lightning.py

Release v2024.1.0

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DOCUMENTATION

`lightning.py` is the python version of the Lightning SED-fitting code. The goal of the project is to maintain Lightning's primary design philosophy of simplicity and physically-based models, while taking advantage of Python's object-oriented nature and the wide array of pre-existing astronomical Python code to improve modularity and user-friendliness.

The IDL version of `Lightning` is now considered the "legacy" version, and will not see further development. Its documentation will remain available at lightning-sed.readthedocs.io, and the source code can still be downloaded from github.com/rafaeleufrasio/lightning.

This new python version contains all the features of IDL `Lightning` with the current notable exception of the Doore+(2021) inclination-dependent attenuation model. Users interested in the properties of highly-inclined disk galaxies are encouraged to continue to use IDL `Lightning` for their analyses, and to let the authors know if it would be nice to access that model through `lightning.py`.

CHAPTER

ONE

INSTALLATION

Currently, `lightning` is not available on PyPI or conda-forge. Until it is uploaded, `lightning` and its dependencies can be installed by cloning the repo, creating a conda environment with the required dependencies, and then installing the package locally:

```
git clone https://github.com/ebmonson/lightningpy.git
cd lightningpy
conda env create -f environment.yml
conda activate lightning
pip install .  --no-deps
```

Model files will then need to be downloaded from Dropbox and dropped in the appropriate directories of the installed package. The folders have readme files to guide you on which files belong where; note that you only need to download a model set if you plan on using it. If you're following the instructions above, the root directory for the models will be

```
path/to/conda/envs/lightning/lib/python3.XX/site-packages/lightning/data/models/
```

where `3.XX` should be replaced with the version of python used by your environment. You can locate your lightning install by opening a python terminal and doing

```
>>> import lightning
>>> print(lightning.__file__)
```

which will show you the root of the lightning install.

CHAPTER

TWO

GETTING STARTED

2.1 Setup

[1]:
```
import matplotlib.pyplot as plt
plt.style.use('lightning.plots.style.lightning-serif')
```

The primary interface to `lightning.py` (hereafter, just `lightning`) is the `Lightning` class.

[1]:
```
from lightning import Lightning
```

This class holds all the information about the models and observations that are needed to perform inference with your chosen models. In its most basic configuration for inference, `Lightning` requires you to specify a set of bandpasses, a distance indicator (either a distance in Mpc or a redshift), and fluxes and uncertainties corresponding to those bandpasses (in mJy).

[2]:
```
import numpy as np
filter_labels = ['SDSS_u', 'SDSS_g', 'SDSS_r', 'SDSS_i', 'SDSS_z']
dist = 7.2
fnu = np.array([237.147, 606.260, 929.869, 1205.353, 1337.25])
fnu_unc = np.array([24.045, 61.632, 94.810, 122.585, 135.481])
lgh = Lightning(filter_labels, lum_dist=dist, flux_obs=fnu, flux_obs_unc=fnu_unc)
```

Note that `filter_labels` is the first and only positional argument, since it's the only argument that's always required: we could specify redshift rather than distance, and it's possible to not specify fluxes and uncertainties (e.g., if you're simulating fluxes). Note also that the `flux_obs` and `flux_unc` keywords should be set by numpy arrays.

The setup here will adopt the defaults: 5 age bins spaced from 0.0-13.4 Gyr, modified Calzetti extinction (as in Noll+2009) and no dust emission (or AGN emission). All of these choices can be modified or made explicit by setting the appropriate keywords when initializing `Lightning`.

We can print the full set of model parameters with

[3]:
```
lgh.print_params()
```

```
['psi_1', 'psi_2', 'psi_3', 'psi_4', 'psi_5']
['Zmet']
['mcalz_tauV_diff', 'mcalz_delta', 'mcalz_tauV_BC']

Total parameters: 9
```

The `verbose` option to `print_params` additionally describes the parameters and gives their allowed ranges.

2.2 Inference

The last step before we can perform Bayesian inference is to define priors for each parameter. In `lightning` priors are passed to the `fit` method as a list of objects from the `lightning.priors` module.

[4]:
```
from lightning.priors import UniformPrior, ConstantPrior
priors = [UniformPrior([0,10]),
          UniformPrior([0,10]),
          UniformPrior([0,10]),
          UniformPrior([0,10]),
          UniformPrior([0,10]),
          ConstantPrior([0.020]),
          UniformPrior([0,3]),
          ConstantPrior([0.0]),
          ConstantPrior([0.0])]
```

Note that the priors are (and must be) in the same order as the parameter list produced by `lgh.print_params`: the first 5 correspond to the SFH coefficients, the next is the stellar metallicity, and the final three are the parameters of the attenuation curve.

To fit with `emcee` we must define an initial state. We can sample this state from the priors of the model:

[5]:
```
Nwalkers = 32
const_dim = np.array([pr.model_name == 'constant' for pr in priors])
p0 = np.stack([pr.sample(Nwalkers) for pr in priors], axis=-1)
print(p0.shape)
```

```
(32, 9)
```

[6]:
```
mcmc = lgh.fit(p0,
               method='emcee',
               priors=priors,
               const_dim=const_dim,
               Nwalkers=Nwalkers,
               Nsteps=10000,
               progress=True)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
100%|##########################################################################################
↪##########################################################| 10000/10000 [00:34<00:00,␣
↪288.13it/s]
```

The `const_dim` keyword is a holdover from previous versions predating `ConstantPrior`. When the MCMC sampling has finished, we can construct the final MCMC chain with the `get_mcmc_chains` method:

[8]:
```
chain, logprob_chain, tau = lgh.get_mcmc_chains(mcmc,
                                                discard=3000,
                                                thin=500,
                                                Nsamples=300,
```

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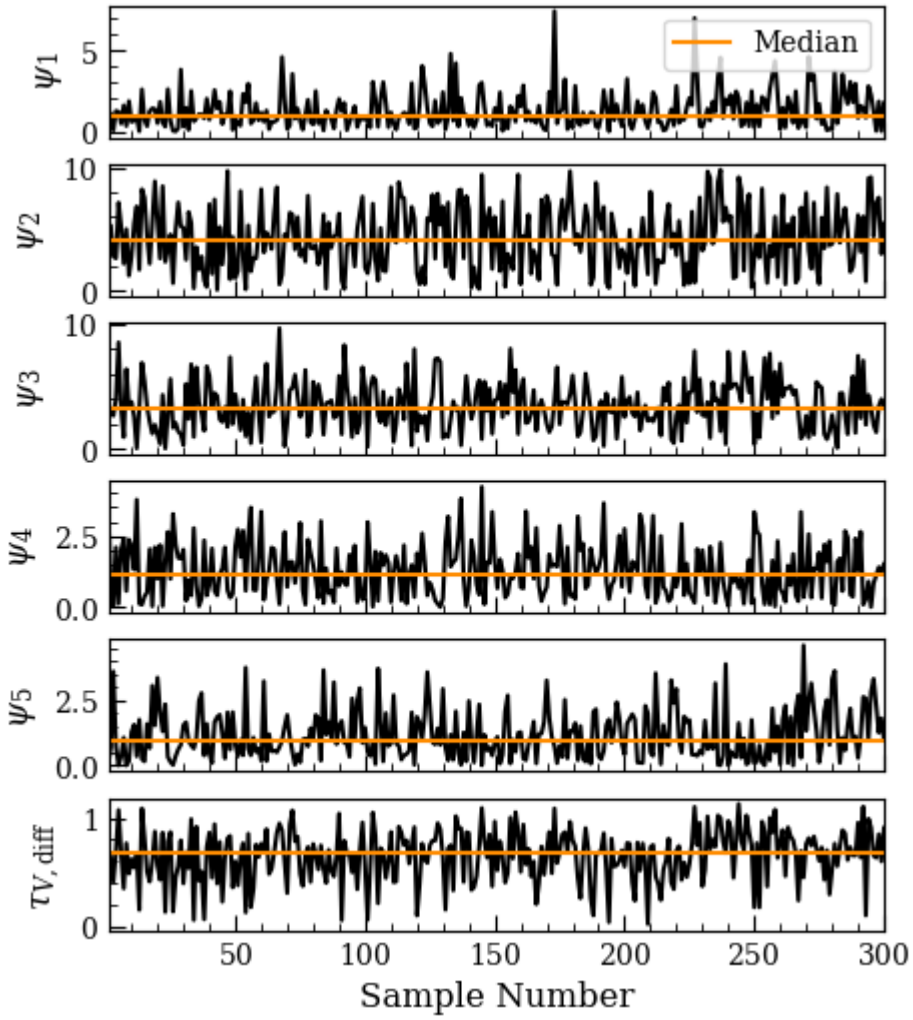
```
                                                const_dim=const_dim,
                                                const_vals=p0[0,const_dim])
```

```
WARNING: The integrated autocorrelation time is longer than N/50.
         The autocorrelation estimate may be unreliable.
```

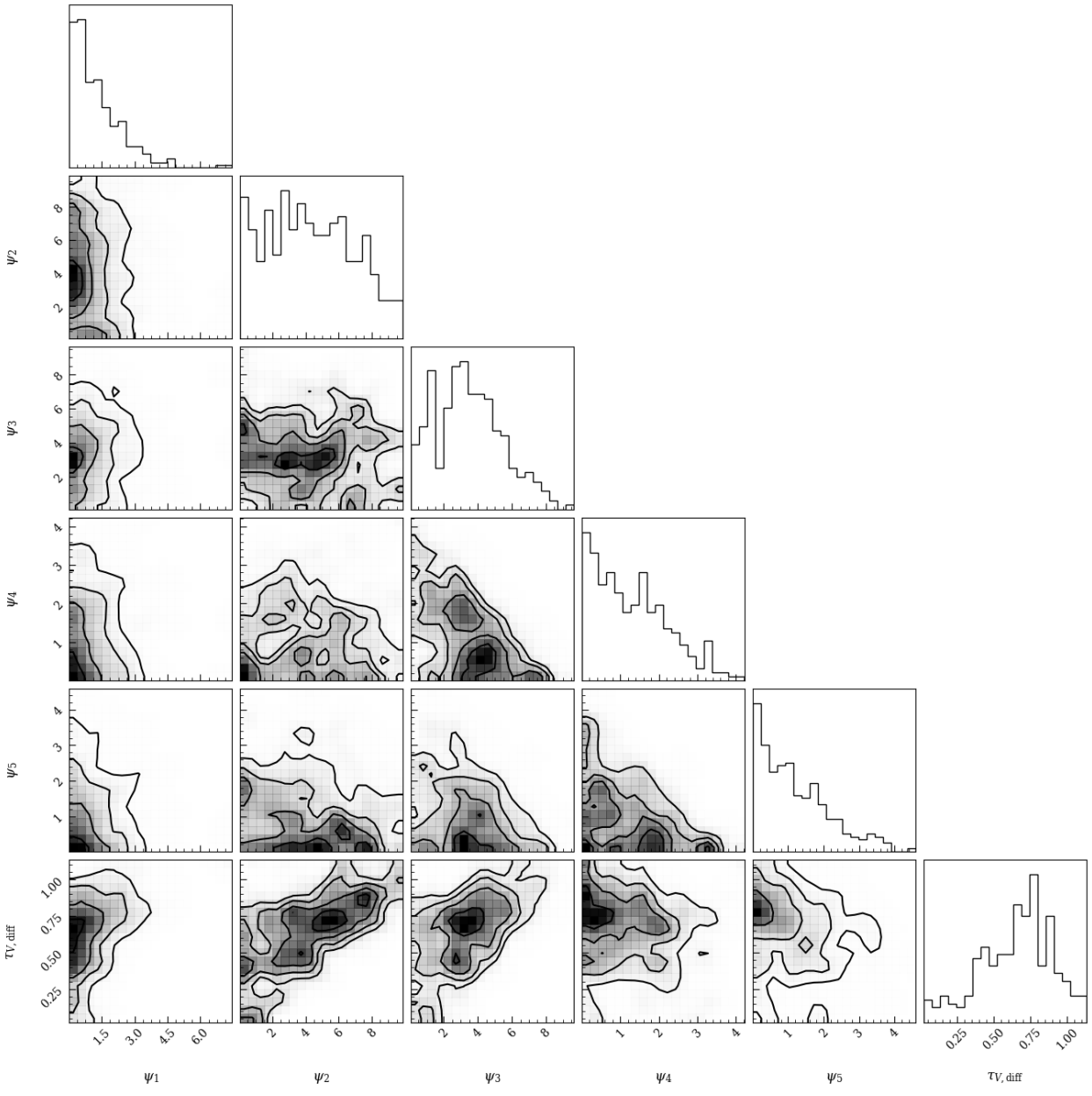
The above command can be read as "discard the first 3000 samples from each walker, retain only every 500th sample after that, and then return the last 1000 samples after merging the separate chains from each walker." The `const_dim` and `const_vals` keywords allow us to add back in the constant dimensions of the model (since they aren't sampled, the `mcmc` sampler object returned by `emcee` doesn't know anything about them) such that the `chain` array has shape (1000, 9). The `tau` returned by the above command is the estimate of the integrated autocorrelation time for each parameter. If the chains were run too short, the estimate may be unreliable (or not available). In that case the MCMC sampling can be continued from its stopping point with `mcmc.run_mcmc(Nsteps)` and then the above command can be run again to construct the chains. In practice the discard and thin factors can be chosen based on the autocorrelation time (~a few times and ~0.5-1 times, are decent choices, respectively), but arbitrarily chosen scales are often fine as long as one inspects the chains for correlated behavior. That can be done with a chain plot:

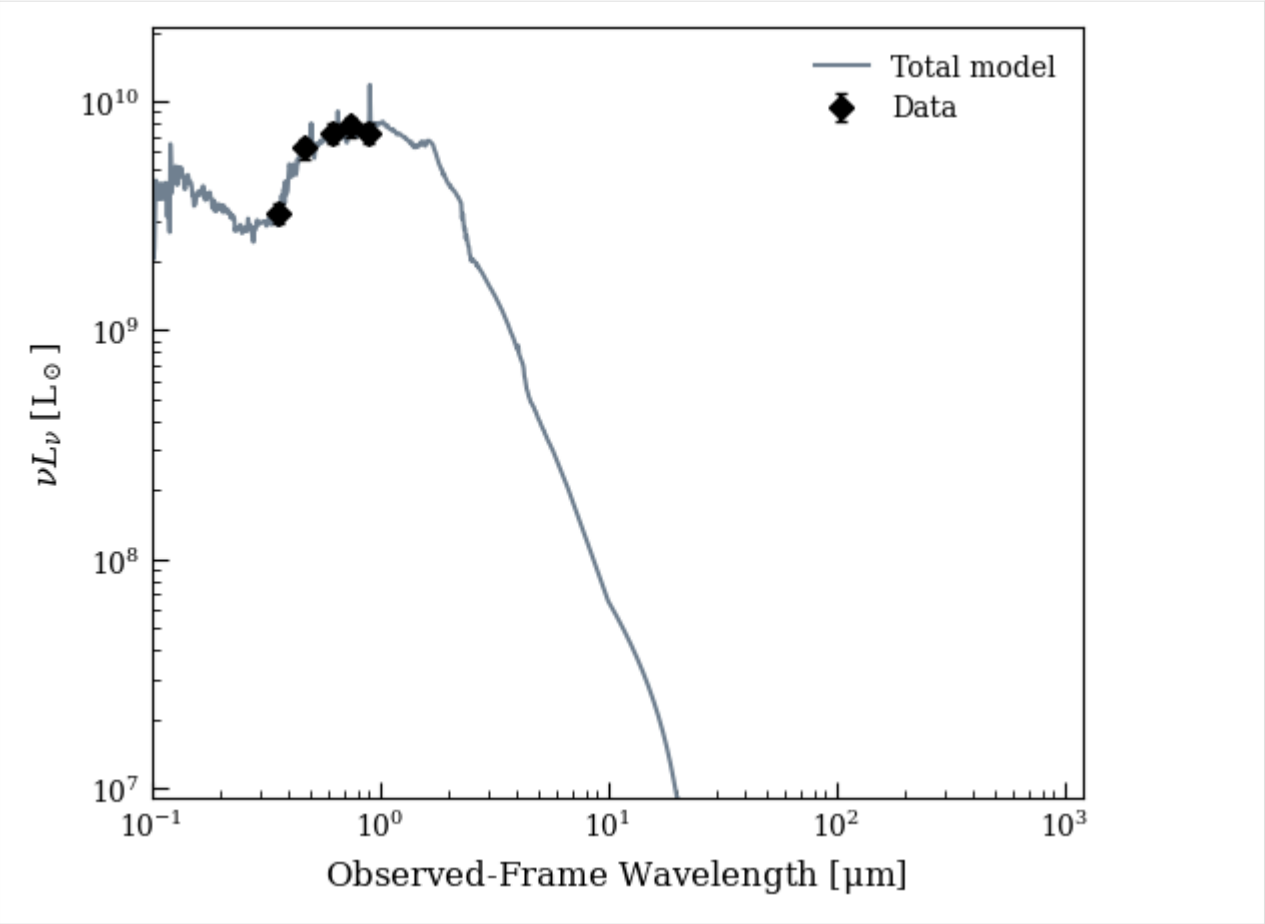
[9]:
```
fig, ax = lgh.chain_plot(chain)
```

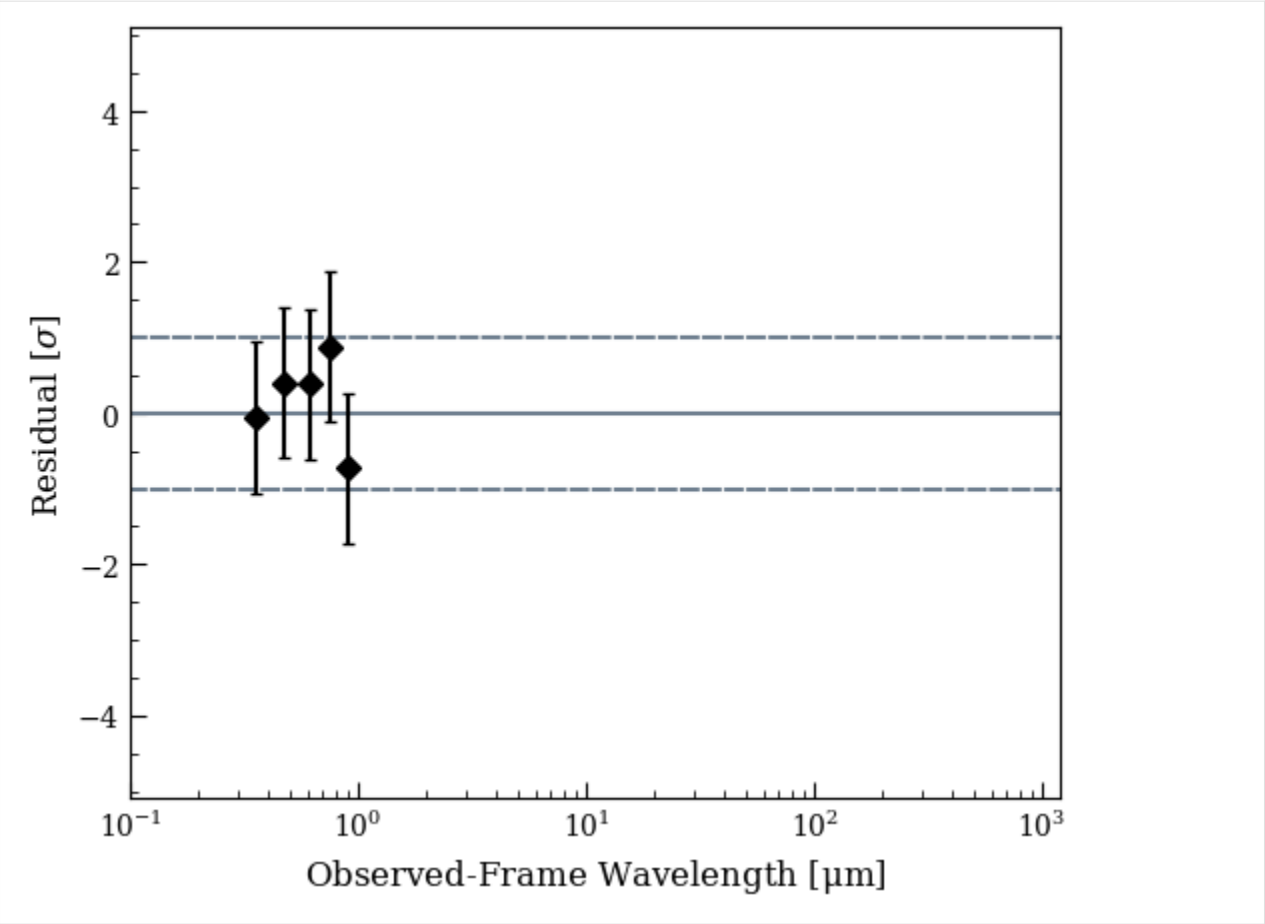


[12]:
```
fig1 = lgh.corner_plot(chain, titles=True, smooth=1)
fig2, ax2 = lgh.sed_plot_bestfit(chain, logprob_chain)
fig3, ax3 = lgh.sed_plot_delchi(chain, logprob_chain)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
```




Total model
Data
10^{10}
10^{9}
10^{8}
10^{7}
νL_ν [L$_\odot$]
10^{-1}
10^{0}
10^{1}
10^{2}
10^{3}
Observed-Frame Wavelength [μm]



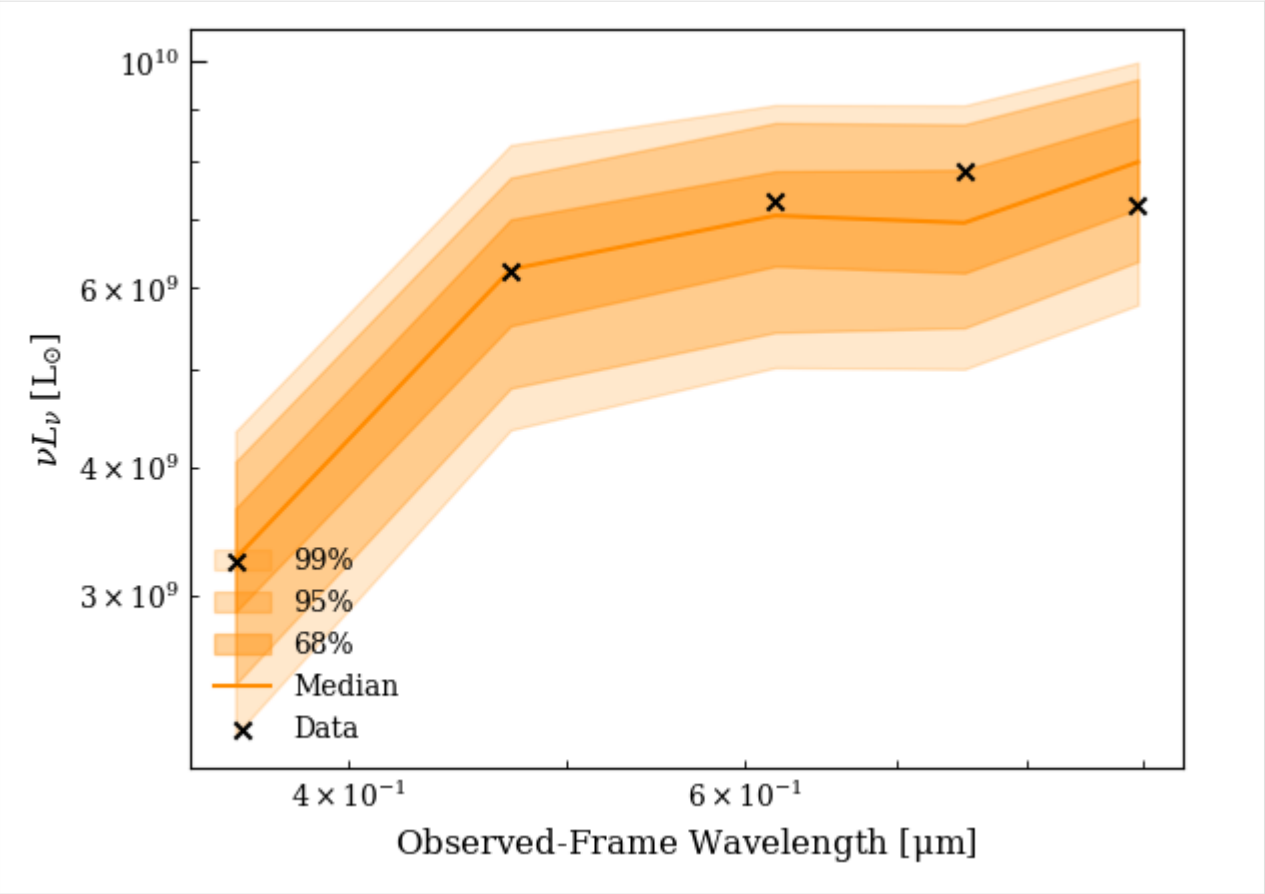
It's worth here considering how well the model can reproduce the observed data. The built in methods for goodness of fit are based on the posterior predictive check, which samples sets of parameters from the chain, uses them to generate a new dataset with the same noise characteristics as the original dataset, and compares this new dataset to the model. The fraction of new datasets that have worse χ^2 than the fit to the observed model is the $p-$value.

[15]:
```
from lightning.ppc import ppc, ppc_sed
pvalue, chi2_rep, chi2_obs = ppc(lgh, chain, logprob_chain)
print('p = %.2f' % pvalue)
```

```
p = 0.60
```

There is also the option to make an SED plot showing the range of data that can be produced by the model:

[16]:
```
fig, ax = ppc_sed(lgh, chain, logprob_chain)
```



All of our data are very well reproduced by the model, yielding a $p-$value of 0.60.

CHAPTER

THREE

CHOOSING A MODEL

Note

For a visual guide to the included models, see the *Model Library*.

3.1 Stellar Model and Star Formation History

Modeling in `lightning.py` is biased toward the use of piecewise-constant (sometimes called "non-parametric") star formation histories (SFH). These are adopted as the default choice for fitting galaxy SEDs. Several other functional SFH forms are provided for toy models and simulations.

Note

The only stellar population models included in the github distribution are the "legacy" PEGASE models used in IDL Lightning. Due to restrictions on file size, the recently developed BPASS + Cloudy and PEGASE + Cloudy models used in Lehmer+(2024) must be downloaded before they can be used with Lightning.

3.1.1 PEGASE

The default stellar population model remains the `PEGASE` models used in IDL `Lightning`, with a slightly expanded range of metallicity. These population models include an analytic prescription for nebular emission. The IMF is locked to the Kroupa et al. (2001) IMF.

3.1.2 PEGASE-A24

This release includes a new set of `PEGASE` models including a nebular emission model derived from single-cloud `Cloudy` simulations run by Amirnezam Amiri (in 2024, hence 'A24'). See Nebular Emission Recipe for a description of the procedure. The IMF remains Kroupa et al. (2001).

3.1.3 BPASS

The BPASS v2.1 release, including *the BPASS collaboration's* Cloudy *simulations*. The IMF is the imf_135_300 option from BPASS.

3.1.4 BPASS-A24

BPASS v2.1 models including a nebular emission model derived from single-cloud Cloudy simulations run by Amirnezam Amiri (in 2024, hence 'A24'). See Nebular Emission Recipe for a description of the procedure. The IMF is Chabrier et al. (2003).

3.1.5 BPASS-ULX-G24

BPASS v2.1 models including a nebular emission model derived from single-cloud Cloudy simulations run by Amirnezam Amiri following the same recipe as above. However, the source SEDs are drawn from the Garofali et al. (2024) (hence 'G24') "Simple X-ray Population" models, which match the BPASS UV-IR spectra with a ULX model. The IMF is the imf_135_100 option from BPASS. We note that our implementation of these models do not extend directly to the X-rays in a self-consistent way. A self-consistent (between X-rays and emission lines) treatment of ULXs is an area of active development. We provide these models mainly as a means for simulating the emission line ratios of composite populations containing ULXs rather than as a component for SED fitting.

3.2 Attenuation Models

The default attenuation curve in Lightning is the Noll et al. (2009) modification of the Calzetti et al. (2000) curve, which adds a Drude profile at 2175 Å, and a parameter δ which controls the deviation from the Calzetti slope in the UV. Note that the IDL Lightning implementation of birth cloud attenuation is no longer included – the tauV_BC parameter is nonfunctional and should be left constant at 0 in any fits. The option to include dust grains in the HII regions adds some element of extra attenuation for young stars, though it shouldn't be applied incautiously, especially at low metallicity.

The featureless Calzetti curve is also preserved as an option.

3.3 Dust Emission Model

The only option for dust emission is the Draine and Li (2007) model, with 5 possible free parameters. **Energy balance between the dust emission and attenuation models is always enforced.**

3.4 UV-IR AGN Model

We implement the SKIRTOR model grid from Stalevski et al. (2016), with 3-4 free parameters, fixing the opening angle of the torus at 40 degrees. There are several quirks to our implementation:

- The UV-IR AGN model sets the normalization of the X-ray model *unless using the* QSOSED *X-ray AGN model* in which case the situation is reversed: the X-ray AGN model sets the normalization of the UV-IR model. For practical purposes this means the UV-IR normalization should be held constant when fitting the QSOSED model.
- When the polar dust model is selected the attenuation of the AGN and stellar population are decoupled - the accretion disk is attenuated only by the torus and polar dust. When the polar dust model *isn't* used, the accretion disk is subject to the same attenuation as the stellar population.

3.5 X-ray Models

3.5.1 Stars

X-ray emission from compact object binaries is modeled as a power law with a high energy exponential cutoff at 100 keV. Γ is available as a free parameter, though in practice we typically leave it fixed. The normalization of the X-ray stellar population model is set using the empirical $L_X - \log(t)$ relationship derived by Gilbertson et al. (2022) from normal galaxies in the Chandra Deep Fields. The hot gas spectral shape is not explicitly included, though the modeling by Gilbertson et al. is such that the *luminosity* of the hot gas is included. This is a weakness of our current implementation, and improvement of the X-ray stellar population models is an active area of development.

We expect that most users of the X-ray fitting capability of `Lightning` will be interested in using it to constrain the overall luminosity of an AGN component. We advise such users that they should still consider the contribution from X-ray binaries by enabling the X-ray stellar population model (perhaps with fixed Γ), especially for fainter AGN.

3.5.2 AGN

Power-Law

We provide a simple power law model with a high-energy exponential cutoff at 300 keV. This model is linked to the luminosity of the UV-IR AGN model at 2500 Å using the Lusso and Risaliti (2017) $L_{2\ \mathrm{keV}} - L_{2500\ \text{Å}}$ relationship, where we allow for a deviation δ from the relationship, representing the scatter in the population. The two sample-able parameters are thus Γ, the power law index, and δ.

QSOSED

We also provide an implementation of the Kubota and Done (2018) QSOSED model family. These physically-motivated models are constructed to reproduce the soft X-ray excess observed in AGN with an accretion disk and two comptonizing components. In our implementation, the parameters are the black hole mass M_{SMBH} and the Eddington ratio $\dot{m} = \dot{M}/\dot{M}_{\mathrm{Edd}}$. As noted above, when this model is selected, the normalization of the entire X-ray-to-IR AGN model is set by the combination of M_{SMBH} and $\dot{m}$ by linking the accretion disk luminosities of the model components at 2500 Å.

The range of Eddington ratios available in this implementation are limited, and thus so is the flexibility of the model for fitting diverse populations of AGN. We've had some success in applying it to relatively obscured, distant AGN. In the future, we may attempt to make this model more flexible by falling back on the AGNSED model family, which allows a greater range of Eddington ratio, and incorporating further physically-motivated AGN models.

3.5.3 Absorption

We provide two X-ray absorption models, familiar to users of `Sherpa` and `Xspec`. We generated the curves on a log-spaced energy grid from 0.01 to 20 keV using `Sherpa`, with default abundances. Both models have a single parameter, the hydrogen column density N_H in units of $10^{20}\ \mathrm{cm}^{-2}$.

phabs

Photoelectric absorption.

tbabs

Tubingen-Boulder absorption model from Wilms et al. (2000), including more metal edges than `phabs`.

CHAPTER

FOUR

CHOOSING A SOLVER

Fitting in `lightning` is biased toward the Bayesian exploration of parameter space rather than maximum likelihood estimation. As such the majority of our plotting and post-processing functions assume that you've used `emcee` for fitting.

We do however include an option for fitting the SED model with the L-BFGS-B minimization algorithm, results from which are compatible with the `lightning_postprocess` function. There is additionally an option to solve the problem with L-BFGS-B and then, if it converges, perform a brief exploration of parameter around the best fitting solution (converting any preexisting bounds on the parameters to uniform priors). This method is potentially much faster than a brute force fit with `emcee`, though it risks getting stuck in a local minimum and is not possible when the solver fails to converge. The results from this MCMC followup are naturally compatible with the MCMC plotting functions.

In the future, we anticipate adding the option to use a nested sampler for exploration of the parameter space.

CHAPTER

FIVE

CATALOG POSTPROCESSING

For samples of galaxies or applications like galaxy mapping, it's desirable to combine the results of all the completed SED fits into a single file. We provide a function for this: `lightning.postprocessing.postprocess_catalog`. The function takes lists of "result" and "model" files and collates the results into a single HDF5 catalog. The result files are expected to be HDF5 files with a specific format.

For `solver_mode='mcmc'`, the chains are also expected to be in HDF5 format, with the following structure:

```
mcmc
├── logprob_samples (Nsamples)
├── samples (Nsamples, Nparams)
└── autocorr (Nparams)
```

Whereas for `solver_mode='mle'`, the results are expected to be formated as:

```
res
├── bestfit (Nparams)
└── chi2_best ()
```

The model files can be either JSON or pickle files, selected by the `model_mode` keyword. The final HDF5 catalog file is generally structured as follows:

```
└──sourcename
    ├── mcmc
    │   ├── logprob_samples (Nsamples)
    │   └── samples (Nsamples, Nparams)
    ├── parameters
    │   ├── modelname
    │   │   └── parametername
    │   │       ├── best ()
    │   │       ├── hi ()
    │   │       ├── lo ()
    │   │       └── med ()
    └── properties
        ├── filter_labels (Nfilters)
        ├── lnu (Nfilters)
        ├── lnu_unc (Nfilters)
        ├── lumdist ()
        ├── mstar
        │   ├── best ()
        │   ├── hi ()
        │   ├── lo ()
        │   ├──
```

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```
│   └── med ()
├── redshift ()
└── pvalue ()
```

where e.g., MCMC keys and parameter quantiles are omitted when dealing with MLE results. See *Postprocessing* in the detailed API reference for further information.

CHAPTER

SIX

EXAMPLES

This collection of notebooks give a few examples of lightning in use: fitting normal galaxies with simple and complex models, comparing results using different stellar population models, and generating grids of line ratios for complex star formation histories.

6.1 Basic Fit - NGC 337

Using the Dale et al. (2017) photometry, fit the SED of NGC 337 with a basic model that would have been the default model in IDL Lightning.

6.1.1 Imports

[7]:
```
import numpy as np
import h5py
rng = np.random.default_rng()
import astropy.units as u
from astropy.table import Table
from corner import corner
import matplotlib.pyplot as plt
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline

from lightning import Lightning
from lightning.priors import UniformPrior, ConstantPrior
```

6.1.2 Initialization

We read in the photometry and information like the distance from a `fits` file and load it into Lightning:

[2]:
```
cat = Table.read('../photometry/ngc337_dale17_photometry.fits')

# Housekeeping to load the photometry:
# strings come in as bytestrings (unencoded)
# The labels are also padded with spaces
filter_labels = np.array([s.decode().strip() for s in cat['FILTER_LABELS'].data[0]])
fnu_obs = cat['FNU_OBS'].data[0]
fnu_unc = cat['FNU_UNC'].data[0]
```

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```
dl = cat['LUMIN_DIST'].data[0]

lgh = Lightning(filter_labels,
                lum_dist=dl,
                stellar_type='PEGASE',
                SFH_type='Piecewise-Constant',
                atten_type='Modified-Calzetti',
                dust_emission=True,
                model_unc=0.10,
                print_setup_time=True)

lgh.flux_obs = fnu_obs * 1e3
lgh.flux_unc = fnu_unc * 1e3

# We could save the configuration like so:
# lgh.save_pickle('ngc337_config.pkl')
```

```
0.023 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
0.558 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.141 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
0.722 s elapsed total
```

Display the parameters and their allowed ranges. This is often useful to do when using a new model configuration for the first time, since the order of the parameters here is the same as that expected when defining the priors and the initial state for the MCMC.

[3]:
```
lgh.print_params(verbose=True)
```

```

============================
Piecewise-Constant
============================
Parameter  Lo  Hi              Description
--------- --- --- ------------------------
    psi_1 0.0 inf SFR in stellar age bin 1
    psi_2 0.0 inf SFR in stellar age bin 2
    psi_3 0.0 inf SFR in stellar age bin 3
    psi_4 0.0 inf SFR in stellar age bin 4
    psi_5 0.0 inf SFR in stellar age bin 5

============================
Pegase-Stellar
============================
Parameter    Lo  Hi                                        Description
--------- ----- --- ------------------------------------------------
     Zmet 0.001 0.1 Metallicity (mass fraction, where solar = 0.020)

============================
Modified-Calzetti
```

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```
============================
      Parameter   Lo                 Hi                                                ␣
↪                             Description
--------------- ---- ------------------ ------------------------------------------------
↪----------------------------------------
mcalz_tauV_diff  0.0                inf                                                ␣
↪         Optical depth of the diffuse ISM
    mcalz_delta -inf 0.4473684210526316 Deviation from the Calzetti+2000 UV power law␣
↪slope (Upper limit set by requiring Eb >= 0)
  mcalz_tauV_BC  0.0                inf                                      Optical depth␣
↪of the birth cloud in star forming regions

============================
DL07-Dust
============================
      Parameter     Lo       Hi                                                        ␣
↪   Description
--------------- ------ -------- ------------------------------------------------------------
↪--------------
dl07_dust_alpha  -10.0      4.0                  Radiation field intensity distribution␣
↪power law index
dl07_dust_U_min    0.1     25.0                                        Radiation field␣
↪minimum intensity
dl07_dust_U_max 1000.0 300000.0                                        Radiation field␣
↪maximum intensity
dl07_dust_gamma    0.0      1.0 Fraction of dust mass exposed to radiation field␣
↪intensity distribution
dl07_dust_q_PAH 0.0047   0.0458                            Fraction of dust mass␣
↪composed of PAH grains

Total parameters: 14
```

[4]:
```
p = np.array([1,1,1,1,1,
              0.02,
              0.3, 0.0, 0.0,
              2, 1, 3e5, 0.1, 0.01])

# Currently the setup is to provide this mask that tells
# lightning which parameters are constant; lightning doesn't yet
# completely recognize the ConstantPrior prior.
const_dim = np.array([False, False, False, False, False,
                      True,
                      False, False, True,
                      True, False, True, False, False])

# This is a little tedious
priors = [UniformPrior([0, 1e1]), # SFH
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          ConstantPrior([0.02]), # Metallicity
```

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```
          UniformPrior([0, 3]), # tauV
          UniformPrior([-2.3, 0.4]), # delta
          ConstantPrior([0.0]), # tauV birth cloud
          ConstantPrior([2]), # alpha
          UniformPrior([0.1, 25]), # Umin
          ConstantPrior([3e5]), # Umax
          UniformPrior([0,1]),
          UniformPrior([0.0047, 0.0458])]

var_dim = ~const_dim

Nwalkers = 64

# Sample an initial state from the priors
p0s = [pr.sample(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)
```

[6]:
```
# Will print a tqdm progress bar
mcmc = lgh.fit(p0, method='emcee', Nwalkers=Nwalkers, Nsteps=20000, priors=priors, const_
↪dim=const_dim)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
100%|##########################################################################################
↪##########################################################| 20000/20000 [09:15<00:00,
↪ 36.01it/s]
```

A first diagnostic of the MCMC is the acceptance fraction, which should typically be > 0.2 and < 0.50.

[8]:
```
print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc.acceptance_fraction)))
```

```
MCMC mean acceptance fraction: 0.320
```

We automatically construct chopped/thinned/flattened chains based on the autocorrelation times of the chains, and retain the last 1000 samples. If we instead got a message here that the autocorrelation times were too long, we could: - Provide a manual scale for burn-in and thinning - Re-run the whole MCMC (expensive) - Simply continue the MCMC where it left off by doing mcmc.run_mcmc(None, Nsteps).

We pass the `const_dim` mask and the corresponding values to `lgh.get_mcmc_chains` so that our reconstructed chain reflects all the parameters (neither `mcmc` nor `lgh` know anything themselves about which parameters were constant or at which value).

[9]:
```
chain, logprob_chain, tau_ac = lgh.get_mcmc_chains(mcmc,
                                                   discard=None,
                                                   thin=None,
                                                   const_dim=const_dim,
                                                   const_vals=p[const_dim])
```

The values of the autocorrelation times are not really actionable as long as they're shorter than N/50. They can be used to estimate the MCMC error.

[10]:
```
print(tau_ac)
print('Nsteps / 50 = %.2f' % (20000 / 50))
```

```
[209.34885177 207.31193192 260.32005758 196.37997666 237.1466256
 181.17688573 261.2378974  141.07647201 117.29100567 178.92168379]
Nsteps / 50 = 400.00
```

Here we could save a checkpoint by outputting the chains. Note that we already saved the configuration in a pickle file at the beginning of this notebook.

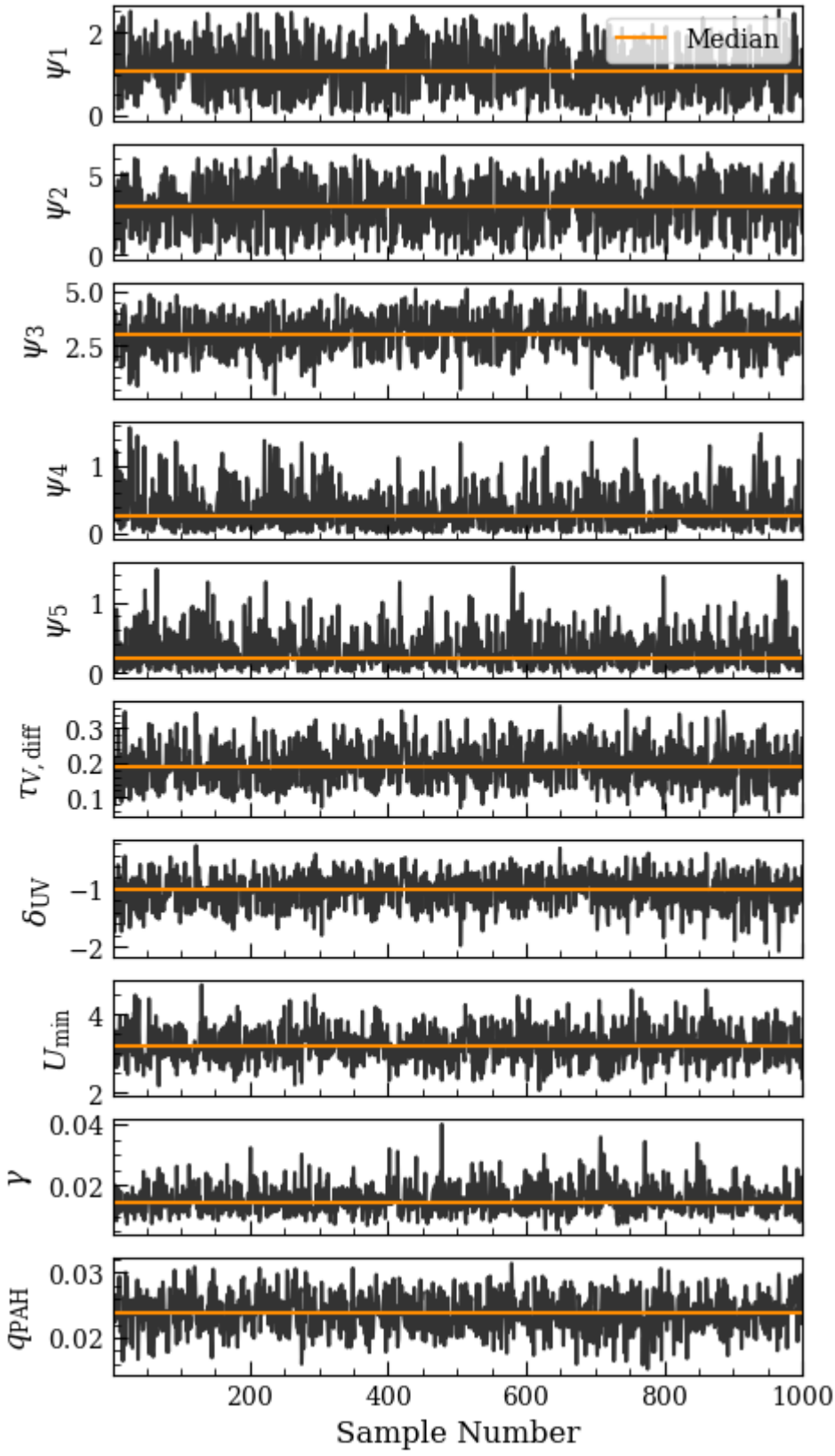
[11]:
```
# with h5py.File('ngc337_chains.hdf5', 'w') as f:
#     f.create_dataset('mcmc/samples', data=chain)
#     f.create_dataset('mcmc/logprob_samples', data=logprob_chain)
```

[12]:
```
# with h5py.File('ngc337_chains.hdf5', 'r') as f:
#     chain = f['mcmc/samples'][:,:]
#     logprob_chain = f['mcmc/logprob_samples'][:]
```

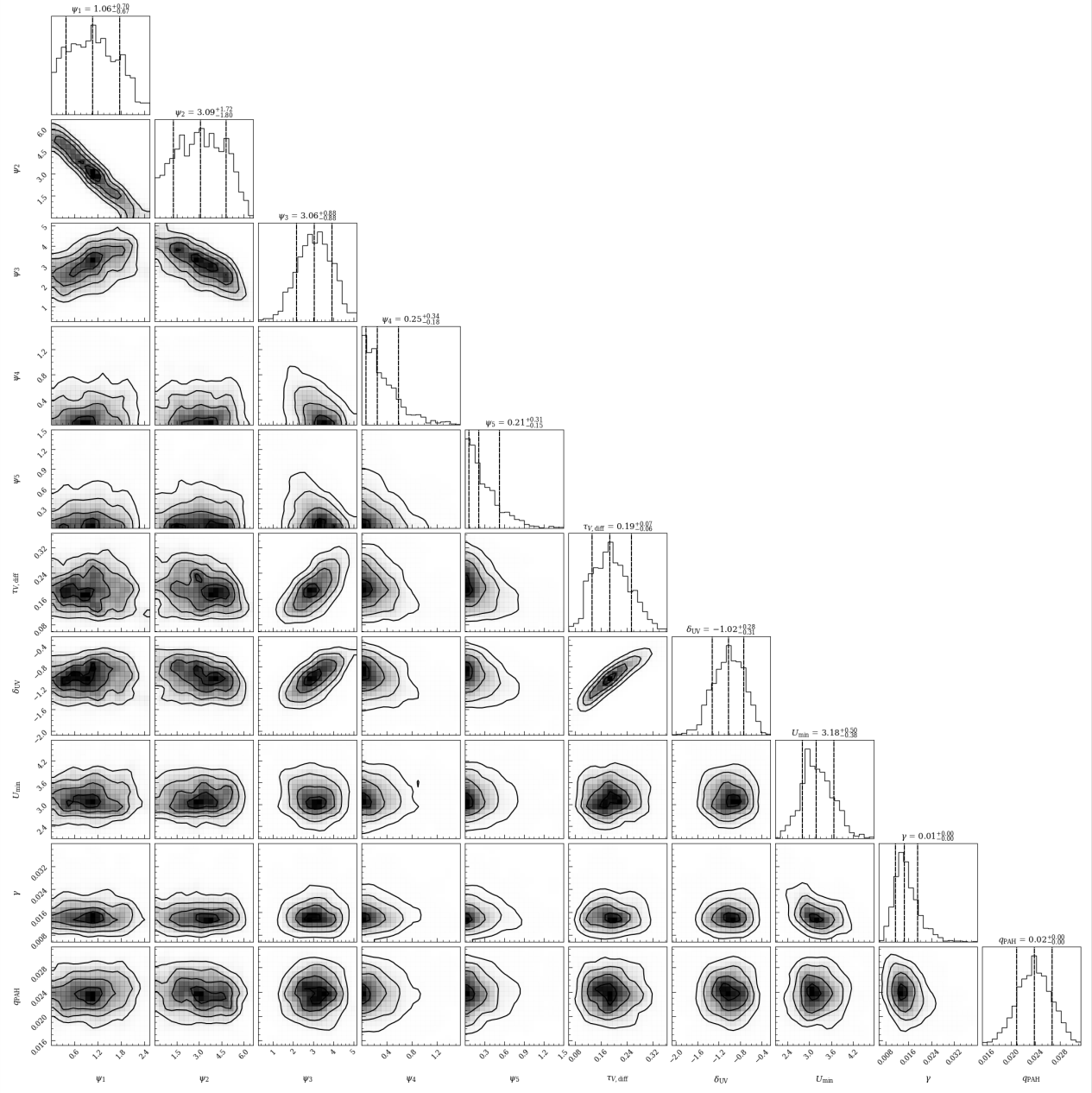
6.1.3 Plots

Now we can visualize the results using the new builtin plotting functions. Note that each of the plotting functions looks for a Lightning object as the first argument and then the parameters (and possibly log probability chain) as the second (third) arguments. Each of the plotting functions return a tuple containing the figure and axes drawn, with the exception of `corner_plot`, which returns only the figure (being a thin wrapper around `corner.corner`).

[13]:
```
fig, axs = lgh.chain_plot(chain, color='black', alpha=0.8)
```


Median
ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
$\tau_{V,\mathrm{diff}}$
δ_{UV}
U_{min}
γ
q_{PAH}
Sample Number

[14]:
```
fig = lgh.corner_plot(chain,
                      quantiles=(0.16, 0.50, 0.84),
                      smooth=1,
                      levels=None,
                      show_titles=True)
```



[15]:
```
# from lightning.plots import sed_plot_bestfit, sed_plot_delchi, sfh_plot

# We could use the builtin plotting functions to make individual figures...
# fig1, ax1 = sed_plot_bestfit(l, param_arr, logprob_chain, plot_components=True)
# fig2, ax2 = sed_plot_delchi(l, param_arr, logprob_chain)
# fig3, ax3 = sfh_plot(l, param_arr)
```

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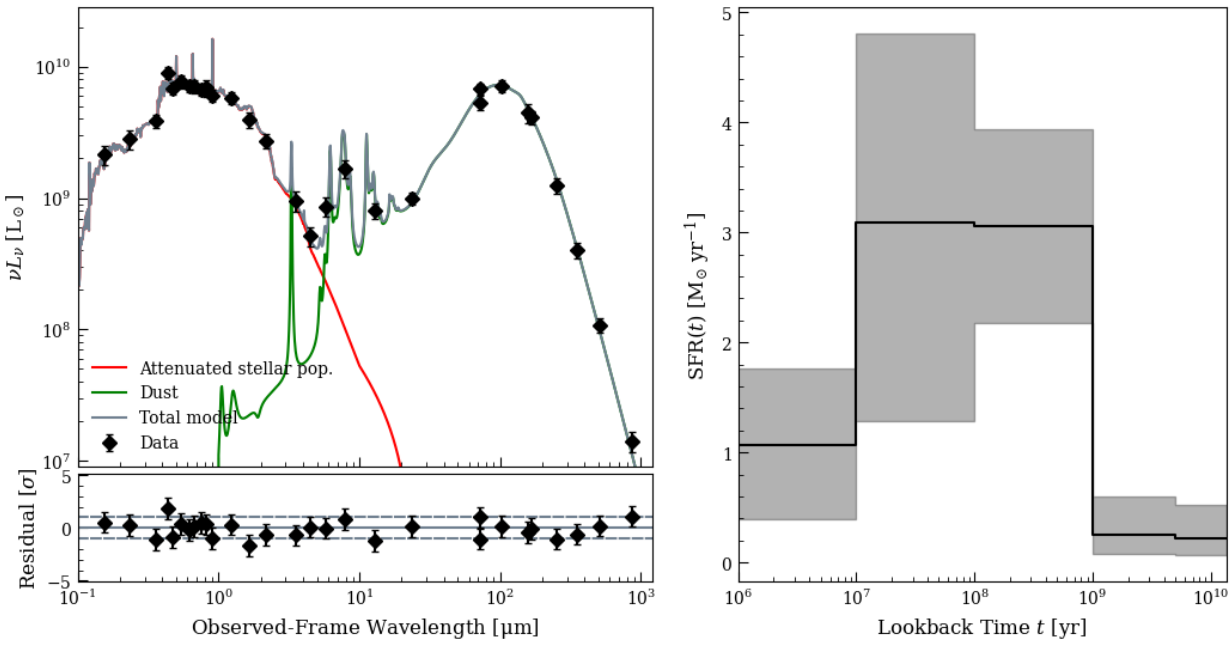
```
# Or we can use them to make a complex publication quality
# figure by laying out our axes and then using the `ax` keyword in each function:
fig4 = plt.figure(figsize=(12,6))
ax41 = fig4.add_axes([0.1, 0.26, 0.4, 0.64])
ax42 = fig4.add_axes([0.1, 0.1, 0.4, 0.15])
ax43 = fig4.add_axes([0.56, 0.1, 0.34, 0.8])

fig4, ax41 = lgh.sed_plot_bestfit(chain, logprob_chain,
                                  plot_components=True,
                                  ax=ax41,
                                  legend_kwargs={'loc': 'lower left', 'frameon': False})
ax41.set_xticklabels([])
fig4, ax42 = lgh.sed_plot_delchi(chain, logprob_chain, ax=ax42)
fig4, ax43 = lgh.sfh_plot(chain, ax=ax43)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
```



[18]:
```
from lightning.plots import sed_plot_morebayesian, sed_plot_delchi_morebayesian, sfh_plot
```

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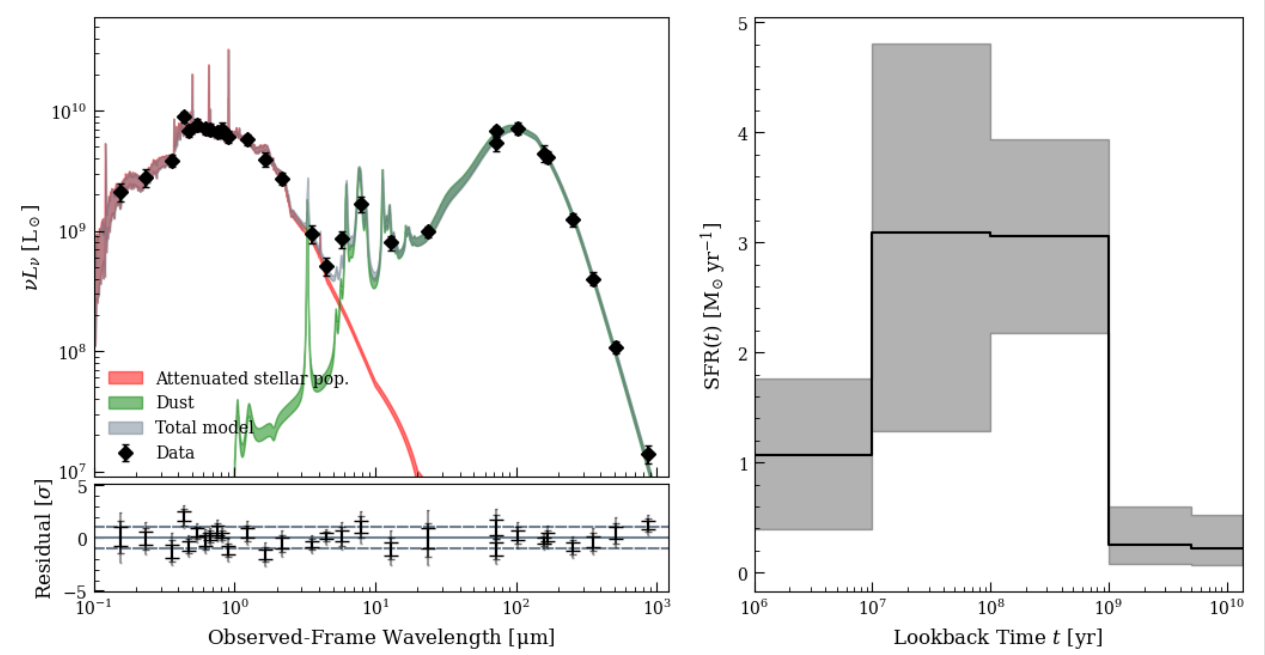
```
fig5 = plt.figure(figsize=(12,6))
ax51 = fig5.add_axes([0.1, 0.26, 0.4, 0.64])
ax52 = fig5.add_axes([0.1, 0.1, 0.4, 0.15])
ax53 = fig5.add_axes([0.56, 0.1, 0.34, 0.8])

fig5, ax51 = sed_plot_morebayesian(lgh, chain, logprob_chain,
                                   plot_components=True,
                                   ax=ax51,
                                   legend_kwargs={'loc': 'lower left', 'frameon': False})
ax51.set_xticklabels([])
fig5, ax52 = sed_plot_delchi_morebayesian(lgh, chain, logprob_chain, ax=ax52)
fig5, ax53 = lgh.sfh_plot(chain, ax=ax53)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/numpy/lib/
↪nanfunctions.py:1095: RuntimeWarning: All-NaN slice encountered
  result = np.apply_along_axis(_nanmedian1d, axis, a, overwrite_input)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/numpy/lib/
↪nanfunctions.py:1583: RuntimeWarning: All-NaN slice encountered
  result = np.apply_along_axis(_nanquantile_1d, axis, a, q,
```



Goodness of Fit

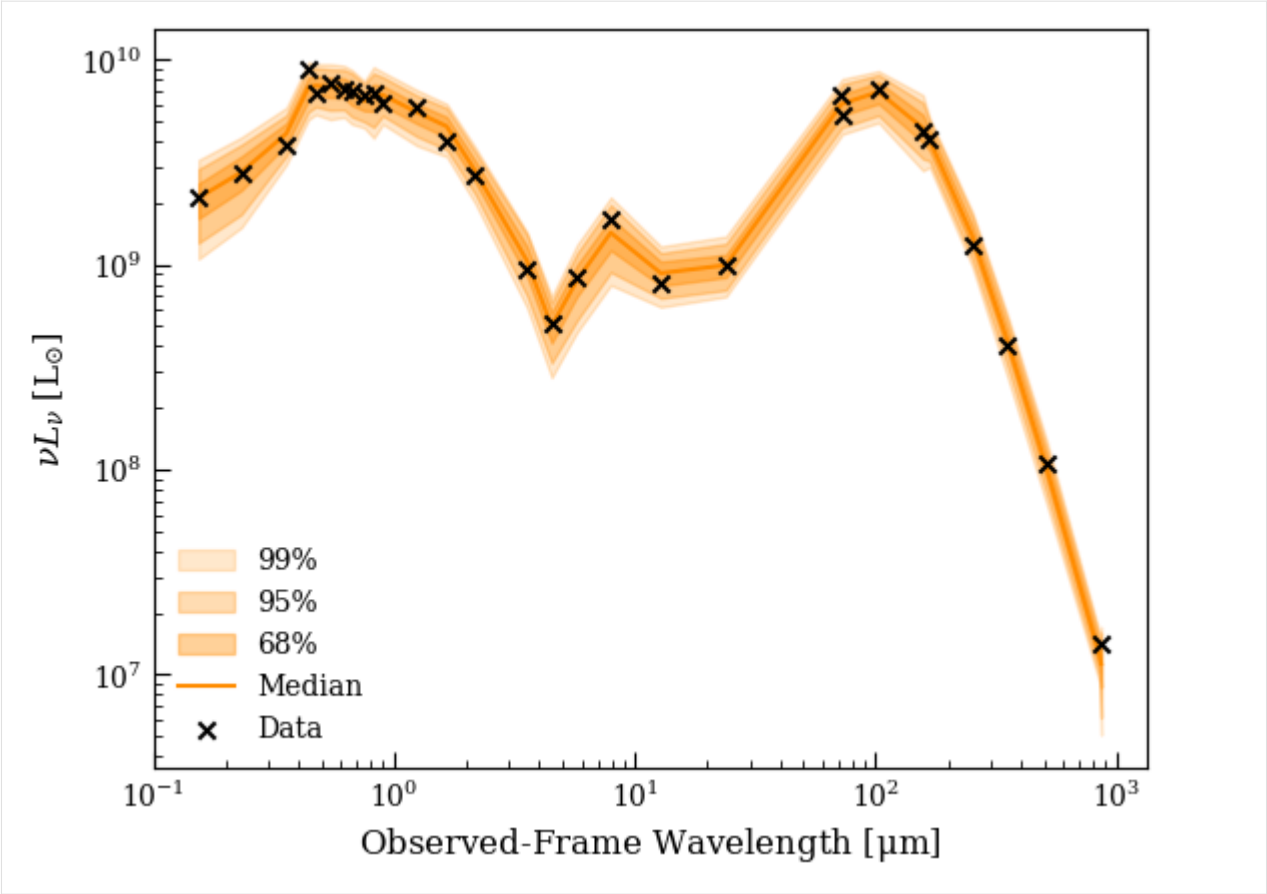
We've seen that we obtained chains without any obvious correlated behavior and fairly nice unimodal posteriors, and we've seen that our normalized residuals look reasonable. We can also use the built-in posterior predictive check functions to see how well our model can reproduce the data.

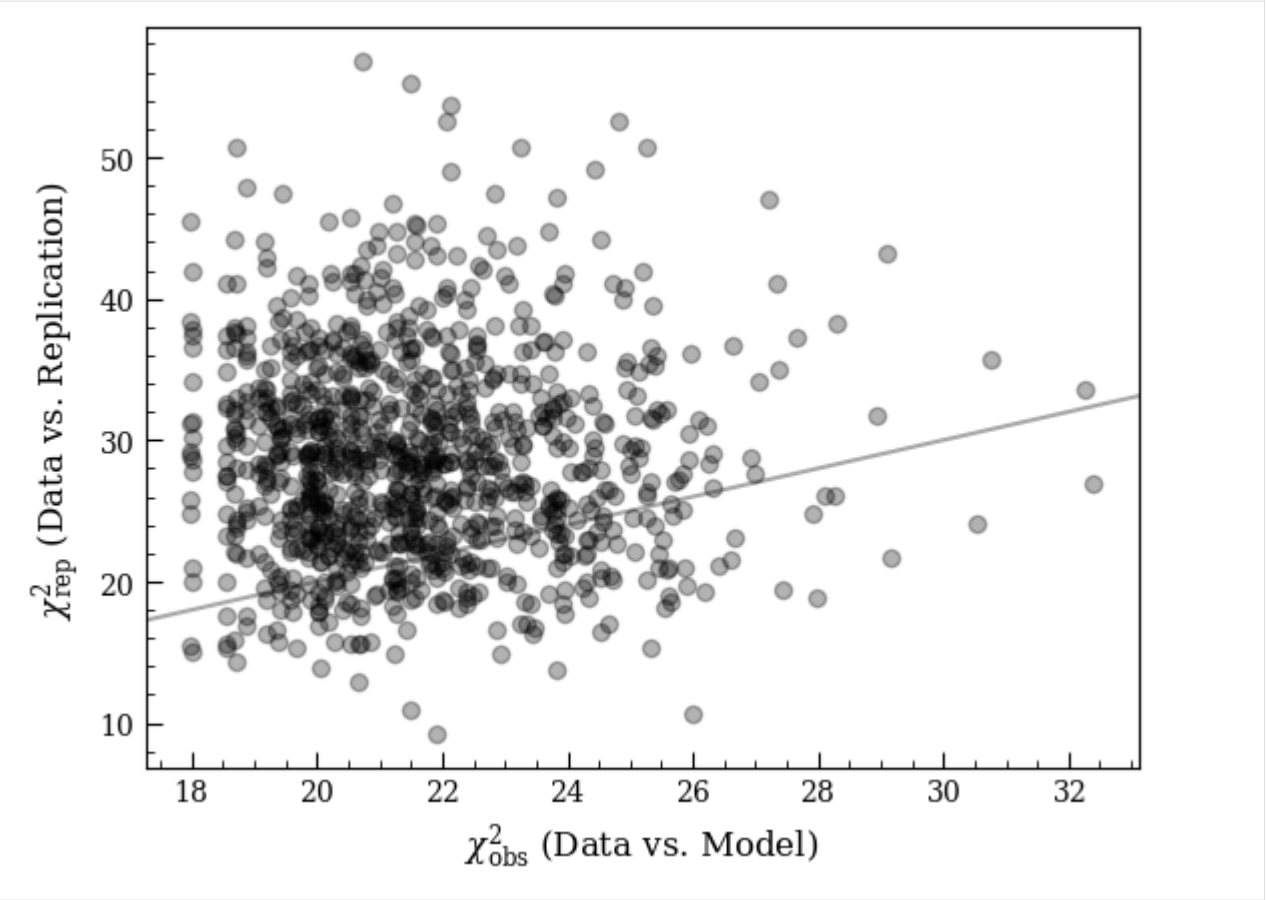
The two plots are two different ways of visualizing the PPC: the first shows you where the model can and cant reproduce the data (effectively, $p-$values for each bandpass) and the second shows the definition of the total $p-$value - the fraction of Monte Carlo experiments producing worse χ^2 than we observe.

[19]:
```
from lightning.ppc import ppc, ppc_sed

pvalue, chi2_rep, chi2_obs = ppc(lgh, chain,
                                 logprob_chain,
                                 Nrep=1000,
                                 seed=12345)
fig, ax = ppc_sed(lgh, chain,
                  logprob_chain,
                  Nrep=1000,
                  seed=12345,
                  normalize=False)

fig2, ax2 = plt.subplots()

ax2.scatter(chi2_obs,
            chi2_rep,
            marker='o',
            alpha=0.3)

xlim = ax2.get_xlim()
ax2.plot(xlim, xlim, linestyle='-', color='darkgray', zorder=-1)
ax2.set_xlim(xlim)

ax2.set_xlabel(r'$\chi_{\rm obs}^2$ (Data vs. Model)')
ax2.set_ylabel(r'$\chi_{\rm rep}^2$ (Data vs. Replication)')


print('p = %.3f' % (pvalue))
```

```
/Users/eqm5663/Research/code/plightning/lightning/ppc.py:77: RuntimeWarning: invalid␣
↪value encountered in divide
  chi2_rep = np.nansum((Lmod - Lmod_perturbed)**2 / total_unc2, axis=-1)
```

```
p = 0.823
```

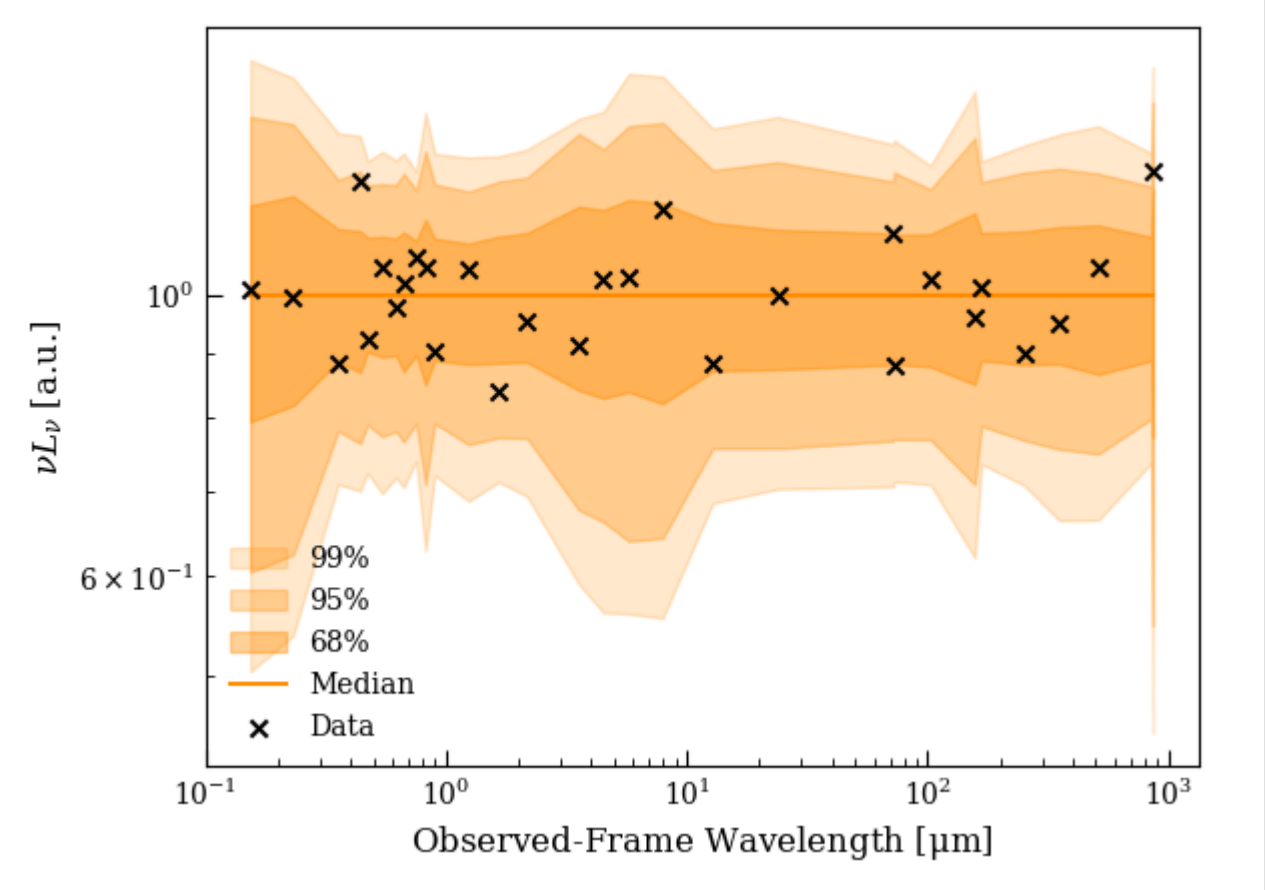

10^{10}
10^{9}
10^{8}
10^{7}
νL_ν [$L_\odot$]
99%
95%
68%
Median
Data
10^{-1}
10^{0}
10^{1}
10^{2}
10^{3}
Observed-Frame Wavelength [μm]



We can see that the model has trouble reproducing one $B-$band point near the 4000 Å break ($p \sim 0.05$ based on the shaded bands) but otherwise we do quite well. It's worth examining both these plots to see if a low $p-$value is driven only by one or two bands, or one component of the model.

We can also plot the PPC-SED plot normalized to the median, which can make individual $p-$values clearer:

[20]:
```
fig, ax = ppc_sed(lgh, chain,
                  logprob_chain,
                  Nrep=1000,
                  seed=12345,
                  normalize=True)
```



6.1.4 Fit with BFGS

Now we fit with the optimization scheme. For this method we provide a single starting point and bounds for the minimizer, as a list of tuples. Constant parameters should have their bounds equal.

[21]:
```
p0 = np.array([5,5,0,0,0,
               0.020,
               0.1, -1.0, 0.0,
               2, 3, 3e5, 0.01, 0.02])

bounds = [(0,10),
          (0,10),
          (0,10),
          (0,10),
          (0,10),
          (0.020, 0.020),
          (0,3),
          (-2.3,0.4),
          (0,0),
          (2,2),
          (0.1,25),
          (3e5,3e5),
          None,
```

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```
          None]

res = lgh.fit(p0,
              method='optimize',
              bounds=bounds,
              disp=False)
print(res)

# res,mcmc = lgh.fit(p0,
#                    method='optimize',
#                    bounds=bounds,
#                    MCMC_followup=True,
#                    MCMC_kwargs={'Nwalkers':128,'Nsteps':1000, 'init_scale':1e-3},
#                    disp=False)
```

```
  message: CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
  success: True
   status: 0
      fun: 8.09302242291625
        x: [ 6.339e-01  3.658e+00 ...  1.325e-02  2.413e-02]
      nit: 210
      jac: [ 1.986e-03  9.187e-04 ...  6.433e-03 -4.183e-03]
     nfev: 3608
     njev: 328
 hess_inv: None
```

We have the option to use the result of the minimization as the starting point for a follow-up MCMC, which saves having to do any estimate of the uncertainties from the minimization results, and can be pretty effective for problems where the likelihood surface is nice and unimodal. There's currently no option to supply new priors for the followup, the bounds are converted to uniform priors.

[22]:
```
res,mcmc2 = lgh.fit(p0,
                    method='optimize',
                    bounds=bounds,
                    MCMC_followup=True,
                    MCMC_kwargs={'Nwalkers':128,'Nsteps':1000, 'init_scale':1e-3,
↪'progress':True},
                    disp=False)
```

```
100%|##########################################################################################
↪##########################################################| 1000/1000 [00:48<00:00,
↪ 20.63it/s]
```

Now we can treat the MCMC result exactly the same as our original MCMC result (since they're functionally identical). However, in theory, there's no burn-in to discard, since we started very near the solution.

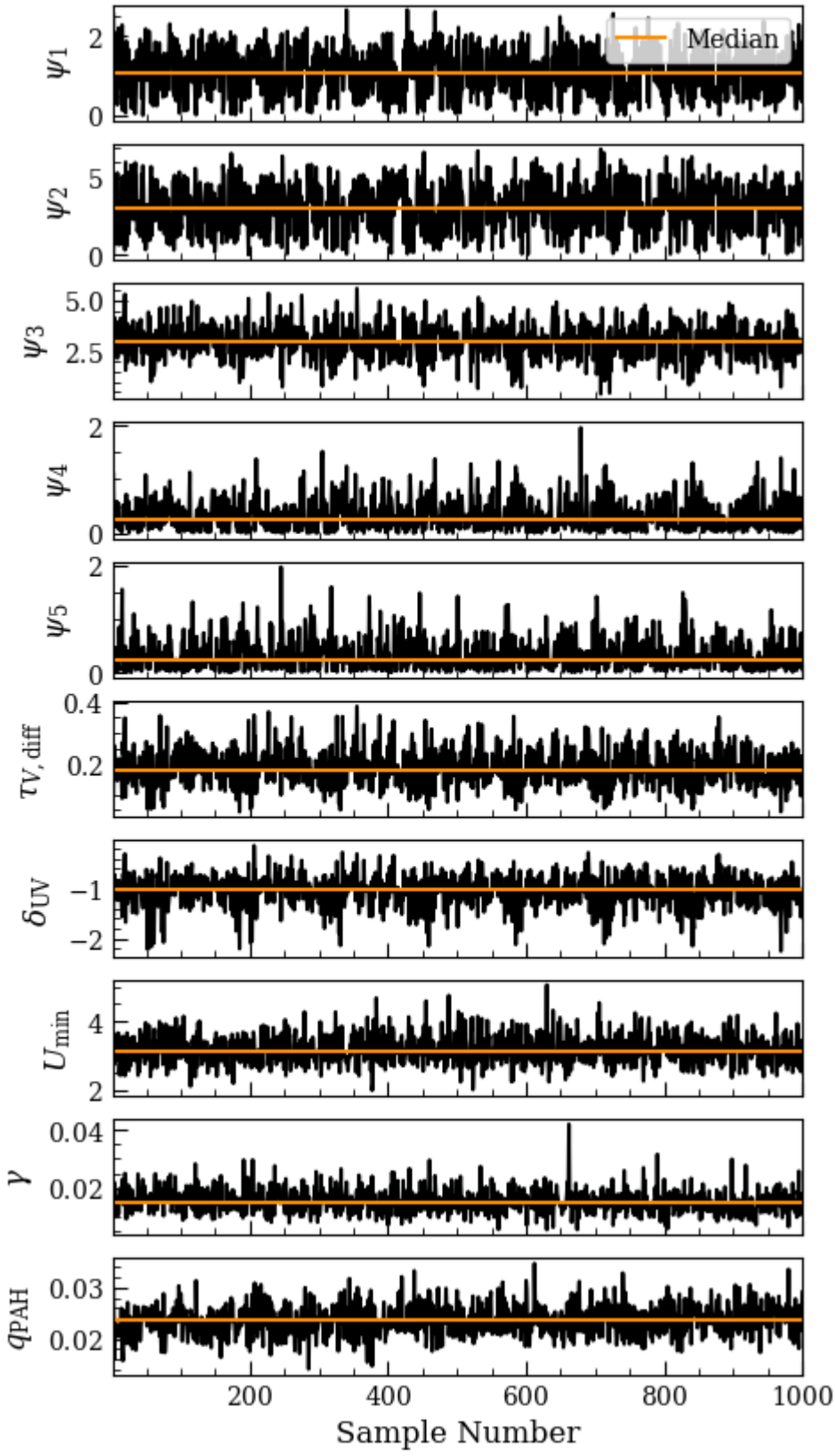
[23]:
```
const_dim = np.array([(b is not None) and (b[1] - b[0] == 0) for b in bounds])

chain2, logprob_chain2, tau_ac2 = lgh.get_mcmc_chains(mcmc2,
                                                      discard=0,
                                                      thin=30,
                                                      const_dim=const_dim,
                                                      Nsamples=1000,
                                                      const_vals=res.x[const_dim])
```

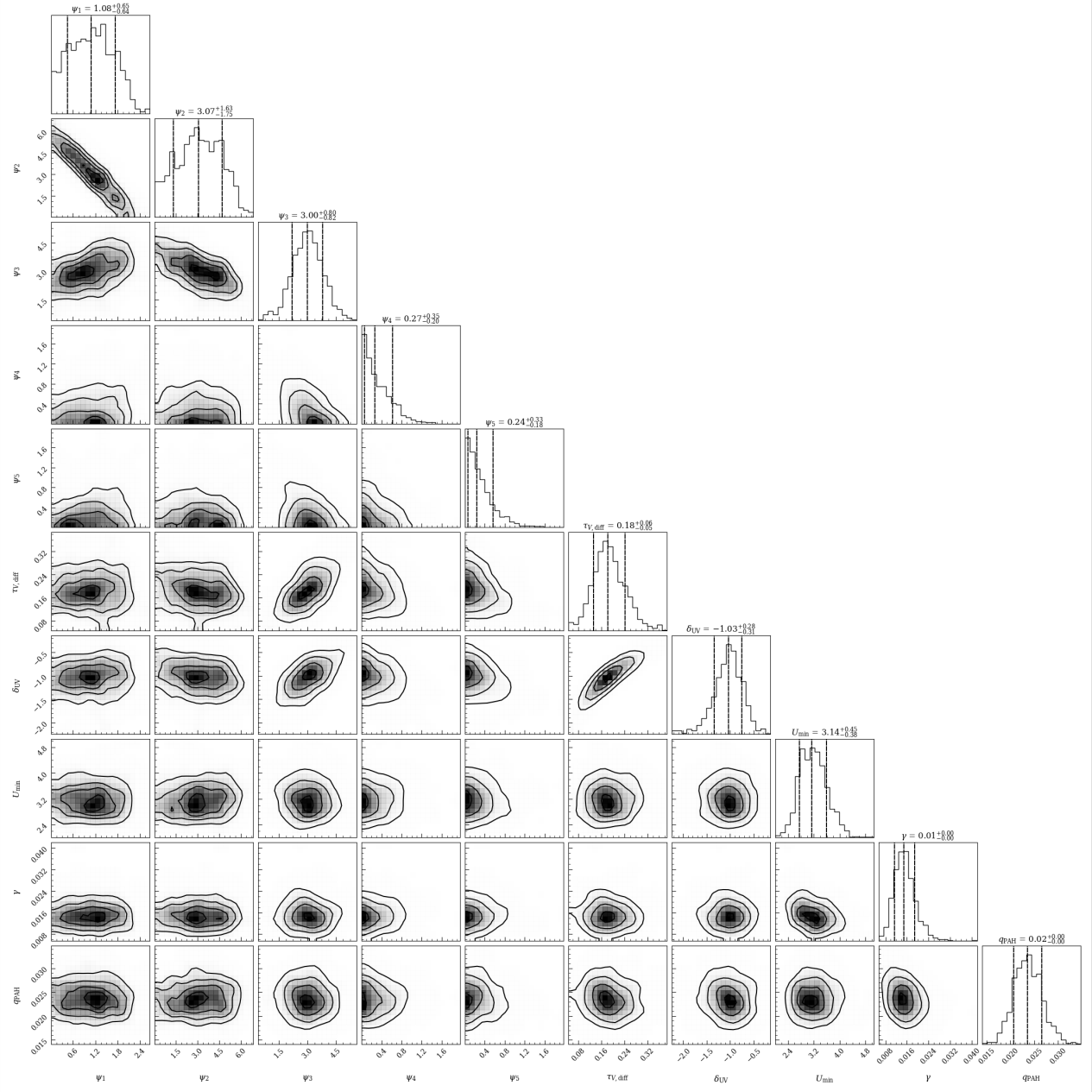
```
WARNING: The integrated autocorrelation time is longer than N/50.
         The autocorrelation estimate may be unreliable.
```

Note that since we ran a very short chain in the follow-up we now see the autocorrelation warning.

[24]:
```
fig, axs = lgh.chain_plot(chain2)
```


Median
ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
$\tau_{V,\mathrm{diff}}$
δ_{UV}
U_{min}
γ
q_{PAH}
Sample Number

[25]:
```
fig = lgh.corner_plot(chain2,
                      quantiles=(0.16, 0.50, 0.84),
                      smooth=1,
                      levels=None,
                      show_titles=True)
```



we can repeat the PPC analysis:

[26]:
```
from lightning.ppc import ppc, ppc_sed

pvalue, chi2_rep, chi2_obs = ppc(lgh, chain2,
                                 logprob_chain2,
                                 Nrep=1000,
```

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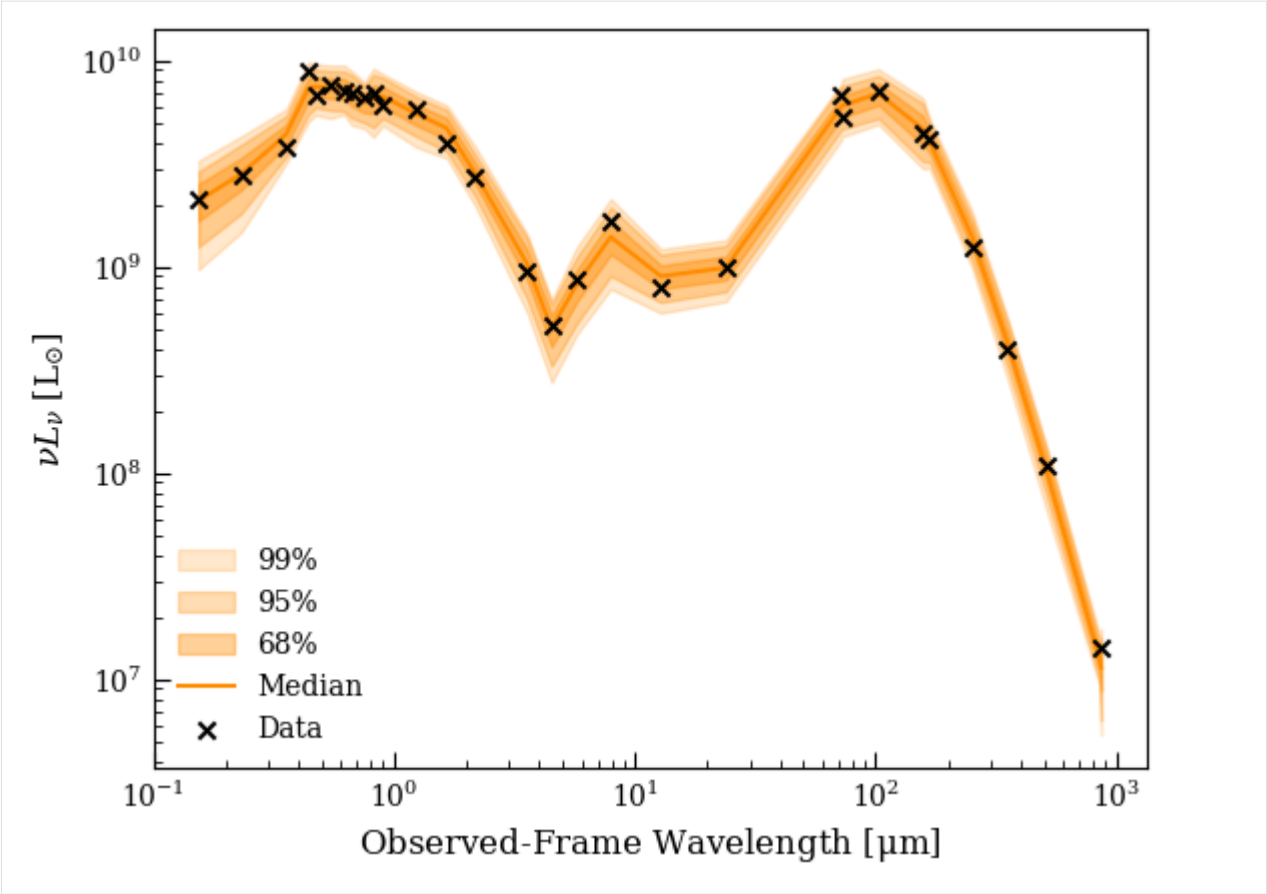
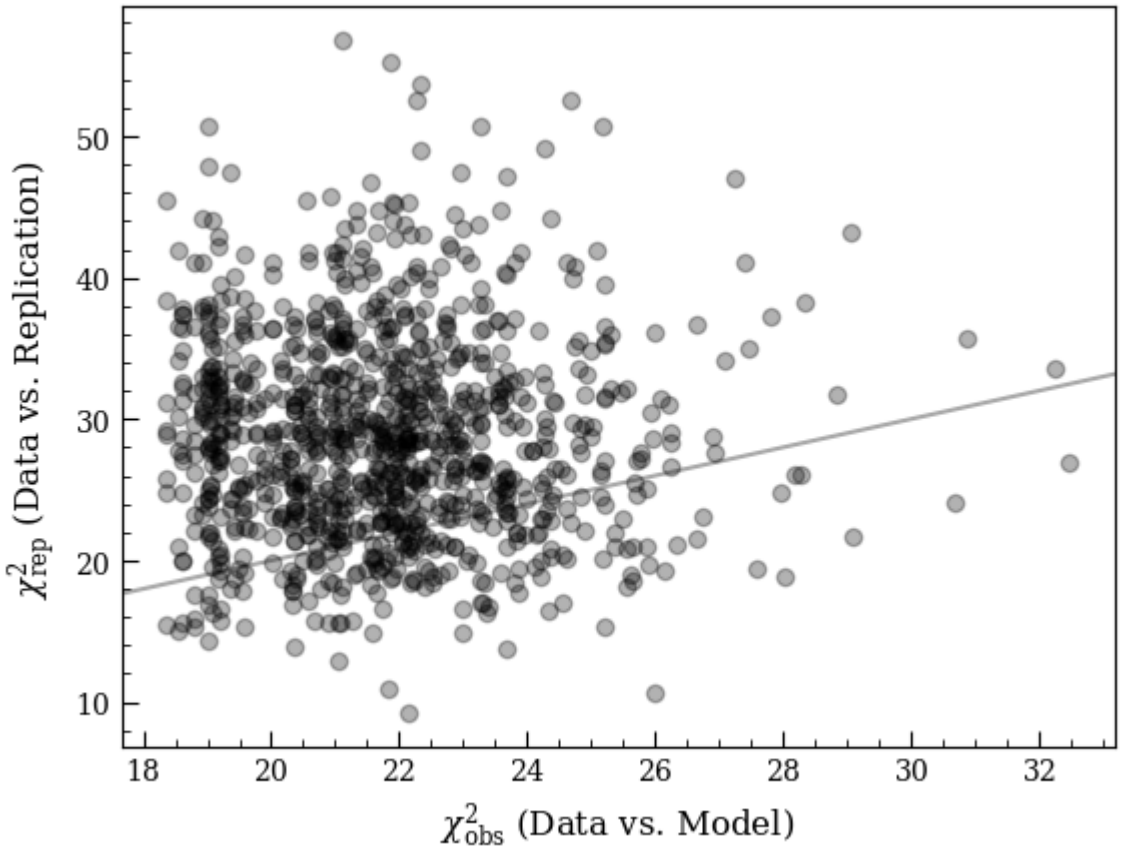
```
                                  seed=12345)
fig, ax = ppc_sed(lgh, chain2,
                  logprob_chain2,
                  Nrep=1000,
                  seed=12345,
                  normalize=False)

fig2, ax2 = plt.subplots()

ax2.scatter(chi2_obs,
            chi2_rep,
            marker='o',
            alpha=0.3)

xlim = ax2.get_xlim()
ax2.plot(xlim, xlim, linestyle='-', color='darkgray', zorder=-1)
ax2.set_xlim(xlim)

ax2.set_xlabel(r'$\chi_{\rm obs}^2$ (Data vs. Model)')
ax2.set_ylabel(r'$\chi_{\rm rep}^2$ (Data vs. Replication)')


print('p = %.3f' % (pvalue))
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
/Users/eqm5663/Research/code/plightning/lightning/ppc.py:77: RuntimeWarning: invalid␣
↪value encountered in divide
  chi2_rep = np.nansum((Lmod - Lmod_perturbed)**2 / total_unc2, axis=-1)
```

```
p = 0.821
```


10^{10}
10^{9}
10^{8}
10^{7}
νL_ν [$L_\odot$]
99%
95%
68%
Median
Data
10^{-1}
10^{0}
10^{1}
10^{2}
10^{3}
Observed-Frame Wavelength [μm]



and get a remarkably similar result. We could save the results like so:

[27]:
```
# with h5py.File('ngc337_mle_res.h5', 'w') as f:
#     f.create_dataset('mcmc/samples', data=chain2)
#     f.create_dataset('mcmc/logprob_samples', data=logprob_chain2)
#     f.create_dataset('res/bestfit', data=res.x)
#     f.create_dataset('res/chi2_best', data=res.fun * 2)
```

6.2 New Stellar Models - NGC 628

Fit NGC 628 with the new BPASS and PEGASE + Cloudy nebular models.

6.2.1 Imports

[1]:
```
import numpy as np
import h5py
rng = np.random.default_rng()
import astropy.units as u
from astropy.table import Table
from corner import corner
import matplotlib.pyplot as plt
```

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```
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline

from lightning import Lightning
from lightning.priors import UniformPrior, NormalPrior, ConstantPrior
```

6.2.2 Initialization

We'll use 7 SFH bins and the new BPASS + Cloudy models to start. Note that we have the option of whether or not we want to include dust grains in the nebular model. We're including them here, but this adds some age dependent attenuation (analogous to the old birth cloud attenuation) and an extra cold dust component to the "intrinsic" stellar spectrum.

[2]:
```
cat = Table.read('../photometry/ngc628_dale17_photometry.fits')

# Housekeeping to load the photometry:
# strings come in as bytestrings (unencoded)
# The labels are also padded with spaces
filter_labels = np.array([s.decode().strip() for s in cat['FILTER_LABELS'].data[0]])
fnu_obs = cat['FNU_OBS'].data[0]
fnu_unc = cat['FNU_UNC'].data[0]
dl = cat['LUMIN_DIST'].data[0]

agebins = [0.0] + list(np.logspace(7, np.log10(13.4e9), 7))

lgh = Lightning(filter_labels,
                lum_dist=dl,
                ages=agebins,
                nebula_lognH=3.5,
                nebula_dust=True,
                stellar_type='BPASS-A24',
                SFH_type='Piecewise-Constant',
                atten_type='Modified-Calzetti',
                dust_emission=True,
                model_unc=0.10,
                print_setup_time=True)


lgh.flux_obs = fnu_obs * 1e3
lgh.flux_unc = fnu_unc * 1e3

# We could save the configuration like so:
# lgh.save_pickle('ngc628_BPASS_config.pkl')
```

```
0.024 s elapsed in _get_filters
0.001 s elapsed in _get_wave_obs
1.152 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.150 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
1.326 s elapsed total
```

[3]:
```
lgh.print_params(verbose=True)
```

```
============================
Piecewise-Constant
============================
Parameter  Lo  Hi              Description
--------- --- --- ------------------------
    psi_1 0.0 inf SFR in stellar age bin 1
    psi_2 0.0 inf SFR in stellar age bin 2
    psi_3 0.0 inf SFR in stellar age bin 3
    psi_4 0.0 inf SFR in stellar age bin 4
    psi_5 0.0 inf SFR in stellar age bin 5
    psi_6 0.0 inf SFR in stellar age bin 6
    psi_7 0.0 inf SFR in stellar age bin 7

============================
BPASS-Stellar-A24
============================
Parameter                   Lo                 Hi                                 ␣
↪           Description
--------- -------------------- ------------------ ------------------------------------
↪------------------------
     Zmet 0.0006471873203208087 0.0257649912911017 Metallicity (mass fraction, where␣
↪solar = 0.020 ~ 10**[-1.7])
     logU                -4.0               -1.5                                log10 of␣
↪the ionization parameter

============================
Modified-Calzetti
============================
      Parameter   Lo                 Hi                                           ␣
↪                            Description
--------------- ---- ------------------ ------------------------------------------------
↪----------------------------------------
mcalz_tauV_diff  0.0                inf                                           ␣
↪         Optical depth of the diffuse ISM
    mcalz_delta -inf 0.4473684210526316 Deviation from the Calzetti+2000 UV power law␣
↪slope (Upper limit set by requiring Eb >= 0)
  mcalz_tauV_BC  0.0                inf                                Optical depth␣
↪of the birth cloud in star forming regions

============================
DL07-Dust
============================
      Parameter     Lo       Hi                                                     ␣
↪   Description
--------------- ------ -------- ------------------------------------------------------------
↪--------------
dl07_dust_alpha  -10.0      4.0                  Radiation field intensity distribution␣
↪power law index
dl07_dust_U_min    0.1     25.0                                      Radiation field␣
↪minimum intensity
```

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```
dl07_dust_U_max 1000.0 300000.0                                    Radiation field␣
↪maximum intensity
dl07_dust_gamma    0.0      1.0 Fraction of dust mass exposed to radiation field␣
↪intensity distribution
dl07_dust_q_PAH 0.0047   0.0458                            Fraction of dust mass␣
↪composed of PAH grains

Total parameters: 17
```

[4]:
```
p0_seed = np.array([5,5,5,0,0,0,0,
                    0.014, -2.0,
                    0.1, -1.0, 0.0,
                    2, 3, 3e5, 0.01, 0.02])

priors = 7 * [UniformPrior([0,20])] + \
             [NormalPrior([0.013, 0.001]), NormalPrior([-2.5,0.75])] + \
             [UniformPrior([0,3]), UniformPrior([-1.5, 0.3]), ConstantPrior([0.0])] + \
             [ConstantPrior([2.0]), UniformPrior([0.1, 25]), ConstantPrior([3e5]),␣
↪UniformPrior([0,1]), UniformPrior([0.0047, 0.0458])]
const_dim = 7 * [False] + \
            [False, False] + \
            [False, False, True] + \
            [True, False, True, False, False]
const_dim = np.array(const_dim)
const_vals = p0_seed[const_dim]

Nwalkers = 64
# p0 = p0_seed[None, :] + rng.normal(loc=0, scale=1e-5, size=(Nwalkers, len(p0_seed)))
# p0[:, const_dim] = p0_seed[const_dim]

p0s = [pr.sample(Nwalkers) if pr is not None else np.zeros(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)
# Metallicity and logU have Normal priors and consequently might sample out
# of the hard bounds on the parameters.
p0[p0[:,7] < 0.001, 7] = 0.001
p0[p0[:,7] > 0.02, 7] = 0.02
p0[p0[:,8] < -3, 8] = -3
p0[p0[:,8] > -1.5, 8] = -1.5


mcmc = lgh.fit(p0,
               method='emcee',
               priors=priors,
               const_dim=const_dim,
               Nwalkers=Nwalkers,
               Nsteps=30000,
               progress=True)

# mcmc = l.fit(p0, method='emcee', Nwalkers=Nwalkers, Nsteps=20000, priors=priors, const_
↪dim=const_dim)
# print(res_bp)
```

```
100%|##########################################################################################
↪##########################################################| 30000/30000 [15:32<00:00,
↪ 32.15it/s]
```

[5]:
```
print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc.acceptance_fraction)))
```

```
MCMC mean acceptance fraction: 0.205
```

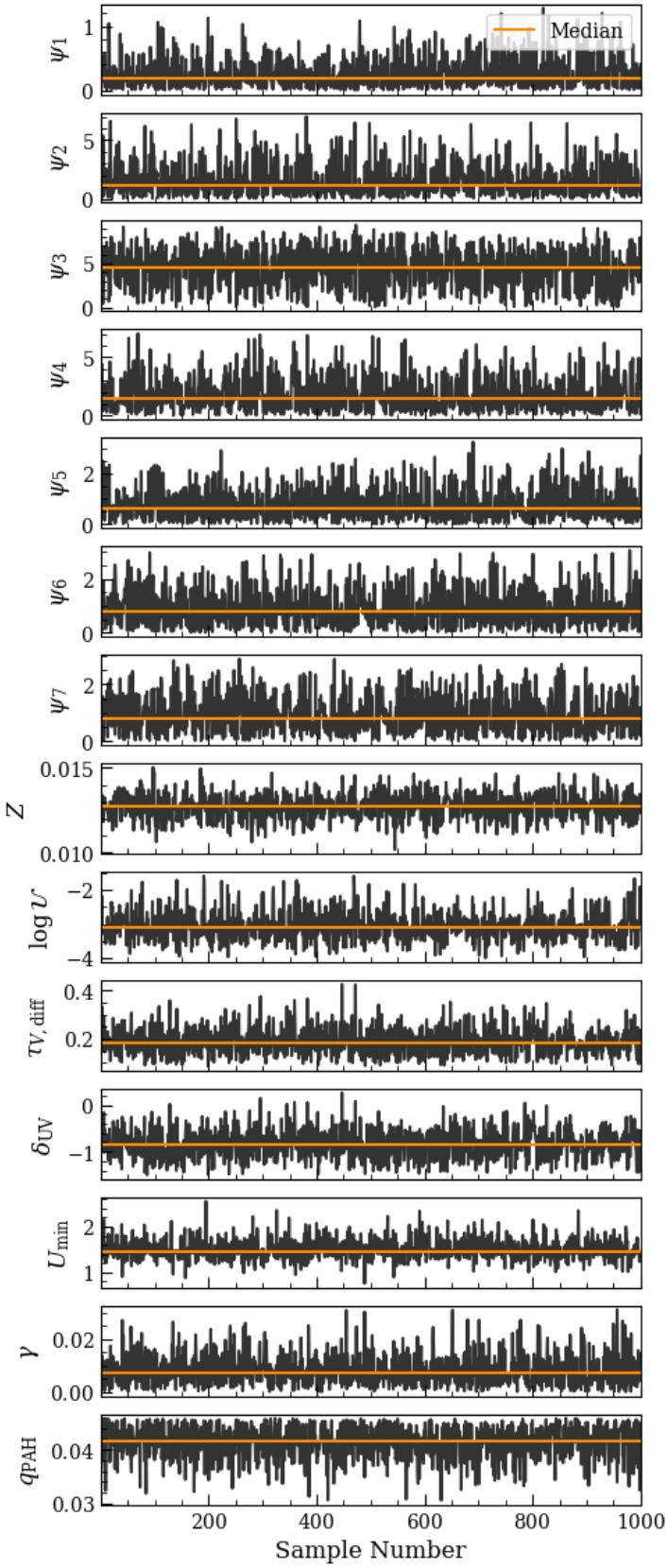
[6]:
```
chain, logprob_chain, tau_ac = lgh.get_mcmc_chains(mcmc, discard=15000, thin=500, const_
↪dim=const_dim, const_vals=p0_seed[const_dim])
```

```
WARNING: The integrated autocorrelation time is longer than N/50.
         The autocorrelation estimate may be unreliable.
```

With this more complicated model `emcee` is going to recommend a longer chain, even beyond what we've already run.

6.2.3 Plots

[7]:
```
fig, axs = lgh.chain_plot(chain, color='k', alpha=0.8)
```

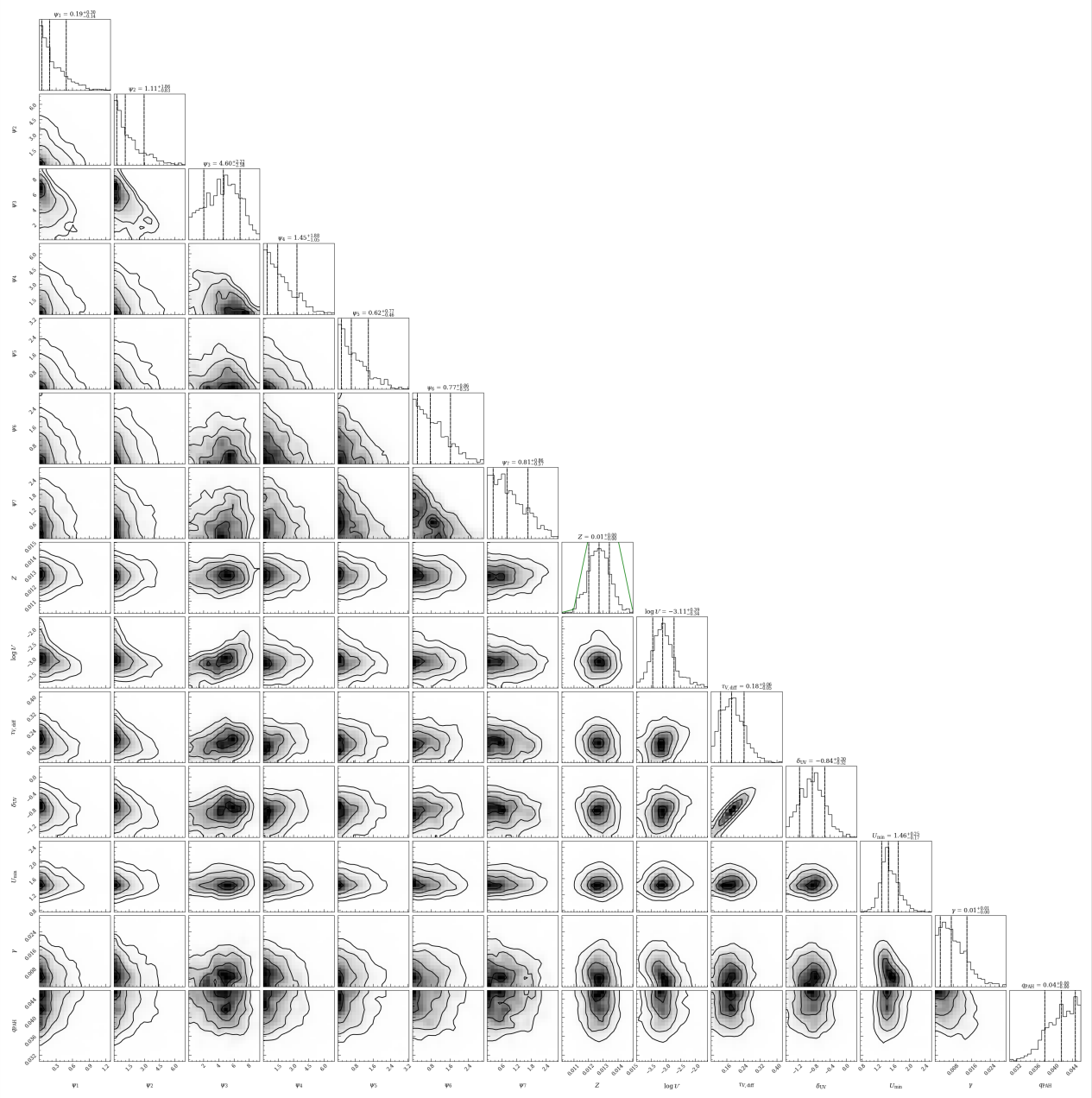

Median
ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
ψ_6
ψ_7
Z
$\log U$
$\tau_{V,\mathrm{diff}}$
δ_{UV}
U_{min}
γ
q_{PAH}
Sample Number

We'll plot the metallicity prior on top, just because we can:

[8]:
```
fig = lgh.corner_plot(chain,
                      quantiles=(0.16, 0.50, 0.84),
                      smooth=1,
                      levels=None,
                      show_titles=True)

ZZ = np.linspace(0.001, 0.03, 30)
Zprior = lambda Z, mu, s: 1 / np.sqrt(2 * np.pi * s**2) * np.exp(-1 * (Z - mu)**2 / s**2)
axs = (np.array(fig.axes)).reshape(14,14)
yy = Zprior(ZZ, 0.013, 0.001)
axs[7,7].plot(ZZ, yy, color='forestgreen')
```

[8]:
```
[<matplotlib.lines.Line2D at 0x338133290>]
```



[9]:
```
from lightning.plots import sed_plot_morebayesian, sed_plot_delchi_morebayesian, sfh_plot

fig5 = plt.figure(figsize=(12,6))
ax51 = fig5.add_axes([0.1, 0.26, 0.4, 0.64])
ax52 = fig5.add_axes([0.1, 0.1, 0.4, 0.15])
ax53 = fig5.add_axes([0.56, 0.1, 0.34, 0.8])

fig5, ax51 = sed_plot_morebayesian(lgh, chain, logprob_chain,
                                   plot_components=True,
                                   ax=ax51,
                                   legend_kwargs={'loc': 'lower left', 'frameon': False})
ax51.set_xticklabels([])
```

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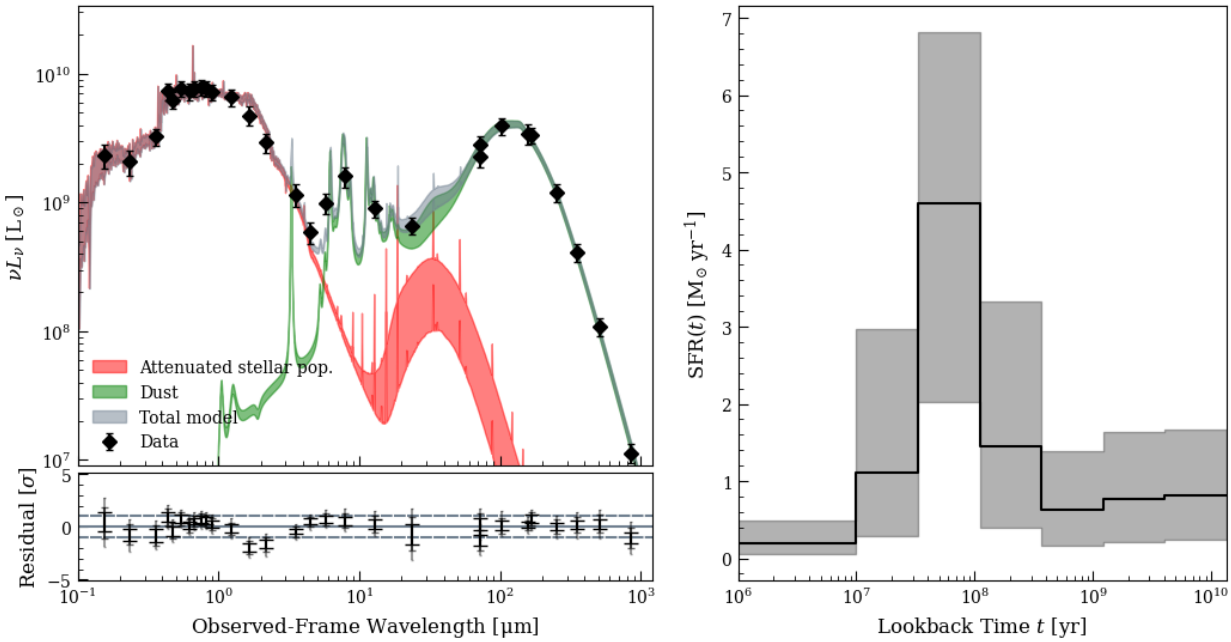
```
fig5, ax52 = sed_plot_delchi_morebayesian(lgh, chain, logprob_chain, ax=ax52)
fig5, ax53 = lgh.sfh_plot(chain, ax=ax53)
```

```
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/numpy/lib/
↪nanfunctions.py:1095: RuntimeWarning: All-NaN slice encountered
  result = np.apply_along_axis(_nanmedian1d, axis, a, overwrite_input)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/numpy/lib/
↪nanfunctions.py:1583: RuntimeWarning: All-NaN slice encountered
  result = np.apply_along_axis(_nanquantile_1d, axis, a, q,
```



6.2.4 Goodness of Fit

[10]:
```
from lightning.ppc import ppc, ppc_sed

pvalue, chi2_rep, chi2_obs = ppc(lgh, chain,
                                 logprob_chain,
                                 Nrep=1000,
                                 seed=12345)
fig, ax = ppc_sed(lgh, chain,
                  logprob_chain,
                  Nrep=1000,
                  seed=12345,
                  normalize=False)

fig2, ax2 = plt.subplots()

ax2.scatter(chi2_obs,
            chi2_rep,
            marker='o',
            alpha=0.3)
```

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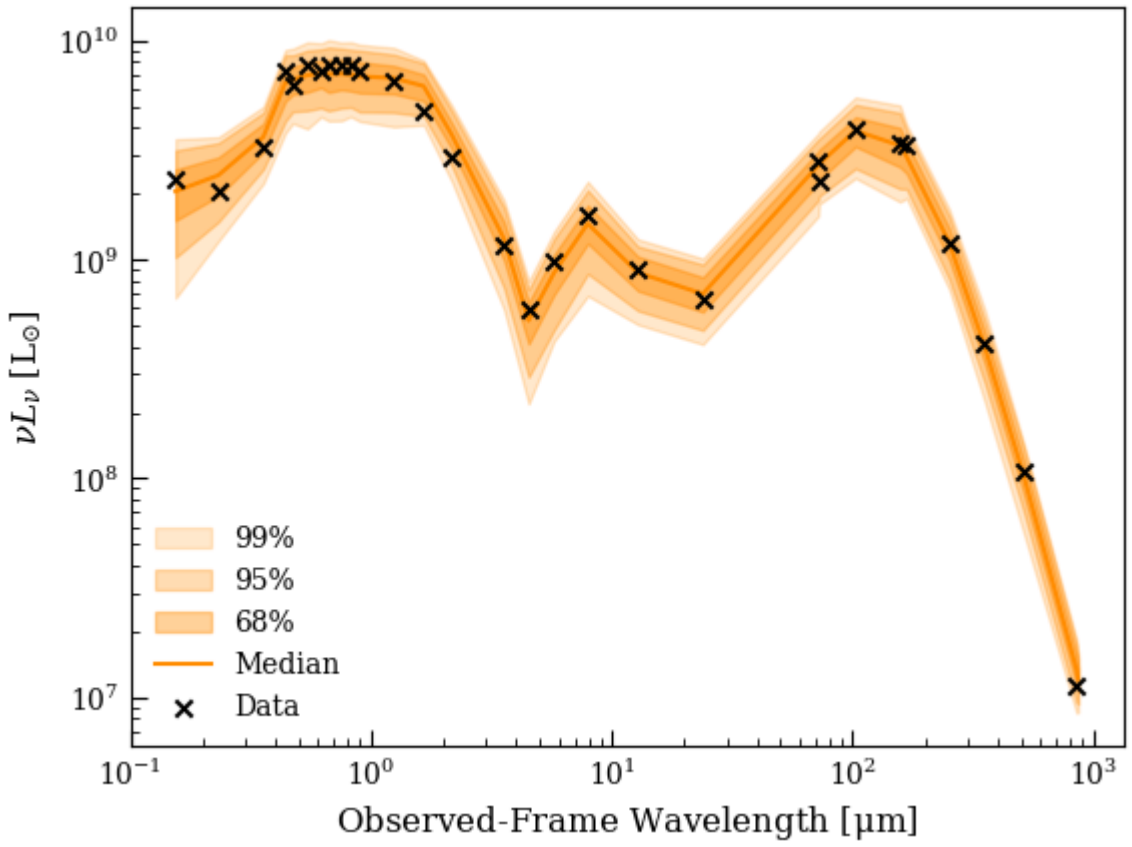
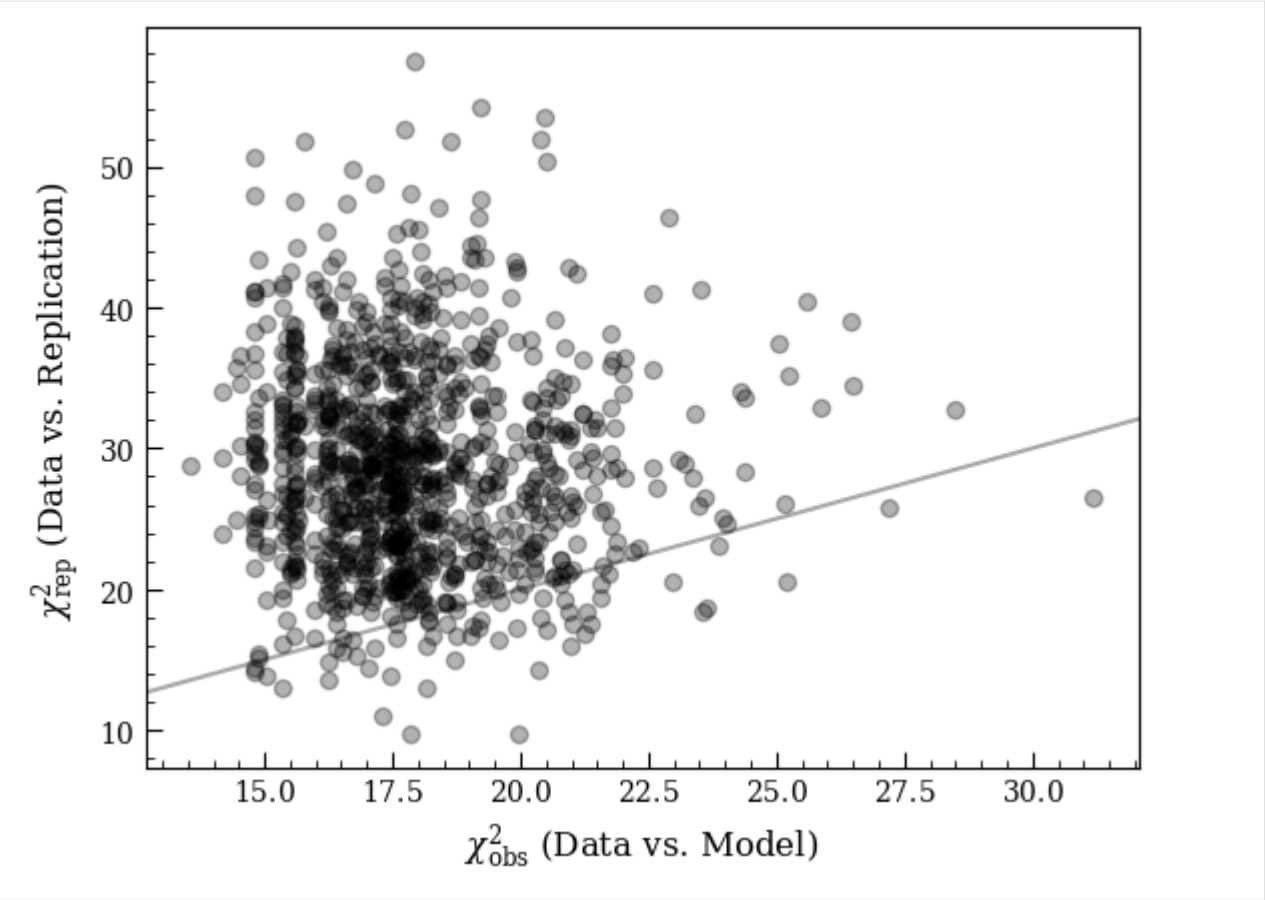
```
xlim = ax2.get_xlim()
ax2.plot(xlim, xlim, linestyle='-', color='darkgray', zorder=-1)
ax2.set_xlim(xlim)

ax2.set_xlabel(r'$\chi_{\rm obs}^2$ (Data vs. Model)')
ax2.set_ylabel(r'$\chi_{\rm rep}^2$ (Data vs. Replication)')


print('p = %.3f' % (pvalue))
```

```
/Users/eqm5663/Research/code/plightning/lightning/ppc.py:77: RuntimeWarning: invalid␣
↪value encountered in divide
  chi2_rep = np.nansum((Lmod - Lmod_perturbed)**2 / total_unc2, axis=-1)
```

```
p = 0.944
```





We're entering the realm of overfitting now, with $> 90\%$ of Monte Carlo trials finding a worse result. This would suggest we need fewer SFH bins, or perhaps to hold $\log U$ constant.

6.2.5 Line ratios

Now we'll have some fun. Even though we didn't fit the line ratios, we can extract the posteriors for the line ratios: the set of line ratios that are consistent with the broadband photometry given our model. We'll compare them to the nebular catalog of Groves+(2023) based on the PHANGS-MUSE survey.

[12]:
```
import corner

# Convenience functions to plot BPT-like diagnostic regions
from lightning.plots import k06_NIIplot, k06_SIIplot, k06_OIplot

from astropy.table import Table

# Line measurements from Groves+(2023) for 2855 individual nebulae
# in NGC 628.
neb = Table.read('../photometry/NGC628_nebula_catalog.fits')

OIIIHbeta_obs = np.log10(neb['OIII5006_FLUX_CORR'] / neb['HB4861_FLUX_CORR'])
NIIHalpha_obs = np.log10(neb['NII6583_FLUX_CORR'] / neb['HA6562_FLUX_CORR'])
SIIHalpha_obs = np.log10((neb['SII6716_FLUX_CORR'] + neb['SII6730_FLUX_CORR']) / neb[
```

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```
↪'HA6562_FLUX_CORR'])
OIHalpha_obs = np.log10(neb['OI6300_FLUX_CORR'] / neb['HA6562_FLUX_CORR'])

linelum, linelum_intr = lgh.get_model_lines(chain)

OIIImask = lgh.stars.line_labels == 'O__3_500684A'
Halphamask = lgh.stars.line_labels == 'H__1_656280A'
Hbetamask = lgh.stars.line_labels == 'H__1_486132A'
NIImask = lgh.stars.line_labels == 'N__2_658345A'
SII6717mask = lgh.stars.line_labels == 'S__2_671644A'
SII6730mask = lgh.stars.line_labels == 'S__2_673082A'
OImask = lgh.stars.line_labels == 'BLND_630000A'

OIIIHbeta = np.log10(linelum[:,OIIImask] / linelum[:,Hbetamask])
NIIHalpha = np.log10(linelum[:,NIImask] / linelum[:,Halphamask])
SIIHalpha = np.log10((linelum[:,SII6717mask] + linelum[:,SII6730mask]) / linelum[:,
↪Halphamask])
OIHalpha = np.log10(linelum[:,OImask] / linelum[:,Halphamask])

OIIIHbeta_intr = np.log10(linelum_intr[:,OIIImask] / linelum_intr[:,Hbetamask])
NIIHalpha_intr = np.log10(linelum_intr[:,NIImask] / linelum_intr[:,Halphamask])
SIIHalpha_intr = np.log10((linelum_intr[:,SII6717mask] + linelum_intr[:,SII6730mask]) /␣
↪linelum_intr[:,Halphamask])
OIHalpha_intr = np.log10(linelum_intr[:,OImask] / linelum_intr[:,Halphamask])

fig, axs = plt.subplots(1,3, figsize=(12,4))

corner.hist2d(NIIHalpha, OIIIHbeta, smooth=1, color='darkorange', levels=[0.50, 0.95, 0.
↪99], ax=axs[0])
corner.hist2d(NIIHalpha_intr, OIIIHbeta_intr, smooth=1, color='dodgerblue', levels=[0.50,
↪ 0.95, 0.99], ax=axs[0])
k06_NIIplot(ax=axs[0])
axs[0].scatter(NIIHalpha_obs, OIIIHbeta_obs, marker='.', color='slategray', alpha=0.2,␣
↪label='Groves+(2023)')

axs[0].set_xlim(-2.2,1)
axs[0].set_ylim(-1,2)
axs[0].set_xlabel(r'$\rm \log([N II] / H\alpha)$')
axs[0].set_ylabel(r'$\rm \log([O III] / H\beta)$')
axs[0].legend(loc='best')

corner.hist2d(SIIHalpha, OIIIHbeta, smooth=1, color='darkorange', levels=[0.50, 0.95, 0.
↪99], ax=axs[1])
corner.hist2d(SIIHalpha_intr, OIIIHbeta_intr, smooth=1, color='dodgerblue', levels=[0.50,
↪ 0.95, 0.99], ax=axs[1])
axs[1].scatter(SIIHalpha_obs, OIIIHbeta_obs, marker='.', color='slategray', alpha=0.2)
k06_SIIplot(ax=axs[1])
axs[1].set_xlim(-1.2,0.8)
axs[1].set_ylim(-1,2)
axs[1].set_yticklabels([])
axs[1].set_xlabel(r'$\rm \log([S II] / H\alpha)$')
```

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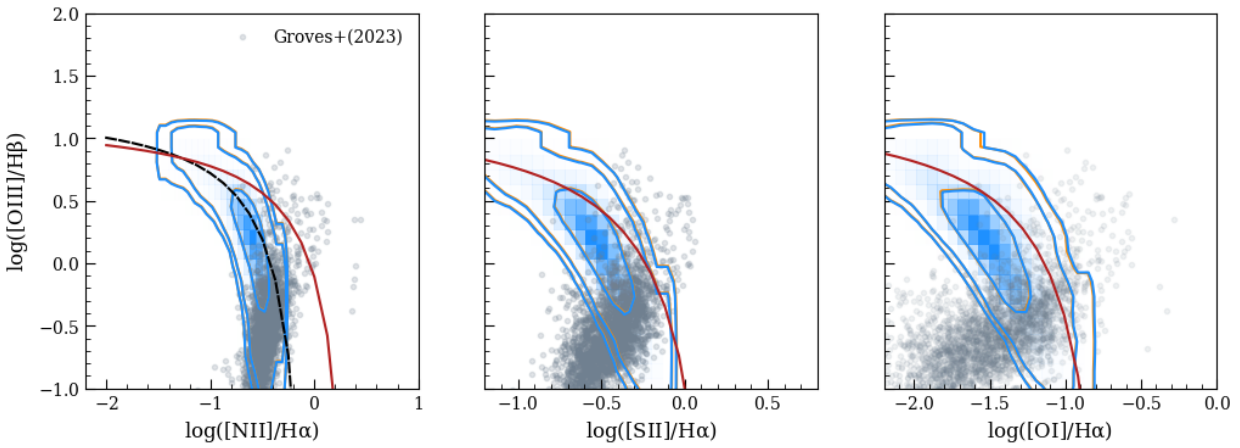
```
corner.hist2d(OIHalpha, OIIIHbeta, smooth=1, color='darkorange', levels=[0.50, 0.95, 0.
↪99], ax=axs[2])
corner.hist2d(OIHalpha_intr, OIIIHbeta_intr, smooth=1, color='dodgerblue', levels=[0.50,␣
↪0.95, 0.99], ax=axs[2])
axs[2].scatter(OIHalpha_obs, OIIIHbeta_obs, marker='.', color='slategray', alpha=0.1)
k06_OIplot(ax=axs[2])
axs[2].set_xlim(-2.2,0.0)
axs[2].set_ylim(-1,2)
axs[2].set_yticklabels([])
axs[2].set_xlabel(r'$\rm \log([O I] / H\alpha)$')
```

```
/var/folders/p6/qlk1ytxd09vf64nrq0vfw06wgg_lcz/T/ipykernel_38318/4253786285.py:12:␣
↪RuntimeWarning: divide by zero encountered in log10
  OIIIHbeta_obs = np.log10(neb['OIII5006_FLUX_CORR'] / neb['HB4861_FLUX_CORR'])
/var/folders/p6/qlk1ytxd09vf64nrq0vfw06wgg_lcz/T/ipykernel_38318/4253786285.py:15:␣
↪RuntimeWarning: divide by zero encountered in log10
  OIHalpha_obs = np.log10(neb['OI6300_FLUX_CORR'] / neb['HA6562_FLUX_CORR'])
/Users/eqm5663/Research/code/plightning/lightning/stellar/bpass.py:1409: RuntimeWarning:␣
↪divide by zero encountered in log10
  np.log10(np.transpose(self.line_lum, axes=[1,2,0,3])),
```

[12]:
```
Text(0.5, 0, '$\\rm \\log([O I] / H\\alpha)$')
```



The excellent agreement of the $[\mathrm{NII}]/\mathrm{H}\alpha$ posterior isn't that surprising, given the narrow posterior we placed on the metallicity was drawn from these same data. In a subsequent notebook we'll fit the line ratios directly.

6.2.6 New PEGASE models

We repeat the fitting and analysis above with the new PEGASE models. We compare the stellar models in more detail in a different notebook.

[13]:
```
cat = Table.read('../photometry/ngc628_dale17_photometry.fits')

filter_labels = np.array([s.decode().strip() for s in cat['FILTER_LABELS'].data[0]])
fnu_obs = cat['FNU_OBS'].data[0]
fnu_unc = cat['FNU_UNC'].data[0]
dl = cat['LUMIN_DIST'].data[0]
```

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```
agebins = [0.0] + list(np.logspace(7, np.log10(13.4e9), 7))

lgh = Lightning(filter_labels,
                lum_dist=dl,
                ages=agebins,
                nebula_lognH=3.5,
                nebula_dust=True,
                stellar_type='PEGASE-A24',
                SFH_type='Piecewise-Constant',
                atten_type='Modified-Calzetti',
                dust_emission=True,
                model_unc=0.10,
                print_setup_time=True)


lgh.flux_obs = fnu_obs * 1e3
lgh.flux_unc = fnu_unc * 1e3

# lgh.save_pickle('ngc628_PEGASE_config.pkl')
```

```
0.025 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
1.617 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.130 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
1.773 s elapsed total
```

[14]:
```
lgh.print_params(verbose=True)
```

```
============================
Piecewise-Constant
============================
Parameter  Lo  Hi              Description
--------- --- --- ------------------------
    psi_1 0.0 inf SFR in stellar age bin 1
    psi_2 0.0 inf SFR in stellar age bin 2
    psi_3 0.0 inf SFR in stellar age bin 3
    psi_4 0.0 inf SFR in stellar age bin 4
    psi_5 0.0 inf SFR in stellar age bin 5
    psi_6 0.0 inf SFR in stellar age bin 6
    psi_7 0.0 inf SFR in stellar age bin 7

============================
PEGASE-Stellar-A24
============================
Parameter                    Lo                Hi                                ␣
↪           Description
--------- -------------------- ------------------ ------------------------------------
```

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```
↪-----------------------
    Zmet 0.0006471873203208087 0.0257649912911017 Metallicity (mass fraction, where␣
↪solar = 0.020 ~ 10**[-1.7])
    logU                -4.0              -1.5                              log10 of␣
↪the ionization parameter

============================
Modified-Calzetti
============================
     Parameter   Lo                Hi                                                ␣
↪                             Description
-------------- ---- ------------------ ------------------------------------------------
↪----------------------------------------
mcalz_tauV_diff  0.0                inf                                               ␣
↪         Optical depth of the diffuse ISM
   mcalz_delta -inf 0.4473684210526316 Deviation from the Calzetti+2000 UV power law␣
↪slope (Upper limit set by requiring Eb >= 0)
  mcalz_tauV_BC  0.0                inf                                  Optical depth␣
↪of the birth cloud in star forming regions

============================
DL07-Dust
============================
     Parameter     Lo       Hi                                                        ␣
↪   Description
-------------- ------ -------- ------------------------------------------------------------
↪--------------
dl07_dust_alpha  -10.0      4.0                  Radiation field intensity distribution␣
↪power law index
dl07_dust_U_min    0.1     25.0                                       Radiation field␣
↪minimum intensity
dl07_dust_U_max 1000.0 300000.0                                       Radiation field␣
↪maximum intensity
dl07_dust_gamma    0.0      1.0 Fraction of dust mass exposed to radiation field␣
↪intensity distribution
dl07_dust_q_PAH 0.0047   0.0458                            Fraction of dust mass␣
↪composed of PAH grains

Total parameters: 17
```

[15]:
```
p0_seed = np.array([5,5,5,0,0,0,0,
                    0.014, -2.0,
                    0.1, -1.0, 0.0,
                    2, 3, 3e5, 0.01, 0.02])

priors = 7 * [UniformPrior([0,20])] + \
             [NormalPrior([0.013, 0.001]), NormalPrior([-2.5,0.75])] + \
             [UniformPrior([0,3]), UniformPrior([-1.5, 0.3]), None] + \
             [ConstantPrior([2]), UniformPrior([0.1, 25]), ConstantPrior([3e5]),␣
↪UniformPrior([0,1]), UniformPrior([0.0047, 0.0458])]
const_dim = 7 * [False] + \
            [False, False] + \
```

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```
            [False, False, True] + \
            [True, False, True, False, False]
const_dim = np.array(const_dim)
const_vals = p0_seed[const_dim]

Nwalkers = 64

p0s = [pr.sample(Nwalkers) if pr is not None else np.zeros(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)
# p0[:, const_dim] = const_vals[None,:]

# Metallicity and logU might sample out of bounds
p0[p0[:,7] < 0.001, 7] = 0.001
p0[p0[:,7] > 0.02, 7] = 0.02
p0[p0[:,8] < -3, 8] = -3
p0[p0[:,8] > -1.5, 8] = -1.5

mcmc = lgh.fit(p0,
               method='emcee',
               priors=priors,
               const_dim=const_dim,
               Nwalkers=Nwalkers,
               Nsteps=30000,
               progress=True)

# mcmc = l.fit(p0, method='emcee', Nwalkers=Nwalkers, Nsteps=20000, priors=priors, const_
↪dim=const_dim)
# print(res_bp)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:1070: RuntimeWarning:
↪ divide by zero encountered in log10
  np.log10(np.transpose(self.Lnu_obs, axes=[1,2,0,3])),
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_rgi.py:418: RuntimeWarning: invalid value encountered in multiply
  term = np.asarray(self.values[edge_indices]) * weight[vslice]
100%|##########################################################################################
↪##########################################################| 30000/30000 [15:35<00:00,
↪ 32.06it/s]
```

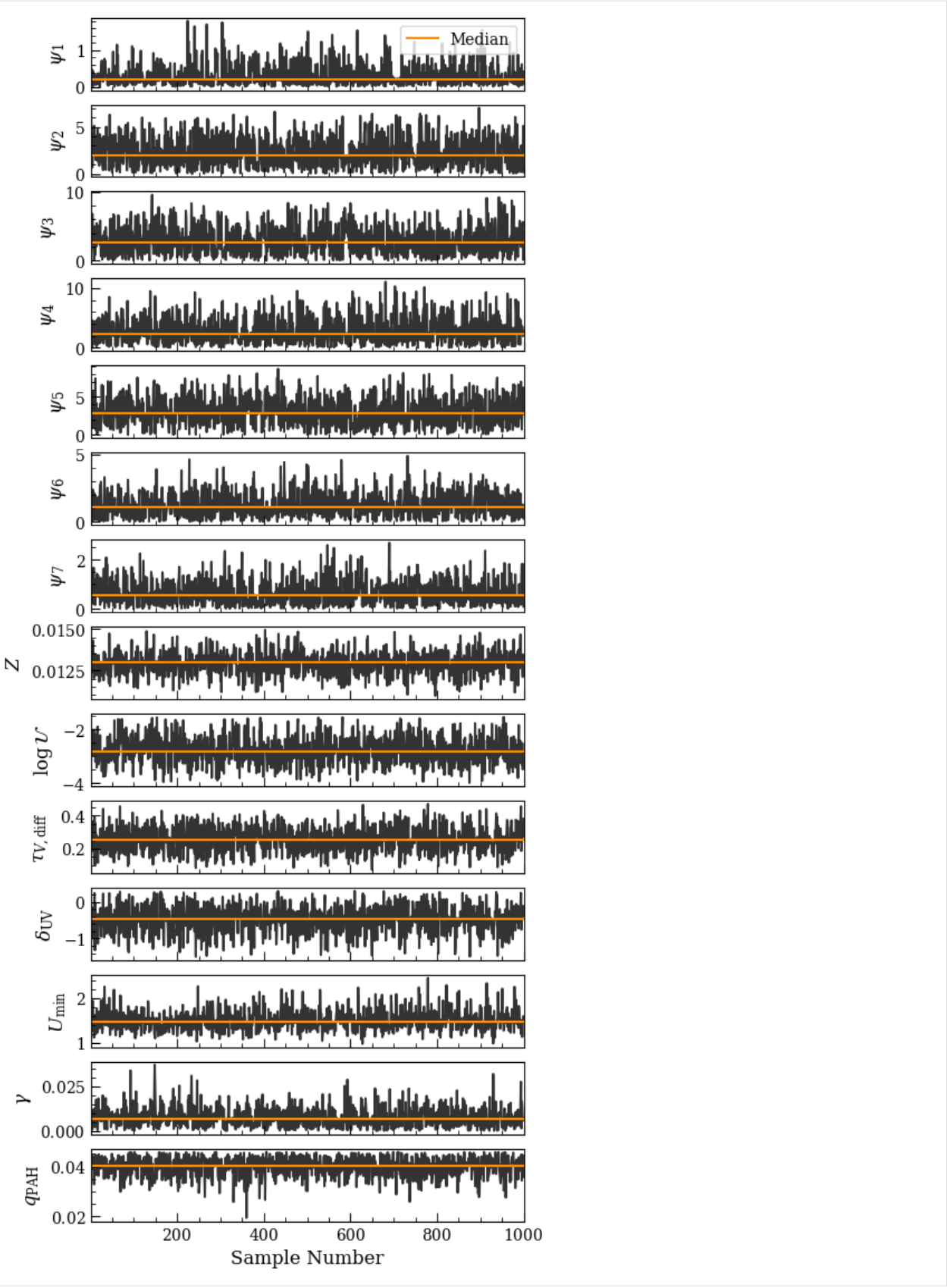
[16]:
```
print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc.acceptance_fraction)))
```

```
MCMC mean acceptance fraction: 0.208
```

[17]:
```
chain, logprob_chain, tau_ac = lgh.get_mcmc_chains(mcmc, discard=2000, thin=500, const_
↪dim=const_dim, const_vals=p0_seed[const_dim])
```

```
WARNING: The integrated autocorrelation time is longer than N/50.
         The autocorrelation estimate may be unreliable.
```

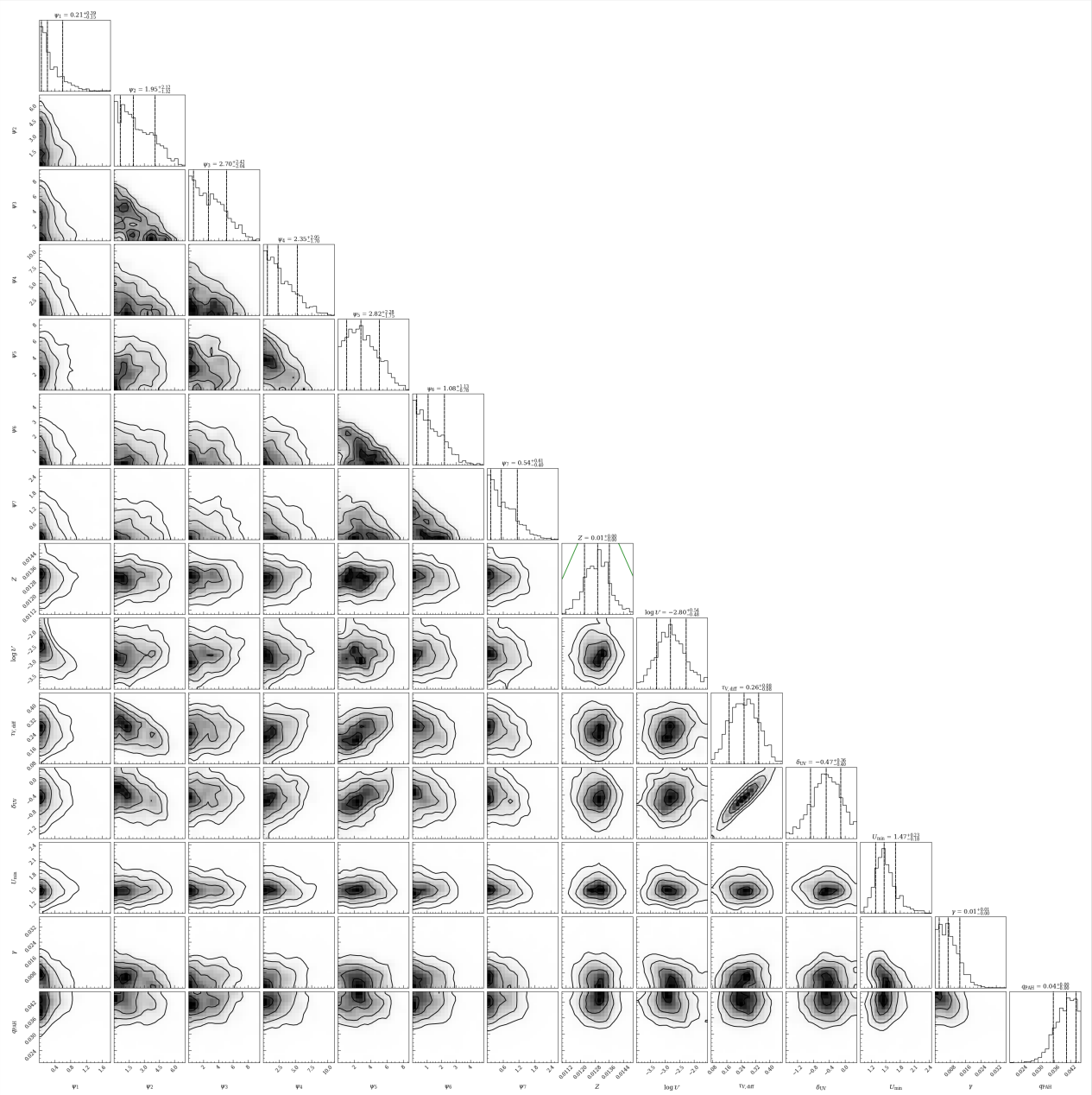
[18]:
```
fig, axs = lgh.chain_plot(chain, color='k', alpha=0.8)
```


Median
ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
ψ_6
ψ_7
Z
$\log U$
$\tau_{V,\mathrm{diff}}$
δ_{UV}
U_{min}
γ
q_{PAH}
Sample Number

[19]:
```
fig = lgh.corner_plot(chain,
                      quantiles=(0.16, 0.50, 0.84),
                      smooth=1,
                      levels=None,
                      show_titles=True)

ZZ = np.linspace(0.001, 0.03, 30)
Zprior = lambda Z, mu, s: 1 / np.sqrt(2 * np.pi * s**2) * np.exp(-1 * (Z - mu)**2 / s**2)
axs = (np.array(fig.axes)).reshape(14,14)
yy = Zprior(ZZ, 0.013, 0.002)
axs[7,7].plot(ZZ, yy, color='forestgreen')
```

[19]:
```
[<matplotlib.lines.Line2D at 0x1572a8810>]
```

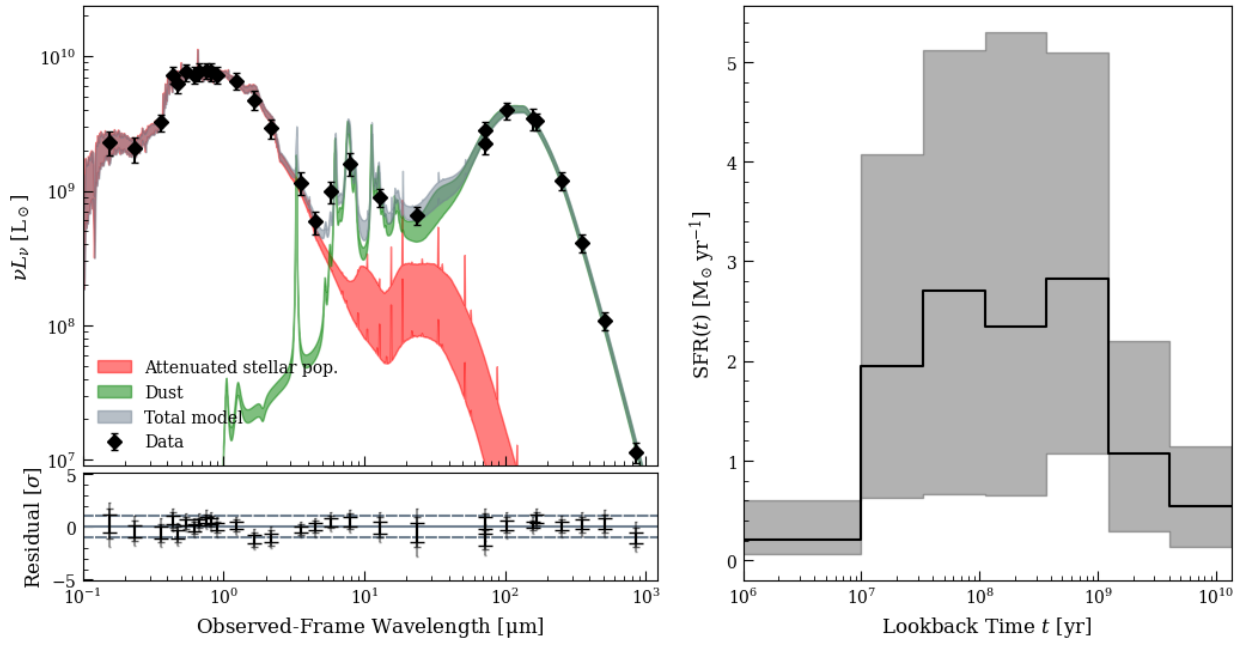


[20]:
```
from lightning.plots import sed_plot_morebayesian, sed_plot_delchi_morebayesian, sfh_plot

fig5 = plt.figure(figsize=(12,6))
ax51 = fig5.add_axes([0.1, 0.26, 0.4, 0.64])
ax52 = fig5.add_axes([0.1, 0.1, 0.4, 0.15])
ax53 = fig5.add_axes([0.56, 0.1, 0.34, 0.8])

fig5, ax51 = sed_plot_morebayesian(lgh, chain, logprob_chain,
                                   plot_components=True,
                                   ax=ax51,
                                   legend_kwargs={'loc': 'lower left', 'frameon': False})
ax51.set_xticklabels([])
fig5, ax52 = sed_plot_delchi_morebayesian(lgh, chain, logprob_chain, ax=ax52)
fig5, ax53 = lgh.sfh_plot(chain, ax=ax53)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:1070: RuntimeWarning:
↪ divide by zero encountered in log10
  np.log10(np.transpose(self.Lnu_obs, axes=[1,2,0,3])),
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:1070: RuntimeWarning:
↪ divide by zero encountered in log10
  np.log10(np.transpose(self.Lnu_obs, axes=[1,2,0,3])),
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/numpy/lib/
↪nanfunctions.py:1095: RuntimeWarning: All-NaN slice encountered
  result = np.apply_along_axis(_nanmedian1d, axis, a, overwrite_input)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/numpy/lib/
↪nanfunctions.py:1583: RuntimeWarning: All-NaN slice encountered
  result = np.apply_along_axis(_nanquantile_1d, axis, a, q,
```



[21]:
```
from lightning.ppc import ppc, ppc_sed

pvalue, chi2_rep, chi2_obs = ppc(lgh, chain,
                                 logprob_chain,
```

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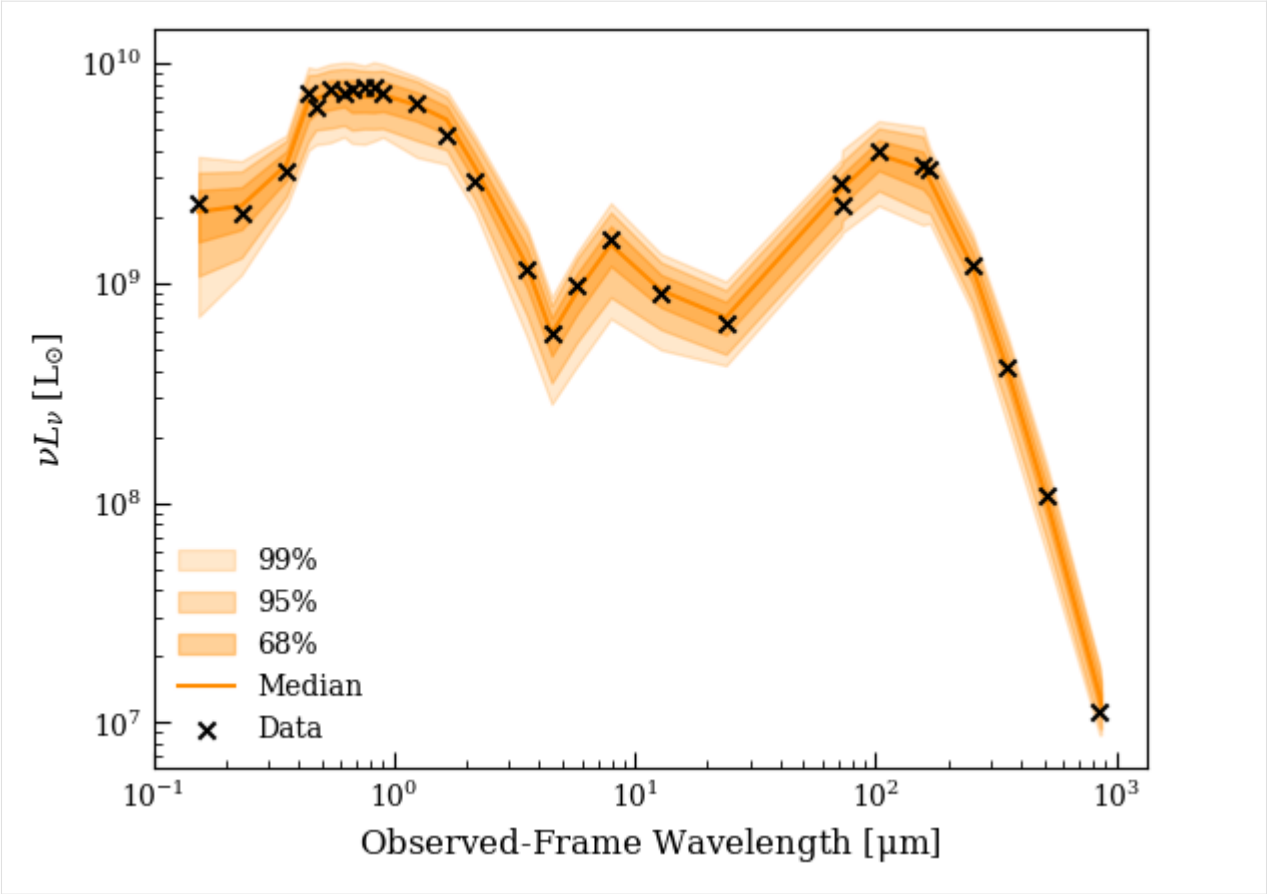
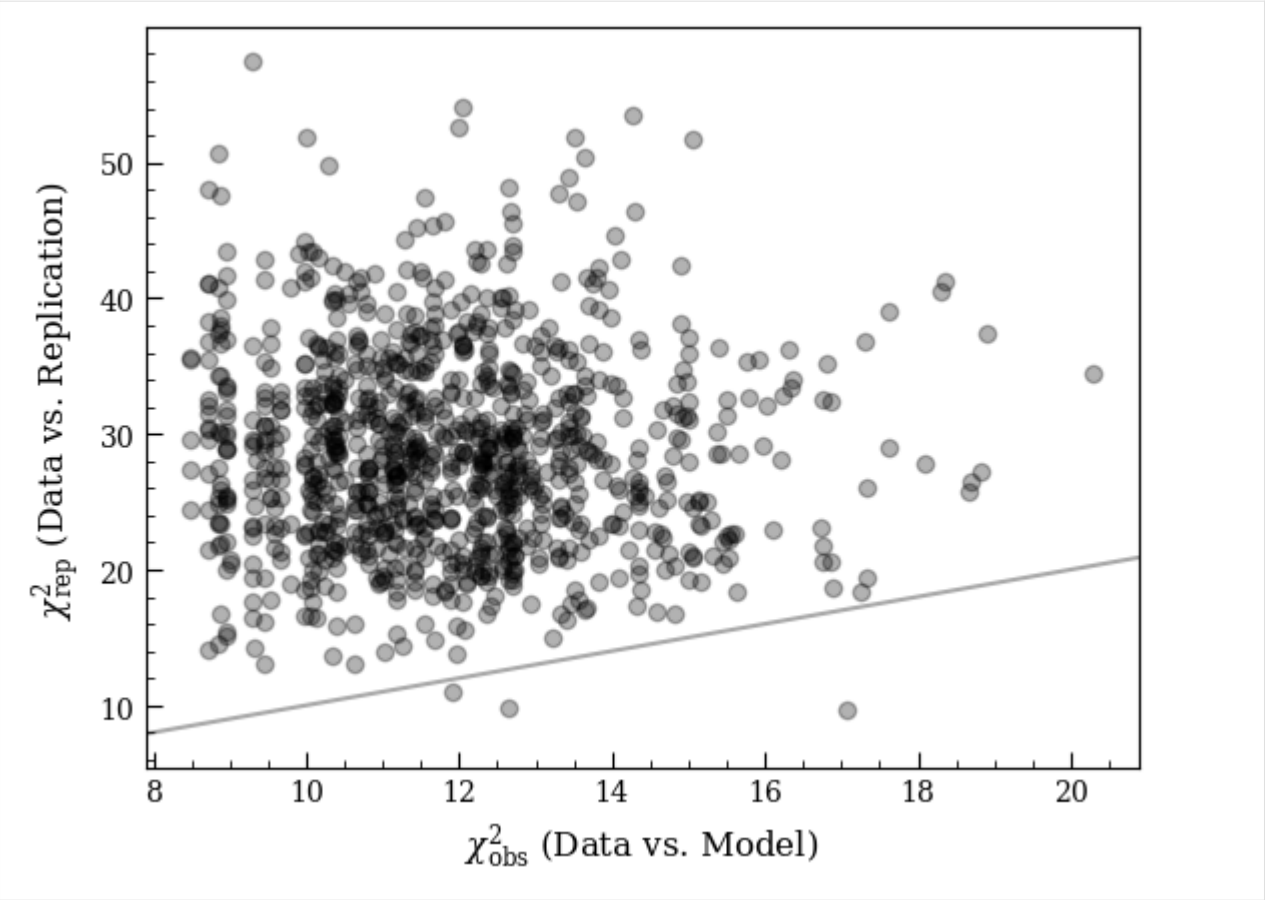
```
                                Nrep=1000,
                                seed=12345)
fig, ax = ppc_sed(lgh, chain,
                  logprob_chain,
                  Nrep=1000,
                  seed=12345,
                  normalize=False)

fig2, ax2 = plt.subplots()

ax2.scatter(chi2_obs,
            chi2_rep,
            marker='o',
            alpha=0.3)

xlim = ax2.get_xlim()
ax2.plot(xlim, xlim, linestyle='-', color='darkgray', zorder=-1)
ax2.set_xlim(xlim)

ax2.set_xlabel(r'$\chi_{\rm obs}^2$ (Data vs. Model)')
ax2.set_ylabel(r'$\chi_{\rm rep}^2$ (Data vs. Replication)')


print('p = %.3f' % (pvalue))
```

```
/Users/eqm5663/Research/code/plightning/lightning/ppc.py:77: RuntimeWarning: invalid␣
↪value encountered in divide
  chi2_rep = np.nansum((Lmod - Lmod_perturbed)**2 / total_unc2, axis=-1)
```

```
p = 0.997
```


10^{10}
10^{9}
10^{8}
10^{7}
νL_ν [$L_\odot$]
99%
95%
68%
Median
Data
10^{-1}
10^{0}
10^{1}
10^{2}
10^{3}
Observed-Frame Wavelength [μm]



Now we're really overfitting.

[22]:
```
import corner
# Convenience functions I made to plot BPT-like diagnostic regions
from lightning.plots import k06_NIIplot, k06_SIIplot, k06_OIplot

from astropy.table import Table

# Line measurements from Groves+(2023) for 2855 individual nebulae
# in NGC 628.
neb = Table.read('../photometry/NGC628_nebula_catalog.fits')

OIIIHbeta_obs = np.log10(neb['OIII5006_FLUX_CORR'] / neb['HB4861_FLUX_CORR'])
NIIHalpha_obs = np.log10(neb['NII6583_FLUX_CORR'] / neb['HA6562_FLUX_CORR'])
SIIHalpha_obs = np.log10((neb['SII6716_FLUX_CORR'] + neb['SII6730_FLUX_CORR']) / neb[
↪'HA6562_FLUX_CORR'])
OIHalpha_obs = np.log10(neb['OI6300_FLUX_CORR'] / neb['HA6562_FLUX_CORR'])

linelum, linelum_intr = lgh.get_model_lines(chain)

OIIImask = lgh.stars.line_labels == 'O__3_500684A'
Halphamask = lgh.stars.line_labels == 'H__1_656280A'
Hbetamask = lgh.stars.line_labels == 'H__1_486132A'
NIImask = lgh.stars.line_labels == 'N__2_658345A'
```

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```
SII6717mask = lgh.stars.line_labels == 'S__2_671644A'
SII6730mask = lgh.stars.line_labels == 'S__2_673082A'
OImask = lgh.stars.line_labels == 'BLND_630000A'

OIIIHbeta = np.log10(linelum[:,OIIImask] / linelum[:,Hbetamask])
NIIHalpha = np.log10(linelum[:,NIImask] / linelum[:,Halphamask])
SIIHalpha = np.log10((linelum[:,SII6717mask] + linelum[:,SII6730mask]) / linelum[:,
↪Halphamask])
OIHalpha = np.log10(linelum[:,OImask] / linelum[:,Halphamask])

OIIIHbeta = np.log10(linelum_intr[:,OIIImask] / linelum_intr[:,Hbetamask])
NIIHalpha = np.log10(linelum_intr[:,NIImask] / linelum_intr[:,Halphamask])
SIIHalpha = np.log10((linelum_intr[:,SII6717mask] + linelum_intr[:,SII6730mask]) /␣
↪linelum_intr[:,Halphamask])
OIHalpha = np.log10(linelum_intr[:,OImask] / linelum_intr[:,Halphamask])

fig, axs = plt.subplots(1,3, figsize=(12,4))

corner.hist2d(NIIHalpha, OIIIHbeta, smooth=1, color='darkorange', levels=[0.50, 0.95, 0.
↪99], ax=axs[0])
corner.hist2d(NIIHalpha_intr, OIIIHbeta_intr, smooth=1, color='dodgerblue', levels=[0.50,
↪ 0.95, 0.99], ax=axs[0])
k06_NIIplot(ax=axs[0])
axs[0].scatter(NIIHalpha_obs, OIIIHbeta_obs, marker='.', color='slategray', alpha=0.2,␣
↪label='Groves+(2023)')

axs[0].set_xlim(-2.2,1)
axs[0].set_ylim(-1,2)
axs[0].set_xlabel(r'$\rm \log([N II] / H\alpha)$')
axs[0].set_ylabel(r'$\rm \log([O III] / H\beta)$')
axs[0].legend(loc='best')

corner.hist2d(SIIHalpha, OIIIHbeta, smooth=1, color='darkorange', levels=[0.50, 0.95, 0.
↪99], ax=axs[1])
corner.hist2d(SIIHalpha_intr, OIIIHbeta_intr, smooth=1, color='dodgerblue', levels=[0.50,
↪ 0.95, 0.99], ax=axs[1])
axs[1].scatter(SIIHalpha_obs, OIIIHbeta_obs, marker='.', color='slategray', alpha=0.2)
k06_SIIplot(ax=axs[1])
axs[1].set_xlim(-1.2,0.8)
axs[1].set_ylim(-1,2)
axs[1].set_yticklabels([])
axs[1].set_xlabel(r'$\rm \log([S II] / H\alpha)$')

corner.hist2d(OIHalpha, OIIIHbeta, smooth=1, color='darkorange', levels=[0.50, 0.95, 0.
↪99], ax=axs[2])
corner.hist2d(OIHalpha_intr, OIIIHbeta_intr, smooth=1, color='dodgerblue', levels=[0.50,␣
↪0.95, 0.99], ax=axs[2])
axs[2].scatter(OIHalpha_obs, OIIIHbeta_obs, marker='.', color='slategray', alpha=0.1)
k06_OIplot(ax=axs[2])
axs[2].set_xlim(-2.2,0.0)
axs[2].set_ylim(-1,2)
axs[2].set_yticklabels([])
```

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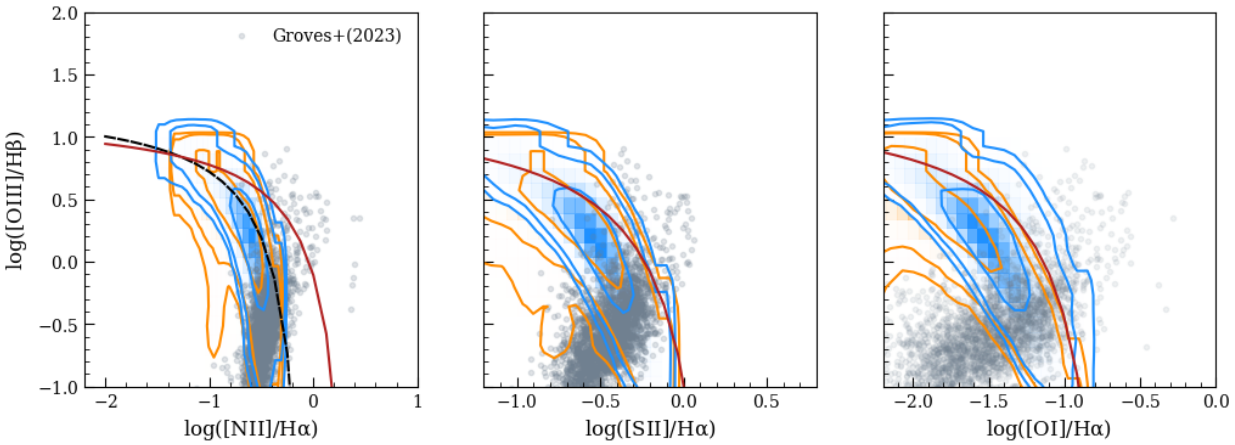
```
axs[2].set_xlabel(r'$\rm \log([O I] / H\alpha)$')
```

```
/var/folders/p6/qlk1ytxd09vf64nrq0vfw06wgg_lcz/T/ipykernel_38318/2227680488.py:11:␣
↪RuntimeWarning: divide by zero encountered in log10
  OIIIHbeta_obs = np.log10(neb['OIII5006_FLUX_CORR'] / neb['HB4861_FLUX_CORR'])
/var/folders/p6/qlk1ytxd09vf64nrq0vfw06wgg_lcz/T/ipykernel_38318/2227680488.py:14:␣
↪RuntimeWarning: divide by zero encountered in log10
  OIHalpha_obs = np.log10(neb['OI6300_FLUX_CORR'] / neb['HA6562_FLUX_CORR'])
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:1278: RuntimeWarning:
↪ divide by zero encountered in log10
  np.log10(np.transpose(self.line_lum, axes=[1,2,0,3])),
```

[22]:
```
Text(0.5, 0, '$\\rm \\log([O I] / H\\alpha)$')
```



The orange contours represent the redenned line ratios, while the blue are intrinsic. The BPASS solution is consistently less attenuated than the PEGASE solution (the BPASS stellar population models are actually just redder, seemingly due to an over-production of AGB stars) so the difference in line ratios is less obvious there. We should be looking for agreement between the blue contour and the background points, which we see again is generally ok, especially where our choice of prior makes it so in $[\mathrm{NII}]/\mathrm{H}\alpha$.

6.3 Stellar Population Model Comparison - NGC 337

In this notebook we compare the models with the new nebular components from Cloudy simulations to each other and to the PEGASE model stellar populations used in the IDL version of Lightning, fitting all the models to the Dale+(2017) photometry for NGC 337 and comparing the results and derived properties.

6.3.1 Imports

[1]:
```
import numpy as np
import h5py
rng = np.random.default_rng()
import astropy.units as u
from astropy.table import Table
from corner import corner
import matplotlib.pyplot as plt
```

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```
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline

from lightning import Lightning
from lightning.priors import UniformPrior, ConstantPrior
```

6.3.2 Setup

We're defining three different Lightning instances that use the same photometry: 1. PEGASE model populations from IDL Lightning 2. PEGASE model populations with Cloudy simulations 3. BPASS model populations with Cloudy simulations

[9]:
```
cat = Table.read('../photometry/ngc337_dale17_photometry.fits')

filter_labels = np.array([s.decode().strip() for s in cat['FILTER_LABELS'].data[0]])
fnu_obs = cat['FNU_OBS'].data[0]
fnu_unc = cat['FNU_UNC'].data[0]
dl = cat['LUMIN_DIST'].data[0]

lgh_pg = Lightning(filter_labels,
                   lum_dist=dl,
                   stellar_type='PEGASE',
                   SFH_type='Piecewise-Constant',
                   atten_type='Modified-Calzetti',
                   dust_emission=True,
                   model_unc=0.10,
                   print_setup_time=True)

lgh_pg.flux_obs = fnu_obs * 1e3
lgh_pg.flux_unc = fnu_unc * 1e3

lgh_pg_cl = Lightning(filter_labels,
                      lum_dist=dl,
                      stellar_type='PEGASE-A24',
                      SFH_type='Piecewise-Constant',
                      atten_type='Modified-Calzetti',
                      dust_emission=True,
                      model_unc=0.10,
                      print_setup_time=True)

lgh_pg_cl.flux_obs = fnu_obs * 1e3
lgh_pg_cl.flux_unc = fnu_unc * 1e3

lgh_bp_cl = Lightning(filter_labels,
                      lum_dist=dl,
                      stellar_type='BPASS-A24',
                      SFH_type='Piecewise-Constant',
                      atten_type='Modified-Calzetti',
                      dust_emission=True,
                      model_unc=0.10,
                      print_setup_time=True)
```

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```
lgh_bp_cl.flux_obs = fnu_obs * 1e3
lgh_bp_cl.flux_unc = fnu_unc * 1e3
```

```
0.018 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
0.551 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.156 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
0.725 s elapsed total
0.008 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
1.703 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.092 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
1.803 s elapsed total
0.008 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
1.249 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.090 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
1.348 s elapsed total
```

Note that the new models have an additional parameter compared to the old models: $\log U$, the ionization parameter.

Fit PEGASE models without Cloudy

[7]:
```
p = np.array([1,1,1,1,1,
              0.02,
              0.3, 0.0, 0.0,
              2, 1, 3e5, 0.1, 0.01])

const_dim = np.array([False, False, False, False, False,
                      True,
                      False, False, True,
                      True, False, True, False, False])

priors = [UniformPrior([0, 1e1]), # SFH
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          ConstantPrior([0.02]), # Metallicity
          UniformPrior([0, 3]), # tauV
          UniformPrior([-2.3, 0.4]), # delta
```

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```
          ConstantPrior([0.0]), # tauV birth cloud
          ConstantPrior([2]), # alpha
          UniformPrior([0.1, 25]), # Umin
          ConstantPrior([3e5]), # Umax
          UniformPrior([0,1]),
          UniformPrior([0.0047, 0.0458])]

var_dim = ~const_dim

Nwalkers = 64

# Sample an initial state from the priors
p0s = [pr.sample(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)

mcmc_pg = lgh_pg.fit(p0, method='emcee', Nwalkers=Nwalkers, Nsteps=20000, priors=priors,␣
↪const_dim=const_dim)

print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc_pg.acceptance_fraction)))
chain_pg, logprob_chain_pg, tau_ac_pg = lgh_pg.get_mcmc_chains(mcmc_pg,
                                                               discard=None,
                                                               thin=None,
                                                               const_dim=const_dim,
                                                               const_vals=p0[0,const_
↪dim])
```

```
100%|##########################################################################################
↪##########################################################| 20000/20000 [10:26<00:00,
↪ 31.94it/s]
```

```
MCMC mean acceptance fraction: 0.320
```

Fit PEGASE models *with* Cloudy

[10]:
```
p = np.array([1,1,1,1,1,
              0.02, -2.0,
              0.3, 0.0, 0.0,
              2, 1, 3e5, 0.1, 0.01])

const_dim = np.array([False, False, False, False, False,
                      True, True,
                      False, False, True,
                      True, False, True, False, False])

priors = [UniformPrior([0, 1e1]), # SFH
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          ConstantPrior([0.02]), # Metallicity
```

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```
          ConstantPrior([-2]), # log U
          UniformPrior([0, 3]), # tauV
          UniformPrior([-2.3, 0.4]), # delta
          ConstantPrior([0.0]), # tauV birth cloud
          ConstantPrior([2]), # alpha
          UniformPrior([0.1, 25]), # Umin
          ConstantPrior([3e5]), # Umax
          UniformPrior([0,1]),
          UniformPrior([0.0047, 0.0458])]

var_dim = ~const_dim

Nwalkers = 64

# Sample an initial state from the priors
p0s = [pr.sample(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)

mcmc_pg_cl = lgh_pg_cl.fit(p0, method='emcee', Nwalkers=Nwalkers, Nsteps=20000,␣
↪priors=priors, const_dim=const_dim)

print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc_pg_cl.acceptance_fraction)))
chain_pg_cl, logprob_chain_pg_cl, tau_ac_pg_cl = lgh_pg_cl.get_mcmc_chains(mcmc_pg_cl,
                                                                           discard=None,
                                                                           thin=None,
                                                                           const_dim=const_dim,
                                                                           const_vals=p0[0,const_
↪dim])
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:1073: RuntimeWarning:
↪ divide by zero encountered in log10
  np.log10(np.transpose(self.Lnu_obs, axes=[1,2,0,3])),
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_rgi.py:418: RuntimeWarning: invalid value encountered in multiply
  term = np.asarray(self.values[edge_indices]) * weight[vslice]
100%|##########################################################################################
↪##########################################################| 20000/20000 [11:39<00:00,
↪ 28.58it/s]
```

```
MCMC mean acceptance fraction: 0.293
```

Fit BPASS Model with Cloudy

[11]:
```
p = np.array([1,1,1,1,1,
              0.02, -2.0,
              0.3, 0.0, 0.0,
              2, 1, 3e5, 0.1, 0.01])

const_dim = np.array([False, False, False, False, False,
                      True, True,
                      False, False, True,
```

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```
                      True, False, True, False, False])

priors = [UniformPrior([0, 1e1]), # SFH
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          ConstantPrior([0.02]), # Metallicity
          ConstantPrior([-2]), # log U
          UniformPrior([0, 3]), # tauV
          UniformPrior([-2.3, 0.4]), # delta
          ConstantPrior([0.0]), # tauV birth cloud
          ConstantPrior([2]), # alpha
          UniformPrior([0.1, 25]), # Umin
          ConstantPrior([3e5]), # Umax
          UniformPrior([0,1]),
          UniformPrior([0.0047, 0.0458])]

var_dim = ~const_dim

Nwalkers = 64

# Sample an initial state from the priors
p0s = [pr.sample(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)

mcmc_bp_cl = lgh_bp_cl.fit(p0, method='emcee', Nwalkers=Nwalkers, Nsteps=20000,␣
↪priors=priors, const_dim=const_dim)

print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc_pg_cl.acceptance_fraction)))
chain_bp_cl, logprob_chain_bp_cl, tau_ac_bp_cl = lgh_bp_cl.get_mcmc_chains(mcmc_bp_cl,
                                                                           discard=None,
                                                                           thin=None,
                                                                           const_
↪dim=const_dim,
                                                                           const_
↪vals=p0[0,const_dim])
```

```
100%|##########################################################################################
↪##########################################################| 20000/20000 [11:40<00:00,
↪ 28.55it/s]
```

```
MCMC mean acceptance fraction: 0.293
```

[22]:
```
fig, axs = lgh_pg_cl.chain_plot(chain_pg_cl, plot_median=False, alpha=0.5)

const_dim = np.array([False, False, False, False, False,
                      True, True,
                      False, False, True,
                      True, False, True, False, False])

for i in range(np.count_nonzero(~const_dim)):
    tmp = (chain_bp_cl[:,~const_dim])[:,i]
```

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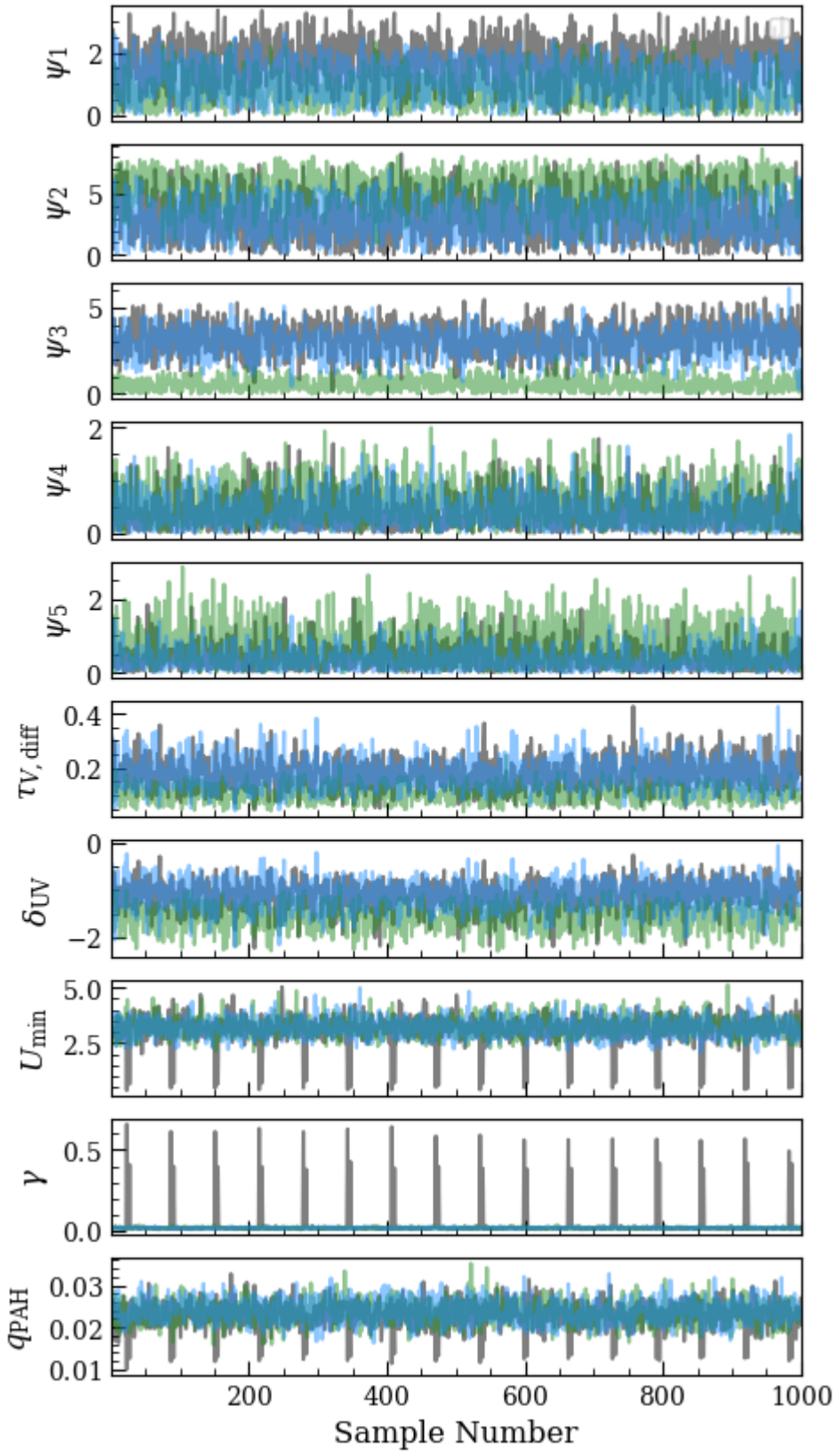
```
    axs[i].plot(np.arange(1000), tmp, color='forestgreen', alpha=0.5)

const_dim = np.array([False, False, False, False, False,
                      True,
                      False, False, True,
                      True, False, True, False, False])

for i in range(np.count_nonzero(~const_dim)):
    tmp = (chain_pg[:,~const_dim])[:,i]
    axs[i].plot(np.arange(1000), tmp, color='dodgerblue', alpha=0.5)
```

```
No artists with labels found to put in legend.  Note that artists whose label start with␣
↪an underscore are ignored when legend() is called with no argument.
```


ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
$\tau_{V,\,\mathrm{diff}}$
δ_{UV}
U_{min}
γ
q_{PAH}
Sample Number

Where gray = PEGASE-Cloudy, blue = PEGASE, green = BPASS-Cloudy.

There's not really a substantial difference except in the third bin of the SFH, which spans 100 Myr to 1 Gyr. The BPASS fit (pale green) puts much less star formation in that stellar age bin. We generally ascribe this to a red excess in the BPASS stellar spectra, which appears to be caused by overproduction of AGB stars, according to the 2018 BPASS release paper. We can overplot all the best-fit SED models and show the confidence regions on the SFHs, which will also make this clear:

[41]:
```
fig = plt.figure(figsize=(12,6))
ax1 = fig.add_axes([0.1, 0.26, 0.4, 0.64])
ax11 = fig.add_axes([0.2, 0.35, 0.2, 0.2])
ax2 = fig.add_axes([0.1, 0.1, 0.4, 0.15])
ax3 = fig.add_axes([0.56, 0.1, 0.34, 0.8])

fig, ax1 = lgh_pg_cl.sed_plot_bestfit(chain_pg_cl, logprob_chain_pg_cl,
                                      plot_components=False,
                                      ax=ax1,
                                      show_legend=False,
                                      total_kwargs={'color':'black', 'alpha':0.5})
fig, ax1 = lgh_pg.sed_plot_bestfit(chain_pg, logprob_chain_pg,
                                      plot_components=False,
                                      ax=ax1,
                                      show_legend=False,
                                      total_kwargs={'color':'dodgerblue', 'alpha':0.5},
                                      data_kwargs={'marker':'', 'linestyle':'', 'color':
↪'none'})
fig, ax1 = lgh_bp_cl.sed_plot_bestfit(chain_bp_cl, logprob_chain_bp_cl,
                                      plot_components=False,
                                      ax=ax1,
                                      show_legend=False,
                                      total_kwargs={'color':'forestgreen', 'alpha':0.5},
                                      data_kwargs={'marker':'', 'linestyle':'', 'color':
↪'none'})

fig, ax11 = lgh_pg_cl.sed_plot_bestfit(chain_pg_cl, logprob_chain_pg_cl,
                                      plot_components=False,
                                      ax=ax11,
                                      show_legend=False,
                                      total_kwargs={'color':'black', 'alpha':0.5})
fig, ax11 = lgh_pg.sed_plot_bestfit(chain_pg, logprob_chain_pg,
                                      plot_components=False,
                                      ax=ax11,
                                      show_legend=False,
                                      total_kwargs={'color':'dodgerblue', 'alpha':0.5},
                                      data_kwargs={'marker':'', 'linestyle':'', 'color':
↪'none'})
fig, ax11 = lgh_bp_cl.sed_plot_bestfit(chain_bp_cl, logprob_chain_bp_cl,
                                      plot_components=False,
                                      ax=ax11,
                                      show_legend=False,
                                      total_kwargs={'color':'forestgreen', 'alpha':0.5},
                                      data_kwargs={'marker':'', 'linestyle':'', 'color':
↪'none'})
```

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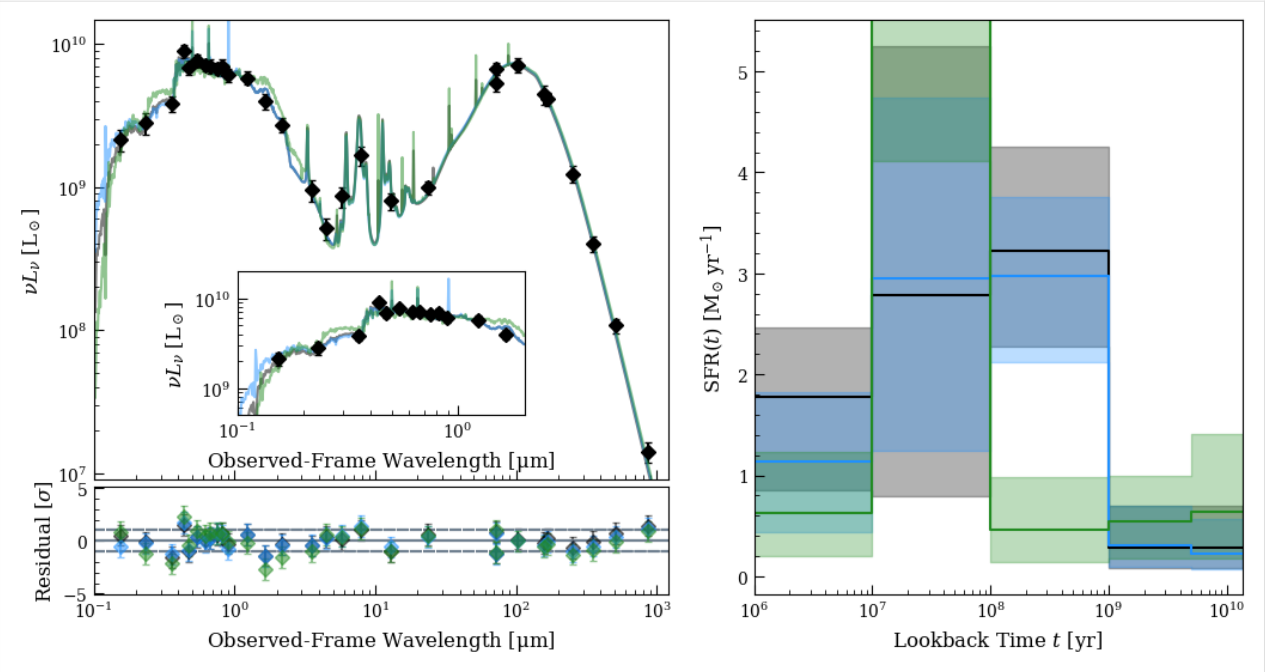
```
ax11.set_xlim(0.1, 2)
ax11.set_ylim(5e8, 2e10)
ax1.set_xticklabels([])

fig, ax2 = lgh_pg_cl.sed_plot_delchi(chain_pg_cl, logprob_chain_pg_cl,
                                     ax=ax2,
                                     data_kwargs={'marker':'D', 'color':'k',
↪'markerfacecolor':'k', 'capsize':2, 'linestyle':'', 'alpha':0.5})
fig, ax2 = lgh_pg.sed_plot_delchi(chain_pg, logprob_chain_pg,
                                     ax=ax2,
                                     data_kwargs={'marker':'D', 'color':'dodgerblue',
↪'markerfacecolor':'dodgerblue', 'capsize':2, 'linestyle':'', 'alpha':0.5})
fig, ax2 = lgh_bp_cl.sed_plot_delchi(chain_bp_cl, logprob_chain_bp_cl,
                                     ax=ax2,
                                     data_kwargs={'marker':'D', 'color':'forestgreen',
↪'markerfacecolor':'forestgreen', 'capsize':2, 'linestyle':'', 'alpha':0.5})


fig, ax3 = lgh_pg_cl.sfh_plot(chain_pg_cl, ax=ax3,
                              shade_kwargs={'color':'k', 'alpha':0.3, 'zorder':0},
                              line_kwargs={'color':'k', 'zorder':1})
fig, ax3 = lgh_pg.sfh_plot(chain_pg, ax=ax3,
                           shade_kwargs={'color':'dodgerblue', 'alpha':0.3, 'zorder':0},
                           line_kwargs={'color':'dodgerblue', 'zorder':1})
fig, ax3 = lgh_bp_cl.sfh_plot(chain_bp_cl, ax=ax3,
                              shade_kwargs={'color':'forestgreen', 'alpha':0.3, 'zorder':
↪0},
                              line_kwargs={'color':'forestgreen', 'zorder':1})
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:1073: RuntimeWarning:
↪ divide by zero encountered in log10
  np.log10(np.transpose(self.Lnu_obs, axes=[1,2,0,3])),
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_rgi.py:418: RuntimeWarning: invalid value encountered in multiply
  term = np.asarray(self.values[edge_indices]) * weight[vslice]
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
```



The color scheme is the same as above: gray = PEGASE-Cloudy, blue = PEGASE, green = BPASS-Cloudy.

The inset in the top panel blows up the optical-NIR portion of the SED to show differences between the models. The red excess from the BPASS models is clearly visible between 1-2 microns. Minimizing this excess leads to suppression of the third SFH bin and a slight enhancement of the second. We can look at the derived $M_\star$ and SFR to see if this has a downstream effect:

[45]:
```
import corner

SFR100_pg_cl = 0.1 * chain_pg_cl[:,0] + 0.9 * chain_pg_cl[:,1]
SFR100_pg = 0.1 * chain_pg[:,0] + 0.9 * chain_pg[:,1]
SFR100_bp_cl = 0.1 * chain_bp_cl[:,0] + 0.9 * chain_bp_cl[:,1]

mstar_coeff_pg_cl = lgh_pg_cl.stars.get_mstar_coeff(chain_pg_cl[:,5])
mstar_coeff_pg = lgh_pg.stars.get_mstar_coeff(chain_pg[:,5])
mstar_coeff_bp_cl = lgh_bp_cl.stars.get_mstar_coeff(chain_bp_cl[:,5])

mstar_pg_cl = np.sum(mstar_coeff_pg_cl * chain_pg_cl[:,:5], axis=1)
mstar_pg = np.sum(mstar_coeff_pg * chain_pg[:,:5], axis=1)
mstar_bp_cl = np.sum(mstar_coeff_bp_cl * chain_bp_cl[:,:5], axis=1)

labels = [r'$\log M_{\star}~[\rm M_{\odot}]$', r'$\rm SFR_{100}~[\rm M_{\odot}~yr^{-1}]$
↪']
fig = corner.corner(np.stack([np.log10(mstar_pg_cl), SFR100_pg_cl], axis=-1),
                    labels=labels,
                    smooth=1,
                    color='k')
fig = corner.corner(np.stack([np.log10(mstar_pg), SFR100_pg], axis=-1),
                    labels=labels,
                    smooth=1,
                    color='dodgerblue', fig=fig)
fig = corner.corner(np.stack([np.log10(mstar_bp_cl), SFR100_bp_cl], axis=-1),
```

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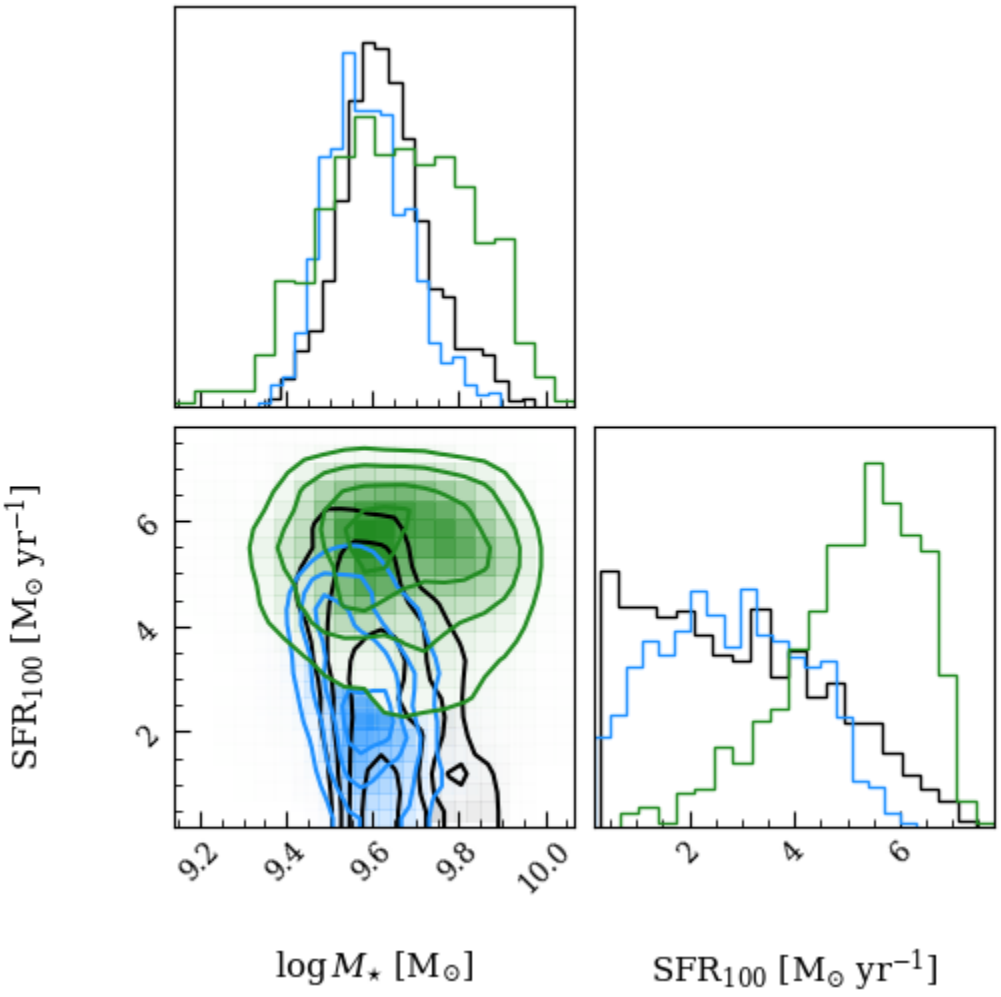
```
                labels=labels,
                smooth=1,
                color='forestgreen', fig=fig)
```



The stellar population differences don't seem to create a strong bias in $M_\star$. However, in this case, we see a slight difference in the SFRs, though they are statistically consistent. See the appendices in Lehmer+(2024) for a somewhat more robust comparison between SFR and stellar masses derived using PEGASE-Cloudy and BPASS-Cloudy models on a diverse sample of ~80 galaxies.

[ ]:

6.4 Line ratio grids

Here, we produce and plot grids of line ratios for a variety of complex star formation histories, both as a demonstration of the range of our nebular model(s) and a demonstration of the simulation capability of Lightning.

6.4.1 Imports

[1]:
```
import numpy as np
import h5py
rng = np.random.default_rng()
import astropy.units as u
from astropy.table import Table
from corner import corner
import matplotlib.pyplot as plt
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline

from lightning import Lightning
from lightning.priors import UniformPrior, NormalPrior
from lightning.plots import step_curve
from lightning.sfh import DelayedExponentialSFH
```

6.4.2 Setup

We create three Lightning objects, loading the Cloudy grids with and without dust grains, and with ULXs from Garofali+(2024) for BPASS stellar population models. Note that the implementation of Garofali et al.'s model doesn't currently extend into the X-rays - we only use the ULX as an ionizing source. A full implementation is planned; using such models for SED fitting is complicated by the stochastic sampling of the XLF. We currently provide them mainly for simulation purposes.

[2]:
```
filter_labels = ['SDSS_u'] # We aren't actually using these, 'None' just isn't an option␣
↪for filter labels.

agebins = [0.0] + list(np.logspace(7, np.log10(13.4e9), 10))

lgh_nodust = Lightning(filter_labels,
                       lum_dist=15, # also isn't going to come up
                       ages=agebins,
                       nebula_lognH=2.0,
                       nebula_dust=False,
                       stellar_type='BPASS-A24',
                       SFH_type='Piecewise-Constant',
                       atten_type='Modified-Calzetti',
                       print_setup_time=True)
print()
lgh_dust = Lightning(filter_labels,
                     lum_dist=15,
                     ages=agebins,
                     nebula_lognH=2.0,
                     nebula_dust=True,
```

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```
                      stellar_type='BPASS-A24',
                      SFH_type='Piecewise-Constant',
                      atten_type='Modified-Calzetti',
                      print_setup_time=True)

print()
lgh_ULX = Lightning(filter_labels,
                      lum_dist=15,
                      ages=agebins,
                      nebula_lognH=2.0,
                      nebula_dust=True,
                      stellar_type='BPASS-ULX-G24',
                      SFH_type='Piecewise-Constant',
                      atten_type='Modified-Calzetti',
                      print_setup_time=True)
```

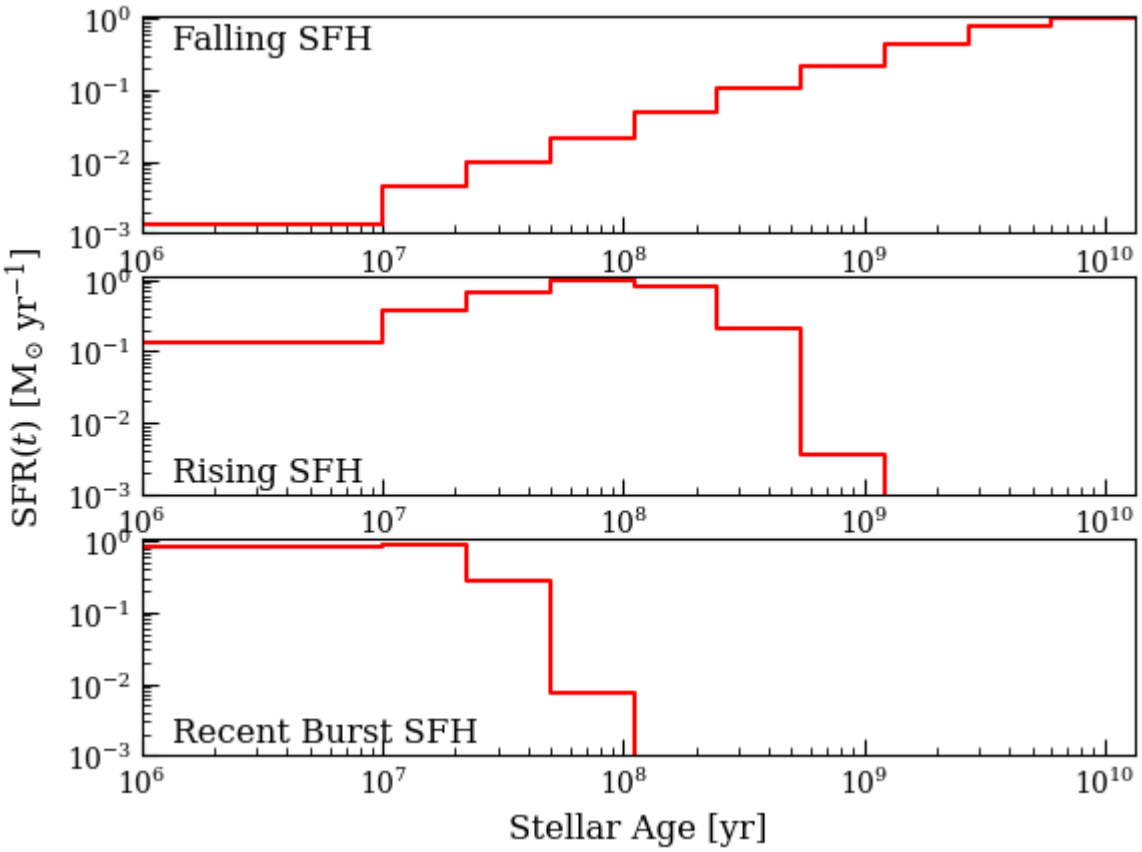
```
0.001 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
1.318 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.000 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
1.319 s elapsed total

0.001 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
1.045 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.000 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
1.046 s elapsed total

0.001 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
0.933 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.000 s elapsed in dust emission model setup
0.000 s elapsed in agn emission model setup
0.000 s elapsed in X-ray model setup
0.934 s elapsed total
```

6.4.3 Define SFH templates

For simplicity we'll convolve a delayed exponential SFH with the age bins to generate SFH templates. We'll choose three: - A "falling" SFH that peaked 10 Gyr ago. - A "rising" SFH that peaked 100 Myr ago. - A "recent" SFH that peaked 10 Myr ago.

[3]:
```
agemid = 0.5 * np.array(agebins[:-1]) + 0.5 * np.array(agebins[1:])
sfh_exp = DelayedExponentialSFH(agemid)


falling_sfh =  sfh_exp.evaluate(np.array([np.exp(1), 1e10]))
rising_sfh = sfh_exp.evaluate(np.array([np.exp(1), 1e8]))
recent_sfh = sfh_exp.evaluate(np.array([np.exp(1), 1e7]))

fig, axs = plt.subplots(3,1)

x,y = step_curve(agebins, falling_sfh)
axs[0].plot(x,y, color='red')

# x,y = step_curve(agebins, rising_sfh)
# axs[1].plot(x,y)
x,y = step_curve(agebins, rising_sfh)
axs[1].plot(x,y, color='red')

# x,y = step_curve(agebins, recent_sfh)
# axs[2].plot(x,y)
x,y = step_curve(agebins, recent_sfh)
axs[2].plot(x,y, color='red')

for i in [0,1,2]:
    axs[i].set_xscale('log')
    axs[i].set_yscale('log')
    axs[i].set_xlim(1e6, 13.4e9)
    axs[i].set_ylim(1e-3, 1.1)

axs[0].text(0.03, 0.97, 'Falling SFH', ha='left', va='top', transform=axs[0].transAxes)
axs[1].text(0.03, 0.03, 'Rising SFH', ha='left', va='bottom', transform=axs[1].transAxes)
axs[2].text(0.03, 0.03, 'Recent Burst SFH', ha='left', va='bottom', transform=axs[2].
↪transAxes)


axs[2].set_xlabel('Stellar Age [yr]')
axs[1].set_ylabel(r'${\rm SFR}(t)~[\rm M_{\odot}~yr^{-1}]$')
```

[3]:
```
Text(0, 0.5, '${\\rm SFR}(t)~[\\rm M_{\\odot}~yr^{-1}]$')
```



And now we'll derive grids of line ratios for our various faked SFHs:

6.4.4 Dusty grid

[4]:
```
from lightning.plots import k06_NIIplot

Npoints = 10

logU_grid = np.linspace(-4, -1.5, Npoints)
Z_grid = np.logspace(np.log10(0.00075), np.log10(0.02), Npoints)

tauV_grid = np.array([0.0])

fig, axs = plt.subplots(2,3, figsize=(12,8))

linestyle=['-','--']

OIIImask = lgh_dust.stars.line_labels == 'O__3_500684A'
Halphamask = lgh_dust.stars.line_labels == 'H__1_656280A'
Hbetamask = lgh_dust.stars.line_labels == 'H__1_486132A'
NIImask = lgh_dust.stars.line_labels == 'N__2_658345A'

HeIImask = lgh_dust.stars.line_labels == 'HE_2_468568A'
```

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```
for m,sfh in enumerate([falling_sfh, rising_sfh, recent_sfh]):
    for k,tauV in enumerate(tauV_grid):

        param_array = np.zeros(15)
        param_array[:10] = sfh
        param_array[-3] = tauV

        line_grid = np.zeros((Npoints,Npoints,len(lgh_nodust.stars.line_labels)))

        for i,logU in enumerate(logU_grid):
            for j,Z in enumerate(Z_grid):

                param_array[10] = Z
                param_array[11] = logU

                lines_ext, lines_intr = lgh_dust.get_model_lines(param_array)

                line_grid[i,j,:] = lines_ext.flatten()

        o3hbeta_grid = np.log10(line_grid[:,:,OIIImask] / line_grid[:,:,Hbetamask])
        n2halpha_grid = np.log10(line_grid[:,:,NIImask] / line_grid[:,:,Halphamask])
        he2hbeta_grid =  np.log10(line_grid[:,:,HeIImask] / line_grid[:,:,Hbetamask])

        for i,_ in enumerate(logU_grid):
            axs[0,m].plot(n2halpha_grid[i,:], o3hbeta_grid[i,:], color='slategray',␣
↪linestyle=linestyle[k])
            axs[1,m].plot(n2halpha_grid[i,:], he2hbeta_grid[i,:], color='slategray',␣
↪linestyle=linestyle[k])

        for j,_ in enumerate(Z_grid):
            axs[0,m].plot(n2halpha_grid[:,j], o3hbeta_grid[:,j], color='forestgreen',␣
↪linestyle=linestyle[k])
            axs[1,m].plot(n2halpha_grid[:,j], he2hbeta_grid[:,j], color='forestgreen',␣
↪linestyle=linestyle[k])

        k06_NIIplot(ax=axs[0,m])
        axs[0,m].set_xlim(-2.2,1)
        axs[0,m].set_ylim(-1,2)

        axs[1,m].set_xlim(-2.2,1)
        axs[1,m].set_ylim(-4,-1)

axs[0,0].set_title('Falling SFH')
axs[0,1].set_title('Rising SFH')
axs[0,2].set_title('Recent Burst SFH')

axs[0,0].set_ylabel(r'$\rm \log([O III] / H\beta)$')
axs[1,0].set_ylabel(r'$\rm \log([He II] / H\beta)$')
for m in [0,1,2]:
    axs[1, m].set_xlabel(r'$\rm \log([N II] / H\alpha)$')
```

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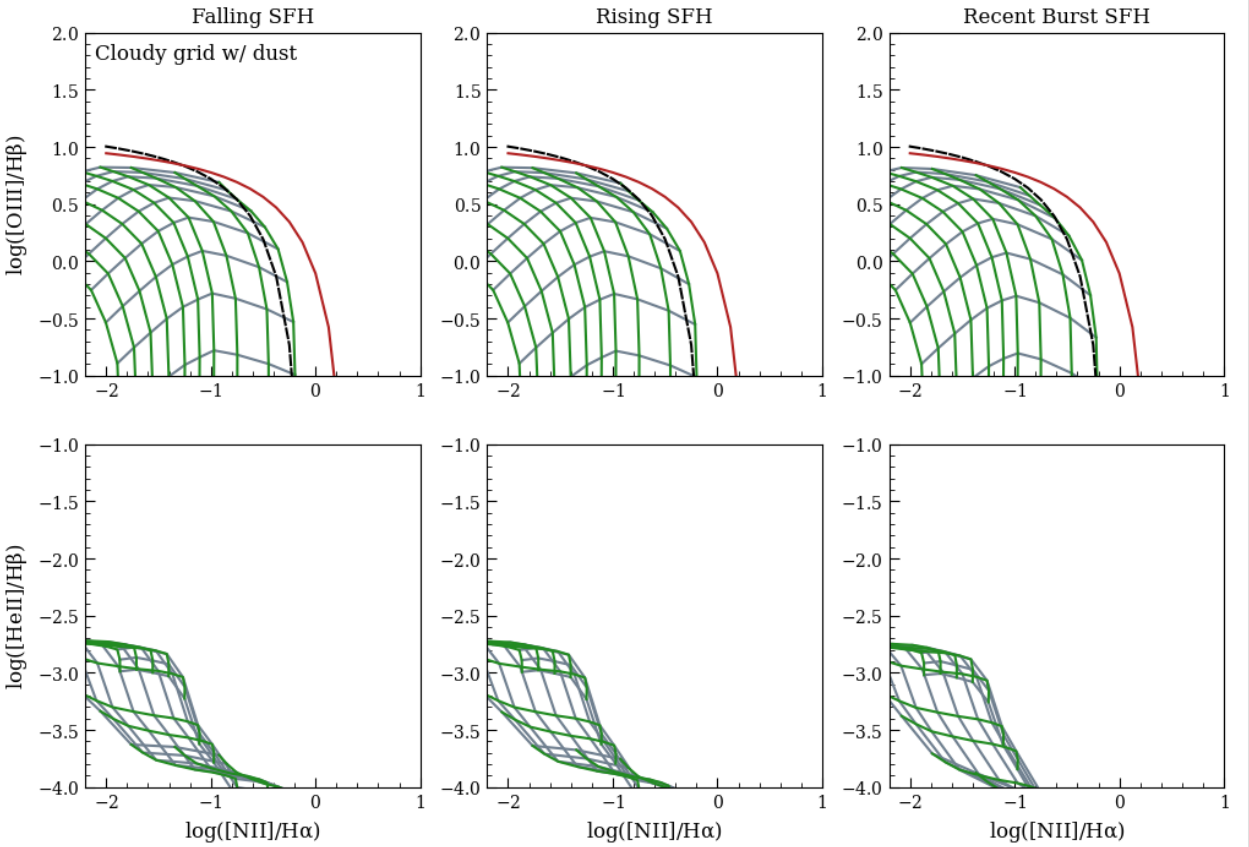
```
axs[0,0].text(0.03, 0.97, 'Cloudy grid w/ dust', ha='left', va='top', transform=axs[0,0].
↪transAxes)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/bpass.py:1409: RuntimeWarning:␣
↪divide by zero encountered in log10
  np.log10(np.transpose(self.line_lum, axes=[1,2,0,3])),
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_rgi.py:418: RuntimeWarning: invalid value encountered in multiply
  term = np.asarray(self.values[edge_indices]) * weight[vslice]
```

[4]:
```
Text(0.03, 0.97, 'Cloudy grid w/ dust')
```



6.4.5 Grid without dust

[5]:
```
from lightning.plots import k06_NIIplot

Npoints = 10

logU_grid = np.linspace(-4, -1.5, Npoints)
Z_grid = np.logspace(np.log10(0.00075), np.log10(0.02), Npoints)

tauV_grid = np.array([0.0])

fig, axs = plt.subplots(2,3, figsize=(12,8))
```

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```
linestyle=['-','--']

OIIImask = lgh_nodust.stars.line_labels == 'O__3_500684A'
Halphamask = lgh_nodust.stars.line_labels == 'H__1_656280A'
Hbetamask = lgh_nodust.stars.line_labels == 'H__1_486132A'
NIImask = lgh_nodust.stars.line_labels == 'N__2_658345A'

HeIImask = lgh_nodust.stars.line_labels == 'HE_2_468568A'

for m,sfh in enumerate([falling_sfh, rising_sfh, recent_sfh]):
    for k,tauV in enumerate(tauV_grid):

        param_array = np.zeros(15)
        param_array[:10] = sfh
        param_array[-3] = tauV

        line_grid = np.zeros((Npoints,Npoints,len(lgh_nodust.stars.line_labels)))

        for i,logU in enumerate(logU_grid):
            for j,Z in enumerate(Z_grid):

                param_array[10] = Z
                param_array[11] = logU

                lines_ext, lines_intr = lgh_nodust.get_model_lines(param_array)

                line_grid[i,j,:] = lines_ext.flatten()

        o3hbeta_grid = np.log10(line_grid[:,:,OIIImask] / line_grid[:,:,Hbetamask])
        n2halpha_grid = np.log10(line_grid[:,:,NIImask] / line_grid[:,:,Halphamask])
        he2hbeta_grid =  np.log10(line_grid[:,:,HeIImask] / line_grid[:,:,Hbetamask])

        for i,_ in enumerate(logU_grid):
            axs[0,m].plot(n2halpha_grid[i,:], o3hbeta_grid[i,:], color='slategray',␣
↪linestyle=linestyle[k])
            axs[1,m].plot(n2halpha_grid[i,:], he2hbeta_grid[i,:], color='slategray',␣
↪linestyle=linestyle[k])

        for j,_ in enumerate(Z_grid):
            axs[0,m].plot(n2halpha_grid[:,j], o3hbeta_grid[:,j], color='forestgreen',␣
↪linestyle=linestyle[k])
            axs[1,m].plot(n2halpha_grid[:,j], he2hbeta_grid[:,j], color='forestgreen',␣
↪linestyle=linestyle[k])

        k06_NIIplot(ax=axs[0,m])
        axs[0,m].set_xlim(-2.2,1)
        axs[0,m].set_ylim(-1,2)

        axs[1,m].set_xlim(-2.2,1)
        axs[1,m].set_ylim(-4,-1)
```

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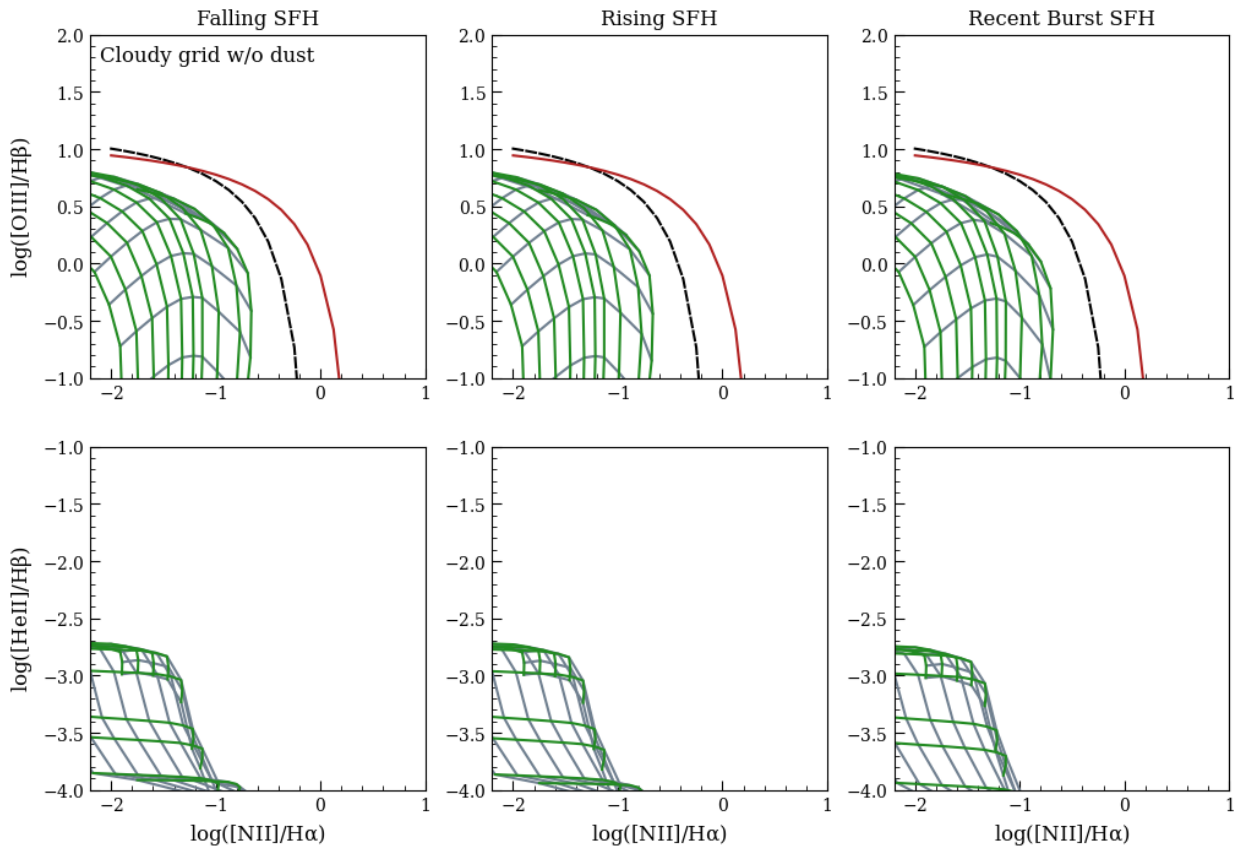
```
axs[0,0].set_title('Falling SFH')
axs[0,1].set_title('Rising SFH')
axs[0,2].set_title('Recent Burst SFH')

axs[0,0].set_ylabel(r'$\rm \log([O III] / H\beta)$')
axs[1,0].set_ylabel(r'$\rm \log([He II] / H\beta)$')
for m in [0,1,2]:
    axs[1, m].set_xlabel(r'$\rm \log([N II] / H\alpha)$')

axs[0,0].text(0.03, 0.97, 'Cloudy grid w/o dust', ha='left', va='top', transform=axs[0,
↪0].transAxes)
```

[5]:
```
Text(0.03, 0.97, 'Cloudy grid w/o dust')
```



6.4.6 Grid with ULXs

[6]:
```
from lightning.plots import k06_NIIplot

Npoints = 10

logU_grid = np.linspace(-4, -1.5, Npoints)
Z_grid = np.logspace(np.log10(lgh_ULX.stars.param_bounds[0,0]), np.log10(lgh_ULX.stars.
↪param_bounds[0,1]), Npoints)
```

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```
tauV_grid = np.array([0.0])

fig, axs = plt.subplots(2,3, figsize=(12,8))

linestyle=['-','--']

OIIImask = lgh_ULX.stars.line_labels == 'O__3_500684A'
Halphamask = lgh_ULX.stars.line_labels == 'H__1_656280A'
Hbetamask = lgh_ULX.stars.line_labels == 'H__1_486132A'
NIImask = lgh_ULX.stars.line_labels == 'N__2_658345A'

HeIImask = lgh_ULX.stars.line_labels == 'HE_2_468568A'

for m,sfh in enumerate([falling_sfh, rising_sfh, recent_sfh]):
    for k,tauV in enumerate(tauV_grid):

        param_array = np.zeros(15)
        param_array[:10] = sfh
        param_array[-3] = tauV

        line_grid = np.zeros((Npoints,Npoints,len(lgh_nodust.stars.line_labels)))

        for i,logU in enumerate(logU_grid):
            for j,Z in enumerate(Z_grid):

                param_array[10] = Z
                param_array[11] = logU

                lines_ext, lines_intr = lgh_ULX.get_model_lines(param_array)

                line_grid[i,j,:] = lines_ext.flatten()

        o3hbeta_grid = np.log10(line_grid[:,:,OIIImask] / line_grid[:,:,Hbetamask])
        n2halpha_grid = np.log10(line_grid[:,:,NIImask] / line_grid[:,:,Halphamask])
        he2hbeta_grid =  np.log10(line_grid[:,:,HeIImask] / line_grid[:,:,Hbetamask])

        for i,_ in enumerate(logU_grid):
            axs[0,m].plot(n2halpha_grid[i,:], o3hbeta_grid[i,:], color='slategray',␣
↪linestyle=linestyle[k])
            axs[1,m].plot(n2halpha_grid[i,:], he2hbeta_grid[i,:], color='slategray',␣
↪linestyle=linestyle[k])

        for j,_ in enumerate(Z_grid):
            axs[0,m].plot(n2halpha_grid[:,j], o3hbeta_grid[:,j], color='forestgreen',␣
↪linestyle=linestyle[k])
            axs[1,m].plot(n2halpha_grid[:,j], he2hbeta_grid[:,j], color='forestgreen',␣
↪linestyle=linestyle[k])

        k06_NIIplot(ax=axs[0,m])
        axs[0,m].set_xlim(-2.2,1)
        axs[0,m].set_ylim(-1,2)
```

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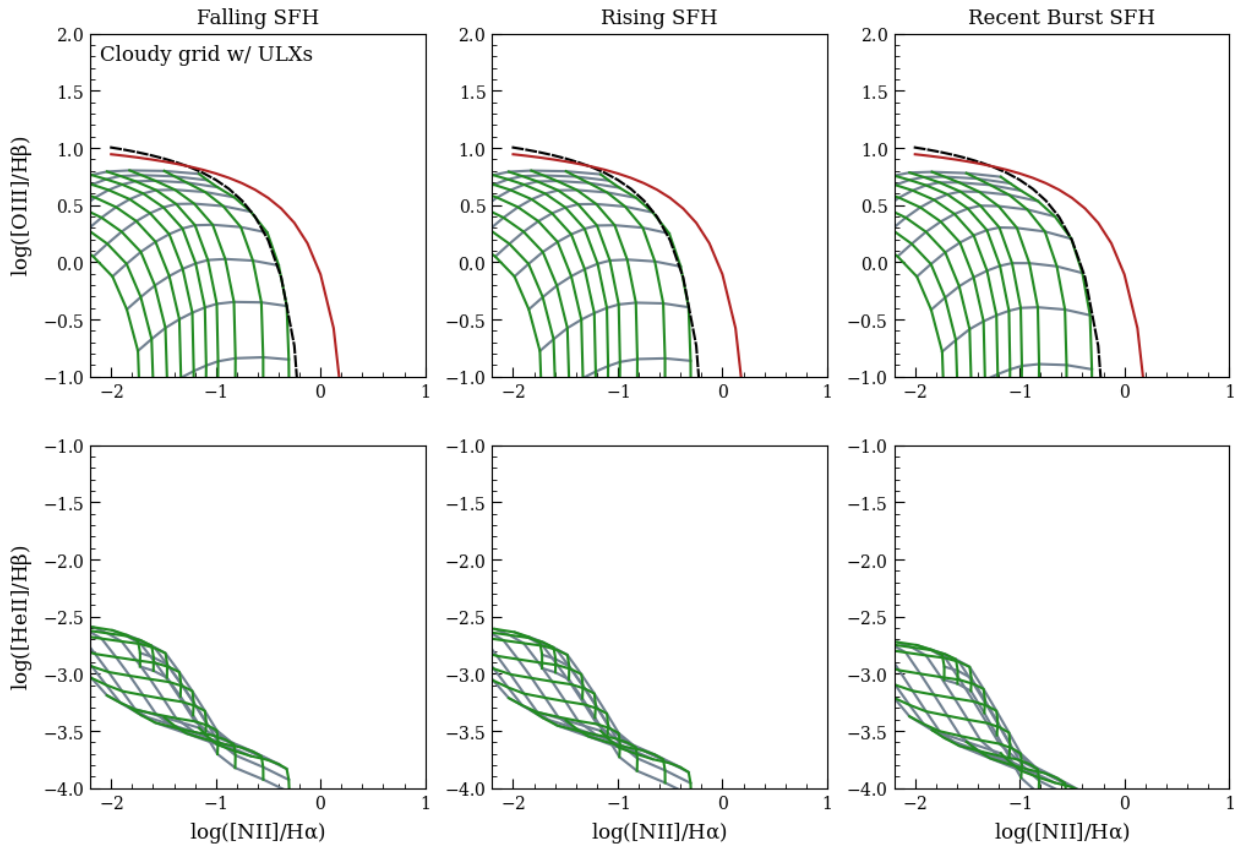
```
        axs[1,m].set_xlim(-2.2,1)
        axs[1,m].set_ylim(-4,-1)

axs[0,0].set_title('Falling SFH')
axs[0,1].set_title('Rising SFH')
axs[0,2].set_title('Recent Burst SFH')

axs[0,0].set_ylabel(r'$\rm \log([O III] / H\beta)$')
axs[1,0].set_ylabel(r'$\rm \log([He II] / H\beta)$')
for m in [0,1,2]:
    axs[1, m].set_xlabel(r'$\rm \log([N II] / H\alpha)$')

axs[0,0].text(0.03, 0.97, 'Cloudy grid w/ ULXs', ha='left', va='top', transform=axs[0,0].
↪transAxes)
```

[6]:
```
Text(0.03, 0.97, 'Cloudy grid w/ ULXs')
```



Even our recent burst SFH includes significant dilution of $[\mathrm{HeII}]/\mathrm{H}\beta$ - it isn't recent enough or bursty enough.

Overall the line ratios are not particularly sensitive to the SFH (as long as it produces *some* ionizing photons), since $\log U$ is an independent parameter from the SFH.

6.5 AGN Fit - J033226

This notebook demonstrates the options for fitting X-ray-IR AGN models to deep observations of a Type-1 AGN, J033226.49-274035.5, in the Chandra Deep Field South. We'll also see some of the complications that come with trying to fit AGN, especially Type-1s, where sometimes the observations are just outside of the space of our models.

We have pulled the data products from the Chandra Source Catalog for the single deepest observation and produced photometry (in instrumental counts) in 10 energy bands. We caution against using full CSC stacked products without extreme care. The remaining photometry comes from the CANDELS catalogs. Note that the UV-IR photometry and the X-ray observation are not simultaneous.

As we'll see, this AGN falls relatively far from the LR17 $L_{2\mathrm{keV}} - L_{2500}$ relationship (about 1 dex) and has some other quirks with its SED, which makes it difficult to fit with the narrow range of Eddington ratios allowed by the QSOSED model. We'll thus focus on the more flexible AGN power law model.

6.5.1 Imports

[48]:
```
import numpy as np
rng = np.random.default_rng()
import astropy.units as u
from astropy.table import Table
from astropy.io import ascii
import astropy.constants as const
import astropy.units as u
import matplotlib.pyplot as plt

from lightning import Lightning
from lightning.priors import UniformPrior, ConstantPrior
plt.style.use('lightning.plots.style.lightning-serif')
```

6.5.2 Setup

Fitting the X-ray model necessarily complicates the setup of Lightning, given that we're now potentially dealing with two different kinds of data (fluxes and counts) and an ancilliary response function (ARF).

[49]:
```
phot = Table.read('../photometry/J033226_lightning_input.fits', hdu=1)
arf = Table.read('../photometry/J033226.arf', hdu=1)
xray_phot = Table.read('../photometry/J033226_xray_photometry.fits', hdu=1)

print(xray_phot['ENERG_LO', 'ENERG_HI', 'NET_COUNTS', 'NET_COUNTS_UNC'])
```

```
     ENERG_LO           ENERG_HI          NET_COUNTS       NET_COUNTS_UNC
----------------- ------------------ ------------------ ------------------
              0.5 0.5900861491455028 103.16080387669922  17.06914388649152
0.5900861491455028 0.6964033268267372  105.2053121208817  17.39261962324014
0.6964033268267372 0.8218759147586129 159.13980601012312 22.506860760889985
0.8218759147586129 0.9699551872306948 220.28320154820105 28.426639814154843
0.9699551872306948 1.1447142425533319 252.40434296418772 31.560538780349464
1.1447142425533319 1.3509600385206135 252.55886556331126  31.66427014408168
1.3509600385206135  1.594365613560178 259.58237594091764 32.537870928706354
 1.594365613560178 1.8816261304714648 237.50699902462856  30.63509272592005
1.8816261304714648   2.22064303492292  108.6541633292519 19.791982010379417
```

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```
  2.22064303492292 2.6207413942088964  76.37598680311142  16.38448381206126
2.6207413942088964  3.092926394429888  90.13244771562292   17.0625173963706
 3.092926394429888  3.650186051359235  63.96931056648404 15.393834234535772
 3.650186051359235  4.307848461422399  79.15847060425958  17.17091023650916
 4.307848461422399  5.084003419406245  63.43539087488492  16.55353507214626
 5.084003419406245                6.0  42.96572103852924 15.947351032754547
```

[50]:
```
filter_labels = [s.decode().strip() for s in phot['FILTER_LABELS'][0]]
fnu_obs = phot['FNU_OBS'][0]
fnu_unc = phot['FNU_UNC'][0]
redshift = phot['REDSHIFT'][0]
galactic_NH = phot['GALACTIC_NH'][0]
```

The X-ray "filters" are uniform sensitive boxes constructed ad-hoc: you can supply any number of X-ray bandpasses, with labels formatted like `"XRAY_[LO]_[HI]_[UNIT]"` where `[UNIT]` is any frequency/energy/wavelength unit. Here we use keV.

[51]:
```
xray_filter_labels = ['XRAY_%.2f_%.2f_keV' % (elo, ehi) for elo,ehi in zip(xray_phot[
↪'ENERG_LO'].data, xray_phot['ENERG_HI'].data)]
xray_counts = xray_phot['NET_COUNTS']
xray_counts_unc = xray_phot['NET_COUNTS_UNC']
```

We now prepend the X-ray counts to the flux array to construct our full "flux" array:

[52]:
```
obs_full = np.zeros(len(xray_filter_labels) + len(filter_labels))
unc_full = np.zeros(len(xray_filter_labels) + len(filter_labels))
exp_full = np.zeros(len(xray_filter_labels) + len(filter_labels))

filter_labels_full = xray_filter_labels + filter_labels
xray_mask = np.array(['XRAY' in s for s in filter_labels_full])
obs_full[xray_mask] = xray_counts
obs_full[~xray_mask] = fnu_obs * 1e3 # IDL Lightning fnu is in Jy, not mJy
unc_full[xray_mask] = xray_counts_unc
unc_full[~xray_mask] = fnu_unc * 1e3 # IDL Lightning fnu is in Jy, not mJy
exp_full[xray_mask] = xray_phot['EXPOSURE']
```

We display the filter labels and the "flux" and uncertainty arrays here:

[53]:
```
t = Table()
t['filter'] = filter_labels_full
t['flux'] = obs_full
t['unc'] = unc_full

ascii.write(t, format='fixed_width_two_line')
```

```
            filter                  flux                   unc
------------------ -------------------- ---------------------
XRAY_0.50_0.59_keV   103.16080387669922     17.06914388649152
XRAY_0.59_0.70_keV    105.2053121208817     17.39261962324014
XRAY_0.70_0.82_keV   159.13980601012312    22.506860760889985
XRAY_0.82_0.97_keV   220.28320154820105    28.426639814154843
XRAY_0.97_1.14_keV   252.40434296418772    31.560538780349464
XRAY_1.14_1.35_keV   252.55886556331126     31.66427014408168
```

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```
XRAY_1.35_1.59_keV   259.58237594091764    32.537870928706354
XRAY_1.59_1.88_keV   237.50699902462856     30.63509272592005
XRAY_1.88_2.22_keV    108.6541633292519    19.791982010379417
XRAY_2.22_2.62_keV    76.37598680311142     16.38448381206126
XRAY_2.62_3.09_keV    90.13244771562292      17.0625173963706
XRAY_3.09_3.65_keV    63.96931056648404    15.393834234535772
XRAY_3.65_4.31_keV    79.15847060425958     17.17091023650916
XRAY_4.31_5.08_keV    63.43539087488492     16.55353507214626
XRAY_5.08_6.00_keV    42.96572103852924    15.947351032754547
         ACS_F435W                  nan                   0.0
         ACS_F606W  0.03874064467041217 0.0007775114528953381
         ACS_F775W 0.046118398755161556 0.0009312075720791517
         ACS_F814W  0.04126685376453945 0.0008364606452776926
        ACS_F850LP  0.05581402261861105 0.0011280738382122932
        WFC3_F098M 0.053161199724363443 0.0010761650524693856
        WFC3_F105W                  nan                   0.0
        WFC3_F125W   0.0633274593161555  0.001269562384159545
        WFC3_F160W  0.06320390974575296 0.0012677310644130264
           VIMOS_U                  nan                   0.0
        MOSAICII_U                  nan                   0.0
          ISAAC_Ks                  nan                   0.0
         HAWK-I_Ks                  nan                   0.0
          IRAC_CH1  0.20377759817500846  0.010189740485754798
          IRAC_CH2   0.2847056678207428  0.014235625916151993
          IRAC_CH3  0.44171788753618635   0.02209056507504984
          IRAC_CH4   0.6298939819335938  0.031498072145069944
          MIPS_CH1    2.303699951171875   0.12405841107268026
          MIPS_CH2    7.647399902343749    0.9605496045803024
        PACS_green   10.149000000000001     1.089519237469138
          PACS_red   19.834999999999997     1.921944825761522
         SPIRE_250               23.663     4.176323212777945
```

We can see that the X-ray bands have the counts, and the UV-IR bands are fluxes in terms of mJy.

We assemble a wavelength grid to integrate the X-ray models on to make sure that the bandpasses are covered at the redshift of the source:

[54]:
```
hc_um = (const.c * const.h).to(u.micron * u.keV).value
lam_05 = hc_um / 0.5
lam_70 = hc_um / 7.0
xray_wave_grid = np.logspace(np.log10(lam_70), np.log10(lam_05), 200) / (1 + redshift)
```

Note that the wavelength grid must be monotonically increasing.

Now, we're ready to assemble the model - we'll use a power law model first.

[55]:
```
lgh = Lightning(filter_labels_full,
                redshift=redshift,
                flux_obs=obs_full,
                flux_obs_unc=unc_full,
                SFH_type='Piecewise-Constant',
                atten_type='Calzetti',
                dust_emission=True,
```

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```
                agn_emission=True,
                agn_polar_dust=True,
                xray_mode='counts',
                xray_stellar_emission='Stellar-Plaw',
                xray_agn_emission='AGN-Plaw',
                xray_absorption='tbabs',
                xray_wave_grid=xray_wave_grid,
                xray_arf=arf,
                xray_exposure=exp_full,
                galactic_NH=galactic_NH,
                model_unc=0.10,
                print_setup_time=True)
```

```
0.033 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
0.551 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.167 s elapsed in dust emission model setup
0.031 s elapsed in agn emission model setup
0.021 s elapsed in X-ray model setup
0.804 s elapsed total
```

```
/Users/eqm5663/Research/code/plightning/lightning/get_filters.py:138: RuntimeWarning:␣
↪invalid value encountered in divide
  transm_norm_interp = transm_interp / trapz(transm_interp, wave_grid)
```

The warning we see above is telling us that our X-ray bandasses don't overlap with the UV-IR models. That's ok.

6.5.3 Fit

[117]:
```
priors = [UniformPrior([0, 1e3]), # SFH
          UniformPrior([0, 1e3]),
          UniformPrior([0, 1e3]),
          UniformPrior([0, 1e3]),
          UniformPrior([0, 1e3]),
          ConstantPrior([0.020]), # Metallicity
          UniformPrior([0, 5]), # tauV
          ConstantPrior([2]), # alpha
          # ConstantPrior([1]), # Umin
          UniformPrior([0.1, 25]), # Umin
          ConstantPrior([3e5]), # Umax
          UniformPrior([0,1]), # Gamma
          ConstantPrior([0.0047]), #qPAH
          UniformPrior([11, 13]), # log L_AGN
          UniformPrior([0.7, 1]), # cos i - Limited to Type-1 views.
          ConstantPrior([7]), # tau 9.7
          UniformPrior([0,1]), # polar dust tauV
          ConstantPrior([1.8]), # stellar pop. pho. index
          UniformPrior([1.0, 2.5]), # AGN pho. index
          UniformPrior([-1.3, 1.3]), # log deviation from Lusso + Risaliti 2017
          UniformPrior([1, 5e4]) # NH
          ]
```

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```
Nwalkers = 64

p0s = [pr.sample(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)

Nsteps = 20000
const_dim = np.array([False, False, False, False, False,
                      True,
                      False,
                      True, True, True, False, True,
                      False, False, True, False,
                      True,
                      False, False,
                      False
                      ])
```

[118]:
```
mcmc = lgh.fit(p0,
               method='emcee',
               Nwalkers=Nwalkers,
               Nsteps=Nsteps,
               priors=priors,
               const_dim=const_dim)
```

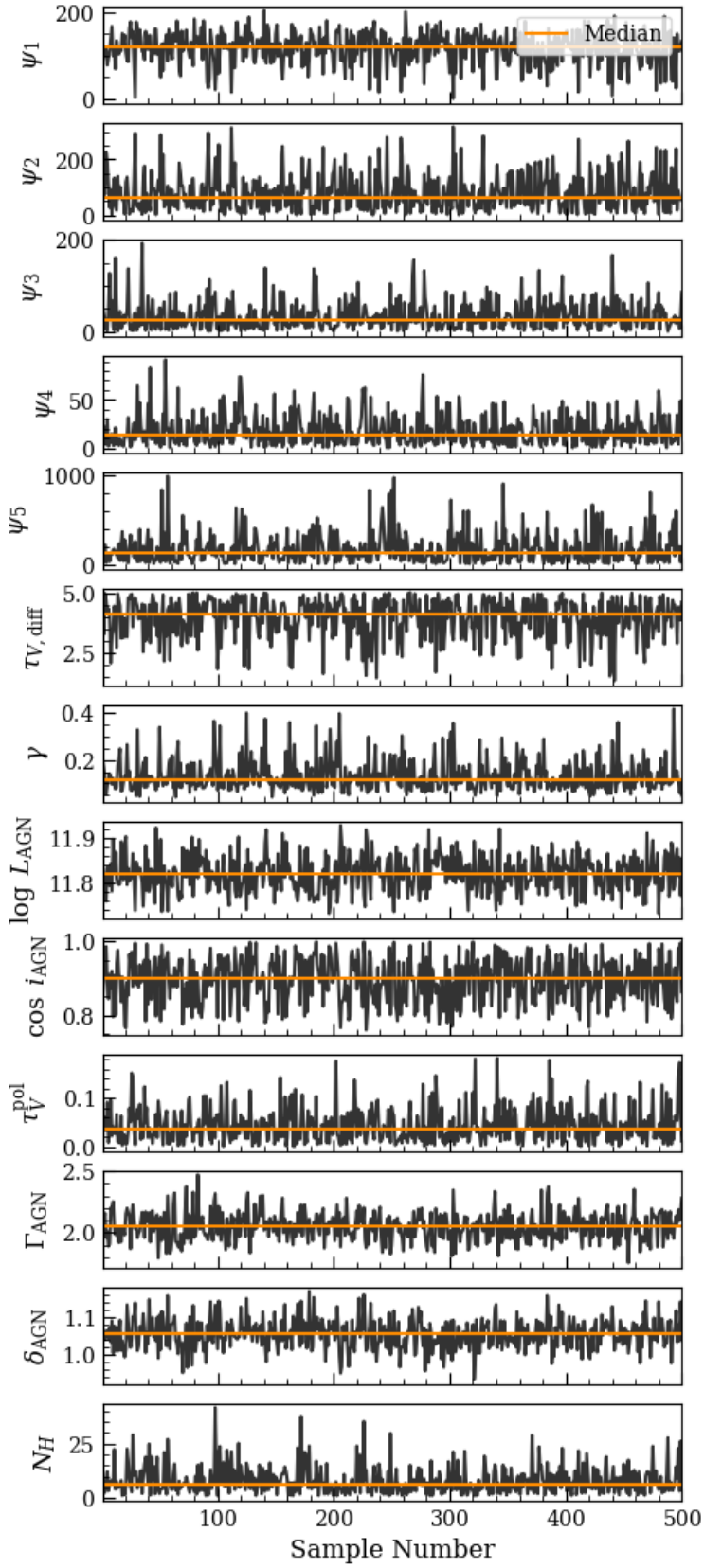
```
/Users/eqm5663/Research/code/plightning/lightning/xray/agn.py:221: RuntimeWarning:␣
↪divide by zero encountered in log10
  np.log10(lnu_obs) + np.log10(self.specresp) - np.log10(self.phot_energ)
100%|##########################################################################################
↪##########################################################| 20000/20000 [10:55<00:00,
↪ 30.51it/s]
```

[58]:
```
print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc.acceptance_fraction)))
chain, logprob_chain, t = lgh.get_mcmc_chains(mcmc,
                                              discard=3000,
                                              thin=500,
                                              Nsamples=500,
                                              const_dim=const_dim,
                                              const_vals=p0[0,const_dim])
```

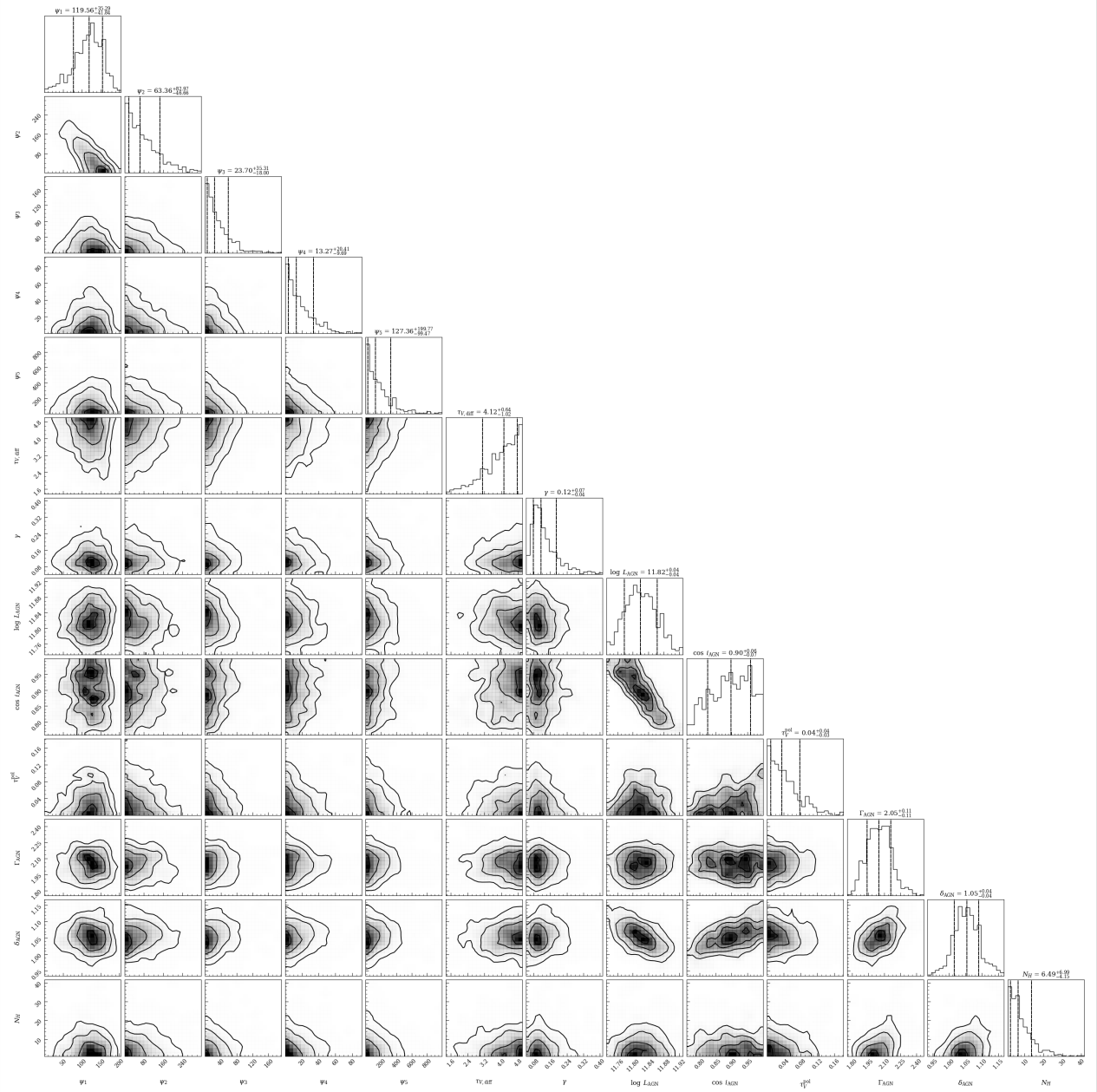
```
MCMC mean acceptance fraction: 0.203
WARNING: The integrated autocorrelation time is longer than N/50.
         The autocorrelation estimate may be unreliable.
```

6.5.4 Plots

[59]:
```
fig, axs = lgh.chain_plot(chain, color='black', alpha=0.8)
```


Median
ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
$\tau_{V,\mathrm{diff}}$
γ
$\log L_{\mathrm{AGN}}$
$\cos i_{\mathrm{AGN}}$
τ_V^{pol}
Γ_{AGN}
δ_{AGN}
N_H
Sample Number

[60]:
```
fig = lgh.corner_plot(chain,
                      quantiles=(0.16, 0.50, 0.84),
                      smooth=1,
                      levels=None,
                      show_titles=True)
```



[119]:
```
from lightning.plots import sed_plot_morebayesian, sed_plot_delchi_morebayesian, sfh_plot

fig5 = plt.figure(figsize=(12,6))
ax51 = fig5.add_axes([0.1, 0.26, 0.4, 0.64])
ax52 = fig5.add_axes([0.1, 0.1, 0.4, 0.15])
ax53 = fig5.add_axes([0.56, 0.1, 0.34, 0.8])
```

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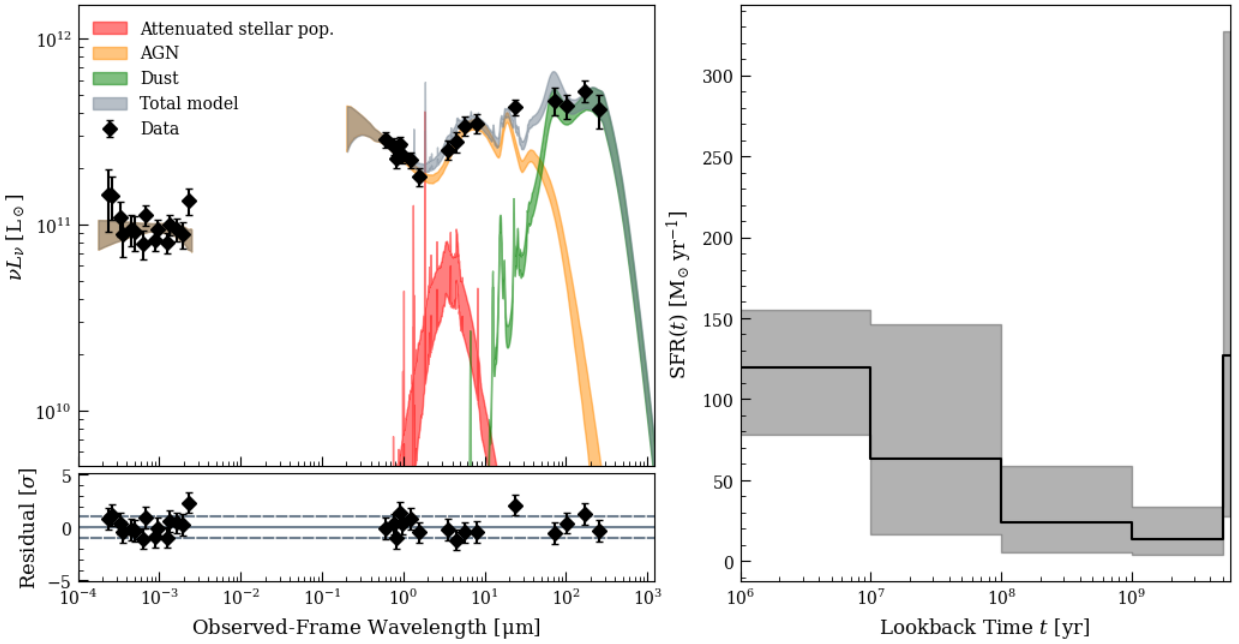
```
fig5, ax51 = sed_plot_morebayesian(lgh, chain, logprob_chain,
                                   plot_components=True,
                                   ax=ax51,
                                   legend_kwargs={'loc': 'upper left', 'frameon': False})
ax51.set_xticklabels([])
ax51.set_xlim(1e-4, 1200)
ax51.set_ylim(5e9,)
fig5, ax52 = lgh.sed_plot_delchi(chain, logprob_chain, ax=ax52)
ax52.set_xlim(1e-4, 1200)
fig5, ax53 = lgh.sfh_plot(chain, ax=ax53)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
```



Notably, this is a *really* different solution from what we would recover with IDL Lightning and is much closer to the xCIGALE solution. This is down to de-coupling the attenuation of the AGN and the stellar population. If we couple the attenuation of the two (assuming, basically, that we're looking through the galaxy to see the AGN) by disabling the polar dust attenuation, we recover the same solution as IDL Lightning. Both are consistent with the data. Fitting the SED of any Type-1 AGN is its own special nightmare, and this one is so incredibly luminous in the far-IR as to imply a large mass of dust *somewhere*. This model assumes that it's between us and the stars, and not between us and the AGN (supported by broad lines in the spectrum), implying in turn a pretty massive SFR. Be cautious in fitting AGN SEDs, and try (and compare) different models.

We can plot the X-ray portion of the SED in count-rate space, as if we'd fit it in Sherpa or Xspec:

[116]:
```
cr = lgh.xray_agn_em.get_model_countrate_hires(chain[:,-3:-1], lgh.agn, chain[:,12:16])
```

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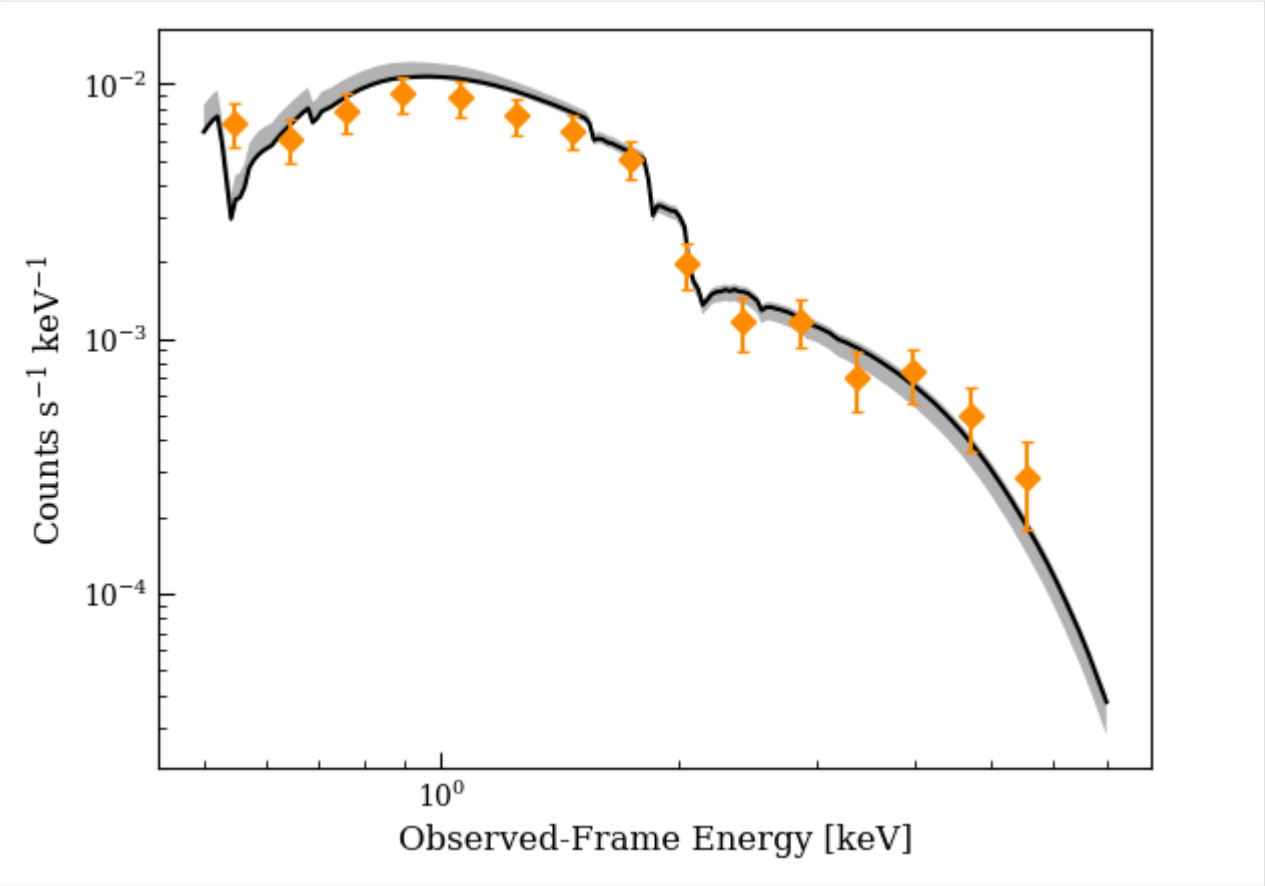
```
# Put the observations in counts s-1 Hz-1
# print(xray_phot['ENERG_LO', 'ENERG_HI', 'NET_COUNTS', 'NET_COUNTS_UNC'])

dE = xray_phot['ENERG_HI'] - xray_phot['ENERG_LO']
Emid = 0.5 * (xray_phot['ENERG_HI'] + xray_phot['ENERG_LO'])
exposure = lgh.xray_exposure[0]

countrate_obs = xray_phot['NET_COUNTS'] / exposure / dE
countrate_obs_unc = np.sqrt((xray_phot['NET_COUNTS_UNC'] / exposure / dE)**2 + 0.10**2 *␣
↪countrate_obs**2)

bestfit = np.argmax(logprob_chain)
cr_best = cr[bestfit,:]
cr_lo, cr_hi = np.quantile(cr, q=(0.16, 0.84), axis=0)

fig, ax = plt.subplots()


ax.fill_between(lgh.xray_agn_em.energ_grid_obs,
                lgh.xray_agn_em.nu_grid_obs * cr_lo / lgh.xray_agn_em.energ_grid_obs,
                lgh.xray_agn_em.nu_grid_obs * cr_hi / lgh.xray_agn_em.energ_grid_obs,
                 alpha=0.3)
ax.plot(lgh.xray_agn_em.energ_grid_obs, lgh.xray_agn_em.nu_grid_obs * cr_best / lgh.xray_
↪agn_em.energ_grid_obs)
ax.errorbar(Emid, countrate_obs, yerr=countrate_obs_unc, linestyle='', marker='D',␣
↪markerfacecolor='darkorange', color='darkorange')
ax.set_xscale('log')
ax.set_yscale('log')
ax.set_xlabel('Observed-Frame Energy [keV]')
ax.set_ylabel(r'Counts s$^{-1}$ keV$^{-1}$')
```

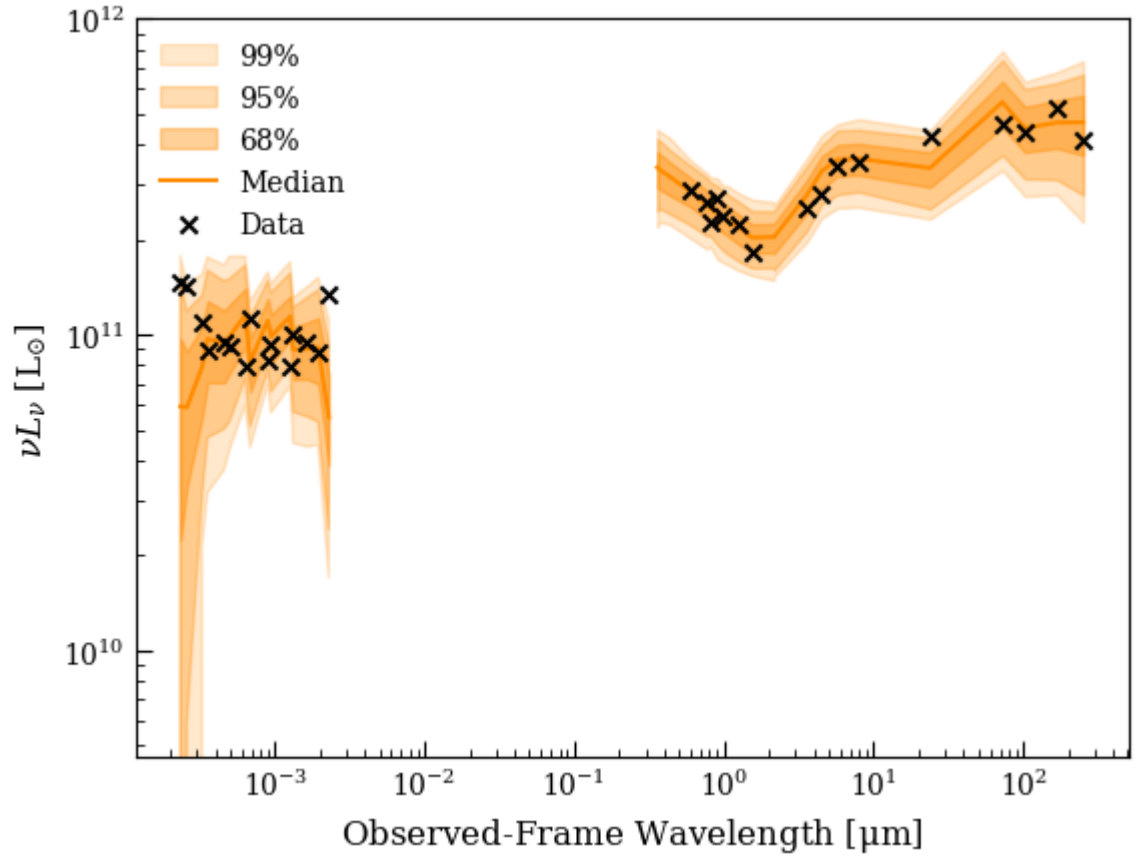
[116]:
```
Text(0, 0.5, 'Counts s$^{-1}$ keV$^{-1}$')
```



[62]:
```
from lightning.ppc import ppc, ppc_sed

pvalue, chi2_rep, chi2_obs = ppc(lgh, chain, logprob_chain)

fig, ax = ppc_sed(lgh, chain, logprob_chain)
ax.legend(loc='upper left')

print('p (power-law) = %.2f' % pvalue)
```

```
/Users/eqm5663/Research/code/plightning/lightning/ppc.py:77: RuntimeWarning: invalid␣
↪value encountered in divide
  chi2_rep = np.nansum((Lmod - Lmod_perturbed)**2 / total_unc2, axis=-1)
```

```
p (power-law) = 0.61
```



6.6 AGN + Host Galaxy Fit - NGC 5728

This notebook demonstrates a fit to the Seyfert galaxy NGC 5728 and its host galaxy, using multiwavelegnth photometry collected in the Brown et al. (2019) 'AGNSEDATLAS'. We collected X-ray photometry for the X-ray point source associated with the nucleus from the Chandra Source Catalog, in four bands: ultrasoft, soft, medium, and hard. Again we note that the X-ray and multiwavelength photometry are not simultaneous.

The mukltiwavelength photometry cover the entire extend of the galaxy, not just the nucleus, meaning that they contain significant contributions from the host galaxy. As we'll see, this dilution is significant enough that we can't conclusively detect the AGN component in our mid-IR photometry, only the X-rays. We use our SED fit to answer a common question, especially at high redshift in cases of obscured AGN: if we assume an Eddington fraction, what is the resulting BH mass?

[46]:
```
import numpy as np
rng = np.random.default_rng()
import astropy.units as u
from astropy.table import Table
from astropy.io import ascii
import astropy.constants as const
import astropy.units as u
import matplotlib.pyplot as plt
```

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```
from lightning import Lightning
from lightning.priors import UniformPrior, ConstantPrior, NormalPrior
plt.style.use('lightning.plots.style.lightning-serif')
```

6.6.1 Setup

Fitting the X-ray model to fluxes is somewhat less complicated than fitting it to an instrumental spectrum, since we will (usually) have fewer bands, and we have a more homegenous dataset.

For this example, our X-ray photometry array already contains the fluxes converted to F_ν in mJy, in addition to the fluxes in erg cm-2 s-1.

[2]:
```
phot = Table.read('../photometry/NGC5728_photometry.fits', hdu=1)
# arf = Table.read('../photometry/Mrk231_arf3.fits', hdu=1)
xray_phot = Table.read('../photometry/NGC5728_xray_photometry.fits', hdu=1)

print(xray_phot['ENERG_LO', 'ENERG_HI', 'FLUX', 'FLUX_UNC', 'FNU', 'FNU_UNC'])
```

```
ENERG_LO ENERG_HI         FLUX               FLUX_UNC                  FNU                ␣
↪  FNU_UNC
-------- -------- ------------------- ---------------------- ---------------------- -----
↪------------------
     0.2      0.5 3.3193209249249e-15   1.19495553297295e-15 4.5758694416451106e-06 1.
↪6473129989922206e-06
     0.5      1.2 3.0089184021393e-14 2.7653864684520005e-15 1.7776980912010367e-05 1.
↪6338170695838985e-06
     1.2      2.0 1.2659455462062e-14 1.9651777694714992e-15  6.544412626887014e-06   1.
↪01591527748952e-06
     2.0      7.0 7.6863430873421e-13 5.0862225098379986e-14  6.357632162758945e-05  4.
↪206985226660801e-06
```

[79]:
```
filter_labels = phot['FILTER_LABELS']
fnu_obs = phot['FNU']
fnu_unc = phot['FNU_UNC']
lumdist = 29 # From NED
galactic_NH = 7.8 # e20 cm-2; from Colden.
```

[4]:
```
xray_filter_labels = xray_phot['FILTER_LABELS']
xray_fnu = xray_phot['FNU']
xray_fnu_unc = xray_phot['FNU_UNC']
```

The X-ray fluxes and filter labels are concatenated to their UV-IR counterparts.

[6]:
```
obs_full = np.zeros(len(xray_filter_labels) + len(filter_labels))
unc_full = np.zeros(len(xray_filter_labels) + len(filter_labels))
exp_full = np.zeros(len(xray_filter_labels) + len(filter_labels))

filter_labels_full = np.array(list(xray_filter_labels) + list(filter_labels))
xray_mask = np.array(['XRAY' in s for s in filter_labels_full])
obs_full[xray_mask] = xray_fnu
obs_full[~xray_mask] = fnu_obs
```

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```
unc_full[xray_mask] = xray_fnu_unc
unc_full[~xray_mask] = fnu_unc
exp_full[xray_mask] = 1
```

[7]:
```
t = Table()
t['filter'] = filter_labels_full
t['flux'] = obs_full
t['unc'] = unc_full

ascii.write(t, format='fixed_width_two_line')
```

```
          filter                    flux                    unc
--------------- ---------------------- ----------------------
XRAY_0.2_0.5_keV 4.5758694416451106e-06 1.6473129989922206e-06
XRAY_0.5_1.2_keV 1.7776980912010367e-05 1.6338170695838985e-06
XRAY_1.2_2.0_keV  6.544412626887014e-06   1.01591527748952e-06
XRAY_2.0_7.0_keV  6.357632162758945e-05  4.206985226660801e-06
       GALEX_FUV                    0.52   0.026000000000000002
       GALEX_NUV                    1.16   0.057999999999999996
       UVOT_UVW2                    0.82                  0.041
       UVOT_UVM2                    0.88   0.044000000000000004
       UVOT_UVW1                    1.35                 0.0675
          UVOT_U                    3.64    0.18200000000000002
          UVOT_B                    9.43    0.47150000000000003
          UVOT_V                    18.4     0.9199999999999999
  Pan-STARRS_gp1                    17.2                    0.86
  Pan-STARRS_rp1                    31.5     1.5750000000000002
  Pan-STARRS_ip1                    42.0                     2.1
  Pan-STARRS_zp1                    53.5     2.6750000000000003
  Pan-STARRS_yp1                    66.4     3.3200000000000003
         2MASS_J                    85.3                    8.53
         2MASS_H                   109.0                    10.9
        2MASS_Ks                    94.8                    9.48
         WISE_W1                    51.3                   3.591
         WISE_W2                    38.6     2.7020000000000004
         WISE_W3                   211.0     14.770000000000001
         WISE_W4                   654.0                   45.78
        MIPS_CH1                   685.0                   34.25
       PACS_blue                  8130.0                   406.5
      PACS_green                  9541.0                  477.05
        PACS_red                  8618.0     430.90000000000003
       SPIRE_250                  3369.0     505.34999999999997
       SPIRE_350                  1390.0                   208.5
       SPIRE_500                   528.0                    79.2
```

The galaxy is 4-5 orders of magnitude fainter in the X-rays than in the UV-optical (in terms of F_ν).

We construct our X-ray wavelength grid to cover the ultrasoft 0.2-0.5 keV band all the way to the hard 2-7 keV band (even though it's probably not helpful to include the ultrasoft band, as we'll see).

[80]:
```
hc_um = (const.c * const.h).to(u.micron * u.keV).value
lam_02 = hc_um / 0.2
lam_70 = hc_um / 7.0
```

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```
xray_wave_grid = np.logspace(np.log10(lam_70), np.log10(lam_02), 200)
```

Our model specification uses the default 5 age bin SFH, the simple Calzetti model (although we have sufficient data quality in the UV and IR to use a more complex model), the QSOSED model, and the power law stellar population X-ray model. Since we're using point source photometry for the nucleus, the X-ray stellar population model will likely overpredict the contribution of the stellar population to the X-rays. We'll trying fitting without it later.

[28]:
```
lgh = Lightning(filter_labels_full,
                lum_dist=lumdist,
                flux_obs=obs_full,
                flux_obs_unc=unc_full,
                SFH_type='Piecewise-Constant',
                atten_type='Calzetti',
                dust_emission=True,
                agn_emission=True,
                agn_polar_dust=True,
                xray_mode='flux',
                xray_stellar_emission='Stellar-Plaw',
                xray_agn_emission='QSOSED',
                xray_absorption='tbabs',
                xray_wave_grid=xray_wave_grid,
                xray_arf={'ENERG_LO':[0,1],'ENERG_HI':[1,2], 'SPECRESP':[1,1]},
                xray_exposure=exp_full,
                galactic_NH=galactic_NH,
                model_unc=0.10,
                print_setup_time=True)
```

```
0.027 s elapsed in _get_filters
0.000 s elapsed in _get_wave_obs
0.550 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.155 s elapsed in dust emission model setup
0.028 s elapsed in agn emission model setup
0.047 s elapsed in X-ray model setup
0.806 s elapsed total
```

```
/Users/eqm5663/Research/code/plightning/lightning/get_filters.py:138: RuntimeWarning:␣
↪invalid value encountered in divide
  transm_norm_interp = transm_interp / trapz(transm_interp, wave_grid)
```

[57]:
```
lgh.print_params(verbose=True)
```

```
============================
Piecewise-Constant
============================
Parameter  Lo  Hi              Description
--------- --- --- ------------------------
    psi_1 0.0 inf SFR in stellar age bin 1
    psi_2 0.0 inf SFR in stellar age bin 2
    psi_3 0.0 inf SFR in stellar age bin 3
    psi_4 0.0 inf SFR in stellar age bin 4
    psi_5 0.0 inf SFR in stellar age bin 5
```

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```
============================
Pegase-Stellar
============================
Parameter    Lo  Hi                                        Description
--------- ----- --- -------------------------------------------------
     Zmet 0.001 0.1 Metallicity (mass fraction, where solar = 0.020)

============================
Calzetti
============================
     Parameter  Lo  Hi                      Description
-------------- --- --- --------------------------------
calz_tauV_diff 0.0 inf Optical depth of the diffuse ISM

============================
DL07-Dust
============================
      Parameter     Lo       Hi                                                  ␣
↪   Description
--------------- ------ -------- ------------------------------------------------------------
↪--------------
dl07_dust_alpha  -10.0      4.0                  Radiation field intensity distribution␣
↪power law index
dl07_dust_U_min    0.1     25.0                                       Radiation field␣
↪minimum intensity
dl07_dust_U_max 1000.0 300000.0                                       Radiation field␣
↪maximum intensity
dl07_dust_gamma    0.0      1.0 Fraction of dust mass exposed to radiation field␣
↪intensity distribution
dl07_dust_q_PAH 0.0047   0.0458                            Fraction of dust mass␣
↪composed of PAH grains

============================
SKIRTOR-AGN
============================
        Parameter Lo Hi                                        Description
----------------- -- -- -------------------------------------------------
SKIRTOR_log_L_AGN  6 15    Integrated luminosity of the model in log Lsun
 SKIRTOR_cosi_AGN  0  1    Cosine of the inclination to the line of sight
   SKIRTOR_tau_97  3 11 Edge-on optical depth of the torus at 9.7 microns
  polar_dust_tauV  0  3 V-band optical depth of the polar dust extinction

============================
Stellar-Plaw
============================
Parameter   Lo  Hi  Description
--------- ---- --- ------------
 PhoIndex -2.0 9.0 Photon index

============================
QSOSED
```

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```
============================
 Parameter   Lo   Hi                                Description
---------- ---- ---- ----------------------------------------
log_M_SMBH  5.0 10.0 log10 of the supermassive black hole mass
  log_mdot -1.5  0.3              log10 of the Eddington ratio

============================
tbabs
============================
Parameter  Lo       Hi             Description
--------- --- -------- ----------------------
       NH 0.0 100000.0 Hydrogen column density

Total parameters: 20
```

Rather than assuming a single, constant value of the Eddington ratio, we'll assume a normal prior centered on -1.0, with a 0.3 dex standard deviation. This uncertainty will thus be propagated to our estimate of the BH mass.

[74]:
```
priors = [UniformPrior([0, 1e1]), # SFH
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          ConstantPrior([0.020]), # Metallicity
          UniformPrior([0, 3]), # tauV
          ConstantPrior([2]), # alpha
          # ConstantPrior([1]), # Umin
          UniformPrior([0.1, 25]), # Umin
          ConstantPrior([3e5]), # Umax
          UniformPrior([0,1]), # Gamma
          UniformPrior([0.0047, 0.0458]), #qPAH
          UniformPrior([10,13]), # log L_AGN
          UniformPrior([0.0, 0.5]), # cos i - Limited to Type-2 views.
          UniformPrior([3,11]), # tau 9.7
          UniformPrior([0,1]), # polar dust tauV
          ConstantPrior([1.8]), # stellar pop. pho. index
          # UniformPrior([1.0, 2.5]), # AGN pho. index
          # UniformPrior([-1.3, 1.3]), # log deviation from Lusso + Risaliti 2017
          UniformPrior([5.0, 9.0]), # log BH mass
          # UniformPrior([-1.5, 0.0]), # log Eddington
          NormalPrior([-1.0, 0.3]), # log Eddington
          UniformPrior([1, 1e3]) # NH
          ]

Nwalkers = 64

p0s = [pr.sample(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)

p0[p0[:,-2] < -1.5, -2] = -1.5
p0[p0[:,-2] > 0.3, -2] = 0.3
```

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```
Nsteps = 40000
const_dim = np.array([False, False, False, False, False,
                      True,
                      False,
                      True, False, True, False, False,
                      True, False, False, False,
                      True,
                      False, False,
                      False
                      ])

# print(p0[0,:])
```

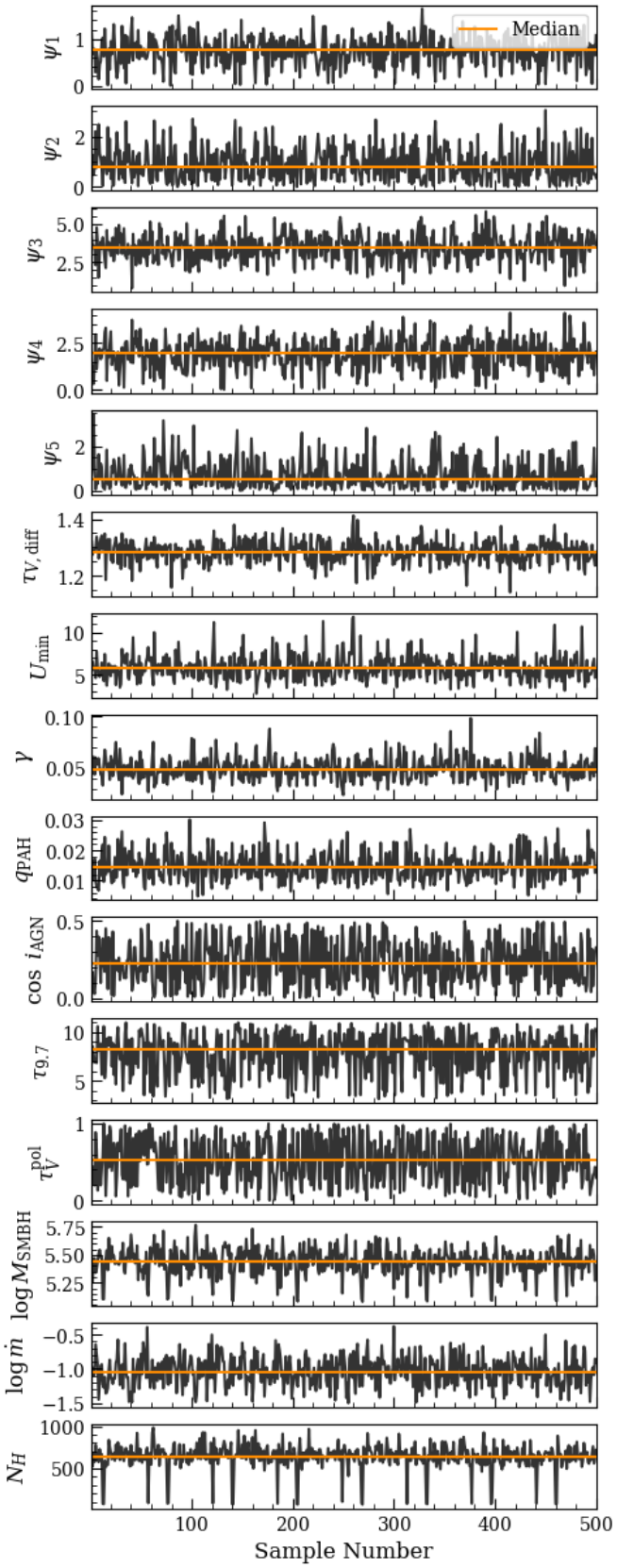
[75]:
```
mcmc = lgh.fit(p0,
               method='emcee',
               Nwalkers=Nwalkers,
               Nsteps=Nsteps,
               priors=priors,
               const_dim=const_dim)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
100%|##########################################################################################
↪#######################| 40000/40000 [23:35<00:00, 28.26it/s]
```

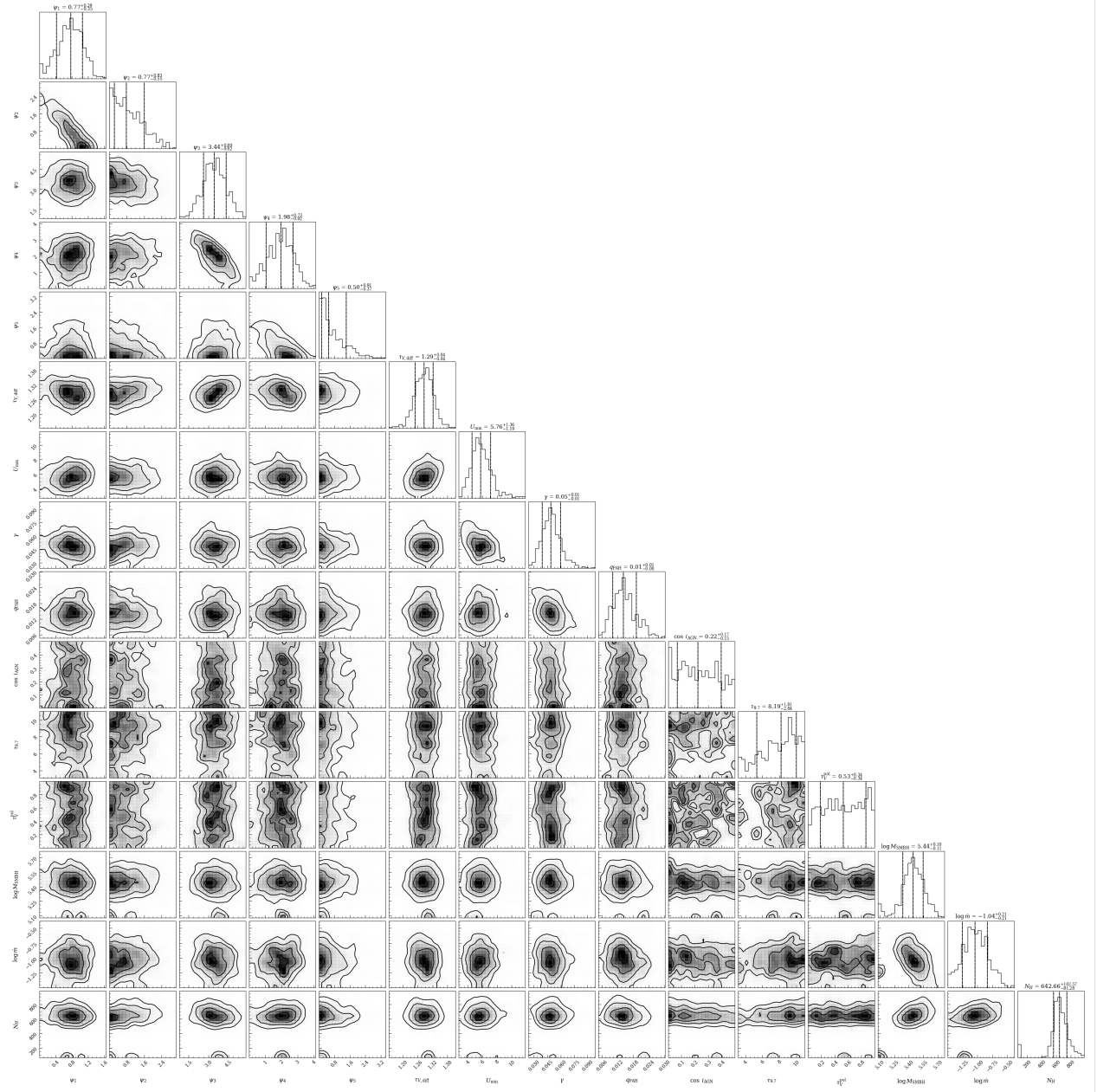
[76]:
```
print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc.acceptance_fraction)))
chain, logprob_chain, t = lgh.get_mcmc_chains(mcmc,
                                              discard=3000,
                                              thin=500,
                                              Nsamples=500,
                                              const_dim=const_dim,
                                              const_vals=p0[0,const_dim])
```

```
MCMC mean acceptance fraction: 0.214
```

[77]:
```
fig, axs = lgh.chain_plot(chain, color='black', alpha=0.8)
```


Median
ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
$\tau_{V,\mathrm{diff}}$
U_{min}
γ
q_{PAH}
$\cos\, i_{\mathrm{AGN}}$
$\tau_{9.7}$
τ_V^{pol}
$\log M_{\mathrm{SMBH}}$
$\log \dot{m}$
N_H
Sample Number

[78]:
```
fig = lgh.corner_plot(chain,
                      quantiles=(0.16, 0.50, 0.84),
                      smooth=1,
                      levels=None,
                      show_titles=True)
```



[71]:
```
from lightning.plots import sed_plot_morebayesian, sed_plot_delchi_morebayesian, sfh_plot

fig5 = plt.figure(figsize=(12,6))
ax51 = fig5.add_axes([0.1, 0.26, 0.4, 0.64])
ax52 = fig5.add_axes([0.1, 0.1, 0.4, 0.15])
ax53 = fig5.add_axes([0.56, 0.1, 0.34, 0.8])
```

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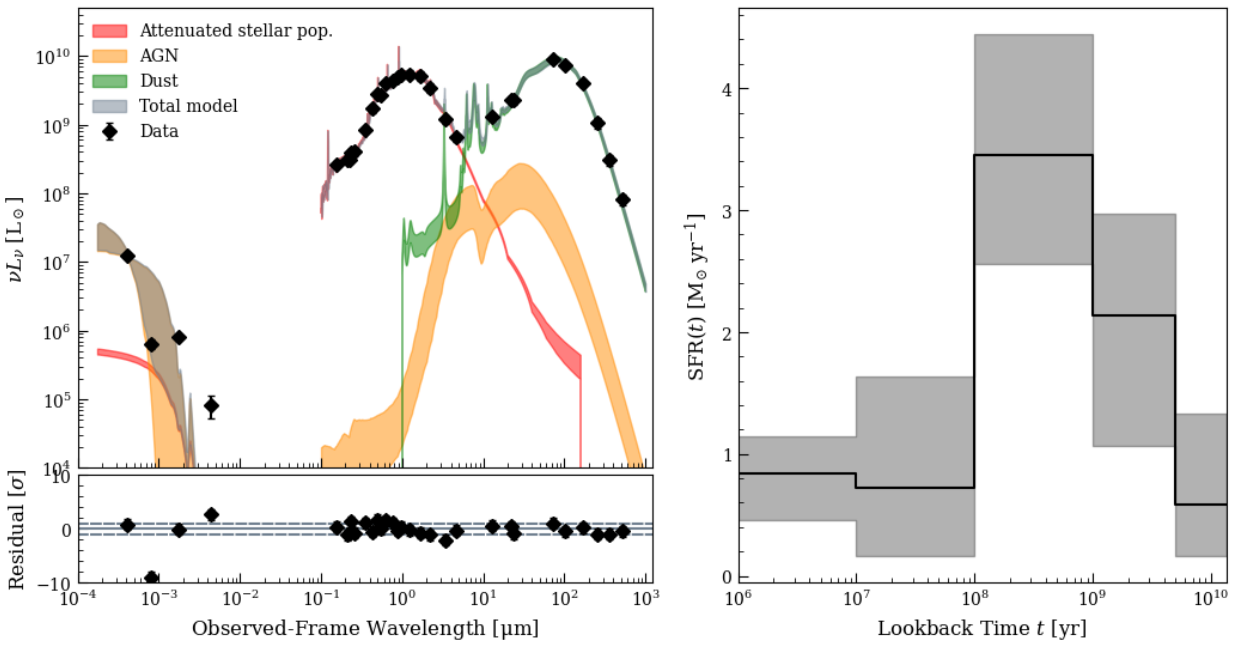
```
fig5, ax51 = sed_plot_morebayesian(lgh, chain, logprob_chain,
                                   plot_components=True,
                                   ax=ax51,
                                   legend_kwargs={'loc': 'upper left', 'frameon': False})
ax51.set_xticklabels([])
ax51.set_xlim(1e-4, 1200)
ax51.set_ylim(1e4,5e10)
fig5, ax52 = lgh.sed_plot_delchi(chain, logprob_chain, ax=ax52)
ax52.set_xlim(1e-4, 1200)
ax52.set_ylim(-10, 10)
fig5, ax53 = lgh.sfh_plot(chain, ax=ax53)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
```



We can see that our model is predicting that a significant chunk of the X-rays come from the stellar population. We also do a very bad job at reproducing the Medium 1.2-2.0 keV flux; this may be due to underestimation of the uncertainties on this relatively narrow band.

Below, we show the posteriors on the stellar mass and BH mass.

[86]:
```
# We need these to determine the posterior on the total stellar mass;
# they are the ratio of the surving stellar mass to star formation
# rate as a function of age. They also depend on metallicity, so the
# stellar population models include a convenience function for extracting
# the appropriate coefficients for each metallicity.
mstar_coeff = lgh.stars.get_mstar_coeff(chain[:,5])
```

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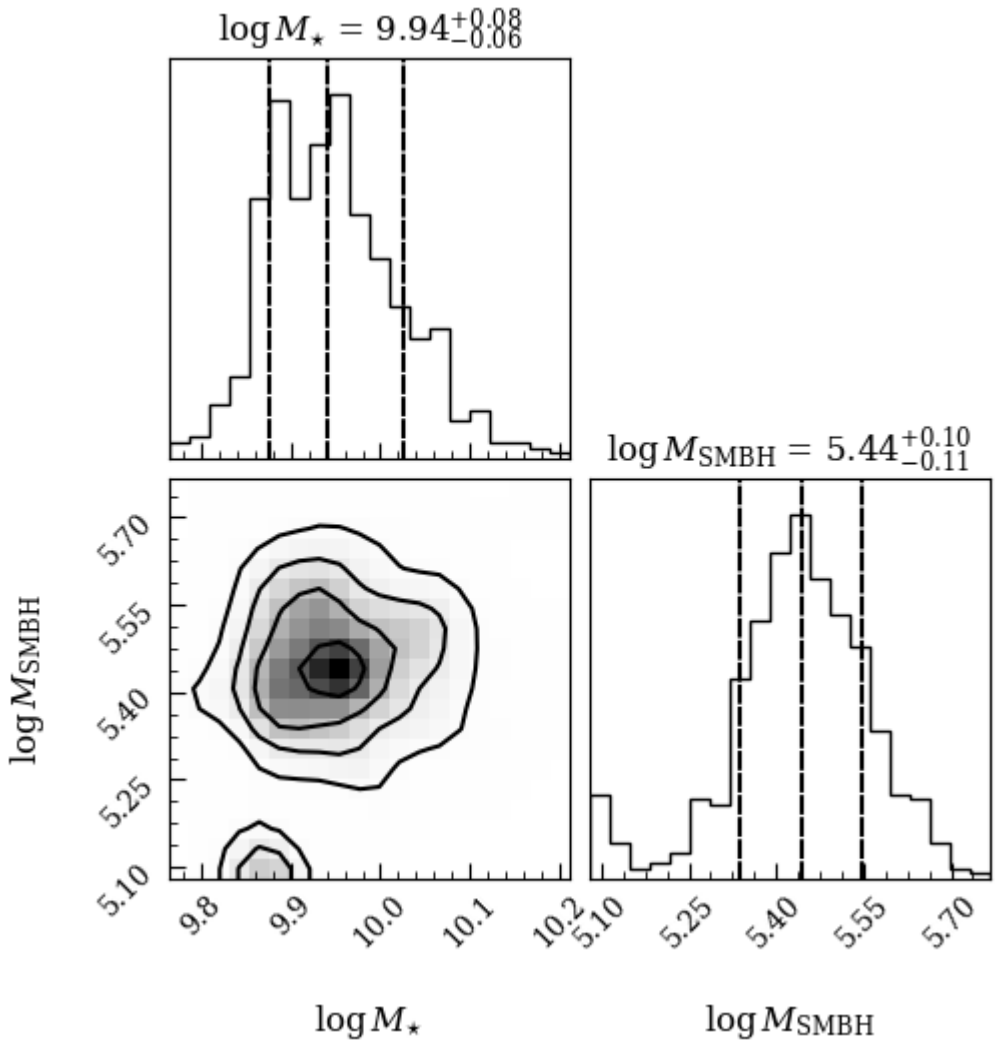
```
mstar_chain = np.sum(mstar_coeff * chain[:,:5], axis=1)

samples = np.stack([np.log10(mstar_chain), chain[:,-3]], axis=-1)
labels = [r'$\log M_{\star}$', r'$\log M_{\rm SMBH}$']

import corner
fig = corner.corner(samples, labels=labels, show_titles=True, quantiles=(0.16, 0.50, 0.
↪84), smooth=1)
```



Our resulting BH mass is a few hundred thousand solar masses, relatively low considering the total stellar mass of the galaxy. We could however, assume an even lower Eddington ratio and find a larger mass.

Note that the stellar mass we're looking at is the entire galaxy, not only the bulge, since we don't have independent photometry for the bulge; we would need to assume a B/T ratio to convert $M_\star$ into a bulge mass.

Below we re-fit the data, now assuming no contributions to the X-ray flux from the stellar population of the galaxy.

[88]:
```
lgh = Lightning(filter_labels_full,
                lum_dist=lumdist,
                flux_obs=obs_full,
                flux_obs_unc=unc_full,
                SFH_type='Piecewise-Constant',
                atten_type='Calzetti',
                dust_emission=True,
                agn_emission=True,
                agn_polar_dust=True,
                xray_mode='flux',
                xray_stellar_emission='None',
                xray_agn_emission='QSOSED',
                xray_absorption='tbabs',
                xray_wave_grid=xray_wave_grid,
                xray_arf={'ENERG_LO':[0,1],'ENERG_HI':[1,2], 'SPECRESP':[1,1]},
                xray_exposure=exp_full,
                galactic_NH=galactic_NH,
                model_unc=0.10,
                print_setup_time=True)
```

```
0.020 s elapsed in _get_filters
0.001 s elapsed in _get_wave_obs
0.547 s elapsed in stellar model setup
0.000 s elapsed in dust attenuation model setup
0.097 s elapsed in dust emission model setup
0.022 s elapsed in agn emission model setup
0.031 s elapsed in X-ray model setup
0.717 s elapsed total
```

```
/Users/eqm5663/Research/code/plightning/lightning/get_filters.py:138: RuntimeWarning:␣
↪invalid value encountered in divide
  transm_norm_interp = transm_interp / trapz(transm_interp, wave_grid)
```

[89]:
```
lgh.print_params(verbose=True)
```

```

============================
Piecewise-Constant
============================
Parameter  Lo  Hi              Description
--------- --- --- ------------------------
    psi_1 0.0 inf SFR in stellar age bin 1
    psi_2 0.0 inf SFR in stellar age bin 2
    psi_3 0.0 inf SFR in stellar age bin 3
    psi_4 0.0 inf SFR in stellar age bin 4
    psi_5 0.0 inf SFR in stellar age bin 5

============================
Pegase-Stellar
============================
Parameter    Lo  Hi                                        Description
--------- ----- --- -------------------------------------------------
     Zmet 0.001 0.1 Metallicity (mass fraction, where solar = 0.020)
```

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```
============================
Calzetti
============================
     Parameter  Lo  Hi                       Description
------------- --- --- -------------------------------
calz_tauV_diff 0.0 inf Optical depth of the diffuse ISM

============================
DL07-Dust
============================
      Parameter     Lo       Hi                                                  ␣
↪   Description
--------------- ------ -------- ------------------------------------------------------------
↪--------------
dl07_dust_alpha  -10.0      4.0                  Radiation field intensity distribution␣
↪power law index
dl07_dust_U_min    0.1     25.0                                       Radiation field␣
↪minimum intensity
dl07_dust_U_max 1000.0 300000.0                                       Radiation field␣
↪maximum intensity
dl07_dust_gamma    0.0      1.0 Fraction of dust mass exposed to radiation field␣
↪intensity distribution
dl07_dust_q_PAH 0.0047   0.0458                           Fraction of dust mass␣
↪composed of PAH grains

============================
SKIRTOR-AGN
============================
        Parameter Lo Hi                                        Description
----------------- -- -- -------------------------------------------------
SKIRTOR_log_L_AGN  6 15    Integrated luminosity of the model in log Lsun
 SKIRTOR_cosi_AGN  0  1    Cosine of the inclination to the line of sight
   SKIRTOR_tau_97  3 11 Edge-on optical depth of the torus at 9.7 microns
  polar_dust_tauV  0  3 V-band optical depth of the polar dust extinction

============================
QSOSED
============================
 Parameter   Lo   Hi                               Description
---------- ---- ---- -----------------------------------------
log_M_SMBH  5.0 10.0 log10 of the supermassive black hole mass
  log_mdot -1.5  0.3              log10 of the Eddington ratio

============================
tbabs
============================
Parameter  Lo       Hi             Description
--------- --- -------- ------------------------
       NH 0.0 100000.0 Hydrogen column density

Total parameters: 19
```

[90]:
```
priors = [UniformPrior([0, 1e1]), # SFH
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          UniformPrior([0, 1e1]),
          ConstantPrior([0.020]), # Metallicity
          UniformPrior([0, 3]), # tauV
          ConstantPrior([2]), # alpha
          # ConstantPrior([1]), # Umin
          UniformPrior([0.1, 25]), # Umin
          ConstantPrior([3e5]), # Umax
          UniformPrior([0,1]), # Gamma
          UniformPrior([0.0047, 0.0458]), #qPAH
          UniformPrior([10,13]), # log L_AGN
          UniformPrior([0.0, 0.5]), # cos i - Limited to Type-2 views.
          UniformPrior([3,11]), # tau 9.7
          UniformPrior([0,1]), # polar dust tauV
          # UniformPrior([1.0, 2.5]), # AGN pho. index
          # UniformPrior([-1.3, 1.3]), # log deviation from Lusso + Risaliti 2017
          UniformPrior([5.0, 9.0]), # log BH mass
          # UniformPrior([-1.5, 0.0]), # log Eddington
          NormalPrior([-1.0, 0.3]), # log Eddington
          UniformPrior([1, 1e3]) # NH
          ]

Nwalkers = 64

p0s = [pr.sample(Nwalkers) for pr in priors]
p0 = np.stack(p0s, axis=-1)

p0[p0[:,-2] < -1.5, -2] = -1.5
p0[p0[:,-2] > 0.3, -2] = 0.3

Nsteps = 40000
const_dim = np.array([False, False, False, False, False,
                      True,
                      False,
                      True, False, True, False, False,
                      True, False, False, False,
                      False, False,
                      False
                      ])

# print(p0[0,:])
```

[91]:
```
mcmc = lgh.fit(p0,
               method='emcee',
               Nwalkers=Nwalkers,
               Nsteps=Nsteps,
               priors=priors,
               const_dim=const_dim)
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
```

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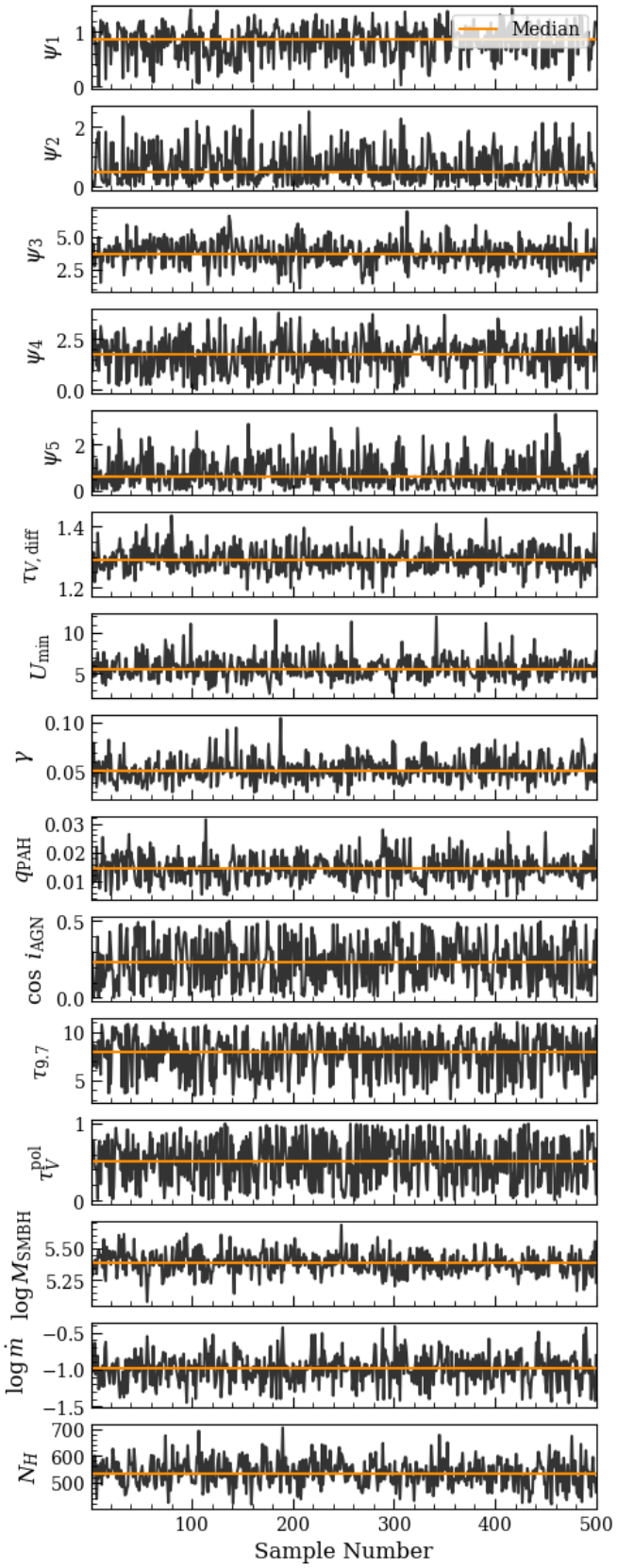
```
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
100%|##########################################################################################
↪######################| 40000/40000 [19:29<00:00, 34.19it/s]
```

[92]:
```
print('MCMC mean acceptance fraction: %.3f' % (np.mean(mcmc.acceptance_fraction)))
chain, logprob_chain, t = lgh.get_mcmc_chains(mcmc,
                                              discard=3000,
                                              thin=500,
                                              Nsamples=500,
                                              const_dim=const_dim,
                                              const_vals=p0[0,const_dim])
```

```
MCMC mean acceptance fraction: 0.219
```

[93]:
```
fig, axs = lgh.chain_plot(chain, color='black', alpha=0.8)
```

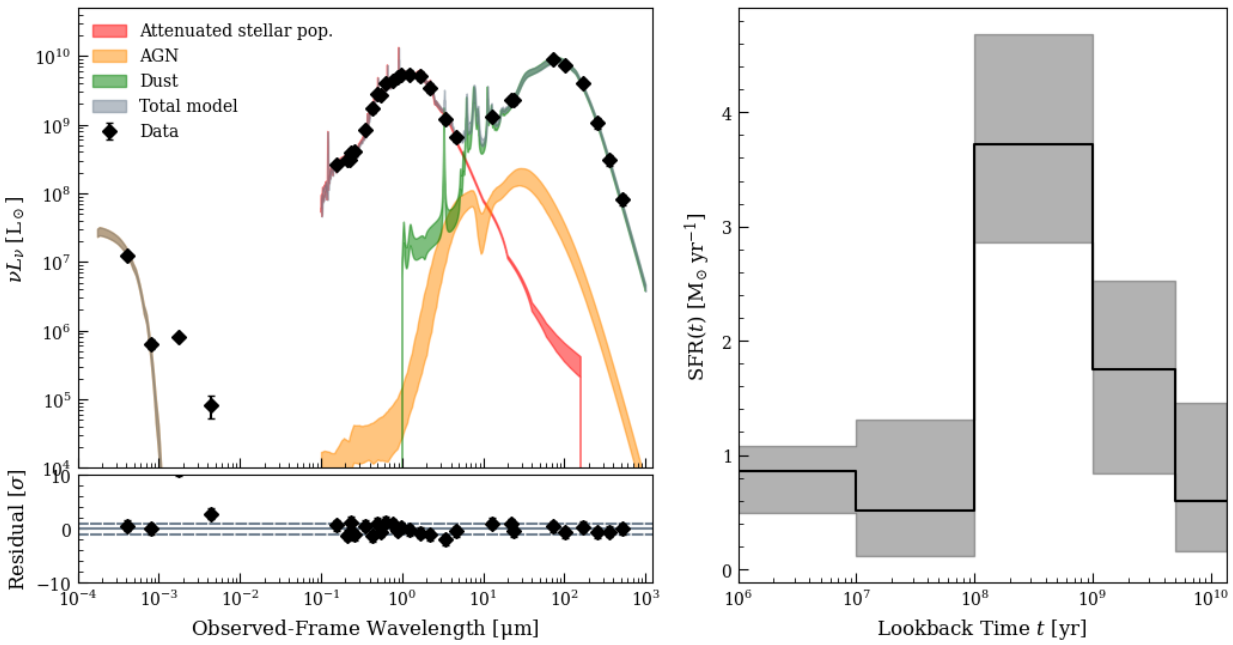

Median
ψ_1
ψ_2
ψ_3
ψ_4
ψ_5
$\tau_{V,\mathrm{diff}}$
U_{min}
γ
q_{PAH}
$\cos i_{\mathrm{AGN}}$
$\tau_{9.7}$
τ_V^{pol}
$\log M_{\mathrm{SMBH}}$
$\log \dot{m}$
N_H
Sample Number

[94]:
```
from lightning.plots import sed_plot_morebayesian, sed_plot_delchi_morebayesian, sfh_plot

fig5 = plt.figure(figsize=(12,6))
ax51 = fig5.add_axes([0.1, 0.26, 0.4, 0.64])
ax52 = fig5.add_axes([0.1, 0.1, 0.4, 0.15])
ax53 = fig5.add_axes([0.56, 0.1, 0.34, 0.8])

fig5, ax51 = sed_plot_morebayesian(lgh, chain, logprob_chain,
                                   plot_components=True,
                                   ax=ax51,
                                   legend_kwargs={'loc': 'upper left', 'frameon': False})
ax51.set_xticklabels([])
ax51.set_xlim(1e-4, 1200)
ax51.set_ylim(1e4,5e10)
fig5, ax52 = lgh.sed_plot_delchi(chain, logprob_chain, ax=ax52)
ax52.set_xlim(1e-4, 1200)
ax52.set_ylim(-10, 10)
fig5, ax53 = lgh.sfh_plot(chain, ax=ax53)
```

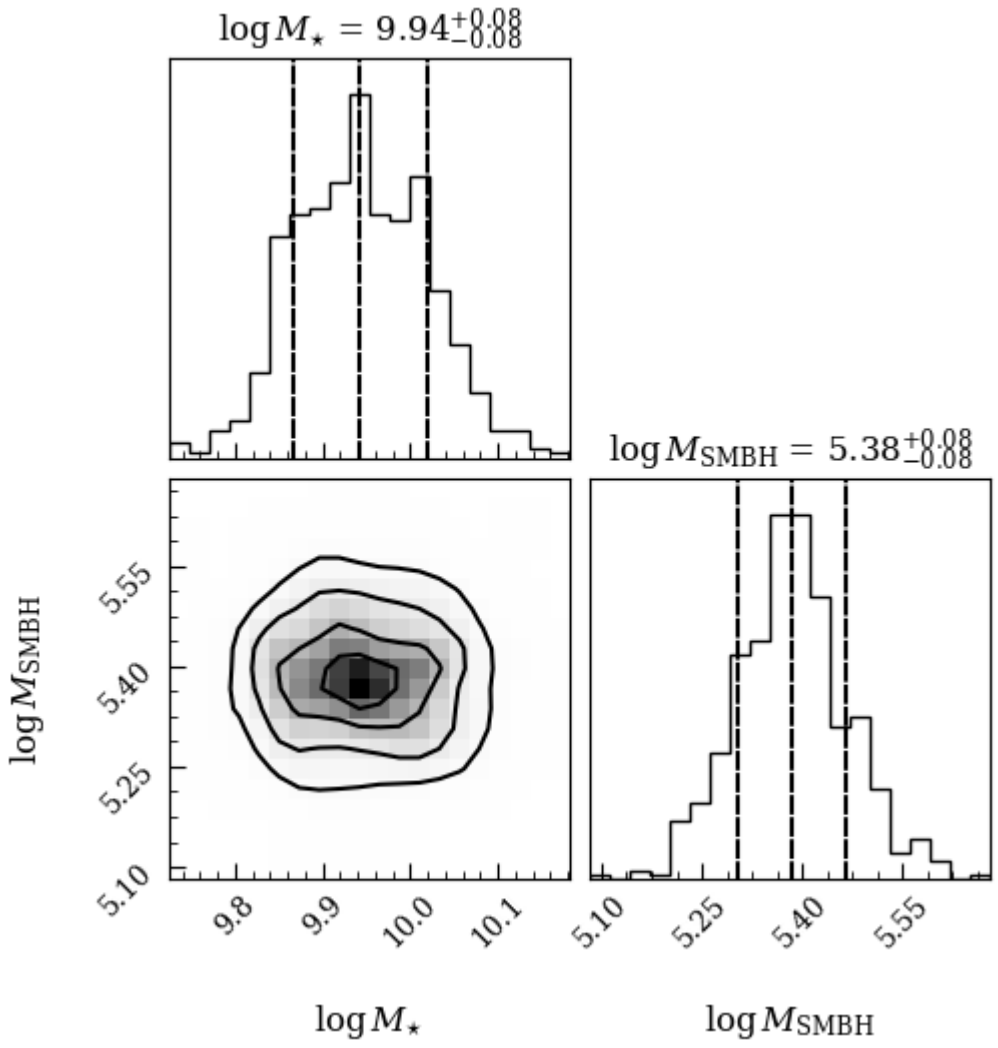
```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
```



[95]:
```
mstar_coeff = lgh.stars.get_mstar_coeff(chain[:,5])
mstar_chain = np.sum(mstar_coeff * chain[:,:5], axis=1)

samples = np.stack([np.log10(mstar_chain), chain[:,-3]], axis=-1)
labels = [r'$\log M_{\star}$', r'$\log M_{\rm SMBH}$']

import corner
fig = corner.corner(samples, labels=labels, show_titles=True, quantiles=(0.16, 0.50, 0.
↪84), smooth=1)
```



We find much the same result as when we included the stellar population model in the X-rays, only now we successfully fit the M and H bands rather than the S and H bands. As a next step, we might try to match the SNR of the X-ray data to the UV-IR data to get a better fit in the X-rays.

CHAPTER

SEVEN

MODEL LIBRARY

This collection of notebooks shows the variation of the the legacy PEGASE models, the BPASS models, the AGN models, and dust models, and are intended to give a quick reference as to where you may or may not have data to constrain a given model.

7.1 Stellar & Nebular Emission - PEGASE

With our Pégase SPS models nebular extinction and continuum emission are essentially built into the stellar emission model.

7.1.1 Imports

[18]:
```
import numpy as np
from scipy.interpolate import interp1d
from lightning.stellar import PEGASEModel as StellarModel
from lightning.sfh import PiecewiseConstSFH
import matplotlib.pyplot as plt
import matplotlib as mpl
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline
```

7.1.2 Initialize Model

Here we'll initialize our sort of 'default' stellar population model, which is integrated over stellar age bins to be used with a piecewise-constant SFH. We'll do it twice, with and without the nebular component, to compare.

[2]:
```
wave_grid = np.logspace(np.log10(0.01),
                        np.log10(10),
                        200)
filter_labels = ['SDSS_u', 'SDSS_g', 'SDSS_r', 'SDSS_i', 'SDSS_z',
                 'MOIRCS_J', 'MOIRCS_H', 'MOIRCS_Ks',
                 'IRAC_CH1', 'IRAC_CH2', 'IRAC_CH3', 'IRAC_CH4']
redshift = 0.0
age = [0, 1e7, 1e8, 1e9, 5e9, 13.4e9]

stars_neb = StellarModel(filter_labels,
                         age=age,
```

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```
                          redshift=redshift,
                          wave_grid=wave_grid,
                          nebular_effects=True)

stars_noneb = StellarModel(filter_labels,
                           age=age,
                           redshift=redshift,
                           wave_grid=wave_grid,
                           nebular_effects=False)
```

[6]:
```
print(stars_neb.Zmet)
print(stars_neb.Lnu_obs.shape)
```

```
[0.001, 0.004, 0.008, 0.013, 0.016, 0.02, 0.05, 0.1]
(5, 8, 200)
```

7.1.3 Simple Stellar Population Models

We've included the left-hand panel of this plot in basically every `Lightning`-related paper for years.

[7]:
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

Nmod = len(age) - 1

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    finterp = interp1d(stars_neb.wave_grid_rest, stars_neb.Lnu_obs[i,-3,:])
    f1 = finterp(1)

    axs[0].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * stars_neb.Lnu_obs[i,-3,:] / f1,
                color=colors_neb[i])

    finterp = interp1d(stars_noneb.wave_grid_rest, stars_noneb.Lnu_obs[i,-3,:])
    f1 = finterp(1)

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * stars_noneb.Lnu_obs[i,-3,:] / f1,
                color=colors_noneb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e9, 5e17)

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
```

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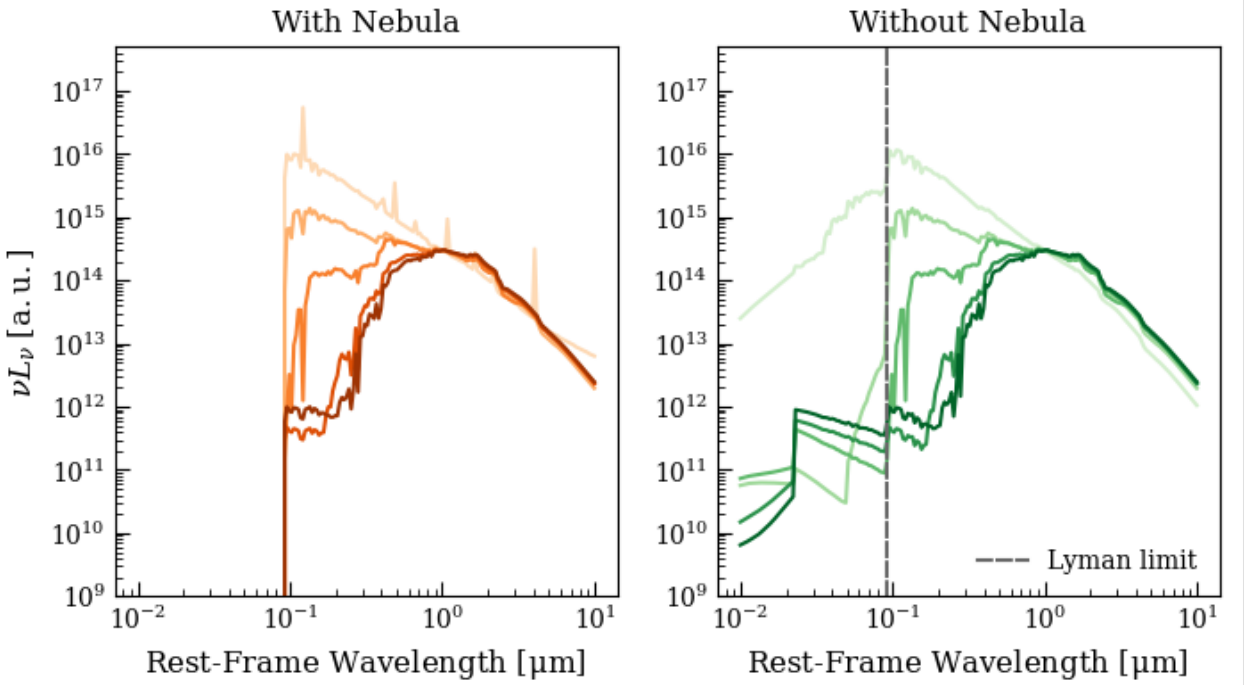
```
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm a.u.]$')
axs[0].set_title('With Nebula')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e9, 5e17)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('Without Nebula')
```

[7]:
```
Text(0.5, 1.0, 'Without Nebula')
```



Where darker shades represent older ages. Note that nebular emission lines are only present for the two models with ages 100 Myr. The effect of free-free nebular continuum emission can be seen by comparing the lightest yellow curve on the left with the lightest green curve on the right.

In python lightning metallicity can be varied as a free parameter (whereas in IDL Lightning it was selected and held fixed), so it's worth looking at the variation of a young population with metallicity:

[17]:
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

Nmod = len(stars_neb.Zmet)

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))
```

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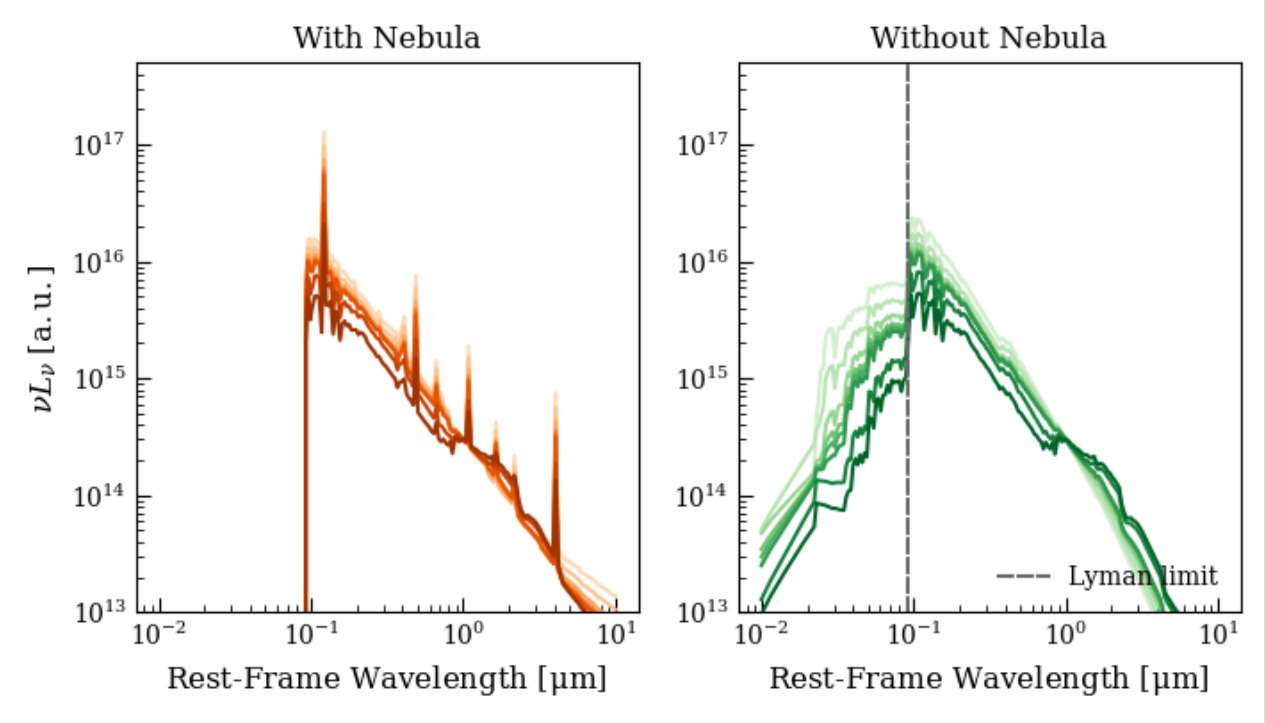
```
for i in np.arange(Nmod):

    finterp = interp1d(stars_neb.wave_grid_rest, stars_neb.Lnu_obs[0,i,:])
    f1 = finterp(1)

    axs[0].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * stars_neb.Lnu_obs[0,i,:] / f1,
                color=colors_neb[i])

    finterp = interp1d(stars_noneb.wave_grid_rest, stars_noneb.Lnu_obs[0,i,:])
    f1 = finterp(1)

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * stars_noneb.Lnu_obs[0,i,:] / f1,
                color=colors_noneb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e13, 5e17)

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm a.u.]$')
axs[0].set_title('With Nebula')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e13, 5e17)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('Without Nebula')
```

[17]:
```
Text(0.5, 1.0, 'Without Nebula')
```



We're looking at the 0-10 Myr population, where lighter colors correspond to lower metallicities. Low-Z populations have a larger ionizing flux, as you would expect.

7.1.4 Composite Stellar Population Models

To construct composite stellar populations we must of course assume a SFH for the population. Since we binned our simple stellar populations, we must use the `PiecewiseConstantSFH` model.

[9]:
```
sfh = PiecewiseConstSFH(age)
```

[11]:
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

Z = np.array([0.02, 0.02])
coeffs= np.array([[1,1,0,0,0],
                  [0,0,1,1,1]])

Nmod = coeffs.shape[0]

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))

lnu_hires_neb,_,_ = stars_neb.get_model_lnu_hires(sfh, coeffs, Z)
lnu_hires_noneb,_,_ = stars_noneb.get_model_lnu_hires(sfh, coeffs, Z)

for i in np.arange(Nmod):
```

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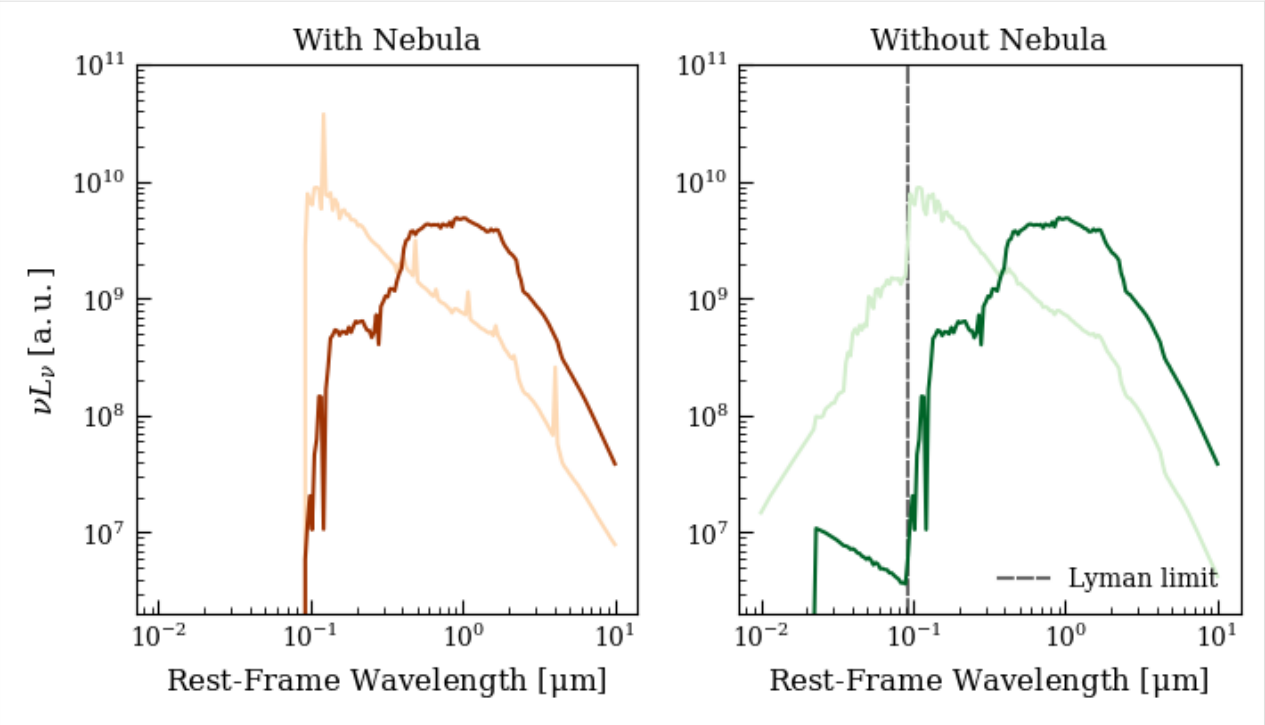
```
    axs[0].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * lnu_hires_neb[i,:],
                color=colors_neb[i])

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * lnu_hires_noneb[i,:],
                color=colors_noneb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(2e6, 1e11)

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm a.u.]$')
axs[0].set_title('With Nebula')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(2e6, 1e11)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit', zorder=-1)
axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('Without Nebula')
```

```
/Users/eqm5663/Research/code/plightning/lightning/stellar/pegase.py:449: RuntimeWarning:␣
↪divide by zero encountered in log10
  finterp = interp1d(self.Zmet, np.log10(self.Lnu_obs), axis=1)
/Users/eqm5663/miniconda3_arm64/envs/ciao-4.16/lib/python3.11/site-packages/scipy/
↪interpolate/_interpolate.py:701: RuntimeWarning: invalid value encountered in subtract
  slope = (y_hi - y_lo) / (x_hi - x_lo)[:, None]
```

[11]:
```
Text(0.5, 1.0, 'Without Nebula')
```



Here the lighter colored populations are star forming, and the darker ones are quiescent. Note that even if you were to use stellar populations without nebular extinction for your SED fitting in Lightning, the resulting galaxy would have no Lyman continuum leakage, as our ISM attenuation models are defined to be opaque to Lyman continuum radiation.

7.2 Stellar & Nebular Emission - BPASS

In the BPASS SPS models nebular extinction and continuum emission were added using Cloudy by the BPASS collaboration using a "sensible set of defaults".

[17]:
```
import numpy as np
from scipy.interpolate import interp1d
from lightning.stellar import BPASSModel, PEGASEModel
from lightning.sfh import PiecewiseConstSFH
import matplotlib.pyplot as plt
import matplotlib as mpl
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline
```

7.2.1 Initialize Model

Here we'll initialize our sort of 'default' stellar population model, which is integrated over stellar age bins to be used with a piecewise-constant SFH. We'll do it three times, with and without binary stellar evolution and the nebular component, to compare.

[3]:
```
wave_grid = np.logspace(np.log10(0.01),
                        np.log10(10),
                        200)
filter_labels = ['SDSS_u', 'SDSS_g', 'SDSS_r', 'SDSS_i', 'SDSS_z',
                 'MOIRCS_J', 'MOIRCS_H', 'MOIRCS_Ks',
                 'IRAC_CH1', 'IRAC_CH2', 'IRAC_CH3', 'IRAC_CH4']
redshift = 0.0
age = [0, 1e7, 1e8, 1e9, 5e9, 13.4e9]

stars_sin = BPASSModel(filter_labels,
                       age=age,
                       redshift=redshift,
                       wave_grid=wave_grid,
                       binaries=False,
                       nebular_effects=False)

stars_neb = BPASSModel(filter_labels,
                       age=age,
                       redshift=redshift,
                       wave_grid=wave_grid,
                       binaries=True,
                       nebular_effects=True)

stars_noneb = BPASSModel(filter_labels,
                         age=age,
                         redshift=redshift,
                         wave_grid=wave_grid,
                         binaries=True,
                         nebular_effects=False)
```

[7]:
```
fig, axs = plt.subplots(1,3, figsize=(12,4))

Nmod = len(age) - 1

cm_sin = mpl.colormaps['Purples']
colors_sin = cm_sin(np.linspace(0.2, 0.9, Nmod))

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    finterp = interp1d(stars_sin.wave_grid_rest, stars_sin.Lnu_obs[i,-3,:])
    # f1 = finterp(1)
```

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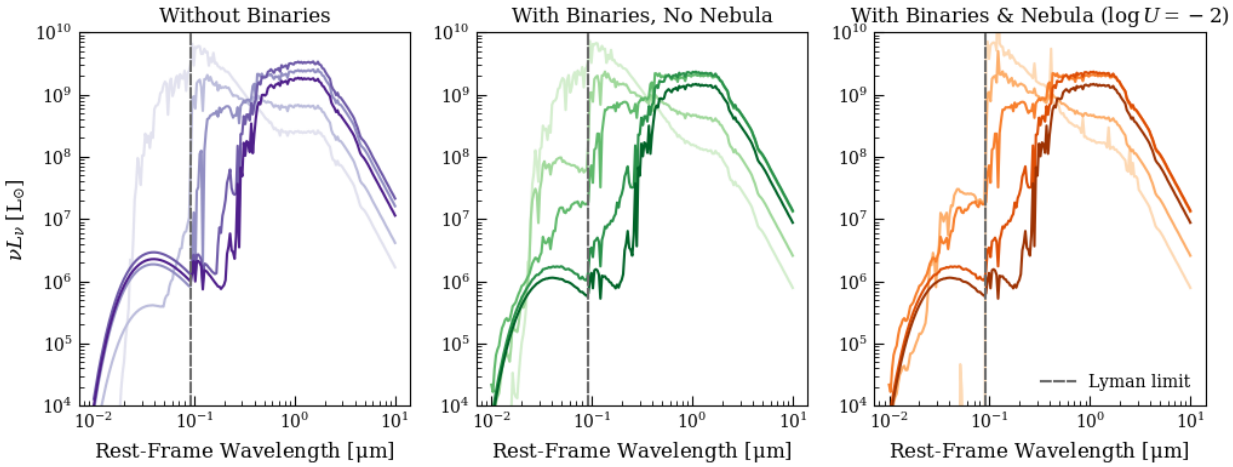
```
    f1 = 1

    axs[0].plot(stars_sin.wave_grid_rest,
                stars_sin.nu_grid_obs * stars_sin.Lnu_obs[i,-3,:] / f1,
                color=colors_sin[i])

    finterp = interp1d(stars_noneb.wave_grid_rest, stars_noneb.Lnu_obs[i,-3,:])
    # f1 = finterp(1)
    f1 = 1

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * stars_noneb.Lnu_obs[i,-3,:] / f1,
                color=colors_noneb[i])

    finterp = interp1d(stars_neb.wave_grid_rest, stars_neb.Lnu_obs[i,-3,2,:])
    # f1 = finterp(1)
    f1 = 1

    axs[2].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * stars_neb.Lnu_obs[i,-3,2,:] / f1,
                color=colors_neb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e4, 1e10)
axs[0].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[0].set_title('Without Binaries')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e4, 1e10)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
# axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('With Binaries, No Nebula')

axs[2].set_xscale('log')
axs[2].set_yscale('log')
axs[2].set_ylim(1e4, 1e10)
axs[2].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[2].legend(loc='lower right')

axs[2].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[2].set_title(r'With Binaries & Nebula ($\log U=-2$)')
```

[7]:
```
Text(0.5, 1.0, 'With Binaries & Nebula ($\\log U=-2$)')
```



Lighter colors here represent the younger age bins. Below, we look at the variation in the youngest age bin with metallicity:

[16]:
```
fig, axs = plt.subplots(1,3, figsize=(12,4))

Nmod = len(stars_neb.Zmet)

cm_sin = mpl.colormaps['Purples']
colors_sin = cm_sin(np.linspace(0.2, 0.9, Nmod))

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    finterp = interp1d(stars_sin.wave_grid_rest, stars_sin.Lnu_obs[0,i,:])
    # f1 = finterp(1)
    f1 = 1

    axs[0].plot(stars_sin.wave_grid_rest,
                stars_sin.nu_grid_obs * stars_sin.Lnu_obs[0,i,:] / f1,
                color=colors_sin[i])

    finterp = interp1d(stars_noneb.wave_grid_rest, stars_noneb.Lnu_obs[0,i,:])
    # f1 = finterp(1)
    f1 = 1

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * stars_noneb.Lnu_obs[0,i,:] / f1,
                color=colors_noneb[i])

    finterp = interp1d(stars_neb.wave_grid_rest, stars_neb.Lnu_obs[0,i,2,:])
    # f1 = finterp(1)
    f1 = 1
```

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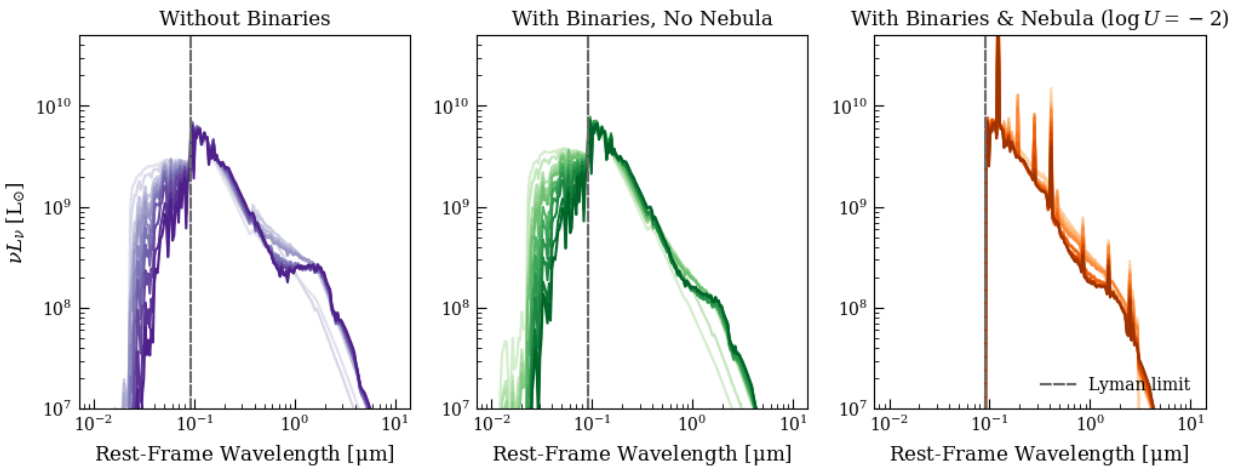
```
    axs[2].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * stars_neb.Lnu_obs[0,i,2,:] / f1,
                color=colors_neb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e7, 5e10)
axs[0].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[0].set_title('Without Binaries')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e7, 5e10)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
# axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('With Binaries, No Nebula')

axs[2].set_xscale('log')
axs[2].set_yscale('log')
axs[2].set_ylim(1e7, 5e10)
axs[2].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[2].legend(loc='lower right')

axs[2].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[2].set_title(r'With Binaries & Nebula ($\log U=-2$)')
```

[16]:
```
Text(0.5, 1.0, 'With Binaries & Nebula ($\\log U=-2$)')
```

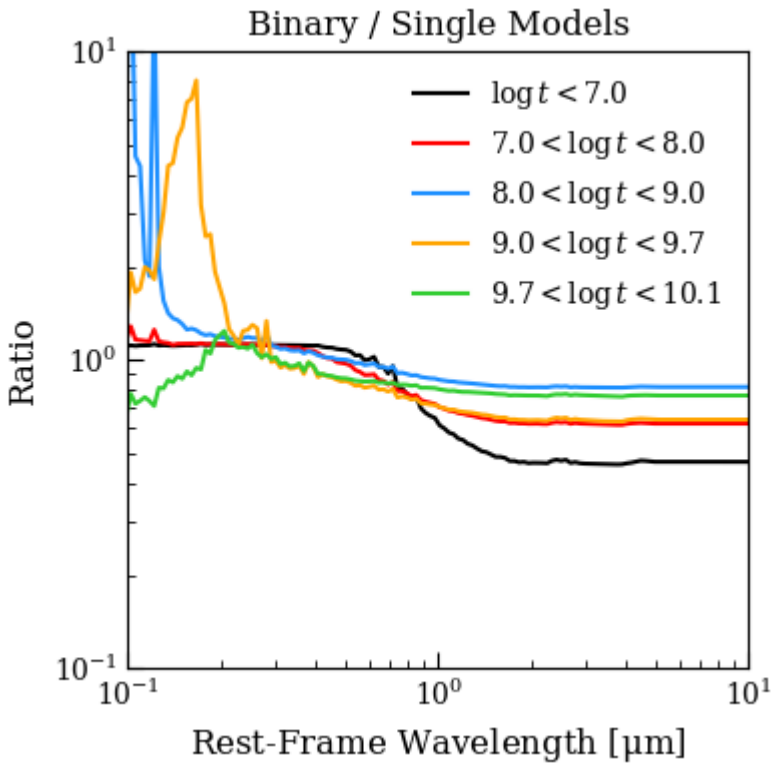


Here, we're looking at the 0-10 Myr population with metallicity ranging from $Z = 10^{-5} - 0.04$. Lighter colors represent lower metallicities.

Now we zoom in on the differences between the models with and without binary stellar evolution in the optical-NIR portion of the spectrum, since they're less obvious than the differences in the Lyman continuum.

[12]:
```
fig, ax = plt.subplots(figsize=(4,4))

# cm_noneb = mpl.colormaps['Greens']
# colors = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    # finterp = interp1d(stars_sin.wave_grid_rest, stars_sin.Lnu_obs[i,:])
    # f1 = finterp(1)
    label = r'$%.1f < \log t < %.1f$' % (np.log10(age[i]), np.log10(age[i+1])) if␣
↪age[i] != 0 else r'$\log t < %.1f$' % (np.log10(age[i+1]))

    ax.plot(stars_sin.wave_grid_rest,
            stars_noneb.Lnu_obs[i,-3,:] / stars_sin.Lnu_obs[i,-3,:],
            label = label)

ax.set_xscale('log')
ax.set_yscale('log')
ax.set_ylim(0.1, 10)
ax.set_xlim(0.1, 10)
ax.legend(loc='upper right')

ax.set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
ax.set_ylabel(r'Ratio')
ax.set_title('Binary / Single Models')
```

[12]:
```
Text(0.5, 1.0, 'Binary / Single Models')
```



A lot of the difference between the two is in the NIR, where the binary stellar evolution prescriptions moderate the overproduction of AGB stars. On the blue side, we see significant differences in the absorption features of the 100 Myr - 1 Gyr population and the shape of the blue continuum in the 1 Gyr - 5 Gyr population.

Finally, we compare the underlying stellar population models to PEGASE, without any modification by the nebula.

[13]:
```
bpass_sin = BPASSModel(filter_labels,
                       age=age,
                       redshift=redshift,
                       wave_grid=wave_grid,
                       binaries=False,
                       nebular_effects=False)

bpass_bin = BPASSModel(filter_labels,
                       age=age,
                       redshift=redshift,
                       wave_grid=wave_grid,
                       binaries=True,
                       nebular_effects=False)

pegase_noneb = PEGASEModel(filter_labels,
                           age=age,
                           redshift=redshift,
                           wave_grid=wave_grid,
                           nebular_effects=False)
```

[14]:
```
fig, axs = plt.subplots(1,3,figsize=(15,5))

Nmod = len(age) - 1

labels = [r'$t < 10^7$ yr',
          r'$10^7 \leq t < 10^8$ yr',
          r'$10^8 \leq t < 10^9$ yr',
          r'$10^9 \leq t < 5 \times 10^9$ yr',
         r'$5 \times 10^9 \leq t < 13.6 \times 10^9$ yr']

for i in np.arange(Nmod):

    l,=axs[0].plot(bpass_sin.wave_grid_rest,
                   bpass_sin.nu_grid_obs * bpass_sin.Lnu_obs[i,-3,:], alpha=0.4)
    axs[0].plot(bpass_bin.wave_grid_rest,
                   bpass_bin.nu_grid_obs * bpass_bin.Lnu_obs[i,-3,:], color=l.get_color(),
                   label=labels[i])
    axs[1].plot(pegase_noneb.wave_grid_rest,
                  pegase_noneb.nu_grid_obs * pegase_noneb.Lnu_obs[i,-3,:])
    l,=axs[2].plot(pegase_noneb.wave_grid_rest,
                  bpass_sin.Lnu_obs[i,-3,:] / pegase_noneb.Lnu_obs[i,-3,:], alpha=0.4)
    axs[2].plot(pegase_noneb.wave_grid_rest,
                  bpass_bin.Lnu_obs[i,-3,:] / pegase_noneb.Lnu_obs[i,-3,:], color=l.get_
↪color())


axs[0].set_xscale('log')
axs[0].set_xlim(0.0912, 10)
```

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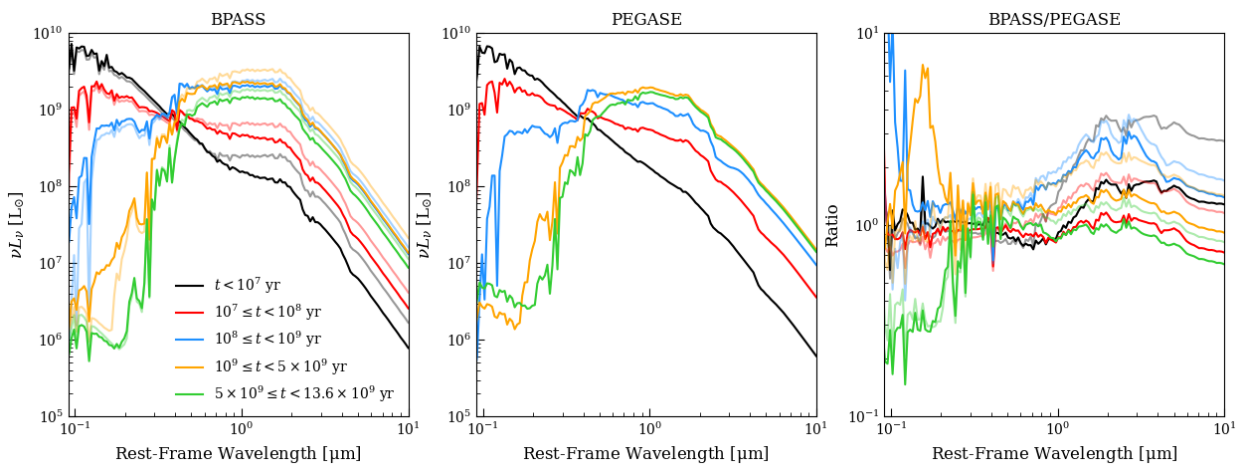
```
axs[0].set_ylim(1e5, 1e10)
axs[0].set_yscale('log')
# axs[0].set_ylim(1e9, 5e17)
axs[0].legend(loc='lower right')

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[0].set_title('BPASS')

axs[1].set_xscale('log')
axs[1].set_xlim(0.0912, 10)
axs[1].set_ylim(1e5, 1e10)
axs[1].set_yscale('log')
# axs[1].set_ylim(1e9, 5e17)
# axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
# axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[1].set_title('PEGASE')

axs[2].set_xscale('log')
axs[2].set_xlim(0.0912, 10)
# axs[2].set_ylim(1e5, 1e10)
axs[2].set_yscale('log')
# axs[2].set_ylim(1e9, 5e17)
# axs[2].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
# axs[2].legend(loc='lower right')

axs[2].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[2].set_ylabel('Ratio')
axs[2].set_title(r'BPASS/PEGASE')
axs[2].set_ylim(0.1,10)
```

[14]:
```
(0.1, 10)
```



In the first and third panels, desaturated colors are single stars. The red excess we can see is driven by evolved massive

stars; it's moderated by the binary evolution prescriptions (e.g. stars are stripped by their companion before they join the AGB) such that we see it primarily in the 100 Myr - 1 Gyr bin, where the AGB stars are really taking over.

7.3 Stellar & Nebular Emission - PEGASE+Cloudy

In these models, the nebular component is generated from Cloudy simulations on a large grid of metallicities and ionization parameters (see Nebular Emission Recipe).

The source models are from PEGASE, assuming a Kroupa et al. (2001) IMF. Since PEGASE models older than 30 Myr produce no Lyman continuum emission by definition, a nebular component is not included at ages older than 30 Myr.

7.3.1 Imports

[1]:
```
import numpy as np
from scipy.interpolate import interp1d
from lightning.stellar import PEGASEModelA24 as StellarModel
from lightning.stellar import PEGASEBurstA24 as BurstModel
from lightning.sfh import PiecewiseConstSFH
import matplotlib.pyplot as plt
import matplotlib as mpl
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline
```

7.3.2 Initialize Model

Here we'll initialize our sort of 'default' stellar population model, which is integrated over stellar age bins to be used with a piecewise-constant SFH. We'll do it twice, with and without the nebular component, to compare.

[2]:
```
wave_grid = np.logspace(np.log10(0.01),
                        np.log10(10),
                        200)
filter_labels = ['SDSS_u', 'SDSS_g', 'SDSS_r', 'SDSS_i', 'SDSS_z',
                 'MOIRCS_J', 'MOIRCS_H', 'MOIRCS_Ks',
                 'IRAC_CH1', 'IRAC_CH2', 'IRAC_CH3', 'IRAC_CH4']
redshift = 0.0
age = [0, 1e7, 1e8, 1e9, 5e9, 13.4e9]

stars_neb = StellarModel(filter_labels,
                         age=age,
                         redshift=redshift,
                         wave_grid=wave_grid,
                         nebular_effects=True)

stars_noneb = StellarModel(filter_labels,
                           age=age,
                           redshift=redshift,
                           wave_grid=wave_grid,
                           nebular_effects=False)
```

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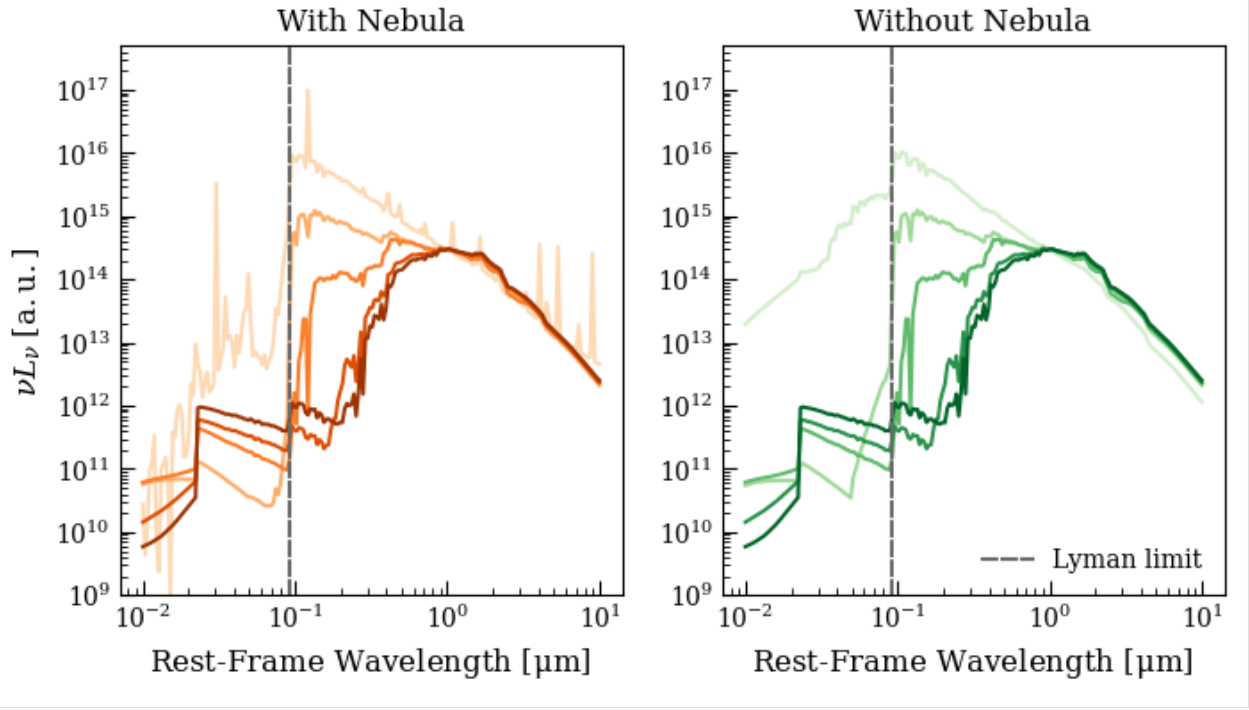
```
burst = BurstModel(filter_labels, redshift=redshift, wave_grid=wave_grid)
```

7.3.3 Simple Stellar Population Models

We've included the left-hand panel of this plot in basically every `Lightning`-related paper for years.

[3]:
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

Nmod = len(age) - 1

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    finterp = interp1d(stars_neb.wave_grid_rest, stars_neb.Lnu_obs[i,-2,1,:])
    f1 = finterp(1)

    axs[0].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * stars_neb.Lnu_obs[i,-2,1,:] / f1,
                color=colors_neb[i])

    finterp = interp1d(stars_noneb.wave_grid_rest, stars_noneb.Lnu_obs[i,-2,:])
    f1 = finterp(1)

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * stars_noneb.Lnu_obs[i,-2,:] / f1,
                color=colors_noneb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e9, 5e17)
axs[0].axvline(0.0912, color='dimgray', linestyle='--')

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm a.u.]$')
axs[0].set_title('With Nebula')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e9, 5e17)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('Without Nebula')
```

[3]:
```
Text(0.5, 1.0, 'Without Nebula')
```



Where darker shades represent older ages. Note that nebular emission lines are only present for the two models with ages 100 Myr. The effect of free-free nebular continuum emission can be seen by comparing the lightest yellow curve on the left with the lightest green curve on the right. Note also that the Lyman continuum emission is not completely attenuated by the nebula (and old stellar populations with hot stripped stars produce low-level Lyman continuum emission). However, our dust models are opaque to the Lyman continuum by definition.

Note that the `PEGASEBurstA24` model class provides a cleaner interface to the single-age population models, and can actually be used to fit SEDs. We'll use it now to look at the variation of the spectrum with Z and $\log U$ for a 1 Myr old population:

[16]:
```
params_Z = np.tile([6.0, 6.0, 0, -2.0], (len(burst.Zmet), 1))
params_Z[:,2] = burst.Zmet

params_logU = np.tile([6.0, 6.0, 0.02, 0.0], (len(burst.logU), 1))
params_logU[:,3] = burst.logU

lnu_burst_Z,_,_ = burst.get_model_lnu_hires(params_Z)
lnu_burst_logU,_,_ = burst.get_model_lnu_hires(params_logU)

fig, axs = plt.subplots(1,2, figsize=(8,4))

Nmod = len(burst.Zmet)
cm_neb = mpl.colormaps['Oranges']
colors_Z = cm_neb(np.linspace(0.2, 0.9, Nmod))

for i in range(Nmod):

    axs[0].plot(burst.wave_grid_obs,
```

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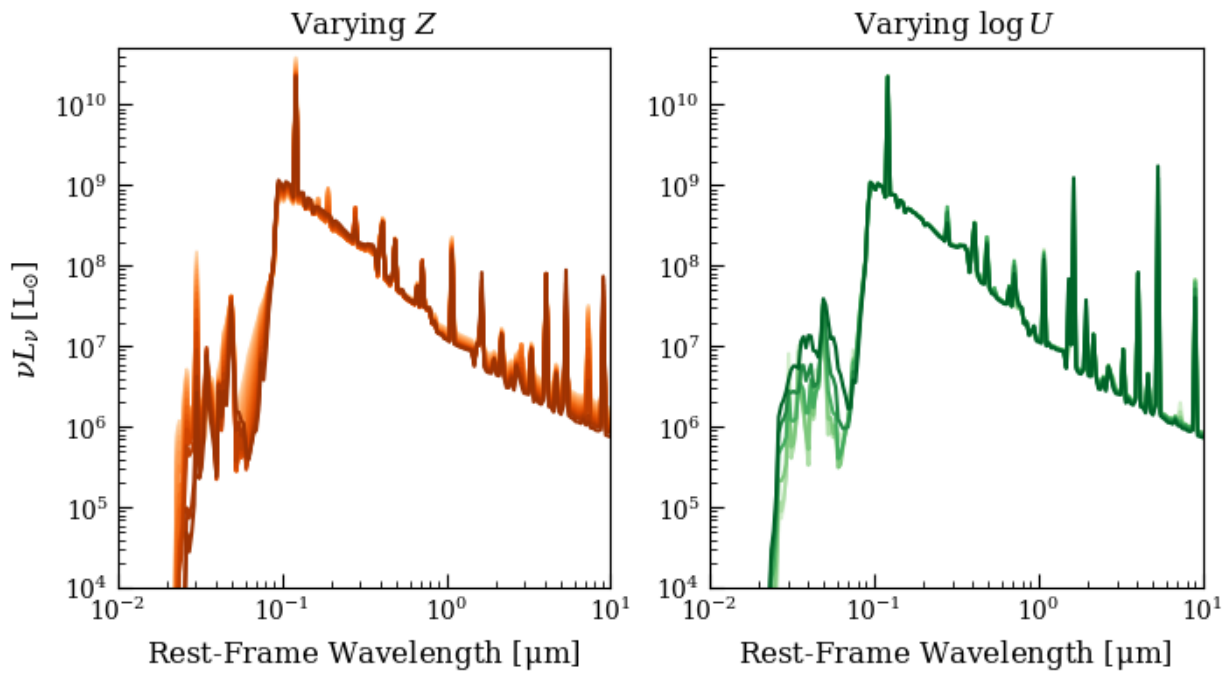
```
                burst.nu_grid_obs * lnu_burst_Z[i,:],
                color=colors_Z[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_xlim(0.01, 10)
axs[0].set_ylim(1e4, 5e10)
axs[0].set_title(r'Varying $Z$')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')

Nmod = len(burst.logU)
cm_noneb = mpl.colormaps['Greens']
colors_logU = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in range(Nmod):

    axs[1].plot(burst.wave_grid_obs,
                burst.nu_grid_obs * lnu_burst_logU[i,:],
                color=colors_logU[i])

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_xlim(0.01, 10)
axs[1].set_ylim(1e4, 5e10)
axs[1].set_title(r'Varying $\log U$')
axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
```

```
[[ 6.00000000e+00  1.00000000e+06  6.47187320e-04 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  8.14760564e-04 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  1.02572278e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  1.29130847e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  1.62566105e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  2.04658600e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  2.57649913e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  3.24362023e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  4.08347593e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  5.14079162e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  6.47187320e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  8.14760564e-03 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  1.02572278e-02 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  1.29130847e-02 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  1.62566105e-02 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  2.04658600e-02 -2.00000000e+00]
 [ 6.00000000e+00  1.00000000e+06  2.57649913e-02 -2.00000000e+00]]
[[ 6.0e+00  1.0e+06  2.0e-02 -1.5e+00]
 [ 6.0e+00  1.0e+06  2.0e-02 -2.0e+00]
 [ 6.0e+00  1.0e+06  2.0e-02 -2.5e+00]
 [ 6.0e+00  1.0e+06  2.0e-02 -3.0e+00]
 [ 6.0e+00  1.0e+06  2.0e-02 -3.5e+00]
 [ 6.0e+00  1.0e+06  2.0e-02 -4.0e+00]]
```

[16]:
```
Text(0.5, 0, 'Rest-Frame Wavelength [$\\rm \\mu m$]')
```



The models with lower metallicity (lighter colors) have more significant ionizing fluxes, while the models with larger ionization parameters have more luminous strong line emission and slightly larger ionizing escape from the nebula.

7.3.4 Composite Stellar Population Models

To construct composite stellar populations we must of course assume a SFH for the population. Since we binned our simple stellar populations, we must use the `PiecewiseConstantSFH` model.

[19]:
```
sfh = PiecewiseConstSFH(age)
```

[20]:
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

coeffs= np.array([[1,1,0,0,0],
                  [0,0,1,1,1]])

Z = np.array([0.02, 0.02])
logU = np.array([-2.0, -2.0])

params = np.stack([Z, logU], axis=-1)

Nmod = coeffs.shape[0]

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))
```

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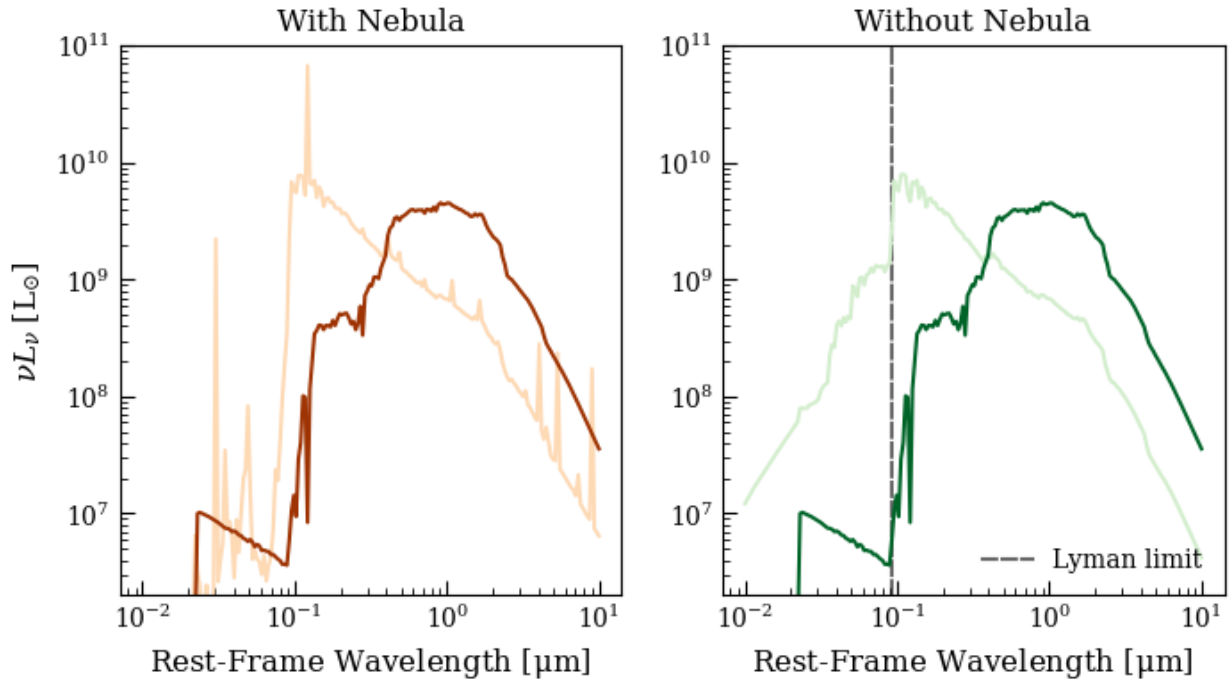
```
lnu_hires_neb,_,_ = stars_neb.get_model_lnu_hires(sfh, coeffs, params)
lnu_hires_noneb,_,_ = stars_noneb.get_model_lnu_hires(sfh, coeffs, Z)

for i in np.arange(Nmod):

    axs[0].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * lnu_hires_neb[i,:],
                color=colors_neb[i])

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * lnu_hires_noneb[i,:],
                color=colors_noneb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(2e6, 1e11)

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[0].set_title('With Nebula')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(2e6, 1e11)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit', zorder=-1)
axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('Without Nebula')
```

[20]:
```
Text(0.5, 1.0, 'Without Nebula')
```



Here the lighter colored populations are star forming, and the darker ones are quiescent. Note that, as implied above, even if you were to use stellar populations without nebular extinction for your SED fitting in Lightning, the resulting galaxy would have no Lyman continuum leakage, as our ISM attenuation models are defined to be opaque to Lyman continuum radiation.

7.4 Stellar & Nebular Emission - BPASS+Cloudy

In these models, the nebular component is generated from Cloudy simulations on a large grid of metallicities and ionization parameters (see Nebular Emission Recipe).

The source models are BPASS v2.2.1, assuming a Chabrier et al. (2013) IMF. We include models of all ages in our Cloudy simulations, since old stellar populations in BPASS continue to produce an ionizing spectrum. The `nebula_old` option allows the user to turn off nebular emission from populations older than 30 Myr.

7.4.1 Imports

[13]:
```
import numpy as np
from scipy.interpolate import interp1d
from lightning.stellar import BPASSModelA24 as StellarModel
from lightning.stellar import BPASSBurstA24 as BurstModel
from lightning.sfh import PiecewiseConstSFH
import matplotlib.pyplot as plt
import matplotlib as mpl
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline
```

7.4.2 Initialize Model

Here we'll initialize our sort of 'default' stellar population model, which is integrated over stellar age bins to be used with a piecewise-constant SFH. We'll do it twice, with and without the nebular component, to compare.

We're passing the special keyword `nebula_old = False` to the first model to ensure that populations older than 30 Myr do not have nebular emission in their spectra. When you select these models when initializing Lightning, nebular emission from old populations is turned off by default. See Byler et al. (2017) for a brief discussion of the effect of post-AGB stars on the line ratios of a composite population.

[14]:
```
wave_grid = np.logspace(np.log10(0.01),
                        np.log10(10),
                        200)
filter_labels = ['SDSS_u', 'SDSS_g', 'SDSS_r', 'SDSS_i', 'SDSS_z',
                 'MOIRCS_J', 'MOIRCS_H', 'MOIRCS_Ks',
                 'IRAC_CH1', 'IRAC_CH2', 'IRAC_CH3', 'IRAC_CH4']
redshift = 0.0
age = [0, 1e7, 1e8, 1e9, 5e9, 13.4e9]

stars_neb = StellarModel(filter_labels,
                         age=age,
                         redshift=redshift,
                         wave_grid=wave_grid,
                         nebula_old=False,
                         nebular_effects=True)

stars_noneb = StellarModel(filter_labels,
                           age=age,
                           redshift=redshift,
                           wave_grid=wave_grid,
                           nebular_effects=False)

burst = BurstModel(filter_labels, redshift=redshift, wave_grid=wave_grid)
```

7.4.3 Simple Stellar Population Models

We've included the left-hand panel of this plot in basically every `Lightning`-related paper for years.

[15]:
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

Nmod = len(age) - 1

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))

cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    finterp = interp1d(stars_neb.wave_grid_rest, stars_neb.Lnu_obs[i,-2,1,:])
    f1 = finterp(1)
```

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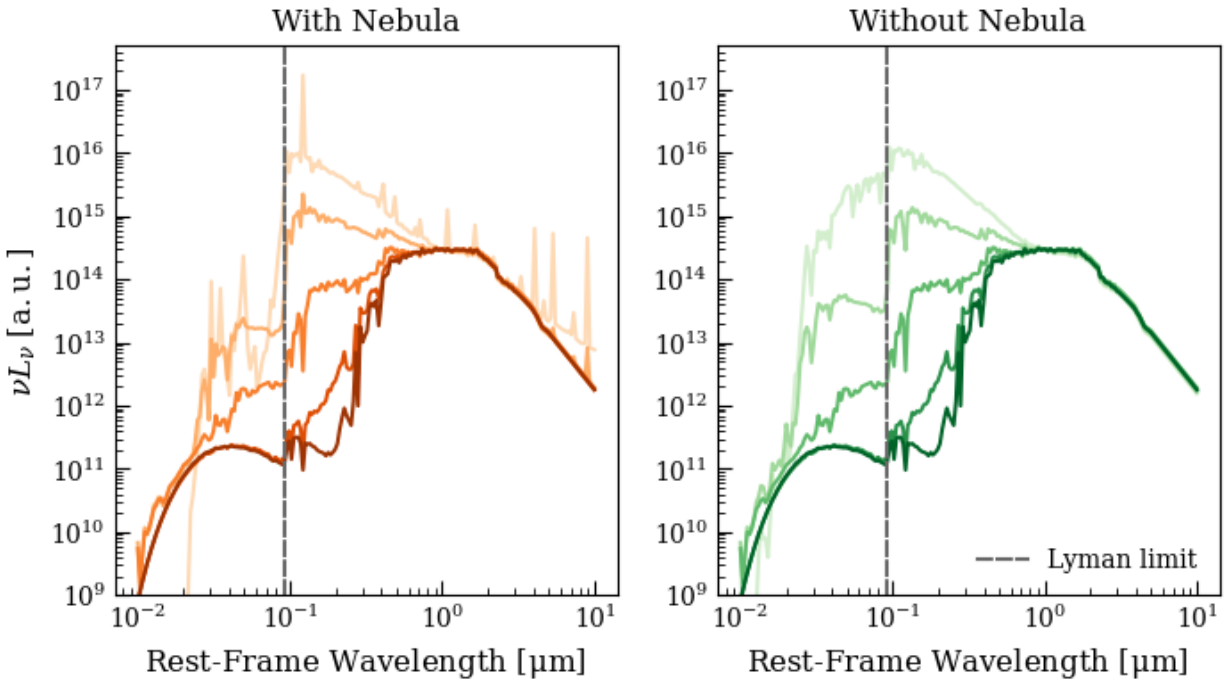
```
    axs[0].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * stars_neb.Lnu_obs[i,-2,1,:] / f1,
                color=colors_neb[i])

    finterp = interp1d(stars_noneb.wave_grid_rest, stars_noneb.Lnu_obs[i,-2,:])
    f1 = finterp(1)

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * stars_noneb.Lnu_obs[i,-2,:] / f1,
                color=colors_noneb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e9, 5e17)
axs[0].axvline(0.0912, color='dimgray', linestyle='--')

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm a.u.]$')
axs[0].set_title('With Nebula')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e9, 5e17)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit')
axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('Without Nebula')
```

[15]:
```
Text(0.5, 1.0, 'Without Nebula')
```



Where darker shades represent older ages. Note that nebular emission lines are only present for the two models with ages 100 Myr. The effect of free-free nebular continuum emission can be seen by comparing the lightest yellow curve on the left with the lightest green curve on the right. Note also that the Lyman continuum emission is not completely attenuated by the nebula (and old stellar populations with hot stripped stars produce low-level Lyman continuum emission). However, our dust models are opaque to the Lyman continuum by definition.

Note that the `BPASSBurstA24` model class provides a cleaner interface to the single-age population models, and can actually be used to fit SEDs. We'll use it now to look at the variation of the spectrum with Z and $\log U$ for a 1 Myr old population:

[16]:
```
params_Z = np.tile([6.0, 6.0, 0, -2.0], (len(burst.Zmet), 1))
params_Z[:,2] = burst.Zmet

params_logU = np.tile([6.0, 6.0, 0.02, 0.0], (len(burst.logU), 1))
params_logU[:,3] = burst.logU

lnu_burst_Z,_,_ = burst.get_model_lnu_hires(params_Z)
lnu_burst_logU,_,_ = burst.get_model_lnu_hires(params_logU)

fig, axs = plt.subplots(1,2, figsize=(8,4))

Nmod = len(burst.Zmet)
cm_neb = mpl.colormaps['Oranges']
colors_Z = cm_neb(np.linspace(0.2, 0.9, Nmod))

for i in range(Nmod):

    axs[0].plot(burst.wave_grid_obs,
                burst.nu_grid_obs * lnu_burst_Z[i,:],
                color=colors_Z[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_xlim(0.01, 10)
axs[0].set_ylim(1e4, 5e10)
axs[0].set_title(r'Varying $Z$')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')

Nmod = len(burst.logU)
cm_noneb = mpl.colormaps['Greens']
colors_logU = cm_noneb(np.linspace(0.2, 0.9, Nmod))

for i in range(Nmod):

    axs[1].plot(burst.wave_grid_obs,
                burst.nu_grid_obs * lnu_burst_logU[i,:],
                color=colors_logU[i])

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_xlim(0.01, 10)
axs[1].set_ylim(1e4, 5e10)
axs[1].set_title(r'Varying $\log U$')
```

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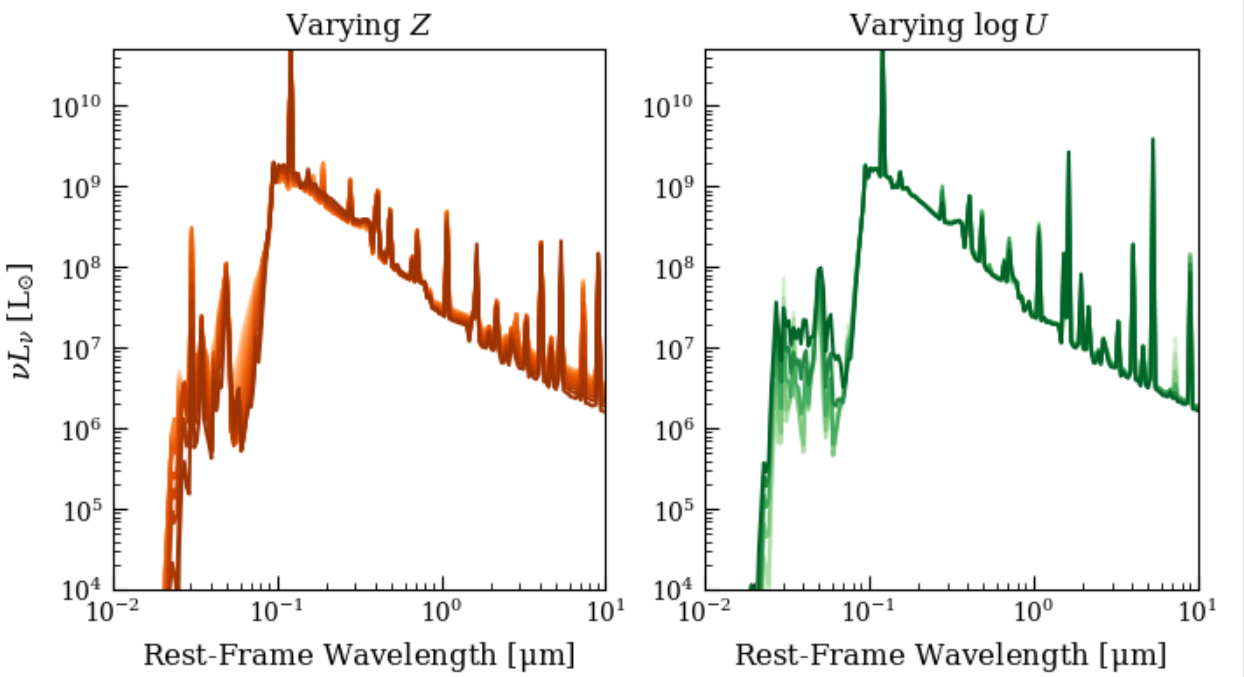
```
axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
```

[16]:
```
Text(0.5, 0, 'Rest-Frame Wavelength [$\\rm \\mu m$]')
```



The models with lower metallicity (lighter colors) have more significant ionizing fluxes, while the models with larger ionization parameters have more luminous strong line emission and slightly larger ionizing escape from the nebula.

7.4.4 Composite Stellar Population Models

To construct composite stellar populations we must of course assume a SFH for the population. Since we binned our simple stellar populations, we must use the `PiecewiseConstantSFH` model.

[8]:
```
sfh = PiecewiseConstSFH(age)
```

[9]:
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

coeffs= np.array([[1,1,0,0,0],
                  [0,0,1,1,1]])

Z = np.array([0.02, 0.02])
logU = np.array([-2.0, -2.0])

params = np.stack([Z, logU], axis=-1)

Nmod = coeffs.shape[0]

cm_neb = mpl.colormaps['Oranges']
colors_neb = cm_neb(np.linspace(0.2, 0.9, Nmod))
```

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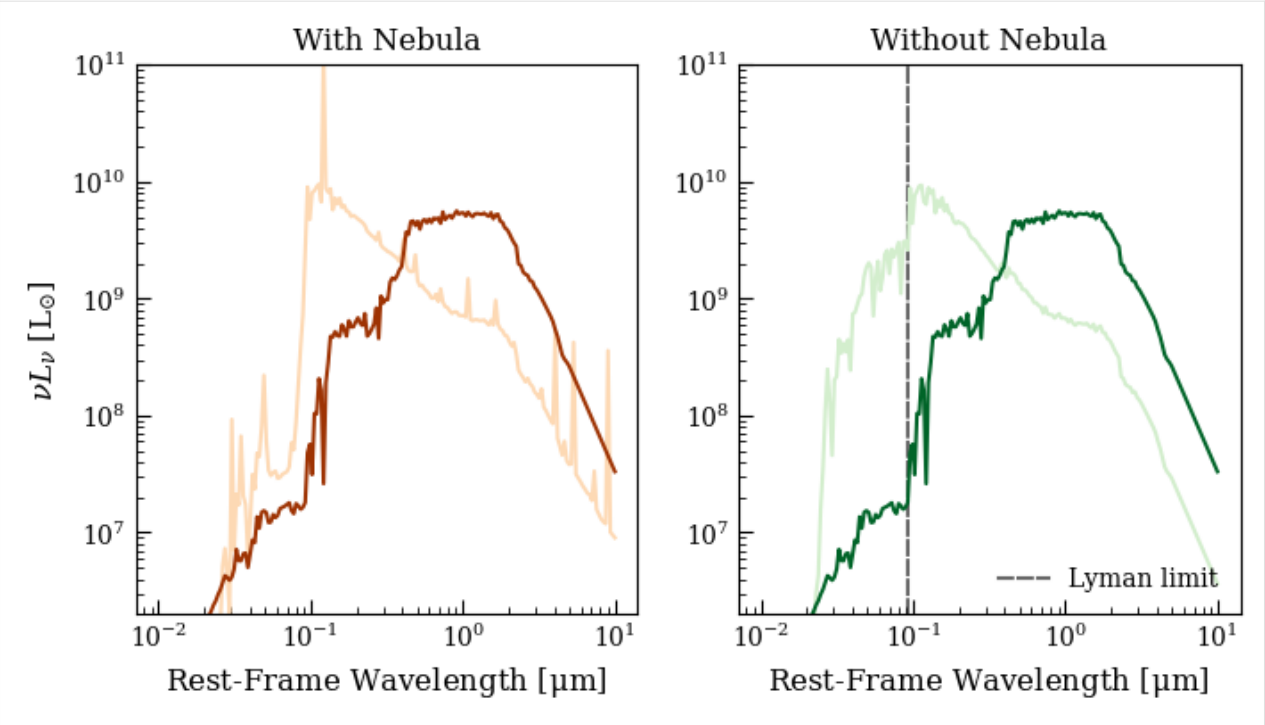
```
cm_noneb = mpl.colormaps['Greens']
colors_noneb = cm_noneb(np.linspace(0.2, 0.9, Nmod))

lnu_hires_neb,_,_ = stars_neb.get_model_lnu_hires(sfh, coeffs, params)
lnu_hires_noneb,_,_ = stars_noneb.get_model_lnu_hires(sfh, coeffs, Z)

for i in np.arange(Nmod):

    axs[0].plot(stars_neb.wave_grid_rest,
                stars_neb.nu_grid_obs * lnu_hires_neb[i,:],
                color=colors_neb[i])

    axs[1].plot(stars_noneb.wave_grid_rest,
                stars_noneb.nu_grid_obs * lnu_hires_noneb[i,:],
                color=colors_noneb[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(2e6, 1e11)

axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_\nu\ [\rm L_{\odot}]$')
axs[0].set_title('With Nebula')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(2e6, 1e11)
axs[1].axvline(0.0912, color='dimgray', linestyle='--', label='Lyman limit', zorder=-1)
axs[1].legend(loc='lower right')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_title('Without Nebula')
```

[9]:
```
Text(0.5, 1.0, 'Without Nebula')
```



Here the lighter colored populations are star forming, and the darker ones are quiescent. Note that, as implied above, even if you were to use stellar populations without nebular extinction for your SED fitting in Lightning, the resulting galaxy would have no Lyman continuum leakage, as our ISM attenuation models are defined to be opaque to Lyman continuum radiation.

7.5 AGN Emission

7.5.1 Imports

[9]:
```
import numpy as np
from lightning.agn import AGNModel
from lightning.xray.agn import AGNPlaw, Qsosed
from astropy.table import Table
import matplotlib.pyplot as plt
import matplotlib as mpl
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline
```

7.5.2 Initialize Model

[2]:
```
wave_grid = np.logspace(np.log10(0.0912),
                        np.log10(100),
                        200)
filter_labels = ['SDSS_u', 'SDSS_g', 'SDSS_r', 'SDSS_i', 'SDSS_z',
                 'MOIRCS_J', 'MOIRCS_H', 'MOIRCS_Ks',
                 'IRAC_CH1', 'IRAC_CH2', 'IRAC_CH3', 'IRAC_CH4',
                 'MIPS_CH1']

redshift = 0.0

agn = AGNModel(filter_labels,
               redshift=redshift,
               wave_grid=wave_grid,
               polar_dust=True)
```

[3]:
```
agn.print_params(verbose=True)
```

```
============================
SKIRTOR-AGN
============================
        Parameter Lo Hi                                          Description
----------------- -- -- ------------------------------------------------------
SKIRTOR_log_L_AGN  6 15    Integrated luminosity of the model in log Lsun
 SKIRTOR_cosi_AGN  0  1    Cosine of the inclination to the line of sight
   SKIRTOR_tau_97  3 11 Edge-on optical depth of the torus at 9.7 microns
  polar_dust_tauV  0  3 V-band optical depth of the polar dust extinction

Total parameters: 4
```

7.5.3 Plots with Varying Model Parameters

[14]:
```
def multi_model_plot(mdl, params, cmap='YlOrRd', labels=None, ax=None):

    Nmod = params.shape[0]
    if labels is None: labels = [None for i in np.arange(Nmod)]

    lnu = mdl.get_model_lnu_hires(params)

    if ax is None:
        fig, ax = plt.subplots()
    else:
        fig = ax.figure

    cm = mpl.colormaps[cmap]
    colors = cm(np.linspace(0.2, 0.9, Nmod))

    for i in np.arange(Nmod):
```

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```
        ax.plot(agn.wave_grid_rest,
                agn.nu_grid_obs * lnu[i,:],
                color=colors[i],
                label=labels[i])

    ax.set_xscale('log')
    ax.set_yscale('log')

    ax.set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
    ax.set_ylabel(r'$\nu L_{\nu}\ [\rm L_{\odot}]$')

    if labels is not None: ax.legend(loc = 'best')

    return fig, ax
```

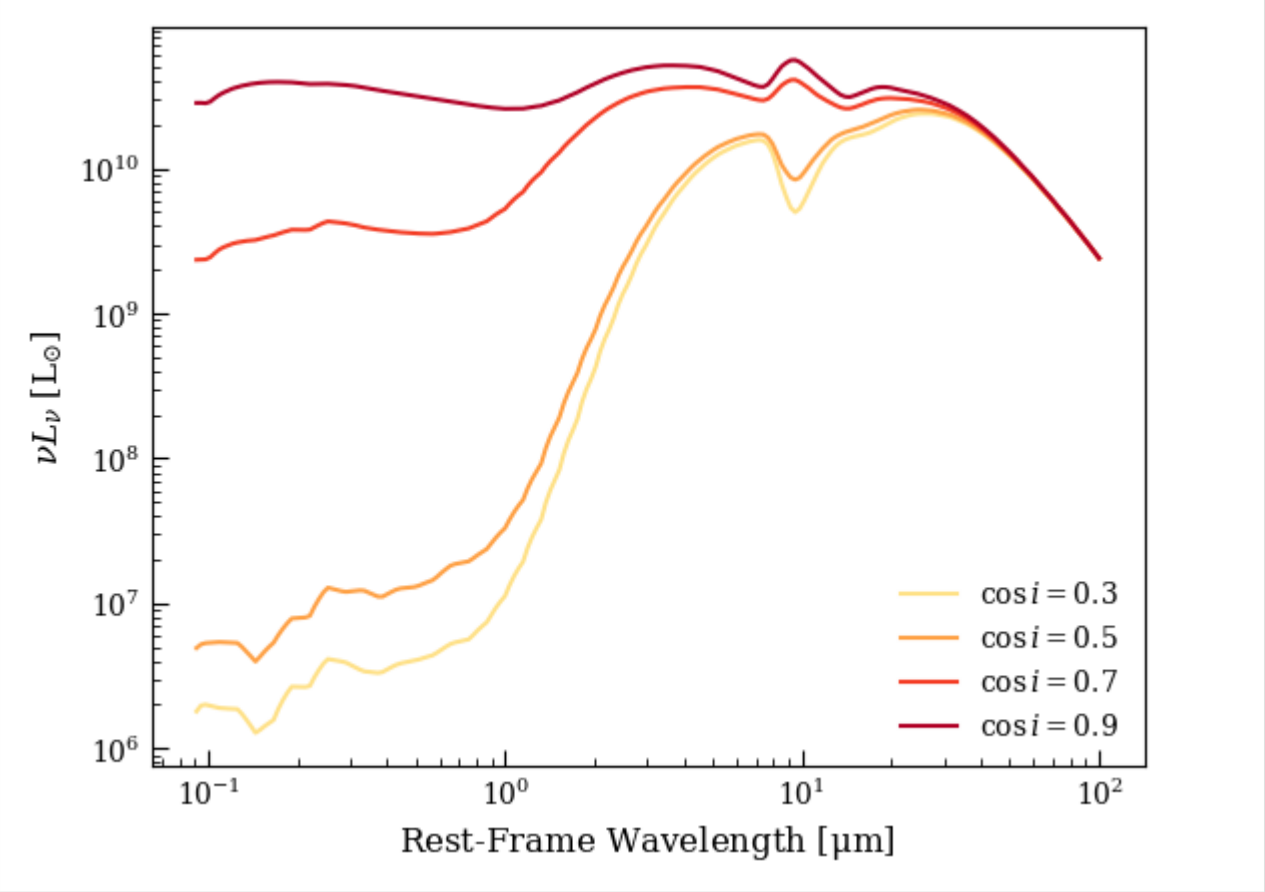
Varying Inclination

The effects of the changing inclination are most pronounced at the sort of edge case, where $i \approx 90 - \Delta$, where Δ is the angle that the dusty torus cone extends upward from the plane of the accretion disk. It will often suffice to fit with inclination fixed or bounded to a small range (in fact this is the recommended strategy for e.g. Cigale) and compare the 'Type 1' and 'Type 2' fits.

[15]:
```
params = np.array([[11, 0.3, 7, 0.1],
                   [11, 0.5, 7, 0.1],
                   [11, 0.7, 7, 0.1],
                   [11, 0.9, 7, 0.1]])

multi_model_plot(agn,
                 params,
                 labels=[r'$\cos i = %.1f$' % p[1] for p in params])
```

[15]:
```
(<Figure size 640x480 with 1 Axes>,
 <Axes: xlabel='Rest-Frame Wavelength [$\\rm \\mu m$]', ylabel='$\\nu L_{\\nu}\\ [\\rm L_
↪{\\odot}]$'>)
```



Varying $\tau_{9.7}$ at Fixed Inclination

Unless we have *really* good data across the MIR it seems unlikely that we could constrain both the inclination and optical depth.

[16]:
```
params1 = np.array([[11, 0.9, 3, 0.1],
                    [11, 0.9, 5, 0.1],
                    [11, 0.9, 7, 0.1],
                    [11, 0.9, 9, 0.1]])

params2 = np.array([[11, 0.3, 3, 0.1],
                    [11, 0.3, 5, 0.1],
                    [11, 0.3, 7, 0.1],
                    [11, 0.3, 9, 0.1]])

fig, axs = plt.subplots(1,2, figsize=(8,4))

multi_model_plot(agn,
                 params1,
                 cmap='Greens',
                 labels=[r'$\tau_{9.7} = %.1f$' % p[2] for p in params1],
                 ax=axs[0]
                 )
```

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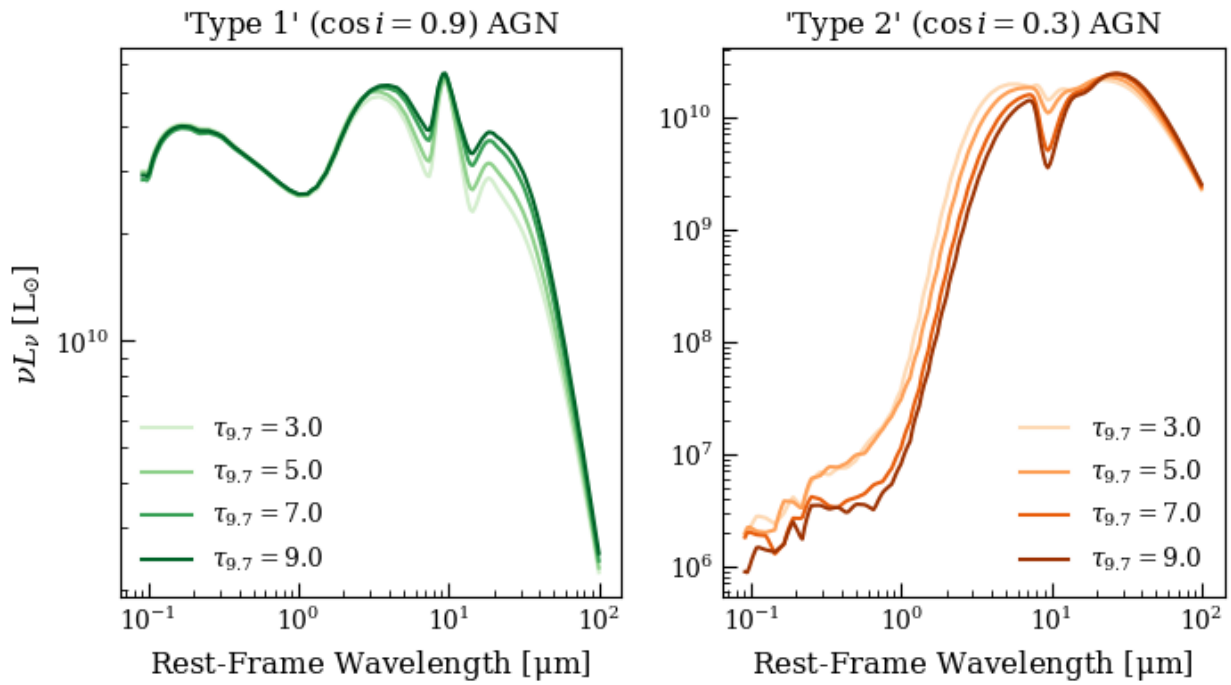
```
axs[0].set_title(r"'Type 1' ($\cos i = 0.9$) AGN")

multi_model_plot(agn,
                 params2,
                 cmap='Oranges',
                 labels=[r'$\tau_{9.7} = %.1f$' % p[2] for p in params2],
                 ax=axs[1]
                 )
axs[1].set_ylabel('')
axs[1].set_title(r"'Type 2' ($\cos i = 0.3$) AGN")
```

[16]:
```
Text(0.5, 1.0, "'Type 2' ($\\cos i = 0.3$) AGN")
```



Varying $\tau_V^{\rm pol}$ at Fixed Inclination

An optically-thick polar-dust obscurer can attenuate nearly all of the optical light from the face-on, 'Type 1' view. In the side-on, 'Type 2' view, we see none of that extra attenuation, but we do still see the isotropic, graybody dust re-emission of that attenuated optical light.

[17]:
```
params1 = np.array([[11, 0.9, 7, 0.0],
                    [11, 0.9, 7, 1],
                    [11, 0.9, 7, 2],
                    [11, 0.9, 7, 3]])

params2 = np.array([[11, 0.3, 7, 0.0],
                    [11, 0.3, 7, 1],
                    [11, 0.3, 7, 2],
                    [11, 0.3, 7, 3]])
```

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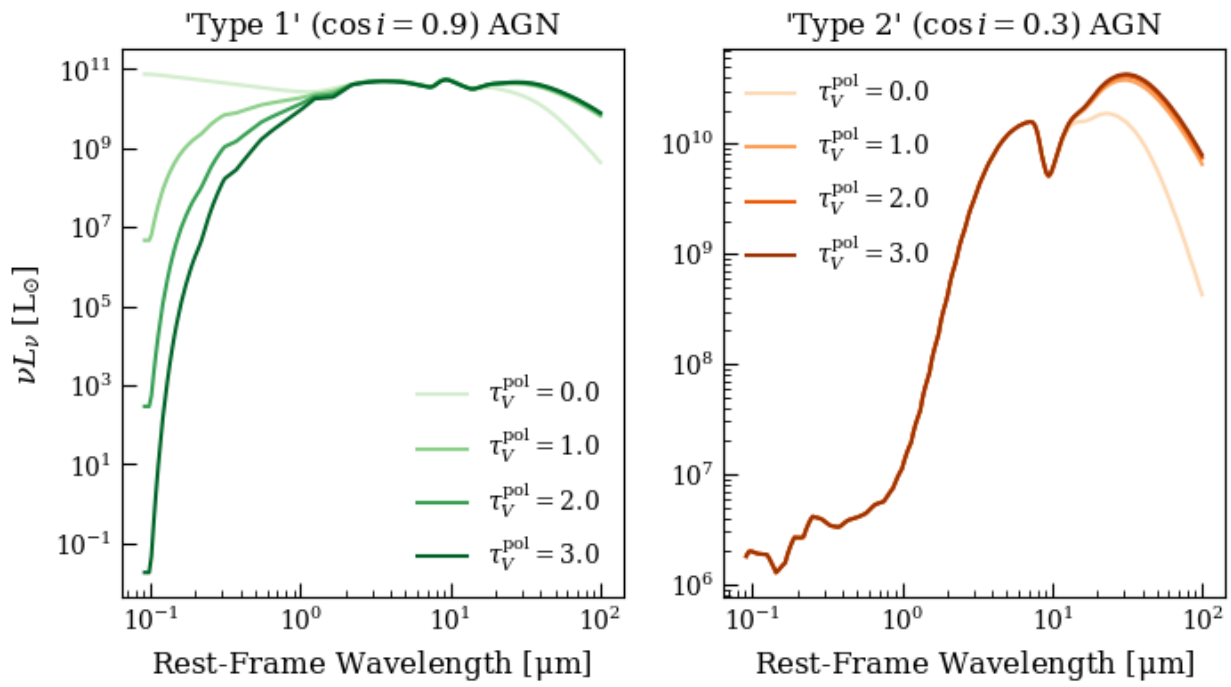
```
fig, axs = plt.subplots(1,2, figsize=(8,4))

multi_model_plot(agn,
                 params1,
                 cmap='Greens',
                 labels=[r'$\tau^{\rm pol}_{V} = %.1f$' % p[3] for p in params1],
                 ax=axs[0]
                 )

axs[0].set_title(r"'Type 1' ($\cos i = 0.9$) AGN")

multi_model_plot(agn,
                 params2,
                 cmap='Oranges',
                 labels=[r'$\tau^{\rm pol}_{V} = %.1f$' % p[3] for p in params2],
                 ax=axs[1]
                 )
axs[1].set_ylabel('')
axs[1].set_title(r"'Type 2' ($\cos i = 0.3$) AGN")
```

[17]:
```
Text(0.5, 1.0, "'Type 2' ($\\cos i = 0.3$) AGN")
```



In principle the "polar dust extinction" does not need to make many assumptions about the physical location of the obscuring dust. With a few changes to the shape of the attenuation curve and the temperature of the re-emission we could use this component to flexibly model "extra" ISM attenuation of a Type 1 AGN. Options for doing this right now are limited but would not be super difficult to expand.

7.5.4 X-ray AGN Model

[12]:
```
filter_labels = ['XRAY_0.5_2.0_keV', 'XRAY_2.0_7.0_keV']
arf = Table.read('../photometry/cdfn_near_aimpoint.arf')

xray_model_pl = AGNPlaw(filter_labels,
                        arf,
                        np.array([1,1]),
                        0.0,
                        lum_dist=10)

xray_model_qso = Qsosed(filter_labels,
                        arf,
                        np.array([1,1]),
                        0.0,
                        lum_dist=10)
```

[13]:
```
xray_model_pl.print_params(verbose=True)
xray_model_qso.print_params(verbose=True)
```

```
============================
AGN-Plaw
============================
 Parameter   Lo  Hi                       Description
---------- ---- --- ---------------------------------
  PhoIndex -2.0 9.0                     Photon index
LR17_delta -inf inf Deviation from LR17 relationship.

Total parameters: 2

============================
QSOSED
============================
 Parameter   Lo   Hi                                Description
---------- ---- ---- ------------------------------------------
log_M_SMBH  5.0 10.0 log10 of the supermassive black hole mass
  log_mdot -1.5  0.3              log10 of the Eddington ratio

Total parameters: 2
```

While practically the deviation from the LR17 relationship can vary between plus and minus infinity, in practice one should probably set it to follow a uniform prior between say, 2 sigma of the scatter in the relationship (or to a normal prior having the scatter), unless one anticipates having e.g. an "X-ray weak" source and wants to fit for delta in an unbiased way.

Because the normalization of the power law model is set by the overall normalization of the UV-IR AGN model, the model functions (`get_model_lnu_hires`, `get_model_lnu`, etc.) need to take the UV-IR model and its parameters as inputs. This isn't something you need to worry about in practice if you're just using the Lightning interface.

[26]:
```
params1 = np.array([[1.4, 0.0],
                    [1.6, 0.0],
                    [1.8, 0.0]])
```

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```
params2 = np.array([[1.8, 0.0],
                    [1.8, 0.3],
                    [1.8,-0.3]])

agn_params = np.array([[11.0, 0.6, 7.0, 0.1],
                       [11.0, 0.6, 7.0, 0.1],
                       [11.0, 0.6, 7.0, 0.1]])



lnu_pl1, _ = xray_model_pl.get_model_lnu_hires(params1,
                                               agn,
                                               agn_params)

lnu_pl2, _ = xray_model_pl.get_model_lnu_hires(params2,
                                               agn,
                                               agn_params)


fig, axs = plt.subplots(1,2, figsize=(8,4))

cm1 = mpl.colormaps['Greens']
colors1 = cm1(np.linspace(0.2, 0.9, 3))

cm2 = mpl.colormaps['Oranges']
colors2 = cm2(np.linspace(0.2, 0.9, 3))

for i in range(3):

    axs[0].plot(xray_model_pl.energ_grid_rest,
                xray_model_pl.nu_grid_obs * lnu_pl1[i,:],
                color=colors1[i],
                label=r'$\Gamma = %.1f$' % (params1[i,0]))

    axs[1].plot(xray_model_pl.energ_grid_rest,
                xray_model_pl.nu_grid_obs * lnu_pl2[i,:],
                color=colors2[i],
                label=r'$\delta = %.1f$' % (params2[i,1]))


axs[0].set_xscale('log')
axs[1].set_xscale('log')
axs[0].set_xlim(1e-1, 300)
axs[1].set_xlim(1e-1, 300)

axs[0].set_yscale('log')
axs[1].set_yscale('log')
axs[0].set_ylim(1e8, 3e10)
axs[1].set_ylim(1e8, 3e10)


axs[0].legend(loc='lower right')
```

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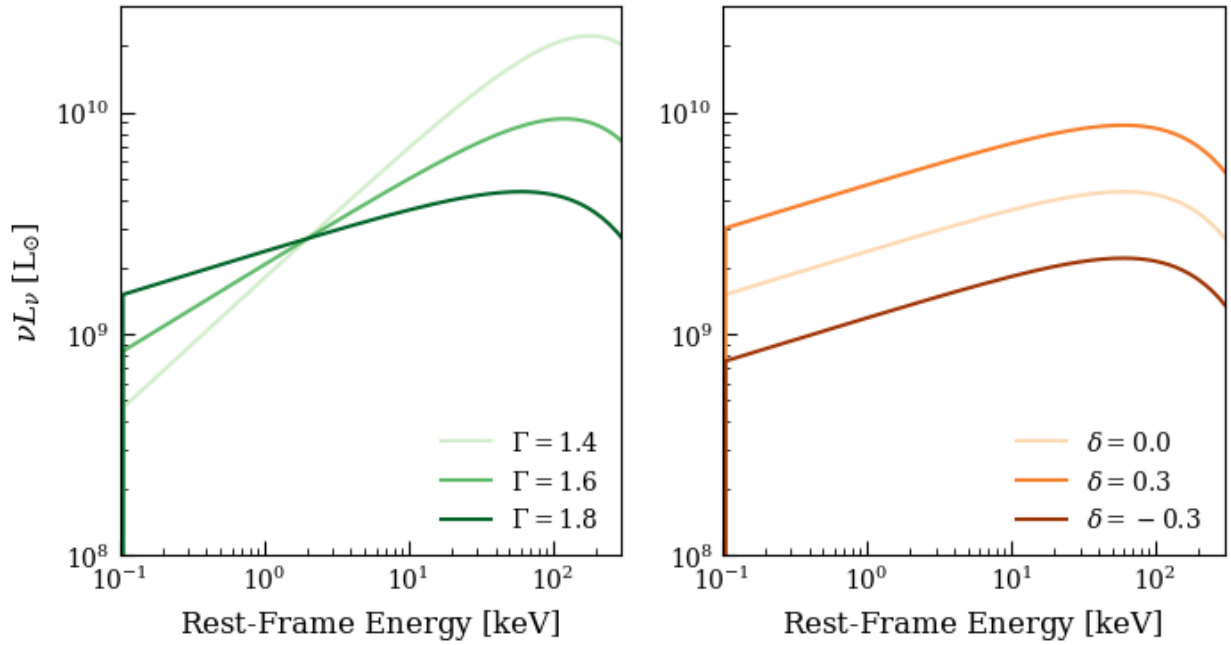
```
axs[1].legend(loc='lower right')

axs[0].set_xlabel(r'Rest-Frame Energy [$\rm keV$]')
axs[1].set_xlabel(r'Rest-Frame Energy [$\rm keV$]')
axs[0].set_ylabel(r'$\nu L_{\nu}\ [\rm L_{\odot}]$')
```

[26]:
```
Text(0, 0.5, '$\\nu L_{\\nu}\\ [\\rm L_{\\odot}]$')
```



It's a power law. The luminosity parameter is fixed at 10^{11} $L_\odot$ here. Note that since the LR17 relationship is between the intrinsic 2500 Angstrom luminosity and 2 keV luminosity, the inclination angle doesn't factor in here. While this ignores any X-ray anisotropy (see discussions of such in the XCigale docs, for example) the effects of anisotropy would be swamped by the δ parameter.

Now, an important distinction: since the QSOSED model *is not* normalized by the UV-IR model, it doesn't take the UV-IR model or its parameters as inputs.

[37]:
```
params1 = np.array([[6.0, -1.0],
                    [7.0, -1.0],
                    [8.0, -1.0],
                    [9.0, -1.0],
                    [10.0, -1.0]])

params2 = np.array([[8.0, -1.3],
                    [8.0, -1.0],
                    [8.0, -0.6],
                    [8.0, -0.3],
                    [8.0,  0.0]])

# agn_params = np.array([[11.0, 0.6, 7.0, 0.1],
#                        [11.0, 0.6, 7.0, 0.1],
#                        [11.0, 0.6, 7.0, 0.1]])
```

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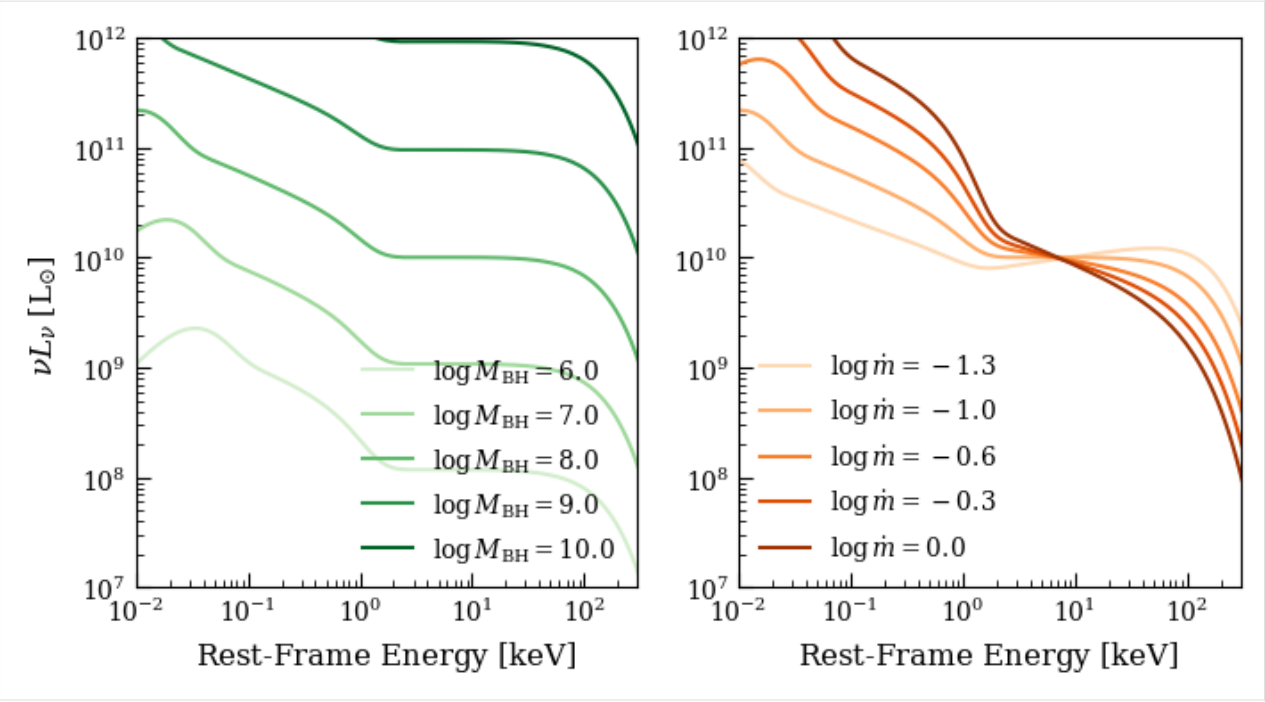
```
lnu_pl1, _ = xray_model_qso.get_model_lnu_hires(params1)

lnu_pl2, _ = xray_model_qso.get_model_lnu_hires(params2)


fig, axs = plt.subplots(1,2, figsize=(8,4))

cm1 = mpl.colormaps['Greens']
colors1 = cm1(np.linspace(0.2, 0.9, 5))

cm2 = mpl.colormaps['Oranges']
colors2 = cm2(np.linspace(0.2, 0.9, 5))

for i in range(5):

    axs[0].plot(xray_model_qso.energ_grid_rest,
                xray_model_qso.nu_grid_obs * lnu_pl1[i,:],
                color=colors1[i],
                label=r'$\log M_{\rm BH} = %.1f$' % (params1[i,0]))

    axs[1].plot(xray_model_qso.energ_grid_rest,
                xray_model_qso.nu_grid_obs * lnu_pl2[i,:],
                color=colors2[i],
                label=r'$\log \dot m = %.1f$' % (params2[i,1]))


axs[0].set_xscale('log')
axs[1].set_xscale('log')
axs[0].set_xlim(1e-2, 300)
axs[1].set_xlim(1e-2, 300)

axs[0].set_yscale('log')
axs[1].set_yscale('log')
axs[0].set_ylim(1e7, 1e12)
axs[1].set_ylim(1e7, 1e12)


axs[0].legend(loc='lower right')
axs[1].legend(loc='lower left')

axs[0].set_xlabel(r'Rest-Frame Energy [$\rm keV$]')
axs[1].set_xlabel(r'Rest-Frame Energy [$\rm keV$]')
axs[0].set_ylabel(r'$\nu L_{\nu}\ [\rm L_{\odot}]$')
```

[37]:
```
Text(0, 0.5, '$\\nu L_{\\nu}\\ [\\rm L_{\\odot}]$')
```



There's significantly more structure to the model, since it is a physical model – you can see the bump from the disk component at low energies, with a multi-temperature comptonized spectrum at higher energies. The model cuts off at slightly lower energies than the power law (which has an exponential cutoff at 300 keV).

It's worth looking at the X-ray AGN models in context with the UV-IR models, as well. The easiest way to do this is to use the main Lightning interface, and to just set all the SFH coefficients to 0 such that we a pure AGN model - note that this is an easy way to fit a pure AGN model to your data, if you so choose.

[70]:
```
from lightning import Lightning
import astropy.constants as const
import astropy.units as u

hc_um = (const.c * const.h).to(u.micron * u.keV).value
lam_05 = hc_um / 0.5
lam_70 = hc_um / 7.0
xray_wave_grid = np.logspace(np.log10(lam_70), np.log10(lam_05), 200) / (1 + redshift)

lgh_pl = Lightning(filter_labels, lum_dist=10,
                   agn_emission=True,
                   agn_polar_dust=True,
                   dust_emission=False,
                   atten_type='Calzetti',
                   xray_agn_emission='AGN-Plaw',
                   xray_arf=arf,
                   xray_mode='counts',
                   xray_wave_grid=xray_wave_grid,
                   xray_exposure=np.array([1,1]))

lgh_qso = Lightning(filter_labels, lum_dist=10,
                   agn_emission=True,
                   agn_polar_dust=True,
```

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```
                    dust_emission=False,
                    atten_type='Calzetti',
                    xray_agn_emission='QSOSED',
                    xray_arf=arf,
                    xray_mode='counts',
                    xray_wave_grid=xray_wave_grid,
                    xray_exposure=np.array([1,1]))
```

[71]:
```
lgh_pl.print_params(verbose=True)
print()
lgh_qso.print_params(verbose=True)
```

```
============================
Piecewise-Constant
============================
Parameter  Lo  Hi              Description
--------- --- --- ------------------------
    psi_1 0.0 inf SFR in stellar age bin 1
    psi_2 0.0 inf SFR in stellar age bin 2
    psi_3 0.0 inf SFR in stellar age bin 3
    psi_4 0.0 inf SFR in stellar age bin 4
    psi_5 0.0 inf SFR in stellar age bin 5

============================
Pegase-Stellar
============================
Parameter    Lo  Hi                                      Description
--------- ----- --- -------------------------------------------------
     Zmet 0.001 0.1 Metallicity (mass fraction, where solar = 0.020)

============================
Calzetti
============================
     Parameter  Lo  Hi                      Description
-------------- --- --- --------------------------------
calz_tauV_diff 0.0 inf Optical depth of the diffuse ISM

============================
SKIRTOR-AGN
============================
        Parameter Lo Hi                                       Description
----------------- -- -- -------------------------------------------------
SKIRTOR_log_L_AGN  6 15    Integrated luminosity of the model in log Lsun
 SKIRTOR_cosi_AGN  0  1    Cosine of the inclination to the line of sight
   SKIRTOR_tau_97  3 11 Edge-on optical depth of the torus at 9.7 microns
  polar_dust_tauV  0  3 V-band optical depth of the polar dust extinction

============================
AGN-Plaw
============================
 Parameter   Lo  Hi                       Description
```

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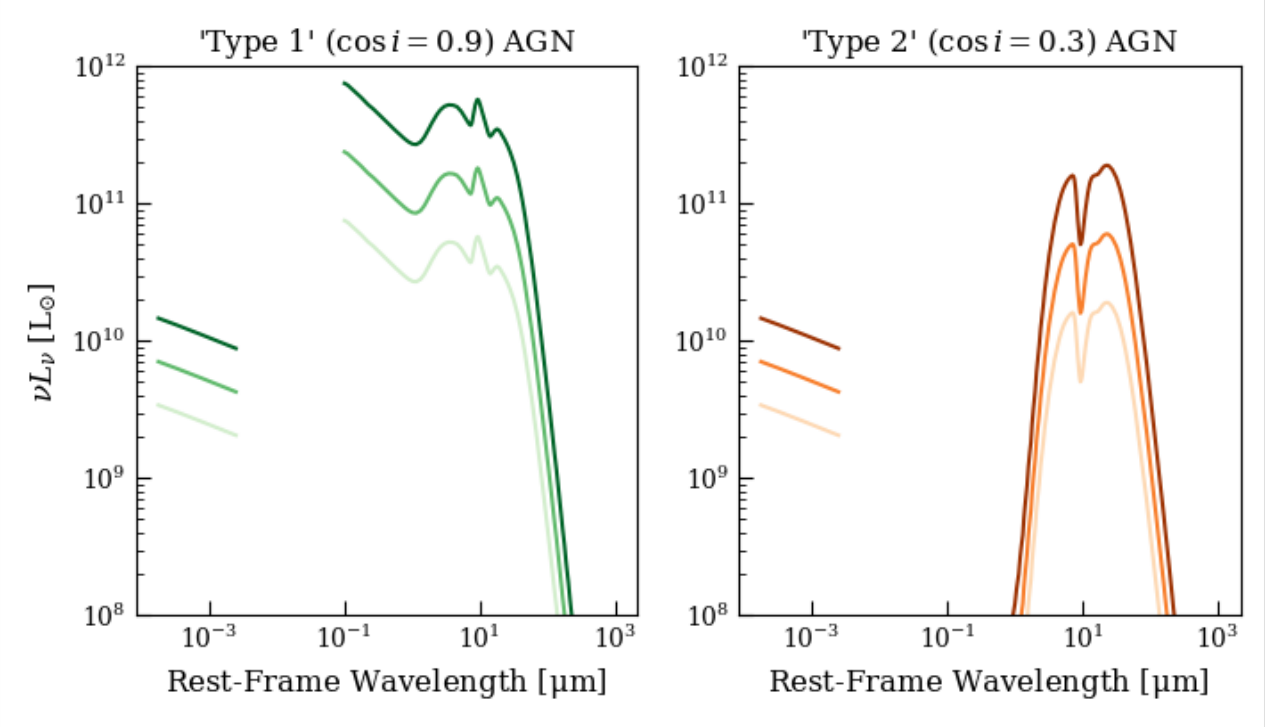
```
---------- ---- --- ---------------------------------
  PhoIndex -2.0 9.0                      Photon index
LR17_delta -inf inf Deviation from LR17 relationship.

Total parameters: 13


============================
Piecewise-Constant
============================
Parameter  Lo  Hi              Description
--------- --- --- ----------------------
    psi_1 0.0 inf SFR in stellar age bin 1
    psi_2 0.0 inf SFR in stellar age bin 2
    psi_3 0.0 inf SFR in stellar age bin 3
    psi_4 0.0 inf SFR in stellar age bin 4
    psi_5 0.0 inf SFR in stellar age bin 5

============================
Pegase-Stellar
============================
Parameter    Lo  Hi                                      Description
--------- ----- --- -------------------------------------------------
     Zmet 0.001 0.1 Metallicity (mass fraction, where solar = 0.020)

============================
Calzetti
============================
     Parameter  Lo  Hi                      Description
------------- --- --- --------------------------------
calz_tauV_diff 0.0 inf Optical depth of the diffuse ISM

============================
SKIRTOR-AGN
============================
        Parameter Lo Hi                                        Description
---------------- -- -- -------------------------------------------------
SKIRTOR_log_L_AGN  6 15    Integrated luminosity of the model in log Lsun
 SKIRTOR_cosi_AGN  0  1    Cosine of the inclination to the line of sight
   SKIRTOR_tau_97  3 11 Edge-on optical depth of the torus at 9.7 microns
  polar_dust_tauV  0  3 V-band optical depth of the polar dust extinction

============================
QSOSED
============================
 Parameter   Lo   Hi                                Description
---------- ---- ---- ----------------------------------------
log_M_SMBH  5.0 10.0 log10 of the supermassive black hole mass
  log_mdot -1.5  0.3              log10 of the Eddington ratio

Total parameters: 13
```

[68]:
```
params = np.array([[0, 0, 0, 0, 0, 0.02, 0.0, 11, 0.9, 7, 0.0, 1.8, 0.0],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 11.5, 0.9, 7, 0.0, 1.8, 0.0],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 12.0, 0.9, 7, 0.0, 1.8, 0.0]])

lnu, _ = lgh_pl.get_model_lnu_hires(params)
lnu_x, _ = lgh_pl.get_xray_model_lnu_hires(params)

cm1 = mpl.colormaps['Greens']
colors1 = cm1(np.linspace(0.2, 0.9, 3))

fig, axs = plt.subplots(1,2, figsize=(8,4))

for i in range(3):
    axs[0].plot(lgh_pl.wave_grid_rest, lgh_pl.nu_grid_obs * lnu[i,:], color=colors1[i])
    axs[0].plot(lgh_pl.xray_wave_grid_rest, lgh_pl.xray_nu_grid_obs * lnu_x[i,:],␣
↪color=colors1[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e8, 1e12)

params = np.array([[0, 0, 0, 0, 0, 0.02, 0.0, 11, 0.3, 7, 0.0, 1.8, 0.0],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 11.5, 0.3, 7, 0.0, 1.8, 0.0],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 12.0, 0.3, 7, 0.0, 1.8, 0.0]])

lnu, _ = lgh_pl.get_model_lnu_hires(params)
lnu_x, _ = lgh_pl.get_xray_model_lnu_hires(params)

cm2 = mpl.colormaps['Oranges']
colors2 = cm2(np.linspace(0.2, 0.9, 3))

for i in range(3):
    axs[1].plot(lgh_pl.wave_grid_rest, lgh_pl.nu_grid_obs * lnu[i,:], color=colors2[i])
    axs[1].plot(lgh_pl.xray_wave_grid_rest, lgh_pl.xray_nu_grid_obs * lnu_x[i,:],␣
↪color=colors2[i])

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e8, 1e12)


axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_{\nu}\ [\rm L_{\odot}]$')
axs[0].set_title(r"'Type 1' ($\cos i = 0.9$) AGN")
axs[1].set_ylabel('')
axs[1].set_title(r"'Type 2' ($\cos i = 0.3$) AGN")
```

[68]:
```
Text(0.5, 1.0, "'Type 2' ($\\cos i = 0.3$) AGN")
```



As mentioned above, the definition of our model is such that the Type 1 and Type 2 viewing angles produce the same X-ray spectrum: the X-ray spectrum is isotropic.

[75]:
```
params = np.array([[0, 0, 0, 0, 0, 0.02, 0.0, 11.0, 0.9, 7, 0.0, 7.5, -1.3],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 11.0, 0.9, 7, 0.0, 7.5, -1.0],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 11.0, 0.9, 7, 0.0, 7.5, -0.6]])

lnu, _ = lgh_qso.get_model_lnu_hires(params)
lnu_x, _ = lgh_qso.get_xray_model_lnu_hires(params)

cm1 = mpl.colormaps['Greens']
colors1 = cm1(np.linspace(0.2, 0.9, 3))

fig, axs = plt.subplots(1,2, figsize=(8,4))

for i in range(3):
    axs[0].plot(lgh_qso.wave_grid_rest, lgh_qso.nu_grid_obs * lnu[i,:], color=colors1[i])
    axs[0].plot(lgh_qso.xray_wave_grid_rest, lgh_qso.xray_nu_grid_obs * lnu_x[i,:],␣
↪color=colors1[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_ylim(1e8, 1e12)

params = np.array([[0, 0, 0, 0, 0, 0.02, 0.0, 11.0, 0.3, 7, 0.0, 7.5, -1.3],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 11.0, 0.3, 7, 0.0, 7.5, -1.0],
                   [0, 0, 0, 0, 0, 0.02, 0.0, 11.0, 0.3, 7, 0.0, 7.5, -0.6]])

lnu, _ = lgh_qso.get_model_lnu_hires(params)
```

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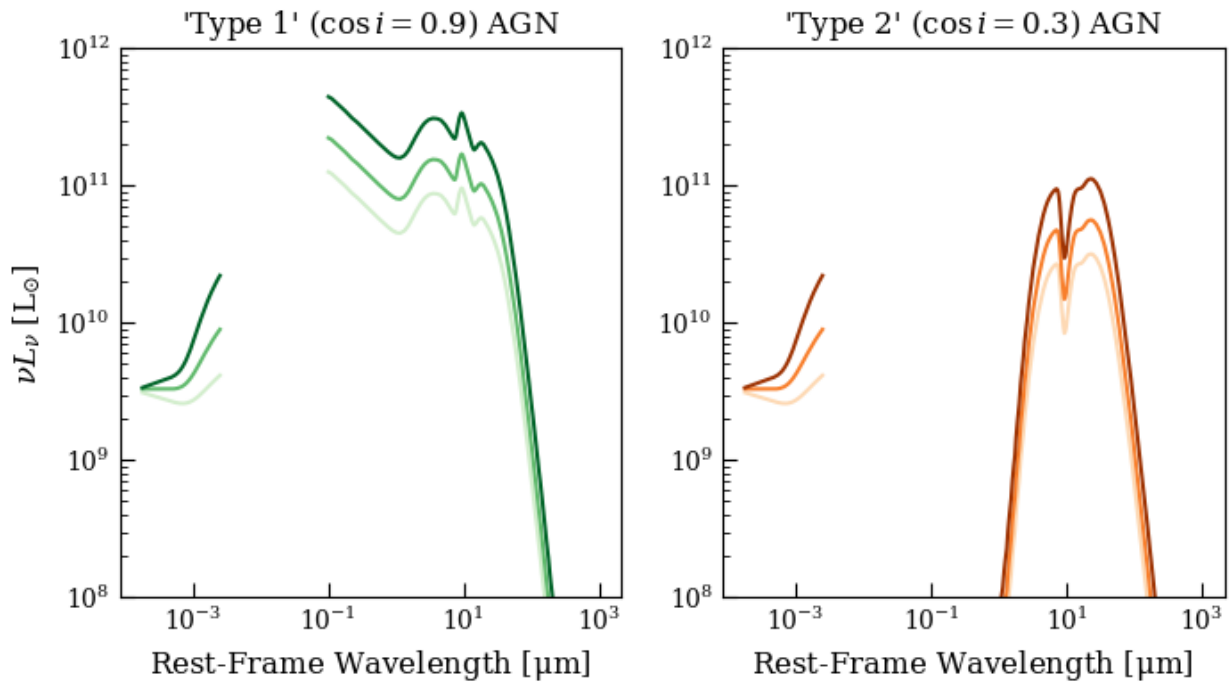
```
lnu_x, _ = lgh_qso.get_xray_model_lnu_hires(params)

cm2 = mpl.colormaps['Oranges']
colors2 = cm2(np.linspace(0.2, 0.9, 3))

for i in range(3):
    axs[1].plot(lgh_qso.wave_grid_rest, lgh_qso.nu_grid_obs * lnu[i,:], color=colors2[i])
    axs[1].plot(lgh_qso.xray_wave_grid_rest, lgh_qso.xray_nu_grid_obs * lnu_x[i,:],␣
↪color=colors2[i])

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_ylim(1e8, 1e12)


axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$\nu L_{\nu}\ [\rm L_{\odot}]$')
axs[0].set_title(r"'Type 1' ($\cos i = 0.9$) AGN")
axs[1].set_ylabel('')
axs[1].set_title(r"'Type 2' ($\cos i = 0.3$) AGN")
```

[75]:
```
Text(0.5, 1.0, "'Type 2' ($\\cos i = 0.3$) AGN")
```



At fixed mass, increasing the Eddington ratio increases the overall luminosity of the AGN model. Again, the X-ray spectrum is isotropic. We can see also here that one of the weaknesses of our implementation of this model is that we can really only produce a pretty narrow range of spectral slopes (compared to the power law model, which is flexible by definition) given the narrow range of Eddington ratios available to the model.

7.6 Dust Attenuation and Emission

A fundamental assumption of our normal galaxy (i.e., non AGN) modeling in `Lightning` is energy balance: the optical power from starlight attenuated by ISM dust is re-radiated in the infrared. As such we present the dust attenuation and emission models side by side here.

7.6.1 Imports

[1]:
```
import numpy as np
from scipy.integrate import trapz

from lightning import Lightning
from lightning.attenuation import CalzettiAtten, ModifiedCalzettiAtten, SMC
from lightning.dust import Graybody, DL07Dust

import matplotlib.pyplot as plt
import matplotlib as mpl
plt.style.use('lightning.plots.style.lightning-serif')
%matplotlib inline
```

7.6.2 Attenuation

`plightning` currently contains three attenuation options: Calzetti+(2000), "Modified Calzetti" (Noll+2009, including variable UV slope and a 2175 Å bump), and the SMC attenuation curve (Gordon+2003). Adding tabulated attenuation curves is pretty trivial (see `lightning.dust.TabulatedAtten`; the SMC curve is an instance of this class). The Doore+(2021) inclination-dependent attenuation curve is coming soon, pending some more testing of computational enhancements I implemented that might not actually be improvements.

[2]:
```
wave = np.logspace(np.log10(0.0912),
                   np.log10(5),
                   200)

calz = CalzettiAtten(wave)
modcalz = ModifiedCalzettiAtten(wave)
smc = SMC(wave)

calz.print_params(verbose=True)
modcalz.print_params(verbose=True)
smc.print_params(verbose=True)
```

```
============================
Calzetti
============================
     Parameter  Lo  Hi                       Description
-------------- --- --- -------------------------------
calz_tauV_diff 0.0 inf Optical depth of the diffuse ISM

Total parameters: 1

============================
```

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```
Modified-Calzetti
============================
      Parameter   Lo                 Hi                                                 ␣
↪                              Description
-------------- ---- ------------------ ---------------------------------------------------
↪---------------------------------------
mcalz_tauV_diff  0.0                inf                                                ␣
↪         Optical depth of the diffuse ISM
    mcalz_delta -inf 0.4473684210526316 Deviation from the Calzetti+2000 UV power law␣
↪slope (Upper limit set by requiring Eb >= 0)
  mcalz_tauV_BC  0.0                inf                                  Optical depth␣
↪of the birth cloud in star forming regions

Total parameters: 3

============================
smc
============================
    Parameter  Lo       Hi                      Description
------------ --- -------- -------------------------------
smc_tauV_diff 0.0 100000.0 Optical depth of the diffuse ISM

Total parameters: 1
```

7.6.3 SMC and Calzetti

[3]:
```
fig, axs = plt.subplots(1,3, figsize=(12,4))
plt.subplots_adjust(wspace=0.3)

tauV_arr = np.linspace(0, 1.5, 6).reshape(-1, 1)
Nmod = len(tauV_arr)

cm_calz = mpl.colormaps['Oranges']
colors_calz = cm_calz(np.linspace(0.2, 0.9, Nmod))

cm_smc = mpl.colormaps['Greens']
colors_smc = cm_smc(np.linspace(0.2, 0.9, Nmod))

calz_models = calz.evaluate(tauV_arr)
smc_models = smc.evaluate(tauV_arr)

for i in np.arange(Nmod):
    axs[0].plot(wave, calz_models[i,:], color=colors_calz[i])
    axs[1].plot(wave, smc_models[i,:], color=colors_smc[i])
    axs[2].plot(wave, calz_models[i,:], color=colors_calz[i])
    axs[2].plot(wave, smc_models[i,:], color=colors_smc[i])

axs[0].set_xscale('log')
axs[0].set_yscale('log')
#axs[0].set_ylim(2e6, 1e11)
```

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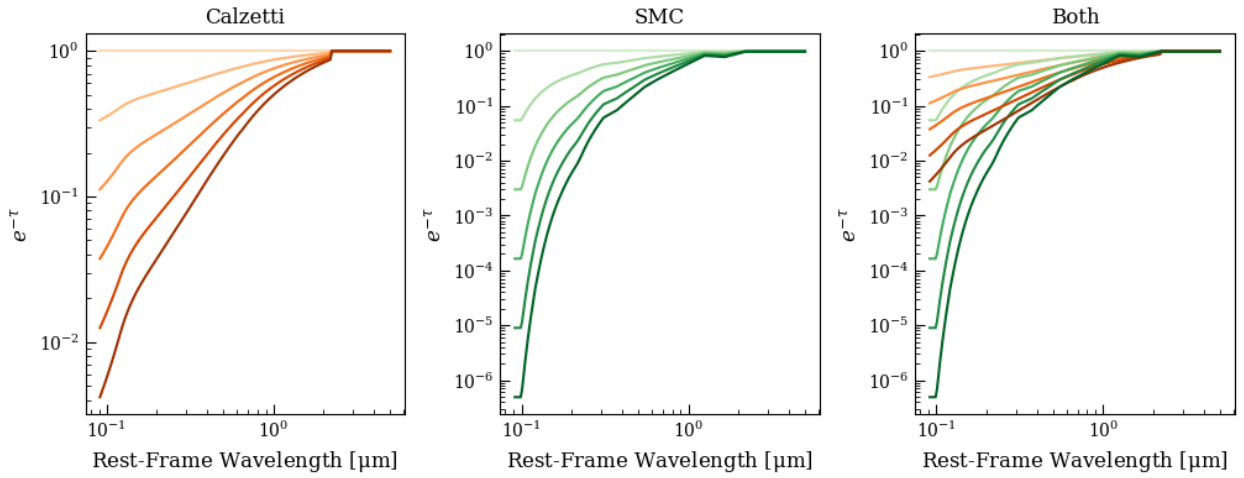
```
axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$e^{- \tau}$')
axs[0].set_title('Calzetti')

axs[1].set_xscale('log')
axs[1].set_yscale('log')

axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_ylabel(r'$e^{- \tau}$')
axs[1].set_title('SMC')

axs[2].set_xscale('log')
axs[2].set_yscale('log')

axs[2].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[2].set_ylabel(r'$e^{- \tau}$')
axs[2].set_title('Both')
```

[3]:
```
Text(0.5, 1.0, 'Both')
```



The SMC curve is steeper at UV wavelengths for the same τ_V. It's used as the default curve for the AGN polar dust model.

7.6.4 Modified Calzetti

The main parameters here are the $V-$band optical depth (as above) and δ the deviation of the UV slope from the Calzetti value. The model also ostensibly allows for extra attenuation for young stars that have not yet blown away their birth cloud ($\tau_{V,\mathrm{BC}}$) but this is not currently implemented, so that parameter doesn't do anything. Working on coming up with a solution I like for flexibly allowing differential attenuation based on stellar age (this is also an issue that affects the Doore+2021 model).

[4]:
```
fig, axs = plt.subplots(figsize=(4,4))
plt.subplots_adjust(wspace=0.3)

param_arr = np.array([[0.1, 0.4, 0.0],
```

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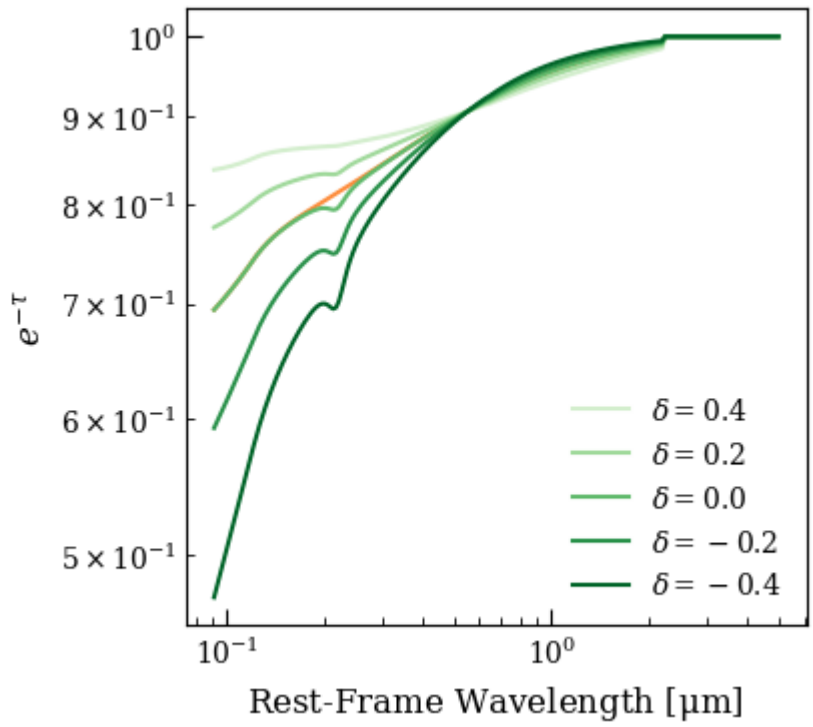
```
                        [0.1, 0.2, 0.0],
                        [0.1, 0.0, 0.0],
                        [0.1, -0.2, 0.0],
                        [0.1, -0.4, 0.0]])

Nmod = param_arr.shape[0]

cm_calz = mpl.colormaps['Oranges']
color_calz = cm_calz(0.5)

cm_modcalz = mpl.colormaps['Greens']
colors_modcalz = cm_smc(np.linspace(0.2, 0.9, Nmod))

calz_models = calz.evaluate(param_arr[:,0])
modcalz_models = modcalz.evaluate(param_arr)

axs.plot(wave, calz_models[0,:], color=color_calz)

for i in np.arange(Nmod):
    axs.plot(wave, modcalz_models[i,:], color=colors_modcalz[i], label=r'$\delta = %.1f$
↪' % (param_arr[i,1]))

axs.set_xscale('log')
axs.set_yscale('log')

axs.set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs.set_ylabel(r'$e^{- \tau}$')
axs.legend(loc='lower right')
```

[4]:
```
<matplotlib.legend.Legend at 0x3218ba910>
```



The modified Calzetti model is in green, where lighter → darker colors indicate δ changing from positive to negative. The strength of the 2175 Å feature is tied to the UV slope parameter, δ. Note that the modified Calzetti model is not exactly equal to the Calzetti model with the same τ_V when $\delta = 0$, due to the presence of the 2175 Å absorption feature.

7.6.5 Emission Models

[5]:
```
wave_grid = np.logspace(np.log10(1),
                        np.log10(1000),
                        200)
filter_labels = ['IRAC_CH1', 'IRAC_CH2', 'IRAC_CH3', 'IRAC_CH4',
                 'MIPS_CH1',
                 'PACS_green', 'PACS_red',
                 'SPIRE_250', 'SPIRE_350', 'SPIRE_500']

redshift = 0.0

dl07 = DL07Dust(filter_labels,
                redshift=redshift,
                wave_grid=wave_grid)
gb = Graybody(filter_labels,
              redshift=redshift,
              wave_grid=wave_grid)

dl07.print_params(verbose=True)
gb.print_params(verbose=True)
```

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```
============================
DL07-Dust
============================
      Parameter     Lo       Hi                                                  ␣
↪   Description
--------------- ------ -------- ------------------------------------------------------------
↪--------------
dl07_dust_alpha  -10.0      4.0                  Radiation field intensity distribution␣
↪power law index
dl07_dust_U_min    0.1     25.0                                       Radiation field␣
↪minimum intensity
dl07_dust_U_max 1000.0 300000.0                                       Radiation field␣
↪maximum intensity
dl07_dust_gamma    0.0      1.0 Fraction of dust mass exposed to radiation field␣
↪intensity distribution
dl07_dust_q_PAH 0.0047   0.0458                            Fraction of dust mass␣
↪composed of PAH grains

Total parameters: 5

============================
GrayBody-Dust
============================
Parameter   Lo     Hi                      Description
--------- ---- ------ --------------------------------
  gb_lam0 10.0 1000.0 Wavelength of unit optical depth
  gb_beta  0.1    5.0    Optical depth power law index
     gb_T 10.0  100.0                 Dust temperature

Total parameters: 3
```

Draine and Li (2017)

The Draine and Li model carries around its own wavelength grid due to some artifact of how the models were constructed in IDL `Lightning`. I should aee an option to interpolate it to some other grid for consistency with every other model class…

[6]:
```
fig, axs = plt.subplots(1,3, figsize=(12,4))

var_umin = np.array([[2, 0.1, 3e5, 0.05, 0.02],
                     [2, 1, 3e5, 0.05, 0.02],
                     [2, 5, 3e5, 0.05, 0.02],
                     [2, 10, 3e5, 0.05, 0.02],
                     [2, 25, 3e5, 0.05, 0.02]])

var_gamma = np.array([[2, 1, 3e5, 0.05, 0.02],
                     [2, 1, 3e5, 0.1, 0.02],
                     [2, 1, 3e5, 0.5, 0.02],
                     [2, 1, 3e5, 0.75, 0.02],
                     [2, 1, 3e5, 1.0, 0.02]])
```

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```
var_qpah = np.array([[2, 1, 3e5, 0.05, 0.0047],
                     [2, 1, 3e5, 0.05, 0.01],
                     [2, 1, 3e5, 0.05, 0.02],
                     [2, 1, 3e5, 0.05, 0.03],
                     [2, 1, 3e5, 0.05, 0.0458]])

mod_var_umin, L_var_umin = dl07.get_model_lnu_hires(var_umin)
Lmod_var_umin, L_var_umin = dl07.get_model_lnu(var_umin)
mod_var_gamma, L_var_gamma = dl07.get_model_lnu_hires(var_gamma)
Lmod_var_gamma, L_var_gamma = dl07.get_model_lnu(var_gamma)
mod_var_qpah, L_var_qpah = dl07.get_model_lnu_hires(var_qpah)
Lmod_var_qpah, L_var_qpah = dl07.get_model_lnu(var_qpah)

Nmod = var_umin.shape[0]

cm_umin = mpl.colormaps['Oranges']
colors_umin = cm_umin(np.linspace(0.2, 0.9, Nmod))

cm_gamma = mpl.colormaps['Greens']
colors_gamma = cm_gamma(np.linspace(0.2, 0.9, Nmod))

cm_qpah = mpl.colormaps['Blues']
colors_qpah = cm_qpah(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    axs[0].plot(dl07.wave_grid_rest, dl07.nu_grid_rest * mod_var_umin[i,:] / L_var_
↪umin[i], color=colors_umin[i], label=r'$U_{\rm min} = %.1f$' % (var_umin[i,1]))
    axs[0].scatter(dl07.wave_obs, dl07.nu_obs * Lmod_var_umin[i,:] / L_var_umin[i],␣
↪color=colors_umin[i], marker='D')
    axs[1].plot(dl07.wave_grid_rest, dl07.nu_grid_rest * mod_var_gamma[i,:] / L_var_
↪gamma[i], color=colors_gamma[i], label=r'$\gamma = %.2f$' % (var_gamma[i,3]))
    axs[1].scatter(dl07.wave_obs, dl07.nu_obs * Lmod_var_gamma[i,:] / L_var_gamma[i],␣
↪color=colors_gamma[i], marker='D')
    axs[2].plot(dl07.wave_grid_rest, dl07.nu_grid_rest * mod_var_qpah[i,:] / L_var_
↪qpah[i], color=colors_qpah[i], label=r'$q_{\rm PAH} = %.4f$' % (var_qpah[i,4]))
    axs[2].scatter(dl07.wave_obs, dl07.nu_obs * Lmod_var_qpah[i,:] / L_var_qpah[i],␣
↪color=colors_qpah[i], marker='D')

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$L_\nu / L_{\rm IR}$ [a.u.]')
axs[0].set_ylim(1e-5, 1)
axs[0].legend(loc='lower left', frameon=True)
#axs[0].set_title(r'$U_{\rm min}=0.1\rightarrow25$')

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_yticklabels([])
axs[1].set_ylim(1e-5, 1)
```

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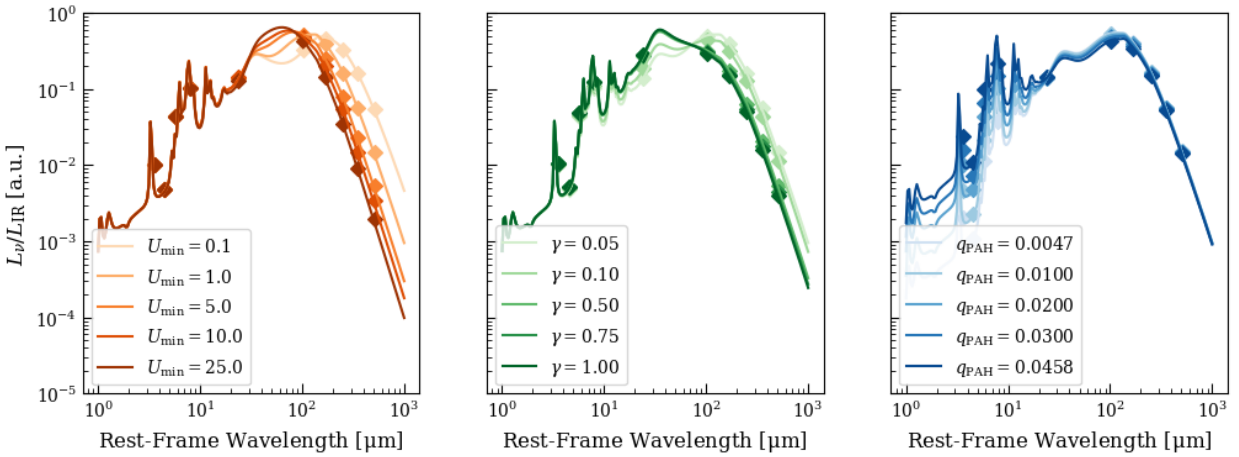
```
axs[1].legend(loc='lower left', frameon=True)
#axs[1].set_title(r'$\gamma=0.05\rightarrow1$')

axs[2].set_xscale('log')
axs[2].set_yscale('log')
axs[2].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[2].set_yticklabels([])
axs[2].set_ylim(1e-5, 1)
axs[2].legend(loc='lower left', frameon=True)
#axs[2].set_title(r'$q_{\rm PAH}=0.0047\rightarrow0.0458$')
```

[6]:
```
<matplotlib.legend.Legend at 0x32189b810>
```



In each of the above plots the changing parameter goes from lighter → darker lines. Note that in practice the normalization of the model is set by the attenuated power from starlight.

7.6.6 Graybody

This model is currently used in our modeling only to represent the re-emission component of the AGN polar dust model.

[7]:
```
fig, axs = plt.subplots(1,3, figsize=(12,4))

var_lam0 = np.array([[10, 1, 10],
                     [100, 1, 10],
                     [200, 1, 10],
                     [500, 1, 10],
                     [1000, 1, 10]])

var_beta = np.array([[100, 0.1, 10],
                     [100, 1, 10],
                     [100, 1.5, 10],
                     [100, 2, 10],
                     [100, 5, 10]])

var_temp = np.array([[100, 1, 10],
```

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```
                     [100, 1, 20],
                     [100, 1, 50],
                     [100, 1, 75],
                     [100, 1, 100]])

mod_var_lam0 = gb.get_model_lnu_hires(var_lam0)
mod_var_beta = gb.get_model_lnu_hires(var_beta)
mod_var_temp = gb.get_model_lnu_hires(var_temp)

Nmod = var_umin.shape[0]

cm_lam0 = mpl.colormaps['Oranges']
colors_lam0 = cm_lam0(np.linspace(0.2, 0.9, Nmod))

cm_beta = mpl.colormaps['Greens']
colors_beta = cm_beta(np.linspace(0.2, 0.9, Nmod))

cm_temp = mpl.colormaps['Blues']
colors_temp = cm_temp(np.linspace(0.2, 0.9, Nmod))

for i in np.arange(Nmod):

    axs[0].plot(gb.wave_grid_rest, gb.nu_grid_rest * mod_var_lam0[i,:], color=colors_
↪lam0[i], label=r'$\lambda_0 = %d$' % (var_lam0[i,0]))
    axs[1].plot(gb.wave_grid_rest, gb.nu_grid_rest * mod_var_beta[i,:], color=colors_
↪beta[i], label=r'$\beta = %.1f$' % (var_beta[i,1]))
    axs[2].plot(gb.wave_grid_rest, gb.nu_grid_rest * mod_var_temp[i,:], color=colors_
↪temp[i], label=r'$T = %d$' % (var_temp[i,2]))

axs[0].set_xscale('log')
axs[0].set_yscale('log')
axs[0].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[0].set_ylabel(r'$L_\nu / L_{\rm IR}$ [a.u.]')
axs[0].set_ylim(1e-5, 5)
axs[0].set_xlim(10, 1000)
#axs[0].set_title(r'$\lambda_{0}=10\rightarrow1000~\rm \mu m$')
axs[0].legend(loc='lower left', frameon=True)

axs[1].set_xscale('log')
axs[1].set_yscale('log')
axs[1].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[1].set_ylim(1e-5, 5)
axs[1].set_xlim(10, 1000)
#axs[1].set_title(r'$\beta=0.1\rightarrow5$')
axs[1].legend(loc='lower left', frameon=True)


axs[2].set_xscale('log')
axs[2].set_yscale('log')
axs[2].set_xlabel(r'Rest-Frame Wavelength [$\rm \mu m$]')
axs[2].set_ylim(1e-5, 5)
axs[2].set_xlim(10, 1000)
```

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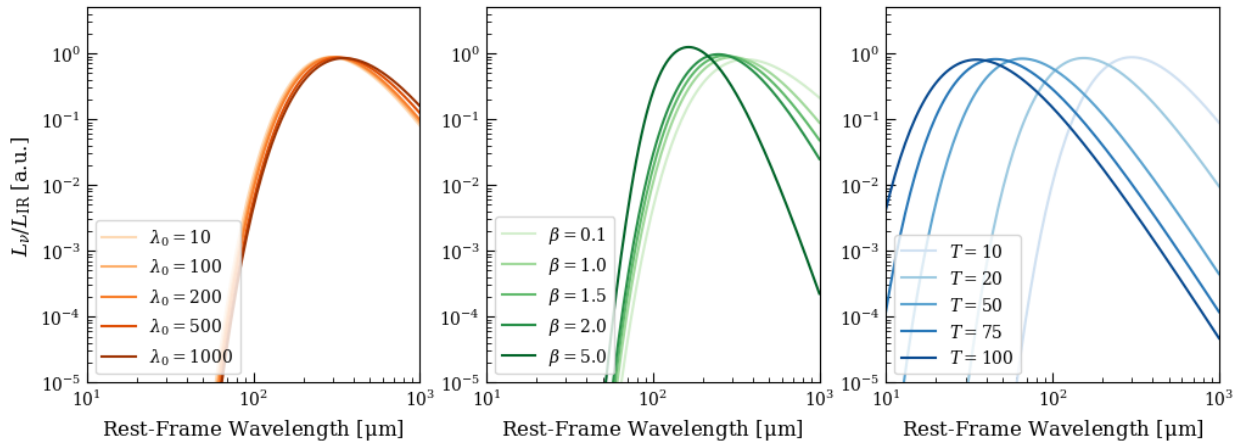
```
#axs[2].set_title(r'$T=10\rightarrow100~\rm K$')
axs[2].legend(loc='lower left', frameon=True)
```

```
/Users/eqm5663/Research/code/plightning/lightning/dust/gray.py:120: RuntimeWarning:␣
↪overflow encountered in exp
  (np.exp(hcoverk / (wave_g1um[None,:] * T[:,None])) - 1)
```

[7]:
```
<matplotlib.legend.Legend at 0x32339dc10>
```



Again, for energy balance the model should be normalized to the total attenuated power.

CHAPTER

EIGHT

NEBULAR EMISSION RECIPE

Our custom nebular emission models are single cloud models, using `Cloudy` simulations assuming:

- An open geometry
- $\log U \in [-4, -1.5]$
- Gas-phase metallicity equal to the stellar metallicity (i.e. the metallicity of the youngest stars)
- Two densities – $\log n_H = 2$ and $\log n_H = 3.5$.
- Constant pressure.

For each spectral template, Q_0 is effectively fixed, and thus varying $\log U$ is equivalent to varying R. We convert the line and continuum intensities produced by `Cloudy` back into luminosities by solving for the appropriate R given Q_0, $\log U$, and $\log n_H$.

We include the option to add dust grains inside the H II region, which we note produces the effect of extra attenuation and warm dust emission in the emitted continuum in addition to affecting the emitted line ratios.

CHAPTER

NINE

FILTER PROFILES

A full list of available filters in Lightning can be found [below](filter_table). All filters are in terms of the spectral response per energy (i.e., equal-energy).

9.1 Directory Structure

The `filters/` directory contains all the current filter profiles available in Lightning. The structure of the directory follows the pattern `filters/observatory/instrument/instrument_band.txt`. In the case of survey specific filters (e.g., 2MASS, SDSS, etc.), the pattern is changed to `filters/survey/survey_band.txt`. Examples for HST WFC3/F125W and 2MASS J band would be `filters/HST/WFC3/WFC3_F125W.txt` and `filters/2MASS/2MASS_J.txt`, respectively.

9.2 File Format

Each filter profile file in Lightning has been edited to a common format. The original source files can be found in the linked URLs in the table [below](filter_table). Each formatted filter profile file has two, space delimited columns giving the wavelength (in microns) and throughput function (normalized to the maximum value). The values in both columns are formatted using the FORTRAN (C) formatting code `E13.7` (`%13.7e`).

For example, the first several lines for the 2MASS J band are:

```
# wave[microns]    norm_trans
  1.0620000E+00    0.0000000E+00
  1.0660000E+00    4.0706800E-04
  1.0700000E+00    1.5429300E-03
  1.0750000E+00    2.6701300E-03
  1.0780000E+00    5.5064300E-03
```

9.3 Addition of New Filters

New filters can be added manually, by formatting them as above and placing them in a subdirectory of the `filters/` directory. Filters must then be added to `filters/filters.json`, where the key is the 'filter_label' which will be used to specify the filter in lightning, and the value is the relative path to the filter.

Note

Adding new filters will make your local git repository out of sync with the remote. It is currently recommended to make a `filters/user/` directory, which you back up before updating the code and replace after updating. Note that paths to your filters need not follow the exact formula as the built-in filters, as long as the path in `filters/filters.json` is correct.

9.4 List of Filters in Lightning

The below table gives a list of all the filters currently available in Lightning, with links to the source and the corresponding filter labels.

Note

Filter labels in the below table may not render correctly in the PDF version of this manual. Check `filters/filters.json` for consistency.

Table 1: Filters available

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
2MASS		J, H, Ks	*2MASS_J*, *2MASS_H*, *2MASS_Ks*
Akari	FIS	N60, WIDE-S, WIDE-L, N160	*FIS_N60*, *FIS_WIDE-S*, *FIS_WIDE-L*, *FIS_N160*
Akari	IRC	N2, N3, N4, S7, S9W, S11, L15, L18W, L24	*IRC_N2*, *IRC_N3*, *IRC_N4*, *IRC_S7*, *IRC_S9W*, *IRC_S11*, *IRC_L15*, *IRC_L18W*, *IRC_L24*
ALMA		band3, band4, band5, band6, band7, band8, band9, band10	*ALMA_band3*, *ALMA_band4*, *ALMA_band5*, *ALMA_band6*, *ALMA_band7*, *ALMA_band8*, *ALMA_band9*, *ALMA_band10*
APEX	LABOCA	LABOCA	*LABOCA_LABOCA*
APEX	SABOCA	SABOCA	*SABOCA_SABOCA*
Apache Point Observatory	Broad	B, V, R, I	*Broad_B*, *Broad_V*, *Broad_R*, *Broad_I*
Apache Point Observatory	FNAL	V, R	*FNAL_V*, *FNAL_R*
Apache Point Observatory	Gunn	g, r, i, z	*Gunn_g*, *Gunn_r*, *Gunn_i*, *Gunn_z*
Apache Point Observatory	Hodge	6563, 6585, 6607, 6629	*Hodge_6563*, *Hodge_6585*, *Hodge_6607*, *Hodge_6629*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Apache Point Observatory	York	5059, 5200, 5684, 5720, 5917, 6007, 6085, 6177, 6409, 6903, 6931, 7740, 8212, 8238, 8678, 9088	*York_5059*, *York_5200*, *York_5684*, *York_5720*, *York_5917*, *York_6007*, *York_6085*, *York_6177*, *York_6409*, *York_6903*, *York_6931*, *York_7740*, *York_8212*, *York_8238*, *York_8678*, *York_9088*
AstrosatUVIT	FUV	F148W, F148Wa, F154W, F169M, F172M	*FUV_F148W*, *FUV_F148Wa*, *FUV_F154W*, *FUV_F169M*, *FUV_F172M*
AstrosatUVIT	NUV	N219M, N242W, N245M, N263M, N279N	*NUV_N219M*, *NUV_N242W*, *NUV_N245M*, *NUV_N263M*, *NUV_N279N*
AstrosatUVIT	VIS	V347M, V391M, V420W, V435ND, V461W	*VIS_V347M*, *VIS_V391M*, *VIS_V420W*, *VIS_V435ND*, *VIS_V461W*
CFHT	CFH12k	B, Custom B, V, R, I, Zprime, HBeta off, HBeta on, OIII, HAlpha off, HAlpha on, TiO, CN, NB92	*CFH12k_B*, *CFH12k_Custom_B*, *CFH12k_V*, *CFH12k_R*, *CFH12k_I*, *CFH12k_Zprime*, *CFH12k_HBeta_off*, *CFH12k_HBeta_on*, *CFH12k_OIII*, *CFH12k_HAlpha_off*, *CFH12k_HAlpha_on*, *CFH12k_TiO*, *CFH12k_CN*, *CFH12k_NB92*
CFHT	MegaCam	U v1, U v3, G v1, G v3, R v1, R v3, I v1, I v2, I v3, Z v1, Z v3	*MegaCam_U_v1*, *MegaCam_U_v3*, *MegaCam_G_v1*, *MegaCam_G_v3*, *MegaCam_R_v1*, *MegaCam_R_v3*, *MegaCam_I_v1*, *MegaCam_I_v2*, *MegaCam_I_v3*, *MegaCam_Z_v1*, *MegaCam_Z_v3*
CFHT	MOCAM	B, V, CFHT V, R, Harris R, I	*MOCAM_B*, *MOCAM_V*, *MOCAM_CFHT_V*, *MOCAM_R*, *MOCAM_Harris_R*, *MOCAM_I*
CFHT	QUIRC	J, H, K, Kprime, Kshort, H+K, Hs, Hl, HeI, n1975, n2131, BrGamma, n2265, CO	*QUIRC_J*, *QUIRC_H*, *QUIRC_K*, *QUIRC_Kprime*, *QUIRC_Kshort*, *QUIRC_H+K*, *QUIRC_Hs*, *QUIRC_Hl*, *QUIRC_HeI*, *QUIRC_n1975*, *QUIRC_n2131*, *QUIRC_BrGamma*, *QUIRC_n2265*, *QUIRC_CO*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
CFHT	WIRCam	Y, J, J v2, H, H v2, Ks, Ks v2, K Cont, Low OH 2, Low OH 1, CH4 On, CH4 Off, H2, BrGamma	*WIRCam_Y*, *WIRCam_J*, *WIRCam_J_v2*, *WIRCam_H*, *WIRCam_H_v2*, *WIRCam_Ks*, *WIRCam_Ks_v2*, *WIRCam_K_Cont*, *WIRCam_Low_OH_2*, *WIRCam_Low_OH_1*, *WIRCam_CH4_On*, *WIRCam_CH4_Off*, *WIRCam_H2*, *WIRCam_BrGamma*
COBE	DIRBE	band1, band2, band3, band4, band5, band6, band7, band8, band9, band10	*DIRBE_band1*, *DIRBE_band2*, *DIRBE_band3*, *DIRBE_band4*, *DIRBE_band5*, *DIRBE_band6*, *DIRBE_band7*, *DIRBE_band8*, *DIRBE_band9*, *DIRBE_band10*
CTIO	ANDICAM	B, B YALO, V, R, R YALO, I, J, H, K	*ANDICAM_B*, *ANDICAM_B_YALO*, *ANDICAM_V* *ANDICAM_R*, *ANDICAM_R_YALO*, *ANDICAM_I*, *ANDICAM_J*, *ANDICAM_H*, *ANDICAM_K*
CTIO	DECam	g, r, i, z, Y	*DECam_g*, *DECam_r*, *DECam_i*, *DECam_z*, *DECam_Y*
CTIO	ISPI	Y 191A, Y 191B, Y 191C, I 81, J 183, J 186, J 192, J 40, J 82a, H 44, H 184, H 187, K 50, K 185, Ks 129, FeII 111, PAlpha 110, 203 134, HeI 135, CIV 136, H2 163, H2 89, H2 130, 214 164, 214w 131, 216 165, BrGamma 132, HeII 138, H2 125	*ISPI_Y_191A*, *ISPI_Y_191B*, *ISPI_Y_191C*, *ISPI_I_81*, *ISPI_J_183*, *ISPI_J_186*, *ISPI_J_192*, *ISPI_J_40*, *ISPI_J_82a*, *ISPI_H_44*, *ISPI_H_184*, *ISPI_H_187*, *ISPI_K_50*, *ISPI_K_185*, *ISPI_Ks_129*, *ISPI_FeII_111*, *ISPI_PAlpha_110*, *ISPI_203_134*, *ISPI_HeI_135*, *ISPI_CIV_136*, *ISPI_H2_163*, *ISPI_H2_89*, *ISPI_H2_130*, *ISPI_214_164*, *ISPI_214w_131*, *ISPI_216_165*, *ISPI_BrGamma_132*, *ISPI_HeII_138*, *ISPI_H2_125*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
CTIO	MOSAICII	U, B, Bj Tyson, V, V old, VR Stubbs, R, I, I Tyson, I old, u SDSS, g SDSS, r SDSS, i SDSS, z SDSS, C Wash, M Wash, D51, OII, OIII, Halpha, Halpha+80, SII	*MOSAICII_U*, *MOSAICII_B*, *MOSAICII_Bj_Tyson*, *MOSAICII_V*, *MOSAICII_V_old*, *MOSAICII_VR_Stubbs*, *MOSAICII_R*, *MOSAICII_I*, *MOSAICII_I_Tyson*, *MOSAICII_I_old*, *MOSAICII_u_SDSS*, *MOSAICII_g_SDSS*, *MOSAICII_r_SDSS*, *MOSAICII_i_SDSS*, *MOSAICII_z_SDSS*, *MOSAICII_C_Wash*, *MOSAICII_M_Wash*, *MOSAICII_D51*, *MOSAICII_OII*, *MOSAICII_OIII*, *MOSAICII_Halpha*, *MOSAICII_Halpha+80*, *MOSAICII_SII*
CTIO	SIO	U Bessel, B Bessel, V Bessel, R Bessel, I Bessel, u sdss, g sdss, r sdss, i sdss, z sdss, u Strom, v Strom, y Strom, HAlpha, SII, TiO, CN	*SIO_U_Bessel*, *SIO_B_Bessel*, *SIO_V_Bessel*, *SIO_R_Bessel*, *SIO_I_Bessel*, *SIO_u_sdss*, *SIO_g_sdss*, *SIO_r_sdss*, *SIO_i_sdss*, *SIO_z_sdss*, *SIO_u_Strom*, *SIO_v_Strom*, *SIO_y_Strom*, *SIO_HAlpha*, *SIO_SII*, *SIO_TiO*, *SIO_CN*
CTIO	Spartan	Y, J, H, K, HeI, FeII, Cont1, HeICIV, H2, Cont2, BrGamma, Cont3, CO	*Spartan_Y*, *Spartan_J*, *Spartan_H*, *Spartan_K*, *Spartan_HeI*, *Spartan_FeII*, *Spartan_Cont1*, *Spartan_HeICIV*, *Spartan_H2*, *Spartan_Cont2*, *Spartan_BrGamma*, *Spartan_Cont3*, *Spartan_CO*
CTIO	SPLUS	u, g, r, i, z, J0378, J0395, J0410, J0430, J0515, J0660, J0861	*SPLUS_u*, *SPLUS_g*, *SPLUS_r*, *SPLUS_i*, *SPLUS_z*, *SPLUS_J0378*, *SPLUS_J0395*, *SPLUS_J0410*, *SPLUS_J0430*, *SPLUS_J0515*, *SPLUS_J0660*, *SPLUS_J0861*
CTIO	Y4KCam	u, r, i, z, B, V, Rc, Ic	*Y4KCam_u*, *Y4KCam_r*, *Y4KCam_i*, *Y4KCam_z*, *Y4KCam_B*, *Y4KCam_V*, *Y4KCam_Rc*, *Y4KCam_Ic*
DENIS		I, J, Ks	*DENIS_I*, *DENIS_J*, *DENIS_Ks*
GAIA	DR2	DR2 G, Gbp, Grp	*DR2_G*, *DR2_Gbp*, *DR2_Grp*
GAIA	EDR3	EDR3 G, Gbp, Grp	*EDR3_G*, *EDR3_Gbp*, *EDR3_Grp*
GALEX		FUV, NUV	*GALEX_FUV*, *GALEX_NUV*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Gemini	AcqCam	U-South, B-South, V-North, V-South, R-North, R-South, I-North, I-South	*AcqCam_U_S*, *AcqCam_B_S*, *AcqCam_V_N*, *AcqCam_V_S*, *AcqCam_R_N*, *AcqCam_R_S*, *AcqCam_I_N*, *AcqCam_I_S*
Gemini	Alopeke-Zorro	u XSDSS, g XSDSS, r XSDSS, i XSDSS, z XSDSS, EO 466, EO 562, EO 716, EO 832, HAlpha	*Alopeke-Zorro_u_XSDSS*, *Alopeke-Zorro_g_XSDSS*, *Alopeke-Zorro_r_XSDSS*, *Alopeke-Zorro_i_XSDSS*, *Alopeke-Zorro_z_XSDSS*, *Alopeke-Zorro_EO_466*, *Alopeke-Zorro_EO_562*, *Alopeke-Zorro_EO_716*, *Alopeke-Zorro_EO_832*, *Alopeke-Zorro_HAlpha*
Gemini	Flamingos-2	Y, J, H, Ks, K blue, K red, Jlow, JH, HK, Klong	*Flamingos-2_Y*, *Flamingos-2_J*, *Flamingos-2_H*, *Flamingos-2_Ks*, *Flamingos-2_K_blue*, *Flamingos-2_K_red*, *Flamingos-2_Jlow*, *Flamingos-2_JH*, *Flamingos-2_HK*, *Flamingos-2_Klong*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Gemini	GMOS	u-North, u-South, g-North, g-South, r-North, r-South, i-North, i-South, z-North, z-South, Y-South, Zcap-South, ri-North, CaT-North, CaT-South, DS920-North, GG455-North, GG455-South, HaC-North, HaC-South, Ha-North, Ha-South, HeIIC-North, HeIIC-South, HeII-North, HeII-South, OG515-North, OG515-South, OIIIC-North, OIIIC-South, OIII-North, OIII-South, OVIC-North, OVIC-South, OVI-North, OVI-South, RG610-North, RG610-South, RG780-South, SII-North, SII-South	*GMOS_u_N*, *GMOS_u_S*, *GMOS_g_N*, *GMOS_g_S*, *GMOS_r_N*, *GMOS_r_S*, *GMOS_i_N*, *GMOS_i_S*, *GMOS_z_N*, *GMOS_Z_S*, *GMOS_Y_S*, *GMOS_Zcap_S*, *GMOS_ri_N*, *GMOS_CaT_N*, *GMOS_CaT_S*, *GMOS_DS920_N*, *GMOS_GG455_N*, *GMOS_GG455_S*, *GMOS_HaC_N*, *GMOS_HaC_S*, *GMOS_Ha_N*, *GMOS_Ha_S*, *GMOS_HeIIC_N*, *GMOS_HeIIC_S*, *GMOS_HeII_N*, *GMOS_HeII_S*, *GMOS_OG515_N*, *GMOS_OG515_S*, *GMOS_OIIIC_N*, *GMOS_OIIIC_S*, *GMOS_OIII_N*, *GMOS_OIII_S*, *GMOS_OVIC_N*, *GMOS_OVIC_S*, *GMOS_OVI_N*, *GMOS_OVI_S*, *GMOS_RG610_N*, *GMOS_RG610_S*, *GMOS_RG780_S*, *GMOS_SII_N*, *GMOS_SII_S*
Gemini	GNIRS	X, J, H, K, Y, J-MK, K-MK, H2, PAH	*GNIRS_X*, *GNIRS_J*, *GNIRS_H*, *GNIRS_K*, *GNIRS_Y*, *GNIRS_J-MK*, *GNIRS_K-MK*, *GNIRS_H2*, *GNIRS_PAH*
Gemini	GSAOI	Z, J, H, Kprime, Kshort, K, Jcont, Hcont, CH4short, CH4long, Kshort cont, Klong cont, HeI, PaBeta, PaGamma, FeII, H2O, HeI_2p2s, BrGamma, H2 1-0, H2 2-1, CO	*GSAOI_Z*, *GSAOI_J*, *GSAOI_H*, *GSAOI_Kprime*, *GSAOI_Kshort*, *GSAOI_K*, *GSAOI_Jcont*, *GSAOI_Hcont*, *GSAOI_CH4short*, *GSAOI_CH4long*, *GSAOI_Kshort_cont*, *GSAOI_Klong_cont*, *GSAOI_HeI*, *GSAOI_PaBeta*, *GSAOI_PaGamma*, *GSAOI_FeII*, *GSAOI_H2O*, *GSAOI_HeI_2p2s*, *GSAOI_BrGamma*, *GSAOI_H2_10*, *GSAOI_H2_21*, *GSAOI_CO*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Gemini	Michelle	N, Nprime, Qa, Q, Si1, Si2, Si3, Si4, Si5, Si6	*Michelle_N*, *Michelle_Nprime*, *Michelle_Qa*, *Michelle_Q*, *Michelle_Si1*, *Michelle_Si2*, *Michelle_Si3*, *Michelle_Si4*, *Michelle_Si5*, *Michelle_Si6*
Gemini	NICI	ED283, ED286, ED299, ED379, ED381, ED449, ED451	*NICI_ED283*, *NICI_ED286*, *NICI_ED299*, *NICI_ED379*, *NICI_ED381*, *NICI_ED449*, *NICI_ED451*
Gemini	NIFS	ZJ, JH, HK	*NIFS_ZJ*, *NIFS_JH*, *NIFS_HK*
Gemini	NIRI	Y, Y cold, Y cold pk50, J, H, HKnotch G0236, Kprime, Kshort, K, Lprime, Mprime, Jcont G0239, HeI, PaGamma, Jcont G0232, PaBeta, PaBeta cold, Hcont, Hcont cold, CH4short, CH4short cold CH4long, CH4long cold, FeII, FeII cold, H2Oice G0242, Kcont G0217, Kcont G0217 cold, H2 1-0, H2 1-0 cold, BrGamma, BrGamma cold, H2 2-1, H2 2-1 cold, Kcont G0219, Kcont G0219 cold, CH4ice, CO2, CO2 cold, H2Oice G0230, Hydrocarbon, BrAlphaCont, BrAlpha, PK50	*NIRI_Y*, *NIRI_Y_cold*, *NIRI_Y_cold_pk50*, *NIRI_J*, *NIRI_H*, *NIRI_HKnotch_G0236*, *NIRI_Kprime*, *NIRI_Kshort*, *NIRI_K*, *NIRI_Lprime*, *NIRI_Mprime*, *NIRI_Jcont_G0239*, *NIRI_HeI*, *NIRI_PaGamma*, *NIRI_Jcont_G0232*, *NIRI_PaBeta*, *NIRI_PaBeta_cold*, *NIRI_Hcont*, *NIRI_Hcont_cold*, *NIRI_CH4short*, *NIRI_CH4short_cold*,`NIRI_CH4long`, *NIRI_CH4long_cold*, *NIRI_FeII*, *NIRI_FeII_cold*, *NIRI_H2Oice_G0242*, *NIRI_Kcont_G0217*, *NIRI_Kcont_G0217_cold*, *NIRI_H2_10*, *NIRI_H2_10_cold*, *NIRI_BrGamma*, *NIRI_BrGamma_cold*, *NIRI_H2_21*, *NIRI_H2_21_cold*, *NIRI_Kcont_G0219*, *NIRI_Kcont_G0219_cold*, *NIRI_CH4ice*, *NIRI_CO2*, *NIRI_CO2_cold*, *NIRI_H2Oice_G0230*, *NIRI_Hydrocarbon*, *NIRI_BrAlphaCont*, *NIRI_BrAlpha*, *NIRI_PK50*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Gemini	TReCS	K, L, M, N, Nprime, Qa, Qb, Qwide, PAH1, PAH2, ArIII, SIV, NeII, NeII cont, Si1, Si2, Si3, Si4, Si5, Si6	*TReCS_K*, *TReCS_L*, *TReCS_M*, *TReCS_N*, *TReCS_Nprime*, *TReCS_Qa*, *TReCS_Qb*, *TReCS_Qwide*, *TReCS_PAH1*, *TReCS_PAH2*, *TReCS_ArIII*, *TReCS_SIV*, *TReCS_NeII*, *TReCS_NeII_cont*, *TReCS_Si1*, *TReCS_Si2*, *TReCS_Si3*, *TReCS_Si4*, *TReCS_Si5*, *TReCS_Si6*
Generic	Bessell	U, B, V, R, I, J, H, K, L, Lp, M	*Bessell_U*, *Bessell_B*, *Bessell_V*, *Bessell_R*, *Bessell_I*, *Bessell_J*, *Bessell_H*, *Bessell_K*, *Bessell_L*, *Bessell_Lp*, *Bessell_M*
Generic	Johnson	U, B, V, R, I, J, H, K, LI, LII, M, N	*Johnson_U*, *Johnson_B*, *Johnson_V*, *Johnson_R*, *Johnson_I*, *Johnson_J*, *Johnson_H*, *Johnson_K*, *Johnson_LI*, *Johnson_LII*, *Johnson_M*, *Johnson_N*
Herschel	PACS	blue, green, red	*PACS_blue*, *PACS_green*, *PACS_red*
Herschel	SPIRE	250, 350, 500	*SPIRE_250*, *SPIRE_350*, *SPIRE_500*
HST	ACS/HRC	F220W, F250W, F330W, F344N, F435W, F475W, F502N, F625W, F775W, 814W, F850LP, F892N, POL UV, POL V	*ACS_HRC_F220W*, *ACS_HRC_F250W*, *ACS_HRC_F330W*, *ACS_HRC_F344N*, *ACS_HRC_F435W*, *ACS_HRC_F475W*, *ACS_HRC_F502N*, *ACS_HRC_F625W*, *ACS_HRC_F775W*, *ACS_HRC_F814W*, *ACS_HRC_F850LP*, *ACS_HRC_F892N*, *ACS_HRC_POL_UV*, *ACS_HRC_POL_V*
HST	ACS/SBC	F115LP, F122M, F125LP, F140LP, F150LP, F165LP	*ACS_F115LP*, *ACS_F122M*, *ACS_F125LP*, *ACS_F140LP*, *ACS_F150LP*, *ACS_F165LP*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
HST	ACS/WFC	F435W, F475W, F502N, F550M, F555W, F606W, F625W, F658N, F660N, F775W, F814W, F850LP, F892N, POL UV, POL V	*ACS_F435W*, *ACS_F475W*, *ACS_F502N*, *ACS_F550M*, *ACS_F555W*, *ACS_F606W*, *ACS_F625W*, *ACS_F658N*, *ACS_F660N*, *ACS_F775W*, *ACS_F814W*, *ACS_F850LP*, *ACS_F892N*, *ACS_POL_UV*, *ACS_POL_V*
HST	WFC3/UVIS	F098M, F105W, F110W, F125W, F126N, F127M, F128N, F130N, F132N, F139M, F140W, F153M, F160W, F164N, F167N	*WFC3_F098M*, *WFC3_F105W*, *WFC3_F110W*, *WFC3_F125W*, *WFC3_F126N*, *WFC3_F127M*, *WFC3_F128N*, *WFC3_F130N*, *WFC3_F132N*, *WFC3_F139M*, *WFC3_F140W*, *WFC3_F153M*, *WFC3_F160W*, *WFC3_F164N*, *WFC3_F167N*
HST	WFC3/IR	F200LP, F218W, F225W, F275W, F280N, F300X, F336W, F343N, F350LP, F373N, F390M, F390W, F395N, F410M, F438W, F467M, F469N, F475W, F475X, F487N, F502N, F547M, F555W, F600LP, F606W, F621M, F625W, F631N, F645N, F656N, F657N, F658N, F665N, F673N, F680N, F689M, F763M, F775W, F814W, F845M, F850LP, F953N	*WFC3_F200LP*, *WFC3_F218W*, *WFC3_F225W*, *WFC3_F275W*, *WFC3_F280N*, *WFC3_F300X*, *WFC3_F336W*, *WFC3_F343N*, *WFC3_F350LP*, *WFC3_F373N*, *WFC3_F390M*, *WFC3_F390W*, *WFC3_F395N*, *WFC3_F410M*, *WFC3_F438W*, *WFC3_F467M*, *WFC3_F469N*, *WFC3_F475W*, *WFC3_F475X*, *WFC3_F487N*, *WFC3_F502N*, *WFC3_F547M*, *WFC3_F555W*, *WFC3_F600LP*, *WFC3_F606W*, *WFC3_F621M*, *WFC3_F625W*, *WFC3_F631N*, *WFC3_F645N*, *WFC3_F656N*, *WFC3_F657N*, *WFC3_F658N*, *WFC3_F665N*, *WFC3_F673N*, *WFC3_F680N*, *WFC3_F689M*, *WFC3_F763M*, *WFC3_F775W*, *WFC3_F814W*, *WFC3_F845M*, *WFC3_F850LP*, *WFC3_F953N*
JCMT	SCUBA2	450, 850	*SCUBA2_450*, *SCUBA2_850*
JWST	MIRI	F560W, F770W, F1000W, F1130W, F1280W, F1500W, F1800W, F2100W, F2550W	*MIRI_F560W*, *MIRI_F770W*, *MIRI_F1000W*, *MIRI_F1130W*, *MIRI_F1280W*, *MIRI_F1500W*, *MIRI_F1800W*, *MIRI_F2100W*, *MIRI_F2550W*

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Observatory/Survey	Instrument	Bands	Lightning Filter Labels
JWST	NIRCam	F070W, F090W, F115W, F140M, F150W, F150W2, F162M, F164N, F182M, F187N, F200W, F210M, F212N, F250M, F277W, F300M, F322W2, F323N, F335M, F356W, F360M, F405N, F410M, F430M, F444W, F460M, F466N, F470N, F480M	*NIRCam_F070W*, *NIRCam_F090W*, *NIRCam_F115W*, *NIRCam_F140M*, *NIRCam_F150W*, *NIRCam_F150W2*, *NIRCam_F162M*, *NIRCam_F164N*, *NIRCam_F182M*, *NIRCam_F187N*, *NIRCam_F200W*, *NIRCam_F210M*, *NIRCam_F212N*, *NIRCam_F250M*, *NIRCam_F277W*, *NIRCam_F300M*, *NIRCam_F322W2*, *NIRCam_F323N*, *NIRCam_F335M*, *NIRCam_F356W*, *NIRCam_F360M*, *NIRCam_F405N*, *NIRCam_F410M*, *NIRCam_F430M*, *NIRCam_F444W*, *NIRCam_F460M*, *NIRCam_F466N*, *NIRCam_F470N*, *NIRCam_F480M*
Keck	DEIMOS	B, R, I, Z	*DEIMOS_B*, *DEIMOS_R*, *DEIMOS_I*, *DEIMOS_Z*
Keck	LRIS	B, V, Rs, R, I, GG495, OG570, RG850, NB4000, NB4325, NB5390, NB6741, NB8185, NB8560, NB9135, NB9148	*LRIS_B*, *LRIS_V*, *LRIS_Rs*, *LRIS_R*, *LRIS_I*, *LRIS_GG495*, *LRIS_OG570*, *LRIS_RG850*, *LRIS_NB4000*, *LRIS_NB4325*, *LRIS_NB5390*, *LRIS_NB6741*, *LRIS_NB8185*, *LRIS_NB8560*, *LRIS_NB9135*, *LRIS_NB9148*
Keck	MOSFIRE	Y, J, J2, J3, H, H1, H2, K, Ks	*MOSFIRE_Y*, *MOSFIRE_J*, *MOSFIRE_J2*, *MOSFIRE_J3*, *MOSFIRE_H*, *MOSFIRE_H1*, *MOSFIRE_H2*, *MOSFIRE_K*, *MOSFIRE_Ks*
Keck	NIRC2	J, H, Kp, Ks, K, Lp, Ms, Hcont, FeII, BrGamma, Kcont	*NIRC2_J*, *NIRC2_H*, *NIRC2_Kp*, *NIRC2_Ks*, *NIRC2_K*, *NIRC2_Lp*, *NIRC2_Ms*, *NIRC2_Hcont*, *NIRC2_FeII*, *NIRC2_BrGamma*, *NIRC2_Kcont*

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Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Keck	NIRSPEC	FeII, H2, KL, Lprime, Mwide, Mprime, Nirspec1, Nirspec2, Nirspec3, Nirspec4, Nirspec5, Nirspec6, Nirspec7, K, Kprime	*NIRSPEC_FeII*, *NIRSPEC_H2*, *NIRSPEC_KL*, *NIRSPEC_Lprime*, *NIRSPEC_Mwide*, *NIRSPEC_Mprime*, *NIRSPEC_Nirspec1*, *NIRSPEC_Nirspec2*, *NIRSPEC_Nirspec3*, *NIRSPEC_Nirspec4*, *NIRSPEC_Nirspec5*, *NIRSPEC_Nirspec6*, *NIRSPEC_Nirspec7*, *NIRSPEC_K*, *NIRSPEC_Kprime*
Keck	OSIRIS	Zbb IMAG, Hbb IMAG, Zn3 IMAG, Jn2 IMAG, Jn3 IMAG, Hn1 IMAG, Hn2 IMAG, Hn3 IMAG, Hn4 IMAG, Hn5 IMAG, Jn1 IMAG, Kn1 IMAG, Kn2 IMAG, Kn3 IMAG, Kn4 IMAG, Kn5 IMAG, Zbb SPEC, Jbb SPEC, Hbb SPEC, Kbb SPEC, Zn4 SPEC, Jn1 SPEC, Jn2 SPEC, Jn3 SPEC, Jn4 SPEC, Hn1 SPEC, Hn2 SPEC, Hn3 SPEC, Hn4 SPEC, Hn5 SPEC, Kn1 SPEC, Kn2 SPEC, Kn3 SPEC, Kn4 SPEC, Kn5 SPEC	*OSIRIS_Zbb_IMAG*, *OSIRIS_Hbb_IMAG*, *OSIRIS_Zn3_IMAG*, *OSIRIS_Jn2_IMAG*, *OSIRIS_Jn3_IMAG*, *OSIRIS_Hn1_IMAG*, *OSIRIS_Hn2_IMAG*, *OSIRIS_Hn3_IMAG*, *OSIRIS_Hn4_IMAG*, *OSIRIS_Hn5_IMAG*, *OSIRIS_Jn1_IMAG*, *OSIRIS_Kn1_IMAG*, *OSIRIS_Kn2_IMAG*, *OSIRIS_Kn3_IMAG*, *OSIRIS_Kn4_IMAG*, *OSIRIS_Kn5_IMAG*, *OSIRIS_Zbb_SPEC*, *OSIRIS_Jbb_SPEC*, *OSIRIS_Hbb_SPEC*, *OSIRIS_Kbb_SPEC*, *OSIRIS_Zn4_SPEC*, *OSIRIS_Jn1_SPEC*, *OSIRIS_Jn2_SPEC*, *OSIRIS_Jn3_SPEC*, *OSIRIS_Jn4_SPEC*, *OSIRIS_Hn1_SPEC*, *OSIRIS_Hn2_SPEC*, *OSIRIS_Hn3_SPEC*, *OSIRIS_Hn4_SPEC*, *OSIRIS_Hn5_SPEC*, *OSIRIS_Kn1_SPEC*, *OSIRIS_Kn2_SPEC*, *OSIRIS_Kn3_SPEC*, *OSIRIS_Kn4_SPEC*, *OSIRIS_Kn5_SPEC*

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Observatory/Survey	Instrument	Bands	Lightning Filter Labels
KPNO	FLAMINGOS	J, JH, H, HK, Ks, K	*FLAMINGOS_J*, *FLAMINGOS_JH*, *FLAMINGOS_H*, *FLAMINGOS_HK*, *FLAMINGOS_Ks*, *FLAMINGOS_K*
KPNO	Mosaic	U, B, V, R, I, Ud, Un, Us, Bw, VR, Rs, C, M, r DECam, Z DECam, g SDSS, r SDSS, i SDSS, z SDSS, white, WR475, 337, 390, 420, 454, 493, 527, 579, 607, 666, 705, 755, 802, 815 v1, 815 v2, 823 v1, 823 v2, 848, 918, 918R, 973, CIII, CIV, D51, Gn, HAlpha, HAlpha12, HAlpha16, HAlpha4, HAlpha8, HeII, OII30, OIII	*Mosaic_U*, *Mosaic_B*, *Mosaic_V*, *Mosaic_R*, *Mosaic_I*, *Mosaic_Ud*, *Mosaic_Un*, *Mosaic_Us*, *Mosaic_Bw*, *Mosaic_VR*, *Mosaic_Rs*, *Mosaic_C*, *Mosaic_M*, *Mosaic_r_DECam*, *Mosaic_Z_DECam*, *Mosaic_g_SDSS*, *Mosaic_r_SDSS*, *Mosaic_i_SDSS*, *Mosaic_z_SDSS*, *Mosaic_white*, *Mosaic_WR475*, *Mosaic_337*, *Mosaic_390*, *Mosaic_420*, *Mosaic_454*, *Mosaic_493*, *Mosaic_527*, *Mosaic_579*, *Mosaic_607*, *Mosaic_666*, *Mosaic_705*, *Mosaic_755*, *Mosaic_802*, *Mosaic_815_v1*, *Mosaic_815_v2*, *Mosaic_823_v1*, *Mosaic_823_v2*, *Mosaic_848*, *Mosaic_918*, *Mosaic_918R*, *Mosaic_973*, *Mosaic_CIII*, *Mosaic_CIV*, *Mosaic_D51*, *Mosaic_Gn*, *Mosaic_HAlpha*, *Mosaic_HAlpha12*, *Mosaic_HAlpha16*, *Mosaic_HAlpha4*, *Mosaic_HAlpha8*, *Mosaic_HeII*, *Mosaic_OII30*, *Mosaic_OIII*
KPNO	NEWFIRM	J1, J2, J3, H1, H2, Ks	*NEWFIRM_J1*, *NEWFIRM_J2*, *NEWFIRM_J3*, *NEWFIRM_H1*, *NEWFIRM_H2*, *NEWFIRM_Ks*
KPNO	WIYN/0.9m	U, B, V, R, I, u Strom, b Strom, v Strom, y Strom, Ca, Hb narrow, Hb wide, HAlpha, HAlpha12, HAlpha16, HAlpha4, HAlpha8	*0.9m_U*, *0.9m_B*, *0.9m_V*, *0.9m_R*, *0.9m_I*, *0.9m_u_Strom*, *0.9m_b_Strom*, *0.9m_v_Strom*, *0.9m_y_Strom*, *0.9m_Ca*, *0.9m_Hb_narrow*, *0.9m_Hb_wide*, *0.9m_HAlpha*, *0.9m_HAlpha12*, *0.9m_HAlpha16*, *0.9m_HAlpha4*, *0.9m_HAlpha8*
KPNO	WIYN/ODI	u, g, r, i, z, NB422, NB659, NB695, NB746	*ODI_u*, *ODI_g*, *ODI_r*, *ODI_i*, *ODI_z*, *ODI_NB422*, *ODI_NB659*, *ODI_NB695*, *ODI_NB746*

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Observatory/Survey	Instrument	Bands	Lightning Filter Labels
KPNO	WIYN/WHIRC	J, H, Ks, Low, HeI, CN, PaBeta, PaBeta45, FeII, FeII45, H2, BrGamma, BrGamma45, CO-n, CO-w	*WHIRC_J*, *WHIRC_H*, *WHIRC_Ks*, *WHIRC_Low*, *WHIRC_HeI*, *WHIRC_CN*, *WHIRC_PaBeta*, *WHIRC_PaBeta45*, *WHIRC_FeII*, *WHIRC_FeII45*, *WHIRC_H2*, *WHIRC_BrGamma*, *WHIRC_BrGamma45*, *WHIRC_CO-n*, *WHIRC_CO-w*
LaSilla	EMMI	Bb, V, R, I, Z, g Gunn, r Gunn, z Gunn, U Bessel, B Bessel, B Tyson, BG38, BG39, EUV, GG375, OG530, RG715, OII, OII10, OII15, OII5, HeII 652, HeII 671, HBeta cont, HBeta, OIII, OIII12, OIII15, OIII3, OIII6, OIII9, HAlpha, HAlpha0, HAlpha12, HAlpha15, HAlpha3, HAlpha6, HAlpha9, NII 653, NII 595, SII, SIII, NeV, Spec 656, Spec 672, Spec 673, Spec 723, Spec 765, Spec 766, Spec 767, Spec 768, Spec 795, Spec 796	*EMMI_Bb*, *EMMI_V*, *EMMI_R*, *EMMI_I*, *EMMI_Z*, *EMMI_g_Gunn*, *EMMI_r_Gunn*, *EMMI_z_Gunn*, *EMMI_U_Bessel*, *EMMI_B_Bessel*, *EMMI_B_Tyson*, *EMMI_BG38*, *EMMI_BG39*, *EMMI_EUV*, *EMMI_GG375*, *EMMI_OG530*, *EMMI_RG715*, *EMMI_OII*, *EMMI_OII10*, *EMMI_OII15*, *EMMI_OII5*, *EMMI_HeII_652*, *EMMI_HeII_671*, *EMMI_HBeta_cont*, *EMMI_HBeta*, *EMMI_OIII*, *EMMI_OIII12*, *EMMI_OIII15*, *EMMI_OIII3*, *EMMI_OIII6*, *EMMI_OIII9*, *EMMI_HAlpha*, *EMMI_HAlpha0*, *EMMI_HAlpha12*, *EMMI_HAlpha15*, *EMMI_HAlpha3*, *EMMI_HAlpha6*, *EMMI_HAlpha9*, *EMMI_NII_653*, *EMMI_NII_595*, *EMMI_SII*, *EMMI_SIII*, *EMMI_NeV*, *EMMI_Spec_656*, *EMMI_Spec_672*, *EMMI_Spec_673*, *EMMI_Spec_723*, *EMMI_Spec_765*, *EMMI_Spec_766*, *EMMI_Spec_767*, *EMMI_Spec_768*, *EMMI_Spec_795*, *EMMI_Spec_796*

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Observatory/Survey	Instrument	Bands	Lightning Filter Labels
LaSilla	SOFI	Js, J, H, Ks, K, NB106, NB108, NB119, NB121, NB171, NB209, NB219, NB225, NB228, NB FeII J, NB Pbeta, NB FeII H, NB HeI K, NB H2, NB BrGamma, NB CO	*SOFI_Js*, *SOFI_J*, *SOFI_H*, *SOFI_Ks*, *SOFI_K*, *SOFI_NB106*, *SOFI_NB108*, *SOFI_NB119*, *SOFI_NB121*, *SOFI_NB171*, *SOFI_NB209*, *SOFI_NB219*, *SOFI_NB225*, *SOFI_NB228*, *SOFI_NB_FeII_J*, *SOFI_NB_Pbeta*, *SOFI_NB_FeII_H*, *SOFI_NB_HeI_K*, *SOFI_NB_H2*, *SOFI_NB_BrGamma*, *SOFI_NB_CO*
LaSilla	SUSI2	U, Uprime, B, B spare, V, R, I, Z, HeII, HBeta, OIII, OIII cont, HAlpha, Halpha cont, WB 490, IB 609, WB 655, IB 662	*SUSI2_U*, *SUSI2_Uprime*, *SUSI2_B*, *SUSI2_B_spare*, *SUSI2_V*, *SUSI2_R*, *SUSI2_I*, *SUSI2_Z*, *SUSI2_HeII*, *SUSI2_HBeta*, *SUSI2_OIII*, *SUSI2_OIII_cont*, *SUSI2_HAlpha*, *SUSI2_Halpha_cont*, *SUSI2_WB_490*, *SUSI2_IB_609*, *SUSI2_WB_655*, *SUSI2_IB_662*
LaSilla	TIMMI2	N79 OCLI, N1, N89 OCLI, N98 OCLI, N104 OCLI, SIV, N2, N119 OCLI, SiC, N129 OCLI, NEII, Q1, Q2, IRWBP	*TIMMI2_N79_OCLI*, *TIMMI2_N1*, *TIMMI2_N89_OCLI*, *TIMMI2_N98_OCLI*, *TIMMI2_N104_OCLI*, *TIMMI2_SIV*, *TIMMI2_N2*, *TIMMI2_N119_OCLI*, *TIMMI2_SiC*, *TIMMI2_N129_OCLI*, *TIMMI2_NEII*, *TIMMI2_Q1*, *TIMMI2_Q2*, *TIMMI2_IRWBP*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
LaSilla	WFI	U, U 38, B, B 99, V, Rc, I, Ic, Z+, Gieren 501, M Wash, MB416, MB445, MB461, MB485, MB513, MB516, MB518, MB531, MB549, MB571, MB604, MB620, MB646, MB679, MB696, MB721, MB753, MB770, MB790, MB815, MB837, MB856, MB884, MB914, NB396, NB504, NB665, NB810, NB817, NB824, OIII, OIII 2, Halpha, SIIr, white	*WFI_U*, *WFI_U_38*, *WFI_B*, *WFI_B_99*, *WFI_V*, *WFI_Rc*, *WFI_I*, *WFI_Ic*, *WFI_Z+*, *WFI_Gieren_501*, *WFI_M_Wash*, *WFI_MB416*, *WFI_MB445*, *WFI_MB461*, *WFI_MB485*, *WFI_MB513*, *WFI_MB516*, *WFI_MB518*, *WFI_MB531*, *WFI_MB549*, *WFI_MB571*, *WFI_MB604*, *WFI_MB620*, *WFI_MB646*, *WFI_MB679*, *WFI_MB696*, *WFI_MB721*, *WFI_MB753*, *WFI_MB770*, *WFI_MB790*, *WFI_MB815*, *WFI_MB837*, *WFI_MB856*, *WFI_MB884*, *WFI_MB914*, *WFI_NB396*, *WFI_NB504*, *WFI_NB665*, *WFI_NB810*, *WFI_NB817*, *WFI_NB824*, *WFI_OIII*, *WFI_OIII_2*, *WFI_Halpha*, *WFI_SIIr*, *WFI_white*
LBT	LBCB	U, B, V, gSloan, rSloan, USpec15, USpec40, USpec65	*LBCB_U*, *LBCB_B*, *LBCB_V*, *LBCB_gSloan*, *LBCB_rSloan*, *LBCB_USpec15*, *LBCB_USpec40*, *LBCB_USpec65*
LBT	LBCR	V, R, I, Y, rSloan, iSloan, zSloan, F972N20, CN, TiO	*LBCR_V*, *LBCR_R*, *LBCR_I*, *LBCR_Y*, *LBCR_rSloan*, *LBCR_iSloan*, *LBCR_zSloan*, *LBCR_F972N20*, *LBCR_CN*, *LBCR_TiO*
LBT	MODS	uMODS1, uMODS2, gMODS1, gMODS2, rMODS1, rMODS2, iMODS1, iMODS2, zMODS1, zMODS2	*MODS_uMODS1*, *MODS_uMODS2*, *MODS_gMODS1*, *MODS_gMODS2*, *MODS_rMODS1*, *MODS_rMODS2*, *MODS_iMODS1*, *MODS_iMODS2*, *MODS_zMODS1*, *MODS_zMODS2*
LSST		u, g, r, i, z, y	*LSST_u*, *LSST_g*, *LSST_r*, *LSST_i*, *LSST_z*, *LSST_y*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Pan-STARRS		open, gp1, rp1, ip1, zp1, yp1, wp1	*Pan-STARRS_open*, *Pan-STARRS_gp1*, *Pan-STARRS_rp1*, *Pan-STARRS_ip1*, *Pan-STARRS_zp1*, *Pan-STARRS_yp1*, *Pan-STARRS_wp1*
Paranal	VISTA/VIRCAM	Y, Z, J, H, Ks, NB980, NB990, NB118	*VIRCAM_Y*, *VIRCAM_Z*, *VIRCAM_J*, *VIRCAM_H*, *VIRCAM_Ks*, *VIRCAM_NB980*, *VIRCAM_NB990*, *VIRCAM_NB118*
Paranal	VLT/FORS	U BESS, B BESS, V BESS, R BESS, I BESS, u HIGH, b HIGH, g HIGH, v HIGH, U GUNN, G GUNN, V GUNN, R GUNN, Z GUNN, U SPECIAL, R SPECIAL, GG3751, GG3752, GG4351, GG4352, IF485, IF691, IF815, IF834, IF915, OG5901, OG5902	*FORS_U_BESS*, *FORS_B_BESS*, *FORS_V_BESS*, *FORS_R_BESS*, *FORS_I_BESS*, *FORS_u_HIGH*, *FORS_b_HIGH*, *FORS_g_HIGH*, *FORS_v_HIGH*, *FORS_U_GUNN*, *FORS_G_GUNN*, *FORS_V_GUNN*, *FORS_R_GUNN*, *FORS_Z_GUNN*, *FORS_U_SPECIAL*, *FORS_R_SPECIAL*, *FORS_GG3751*, *FORS_GG3752*, *FORS_GG4351*, *FORS_GG4352*, *FORS_IF485*, *FORS_IF691*, *FORS_IF815*, *FORS_IF834*, *FORS_IF915*, *FORS_OG5901*, *FORS_OG5902*
Paranal	VLT/HAWK-I	Y, J, H, Ks, CH4, H2, BrGamma, NB1060, NB1190, NB2090	*HAWK-I_Y*, *HAWK-I_J*, *HAWK-I_H*, *HAWK-I_Ks*, *HAWK-I_CH4*, *HAWK-I_H2*, *HAWK-I_BrGamma*, *HAWK-I_NB1060*, *HAWK-I_NB1190*, *HAWK-I_NB2090*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Paranal	VLT/ISAAC	SZ, Js, J, H, Ks, L, M, NB1061, NB1083, NB1187, NB1215, NB1257, NB1282, NB1644, NB1710, NB2058, NB2090, NB2122, NB2188, NB2195, NB2248, NB2280, NB2336, NB3200, NB3280, NB3800, NB4050	*ISAAC_SZ*, *ISAAC_Js*, *ISAAC_J*, *ISAAC_H*, *ISAAC_Ks*, *ISAAC_L*, *ISAAC_M*, *ISAAC_NB1061*, *ISAAC_NB1083*, *ISAAC_NB1187*, *ISAAC_NB1215*, *ISAAC_NB1257*, *ISAAC_NB1282*, *ISAAC_NB1644*, *ISAAC_NB1710*, *ISAAC_NB2058*, *ISAAC_NB2090*, *ISAAC_NB2122*, *ISAAC_NB2188*, *ISAAC_NB2195*, *ISAAC_NB2248*, *ISAAC_NB2280*, *ISAAC_NB2336*, *ISAAC_NB3200*, *ISAAC_NB3280*, *ISAAC_NB3800*, *ISAAC_NB4050*
Paranal	VLT/MIDI	Nband, SiC, N87, ArIII, SIV, N113, NeII	*MIDI_Nband*, *MIDI_SiC*, *MIDI_N87*, *MIDI_ArIII*, *MIDI_SIV*, *MIDI_N113*, *MIDI_NeII*
Paranal	VLT/NACO	J, H, Ks, Lprime, Mprime, NB104, NB108, NB109, NB124, NB126, NB128, NB164, NB175, NB212, NB217, NB374, NB405, IB200, IB203, IB206, IB209, IB212, IB215, IB218, IB221, IB224, IB227, IB230, IB233, IB236, IB239, IB242, IB245, IB248	*NACO_J*, *NACO_H*, *NACO_Ks*, *NACO_Lprime*, *NACO_Mprime*, *NACO_NB104*, *NACO_NB108*, *NACO_NB109*, *NACO_NB124*, *NACO_NB126*, *NACO_NB128*, *NACO_NB164*, *NACO_NB175*, *NACO_NB212*, *NACO_NB217*, *NACO_NB374*, *NACO_NB405*, *NACO_IB200*, *NACO_IB203*, *NACO_IB206*, *NACO_IB209*, *NACO_IB212*, *NACO_IB215*, *NACO_IB218*, *NACO_IB221*, *NACO_IB224*, *NACO_IB227*, *NACO_IB230*, *NACO_IB233*, *NACO_IB236*, *NACO_IB239*, *NACO_IB242*, *NACO_IB245*, *NACO_IB248*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Paranal	VLT/SPHERE/IRDIS	Y, J, H, Ks, Y23, J23, H23, ND_H23, H34, K12, HeI, CntJ, PaB, CntH, FeII, CntK1, H2, BrG, CntK2, CO	*IRDIS_Y*, *IRDIS_J*, *IRDIS_H*, *IRDIS_Ks*, *IRDIS_Y23*, *IRDIS_J23*, *IRDIS_H23*, *IRDIS_ND_H23*, *IRDIS_H34*, *IRDIS_K12*, *IRDIS_HeI*, *IRDIS_CntJ*, *IRDIS_PaB*, *IRDIS_CntH*, *IRDIS_FeII*, *IRDIS_CntK1*, *IRDIS_H2*, *IRDIS_BrG*, *IRDIS_CntK2*, *IRDIS_CO*
Paranal	VLT/SPHERE/ZIMP(	VBB, R PRIM, I PRIM, V, V S, V L, N R, NB730, N I, I L, KI, TiO, CH4, Cnt748, Cnt820, Ha B, Ha Cnt, HeI, OI 630, N Ha	*ZIMPOL_VBB*, *ZIMPOL_R_PRIM*, *ZIMPOL_I_PRIM*, *ZIMPOL_V*, *ZIMPOL_V_S*, *ZIMPOL_V_L*, *ZIMPOL_N_R*,`ZIMPOL_NB730`, *ZIMPOL_N_I*, *ZIMPOL_I_L*, *ZIMPOL_KI*, *ZIMPOL_TiO*, *ZIMPOL_CH4*, *ZIMPOL_Cnt748*, *ZIMPOL_Cnt820*, *ZIMPOL_Ha_B*, *ZIMPOL_Ha_Cnt*, *ZIMPOL_HeI*, *ZIMPOL_OI_630*, *ZIMPOL_N_Ha*
Paranal	VLT/VIMOS	U, B, V, R, I, z	*VIMOS_U*, *VIMOS_B*, *VIMOS_V*, *VIMOS_R*, *VIMOS_I*, *VIMOS_z*
Paranal	VLT/VISIR	M, J79, PAH1, J89, B87, ArIII, SIV 1, B97, SIV, B107, SIV 2, PAH2, B117, PAH2 2, J122, NeII 1, B124, NeII, NeII 2, Q1, Q2, Q3	*VISIR_M*, *VISIR_J79*, *VISIR_PAH1*, *VISIR_J89*, *VISIR_B87*, *VISIR_ArIII*, *VISIR_SIV_1*, *VISIR_B97*, *VISIR_SIV*, *VISIR_B107*, *VISIR_SIV_2*, *VISIR_PAH2*, *VISIR_B117*, *VISIR_PAH2_2*, *VISIR_J122*, *VISIR_NeII_1*, *VISIR_B124*, *VISIR_NeII*, *VISIR_NeII_2*, *VISIR_Q1*, *VISIR_Q2*, *VISIR_Q3*
Paranal	VST/OmegaCAM	B, V, V Strom, u, g, r, i, z, HAlpha, Cal	*OmegaCAM_B*, *OmegaCAM_V*, *OmegaCAM_V_Strom*, *OmegaCAM_u*, *OmegaCAM_g*, *OmegaCAM_r*, *OmegaCAM_i*, *OmegaCAM_z*, *OmegaCAM_HAlpha*, *OmegaCAM_Cal*
Planck	HFI	F100, F143, F217, F353, F545, F857	*HFI_F100*, *HFI_F143*, *HFI_F217*, *HFI_F353*, *HFI_F545*, *HFI_F857*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Planck	LFI	F030, F044, F070	*LFI_F030*, *LFI_F044*, *LFI_F070*
SDSS		u, g, r, i, z	*SDSS_u*, *SDSS_g*, *SDSS_r*, *SDSS_i*, *SDSS_z*
SOFIA	FLITECAM	J, H, K, Lprime, L, M, PaAlpha, PaAlphaCont, Ice, PAH, LNarrow, MNarrow, Hwide, Kwide, Klong, KplusM	*FLITECAM_J*, *FLITECAM_H*, *FLITECAM_K*, *FLITECAM_Lprime*, *FLITECAM_L*, *FLITECAM_M*, *FLITECAM_PaAlpha*, *FLITECAM_PaAlphaCont*, *FLITECAM_Ice*, *FLITECAM_PAH*, *FLITECAM_LNarrow*, *FLITECAM_MNarrow*, *FLITECAM_Hwide*, *FLITECAM_Kwide*, *FLITECAM_Klong*, *FLITECAM_KplusM*
SOFIA	FORCAST	F054, F064, F066, F077, F111, F113, F197, F242, F315, F336, F348, F371	*FORCAST_F054*, *FORCAST_F064*, *FORCAST_F066*, *FORCAST_F077*, *FORCAST_F111*, *FORCAST_F113*, *FORCAST_F197*, *FORCAST_F242*, *FORCAST_F315*, *FORCAST_F336*, *FORCAST_F348*, *FORCAST_F371*
SOFIA	HAWC+	bandA, bandB, bandC, bandD, bandE	*HAWC+_bandA*, *HAWC+_bandB*, *HAWC+_bandC*, *HAWC+_bandD*, *HAWC+_bandE*
Spitzer	IRAC	CH1, CH2, CH3, CH4	*IRAC_CH1*, *IRAC_CH2*, *IRAC_CH3*, *IRAC_CH4*
Spitzer	IRS	BLUE-PeakUp, RED-PeakUp	*IRS_BLUE-PU*, *IRS_RED-PU*
Spitzer	MIPS	CH1, CH2, CH3	*MIPS_CH1*, *MIPS_CH2*, *MIPS_CH3*
SPT	SPT-SZ	150, 220	*SPT-SZ_150*, *SPT-SZ_220*
Steward	Bok/90Prime	U, uprime, B, V, R, I, zprime, Washington M	*90prime_U.txt*, *90prime_uprime.txt*, *90prime_B.txt*, *90prime_V.txt*, *90prime_R.txt*, *90prime_I.txt*, *90prime_zprime.txt*, *90Prime_Washington_M.txt*
Subaru	CIAO	J, H, K, Lprime, Mprime, PAH	*CIAO_J*, *CIAO_H*, *CIAO_K*, *CIAO_Lprime*, *CIAO_Mprime*, *CIAO_PAH*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Subaru	CISCO-OHS	z, J, H, Kprime, K, N204, H2 1-0, N215, H2 2-1	*CISCO_OHS_z*, *CISCO_OHS_J*, *CISCO_OHS_H*, *CISCO_OHS_Kprime*, *CISCO_OHS_K*, *CISCO_OHS_N204*, *CISCO_OHS_H2_10*, *CISCO_OHS_N215*, *CISCO_OHS_H2_21*
Subaru	FOCAS	U, B, V, R, I, N373, N386, N487, N502, N512, N642, N658, N670	*FOCAS_U*, *FOCAS_B*, *FOCAS_V*, *FOCAS_R*, *FOCAS_I*, *FOCAS_N373*, *FOCAS_N386*, *FOCAS_N487*, *FOCAS_N502*, *FOCAS_N512*, *FOCAS_N642*, *FOCAS_N658*, *FOCAS_N670*
Subaru	HSC	g, r, r new, i, i new, z, Y, IB945, NB387, NB391, NB395, NB400, NB430, NB468, NB497, NB515, NB527, NB656, NB718, NB816, NB921, NB926, NB973, NB1010	*HSC_g*, *HSC_r*, *HSC_r_new*, *HSC_i*, *HSC_i_new*, *HSC_z*, *HSC_Y*, *HSC_IB945*, *HSC_NB387*, *HSC_NB391*, *HSC_NB395*, *HSC_NB400*, *HSC_NB430*, *HSC_NB468*, *HSC_NB497*, *HSC_NB515*, *HSC_NB527*, *HSC_NB656*, *HSC_NB718*, *HSC_NB816*, *HSC_NB921*, *HSC_NB926*, *HSC_NB973*, *HSC_NB1010*
Subaru	IRCS	J, H, Kprime, K, Lprime, Mprime, NB1189, CH4 long, CH4 short, FeII, NB1984, H2, BrGamma, H2Oice	*IRCS_J*, *IRCS_H*, *IRCS_K*, *IRCS_Kprime*, *IRCS_Lprime*, *IRCS_Mprime*, *IRCS_NB1189*, *IRCS_CH4_long*, *IRCS_CH4_short*, *IRCS_FeII*, *IRCS_NB1984*, *IRCS_H2*, *IRCS_BrGamma*, *IRCS_H2Oice*
Subaru	MOIRCS	Y, J, H, Ks, K, NB119, NB1550, NB1657, FeII, NB2071, NB2083, NB2095, H2, BrGamma, Kcont, CO, NB2315	*MOIRCS_Y*, *MOIRCS_J*, *MOIRCS_H*, *MOIRCS_Ks*, *MOIRCS_K*, *MOIRCS_NB119*, *MOIRCS_NB1550*, *MOIRCS_NB1657*, *MOIRCS_FeII*, *MOIRCS_NB2071*, *MOIRCS_NB2083*, *MOIRCS_NB2095*, *MOIRCS_H2*, *MOIRCS_BrGamma*, *MOIRCS_Kcont*, *MOIRCS_CO*, *MOIRCS_NB2315*

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Table 1 – continued from previous page

Observatory/Survey	Instrument	Bands	Lightning Filter Labels
Subaru	SuprimeCam	B, V, Rc, Ic, gprime, iprime, rprime, zprime, Y, NA656, NB711, NB816, NB921	*SuprimeCam_B*, *SuprimeCam_V*, *SuprimeCam_Rc*, *SuprimeCam_Ic*, *SuprimeCam_gprime*, *SuprimeCam_iprime*, *SuprimeCam_rprime*, *SuprimeCam_zprime*, *SuprimeCam_Y*, *SuprimeCam_NA656*, *SuprimeCam_NB711*, *SuprimeCam_NB816*, *SuprimeCam_NB921*
Swift	UVOT	UVW2, UVM2, UVW1, U, B, V, white	*UVOT_UVW2*, *UVOT_UVM2*, *UVOT_UVW1*, *UVOT_U*, *UVOT_B*, *UVOT_V*, *UVOT_white*
UKIRT	WFCAM	Z, Y, J, H, K, H2, BrGamma	*WFCAM_Z*, *WFCAM_Y*, *WFCAM_J*, *WFCAM_H*, *WFCAM_K*, *WFCAM_H2*, *WFCAM_BrGamma*
WISE		W1, W2, W3, W4	*WISE_W1*, *WISE_W2*, *WISE_W3*, *WISE_W4*

CHAPTER

TEN

FAQ / PLANNED CHANGES

10.1 X-ray Model

- The rest-frame X-ray wavelength grid should be produced in a very specific way to ensure that your bandpasses are covered, especially at high-z. I currently recommend something like:

```
import astropy.constants as const
import astropy.units as u

hc = (const.c * const.h).to(u.micron * u.keV).value
E_lo = 0.5
E_hi = 7.0 # Or whatever is appropriate for you
xray_wave_grid = np.logspace(np.log10(hc / E_hi),
                             np.log10(hc / E_lo),
                             200)
xray_wave_grid /= (1 + redshift)
```

  Note that the wavelength *must be monotonically increasing*. This construction will probably be done by default in the future; I'll also probably change the specification to energy rather than wavelength just to make it more sensible.

10.2 Upper Limits and Missing Bands

- Upper limits should be specified by setting their flux to 0 and the corresponding uncertainty to the 1σ-equivalent limiting flux.
  - The `'exact'` upper limit handling should be approached with caution - it needs further testing on real-world data.
  - The `'approx'` handling generally suffices to make upper limits behave like upper limits.
- Missing bands, on the other hand, should be specified by setting the flux to `NaN` and corresponding uncertainty to 0. Take care when using masked arrays to fill in masked bands - in particular, `astropy` methods for reading fits tables may convert your data to masked arrays without your knowledge, producing unintended results.

CHAPTER

ELEVEN

API REFERENCE

11.1 Lightning

class lightning.**Lightning**

The main interface for fitting a galaxy SED model.

Holds information about the filters, observed flux, type of model. Model components are set by keyword choices.

The only strictly required parameters are `filter_labels` and one of `redshift` or `lum_dist`. For inference/fitting, both `flux_obs` and `flux_unc` must also be set.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model. If set, `lum_dist` is ignored. (Default: None)

lum_dist
[float] Luminosity distance to the model. If `redshift` is not set, this parameter must be. If a luminosity distance is provided instead of a redshift, the redshift is set to 0 (as we assume the galaxy is very nearby). (Default: None)

flux_obs
[np.ndarray, (Nfilters,) or (Nfilters, 2), float32, optional] The observed flux densities in *mJy*, or, optionally, the observed flux densities and associated uncertainties as a 2D array. (Default: None)

flux_unc
[np.ndarray, (Nfilters,), float32, optional] The uncertainties associated with `flux_obs`, in *mJy*. (Default: None)

wave_grid
[tuple (3,), or np.ndarray, (Nwave,), float32, optional] Either a tuple of (lo, hi, Nwave) specifying a log-spaced rest-frame wavelength grid, or an array giving the wavelengths directly. (Default: (0.1, 1000, 1200))

stellar_type
[{'PEGASE', 'PEGASE-A24', 'BPASS', 'BPASS-A24', 'BPASS-ULX-G24'}] String specifying the simple stellar population models to use. 'PEGASE' gives the stellar population models used in IDL Lightning (Doore+2023). (Default: 'PEGASE')

line_labels
[np.ndarray, (Nlines,), string, optional] Line labels in the format used by pyCloudy. See

lightning/models/linelist_full.txt for the complete list of available lines in the grid and their format. (Default: None)

line_flux
[np.ndarray, (Nlines,) or (Nlines, 2), float32, optional] Observed integrated fluxes of the lines in *erg cm-2 s-1* (unless the `line_index` keyword is set, in which case they should be normalized by the appropriate line). (Default: None)

line_flux_unc
[np.ndarray,(Nlines,), float32, optional] Uncertainties on the integrated line fluxes in *erg cm-2 s-1* (unless `line_index` is set, see above) (Default: None)

line_index
[string] Label for the line to index the line fluxes by. You would normally want this to be `'H__1_486132A'` or `'H__1_656280A'` for Hbeta and Halpha, respectively, but the highest SNR line could be a good choice. If this is set to `None` then the model line fluxes are not normalized for fitting. (Default: None)

nebula_lognH
[float] log of the Hydrogen density in cm-3 for the Cloudy grids. (Default: 2.0)

nebula_dust
[bool] If `True`, then dust grains are included in the Cloudy grids. (Default: False)

SFH_type
[{'Piecewise-Constant', 'Delayed-Exponential', 'Single-Exponential', 'Burst'}] String specifying the SFH type to use. (Default: 'Piecewise-Constant')

ages
[np.ndarray, (Nages,), float32] Array giving the stellar ages (or stellar age bins) of the stellar population models. Default depends on the model and redshift.

atten_type
[{'Modified-Calzetti', 'Calzetti'}] String specifying the dust attenuation model to use. (Default: 'Modified-Calzetti')

dust_emission
[bool] If `True`, a Draine & Li (2007) dust emission model is included, in energy balance with the attenuated power. (Default: False)

agn_emission
[bool] If `True`, a Stalevski et al. (2016) UV-IR AGN emission model is included. (Default: False)

agn_polar_dust
[bool] If `True`, AGN polar dust extinction and re-emission are implemented following the recipe from X-Cigale. Note that even if this keyword is set to `False`, the polar dust optical depth remains a parameter of the model - it just doesn't do anything, and should held at 0 in any fitting. (Default: False)

xray_mode
[{'flux', 'counts', 'None', None}] String specifying the mode for X-ray model fitting - fluxes are fit like any other point in the SED, while counts are folded through the instrumental response. Expect counts mode to be more flexible but harder to set up. If you are fitting X-ray data from multiple instruments simultaneously, you must set this to 'flux' (and should convert your instrumental countrates to fluxes assuming the same spectrum for every instrument). (Default: None)

xray_stellar_emission
[{'Stellar-Plaw', 'None', None}] String specifying the X-ray stellar model. Currently the only

available model is 'Stellar-Plaw', which uses the Gilbertson+(2022) LX-stellar age scaling relation to calculate the luminosity. (Default: None)

xray_agn_emission
[{'AGN-Plaw', 'QSOSED', 'None', None}] String specifying the X-ray AGN model. The 'AGN-Plaw' model is a power law sclaed by the Lusso & Risaliti (2017) empirical L2500-L2keV relationship; the QSOSED model is a theoretical accretion disk + comptonization model that sets the normalization of the whole X-ray-to-IR AGN model as a function of M and mdot. (Default: None)

xray_absorption
[{'tbabs', 'phabs', 'None', None}] String specifying the X-ray absorption model to use. Two instances are used, one in the rest frame describing the intrinsic absorption, and one in the observed frame with a constant Galactic NH. (Default: None)

xray_wave_grid
[tuple (3,), or np.ndarray, (Nwave,), float32, optional] Either a tuple of (lo, hi, Nwave) specifying a log-spaced rest-frame wavelength grid, or an array giving the wavelengths directly. At high redshift this should be constructed carefully to ensure that your bands are covered. (Default: (1e-6, 1e-1, 200))

xray_arf
[dict or astropy.table.Table or numpy structured array] A structure defining the anciliary response function (ARF) of your X-ray observations. The structure must have three keys, *'ENERG_LO'*, *'ENERG_HI'*, and *'SPECRESP'*, which given the energy bins and binned spectral response respectively. Only used if *xray_mode='counts'* `. (Default: None)

xray_exposure
[float or np.ndarray (Nfilters)] A scalar or array giving the exposure time of the X-ray observations. If an array, it should have the same length as `filter_labels`, with all non-X-ray bands having their exposure time set to 0. Note that you almost certainly don't need to give exposure time as an array, since the energy dependence of the effective area is explicitly given by the ARF. Only used if `xray_mode='counts'`. (Default: None)

galactic_NH
[float] A scalar giving the Galactic column density along the line of sight to the source in *1e20 cm-2*. (Default: 0.0)

print_setup_time
[bool] If `True`, the setup time will be printed. (Default: False)

model_unc
[np.ndarray, (Nfilters,), float, or float] Fractional (i.e. [0,1)) model uncertainty to include in the fits. If a scalar is provided, the same model uncertainty is applied to each filter. Alternately, model uncertainties can be provided as an array, one per filter. The smarter way to do this in the future may be to set model uncertainties per component, rather than per filter. (Default: None)

model_unc_lines
[np.ndarray, (Nlines,), float, or float] Fractional (i.e. [0,1)) model uncertainty to include in the line fits. (Default: None)

cosmology
[astropy.cosmology.FlatLambdaCDM] The cosmology to assume. Lightning defaults to a flat cosmology with `h=0.7 and Om0=0.3`.

uplim_handling
[{'exact', 'approx'}] A string specifying how upper limits are to be handled. In the case of 'exact' we treat them as derived in e.g. Appendix A of Sawicki et al. (2012). In the

case of 'approx', upper limits are treated as measurements of 0 with a 1 sigma uncertainty equal to the 1 sigma flux limit. This option is provided for consistency with the handling of limits in IDL lightning. Our convention for inputting upper limits remains that they should be specified as a measurement of 0 with a 1 sigma uncertainty equal to the 1 sigma flux limit. (Default: 'exact')

Attributes

flux_obs
Observed flux-densities in mJy.

flux_unc
Uncertainties associated with `flux_obs`.

Lnu_obs
[None or numpy.ndarray, (Nfilters,), float32] Observed-frame luminosity densities, converted from the given fluxes.

Lnu_unc
[None or numpy.ndarray, (Nfilters,), float32] Uncertainties associated with `Lnu_obs`.

filter_labels
[list, str] List of filter labels.

filters
[dict, len=Nfilters, float32] A dict of numpy float32 arrays. The keys are *filter_labels* and the values correspond to the normalized transmission evaluated on *wave_grid*.

wave_obs
[numpy.ndarray, (Nfilters,), float32] Mean wavelength of the the supplied filters.

redshift
[float] Redshift of the model. Assumed to be 0 if *lum_dist* was set.

DL
[float] Luminosity distance to the model, in Mpc

wave_grid_rest
[numpy.ndarray, (Nwave,), float32] Unified rest-frame wavelength grid for the models.

wave_grid_obs
nu_grid_rest
nu_grid_obs
path_to_filters
[str] The path (relative or absolute, should just make it absolute) to the top filter directory.

model_unc

Methods

chain_plot(samples, **kwargs)	Make chain plot.
corner_plot(samples, **kwargs)	Make corner plot.
fit(p0, **kwargs)	Fit the model to the data.
from_json(fname)	Construct a Lightning object with the configuration specified by a json file.
get_mcmc_chains(sampler[, thin, discard, ...])	Reduce the emcee sampler object into chains.
get_model_components_lnu_hires(params[, ...])	Construct the individual components of the high-resolution spectral model.
get_model_likelihood(params[, negative])	Calculate the log-likelihood of the model under the given parameters.
get_model_lines(params[, stepwise])	Construct the absorbed and intrinsic model lines.
get_model_lnu(params[, stepwise])	Construct the low-resolution SED model.
get_model_lnu_hires(params[, stepwise])	Construct the high-resolution spectral model.
get_model_log_prob(params[, priors, ...])	Calculate the log-probability of the model under the given parameters.
get_xray_model_counts(params)	Construct the low-resolution X-ray instrumental SED.
get_xray_model_lnu(params)	Construct the low-resolution X-ray SED model.
get_xray_model_lnu_hires(params)	Construct the high-resolution X-ray spectral model.
print_params([verbose])	Print all the parameters of the current model.
save_json(fname)	Save the information needed to reconstruct this Lightning object to a json file.
save_pickle(fname)	Save this whole Lightning object to a pickle.
sed_plot_bestfit(samples, logprob_samples, ...)	Make plot of the best-fitting SED.
sed_plot_delchi(samples, logprob_samples, ...)	Make residual plot.
sfh_plot(samples, **kwargs)	Make SFH plot.

__init__(*filter_labels*, *redshift=None*, *lum_dist=None*, *flux_obs=None*, *flux_obs_unc=None*, *wave_grid=(0.1, 1000, 1200)*, *stellar_type='PEGASE'*, *line_labels=None*, *line_flux=None*, *line_flux_unc=None*, *line_index=None*, *nebula_lognH=2.0*, *nebula_dust=False*, *SFH_type='Piecewise-Constant'*, *ages=None*, *atten_type='Modified-Calzetti'*, *dust_emission=False*, *agn_emission=False*, *agn_polar_dust=False*, *xray_mode=None*, *xray_stellar_emission=None*, *xray_agn_emission=None*, *xray_absorption=None*, *xray_wave_grid=(1e-06, 0.1, 200)*, *xray_arf=None*, *xray_exposure=None*, *galactic_NH=0.0*, *print_setup_time=False*, *model_unc=None*, *model_unc_lines=None*, *cosmology=None*, *uplim_handling='approx'*)

chain_plot(*samples*, ***kwargs*)

Make chain plot.

See lightning.plots.chain_plot

corner_plot(*samples*, ***kwargs*)

Make corner plot.

See lightning.plots.corner_plot

fit(*p0*, ***kwargs*)

Fit the model to the data.

Parameters

p0
[np.ndarray, (Nwalkers, Nparam) or (Nparam,), float32] Initial parameters. In the case of the affine invariant MCMC sampler, this should be a 2D array initializing the entire ensemble.

method
[{'emcee', 'optimize'}] Fitting method.

Returns

emcee ensemble sampler object or scipy.opt.minimize result, depending on `method`.

`property flux_obs`

Observed flux-densities in mJy.

Flux densities are converted to observed-frame luminosity densities.

`property flux_unc`

Uncertainties associated with `flux_obs`.

Flux densities are converted to observed-frame luminosity densities.

`static from_json`(*fname*)

Construct a Lightning object with the configuration specified by a json file.

This was a nice idea when the model was simple enough that it could just be `Lightning(**config)` but now it's kind of a nightmare. Should move to binary only. Or come up with a better scheme for ascii serialization, so that I don't have to update this function every time I change anything about the model.

`get_mcmc_chains`(*sampler*, *thin=None*, *discard=None*, *flat=True*, *Nsamples=1000*, *const_dim=None*, *const_vals=None*)

Reduce the emcee sampler object into chains.

Parameters

sampler
[emcee.EnsembleSampler] Sampler from completed MCMC run, as returned by lightning.fit(method='emcee')

thin
[int] Thin factor for chains. Note that *None* means that the thin factor will be determined from the autocorrelation time; if you instead want no thinning, use thin=1. (Default: None)

discard
[int] Number of trials (i.e. burn-in) to discard from the beginning of MCMC chains. Note that *None* means that the burn-in will be determined from the autocorrelation time; if you instead want no discard, use discard=0. (Default: None)

flat
[bool] If True, collapse the ensemble sampler to a single MCMC chain. Otherwise one chain per walker is retained (Default: True)

Nsamples
[int] Number of posterior samples to retain after discarding/thinning/flattening (Default: 1000)

const_dim
[np.array, boolean] An array of length Nparams showing which model parameters were constant (since emcee doesn't know anything about these dimensions, we must provide

them separately). If None, these dimensions will be excluded from the output (as if there were no constant dimensions).

const_vals
[np.array, float] An array giving the values of the constant model parameters, if any.

Returns

samples
[np.ndarray(Nsamples, Nparam)] Sampled posterior chain(s) for parameters.

logprob_samples
[np.ndarray(Nsamples, Nparam)] Sampled logprob chain(s).

t
[np.ndarray(Nparams,)] Autocorrelation time computed *before* thinning and discarding burn-in. Preserved as a diagnostic, since it sets the scale for thinning and burn-in.

`get_model_components_lnu_hires`(*params*, *stepwise=False*)

Construct the individual components of the high-resolution spectral model.

This function returns a dictionary (or an array, I haven't decided yet) containing the indiviudal model components interpolated to the same wavelength grid.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stepwise
[bool] If true, this function returns the spectral model as a function of stellar age.

Returns

hires_models
[dict] Keys are {'stellar_attenuated', 'stellar_unattenuated', 'attenuation', 'dust', 'agn'} where 'dust' and 'agn' are only included if the model includes these components. Each key points to a numpy array containing the high-resolution models.

`get_model_likelihood`(*params*, *negative=True*)

Calculate the log-likelihood of the model under the given parameters.

If `negative` flag is set (on by default), returns the negative log likelihood (i.e. chi2 / 2).

Parameters

params
[np.ndarray(Nmodels, Nparams)] An array of the parameters expected by the model. See `Lightning.print_params()` for details on the current model parameters.

negative
[bool] A flag setting whether the log probability or its opposite is returned (as e.g. when using a minimization method). (Default: `True`)

Returns

log_like
[np.ndarray(Nmodels,)] The log of the likelihood.

`get_model_lines`(*params*, *stepwise=False*)

Construct the absorbed and intrinsic model lines.

Only available if the model *has* lines

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stepwise
[bool] If true, this function returns the spectral model as a function of stellar age.

Returns

lines_ext
[np.ndarray(Nmodels, Nlines) or np.ndarray(Nmodels, Nlines, Nages)] Model line luminosities in Lsun after multiplication by the galaxy attenuation curve.

lnu_intrinsic
[np.ndarray(Nmodels, Nlines) or np.ndarray(Nmodels, Nlines, Nages)] Intrinsic model line luminosities in Lsun.

`get_model_lnu`(*params*, *stepwise=False*)

Construct the low-resolution SED model.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stepwise
[bool] If true, this function returns the spectral model as a function of stellar age.

Returns

lnu_processed
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] Model including the effects of ISM dust, convolved with the filters.

lnu_intrinsic
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] Model not including the effects of ISM dust, convolved with the filters.

`get_model_lnu_hires`(*params*, *stepwise=False*)

Construct the high-resolution spectral model.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stepwise
[bool] If true, this function returns the spectral model as a function of stellar age.

Returns

lnu_processed
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] High resolution spectral model including the effects of ISM dust.

lnu_intrinsic
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] High resolution spectral model not including the effects of ISM dust.

`get_model_log_prob`(*params*, *priors=None*, *negative=True*, *p_bound=inf*)

Calculate the log-probability of the model under the given parameters.

If `negative` flag is set (on by default), returns the negative log probability (i.e. chi2 / 2 + log(prior)).

Parameters

params
[np.ndarray(Nmodels, Nparams)] An array of the parameters expected by the model. See `Lightning.print_params()` for details on the current model parameters.

priors
[list of Nparams callables] Priors on the parameters.

negative
[bool] A flag setting whether the log probability or its opposite is returned (as e.g. when using a minimization method). (Default: `True`)

p_bound
[float] The magnitude of the log probability for models outside of the parameter space. (Default: `np.inf`)

Returns

log_prob
[np.ndarray(Nmodels,)] The log of the probability, prior * likelihood.

`get_xray_model_counts`(*params*)

Construct the low-resolution X-ray instrumental SED.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

Returns

counts_absorbed
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] Model including the effects of the chosen absorption model, convolved with the filters.

counts_unabsorbed
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] Model not including the effects of the chosen absorption model, convolved with the filters.

`get_xray_model_lnu`(*params*)

Construct the low-resolution X-ray SED model.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters.

For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

Returns

lnu_absorbed
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] Model including the effects of the chosen absorption model, convolved with the filters.

lnu_unabsorbed
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] Model not including the effects of the chosen absorption model, convolved with the filters.

`get_xray_model_lnu_hires`(*params*)

Construct the high-resolution X-ray spectral model.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stepwise
[bool] If true, this function returns the spectral model as a function of stellar age.

Returns

lnu_absorbed: np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)
High resolution spectral model including the effects of the chosen absorption model.

lnu_unabsorbed
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nmodels, Nwave, Nages)] High resolution spectral model not including the effects of the chosen absorption model.

`property line_flux`

Observed line fluxes in erg cm-2 s-1.

Fluxes are converted to apparent luminosities.

`property line_flux_unc`

Observed line fluxes in erg cm-2 s-1.

Fluxes are converted to apparent luminosities.

`print_params`(*verbose=False*)

Print all the parameters of the current model.

If `verbose`, print a nicely formatted table of the models, their parameters, and the description of the parameters. Otherwise, just print the names of the parameters.

`save_json`(*fname*)

Save the information needed to reconstruct this Lightning object to a json file.

The Lightning object can be remade using `Lightning.from_json`.

The json configuration file is in theory human readable but note that the wavelength grids are reproduced in their entirety, so the file will likely be thousands of lines long.

`save_pickle`(*fname*)

Save this whole Lightning object to a pickle.

This will be larger than just saving the configuration to a json file, since it contains the whole object, all of the models, etc.

The normal caveats with pickles apply.

sed_plot_bestfit(*samples*, *logprob_samples*, ***kwargs*)

Make plot of the best-fitting SED.

See lightning.plots.sed_plot_bestfit

sed_plot_delchi(*samples*, *logprob_samples*, ***kwargs*)

Make residual plot.

See lightning.plots.sed_plot_delchi

sfh_plot(*samples*, ***kwargs*)

Make SFH plot.

See lightning.plots.sfh_plot

11.2 Attenuation Curves

The default attenuation model in lightning is the "modified Calzetti" curve from Noll+(2009) with a 2175 Angstrom bump and a variable UV slope linked to the bump strength. This model is implemented in the `ModifiedCalzettiAtten` class.

class lightning.attenuation.**ModifiedCalzettiAtten**

Bases: *AnalyticAtten*

The Noll+(2009) modification of the Calzetti+(2000) attenuation curve, including a Drude-profile bump at 2175 Å and a variable UV slope.

Linearly extrapolated from 1200 Å down to 912 Å.

Parameters

wave
[np.ndarray, (Nwave,), float] Rest frame wavelength grid to evaluate the model on.

Methods

evaluate(params)	Evaluate the attenuation as a function of wavelength for the given parameters.
get_AV(params)	Helper function to convert tauV -> AV
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

__init__(*wave*)

evaluate(*params*)

Evaluate the attenuation as a function of wavelength for the given parameters.

Model includes a featureless Calzetti law, with the addition of a UV bump at 2175 A and optionally extra birth cloud extinction. The same attenuation model used in most cases by Lightning; I ported it from the Lightning IDL source.

As of right now the birth cloud component should be ignored, it isn't really implemented properly at the moment – it'll be applied to all ages if you set tauV_BC > 0.

If I were willing to be a little more clever, I would define this more obviously as an extension of the Calzetti-Atten class.

Parameters

params
[np.ndarray, (Nmodels, 3) or (3,)] Parameters of the model.

Returns

expminustau
[(Nmodels, Nwave)]

`get_AV`(*params*)

Helper function to convert tauV -> AV

For toy models and instances where there is insufficient data to constrain the variable UV slope of the `ModifiedCalzettiAtten` model, we also implement the pure Calzetti featureless attenuation curve in the `CalzettiAtten` class.

`class lightning.attenuation.CalzettiAtten`

Bases: *AnalyticAtten*

Featureless Calzetti+(2000) attenuation curve.

Linearly extrapolated from 1200 Å down to 912 Å.

Parameters

wave
[np.ndarray, (Nwave,), float] Rest frame wavelength grid to evaluate the model on.

Methods

evaluate(params)	Evaluate the attenuation as a function of wavelength for the given parameters.
get_AV(params)	Helper function to convert tauV -> AV
`print_params`([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

`__init__`(*wave*)

`evaluate`(*params*)

Evaluate the attenuation as a function of wavelength for the given parameters.

Parameters

params
[np.ndarray, (Nmodels, 1) or (1,)] Values for tauV.

Returns

expminustau
[(Nmodels, Nwave)]

get_AV(*params*)

Helper function to convert tauV -> AV

The SMC extinction curve is also implemented in the SMC class for internal use by the polar dust attenuation model, as in X-Cigale.

class lightning.attenuation.**SMC**

Bases: *TabulatedAtten*

Small Magellanic Cloud extinction curve from Gordon et al. (2003)

Parameters

wave
[np.ndarray, (Nwave,), float] Rest frame wavelength grid to evaluate the model on.

References

- Gordon et al. (2003)
- https://www.stsci.edu/hst/instrumentation/reference-data-for-calibration-and-tools/astronomical-catalogs/interstellar-extinction-curves

Methods

evaluate(params)	Evaluate the attenuation as a function of wavelength for the given parameters.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

evaluate(*params*)

Evaluate the attenuation as a function of wavelength for the given parameters.

Parameters

params
[np.ndarray, (Nmodels, 1) or (1,)] Values for tauV.

Returns

expminustau
[(Nmodels, Nwave)]

The above attenuation and extinction models extend the AnalyticAtten and TabulatedAtten classes.

class lightning.attenuation.base.**AnalyticAtten**

Base class for analytic (i.e., not tabulated) attenuation curves.

__init__(*wave*)

__new__(**args*, ***kwargs*)

class lightning.attenuation.base.**TabulatedAtten**

Base class for tabulated attenuation curves.

__init__(*wave=None*)

__new__(*args, **kwargs)

11.3 SFH Models

SFH modeling in Lightning is biased toward the use of the "non-parametric" PiecewiseConstSFH as in every previous Lightning publication.

class lightning.sfh.PiecewiseConstSFH

Bases: object

Class for piecewise-constant star formation histories.

$$\psi(t) = \psi_i,\ t_i \leq t < t_{i+1}$$

Parameters

age
[array-like, (Nbins+1)] This array should define the edges of the stellar age bins.

Methods

evaluate(params)	Return the SFR as a function of time.
multiply(params, arr)	Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).
sum(params, arr[, cumulative])	Multiply the SFR in each bin by a supplied array and sum along the age axis.

__init__(*age*)

__new__(*args, **kwargs)

evaluate(*params*)

Return the SFR as a function of time.

For this piecewise constant SFH, it's just a pass-through for *params* after checking that it's the right shape.

Parameters

params
[array-like (Nmodels, Nbins)] SFR in each bin.

Returns

sfrt

multiply(*params*, *arr*)

Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of arr (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nbins)] SFR in each bin.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

Returns

res
[array-like] Product of sfh and `arr` broadcast to whatever shape was deemed appropriate.

sum(*params*, *arr*, *cumulative=False*)

Multiply the SFR in each bin by a supplied array and sum along the age axis.

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of `arr` (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nbins)] SFR in each bin.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

cumulative
[bool] If `True`, return the cumulative sum as a function of age.

Returns

res
[array-like, (Nmodels, ...)] Product of sfh and `arr`, summed along the age axis.

Several parametric SFH models are also included in the code for implementing toy models, simulating populations, reproducing literature results, etc.

class lightning.sfh.**DelayedExponentialSFH**

Bases: *FunctionalSFH*

Delayed exponential burst of star formation

$$\psi(t) = A(t/\tau)\exp(-t/\tau)$$

Methods

evaluate(params)	Returns the SFR as a function of time.
integrate(params, arr[, cumulative])	Multiply the SFR in each bin by a supplied array and integrate along the age axis.
multiply(params, arr)	Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).

__init__(*age*)

__new__(**args*, ***kwargs*)

`evaluate`(*params*)

Returns the SFR as a function of time.

`integrate`(*params*, *arr*, *cumulative=False*)

Multiply the SFR in each bin by a supplied array and integrate along the age axis.

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of `arr` (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nbins)] SFR in each bin.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

cumulative
[bool] If `True`, return the cumulative intgral as a function of age.

Returns

res
[array-like, (Nmodels, ...)] Product of sfh and `arr`, integrated along the age axis.

`multiply`(*params*, *arr*)

Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of `arr` (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nparams)] Model parameters.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

Returns

res
[array-like] Product of sfh and `arr` broadcast to whatever shape was deemed appropriate.

`class lightning.sfh.SingleExponentialSFH`

Bases: *FunctionalSFH*

Exponentially decaying burst of star formation

$$\psi(t) = \begin{cases} A \exp[(t - t_{burst})/\tau]/k, & t \leq t_{burst} \\ 0, & t > t_{burst} \end{cases}$$

where

$$k = \tau * [1 - \exp(-t_{burst}/\tau)]$$

Methods

evaluate(params)	Returns the SFR as a function of time.
integrate(params, arr[, cumulative])	Multiply the SFR in each bin by a supplied array and integrate along the age axis.
multiply(params, arr)	Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).

__init__(*age*)

__new__(**args*, ***kwargs*)

evaluate(*params*)

Returns the SFR as a function of time.

integrate(*params*, *arr*, *cumulative=False*)

Multiply the SFR in each bin by a supplied array and integrate along the age axis.

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of `arr` (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nbins)] SFR in each bin.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

cumulative
[bool] If `True`, return the cumulative intgral as a function of age.

Returns

res
[array-like, (Nmodels, ...)] Product of sfh and `arr`, integrated along the age axis.

multiply(*params*, *arr*)

Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of `arr` (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nparams)] Model parameters.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

Returns

res
[array-like] Product of sfh and `arr` broadcast to whatever shape was deemed appropriate.

New user-specific parametric SFHs can be added by defining classes that extend the `FunctionalSFH` class and define the `evaluate` method.

class lightning.sfh.base.**FunctionalSFH**

Base class for functional (delayed exponential, double exponential, etc.) star formation histories.

Parameters

age
[array-like] Grid of stellar ages on which to evaluate the SFH.

Methods

evaluate(params)	Return the SFR as a function of time.
integrate(params, arr[, cumulative])	Multiply the SFR in each bin by a supplied array and integrate along the age axis.
multiply(params, arr)	Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).

__init__(*age*)

__new__(**args*, ***kwargs*)

evaluate(*params*)

Return the SFR as a function of time.

Parameters

params
[array-like (Nmodels, Nparams)] Model parameters.

Returns

sfrt
[array-like (Nmodels, Nages)]

integrate(*params*, *arr*, *cumulative=False*)

Multiply the SFR in each bin by a supplied array and integrate along the age axis.

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of `arr` (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nbins)] SFR in each bin.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

cumulative
[bool] If `True`, return the cumulative intgral as a function of age.

Returns

res
[array-like, (Nmodels, ...)] Product of sfh and `arr`, integrated along the age axis.

`multiply`(*params*, *arr*)

Multiply the SFR in each bin by a supplied array (to determine, e.g., the stellar mass in each bin).

For normal internal use this function determines the appropriate broadcast shape of the output based on the shape of `arr` (which could be, e.g. stellar mass as a function of time, or luminosity density as a function of time *and* wavelength). If you find yourself using this function on its own, check the shape of the outputs carefully.

Parameters

params
[array-like (Nmodels, Nparams)] Model parameters.

arr
[array-like, (..., Nbins, ...) (up to three dimensions)] Array to multiply by the SFH.

Returns

res
[array-like] Product of sfh and `arr` broadcast to whatever shape was deemed appropriate.

11.4 Stellar Model

Available stellar models in Lightning are based on the PEGASE and BPASS spectral population synthesis codes; models with the A24 suffix include a nebular component generated from custom Cloudy simulations run by Amirnezam Amiri in 2024 (hence, A24). The `PEGASEModel` class is the same set of stellar population models used in IDL `Lightning`, with a Kroupa IMF and Z = 0.001-0.1

`class lightning.stellar.PEGASEModel`

Bases: `BaseEmissionModel`

Stellar emission models generated using Pégase.

These models are either:

- A single burst of star formation at 1 solar mass yr-1, evaluated on a grid of specified ages
- A binned stellar population, representing a constant epoch of star formation in a specified set of stellar age bins. These models are integrated from the above.

Nebular extinction + continuum are included by default, lines are optional, added by hand.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model.

age
[np.ndarray, (Nsteps + 1,) or (Nages,), float] Either the bounds of `Nsteps` age bins for a piecewise-constant SFH model, or `Nages` stellar ages for a continuous SFH model.

step
[bool] If `True`, `age` is interpreted as age bounds for a piecewise-constant SFH model. Otherwise `age` is interpreted as the age grid for a continuous SFH.

add_lines
[bool] If `True`, emission lines are added to the spectral models at ages < `1e7` yr.

wave_grid
[np.ndarray, (Nwave,), float, optional] If set, the spectra are interpreted to this wavelength grid.

Attributes

filter_labels
redshift
age
step
metallicity
mstar
[np.ndarray, (Nages,), float] Surviving stellar mass as a function of age.

Lbol
[np.ndarray, (Nages,), float] Bolometric luminosity as a function of age.

q0
[np.ndarray, (Nages,), float] Lyman-continuum photon production rate (yr-1) as a function of age.

wave_grid_rest
[np.ndarray, (Nwave,), float] Rest-frame wavelength grid.

wave_grid_obs
nu_grid_rest
nu_grid_obs
Lnu_obs
[np.ndarray, (Nages, Nwave), float] `(1 + redshift)` times the rest-frame spectral model, as a function of age.

Methods

get_model_lines(sfh, sfh_param, params[, ...])	Get the integrated luminosity of all the lines available to the nebular model.
get_model_lnu(sfh, sfh_param[, params, ...])	Construct the stellar SED as observed in the given filters.
get_model_lnu_hires(sfh, sfh_param, params)	Construct the high-res stellar spectrum.
get_mstar_coeff(Z)	Return the Mstar coefficients as a function of age for a given metallicity.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_lines(*sfh*, *sfh_param*, *params*, *stepwise=False*)

Get the integrated luminosity of all the lines available to the nebular model.

See self.line_names for a full list of lines. In the future we'll need to redden these lines to compare them to the observed lines, such that our line attenuation is consistent with the attenuation of the stellar population model broadly.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for Z.

stepwise
[bool] If true, the lines are returned as a function of stellar age.

Returns

Lmod_lines
[np.ndarray, (Nmodels, Nlines) or (Nmodels, Nages, Nlines)] Integrated line luminosities, optionally as a function of age.

`get_model_lnu`(*sfh*, *sfh_param*, *params=None*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the stellar SED as observed in the given filters.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed and convolved with the filters. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[None] Empty placeholder for compatibility.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_model_lnu_hires`(*sfh*, *sfh_param*, *params*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the high-res stellar spectrum.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[None] Empty placeholder for compatibility.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_mstar_coeff`(*Z*)

Return the Mstar coefficients as a function of age for a given metallicity.

Parameters

Z
[array-like (Nmodels,)] Stellar metallicity

Returns

Mstar
[(Nmodels, Nages)] Surviving stellar mass as function of age per 1 Msun yr-1 of SFR.

`class lightning.stellar.`**PEGASEModelA24**

Bases: `BaseEmissionModel`

Stellar emission models generated using PEGASE, including nebular emission calculated with Cloudy using a custom recipe with an ionization bounded nebula and an open geometry. See the README in the models folder for an outline of the Cloudy setup and links to more detailed documentation.

These models are either:

- A single burst of star formation at 1 solar mass yr-1, evaluated on a grid of specified ages
- A binned stellar population, representing a constant epoch of star formation in a specified set of stellar age bins. These models are integrated from the above.

Nebular extinction, lines, and continuum are included by default.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model.

age
[np.ndarray, (Nsteps + 1,) or (Nages,), float] Either the bounds of `Nsteps` age bins for a piecewise-constant SFH model, or `Nages` stellar ages for a continuous SFH model.

step
[bool] If `True`, `age` is interpreted as age bounds for a piecewise-constant SFH model. Otherwise `age` is interpreted as the age grid for a continuous SFH.

binaries
[bool] If `True`, the spectra include the effects of binary stellar evolution. If `False`, the nebular model cannot be applied.

nebular_effects
[bool] If `True`, the spectra will include nebular extinction, continua, and lines.

line_labels
[np.ndarray, (Nlines,), string, optional] Line labels in the format used by pyCloudy. See *lightning/models/linelist_full.txt* for the complete list of lines in the grid and their format.

dust_grains
[bool] If `True`, then dust grains are included in the Cloudy grids. (Default: False)

wave_grid
[np.ndarray, (Nwave,), float, optional] If set, the spectra are interpreted to this wavelength grid.

Attributes

filter_labels
redshift
age
step
metallicity
mstar
[np.ndarray, (Nages,), float] Surviving stellar mass as a function of age.

Lbol
[np.ndarray, (Nages,), float] Bolometric luminosity as a function of age.

q0
[np.ndarray, (Nages,), float] Lyman-continuum photon production rate (yr-1) as a function of age.

wave_grid_rest
[np.ndarray, (Nwave,), float] Rest-frame wavelength grid.

wave_grid_obs
nu_grid_rest
nu_grid_obs
Lnu_obs
[np.ndarray, (Nages, Nwave), float] `(1 + redshift)` times the rest-frame spectral model, as a function of age.

Methods

get_model_lines(sfh, sfh_param, params[, ...])	Get the integrated luminosity of all the lines available to the nebular model.
get_model_lnu(sfh, sfh_param[, params, ...])	Construct the stellar SED as observed in the given filters.
get_model_lnu_hires(sfh, sfh_param, params)	Construct the high-res stellar spectrum.
get_mstar_coeff(Z)	Return the Mstar coefficients as a function of age for a given metallicity.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_lines(*sfh*, *sfh_param*, *params*, *exptau=None*, *stepwise=False*)

Get the integrated luminosity of all the lines available to the nebular model.

See self.line_names for a full list of lines. In the future we'll need to redden these lines to compare them to the observed lines, such that our line attenuation is consistent with the attenuation of the stellar population model broadly.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 2)] Values for Z and logU.

stepwise
[bool] If true, the lines are returned as a function of stellar age.

Returns

Lmod_lines
[np.ndarray, (Nmodels, Nlines) or (Nmodels, Nages, Nlines)] Integrated line luminosities, optionally as a function of age.

get_model_lnu(*sfh*, *sfh_param*, *params=None*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the stellar SED as observed in the given filters.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed and convolved with the filters. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for logU, if the model includes a nebular component.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_model_lnu_hires`(*sfh*, *sfh_param*, *params*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the high-res stellar spectrum.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for logU, if the model includes a nebular component.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_mstar_coeff`(*Z*)

Return the Mstar coefficients as a function of age for a given metallicity.

Parameters

Z
[array-like (Nmodels,)] Stellar metallicity

Returns

Mstar
[(Nmodels, Nages)] Surviving stellar mass as function of age per 1 Msun yr-1 of SFR.

`class lightning.stellar.`**PEGASEBurstA24**

Bases: *PEGASEModelA24*

SFH-free model representing a single instantaneous burst of star formation with a given mass and age.

Methods

get_model_lines(params[, exptau])	
get_model_lnu(params[, exptau])	
get_model_lnu_hires(params[, exptau])	
`get_mstar_coeff`(Z)	Return the Mstar coefficients as a function of age for a given metallicity.
`print_params`([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

__init__(*filter_labels*, *redshift*, *wave_grid=None*, *age=None*, *lognH=2.0*, *cosmology=None*, *line_labels=None*, *dust_grains=False*)

Generic initialization. Actual model-building should be handled by implementing the *construct_model* and *construct_model_grid* methods.

get_model_lines(*params*, *exptau=None*)

Parameters

params
[array-like (Nmodels, 4)] The parameters are, in order, Mburst, tburst, Z, and logU. In practice we'll probably sample log(Mburst) and log(tburst).

exptau
[array-like (Nmodels, Nwave)] Attenuation curve(s) evaluated at model wavelengths; really it's exp(-tau). Currently unused, i.e. line luminosities returned are intrinsic, unreddened.

Returns

lmod_lines

get_model_lnu(*params*, *exptau=None*)

Parameters

params
[array-like (Nmodels, 4)] The parameters are, in order, Mburst, tburst, Z, and logU. In practice we'll probably sample log(Mburst) and log(tburst).

exptau
[array-like (Nmodels, Nwave)] Attenuation curve(s) evaluated at model wavelengths; really it's exp(-tau)

Returns

lmod_unattenuated
lmod_unattenuated
L_TIR

get_model_lnu_hires(*params*, *exptau=None*)

Parameters

params
[array-like (Nmodels, 4)] The parameters are, in order, Mburst, tburst, Z, and logU. In practice we'll probably sample log(Mburst) and log(tburst).

exptau
[array-like (Nmodels, Nwave)] Attenuation curve(s) evaluated at model wavelengths; really it's exp(-tau)

Returns

lnu_unattenuated
lnu_unattenuated
L_TIR

class lightning.stellar.**BPASSModel**

Bases: BaseEmissionModel

Stellar emission models generated using BPASS, including nebular emission calculated with Cloudy, as generated by the BPASS team. See the README in the models folder for an outline of the Cloudy setup and

links to more detailed documentation. For the custom BPASS+Cloudy models used in e.g. Lehmer+(2024), see `BPASSModelA24`.

These models are either:

- A single burst of star formation at 1 solar mass yr-1, evaluated on a grid of specified ages
- A binned stellar population, representing a constant epoch of star formation in a specified set of stellar age bins. These models are integrated from the above.

Nebular extinction, lines, and continuum are included by default. IMF is only 'imf_135_300'; a Kroupa-like two-slope IMF with an upper mass cutoff at 300 Msun.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model.

age
[np.ndarray, (Nsteps + 1,) or (Nages,), float] Either the bounds of `Nsteps` age bins for a piecewise-constant SFH model, or `Nages` stellar ages for a continuous SFH model.

step
[bool] If `True`, `age` is interpreted as age bounds for a piecewise-constant SFH model. Otherwise `age` is interpreted as the age grid for a continuous SFH.

binaries
[bool] If `True`, the spectra include the effects of binary stellar evolution. If `False`, the nebular model cannot be applied (and as a result the `dust_grains` switch has no effect).

nebular_effects
[bool] If `True`, the spectra at ages <1e7.5 years will include nebular extinction, continua, and lines.

dust_grains
[bool] If `True`, the Cloudy models include the effects of dust grain depletion. This option has no effect unless `nebular_effects` is True. By default, we set this option to `False`, for parity with the treatment of nebular emission in the Pégase stellar population models.

wave_grid
[np.ndarray, (Nwave,), float, optional] If set, the spectra are interpreted to this wavelength grid.

Attributes

filter_labels
redshift
age
step
metallicity
mstar
[np.ndarray, (Nages,), float] Surviving stellar mass as a function of age.

Lbol
[np.ndarray, (Nages,), float] Bolometric luminosity as a function of age.

q0
[np.ndarray, (Nages,), float] Lyman-continuum photon production rate (yr-1) as a function of age.

wave_grid_rest
[np.ndarray, (Nwave,), float] Rest-frame wavelength grid.

wave_grid_obs
nu_grid_rest
nu_grid_obs
Lnu_obs
[np.ndarray, (Nages, Nwave), float] `(1 + redshift)` times the rest-frame spectral model, as a function of age.

Methods

get_model_lines(sfh, sfh_param, params[, ...])	Get the integrated luminosity of all the lines available to the nebular model.
get_model_lnu(sfh, sfh_param, params[, ...])	Construct the stellar SED as observed in the given filters.
get_model_lnu_hires(sfh, sfh_param, params)	Construct the high-res stellar spectrum.
get_mstar_coeff(Z)	Return the Mstar coefficients as a function of age for a given metallicity.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_lines(*sfh*, *sfh_param*, *params*, *stepwise=False*)

Get the integrated luminosity of all the lines available to the nebular model.

See self.line_names for a full list of lines. In the future we'll need to redden these lines to compare them to the observed lines, such that our line attenuation is consistent with the attenuation of the stellar population model broadly.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 2)] Values for Z and logU.

stepwise
[bool] If true, the lines are returned as a function of stellar age.

Returns

Lmod_lines
[np.ndarray, (Nmodels, Nlines) or (Nmodels, Nages, Nlines)] Integrated line luminosities, optionally as a function of age.

get_model_lnu(*sfh*, *sfh_param*, *params*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the stellar SED as observed in the given filters.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed and convolved with the filters. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for logU, if the model includes a nebular component.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_model_lnu_hires`(*sfh*, *sfh_param*, *params*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the high-res stellar spectrum.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for logU, if the model includes a nebular component.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_mstar_coeff`(*Z*)

Return the Mstar coefficients as a function of age for a given metallicity.

Parameters

Z
[array-like (Nmodels,)] Stellar metallicity

Returns

Mstar
[(Nmodels, Nages)] Surviving stellar mass as function of age per 1 Msun yr-1 of SFR.

class lightning.stellar.**BPASSModelA24**

Bases: `BaseEmissionModel`

Stellar emission models generated using BPASS, including nebular emission calculated with Cloudy using a custom recipe with an ionization bounded nebula and an open geometry. See the README in the models folder for an outline of the Cloudy setup and links to more detailed documentation.

These models are either:

- A single burst of star formation at 1 solar mass yr-1, evaluated on a grid of specified ages
- A binned stellar population, representing a constant epoch of star formation in a specified set of stellar age bins. These models are integrated from the above.

Nebular extinction, lines, and continuum are included by default. IMF is Chabrier by default, with high mass cutoff at 300 Msun (chab300). If the grids based on the SSP+ULX SED files from Garofali+(2024) are selected, the IMF is instead 'imf_135_100', a Kroupa-like two-slope IMF with a high mass cutoff at 100 Msun.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model.

age
[np.ndarray, (Nsteps + 1,) or (Nages,), float] Either the bounds of `Nsteps` age bins for a piecewise-constant SFH model, or `Nages` stellar ages for a continuous SFH model.

step
[bool] If `True`, `age` is interpreted as age bounds for a piecewise-constant SFH model. Otherwise `age` is interpreted as the age grid for a continuous SFH.

binaries
[bool] If `True`, the spectra include the effects of binary stellar evolution. If `False`, the nebular model cannot be applied.

ULX
[bool] If `True`, the spectra loaded will be the SXP+SSP models from Garofali+(2024), postprocessed with Cloudy following the same recipe as we typically adopt (see `lightning_models/models/BPASS_Cloudy/README.md`). Note that this fixes the IMF to the BPASS *imf_135_100* adopted in Garofali+. Note that this model doesn't extend fully to the X-rays yet, it just modifies the line emission due to the considerably larger Q(He II).

nebular_effects
[bool] If `True`, the spectra will include nebular extinction, continua, and lines.

line_labels
[np.ndarray, (Nlines,), string, optional] Line labels in the format used by pyCloudy. See *lightning/models/linelist_full.txt* for the complete list of lines in the grid and their format.

nebula_old
[bool] If `True`, the spectra will include nebular extinction and emission at ages older than 50 Myr, modeling the nebular contributions of the hot, stripped cores of evolved massive stars. While the the conditions we assume for the nebula are most appropriate for massive H II regions, Byler+(2017) found that nebular emission from post-AGB stars is not super sensitive to the geometry/density of the nebula, but it may be worth fitting your galaxies with and without this component if you're concerned.

dust_grains
[bool] If `True`, then dust grains are included in the Cloudy grids. (Default: False)

wave_grid
[np.ndarray, (Nwave,), float, optional] If set, the spectra are interpreted to this wavelength grid.

Attributes

filter_labels
redshift
age
step
metallicity
mstar
[np.ndarray, (Nages,), float] Surviving stellar mass as a function of age.

Lbol
[np.ndarray, (Nages,), float] Bolometric luminosity as a function of age.

q0
[np.ndarray, (Nages,), float] Lyman-continuum photon production rate (yr-1) as a function of age.

wave_grid_rest
[np.ndarray, (Nwave,), float] Rest-frame wavelength grid.

wave_grid_obs
nu_grid_rest
nu_grid_obs
Lnu_obs
[np.ndarray, (Nages, Nwave), float] `(1 + redshift)` times the rest-frame spectral model, as a function of age.

Methods

get_model_lines(sfh, sfh_param, params[, ...])	Get the integrated luminosity of all the lines available to the nebular model.
get_model_lnu(sfh, sfh_param[, params, ...])	Construct the stellar SED as observed in the given filters.
get_model_lnu_hires(sfh, sfh_param, params)	Construct the high-res stellar spectrum.
get_mstar_coeff(Z)	Return the Mstar coefficients as a function of age for a given metallicity.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_lines(*sfh*, *sfh_param*, *params*, *exptau=None*, *stepwise=False*)

Get the integrated luminosity of all the lines available to the nebular model.

See self.line_names for a full list of lines. In the future we'll need to redden these lines to compare them to the observed lines, such that our line attenuation is consistent with the attenuation of the stellar population model broadly.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for Z and logU

stepwise
[bool] If true, the lines are returned as a function of stellar age.

Returns

Lmod_lines
[np.ndarray, (Nmodels, Nlines) or (Nmodels, Nages, Nlines)] Integrated line luminosities, optionally as a function of age.

get_model_lnu(*sfh*, *sfh_param*, *params=None*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the stellar SED as observed in the given filters.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed and convolved with the filters. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for logU, if the model includes a nebular component.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_model_lnu_hires`(*sfh*, *sfh_param*, *params*, *exptau=None*, *exptau_youngest=None*, *stepwise=False*)

Construct the high-res stellar spectrum.

Given a SFH instance and set of parameters, the corresponding high-resolution spectrum is constructed. Optionally, attenuation is applied and the attenuated power is returned.

Parameters

sfh
[instance of lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] Star formation history model.

sfh_params
[np.ndarray, (Nmodels, Nparam) or (Nparam,), float32] Parameters for the star formation history.

params
[np.ndarray, (Nmodels, 1) or (Nmodels,)] Values for logU, if the model includes a nebular component.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] `exp(-tau)` as a function of wavelength. If this is 2D, the size of the first dimension must match the size of the first dimension of `sfh_params`.

exptau_youngest
[np.ndarray, (Nmodels, Nwave) or (Nwave,), float32] This doesn't do anything at the moment, until I figure out how to flexibly decide which ages to apply the birth cloud attenuation to.

stepwise
[bool] If true, the spectrum is returned as a function of stellar age.

Returns

lnu_attenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The stellar spectrum as seen after the application of the ISM dust attenuation model.

lnu_unattenuated
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The intrinsic stellar spectrum.

L_TIR
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total attenuated power of the stellar population.

`get_mstar_coeff(Z)`

Return the Mstar coefficients as a function of age for a given metallicity.

Parameters

Z
[array-like (Nmodels,)] Stellar metallicity

Returns

Mstar
[(Nmodels, Nages)] Surviving stellar mass as function of age per 1 Msun yr-1 of SFR.

`class lightning.stellar.BPASSBurstA24`

Bases: *BPASSModelA24*

SFH-free model representing a single instantaneous burst of star formation with a given mass and age.

Methods

get_model_lines(params[, exptau])	
get_model_lnu(params[, exptau])	
get_model_lnu_hires(params[, exptau])	
get_mstar_coeff(Z)	Return the Mstar coefficients as a function of age for a given metallicity.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

`__init__`(*filter_labels*, *redshift*, *wave_grid=None*, *age=None*, *lognH=2.0*, *cosmology=None*, *line_labels=None*, *dust_grains=False*, *ULX=False*)

Generic initialization. Actual model-building should be handled by implementing the *construct_model* and *construct_model_grid* methods.

`get_model_lines`(*params*, *exptau=None*)

Parameters

params
[array-like (Nmodels, 4)] The parameters are, in order, Mburst, tburst, Z, and logU. In practice we'll probably sample log(Mburst) and log(tburst).

exptau
[array-like (Nmodels, Nwave)] Attenuation curve(s) evaluated at model wavelengths; really it's exp(-tau).

Returns

lmod_lines

`get_model_lnu`(*params*, *exptau=None*)

Parameters

params
[array-like (Nmodels, 4)] The parameters are, in order, Mburst, tburst, Z, and logU. In practice we'll probably sample log(Mburst) and log(tburst).

exptau
[array-like (Nmodels, Nwave)] Attenuation curve(s) evaluated at model wavelengths; really it's exp(-tau)

Returns

lmod_unattenuated
lmod_unattenuated
L_TIR

`get_model_lnu_hires`(*params*, *exptau=None*)

Parameters

params
[array-like (Nmodels, 4)] The parameters are, in order, Mburst, tburst, Z, and logU. In practice we'll probably sample log(Mburst) and log(tburst).

exptau
[array-like (Nmodels, Nwave)] Attenuation curve(s) evaluated at model wavelengths; really it's exp(-tau)

Returns

lnu_unattenuated
lnu_unattenuated
L_TIR

11.5 Dust Model

Dust emission powered by the stellar radiation field is modeled in lightning using the Draine & Li (2007) models. Setting `dust_emission=True` when initializing `Lightning` automatically selects this model; we do not currently provide an alternative.

class lightning.dust.**DL07Dust**

Bases: `BaseEmissionModel`

An implementation of the Draine & Li (2007) dust emission models.

A fraction `gamma` of the dust is exposed to a radiation field such that the mass of dust `dM` exposed to a range of intensities `[U, U + dU]` is

$$dM = \text{const}\ U^{-\alpha} dU,$$

where `U` is in `[Umin, Umax]`. The remaining portion `(1 - gamma)` is exposed to a radiation field with intensity `Umin`.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model.

wave_grid
[np.ndarray] Rest frame wavelength grid to interpolate the model on.

Attributes

Lnu_rest
[numpy.ndarray, (29, 7, Nwave), float] High-res spectral model grid. First dimension covers U, the second q_PAH, and the third covers wavelength.

Lnu_obs
[numpy.ndarray, (29, 7, Nwave), float] `(1 + redshift) * Lnu_rest`

mean_Lnu
[numpy.ndarray, (29, 7, Nfilters), float] The `Lnu_obs` grid integrated against the filters.

Lbol
[numpy.ndarray, (29, 7), float] Total luminosity of each model in the grid.

wave_grid_rest
[numpy.ndarray, (Nwave,), float] Rest-frame wavelength grid for the models.

wave_grid_obs
nu_grid_rest
nu_grid_obs

Methods

get_model_lnu(params)	Construct the dust SED as observed in the given filters.
get_model_lnu_hires(params)	Construct the high-resolution dust SED.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_lnu(*params*)

Construct the dust SED as observed in the given filters.

Given a set of parameters, the corresponding high-resolution spectrum is constructed and convolved with the filters.

Parameters

params
[np.ndarray, (Nmodels, 5) or (5,) float32] The dust model parameters.

Returns

Lnu_obs
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The dust spectrum as seen through the given filters

Lbol
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total luminosity of the dust model.

get_model_lnu_hires(*params*)

Construct the high-resolution dust SED.

Given a set of parameters, the high-resolution spectrum is constructed.

Parameters

params
[np.ndarray, (Nmodels, 5) or (5,) float32] The dust model parameters.

Returns

Lnu_obs
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The dust spectrum as seen through the given filters

Lbol
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total luminosity of the dust model.

The GrayBody class is used internally to add an additional cold dust component to the AGN emission spectra, balanced with the attenuated power of the "polar dust" component. It cannot currently be selected to replace the Draine & Li model to model the dust emission powered by attenuated stars. It is documented here for completeness; note that it can be initialized on its own and used to build your own custom models.

class lightning.dust.**Graybody**

Bases: BaseEmissionModel

A gray-body dust emission model.

The gray body is a modified blackbody accounting for variations in opacity and emissivity, such that (Casey et al. 2012):

$$L_\nu \propto [1 - \exp(-\tau(\nu))] B_\nu(T) = [1 - \exp(-\tau(\nu))] \frac{\nu^3}{\exp(h\nu/kT) - 1}$$

where the optical depth is taken to be a power law in frequency: `tau(nu) = (nu / nu0)^beta` for some `nu0` where the optical depth is 1. In practice this is usually assumed to be around 100-200 um. Beta is expected to range between ~1–2.5.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model.

wave_grid
[np.ndarray] Rest frame wavelength grid to evaluate the model on.

Methods

get_model_lnu(params)	Construct the dust SED as observed in the given filters.
get_model_lnu_hires(params)	Construct the high-resolution dust SED.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_lnu(*params*)

Construct the dust SED as observed in the given filters.

Note that the model Lnu is normalized to the total luminosity.

Parameters

params
[np.ndarray, (Nmodels, 3) or (3,) float32] The dust model parameters.

Returns

Lnu_obs
[np.ndarray, (Nmodels, Nfilters), (Nmodels, Nages, Nfilters), or (Nfilters,), float32] The dust spectrum as seen through the given filters

Lbol
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total luminosity of the dust model.

get_model_lnu_hires(*params*)

Construct the high-resolution dust SED.

Note that the model Lnu is normalized to the total luminosity.

Parameters

params
[np.ndarray, (Nmodels, 3) or (3,) float32] The dust model parameters.

Returns

Lnu_obs
[np.ndarray, (Nmodels, Nwave), (Nmodels, Nages, Nwave), or (Nwave,), float32] The dust spectrum as seen through the given filters

Lbol
[np.ndarray, (Nmodels,) or (Nmodels, Nages)] The total luminosity of the dust model.

11.6 AGN Model

`class lightning.agn.AGNModel`

Bases: `BaseEmissionModel`

An implementation of the Stalevski (2016) SKIRTOR models.

The broken power law accretion disk model is the SKIRTOR default. Future versions may include an option to swap in the Schartman+(2005) power law model as in X-Cigale. Optionally includes the X-Cigale recipe for polar dust extinction.

Parameters

filter_labels
[list, str] List of filter labels.

redshift
[float] Redshift of the model.

wave_grid
[np.ndarray, (Nwave,), float, optional] If set, the spectra are interpreted to this wavelength grid.

polar_dust
[bool] If `True`, AGN polar dust extinction and re-emission are implemented following the recipe from X-Cigale Note that even if this keyword is set to `False`, the polar dust optical depth remains a parameter of the model - it just doesn't do anything, and should held at 0 in any fitting. (Default: True)

References

- https://ui.adsabs.harvard.edu/abs/2016MNRAS.458.2288S/abstract
- https://sites.google.com/site/skirtorus

Attributes

Lnu_rest
[numpy.ndarray, (29, 7, 132), float] High-res spectral model grid. First dimension covers U, the second q_PAH, and the third covers wavelength.

Lnu_obs
[numpy.ndarray, (29, 7, 132), float] `(1 + redshift) * Lnu_rest`

mean_Lnu
[numpy.ndarray, (29, 7, Nfilters), float] The `Lnu_obs` grid integrated against the filters.

Lbol
[numpy.ndarray, (29, 7), float] Total luminosity of each model in the grid.

wave_grid_rest
[numpy.ndarray, (132,), float] Rest-frame wavelength grid for the models.

wave_grid_obs
nu_grid_rest
nu_grid_obs

Methods

get_model_lnu(params[, exptau])	Produce the AGN model as observed in the given filters.
get_model_lnu_hires(params[, exptau])	Produce the high-resolution AGN spectral model.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_lnu(*params*, *exptau=None*)

Produce the AGN model as observed in the given filters.

Given a set of parameters, produce the observed AGN SED, optionally attenuating it with the ISM dust attenuation model and a polar dust model, a là CIGALE.

Parameters

params
[np.ndarray, (Nmodels, 3) or (3,) float] The AGN model parameters.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,) float] The ISM attenuation curve.

Returns

lnu_hires
[np.ndarray, (Nmodels, Nfilters) or (Nfilters,) float] The high resolution AGN models.

get_model_lnu_hires(*params*, *exptau=None*)

Produce the high-resolution AGN spectral model.

Given a set of parameters, produce the AGN spectrum, optionally attenuating it with the ISM dust attenuation model and a polar dust model, a là CIGALE.

Parameters

params
[np.ndarray, (Nmodels, 3) or (3,) float] The AGN model parameters.

exptau
[np.ndarray, (Nmodels, Nwave) or (Nwave,) float] The ISM attenuation curve.

Returns

lnu_hires
[np.ndarray, (Nmodels, Nwave) or (Nwave,) float] The high resolution AGN models.

11.7 X-ray Models

11.7.1 X-ray Emission

The X-ray fitting module implements two simple power law models for XRB populations and AGN, as well as a version of the `QSOSED` model of Kubota & Done (2018).

One noteworthy point about the `StellarPlaw` and `AGNPlaw` models is that they both rely on knowledge of the corresponding UV-IR models to set their normalization. You'll thus see that the `StellarPlaw` `get_*` functions all require a stellar model and its parameters as input, while their equivalents for the `AGNPlaw` model require the AGN model and its parameters.

class lightning.xray.**StellarPlaw**

Bases: *XrayPlawExpcut*

Simple model for stellar X-ray emission.

Inclues a stellar-age parameterization of the luminosity, such that the model normalization is a function of the SFH. The high energy cutoff is fixed, but the photon index can vary.

The luminosity is determined from the SFH model based on the empirical Lx/M - stellar age relationship from Gilbertson+(2022).

Parameters

filter_labels
[list, str] List of filter labels.

arf
[dict or astropy.table.Table or numpy structured array] A structure defining the anciliary response function (ARF) of your X-ray observations. The structure must have three keys, *'ENERG_LO'*, *'ENERG_HI'*, and *'SPECRESP'*, which given the energy bins and binned spectral response respectively. Only used if *xray_mode='counts'* `.

exposure
[float or np.ndarray (Nfilters)] A scalar or array giving the exposure time of the X-ray observations. If an array, it should have the same length as `filter_labels`, with all non-X-ray bands having their exposure time set to 0. Note that you almost certainly don't need to give exposure time as an array, since the energy dependence of the effective area is explicitly given by the ARF. Only used if `xray_mode='counts'`.

redshift
[float] Redshift of the model. If set, `lum_dist` is ignored.

lum_dist
[float] Luminosity distance to the model. If not set, this will be calculated from the redshift and cosmology. (Default: None)

cosmology
[astropy.cosmology.FlatLambdaCDM] The cosmology to assume. Lightning defaults to a flat cosmology with `h=0.7 and Om0=0.3`.

path_to_models
[str] Path to lightning models. Not actually used in normal circumstances.

path_to_filters
[str] Path to lightning filters. Not actually used in normal circumstances.

wave_grid
[tuple (3,), or np.ndarray, (Nwave,), float32, optional] Either a tuple of (lo, hi, Nwave) specifying a log-spaced rest-frame wavelength grid, or an array giving the wavelengths directly. At high redshift this should be constructed carefully to ensure that your bands are covered. (Default: (1e-6, 1e-1, 200))

References

- Gilbertson et al. (2022)

Methods

get_model_countrate(params, stellar_model, ...)	Construct the bandpass-convolved SED in count-rate.
get_model_countrate_hires(params, ...[, exptau])	Construct the high-resolution countrate-density spectrum.
get_model_counts(params, stellar_model, ...)	Construct the bandpass-convolved SED in counts.
get_model_lnu(params, stellar_model, ...[, ...])	Construct the bandpass-convolved SED in Lnu.
get_model_lnu_hires(params, stellar_model, ...)	Construct the high-resolution spectrum in Lnu.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_countrate(*params*, *stellar_model*, *stellar_params*, *sfh*, *sfh_params*, *exptau=None*)

Construct the bandpass-convolved SED in count-rate.

This function takes in the stellar and SFH models in order to use the stellar-age parametrization of Lx / M from Gilbertson et al. (2022).

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stellar_model
[lightning.stellar model] The stellar model.

stellar_params
[np.ndarray(Nmodels, Nparams_st) or np.ndarray(Nparams_st)] The stellar model parameters (i.e. metallicity and possible logU).

sfh
[lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] The star formation history model.

sfh_params
[np.ndarray(Nmodels, Nparams_sfh) or np.ndarray(Nparams_sfh)] The parameters for the SFH.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free count-rate is not returned by default. It can be accessed by setting exptau to `None`.

`get_model_countrate_hires`(*params*, *stellar_model*, *stellar_params*, *sfh*, *sfh_params*, *exptau=None*)

Construct the high-resolution countrate-density spectrum.

This function takes in the stellar and SFH models in order to use the stellar-age parametrization of Lx / M from Gilbertson et al. (2022).

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stellar_model
[lightning.stellar model] The stellar model.

stellar_params
[np.ndarray(Nmodels, Nparams_st) or np.ndarray(Nparams_st)] The stellar model parameters (i.e. metallicity and possible logU).

sfh
[lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] The star formation history model.

sfh_params
[np.ndarray(Nmodels, Nparams_sfh) or np.ndarray(Nparams_sfh)] The parameters for the SFH.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free count-rate spectrum is not returned by default. It can be accessed by setting exptau to `None`.

`get_model_counts`(*params*, *stellar_model*, *stellar_params*, *sfh*, *sfh_params*, *exptau=None*)

Construct the bandpass-convolved SED in counts.

This function takes in the stellar and SFH models in order to use the stellar-age parametrization of Lx / M from Gilbertson et al. (2022).

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stellar_model
[lightning.stellar model] The stellar model.

stellar_params
[np.ndarray(Nmodels, Nparams_st) or np.ndarray(Nparams_st)] The stellar model parameters (i.e. metallicity and possible logU).

sfh
[lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] The star formation history model.

sfh_params
[np.ndarray(Nmodels, Nparams_sfh) or np.ndarray(Nparams_sfh)] The parameters for the SFH.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free counts are not returned by default. They can be accessed by setting exptau to `None`.

`get_model_lnu`(*params*, *stellar_model*, *stellar_params*, *sfh*, *sfh_params*, *exptau=None*)

Construct the bandpass-convolved SED in Lnu.

This function takes in the stellar and SFH models in order to use the stellar-age parametrization of Lx / M from Gilbertson et al. (2022).

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stellar_model
[lightning.stellar model] The stellar model.

stellar_params
[np.ndarray(Nmodels, Nparams_st) or np.ndarray(Nparams_st)] The stellar model parameters (i.e. metallicity and possible logU).

sfh
[lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] The star formation history model.

sfh_params
[np.ndarray(Nmodels, Nparams_sfh) or np.ndarray(Nparams_sfh)] The parameters for the SFH.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

`get_model_lnu_hires`(*params*, *stellar_model*, *stellar_params*, *sfh*, *sfh_params*, *exptau=None*)

Construct the high-resolution spectrum in Lnu.

This function takes in the stellar and SFH models in order to use the stellar-age parametrization of Lx / M from Gilbertson et al. (2022).

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

stellar_model
[lightning.stellar model] The stellar model.

stellar_params
[np.ndarray(Nmodels, Nparams_st) or np.ndarray(Nparams_st)] The stellar model parameters (i.e. metallicity and possible logU).

sfh
[lightning.sfh.PiecewiseConstSFH or lightning.sfh.FunctionalSFH] The star formation history model.

sfh_params
[np.ndarray(Nmodels, Nparams_sfh) or np.ndarray(Nparams_sfh)] The parameters for the SFH.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

`class lightning.xray.AGNPlaw`

Bases: *XrayPlawExpcut*

Simple model for AGN X-ray emission.

Uses the Lusso and Risaliti (2017) relationship to connect the intrinsic accretion disk luminosity at 2500 Angstroms to the X-ray luminosity at 2 keV. The high energy cutoff is fixed, but the photon index can vary.

The model includes a parameter representing the deviation from the LR17 relationship. Similar parameters are sometimes called 'x-ray weakness' - an underluminous X-ray spectrum compared to the prediction may be a result of mass loading in the corona providing an alternate source of cooling.

Parameters

filter_labels
[list, str] List of filter labels.

arf
[dict or astropy.table.Table or numpy structured array] A structure defining the anciliary response function (ARF) of your X-ray observations. The structure must have three keys, *'ENERG_LO'*, *'ENERG_HI'*, and *'SPECRESP'*, which given the energy bins and binned spectral response respectively. Only used if *xray_mode='counts'* `.

exposure
[float or np.ndarray (Nfilters)] A scalar or array giving the exposure time of the X-ray observations. If an array, it should have the same length as `filter_labels`, with all non-X-ray bands having their exposure time set to 0. Note that you almost certainly don't need to give exposure time as an array, since the energy dependence of the effective area is explicitly given by the ARF. Only used if `xray_mode='counts'`.

redshift
[float] Redshift of the model. If set, `lum_dist` is ignored.

lum_dist
[float] Luminosity distance to the model. If not set, this will be calculated from the redshift and cosmology. (Default: None)

cosmology
[astropy.cosmology.FlatLambdaCDM] The cosmology to assume. Lightning defaults to a flat cosmology with `h=0.7 and Om0=0.3`.

wave_grid
[tuple (3,), or np.ndarray, (Nwave,), float32, optional] Either a tuple of (lo, hi, Nwave) specifying a log-spaced rest-frame wavelength grid, or an array giving the wavelengths directly.

At high redshift this should be constructed carefully to ensure that your bands are covered. (Default: (1e-6, 1e-1, 200))

References

- Lusso and Risaliti (2018)

Methods

get_model_countrate(params, agn_model, ...)	Construct the bandpass-convolved SED in count-rate.
get_model_countrate_hires(params, agn_model, ...)	Construct the high-resolution spectrum in count-rate density.
get_model_counts(params, agn_model, agn_params)	Construct the high-resolution spectrum in Lnu.
get_model_lnu(params, agn_model, agn_params)	Construct the bandpass-convolved SED in Lnu.
get_model_lnu_hires(params, agn_model, ...)	Construct the high-resolution spectrum in Lnu.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_countrate(*params*, *agn_model*, *agn_params*, *exptau=None*)

Construct the bandpass-convolved SED in count-rate.

This function takes in the agn model to normalize the X-ray spectrum with the Lusso & Risaliti (2017) L2keV - L2500 relationship.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

agn_model
[lightning.agn.AGNModel] The AGN model.

agn_params
[np.ndarray(Nmodels, Nparams_agn) or np.ndarray(Nparams_agn)] The parameters for the AGN model.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free count-rate is not returned by default. It can be accessed by setting exptau to `None`.

get_model_countrate_hires(*params*, *agn_model*, *agn_params*, *exptau=None*)

Construct the high-resolution spectrum in count-rate density.

This function takes in the agn model to normalize the X-ray spectrum with the Lusso & Risaliti (2017) L2keV - L2500 relationship.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

agn_model
[lightning.agn.AGNModel] The AGN model.

agn_params
[np.ndarray(Nmodels, Nparams_agn) or np.ndarray(Nparams_agn)] The parameters for the AGN model.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free count-rate spectrum is not returned by default. It can be accessed by setting exptau to `None`.

`get_model_counts`(*params*, *agn_model*, *agn_params*, *exptau=None*)

Construct the high-resolution spectrum in Lnu.

This function takes in the agn model to normalize the X-ray spectrum with the Lusso & Risaliti (2017) L2keV - L2500 relationship.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

agn_model
[lightning.agn.AGNModel] The AGN model.

agn_params
[np.ndarray(Nmodels, Nparams_agn) or np.ndarray(Nparams_agn)] The parameters for the AGN model.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free counts are not returned by default. They can be accessed by setting exptau to `None`.

`get_model_lnu`(*params*, *agn_model*, *agn_params*, *exptau=None*)

Construct the bandpass-convolved SED in Lnu.

This function takes in the agn model to normalize the X-ray spectrum with the Lusso & Risaliti (2017) L2keV - L2500 relationship.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters.

For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

agn_model
[lightning.agn.AGNModel] The AGN model.

agn_params
[np.ndarray(Nmodels, Nparams_agn) or np.ndarray(Nparams_agn)] The parameters for the AGN model.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

`get_model_lnu_hires`(*params*, *agn_model*, *agn_params*, *exptau=None*)

Construct the high-resolution spectrum in Lnu.

This function takes in the agn model to normalize the X-ray spectrum with the Lusso & Risaliti (2017) L2keV - L2500 relationship.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

agn_model
[lightning.agn.AGNModel] The AGN model.

agn_params
[np.ndarray(Nmodels, Nparams_agn) or np.ndarray(Nparams_agn)] The parameters for the AGN model.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

The `QSOSED` model, however, doesn't need to know about the UV-IR AGN model, because the opposite is true: the UV-IR AGN component is normalized by the `QSOSED` model, allowing the black hole mass and Eddington ratio to set the overall luminosity of the entire AGN model.

`class lightning.xray.Qsosed`

Bases: *XrayEmissionModel*

Physically motivated quasar model for X-ray emission.

Parametrized by the black hole mass and Eddington ratio (here called mdot). See Kubota & Done (2018) for details.

The model is available in XSpec, and the implementation here was generated using Sherpa.

Parameters

filter_labels
[list, str] List of filter labels.

arf
[dict or astropy.table.Table or numpy structured array] A structure defining the anciliary response function (ARF) of your X-ray observations. The structure must have three keys, *'ENERG_LO'*, *'ENERG_HI'*, and *'SPECRESP'*, which given the energy bins and binned spectral response respectively. Only used if *xray_mode='counts'* `.

exposure
[float or np.ndarray (Nfilters)] A scalar or array giving the exposure time of the X-ray observations. If an array, it should have the same length as `filter_labels`, with all non-X-ray bands having their exposure time set to 0. Note that you almost certainly don't need to give exposure time as an array, since the energy dependence of the effective area is explicitly given by the ARF. Only used if `xray_mode='counts'`.

redshift
[float] Redshift of the model. If set, `lum_dist` is ignored.

lum_dist
[float] Luminosity distance to the model. If not set, this will be calculated from the redshift and cosmology. (Default: None)

cosmology
[astropy.cosmology.FlatLambdaCDM] The cosmology to assume. Lightning defaults to a flat cosmology with `h=0.7 and Om0=0.3`.

wave_grid
[tuple (3,), or np.ndarray, (Nwave,), float32, optional] Either a tuple of (lo, hi, Nwave) specifying a log-spaced rest-frame wavelength grid, or an array giving the wavelengths directly. At high redshift this should be constructed carefully to ensure that your bands are covered. (Default: (1e-6, 1e-1, 200))

References

- Kubota and Done (2018)

Methods

get_model_L2500(params)	Calculate the intrinsic L2500
get_model_countrate(params[, exptau])	Construct the bandpass-convolved SED in count-rate.
get_model_countrate_hires(params[, exptau])	Construct the high-resolution spectrum in count-rate density.
get_model_counts(params[, exptau])	Construct the high-resolution spectrum in Lnu.
get_model_lnu(params[, exptau])	Construct the bandpass-convolved SED in Lnu.
get_model_lnu_hires(params[, exptau])	Construct the high-resolution spectrum in Lnu.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_L2500(*params*)
Calculate the intrinsic L2500

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

get_model_countrate(*params*, *exptau=None*)
Construct the bandpass-convolved SED in count-rate.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free count-rate is not returned by default. It can be accessed by setting exptau to `None`.

`get_model_countrate_hires`(*params*, *exptau=None*)

Construct the high-resolution spectrum in count-rate density.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free count-rate spectrum is not returned by default. It can be accessed by setting exptau to `None`.

`get_model_counts`(*params*, *exptau=None*)

Construct the high-resolution spectrum in Lnu.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

Notes

- The absorption free counts are not returned by default. They can be accessed by setting exptau to `None`.

`get_model_lnu`(*params*, *exptau=None*)

Construct the bandpass-convolved SED in Lnu.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

`get_model_lnu_hires`(*params*, *exptau=None*)

Construct the high-resolution spectrum in Lnu.

Parameters

params
[np.ndarray(Nmodels, Nparams) or np.ndarray(Nparams)] An array of model parameters. For purposes of vectorization this can be a 2D array, where the first dimension cycles over different sets of parameters.

exptau
[np.ndarray(Nmodels, Nwave) or np.ndarray(Nwave)] The e(-tau) absorption curve.

The emission models above extend the `XrayPlaw` and `XrayEmissionModel` classes documented at the bottom of this page for the sake of completeness.

11.7.2 X-ray Absorption

Two absorption models are implemented: the Tubingen-Boulder absorption model (`tbabs`) which includes more atomic physics and extends to the UV, and the photoelectric absorption model from XSpec (`phabs`) which covers only the X-rays.

`class lightning.xray.Tbabs`

Bases: *TabulatedAtten*

Tubingen-Boulder absorption model.

Includes cross sections from gas phase ISM, grains, and molecular hydrogen. Atomic abundances are fixed to the default.

Parameters

wave
[np.ndarray, (Nwave,), float] Rest frame wavelength grid to evaluate the model on.

path_to_models
[str] Path to lightning models. Not actually used in normal circumstances.

References

- https://heasarc.gsfc.nasa.gov/xanadu/xspec/manual/XSmodelTbabs.html
- https://ui.adsabs.harvard.edu/abs/2000ApJ...542..914W/abstract

Methods

evaluate(params)	Evaluate the absorption as a function of wavelength for the given parameters.
`print_params`([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

evaluate(*params*)

Evaluate the absorption as a function of wavelength for the given parameters.

Parameters

params
[np.ndarray, (Nmodels, 1) or (1,)] Values for NH.

Returns

expminustau
[(Nmodels, Nwave)]

class lightning.xray.**Phabs**

Bases: *TabulatedAtten*

Photo-electric absorption model.

Abundances are fixed to the default.

Parameters

wave
[np.ndarray, (Nwave,), float] Rest frame wavelength grid to evaluate the model on.

path_to_models
[str] Path to lightning models. Not actually used in normal circumstances.

References

- https://heasarc.gsfc.nasa.gov/xanadu/xspec/manual/node264.html

Methods

evaluate(params)	Evaluate the absorption as a function of wavelength for the given parameters.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

evaluate(*params*)

Evaluate the absorption as a function of wavelength for the given parameters.

Parameters

params
[np.ndarray, (Nmodels, 1) or (1,)] Values for NH.

Returns

expminustau
[(Nmodels, Nwave)]

11.7.3 X-ray Base Classes

class lightning.xray.**XrayPlawExpcut**

Bases: *XrayEmissionModel*

Power law emission model with an exponential cutoff at high energy.

Methods

get_model_countrate(params[, exptau])	Produce the mean model countrate density in the bandpass.
get_model_countrate_hires(params[, exptau])	Produce the high-resolution model countrate density in counts s-1 Hz-1.
get_model_counts(params[, exptau])	Produce the model counts in the bandpass.
get_model_lnu(params[, exptau])	Overwrite this method to provide the actual evaluation of the model as observed in the given filters.
get_model_lnu_hires(params[, exptau])	Overwrite this method to provide the actual evaluation of the high-res spectral model.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

get_model_countrate(*params*, *exptau=None*)

Produce the mean model countrate density in the bandpass.

get_model_countrate_hires(*params*, *exptau=None*)

Produce the high-resolution model countrate density in counts s-1 Hz-1. Note that these could probably be implemented here; the only thing that's specific to each individual model is the high-resolution Lnu spectrum.

get_model_counts(*params*, *exptau=None*)

Produce the model counts in the bandpass.

get_model_lnu(*params*, *exptau=None*)

Overwrite this method to provide the actual evaluation of the model as observed in the given filters.

get_model_lnu_hires(*params*, *exptau=None*)

Overwrite this method to provide the actual evaluation of the high-res spectral model.

class lightning.xray.base.**XrayEmissionModel**

Bases: BaseEmissionModel

Base class for X-ray emission models.

Methods

get_model_countrate(params)	Produce the mean model countrate density in the bandpass.
get_model_countrate_hires(params)	Produce the high-resolution model countrate density in counts s-1 Hz-1.
get_model_counts(params)	Produce the model counts in the bandpass.
get_model_lnu(params)	Overwrite this method to provide the actual evaluation of the model as observed in the given filters.
get_model_lnu_hires(params)	Overwrite this method to provide the actual evaluation of the high-res spectral model.
print_params([verbose])	If *verbose*, print a nicely formatted table of the models, their parameters, and the description of the parameters.

__init__(*filter_labels*, *arf*, *exposure*, *redshift*, *lum_dist=None*, *cosmology=None*, ***kwargs*)

Generic initialization. Actual model-building should be handled by implementing the *construct_model* and *construct_model_grid* methods.

get_model_countrate(*params*)

Produce the mean model countrate density in the bandpass.

get_model_countrate_hires(*params*)

Produce the high-resolution model countrate density in counts s-1 Hz-1. Note that these could probably be implemented here; the only thing that's specific to each individual model is the high-resolution Lnu spectrum.

get_model_counts(*params*)

Produce the model counts in the bandpass.

11.8 Prior Distributions

Priors in `Lightning` are built around two base classes: `AnalyticPrior` for priors with a functional form and `TabulatedPrior` for empirically derived priors. New user-specific priors can be added by defining classes that inherit from one of these base classes and define the `evaluate`, `quantile`, and `sample` methods.

In the course of normal use, the `sample` method is the only one likely to be used regularly, in initializing the mcmc.

class lightning.priors.base.**AnalyticPrior**

Base class for priors with a functional form.

Need only be overwritten if there's specific requirements for the prior parameters (i.e. b > a for the uniform prior).

Methods

evaluate(x)	This function must be overwritten by each specific prior, implementing the PDF.
quantile(q)	This function must be overwritten by each specific prior, implementing the quantile function/PPF (the inverse of the CDF).
sample(size[, rng, seed])	Sample from the prior.

__init__(*params*)

__new__(**args*, ***kwargs*)

evaluate(*x*)

This function must be overwritten by each specific prior, implementing the PDF.

quantile(*q*)

This function must be overwritten by each specific prior, implementing the quantile function/PPF (the inverse of the CDF).

sample(*size*, *rng=None*, *seed=None*)

Sample from the prior.

Parameters

size
[int] Number of samples to draw

rng
[numpy.random.Generator] Numpy object for random number generation; see `numpy.random.default_rng()`

seed
[int] Seed for random number generation. If you pass a pre-constructed generator this is ignored.

Returns

samples
[numpy array] Random samples

class lightning.priors.base.**TabulatedPrior**

Base class for tabulated priors.

Keywords are passed on to scipy.interpolate.interp1d.

Methods

evaluate(x)	Evaluate the scipy.interpolate.interp1d object representing the PDF on `x`.
quantile(q)	Evaluate the scipy.interpolate.interp1d object representing the quantile function on `q`.
sample(size[, rng, seed])	Sample from the prior.

__init__(*x*, *y*, ***kwargs*)

__new__(**args*, ***kwargs*)

evaluate(*x*)

Evaluate the scipy.interpolate.interp1d object representing the PDF on `x`.

quantile(*q*)

Evaluate the scipy.interpolate.interp1d object representing the quantile function on `q`.

sample(*size*, *rng=None*, *seed=None*)

Sample from the prior.

Parameters

size
[int] Number of samples to draw

rng
[numpy.random.Generator] Numpy object for random number generation; see `numpy.random.default_rng()`

seed
[int] Seed for random number generation. If you pass a pre-constructed generator this is ignored.

Returns

samples
[numpy array] Random samples

The `UniformPrior` and `NormalPrior` classes inherent from `AnalyticPrior` and define the uniform and normal distributions, respectively.

class lightning.priors.**UniformPrior**

Bases: *AnalyticPrior*

Uniform prior. Parameters are lower bound a and upper bound b, in that order.

PDF:

$$p(x) = \begin{cases} \frac{1}{b-a} & , \ x \in [a, b) \\ 0 & , \ \text{otherwise} \end{cases}$$

Quantile function:

$$x(q) = q(b - a) + a$$

__init__(*params*)

__new__(**args*, ***kwargs*)

class lightning.priors.**NormalPrior**

Bases: *AnalyticPrior*

Normal prior. Parameters are mu and sigma, in that order.

PDF:

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp[-\frac{(x-\mu)^2}{\sigma^2}]$$

Quantile function:

$$x(q) = \mu + \sigma\sqrt{2}\text{erfinv}(2q - 1)$$

__init__(*params*)

__new__(**args*, ***kwargs*)

Constant parameters in Lightning can be fixed to a single value using the `ConstantPrior`, which implements a delta-function-like prior. In practice this isn't a true prior, but it tells `Lightning` not to bother sampling the given parameter and what its value should be.

class lightning.priors.**ConstantPrior**

Bases: *AnalyticPrior*

Delta function prior. The single parameter is value a.

PDF:

$$p(x) = \begin{cases} 1 & , x = a \\ 0 & , \text{otherwise} \end{cases}$$

Quantile function:

$$x(q) = a \forall q$$

Holding a parameter constant is not really a prior so much as a reduction in the dimensionality of the problem, so this is basically a dummy prior, which tells the sampler to hold a parameter constant and what its value should be.

__init__(*params*)

__new__(**args*, ***kwargs*)

11.9 Plotting

We have implemented a number of plotting functions in lightning to make visualizing results easy. These are typically implemented such that they take a `Lightning` object as their first argument, followed by an MCMC chain (and the chain of log-probability values, where necessary). Most plotting functions can accept dictionaries of keyword arguments describing the colors and styles of lines, markers, etc. These are passed through to the relevant `matplotlib` functions. All the plotting functions can also plot into existing axes by supplying the `ax` keyword (for `corner_plot`, set the `fig` keyword instead to a figure containing the appropriate number of axes).

Two convenience items are also implemented in this module: the `ModelBand` class adapted from `Ultranest`, and the `step_curve` function designed to make plotting step functions with shaded uncertainties easier. Both are mostly meant for internal use, but are documented below for completeness.

We also provide three `matplotlib` style sheets (mainly for consistency across the examples) which can be loaded using `matplotlib.pyplot.style.use(name)` where `name` is one of `[lightning-serif, lightning-sans, lightning-dark]`.

class lightning.plots.**ModelBand**

Bases: `object`

A class interface for storing a bunch of model realizations and plotting them, as shaded bands, quantiles, or individual realizations.

This is very much taken from UltraNest's `PredictionBand` class with some tweaks. Ultranest is (c) 2019 by Johannes Buchner, and is available under GPL v3. Find it here: https://johannesbuchner.github.io/UltraNest/

All plotting functions (`shade`, `line`, `realizations`) draw into the current axes unless the `ax` keyword is set. The plotting functions also all pass through keyword arguments, allowing you to modify color, alpha, etc.

Methods

add(y)	Add a realization to the band.
line([q, ax])	Draw a line at the specified quantile `q`.
realizations([num, replace, ax])	Plot `num` randomly chosen model realizations.
shade([q, ax])	Draw a shaded region between the quantiles specified by `q`.

__init__(*x*, *seed=None*)

add(*y*)

Add a realization to the band. Currently limited to one at a time.

line(*q=0.5*, *ax=None*, ***kwargs*)

Draw a line at the specified quantile `q`. Defaults to the median.

realizations(*num=1*, *replace=False*, *ax=None*, ***kwargs*)

Plot `num` randomly chosen model realizations. If `replace` is set, the same realization can be chosen multiple times.

shade(*q=(0.16, 0.84)*, *ax=None*, ***kwargs*)

Draw a shaded region between the quantiles specified by `q`. Defaults to the 68% interval.

lightning.plots.**chain_plot**(*lgh*, *samples*, *plot_median=True*, *median_color='darkorange'*, ***kwargs*)

Produce a chain plot of samples from an SED fit.

The chain plots are placed in a single matplotlib figure, all in a single column. Not that this may (will) be unwieldy in cases with many free parameters.

Parameters

lgh
[lightning.Lightning object] Used to assign names (and maybe units) to the sample dimensions.

samples
[np.ndarray, (Nsamples, Nparam), float] The sampled parameters. Note that this should also include any constant parameters.

plot_median
[bool] If true, draw a horizontal line at the median of the chain.

median_color
[string] The color to plot the median line with.

****kwargs**
[dict] Keyword arguments are passed on to *plt.plot* for the chain plot.

Returns

fig
[Matplotlib figure containing the plot]

axs
[List of axes in the plot]

lightning.plots.**corner_plot**(*lgh*, *samples*, ***kwargs*)

Produce a corner plot of samples from an SED fit.

This is just a thin wrapper around corner that just figures out which dimensions are constant and assigns parameter labels to the chains. See the link below for a complete listing of keywords understood by corner.

Parameters

lgh
[lightning.Lightning object] Used to assign names (and maybe units) to the sample dimensions.

samples
[np.ndarray, (Nsamples, Nparam), float] The sampled parameters. Note that this should also include any constant parameters.

****kwargs**
[dict] Keyword arguments are passed on to *corner.corner*.

Returns

fig
[Matplotlib figure containing the plot]

References

- https://corner.readthedocs.io/en/latest/api/

lightning.plots.**sed_plot_bestfit**(*lgh*, *samples*, *logprob_samples*, *plot_components=False*, *plot_unatt=False*, *ax=None*, *xlim=(0.1, 1200)*, *ylim=(9000000.0, None)*, *xlabel='Observed-Frame Wavelength $[\\rm \\mu m]$'*, *ylabel='$\\nu L_{\\nu}\\ [\\rm L_\\odot]$'*, *stellar_unatt_kwargs={'color': 'dodgerblue', 'label': 'Unattenuated stellar pop.'}*, *stellar_att_kwargs={'color': 'red', 'label': 'Attenuated stellar pop.'}*, *agn_kwargs={'color': 'darkorange', 'label': 'AGN'}*, *dust_kwargs={'color': 'green', 'label': 'Dust'}*, *total_kwargs={'color': 'slategray', 'label': 'Total model'}*, *data_kwargs={'capsize': 2, 'color': 'k', 'label': 'Data', 'linestyle': '', 'marker': 'D', 'markerfacecolor': 'k'}*, *show_legend=True*, *legend_kwargs={'frameon': False, 'loc': 'upper right'}*, *uplim_sigma=3*, *uplim_kwargs={'color': 'k', 'marker': '$\\downarrow$'}*)

Best-fit SED plot.

Selects the highest log-probability model from the chain. Individual components may be plotted.

Parameters

lgh
[lightning.Lightning object] Used to assign names (and maybe units) to the sample dimensions.

samples
[np.ndarray, (Nsamples, Nparam), float] The sampled parameters. Note that this should also include any constant parameters.

logprob_samples
[np.ndarray, (Nsamples,), float] Log-probability chain.

plot_components
[bool] If `True`, plot the components of the SED.

plot_unatt
[bool] If `True`, also plot the unattenuated stellar SED.

ax
[matplotlib.axes.Axes] Axes to draw the plot in. (Default: None)

xlim
[tuple]

ylim
[tuple]

xlabel
[str]

ylabel
[str]

stellar_unatt_kwargs
[dict]

stellar_att_kwargs
[dict]

agn_kwargs
[dict]

dust_kwargs
[dict]

total_kwargs
[dict]

data_kwargs
[dict]

show_legend
[bool]

legend_kwargs
[dict]

uplim_sigma
[int] How many sigma should upper limits be drawn at? (Default: 3)

uplim_kwargs
[dict] Each of the above `*_kwargs` parameters is a dict containing keyword arguments describing the color, style, label, etc. of the corresponding plot element, passed through to the appropriate `matplotlib` function.

Returns

fig
[Matplotlib figure containing the plot]

ax
[Axes containing the plot]

lightning.plots.**sed_plot_delchi**(*lgh*, *samples*, *logprob_samples*, *ax=None*, *xlim=(0.1, 1200)*, *ylim=(-5.1, 5.1)*, *lines=[0, -1, 1]*, *linecolors=['slategray']*, *linestyles=['-', '--', '--']*, *xlabel='Observed-Frame Wavelength $[\\rm \\mu m]$'*, *ylabel='Residual $[\\sigma]$'*, *data_kwargs={'capsize': 2, 'color': 'k', 'label': 'Data', 'linestyle': '', 'marker': 'D', 'markerfacecolor': 'k'}*, *uplim_sigma=3*, *uplim_kwargs={'color': 'k', 'marker': '$\\downarrow$'}*)

Delta-chi residuals for the best-fit SED.

$$\delta\chi = (L_\nu^{\rm obs} - L_\nu^{\rm mod})/\sigma$$

Selects the highest log-probability model from the chain.

Parameters

lgh
[lightning.Lightning object] Used to assign names (and maybe units) to the sample dimensions.

samples
[np.ndarray, (Nsamples, Nparam), float] The sampled parameters. Note that this should also include any constant parameters.

logprob_samples
[np.ndarray, (Nsamples,), float] Log-probability chain.

xlim
[tuple]

ylim
[tuple]

lines
[list or tuple] Values to draw horizontal guide lines at (in sigma). (Default: [-1,0,1])

linecolors
[list or str] Corresponding colors for the guide lines. (Default: 'slategray')

linestyles
[list or str] Corresponding styles for the guide lines. (Default: ['-', '–', '–'])

xlabel
[str]

ylabel
[str]

data_kwargs
[dict]

uplim_sigma
[int] How many sigma should upper limits be drawn at? (Default: 3)

uplim_kwargs
[dict] Each of the above `*_kwargs` parameters is a dict containing keyword arguments describing the color, style, label, etc. of the corresponding plot element, passed through to the appropriate `matplotlib` function.

Returns

fig
[Matplotlib figure containing the plot]

ax
[Axes containing the plot]

lightning.plots.**sed_plot_morebayesian**(*lgh*, *samples*, *logprob_samples*, *plot_components=False*, *plot_unatt=False*, *ax=None*, *xlim=(0.1, 1200)*, *ylim=(9000000.0, None)*, *xlabel='Observed-Frame Wavelength $[\\rm \\mu m]$'*, *ylabel='$\\nu L_{\\nu}\\ [\\rm L_\\odot]$'*, *stellar_unatt_kwargs={'alpha': 0.5, 'color': 'dodgerblue', 'label': 'Unattenuated stellar pop.'}*, *stellar_att_kwargs={'alpha': 0.5, 'color': 'red', 'label': 'Attenuated stellar pop.'}*, *agn_kwargs={'alpha': 0.5, 'color': 'darkorange', 'label': 'AGN'}*, *dust_kwargs={'alpha': 0.5, 'color': 'green', 'label': 'Dust'}*, *total_kwargs={'alpha': 0.5, 'color': 'slategray', 'label': 'Total model'}*, *data_kwargs={'capsize': 2, 'color': 'k', 'label': 'Data', 'linestyle': '', 'marker': 'D', 'markerfacecolor': 'k'}*, *show_legend=True*, *legend_kwargs={'frameon': False, 'loc': 'upper right'}*, *uplim_sigma=3*, *uplim_kwargs={'color': 'k', 'marker': '$\\downarrow$'}*)

More bayesian visualization of the fit, agnostic of the best fit. Better name TBD

Shows the 16th-84th percentile range of the model Lnu. Currently this doesn't show the median or best-fit, just shaded polygons indicating the range.

Parameters

lgh
[lightning.Lightning object] Used to assign names (and maybe units) to the sample dimensions.

samples
[np.ndarray, (Nsamples, Nparam), float] The sampled parameters. Note that this should also include any constant parameters.

logprob_samples
[np.ndarray, (Nsamples,), float] Log-probability chain.

plot_components
[bool] If `True`, plot the components of the SED.

plot_unatt
[bool] If `True`, also plot the unattenuated stellar SED.

ax
[matplotlib.axes.Axes] Axes to draw the plot in. (Default: None)

xlim
[tuple]

ylim
[tuple]

xlabel
[str]

ylabel
[str]

stellar_unatt_kwargs
[dict]

stellar_att_kwargs
[dict]

agn_kwargs
[dict]

dust_kwargs
[dict]

total_kwargs
[dict]

data_kwargs
[dict]

show_legend
[bool]

legend_kwargs
[dict]

uplim_sigma
[int] How many sigma should upper limits be drawn at? (Default: 3)

uplim_kwargs
[dict] Each of the above `*_kwargs` parameters is a dict containing keyword arguments describing the color, style, label, etc. of the corresponding plot element, passed through to the appropriate `matplotlib` function.

Returns

fig
[Matplotlib figure containing the plot]

ax
[Axes containing the plot]

`lightning.plots.`**`sfh_plot`**(*lgh*, *samples*, *xlabel='Lookback Time t [yr]'*, *ylabel='SFR(t) $[\\rm M_{\\odot}\\ yr^{-1}]$'*, *ax=None*, *shade_band=True*, *shade_q=(0.16, 0.84)*, *shade_kwargs={'alpha': 0.3, 'color': 'k', 'zorder': 0}*, *plot_line=True*, *line_q=0.5*, *line_kwargs={'color': 'k', 'zorder': 1}*, *ylim=None*)

A plot of the posterior SFR as a function of time.

The default behavior is to plot the median of the posterior along with the shaded 16th to 84th percentiles.

Parameters

lgh
[lightning.Lightning object] Used to assign names (and maybe units) to the sample dimensions.

samples
[np.ndarray, (Nsamples, Nparam), float] The sampled parameters. Note that this should also include any constant parameters.

xlabel
[str]

ylabel
[str]

ax
[matplotlib.axes.Axes] Axes to draw the plot in. (Default: None)

shade_band
[bool] Should the uncertainty band be shaded?

shade_q
[tuple] Quantiles to shade between. (Default: (0.16, 0.84))

shade_kwargs
[dict]

plot_line
[bool] Should a line be plotted?

line_q
Quantile to plot the line at (Default: 0.5)

line_kwargs
[dict] Each of the above `*_kwargs` parameters is a dict containing keyword arguments describing the color, style, label, etc. of the corresponding plot element, passed through to the appropriate `matplotlib` function.

ylim
[tuple]

Returns

fig
[Matplotlib figure containing the plot]

ax
[Axes containing the plot]

`lightning.plots.step_curve`(*bin_edges*, *y_values*, *anchor=False*)

From a histogram (bin edges and count values) generate a step curve for use with matplotlib's `plot` function.

This function takes an array of N + 1 bin edges and an array of N values and turns them into a list of 2N vertices so that you can make a step plot with the `plot` command rather than `step`, `hlines` and `vlines`, etc.

Parameters

bin_edges
[numpy array, (N+1), float] Array defining the edges of the histogram bins (i.e., the locations of the steps). Assumed to be a monotonically increasing sequence.

y_values
[numpy array, (..., N), float] Array containing the y values corresponding to bin_edges: the value of the function on (bin_edges[i], bin_edges[i+1]) is y_values[...,i]. Note that this can be a 2D array, where the first axis cycles among different curves.

anchor
[bool (default False)] If True, the returned curve will be anchored to 0 on both sides.

Returns

x
[np.ndarray]

y
[np.ndarray] Two numpy arrays containing the x- and y-values of the step curve, respectively. See note on size below.

Notes

If anchor is False, each curve has 2N points, where N is the number of y-values.

If anchor is True, each curve has 2N + 2 points.

This function actually doesn't do any plotting, it just makes arrays to feed into `plot`.

11.10 Postprocessing

lightning.postprocessing.**postprocess_catalog**(*res_filenames*, *model_filenames*, *solver_mode='mcmc'*, *model_mode='json'*, *names=None*, *catalog_name='postprocessed_catalog.hdf5'*)

Given lists of result files and model files, merge the results into a postprocessed catalog.

This script uses h5py to produce an output file in HDF5 format. We've made this choice to easily allow for non-homogeneous model setups, e.g. different numbers of bandpasses and parameters per source. The structure and content of the HDF5 file is as follows (for each source):

```
└──sourcename
    ├── mcmc
    │   ├── logprob_samples (Nsamples)
    │   └── samples (Nsamples, Nparams)
    ├── parameters
    │   ├── modelname
    │   │   └── parametername
    │   │       ├── best ()
    │   │       ├── hi ()
    │   │       ├── lo ()
    │   │       └── med ()
    └── properties
        ├── filter_labels (Nfilters)
        ├── lnu (Nfilters)
        ├── lnu_unc (Nfilters)
        ├── lumdist ()
        ├── mstar
        │   ├── best ()
        │   ├── hi ()
        │   ├── lo ()
        │   └── med ()
        ├── redshift ()
        └── pvalue ()
```

The "modelname" and "parametername" groups under the "parameters" group repeat for every model and parameter. For piecewise-constant SFHs the "properties" group also contains the age bin edges for the SFH. Quantiles ("*/lo" and "*/hi") are computed at the 16 and 84th percentile.

For solver_mode='mcmc', the chains are also expected to be in HDF5 format, with the following structure:

```
mcmc
├── logprob_samples (Nsamples)
├── samples (Nsamples, Nparams)
└── autocorr (Nparams)
```

Whereas for solver_mode='mle', the results are expected to be formated as:

```
res
├── bestfit (Nparams)
└── chi2_best ()
```

I'll provide a function to make such HDF5 result files soon if I haven't already.

Parameters

res_filenames
[array-like, str] A list of filenames pointing to the result files.

model_filenames
[array-like, str] A list of filenames poitning to the model files (either json or pickles).

model_mode
[str] Method for model serialization, either "json" or "pickle". (Default: "json")

names
[array-like, str] Names for each of the galaxies. If None (default), we'll just guess based on the filenames of the chains assuming that they're named something like [NAME]_chain.h5.

catalog_name
[str] (Default: "postprocessed_catalog.hdf5")

Returns

None

Notes

TODO:

- Allow user-supplied quantiles.
- Add additional properties; allow user specification of properties? That might be a whole chore.

11.11 Posterior Predictive Checks

lightning.ppc.**ppc**(*lgh*, *samples*, *logprob_samples*, *Nrep=1000*, *seed=None*, *counts_dist='gaussian'*)

Compute the posterior predictive check p-value given a set of samples and a Lightning object

Parameters

lgh
[lightning.Lightning object] Used to compute chi2 values.

samples
[np.ndarray, (Nsamples, Nparam), float] The samples to compute the PPC with. Note that this must also include any constant parameters, since we need them to compute the model luminosities.

logprob_samples
[np.ndarray, (Nsamples,), float] The logprob corresponding to each sample. Used to weight samples.

Nrep
[int] Number of realizations of the data to compute from the model.

seed
[float] Seed for random number generation.

Returns

p-value
[float] A single p-value for the given chain. Extremely low p-values indicate underfitting, that the model is not flexible enough to produce the observed variation in the data (or that the uncertainties on the data are too small), while extremely high p-values (close to 1) may indicate over-fitting, where the model is *too* flexible (or the uncertainties overly conservative).

Notes

The implementation of PPC here is ported from IDL Lightning.

lightning.ppc.**ppc_sed**(*lgh*, *samples*, *logprob_samples*, *Nrep=1000*, *seed=None*, *ax=None*, *normalize=False*, *counts_dist='gaussian'*)

Make an SED plot representing the posterior predictive check.

The idea is that this can serve as a diagnostic plot showing where the model may be too inflexible to reproduce individual datapoints. This may show you if, e.g. your low p-value is driven by an individual band.

Parameters

lgh
[lightning.Lightning object] Used to compute chi2 values.

samples
[np.ndarray, (Nsamples, Nparam), float] The samples to compute the PPC with. Note that this must also include any constant parameters, since we need them to compute the model luminosities.

logprob_samples
[np.ndarray, (Nsamples,), float] The logprob corresponding to each sample. Used to weight samples.

Nrep
[int] Number of realizations of the data to compute from the model.

seed
[float] Seed for random number generation. Useful for matching your PPC p-value to the plot.

ax
[matplotlib.axis.Axes] Axes to draw the plot into.

normalize
[bool] If True, the data and quantiles of the reproduced data are divided by the median of the reproduced data before plotting.

Returns

PPC SED plot figure: an SED plot showing the quantile bands of the reproduced data, with the observed data overplotted.

CHAPTER

TWELVE

ATTRIBUTION

A paper describing `lightning.py` is forthcoming by Monson et al.; this page will be updated on submission. In the meantime, work using the new PEGASE+Cloudy and BPASS+Cloudy models are encouraged to also cite Lehmer et al. (2024), while work using models described in Doore et al. (2023) should also cite that paper:

```
@ARTICLE{2023ApJS..266...39D,
    author = {{Doore}, Keith and {Monson}, Erik B. and {Eufrasio}, Rafael T. and {Lehmer}
↪, Bret D. and {Garofali}, Kristen and {Basu-Zych}, Antara},
    title = "{Lightning: An X-Ray to Submillimeter Galaxy SED-fitting Code with␣
↪Physically Motivated Stellar, Dust, and AGN Models}",
    journal = {\apjs},
    keywords = {Extragalactic astronomy, Galaxy properties, Star formation, Spectral␣
↪energy distribution, 506, 615, 1569, 2129, Astrophysics - Astrophysics of Galaxies},
    year = 2023,
    month = jun,
    volume = {266},
    number = {2},
    eid = {39},
    pages = {39},
    doi = {10.3847/1538-4365/accc29},
    archivePrefix = {arXiv},
    eprint = {2304.06753},
    primaryClass = {astro-ph.GA},
    adsurl = {https://ui.adsabs.harvard.edu/abs/2023ApJS..266...39D},
    adsnote = {Provided by the SAO/NASA Astrophysics Data System}
}
```

CHAPTER

THIRTEEN

LICENSE

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CHAPTER

FOURTEEN

ACKNOWLEDGMENTS

`lightning.py` has been developed by Erik B. Monson, Amirnezam Amiri, Keith Doore, and Rafael Eufrasio. Much of `lightning.py` is ported from or based on code from IDL `Lightning`, which was developed by Rafael Eufrasio, Keith Doore, and Erik B. Monson.

CHAPTER

FIFTEEN

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