Oracle: A family of Real-Time, Hierarchical, Multi-modal classifiers for LSST and ZTF

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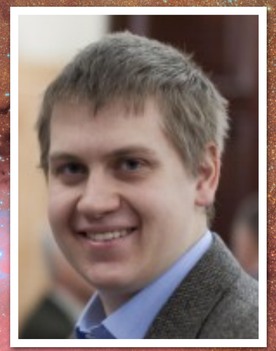
CIERA
CENTER FOR INTERDISCIPLINARY EXPLORATION AND RESEARCH IN ASTROPHYSICS

SkAI
Funded by the U.S. National Science Foundation and the Simons Foundation

Oracle v1 (for LSST)

Alex Gagliano

Gautham Narayan



Konstantin Malanchev

Alex Malz

Oracle v2 (for ZTF and LSST) + Model Deployment

Nabeel Rehemtulla

Adam Miller

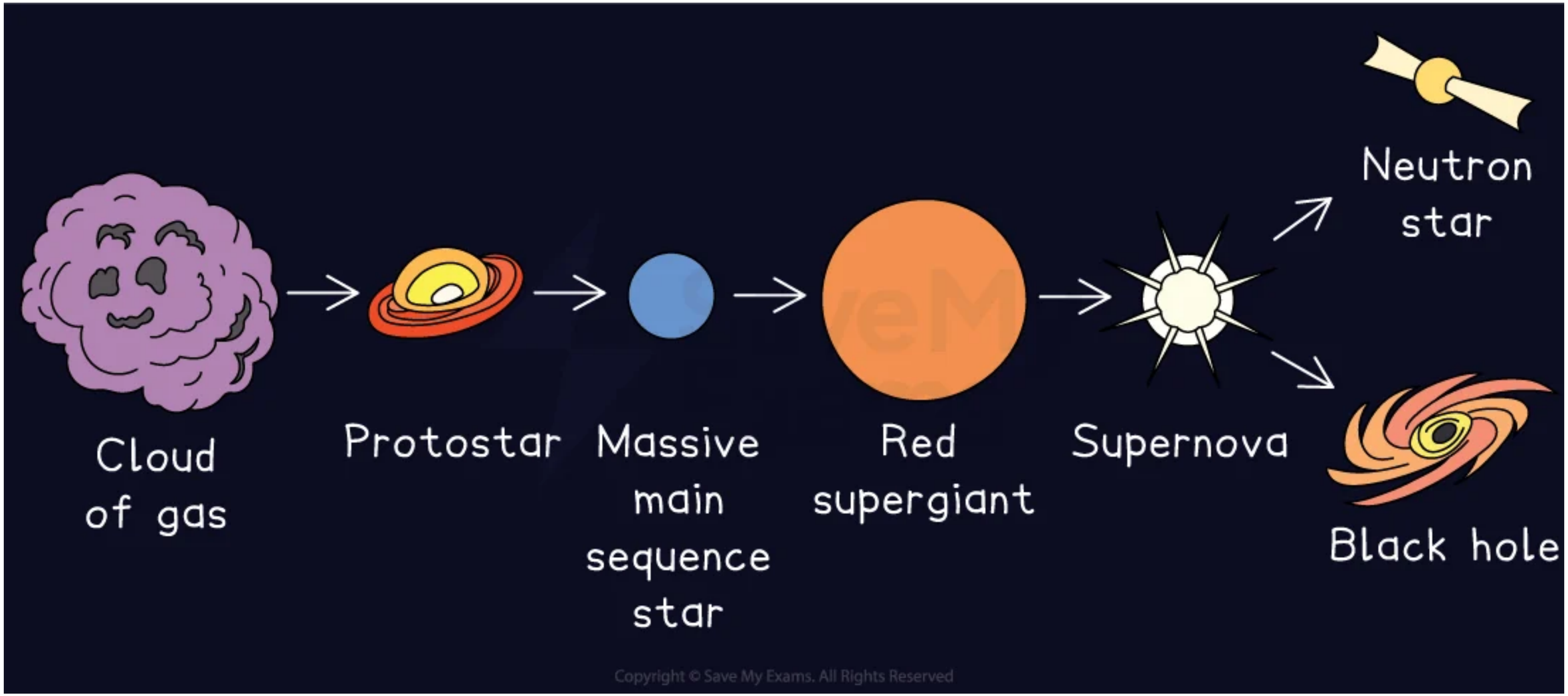
Michael Coughlin

Sushant Sharma Chaudhary

+ The BOOM Team

1. Introduction and Motivation

All of Supernova science in 30 seconds



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Outline

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- The need for **multi-modality** in astronomy.

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- Lessons from **deployment** of models on real alerts.

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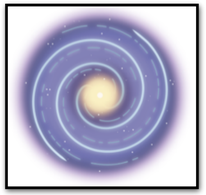
- Lessons from **deployment** of models on real alerts.
- Outstanding **challenges** for astronomy in the real world.

Why use hierarchical classification?

Time t1



Science

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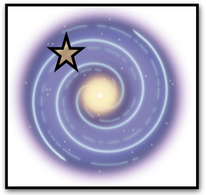

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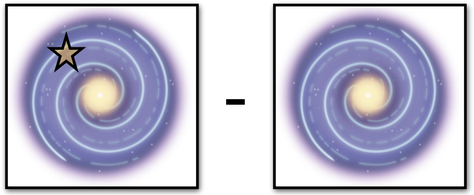

Science

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Reference

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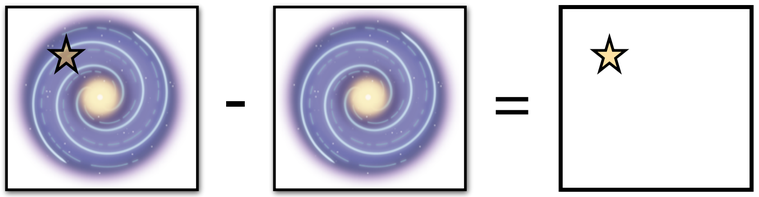

Science - Reference = Difference

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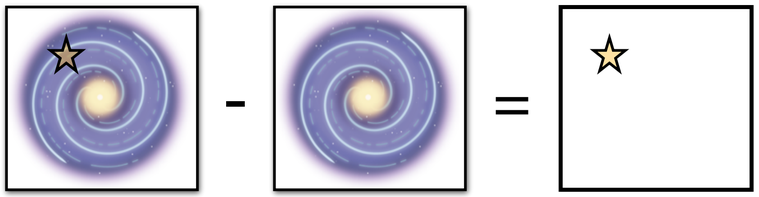

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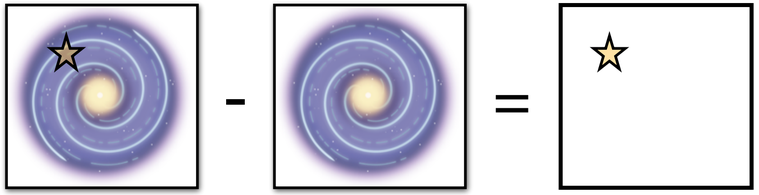
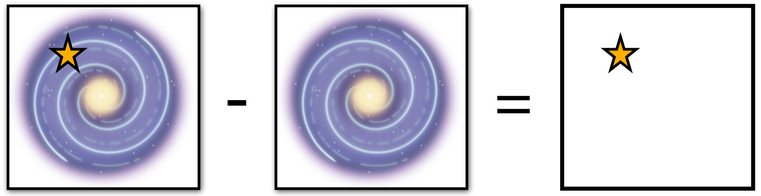


Time t2



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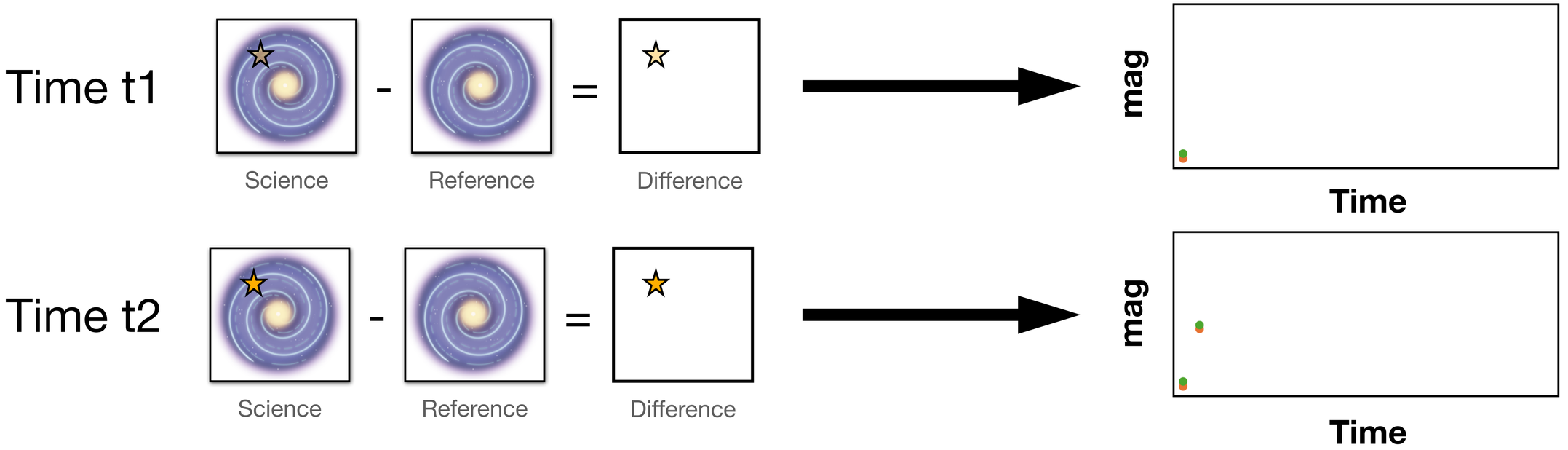

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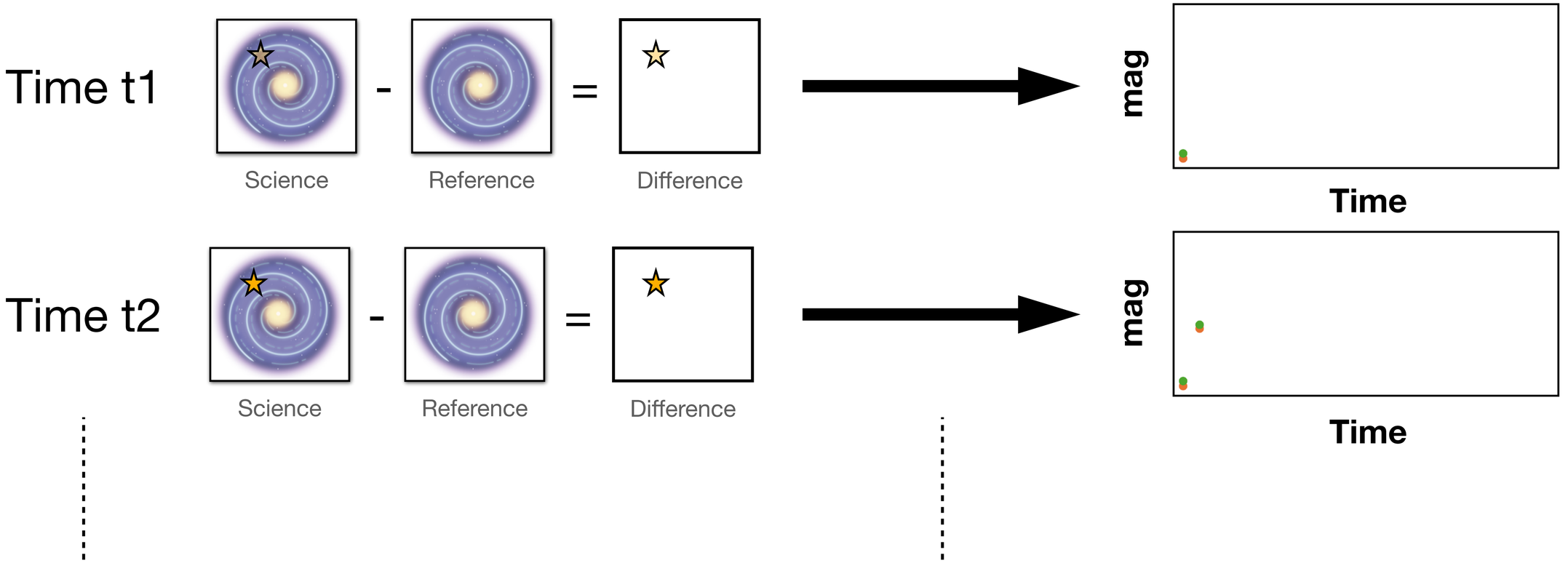

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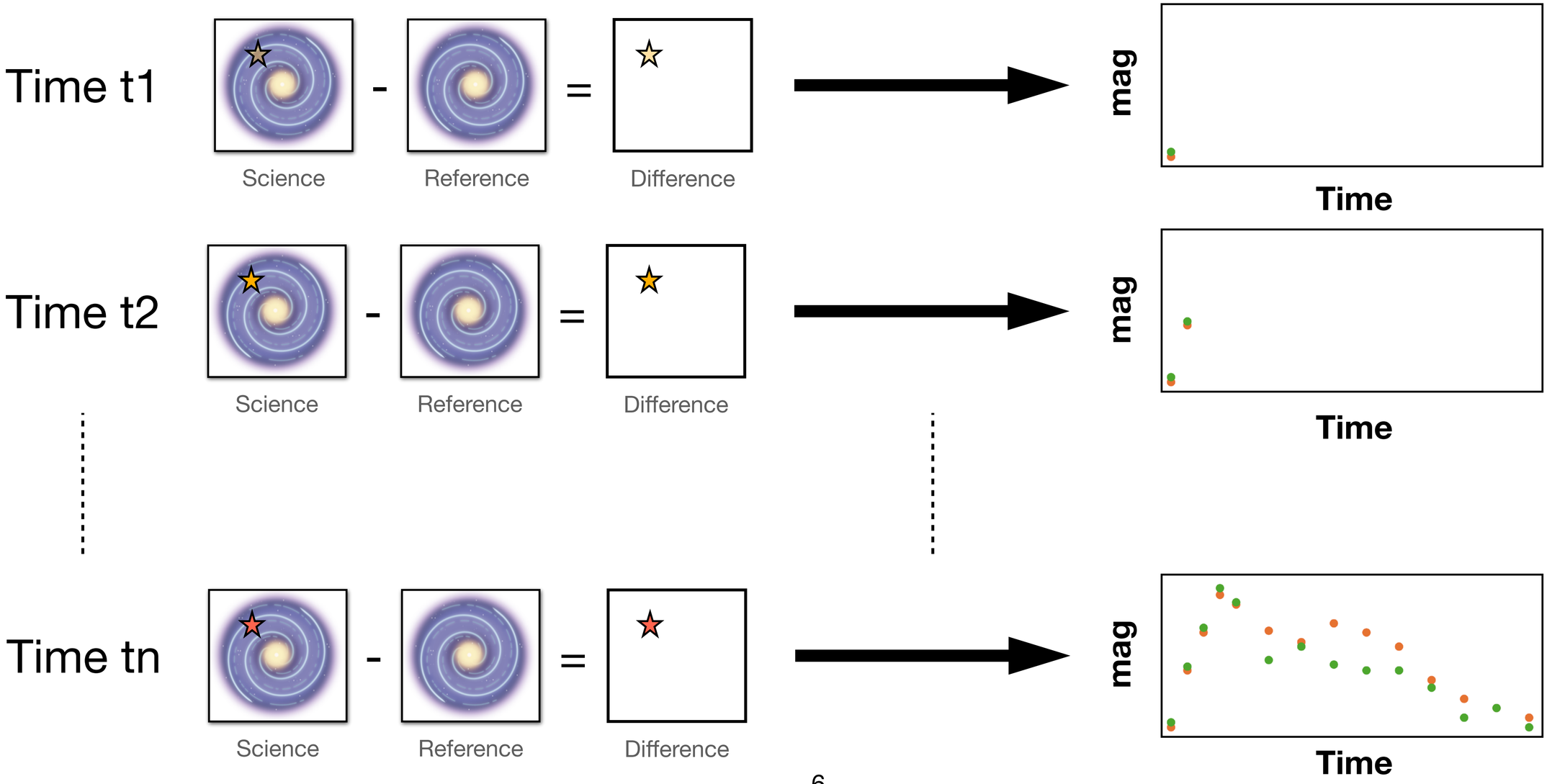

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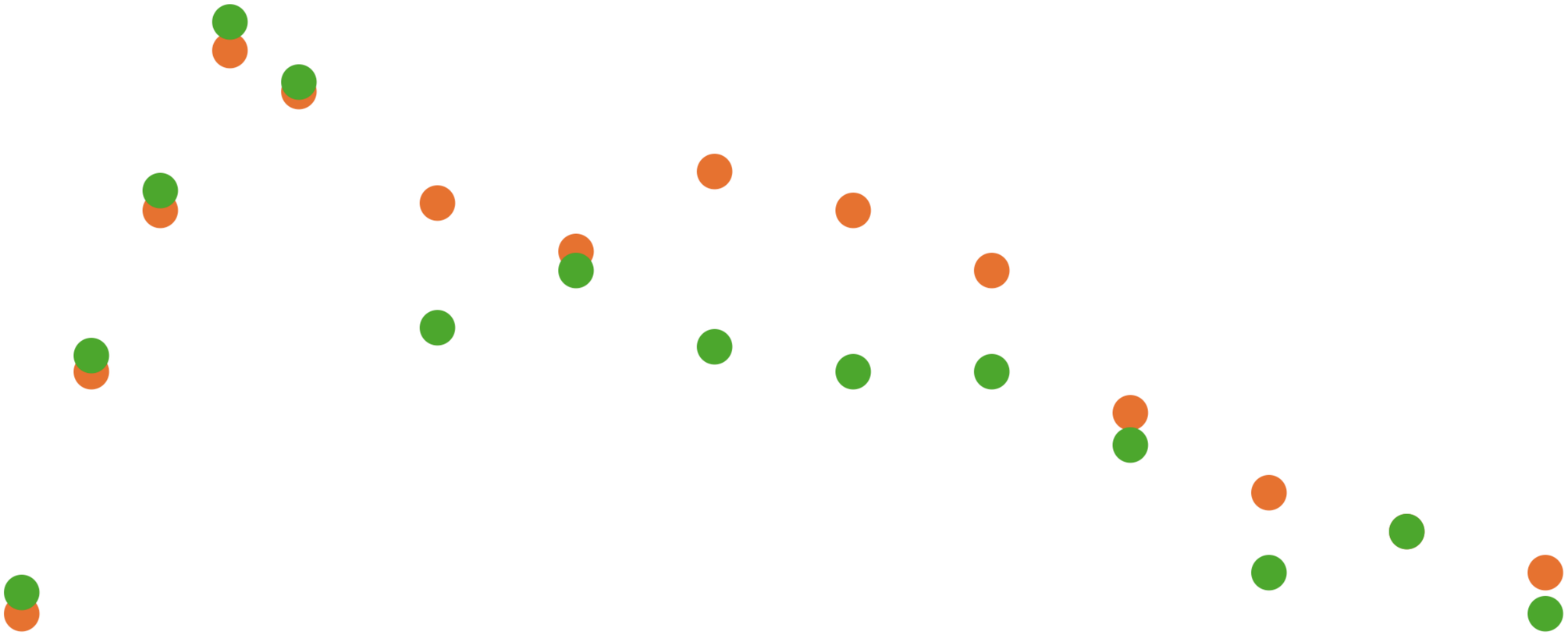

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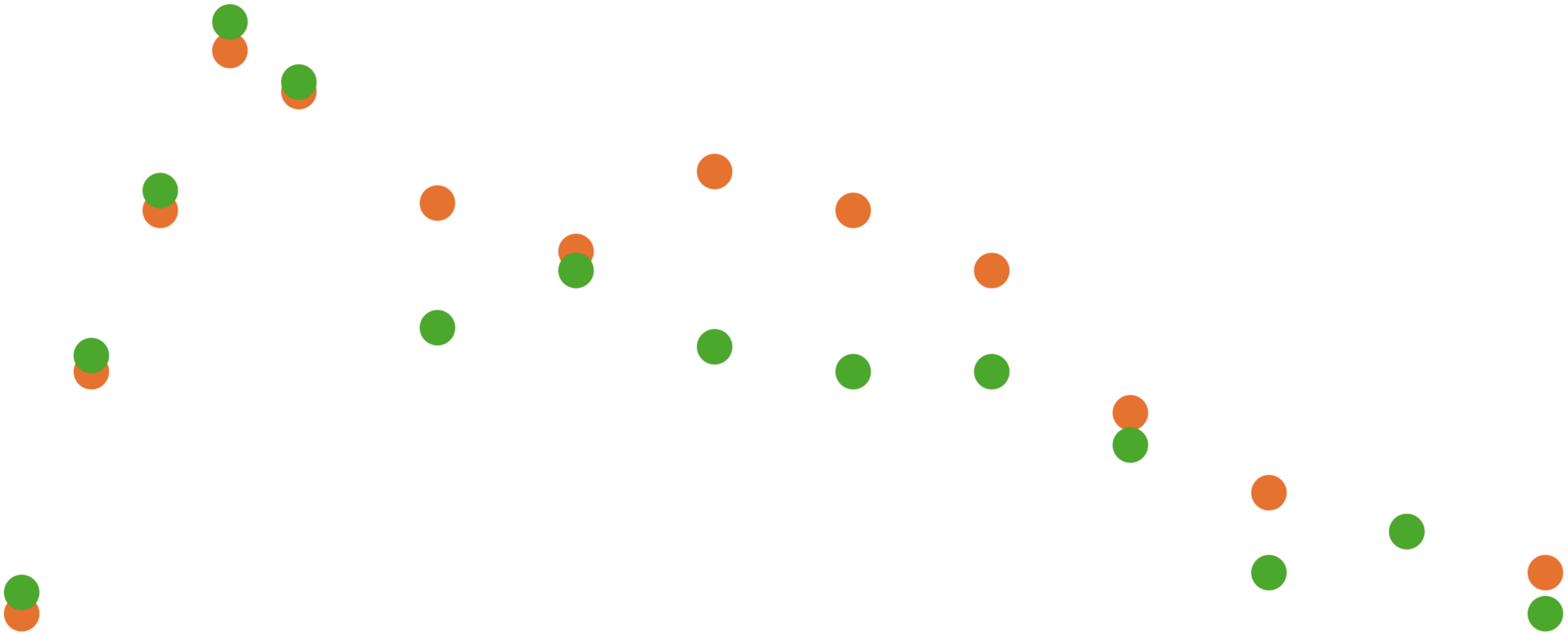

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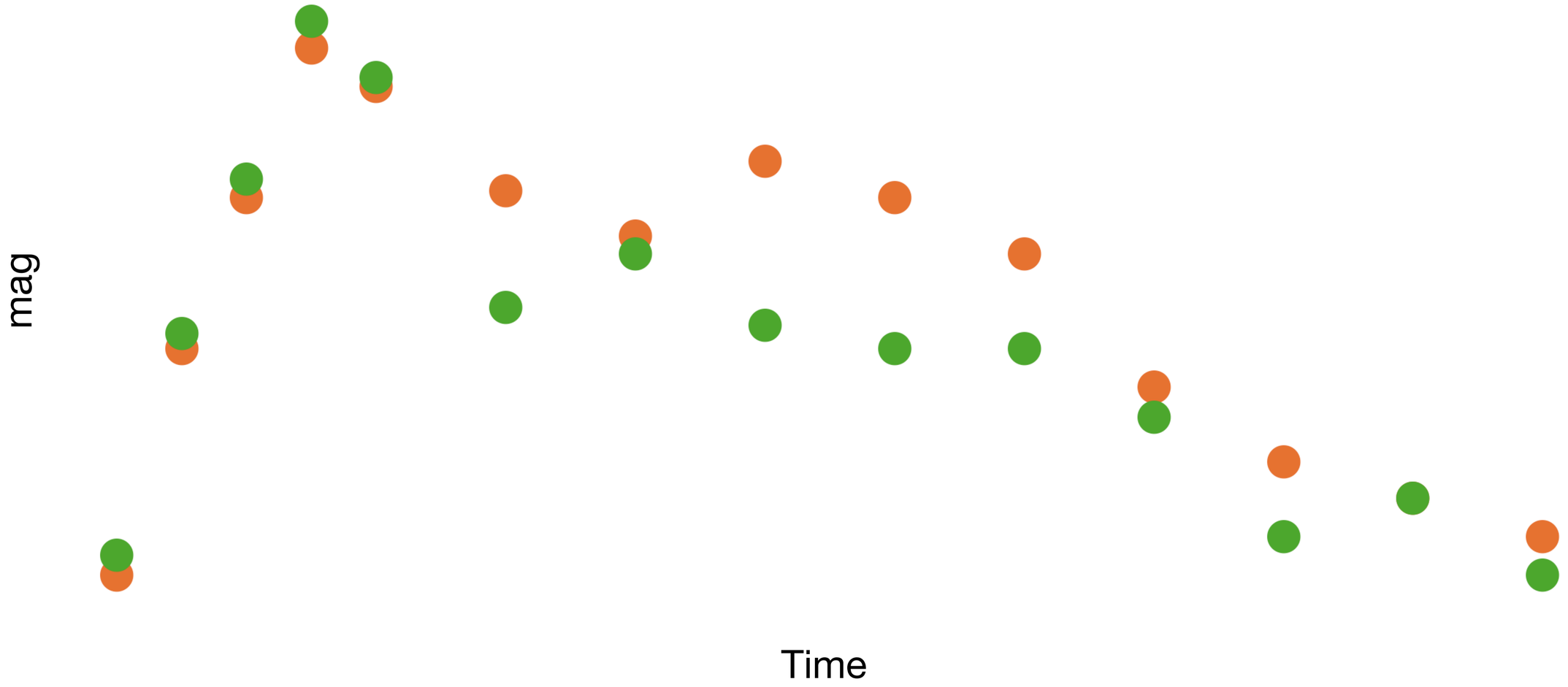

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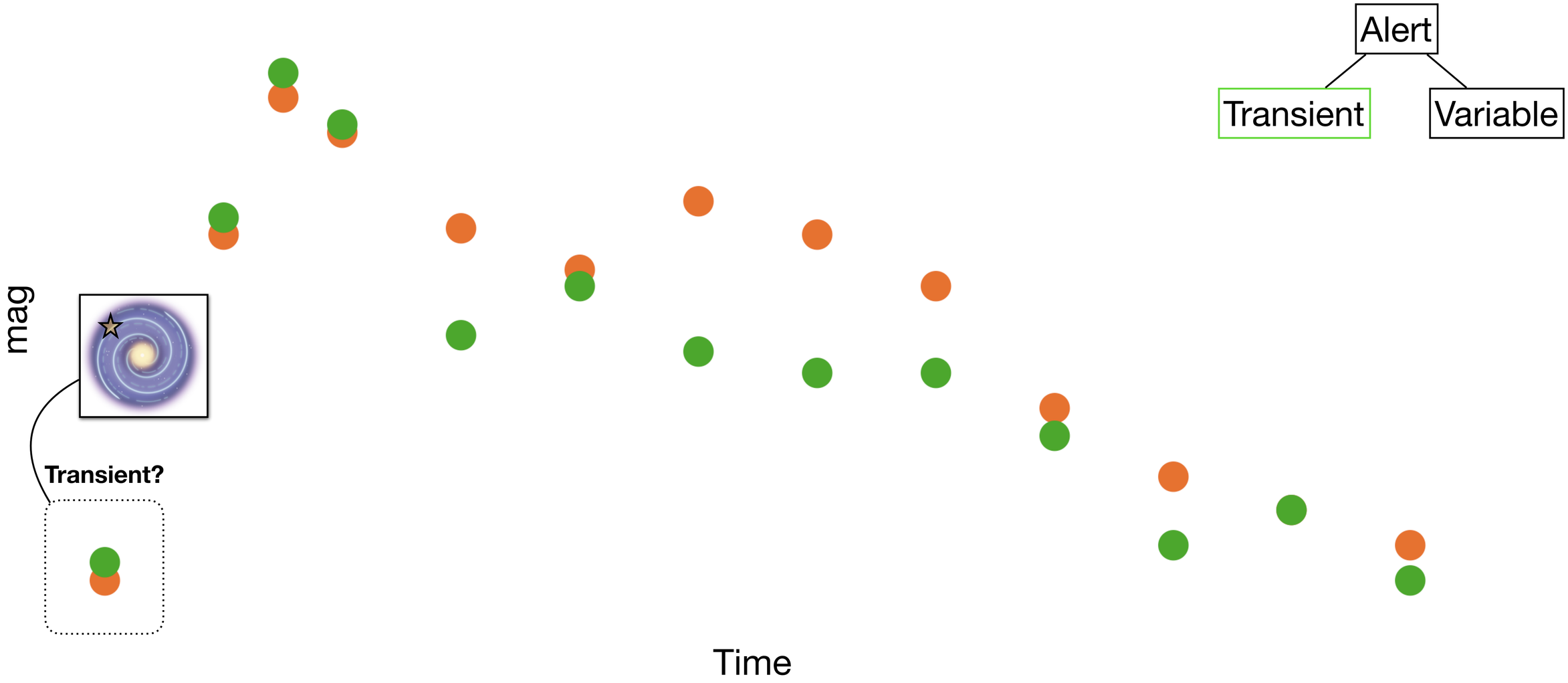

*For illustrative purposes only

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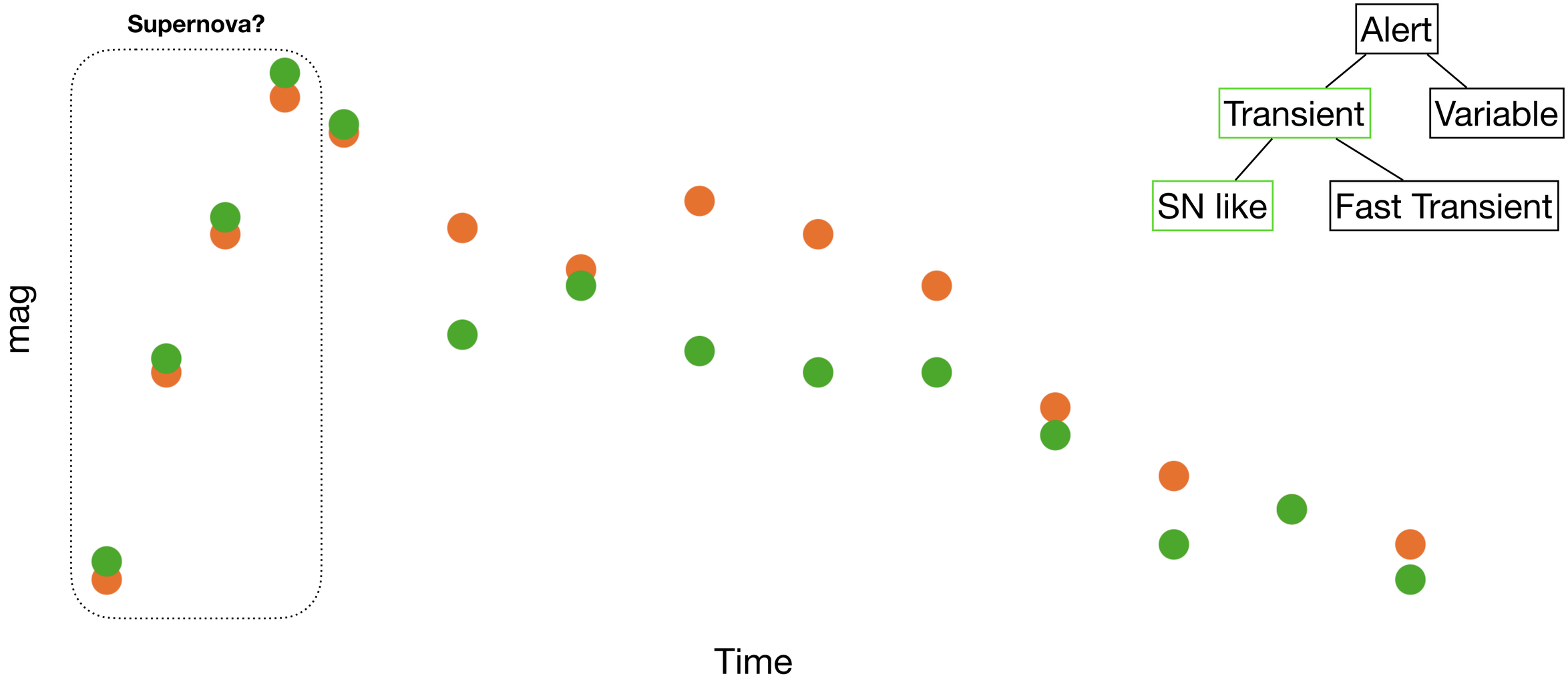

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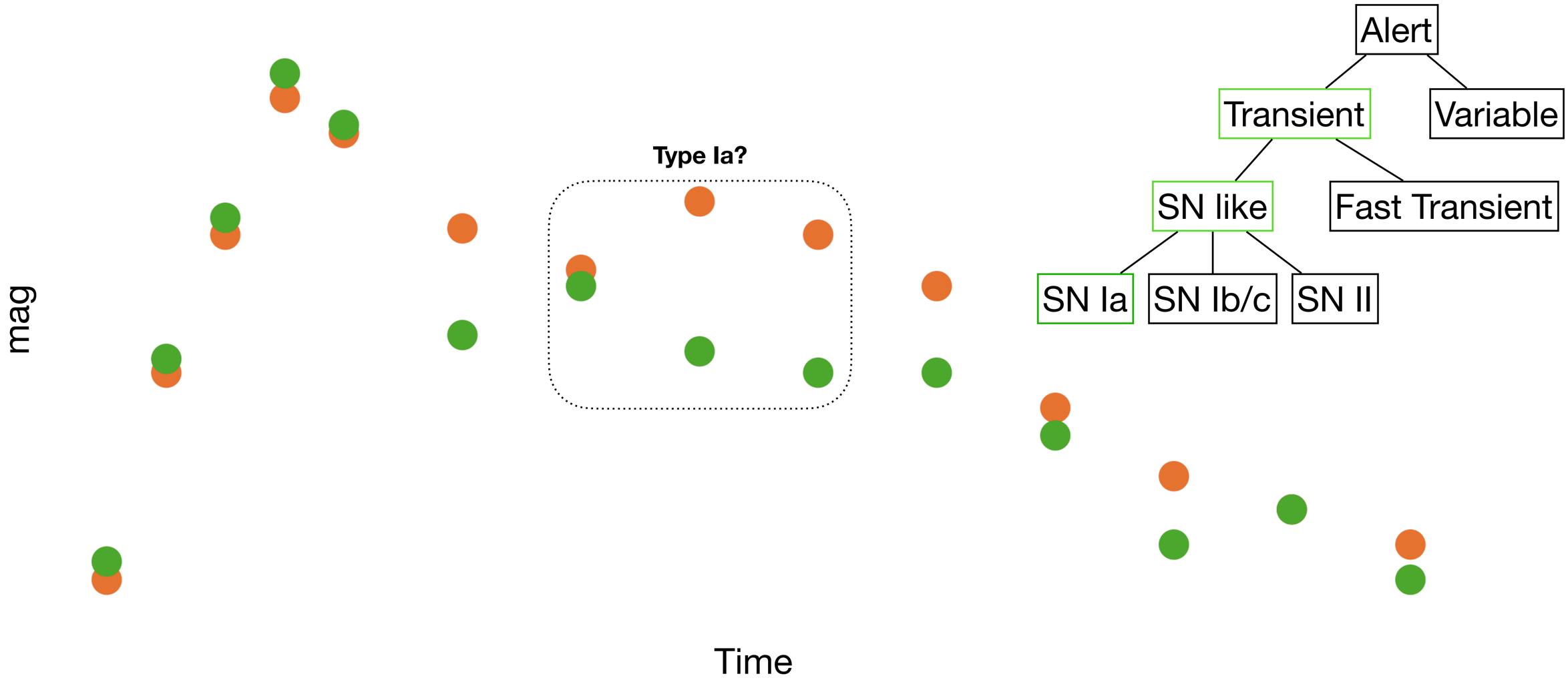

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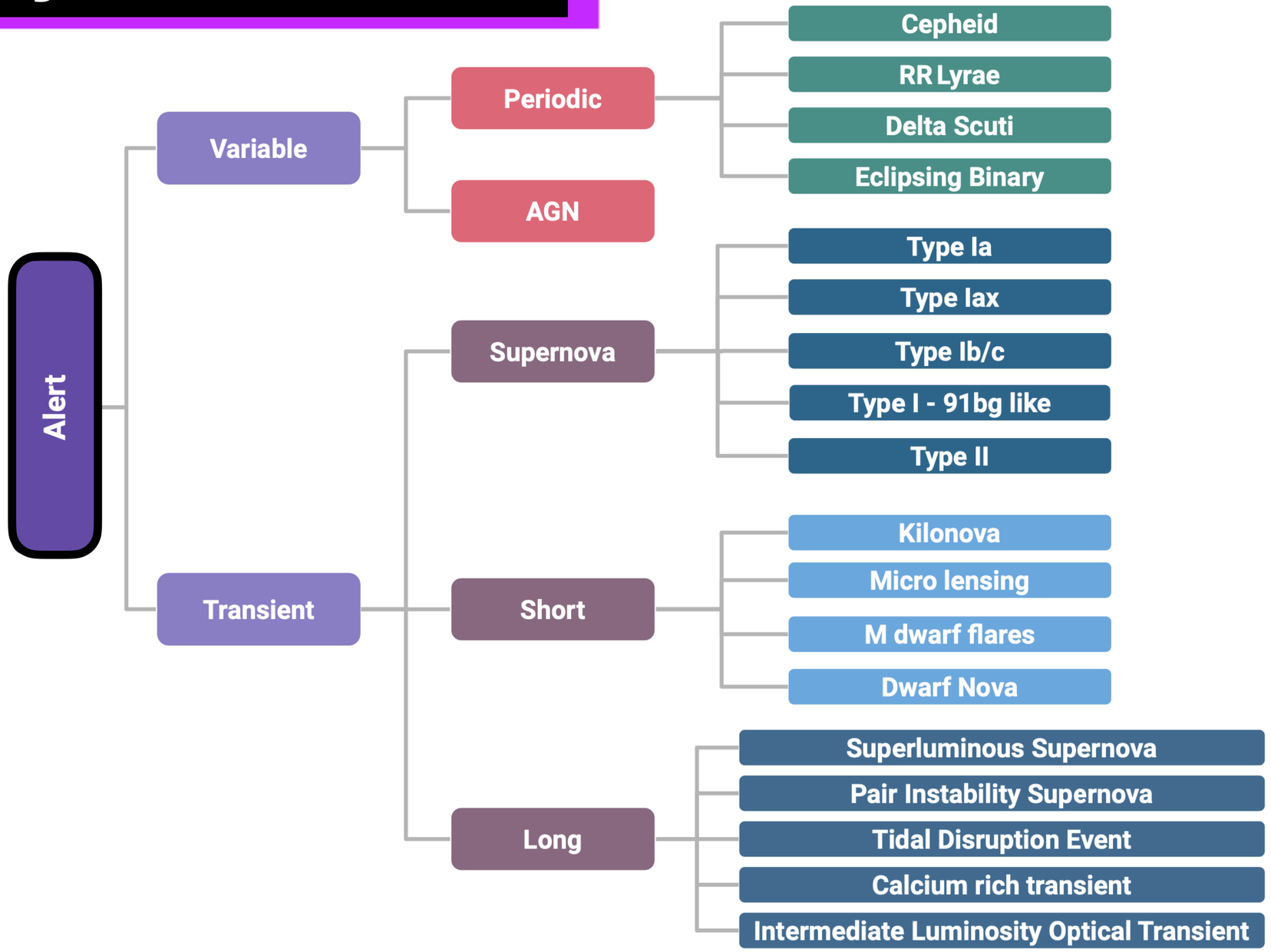
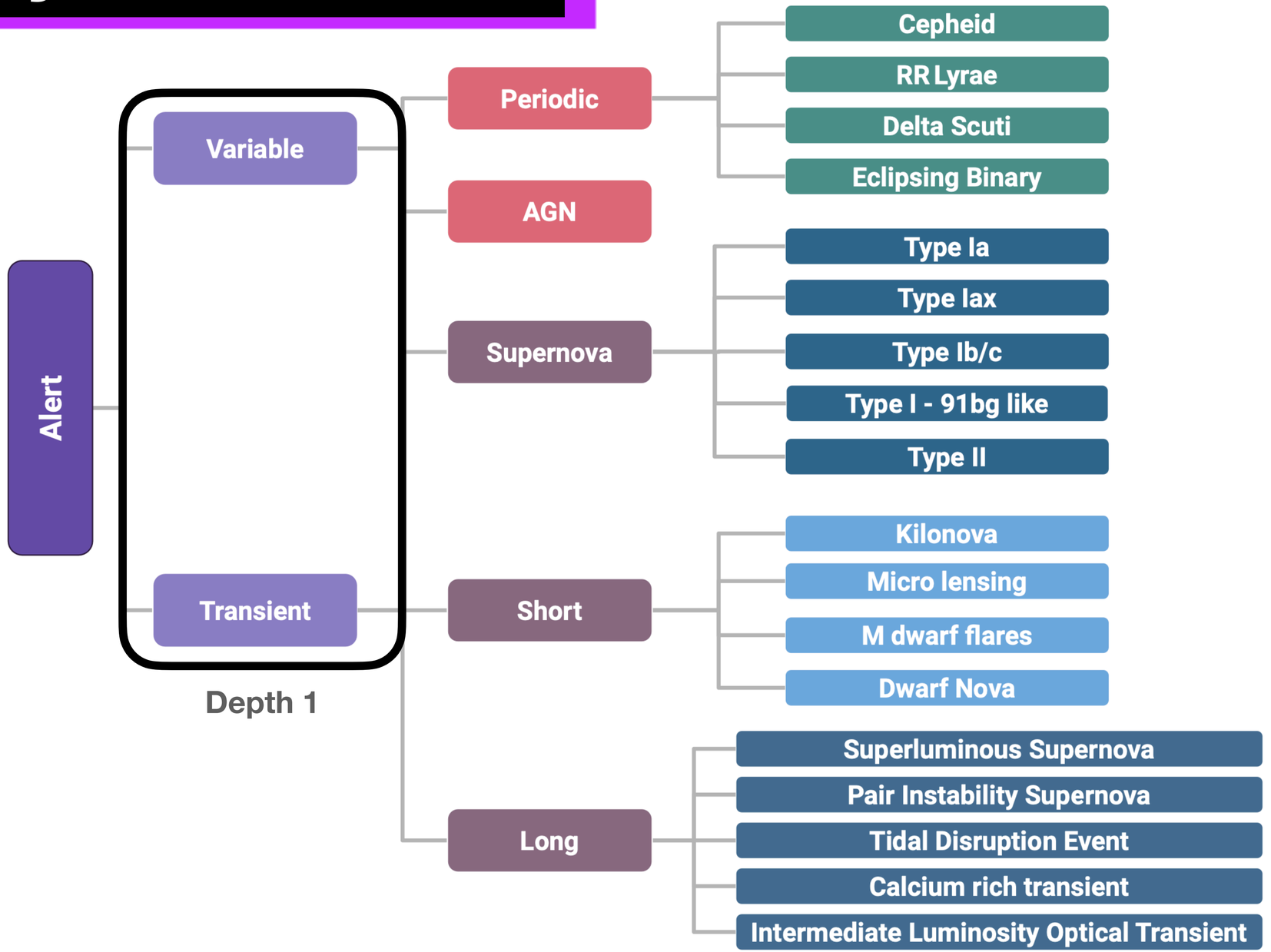
Taxonomy for ELAsTiCC



Shah et al. (2025b)

Taxonomy for ELAsTiCC



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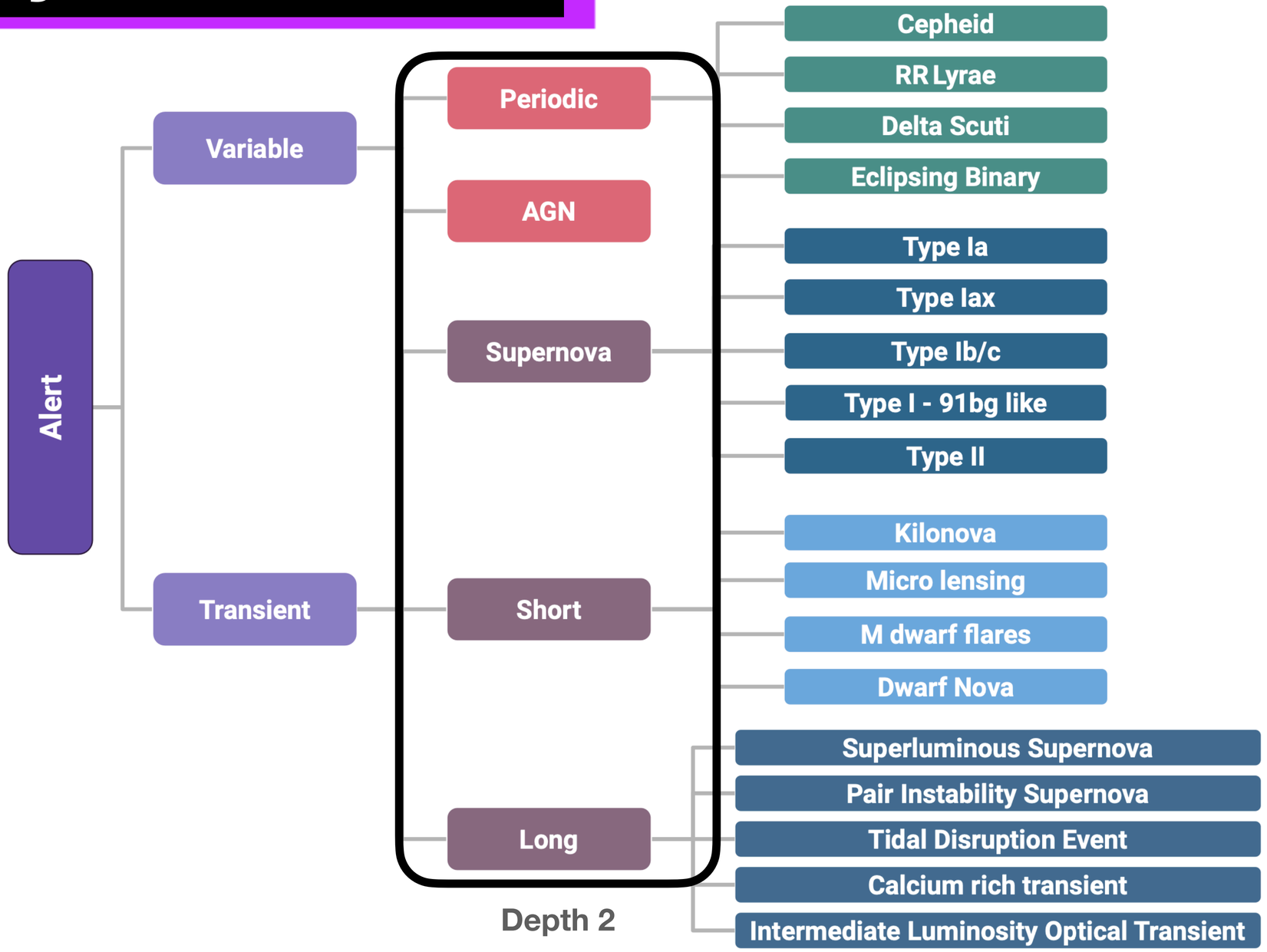

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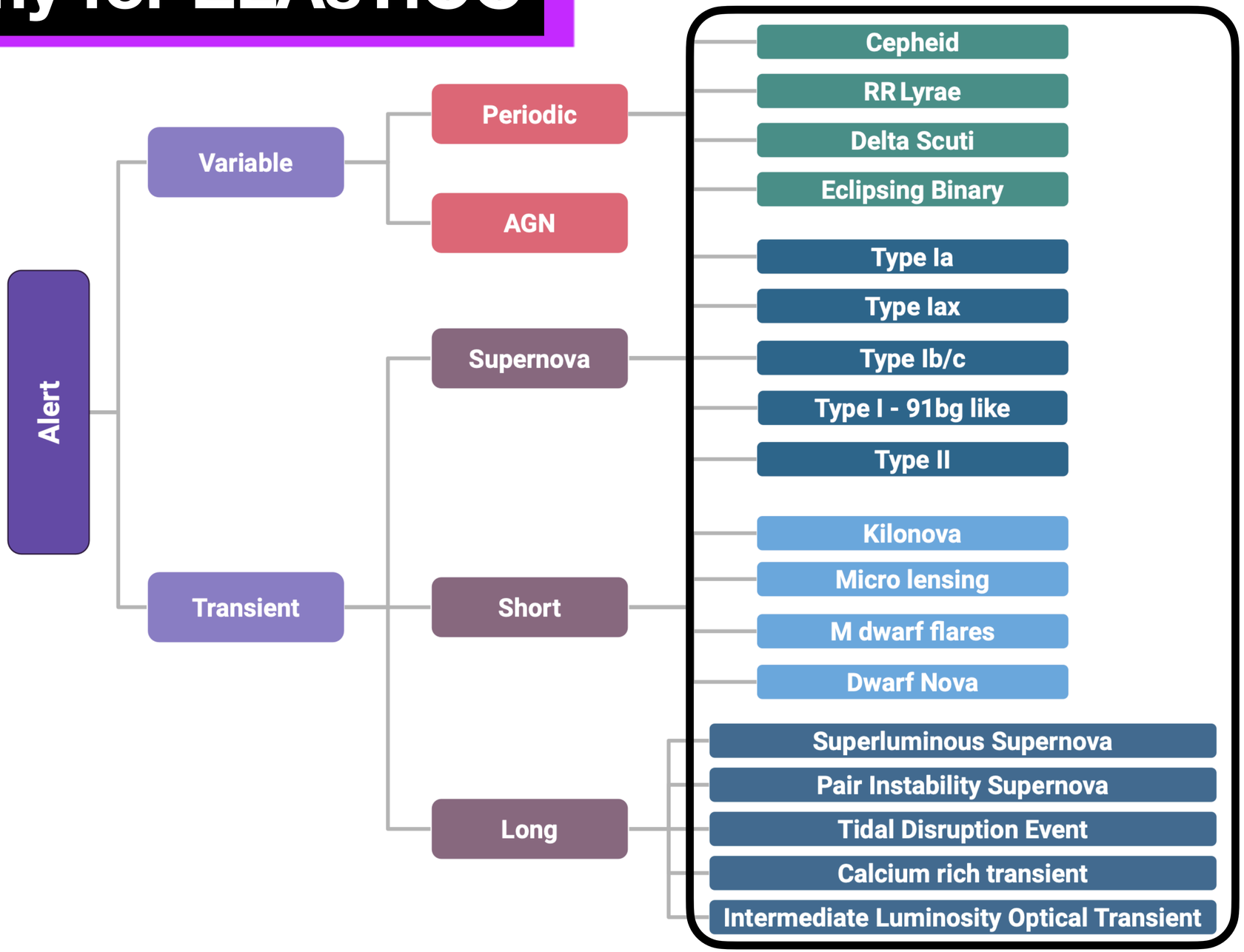
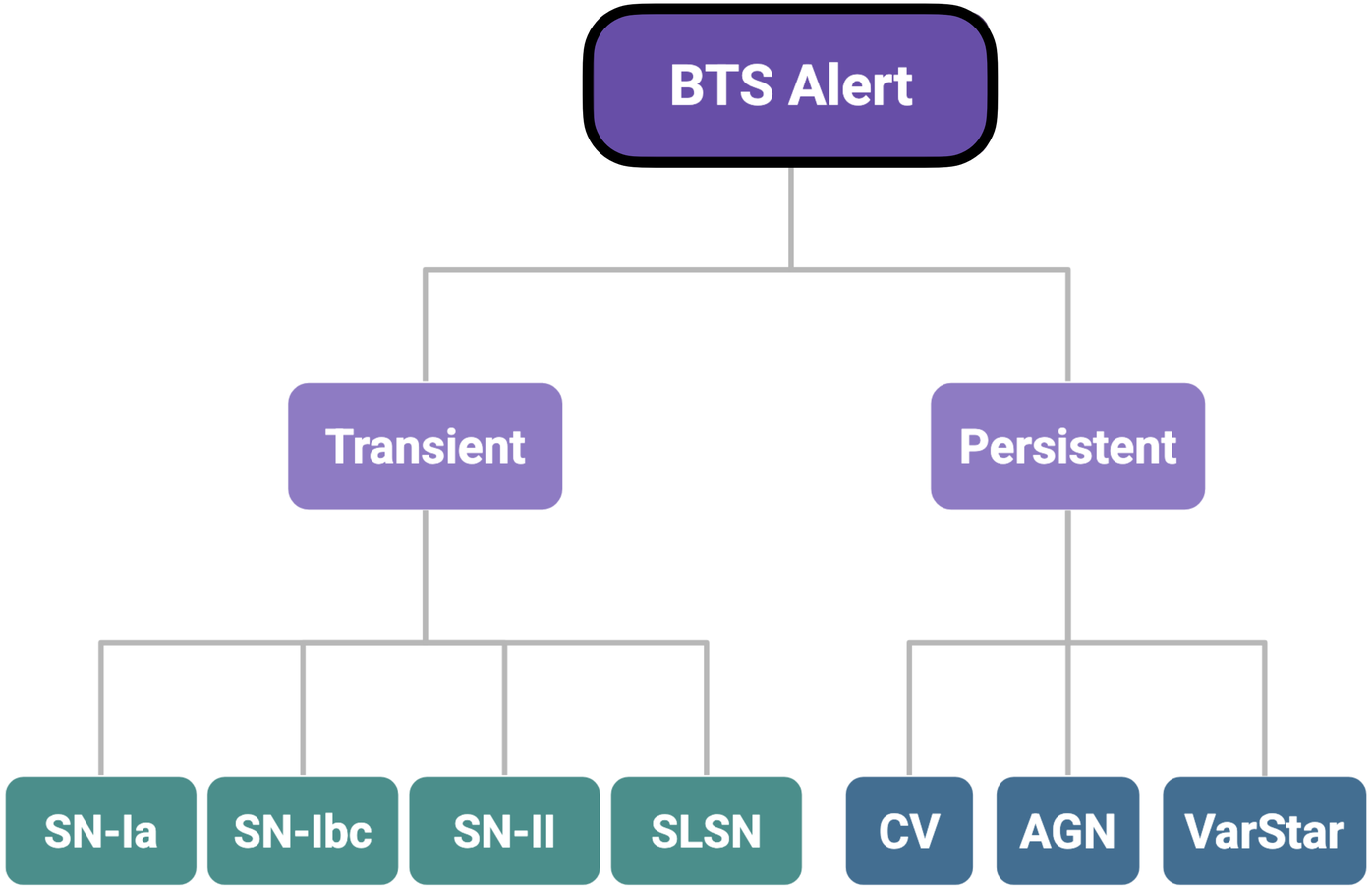


Depth Leaf

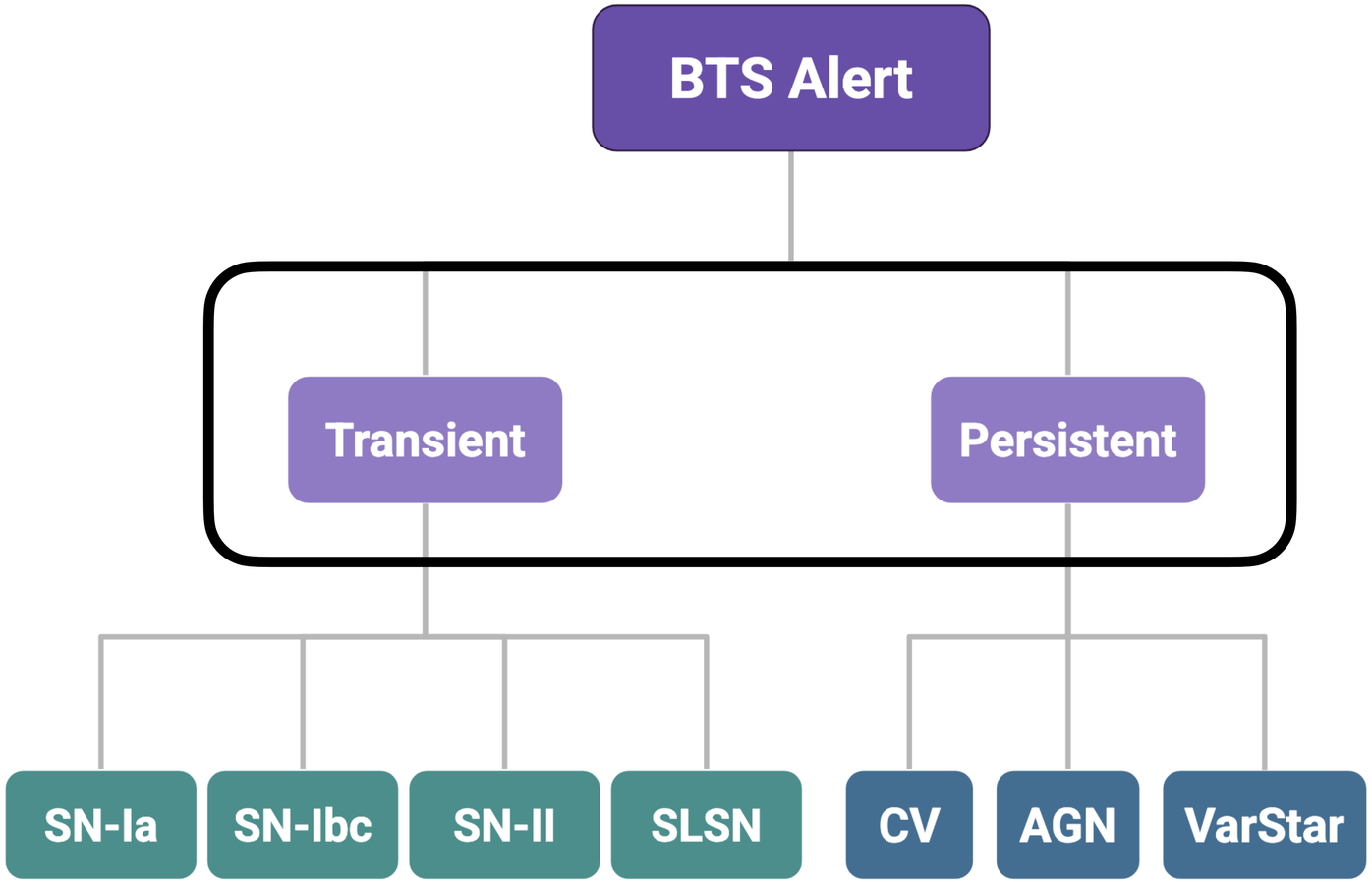
Shah et al. (2025b)

Taxonomy for ZTF model



Shah+26 (in prep)

Taxonomy for ZTF model



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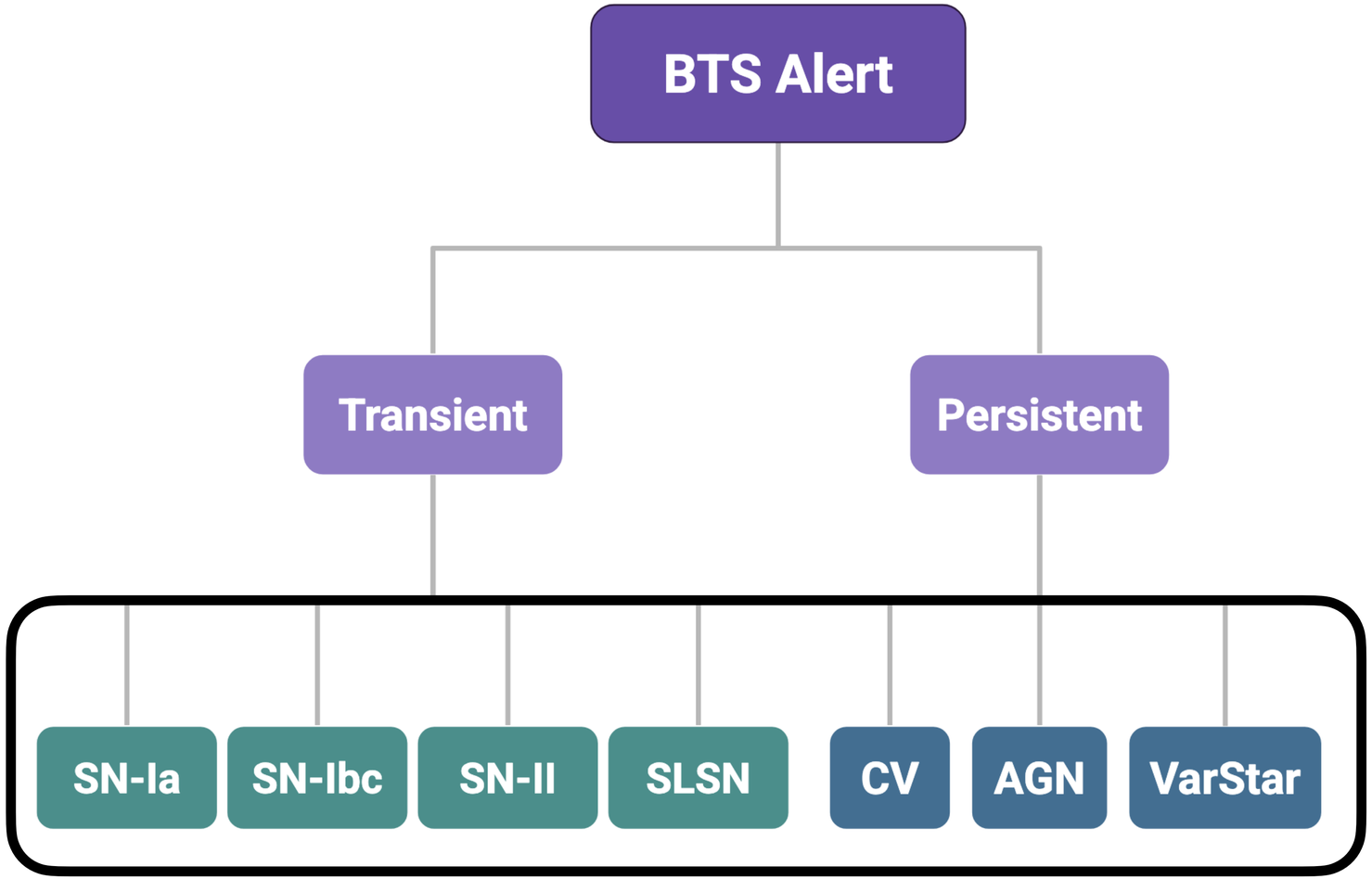

Shah+26 (in prep)

The need for multi-modality

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Core Collapse SNe:

- Preferentially occur in galaxies that have active star formation

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Superluminous SNe-I:

- Preferentially occur in low metallicity dwarf galaxies

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Core Collapse SNe:

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Superluminous SNe-I:

- Preferentially occur in low metallicity dwarf galaxies

Variable Stars:

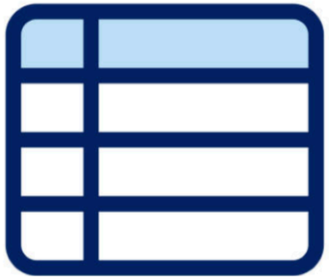
- A large fraction of alerts occur in crowded fields

2. Methods

Multi-modal Architecture

5 feature time series

Contextual Information



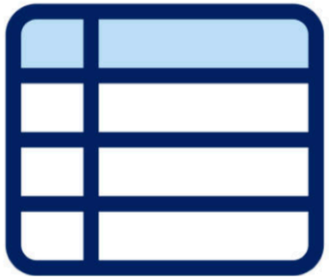
Multi-band Images

Shah+26 (in prep)

Multi-modal Architecture

5 feature time series

Contextual Information



Multi-band Images

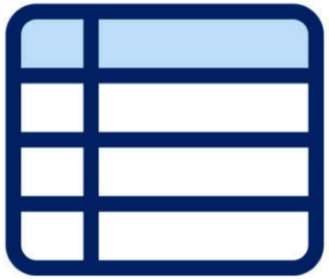
Oracle-2 Lite (RNN)

Shah+26 (in prep)

Multi-modal Architecture

5 feature time series

Contextual Information



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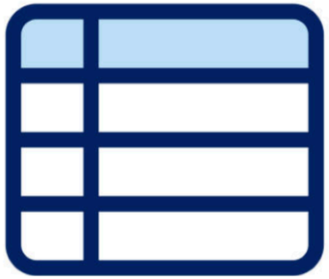

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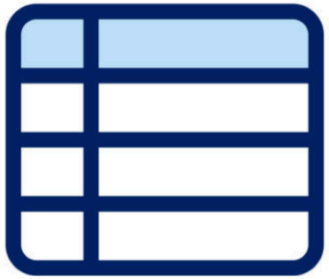


Multi-band Images

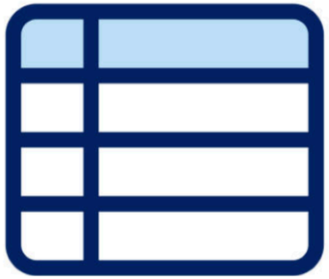
Oracle-2
(RNN + MLP)

Shah+26 (in prep)

Multi-modal Architecture

5 feature time series

Contextual Information



Multi-band Images

Shah+26 (in prep)

Multi-modal Architecture

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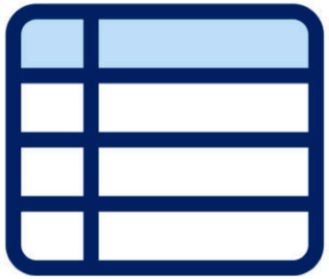

Multi-band Images

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Multi-modal Architecture

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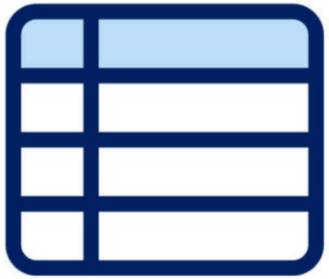
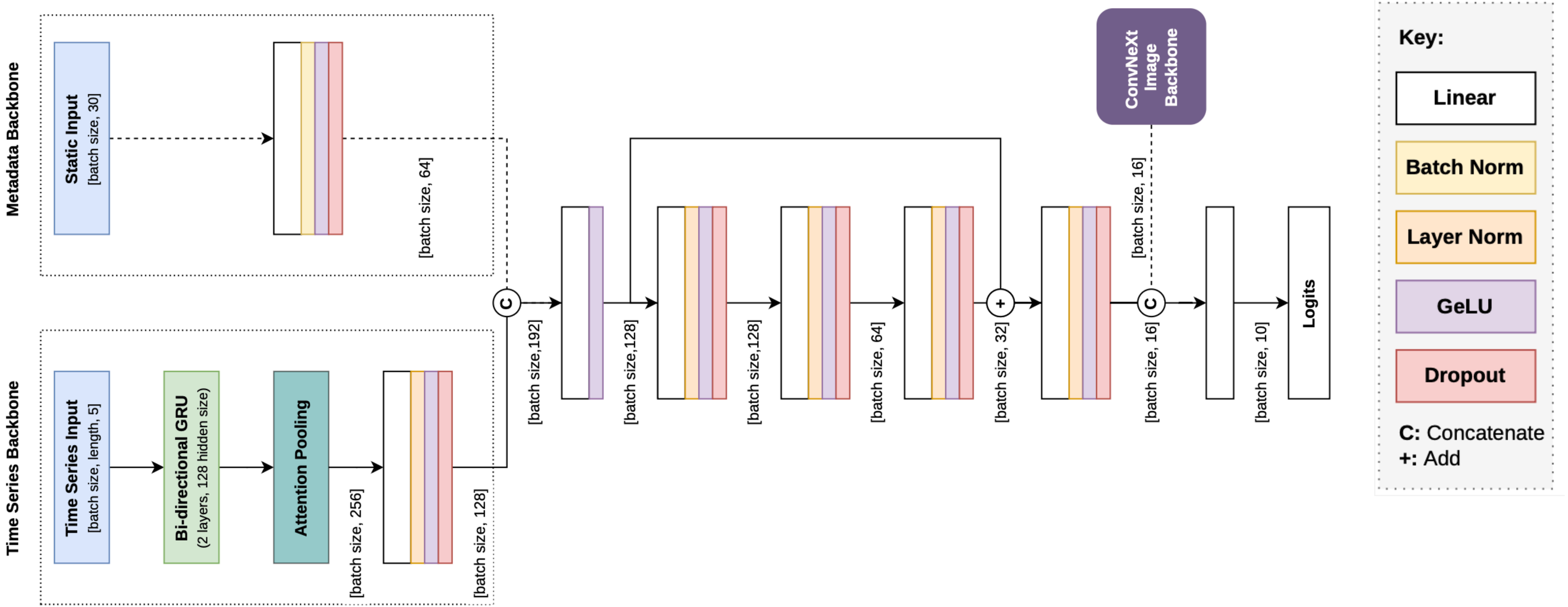


Multi-band Images

Oracle-2 Omni (for ZTF only)
(RNN + MLP + CNN)

Shah+26 (in prep)

Multi-modal Architecture



X

Shah+26 (in prep)

The Loss Function

Hierarchical Cross Entropy (HXE) - Bertinetto et al. (2019)

$$L_{\text{HXE}}(p, C) = -\sum_{l=0}^{h-1} \lambda(C^{(l)}) \log p(C^{(l)} \mid C^{(l+1)})$$

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Hierarchical Cross Entropy (HXE) - Bertinetto et al. (2019)

$$L_{\text{HXE}}(p, C) = -\underbrace{\sum_{l=0}^{h-1} \lambda(C^{(l)}) \log p(C^{(l)} \mid C^{(l+1)})}$$

Sum over all layers of taxonomy

The Loss Function

Hierarchical Cross Entropy (HXE) - Bertinetto et al. (2019)

$$L_{\text{HXE}}(p, C) = -\sum_{l=0}^{h-1} \underbrace{\lambda(C^{(l)})}_{\text{Level weight term}} \log p(C^{(l)} \mid C^{(l+1)})$$

where $\lambda(C^{(l)}) = \exp(-\alpha d(C))$

The Loss Function

Weighted Hierarchical Cross Entropy (WHXE) - Villar et al. (2023)

$$L_{\text{WHXE}}(p, C) = -\sum_{l=0}^{h-1} W(C^{(l)})\ \lambda(C^{(l)})\ \ \log p(C^{(l)} \mid C^{(l+1)})$$

The Loss Function

Weighted Hierarchical Cross Entropy (WHXE) - Villar et al. (2023)

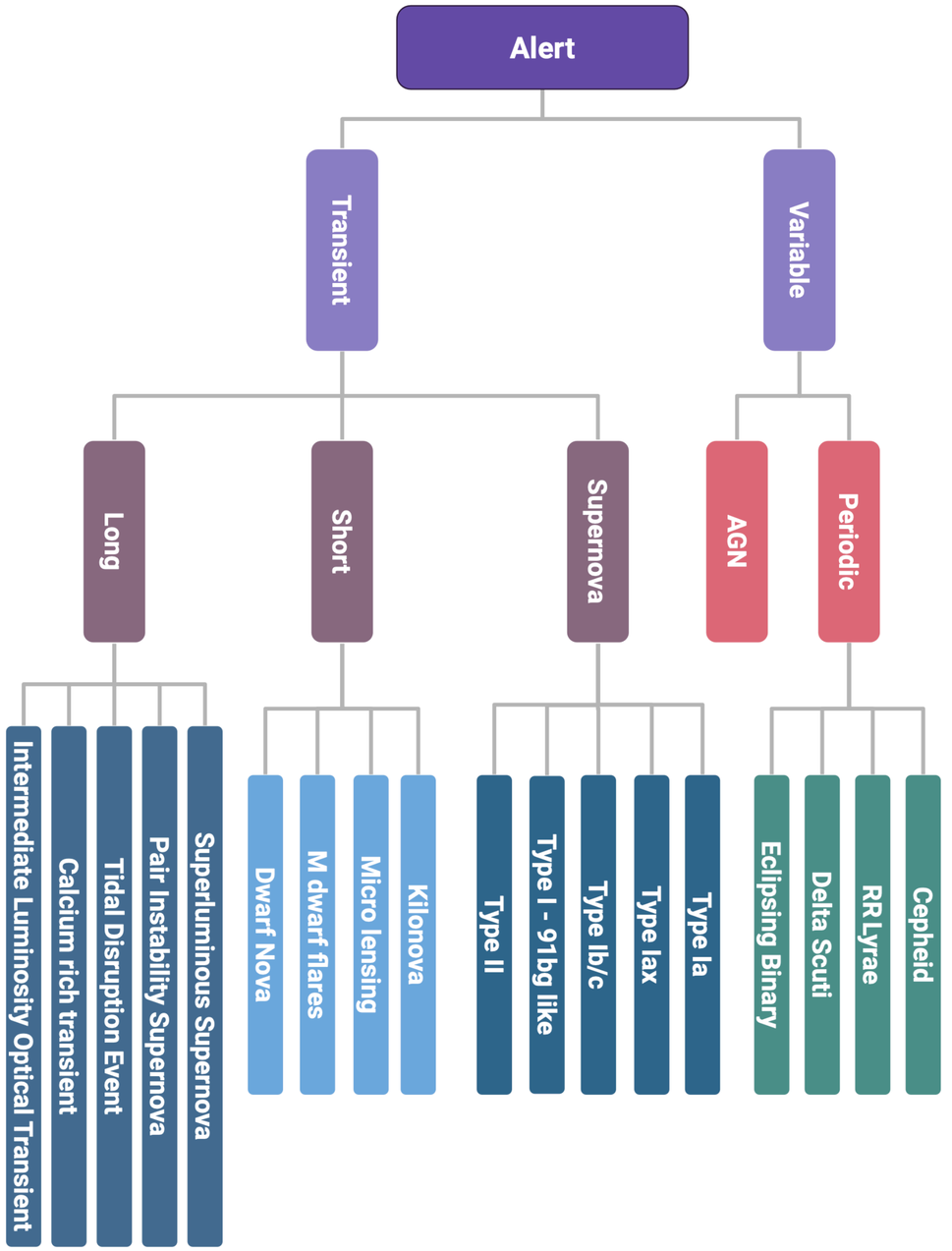
$$L_{\text{WHXE}}(p, C) = -\sum_{l=0}^{h-1} \underbrace{W(C^{(l)})}\ \lambda(C^{(l)})\ \log p(C^{(l)} \mid C^{(l+1)})$$

Class weight term

$$\text{where } W(C^{(l)}) \propto \frac{1}{N_c}$$

Computing class probabilities

$$p(C) = \prod_{l=0}^{h(C)-1} p(C^{(l)} \mid C^{(l+1)})$$



x

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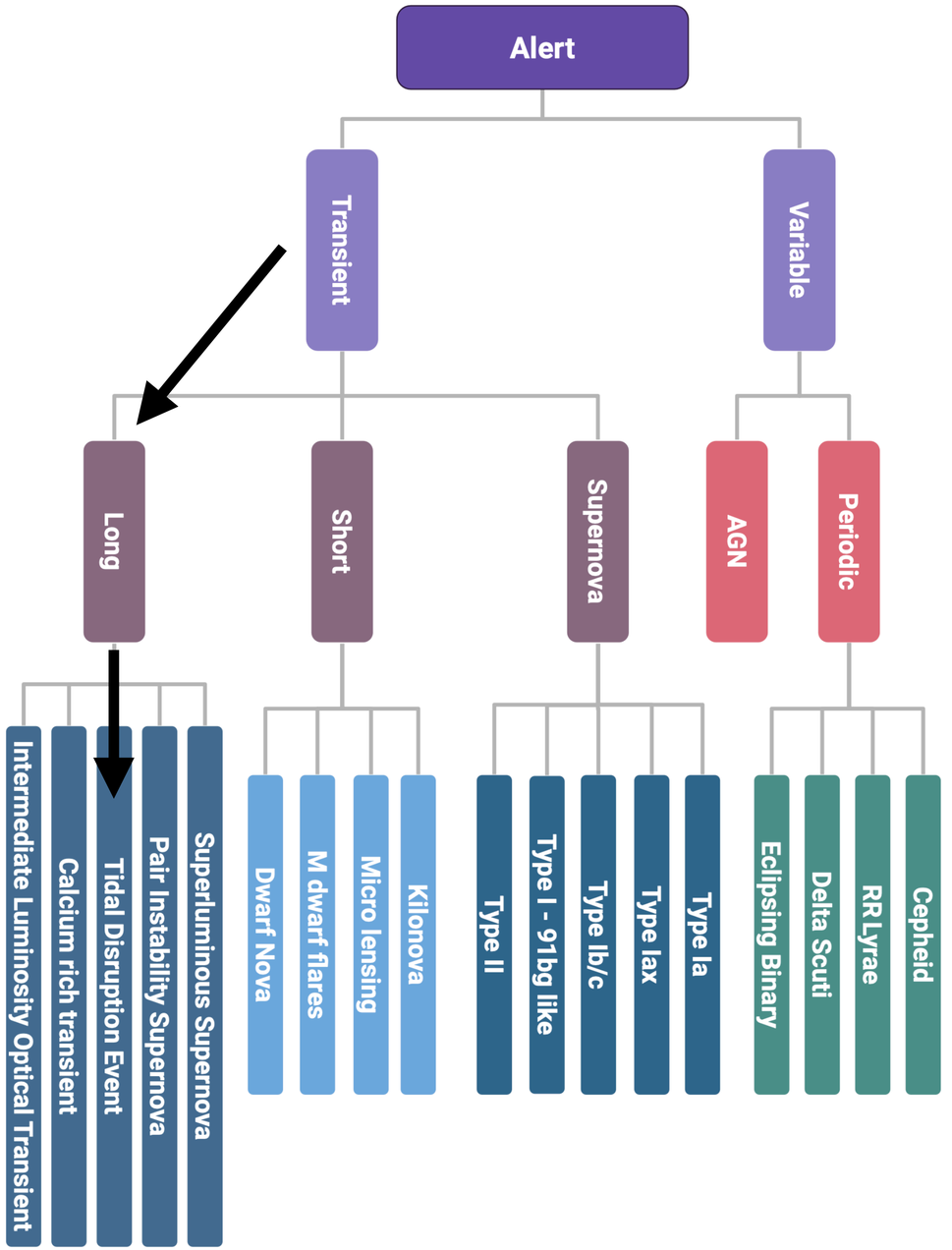

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Dataset

ELAsTiCC for LSST:

- Used ~500,000 simulated sources from the ELAsTiCC data set across 19 classes.
- 70:30% split for training/testing. 5% of the training data for left aside for validation.
- Combination of light curves and metadata.

ZTF:

- Used ~15,000 transients and variables from ZTF organized across 7 classes.
- 80%/10%/10% split for train/test/validation.
- Combination of light curves, metadata, and images.

Data Augmentation

- Since we want **Oracle** to classify observations in real time, we explicitly trained the model to classify partial light curves.
- For the omni models, we add random rotations and flips to the images in order to promote rotational invariance and prevent overfitting.

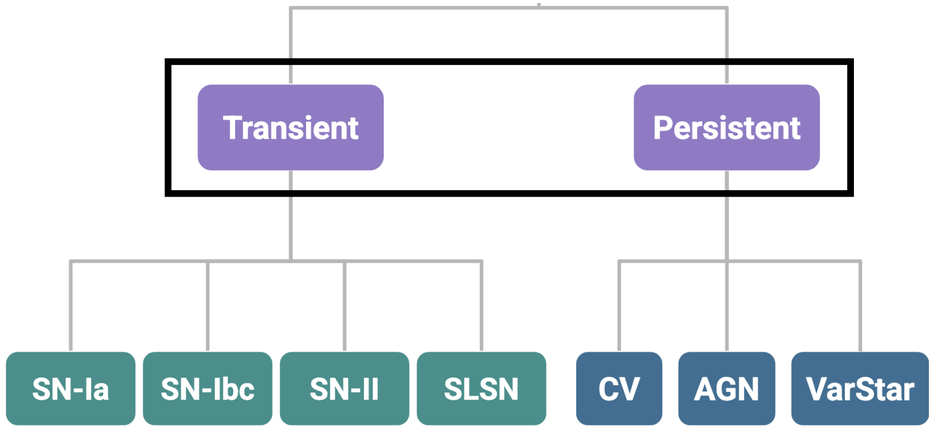
Hyperparameters

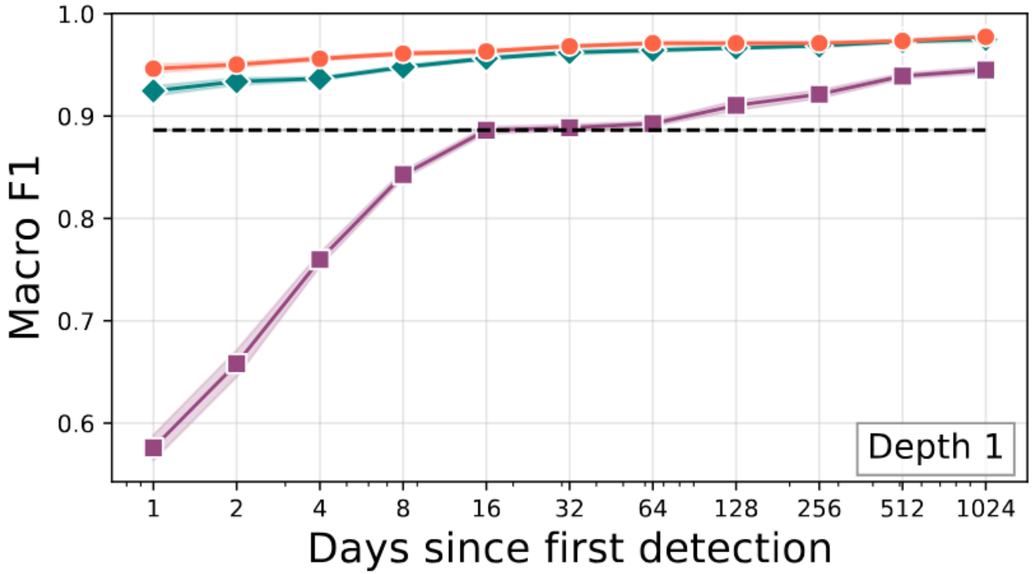
Parameter	Value
Epochs	1000
Batch Size	1024
Learning rate	2e-4
Non linearity	tanh, ReLU
Optimizer	Adam
Alpha (For loss function)	0.5

Table 4. Hyper-parameters used for training ORACLE.

3. Results for ZTF

Real time performance for ZTF

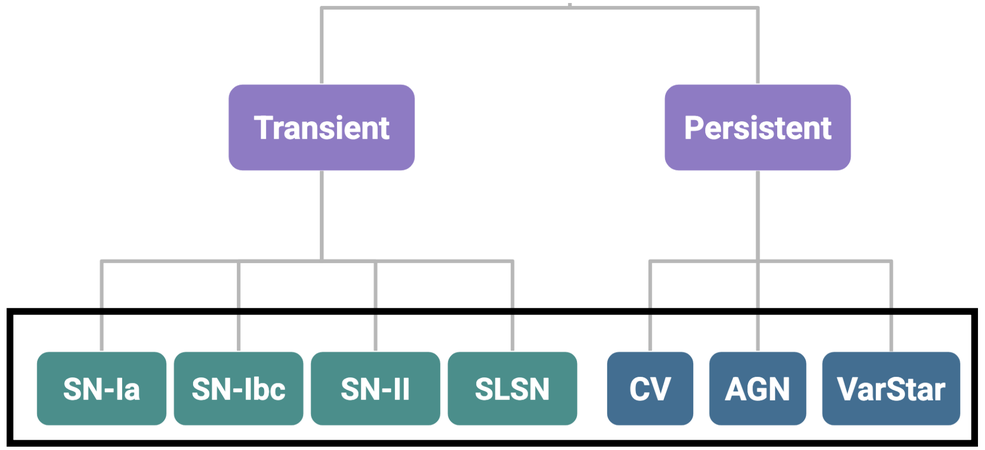


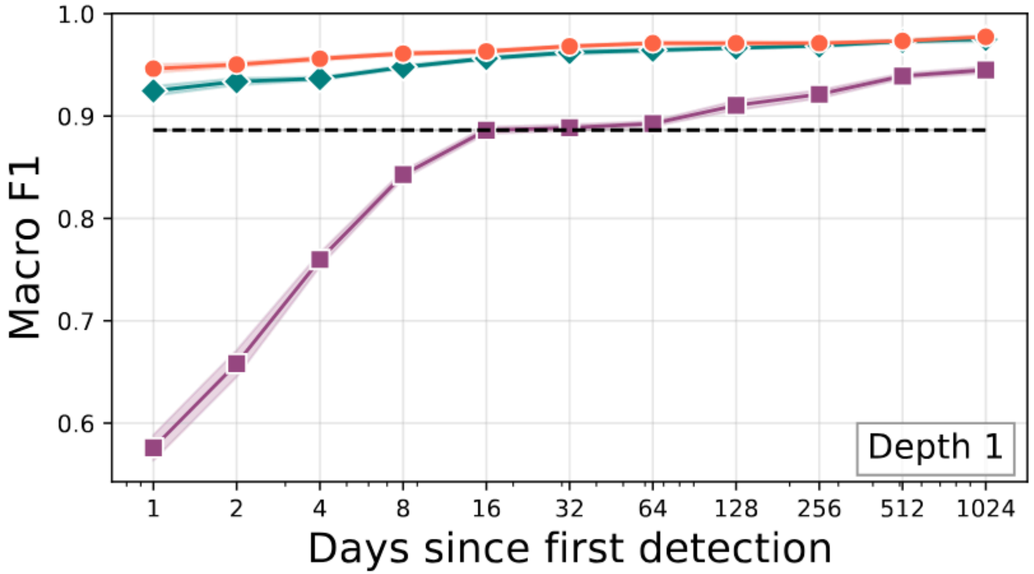


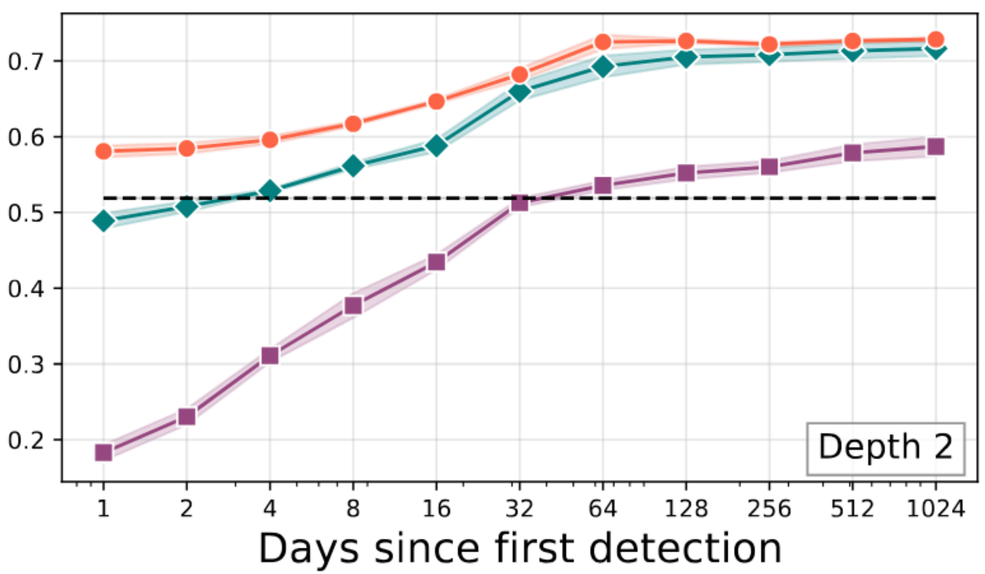
Oracle-2 Lite Oracle-2 Oracle-2 Omni Image Backbone

Shah+26 (in prep)

Real time performance for ZTF





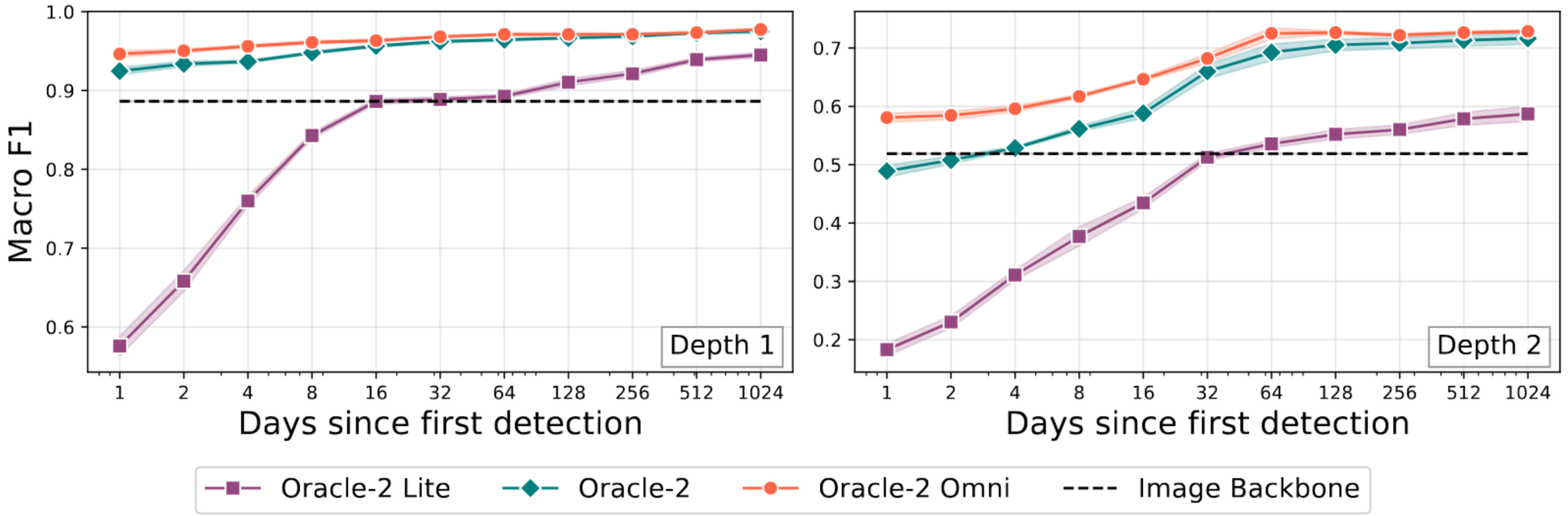


Oracle-2 Lite Oracle-2 Oracle-2 Omni Image Backbone

Shah+26 (in prep)

Real time performance for ZTF

Oracle-2 Omni > Oracle-2 > Oracle-2 Lite



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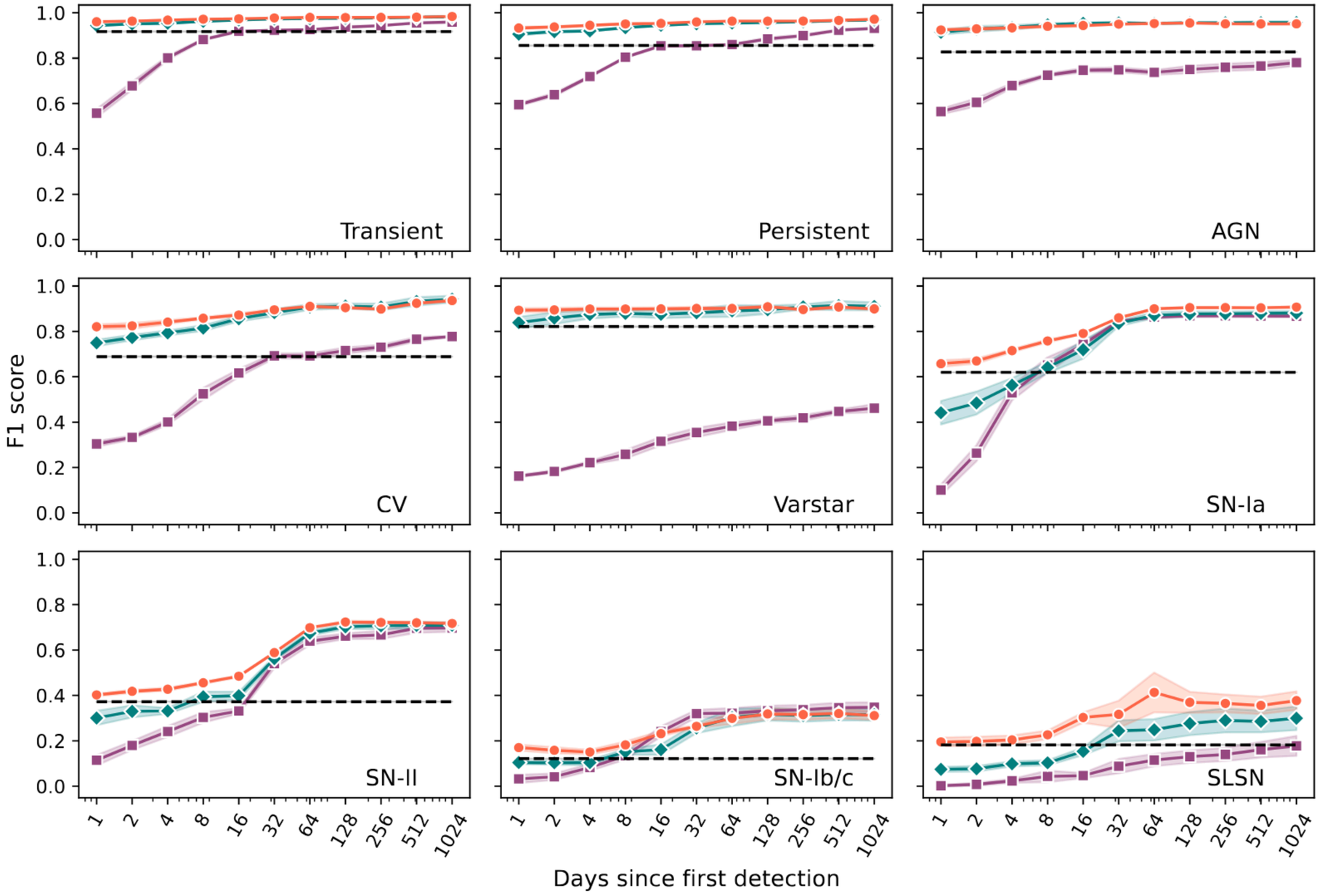
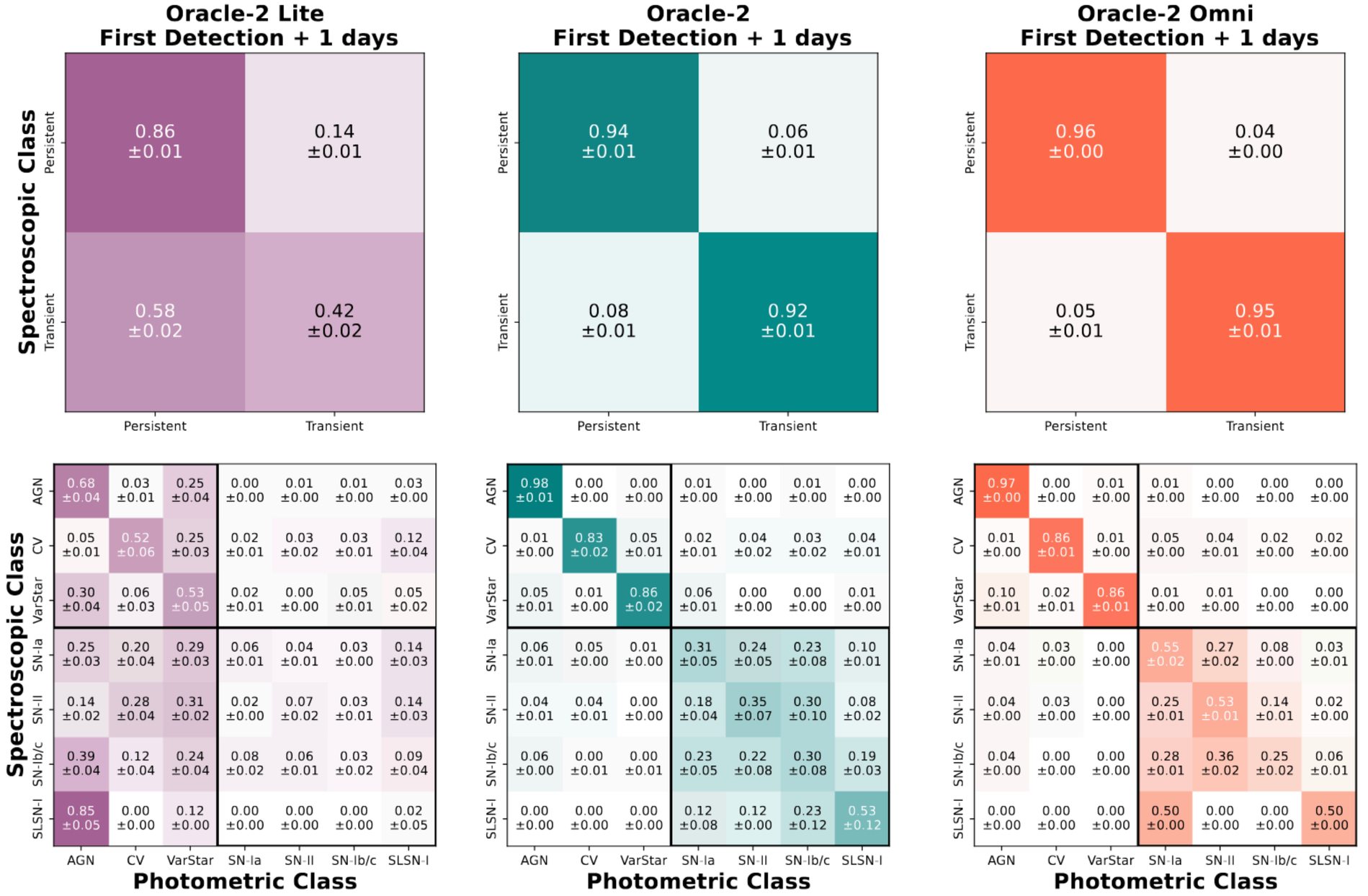


X

Shah+26 (in prep)

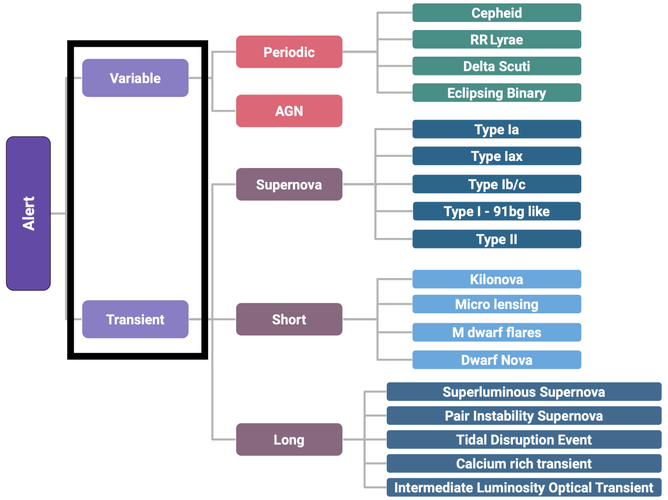
Confusion matrices at 1 day

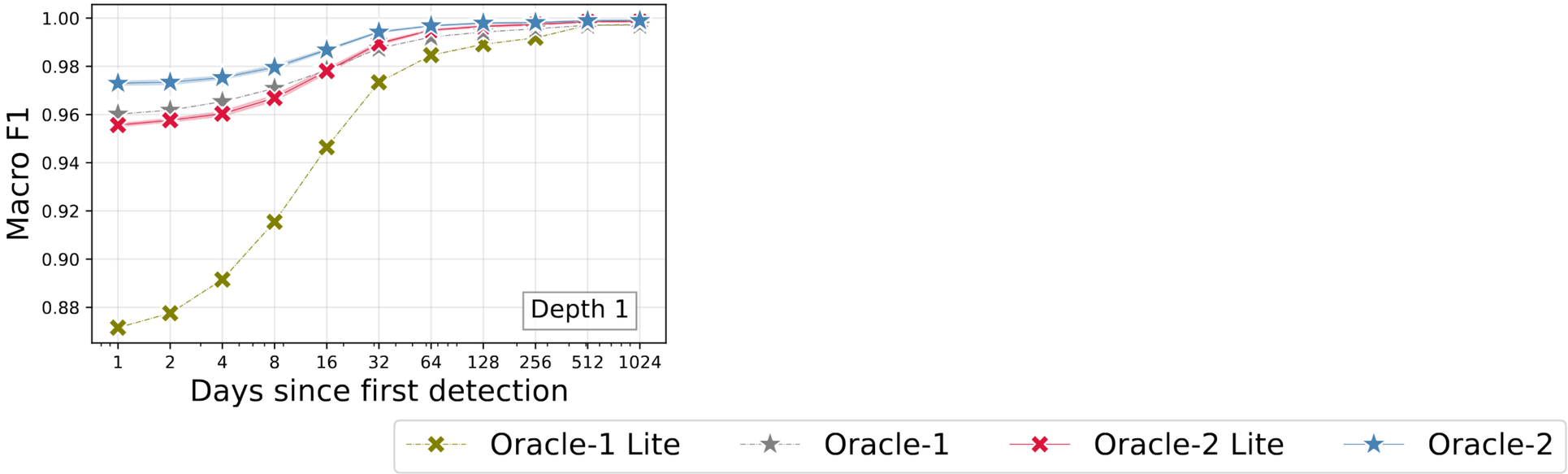


Shah+26 (in prep)

3.5 Results for LSST (using ELAsTiCC)

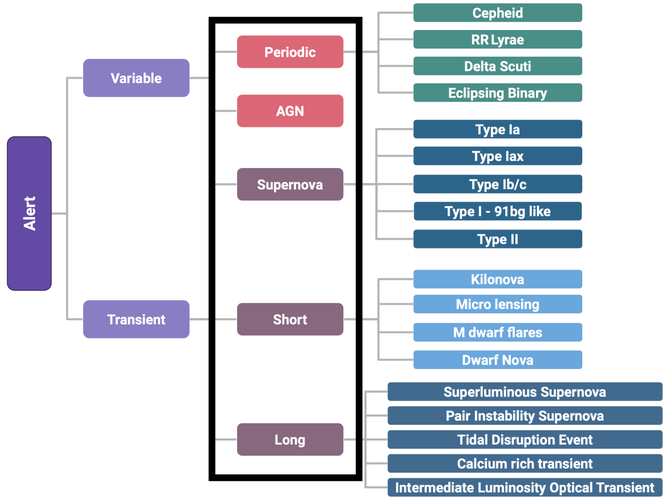
Real time performance on ELAsTiCC

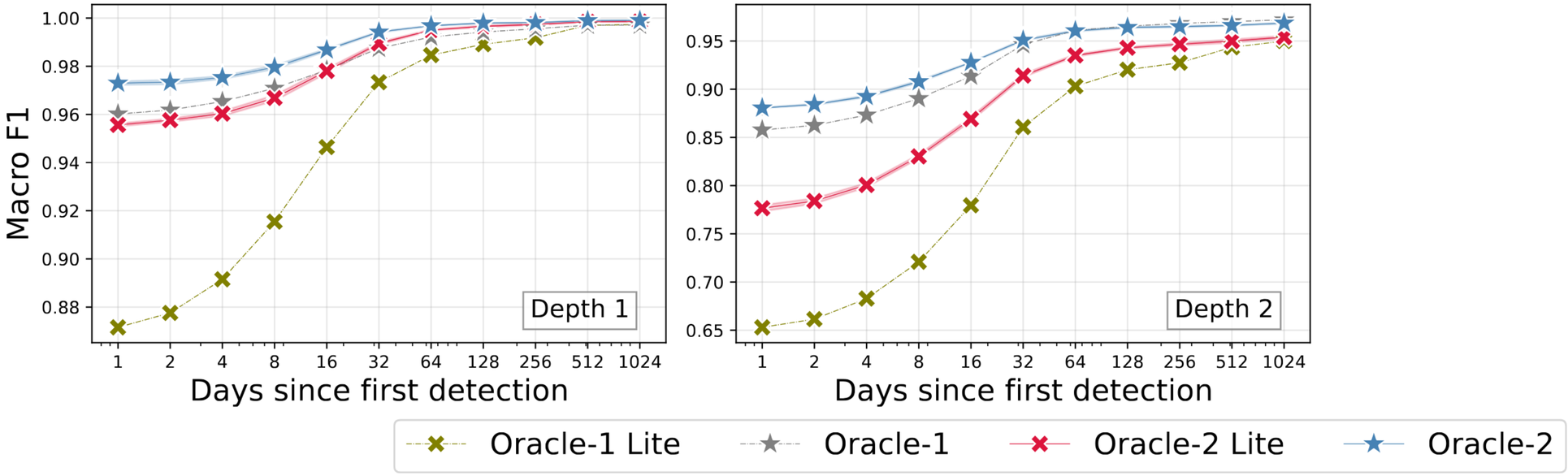




Shah+26 (in prep)

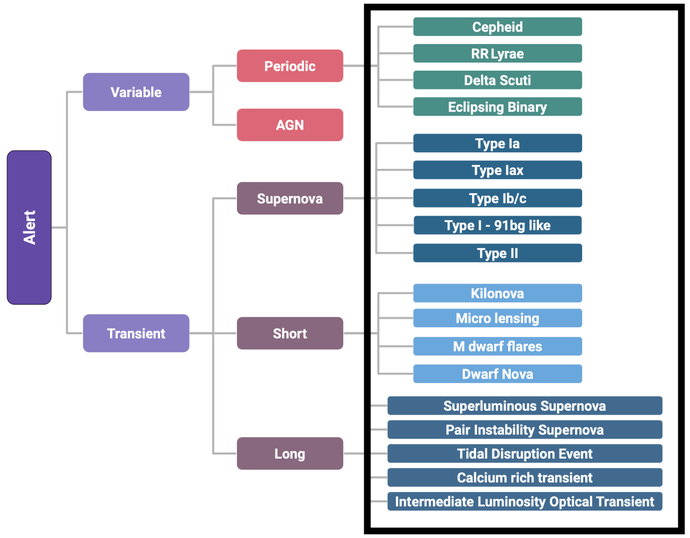
Real time performance on ELAsTiCC

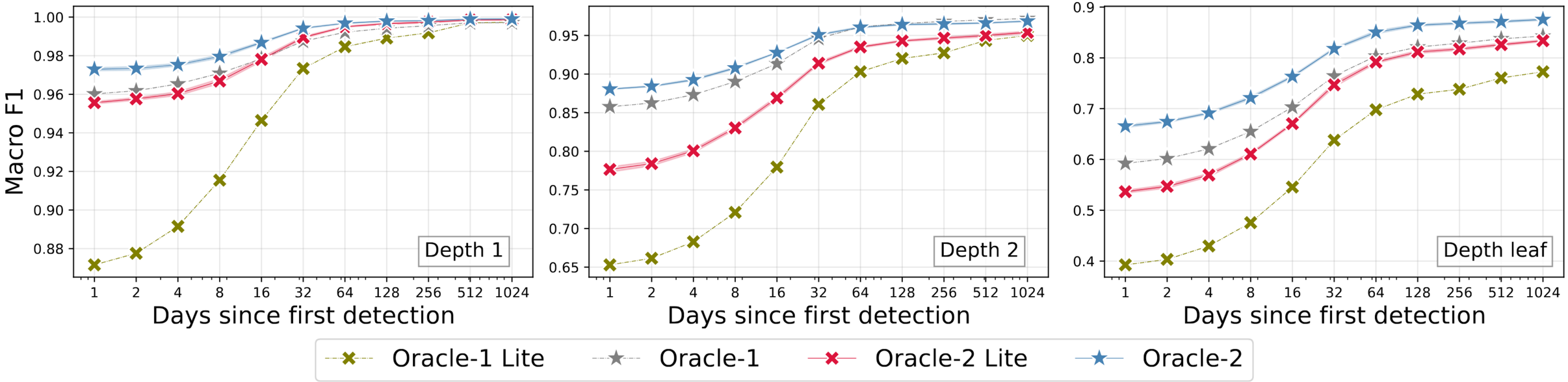




Shah+26 (in prep)

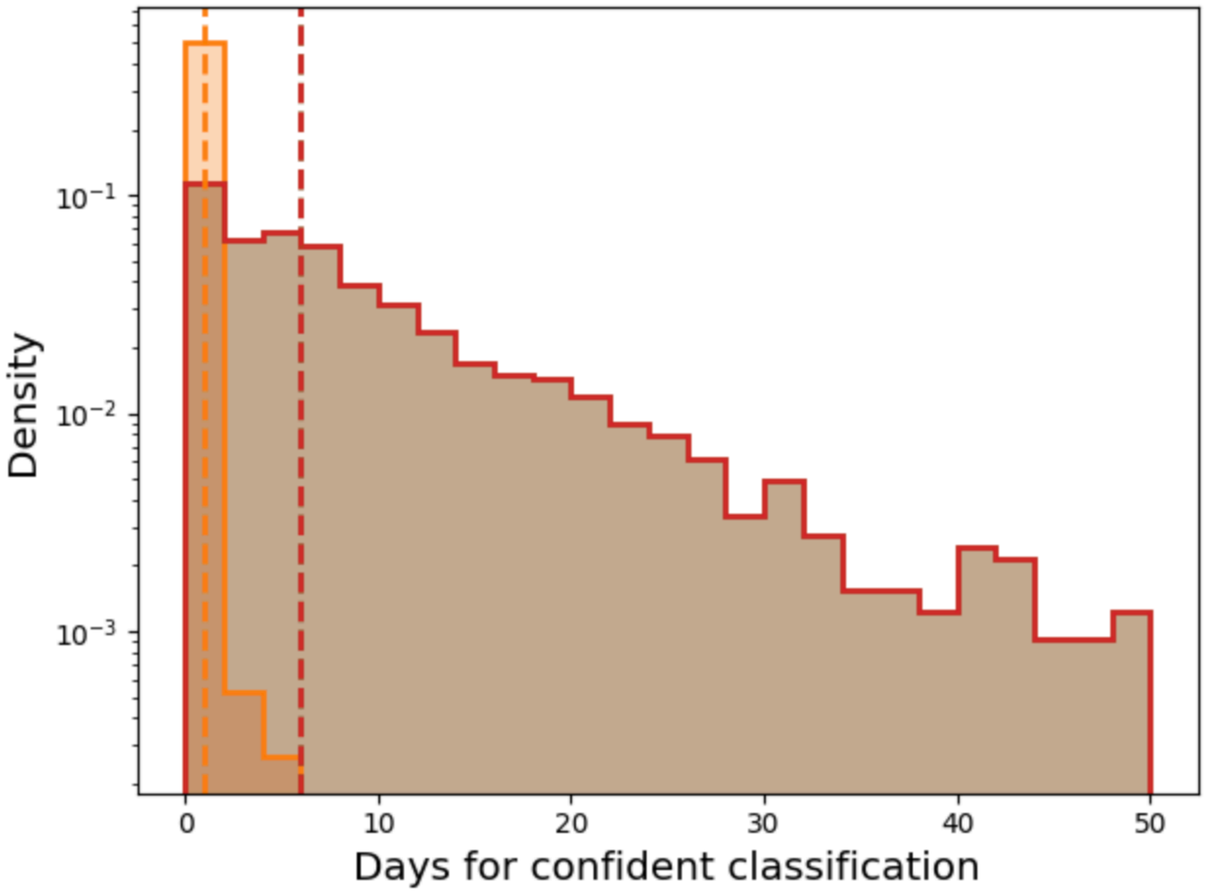
Real time performance on ELAsTiCC





Shah+26 (in prep)

Example: Kilonovae



Shah+24:

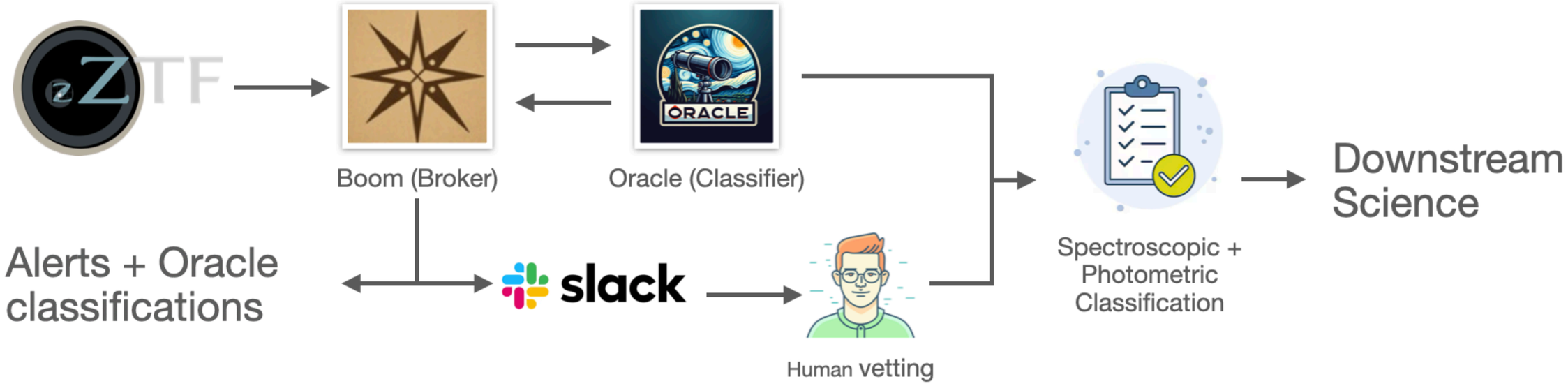
Discovery windows (days)

BNS mass model	N	90% credible	Mean
Galaudage et al. (2021)	1	$3.4^{+3.4}_{-2.0}$	3.60
	2	$3.2^{+3.4}_{-2.0}$	3.45
	3	$4.4^{+3.8}_{-2.2}$	4.82
Farrow et al. (2019)	1	$4.0^{+3.0}_{-2.0}$	4.29
	2	$4.0^{+3.0}_{-2.2}$	4.13
	3	$5.8^{+3.2}_{-3.4}$	5.82

Table 8. Discovery windows (in days) for KNe during LVK O4 for N = 1, 2, and 3 detector events in DECam r-band. The missing statistics for the 4-detector events is due to a negligible number of mergers having coincidental detections on 4 instruments. All these discovery windows are significantly shorter than the 10+ days for which SSS17a was discoverable.

4. Real-time Deployment

Real-time Deployment



*In beta testing

Shah+26 (in prep)

Real-time Deployment

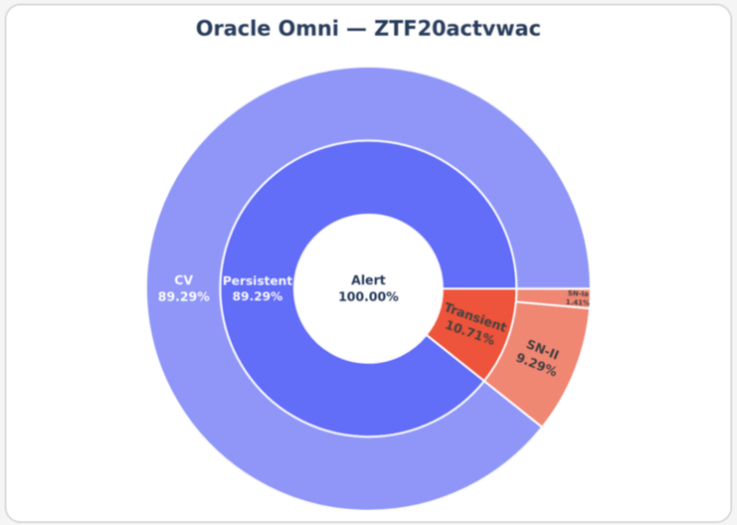
Oracle Bot APP 5:36 AM

Oracle Omni — ZTF20actvwac

Alert	100.00%
Persistent	89.29%
CV	89.29%
Transient	10.71%
SN-II	9.29%
SN-Ia	1.41%
SLSN	<0.01%
SN-Ib/c	<0.01%

Fritz: Cataclysmic (0.90)

ZTF20actvwac Oracle Omni



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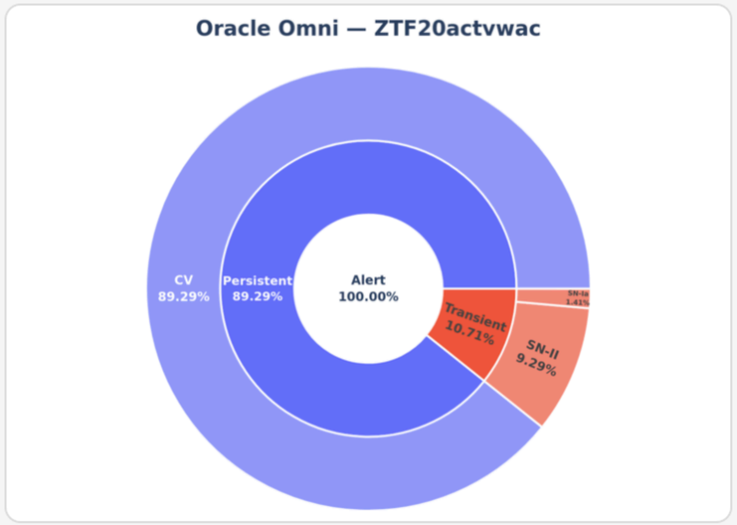


*In beta testing

Shah+26 (in prep)

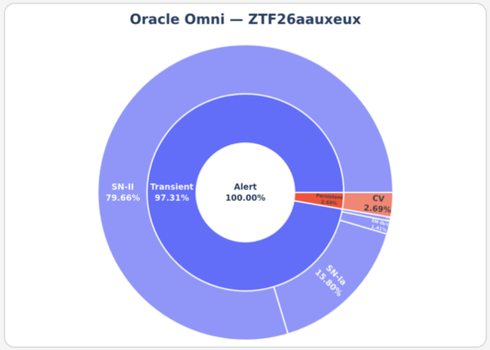
Real-time Deployment

4:58 **Oracle Omni — ZTF26aauxeux**

Alert	100.00%
Transient	97.31%
SN-II	79.66%
SN-Ia	15.80%
Persistent	2.69%
CV	2.69%
SN-Ib/c	1.41%
SLSN	0.43%

Fritz: Type II (0.33)

ZTF26aauxeux Oracle Omni



Oracle Bot APP 5:36 AM

Oracle Omni — ZTF20actv

Alert	100
Persistent	89
CV	89
Transient	10
I	9
a	1
	<0
b/c	<0

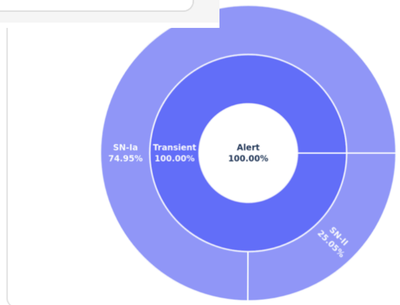
Cataclysmic (0.90)

actvwac Oracle Omni

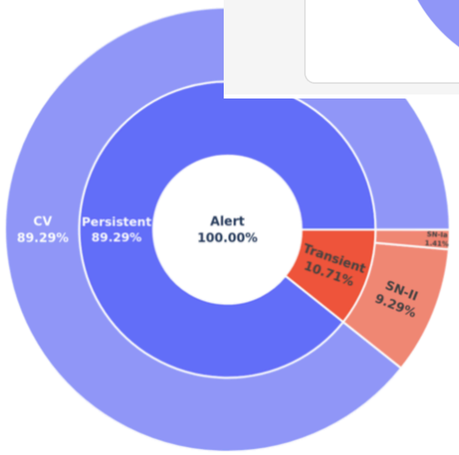
ajugdc

	100.00%
	100.00%
	74.95%
	25.05%
	<0.01%
	<0.01%
	<0.01%
	<0.01%

ni — ZTF26aajugdc



Oracle Omni —



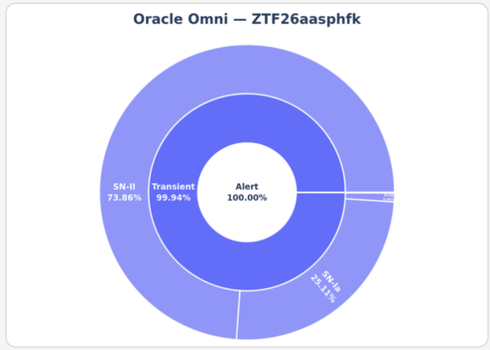
Oracle Bot APP 5:17 AM

Oracle Omni — ZTF26aasphfk

Alert	100.00%
Transient	99.94%
SN-II	73.86%
SN-Ia	25.11%
SLSN	0.96%
Persistent	0.06%
CV	0.06%
SN-Ib/c	0.01%

Fritz: IIn (0.55)

ZTF26aasphfk Oracle Omni



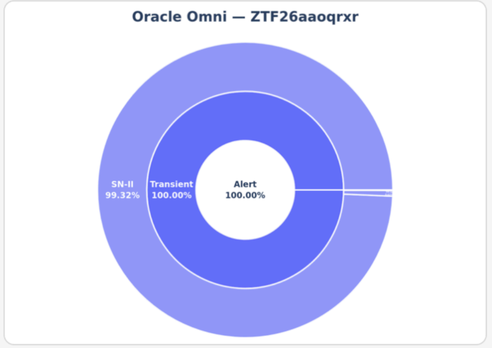
Oracle Bot APP 4:43 AM

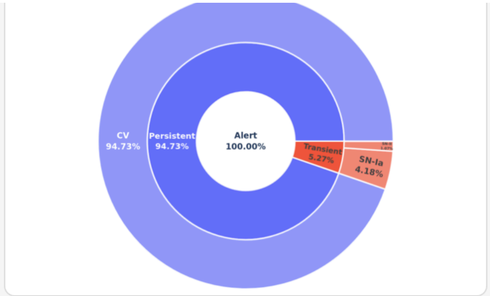
Oracle Omni — ZTF26aaoqrxr

Alert	100.00%
Transient	100.00%
SN-II	99.32%
SN-Ia	0.62%
SN-Ib/c	0.05%
Persistent	<0.01%
CV	<0.01%
SLSN	<0.01%

Fritz: Type II (0.77)

ZTF26aaoqrxr Oracle Omni

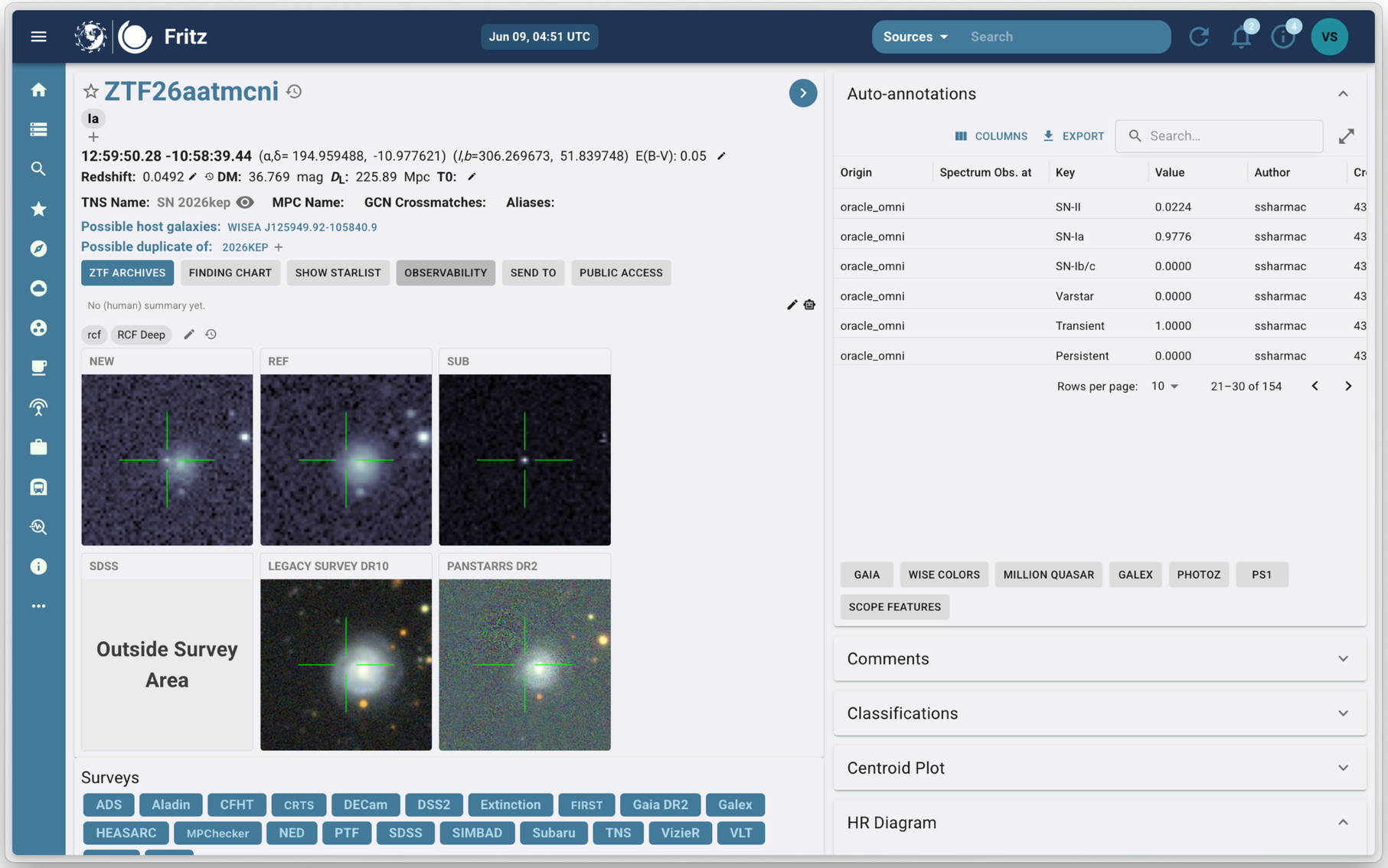




*In beta testing

SNAPS20 (in prep)

Real-time Deployment

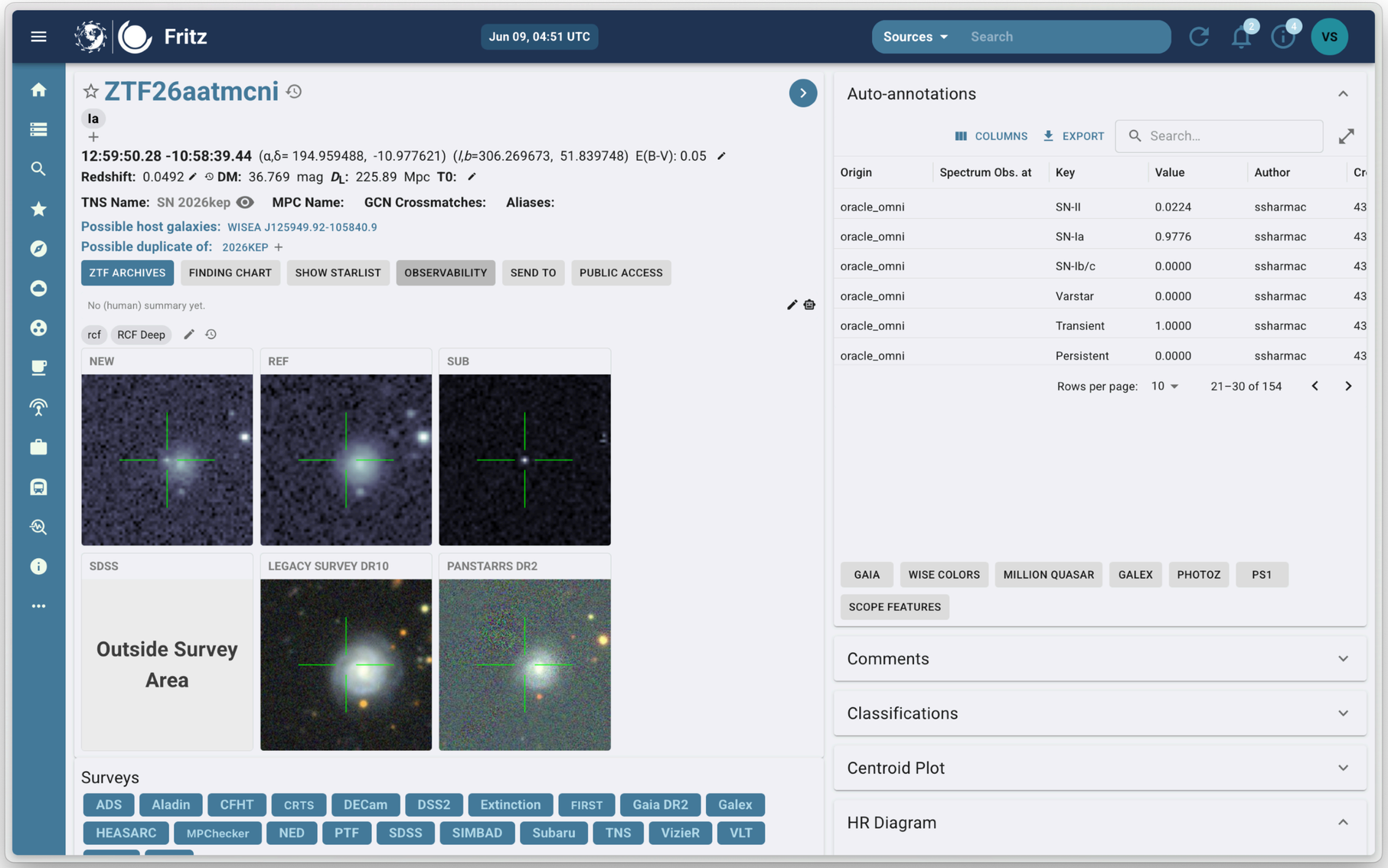


Sushant Sharma Chaudhary

***In beta testing**

Shah+26 (in prep)

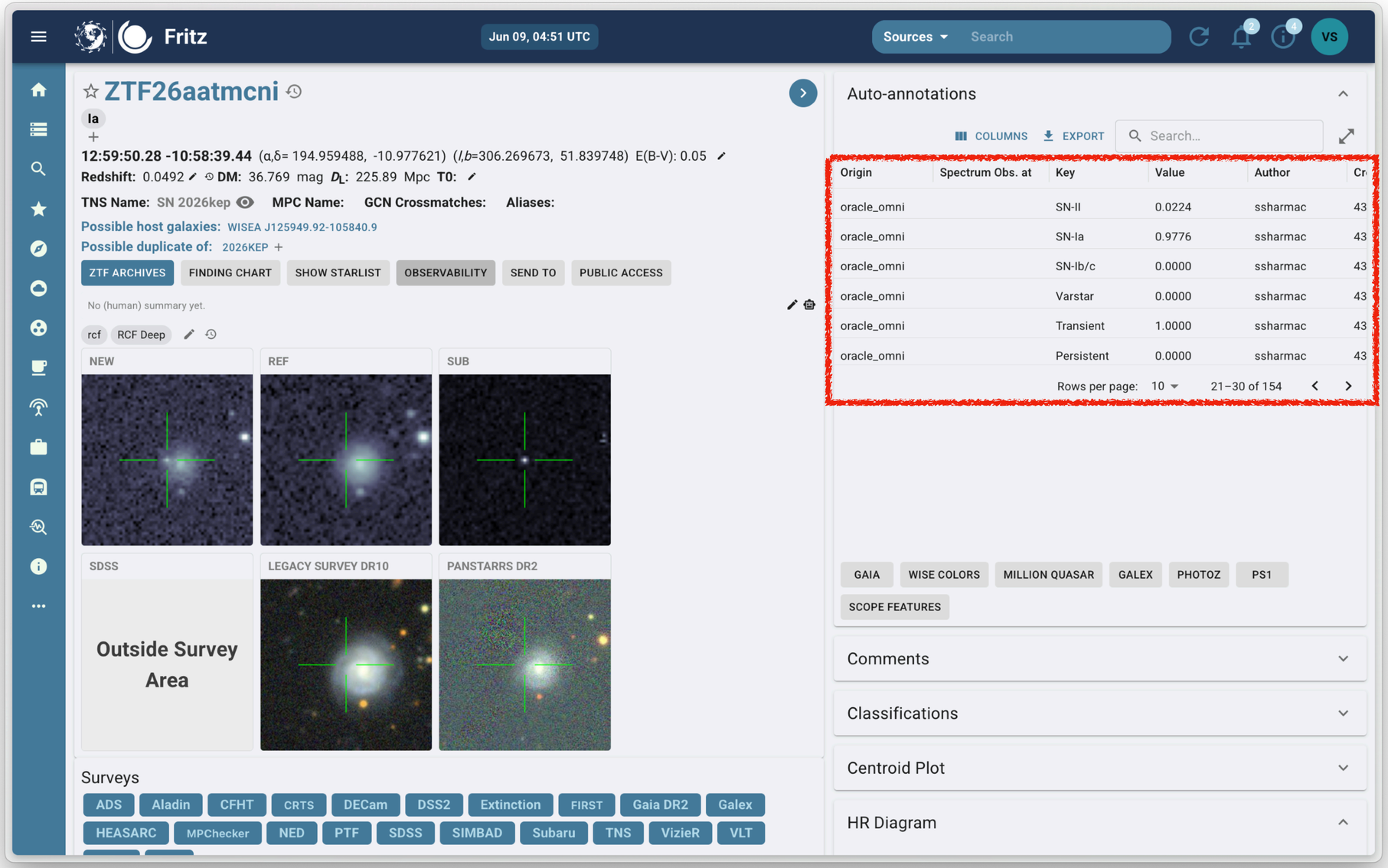
Real-time Deployment



*In beta testing

Shah+26 (in prep)

Real-time Deployment



*In beta testing

Shah+26 (in prep)

Real-time Deployment

Origin	Spectrum Obs. at	Key	Value	Author	Cr
oracle_omni		SN-II	0.0224	ssharmac	43
oracle_omni		SN-Ia	0.9776	ssharmac	43
oracle_omni		SN-Ib/c	0.0000	ssharmac	43
oracle_omni		Varstar	0.0000	ssharmac	43
oracle_omni		Transient	1.0000	ssharmac	43
oracle_omni		Persistent	0.0000	ssharmac	43

Rows per page: 10 21–30 of 154

***In beta testing**

Shah+26 (in prep)

Real-time Deployment

Origin	Spectrum Obs. at	Key	Value	Author	Cr
oracle_omni		SN-II	0.0224	ssharmac	43
oracle_omni		SN-Ia	0.9776	ssharmac	43
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oracle_omni		Persistent	0.0000	ssharmac	43

Rows per page: 10 21–30 of 154

***In beta testing**

Shah+26 (in prep)

5. Outstanding Challenges

Challenges

Challenges

- Real time deployment remains difficult

Challenges

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  - Personnel requirements

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- Real time deployment remains difficult
  - Personnel requirements
  - Distribution shifts
- There remains a huge gap between a models performance on simulations vs a models on real data
- Muti-modality comes at the cost of throughput
- Learning how to turn model outputs into actionable insights is non trivial

6. Summary

Summary

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- Adding **multi-modal inputs** can **significantly improve performance** without adding any labelling cost

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- Adding **multi-modal inputs** can **significantly improve performance** without adding any labelling cost
- Hierarchical classification gives us a way to build in **astrophysical structure into the classification problem**

Thank you!

Shah et al. (2025b)

THE ASTROPHYSICAL JOURNAL

OPEN ACCESS

ORACLE: A Real-time, Hierarchical, Deep Learning Photometric Classifier for the LSST

Ved G. Shah, Alex Gagliano, Konstantin Malanchev, Gautham Narayan, Alex I. Malz, and and the LSST Dark Energy Science Collaboration

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The Astrophysical Journal, Volume 995, Number 1

Citation Ved G. Shah *et al* 2025 *ApJ* **995** 4

DOI 10.3847/1538-4357/ae1130

GitHub

https://github.com/dev-ved30/Oracle

ZTF paper + models to follow!

Funded by the U.S. National Science Foundation and the Simons Foundation

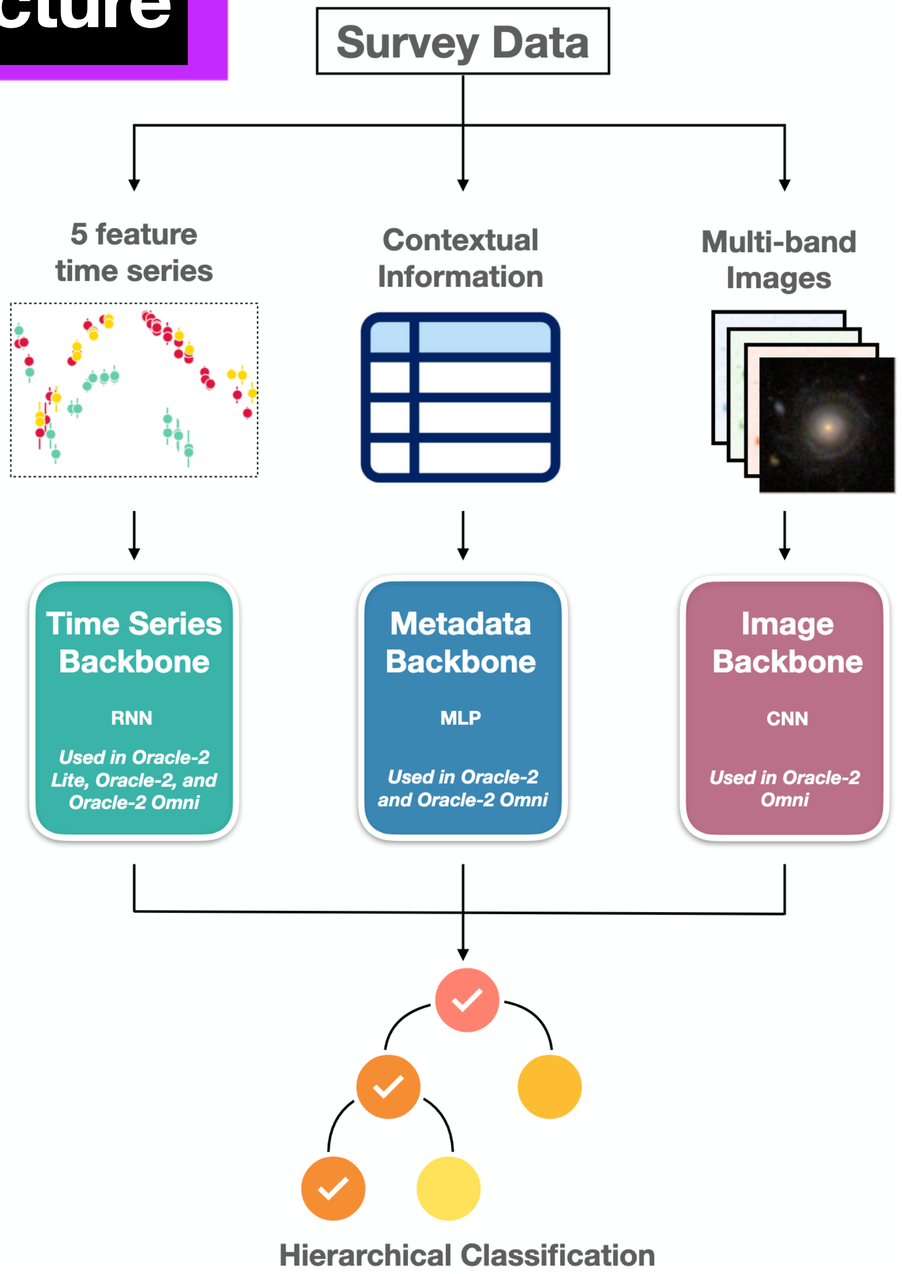
Northwestern University

Northwestern CIERA CENTER FOR INTERDISCIPLINARY EXPLORATION AND RESEARCH IN ASTROPHYSICS

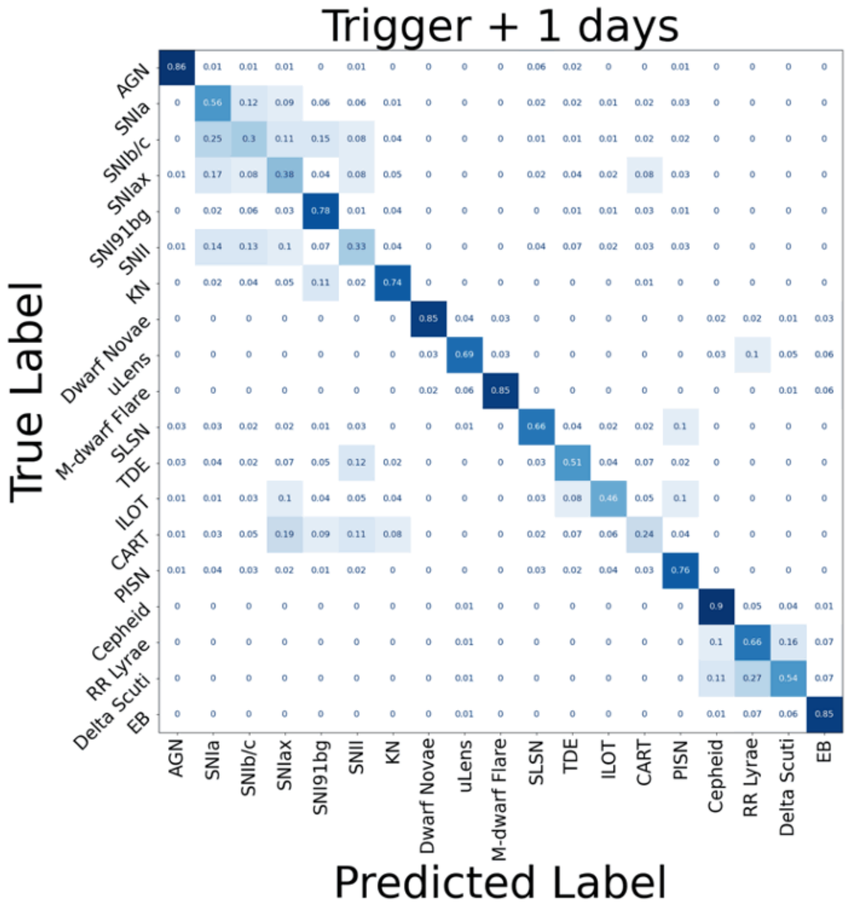
UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

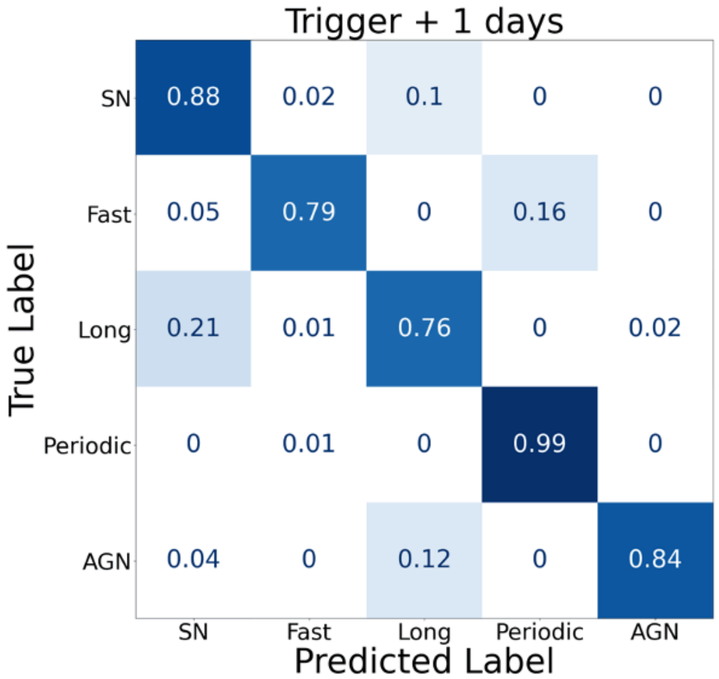
Questions?

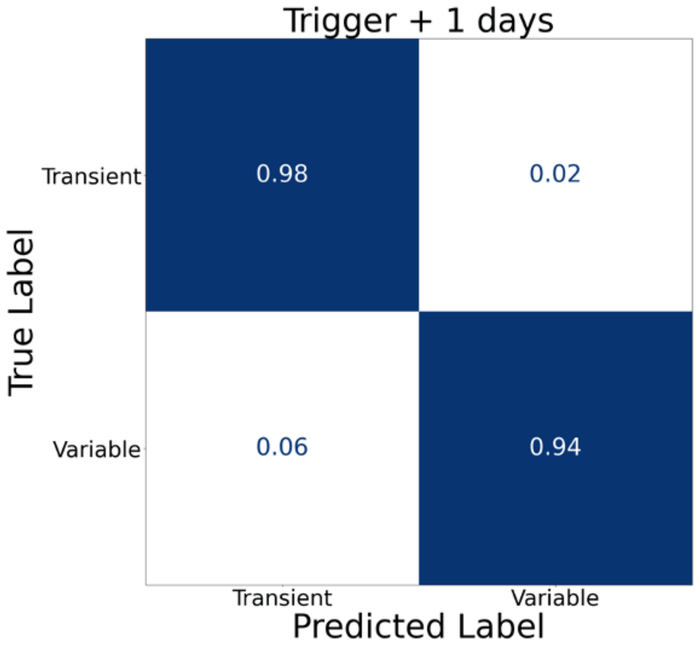
Multi-modal Architecture



Real time Confusion Matrices







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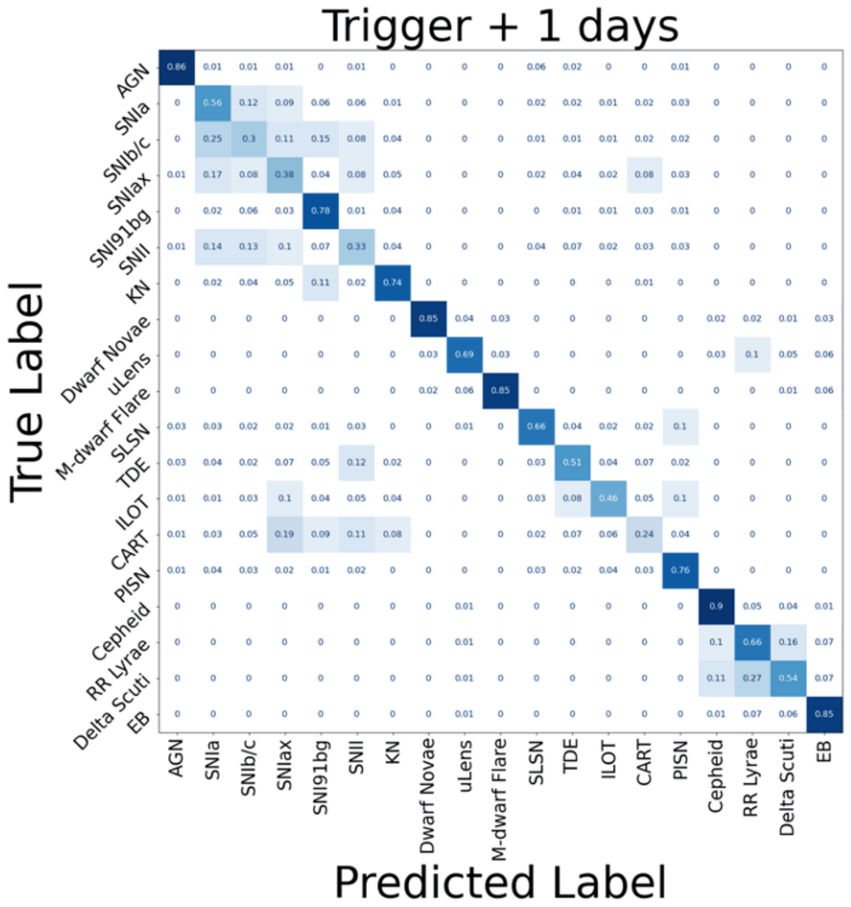
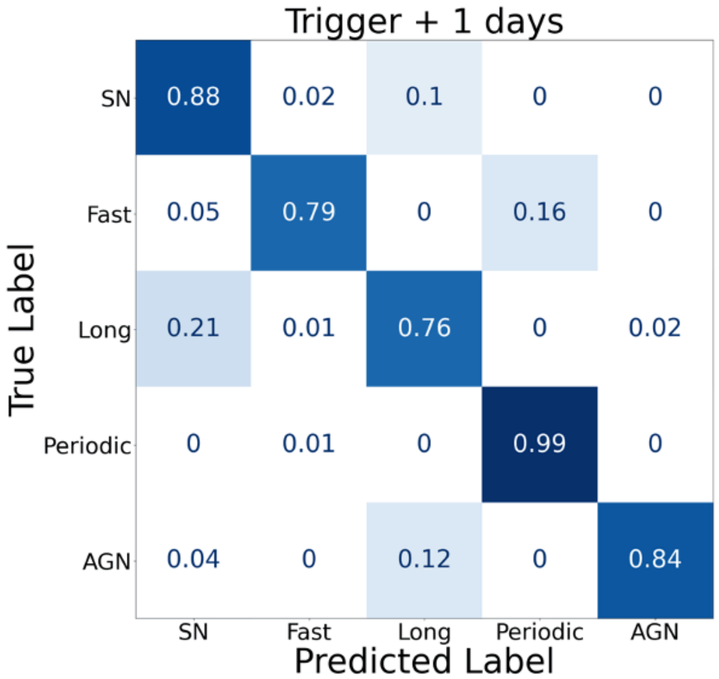
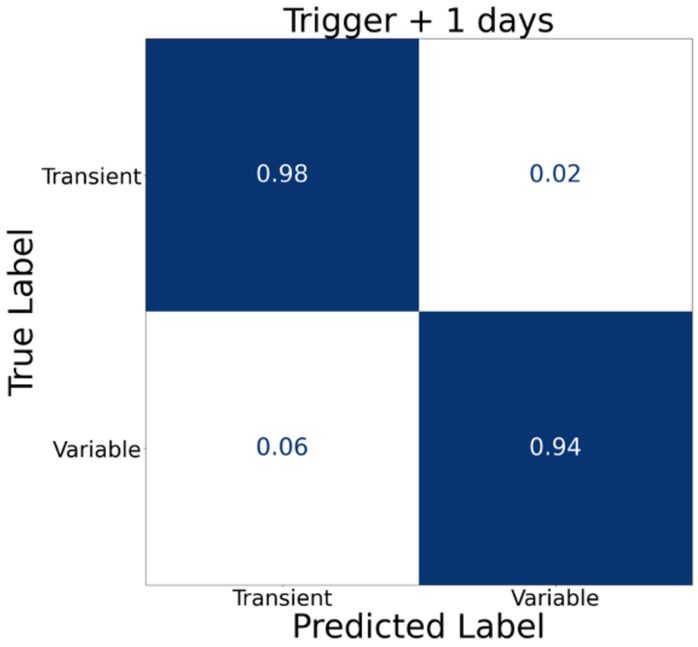
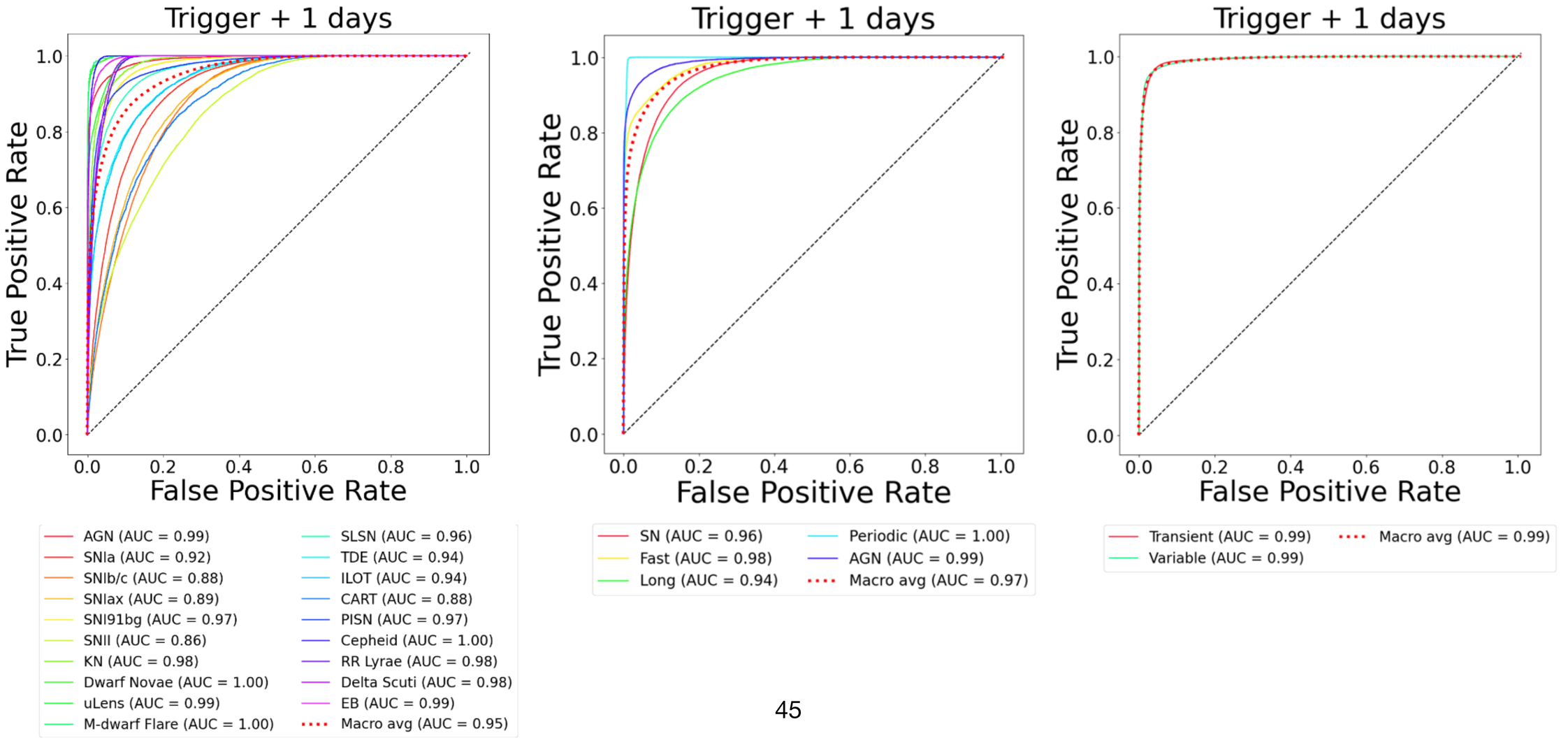






Real time ROC curves



Real time ROC curves