actsnclass

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Contents

CHAPTER 1

Recommendation System for Spectroscopic Follow-up

This tool allows the constructon of an optimized spectroscopic observation strategy which enables photometric supernova cosmology. It was developed as a collaboration between the LSST DESC and the Cosmostatistics Initiative.

This grew from the work presented in Ishida et al., 2019

The code has been updated to allow a friendly use and expansion.

1.1 Getting started

This code was developed for `Python3` and was not tested in Windows.

We recommend that you work within a virtual environment.

You will need to install the *Python* package `virtualenv`. In MacOS or Linux, do

```
>>> python3 -m pip install --user virtualenv
```

Navigate to a `working_directory` where you will store the new virtual environment and create it:

```
>>> python3 -m venv ActSNClass
```

Hint: Make sure you deactivate any `conda` environment you might have running before moving forward.

Once the environment is set up you can activate it:

You should see a `(ActSNClass)` flag in the extreme left of terminal command line.

Next, clone this repository in another chosen location:

```
(ActSNClass) >>> git clone https://github.com/COINtoolbox/ActSNClass
```

Navigate to the repository folder and do

```
(ActSNClass) >>> pip install -r requirements.txt
```

You can now install this package with:

```
(ActSNClass) >>> python setup.py develop
```

Hint: You may choose to create your virtual environment within the folder of the repository. If you choose to do this, you must remember to exclude the virtual environment directory from version control using e.g., `.gitignore`.

1.1.1 Setting up a working directory

In a your choosing, create the following directory structure:

```
work_dir
├── plots
├── results
```

The outputs of `ActSNClass` will be stored in these directories.

In order to set things properly, navigate to the repository you just cloned and move the data directory to your chosen working directory and unpack the data.

```
>>> mv -f actsnclass/data/ work_dir/
>>> cd work_dir/data
>>> tar -xzvf SIMGEN_PUBLIC_DES.tar.gz
```

This data was provided by Rick Kessler, after the publication of results from the SuperNova Photometric Classification Challenge. It allows you to run tests and validate your installation.

For the RESSPECT project data can be found in the COIN server. Check the minutes document for the module you are interested in for information about the exact location.

1.2 Analysis steps

The active learning pipeline is composed of 4 important steps:

1. Feature extraction
2. Classifier
3. Query Strategy
4. Metric evaluation

These are arranged in the adaptable learning process (figure to the right).

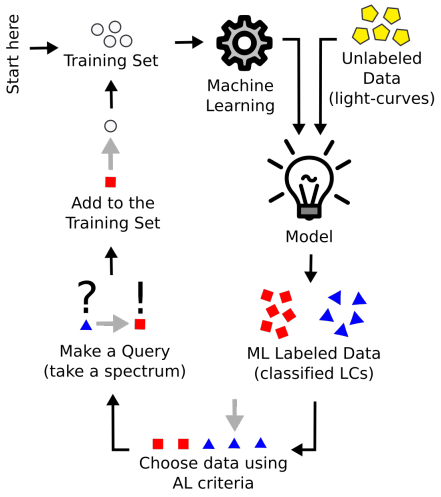

Fig. 1: Figure by Bruno Quint.

1.2.1 Using this package

Step 1 is considered pre-processing. The current code does the feature extraction using the Bazin parametric function for the complete training and test sample before any machine learning application is used.

Details of the tools available to evaluate different steps on feature extraction can be found in the *Feature extraction page*.

Alternatively, you can also perform the full light curve fit for the entire sample from the command line:

```
>>> fit_dataset.py -s RESSPECT -p <path_to_photo_
↪file> -hd <path_to_header_file> -o <output_file>
```

Once the data has been processed you can apply the full Active Learning loop according to your needs. A detail description on how to use this tool is provided in the *Learning Loop page*.

The command line option require a few more inputs than the feature extraction stage, but it is also available:

```
>>> run_loop.py -i <input␣
↪features file> -b <batch size> -n <number of loops>
>>>              -d <output␣
↪metrics file> -q <output queried sample file>
>>>              -s␣
↪<learning strategy> -t <choice of initial training>
```

We also provide detail explanation on how to use this package to produce other stages of the pipeline like: *prepare the Canonical sample*, *prepare data for time domain* and *produce plots*.

We also provide detail descriptions on how to contribute with other modules in the *How to contribute* tab.

Enjoy!!

Acknowledgements

This work is heavily based on the first prototype developed during COIN Residence Program (CRP#4), held in Clermont Ferrand, France, 2017 and financially supported by Universite Clermont Auvergne and La Region Auvergne-Rhone-Alpes. We thank Emmanuel Gangler for encouraging the realization of this event.

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This work would not be possible without intensive consultation to online platforms and discussion forums. Although it is not possible to provide a complete list of the open source material consulted in the construction of this material, we recognize their importance and **deeply thank all those who contributes to open learning platforms**.

1.2.2 Dependencies

`actsnclass` was developed under `Python3`. The complete list of dependencies is given below:

- Python>=3.7
- astropy>4.0
- matplotlib>=3.1.1
- numpy>=1.17.0
- pandas>=0.25.0
- setuptools>=41.0.1

- scipy>=1.3.0
- sklearn>=0.20.3
- seaborn>=0.9.0

1.3 Table of Contents

1.3.1 Feature Extraction

The first stage in consists in transforming the raw data into a uniform data matrix which will subsequently be given as input to the learning algorithm.

The original implementation of `actsnclass` can handle text-like data from the SuperNova Photometric Classification Challenge (SNPCC) which is described in Kessler et al., 2010.

This version is equiped to input `RESSPECT` simulatons made with the SNANA simulator.

Load 1 light curve:

For RESSPECT

In order to fit a single light curve from the RESSPECT simulations you need to have its identification number. This information is stored in the header SNANA files. One of the possible ways to retrieve it is:

```
>>> import io
>>> import pandas as pd
>>> import tarfile

>>> path_to_header = '~/RESSPECT_PERFECT_V2_TRAIN_HEADER.tar.gz'

# openning '.tar.gz' files requires some juggling ...
>>> tar = tarfile.open(path_to_header, 'r:gz')
>>> fname = tar.getmembers()[0]
>>> content = tar.extractfile(fname).read()
>>> header = pd.read_csv(io.BytesIO(content))
>>> tar.close()

# get keywords
>>> header.keys()
Index(['objid', 'redshift', 'type', 'code', 'sample'], dtype='object')

# check the first chunks of ids and types
>>> header[['objid', 'type']].iloc[:10]
   objid     type
0   3228  Ibc_V19
1   2241      IIn
2   6770       Ia
3    302      IIn
4   7948       Ia
5   4376   II_V19
6    337   II_V19
7   6017       Ia
8   1695       Ia
9   1660   II-NMF
```

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```
>> snid = header['objid'].values[4]
```

Now that you have selected on object, you can fit its light curve using the LightCurve class :

```
>>> from actsnclass.fit_lightcurves import LightCurve

>>> path_to_lightcurves = '~/RESSPECT_PERFECT_V2_TRAIN_LIGHTCURVES.tar.gz'

>>> lc = LightCurve()
>>> lc.load_resspect_lc(photo_file=path_to_lightcurves, snid=snid)

# check light curve format
>>> lc.photometry
          mjd band      flux    fluxerr        SNR
0     53058.0    u  0.138225  0.142327   0.971179
1     53058.0    g -0.064363  0.141841  -0.453768
...       ...  ...       ...       ...        ...
1054  53440.0    z  1.173433  0.145918   8.041707
1055  53440.0    Y  0.980438  0.145256   6.749742
```

[1056 rows x 5 columns]

For PLAsTiCC:

Similar to the case presented below, reading only 1 light curve from PLAsTiCC requires an object identifier. This can be done by:

```
>>> from actsnclass.fit_lightcurves import LightCurve
>>> import pandas as pd

>>> path_to_metadata = '~/plasticc_train_metadata.csv.gz'
>>> path_to_lightcurves = '~/plasticc_train_lightcurves.csv.gz'

# read metadata for the entire sample
>>> metadata = pd.read_csv(path_to_metadata)

# check keys
metadata.keys()
Index(['object_id', 'ra', 'decl', 'ddf_bool', 'hostgal_specz',
       'hostgal_photoz', 'hostgal_photoz_err', 'distmod', 'mwebv', 'target',
       'true_target', 'true_submodel', 'true_z', 'true_distmod',
       'true_lensdmu', 'true_vpec', 'true_rv', 'true_av', 'true_peakmjd',
       'libid_cadence', 'tflux_u', 'tflux_g', 'tflux_r', 'tflux_i', 'tflux_z',
       'tflux_y'],
     dtype='object')

# choose 1 object
snid = metadata['object_id'].values[0]

# create light curve object and load data
lc = LightCurve()
lc.load_plasticc_lc(photo_file=path_to_lightcurves, snid=snid)
```

For SNPCC:

The raw data looks like this:

```
SURVEY: DES
SNID:   848233
IAUC:    UNKNOWN
PHOTOMETRY_VERSION: DES
SNTYPE:  22
FILTERS: griz
RA:      36.750000  deg
DECL:    -4.500000  deg
MAGTYPE: LOG10
MAGREF:  AB
FAKE:    2   (=> simulated LC with snlc_sim.exe)
MWEBV:   0.0283    MW E(B-V)
REDSHIFT_HELIO:   0.50369 +- 0.00500  (Helio, z_best)
REDSHIFT_FINAL:   0.50369 +- 0.00500  (CMB)
REDSHIFT_SPEC:    0.50369 +- 0.00500
REDSHIFT_STATUS: OK

HOST_GALAXY_GALID:   17173
HOST_GALAXY_PHOTO-Z:   0.4873  +- 0.0318



SIM_MODEL:  NONIA  10  (name index)
SIM_NON1a:      30   (non1a index)
SIM_COMMENT:  SN Type = II , MODEL = SDSS-017564
SIM_LIBID:  2
SIM_REDSHIFT:  0.5029
SIM_HOSTLIB_TRUEZ:  0.5000  (actual Z of hostlib)
SIM_HOSTLIB_GALID:  17173
SIM_DLMU:      42.276020  mag   [ -5*log10(10pc/dL) ]
SIM_RA:        36.750000 deg
SIM_DECL:      -4.500000 deg
SIM_MWEBV:   0.0256   (MilkyWay E(B-V))
SIM_PEAKMAG:   22.48  22.87  22.70  22.82  (griz obs)
SIM_EXPOSURE:     1.0    1.0    1.0    1.0  (griz obs)
SIM_PEAKMJD:   56251.609375  days
SIM_SALT2x0:   1.229e-17
SIM_MAGDIM:    0.000
SIM_SEARCHEFF_MASK:  3  (bits 1,2=> found by software,humans)
SIM_SEARCHEFF:  1.0000  (spectro-search efficiency (ignores pipelines))
SIM_TRESTMIN:   -38.24   days
SIM_TRESTMAX:    64.80   days
SIM_RISETIME_SHIFT:   0.0 days
SIM_FALLTIME_SHIFT:   0.0 days

SEARCH_PEAKMJD:   56250.734


# ============================================
# TERSE LIGHT CURVE OUTPUT:
#
NOBS: 108
NVAR: 9
```

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```
VARLIST:  MJD  FLT FIELD   FLUXCAL   FLUXCALERR   SNR     MAG     MAGERR  SIM_MAG
OBS:  56194.145  g NULL   7.600e+00   4.680e+00   1.62   99.000    5.000   98.926
OBS:  56194.156  r NULL   3.875e+00   2.752e+00   1.41   99.000    5.000   98.953
OBS:  56194.172  i NULL   3.585e+00   4.628e+00   0.77   99.000    5.000   99.033
OBS:  56194.188  z NULL  -2.203e+00   4.463e+00  -0.49   99.000    5.000   98.983
OBS:  56207.188  g NULL  -7.008e+00   4.367e+00  -1.60   99.000    5.000   98.926
OBS:  56207.195  r NULL  -1.189e+00   3.459e+00  -0.34   99.000    5.000   98.953
OBS:  56207.203  i NULL   8.799e+00   6.249e+00   1.41   99.000    5.000   99.033
```

You can load this data using:

```
>>> from actsnclass.fit_lightcurves import LightCurve

>>> path_to_lc = 'data/SIMGEN_PUBLIC_DES/DES_SN848233.DAT'

>>> lc = LightCurve()                          # create light curve instance
>>> lc.load_snpcc_lc(path_to_lc)               # read data
```

Fit 1 light curve:

Once the data is properly loaded, the photometry can be recovered by:

```
>>> lc.photometry                                # check structure of photometry
          mjd band     flux  fluxerr   SNR
 0    56194.145    g   7.600    4.680   1.62
 1    56194.156    r   3.875    2.752   1.41
 ...        ...  ...     ...      ...   ...
 106  56348.008    z  70.690    6.706  10.54
 107  56348.996    g  26.000    5.581   4.66
```

You can now fit each individual filter to the parametric function proposed by Bazin et al., 2009 in one specific filter.

```
>>> rband_features = lc.fit_bazin('r')
>>> print(rband_features)
[159.25796385, -13.39398527,  55.16210333, 111.81204143, -20.13492354]
```

The designation for each parameter are stored in:

It is possible to perform the fit in all filters at once and visualize the result using:

```
>>> lc.fit_bazin_all()                              # perform Bazin fit in all filters
>>> lc.plot_bazin_fit(save=True, show=True,
                      output_file='plots/SN' + str(lc.id) + '.png')    # save to file
```

Processing all light curves in the data set

There are 2 way to perform the Bazin fits for the entire SNPCC data set. Using a python interpreter,

```
>>> from actsnclass import fit_snpcc_bazin

>>> path_to_data_dir = 'data/SIMGEN_PUBLIC_DES/'            # raw data directory
>>> output_file = 'results/Bazin.dat'                          # output file
>>> fit_snpcc_bazin(path_to_data_dir=path_to_data_dir, features_file=output_file)
```

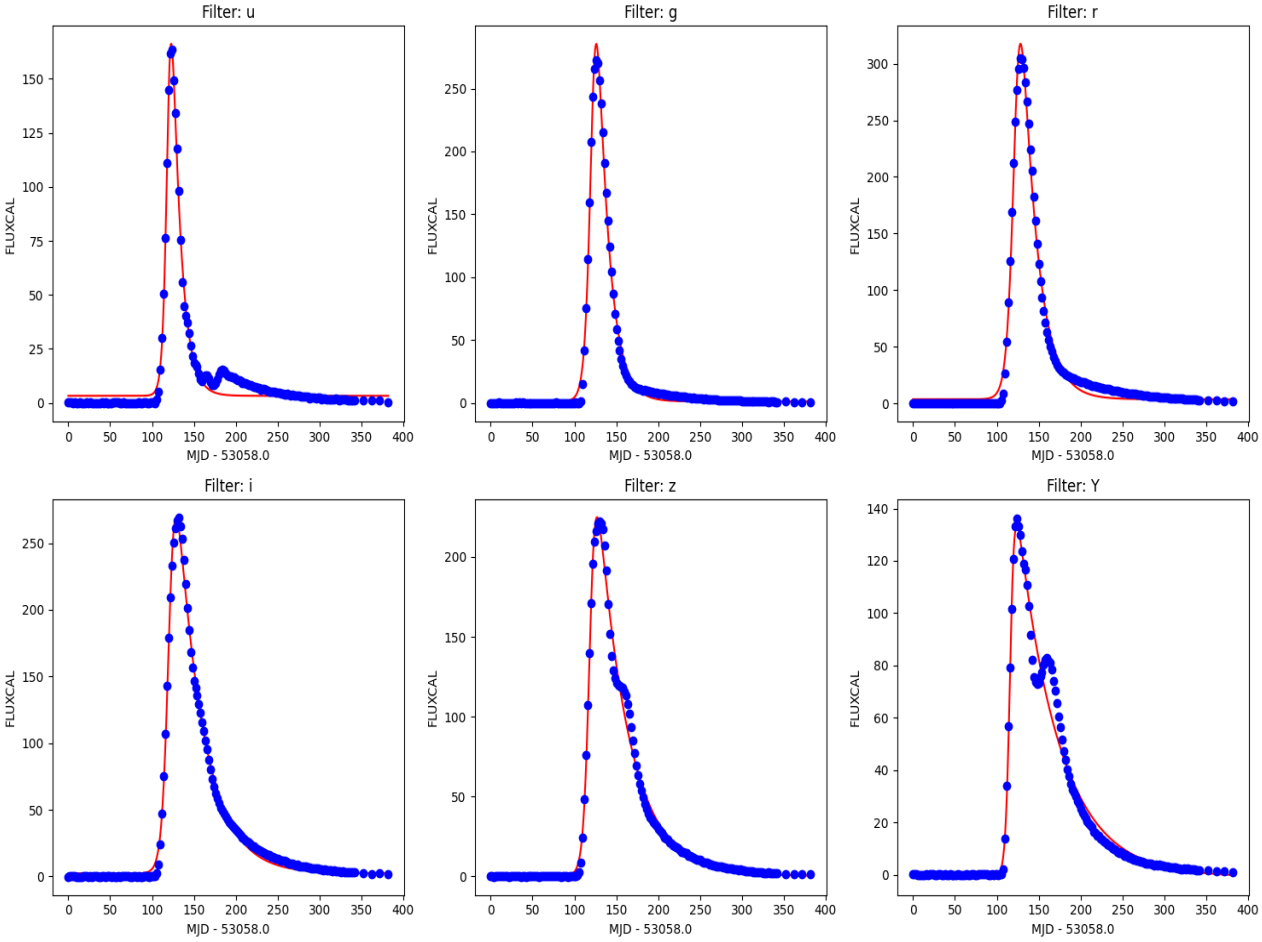


Fig. 2: Example of light curve from RESSPECT perfect simulations.

The above will produce a file called `Bazin.dat` in the *results* directory.

The same result can be achieved using the command line:

```
# for SNPCC
 >>> fit_dataset.py -s SNPCC -dd <path_to_data_dir> -o <output_file>

 # for RESSPECT or PLAsTiCC
 >>> fit_dataset.py -s <dataset_name> -p <path_to_photo_file>
          -hd <path_to_header_file> -o <output_file>
```

1.3.2 Building the Canonical sample

According to the nomenclature used in Ishida et al., 2019, the Canonical sample is a subset of the test sample chosen to hold the same characteristics of the training sample. It was used to mimic the effect of continuously adding elements to the training sample under the traditional strategy.

It was constructed using the following steps:

1. From the raw light curve files, build a metadata matrix containing: `[snid, sample, sntype, z, g_pkmag, r_pkmag, i_pkmag, z_pkmag, g_SNR, r_SNR, i_SNR, z_SNR]` where `z` corresponds to redshift, `x_pkmag` is the simulated peak magnitude and `x_SNR` denotes the mean SNR, both in filter x;
2. Separate original training and test set in 3 subsets according to SN type: [Ia, Ibc, II];
3. For each object in the training sample, find its nearest neighbor within objects of the test sample of the same SN type and considering the photometric parameter space built in step 1.

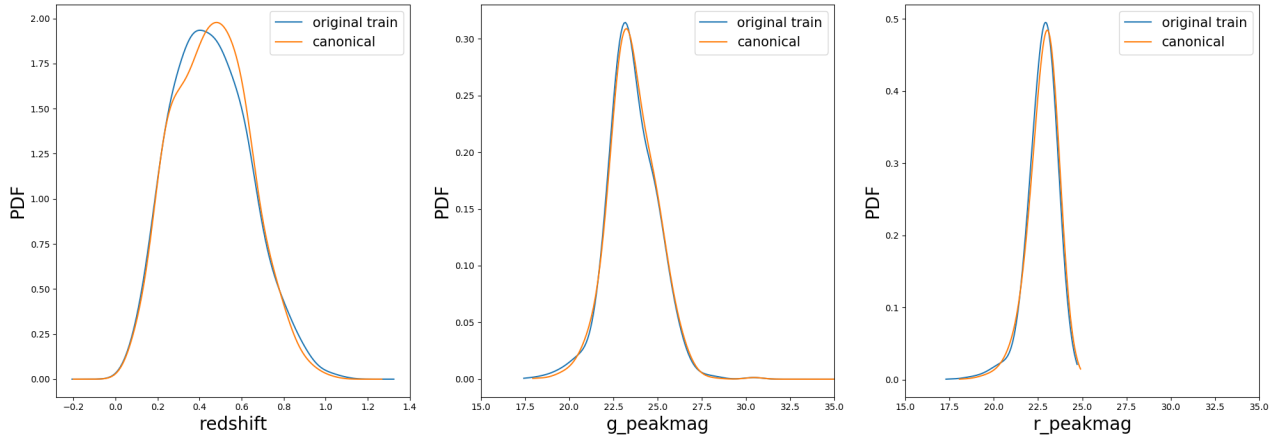
This will allow you to construct a Canonical sample holding the same characteristics and size of the original training sample but composed of different objects.

`actsnclass` allows you to perform this task using the py:mod:*actsnclass.build_snpcc_canonical* module:

```
>>> from snactclass import build_snpcc_canonical

>>> # define variables
>>> data_dir = 'data/SIMGEN_PUBLIC_DES/'
>>> output_sample_file = 'results/Bazin_SNPCC_canonical.dat'
>>> output_metadata_file = 'results/Bazin_metadata.dat'
>>> features_file = 'results/Bazin.dat'

>>> sample = build_snpcc_canonical(path_to_raw_data: data_dir, path_to_
↪features=features_file,
>>>                                output_canonical_file=output_sample_file,
>>>                                output_info_file=output_metadata_file,
>>>                                compute=True, save=True)
```

Once the samples is constructed you can compare the distribution in `[z, g_pkmag, r_pkmag]` with a plot:

```
>>> from actsnclass import plot_snpcc_train_canonical

>>> plot_snpcc_train_canonical(sample, output_plot_file='plots/compare_canonical_
↪train.png')
```



In the command line, using the same parameters as in the code above, you can do all at once:

```
>>> build_canonical.py -c <if True compute metadata>
>>>        -d <path to raw data dir>
>>>        -f <input features file> -m <output file for metadata>
>>>        -o <output file for canonical sample> -p <comparison plot file>
>>>        -s <if True save metadata to file>
```

You can check that the file `results/Bazin_SNPCC_canonical.dat` is very similar to the original features file. The only difference is that now a few of the `sample` variables are set to `queryable`:

```
id redshift type code sample gA gB gt0 gtfall gtrise rA rB rt0 rtfall rtrise iA iB␣
↪it0 itfall itrise zA zB zt0 ztfall ztrise
116537 0.5547 II 36 test 10.969309008063526 -2.505571025776927 33.36879338510094 89.
↪92091344407919 -1.4070121479476083 35.57261257957346 -0.97172916012906 47.
↪691951316763436 37.48483229249487 -7.146619117223875 41.16723042762342 0.
↪14005823764049471 47.983238664813264 39.02626334489017 -6.096248676680143 36.
↪82968789062783 -0.373638211418927 48.438610651533445 41.8848763303308 -7.
↪169183522127793
855370 0.5421 Ibc 23 test -5.514648646328689 3.370545820694393 6.890703579070343 127.
↪00223553079377 -0.04721760599586505 27.987087830949765 -0.4446376337515848 51.
↪06299616763716 13.46475077451422 -0.7802021055103384 42.50390337399486 1.
↪217778587283846 63.88727539461748 4.425762504064253 -2.826164280709543 57.
↪08358377564619 -0.9866672975549484 65.3976378960504 2.88096954432307 -2.
↪211749860376304
328118 0.3131 II 37 test 28.134338786167365 0.7147372066065217 45.830405214215425 15.
↪850284787778433 -0.0005766632993162762 29.225476277548275 -1.9734118280637896 45.
↪83230493446332 87.25700882127312 -0.00025821702716214264 24.95217257542528 -0.
↪3731568724509137 40.527255841246365 311.42509172517947 -3.099534332677601 46.
↪782672798921226 -0.05678675661798624 53.51739930097104 50.76716462668245 -4.
↪572685479766832
704481 0.4665 Ia 0 queryable -50.86850174812521 2.4148469184147547 16.05240678384717␣
↪3.5459318666713298 -0.4734666030325012 74.65602268994473 -3.763616485144308 48.
↪208444944828855 24.3318092539982 -4.452287612782472 83.29745588526693 -7.
↪371877954771961 50.92270461365078 38.76468635410394 -10.931632426569717 73.
↪35112115534632 -1.2509966370291774 40.053959252846106 44.453394158157614 -0.
↪18674652754319326
43679 0.5756 II 33 test 28.24271470397688 -3.438072722932048 23.521675700587007 32.
↪4401288159836 -0.2295765027048151 -37.86668398190429 6.8580060036559365 22.
↪252525376185087 2.3940753934318044 -1.611409074593934 -20.420915833911547 9.
↪2659565057976 7.0218302478113035 23.713442135755557 -0.027609543521757457 14.
↪76124690750807 -5.175821286895905 32.58560788340983 115.86494837233313 -0.
↪2587648450330448
```

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```
172648 0.7592 II 31 test -5.942021205498 2.5808480681448858 72.24216865162195 83.
↪43696533883242 -0.04052830859563986 17.05919635984848 1.005755998955811 18.
↪148318002391164 33.16119808959254 -0.12803412647871454 12.153694246253906 -1.
↪2962293252577974 17.493068792921502 89.98548146319197 -0.14950758787782462 13.
↪355316206445695 -2.4143982246591293 23.84002028961246 118.87985827861259 -1.
↪4858837093947788
762146 0.7245 Ibc 22 test 10.734014319410377 -0.696725251384634 92.36623187978644 0.
↪5112285753252996 -0.4900012400030447 12.968161724599275 -0.94670057528261 55.
↪7516252880299 25.59410571631452 -1.971658945324412 19.03779421586546 -2.
↪228264147418322 57.66412361316971 35.09222360219662 -3.325944814741228 22.
↪877393161444374 0.3070939958786501 57.9675613727551 49.63155574417528 -1.
↪8832424871891025
```

This means that you can use the *actsnclass.learn_loop* module in combination with a `RandomSampling` strategy but reading data from the canonical sample. In this way, at each iteration the code will select a random object from the test sample but a query will only be made is the selected object belongs to the canonical sample.

In the command line, this looks like:

```
>>> run_loop.py -i results/Bazin_SNPCC_canonical.dat -b <batch size> -n <number of␣
↪loops>
>>>              -d <output metrics file> -q <output queried sample file>
>>>              -s RandomSampling -t <choice of initial training>
```

1.3.3 Prepare data for time domain

In order to mimic the realistic situation where only a limited number of observed epochs is available at each day, it is necessary to prepare our simulate data resemble this scenario. In `actsnclass` this is done in 5 steps:

1. Determine minimum and maximum MJD for the entire SNPCC sample;
2. For each day of the survey, run through the entire data sample and select only the observed epochs which were obtained prior to it;
3. Perform the feature extraction process considering only the photometric points which survived item 2.
4. Check if in the MJD in question the object is available for querying.
5. Join all information in a standard features file.

You can perform the entire analysis for one day of the survey using the `actsnclass.time_domain` module:

```
>>> from actsnclass.time_domain import SNPCCPhotometry

>>> path_to_data = 'data/SIMGEN_PUBLIC_DES/'
>>> output_dir = 'results/time_domain/'
>>> day = 20

>>> data = SNPCCPhotometry()
>>> data.create_daily_file(output_dir=output_dir, day=day)
>>> data.build_one_epoch(raw_data_dir=path_to_data, day_of_survey=day,
                         time_domain_dir=output_dir)
```

Alternatively you can use the command line to prepare a sequence of days in one batch:

```
>>> build_time_domain.py -d 20 21 22 23 -p <path to raw data dir> -o <path to output␣
↪time domain dir>
```

1.3.4 Active Learning loop

Details on running 1 loop

Once the data has been pre-processed, analysis steps 2-4 can be performed directly using the `DataBase` object.

For start, we can load the feature information:

```
>>> from actsnclass import DataBase

>>> path_to_features_file = 'results/Bazin.dat'

>>> data = DataBase()
>>> data.load_features(path_to_features_file, method='Bazin')
Loaded  21284  samples!
```

Notice that this data has some pre-determine separation between training and test sample:

```
>>> data.metadata['sample'].unique()
array(['test', 'train'], dtype=object)
```

You can choose to start your first iteration of the active learning loop from the original training sample flagged int he file OR from scratch. As this is our first example, let's do the simple thing and start from the original training sample. The code below build the respective samples and performs the classification:

```
>>> data.build_samples(initial_training='original', nclass=2)
Training set size:  1093
Test set size:  20191

>>> data.classify(method='RandomForest')
>>> data.classprob                          # check classification probabilities
array([[0.461, 0.539],
       [0.346, 0.654],
       ...,
       [0.398, 0.602],
       [0.396, 0.604]])
```

Hint: If you wish to start from scratch, just set the *initial_training=N* where *N* is the number of objects in you want in the initial training. The code will then randomly select *N* objects from the entire sample as the initial training sample. It will also impose that at least half of them are SNe Ias.

For a binary classification, the output from the classifier for each object (line) is presented as a pair of floats, the first column corresponding to the probability of the given object being a Ia and the second column its complement.

Given the output from the classifier we can calculate the metric(s) of choice:

```
>>> data.evaluate_classification(metric_label='snpcc')
>>> print(data.metrics_list_names)           # check metric header
['acc', 'eff', 'pur', 'fom']

>>> print(data.metrics_list_values)          # check metric values
[0.5975434599574068, 0.9024767801857585,
0.34684684684684686, 0.13572404702012383]
```

and save results for this one loop to file:

```
 >>> path_to_features_file = 'results/Bazin.dat'
 >>> metrics_file = 'results/metrics.dat'
 >>> queried_sample_file = 'results/queried_sample.dat'

>>> data.save_metrics(loop=0, output_metrics_file=metrics_file)
>>> data.save_queried_sample(loop=0, queried_sample_file=query_file,
>>>                          full_sample=False)
```

You should now have in your `results` directory a `metrics.dat` file which looks like this:

```
day accuracy efficiency purity fom query_id
0 0.4560942994403447 0.5545490350531705 0.23933367329593744 0.05263972502898026 81661
```

Running a number of iterations in sequence

We provide a function where all the above steps can be done in sequence for a number of iterations. In interactive mode, you must define the required variables and use the *actsnclass.learn_loop* function:

```
>>> from actsnclass.learn_loop import  learn_loop

>>> nloops = 1000                                  # number of iterations
>>> method = 'Bazin'                               # only option in v1.0
>>> ml = 'RandomForest'                            # only option in v1.0
>>> strategy = 'RandomSampling'                    # learning strategy
>>> input_file = 'results/Bazin.dat'               # input features file
>>> metric = 'results/metrics.dat'                 # output metrics file
>>> queried = 'results/queried.dat'                # output query file
>>> train = 'original'                             # initial training
>>> batch = 1                                      # size of batch

>>> learn_loop(nloops=nloops, features_method=method, classifier=ml,
>>>            strategy=strategy, path_to_features=input_file, output_metrics_
↪file=metrics,
>>>            output_queried_file=queried, training=train, batch=batch)
```

Alternatively you can also run everything from the command line:

```
>>> run_loop.py -i <input features file> -b <batch size> -n <number of loops>
>>>              -d <output metrics file> -q <output queried sample file>
>>>              -s <learning strategy> -t <choice of initial training>
```

The queryable sample

In the example shown above, when reading the data from the features file there was only 2 possibilities for the *sample* variable:

```
>>> data.metadata['sample'].unique()
array(['test', 'train'], dtype=object)
```

This corresponds to an unrealistic scenario where we are able to obtain spectra for any object at any time.

Hint: If you wish to restrict the sample available for querying, just change the *sample* variable to *queryable* for the objects available for querying. Whenever this keywork is encountered in a file of extracted features, the code

automatically restricts the query selection to the objects flagged as *queryable*.

1.3.5 Active Learning loop in time domain

Considering that you have previously prepared the time domain data, you can run the active learning loop in its current form either by using the `actsnclass.time_domain_loop` or by using the command line interface:

```
>>> run_time_domain.py -d <first day of survey> <last day of survey>
>>>         -m <output metrics file> -q <output queried file> -f <features directory>
>>>         -s <learning strategy> -t <choice of initial training>
```

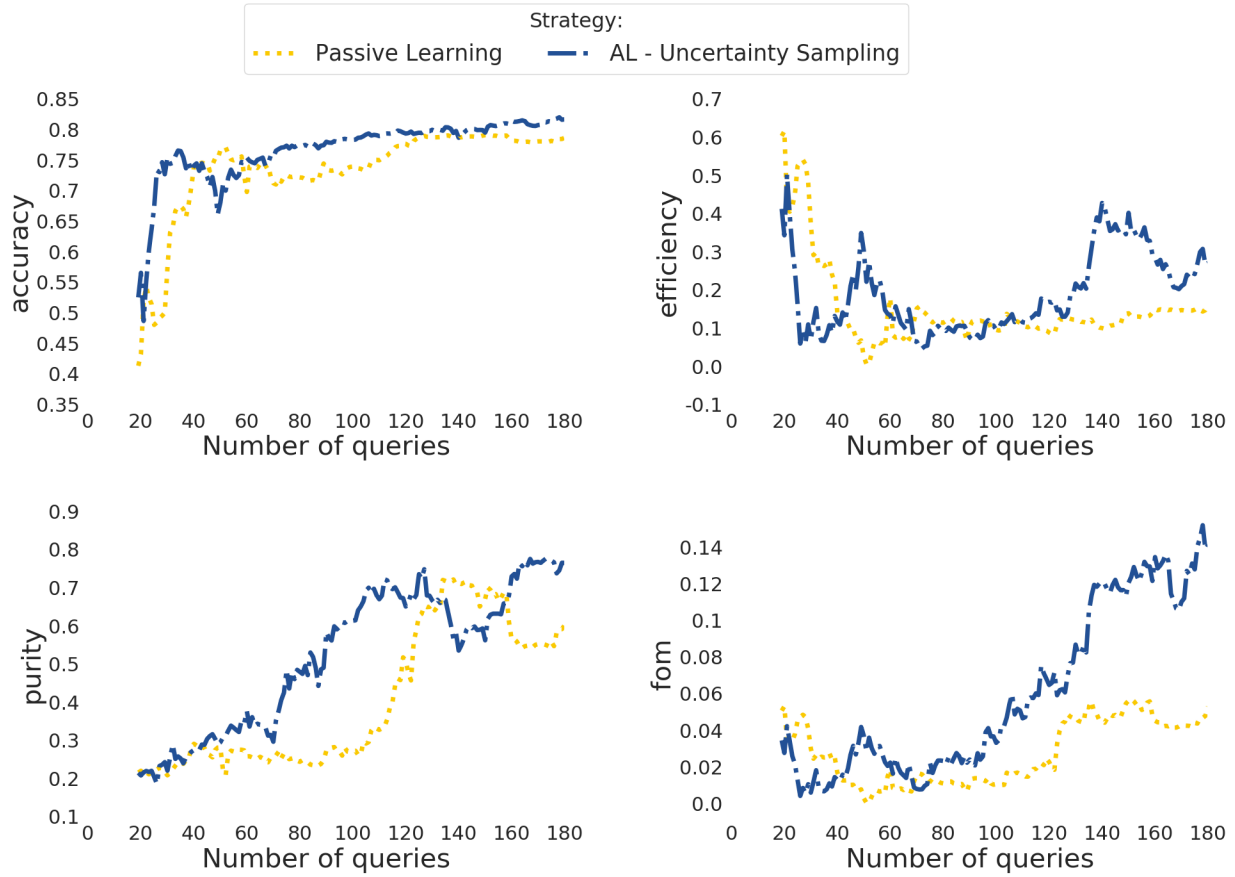
Make sure you check the full documentation of the module to understand which variables are required depending on the case you wish to run.

For example, to run with SNPCC data, the larges survey interval you can run is between 20 and 182 days, the corresponding option will be *-d 20 182*.

In the example above, if you choose to start from the original training sample, *-t original* you must also input the path to the file containing the full light curve analysis - so the full initial training can be read. This option corresponds to *-t original -fl <path to full lc features>*.

More details can be found in the corresponding docstring.

Once you ran one or more options, you can use the `actsnclass.plot_results` module, as described in the *produce plots* page. The result will be something like the plot below (accounting for variations due to initial training).



Warning: At this point there is no *Canonical sample* option implemented for the time domain module.

1.3.6 Plotting

Once you have the metrics results for a set of learning strategies you can plot the behaviour the evolution of the metrics:

- Accuracy: fraction of correct classifications;
- Efficiency: fraction of total SN Ia correctly classified;
- Purity: fraction of correct Ia classifications;
- Figure of merit: efficiency x purity with a penalty factor of 3 for false positives (contamination).

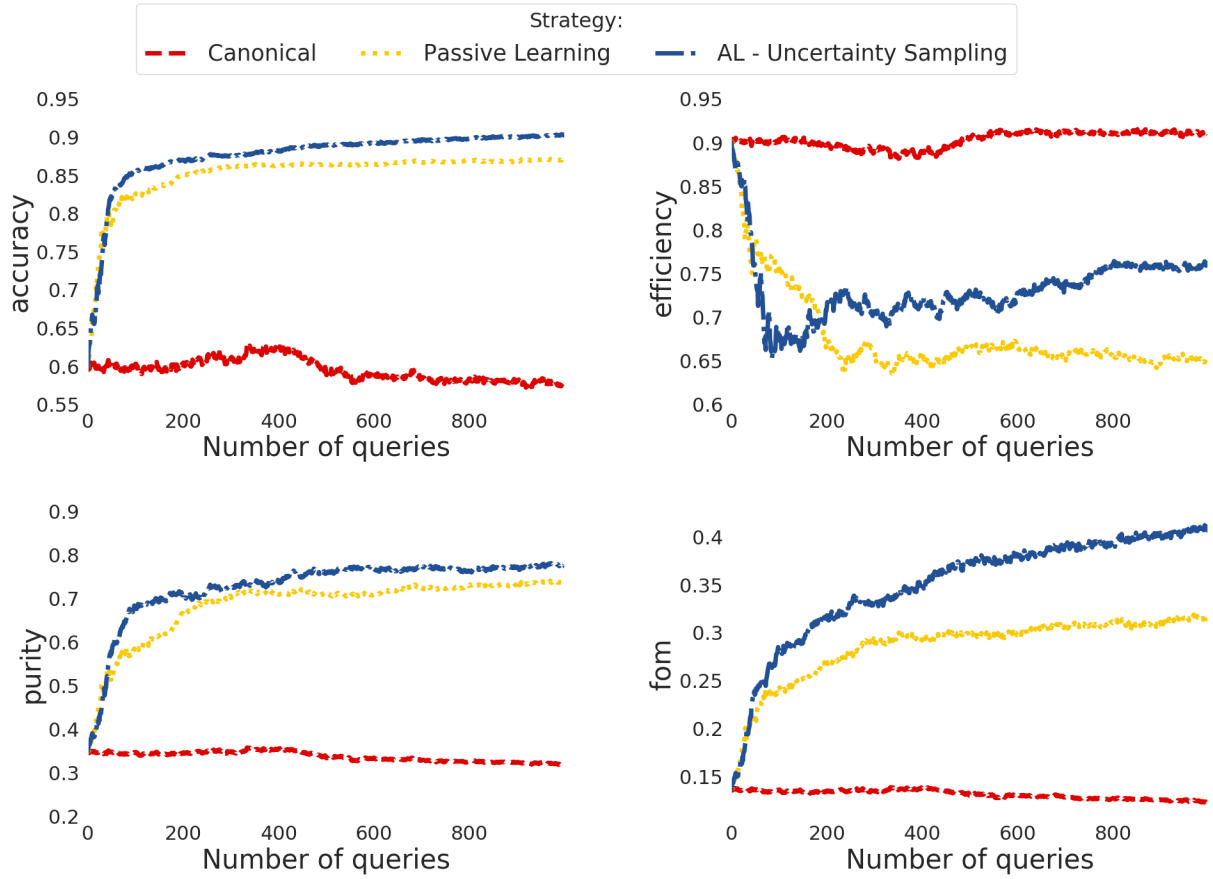
The class *Canvas <https://actsnclass.readthedocs.io/en/latest/api/actsnclass.Canvas.html#actsnclass.Canvas>_* enables you do to it using:

```
>>> from actsnclass.plot_results import Canvas

>>> # define parameters
>>> path_to_files = ['results/metrics_canonical.dat',
>>>                  'results/metrics_random.dat',
>>>                  'results/metrics_unc.dat']
>>> strategies_list = ['Canonical', 'RandomSampling', 'UncSampling']
>>> output_plot = 'plots/metrics.png'

>>> #Initiate the Canvas object, read and plot the results for
>>> # each metric and strategy.
>>> cv = Canvas()
>>> cv.load_metrics(path_to_files=path_to_files,
>>>                     strategies_list=strategies_list)
>>> cv.set_plot_dimensions()
>>> cv.plot_metrics(output_plot_file=output_plot,
>>>                     strategies_list=strategies_list)
```

This will generate:



Alternatively, you can use it directly from the command line.

For example, the result above could also be obtained doing:

```
>>> make_metrics_plots.py -m <path to canonical metrics> <path to rand sampling␣
↪metrics>  <path to unc sampling metrics>
>>>        -o <path to output plot file> -s Canonical RandomSampling UncSampling
```

OBS: the color pallete for this project was chosen to honor the work of Piet Mondrian.

1.3.7 How to contribute

Below you will find general guidance on how to prepare your piece of code to be integrated to the `actsnclass` environment.

Add a new data set

The main challenge of adding a new data set is to build the infrastructure necessary to handle the new data.

The function below show how the basic structure required to deal with 1 light curve:

```
>>> import pandas as pd

>>> def load_one_lightcurve(path_to_data, *args):
>>>     """Load 1 light curve at a time.
```

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```
>>>
>>>     Parameters
>>>     ----------
>>>     path_to_data: str
>>>         Complete path to data file.
>>>     ...
>>>         ...
>>>
>>>     Returns
>>>     -------
>>>     pd.DataFrame
>>>     """
>>>
>>>     ####################
>>>     # Do something #####
>>>     ####################
>>>
>>>     # structure of light curve
>>>     lc = {}
>>>     lc['dataset_name'] = XXXX                # name of the data set
>>>     lc['filters'] = [X, Y, Z]                # list of filters
>>>     lc['id'] = XXX                           # identification number
>>>     lc['redshift'] = X                       # redshift (optional, important for␣
↪building canonical)
>>>     lc['sample'] = XXXXX                     # train, test or queryable (none is␣
↪mandatory)
>>>     lc['sntype'] = X                         # Ia or non-Ia
>>>     lc['photometry' = pd.DataFrame()         # min keys: MJD, filter, FLUX, FLUXERR
>>>                                              # bonus: MAG, MAGERR, SNR
>>>     return lc
```

Feel free to also provide other keywords which might be important to handle your data. Given a function like this we should be capable of incorporating it into the pipeline.

Please refer to the `actsnclass.fit_lightcurves` module for a closer look at this part of the code.

Add a new feature extraction method

Currently `actsnclass` only deals with Bazin features. The snipet below show an example of friendly code for a new feature extraction method.

```
>>> def new_feature_extraction_method(time, flux, *args):
>>>     """Extract features from light curve.
>>>
>>>     Parameters
>>>     ----------
>>>     time: 1D - np.array
>>>         Time of observation.
>>>     flux: 1D - np.array of floats
>>>         Measured flux.
>>>     ...
>>>         ...
>>>
>>>     Returns
>>>     -------
>>>     set of features
```

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```
>>>     """
>>>
>>>         ################################
>>>         ###   Do something    ##########
>>>         ################################
>>>
>>>     return features
```

You can check the current feature extraction tools for the Bazin parametrization at `actsnclass.bazin` module.

Add a new classifier

A new classifier should be warp in a function such as:

```
>>> def new_classifier(train_features, train_labels, test_features, *args):
>>>     """Random Forest classifier.
>>>
>>>     Parameters
>>>     ----------
>>>     train_features: np.array
>>>         Training sample features.
>>>     train_labels: np.array
>>>         Training sample classes.
>>>     test_features: np.array
>>>         Test sample features.
>>>     ...
>>>         ...
>>>
>>>    Returns
>>>     -------
>>>     predictions: np.array
>>>         Predicted classes - 1 class per object.
>>>     probabilities: np.array
>>>         Classification probability for all objects, [pIa, pnon-Ia].
>>>     """
>>>
>>>     ######################################
>>>     #######  Do something     #############
>>>     ######################################
>>>
>>>     return predictions, probabilities
```

The only classifier implemented at this point is a Random Forest and can be found at the `actsnclass.classifiers` module.

Important: Remember that in order to be effective in the active learning frame work a classifier should not be heavy on the required computational resources and must be sensitive to small changes in the training sample. Otherwise the evolution will be difficult to tackle.

Add a new query strategy

A query strategy is a protocol which evaluates the current state of the machine learning model and makes an informed decision about which objects should be included in the training sample.

This is very general, and the function can receive as input any information regarding the physical properties of the test and/or target samples and current classification results.

A minimum structure for such function would be:

```
>>> def new_query_strategy(class_prob, test_ids, queryable_ids, batch, *args):
>>>     """New query strategy.
>>>
>>>     Parameters
>>>     ----------
>>>     class_prob: np.array
>>>         Classification probability. One value per class per object.
>>>     test_ids: np.array
>>>         Set of ids for objects in the test sample.
>>>     queryable_ids: np.array
>>>         Set of ids for objects available for querying.
>>>     batch: int
>>>         Number of objects to be chosen in each batch query.
>>>     ...
>>>         ...
>>>
>>>     Returns
>>>     -------
>>>     query_indx: list
>>>         List of indexes identifying the objects from the test sample
>>>         to be queried in decreasing order of importance.
>>>     """
>>>
>>>        ##########################################
>>>        #####   Do something              ##########
>>>        ##########################################
>>>
>>>     return list of indexes of size batch
```

The current available strategies are Passive Learning (or Random Sampling) and Uncertainty Sampling. Both can be scrutinized at the :py:mod:actsnclass.‘query_strategies‘ module.

Add a new diagnostic metric

Beyond the criteria for choosing an object to be queried one could also think about the possibility to test different metrics to evaluate the performance of the classifier at each learning loop.

A new diagnostic metrics can then be provided in the form:

```
>>> def new_metric(label_pred: list, label_true: list, ia_flag, *args):
>>>     """Calculate efficiency.
>>>
>>>     Parameters
>>>     ----------
>>>     label_pred: list
>>>         Predicted labels
>>>     label_true: list
>>>         True labels
>>>     ia_flag: number, symbol
>>>         Flag used to identify Ia objects.
>>>     ...
>>>         ...
```

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```
>>>
>>>     Returns
>>>     -------
>>>     a number or set of numbers
>>>         Tells us how good the fit was.
>>>     """
>>>
>>>     ##########################################
>>>     #####  Do something !    ##################
>>>     ##########################################
>>>
>>>     return a number or set of numbers
```

The currently implemented diagnostic metrics are those used in the SNPCC (Kessler et al., 2009) and can be found at the `actsnclass.metrics` module.

1.3.8 Reference / API

Pre-processing

Light curve analysis

Performing feature extraction for 1 light curve

LightCurve()	Light Curve object, holding meta and photometric data.
LightCurve.load_snpcc_lc(path_to_data)	Reads one LC from SNPCC data.
LightCurve.fit_bazin(band)	Extract Bazin features for one filter.
LightCurve.fit_bazin_all()	Perform Bazin fit for all filters independently and concatenate results.
LightCurve.plot_bazin_fit([save, show, ...])	Plot data and Bazin fitted function.

actsnclass.LightCurve

class actsnclass.**LightCurve**

Light Curve object, holding meta and photometric data.

Variables

- **bazin_features_names** (*list*) – List of names of the Bazin function parameters.
- **bazin_features** (*list*) – List with the 5 best-fit Bazin parameters in all filters. Concatenated from blue to red.
- **dataset_name** (*str*) – Name of the survey or data set being analyzed.
- **filters** (*list*) – List of broad band filters.
- **id** (*int*) – SN identification number
- **id_name** – Column name of object identifier.
- **photometry** (*pd.DataFrame*) – Photometry information. Keys –> [mjd, band, flux, fluxerr, SNR, MAG, MAGERR].
- **redshift** (*float*) – Redshift

- **sample** (*str*) – Original sample to which this light curve is assigned
- **sim_peakmag** (*np.array*) – Simulated peak magnitude in each filter
- **sncode** (*int*) – Number identifying the SN model used in the simulation
- **sntype** (*str*) – General classification, possibilities are: Ia, II or Ibc

check_queryable (*mjd: float*, *r_lim: float*)
Check if this light can be queried in a given day.

evaluate_bazin (*param: list*, *time: np.array*) → np.array
Evaluate the Bazin function given parameter values.

load_snpcc_lc (*path_to_data: str*)
Reads header and photometric information for 1 light curve

load_plasticc_lc (*photo_file: str*, *snid: int*)
Load photometric information for 1 PLAsTiCC light curve

load_resspect_lc (*photo_file: str*, *snid: int*)
Load photometric information for 1 RESSPECT light curve

fit_bazin (*band: str*) → list
Calculates best-fit parameters from the Bazin function in 1 filter

fit_bazin_all ()
Calculates best-fit parameters from the Bazin func for all filters

plot_bazin_fit (*save: bool*, *show: bool*, *output_file: srt*)
Plot photometric points and Bazin fitted curve

Examples

for RESSPECT and PLAsTiCC light curves it is necessary to ##### input the object identification for dealing with 1 light curve

```
>>> import io
>>> import pandas as pd
>>> import tarfile
```

```
>>> from actsnclass import LightCurve
```

path to header file >>> path_to_header = '~/RESSPECT_PERFECT_V2_TRAIN_HEADER.tar.gz'

openning '.tar.gz' files requires some juggling ... >>> tar = tarfile.open(path_to_header, 'r:gz') >>> fname = tar.getmembers()[0] >>> content = tar.extractfile(fname).read() >>> header = pd.read_csv(io.BytesIO(content)) >>> tar.close()

choose one object >>> snid = header['objid'].values[4]

once you have the identification you can use this class >>> path_to_lightcurves = '~/RESSPECT_PERFECT_V2_TRAIN_LIGHTCURVES.tar.gz'

```
>>> lc = LightCurve()                          # create light curve instance
>>> lc.load_snpcc_lc(path_to_lightcurves)      # read data
>>> lc.photometry
         mjd band       flux   fluxerr         SNR
0    53214.0    u   0.165249  0.142422    1.160276
1    53214.0    g  -0.041531  0.141841   -0.292803
```

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```
..       ...  ...        ...       ...         ...
472  53370.0    z  68.645930  0.297934  230.406460
473  53370.0    Y  63.254270  0.288744  219.067050
```

```
>>> lc.fit_bazin_all()                # perform Bazin fit in all filters
>>> lc.bazin_features                 # display Bazin parameters
[198.63302952843623, -9.38297128588733, 43.99971014717201,
... ...
-1.546372806815066]
```

for fitting the entire sample . . .

```
>>> output_file = 'RESSPECT_PERFECT_TRAIN.DAT'
>>> fit_resspect_bazin(path_to_lightcurves, path_to_header,
                       output_file, sample='train')
```

__init__()
Initialize self. See help(type(self)) for accurate signature.

Methods

__init__()	Initialize self.
check_queryable(mjd, r_lim)	Check if this light can be queried in a given day.
evaluate_bazin(param, time)	Evaluate the Bazin function given parameter values.
fit_bazin(band)	Extract Bazin features for one filter.
fit_bazin_all()	Perform Bazin fit for all filters independently and concatenate results.
load_plasticc_lc(photo_file, snid)	Return 1 light curve from PLAsTiCC simulations.
load_resspect_lc(photo_file, snid)	Return 1 light curve from RESSPECT simulations.
load_snpcc_lc(path_to_data)	Reads one LC from SNPCC data.
plot_bazin_fit([save, show, output_file, . . .])	Plot data and Bazin fitted function.

actsnclass.LightCurve.load_snpcc_lc

LightCurve.**load_snpcc_lc**(*path_to_data: str*)
Reads one LC from SNPCC data.

Populates the attributes: dataset_name, id, sample, redshift, sncode, sntype, photometry and sim_peakmag.

Parameters **path_to_data** (*str*) – Path to text file with data from a single SN.

actsnclass.LightCurve.fit_bazin

LightCurve.**fit_bazin**(*band: str*)
Extract Bazin features for one filter.

Parameters **band** (*str*) – Choice of broad band filter

Returns **bazin_param** – Best fit parameters for the Bazin function: [a, b, t0, tfall, trise]

Return type list

actsnclass.LightCurve.fit_bazin_all

LightCurve.**fit_bazin_all**()
Perform Bazin fit for all filters independently and concatenate results.

Populates the attributes: bazin_features.

actsnclass.LightCurve.plot_bazin_fit

LightCurve.**plot_bazin_fit**(*save=True*, *show=False*, *output_file=' '*, *figscale=1*)
Plot data and Bazin fitted function.

Parameters

- **save** (*bool (optional)*) – Save figure to file. Default is True.
- **show** (*bool (optinal)*) – Display plot in windown. Default is False.
- **output_file** (*str (optional)*) – Name of file to store the plot.
- **figscale** (*float (optional)*) – Allow to control the size of the figure.

Fitting an entire data set

fit_snpcc_bazin(path_to_data_dir, features_file)	Perform Bazin fit to all objects in the SNPCC data.

actsnclass.fit_snpcc_bazin

actsnclass.**fit_snpcc_bazin**(*path_to_data_dir: str*, *features_file: str*)
Perform Bazin fit to all objects in the SNPCC data.

Parameters

- **path_to_data_dir** (*str*) – Path to directory containing the set of individual files, one for each light curve.
- **features_file** (*str*) – Path to output file where results should be stored.

Basic light curve analysis tools

bazin(time, a, b, t0, tfall, trise)	Parametric light curve function proposed by Bazin et al., 2009.
errfunc(params, time, flux)	Absolute difference between theoretical and measured flux.
fit_scipy(time, flux)	Find best-fit parameters using scipy.least_squares.

Canonical sample

The Canonical object for holding the entire sample.

Canonical()	Canonical sample object.
Canonical.snpcc_get_canonical_info(...[, ...])	Load SNPCC metada data required to characterize objects.
Canonical.snpcc_identify_samples()	Identify training and test sample.

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Table 5 – continued from previous page

Canonical.find_neighbors()	Identify 1 nearest neighbor for each object in training.

actsnclass.Canonical

class actsnclass.**Canonical**

Canonical sample object.

Variables

- **canonical_ids** (*list*) – List of ids for objects in the canonical sample.
- **canonical_sample** (*list*) – Complete data matrix for the canonical sample.
- **meta_data** (*pd.DataFrame*) – Metadata on sim peakmag and SNR for all objects in the original data set.
- **test_ia_data** (*pd.DataFrame*) – Metadata on sim peakmag and SNR for SN Ias in the test sample.
- **test_ia_id** (*np.array*) – Set of ids for all SN Ia in the test sample.
- **test_ibc_data** (*pd.DataFrame*) – Metadata on sim peakmag and SNR for SN Ibcs in the test sample.
- **test_ibc_id** (*np.array*) – Set of ids for all SN Ibc in the test sample.
- **test_ii_data** (*pd.DataFrame*) – Metadata on sim peakmag and SNR for SN IIs in the test sample.
- **test_ii_id** (*np.array*) – Set of ids for all SN II in the test sample.
- **train_ia_data** (*pd.DataFrame*) – Metadata on sim peakmag and SNR for SN Ias in the train sample.
- **train_ia_id** (*np.array*) – Set of ids for all SN Ia in the train sample.
- **train_ibc_data** (*pd.DataFrame*) – Metadata on sim peakmag and SNR for SN Ibcs in the train sample.
- **train_ibc_id** (*np.array*) – Set of ids for all SN Ibc in the train sample.
- **train_ii_data** (*pd.DataFrame*) – Metadata on sim peakmag and SNR for SN IIs in the train sample.
- **train_ii_id** (*np.array*) – Set of ids for all SN II in the train sample.

snpcc_get_canonical_info(*path_to_rawdata_dir: str*, *canonical_output_file: st*, *compute: bool*, *save: bool*, *canonical_input_file: str*)

Load SNPCC metada data required to characterize objects.

snpcc_identify_samples()

Identify training and test sample.

find_neighbors()

Identify 1 nearest neighbor for each object in training.

__init__()

Initialize self. See help(type(self)) for accurate signature.

Methods

__init__()	Initialize self.
find_neighbors()	Identify 1 nearest neighbor for each object in training.
snpcc_get_canonical_info(...[, compute, ...])	Load SNPCC metada data required to characterize objects.
snpcc_identify_samples()	Identify training and test sample.

actsnclass.Canonical.snpcc_get_canonical_info

Canonical.**snpcc_get_canonical_info**(*path_to_rawdata_dir: str*, *canonical_output_file: str*, *compute=True*, *save=True*, *canonical_input_file=''*)

Load SNPCC metada data required to characterize objects.

Populates attribute: data.

Parameters

- **path_to_rawdata_dir** (*str*) – Complete path to directory holding raw data files.
- **canonical_output_file** (*str*) – Complete path to output canonical sample file.
- **compute** (*bool (optional)*) – Compute required metada from raw data files. Default is True.
- **save** (*bool (optional)*) – Save metadata to file. Default is True.
- **canonical_input_file** (*str (optional)*) – Path to input file if required metadata was previously calculated. If name is give, 'compute' must be False.

actsnclass.Canonical.snpcc_identify_samples

Canonical.**snpcc_identify_samples**()

Identify training and test sample.

Populates attributes: train_ia_data, train_ia_id, train_ibc_data, train_ibc_id, train_ii_data, train_ibc_id, test_ia_data, test_ia_id, test_ibc_data, test_ibc_id, test_ii_data and test_ii_id.

actsnclass.Canonical.find_neighbors

Canonical.**find_neighbors**()

Identify 1 nearest neighbor for each object in training.

Populates attribute: canonical_ids.

Functions to populate the Canonical object

build_snpcc_canonical(path_to_raw_data, ...)	Build canonical sample for SNPCC data.
plot_snpcc_train_canonical(sample[, ...])	Plot comparison between training and canonical samples.

actsnclass.build_snpcc_canonical

actsnclass.**build_snpcc_canonical**(*path_to_raw_data: str*, *path_to_features: str*, *output_canonical_file: str*, *output_info_file=''*, *compute=True*, *save=True*, *input_info_file=''*, *features_method='Bazin'*)

Build canonical sample for SNPCC data.

Parameters

- **path_to_raw_data** (*str*) – Complete path to raw data directory.
- **path_to_features** (*str*) – Complete path to Bazin features files.
- **output_canonical_file** (*str*) – Complete path to output canonical sample file.
- **output_info_file** (*str*) – Complete path to output metadata file for canonical sample. This includes SNR and simulated peak magnitude for each filter.
- **compute** (*bool (optional)*) – If True, compute metadata information on SNR and sim peak mag. If False, read info from file. Default is True.
- **save** (*bool (optional)*) – Save simulation metadata information to file. Default is True.
- **input_info_file** (*str (optional)*) – Complete path to sim metadata file. This must be provided if save == False.
- **features_method** (*str (optional)*) – Method for feature extraction. Only 'Bazin' is implemented.

Returns **actsnclass.Canonical** – Updated canonical object with the attribute 'canonical_sample'.

Return type obj

actsnclass.plot_snpcc_train_canonical

actsnclass.**plot_snpcc_train_canonical**(*sample: actsnclass.build_snpcc_canonical.Canonical*, *output_plot_file=False*)

Plot comparison between training and canonical samples.

Parameters

- **sample** (*actsnclass.Canonical*) – Canonical object holding infor for canonical sample
- **output_plot_file** (*str (optional)*) – Complete path to output plot. If not provided, plot is displayed on screen only.

Build time domain data base

SNPCCPhotometry()	Handles photometric information for entire SNPCC data.
SNPCCPhotometry.get_lim_mjds(raw_data_dir)	Get minimum and maximum MJD for complete sample.
SNPCCPhotometry.create_daily_file(... [, header])	Create one file for a given day of the survey.
SNPCCPhotometry.build_one_epoch(... [, ...])	Fit bazin for all objects with enough points in a given day.

actsnclass.SNPCCPhotometry

class actsnclass.**SNPCCPhotometry**

Handles photometric information for entire SNPCC data.

This class only works for Bazin feature extraction method.

Variables

- **bazin_header** (*str*) – Header to be added to features files for each day.
- **max_epoch** (*float*) – Maximum MJD for the entire data set.
- **min_epoch** (*float*) – Minimum MJD for the entire data set.
- **rmag_lim** (*float*) – Maximum r-band magnitude allowing a query.

get_lim_mjds(*raw_data_dir*)

Get minimum and maximum MJD for complete sample.

create_daily_file(*raw_data_dir: str*, *day: int*, *output_dir: str*, *header: str*)

Create one file for a given day of the survey. Only populates the file with header. It will erase existing files!

build_one_epoch(raw_data_dir: str, day_of_survey: int, time_domain_dir: str,

feature_method: str, dataset: str)

Selects objects with observed points until given MJD, performs feature extraction and evaluate if query is possible. Save results to file.

__init__()

Initialize self. See help(type(self)) for accurate signature.

Methods

__init__()	Initialize self.
build_one_epoch(raw_data_dir, day_of_survey, ...)	Fit bazin for all objects with enough points in a given day.
create_daily_file(output_dir, day[, header])	Create one file for a given day of the survey.
get_lim_mjds(raw_data_dir)	Get minimum and maximum MJD for complete sample.

actsnclass.SNPCCPhotometry.get_lim_mjds

SNPCCPhotometry.**get_lim_mjds**(*raw_data_dir*)

Get minimum and maximum MJD for complete sample.

This function is not necessary if you are working with SNPCC data. The values are hard coded in the class.

Parameters **raw_data_dir** (*str*) – Complete path to raw data directory.

Returns **limits** – List of extreme MJDs for entire sample: [min_MJD, max_MJD].

Return type list

actsnclass.SNPCCPhotometry.create_daily_file

SNPCCPhotometry.**create_daily_file**(*output_dir: str*, *day: int*, *header='Bazin'*)

Create one file for a given day of the survey.

The file contains only header for the features file.

Parameters

- **output_dir** (*str*) – Complete path to raw data directory.
- **day** (*int*) – Day passed since the beginning of the survey.
- **header** (*str (optional)*) – List of elements to be added to the header. Separate by 1 space. Default option uses header for Bazin features file.

actsnclass.SNPCCPhotometry.build_one_epoch

SNPCCPhotometry.**build_one_epoch**(*raw_data_dir: str*, *day_of_survey: int*, *time_domain_dir: str*, *feature_method='Bazin'*, *dataset='SNPCC'*)

Fit bazin for all objects with enough points in a given day.

Generate 1 file containing best-fit Bazin parameters for a given day of the survey.

Parameters

- **raw_data_dir** (*str*) – Complete path to raw data directory
- **day_of_survey** (*int*) – Day since the beginning of survey.
- **time_domain_dir** (*str*) – Output directory to store time domain files.
- **feature_method** (*str (optional)*) – Feature extraction method. Only possibility is 'Bazin'.
- **dataset** (*str (optional)*) – Name of the data set. Only possibility is 'SNPCC'.

DataBase

Object upon which the learning process is performed

DataBase()	DataBase object, upon which the active learning loop is performed.
DataBase.load_bazin_features(path_to_bazin_file)	Load Bazin features from file.
DataBase.load_features(path_to_file[, ...])	Load features according to the chosen feature extraction method.
DataBase.build_samples([initial_training, ...])	Separate train and test samples.
DataBase.classify(method, **kwargs)	Apply a machine learning classifier.
DataBase.evaluate_classification([metric_label])	Evaluate results from classification.
DataBase.make_query([strategy, batch, ...])	Identify new object to be added to the training sample.
DataBase.update_samples(query_indx, loop[, ...])	Add the queried obj(s) to training and remove them from test.
DataBase.save_metrics(loop, ...[, batch])	Save current metrics to file.
DataBase.save_queried_sample(...[, ...])	Save queried sample to file.

actsnclass.DataBase

class actsnclass.**DataBase**

DataBase object, upon which the active learning loop is performed.

Variables

- **classprob** (*np.array*) – Classification probability for all objects, [pIa, pnon-Ia].
- **data** (*pd.DataFrame*) – Complete information read from features files.
- **features** (*pd.DataFrame*) – Feature matrix to be used in classification (no metadata).
- **features_names** (*list*) – Header for attribute *features*.
- **metadata** (*pd.DataFrame*) – Features matrix which will not be used in classification.
- **metadata_names** (*list*) – Header for metadata.
- **metrics_list_names** (*list*) – Values for metric elements.
- **output_photo_Ia** (*pd.DataFrame*) – Returns metadata for photometrically classified Ia.
- **photo_Ia_metadata** (*pd.DataFrame*) – Metadata for photometrically classified object ids.
- **plasticc_mjd_lim** (*list*) – [min, max] mjds for plasticc data
- **predicted_class** (*np.array*) – Predicted classes - results from ML classifier.
- **queried_sample** (*list*) – Complete information of queried objects.
- **queryable_ids** (*np.array()*) – Flag for objects available to be queried.
- **test_features** (*np.array()*) – Features matrix for the test sample.
- **test_metadata** (*pd.DataFrame*) – Metadata for the test sample
- **test_labels** (*np.array()*) – True classification for the test sample.
- **train_features** (*np.array()*) – Features matrix for the train sample.
- **train_metadata** (*pd.DataFrame*) – Metadata for the training sample.
- **train_labels** (*np.array*) – Classes for the training sample.

build_samples(*initial_training: str or int*, *nclass: int*)

Separate train and test samples.

classify(*method: str*)

Apply a machine learning classifier.

classify_bootstrap(*method: str*)

Apply a machine learning classifier bootstrapping the classifier

evaluate_classification(*metric_label: str*)

Evaluate results from classification.

identify_keywords()

Break degenerescency between keywords with equal meaning.

load_bazin_features(*path_to_bazin_file: str*)

Load Bazin features from file

load_photometry_features(*path_to_photometry_file:str*)

Load photometric light curves from file

load_plasticc_mjd (*path_to_data_dir: str*)
Get min and max mjds for PLAsTiCC data

load_features (*path_to_file: str*, *method: str*)
Load features according to the chosen feature extraction method.

make_query (*strategy: str*, *batch: int*) → list
Identify new object to be added to the training sample.

save_metrics (*loop: int*, *output_metrics_file: str*)
Save current metrics to file.

save_queried_sample (*queried_sample_file: str*, *loop: int*, *full_sample: str*)
Save queried sample to file.

update_samples (*query_indx: list*)
Add the queried obj(s) to training and remove them from test.

Examples

```
>>> from actsnclass import DataBase
```

Define the necessary paths

```
>>> path_to_bazin_file = 'results/Bazin.dat'
>>> metrics_file = 'results/metrics.dat'
>>> query_file = 'results/query_file.dat'
```

Initiate the DataBase object and load the data. >>> data = DataBase() >>> data.load_features(path_to_bazin_file, method='Bazin')

Separate training and test samples and classify

```
>>> data.build_samples(initial_training='original', nclass=2)
>>> data.classify(method='RandomForest')
>>> print(data.classprob)          # check predicted probabilities
[[0.461 0.539]
[0.346print(data.metrics_list_names)           # check metric header
['acc', 'eff', 'pur', 'fom']
```

```
>>> print(data.metrics_list_values)          # check metric values
[0.5975434599574068, 0.9024767801857585,
0.34684684684684686, 0.13572404702012383] 0.654]
...
[0.398 0.602]
[0.396 0.604]]
```

Calculate classification metrics

```
>>> data.evaluate_classification(metric_label='snpcc')
>>>
```

Make query, choose object and update samples

```
>>> indx = data.make_query(strategy='UncSampling', batch=1)
>>> data.update_samples(indx)
```

Save results to file

```
>>> data.save_metrics(loop=0, output_metrics_file=metrics_file)
>>> data.save_queried_sample(loop=0, queried_sample_file=query_file,
>>>                          full_sample=False)
```

__init__()
Initialize self. See help(type(self)) for accurate signature.

Methods

__init__()	Initialize self.
build_orig_samples([nclass, screen, ...])	Construct train and test samples as given in the original data set.
build_previous_runs(path_to_train, ...[, ...])	Build train, test and queryable samples from previous runs.
build_random_training(initial_training[, ...])	Construct initial random training and corresponding test sample.
build_samples([initial_training, nclass, ...])	Separate train and test samples.
classify(method, **kwargs)	Apply a machine learning classifier.
classify_bootstrap(method, **kwargs)	Apply a machine learning classifier bootstrapping the classifier.
evaluate_classification([metric_label])	Evaluate results from classification.
identify_keywords()	Break degenerescency between keywords with equal meaning.
load_bazin_features(path_to_bazin_file[, ...])	Load Bazin features from file.
load_features(path_to_file[, method, ...])	Load features according to the chosen feature extraction method.
load_photometry_features(path_to_photometry_file)	Load photometry features from file.
load_plasticc_mjd(path_to_data_dir)	Return all MJDs from 1 file from PLAsTiCC simulations.
make_query([strategy, batch, screen, ...])	Identify new object to be added to the training sample.
output_photo_Ia(threshold[, to_file, filename])	Returns the metadata for photometrically classified SN Ia.
save_metrics(loop, output_metrics_file, epoch)	Save current metrics to file.
save_queried_sample(queried_sample_file, loop)	Save queried sample to file.
update_samples(query_indx, loop[, epoch])	Add the queried obj(s) to training and remove them from test.

actsnclass.DataBase.load_bazin_features

DataBase.**load_bazin_features**(*path_to_bazin_file: str*, *screen=False*, *survey='DES'*, *sample=None*)

Load Bazin features from file.

Populate properties: features, feature_names, metadata and metadata_names.

Parameters

- **path_to_bazin_file** (*str*) – Complete path to Bazin features file.
- **screen** (*bool (optional)*) – If True, print on screen number of light curves processed. Default

is False.

- **survey** (*str (optional)*) – Name of survey. Used to infer the filter set. Options are DES or LSST. Default is DES.
- **sample** (*str (optional)*) – If None, sample is given by a column within the given file. else, read independent files for 'train' and 'test'. Default is None.

actsnclass.DataBase.load_features

DataBase.**load_features**(*path_to_file: str*, *method='Bazin'*, *screen=False*, *survey='DES'*, *sample=None*)

Load features according to the chosen feature extraction method.

Populates properties: data, features, feature_list, header and header_list.

Parameters

- **path_to_file** (*str*) – Complete path to features file.
- **method** (*str (optional)*) – Feature extraction method. The current implementation only accepts method=='Bazin' or 'photometry'. Default is 'Bazin'.
- **screen** (*bool (optional)*) – If True, print on screen number of light curves processed. Default is False.
- **survey** (*str (optional)*) – Survey used to obtain the data. The current implementation only accepts survey='DES' or 'LSST'. Default is 'DES'.
- **sample** (*str (optional)*) – If None, sample is given by a column within the given file. else, read independent files for 'train' and 'test'. Default is None.

actsnclass.DataBase.build_samples

DataBase.**build_samples**(*initial_training='original'*, *nclass=2*, *screen=False*, *Ia_frac=0.5*, *queryable=False*, *save_samples=False*, *sep_files=False*, *survey='DES'*, *output_fname=' '*, *path_to_train=' '*, *path_to_queried=' '*, *method='Bazin'*)

Separate train and test samples.

Populate properties: train_features, train_header, test_features, test_header, queryable_ids (if flag available), train_labels and test_labels.

Parameters

- **initial_training** (*str or int*) – Choice of initial training sample. If 'original': begin from the train sample flagged in original file elif 'previous': continue from a previously run loop elif int: choose the required number of samples at random, ensuring that at least half are SN Ia.
- **Ia_frac** (*float in [0,1] (optional)*) – Fraction of Ia required in initial training sample. Default is 0.5.
- **method** (*str (optional)*) – Feature extraction method. The current implementation only accepts method=='Bazin' or 'photometry'. Default is 'Bazin'. Only used if initial_training == 'previous'.
- **nclass** (*int (optional)*) – Number of classes to consider in the classification Currently only nclass == 2 is implemented.
- **path_to_train** (*str (optional)*) – Path to initial training file from previous run. Only used if initial_training == 'previous'.

- **path_to_queried** (*str(optional)*) – Path to queried sample from previous run. Only used if initial_training == 'previous'.
- **queryable** (*bool (optional)*) – If True build also queryable sample for time domain analysis. Default is False.
- **screen** (*bool (optional)*) – If True display the dimensions of training and test samples.
- **save_samples** (*bool (optional)*) – If True, save training and test samples to file. Default is False.
- **survey** (*str (optional)*) – Survey used to obtain the data. The current implementation only accepts survey='DES' or 'LSST'. Default is 'DES'.
- **sep_files** (*bool (optional)*) – If True, consider train and test samples separately read from independent files. Default is False.
- **output_fname** (*str (optional)*) – Complete path to output file where initial training will be stored. Only used if save_samples == True.

actsnclass.DataBase.classify

DataBase.**classify**(*method: str*, ***kwargs*)

Apply a machine learning classifier.

Populate properties: predicted_class and class_prob

Parameters

- **method** (*str*) – Chosen classifier. The current implementation accepts *RandomForest*, 'GradientBoostedTrees', 'KNN', 'MLP', 'SVM' and 'NB'.
- **kwargs** (*extra parameters*) – Parameters required by the chosen classifier.

actsnclass.DataBase.evaluate_classification

DataBase.**evaluate_classification**(*metric_label='snpcc'*)

Evaluate results from classification.

Populate properties: metric_list_names and metrics_list_values.

Parameters **metric_label** (*str*) – Choice of metric. Currenlty only *snpcc* is accepted.

actsnclass.DataBase.make_query

DataBase.**make_query**(*strategy='UncSampling'*, *batch=1*, *screen=False*, *queryable=False*, *query_thre=1.0*) → list

Identify new object to be added to the training sample.

Parameters

- **strategy** (*str (optional)*) – Strategy used to choose the most informative object. Current implementation accepts 'UncSampling' and 'RandomSampling', 'UncSamplingEntropy', 'UncSamplingLeastConfident', 'UncSamplingMargin', 'QBDMI', 'QBDEntropy', . Default is *UncSampling*.
- **batch** (*int (optional)*) – Number of objects to be chosen in each batch query. Default is 1.
- **queryable** (*bool (optional)*) – If True, consider only queryable objects. Default is False.

- **query_thre** (*float (optional)*) – Percentile threshold where a query is considered worth it. Default is 1 (no limit).
- **screen** (*bool (optional)*) – If true, display on screen information about the displacement in order and classificaion probability due to constraints on queryable sample.

Returns **query_indx** – List of indexes identifying the objects to be queried in decreasing order of importance. If strategy=='RandomSampling' the order is irrelevant.

Return type list

actsnclass.DataBase.update_samples

DataBase.**update_samples**(*query_indx: list*, *loop: int*, *epoch=0*)

Add the queried obj(s) to training and remove them from test.

Update properties: train_headers, train_features, train_labels, test_labels, test_headers and test_features.

Parameters

- **query_indx** (*list*) – List of indexes identifying objects to be moved.
- **loop** (*int*) – Store number of loop when this query was made.

actsnclass.DataBase.save_metrics

DataBase.**save_metrics**(*loop: int*, *output_metrics_file: str*, *epoch: int*, *batch=1*)

Save current metrics to file.

If loop == 0 the 'output_metrics_file' will be created or overwritten. Otherwise results will be added to an existing 'output_metrics file'.

Parameters

- **loop** (*int*) – Number of learning loops finished at this stage.
- **output_metrics_file** (*str*) – Full path to file to store metrics results.
- **batch** (*int*) – Number of queries in each loop.
- **epoch** (*int*) – Days since the beginning of the survey.

actsnclass.DataBase.save_queried_sample

DataBase.**save_queried_sample**(*queried_sample_file: str*, *loop: int*, *full_sample=False*, *batch=1*)

Save queried sample to file.

Parameters

- **queried_sample_file** (*str*) – Complete path to output file.
- **loop** (*int*) – Number of learning loops finished at this stage.
- **full_sample** (*bool (optional)*) – If true, write down a complete queried sample stored in property 'queried_sample'. Otherwise append 1 line per loop to 'queried_sample_file'. Default is False.

Classifiers

random_forest(train_features, train_labels, ...)	Random Forest classifier.

actsnclass.random_forest

actsnclass.**random_forest**(*train_features: numpy.array*, *train_labels: numpy.array*, *test_features: numpy.array*, ***kwargs*)

Random Forest classifier.

Parameters

- **train_features** (*np.array*) – Training sample features.
- **train_labels** (*np.array*) – Training sample classes.
- **test_features** (*np.array*) – Test sample features.
- **kwargs** (*extra parameters*) – All keywords required by sklearn.ensemble.RandomForestClassifier function.

Returns

- **predictions** (*np.array*) – Predicted classes.
- **prob** (*np.array*) – Classification probability for all objects, [pIa, pnon-Ia].

Query strategies

random_sampling(test_ids, queryable_ids[, ...])	Randomly choose an object from the test sample.
uncertainty_sampling(class_prob, test_ids, ...)	Search for the sample with highest uncertainty in predicted class.

actsnclass.random_sampling

actsnclass.**random_sampling**(*test_ids: numpy.array*, *queryable_ids: numpy.array*, *batch=1*, *queryable=False*, *query_thre=1.0*, *seed=42*) → list

Randomly choose an object from the test sample.

Parameters

- **test_ids** (*np.array*) – Set of ids for objects in the test sample.
- **queryable_ids** (*np.array*) – Set of ids for objects available for querying.
- **batch** (*int (optional)*) – Number of objects to be chosen in each batch query. Default is 1.
- **queryable** (*bool (optional)*) – If True, check if randomly chosen object is queryable. Default is False.
- **query_thre** (*float (optinal)*) – Threshold where a query is considered worth it. Default is 1.0 (no limit).
- **seed** (*int (optional)*) – Seed for random number generator. Default is 42.

Returns **query_indx** – List of indexes identifying the objects from the test sample to be queried. If there are less queryable objects than the required batch it will return only the available objects – so the list of objects to query can be smaller than 'batch'.

Return type list

actsnclass.uncertainty_sampling

actsnclass.**uncertainty_sampling**(*class_prob: numpy.array*, *test_ids: numpy.array*, *queryable_ids: numpy.array*, *batch=1*, *screen=False*, *query_thre=1.0*) → list

Search for the sample with highest uncertainty in predicted class.

Parameters

- **class_prob** (*np.array*) – Classification probability. One value per class per object.
- **test_ids** (*np.array*) – Set of ids for objects in the test sample.
- **queryable_ids** (*np.array*) – Set of ids for objects available for querying.
- **batch** (*int (optional)*) – Number of objects to be chosen in each batch query. Default is 1.
- **screen** (*bool (optional)*) – If True display on screen the shift in index and the difference in estimated probabilities of being Ia caused by constraints on the sample available for querying.
- **query_thre** (*float (optional)*) – Maximum percentile where a spectra is considered worth it. If not queryable object is available before this threshold, return empty query. Default is 1.0.

Returns **query_indx** – List of indexes identifying the objects from the test sample to be queried in decreasing order of importance. If there are less queryable objects than the required batch it will return only the available objects – so the list of objects to query can be smaller than 'batch'.

Return type list

Metrics

Individual metrics

accuracy(label_pred, label_true)	Calculate accuracy.
efficiency(label_pred, label_true[, ia_flag])	Calculate efficiency.
purity(label_pred, label_true[, ia_flag])	Calculate purity.
fom(label_pred, label_true[, ia_flag, penalty])	Calculate figure of merit.

actsnclass.accuracy

actsnclass.**accuracy**(*label_pred: list*, *label_true: list*)

Calculate accuracy.

Parameters

- **label_pred** (*list*) – predicted labels
- **label_true** (*list*) – true labels

Returns **Accuracy** – Global fraction of correct classifications.

Return type float

actsnclass.efficiency

actsnclass.**efficiency**(*label_pred: list*, *label_true: list*, *ia_flag=1*)
Calculate efficiency.

Parameters

- **label_pred** (*list*) – Predicted labels
- **label_true** (*list*) – True labels
- **ia_flag** (*int (optional)*) – Flag used to identify Ia objects. Default is 1.

Returns **efficiency** – Fraction of correctly classified SN Ia.

Return type float

actsnclass.purity

actsnclass.**purity**(*label_pred: list*, *label_true: list*, *ia_flag=1*)
Calculate purity.

Parameters

- **label_pred** (*list*) – Predicted labels
- **label_true** (*list*) – True labels
- **ia_flag** (*int (optional)*) – Flag used to identify Ia objects. Default is 1.

Returns **Purity** – Fraction of true SN Ia in the final classified Ia sample.

Return type float

actsnclass.fom

actsnclass.**fom**(*label_pred: list*, *label_true: list*, *ia_flag=1*, *penalty=3.0*)
Calculate figure of merit.

Parameters

- **label_pred** (*list*) – Predicted labels
- **label_true** (*list*) – True labels
- **ia_flag** (*bool (optional)*) – Flag used to identify Ia objects. Default is 1.
- **penalty** (*float*) – Weight given for non-Ias wrongly classified.

Returns **figure of merit** – Efficiency x pseudo-purity (purity with a penalty for false positives)

Return type float

Metrics agregated by category or use

get_snpcc_metric(label_pred, label_true[, ...])	Calculate the metric parameters used in the SNPCC.

actsnclass.get_snpcc_metric

actsnclass.**get_snpcc_metric**(*label_pred: list*, *label_true: list*, *ia_flag=1*, *wpenalty=3*)

Calculate the metric parameters used in the SNPCC.

Parameters

- **label_pred** (*list*) – Predicted labels
- **label_true** (*list*) – True labels
- **ia_flag** (*bool (optional)*) – Flag used to identify Ia objects. Default is 1.
- **wpenalty** (*float*) – Weight given for non-Ias wrongly classified.

Returns

- **metric_names** (*list*) – Name of elements in metrics: [accuracy, eff, purity, fom]
- **metric_values** (*list*) – list of calculated metrics values for each element

Active Learning loop

Full light curve

learn_loop(nloops, strategy, . . . [, . . .])	Perform the active learning loop.

actsnclass.learn_loop

actsnclass.**learn_loop**(*nloops: int*, *strategy: str*, *path_to_features: str*, *output_metrics_file: str*, *output_queried_file: str*, *features_method='Bazin'*, *classifier='RandomForest'*, *training='original'*, *batch=1*, *screen=True*, *survey='DES'*, *nclass=2*, *photo_class_thr=0.5*, *photo_ids=False*, *photo_ids_tofile=False*, *photo_ids_froot=' '*, *classifier_bootstrap=False*, ***kwargs*)

Perform the active learning loop. All results are saved to file.

Parameters

- **nloops** (*int*) – Number of active learning loops to run.
- **strategy** (*str*) – Query strategy. Options are 'UncSampling' and 'RandomSampling'.
- **path_to_features** (*str or dict*) – Complete path to input features file. if dict, keywords should be 'train' and 'test', and values must contain the path for separate train and test sample files.
- **output_metrics_file** (*str*) – Full path to output file to store metric values of each loop.
- **output_queried_file** (*str*) – Full path to output file to store the queried sample.
- **features_method** (*str (optional)*) – Feature extraction method. Currently only 'Bazin' is implemented.
- **classifier** (*str*) – Machine Learning algorithm. Currently implemented options are 'RandomForest', 'GradientBoostedTrees', 'K-NNclassifier','MLPclassifier','SVMclassifier' and 'NBclassifier'.
- **training** (*str or int (optional)*) – Choice of initial training sample. If 'original': begin from the train sample flagged in the file If int: choose the required number of samples at random, ensuring that at least half are SN Ia Default is 'original'.

- **batch** (*int (optional)*) – Size of batch to be queried in each loop. Default is 1.
- **photo_class_thr** (*float (optional)*) – Threshold for photometric classification. Default is 0.5. Only used if photo_ids is True.
- **photo_ids** (*bool (optional)*) – Get photometrically classified ids. Default is False.
- **photo_ids_to_file** (*bool (optional)*) – If True, save photometric ids to file. Default is False.
- **photo_ids_froot** (*str (optional)*) – Output root of file name to store photo ids. Only used if photo_ids is True.
- **screen** (*bool (optional)*) – If True, print on screen number of light curves processed.
- **survey** (*str (optional)*) – 'DES' or 'LSST'. Default is 'DES'. Name of the survey which characterizes filter set.
- **nclass** (*int (optional)*) – Number of classes to consider in the classification Currently only nclass == 2 is implemented.
- **bootstrap** (*bool (optional)*) – Flag for bootstrapping on the classifier Must be true if using disagreement based strategy
- **kwargs** (*extra parameters*) – All keywords required by the classifier function.

Time domain

`get_original_training`	
time_domain_loop(days, output_metrics_file, ...)	Perform the active learning loop.

actsnclass.time_domain_loop

actsnclass.**time_domain_loop**(*days: list*, *output_metrics_file: str*, *output_queried_file: str*, *path_to_features_dir: str*, *strategy: str*, *fname_pattern: list*, *batch=1*, *canonical=False*, *classifier='RandomForest'*, *cont=False*, *first_loop=20*, *features_method='Bazin'*, *nclass=2*, *Ia_frac=0.5*, *output_fname=''*, *path_to_canonical=''*, *path_to_full_lc_features=''*, *path_to_train=''*, *path_to_queried=''*, *queryable=True*, *query_thre=1.0*, *save_samples=False*, *sep_files=False*, *screen=True*, *survey='LSST'*, *initial_training='original'*)

Perform the active learning loop. All results are saved to file.

Parameters

- **days** (*list*) – List of 2 elements. First and last day of observations since the beginning of the survey.
- **output_metrics_file** (*str*) – Full path to output file to store metrics for each loop.
- **output_queried_file** (*str*) – Full path to output file to store the queried sample.
- **path_to_features_dir** (*str*) – Complete path to directory holding features files for all days.
- **strategy** (*str*) – Query strategy. Options are 'UncSampling' and 'RandomSampling'.
- **fname_pattern** (*str*) – List of strings. Set the pattern for filename, except day of survey. If file name is 'day_1_vx.dat' -> ['day_', '_vx.dat']
- **batch** (*int (optional)*) – Size of batch to be queried in each loop. Default is 1.
- **canonical** (*bool (optional)*) – If True, restrict the search to the canonical sample.

- **continue** (*bool (optional)*) – If True, read the initial states of previous runs from file. Default is False.
- **classifier** (*str (optional)*) – Machine Learning algorithm. Currently 'RandomForest', 'GradientBoostedTrees', 'KNN', 'MLP', 'SVM' and 'NB' are implemented. Default is 'RandomForest'.
- **first_loop** (*int (optional)*) – First day of the survey already calculated in previous runs. Only used if initial_training == 'previous'. Default is 20.
- **features_method** (*str (optional)*) – Feature extraction method. Currently only 'Bazin' is implemented.
- **Ia_frac** (*float in [0,1] (optional)*) – Fraction of Ia required in initial training sample. Default is 0.5.
- **nclass** (*int (optional)*) – Number of classes to consider in the classification Currently only nclass == 2 is implemented.
- **path_to_canonical** (*str (optional)*) – Path to canonical sample features files. It is only used if "strategy==canonical".
- **path_to_full_lc_features** (*str (optional)*) – Path to full light curve features file. Only used if training is a number.
- **path_to_train** (*str (optional)*) – Path to initial training file from previous run. Only used if initial_training == 'previous'.
- **path_to_queried** (*str(optional)*) – Path to queried sample from previous run. Only used if initial_training == 'previous'.
- **queryable** (*bool (optional)*) – If True, allow queries only on objects flagged as queryable. Default is True.
- **query_thre** (*float (optional)*) – Percentile threshold for query. Default is 1.
- **save_samples** (*bool (optional)*) – If True, save training and test samples to file. Default is False.
- **screen** (*bool (optional)*) – If True, print on screen number of light curves processed.
- **sep_files** (*bool (optional)*) – If True, consider train and test samples separately read from independent files. Default is False.
- **survey** (*str (optional)*) – Name of survey to be analyzed. Accepts 'DES' or 'LSST'. Default is LSST.
- **initial_training** (*str or int (optional)*) – Choice of initial training sample. If 'original': begin from the train sample flagged in the file eilf 'previous': read training and queried from previous run. If int: choose the required number of samples at random, ensuring that at least half are SN Ia Default is 'original'.
- **output_fname** (*str (optional)*) – Complete path to output file where initial training will be stored. Only used if save_samples == True.

Plotting

Canvas()	Canvas object, handles and plot information from multiple strategies.
Canvas.load_metrics(path_to_files, ...)	Load and identify set of metrics.

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Canvas.set_plot_dimensions()	Set directives for plot sizes.
Canvas.plot_metrics(output_plot_file, ...[, ...])	Generate plot for all metrics in files and strategies given as input.

actsnclass.Canvas

class actsnclass.**Canvas**

Canvas object, handles and plot information from multiple strategies.

Variables

- **axis_label_size** (*int*) – Size of font in axis labels.
- **canonical** (*pd.DataFrame*) – Data from Canonical strategy.
- **fig_size** (*tuple*) – Figure dimensions.
- **rand_sampling** (*pd.DataFrame*) – Data from Random Sampling strategy.
- **tick_label_size** (*int*) – Size of tick labels in both axis.
- **ncolumns** (*int*) – Number of columns in panel grid.
- **nlines** (*int*) – Number of lines in panel grid.
- **nmetrics** (*int*) – Number of metric elements (panels in plot).
- **metrics_names** (*list*) – List of names for metrics to be plotted.
- **unc_sampling** (*pd.DataFrame*) – Data from Uncertainty Sampling strategy.
- **colors** (*dict*) – Colors corresponding to each strategy. They were chosen to follow Mondrian's color palette. Do not change and try to keep the same palette in adding new elements.
- **labels** (*dict*) – Labels to appear on plot for each strategy.
- **markers** (*dict*) – Plot markers for each strategy.
- **strategies** (*dict*) – Dictionary connecting each data frame to its standard nomenclature (not the plot labels).

load_metrics(*path_to_files: list*, *strategy_list: list*)

Load metrics and identify set of metrics.

set_plot_dimensions()

Set directives for plot sizes based on number of metrics.

plot_metrics(*output_plot_file: str*, *strategies_list: list*)

Generate plot for all metrics in files and strategies given as input.

Examples

Define input variables

```
>>> path_to_files = ['results/metrics_canonical.dat',
>>>                  'results/metrics_random.dat',
>>>                  'results/metrics_unc.dat']
>>> strategies_list = ['Canonical', 'RandomSampling', 'UncSampling']
>>> output_plot = 'plots/metrics1_unc.png'
```

Initiate the Canvas object, read and plot the results for each metric and strategy.

```
>>> cv = Canvas()
>>> cv.load_metrics(path_to_files=path_to_files,
>>>                     strategies_list=strategies_list)
>>> cv.set_plot_dimensions()
>>> cv.plot_metrics(output_plot_file=output_plot,
>>>                 strategies_list=strategies_list)
```

__init__()
Initialize self. See help(type(self)) for accurate signature.

Methods

__init__()	Initialize self.
load_metrics(path_to_files, strategies_list)	Load and identify set of metrics.
plot_metrics(output_plot_file, strategies_list)	Generate plot for all metrics in files and strategies given as input.
set_plot_dimensions()	Set directives for plot sizes.

actsnclass.Canvas.load_metrics

Canvas.**load_metrics**(*path_to_files: list*, *strategies_list: list*)
Load and identify set of metrics.

Populates attributes: canonical, unc_sampling or rand_sampling, depending on choice of 'sample'.

Parameters

- **path_to_files** (*str*) – List of paths to metrics files for different strategies.
- **strategies_list** (*list*) – List of all strategies to be included in the same plot. Current possibilities are: ['canonical', 'rand_sampling', 'unc_sampling'].

actsnclass.Canvas.set_plot_dimensions

Canvas.**set_plot_dimensions**()
Set directives for plot sizes.

Populates attributes: nmetrics, ncolumns, and fig_size.

actsnclass.Canvas.plot_metrics

Canvas.**plot_metrics**(*output_plot_file: str*, *strategies_list: list*, *lim_queries=None*)
Generate plot for all metrics in files and strategies given as input.

Parameters

- **output_plot_file** (*str*) – Complete path to file to store plot.
- **strategies_list** (*list*) – List of all strategies to be included in the same plot. Current possibilities are: ['canonical', 'rand_sampling', 'unc_sampling'].
- **lim_queries** (*int or None (optional)*) – If int, maximum number of queries to be plotted. If None no limits are imposed. Default is None.

Scripts

`build_canonical`(user_choices)	Build canonical sample for SNPCC data set fitted with Bazin features.
`build_time_domain`(user_choice)	Generates features files for a list of days of the survey.
`fit_dataset`(user_choices)	Fit the entire sample with the Bazin function.
`make_metrics_plots`(user_input)	Generate metric plots.
`run_loop`(args)	Command line interface to run the active learning loop.
`run_time_domain`(user_choice)	Command line interface to the Time Domain Active Learning scenario.

1.4 Indices and tables

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