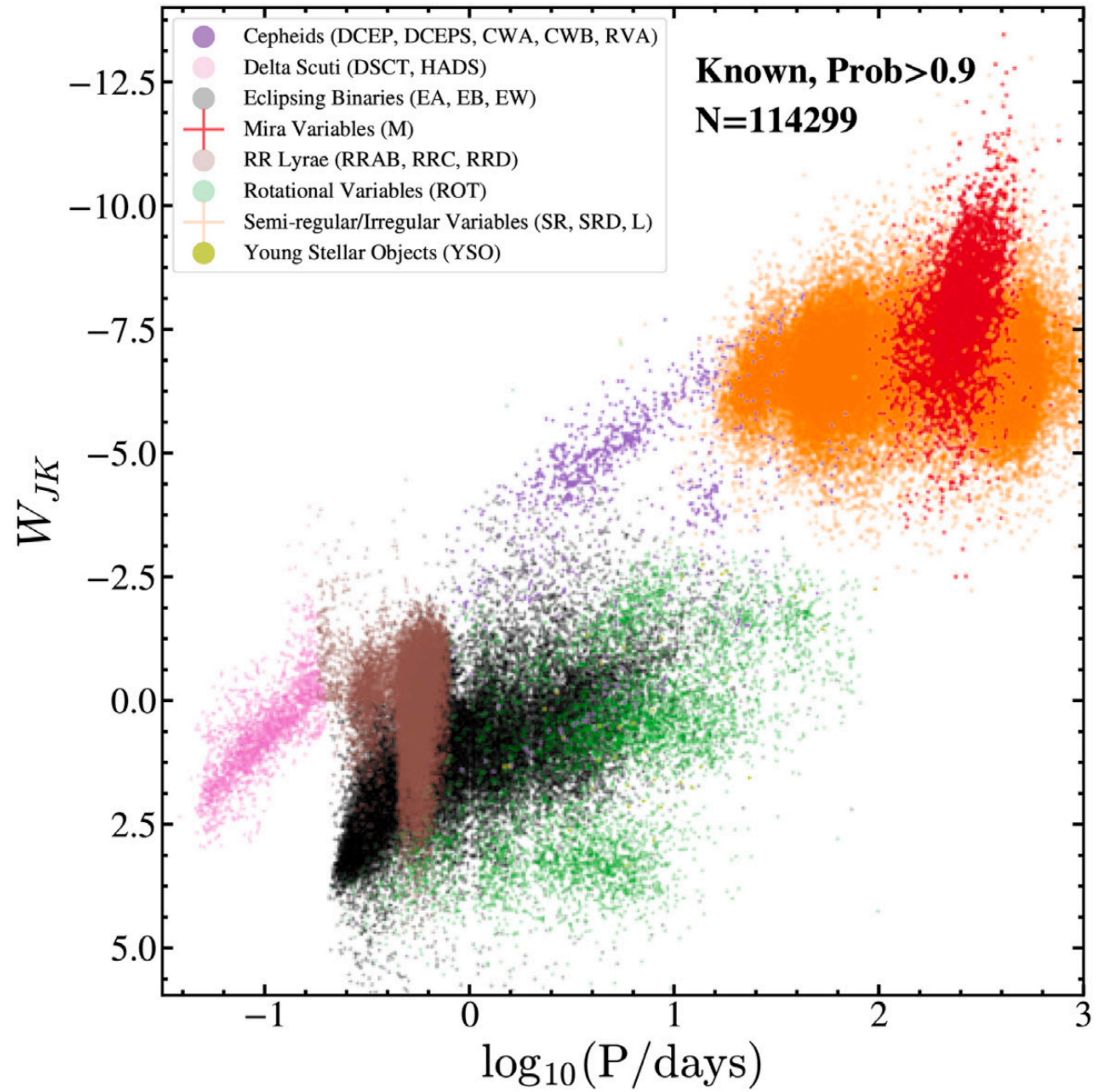
Photometric Classification of Transients and Variables

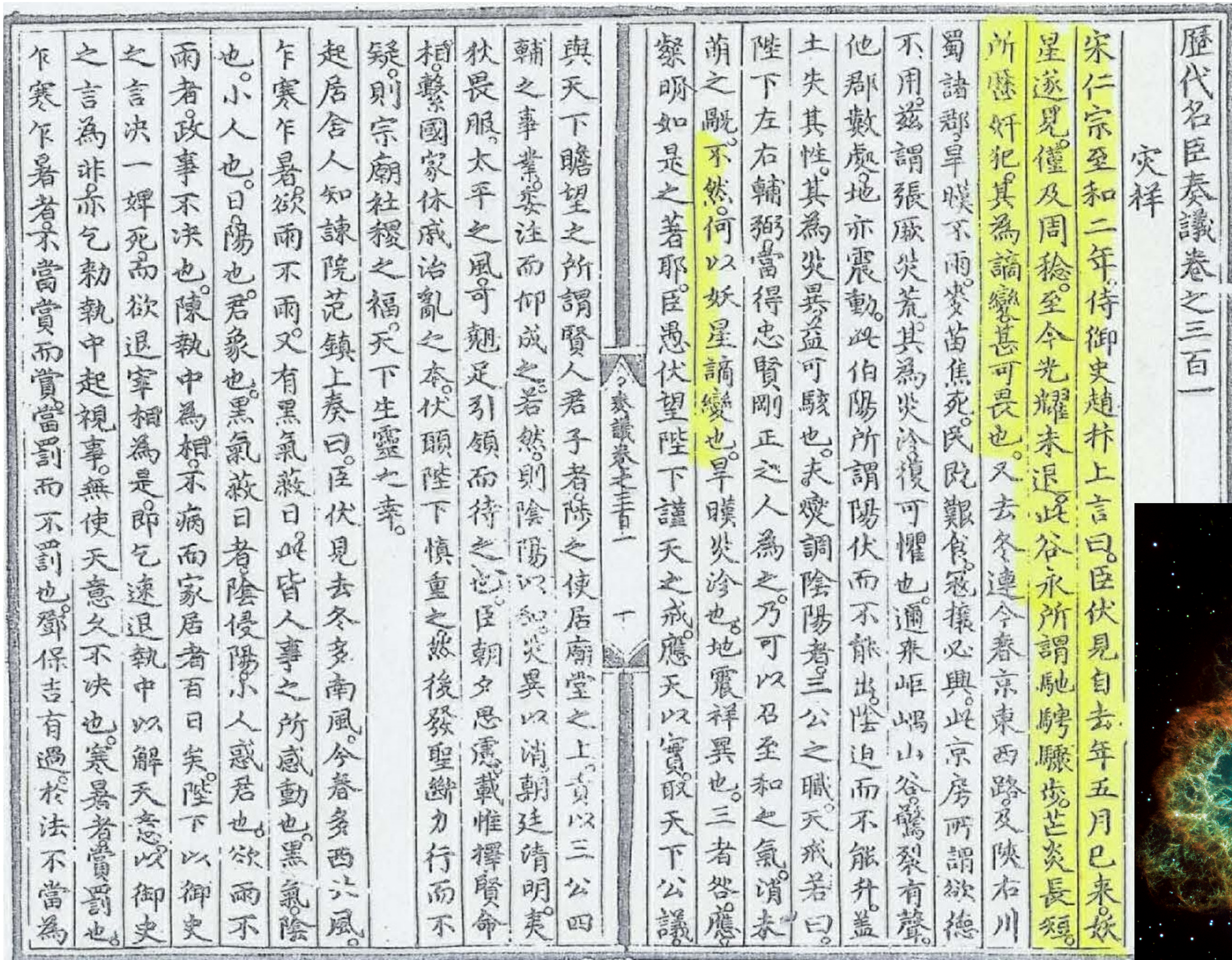


Jayasinghe+20

Eric Bellm

ASTR 597A, Winter 2023

Time-domain classification is foundational to astronomical science.



歷代名臣奏議卷之三百一

災祥

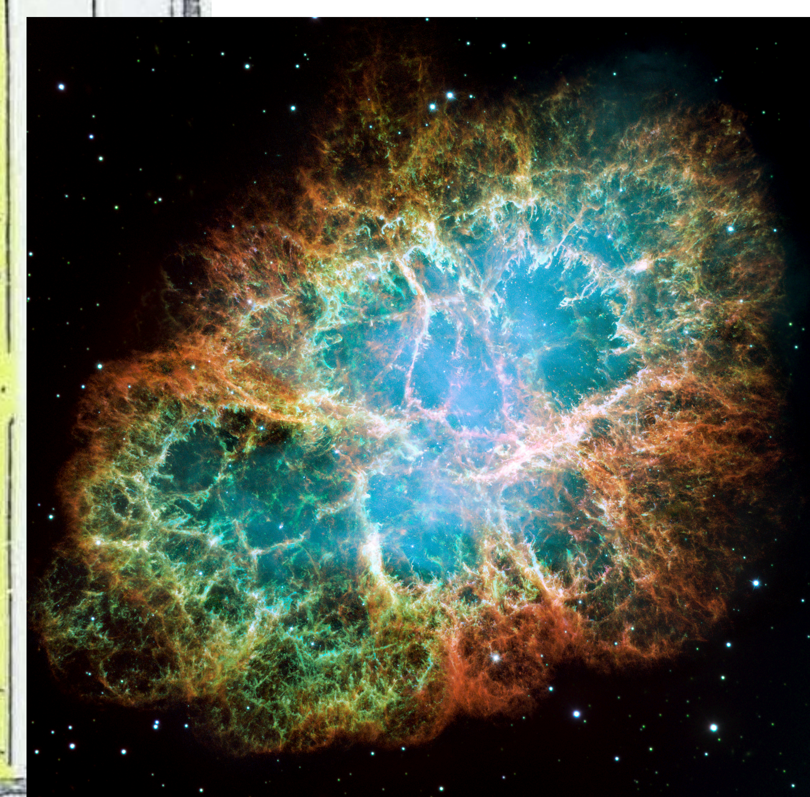
宋仁宗至和二年侍御史趙抃上言曰臣伏見自去年五月巳來妖星遂見僅及周稔至今光耀未退此谷永所謂馳騁驟步芒炎長縟所曆奸犯其為譴變甚可畏也又去冬達今春京東西路及陝右川蜀諸郡旱暵不雨麥苗焦死民既艱食寇攘必興此京房所謂欲德不用茲謂張厥災荒其為災沴復可懼也通來岷嶠山谷驚裂有聲他郡數處地亦震動此伯陽所謂陽伏而不能出陰迫而不能升蓋土失其性其為災異益可駭也夫變調陰陽者三公之職天戒若曰陛下左右輔弼當得忠賢剛正之人為之乃可以召至和之氣消弭萌之戚不然何以妖星譴變也旱暵災沴也地震祥異也三者咎應粲明如是之著耶臣愚伏望陛下謹天之戒應天以實取天下公議

奏議卷三百一　十一

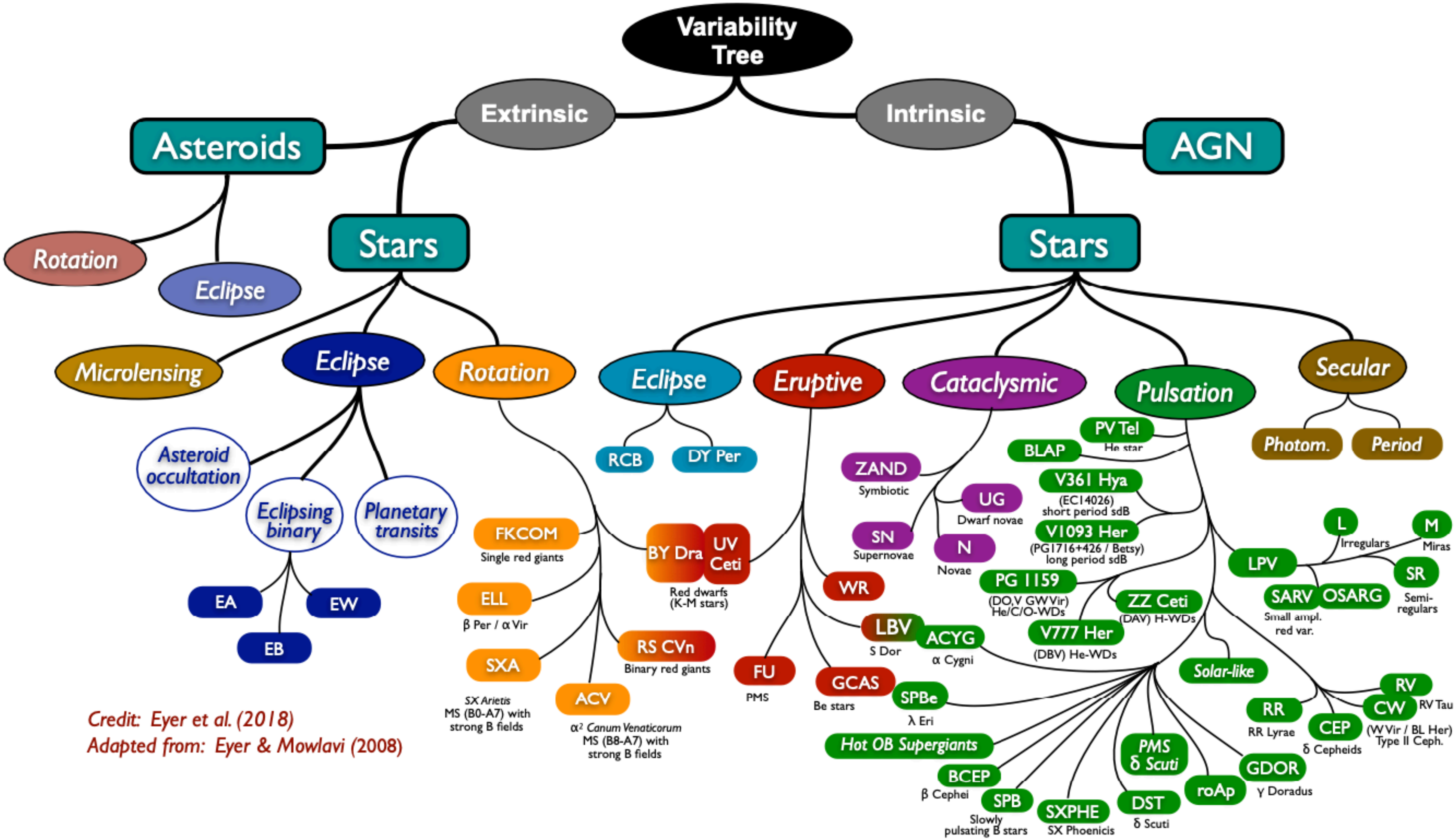
與天下瞻望之所謂賢人君子者陟之使居廟堂之上貢以三公四輔之事業委注而仰成之若然則陰陽以和災異以消朝廷清明矣狀畏服太平之風可翹足引領而待之也臣朝夕思慮載惟擇賢命相繫國家休戚治亂之本伏願陛下慎重之然後發聖斷力行而不疑則宗廟社稷之福天下生靈之幸

起居舍人知諫院范鎮上奏曰臣伏見去冬多南風今春多西北風乍寒乍暑欲雨不雨又有黑氣蔽日此皆人事之所感動也黑氣陰也小人也日陽也君象也黑氣蔽日者陰侵陽小人惑君也欲雨不雨者政事不決也陳執中為相不病而家居者百日矣陛下以御史之言決一婢死而欲退宰相為是邪乞速退執中以解天意以御史之言為非亦乞勅執中起視事無使天意久不決也寒暑者賞罰也乍寒乍暑者不當賞而賞當罰而不罰也鄧保吉有過於法不當為

"guest star"
SN 1054

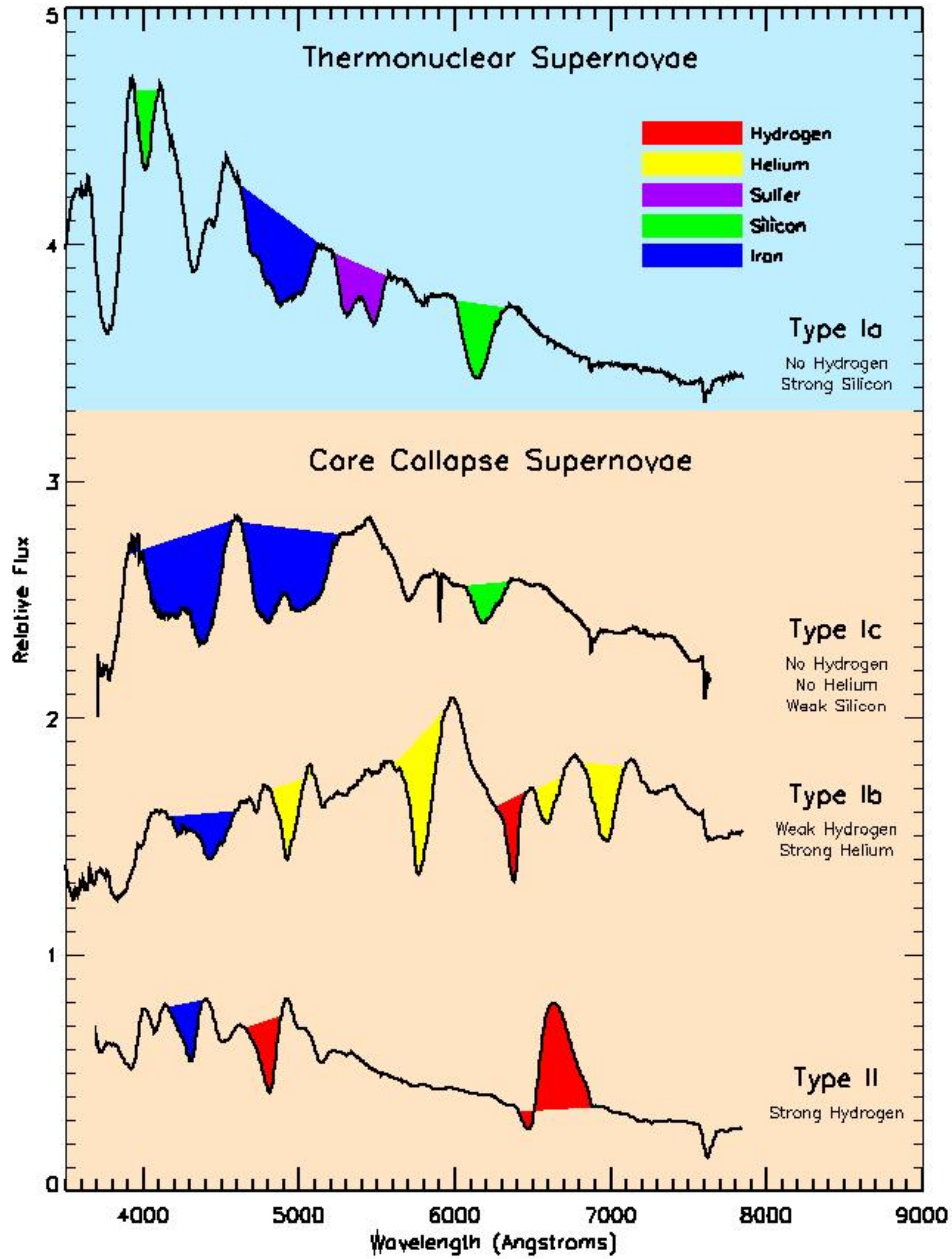


How far down the classification tree you descend depends on your scientific interest.



Credit: Eyer et al. (2018)
Adapted from: Eyer & Mowlavi (2008)

Photometric variability alone does not distinguish all astrophysical classes.



Astronomers use a range of classification methods.

Simple cuts on event properties

Spectroscopy

Template fitting

Host/environment

Parametric fitting

Featurized Machine Learning

Deep Learning & friends

"Physics-aware ML"

Astronomers use a range of classification methods.

Simple cuts on event properties

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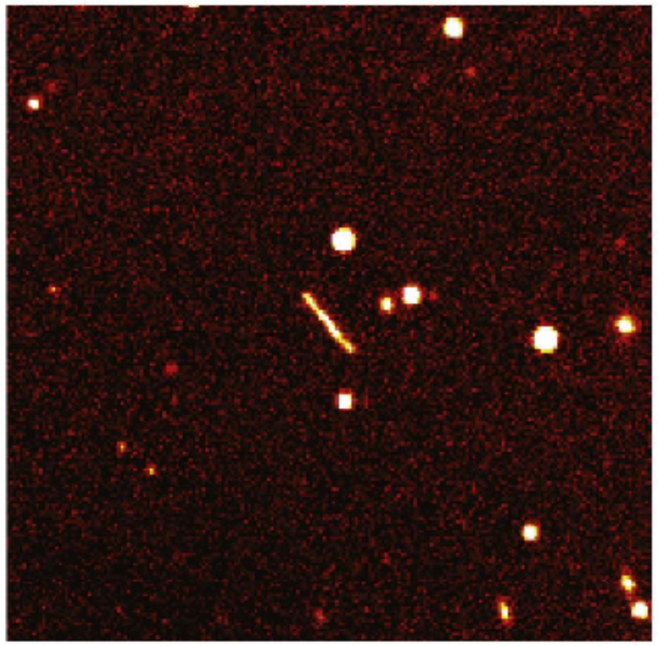
Featurized Machine Learning

Deep Learning & friends

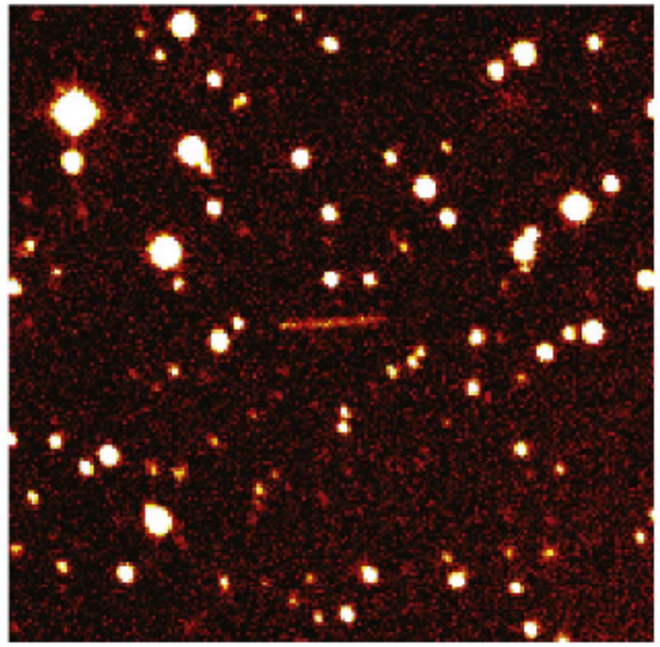
"Physics-aware ML"

BIASED & INCOMPLETE

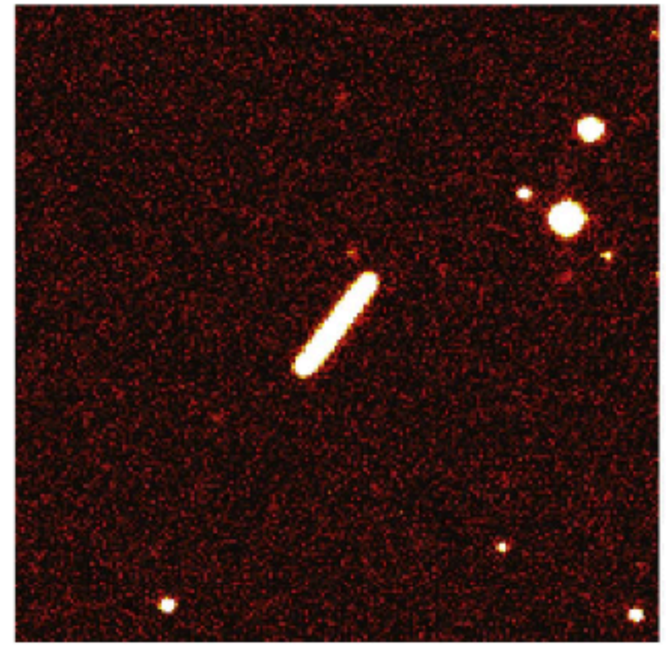
Simple cuts can be surprisingly effective.



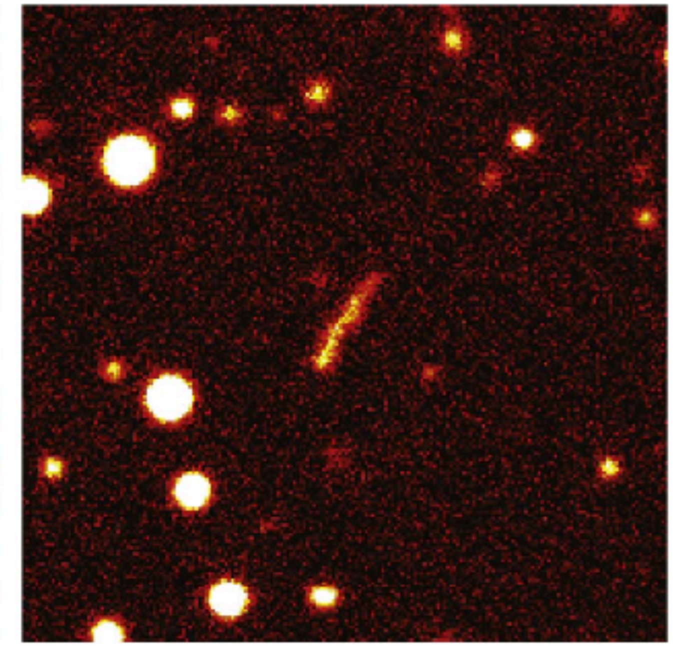
2009 HK73
V~17.5 length=24″ FWHM=2.1″



2010 UC7
V~18.5 length=32″ FWHM=2.6″

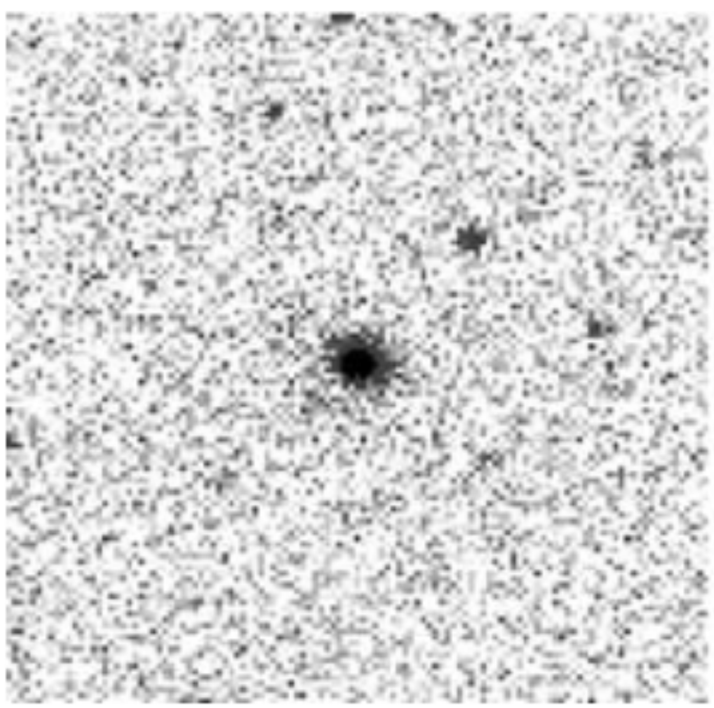


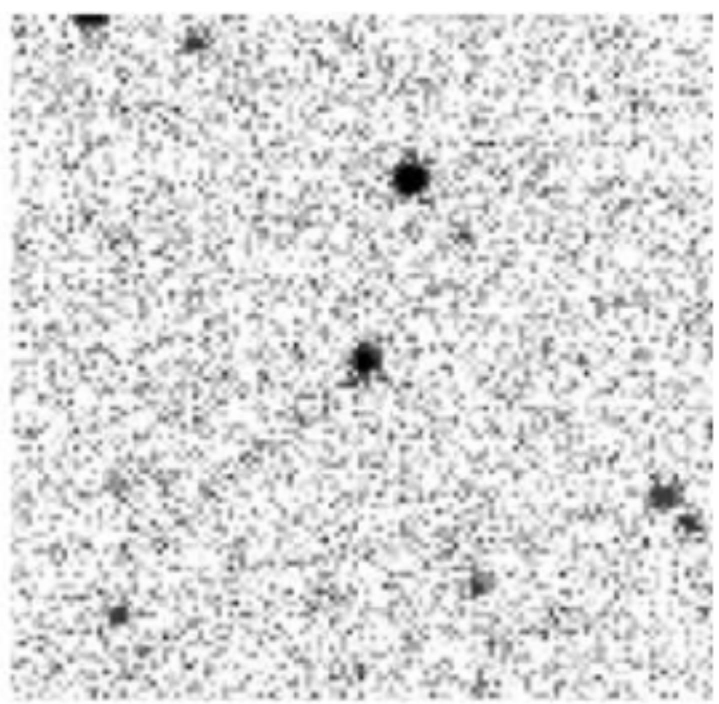
(277475) 2005 WK4
V~14.3 length=34″ FWHM=2.4″



2013 SU24
V~16.6 length=36″ FWHM=5.0″

Waszczak+17





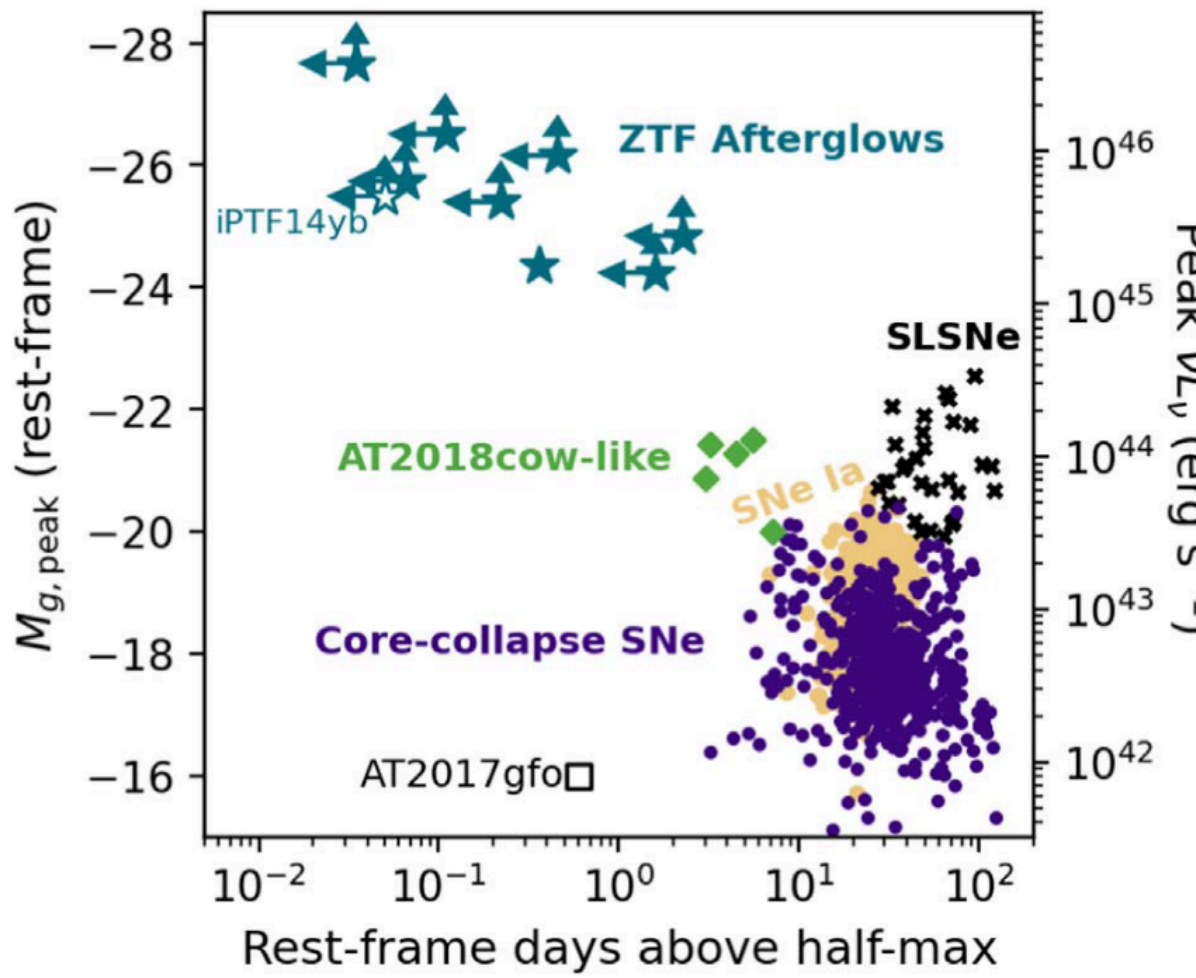
Waszczak+13

Simple cuts can be surprisingly effective.

2.2. Search Procedure

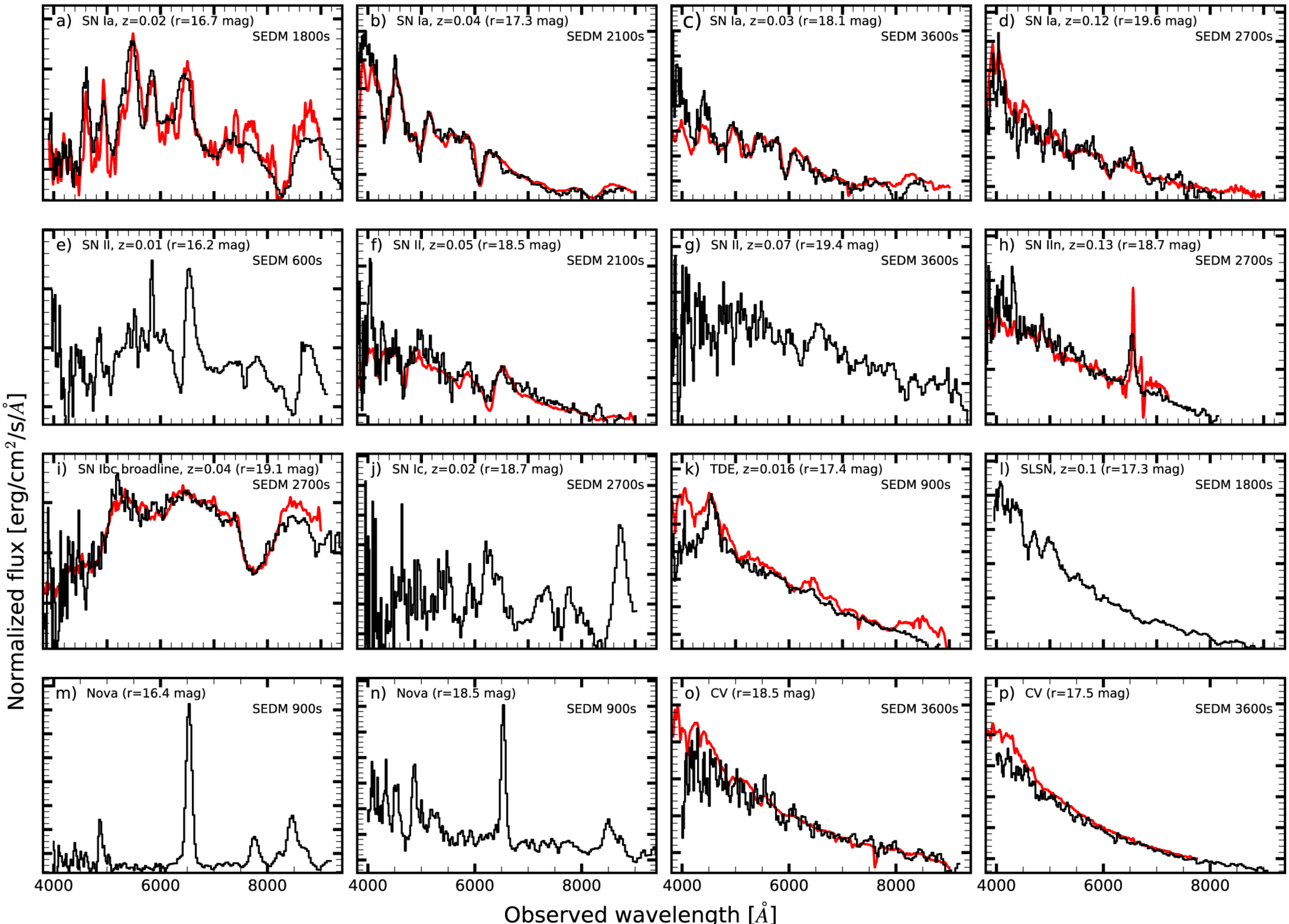
Every night, the ZTF alert stream is filtered by several independent pipelines to identify young or fast-evolving transients. In this paper we focus on events discovered via the approach described by Ho et al. (2020a) and Perley et al. (2021b). In short, basic cuts are applied to remove artifacts, asteroids, and stellar flares. Remaining transients are divided into several groups, including new transients (those with no detections prior to the current night). One of us (A.Y.Q.H., D.A.P., or Y.Y.) visually inspects the new transients and determines whether any meet the following criteria for afterglows.

1. A fast rise from the previous nondetection ($\gtrsim 0.5$ mag day^{-1}).
2. Red colors ($g - r > 0$ mag) expected from optically thin synchrotron radiation (see Ho et al. 2020a) *or* rapid intranight fading in a single band.
3. Either no, or a very faint, associated host in deep archival imaging from the Legacy Survey (Dey et al. 2019) or Pan-STARRS1 (Chambers et al. 2016).

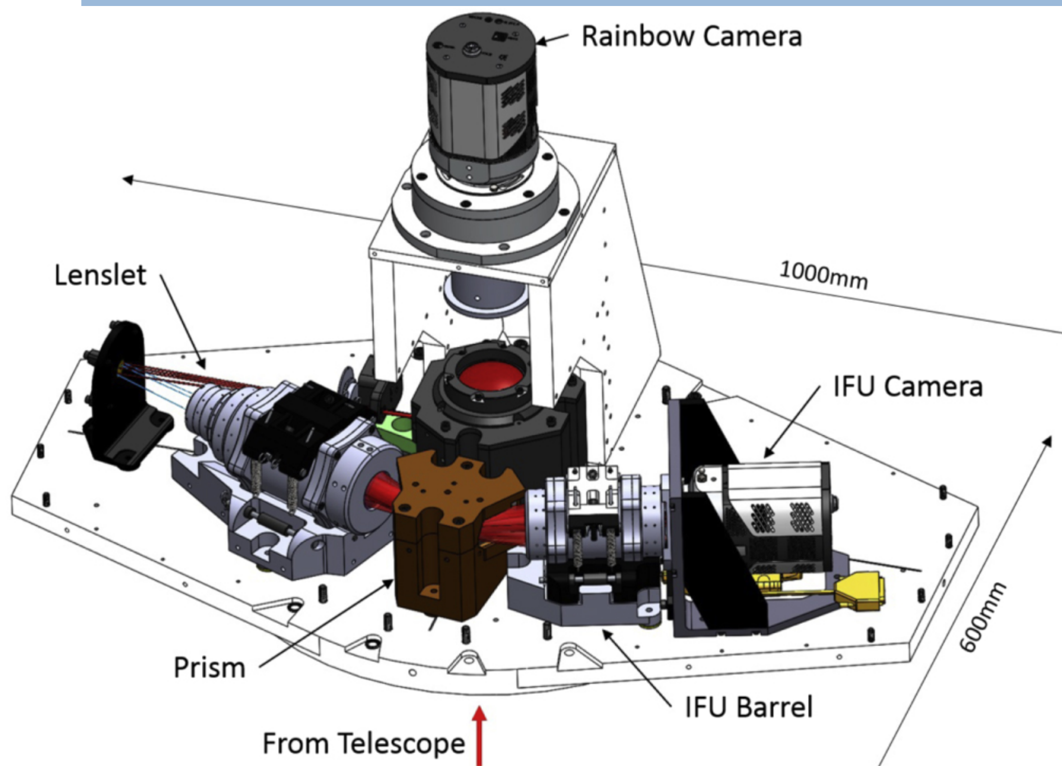


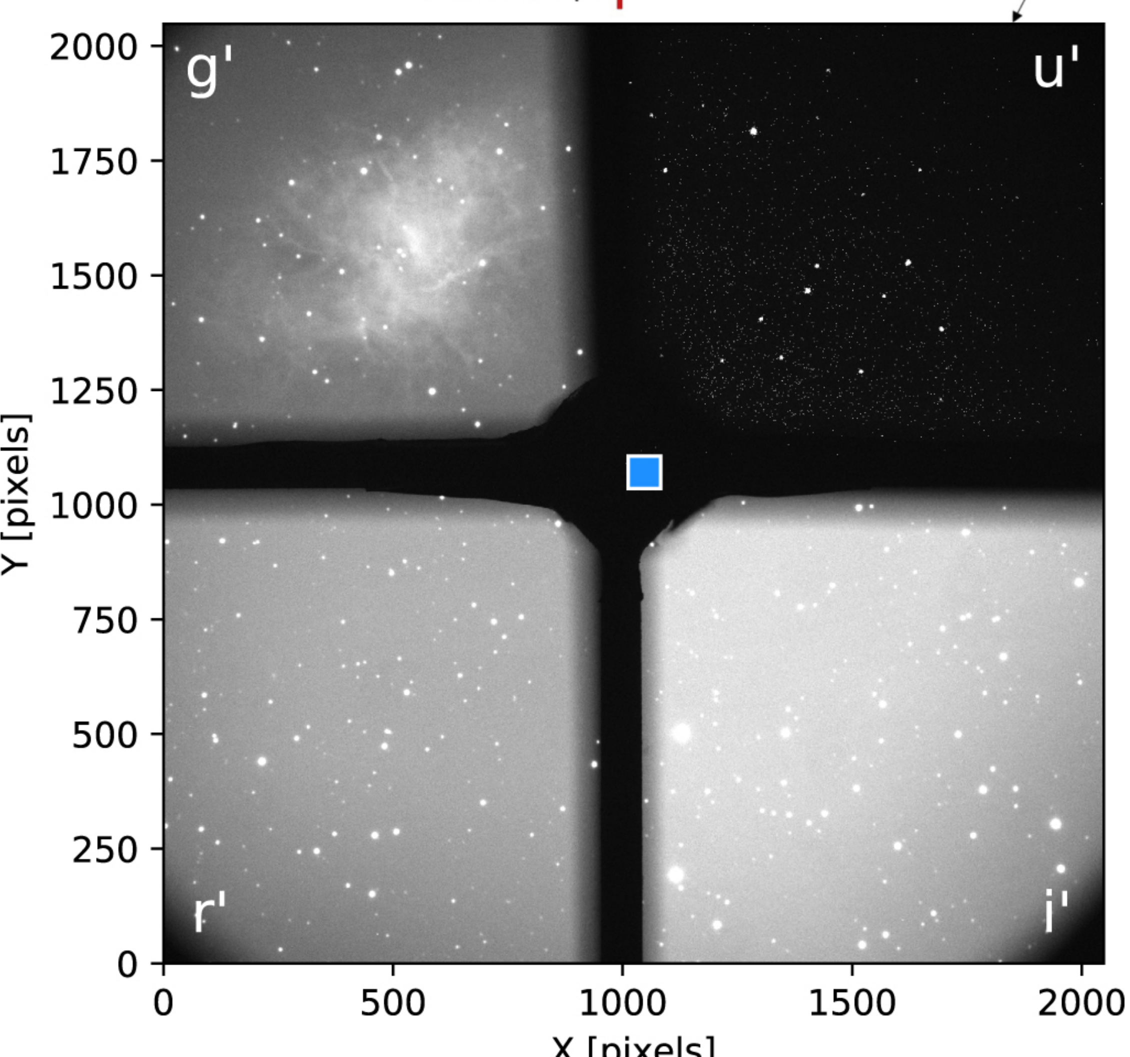
Ho+22

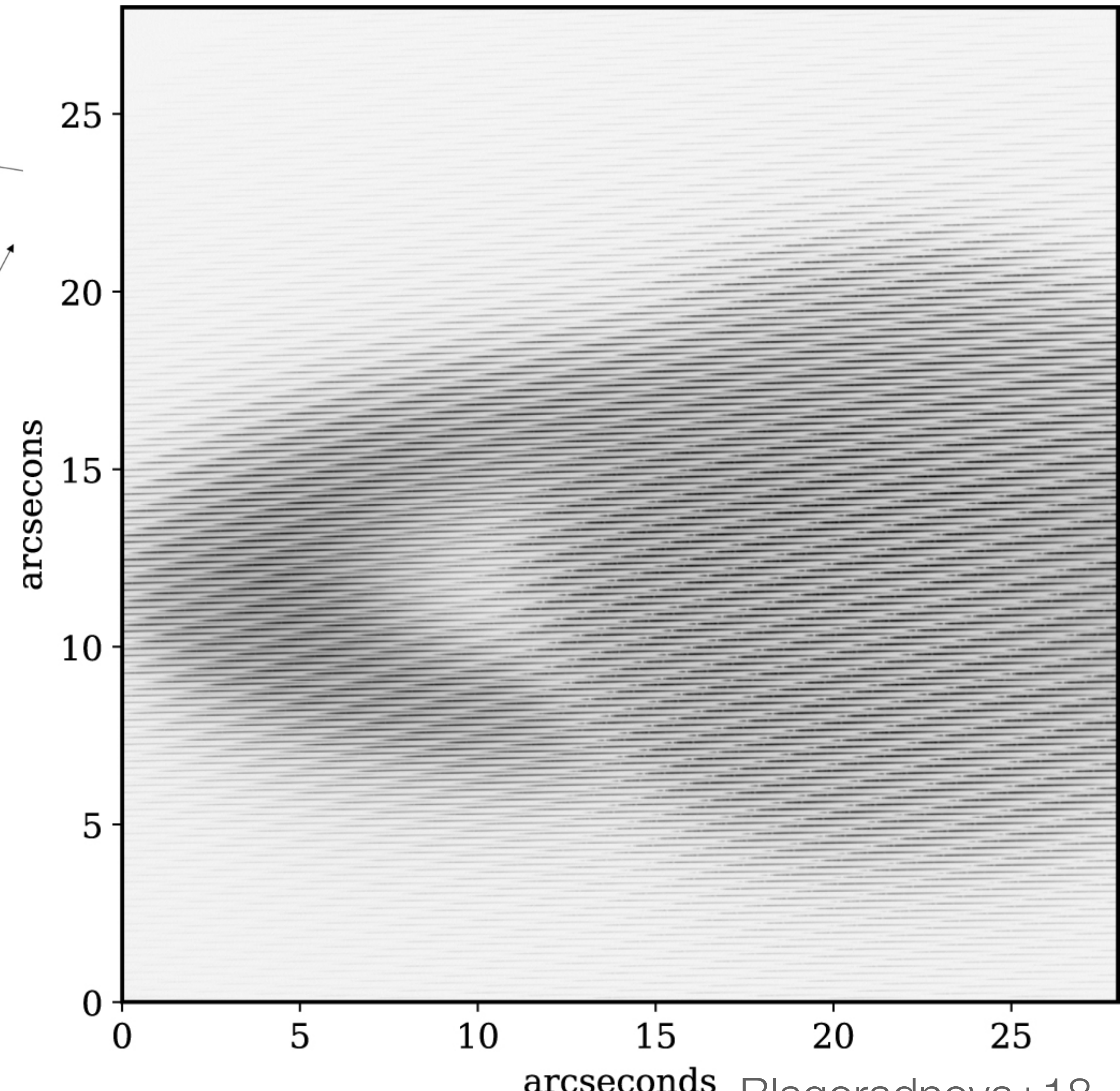
For supernovae spectroscopy provides the best classification.



Robotic followup with the SEDM on P60 provides world-leading transient classification throughput.



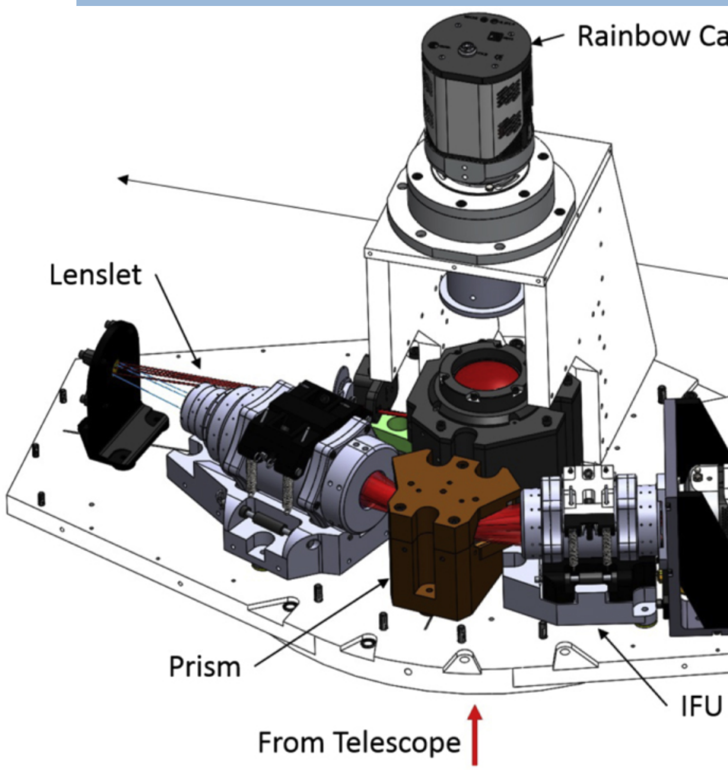




Blagoradnova+18

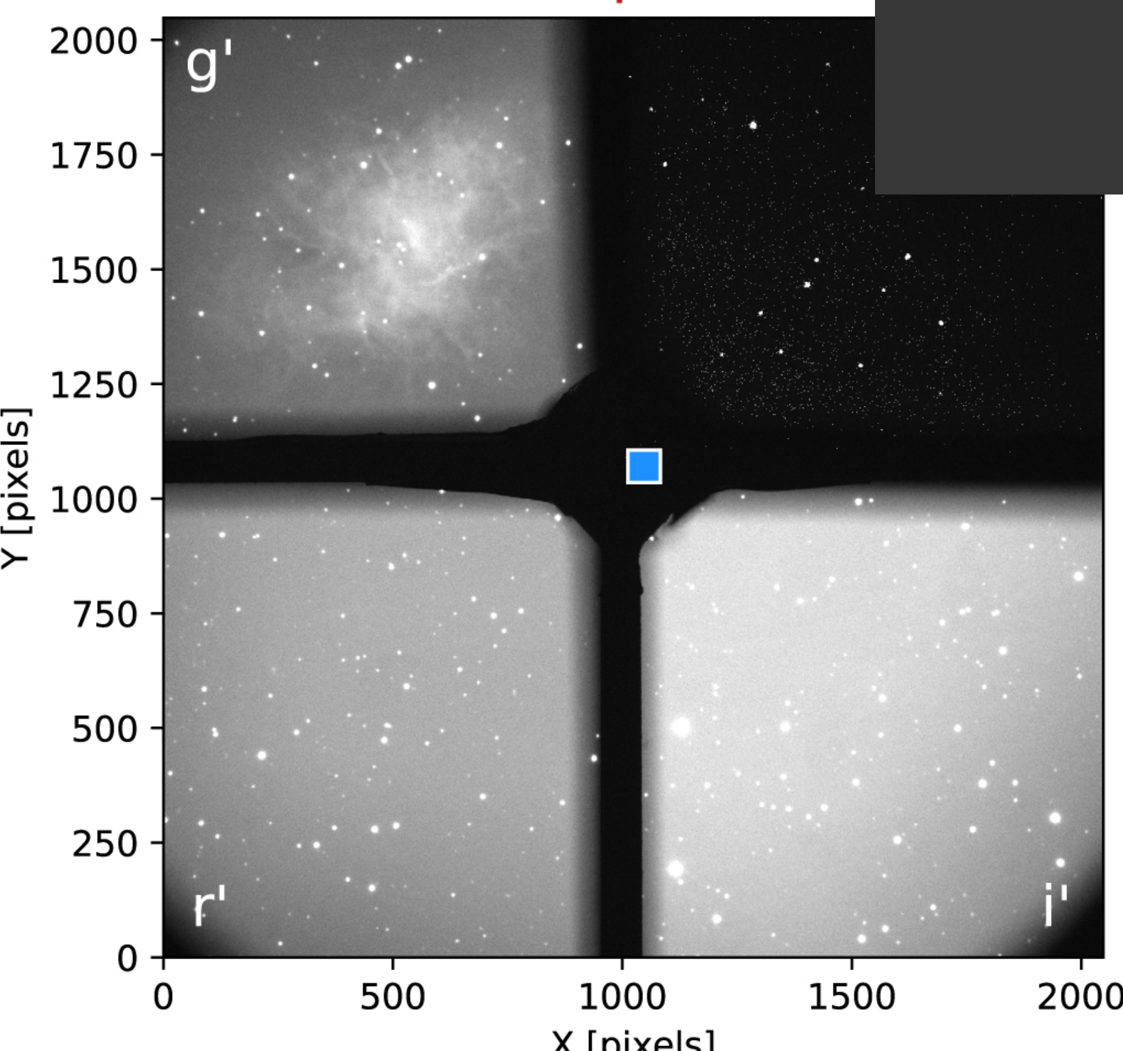
SEDM v2 on KP88 soon!

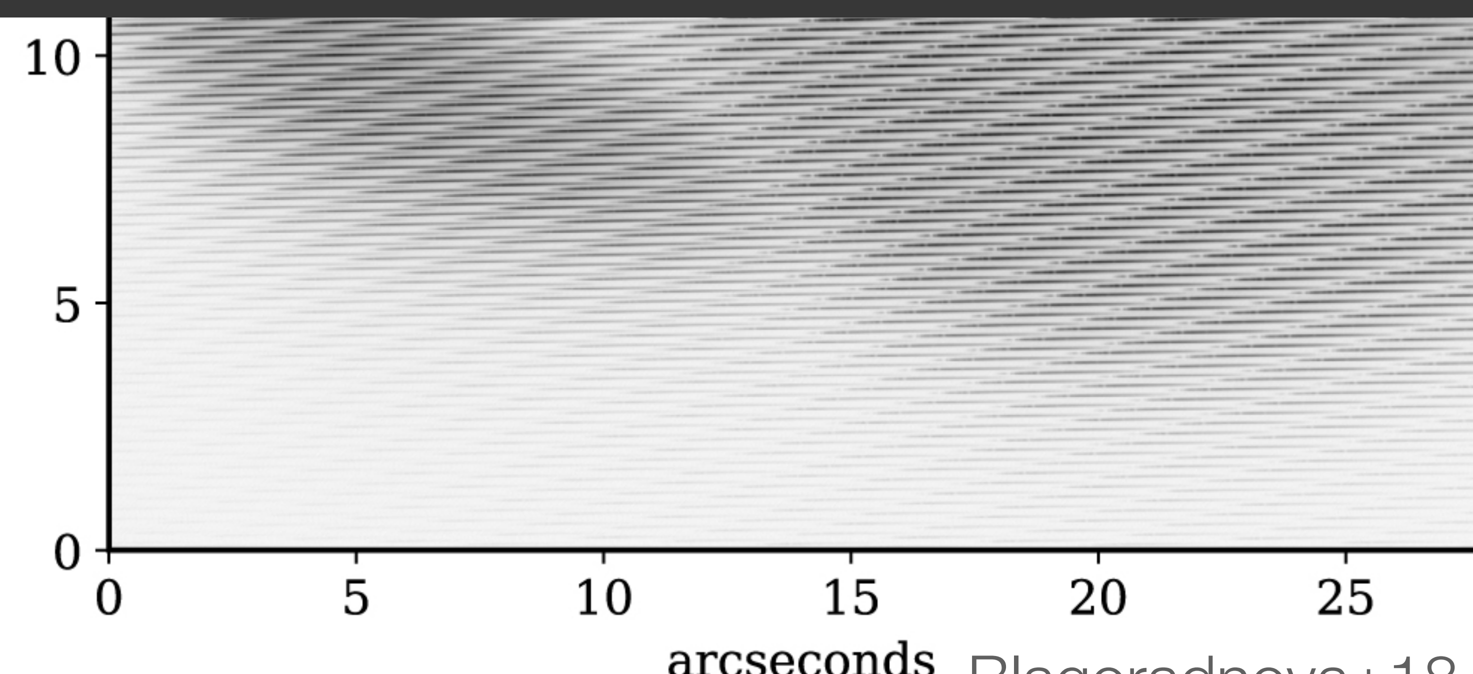
Robotic followup with the SEDM on P60 provides world-leading transient classification throughput.



PUBLIC classified SNe for the top 5 data source groups	ZTF	4416
	ATLAS	2166
	ASAS-SN	734
	Pan-STARRS1	571
	GaiaAlerts	506

ALL spectra reported to the TNS	11169	
PUBLIC spectra reported to the TNS	10849	
PUBLIC classifications for the top 5 contributing groups	ZTF	4312
	ePESSTO+	927
	ePESSTO	723
	SCAT	648
	PESSTO	277





Blagoradnova+18

SEDM v2 on KP88 soon!

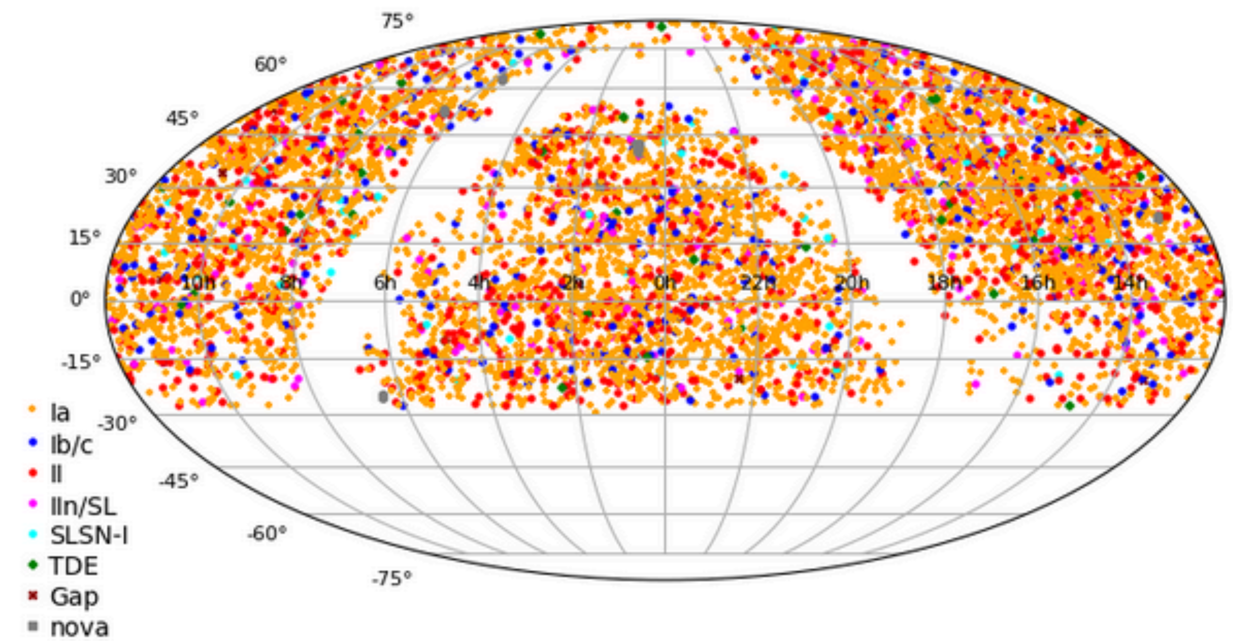
The ZTF Bright Transient Survey is the largest spectroscopic supernova survey ever.

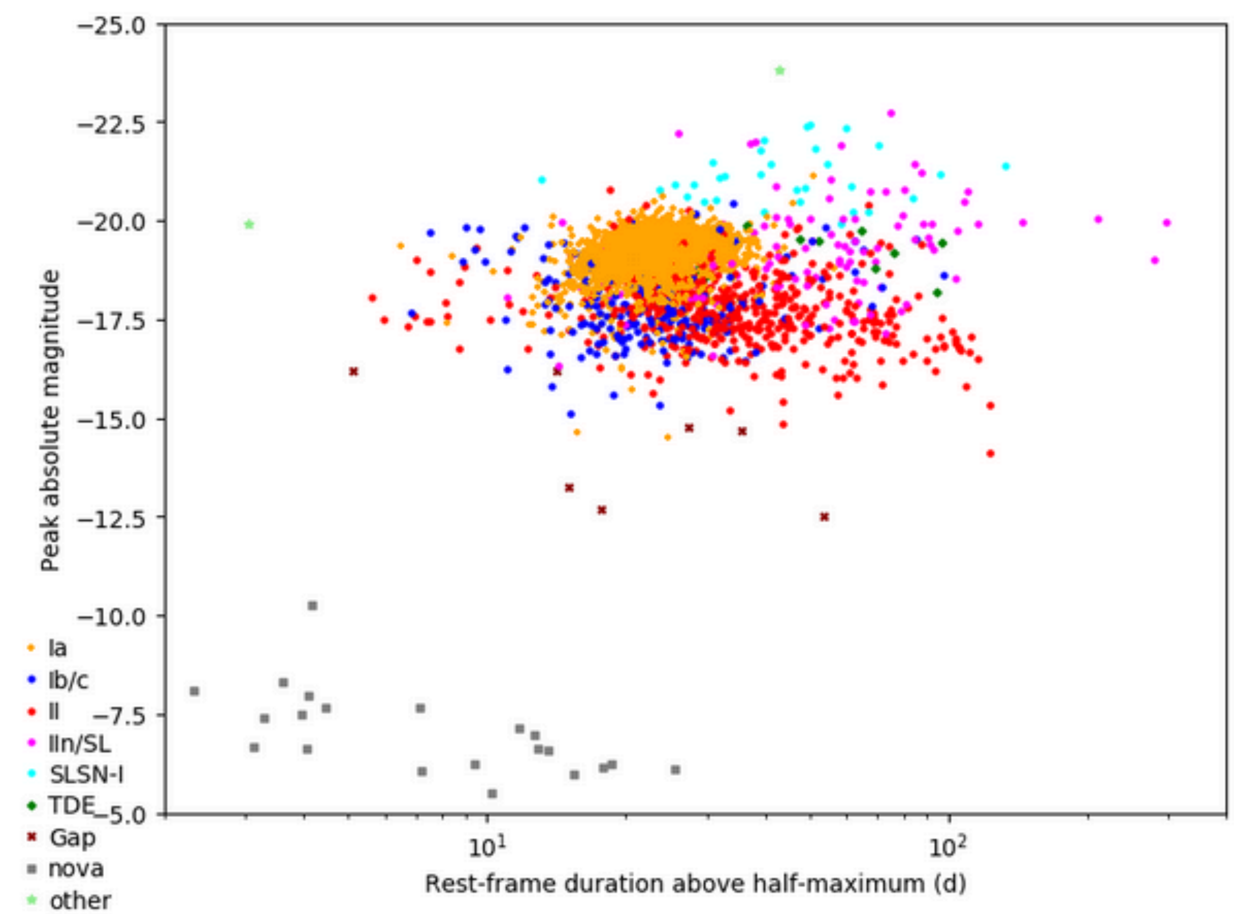
Spectroscopic followup of all ZTF transients brighter than 18.5 mag
Over 7000 classified objects to date

All events:

mag ≤	19.0	18.5	18.0	17.5	17.0
All typed	7368	4947	2614	1424	716
All SNe	7266	4867	2562	1394	698
Ia	5370	3606	1885	1035	529
Ia-CSM	12	10	5	4	4
Iax	14	11	7	5	4
Ib/c	371	256	142	70	32
Ibn	24	18	12	6	2
Ic-BL	57	44	23	11	7
SLSN-I	59	29	15	11	2
II	1466	976	520	278	135
IIb	100	63	39	21	11
IIn	198	139	75	38	17
SLSN-II	35	20	6	1	0
TDE	43	30	15	5	4
Gap	15	12	8	4	3

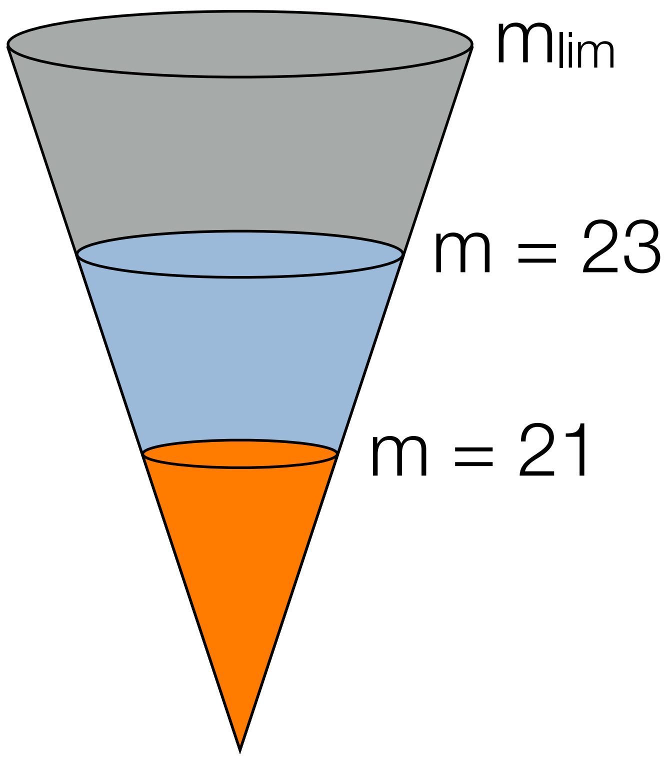
Fremling+20, Perley+20

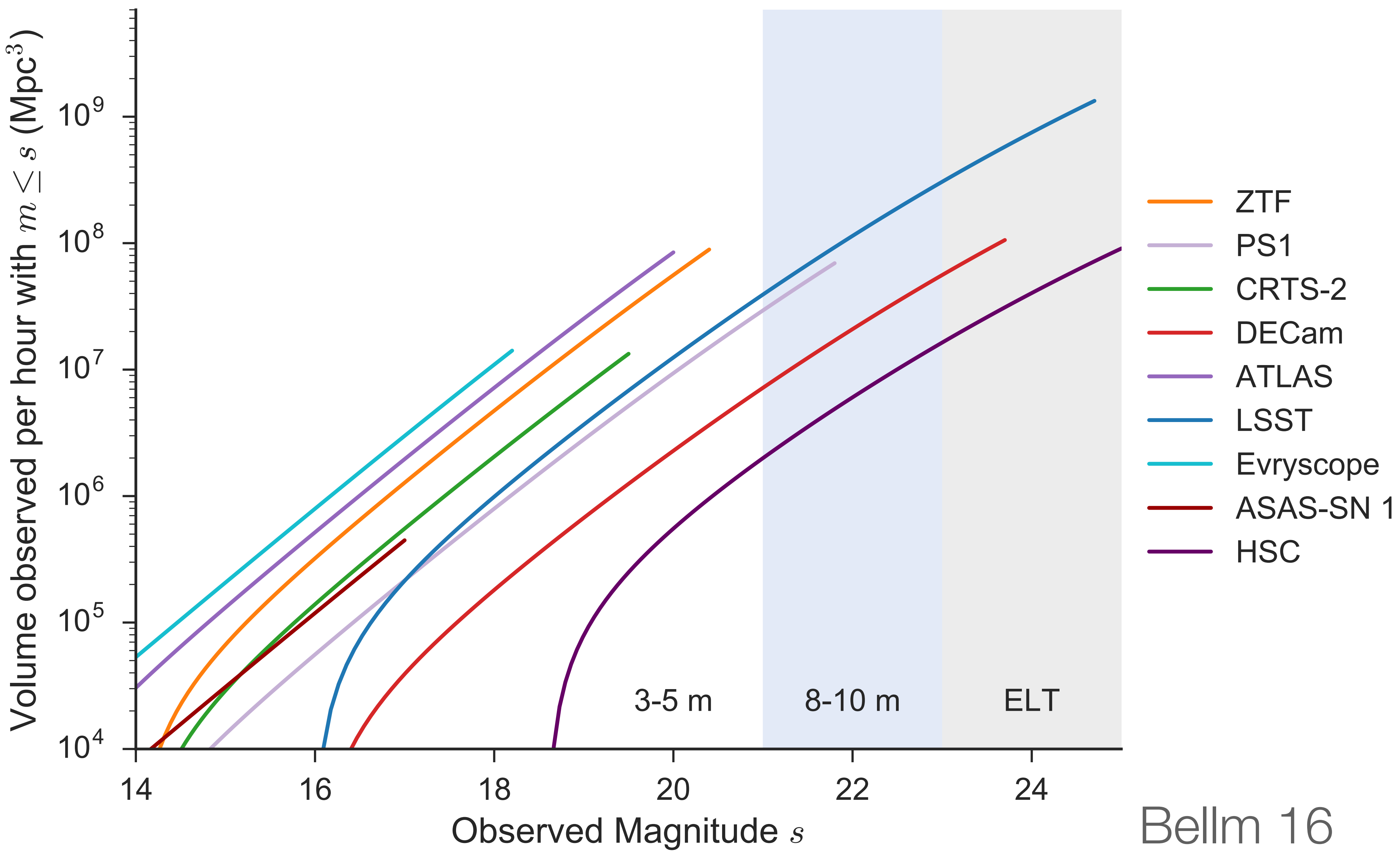




https://sites.astro.caltech.edu/ztf/bts/

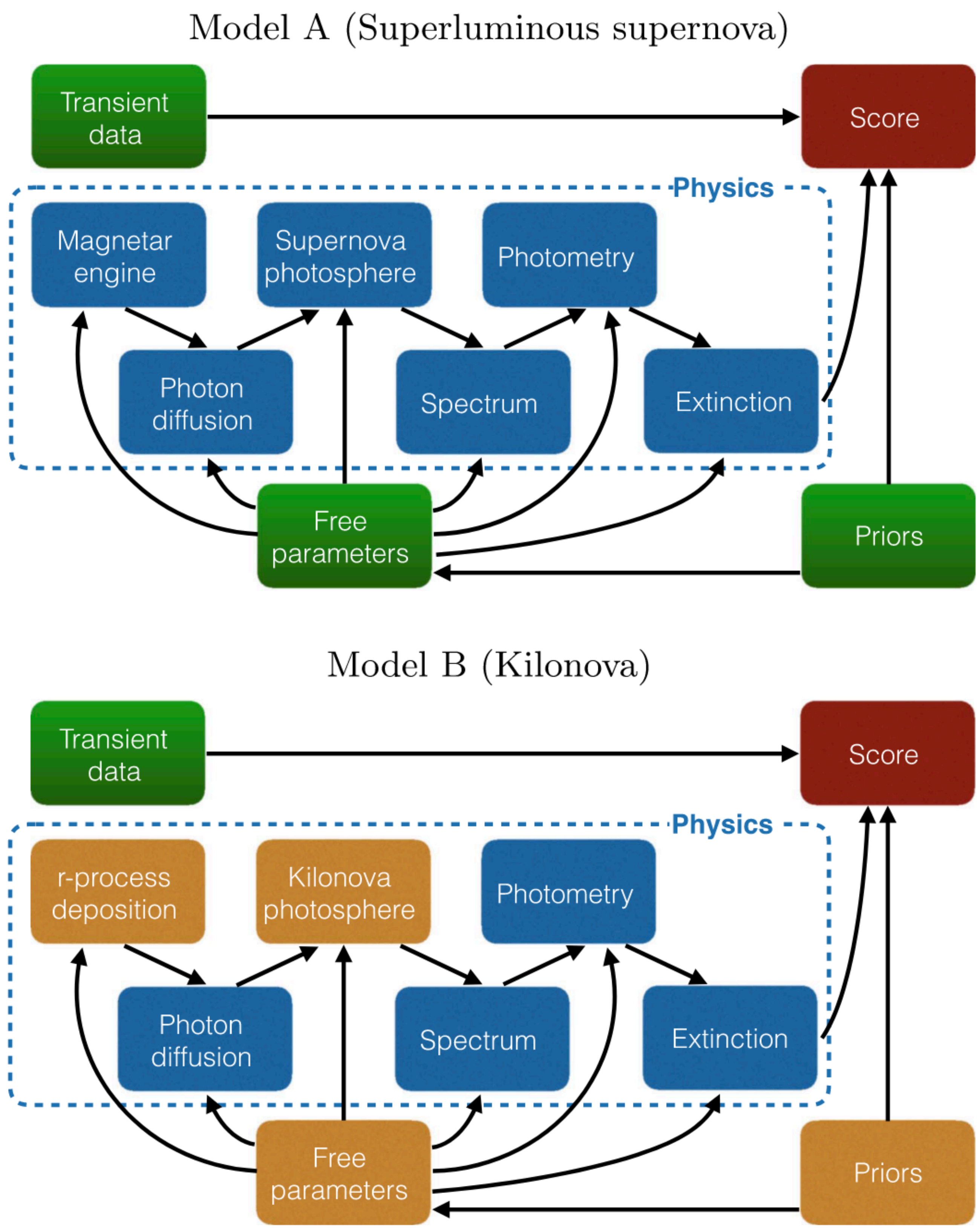
Most LSST transients will be too faint for routine spectroscopy!





Bellm 16

Template fitting compares lightcurves to models or examplars of known transients.



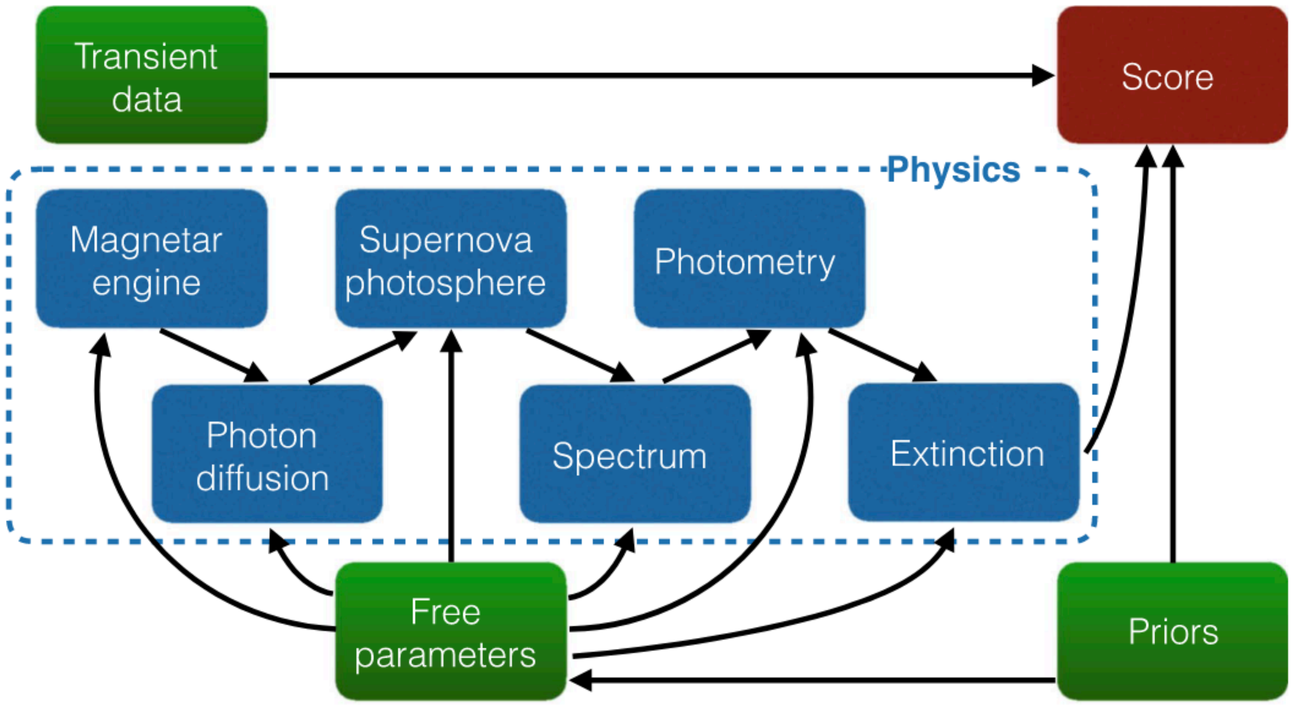
MOSFIT: Guillochon+18

List of built-in models

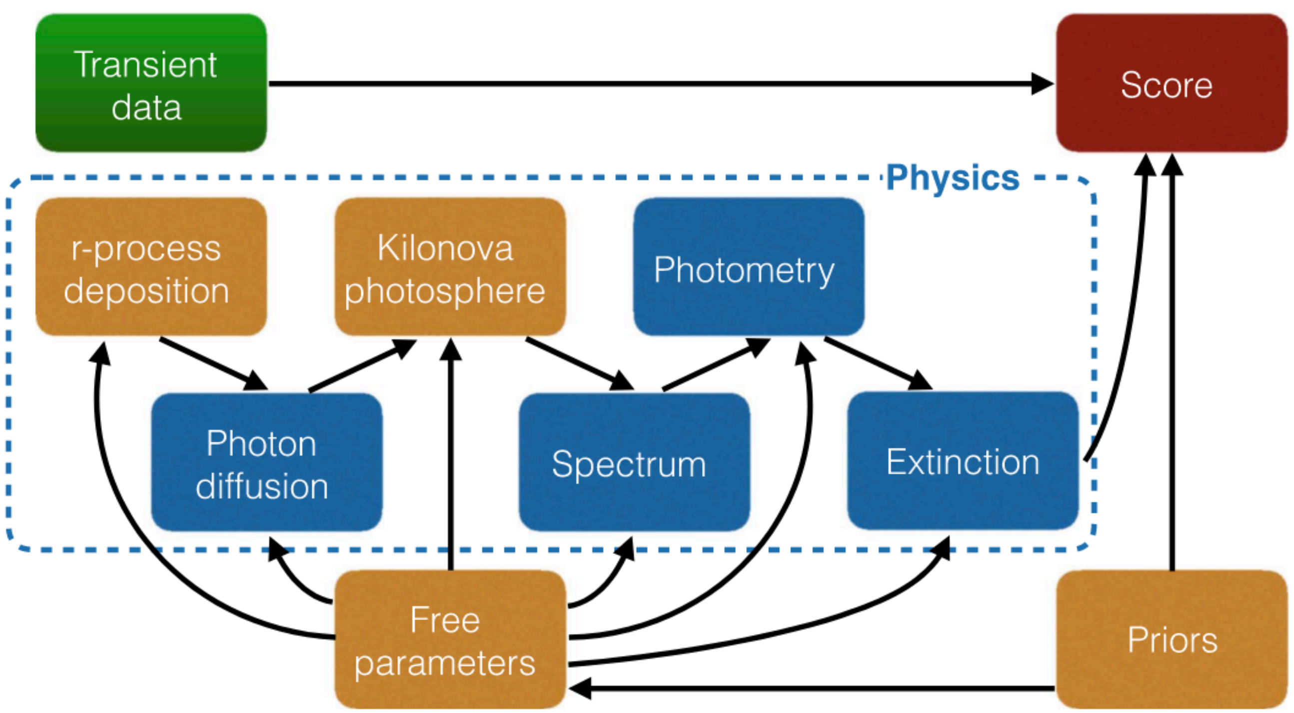
Model name	Description	Reference(s)
`default`	Nickel-cobalt decay	1994ApJS...92..527N
`csm`	Interacting CSM-SNe	2013ApJ...773...76C, 2020RNAAS...4...16J
`csmni`	CSM + NiCo decay	See `default` & `csm`
`exppow`	Analytical engine	
`ia`	NiCo decay + I-band	
`ic`	NiCo decay + radio	
`magnetar`	Magnetar engine w/ simple SED	2017ApJ...850...55N
`magni`	Above + NiCo decay	
`rprocess`	Kilonova	2017ApJ...851L..21V
`kilonova`	Kilonova	2017ApJ...851L..21V
`bns`	Kilonova + binary params + angle	2021arXiv21020222
`slsn`	Magnetar + modified SED + constraints	2017ApJ...850...55N
`tde`	Tidal disruption events	2018arXiv18010822

Template fitting compares lightcurves to models or examplars of known transients.

Model A (Superluminous supernova)



Model B (Kilonova)

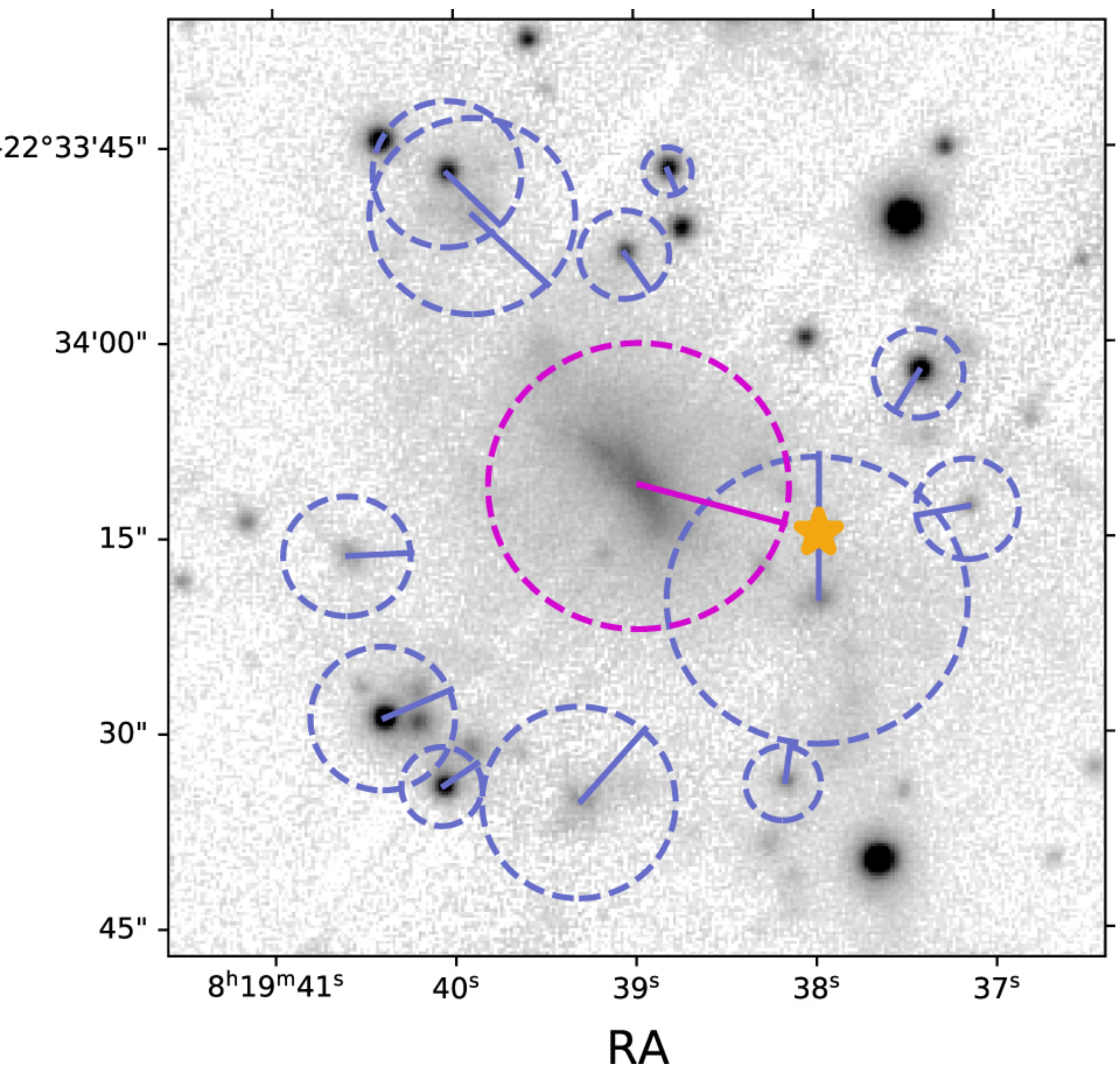


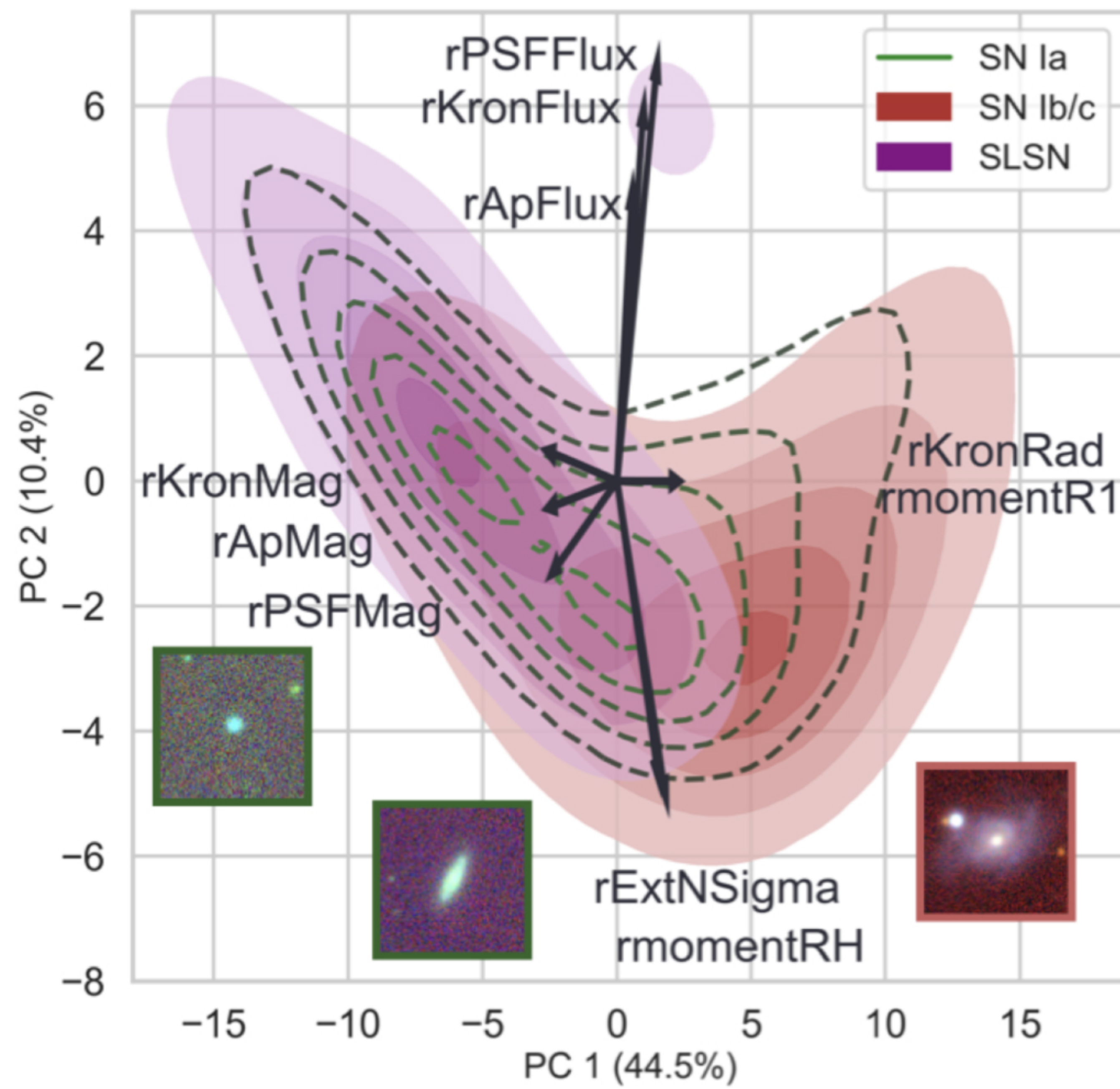
Pros:
- Conceptually straightforward
- Can sometimes constrain physical parameters

Cons:
- Can be slow to execute
- Need really good data/models
- "Searching under the lamppost"

MOSFIT: Guillochon+18

Contextual/host galaxy information can aid classification.



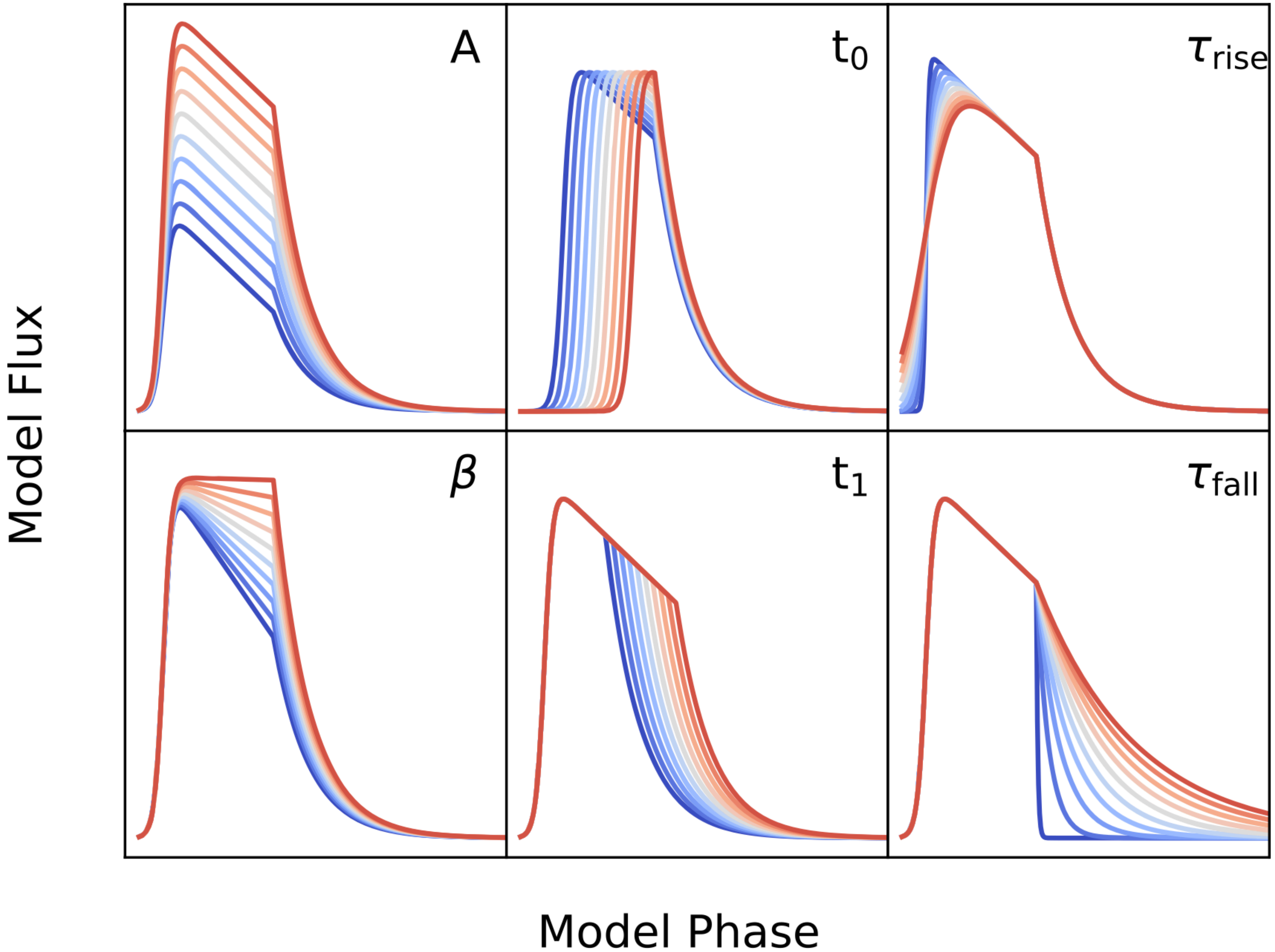


GHOST: Gagliano+21

Parametric models can fit a variety of object types.

$$F = \begin{cases} \dfrac{A + \beta(t - t_0)}{1 + e^{-(t-t_0)/\tau_{\rm rise}}} & t < t_1 \\[2ex] \dfrac{(A + \beta(t_1 - t_0))e^{-(t-t_1)/\tau_{\rm fall}}}{1 + e^{-(t-t_0)/\tau_{\rm rise}}} & t \geqslant t_1. \end{cases}$$

Villar+19



Fit parameters and other lightcurve statistics can be used as features for machine learning models.

Sanchez-Saiz+21

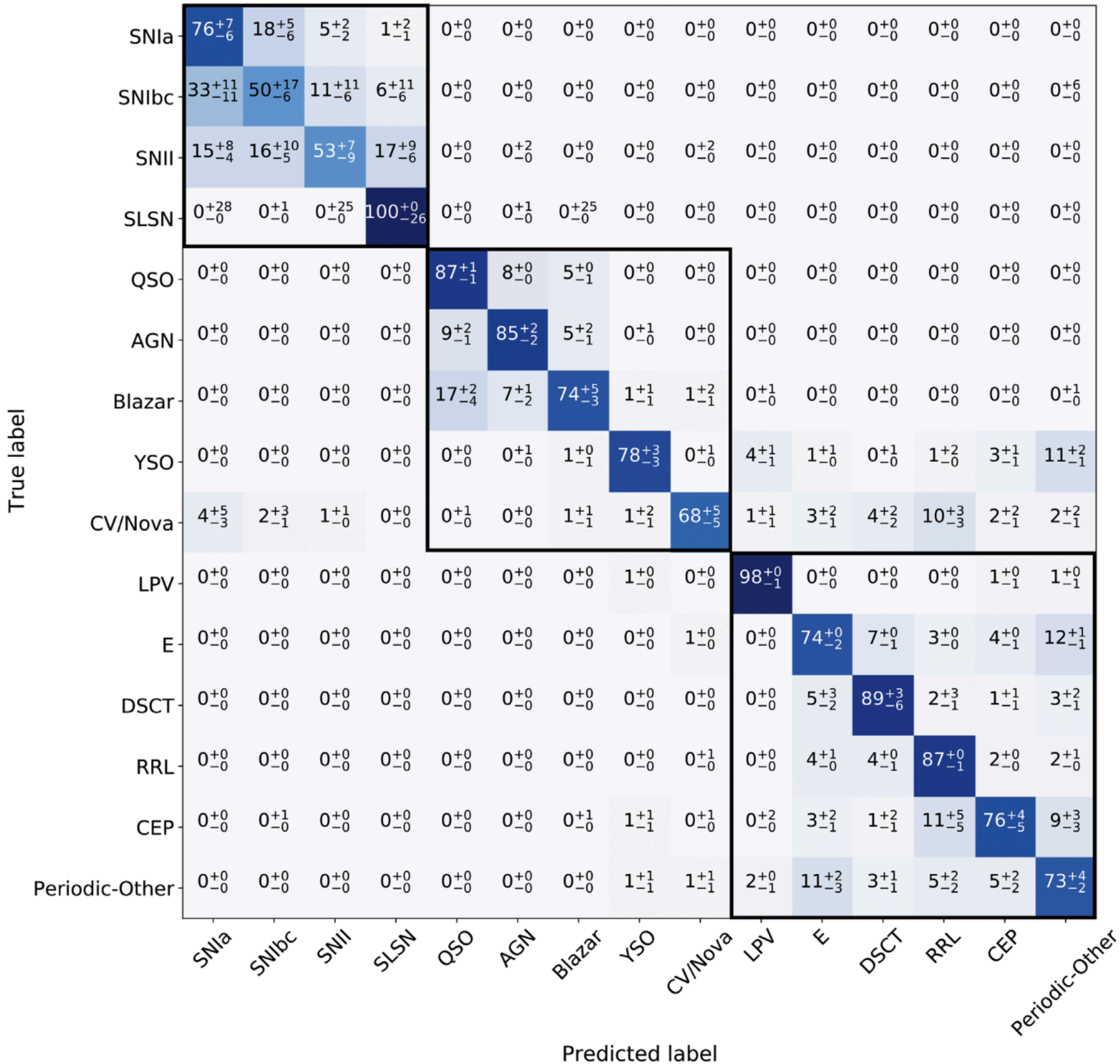
Table 2
List of Detection Features Used by the Light Curve Classifier

Feature	Description	References
`delta_period`	Absolute value of the difference between the `Multiband_period` and the MHAOV period obtained using a single band	This work
`IAR_phi`*	Level of autocorrelation using a discrete-time representation of a DRW model	Eyheramendy et al. (2018)
MHPS parameters*	Obtained from an MHPS analysis (three in total)	Arévalo et al. (2012)
`positive_fraction`	Fraction of detections in the difference images of a given band which are brighter than the template image	This work
`Power_rate`* ♦	Ratio between the power of the multiband periodogram obtained for the best period candidate (P) and $2 \times P$, $3 \times P$, $4 \times P$, $P/2$, $P/3$, or $P/4$	This work
`PPE`* ♦	Multiband Periodogram Pseudo Entropy	This work
$(g-r)$`_max` ♦	$g-r$ color obtained using the brightest `lc_diff` magnitude in each band	This work
$(g-r)$`_max_corr` ♦	$g-r$ color obtained using the brightest `lc_corr` magnitude in each band	This work
$(g-r)$`_mean` ♦	$g-r$ color obtained using the mean `lc_diff` magnitude of each band	This work
$(g-r)$`_mean_corr` ♦	$g-r$ color obtained using the mean `lc_corr` magnitude of each band	This work
`delta_mag_fid`	Difference between maximum and minimum observed magnitude in a given band	This work
`ExcessVar`**	Measure of the intrinsic variability amplitude	Allevato et al. (2013)
`GP_DRW_tau`**	Relaxation time τ from DRW modeling	Graham et al. (2017)
`GP_DRW_sigma`**	Amplitude of the variability at short timescales ($t \ll \tau$), from DRW modeling	Graham et al. (2017)
Harmonics parameters**	Obtained by fitting a harmonic series up to the seventh harmonic (14 in total)	(Stellingwerf & Donohoe 1986)
`Multiband_period`** ♦	Period obtained using the multiband MHAOV periodogram	Mondrik et al. (2015)
`Pvar`**	Probability that the source is intrinsically variable	McLaughlin et al. (1996)
`SF_ML_amplitude`**	rms magnitude difference of the SF, computed over a 1 yr timescale	Schmidt et al. (2010)
`SF_ML_gamma`**	Logarithmic gradient of the mean change in magnitude	Schmidt et al. (2010)
SPM features**	Supernova parametric model features (seven in total)	Villar et al. (2019)
`Amplitude`	Half of the difference between the median of the maximum 5% and of the minimum 5% magnitudes	Richards et al. (2011)
`AndersonDarling`	Test of whether a sample of data comes from a population with a specific distribution	Nun et al. (2015)
`Autocor_length`	Lag value where the autocorrelation function becomes smaller than `Eta_e`	Kim et al. (2011)
`Beyond1Std`	Percentage of points with photometric mag that lie beyond 1σ from the mean	Richards et al. (2011)
`Con`	Number of three consecutive data points brighter/fainter than 2σ of the light curve	Kim et al. (2011)
`Eta_e`	Ratio of the mean of the squares of successive mag differences to the variance of the light curve	Kim et al. (2014)
`Gskew`	Median-based measure of the skew	
`LinearTrend`	Slope of a linear fit to the light curve	
`MaxSlope`	Maximum absolute magnitude slope between two consecutive observations	
`Meanvariance`	Ratio of the standard deviation to the mean magnitude	
`MedianAbsDev`	Median discrepancy of the data from the median data	
`MedianBRP`	Fraction of photometric points within amplitude/10 of the median mag	

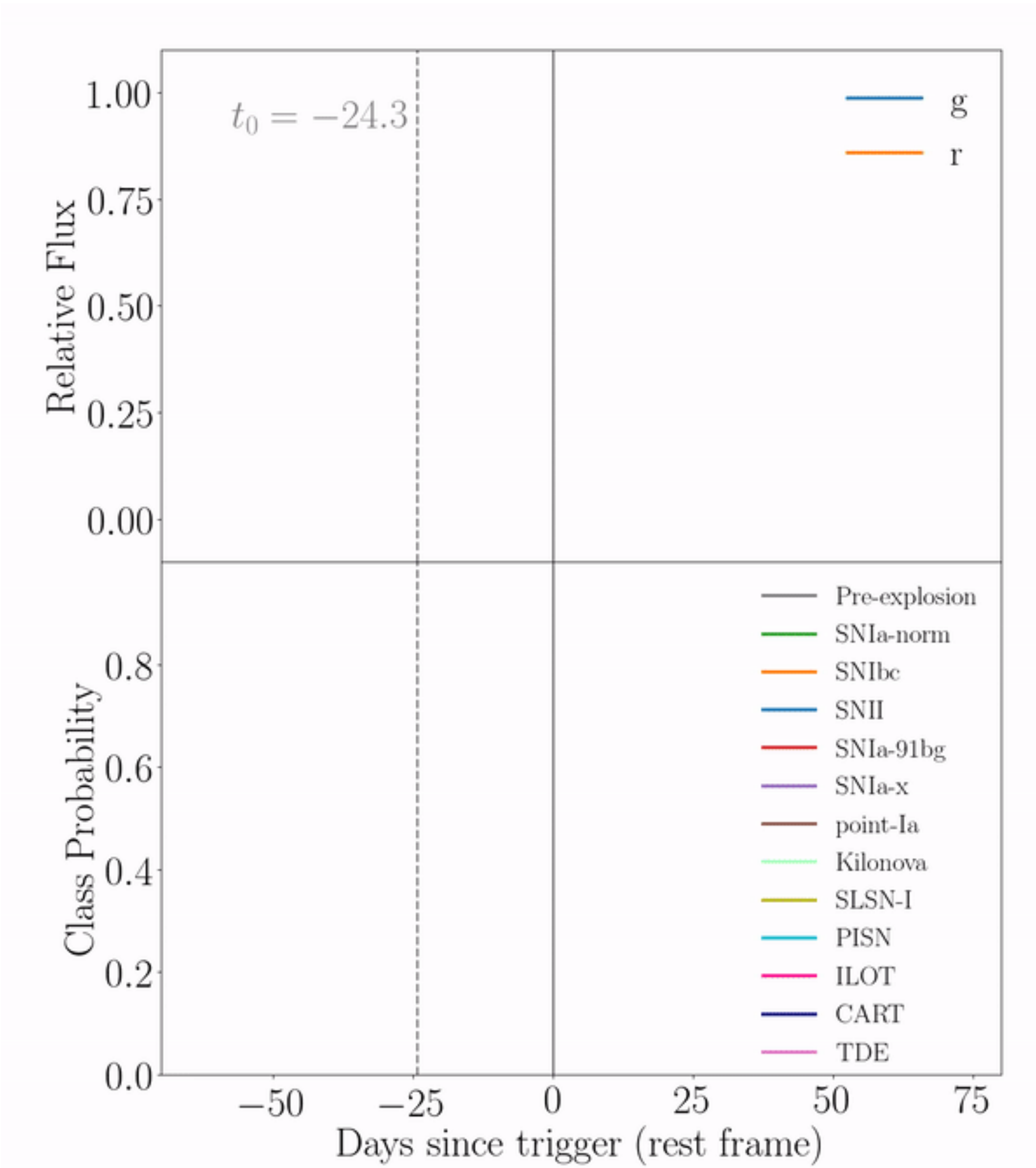
See dmtn-118.lsst.io for a review of timeseries features

Fit parameters and other lightcurve statistics can be used as features for machine learning models.

Sanchez-Saiz+21



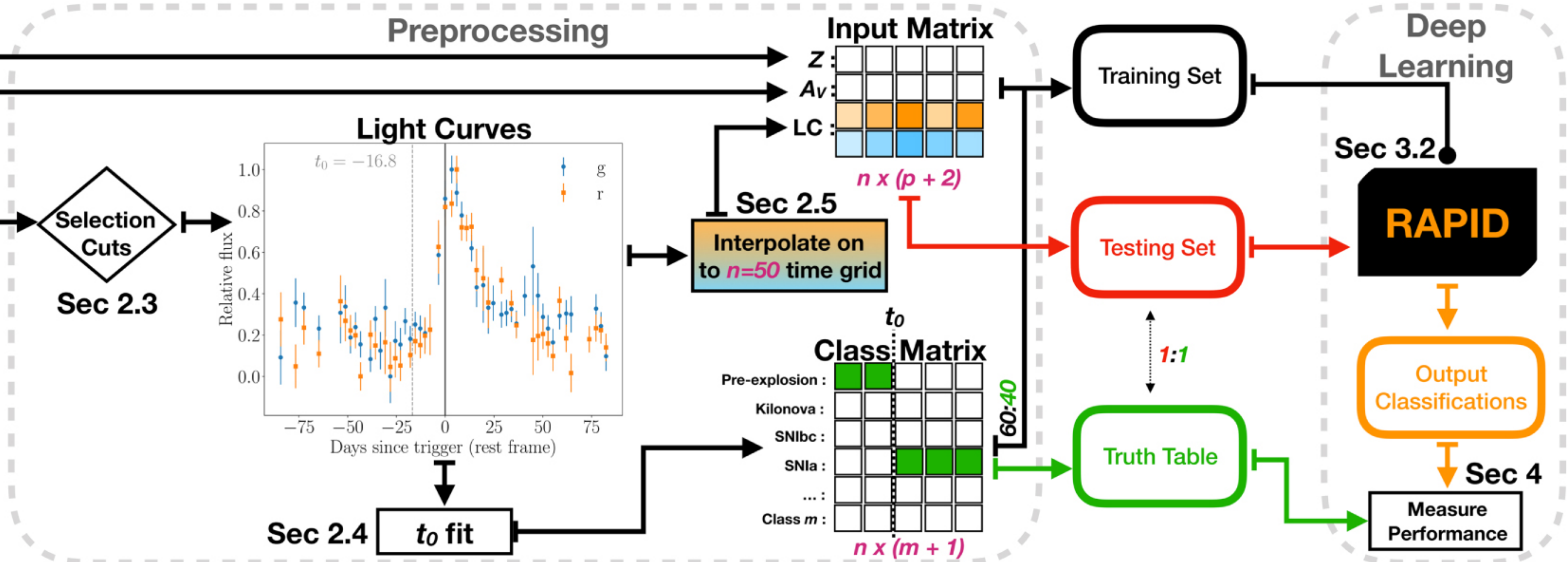
Deep learning approaches avoid the need for feature engineering.



RAPID
Muthukrishna+19

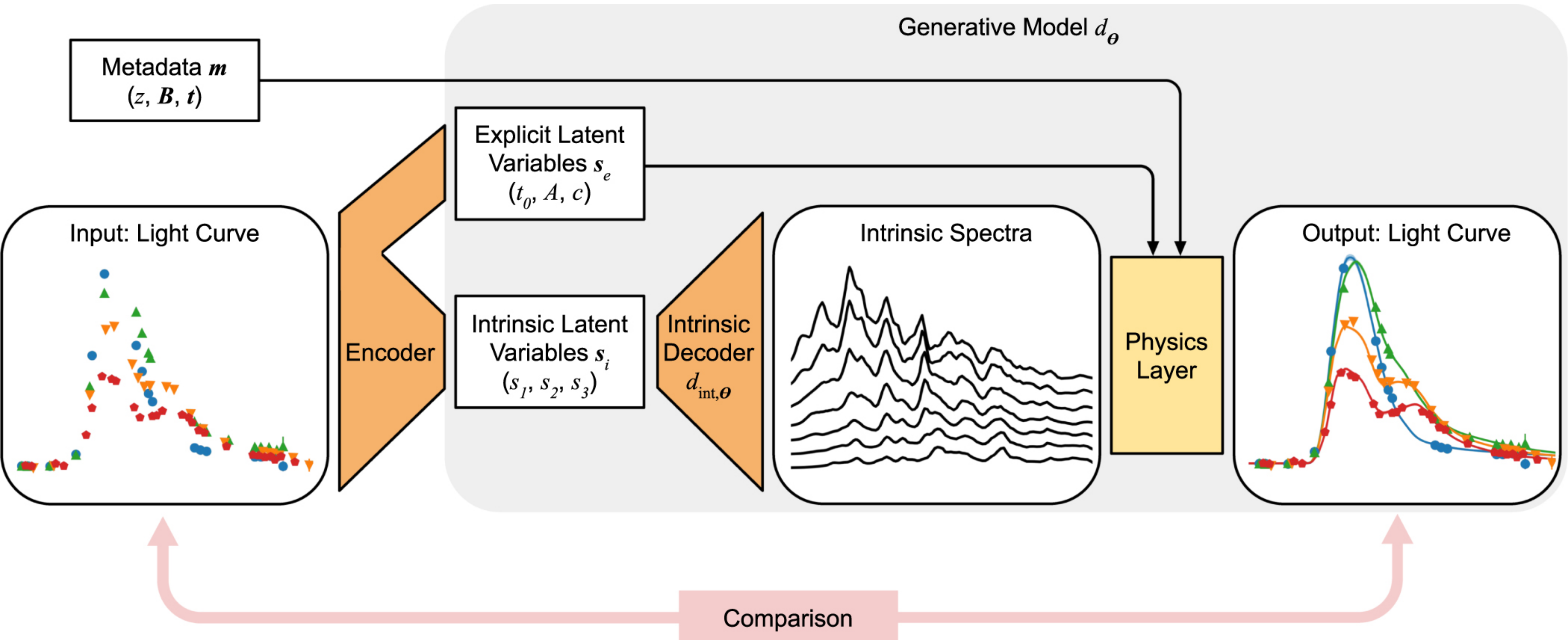
Deep learning approaches avoid the need for feature engineering.

RAPID
Muthukrishna+19



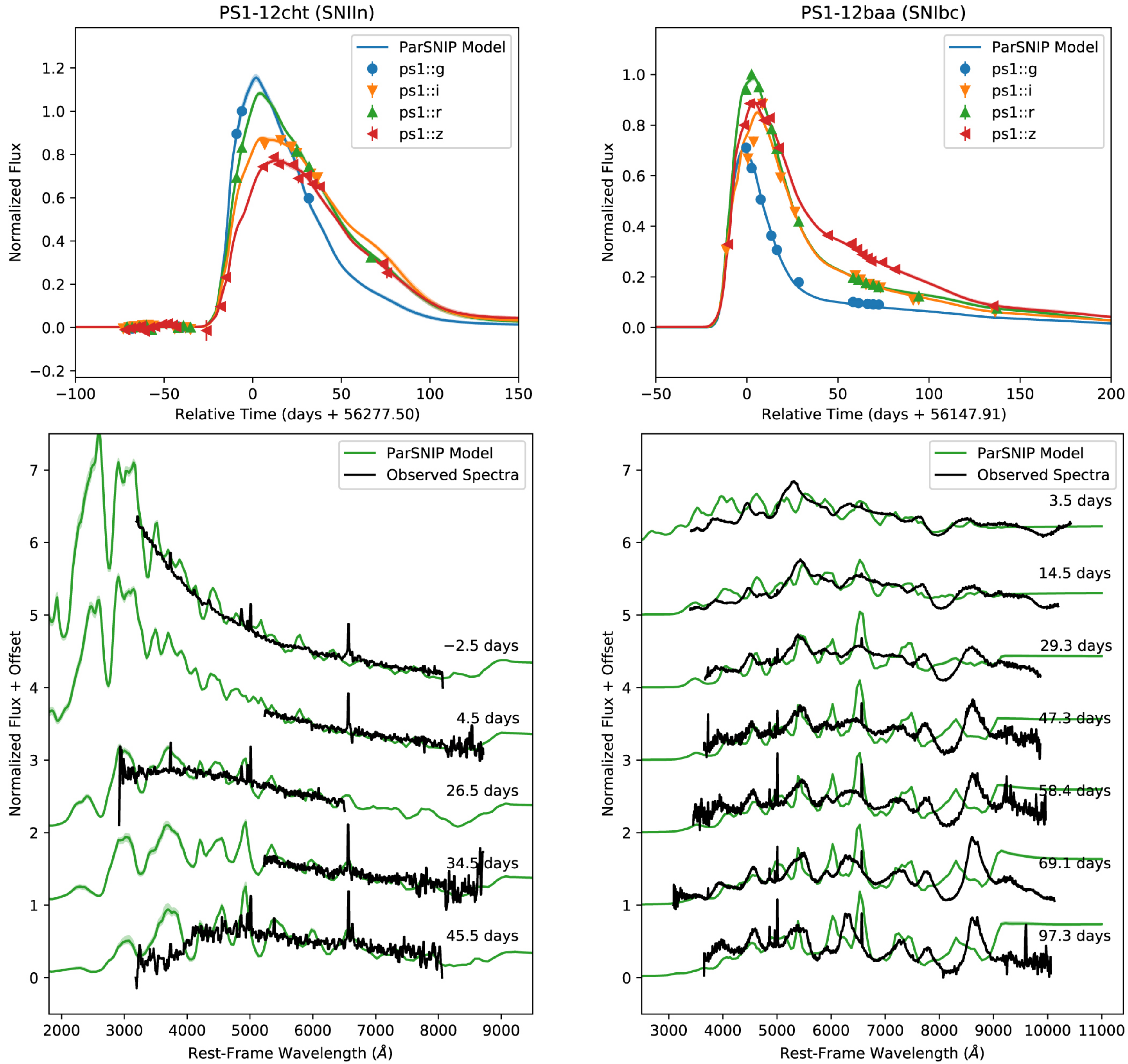
See Jamal & Bloom 2020 for a review of network architectures.

Separating known physics from unknown or nuisance parameters appears powerful.



ParSNIP
Boone 2021

Separating known physics from unknown or nuisance parameters appears powerful.



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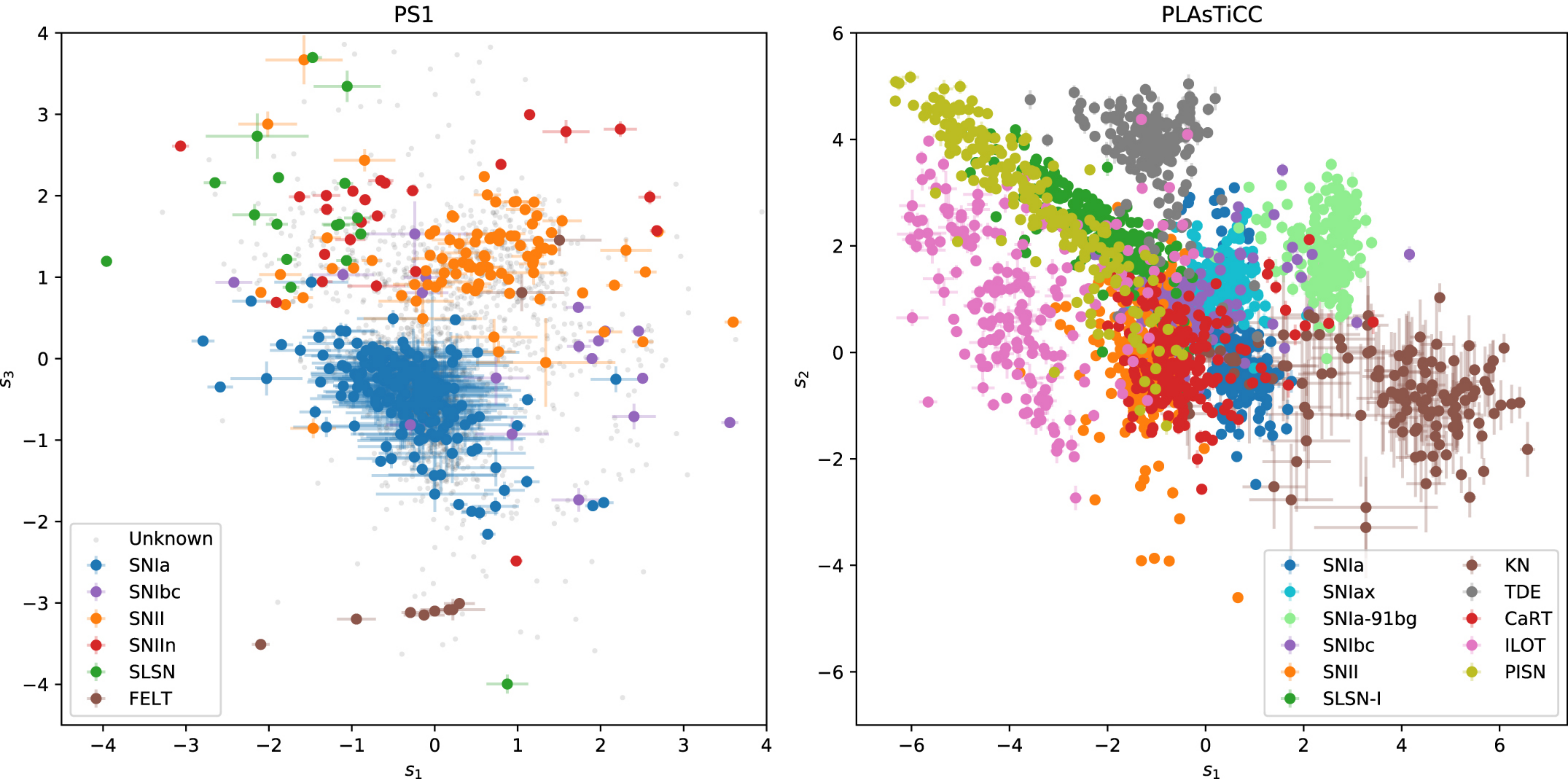
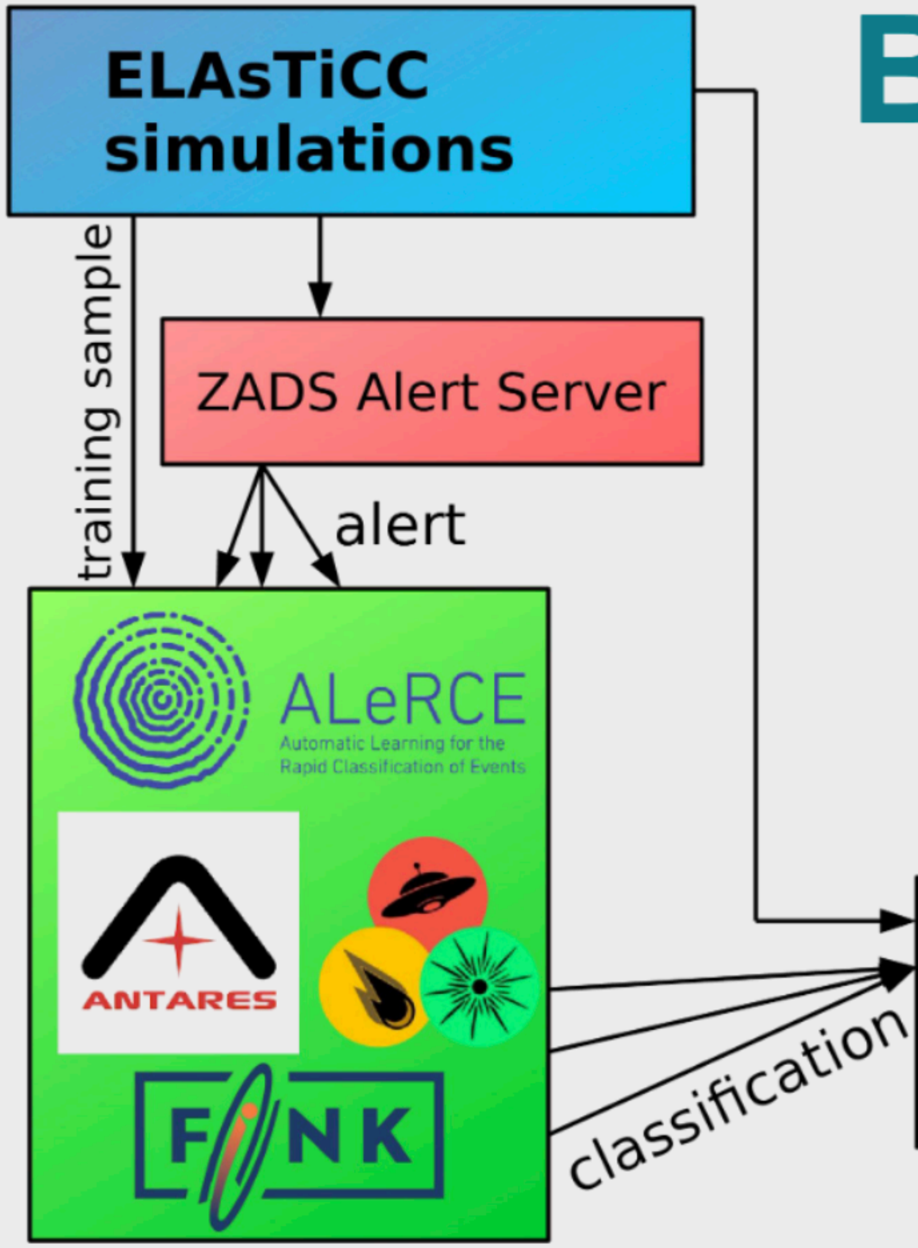


ParSNIP
Boone 2021

& can aid Ia cosmology by marginalizing over classification

The ELAsTiCC classification challenge is currently preparing community alert brokers for LSST.



Brokers & Alerts

Alerts generated from simulations are streamed to the **ZTF alert distribution server**, and from there to brokers. DESC ingests classifications into a database which also holds truth tables from the original simulation.

https://portal.nersc.gov/cfs/lsst/DESC_TD_PUBLIC/ELASTICC/

The ELAsTiCC classification challenge is currently preparing community alert brokers for LSST.

AMPEL v0.4

Show ElasticcLiveSNGuess (XGBUnified+Parsnip05)

Show ElasticcLiveSNGuessParsnip (XGBUnified+Parsnip05)

Show ElasticcLiveSNGuessParsnipPrior (XGBUnified+Parsnip05)

ANTARES 2.0.0

Show Astrorapid_filter (known_redshift=True)

Show LiCuParsnip_filter (v2)

Show LightGBM_filter (v3)

Show REFLECT_subclass_v1 (v1)

Show REFLECT_v1 (v1)

Fink 2.4

Show AGN classifier version 1.0 (Probability to NOT be an AGN based on a Random Forest classifier)

Show AGN classifier version 1.0 (Probability to be an AGN based on a Random Forest classifier)

Show CATS broad classifier version 1.0 (Level 1 classifier based on the CBPF Algorithm for Transient Search)

The ELAsTiCC classification challenge is currently preparing community alert brokers for LSST.