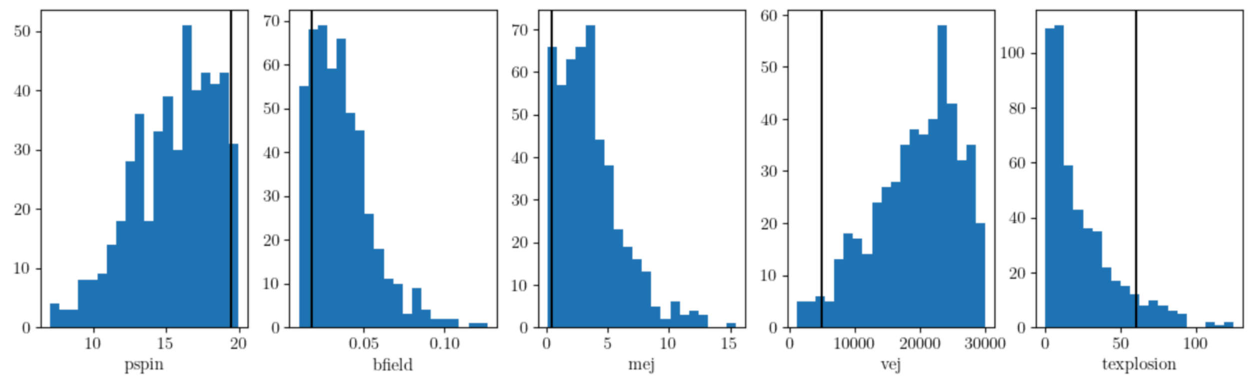
Abstract

The Vera A. Rubin Observatory will begin the Legacy Survey of Space and Time (LSST) in April of 2025 in which it will discover over one million supernovae annually. LSST will therefore play a critical role in resolving the intense contention concerning the progenitors and dynamics of superluminous supernovae (SLSNe)—a very rare supernova class. Conventional methods for classifying and studying supernova light curves, however, are far too computationally expensive for the unprecedented volume of data and rate of collection that we will see with LSST. Simulation based inference (SBI) using normalizing flows has been shown to be well-calibrated at inferring toy supernova parameters compared to traditional methods such as MCMC in order one-ten-thousand the time. Here, we build upon this work by training a similar SBI architecture to infer the parameters of SLSNe from highly realistic simulations of Rubin light curves. Preliminary results indicate that our SBI model does indeed learn the parameter posteriors from a subset of our lightcurve dataset, however there appears to be room for improvement. Steps forward include adding magnitude uncertainties and supernova redshift into the input, tuning the network hyperparameters, using a compressed version of the lightcurve as the SBI input, and normalizing the dataset before training.

Project Updates

Overall, I have been able to successfully implement a baseline SBI architecture that infers SLSN parameters. Professor Villar sent me 32643 simulated Rubin-like SLSN light curves. Due to their realistic sampling patterns, the light curves were highly heterogeneous, so I needed to interpolate them before passing them into a normalizing flow. Following professor Villar's methodology in the original study, I used a 3/2 Matern Gaussian process to interpolate the *ugrizy* light curves onto a 100-day grid with a one day cadence.

I constructed a preliminary normalizing flow network of 5 MADE blocks with 200 hidden layers. For preliminary training, I conducted a train_test_split on a subset of 1000 simulated SLSN light curves and trained the network to predict the spin period P, magnetic field component perpendicular to the spin axis $B_{\perp}$, ejecta mass M_{ej}, ejecta velocity v_{ej}, and explosion time t_{exp} of the supernovae. For these parameters, I chose uniform, log-uniform, log-uniform, normal, and exponential priors, respectively. Below, I show the model's posterior approximation for one of the test light curves (the true values are plotted in black).



The model certainly seems to be learning the data, but there is room for improvement. The maximum posterior estimate is relatively poor for the ejecta velocity and explosion time. I think that this may have to do with numerical instability resulting from the relative parameter magnitudes (i.e. v_{ej} is of order 10000 while $b_{\perp}$ is of order 0.01). I will therefore try normalizing the parameters (and maybe the light curves), which will also entail transforming the priors.

Furthermore, I have thus far only input the interpolated lightcurve magnitudes to the normalizing flow. I will see how adding the interpolation uncertainties and supernova redshift impacts performance. With our large input size, the network may be less efficient than desired. I will therefore compare the performance to a network where the inputs are a lower-dimensional compression of the lightcurve using an autoencoder.

Finally, I will tune the normalizing flow hyperparameters and use the entire dataset (as opposed to the 1000 light curve sample). I will then evaluate our performance by comparing the marginalized posterior to that of a traditional MCMC model using the emcee package. The current results are promising, and the steps that I have outlined should ultimately produce an impressive SLSN parameter inference pipeline.