

An Overview of Deep Learning in Astronomy



SO MUCH OF "AI" IS JUST FIGURING OUT WAYS
TO OFFLOAD WORK ONTO RANDOM STRANGERS.

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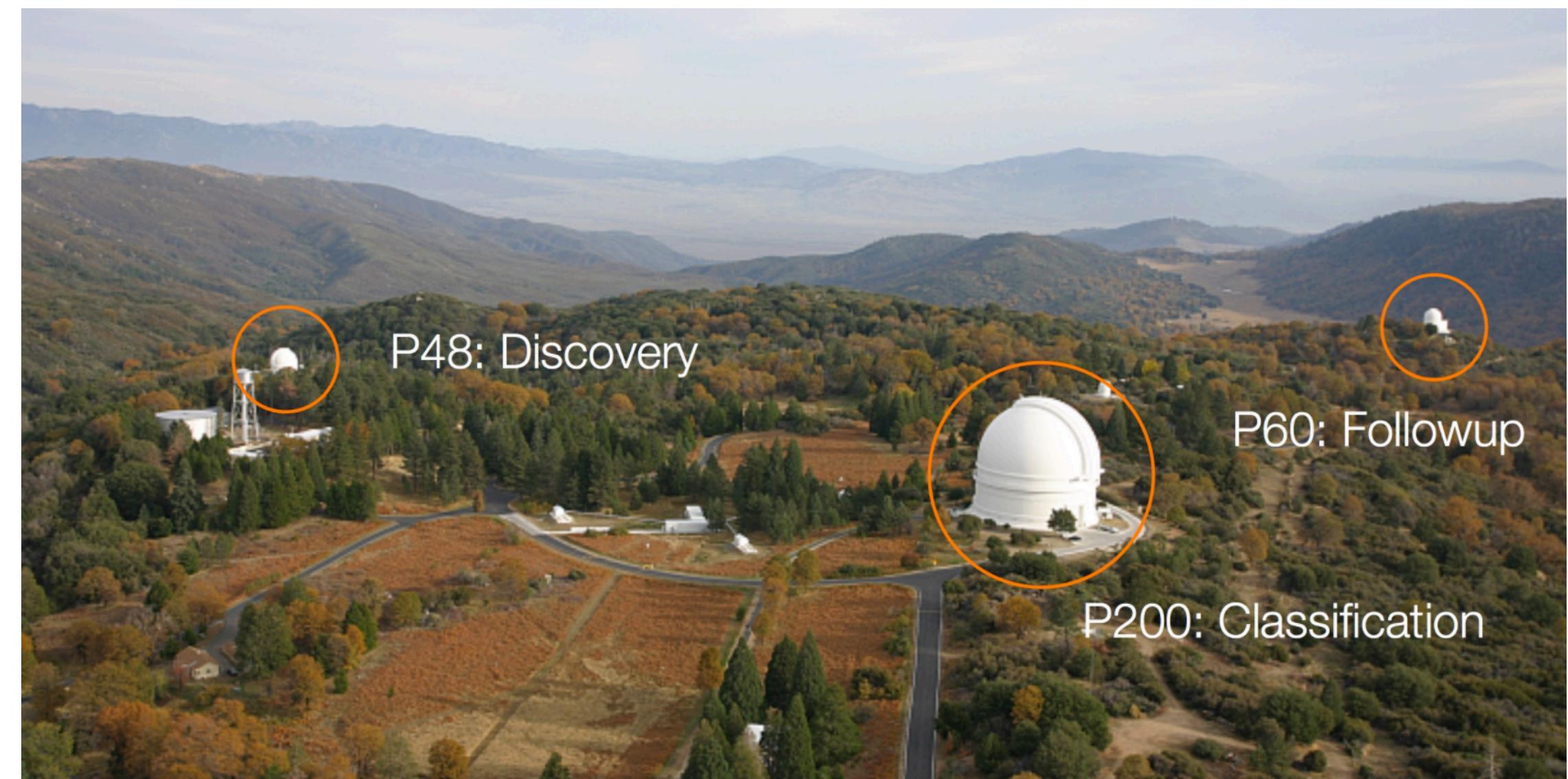
Center for Data Driven Discovery, Caltech

ML Lead ZTF

M Topinka's ML Class, University of Brno, 15 Dec 2020

Outline

- Intro to ZTF
- ML/DL avenues within ZTF
- Multi Messenger Astronomy
- LSST/Rubin brokers, transfer learning
- Good practices and tricks

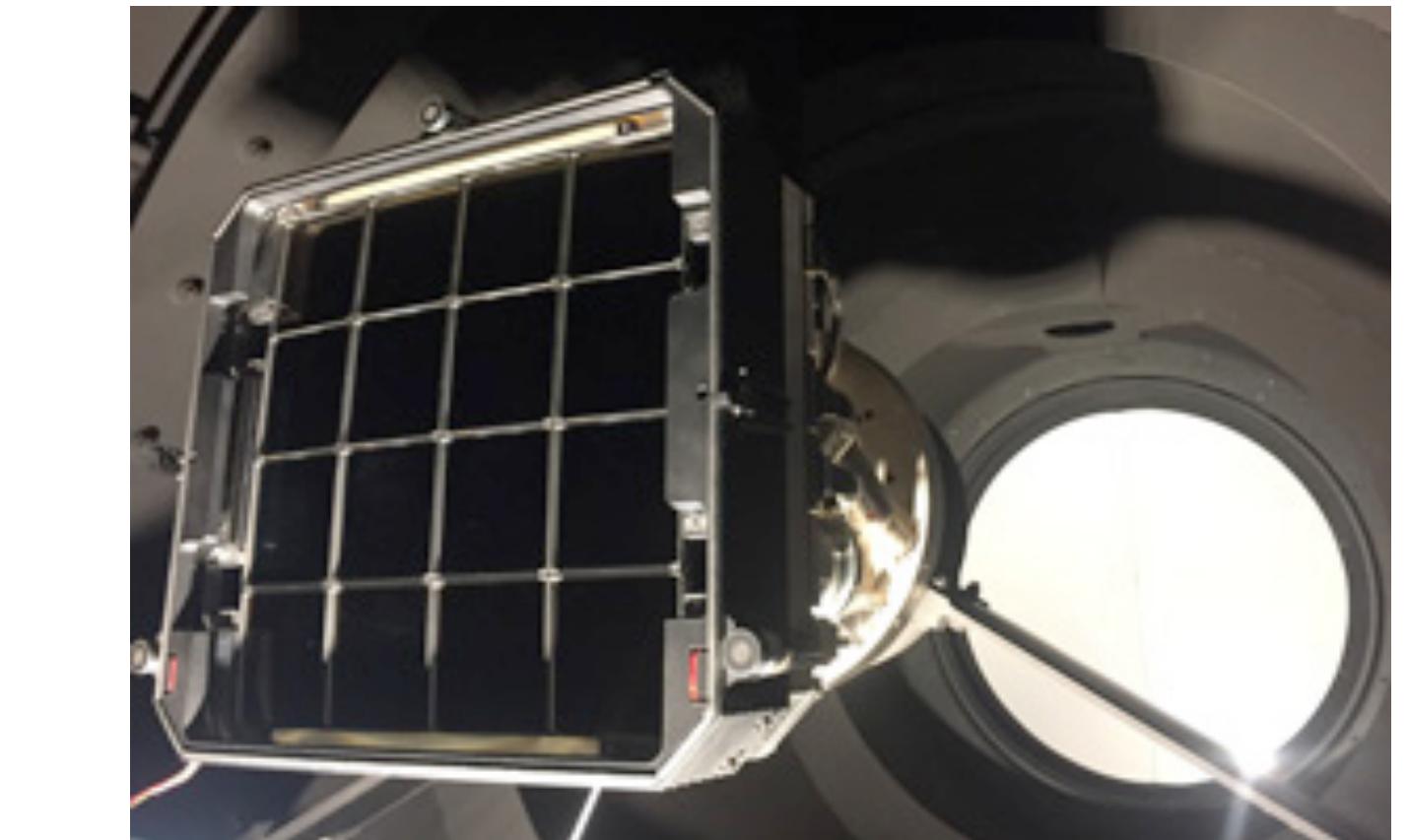


Bryan Penprase

- Exoplanets
- Deep Space Data Fusion



Brief intro to ZTF

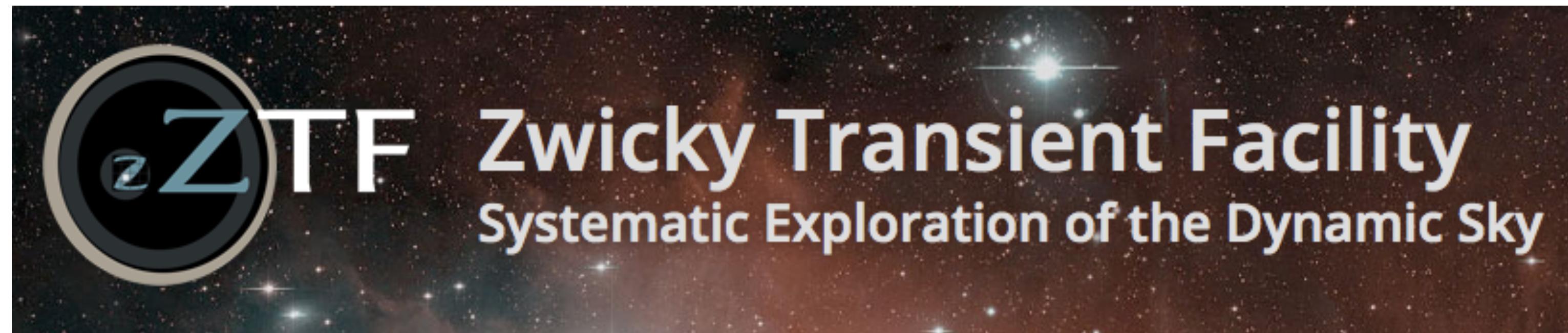


47 deg² FOV, m_{lim}~20.5 in

30 sec:

- g, r, i filters
- Well-tested subtraction/detection pipeline

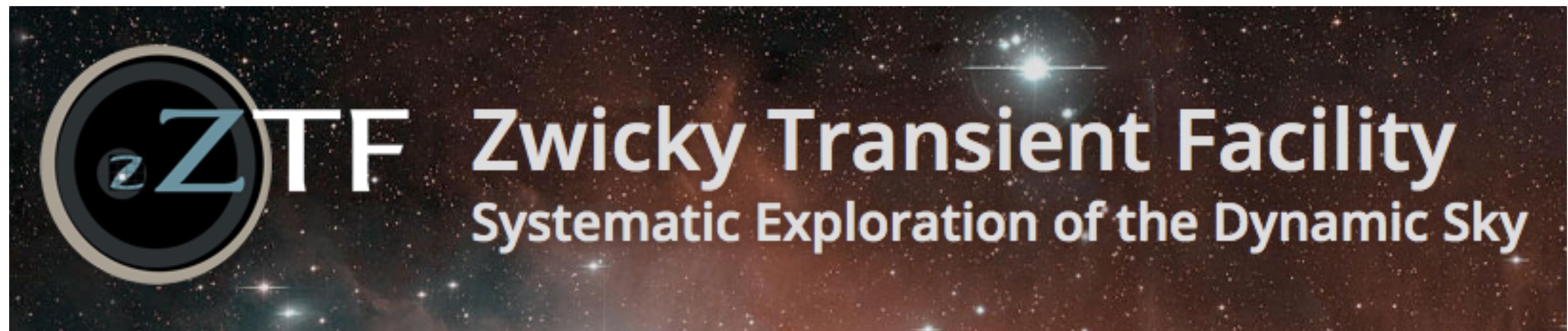
~20000 sq deg every 3 nights in two filters (g and r)



DR3 <https://www.ztf.caltech.edu/page/dr3>

Filter(s)	#PSFcat- sci sources	#Aperturecat- sci sources	#PSFcat- refsources	#Aperturecat- refsources
<i>g</i>	59,554,633,211	37,972,012,960	2,066,428,459	659,475,989
<i>r</i>	171,101,170,546	105,544,929,811	2,981,010,701	1,022,102,891
<i>i</i>	2,759,684,746	1,688,197,984	561,942,811	164,121,447
<i>g + r + i</i>	233,415,488,503	145,205,140,755	5,609,381,971	1,845,700,327

Table 3: Number of sources in CCD-quadrant-based catalog files in DR3, according to extraction and image type



DR3 <https://www.ztf.caltech.edu/page/dr3>

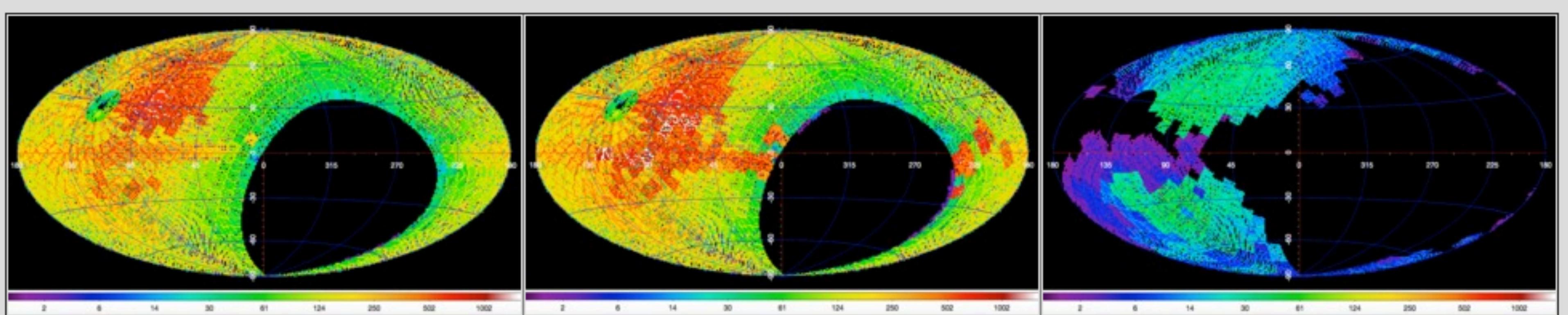
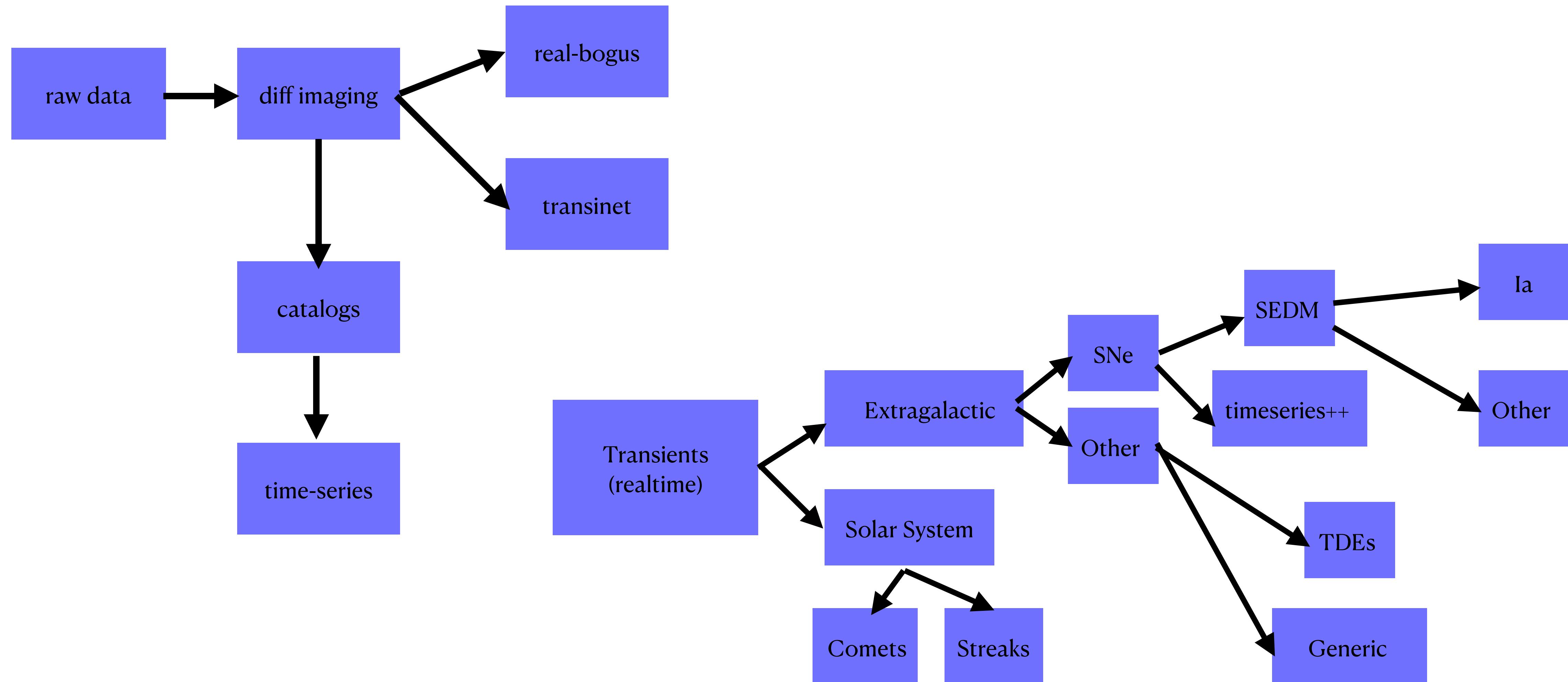


Figure 1 - Sky coverage and number of observation epochs per approximate CCD-quadrant footprint represented in DR3, in Galactic coordinates centered at $l, b = 0, 0$. **Left:** g -filter; **Center:** r -filter; **Right:** i -filter. Color bar represents the number of observation epochs. Dark regions on small scales are not holes in coverage, but due to the coarse resampling of CCD-quadrant centers on 1° scales. This resampling also distorts the true number of epochs per pointing (see Figure 3a for the true epoch distribution). **Click on a panel to enlarge.**

Example Query using the APIs

```
wget "https://irsa.ipac.caltech.edu/ibe/search/ztf/products/sci?  
POS=255.9302,11.8654&WHERE=obsjd>2458219.9678+AND+obsjd<2458228.8155+  
AND+infobits<33554432" -O out.tbl
```

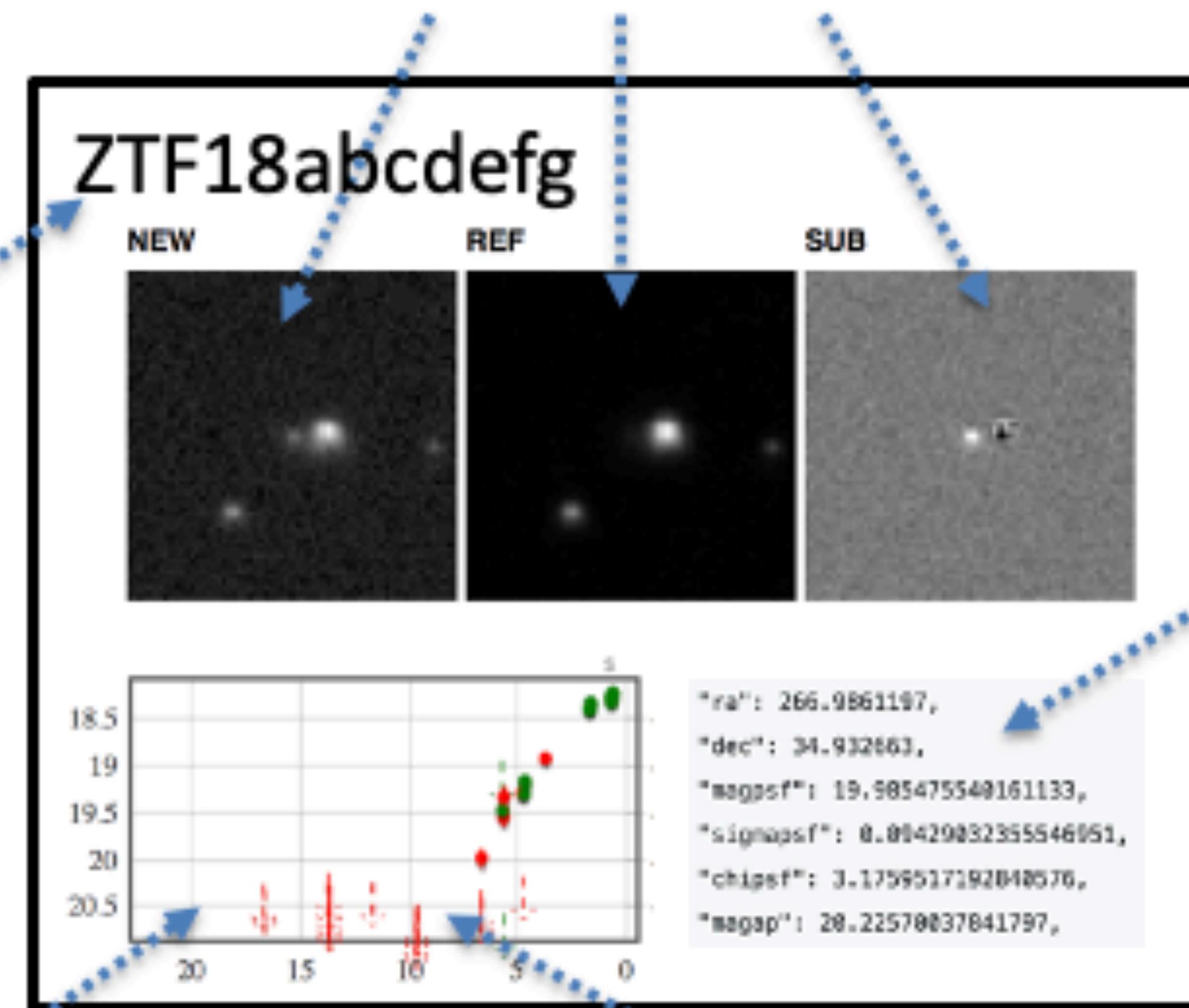
A few ZTF ML Avenues



ZTF Alert Packet

63 x 63 pixel 32-bit images

Unique spatially
matched alert name
(1.5" radius)



Rolling 30-day window
light curve

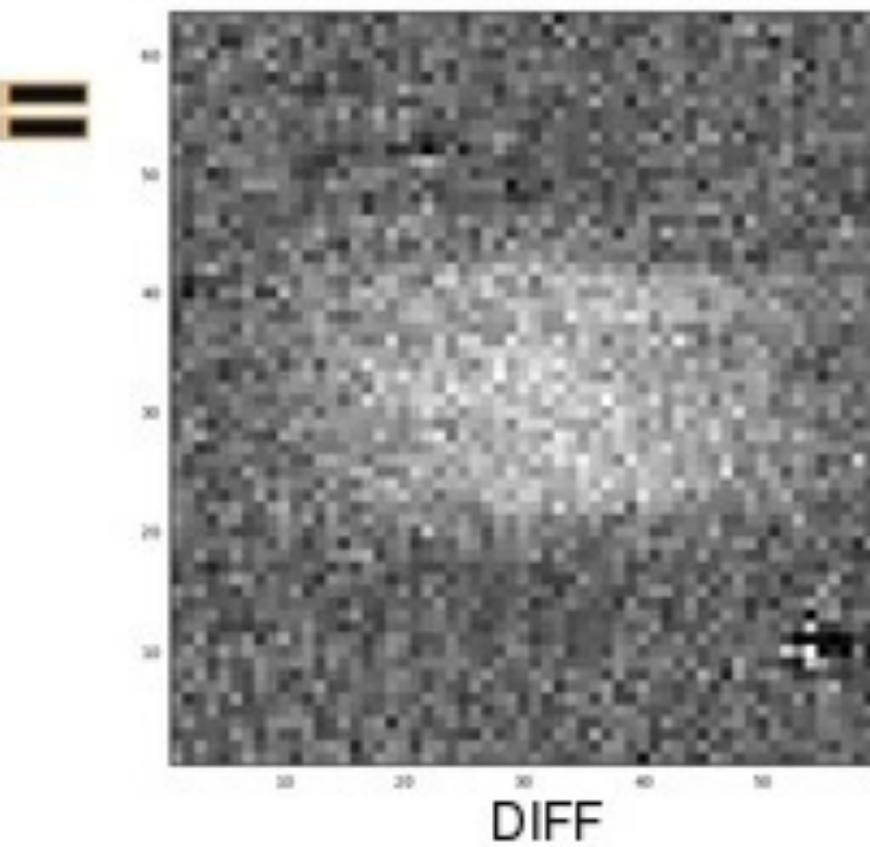
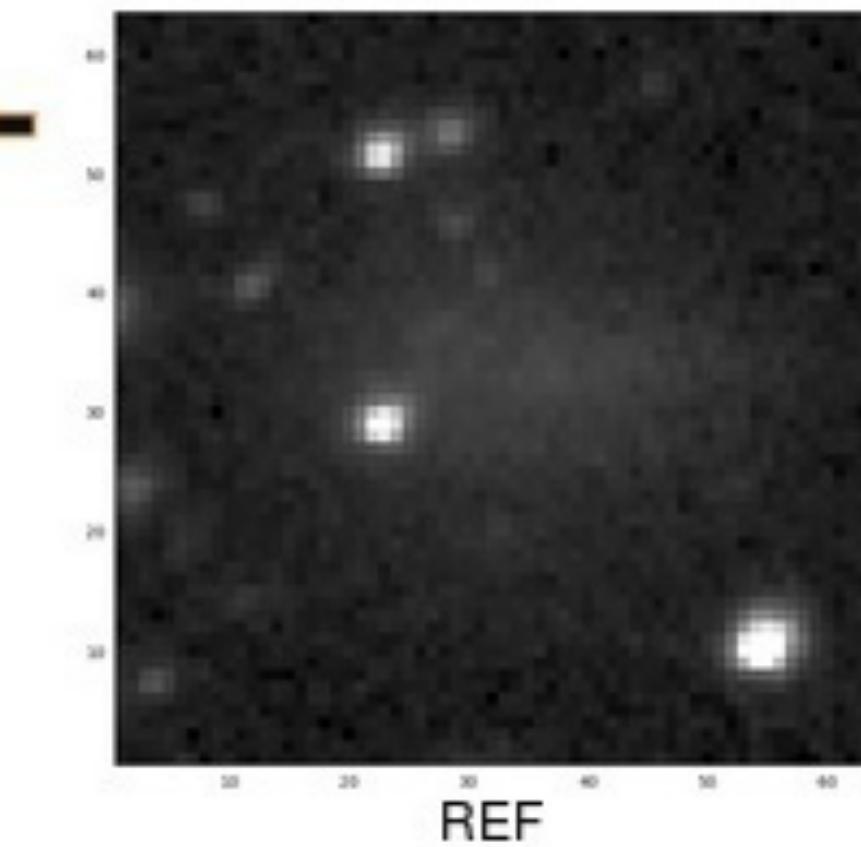
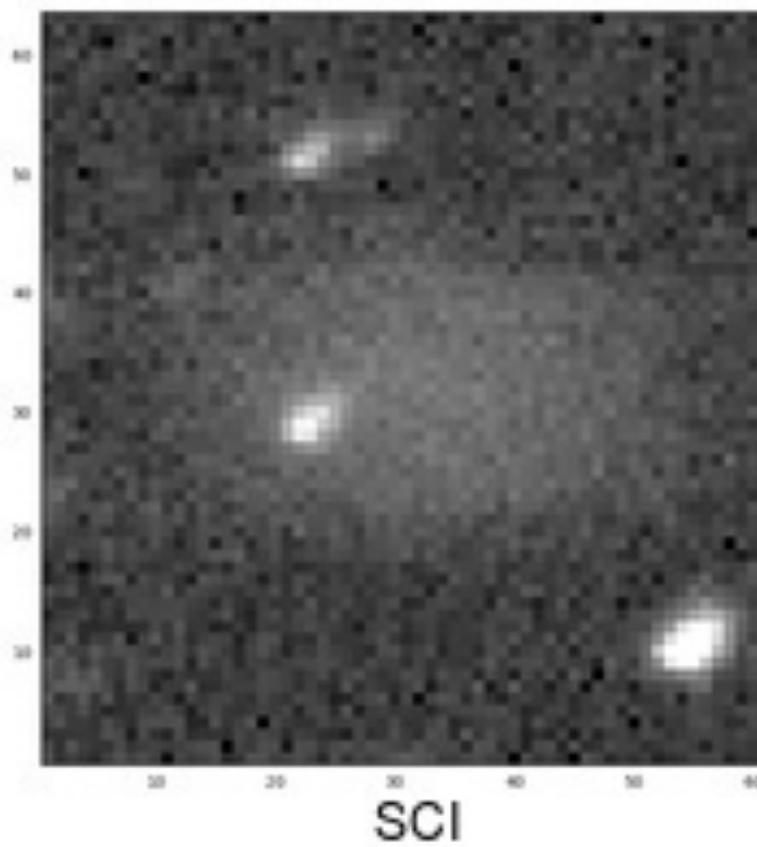
Forced photometry
instead of upper limits

- ZOGY parameters
- Real-bogus score
- Star/galaxy score
- 3 nearest PS1 sources
- Nearest SS object
- Alert history

Smears - bogus

Labeling Objects for training

metadata from ZTF alerts



FWHM
isdiffpos
magpsf
...

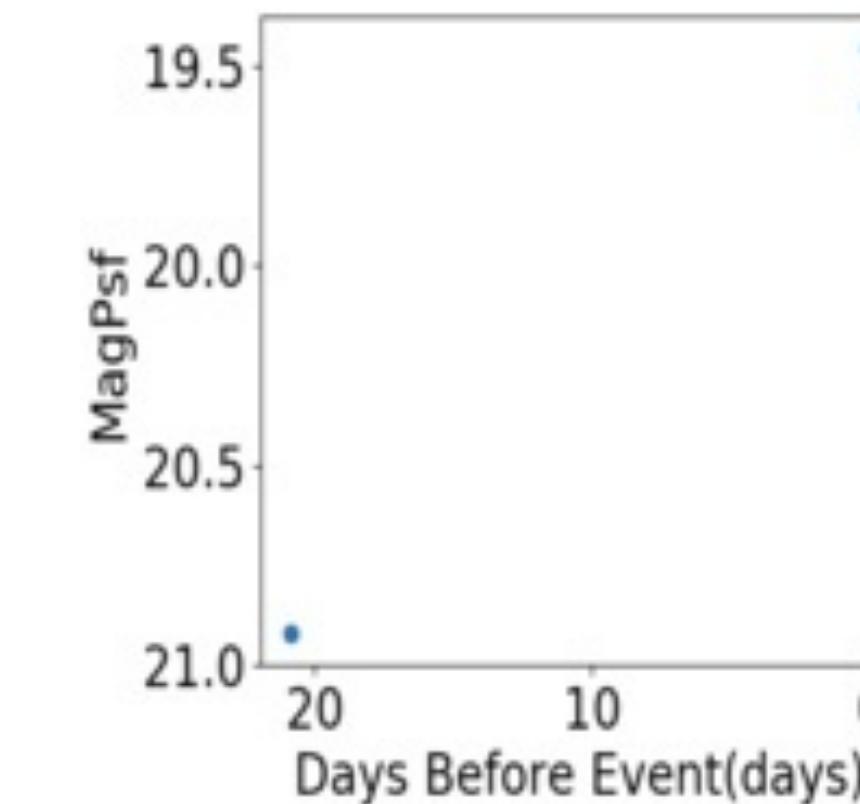
fwhm: 44.73"
magpsf: 19.46
sigmapsf: 0.07
magdiff: -0.81
elong: 1.42
classtar: 0.0
sgscore: 0.99
isdiffpos: t



Pan-STARRS

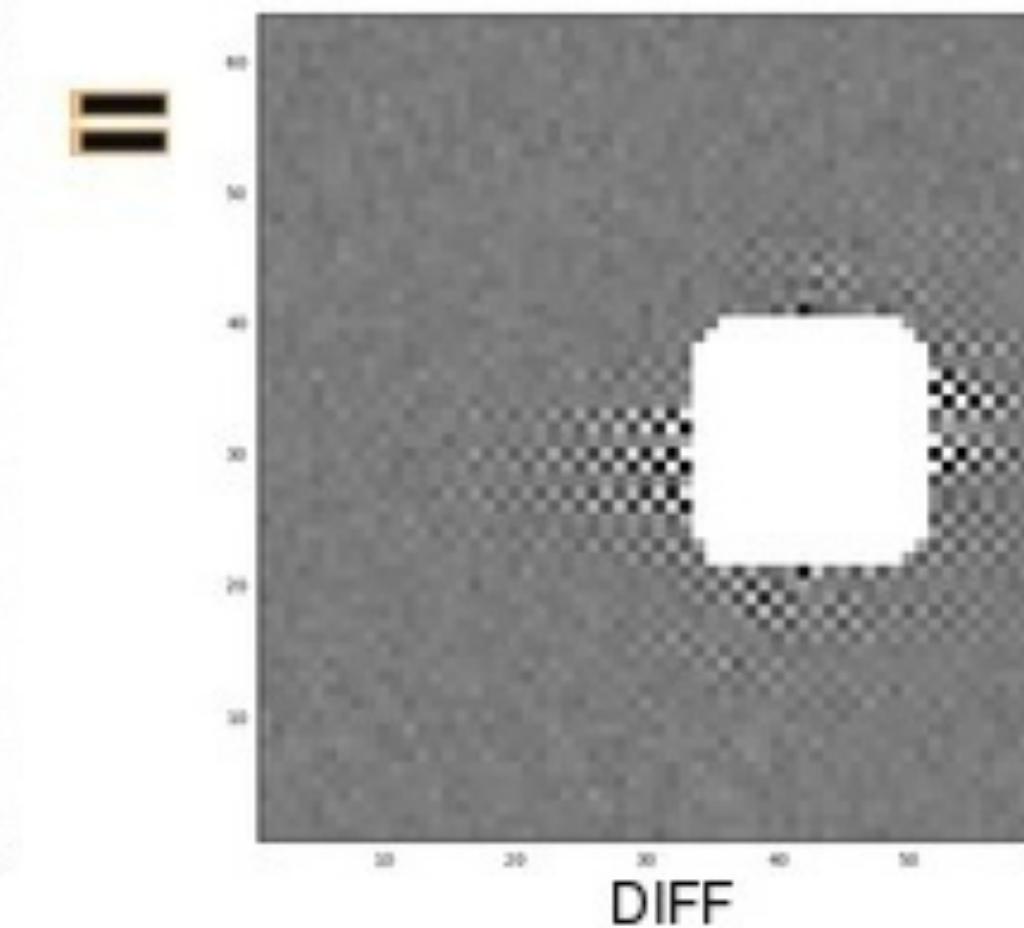
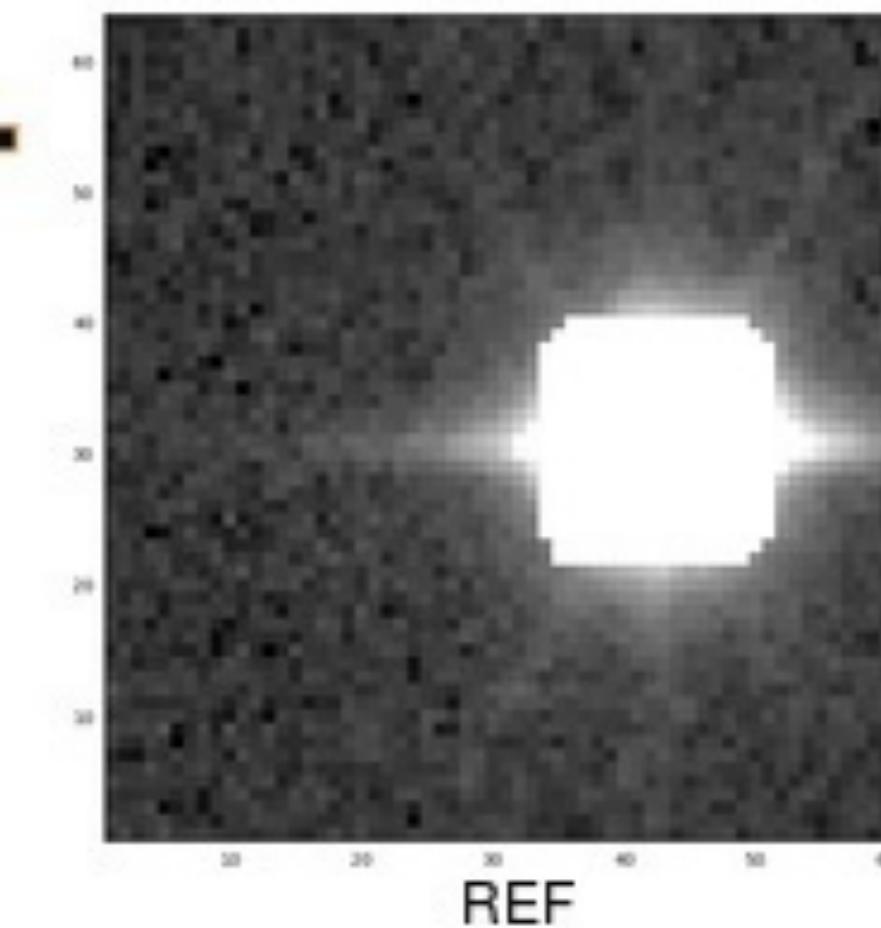
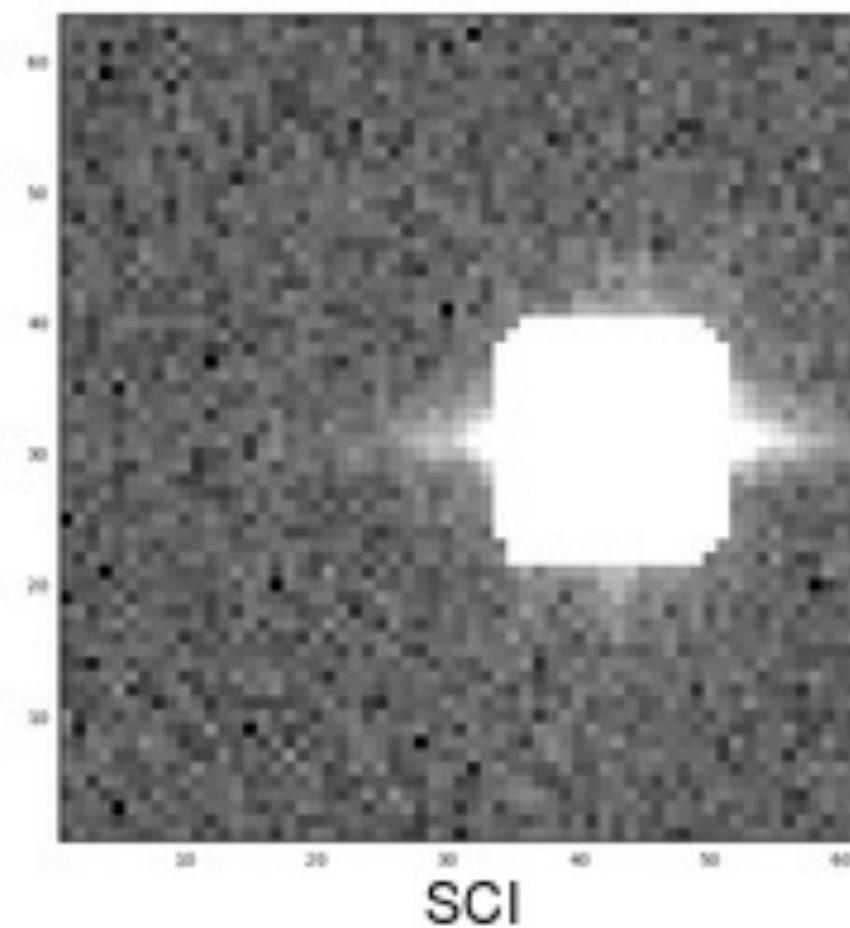
archival data

Easy to remove artifact with enough examples

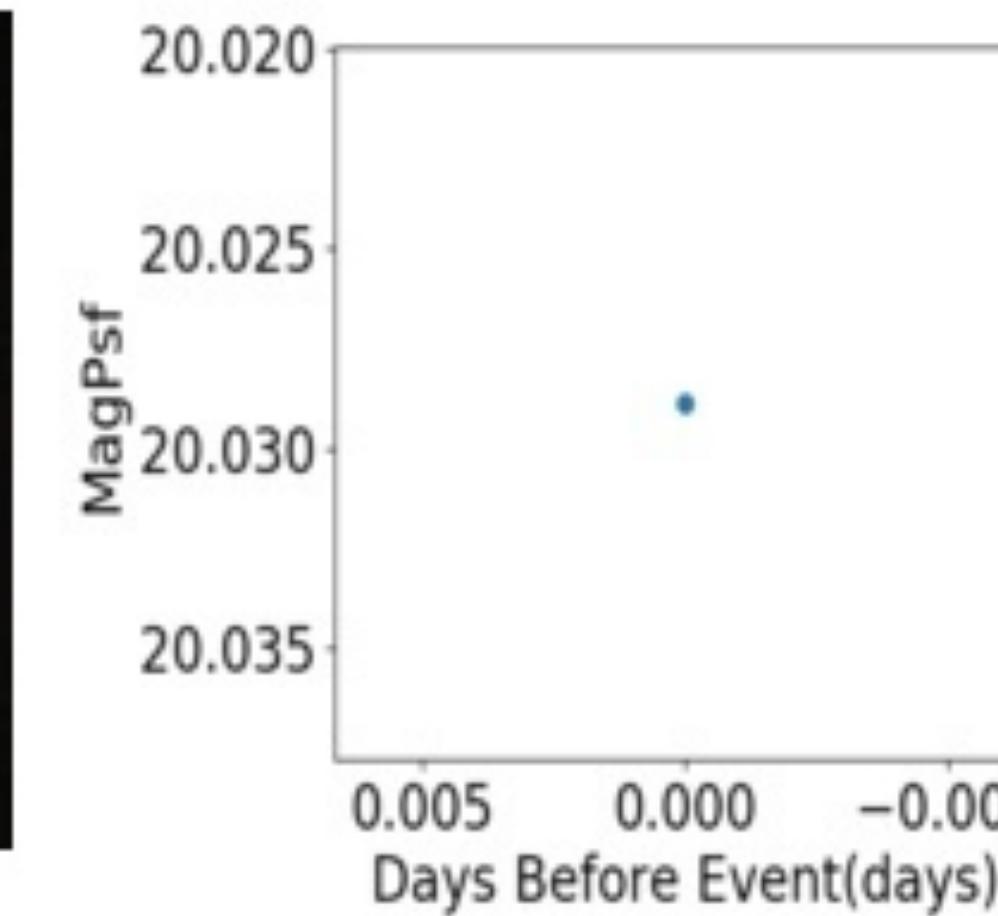
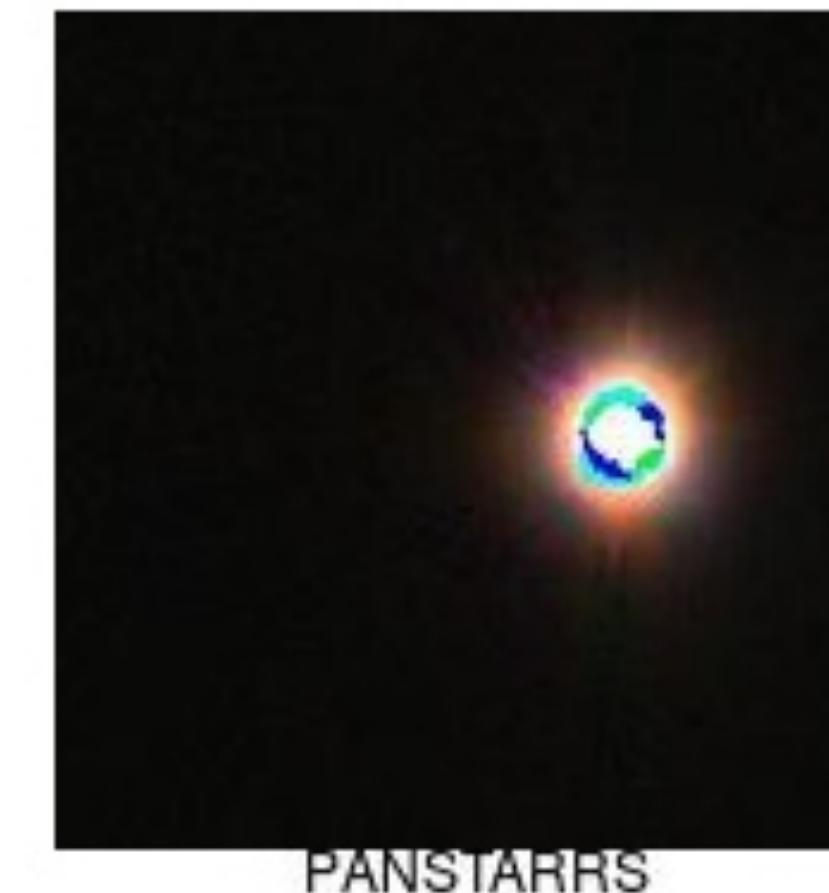


**light
curve**

Bogus - streak from masked star



fwHM: 5.37"
magPSF: 20.03
sigmapSF: 0.12
magDiff: -0.42
elong: 1.33
clasStar: 0.99
sgScore: 0.5
isDiffPos: t



Easy to remove artifact with enough examples

Zooniverse campaigns

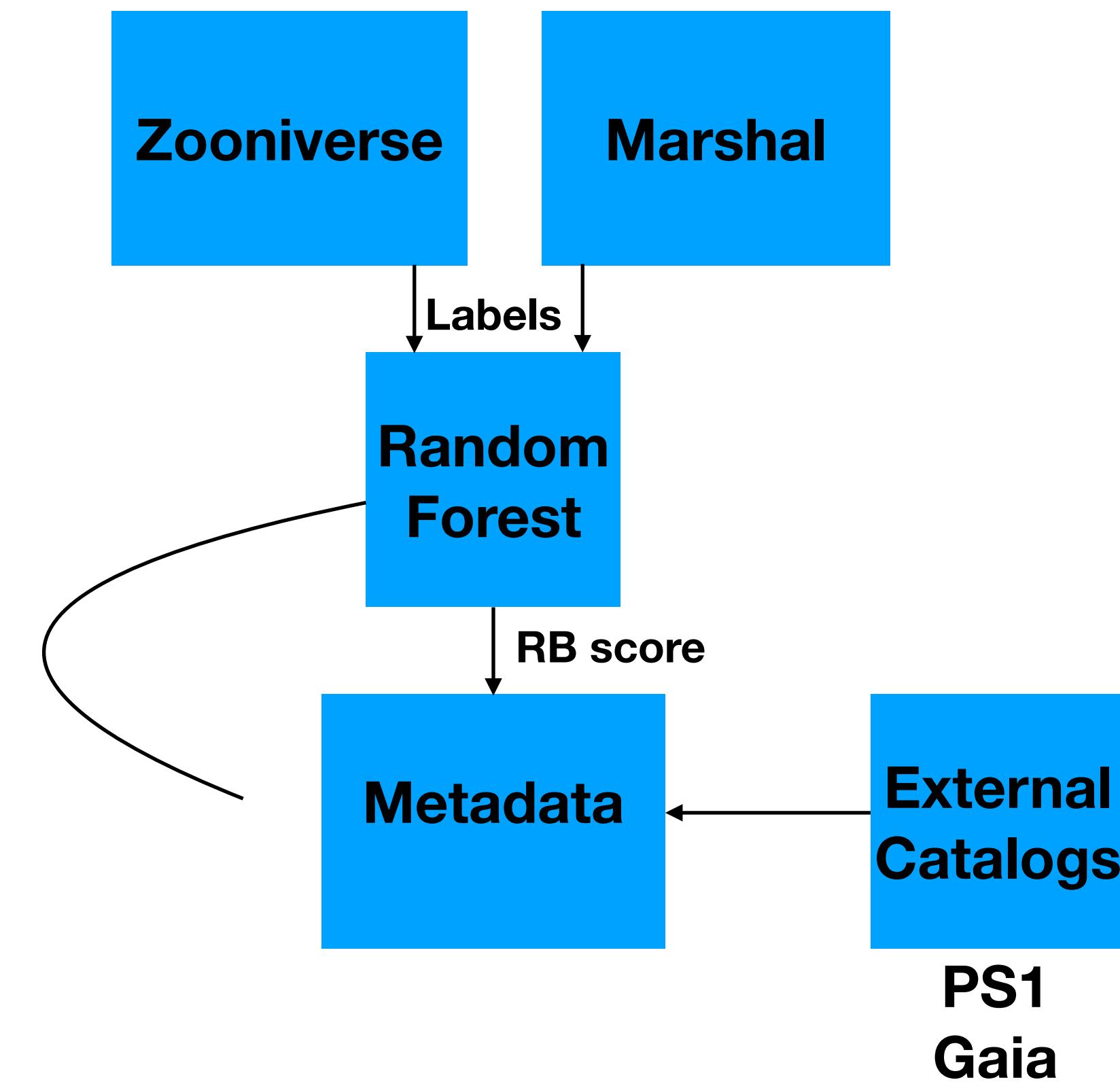
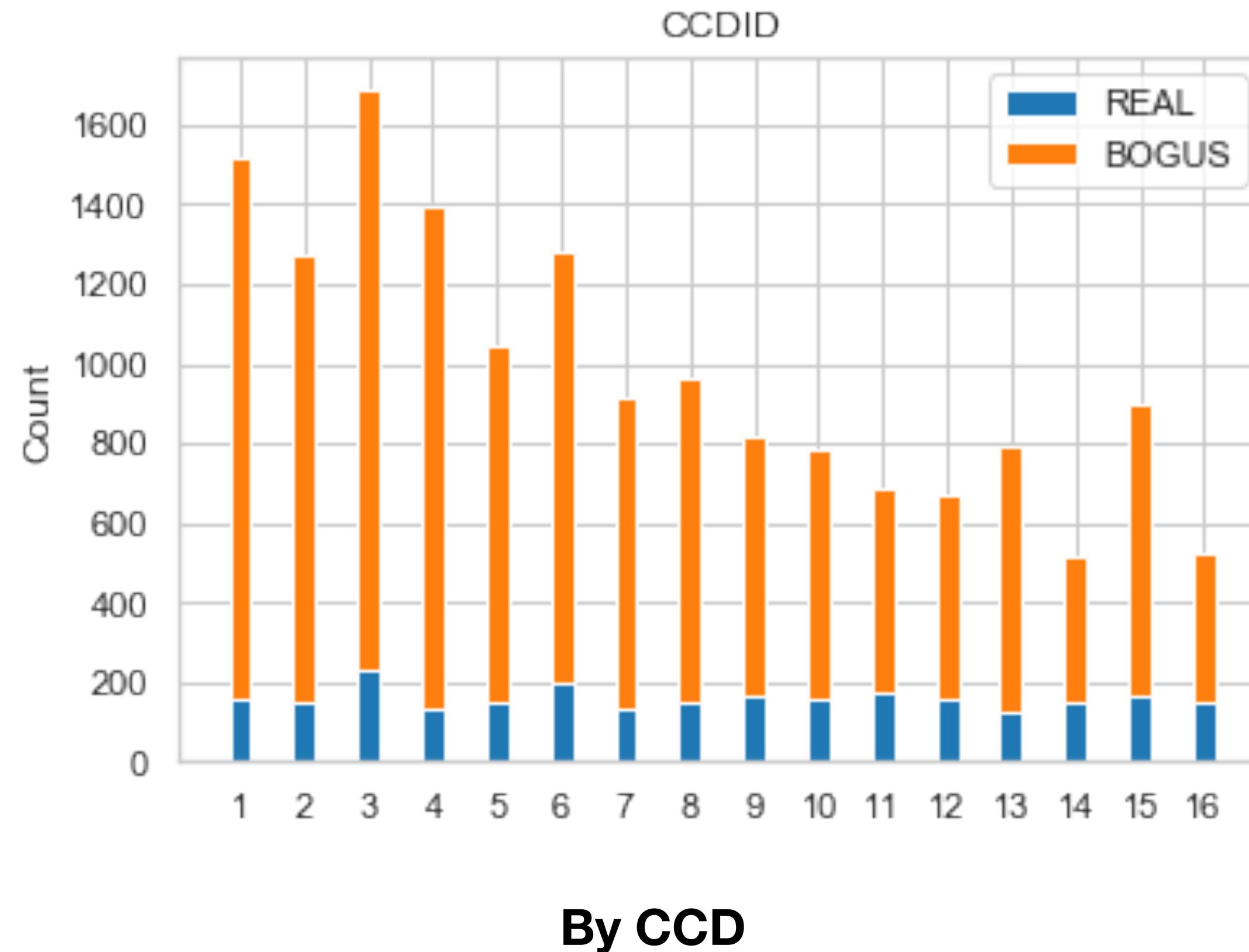
Richard Walters++

The screenshot shows a user interface for a Zooniverse campaign. On the left, there is a row of three astronomical images: 'SCIENCE' (a noisy image with several bright stars), a minus sign, 'REFERENCE' (a clearer image of the same stars), an equals sign, and 'DIFFERENCE' (the difference image where only the stars from the science image remain). To the right of these images is a vertical toolbar with zoom (+/-) and crop (C) controls. Above the toolbar is a 'TASK' tab, which is selected, and a 'TUTORIAL' tab. The task area contains the question: 'Is the object seen in the center of the difference image real or bogus.' Below the question are three options: 'Real', 'Bogus', and 'Skip'. A blue box labeled 'NEED SOME HELP WITH THIS TASK?' is positioned below the options. At the bottom are two buttons: 'Done & Talk' (blue) and 'Done' (green), followed by a gear icon.

Had to dumb down what we show

$b > .4$ (No upper limit cutoff)
programid = 1 = MSIP
 $ssdnr > 8$
isdiffpos = true
 $n > 1$

Sources of labels



Low Galactic rb

[edit](#)[remove](#)

id: 5c58cd4c67b6e500be33b6f3

Training data-sets for low Galactic real/bogus classification in ZTF

[Project metadata](#)

[Classes](#)

[Users](#)

[Datasets](#)

20181115_0.2<rb<0.4

[classify](#)[inspect](#)[edit](#)[remove](#)

id: 5c5aa5b367b6e500be33b6f4

299 random alerts from 20181115 with $0.2 < rb < 0.4$

Number of objects: 299

Number of classifications: 0

Number of classifications by all users: 297

[Dataset](#)

[Classifications](#)

[Classifications from all users](#)

20181126_0.2<rb<0.4

[classify](#)[inspect](#)[edit](#)[remove](#)

id: 5c5acbb667b6e500c117d63a

304 random alerts from 20181126 with $0.2 < rb < 0.4$

Number of objects: 304

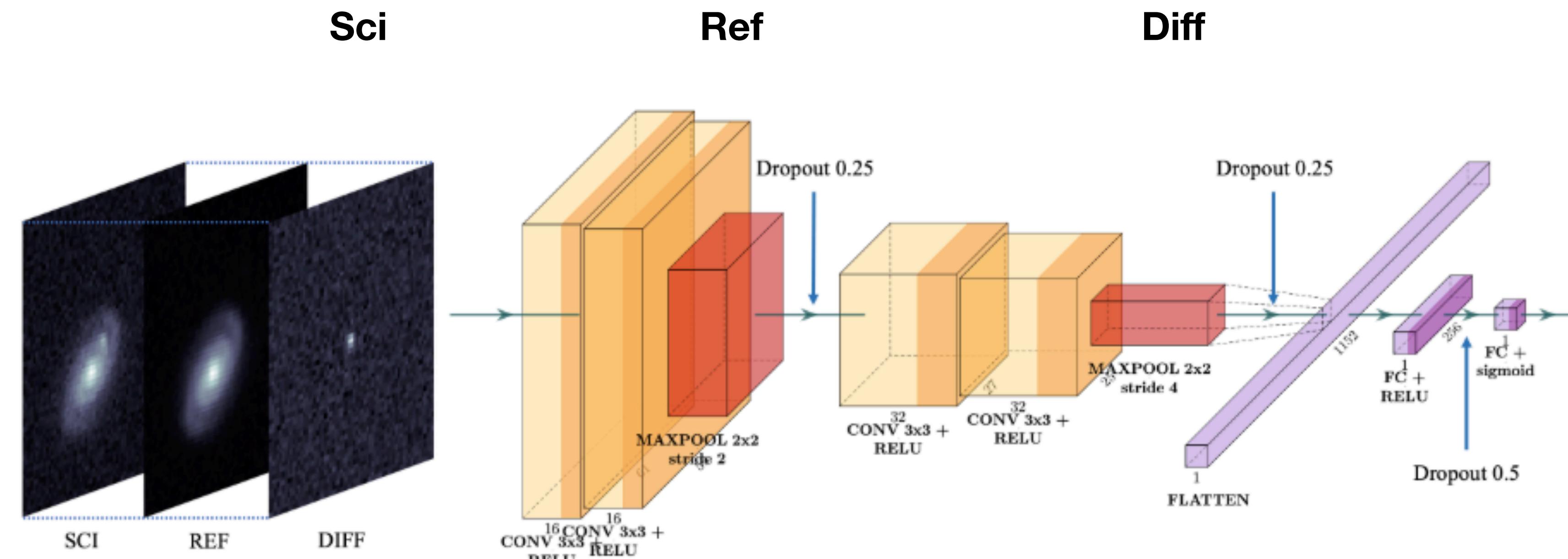
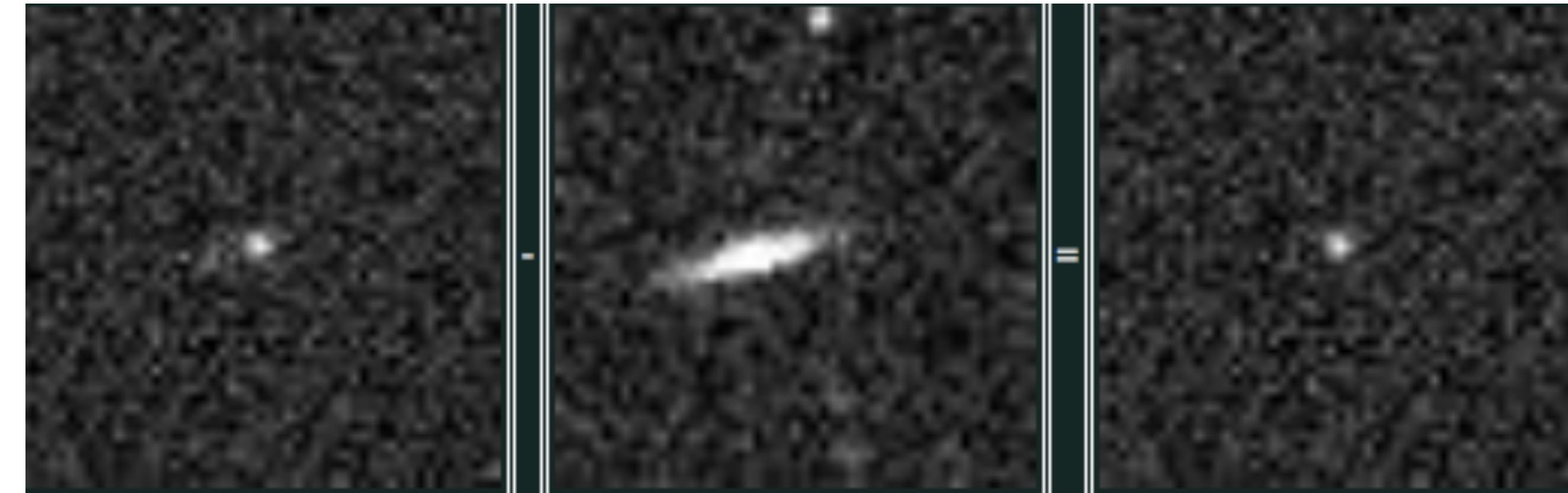
Number of classifications: 0

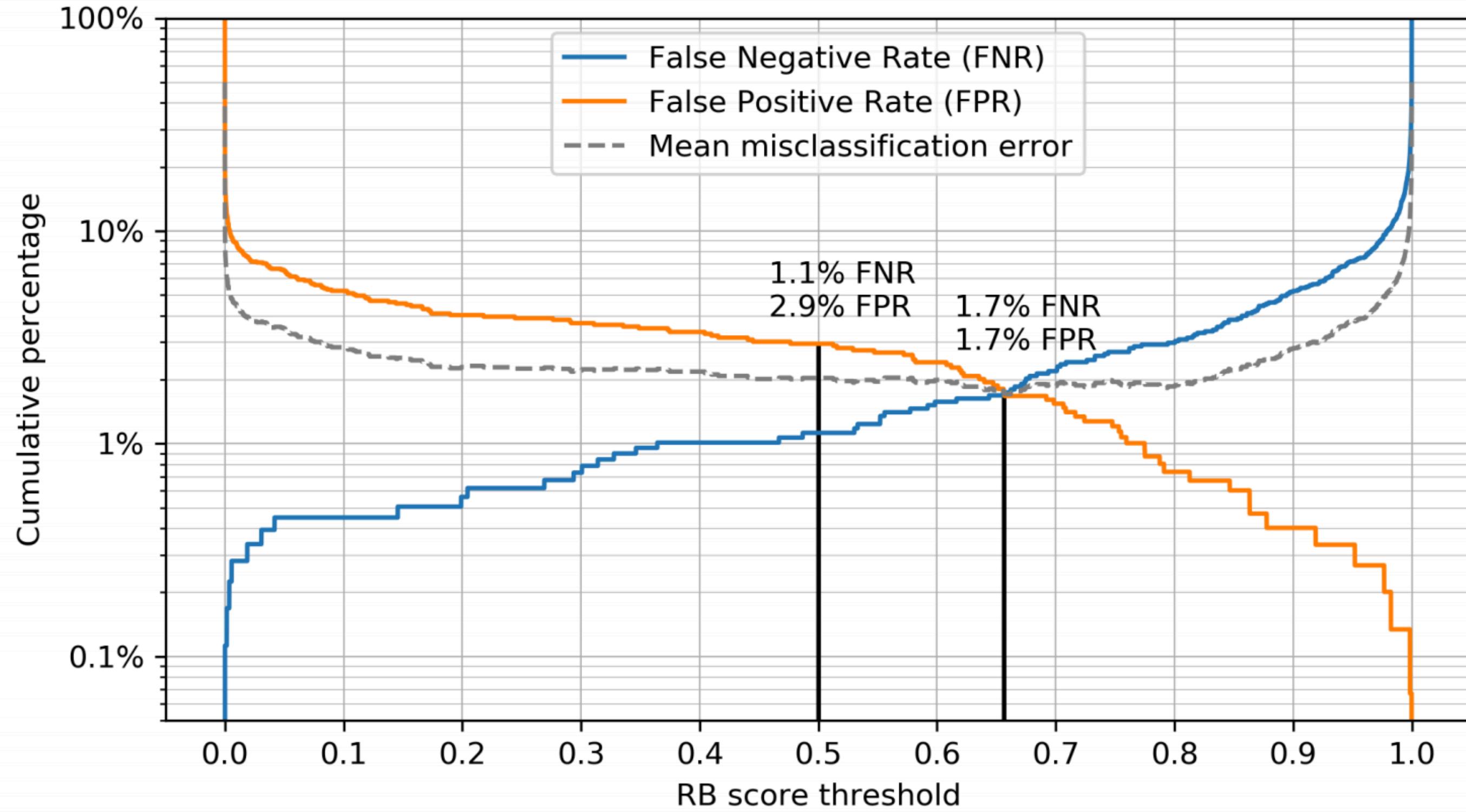
Number of classifications by all users: 304

[private.caltech.edu](#)

Dmitry Duev

Real-Bogus separation ('braai')





$$A = \frac{TP + TN}{TP + FP + TN + FN}$$

Total predictions

How often is the model correct?

$$P = \frac{TP}{TP + FP}$$

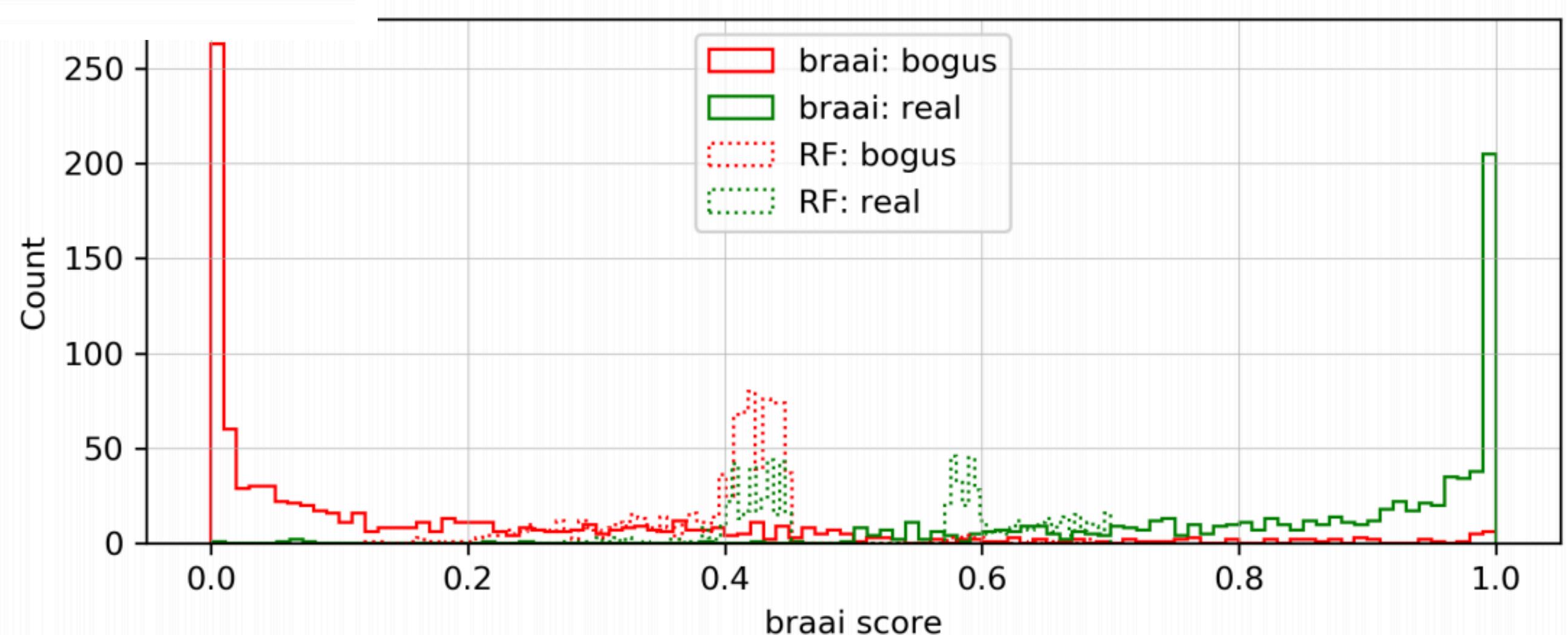
Predicted positives

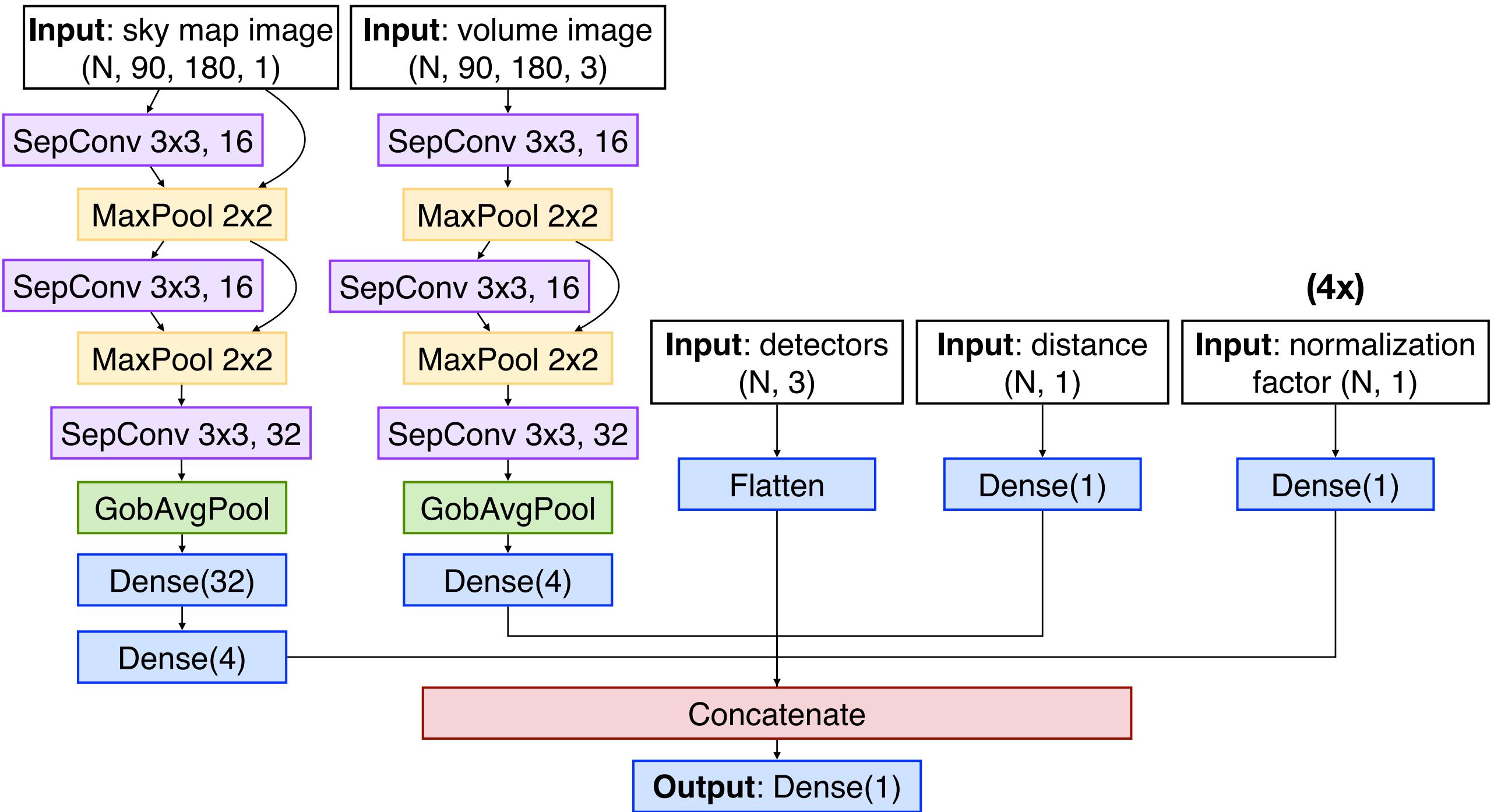
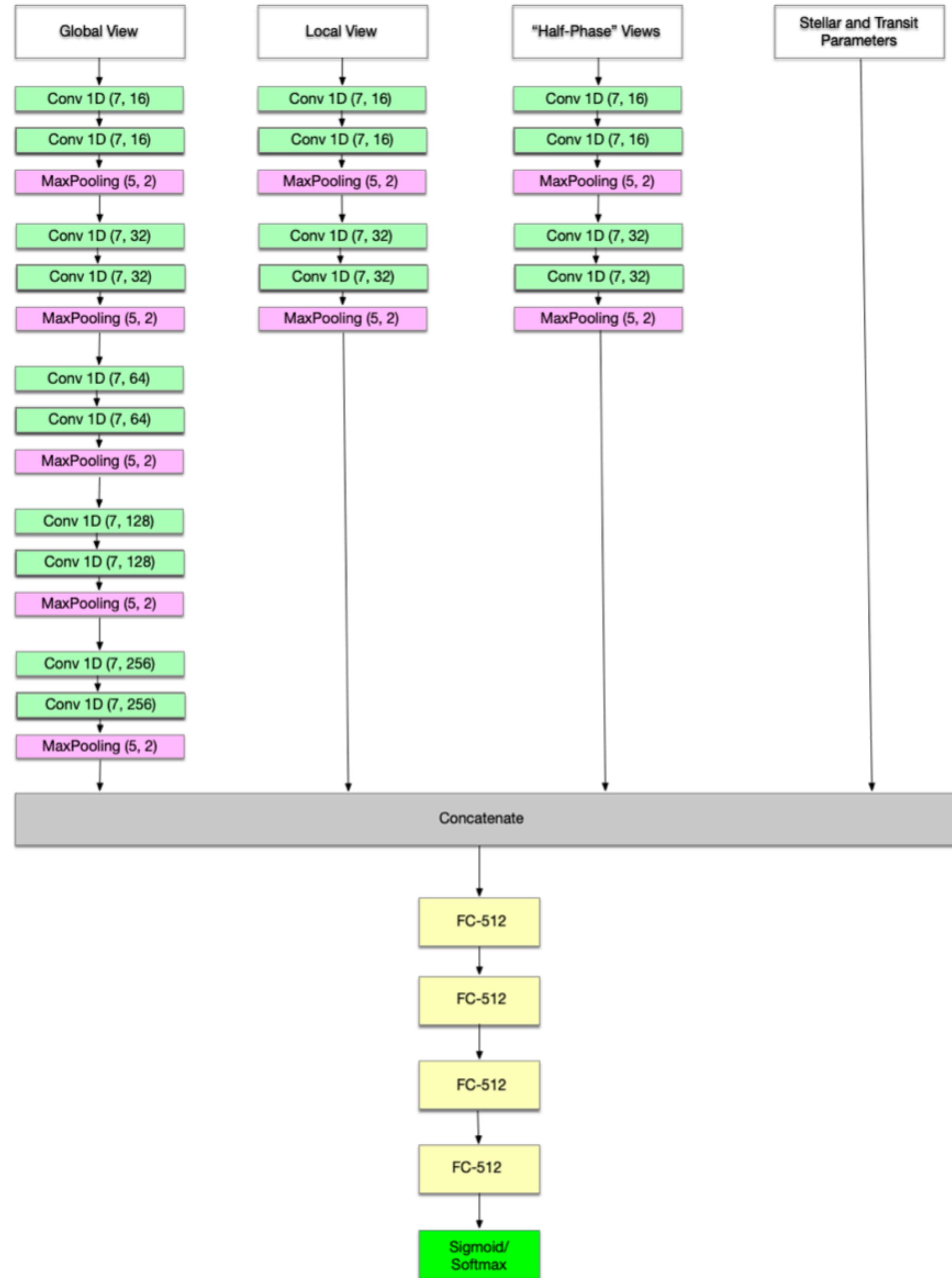
How often is the model correct when it predicts that the candidate is real?

$$R = \frac{TP}{TP + FN}$$

Actual positives

How many real candidates are predicted correctly?

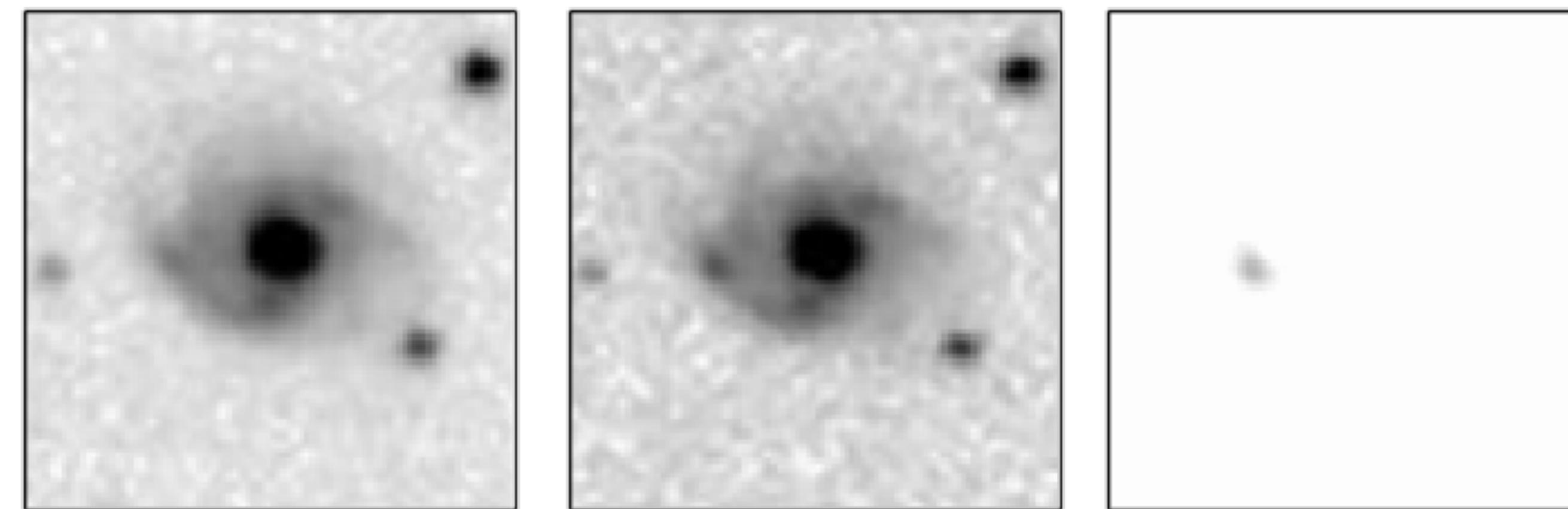
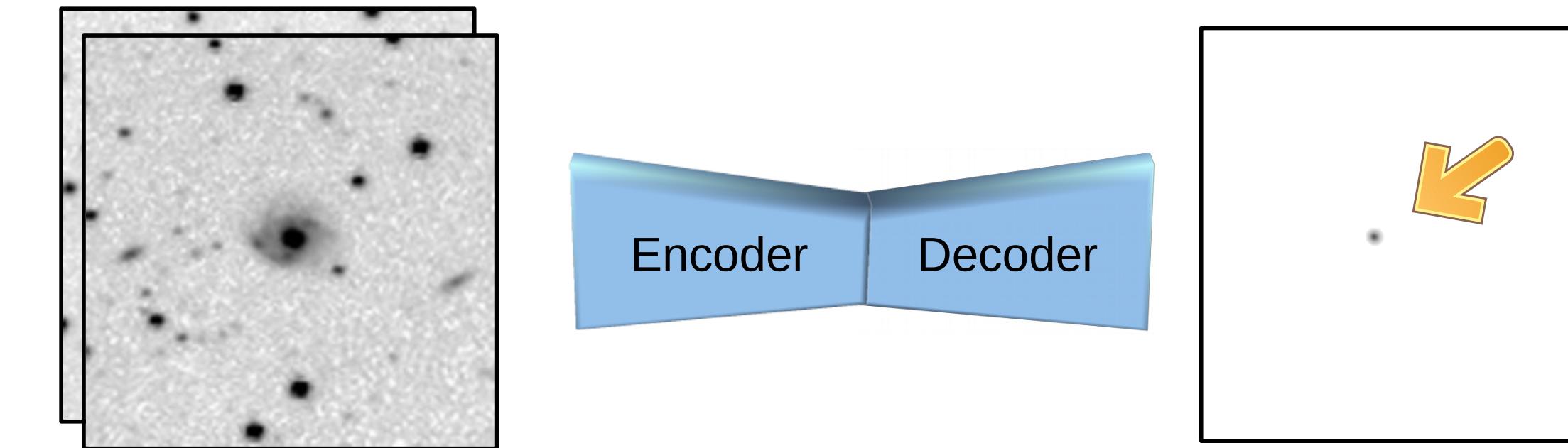




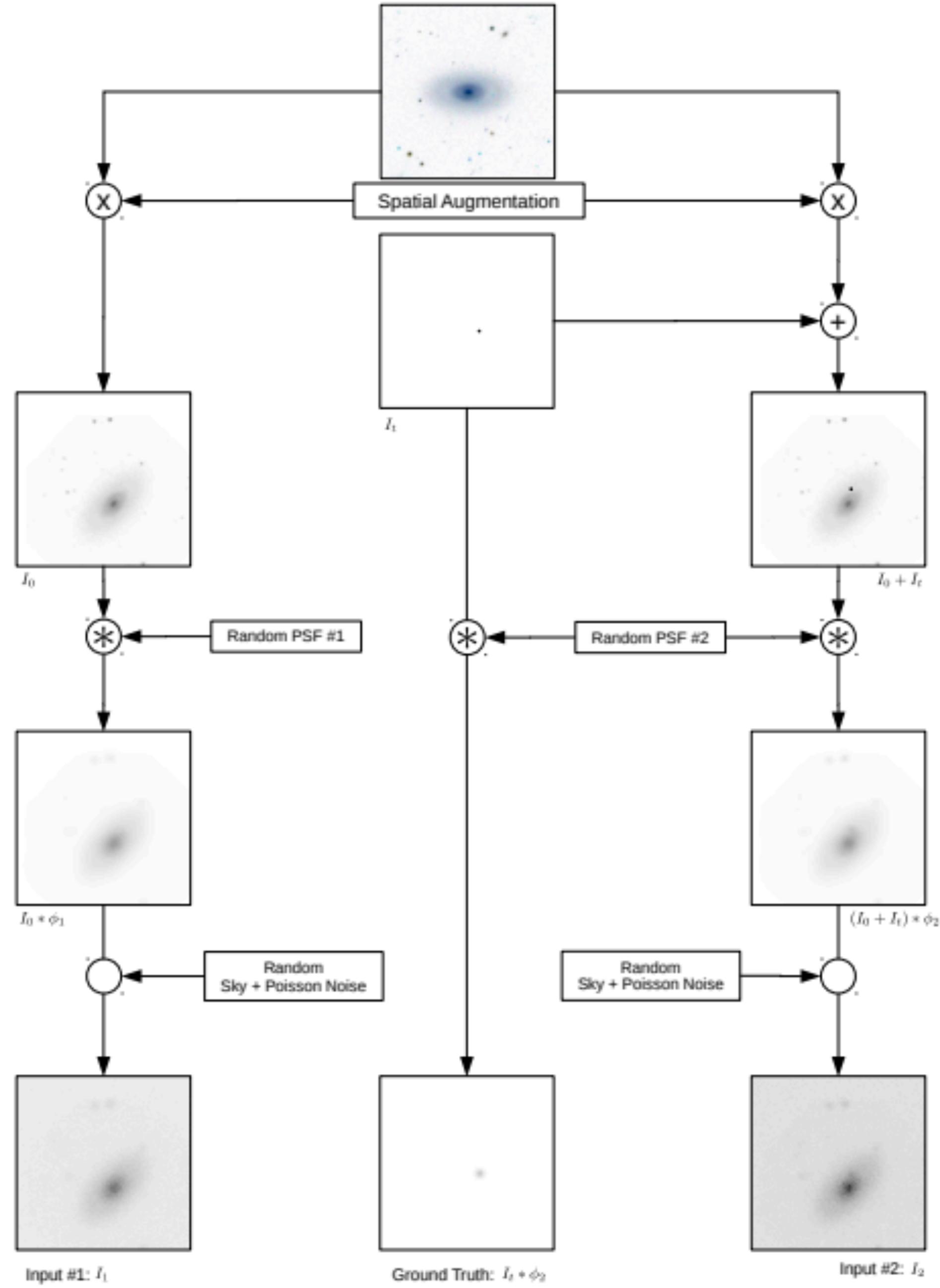
Examples with multiple inputs

Similarly one can build models with multiple outputs
e.g. classification and regression

Image subtraction for hunting transients without subtraction



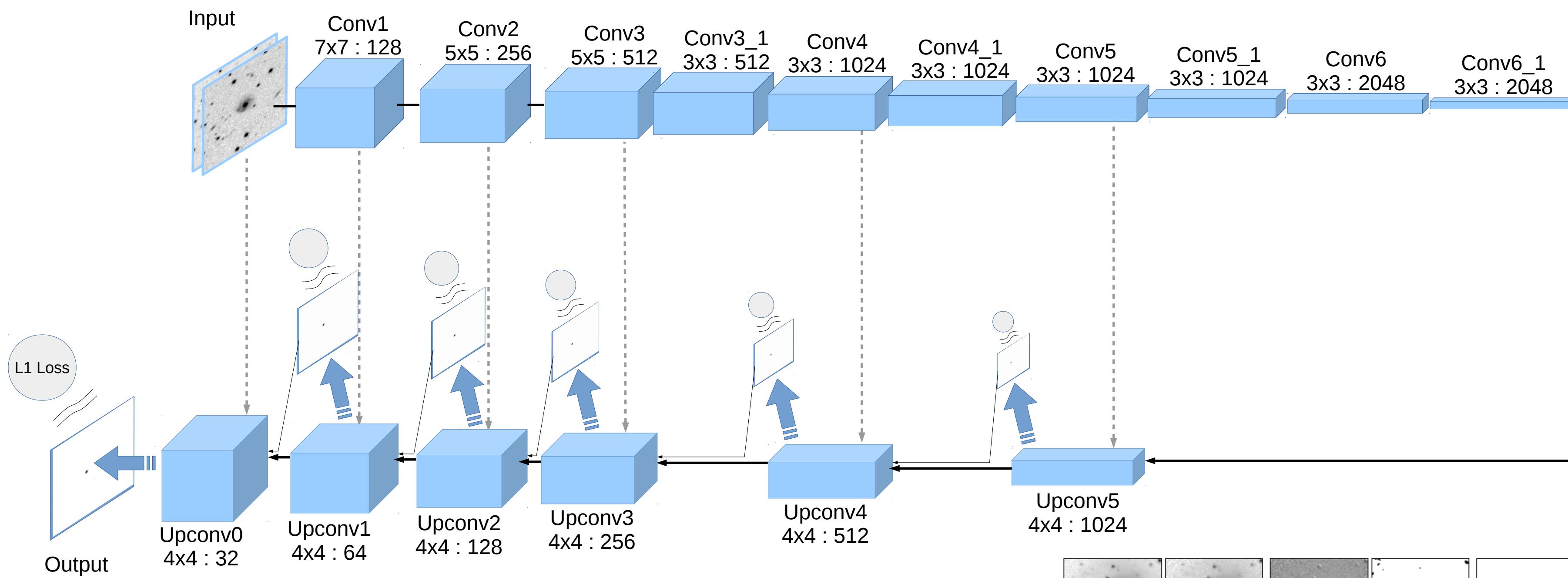
Sedaghat and Mahabal, 2017
arXiv:1710.01422



Training cycles involving different PSFs

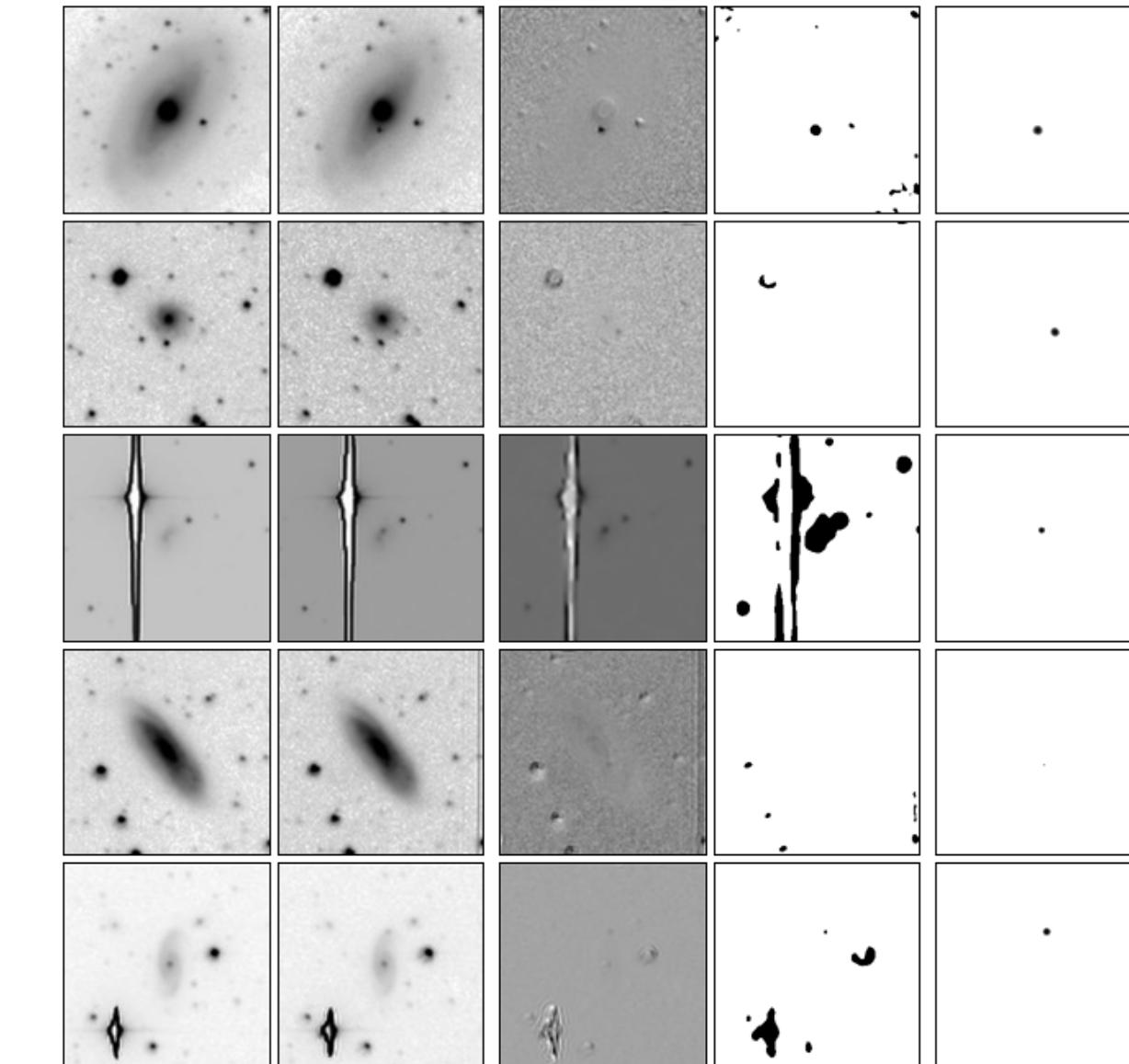
Figure 5. The synthetic sample generation procedure. The notations used here are described in Equations (1) and (2).

Encoder-decoder network (fully convolutional)



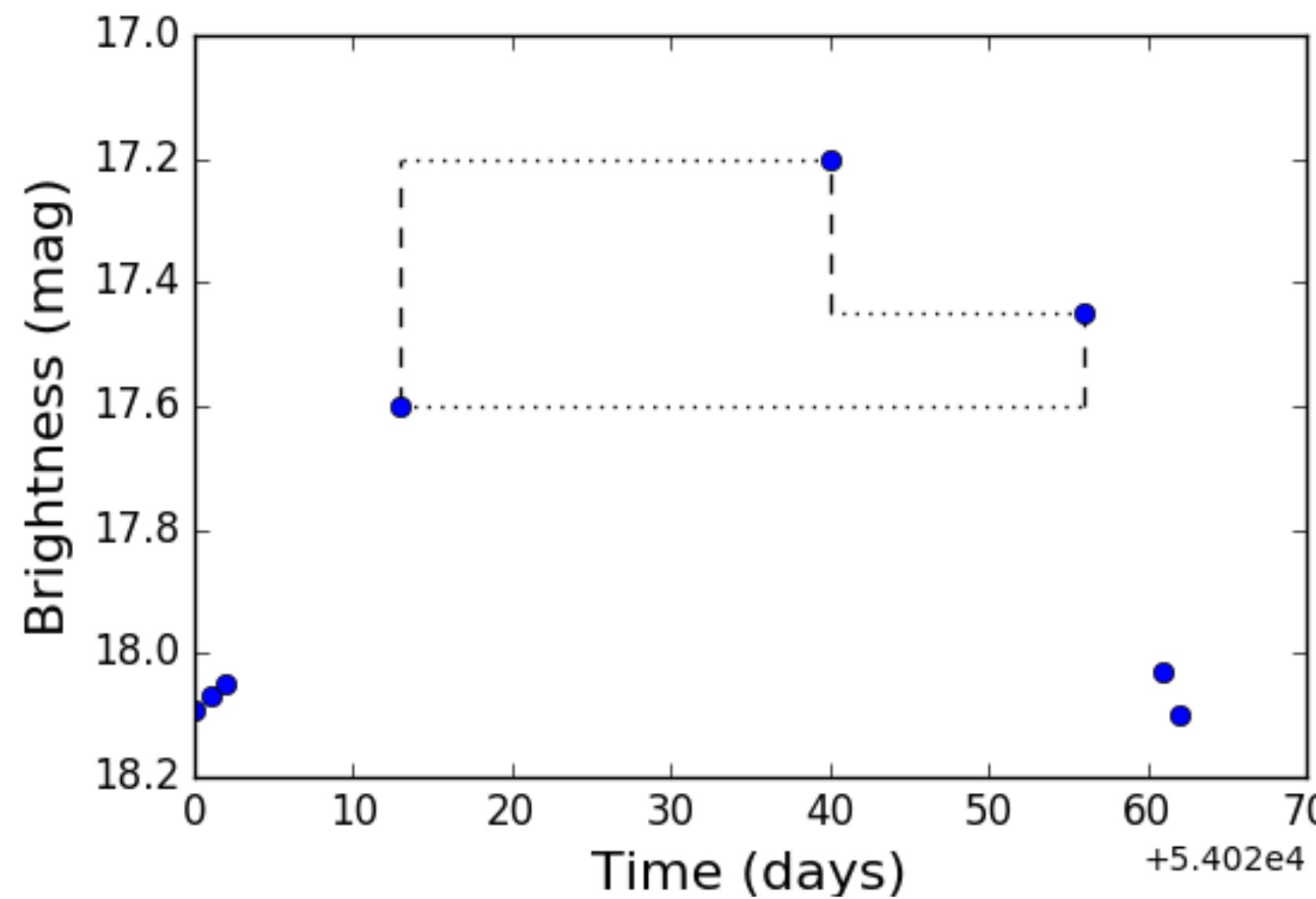
Sedaghat and Mahabal, 2017

arXiv:1710.01422



(dmdt) Image representation

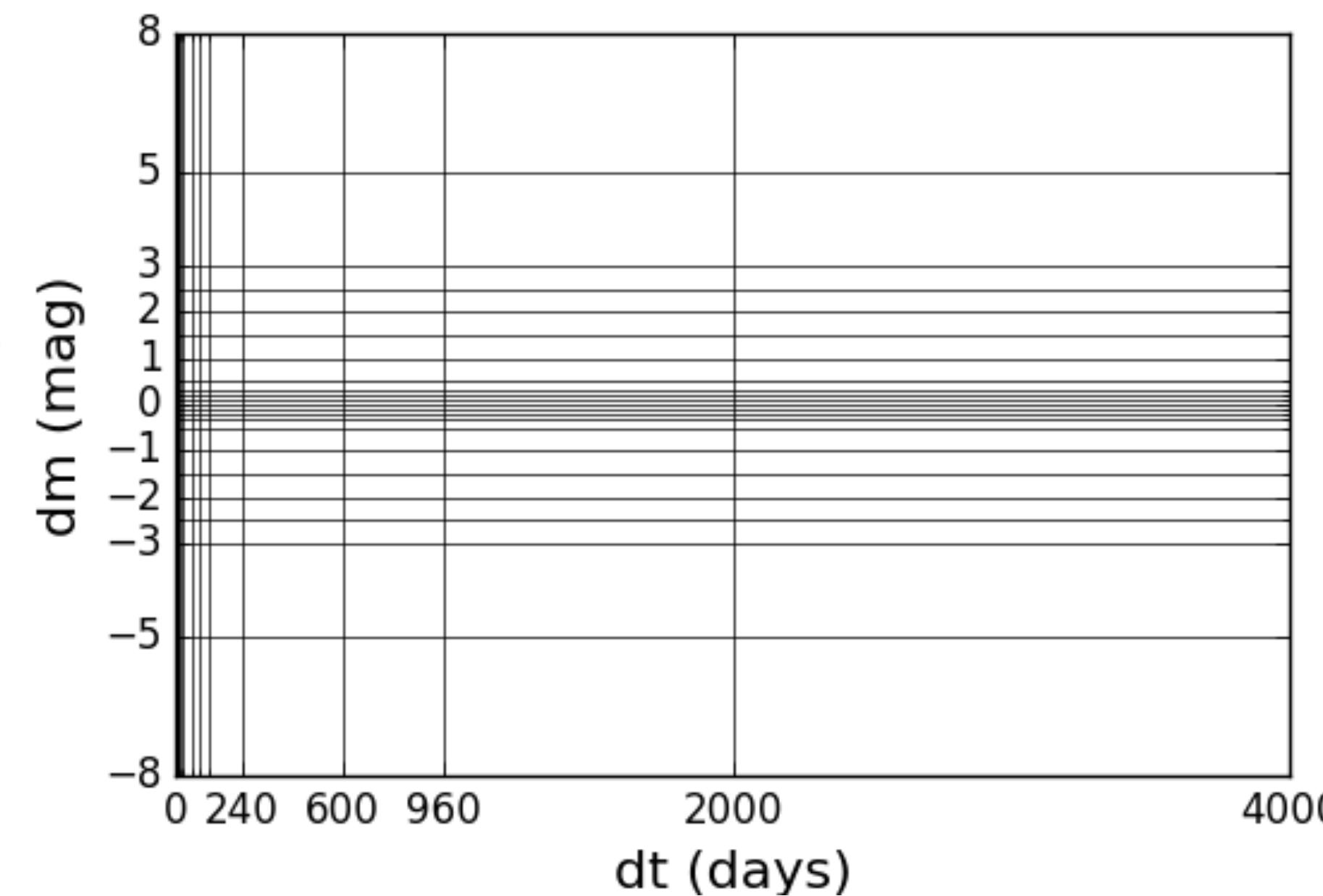
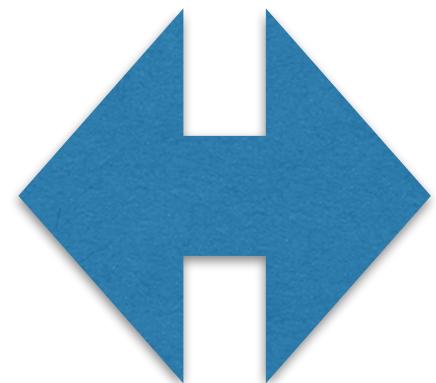
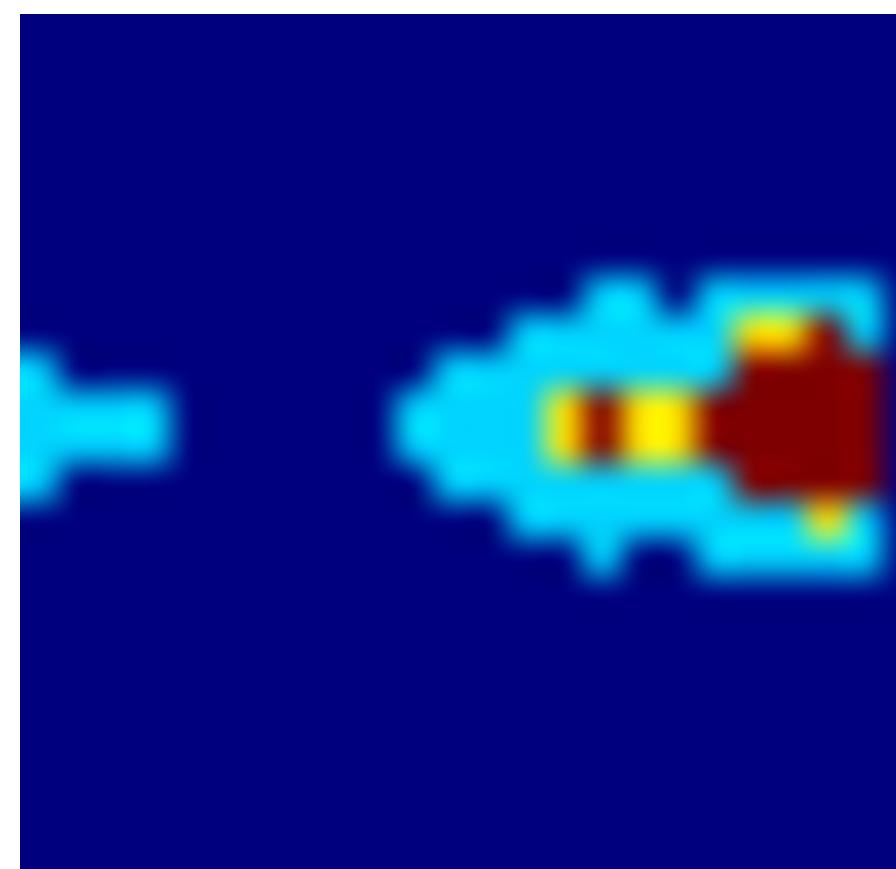
Mahabal et al., 2017



light curve with n points

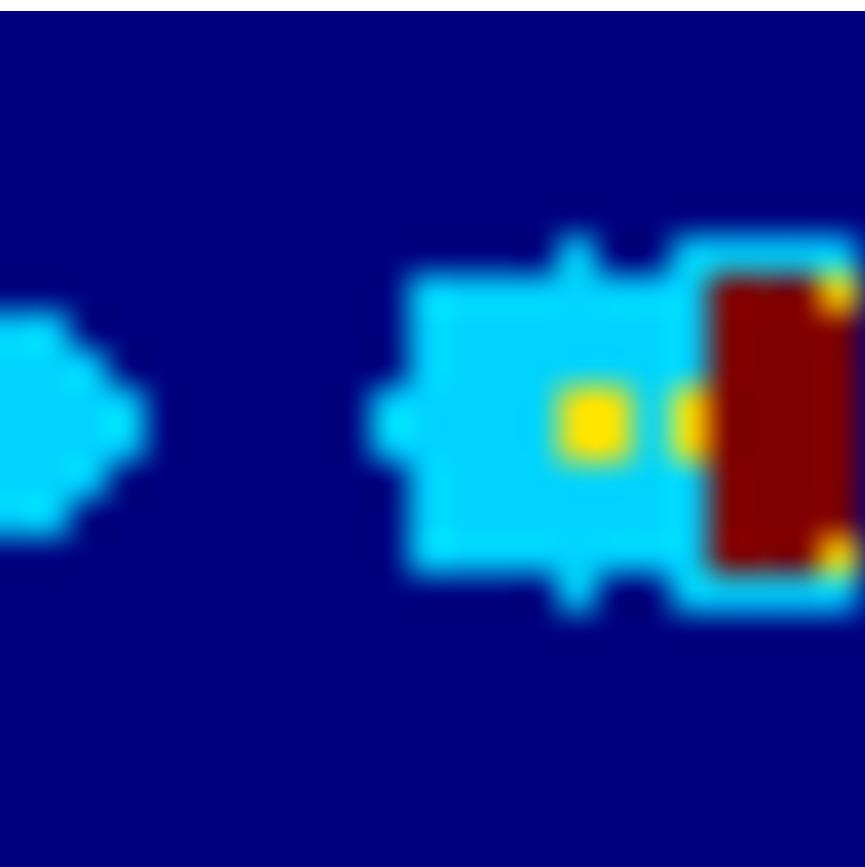
**23 x 24
output grid**

$n * (n-1)/2$ points

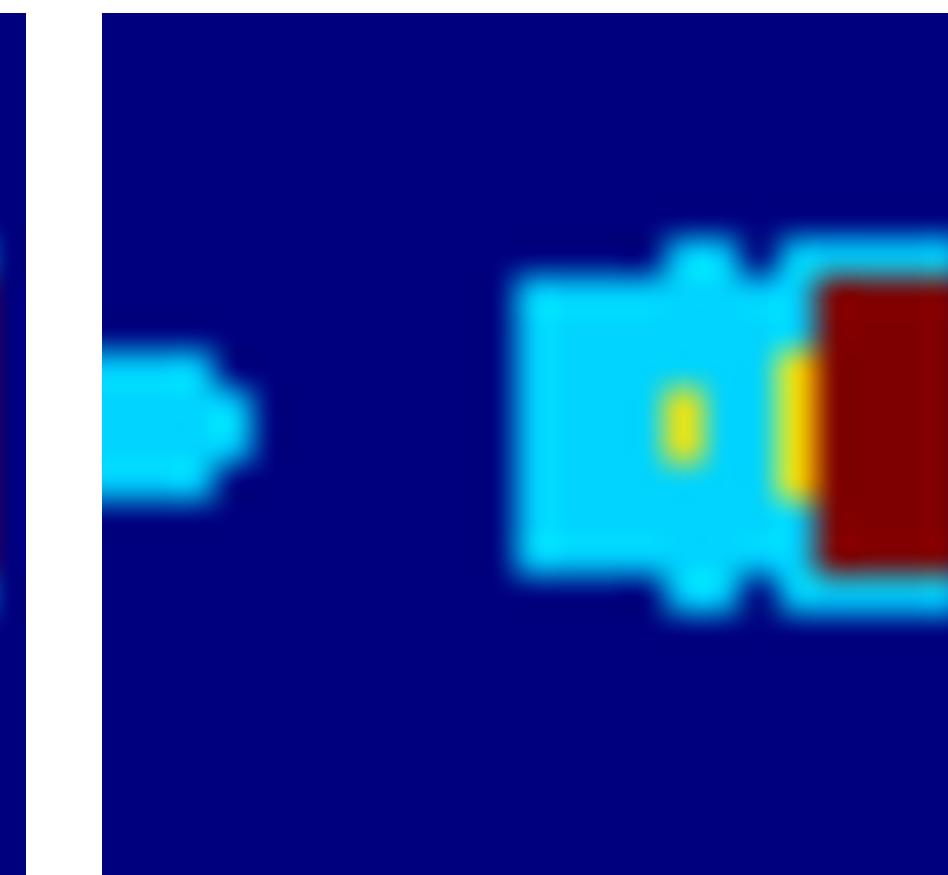
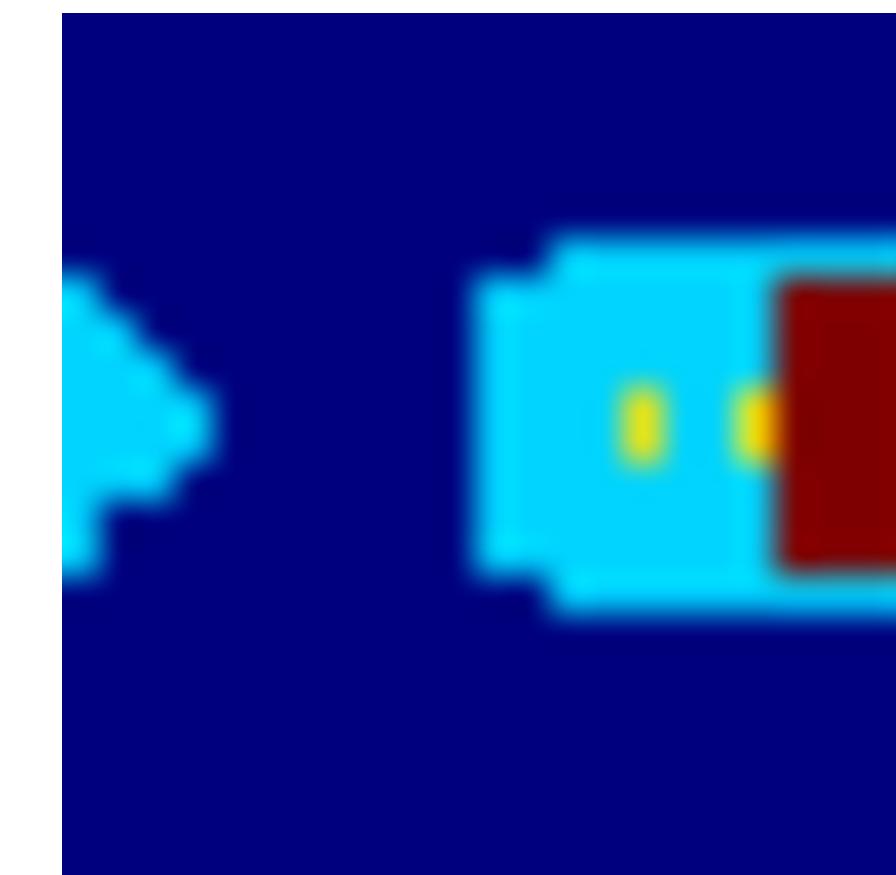
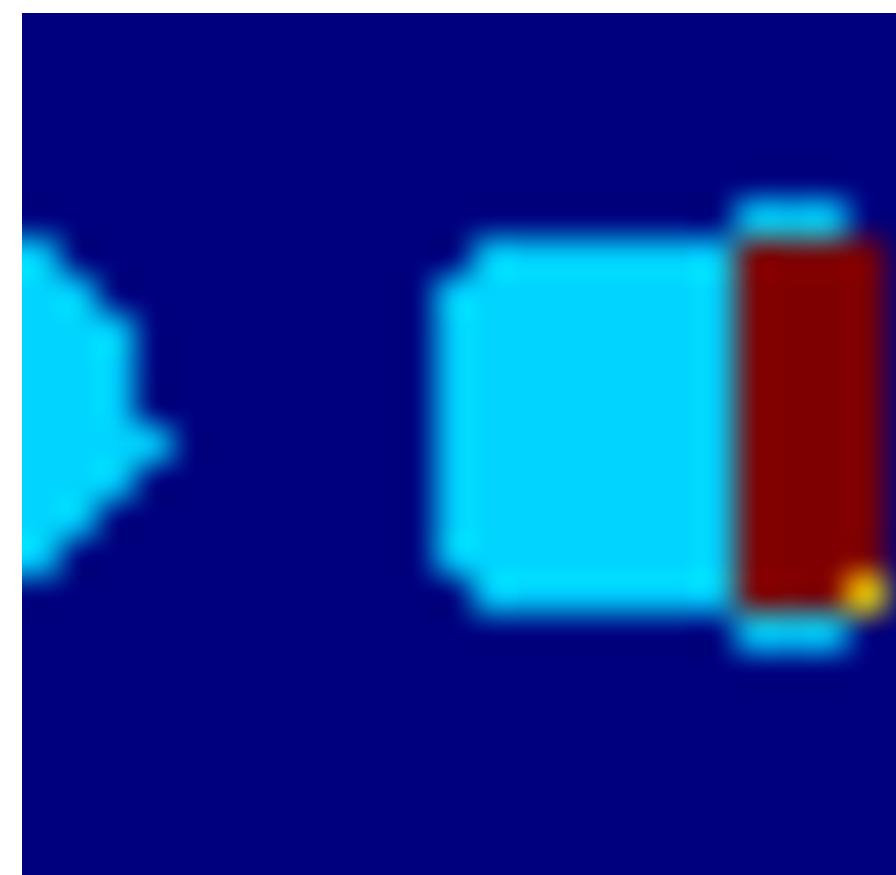
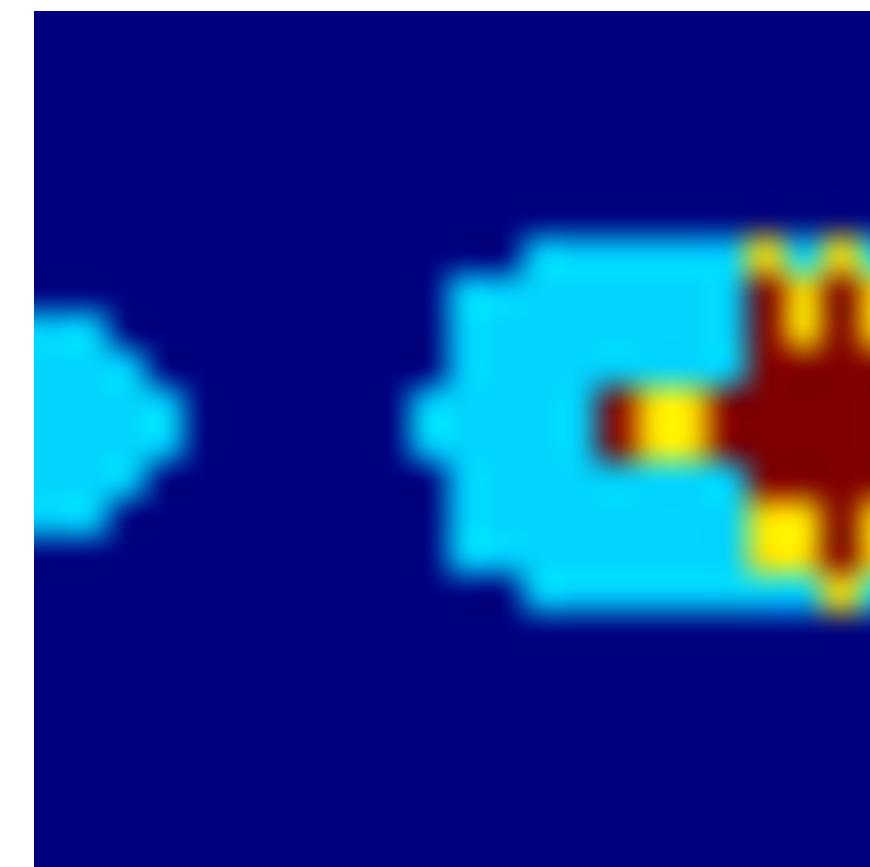


Area equalized pixels

EW

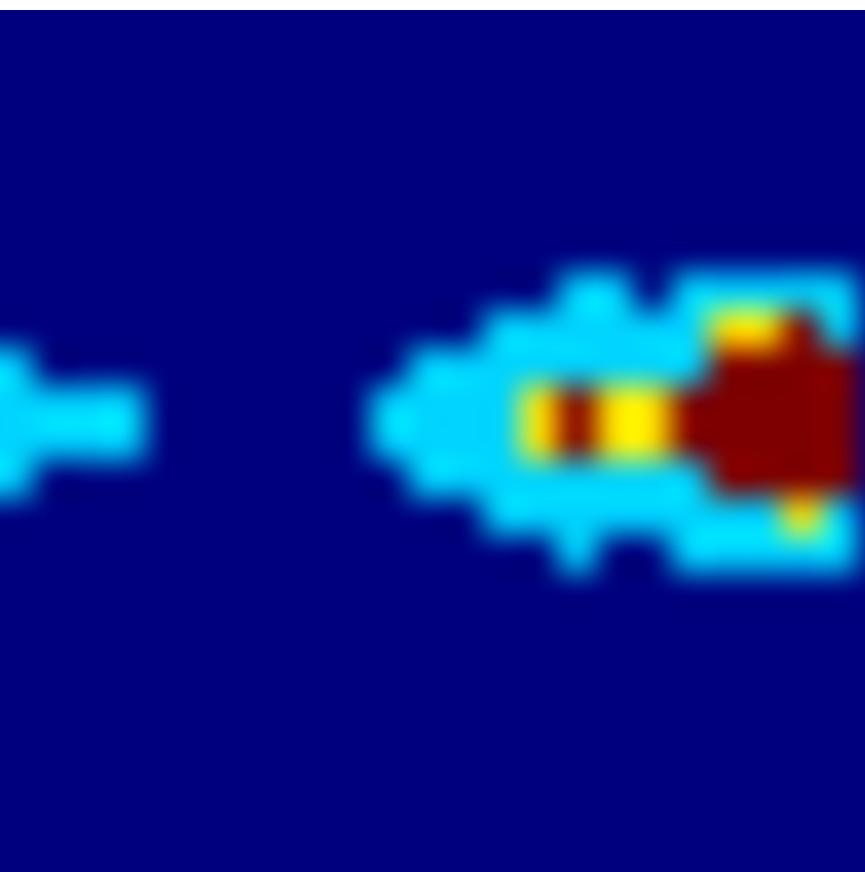


EA

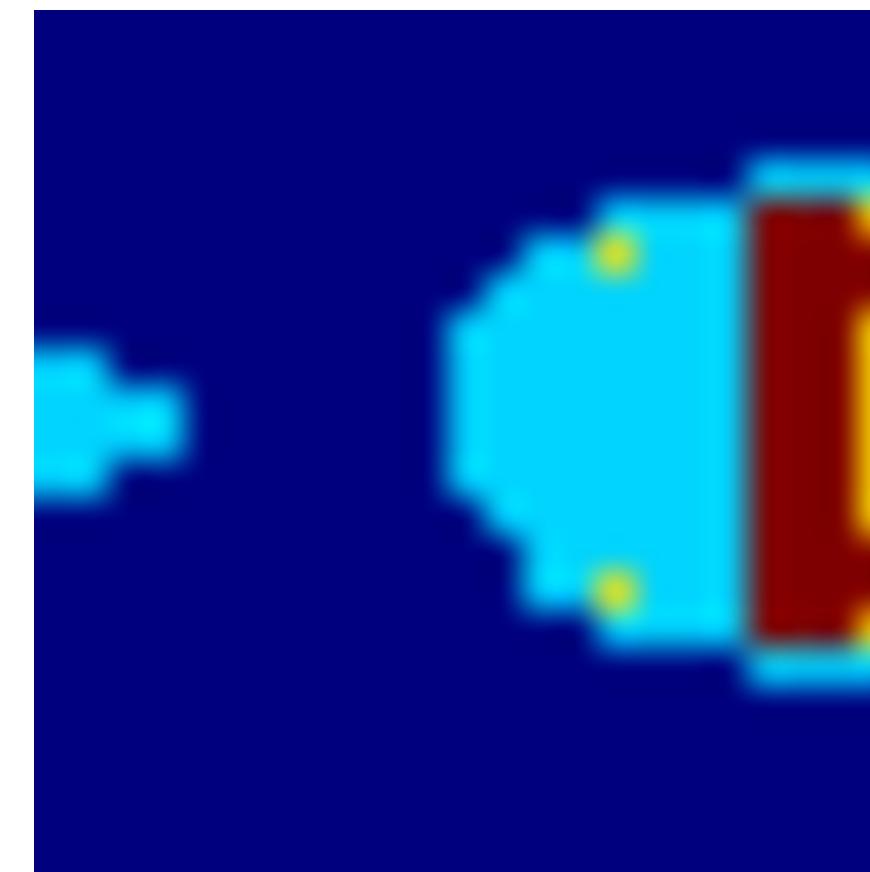


RR

RS CVn



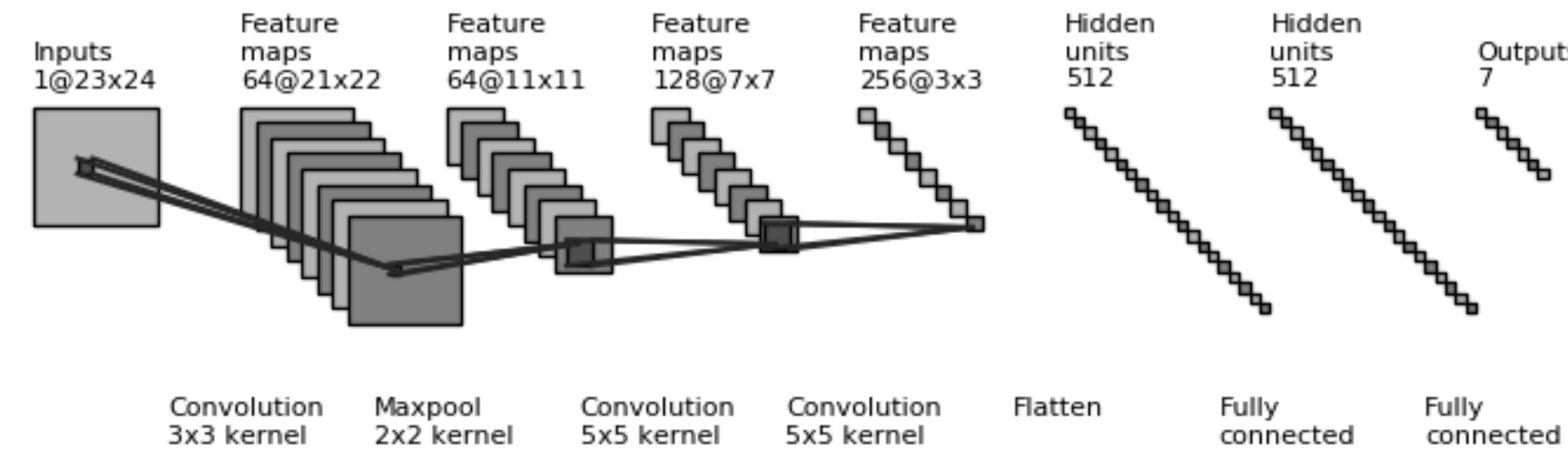
LPV



Kshiteej Sheth

medians

Network architecture



In this case
shallow works
well too

```
layers = [  
    InputLayer,  
    Conv2DLayer(32, size:3x3, rectify),  
    DropoutLayer(0.1),  
    DenseLayer(128),  
    DropoutLayer(0.25),  
    DenseLayer(128),  
    DenseLayer(all, softmax).
```



	1	2	4	5	6	8	13
True Class	94	2	0	2	0	0	0
	1	2	4	5	6	8	13
1	15	84	0	0	0	0	0
2	31	0	57	10	0	0	0
4	43	0	2	54	0	0	0
5	43	0	8	38	10	0	0
6	97	0	0	1	0	0	0
8	22	0	5	0	0	0	71
Prediction	1	2	4	5	6	8	13



Binary probabilities are better

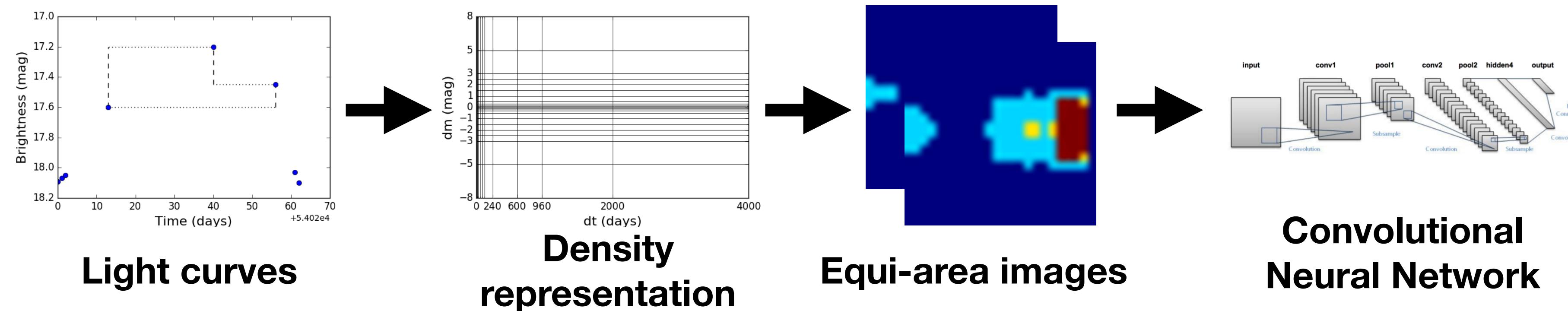
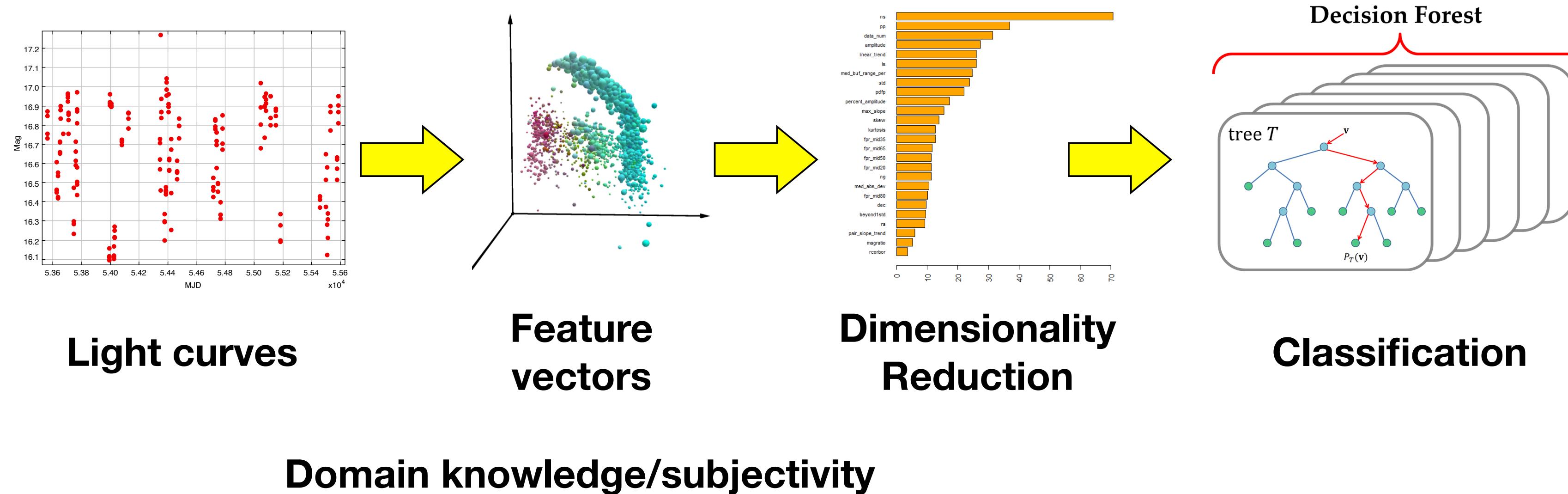
Random Forest
using standard
features

no features
no dimensionality reduction
comparable results

Convolutional Network

	1	2	4	5	6	8	13
True Class	94	2	0	2	0	0	0
	1	2	4	5	6	8	13
1	18	81	0	0	0	0	0
2	32	0	53	14	0	0	0
4	32	0	1	65	0	0	0
5	26	0	5	66	0	1	0
6	78	0	0	4	0	13	0
8	1	1	5	1	2	3	83
Prediction	1	2	4	5	6	8	13

Classification Workflow



Improving LIGO detector duty cycle

New methods to assess and improve LIGO detector duty cycle

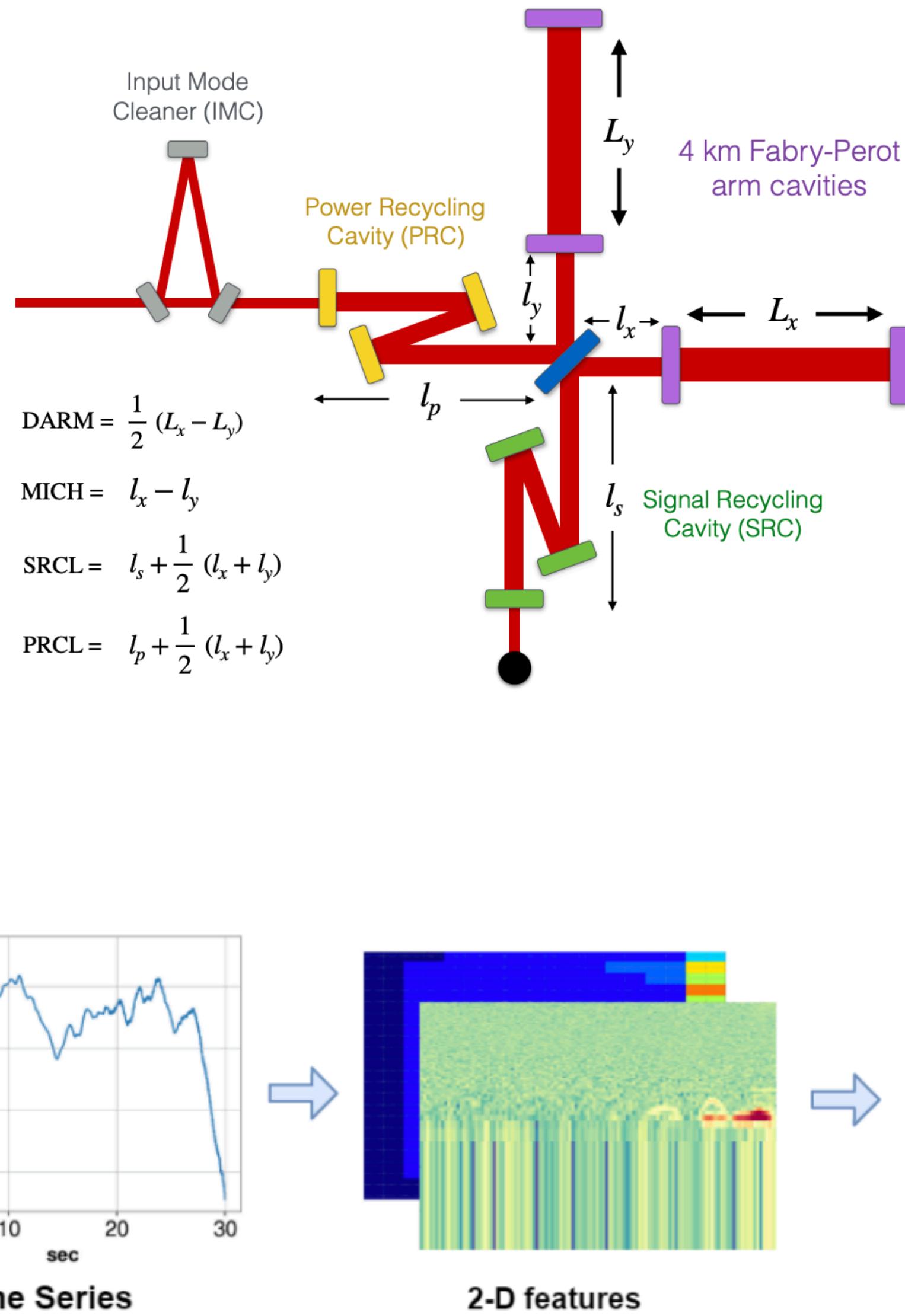
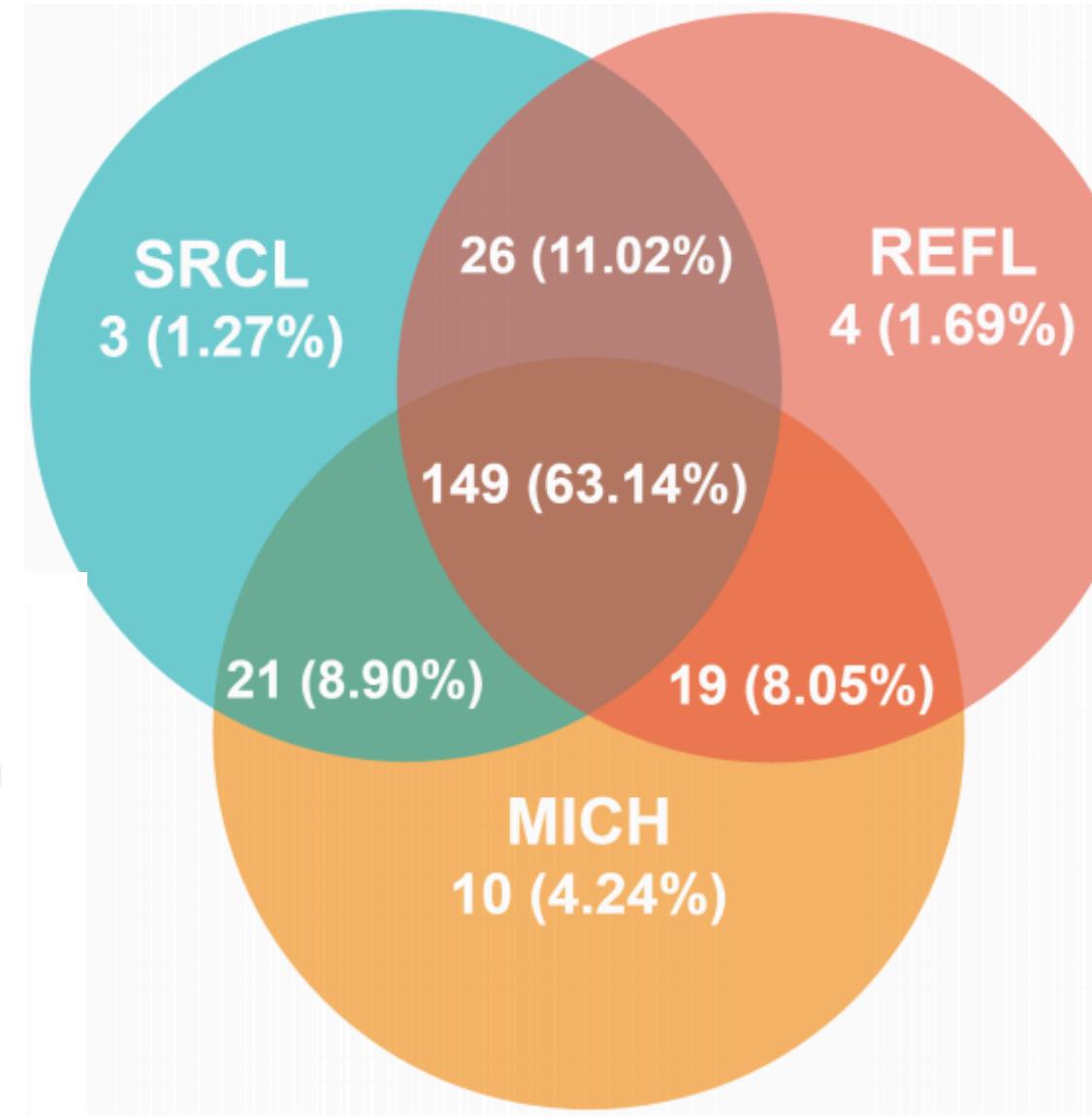


Table 8: Performance metrics for stacked $dmdt$ of multiple channels.

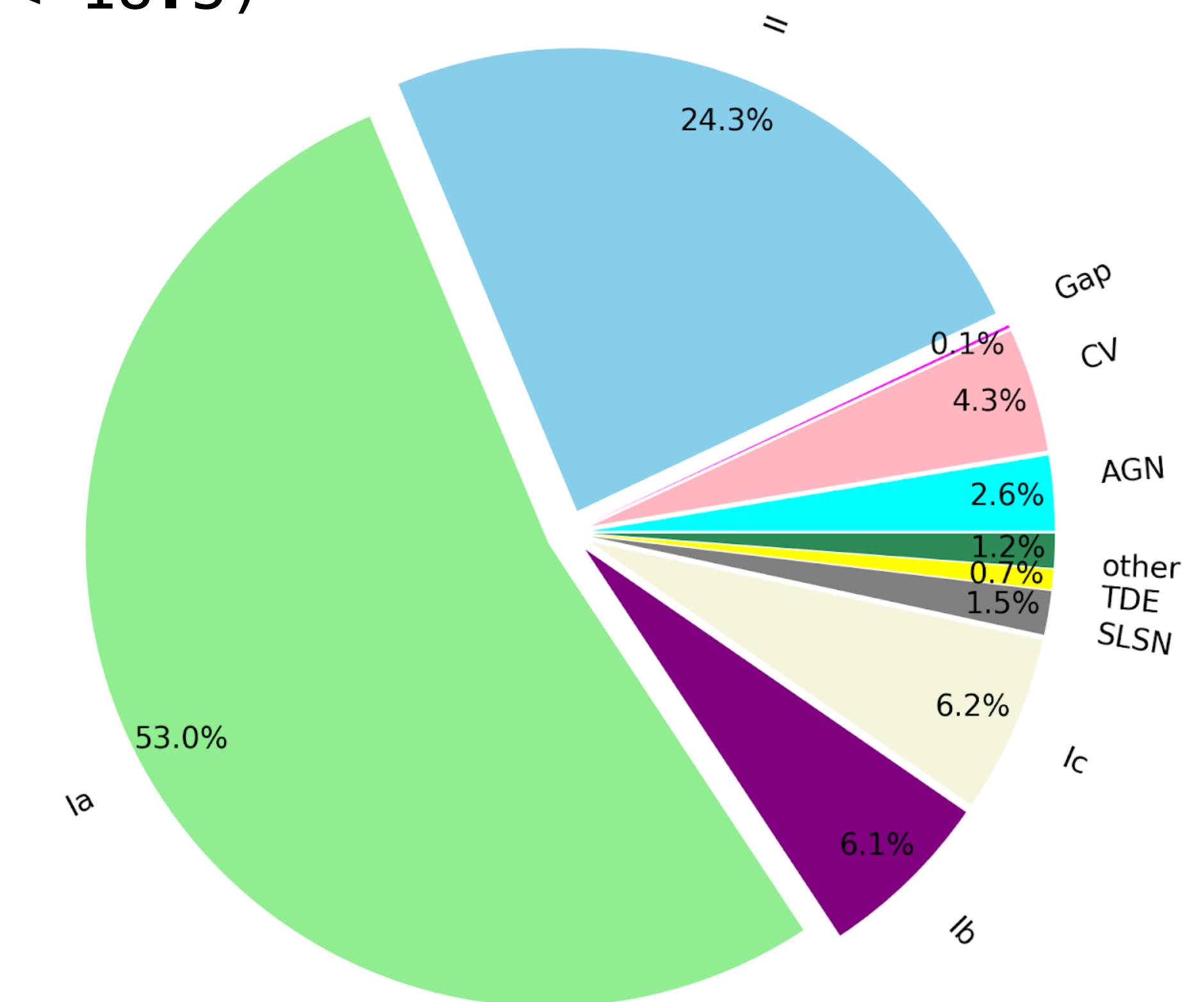
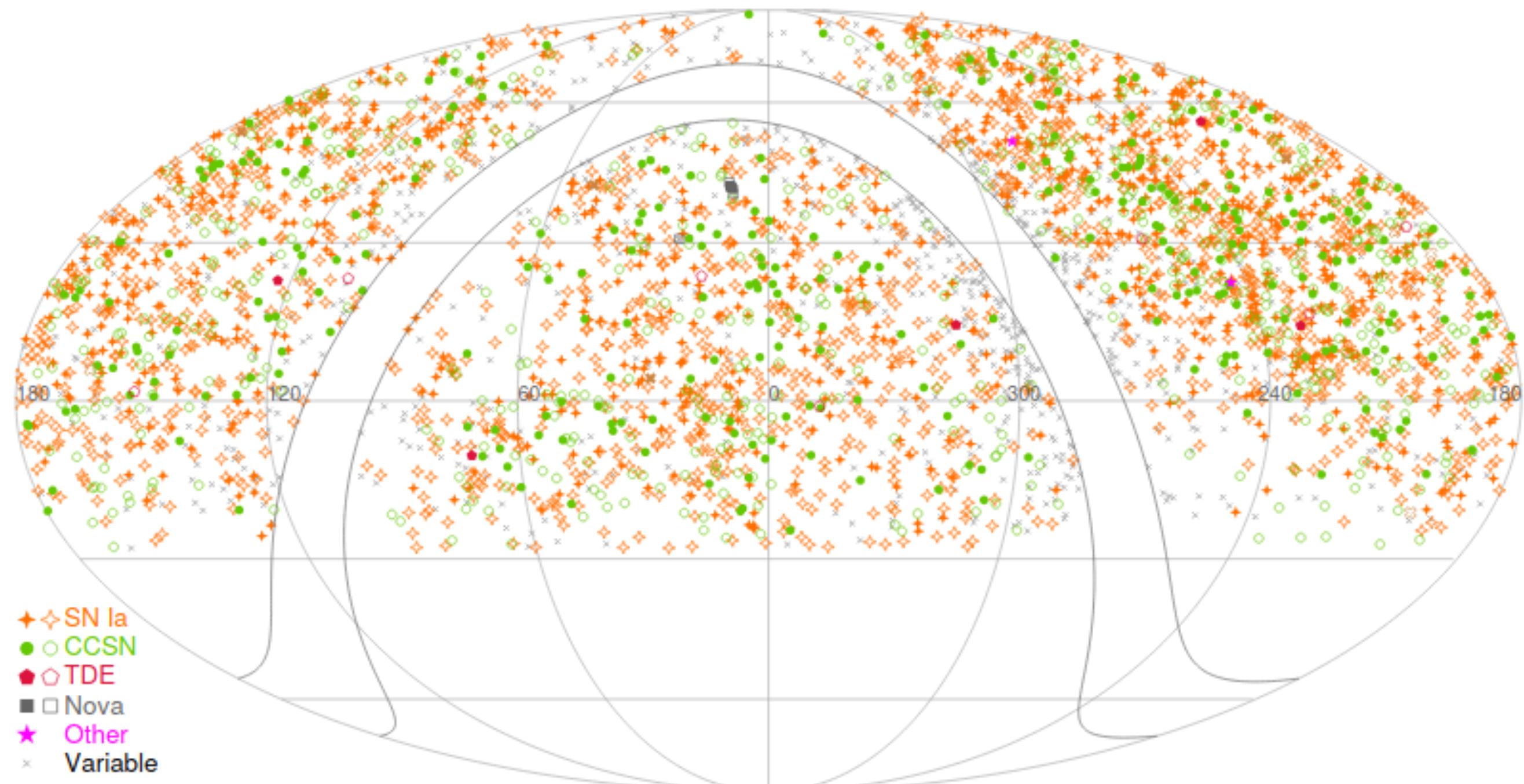
channels	Test accuracy	Matthew's coefficient	F1 score	Specificity	Recall	Precision
MICH+POP	0.971	0.941	0.968	0.985	0.953	0.983
MICH+REFL	0.975	0.949	0.972	0.996	0.949	0.996
MICH+SRCL	0.971	0.941	0.968	0.989	0.949	0.987
MICH+POP+SRCL	0.984	0.969	0.983	1.000	0.966	1.000
MICH+PRCL+REFL	0.984	0.969	0.983	0.996	0.970	0.996
MICH+REFL+SRCL	0.986	0.973	0.985	0.996	0.975	0.996
IMC+MICH+POP+SCRL	0.988	0.976	0.987	0.996	0.979	0.996
IMC+MICH+PRCL+REFL	0.986	0.973	0.985	1.000	0.970	1.000
MICH+PRCL+REFL+SRCL	0.986	0.973	0.985	0.996	0.975	0.996
IMC+MICH+POP+PRCL+SCRL	0.990	0.980	0.989	1.000	0.979	1.000

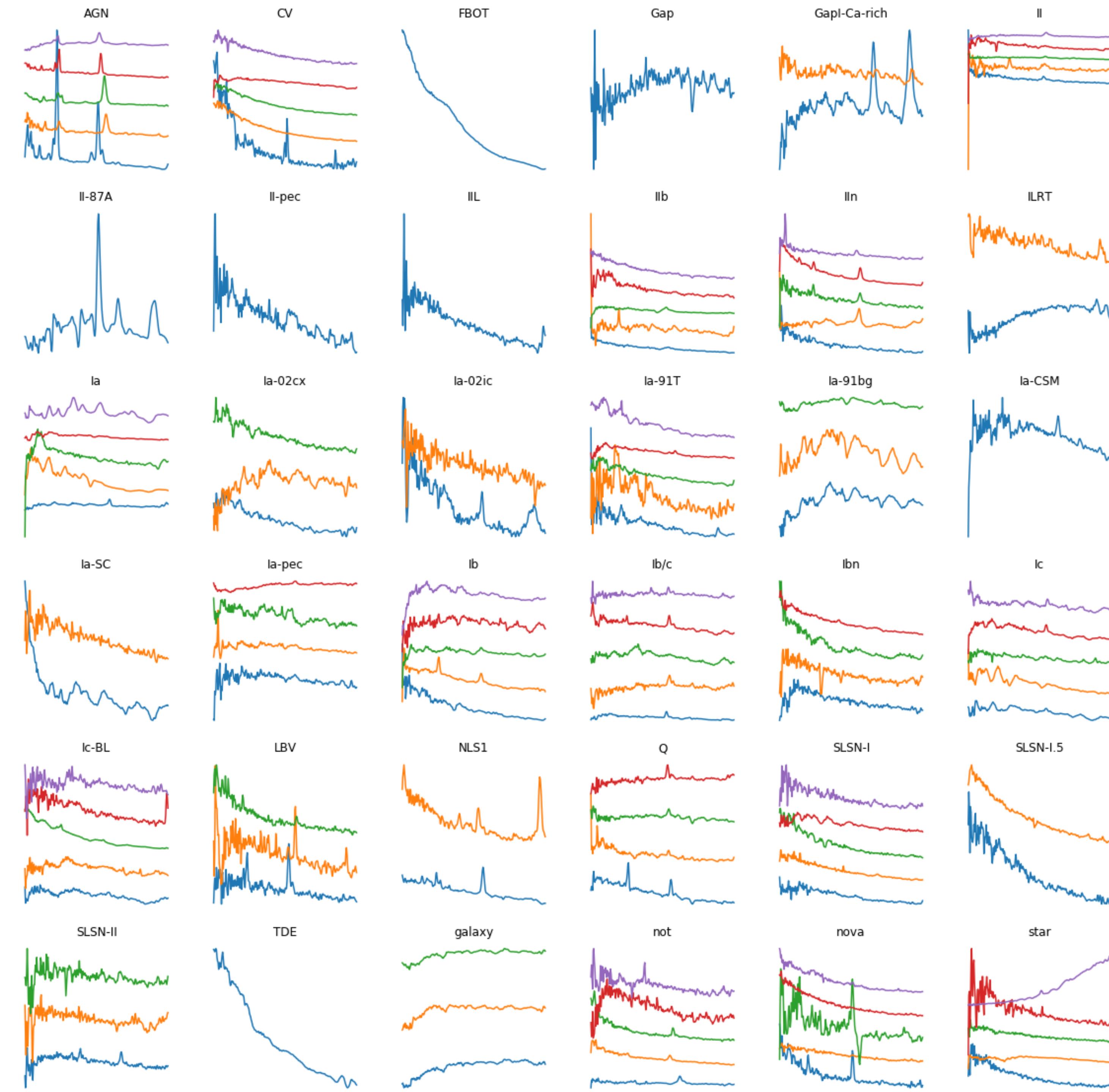


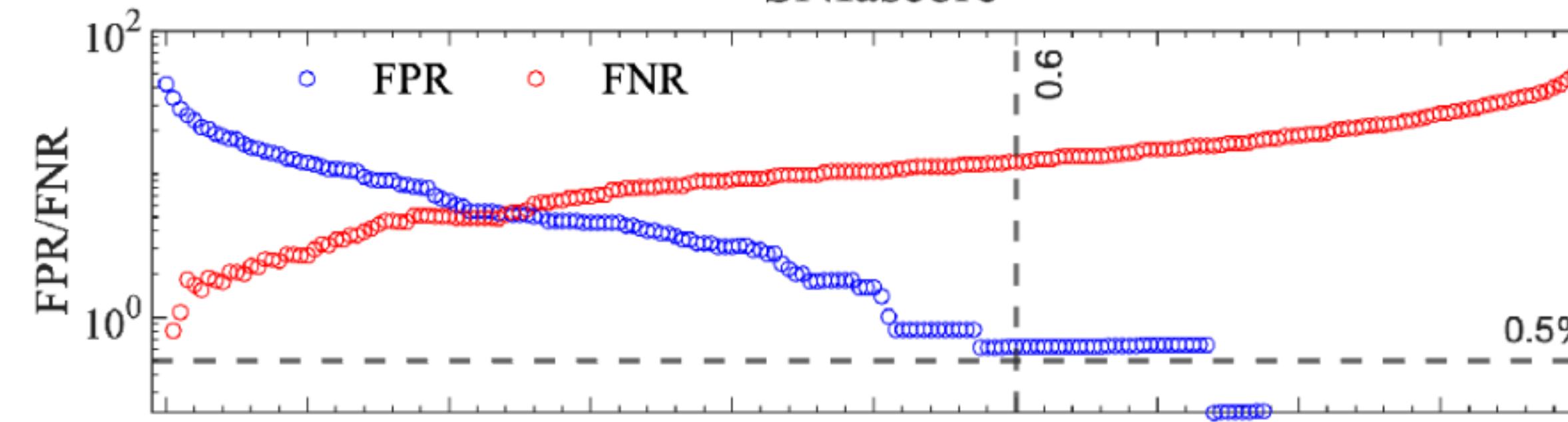
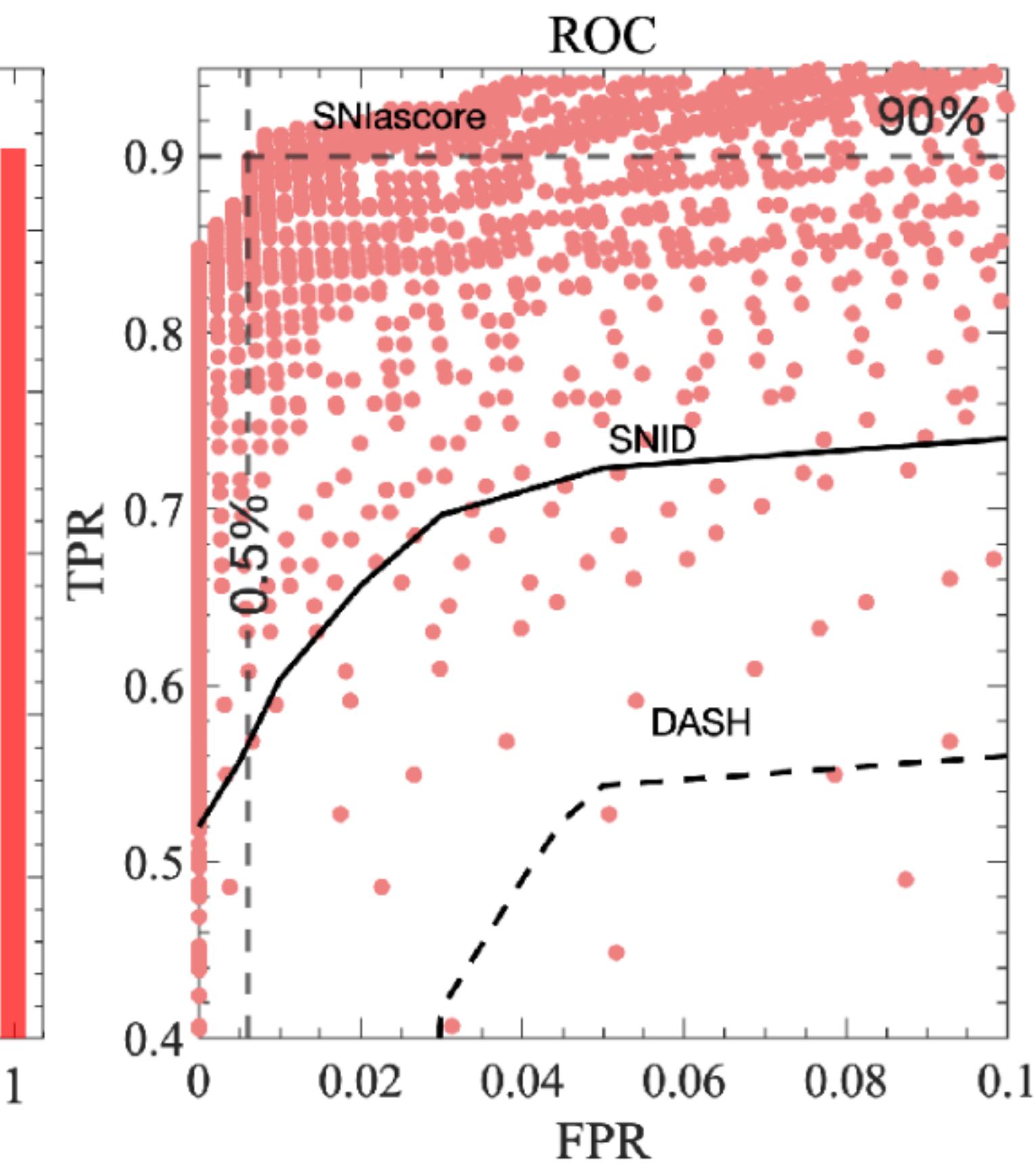
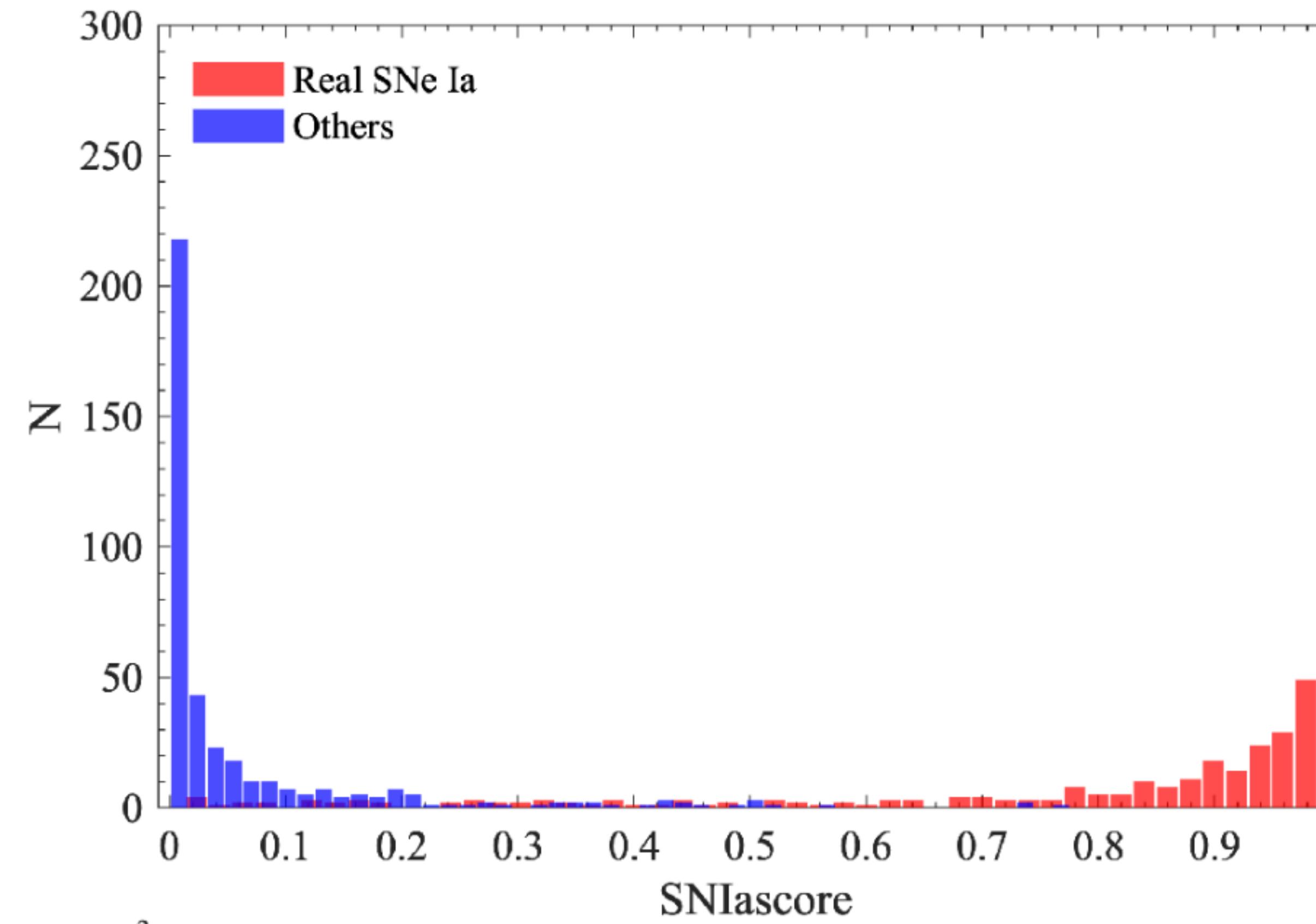
```
Layers = [
    InputLayer,
    Conv2DLayer(16,3x3,ReLU),
    Conv2DLayer(32,3x3,ReLU),
    MaxPoolLayer(3x3),
    DropoutLayer(0.25),
    DenseLayer(16),
    DropoutLayer(0.5),
    DenseLayer(2)
]
```

BTS : An unbiased view of transient night sky!

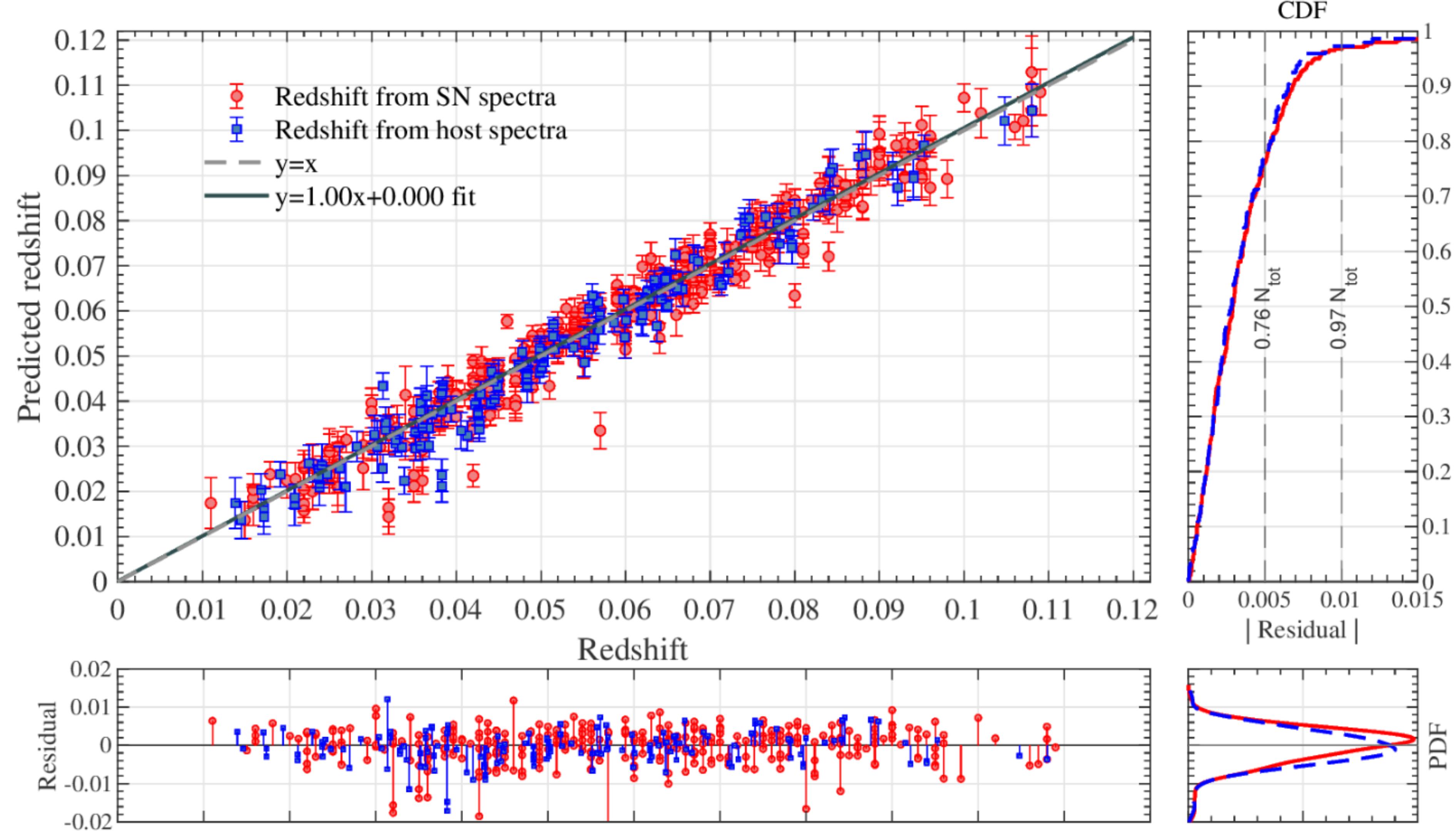
Untargeted and flux limited ($m < 19$)
No strong variables (like CV, AGN) or moving objects
Spectroscopically complete ($m < 18.5$)





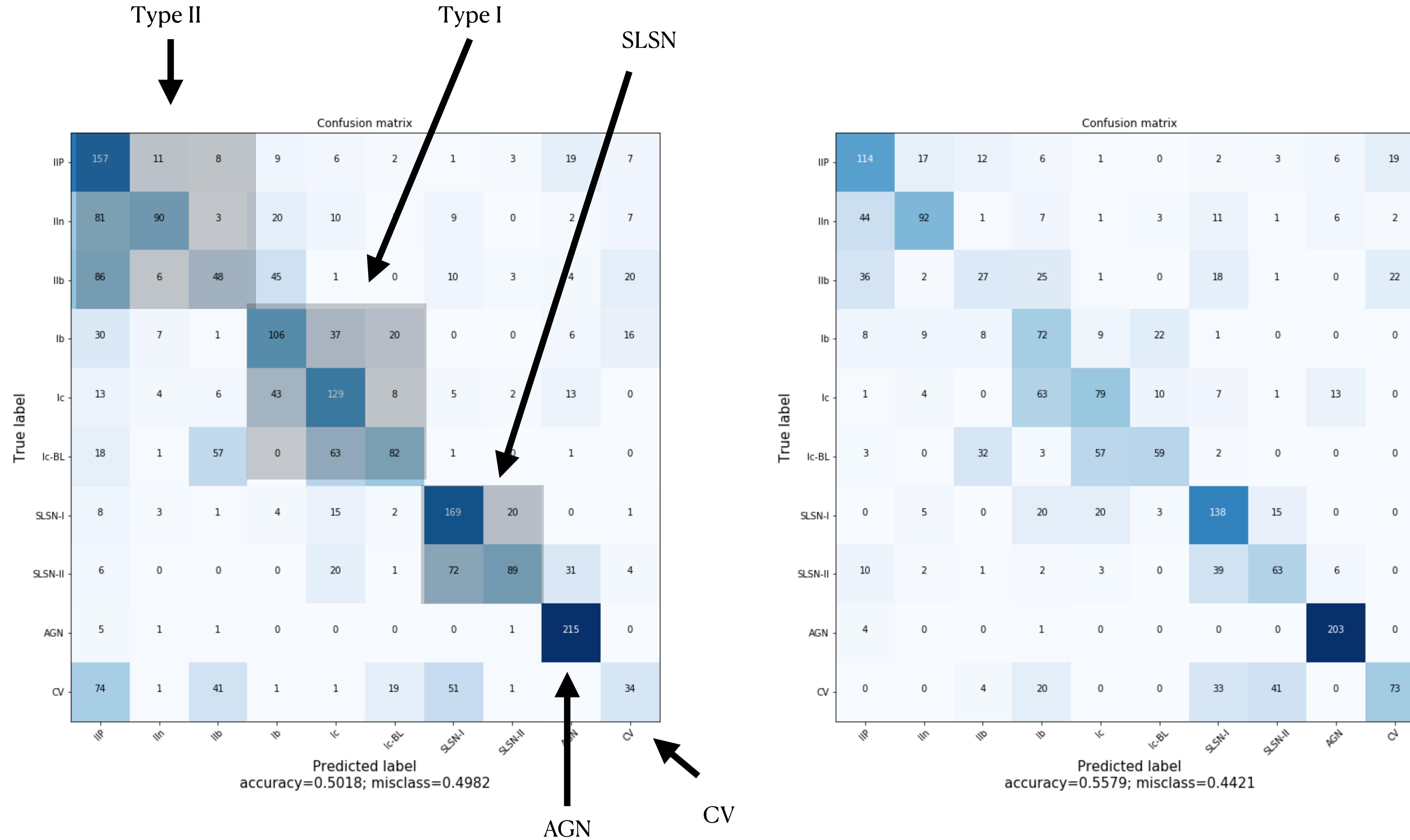


Redshift Regression



Model with two outputs

Multiclass, and binary non-SNIa SEDM classifiers

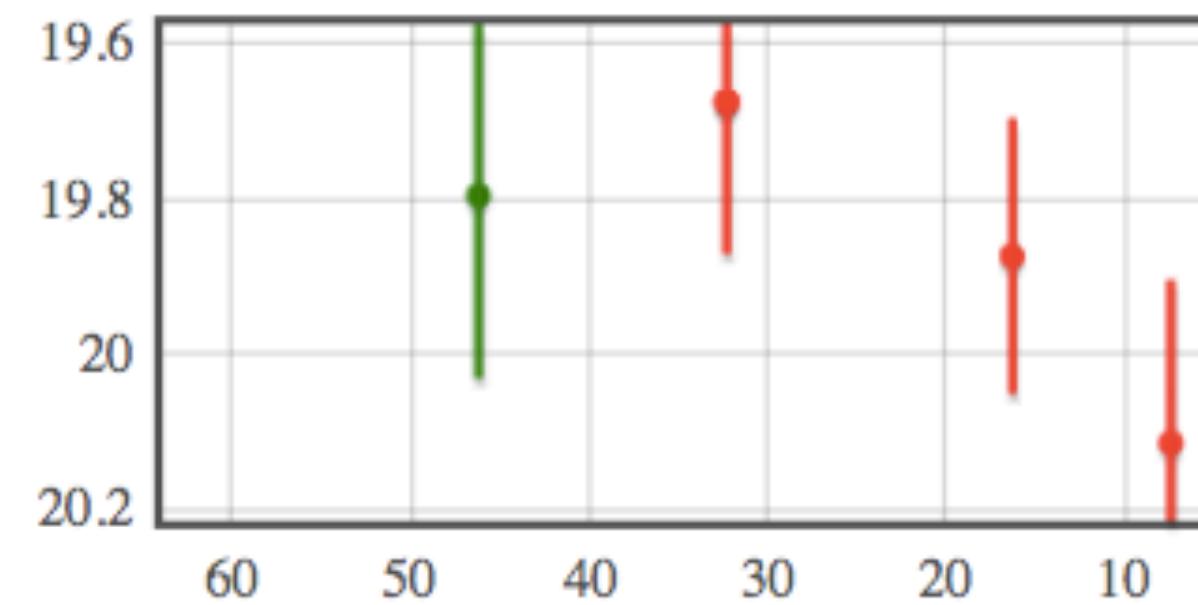
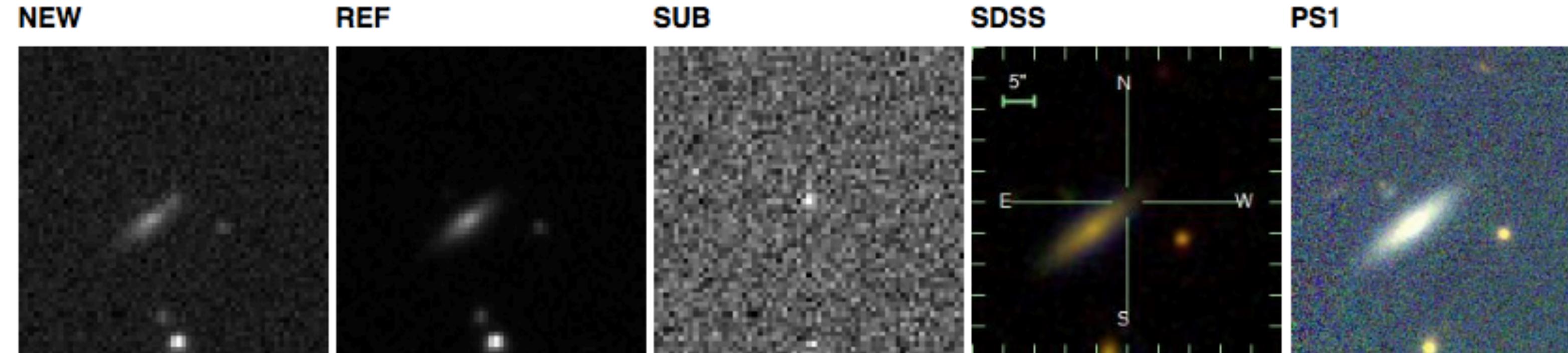
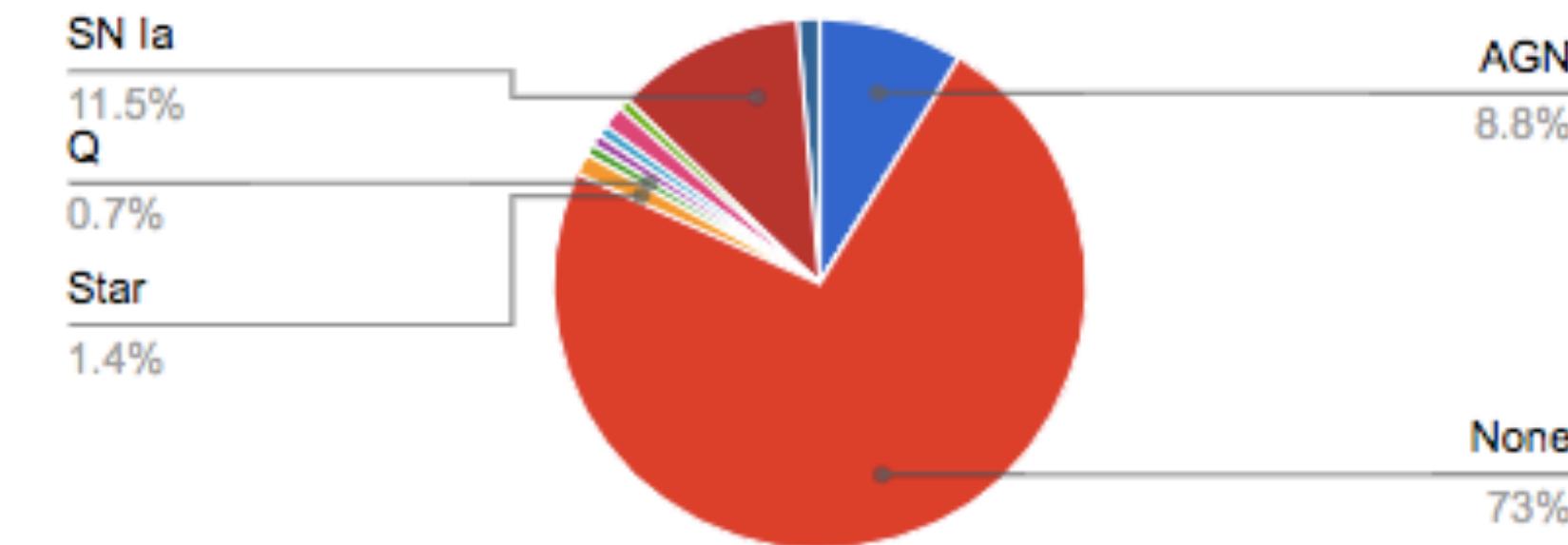


Analysis of Zooniverse data for fainter transients

**different campaigns
science groups still after
low hanging fruit
help with completeness
but also rare objects
automating analysis**

Subtypes:

Any Type: 148
AGN: 13
None: 108
Star: 2
Q: 1
LINER: 1
stellar: 1
SN Ic: 2
SN Ib: 1
SN Ia: 17



r = 20.1 (7.4 d) | Upload New Photometry

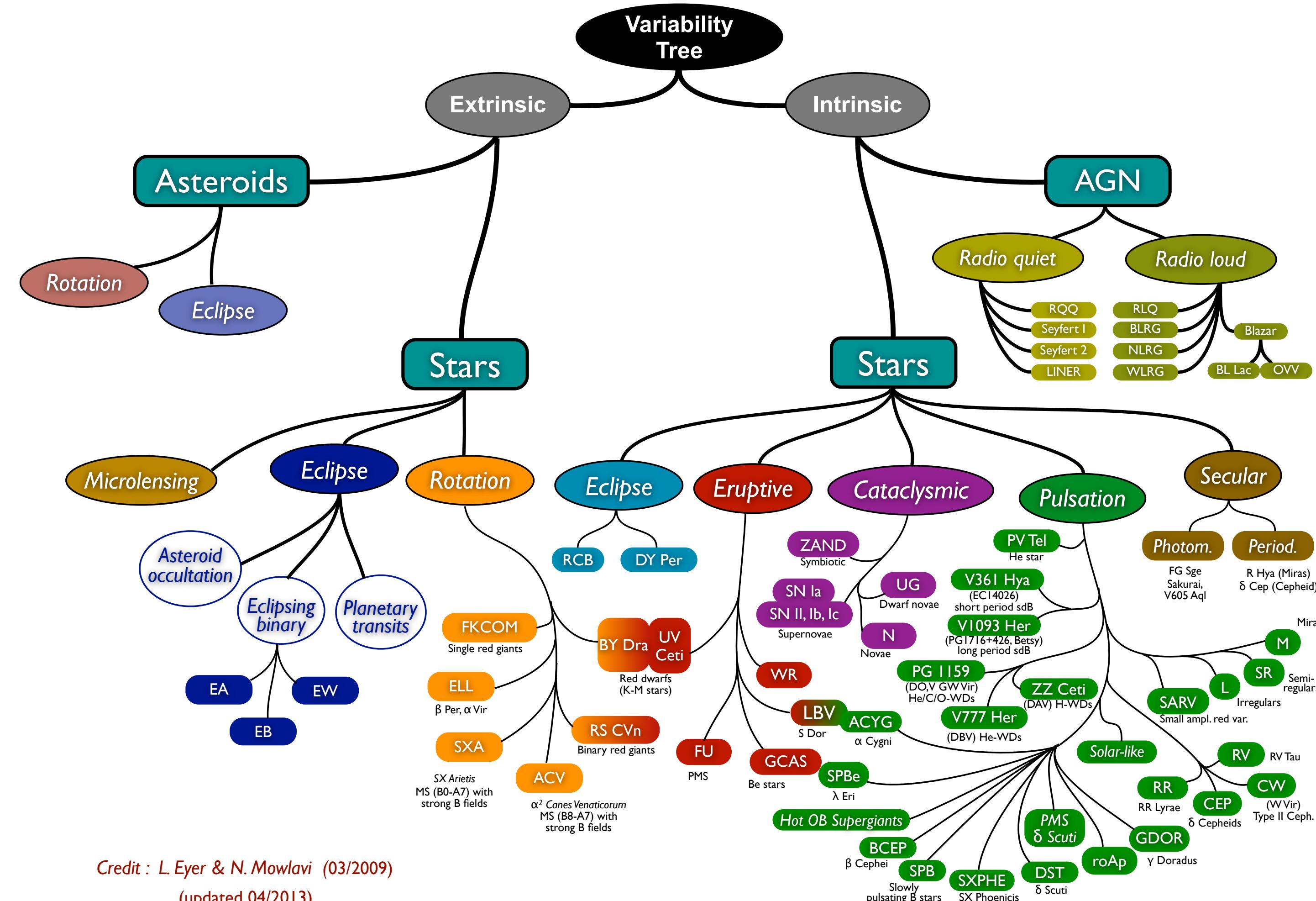
Upload New Spectroscopy

Fainter transients - no spectra

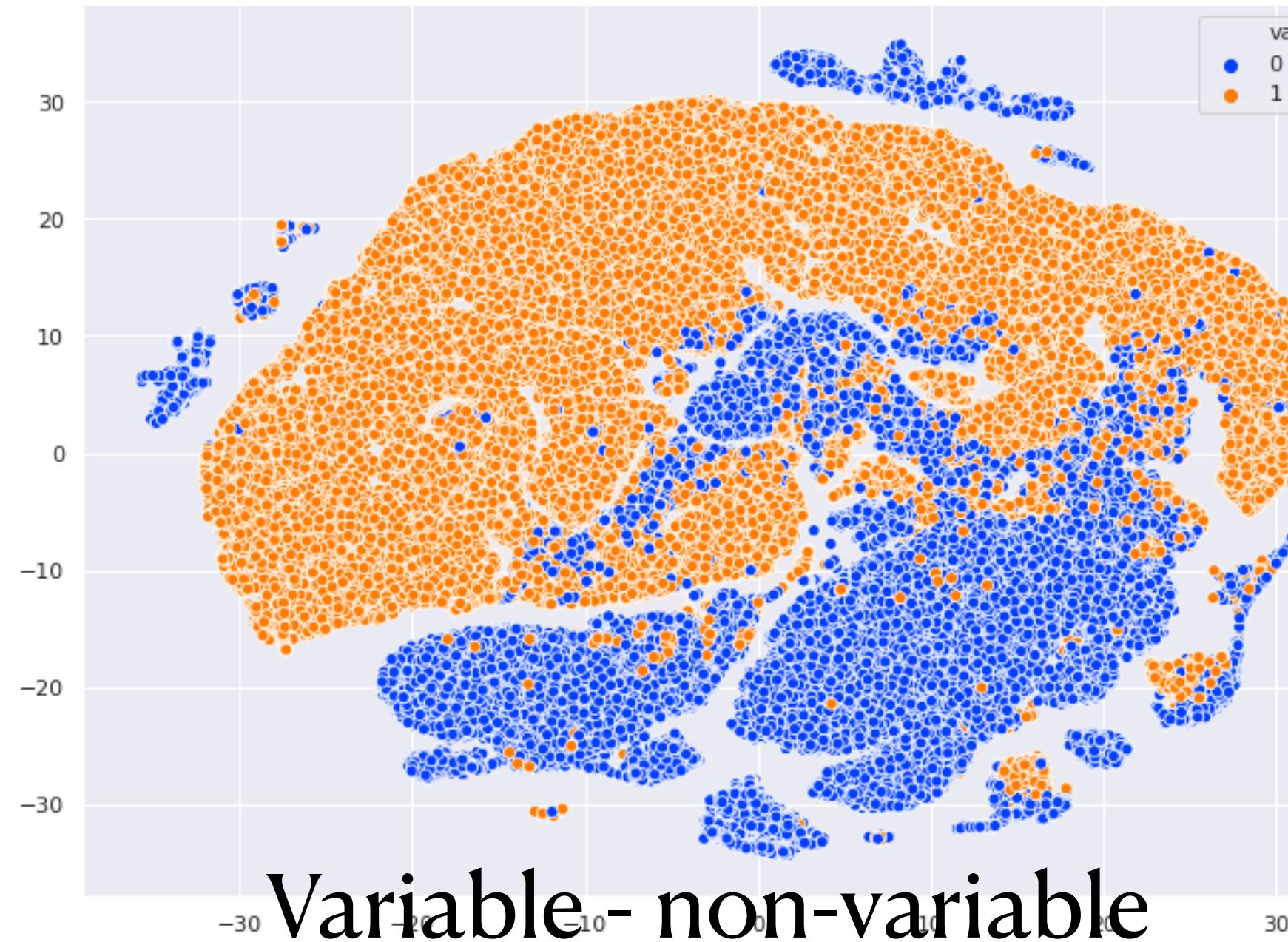
Faint LSST/Rubin objects will have to rely on ML

Classification of variables and transients

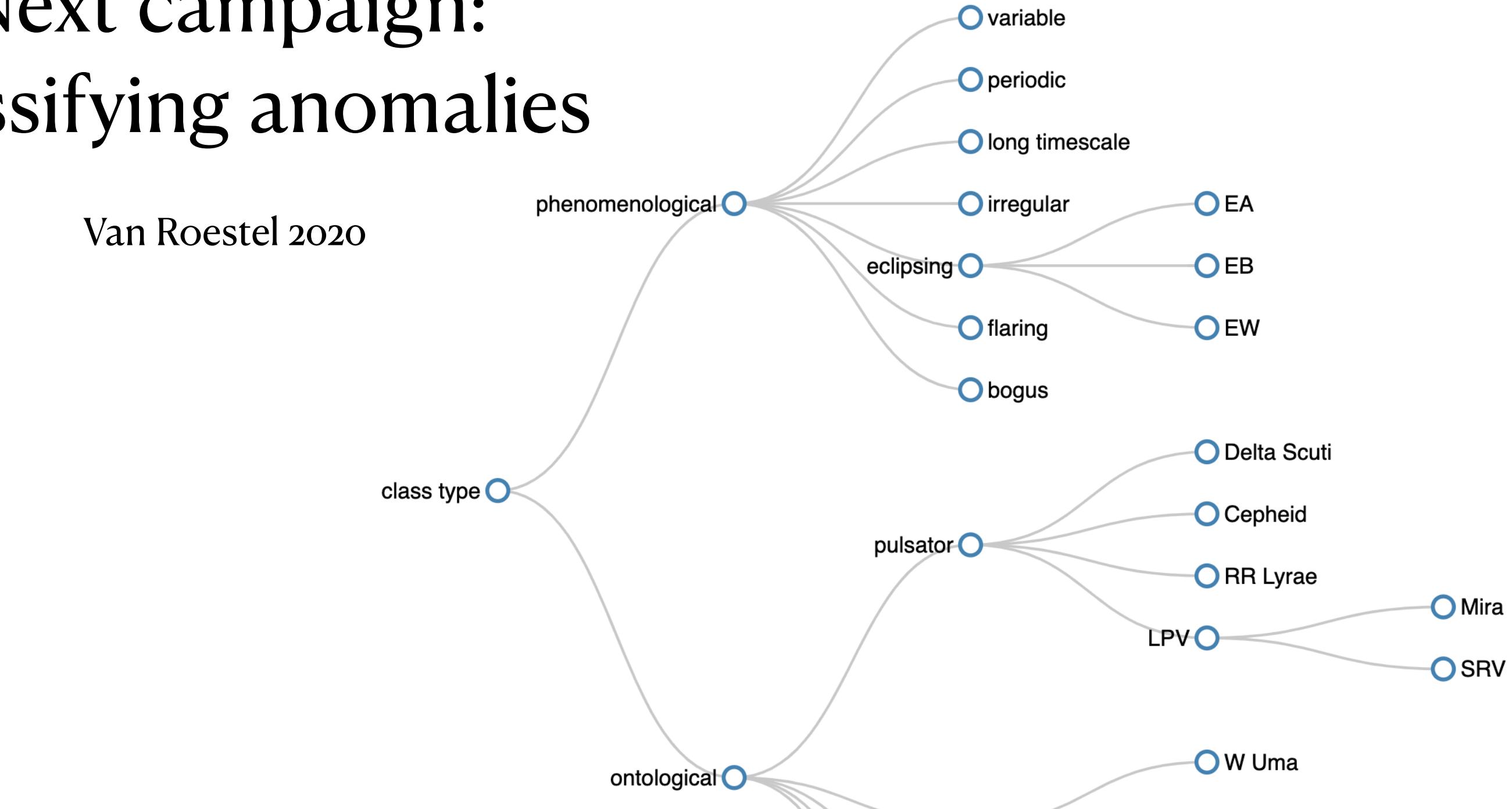
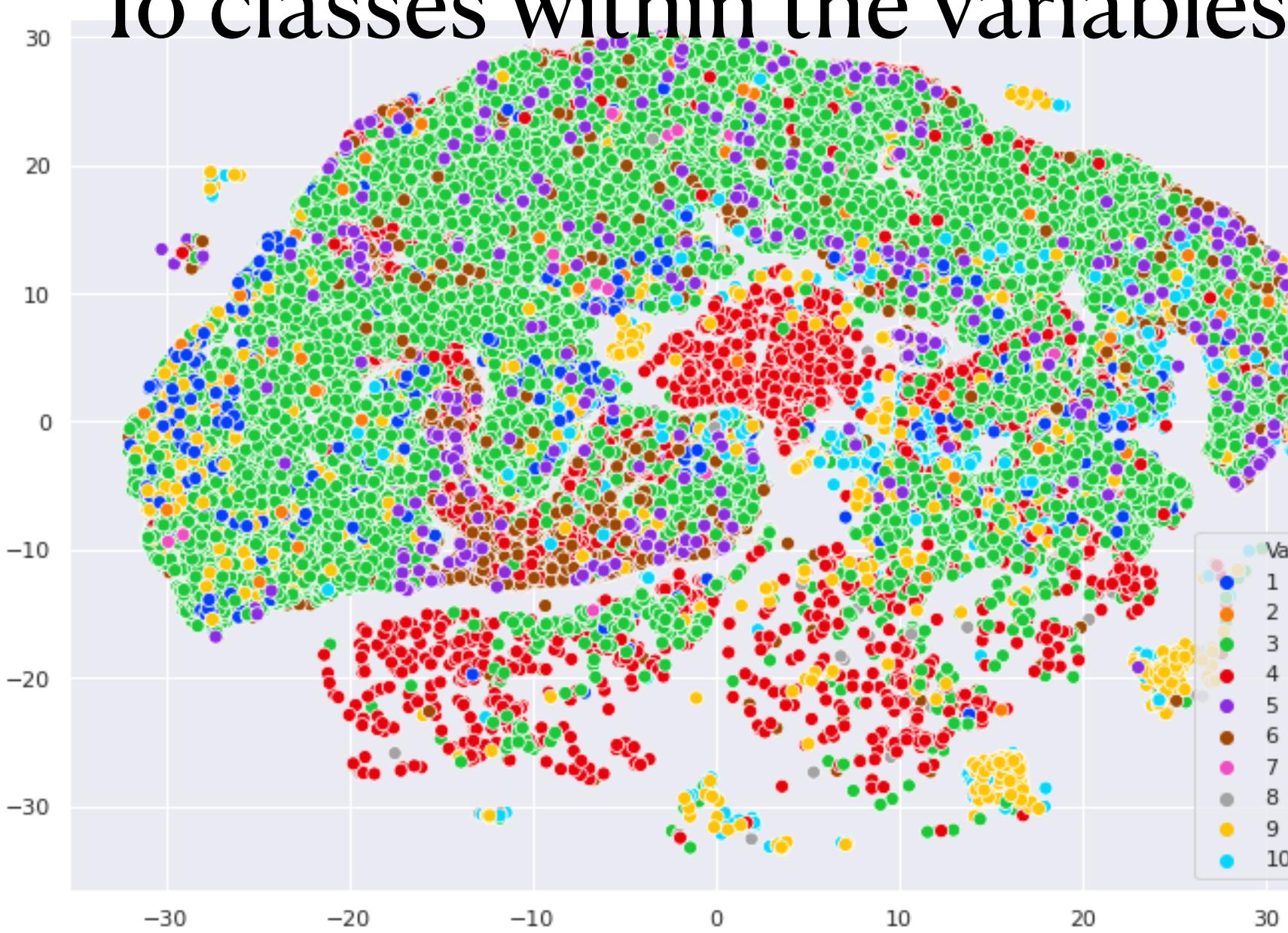
100K alerts a night -
published in real-time



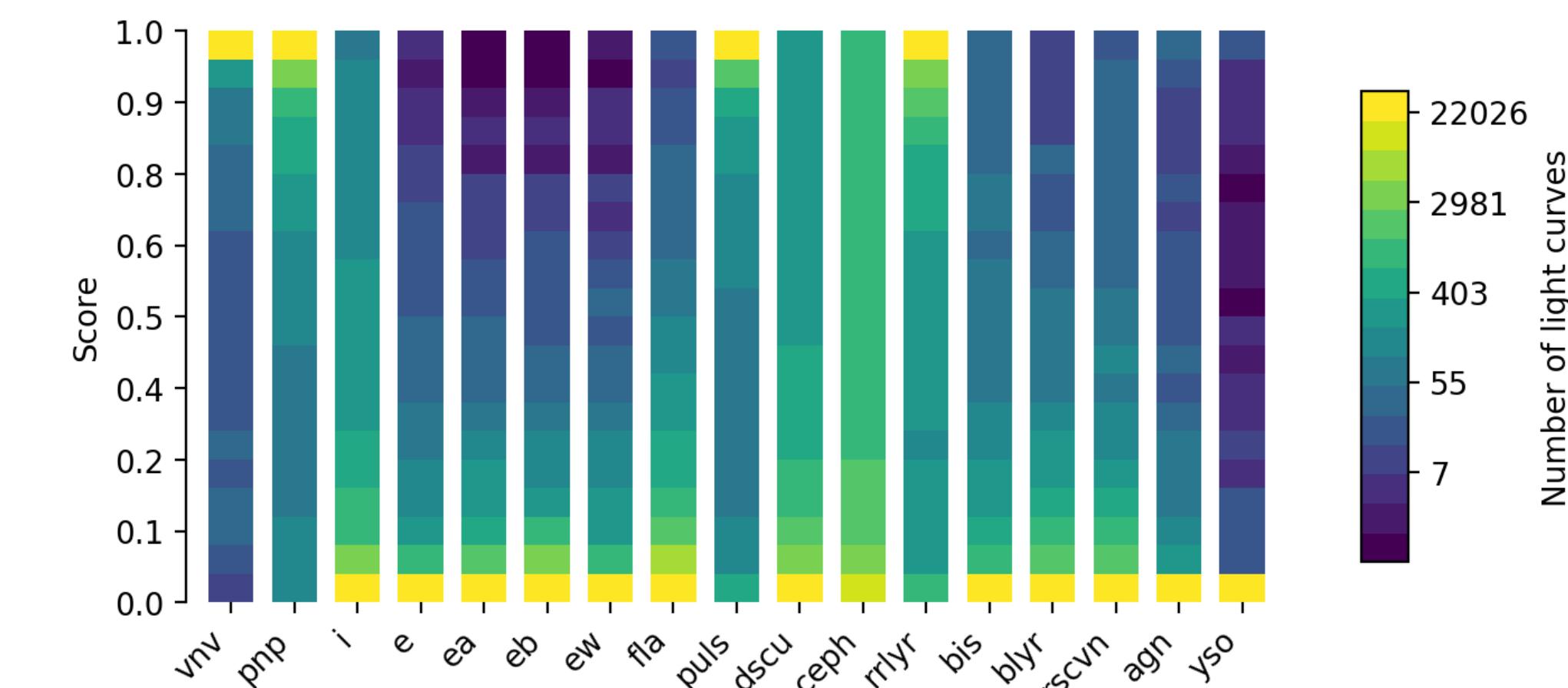
Next campaign: Classifying anomalies



Variable- non-variable
10 classes within the variables



XGBoost, DNN (dmdt + features)



Streaking asteroids

Internal project

Type	Count
Masked bright star	1526
Skip (Includes 'Not Sure' and seemingly 'Blank Images')	1051
Yin-Yang (multiple badly subtracted stars)	437
Dementors and ghosts	207
Satellite (long streak – could be partially masked)	89
Satellite flashes	32
Cosmic rays	28
Asteroid (short streak)	3
Plausible Asteroid (short streak)	3
Naked stars	1

ZTF DeepStreaks

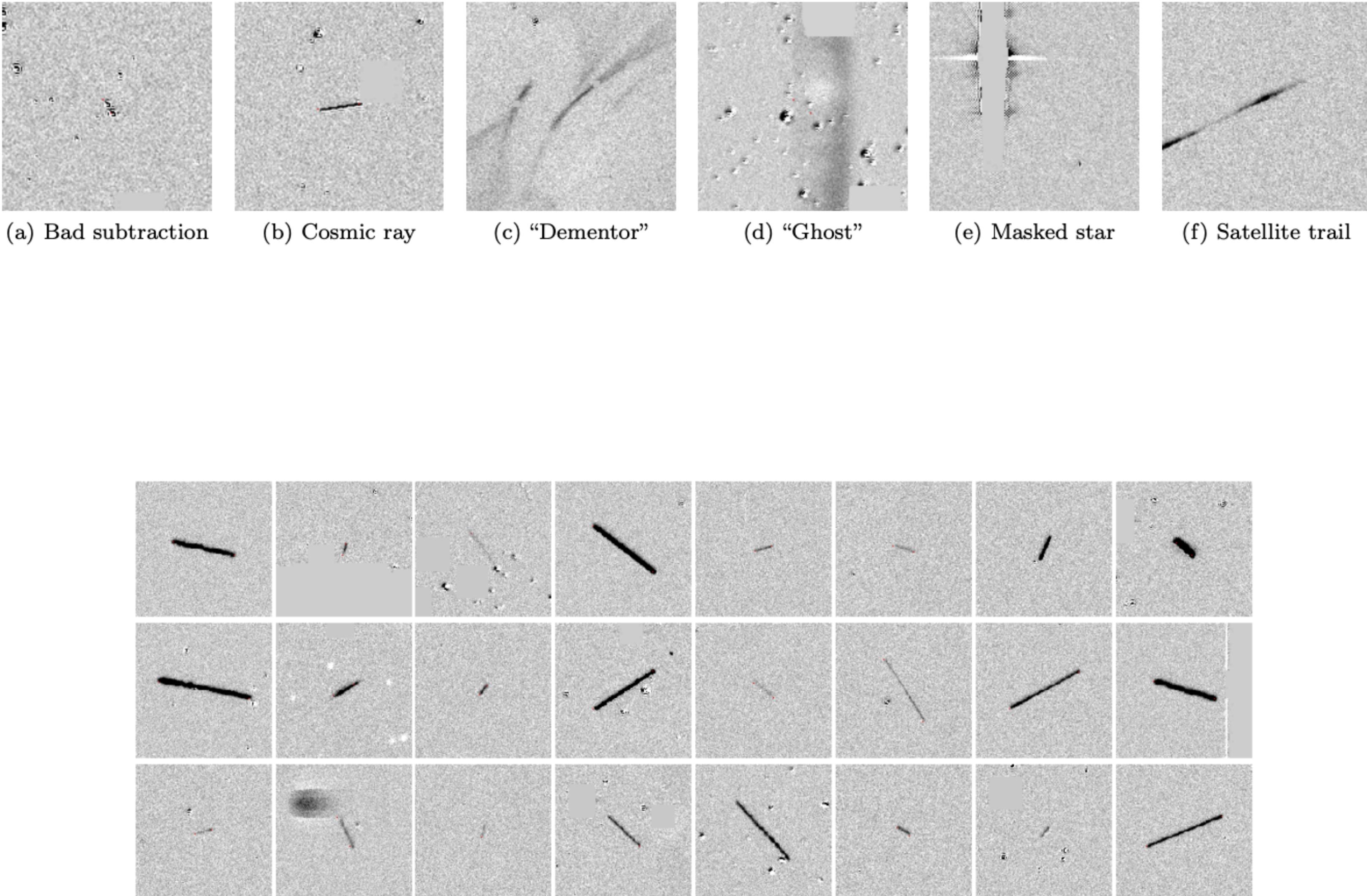
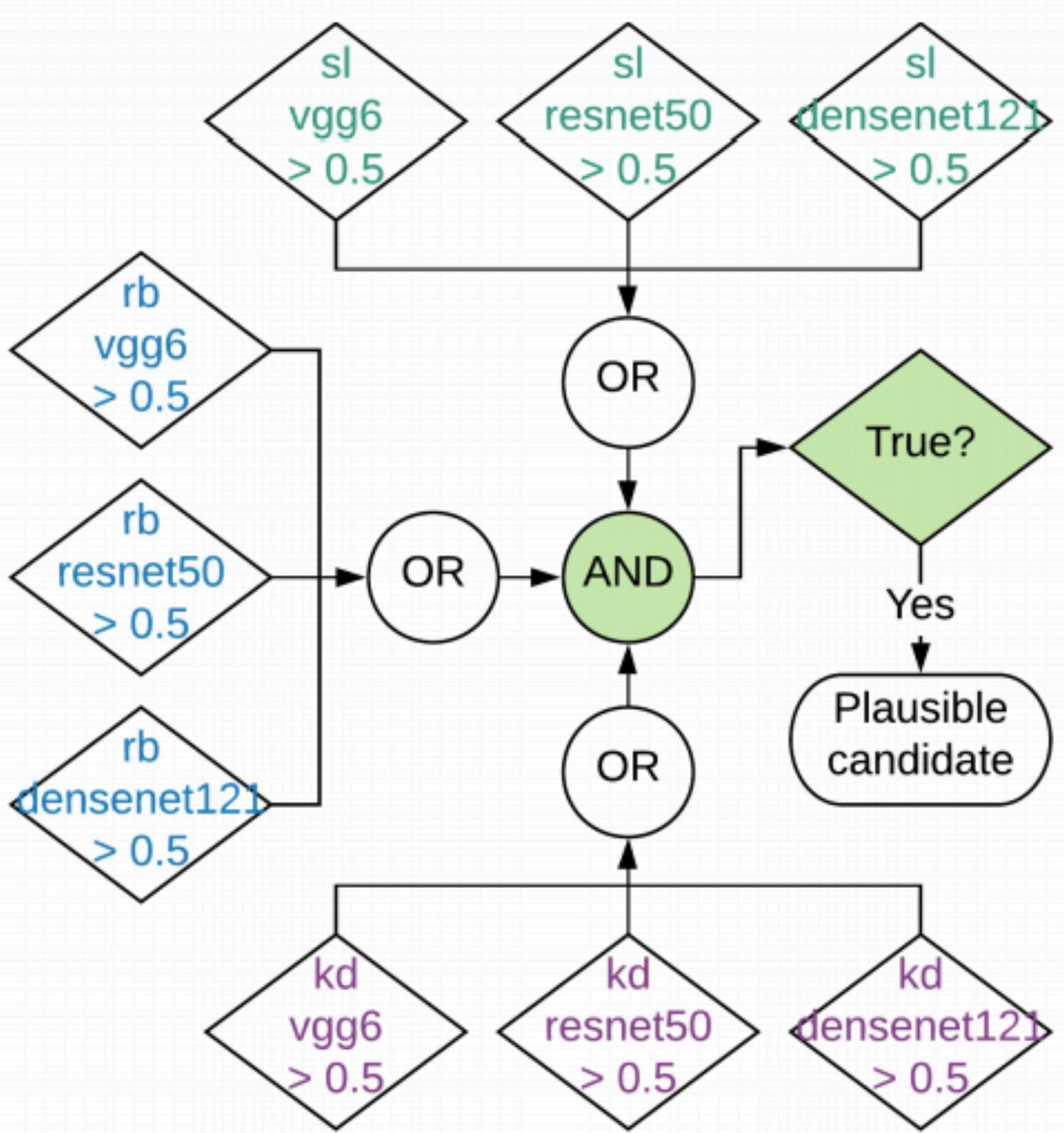


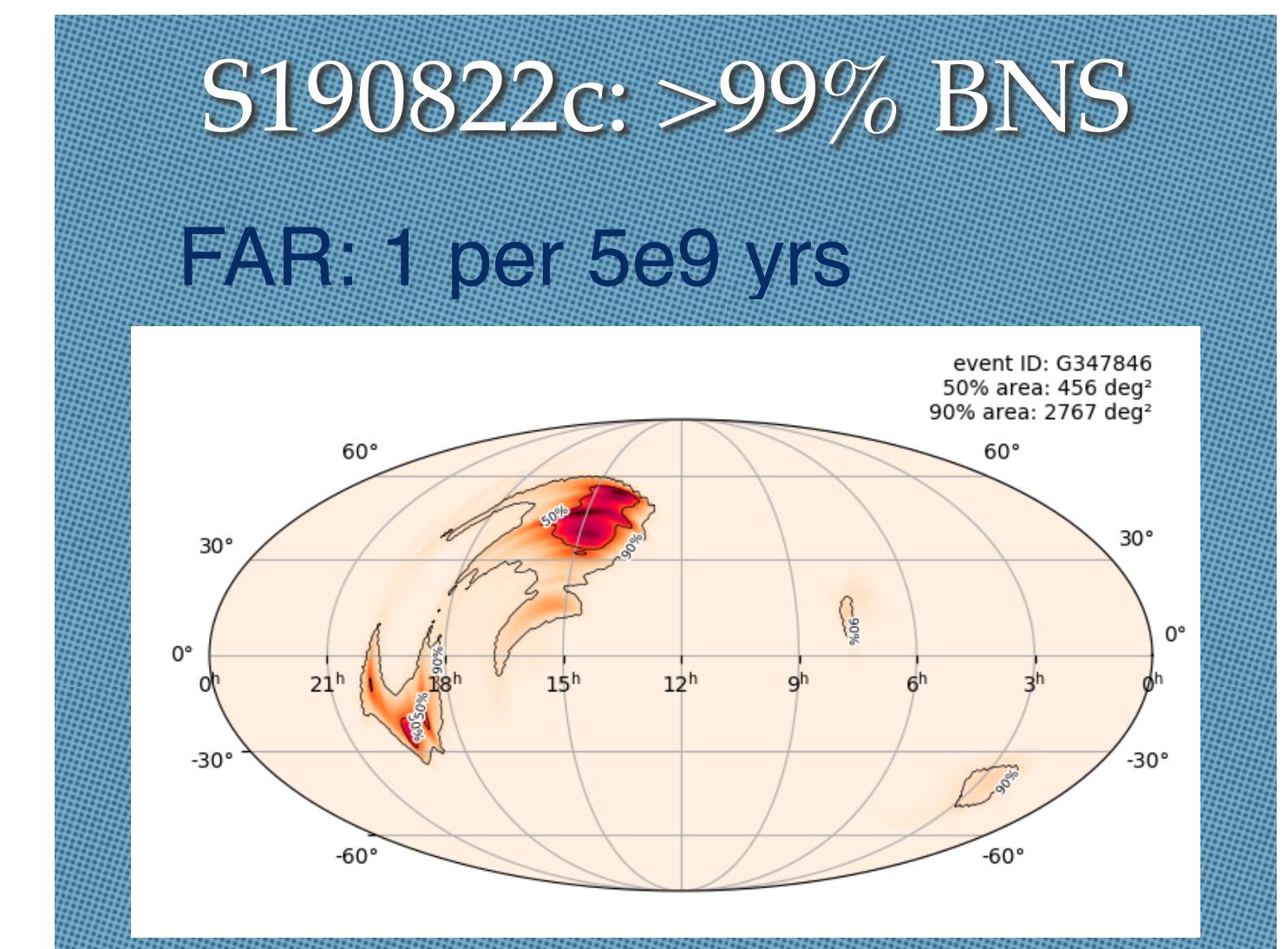
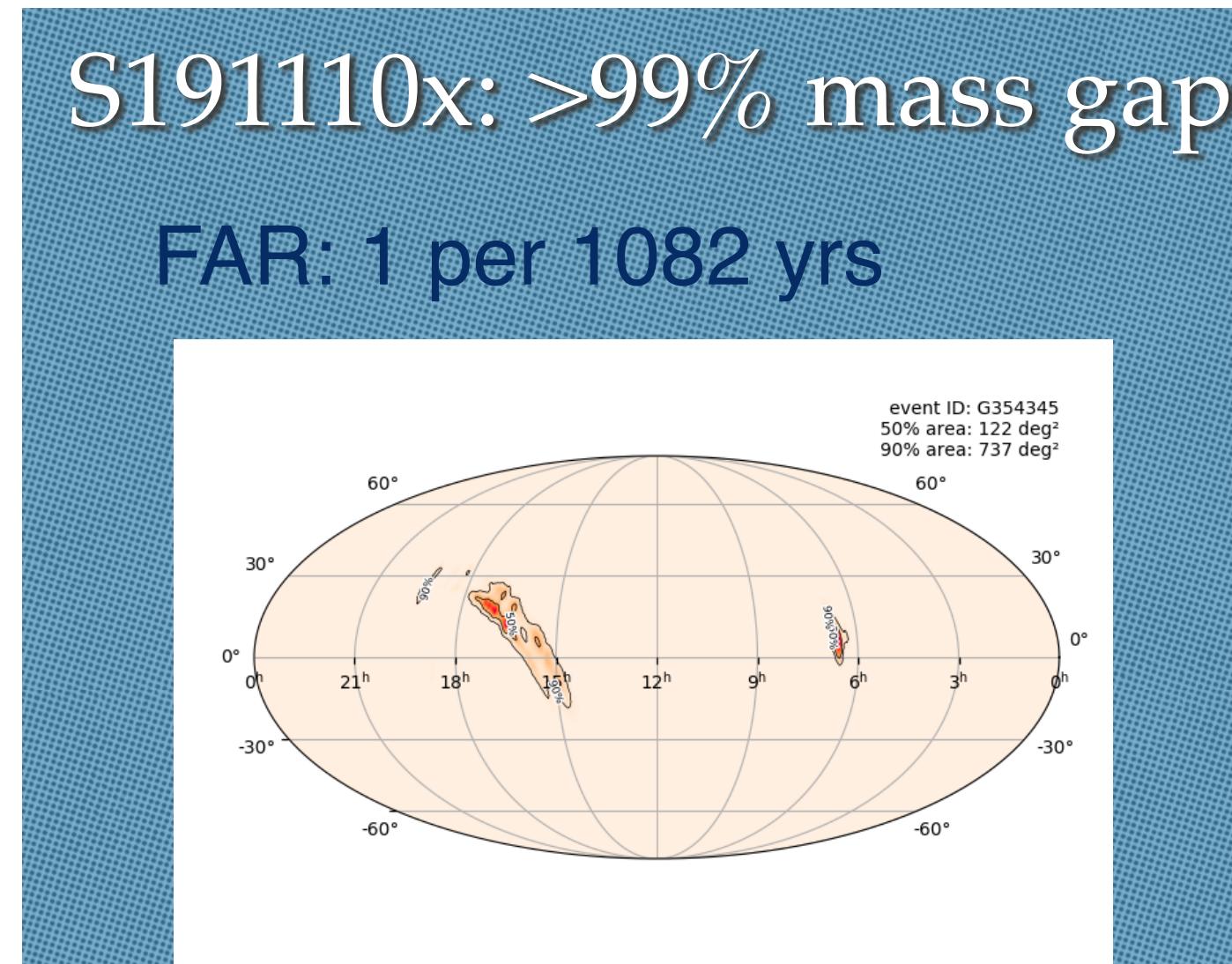
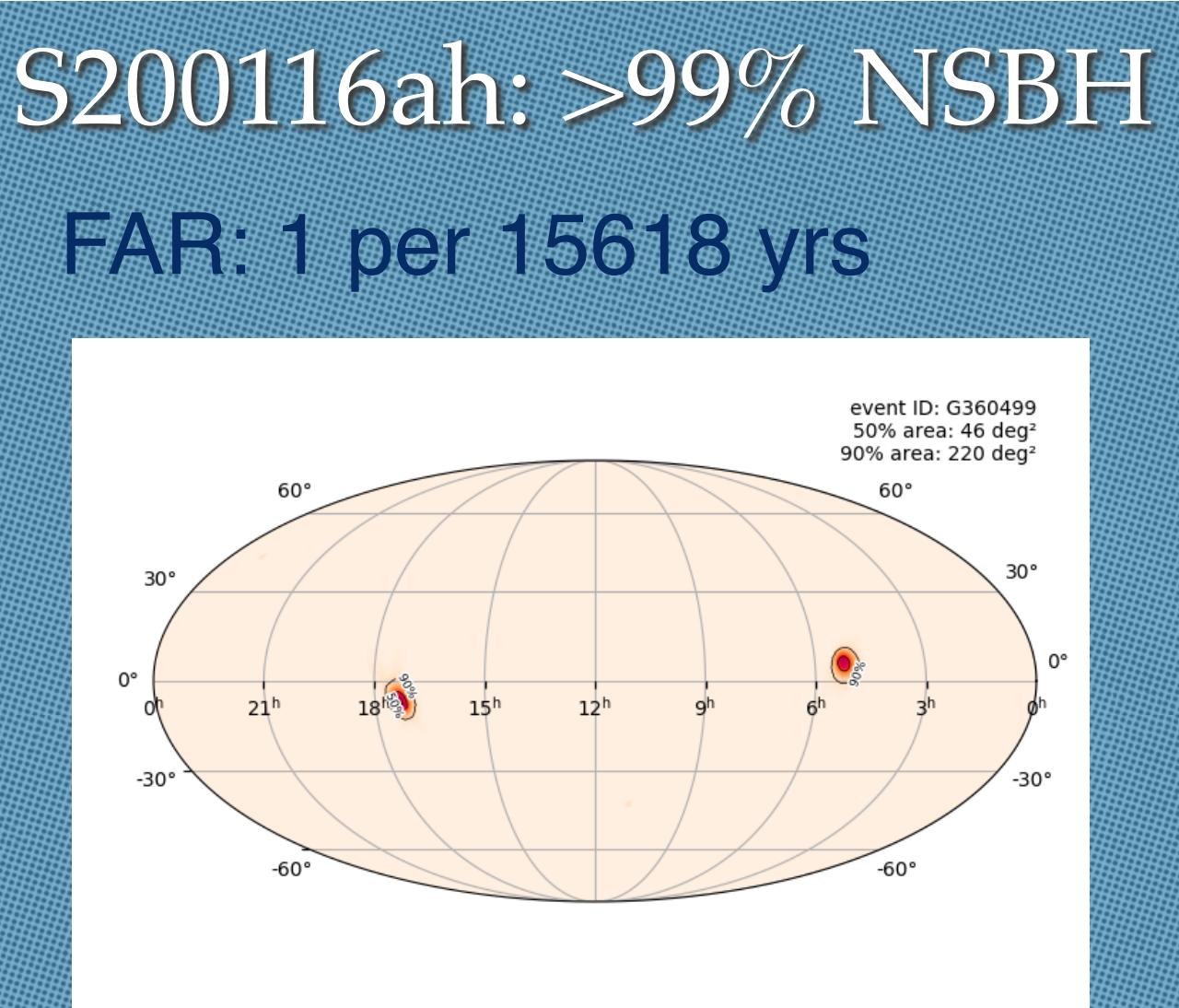
Figure 2. Decision logic used by DeepStreaks to identify plausible streaks. The problem is split into three simpler sub-problems, each solved by a dedicated group of classifiers assigning real vs. bogus (“rb”), short vs. long (“sl”), and keep vs. ditch (“kd”) scores. At least one member of each group must output a score that passes a pre-defined threshold. See Section 2.1 for details.

CNNs

Duev, Mahabal, ... arXiv:1904.05920

Multi Messenger Astronomy and GW follow-up

Several GraceDB alerts were later retracted

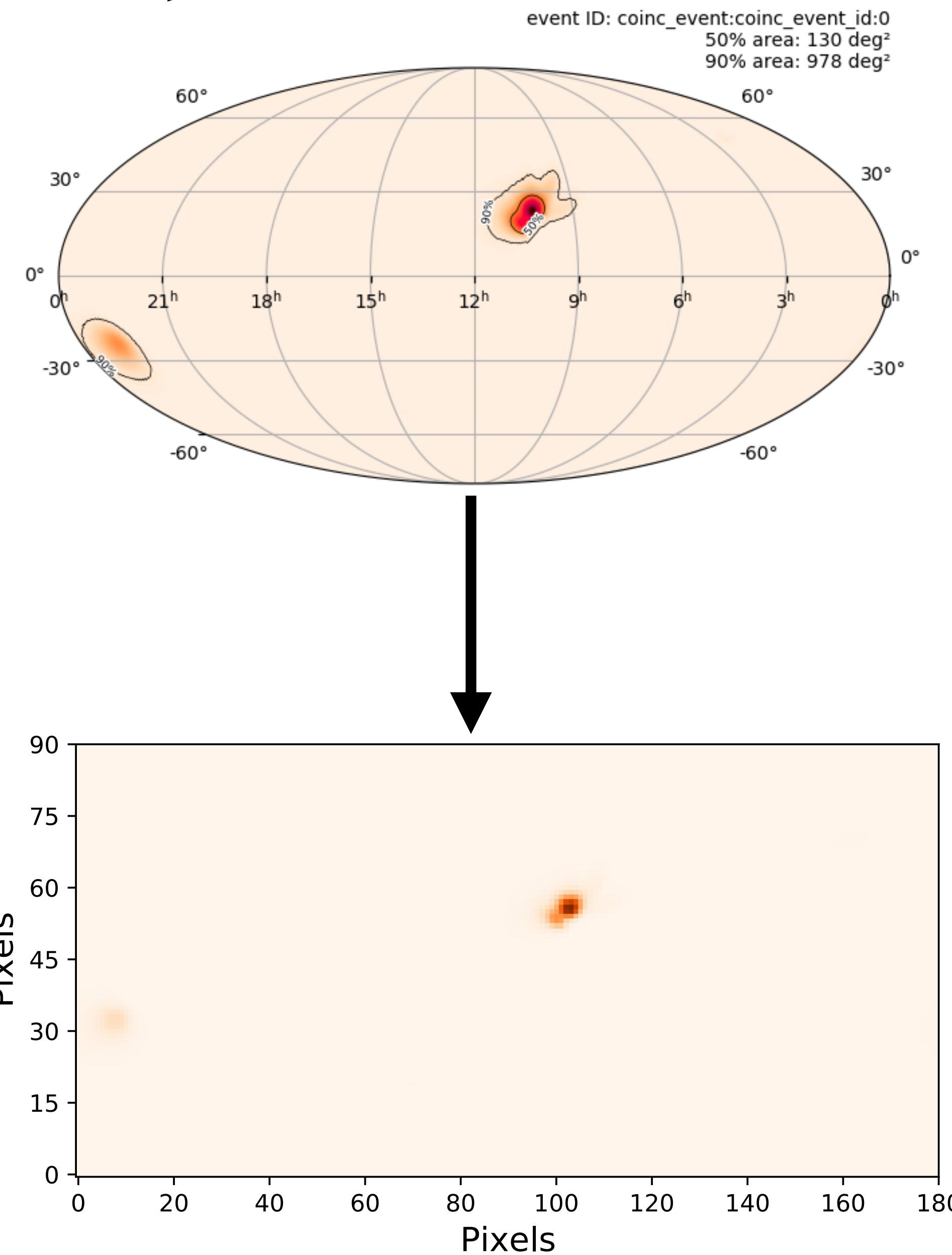


End of O3 GraceDB stats

Candidates: 56
Retracted: 24

Can we classify these based on skymaps?

Reproject
and Bin



The data

Bogus set: glitches

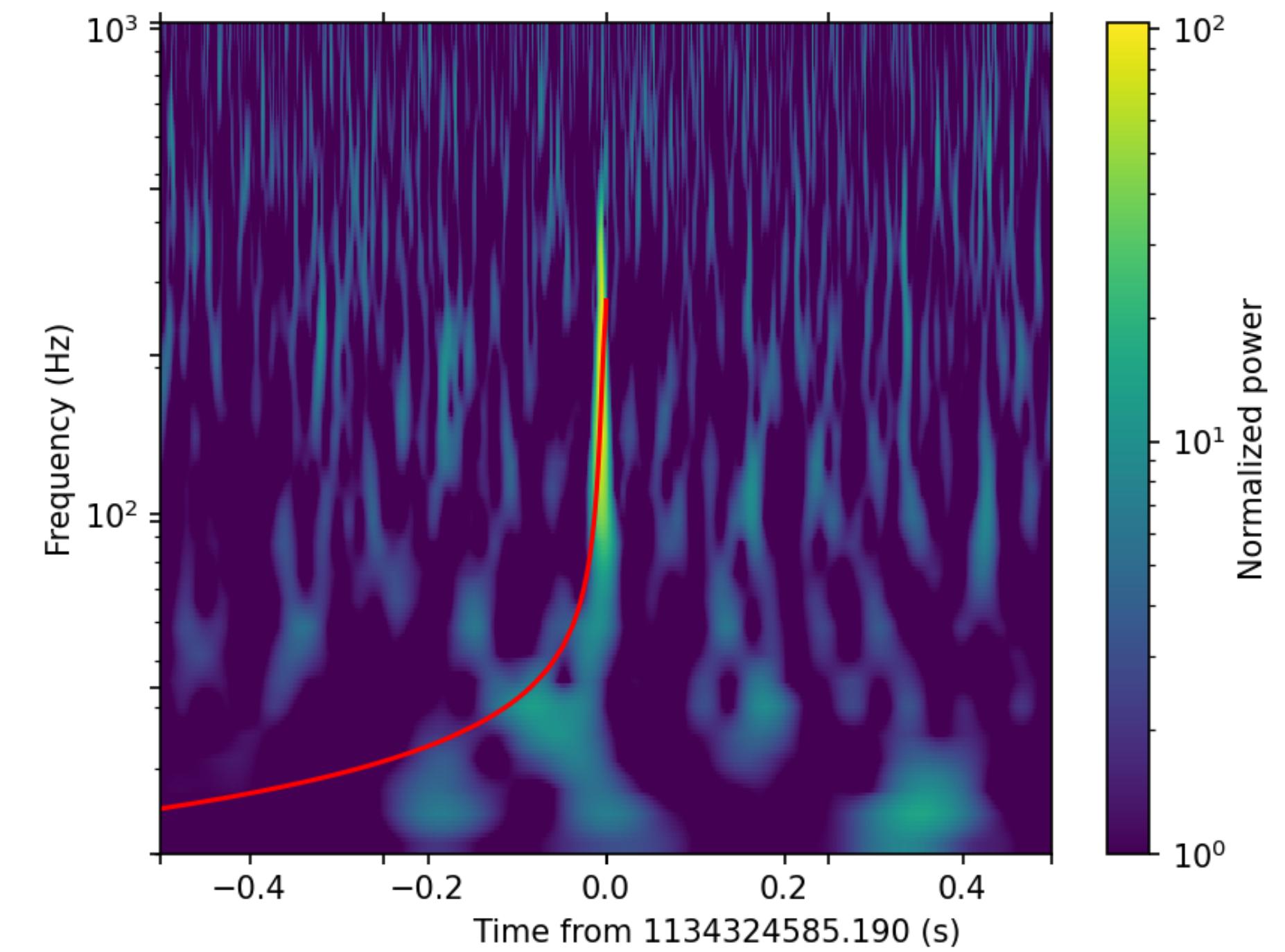
- NS $m \in [1.2, 2.2]M_{\odot}; \chi \leq 0.05$
- BH $m \in [3, 100]M_{\odot}; \chi \leq 0.99$

Combine glitches with
2-OGC triggers

	O1	O2a	O2b
Network	H1, L1	H1, L1	H1, L1, V1 (4 options)
PSD	GW151012	GW170104	GW170729

Single detector SNR ≥ 4.5
Network SNR ≥ 7

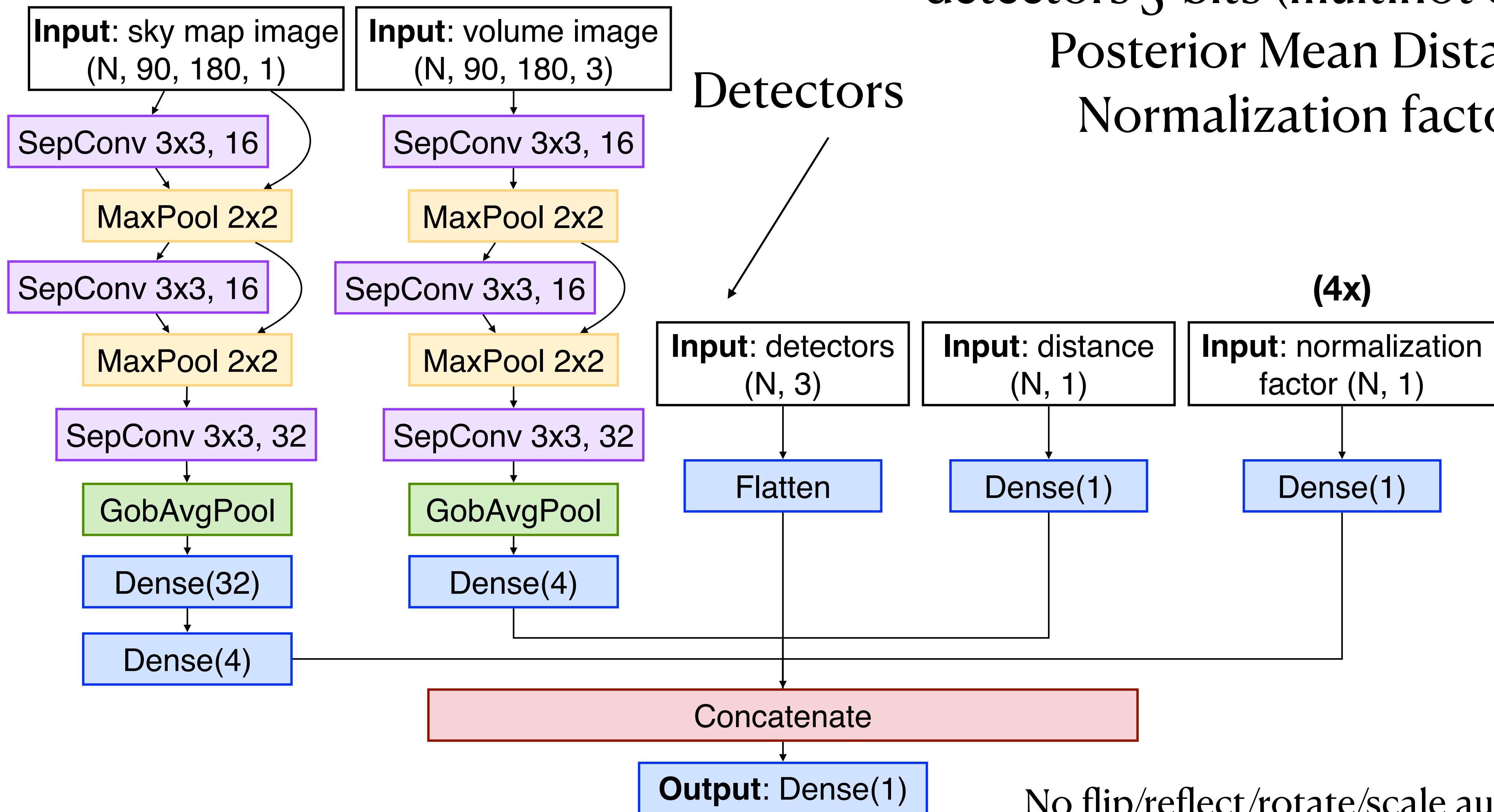
2857 examples



1267 examples

The model

SkyMap



Sky map: 90 x 180

Stacked volume: 90 x 180 x 3

detectors 3-bits (multihot encoding)

Posterior Mean Distance

Normalization factors

(4x)

Input: distance
(N, 1)

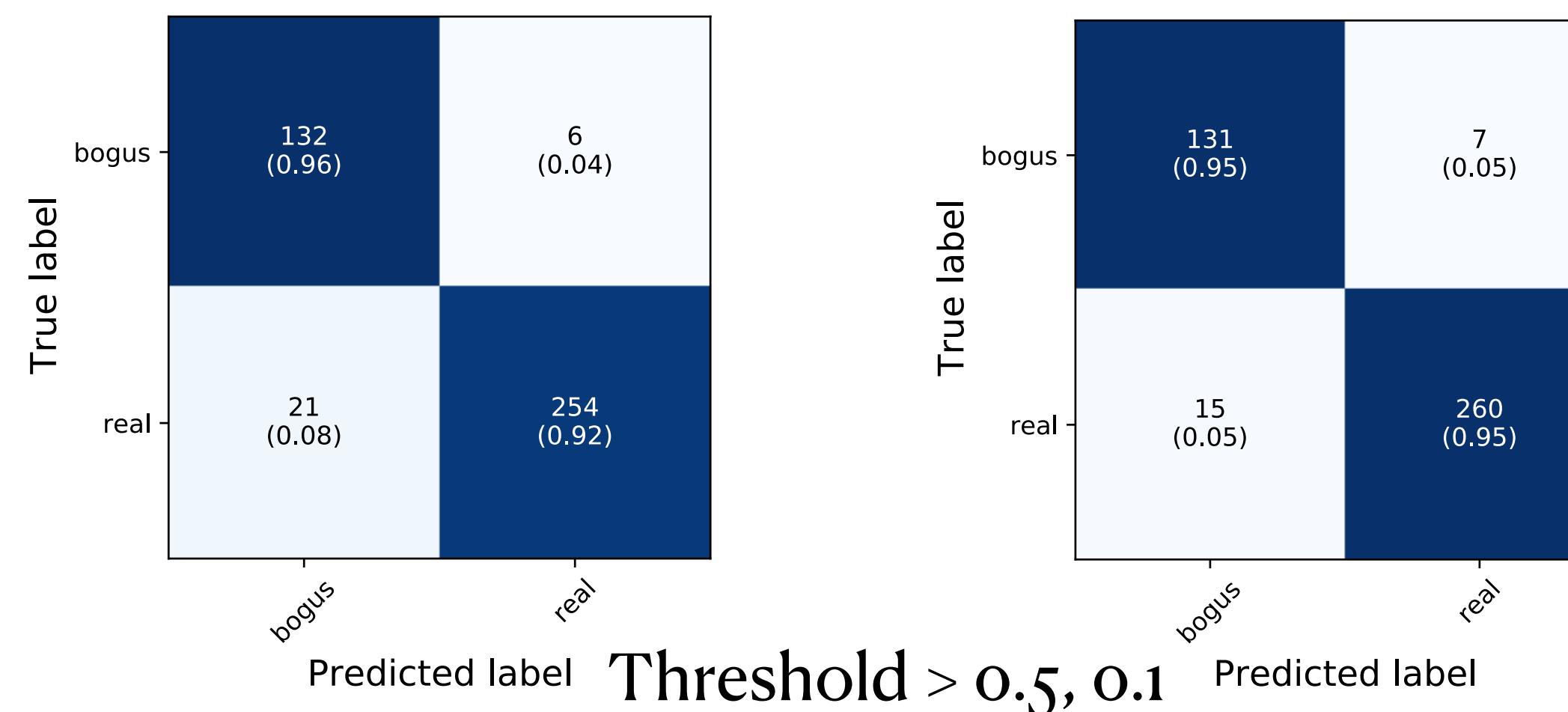
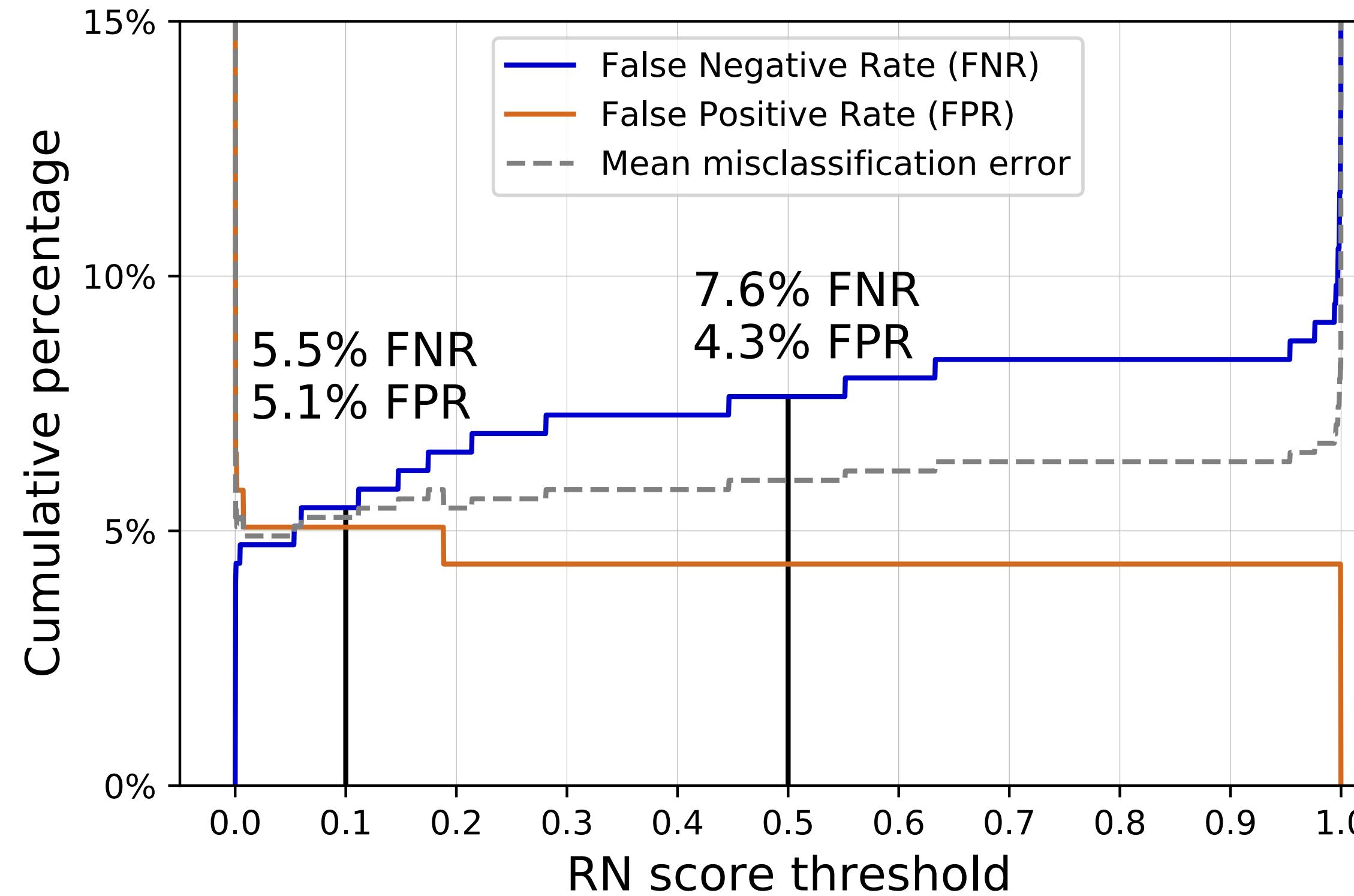
Input: normalization
factor (N, 1)

Concatenate

Output: Dense(1)

No flip/reflect/rotate/scale augmentations

GW Sky Map Network Performance



$$A = \frac{TP + TN}{TP + FP + TN + FN}$$

Total predictions

How often is the model correct?

$$P = \frac{TP}{TP + FP}$$

Predicted positives

How often is the model correct when it predicts that the candidate is real?

$$R = \frac{TP}{TP + FN}$$

Actual positives

How many real candidates are predicted correctly?

Accuracy: 93.5%
Precision: 97.7%
Recall: 92.4%

arXiv:[2010.11829](https://arxiv.org/abs/2010.11829) Cabero, Mahabal, McIver

Predictions (Threshold > 0.5)

O3 GraceDB events from CBC pipelines

Prediction	Real	Bogus
4 published GW	4	-
22 retracted events	12	10
51 non-published GW candidates	41	10

Misclassifications: Many were identified by the GstLal and MBTAOnline pipelines, training noise examples are from PyCBC

70% retracted had Virgo data

GWTC-2
the O3a catalog

4 Published GW

13 new

22 confirmed

7 retracted

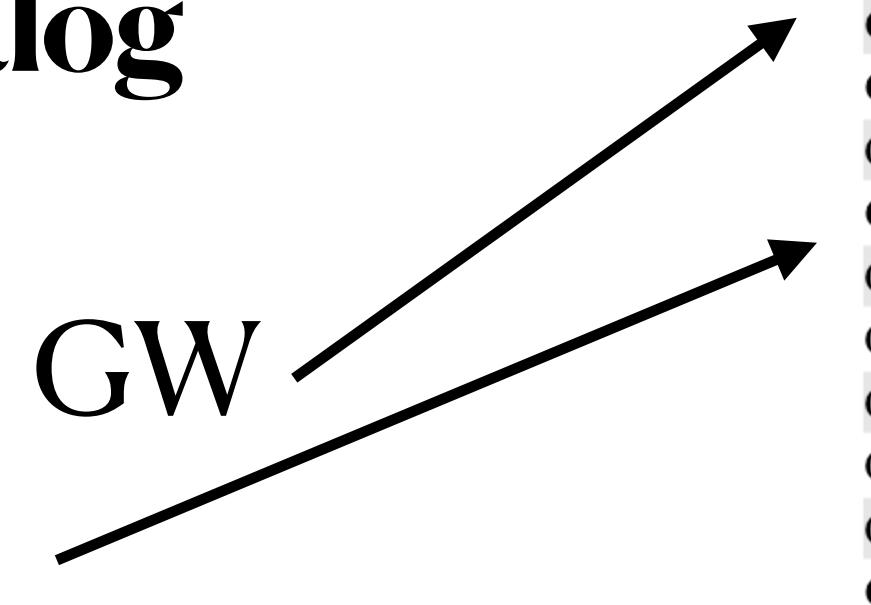
GWSkyNet verdict:

23 real

6 non-astrophysical

28/29 correct

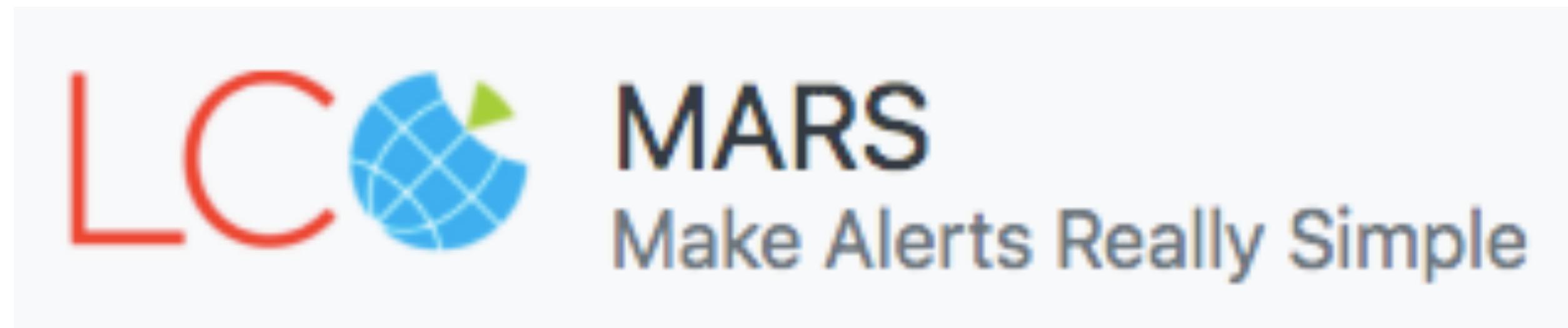
no reals called bogus



Name	Inst.	cWB		GstLAL		PyCBC		PyCBC BBH				
		FAR (yr ⁻¹)	SNR*	FAR (yr ⁻¹)	SNR <i>p</i> _{astro}	FAR (yr ⁻¹)	SNR*	<i>p</i> _{astro}	FAR (yr ⁻¹)	SNR*		
GW190408-181802	HLV	$< 9.5 \times 10^{-4}$	14.8	$< 1.0 \times 10^{-5}$	14.7	1.00	$< 2.5 \times 10^{-5}$	13.5	1.00	$< 7.9 \times 10^{-5}$	13.6	
GW190412	HLV	$< 9.5 \times 10^{-4}$	19.7	$< 1.0 \times 10^{-5}$	18.9	1.00	$< 3.1 \times 10^{-5}$	17.9	1.00	$< 7.9 \times 10^{-5}$	17.8	
GW190413_052954	HLV	—	—	—	—	—	—	—	7.2×10^{-2}	8.6	0.98	
GW190413_134308	HLV	—	—	3.8×10^{-1}	10.0	0.95	—	—	4.4×10^{-2}	9.0	0.98	
GW190421-213856	HL	3.0×10^{-1}	9.3	7.7×10^{-4}	10.6	1.00	1.9×10^0	10.2	0.89	6.6×10^{-3}	10.2	1.00
GW190424_180648	L	—	—	$7.8 \times 10^{-1\dagger}$	10.0	0.91	—	—	—	—	—	
GW190425	LV	—	—	$7.5 \times 10^{-4\dagger}$	13.0	—	—	—	—	—	—	
GW190426-152155	HLV	—	—	1.4×10^0	10.1	—	—	—	—	—	—	
GW190503-185404	HLV	1.8×10^{-3}	11.5	$< 1.0 \times 10^{-5}$	12.1	1.00	3.7×10^{-2}	12.2	1.00	$< 7.9 \times 10^{-5}$	12.2	1.00
GW190512-180714	HLV	8.8×10^{-1}	10.7	$< 1.0 \times 10^{-5}$	12.3	1.00	3.8×10^{-5}	12.2	1.00	$< 5.7 \times 10^{-5}$	12.2	1.00
GW190513-205428	HLV	—	—	$< 1.0 \times 10^{-5}$	12.3	1.00	3.7×10^{-4}	11.8	1.00	$< 5.7 \times 10^{-5}$	11.9	1.00
GW190514_065416	HL	—	—	—	—	—	—	—	5.3×10^{-1}	8.3	0.96	
GW190517-055101	HLV	6.5×10^{-3}	10.7	9.6×10^{-4}	10.6	1.00	1.8×10^{-2}	10.4	1.00	$< 5.7 \times 10^{-5}$	10.2	1.00
GW190519-153544	HLV	3.1×10^{-4}	14.0	$< 1.0 \times 10^{-5}$	12.0	1.00	$< 1.8 \times 10^{-5}$	13.0	1.00	$< 5.7 \times 10^{-5}$	13.0	1.00
GW190521	HLV	2.0×10^{-4}	14.4	1.2×10^{-3}	14.7	1.00	1.1×10^0	12.6	0.93	—	—	
GW190521-074359	HL	$< 1.0 \times 10^{-4}$	24.7	$< 1.0 \times 10^{-5}$	24.4	1.00	$< 1.8 \times 10^{-5}$	24.0	1.00	$< 5.7 \times 10^{-5}$	24.0	1.00
GW190527_092055	HL	—	—	6.2×10^{-2}	8.9	0.99	—	—	—	—	—	
GW190602-175927	HLV	1.5×10^{-2}	11.1	1.1×10^{-5}	12.1	1.00	—	—	1.5×10^{-2}	11.4	1.00	
GW190620_030421	LV	—	—	$2.9 \times 10^{-3\dagger}$	10.9	1.00	—	—	—	—	—	
GW190630-185205	LV	—	—	$< 1.0 \times 10^{-5}$	15.6	1.00	—	—	—	—	—	
GW190701-203306	HLV	5.5×10^{-1}	10.2	1.1×10^{-2}	11.6	1.00	—	—	—	—	—	
GW190706-222641	HLV	$< 1.0 \times 10^{-3}$	12.7	$< 1.0 \times 10^{-5}$	12.3	1.00	6.7×10^{-5}	11.7	1.00	$< 4.6 \times 10^{-5}$	12.3	1.00
GW190707-093326	HL	—	—	$< 1.0 \times 10^{-5}$	13.0	1.00	$< 1.0 \times 10^{-5}$	12.8	1.00	$< 4.6 \times 10^{-5}$	12.8	1.00
GW190708_232457	LV	—	—	$2.8 \times 10^{-5\dagger}$	13.1	1.00	—	—	—	—	—	
GW190719_215514	HL	—	—	—	—	—	—	—	1.6×10^0	8.0	0.82	
GW190720-000836	HLV	—	—	$< 1.0 \times 10^{-5}$	11.7	1.00	$< 2.0 \times 10^{-5}$	10.6	1.00	$< 3.7 \times 10^{-5}$	10.5	1.00
GW190727-060333	HLV	8.8×10^{-2}	11.4	$< 1.0 \times 10^{-5}$	12.3	1.00	3.5×10^{-3}	11.5	1.00	$< 3.7 \times 10^{-5}$	11.8	1.00
GW190728-064510	HLV	—	—	$< 1.0 \times 10^{-5}$	13.6	1.00	$< 1.6 \times 10^{-5}$	13.4	1.00	$< 3.7 \times 10^{-5}$	13.4	1.00
GW190731_140936	HL	—	—	2.1×10^{-1}	8.5	0.97	—	—	2.8×10^{-1}	8.2	0.96	
GW190803_022701	HLV	—	—	3.2×10^{-2}	9.0	0.99	—	—	2.7×10^{-2}	8.6	0.99	
GW190814	LV	—	—	$< 1.0 \times 10^{-5}$	22.2	1.00	—	—	—	—	—	
GW190828-063405	HLV	$< 9.6 \times 10^{-4}$	16.6	$< 1.0 \times 10^{-5}$	16.0	1.00	$< 1.5 \times 10^{-5}$	15.3	1.00	$< 3.3 \times 10^{-5}$	15.3	1.00
GW190828-065509	HLV	—	—	$< 1.0 \times 10^{-5}$	11.1	1.00	5.8×10^{-5}	10.8	1.00	$< 3.3 \times 10^{-5}$	10.8	1.00
GW190909_114149	HL	—	—	1.1×10^0	8.5	0.89	—	—	—	—	—	
GW190910_112807	LV	—	—	$1.9 \times 10^{-5\dagger}$	13.4	1.00	—	—	—	—	—	
GW190915-235702	HLV	$< 1.0 \times 10^{-3}$	12.3	$< 1.0 \times 10^{-5}$	13.1	1.00	8.6×10^{-4}	13.0	1.00	$< 3.3 \times 10^{-5}$	12.7	1.00
GW190924-021846	HLV	—	—	$< 1.0 \times 10^{-5}$	13.2	1.00	$< 6.3 \times 10^{-5}$	12.5	1.00	$< 3.3 \times 10^{-5}$	12.4	1.00
GW190929_012149	HLV	—	—	2.0×10^{-2}	9.9	1.00	—	—	—	—	—	
GW190930-133541	HL	—	—	5.8×10^{-1}	10.0	0.92	3.4×10^{-2}	9.7	1.00	3.3×10^{-2}	9.8	0.99

Table 4
Bogus:
S190510g
S190718y
S190901ap
S190910d
S190910h
S190930t
Missed:
S190923y

Several brokers



Fink

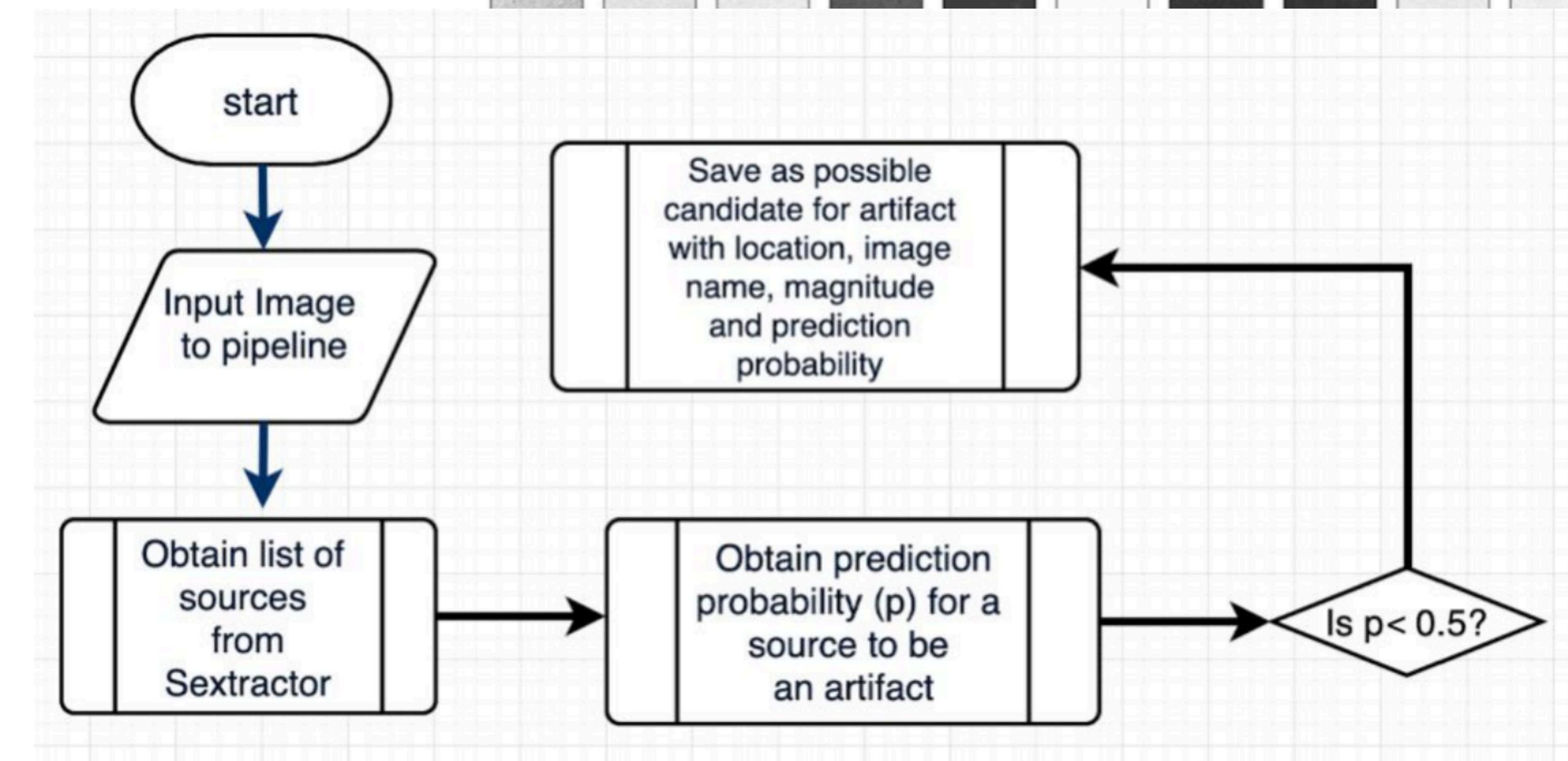
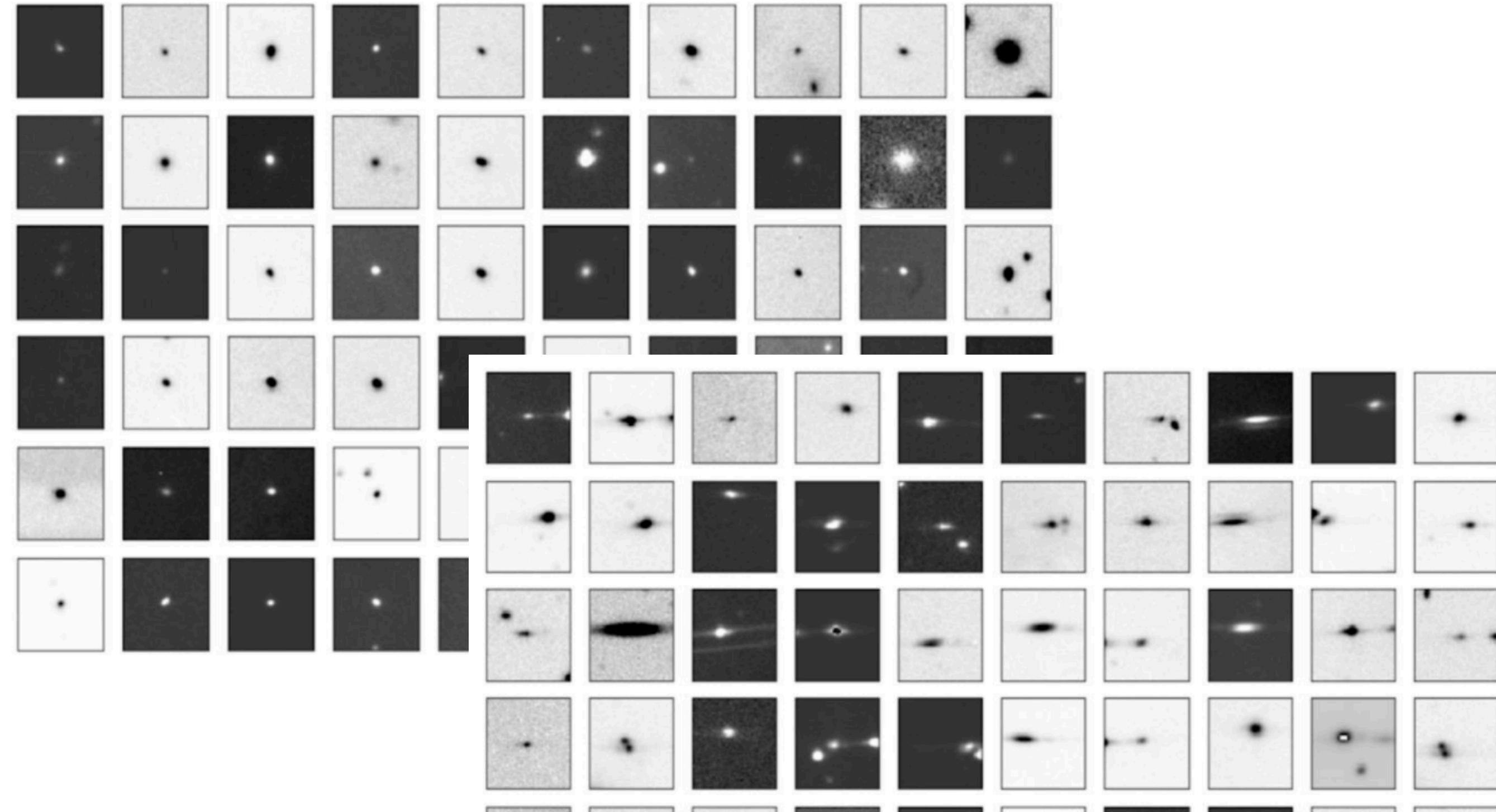
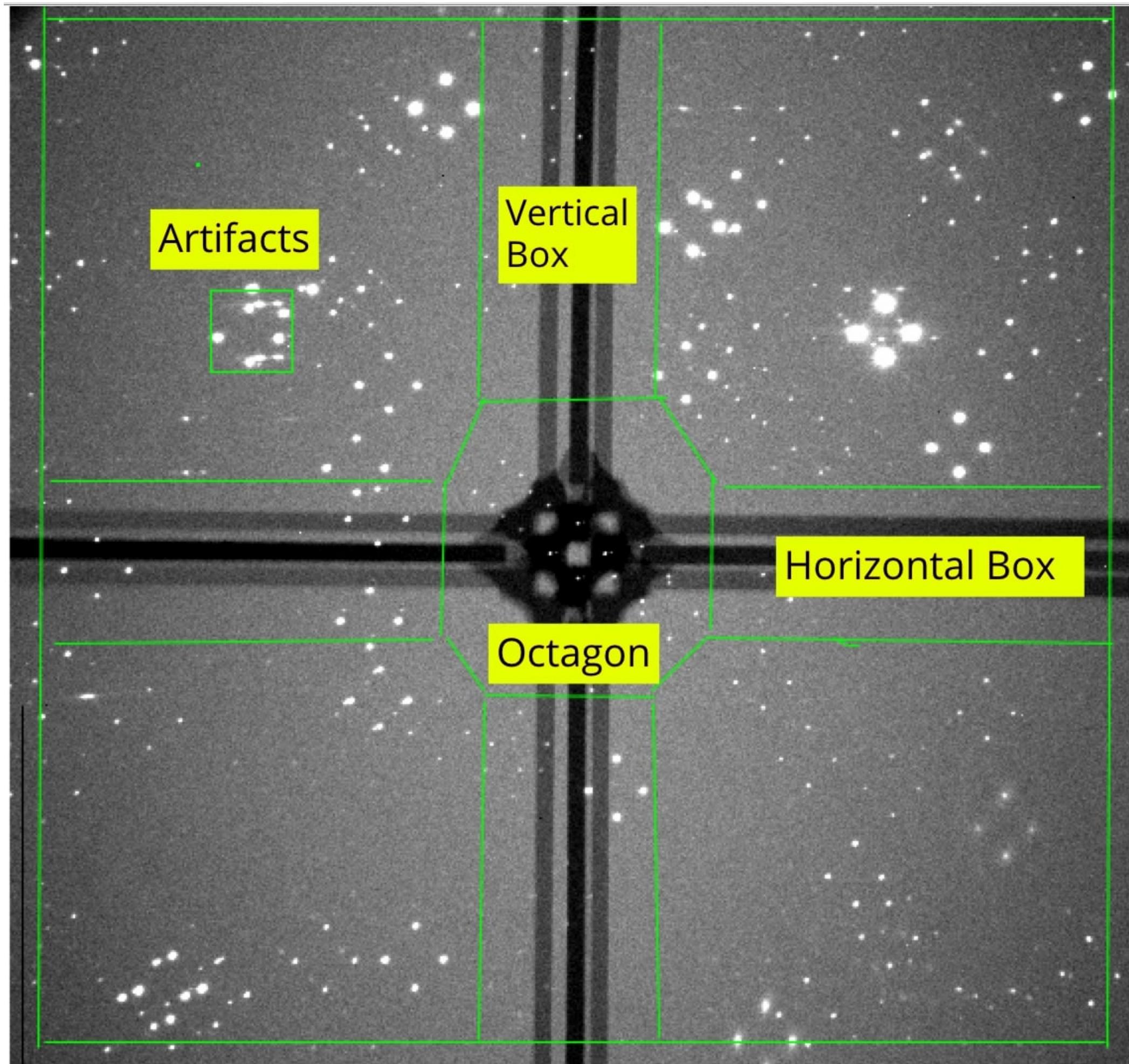
Lasair

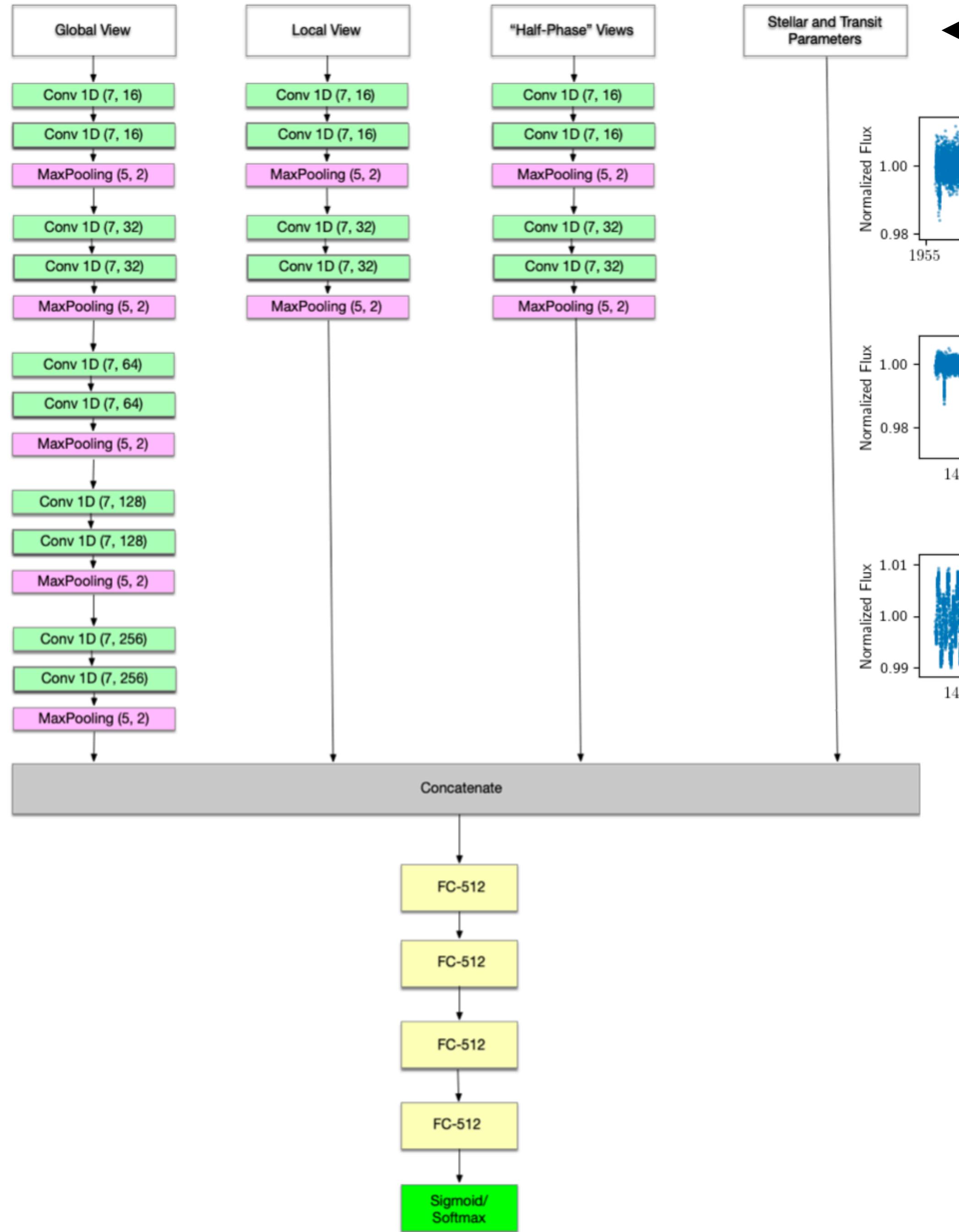
Getting ready for LSST/VRO
with ZTF data



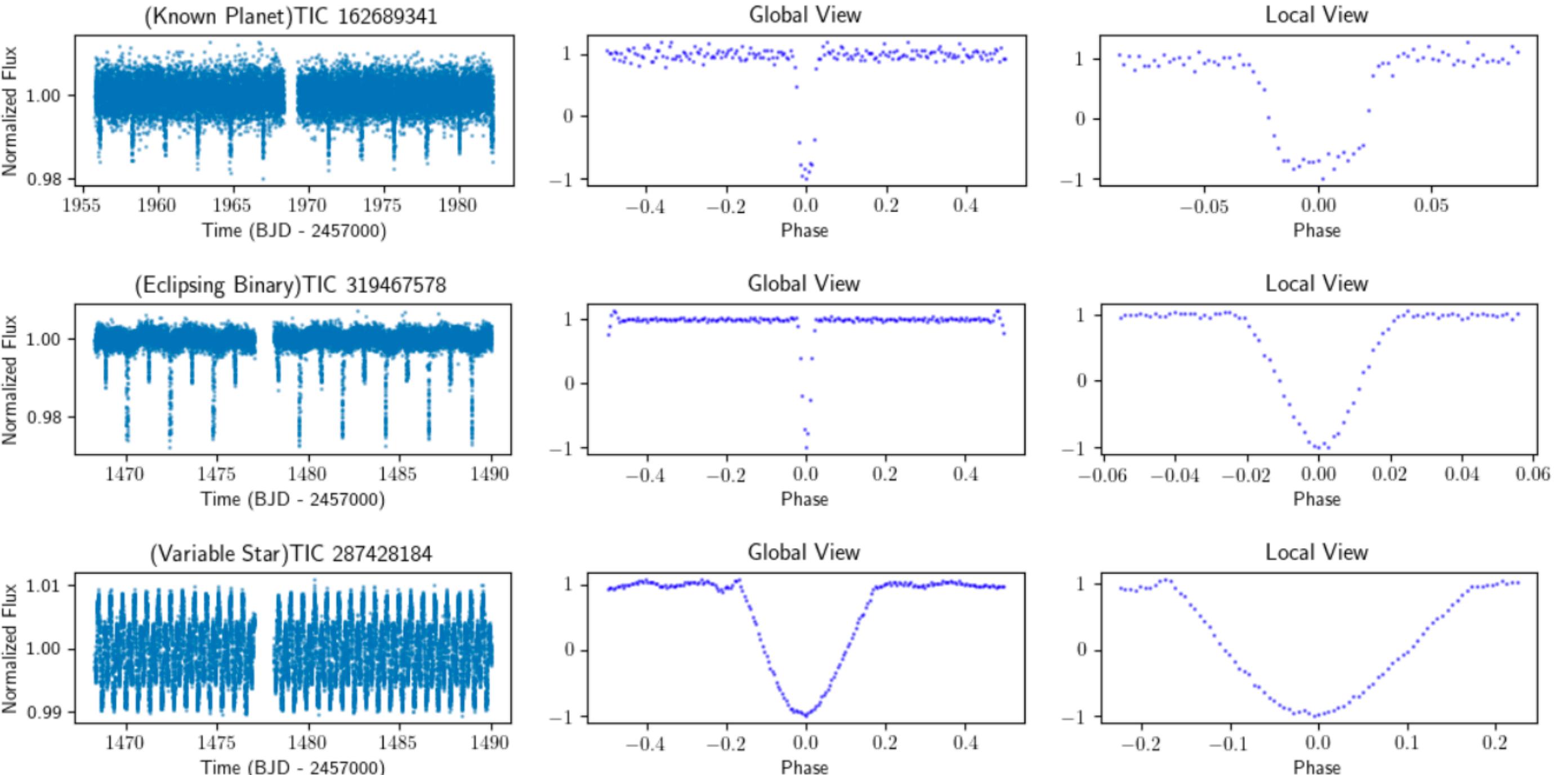
- Cross-matches
- Value additions
- Classifications

Robopol





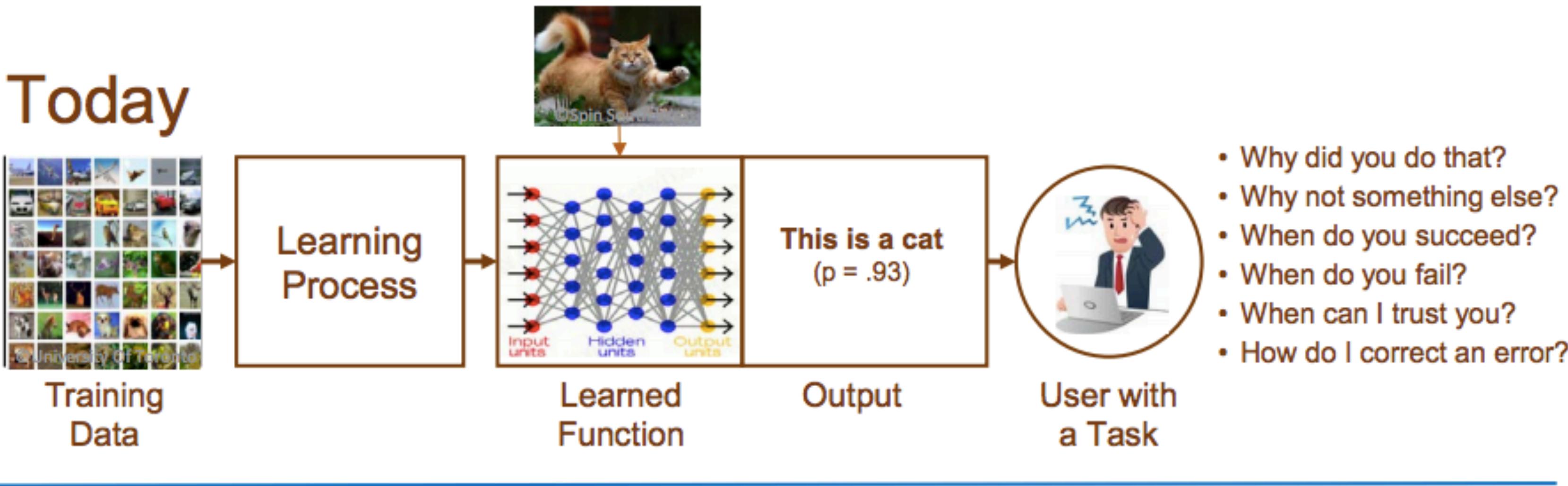
Metadata



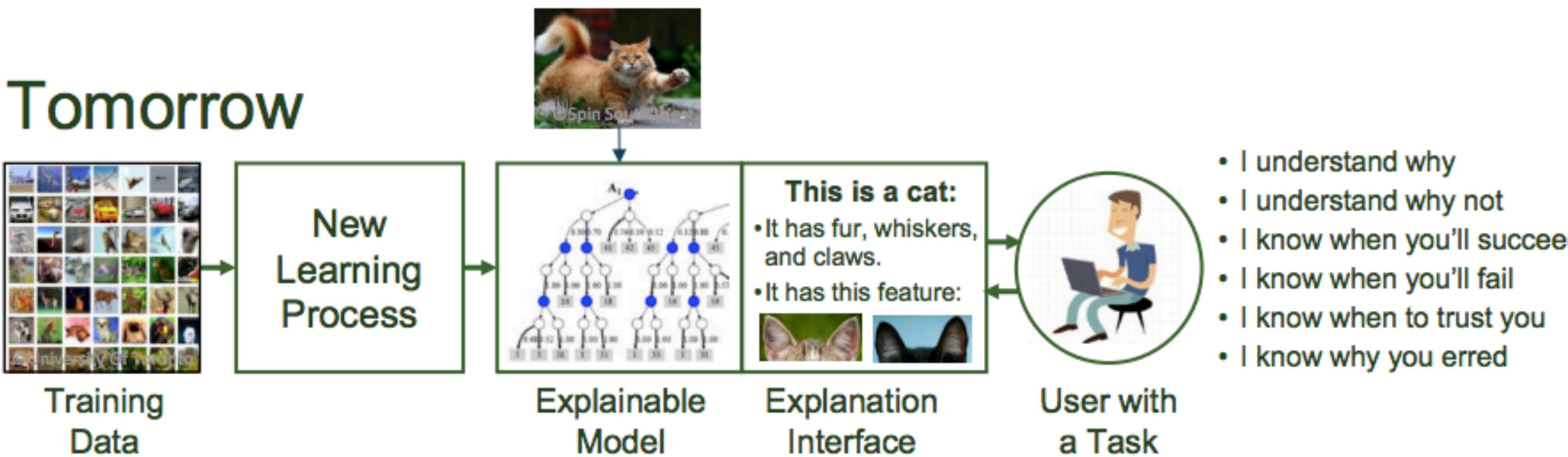
Hunting for Exoplanets
S Rao, Mahabal, ...

Interpretability

Today

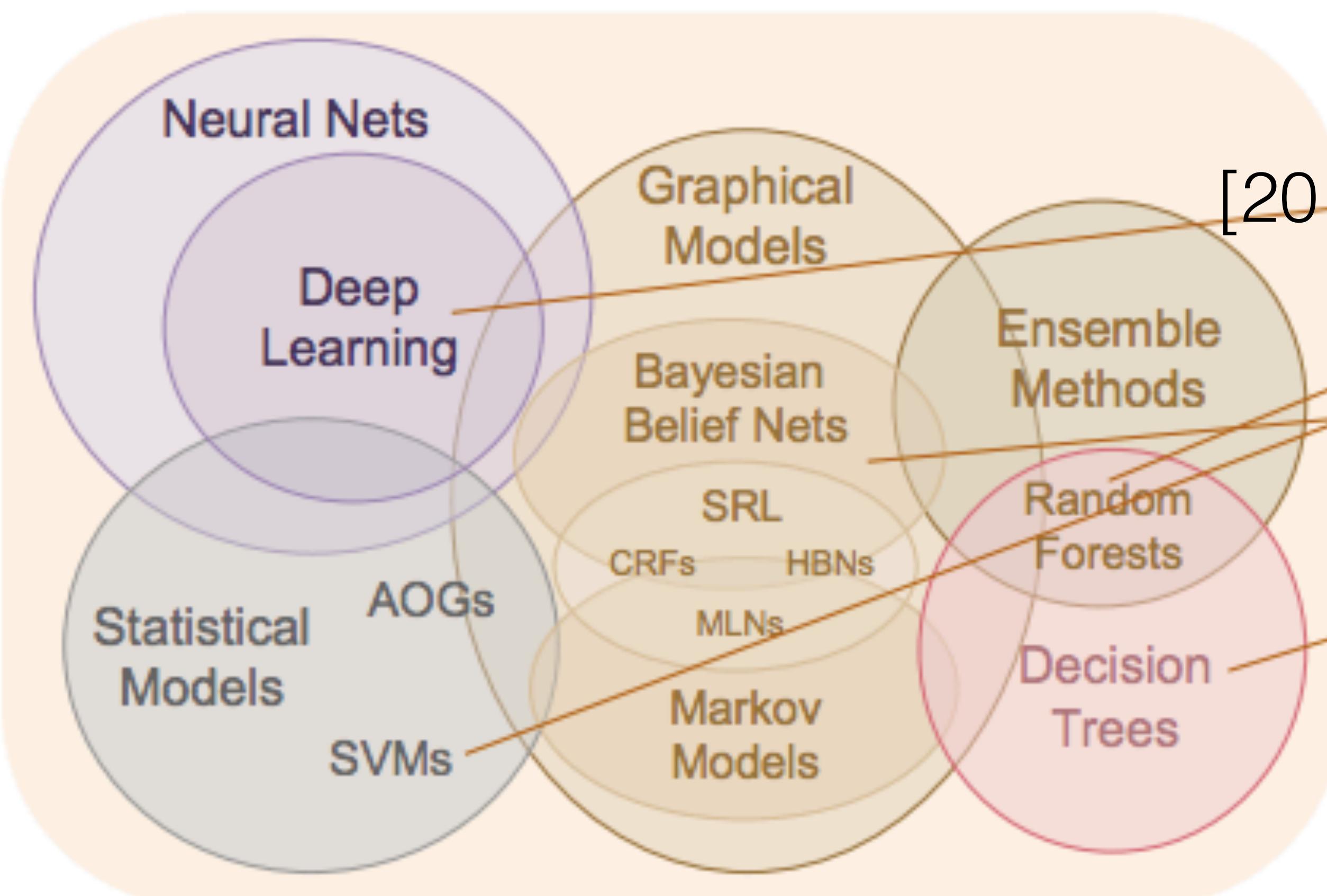


Tomorrow

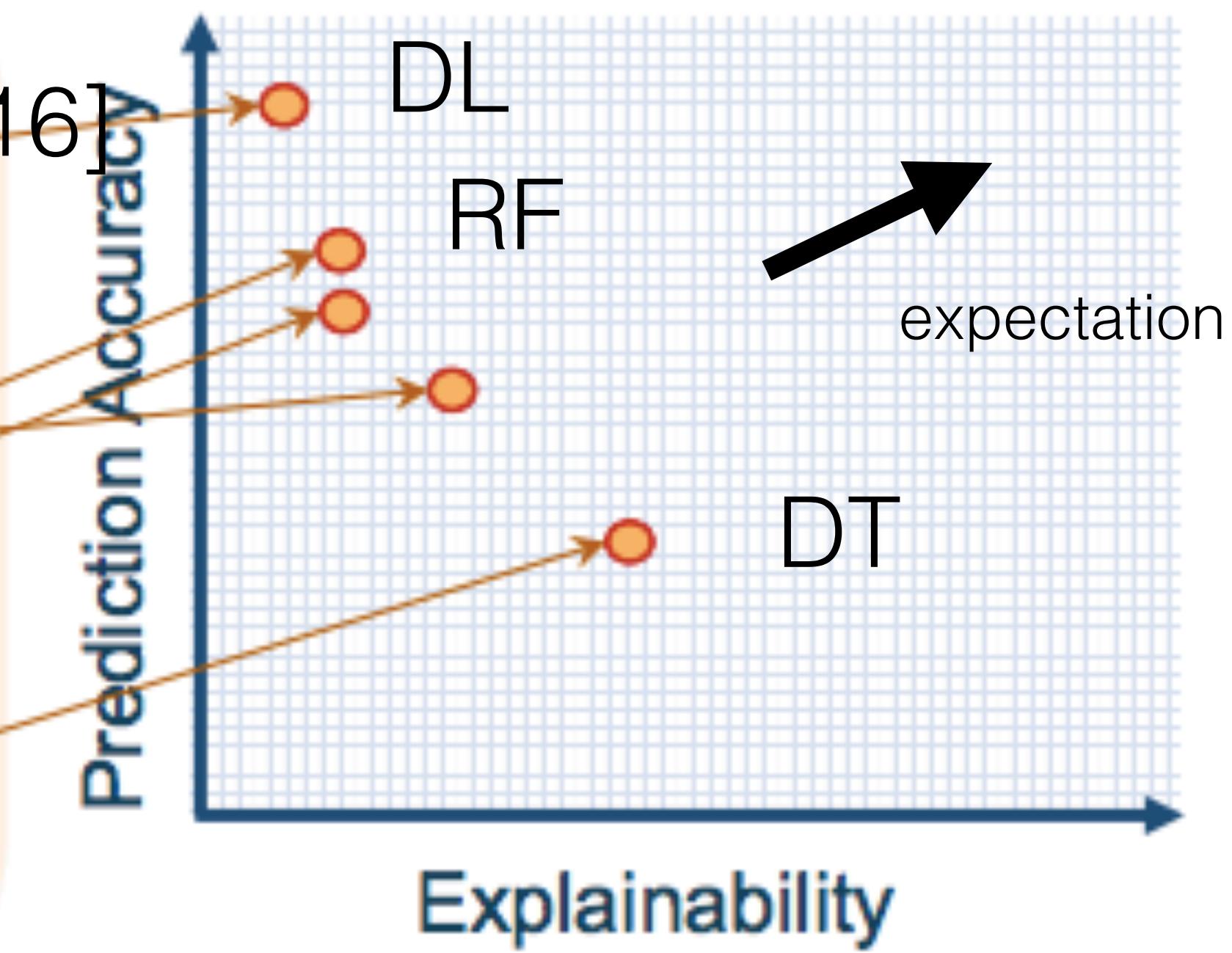


David Gunning (DARPA/I2O)

Learning Techniques (today)



Explainability (notional)

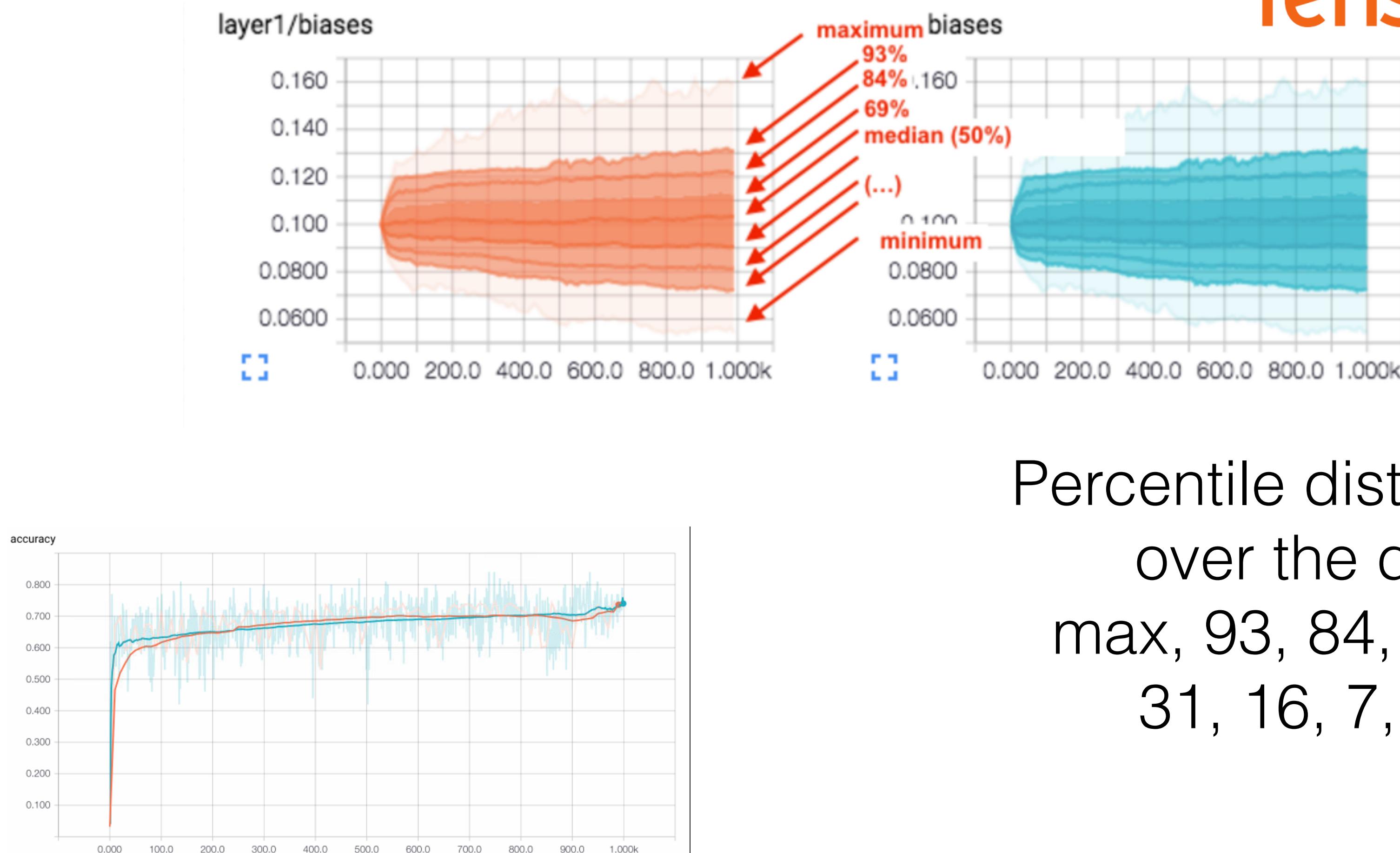


David Gunning (DARPA/I2O)

Distribution Summaries



TensorFlow



Percentile distributions
over the data:
max, 93, 84, 69, 50,
31, 16, 7, min



Before

After

fromthegrapevine.com



telegraph.co.uk

Visualization for interpretability

A. Activation Maximization

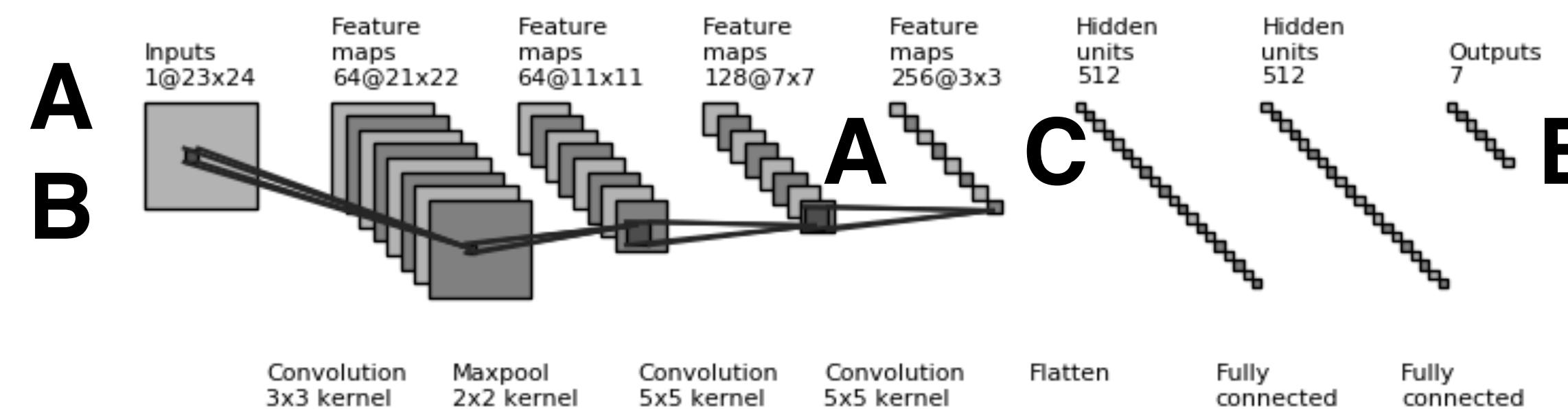
- Initial layer filters easy to visualize
- Generate input image that activates later filters

B. Saliency Maps

- Gradient of o/p category wrt input image
- Understanding attention of the classifier

C. Class Activation Maps

- Gradients based on first dense layer
- Spatial information still intact



<https://raghakot.github.io/keras-vis/>

Bias in Machine Learning

Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*

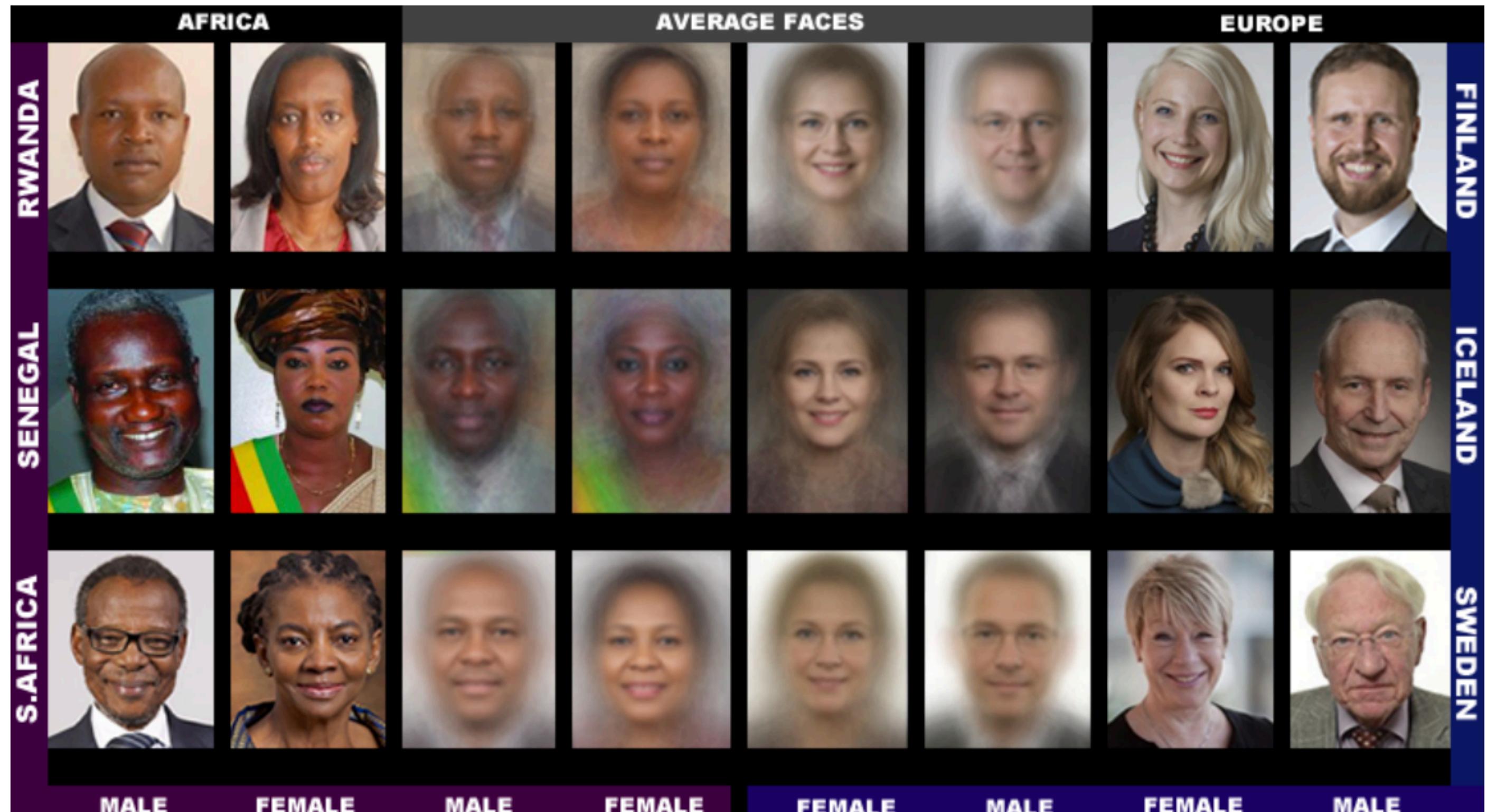
Automated systems are not inherently neutral. They reflect the priorities, preferences, and prejudices—the coded gaze—of those who have the power to mold artificial intelligence.

(MIT Media Lab)

Gebru - Yann Lecun debate

We should all be wary
of the bias in our data
and the methodology

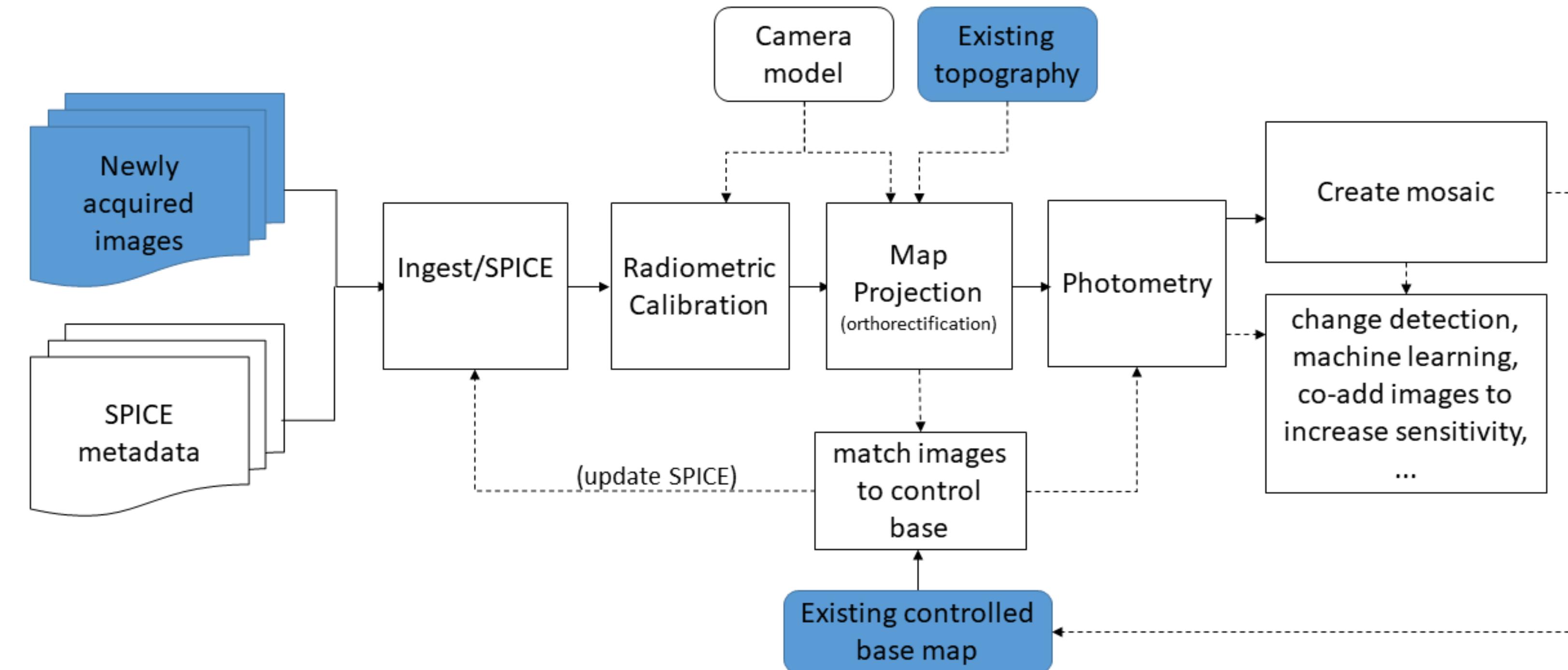
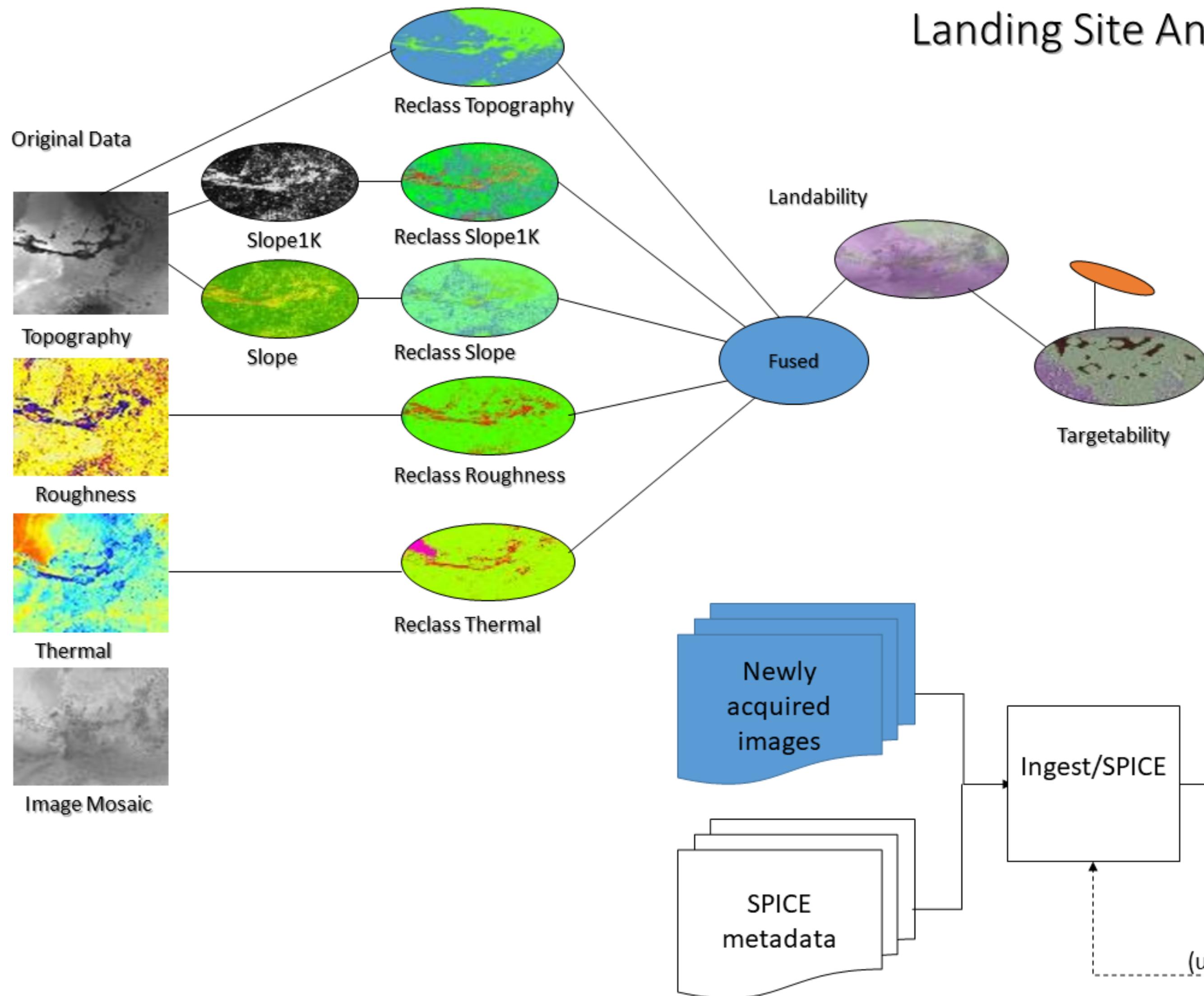
Buolamwini and Gebru



Pilot Parliaments Benchmark (PPB)

Recently Google expelled
Gebru for raising valid
questions regarding bias

Landing Site Analysis



From Data Fusion for In-space Nebulae

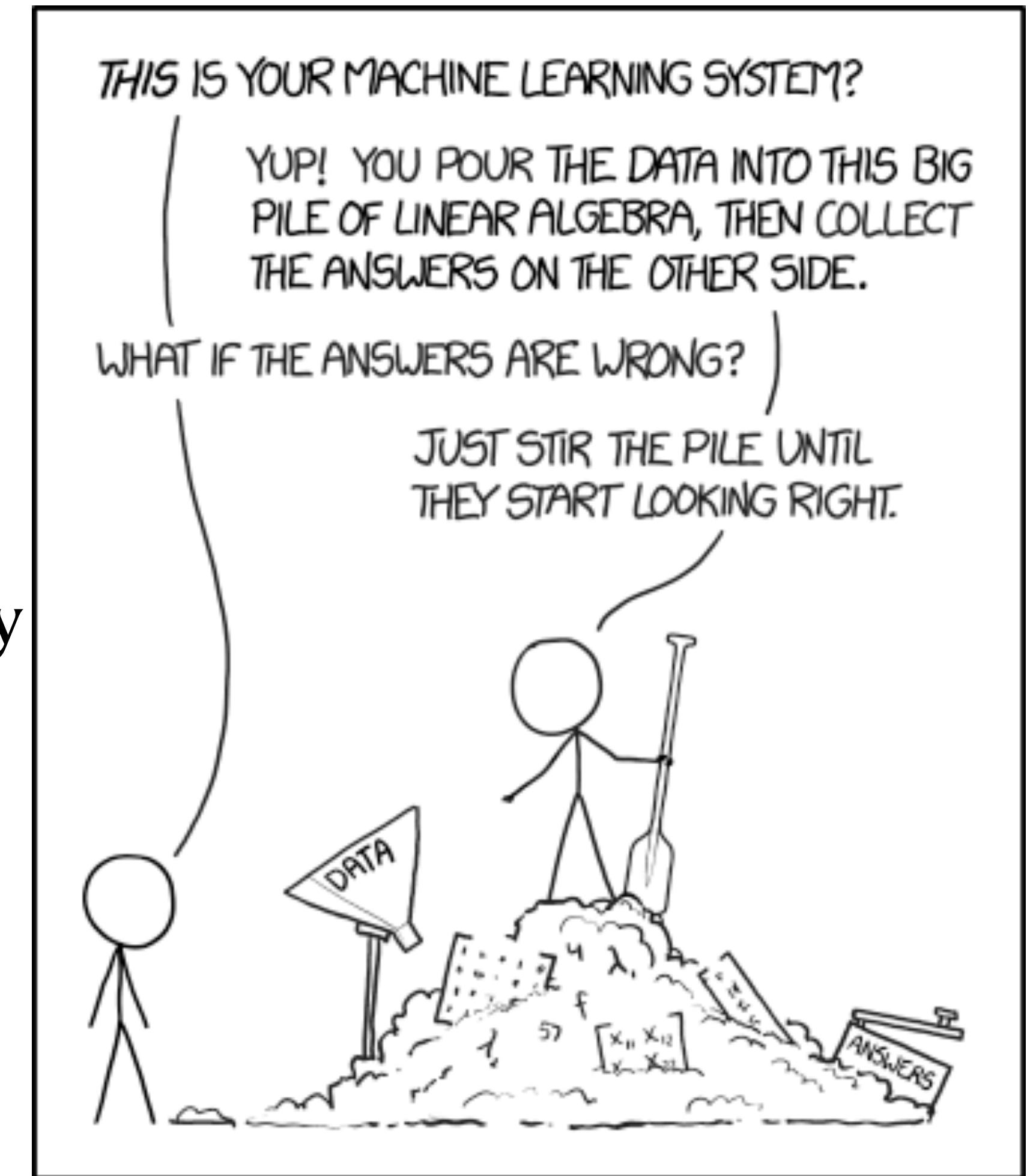
Mahabal, Hare, Fox, Hallinan 2020

Based on a Keck Institute for Space Studies workshop

Summary

- Deep Learning has entered almost every aspect of astronomy
- Good training sets are critical
- Models should be as simple as possible
- Building in interpretability is critical (though not easy yet)
- Many examples, codes available

Don't do this!



Hands-on Exercises

- Trivial example (colors, galaxies): <https://github.com/AshishMahabal/BasicDLTute>
- ZTF Real-Bogus classifier: <https://github.com/dmitryduev/braai>
- Real-Bogus predictions for GW events: <https://github.com/GWML/GWSkyNet>