Proposal for Amortized Inference of Superluminous Supernovae Using Normalizing Flows in the Era of Vera Rubin

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When stars die they produce highly energetic explosions called supernovae (SNe). Not all stars die in the same fashion, however, and astronomers have therefore defined several supernova (SN) classes. The progenitors and dynamics of one of these classes, superluminous supernovae (SLSNe), have been a topic of intense contention since their first observation in 2007, largely as a result of high variability in the (small) set of observations [1]. Understanding the physical distribution of SLSNe is therefore of principal importance to the SN science community [See 1 and references therein].

Traditional Bayesian techniques such as Markov Chain Monte Carlo (MCMC) have been the most common method for inferring the demographics of the order 10k collection of observed SN lightcurves. Depending on model complexity, current methods take anywhere on the order of 10s of minutes to one week to sample the full posterior. When the Vera C. Rubin Observatory begins its ten year survey of the southern sky known as the Legacy Survey of Space and Time (LSST) in April 2025, it will produce roughly 10 million SN alerts *per night* [2]. This drastic increase in the SN dataset volume motivates the development of cheaper methods for fitting SN lightcurves, especially for classes like SLSNe which are less than 1% all SNe.

We will use simulation based inference (SBI) with normalizing flows to estimate the posterior $p(\theta|y)$ where θ are the model parameters of our SNe and y are the lightcurve observations. Conveniently, supernovae are highly deterministic: their lightcurve is an analytic function of a 4-dimensional vector θ composed of redshift, ejecta mass, ejecta velocity, and fraction of radioactive material at explosion time. In [3], Professor Villar found that conducting SBI with masked autoregressive normalizing flows (MAFs) produced well-calibrated results compared to traditional MCMC methods with a computational cost of 5-10 ms per SN for a dataset simulated with the relatively-simplified Arnett model of “stripped” core-collapse SNe [4].

Following her methodology, we will train a MAF model by minimizing the Kullback-Leibler divergence between the model’s distribution and a set of SN lightcurve simulations. To build on her work, we will focus on inferring the 4D posteriors of SLSNe instead of type I. Our dataset will consist of a set of simulations conducted by Professor Villar (she is sending them to me soon). We will begin by showing proof-of-concept with her exact architecture, and then tune by conducting a grid search over the hyperparameters. Time permitting, we will create a pipeline that infers the posterior for SNe of multiple different classes. The primary challenge for me will likely be learning the necessary topics to complete this project, but I already have a good start on this.

References

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