Prioritising Follow-up in Transient Surveys with TESS and ZTF

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Criteria for Prioritising Follow-up

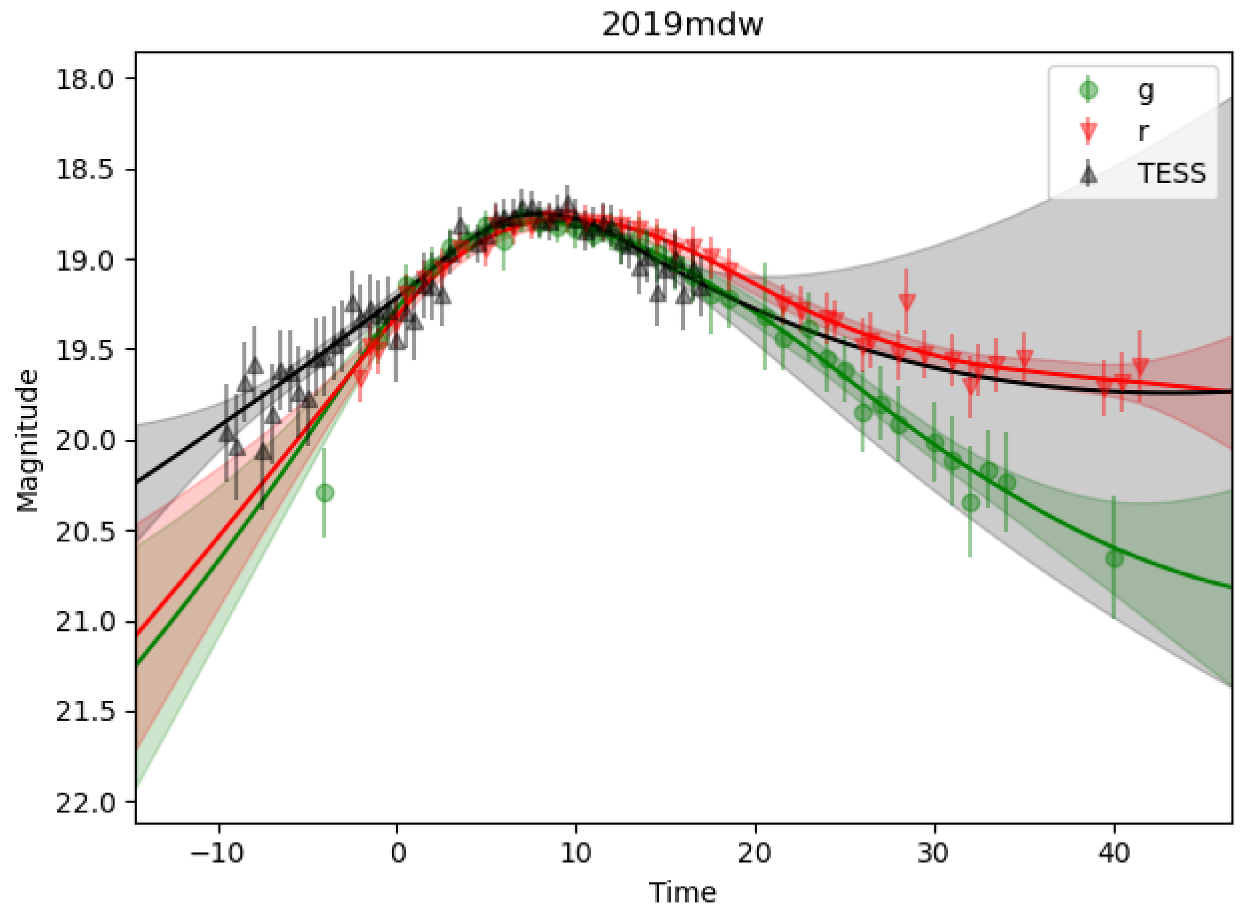
Modern surveys such as the Vera Rubin LSST will record millions of transient alerts per night, making standard approaches of visually identifying new and interesting transients infeasible. Three challenges for deciding which alerts are most suitable for follow-up observations are:

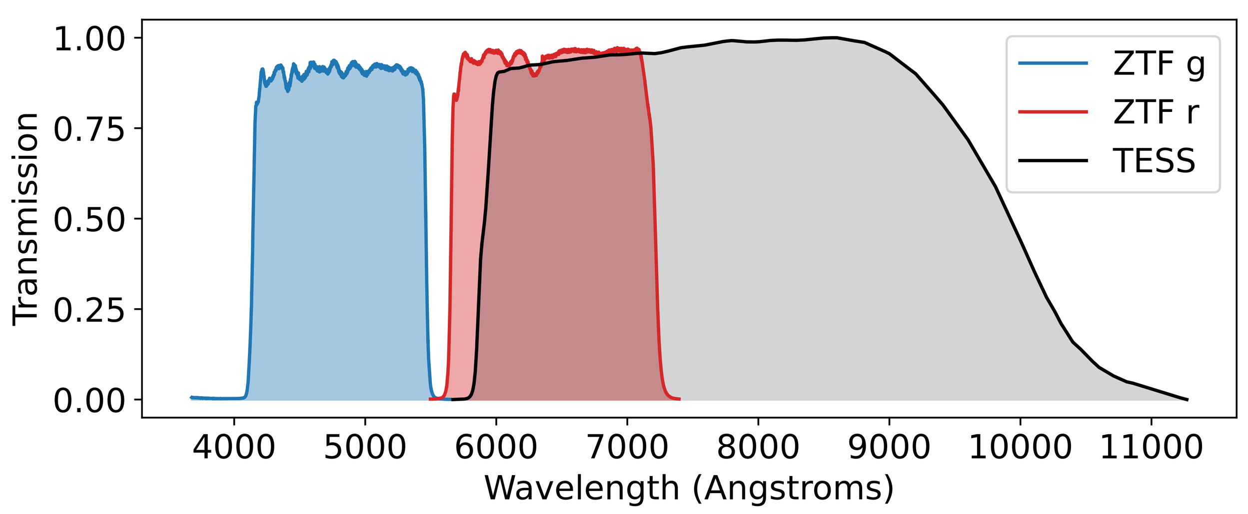
1. Automated real-time **classification**
2. Automated real-time **anomaly detection**
3. Automated prediction of **epoch time**

Classifying what type of transient has been observed is the first step to deciding whether further follow-up is required. Discovery in astronomy has been driven by serendipity. Thus, being prepared for discovering entirely new or rare classes of transients requires dedicated anomaly detection frameworks, and prioritising follow-up based on the likelihood of an alert being novel and interesting. Finally, observing transients early is necessary to understand the central engine and progenitor systems, and we should prioritise resources based on the epoch of observation.

Data

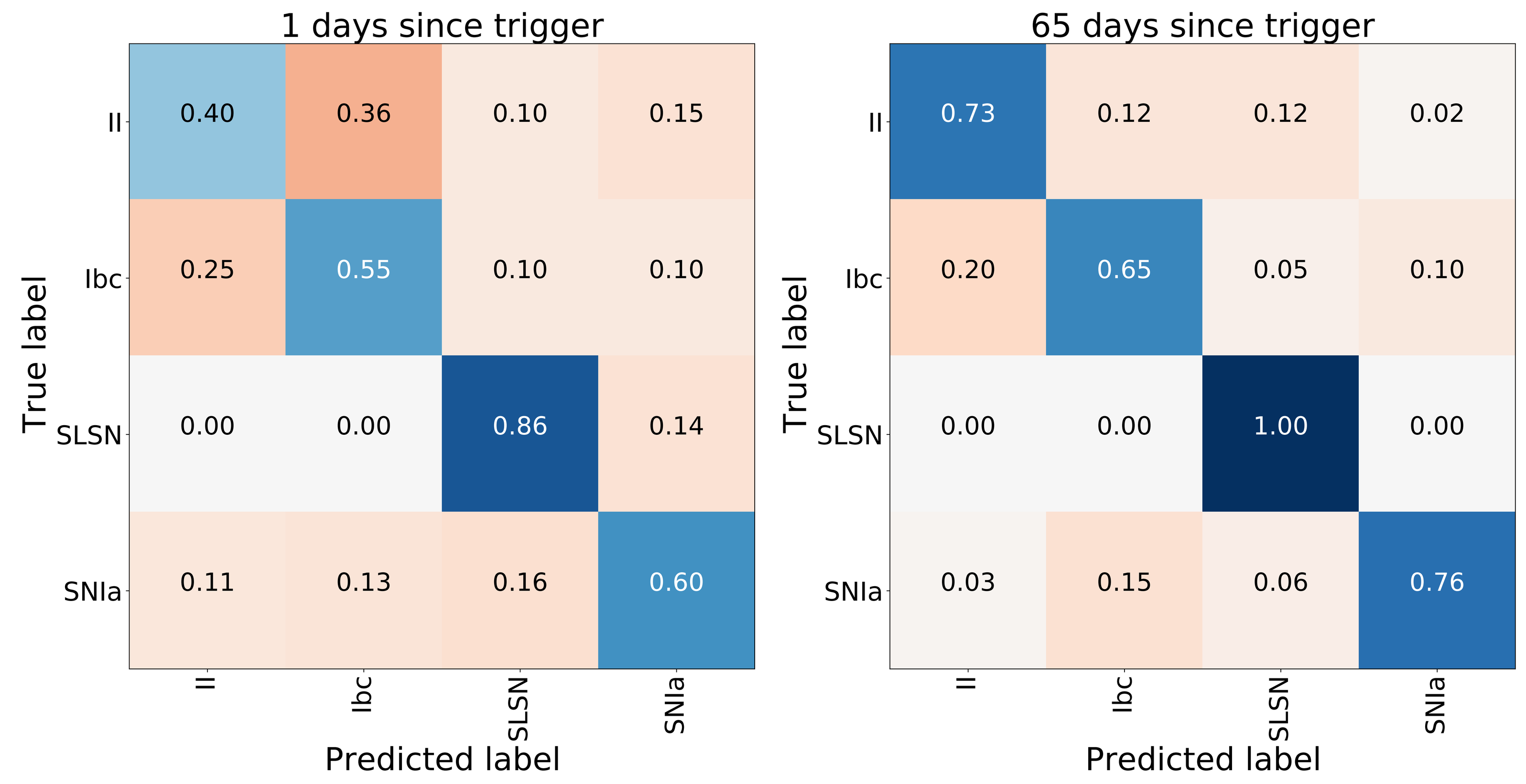
We collected 1909 known transients observed by both TESS and ZTF as the dataset for this work. TESS enables discovery of short time-scale transients and the early rise and shape of a light curve. ZTF observes long term trends in a light curve and enables discovery of fainter objects. An example transient with a combined ZTF and TESS Gaussian Process model is shown below.





1. Real-Time Classification

We use a semi-supervised classification algorithm to to capture information from both unlabelled and labelled transients in our dataset. First, all transients are passed into an unsupervised Variational Recurrent Neural Network Autoencoder to encode each light curve into a lower dimensional representation. The latent space of this autoencoder is then passed into a supervised Random Forest classifier. Classifications on our small labelled dataset are illustrated in the confusion matrix. Methods are based on Muthukrishna et al. (2019) and Villar et al. (2020).

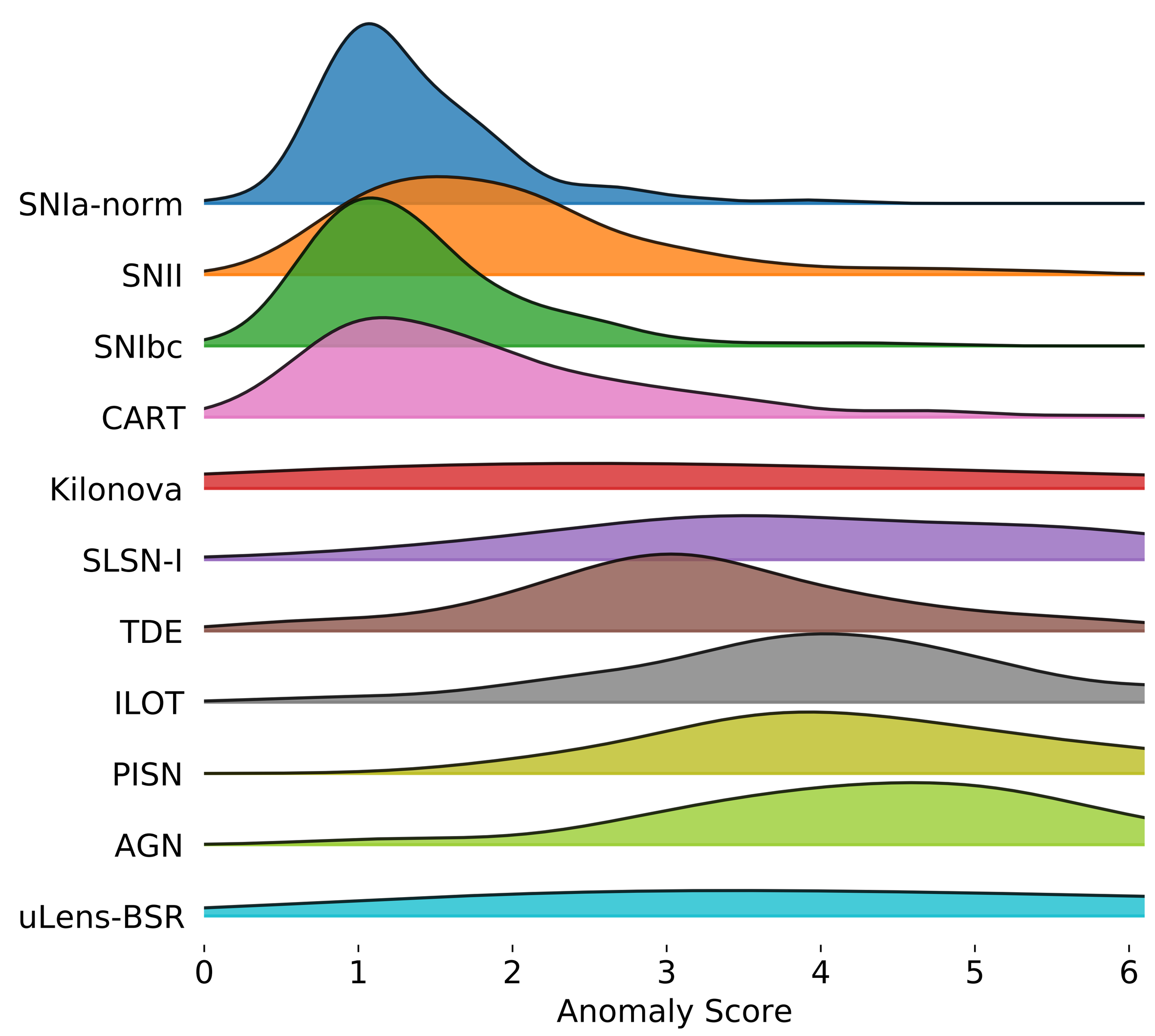


1 days since trigger	II	Ibc	SLSN	SNIa
II	0.40	0.36	0.10	0.15
Ibc	0.25	0.55	0.10	0.10
SLSN	0.00	0.00	0.86	0.14
SNIa	0.11	0.13	0.16	0.60

65 days since trigger	II	Ibc	SLSN	SNIa
II	0.73	0.12	0.12	0.02
Ibc	0.20	0.65	0.05	0.10
SLSN	0.00	0.00	1.00	0.00
SNIa	0.03	0.15	0.06	0.76

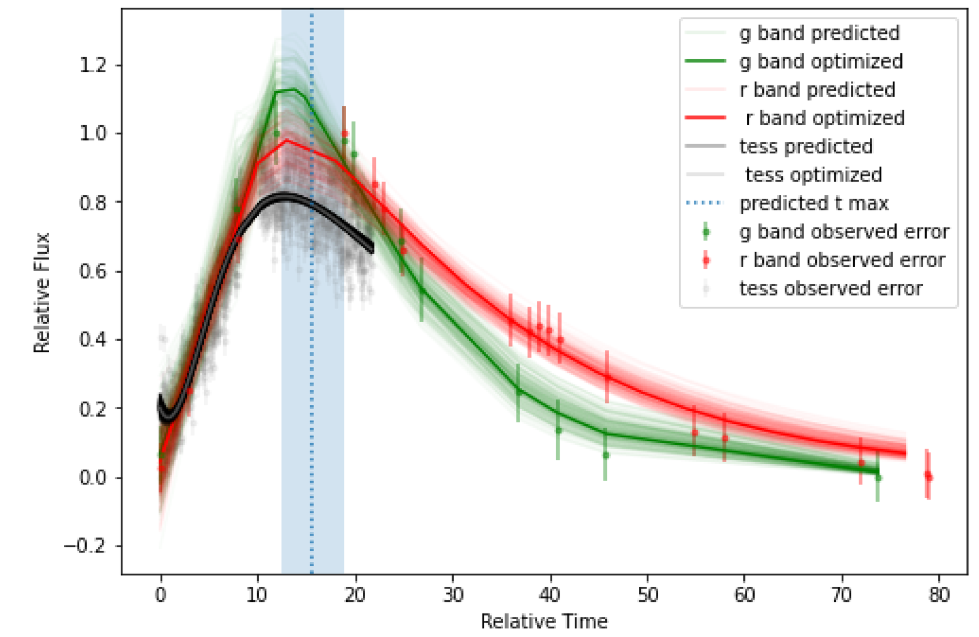
2. Anomaly Detection

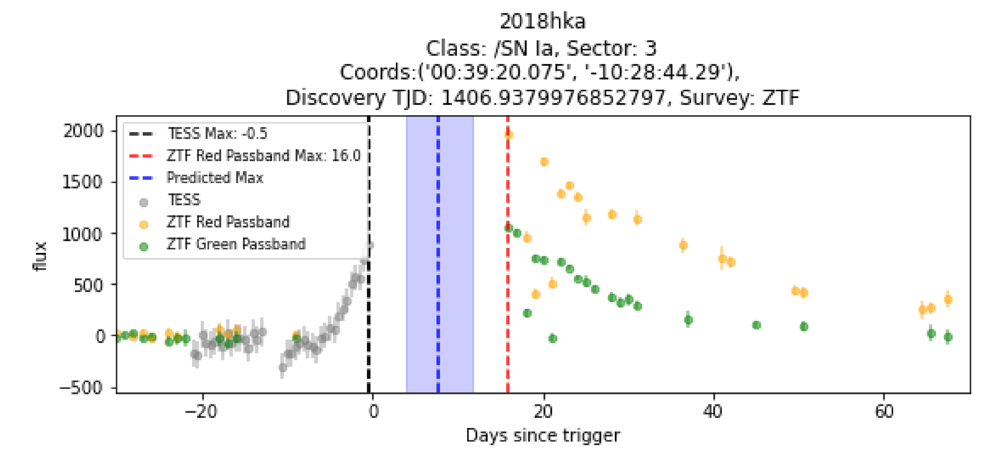
Classification approaches are limited because they require that an observed transient resembles a known class of objects. However, modern surveys will probe entirely new regimes in the time-varying universe, possibly observing completely new classes of astronomical objects. We have developed a machine-learning-based anomaly detection framework that scores each incoming transient alert based on how anomalous it is. See Muthukrishna et al. (2021) for the method our approach is based on. The below plot is based on a simulated dataset of ZTF light curves.

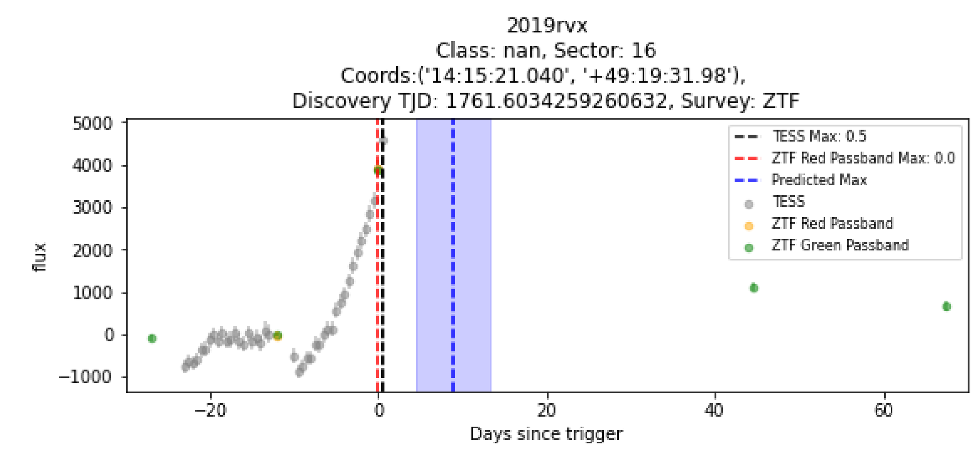


3. Predicting the Epoch Time

Discovering a transient early in its evolution is necessary for understanding more about its central engine and progenitor system. Prioritising the millions of alerts by how early they have been detected will be important for follow-up in large-scale transient surveys. We have built two methods for predicting the time of maximum in real-time observations. The first approach uses a Recurrent Neural Network to regress over past data and predict the time of maximum. The second approach uses a simple Supernova Parametric Model from Sánchez-Sáez et al. (2021) based on the Bazin et al. (2009) model. We make predictions of the time of maximum conditioned on only a partial light curve. Predictions on example light curves are shown where the blue vertical line shows the predicted time of maximum and the uncertainty in that prediction.







Conclusions

We present preliminary solutions to three of most important challenges facing the big data era of time-domain astronomy. The sheer number of transient alerts from new surveys will require that follow-up resources are allocated based on a range of criteria. This work and other recent approaches addressing classification, anomaly detection, and epoch-time predictions are going to be critical for discovery in the new era of large-scale astronomical surveys.