SIMULTANEOUS ESTIMATION OF PHOTOMETRIC REDSHIFTS AND SED PARAMETERS: IMPROVED TECHNIQUES AND A REALISTIC ERROR BUDGET

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ABSTRACT

We seek to improve the accuracy of joint galaxy photometric redshift estimation and spectral energy distribution (SED) fitting. By simulating different sources of uncorrected systematic errors, we demonstrate that if the uncertainties in the photometric redshifts are estimated correctly, so are those on the other SED fitting parameters, such as stellar mass, stellar age, and dust reddening. Furthermore, we find that if the redshift uncertainties are over(under)-estimated, the uncertainties in SED parameters tend to be over(under)-estimated by similar amounts. These results hold even in the presence of severe systematics and provide, for the first time, a mechanism to validate the uncertainties on these parameters via comparison with spectroscopic redshifts. We propose a new technique (annealing) to re-calibrate the joint uncertainties in the photo-z and SED fitting parameters without compromising the performance of the SED fitting + photo-z estimation. This procedure provides a consistent estimate of the multi-dimensional probability distribution function in SED fitting + z parameter space, including all correlations. While the performance of joint SED fitting and photo-z estimation might be hindered by template incompleteness, we demonstrate that the latter is “flagged” by a large fraction of outliers in redshift, and that significant improvements can be achieved by using flexible stellar populations synthesis models and more realistic star formation histories. In all cases, we find that the median stellar age is better recovered than the time elapsed from the onset of star formation. Finally, we show that using a photometric redshift code such as EAZY to obtain redshift probability distributions that are then used as priors for SED fitting codes leads to only a modest bias in the SED fitting parameters and is thus a viable alternative to the simultaneous estimation of SED parameters and photometric redshifts.

Key words: galaxies: distances and redshifts – galaxies: fundamental parameters – galaxies: statistics

1. INTRODUCTION

Spectral energy distribution (SED) fitting is a useful tool to infer the physical properties of galaxies, such as mass, stellar age, star formation history (SFH), and dust content, starting from photometric observations. The basic idea is to use stellar population synthesis (SPS) models to create templates whose properties are known, and then explore the parameter space of possible templates to find models that resemble the data. The success rate of this technique relies crucially on the accuracy of the chosen templates, while its efficiency depends mostly on the algorithm used for the exploration of the parameter space.

A problem that is fundamentally related to SED fitting is the determination of the redshift of galaxies (called photo-z) on the basis of the same photometric data. This problem will become increasingly important since the large imaging surveys of the future (e.g., the Large Synoptic Survey Telescope, Ivezić et al. 2008) will provide photometric broadband coverage for a very large number of galaxies, but spectroscopic follow-up will only be available for a small fraction of them.

There are a number of publicly available algorithms to estimate photo-z (see, e.g., the discussion in Walcher et al. 2011 and http://sedfitting.org/SED08/Fitting.html for a complete list). These codes use linear combinations of empirical templates or SPS templates (e.g., EAZY, Brammer et al. 2008; HYPERZ, Bolzonella et al. 2000), or adopt supervised machine learning techniques (e.g., AnnZ, Firth et al. 2003; TPZ, Carrasco Kind & Brunner 2013) to optimize the estimation of the photometric redshifts.

A common practice is to perform the estimation of the photometric redshifts and the SED fitting in two steps, by determining the photo-z first and then fixing the redshift at the best-fit value to estimate the other physical properties of the galaxy. However, this procedure causes an underestimation of the uncertainties in the SED fitting parameters since the uncertainty in redshift is not propagated correctly. Even when the latter is taken into account in the SED fitting algorithm, parameter estimation might still be biased because the templates used in the photo-z estimation and SED fitting differ or if the SED fitting code does not utilize the full information from the redshift probability distribution (see, e.g., Kotulla 2013; Pirzkal et al. 2013). A different example of parameter estimation where the results of a two-step process differ significantly from the fully covariant exploration of parameter space is discussed in Andreon (2012). Here we seek to develop a strategy to estimate photometric redshift and perform SED fitting simultaneously by using the same algorithm and the same templates, and to improve the accuracy of the error estimation on redshift and other physical properties of galaxies by using a novel technique (annealing) to calibrate the uncertainties.

One important difference between photo-z estimation and SED fitting is that if spectroscopic redshifts are available, at least for a subset of the data, it is possible to test the performance of the photo-z algorithm, and this information can
Figure 1. Distribution of input parameters for the two mock catalogs characterized by constant SFH (left), and exponentially declining SFH (right).

be used to iteratively improve the redshift estimation method.
This luxury is usually not available for SED fitting parameters,
since the “true” values are unknown. A notable exception is the
(few) galaxies for which Lick indices or spectroscopic line
widths or ratios are available and provide an alternative
estimate of age, mass, or metallicity. For mass or stellar age,
tests conducted on mock catalogs will reveal systematic biases
introduced by imperfect exploration of the parameter space
(“algorithmic systematics”), but will be blind to systematic
biases caused by, e.g., catastrophic failures in the photometry
or excessively simplistic SPS models. On the other hand, those
causes of systematic uncertainties in parameter determination
are often dominant with respect to those arising from
uncertainties in the photometry (e.g., Lee et al. 2009; Conroy
2013; Simha et al. 2014; Mobasher et al. 2015).

In this paper, we show that the performance of photo-z estimation in a joint SED fitting+photo-z approach is a good tracer of these “non-algorithmic systematics.” We then demonstrate how these pieces of information can be used to improve the determination of the SED fitting parameters. We propose a technique to correct the estimation of uncertainties in redshift and other SED fitting parameters with minimal information loss, i.e., without degrading the quality of parameter fitting.

The paper is organized as follows. We use mock data in Sections 2, 3, and 4. In Section 2 we show that the code we use, SpeedyMC, is able to recover redshifts and SED fitting parameters correctly in the absence of “non-algorithmic systematics.” In Section 3 we investigate the separate and combined effects of adding catastrophic failures to the photometry, adding uncorrected zero-point errors, and of using incomplete libraries of SPS models. In Section 4 we provide a strategy to recalibrate uncertainties in all parameters on the basis of photo-z information, and we estimate the effect of using empirical offsets, which are common in photo-z algorithms. In Section 5 we show that it is possible to apply the same strategy to data, for joint SED fitting and photo-z estimation, and for a two-step process where a photo-z algorithm is used before SED fitting. Section 6 summarizes our findings and our prescription for calibrating uncertainties in SED fitting parameters on the basis of uncertainties in photo-z.

2. JOINT SED–PHOTO-z FITTING WITH SPEEDYMC

We use the SpeedyMC code (Acquaviva et al. 2011a) to jointly perform SED and photo-z fitting. SpeedyMC is a Markov Chain Monte Carlo code based on GaMC (Acquaviva et al. 2011b). It uses a Metropolis–Hastings algorithm with adaptive proposal density to explore the parameter space, and it employs Bayesian statistics to calculate the posterior probability as a product of likelihood and priors. In the case of redshift, we adopt a luminosity function prior based on the evolving cosmological volume in a ΛCDM cosmology.

We create two mock catalogs, one characterized by constant star formation (CSF) history, and one characterized by exponentially declining star formation (ESF) history; these two star formation histories are among the most common ones used in SED fitting.

The model parameters are stellar mass, stellar age, dust content parameterized by the excess color $E(B - V)$, redshift, and e-folding time $\tau$, in the case of ESF. We define age as the median stellar age of the galaxy, i.e., the lookback time in which 50% of the stellar mass has been built. Whenever there is a mismatch between the “true” and “assumed” functional form for the SFH, we compare two definitions of age: the median stellar age and the time elapsed since the onset of star formation. We demonstrate that in all cases the median stellar age is better recovered and is more robust to incorrect assumptions in the star formation history of the galaxy. We adopt uniform priors in $\log(Age)$, $\log(Mass)$, $\log(\tau)$, and $E(B - V)$.

For both sets of models, the input physical properties and broadband coverage are modeled after a bright subset of the Cosmic Assembly Near-Infrared Deep Extragalactic Survey (CANDELS, Grogin et al. 2011) GOODS-S photometric catalog described in Guo et al. (2013). The model galaxies are at $0 < z < 3$, and the UV-to-mid-infrared multi-wavelength SED allows one to obtain deep coverage in the rest-frame UV to rest-frame NIR, which is essential for SED fitting. The distribution of input parameters for the two catalogs is shown in Figure 1; for ESF we show the ratio age/$\tau$ since it is more representative of the star formation mode of the galaxy.

Both catalogs comprise several hundred galaxies. We perturb the photometry in each band by a random Gaussian
scatter of an amplitude equal to 10% of the flux in that band. We also verified that varying the fractional errors across the range of photometric bands does not affect our results. In particular, the ranking of the severity of systematics (with uncorrected zero-point errors being the mildest, and template incompleteness being the most severe) is unaltered, and the degree of correlation between the underestimation of the uncertainties in different parameters is unchanged. Additionally, an example application with a fully realistic distribution of uncertainties in different parameters is unchanged. Addition-}

\[ \text{Figure 2. Recovery of input parameters shown for several hundred mock galaxies generated with constant (left) and exponentially declining (right) star formation history. Noise and scatter are added to the photometry, but the mock data are fit using the correct functional form for the SFH and the photometry is immune from catastrophic errors. In the absence of "non-algorithmic systematics," SpeedyMC is able to correctly recover the input parameter values, as well as to correctly estimate the size of the uncertainties.} \]

3. SED FITTING IN THE PRESENCE OF NON-ALGORITHMIC SYSTEMATICS

In this section we analyze the effect of three common sources of systematic bias: catastrophic failures in the photometry (i.e., photometric measurements that are far off from the “true” value), uncorrected zero-point errors in the photometry, and the use of incomplete or inadequate libraries of stellar population templates. The results for all these tests are summarized in Table 1.

3.1. Effect of catastrophic failures

We use the same set of mock galaxies with CSF history considered above, and revise the photometry so that every
photometric point has a 3% probability of being replaced by a 10σ outlier. The results of this test are shown in the left panel of Figure 3. With respect to the systematics-free case (left panel of Figure 2), we note that the best-fit values now suffer from a (very) slight bias and the sizes of the uncertainties in all parameters are moderately underestimated (by about 15%). The fraction of outliers in redshift, age, and $E(B-V)$ increases significantly, from 1.5% or less to 6.7%, 7.5%, and 5.0%, respectively. Finally, the overall scatter of true versus estimated parameters (in other words, the size of the uncertainties in the SED fitting parameters), which summarizes how well parameters can be measured, increases by 20%–30% in each parameter.

3.2. Effect of uncorrected zero-point errors

For the mock catalog with CSF history, we introduce a band-dependent systematic bias in order to mimic the effect of uncorrected zero-point errors in the photometry. We assume that the amplitude of this effect is 2% of the flux in UV, optical, and NIR bands; 5% in K-band; and 8% in IRAC, as suggested by, e.g., the analysis in Guo et al. (2013). The sign of the bias is random, but consistent within filters belonging to the same instrument. The results of this test can be found in Table 1. The best-fit values suffer from a slight bias (between 1% and 3%) and the sizes of uncertainties in all parameters are underestimated by 10%–15%. The fraction of outliers in redshift, age, and $E(B-V)$ is low, 1%, 5%, and 2.5%, respectively, and negligible in mass. The overall scatter of true versus estimated parameters again increases moderately, by 20%–30%.

3.3. Effect of using an incorrect SFH

Most SPS models used in SED fitting have relatively simple star formation histories. To capture the effect of this simplifying assumption on the parameter estimation, we generate models with a given SFH, and then assume a different, incorrect SFH when performing SED fitting. We run this test for two sets of mock galaxies: for models generated with CSF and fit assuming a linearly increasing star formation rate ($\Psi(t) \propto t$), and for models generated with ESF and fit by assuming a CSF rate. We expect the bias introduced by our wrong assumptions to be mild in the first case and severe in the second case.

The results of these tests confirm our expectations. Assuming a linearly increasing SFH (when the correct one is constant) does not impact the correct recovery of mean values and credible regions for photo-z, stellar mass, and $E(B-V)$. If age is defined as the time elapsed from the beginning of star formation, the incorrect assumption on the SFH induces a moderate but significant bias in this parameter (3%, versus a scatter of 5%) and increased scatter. The fraction of objects for which the input age values lie within the 68% and 95% regions is significantly smaller than 68% and 95%, as a result of the systematic bias. Conversely, the median stellar age is less sensitive to the mismatch between true and assumed SFH, and the estimation of mean values and credible regions for median stellar age remains correct.

Fitting models whose SFH is exponential using a CSF has more drastic consequences. All parameters are affected and the underestimation of the uncertainties is quite dramatic (around 50%). Redshift and mass are the parameters for which the effect is largest. The outlier fractions in redshift and $E(B-V)$ are as high as 15% and 24%, respectively. The bias and scatter found in the distribution of estimated-versus-true parameters are also higher, with respect to the case in which ESF models are fit using the correct SFH, although the numbers change moderately because these calculations are made excluding outliers. Once again, the median stellar age is recovered from SED fitting much better than the time elapsed since the onset of star formation.

3.4. Combined effect of several sources of modeling error in realistic simulations

While the previous cases were aimed at estimating the effect of individual sources of systematic errors, when using data, the most common scenario is that several simplifying hypotheses are used at once. We attempt to simulate the effect of these combined factors by generating a new mock catalog, comprised...
Table 1

Results for Different Tests on Mock Catalogs whose Photometry is Affected by “Non-algorithmic Systematics”
(Catastrophic Failures in the Photometry, Template Incompleteness, Uncorrected Zero-point Errors, or All of Them)

| Parameter | % of Objects in 68% Region | % of Objects in 95% Region | Median Bias | Scatter | OLF |
|-----------|-----------------------------|-----------------------------|-------------|---------|-----|
| z         | 67                          | 94                          | 0.002       | 0.03    | 0.008 |
| CSF       |                             |                             |             |         |     |
| Mass      | 93                          |                             | -0.0001     | 0.03    |     |
| Age (median) | 94                          |                             | -0.0003     | 0.05    | 0.015 |
| E(B - V)  | 94                          |                             | 0.001       | 0.04    | 0.01 |
| z         | 57                          | 84                          | 0.0008      | 0.04    | 0.07 |
| CSF       |                             |                             |             |         |     |
| + Cat fail | 85                          |                             | -0.001      | 0.04    | 0.02 |
| Age (median) | 87                          |                             | -0.003      | 0.06    | 0.08 |
| E(B - V)  | 87                          |                             | 0.002       | 0.05    | 0.05 |
| z         | 55                          | 90                          | -0.01       | 0.03    | 0.01 |
| CSF       |                             |                             |             |         |     |
| + ZP errors | 91                          |                             | 0.01        | 0.04    |     |
| Age (median) |                             |                             | 0.03        | 0.06    | 0.05 |
| E(B - V)  |                             |                             | 0.002       | 0.05    | 0.03 |
| z         | 67                          | 94                          | -0.0002     | 0.03    | 0.008 |
| CSF       |                             |                             |             |         |     |
| fit as Lin Inc | 90                          |                             | 0.002       | 0.03    |     |
| Age (onset) | 88                          |                             | 0.03        | 0.05    | 0.02 |
| Age (median) | 88                          |                             | 0.0007      | 0.05    | 0.015 |
| E(B - V)  | 88                          |                             | 0.003       | 0.04    | 0.01 |
| z         | 61                          | 91                          | -0.003      | 0.05    | 0.003 |
| ESF       |                             |                             |             |         |     |
| Mass      | 96                          |                             | -0.01       | 0.04    | 0.02 |
| Age (median) | 94                          |                             | 0.003       | 0.04    | 0.005 |
| E(B - V)  | 84                          |                             | 0.001       | 0.05    | 0.009 |
| z         | 38                          | 67                          | -0.02       | 0.05    | 0.15 |
| ESF       |                             |                             |             |         |     |
| fit as CSF | 78                          |                             | -0.01       | 0.04    | 0.01 |
| Age (onset) | 82                          |                             | 0.03        | 0.05    | 0.01 |
| Age (median) | 88                          |                             | 0.002       | 0.05    | 0.007 |
| E(B - V)  | 81                          |                             | 0.01        | 0.05    | 0.24 |
| z         | 38                          | 68                          | -0.02       | 0.05    | 0.18 |
| ESF       |                             |                             |             |         |     |
| fit as CSF | 72                          |                             | -0.01       | 0.04    | 0.02 |
| Age (median) | 71                          |                             | 0.02        | 0.06    | 0.06 |
| E(B - V)  | 80                          |                             | 0.015       | 0.05    | 0.04 |
| z         | 46                          | 86                          | -0.01       | 0.05    | 0.07 |
| ESF       |                             |                             |             |         |     |
| + Cat fail | 84                          |                             | 0.006       | 0.04    | 0.01 |
| Age (median) | 85                          |                             | 0.02        | 0.05    | 0.04 |
| E(B - V)  | 85                          |                             | 0.002       | 0.06    | 0.11 |
| z         | 38                          | 67                          | -0.004      | 0.04    | 0.125 |
| ESF       |                             |                             |             |         |     |
| + ZP errors |                             |                             | 0.005       | 0.03    | 0.01 |
| Age (median) |                             |                             | 0.03        | 0.06    | 0.13 |
| E(B - V)  |                             |                             | 0.004       | 0.05    | 0.12 |
| z         | 35                          | 46                          | 0.05        | 0.21    | 0.39 |
| Realistic SFH |                             |                             |             |         |     |
| fit as single-pop; incorrect dust law |                             |                             | 0.004       | 0.08    | 0.26 |
| Age (onset) |                             |                             | -0.08       | 0.05    | 0.58 |
| Age (median) |                             |                             | -0.02       | 0.06    | 0.12 |
| E(B - V)  |                             |                             | -0.03       | 0.06    | 0.13 |
| z         | 33                          | 43                          | 0.07        | 0.24    | 0.34 |
| Realistic SFH |                             |                             |             |         |     |
| fit as single-pop; correct dust law |                             |                             | 0.002       | 0.05    | 0.08 |
| Age (onset) |                             |                             | -0.02       | 0.02    | 0.003 |
| Age (median) |                             |                             | -0.03       | 0.05    | 0.1 |
| E(B - V)  |                             |                             | -0.003      | 0.05    | 0.09 |
| z         | 32                          | 57                          | -0.03       | 0.07    | 0.2 |
| ESF       |                             |                             | -0.004      | 0.05    | 0.02 |
| + Cat fail + ZP errors |                             |                             | 0.06        | 0.06    | 0.08 |
| Age (median) |                             |                             | 0.05        | 0.06    | 0.05 |
| E(B - V)  |                             |                             | 0.003       | 0.06    | 0.26 |

Note. When there is an ambiguity in the definition of age, we report results using both the median stellar age and the age since the onset of star formation to show that the former is recovered better in all cases. When flexible dust laws are used, the input parameter $E(B - V)$ is not well defined.
of 1000 galaxies, as follows. The SFH of each galaxy is simulated as the combination of either an exponentially decreasing model \( \text{SFH} \propto e^{-t} \) or a delayed \( \tau \) model \( \text{SFH} \propto t e^{-t} \), combined with a burst. The fraction of mass in the burst is a random variable uniformly distributed between zero and one and the age of the burst is randomly sampled from a uniform logarithmic distribution between 10 Myr and 1 Gyr. For the smooth SF component, the logarithms of ages and masses follow a uniform distribution (between 6.5 and 10 and between 8 and 12, respectively), and the ratio \( \tau \)/age for the SFH or DSF model is randomly selected within the \([0.1–10] \) interval. We also consider three possible (randomly selected) dust laws for the galaxies: the Calzetti law (Calzetti et al. 2000), the Milky Way dust law from Cardelli et al. (1989), and the two-component model of Charlot & Fall (2000) where the birth cloud parameters \( \eta_C \) and \( \mu_{BC} \) follow a Gaussian distribution with mean values 1.0 and 0.3 and standard deviations equal to 0.2 and 0.1, respectively.

To include a realistic model of photometric noise, we use the CANDELS GOODS-S photometric catalog, fit the distribution of photometric uncertainties as a function of flux density in each band, and apply it to our mock catalog. We perform SED fitting on these catalogs using a single stellar population model with an ESF history, and assuming that the dust attenuation law is the Calzetti law with the variable parameter \( E(B - V) \). To show the effect of using a single stellar population and an incorrect dust law separately, we split the two cases into the full catalog and a subset where the Calzetti law is used both in simulations and fitting (dubbed “correct dust law” in Table 1).

For the case where the incorrect functional form for the dust law is used, we do not report a significant bias for any of our SED fitting parameters other than \( \tau \), which is poorly constrained. However, we observe a significant fraction of outliers (about one in eight objects) for all parameters. The uncertainties in all parameters are significantly underestimated, by a factor of 30%–40%. In the case where multiple stellar populations are present, it is especially preferable to use the median stellar age to define the age of the galaxy; using time since the beginning of star formation would lead to a bias at least +8%.

These unsatisfactory behaviors (underestimation of uncertainties, high OLF) are mitigated significantly when the correct functional form for the dust absorption law is used, with OLFs decreasing by 30%–40% and milder underestimation of the uncertainties in all other parameters.

We also attempted to model another source uncertainty in stellar evolution, the contribution of TP-AGB stars, by using the stellar population models from G. Bruzual & S. Charlot (2007, private communication) to fit the mock catalogs obtained with the 2003 SPS models. We note that this issue (as well as the well-known uncertainty in the IMF) leads to a systematic shift in the estimate stellar masses rather than to a true underestimation of the uncertainties related to a certain measurement, and therefore we have not included it in our prescription for calculating the annealing temperature. Using the CB07 models to fit a CB03 “truth” causes an increase in the fraction of outliers in redshift of a factor of two (to a total of 26%), producing a notable “red flag” in the results of the SED fitting.

### 3.5. Effect of combined systematics

Our final scenario is the “worst-case” one in which catastrophic failures in the photometry, uncorrected zero-point errors, and template incompleteness all affect the SED fitting. Unfortunately, unless our treatment of the systematics is pessimistic, this is also the most realistic scenario when using data, and is therefore particularly worthy of our consideration. As anticipated and shown in the last row of Table 1, the combined effect of these three systematics makes the results even worse than the previous case, with outlier fractions in redshift and \( E(B - V) \) reaching 21% and 29%, respectively, and even more severely underestimated uncertainties in all cases. This case is illustrated in the right panel of Figure 3.

### 4. Improved estimation of uncertainties on SED fitting parameters

The results from the tests on mock galaxies described in the previous sections (and the parallel ones we conducted with a different prescription for simulated noise which confirm these findings without adding new information) teach us some lessons about the effect of “non-algorithmic” systematics on SED fitting. In particular, we note the following.

1. The fraction of outliers in redshift is a meaningful “red flag” for the presence and gravity of these systematics. In our tests, the fraction of outliers rose from less than 1.5% in the case of no catastrophic failures and correct SPS templates, to a few percent when catastrophic failures were added, to over 20% in the case of combined catastrophic failures, uncorrected zero-point errors, and incorrect SPS templates. If the expected levels of catastrophic photometric failures and zero-point errors are known, the expected OLF from those can be calculated from simulations, and one could use any discrepancy to evaluate, and possibly correct, residual systematics deriving from template incompleteness.

2. Whenever non-algorithmic systematics are present, the size of the uncertainties in photometric redshift as well as in SED fitting parameters is underestimated. The extent of this underestimation can be severe even in very common circumstances. Therefore, it is important to find a way to test and correct the size of the uncertainties.

3. The size of the estimated uncertainties in redshift is strongly correlated with the size of the estimated uncertainties in other parameters, as shown in Figure 4, even in critical cases of several incorrect assumptions made in SED fitting. For the 11 tests shown in Table 1, we calculated the Pearson correlation coefficient between the percentage of objects within the 68% and 95% credible intervals in redshift, and those of age, stellar mass, and \( E(B - V) \). The correlation is highest for mass (0.86 and 0.92 for the 68% and 95% intervals, respectively) and \( E(B - V) \) (0.87 and 0.92), and is strong for age (0.65 and 0.63). In other words, if the size of the uncertainties in redshift are correctly estimated, so are the ones in SED fitting parameters; and if they are underestimated in redshift, they will be underestimated in the other parameters, especially stellar mass, by approximately the same amount. This is a useful piece of information because the relation between the estimated and true size of uncertainties in redshift can be measured if spectroscopic redshifts are available for a subset of
are underestimated by the same amount. Small symbols refer to 68\%-age, or $\approx$,

Figure 4. Percentage of objects within the estimated credible intervals for all of the example cases considered in Section 3. The legend shows the Pearson correlation coefficients of the values obtained for redshift (x-axis) and other SED fitting parameters. A perfect correlation would indicate that if the uncertainties in redshift are underestimated by a certain amount, those in mass, age, or $E(B-V)$ are underestimated by the same amount. Small (large) symbols refer to 68\% (95\%) credible intervals.

galaxies. As a result, we argue that it is possible to use the estimated-versus-true size of uncertainties in redshift to approximately calibrate the size of uncertainties in other parameters, even in the presence of non-algorithmic systematics.

Based on these results, we seek a method to simultaneously correct the size of uncertainties in photo-zs and SED fitting parameters. We assume that the factor by which the uncertainties are mis-estimated in redshift can be obtained by testing the performance of the photo-zs against a control sample with spectroscopic redshifts.

A first step in this direction is to estimate the unknown systematic errors by investigating the distribution of residuals between templates and observed photometry in each band. The width of this distribution provides a band-dependent smoothing error that can be added in quadrature to the photometric errors (e.g., Dahlen et al. 2013). However, as further discussed in Section 5, there is no guarantee that this procedure will bring the uncertainties to a realistic level. In this case, a prescription is needed to modify uncertainties so that (1) the size of predicted and true uncertainties in redshift match (i.e., the reported values lie within the N\% confidence errors N\% of the time); and, (2) there is no information loss in terms of bias, scatter, and OLF. Our question then becomes: is it possible to modify the multi-dimensional PDF itself in a way that does not affect the relative weight of each band, yet still achieves the goal of re-sizing the uncertainties? Our proposed answer is to apply a technique called “MCMC sampling at high temperatures” or, more often, annealing.

4.1. Annealing

Annealing (e.g., MacKay 2003) is a technique used in MCMC sampling to speed up convergence in multi-modal probability distributions. In MCMC parlance, this process is described as increasing the “temperature” T of the chains; the standard temperature is $T = 1$. This is achieved by replacing the likelihood of each model, $\mathcal{L}$, with $\mathcal{L}^{(1/T)}$. The effect of annealing is to increase the likelihood of improbable transitions. As a result, points occupying the tail of a probability distribution are sampled more often than they would be at low temperatures. Because in MCMC the density of visited points is proportional to the probability distribution function; for single-peak distributions the PDF inferred from high-temperature chains has a similar mean and location of maximum as its low-temperature equivalent, but has wider tails. In the presence of multiple local minima, the secondary ones might get “boosted” to higher significance. The practical effect on the marginalized distributions is to increase the size of the credible regions, achieving our objective of re-sizing the uncertainties of photo-zs as well as SED fitting parameters, but without information loss in the form of an increased bias or a significantly higher fraction of outliers.

By sampling the chains for the tests described above at different temperatures, we were able to verify that the width of the PDF distributions increased, but the bias and OLF did not become significantly worse when chains were run at higher temperatures. For example, for the case of CSF with catastrophic failures, the fraction of objects for which the true value of the redshift is within the 68\% (95\%) estimated credible region is 56\% (83\%) at $T = 1$, becomes 68\% (90\%) at $T = 2$, and 75\% (94\%) at $T = 3$. More importantly for our purpose, the correlation between the size of the credible regions in redshift and other SED fitting parameters holds. For example, the fraction of objects for which the true value of the mass is within the 68\% (95\%) estimated credible region varies from 59\% (84\%) at $T = 1$, to 70\% (90\%) at $T = 2$, to 73\% (93\%) at $T = 3$. In each of the three cases, the bias and OLF do not change significantly. An example of the effect of sampling at higher temperatures on the recovered marginalized PDFs in redshift and mass is shown in Figure 5 for the first 16 objects in our mock catalog with constant SFH and added catastrophic failures in the photometry.

We ran MCMC chains using annealing for seven problematic cases described in Table 1, and we show our results in Table 2. In each instance (catastrophic failures, template incompleteness, incorrect assumptions in modeling the stellar populations, uncorrected zero-point errors, combined effect) annealing was useful in improving the accuracy of the reported error bars on photo-zs and SED fitting parameters, without compromising the performance of SED fitting (i.e., without introducing further biases or increasing the fraction of outliers). A rule-of-thumb to determine the correct temperature for MCMC sampling (e.g., the temperature for which the uncertainties will be close to their nominal value) is the following. In the chains, the comparison between the different models that decided whether to accept or reject a step is done by comparing $\mathcal{L}^{(1/T)}$, where $\mathcal{L}$ is the likelihood of each model and $T$ is the temperature of the chains. If the likelihood function was represented by a Gaussian function, an N-fold increase in temperature would correspond to an increase of $\sqrt{N}$ in the width of the likelihood (and therefore, in the size of the uncertainties). Because the likelihood function is not Gaussian, and because of the presence of priors, the actual increase factor is different, and finding the ideal temperature for annealing might require some further trial-and-error.

Furthermore, since the annealing temperature is calibrated using subsets of objects with spectroscopic redshifts, which might be on average brighter than photometric catalogs, we
investigated how a signal-to-noise ratio (S/N) affects the annealing temperature. We divided our mock catalogs into the high- and low- S/N halves, ran chains with the same annealing temperature, and calculated the accuracy of the uncertainties for the two subsets. We found a mild dependence of the uncertainties on signal-to-noise, with uncertainties tending to

| Parameter | % of Objects in 68% Region | % of Objects in 95% Region | Median Bias | Scatter | OLF |
|-----------|----------------------------|----------------------------|-------------|---------|-----|
| z         | 67 (57)                    | 89 (84)                    | 0.003 (0.002) | 0.07 (0.05) | 0.07 (0.07) |
| CSF Age (median) | 72 (62) | 91 (87) | 0.03 (0.003) | 0.06 (0.06) | 0.08 (0.08) |
| + Cat fail Mass | 69 (60) | 90 (85) | 0.002 (-0.002) | 0.04 (0.04) | 0.02 (0.02) |
| $T = 1.5$ $E(B - V)$ | 69 (59) | 91 (87) | 0.003 (0.002) | 0.05 (0.05) | 0.05 (0.05) |
| z         | 67 (38)                    | 91 (67)                    | 0.03 (-0.02)  | 0.06 (0.05) | 0.15 (0.15) |
| ESF Age (median) | 69 (60) | 87 (88) | 0.02 (0.02)  | 0.05 (0.05) | 0.01 (0.01) |
| fit as CSF Mass | 65 (51) | 84 (78) | 0.009 (-0.01) | 0.04 (0.04) | 0.02 (0.01) |
| $T = 5$ $E(B - V)$ | 65 (58) | 83 (81) | 0.01 (0.01)  | 0.05 (0.05) | 0.24 (0.24) |
| z         | 62 (37)                    | 88 (59)                    | 0.03 (0.02)  | 0.09 (0.09) | 0.22 (0.21) |
| ESF Age (median) | 85 (54) | 95 (81) | 0.02 (0.03)  | 0.06 (0.06) | 0.09 (0.08) |
| fit as CSF Mass | 63 (46) | 81 (69) | 0.01 (-0.01) | 0.05 (0.05) | 0.05 (0.04) |
| $T = 5$ $E(B - V)$ | 71 (52) | 89 (78) | 0.01 (0.01)  | 0.06 (0.06) | 0.31 (0.29) |
| z         | 58 (32)                    | 86 (57)                    | 0.04 (-0.03) | 0.08 (0.07) | 0.21 (0.20) |
| ESF Age (median) | 57 (43) | 79 (65) | 0.005 (-0.004) | 0.05 (0.05) | 0.03 (0.02) |
| fit as CSF Mass | 86 (39) | 95 (74) | 0.05 (0.05)  | 0.06 (0.06) | 0.06 (0.04) |
| $T = 5$ $E(B - V)$ | 69 (47) | 86 (74) | 0.006 (-0.003) | 0.06 (0.06) | 0.27 (0.26) |
| z         | 64 (46)                    | 87 (67)                    | 0.004 (-0.004) | 0.04 (0.04) | 0.124 (0.125) |
| Realistic SFH Mass | 59 (38) | 84 (61) | 0.005 (-0.005) | 0.03 (0.03) | 0.02 (0.01) |
| fit as single-pop Age (median) | 56 (40) | 79 (60) | 0.005 (-0.004) | 0.05 (0.05) | 0.13 (0.12) |
| $T = 5$ $E(B - V)$ | ... | ... | ... | ... | ... |
| $T = 5$ $\tau$ | 43 (35) | 51 (46) | 0.06 (0.05)  | 0.21 (0.21) | 0.38 (0.39) |
| z         | 77 (61)                    | 92 (80)                    | 0.002 (0.002) | 0.03 (0.03) | 0.09 (0.08) |
| Realistic SFH Mass | 73 (56) | 90 (84) | 0.002 (0.006) | 0.03 (0.04) | 0.01 (0.01) |
| fit as single-pop Age (median) | 60 (48) | 81 (69) | 0.002 (-0.003) | 0.05 (0.05) | 0.1 (0.1) |
| $T = 5$ $E(B - V)$ | 75 (62) | 93 (81) | 0.004 (0.003) | 0.03 (0.03) | 0.022 (0.025) |
| $T = 5$ $\tau$ | 37 (34) | 47 (44) | 0.04 (0.08)  | 0.22 (0.19) | 0.35 (0.38) |

Note. In all cases, the estimation of uncertainties can be improved by using the spectroscopic redshifts control sample as a calibration tool. The numbers in parentheses indicate the results obtained without annealing.
be more severely underestimated (by about 20%) for the high S/N objects than for the low S/N objects. As a result, the calibration obtained through annealing on a spectroscopic sample can be considered as an upper limit to the true uncertainties.

It is worth noting that as non-algorithmic systematics become more severe, the correlation between the under uncertainties.

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5. Example Application to Data

The last step of our analysis is to verify that using annealing on real data, rather than on simulated galaxies, is still helpful in calibrating the uncertainties and does not introduce additional bias and/or worsen the fraction of outliers. In this case, we can only test the effect of annealing on redshift, since it’s the only parameter for which the “true” value can be learned via spectroscopic observations.

In order to perform joint SED and photo-z fitting on real data, we used the publicly available multi-wavelength catalog obtained by CANDELS in the GOODS-S field, described in Guo et al. (2013). The spectroscopic sample from this catalog comprises 1338 galaxies; we selected a subsample of 585 objects characterized by a S/N of at least eight in at least 13 bands from observed-frame UV to IR. To determine photometric redshift and other physical properties using SpeedyMC, we adopt the following pipeline.

1. Perform photo-z estimation and SED fitting jointly, including a luminosity function prior that takes into account the cosmological volume as a function of redshift. The distribution of estimated redshifts will have bias and scatter.
2. Calculate the distribution of residuals in each observed band as described in the previous section.
3. Use the width of the residual distribution as an estimate of the smoothing error in each band, to be added in quadrature to the photometric error.
4. Increase the uncertainties in the data by incorporating the smoothing errors in the photometry.
5. Evaluate any mismatch of the calculated and true uncertainties in redshift (i.e., calculate for how many objects the spectroscopic redshift value lies within the 68% and 95% estimated credible intervals).
6. Run MCMC chains at higher temperature as appropriate.

For these data, using a CSF history leads to a sizable median bias, scatter, and outlier fraction of −0.025%, 0.06%, and 16%. The sizes of the 68% and 95% credible intervals are also quite severely underestimated, at 42% and 66%, respectively. We note that this result is obtained after applying the smoothing errors; those are insufficient to ensure that the uncertainties in the SED fitting parameters will be estimated correctly, as mentioned in Section 4. The high OLF alone is a sign of template incompleteness, and a strong invitation to explore more flexible models, as suggested in Section 4.1. Indeed, using exponential star formation histories leads to much better results, with a median bias, scatter, and outlier fraction of −0.01%, 0.06%, and 7.5%, respectively, without applying any zero-point corrections. On the basis of our results in the previous section, we chose not to apply offsets to these templates. We note that our results are of comparable quality to the ones obtained by the teams participating in the CANDELS photo-z challenge (Dahlen et al. 2013) in terms of correspondence between spectroscopic and photometric redshifts, scatter, and outlier fraction in redshift. The sizes of the 68% and 95%
The choice of SFHs and annealing temperatures are driven by the lessons learned on simulated catalogs. In particular, we consider the data, EAZY + SpeedyMC, EAZY, and SpeedyMC. Table 3 shows the comparison of results for photometric redshift estimation and SED fitting with SpeedyMC.

### Table 3
Comparison of Results for Photo-\(z\) + SED Fitting Runs on CANDELS Data

| Settings                  | % of Objects with \(\text{Photo-}z\) in 68% Region | % of Objects with \(\text{Photo-}z\) in 95% Region | Average Bias in \(\text{Photo-}z\) | Scatter in \(\text{Photo-}z\) | OLF in \(\text{Photo-}z\) |
|---------------------------|-----------------------------------------------|-----------------------------------------------|-------------------------------|-----------------------------|-----------------|
| Data, CSF, SpeedyMC       | 42                                           | 66                                           | −0.03                         | 0.06                        | 0.16            |
| Data, EAZY, SpeedyMC      | 51                                           | 83                                           | −0.005                        | 0.06                        | 0.075           |
| Data, EAZY, SpeedyMC, \(T = 3\) | 65                                           | 94                                           | −0.005                        | 0.06                        | 0.079           |
| Data, EAZY + SpeedyMC     | 44                                           | 74                                           | 0.002                         | 0.049                       | 0.057           |
| Data, EAZY + SpeedyMC, \(T = 3\) | 60                                           | 93                                           | 0.001                         | 0.049                       | 0.063           |
| Data, EAZY + FAST         | 67                                           | 93                                           | −0.004                        | 0.046                       | 0.089           |

**Note.** The choice of SFHs and annealing temperatures are driven by the lessons learned on simulated catalogs. In particular, we confirm on data the following findings: (i) using more flexible SFHs improves the fitting performance and (ii) annealing does not significantly increase the values of bias, OLF and scatter.

credible intervals are also not far from their nominal value, with 51% and 83% of objects falling in these regionally credible intervals. We can apply annealing to obtain more accurate credible regions; sampling at a temperature \(T = 3\) causes these numbers to shift to 65% and 94%, respectively, while leaving bias, scatter, and OLF basically unaltered, as shown in Table 3.

5.1. **Photometric Redshift Estimation with EAZY and SED Fitting with SpeedyMC**

As a final experiment in the joint photo-\(z\) estimation and SED fitting, we considered combining the use of the publicly available photometric redshift code EAZY (Brammer et al. 2008) with SpeedyMC. EAZY is known to produce accurate photometric redshifts and we wanted to investigate the following two issues:

1. Whether using the probability distributions obtained by EAZY as priors for the photo-\(z\) + SED fitting could further reduce the OLF and scatter obtained by using SpeedyMC alone;
2. Whether combining two different sets of templates (the empirical templates used by EAZY and the SPS templates used by SpeedyMC) would introduce a significant bias in the recovered SED fitting parameters.

We used EAZY to compute the \(P(z)\) distributions for the same catalog described above, adjusting the photometric uncertainties to reproduce the 68% and 95% credible intervals correctly. These \(P(z)\) curves were then used as a prior probability distribution for redshift by SpeedyMC in place of the luminosity function prior; in other words, SpeedyMC would sample each redshift value from these probability distributions. The results were slightly better than the case in which SpeedyMC was used by itself, with a bias varying from −0.005 to 0.001, and OLF and scatter both decreasing by about 20%. Since the size of the 68% and 95% estimated credible regions were still underestimated, we used annealing at \(T = 3\) to correct the size of the error bars. Once again, annealing did not negatively impact the performance of the photo-\(z\) + SED fitting, as shown in Table 3.

We were also able to verify that the mean values of SED fitting parameters did not change significantly whether they were estimated using SpeedyMC (i.e., consistently using the same set of templates) or using EAZY to determine the \(P(z)\) first and “feeding” them into SpeedyMC as a prior. The median difference (percentage of objects for which the difference was larger than the 68% error) in stellar mass, stellar age, redshift, and \(E(B−V)\) in the two cases were found to be −0.01 (12%), −0.005 (9%), −0.006 (13%), and 0.003 (4%). The main driver of the disagreement is the different estimate of redshift, which immediately translates into a different estimate of mass because of the change in luminosity distance. Of course, there is no telling, in general, which one is correct, but the rule is that if the redshift estimate agrees, the estimates of the other parameters also agree. These results are also in agreement with the similar analysis conducted in Finkelstein et al. (2010).

We also compared the performance of SpeedyMC with annealing to that obtained by using EAZY (Brammer et al. 2008) with the publicly available SED fitting code FAST (Kriek et al. 2009). We used FAST with input values as close as possible to those used by SpeedyMC (e.g., using the same SPS models, initial mass function, dust law, and SFH); however, some differences persist, such as the inclusion of the nebular emission contribution in SpeedyMC, which is not available in FAST. The performance of these two combined codes is similar to that obtained when SpeedyMC was used by itself, and was slightly worse than that obtained by using SpeedyMC with EAZY, with a median bias of −0.004 (versus 0.001), an outlier fraction of 8.9% (versus 6.3%) and similar scatter of 0.05. The difference in the estimate of the SED fitting parameters from EAZY + FAST and EAZY + SpeedyMC was also examined, and was found to be within the 68% uncertainties in 90%–95% of cases for all parameters. The size of 68% and 95% credible regions were estimated correctly by FAST once the outliers were eliminated.

6. **CONCLUSIONS**

We have investigated the relationship between photometric redshift estimation and SED fitting and assessed performance in both cases through bias, scatter, outlier fraction, and whether the uncertainties were evaluated correctly. We concluded that the performance of photometric redshift determination is strongly correlated with that of SED fitting, and that because the former can be tested on data by analyzing validation samples with spectroscopic redshifts, the latter can be improved accordingly. We tested our hypothesis on various types of mock catalogs, making sure we included severely problematic (but rather common) sources of systematic errors in the photo-\(z\)+SED fitting setup. Our main conclusions are as follow.

1. “Non-algorithmic” (i.e., code-independent) systematics, such as catastrophic failures in the photometry or template incompleteness, will result in an underestimation of the uncertainties both in photo-\(z\)s and SED fitting parameters.
2. The presence and severity of these systematics is signaled by a high fraction of redshift outliers.
3. The performance of the joint SED fitting-photo-$z$ estimation can be significantly improved by using more flexible SPS models and more realistic star formation histories.
4. In the presence of systematics, the median stellar age of a galaxy is a more robust parameter than the time elapsed from the beginning of star formation.
5. We could not reach a conclusion about whether adding offsets to the photometry, as customary in photometric redshift codes, might be detrimental to the estimation of SED fitting parameters, but we did not find evidence that it is beneficial.
6. Even when severe non-algorithmic systematics are present, the extent to which uncertainties in redshift and other SED fitting parameters are underestimated is strongly correlated. Therefore, if uncertainties in photo-$z$s can be recalibrated by using a validation sample with spectroscopic redshifts, those in SED fitting parameters can also be corrected.
7. Annealing (running MCMC chains at higher temperatures, by substituting the likelihood $L$ with $L^{1/T}$) is a valid method of calibrating the joint uncertainties on photo-$z$s and other SED fitting parameters without sacrificing accuracy.
8. Using the same code and set of templates for photometric redshift estimation and SED fitting has the advantage of internal consistency and allows one to reconstruct the full multi-dimensional probability distribution. However, we found that photometric redshift codes such as EAZY can also be used in combination with SED fitting codes. We obtained a competitive performance by using the $P(z)$ from EAZY as a prior in the SED fitting, and using annealing to re-size the uncertainties. The difference in the estimation of SED parameters in the two cases was within the uncertainty for the vast majority of cases.

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