Polarimetric Studies of Galaxies
Reducing the Computational Cost of MCRT Simulations via Bayesian Inference

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PhD Brief

- **Objectives:**
  - Explore influence of magnetic fields, scattering and dust in the linear polarization of galaxies;
  - Extract and understand dust properties and distributions to correct systematics in extinction laws

- **Methods**
  1. Data reduction and analysis
  2. Apply Bayesian inference and other statistical learning methods
  3. Model the observed galaxies using MCRT models
  4. Compare with models with observations

Modeling with MCRT - Monte Carlo Radiative Transfer

Mattila, 1970

- Define an emitting body and a dust structure
- Simulate the emission of N photons by the body and their interaction with the dust
- Check the photon maps for different wavelengths

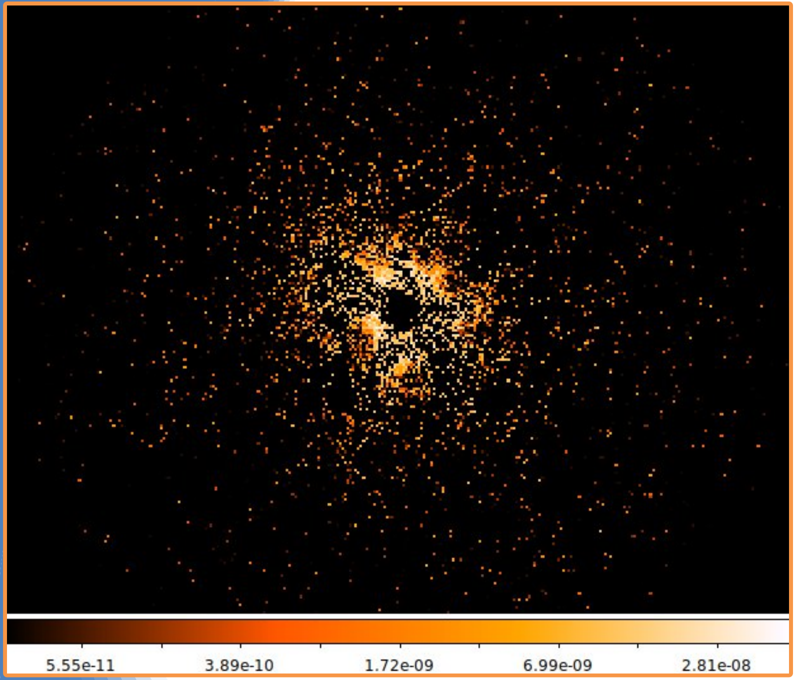
SKIRT

Baes et al., 2011

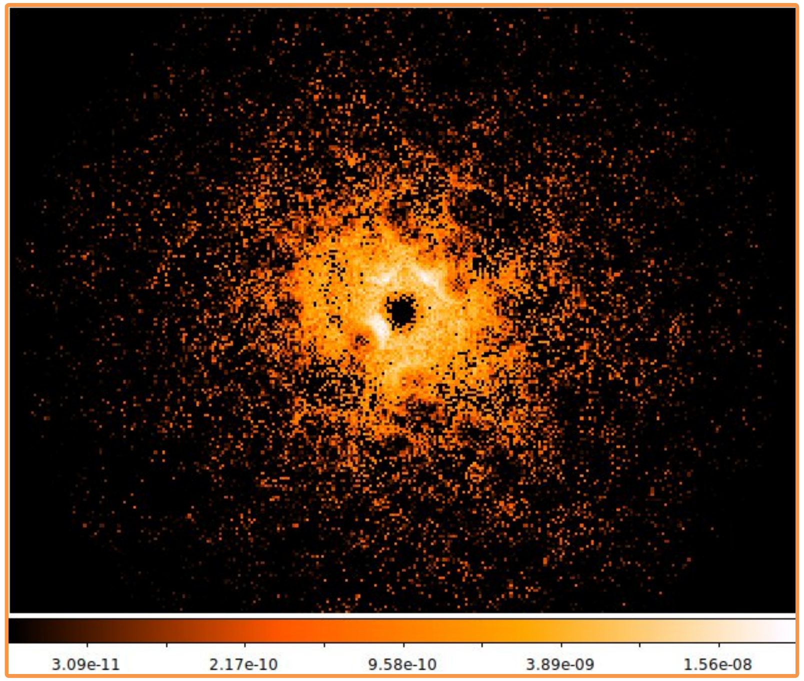
- MCRT suite that has tunable body and dust distribution templates
- Easier to simulate distinct scenes from different perspectives
- Simulates K photons per wavelength bin

SKIRT

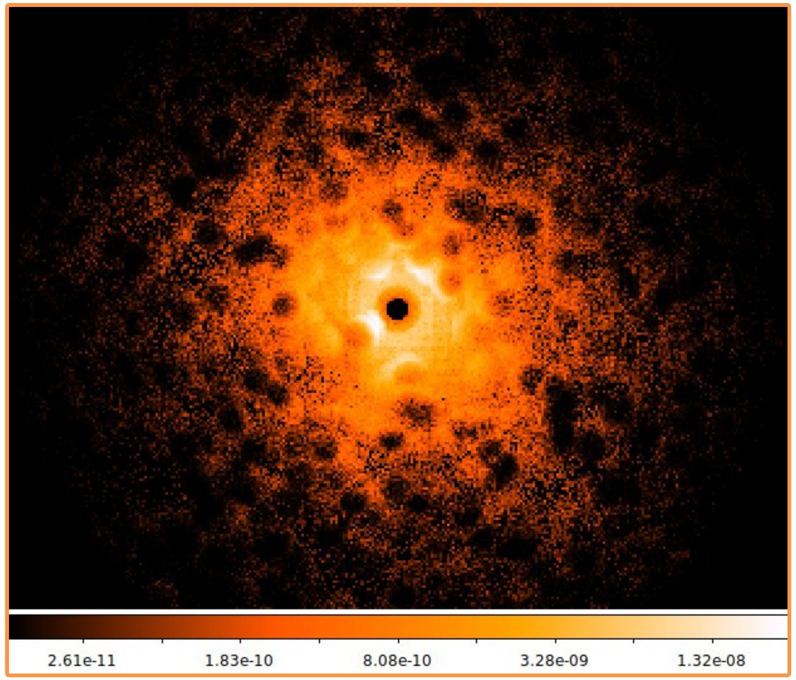
Simulations of face-on AGN, at 9.72 μm
(by Marko Stalevski, on a cluster using 20 threads)



10^4 photons per bin
~30min per cube



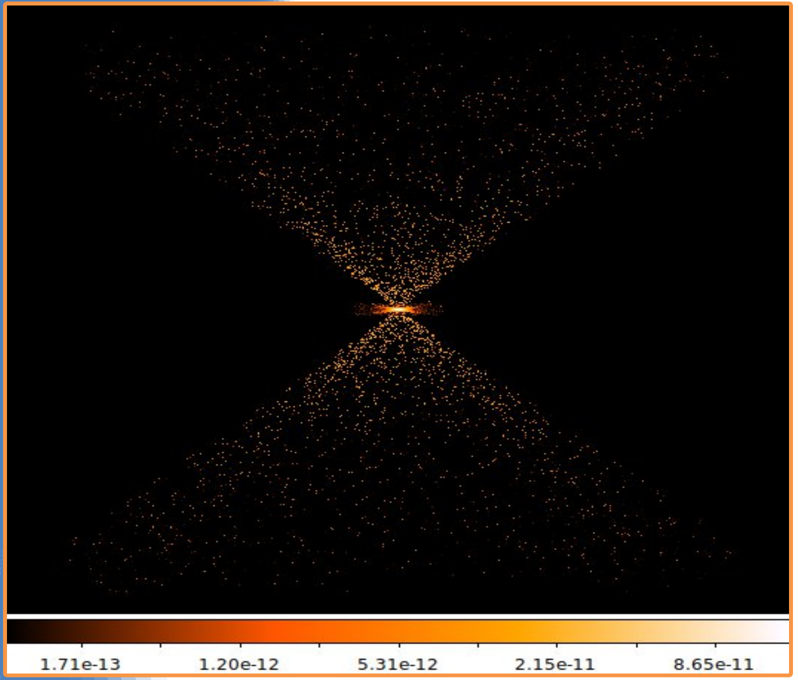
10^5 photons per bin
0.5-2h per cube



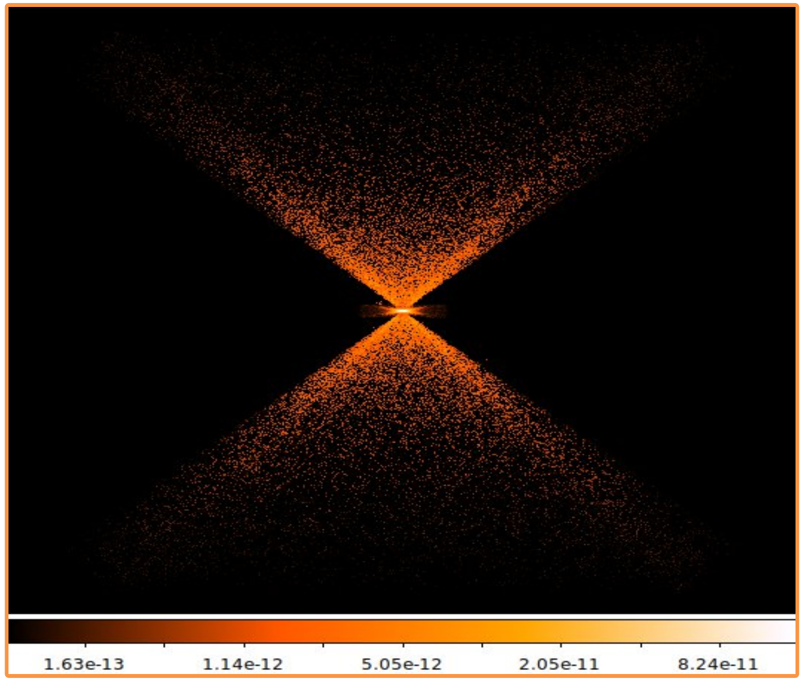
10^6 photons per bin
3-16h per cube

SKIRT

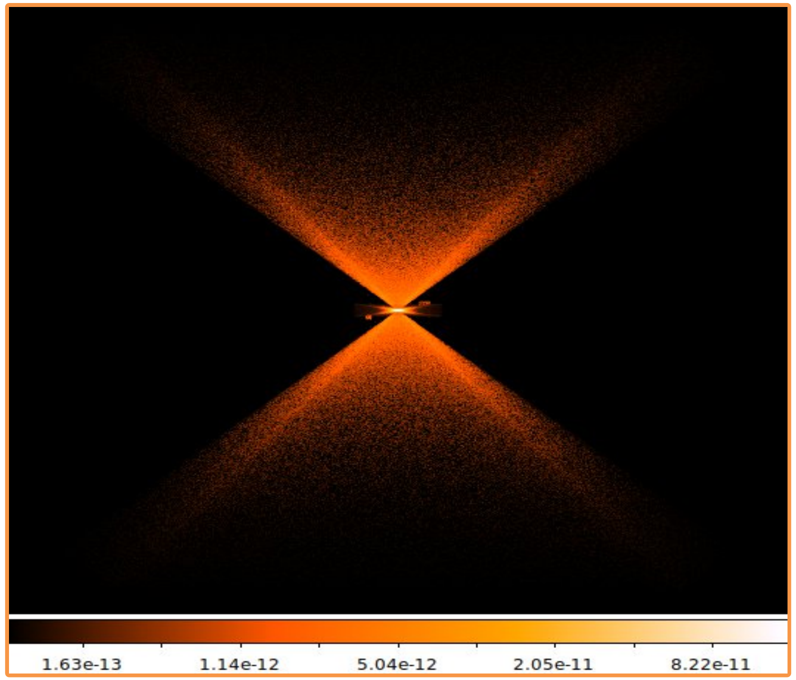
Simulations of edge-on AGN, at 9.82 μm
(by Marko Stalevski, on a cluster using 20 threads)



10^4 photons per bin
~25min per cube



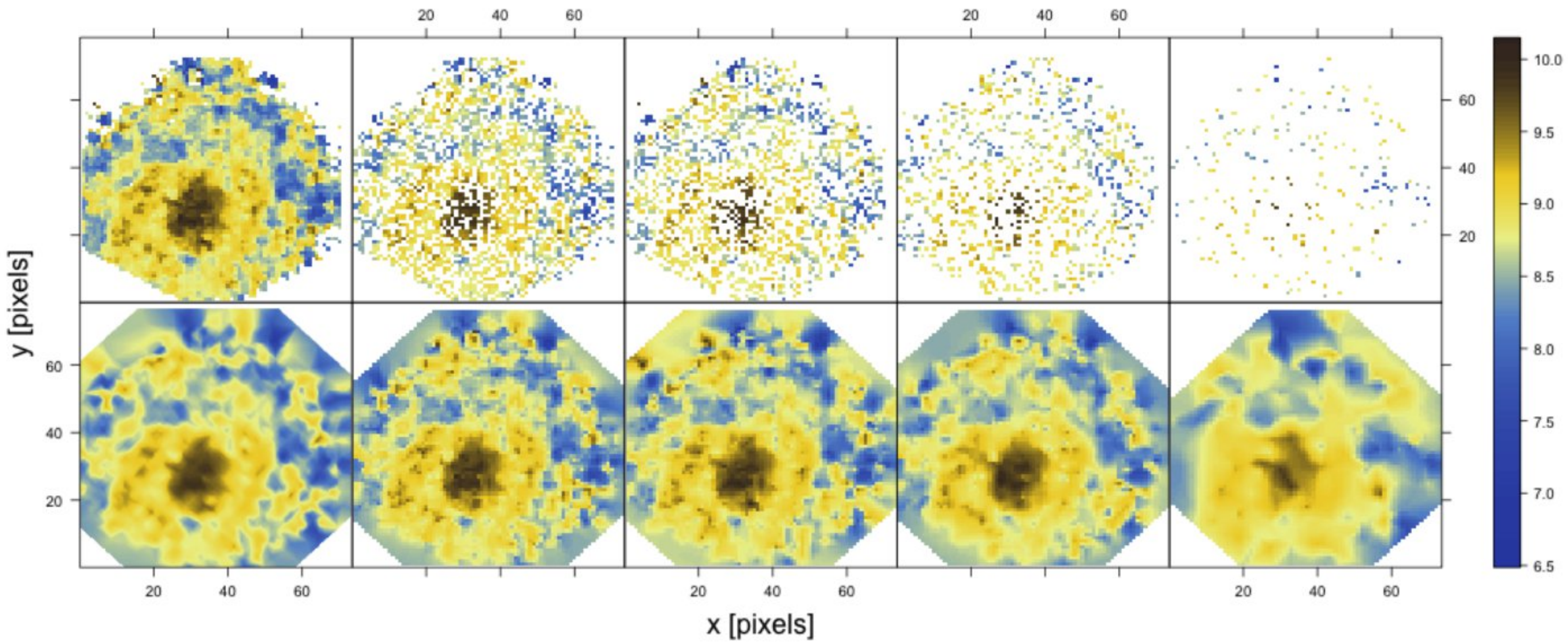
10^5 photons per bin
~35min per cube



10^6 photons per bin
~3h per cube

INLA

Rue et al., 2009



Predictions from INLA for input starlight age of NGC 0309 when 100, 75, 50, 25 and 5% (left to right) of the data is used. Upper panels show the starlight input, bottom the INLA prediction [González-Gaitán et al., 2018].

INLA

- Bayesian inference of a latent field from a dataset
- Considers spatial correlations
- Applies a sequential set of approximations to the variable and hyperparameter distributions

INLA

- Predictions account for spatial correlation
- Faster and lower error than MCMC methods*
- Noise resistant
- Readily available as an R package
- Small number of hyperparameters (m<6)
- The field we want to infer must be a GMRF

SKIRT + INLA

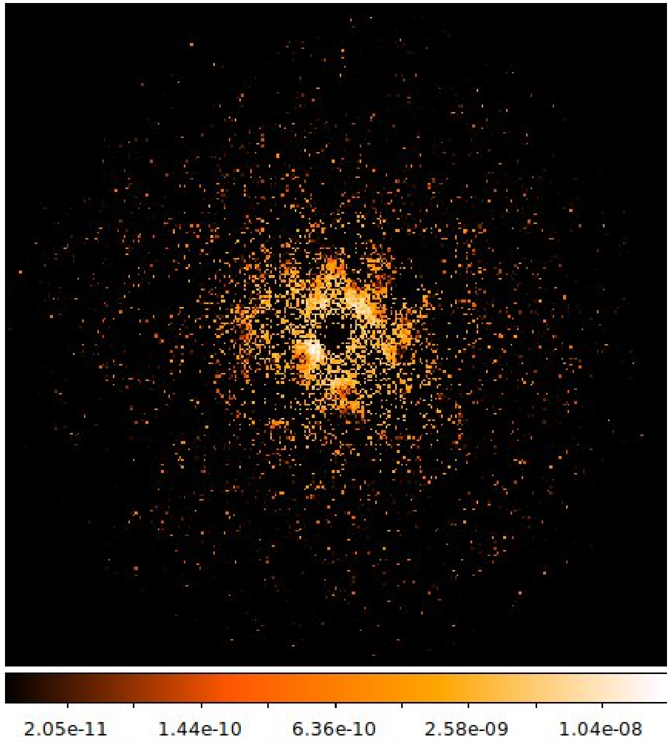
1. Generate low photon count simulations using SKIRT

2. Pre-process output files

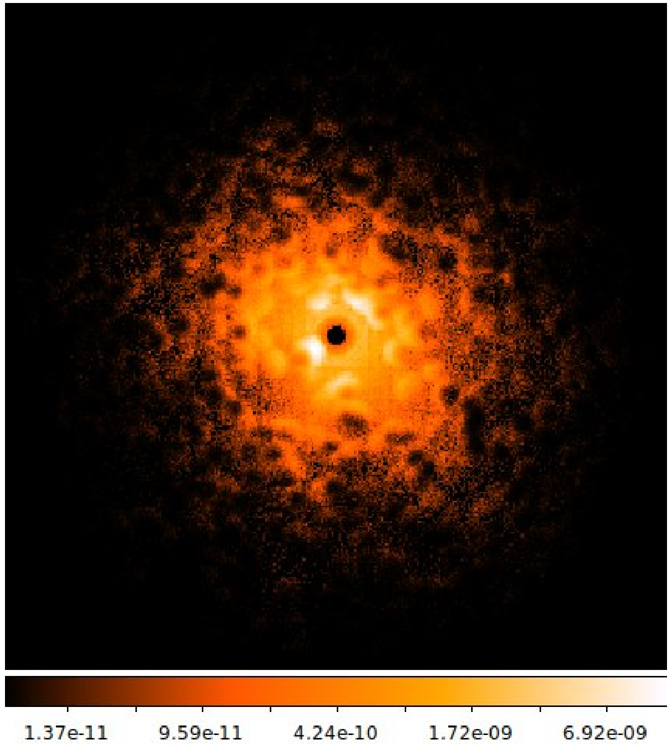
3. Feed (2.) results as priors to INLA

4. Get high resolution posteriors in a fraction of the time

SKIRT + INLA

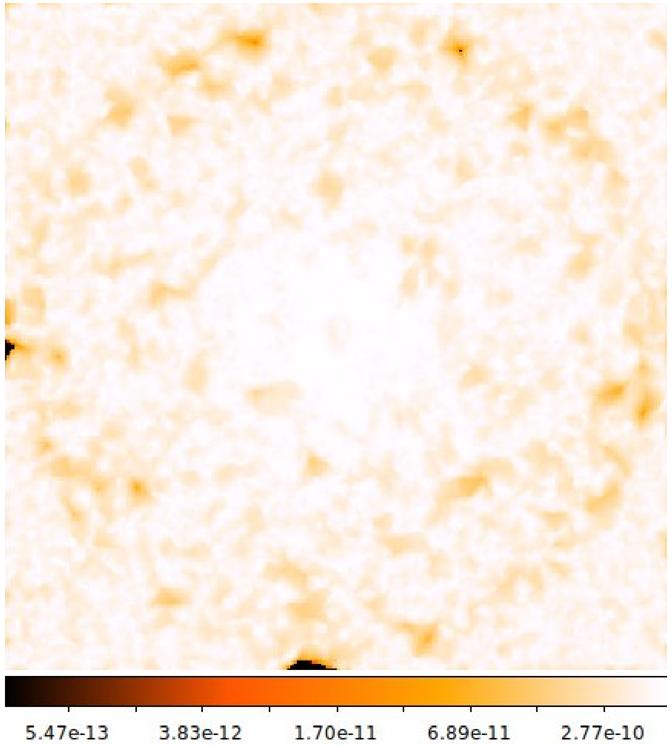


10^4 photons, ~15s/slice
(cluster, 20 threads)

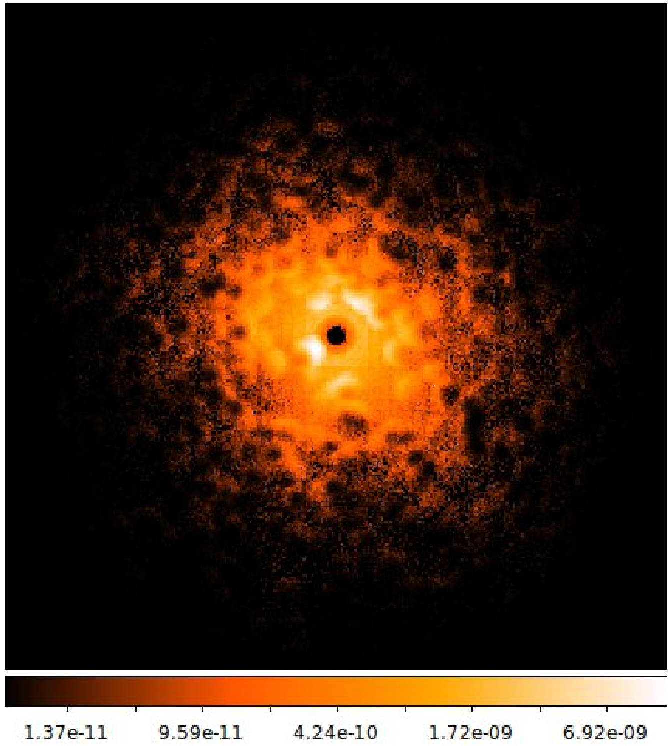


10^6 photons, 100-600s/slice
(cluster, 20 threads)

SKIRT + INLA

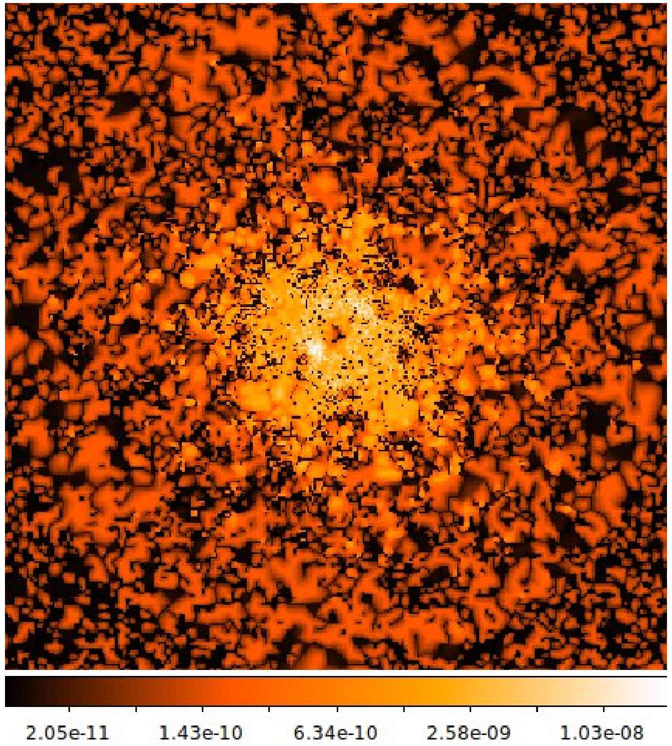


10^4 photons -> INLA, ~150s/slice
(laptop, 3-6 threads)

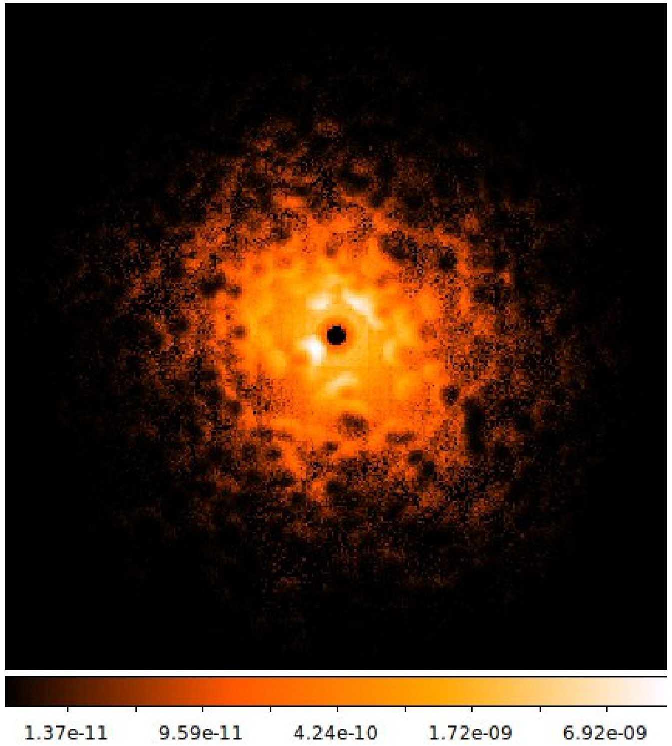


10^6 photons, 100-600s/slice
(cluster, 20 threads)

SKIRT + INLA

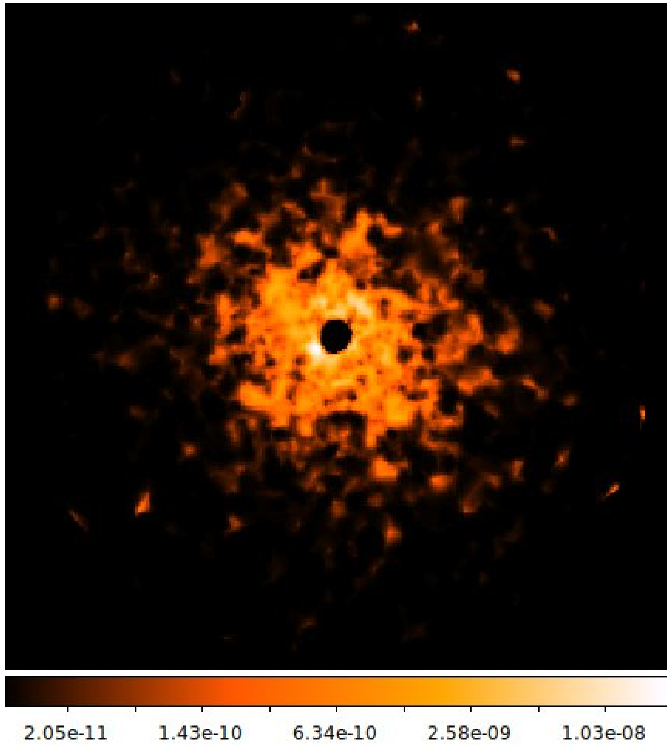


10^4 photons -> normalize -> INLA, ~150s/slice
(laptop, 3-6 threads)

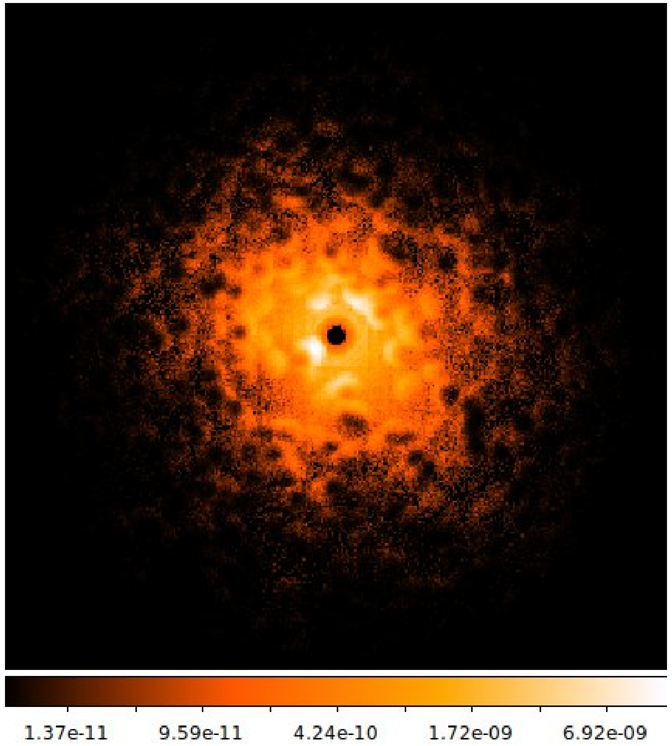


10^6 photons, 100-600s/slice
(cluster, 20 threads)

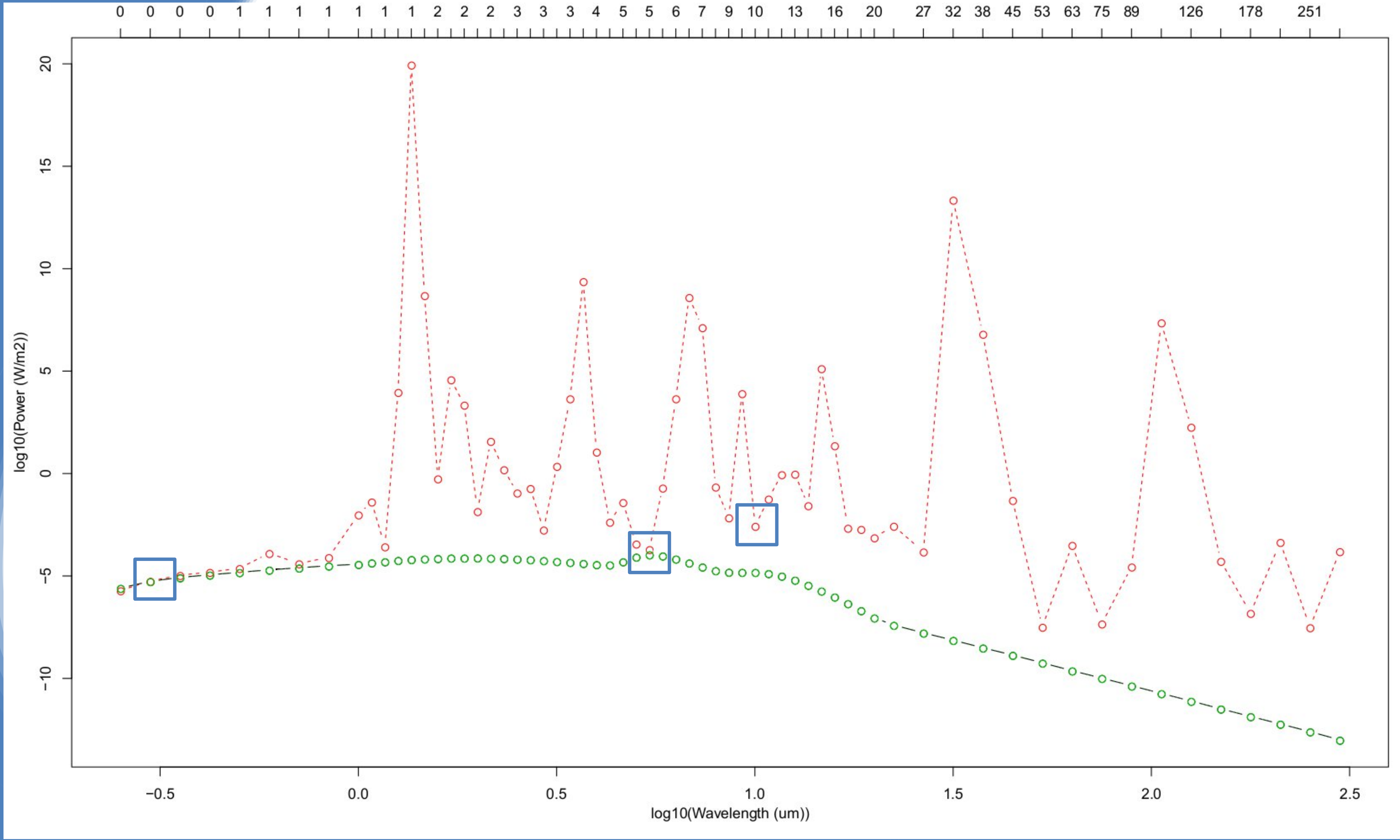
SKIRT + INLA



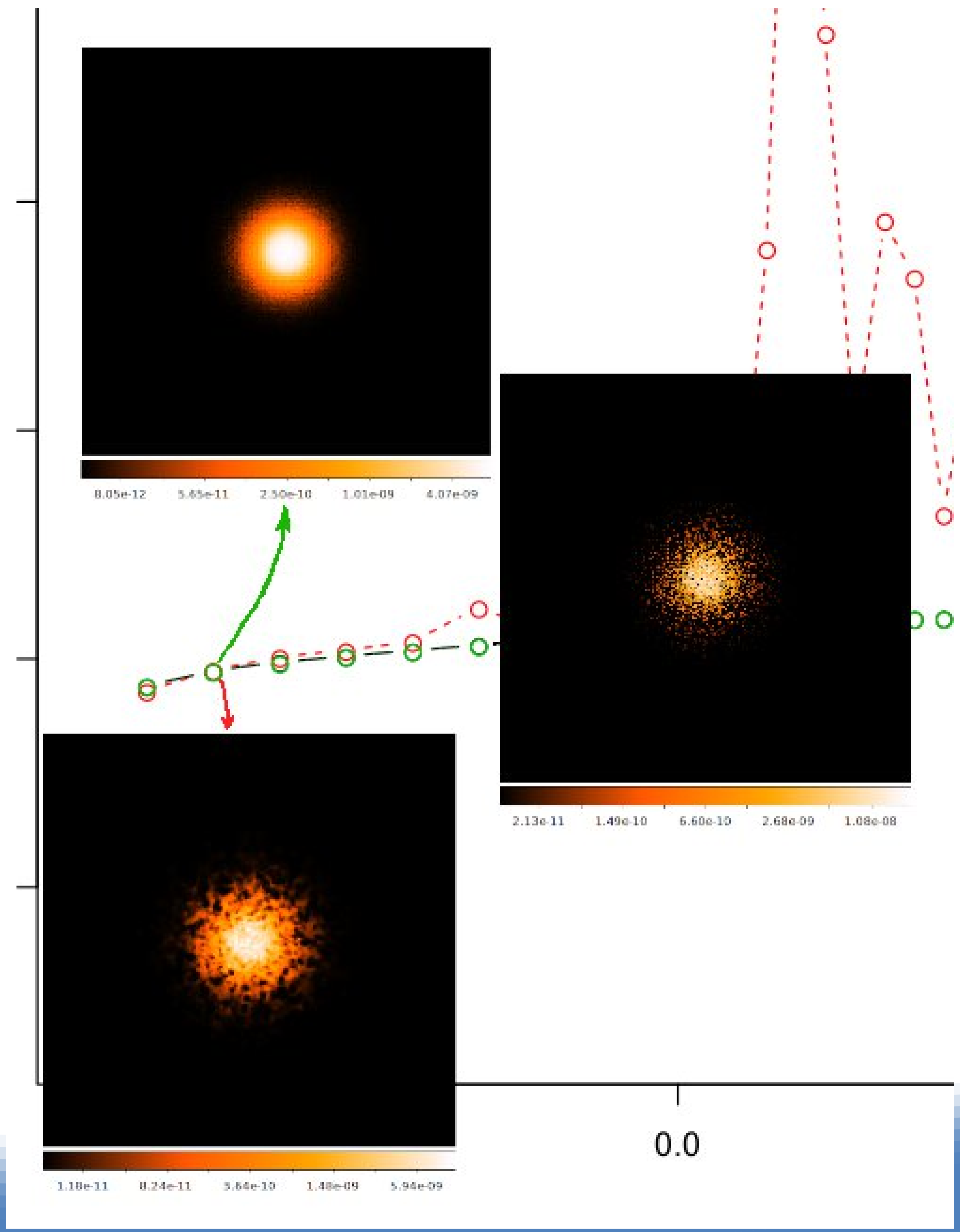
10^4 photons -> $\log_{10}$ -> INLA, ~150s/slice
(laptop, 3-6 threads)



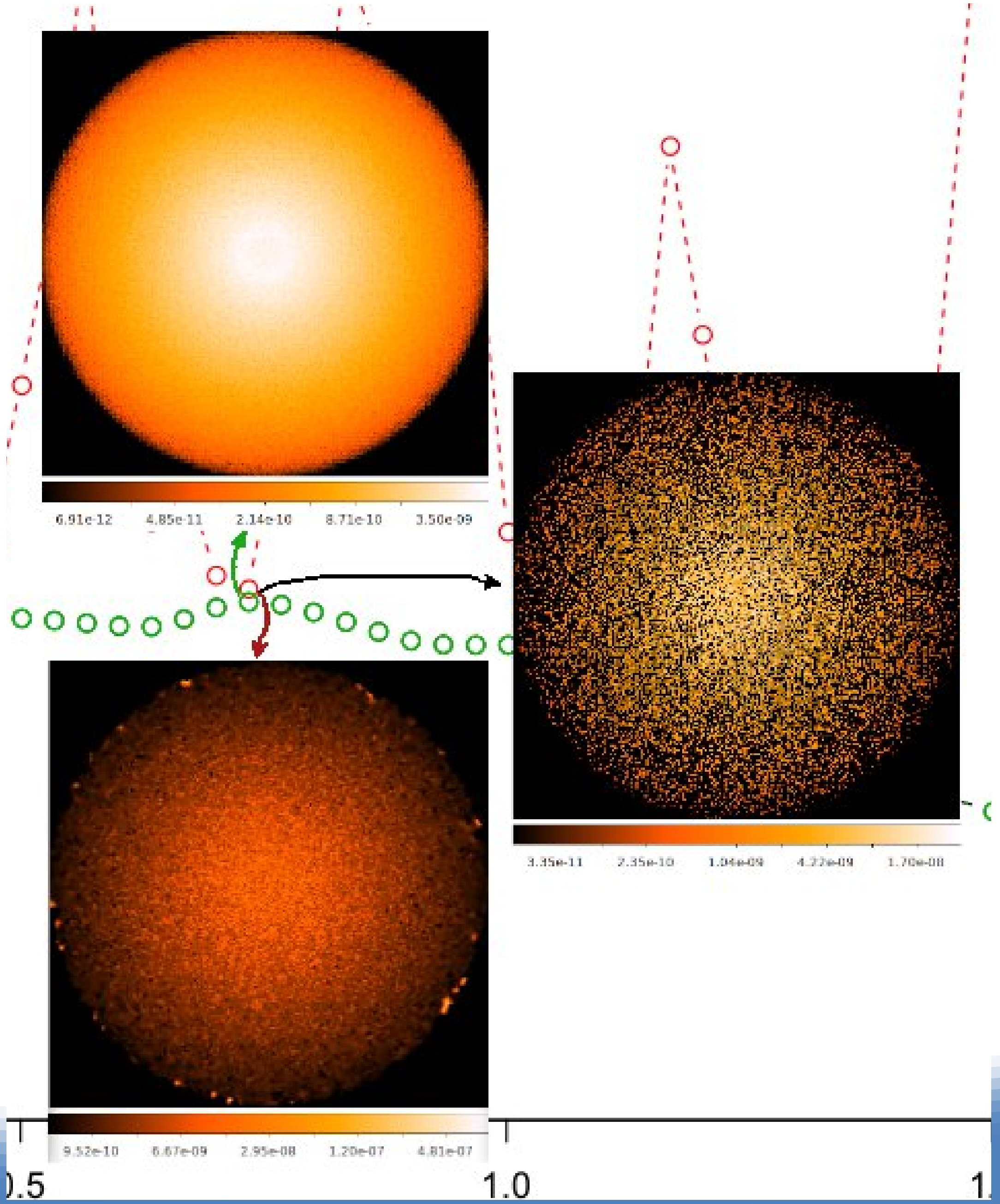
10^6 photons, 100-600s/slice
(cluster, 20 threads)



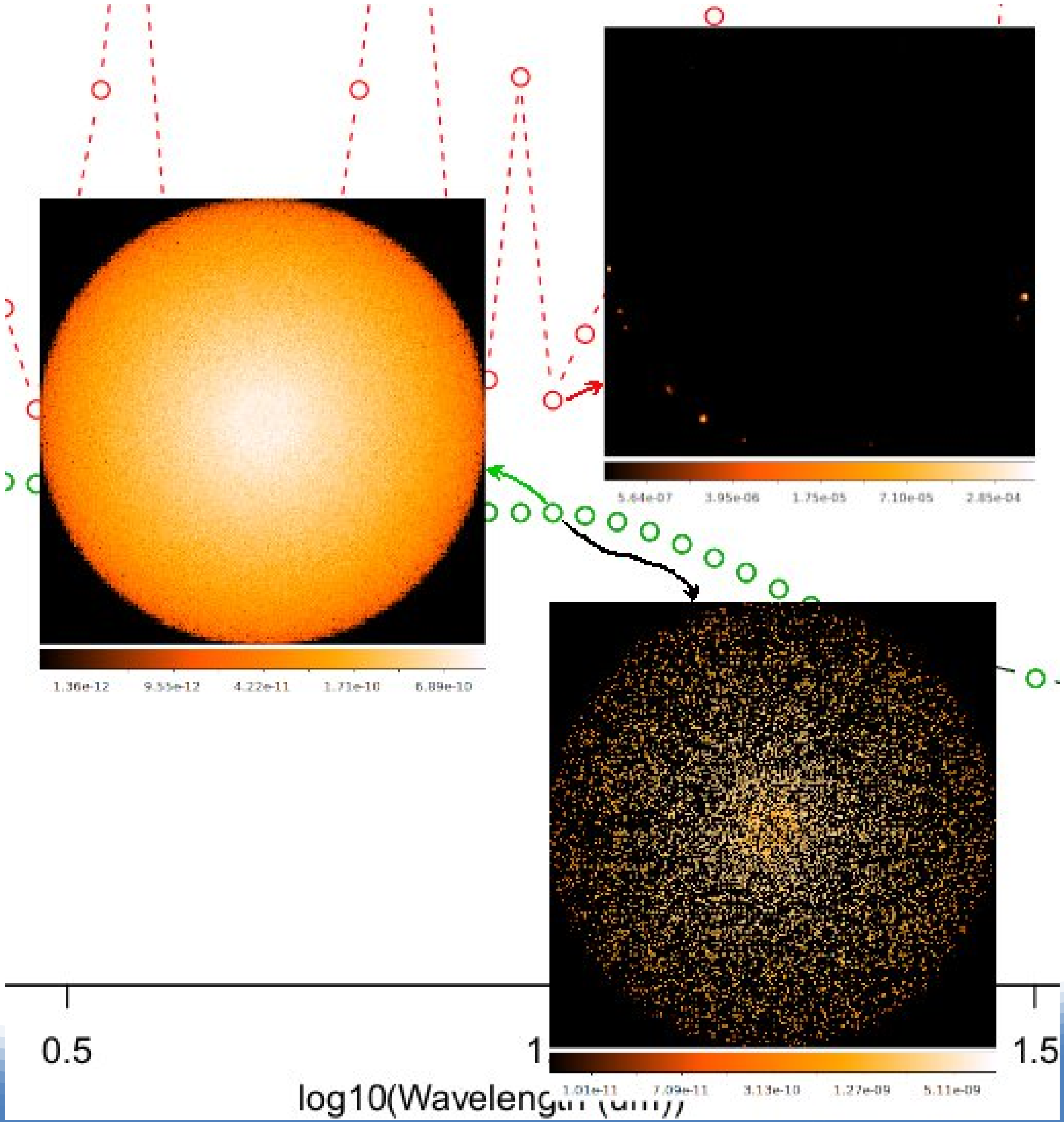
0 0 0 0 1 1 1 1 1 1 1 2 2 2 3 3 3 4 5 5 6 7 9 10 13 16 20 27 32 38 45 53 63 75 89 126 178 251
log10(Power (W/m2))
20
15
10
5
0
−5
−10
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
log10(Wavelength (um))



8.05e-12
5.65e-11
2.50e-10
1.01e-09
4.07e-09
2.13e-11
1.49e-10
6.60e-10
2.68e-09
1.08e-08
1.18e-11
8.24e-11
3.64e-10
1.48e-09
5.94e-09
0.0



6.91e-12
4.85e-11
2.14e-10
8.71e-10
3.50e-09
3.35e-11
2.35e-10
1.04e-09
4.22e-09
1.70e-08
9.52e-10
6.67e-09
2.95e-08
1.20e-07
4.81e-07
1.0


5.64e-07
3.95e-06
1.75e-05
7.10e-05
2.85e-04
1.36e-12
9.55e-12
4.22e-11
1.71e-10
6.89e-10
1.01e-11
7.09e-11
3.13e-10
1.27e-09
5.11e-09
0.5
1.5
log10(Wavelen

Final Remarks

- INLA's performance appears to be highly sensitive to input's span and magnitude of values

- Computational performance improvement is not yet clear

Thank you!