

Transient Classification with ParSNIP

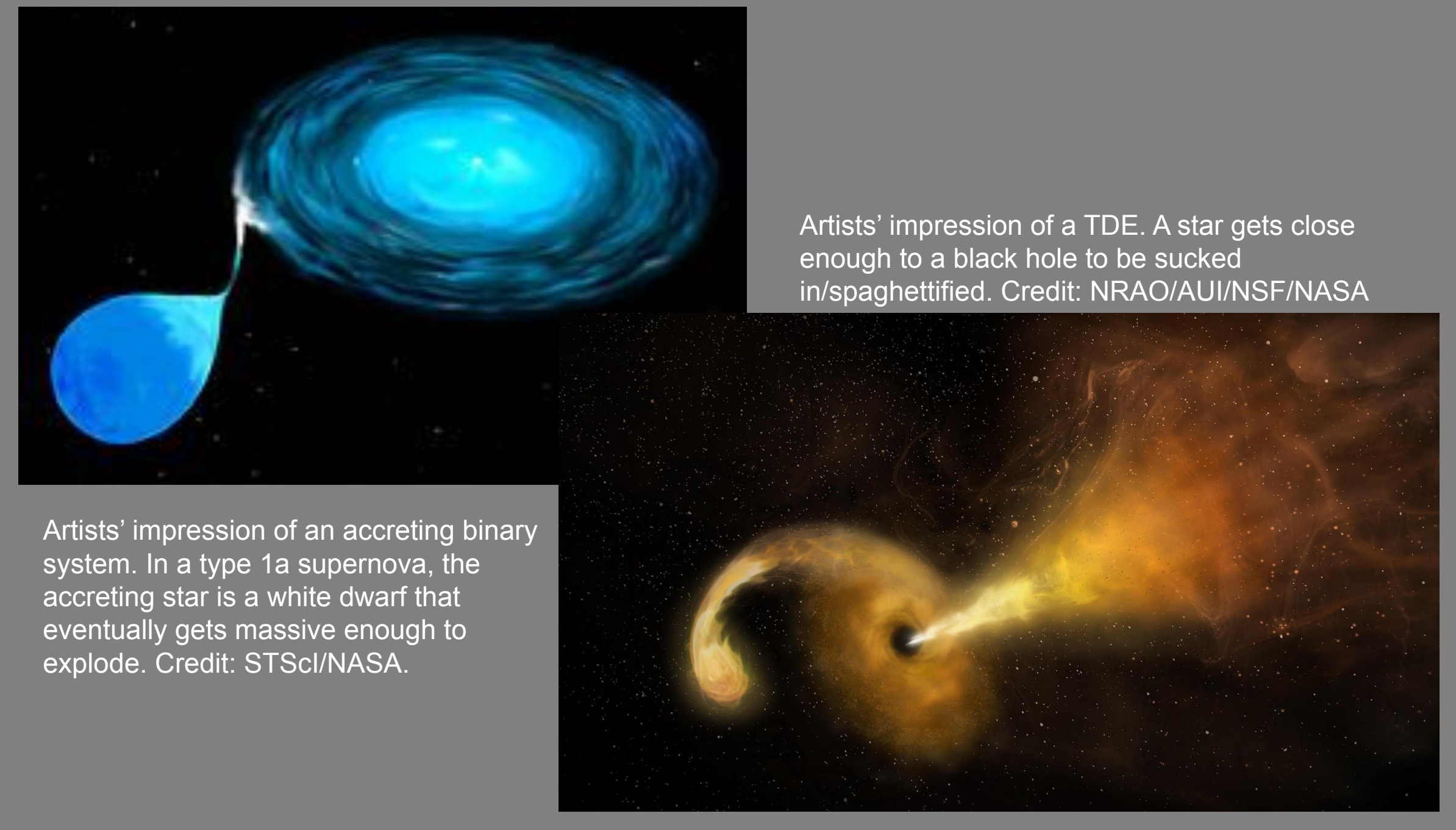
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Abstract

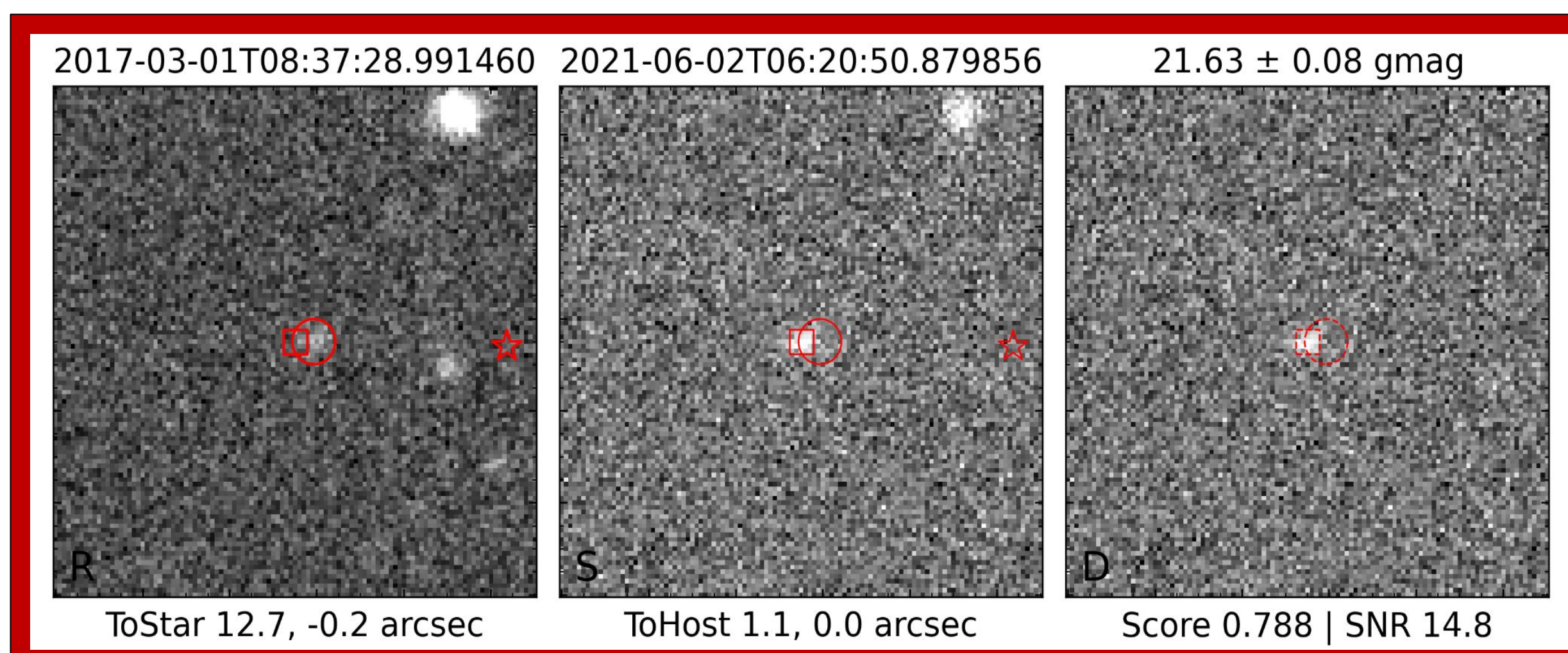
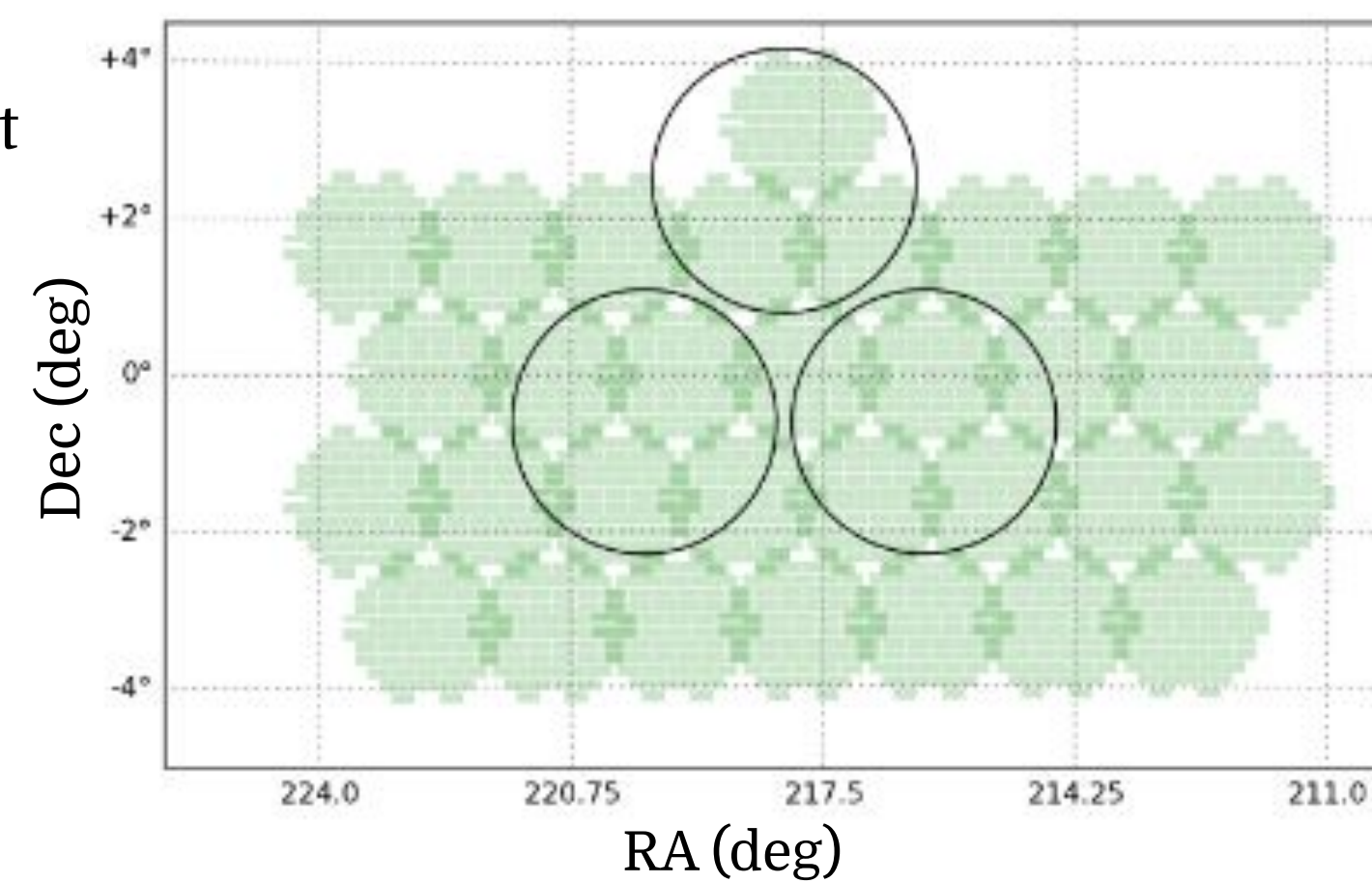
Classifying transients, astrophysical phenomena lasting for a short period of time, is vital due to time constraints on follow-up observations. In preparation for Vera C. Rubin Observatory Legacy Survey of Space and Time (LSST), DESIRT (DECam Survey of Intermediate Redshift Transients) aims to study and identify transients from DECam data (Palmese et al. 2022). The classification process is difficult; spectroscopic follow-up is expensive and constrained by the amount of time a transient is observable, and even when follow-up data is obtained, only the brightest transients are classifiable. Thus, we aim to utilize ParSNIP (Boone 2021), a neural network built to photometrically classify transients, to aid our DECam classifications, by training a model with ELAsTiCC, a simulated dataset of transients (LSST DESC 2023).

Background

Transient: Astrophysical phenomena lasting for a short period of time. Examples include supernovae, TDE (Tidal Disruption Events), and KN (kilanovae).

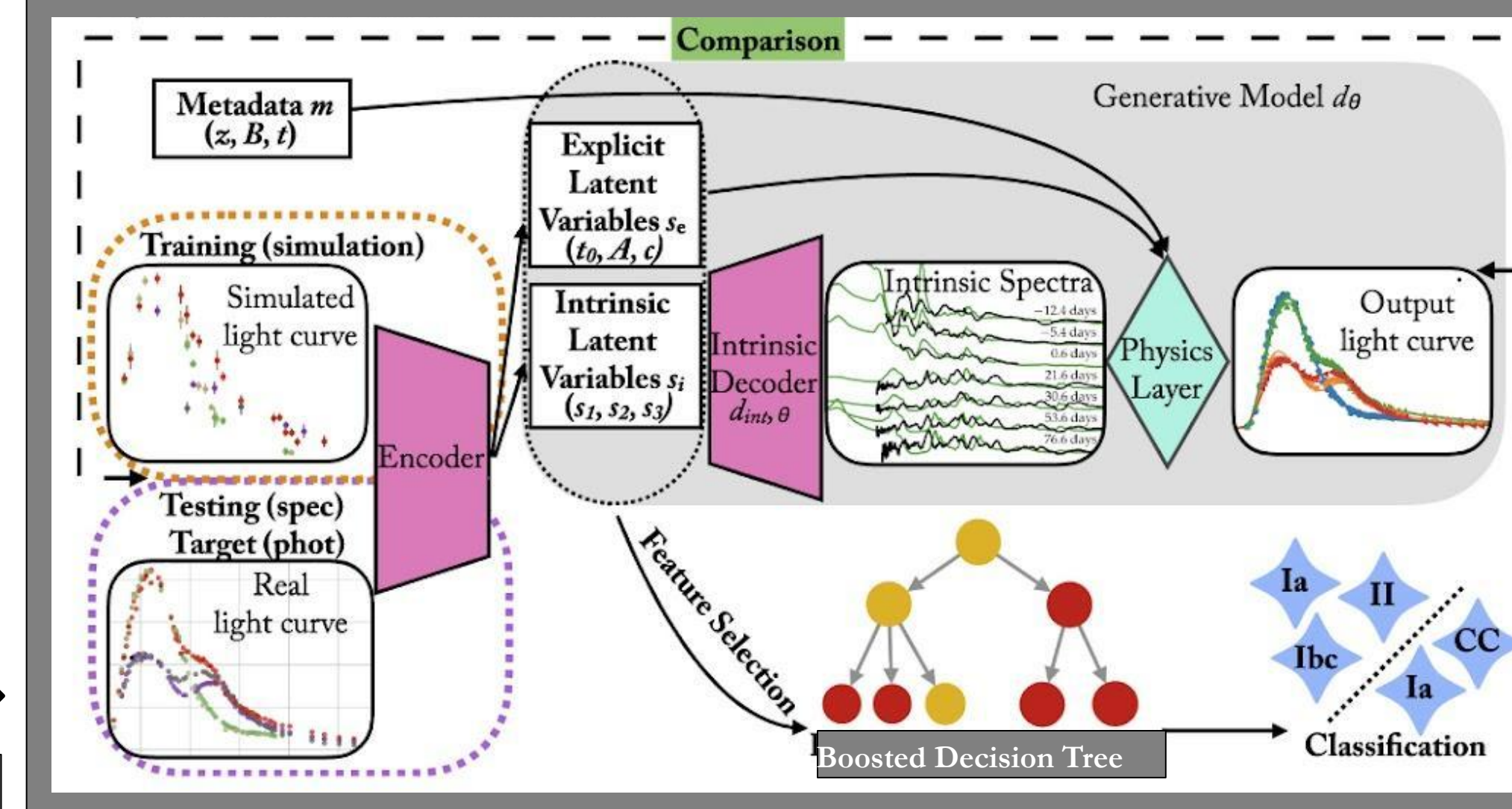


DECam (Dark Energy Camera) is a powerful camera with a large field of view and high sensitivity (Flaugher et al. 2015). We use it to observe in primarily *grz* bands. All DESIRT observations have corresponding DESI (Dark Energy Spectroscopic Instrument) spectroscopic data (Levi et al. 2019). DESI's follow-up gets additional information, particularly host galaxy redshift. Right: Sample sky coverage of DECam and DESI, with DECam in green and DESI in black.



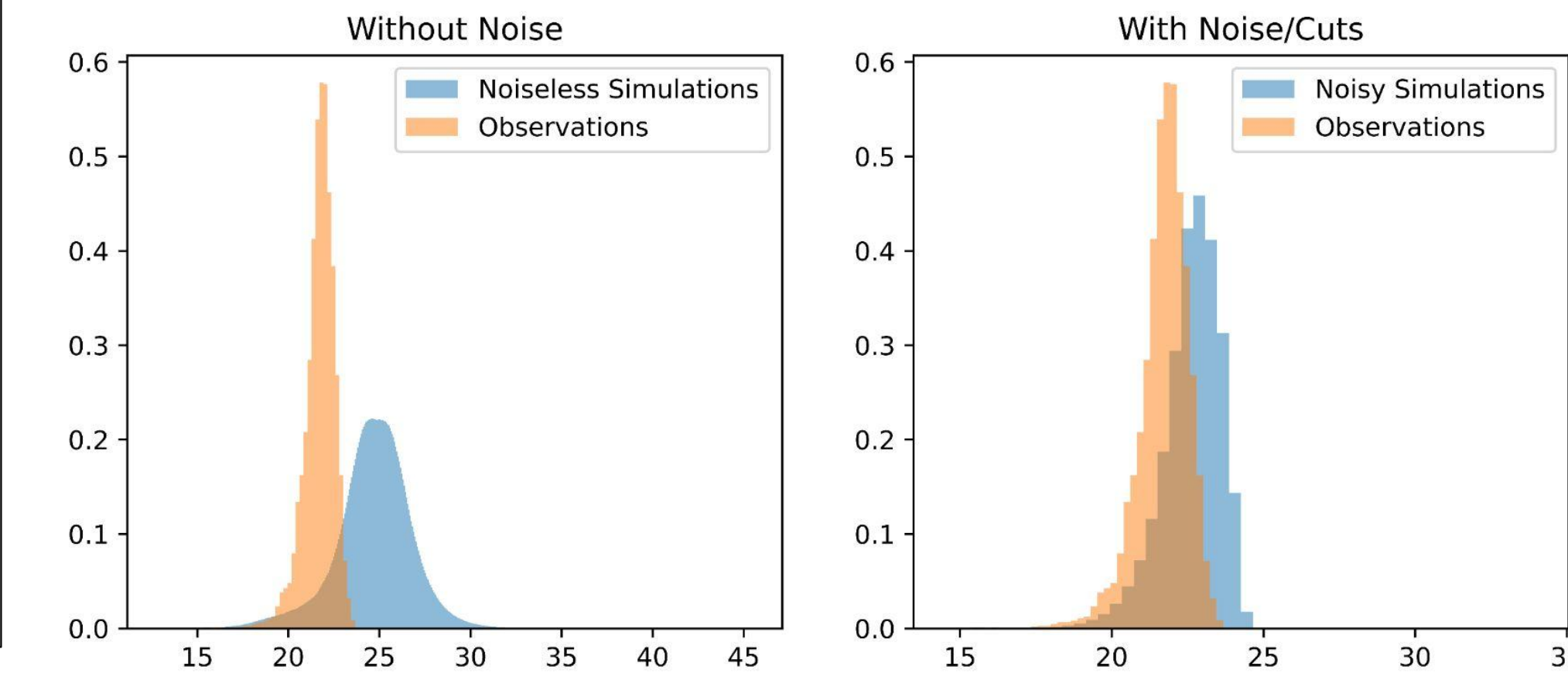
Above: Panels displaying difference imaging, when search images are aligned to reference images, subtracted, then visually examined for potential objects of interest (such as transients)

ParSNIP: A neural network built to model and classify transients given a light curve. Trains using a convolutional variational encoder/autoencoder. See figure to the right for more details on its training architecture (Boone 2021). To classify, it uses a boosted decision tree. See figure below for full ParSNIP architecture, a recaptioned image from (Alio et al. 2023).



Methods

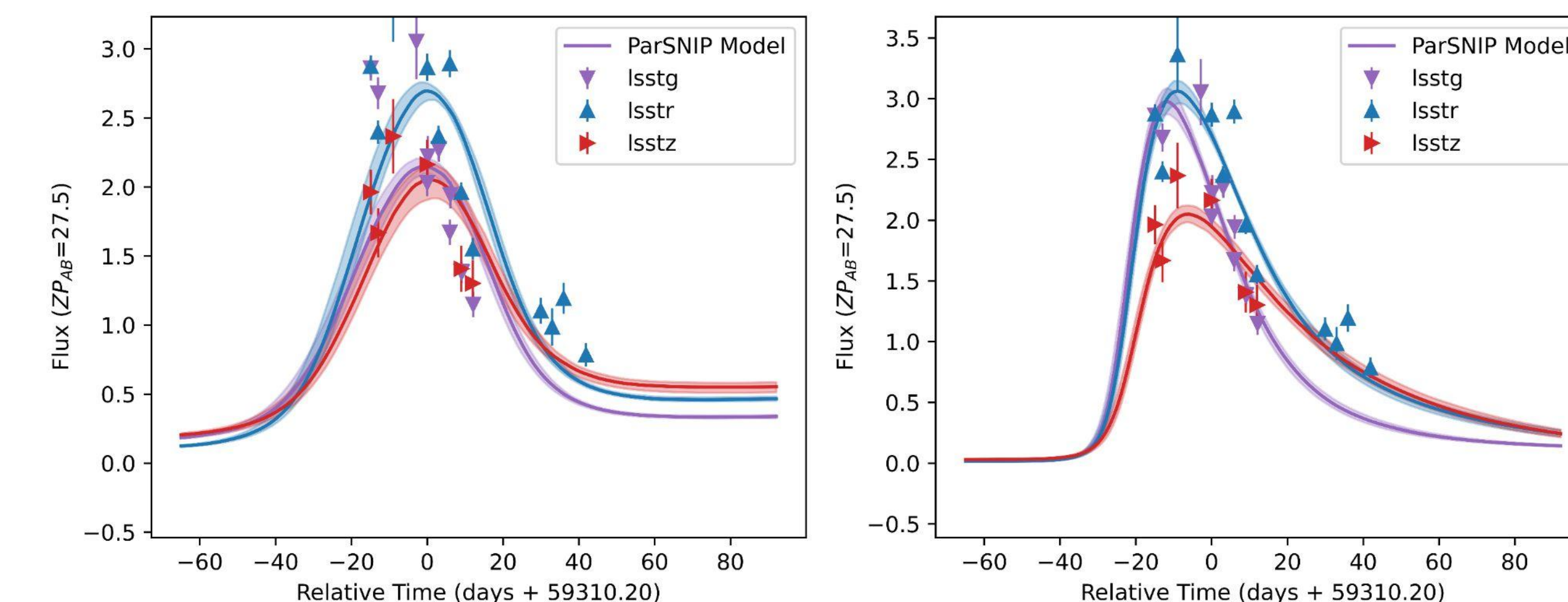
We retrain ParSNIP using ELAsTiCC – a dataset of simulated transients. These simulations were created with SNANA (Supernova Analysis Software) (Kessler et al. 2009) and emulate LSST data. We aim to utilize it to model and classify DESIRT light curves, so we make the following modifications to increase simulation similarity to DECam data:



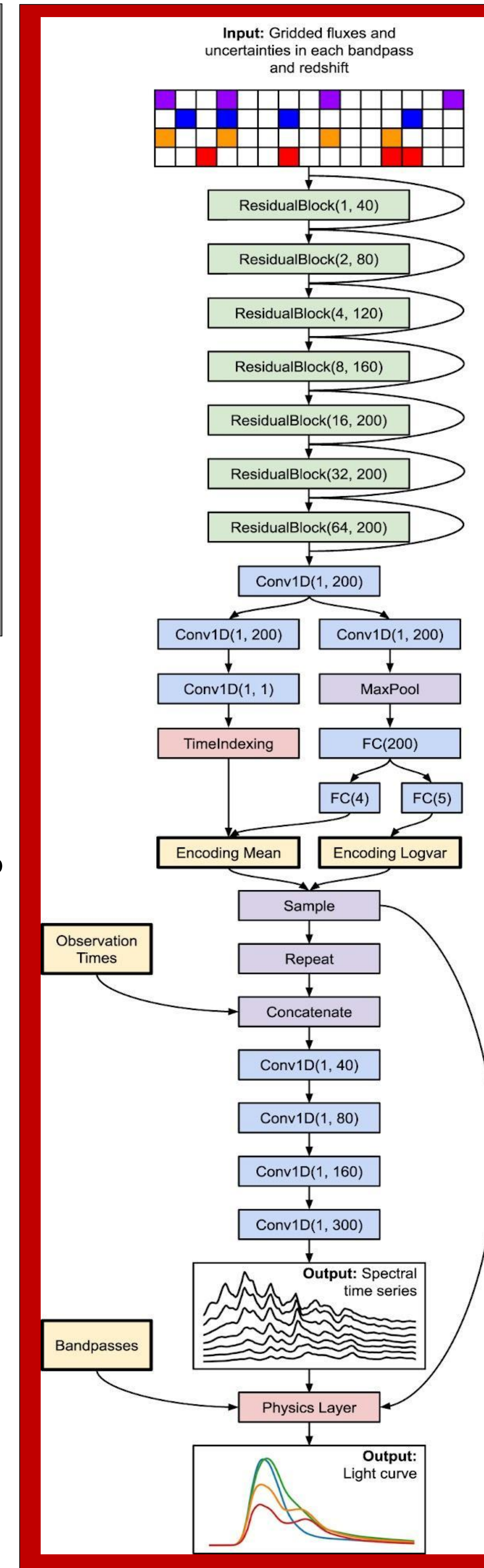
Above: Comparison of ELAsTiCC data without noise to DECam observations (left) and comparison with noise and an SNR cut added to simulation data (right)

- Add noise randomly generated on a gaussian distribution based on a linear fit of flux vs flux error in DECam observations
- Cut simulation data by band (only keeping *grz* bands, and simulating the noise per band), SNR (signal-to-noise ratio), and potentially cadence (frequency of observations)

Once the data is finalized, we train models on extragalactic sources to examine their viability. This requires ~300 neural network training epochs. We've attempted three retrains – two on uncut data with simulated linear noise, and one with noise simulated with an alternative CDF method and cut for SNR >= 5. Additionally, we trained one classifier based on the predictions of our second model, which identifies extragalactic transients with categories for KN, SLSN (superluminous supernovae), TDE, and various kinds of supernovae (see classification matrix)



Left: Light curves produced by models trained on linear noise simulation training datasets without SNR cuts. Left model trained with only 5 training epochs, right trained with ~115.



Results and Conclusions

Though imperfect, the second model trained on uncut ELAsTiCC data with simulated noise performed the best. However, we've only trained it through ~115 training epochs out of the desired 300. The classifier performed with a macro average completeness of 0.55 and fraction correct of 0.50. The below confusion matrix displays the classifier's performance when identifying different types of transients. It performed the best on the brightest objects, KN, SLSN-I, and TDE, but struggled to identify types of supernovae, particularly SNIb and SNIib.

True Type	KN	SLSN-I	SNIi	SNIib	SNIa	SNIa-91	SNIax	SNIb	SNIc	TDE
KN	0.94	0.00	0.01	0.00	0.00	0.03	0.01	0.00	0.00	0.00
SLSN-I	0.00	0.82	0.05	0.01	0.03	0.01	0.02	0.01	0.03	0.02
SNIi	0.03	0.07	0.48	0.06	0.09	0.02	0.09	0.03	0.04	0.09
SNIib	0.03	0.02	0.12	0.22	0.09	0.14	0.17	0.08	0.12	0.01
SNIa	0.01	0.02	0.05	0.04	0.61	0.05	0.11	0.03	0.07	0.01
SNIa-91	0.04	0.01	0.01	0.05	0.02	0.76	0.04	0.01	0.06	0.00
SNIax	0.03	0.04	0.09	0.11	0.17	0.07	0.37	0.07	0.04	0.01
SNIb	0.03	0.03	0.07	0.14	0.14	0.09	0.17	0.14	0.18	0.01
SNIc	0.03	0.03	0.06	0.10	0.12	0.12	0.10	0.07	0.37	0.01
TDE	0.02	0.02	0.09	0.01	0.02	0.01	0.03	0.01	0.00	0.80

The previously utilized model, which was trained on PLAsTiCC, another simulated transient dataset, performed better with a macro averaged completeness of 0.81 and fraction correct of 0.80. We still hope to improve on the PLAsTiCC model's performance for DECam identification specifically through modified ELAsTiCC data, as to better optimize our models for DECam observations. Next steps include training with more epochs and perfecting the simulated noise and SNR/cadence cuts. Along with this model, which is trained on data with spectroscopic redshifts, we will train a second model with simulation data at a fixed $z=0.01$, as we only have photometric redshifts for ~50% of the data. If these methods are not successful, we may simulate our own dataset of DECam transients using SNANA.

Citations

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