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SN-BHM: A hierarchical Bayesian model for Supernova Cosmology

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ABSTRACT
Abstract Abstract

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1 INTRODUCTION

Almost two decades have passed since the discovery of the accelerating universe (Riess et al. 1998; Perlmutter et al. 1999). Since that time, of the number of observed Type Ia supernovae (SN Ia) have increased by more than an order of magnitude thanks to modern surveys at both low redshift (Bailey et al. 2008; Freedman et al. 2009; Hicken et al. 2009; Contreras et al. 2010; Conley et al. 2011), and higher redshift (Astier et al. 2006; Wood-Vasey et al. 2007; Balland et al. 2009; Amanullah et al. 2010). Cosmological analysis of these supernova samples (Kowalski et al. 2008; Conley et al. 2011; Suzuki et al. 2012; Betoule et al. 2014; Rest et al. 2014) have been combined with complimentary probes of large scale structure (Alam et al. 2017) and the CMB (Hinshaw et al. 2013; Planck Collaboration et al. 2013), and yet, despite these prodigious efforts, the nature of dark energy remains an unsolved mystery.

In attempts to tease out the nature of dark energy, currently running and planned surveys are once again ramping up their statistical power. The Dark Energy Survey (DES, Bernstein et al. 2012; Abbott et al. 2016) will be observing thousands of Type Ia supernova, attaining both spectroscopic and photometric confirmation. The Large Synoptic Survey Telescope (LSST, Ivezic et al. 2008; LSST Science Collaboration et al. 2009) will produce scores of thousands of photometrically classified supernovae. Such increased statistical power demands a similarly increased fidelity and flexibility in modelling the supernovae for cosmological purposes, as systematic uncertainty will prove to be the limiting factor in our analyses.

As such, staggering effort is being put into developing more sophisticated supernovae analyses. Scolnic & Kessler (2016) and Kessler & Scolnic (2017) explore sophisticated simulation corrections to traditional analyses. Approximate Bayesian computation methods also make use of simulations, trading traditional likelihoods and analytic approximations for more robust models with only the cost of increased computational time (Weyant et al. 2013; Jennings et al. 2016). Hierarchical Bayesian Models abound (Mandel et al. 2009; March et al. 2011, 2014; Rubin et al. 2015; Shariff et al. 2016; Roberts et al. 2017), however often face difficulties finding sufficient analytic approximations for complicated effects such as Malmquist bias.

In this paper, we lay out a new hierarchical model that extends on past work. Section 2 is dedicated to a quick review of the supernovae cosmology. In Section 3 we outline our methodology and apply it to simulated datasets. Forecasts for the impending DES three year spectroscopic supernova survey are contain in Section 4. Section 5 investigates the effect of various systematics on our model, and Section 6 provides details on potential areas of improvement and unsuccessful methodologies.

2 REVIEW

Whilst supernova observations take the form of time-series photometric measurements of brightness in many photometric bands, most analyses do not work from these measurements of apparent magnitude and colour. Instead, most techniques fit these observations of magnitude (along with red-

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shift) to a supernova model, with the most widely used being that of the empirical SALT2 model (Guy et al. 2007, 2010). This model is trained separately before fitting the supernovae light curves for the cosmology selected supernova sample (Guy et al. 2010; Mosher et al. 2014). The resulting output from the model is, for each supernova, a characterised amplitude x_0 (which can be converted into apparent magnitude $m_B = -2.5\log(x_0)$), a stretch term x_1 and colour term c, along with a covariance matrix describing the uncertainty on these summary statistics. As such, the product at the end is a (redshift dependent) population of m_B, x_1 and c.

The underlying actual supernova population is not as clear cut, and indeed accurately characterising this population, its evolution over redshift and effects from environment is one of the challenges of supernova cosmology. However, given some modelled underlying population that lives in the redshift dependent space M_B, x_1 and c, the introduction of cosmology into the model is simple – it is encoded in the functional map between those two populations, from apparent magnitude space to absolute magnitude. Specifically, for any given supernova our functional map may take the traditional form:

$$M_B = m_B + \alpha x_1 - \beta c - \mu(z) + \text{corrections}, \tag{1}$$

where α is the stretch correction (Phillips 1993), and β is the colour correction (Tripp 1998) that respectively encapsulate the empirical relation that broader and bluer supernovae are brighter. The corrections term at the end often includes corrections for host galaxy environment, as this has statistically significant effects on supernova properties (Kelly et al. 2010; Lampeitl et al. 2010; Sullivan et al. 2010; Rigault et al. 2013; Uddin et al. 2017). The cosmological term, $\mu(z)$ represents the distance modulus, and is precisely known given cosmological parameters and an input redshift.

For traditional χ^2 analyses such as that found in Kowalski et al. (2008); Conley et al. (2011); Betoule et al. (2014), minimise the difference in distance modulus between the cosmologically predicted values μ_C and the observed distance modulus $\mu_{\rm obs}$, shown respectively below:

$$\mu_C = 5\log\left[\frac{(1+z)r}{10}\right] \tag{2}$$

$$r = \frac{c}{H_0}\int_0^z \frac{dz'}{\sqrt{\Omega_m(1+z')^3 + \Omega_k(1+z')^2 + \Omega_\Lambda(1+z')^{3(1+w)}}} \tag{3}$$

$$\mu_{\rm obs} = m_B + \alpha x_1 - \beta c - M_B \tag{4}$$

The minimising function is then given as

$$\chi^2 = (\mu_{\rm obs} - \mu_C)^\dagger C^{-1} (\mu_{\rm obs} - \mu_C) \tag{5}$$

where C^{-1} is an uncertainty matrix which combined the uncertainty from the SALT2 fits, intrinsic dispersion, calibration, dust, peculiar velocity and many other factors (see Betoule et al. (2014) for a review). The benefit this analysis methodology provides is speed - for samples of hundreds of supernova, efficient matrix inversion algorithms allow the likelihood to be evaluated quickly. The speed comes with two costs. Firstly, formulating a χ^2 likelihood requires a loss of model flexibility by building into the model assumptions of uncertainty Gaussianity. Secondly, the computational efficiency is dependent on inverting a covariance matrix with dimensionality linearly proportional to the number of supernovae. As this number increases, the cost of inversion rises quickly, and is not viable for samples with thousands of supernovae.

Review old methods done

Review current methods not done

Potential places for improvement not done

3 OUR METHOD

General comments about the method (BHM), Stan

3.1 General Description

Mapping population of observables on a population of underlying SN, where the map function encodes cosmology. Difficulty is creating an underlying SN population that is flexible enough to not introduce bias whilst still being physically motivated.

Observables -> Transformation function (latent, mass, cosmology, systematics) -> Underlying pop (and outlier)

3.2 Applied to Spectroscopic Sample

Minimal outliers

4 APPLICATION TO DES

4.1 Simulating DES SN data

4.2 Model validation

appoximate_simple_test.py

multisim

bulk

4.3 Results on simulated data (ie projections)

4.3.1 Spectroscopic Sample

4.3.2 Photometric sample

4.4 Comparison with bells and whistles fixed

5 SYSTEMATICS STRENGTH TEST

systematics test

6 INTERESTING IMPLEMENTATION DETAILS

Anything interesting.

Also talk about non-analytic correction factors (and their failure - mc integration, GP, NNGP)

7 CONCLUSIONS

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APPENDIX A: PAPERS

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