

# BayeSN: Scaling Bayesian Inference for Next Generation Surveys

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# Part 1: The BayeSN Model

### **Motivation**





NASA/JPL-Caltech/ESO/R. Hurt Nicholas B. Suntzeff



- Correctly handling dust (and SN Ia colour–luminosity correlations more generally) is key to correctly estimating SN Ia distances
- Observed correlation ("mass step") between SN Ia magnitudes and host mass
   → dust would be one explanation
- If dust correlates with host mass, could create *z*-dependent biases if not accounted for
- If intrinsic effect misattributed to dust, could lead to bias

### The BayeSN Model





Mandel (2020)

### The BayeSN Model





Mandel (2020)

### Why include intrinsic colour variation?





### Why include intrinsic variation?





### Why use Optical + NIR?





### Advantages of BayeSN



#### • Hierarchical Bayesian Model

- Allows for joint inference of global and individual SN properties
- Better estimation of global Rv distribution using hierarchical approach than just taking mean/standard deviation of individual estimates
- Can constrain/marginalise over intrinsic SN colour variation
- Model extends into NIR wavelengths, allowing for better constraint of host galaxy dust
- Improved Hubble diagram scatter (~20-30% better than SALT2 and SNooPy)

### **Disadvantages of BayeSN**



• Lots of parameters!



# Part 2: Scaling to Next Generation Surveys





Problem:

Scaling BayeSN for next generation data sets without compromising functionality





#### Problem:

Scaling BayeSN for next generation data sets without compromising functionality Solution:

### pyro-ppl/numpyro

Probabilistic programming with NumPy powered by JAX for autograd and JIT compilation to

GPU/TPU/CPU.

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Contributors	Used by	Stars	Forks	



#### Jax

• Python package very similar to numpy, but includes JIT compilation at runtime for any device including GPUs

Numpyro

• Probabilistic programming package for Python built on Jax

Vectorized posterior evaluation + GPUs = Fast Bayesian inference





#### Mandel+20:

- Trained on 79 *BVriYJH* light curves compiled in Avelino+19
- Approximately 4600 parameters
- Previous training  $\sim$ 5 days  $\rightarrow$  now  $\sim$ 20 minutes

Thorp+21:

- Trained on 157 *griz* light curves from Foundation DR1
- Approximately 4600 parameters
- Previous training  $\sim 1 \text{ day} \rightarrow \text{now} \sim 10 \text{ minutes}$

### Examples



1000 simulated Foundation-like SNe:

- Training (conditioning global parameters on data)
  - 27,500 parameters
  - $\circ$  45 mins
- Fitting (inference of supernova properties)
  - 27,000 parameters
  - $\circ$  15 mins

### **Applications to Next Generation Surveys**



- Previously, training and fitting on data-sets > 10,000 SNe would have been computationally unfeasible
- The use of numpyro + GPUs makes this achievable in relatively short timescales
- We are able to scale Bayesian inference approaches to LSST-size data sets

LSST



8 6 - Z const. colour + 2 u - gmean intrinsic colour 0 intrinsic colour scatter ---- $A_B = 0.75, R_V = 1.5, E(B - V) = 0.30$ --  $A_B = 1.20, R_V = 3.0, E(B - V) = 0.30$ -----  $A_B = 1.20, R_V = 1.5, E(B - V) = 0.48$ BayeSN 10 20 30 0

#### rest frame phase (days)

Wealth of colour information in LSST data!

Will get rest frame z-band out to  $z \approx 0.15$ , rest frame *i*-band out to  $z \approx 0.35$ 

SN Ia Colour Curves Simulated Using BayeSN (in LSST passbands)

### Ongoing Work



#### Improving the model:

- Replacing HMC with variational inference (Ana-Sofia Uzsoy)
  - Rather than trying to sample from posterior, assume its shape and match to the true posterior
    turns Bayesian inference into an optimisation problem
- Using Gaussian Markov random fields and Integrated Nested Laplace Approximation (Collin Politsch)
  - Reduces intrinsic colour variation to far fewer parameters while maintaining complexity, alternative approach for fitting
- Improving and incorporating spectroscopy (Ben Boyd)
  - Training on spectra and using new spectroscopic templates
- Implementing BayeSN within SNANA (Stephen Thorp)
  - Will allow for full BayeSN cosmological analysis

### Ongoing Work



#### Applying the model:

- A BayeSN distance ladder (Suhail Dhawan)
- Hierarchical analysis of SN siblings (Sam Ward)
- Analysis of dust and intrinsic colour distributions (Erin Hayes)
- Training BayeSN using YSE DR1 (Matt Grayling)
- Analysis of environmental dependence on intrinsic colour (Matt Grayling + Suhail Dhawan)

### Conclusions



- BayeSN is a powerful Bayesian hierarchical model for standardising type Ia supernovae
- LSST will provide a fantastic sample of *ugrizy* light curves and allow for good constraint of host galaxy dust
- Our work on scaling BayeSN means that it can be applied to next generation surveys
- Lots of ongoing work to improve and apply BayeSN