Simulation Based Inference of BNS Kilonova Properties: A Case Study with AT2017gfo

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1 Introduction

Kilonovae are a class of astronomical transients observed as counterparts to mergers of compact binary systems, such as a binary neutron star (BNS) or black hole-neutron star (BHNS) inspirals. They serve as probes for heavy-element nucleosynthesis in astrophysical environments, while together with gravitational wave emission constraining the distance to the merger itself, they can place constraints on the Hubble constant.

We propose here to use a Simulation-based Inference (SBI) technique to infer the physical parameters of BNS kilonovae from their spectra, using simulations produced with *KilonovaNet* (Simulator). Our model uses Amortized Neural Posterior Estimation (ANPE) together with an embedding neural network to accurately predict posterior distributions from simulated spectra. We further test our model with real observations from **AT 2017gfo,** the only kilonova with multi-messenger data.

3 Methodology

The basic idea behind an Amortized Neural posterior estimation is to first train a model (training phase) – specifically, a density estimator – that is not focused on any particular observation (Thus, *Amortized*). Instead, it learns to be a versatile estimator that attempts to approximate all posteriors supported by the prior. Once trained, the density estimator can, in the second phase (Inference), quickly and continually infer parameters of BNS kilonovae from their spectra. To train the Network, we can simulate using prior-draw parameters to build a dataset, of kilonova parameters (**θj**) and their respective spectra (**Xj**), and minimize the Loss function over the weights. Once the density estimator has been trained on simulated data (**X**), it can then be applied to empirical data **Xobs** (ATF2017gfo) to compute the posterior.

3.1 Amortized Neural Posterior Estimation Model

We implemented an **embedding network** in our model, composed of convolutional layers, followed by a max pooling layer, Long Short-Term memory (LSTM) layers and an output dense layer with 100 neurons. The use of Convolutional layers and LSTM layers are essential to extract specific patterns or trends in the spectral data, which can be indicative of certain physical properties, such as the lanthanide composition of the ejecta and the viewing angle.

Our model takes as input spectras at 3 different times differing by one day (E.g: 1.5, 2.5 and 3.5 days after the merger), ranging from 5000 and 8000 Å. Each spectrum was interpolated to have 550 points, and the flux was normalized to zero mean and unit variance.

The parameter sets consist of the mass of the dynamical ejecta (**Mej,dyn**), the mass of the post-merger ejecta (**Mej,pm**), the half-opening angle of the lanthanide-rich tidal dynamical ejecta **ϕ**, and the cosine of the observer viewing angle **cos(θobs)**.

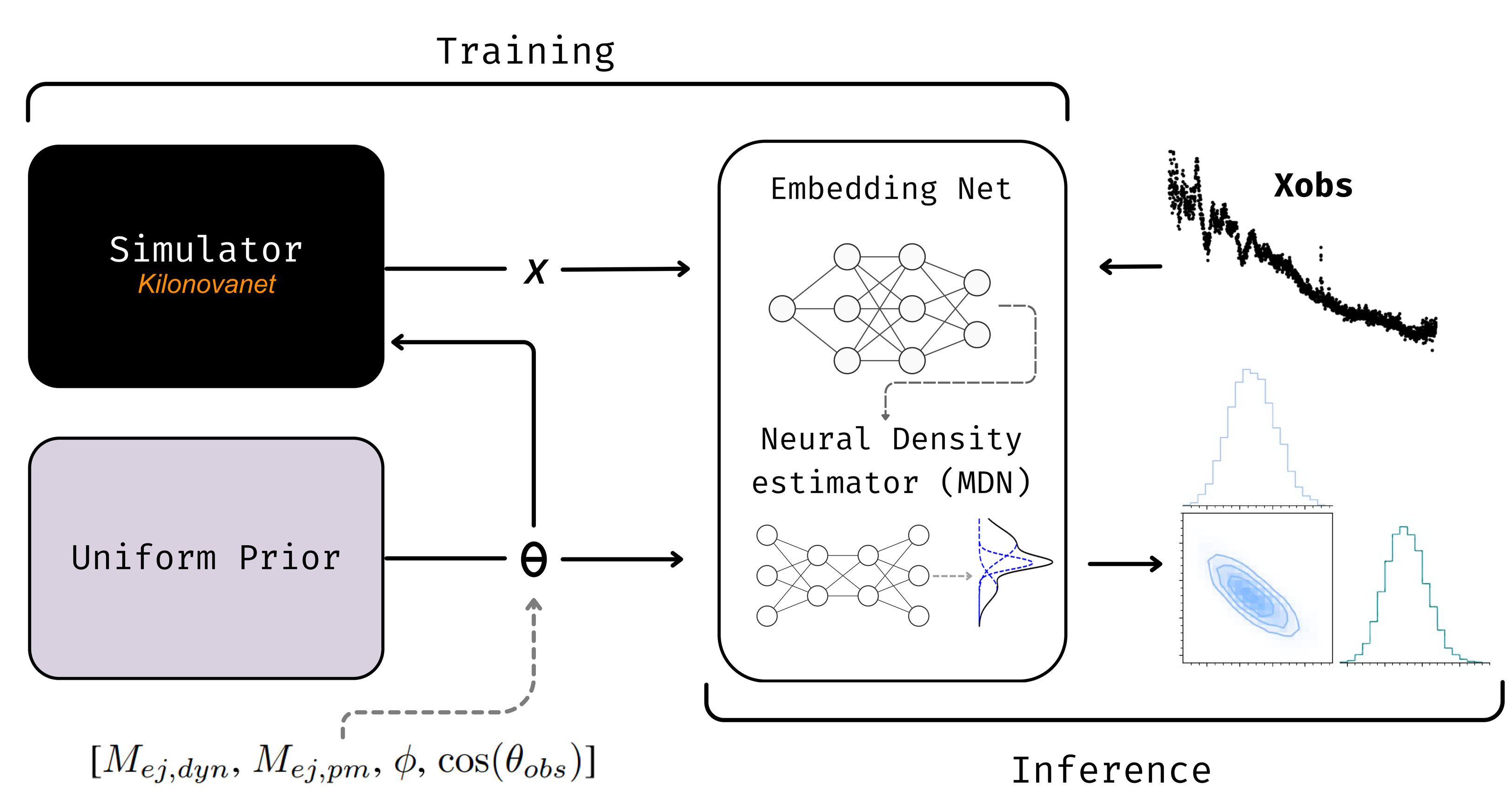

Fig.1: Inference pipeline using amortized neural posterior estimation.

5 Results

We demonstrate the capacity of our model to reproduce observables, spectra, and light curves of the synthetic data and the AT2017gfo event, exhibiting the capability and reliability of using an SBI approach to constrain the parameters of kilonova models.

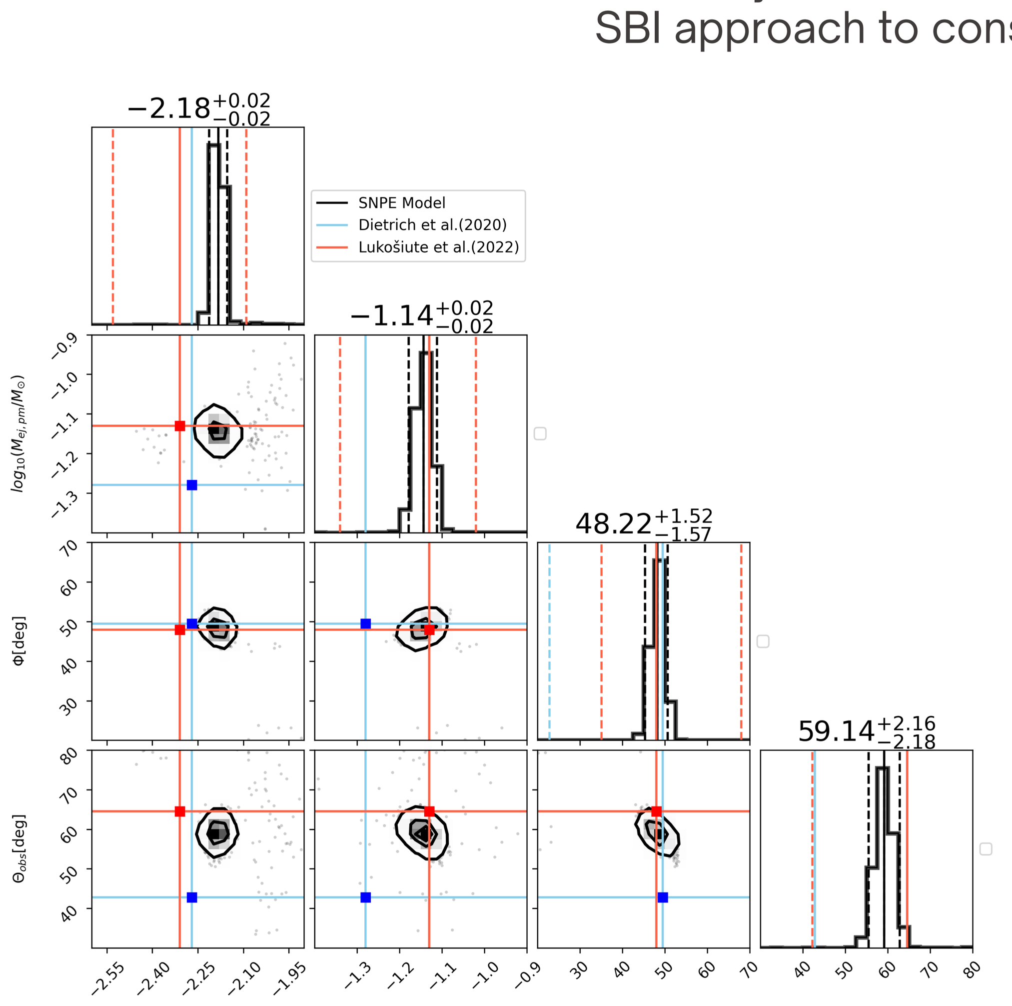

Fig.2: Inferred posteriors for the model parameters at 10%, 32%, 68% and 95% confidence intervals. The median and 90% interval are shown in vertical solid and dashed lines, respectively, and reported above each column. Results from Dietrich, Coughlin, et al. 2020 (**blue**) and Lukošiute et al. 2022 (**orange**) are also shown for comparison.

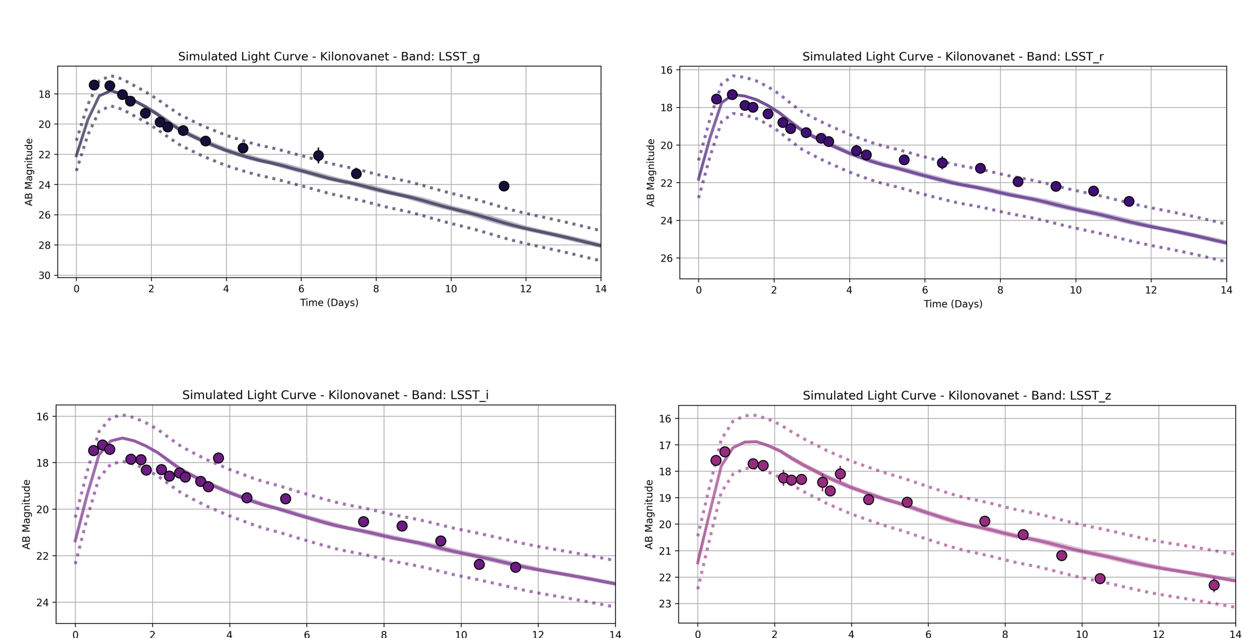

Fig.3: Light curves for AT 2017gfo. Observed values (points) and the prediction based inferred parameters using the NPE model (solid lines). The dashed lines represent the 1 mag tolerance typically used to represent modelling error of kilonova light curves (Lukošiute et al. 2022).

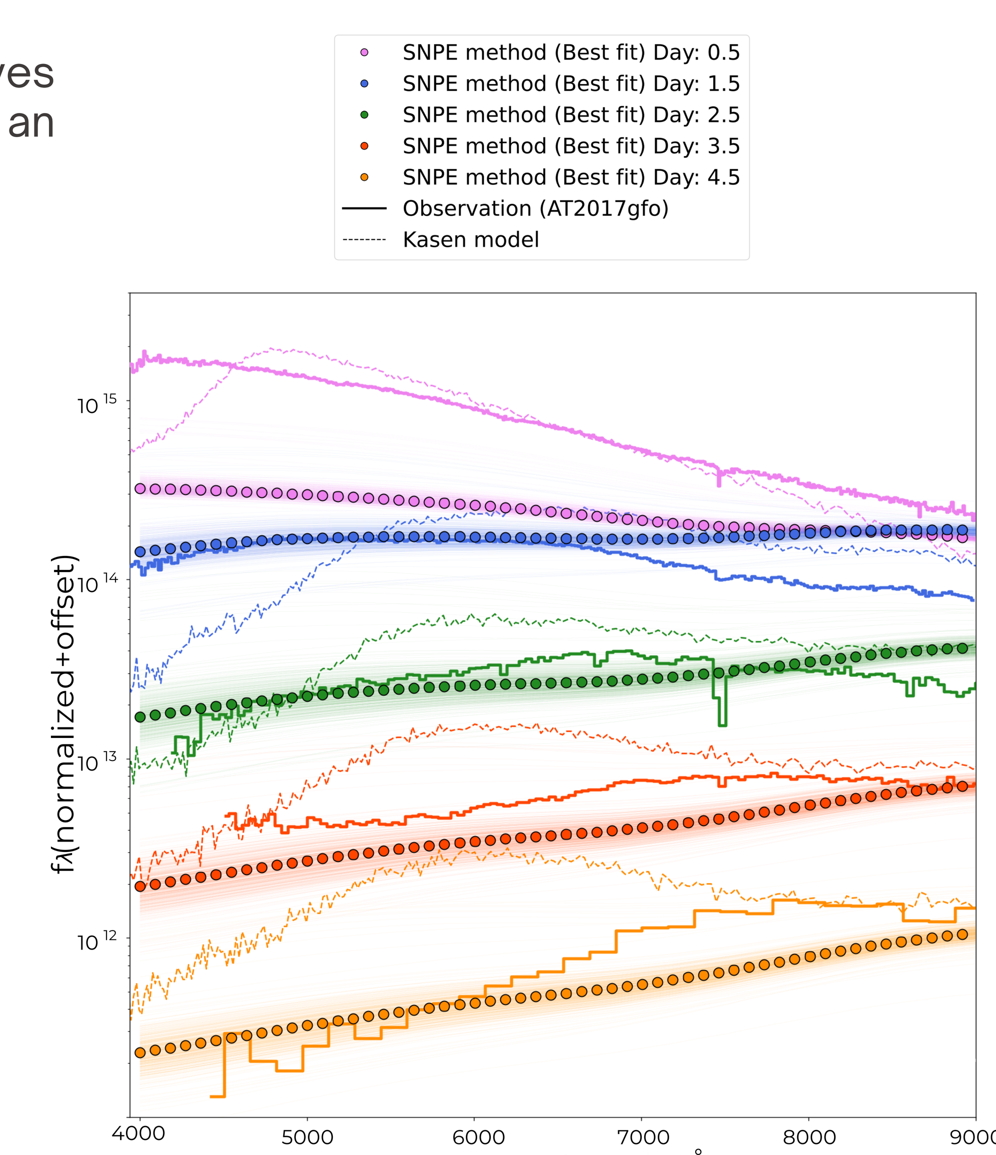

Fig.4: Spectroscopic time series of AT2017gfo (solid lines), the spectra generated by *KilonovaNet* using the Best fit of our NPE model (dotted lines) and the Kasen model best fit (dashed lines) made by Shappee et al. 2017, the vertical axis is observed flux (fλ).

6 Conclusion

SBI is particularly useful when the likelihood function is intractable or computationally expensive to evaluate. Given the speed with which the ANPE model performs during parameter inference, it will serve as a useful tool in future gravitational wave observing runs to **quickly** analyze potential kilonova candidates. The speed-up provided in the parameter inference and spectra retrieval also enables the exploration of several different simulation models over limited observations in a reasonable time.

References

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