

Bayesian multiband imaging of SN1987A in the Large Magellanic Cloud with SRG/eROSITA

Vincent Eberle
Information Field Theory Group

Machine Learning for Astrophysics
3rd Edition, Valetta
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Acknowledgements:

Matteo Guardiani, Margret Westerkamp,
Philipp Frank, Michael Freyberg,
Mara Salvato, Torsten Enßlin

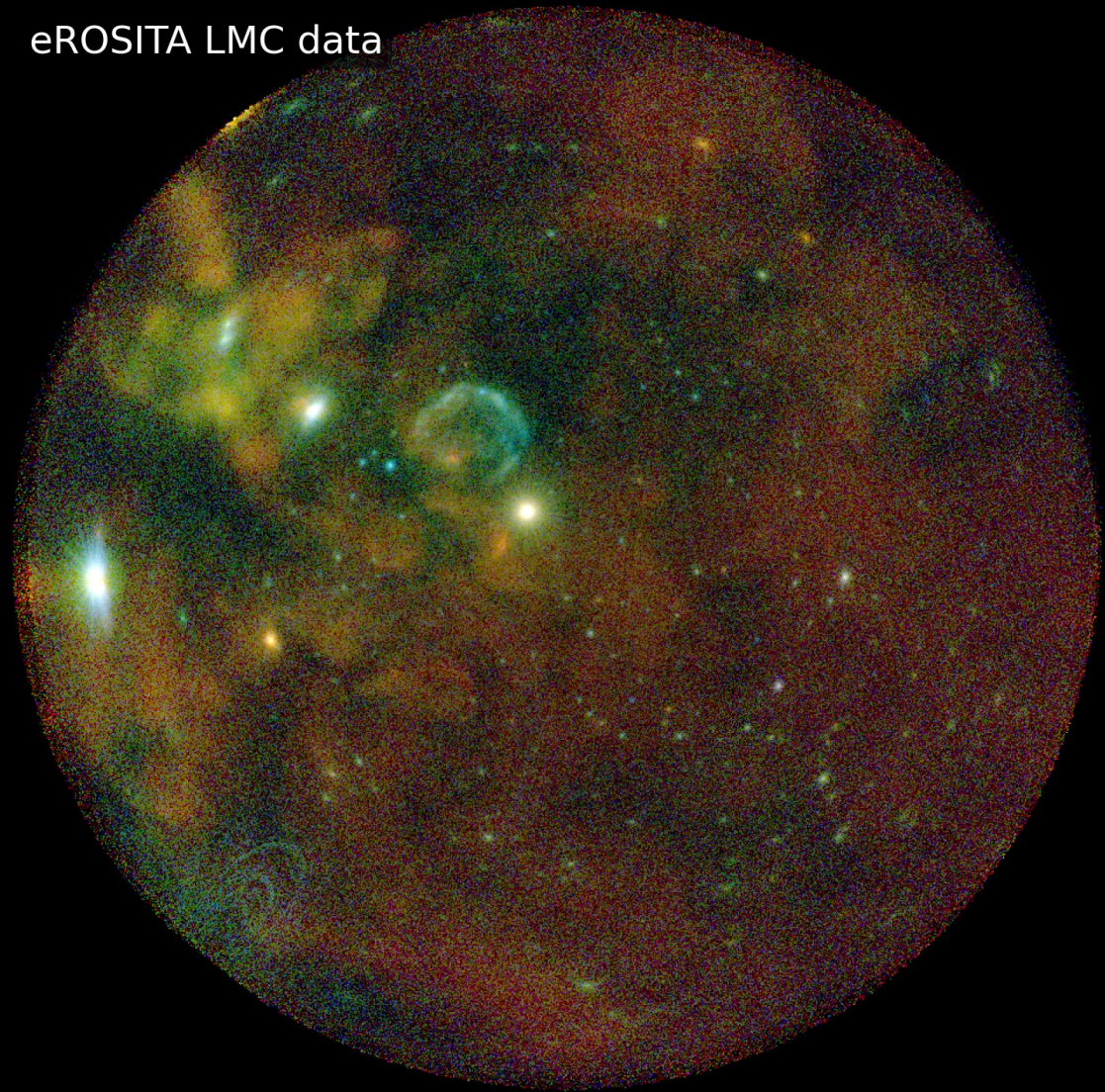


MAX PLANCK INSTITUTE
FOR ASTROPHYSICS



Motivation

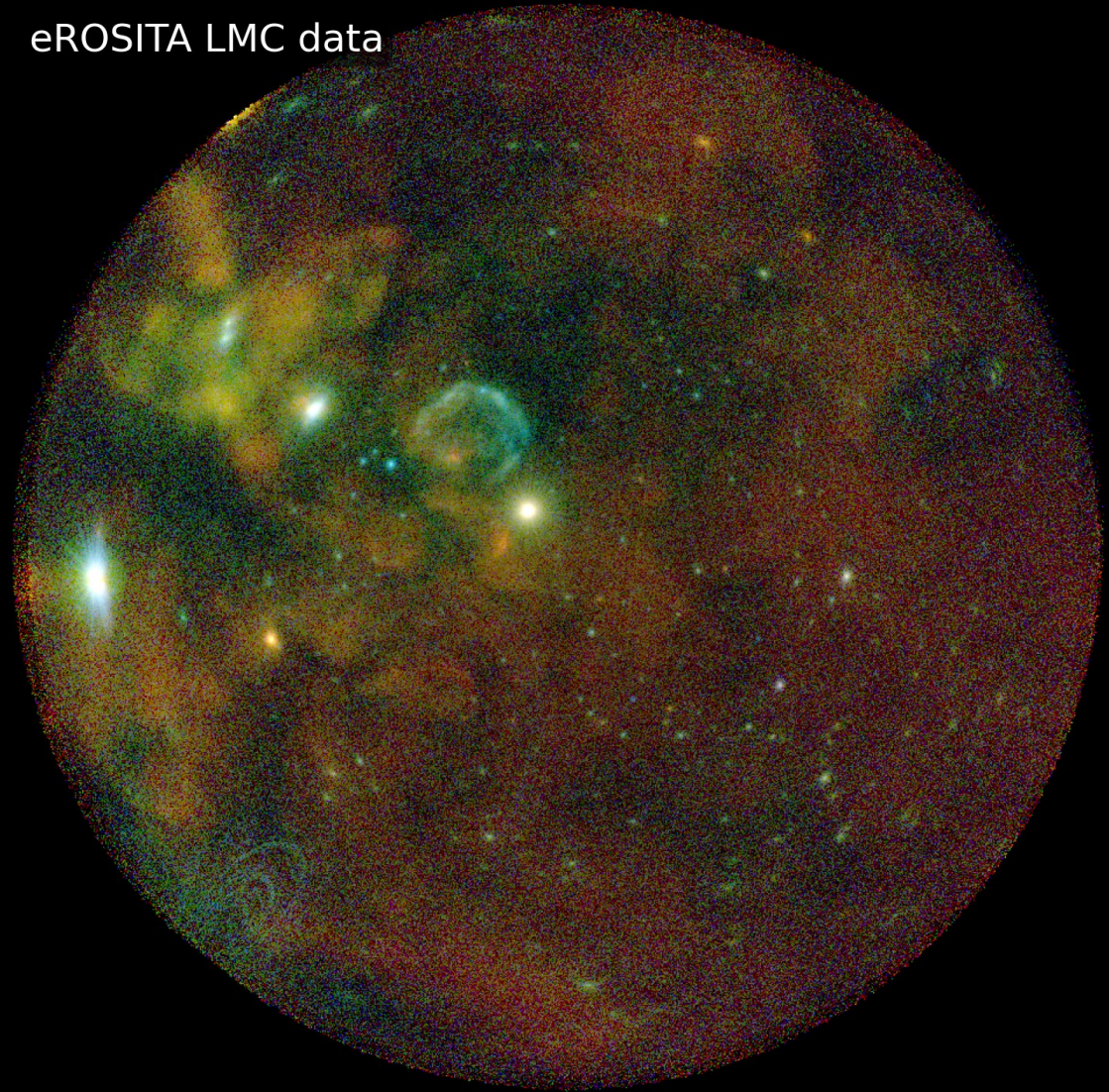
eROSITA LMC data



Motivation

X-ray telescopes suffer from nuisance effects

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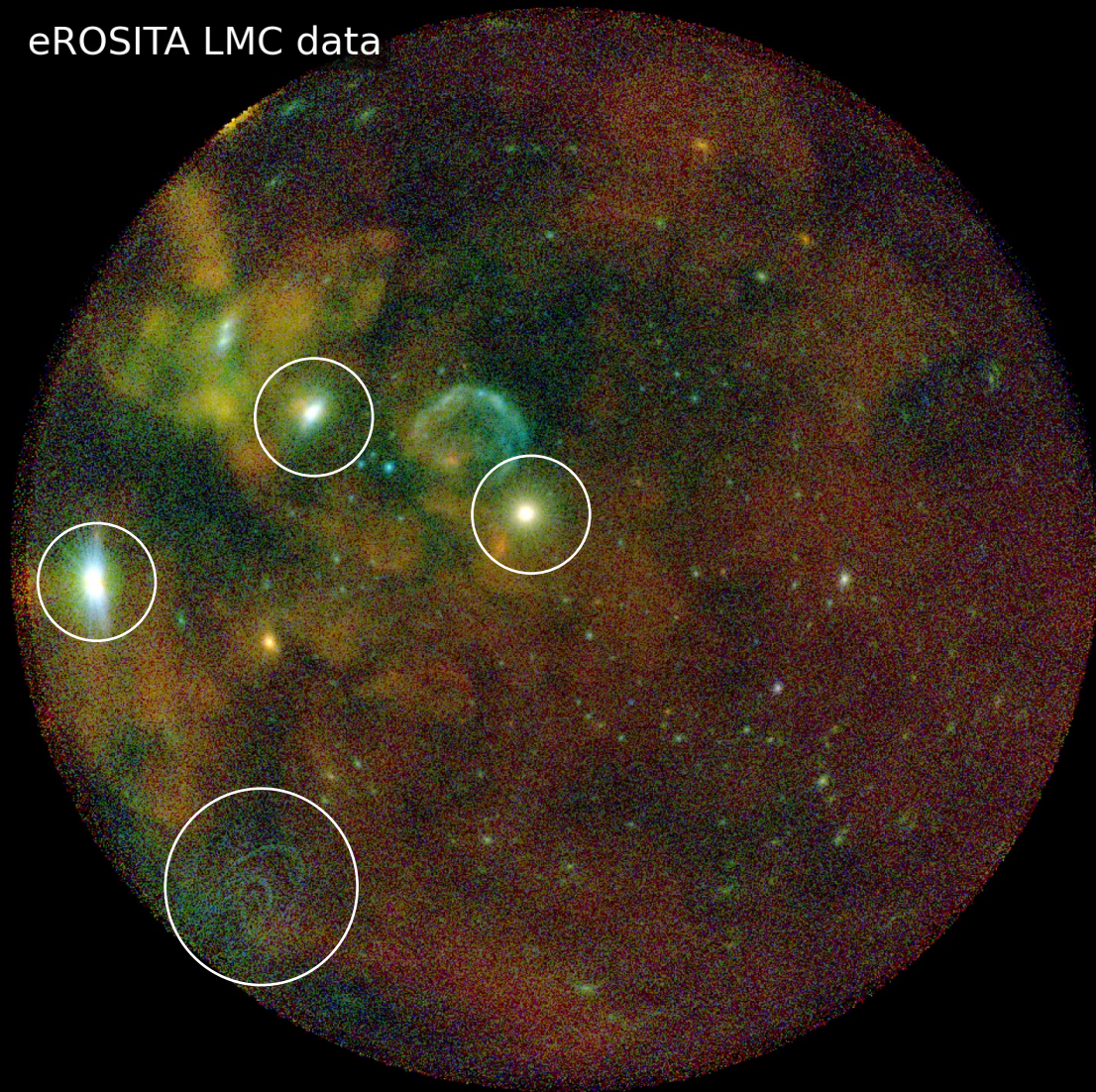


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X-ray telescopes suffer from nuisance effects

- Spatially Variant Point Spread Functions (PSF)

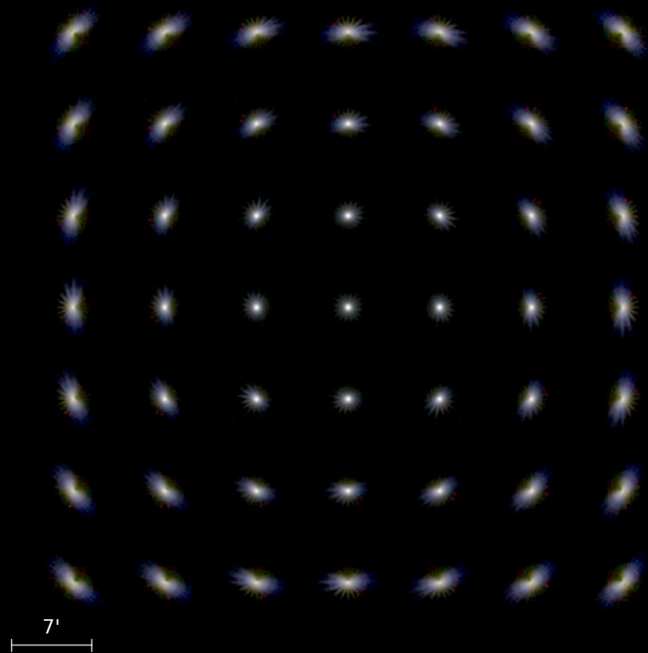
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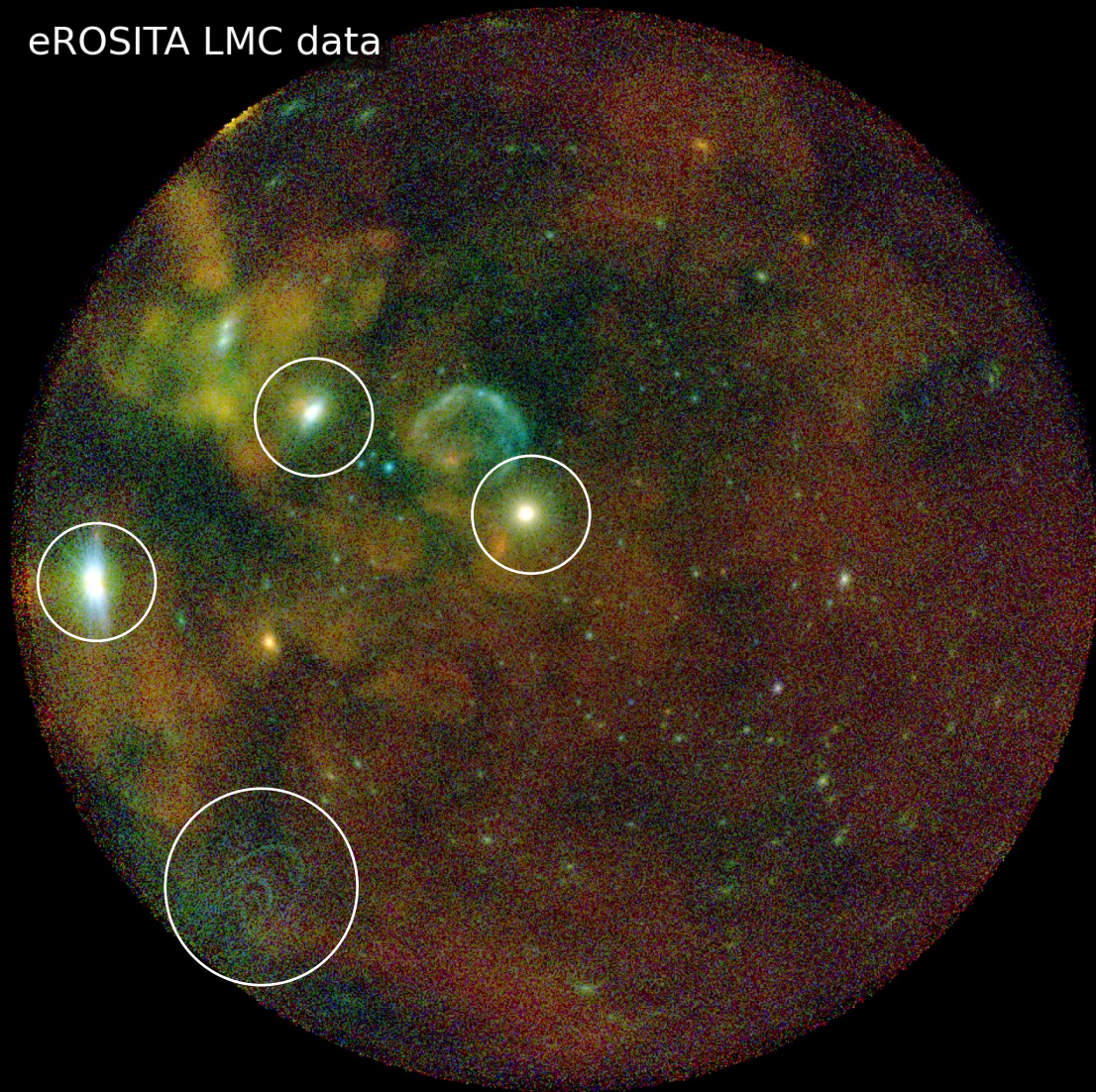
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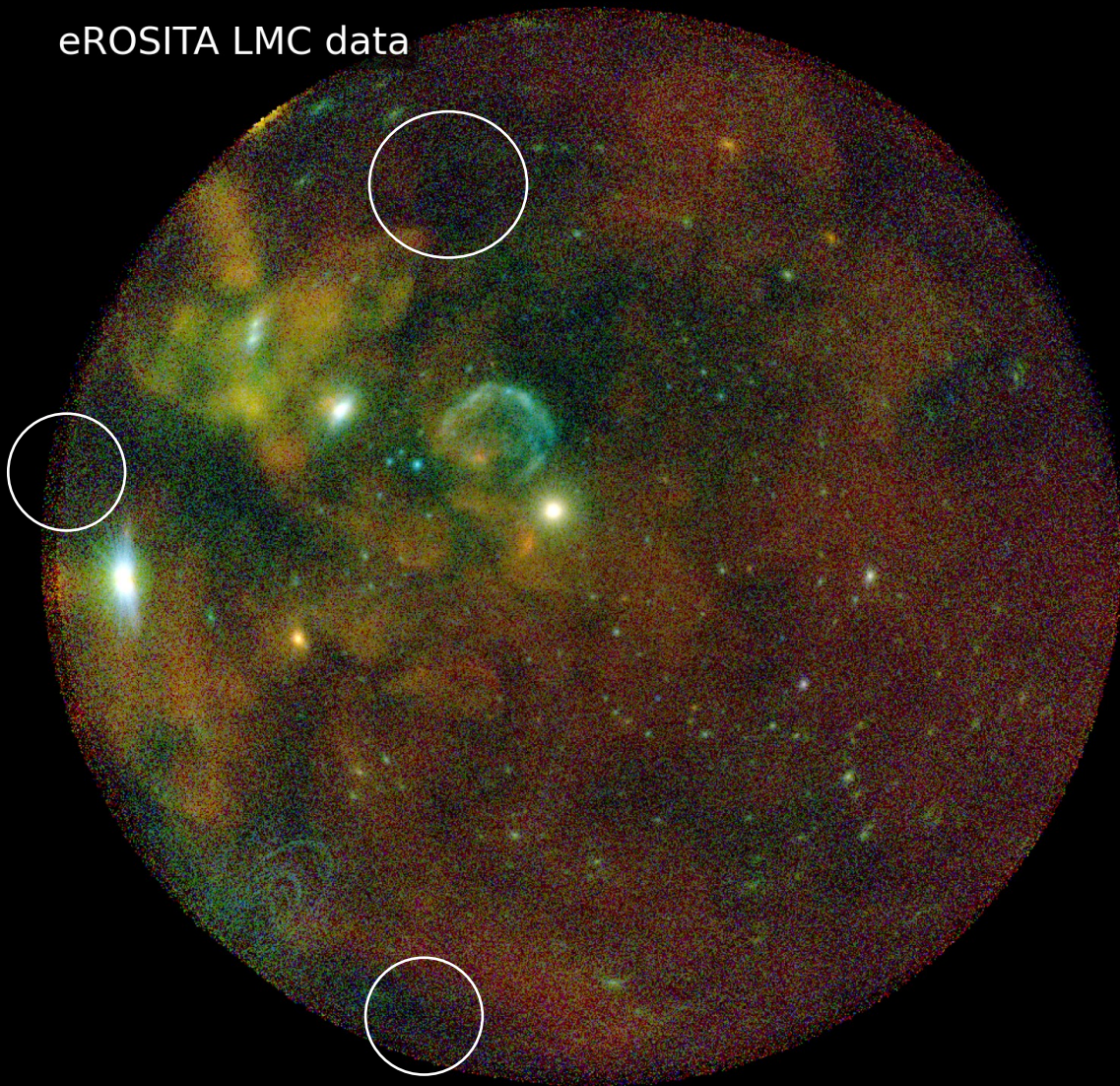


Motivation

X-ray telescopes suffer from nuisance effects

- Spatially Variant Point Spread Functions (PSF)
- Shot noise

eROSITA LMC data

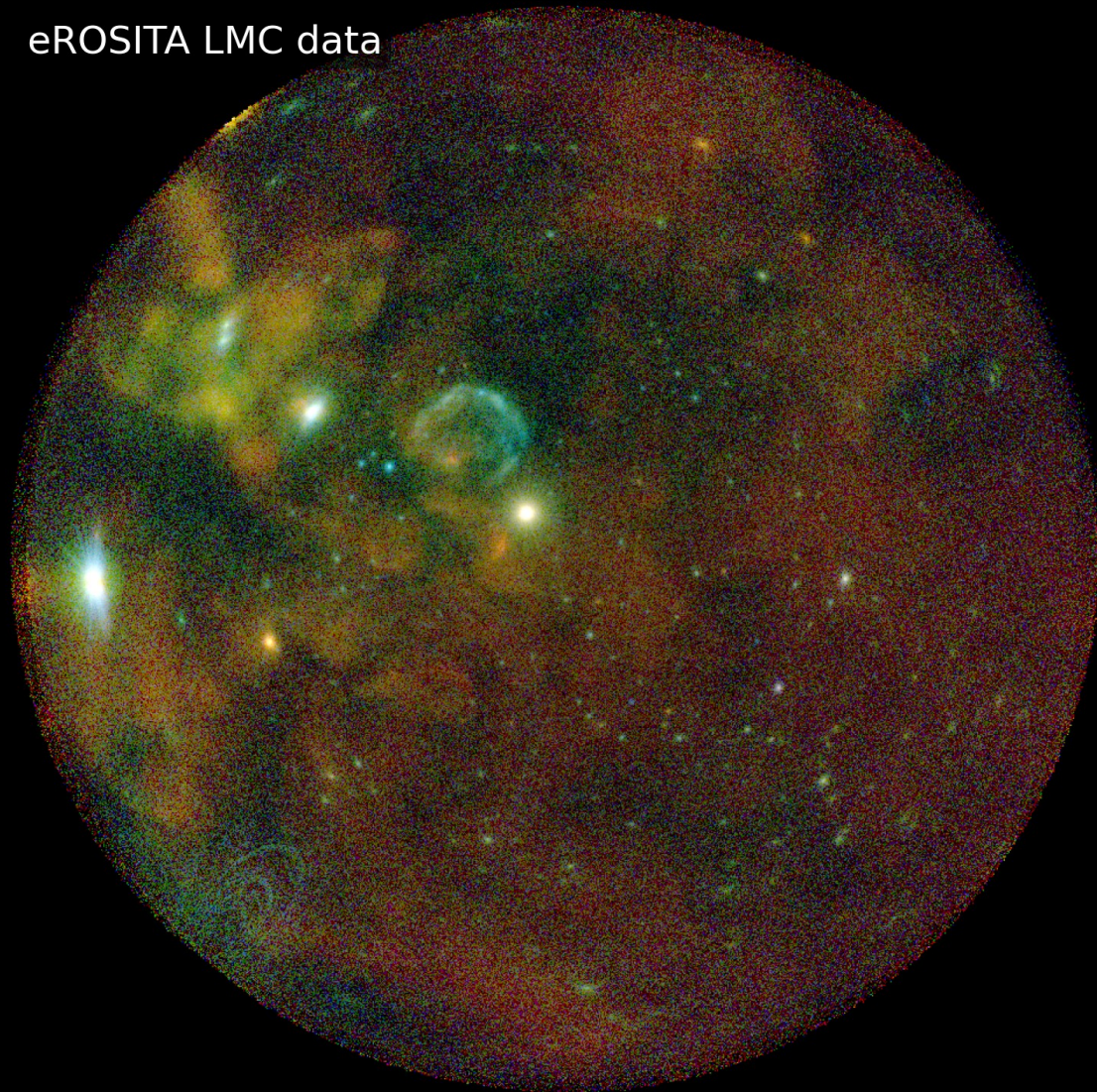


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X-ray telescopes suffer from nuisance effects

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- Background

eROSITA LMC data

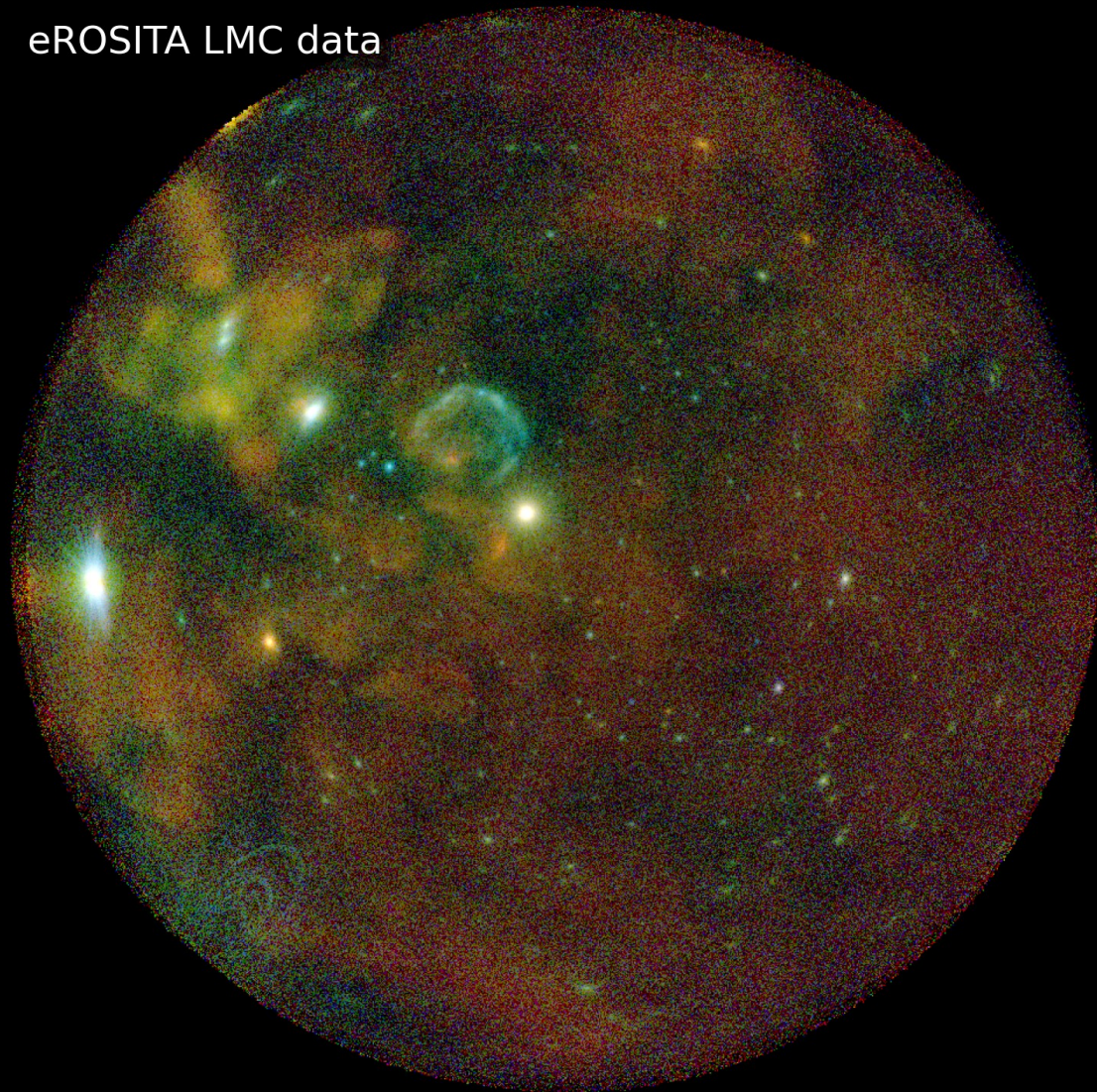


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- Other detector effects (light leaks, pile up, ...)

eROSITA LMC data



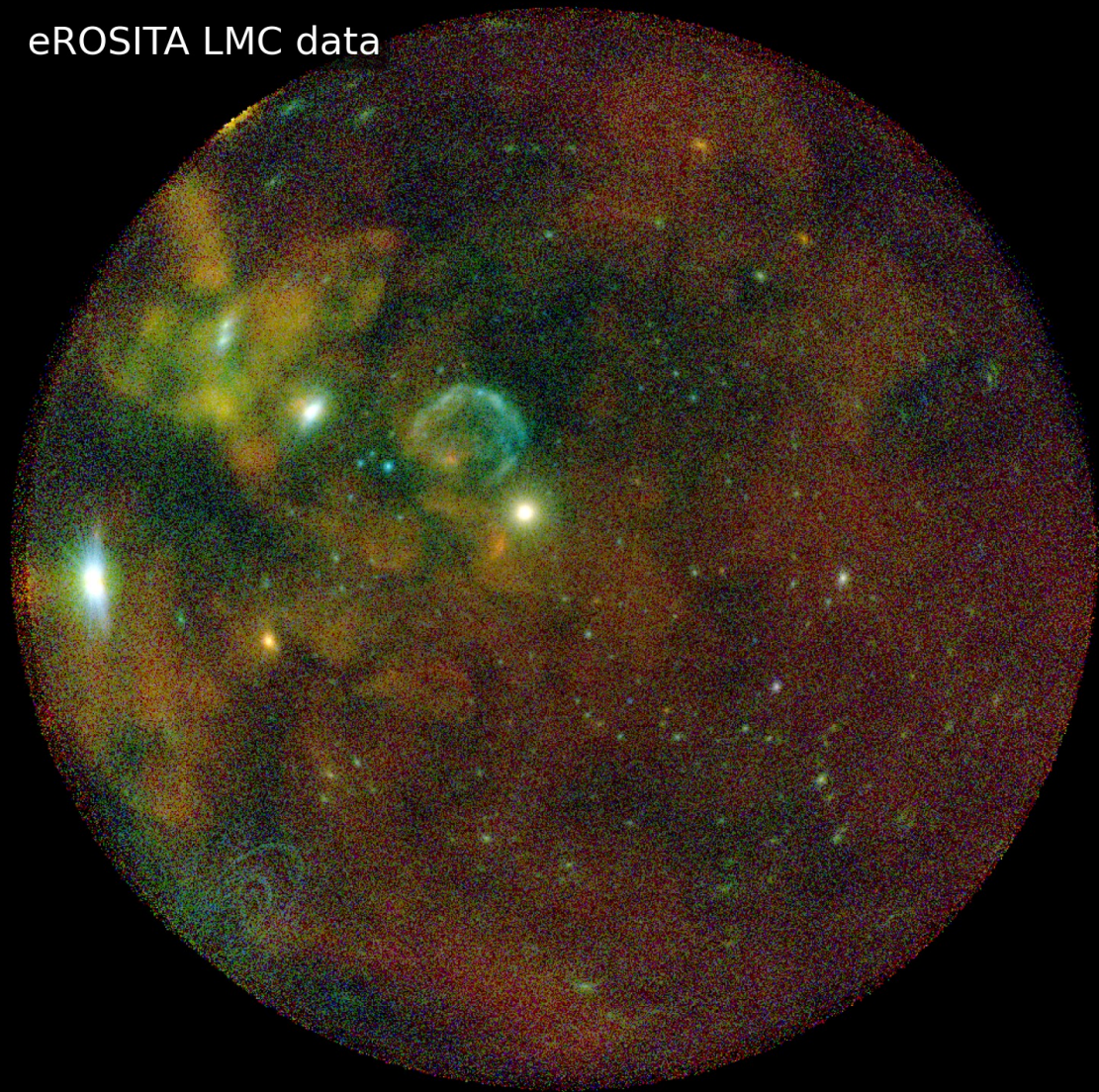
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Ill-posed problem

eROSITA LMC data



Motivation

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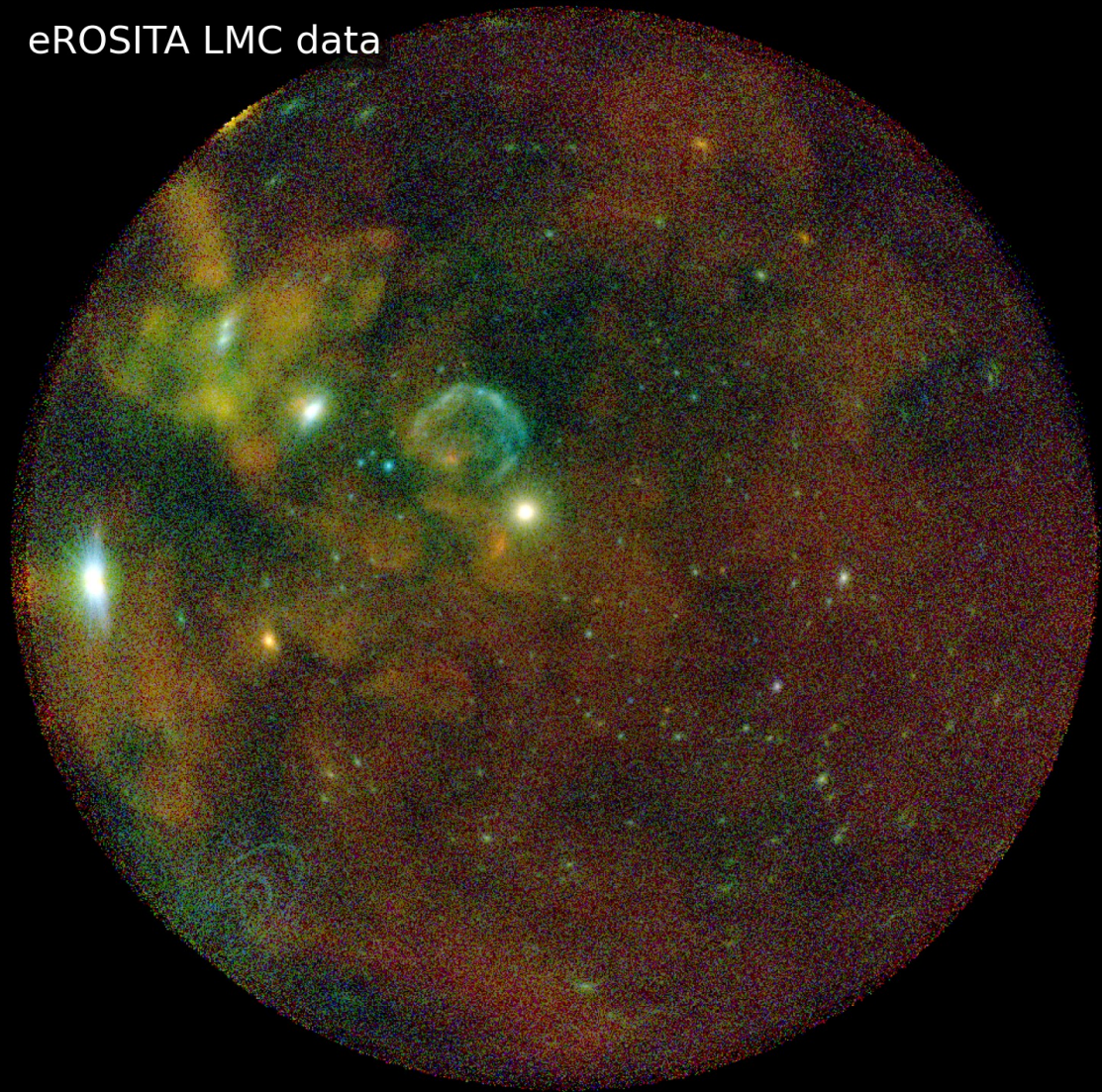
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**Bayesian Imaging
&
Generative Models**

eROSITA LMC data



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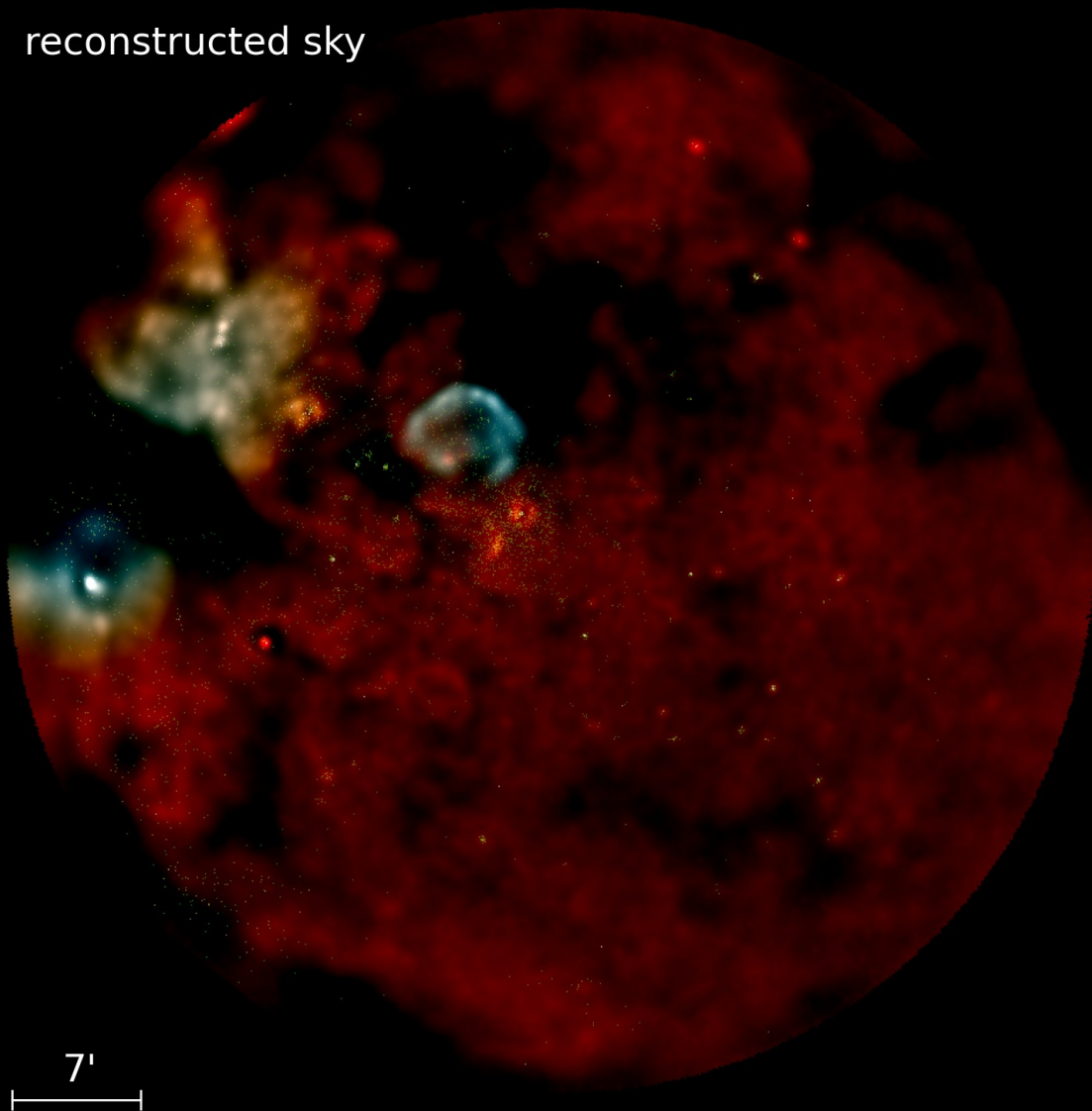
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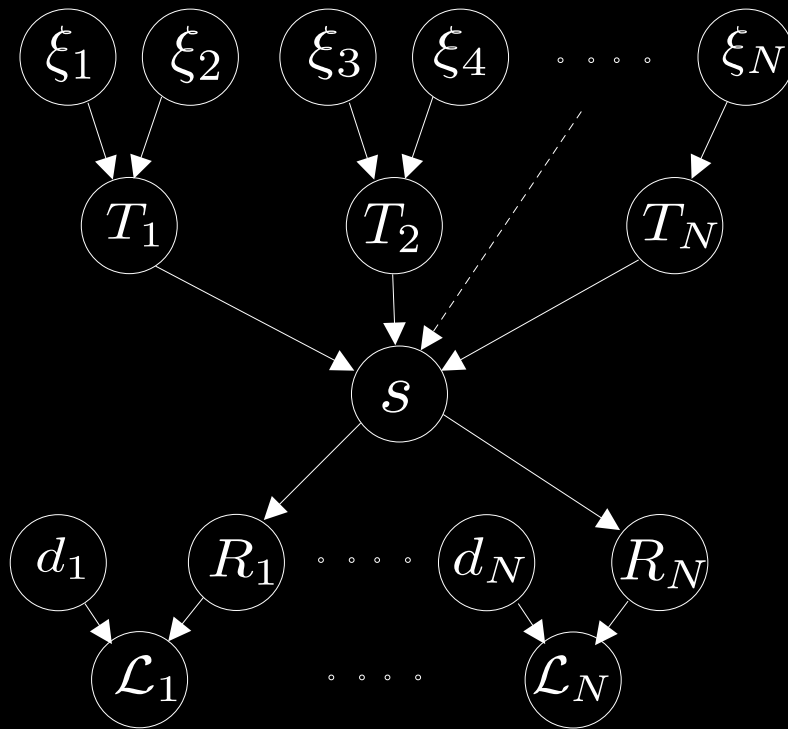
**Bayesian Imaging
&
Generative Models**

reconstructed sky



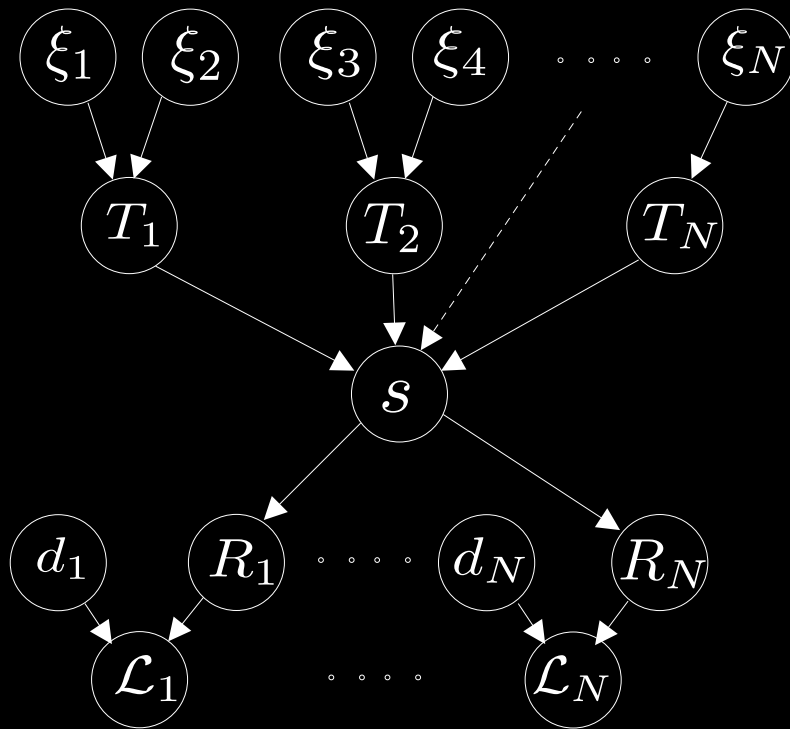
Generative Models for Bayesian Imaging

Generative Models for Bayesian Imaging



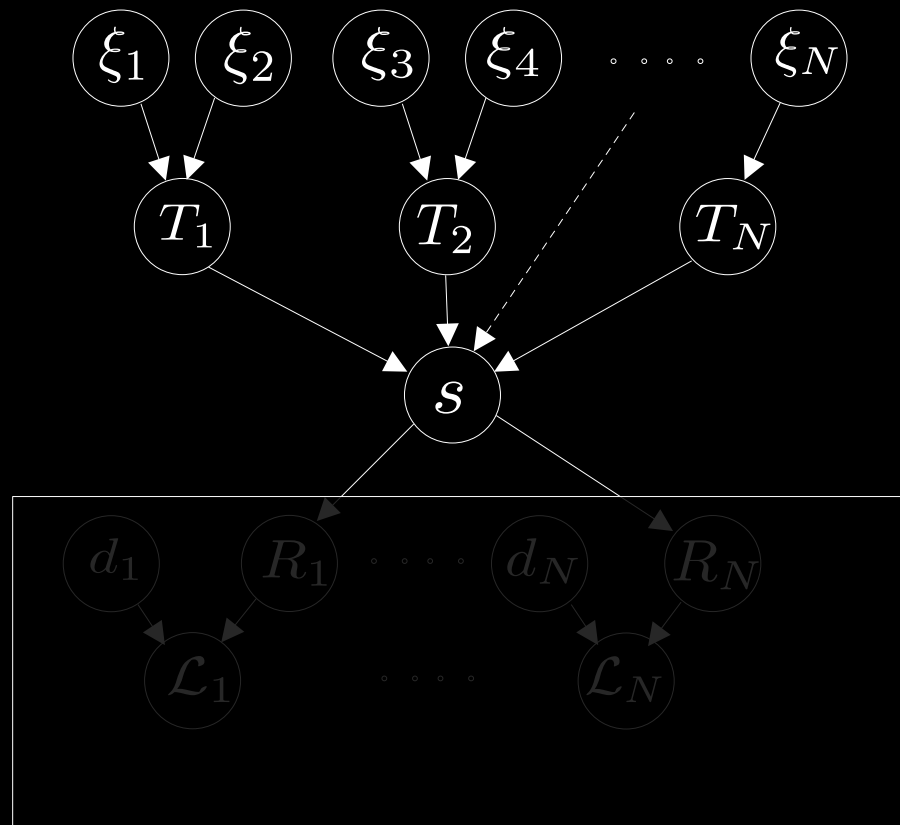
Generative Models for Bayesian Imaging

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



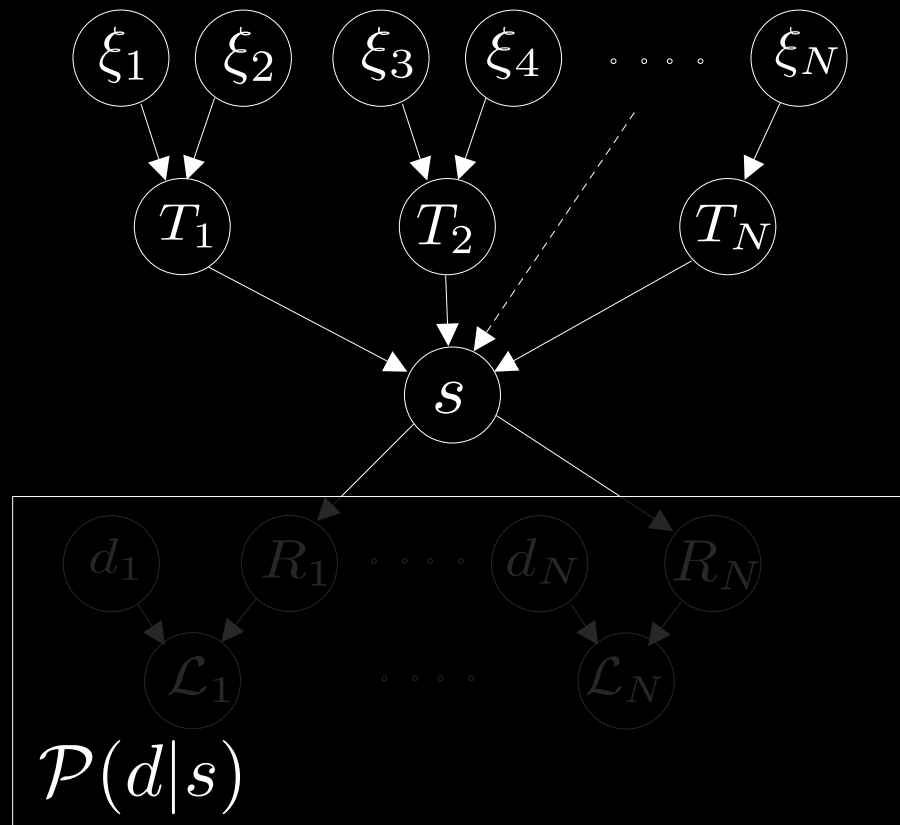
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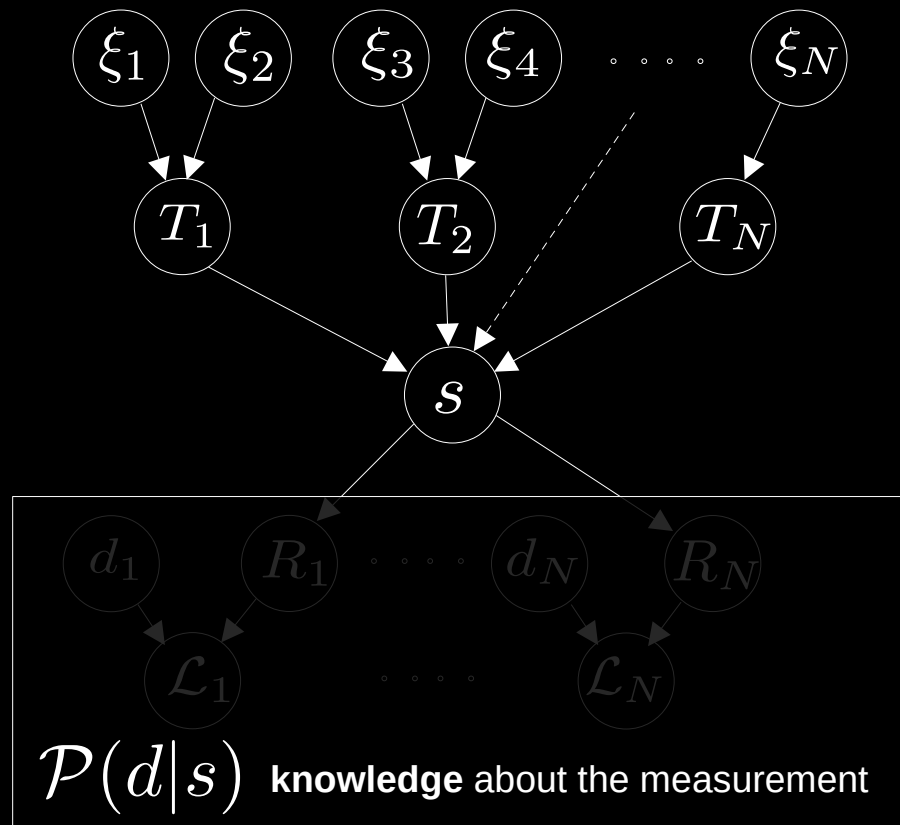
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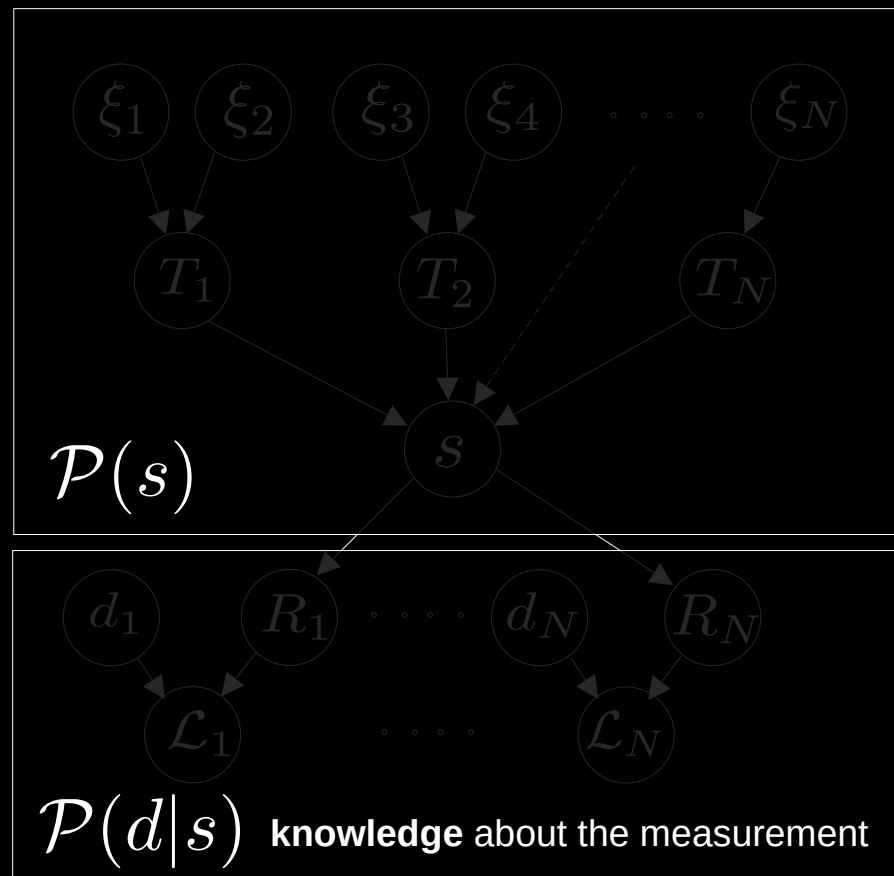
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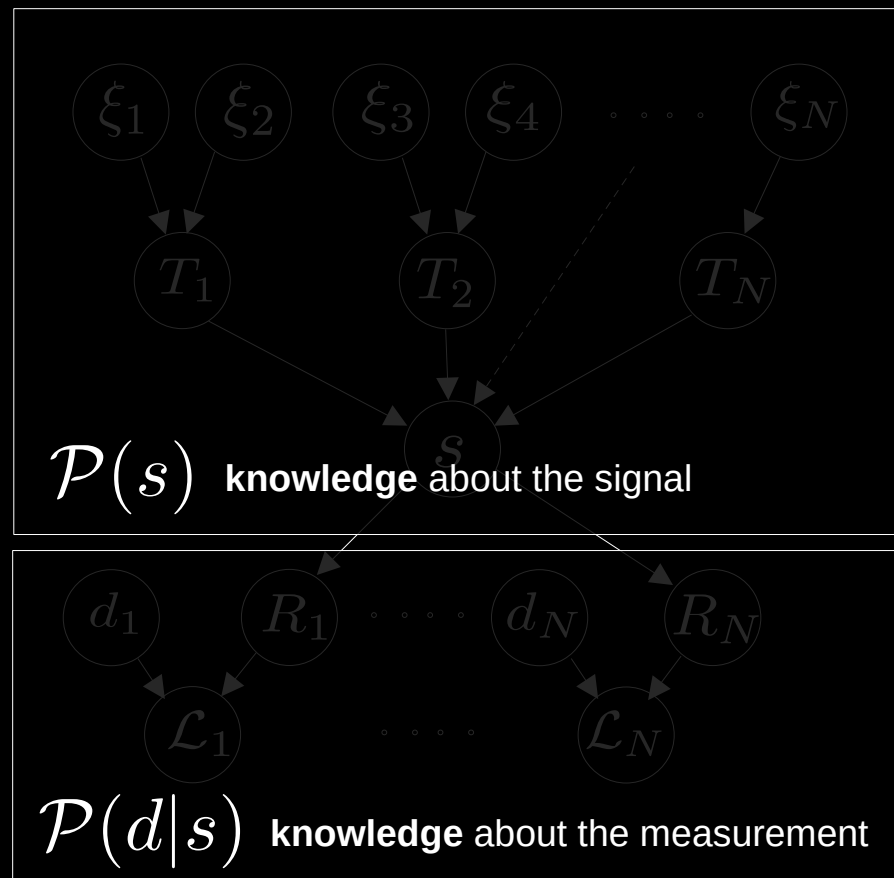
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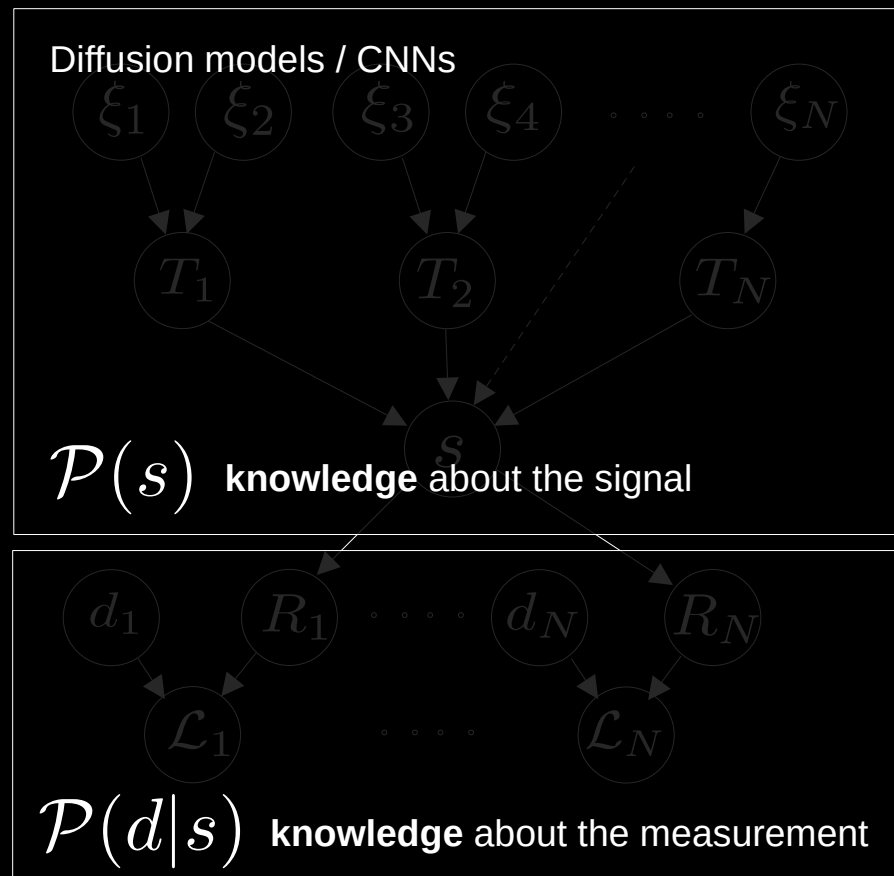
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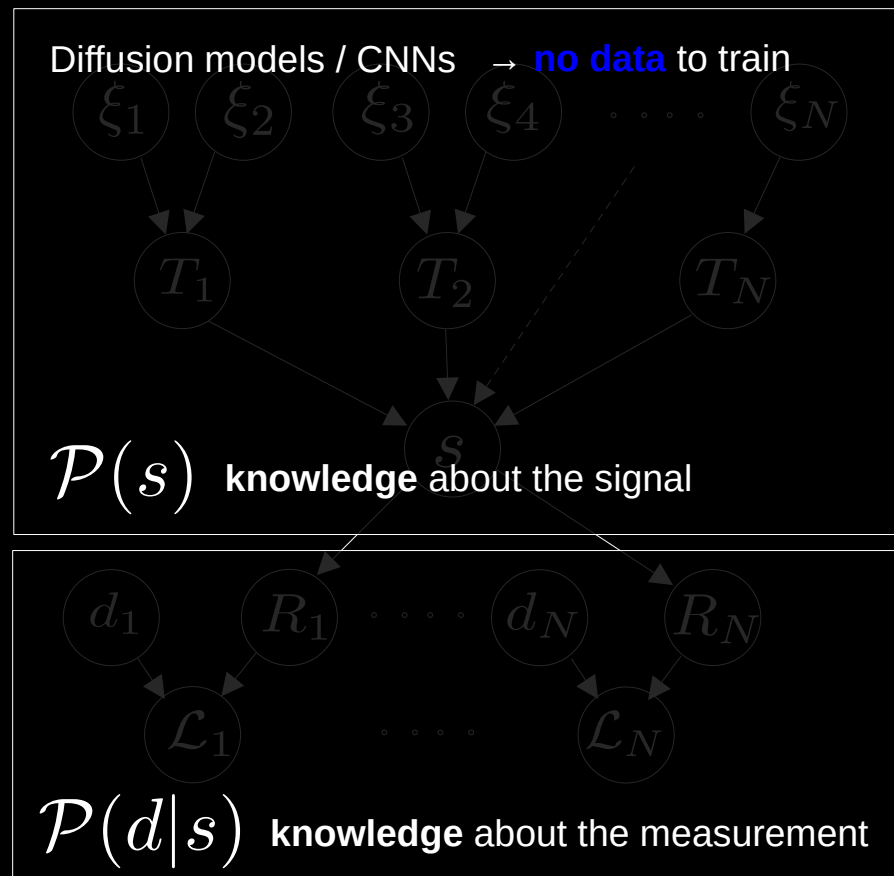
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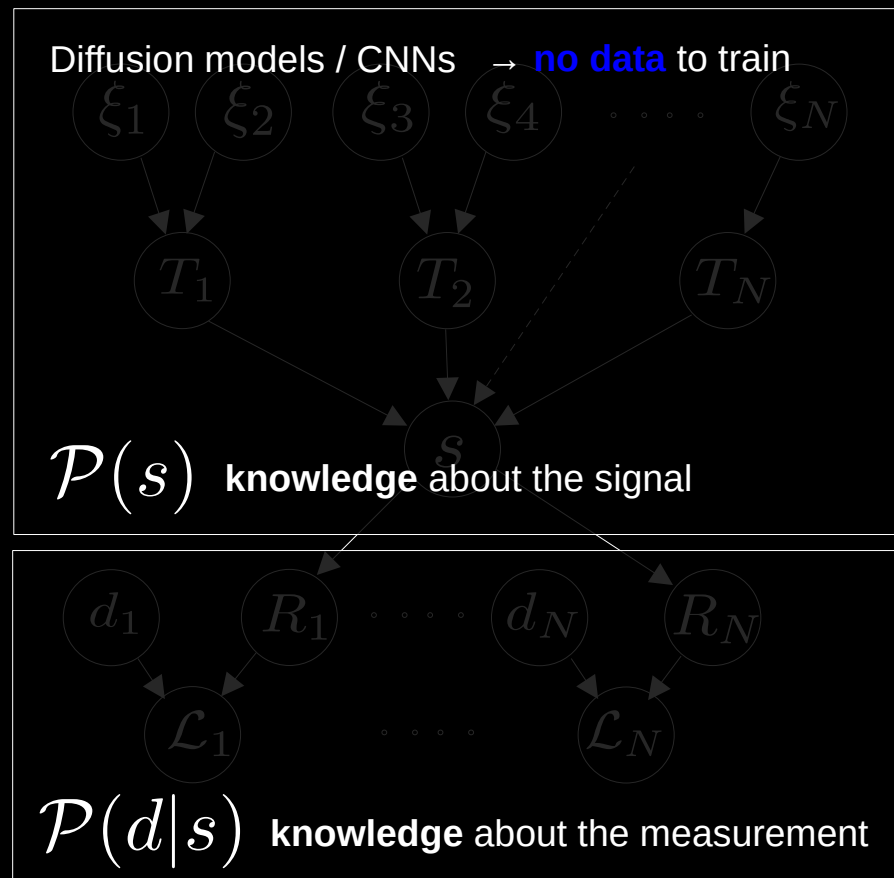
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Generative Models for Bayesian Imaging

How can we include
domain knowledge
about the signal?

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



Generative Models for Bayesian Imaging

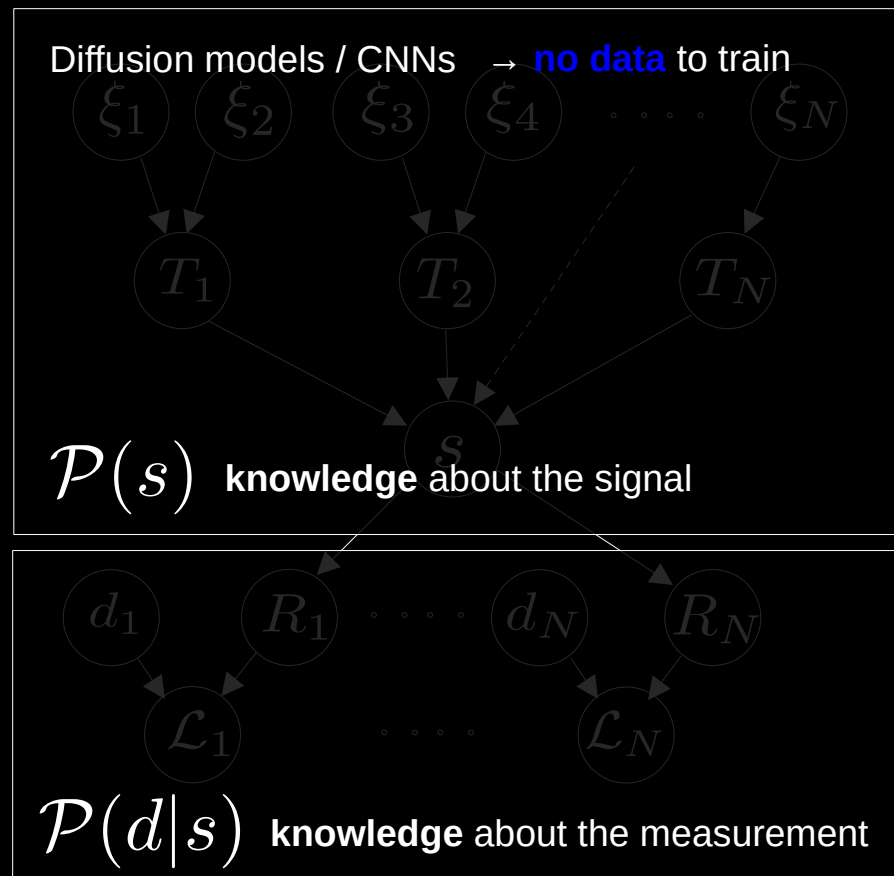
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Structure!

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Generative Models for Bayesian Imaging

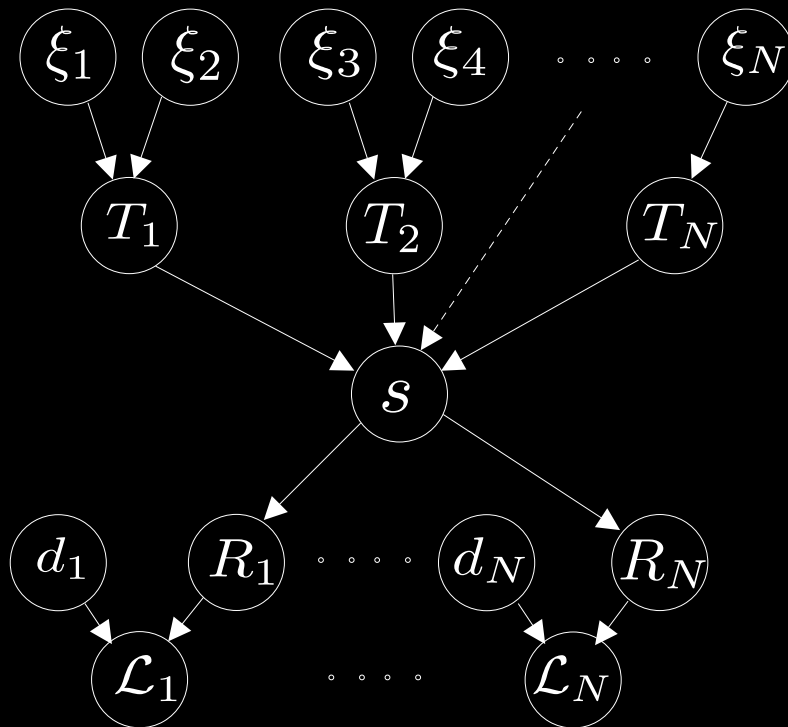
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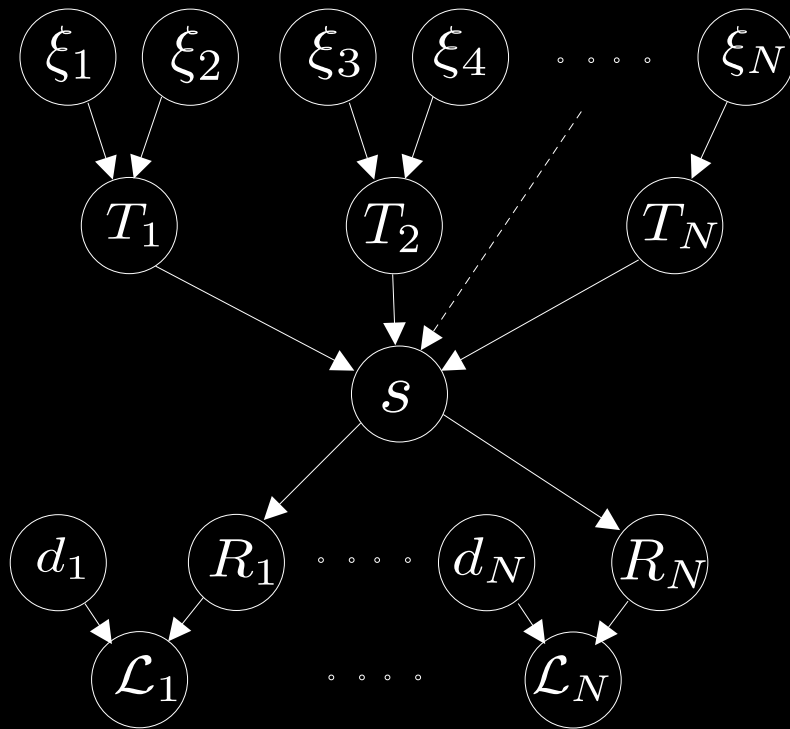
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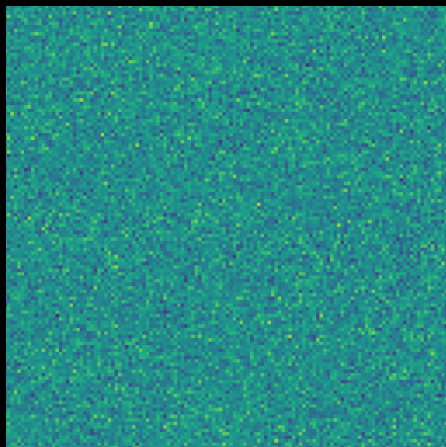
Generative Models for Bayesian Imaging

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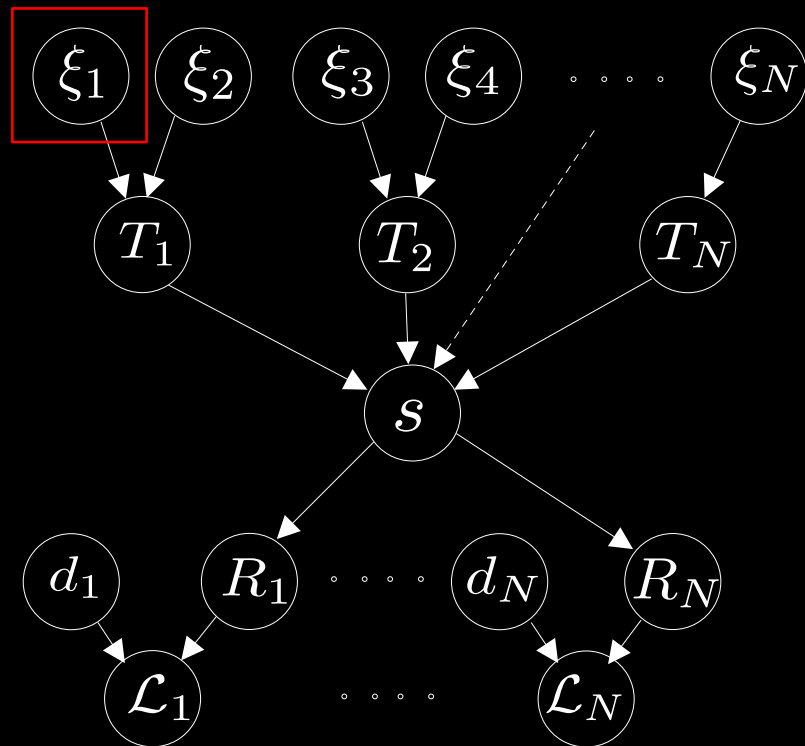


Generative Models for Bayesian Imaging

$$\mathcal{N}(\xi; 0, 1)$$

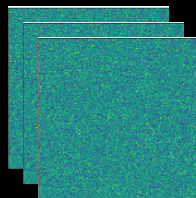


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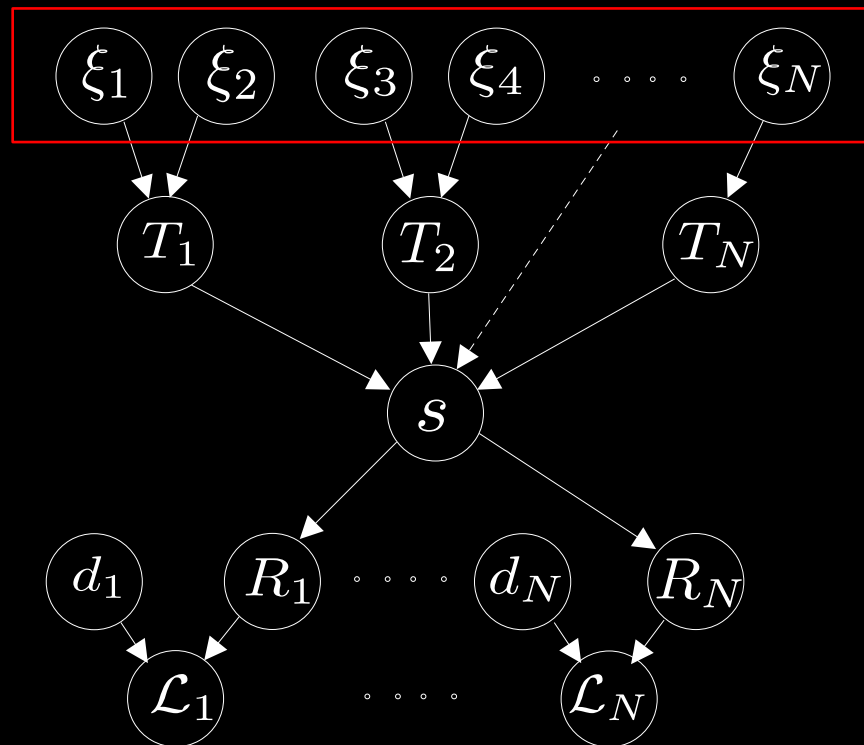


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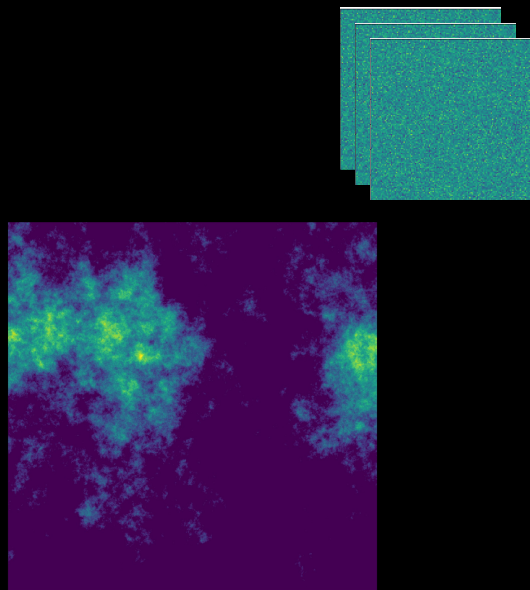


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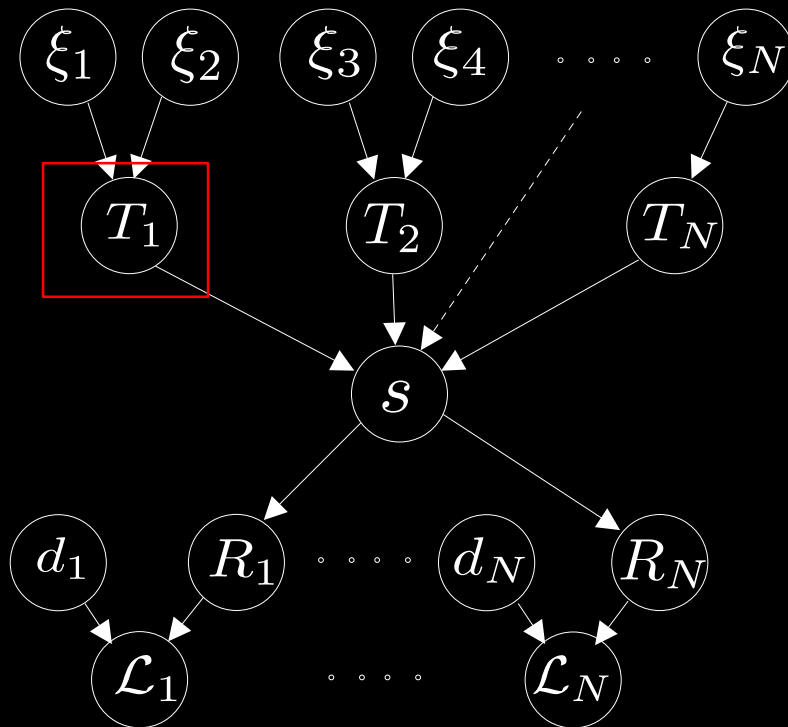


Generative Models for Bayesian Imaging

GP

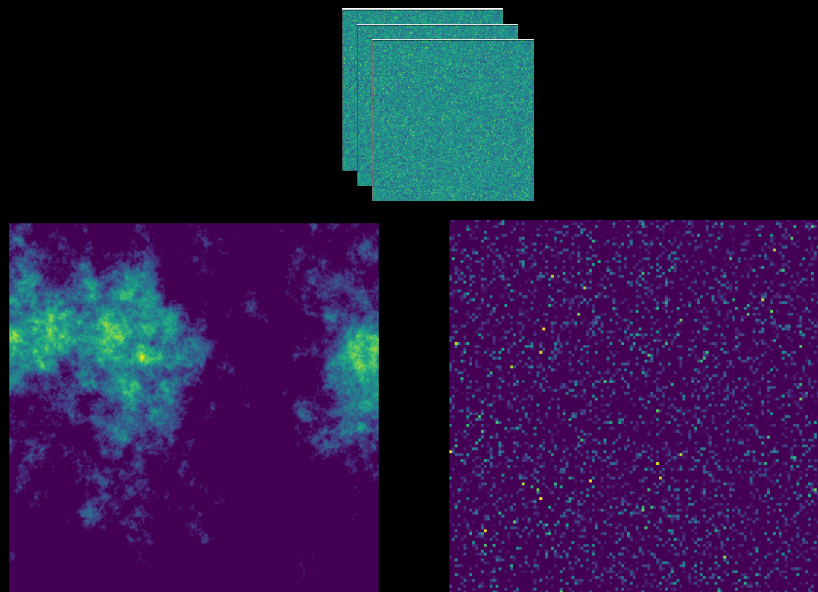


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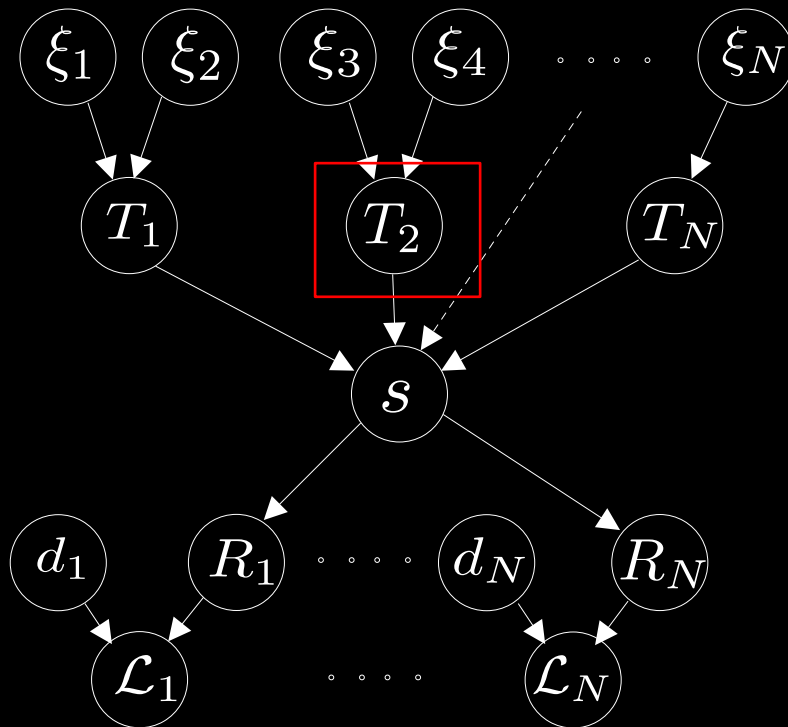


Generative Models for Bayesian Imaging

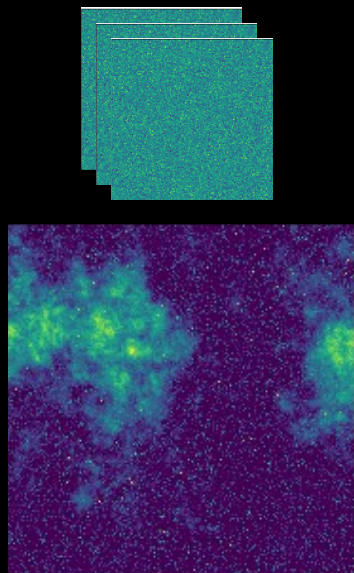
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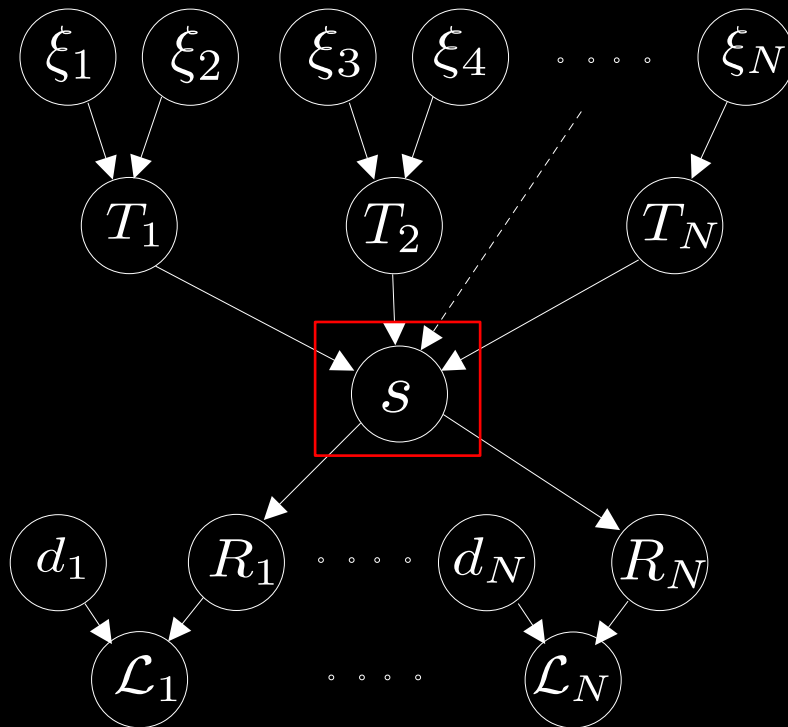
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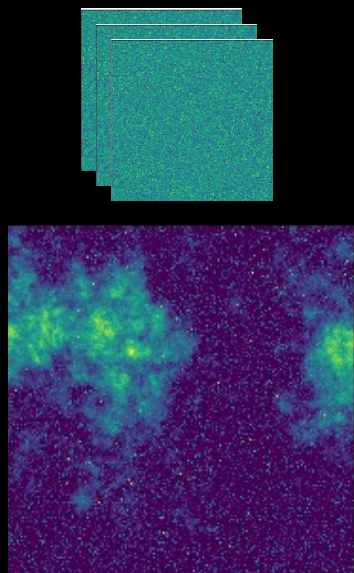
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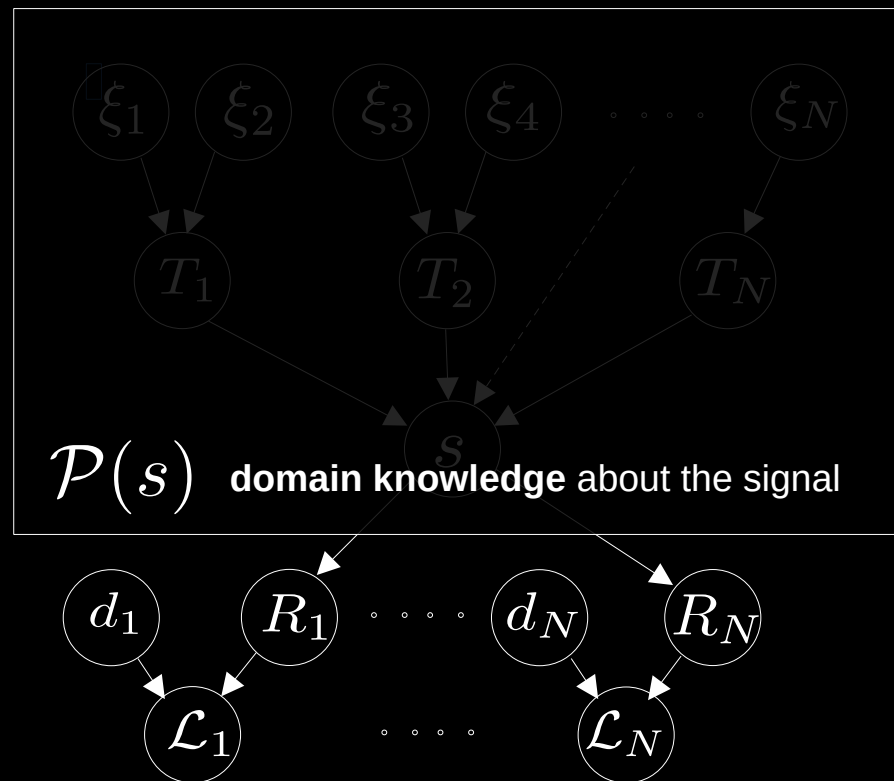
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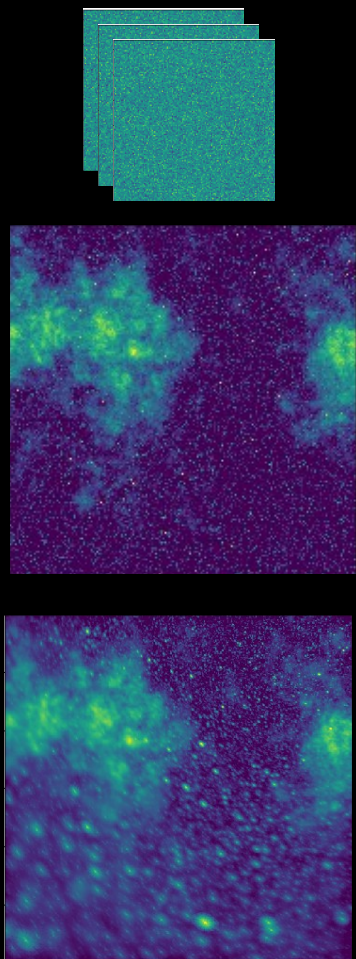
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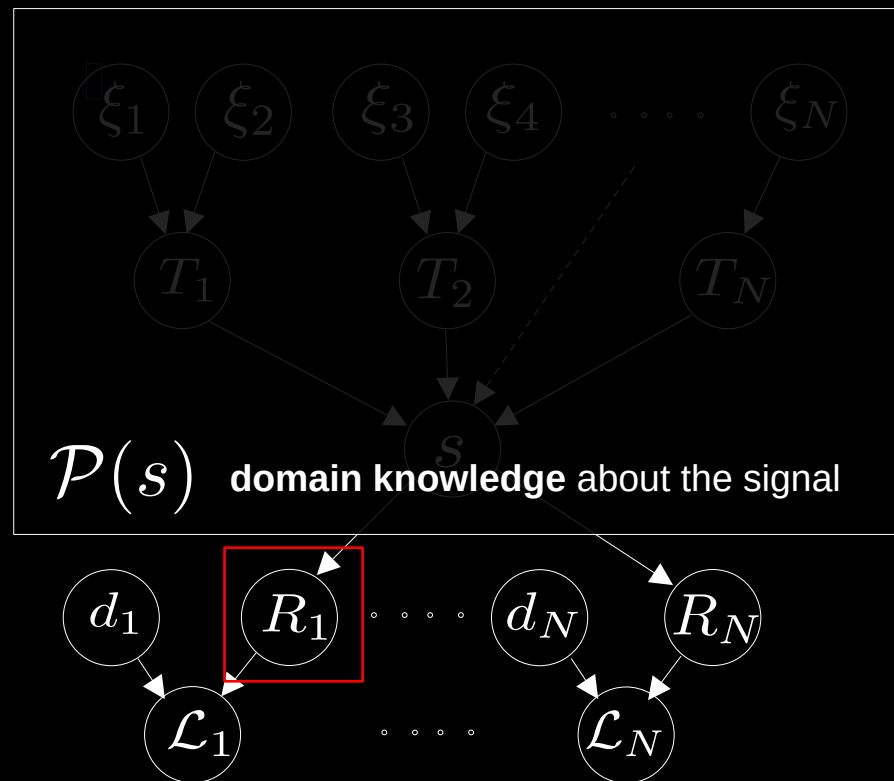
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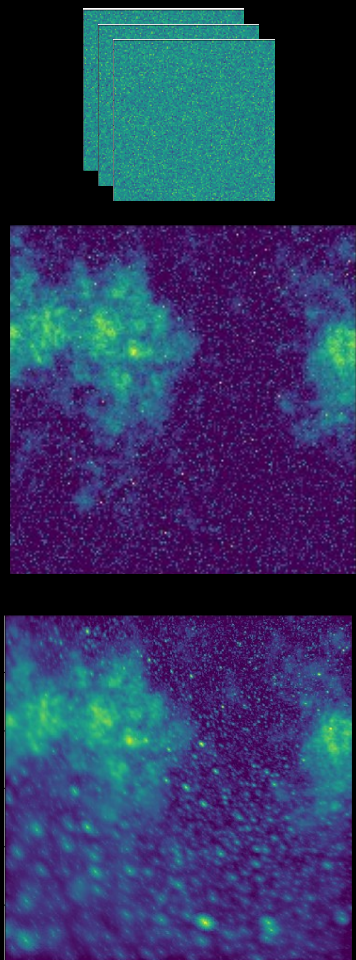
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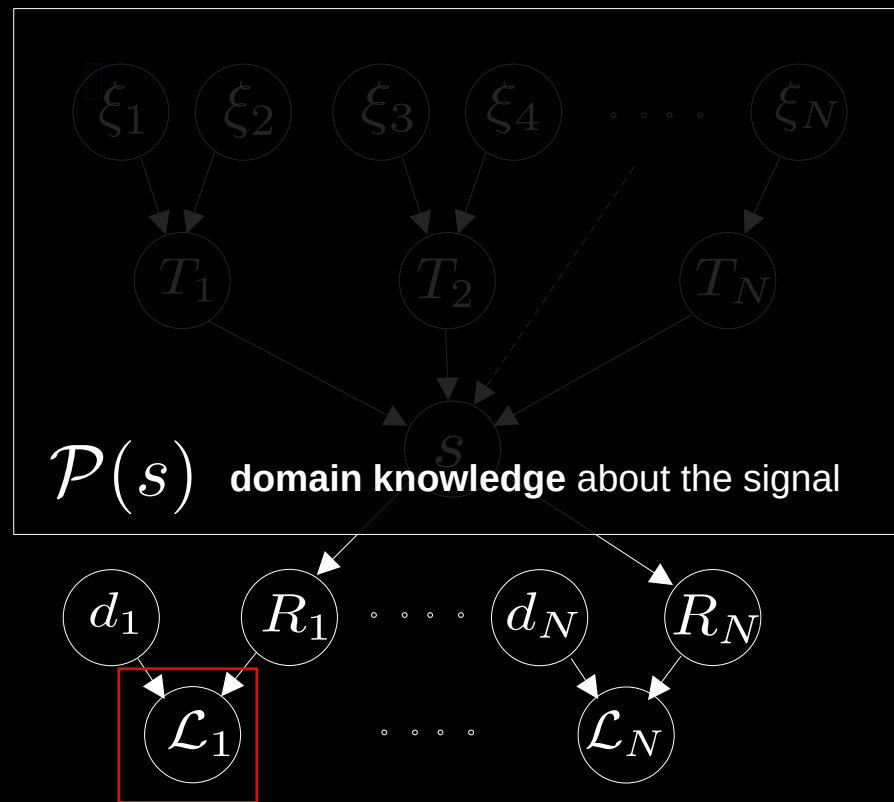
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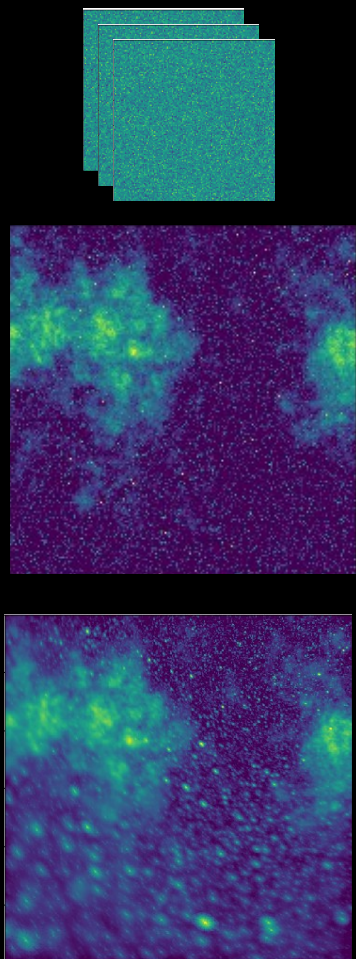
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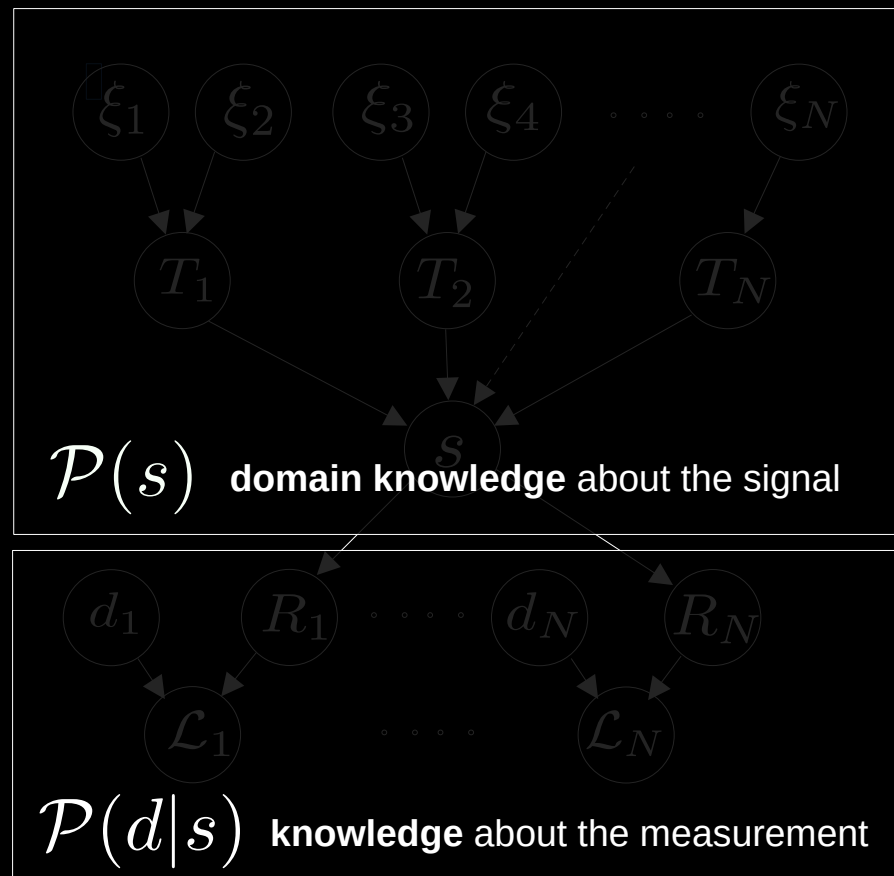
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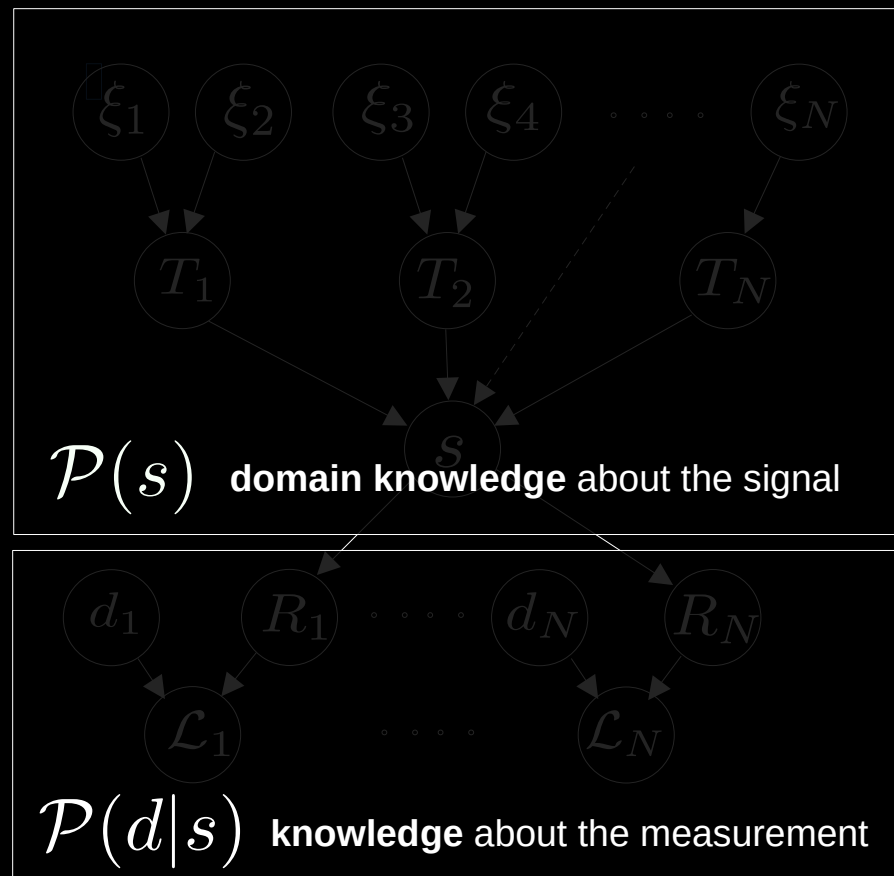


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Inference with Generative Models

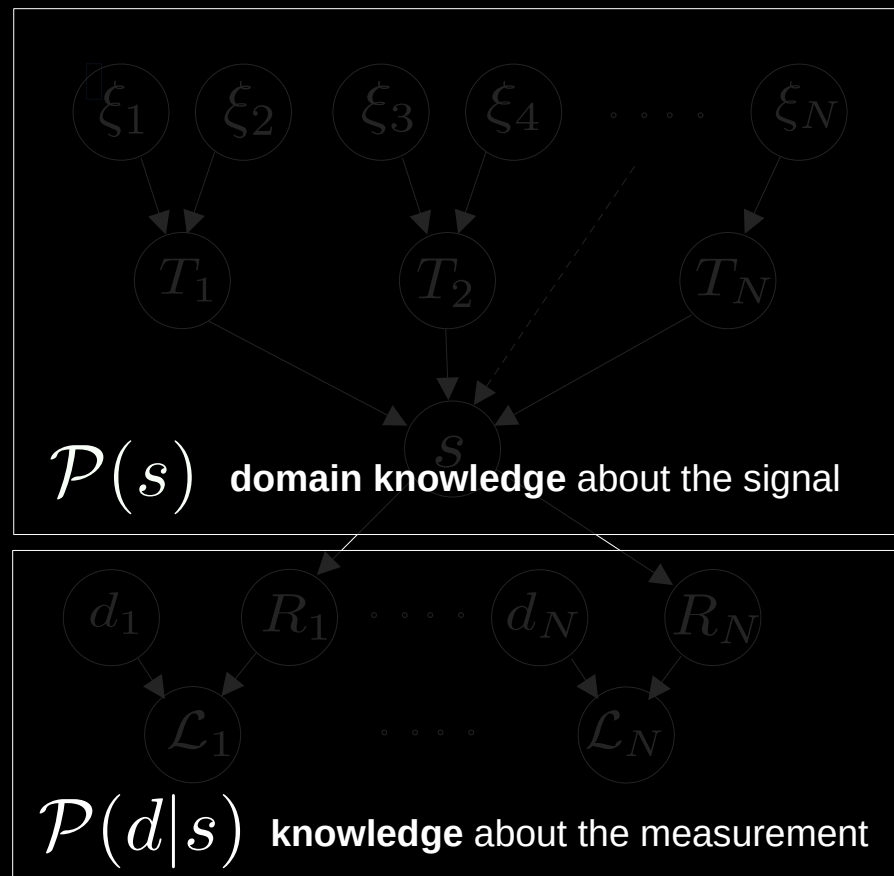
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Inference with Generative Models

- Maximum posterior

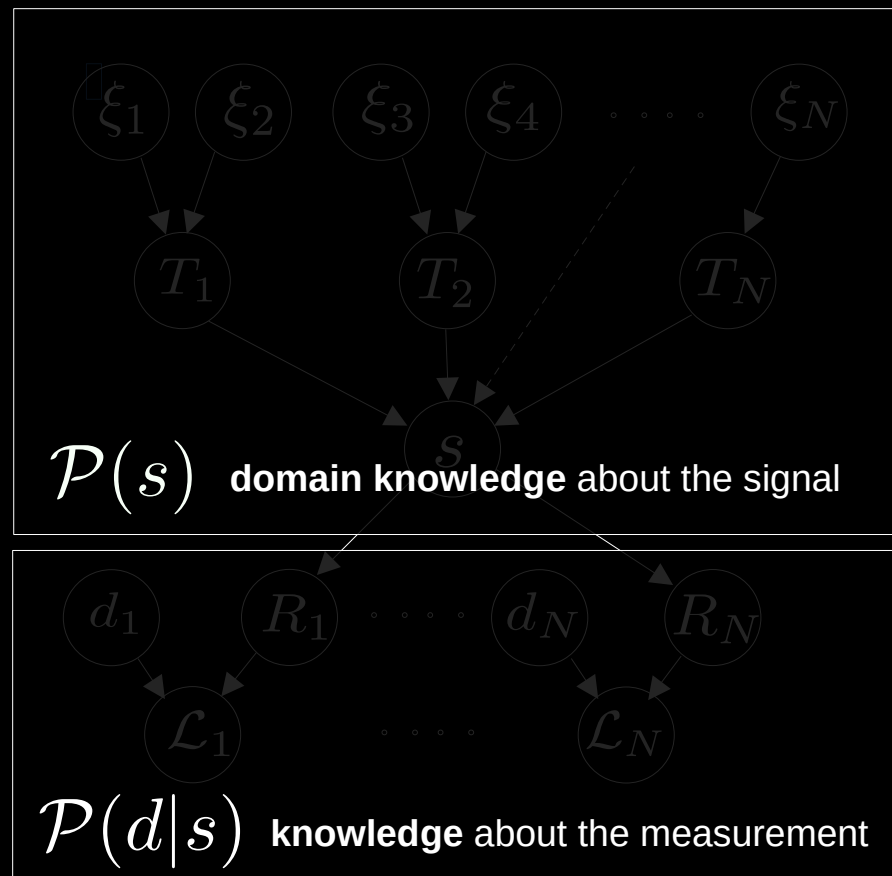
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Inference with Generative Models

- Maximum posterior
 $-\log \mathcal{P}(s, d)$

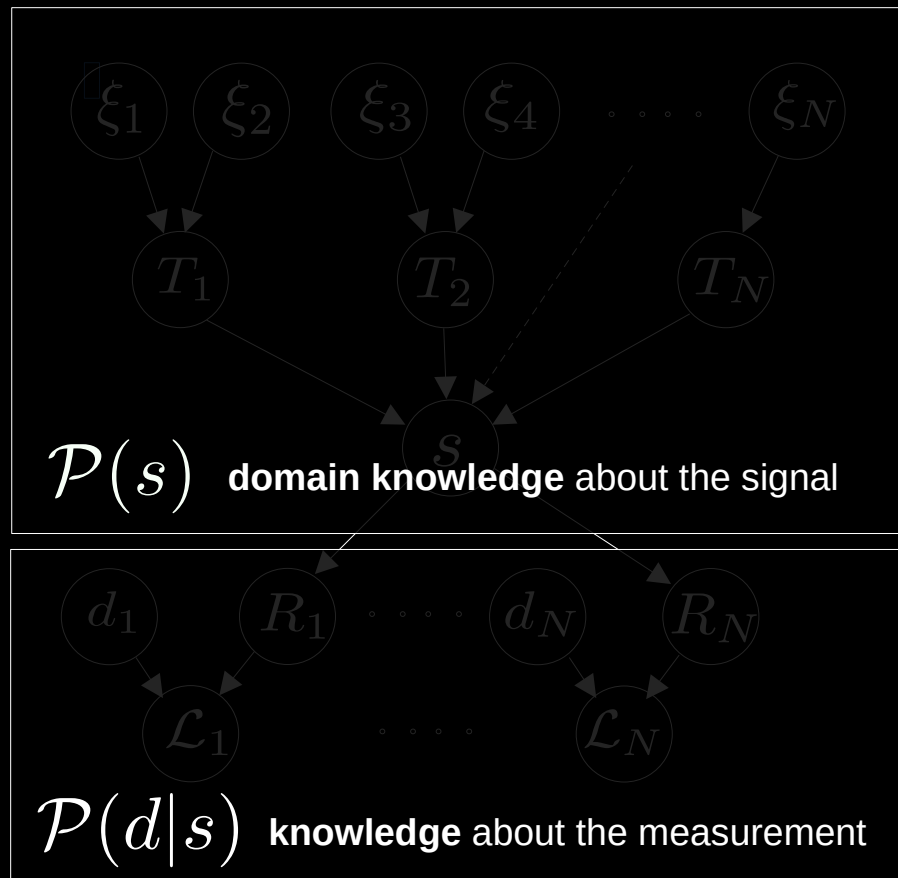
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Inference with Generative Models

- Maximum posterior
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- Metric Gaussian Variational Inference

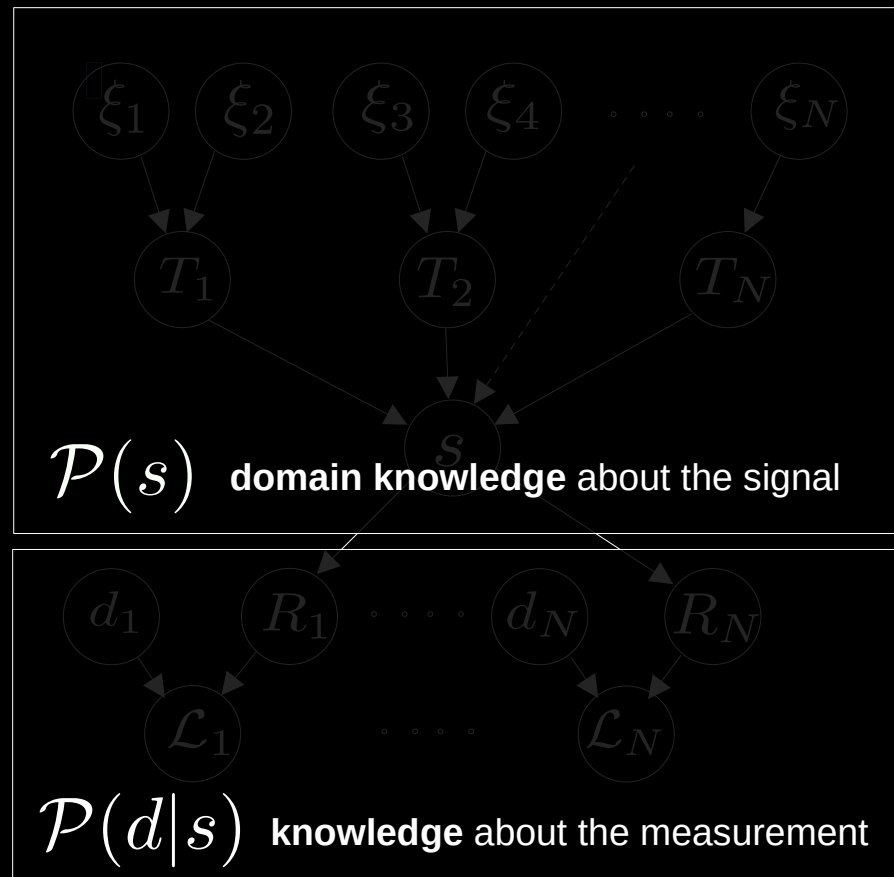
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Inference with Generative Models

- Maximum posterior
 $-\log \mathcal{P}(s, d)$
- Metric Gaussian Variational Inference
 $D_{\text{KL}}(Q_{\bar{\xi}, \Xi}(\xi) \| \mathcal{P}(\xi \mid d))$

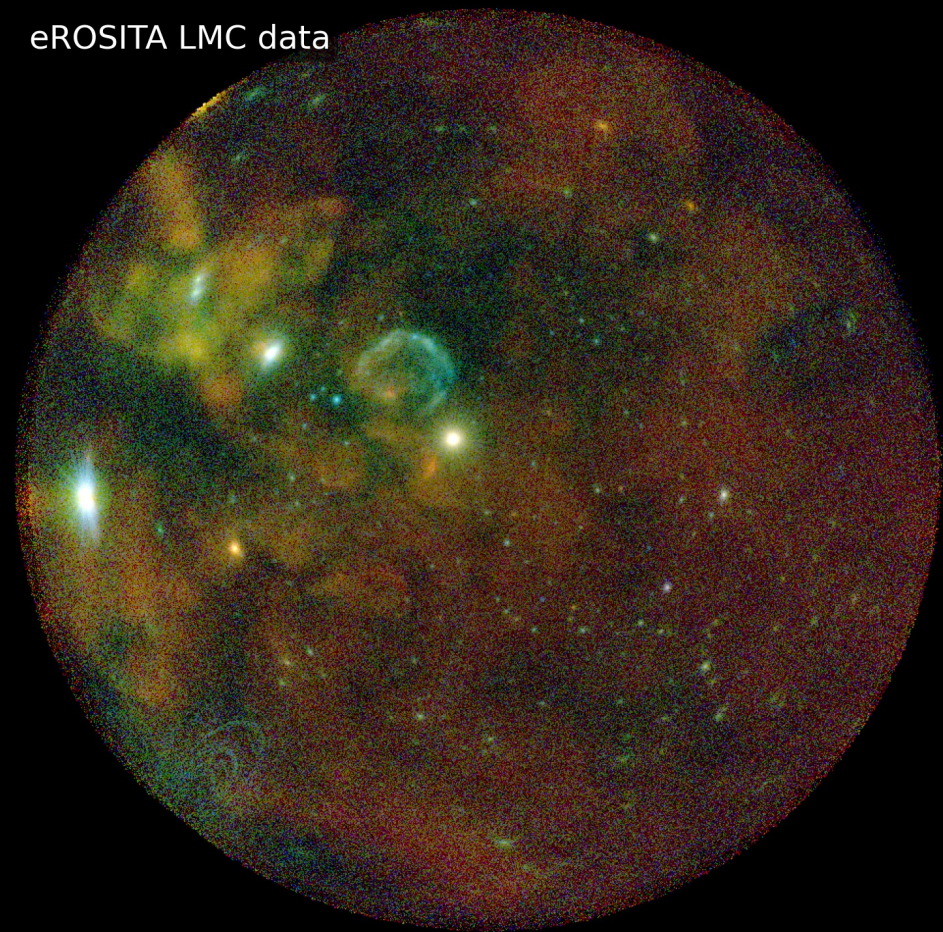
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How do we apply this to SN1987A data?

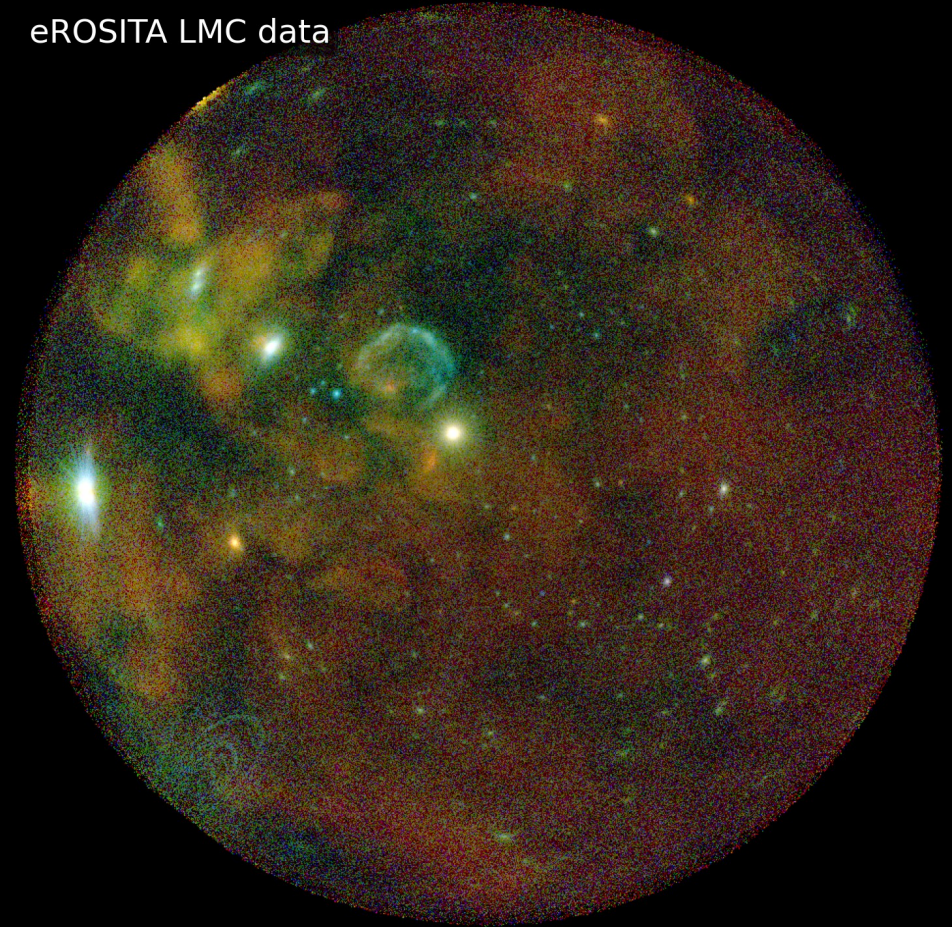
Example

eROSITA LMC data



Modeling the X-ray Sky – the Prior

eROSITA LMC data

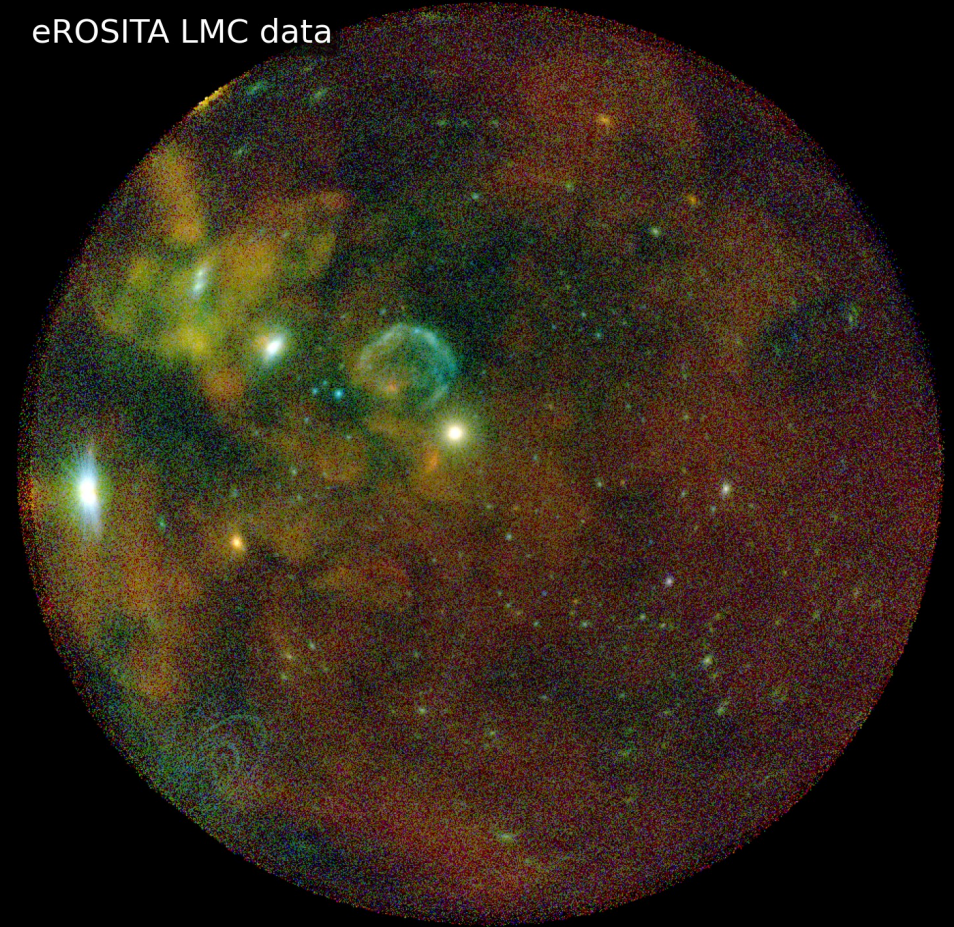


Modeling the X-ray Sky – the Prior

LMC 1987A dataset

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

eROSITA LMC data



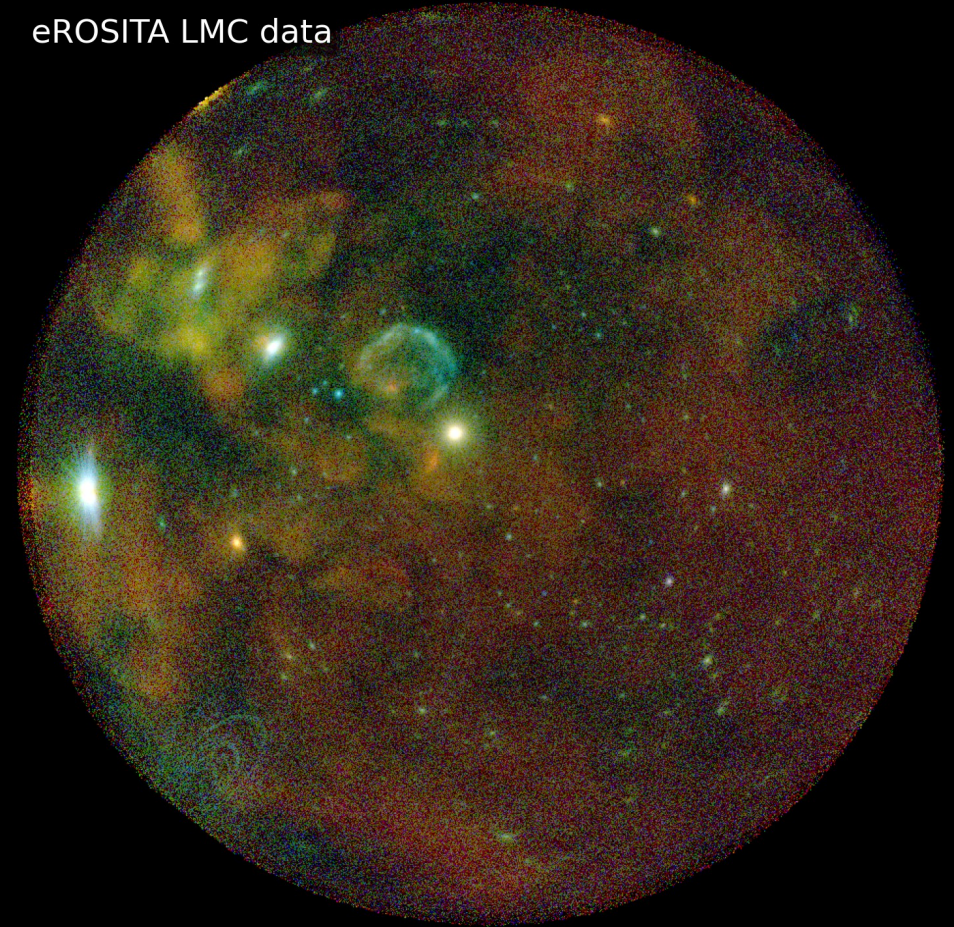
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Components

eROSITA LMC data



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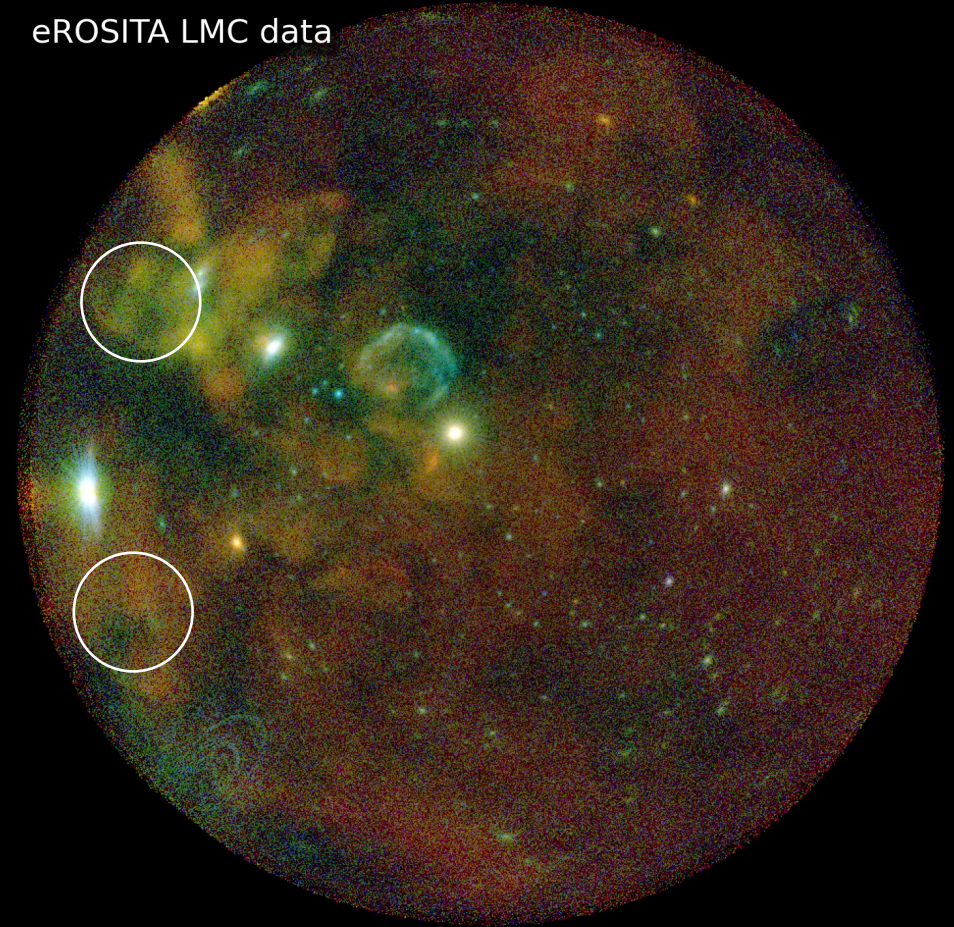
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Components

- diffuse emission

eROSITA LMC data



Modeling the X-ray Sky – the Prior

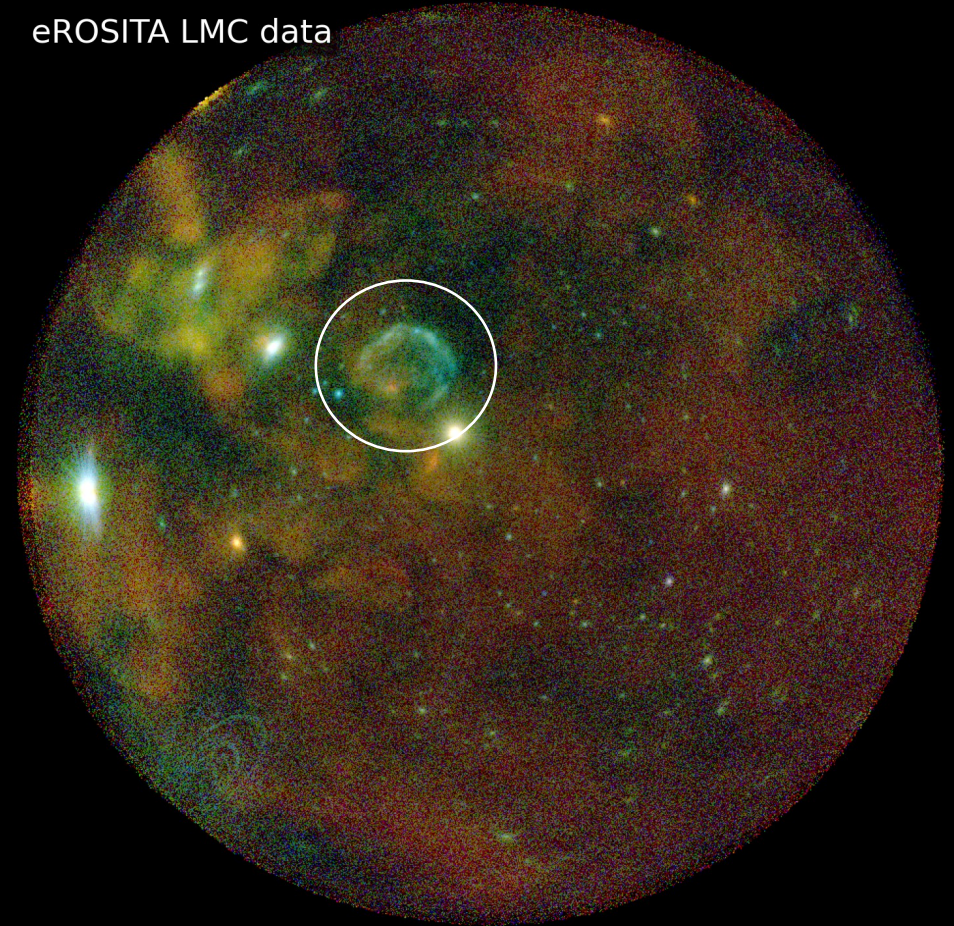
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Components

- diffuse emission
- extended sources (30 Doradus)

eROSITA LMC data



Modeling the X-ray Sky – the Prior

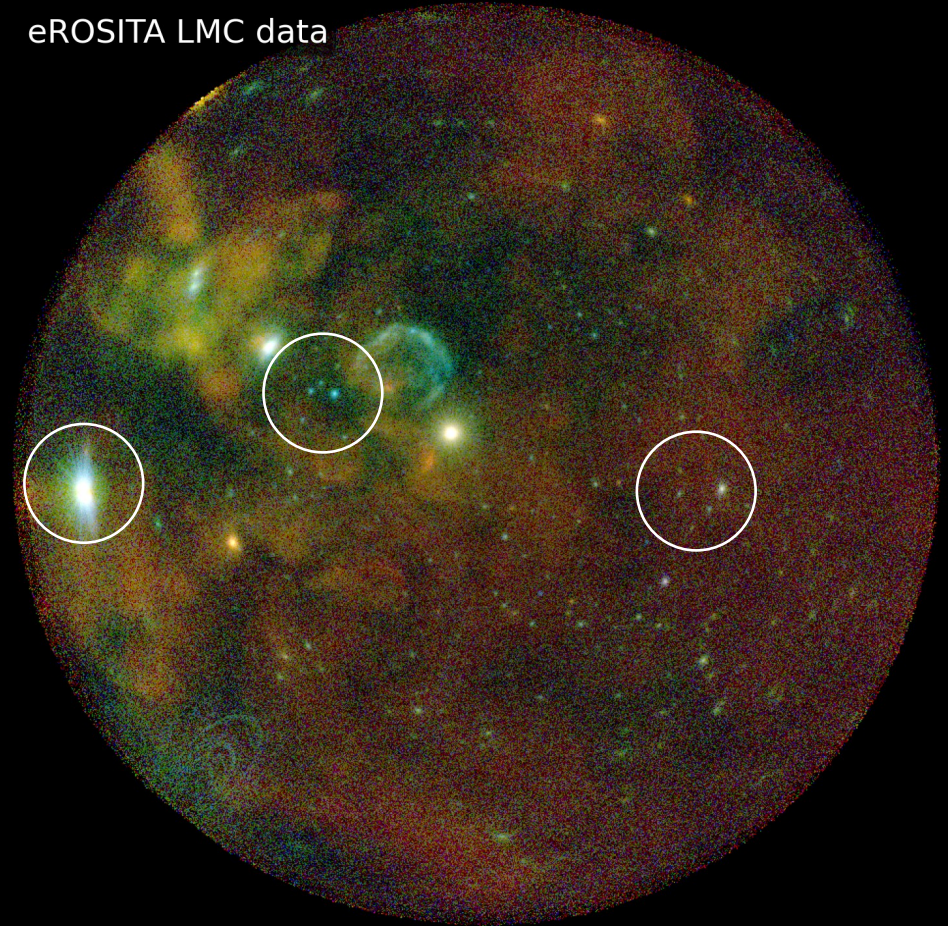
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Components

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

eROSITA LMC data



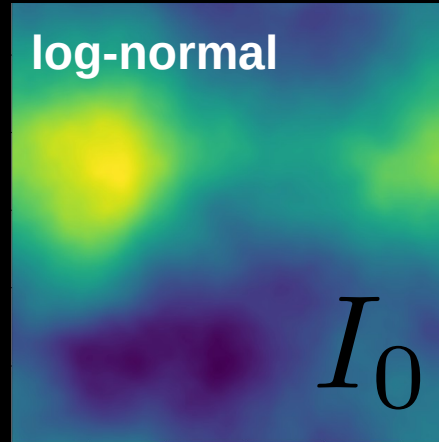
Modeling the Diffuse X-ray Sky

Modeling the Diffuse X-ray Sky

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

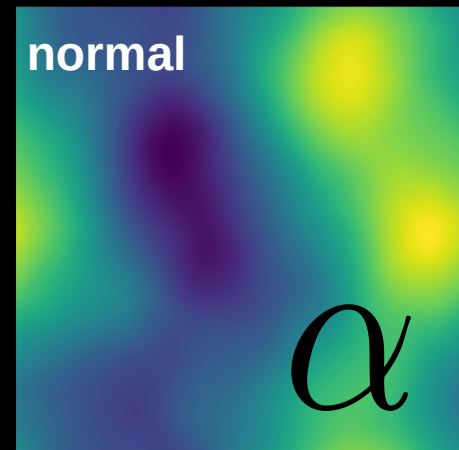
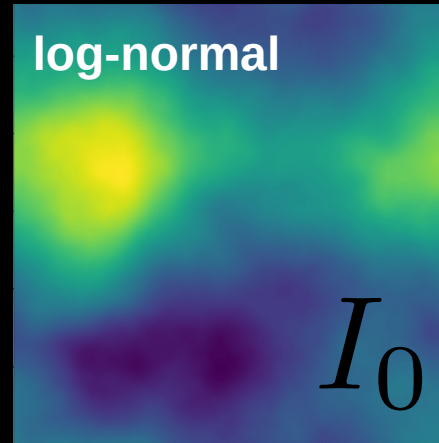
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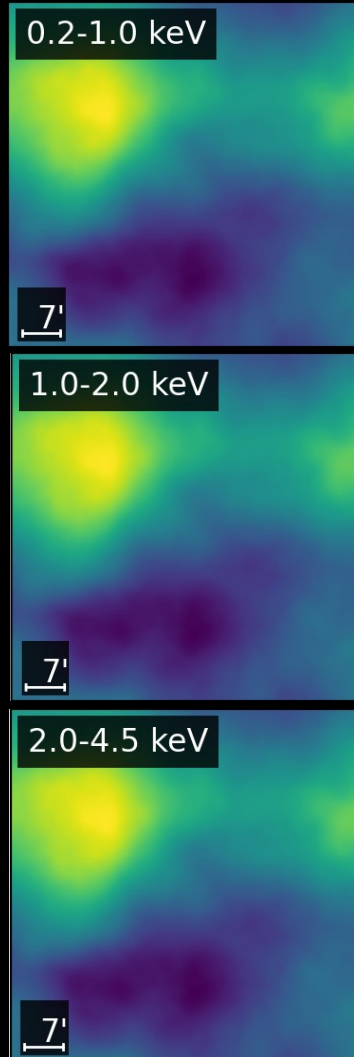


Modeling the Diffuse X-ray Sky

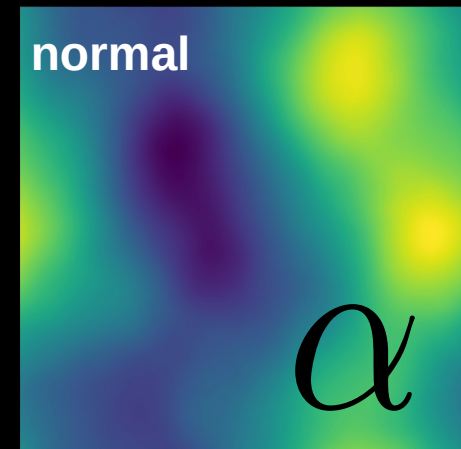
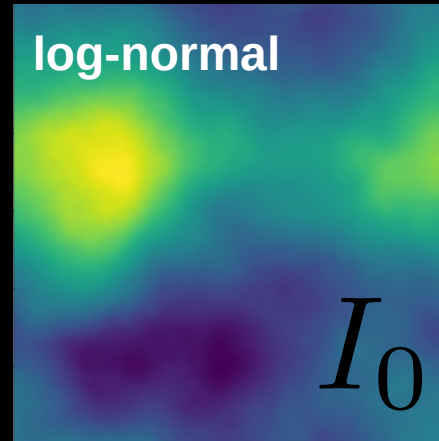
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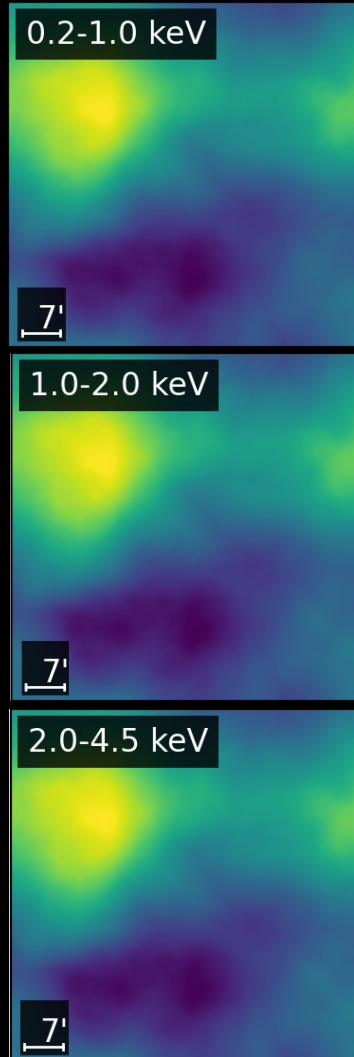
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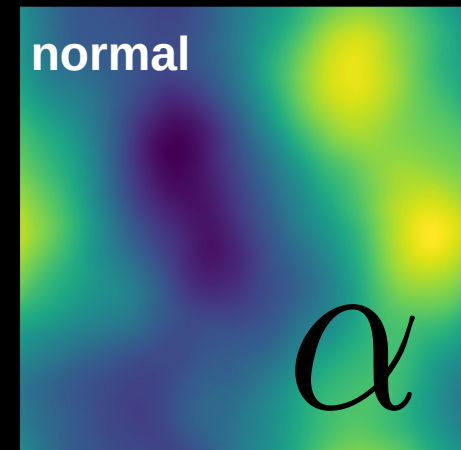
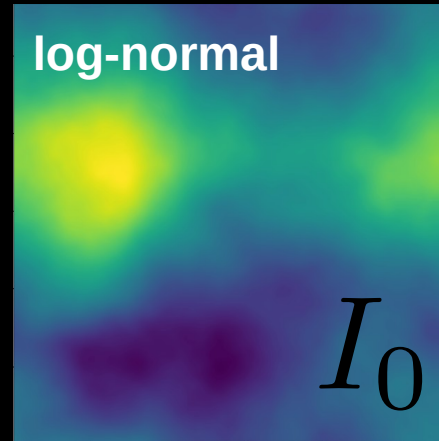
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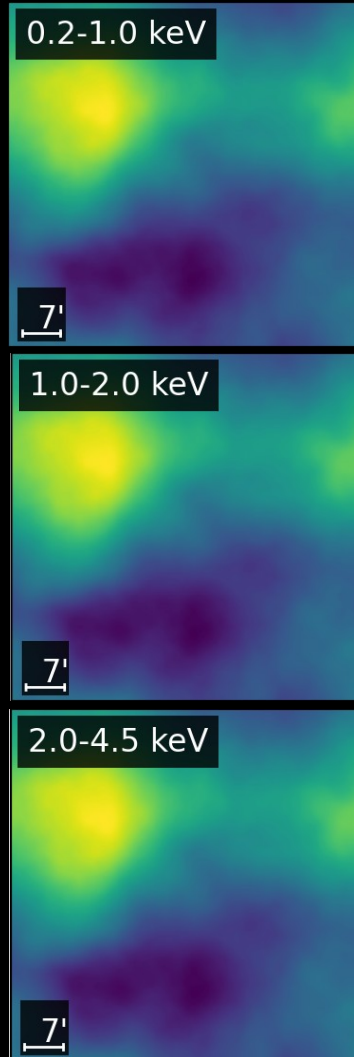
Modeling the Diffuse X-ray Sky & Extended Sources



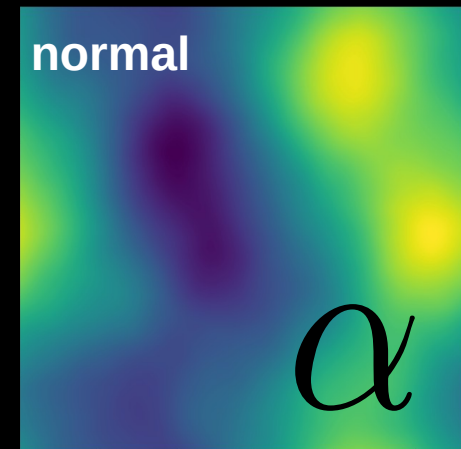
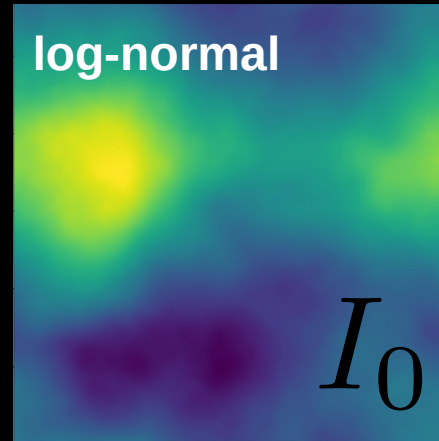
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Modeling the Diffuse X-ray Sky & Extended Sources

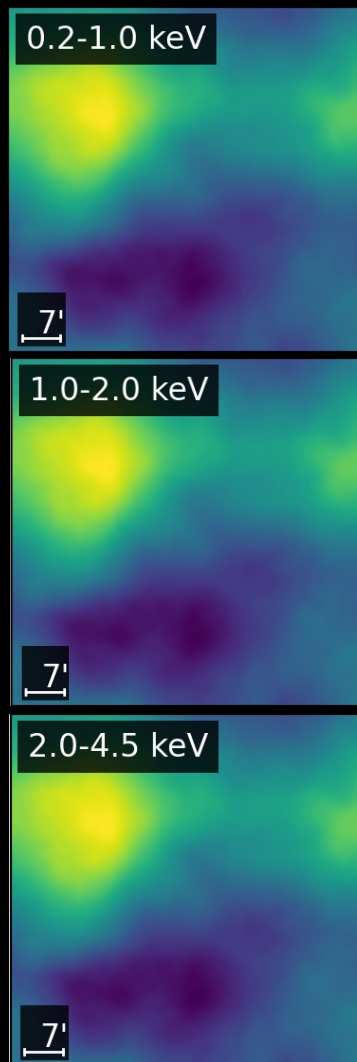


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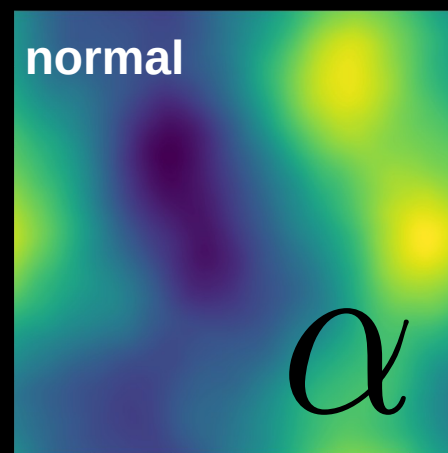
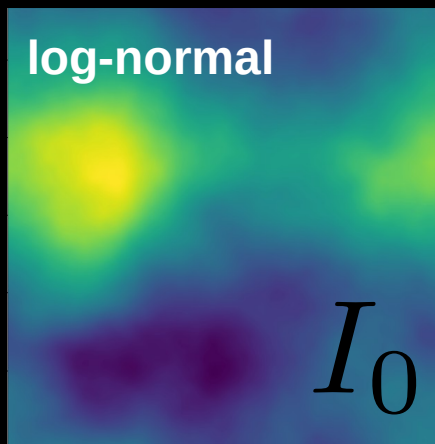


Assumptions in the generative model:

Modeling the Diffuse X-ray Sky & Extended Sources



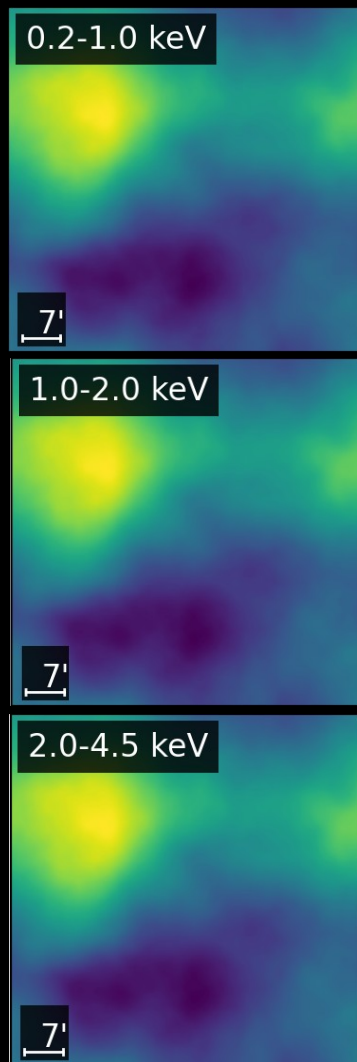
$$d(x, \nu) = I_0(x) \cdot \exp(\alpha(x) \cdot \nu)$$



Assumptions in the generative model:

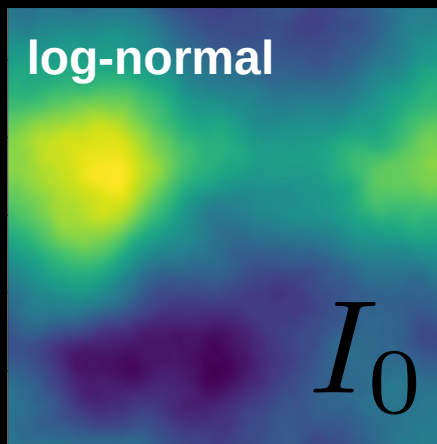
- **Positivity** of flux

Modeling the Diffuse X-ray Sky & Extended Sources

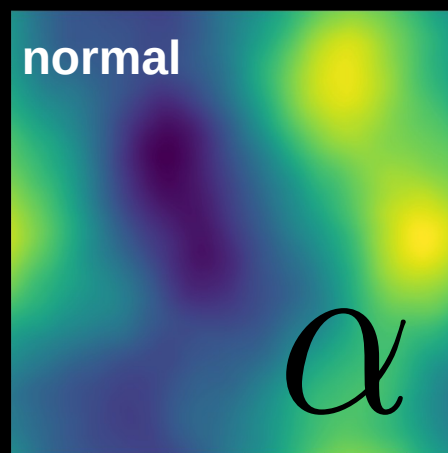


$$d(x, \nu) = I_0(x) \cdot \exp(\alpha(x) \cdot \nu)$$

log-normal



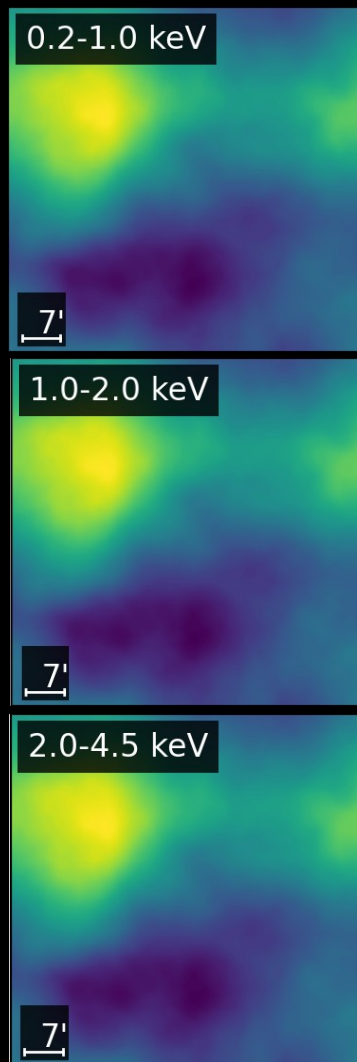
normal



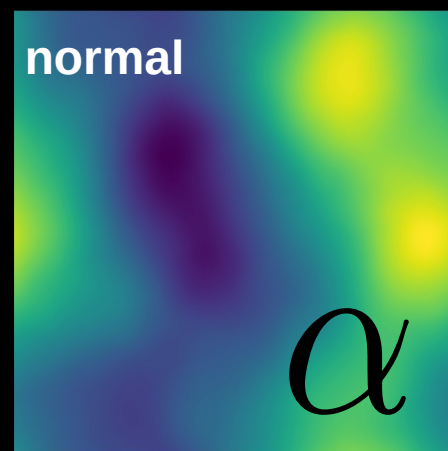
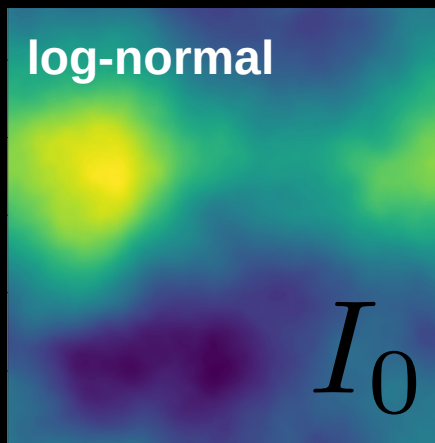
Assumptions in the generative model:

- **Positivity** of flux
- Statistical **homogeneity** & **isotropy**

Modeling the Diffuse X-ray Sky & Extended Sources



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



Assumptions in the generative model:

- **Positivity** of flux
- Statistical **homogeneity** & **isotropy**
- **Spectral** behavior

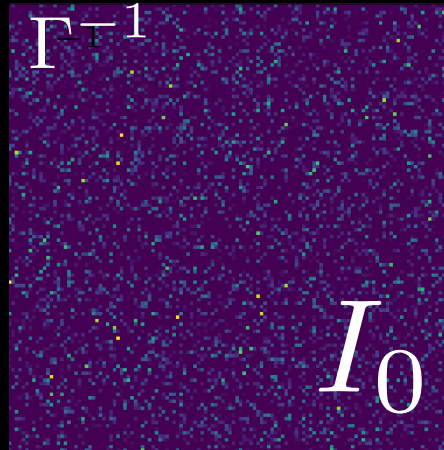
Modeling Point Sources

Modeling Point Sources

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

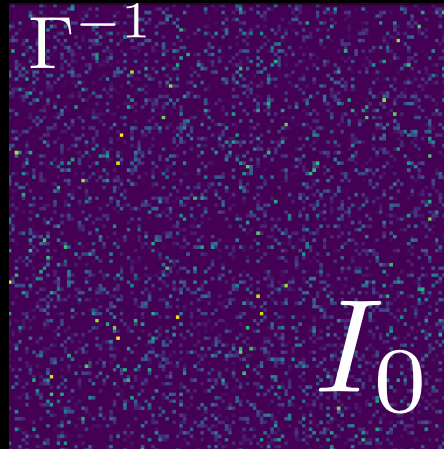
Modeling Point Sources

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



Modeling Point Sources

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



Modeling Point Sources

0.2-1.0 keV

$\underline{I'}$

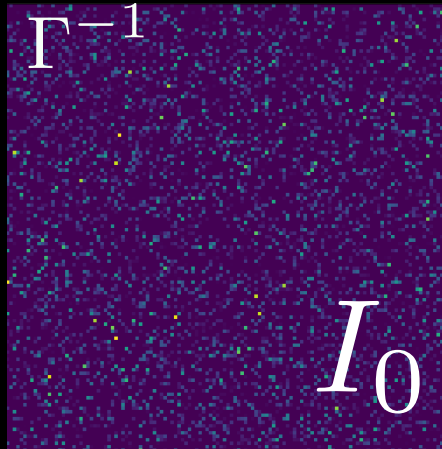
1.0-2.0 keV

$\underline{I'}$

2.0-4.5 keV

$\underline{I'}$

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



Modeling Point Sources

0.2-1.0 keV

$\underline{I'}$

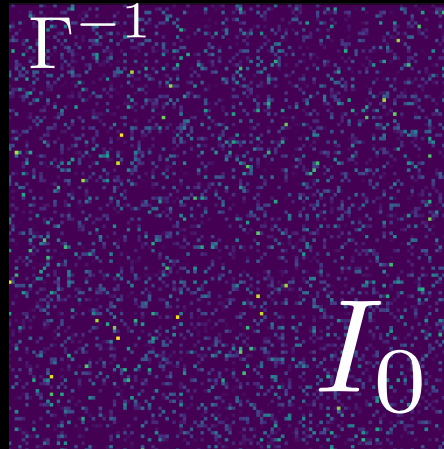
1.0-2.0 keV

$\underline{I'}$

2.0-4.5 keV

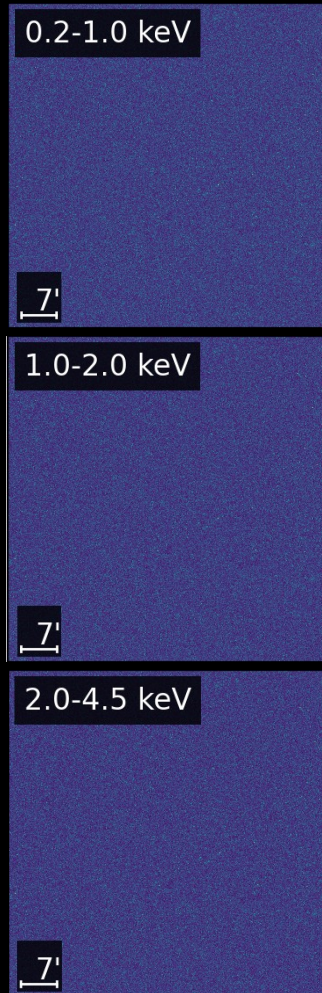
$\underline{I'}$

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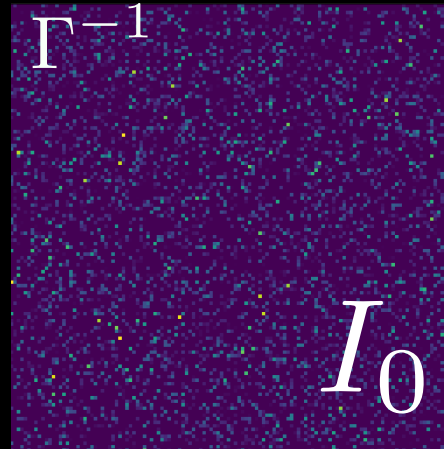


Assumptions in the generative model:

Modeling Point Sources

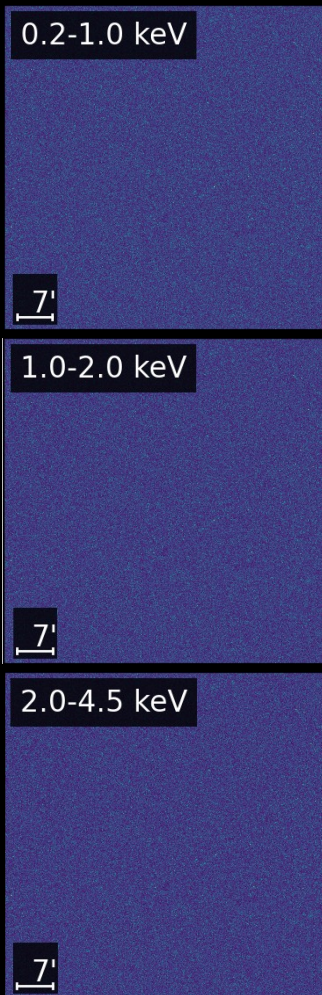


$$p(x, \nu) = I_0(x) \cdot \exp(\alpha_p(x) \cdot \nu)$$

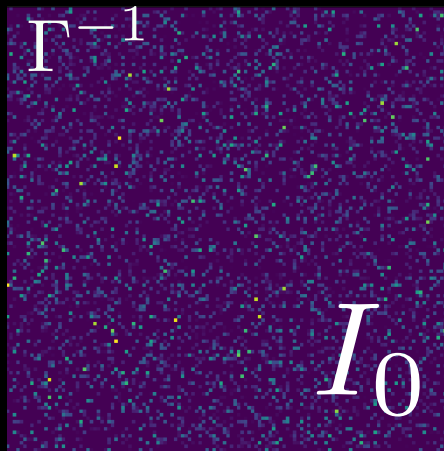


- Assumptions** in the generative model:
- **Positivity** of flux

Modeling Point Sources

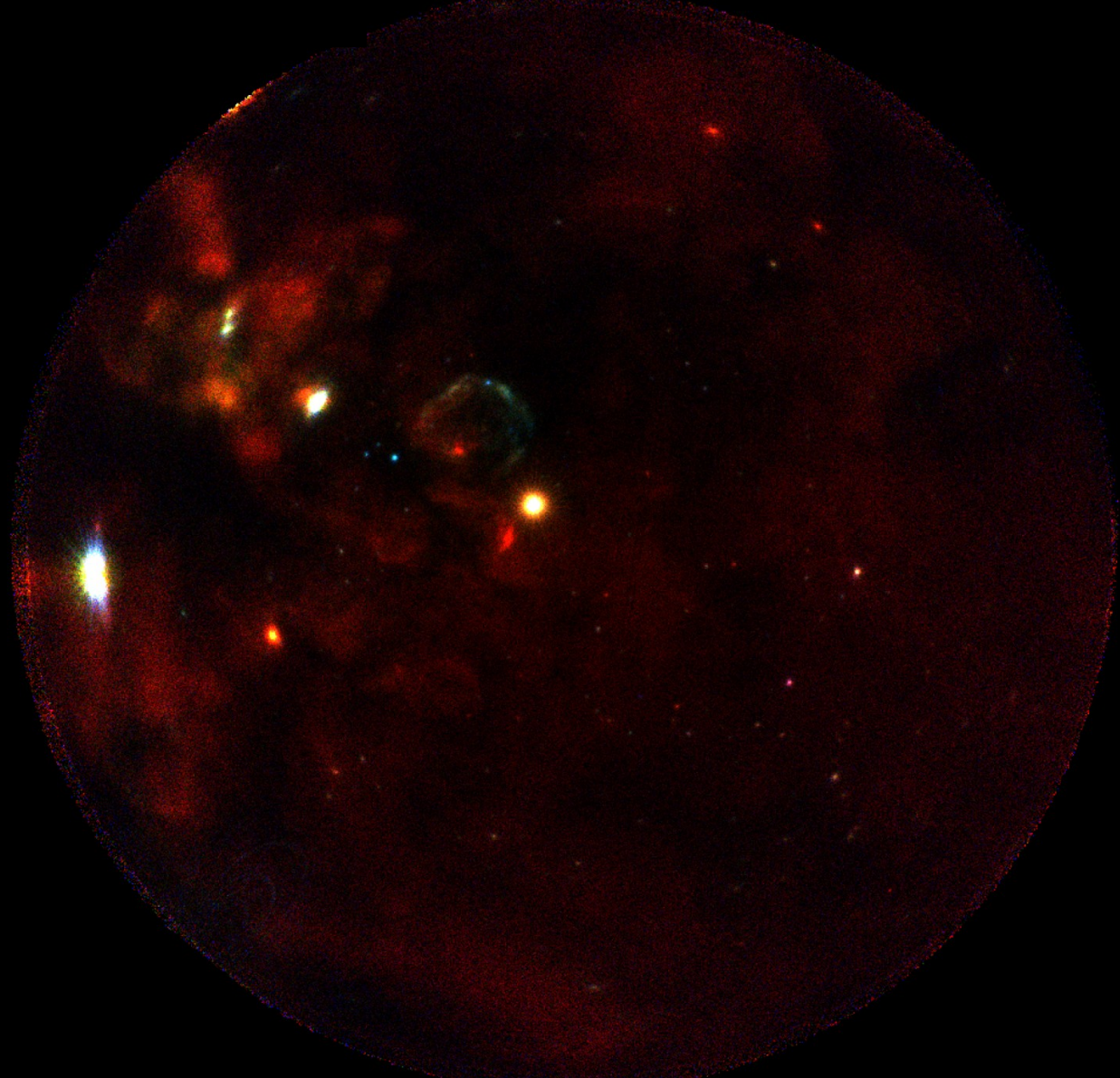


$$p(x, \nu) = I_0(x) \cdot \exp(\alpha_p(x) \cdot \nu)$$



Assumptions in the generative model:

- **Positivity** of flux
- **Spectral** behavior



Generative Models for Bayesian Imaging

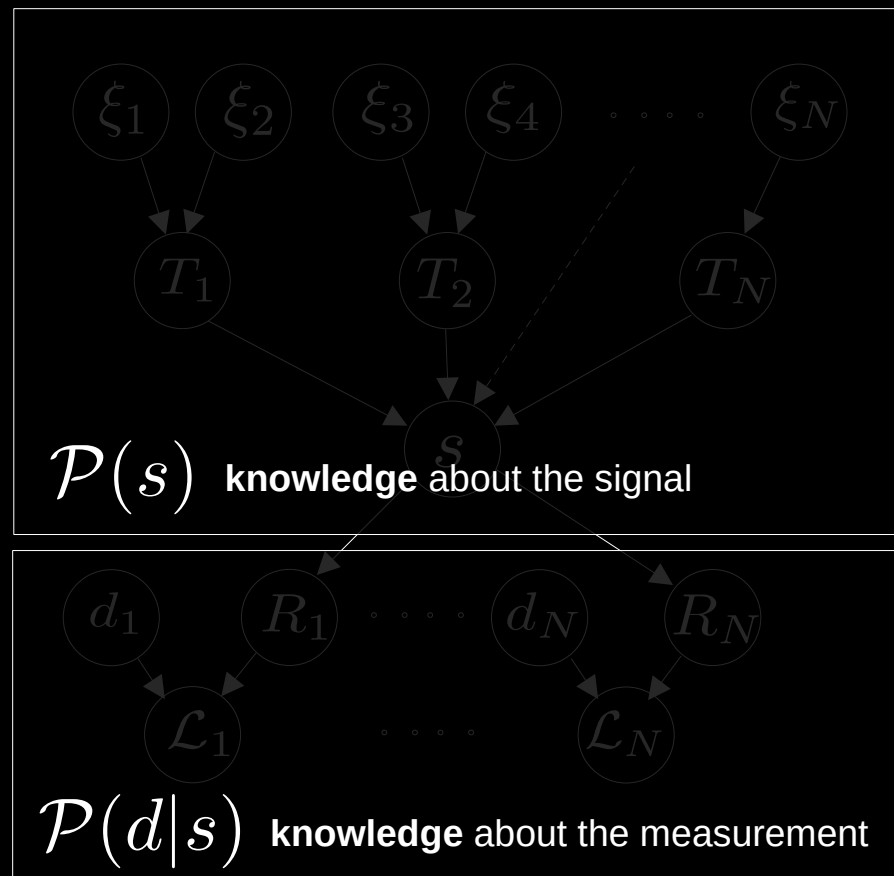
How can we include

domain knowledge

about the signal?

Structure!

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



Generative Models for Bayesian Imaging

How can we include

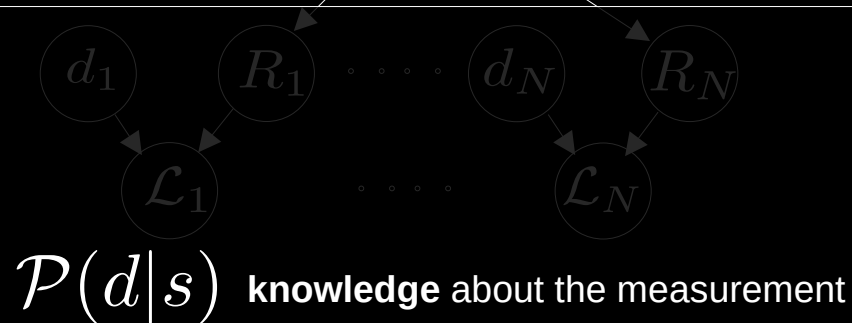
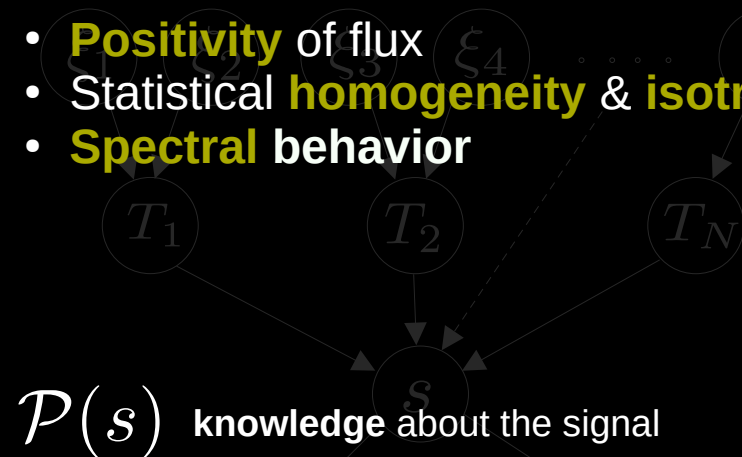
domain knowledge

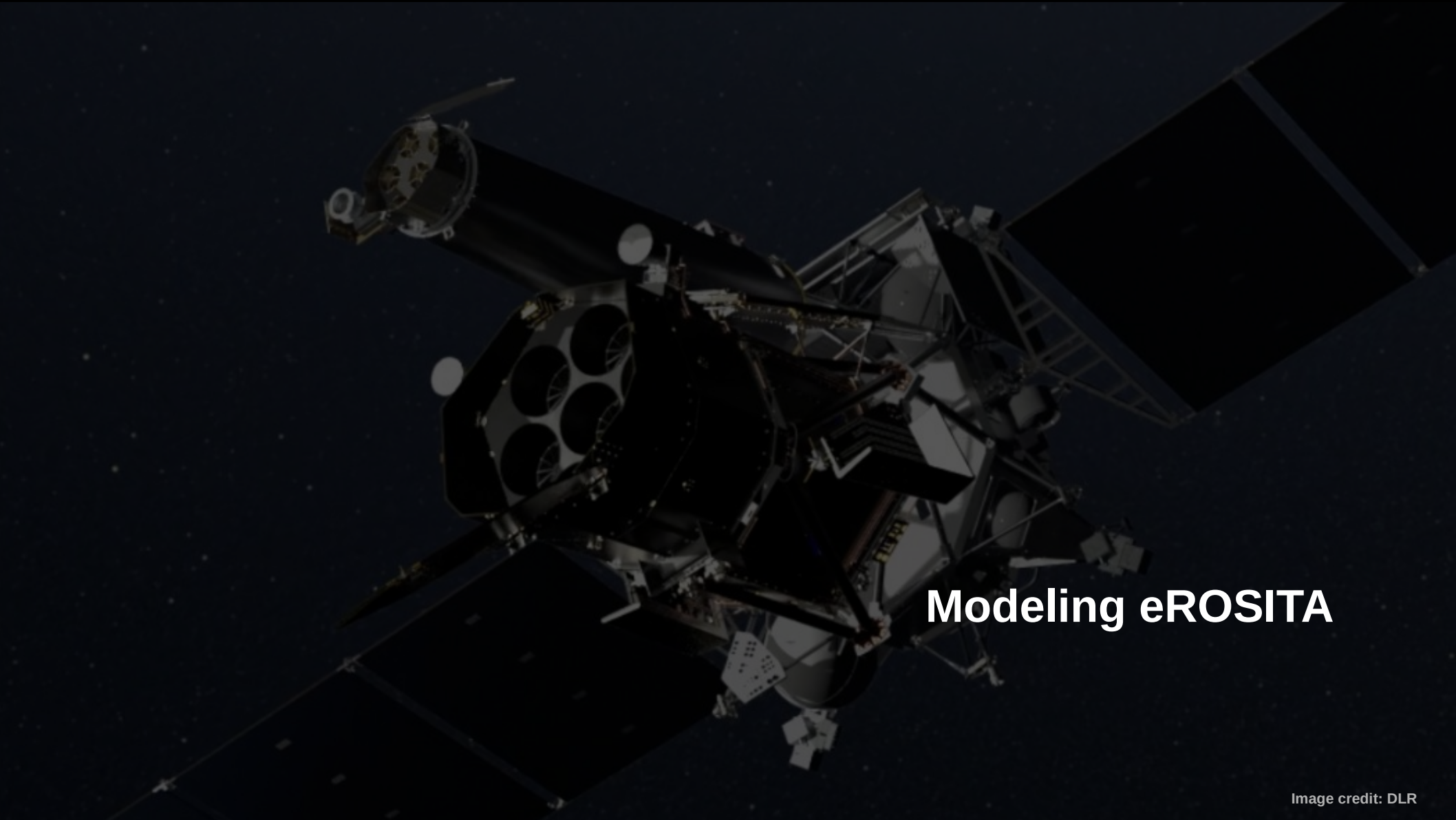
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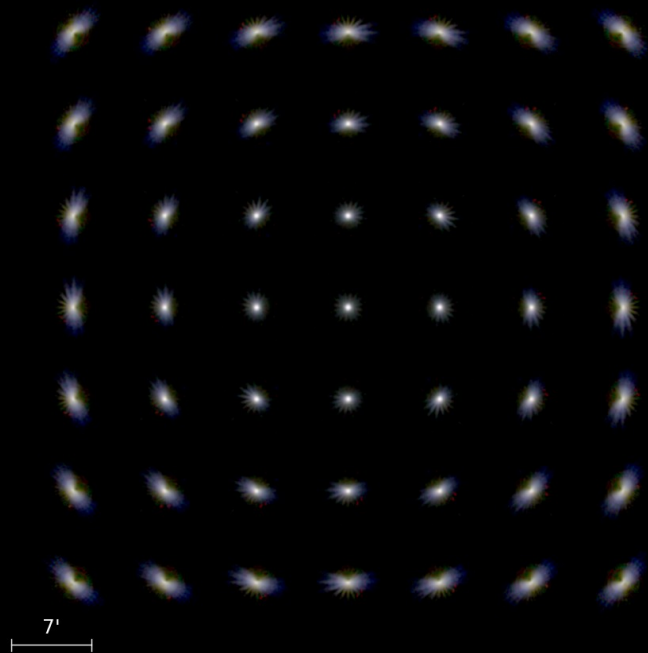
- **Positivity** of flux
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A detailed 3D computer-generated model of the eROSITA (extended Roentgen Surveyor for Telescopes and Imaging) satellite. The satellite is shown in a three-quarter view against a black background filled with numerous small white dots representing distant stars. The main body of the satellite is a complex assembly of metallic structures, including a large cylindrical section with several circular apertures. A long, thin boom extends from the main body, supporting a large, rectangular solar panel. Another boom extends from the side, supporting a smaller, circular instrument. The overall design is intricate, showing various sensors, antennas, and structural supports.

Modeling eROSITA

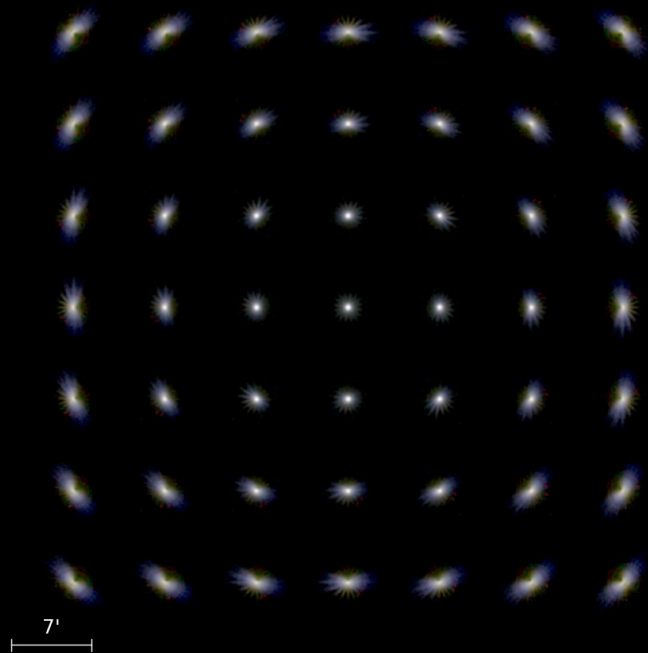
Modeling the Instrument



Point spread functions measured at PANTER (CaIDB)

Modeling the Instrument

Spatially invariant PSF:

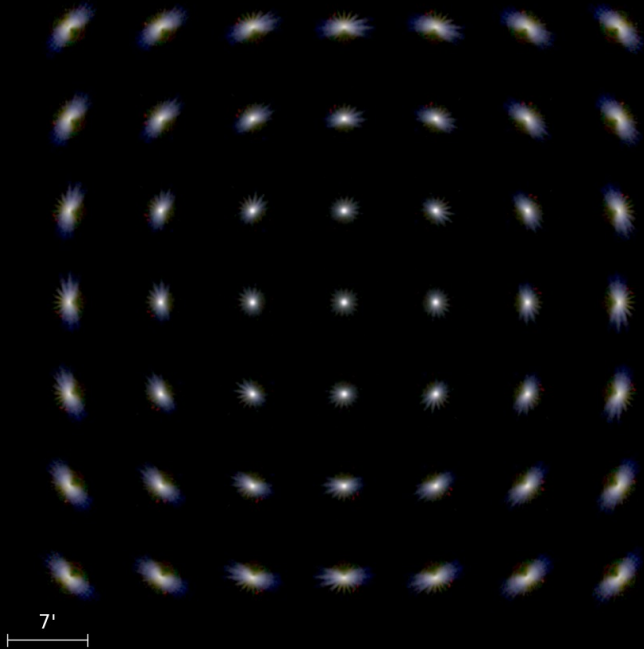


Point spread functions measured at PANTER (CalDB)

Modeling the Instrument

Spatially **invariant** PSF:

- **Convolution** with one PSF kernel
- $O(N \log N)$ Fast Fourier Transform



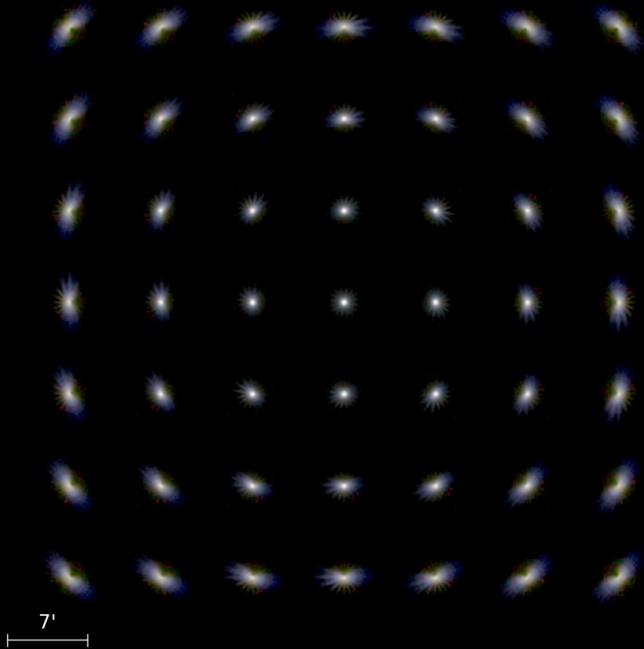
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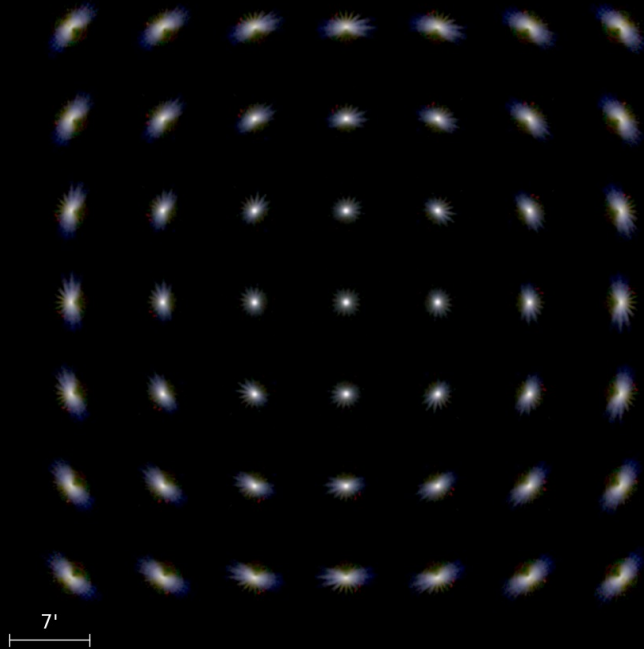
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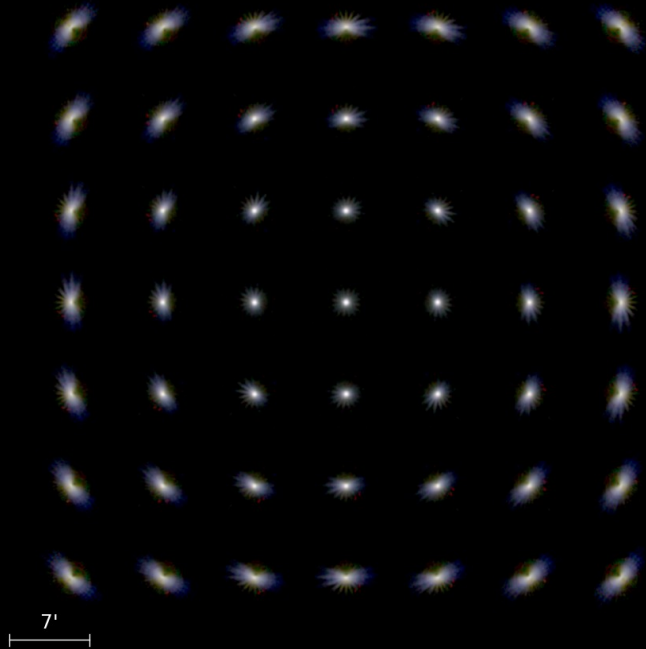
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- Naive: Full Matrix? [$O(N^2)$]
 - Huge memory consumption
 - Slow execution

Modeling the Instrument



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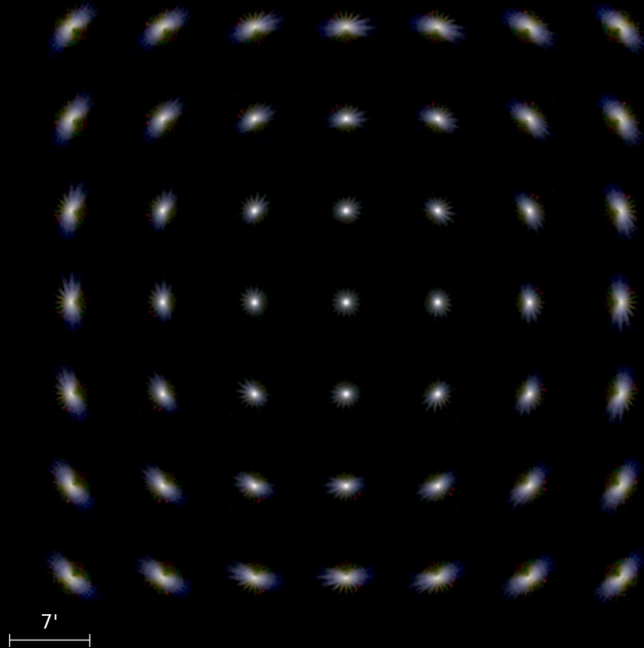
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Strategies for spatially variant PSF de-blurring:

Modeling the Instrument



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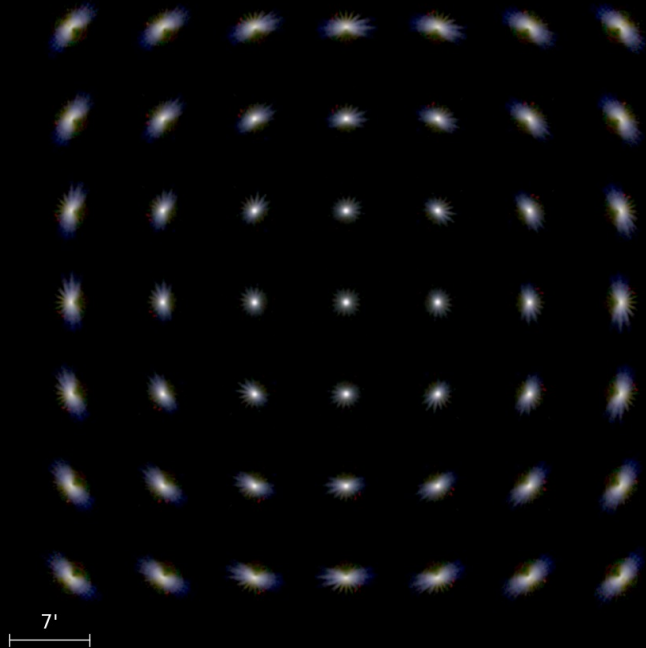
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Modeling the Instrument



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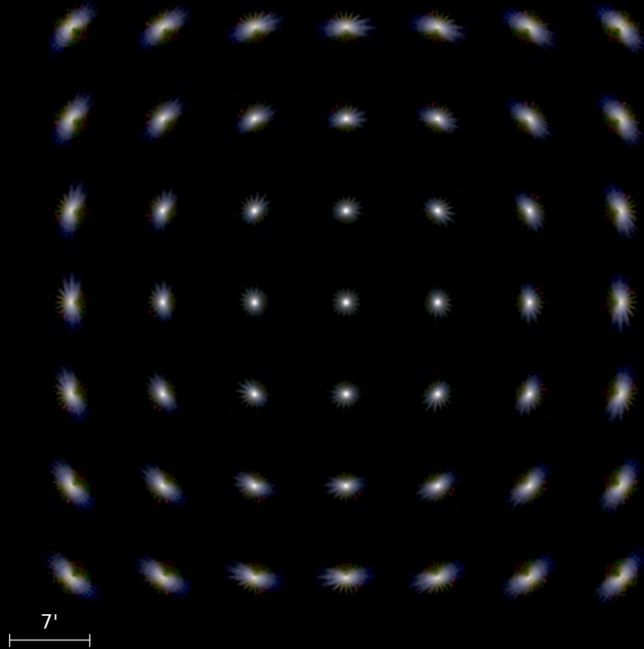
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Strategies for spatially variant PSF de-blurring:

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- Remove off-axis data

Modeling the Instrument



Point spread functions measured at PANTER (CalDB)

Patched Interpolated Convolution

[Nagy, James G., and Dianne P. O'Leary. "Fast iterative image restoration with a spatially varying PSF."

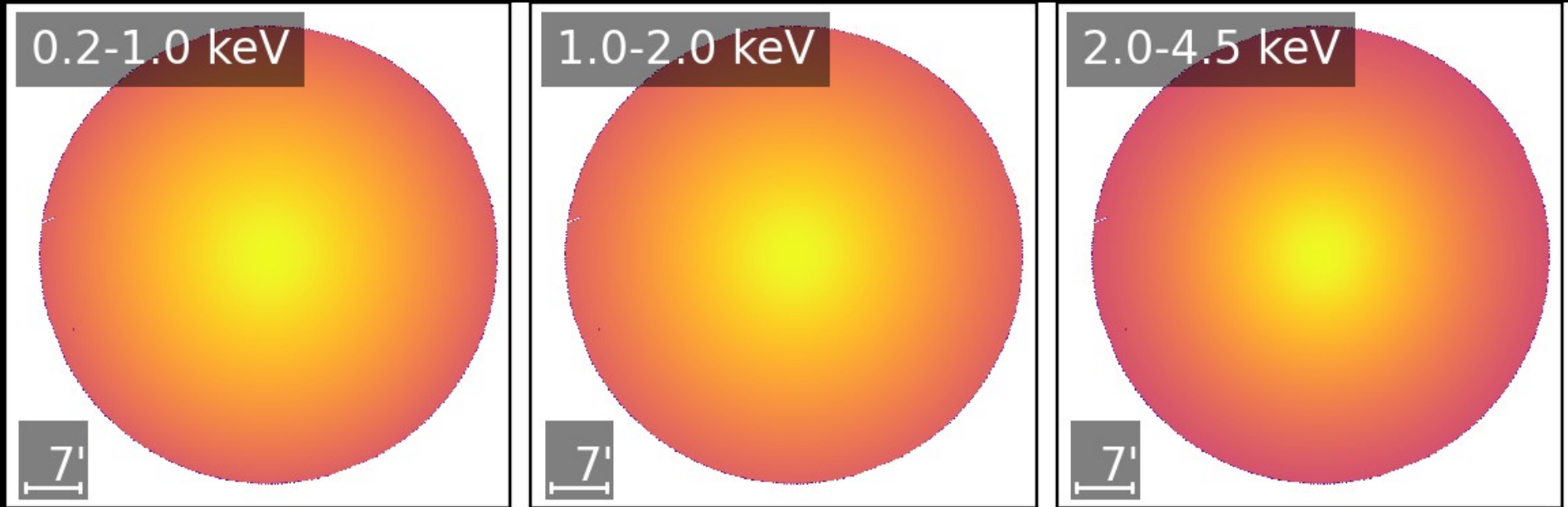
Advanced Signal Processing: Algorithms, Architectures, and Implementations VII. Vol. 3162. SPIE, 1997.]

Modeling the Instrument

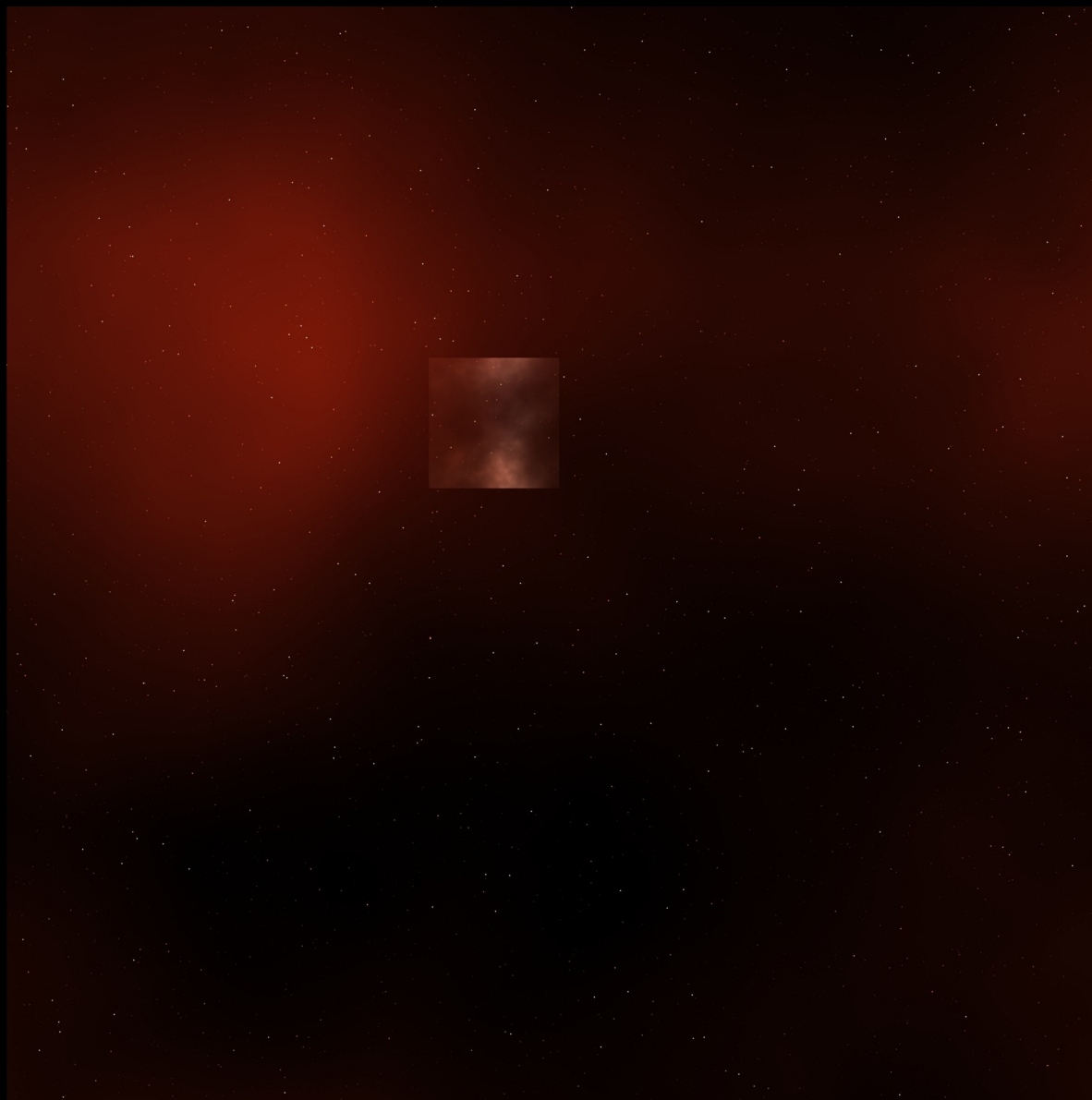
Exposure and Detmaps information from eSASS and CALDB

Modeling the Instrument

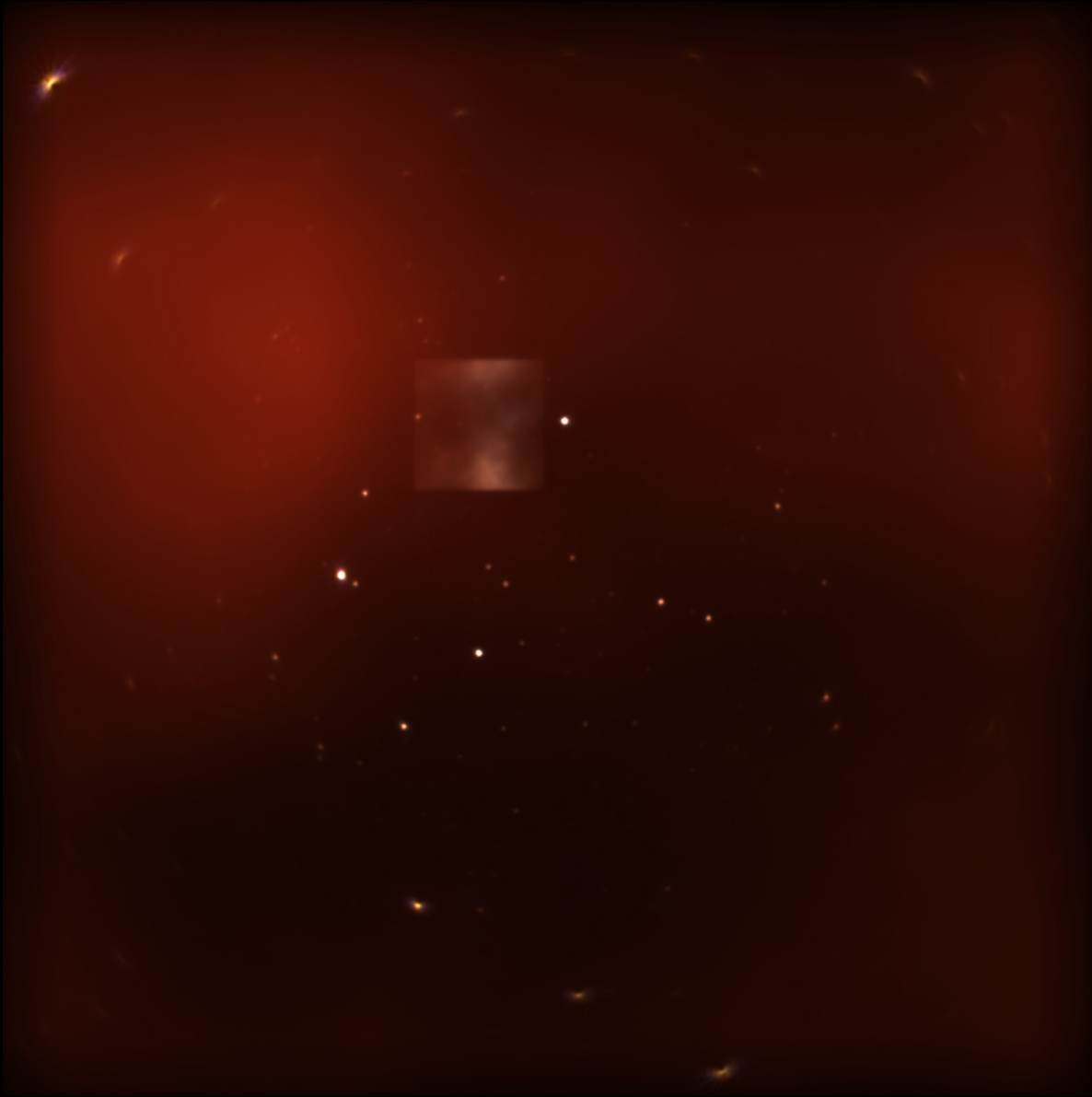
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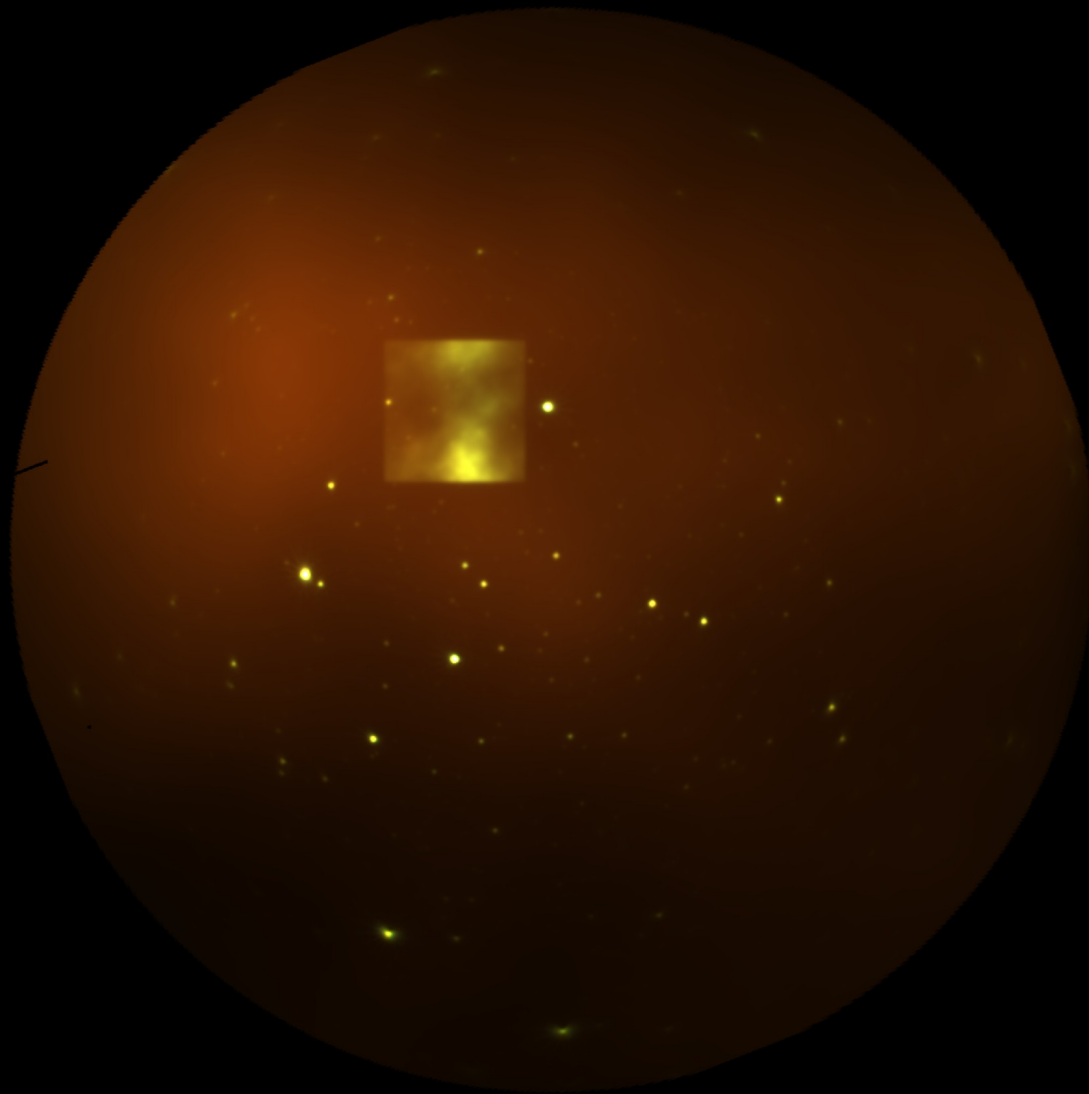
Sky

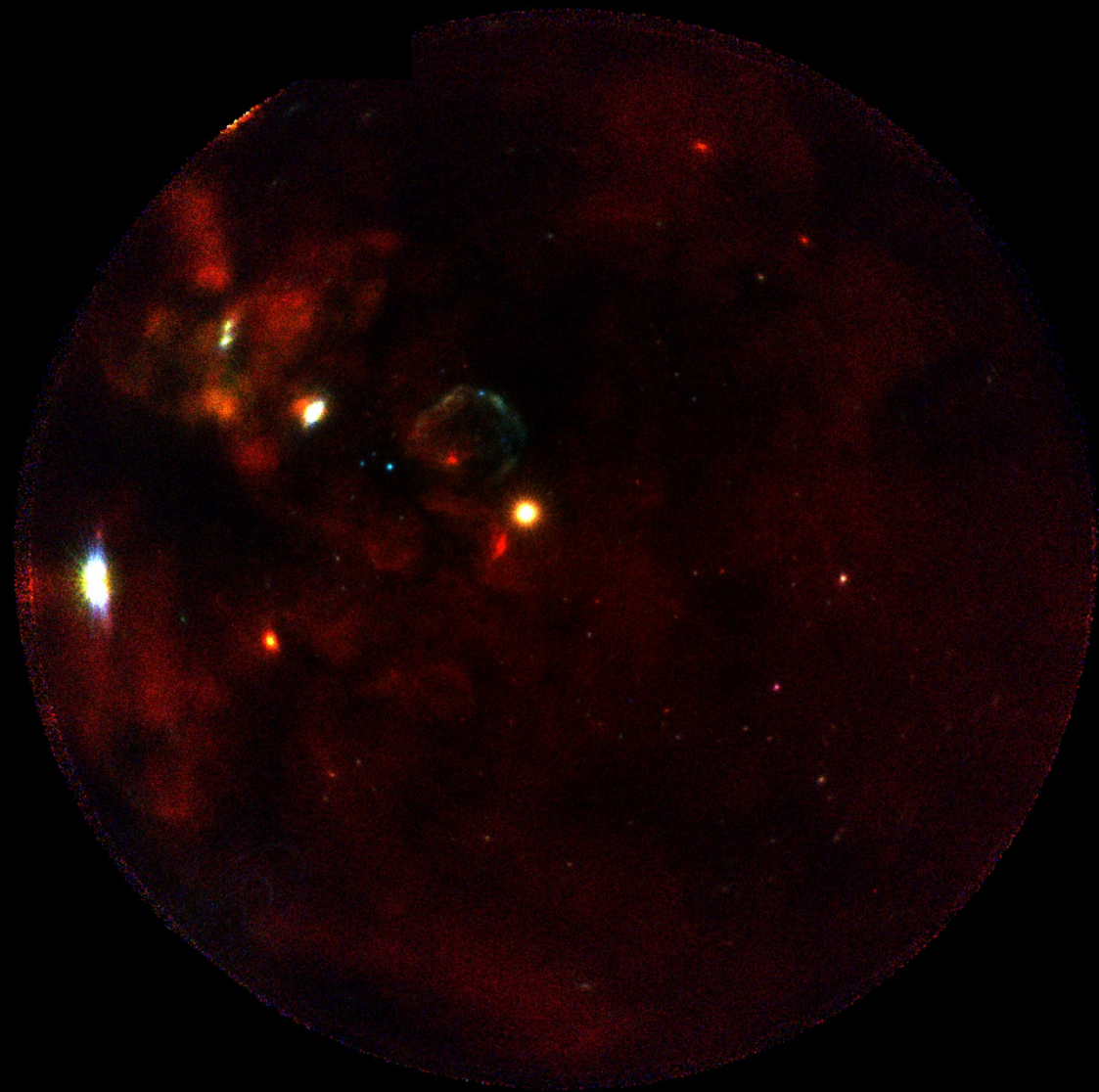


PSF(Sky)



$E(\text{PSF}(\text{Sky}))$





Generative Models for Bayesian Imaging

How can we include

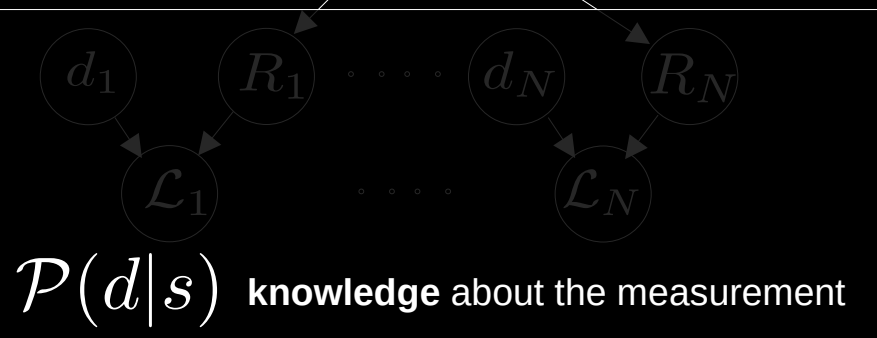
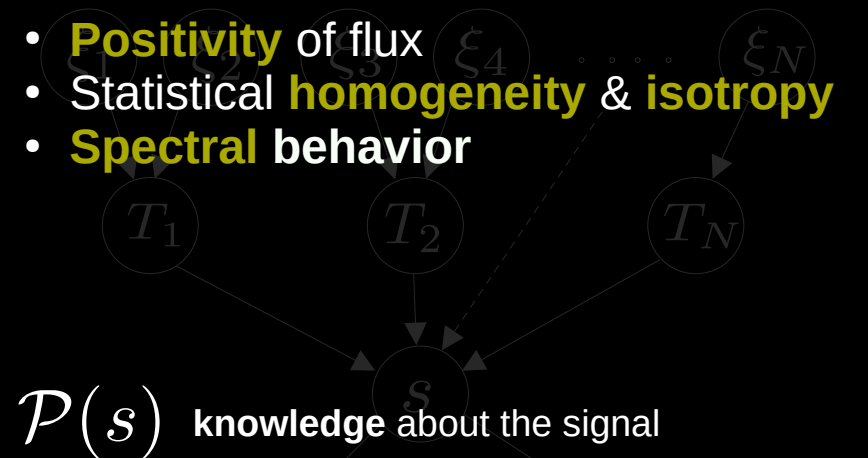
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Generative Models for Bayesian Imaging

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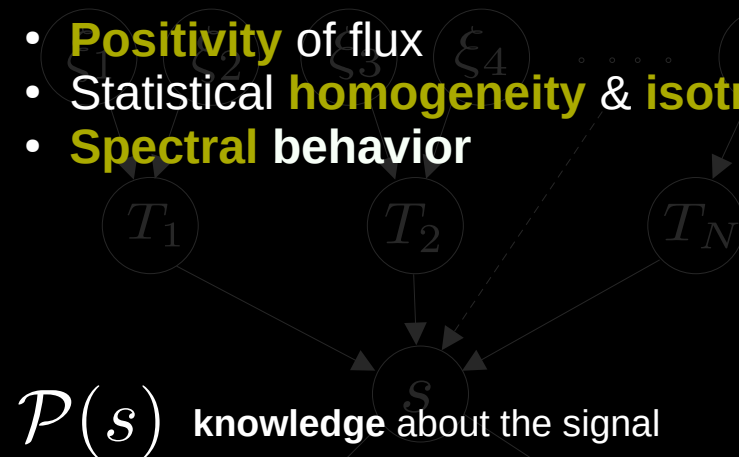
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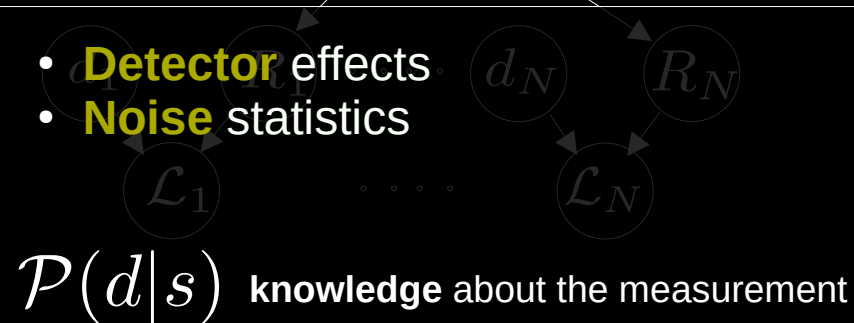
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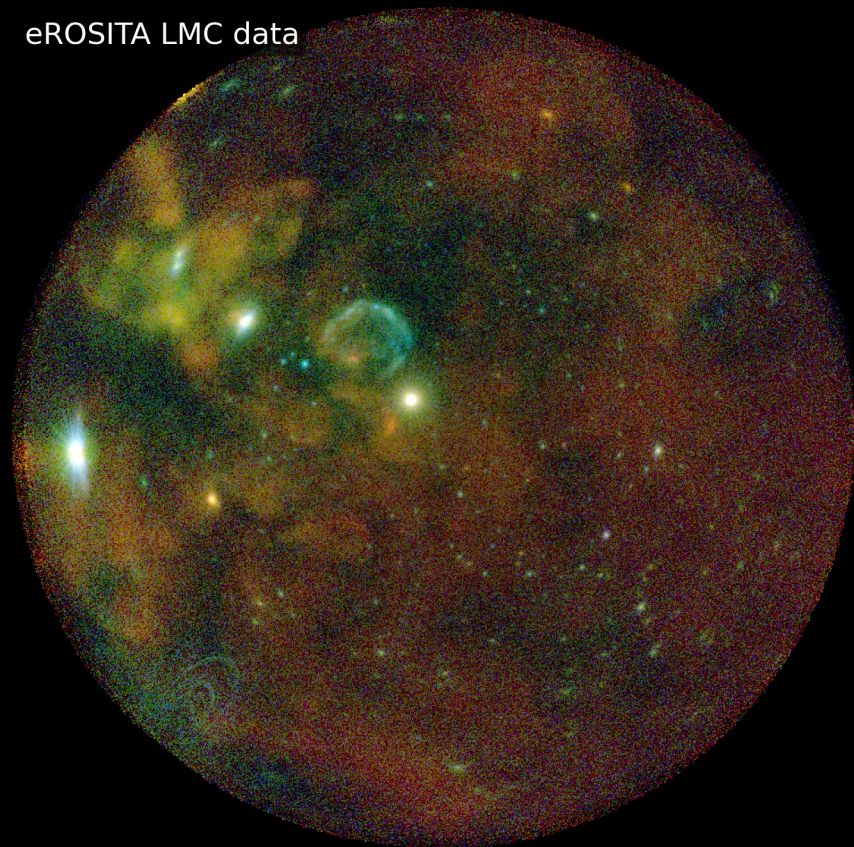


- **Detector** effects
- **Noise** statistics

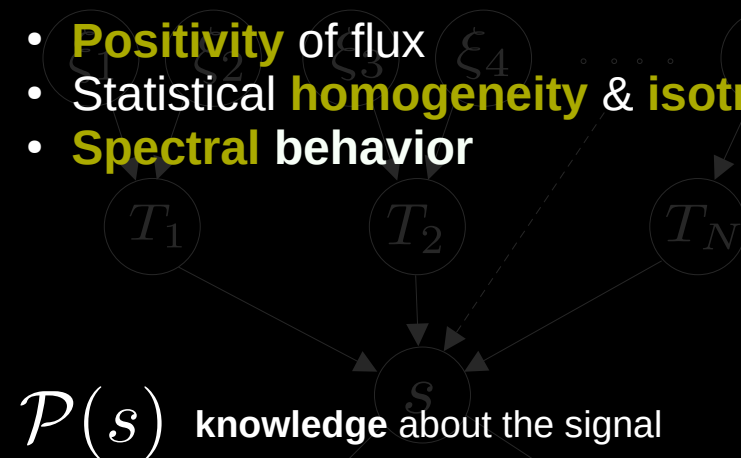


SN1987A with eROSITA

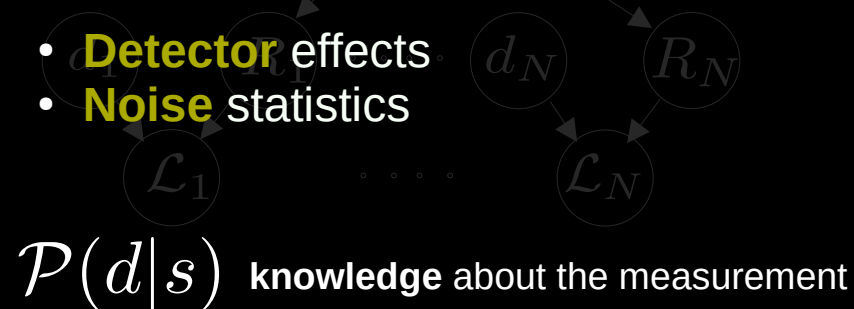
eROSITA LMC data



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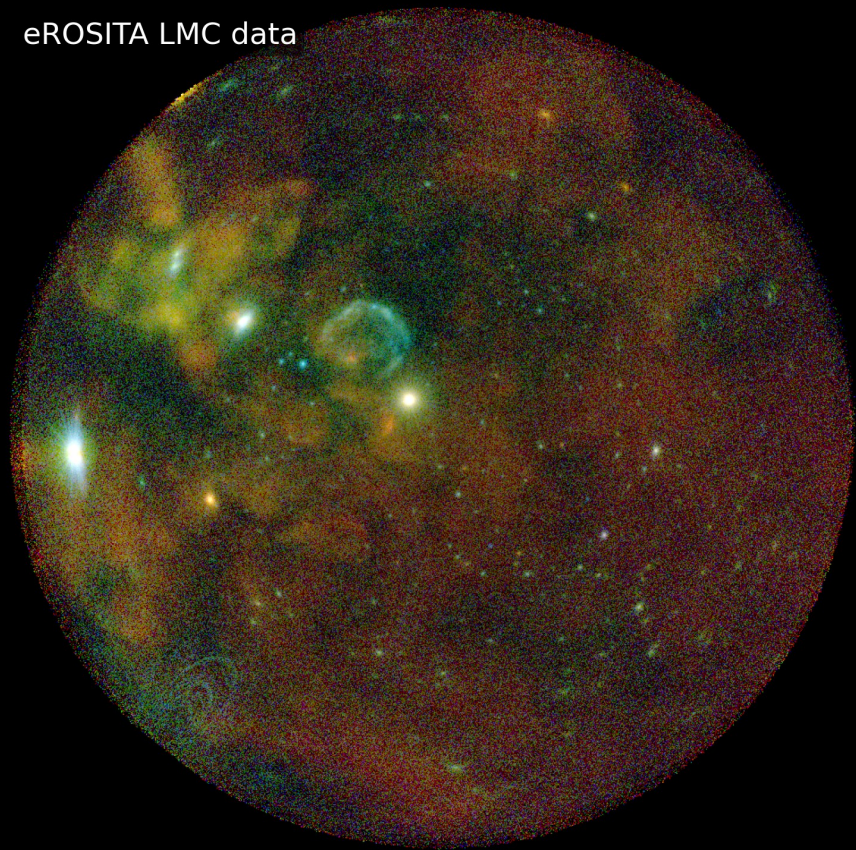


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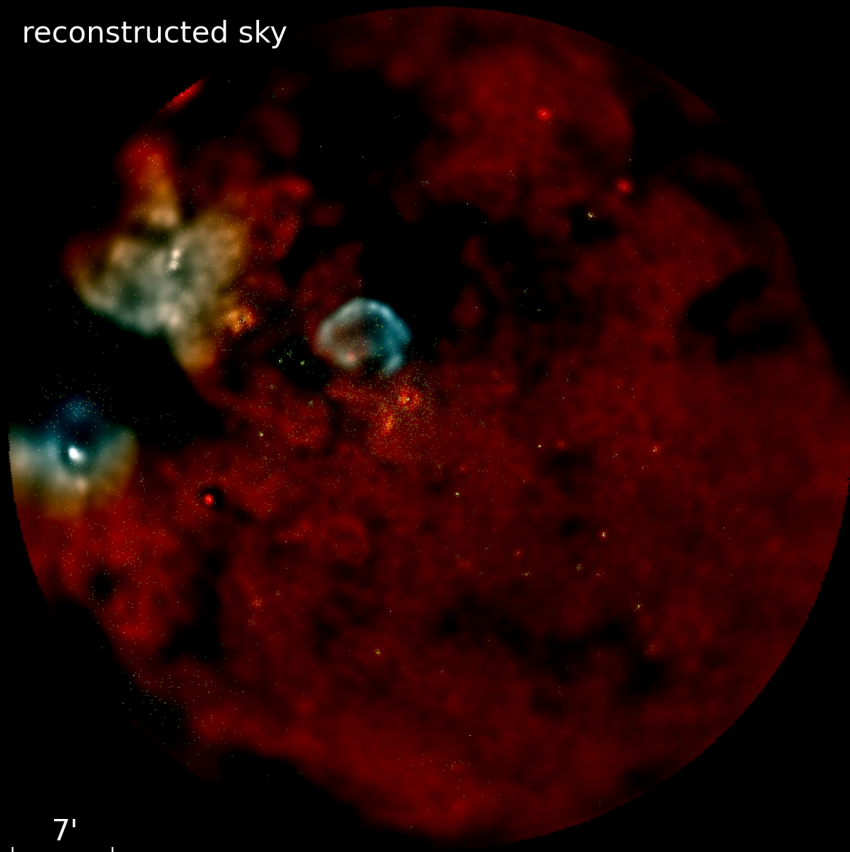


SN1987A with eROSITA

eROSITA LMC data



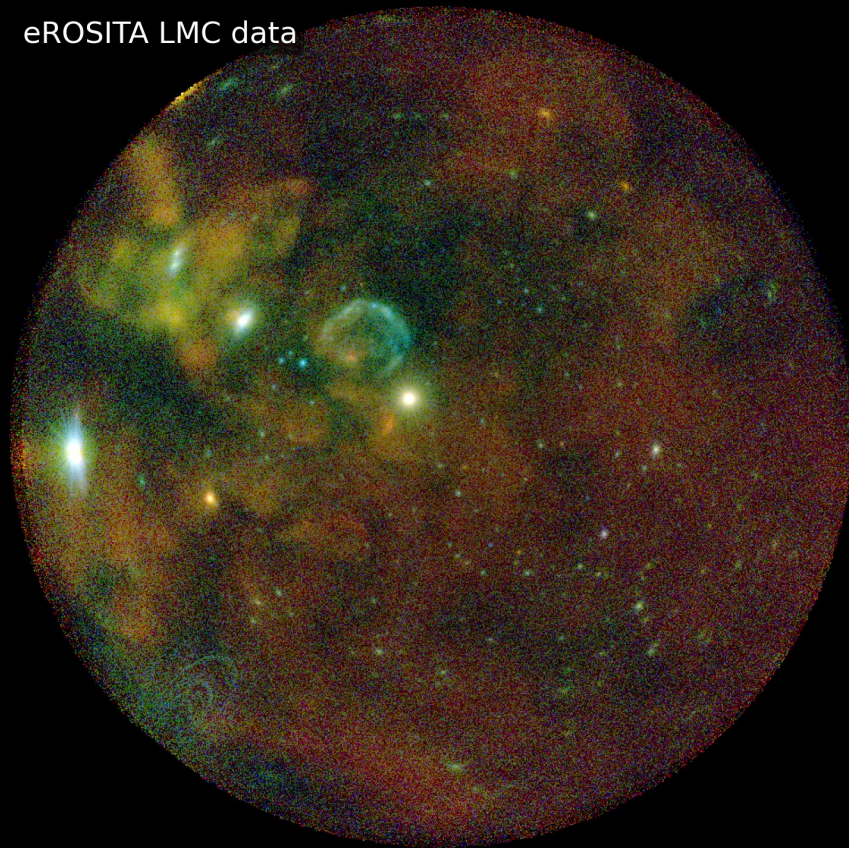
reconstructed sky



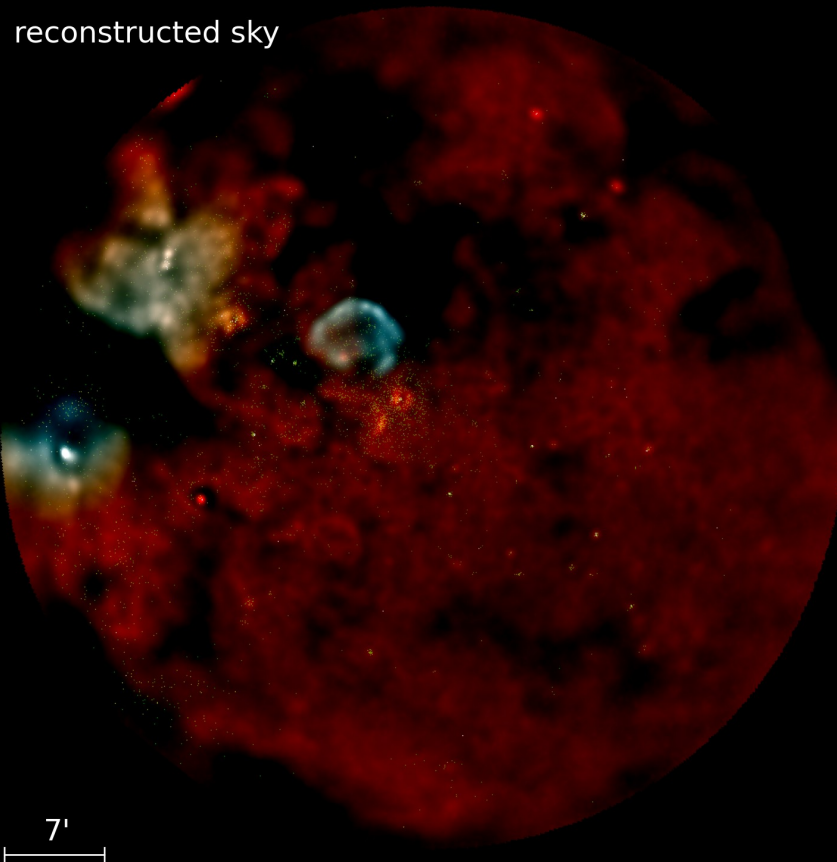
7'

SN1987A with eROSITA

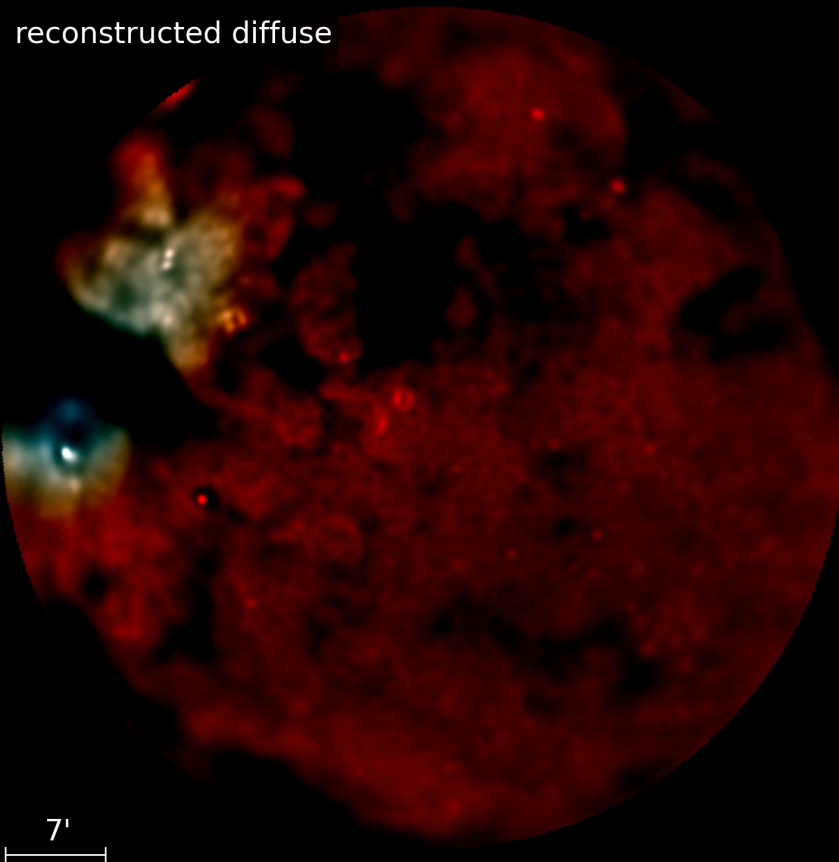
eROSITA LMC data



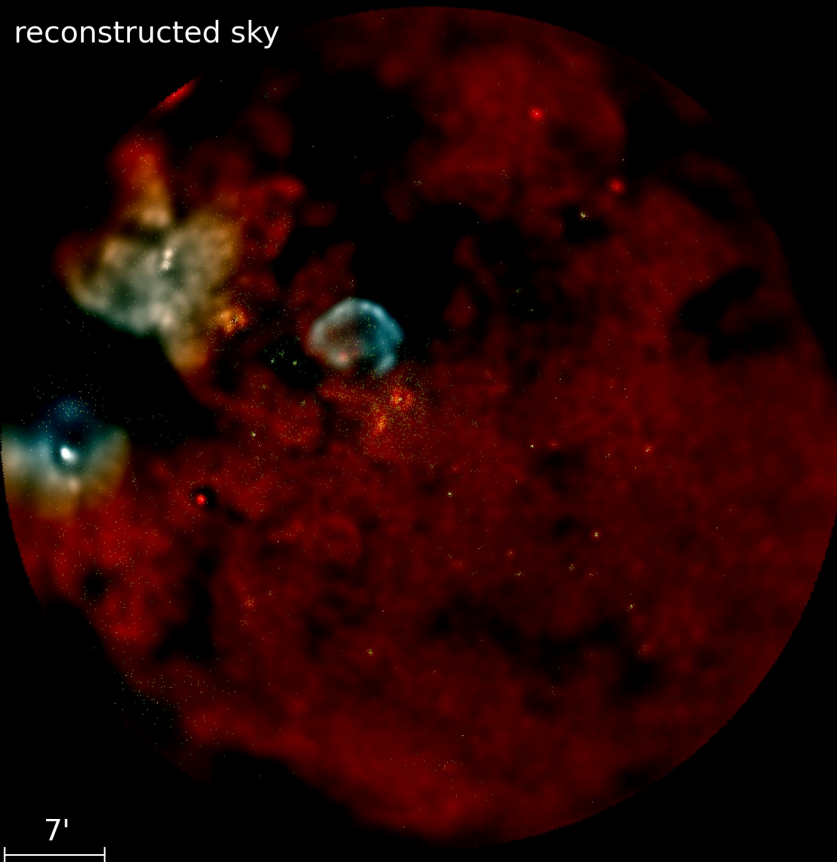
SN1987A with eROSITA



SN1987A with eROSITA



SN1987A with eROSITA

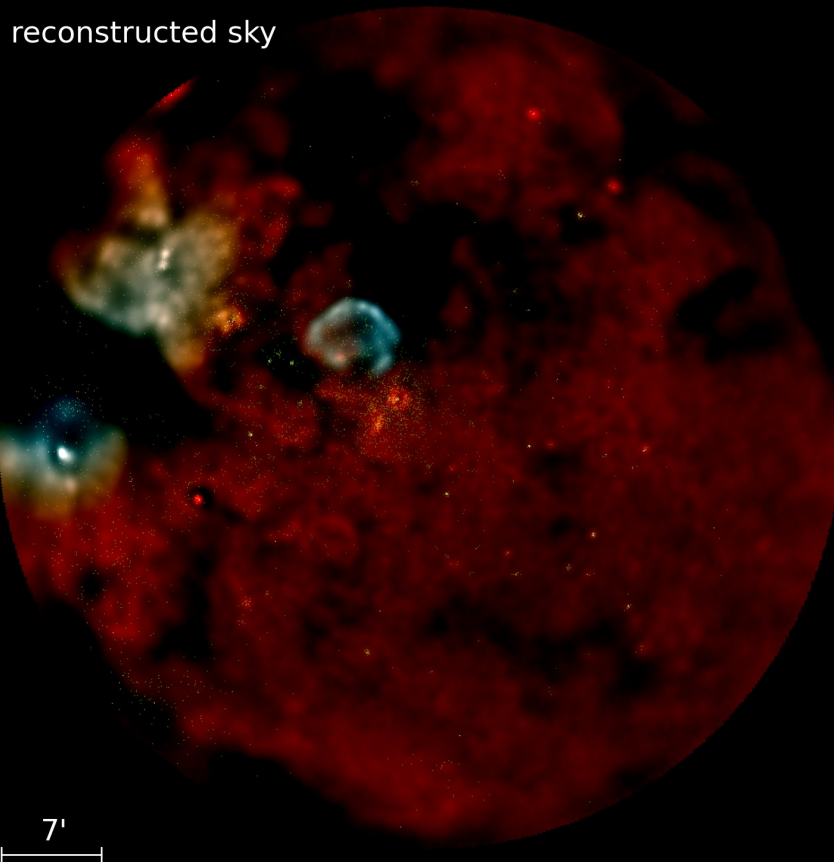


SN1987A with eROSITA

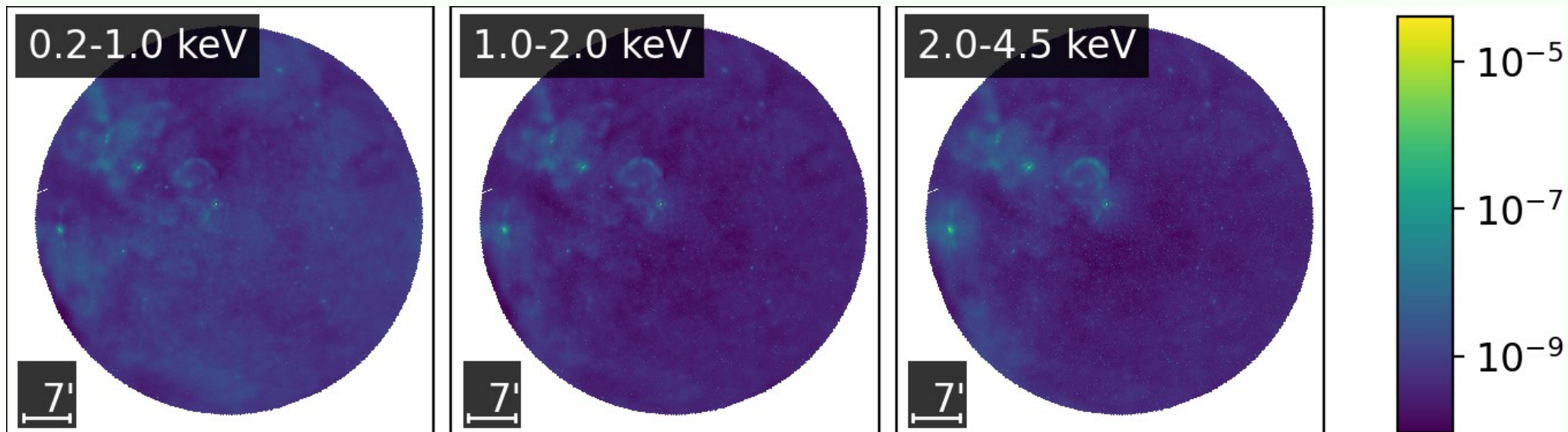
reconstructed points



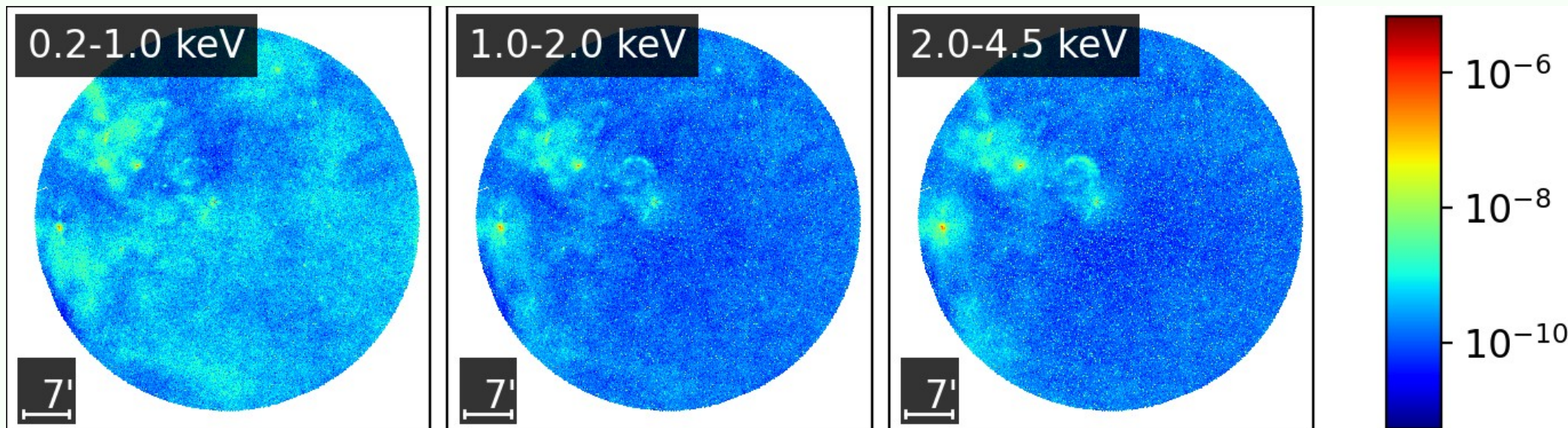
SN1987A with eROSITA



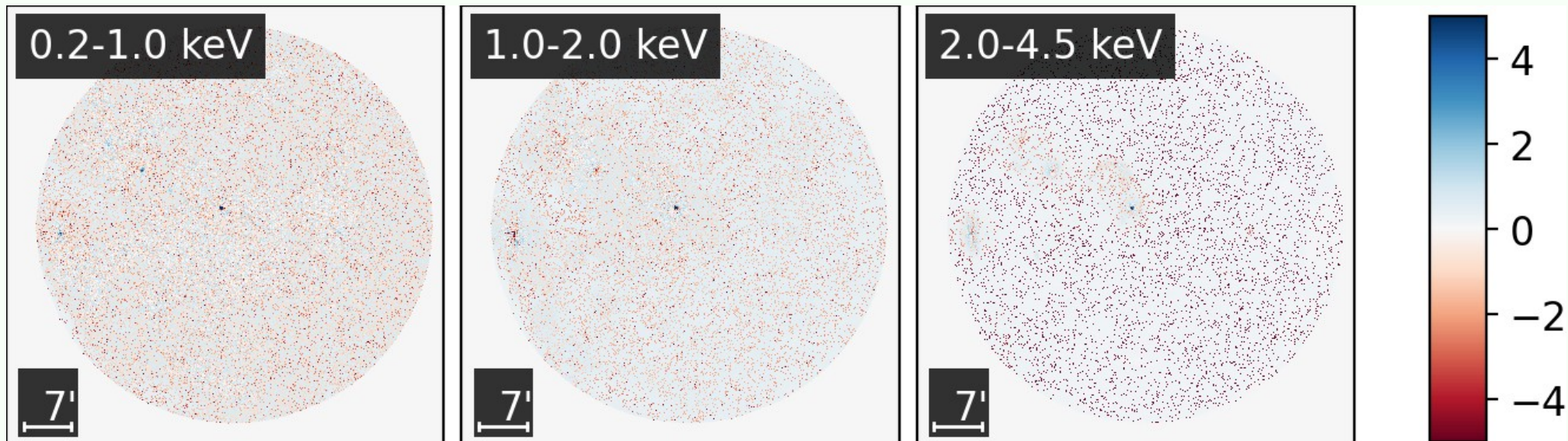
Posterior Mean Flux per Energy bin



Standard deviations of Flux per Energy bin



Noise weighted residuals



Conclusion

Conclusion

Structured generative networks can

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Structured generative networks can

- encode $\mathcal{P}(s)$ with minimal **assumptions** and **domain knowledge** instead of **training data**

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A combination of classical ML Networks and this approach:

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A combination of classical ML Networks and this approach:

Aim-resolve, Fuchs et al.
U-Net for component identification



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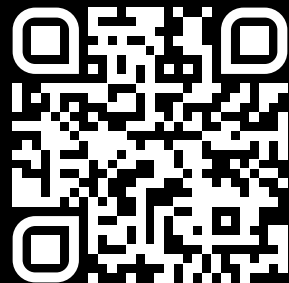
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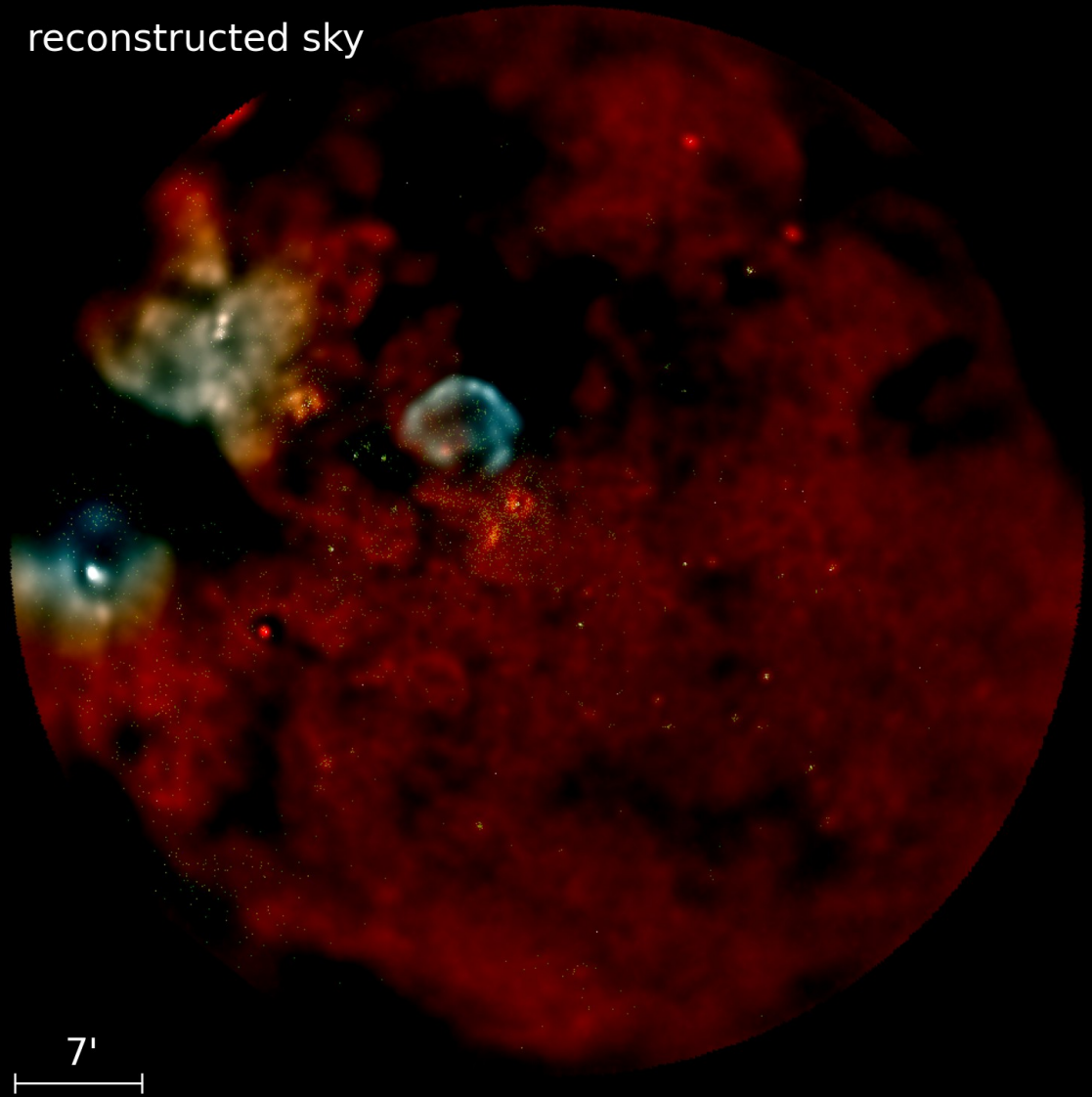


*Bayesian Reasoning with
Trained Neural Networks,
Knollmüller et al.*
Prior encoded in network



Got interested? - Let's talk

reconstructed sky



Vincent Eberle
mail: veberle@mpa-garching.mpg.de

Backup Slides



Essential building blocks

Inference algorithms



Essential building blocks

Inference algorithms

UBIK – Universal Bayesian Imaging Kit



Essential building blocks

Inference algorithms

UBIK – Universal Bayesian Imaging Kit





Essential building blocks

Inference algorithms

UBIK – Universal Bayesian Imaging Kit

Extension of NIFTy

Prior models

Instrument interfaces

Methods for response representation

Methods for component separation

...



UBIK



DLR Funding (ca. 2022-2024)

Team:

Vincent Eberle
Matteo Guardiani
Margret Westerkamp

Content:

- Develop interface for X-Ray Instruments (Chandra, eROSITA, [XMM-Newton](#))
- Develop methods for instrument responses
- Sky Models



UBIK



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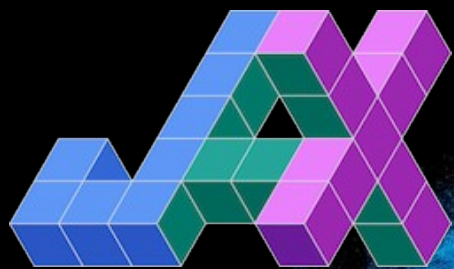
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J-UBIK





J-UBIK: The JAX-accelerated Universal Bayesian Imaging Kit

Vincent Eberle ^{1,2*}, Matteo Guardiani ^{1,2*}, Margret Westerkamp ^{1,2*},
Philipp Frank ¹, Julian Rüstig ^{2,3}, Julia Stadler ^{1,4}, and Torsten A.
Enßlin ^{1,2,3,4}

1 Max Planck Institute for Astrophysics, Karl-Schwarzschild-Straße 1, 85748 Garching bei München, Germany 2 Ludwig Maximilian University of Munich, Geschwister-Scholl-Platz 1, 80539 München, Germany 3 Deutsches Zentrum für Astrophysik, Postplatz 1, 02826 Görlitz, Germany 4 ORIGINS Excellence Cluster, Boltzmannstr. 2, D-85748 Garching, Germany  Corresponding author * These authors contributed equally.



main ▾

33 Branches 2 Tags

Go to file

<> Code ▾

	Merge branch 'cosmetics' into 'main'	9666fb7 · last week	1,939 Commits
data	add empty data folder	2 years ago	
demos	fix_documentation: small typo.	last month	
docs	better docstrings better api	2 weeks ago	
paper	add new plots	2 months ago	
src	requested change	last week	
test	better test documentation and skip of chandra tests	2 months ago	
.gitignore	change package name	2 years ago	
.gitlab-ci.yml	changes	last month	
CONTRIBUTION.md	black as formatter	5 months ago	
LICENSE	Add LICENSE	last year	
README.md	add link	2 months ago	
jubik0	change package name	2 years ago	
pyproject.toml	changes	last month	

README BSD-2-Clause license

About

Universal Bayesian Imaging Kit for the removal of instrument caused degradations and calibration

ift.pages.mpcdf.de/j-ubik/

astronomy bayesian bayesian-inference imaging

Readme

BSD-2-Clause license

Activity

Custom properties

4 stars

2 watching

1 fork

Report repository

Releases

2 tags

Packages

No packages published

Contributors 8





Section Navigation

[What is Information Field Theory?](#)[What is NIFTy?](#)[What is J-UBIK?](#)[Citing J-UBIK](#)[🏠 > J-UBIK User Guide](#)

J-UBIK User Guide

This guide is an overview and explains the main conceptual idea behind J-UBIK (JAX-accelerated Universal Bayesian Imaging Kit for X-ray), NIFTy.re and IFT.

The foundation of J-UBIK and NIFTy.re is the theoretical framework of information field theory (IFT), which applies Bayesian inference to address the underconstrained problem of reconstructing continuous physical fields from finite datasets.

However, J-UBIK is more driven by real instrument and their data. It facilitates the implementation of the central components of Bayesian inference, namely likelihood models for different instruments. It currently includes implementations for X-ray telescopes (Chandra and eROSITA) as well as the infrared observatory JWST. Several demos show how different likelihood implementations (Chandra & eROSITA):

Further information on these topics, as well as on the role of prior and likelihood models in Bayesian inference, can be found here:

[What is Information Field Theory?](#)[What is NIFTy?](#)[What is J-UBIK?](#)

More details on the API and the demos for the different instruments can be found at the [API reference](#).

Details on how to cite the J-UBIK package can be found at

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James Webb Space Telescope



Radio Telescopes (VLA, Meerkat, ALMA)