ZTF Source Classification Project (SCoPe)

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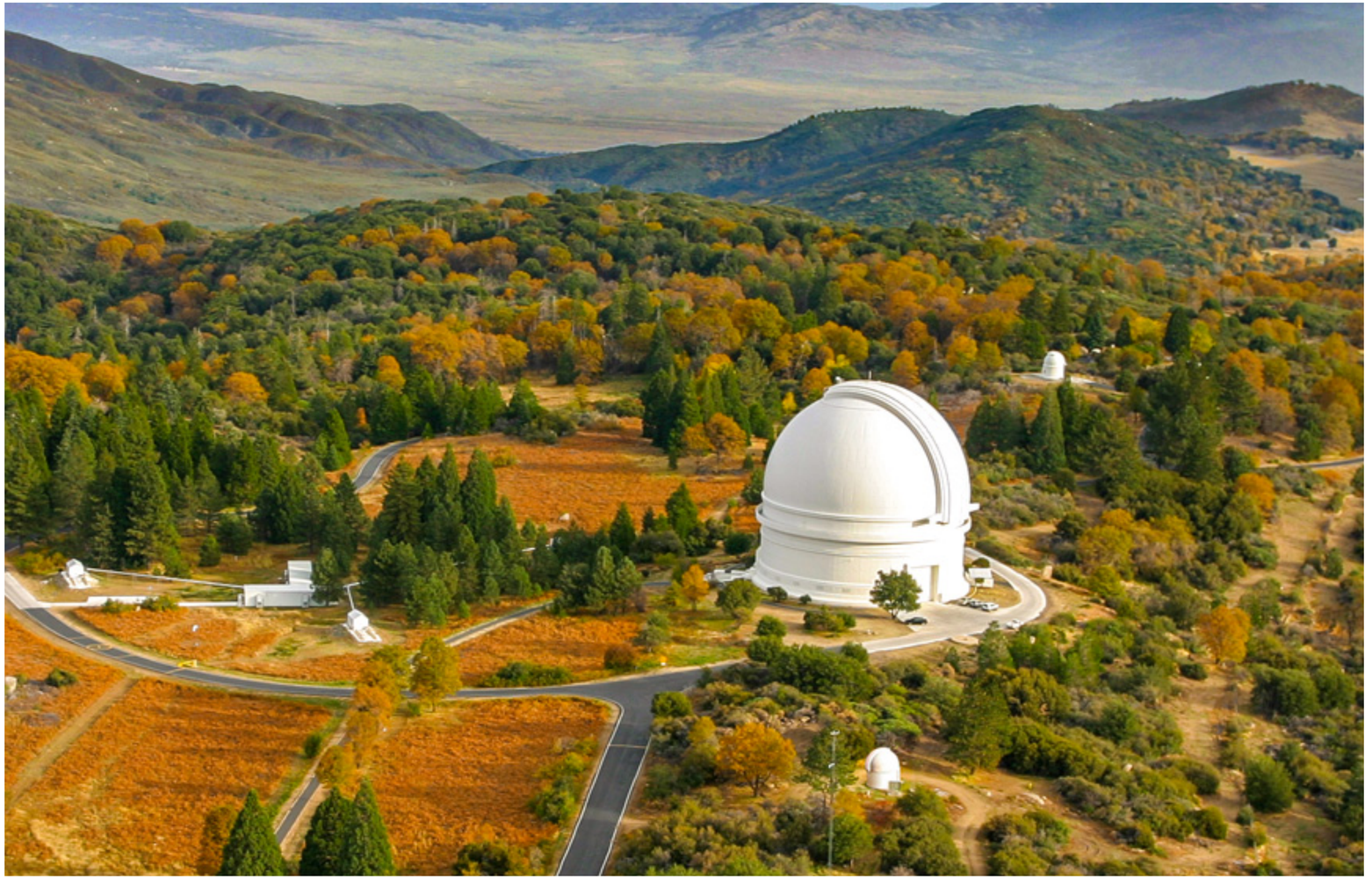
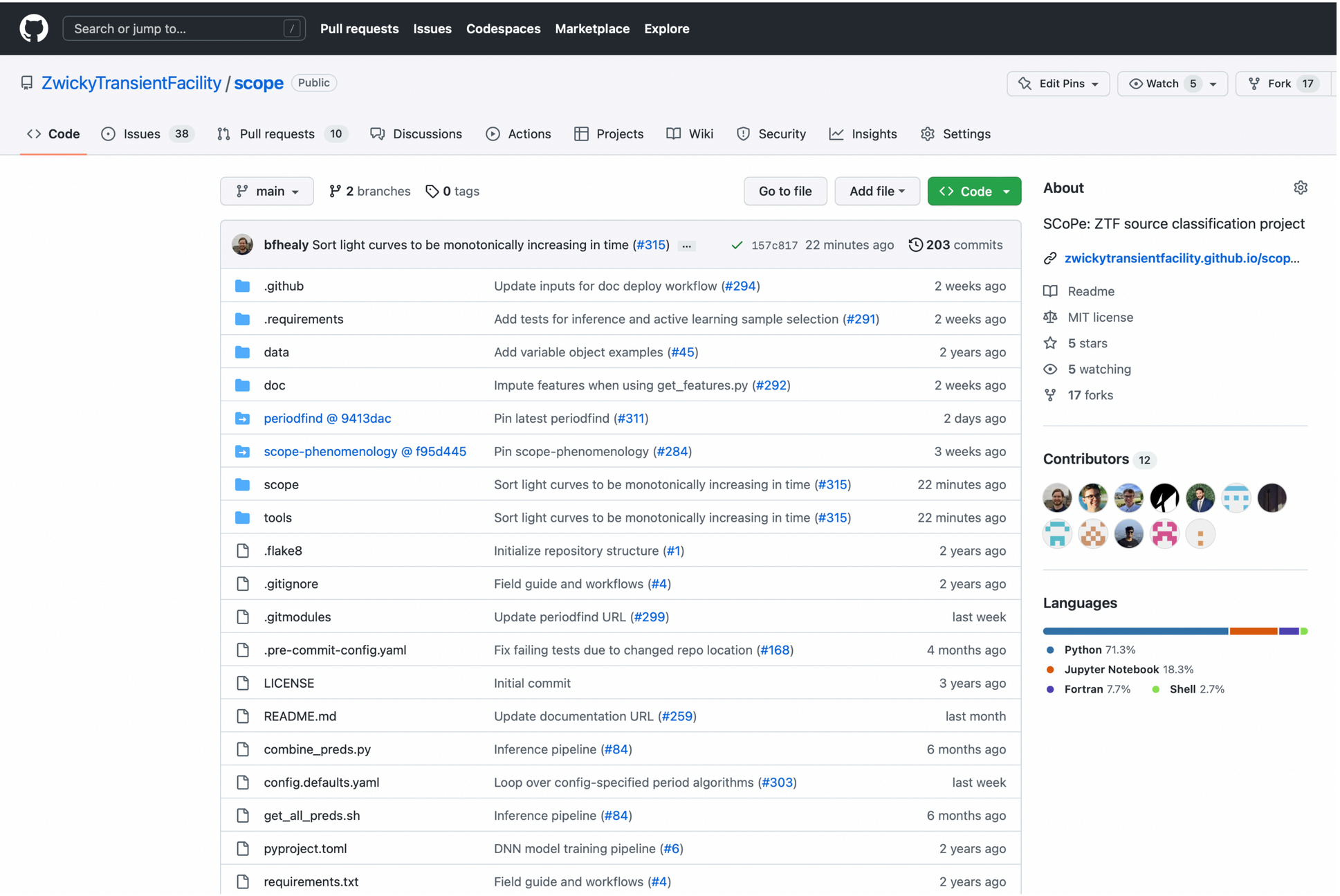
A3D3 Hackathon topic intro (MMA)

Zwicky Transient Facility (ZTF)



(Palomar Observatory/Caltech)

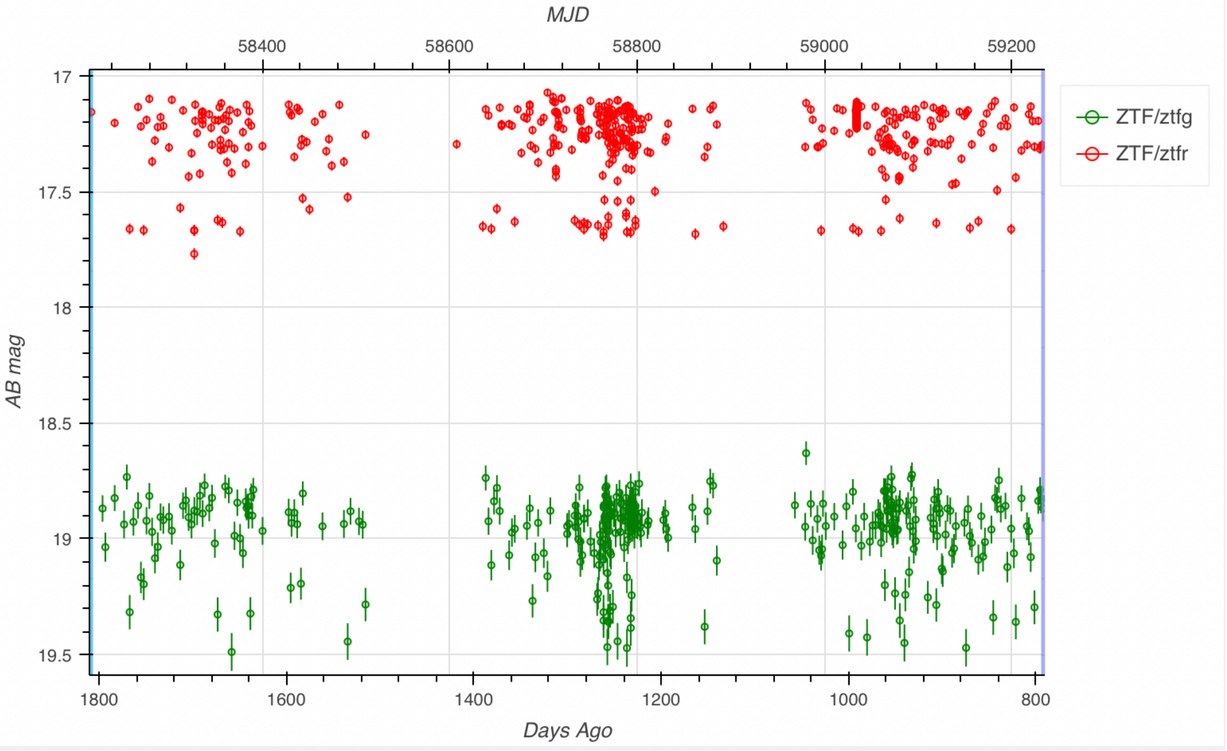
ZTF Source Classification Project (SCoPe)



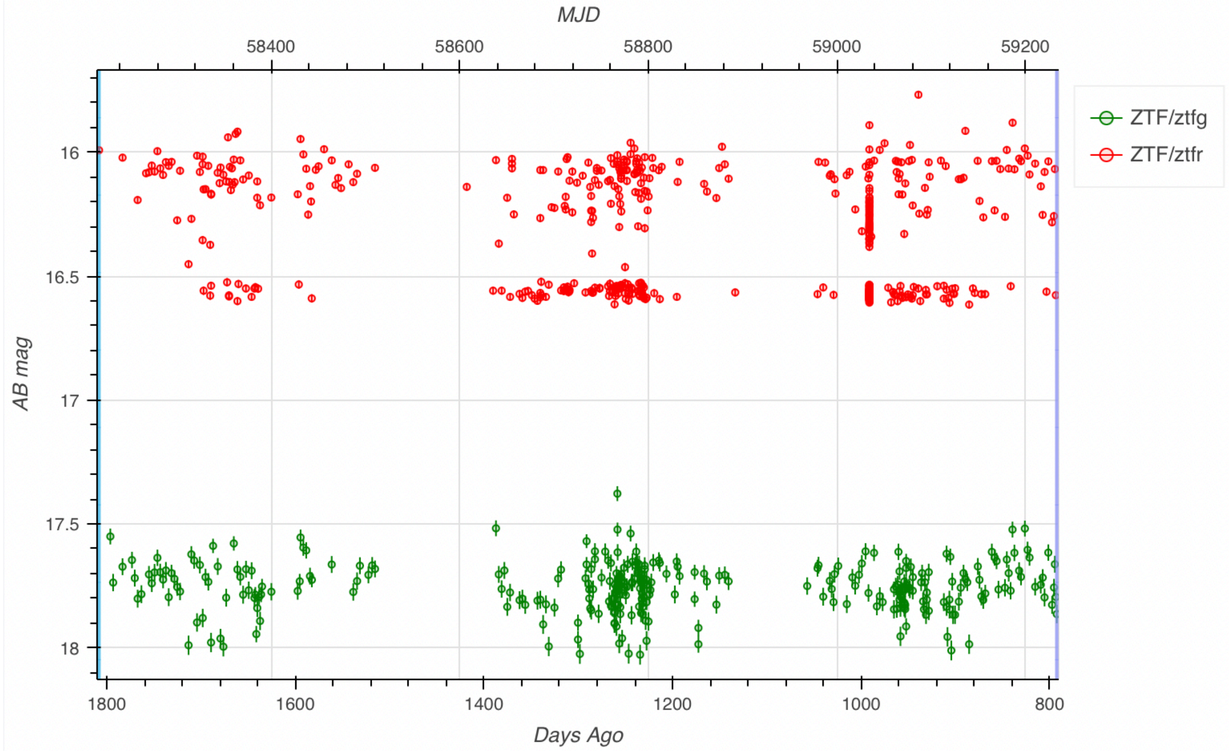
- Open-source
- Python-based
- CI/CD pipeline
- Regularly updated docs
- Hackathon topic!

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

Example ZTF Data

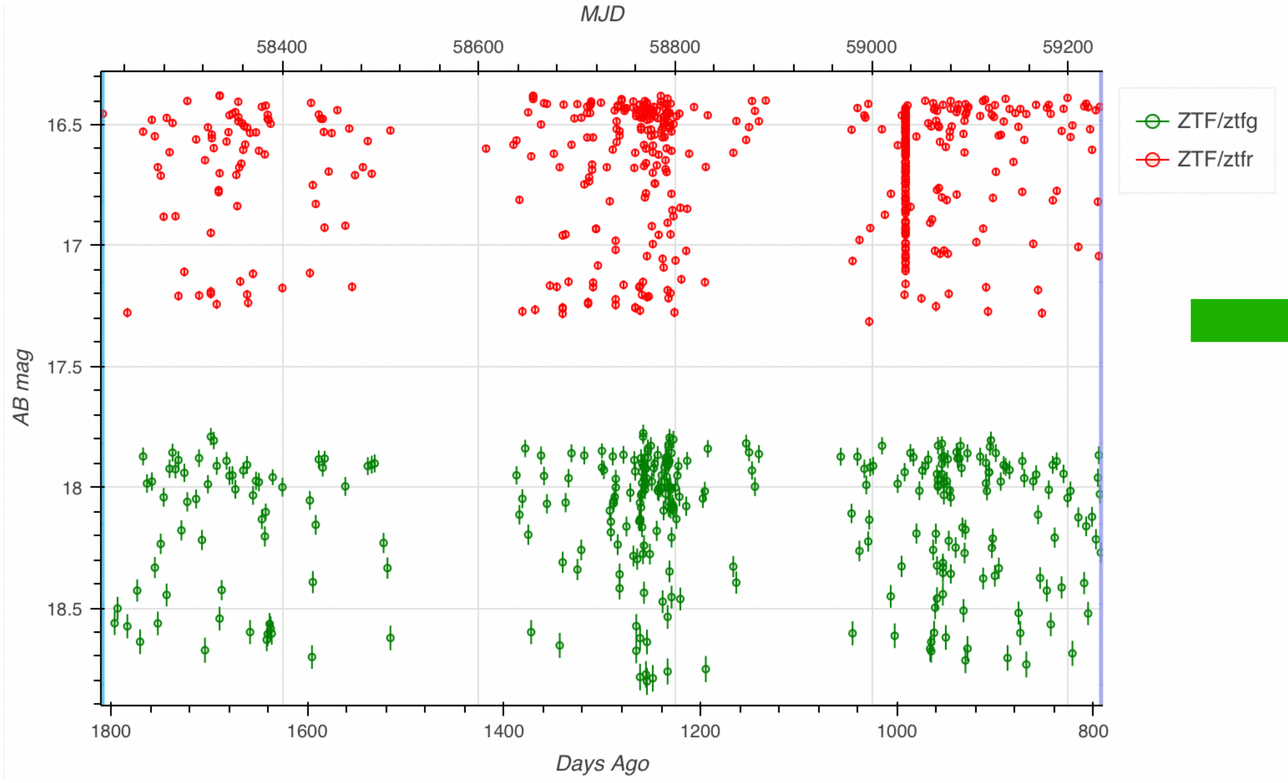


Eclipsing binary



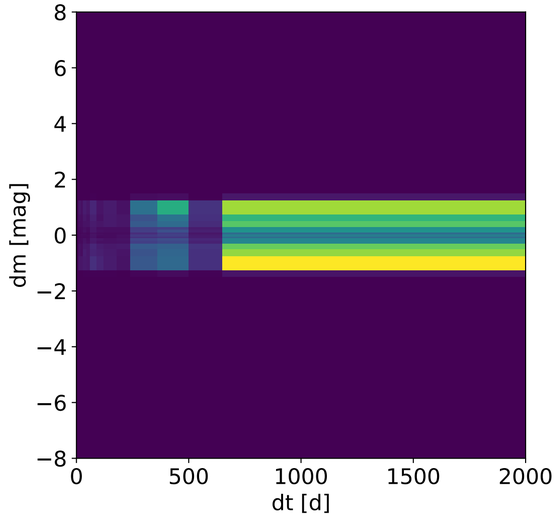
Blend

Input Features



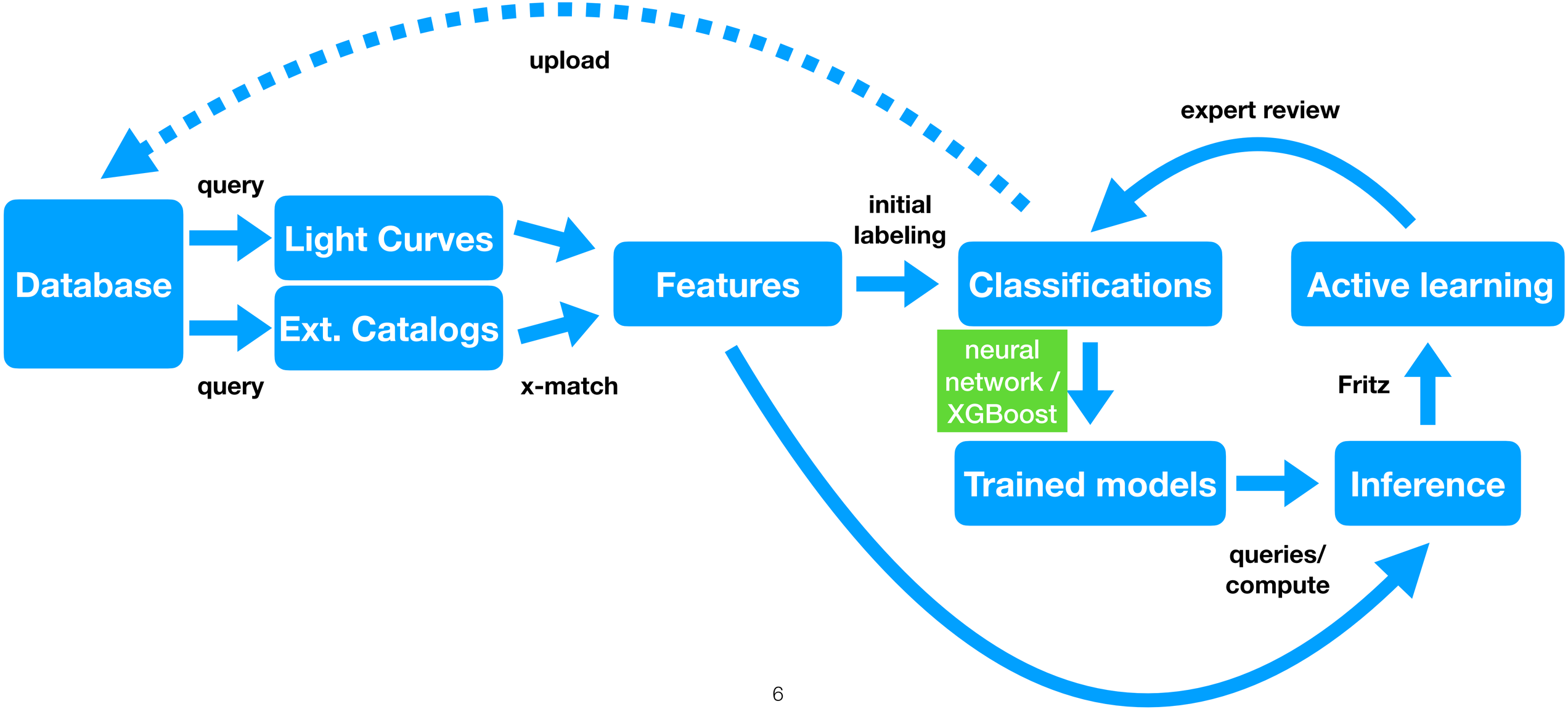
Summary statistics

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

SCoPe workflow



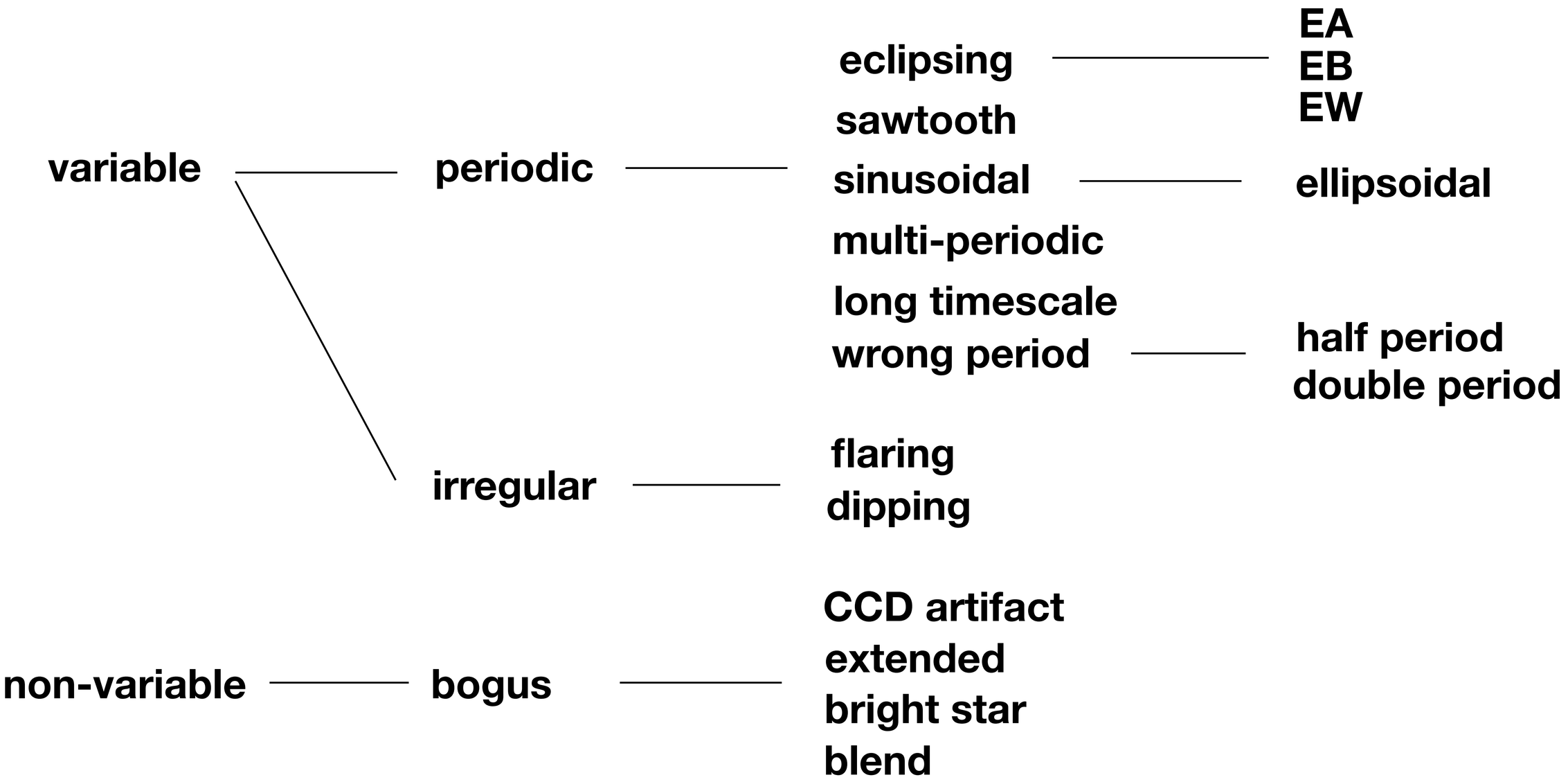
SCoPe Details

- **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

Phenomenological Taxonomy



Ontological Taxonomy

- pulsator
  - Cepheid
    - Fundamental
    - Overtone
  - Delta Scu
  - Pop II Cepheid
    - BL Her
    - W Vir
  - RV Tau
  - RR Lyr
    - RRab
    - RRc
    - RRd
    - RRe
    - Blazhko
- AGN
- YSO
- CV
- LPV
  - Mira
  - SRV
  - OSARG
- binary
  - MS-MS
  - HW Vir
  - W UMa
  - Beta Lyr
  - Compact
    - Redback pulsar
    - NN Ser
  - RS CVn

Hackathon goals

- Modify/introduce ML classifiers
  - Adjust architecture of DNN, XGB (see scope/nn.py, scope/xgb.py)
  - Incorporate RNN or other algorithms (follow pattern of scope/nn.py, or start from scratch)
  - Training plots and results are saved to evaluate performance (models_dnn, models_xgb)
    - Compare these to current performance stats

SCoPe data on Google Drive

https://drive.google.com/drive/folders/13cm3Tf3RtudlVA5fBaMcHVi8anOnn8Gy?usp=sharing

- **Full training set (170632 rows × 247 columns)**
  - Parquet file (see SCoPe docs for comparison with CSV, HDF5)
  - Columns: obj_id, ra, dec; labels; features
  - See **SCoPe training set column guide** Google Sheet
- **10% training set (17063 rows × 247 columns)**
  - `full_training_set.sample(frac=0.1, \ random_state=9).reset_index(drop=True)`
- **SCoPe model performance JSON files (DNN and XGB)**

SCoPe Installation

- Follow documentation here: https://zwickytransientfacility.github.io/scope-docs/
- Create your own fork of the SCoPe repo: https://github.com/ZwickyTransientFacility/scope
  - Also a version on the hackathon organization, but may not always be up-to-date
- `git clone` <link to your forked repo>
- `git remote add upstream` <link to ZTF SCoPe repo>
- Use conda/pip to install requirements in a new `scope-env`
- Test by running `./scope.py test_limited`

Use config.yaml to specify training details

- Copy config.defaults.yaml to a new config.yaml file
- Use `training:` config section to set and modify training details
    - Training set path, features to include, classification thresholds, hyperparameters, etc.

config.defaults.yaml

```yaml
training:
  # Below, enter path to training set
  dataset: tools/fritzDownload/merged_classifications_features.parquet
  xgboost:
    # See scope.py train for descriptions of these parameters
    gridsearch_params_start_stop_step:
      max_depth: [3, 8, 2]
      min_child_weight: [1, 6, 2]
      # subsample, colsample values get divided by 10
      # (default values produce .6, .8, 1.0)
      subsample: [6, 11, 2]
      colsample_bytree: [6, 11, 2]
    other_training_params:
      eta: [0.3, 0.2, 0.1, 0.05]
      seed: 42
      nfold: 5
      metrics: ['auc']
      objective: 'binary:logistic'
      eval_metric: 'auc'
      early_stopping_rounds: 10
      num_boost_round: 999
  classes:
    # phenomenological classes
    vnv:
      # value of label should refer to dataset.dN.csv
      label: variable
      # conv_branch: false
      # value should refer to features section of this config
      features: phenomenological
      # our "labels" are floats [0., 0.25, 0.5, 0.75, 1.]
      threshold: 0.7
      # balance ratio for the prevalent class. leave null to use all available data
      balance:
      weight_per_class: false
      amsgrad: 0.0003724
      epsilon: 1.945e-8
      lr: 0.02229
```

Training ML algorithms with SCoPe

- Default train/val/test split: 0.81/0.09/0.10

- `./scope.py train --tag=vnv --path_dataset=/path/to/trainingset.parquet --verbose --save --plot --group=group_name --period_suffix=ELS_ECE_EAOV`

- `./scope.py train --tag=vnv --algorithm=xgb --path_dataset=/path/to/trainingset.parquet --verbose --save --plot --group=xgb_group_name --period_suffix=ELS_ECE_EAOV`

Other notes

- SCoPe has utilities to read parquet files, manage datasets
  - `from scope.utils import read_parquet, Dataset`
- Some labels in training set can are inconsistently applied
  - Many sources with incorrect periods are not labeled “wrong period”
- Use caution when improving stats by selectively reducing size of training data (e.g. the `balance` hyperparameter)
  - Can get deceptively good results because classifier is not exposed to enough types of negative examples