Electromagnetic Counterpart Identification of Gravitational-wave candidates using deep-learning

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Abstract

Both time-domain and gravitational-wave (GW) astronomy have gone through a revolution in the last decade. These two previously disjoint fields converged when the electromagnetic (EM) counterpart of a binary neutron star merger, GW170817, was discovered in 2017. However, despite the discovery rate of GWs steadily increasing, by several folds in each observing run of the LIGO/Virgo GW instruments, GW170817 remains the only success story of EMGW astronomy. While future GW detectors will detect even larger number of events, this does not guarantee corresponding increase in the number of EM counterparts discovered. In fact, the growing number is overwhelming since wide-field telescope surveys will have to contend with distinguishing the optical EM counterpart, called a kilonova, from the ever increasing number of "vanilla" transients objects they encounter during a GW follow-up operation. To this end, we present a novel tool based on a temporal convolutional network (TCN) architecture for Electromagnetic Counterpart Identification (El-CID). The overarching goal of El-CID is to slice through list of objects that are consistent with the GW sky localization, and determine which sources are consistent with kilonovae, allowing limited and judicious use of telescope and spectroscopic resources. Our classifier is trained on sparse early-time photometry and contextual information available during discovery. Apart from verifying our model on an extensive testing sample, we also show succesful results on real events during the previous LIGO/Virgo observing runs.

1 Introduction

The field of gravitational waves (GWs) has moved swiftly since the discovery in 2015 [1]. The number of discovered events have increased more than an order of magnitude over the last five years, from

Fourth Workshop on Machine Learning and the Physical Sciences (NeurIPS 2021).

three events in the first observing run of the LIGO/Virgo GW instruments, to more than thirty in the most recent catalog [2]. One of the more interesting topics related to GWs today is the prospect to do multi-messenger astronomy with them – observing the same source in GWs, EM radiation, and other high-energy astrophysical probes. Of relevance to this work is the joint detection of GWs from binary neutron star mergers and the optical component of the EM radiation resulting from the radioactive decay of heavy elements produced in the aftermath, called a kilonova [3]. While this was hypothesized decades back [4], the first discovery happened in 2017 when GWs from a binary neutron star merger, GW170817, [5, 6] was followed by the exhaustive observation of the kilonova, AT 2017gfo, in the hours through days following discovery [7, 8, 9, 10, 11, 12, 13]. Such joint observations provide rich observational data for astronomy, astrophysics, cosmology, and fundamental physics [14, 15, 16, 17]. Starting from the third LIGO/Virgo observing run, O3, in 2019-2020, there has been been several efforts towards coordinating GW follow-up [18, 19]. However, it can be safely said that there was disappointment when O3 concluded without another coincident kilonova observation.

While the growing number of GW discoveries brings hope to detect more counterparts, we are also in the era of where transient discovery is profuse [20]. Today, a typical photometric telescope survey detects several thousands of new supernovae yearly for example. Therefore, it is challenging to detect the more exotic transients like kilonovae even in the case of targeted searches. Going ahead, follow-up teams will have to contend with the fact that a search for the kilonova will be confounded by several other, more "vanilla" objects, like supernovae whose astrophysical rates are several orders of magnitude greater than binary neutron star (BNS) mergers. This was already witnessed during O3. A visual description of the scenario we envision is shown in left panel of Fig. 1. Here, we show a fiducial GW sky-localization (skymap) along with the true location of the kilonova using symbol 'x'. But there maybe several objects, like supernovae, represented by solid circles that maybe temporally coincident with high-confidence portions of the skymap. It may not be possible to perform spectroscopic analysis on all the candidates in a timely manner. Hence the motivation of creating a classifier that will be able to distinguish the kilonova from other objects using the initial sparse photometric data, and other contextual information that is available during discovery time.

2 Methodology

2.1 Dataset preparation: Connecting binaries to observed lightcurves

We build an end-to-end dataset starting with an ensemble of BNS mergers. From this ensemble, we determine which systems are detected in GWs by the LIGO/Virgo/KAGRA instuments based on their sensitivity in future observing runs. This step involves determining whether the system produces a GW strain that produces a signal-to-noise (S/N) ratio ≥ 8 (typical threshold) in at least two GW detectors. The result depends on the noise realization of the era. We consider both the upcoming fourth observing run, O4, and the design sensitivity era independently. The results presented here are the for the former case, but the results are qualitatively similar for the latter case. In the event the signal is detected, the S/N time-series is used to produce a GW sky-localization (skymap). The fundamental principle utilizes the timing difference in arrival of the signal in different detectors to create a probability density map in sky coordinates. This is done using the rapid sky-localization algorithm, BAYESTAR [21] that is used in LIGO/Virgo realtime discoveries. Next, we connect the binary properties to the ejecta properties. Among the factors affecting the properties of the kilonova the most important is the

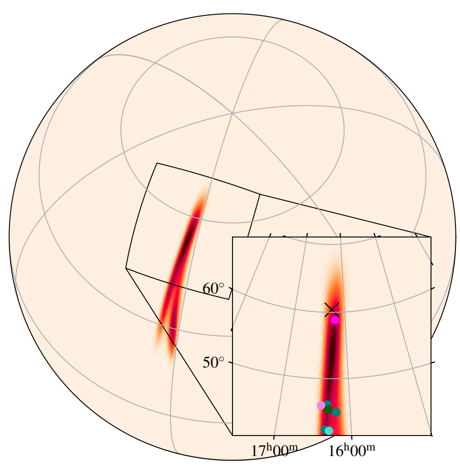

Figure 1: An hypothetical scenario of a targeted GW follow-up – the true EM counterpart to the GW, the kilonova, is shown using the "x" symbol. There maybe other objects, like supernovae, in the field of view. These are shown using the solid circles.

mass ejected from the aftermath of the merger of two stars and equation of state of the star. In order to map the binary parameters like masses and spins of the components to the ejected mass, we use an empirical fit developed in Ref. [22] from numerical relativity merger simulations of BNSs. The ejecta properties then determine the spectral evolution of the kilonova in time in different filters i.e., its lightcurve. Theoretical modeling of kilonovae is still in its infancy – several models and parameterizations exist to describe the same physical system. We use the models by Bulla [23] and Kasen [24] which have been widely used in the literature earlier in the analysis of AT 2017gfo [9, 25]. Hence for every binary, we are able to obtain a kilonova spectral energy density (SED). To get the observed lightcurve, we use the Supernova Analysis library, SNANA. One of the primary use case of SNANA is in simulating observed lightcurves given a survey cadence accounting for instrument detection uncertainties and sky noise. A notable effort in supervised classification of lightcurves using SNANA is the Photometric LSST Astronomical Time Series Classification Challenge (PLAsTiCC) [26, 27]. This challenge was hosted publicly on the Kaggle platform [1] to classify millions of lightcurves in the era of the Rubin Observatory [28]. In this study, however, we use the observing schedule of the Zwicky Transient Facility's (ZTF) from its third data release. ZTF has participated actively in the follow-up of GWs, and therefore we make the choice for this work. Also, ZTF will be participating in the GW follow-up in the coming observing run. In the Appendix, we show some examples of lightcurves of the KNe and other objects (see Fig. 5). We also verify that there is no selection effect in choosing one model over the other in the data preparation step (see bottom panel of Fig. 5).

2.2 Simulating rest of the sky

The steps in the above section provides us with a skymap and a KN lightcurve for each BNS simulation that is detected i.e., analogous to the skymap and the 'x' symbol in Fig. 1. To simulate other objects that will pollute the search for a KN, we use SNANA along with the same ZTF DR3 cadence for a variety of supernova models and tidal disruption events.[2] In this study, we restrict to extragalactic transients, but this will be extended in the future to include galactic transients like M-dwarf flares which could have similar time scales as KNe. For each of the detected GW event, we use a window of a week to select other objects that had their first detection in this period. This is because we expect a typical KN to reach peak brightness within a few days from the time of the GW trigger. If the first detection is outside this window the new object is unrelated to the GW event. We rank the objects based on the line-of-sight probability value of the skymap, and select the top 20 to be contaminant. While is this an empirical choice, we have verified that changing this number does not have a significant effect on the performance of the classifier. Details of breakdown of the object types and numbers is presented in Appendix A.2.

3 Binary classification using TCN

During the early hours through days following a BNS GW candidate, the primary question for a new EM candidate is whether it is/isn't associated with the GW event. We, therefore, consider the problem from a binary classification standpoint. For our feature set we consider the ~ 1 week lightcurve data of the objects from Table 1. Every object has different timescale features e.g., rise/fall, and color evolution in different passbands which the network is able to learn with more incoming data. In addition to the lightcurves, we also supply important contextual information in the form certain feature of the skymap. We have this because all objects in our dataset have a skymap just like the scenario for a real GW follow-up. We use the line-of-sight probability for the object, and the angular offset from the mode of the distribution. This is important contextual information since KN are expected to have high correlation with the high-probability regions of the skymap compared to the other objects which would be uncorrelated. The offset is important since for GWs detected in two-detectors, the skymap can have a ring-like profile in the sky. We additionally supply the 90% sky-localization area as another feature. Note that, unlike the time-series data of the lightcurve, the contextual information are constant, repeating arrays of the same length as the lightcurve. The contextual information allows the network to put a *prior* score to candidates even in absence of photometric data. We use a temporal convolutional network (TCN) [29] as implemented in Ref. [30] using the open-source library Tensorflow [31]. The network is similar to that used in Ref. [32] for

[1] `https://www.kaggle.com/c/PLAsTiCC-2018`

[2] These are a subset of the types used in for PLAsTiCC [26] – SALT2 SNIa, SNII NMF model, SNII Vincenzi model, SNIa 91bg, SLSN, SNIax, SNIbc.

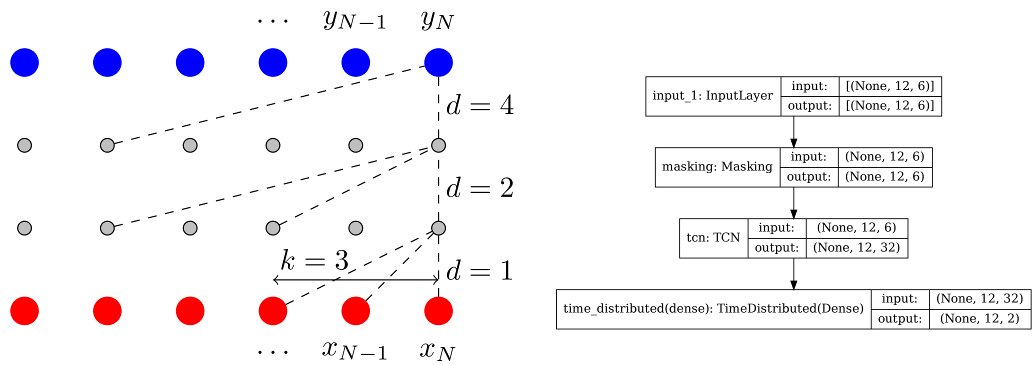

Figure 2: **Left**: Basic architecture of a TCN (see Ref. [29]). The convolutions are causal and therefore suited to learn temporal features. **Right**: The block diagram of our network.

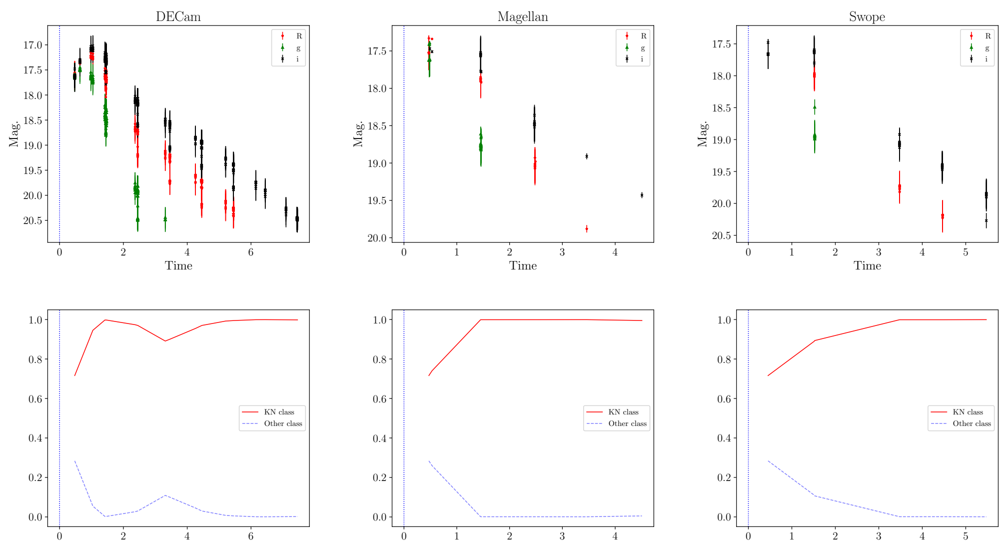

Figure 3: **Top**: Photometry of AT 2017gfo from different instruments **Bottom**: Binary classification score of being a “Kilonova” or “Other”.

realtime classification of different classes of supernovae. The convolutions of a TCN are causal and therefore suited to learn temporal features which is of interest here (see Fig. 2). We linearly interpolate the lightcurves with a periodic interval of ~ 0.7 days. This choice was made by analyzing the distribution of time difference between consecutive observations of the KNe and considering the 80-percentile. While this is an empirical choice, excessively larger time steps decimate temporal features and excessively smaller time steps cause unexpected, jittery behavior. This pre-processing step is required to prepare uniformly sampled arrays of the lightcurve. We consider a total length of 12 i.e., about a week post the GW trigger. Our temporal array is 3-dimensional – one each for the flux in each ZTF filter (g, R, and i). Additionally, we supply the 3 contextual information mentioned above. Thus, our input arrays have the shape 6x12. The labels are “Kilonova” or “Other”. We use 32 channels for the TCN with a droptout rate of 5% during training. We use a convolution kernel of size of two, two dilation layers, and also a stack size of two. During training, we use the categorical cross-entropy loss and the Adam stochastic optimizer as implemented in Tensorflow. We show a block diagram of our network in the right panel of Fig. 2. We train our network for 20 epochs using 60% of the dataset for training and 40% for validation.

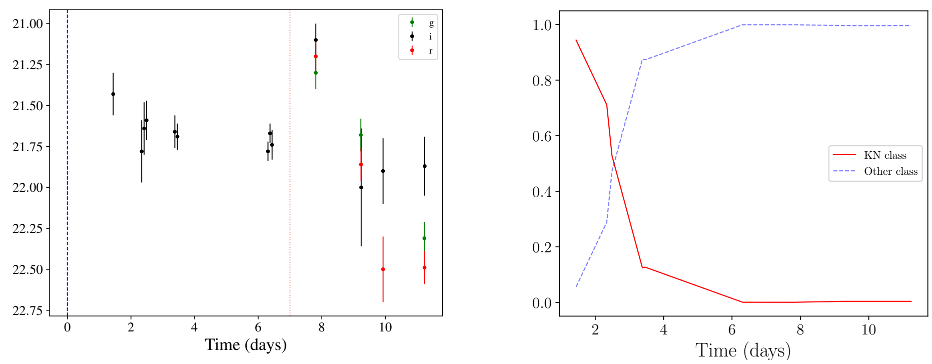

Figure 4: **Left**: Observational data of AT 2019npv taken from Ref. [33]. **Right**: El-CID score.

4 Results

The classifier achieves $\geq 99\%$ accuracy at ~ 3 days, i.e., in about 3 days of photometric data, the classifier is able to distinguish a KN. We verified that increasing the number of channels does not have significant performance improvement. To verify the accuracy on unseen data, we used kilonovae lightcurves swapping out the ZTF observing schedule with that of the Rubin Observatory as used in PLAsTiCC. This would corresponding the hypothetical situation if Rubin was in operation during LIGO/Virgo fourth observing run, and also verify that the classifier is not learning cadence. We found that performance is not affected and verifies the fact that the classifier is learning temporal features as desired. We provide more details in Appendix A.3. Finally, we test our trained classifier on the real data. Unfortunately, AT 2017gfo remains the only exhaustively studied KN till date with data from instruments all over the world. We use the photometric data publicly available at the Open Kilonova catalog. [3] Note that this data was not a part of the training sample. In Fig. 3 we show data from a few different instruments. We find that the correct classification in obtained within a few epochs of data acquisition. Note that this once again verifies the robustness to instrument cadence as the observations are not only from different instruments, but also likely taken at an aggressive targeted cadence which can be significantly different from the usual nightly cadence of a survey. We also test our classifier on AT 2019npv, [33] which was a SNIbc that was coincidentally discovered at a high confidence region of the skymap of GW190814, [34] and raised interest as a KN doppelganger during the first few days of discovery [35, 36, 37, 38, 39, 40] (see Appendix A.4). We find that the classifier is able to rule out the object as not a KN within the first few days of data acquisition. This showcases the use case of a tool like El-CID.

5 Societal and negative impacts

Our dataset, scope, and purpose is entirely limited to astrophysical processes and therefore we don't envision any impact on society. If our classifier is adopted by astronomical broker teams for nightly operations, the event of erroneous results from our classifier might lead to telescope and spectroscopic resources following-up candidates that are not related to a GW merger.

Acknowledgments and Disclosure of Funding

D. C. is supported by the Illinois Survey Science Fellowship by the Center for AstroPhysical Surveys, National Center for Supercomputing Applications at University of Illinois at Urbana-Champaign. The authors would like to thank Rick Kessler for help with SNANA simulations. The authors would also like to thank Mattia Bulla and Michael Coughlin for help with the models. This work made use of the Illinois Campus Cluster, a computing resource that is operated by the Illinois Campus Cluster Program (ICCP) in conjunction with NCSA which is supported by funds from the University of Illinois at Urbana-Champaign. This research also used resources of the National Energy Research Scientific

[3] `https://kilonova.org/data.html`

Computing Center (NERSC), a U.S. Department of Energy Office of Science User Facility located at Lawrence Berkeley National Laboratory, operated under Contract No. DE-AC02-05CH11231.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Sec. 2.2
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Sec. 5
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See Appendix A.5

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Sec. 3

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] Extensive validation and sanity is presented on unseen and real data instead

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Sec. A.5

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

   (a) If your work uses existing assets, did you cite the creators? [Yes]

   (b) Did you mention the license of the assets? [Yes] Mentioned in repository of the corresponding projects

   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] See Appendix A.5

   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A] All data was created as a part of this work

   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] See Sec. 5

5. If you used crowdsourcing or conducted research with human subjects...

   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

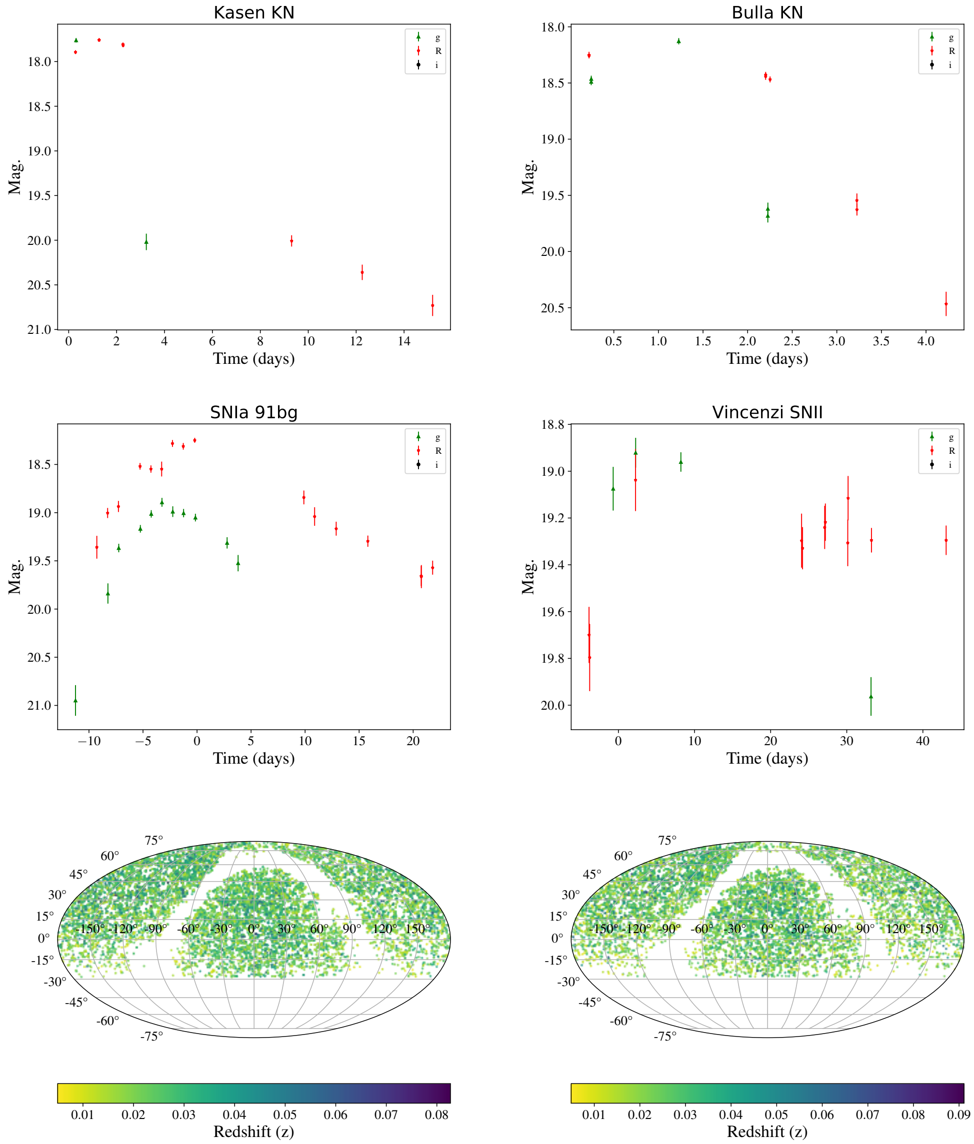

Figure 5: **Top**: Example lightcurves of KN from the Bulla and Kasen models. **Middle**: Example lightcurves from two supernova models. **Bottom**: The distribution of detected Bulla KNe (left) and Kasen KNe (right). We observe that there is no bias in selecting one KN model over the other in the dataset.

A Appendix

A.1 Example lightcurves

In Fig. 5 top panel we show some example KN lightcurves from both Bulla and Kasen models, in the middle panel, we show example of other objects, and in the bottom we show the distribution of the recovered Kasen and Bulla KNe in the sky, colored by their cosmological redshift. We note the empty patch being the galactic plane where there are no extra-galactic observations. We also verify that there is no preference towards either model in this step of data preparation i.e., the distribution is not model specific.

Table 1: The table lists the number count of different types of objects used for training

Object Type	Number count
Bulla KN	5126
Kasen KN	3707
SALT2 SNIa	24670
SLSN	16926
SNII NMF	24232
SNIa 91bg	28620
SNIax	21686
SNIbc	21258
TDE	19359
Vincenzi SNII	19909

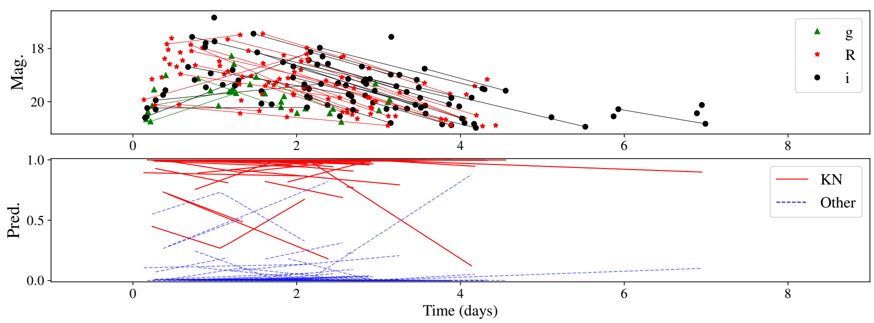

Figure 6: **Top**: Lightcurves generated in g, R, i bands using the Rubin Observatory observing schedule. **Bottom**: The prediction of trained classifier on unseen data generated using Rubin Observatory observing schedule. We observe that most of the objects (113/115 here) have been correctly classified as KNe.

A.2 Object counts

In table 1, we show the number count of the different object type in our dataset.

A.3 Performance on unseen LSST lightcurves

To verify that the classifier is not learning the cadence of the training set, we verify by preparing a dataset of KNe that with the LSST observing strategy. In Fig. 6 we show the performance of the classifier on unseen LSST lightcurves. We find that most of the objects are correctly classified.

A.4 Skymaps of GW170817 & GW190814

In this section we show the skymaps of the GW events GW170817 & GW190814. GW170817 was a merger of two neutron stars that produced the kilonova AT 2017gfo. GW190814 was a merger of a black-hole with a low-mass component compoenent, the nature of which is still unknown. AT 2019npv was consistent with the skymap of GW190814. From visual inspection of the initial photometry it was considered an object of interest and followed up. Later spectroscopy revealed it to be a type Ibc supernova, unrelated to the GW event.

A.5 Code and data

El-CID is based on the architecture used for the real-time supernova classification code RAPID [32]. At the time of submission, the source code exists as a branch in the following repository: `https://github.com/deepchatterjeeligo/astrorapid/tree/kn-rapid`. GW binaries were simulated using `lalapps_inspinj` tool which is a part of LALSuite [41]. Noise curves for GW instruments were used from LIGO DCC: `https://dcc.ligo.org/LIGO-T2000012/public`. Mock S/N time-series was generated using the `bayestar-realize-coincs` tool from the

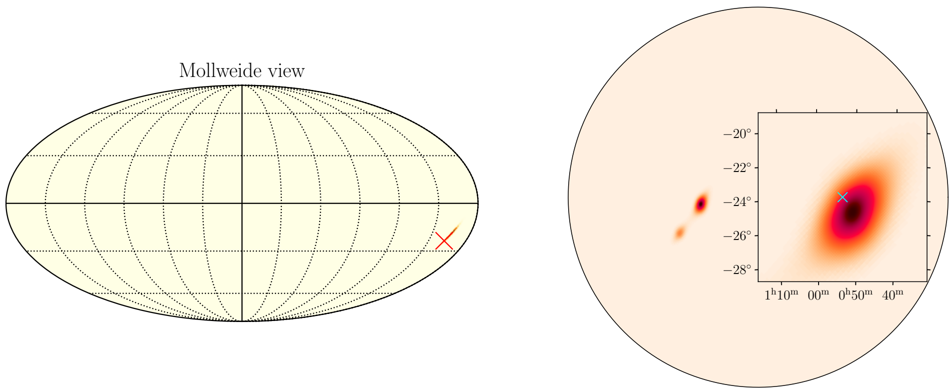

Figure 7: **Left**: The skymap of GW170817. The 'x' shows the location of AT 2017gfo. **Right**: The skymp of GW190814. The inset shows a zoomed-in image of the primary mode, and 'x' shows the location of AT 2019npv.

ligo.skymap (`https://lscsoft.docs.ligo.org/ligo.skymap/`). Mock skymaps were created using the BAYESTAR algorithm [21]. Bulla and Kasen kilonova SED models are available as package data of SNANA available at `https://doi.org/10.5281/zenodo.4728252`. SNANA project is publicly available at `https://github.com/RickKessler/SNANA` with installation instruction.

The computationally expensive part of this work was the data generation. Kilonova and other lightcurves were created at the Cori cluster at the National Energy Research Scientific Computing Center (NERSC). The sky-localizations were created at the Illinois Campus Cluster maintained by NCSA. Training the neural network takes considerably less resources – ~ 5 minutes on 8 Intel core-i7 processors.