Parameter Posteriors for Supernova Spectral Models with Simulation-Based Inference

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Modeling supernova spectra: a high-dimensional problem

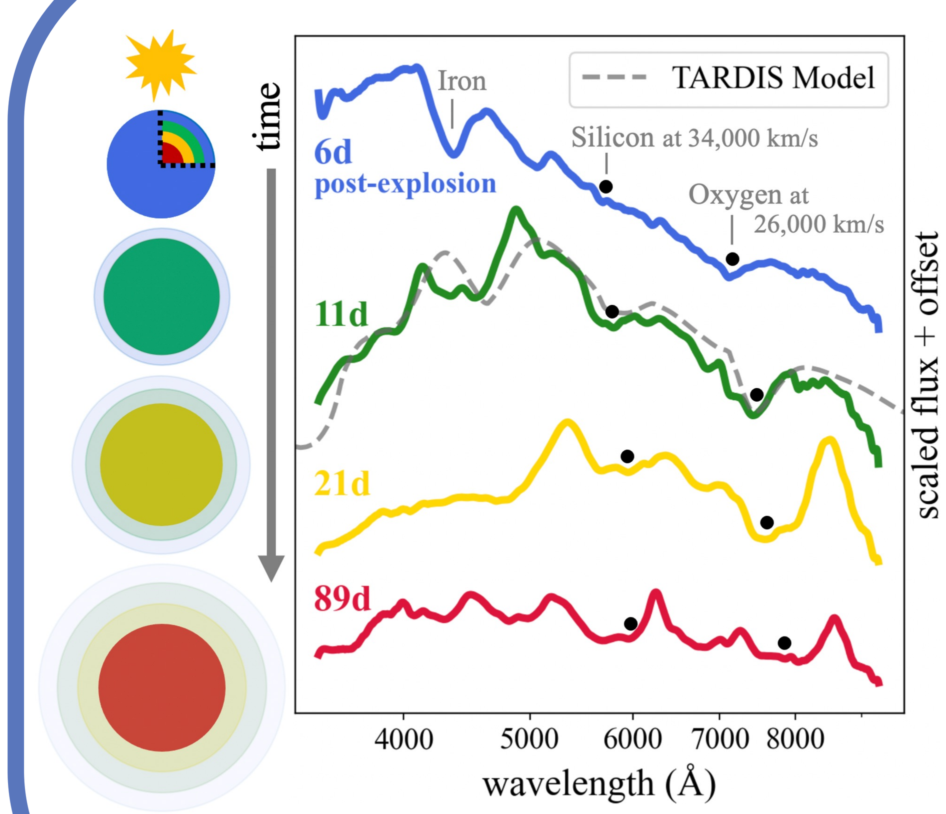


Figure 1: Supernova spectra evolve over time as the ejecta expands and cools, revealing interior layers. Spectral lines can reveal the velocity, temperature, & composition of the ejecta.

Why model supernova spectra?

- Modeling supernova spectra can reveal the velocities, temperatures, densities, and element composition of the ejecta.
- Over time, as the supernova expands and cools, the outer layers of the ejecta become transparent, and we can see into the interior of the supernova.
- Understanding the structure of the supernova helps us constrain progenitor systems and explosion mechanisms.

TARDIS: radiative transfer code

- Open-source Monte Carlo radiative-transfer spectral synthesis code for 1D models of supernova ejecta [1,2].
- Running in minutes, TARDIS simulations are less computationally expensive than full hydrodynamical simulations and more physically realistic than simple line-identification codes.

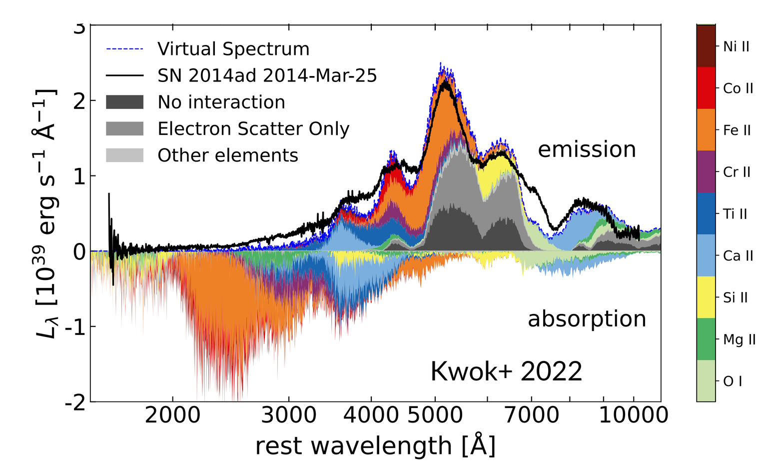


Figure 2: Example TARDIS model spectrum for observed spectrum of SN 2014ad. TARDIS tracks photon/ejecta interactions and can show which elements are responsible for spectral features.

Machine learning applications

- TARDIS simulations have >13 parameters, making manual investigation of the parameter space difficult and time consuming.
- Need parameter posteriors to quantify errors and degeneracies.
- Development of a machine-learning emulator for TARDIS is ongoing [3].

Simulation-based inference: recovering parameter posteriors

Why simulation-based inference?

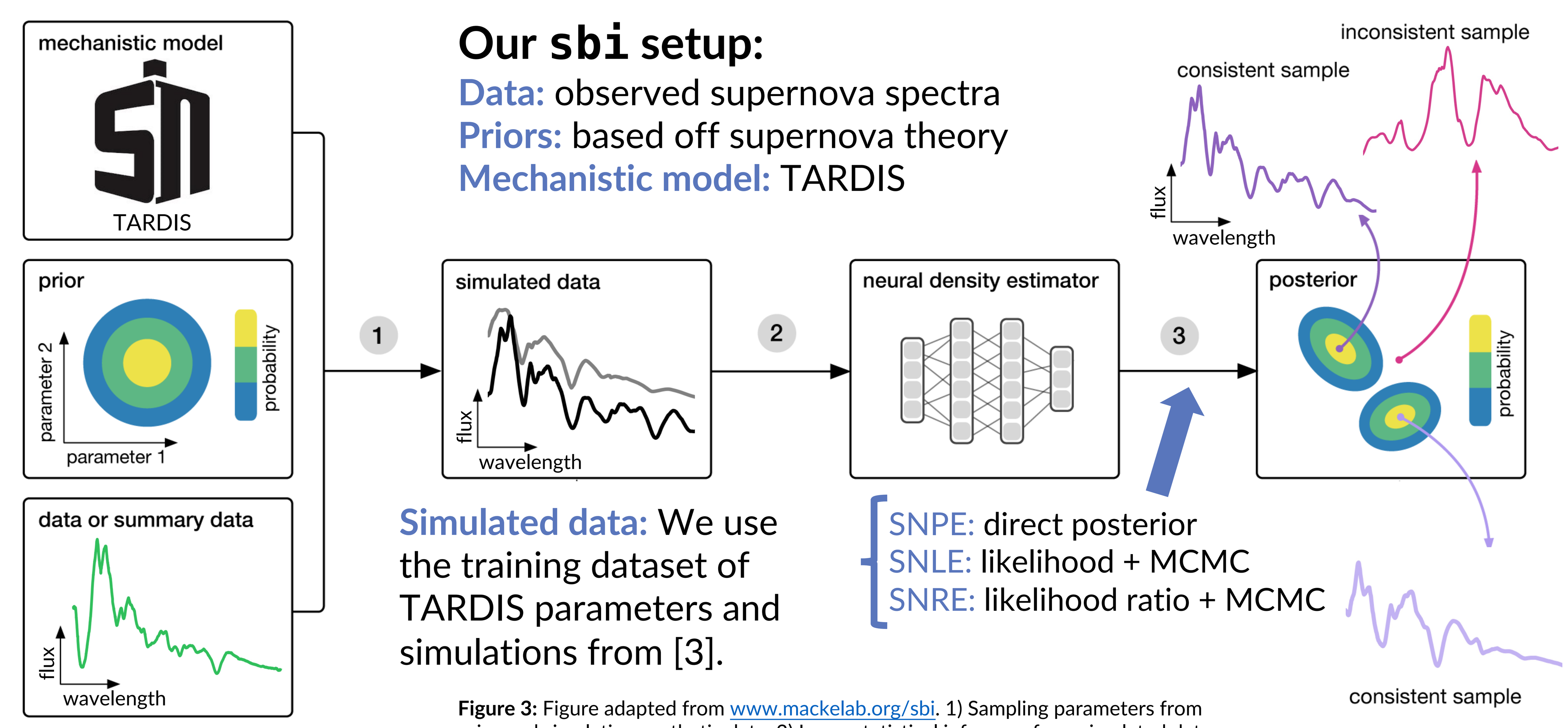
- We want to input an observed supernova spectrum and get out the most likely model parameters.
- Simulation-based inference (`sbi`) derives parameter posterior distributions from empirical data and model parameter priors.
- `sbi` uses deep neural networks to learn the probabilistic association between data and underlying parameters.
- We want to compare the performance of `sbi` as an alternative or addition to the current TARDIS emulator [3].

Machine-learning inference methods

- We use `sbi`: a python toolbox for simulation-based inference [4]
- SNPE (Sequential Neural Posterior Estimation) [5,6,7]
- SNLE (Sequential Neural Likelihood Estimation) [8]
- SNRE (Sequential Neural Ratio Estimation) [9,10]

Our `sbi` setup:

Data: observed supernova spectra
Priors: based off supernova theory
Mechanistic model: TARDIS



Simulated data: We use the training dataset of TARDIS parameters and simulations from [3].

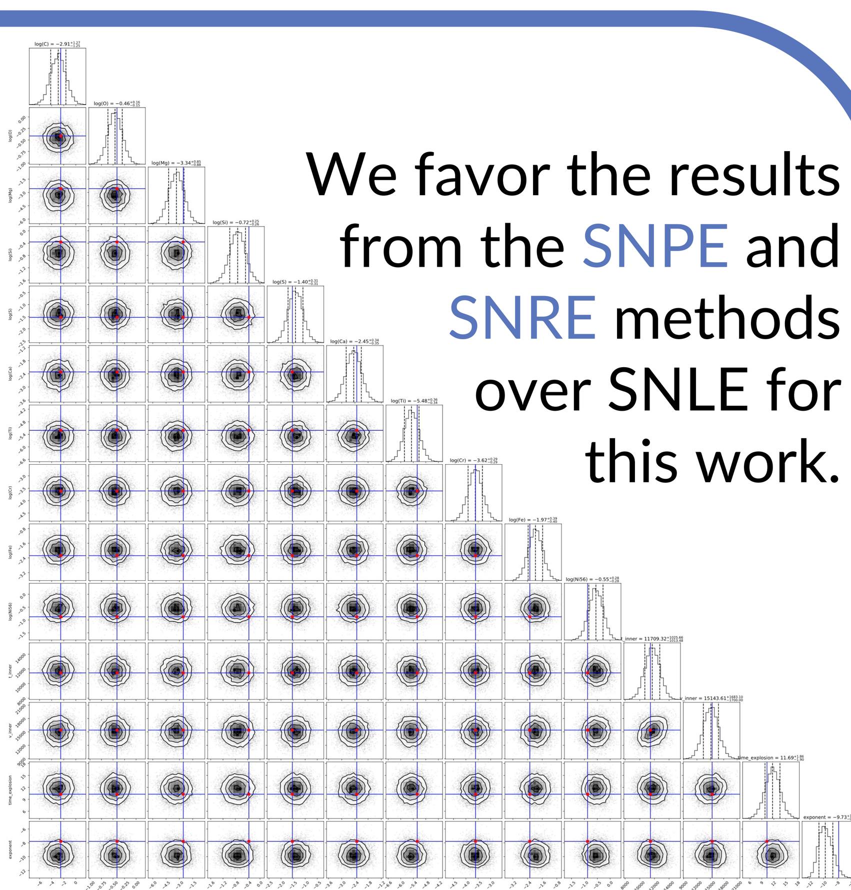
SNPE: direct posterior
SNLE: likelihood + MCMC
SNRE: likelihood ratio + MCMC

Figure 3: Figure adapted from www.mackelab.org/sbi. 1) Sampling parameters from prior and simulating synthetic data. 2) Learn statistical inference from simulated data. 3) Apply neural network to empirical data to construct posterior distribution.

Results

Preliminary results show close agreement with ground truth parameters.

We favor the results from the SNPE and SNRE methods over SNLE for this work.



`sbi` parameter posteriors from the SNRE method.

Figure 5: Corner plot of parameter posteriors for the SNRE method. The ground truth is shown as a red dot with blue lines and is from the same randomly selected simulation as shown in Figure 4. Parameters are unexpectedly uncorrelated and will require further investigation.

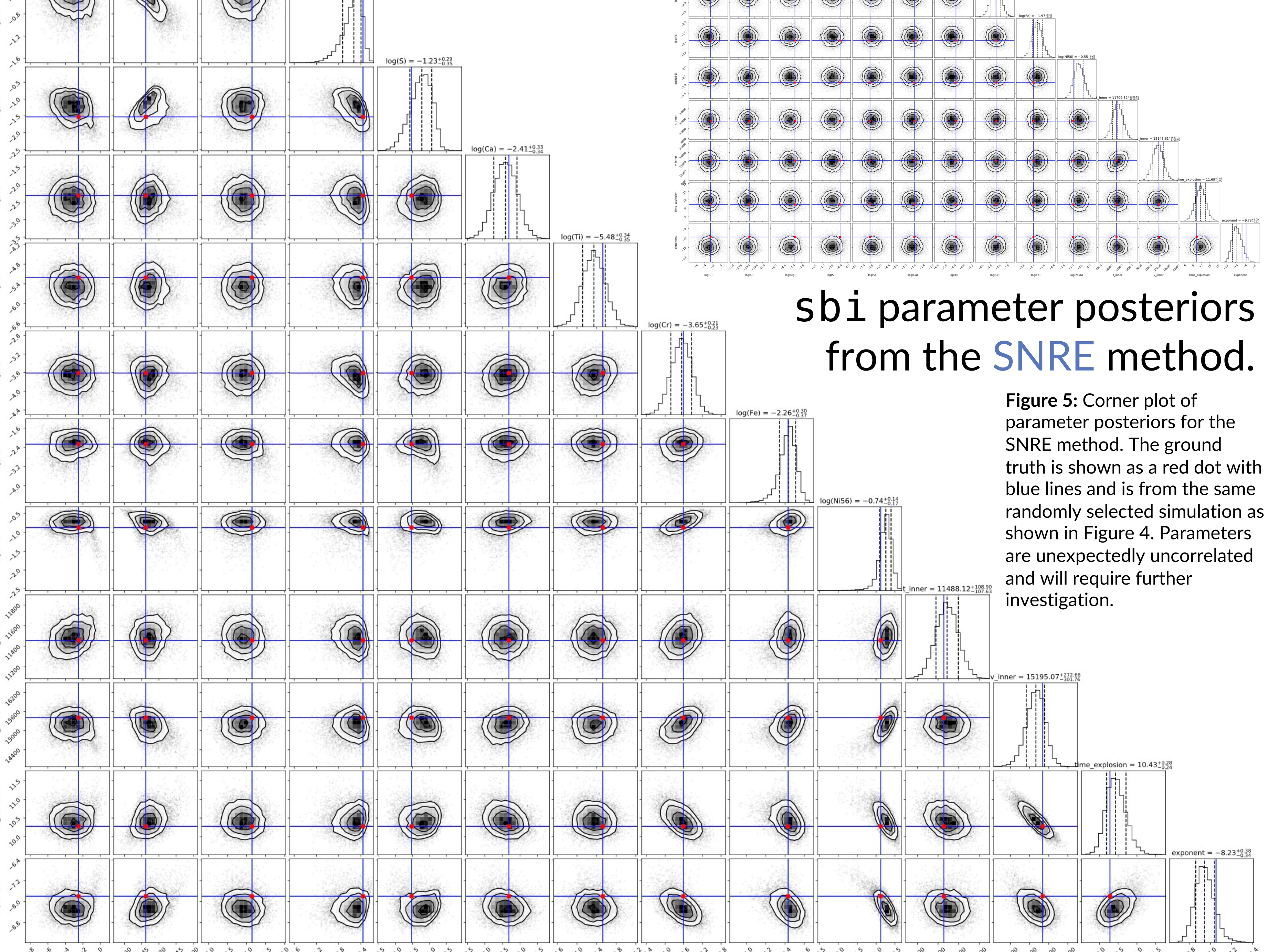


Figure 4: Corner plot of parameter posteriors for the SNPE method. The ground truth is shown as a red dot with blue lines and is from a randomly selected simulation.

`sbi` parameter posteriors from the SNPE method.

Conclusions & Future Work

`sbi` offers a fast, promising avenue for recovering TARDIS model parameters from observed supernova spectra.

SNPE and SNRE methods appear to outperform SNLE.

Future Work

- Currently, we have used one of the training simulations as the "ground truth" to see how well `sbi` is performing but we will use a real, observed supernova spectrum in future implementations.
- We aim to make our work publicly available as a tool in TARDIS to estimate model parameters for an observed supernova spectra.
- We plan to compare performance of our completed `sbi` pipeline to results from the current TARDIS emulator [3].

Acknowledgments

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