Towards Bayesian Imaging of the eROSITA sky

Vincent Eberle, Matteo Guardiani, Margret Westerkamp,
Philipp Frank, Torsten Enßlin

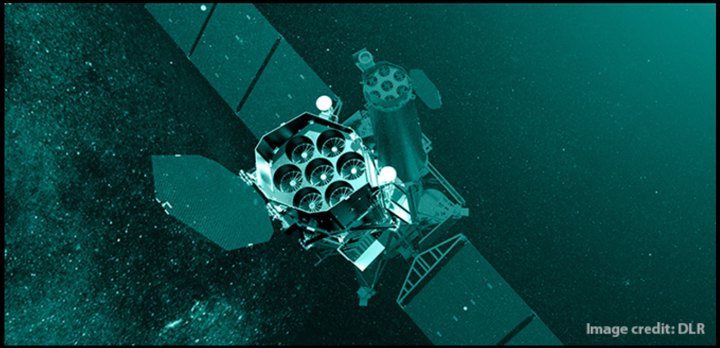
First Results from the
SRG/eROSITA All-Sky Survey:
From Stars to Cosmology

Garching, Germany
15Th - 20th September 2024

MAX PLANCK INSTITUTE
FOR ASTROPHYSICS

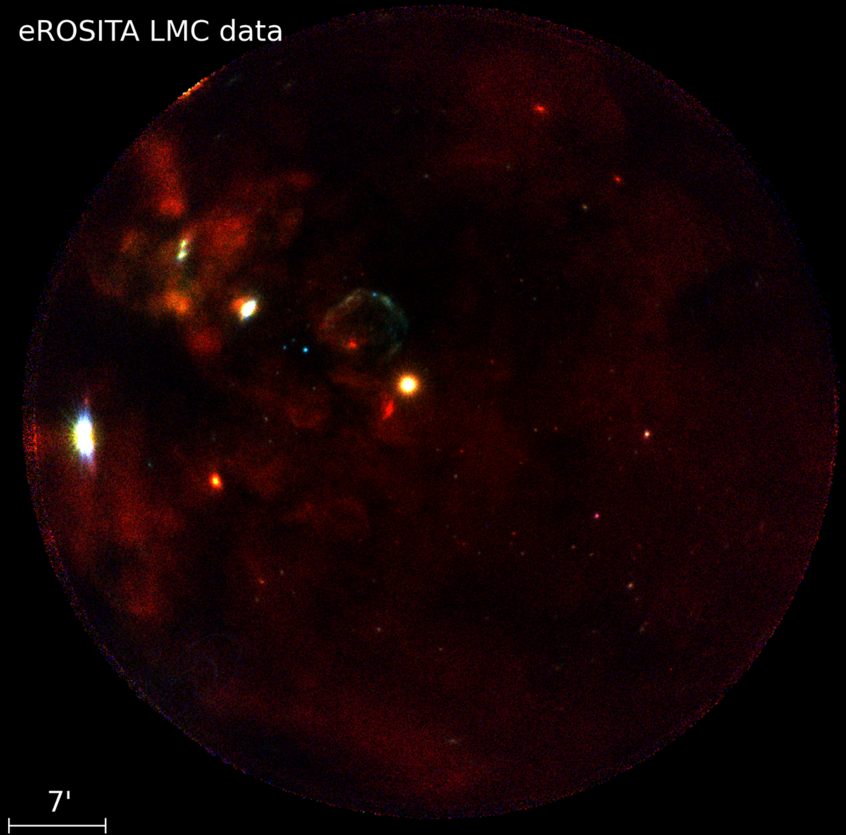
DLR

Motivation



X-ray telescopes (e.g. eROSITA, Chandra) suffer from nuisance effects, e.g.

eROSITA LMC data



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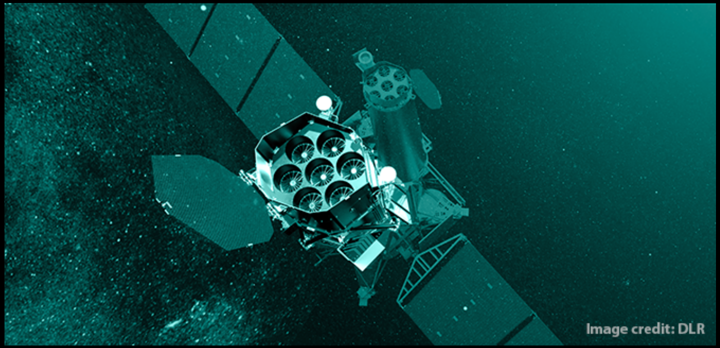

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Problems Spatially Variant Point Spread Functions (PSF)

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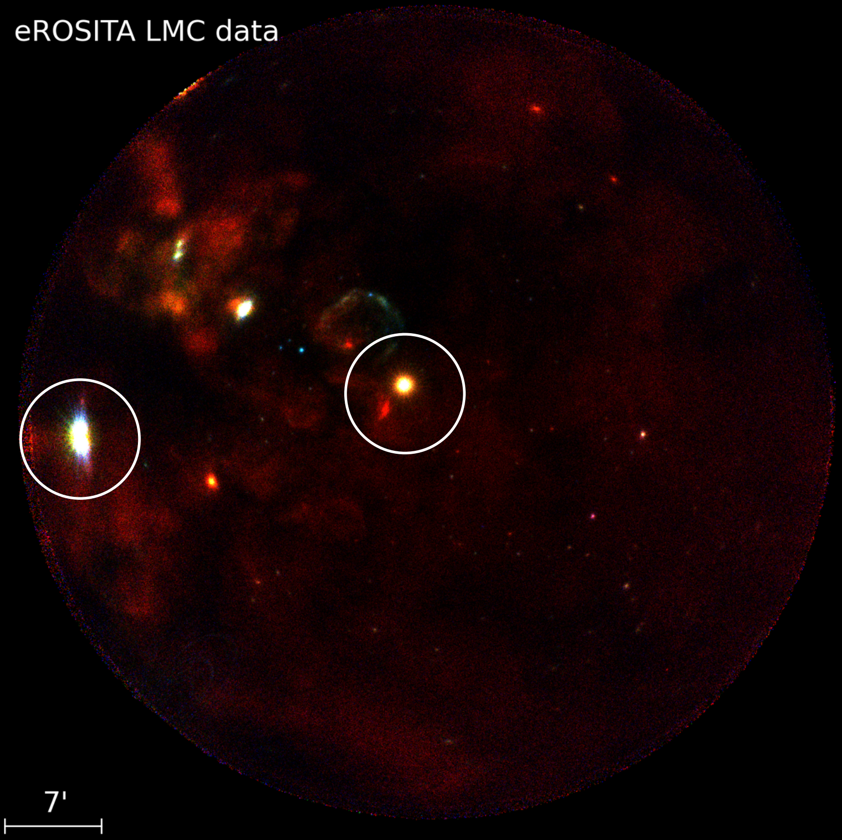

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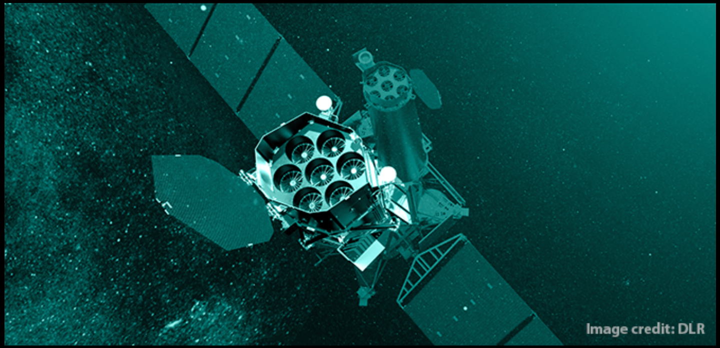

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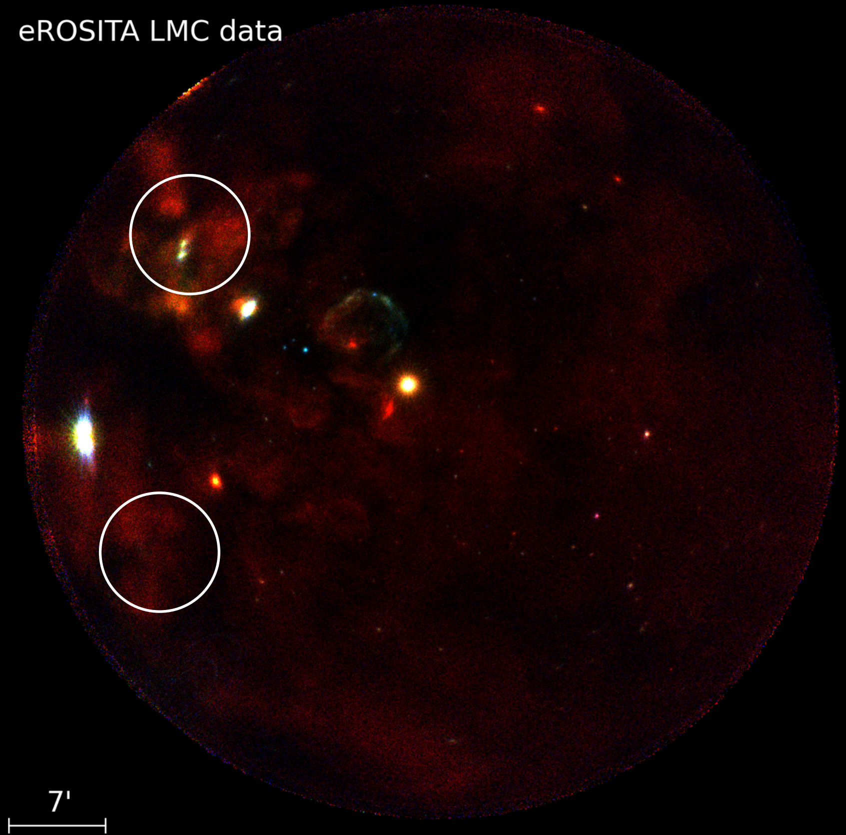

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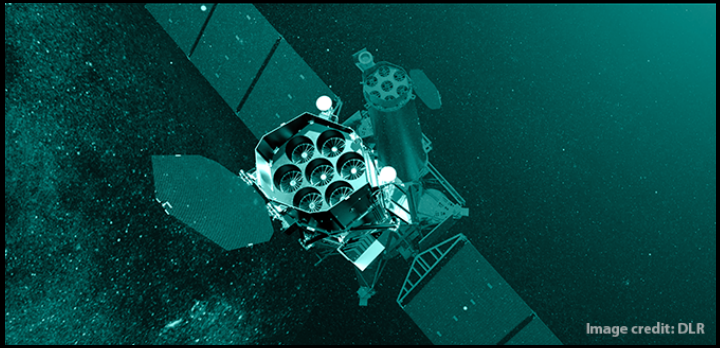
Problems

Spatially Variant Point Spread Functions (PSF)

Shot Noise

Motivation



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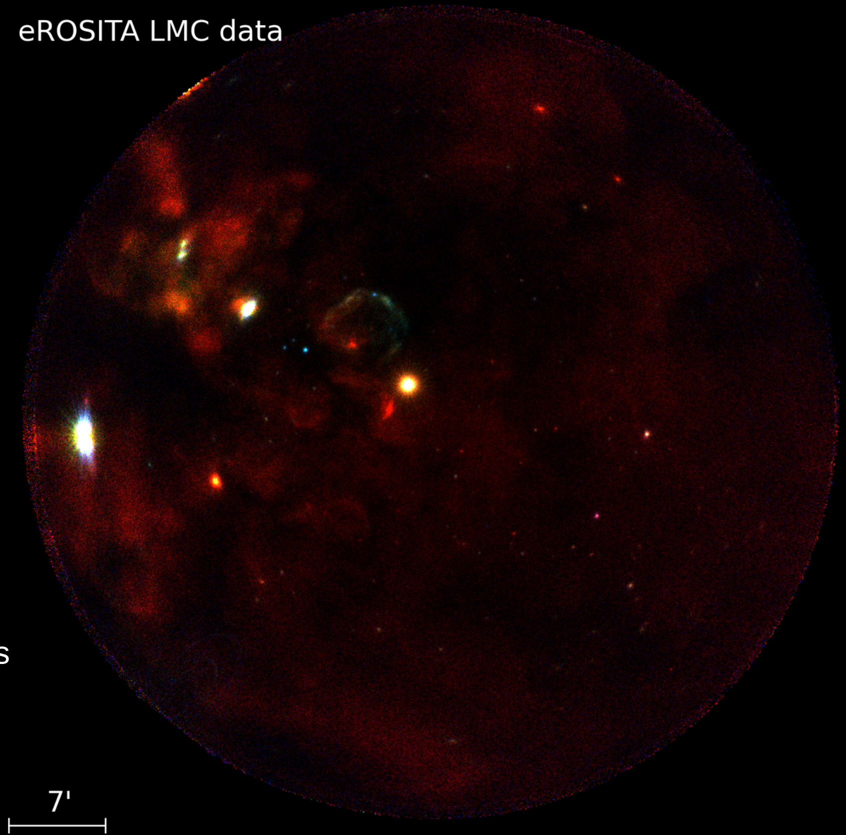

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Problems

- Spatially Variant Point Spread Functions (PSF)
- Shot Noise
- others

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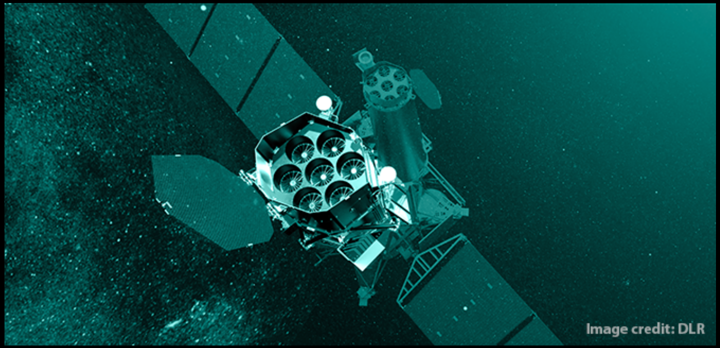

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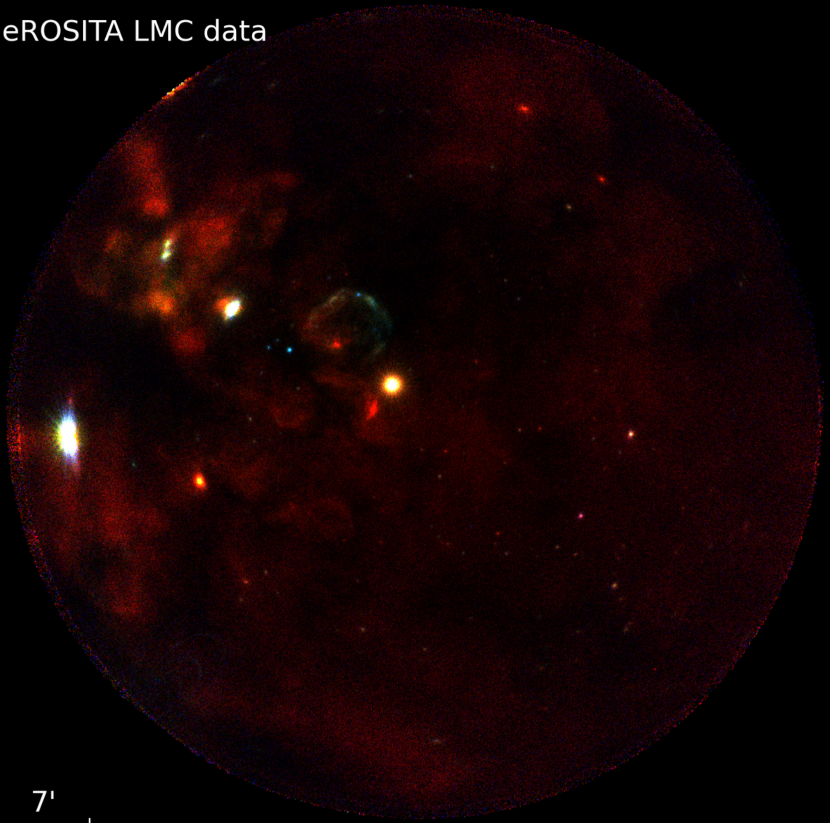


7'

X-ray telescopes (e.g. eROSITA, Chandra) suffer from nuisance effects, e.g.

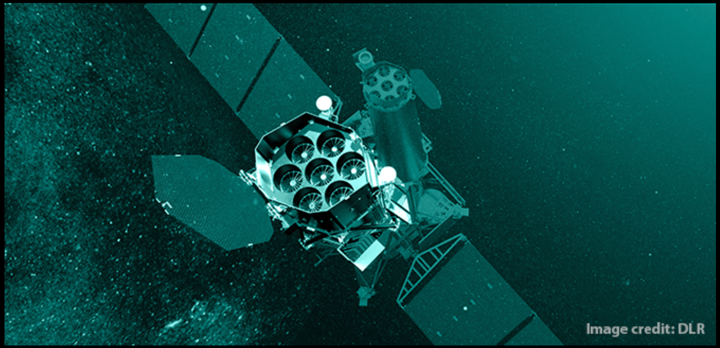
Problems

Spatially Variant Point Spread Functions (PSF) | Shot Noise | others

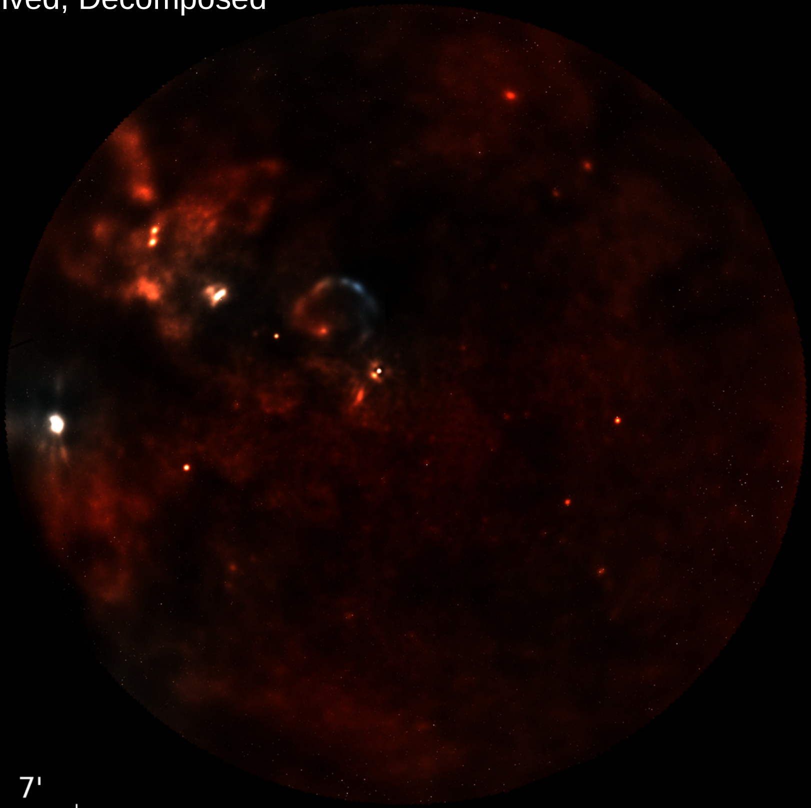
Approach

Bayesian Imaging
&
Generative Models

Motivation



Denoised, Deconvolved, Decomposed



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Generative Models for Bayesian Imaging

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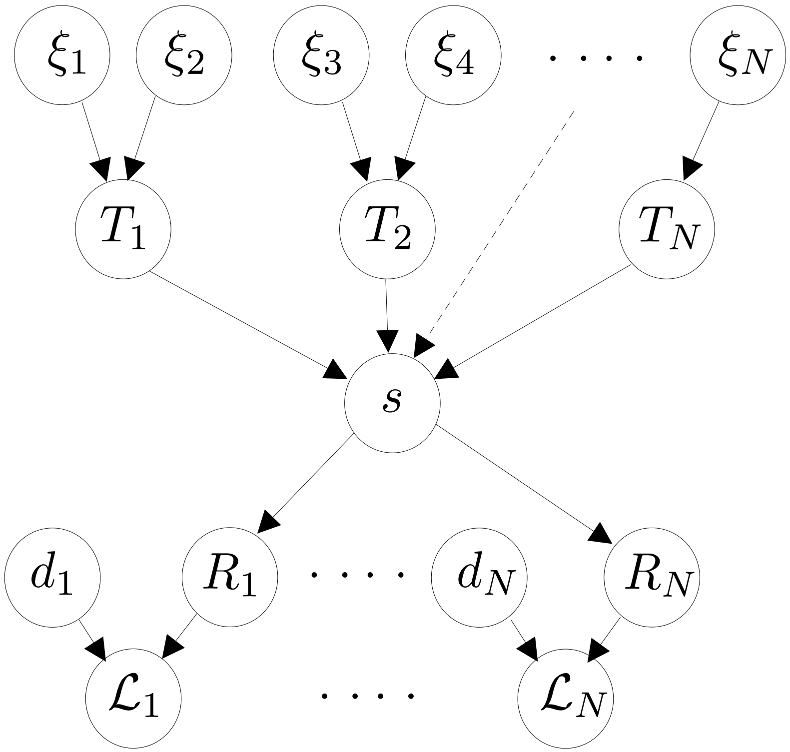

NIFTy

Generative Models for Bayesian Imaging

Framework: Numerical **I**nformation **F**ield **T**heory

https://github.com/NIFTy-PPL/NIFTy

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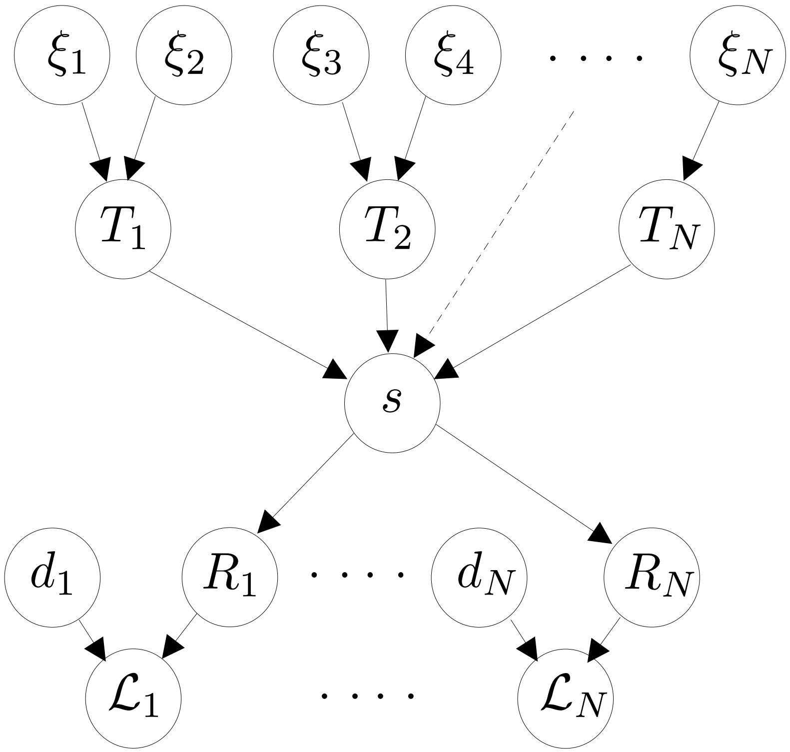

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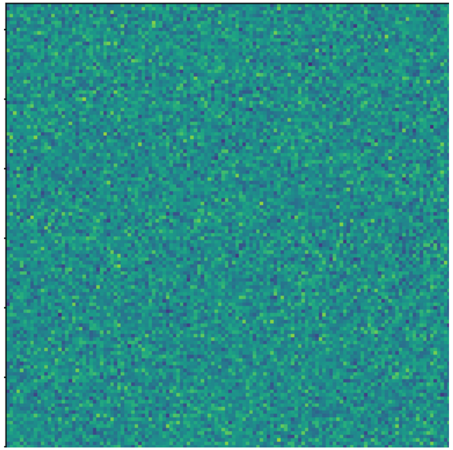

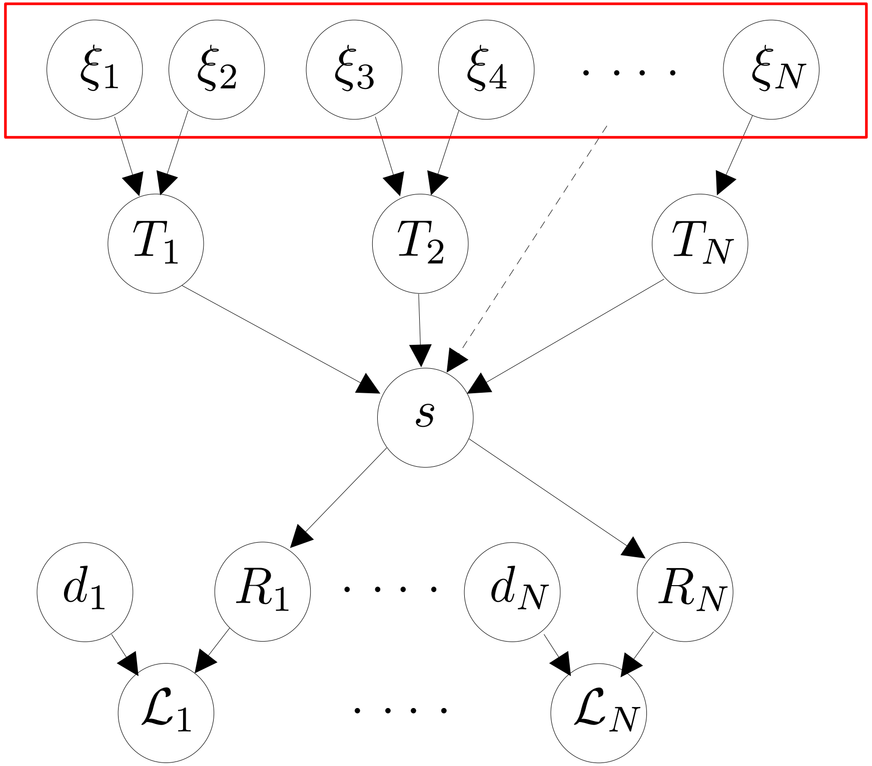

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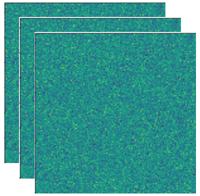

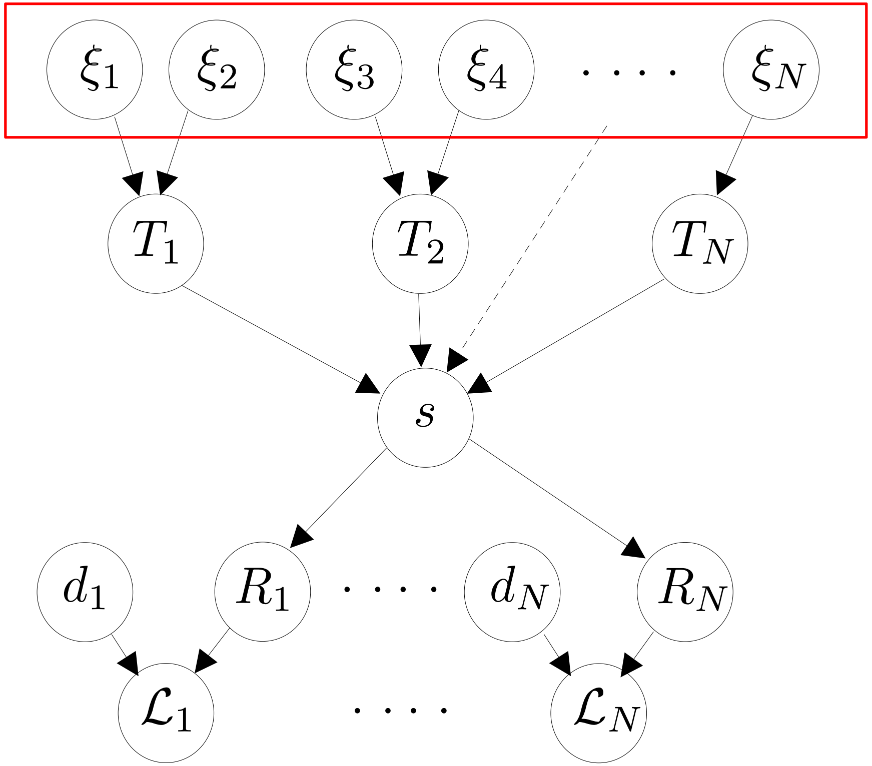

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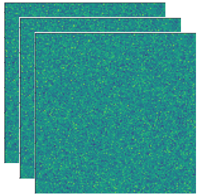

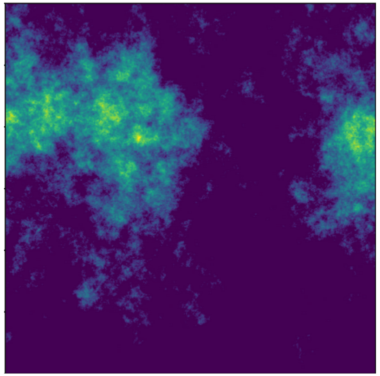

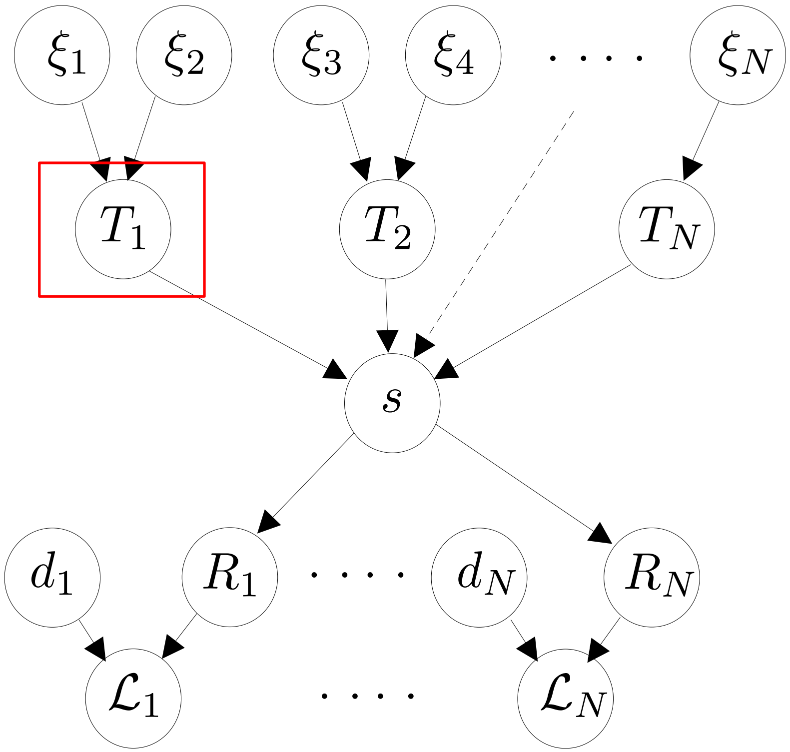

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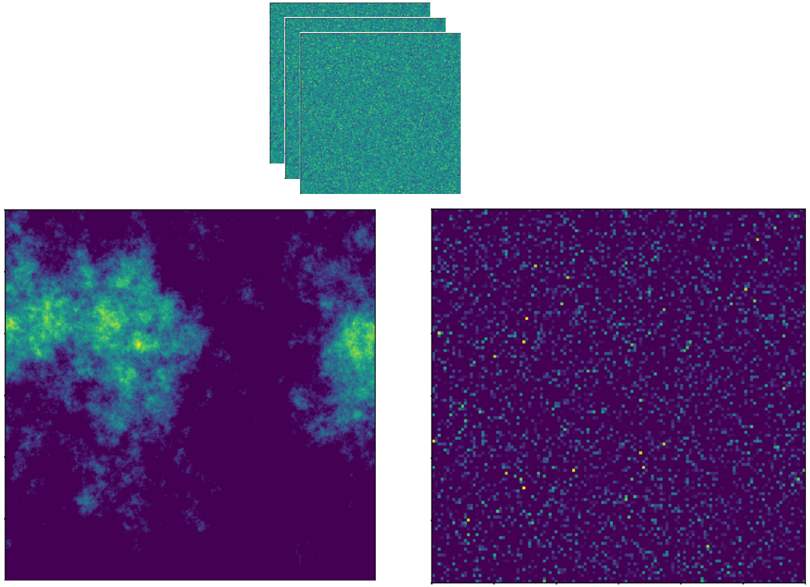

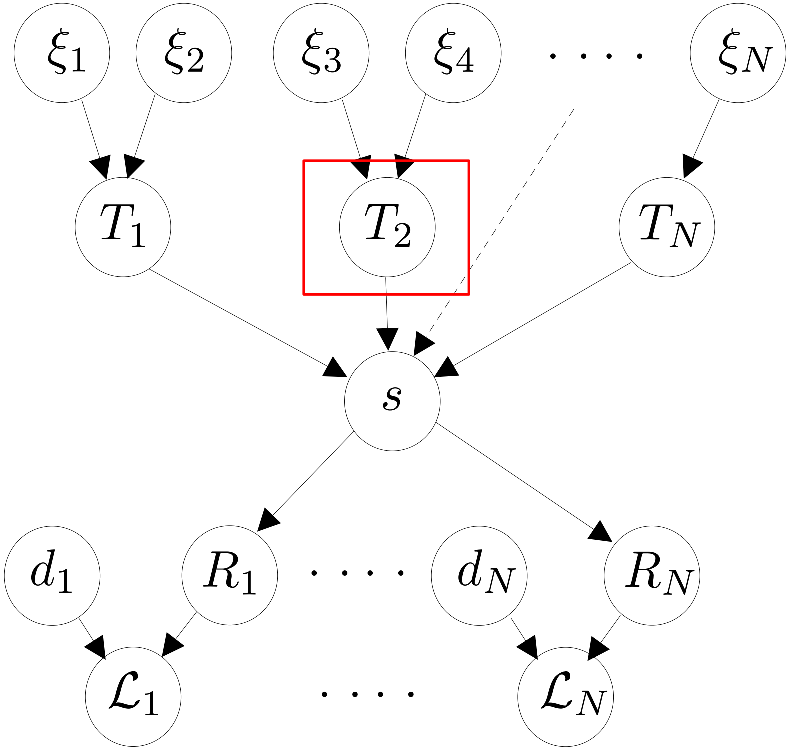

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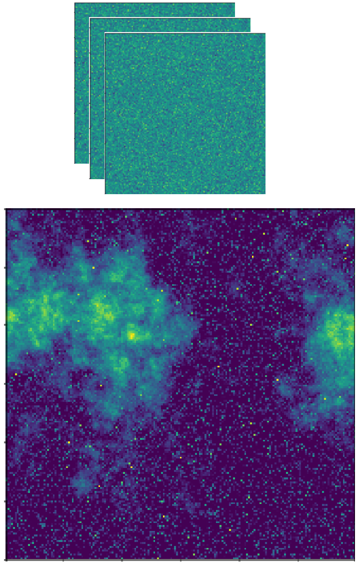

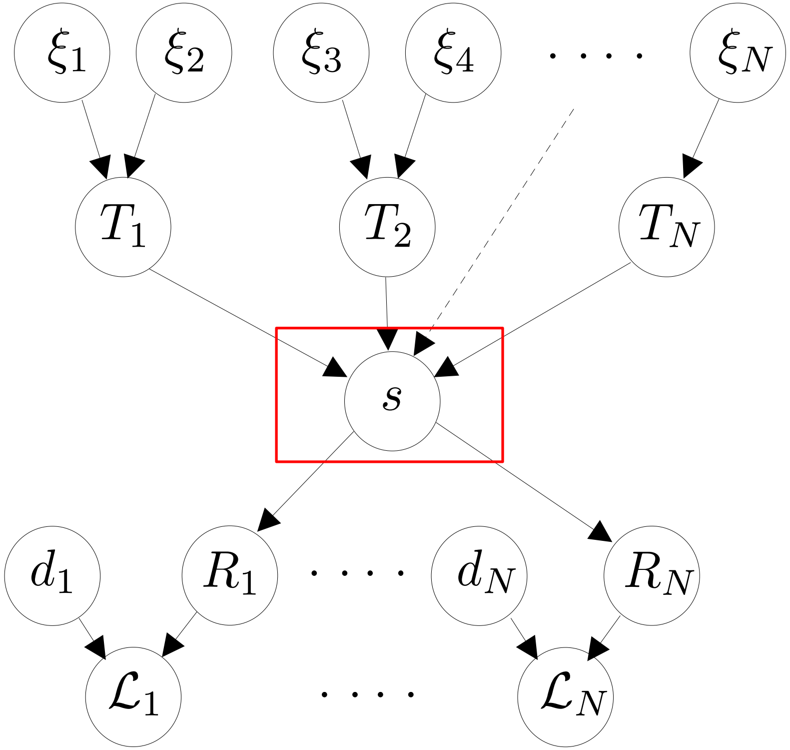

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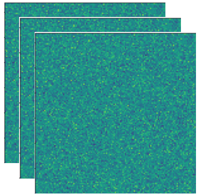

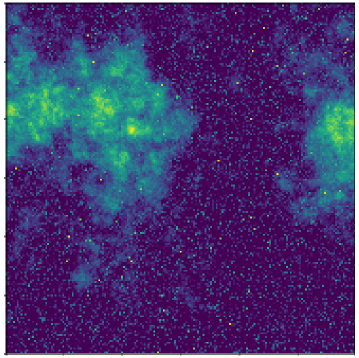

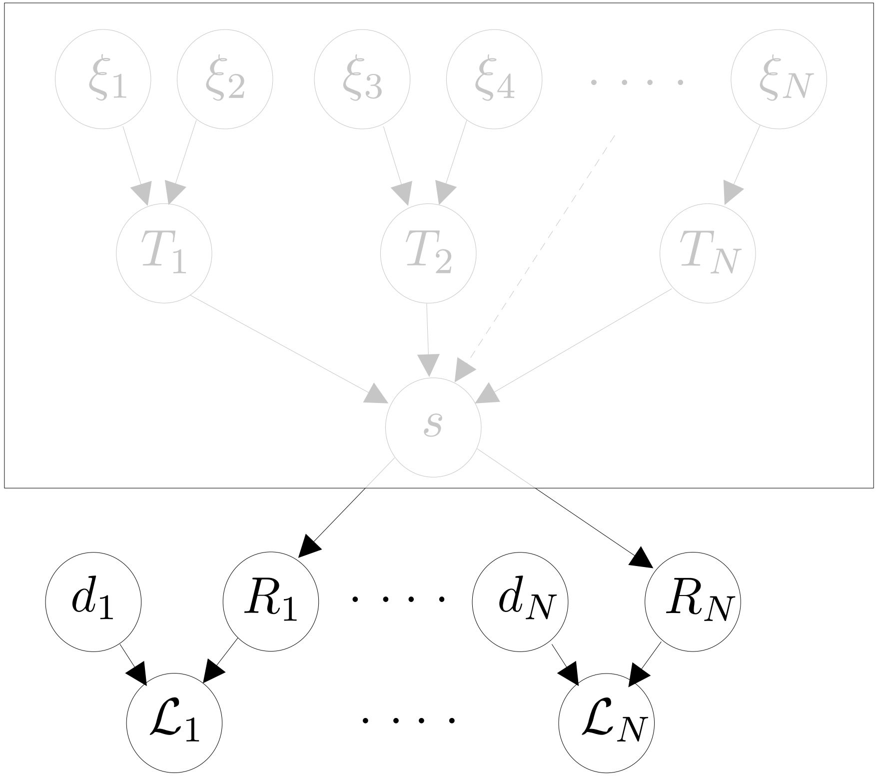

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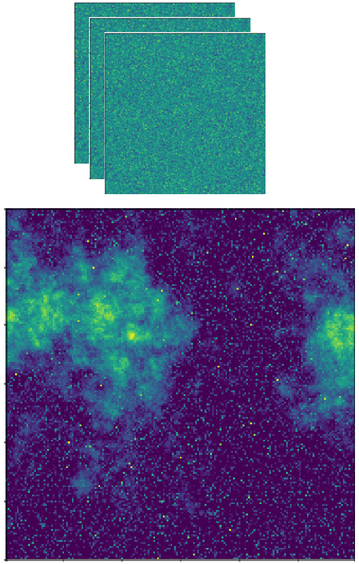

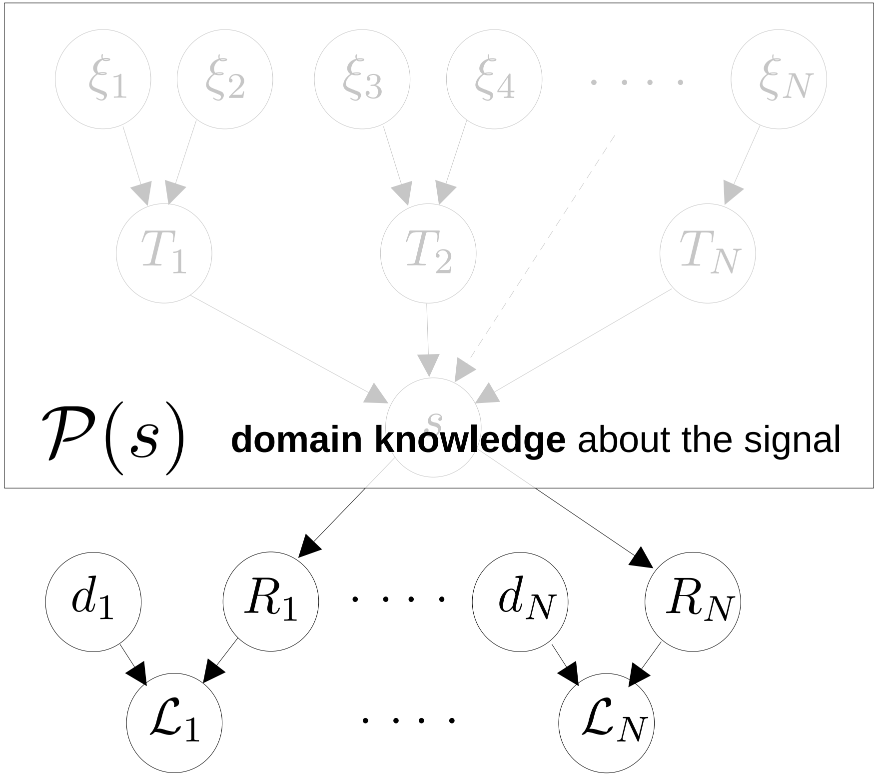

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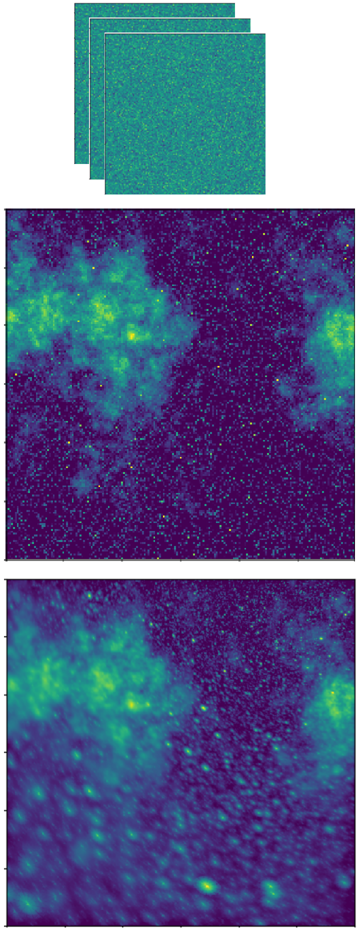

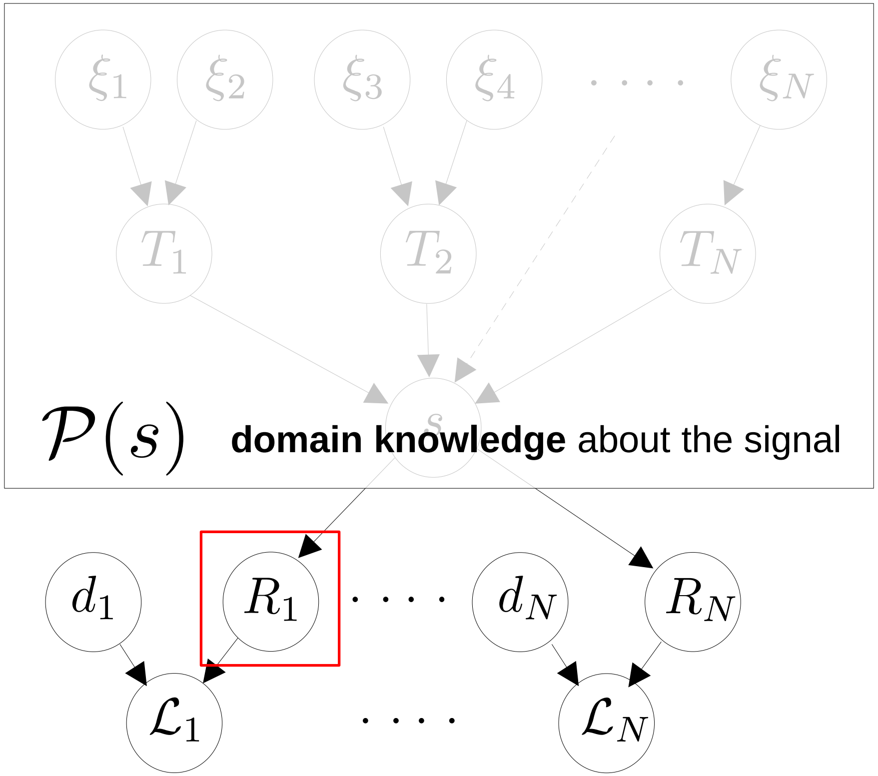

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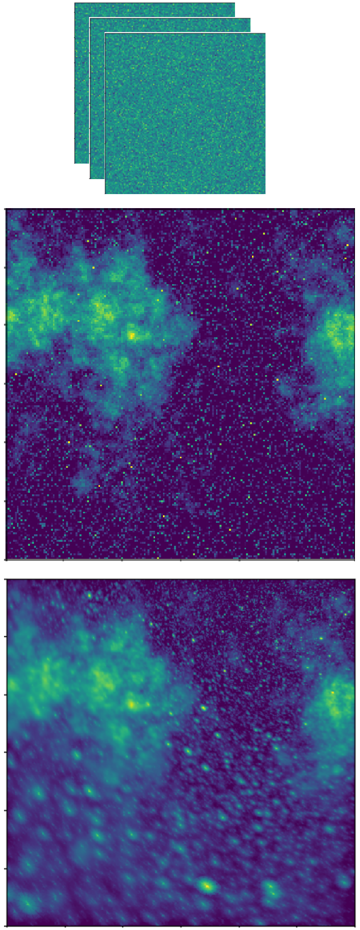
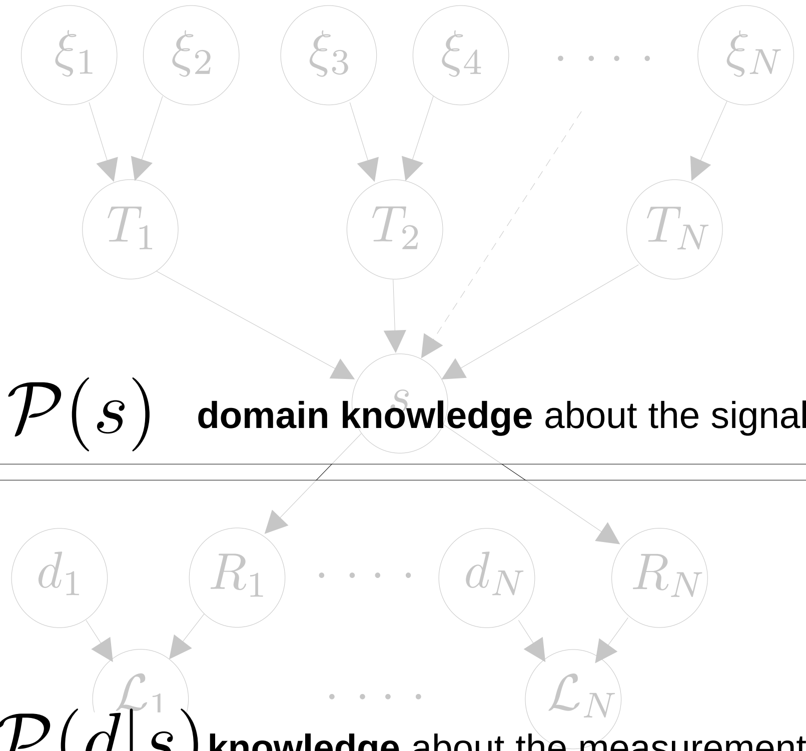


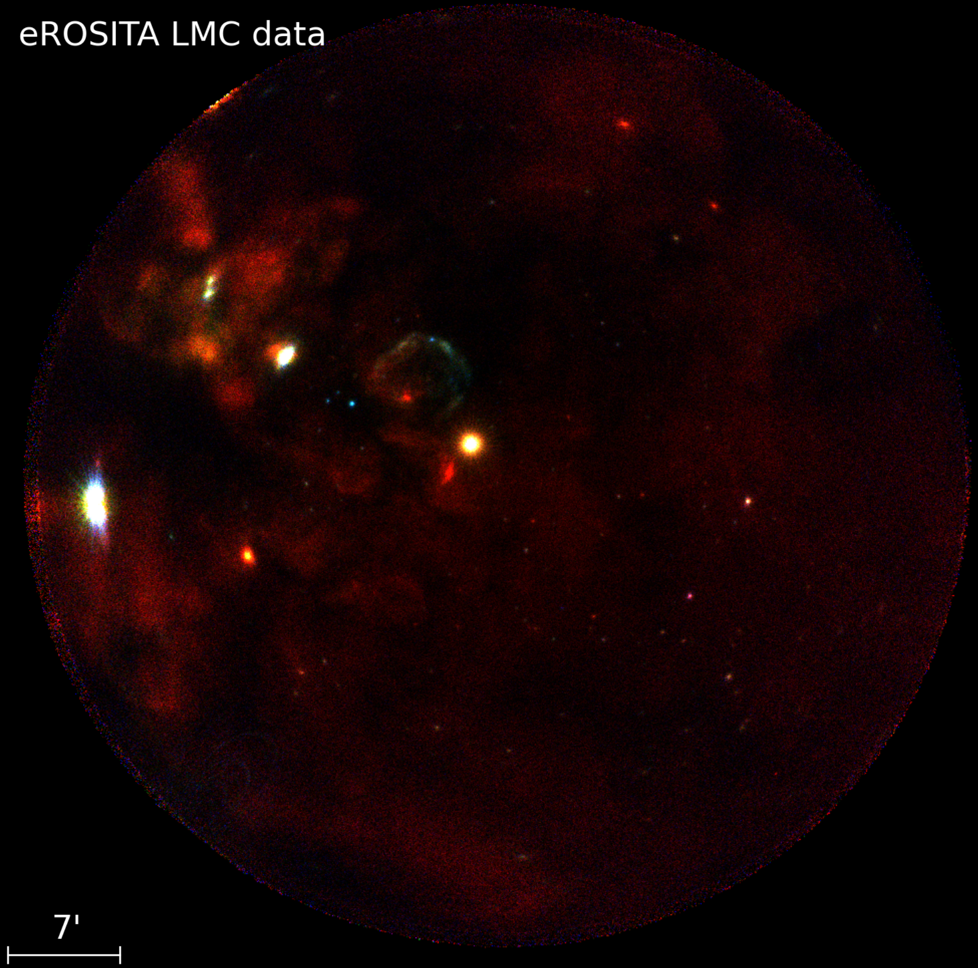


$\mathcal{P}(s)$ **domain knowledge** about the signal

$\mathcal{P}(d|s)$ **knowledge** about the measurement

Modeling the X-ray Sky – the Prior

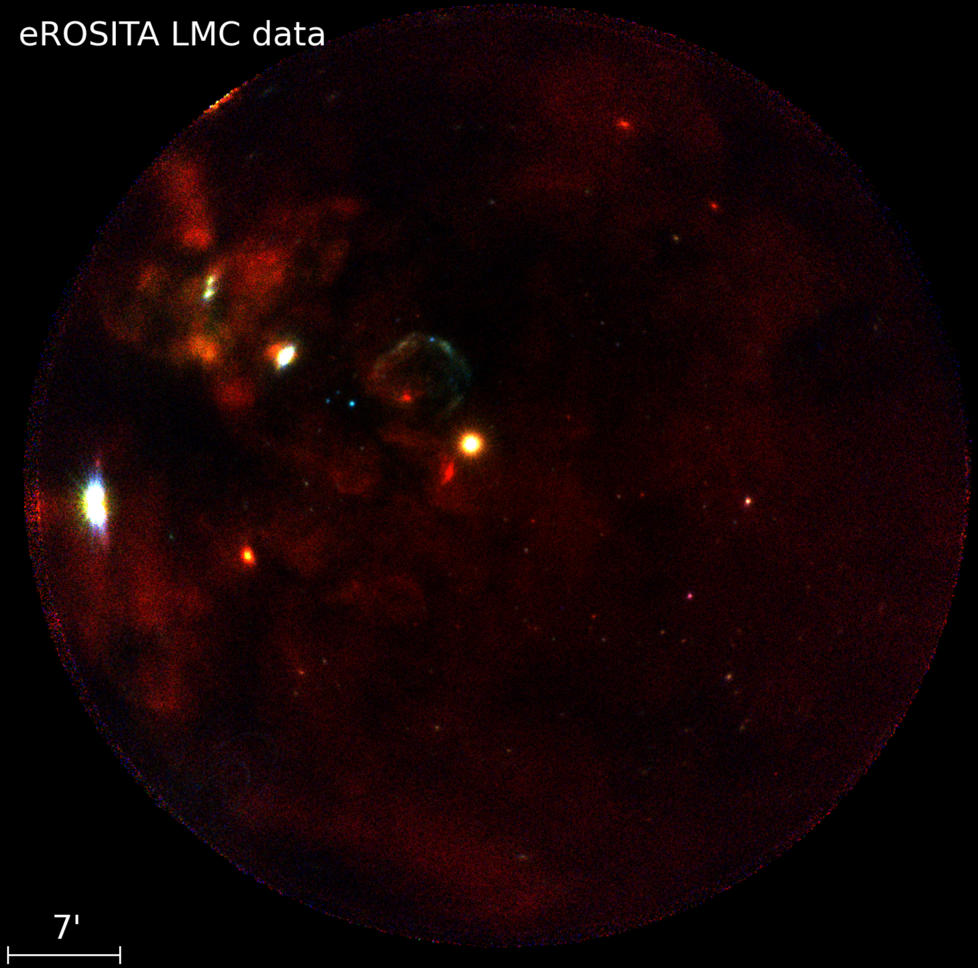
eROSITA LMC data



Modeling the X-ray Sky – the Prior

LMC 1987A dataset

- 0.2 - 1.0 keV (red)
- 1.0 - 2.0 keV (green)
- 2.0 - 4.5 keV (blue)



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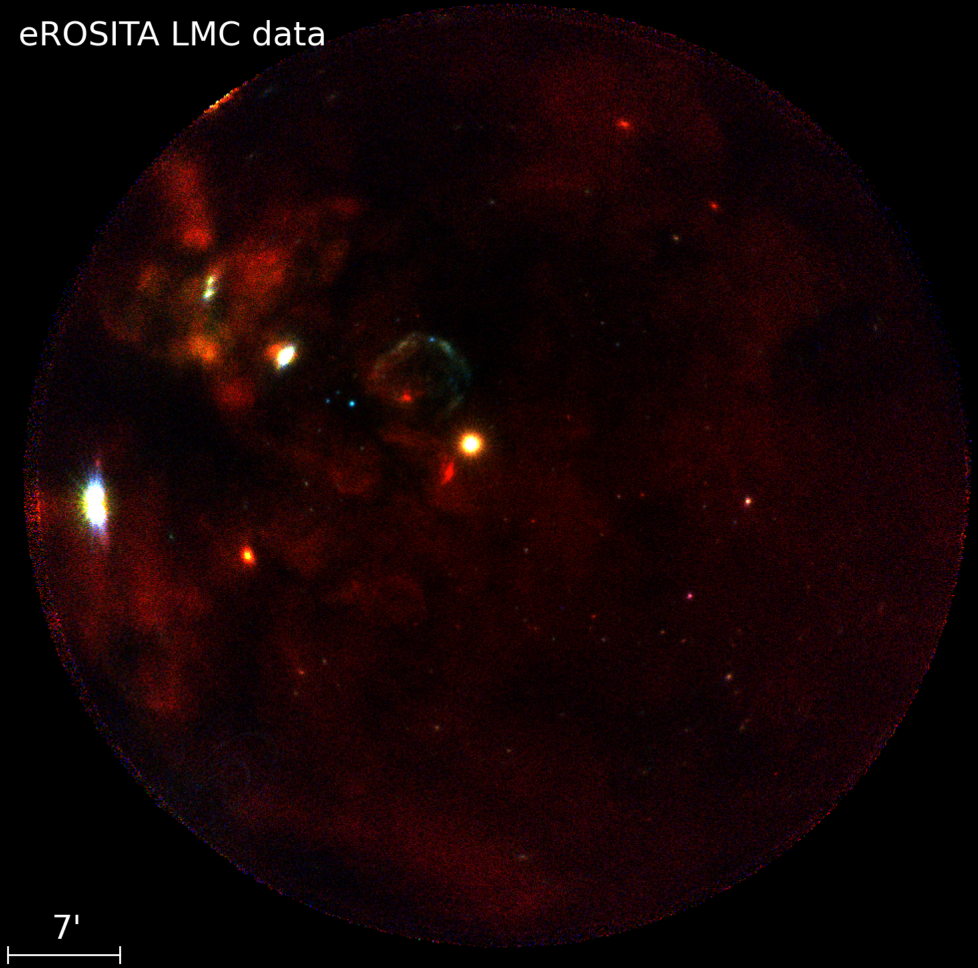

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Components

- diffuse emission

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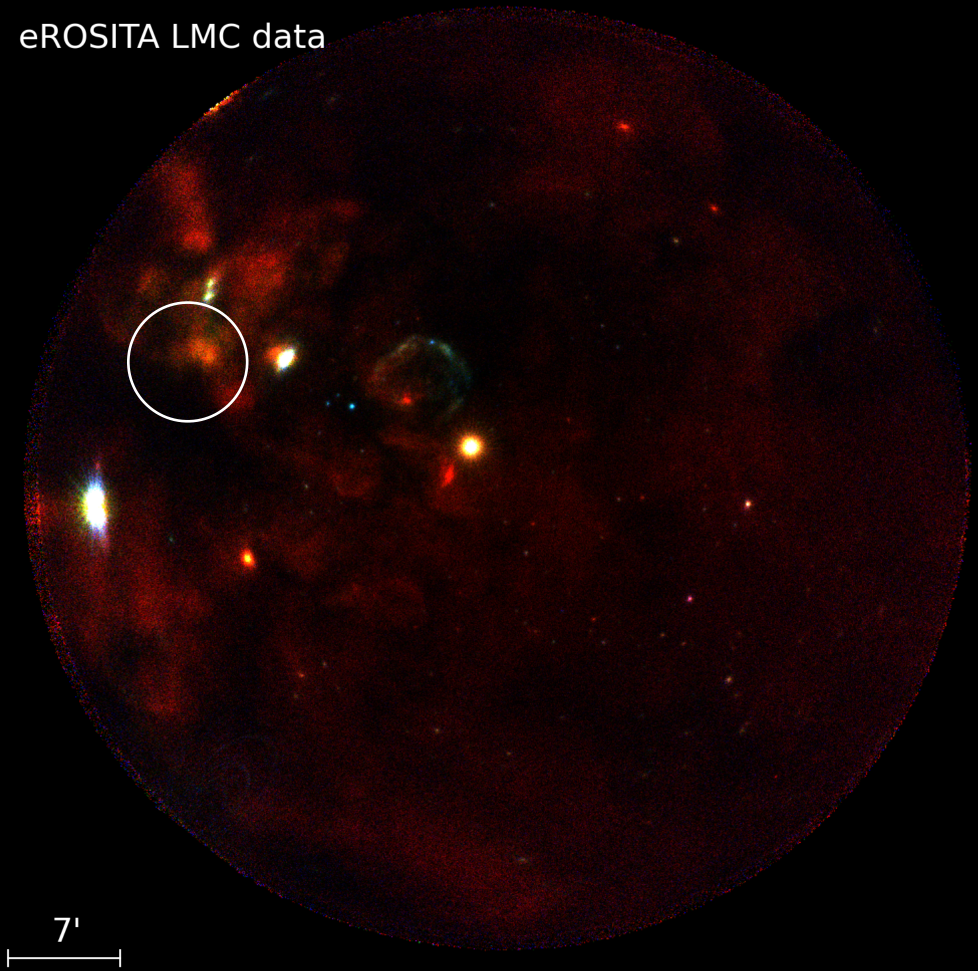

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Components

- diffuse emission
- extended sources (30 Doradus)

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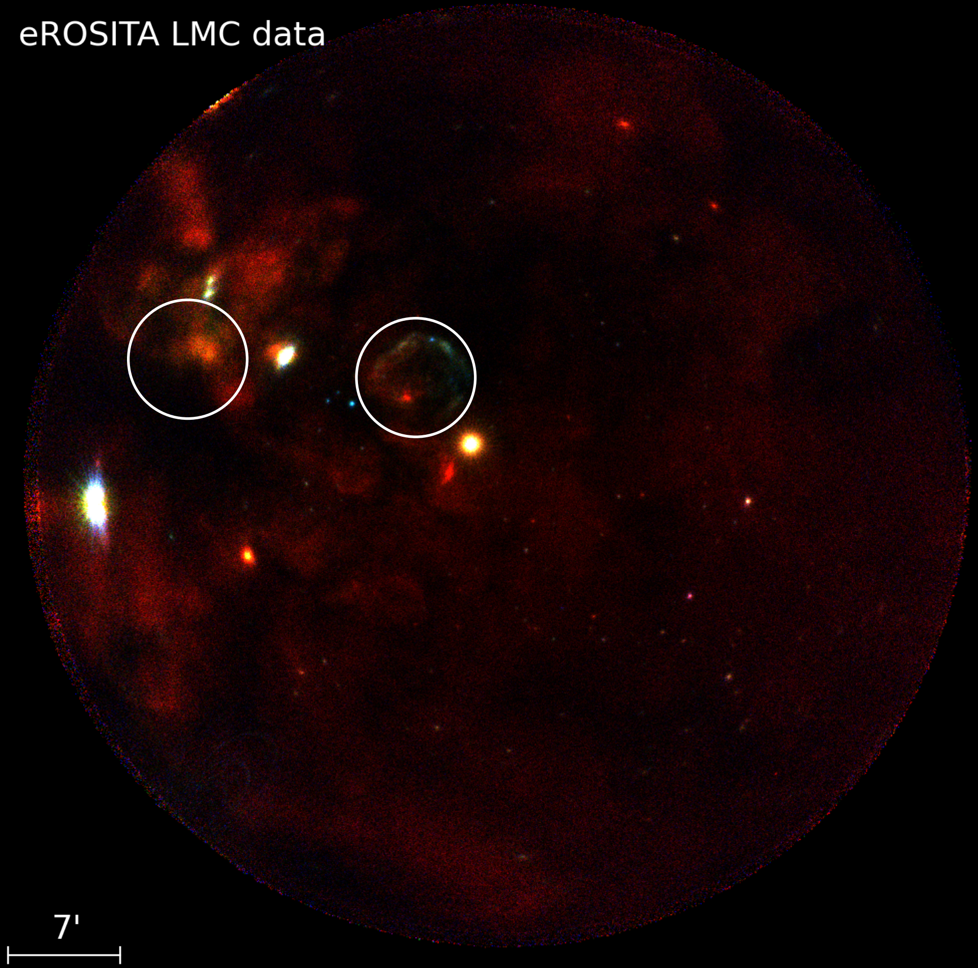

Modeling the X-ray Sky – the Prior

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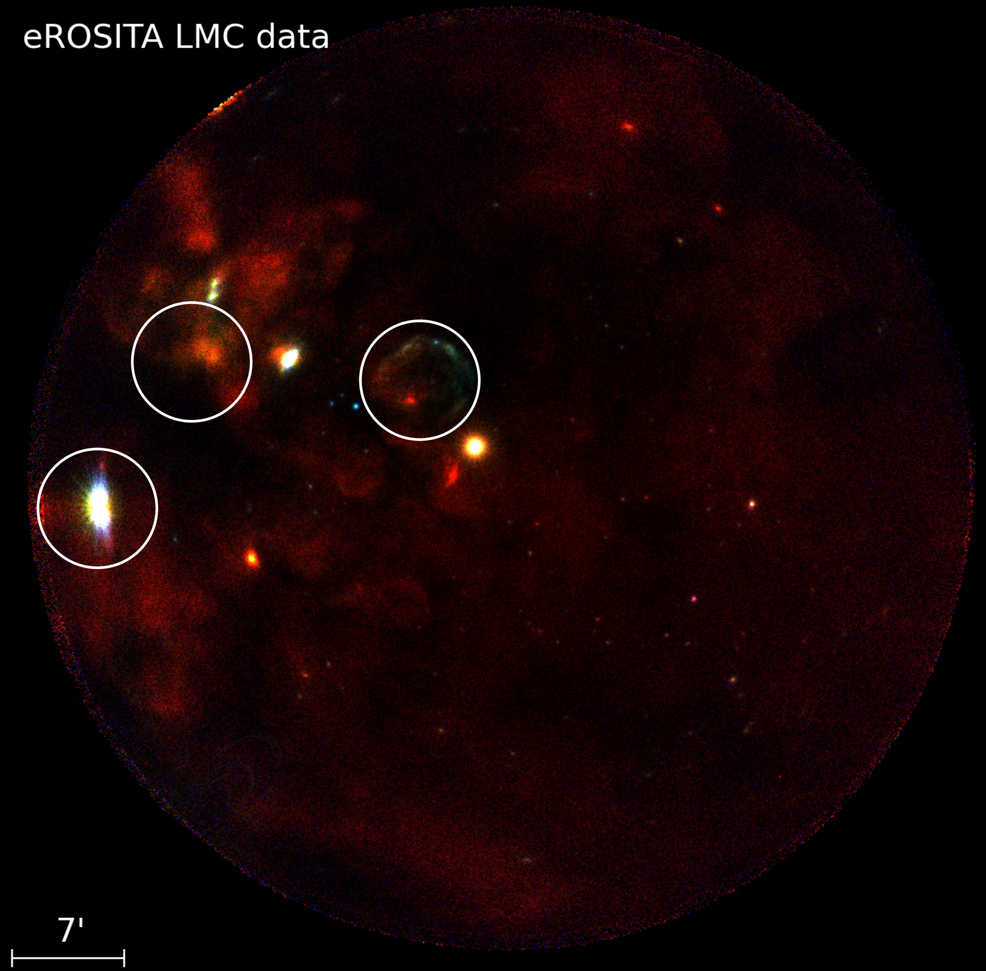
Components

- diffuse emission
- extended sources (30 Doradus)
- point sources



Modeling the Diffuse X-ray Sky

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$$d(x, \nu) = I_0(x) \cdot exp(\alpha(x) \cdot \nu)$$

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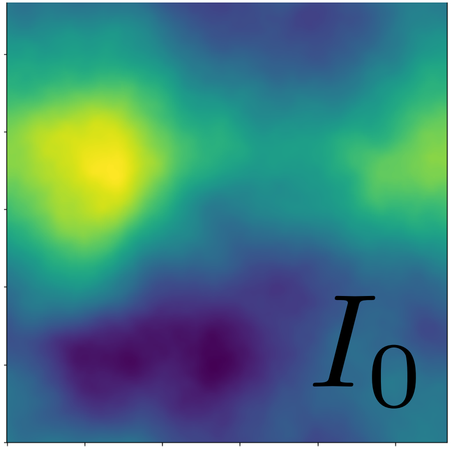

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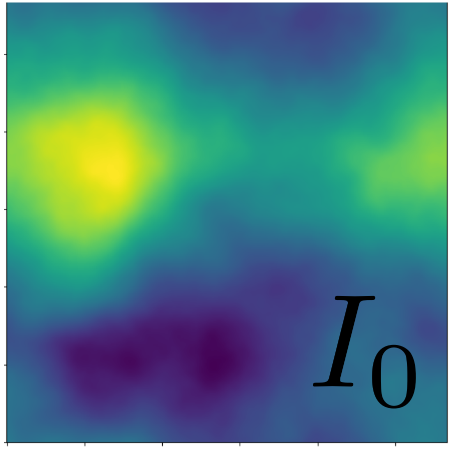

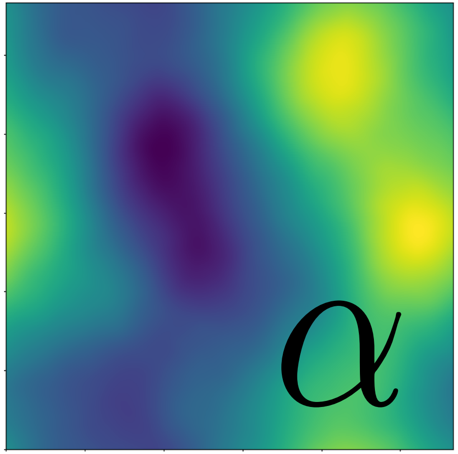

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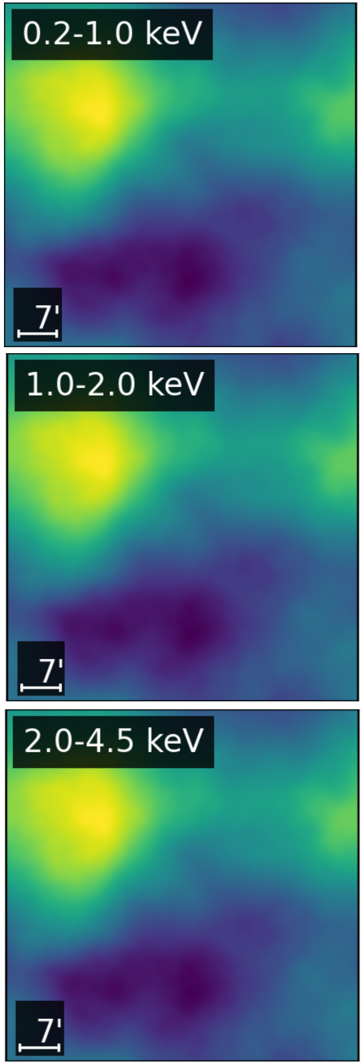

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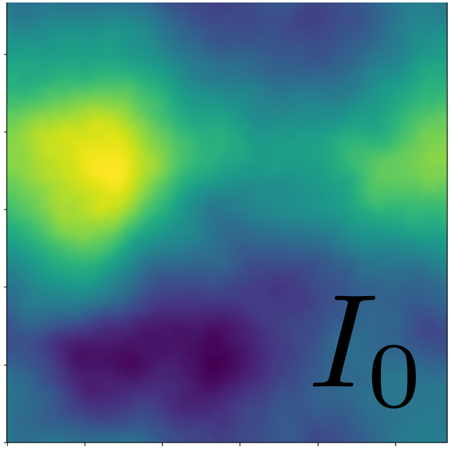
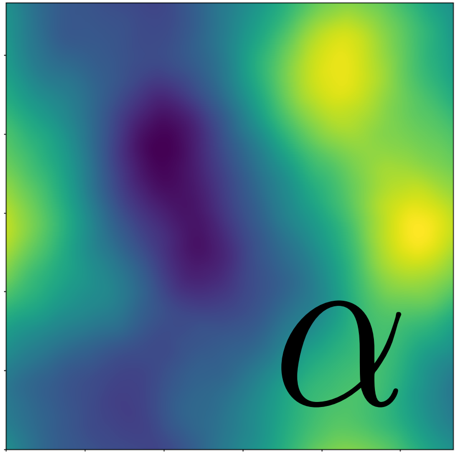
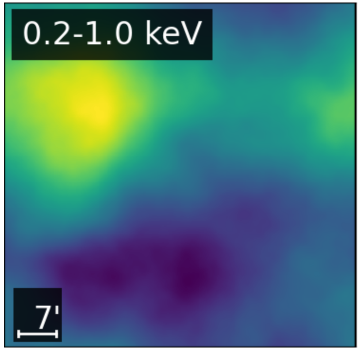
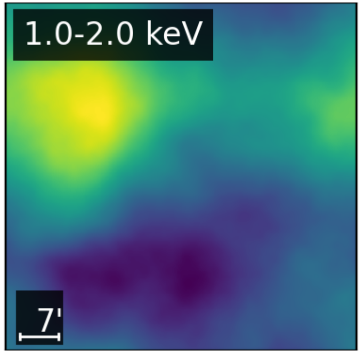
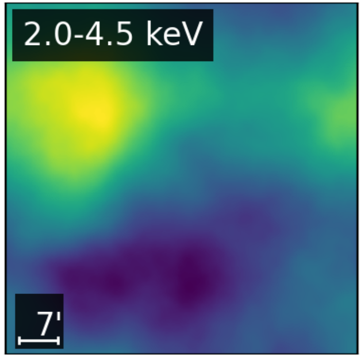




Modeling the Diffuse X-ray Sky & Extended Sources







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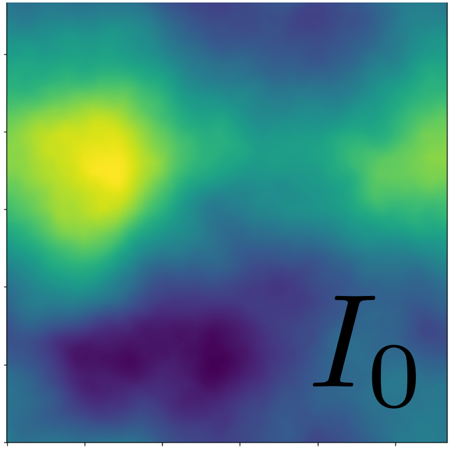

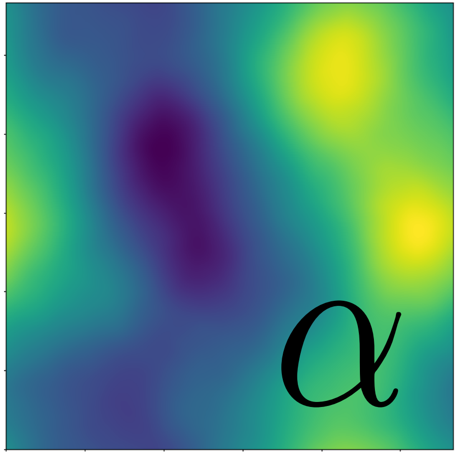

Modeling Point Sources

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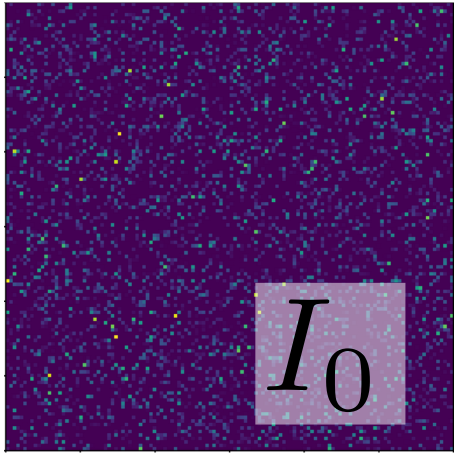

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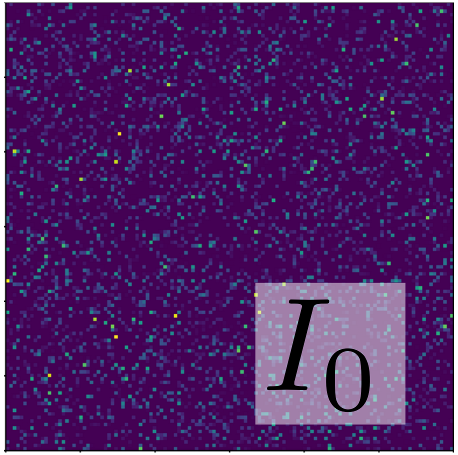

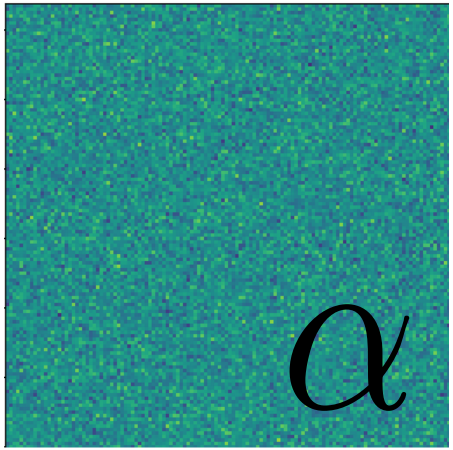

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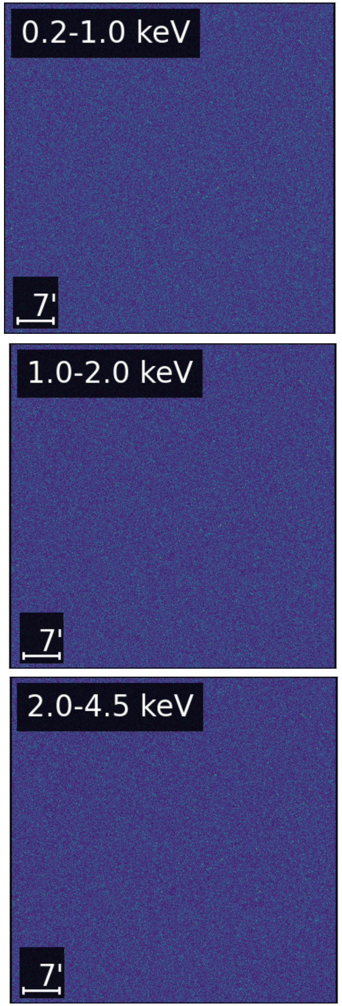

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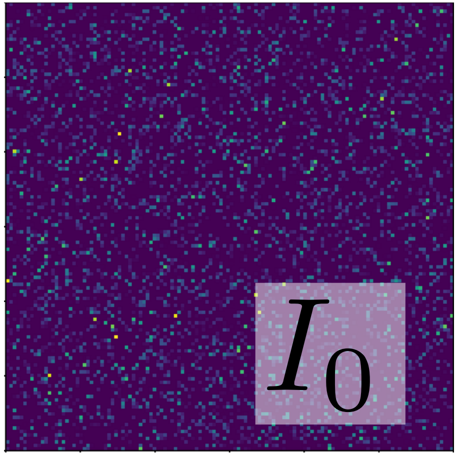
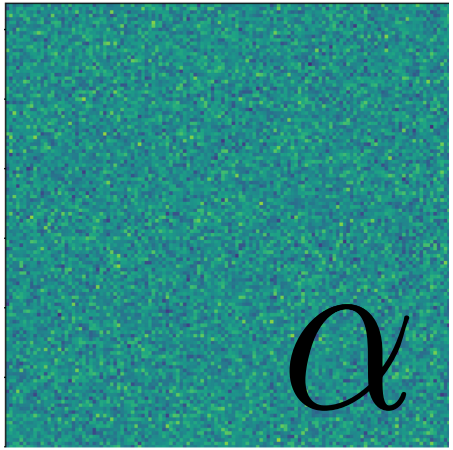
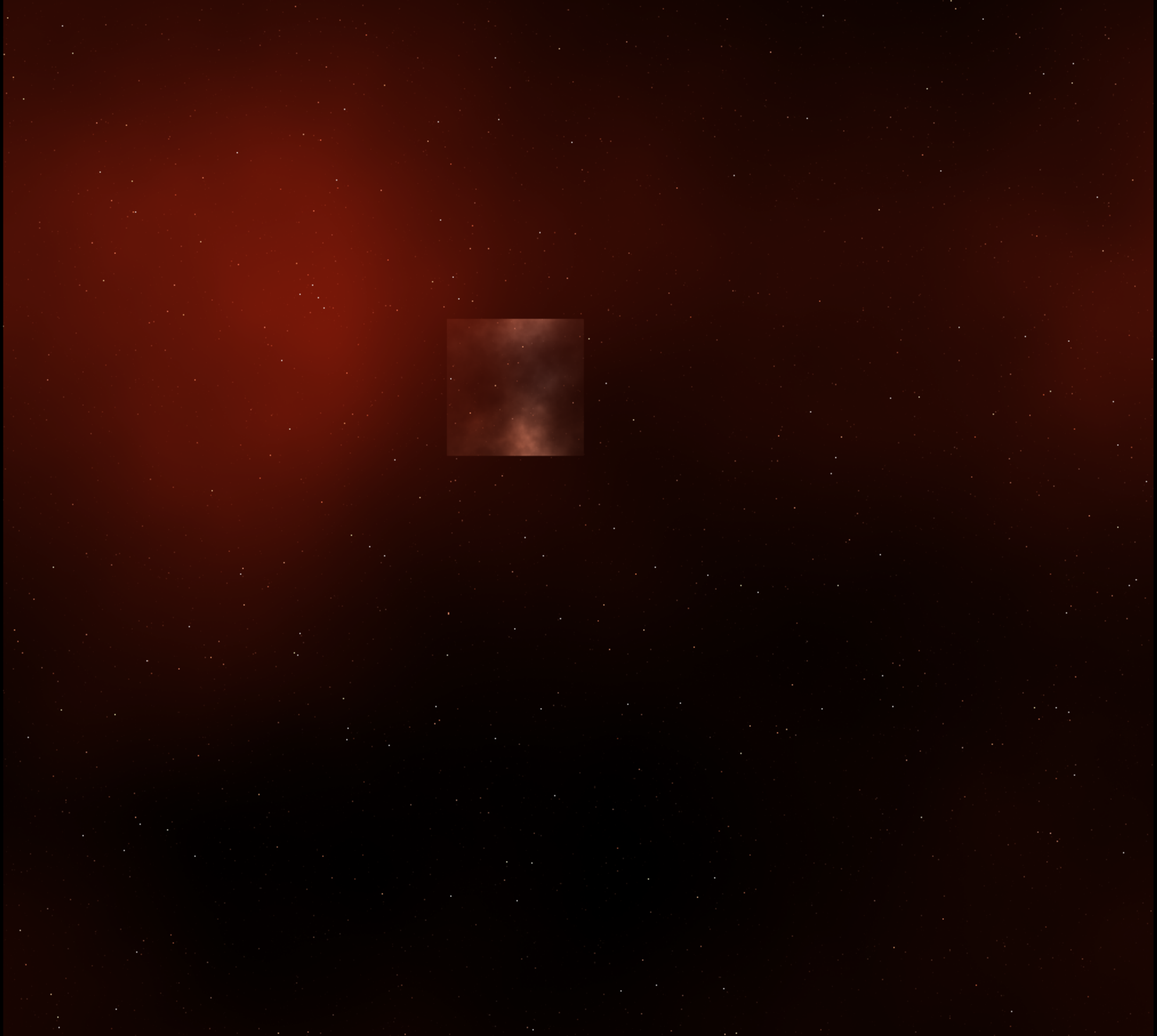
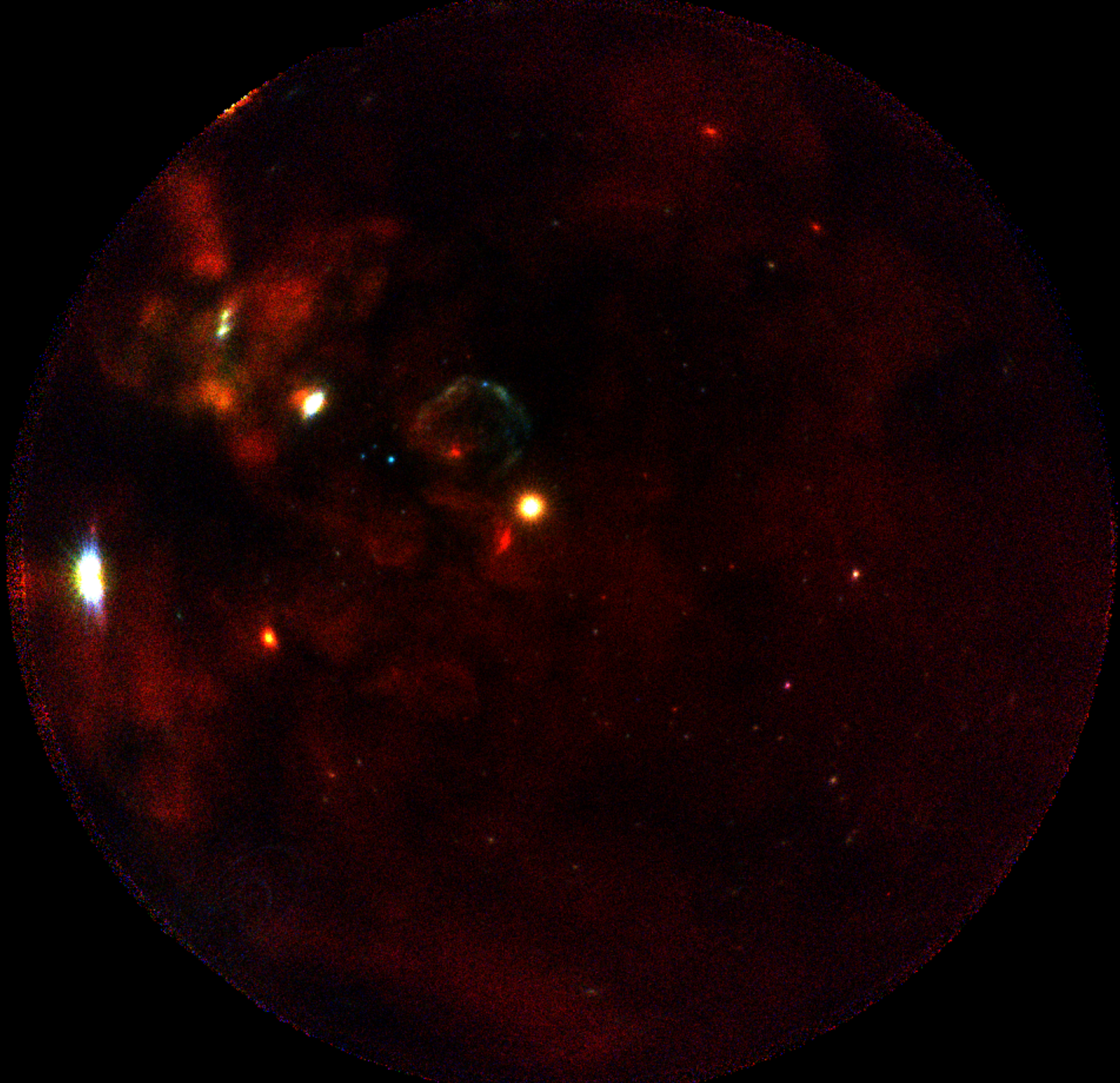
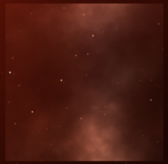






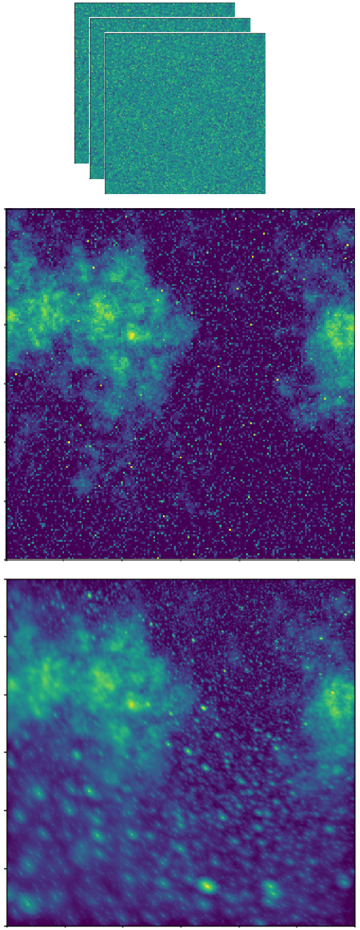


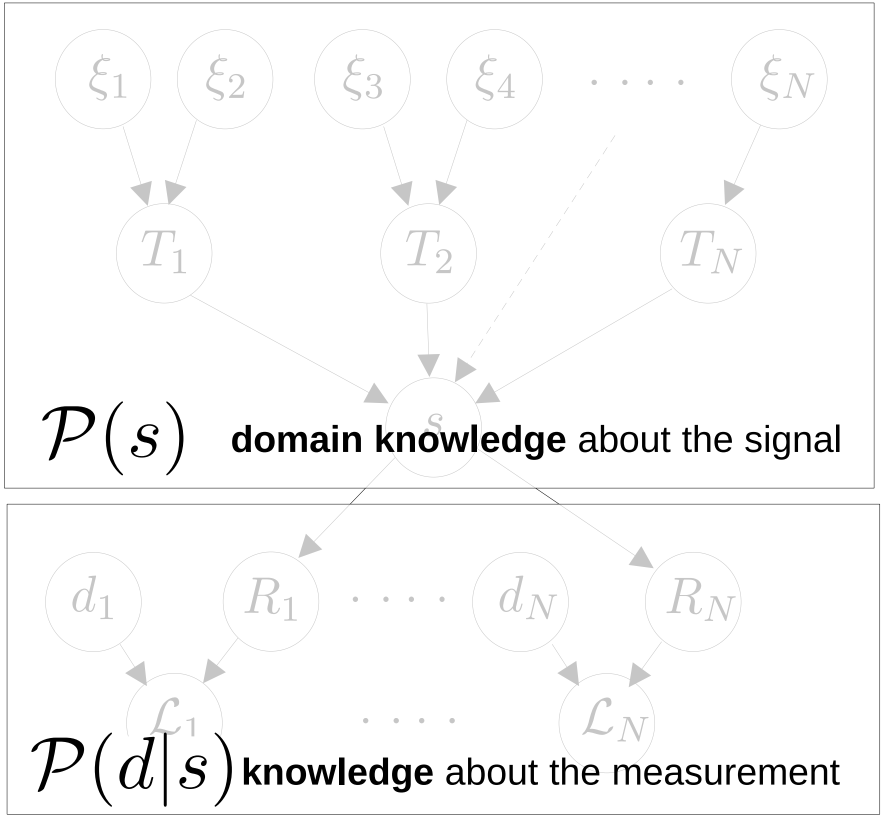


Generative Models for Bayesian Imaging

Framework: Numerical **I**nformation **F**ield **T**heory
https://github.com/NIFTy-PPL/NIFTy

$$\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$$





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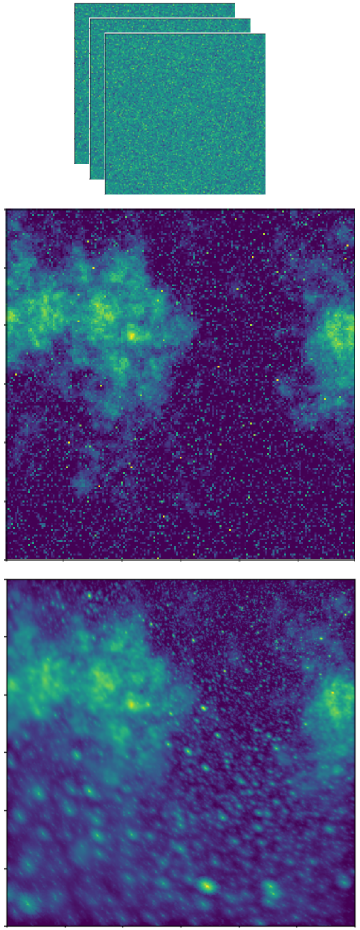

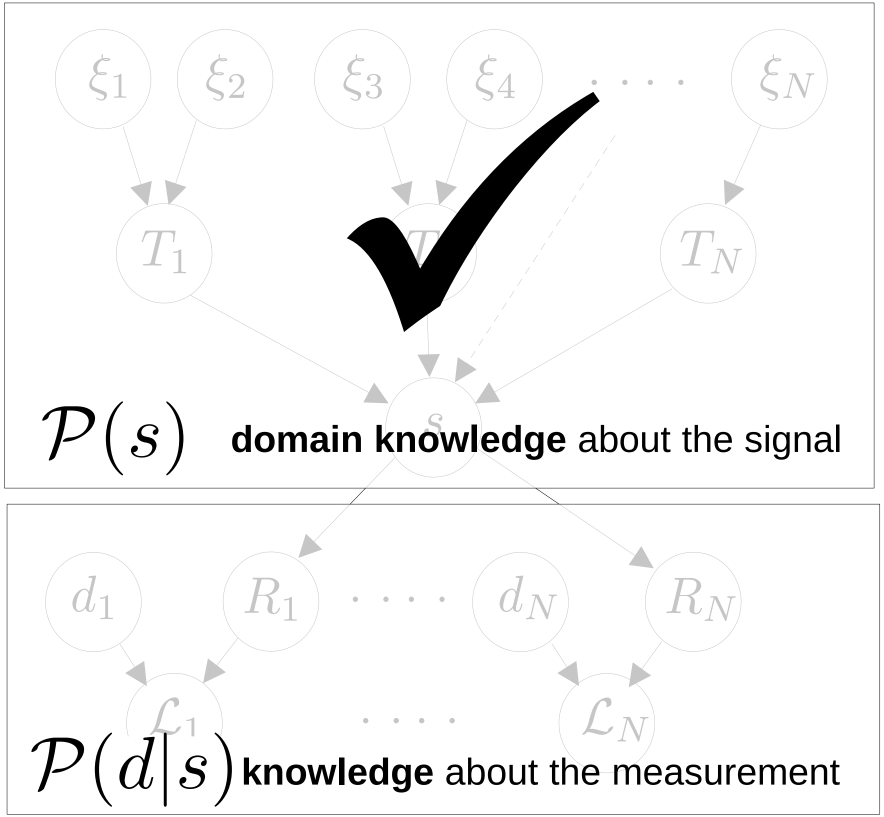

Modeling the Instrument

Modeling the Instrument

Point spread functions from CALDB

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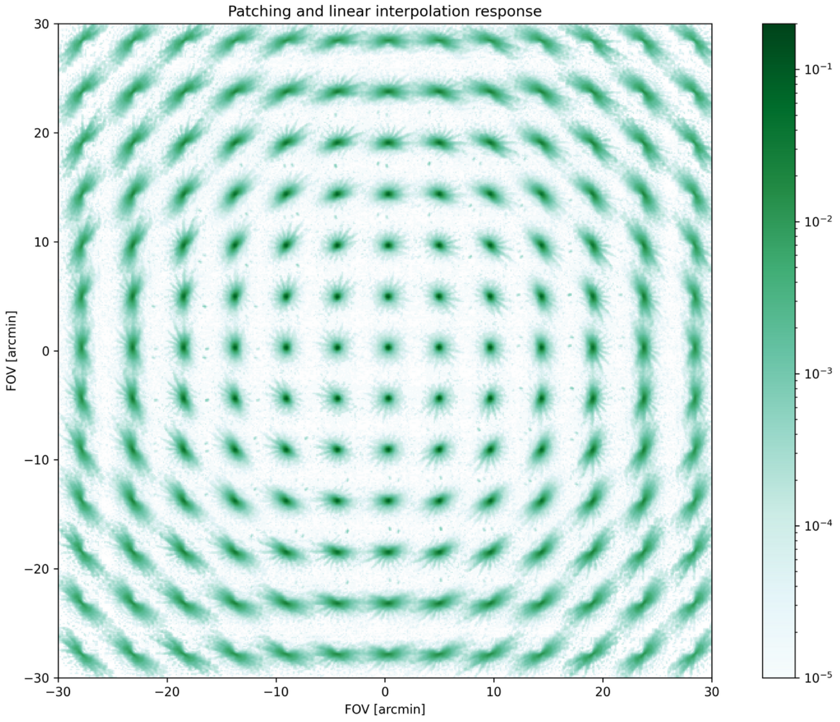

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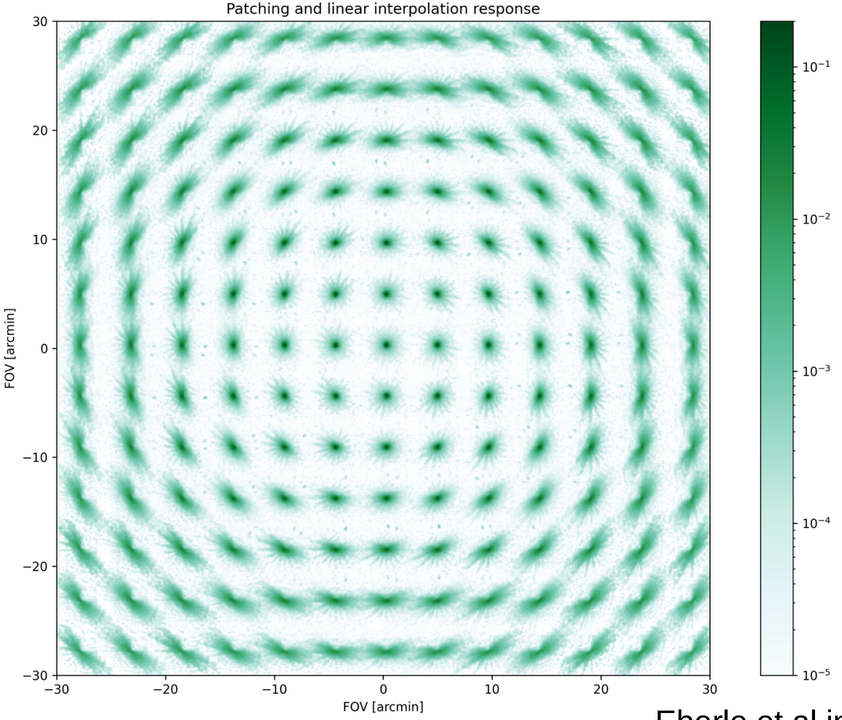

Eberle et al in prep.

Patched Interpolated Convolution

[Nagy, James G., and Dianne P. O'Leary. "Fast iterative image restoration with a spatially varying PSF."
Advanced Signal Processing: Algorithms, Architectures, and Implementations VII. Vol. 3162. SPIE, 1997.]

Modeling the Instrument

Exposure and Detmaps information from eSASS and CALDB

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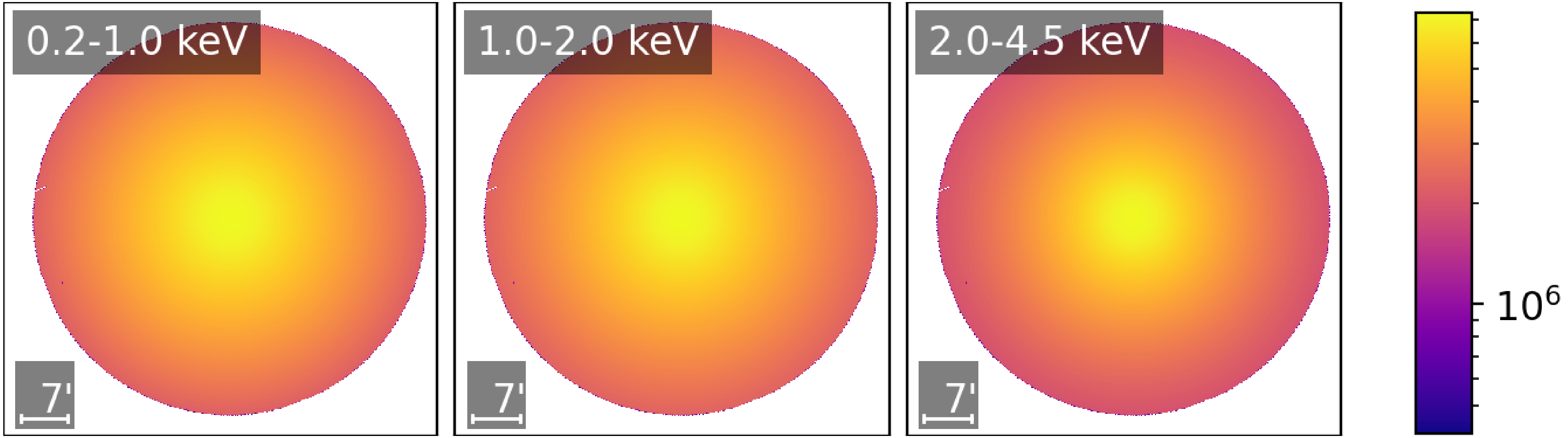

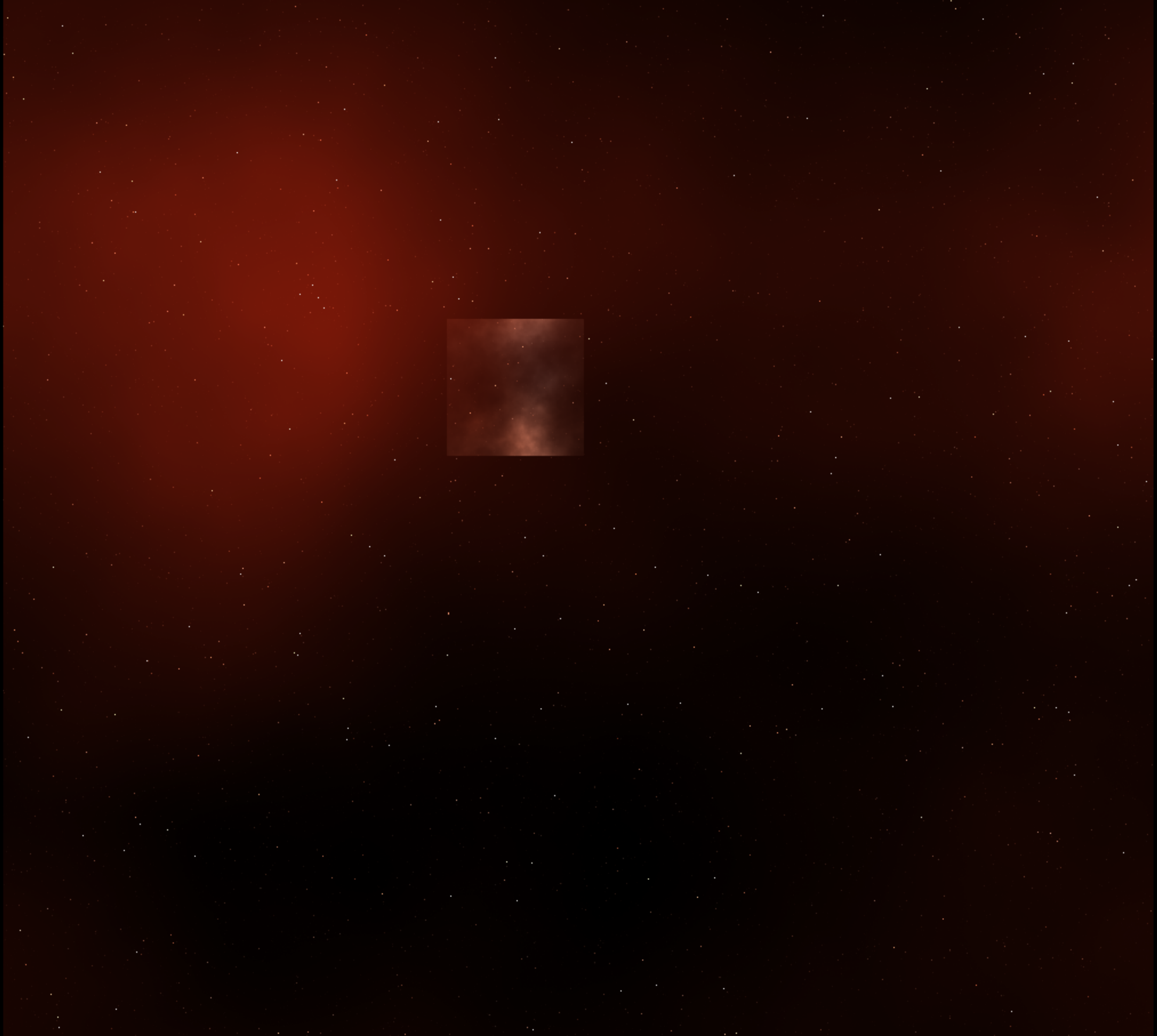

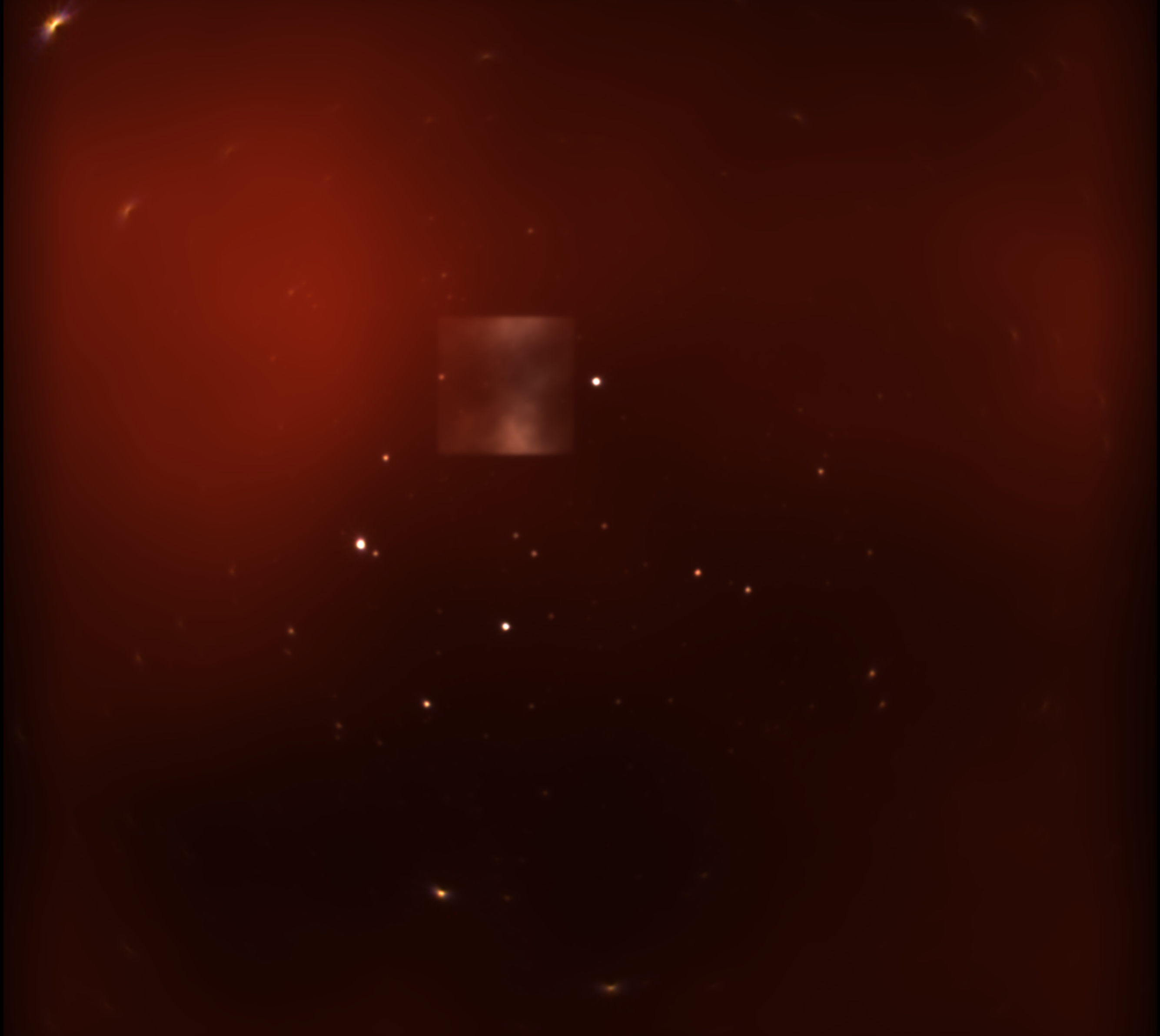

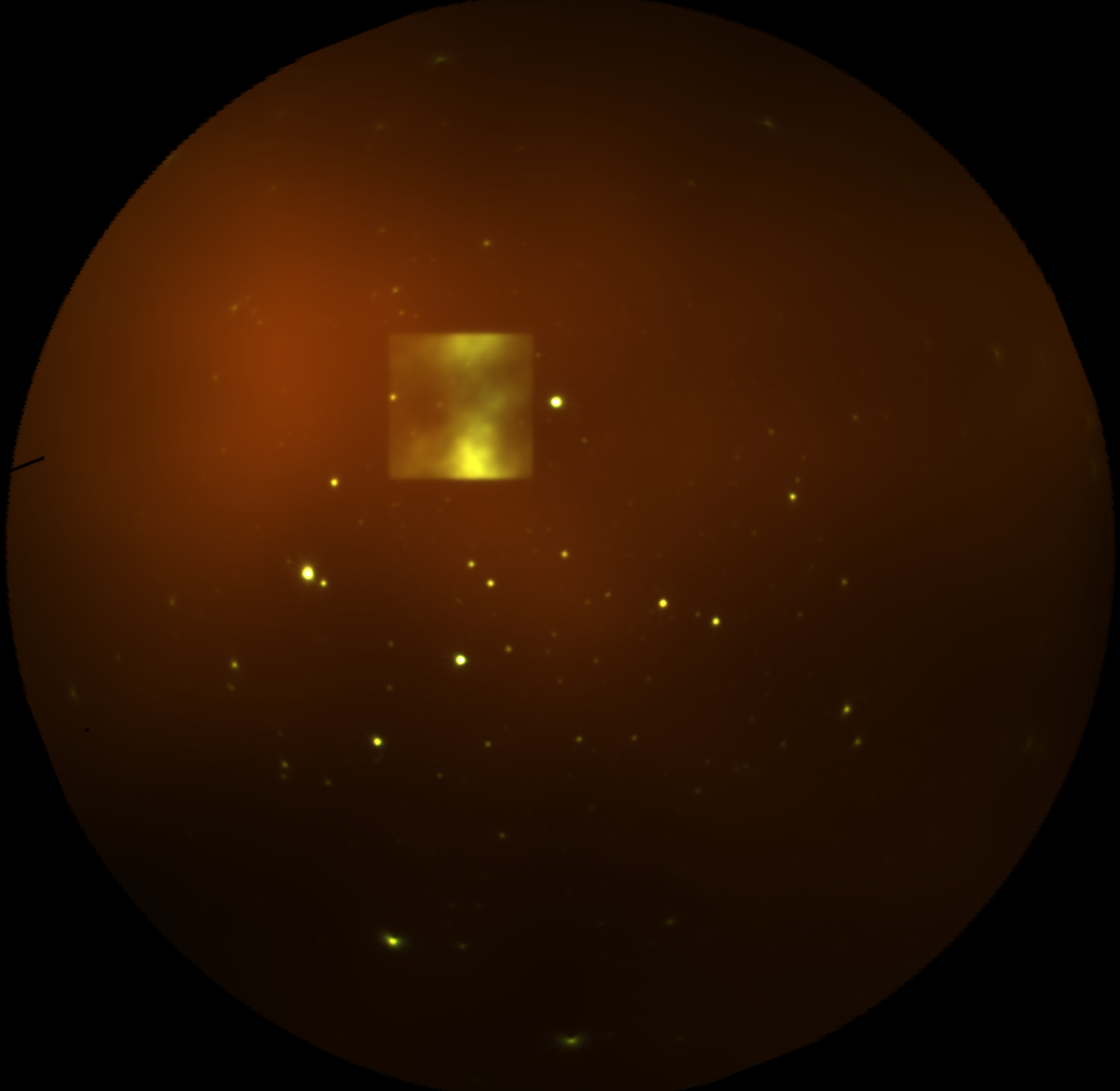

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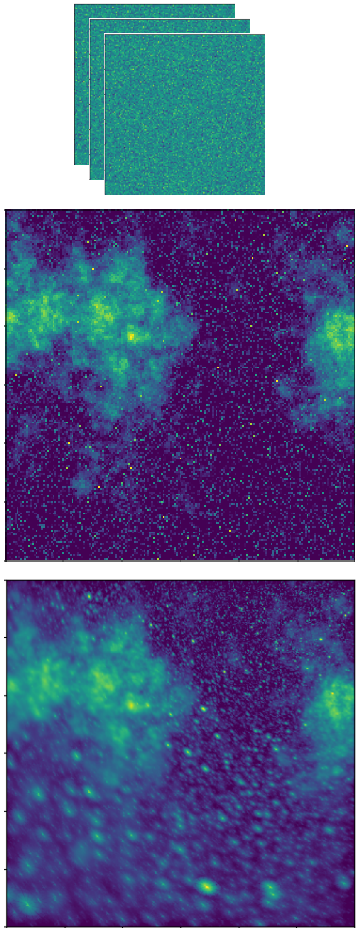

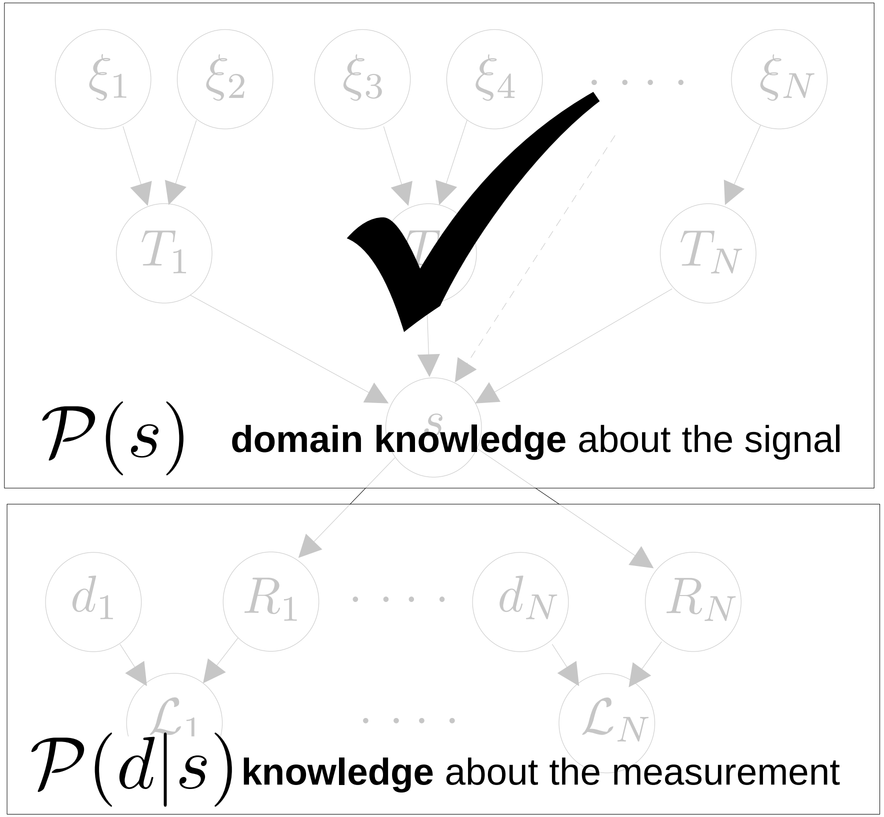

$\mathcal{P}(s)$ **domain knowledge** about the signal

$\mathcal{P}(d|s)$ **knowledge** about the measurement

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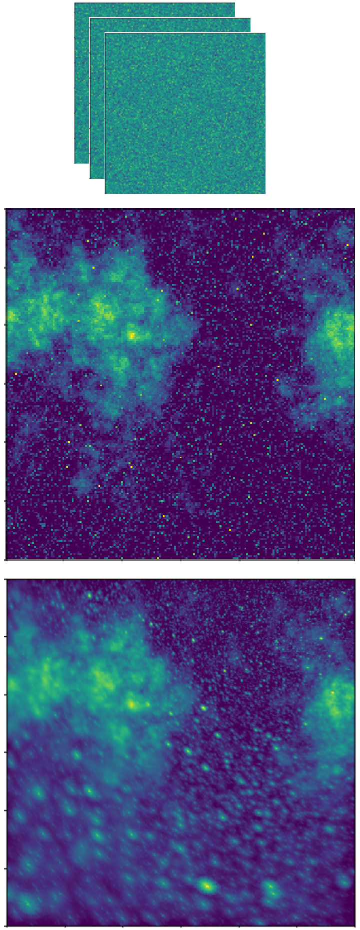

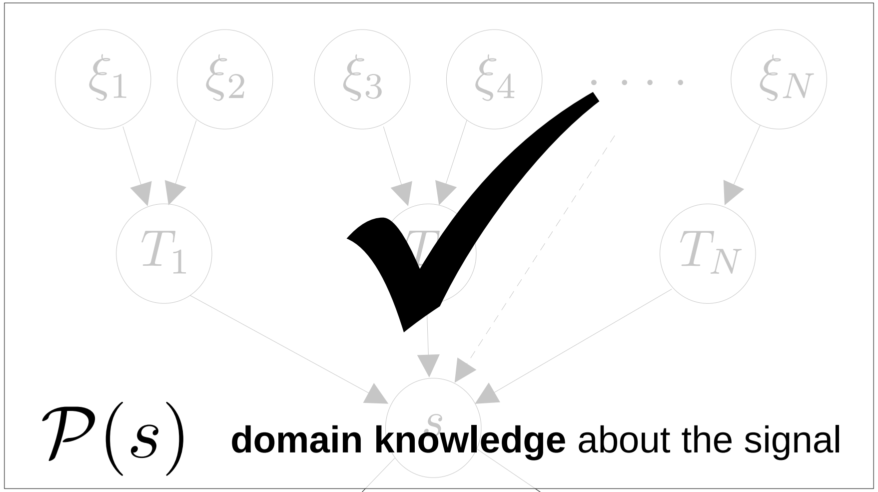

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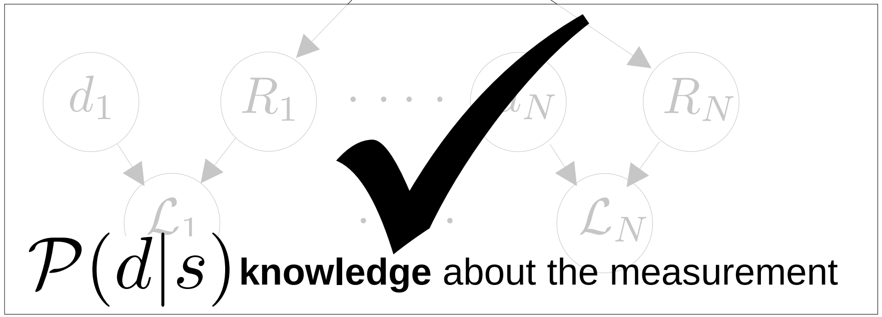

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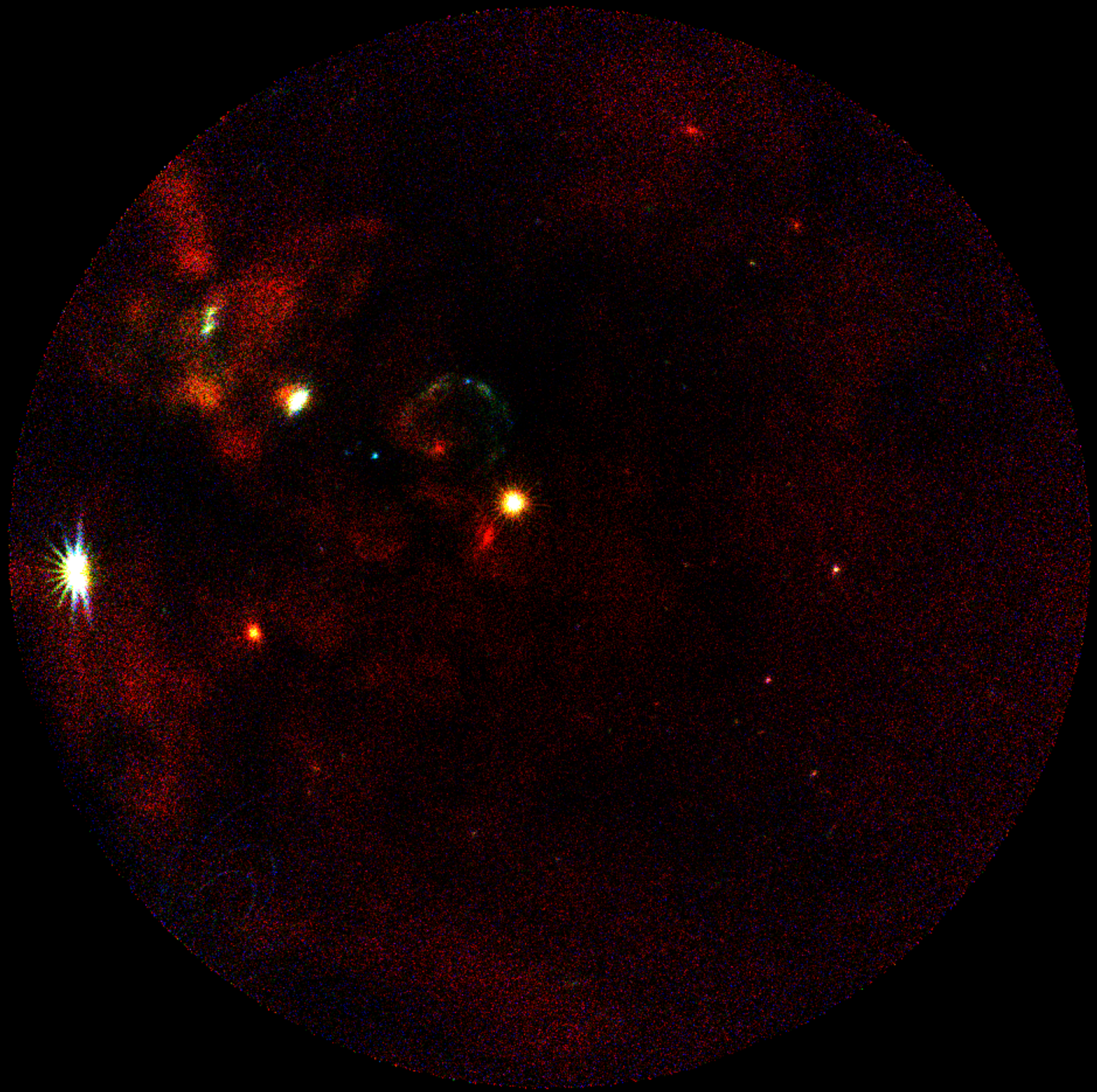
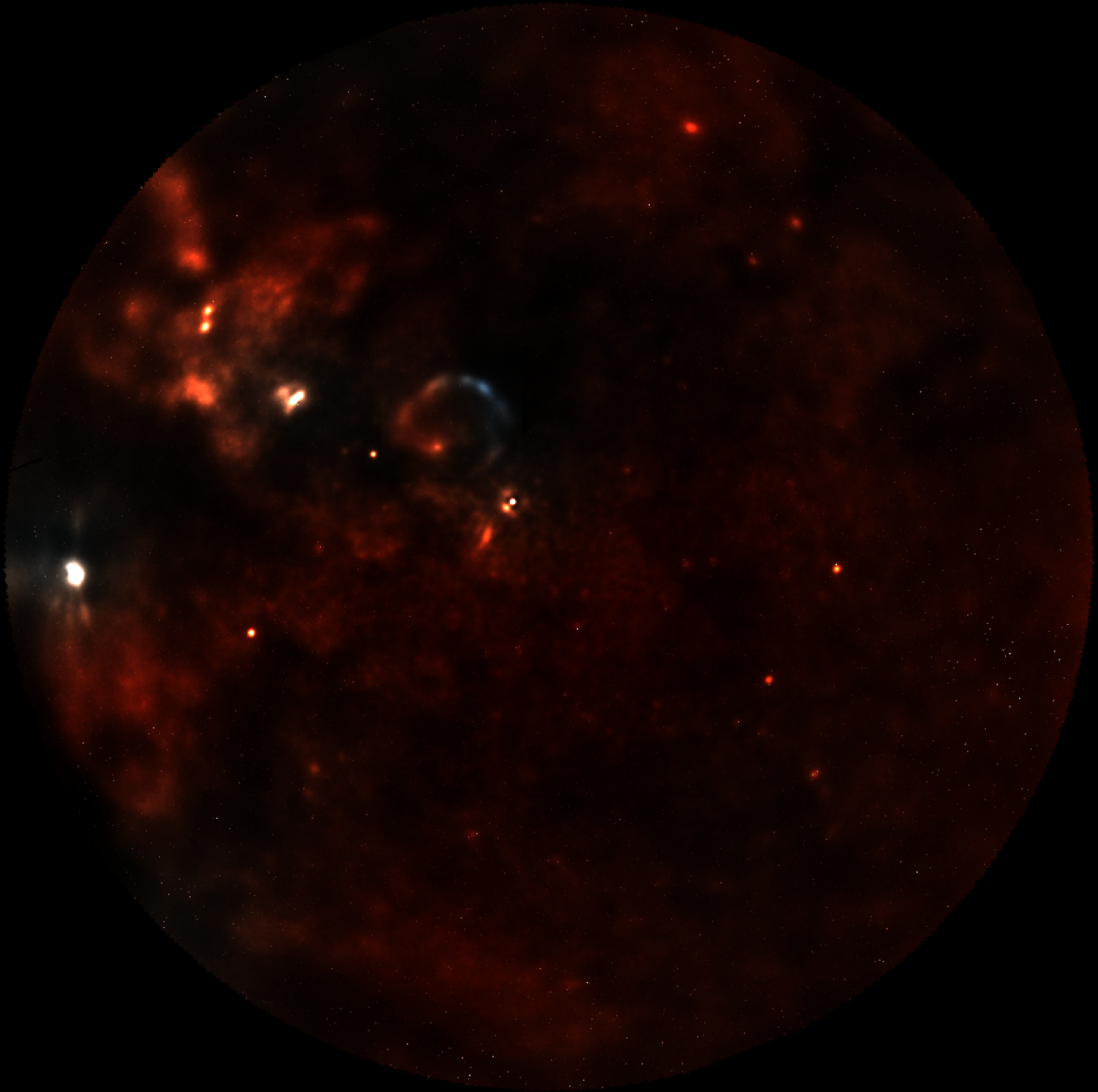
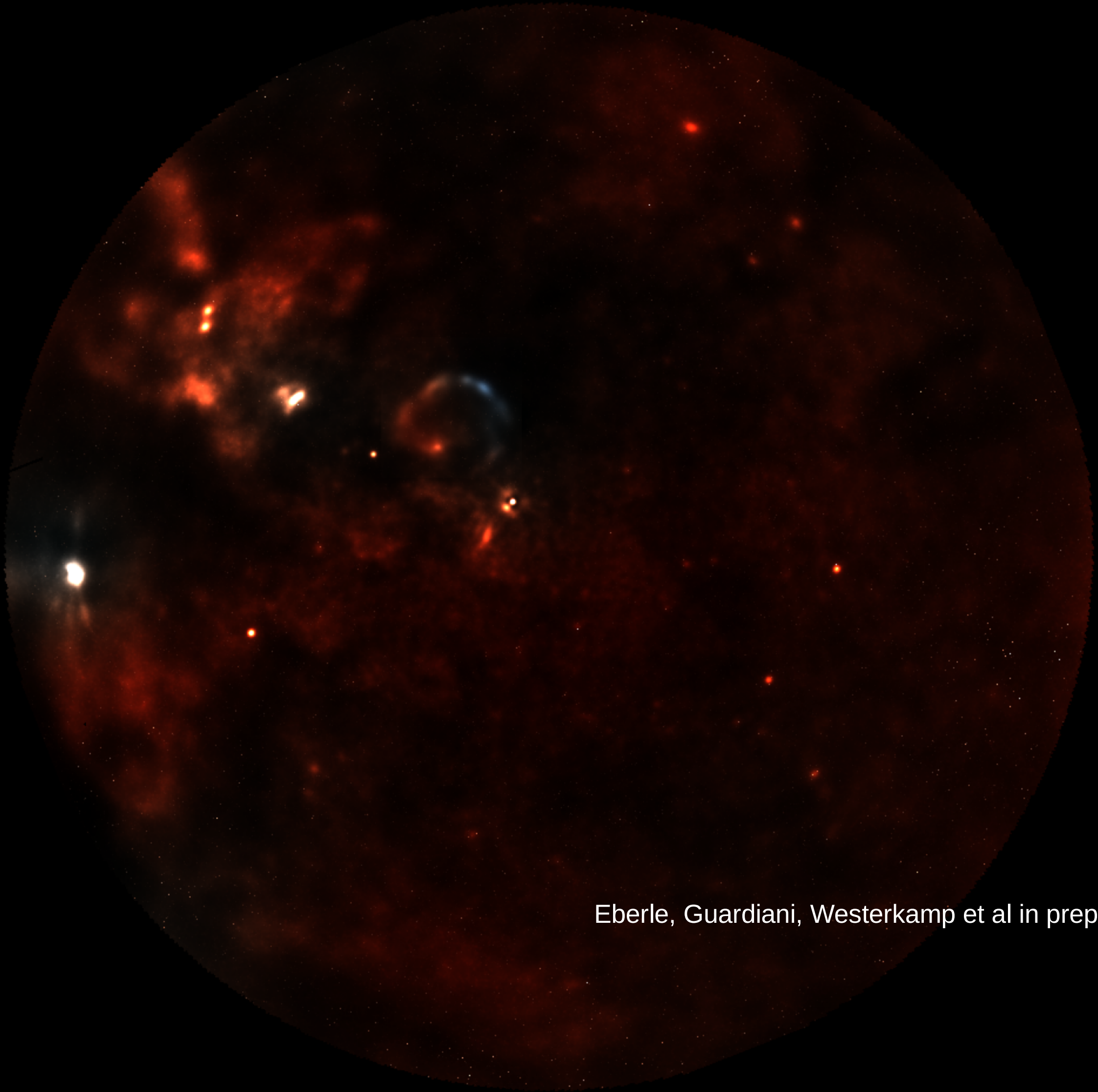
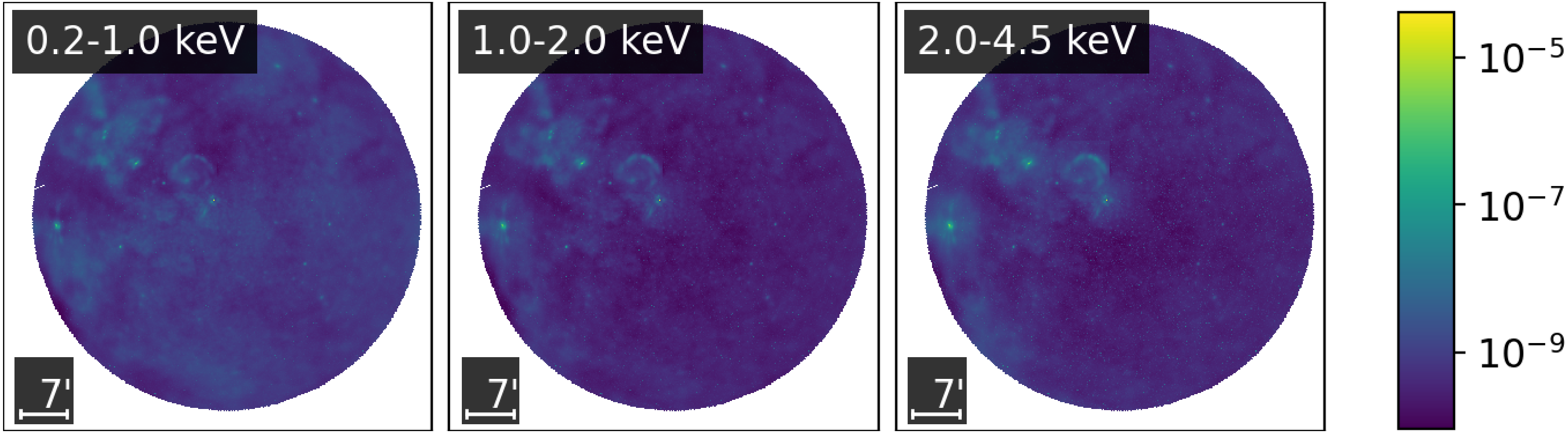




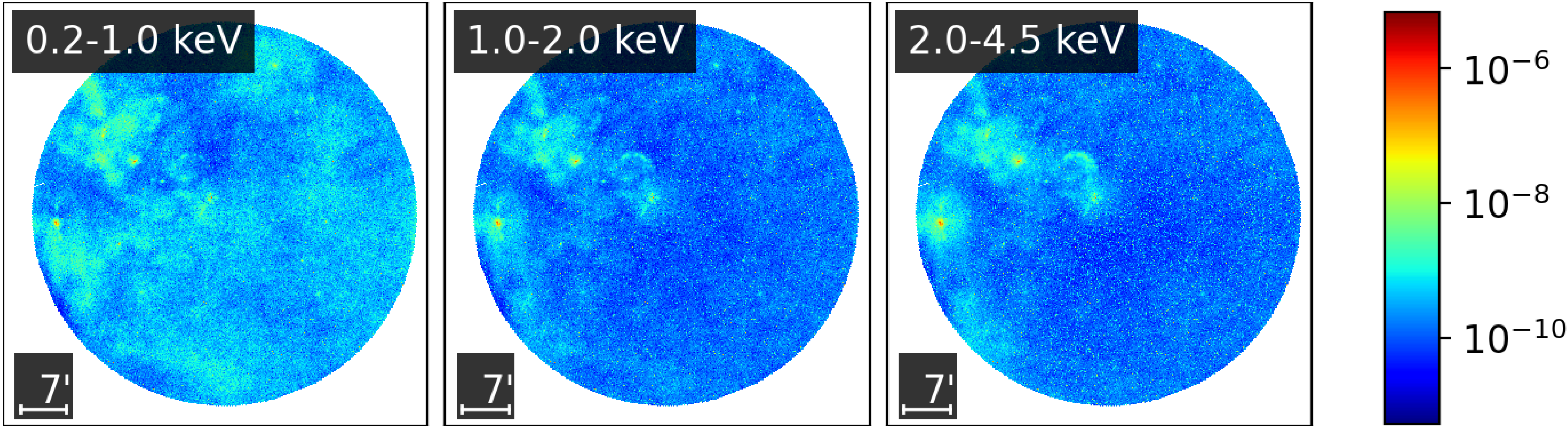


Eberle, Guardiani, Westerkamp et al in prep

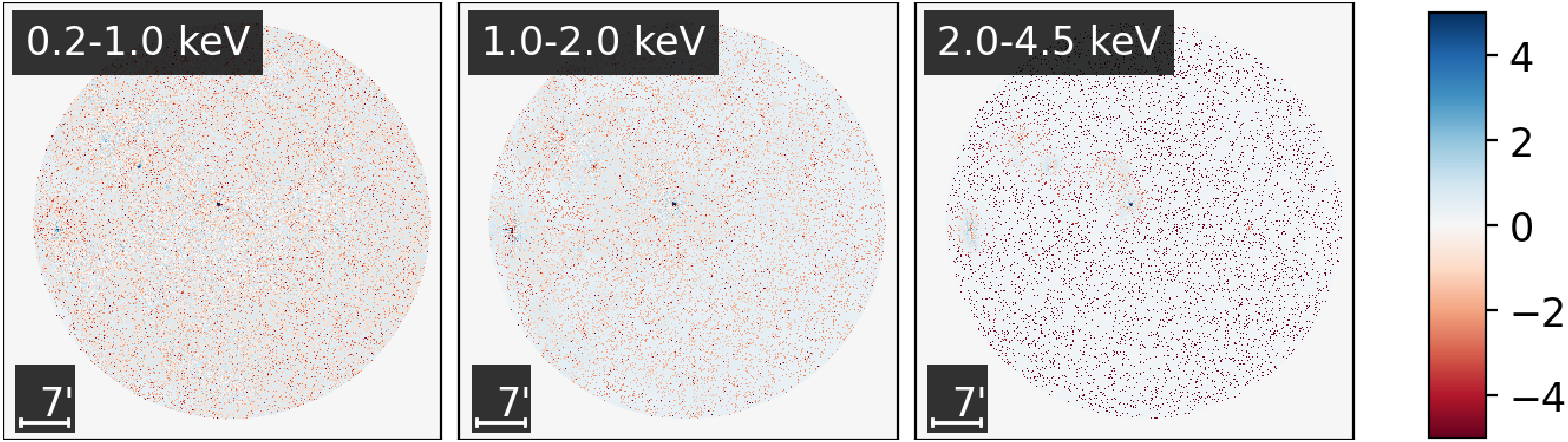
Posterior Mean Flux



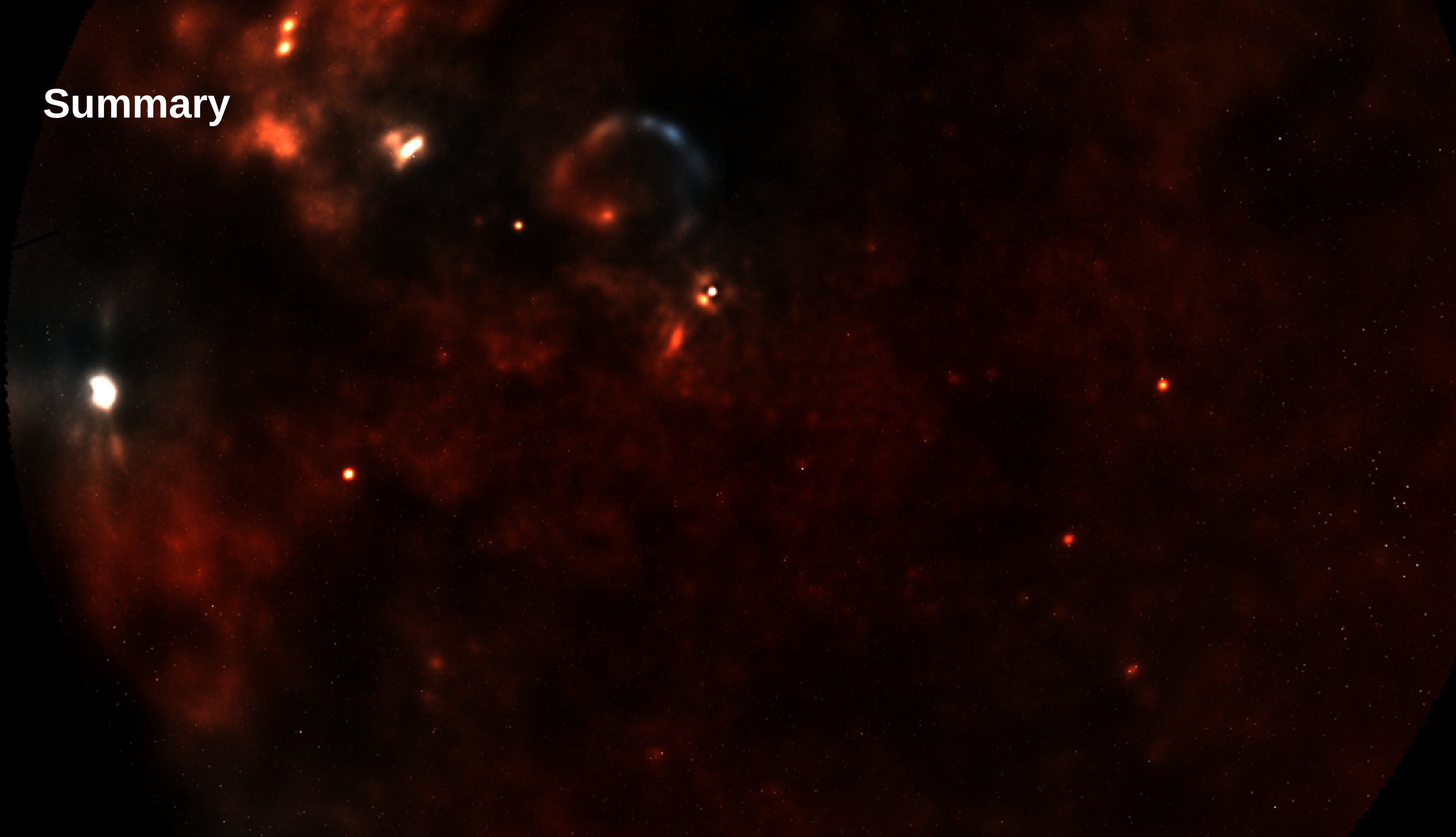
Uncertainties



Noise weighted residuals



Summary



Summary

Using generative models and Bayesian inference, it is possible to:

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Using generative models and Bayesian inference, it is possible to:

- denoise

Summary

Using generative models and Bayesian inference, it is possible to:

- denoise
- deconvolve

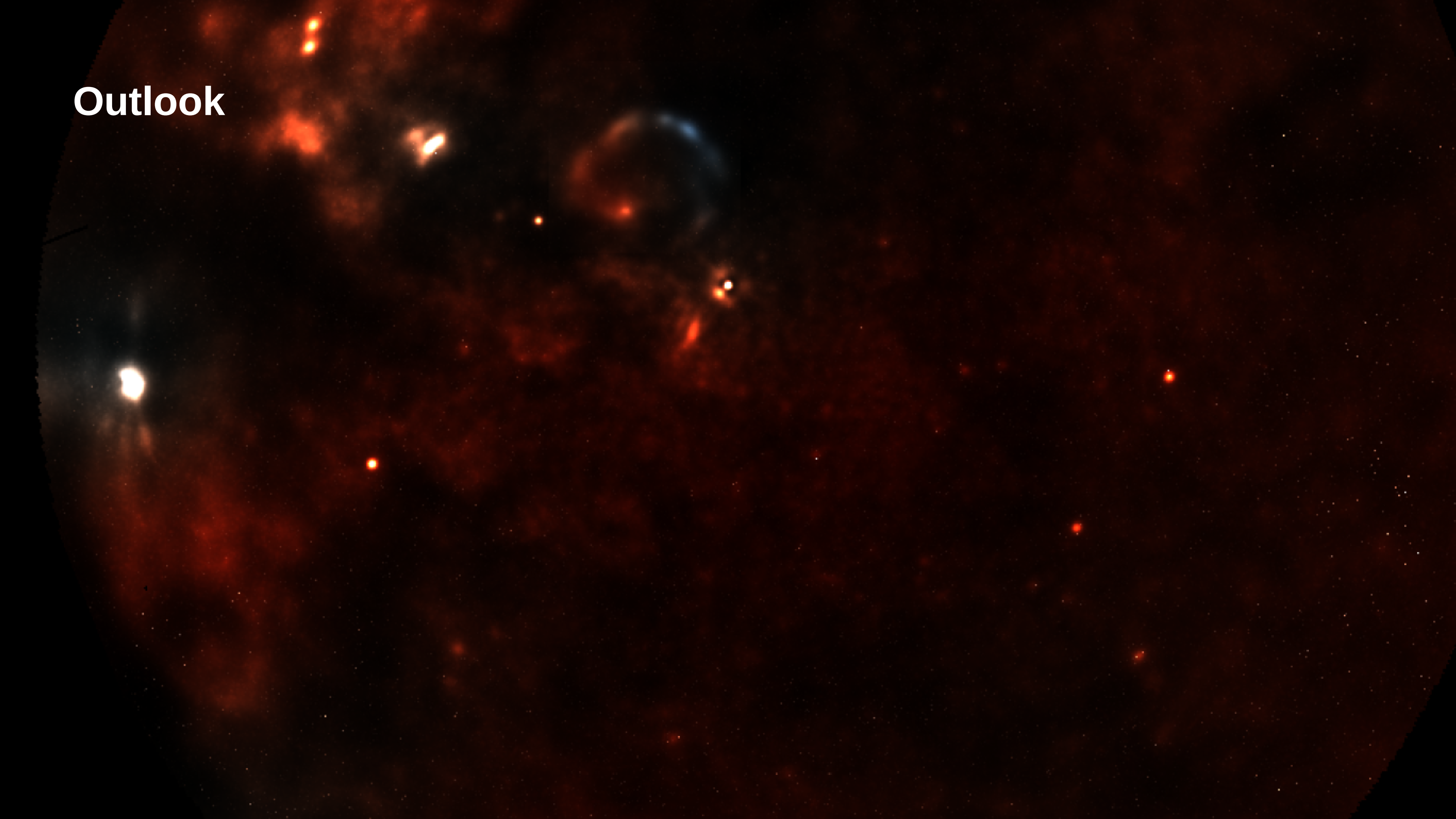
Summary

Using generative models and Bayesian inference, it is possible to:

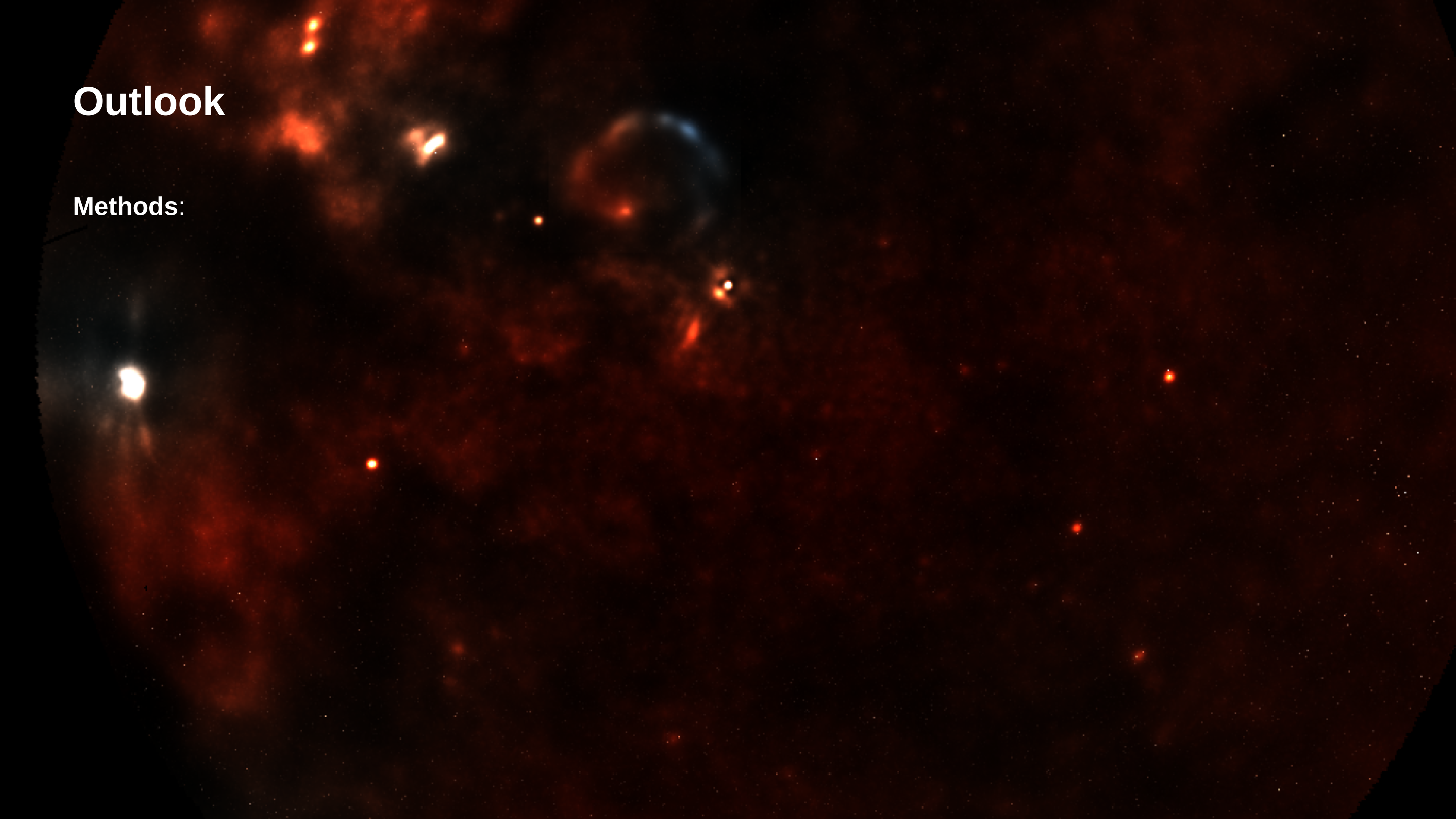
- denoise
- deconvolve
- decompose

observations from X-ray observatories.

Outlook



Outlook

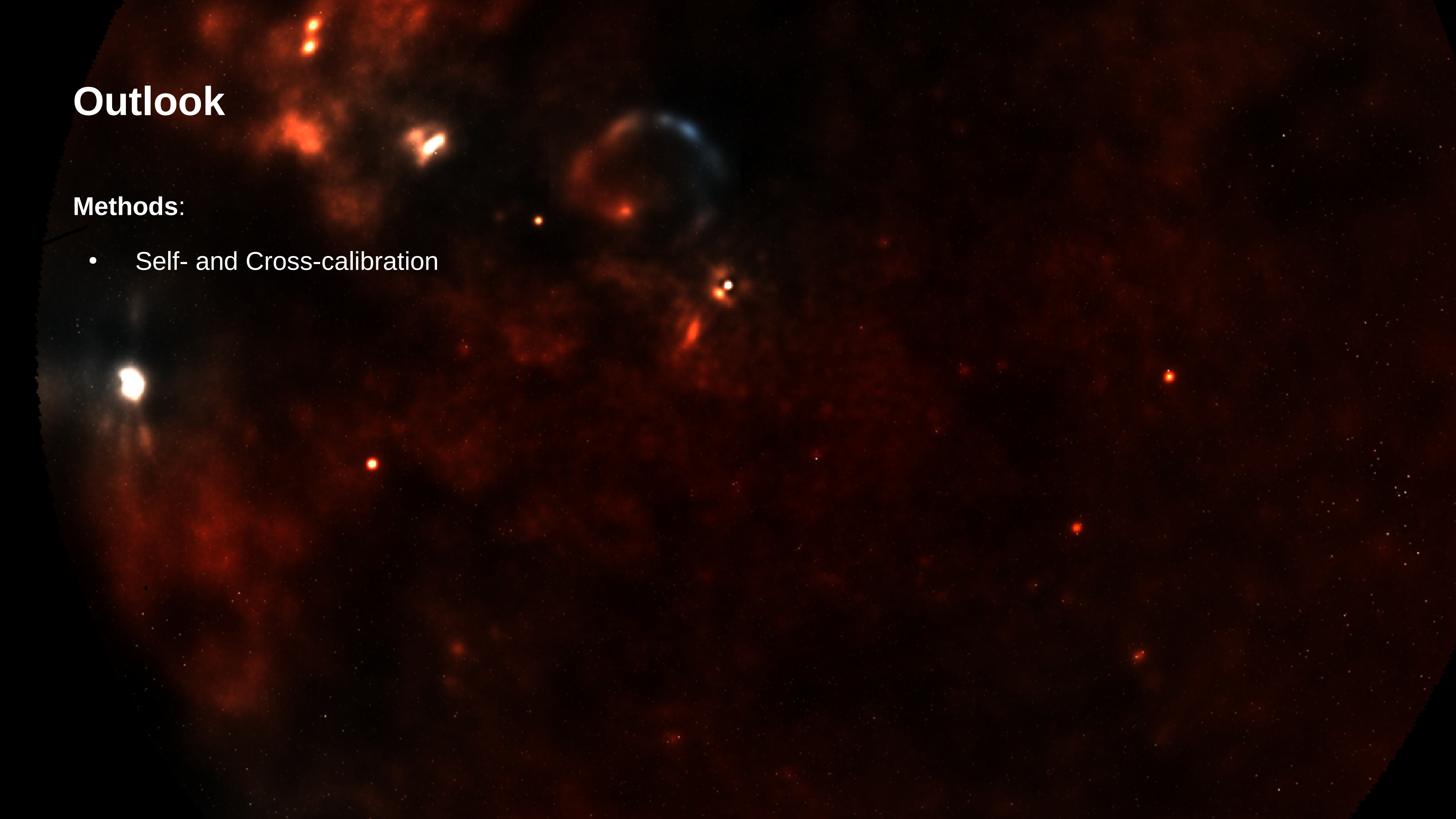


Methods:

Outlook

Methods:

- Self- and Cross-calibration



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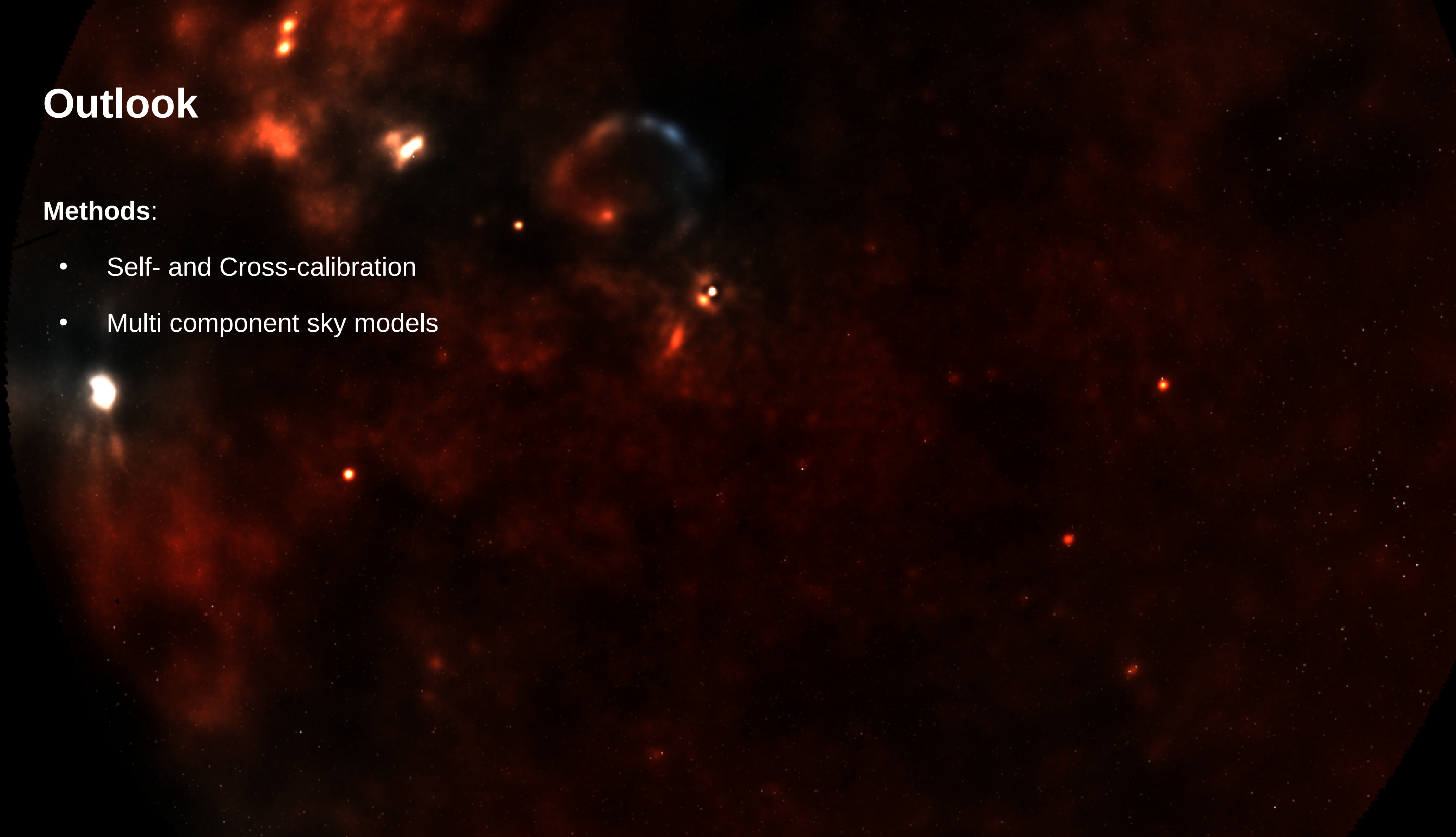

Methods:

- Self- and Cross-calibration
- Multi component sky models

Outlook

Methods:

- Self- and Cross-calibration
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- Automatic detection of extended components

Outlook

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Data:

Outlook

Methods:

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Data:

- eFEDs

Outlook

Methods:

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more about the details:

The **U**niversal **B**ayesian **I**maging **K**it [Margret Westerkamp]

Automatic Point Source Detection through Model Stress [Matteo Guardiani]