GalaPy: the highly optimized C++/Python spectral modelling tool for galaxies

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Why a new SED fitting code?

✓ Flexible modeling

- self-consistent evolution of gas, stars, metals and dust inspired from in-situ GFE scenarios
- 2-components dust models with age-dependent energy balance
- aimed also at (very) high-z sources, including strongly obscured ones

✓ High performance

- hybrid C++/Python implementation (fast speed + user friendly)
- vectorized programming, register proximity, advanced interpolation techniques
- shared memory parallelization from Python (more to come…)

✓ Bayesian inference

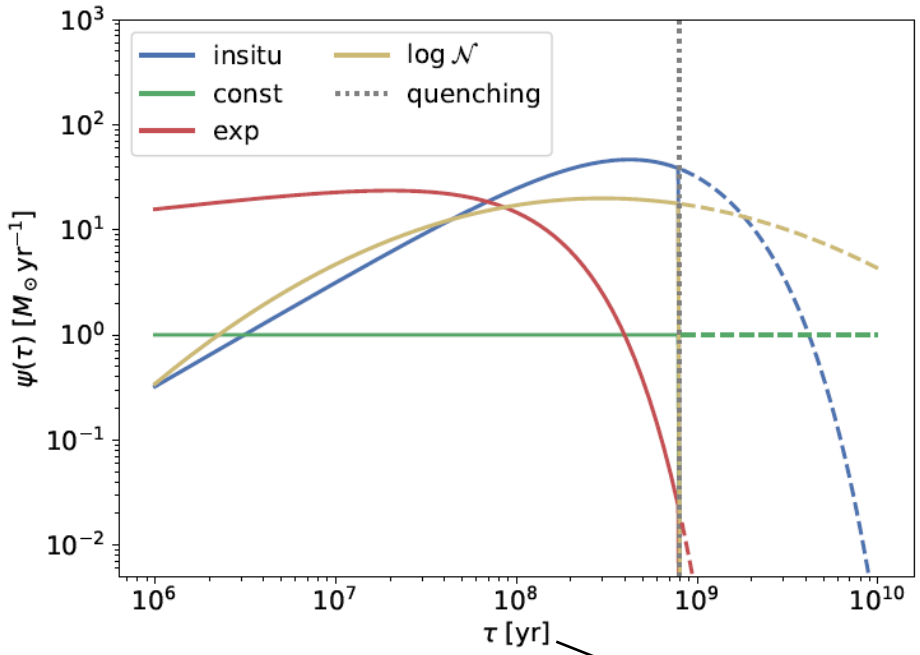
- Markov Chain MonteCarlo
- dynamic nested sampling
- soon: hierarchical Bayesian, active learning, hamiltonian MC

Star formation histories

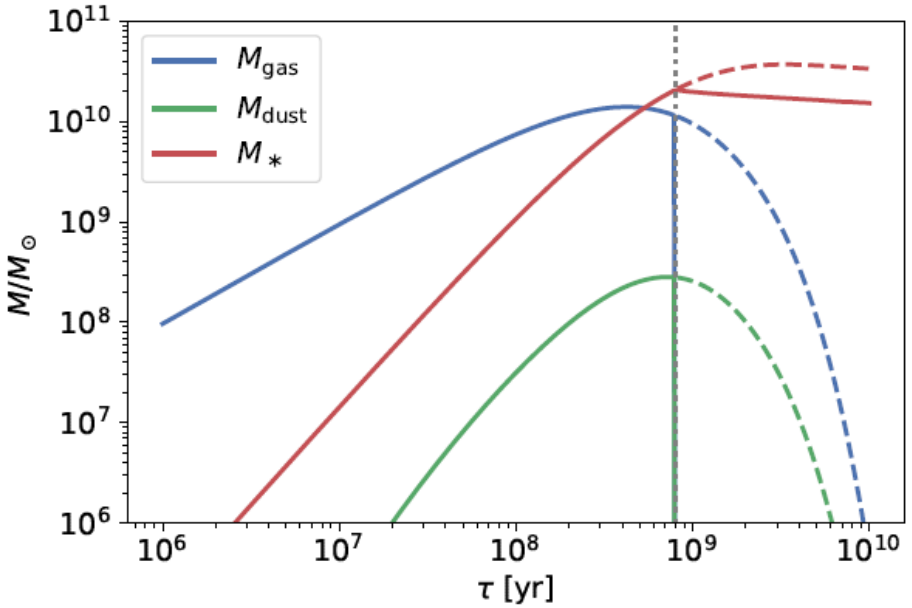
✓ empirical models
- constant
- delayed exp.
- lognormal
- non-parametric

→ need time-averaged Z and DGR

SFR



galaxy age



masses

Lapi+18,20; Pantoni+19

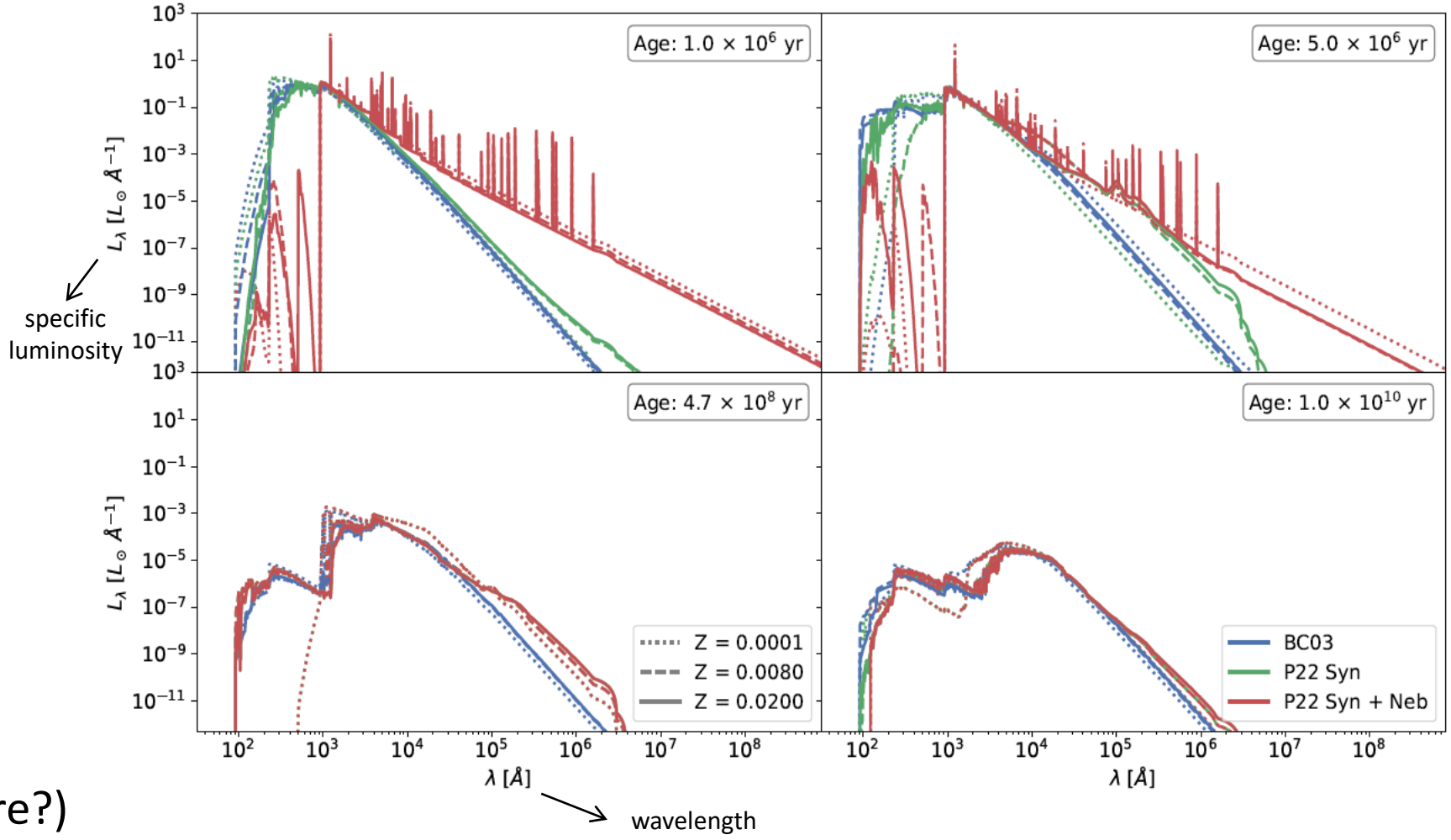
✓ in-situ GFE model
- self-consistent SFR(t), Z(t), D(t)
- physically motivated
- more constraining power

+ quenching, bursts

Stellar emission

- ✓ SSP - B&C03 Bruzual & Charlot 03,16
  - continuum
- ✓ SSP - Parsec22 Bressan+12
  - continuum
  - emission lines
  - nebular
  - synchrotron
- ✓ IMF
  - Chabrier
  - Salpeter
  - Kroupa
  - Larson (top-heavy)
  - Non-universal (future?)

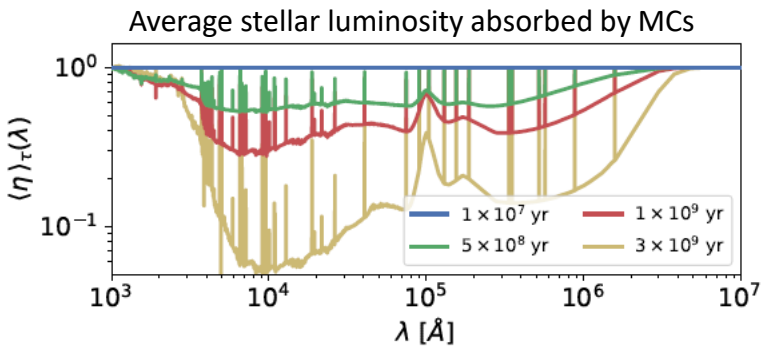
Single stellar populations (SSP)



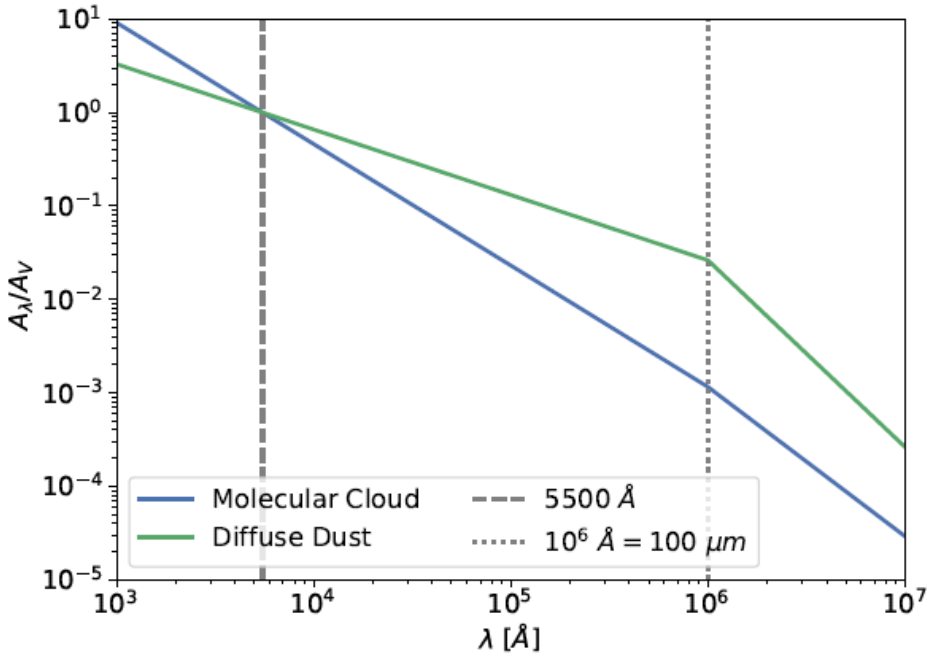
Dust extinction and attenuation

- ✓ Two components dust model:
  - molecular (birth) clouds
  - diffuse dust (cirrus)

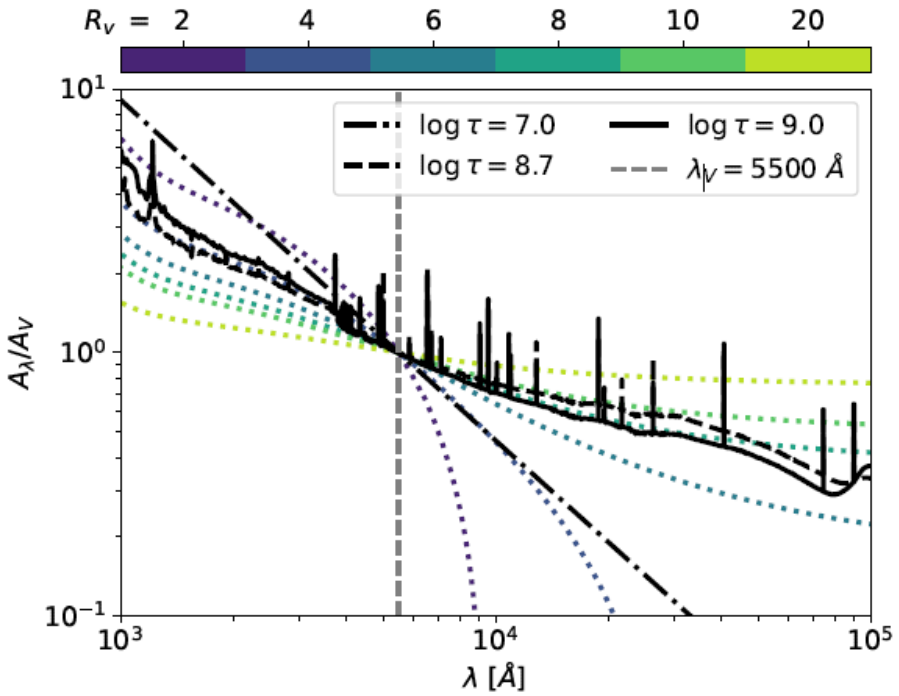
→ age-dependent extinction, inspired from GRASIL Silva+98



extinction curves

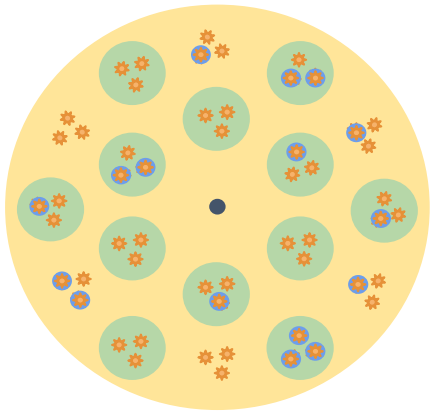


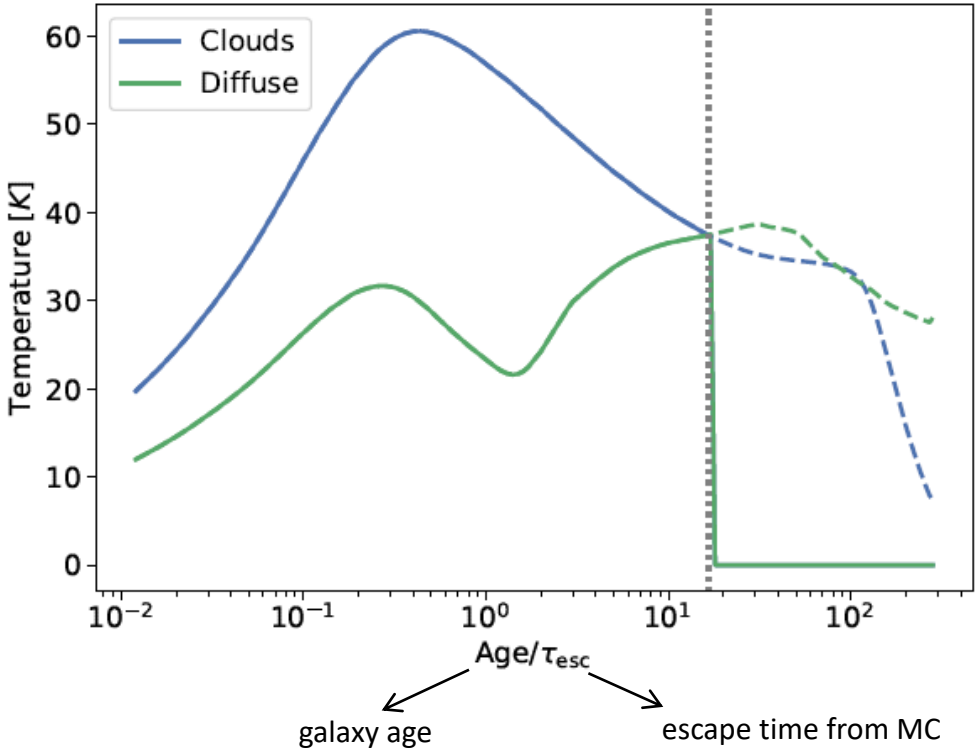
attenuation curves

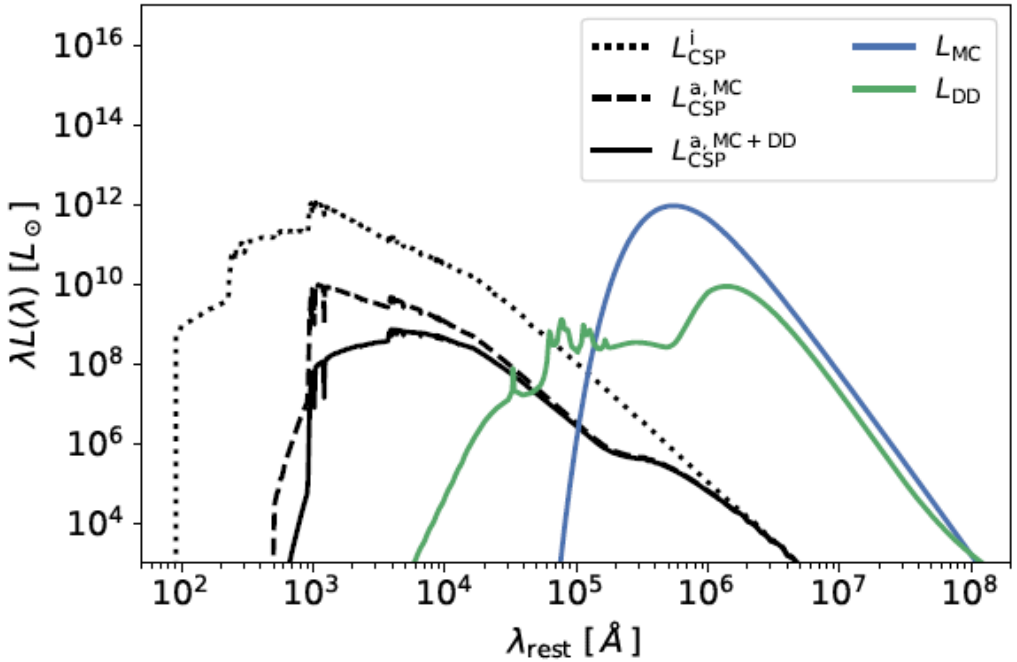


Dust emission

- ✓ Innovative approach
  - two optically-thick grey-body emissions
  - temperatures from age-dependent energy balance
  - template PAH emission (associated to cirrus)



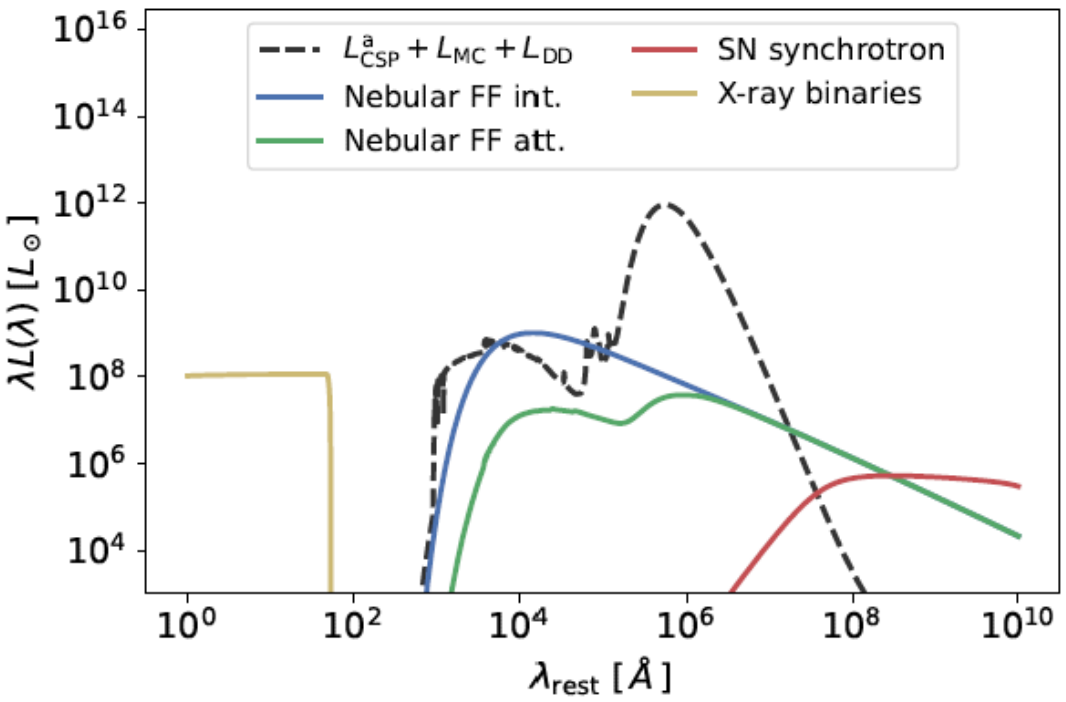


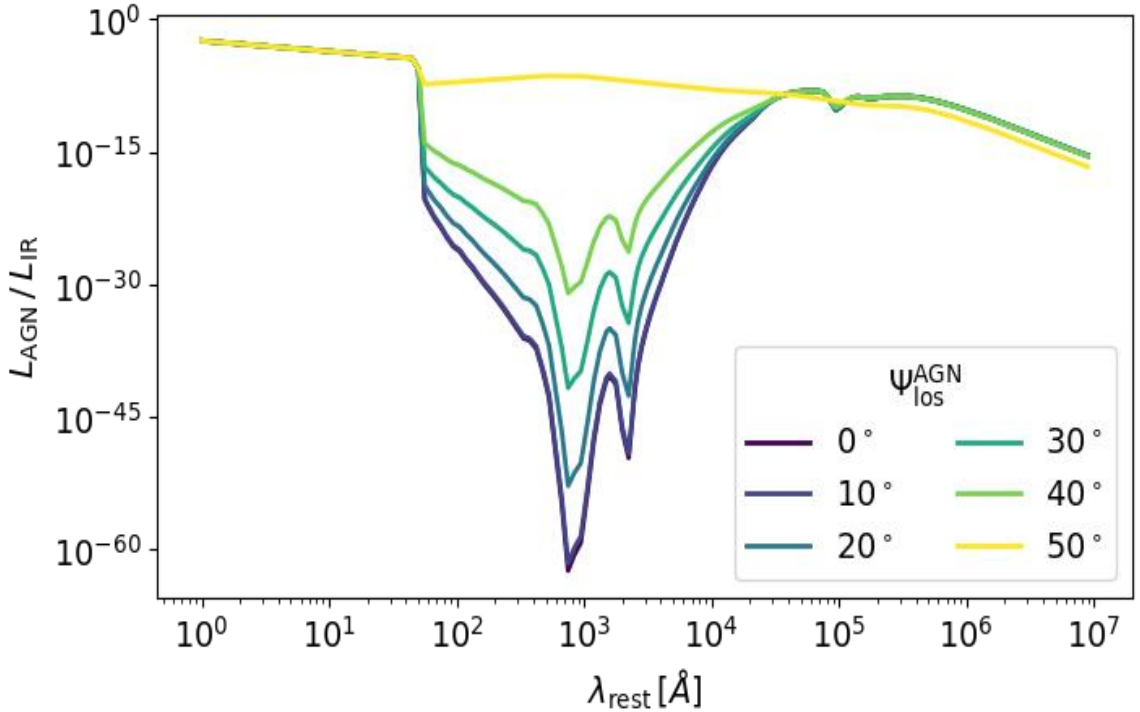


Optional components

- ✓ Extension for stellar continuum
  - nebular emission (including free-free) Mancuso+17
  - X-ray binaries (both high and low mass) Fragos+13

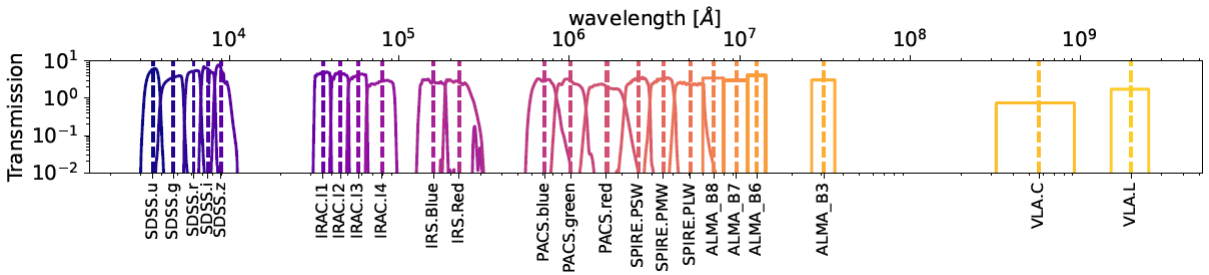
- ✓ Active Galactic Nucleus Fritz+06
  - 24K templates
  - + X-ray emission

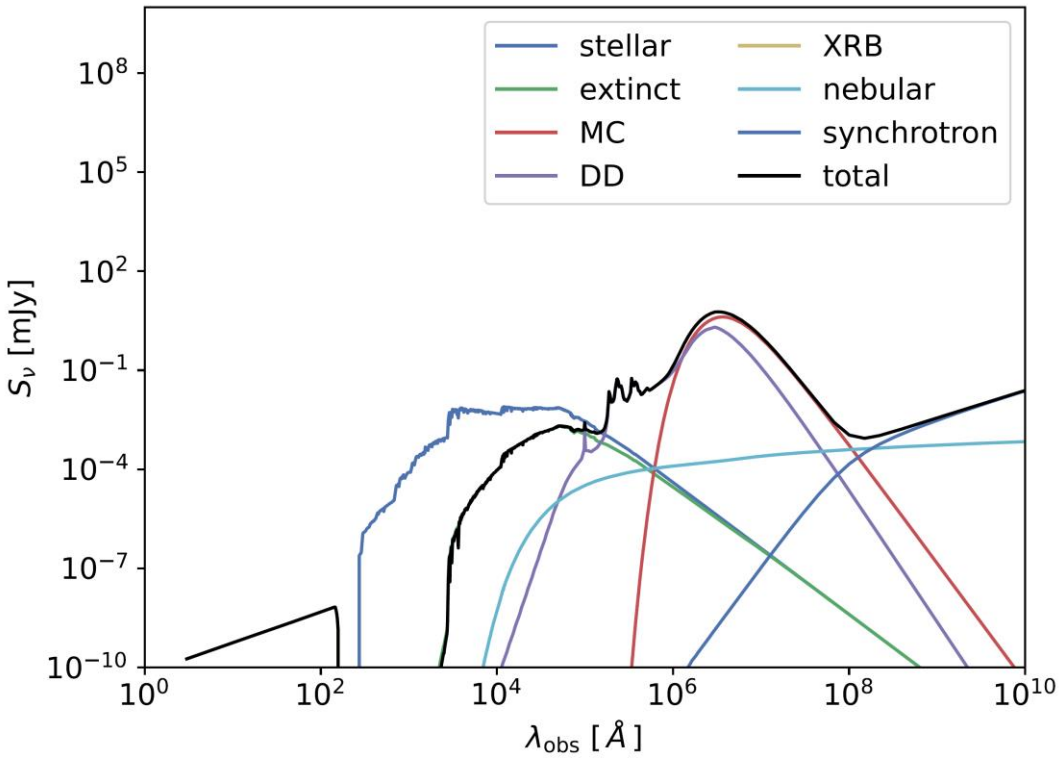




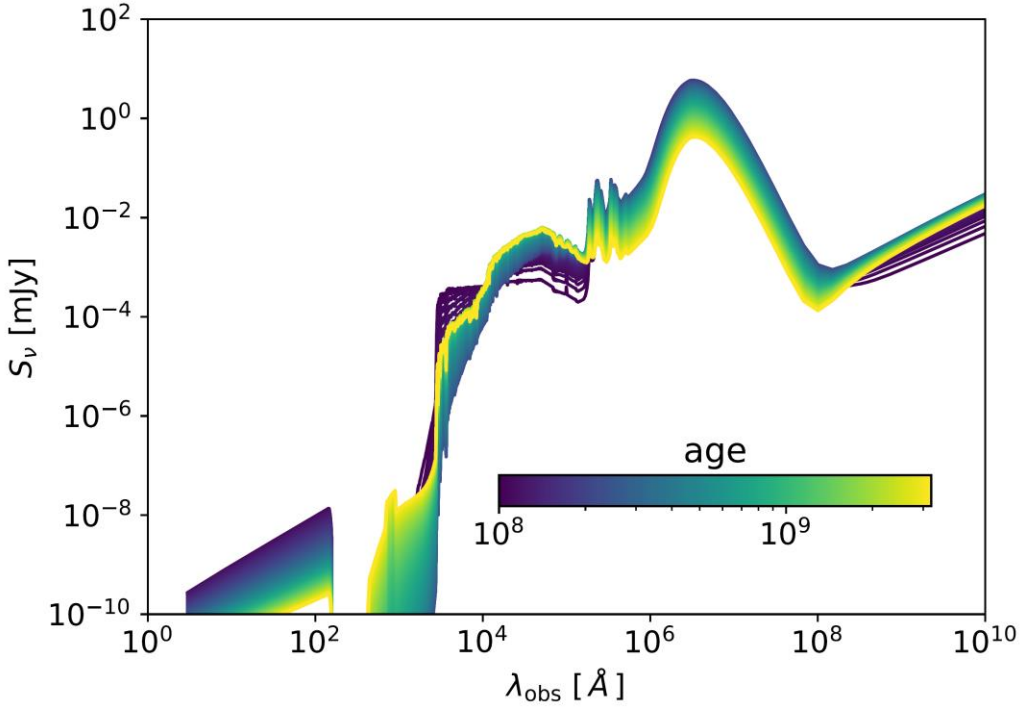
Galaxy SED

- ✓ Putting all together:
  - sum up all contributions to restframe SED
  - select cosmology, apply redshifting
  - IGM transmission
  - select spectra resolution and passband filters (many available, easy to add yours)





Evolution with galactic age

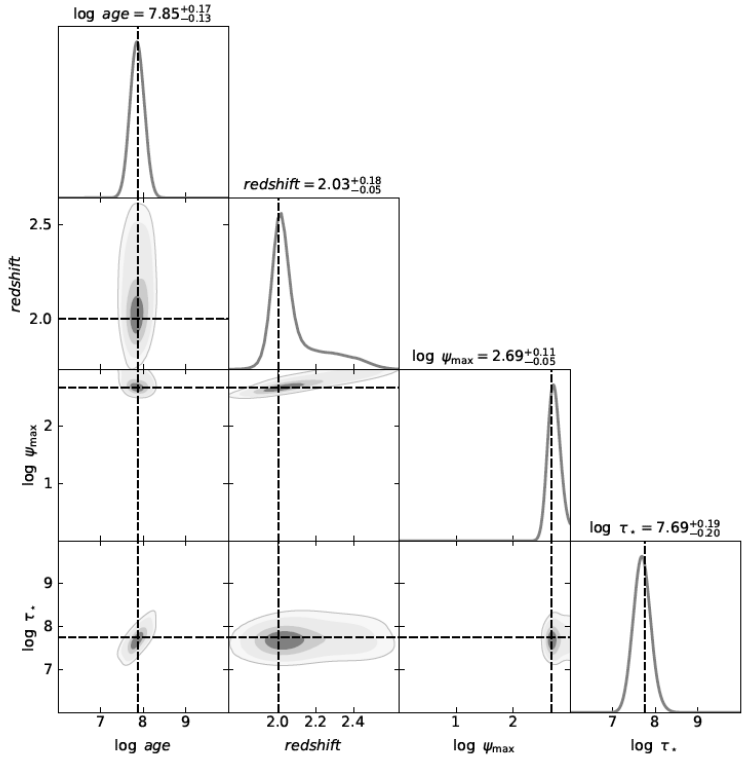


Bayesian inference

✓ Likelihood

$$\ln \mathcal{L}\left(\overline{S} \mid \theta, f_{\rm sys}\right) \equiv -\frac{1}{2} \sum_i \left\{ \frac{\left[\overline{S}_i - \overline{S}_i(\theta)\right]^2}{\tilde{\sigma}_i^{\,2}(\theta, f_{\rm sys})} + \ln\left[2\pi\,\tilde{\sigma}_i^2(\theta, f_{\rm sys})\right] \right\}$$

$$\tilde{\sigma}_i^{\,2}(\theta, f_{\rm sys}) \equiv \sigma_i^2 + f_{\rm sys}^2 \overline{S}_i^{\,2}(\theta)$$

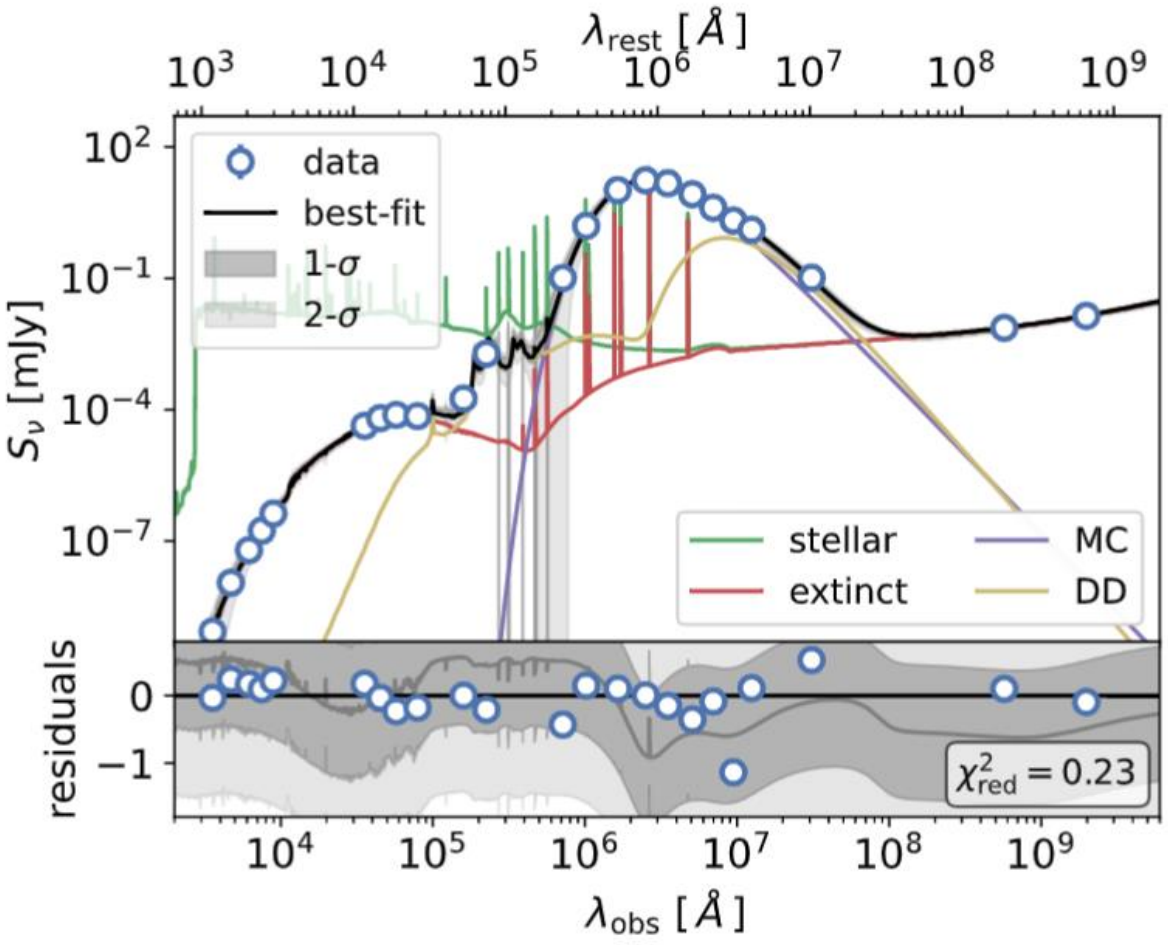


✓ Samplers

- emcee : affine-invariant MCMC → faster on smaller and well-behaved parameter space, easy inclusion of sophisticated priors Foreman-Mackey+13

- dynesty : dynamic nested sampling → apt for large and multimodal parameter space Speagle+19

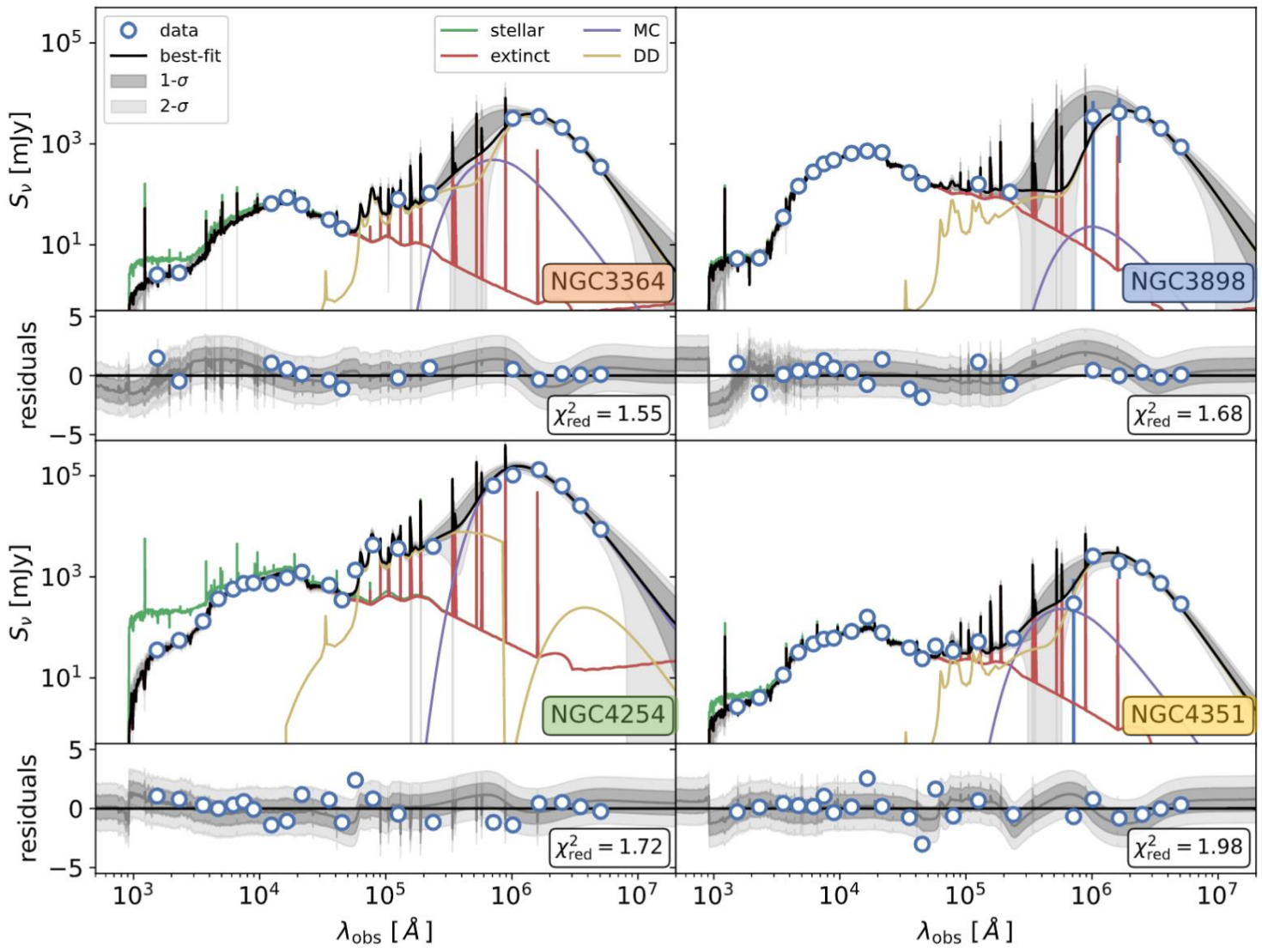
Validation : mock source



	Real	Prior	Bestfit	Mean ± 1σ
Log age	8.00	[6 , 10]	7.88	7.9 ± 0.2
redshift	2.00	[0 , 10]	2.00	2.1 ± 0.1
Log SFR	2.70	[0 , 3]	2.68	2.7 ± 0.1
f_{MC}	0.5	[0 , 1]	0.24	0.49 ± 0.17
Log τ_{MC}	7.70	[4 , 8]	7.60	7.6 ± 0.2
f_{PAH}	0.1	[0 , 1]	0.1	0.15 ± 0.08
...	...	...	...	...
T_{MC}	41.46	derived	43.84	45.6 ± 3.1
T_{DD}	10.25	derived	10.56	10.3 ± 1.4
Log M_{dust}	8.37	derived	8.25	8.3 ± 0.2
Log M_{gas}	10.25	derived	10.03	10.0 ± 0.2
Log M_{star}	9.94	derived	9.88	9.9 ± 0.2
Z_{gas}	0.02	derived	0.02	0.03±0.01
Z_{star}	0.01	derived	0.01	0.01±0.01

Validation: local SFGs

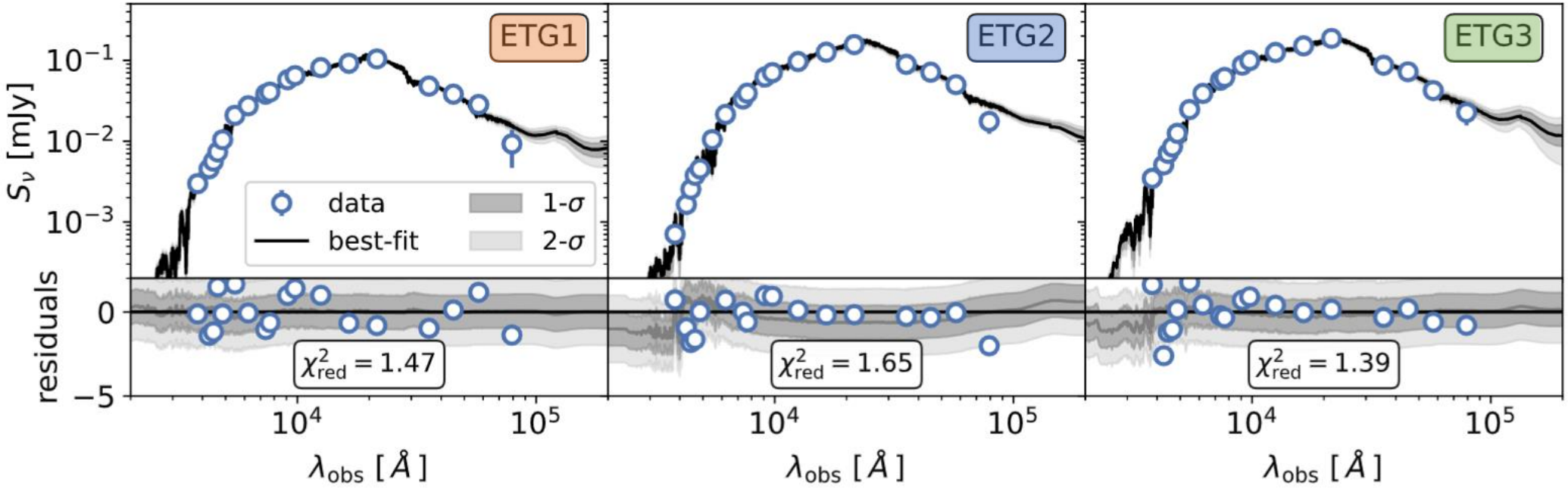
Casasola+20



	NGC 3364	NGC 3898	NGC 4254	NGC 4351
Log age	10.15	9.72	9.74	9.35
Log SFR	0.73	0.16	24.42	0.45
T_{MC}	47.96	33.09	28.48	58.65
T_{DD}	20.55	16.02	7.72	20.51
Log M_{dust}	7.36	6.10	8.97	6.27
Log M_{gas}	9.18	7.67	10.51	7.93
Log M_{star}	10.18	10.30	11.05	9.81
Z_{gas}	0.02	0.04	0.04	0.03
Z_{star}	0.02	0.03	0.03	0.02

Validation: local ETGs

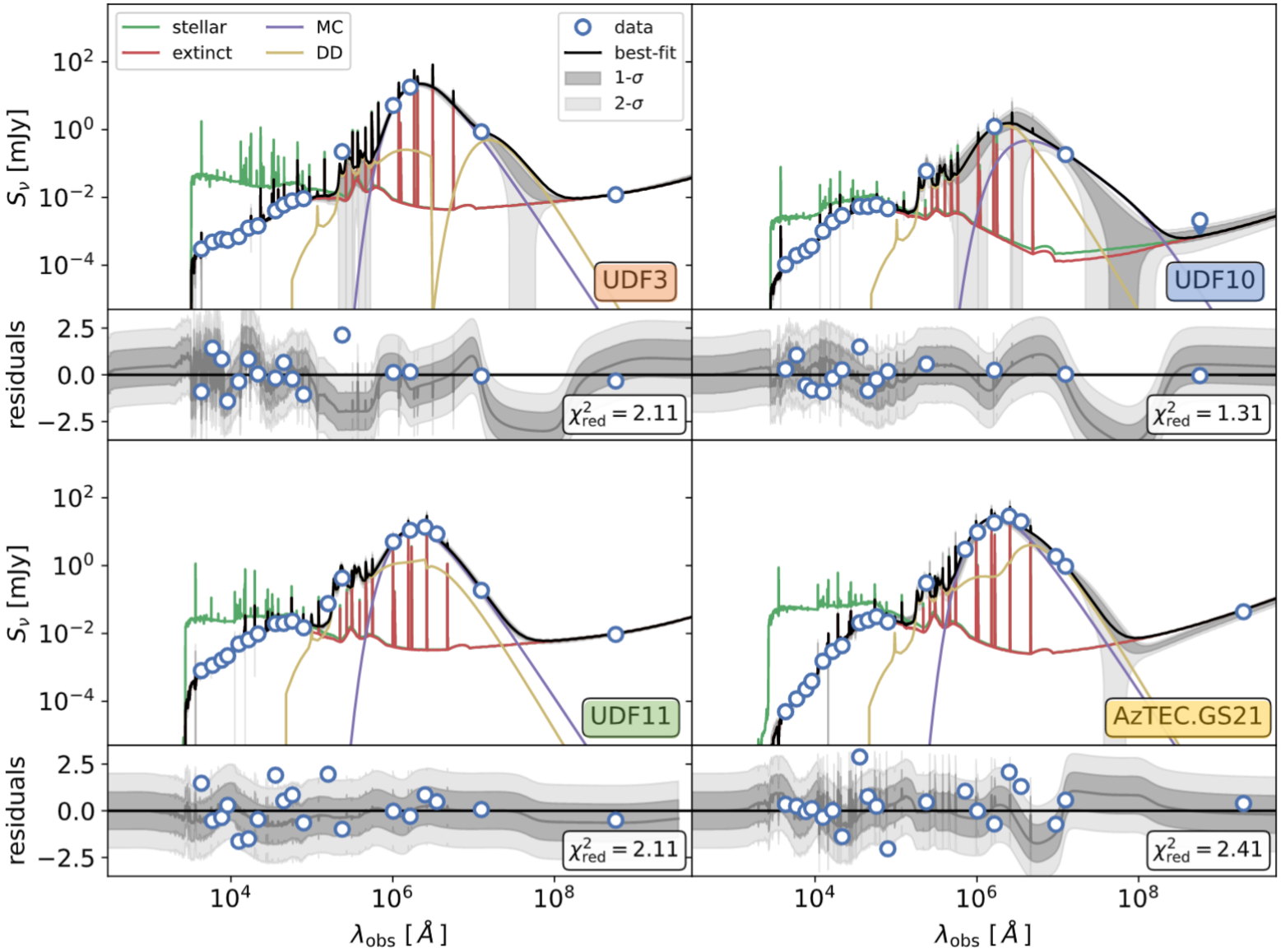
Donevski+22



	ETG 1	ETG 2	ETG 3
Log age	9.66	9.90	9.75
Log M_{star}	9.78	10.94	10.57
Z_{star}	0.03	0.04	0.04

Validation : high-z dusty SFGs

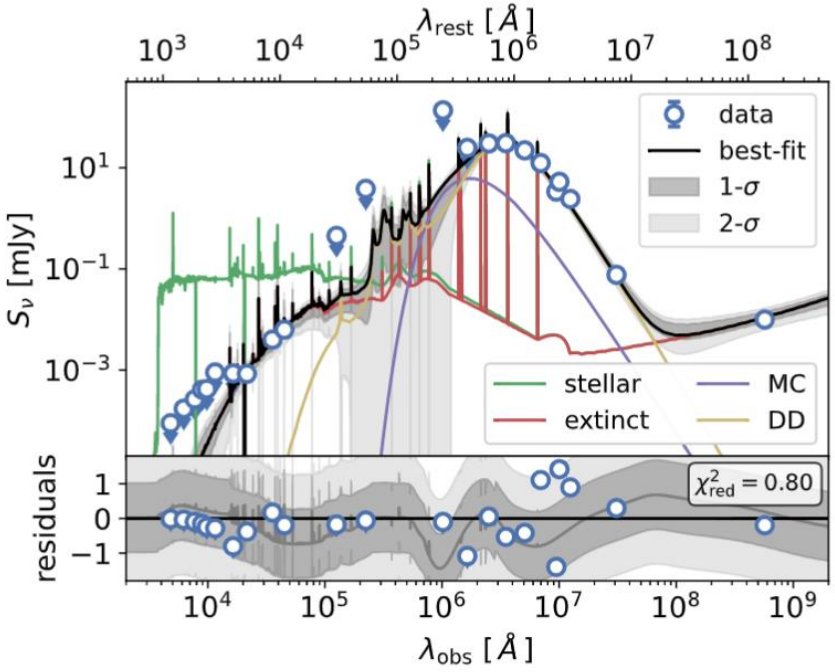
Pantoni+21



	UDF 3	UDF 10	UDF 11	AzTEC GS21
Log age	7.52	9.52	8.83	7.79
Log SFR	623	21	182	128
T_{MC}	54.97	36.34	53.34	54.82
T_{DD}	6.58	55.15	32.16	18.21
Log M_{dust}	8.43	8.72	9.21	7.79
Log M_{gas}	10.08	10.34	11.56	8.92
Log M_{star}	10.09	10.65	10.67	10.78
Z_{gas}	0.03	0.03	0.01	0.09
Z_{star}	0.02	0.02	0.01	0.05

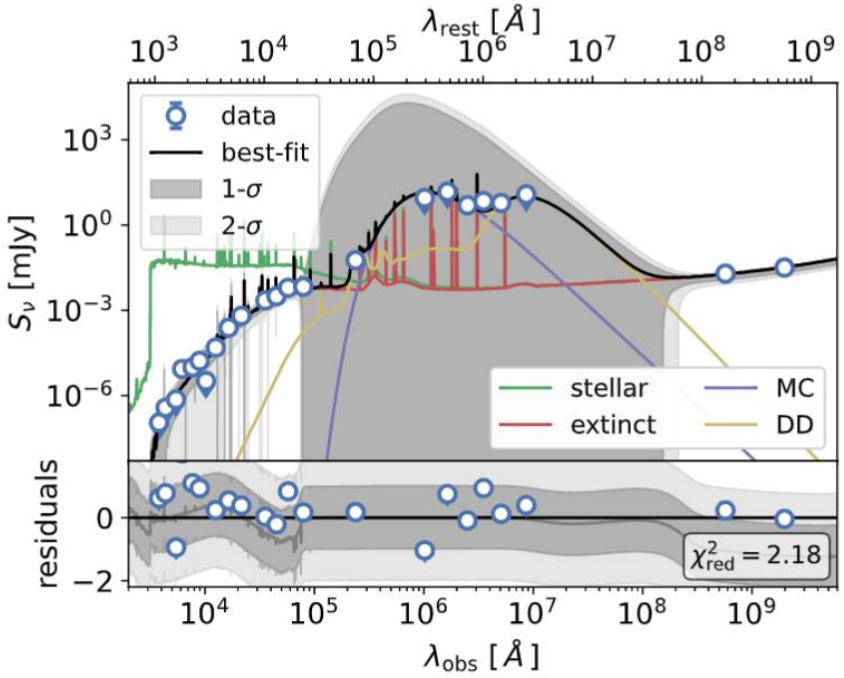
Validation: more challenging cases

Strongly-lensed O/NIR dark @ z=3



Giulietti+23

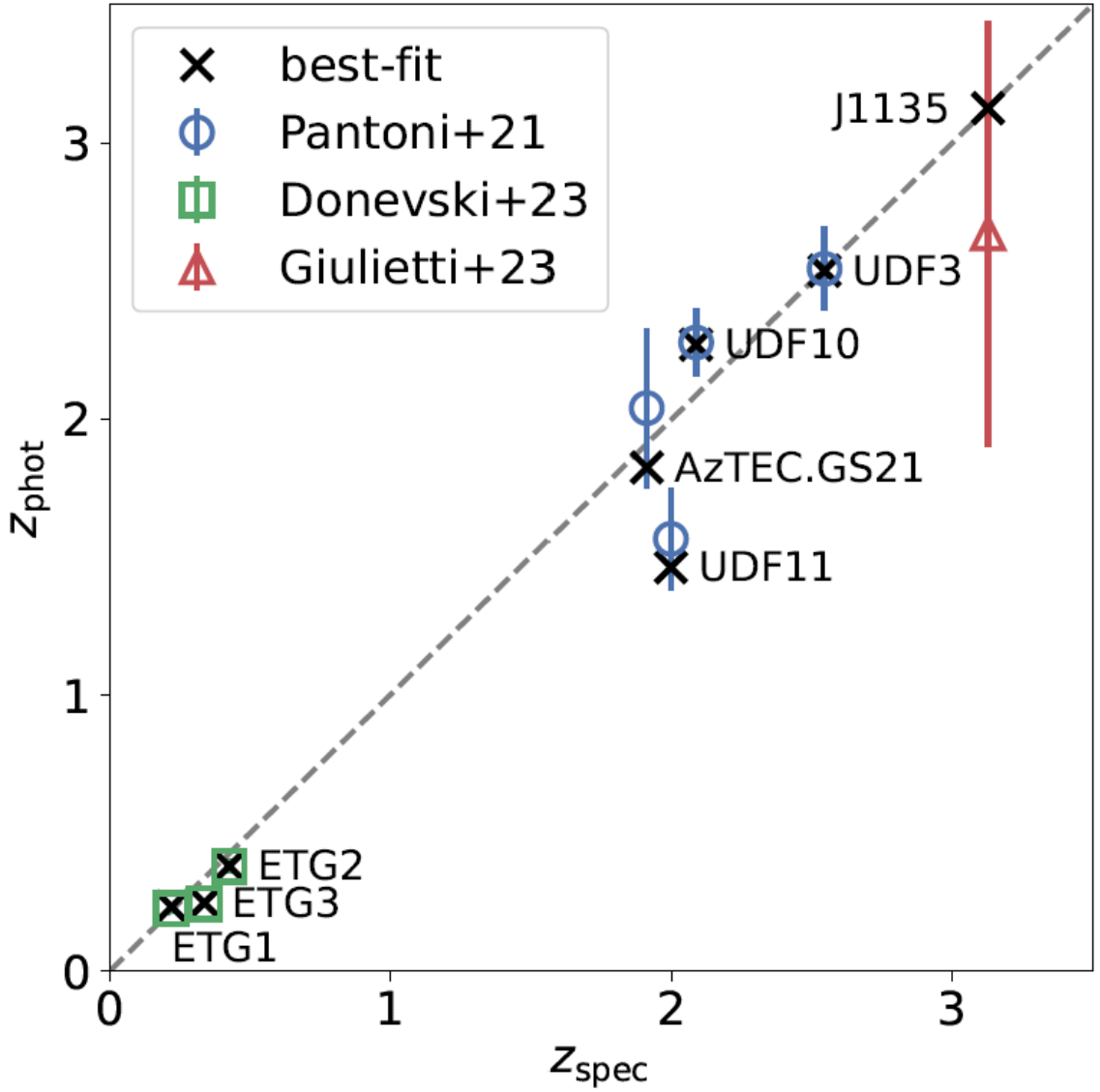
Stacked SED of RS-NIR dark sample

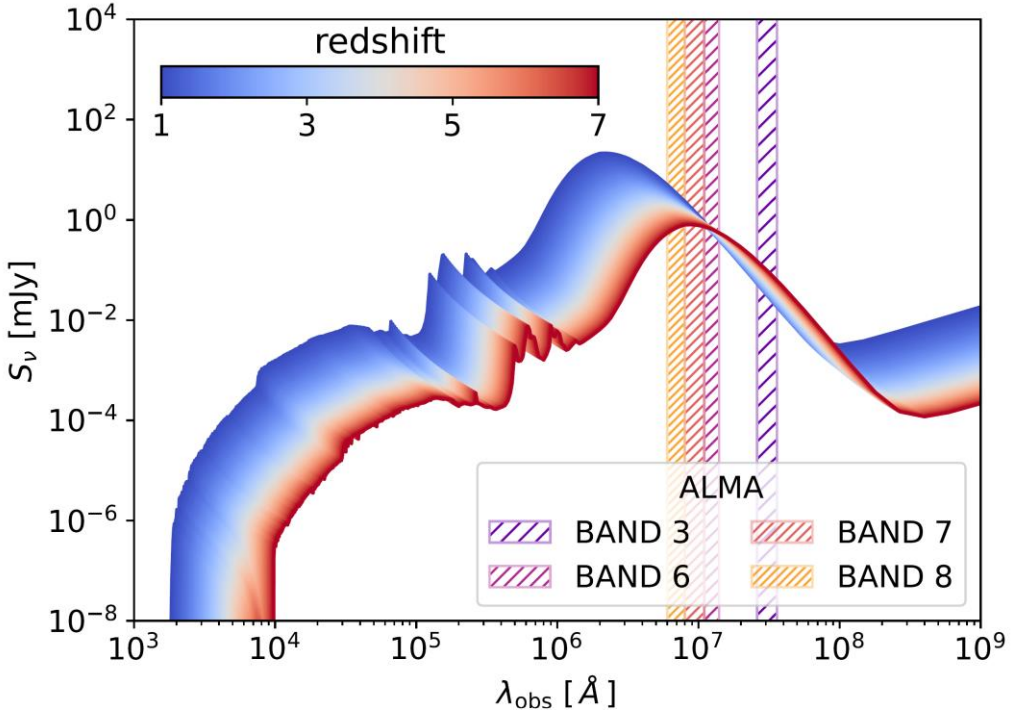


Talia+21; Behiri+23

	J1135 lensed	RS-NIR dark
Log age	8.56	8.01
SFR	1084.08	641.85
T_{MC}	80.85	110.49
T_{DD}	44.02	12.16
Log M_{dust}	9.63	8.95
Log M_{gas}	10.96	11.02
Log M_{star}	11.52	10.46
Z_{gas}	0.06	0.01
Z_{star}	0.04	0.01

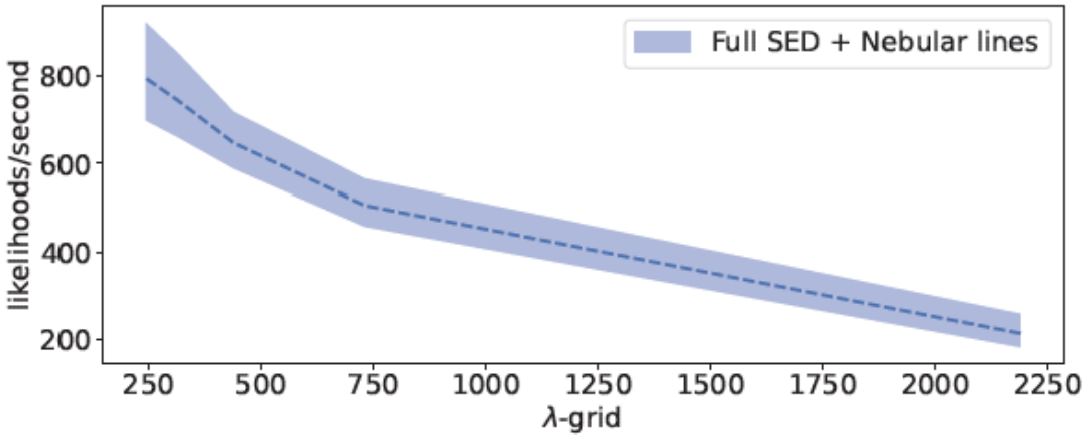
Validation : photo-z fitting



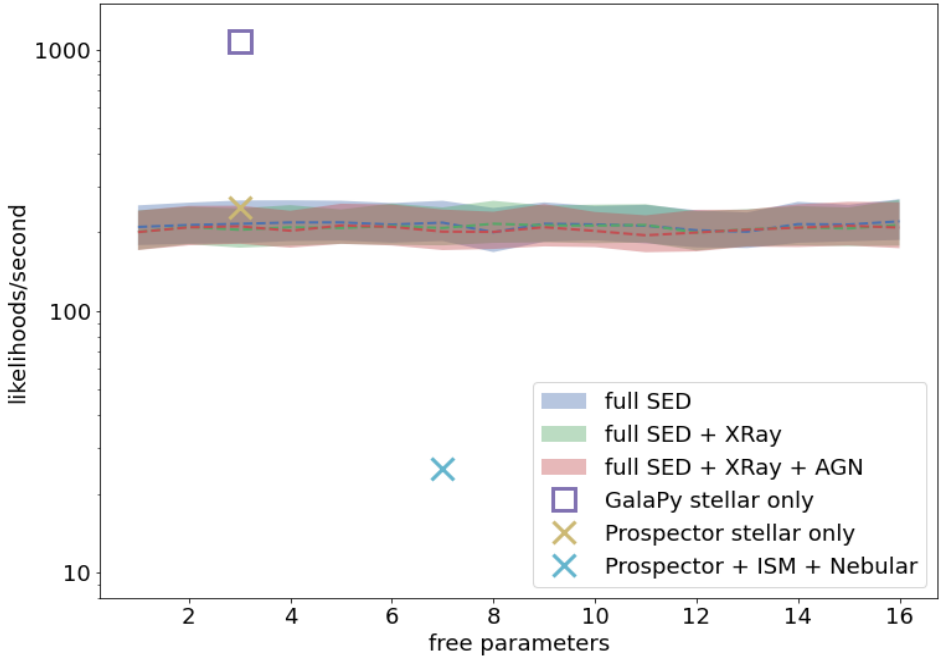


Testing performances

✓ mild dependence on spectral resolution:
- low-res : 800-900 likelihood/s
- high-res : 200-300 likelihood/s



✓ weak dependence on # parameters:



✓ GalaPy vs. other SED-fitting codes
- model time > 100 times faster than CIGALE Boquien+19
- likelihood time > 10 times faster than Prospector Johnson+21

- Magphys + photo-z da Cunha+08
- BEAGLE Vidal-Garcia+22
- BAGPIPES Carnali+18
- others

} comparison ongoing!

Outlook

✓ Short term
- fixing cosmetics in user-interface
- finalizing documentation and wiki
- first paper out + code release (open source)

✓ Mid term
- hierarchical Bayesian scheme (for huge datasets)
- parametric modeling of AGN from coevolution
- variable-resolution spectroscopic fitting

✓ Long term
- active learning direct posterior inference
- internally compiled sampling + sequential Hamiltonian MC
- detailed SED-fitting code performance comparison

Fondazione "Centro Nazionale di Ricerca in HPC, Big Data and Quantum Computing"