Developing AGN models with INLA

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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

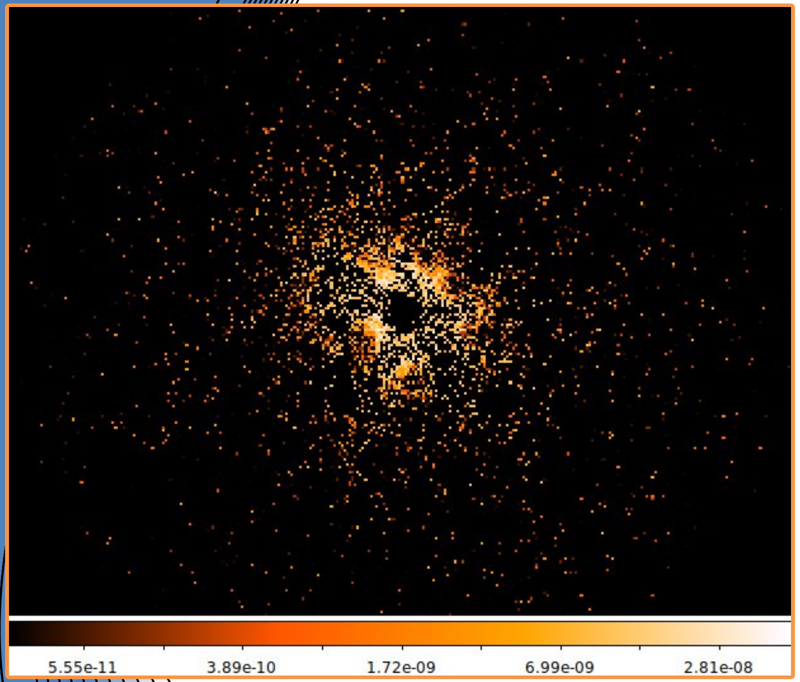
SKIRT

Baes et al., 2011

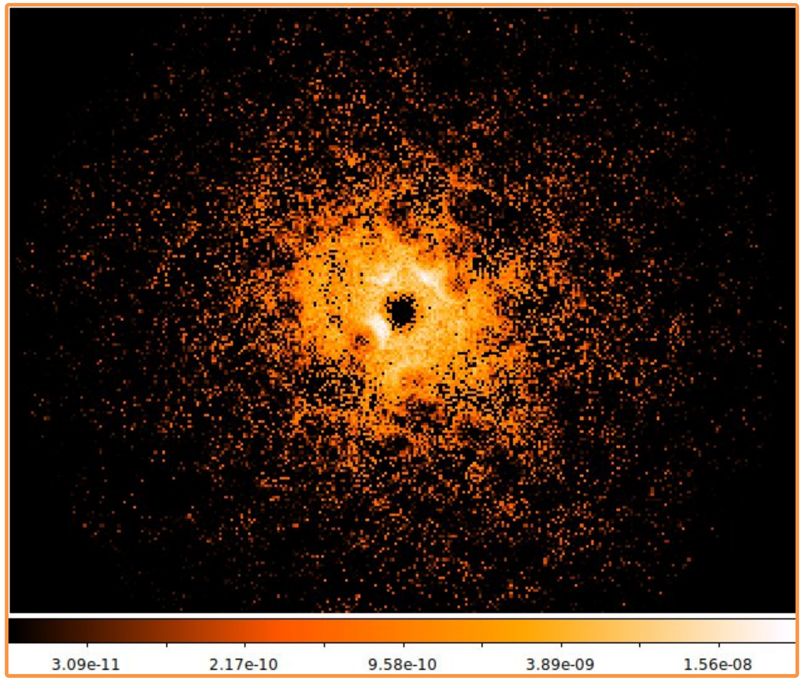
- MCRT suite that has tunable body and dust distribution templates
- Easier to simulate distinct scenes from different perspectives
- Simulates K photon packets distributed by wavelength bins

SKIRT

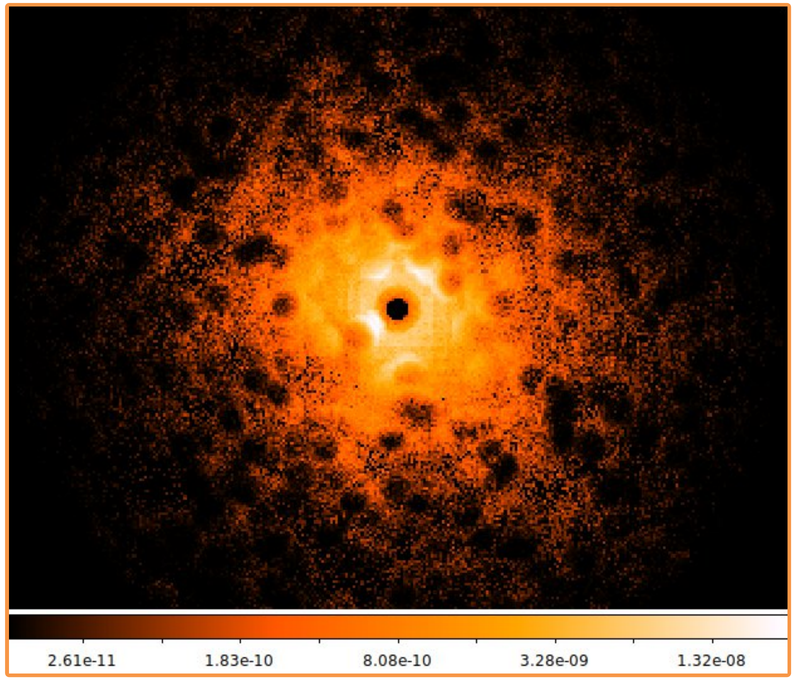
Simulations of face-on AGN, at 9.72 m
(by Marko Stalevski, on a cluster using 20 threads)



10^4 photons per bin
~30min per cube



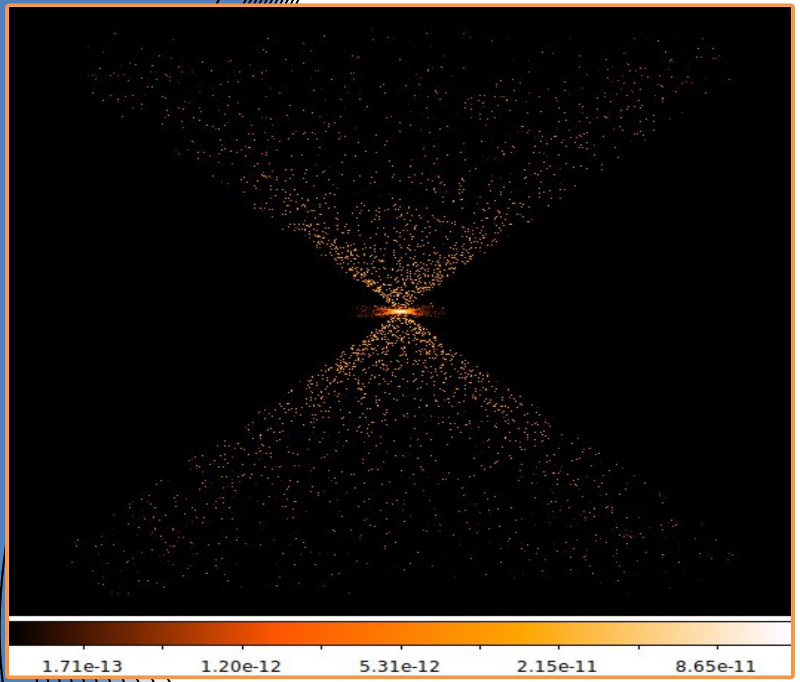
10^5 photons per bin
0.5-2h per cube



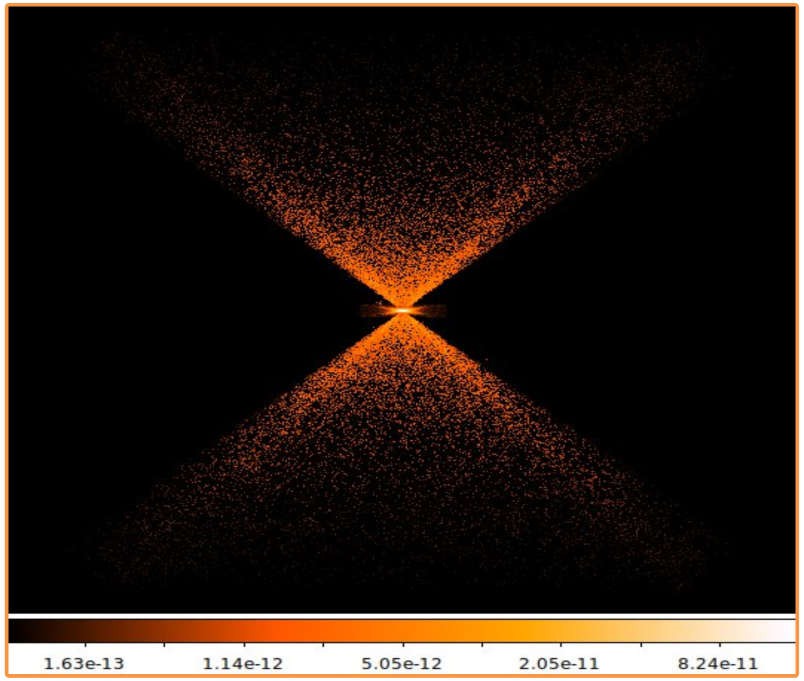
10^6 photons per bin
3-16h per cube

SKIRT

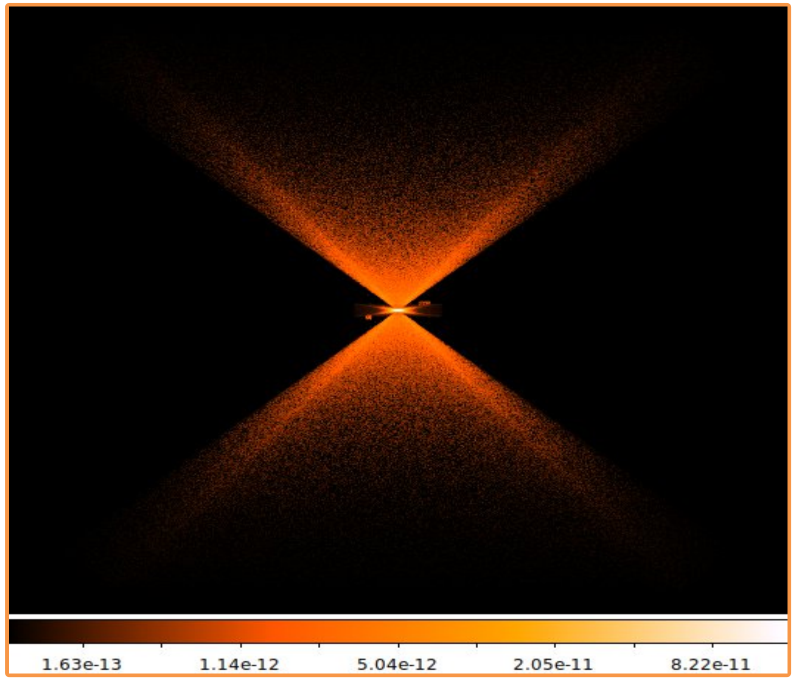
Simulations of edge-on AGN, at 9.82 m
(by Marko Stalevski, on a cluster using 20 threads)



10^4 photons per bin
~25min per cube



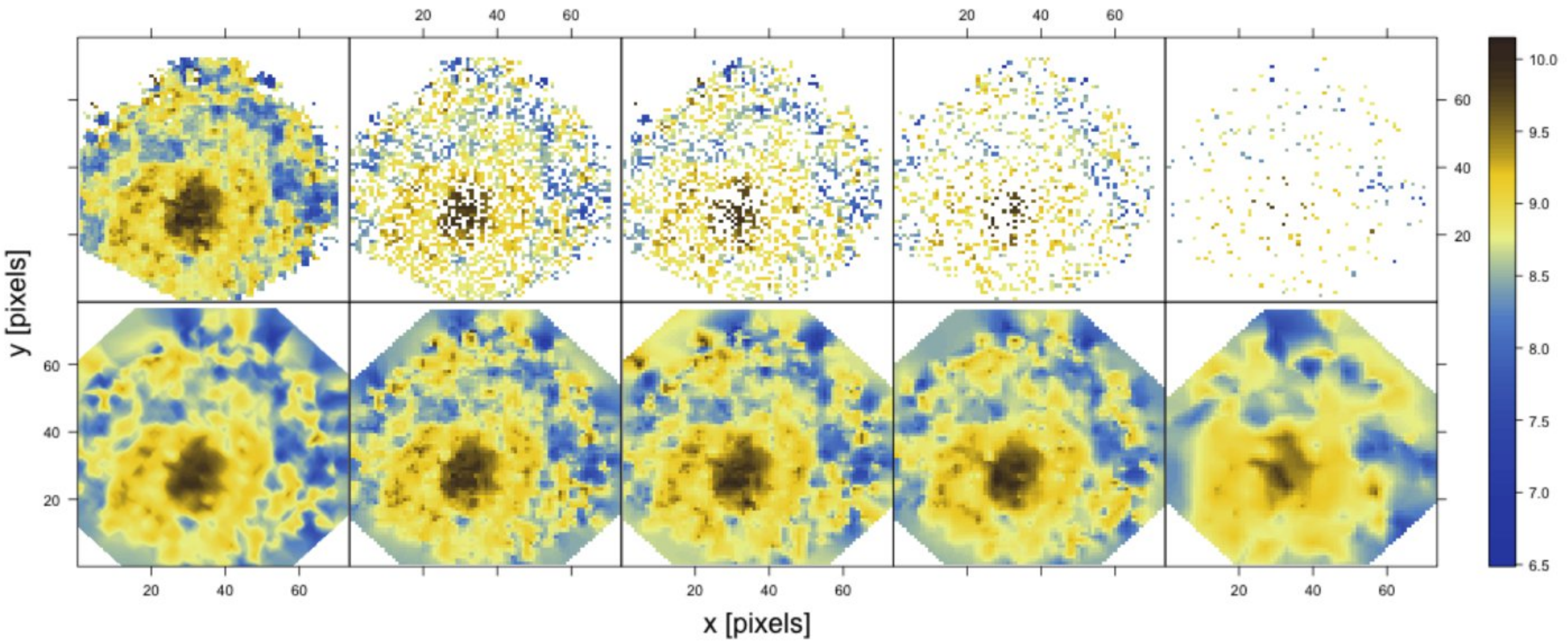
10^5 photons per bin
~35min per cube



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

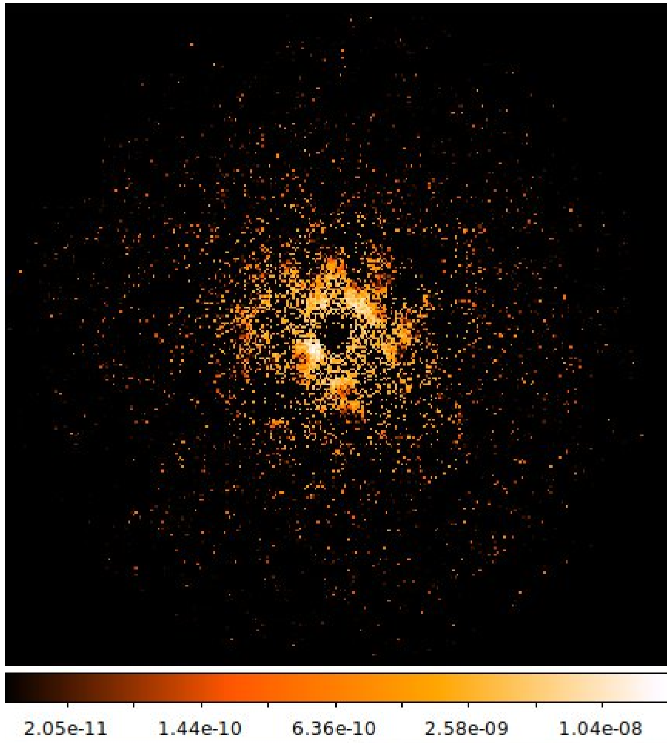
1. Generate low photon count simulations using SKIRT

1. Pre-process output files

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

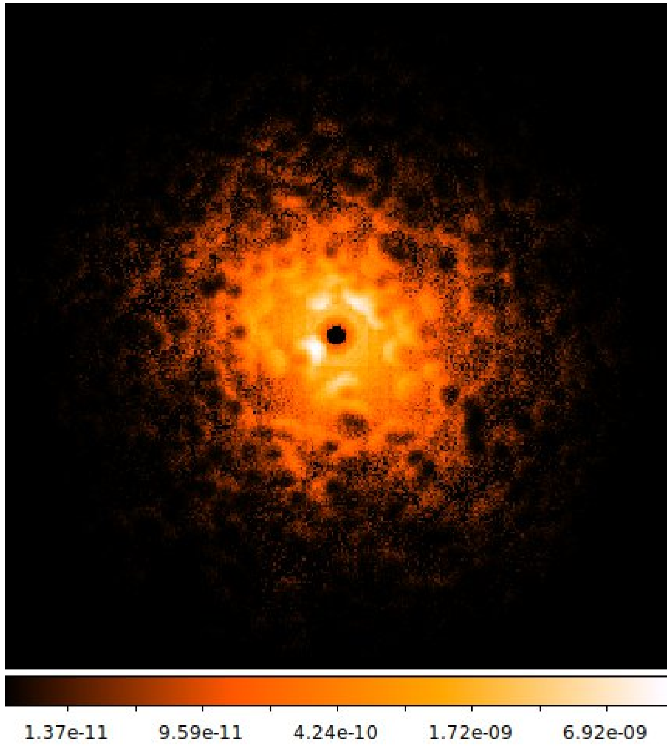
1. Get high resolution posteriors in a fraction of the time

SKIRT + INLA



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

INLA



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

Data differences & Strategies

1. Transform Input ($\log_{10}$, normalize by max)

1. Focused 0 imputation

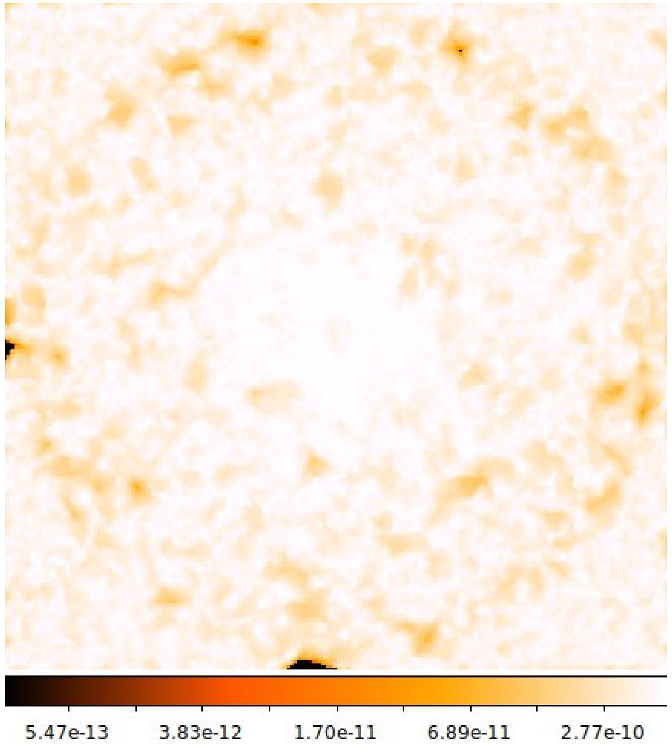
1. Statistical Brute-forcing

1. Smart 0 imputation

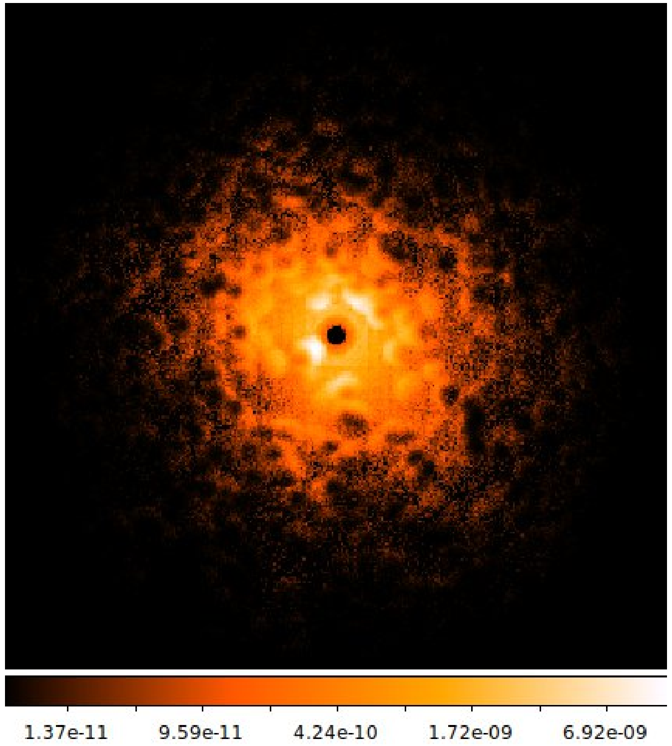
1. Change of Perspective

1. Non-0-Blind Transform Input

Transforming Input

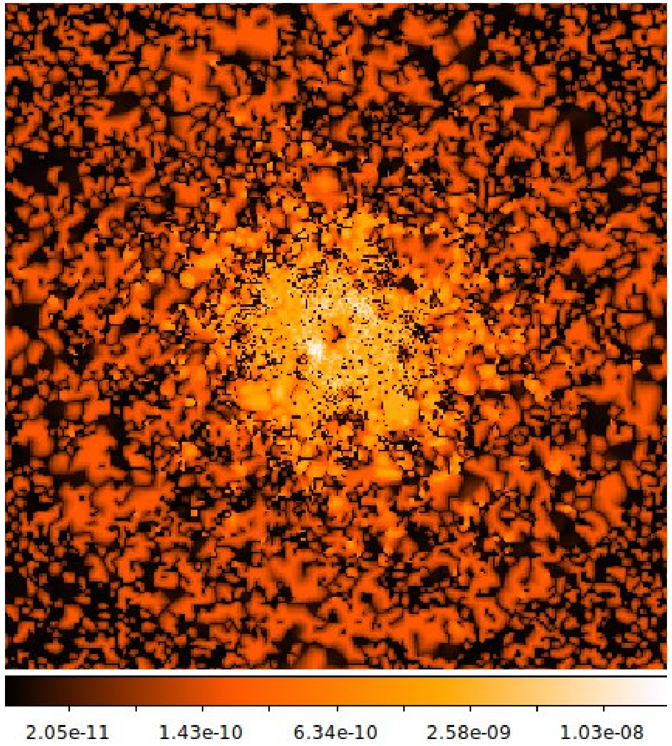


10⁴ photon packets -> INLA, ~150s/slice
(laptop, 3-6 threads)

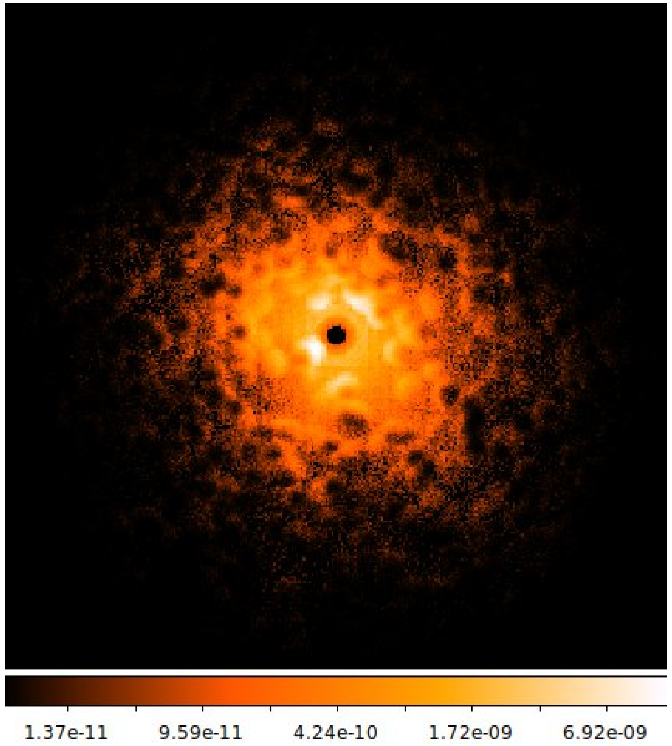


10⁶ photon packets, 100-600s/slice
(cluster, 20 threads)

Transforming Input

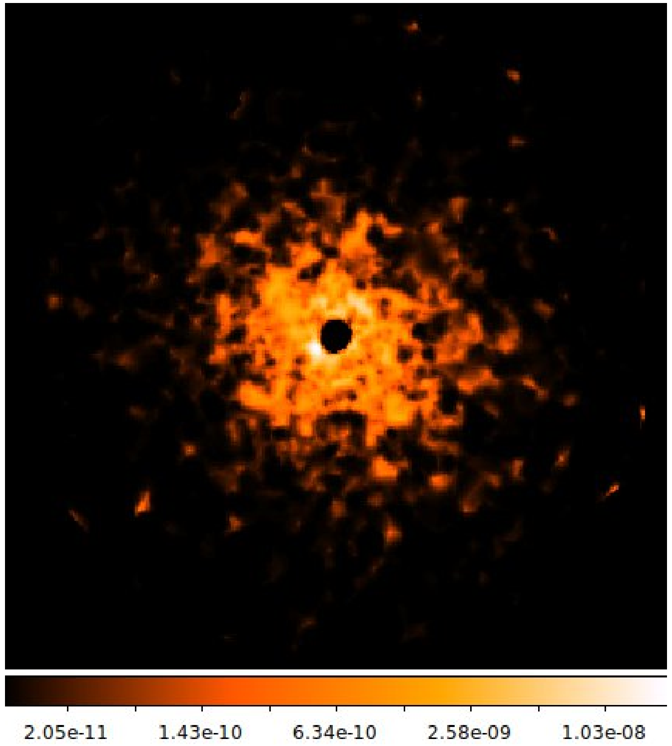


10^4 photon packets -> normalize -> INLA,
~150s/slice
(laptop, 3-6 threads)

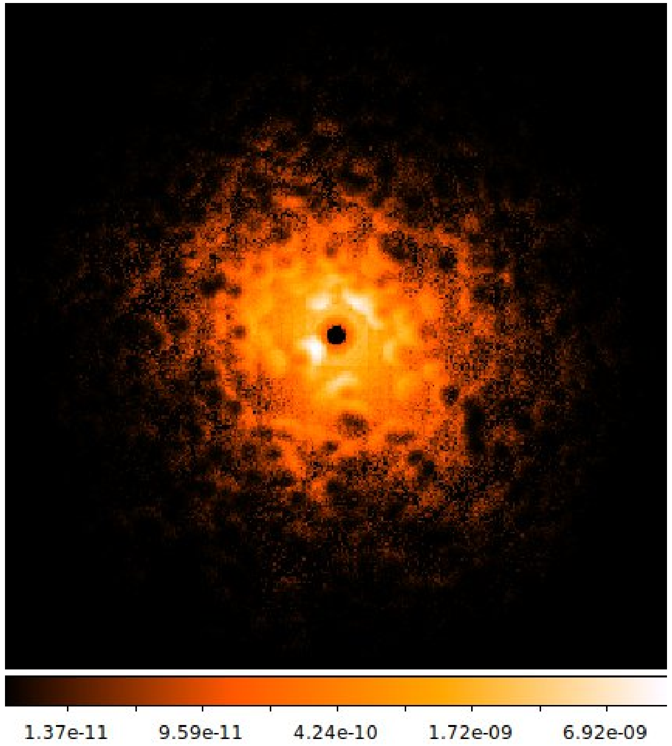


10^6 photon packets, 100-600s/slice
(cluster, 20 threads)

Transforming Input



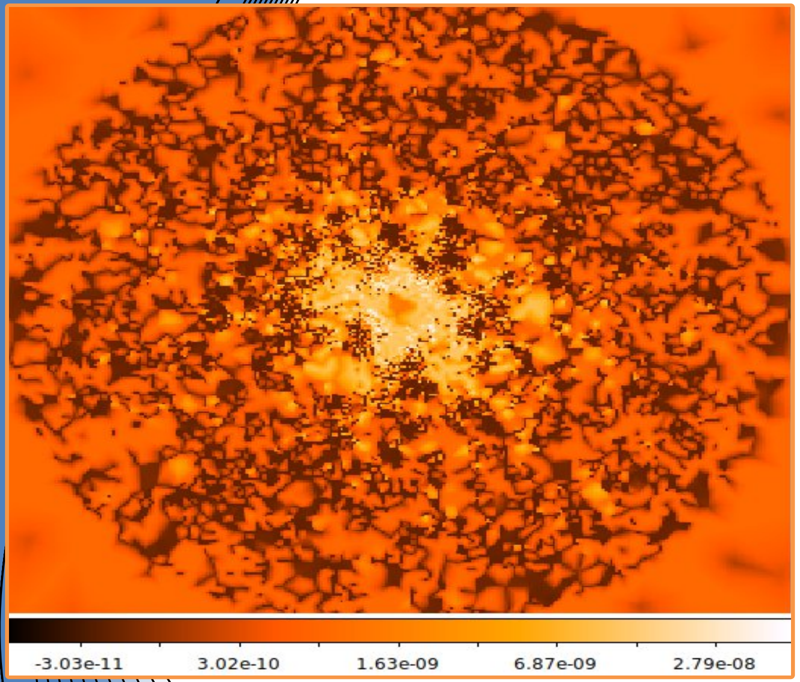
10^4 photon packets -> $\log_{10}$ -> INLA, ~150s/slice
(laptop, 3-6 threads)



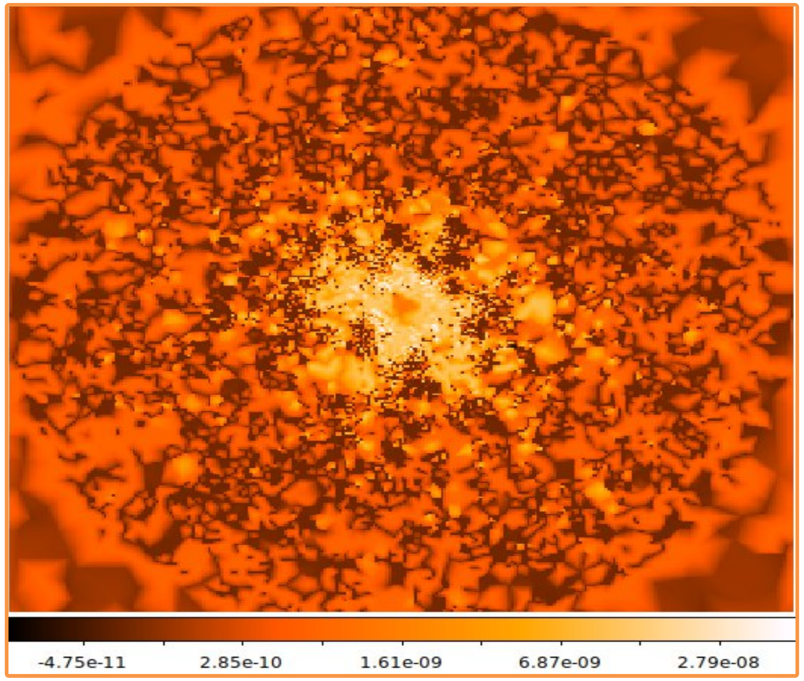
10^6 photon packets, 100-600s/slice
(cluster, 20 threads)

Focused 0 imputation

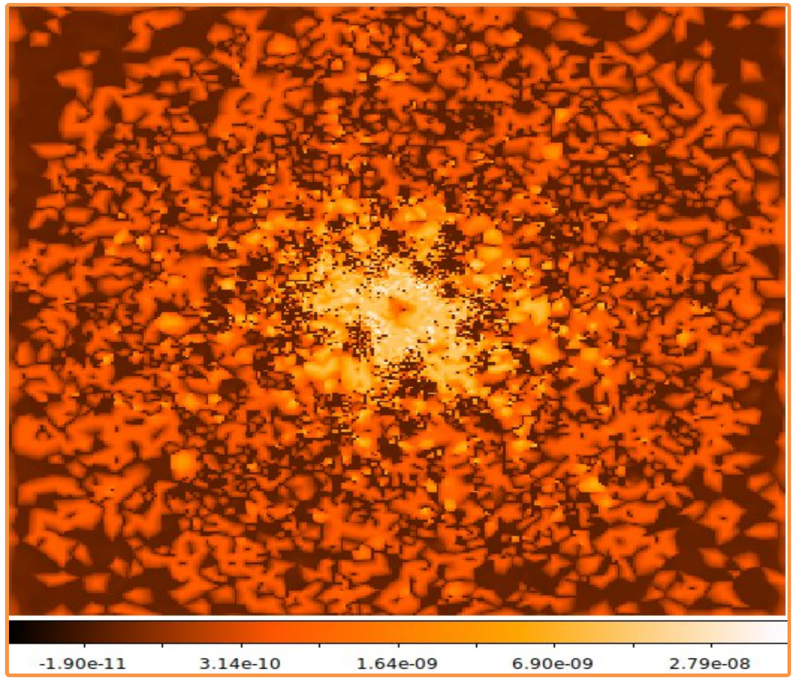
Upscaling face-on AGN, at 9.72 m, with imputation of 0's on regular input before INLA



Imputation freq: 1/900



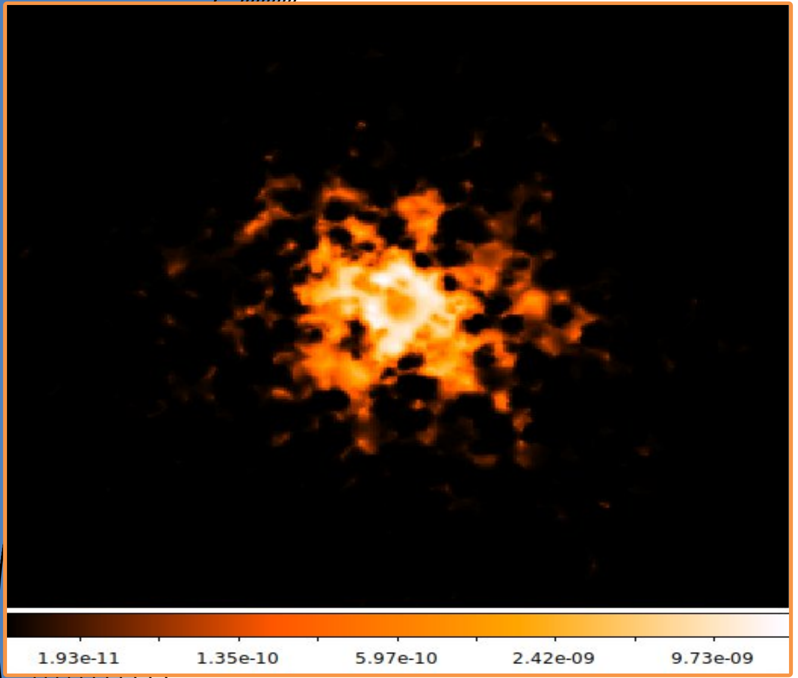
Imputation freq: 1/144



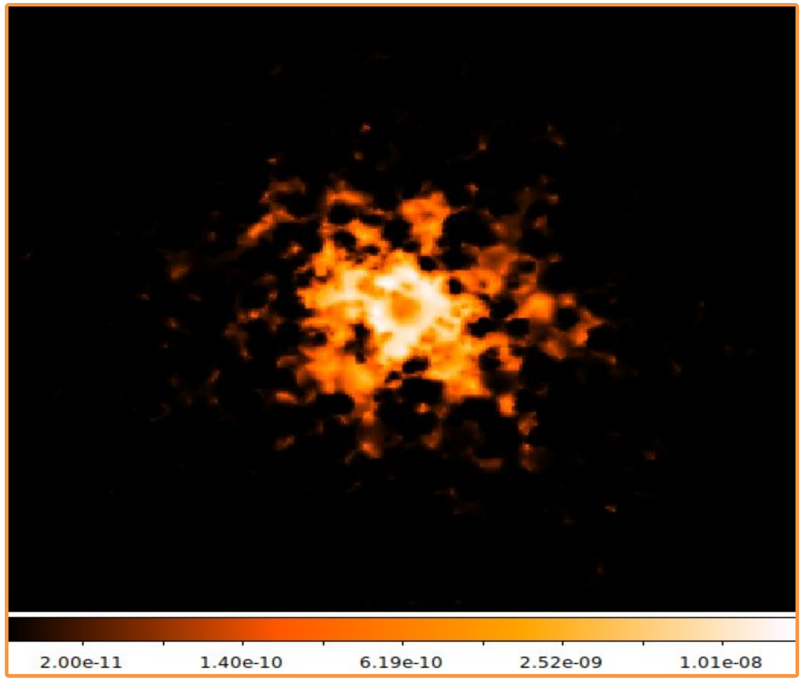
Imputation freq: 1/36

Focused 0 imputation

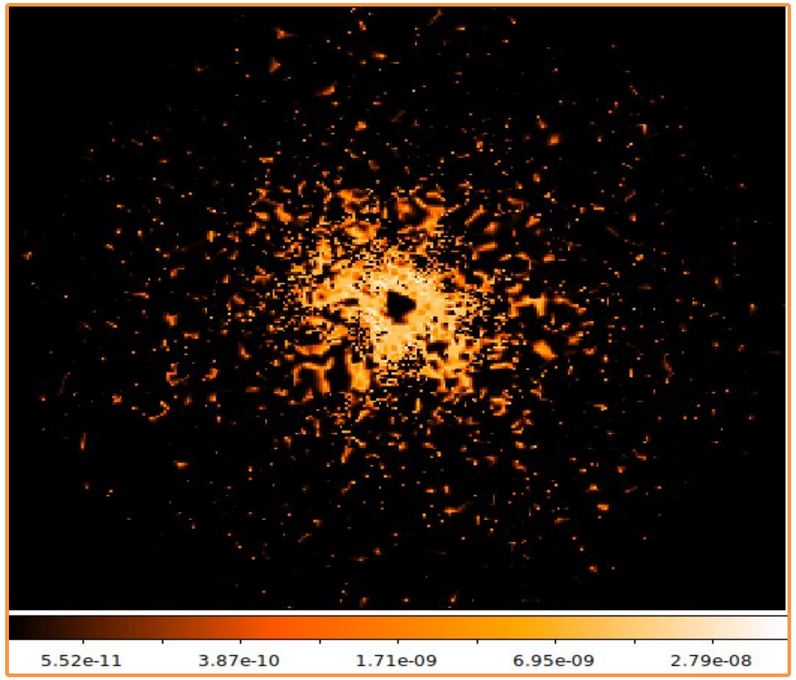
Upscaling face-on AGN, at 9.72 m, with imputation of -15's on $\log_{10}$ input before INLA



Imputation freq: 1/900

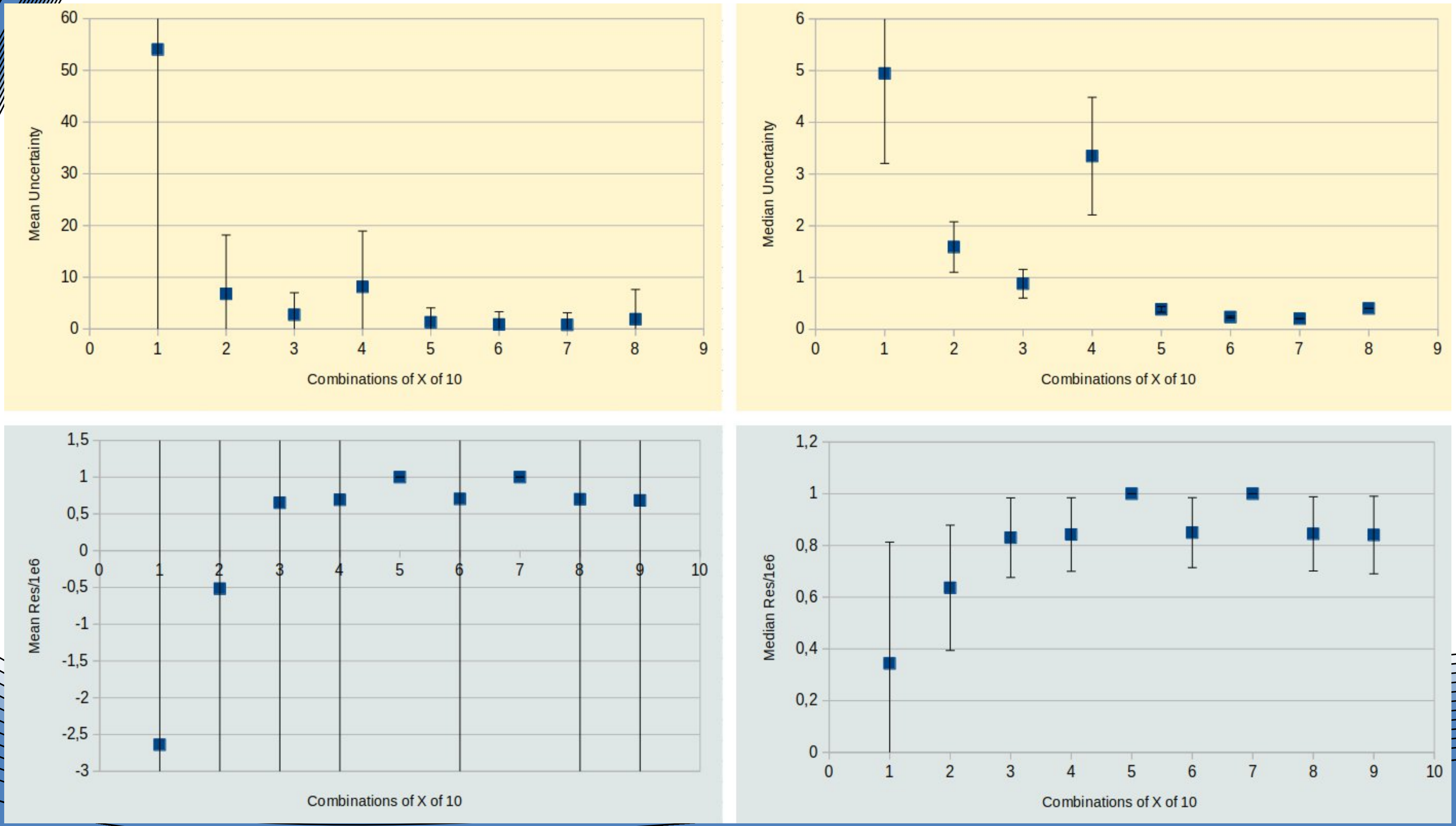


Imputation freq: 1/144



Imputation freq: 1/36

Statistical Brute-forcing



Statistical Brute-forcing

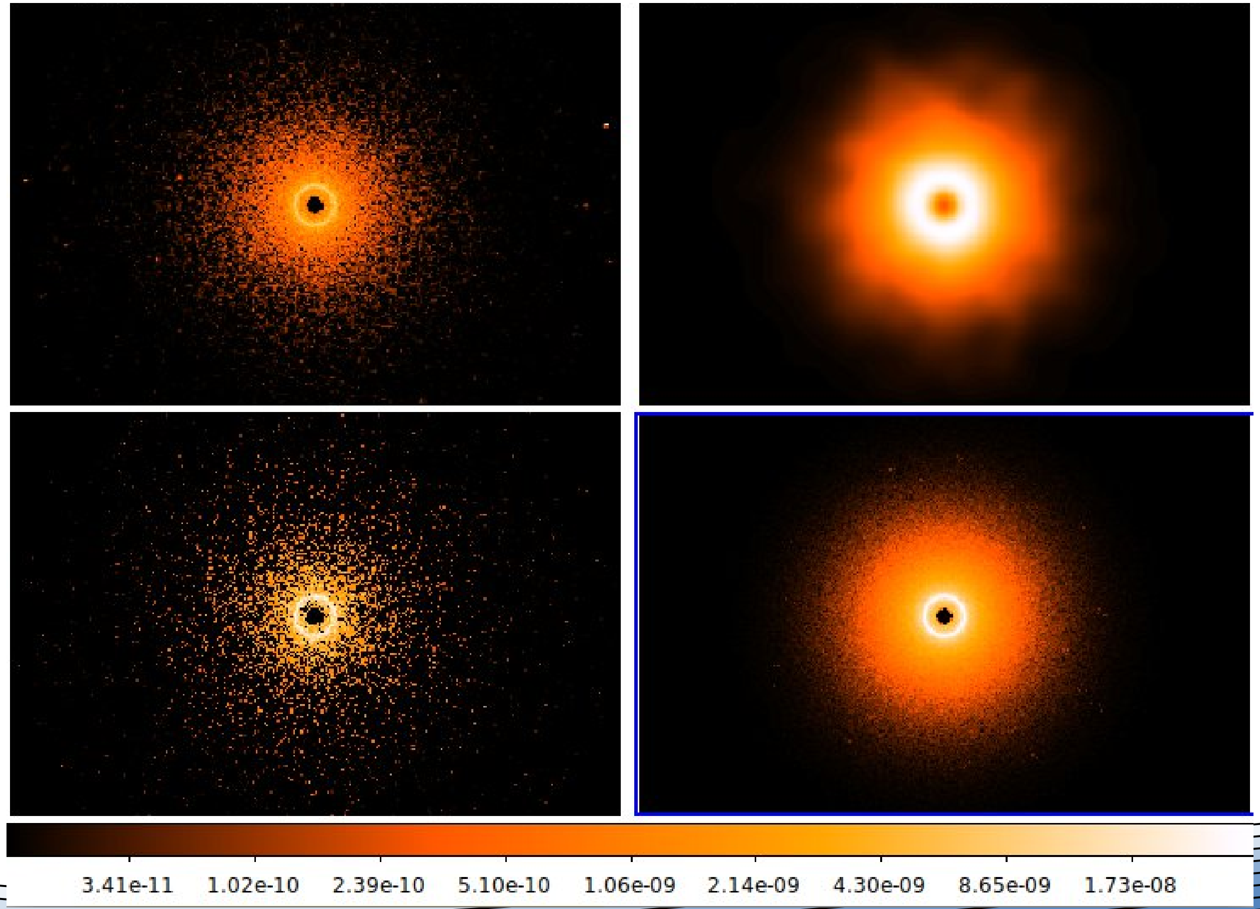
face-on AGN, at 9.72 m

Avg of 2 INLA reconstructions; each using a distinct comb. of 4 (of 10) 1e4 SKIRT simulations

Avg of 210 INLA reconstructions; each using a distinct comb. of 4 (of 10) 1e4 SKIRT simulations

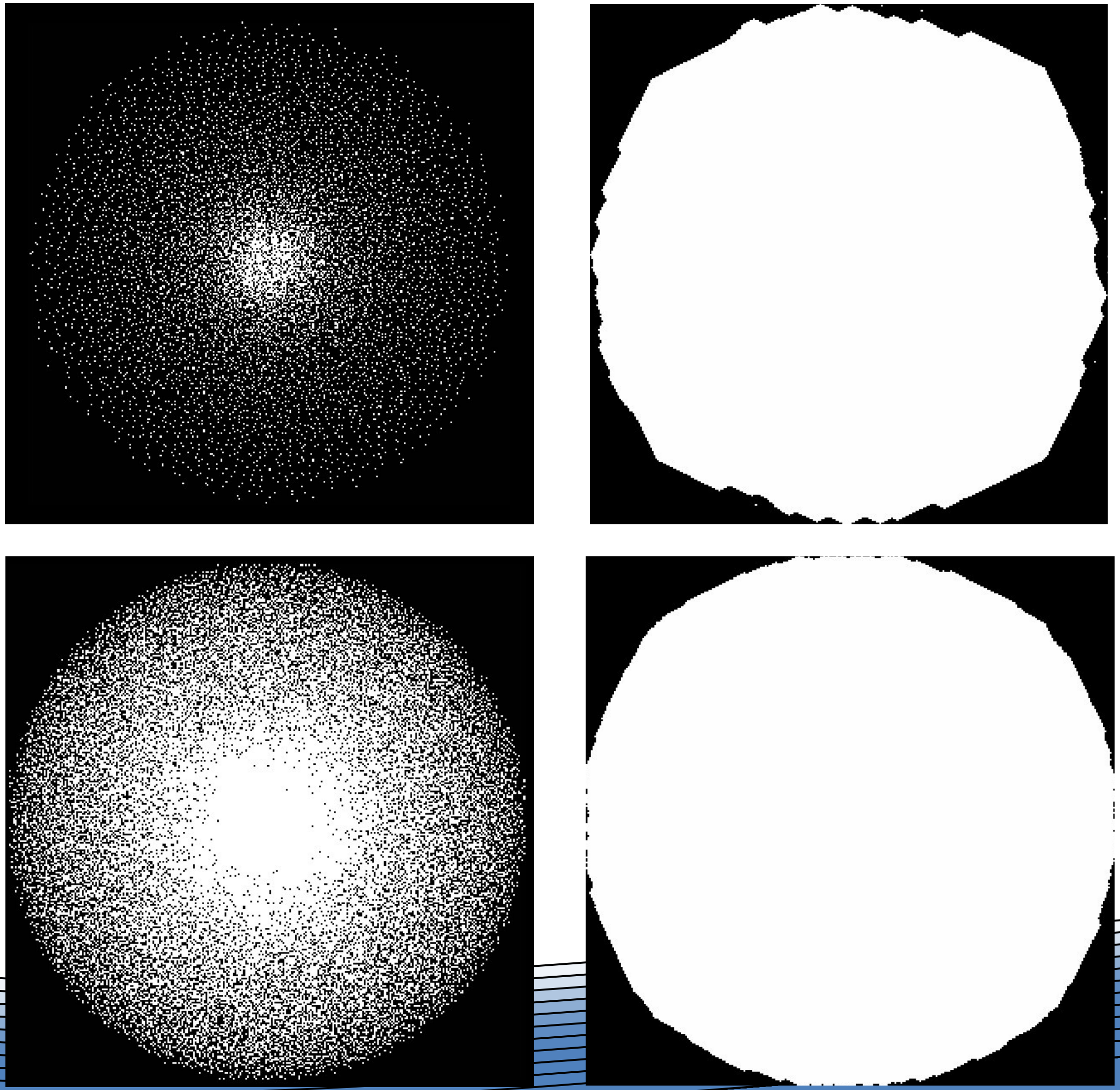
SKIRT: 1e4 (1 of 10)

SKIRT: 1e6



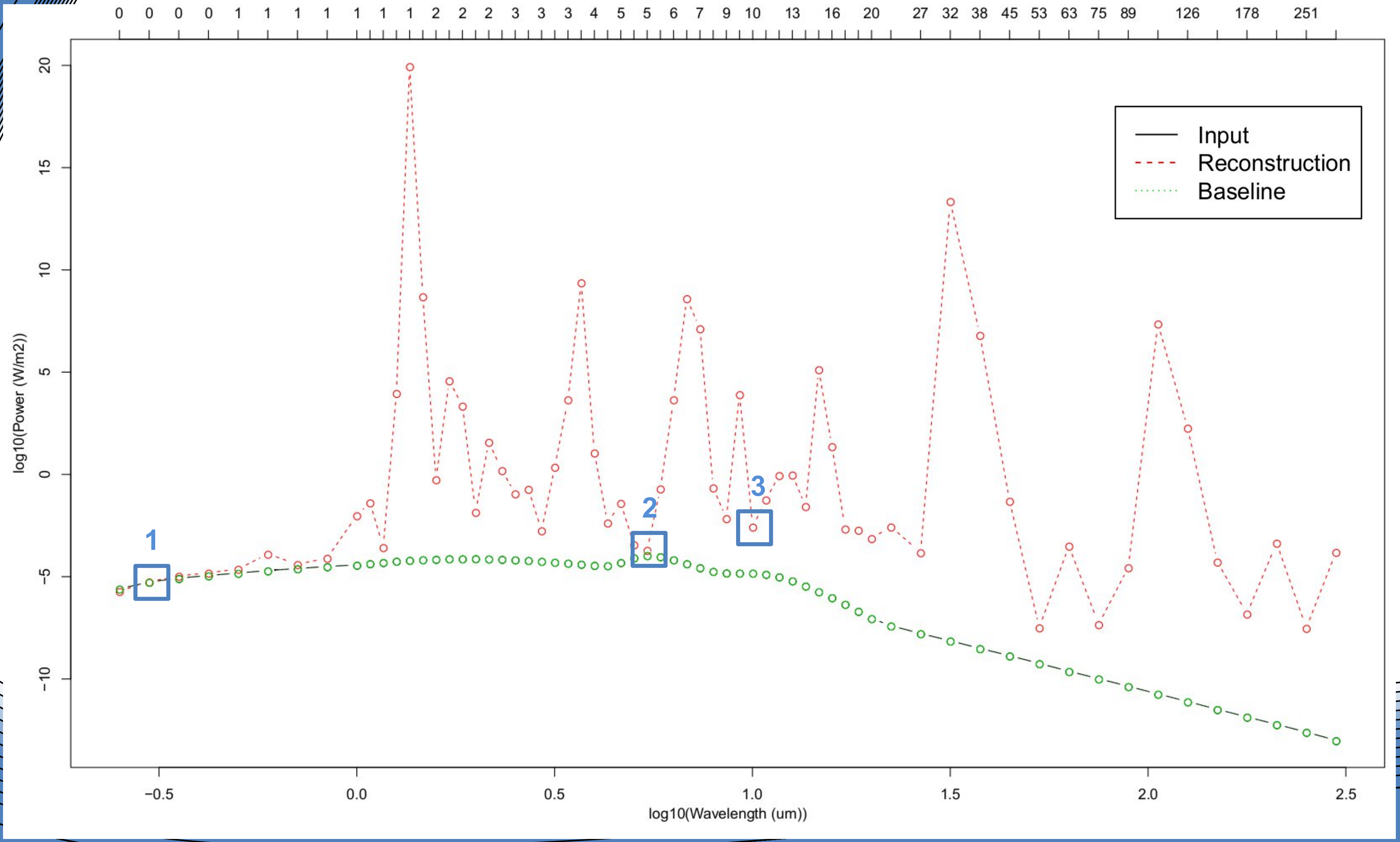
Smart 0 Imputation

'True' 0s from SED inspection

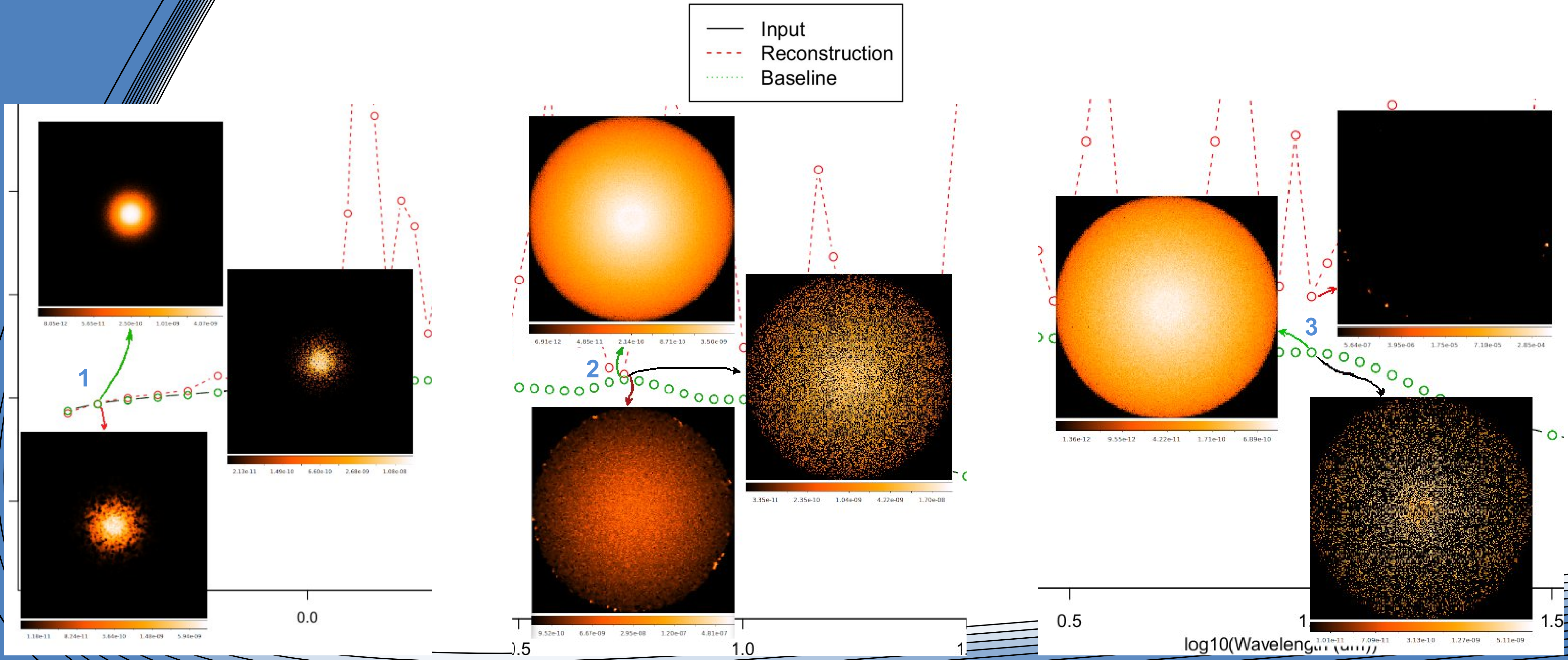


'True' 0s from SED & neighborhood inspection

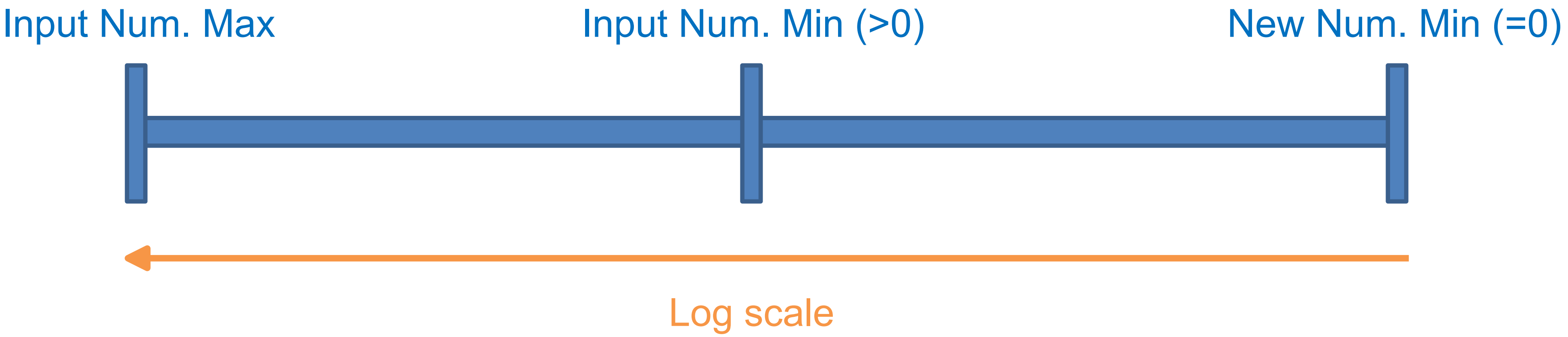
Change of Perspective



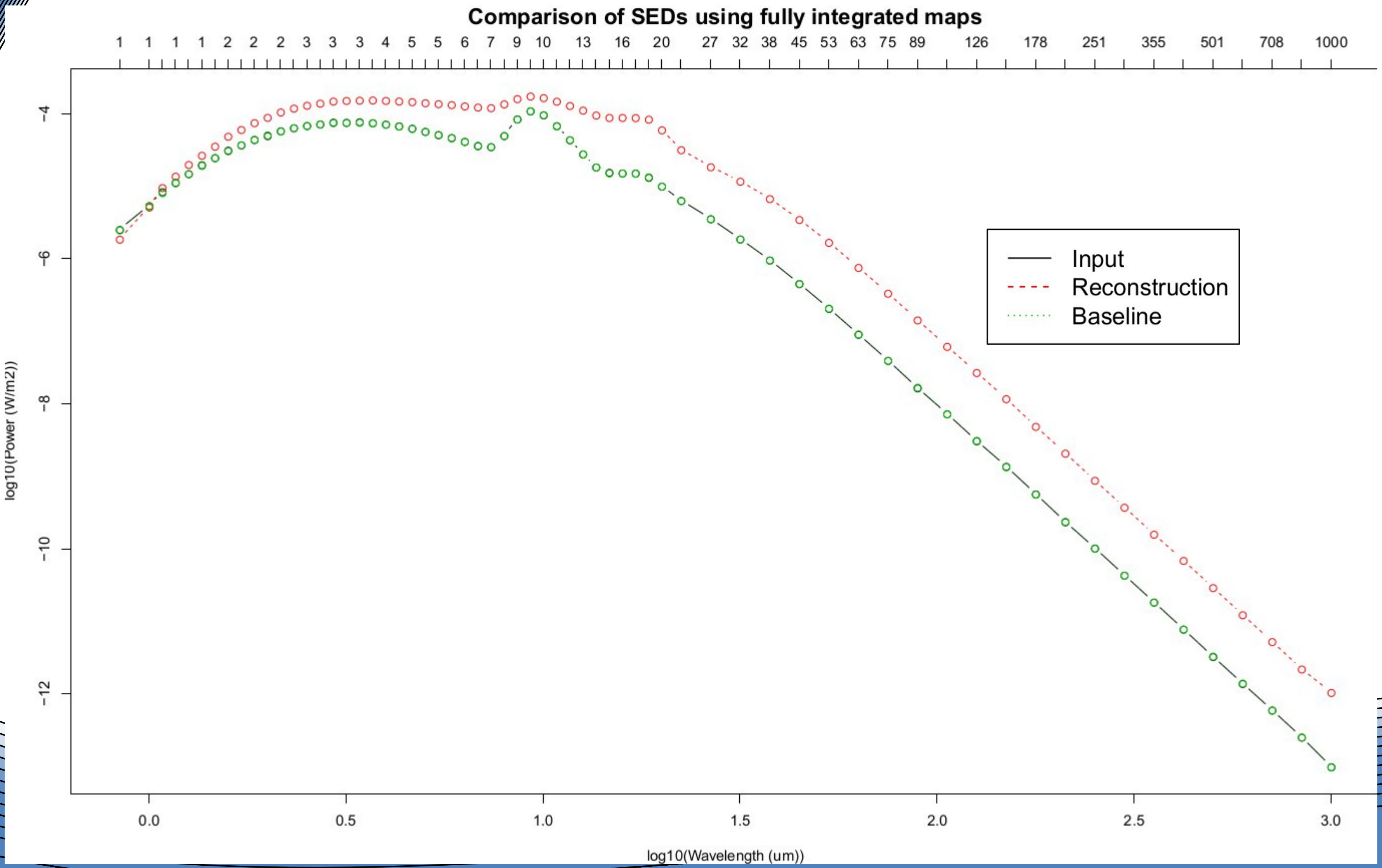
Change of Perspective



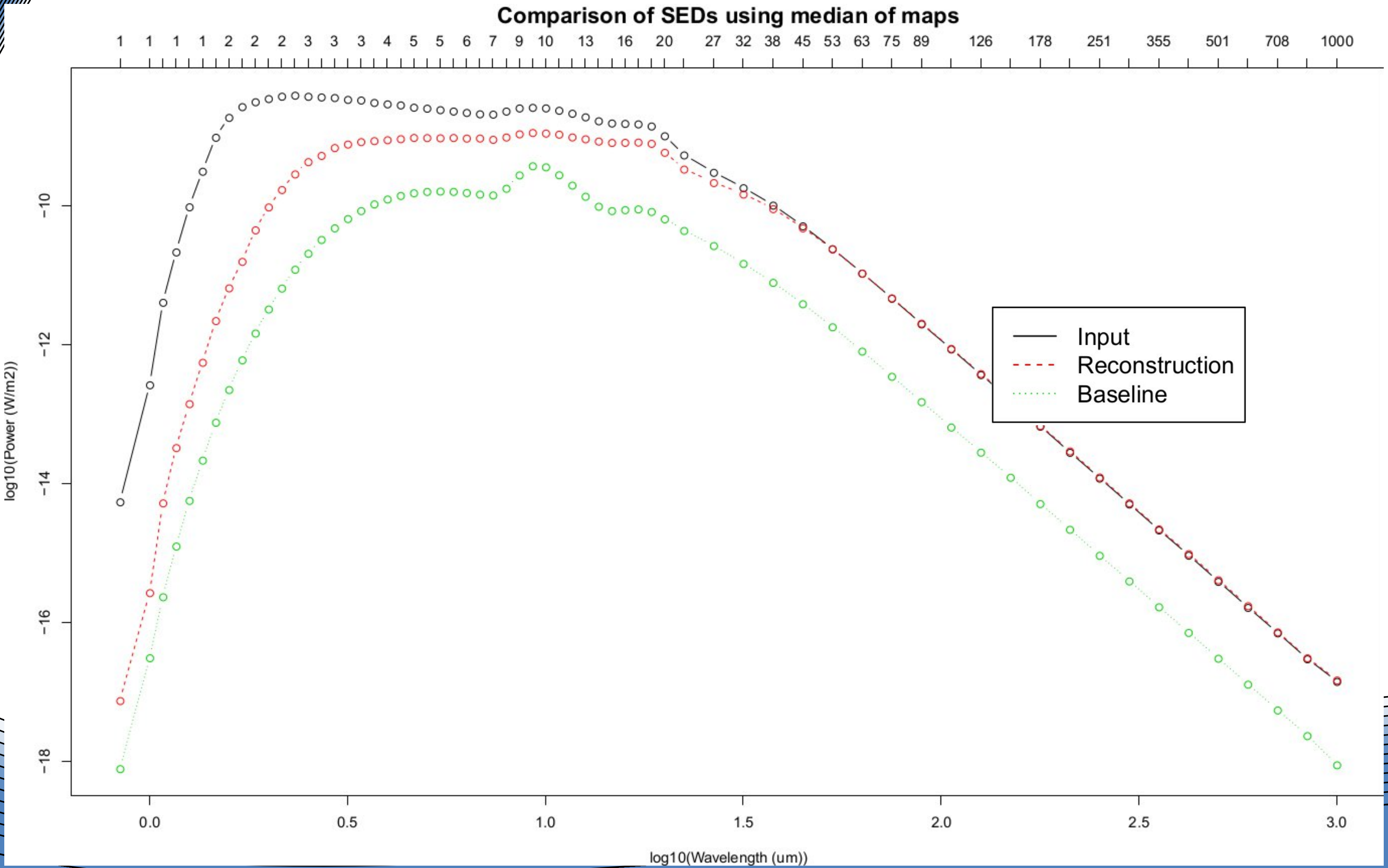
Non-0-Blind Transform Input



Non-0-Blind Transform Input



Non-0-Blind Transform Input



Final Remarks

- INLA's performance is highly sensitive to input's span and order of magnitude of values
  - Treat it like a baby, give it the kind of input it needs
- SD maps' values are 3 to 8 orders of magnitude higher than Mean maps'
  - Why?
- Computational performance improvement is not yet clear
  - Thanks COVID-19

Thank you!