Using Synthetic Photometry to Predict the SN Ia CMAGIC Diagrams and Cosmological Results of LSST

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Research Objective

We aim to produce synthetic photometry with the aid of a predictive neural network, requiring only one input spectrum, in order to mimic the data we expect from LSST. Then, we will use the simulated photometry to predict cosmological results from LSST using CMAGIC [2], a standardization method that relies on brightness at a fixed color rather than maximum brightness.

Background

LSST is expected to find ~10^5 well-sampled SNe Ia, a critical sample for reducing systematic error in cosmological parameters. By using a standardization method that does not require observations at maximum brightness and utilizes minimal data, we will be able to push the boundary of the utility of the LSST SN Ia sample by reducing the need for follow-up observations.

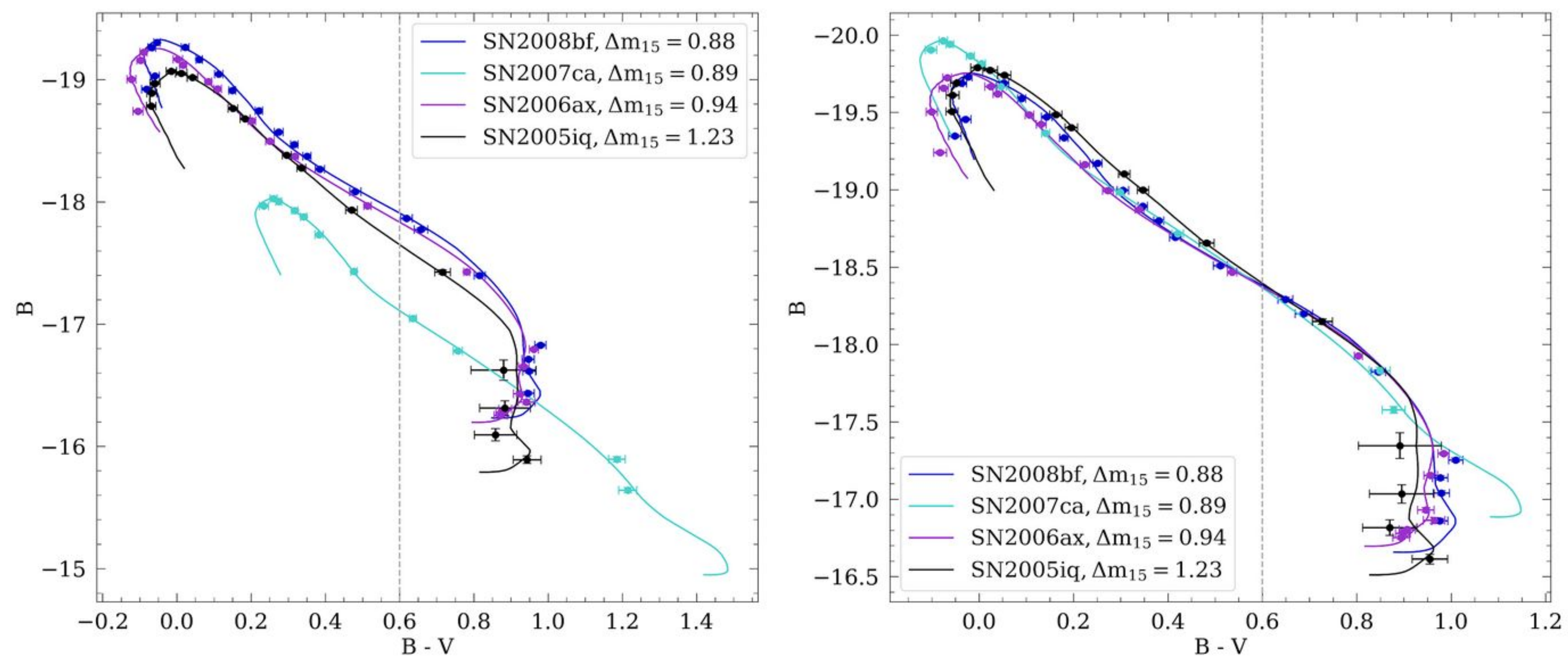

Figure 1. *Left*: CMAGIC curves for four Carnegie Supernova Project objects, corrected for Milky Way extinction and in absolute magnitudes using an assumed cosmology. *Right*: The same as the left panel, but after CMAGIC standardization. In both panels, the vertical dotted line shows where *B-V = 0.6*, the value of interest in CMAGIC.

Methods

We use the principal component (PC) parameterization from the neural network presented in [1], with modifications to include a normalization constant as a parameter so that it accounts for brightness evolution over time. Once the neural network model has been generated, PC components will be calculated for all SNe at every phase. Then, probability distributions will be constructed for each PC component at each phase. Monte Carlo methods will be used to simulate the expected ~10^5 SNe Ia from these probability distributions, drawing samples over the range of expected LSST redshifts at both rapid- and deep-drilling cadences. Synthetic photometry will be generated for the mock data set, followed by a cosmological analysis using CMAGIC [2].

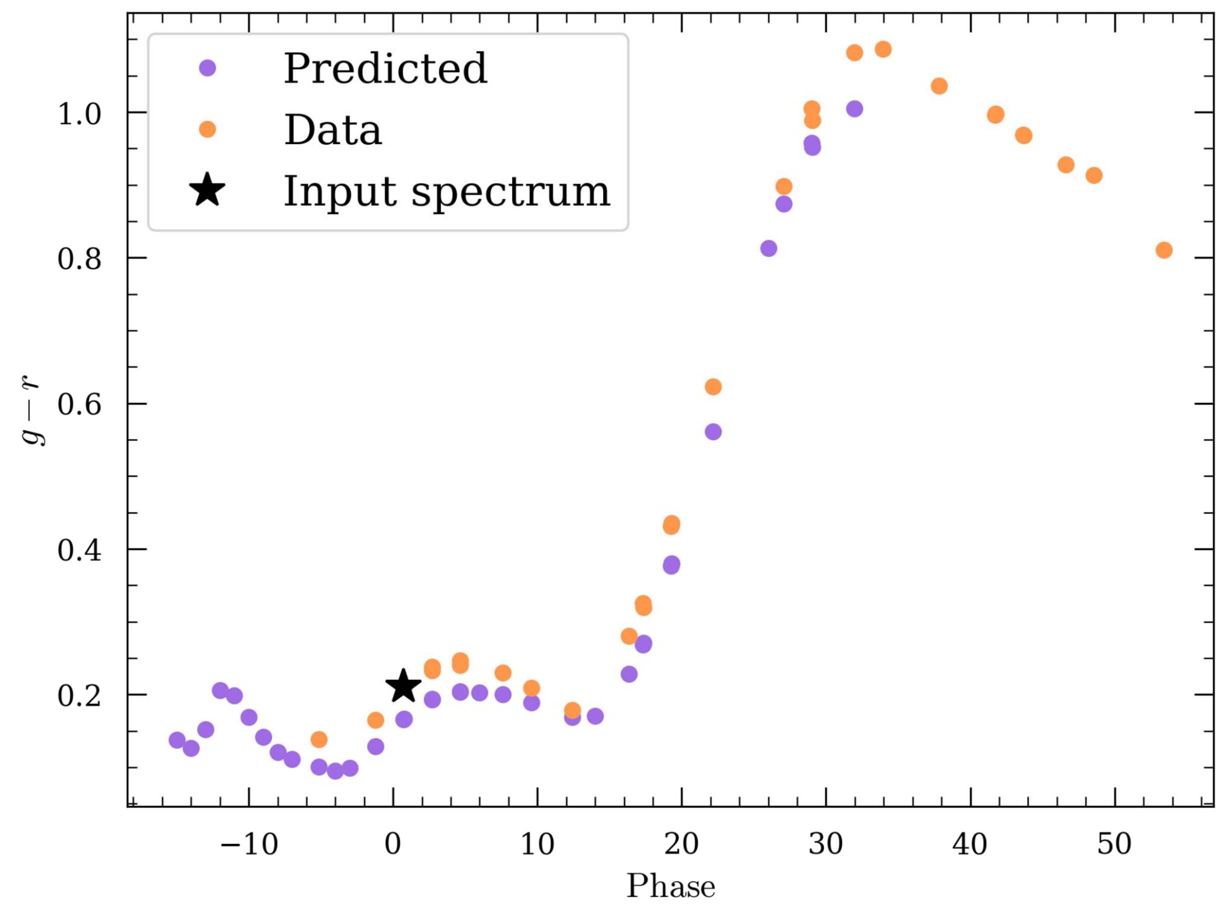

Figure 2. An example SNIFS SN showing that the neural network in [1] is able to reproduce the observed colors of SNe, as viewed through LSST filters, accurately between 15 and 30 days post-maximum. There is some discrepancy between -10 and 10 days; this is because the neural network was calibrated using Johnson *B* and *V* filters. We expect improvement once brightness over time is tracked.

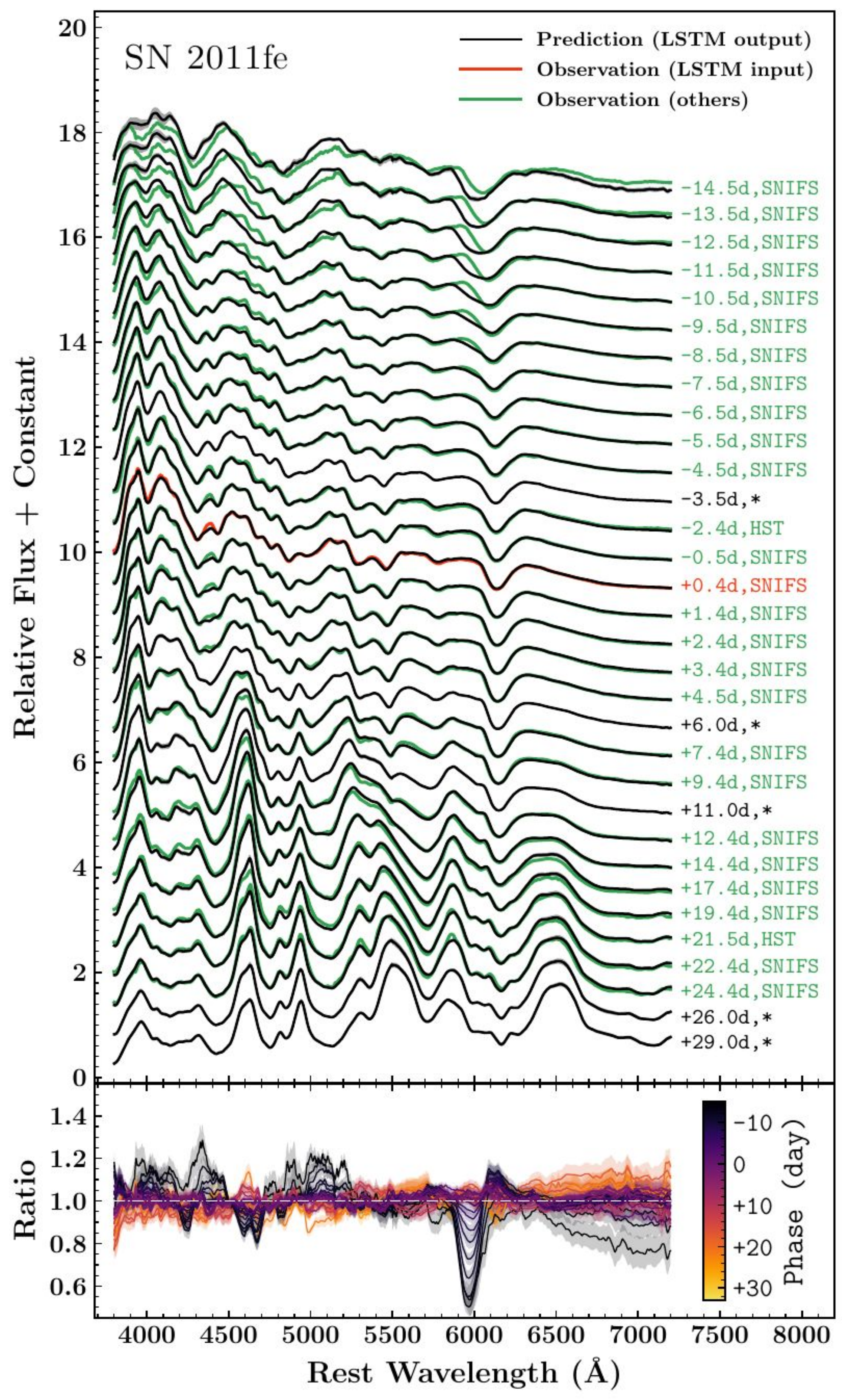

Figure 3. Predicted and observed spectra from SN 2011fe. Black lines represent predictions, green shows observations, and red shows the input observation. Text to the right of each spectrum indicates phase and instrument. "*" indicates no available observations. Figure from [1].

Results

- As-is, the neural network is able to accurately reproduce LSST photometric colors for SNe Ia between 20 and 40 days after maximum brightness.
- We are able to simulate a sample of SNe Ia based on the principal component decompositions of a training sample.

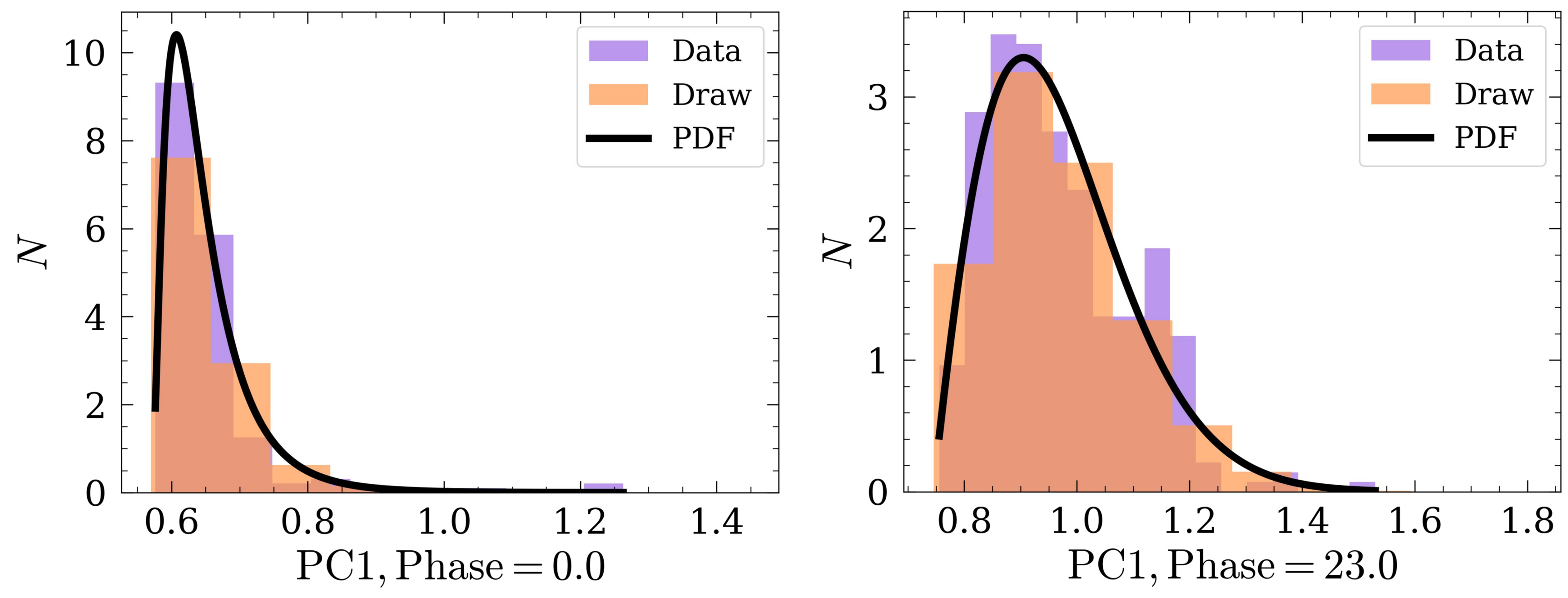

Figure 4. Examples of the distribution of the first principal component score at different phases based on 228 SNIFS SNe Ia (purple). Gaps in data are filled using predicted spectra from the neural network. Gamma distributions are fit to the histograms (black line), and 10^5 draws are taken from the fit (orange).

Next steps

The neural network needs to be re-trained so that it is able to track brightness evolution over time. It currently only accepts normalized inputs, and only outputs normalized spectra. The normalization constant (mean flux) will be tracked as an additional PC score.

Future work

- Once real LSST data are available, we will be able to use the same neural network to fill in gaps in data to allow for better fitting to photometric data.
- Currently, the neural network is trained for a wavelength range of 3,800-7,200Å, only allowing use of the *gr* filters. This could be expanded to 2,000-10,000Å given data availability, enabling incorporation of *ugriz* filters into the analysis.

References

[1] Hu, L., Chen, X., & Wang, L. (2022). *The Astrophysical Journal*, *930*(1), 70. https://doi.org/10.3847/1538-4357/AC5C48

[2] Wang, L., Goldhaber, G., Aldering, G., & Perlmutter, S. (2003). *The Astrophysical Journal*, *590*(2), 944–970. https://doi.org/10.1086/375020

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