The Astrophysical Journal, 949:114 (7pp), 2023 June 1 https://doi.org/10.3847/1538-4357/acc536

The First Two Years of FLEET: An Active Search for Superluminous Supernovae

Sebastian Gomez[1], Edo Berger[2,3], Peter K. Blanchard[4], Griffin Hosseinzadeh[5], Matt Nicholl[6], Daichi Hiramatsu[2,3], V. Ashley Villar[7,8,9], and Yao Yin[2]

[1] Space Telescope Science Institute, 3700 San Martin Drive, Baltimore, MD 21218, USA; sgomez@stsci.edu
[2] Center for Astrophysics | Harvard & Smithsonian, 60 Garden Street, Cambridge, MA 02138-1516, USA
[3] The NSF AI Institute for Artificial Intelligence and Fundamental Interactions, USA
[4] Center for Interdisciplinary Exploration and Research in Astrophysics and Department of Physics and Astronomy, Northwestern University, 1800 Sherman Avenue, 8th Floor, Evanston, IL 60201, USA
[5] Steward Observatory, University of Arizona, 933 North Cherry Avenue, Tucson, AZ 85721, USA
[6] Birmingham Institute for Gravitational Wave Astronomy and School of Physics and Astronomy, University of Birmingham, Birmingham B15 2TT, UK
[7] Department of Astronomy & Astrophysics, The Pennsylvania State University, University Park, PA 16802, USA
[8] Institute for Computational & Data Sciences, The Pennsylvania State University, University Park, PA 16802, USA
[9] Institute for Gravitation and the Cosmos, The Pennsylvania State University, University Park, PA 16802, USA
Received 2022 October 19; revised 2023 March 1; accepted 2023 March 3; published 2023 June 2

Abstract

In 2019 November, we began operating Finding Luminous and Exotic Extragalactic Transients (FLEET), a machine-learning algorithm designed to photometrically identify Type I superluminous supernovae (SLSNe) in transient alert streams. Through this observational campaign, we spectroscopically classified 21 of the 50 SLSNe identified worldwide between 2019 November and 2022 January. Based on our original algorithm, we anticipated that FLEET would achieve a purity of about 50% for transients with a probability of being an SLSN, P(SLSN-I) > 0.5; the true on-sky purity we obtained is closer to 80%. Similarly, we anticipated FLEET could reach a completeness of about 30%, and we indeed measure an upper limit on the completeness of $\lesssim$33%. Here we present FLEET 2.0, an updated version of FLEET trained on 4780 transients (almost three times more than FLEET 1.0). FLEET 2.0 has a similar predicted purity to FLEET 1.0 but outperforms FLEET 1.0 in terms of completeness, which is now closer to $\approx$40% for transients with P(SLSN-I) > 0.5. Additionally, we explore the possible systematics that might arise from the use of FLEET for target selection. We find that the population of SLSNe recovered by FLEET is mostly indistinguishable from the overall SLSN population in terms of physical and most observational parameters. We provide FLEET as an open source package on GitHub: https://github.com/gmzsebastian/FLEET.

Unified Astronomy Thesaurus concepts: Supernovae (1668); Core-collapse supernovae (304); Surveys (1671)

1. Introduction

Type I superluminous supernovae (SLSNe) can be up to 100 times more luminous than "normal" Type Ic SNe (SNe Ic). They are identified by their high luminosity and blue spectra, and, much like their normal-luminosity SN Ic counterparts, SLSNe are thought to be the end stage of massive stripped-envelope stars (Chomiuk et al. 2011; Quimby et al. 2011). To date, we know of ∼200 spectroscopically classified SLSNe (Chen et al. 2023; S. Gomez et al. 2023, in preparation). Many open questions remain about the nature of SLSNe, what powers them, their environments, their progenitors, and their connection to other transients (e.g., Ofek et al. 2007; Pastorello et al. 2010; Dessart et al. 2012; Gal-Yam 2012; Inserra et al. 2013; Lunnan et al. 2014; Nicholl et al. 2017; Blanchard et al. 2020b; Ørum et al. 2020; Yan et al. 2020c; Könyves-Tóth & Vinkó 2021; Gomez et al. 2022a; Hosseinzadeh et al. 2022). To address these questions, it is imperative that we find SLSNe early and efficiently.

Telescope resources worldwide can only spectroscopically classify ∼10% of all transients discovered by current optical time-domain surveys. Since SLSNe only make up ∼1.5% of all discovered transients (Perley et al. 2020b), we need efficient methods to select the most likely SLSN candidates for spectroscopic follow-up and make the most efficient use of limited telescope time. Toward this end, we developed Finding Luminous and Exotic Extragalactic Transients (FLEET), a machine-learning algorithm that can determine the probability of being an SLSN, P(SLSN-I), for any transient, calculated using the properties of both its light curve and host galaxy (Gomez et al. 2020a). We presented three versions of FLEET, a rapid version trained on the first 20 days of photometry, a late-time version that uses the first 70 days of photometry, and a redshift version, the only one that includes the redshift as a required parameter. The rapid version is meant to be used for real-time classification, including additional photometry as it becomes available, before the SN fades. The late-time version, on the other hand, can provide more robust predictions and be used to create photometric samples for population studies at the expense of the SN being either dimmer or having faded. The redshift version is the most accurate of the three but requires knowing the redshift of the transient a priori.

The structure of this paper is as follows. In Section 2, we present the results from our first 2 yr of FLEET operations and confirm that we have been able to accurately and efficiently discover SLSNe. In Section 3, we describe the expanded training set used for FLEET, present updated performance metrics of purity and completeness, and explore how FLEET can be used to generate photometric samples of SLSNe. In Section 4, we compare the SLSNe from FLEET to the overall sample of SLSNe and explore possible selection effects from FLEET in terms of both physical and observational parameters. Finally, we summarize our conclusions in Section 5. FLEET is provided as a Python package on GitHub[10] and Zenodo (Gomez et al. 2020b), as well as included in the Python Package Index under the name `fleet-pipe`.

2. FLEET 1.0: Operations and Discoveries

We began operating FLEET in 2019 November with the aim of finding SLSNe in ongoing transient alert streams. We selected candidates from transients reported to the Transient Name Server (TNS)[11] and followed up the ones that were most likely to be SLSNe using the Blue Channel (Schmidt et al. 1989) and Binospec (Fabricant et al. 2019) spectrographs on the MMT 6.5 m telescope and the Low Dispersion Survey Spectrograph (Stevenson et al. 2016) and Inamori-Magellan Areal Camera and Spectrograph (Dressler et al. 2011) on the Magellan 6.5 m telescopes. Since we began running FLEET and up to 2022 January, there have been 50 SLSNe spectroscopically classified worldwide, and FLEET is responsible for classifying 21 of them (42%); the full list is shown in Table 1. For completeness, in Table 2, we include a list of 17 transients classified by FLEET that turned out to be something other than SLSNe (six SNe IIn, six SNe Ia, three SNe II, and two SLSNe II). We define an SLSN-II as an SN IIn with a peak absolute magnitude $M_r < -20$. The classifications and spectra of all SNe classified as part of this program were published on the TNS.

FLEET is a binary classifier that can determine if a transient either is an SLSN with a probability $P(\text{SLSN-I}) \geqslant 0.5$ or, if the probability is lower, is not. Purity is defined as the number of true-positive SLSNe divided by the sum of true- and false-positive SLSNe. For our purity measurements, we only consider transients with $P(\text{SLSN-I}) \geqslant 0.5$, whether they are SLSNe ($N = 14$) or not ($N = 4$). Completeness is defined as the number of true-positive SLSNe divided by the sum of true-positive and false-negative SLSNe. Since we do not know the true number of undiscovered SLSNe, we cannot measure the true completeness of the classifier. Nevertheless, we can obtain an upper limit on the completeness by considering all SLSNe discovered by FLEET with $P(\text{SLSN-I}) \geqslant 0.5$ ($N = 14$) divided by the total number of SLSNe discovered worldwide ($N = 46$), whether classified by FLEET or by someone else in the community. We do not include the four SLSNe with $P(\text{SLSN-I}) \geqslant 0.5$ discovered by others in our estimate of completeness to be more conservative about our estimates. We find that the on-sky performance surpassed the expected performance for almost every metric:

1. rapid purity = 85% (predicted 50%),
2. late-time purity = 78% (predicted 59%),
3. rapid completeness $\lesssim$ 33% (predicted 30%), and
4. late-time completeness $\lesssim$ 30% (predicted 44%).

The on-sky measurements of purity are particularly successful, given that FLEET was originally designed to optimize for purity as opposed to completeness. Additionally, it is reassuring to see that even when optimizing for purity, the measured completeness is consistent with the predicted level. In addition to the SLSN candidates with high $P(\text{SLSN-I})$ values, we observed some transients that had $P(\text{SLSN-I}) < 0.5$ when other methods independent of FLEET suggested that they could be possible SLSNe. For example, we targeted SN 2021jmm, SN 2021jtu, and SN 2021owc because they were part of the Zwicky Transient Facility (ZTF) SLSN candidate reports (Perley et al. 2021a; Yan et al. 2021b, 2021c). We also observed a few targets as part of an experimental attempt to target Type II SLSNe, which, although they had low $P(\text{SLSN-I})$ values, had $P(\text{SLSN-II})$ values above 0.7: SN 2019itq, SN 2019otl, SN 2019pvs, SN 2019sgh, SN 2021xfu (all spectroscopically classified as Type I SLSNe), SN 2021owc, SN 2021srg (SN IIn), and SN 2020mad (SLSN-II). We manually vetted every transient before triggering spectroscopic follow-up, removing transients with very poor or erroneous data or misidentified host galaxies or that were clearly stellar in nature. This means that we did not observe every transient with $P(\text{SLSN-I}) > 0.5$, which might have lowered our measured purity.

The redshift classifier was originally designed with the goal of using it with data from the Legacy Survey of Space and Time once it provides photometric redshift estimates for galaxies down to $i \approx 25$ mag (Graham et al. 2018). Therefore, we do not include a comparable validation of the redshift classifier, since we have not yet tested it on active surveys.

3. FLEET 2.0: Updates and Predictions

The original version of FLEET was trained on 1813 spectroscopically classified transients. Here we retrain FLEET on an updated and more extensive list of 4780 spectroscopically classified transients with the following distinct labels from the TNS: 2983 SNe Ia, 749 SNe II, 187 SLSNe I, 157 SNe IIn, 143 CVs, 105 SNe Ic, 89 SNe IIP, 80 SNe Ib, 68 SNe IIb, 52 SLSNe II, 46 tidal disruption events (TDEs), 35 SNe Ic-BL, 26 SNe Ibc, 23 active galactic nuclei (AGNs), 19 SNe Ibn, and 18 variable stars. We retrain the algorithm using the same procedures outlined in Gomez et al. (2020a), where we optimize the depth of the random forest trees, the features included, and the number of days of photometry to consider. We find that the optimal parameters we determined for FLEET 1.0 still perform best for FLEET 2.0, with the exception that a tree depth of 11 branches now results in a higher completeness than the original depth of seven branches.

Given that the number of transients per class varies substantially, the classification would tend to be biased toward selecting the more common classes. To prevent this, we oversample each class to have a total of number of objects as the most common class (i.e., 2983 SNe Ia) using the Synthetic Minority Over-sampling Technique (Chawla et al. 2002). This algorithm draws random samples from a vector connecting every pair of objects across their parameter space until the desired number of events is reached.

In Figure 1, we show the updated purity and completeness obtained from the new FLEET 2.0 compared to those of FLEET 1.0 for all three classifiers. The uncertainties for all predictions represent the 1σ scatter of 25 different realizations of each model generated using a different initial random seed. We find that for transients with $P(\text{SLSN-I}) \geqslant 0.5$, the expected purity is ≈50% for both the rapid and late-time classifiers. The expected completeness for the same threshold is ≈50% for the late-time classifier and ≈40% for the rapid classifier. FLEET 1.0 had a comparable purity to FLEET 2.0 but a completeness ≈10% lower for both classifiers. For the redshift classifier, the purity increased in FLEET 2.0 compared to FLEET 1.0, from

[10] https://github.com/gmzsebastian/FLEET
[11] https://www.wis-tns.org/

Table 1
Spectroscopically Classified SLSNe

SLSNe with P(SLSN-I) $\geqslant$ 0.5

Classified by FLEET				Classified by Others			
Name	Redshift	P(SLSN-I)	References	Name	Redshift	P(SLSN-I)	References
SN 2019zbv	0.370	0.77	(1)	SN 2019sgg	0.573	0.62	(14)
SN 2019zeu	0.390	0.87	(1)	SN 2020abjx	0.390	0.56	(15)
SN 2020abjc	0.219	0.51	(2)	SN 2020auv	0.250	0.83	(16)
SN 2020adkm	0.226	0.62	(3)	SN 2020rmv	0.270	0.64	(17)
SN 2020jii	0.396	0.84	(4)				
SN 2020myh	0.283	0.67	(4)				
SN 2020onb	0.153	0.85	(4)				
SN 2020xgd	0.454	0.86	(5), (6)				
SN 2021ejo	0.440	0.65	(7)				
SN 2021gtr	0.303	0.47	(8)				
SN 2021hpc	0.240	0.63	(9)				
SN 2021txk	0.460	0.75	(10)				
SN 2021vuw	0.200	0.81	(11)				
SN 2021yrp	0.300	0.65	(12)				

SLSNe with P(SLSN-I) < 0.5

Classified by FLEET				Classified by Others			
Name	Redshift	P(SLSN-I)	References	Name	Redshift	P(SLSN-I)	References
SN 2019itq	0.481	0.03	(1)	SN 2019pud	0.114	0.16	(18)
SN 2019otl	0.514	0.11	(1)	SN 2019szu	0.213	0.02	(19)
SN 2019pvs	0.167	0.03	(1)	SN 2019unb	0.064	0.12	(20)
SN 2019sgh	0.344	0.06	(1)	SN 2020aewh	0.345	0.06	(21)
SN 2019ujb	0.165	0.04	(1)	SN 2020ank	0.249	0.28	(22), (23)
SN 2019xaq	0.200	0.02	(1)	SN 2020exj	0.133	0.04	(24)
SN 2021xfu	0.320	0.06	(13)	SN 2020qef	0.183	0.09	(25)
				SN 2020qlb	0.159	0.03	(26)
				SN 2020tcw	0.065	0.08	(27)
				SN 2020vpg	0.257	0.06	(28)
				SN 2020wfh	0.330	0.20	(15)
				SN 2020xga	0.440	0.11	(29)
				SN 2020znr	0.100	0.16	(30)
				SN 2020zzb	0.166	0.10	(15)
				SN 2021bnw	0.098	0.06	(31)
				SN 2021een	0.160	0.08	(32)
				SN 2021ek	0.193	0.13	(33)
				SN 2021fpl	0.115	0.11	(34)
				SN 2021hpx	0.213	0.06	(35)
				SN 2021kty	0.159	0.09	(36)
				SN 2021lwz	0.065	0.00	(37)
				SN 2021mkr	0.280	0.06	(38), (39)
				SN 2021nxq	0.150	0.03	(40)
				SN 2021rwz	0.190	0.24	(41)
				SN 2021ybf	0.130	0.07	(42)

Note. All SLSNe spectroscopically classified between 2019 November and 2021 November either by FLEET or by other groups. We include the spectroscopic redshifts and P(SLSN-I) values from the late-time FLEET classifier, sorted alphabetically. Only the SLSNe with P(SLSN-I) $\geqslant$ 0.5 were used for measuring the purity. All of the SLSNe with P(SLSN-I) $\geqslant$ 0.5, excluding the ones discovered by other groups, were used to estimate the completeness. (1) Gomez et al. (2021b); (2) Blanchard et al. (2020a); (3) Blanchard et al. (2021a); (4) Gomez et al. (2020c); (5) Gomez et al. (2020d); (6) Weil & Milisavljevic (2020); (7) Gomez et al. (2021a); (8) Gomez et al. (2021d); (9) Gomez et al. (2021c); (10) Gomez et al. (2021e); (11) Gomez et al. (2021j); (12) Gomez et al. (2021h); (13) Gomez et al. (2021g); (14) Yan et al. (2019); (15) Yan et al. (2020a); (16) Yan et al. (2020b); (17) Terreran (2020b); (18) Fremling et al. (2019); (19) Dahiwale & Fremling (2019); (20) Dahiwale & Fremling (2020b); (21) Yan et al. (2021a); (22) Poidevin et al. (2020); (23) Dahiwale & Fremling (2020a); (24) Dahiwale & Fremling (2020c); (25) Terreran (2020a); (26) Perez-Fournon et al. (2020); (27) Perley et al. (2020a); (28) Terreran (2020c); (29) Gromadzki et al. (2020); (30) Ihanec et al. (2020); (31) Magee et al. (2021); (32) Dahiwale & Fremling (2021); (33) Gillanders et al. (2021); (34) Deckers et al. (2021); (35) Padilla Gonzalez et al. (2021); (36) Yao et al. (2021); (37) Perley et al. (2021b); (38) Chu et al. (2021b); (39) Poidevin et al. (2021); (40) Weil et al. (2021); (41) Weil & Milisavljevic (2021); (42) Bruch et al. (2021).

≈50% to ≈60%, and the completeness increased from ≈55% to ≈60%. The drop seen in the FLEET 1.0 rapid classifier at P(SLSN-I) > 0.9, which was due to the small sample size, is now not present in FLEET 2.0.

3.1. Photometric Sample of SLSNe

We use FLEET 2.0 to generate a photometric sample of SLSN candidates by running it on every optical transient reported to the TNS and searching for unclassified SLSNe.

Table 2
Non-SLSNe Classified by FLEET

Name	Type	Redshift	P(SLSN-I)	References
		SNe with P(SLSN-I) $\geqslant$ 0.5		
SN 2020mad	SLSN-II	0.123	0.60	(1)
SN 2020tyk	SN IIn	0.087	0.73	(2), (3)
SN 2021abjs	SN Ia	0.160	0.52	(6)
SN 2021ali	SLSN-II	0.192	0.80	(8)
		SNe with P(SLSN-I) $<$ 0.5		
SN 2020hvw	SN II	0.093	0.41	(1)
SN 2020oqy	SN Ia	0.135	0.12	(1)
SN 2021aeaj	SN Ia	0.205	0.47	(7)
SN 2021jmm	SN IIn	0.190	0.45	(4)
SN 2021jtu	SN IIn	0.113	0.48	(4)
SN 2021osr	SN IIn	0.085	0.01	(8), (9)
SN 2021owc	SN IIn	0.127	0.42	(8)
SN 2021rcn	SN Ia	0.121	0.05	(10)
SN 2021srg	SN IIn	0.069	0.07	(5)
SN 2021stu	SN II	0.034	0.27	(11)
SN 2021uuz	SN II	0.175	0.36	(12)
SN 2021wkg	SN Ia	0.120	0.06	(13)
SN 2021zqa	SN Ia	0.120	0.34	(13)

Note. All transients spectroscopically classified by FLEET that turned out to not be SLSNe, including their redshift and P(SLSN-I) estimate from the late-time classifier, sorted alphabetically. Only the SNe with P(SLSN-I) $\geqslant$ 0.5 were used to calculate our purity estimates. (1) Gomez et al. (2020c); (2) Gomez et al. (2020d); (3) Weil & Milisavljevic (2020); (4) Gomez et al. (2021c); (5) Gomez et al. (2021e); (6) Gomez et al. (2021k); (7) Gomez et al. (2022b); (8) Hosseinzadeh et al. (2021); (9) Chu et al. (2021a); (10) Gomez et al. (2021e); (11) Gomez et al. (2021f); (12) Gomez et al. (2021i); (13) Gomez et al. (2021l).

Since these are mostly transients that have faded away by the time of this analysis, we use the late-time classifier that was trained on the first 70 days of photometry. For this reason, we exclude transients that were too young, discovered after 2022 March 1. At that time, there were a total of 95,729 transients reported to the TNS. Of these, 83,589 have a decl. $> -32°$, required for FLEET to query the PS1/3π (Chambers & Pan-STARRS Team 2018) or Sloan Digital Sky Survey (SDSS) catalogs (Alam et al. 2015; Ahumada et al. 2020). Of these, 34,805 were discovered before ZTF began operations and have either only one data point or minimal discovery photometry available. An additional 2078 transients were excluded because they only had coverage in one band, despite having tens to hundreds of detections in ZTF. Of the remaining transients, 31,922 had at least two g-band and two r-band points, required for FLEET to fit a model to their light curve. Finally, we excluded 30 transients that were located in regions with a Galactic extinction $\gtrsim$1.5 mag. The final list of transients on which we run FLEET contains 31,892 transients.

In Figure 2, we show the P(SLSN-I) values from FLEET 2.0 compared to the estimates from FLEET 1.0 for all 31,892 transients. The increase in completeness of FLEET 2.0 is evident in the cluster of transients that had low P(SLSN-I) values in FLEET 1.0 that now lie at P(SLSN-I) $>$ 0.5. In Figure 2, we also include the sample of 106 spectroscopically classified SLSNe, shown in blue. A total of 69 of these SLSNe had P(SLSN-I) $<$ 0.2 in FLEET 1.0, 20 of which now have P(SLSN-I) $>$ 0.5 in FLEET 2.0, representing the improvement in completeness. While 21 SLSNe now have a lower P(SLSN-I) in FLEET 2.0, 85 have a higher P(SLSN-I) in FLEET 2.0

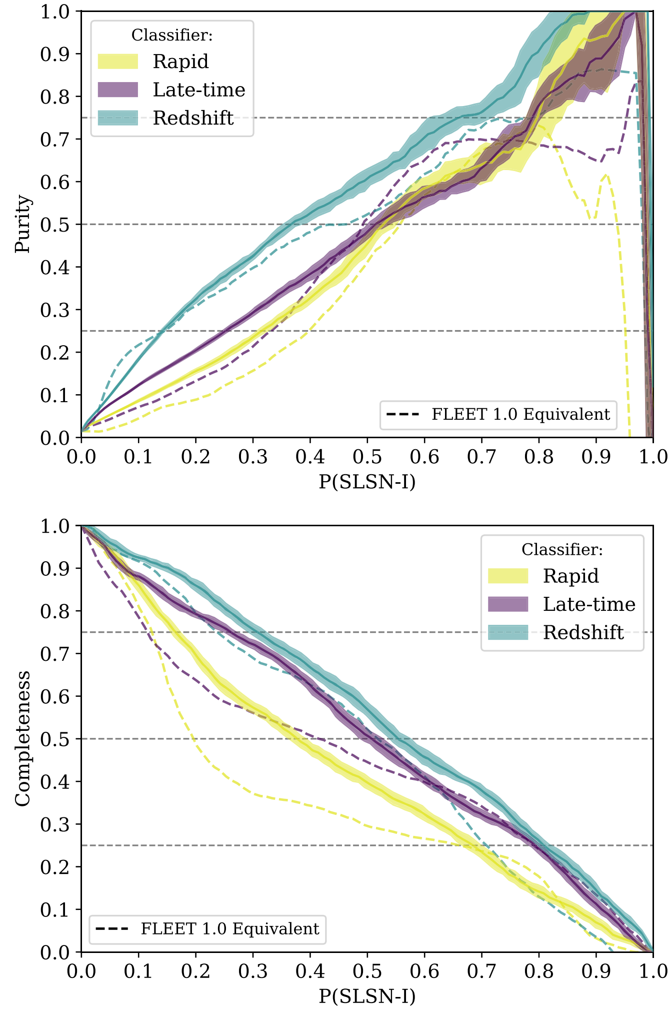

Figure 1. Purity and completeness estimates for FLEET 2.0. Top: purity as a function of classification confidence for the rapid, late-time, and redshift versions of the classifier. Bottom: completeness as a function of classification confidence for the same classifiers. The dashed lines show the equivalent measurements from FLEET 1.0 taken directly from Gomez et al. (2020a) but without the uncertainty regions for clarity.

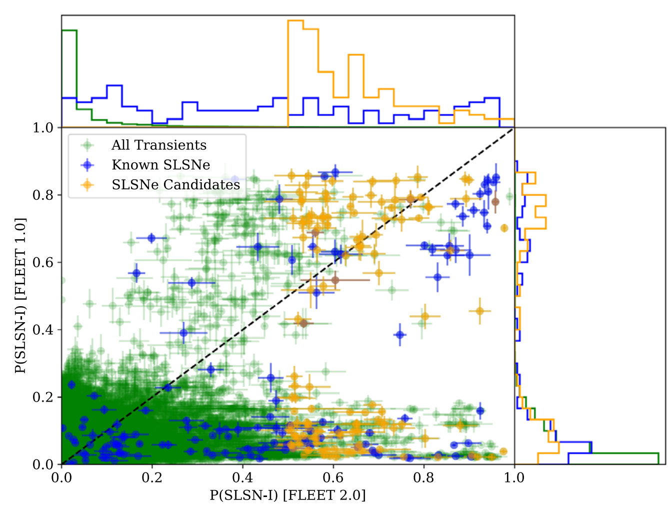

Figure 2. Classification confidence P(SLSN-I) for both the new and old versions of FLEET using the late-time classifier. We find that some SLSNe that had low values of P(SLSN-I) in FLEET 1.0 are now well above 0.5 in FLEET 2.0. Both histograms showing the distribution of the distinct samples have been normalized by sample size.

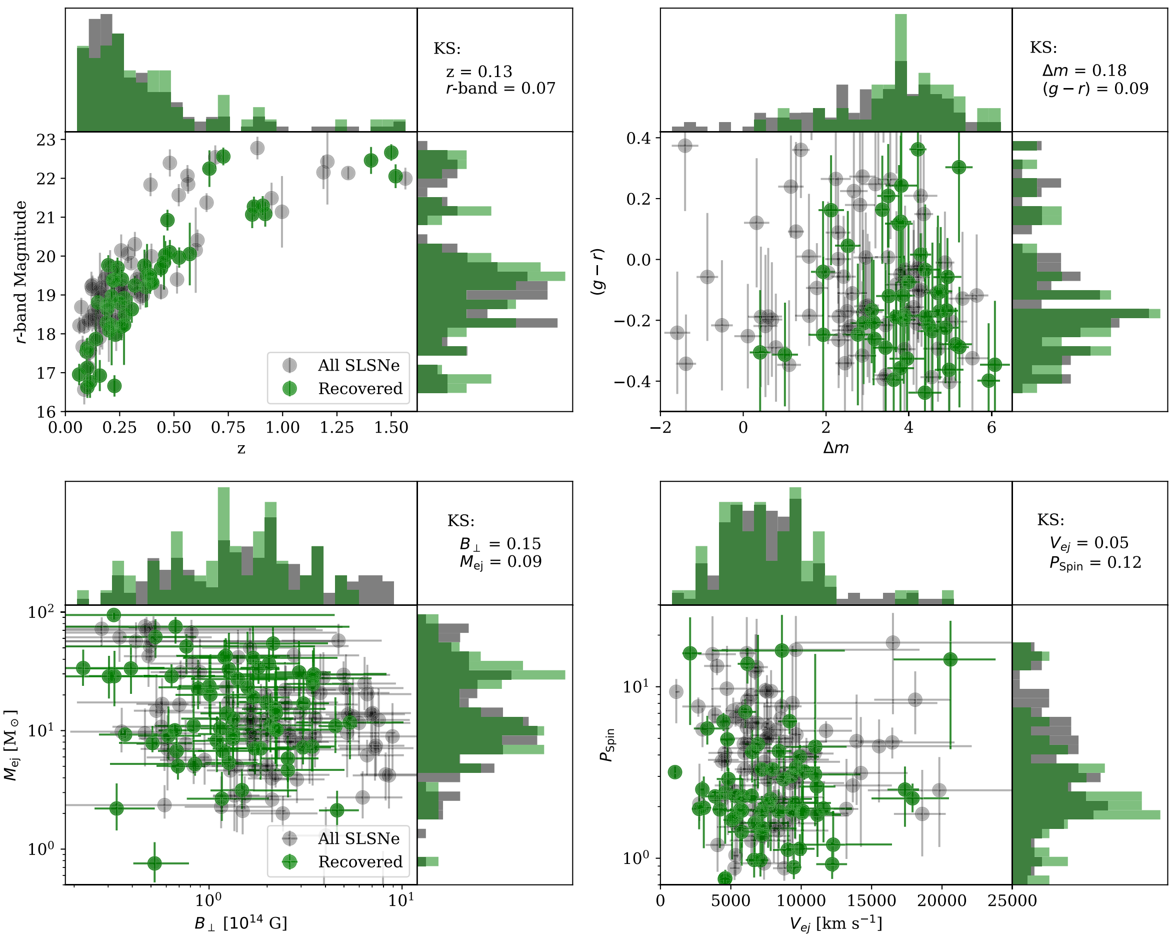

Figure 3. Gray data points represent the parameters of the full sample of SLSNe, while the green points are SLSNe that were recovered by FLEET using the late-time classifier with $P(\text{SLSN-I}) > 0.5$. We show distributions of the most relevant physical and observational parameters. Top left: peak apparent r-band magnitude and redshift. Top right: $(g - r)$ color during peak and the host minus transient magnitude, Δm. Bottom left: ejecta mass and neutron star magnetic field. Bottom right: magnetar spin period and ejecta velocity. We include the K-S metric for each parameter in the upper right corner of each panel.

compared to FLEET 1.0, indicating a net gain. Of the 21 SLSNe that lowered in confidence, only six decreased significantly from $P(\text{SLSN-I}) > 0.5$ in FLEET 1.0 to $P(\text{SLSN-I}) < 0.5$ in FLEET 2.0.

There were 25 SLSNe classified by other groups, which had $P(\text{SLSN-I}) < 0.5$ in FLEET 1.0. Of these, nine have $P(\text{SLSN-I}) > 0.5$ in FLEET 2.0. Of the remaining ones, nine still have significantly low values of $P(\text{SLSN-I}) < 0.25$. These low $P(\text{SLSN-I})$ values are mostly due to sparse or noisy light curves and, in the case of SN 2021lwz, a very quickly evolving light curve.

Of the 106 spectroscopically confirmed SLSNe in the sample shown in Figure 2, 45 have $P(\text{SLSN-I}) > 0.5$, corresponding to a completeness of 43%. We find a total of 382 transients with $P(\text{SLSN-I}) > 0.5$, including the 45 known SLSNe. This corresponds to a purity of 12%, much lower than the on-sky purity presented in Section 2, for two main reasons. First, obvious failure modes still exist that pollute the sample (e.g., variable AGNs or variable stars with long light curves, and no detected host can be misclassified as an SLSN). We can visually purge these obvious failure modes to increase the purity of our sample, as was done during the first 2 yr of operations to obtain the observed purity cited in Section 2. Second, there are likely still some SLSNe in those 382 transients that have not been classified but can be considered to create a photometrically selected sample of SLSNe. Of those 382 transients, we exclude 139 from being possible SLSNe because either their light curves are too noisy or sparse or they strongly resemble a stellar transient or AGN (these are the green points in Figure 2 with $P(\text{SLSN-I}) > 0.5$ in FLEET 2.0). That leaves 243 transients as possible SLSNe, noting that none of the 45 spectroscopic classified SLSNe were rejected in the manual purging process. Of these, 70 transients are already classified: 2 AGNs, 2 CVs, 11 SLSNe II, 1 SN I, 13 SNe II, 2 SNe IIP, 17 SNe IIn, 16 SNe Ia, 2 SNe Ia-91T-like, 1 SN Ia-CSM, 2 SNe Ic, and 1 TDE. Finally, 128 remain unclassified SLSN candidates. We show the 128 photometrically selected SLSN candidates in orange in Figure 2. We find that 45% of these candidates also had $P(\text{SLSN-I}) > 0.5$ in FLEET 1.0, whereas the other half were previously below this threshold. If we were to spectroscopically classify these 128 SLSN candidates, assuming that the likelihood of any one target being an SLSN is equal to their $P(\text{SLSN-I})$, we expect that about 82 of them would be true SLSNe, or an ∼40% increase of the current total population size of SLSNe. A full exploration of this population will be presented in future work.

4. Selection Effects

In this section, we explore whether the use of FLEET introduces biases or selection effects in terms of observed or physical SLSN parameters. For this test, we use the sample of

187 SLSNe used for training FLEET. We run these SLSNe through the late-time classifier in FLEET and compare the observational parameters of the SLSN population at large, with those of 74 "recovered" SLSN with $P(\text{SLSN-I}) > 0.5$. To quantify how different the parameter distributions are, we implement a two-sample Kolmogorov–Smirnov (K-S), where a K-S metric of $D = 0.0$ indicates that the two samples are drawn from the same distribution, and $D = 1.0$ means that there is no overlap between the distributions. We show how the apparent r-band magnitude, redshift, $(g - r)$ color, and Δm compare between the two samples in the top panels of Figure 3, where Δm is defined as the host magnitude minus the transient peak magnitude. We find no obvious selection effects in terms of redshift r-band magnitude or $(g - r)$ color, which have K-S metrics (and p values) of 0.13 (0.4), 0.07 (0.96), and 0.09 (0.3), respectively. The only observational parameter for which we do find a possible difference between the full and recovered sample is Δm, where SLSNe with $\Delta m < 0$ are generally not selected as likely SLSNe. This is reflected in its K-S metric of 0.18 (0.09). To calculate Δm, we use as reference the r-band magnitudes of the host galaxies obtained from either PS1/3π, SDSS, or values published in compilation studies of the hosts of SLSNe (Inserra et al. 2013; Lunnan et al. 2014; Angus et al. 2016, 2019; Perley et al. 2016; Schulze et al. 2018, 2021) or studies of individual SLSNe (Leloudas et al. 2012; Vreeswijk et al. 2014; Lunnan et al. 2016, 2018; Yan et al. 2017; Blanchard et al. 2018, 2021b; Yin et al. 2022).

The power source behind SLSNe is still a debated topic, but the most likely one appears to be a magnetar central engine (Angus et al. 2016; Nicholl et al. 2017; Margalit et al. 2018). When a millisecond magnetar is born after the explosion of the progenitor, it will spin down and deposit this energy into the ejecta, powering the bright optical light curves observed in SLSNe (Kasen & Bildsten 2010; Woosley 2010). Therefore, we explore the selection effects in terms of the physical parameters of the SLSN population, assuming these are powered by magnetars. We derive the physical parameters of the 187 SLSNe from light-curve fits using `MOSFiT`, a Python code designed to model the light curves of transients using a variety of different power sources and derive their physical parameters (Guillochon et al. 2018). We show how the population of recovered SLSNe compares to the overall population in the bottom panels of Figure 3. We find a K-S metric (and p value) of 0.15 (0.26) for the magnetic field $B_{\perp}$, 0.09 (0.79) for the ejecta mass M_{ej}, 0.05 (0.99) for the ejecta velocity V_{ej}, and 0.12 (0.03) for the spin period P_{spin}. This shows that the two populations are very similar at the 5%–10% level and that FLEET is not introducing a bias in terms of physical parameters. We note that here we are concerned mostly with the relative distribution of physical parameters, and the specific choice of physical model is not the discerning factor.

In conclusion, we find that even if FLEET is less likely to select SLSNe with low values of Δm, this does not translate into a bias on the derived physical parameters.

5. Conclusion

We have provided an evaluation of the on-sky performance of FLEET during our first 2 yr of operations. We include the list of 21 SLSNe found by FLEET 1.0 from 2019 November to 2022 January, which represent 42% of all SLSNe discovered worldwide in the same time period. We show that our estimate for purity of ≈50% from FLEET 1.0 was surpassed with a measured purity of ≈80%. The measured completeness was in line with our predicted value of ≈30%.

We describe an updated version, FLEET 2.0, trained on 4780 transients, or almost three times as many as FLEET 1.0. The updated estimates for purity and completeness are both ≈50% for the late-time classifier and ≈50% purity and ≈40% completeness for the rapid classifier. The estimated purity and completeness for the redshift classifier are both ≈60%. It is of course possible that the on-sky purity will be higher, as was the case for FLEET 1.0. We test whether FLEET might be introducing selection effects into the recovered SLSN population and find no significant biases against any physical or most observational parameters.

Finally, we generate a photometric sample of 128 likely SLSN candidates selected by FLEET from ZTF archival data. We find that if we were to spectroscopically classify all of these candidates, assuming that the likelihood of any transient being an SLSN is equal to its $P(\text{SLSN-I})$ value, ∼80 of them would result in true SLSNe, which would represent an ∼40% increase in the current population size of SLSNe.

S.G. is supported by an STScI Postdoctoral Fellowship. The Berger Time Domain group at Harvard is supported in part by NSF and NASA grants, including support by the NSF under grant AST-2108531, as well as by the NSF under Cooperative Agreement PHY-2019786 (The NSF AI Institute for Artificial Intelligence and Fundamental Interactions; http://iafi.org/). M. N. is supported by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No. 948381) and a fellowship from the Alan Turing Institute. This research has made use of NASA's Astrophysics Data System. This research has made use of the SIMBAD database, operated at CDS, Strasbourg, France. Operation of the Pan-STARRS1 telescope is supported by the National Aeronautics and Space Administration under grant Nos. NNX12AR65G and NNX14AM74G issued through the NEO Observation Program.

Facilities: ADS, TNS.

Software: Astropy (Astropy Collaboration et al. 2018), extinction (Barbary 2016), Matplotlib (Hunter 2007), emcee (Foreman-Mackey et al. 2013), NumPy (van der Walt et al. 2011), scikit-learn (Pedregosa et al. 2011), SMOTE (Chawla et al. 2002), FLEET (Gomez et al. 2020b).

ORCID iDs

Sebastian Gomez https://orcid.org/0000-0001-6395-6702
Edo Berger https://orcid.org/0000-0002-9392-9681
Peter K. Blanchard https://orcid.org/0000-0003-0526-2248
Griffin Hosseinzadeh https://orcid.org/0000-0002-0832-2974
Matt Nicholl https://orcid.org/0000-0002-2555-3192
Daichi Hiramatsu https://orcid.org/0000-0002-1125-9187
V. Ashley Villar https://orcid.org/0000-0002-5814-4061
Yao Yin https://orcid.org/0000-0002-5723-8023

References

Ahumada, R., Allende Prieto, C., Almeida, A., et al. 2020, ApJS, 249, 3
Alam, S., Albareti, F. D., Allende Prieto, C., et al. 2015, ApJS, 219, 12
Angus, C. R., Levan, A. J., Perley, D. A., et al. 2016, MNRAS, 458, 84
Angus, C. R., Smith, M., Sullivan, M., et al. 2019, MNRAS, 487, 2215
Astropy Collaboration, Price-Whelan, A. M., Sipőcz, B. M., et al. 2018, AJ, 156, 123

Barbary, K. 2016, Extinction V0.3.0, Zenodo, doi:10.5281/zenodo.804967
Blanchard, P., Berger, E., Gomez, S., & Hosseinzadeh, G. 2021a, TNSCR, 276, 1
Blanchard, P., Gomez, S., Hosseinzadeh, G., & Berger, E. 2020a, TNSCR, 3871, 1
Blanchard, P. K., Berger, E., Nicholl, M., & Villar, V. A. 2020b, ApJ, 897, 114
Blanchard, P. K., Berger, E., Nicholl, M., et al. 2021b, ApJ, 921, 64
Blanchard, P. K., Nicholl, M., Berger, E., et al. 2018, ApJ, 865, 9
Bruch, R., Anderson, J., Gutierrez, C., & Irani, I. 2021, TNSCR, 3392, 1
Chambers, K. & Pan-STARRS Team 2018, AAS Meeting Abstracts, 231, 102.01
Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. 2002, J. Artif. Intell. Res., 16, 321
Chen, Z. H., Yan, L., Kangas, T., et al. 2023, ApJ, 943, 41
Chomiuk, L., Chornock, R., Soderberg, A. M., et al. 2011, ApJ, 743, 114
Chu, M., Dahiwale, A., & Fremling, C. 2021a, TNSCR, 2593, 1
Chu, M., Dahiwale, A., & Fremling, C. 2021b, TNSCR, 2748, 1
Dahiwale, A., & Fremling, C. 2019, TNSCR, 2889, 1
Dahiwale, A., & Fremling, C. 2020a, TNSCR, 1494, 1
Dahiwale, A., & Fremling, C. 2020b, TNSCR, 1504, 1
Dahiwale, A., & Fremling, C. 2020c, TNSCR, 1756, 1
Dahiwale, A., & Fremling, C. 2021, TNSCR, 1234, 1
Deckers, M., Prentice, S., Maguire, K., et al. 2021, TNSCR, 1365, 1
Dessart, L., Hillier, D. J., Waldman, R., Livne, E., & Blondin, S. 2012, MNRAS Lett., 426, L76
Dressler, A., Bigelow, B., Hare, T., et al. 2011, PASP, 123, 288
Fabricant, D., Fata, R., Epps, H., et al. 2019, PASP, 131, 075004
Foreman-Mackey, D., Hogg, D. W., Lang, D., & Goodman, J. 2013, PASP, 125, 306
Fremling, C., Dahiwale, A., & Dugas, A. 2019, TNSCR, 1923, 1
Gal-Yam, A. 2012, Sci, 337, 927
Gillanders, J., Srivastav, S., Fulton, M., et al. 2021, TNSCR, 86, 1
Gomez, S., Berger, E., Blanchard, P., & Nicholl, M. 2021a, TNSCR, 1675, 1
Gomez, S., Berger, E., Blanchard, P. K., et al. 2020a, ApJ, 904, 74
Gomez, S., Berger, E., Blanchard, P. K., et al. 2020b, FLEET Finding Luminous and Exotic Extragalactic Transients, v1.0.0, Zenodo, doi:10.5281/zenodo.4013965
Gomez, S., Berger, E., Nicholl, M., Blanchard, P. K., & Hosseinzadeh, G. 2022a, ApJ, 941, 107
Gomez, S., Blanchard, P., Hiramatsu, D., & Berger, E. 2022b, TNSCR, 143, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2020c, TNSCR, 3149, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2020d, TNSCR, 3506, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2021b, TNSCR, 565, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2021c, TNSCR, 1647, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2021d, TNSCR, 1716, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2021e, TNSCR, 2719, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2021f, TNSCR, 2965, 1
Gomez, S., Hosseinzadeh, G., Berger, E., & Blanchard, P. 2021g, TNSCR, 3270, 1
Gomez, S., Hosseinzadeh, G., Blanchard, P., & Berger, E. 2021h, TNSCR, 3444, 1
Gomez, S., Hosseinzadeh, G., Blanchard, P., & Berger, E. 2021i, TNSCR, 3483, 1
Gomez, S., Hosseinzadeh, G., Blanchard, P., & Berger, E. 2021j, TNSCR, 3662, 1
Gomez, S., Hosseinzadeh, G., Blanchard, P., & Berger, E. 2021k, TNSCR, 4047, 1
Gomez, S., Hosseinzadeh, G., Blanchard, P., Hiramatsu, D., & Berger, E. 2021l, TNSCR, 3788, 1
Graham, M. L., Connolly, A. J., Ivezić, Ž., et al. 2018, AJ, 155, 1
Gromadzki, M., Ihanec, N., Moran, S., & Yaron, O. 2020, TNSCR, 3372, 1
Guillochon, J., Nicholl, M., Villar, V. A., et al. 2018, ApJS, 236, 6
Hosseinzadeh, G., Berger, E., Metzger, B. D., et al. 2022, ApJ, 933, 14
Hosseinzadeh, G., Gomez, S., Berger, E., & Blanchard, P. 2021, TNSCR, 2441, 1
Hunter, J. D. 2007, CSE, 9, 90
Ihanec, N., Gromadzki, M., Wevers, T., & Irani, I. 2020, TNSCR, 3486, 1
Inserra, C., Smartt, S. J., Jerkstrand, A., et al. 2013, ApJ, 770, 128
Kasen, D., & Bildsten, L. 2010, ApJ, 717, 245
Könyves-Tóth, R., & Vinkó, J. 2021, ApJ, 909, 24
Leloudas, G., Chatzopoulos, E., Dilday, B., et al. 2012, A&A, 541, A129
Lunnan, R., Chornock, R., Berger, E., et al. 2014, ApJ, 787, 138
Lunnan, R., Chornock, R., Berger, E., et al. 2016, ApJ, 831, 144
Lunnan, R., Fransson, C., Vreeswijk, P. M., et al. 2018, NatAs, 2, 887
Magee, M., Terwel, J., Prentice, S., Harvey, L., & Strotjohann, N. L. 2021, TNSCR, 338, 1
Margalit, B., Metzger, B. D., Berger, E., et al. 2018, MNRAS, 481, 2407
Nicholl, M., Guillochon, J., & Berger, E. 2017, ApJ, 850, 55
Ofek, E. O., Cameron, P. B., Kasliwal, M. M., et al. 2007, ApJL, 659, L13
Ørum, S. V., Ivens, D. L., Strandberg, P., et al. 2020, A&A, 643, A47
Padilla Gonzalez, E., Hiramatsu, D., Burke, J., et al. 2021, TNSCR, 1220, 1
Pastorello, A., Smartt, S. J., Botticella, M. T., et al. 2010, ApJL, 724, L16
Pedregosa, F., Varoquaux, G., Gramfort, A., et al. 2011, J. Mach. Learn. Res., 12, 2825
Perez-Fournon, I., Poidevin, F., Angel, C. J., et al. 2020, TNSCR, 2456, 1
Perley, D., Sollerman, J., Fremling, C., Dahiwale, A., & Walters, R. 2020a, TNSCR, 3125, 1
Perley, D. A., Chen, T., Schulze, S., et al. 2021a, TNSAN, 154, 1
Perley, D. A., Fremling, C., Sollerman, J., et al. 2020b, ApJ, 904, 35
Perley, D. A., Quimby, R. M., Yan, L., et al. 2016, ApJ, 830, 13
Perley, D. A., Yao, Y., Chen, T., et al. 2021b, TNSCR, 1649, 1
Poidevin, F., Marques-Chaves, R., Perez-Fournon, I., et al. 2020, TNSCR, 500, 1
Poidevin, F., Perez-Fournon, I., Angel, C. J., et al. 2021, TNSCR, 2271, 1
Quimby, R. M., Kulkarni, S. R., Kasliwal, M. M., et al. 2011, Natur, 474, 487
Schmidt, G. D., Weymann, R. J., & Foltz, C. B. 1989, PASP, 101, 713
Schulze, S., Krühler, T., Leloudas, G., et al. 2018, MNRAS, 473, 1258
Schulze, S., Yaron, O., Sollerman, J., et al. 2021, ApJS, 255, 29
Stevenson, K. B., Bean, J. L., Seifahrt, A., et al. 2016, ApJ, 817, 141
Terreran, G. 2020a, TNSCR, 2618, 1
Terreran, G. 2020b, TNSCR, 2902, 1
Terreran, G. 2020c, TNSCR, 3507, 1
van der Walt, S., Colbert, S. C., & Varoquaux, G. 2011, CSE, 13, 22
Vreeswijk, P. M., Savaglio, S., Gal-Yam, A., et al. 2014, ApJ, 797, 24
Weil, K. E., & Milisavljevic, D. 2020, TNSCR, 3413, 1
Weil, K. E., & Milisavljevic, D. 2021, TNSCR, 2881, 1
Weil, K. E., Subrayan, B. M., & Milisavljevic, D. 2021, TNSCR, 2270, 1
Woosley, S. E. 2010, ApJL, 719, L204
Yan, L., Chen, Z., Perley, D., et al. 2019, TNSCR, 2041, 1
Yan, L., Lunnan, R., Perley, D., Schulze, S., & Chen, T. W. 2020a, TNSCR, 3639, 1
Yan, L., Lunnan, R., Perley, D., Schulze, S., & Chen, T. W. 2021a, TNSCR, 451, 1
Yan, L., Lunnan, R., Perley, D. A., et al. 2017, ApJ, 848, 6
Yan, L., Perley, D., Lunnan, R., et al. 2021b, TNSAN, 119, 1
Yan, L., Perley, D., Schulze, S., et al. 2020b, TNSCR, 1736, 1
Yan, L., Perley, D. A., Lunnan, R., et al. 2021c, TNSAN, 172, 1
Yan, L., Perley, D. A., Schulze, S., et al. 2020c, ApJL, 902, L8
Yao, Y., Hammerstein, E., Gezari, S., et al. 2021, TNSCR, 2535, 1
Yin, Y., Gomez, S., Berger, E., et al. 2022, ApJ, 931, 32