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University of Delaware
Department of Physics and Astronomy
Biden School of Public Policy and Administration
Data Science Institute
Rubin Legacy Survey of Space and Time
Deputy Project Scientist, Rubin Construction
Interim Head of Science, Rubin Operations
Applications of and opportunities for AI in the new era of time-domain astronomy

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this slide deck is live at

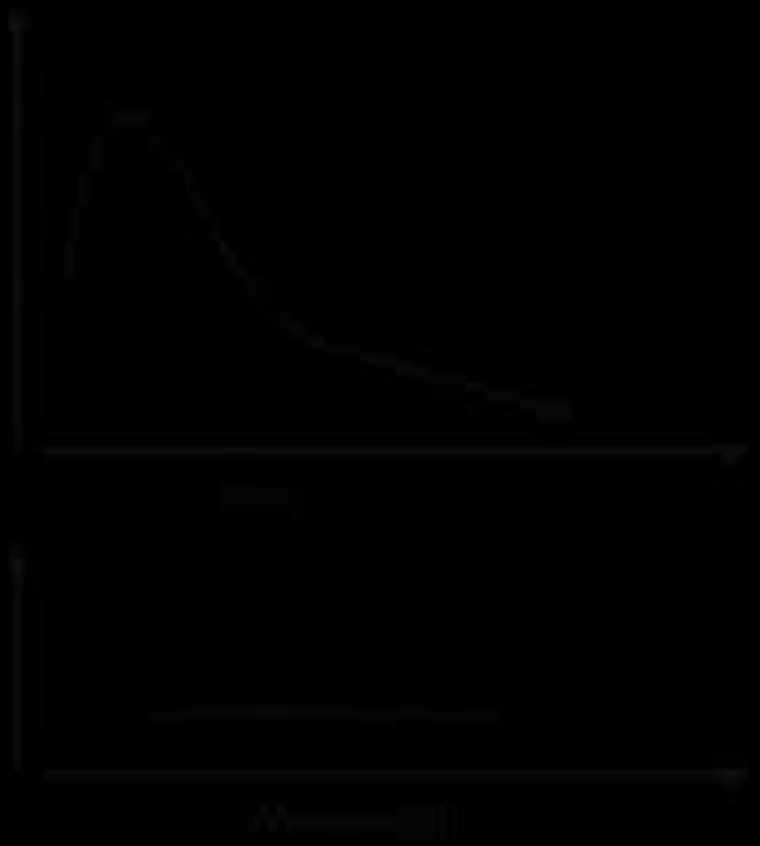
https://slides.com/federicabianco/aimlaw

The best way to view the slides is on the web (to see videos and animations). A flat (PDF) version of this deck would be largely diminished

Applications of and opportunities for AI in the new era of time-domain astronomy

explosions in the sky

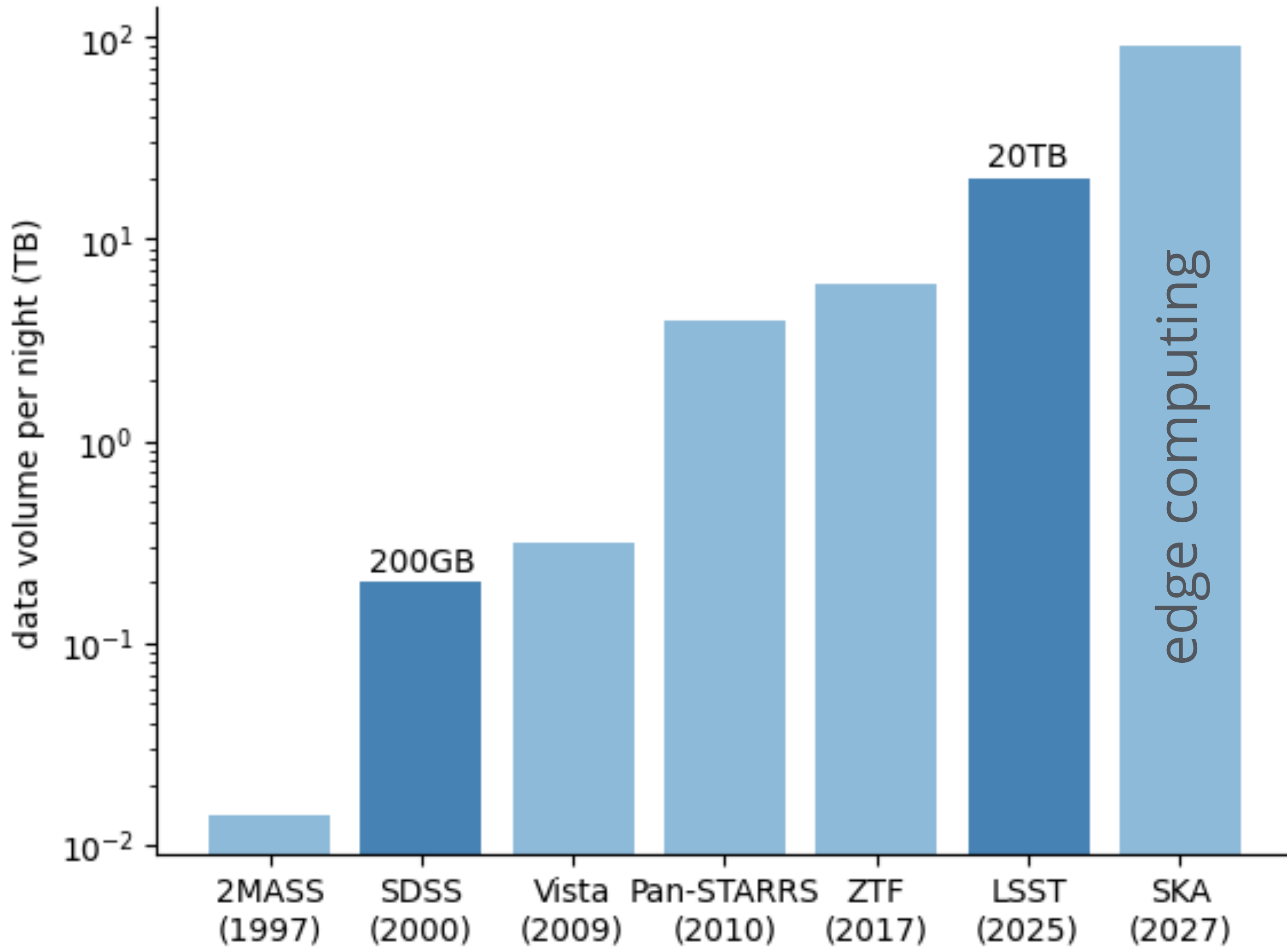
how we study SNe



https://www.youtube.com/watch?v=aIAQqzIB-O8

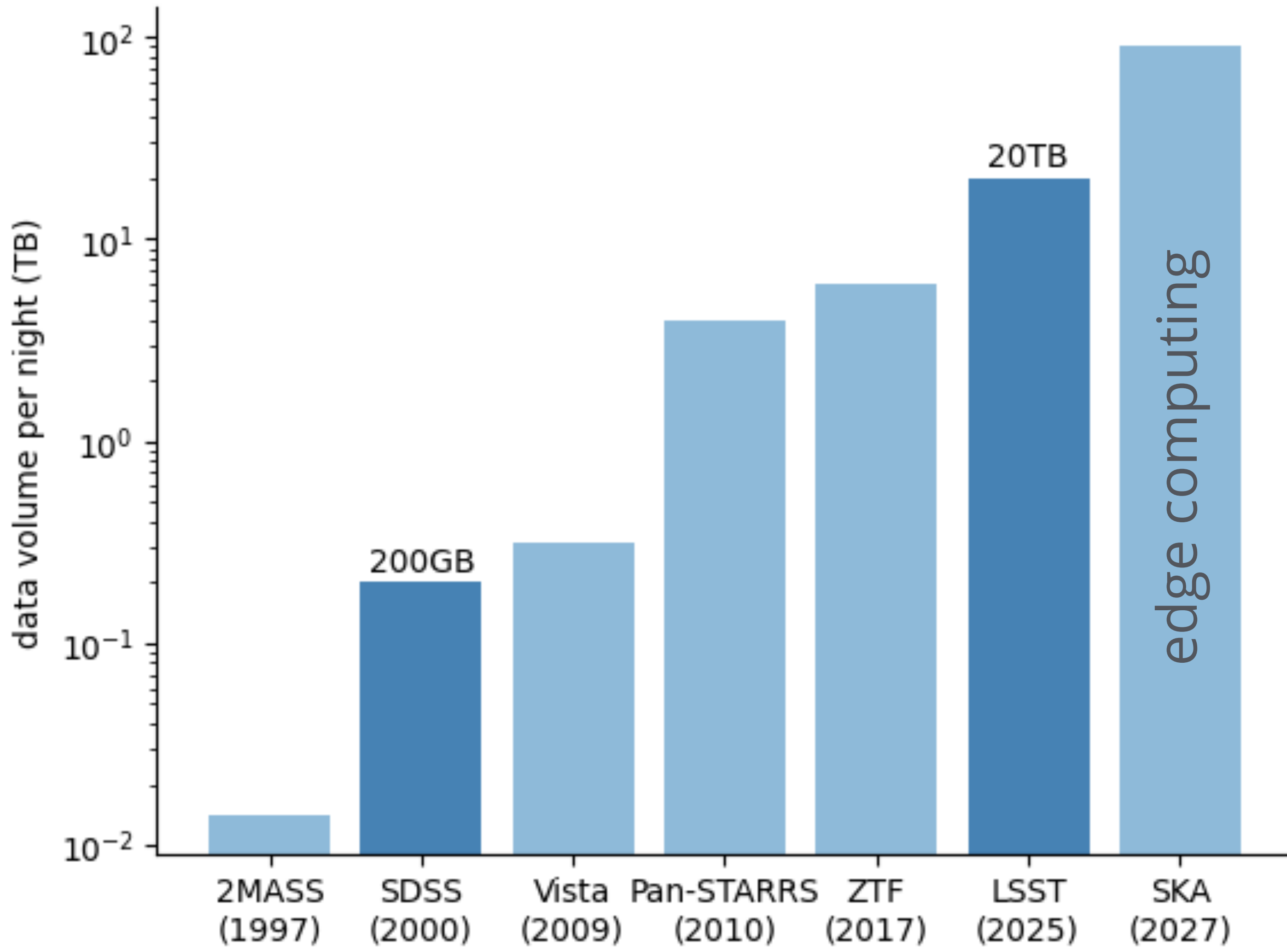
Do we want more data??

HELL YEAH!



Rubin LSST Transients by the numbers

17B stars Ivezic+19



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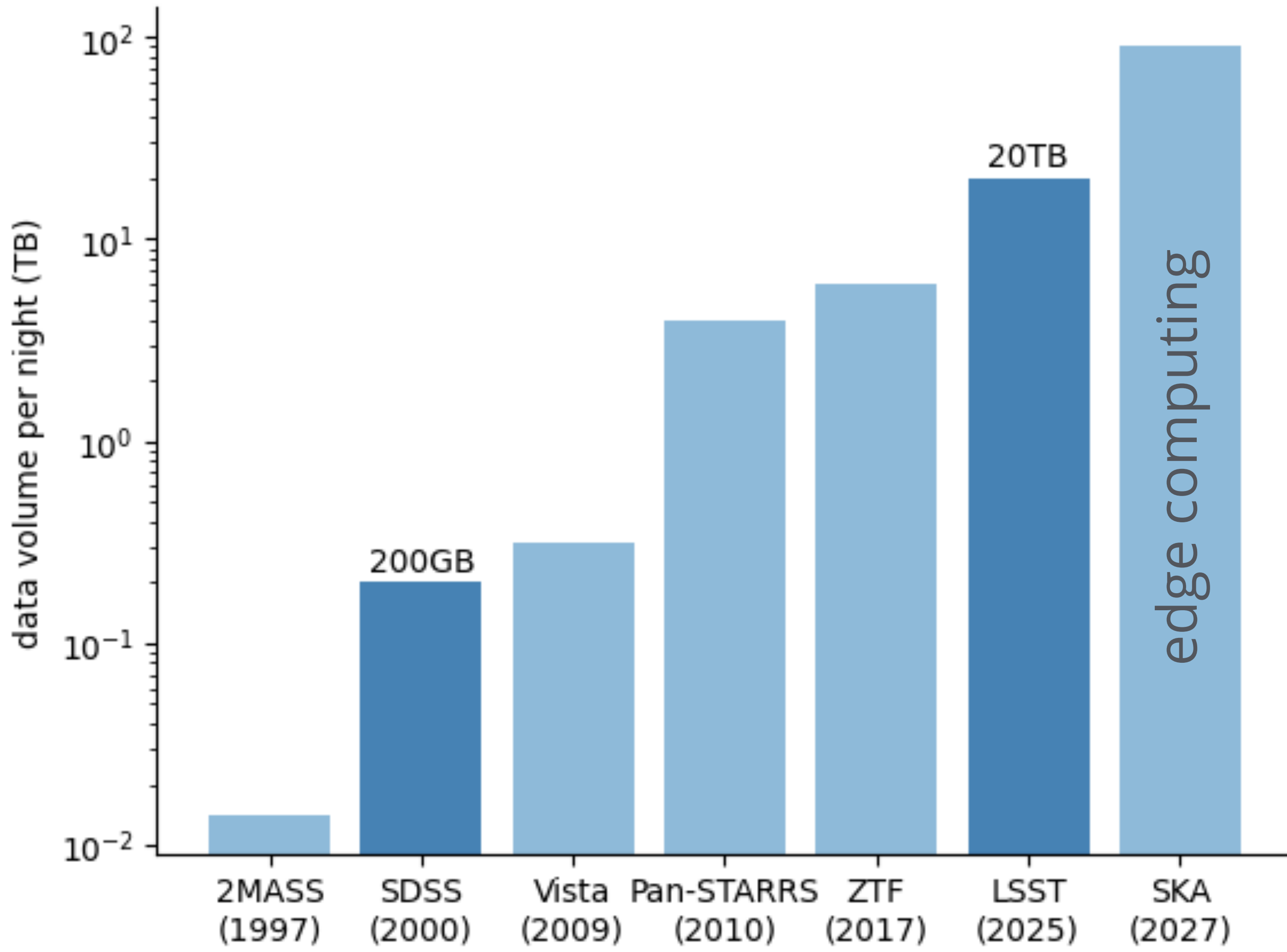
~10 million QSO Mary Loli+21



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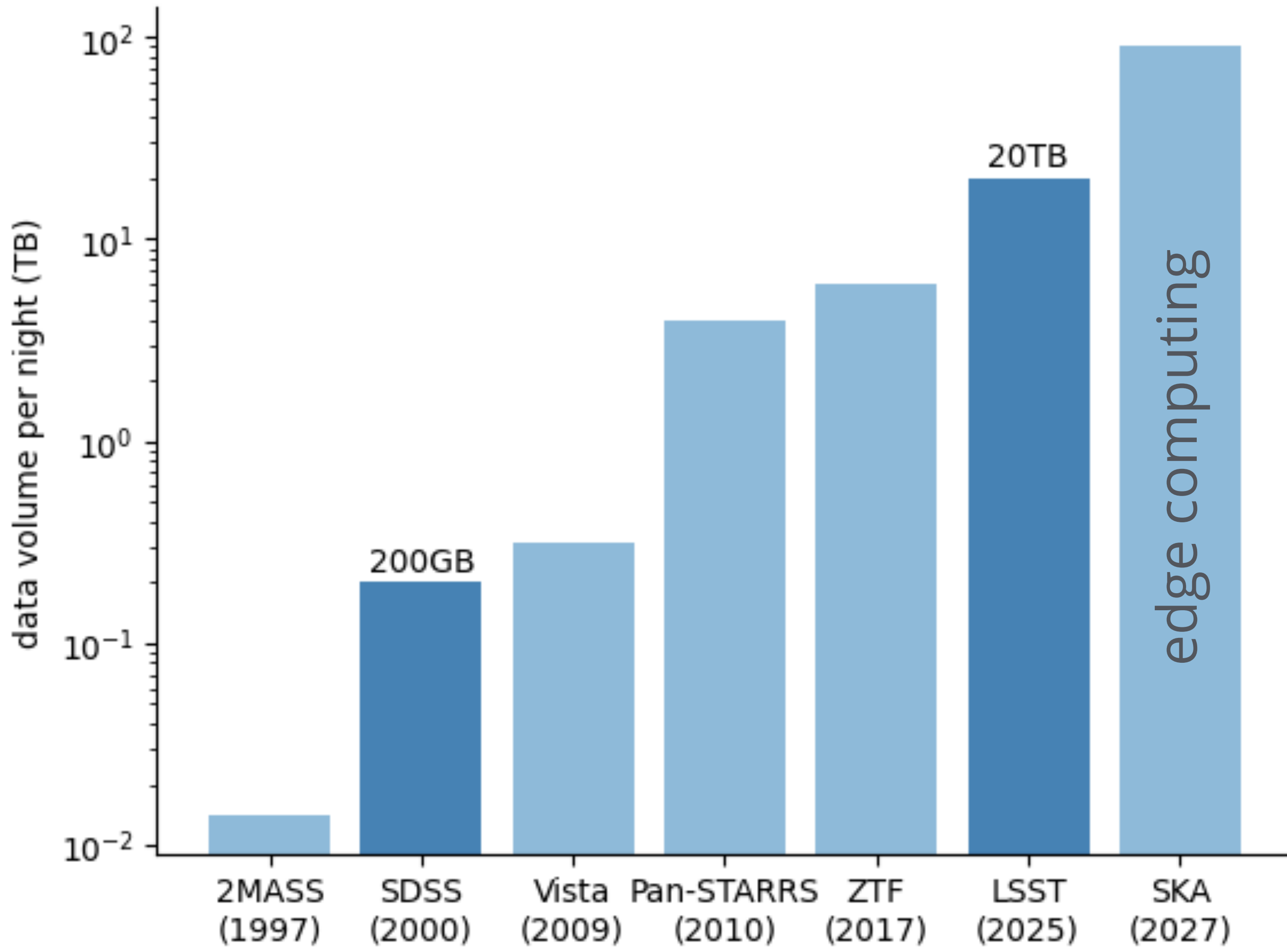

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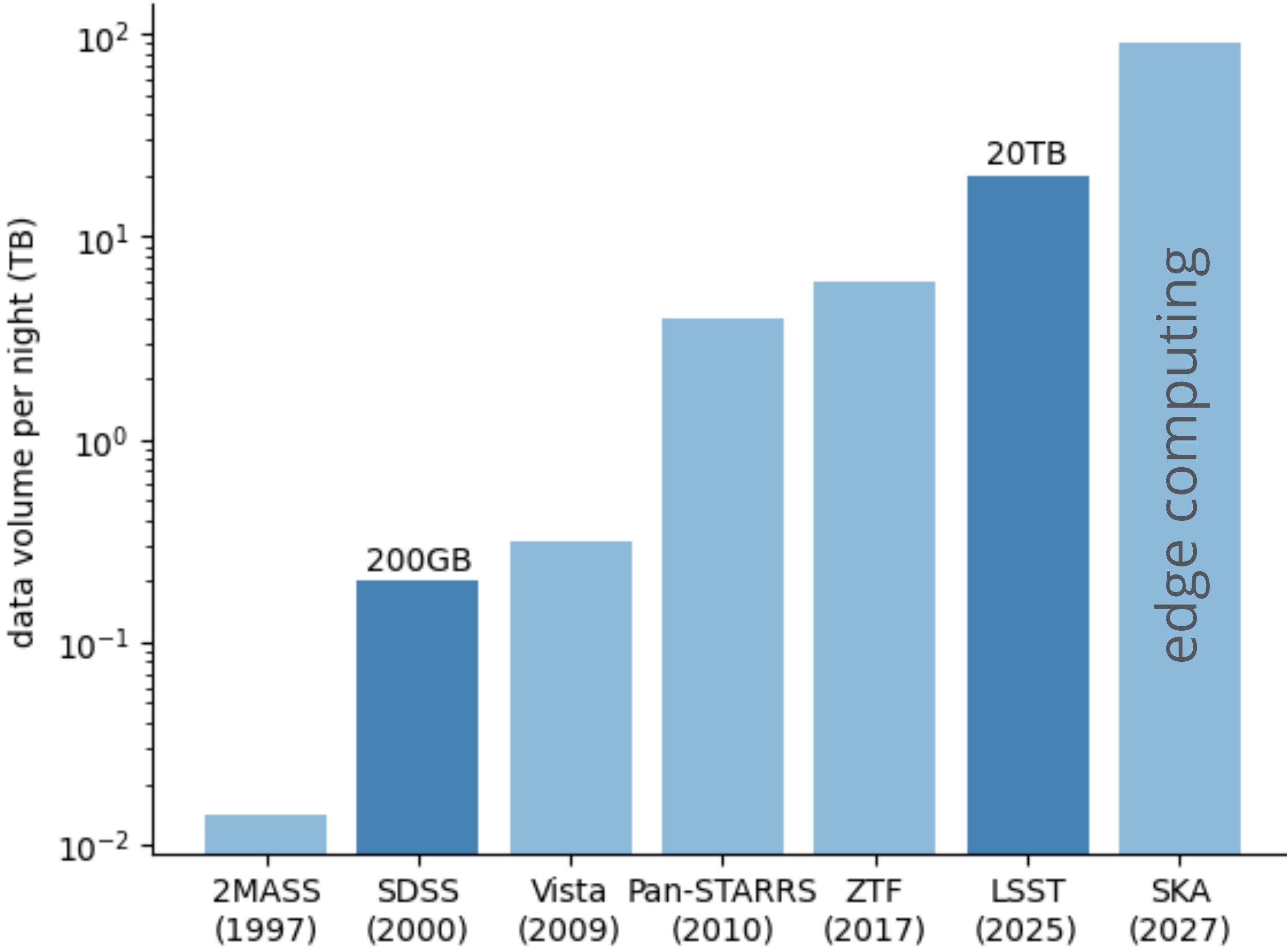

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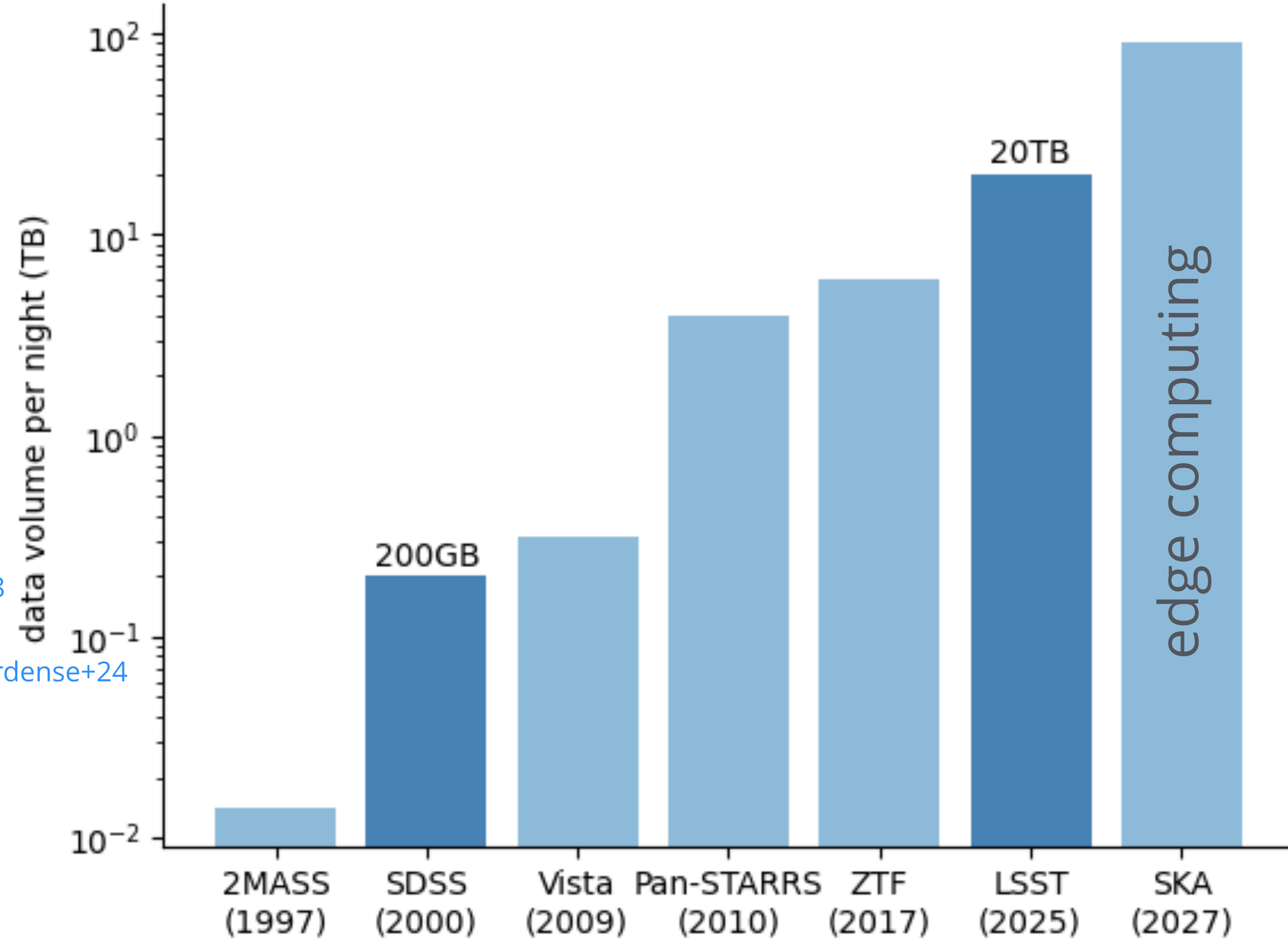

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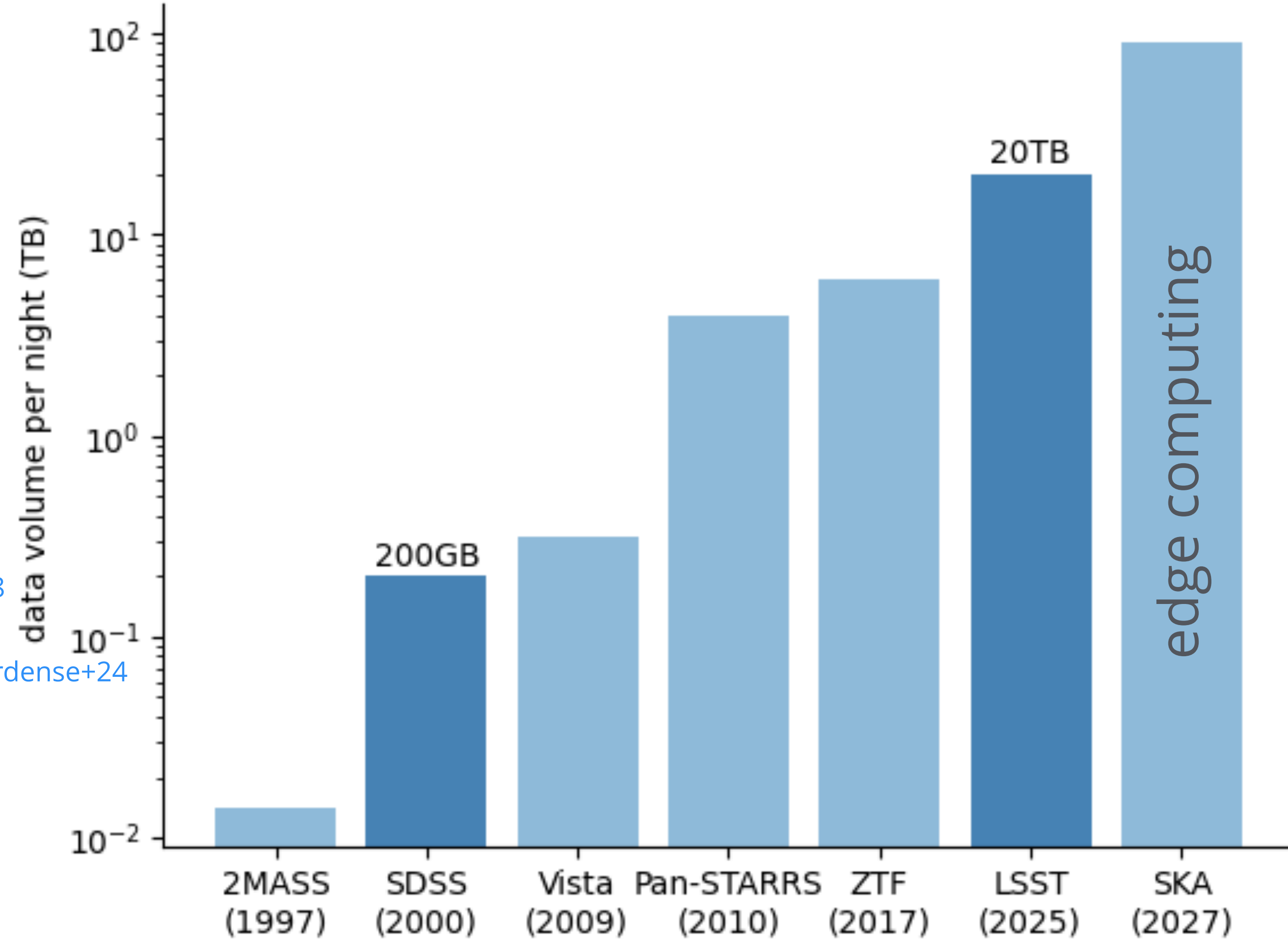

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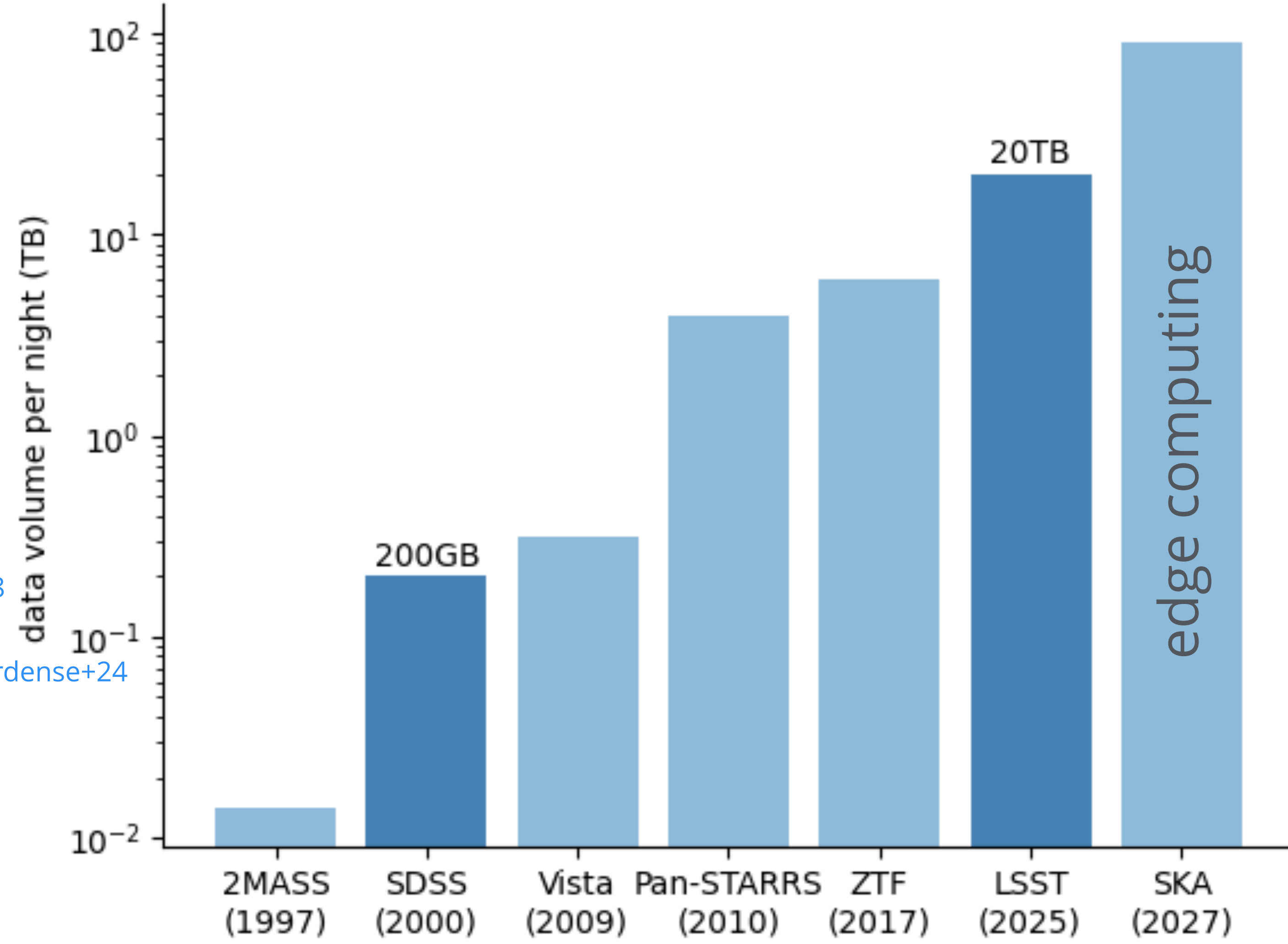
> 10 Interstellar Objects (👽?)



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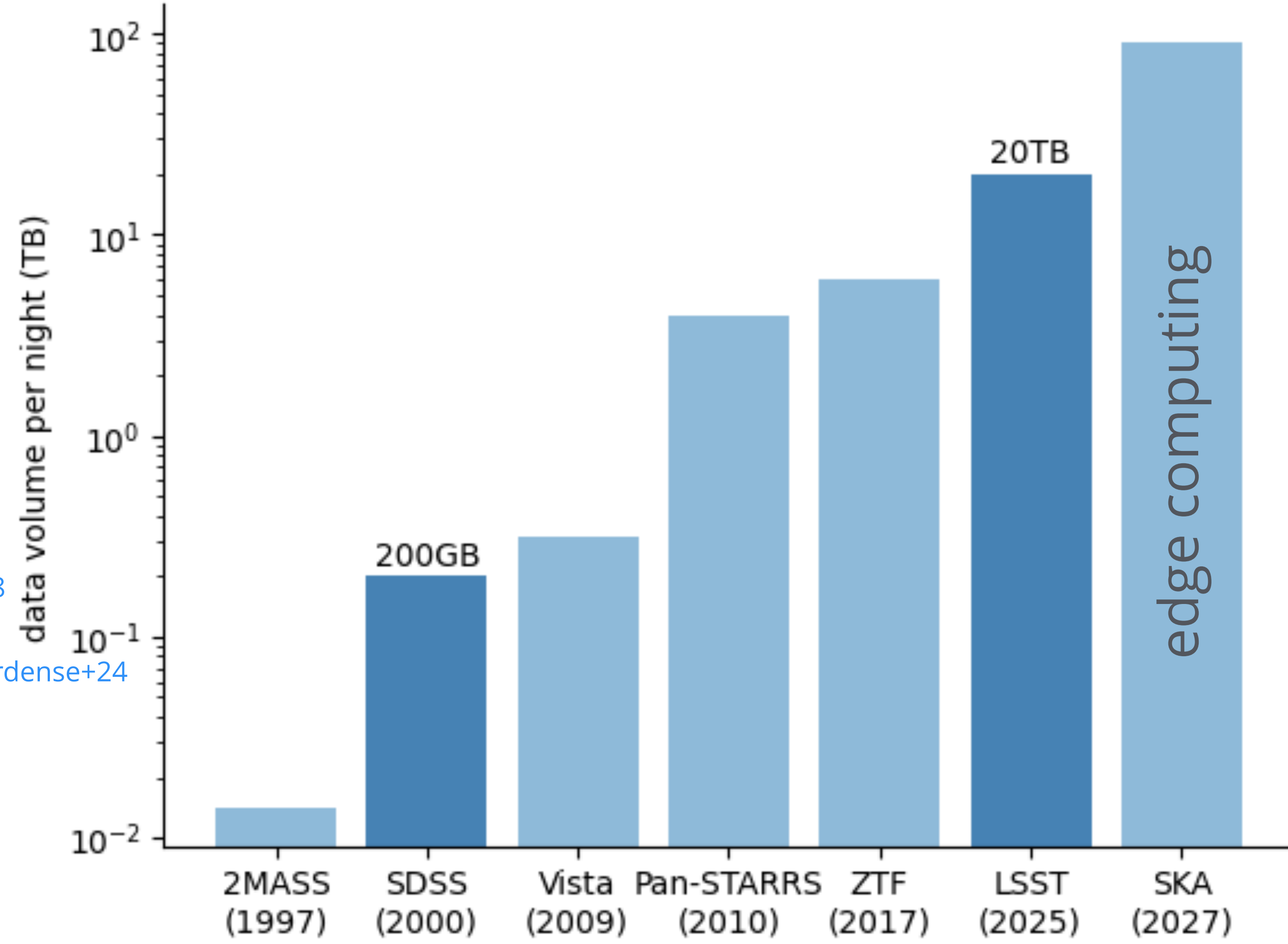
True Novelties!



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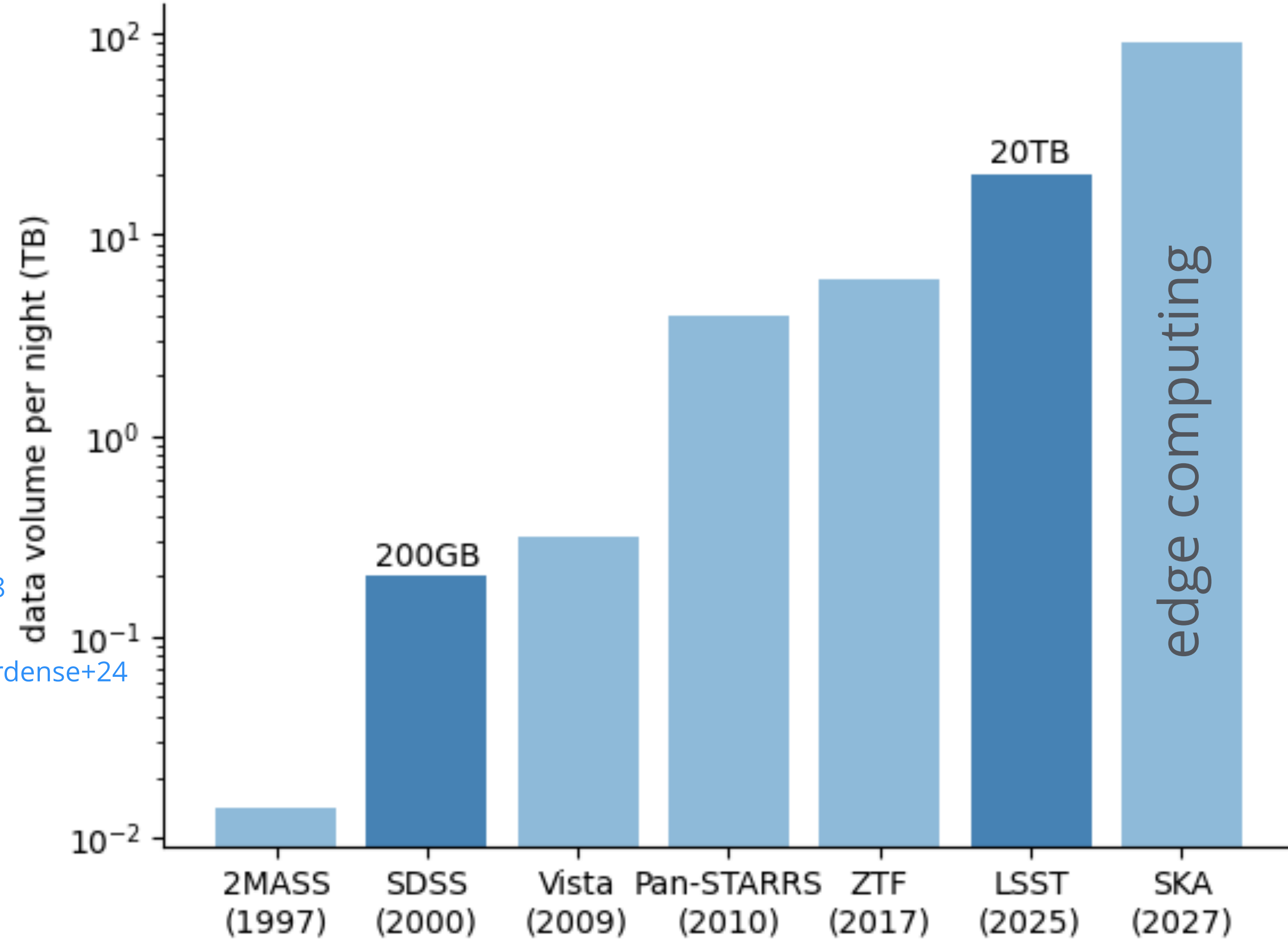
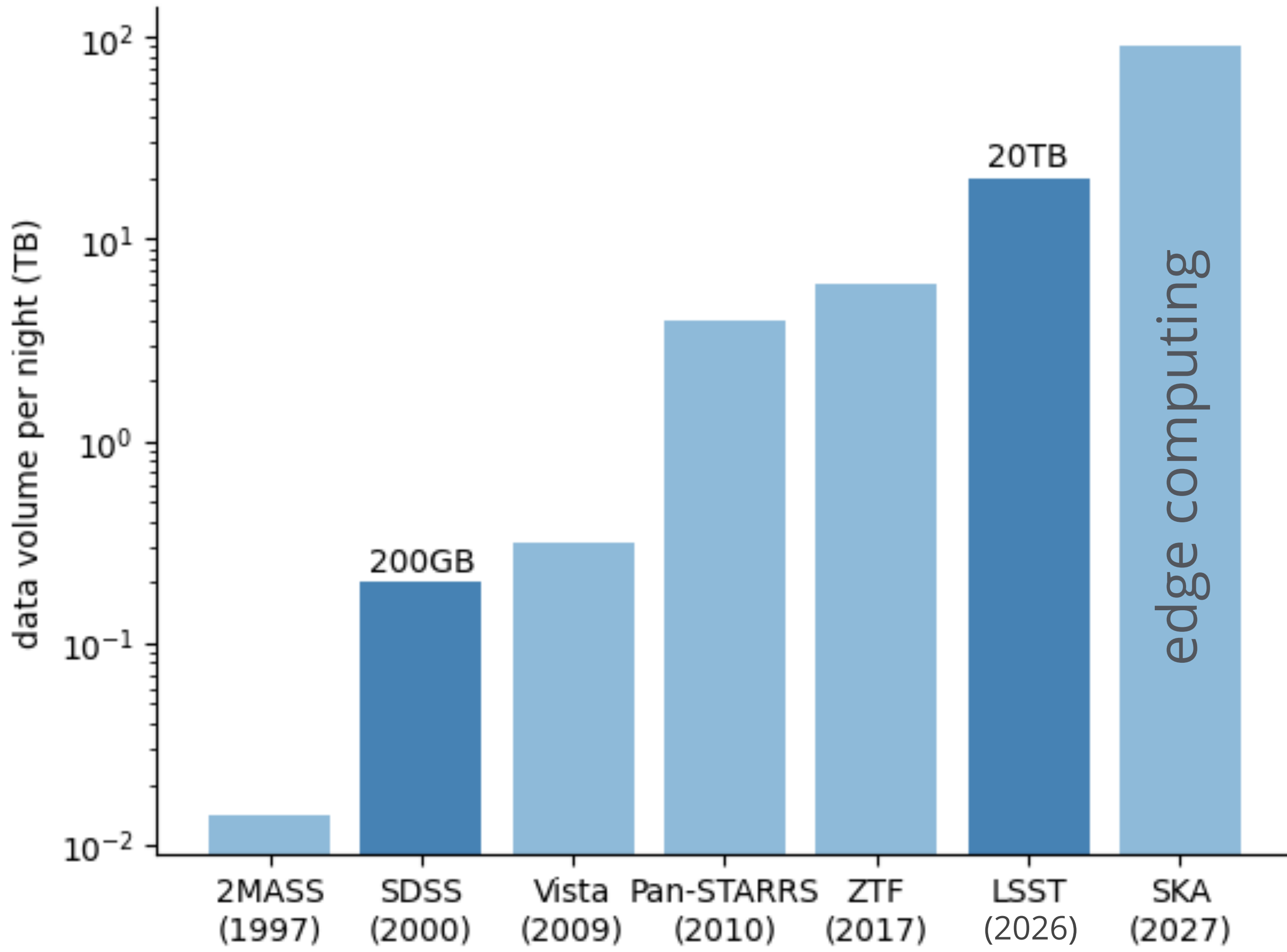
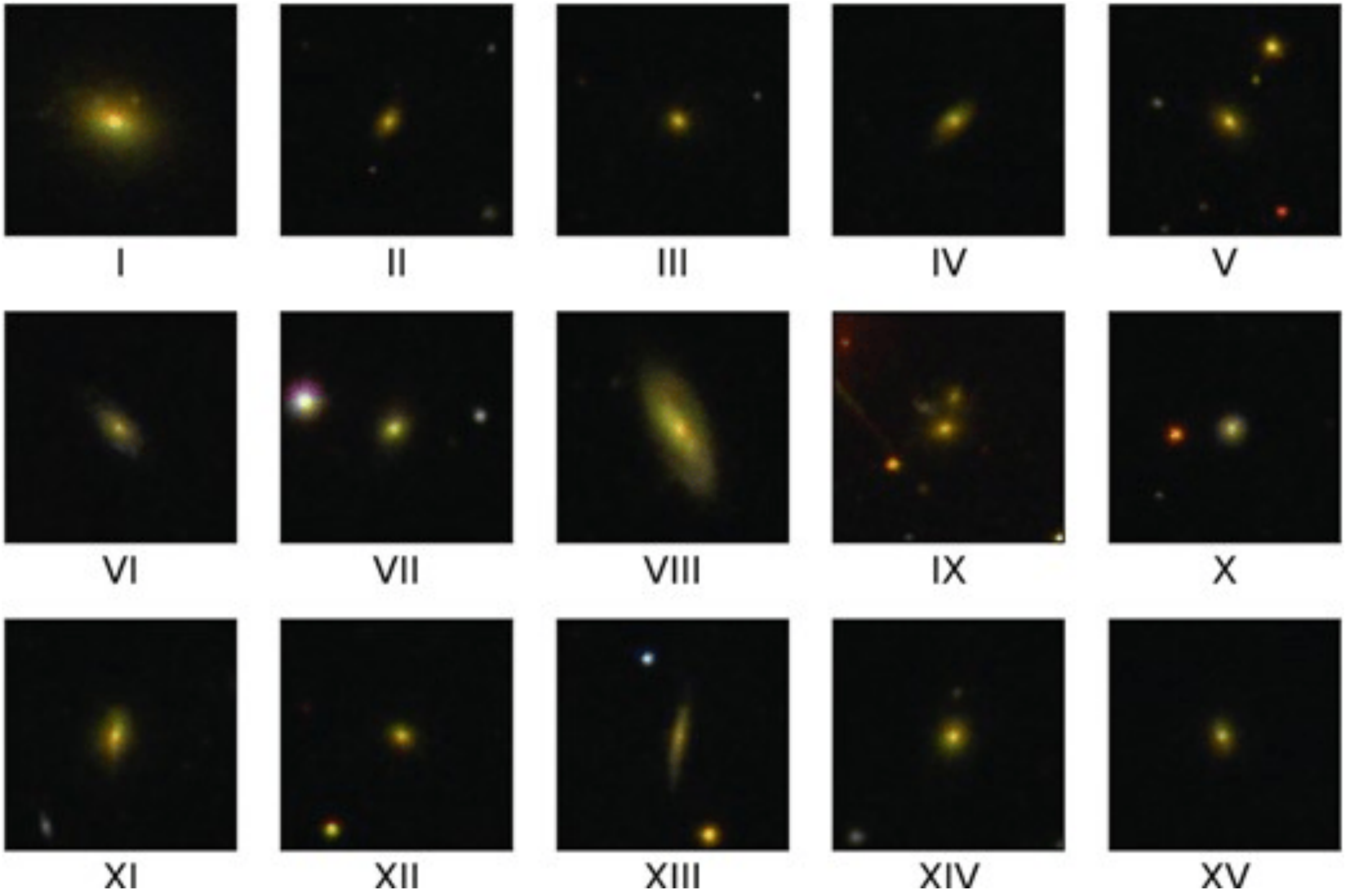


Is the data gonna also be better?

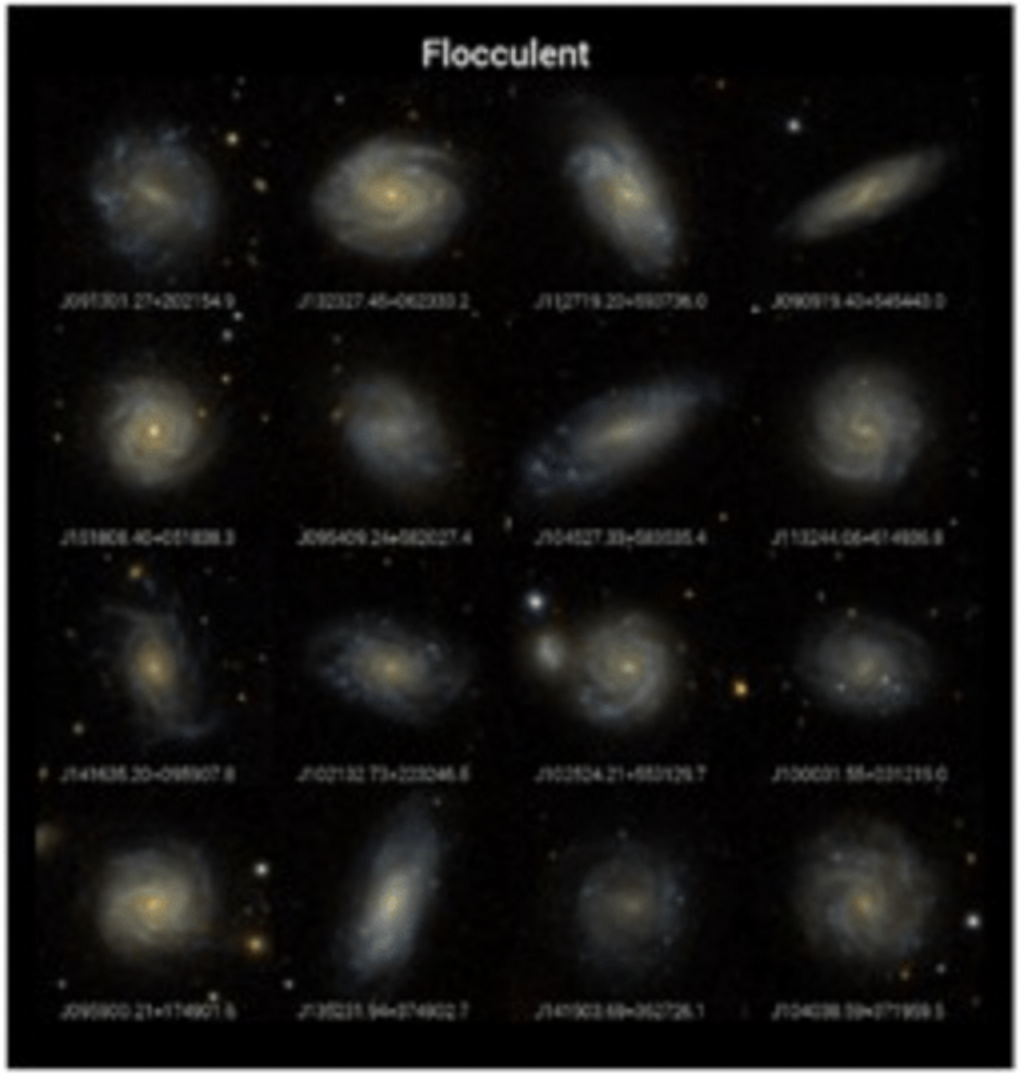
well... it depends

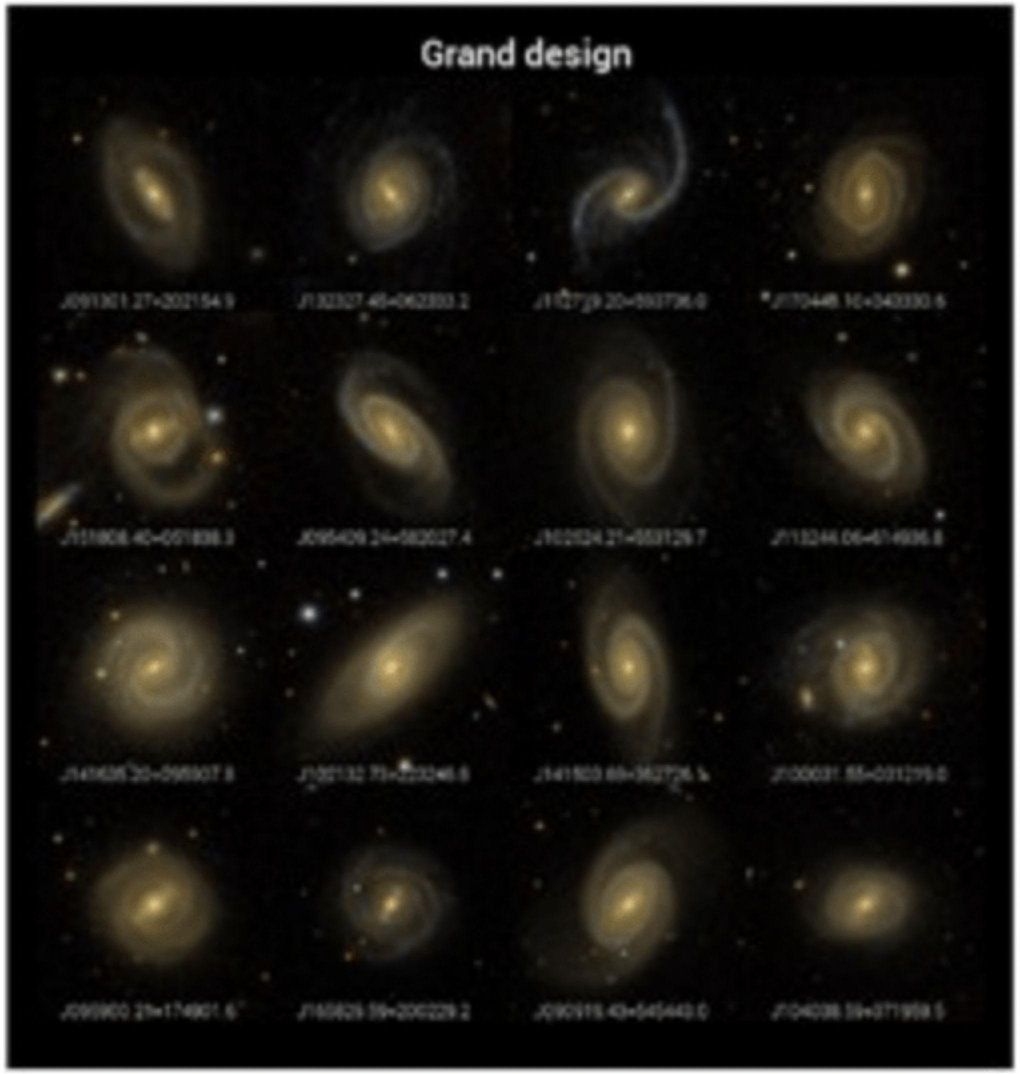




Grover+ 2021 https://doi.org/10.1093/mnras/stab1935

thank you Yogesh!

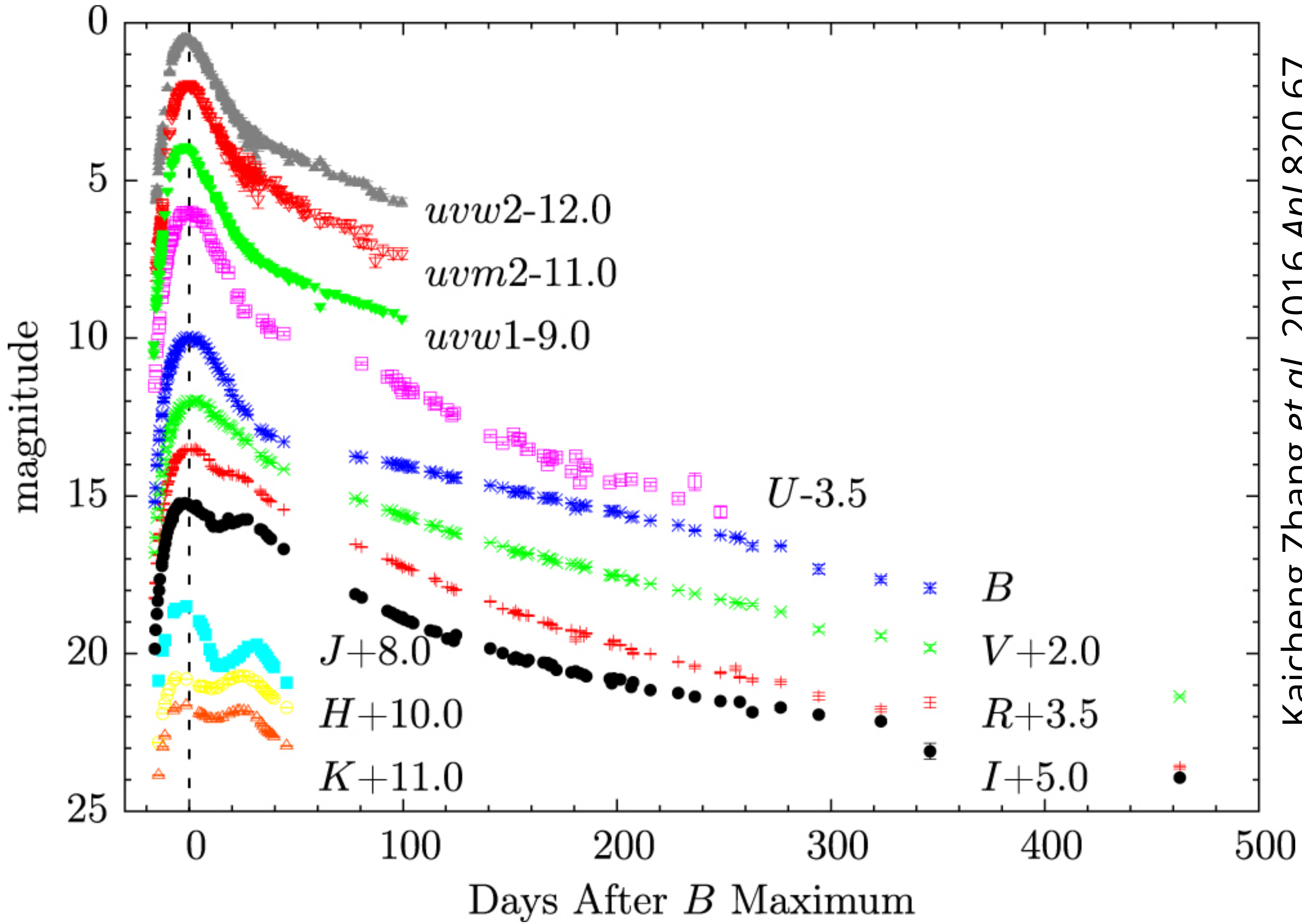




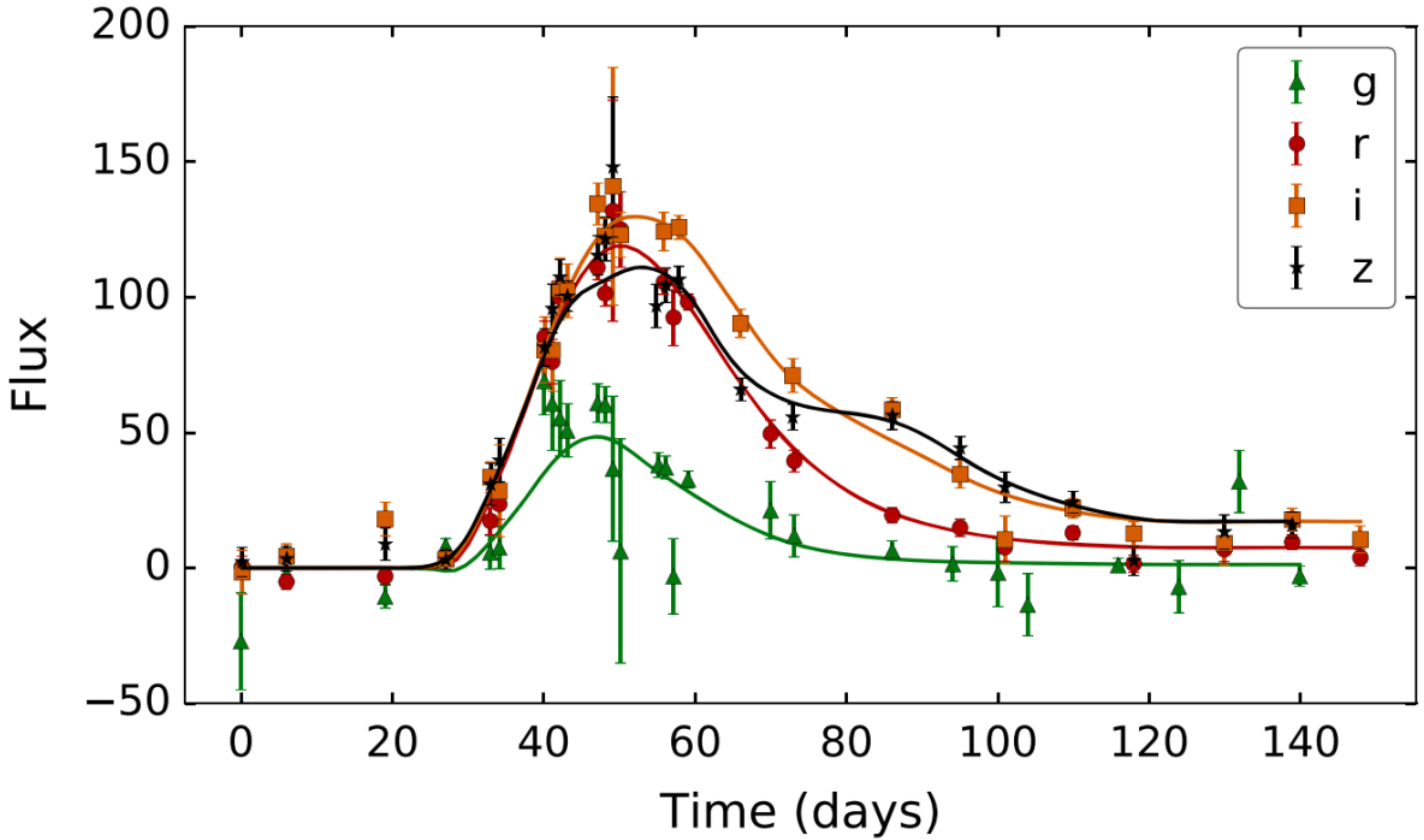
Sarkar+ 2023, https://doi.org/10.1093/mnras/stac3096

thank you Arumina

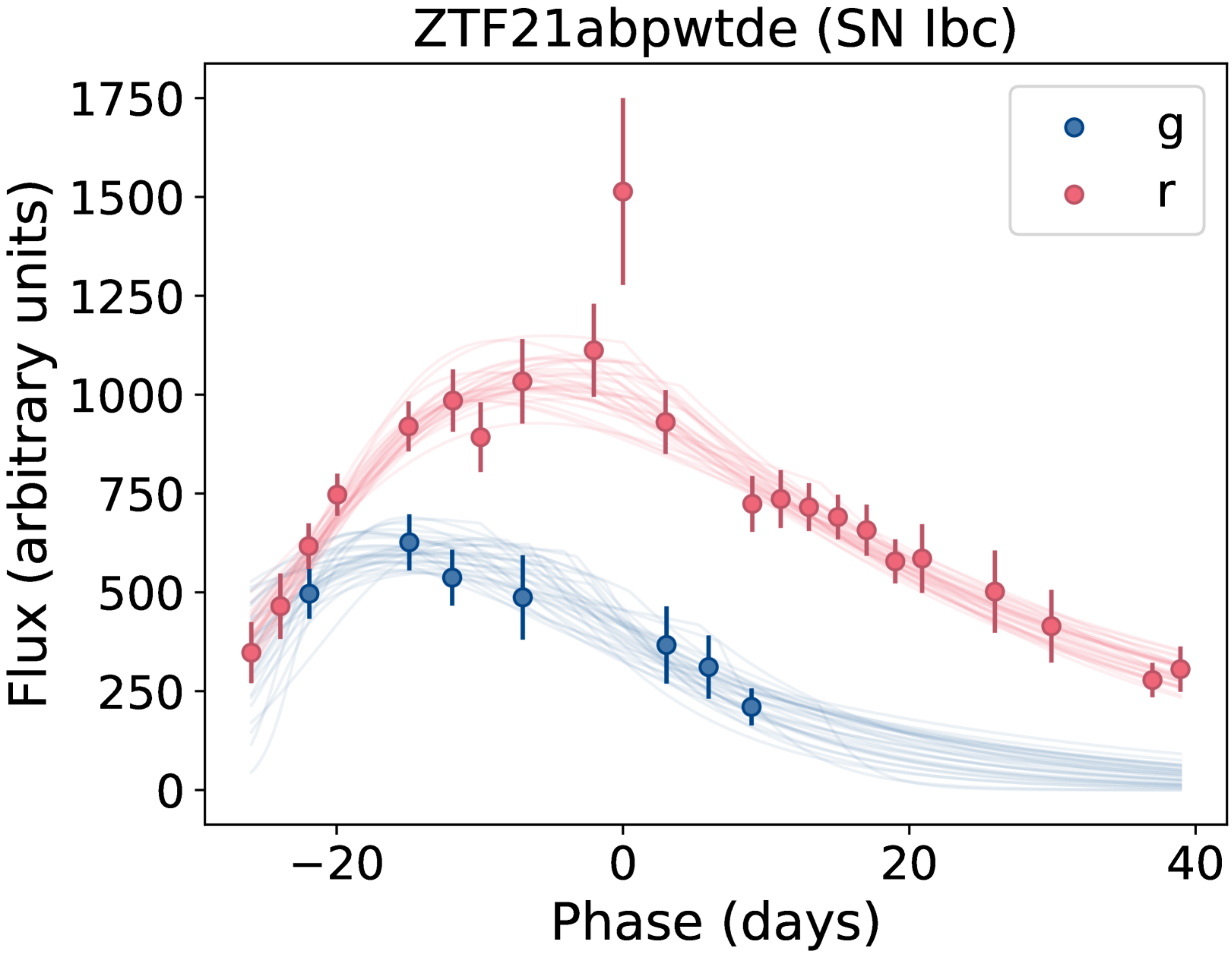
visualizatoin and concept credit: Alex Razim



Kaicheng Zhang *et al* 2016 *ApJ* 820 67

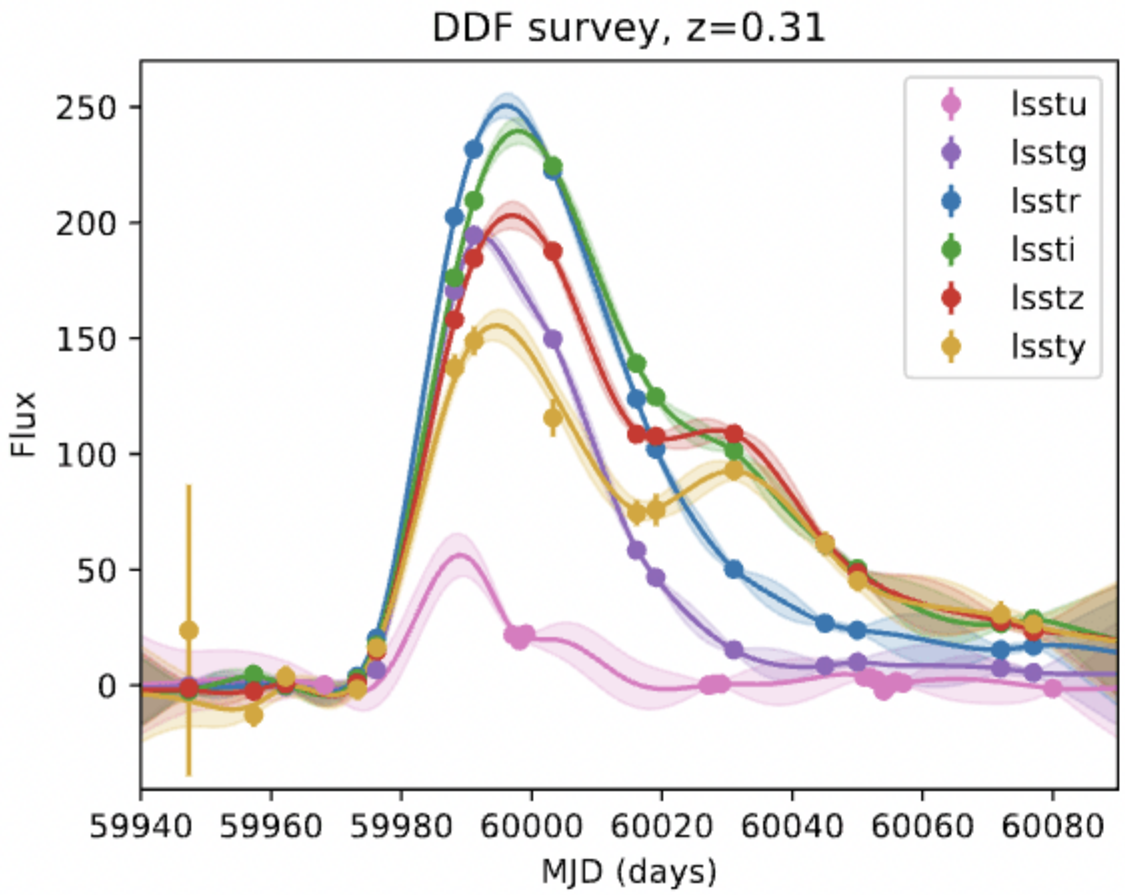


https://plasticc.org/data-release



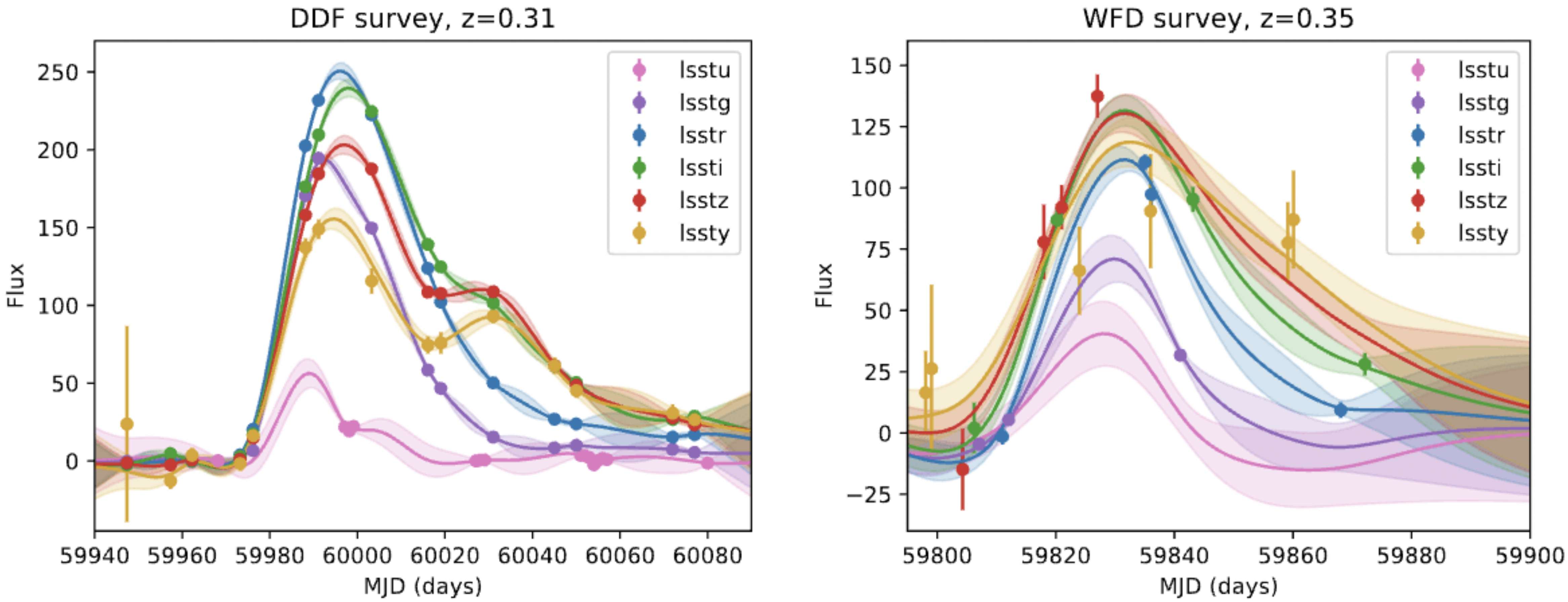
ZTF21abpwtde (SN Ibc)
Flux (arbitrary units)
Phase (days)
g
r
0
250
500
750
1000
1250
1500
1750
−20
0
20
40

deSoto+2024



7% of LSST data

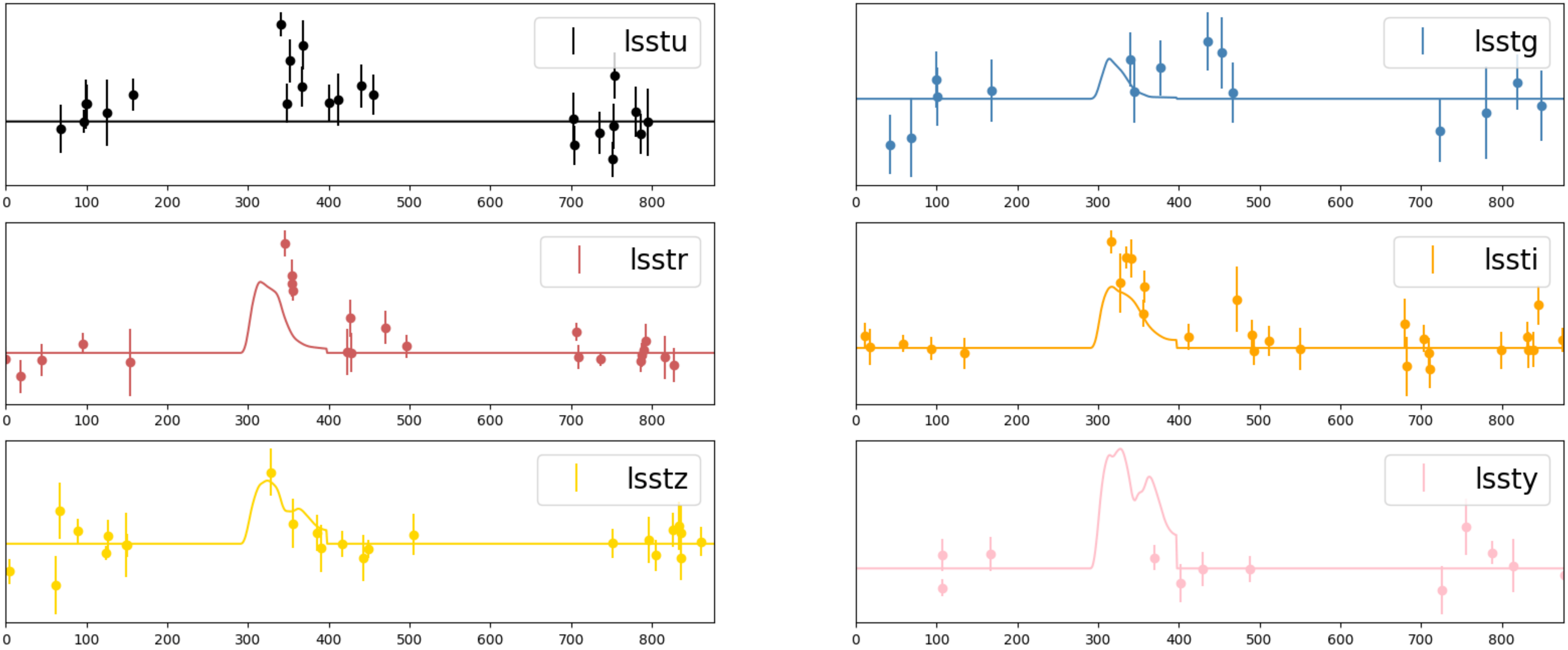
Boone 2017



7% of LSST data

The rest

Boone 2017

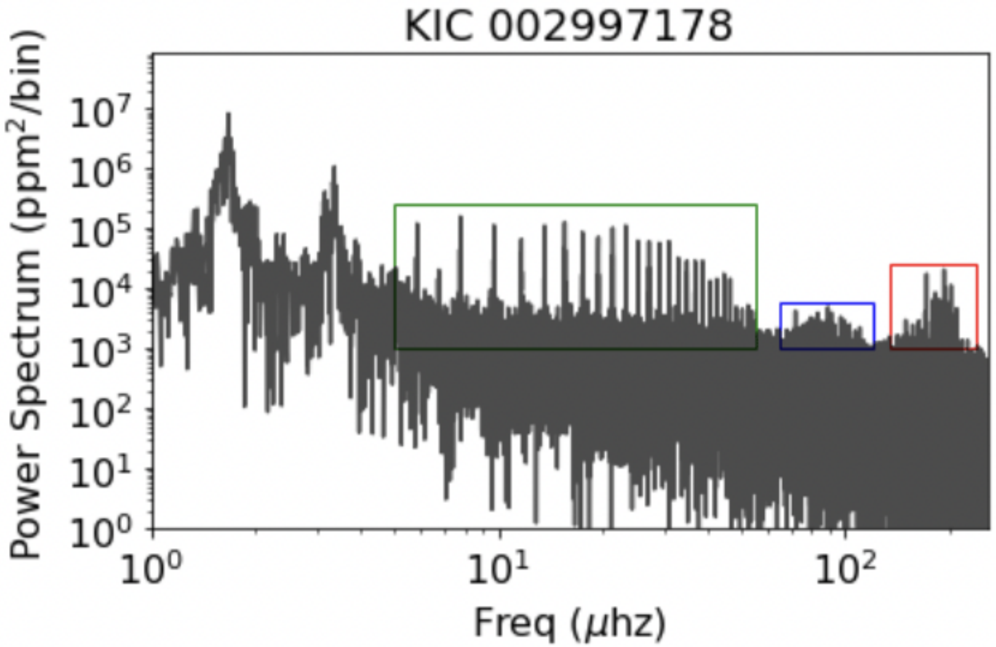


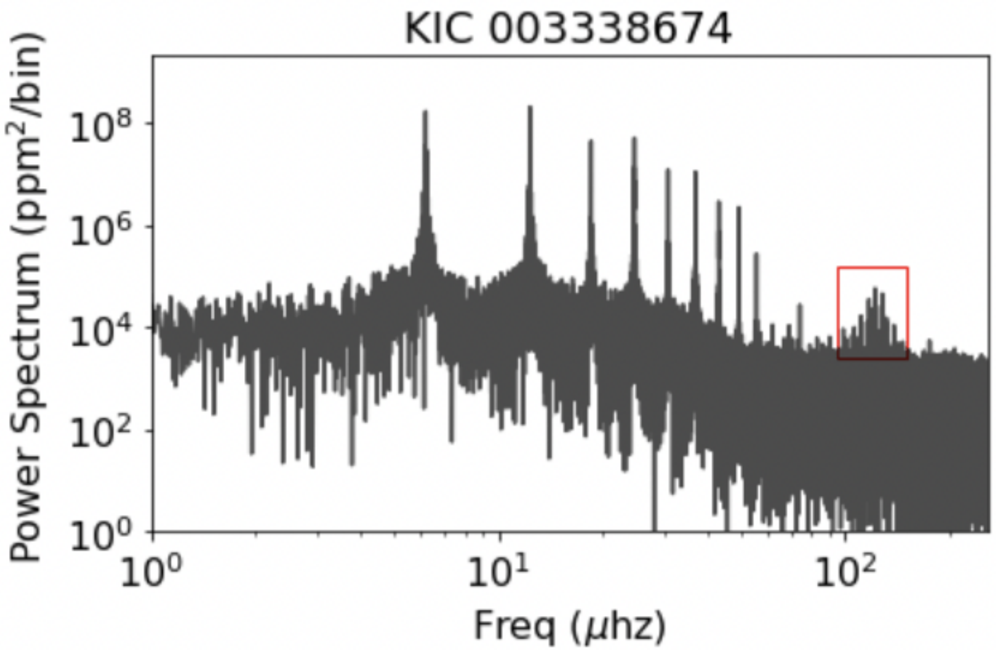
Data: PLAsTiCC

Model: *salt2 (Guy+07)* implemented with SNCOSMO (*Barbary+2012*) *transient data AI ready (see Alex's talk)*

lightcurves make really bad tensors

- Variable sizes of data vectors
- Uneven sampling
- Different sampling at different wavelengths
- Phase gaps can be months long over ~1 year relevant time scales
- Multiple relevant time scales (Long Sort Medium.... need all memory)
- Heteroscedastic errors

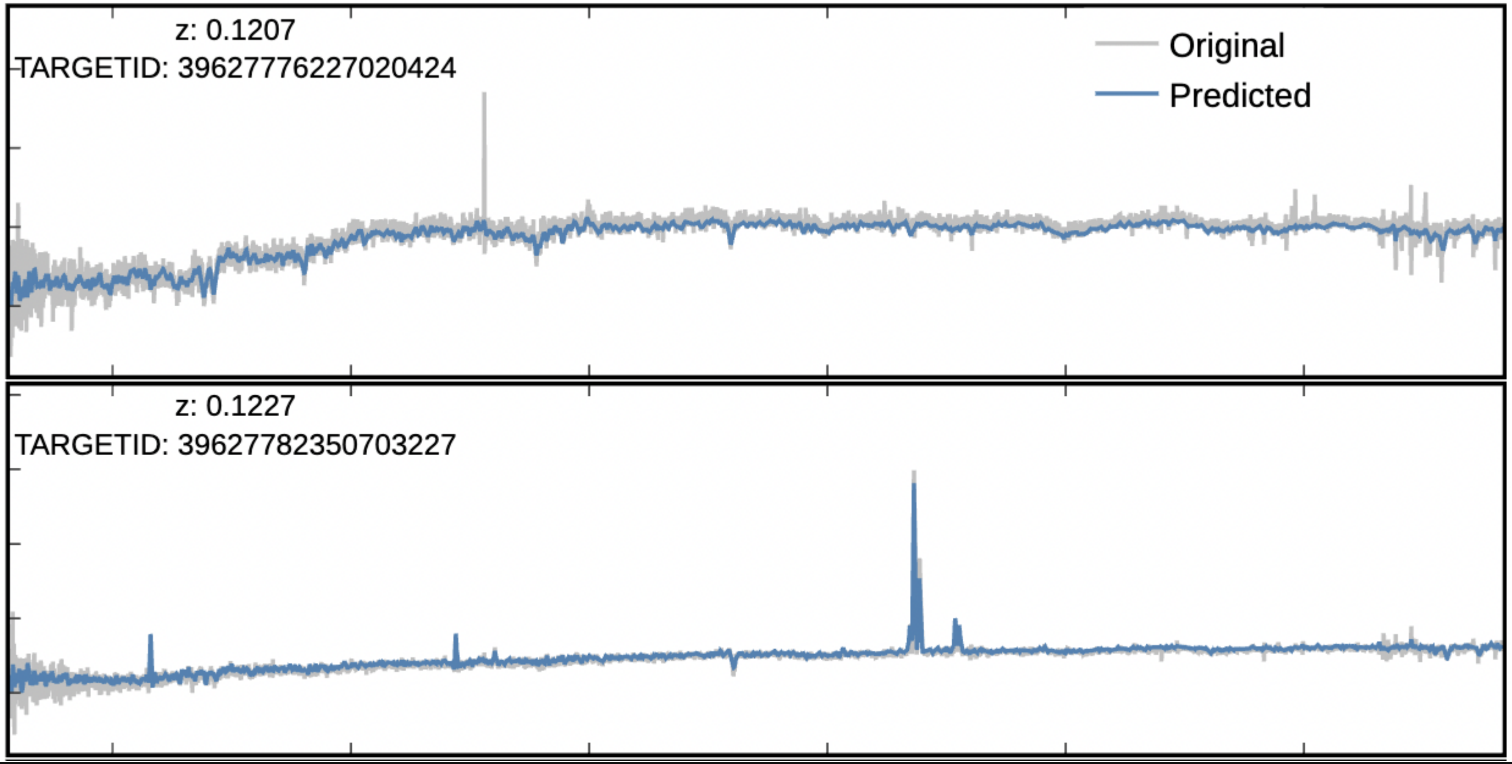




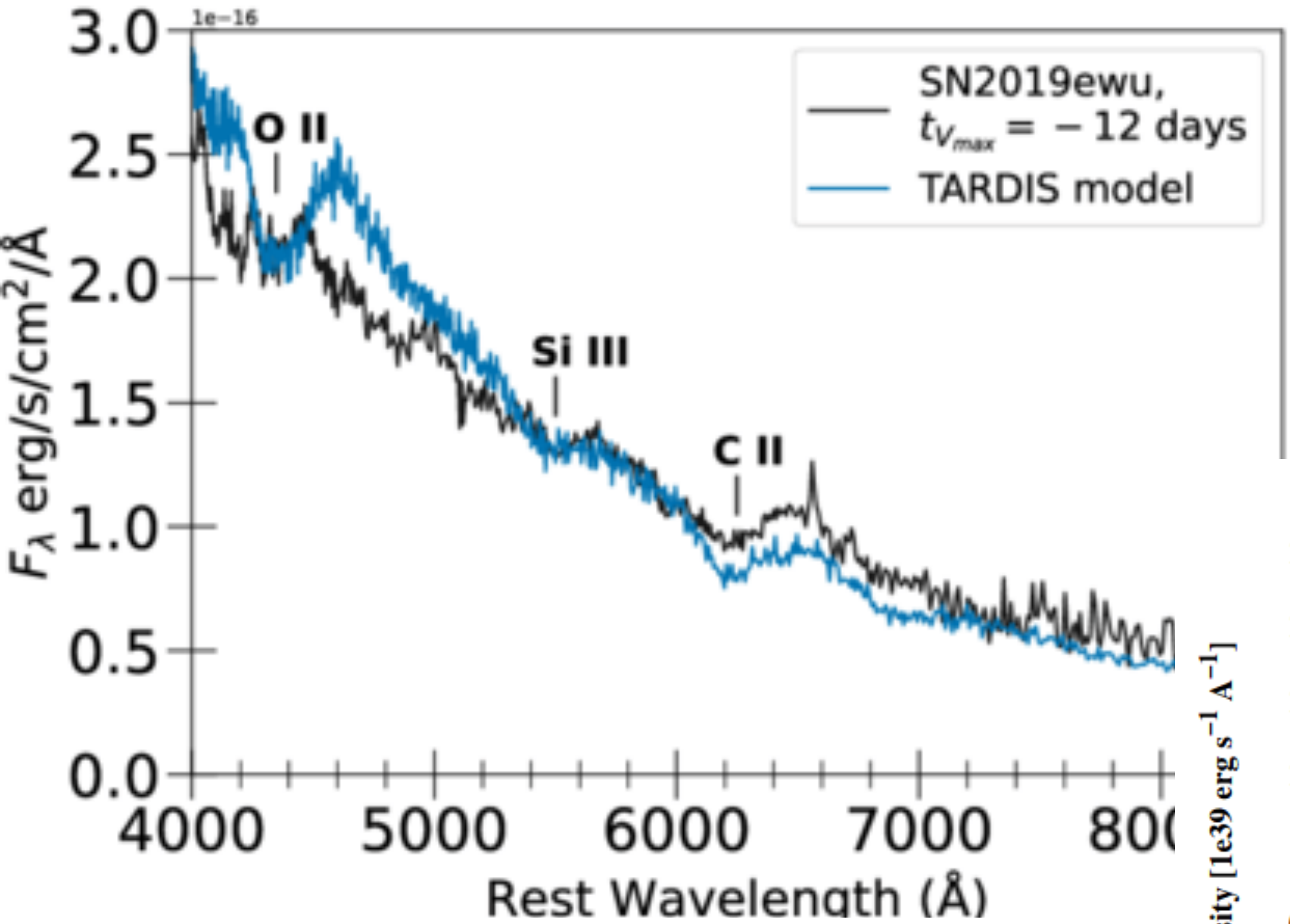
Dhanpal+2022

thank you Shravan

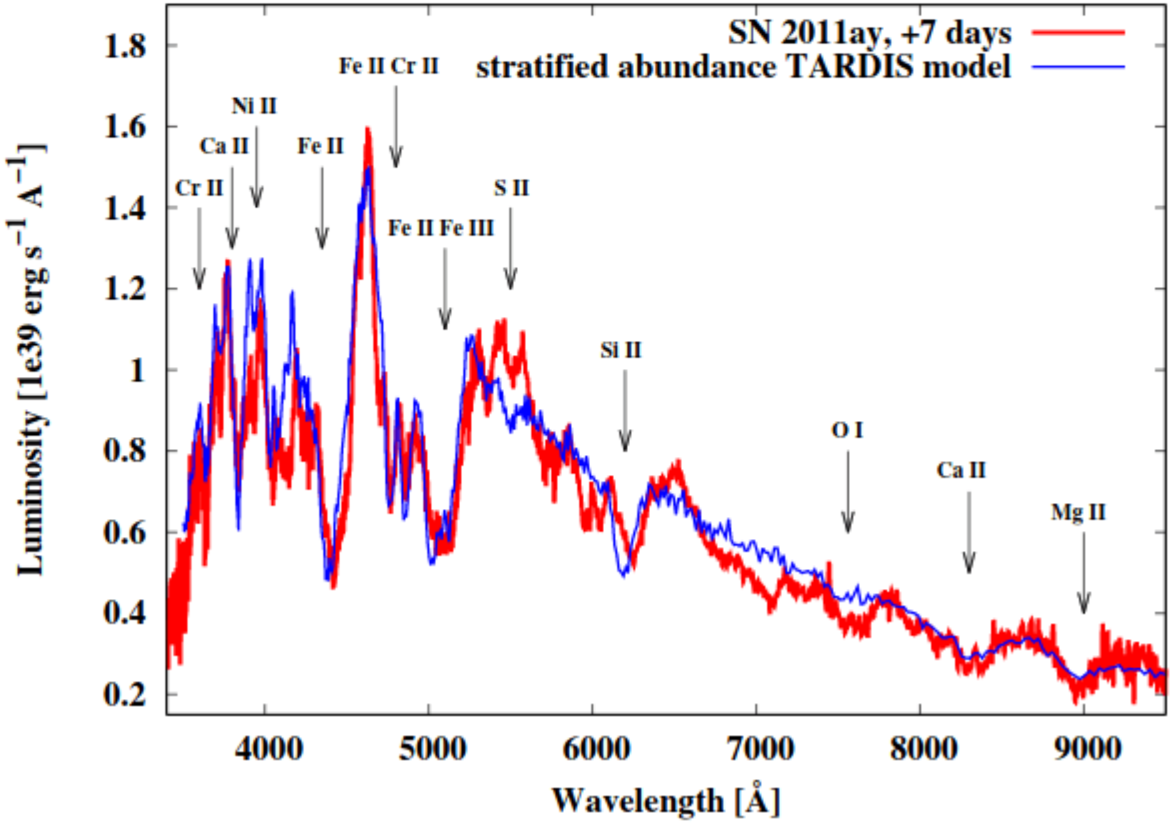
Rohan Pattnaik+ 2025



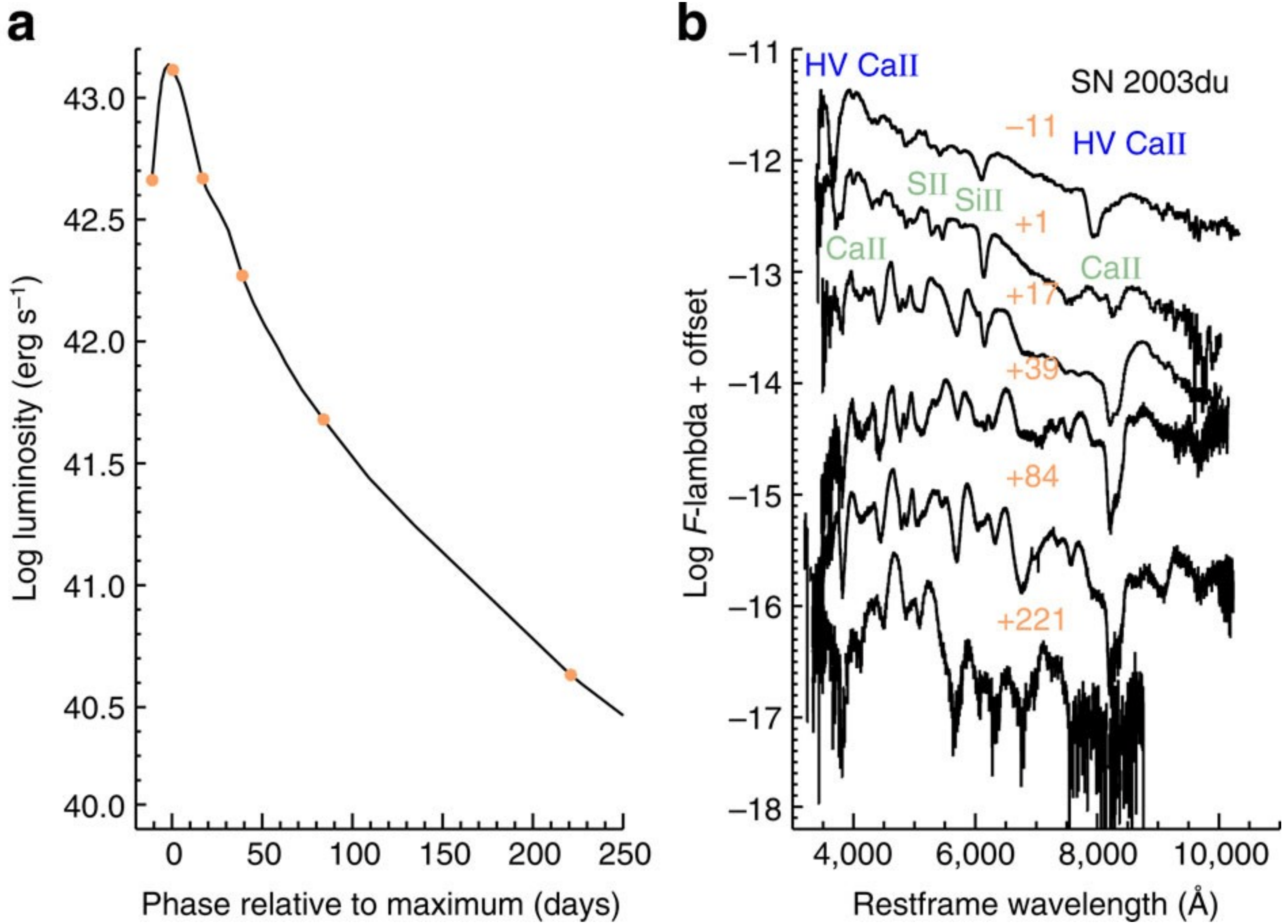
thank you Rohan



Willimamson+23



Barna+ 2017


a
b
Log luminosity (erg s⁻¹)
43.0
42.5
42.0
41.5
41.0
40.5
40.0
0
50
100
150
200
250
Phase relative to maximum (days)
HV CaII
SN 2003du
−11
HV CaII
SII
SiII
+1
CaII
CaII
+17
+39
+84
+221
Log F-lambda + offset
−11
−12
−13
−14
−15
−16
−17
−18
4,000
6,000
8,000
10,000
Restframe wavelength (Å)

Howell 2011

time-domain spectra are just painful

transients spectra are just painful

- feature broadening -> blending
- time evolving
- redshift moves features in different regions of a detector (systematics)
- in the LSST era we work at the limit of SNR
- we do not nearly have enough glass in the sky to collect spectra!

Rubin will see ~1000 SN every night!

Credit: Alex Gagliano IAIFI fellow MIT/CfA

Rubin Observatory

Site: Cerro Pachon, Chile

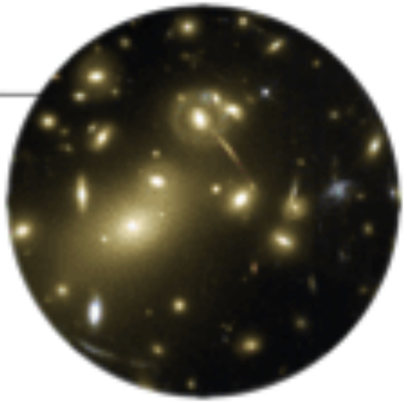
Funding: US NSF + DOE

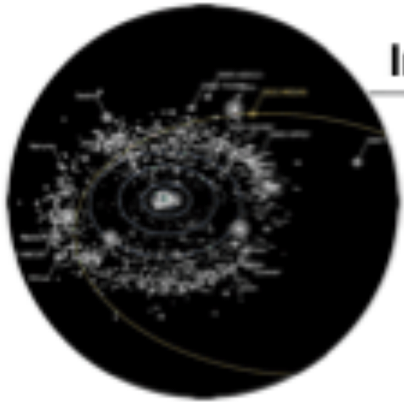
LSST Science Drivers

Four science programs as the key drivers of the science requirements

Probing Dark Matter & Dark Energy

- Strong & Weak Lensing
- Large Scale Structure
- Galaxy Clusters, Supernovae



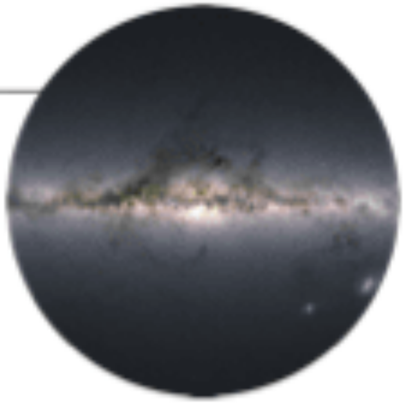


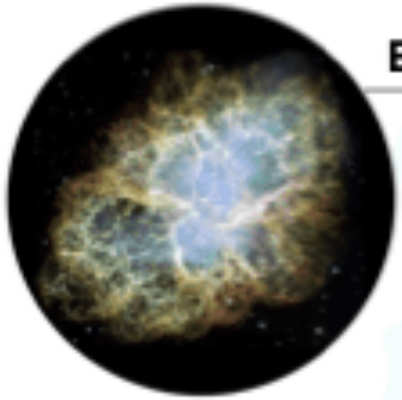
Inventory of the Solar System

- Comprehensive small body census
- Comets & ISOs
- Planetary defence

Mapping the Milky Way

- Structure and evolutionary history
- Spatial maps of stellar characteristics
- Reach well into the halo





Exploring the Transient Optical Sky

- Variable stars, Supernovae
- Fill in the variability phase-space
- Discovery of new classes of transients

LSST Science Drivers

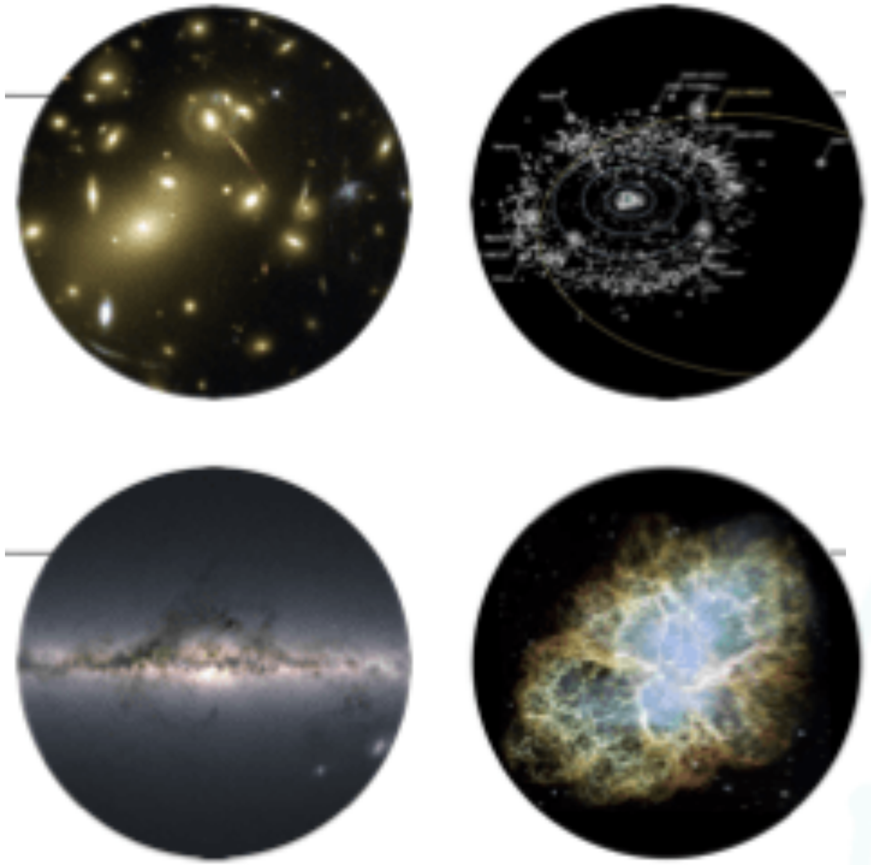
VERA C. RUBIN OBSERVATORY

Four science programs as the key drivers of the science requirements

To be transformational simultaneously in the four scientific areas Rubin needs:

1) a large telescope mirror to be sensitive - 8m (6.7m) **deep survey**

2) a large field-of-view for sky-scanning speed - 10 deg2 **wide survey**



3) high spatial resolution, high quality images - 0.2''/pixels **exquisite image quality**

4) process images in realtime and offline to produce live alerts and catalogs of all 37B objects

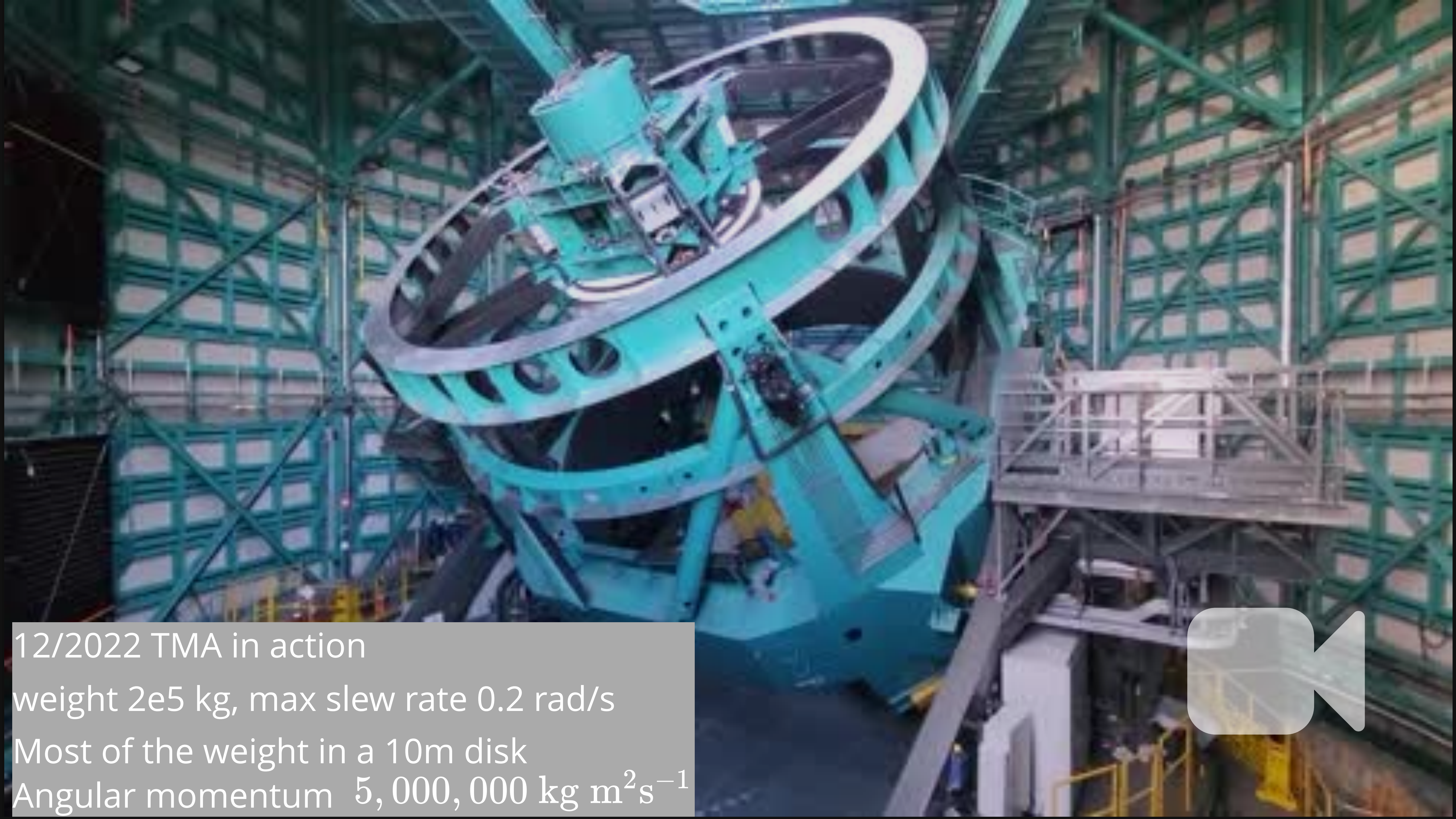
massive time domain dataset

Rubin Observatory Status


September 2016
@fedhere


5 / 2019

May 2022 - Telescope Mount Assembly



12/2022 TMA in action

weight 2e5 kg, max slew rate 0.2 rad/s

Most of the weight in a 10m disk

Angular momentum $5,000,000\ \mathrm{kg\ m^2 s^{-1}}$

The DOE LSST Camera - 3.2 Gigapixel

3024 science raft amplifier channels

Camera and Cryostat integration completed at SLAC in May 2022,

Shutter and filter auto-changer integrated into camera body

LSSTCam undergoing final stages of testing at SLAC


Sphere Entertainment
The Company behind the
$2.3 billion concert venue ...

rgill Ranpal GIll LSST Oct 25

Versión en Español más abajo

All,

https://ls.st/comcamcommissioning

What an incredible milestone we've reached together! Last night, on October 24, 2024, we passed our first end-to-end engineering test, marking a historic moment for all of us. Using the Commissioning Camera, we successfully captured and transferred our first on-sky data from Chile to the US Data Facility at SLAC. The excitement in the control rooms and online was electric, as decades of dedication and innovation came to life. Look out for the public announcement coming soon.

artist (me) impression of the first image taken by ComCam

rgill Ranpal GIll LSST

Versión en Español más abajo

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Is the data gonna also be better?

magnitude limit single image r~24

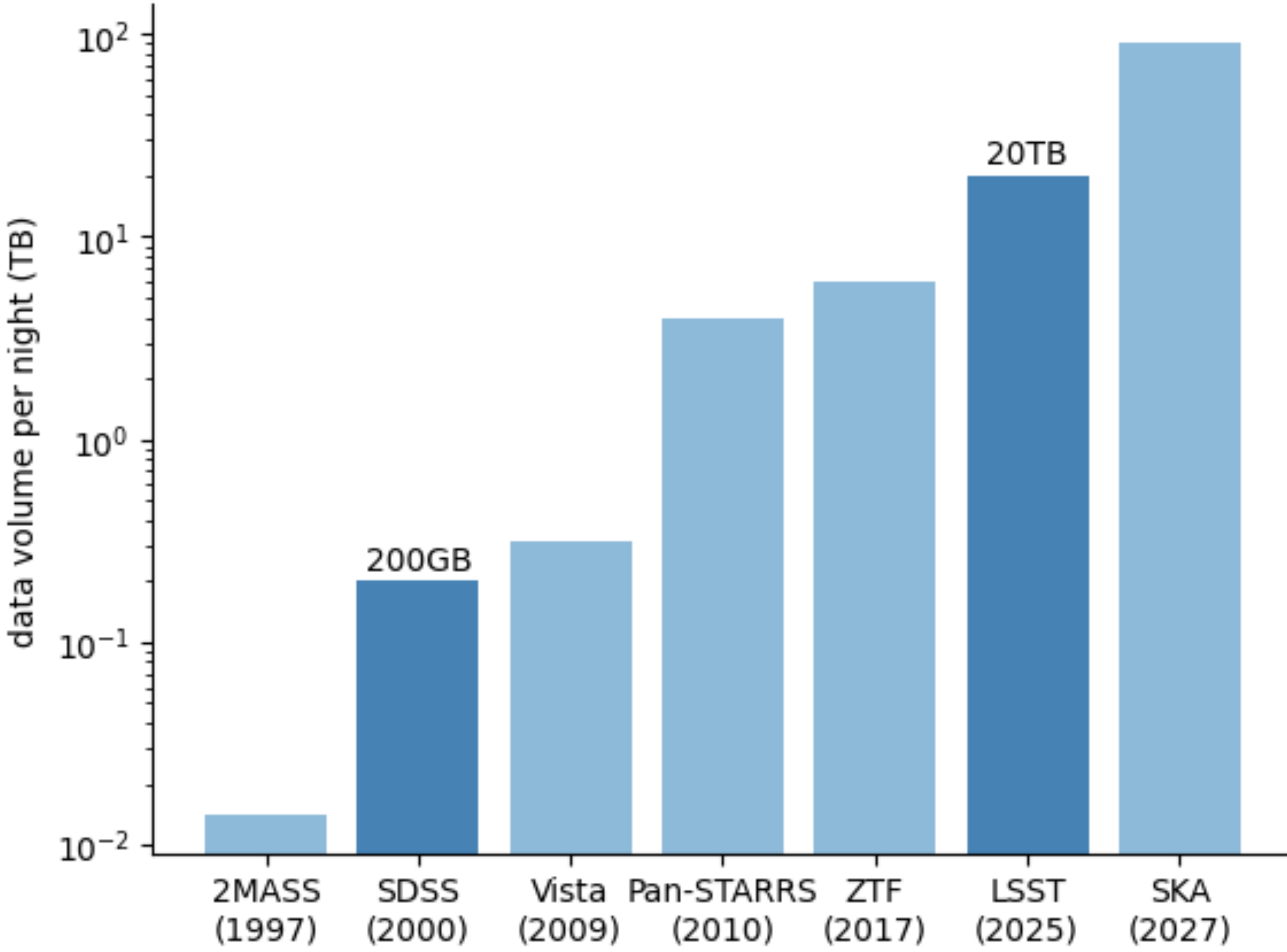
magnitude limit 10 year stacks r~27

spatial resolution 0.2'' (seeing limited)

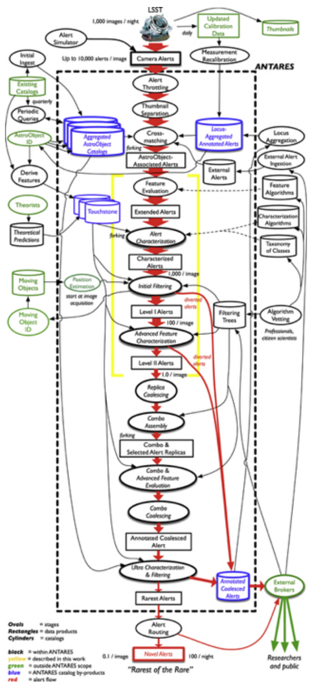
photometric precision 5mmag

photometric accuracy 10mmag

cadence.... that's a long story



the astronomy discovery chain

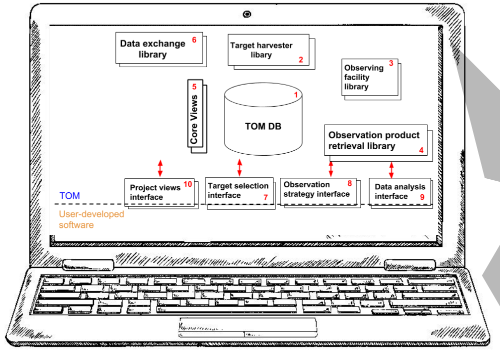


ALeRCE
Automatic Learning for the Rapid Classification of Events

ANTARES
beta

Lasair

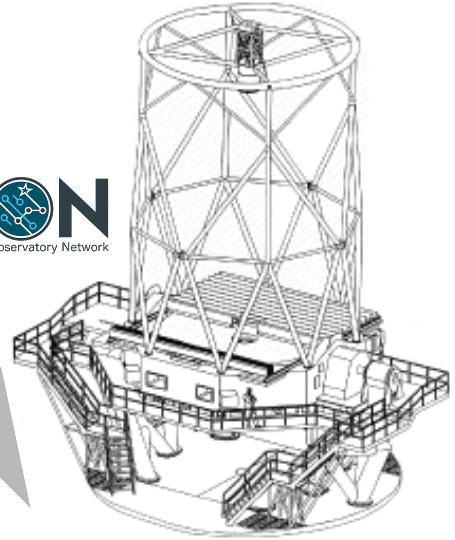
FINK

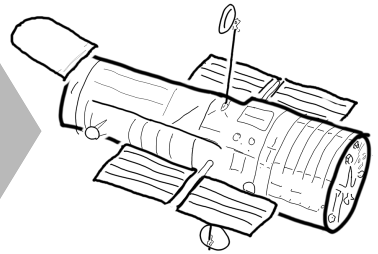


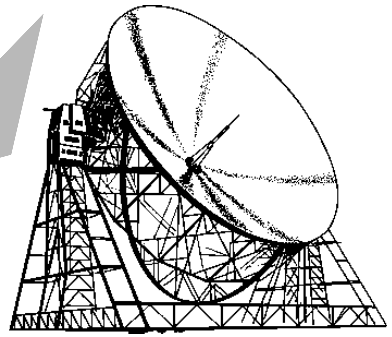
TOM
TOM TOOLKIT

SkyPortal
An Astronomical Data Platform

AEON
Astronomical Event Observatory Network







Discovery

Distribution

Classification

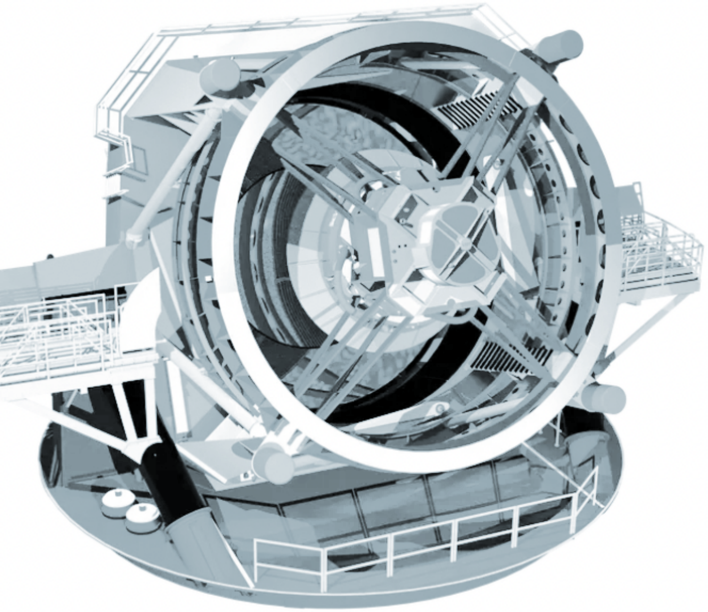
Data Integration and Follow up

Ensamble Inference

Prediction

Discovery of Novelties

(A.K.A science!)



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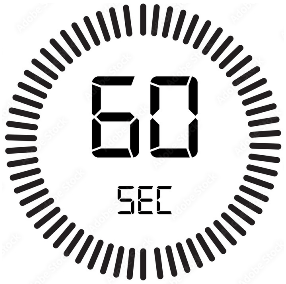
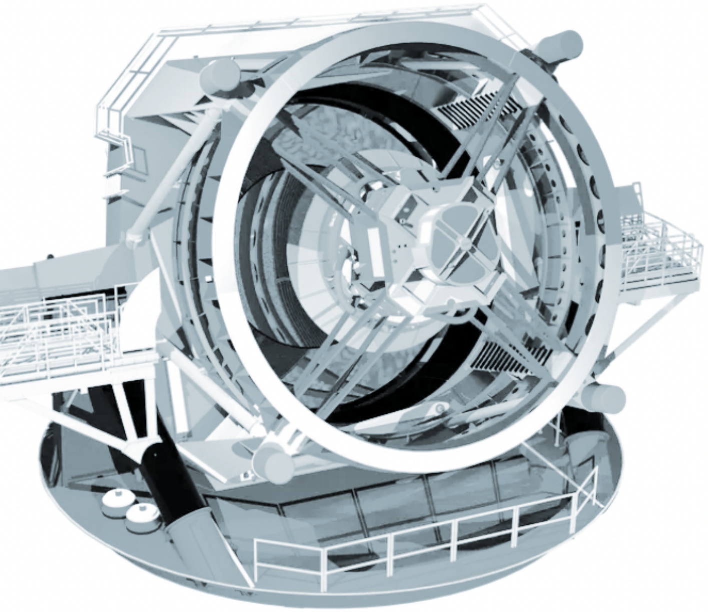
Distribution



Discovery



Data Integration and Follow up

Ensamble Inference

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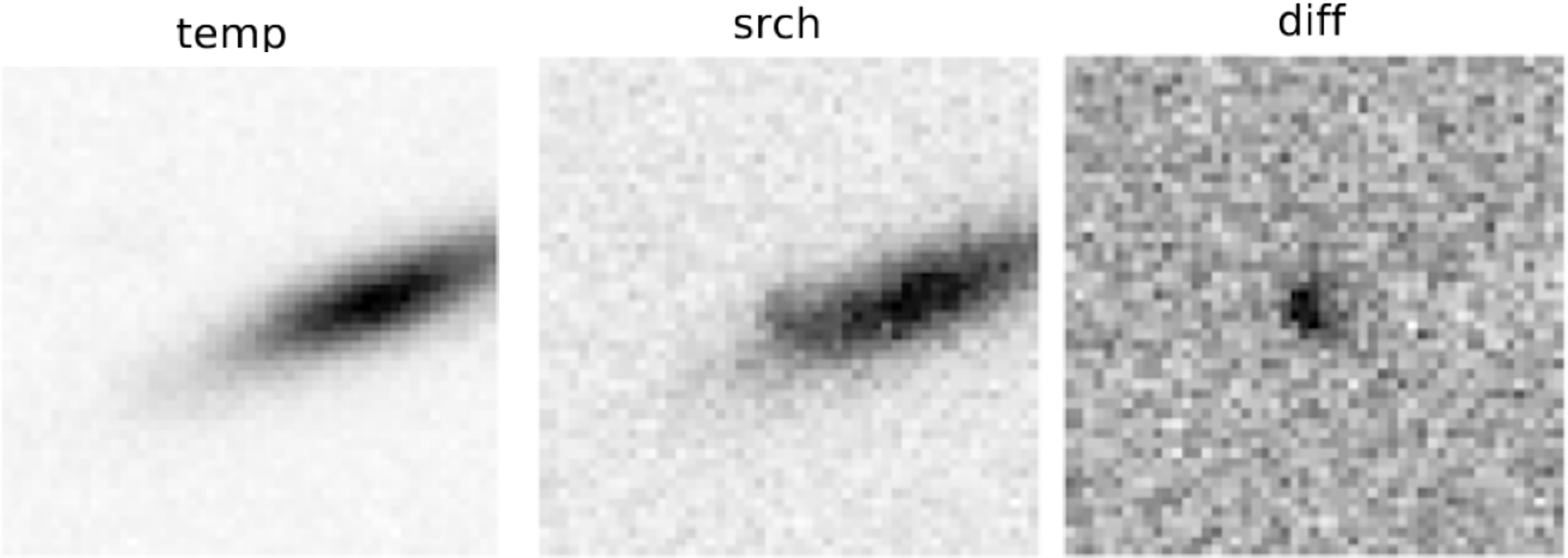
(A.K.A science!)

in <60 seconds:
Difference Image Analysis

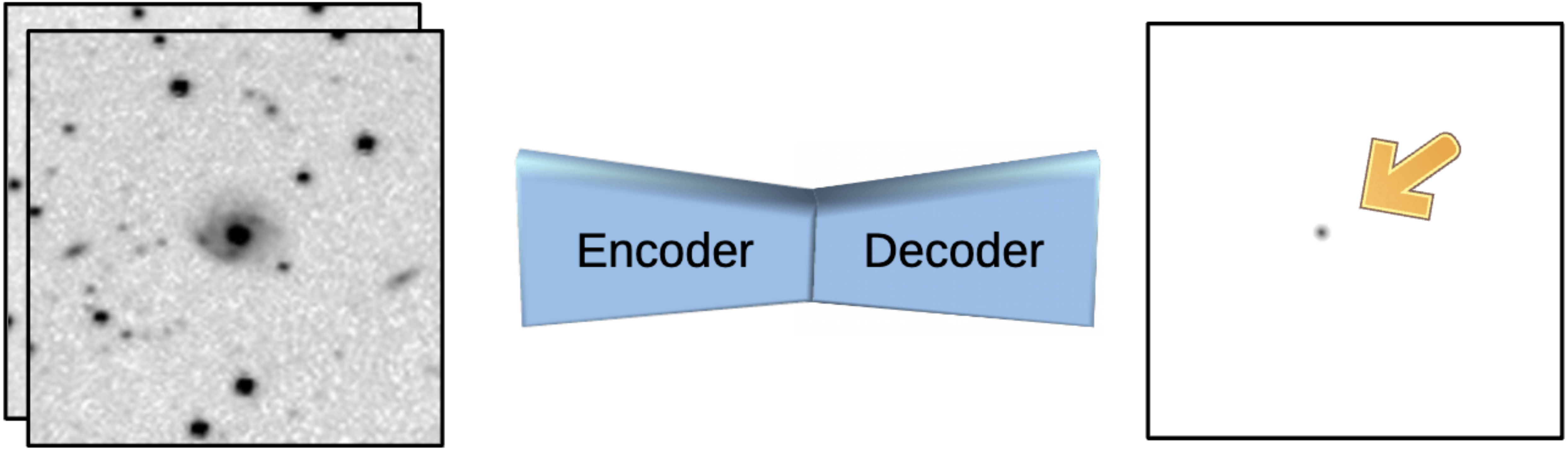


$$\mathrm{tmpl}(x, y) \otimes \mathrm{Kernel}(x, y, u, v) = \mathrm{srch}(x, y)$$

$$\mathrm{Kernel}\,(x, y, u, v) = \sum_n \sum_{d_n^x} \sum_{d_n^y} \sum_{\delta^x} \sum_{\delta^y} a_k x^{\delta^x} y^{\delta^y} \times e^{-(u^2+v^2)/2\sigma_n^2} u^{d_n^x} v^{d_n^y}$$

in <60 seconds:
Difference Image Analysis

Can we replace DIA with ANN?



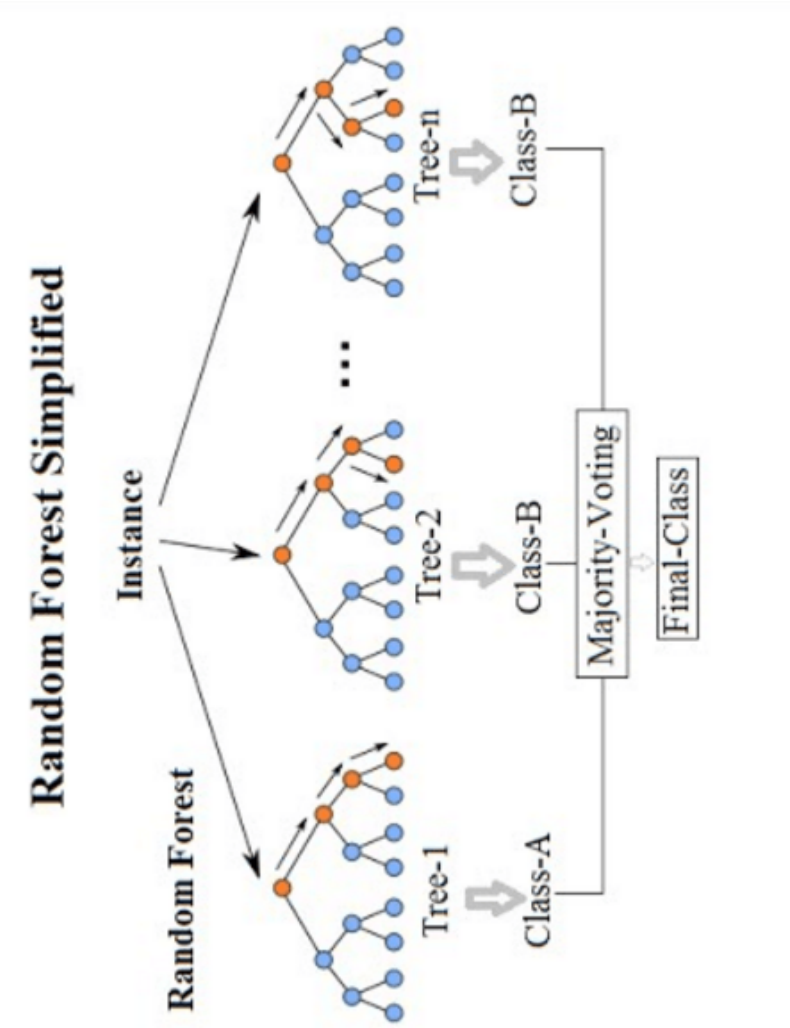
TANSINET: Sedhagat + Mahabal 2017

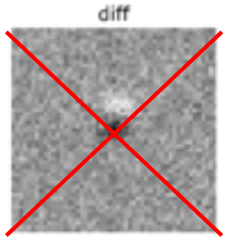
in 60 seconds:

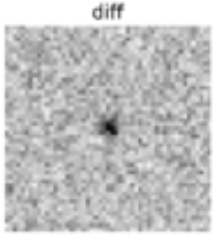
Difference Image Analysis + Bogus rejection

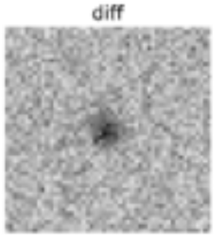
feature extraction + Random Forest

Object	MAG	···	30.0	Mag
	A_IMAGE	···	1.5 pix.	Len SEx
	SPREAD_MODEL	···	$3\sigma_S + 1.0$	Star fron SPR
	CHISQ	···	10^4	χ^2 arou
	SNR	3.5	···	Flu cut cert
	VETOMAG[a]	21.0	···	Mag cata
	VETOTOL[a]	Magnitude-dependent	···	Sep alog
	DIPOLE6	···	2	N_{pi} at l
	DIPOLE4	···	20	N_{pi} at l
	DIPOLE2	···	200	N_{pi} at l









AUTOSCAN: Goldstein+ 2017

OPEN ACCESS

What's the Difference? The Potential for Convolutional Neural Networks for Transient Detection without Template Subtraction

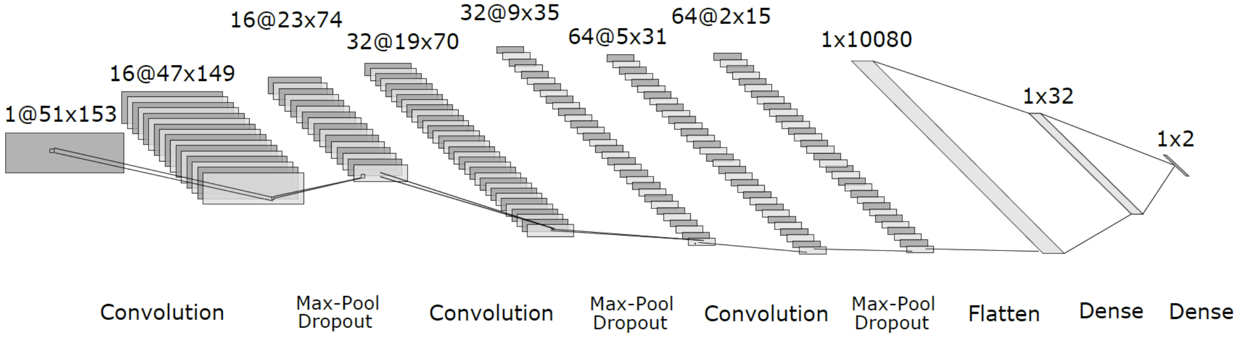
Tatiana Acero-Cuellar[1,2], Federica Bianco[1,3,4,5], Gregory Dobler[1,3,4], Masao Sako[6], Helen Qu[6], and The LSST Dark Energy Science Collaboration

Published 2023 August 18 •

The Astronomical Journal, Volume 166, Number 3

Citation Tatiana Acero-Cuellar *et al* 2023 *AJ* **166** 115

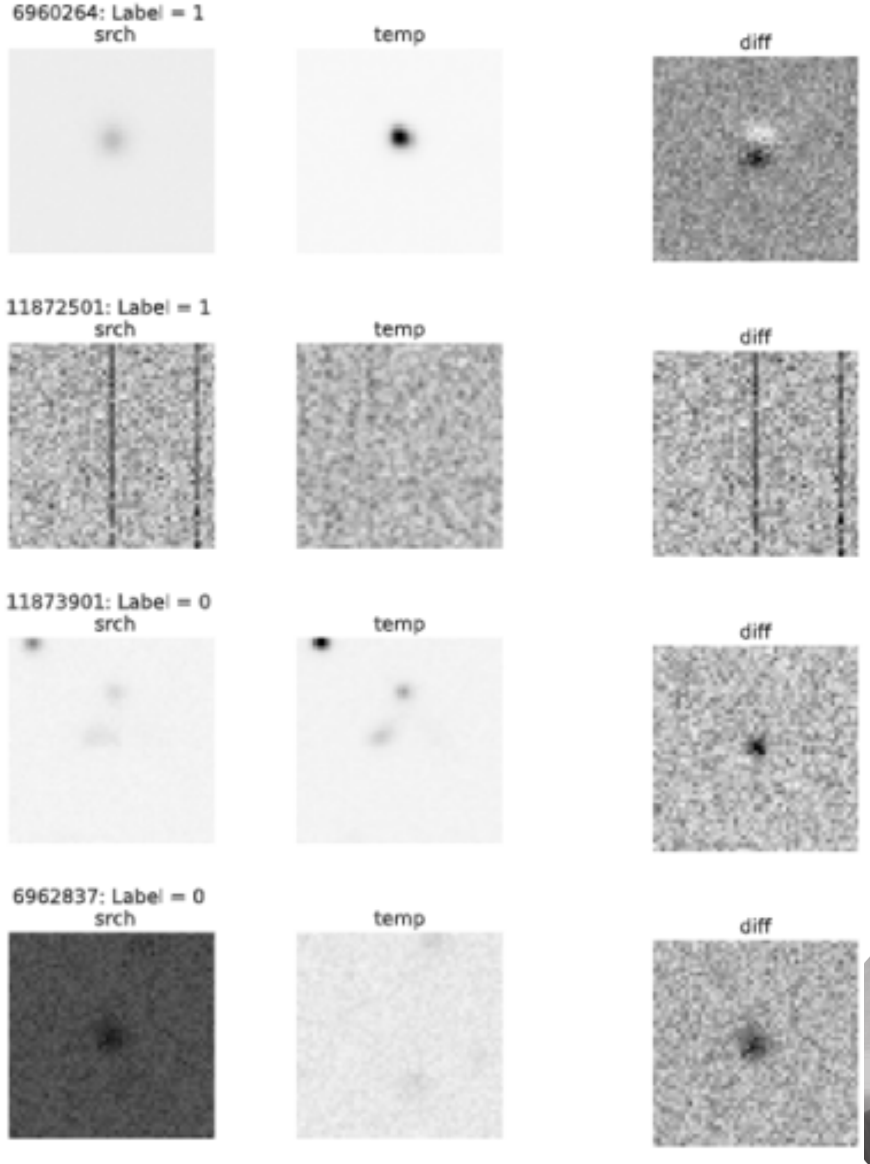
DOI 10.3847/1538-3881/ace9d8

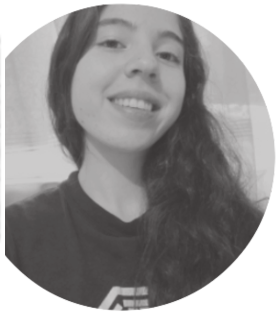


Model	Accuracy		Train time (CPU hours)	Prediction* (Clock-time, ms)
	Train	Test		
DIA-based	0.962	0.959 ± 0.004	~35	1.00 ± 0.03

96% accurate

search - template = difference





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Tatiana Acero-Cuellar[1,2], Federica Bianco[1,3,4,5], Gregory Dobler[1,3,4], Masao Sako[6], Helen Qu[6], and The LSST Dark Energy Science Collaboration

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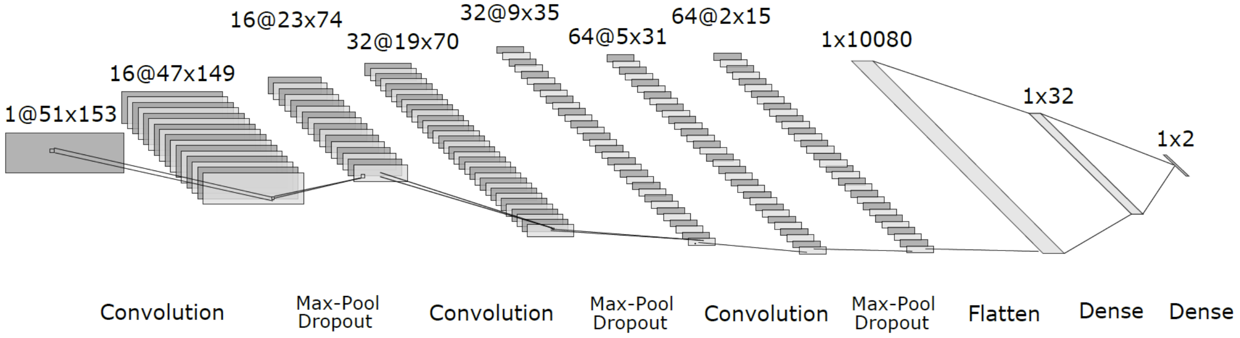
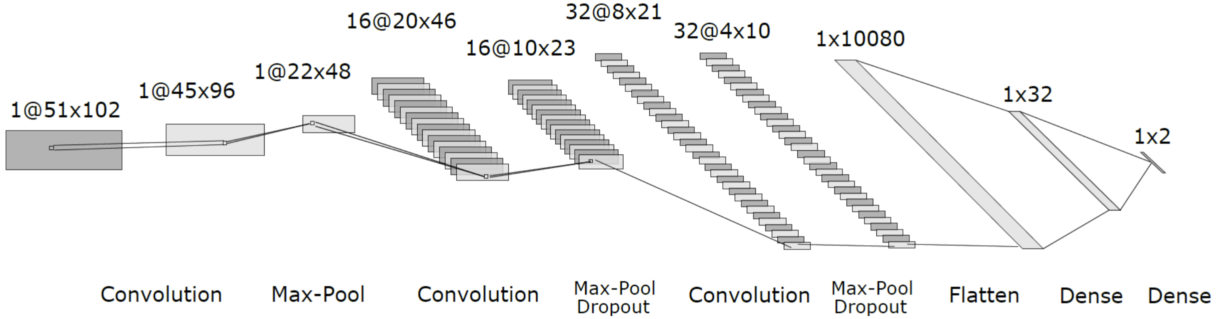
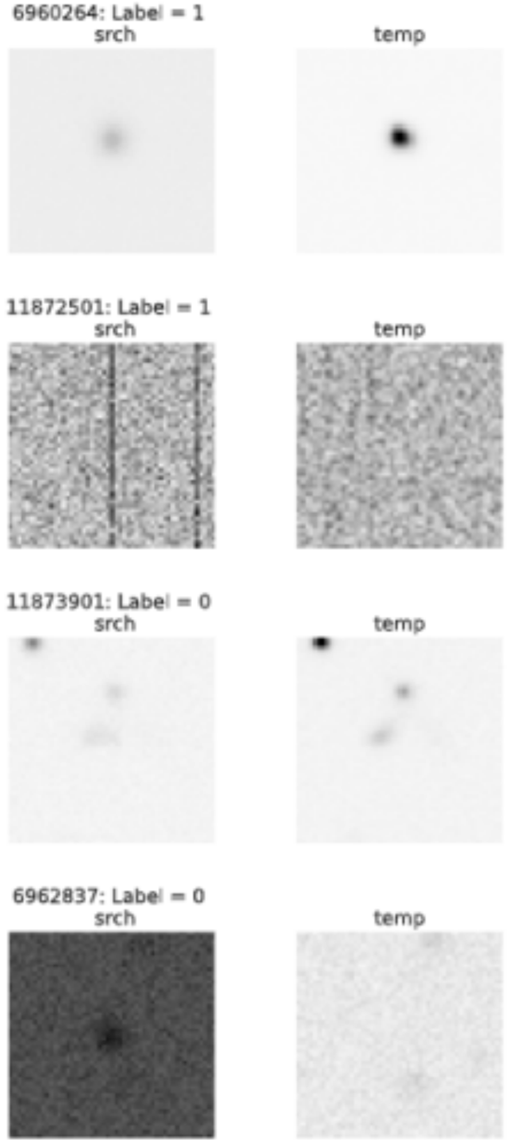




Model	Accuracy		Train time (CPU hours)	Prediction* (Clock-time, ms)
	Train	Test		
DIA-based	0.962	0.959 ± 0.004	~35	1.00 ± 0.03
noDIA	0.915	0.916 ± 0.007	~56	0.30 ± 0.01

92% accurate

search - template = difference



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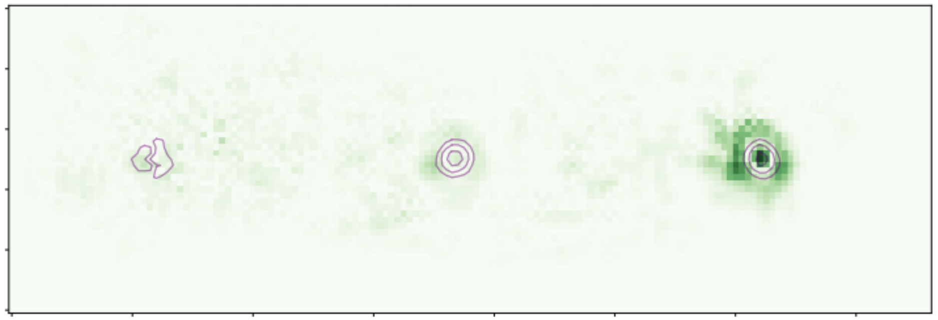
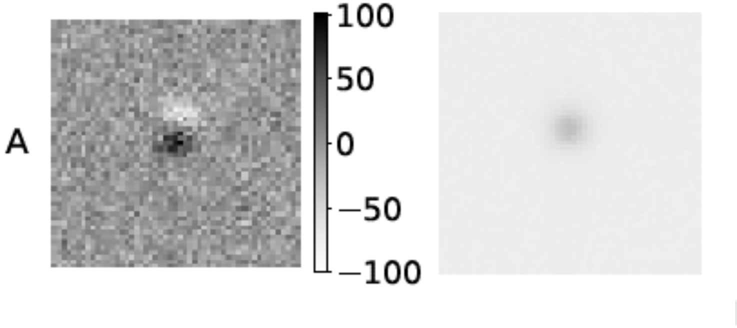
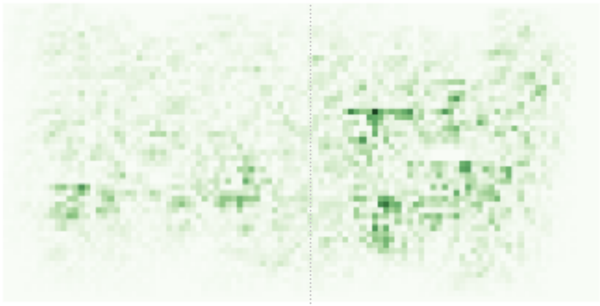
What is the network learning?

What can we learn from the AI?







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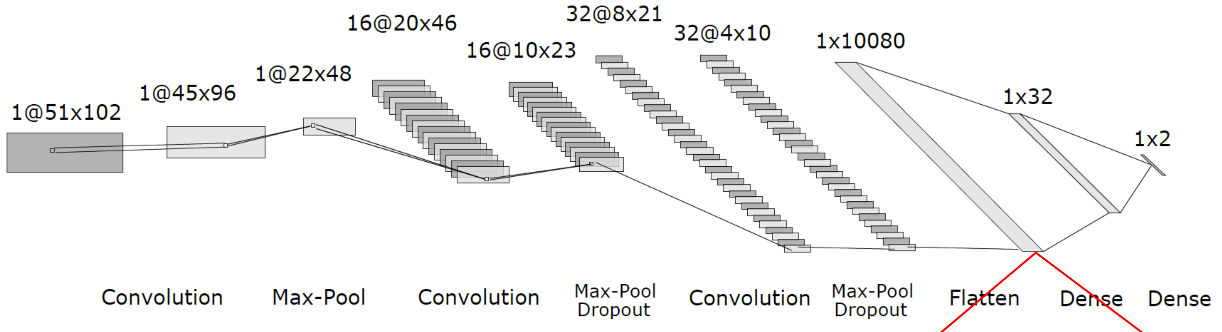
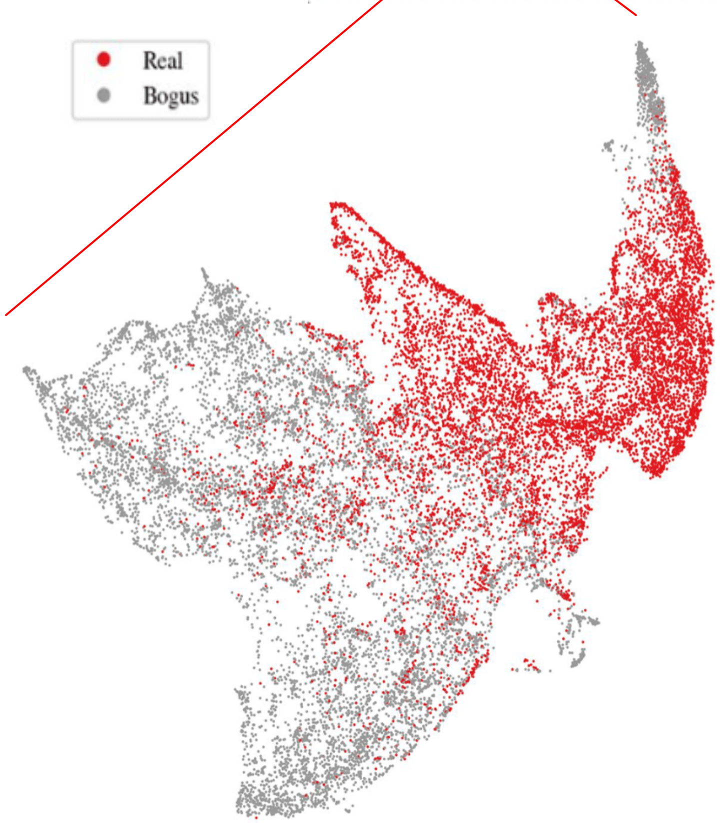
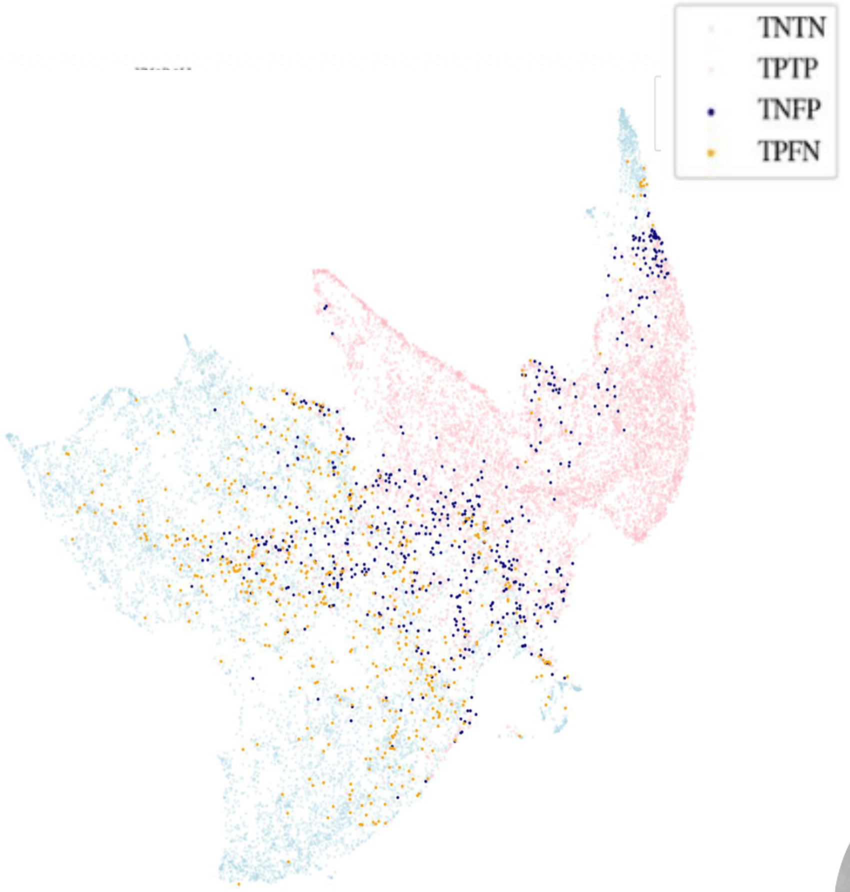


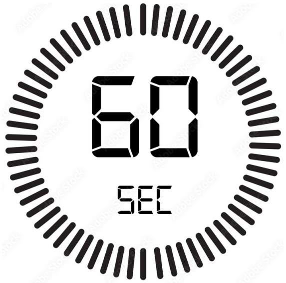




Classification

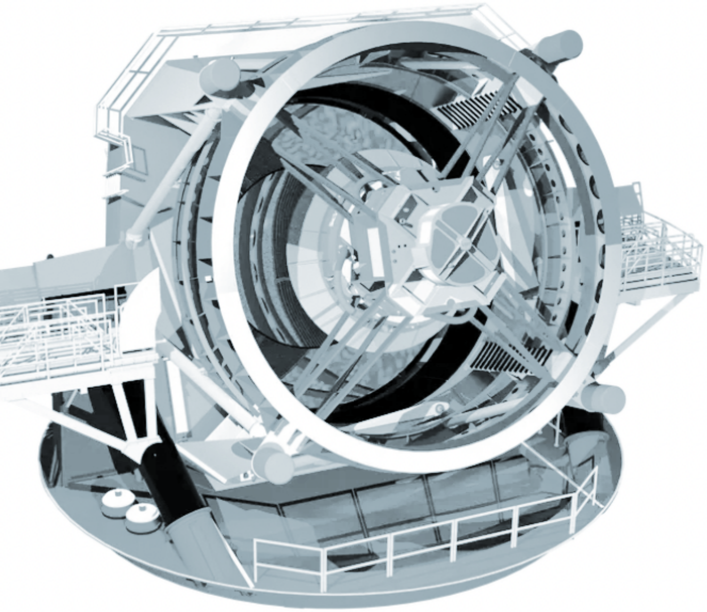
Distribution

ALeRCE
ANTARES
AMPEL
BABA-MUL
FINK
LASAIR



Discovery

Data Integration and Follow up

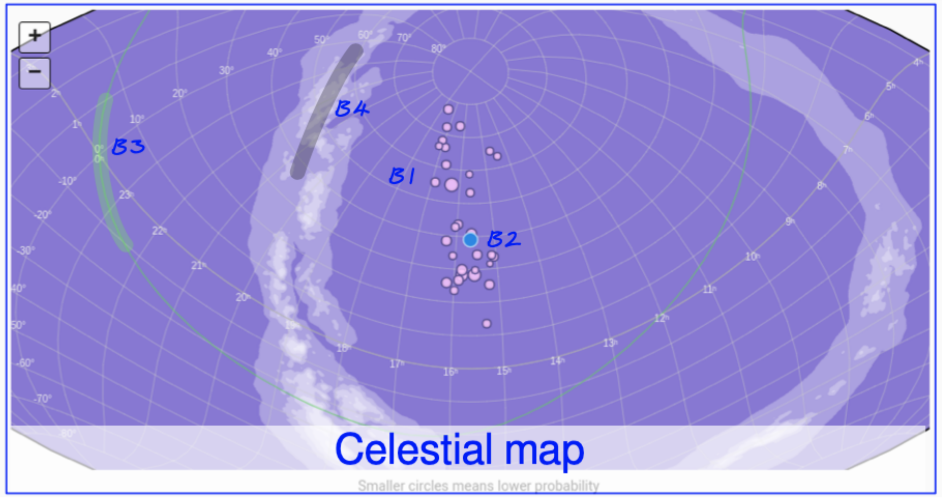


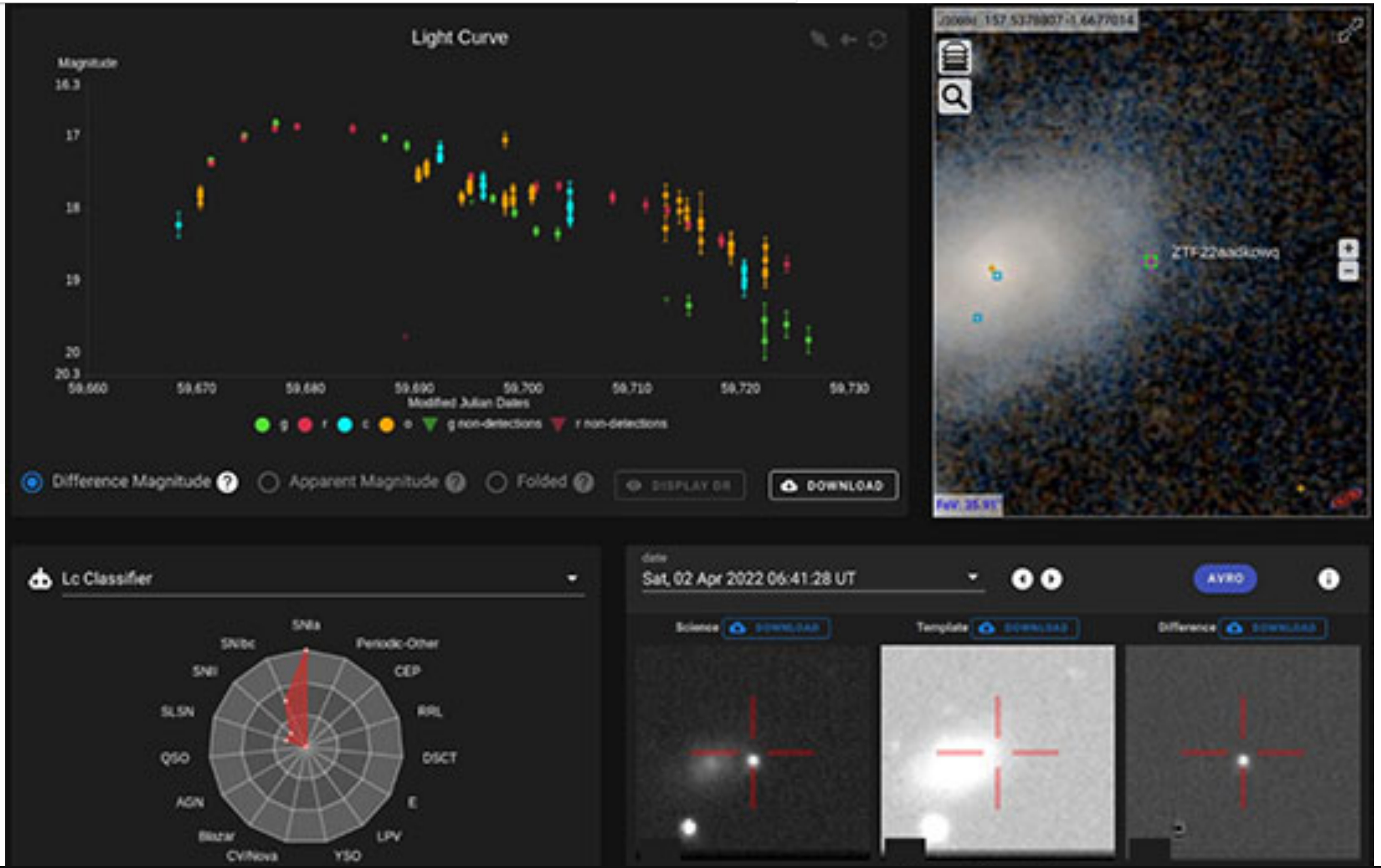
Ensamble Inference

Prediction

Discovery of Novelties

(A.K.A science!)

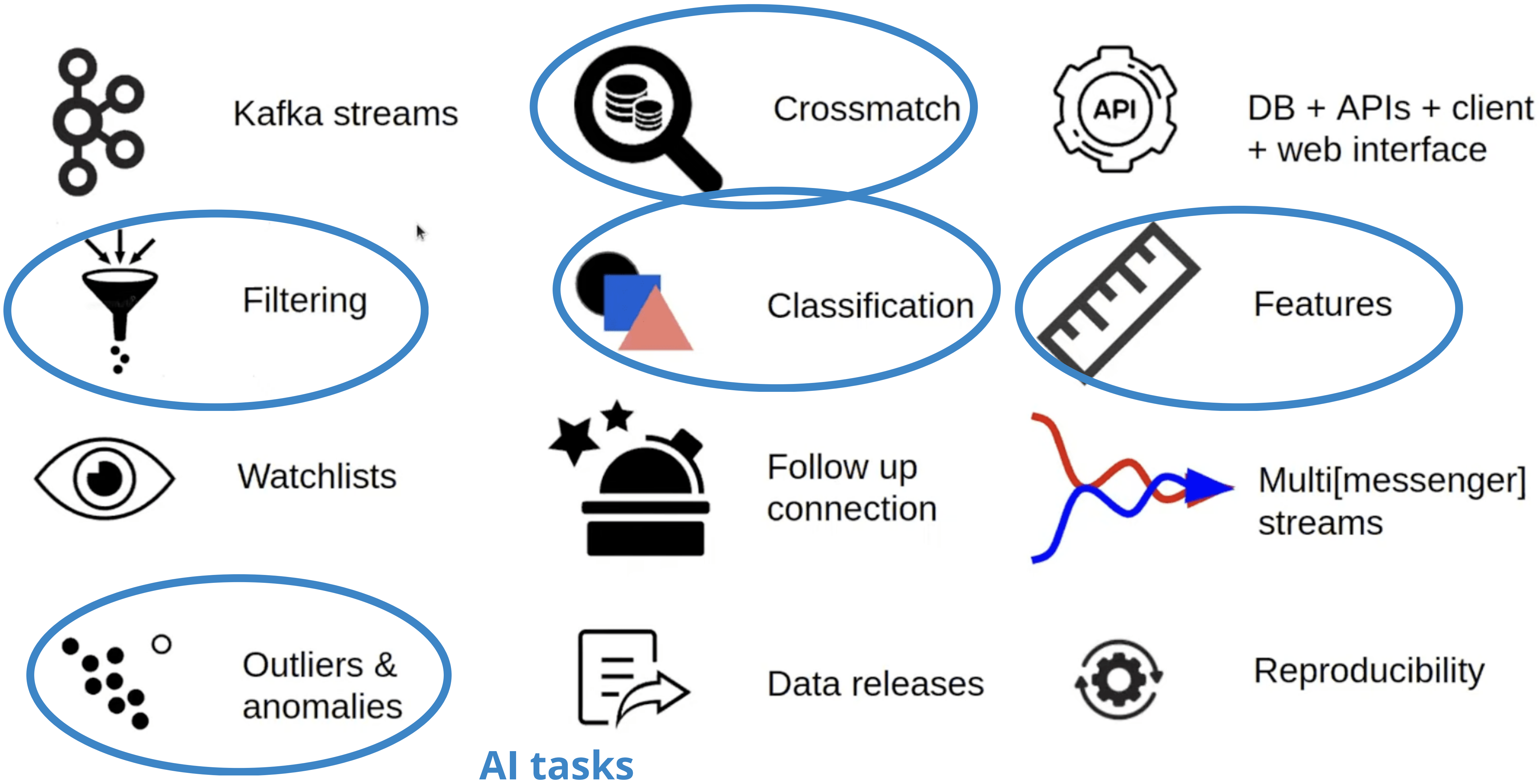


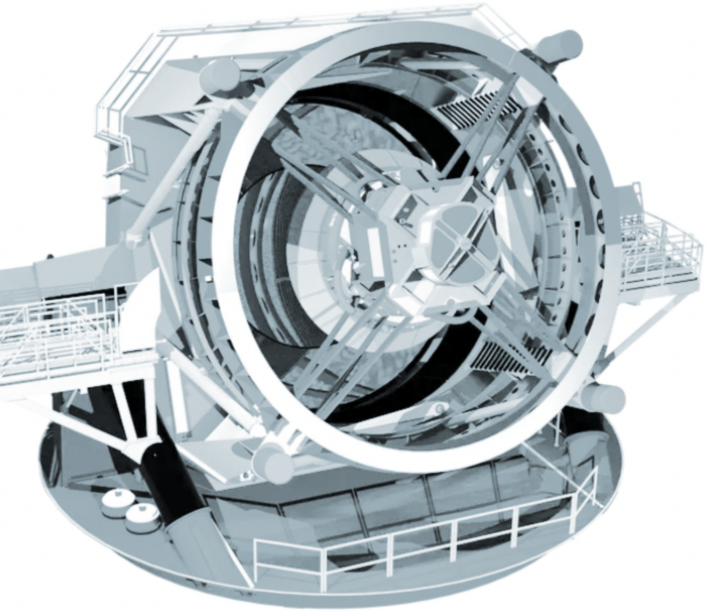


The Automatic Learning for the Rapid Classification of Events (ALeRCE) Alert Broker

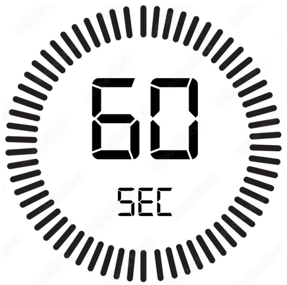
F. Förster et al 2021 AJ 161 242

Products / services offered by brokers



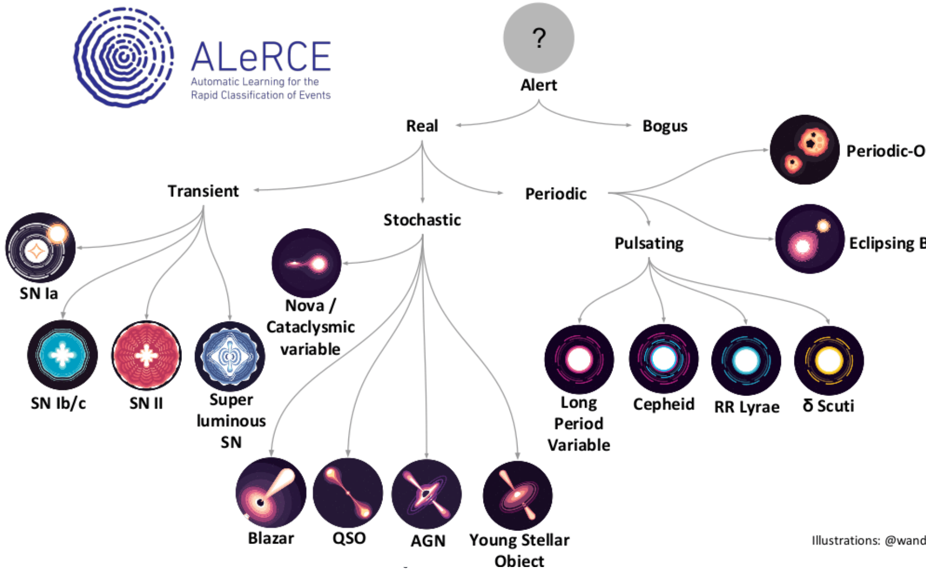


Discovery



Distribution

Classification



Data Integration and Follow up

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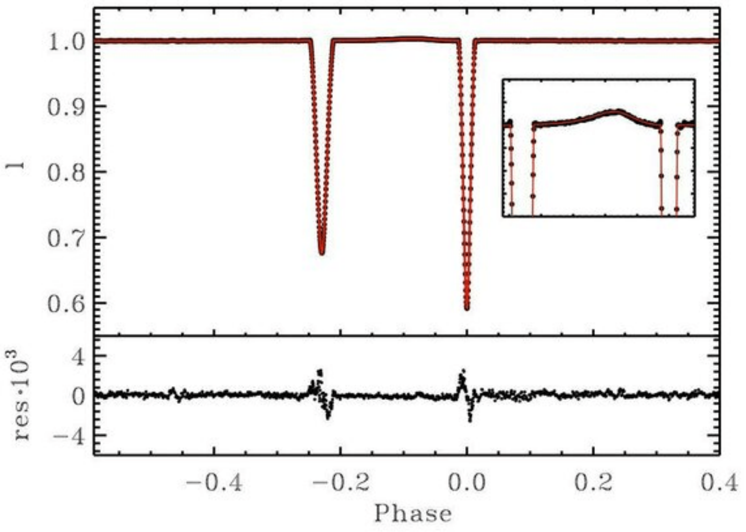
Discovery of Novelties

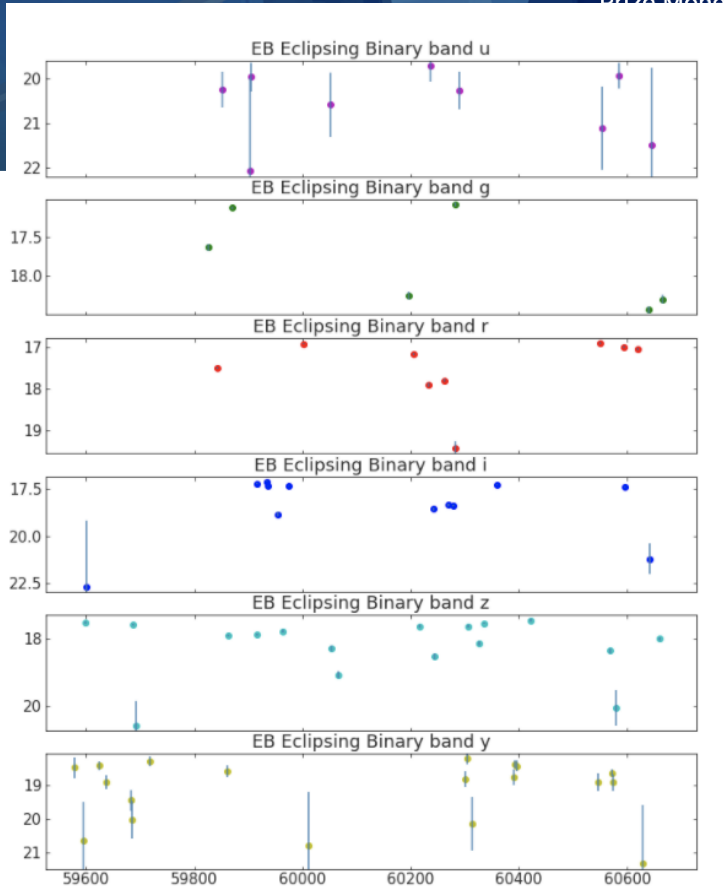
(A.K.A science!)

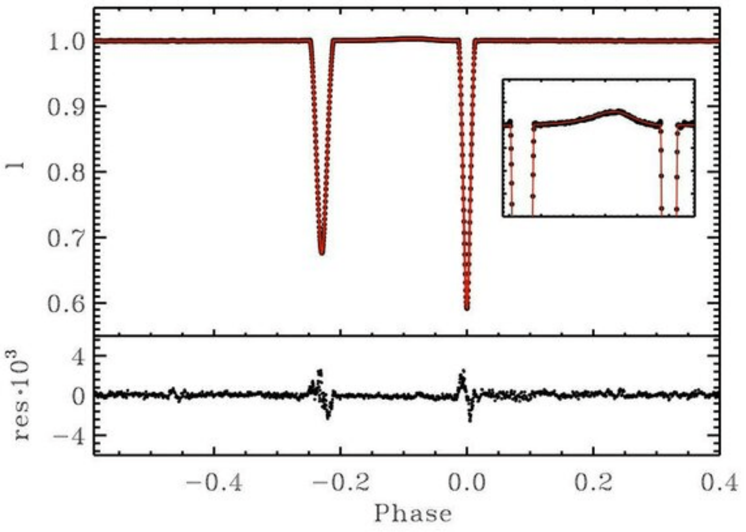
Photometric Classification of transients



KIC 3858884: A hybrid δ Scuti pulsator in a highly eccentric eclipsing binary

Photometric Classification of transients



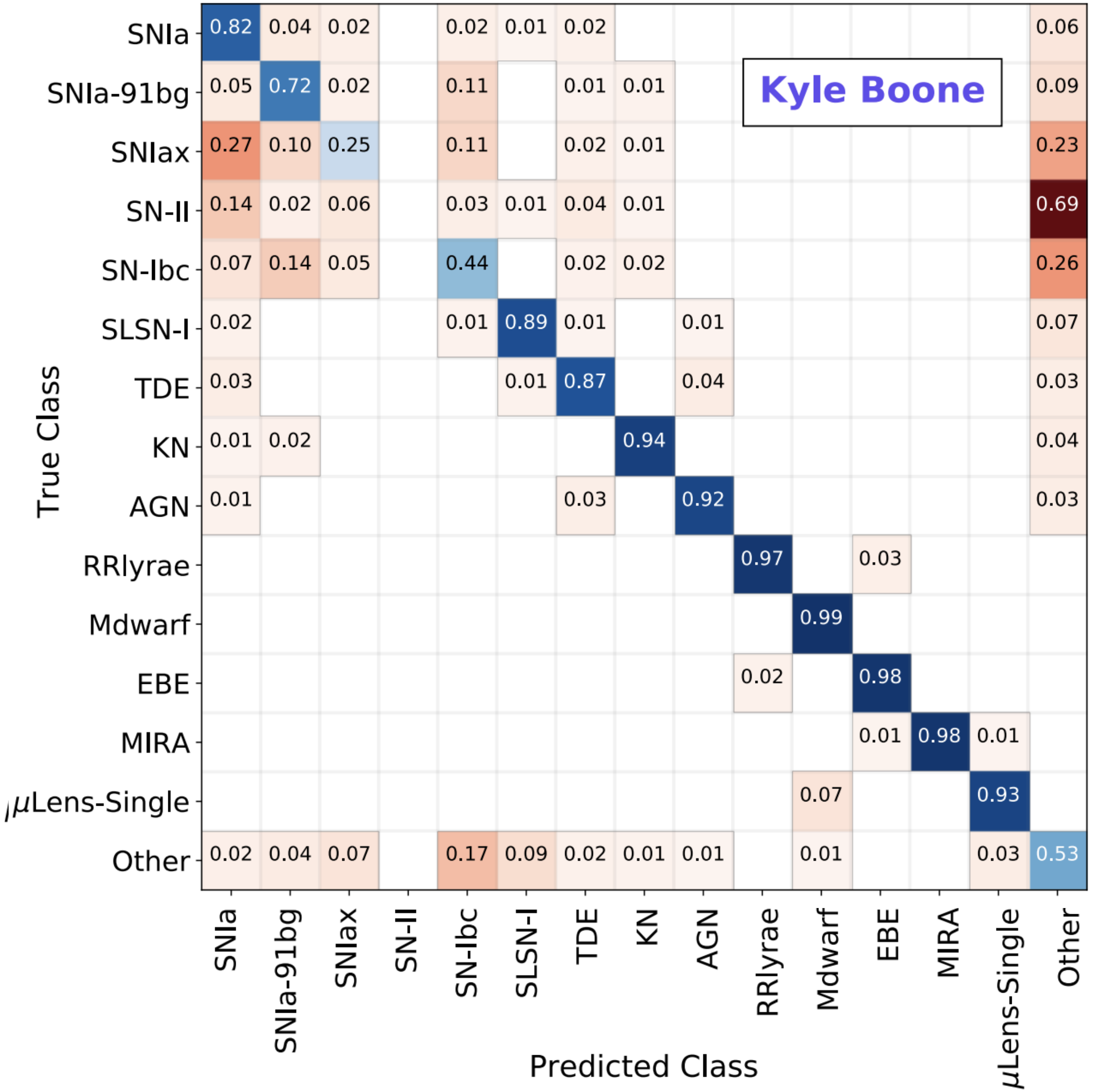


Classification from sparse data: Lightcurves

https://arxiv.org/abs/1907.04690

The PLAsTiCC challenge winnre, Kyle Boone was a grad student at Berkeley, and did not sue a Neural Network!

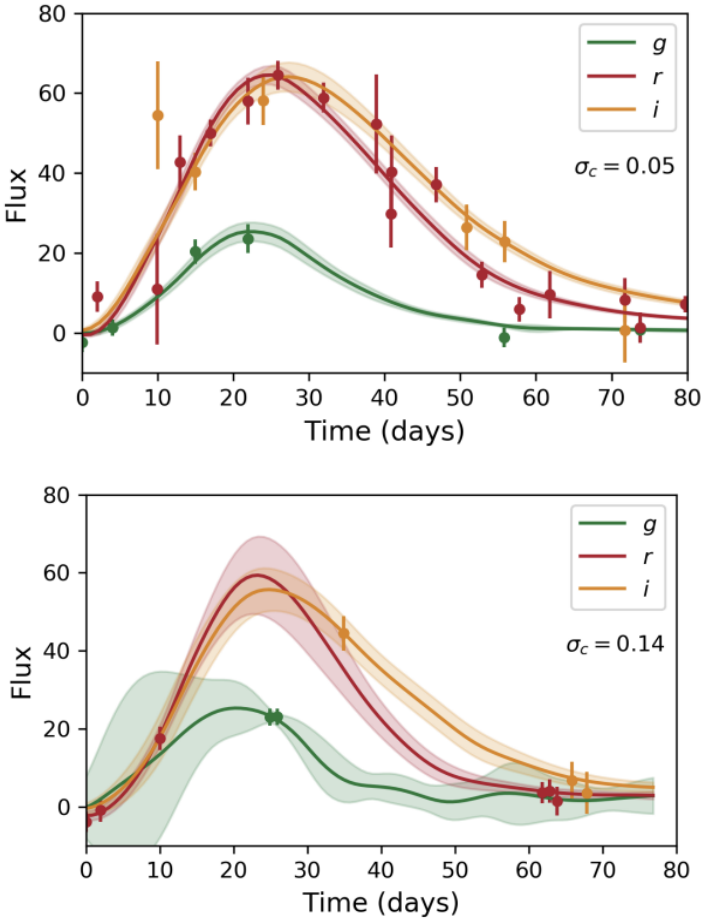
He won $2,000



Classification from sparse data: Lightcurves

https://arxiv.org/abs/1907.04690

https://arxiv.org/pdf/1812.00515.pdf



Avocado: Photometric Classification of Astronomical Transients with Gaussian Process Augmentation

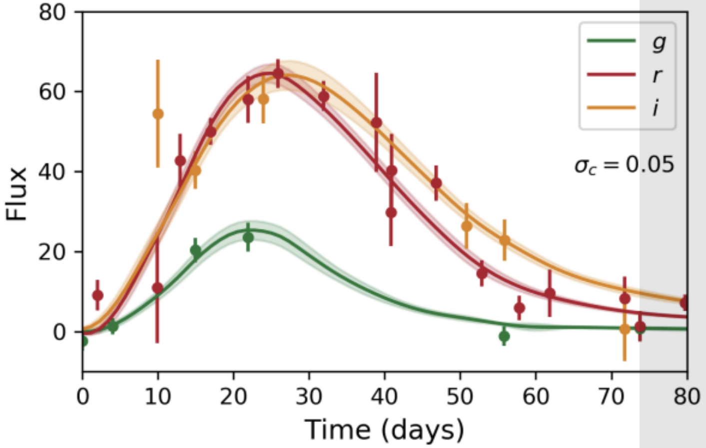
Kyle Boone[1,2]

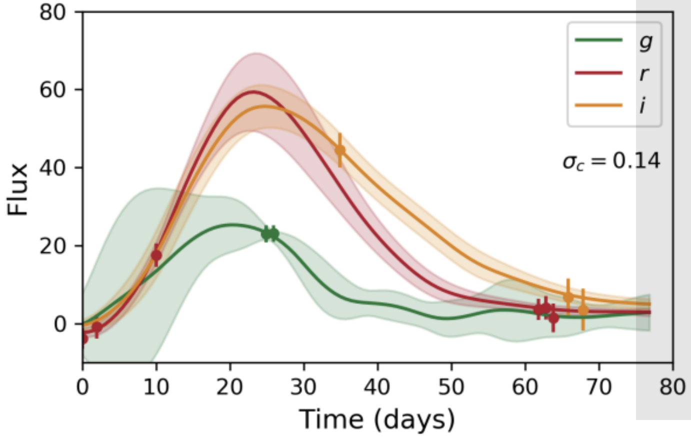
[1] *Physics Division, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA, 94720, USA*
[2] *Department of Physics, University of California Berkeley, 366 LeConte Hall MC 7300, Berkeley, CA, 94720-7300, USA*

ABSTRACT

Upcoming astronomical surveys such as the Large Synoptic Survey Telescope (LSST) will rely on photometric classification to identify the majority of the transients and variables that they discover. We present a set of techniques for photometric classification that can be applied even when the training set of spectroscopically-confirmed objects is heavily biased towards bright, low-redshift objects. Using Gaussian process regression to model arbitrary light curves in all bands simultaneously, we "augment" the training set by generating new versions of the original light curves covering a range of redshifts and observing conditions. We train a boosted decision tree classifier on features extracted from the augmented light curves, and we show how such a classifier can be designed to produce classifications that are independent of the redshift distributions of objects in the training sample. Our classification algorithm was the best-performing among the 1,094 models considered in the blinded phase of the Photometric LSST Astronomical Time-Series Classification Challenge (PLAsTiCC), scoring 0.468 on the organizers' logarithmic-loss metric with flat weights for all object classes in the training set, and achieving an AUC of 0.957 for classification of Type Ia supernovae. Our results suggest that spectroscopic campaigns used for training photometric classifiers should focus on typing large numbers of well-observed, intermediate redshift transients instead of attempting to type a sample of transients that is directly representative of the full dataset being classified. All of the algorithms described in this paper are implemented in the avocado software package[a].

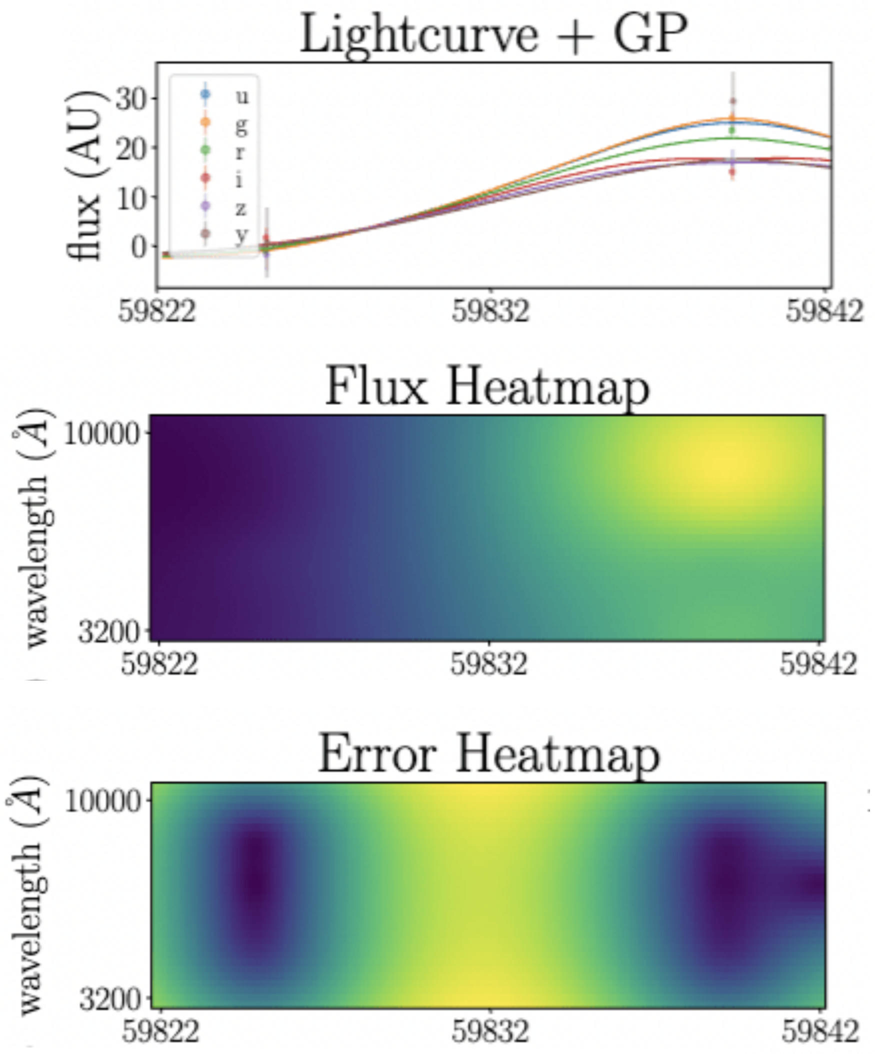
https://arxiv.org/pdf/1812.00515.pdf





https://smlbook.org/GP/

Classification from sparse data: Lightcurves



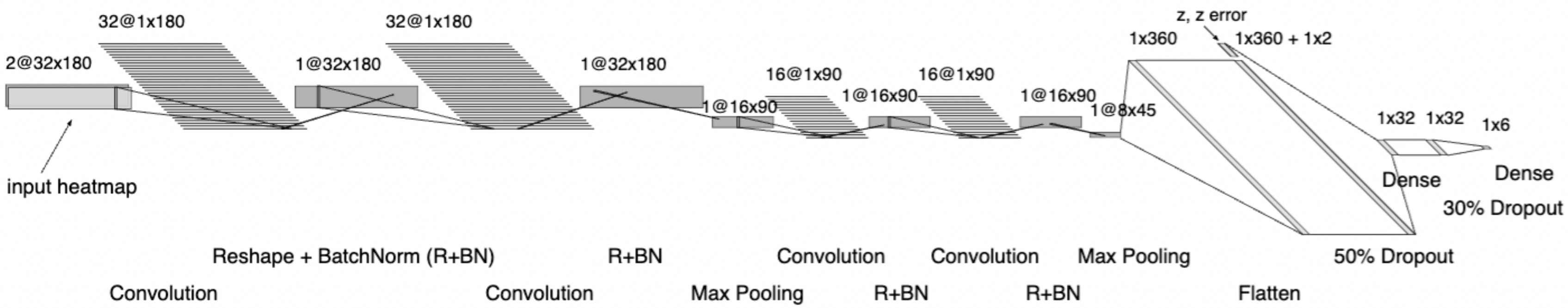
Photometric Classification of Early-Time Supernova Lightcurves with SCONE

Helen Qu[1] and Masao Sako[1]

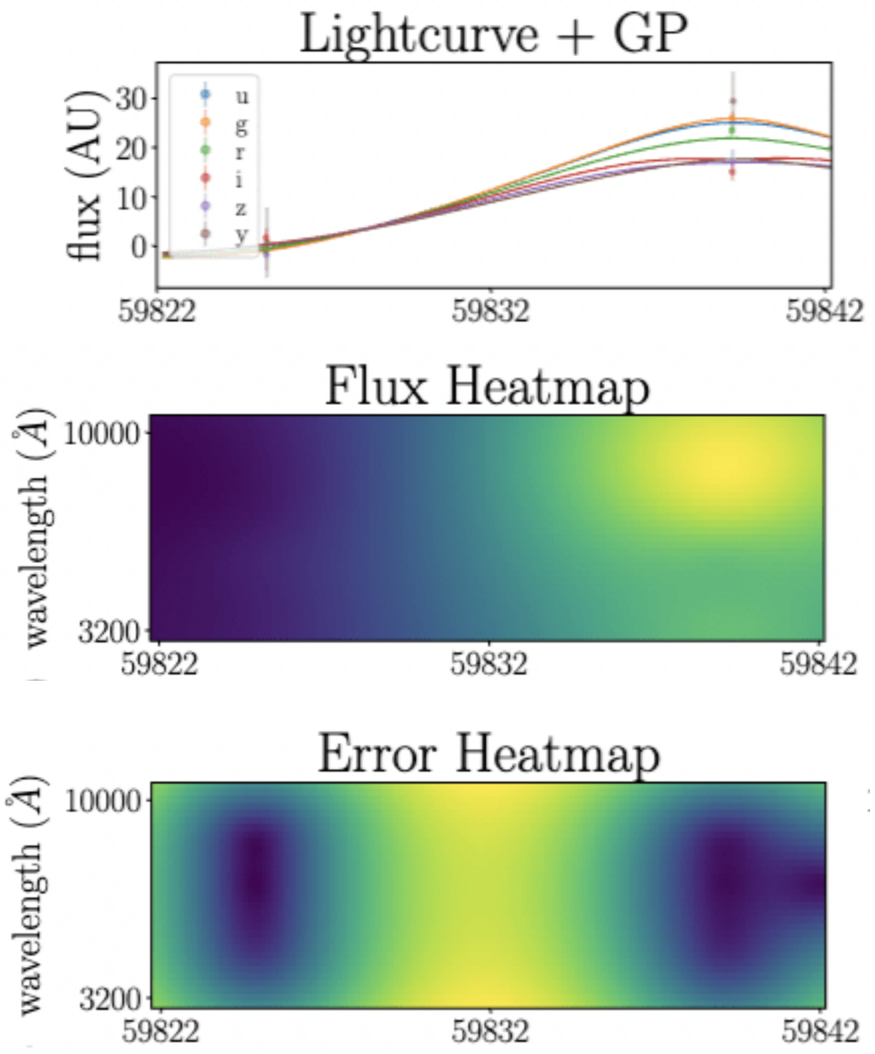
[1] *Department of Physics and Astronomy, University of Pennsylvania, Philadelphia, PA 19104, USA*

ABSTRACT

In this work, we present classification results on early supernova lightcurves from SCONE, a photometric classifier that uses convolutional neural networks to categorize supernovae (SNe) by type using lightcurve data. SCONE is able to identify SN types from lightcurves at any stage, from the night of initial alert to the end of their lifetimes. Simulated LSST SNe lightcurves were truncated at 0, 5, 15, 25, and 50 days after the trigger date and used to train Gaussian processes in wavelength and time space to produce wavelength-time heatmaps. SCONE uses these heatmaps to perform 6-way classification between SN types Ia, II, Ibc, Ia-91bg, Iax, and SLSN-I. SCONE is able to perform classification with or without redshift, but we show that incorporating redshift information improves performance at each epoch. SCONE achieved 75% overall accuracy at the date of trigger (60% without redshift), and 89% accuracy 50 days after trigger (82% without redshift). SCONE was also tested on bright subsets of SNe ($r < 20$ mag) and produced 91% accuracy at the date of trigger (83% without redshift) and 95% 5 days after trigger (94.7% without redshift). SCONE is the first application of convolutional neural networks to the early-time photometric transient classification problem. All of the data processing and model code developed for this paper can be found in the SCONE software package located at github.com/helenqu/scone (Qu 2021).



Classification from sparse data: Lightcurves



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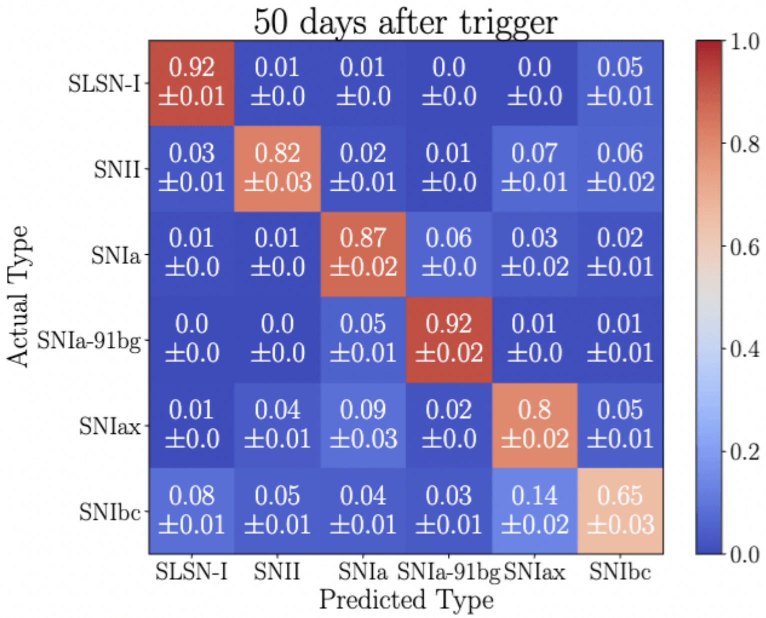
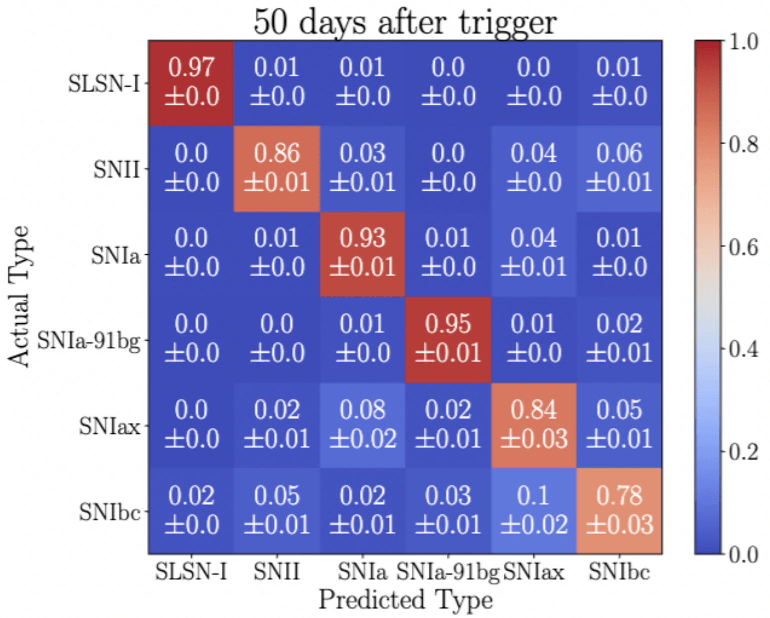
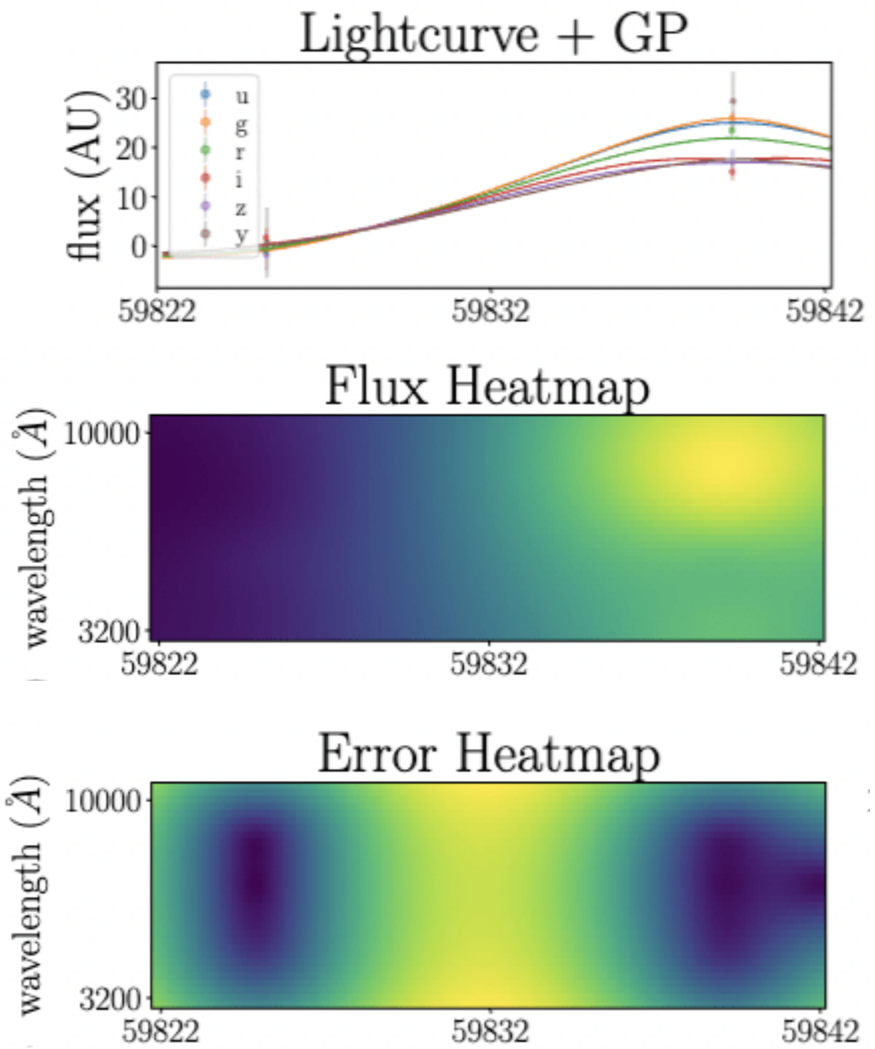
without redshift



with redshift



Classification from sparse data: Lightcurves



Photometric Classification of Early-Time Supernova Lightcurves with SCONE

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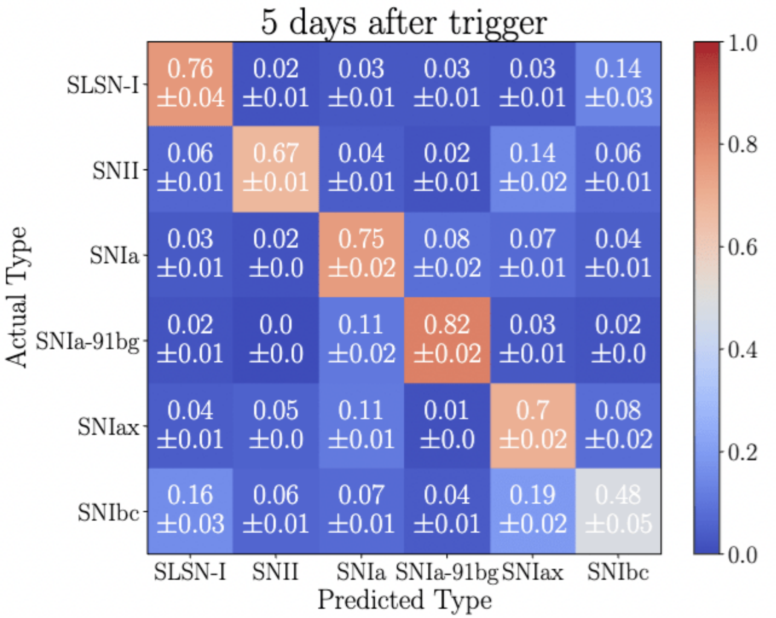
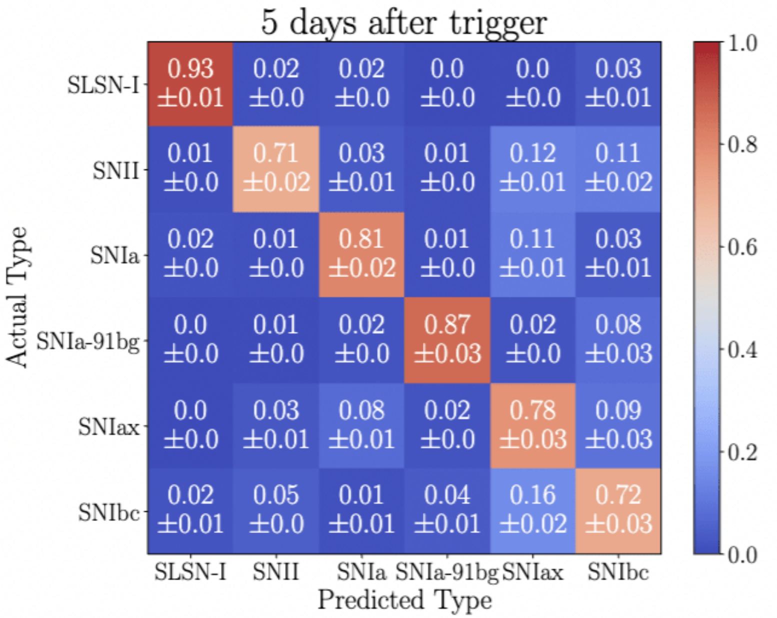
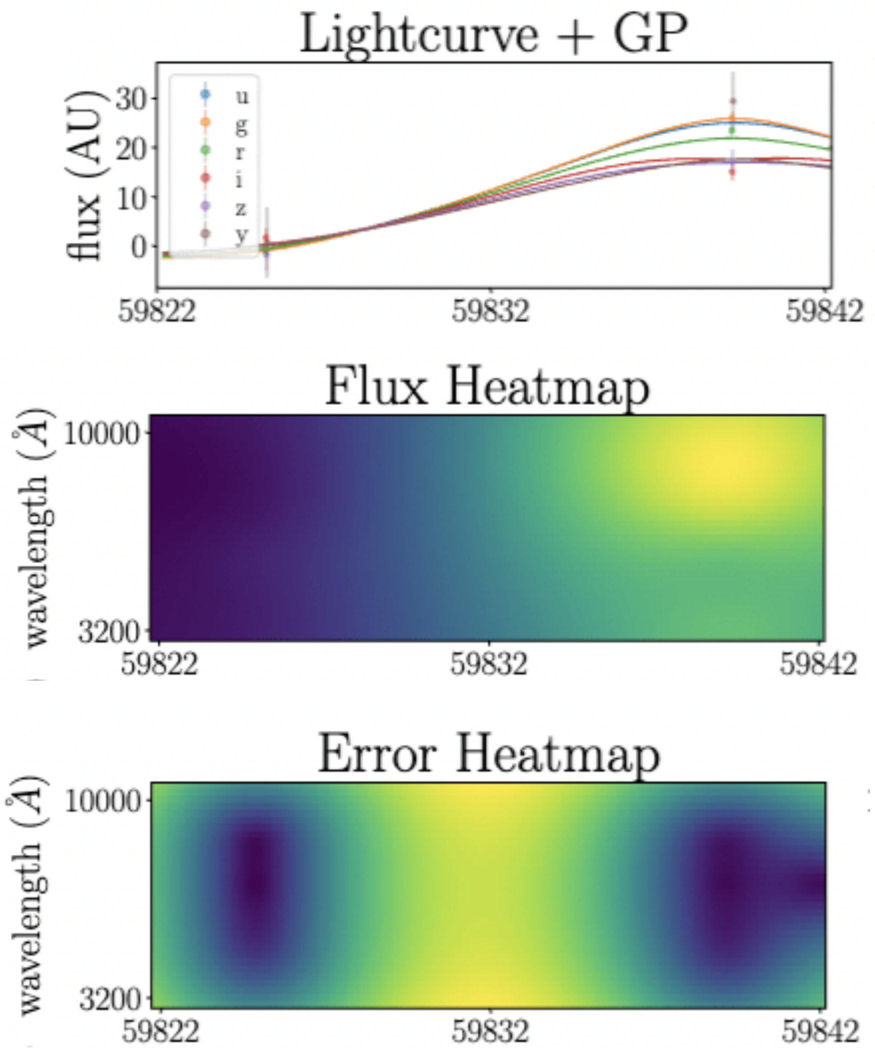
without redshift



with redshift



Classification from sparse data: Lightcurves



Photometric Classification of Early-Time Supernova Lightcurves with SCONE

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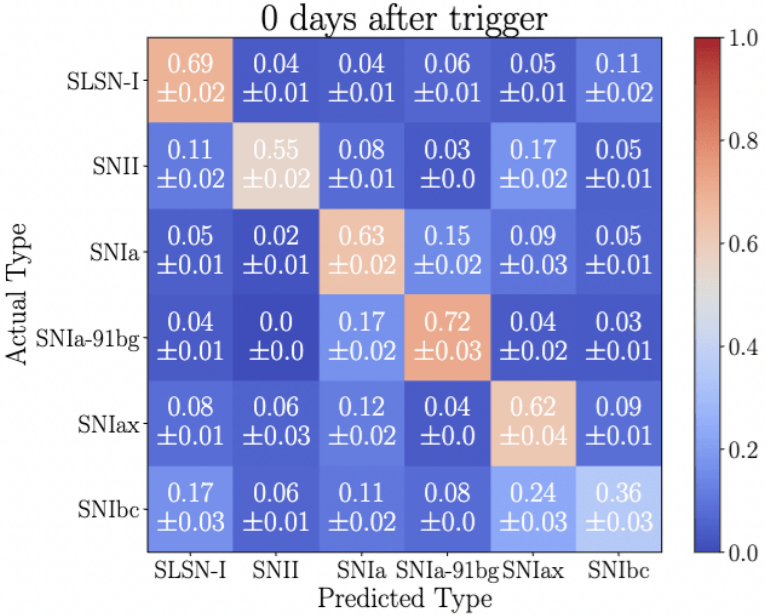
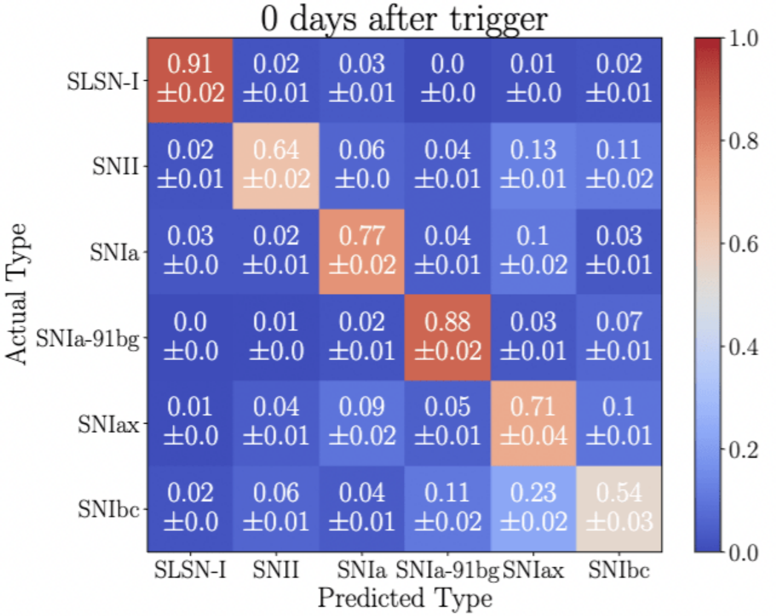
without redshift



with redshift



Classification from sparse data: Lightcurves

THE ASTRONOMICAL JOURNAL

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Deep Attention-based Supernovae Classification of Multiband Light Curves

Óscar Pimentel, Pablo A. Estévez, and Francisco Förster

Published 2022 December 16 • © 2022. The Author(s). Published by the American Astronomical Society.

The Astronomical Journal, Volume 165, Number 1

Citation Óscar Pimentel *et al* 2023 *AJ* **165** 18

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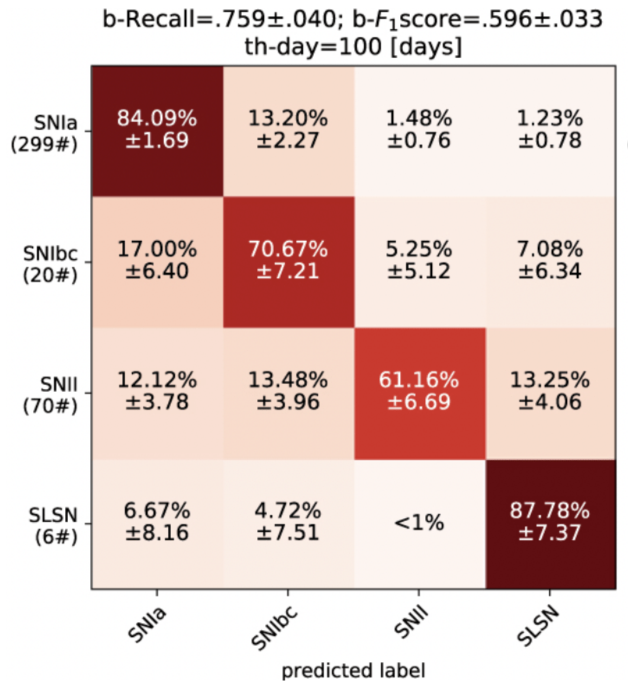

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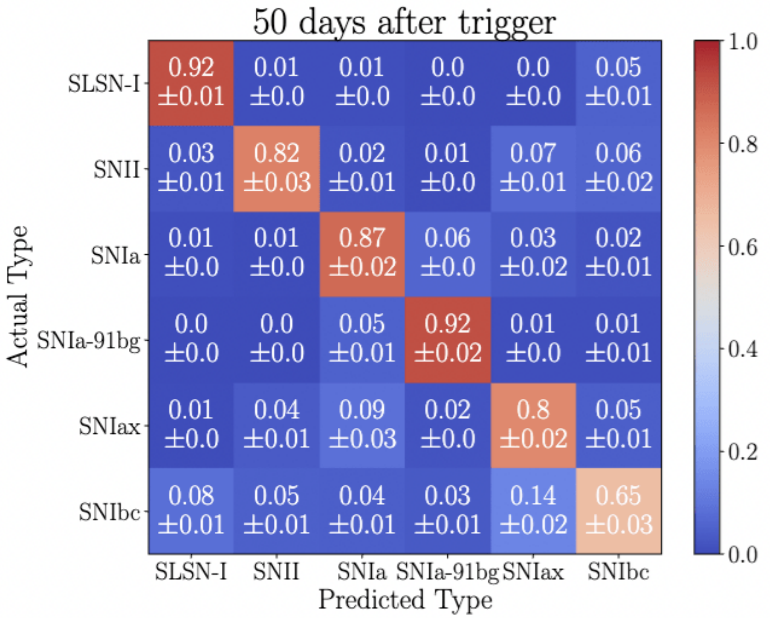

Methodological issues with these approaches

CNNs are not designed to ingest uncertainties. Passing them as an image layer "works" but it is not clear why since the convolution on the flux and error space are averaged after the first layer

Methodological issues with these approaches

Gaussian processes work by imposing a kernel that represents the covariance in the data (how data depend on time or time/wavelength). Imposing the same kernel for different time-domain phenomena is principally incorrect

=> bias toward known classes!

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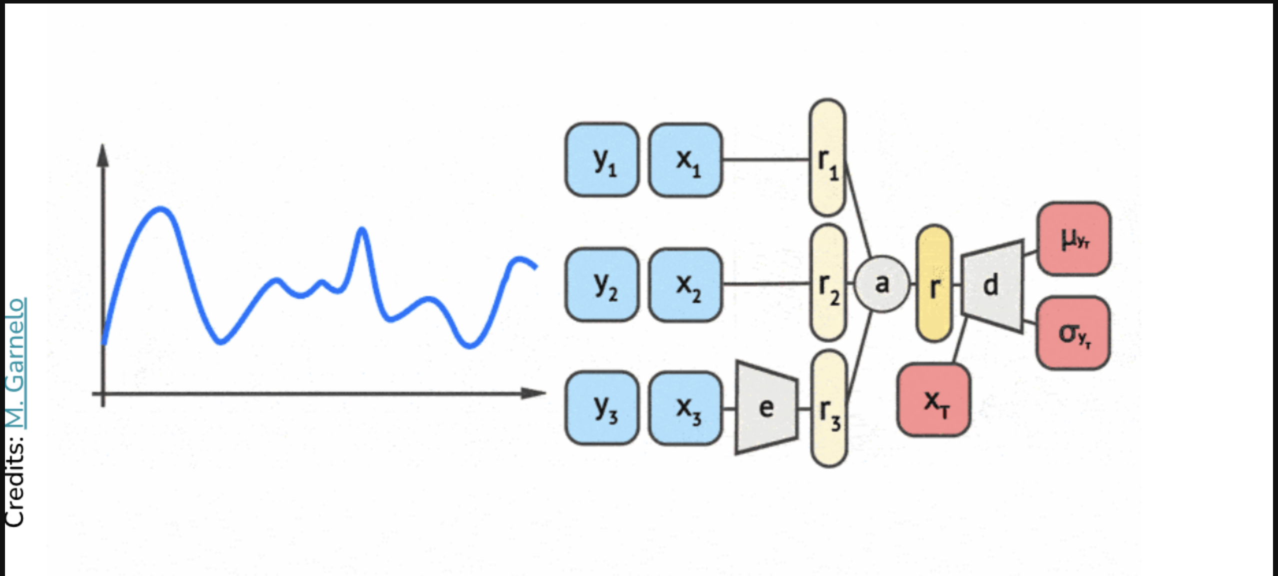
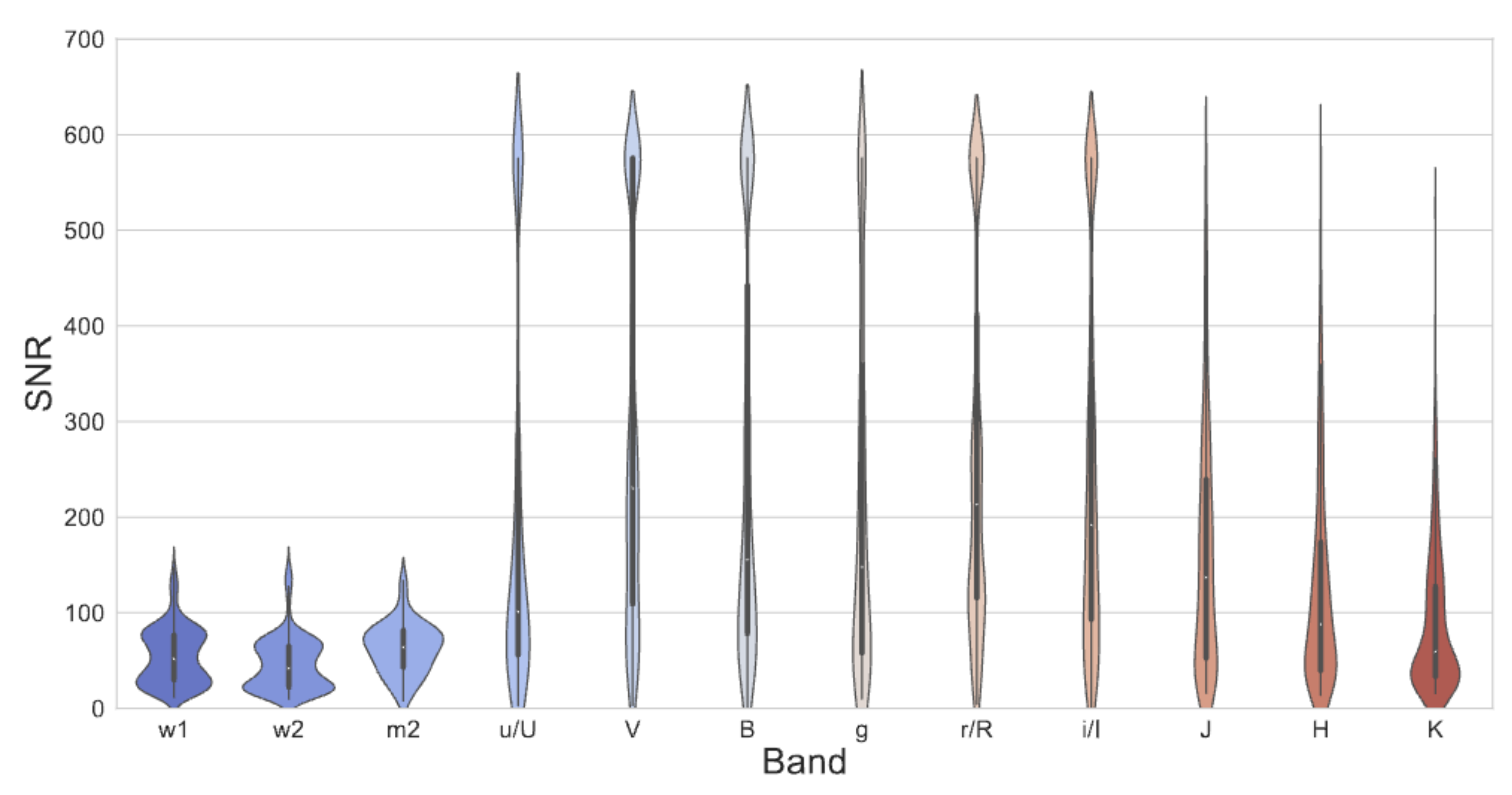
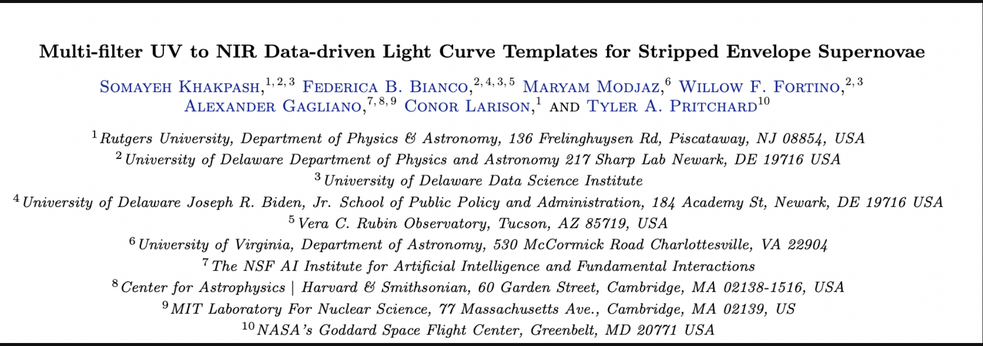


Neural processes replace the imposed kernel with a learned one - ask Siddharth Chaini!

Data-Driven Photometric Templates for stripped SESN

FASTlab Flash highlight





Multi-filter UV to NIR Data-driven Light Curve Templates for Stripped Envelope Supernovae

Somayeh Khakpash,[1,2,3] Federica B. Bianco,[2,4,3,5] Maryam Modjaz,[6] Willow F. Fortino,[2,3]
Alexander Gagliano,[7,8,9] Conor Larison,[1] and Tyler A. Pritchard[10]

[1] Rutgers University, Department of Physics & Astronomy, 136 Frelinghuysen Rd, Piscataway, NJ 08854, USA
[2] University of Delaware Department of Physics and Astronomy 217 Sharp Lab Newark, DE 19716 USA
[3] University of Delaware Data Science Institute
[4] University of Delaware Joseph R. Biden, Jr. School of Public Policy and Administration, 184 Academy St, Newark, DE 19716 USA
[5] Vera C. Rubin Observatory, Tucson, AZ 85719, USA
[6] University of Virginia, Department of Astronomy, 530 McCormick Road Charlottesville, VA 22904
[7] The NSF AI Institute for Artificial Intelligence and Fundamental Interactions
[8] Center for Astrophysics | Harvard & Smithsonian, 60 Garden Street, Cambridge, MA 02138-1516, USA
[9] MIT Laboratory For Nuclear Science, 77 Massachusetts Ave., Cambridge, MA 02139, US
[10] NASA's Goddard Space Flight Center, Greenbelt, MD 20771 USA

Khakpash et al. 2024 ApJS
https://arxiv.org/pdf/2405.01672

Rare classes will become common, but how do we know what we are looking at and classify different objects for sample studies?

on the job market!

Dr. Somayeh Khakpash
LSSTC Catalyst Fellow, Rutgers

Methodological issues with these approaches

Attetion requires positional encoding

Positional Encodings for Light Curve Transformers: Playing with Positions and Attention

Daniel Moreno-Cartagena [1] Guillermo Cabrera-Vives [1 2 3 4] Pavlos Protopapas [5] Cristobal Donoso-Oliva [3 2]
Manuel Pérez-Carrasco [2 1 4] Martina Cádiz-Leyton [1]

Table 1. Performance of different positional encodings in the pretraining stage and classification task.

PE TYPE	MACHO UNLAB.		MACHO LAB.				OGLE	ATLAS
			FULL	3/4	1/2	1/4		
	RMSE	TIME (EPOCHS)	F1 (%)	F1 (%)	F1 (%)	F1 (%)	F1 (%)	F1 (%)
BASELINE	.170	6D 14H (523)	71.6 ± 1.9	69.2 ± 1.9	66.2 ± 1.9	63.3 ± 1.5	71.3 ± 1.1	65.8 ± 1.4
TRAINABLE	**.169**	2D 13H (202)	72.9 ± 2.1	72.3 ± 1.0	$\mathbf{71.0 \pm 1.0}$	$\mathbf{69.0 \pm 0.5}$	74.9 ± 1.4	65.4 ± 1.8
FOURIER	.170	1D 20H (142)	73.0 ± 1.1	70.2 ± 1.9	67.8 ± 0.9	62.9 ± 2.0	72.0 ± 0.8	$\mathbf{69.6 \pm 0.1}$
RECURRENT	.197	0D 16H (048)	67.1 ± 1.8	63.5 ± 2.5	59.7 ± 1.9	54.6 ± 1.3	70.7 ± 1.1	68.3 ± 0.9
TUPE-A	.219	0D 17H (084)	67.3 ± 1.6	66.1 ± 1.4	64.9 ± 1.0	60.8 ± 0.9	71.0 ± 1.0	67.5 ± 0.9
CONCAT	.170	3D 01H (237)	$\mathbf{73.4 \pm 1.1}$	$\mathbf{73.1 \pm 1.7}$	70.9 ± 1.7	$\mathbf{69.0 \pm 1.8}$	74.5 ± 1.3	68.1 ± 0.6
PEA	.199	0D 17H (058)	69.7 ± 0.9	68.9 ± 1.8	68.0 ± 1.0	65.5 ± 2.5	$\mathbf{76.3 \pm 1.2}$	66.9 ± 1.0

we badly need better benchmark datasets

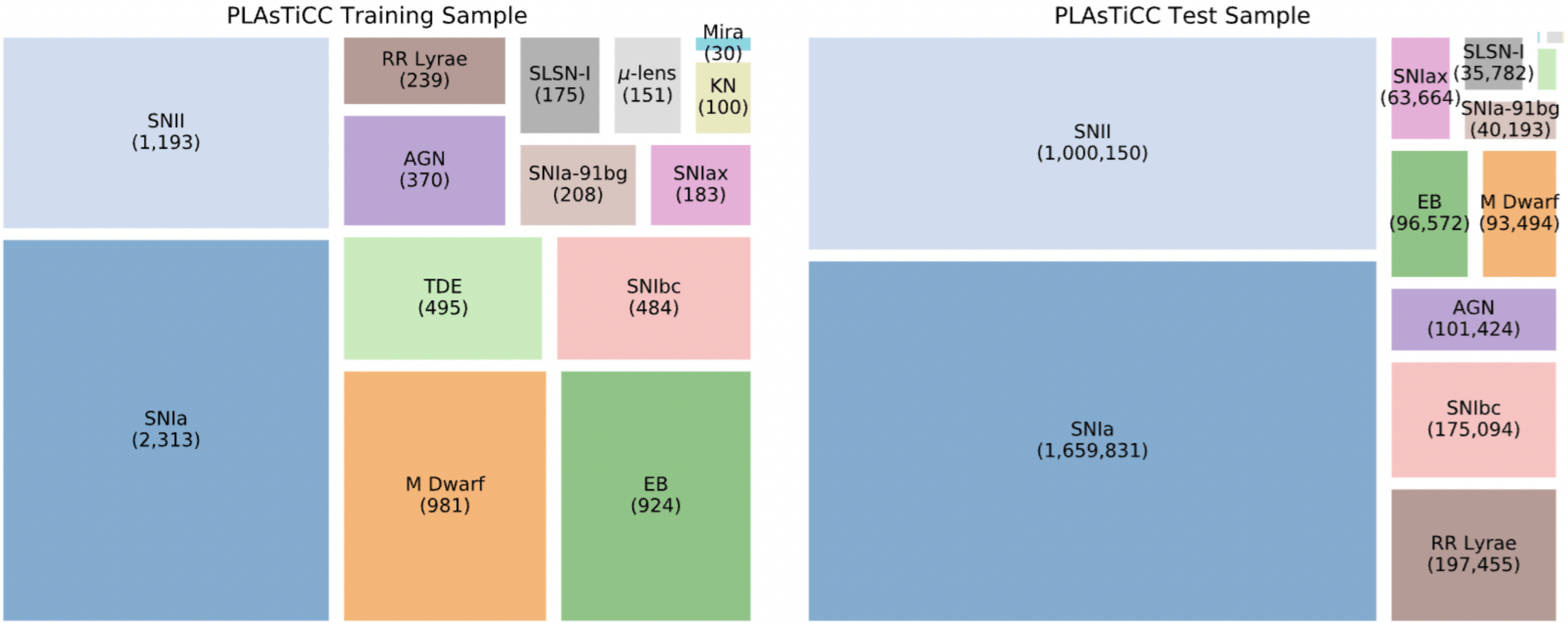


Figure 1. Relative numbers of objects of each class between the training (left) and test (right) data of PLAsTiCC. The size of the boxes are proportional to the relative numbers in each set and the absolute numbers are in parentheses. The simulated $\simeq$ 8000 objects in the training set were distributed across the data classes in a different ratio compared to the test data of over 3.5 M objects.

Hlozek et al, 2020

DATA CURATION IS THE BOTTLE NECK

models contributed by the community were in

- different format (spectra, lightcurves, theoretical, data-driven)
- the people that contributed the models were included in 1 paper at best
- *incompleteness*
- *systematics*
- *imbalance*

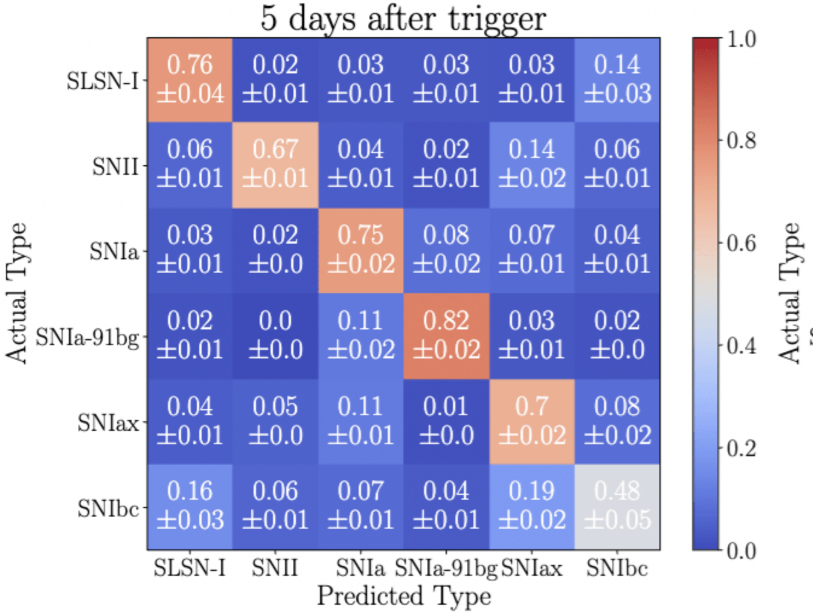
Multi-filter UV to NIR Data-driven Light Curve Templates for Stripped Envelope Supernovae

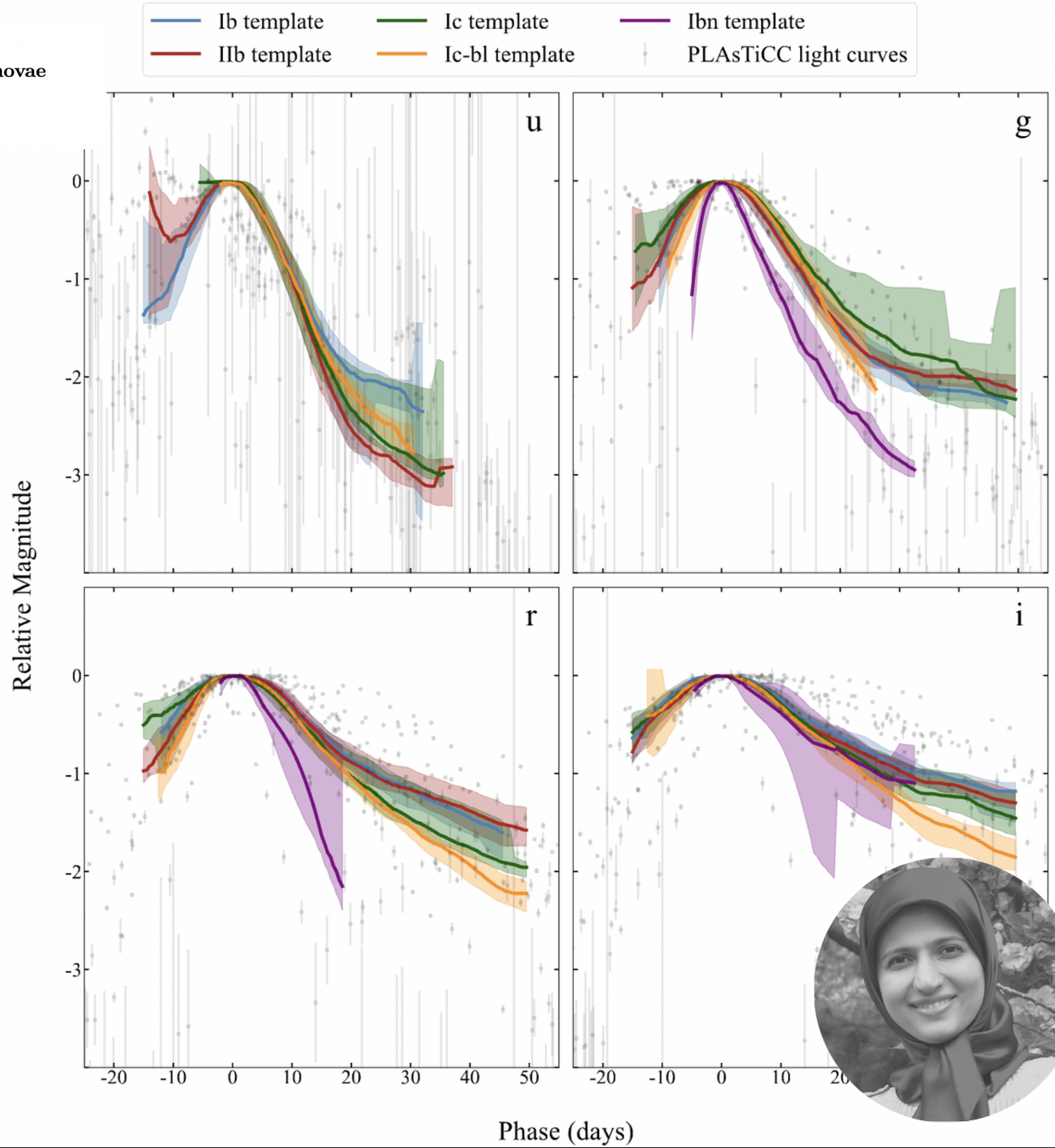
Somayeh Khakpash,[1,2,3] Federica B. Bianco,[2,4,3,5] Maryam Modjaz,[6] Willow F. Fortino,[2,3]
Alexander Gagliano,[7,8,9] Conor Larison,[1] and Tyler A. Pritchard[10]

Ibc data-driven templates *vs* PLAsTiCC

khakpash+ 2024 showed that the models were biased for SN Ibc

AVOCADO, SCONE, all these models are trained on a biased dataset and are being currently used for classification





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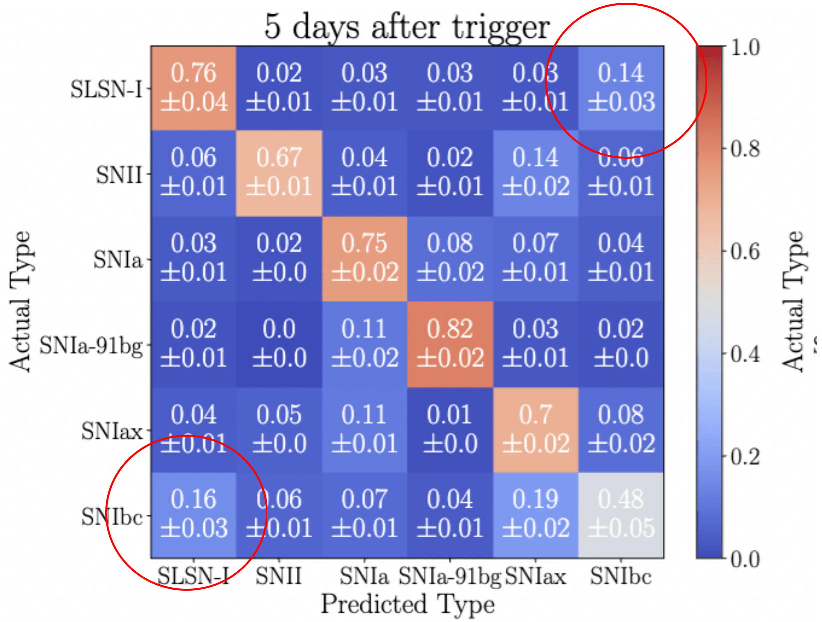

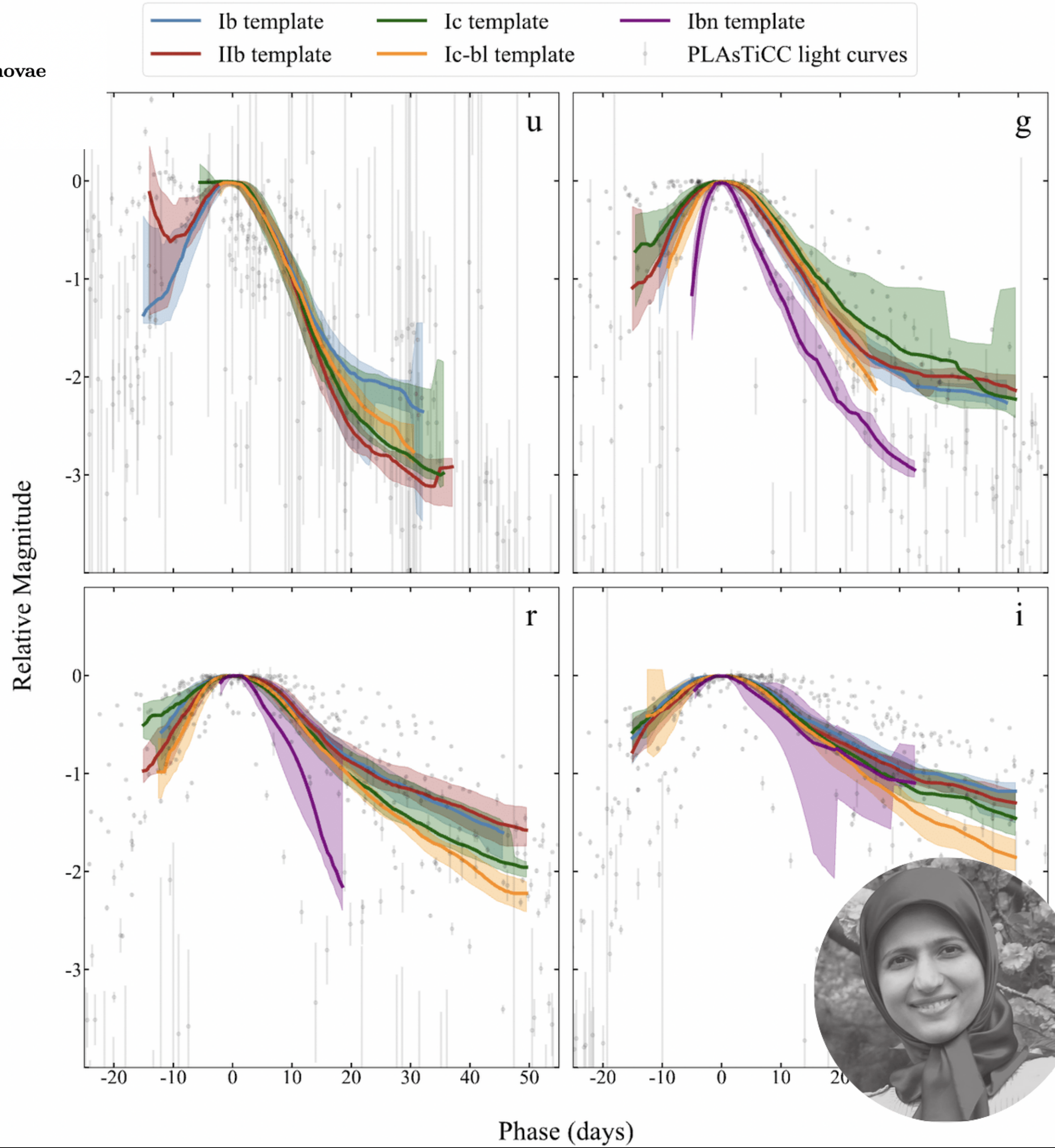

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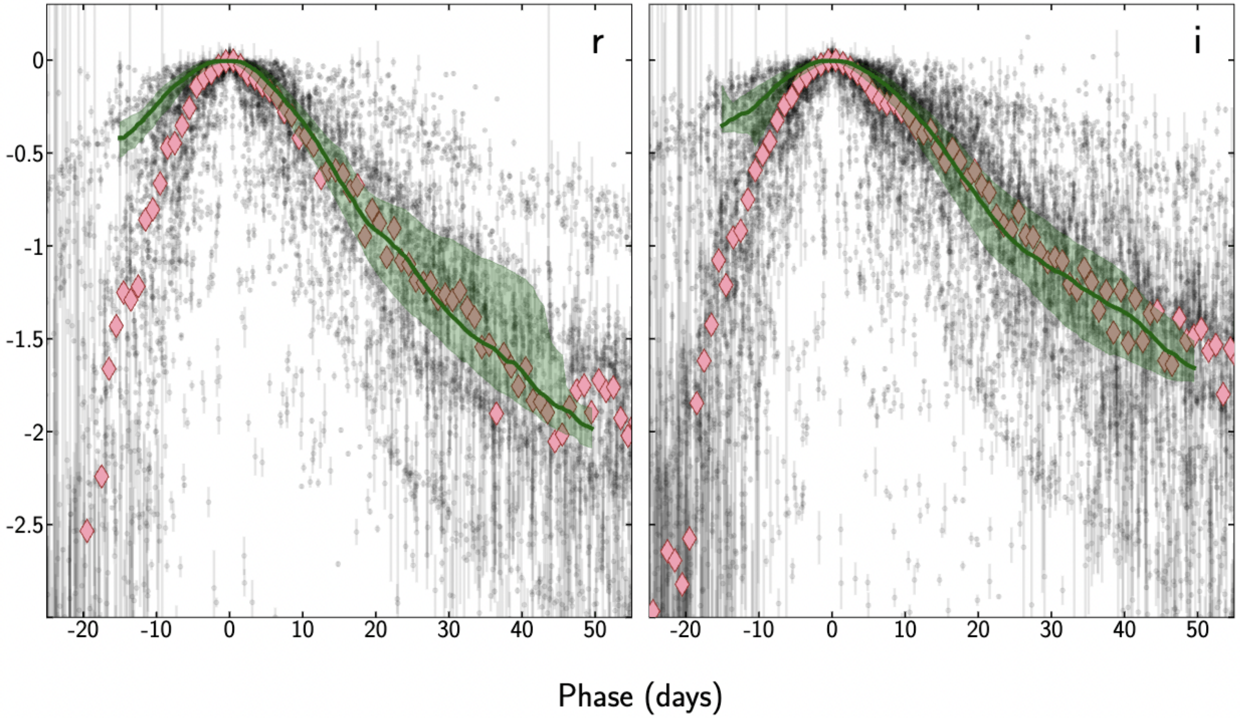
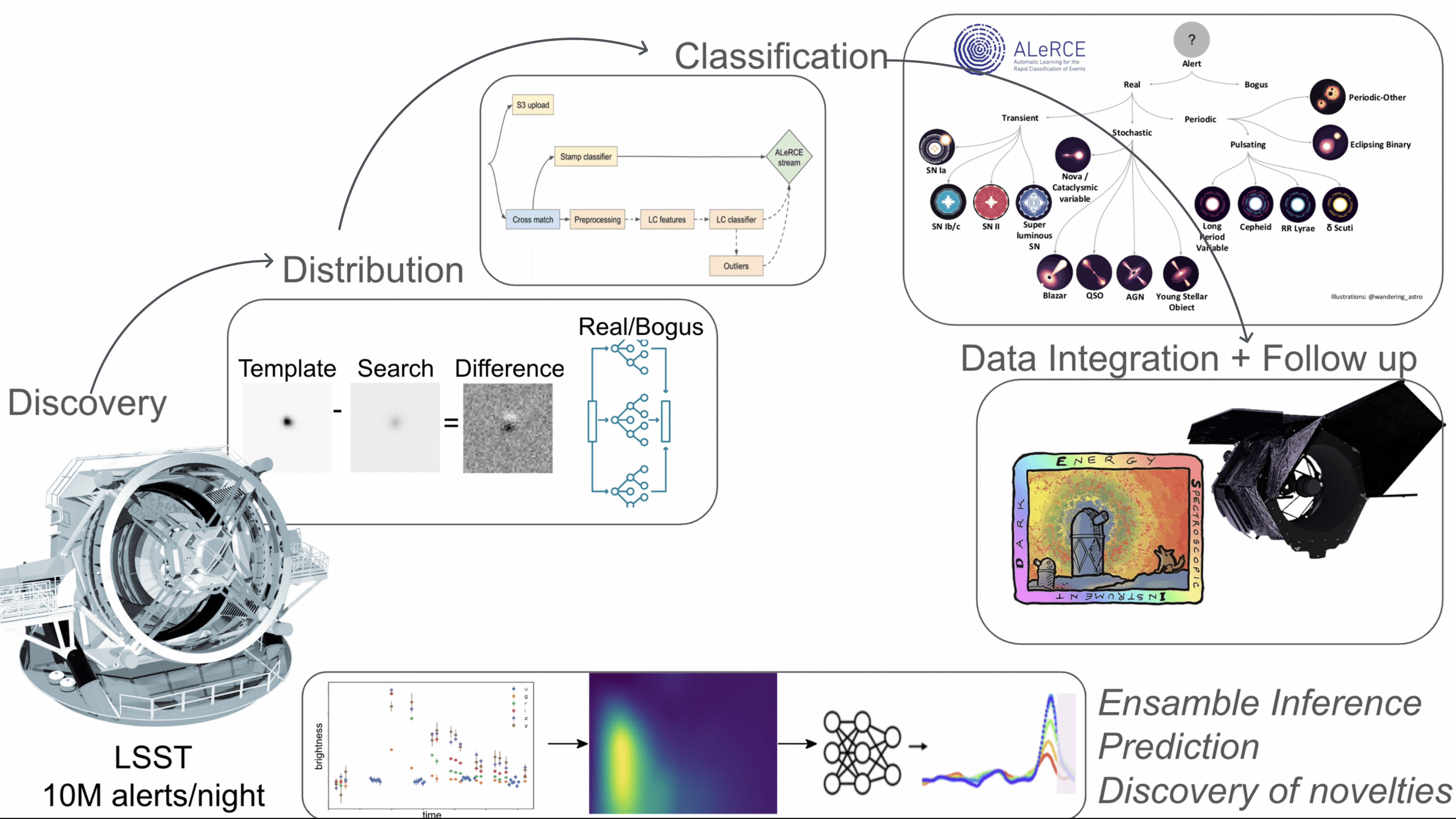
Ic templates *vs* ELAsTiCC




Classification
ALeRCE
Automatic Learning for the Rapid Classification of Events
Alert
Real
Bogus
Transient
Stochastic
Periodic
Periodic-Other
Eclipsing Binary
Pulsating
SN Ia
SN Ib/c
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Illustrations: @wandering_astro
S3 upload
Stamp classifier
ALeRCE stream
Cross match
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LC features
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Template
Search
Difference
Discovery
Data Integration + Follow up
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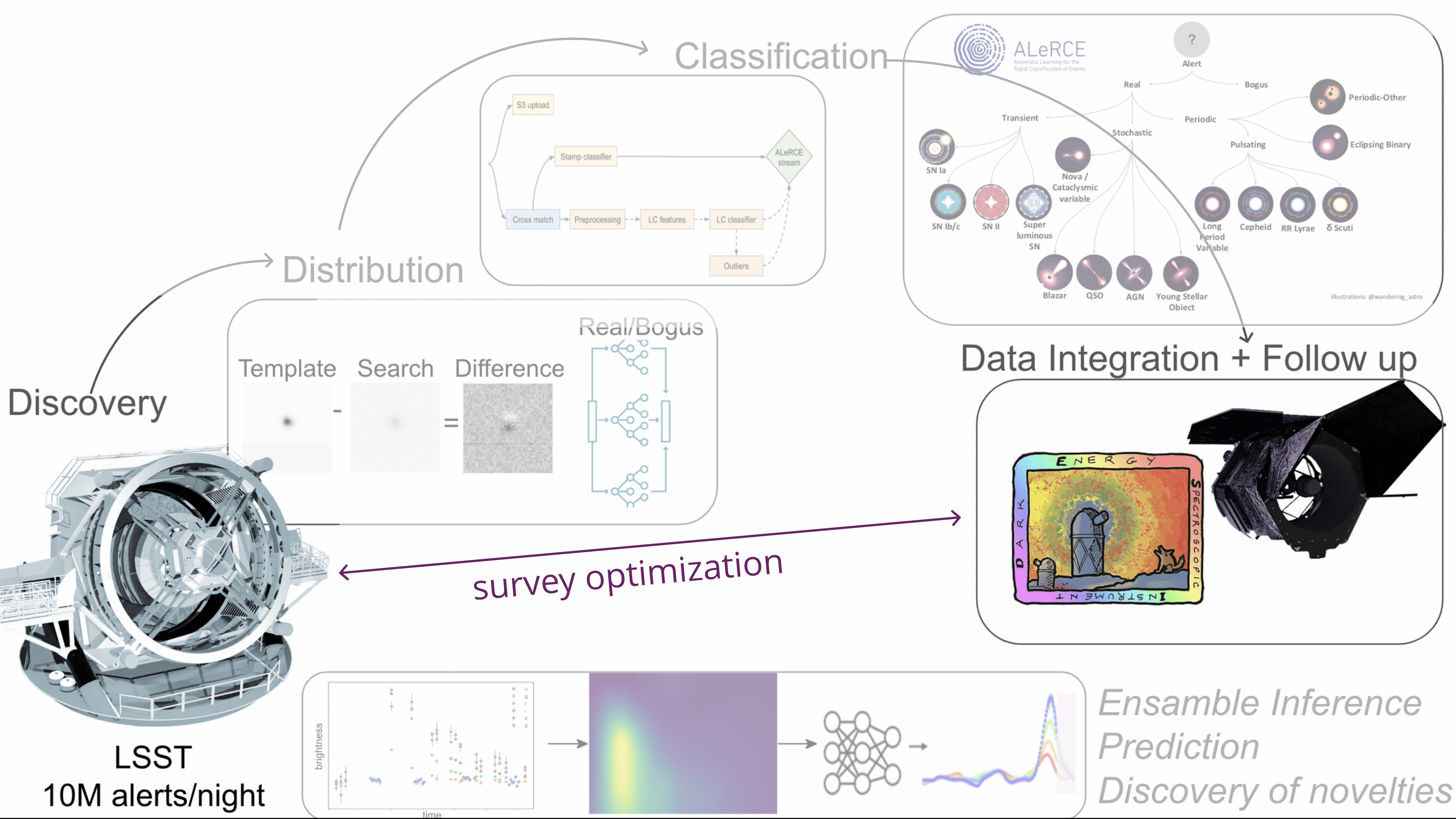
DARK
SPECTROSCOPIC
INSTRUMENT
LSST
10M alerts/night
brightness
time
Ensamble Inference
Prediction
Discovery of novelties



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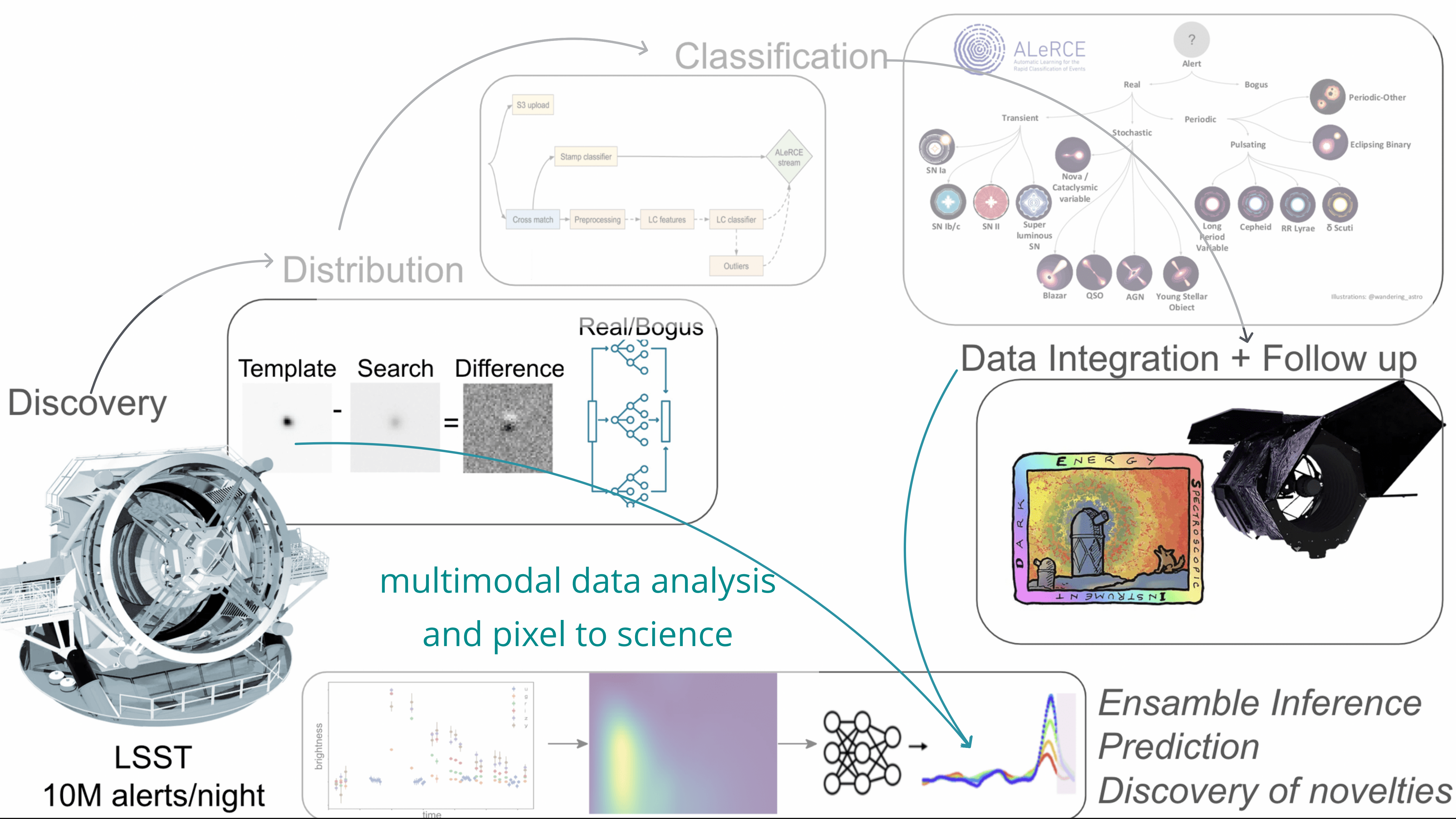

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MACHINE LEARNING
Science and Technology

PAPER • OPEN ACCESS

Maven: a multimodal foundation model for supernova science

Gemma Zhang[7,*], Thomas Helfer[7,*], Alexander T Gagliano, Siddharth Mishra-Sharma[8] and V Ashley Villar

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Focus on ML and the Physical Sciences
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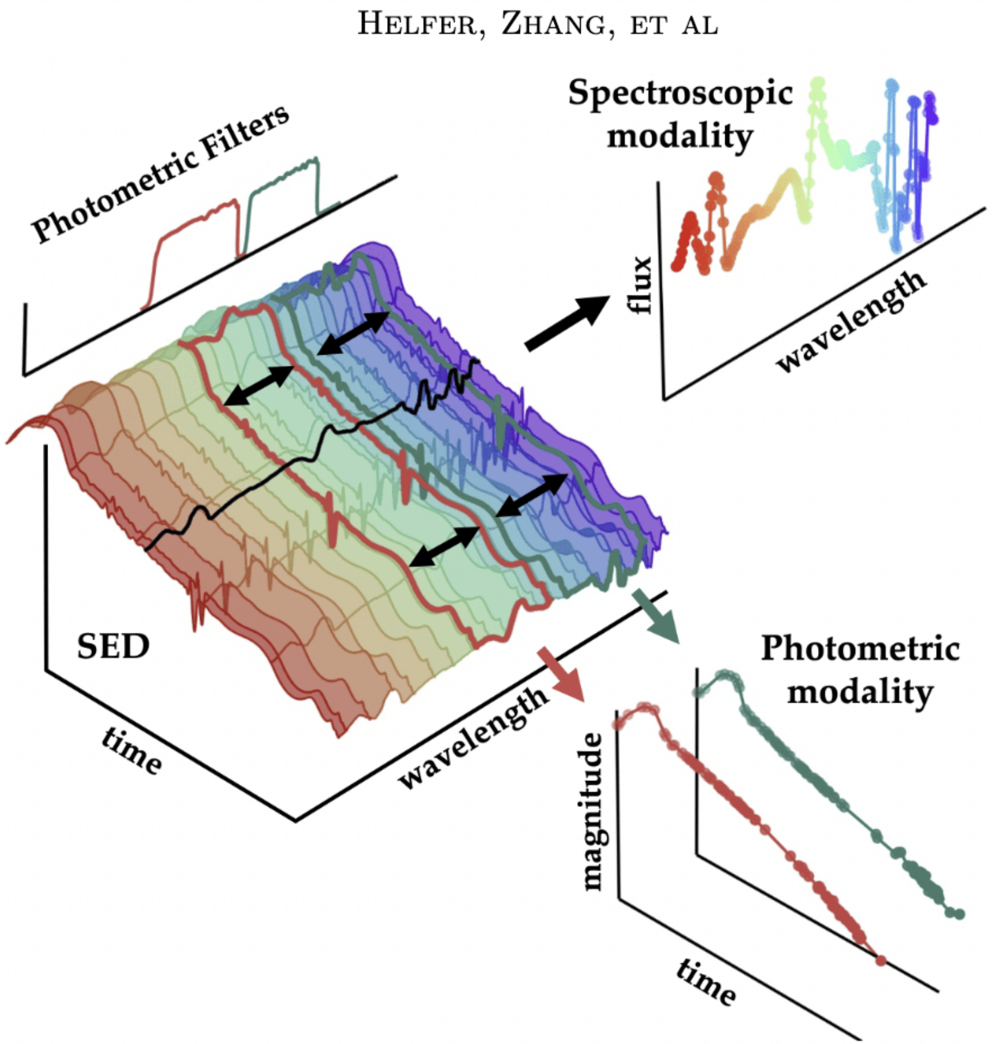
DOI 10.1088/2632-2153/ad990d

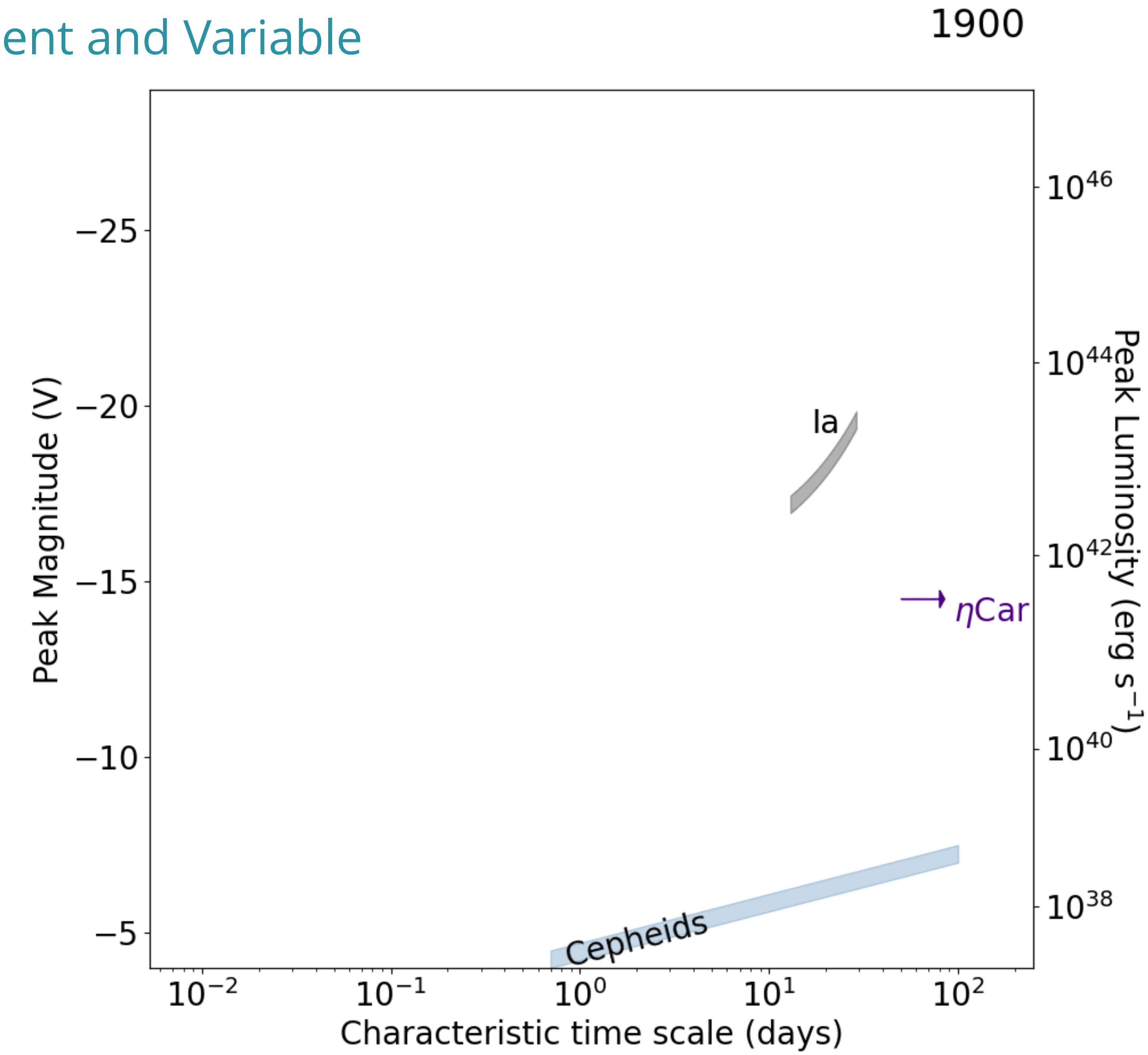
Abstract

A common setting in astronomy is the availability of a small number of high-quality observations, and larger amounts of either lower-quality observations or synthetic data from simplified models. Time-domain astrophysics is a canonical example of this imbalance, with the number of supernovae observed photometrically outpacing the number observed spectroscopically by multiple orders of magnitude. At the same time, no data-driven models exist to understand these photometric and spectroscopic observables in a common context. Contrastive learning objectives, which have grown in popularity for aligning distinct data modalities in a shared embedding space, provide a potential solution to extract information from these modalities. We present Maven, the first foundation model for supernova science. To construct Maven, we first pre-train our model to align photometry and spectroscopy from 0.5 M synthetic supernovae using a contrastive objective. We then fine-tune the model on 4702 observed supernovae from the Zwicky transient facility. Maven reaches state-of-the-art performance on both classification and redshift estimation, despite the embeddings not being explicitly optimized for these tasks. Through ablation studies, we show that pre-training with synthetic data improves overall performance. In the upcoming era of the Vera C. Rubin observatory, Maven will serve as a valuable tool for leveraging large, unlabeled and multimodal time-domain datasets.

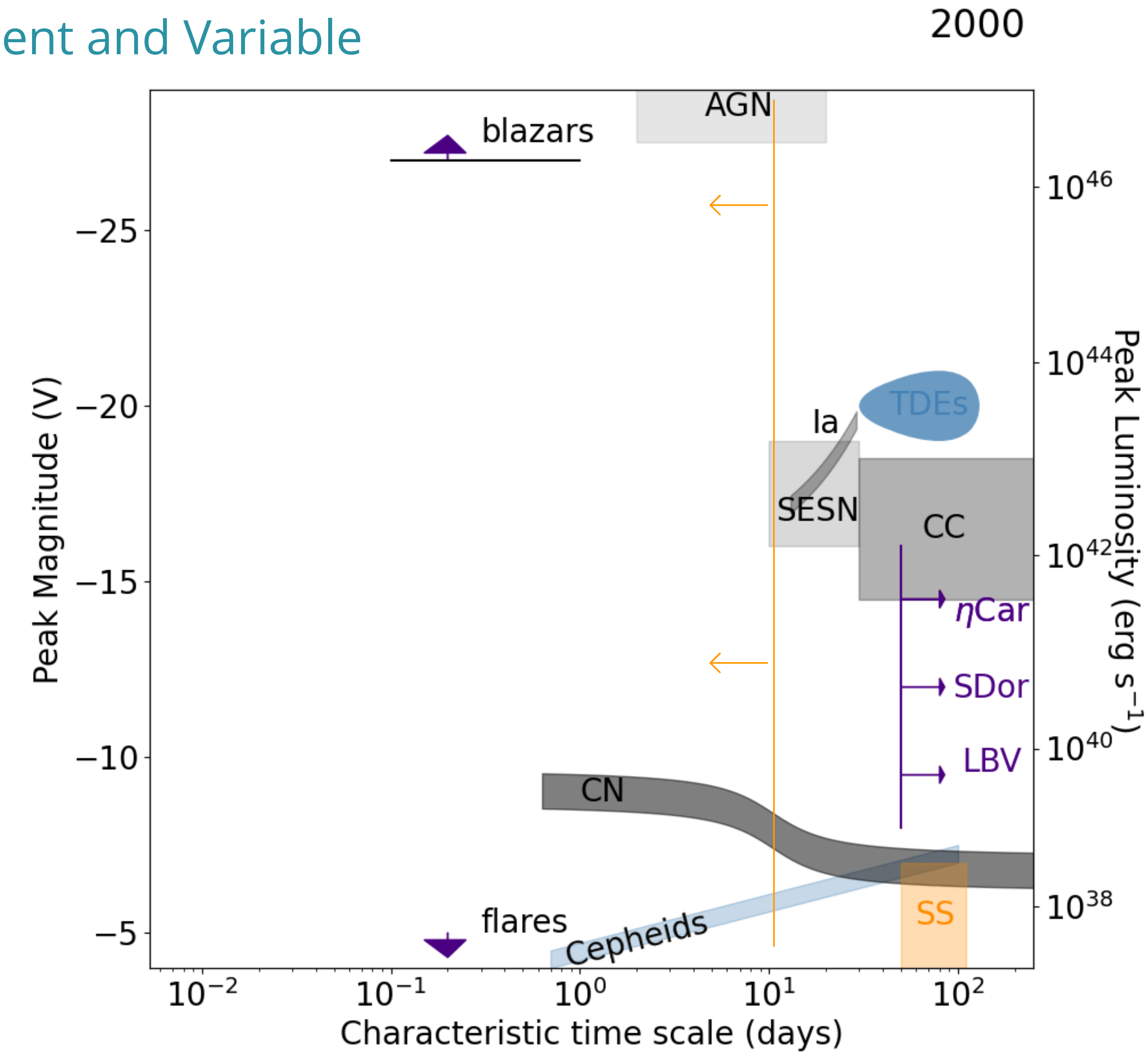


LSST survey strategy optimization

Exploring the Transient and Variable Optical Sky

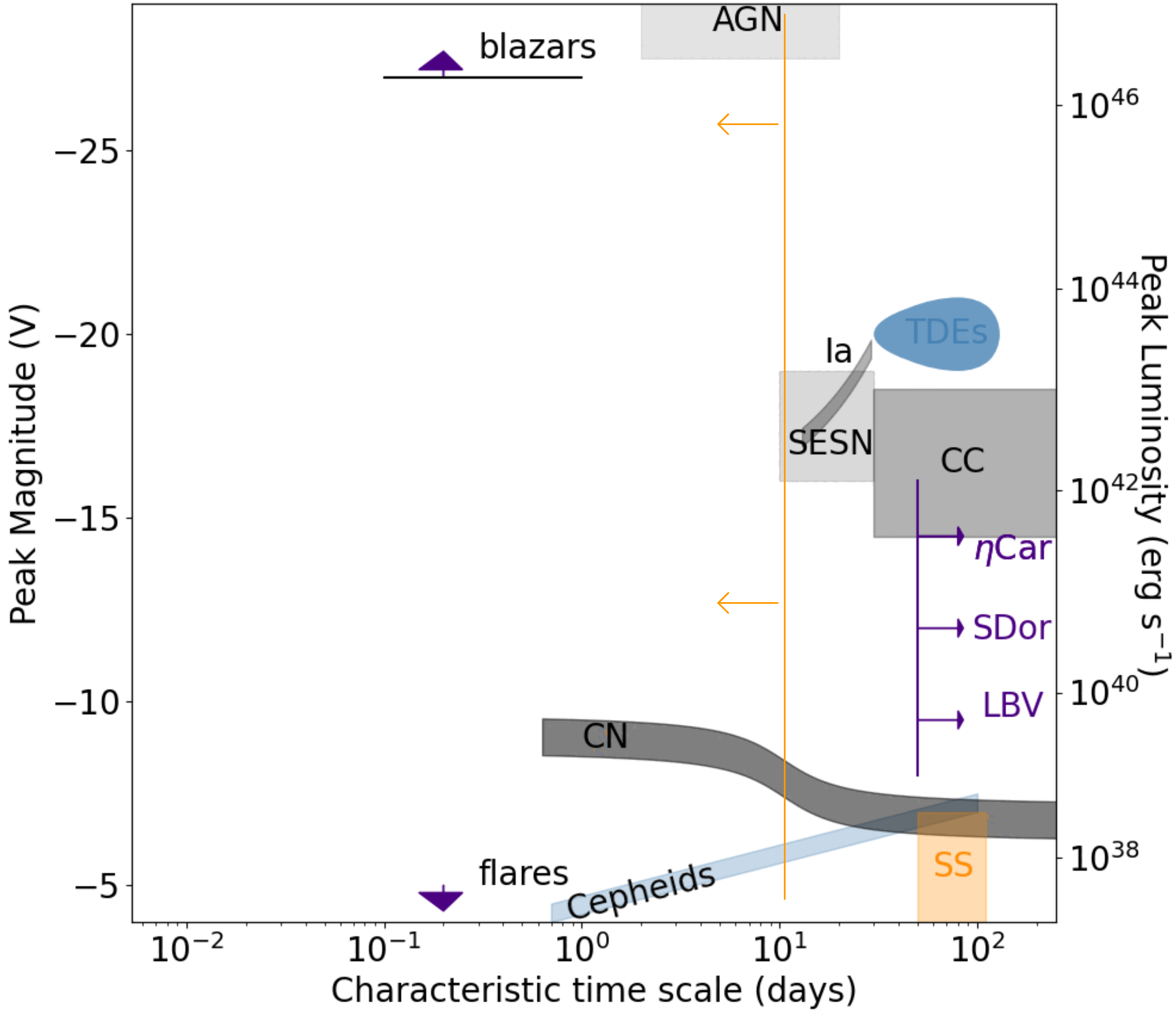


Exploring the Transient and Variable Optical Sky



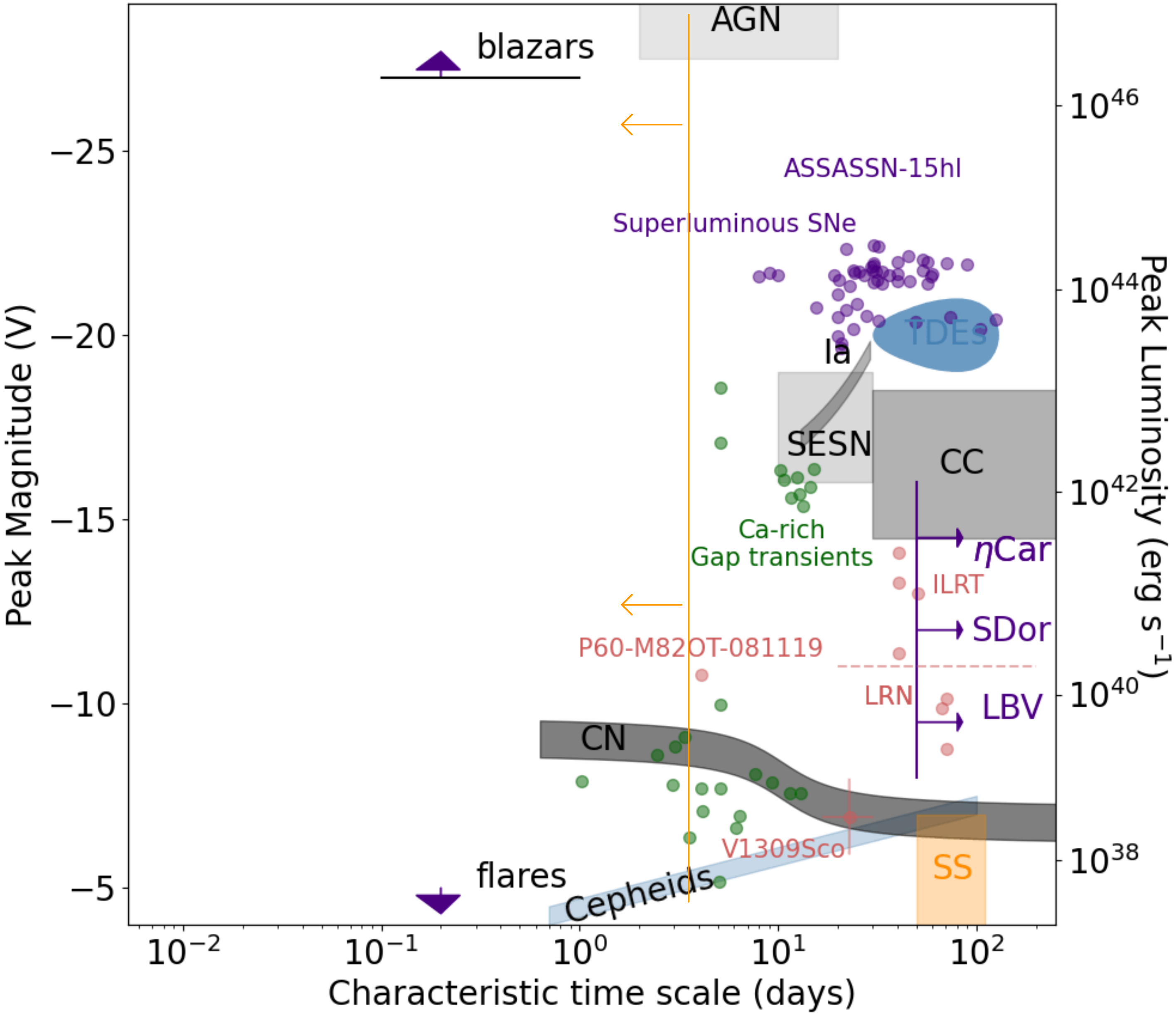
Exploring the Transient and Variable Optical Sky

2000



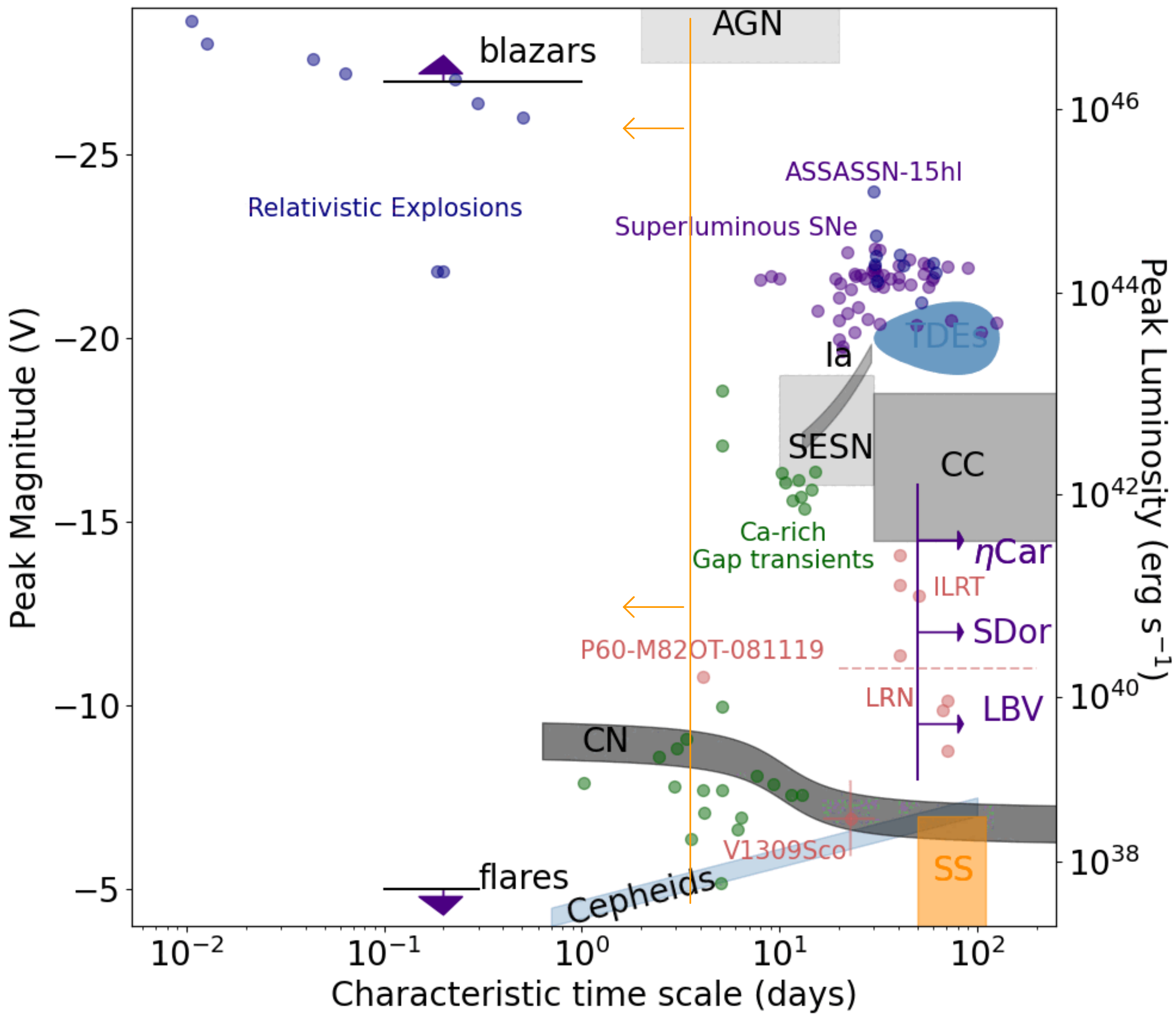
Exploring the Transient and Variable Optical Sky

2009



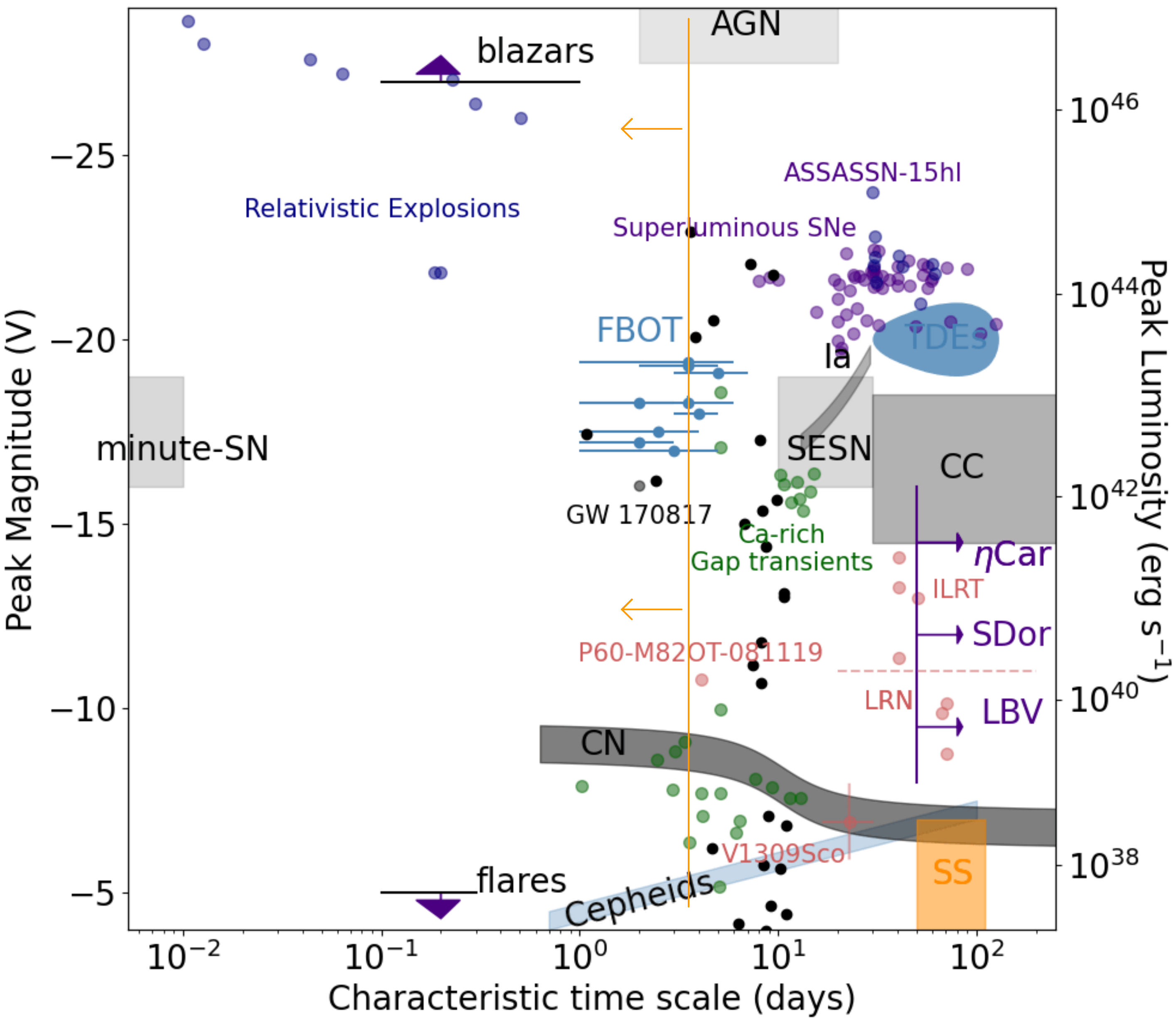
Exploring the Transient and Variable Optical Sky

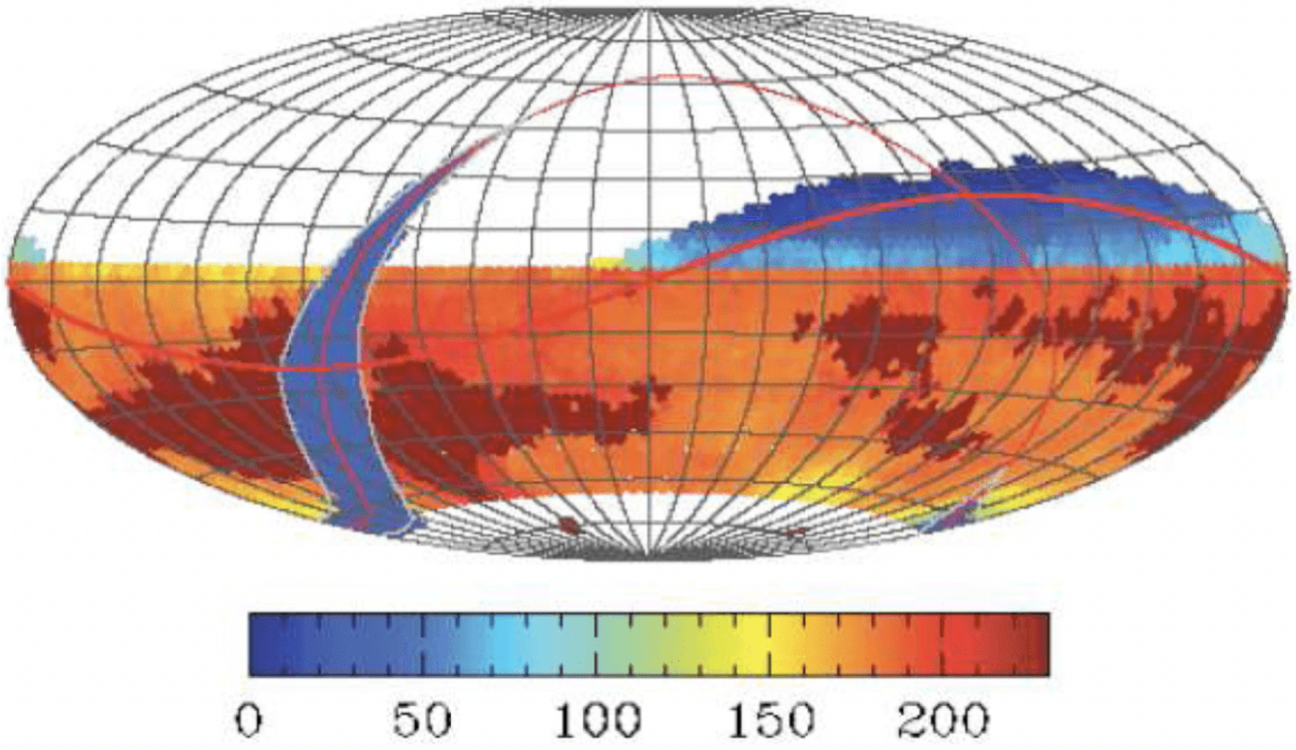
2010



Exploring the Transient and Variable Optical Sky

2024

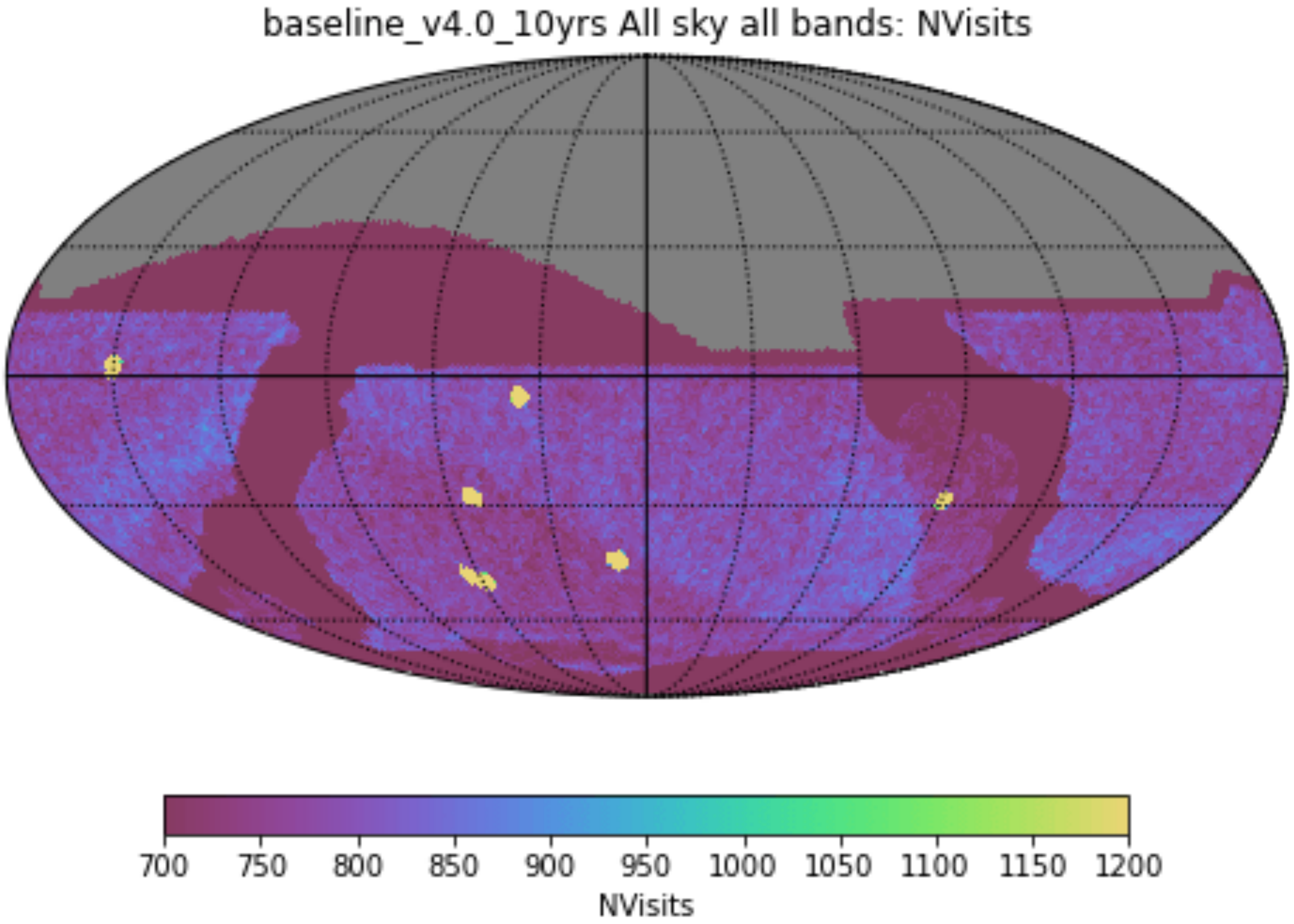




A vigorous and systematic research effort is underway to explore the enormously large parameter space of possible survey cadences, using the Operations Simulator tool described in § 3.1. The commissioning period will be used to test the usefulness of various observing modes and to explore alternative strategies. Proposals from the community and the Science Collaborations for specialized cadences (such as mini-surveys and micro-surveys) will also be considered.

LSST Science Book (2009)

Rubin LSST survey design



ethics of AI in astro

the butterfly effect

NGC 4565 is an edge-on spiral galaxy about 30 to 50 million light-years away. The faculty at the IUCAA used a AI model (emulator) to predict the hidden physical parameters of the Galaxy wrongfully estimating the DM content of NCG 4565 and claimed a novel process for Galaxy formation should be taken under consideration.

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Unfortunately, this was the result of a model hallucination.

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Unfortunately, this was the result of a model hallucination.

The galaxy was featured in many social media posts gaining rapid notoriety, but upon retraction it was canceled. The galaxy is suing IUCAA claiming emotional damage and loss of revenue

the butterfly effect

Robert Williams, a 43-year-old father who resides in the Detroit suburb of Farmington Hills, was arrested in early January on charges that he stole watches from Shinola, a trendy accessories store in the city. Detroit Police used facial recognition software on the store's surveillance camera footage and wrongfully identified him as the thief.

Robert Williams has sued Detroit Police after a false facial recognition match led to him being wrongfully identified and subsequently arrested as a shoplifting suspect. (ACLU)

the butterfly effect

We use astrophyiscs as a neutral and safe sandbox to learn how to develop and apply powerful tool.

Deploying these tools in the real worlds can do harm.

Ethics of AI is essential training that all data scientists shoudl receive.

models are neutral, the bias is in the data (or is it?)

Why does this AI model whitens Obama face?

Simple answer: the data is biased. The algorithm is fed more images of white people

But really, would the opposite have been acceptable? *The bias is in society*

https://www.theverge.com/21298762/face-depixelizer-ai-machine-learning-tool-pulse-stylegan-obama-bias

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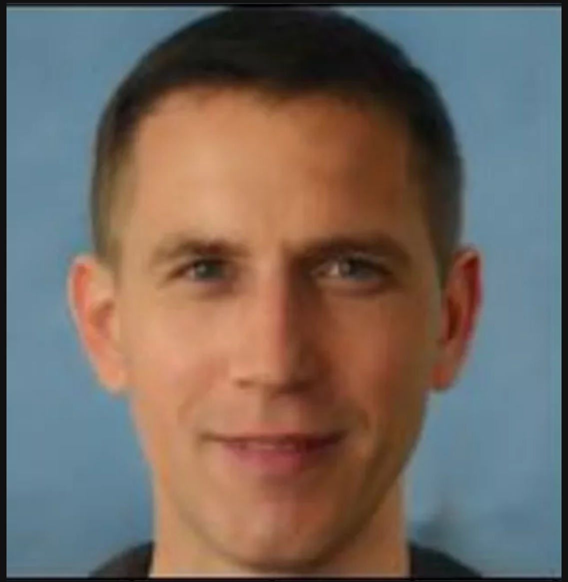

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Joy Boulamwini

https://www.youtube.com/embed/TWWsW1w-BVo?enablejsapi=1

thank you!

federica bianco

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Department of Physics and Astronomy

Biden School of Public Policy and Administration
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https://slides.com/federicabianco/aimlaw