Hierarchical Simulation-Based Inference of Supernova Power Sources and their Physical Properties

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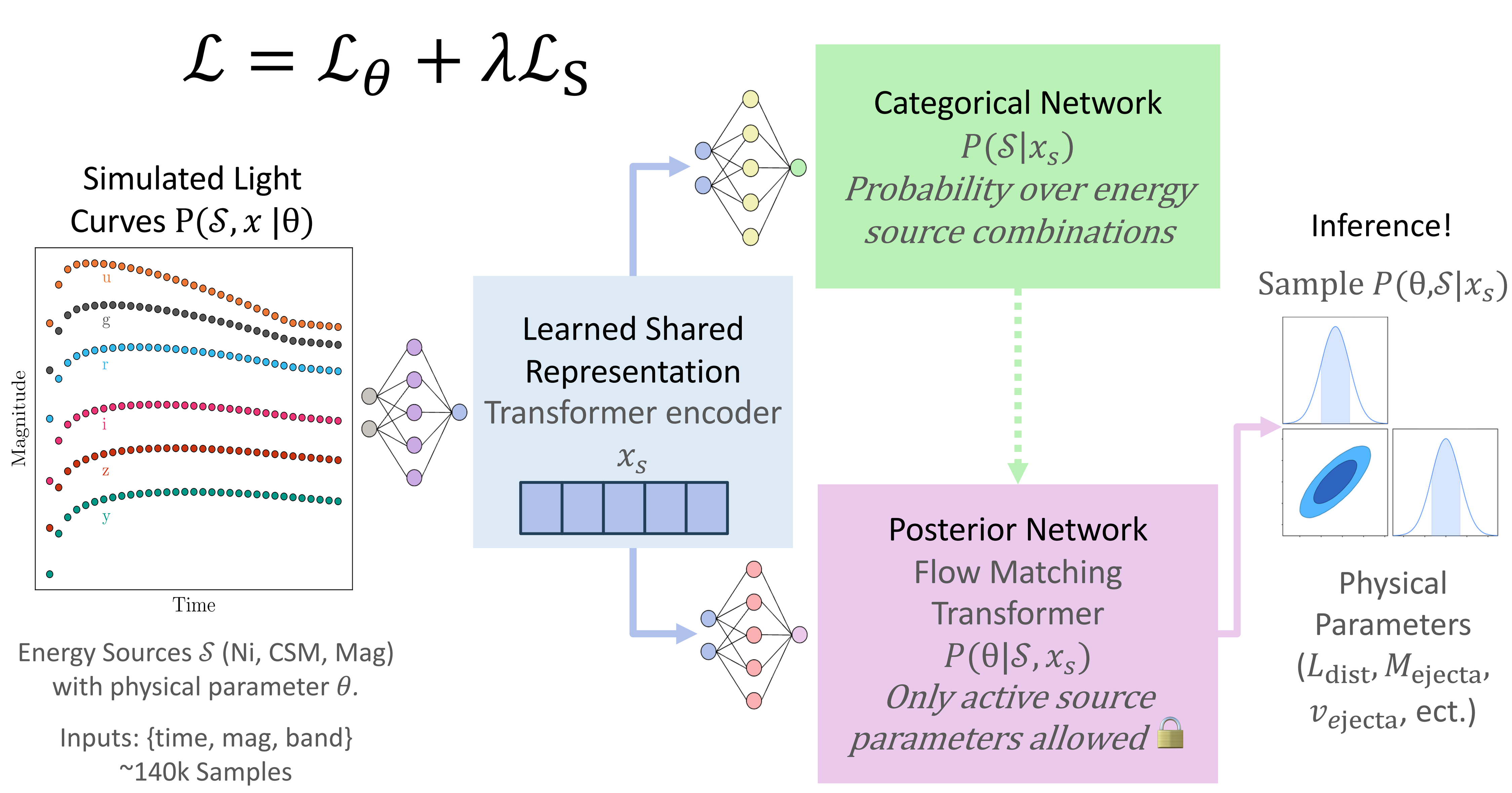
Introduction

The Vera C. Rubin Observatory will discover millions of transients each year, demanding fast and automated physical characterization. Traditional approaches to likelihood-based inference are computationally expensive and ignore the multi-component energy sources powering astrophysical phenomena. We introduce a hierarchical simulation-based inference model for multi-band light curves that identifies the energy sources powering an event, infers physical parameters, and highlights anomalies in a learned latent space. Our framework enables scalable population studies and the discovery of rare or novel transients.

Simulated Light Curves

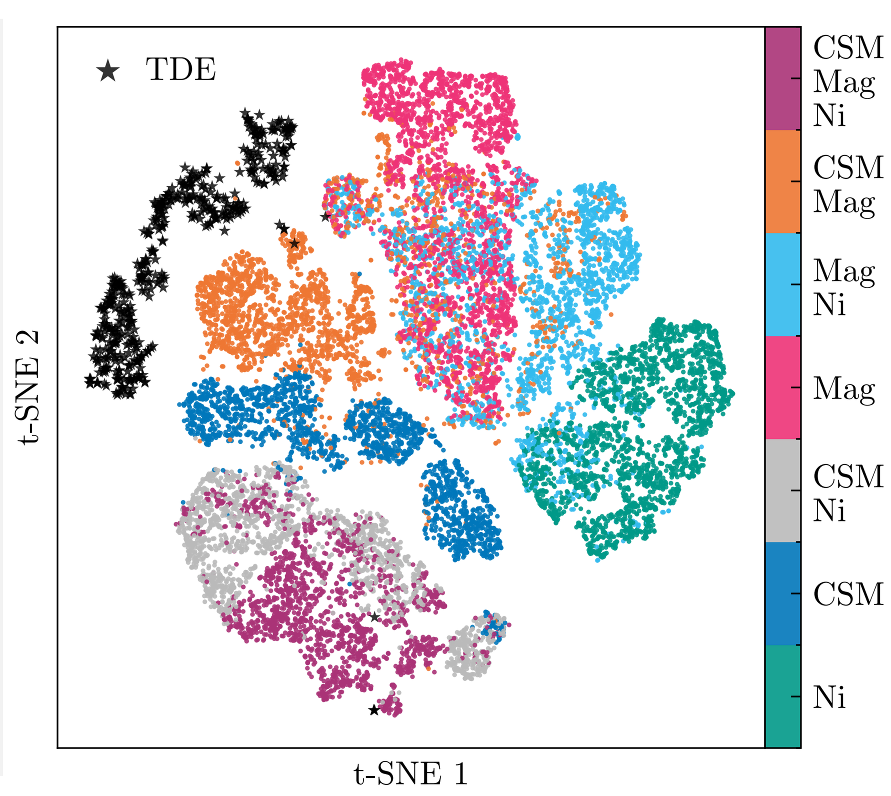
To generate a realistically diverse sample of physical phenomena, we generate synthetic *ugrizy* LSST light curves from the Modular Open Source Fitter for Transients (MOSFiT). We consider three energy sources in MOSFiT: the radioactive decay of $^{56}\boldsymbol{Ni}$, interaction with circumstellar material (**CSM**), and spin-down by a central magnetar (**Mag**). We define seven total Supernovae (**SN**) models consisting of all combinations of these three components. We also simulate an anomalous Tidal Disruption Event (**TDE**) class.

Hierarchical SBI Training Workflow



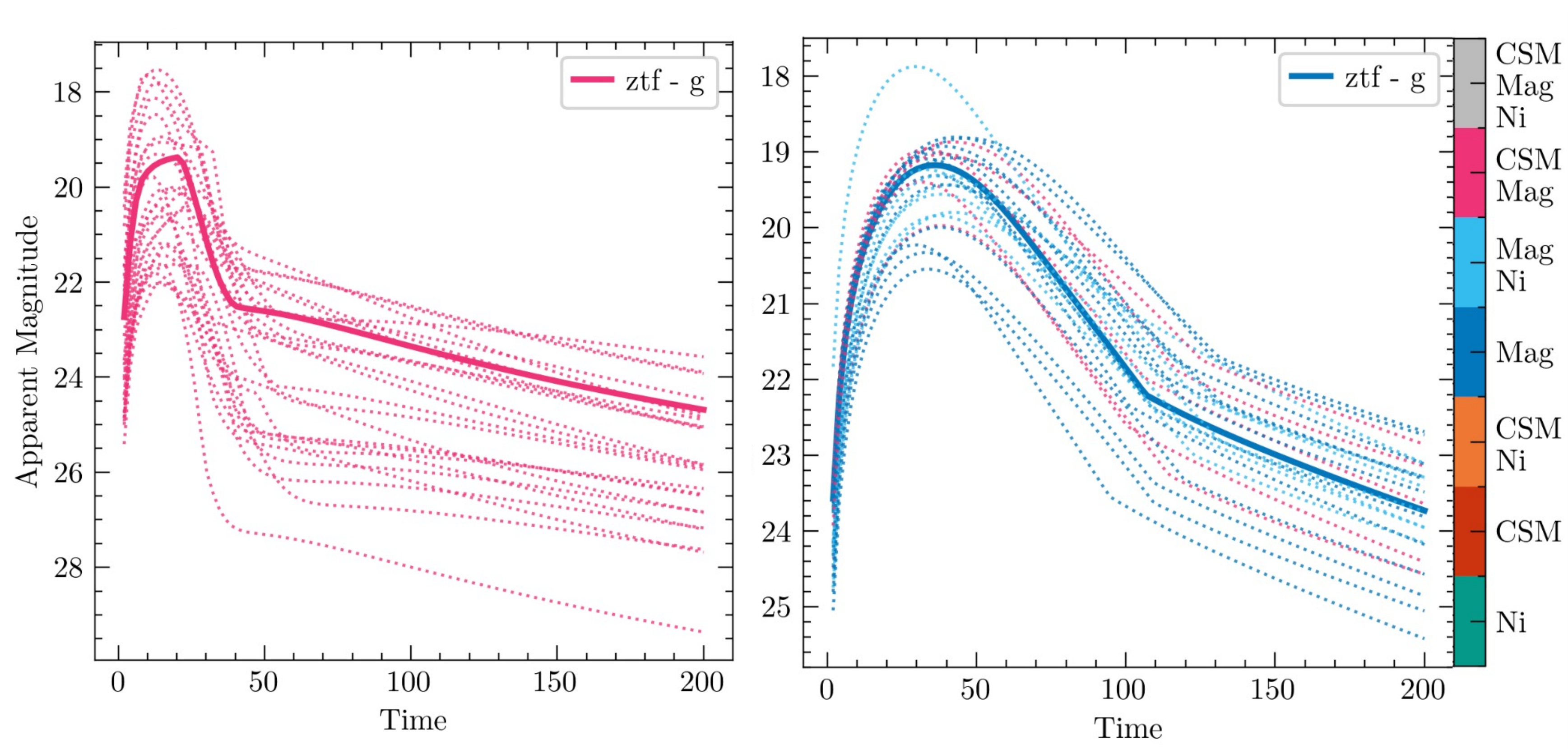
Learned Shared Latent Representation

- Generate embeddings for both SN and TDE light curves, then project them into a 2D space using t-SNE
- Identify natural structure in the embedding space, including clusters
- Isolate physically anomalous events based on their embedding positions
- Estimate the conditional probability $p(x_s|\ \mathcal{S})$ from embeddings



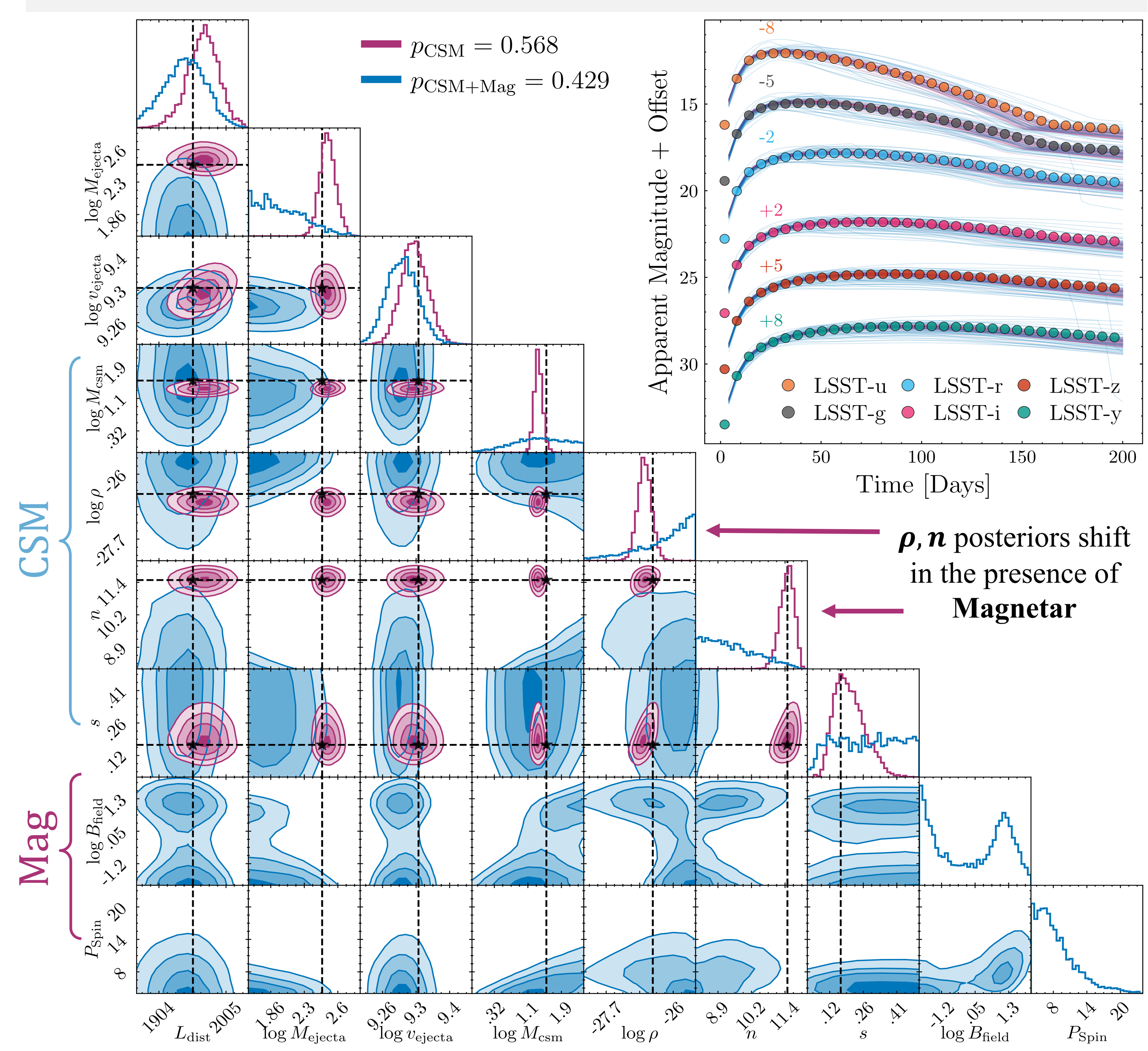
Similarity Search

We compare nearest neighbors in the learned latent space (x_s) to their observed light curves (x) to assess whether the embedding preserves meaningful structure. We find that close neighbors show strong similarity in temporal behavior.



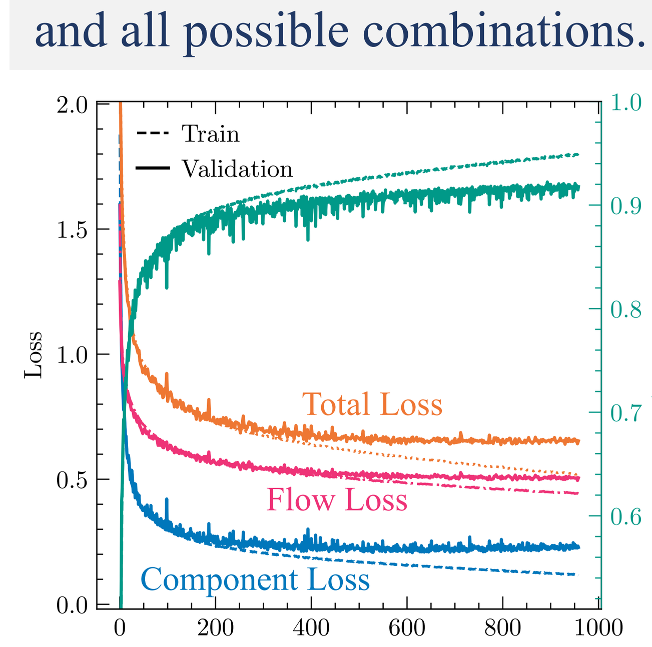
Joint Inference of Supernova Lightcurves

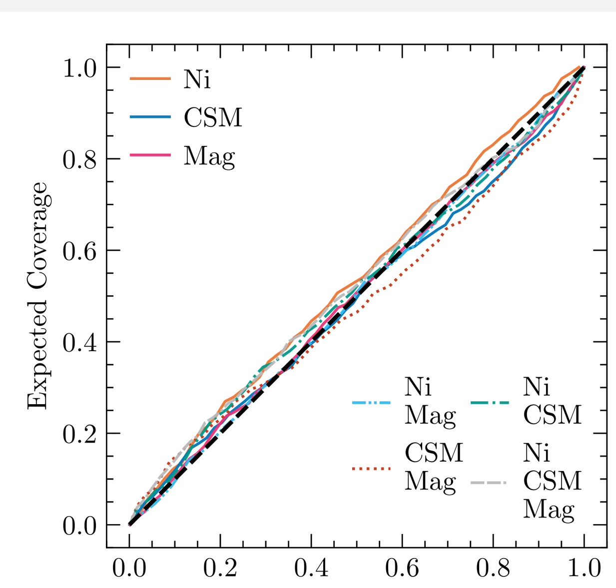
Example joint inference of power sources and their physical properties for a supernova light curve. On the left, we show the posterior samples for the two most likely source combinations powering the light curve, CSM (pink) and CSM+Mag (blue). We show that the presence of the magnetar engine can significantly alter the posteriors for the CSM parameters. In the upper right corner, we show the observed light curve and overlay the light curves drawn from the posteriors of the two power sources.



Model Performance and Calibration

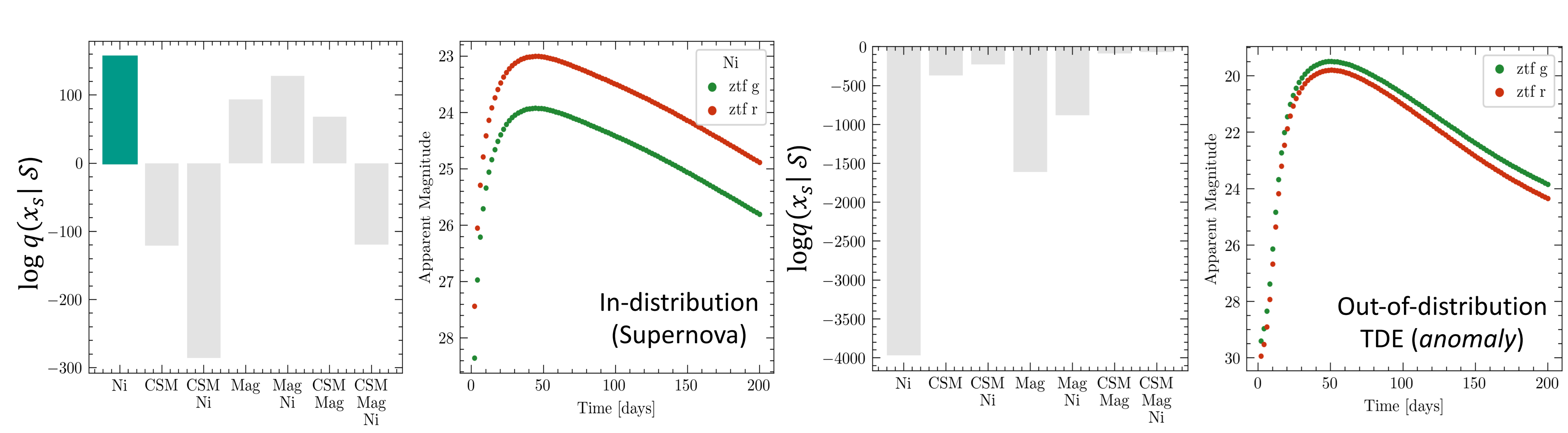
Training and validation loss curves, along with the accuracy curves added for comparison. We also show a coverage test for the primary physical components (Ni, CSM, and Mag) and all possible combinations.





The Way Forward: Future Work

Anomaly Detection: Train Normalizing Flow to approximate $q(x_s|\ \mathcal{S}) \approx\ p(x_s|\ \mathcal{S})$. Use the learned density to quantify both in-class and global anomalies. **Real observations** include irregular sampling and photometric uncertainties from weather and instrumental systematics. We will simulate these conditions with SkySurvey and evaluate model performance on real **ZTF** light curves.



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