MMA Subgroup Talk - Michael Coughlin Group

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Coughlin Group members

Postdocs:

- Brian Healy
- Saleem Muhammed

Grad students:

- Tyler Barna
- William Benoit
- Brendan King
- Rafia Omer
- Andrew Toivonen

Postbac:

- Abigail Gray

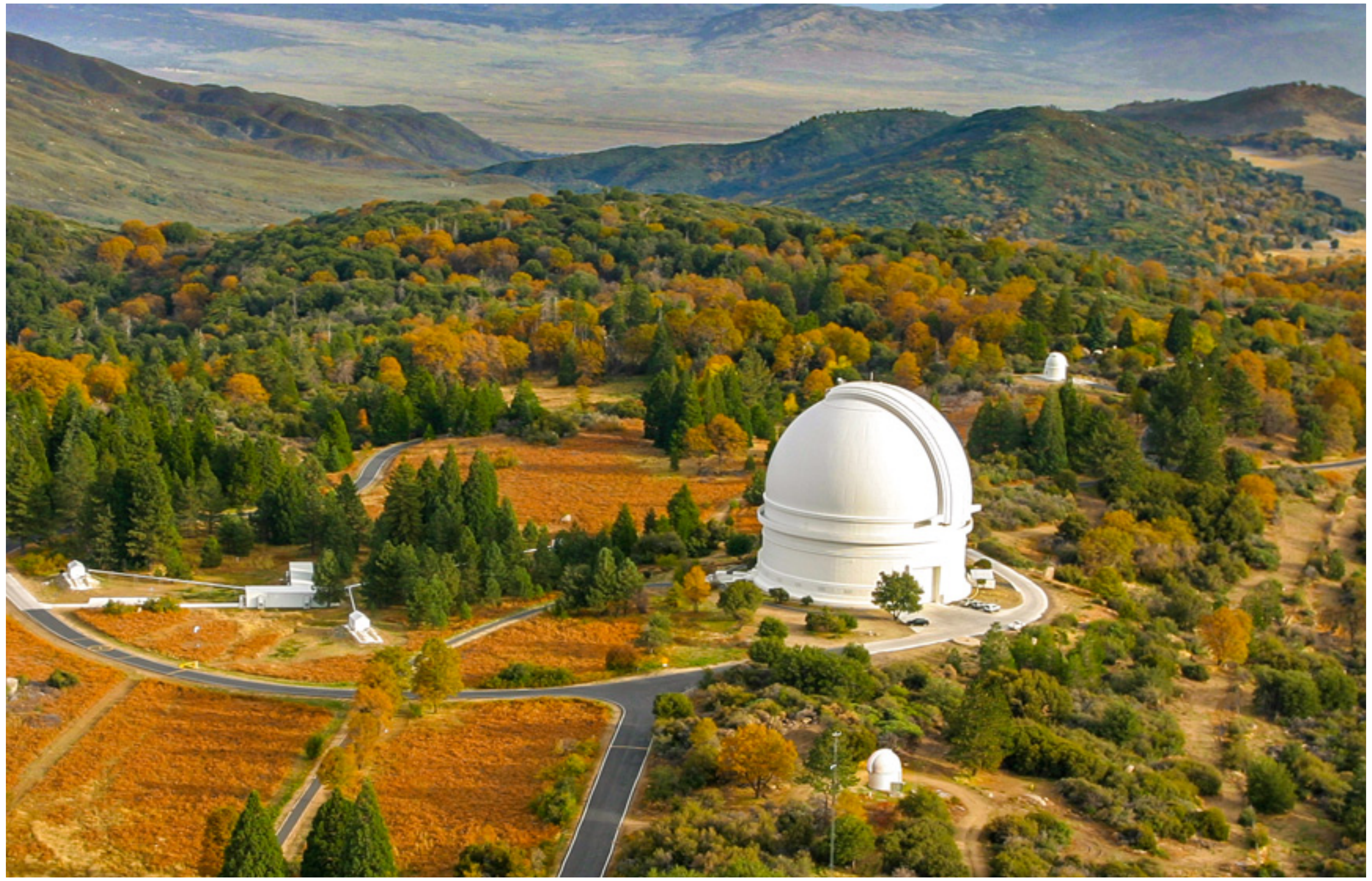
- *See also talks by Alec Gunny, Eric Moreno about GW efforts*

Time-domain Astronomy

- Many astronomical objects show brightness variations on short timescales
  - Persistent variables, transients
- To study time-domain astronomy at scale:

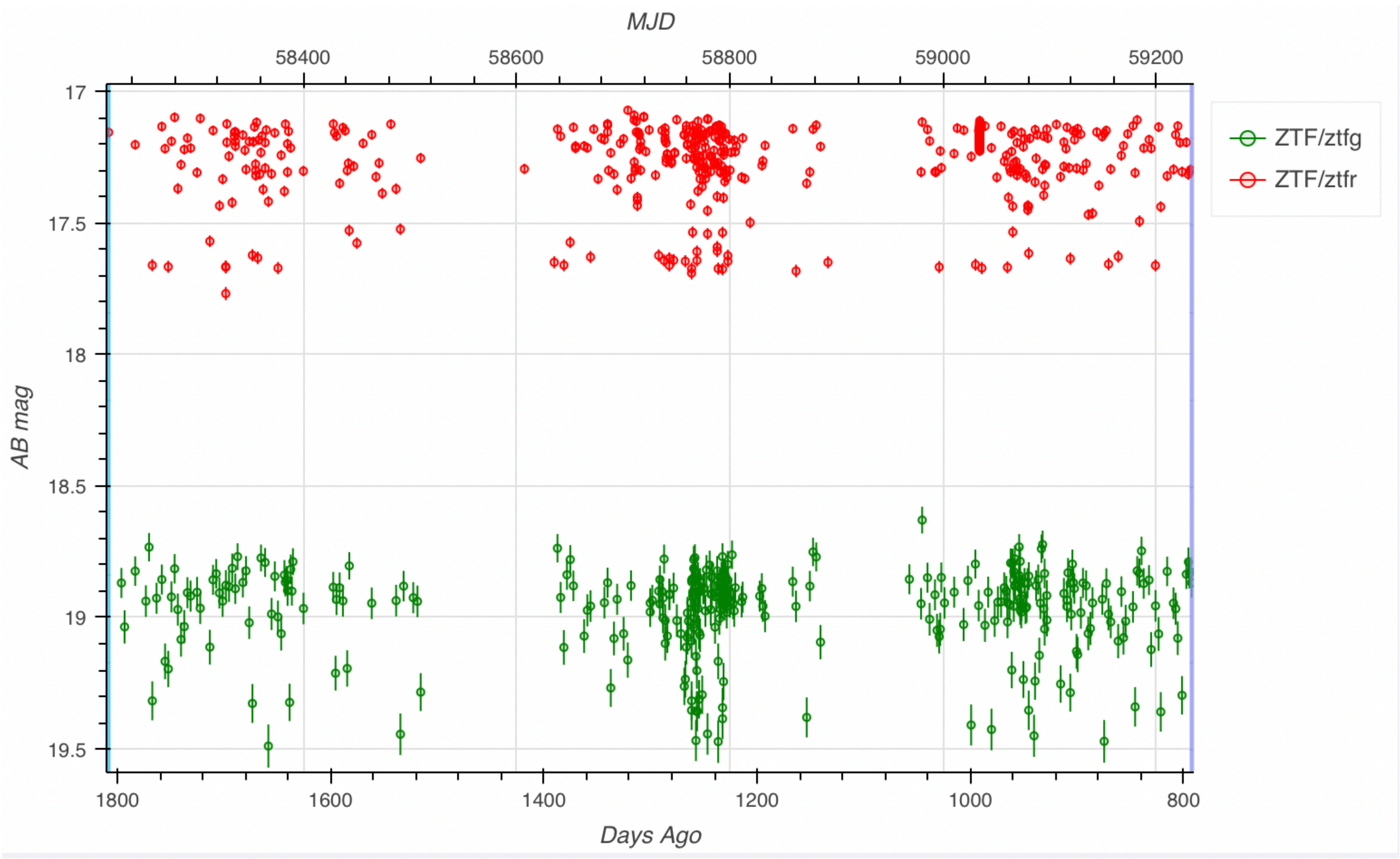
Zwicky Transient Facility (ZTF)

- Northern sky survey @ Palomar Observatory, CA
  - Wide field of view (47 deg^2)
  - Fast survey rate (4300 deg^2/hr)
  - Observes faint sources in multiple colors; median single visit depth 20.6 mag (5σ, r)
- Full-sky coverage every 2 days
  - DR16: 4.64 billion light curves

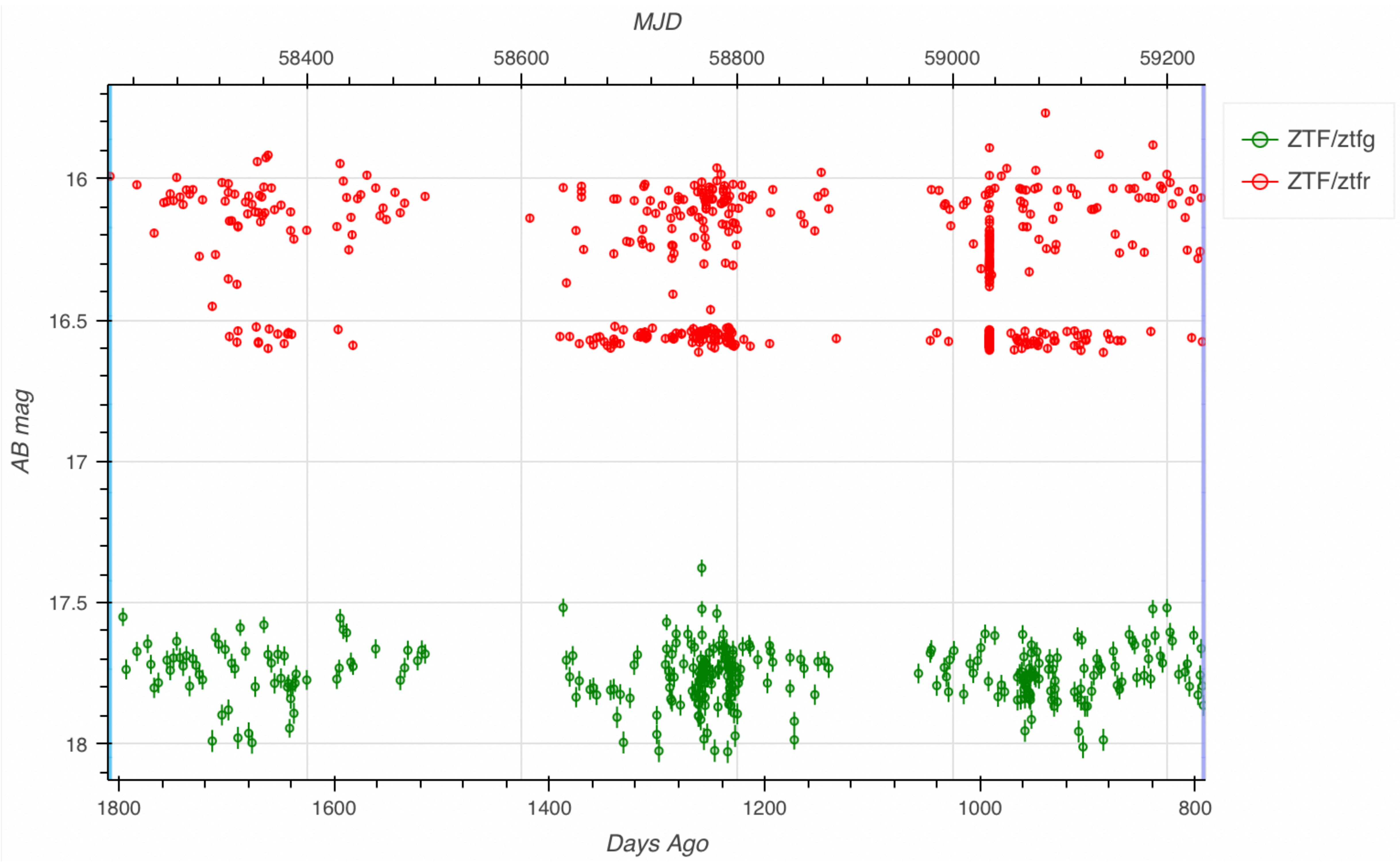


(Palomar Observatory/Caltech)

Example ZTF Data



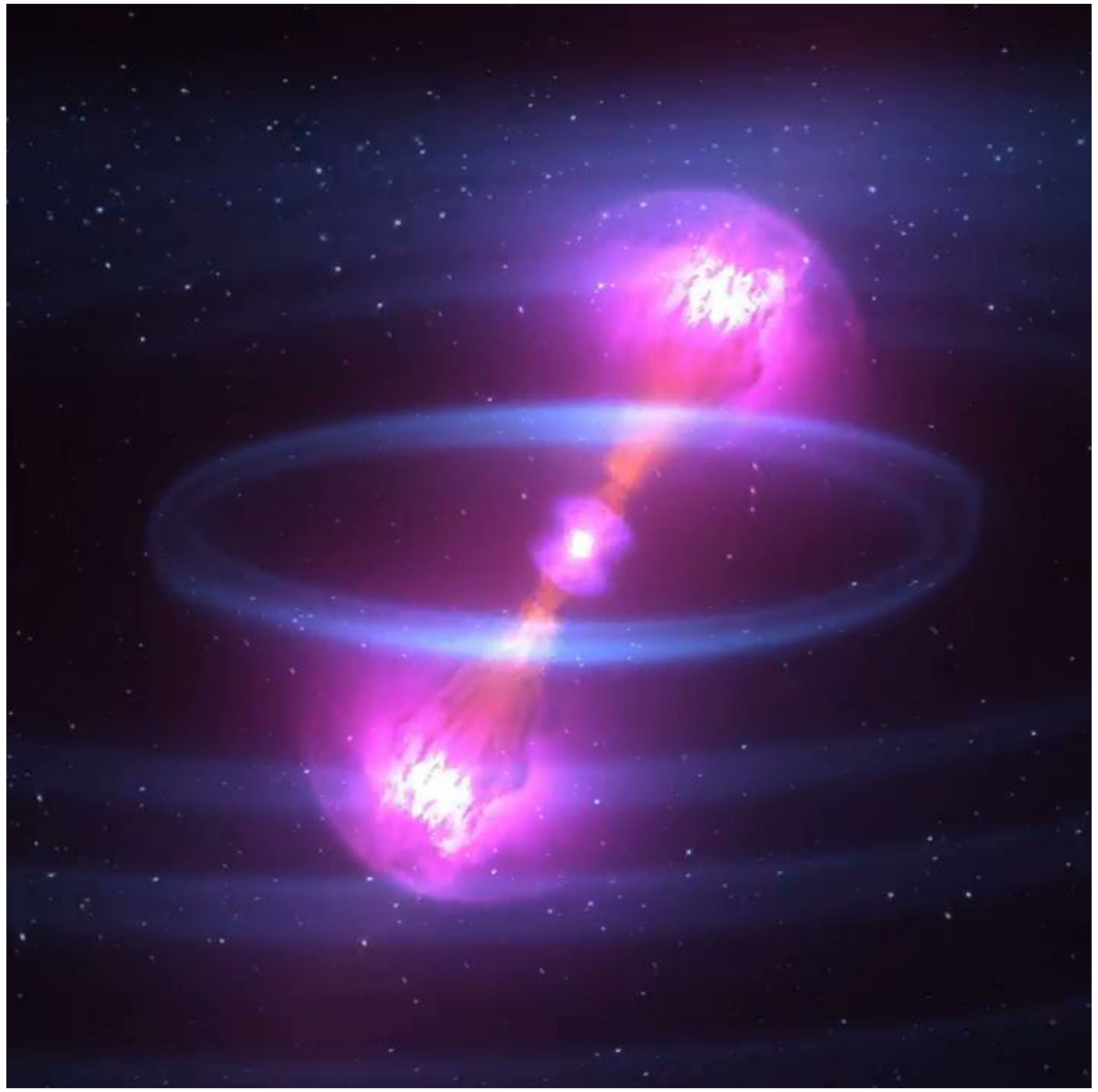
Astrophysical source (eclipsing binary)



Artifact (blend)

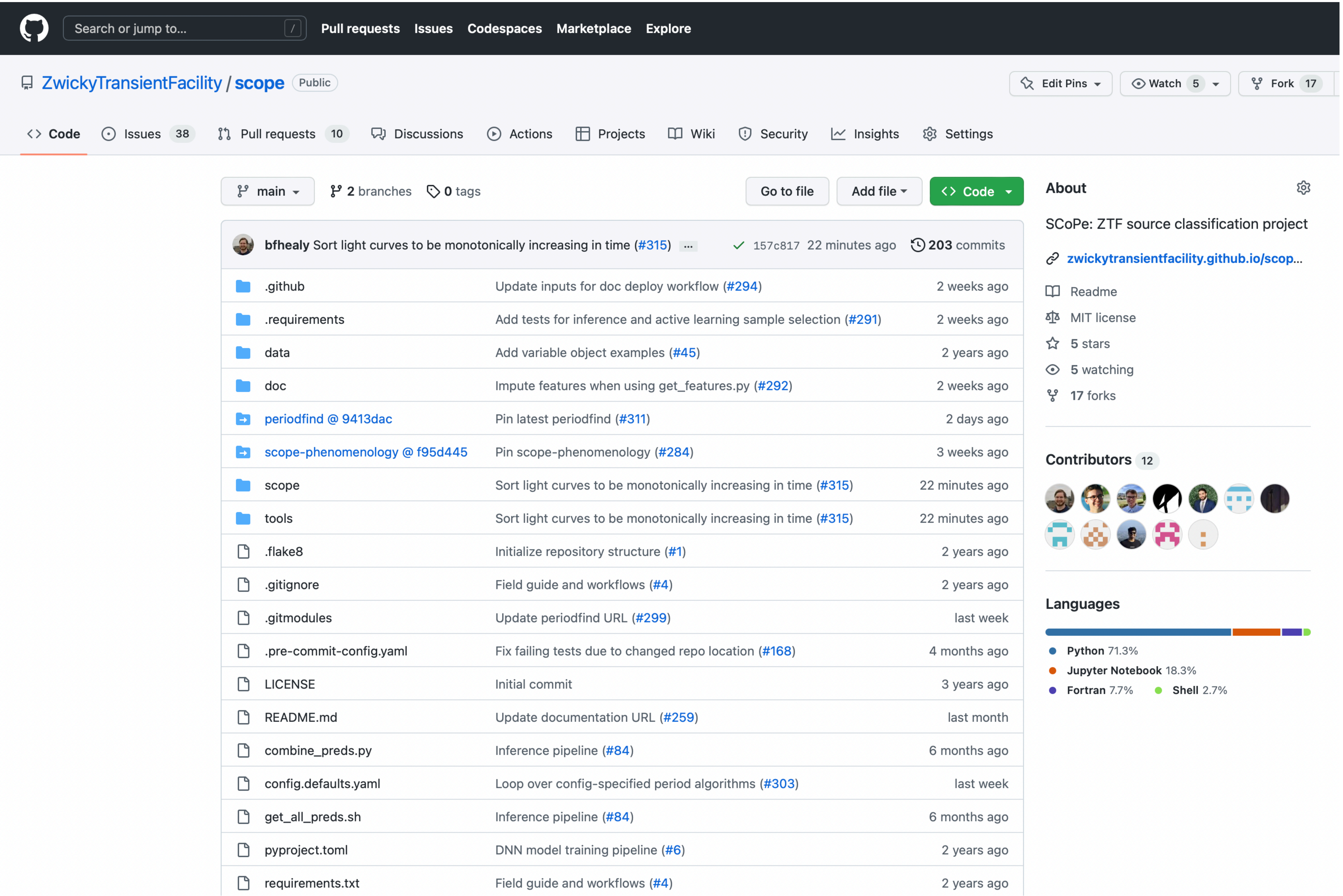
Motivating Source Classification

- Source classification benefits:
  - Variable star studies
    - Enable ensemble studies
  - Transient follow-up, esp. kilonovae (neutron star mergers)
    - Exclude sources observed to exhibit past variability
  - Anomaly detection
    - Discover new sources by searching for anomalous outliers



(NASA GSFC/CI Lab)

ZTF Source Classification Project (SCoPe)



- Open-source
- Python-based
- CI/CD pipeline
- Regularly updated docs
- Hackathon topic!

(van Roestel et al. 2021, Coughlin et al. 2021)

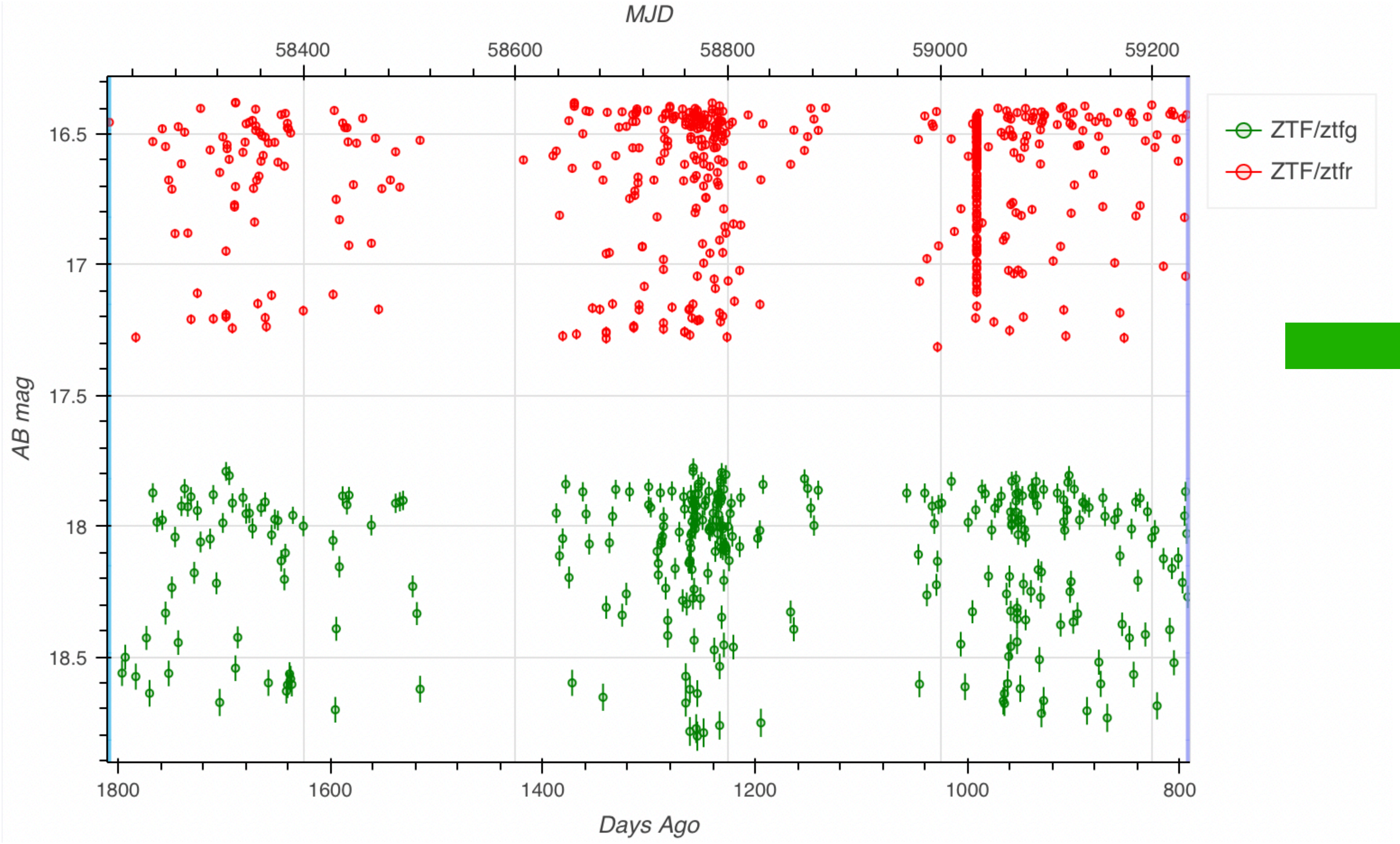
SCoPe Details

- **Supervised, active learning:** training set built up over time (w/human input)
- **Two taxonomies:** ontological (intrinsic), phenomenological (light curve shape)
  - Provides useful information for anomalous sources
  - Avoids complications of overlapping classes

SCoPe Details

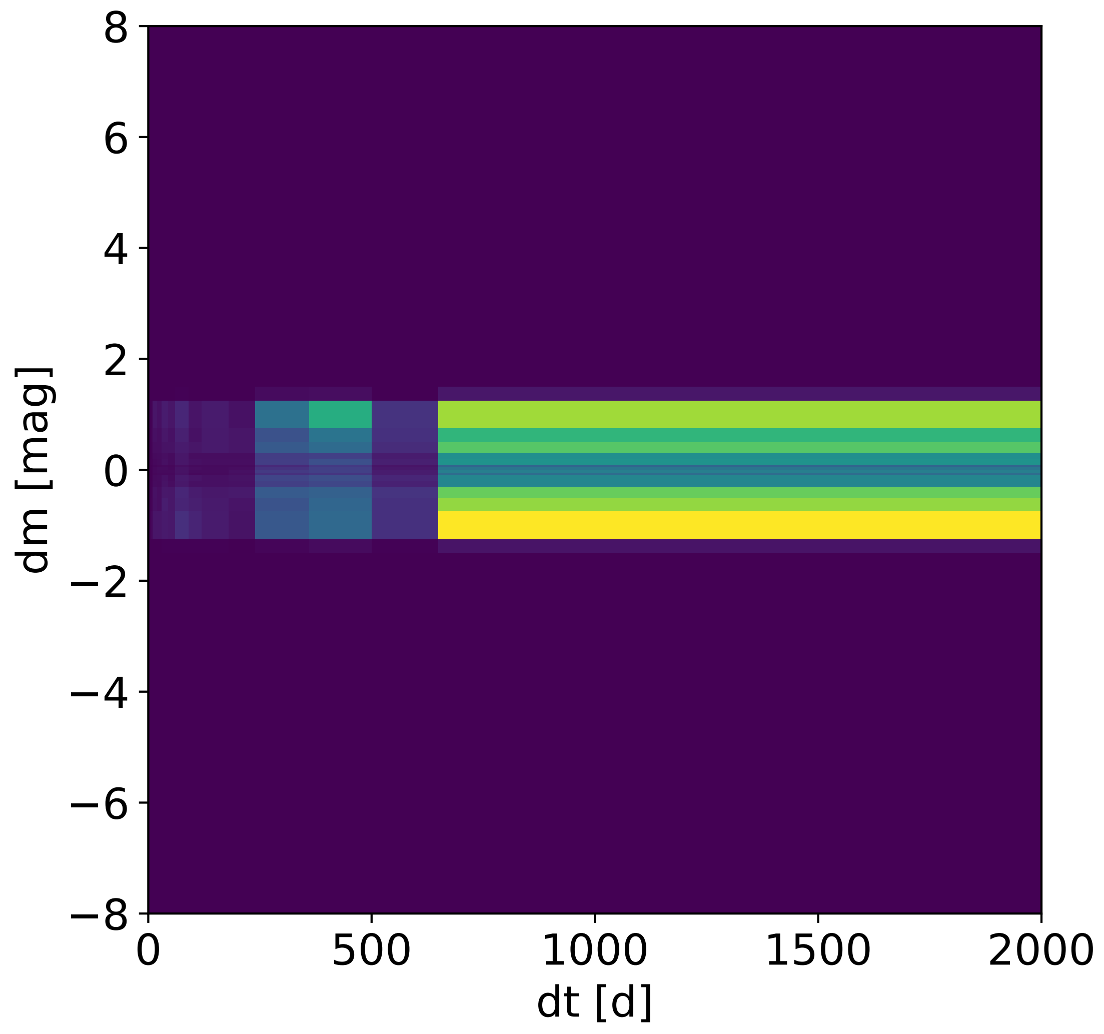
- **Binary classification:** independent predictions for each class
    - Supports multiple labels per source (varying specificity)
    - Flexible to new labels
- Train **convolutional neural network** and **XGBoost** algorithms on each label

Input Features



Summary statistics

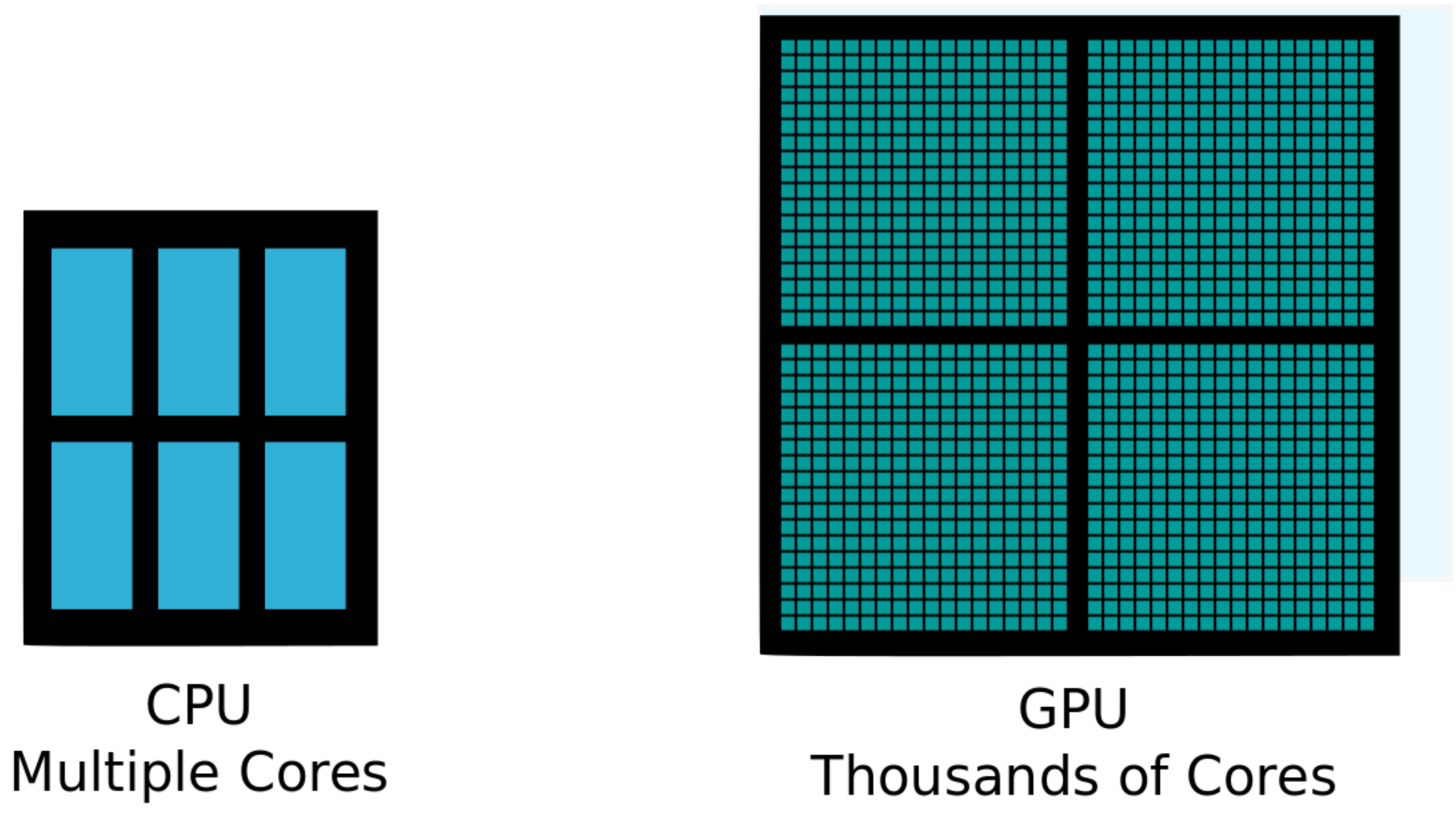
f1_a	18.137365
f1_amp	0.284065
f1_b	-0.000034
f1_phi0	-0.098306
f1_power	0.93193
f1_relamp1	0.082111
f1_relamp2	0.024026
f1_relamp3	0.0
f1_relamp4	0.0
f1_relphi1	-0.075452
f1_relphi2	-0.03388
f1_relphi3	0.0
f1_relphi4	0.0
field	853
i60r	0.316
i70r	0.3674
i80r	0.4464
i90r	0.5692
inv_vonneumannratio	0.71049
iqr	0.25
mean_ztf_alert_braai	0.99176
median	18.014
median_abs_dev	0.101
n	137.0
n_ztf_alerts	406
norm_excess_var	0.000093
norm_peak_to_peak_amp	0.016749
pdot	0.0
period	0.175088
quad	1
ra	355.275604
roms	3.267903
significance	167.419434
skew	67.574478
smallkurt	826.596439
stetson_j	-1.10259
stetson_k	0.815673
sw	0.882065
welch_i	71.02061
wmean	18.050412



Magnitude-time histograms

Finding Periods

- Lomb-Scargle periodogram takes ~1s per light curve on laptop CPU
  - ~10^9 LCs: every second counts
- GPU-accelerated algorithms reduce runtime to ~0.1s / LC
- Run in parallel on high-performance compute (HPC) cluster to further accelerate

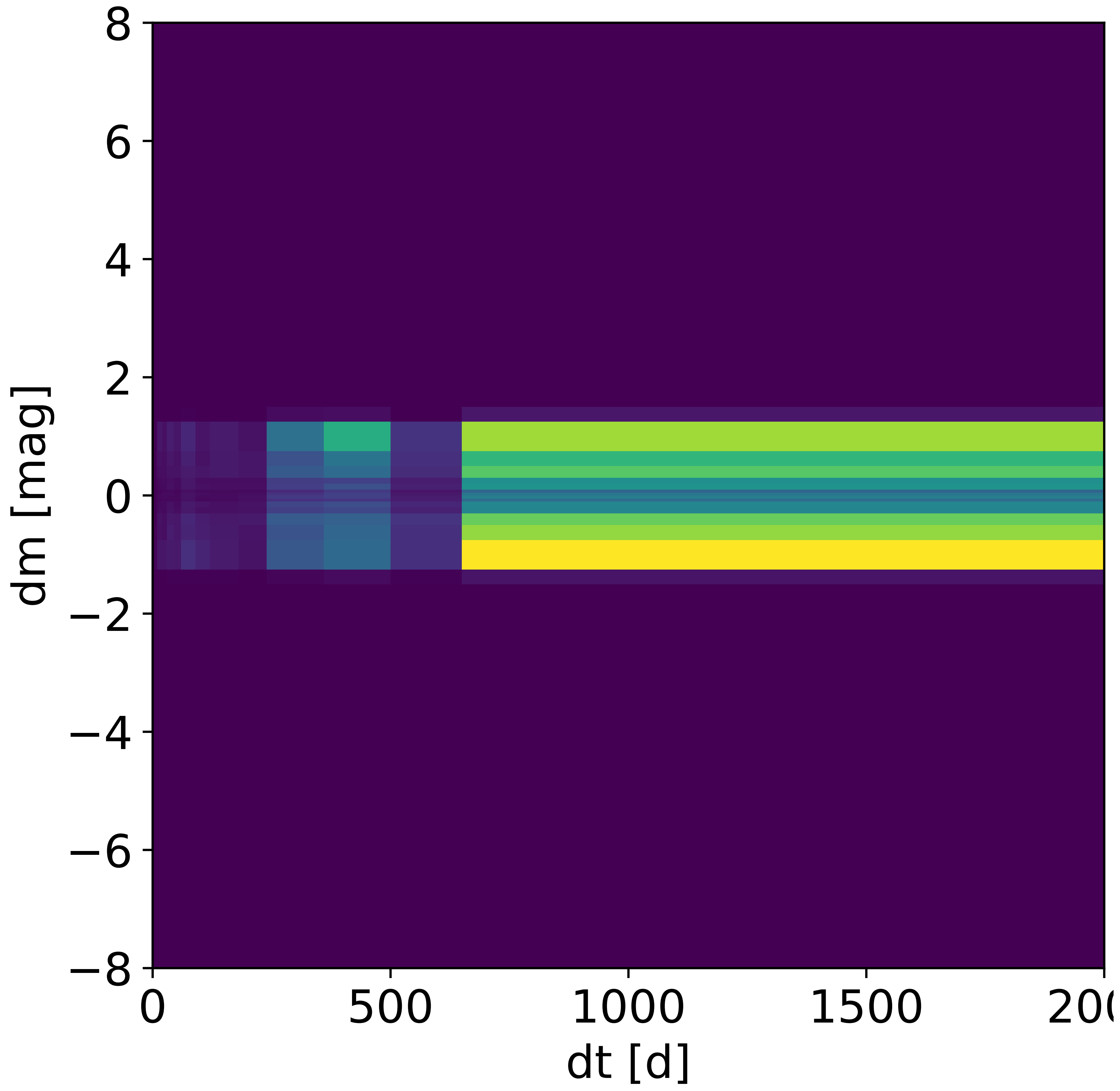


(cherryservers.com)

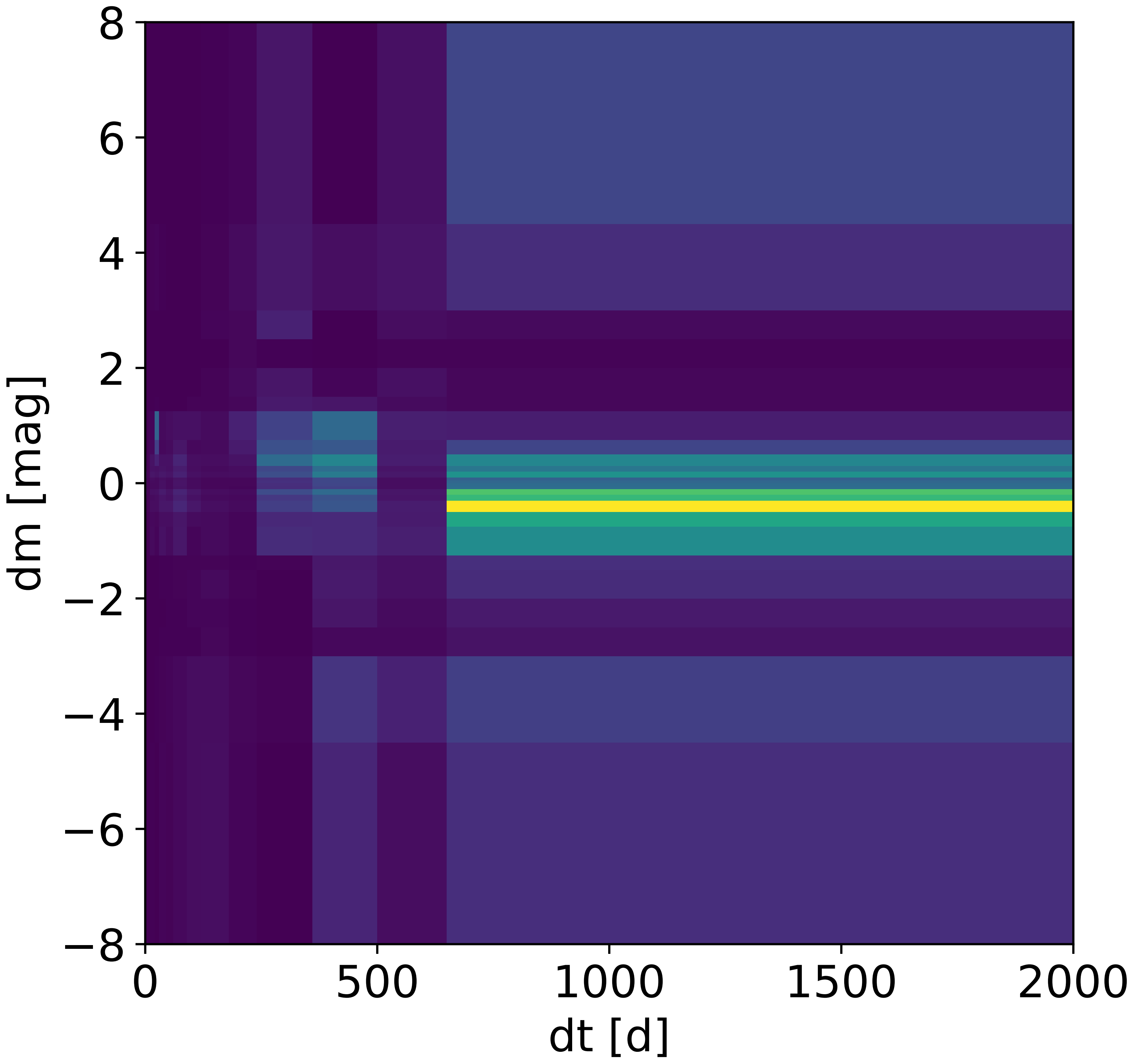
(expanse.sdsc.edu)

Magnitude-Time Histograms (dmdt)

- Map changes in magnitude (brightness), time to 26 bins
- Create standardized "image" as additional feature
- Improves classifier performance (Mahabal et al. 2017)



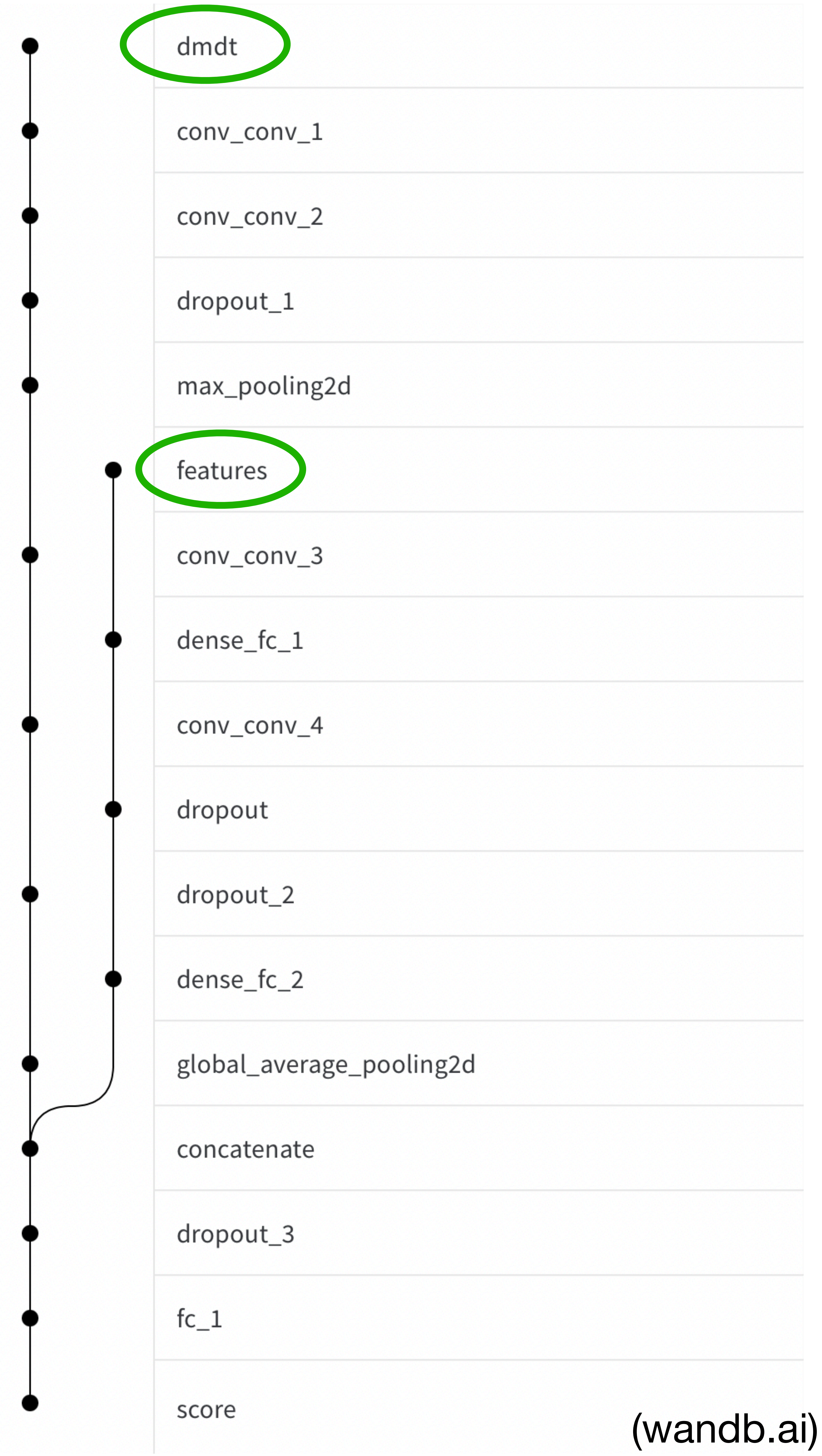
Eclipsing binary



Flaring

SCoPe Neural Network Architecture

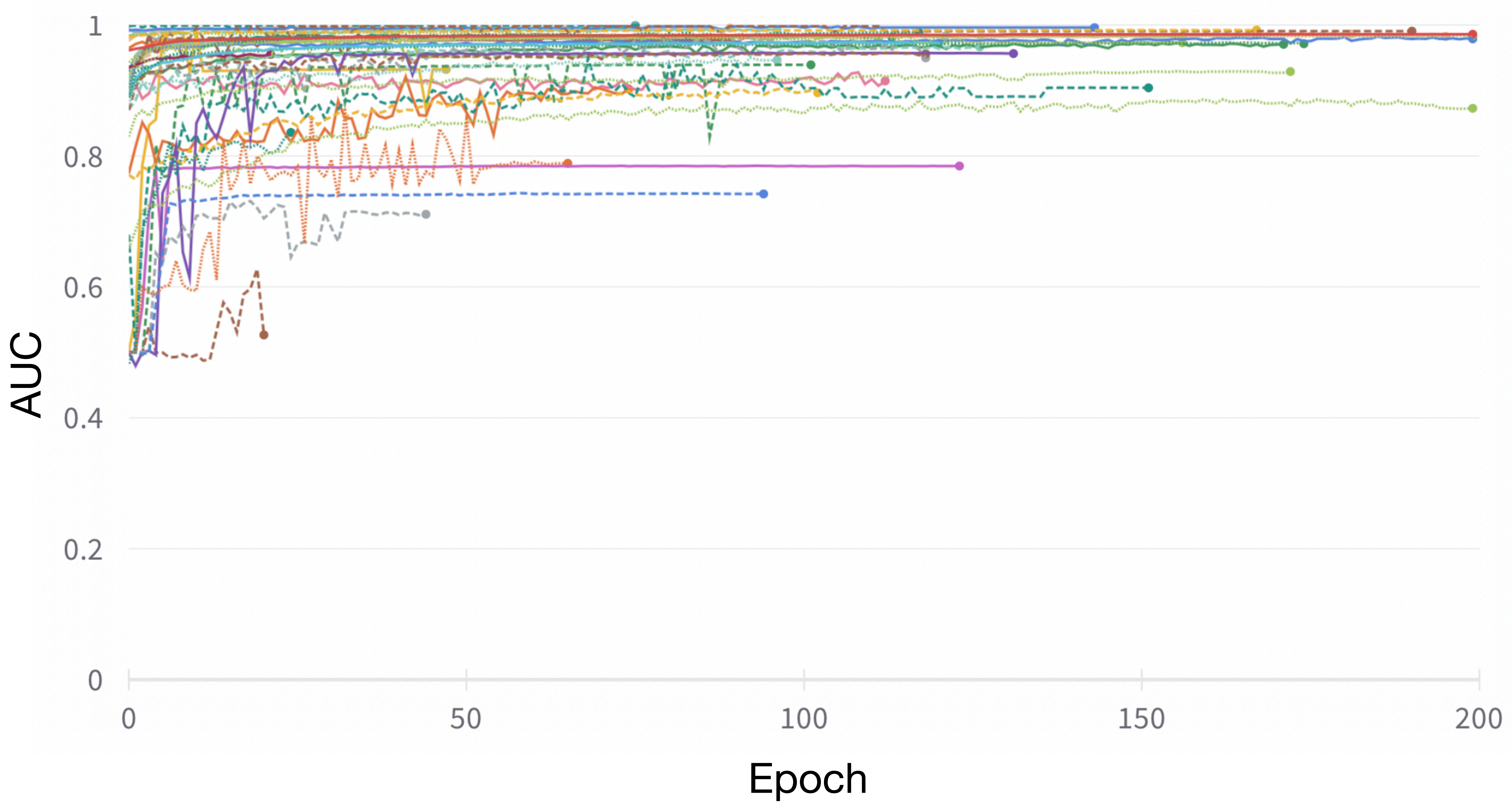
- Most features pass through fully-connected layers
- dmdt histograms input to convolutional branch
- Dropout layers help avoid overfitting
- One output per classifier (probability)



(wandb.ai)

NN Training Details

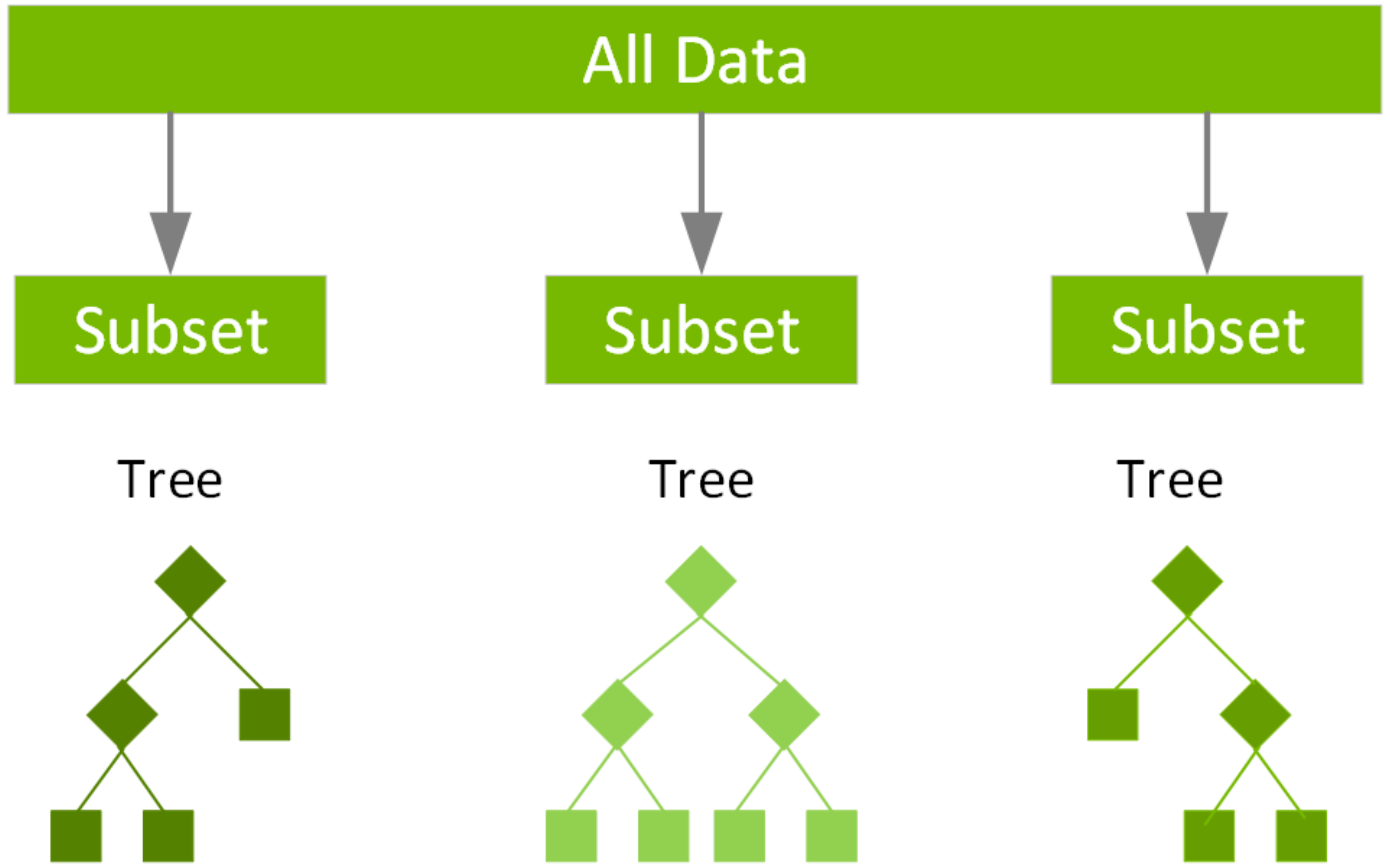
- ~80,000 sources in training set
    - ~180,000 light curves
- 44 binary classifiers
    - Some labels well-represented, others highly imbalanced



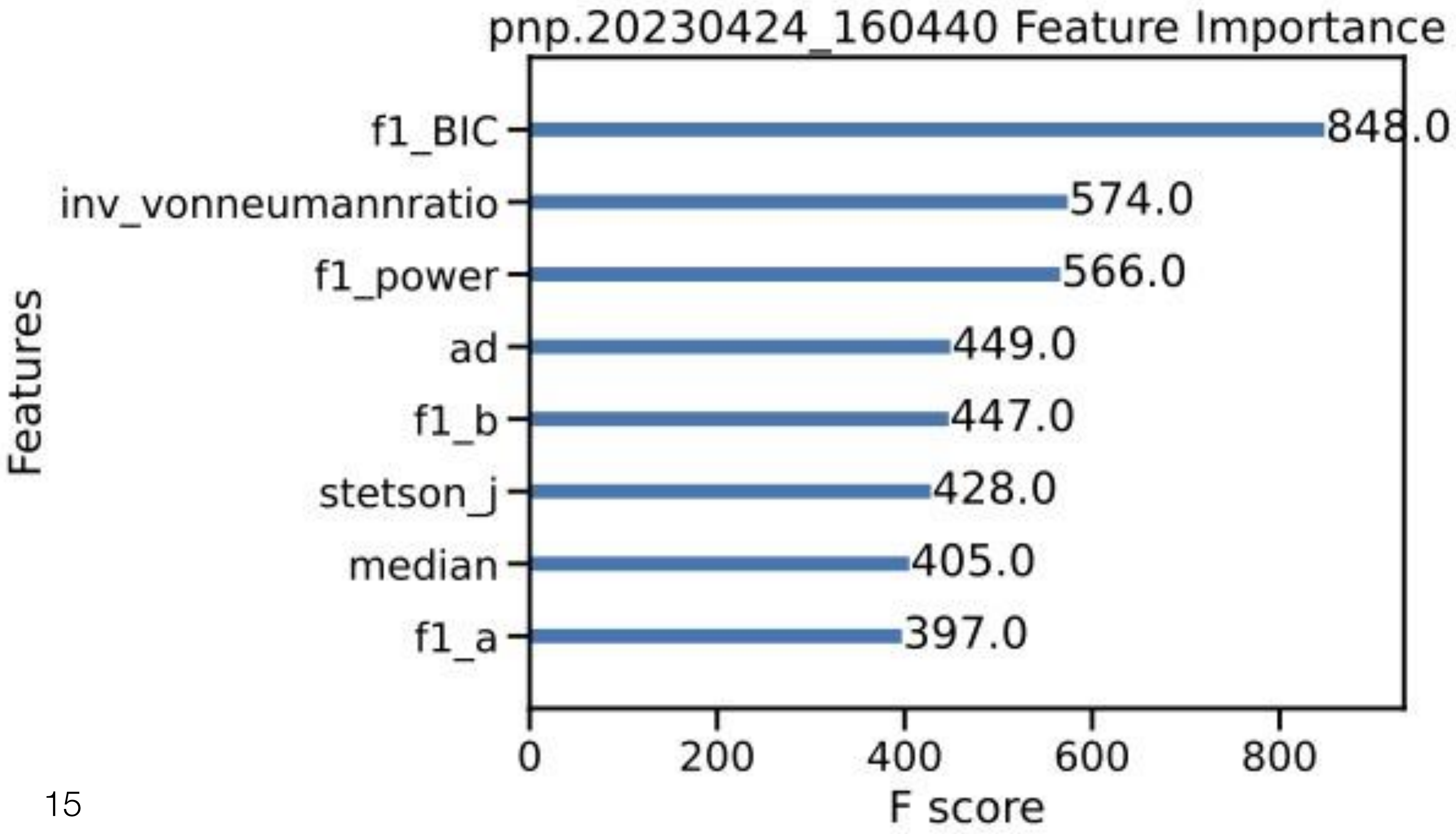
(wandb.ai)

XGBoost

- Combines individual decision trees sequentially, minimizing underfitting
- Feature importance plots generated for each label
- Achieves similar or better performance vs. DNN



(nvidia.com)



Current SCoPe status

- DR16 features generated for 20 ZTF fields on SDSC Expanse GPUs
- Classifications obtained from DNN and XGB algorithms
- Trained models run on sources near transient candidates to assist with follow-up decisions
- Paper in prep to report methods, classifications
    - Catalog of classifications to be made public

Nuclear Multi-Messenger Astronomy (NMMA)

NMMA

NMMA

a pythonic library for probing nuclear physics and cosmology with multimessenger analysis

Please check our official documentation here: https://nuclear-multimessenger-astronomy.github.io/nmma/

How to contribute: https://nuclear-multimessenger-astronomy.github.io/nmma/contributing.html

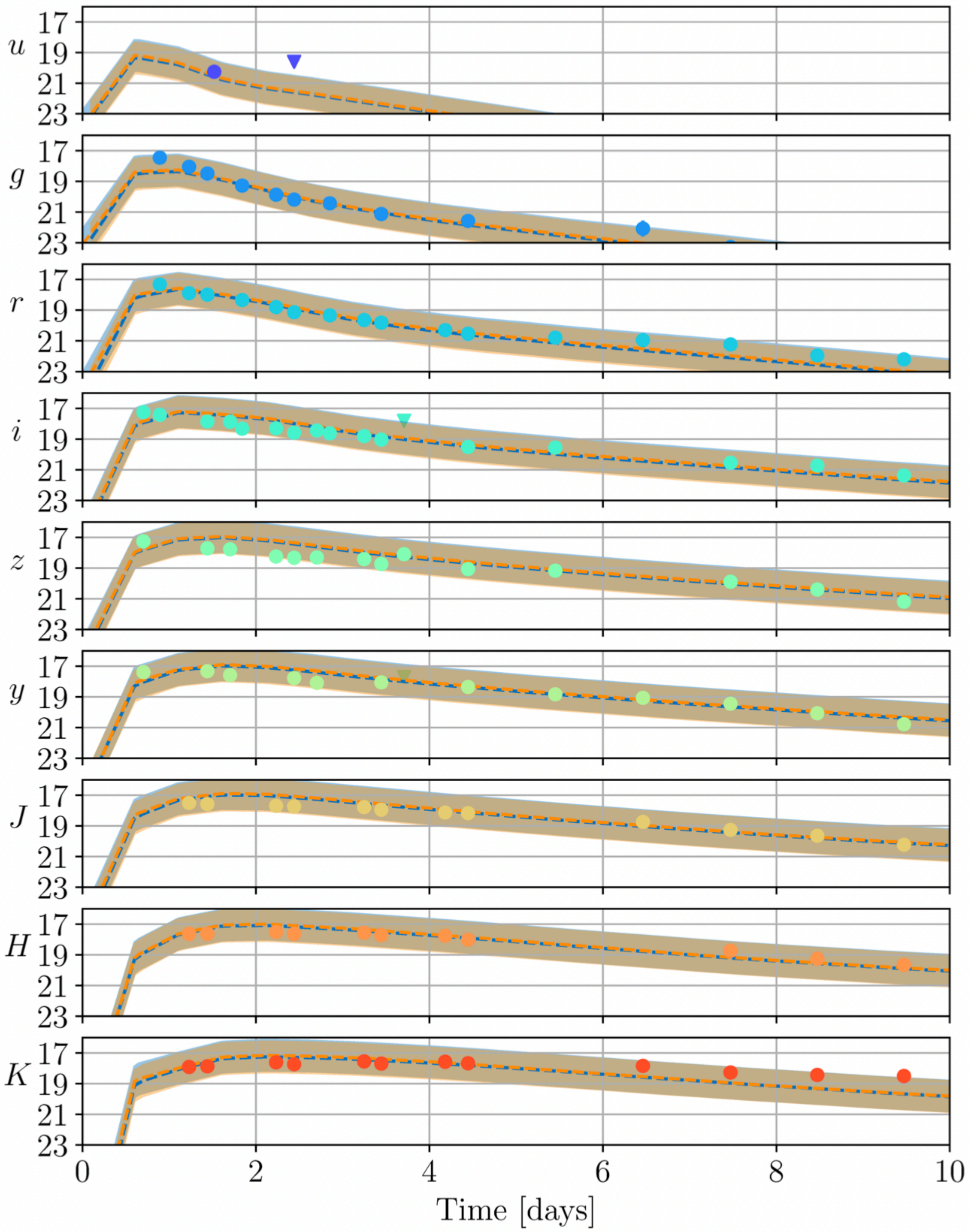
A tutorial about how to produce simulations of lightcurves is given in nmma/tutorials/tutorial-lightcurve_simulation.ipynb

- Open-source
- Python-based
- CI/CD pipeline
- Regularly updated docs

(Pang et al. 2022)

NMMA basics

- MMA pipeline for Bayesian analysis of GW, EM data
- Includes models of KNe, GRB, SNe, etc.
- Workflow: train models on simulated data, download when needed, sample from priors to fit observations and determine event parameters
    - Use cluster resources to run at scale

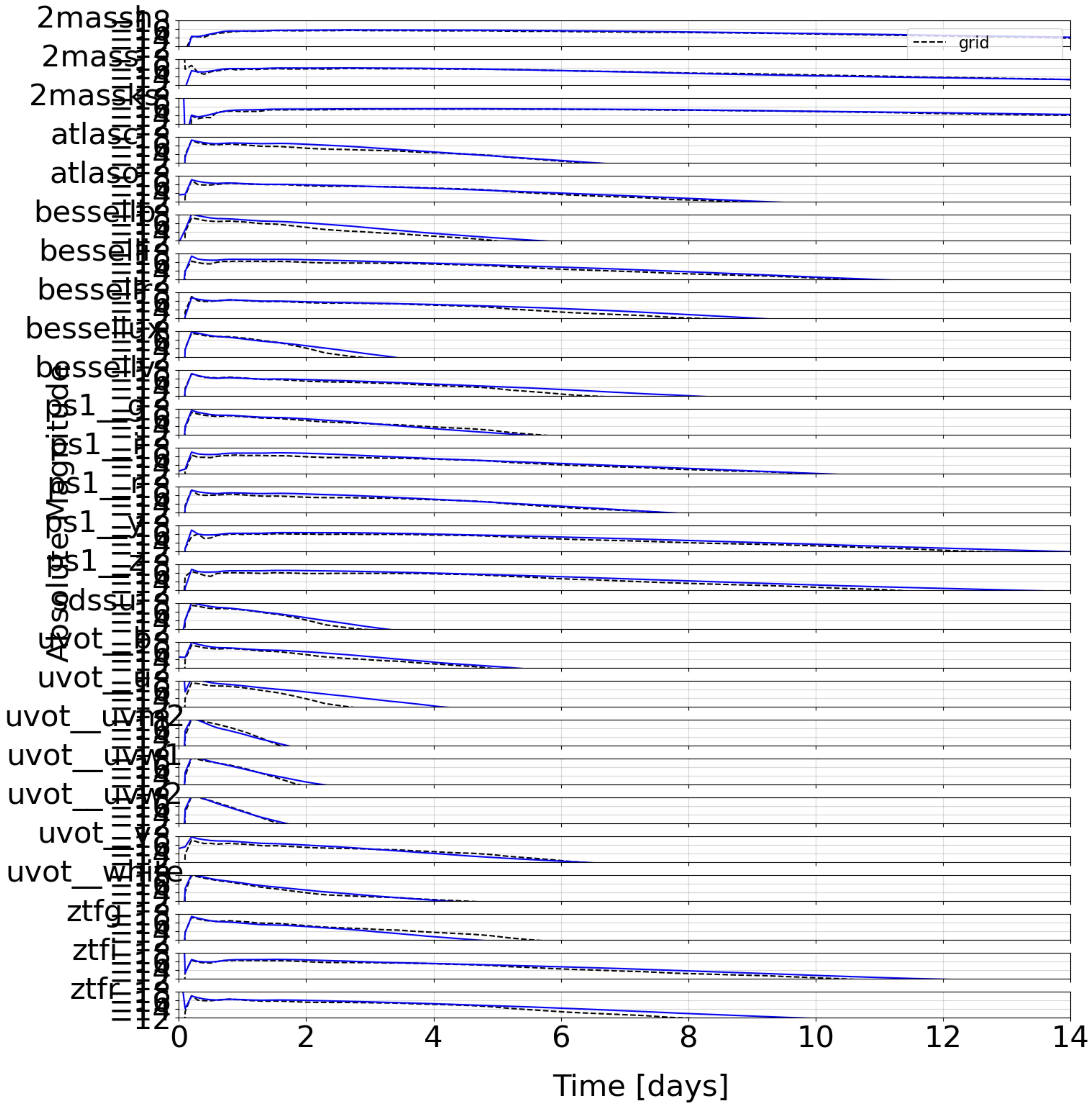


AT2017gfo
(Pang et al. 2022)

Training NMMA models

- Grid of physical parameters produces simulated light curves
  - Want continuous mapping between parameters, light curves
- LCs mapped to eigenvalues using PCA
- Gaussian process/neural network maps between input params, eigenvalues
  - Broad, few-layer NN approximates GP in less compute time

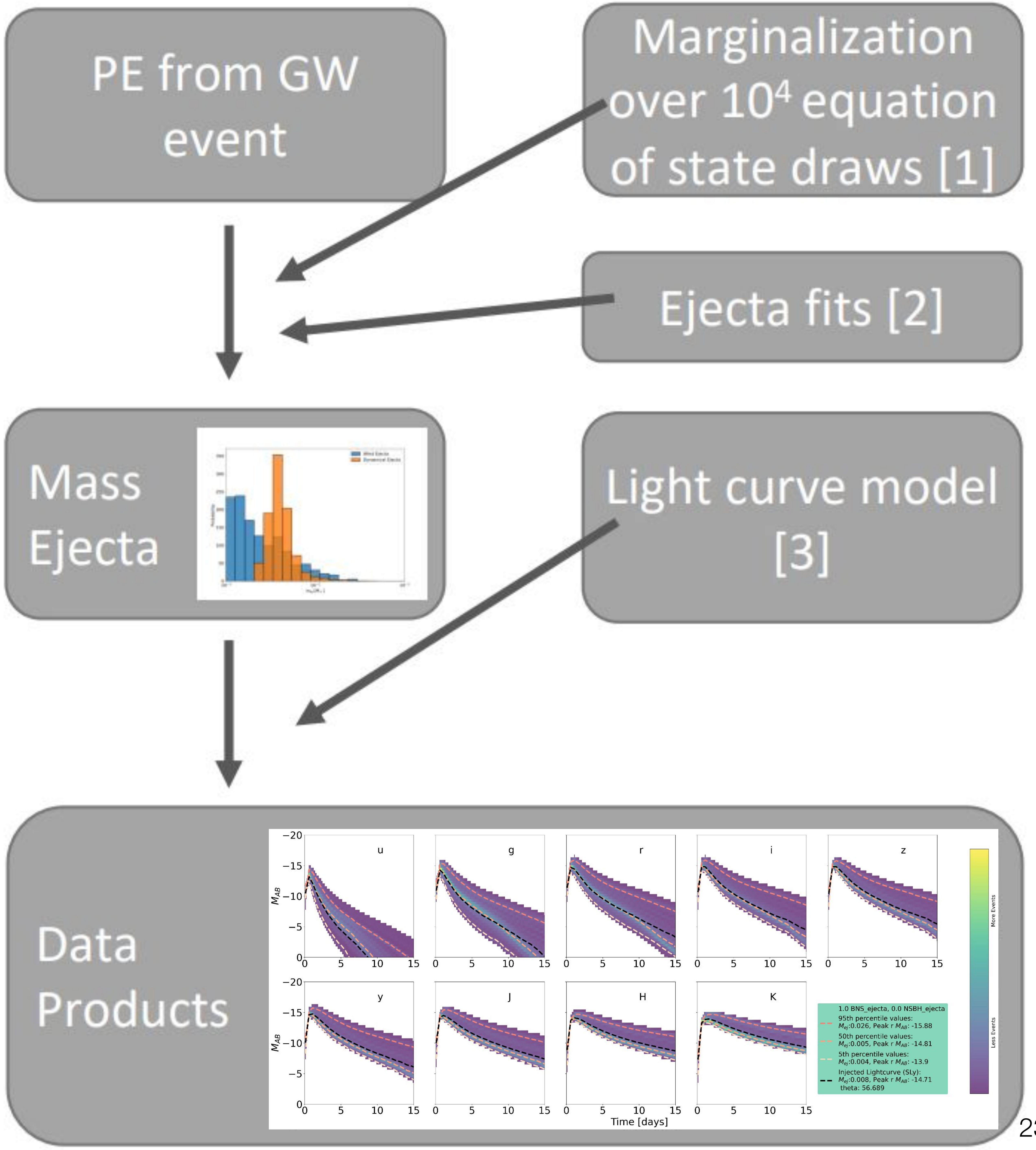
NN training results for new model



Status/goals for NMMA

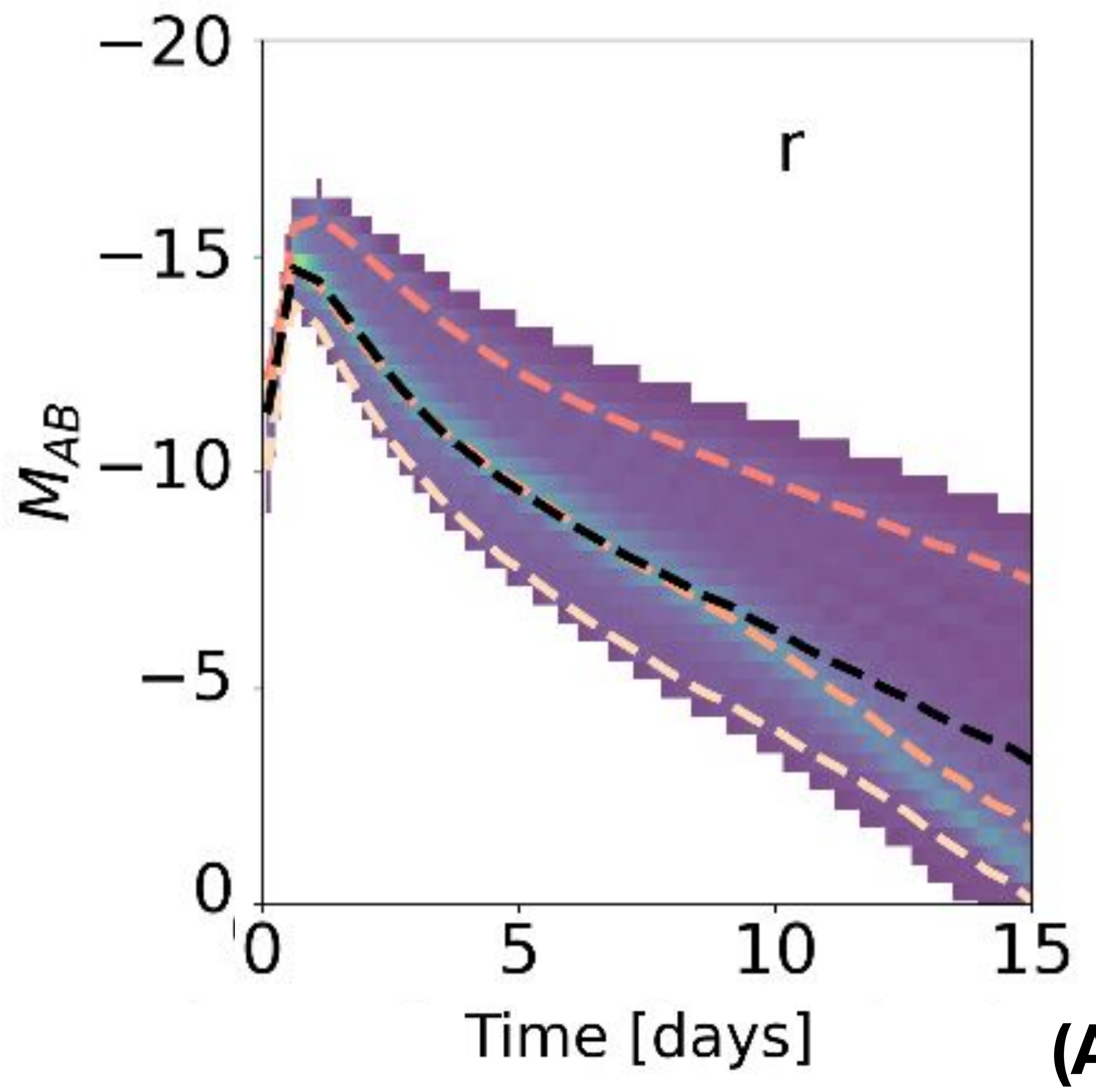
- Updated models being used for analyses of past events
  - New tensorflow training runs faster than GP
- Adding new features as needed, expanding documentation
- Run on GW, EM data as fast as they become available
- Use API service to start automated analyses
- Submit paper $\leq$ 48 hrs after event detected

Kilonova Lightcurves



Data products:

- BNS_ejecta: probability of BNS and $m_{ej} > 10^{-3}\ M_\odot$
- NSBH_ejecta: probability of NSBH and $m_{ej} > 10^{-3}\ M_\odot$
- Peak UVOIR M_{AB} estimate and m_{ej} estimate (90 percent credible interval)



~1.4, 1.4 $M_\odot$
BNS example

(Andrew Toivonen)