imposes a uniform prior: $p(\Omega, \mathcal{B}) = 1$. Thus, we use a total of 100,000 CAMELS-TNG galaxies.

Since the goal of this work is to analyze the observed photometry of NSA galaxies, we forward model observed photometry for the simulated galaxies. CAMELS-TNG already provides synthetic dust attenuated stellar photometry for each simulated galaxy calculated using the same procedure as (Nelson et al., 2018). The unattenuated spectral energy distribution (SED) of a galaxy is computed by combining the SEDs of every member star particle of the host subhalo. Each star particle SED is modeled as a single-burst simple stellar population using stellar population synthesis (SPS) based on the recorded birth time, metallicity, and mass. The SPS uses FSPS (Conroy et al., 2009; ?), Padova isochrones, MILES stellar library, and assumes a Chabrier initial mass function. The unattenuated galaxy SEDs are then attenuated using a dust model based on the metal content of the neutral gas distribution in and around each galaxy (Model C in Nelson et al., 2018). Afterwards, the SED is convolved with SDSS g, r, i, z -band photometric bandpasses to produce the photometry: X_i .

Next, we add noise to the CAMELS-TNG synthetic photometry based on the measured uncertainties, σ_X , of NSA galaxies. For each galaxy, we randomly sample $\sigma_{X,i}$ from

the range of uncertainties measured in NSA. Afterwards, we apply the uncertainty using a Gaussian with standard deviation $\sigma_{X,i}$: $\hat{X}_i \sim \mathcal{N}(X_i, \sigma_{X,i})$. Although our noise model is overly simplistic, this is not an issue in our approach because the posteriors we ultimately evaluate are conditioned on the uncertainties (Hahn & Melchior, 2022). In Fig. 1, we present the color-magnitude distribution of the forward modeled CAMELS-TNG galaxies in blue.

3. Methods

3.1. Hierarchical Bayesian Inference

Our goal in this paper is to infer the posterior of cosmological parameters $\Omega = \{\Omega_m, \sigma_8\}$ and baryonic feedback parameters $\mathcal{B} = \{A_{\text{SN1}}, A_{\text{SN2}}, A_{\text{AGN1}}, A_{\text{AGN2}}\}$ from the observed photometry of galaxies in the NSA catalog, $\{X_i\}$: $p(\Omega, \mathcal{B} | \{X_i\})$. X_i represents both the measured absolute magnitudes and uncertainties: $\{\hat{X}_i, \sigma_{X,i}\}$. With our forward model, based on CAMELS-TNG, we can simulate noisy galaxy photometry from Ω and \mathcal{B} . Hence, the cosmological inference from photometry can be reformulated as a hierarchical population inference problem.

To illustrate this, we graphically represent our forward model in Figure 2. Circles, shaded circles, and dots represent random variables, observed quantities, and random variables that are deterministic. θ_i^g represents the physical properties of galaxies (e.g. M_* , star-formation history), which are determined from Ω and \mathcal{B} through the CAMELS-TNG simulation. Then the noisy photometry \hat{X}_i is determined from θ_i^g through SPS and our noise model.

Given this hierarchical model, we can rewrite the posterior as:

$$p(\Omega, \mathcal{B} | \{X_i\}) = \frac{p(\Omega, \mathcal{B}) p(\{X_i\} | \Omega, \mathcal{B})}{p(\{X_i\})} \quad (1)$$

$$= \frac{p(\Omega, \mathcal{B})}{p(\{X_i\})} \prod_{i=1}^N p(X_i | \Omega, \mathcal{B}) \quad (2)$$

$$= \frac{p(\Omega, \mathcal{B})}{p(\{X_i\})} \prod_{i=1}^N \frac{p(X_i) p(\Omega, \mathcal{B} | X_i)}{p(\Omega, \mathcal{B})} \quad (3)$$

$$= \frac{1}{p(\Omega, \mathcal{B})^{N-1}} \prod_{i=1}^N p(\Omega, \mathcal{B} | X_i) \quad (4)$$

We downsampled the galaxies in the CAMELS-TNG simulations to impose $p(\Omega, \mathcal{B}) = 1$ (Sec. 2.2), so the posterior simply becomes:

$$= \prod_{i=1}^N p(\Omega, \mathcal{B} | X_i). \quad (5)$$

Hence, we can evaluate $p(\Omega, \mathcal{B} | \{X_i\})$, and sample it, as long as we can accurately estimate $p(\Omega, \mathcal{B} | X_i)$, the posterior for photometry from an individual galaxy.

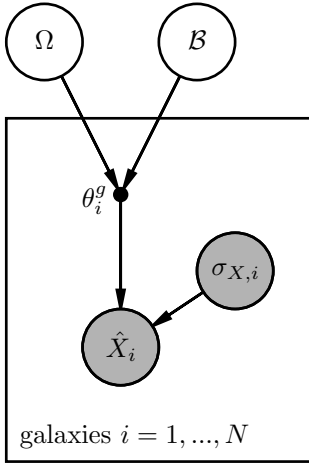


Figure 2. Graphical representation of our hierarchical approach that illustrate the relationship among the parameters of our model. Circles are inferred random variables, shaded circles are observed quantities, and dots indicate random variables that are deterministic. The physical properties of galaxies, θ_i^g , are determined from the cosmological and hydrodynamical parameters Ω and \mathcal{B} through the CAMELS-TNG simulation. Then the noisy optical photometry, \hat{X}_i , is derived from θ_i^g using SPS and our noise model.

3.2. Neural Density Estimation

One way to accurately estimate $p(\Omega, \mathcal{B} | X_i)$ is by applying neural density estimation (NDE) to the CAMELS-TNG. The CAMELS-TNG forward model provides a training dataset of 100,000 parameter-photometry pairs: $\{(\Omega, \mathcal{B}, X_i)\}$. With NDE, we can use this data to train a neural network q with parameters ϕ to estimate $p(\Omega, \mathcal{B} | X_i) \approx q_\phi(\Omega, \mathcal{B} | X_i)$. This type of simulation-based inference using NDE has now been applied to a broad range of astronomical applications: *e.g.* analyzing gravitational waves (Wong et al., 2020; Dax et al., 2021), binary microlensing lensing (?), galaxy SEDs (Hahn & Melchior, 2022), and galaxy clustering (Hahn et al., 2022; 2023).

In this work, our NDE is based on “normalizing flow” models (Tabak & Vanden-Eijnden, 2010; Tabak & Turner, 2013), which use neural networks to learn a flexible and bijective transformation, f , that maps a complex target distribution to a simple base distribution that is fast to evaluate. f is defined to be invertible and have a tractable Jacobian so that the target distribution can be evaluated with change of variables. In our case, the target distribution is $p(\Omega, \mathcal{B} | X_i)$ and we set the base distribution to be a multivariate Gaussian. Among different flow architectures, we use Masked Autoregressive Flow (MAF; Papamakarios et al., 2017) models

implemented in the `sbi` Python package² (Greenberg et al., 2019; Tejero-Cantero et al., 2020).

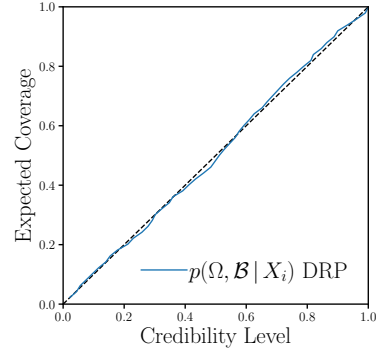


Figure 3. DRP coverage test validating the accuracy of our $q_\phi(\Omega, \mathcal{B} | X_i)$ posterior estimate trained using the forward modeled CAMELS-TNG data (blue). The black-dashed line represents an optimal estimate of the posterior. The coverage test demonstrates that q_ϕ provides a near optimal estimate of the true posterior.

Our goal in training is to determine q_ϕ that best approximates $p(\Omega, \mathcal{B} | X_i)$. We can reformulate this into an optimization problem: determining ϕ that minimizes the KL divergence between $p(\Omega, \mathcal{B}, X_i) = p(\Omega, \mathcal{B} | X_i)p(X_i)$ and $q_\phi(\Omega, \mathcal{B} | X_i)p(X_i)$. In practice, we split the $\{(\Omega, \mathcal{B}, X_i)\}$ data from CAMELS-TNG into a training and validation set with a 90/10 split. Then, we maximize the total log-likelihood $\sum_i \log q_\phi(\Omega, \mathcal{B} | X_i)$ over the training set, which is equivalent to the KL divergence, using the ADAM optimizer (Kingma & Ba, 2017) with a learning rate of 5×10^{-4} . To prevent overfitting, we evaluate the total log-likelihood on the validation data at every training epoch and stop the training when the validation log-likelihood fails to increase after 20 epochs.

We determine the architecture of our flow by training a large number of flows with architectures determined using the (Akiba et al., 2019) hyperparameter optimization framework. Afterwards, we define our final flow as an equally weighted ensemble of five flows with the lowest validation losses: $q_\phi(\Omega, \mathcal{B} | X_i) = \sum_{j=1}^5 q_{\phi,j}(\Omega, \mathcal{B} | X_i)/5$. Ensembling flows with different initializations and architectures improves the overall robustness of our normalizing flow (Alsing et al., 2019). To validate the accuracy of q_ϕ , we use the “distance to random point” (DRP) coverage test from (Lemos et al., 2023), which is necessary and sufficient to show that a posterior estimator is optimal. In Fig 3, we present the DRP coverage of q_ϕ (blue) and find that it provides a near optimal estimate of the true posterior.

In Fig. 4, we present $q_\phi(\Omega, \mathcal{B} | X_i)$ for three arbitrarily se-

²<https://github.com/mackelab/sbi/>

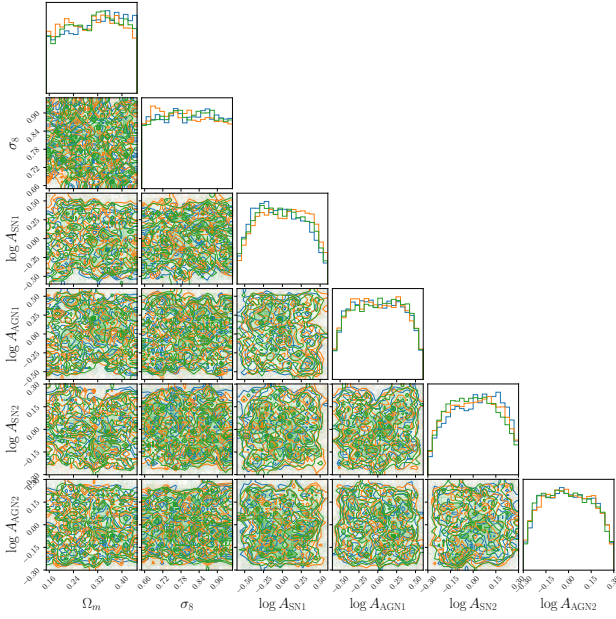


Figure 4. Estimated posteriors of the cosmological and hydrodynamical parameters (Ω , σ_8) from photometry, $q_\phi(\Omega, \mathcal{B} | X_i)$, for three arbitrarily selected NSA galaxies. The posteriors correspond to the galaxies marked in Fig. 1.

lected NSA galaxies. The selected galaxies are also marked in Fig. 1. The individual posteriors reveal that there is very little cosmological information in the photometry of a single galaxy. However, with Eq. 5, we can extract the cosmological information from *thousands* of galaxies.

4. Results

Our posterior on Ω_m and σ_8 is inferred assuming a galaxy formation model and a SED model. This is illustrated in Eq. ?? where $p(\Omega, \mathcal{B} | \theta_i^g)$ is determined by the galaxy formation model and $p(\theta_i^g | X_i)$ is determined by the SED model. Below we discuss the caveats of these assumptions and how they can be accounted for in future research.

4.1. Galaxy Formation Model

Some interpretation of cosmology with one galaxy here and what that may actually imply for $p(\Omega, \mathcal{B} | \theta_i^g)$

4.2. SED Modeling

The forward modeled photometry for the simulated galaxies in our training data are constructed using SED modeling (Section 2.2).

dust modeling is unrealistic, which could bias the inferred θ^g

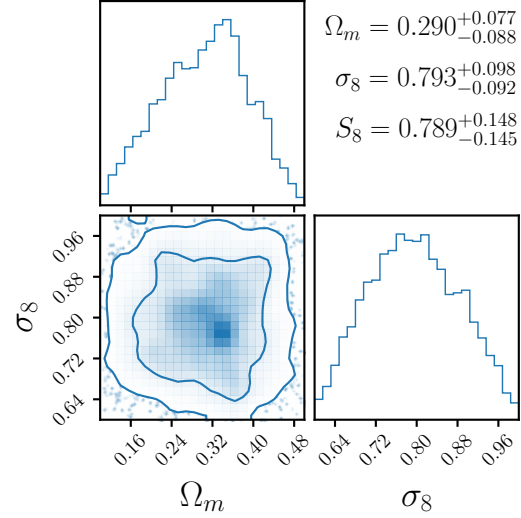


Figure 5.

emission lines are crap

hard assumptions on the IMF

Despite these serious limitations, we can identify subpopulations of galaxies that are the least sensitive to them. For example, quiescent galaxies do not have emission lines and we can identify ones without dust attenuation from XXXX (galaxy zoo? emission lines?). Furthermore, recent studies using both lensing and IR spectral features also find no IMF variations in the bulk populations of nearby quiescent galaxies. Hence, although $p(\theta_i^g | X_i)$ is not robust over the full space of X , it is robust for dustless quiescent galaxies.

In principle, $p(\Omega, \mathcal{B} | X_i) = \int p(\Omega, \mathcal{B} | \theta_i^g) p(\theta_i^g | X_i) d\theta_i^g$, where θ_i^g is a latent variable that is marginalized.

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A. You *can* have an appendix here.

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