

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

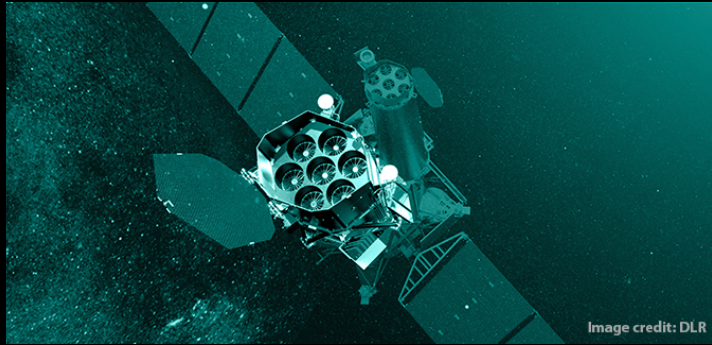
Garching, Germany
15th - 20th September 2024



MAX PLANCK INSTITUTE
FOR ASTROPHYSICS

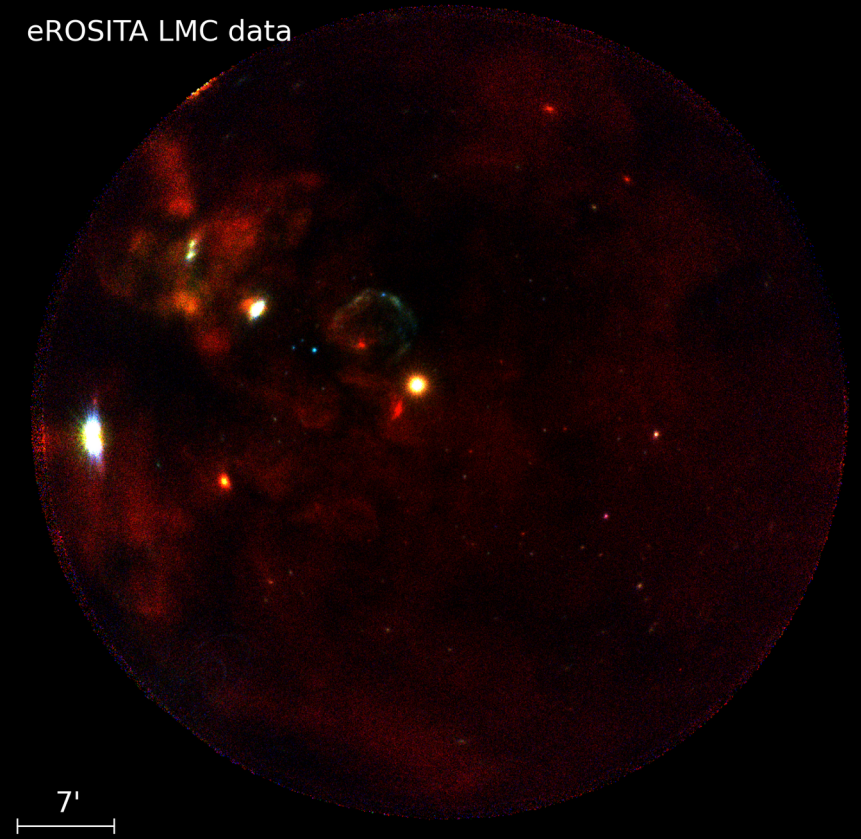


Motivation

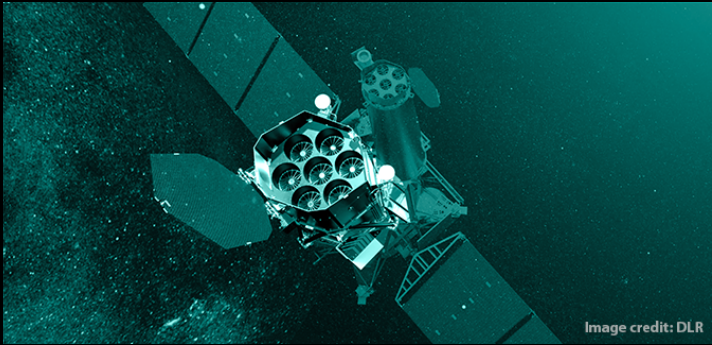


X-ray telescopes (e.g. eROSITA, Chandra) suffer from nuisance effects, e.g.

eROSITA LMC data



Motivation



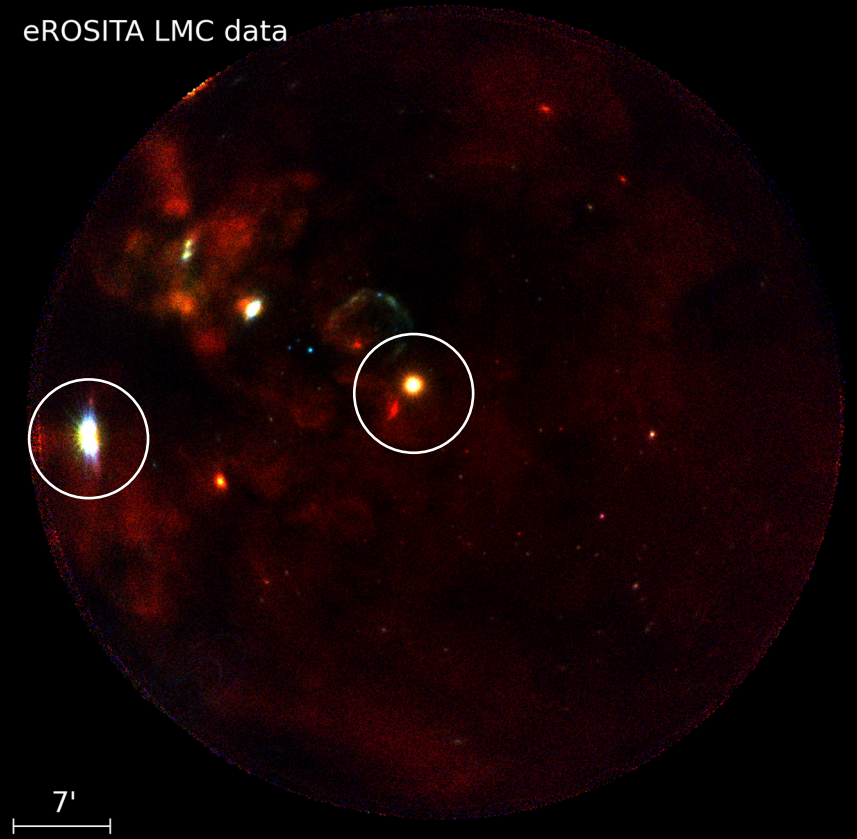
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Problems

Spatially Variant Point Spread Functions (PSF)

eROSITA LMC data



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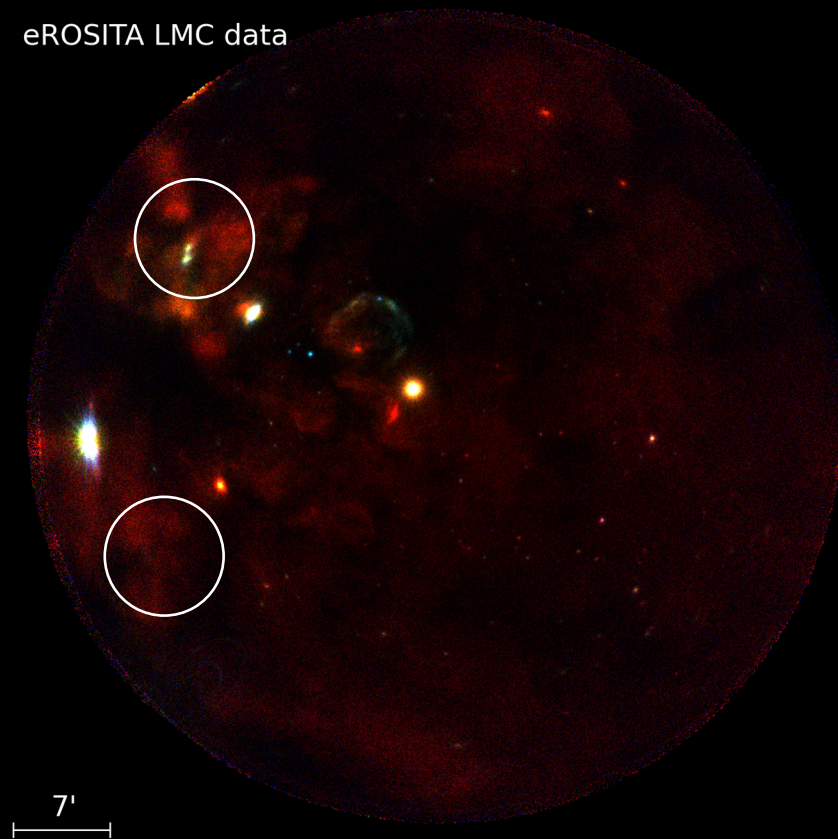


Problems

Spatially Variant Point Spread Functions (PSF)

Shot Noise

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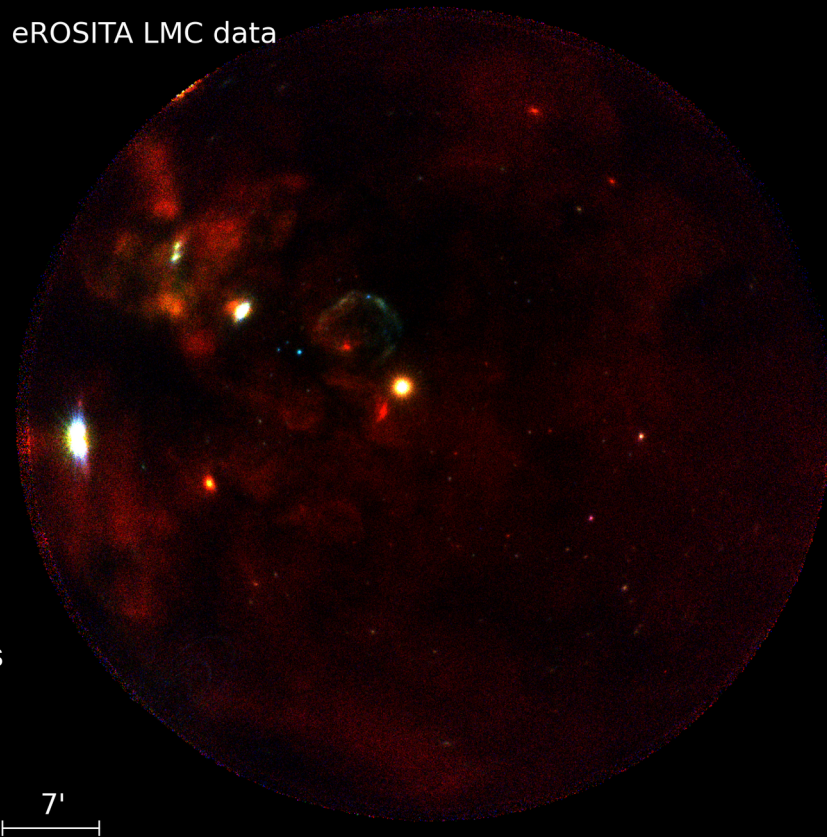


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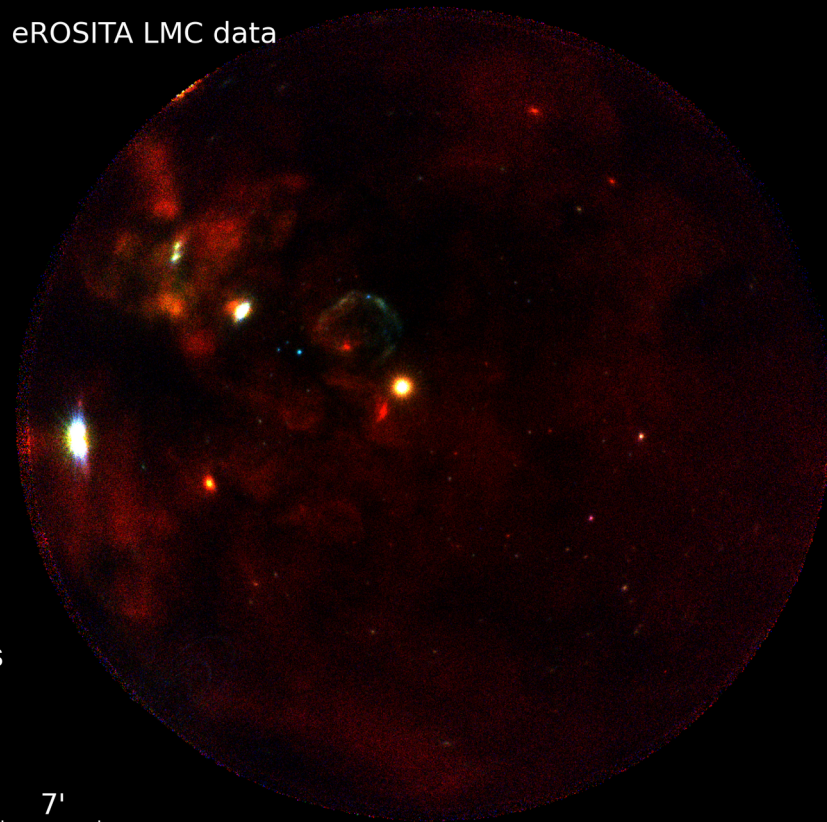
others



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eROSITA LMC data



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Problems

Spatially Variant Point Spread Functions (PSF)

Shot Noise

others

Approach

Bayesian Imaging
&
Generative Models

7'

Motivation

Denoised, Deconvolved, Decomposed



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

Problems

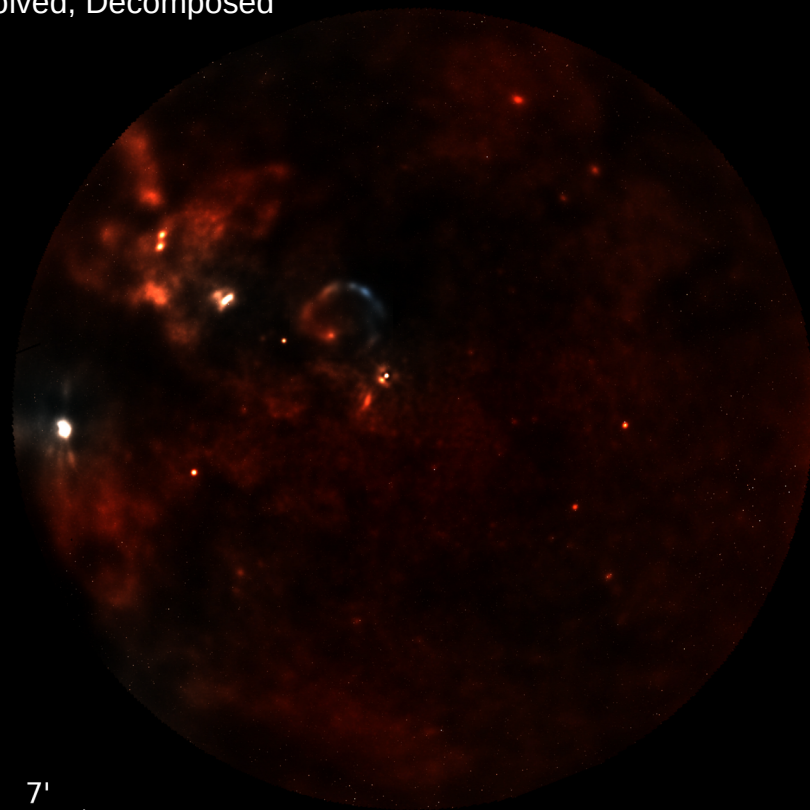
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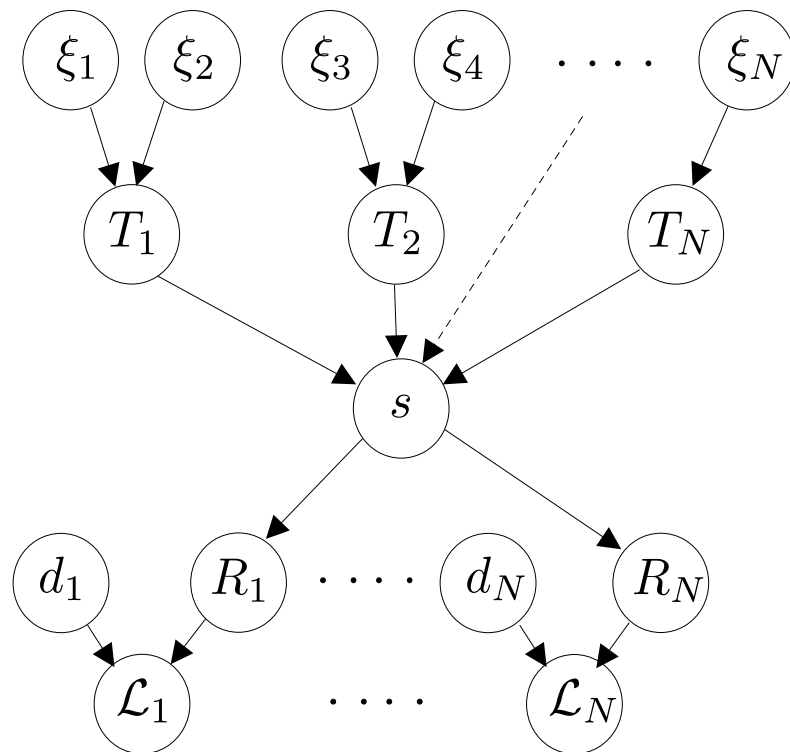
Generative Models for Bayesian Imaging

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

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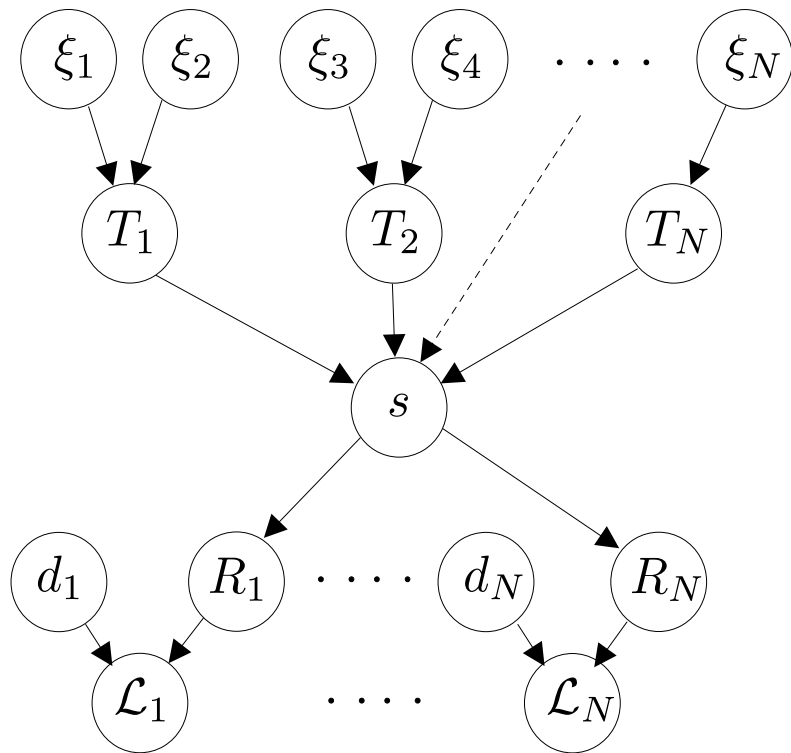


Generative Models for Bayesian Imaging

Framework: Numerical Information Field Theory

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

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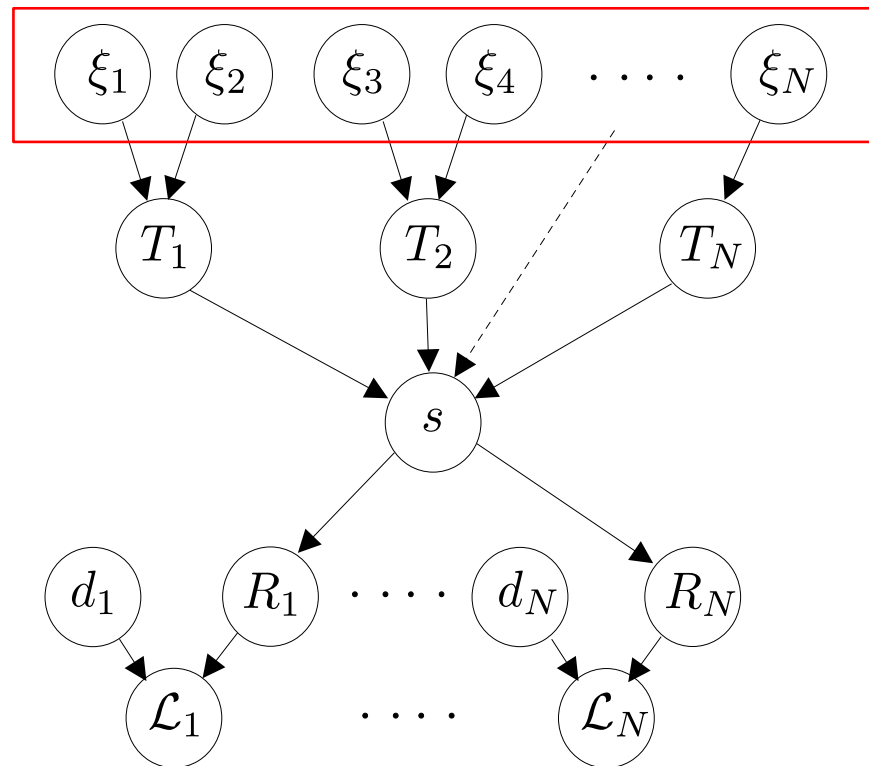
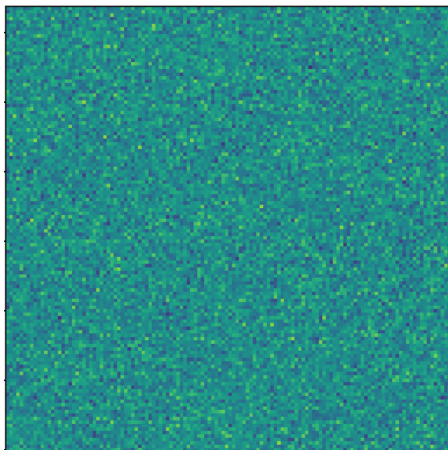


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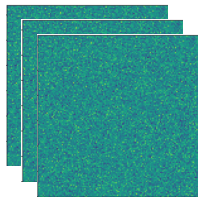




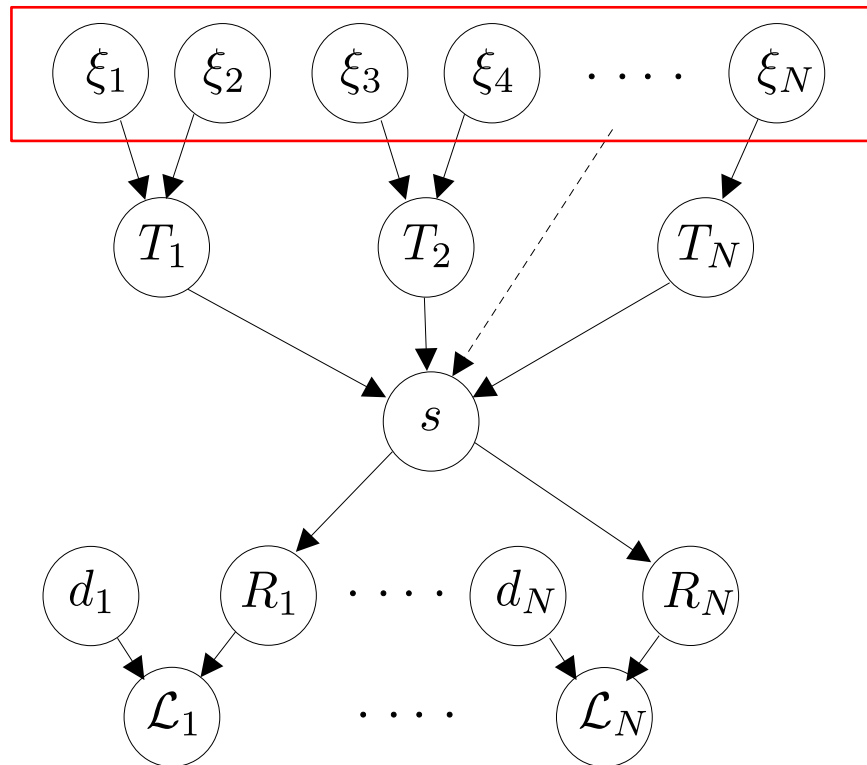
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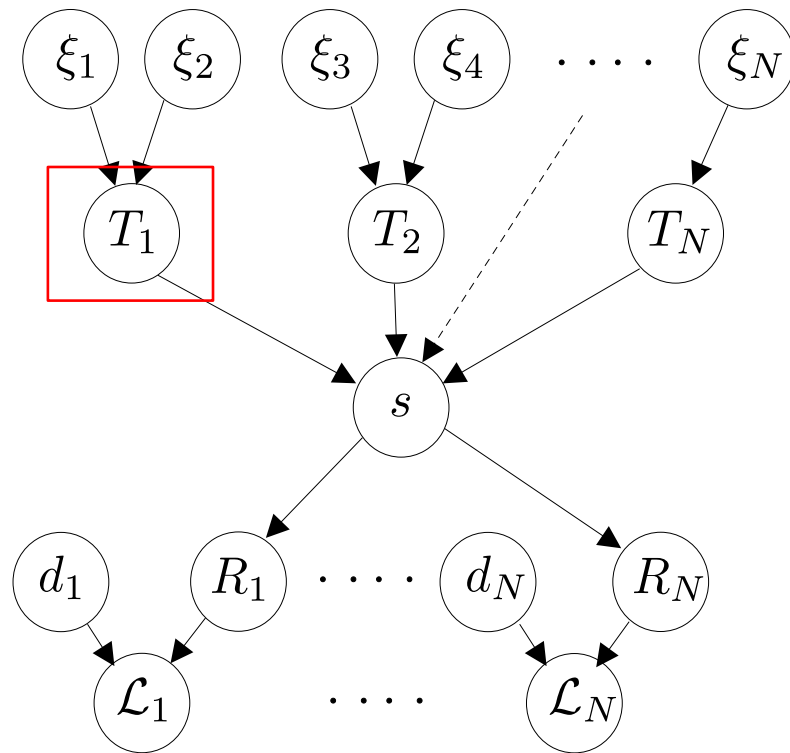
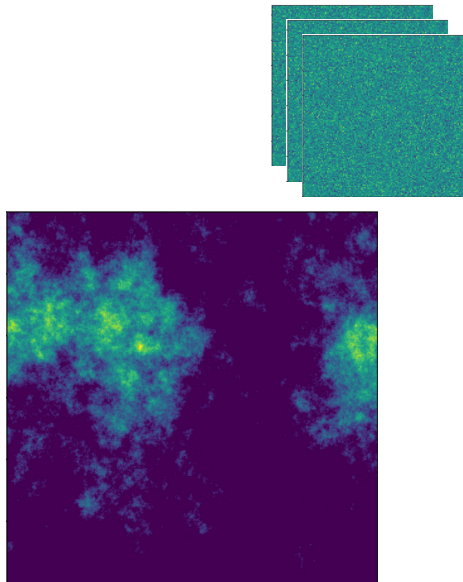


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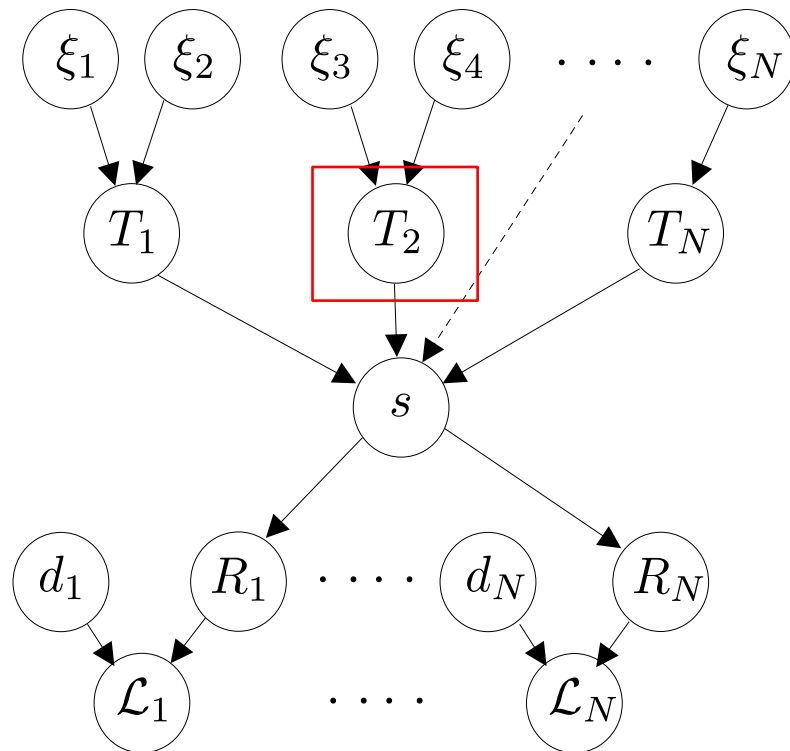
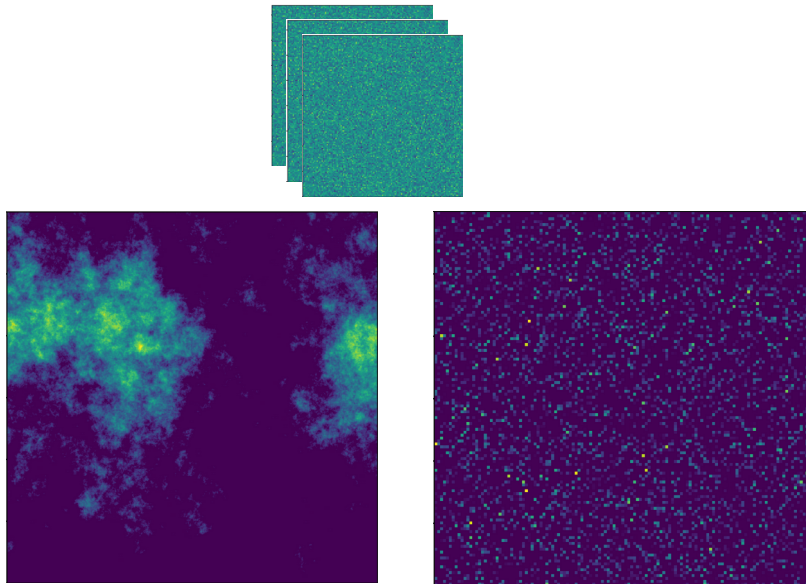


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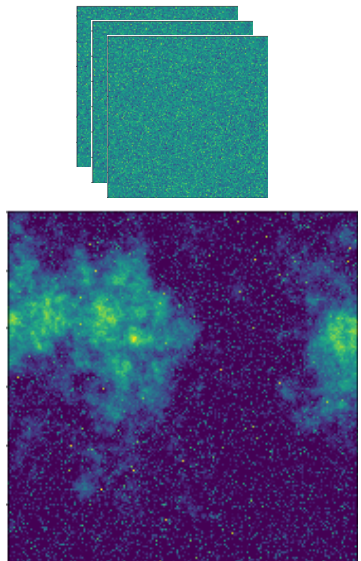




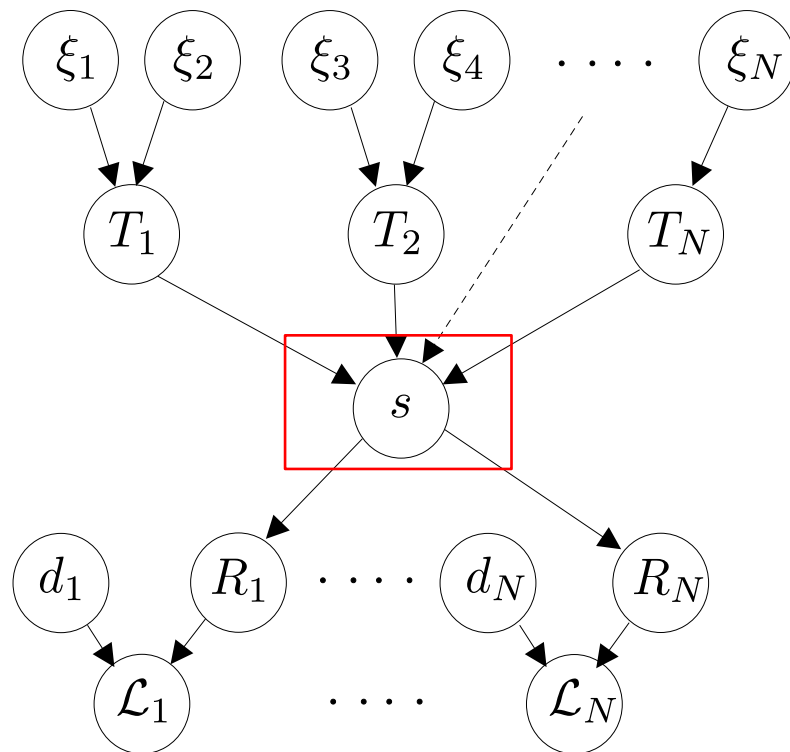
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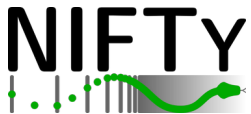
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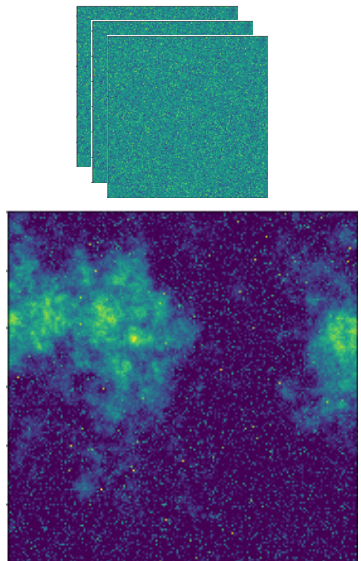




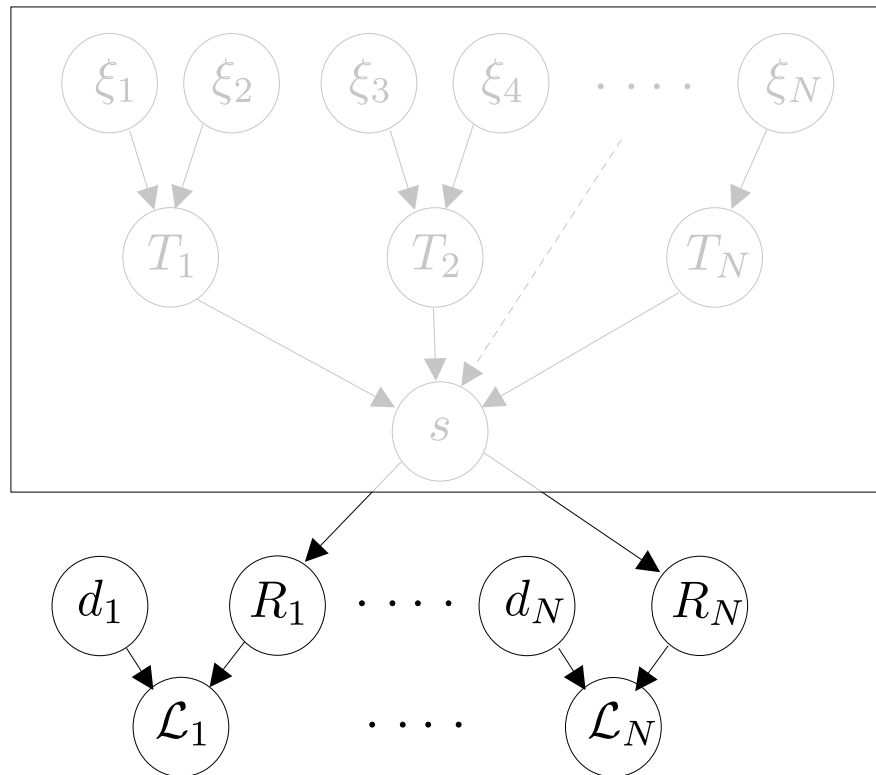
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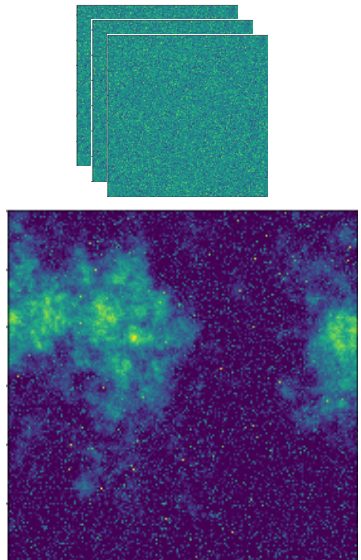




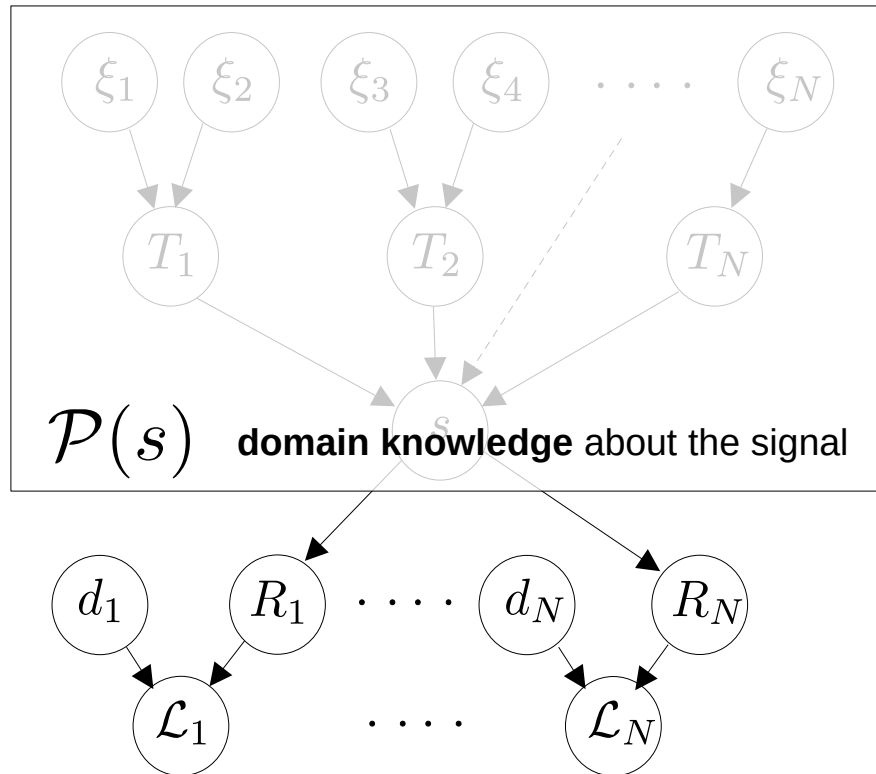
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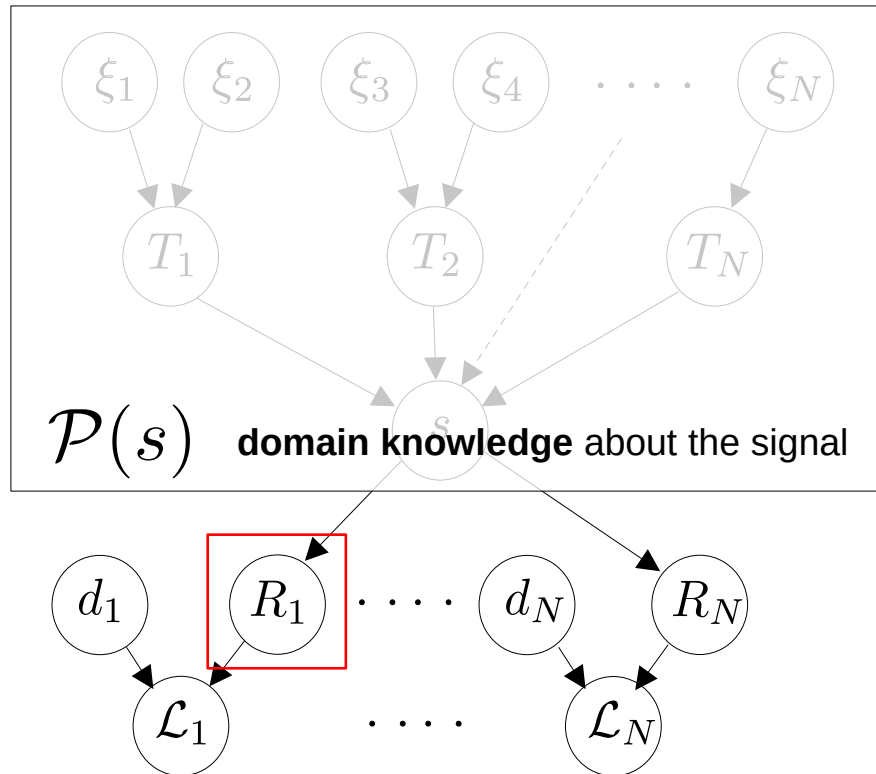
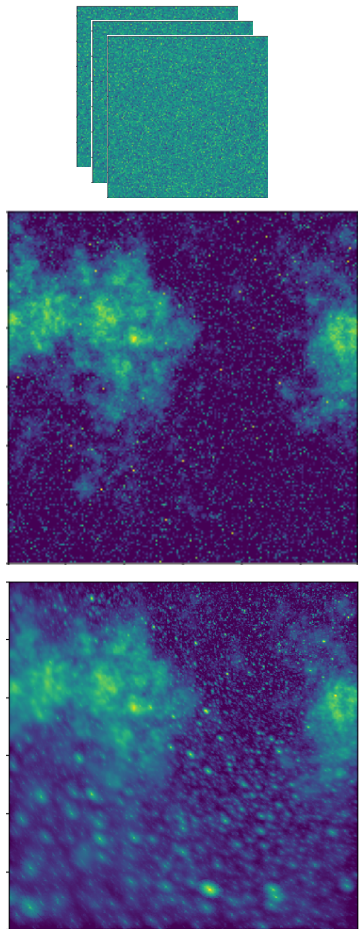


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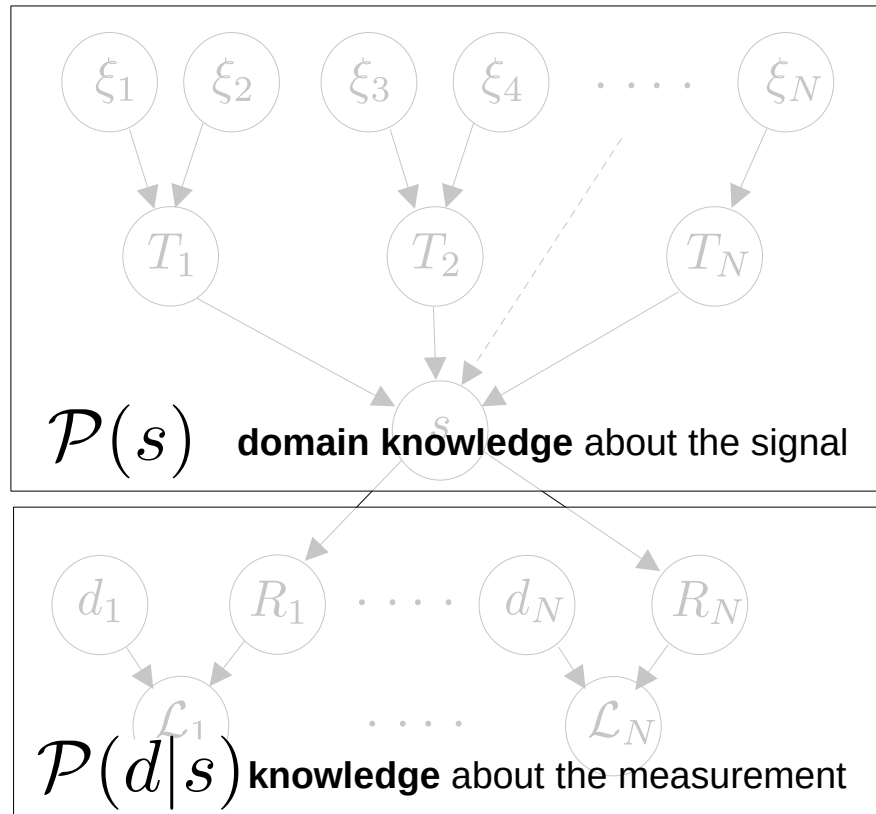
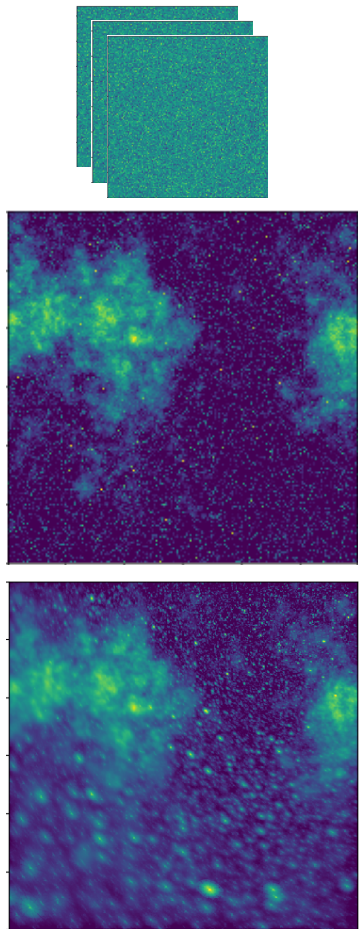


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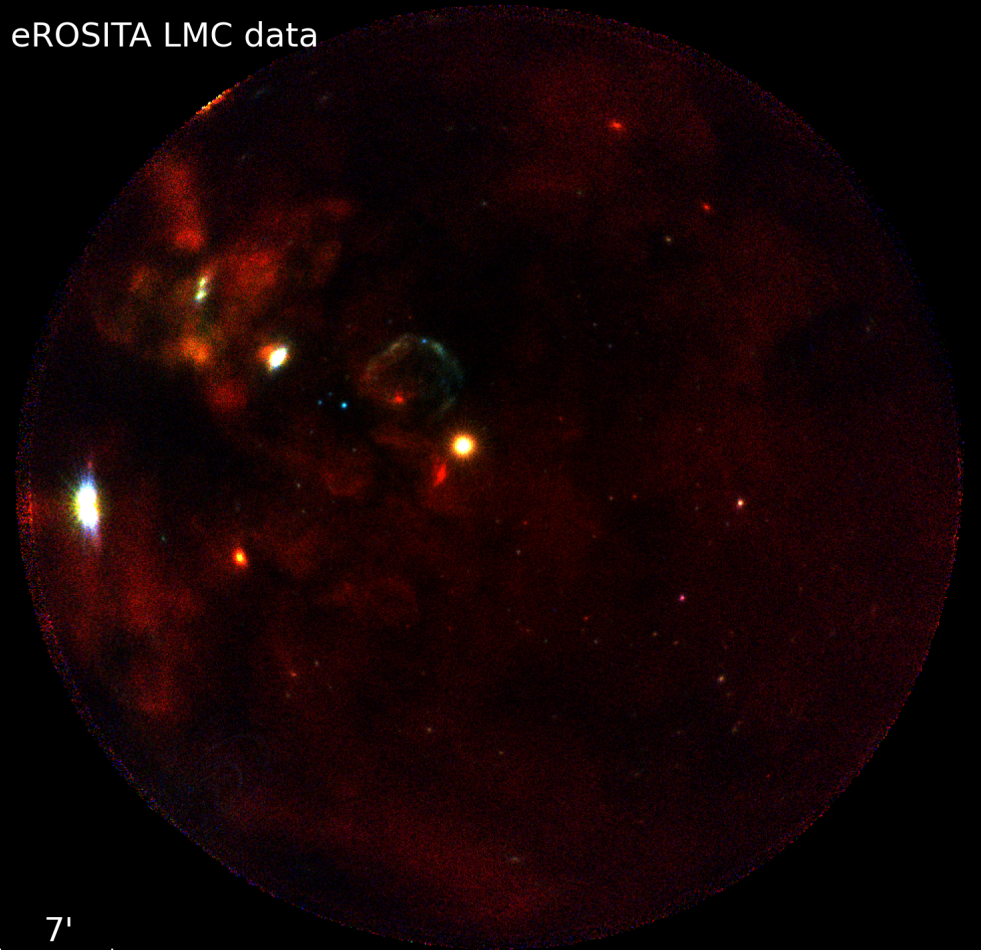
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Modeling the X-ray Sky – the Prior

eROSITA LMC data



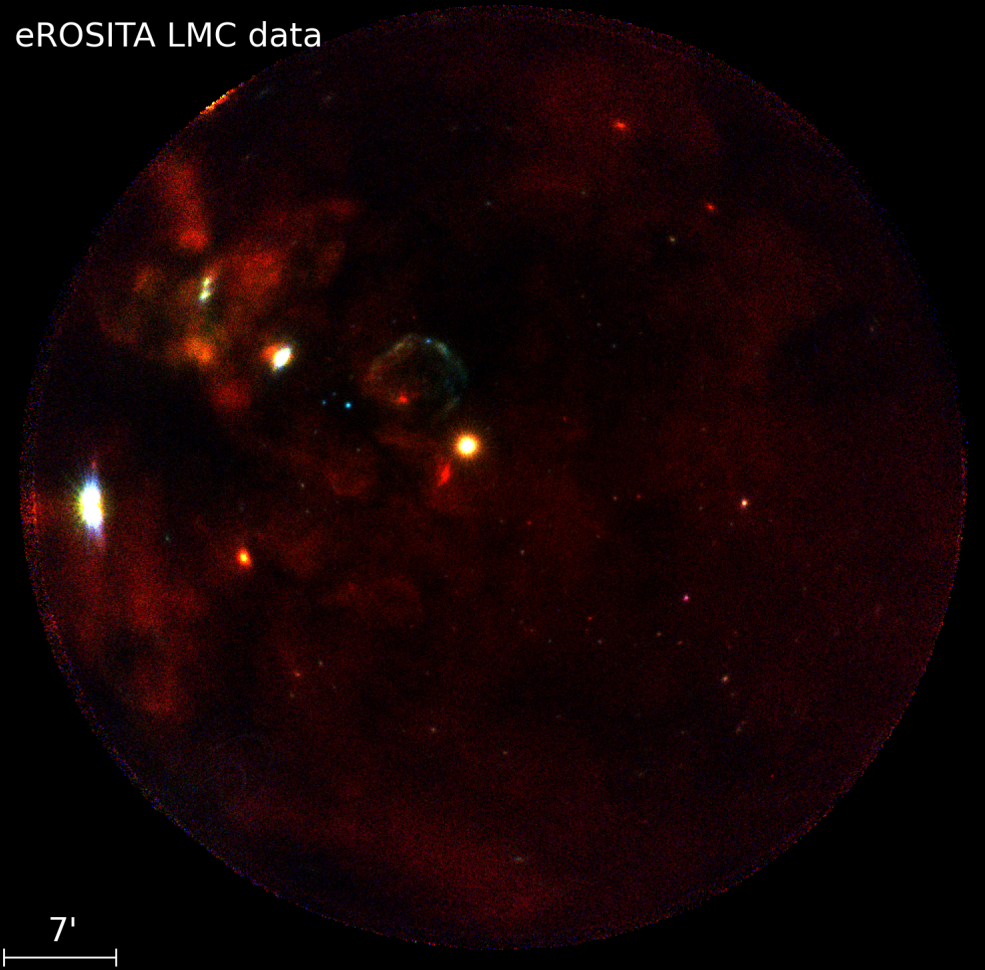
7'

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)

eROSITA LMC data



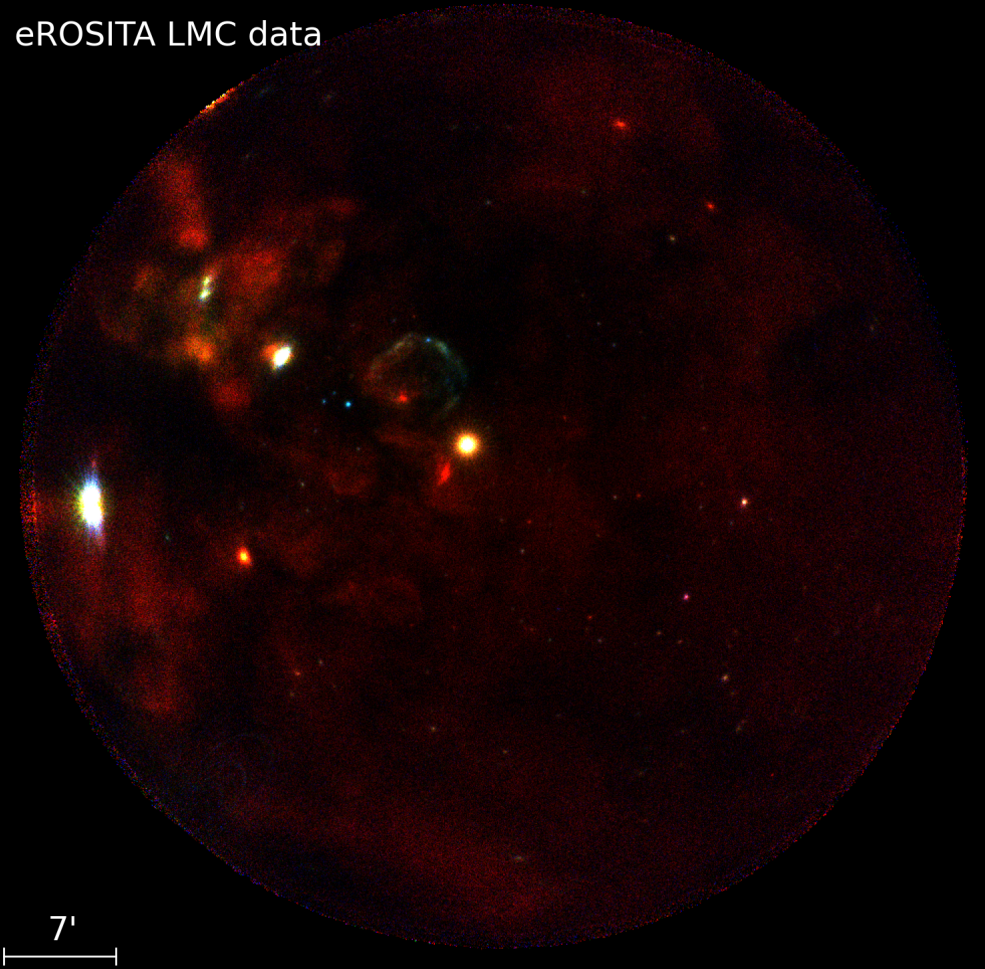
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Components

eROSITA LMC data



Modeling the X-ray Sky – the Prior

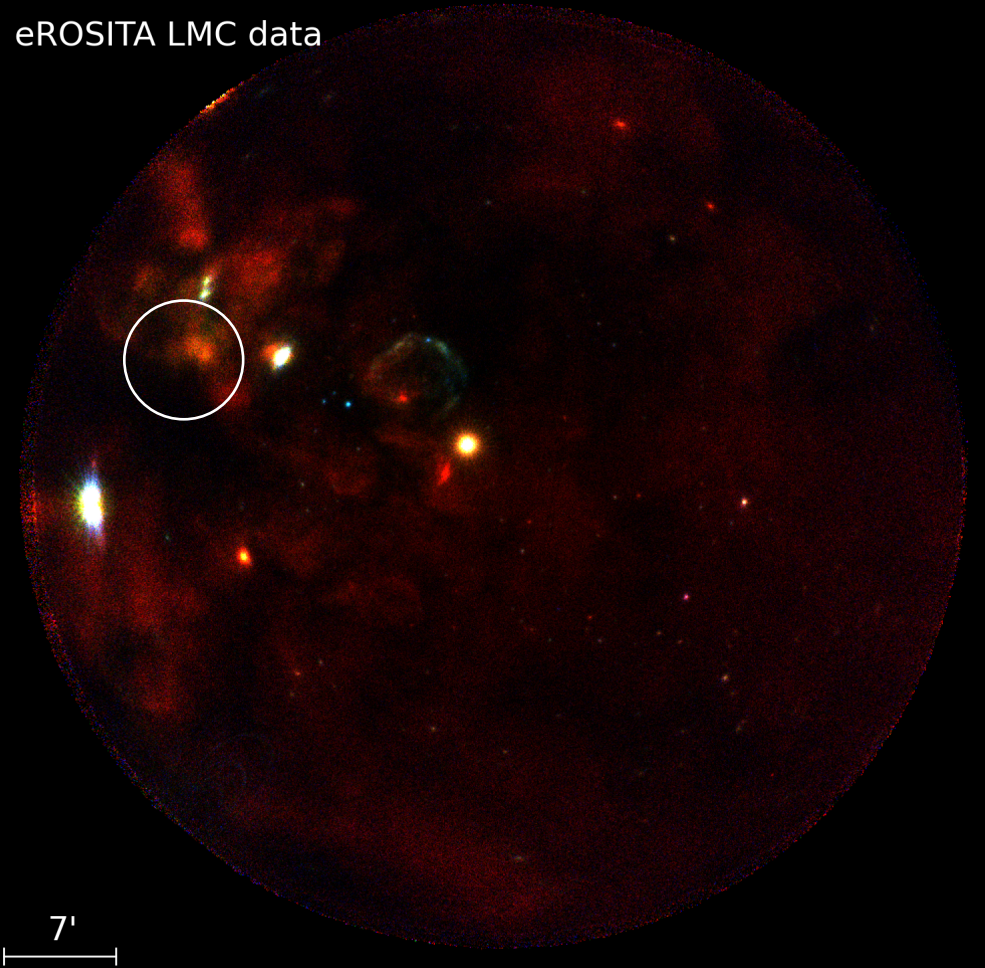
LMC 1987A dataset

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Components

- diffuse emission

eROSITA LMC data



Modeling the X-ray Sky – the Prior

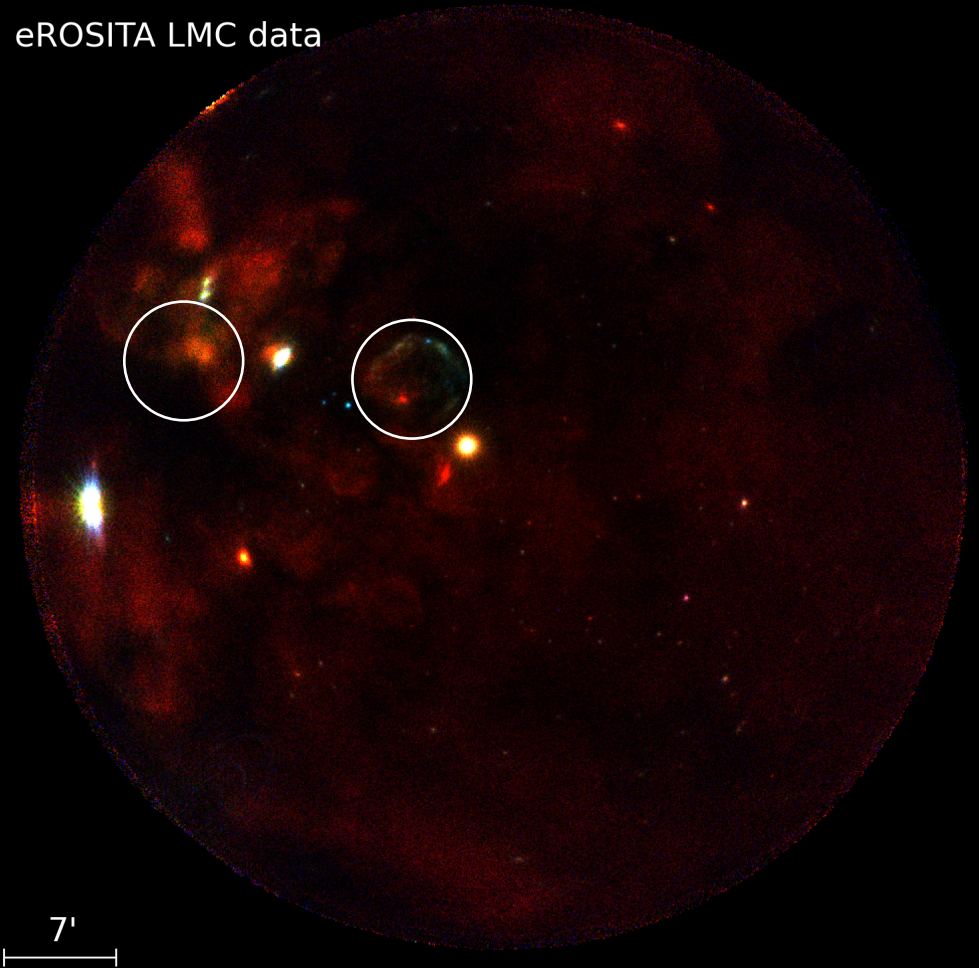
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Components

- diffuse emission
- extended sources (30 Doradus)

eROSITA LMC data



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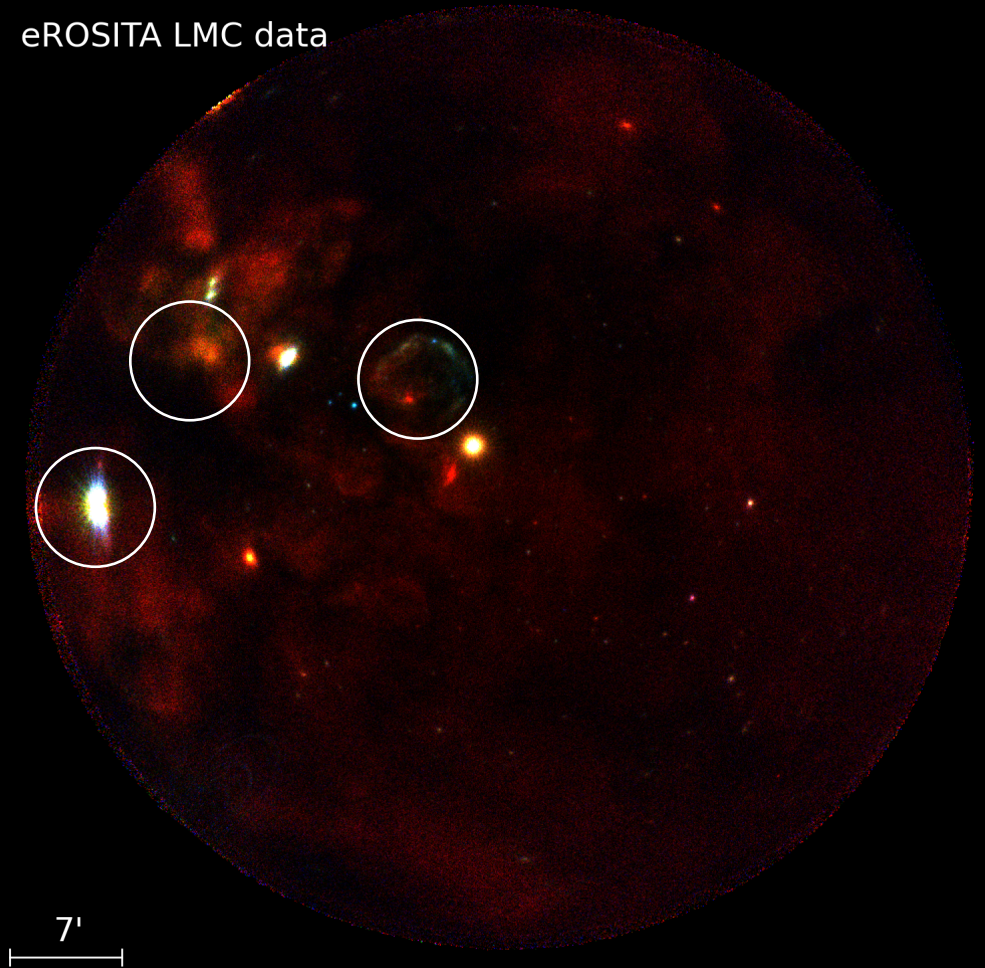
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Components

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

eROSITA LMC data



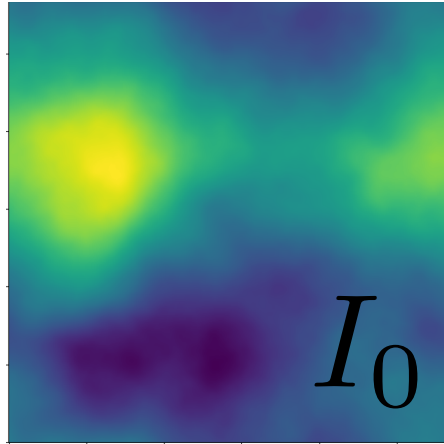
Modeling the Diffuse X-ray Sky

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

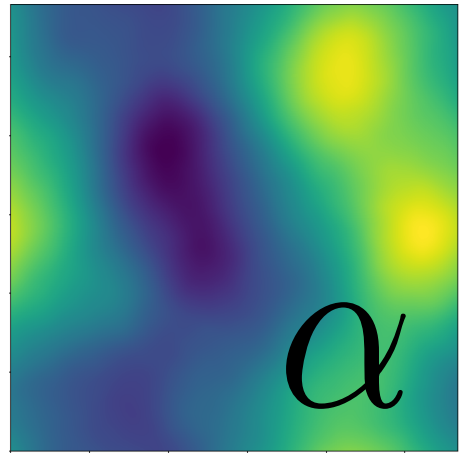
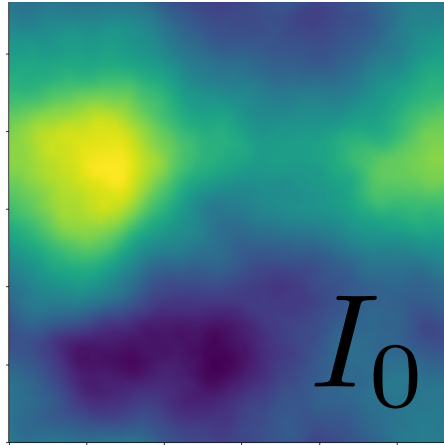
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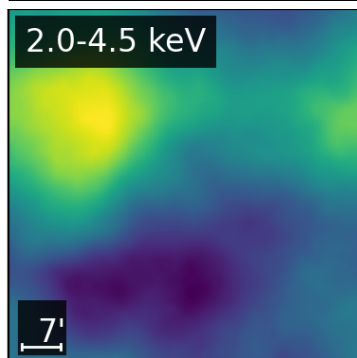
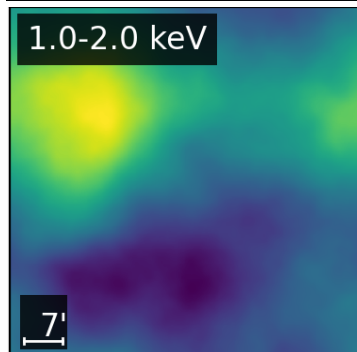
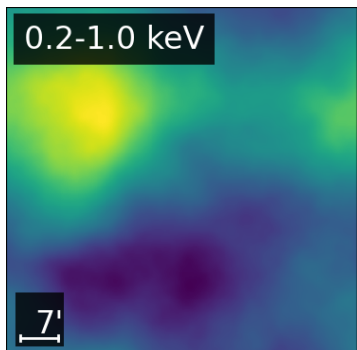


Modeling the Diffuse X-ray Sky

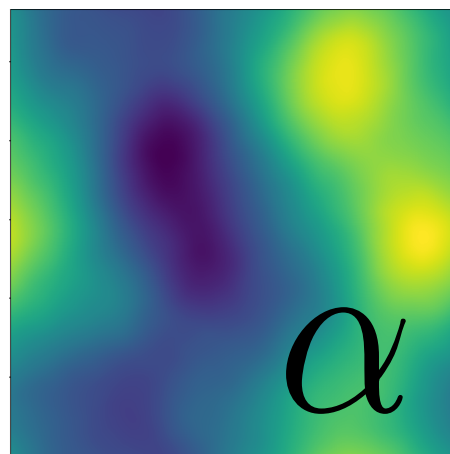
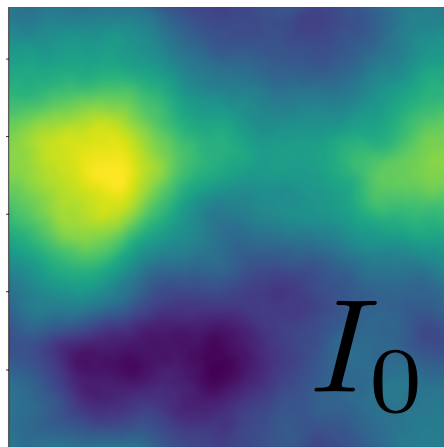
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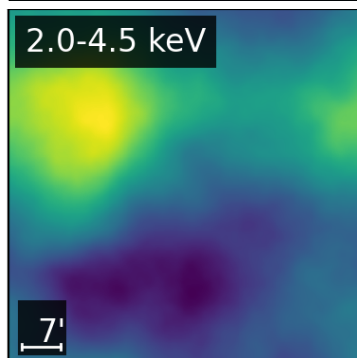
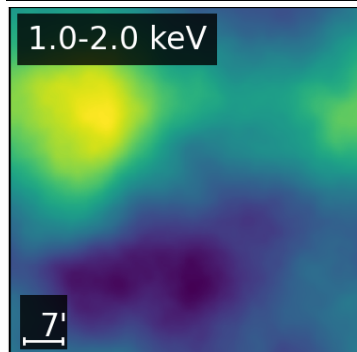
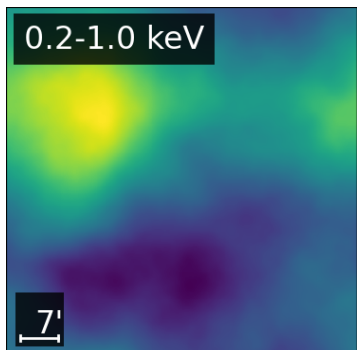
Modeling the Diffuse X-ray Sky



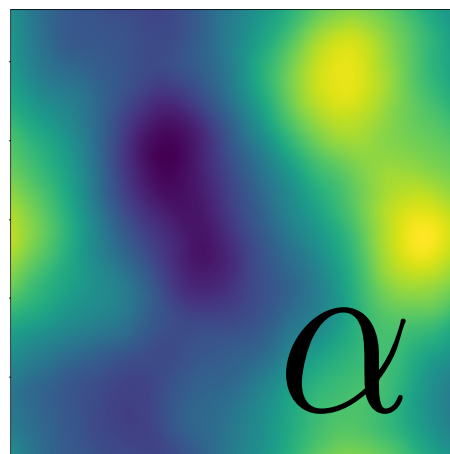
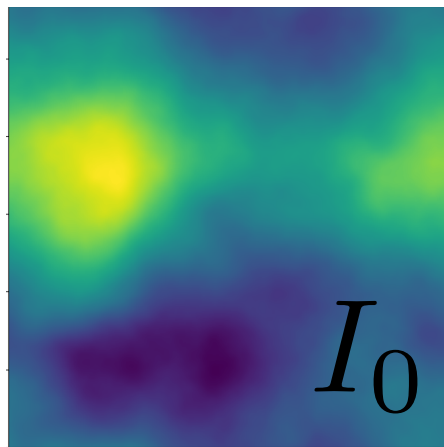
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Modeling the Diffuse X-ray Sky & Extended Sources



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



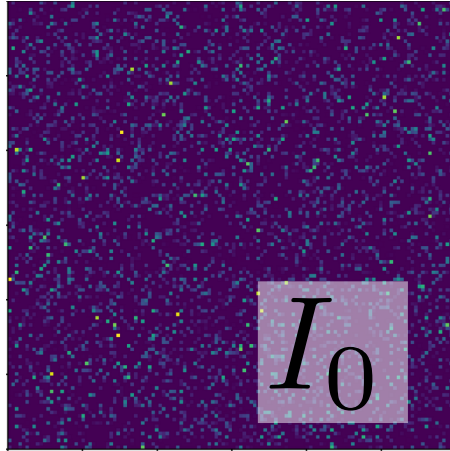
Modeling Point Sources

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$$p(x, \nu) = I_0(x) \cdot \exp(\alpha_p(x) \cdot \nu)$$

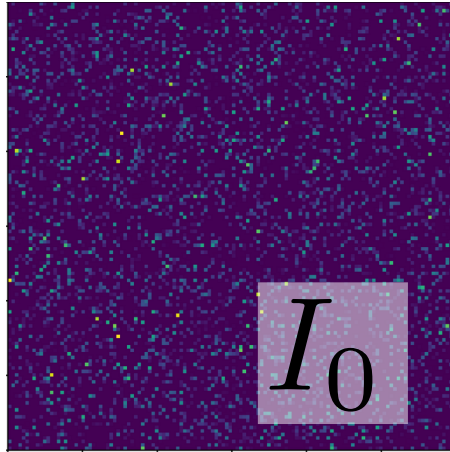
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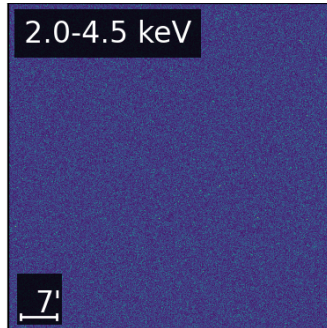
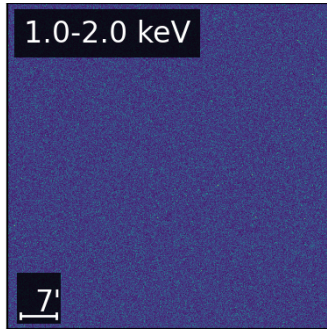
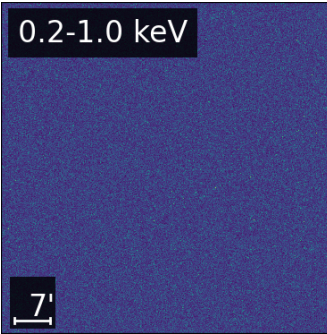


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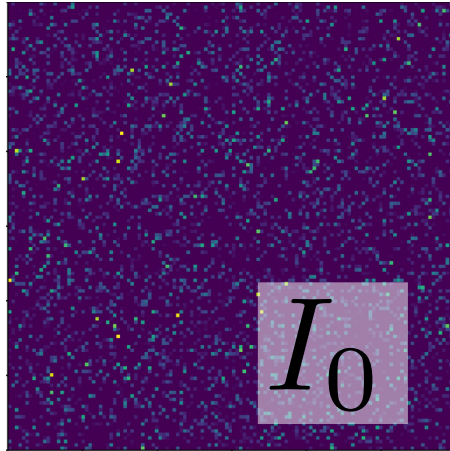
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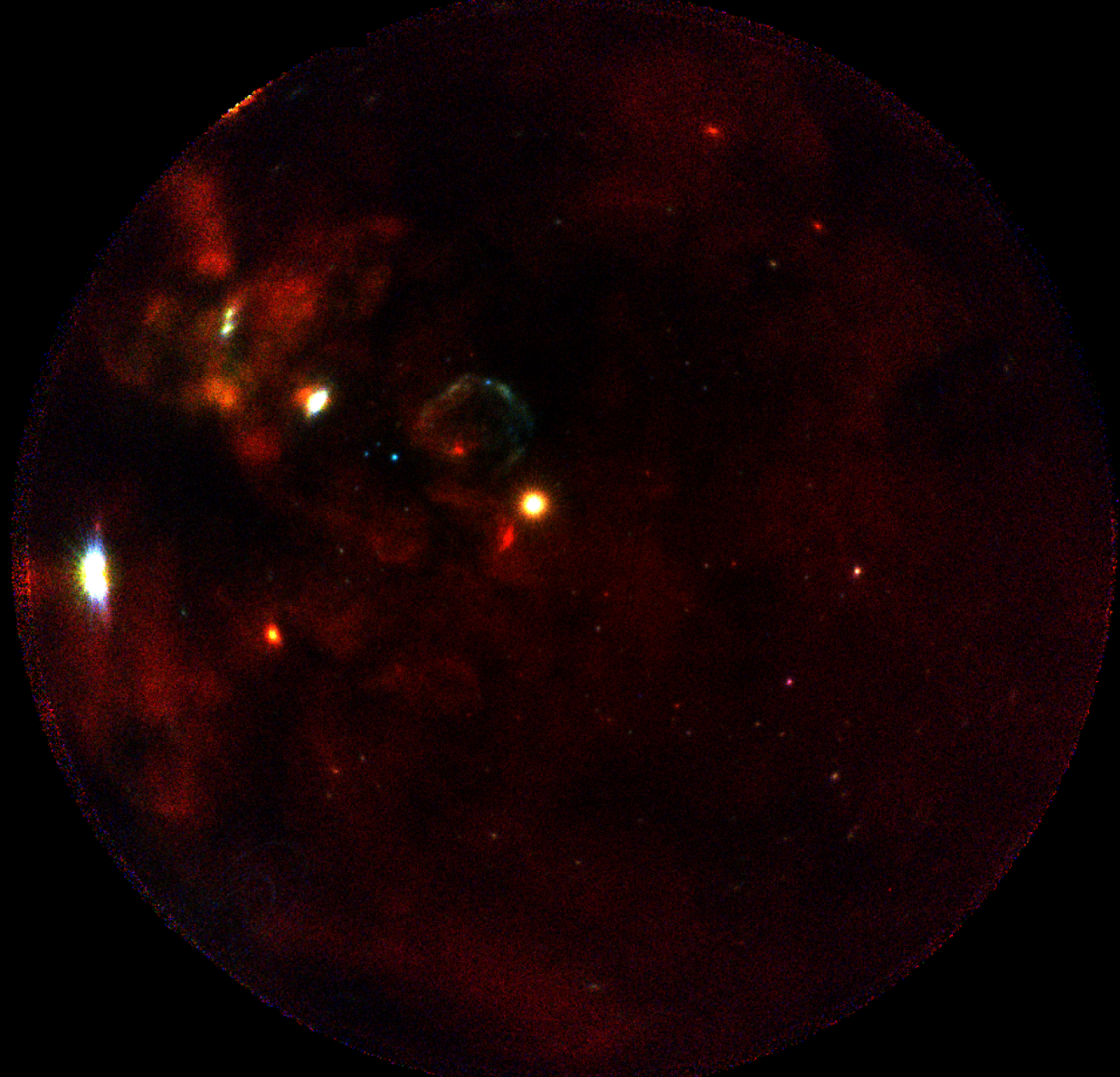


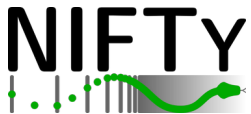
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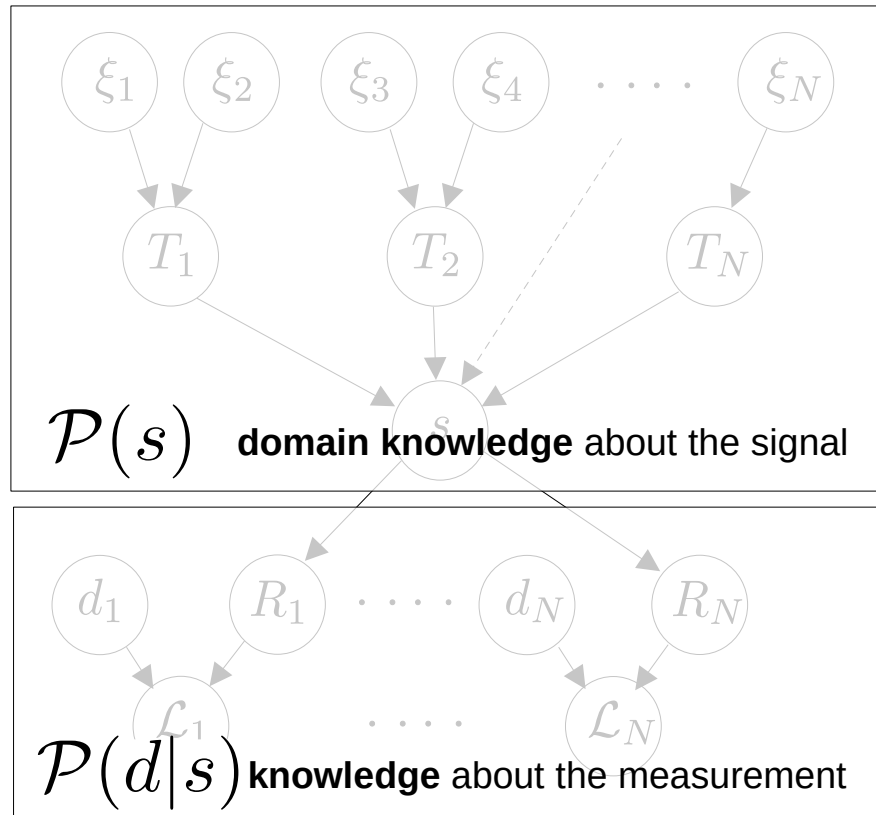
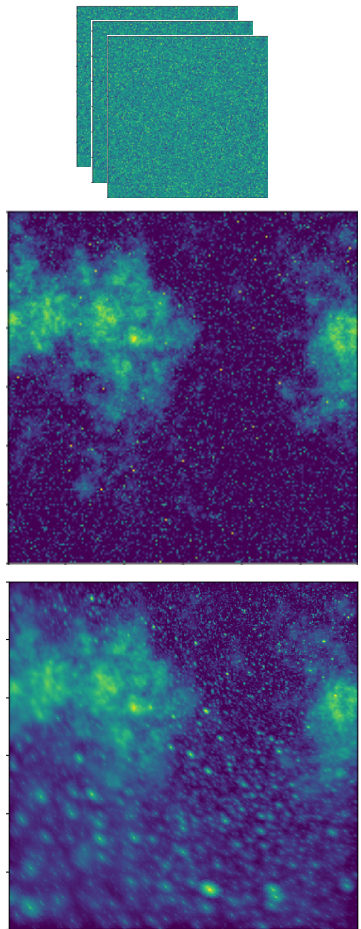


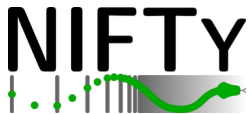
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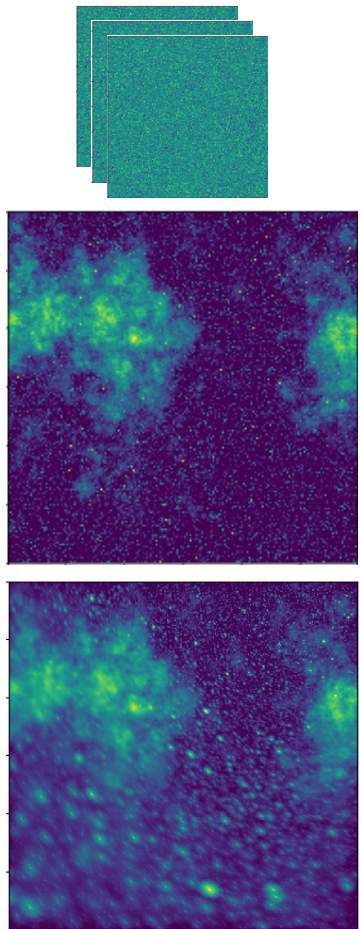




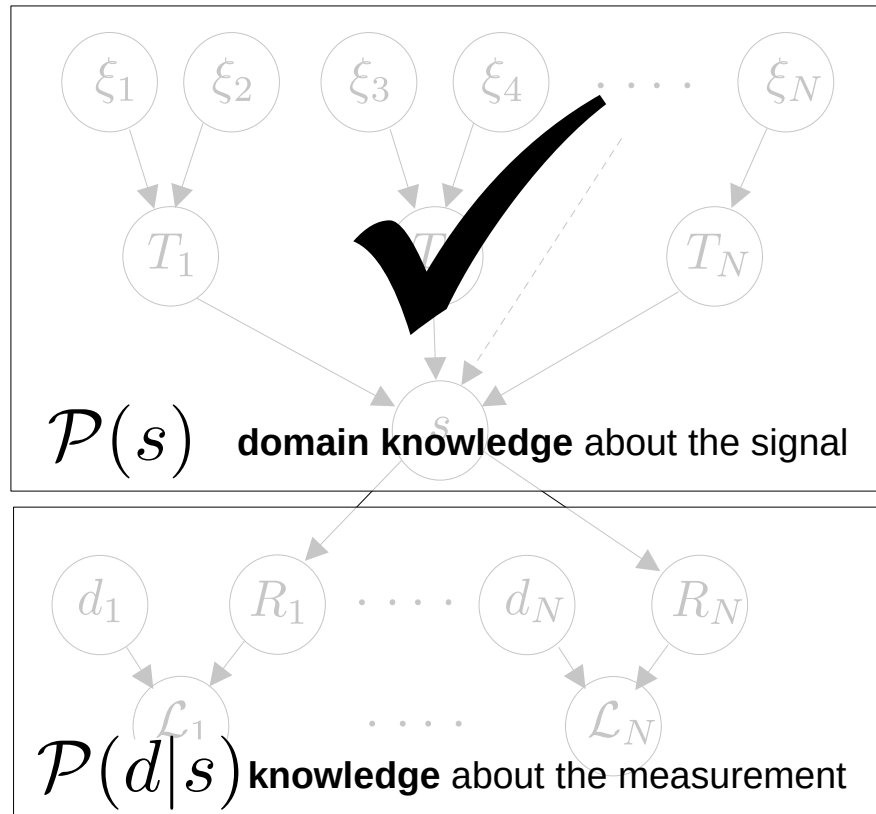
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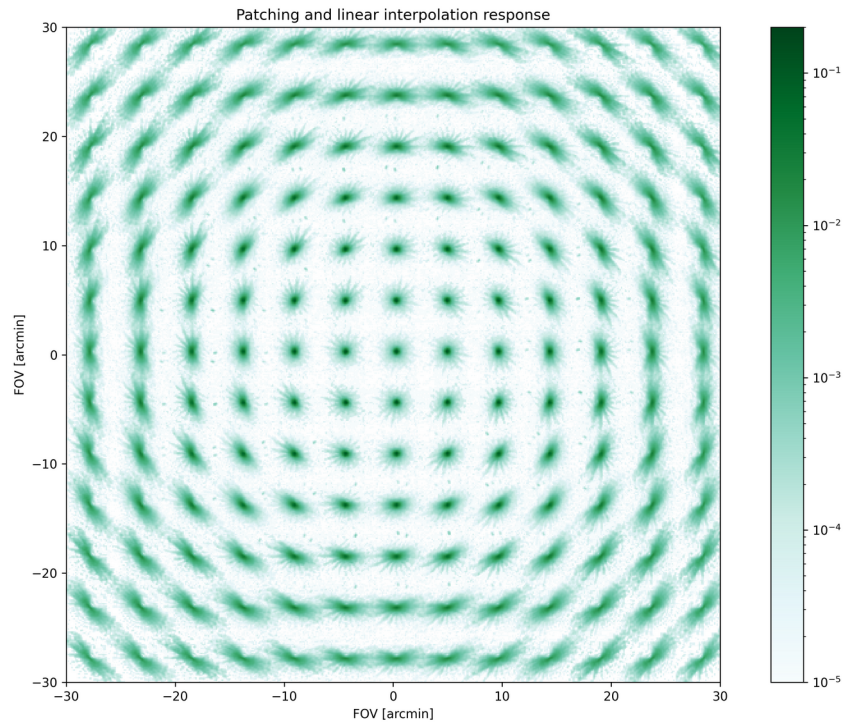
Modeling the Instrument

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Point spread functions from CALDB

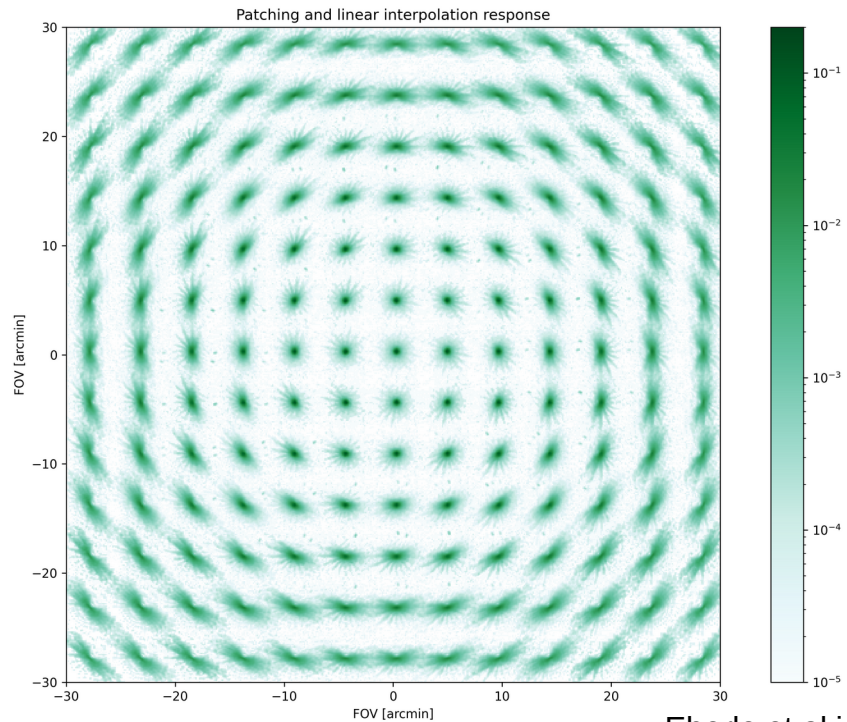
Modeling the Instrument

Point spread functions from CALDB



Modeling the Instrument

Point spread functions from CALDB



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.]

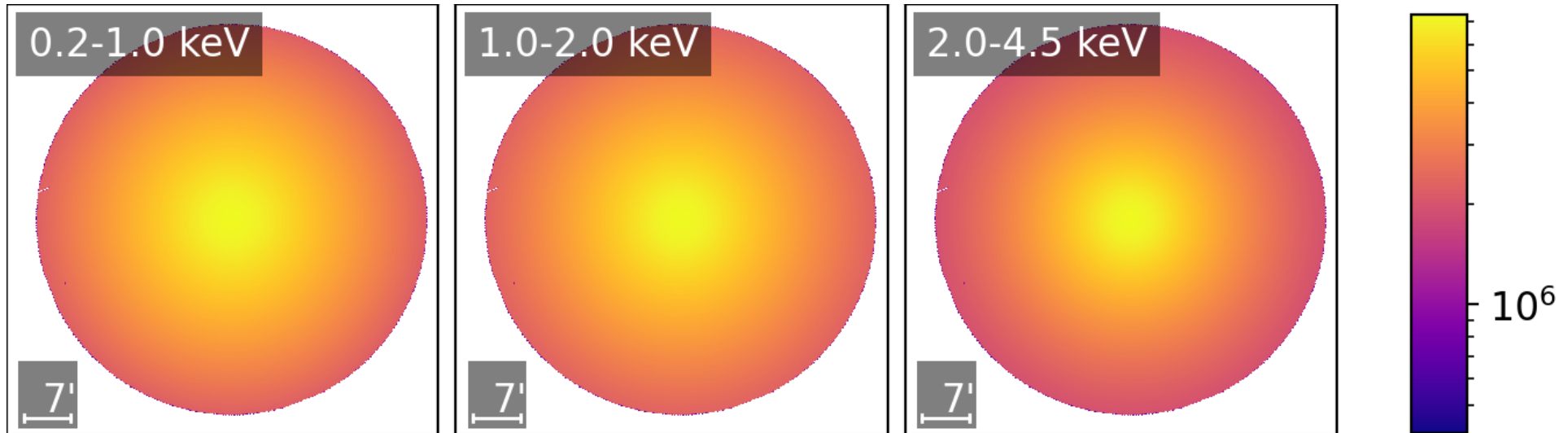
Eberle et al in prep.

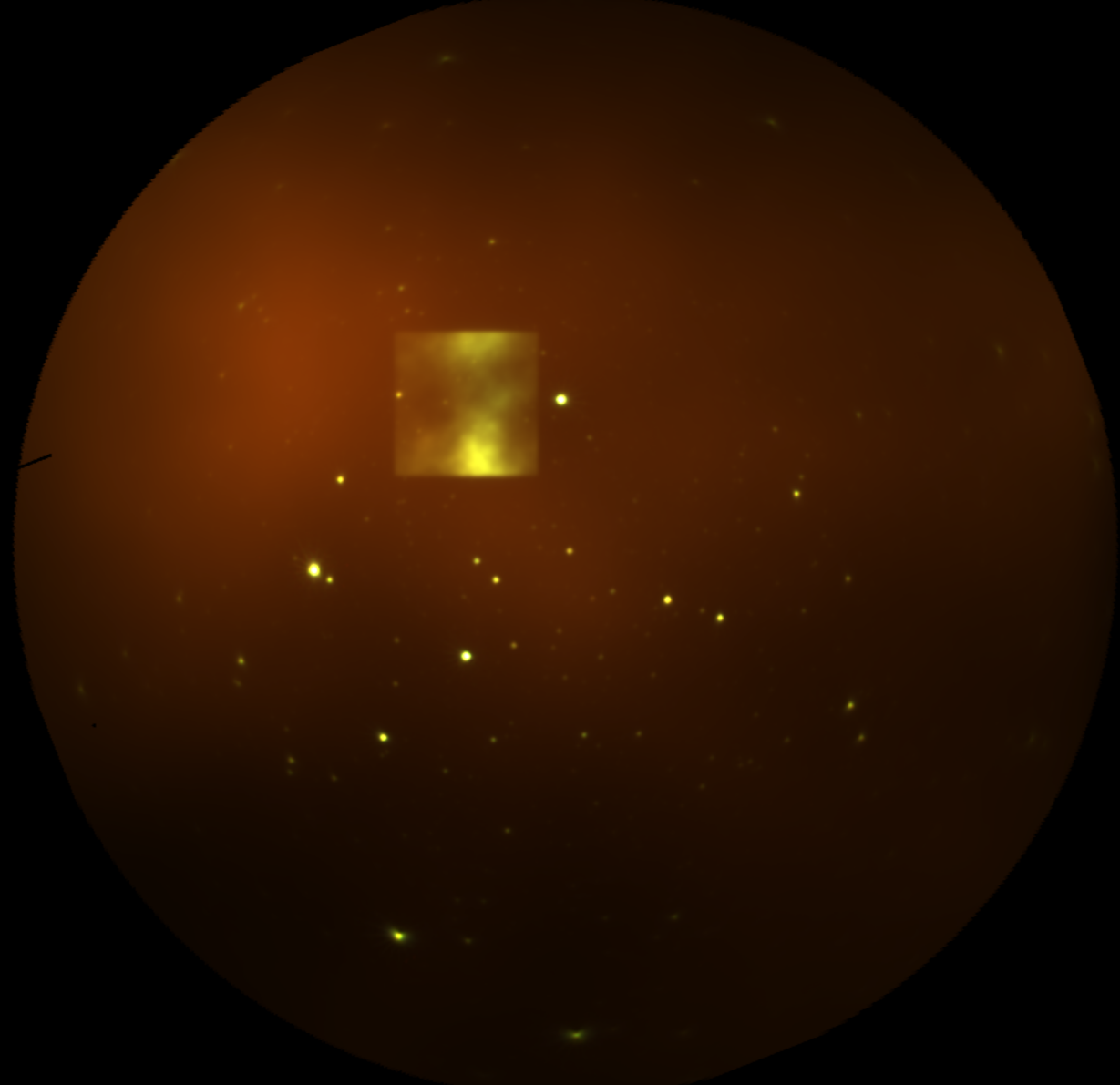
Modeling the Instrument

Exposure and Detmaps information from eSASS and CALDB

Modeling the Instrument

Exposure and Detmaps information from eSASS and CALDB





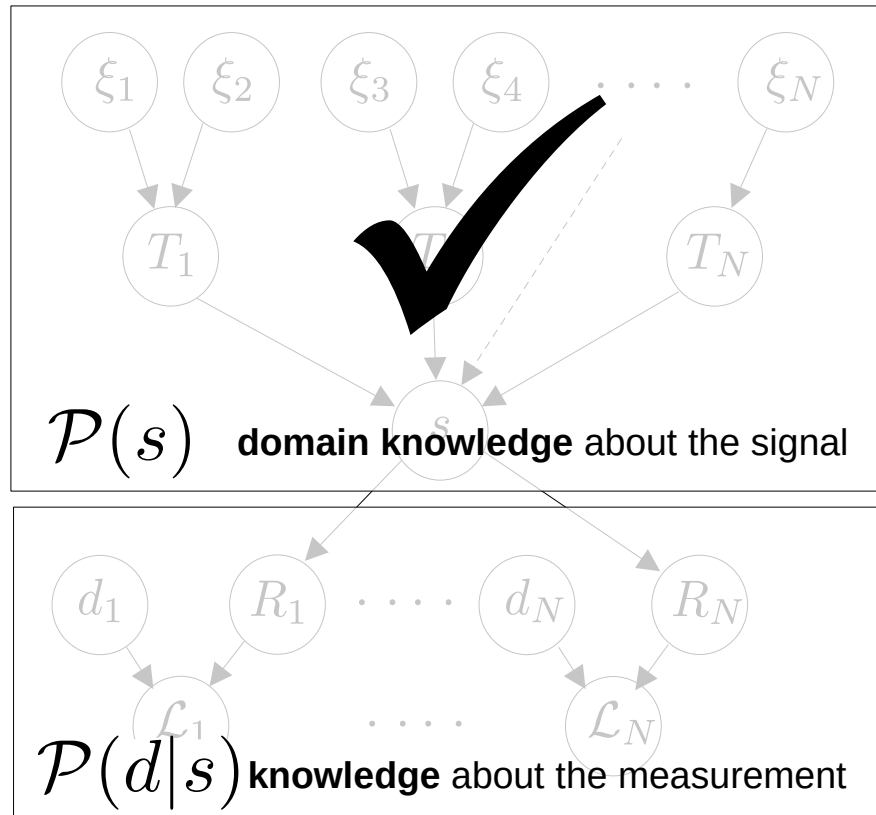
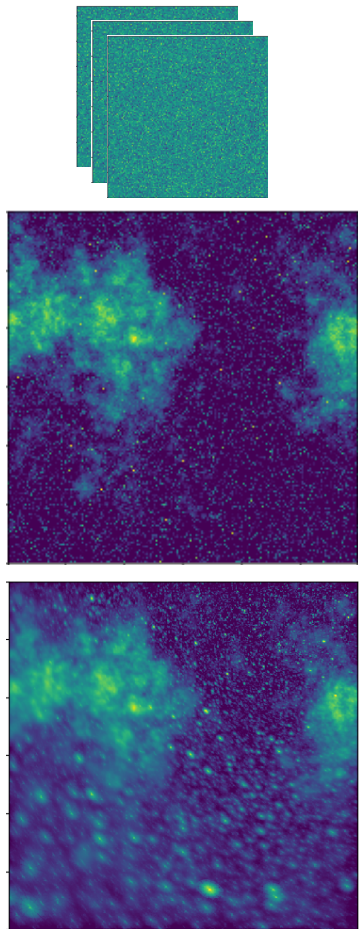


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$$\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$$



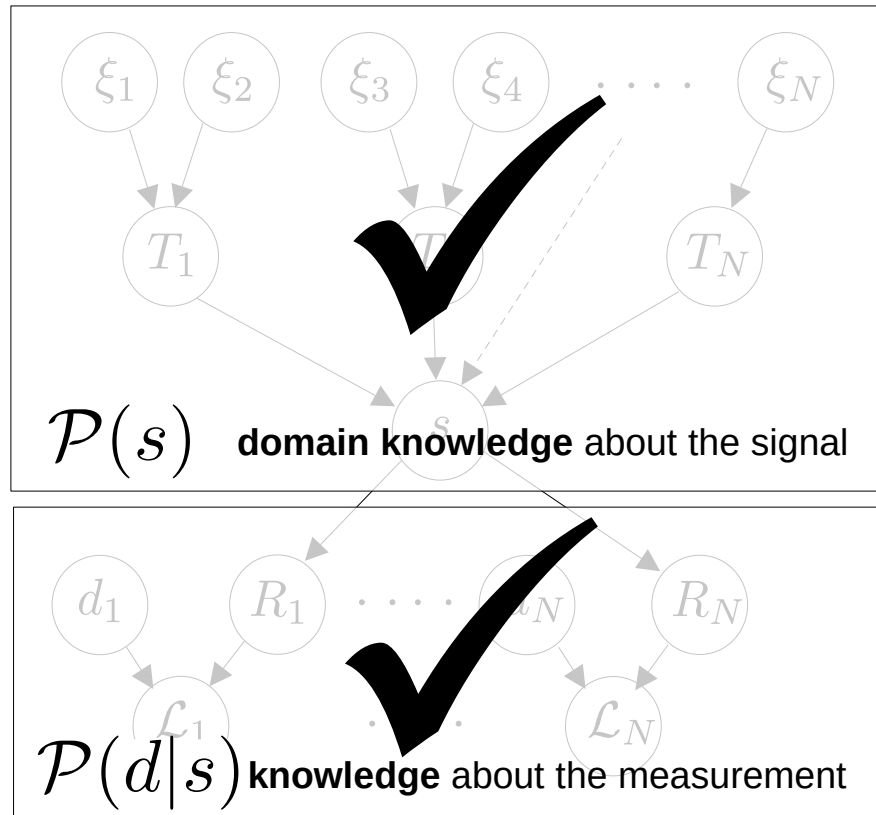
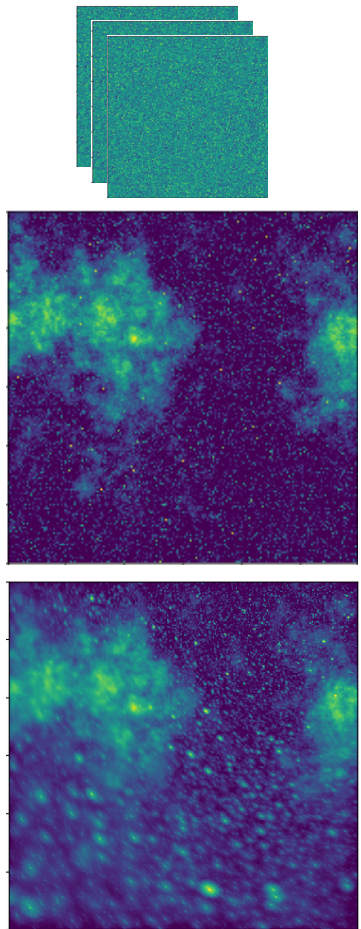


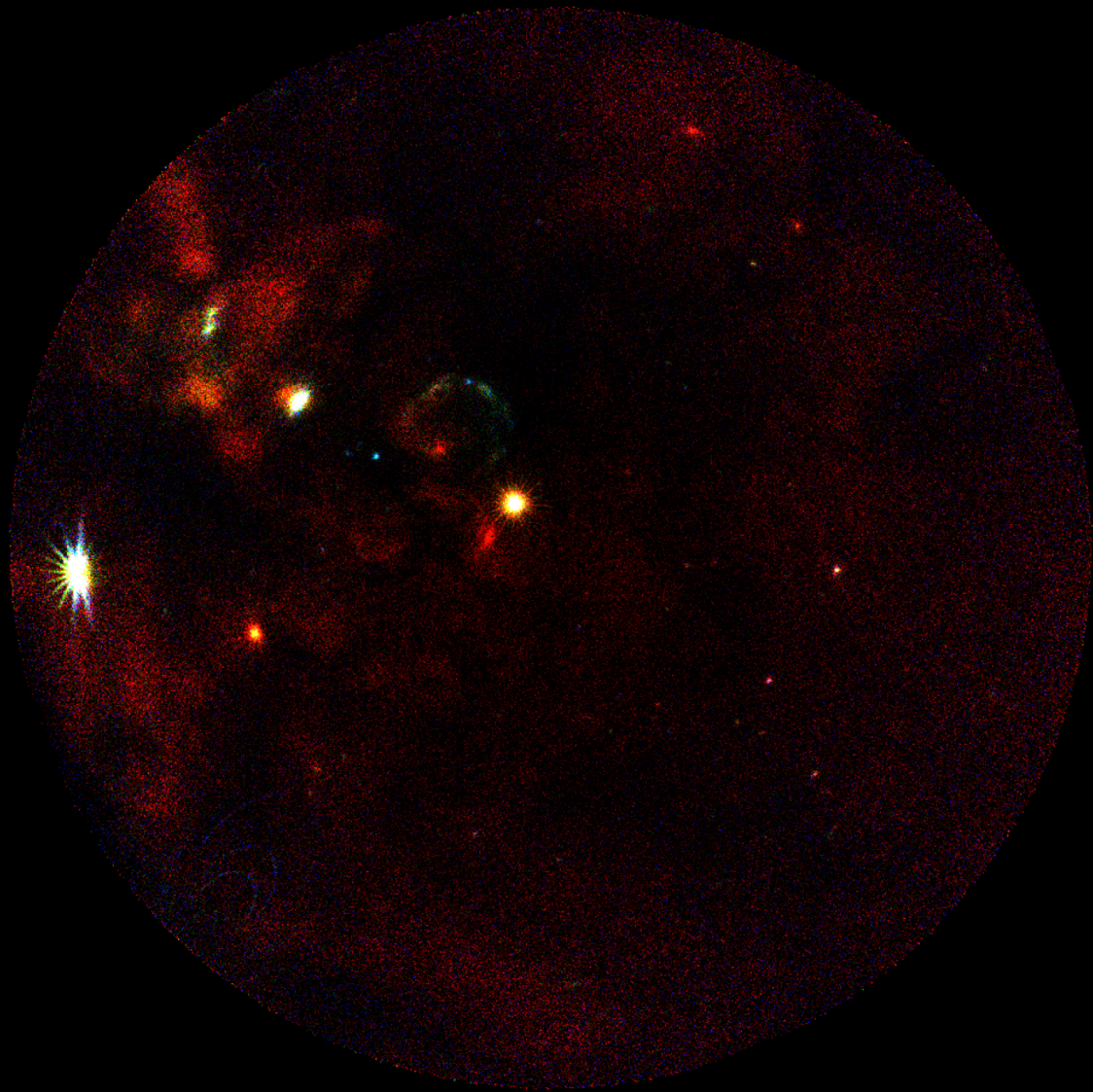
Generative Models for Bayesian Imaging

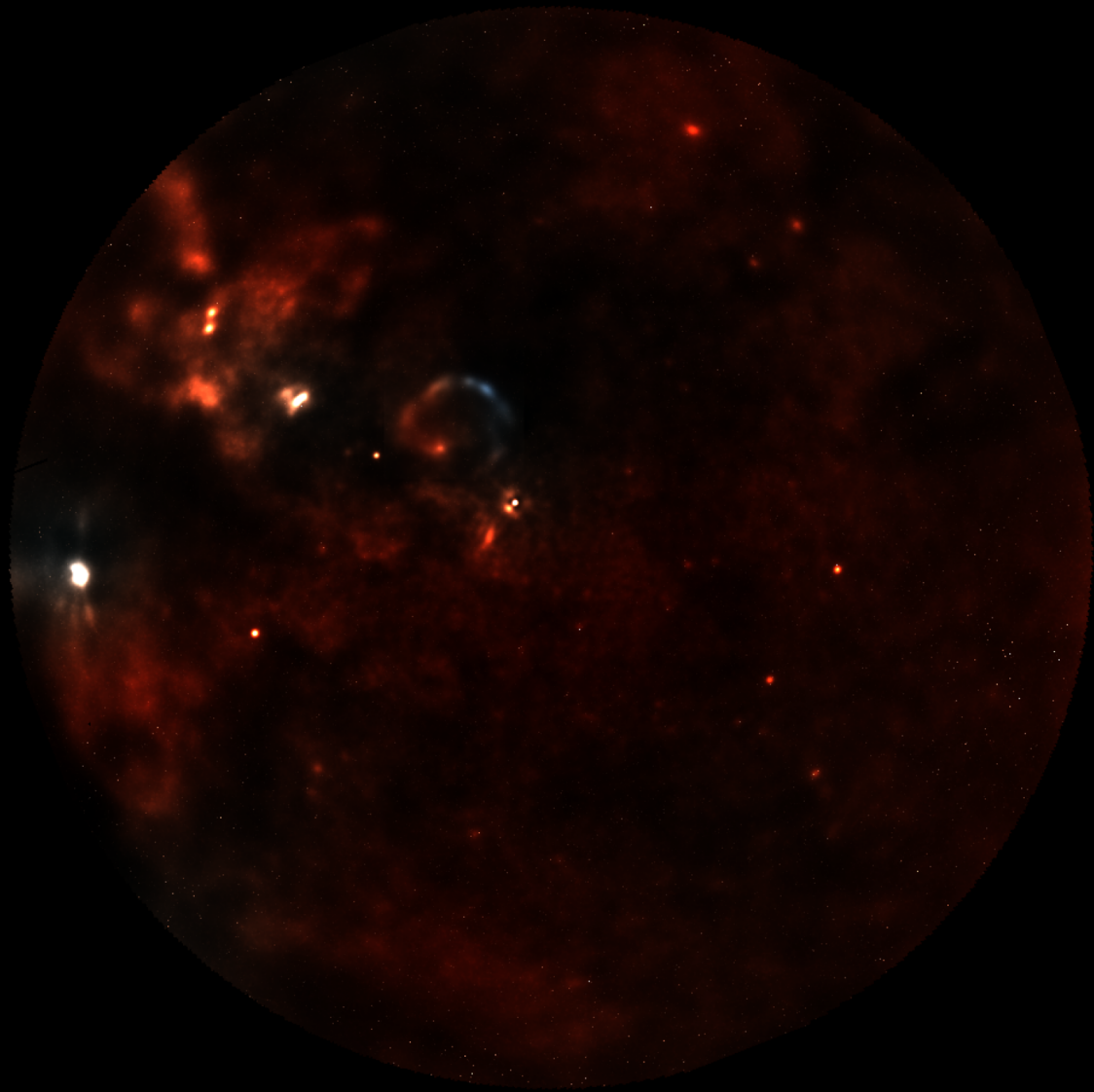
Framework: Numerical Information Field Theory

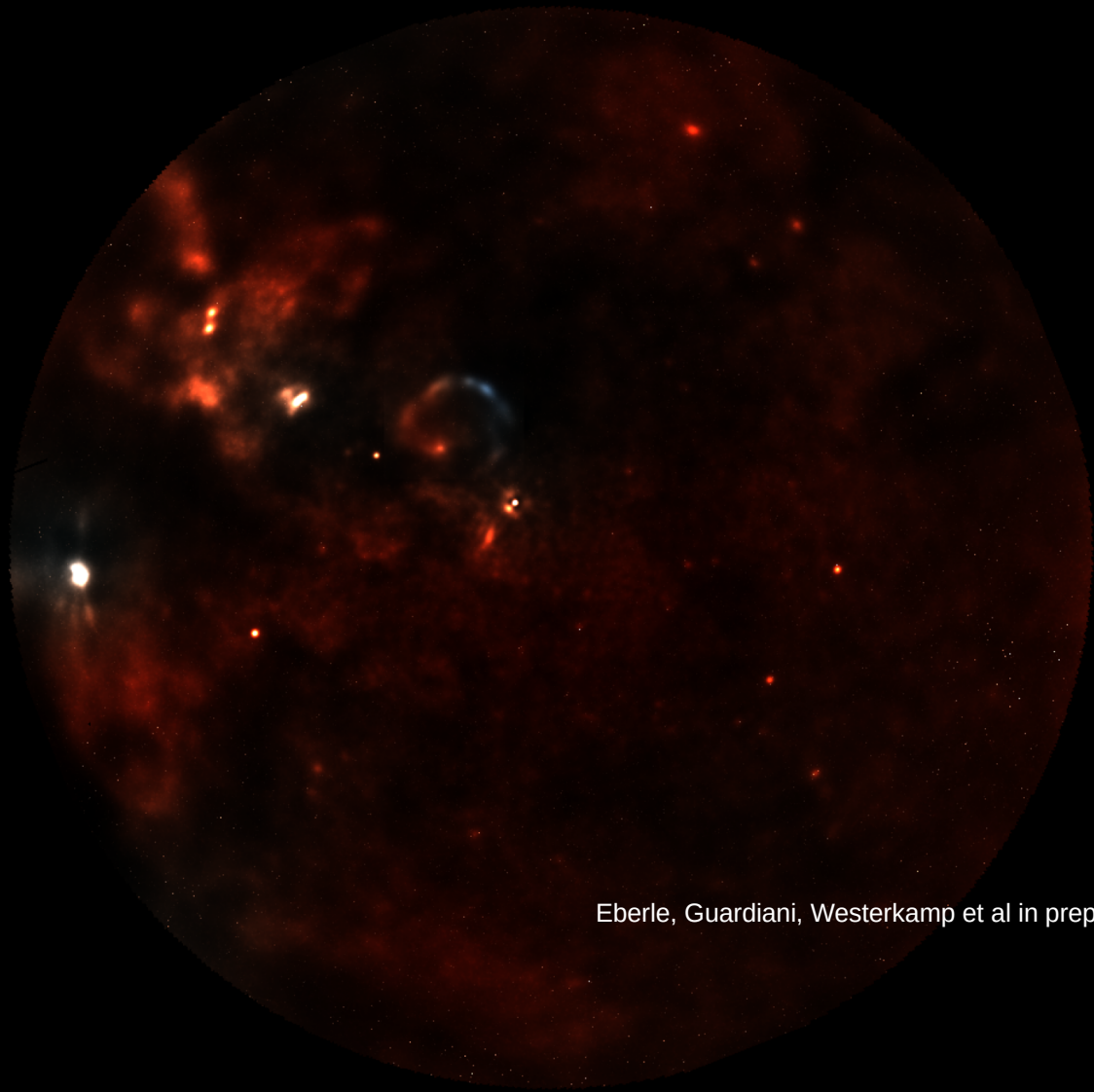
<https://github.com/NIFTy-PPL/NIFTy>

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



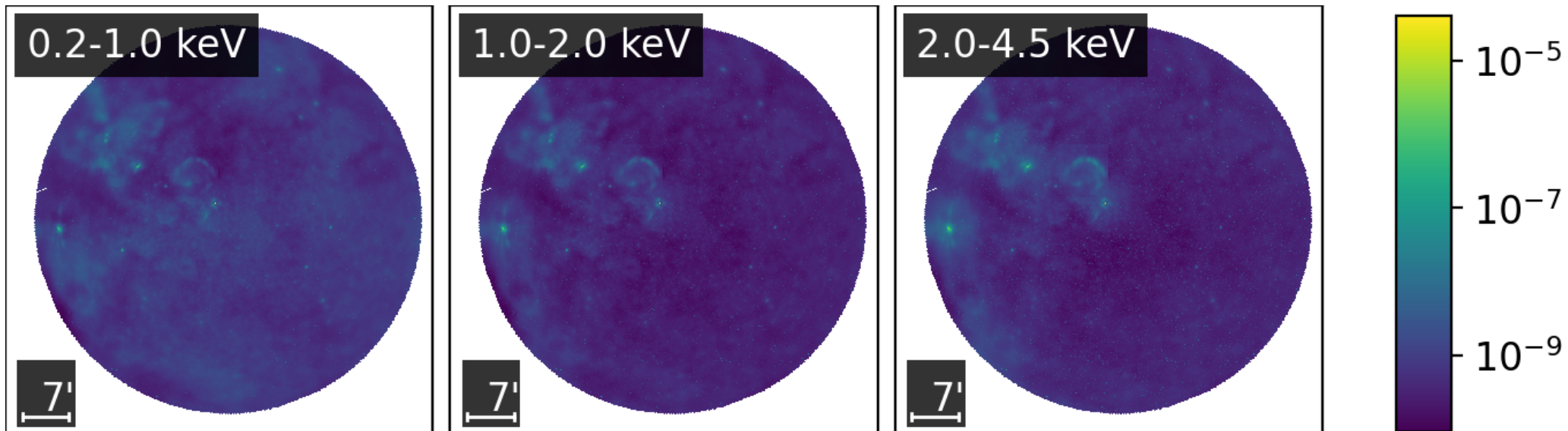




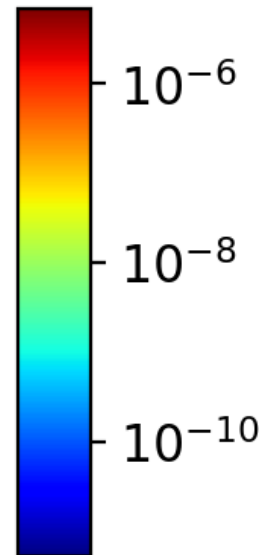
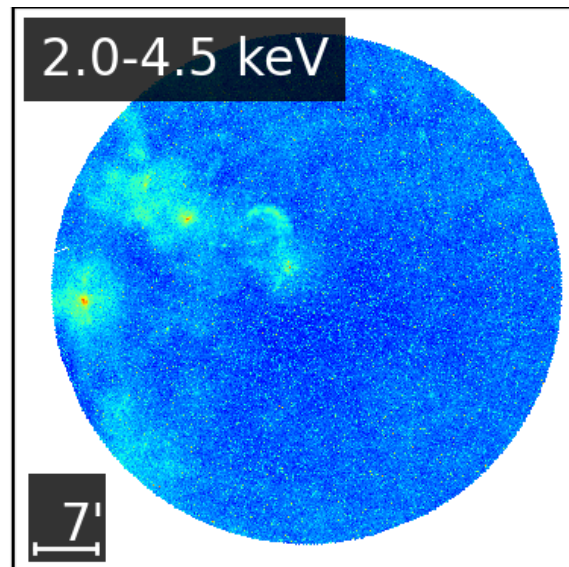
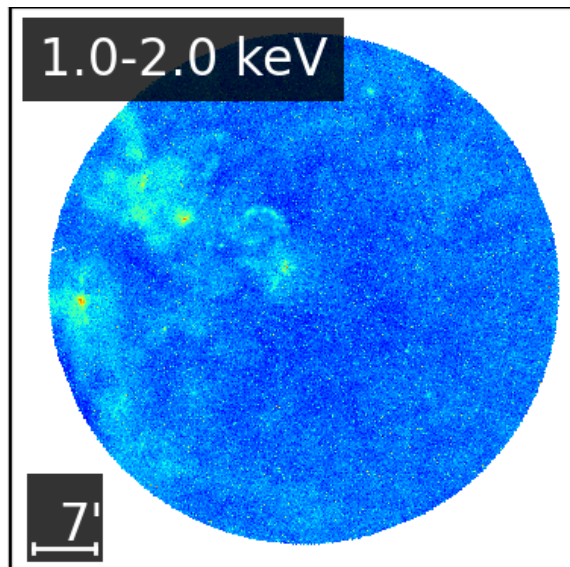
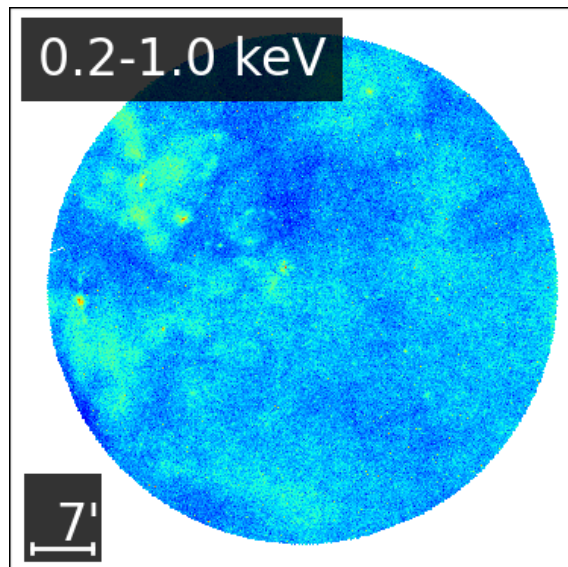


Eberle, Guardiani, Westerkamp et al in prep

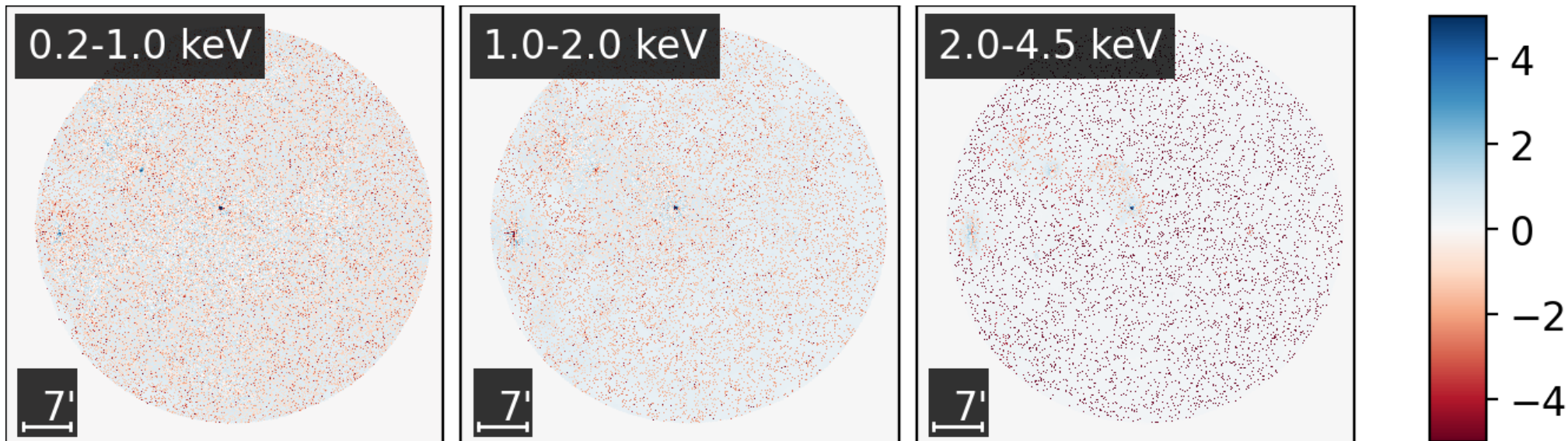
Posterior Mean Flux



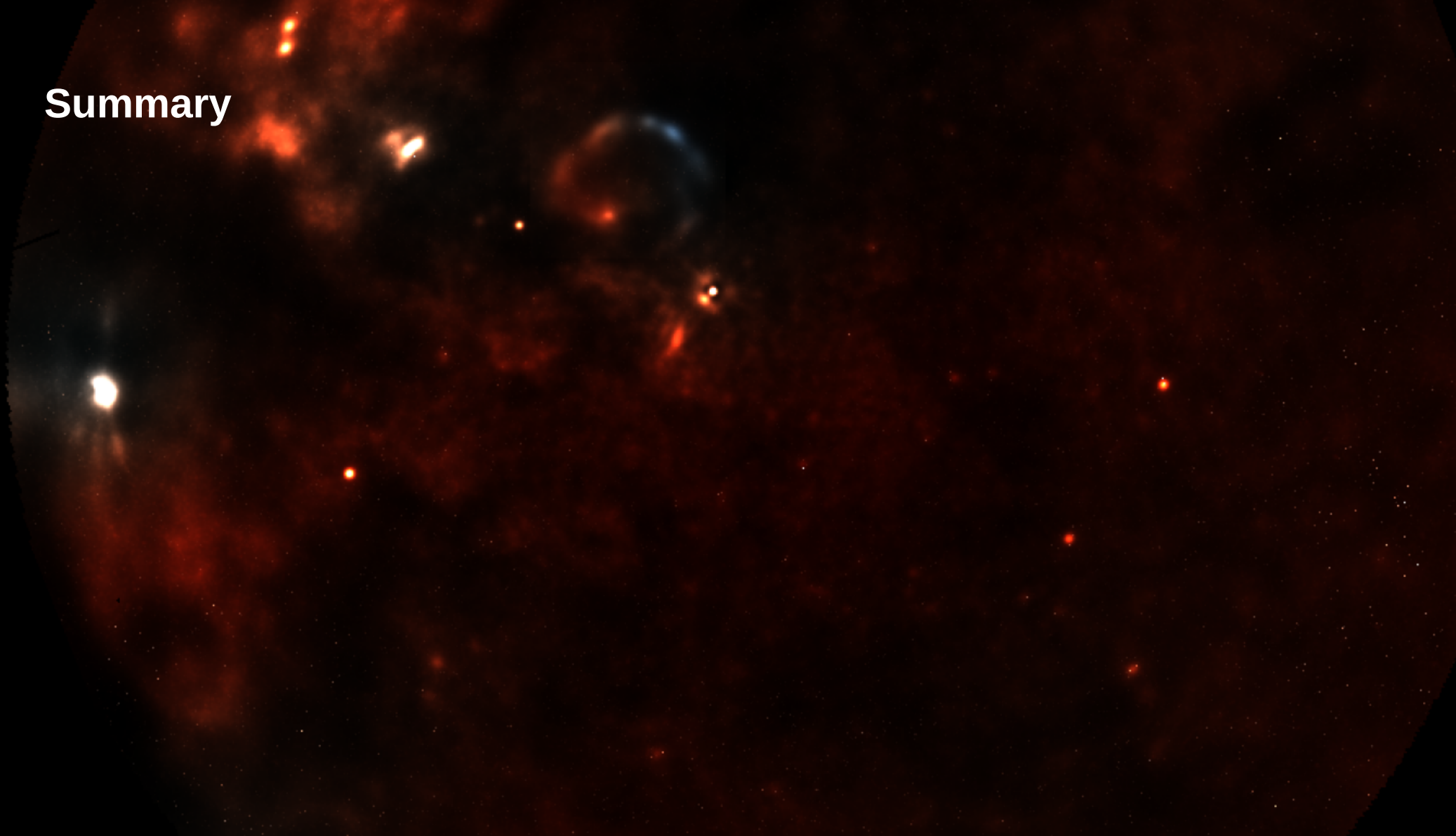
Uncertainties



Noise weighted residuals



Summary



Summary

A circular astronomical image showing a star field. The background is dark with a reddish, diffuse nebula or star-forming region. Several bright stars are visible, including a prominent white star on the left and a blue arc in the upper center. The overall color palette is dominated by reds and oranges, with some blue highlights.

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

Summary

A circular astronomical image showing a star field. The stars are mostly reddish-orange, with a few brighter white and yellow stars. A prominent blue arc is visible in the upper left quadrant. The background is dark with some faint, diffuse reddish structures.

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

- denoise

Summary

A circular astronomical image showing a field of stars. The stars are mostly reddish-orange, with a few brighter white and yellow stars. A prominent blue arc is visible in the upper left quadrant. The background is dark with some faint, diffuse reddish structures.

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

- denoise
- deconvolve

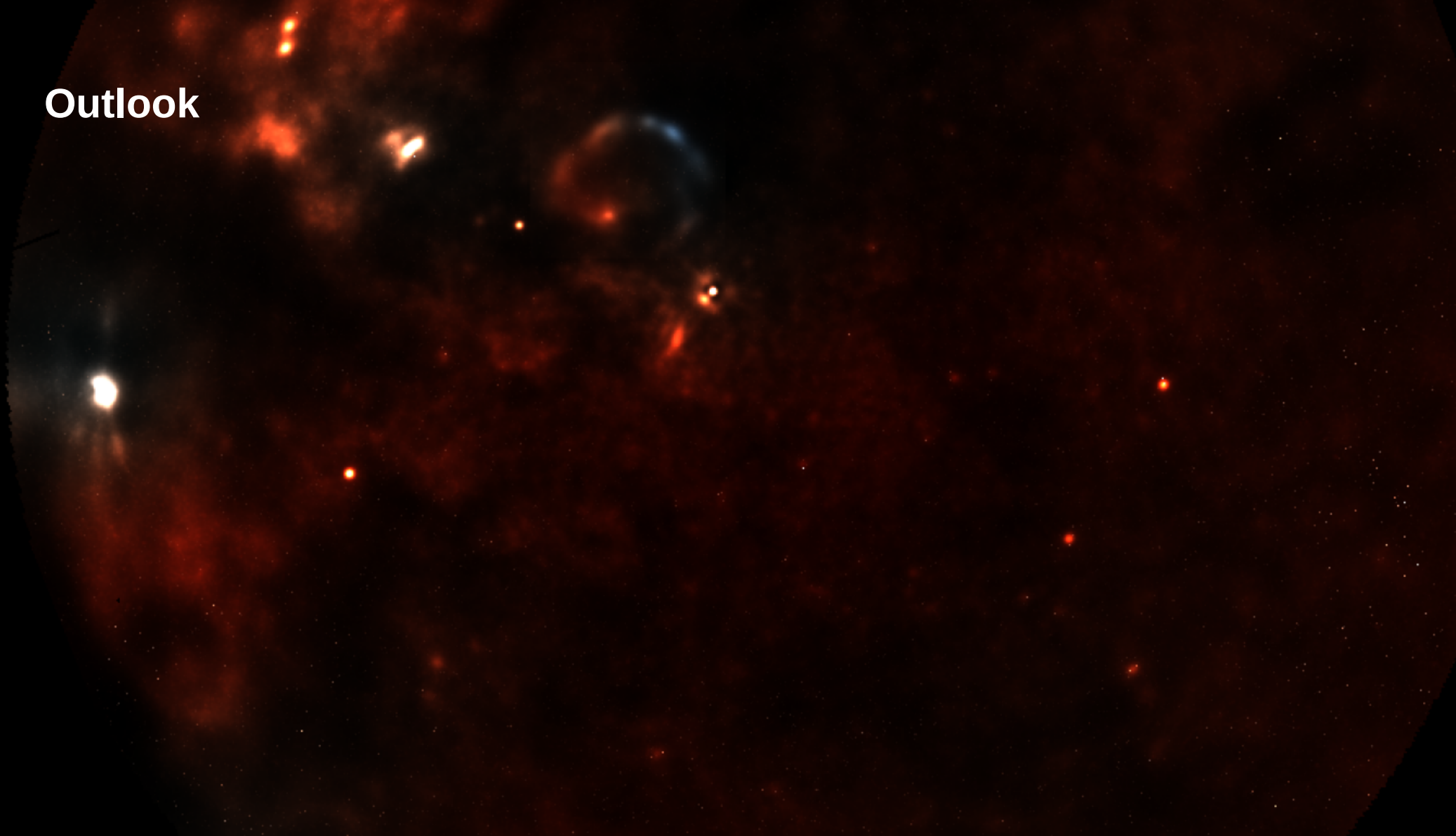
Summary

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

- denoise
- deconvolve
- decompose

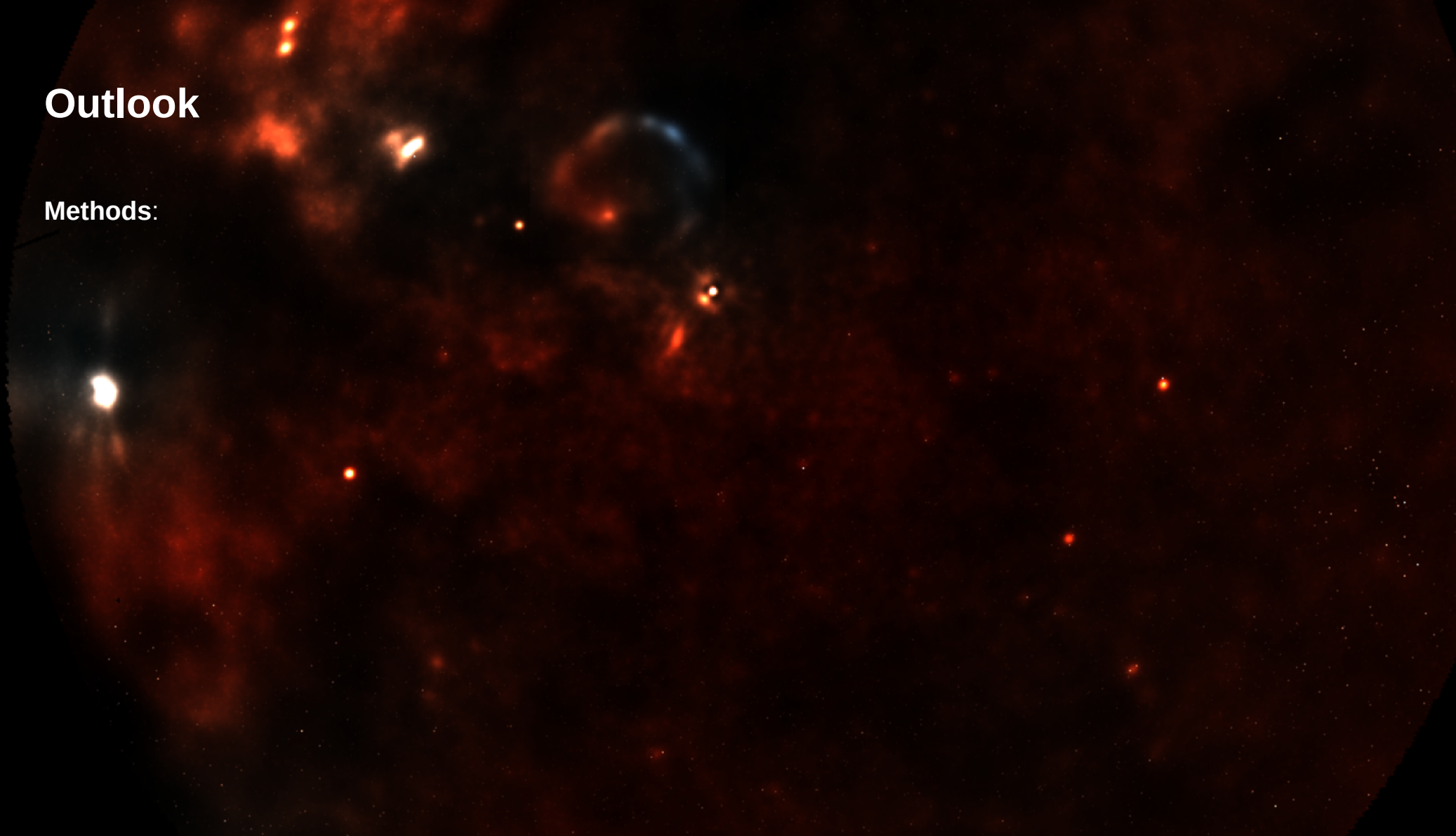
observations from X-ray observatories.

Outlook



Outlook

Methods:



Outlook



Methods:

- Self- and Cross-calibration

Outlook



Methods:

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

Outlook

The background of the slide is a circular astronomical image. It features a dense field of stars, with a prominent reddish-brown color palette. A faint, blue, ring-like structure is visible in the upper-middle portion of the image. The overall appearance is that of a deep-sky or multi-wavelength astronomical observation.

Methods:

- Self- and Cross-calibration
- Multi component sky models
- Automatic detection of extended components

Outlook

The background of the slide is a dark, reddish-brown astronomical image. It shows a dense field of stars, with some appearing as bright, distinct points of light and others as faint, diffuse clouds. In the upper central region, there is a prominent, faint blue ring-like structure, possibly a nebula or a specific astronomical feature. The overall color palette is dominated by dark reds and browns, with the blue ring providing a sharp contrast.

Methods:

- Self- and Cross-calibration
- Multi component sky models
- Automatic detection of extended components

Data:

Outlook



Methods:

- Self- and Cross-calibration
- Multi component sky models
- Automatic detection of extended components

Data:

- eFEDs

Outlook

The background of the slide is a deep red and orange astronomical image, likely a galaxy cluster. It features numerous bright, point-like sources of light, some appearing as white or yellow stars, and others as reddish-orange spots. A prominent, faint blue arc is visible in the upper central region. The overall texture is grainy and filled with smaller, dimmer red and orange specks, suggesting a rich field of galaxies or stars.

Methods:

- Self- and Cross-calibration
- Multi component sky models
- Automatic detection of extended components

Data:

- eFEDs
- Survey data

Outlook

Methods:

- Self- and Cross-calibration
- Multi component sky models
- Automatic detection of extended components

Data:

- eFEDs
- Survey data

more about the details:

The **Universal Bayesian Imaging Kit** [Margret Westerkamp]

Automatic Point Source Detection through Model Stress [Matteo Guardiani]