Implementation of the redshift evolution of type la supernovae in SNANA

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ABSTRACT

The use of Type Ia supernovae (SNe Ia) as standard candles lead to a huge improvement on the constraints on cosmological parameters. In order to continue refining these values in a era of increasingly bigger datasets, systematic uncertainties have to be dealt with. Following previous work on the link between supernovae and their environment, we aim at finding the precise impact of a redshift-evolving underlying stretch distribution of SNe Ia compared to the currently-used distributions in SNANA.

Key words. Cosmology – Type Ia Supernova – Systematic uncertainties

1. Introduction

General talk about SNe Ia, Hubble diagram, constraints and assumptions from BBC to fit HD.

Standardizing SNe Ia led to the discovery of the acceleration of the Universe's expansion: thanks to their color and stretch parameters, the systematic uncertainty on their absolute magnitude and thus their distance was greatly reduced. Dark energy is commonly thought to be the cause of this expansion, and its equation-of-state parameter, w, is currently know down to $\approx 4\%$ by combining constraints from both SNe Ia and the Cosmic Microwave Background. If we want to enhance that knowledge, apart from the statistical part it's the systematic budget that needs to go lower.

With that goal in mind, some recent studies try to improve the known correlations. In NR21, we presented an initial study of the drift of the underlying SNe Ia stretch distribution as the function of redshift. We based this study on the assumption of two populations of SNe Ia, young and old, and implemented different modelings of their distributions to better represent the observed data. For that end we took SNe Ia data and created a complete sample by applying redshift cuts corresponding to the expected distance where no selection effects should impact each survey. This approach was at the time the simplest one to implement but does not allow to ponder the impact such a modeling has on the cosmology, and mainly on w, and skips all selection effects altogether.

Other studies tend to define and refine other correlations between a SN's brightness and some observable properties, such as their host-galaxy's mass or Star Formation Rate. One of the most common ways to test these correlations is to simulate surveys by using underlying distributions of parameters and correlations between them with the aim to find which ones come closest to the actual data. In the SNANA framework, it's a galaxy's stellar mass ($M_{\rm stellar}$) that is assumed as the main observable responsible for its environmental effects on SNe Ia. Selection effects are simulated for each survey with great accuracy, and the goal is to correct the values of SNe affected by Malmquist bias by computing the average

2. Modeling

In our previous work N21, we had determined a relationship between SNe Ia stretches and redshift by using the evolution of the fraction of young SNe Ia, $\delta(z)$, after having modelized each subpopulation's underlying stretch populations based on LsSFR, a tracer for the age of a supernova.

In order to simulate SNe, we require a host galaxy to follow the distributions of what has been observed by different surveys. While we argue that LsSFR is a better tracer of a SNe's environment (Briday 21), most survey characterize galaxies using their stellar mass. Therefore, to compare the implication of our modeling based on LsSFR with what other surveys observed, we need to modelize galaxy masses with respect to LsSFR.

2.1. Modeling the mass

Following NR21, we use the LsSFR as the tracer of the age of a SN on the mass estimates from SNf, then model the young and old population through a series of different parameterizations and pick the lowest AIC one. However, different techniques of mass estimation give different output value for a same galaxy and could imply a shift between surveys. SNf masses where com-

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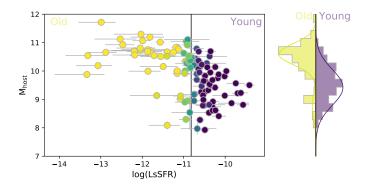


Fig. 1. *Main*: SED-fitted host mass (M_{host}) as a function of the LsSFR for SNfactory SNe. The color corresponds to the probability, p_y , for the SNe Ia to be young, i.e., to have log LsSFR ≥ -10.82 (see ?). *Right*: p_y -weighted histogram of the SN masses, as well as the adjusted model; contributions of the younger and older population are shown in purple and yellow, respectively.

puted using Eq. 8 of Taylor 2011 (see Rigault 20). It involves the absolute i-band AB-agnitude M_i , deduced from the apparent magnitude m_i knowing the galaxy's redshift but assumes that the observed i band is close to the restframe one, which is true for the redshifts on the survey which are below 0.05. However, surveys from the Pantheon sample are at higher redshifts and used SED to avoid K-corrections in that procedure. In order to maintain coherence between the mass modeling based on SNf data and the masses measured in the Pantheon surveys we will simulate, we needed to use the same method for each object. We thus chose to use SED fitting for everyone.

Having done that, the best, lowest-AIC model for the mass distribution of the younger population (log(LsSFR) \geq -10.82) is modeled as a single normal distribution $\mathcal{N}(\mu_y, \sigma_y^2)$, and the stretch distribution of the older population (log(LsSFR) < -10.82) is modeled as a bimodal Gaussian mixture $a \times \mathcal{N}(\mu_{0,1}, \sigma_{0,1}^2) + (1-a) \times \mathcal{N}(\mu_{0,2}, \sigma_{0,2}^2)$, a representing the relative effect of the two modes.

2.2. Input generation

Then, from a redshift, we can generate a mass and a stretch. This is done with the *SNprop* Python module (INSERT URL). Given a redshift or lists of redshift, it takes the expected fraction of young stars using $\delta(z) = \left(K^{-1} \times (1+z)^{-2.8} + 1\right)^{-1}$ (Fig. 2 from ? then sets a "young" or "old" flag by picking a random value between 0 and 1 and comparing it to said fraction. If the random value is lower, the SN that will be simulated is young. The higher the z, the higher the $\delta(z)$, and thus the lower the probability to flag it young. Stretch values are then generated with the previous NR21 model depending whether the progenitor is considered young or old, same for old. We also include the magnitude shift which we intend to be the underlying reason behind the mass step.

2.3. Generating HOSTLIBs

Generate z, take closest M entry in a table of host galaxies (HOSTLIB), then pick x_1 , c assuming underlying relationships defined by the BBC team. Because we want to make these simulations with an evolving underlying distribution, we have to replace then x_1 values by what is estimated by our previous model.

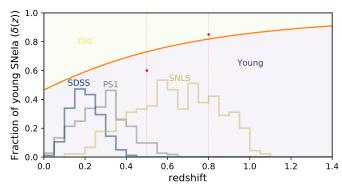


Fig. 2. *Orange*: Estimated fraction of young SNe as a function of redshift. *Histograms*: Number of SNe in bins of redshift for the 3 main surveys of the Pantheon sample, not scaled. *Red vertical lines*: For each z, a random number a between 0 and 1 is picked: if it's lower (higher) than $\delta(z)$ at that redshift then the SN will be young (old), and the distributions of mass and stretch to pick from will follow this flag.

3. SNANA

What is SNANA doing generally: 3 steps.

Model SN and what will a survey look like: lightcurves Fitting with SALT.2 Compute distance

In the simulation you take an underlying model of how a SN works and run that through an obversing lens of a survey to use them like data then fit, and infer deistances. Basic SNANA. Key is saying what is the definition of a realistic model? SK16, but no relation with galaxy. P21 or M20 introduced a link between the two thanks to a HOSTLIB: take a model and turn them into objects. SK16 is galaxy distribution from which you draw, P21 is a list with the distrubtion already in it, linking the relationships and x_1 and stuff already drawn. But there's no evolution in it, and we want to do that. Forward model that through. PREDICTIVE.

SK16: SNe independent galaxies P21: There is a relationship, we'll try to guess it. Take data bns of mass, and calculate what the distribtion of stretch is for each. Looks differently in different bins: as a function of mass they have distribution. Backward models. N21: our data is independent and we use it to show tht it work on other data at higher redshift, is predictive.

General, Brodie, us; no lightcurve fitting, and at the end of hostlib section w simulate antheon

Compare the , x, c distributons we use wih data Section 3

Having mass isn't constitutive of SNANA, not a requirment, but we use it because the actual data we compare our simulated data to is described using mass. So we need a link between LsSFR to mass: high-redshift galaxies only have mass measurments, not LsSFR. Quote Martin's paper.

given model and observation strategy, what do you see like SIMSURVEY.

SImulation part of SNANA separate from distance.

4. Results of modeling

- Recreate non-evolving, POPOVIC 21 model;
- Test different inputs to reproduce what we want to test.

How to check validity of results: SNprop module, copute probability of fit with a 2D gaussian KDE.

Table 1. Best-fit values of the parameters for the mass distribution model when applied to the SNfactory dataset only (114 SNe Ia).

Sample	$\mu_{ m y}$	$\sigma_{ m y}$	$\mu_{ m o,1}$	$\sigma_{ m o,1}$	$\mu_{\mathrm{o},2}$	$\sigma_{ m o,2}$	a
SNfactory	9.41±????	0.62±????	10.60±????	0.38±????	8.74±????	0.43±????	0.90±????

5. Impact on cosmology

What we want is not so much w than Δw wrt. best current work. We find x% and here are the contours.

6. Discussion

We expected to have a higher/lower, and we got that.

7. Conclusion

Should be nice.

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