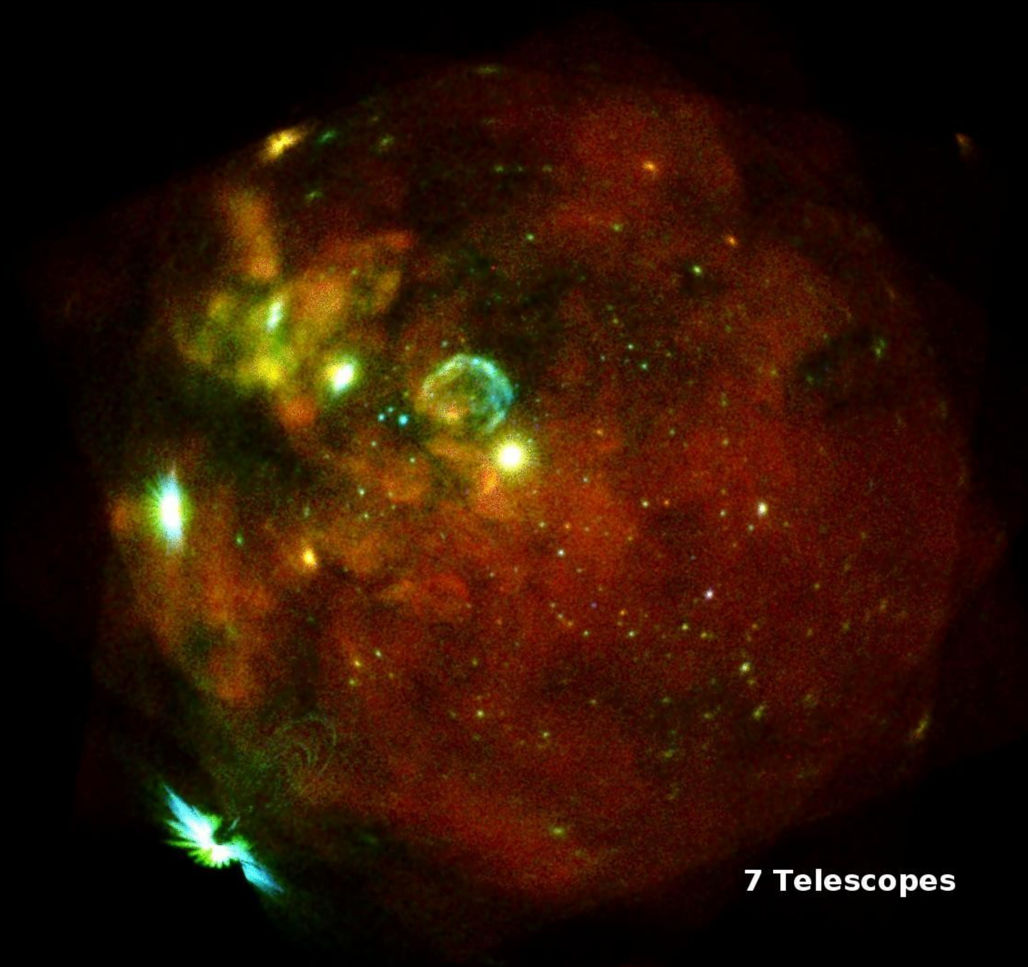
Spatially Variant Point Spread Functions for Bayesian Imaging

Vincent Eberle, Margret Westerkamp, Matteo Guardiani,
Julia Stadler, Philipp Frank, Philipp Arras,
Torsten Enßlin

ML-IAP/CCA-2023
Paris, France
1st December

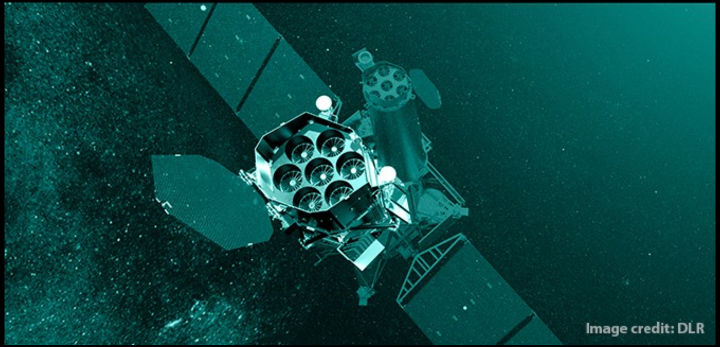
DLR
MAX-PLANCK-INSTITUT
FÜR ASTROPHYSIK

Motivation

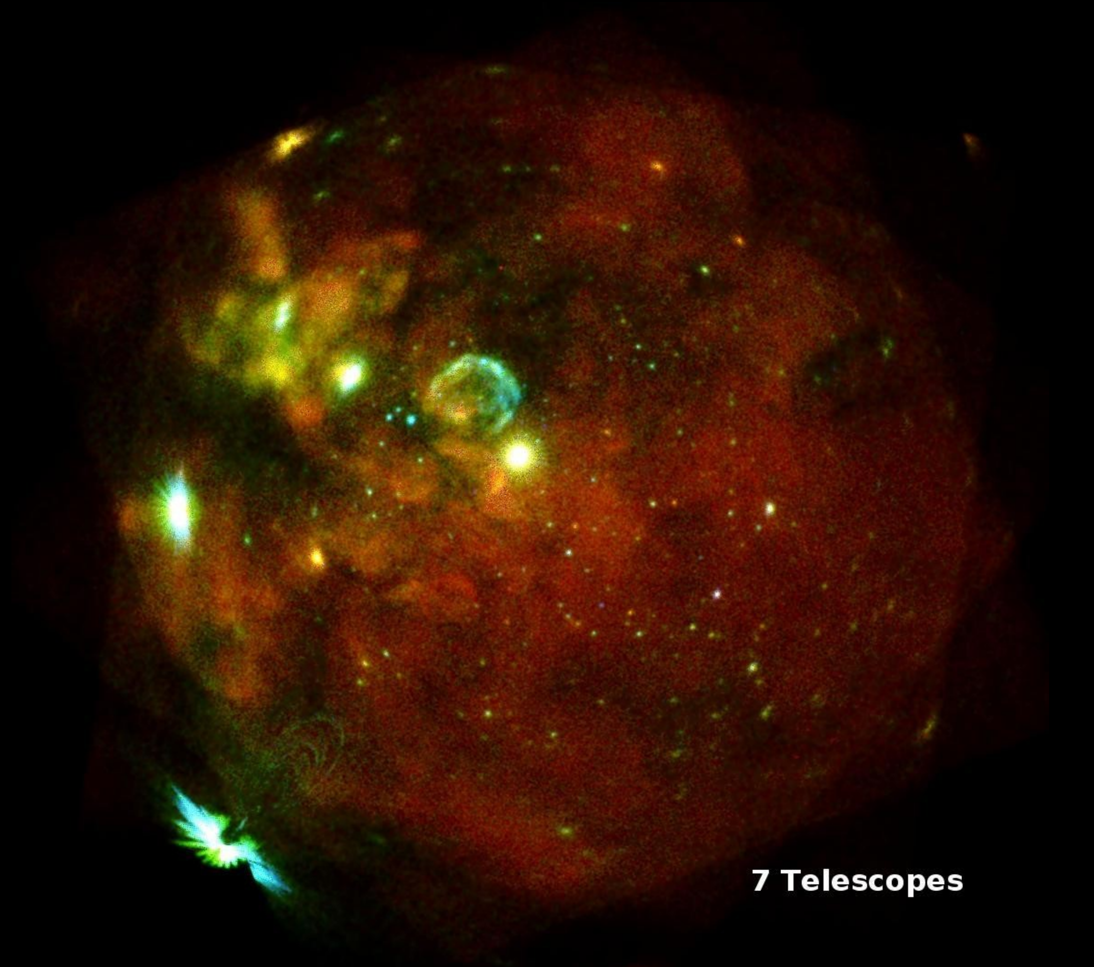


© F.Haberl, M. Freyberg und C. Maitra, MPE/IKI

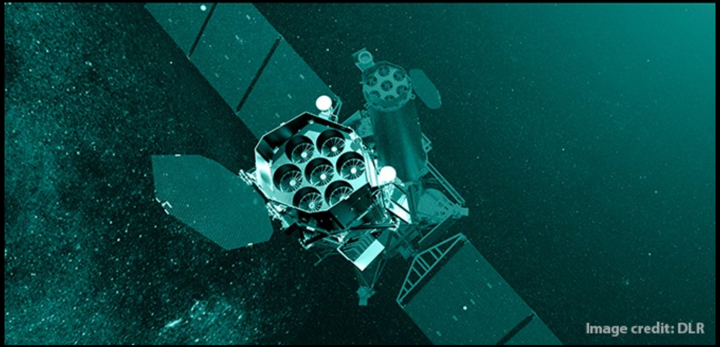
Motivation



eROSITA – X-ray telescope



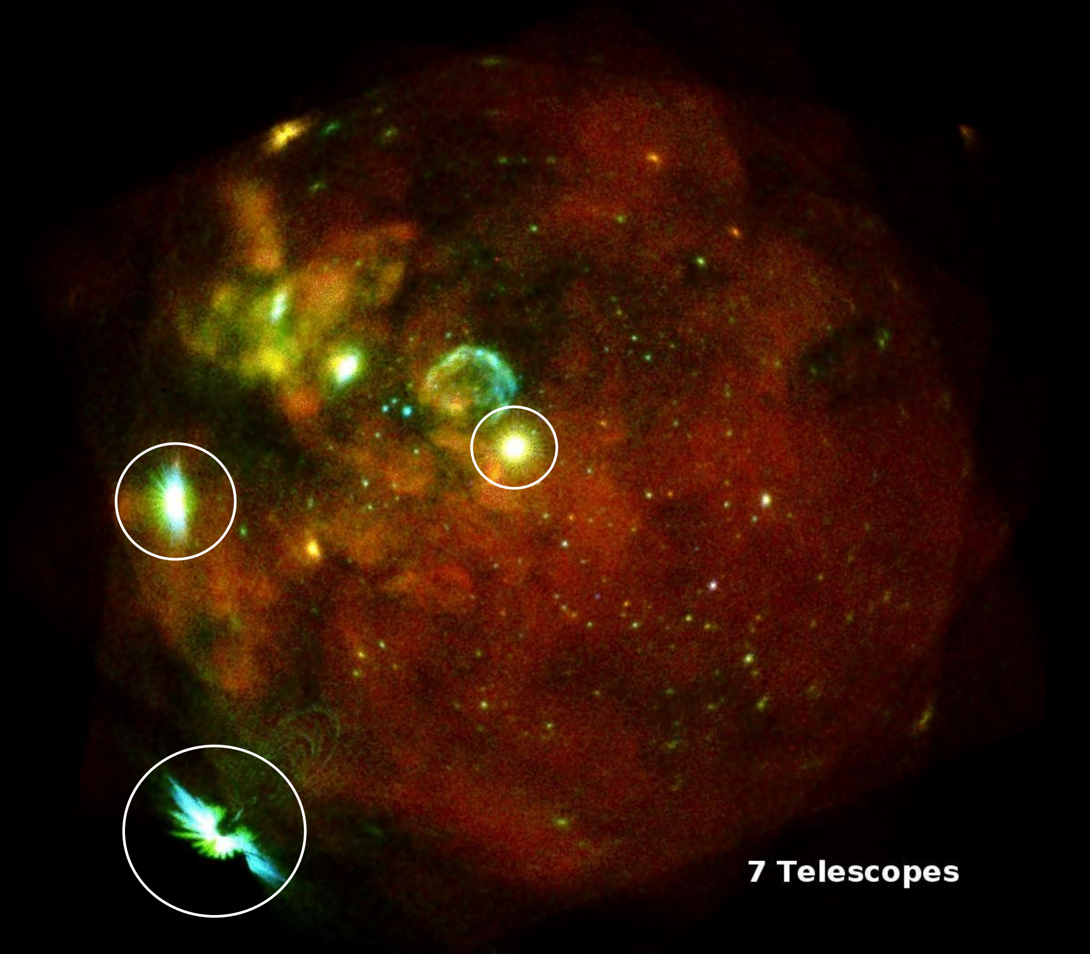
Motivation



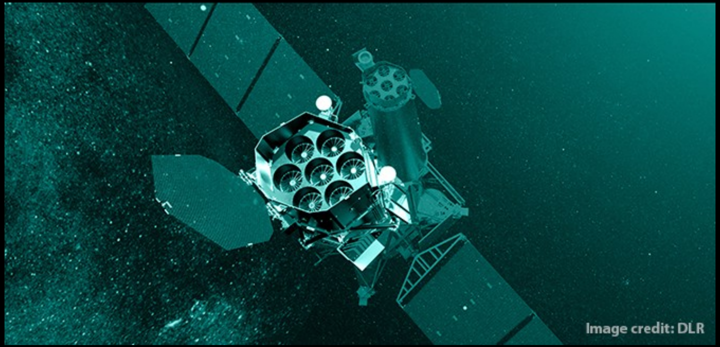
eROSITA – X-ray telescope

Effects of point spread functions (PSF)

distort X-ray Observations



Motivation

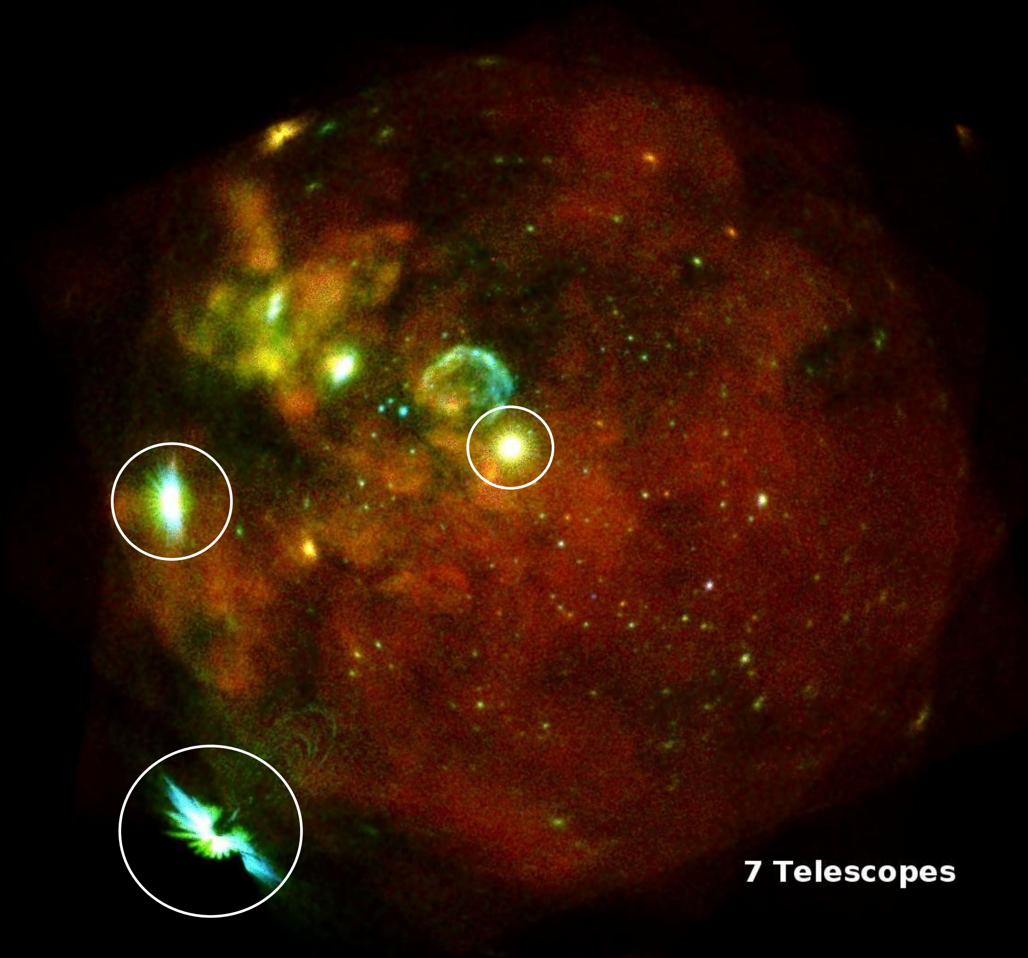


eROSITA – X-ray telescope

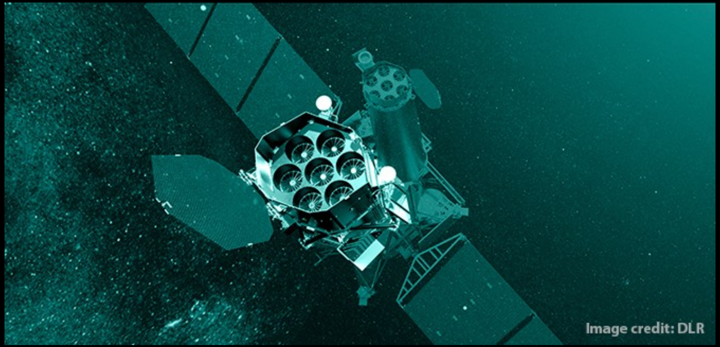
Effects of point spread functions (PSF)

distort X-ray Observations

- Spatially **in**variant PSF



Motivation

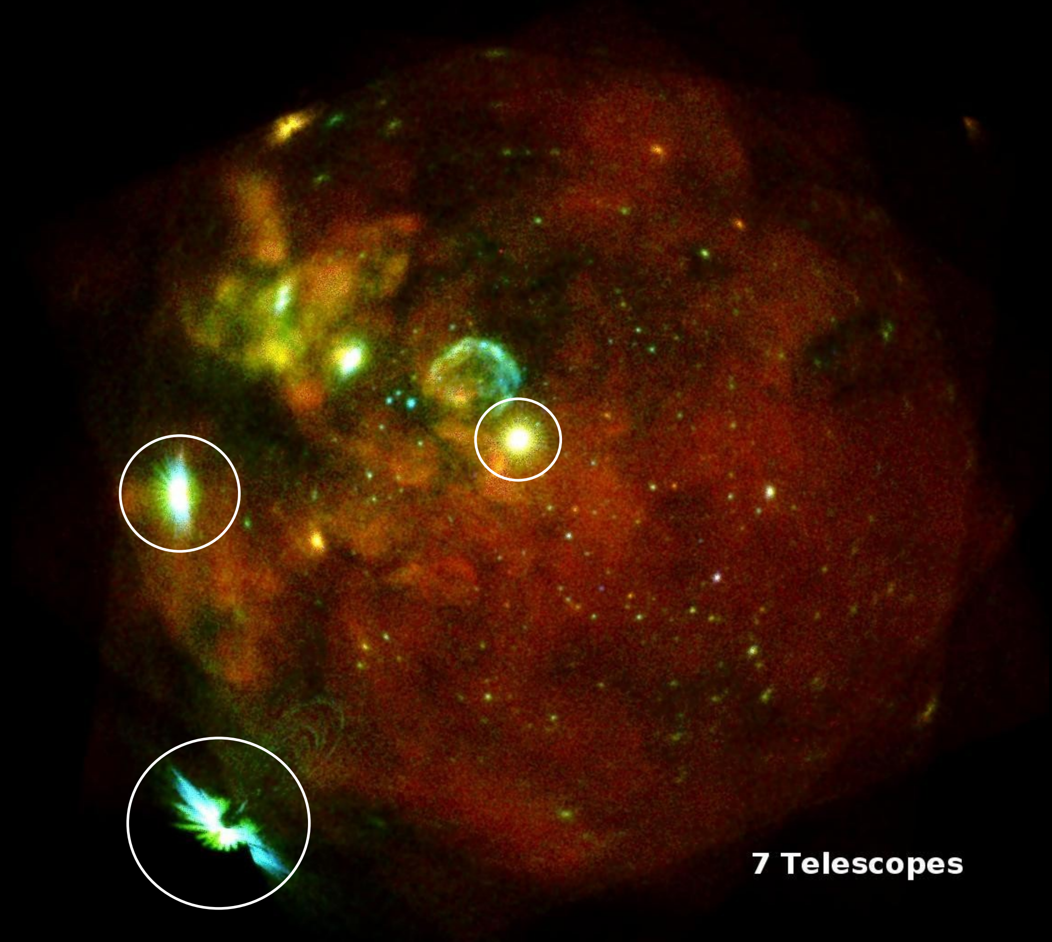


eROSITA – X-ray telescope

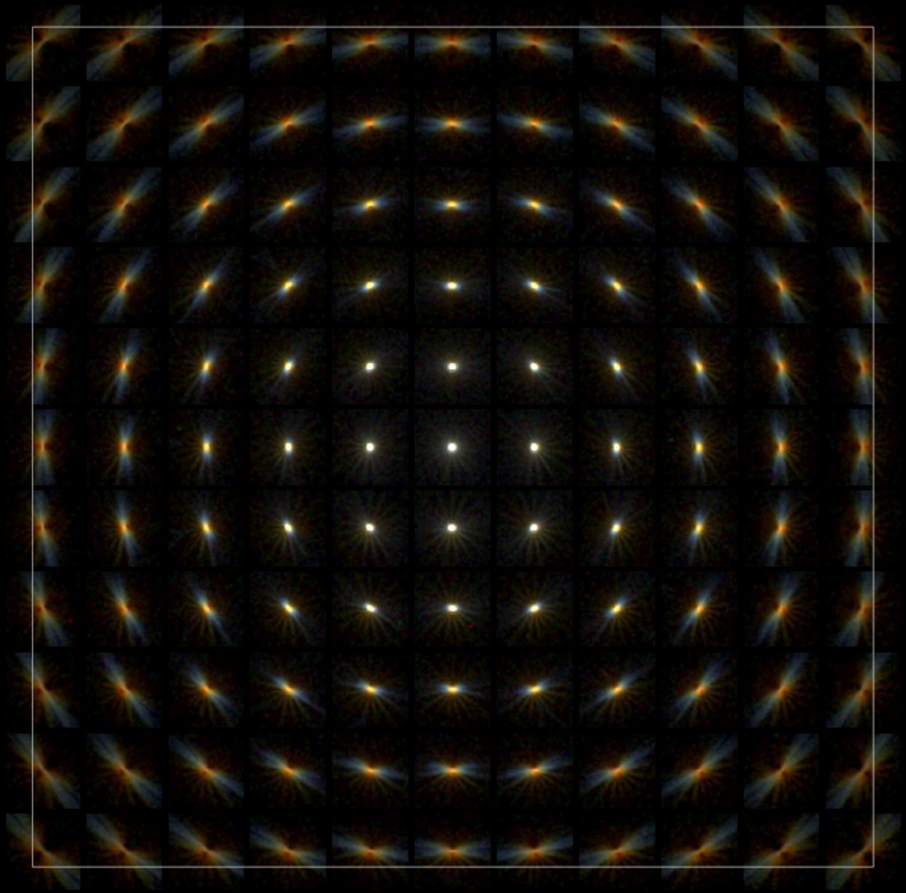
Effects of point spread functions (PSF)

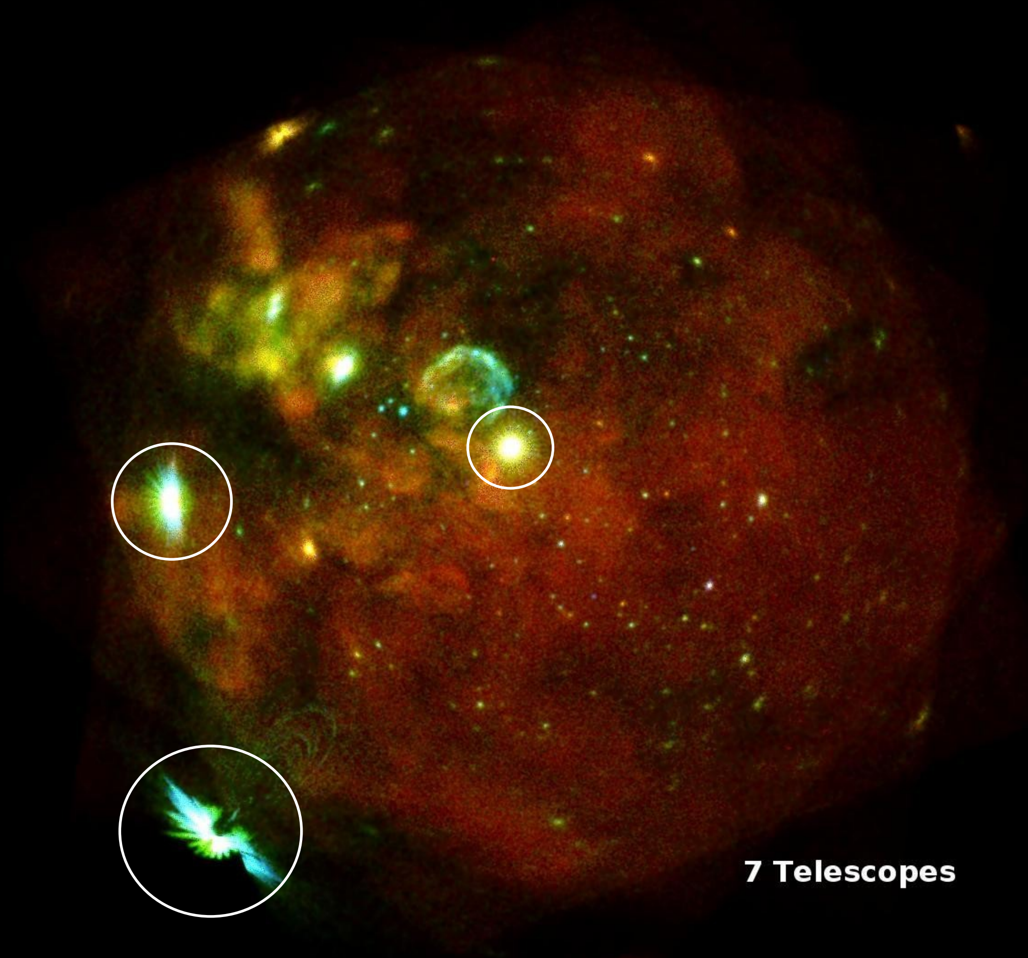
distort X-ray Observations

- Spatially **in**variant PSF
- Spatially **variant** PSF
  (off-axis-angle, azimuth and energy)



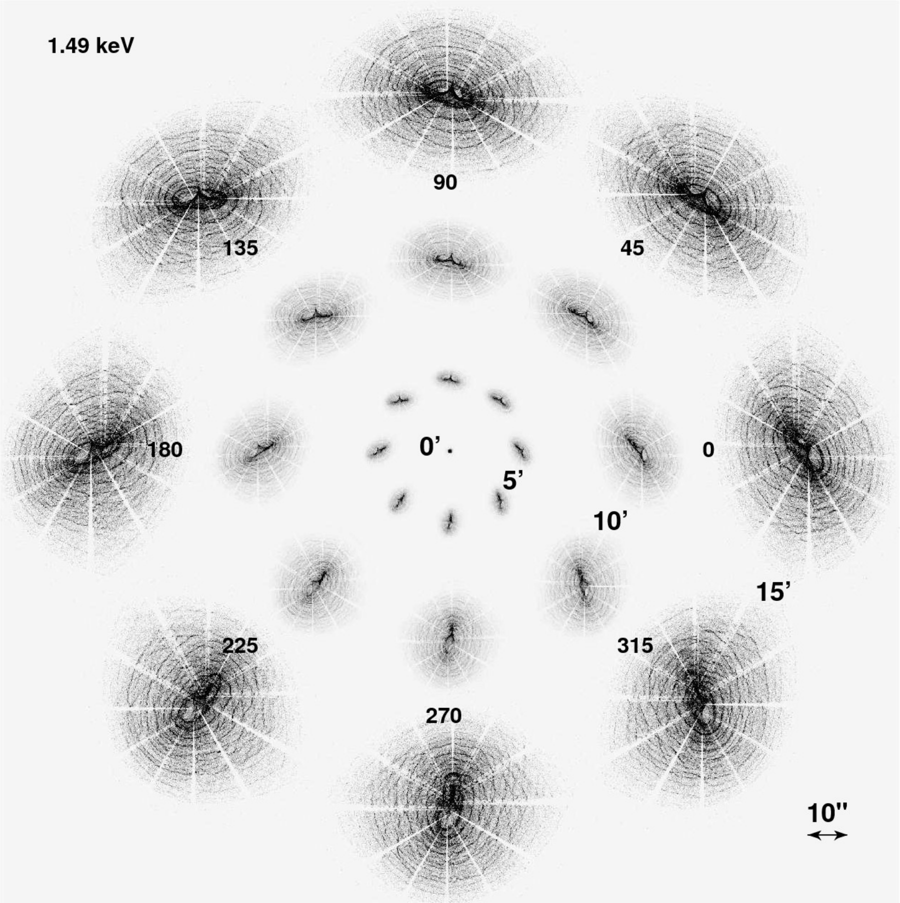
eROSITA PSF

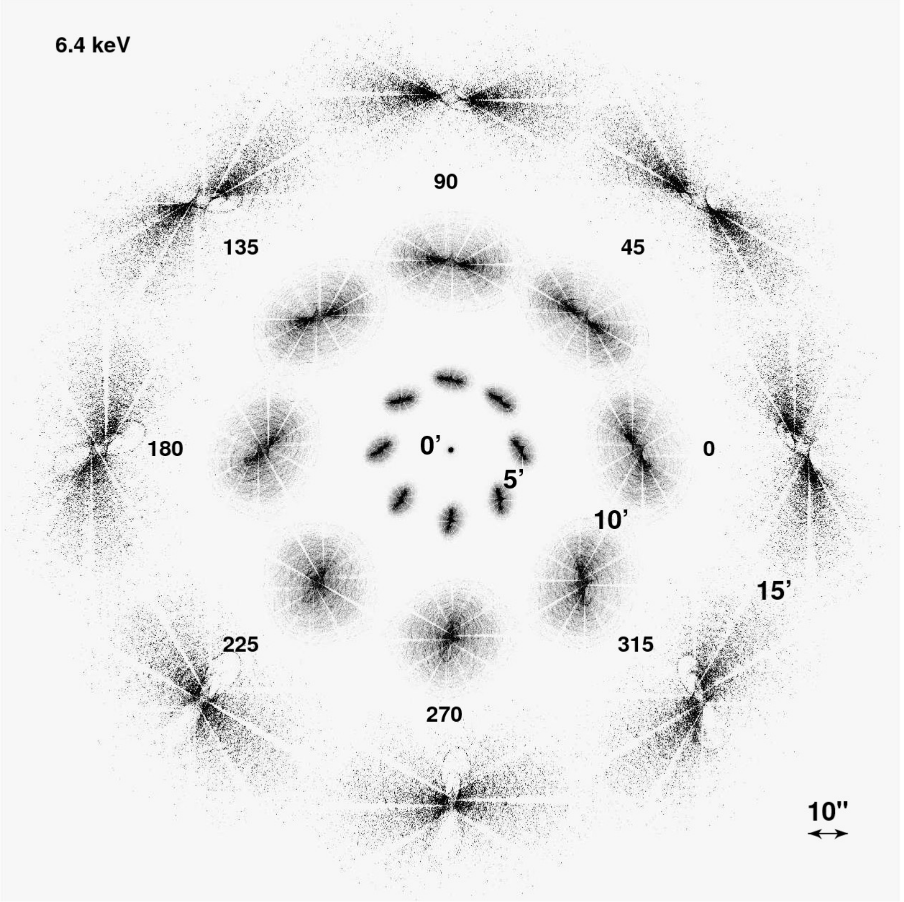




Predehl, Peter, et al. "The eROSITA X-ray telescope on SRG." Astronomy & Astrophysics 647 (2021): A1.

Chandra PSF





https://cxc.harvard.edu/proposer/POG/html/chap4.html

This affects many optical systems.

This affects many optical systems.

Will we have instruments without this effect in the future?

This affects many optical systems.

Will we have instruments without this effect in the future?

….we don’t want to wait!

Why is it non-trivial to remove the PSF?

Why is it non-trivial to remove the PSF?

De-blurring noisy images

Why is it non-trivial to remove the PSF?

De-blurring noisy images

PSF **Representation**

Why is it non-trivial to remove the PSF?

De-blurring noisy images

Information Field Theory
&
Generative Modeling

PSF **Representation**

Information Field Theory

Information Field Theory

- Information theory for fields using **Bayes' Theorem** $\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$

Information Field Theory

- Information theory for fields using **Bayes' Theorem** $\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$
- $m =< s >_{\mathcal{P}(s|d)}$ $\sigma = \sqrt{< (s-m)^2 >_{\mathcal{P}(s|d)}}$ or posterior samples

Information Field Theory

- Information theory for fields using **Bayes' Theorem** $\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$
- $m = < s >_{\mathcal{P}(s|d)}$ $\sigma = \sqrt{< (s-m)^2 >_{\mathcal{P}(s|d)}}$ or posterior samples
- $\mathcal{P}(s)$: **domain knowledge** about the signal

Information Field Theory

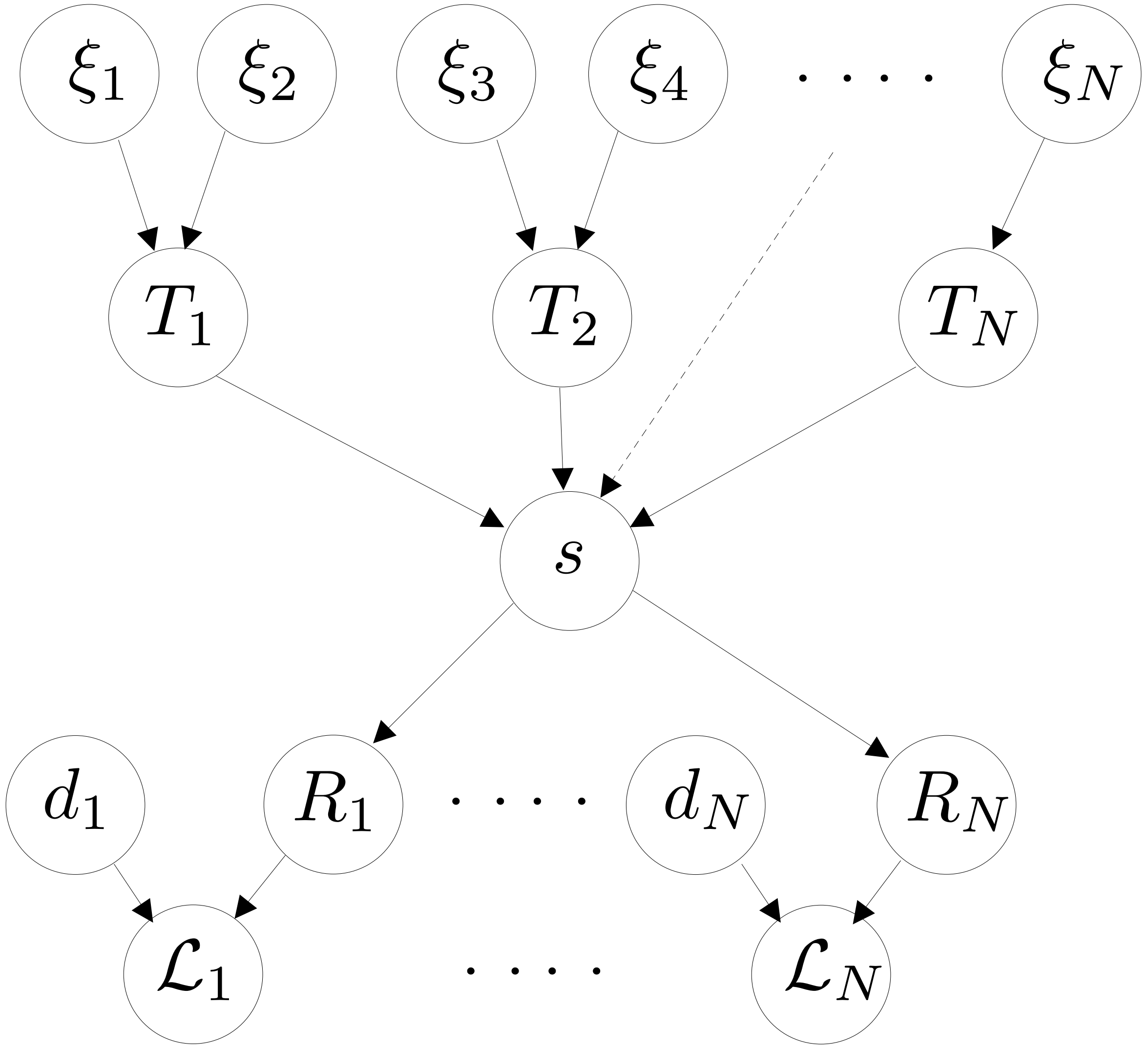
- Information theory for fields using **Bayes' Theorem** $\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$
- $m = < s >_{\mathcal{P}(s|d)}$ $\sigma = \sqrt{< (s-m)^2 >_{\mathcal{P}(s|d)}}$ or posterior samples
- $\mathcal{P}(s)$: **domain knowledge** about the signal
- $\mathcal{P}(d|\lambda) = \prod_{i=1}^{N} \frac{(\lambda^i)^{d^i} e^{-\lambda^i}}{d^i!}, \quad \lambda = \mathcal{R}s$: knowledge about the **instrument** and the noise

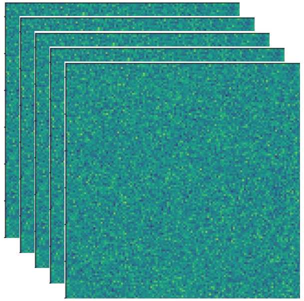
Information Field Theory

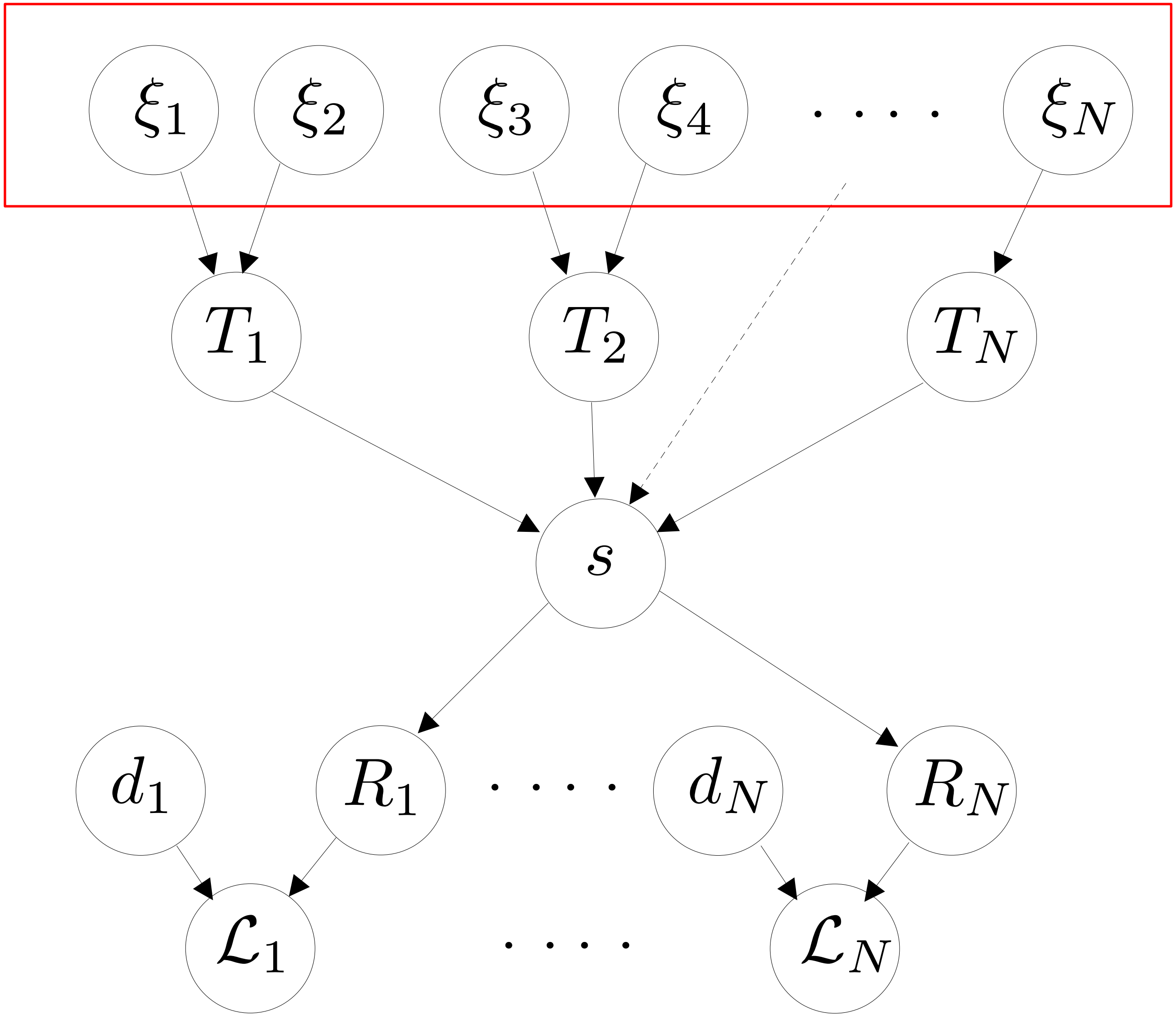
- Information theory for fields using **Bayes' Theorem** $\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$
- $m =< s >_{\mathcal{P}(s|d)}$ $\sigma = \sqrt{< (s-m)^2 >_{\mathcal{P}(s|d)}}$ or posterior samples
- $\mathcal{P}(s)$: **domain knowledge** about the signal
- $\mathcal{P}(d|\lambda) = \prod_{i=1}^{N} \frac{(\lambda^i)^{d^i} e^{-\lambda^i}}{d^i!}, \quad \lambda = \mathcal{R}s$: knowledge about the **instrument** and the noise
- NIFTY [Framework to build generative models for Bayesian inference]

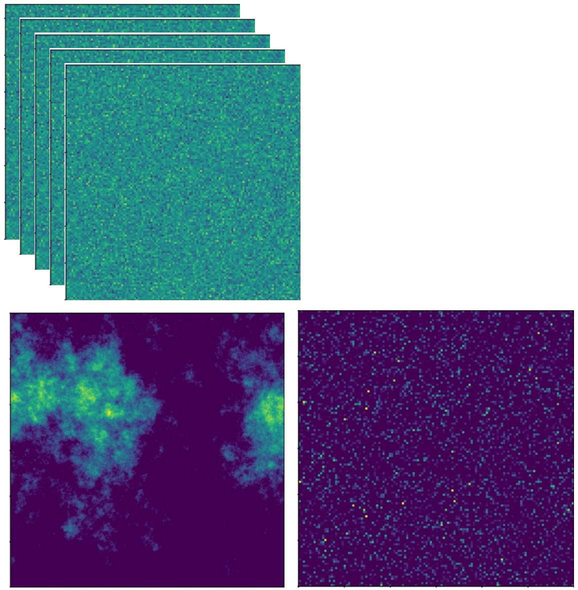
Information Field Theory

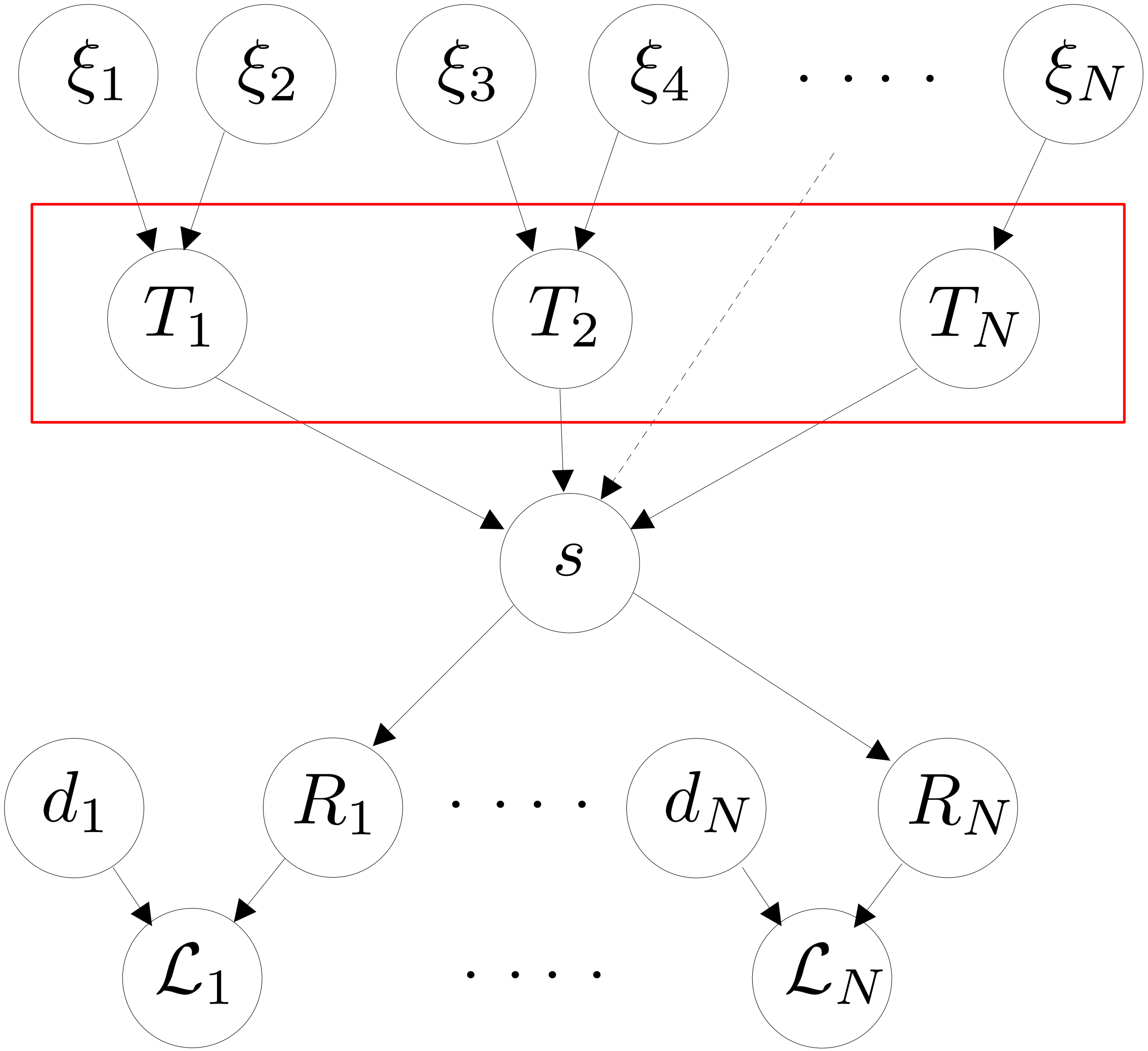
- Information theory for fields using **Bayes' Theorem** $\mathcal{P}(s|d) \propto \mathcal{P}(d|s)\mathcal{P}(s)$
- $m =< s >_{\mathcal{P}(s|d)}$ $\sigma = \sqrt{< (s-m)^2 >_{\mathcal{P}(s|d)}}$ or posterior samples
- $\mathcal{P}(s)$: **domain knowledge** about the signal
- $\mathcal{P}(d|\lambda) = \prod_{i=1}^{N} \frac{(\lambda^i)^{d^i} e^{-\lambda^i}}{d^i!}, \quad \lambda = \mathcal{R}s$: knowledge about the **instrument** and the noise
- NIFTy [Framework to build generative models for Bayesian inference]
- **Geo**metric **V**ariational **I**nference [P. Frank et al. 2021]


ξ_1
ξ_2
ξ_3
ξ_4
ξ_N
T_1
T_2
T_N
s
d_1
R_1
d_N
R_N
$\mathcal{L}_1$
$\mathcal{L}_N$

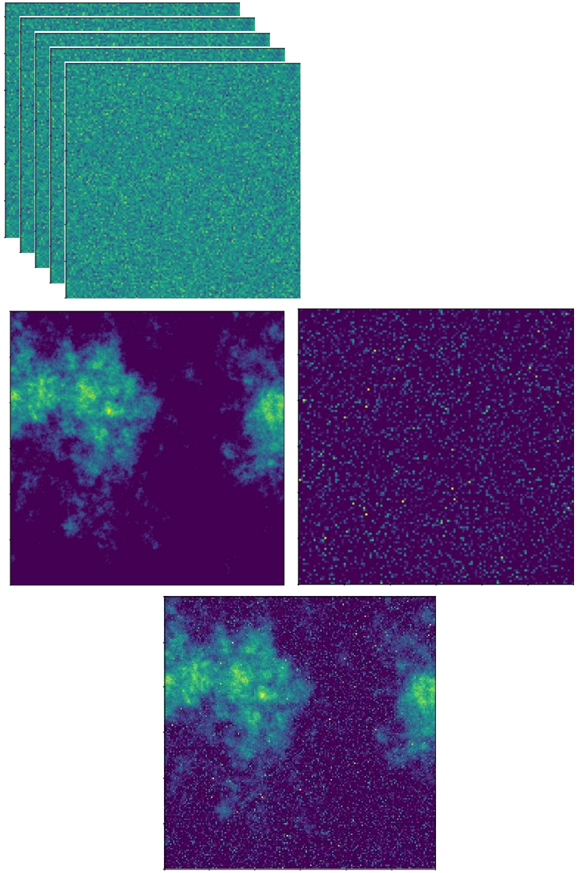


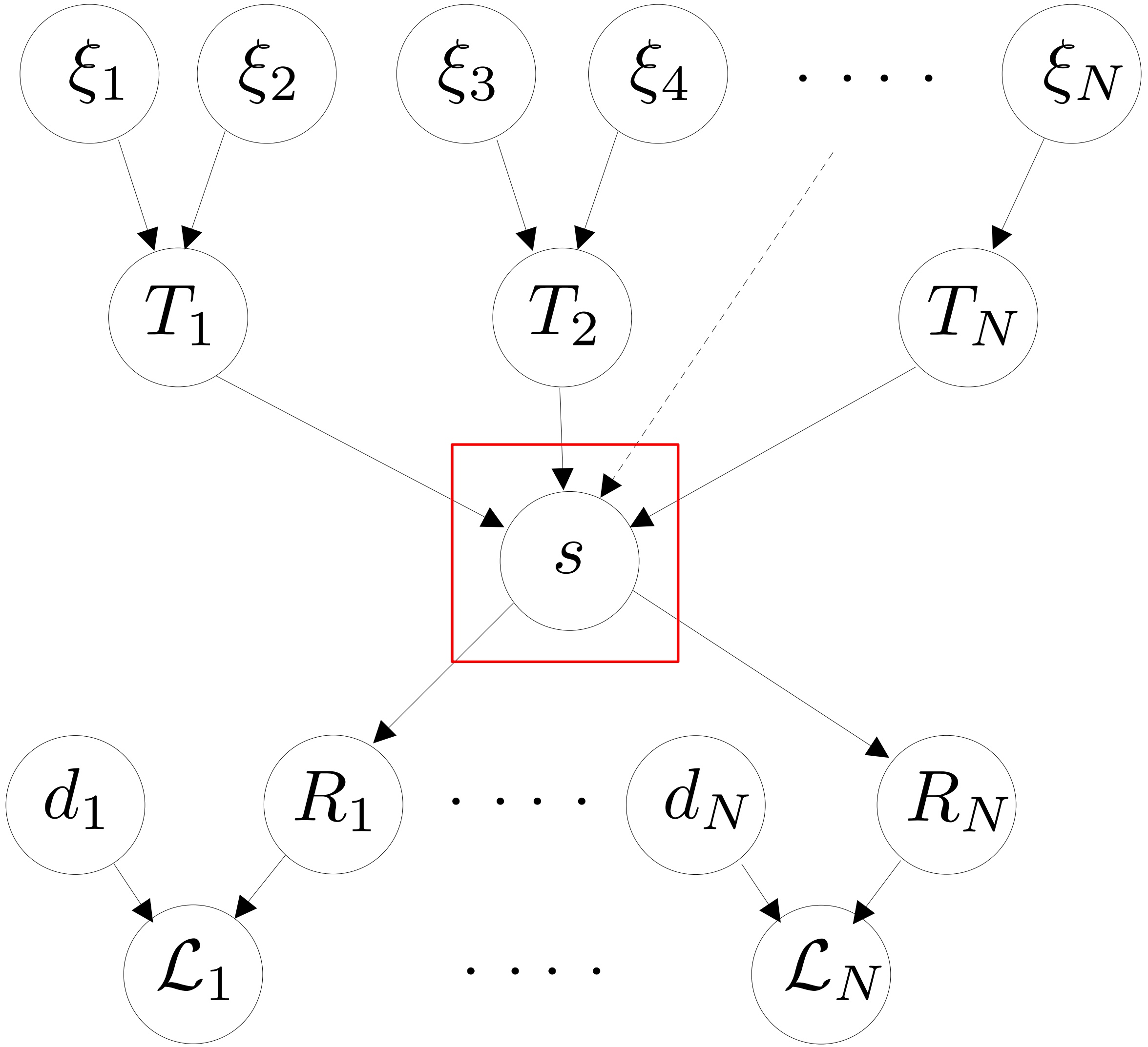

ξ_1
ξ_2
ξ_3
ξ_4
....
ξ_N
T_1
T_2
T_N
s
d_1
R_1
....
d_N
R_N
$\mathcal{L}_1$
....
$\mathcal{L}_N$



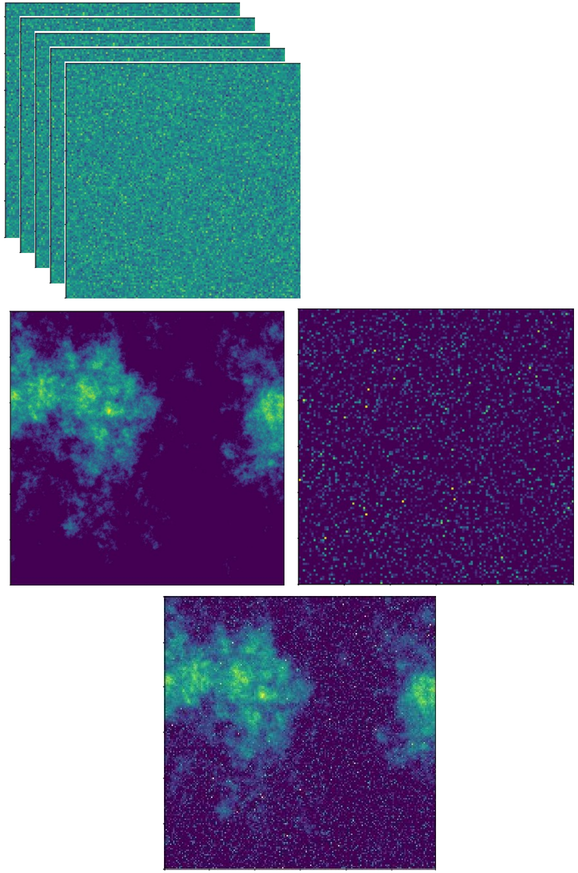


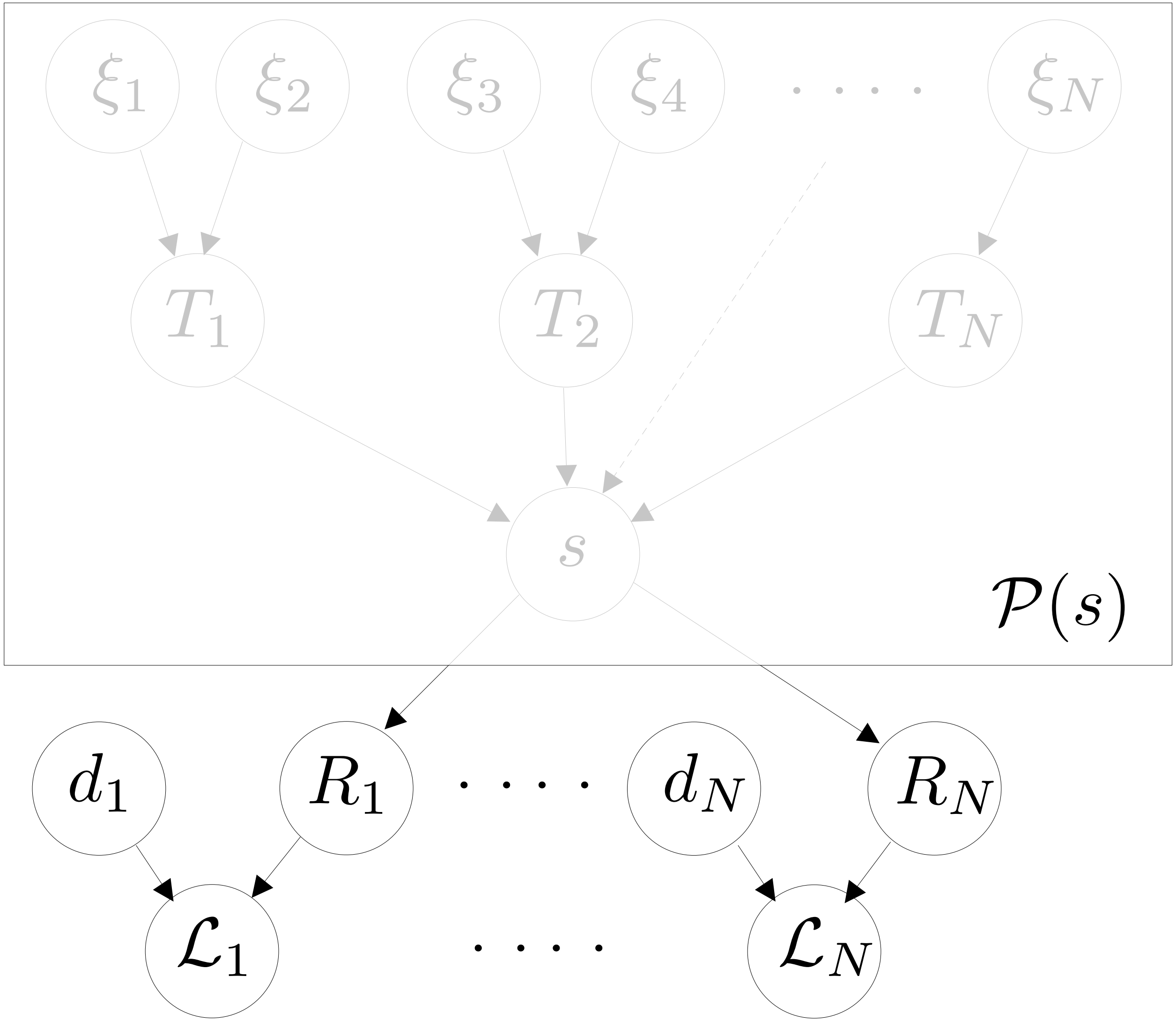
ξ_1
ξ_2
ξ_3
ξ_4
$\cdots$
ξ_N
T_1
T_2
T_N
s
d_1
R_1
$\cdots$
d_N
R_N
$\mathcal{L}_1$
$\cdots$
$\mathcal{L}_N$

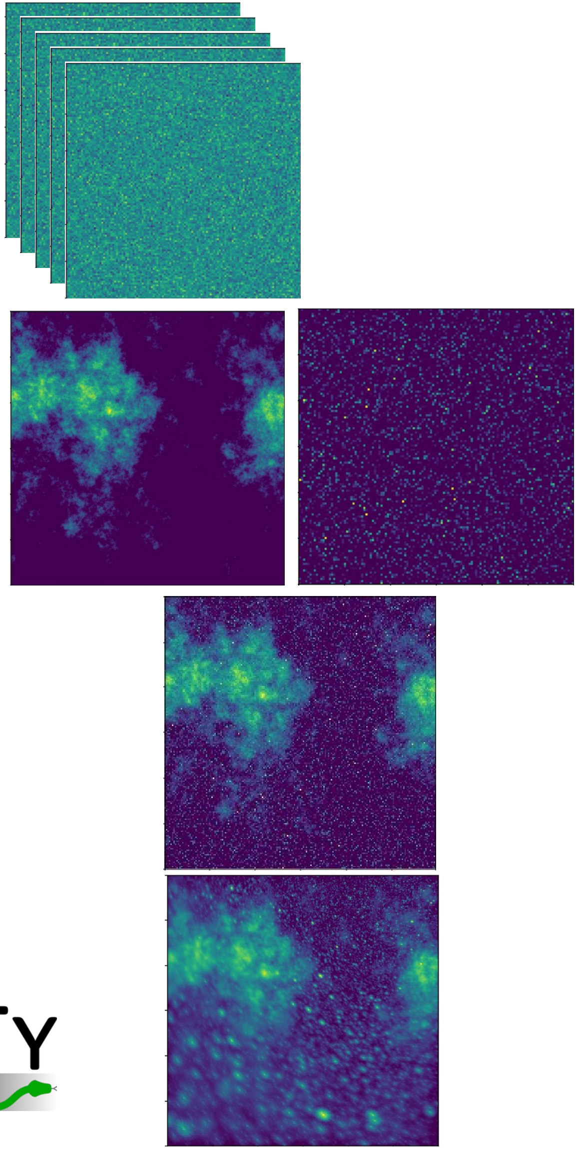


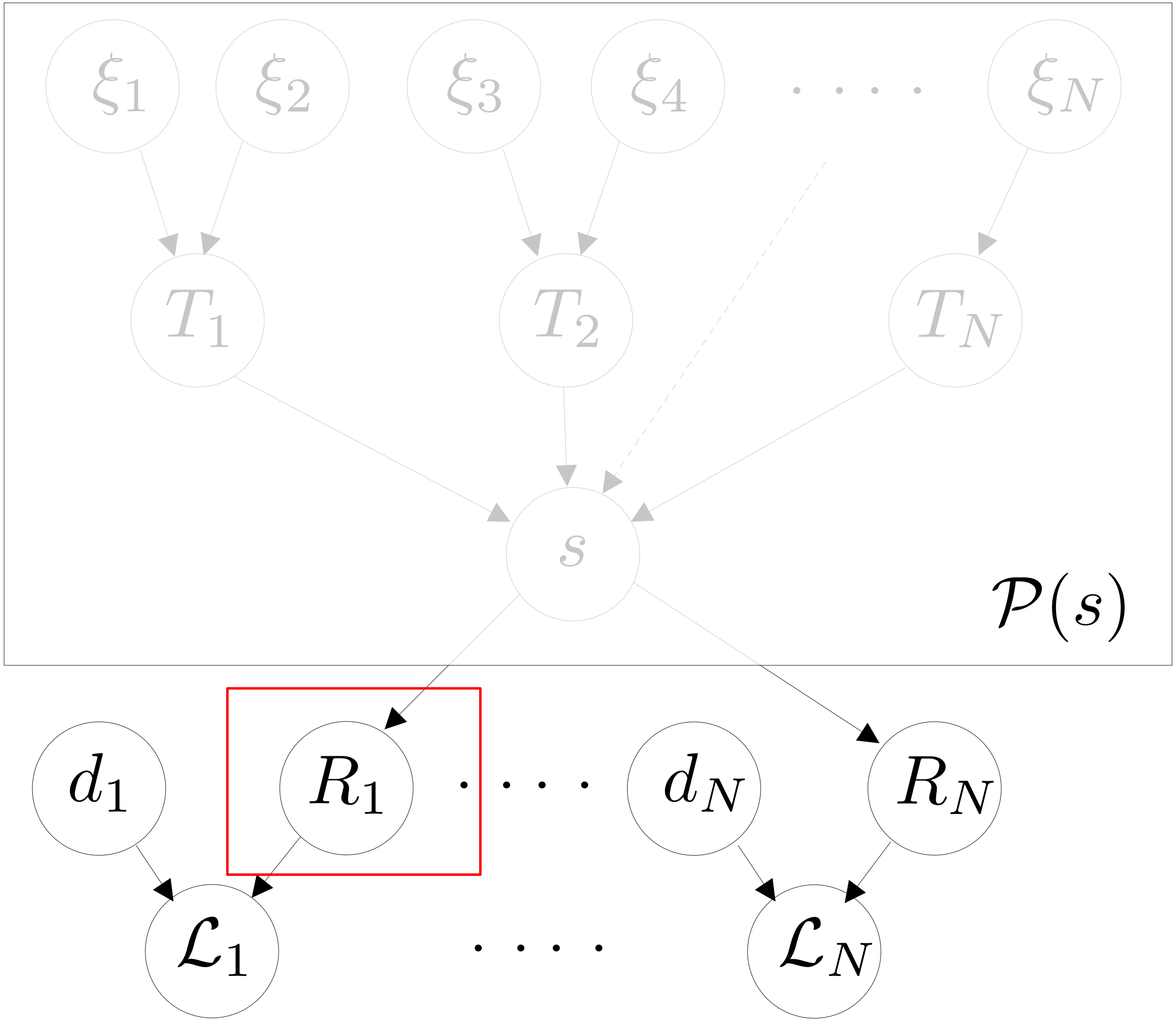


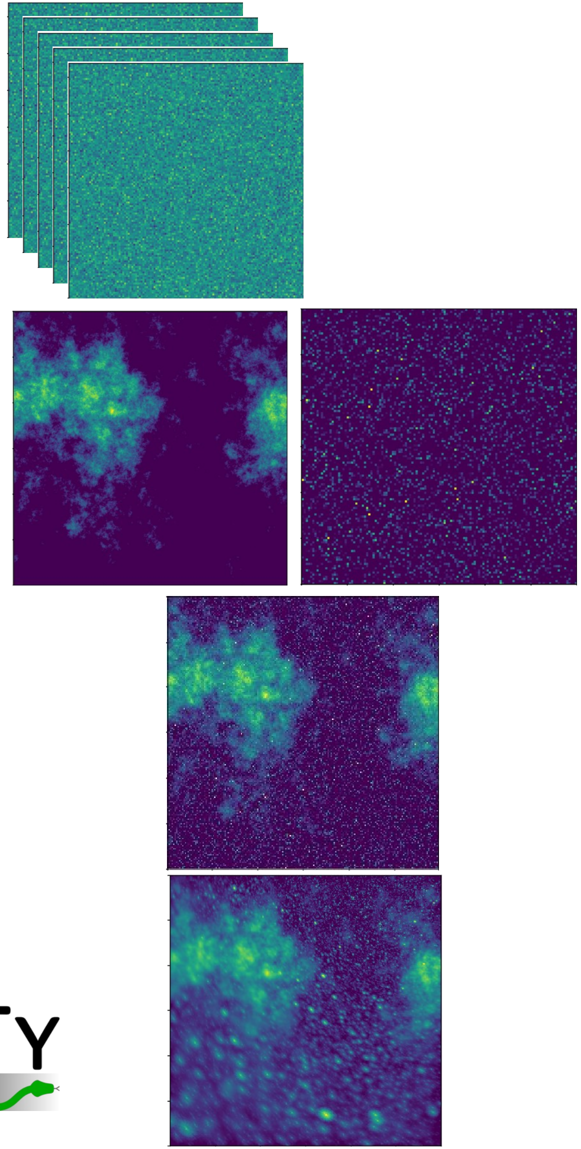
ξ_1
ξ_2
ξ_3
ξ_4
ξ_N
T_1
T_2
T_N
s
d_1
R_1
d_N
R_N
$\mathcal{L}_1$
$\mathcal{L}_N$

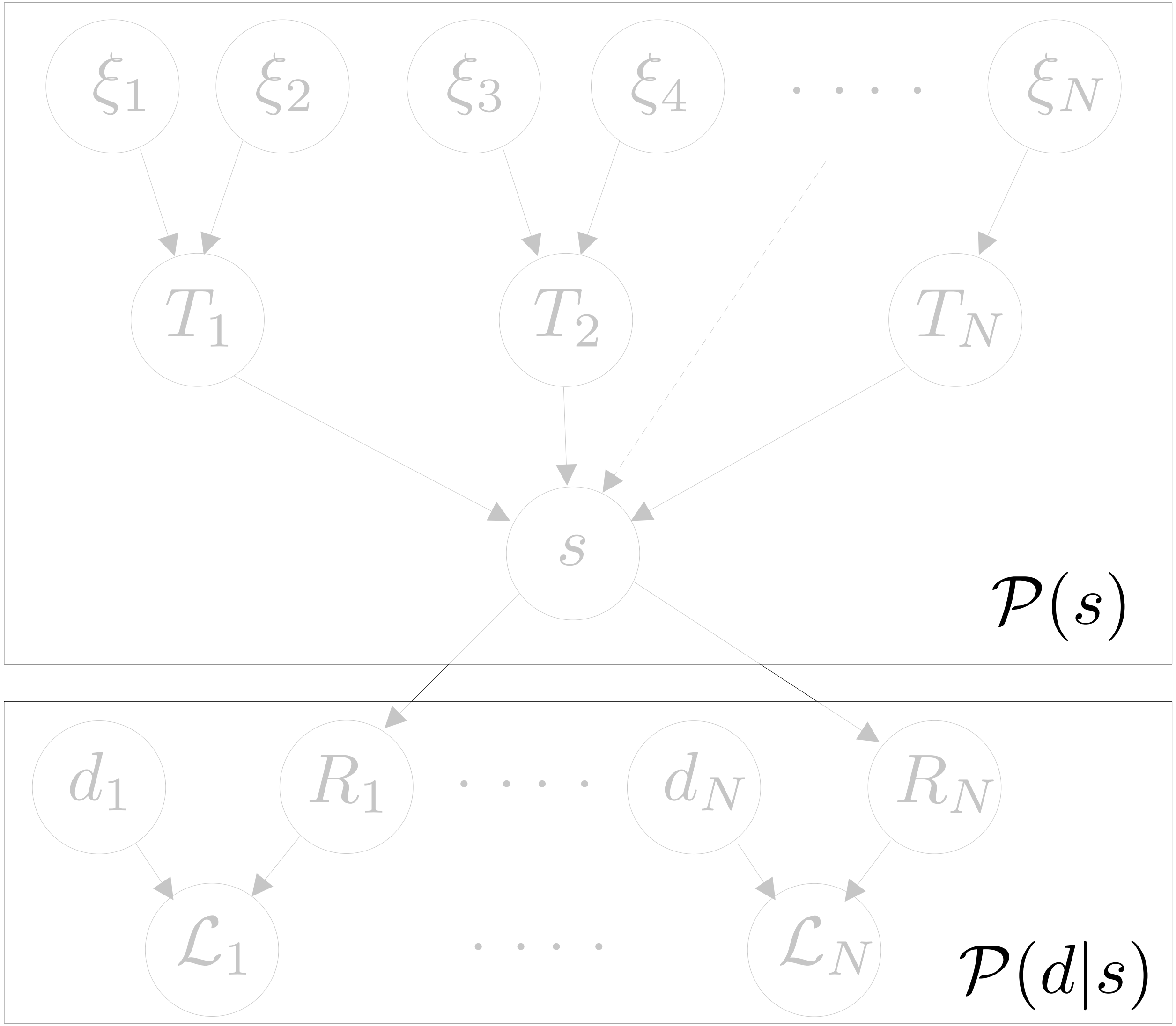



ξ_1 ξ_2 ξ_3 ξ_4 .... ξ_N
T_1 T_2 T_N
s
$\mathcal{P}(s)$
d_1 R_1 .... d_N R_N
$\mathcal{L}_1$ .... $\mathcal{L}_N$




ξ_1 ξ_2 ξ_3 ξ_4 $\cdots$ ξ_N
T_1 T_2 T_N
s
$\mathcal{P}(s)$
d_1 R_1 $\cdots$ d_N R_N
$\mathcal{L}_1$ $\cdots$ $\mathcal{L}_N$




ξ_1 ξ_2 ξ_3 ξ_4 ξ_N
T_1 T_2 T_N
s
$\mathcal{P}(s)$
d_1 R_1 d_N R_N
$\mathcal{L}_1$ $\mathcal{L}_N$
$\mathcal{P}(d|s)$

Why is it non-trivial to remove the PSF?

De-blurring noisy images

Information Field Theory
&
Generative Modeling

PSF **Representation**

PSF Representation

PSF Representation

Spatially **in**variant PSF:

Spatially **variant** PSF:

PSF Representation

Spatially **in**variant PSF:

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

Spatially **variant** PSF:

PSF Representation

Spatially **in**variant PSF:

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

Spatially **variant** PSF:

- **Not** a convolution.
- Naive: Full Matrix? [$O(N^2)$]
  → Huge memory consumption
  → Slow execution

PSF Representation

Spatially **in**variant PSF:

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

Spatially **variant** PSF:

- **Not** a convolution.
- Naive: Full Matrix? [$O(N^2)$]
  → Huge memory consumption
  → Slow execution

Strategies for spatially variant PSF de-blurring:

PSF Representation

Spatially **in**variant PSF:

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

Spatially **variant** PSF:

- **Not** a convolution.
- Naive: Full Matrix? [$O(N^2)$]
  → Huge memory consumption
  → Slow execution

Strategies for spatially variant PSF de-blurring:

- Deconvolution with averaged PSF
- Remove off-axis data

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.]

Patched Interpolated Convolution

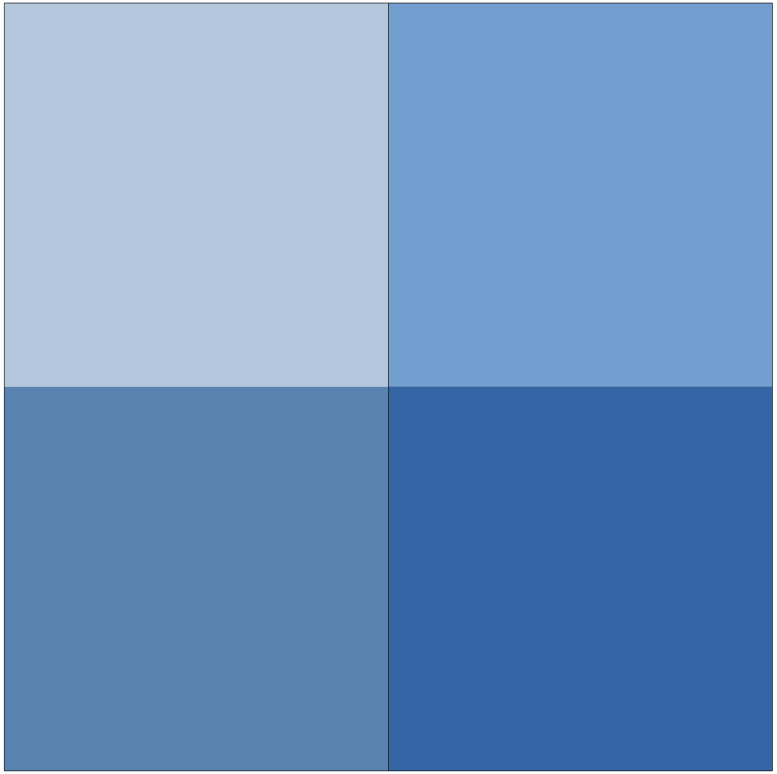
Image

Patched Interpolated Convolution

Image

↓

Select Patches

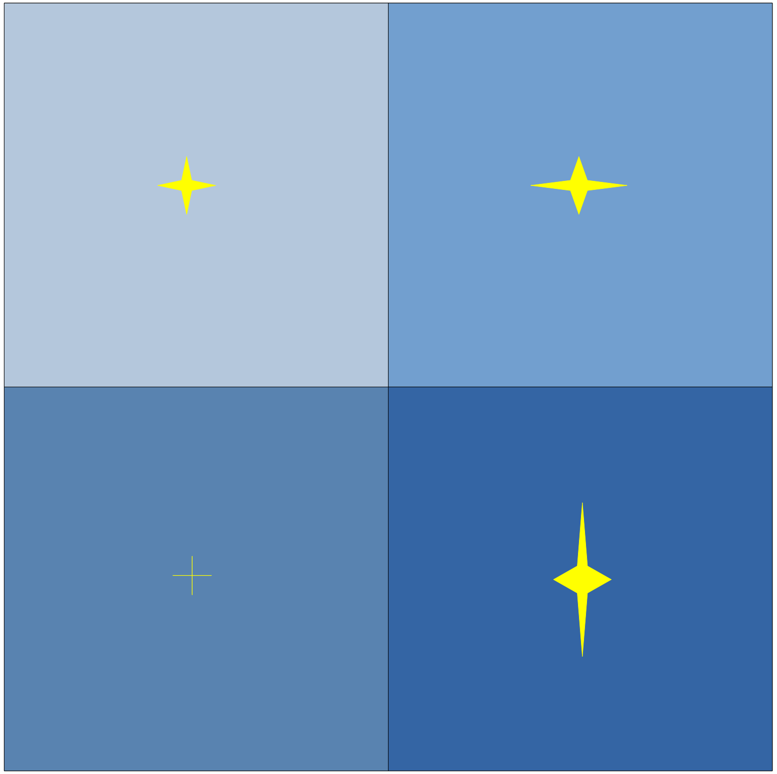


Patched Interpolated Convolution

Image

Select Patches

PSF of patch center



Patched Interpolated Convolution

Image

↓

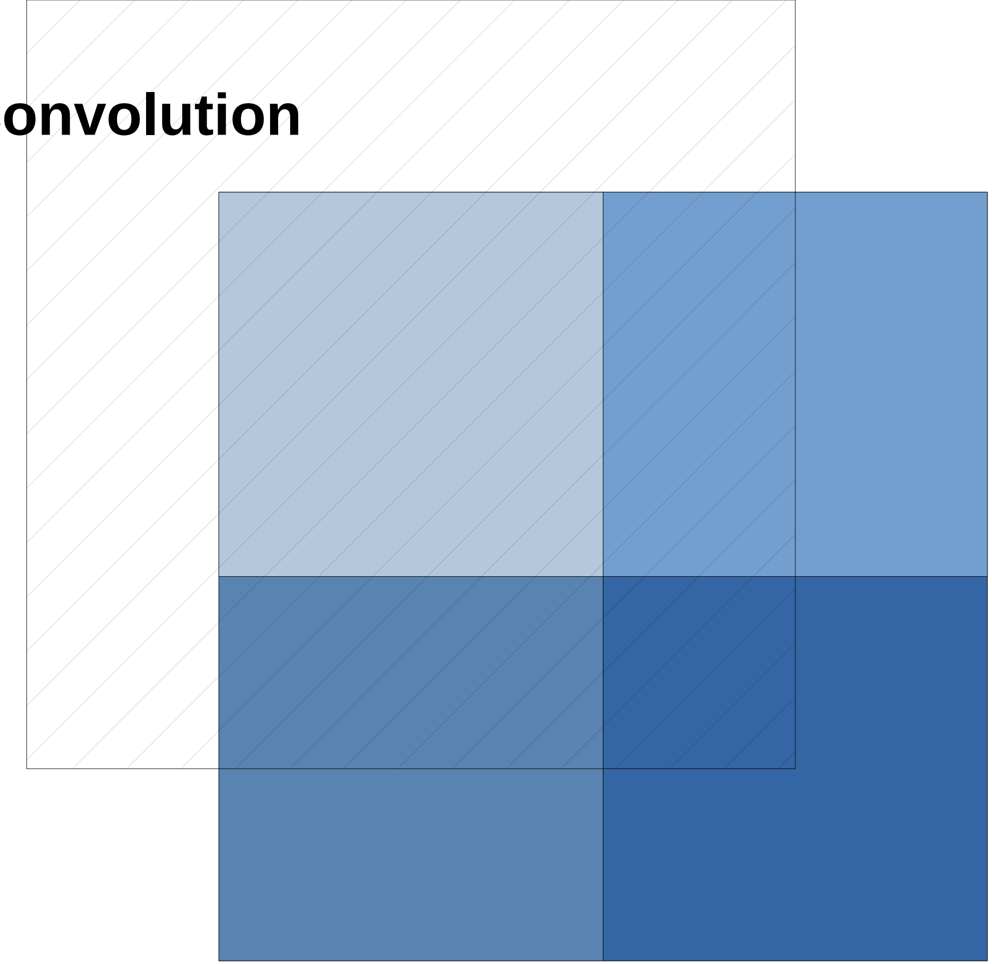
Select Patches

↓

PSF of patch center

↓

Cut out with overlap



Patched Interpolated Convolution

Image

↓

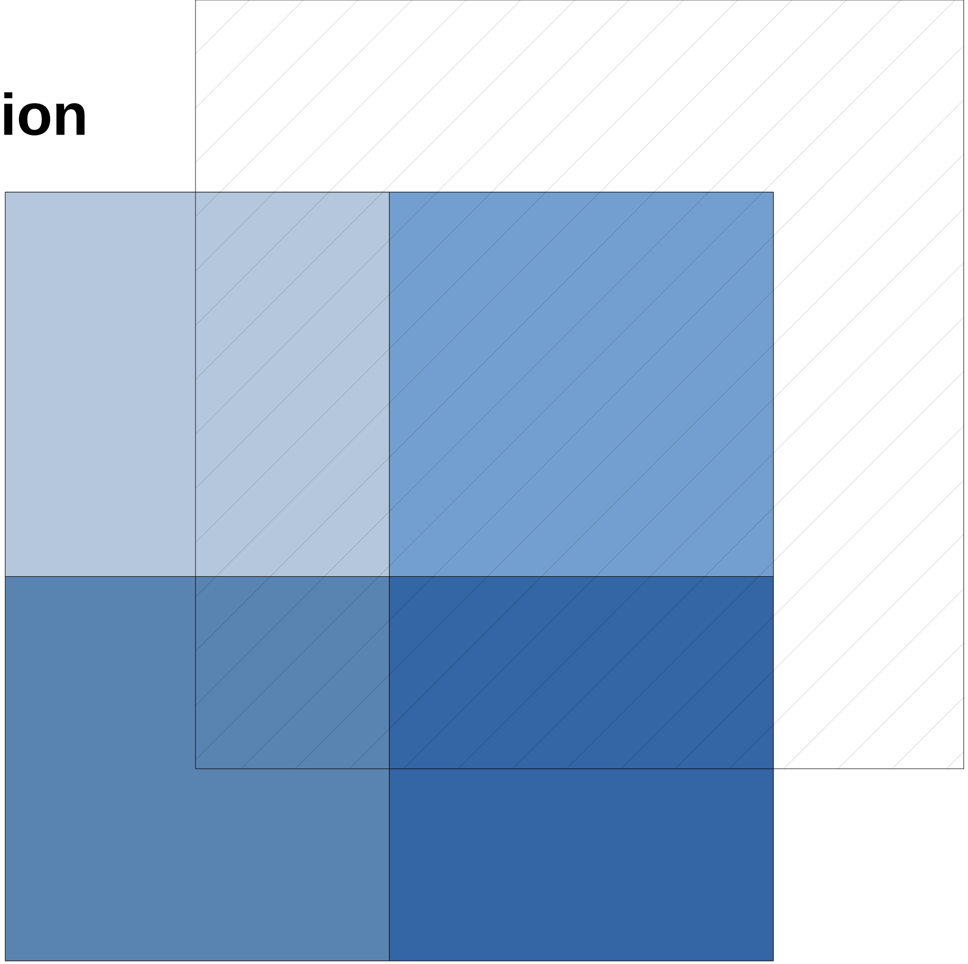
Select Patches

↓

PSF of patch center

↓

Cut out with overlap



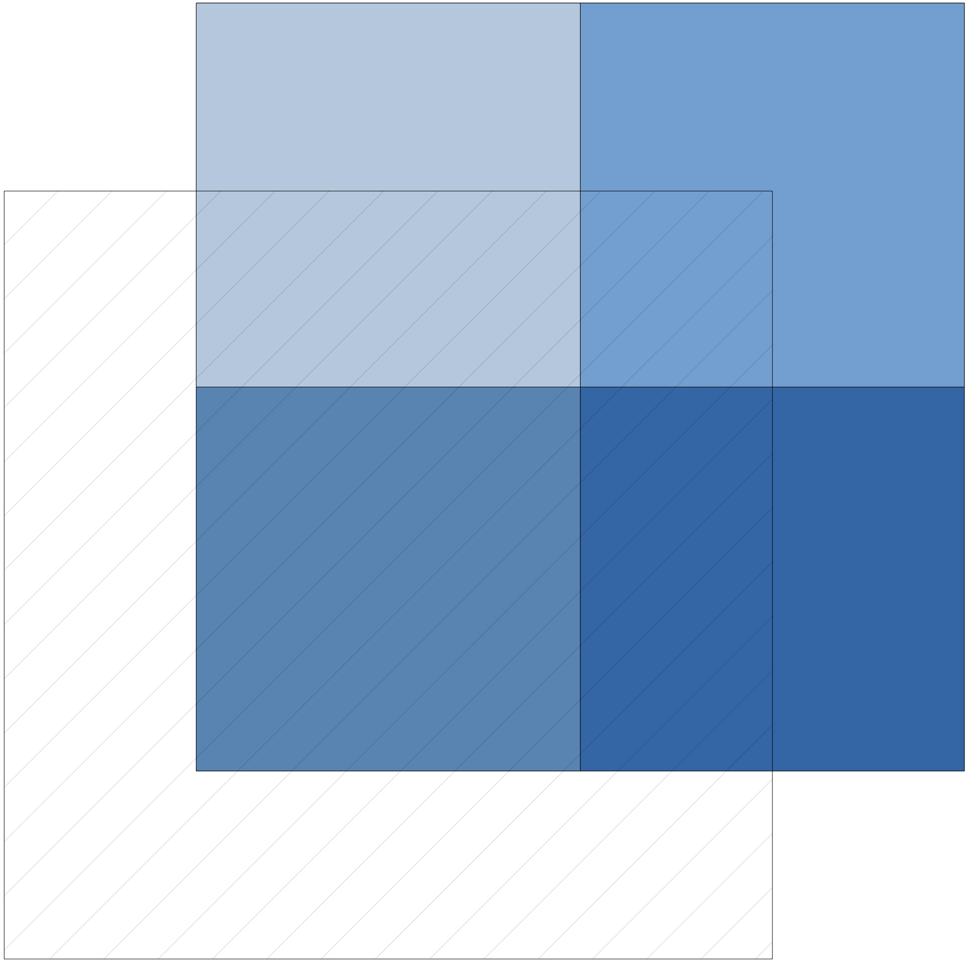
Patched Interpolated Convolution

Image

Select Patches

PSF of patch center

Cut out with overlap



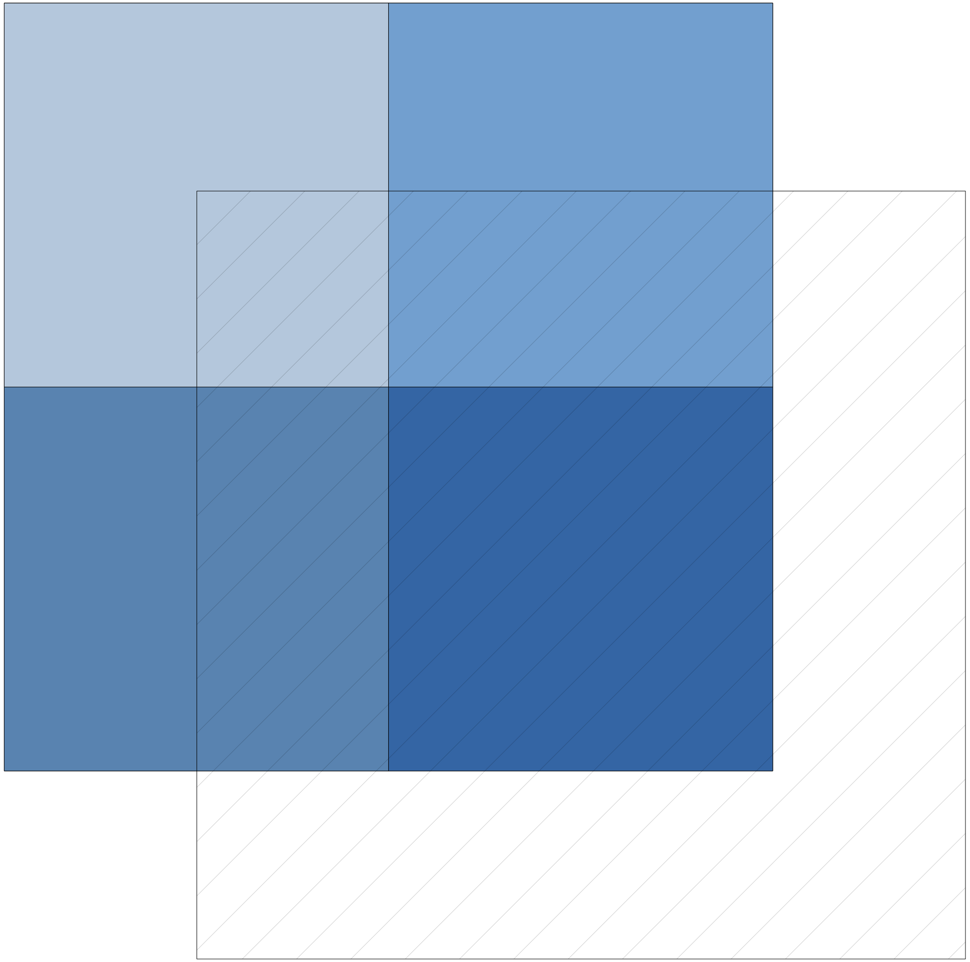
Patched Interpolated Convolution

Image

Select Patches

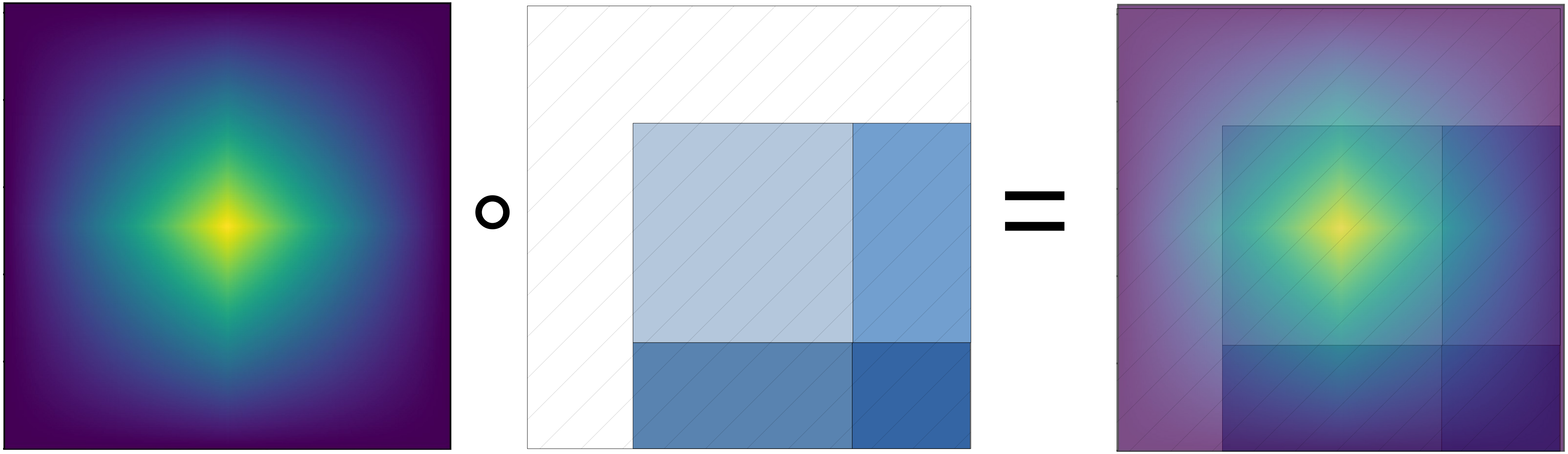
PSF of patch center

Cut out with overlap



Patched Interpolated Convolution

Weight cut outs bilinearly



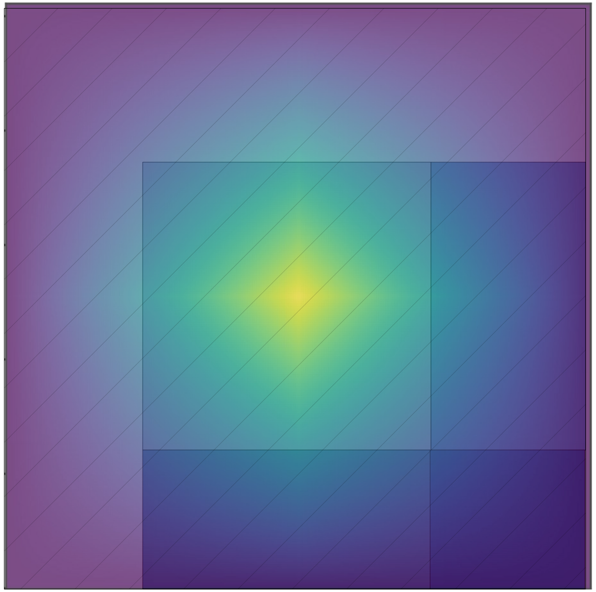
Interpolation weights

Cut out

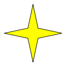
Weighted cut out

Patched Interpolated Convolution

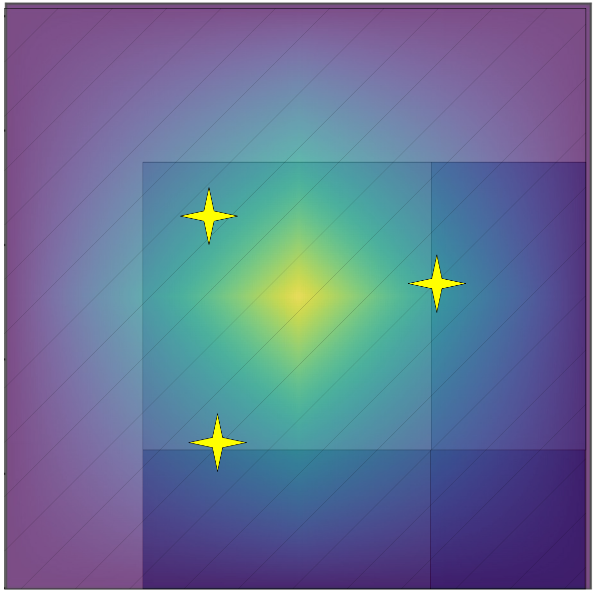
Convolve weighted cut outs with local PSF



*



=



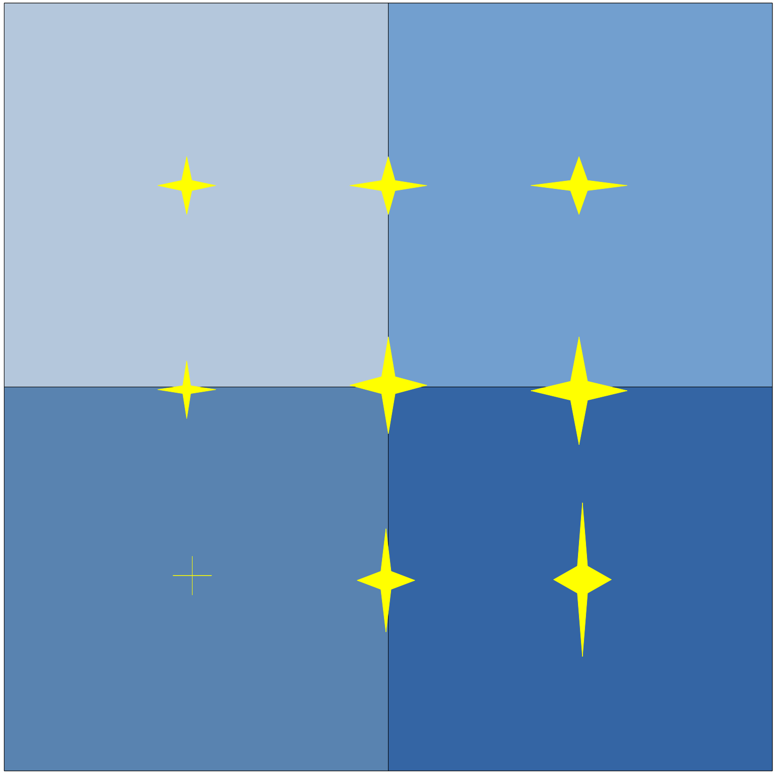
Weighted cut out

Local PSF

Weighted convolved cut out

Patched Interpolated Convolution

Add up the patches...



Why is it non-trivial to remove the PSF?

De-blurring noisy images

Information Field Theory
&
Generative Modeling

PSF **Representation**

Why is it non-trivial to remove the PSF?

De-blurring noisy images

Information Field Theory
&
Generative Modeling

PSF **Representation**

Patched Interpolated Convolution

Why is it non-trivial to remove the PSF?

De-blurring noisy images

Information Field Theory
&
Generative Modeling

PSF **Representation**

Patched Interpolated Convolution

Why is it non-trivial to remove the PSF?

De-blurring noisy images

Information Field Theory
&
Generative Modeling

PSF **Representation**

Patched Interpolated Convolution

Bayesian
De**noising**, De**composition** and De**convolution**
with spatially **variant** PSF

Chandra PSF

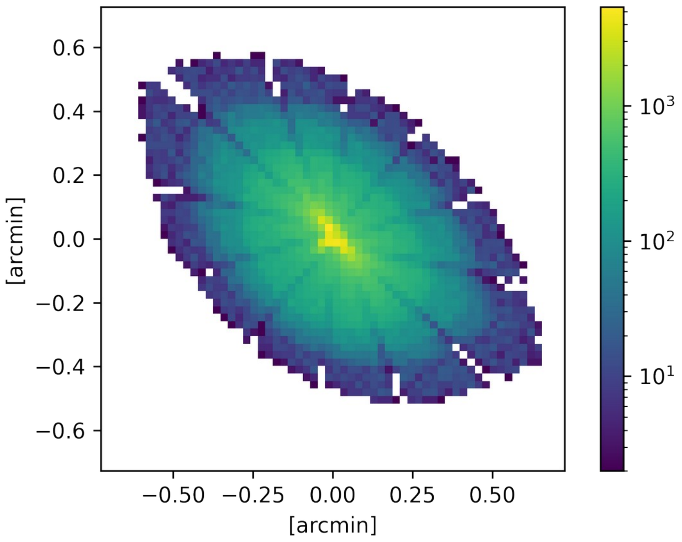
Chandra PSF

PSFs for patches from Marx [1] simulation, about 1e6 simulated photons, remove 1 photon events

1) Raytracing with MARX: x-ray observatory design, calibration, and support (Davis et al. 2012, SPIE 8443, 84431A)

Chandra PSF

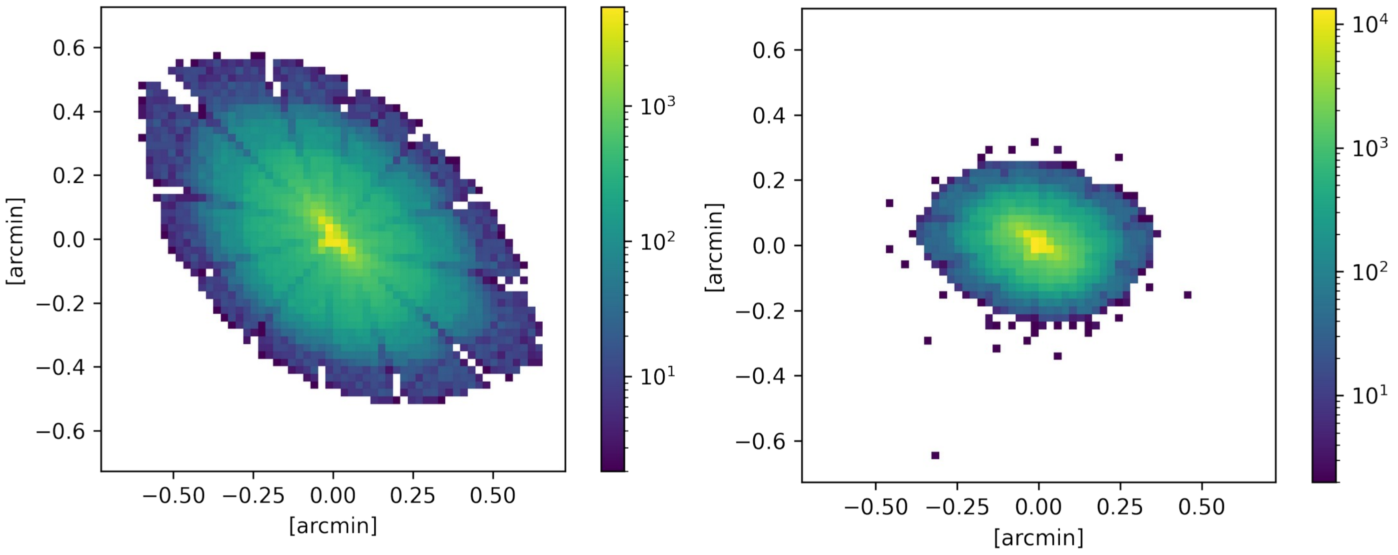
PSFs for patches from Marx [1] simulation, about 1e6 simulated photons, remove 1 photon events



1) Raytracing with MARX: x-ray observatory design, calibration, and support (Davis et al. 2012, SPIE 8443, 84431A)

Chandra PSF

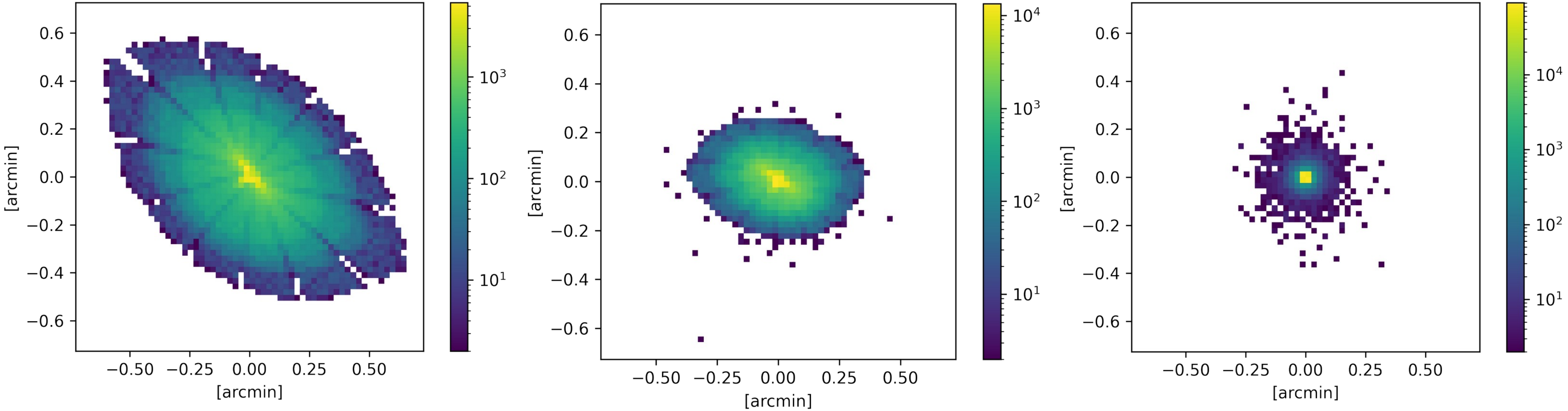
PSFs for patches from Marx [1] simulation, about 1e6 simulated photons, remove 1 photon events



1) Raytracing with MARX: x-ray observatory design, calibration, and support (Davis et al. 2012, SPIE 8443, 84431A)

Chandra PSF

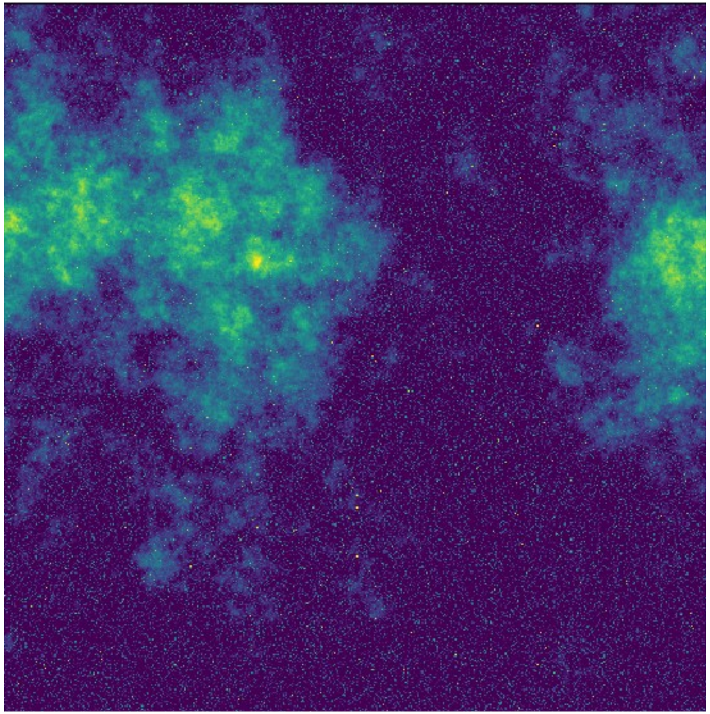
PSFs for patches from Marx [1] simulation, about 1e6 simulated photons, remove 1 photon events



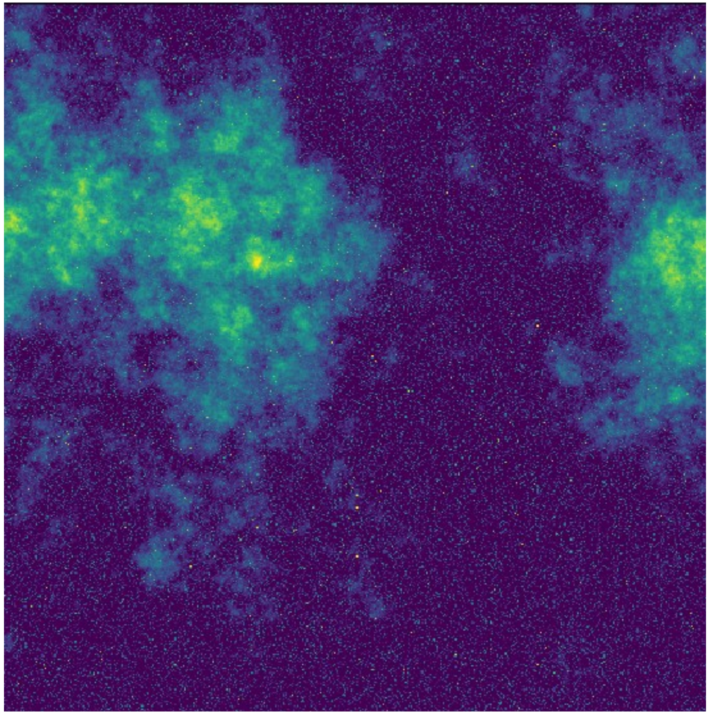
1) Raytracing with MARX: x-ray observatory design, calibration, and support (Davis et al. 2012, SPIE 8443, 84431A)

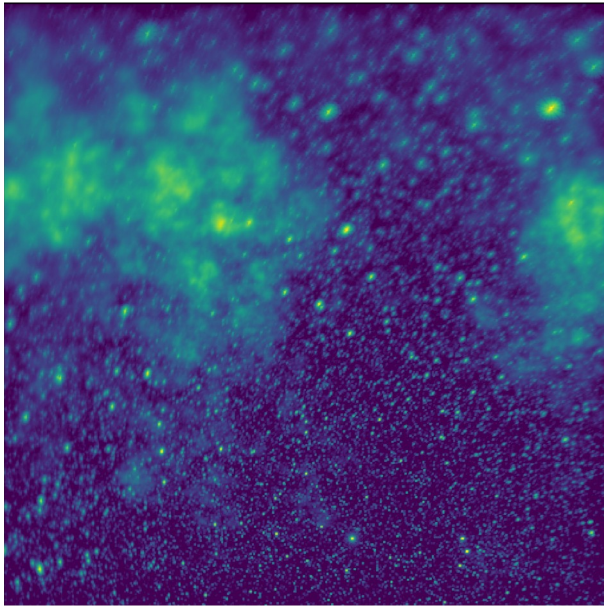
Application to
a synthetic example

Application to a synthetic example

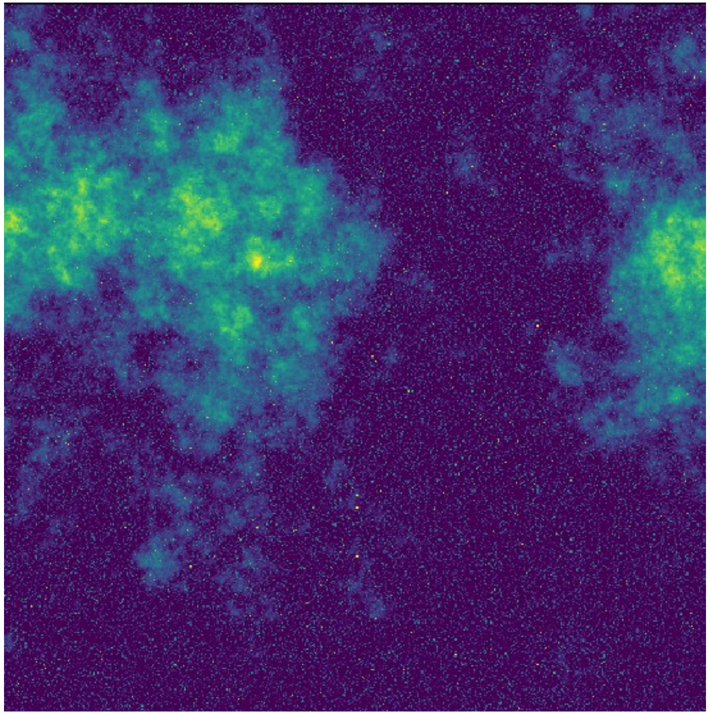


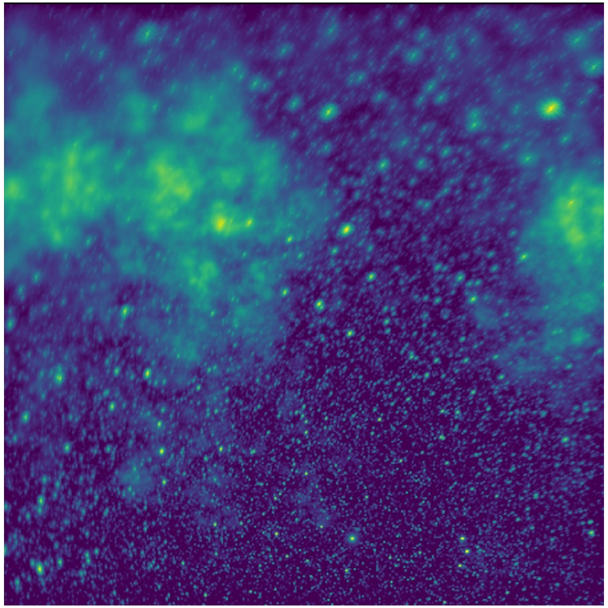
Application to a synthetic example

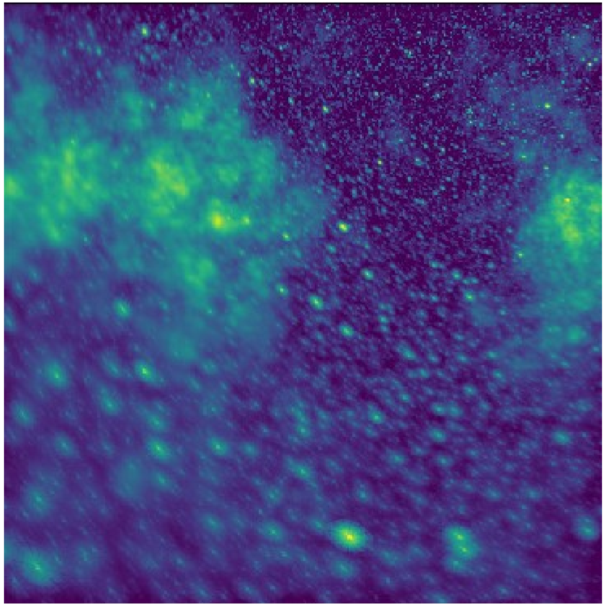




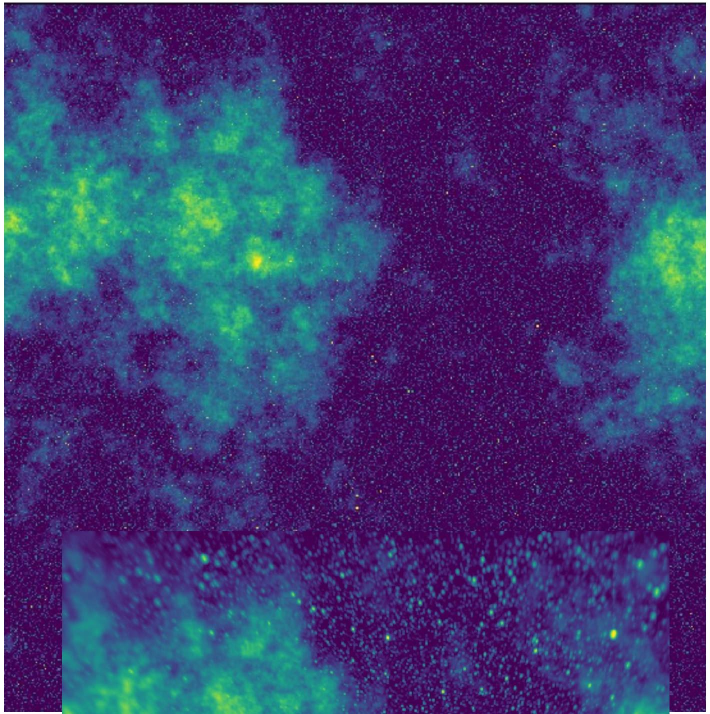
Application to a synthetic example

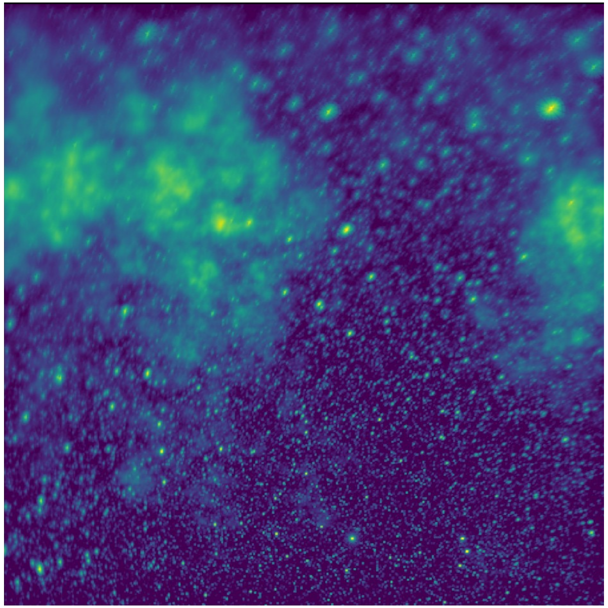


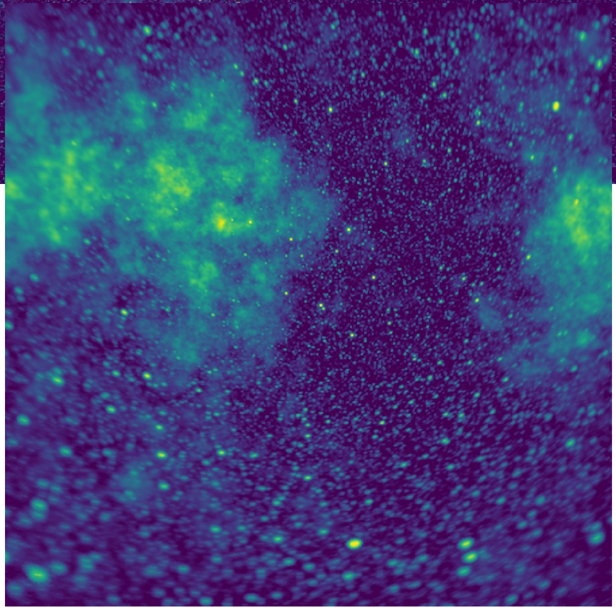


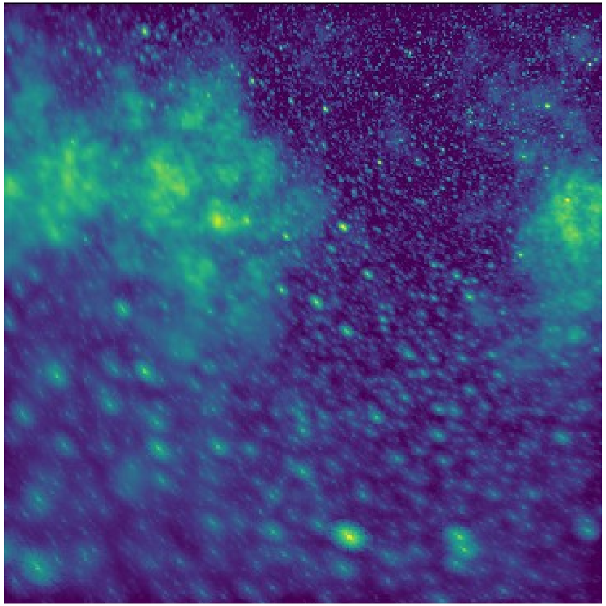


Application to a synthetic example

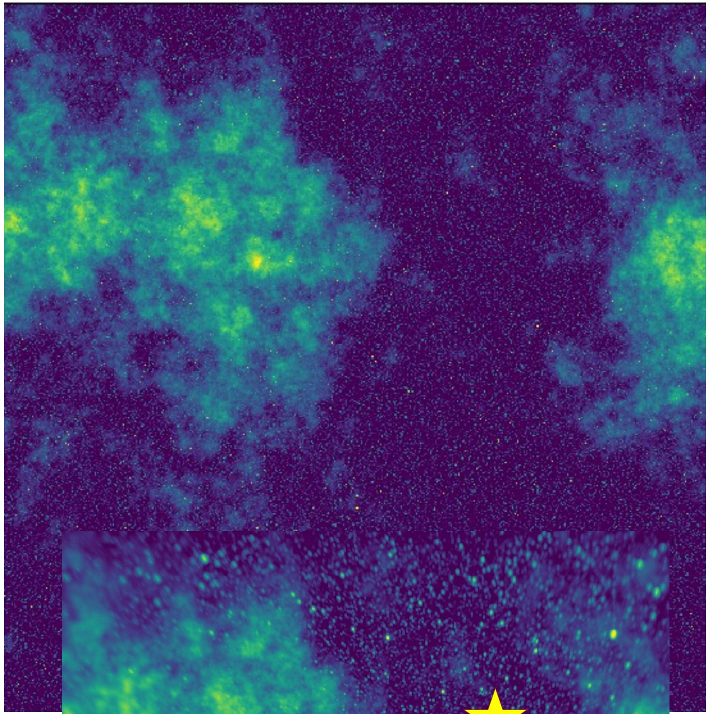


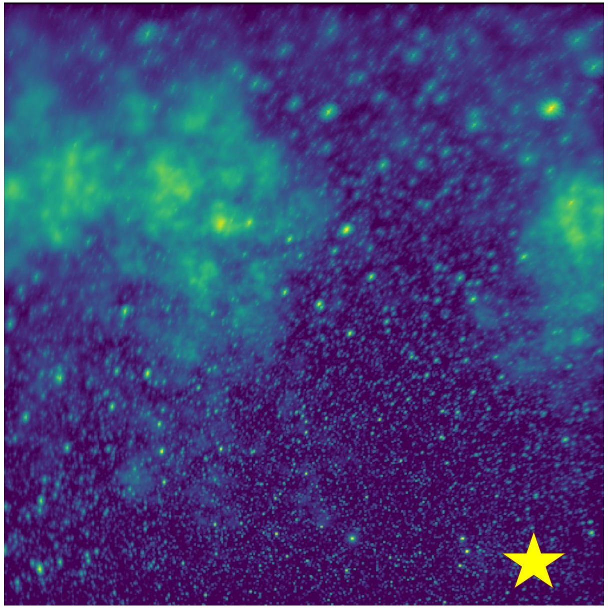


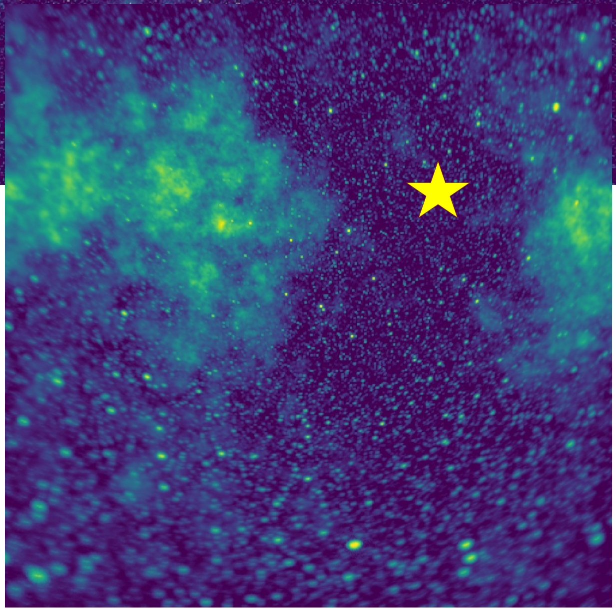


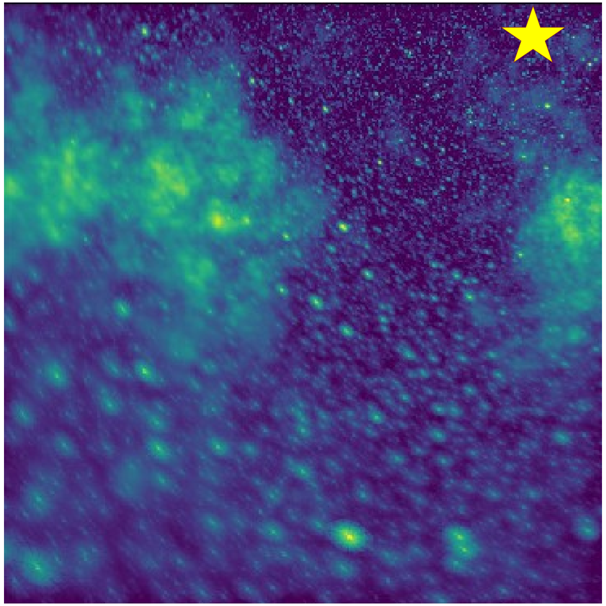


Application to a synthetic example









Bayesian Reconstruction of Perseus Cluster

with observation off-axis observation [11713]

Bayesian Reconstruction of Perseus Cluster

with observation off-axis observation [11713]

- Energy bins:
  - 0.5 – 1.2 keV
  - 1.2 – 2.9 keV
  - 2.9 - 7 keV

Bayesian Reconstruction of Perseus Cluster

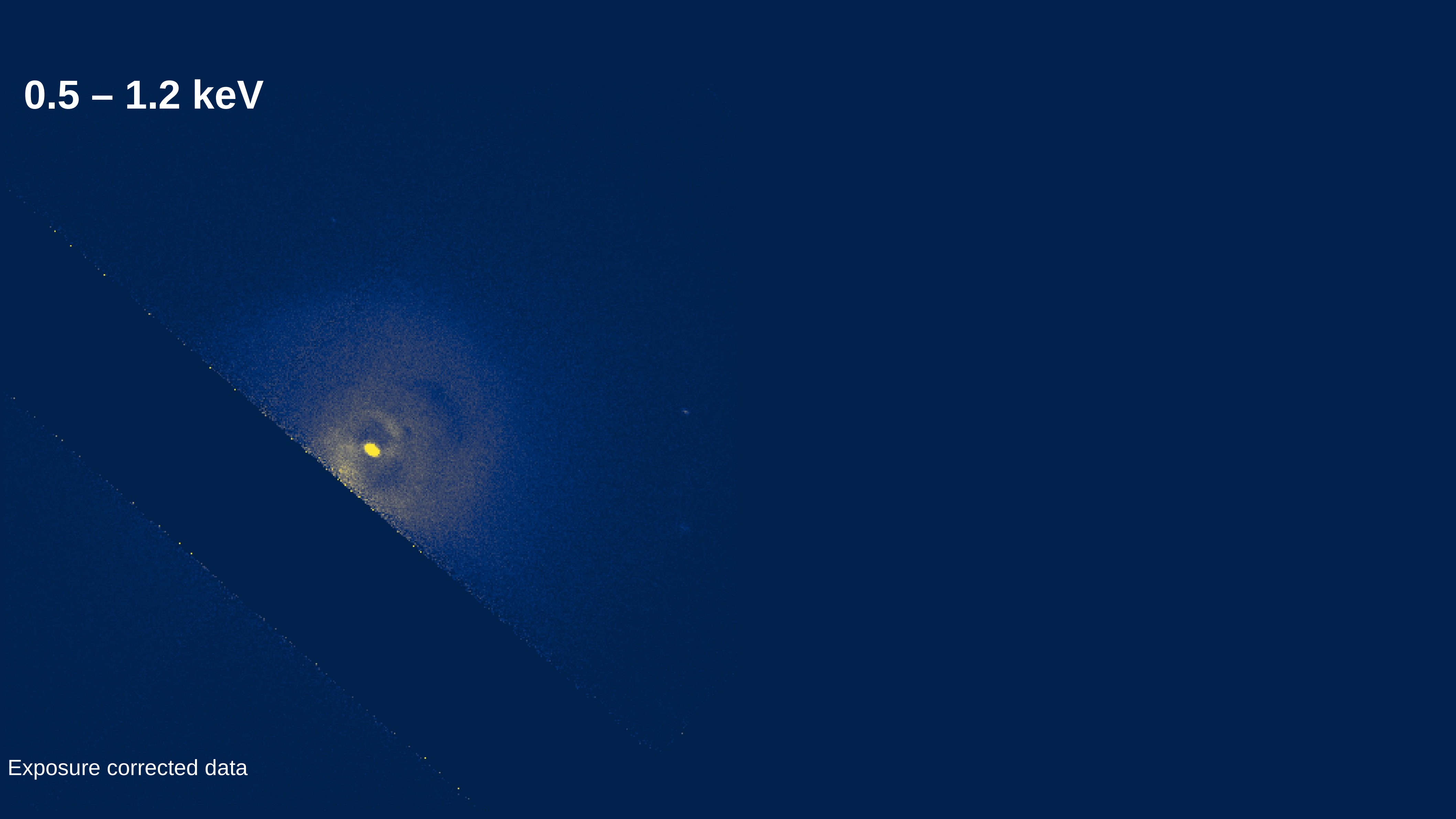
with observation off-axis observation [11713]

- Energy bins:
  - 0.5 – 1.2 keV
  - 1.2 – 2.9 keV
  - 2.9 - 7 keV
- Generative Model with diffuse & point-source component

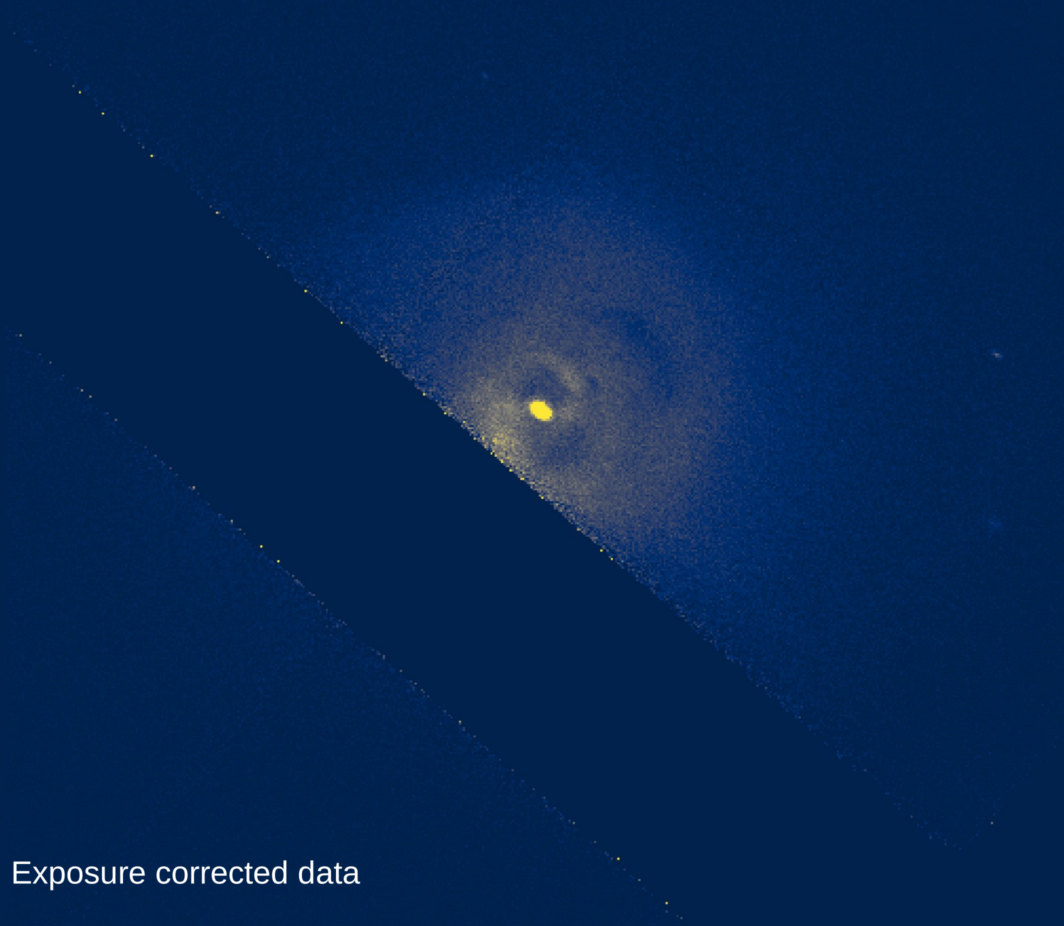
Bayesian Reconstruction of Perseus Cluster

with observation off-axis observation [11713]

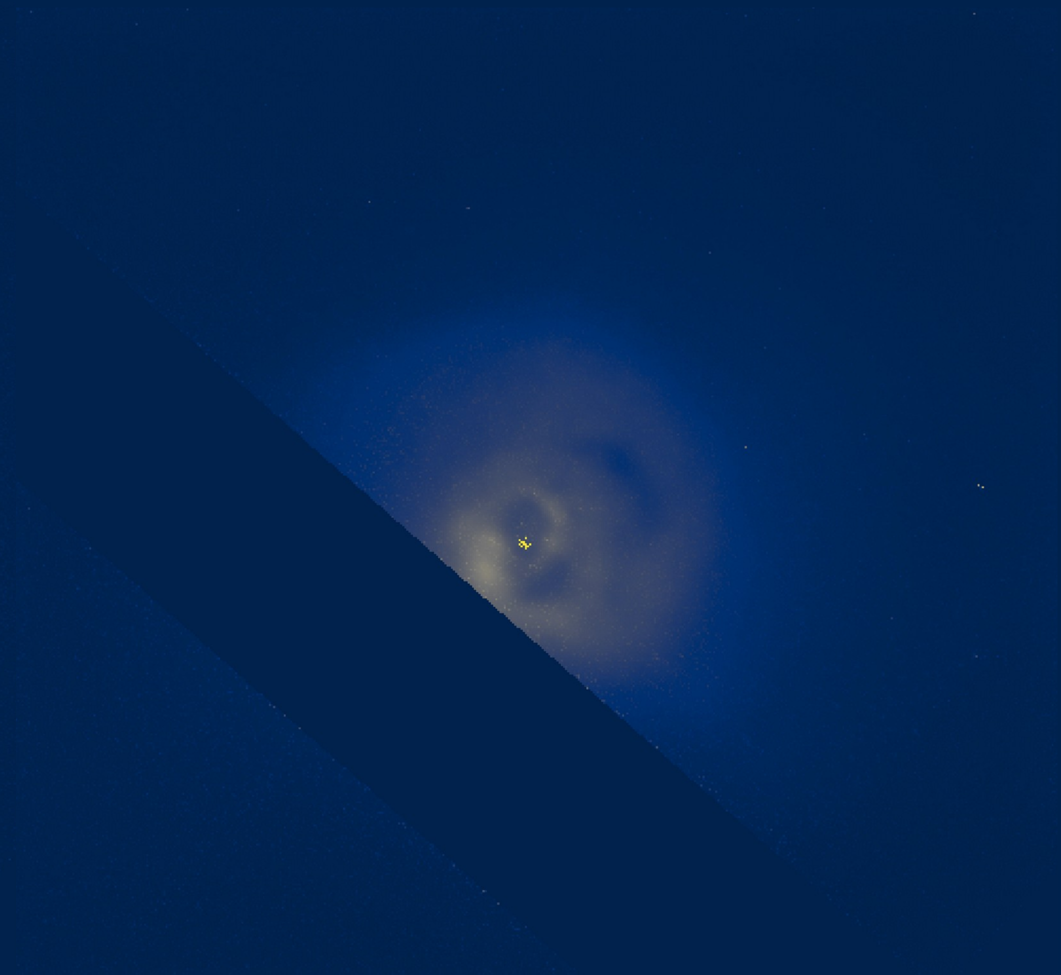
- Energy bins:
  - 0.5 – 1.2 keV
  - 1.2 – 2.9 keV
  - 2.9 - 7 keV
- Generative Model with diffuse & point-source component
- Assuming spatial and spectral correlations


0.5 – 1.2 keV
Exposure corrected data

0.5 – 1.2 keV

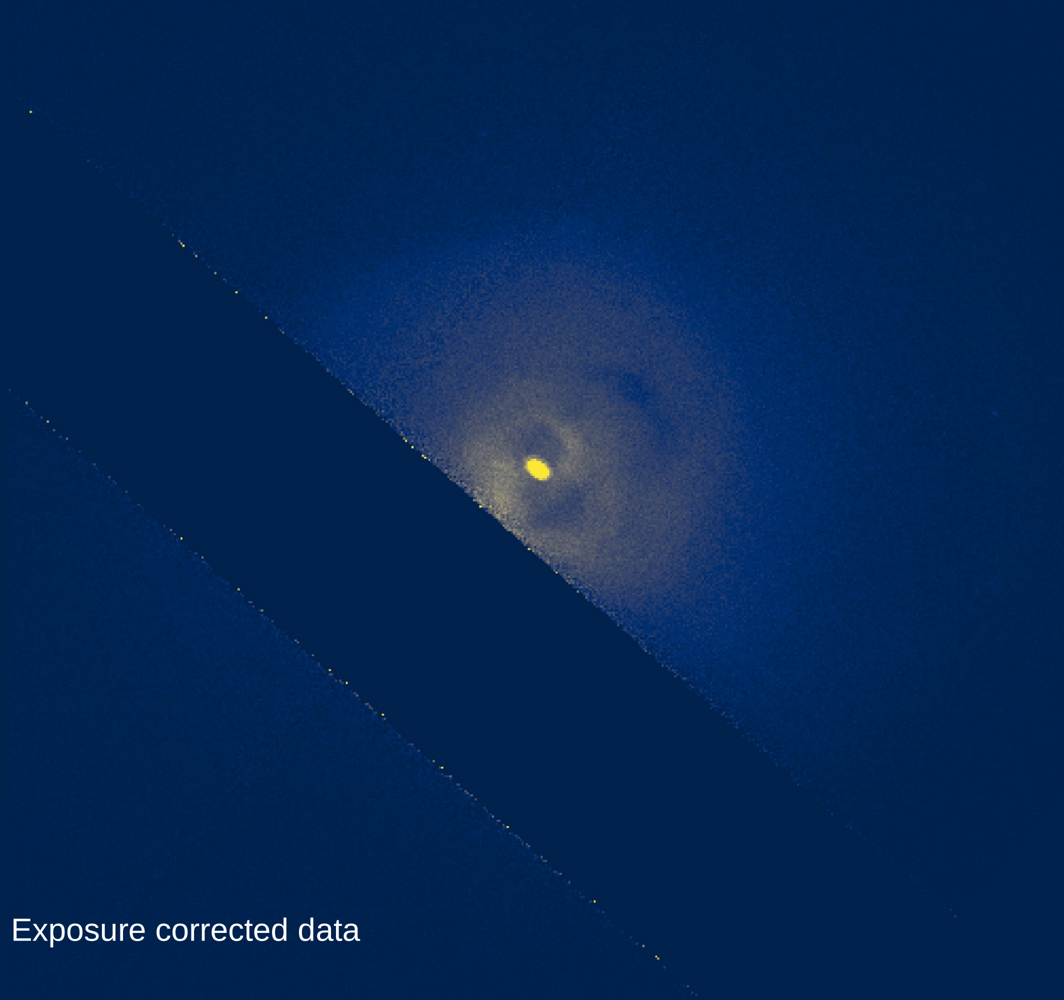


Exposure corrected data

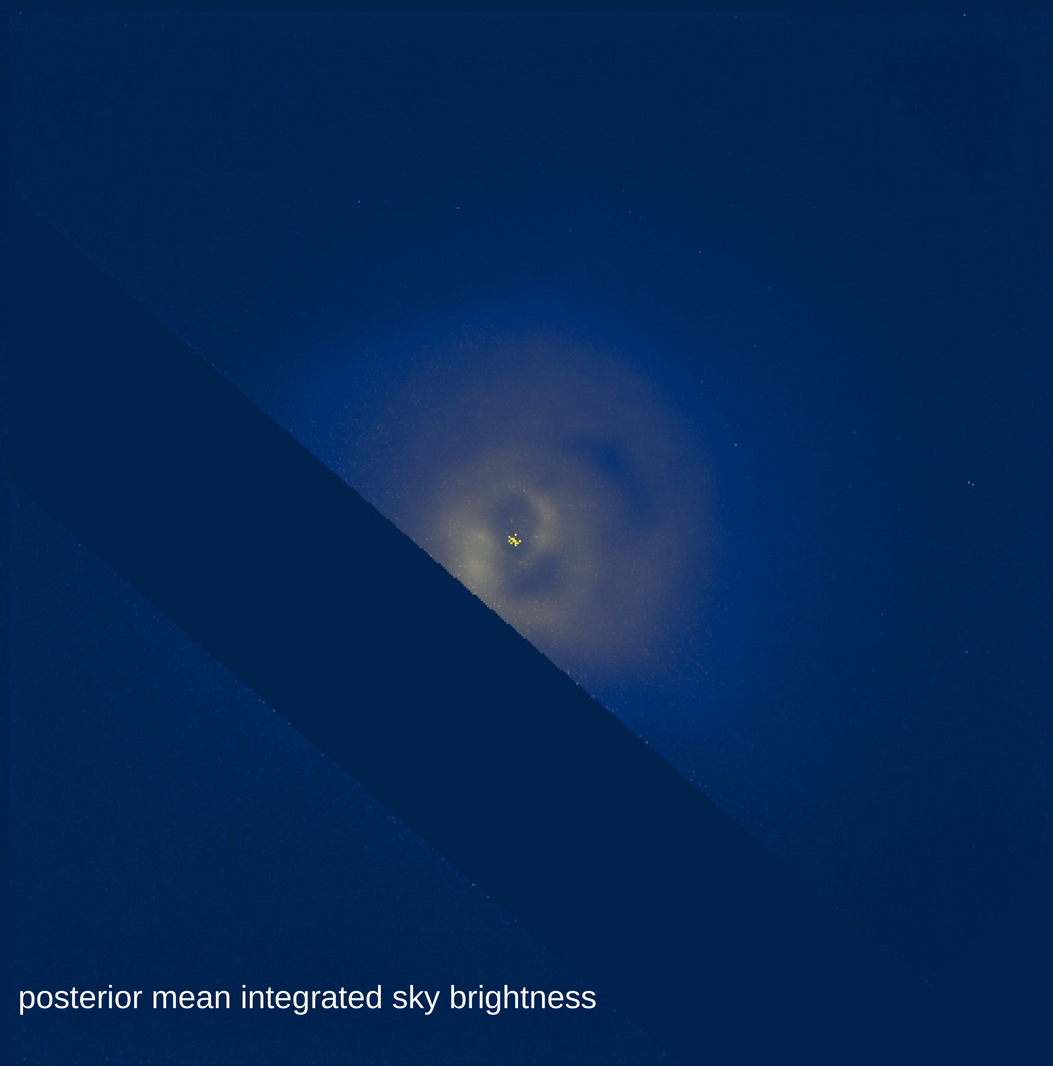


posterior mean integrated sky brightness

1.2 – 2.9 keV

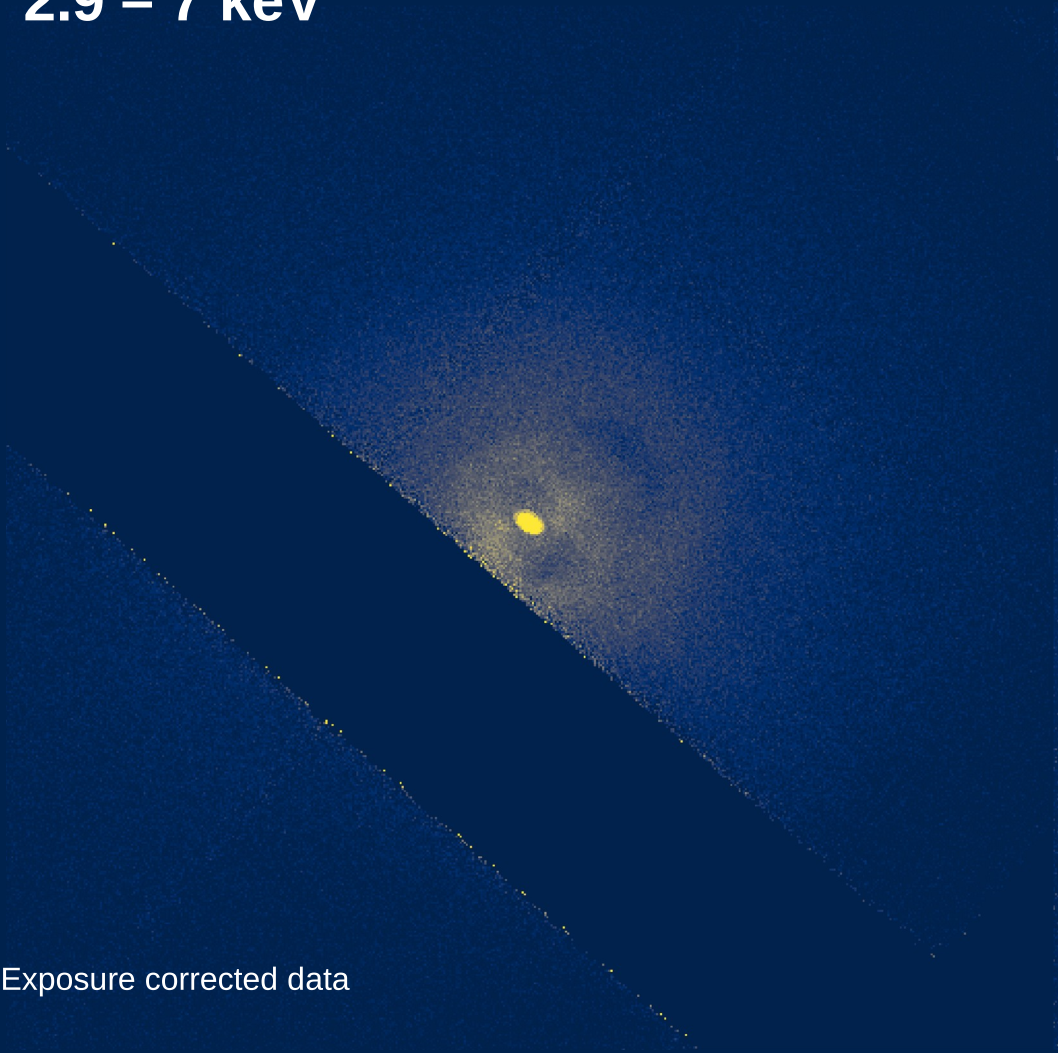


Exposure corrected data

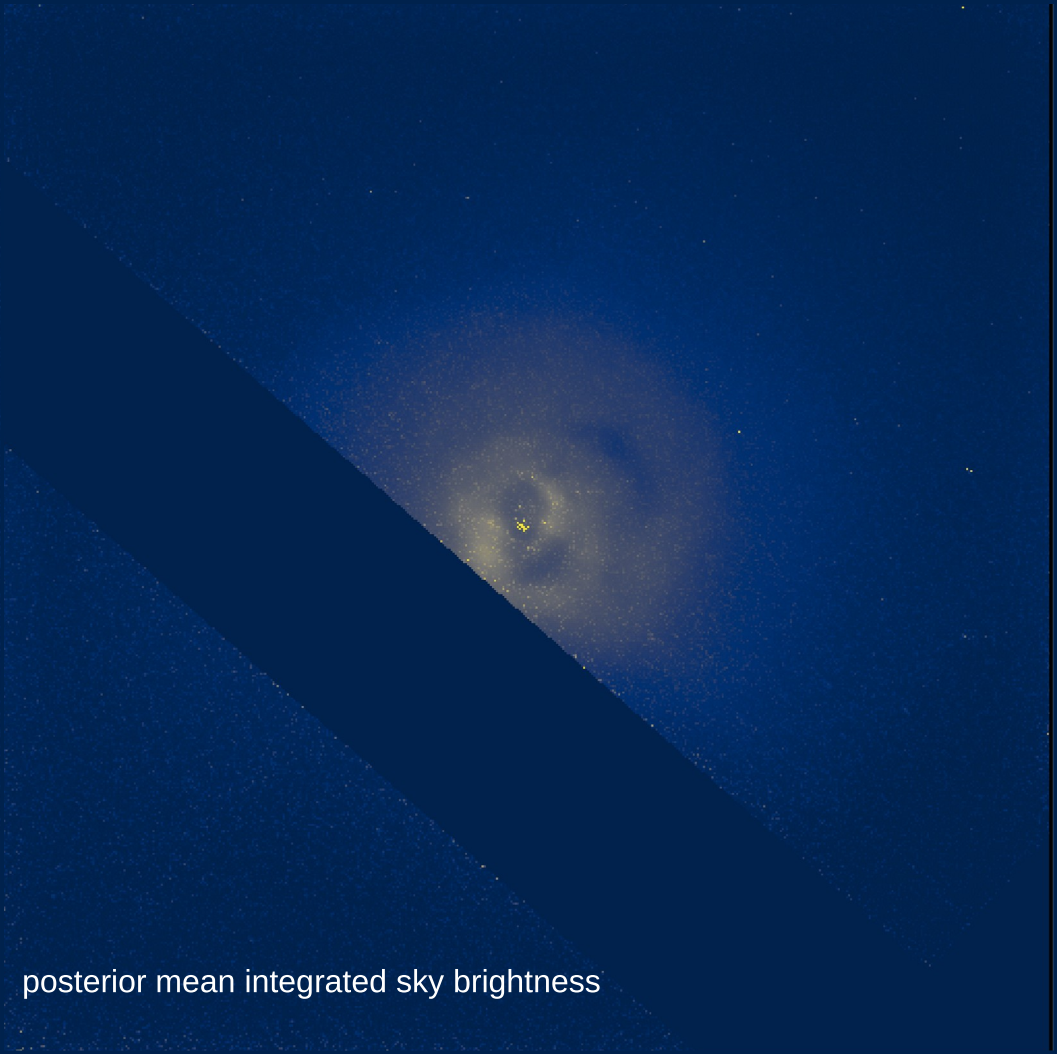


posterior mean integrated sky brightness

2.9 – 7 keV



Exposure corrected data



posterior mean integrated sky brightness

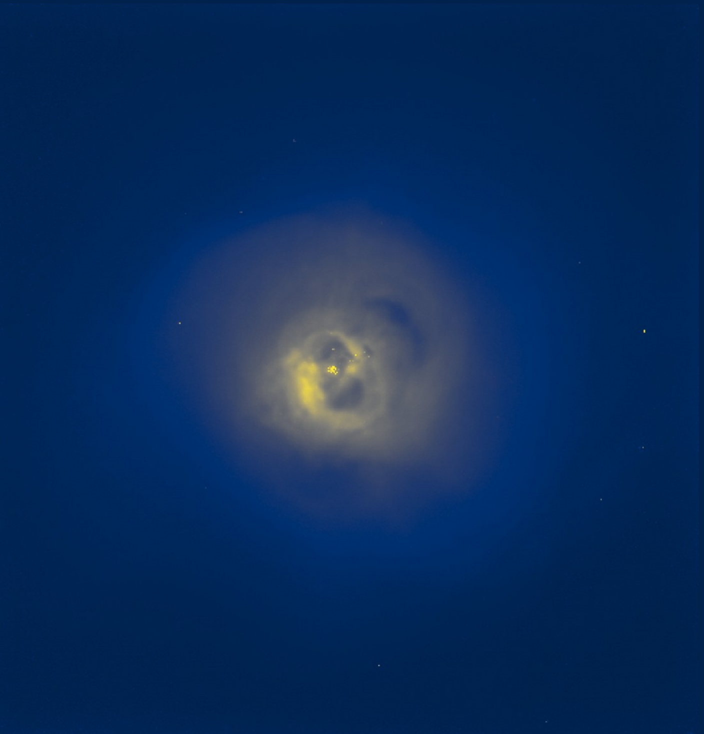
More data? No Problem!

Observations: 11713-11716, 3209, 4289, 4948, 4952

More data? No Problem!

Observations: 11713-11716, 3209, 4289, 4948, 4952

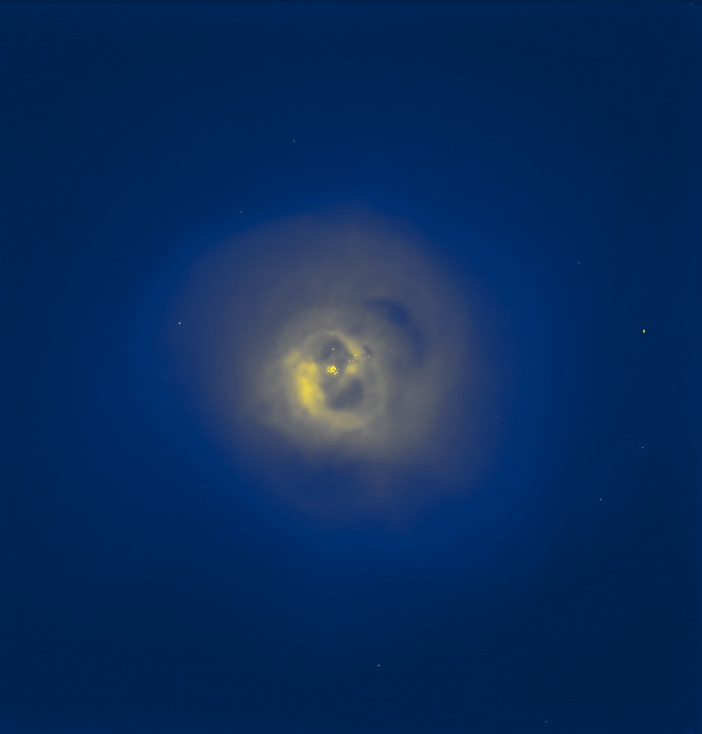
Sky Reconstruction



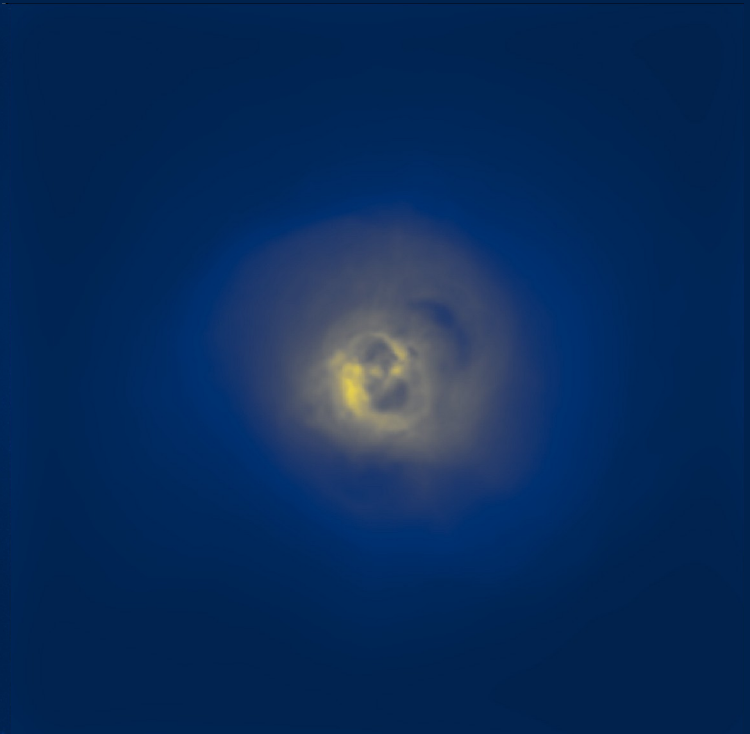
More data? No Problem!

Observations: 11713-11716, 3209, 4289, 4948, 4952

Sky Reconstruction



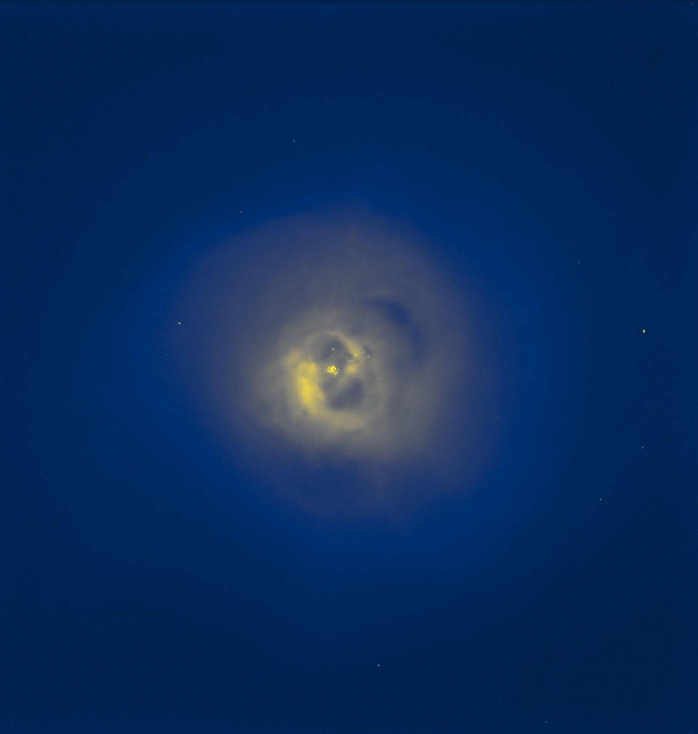
diffuse / correlated



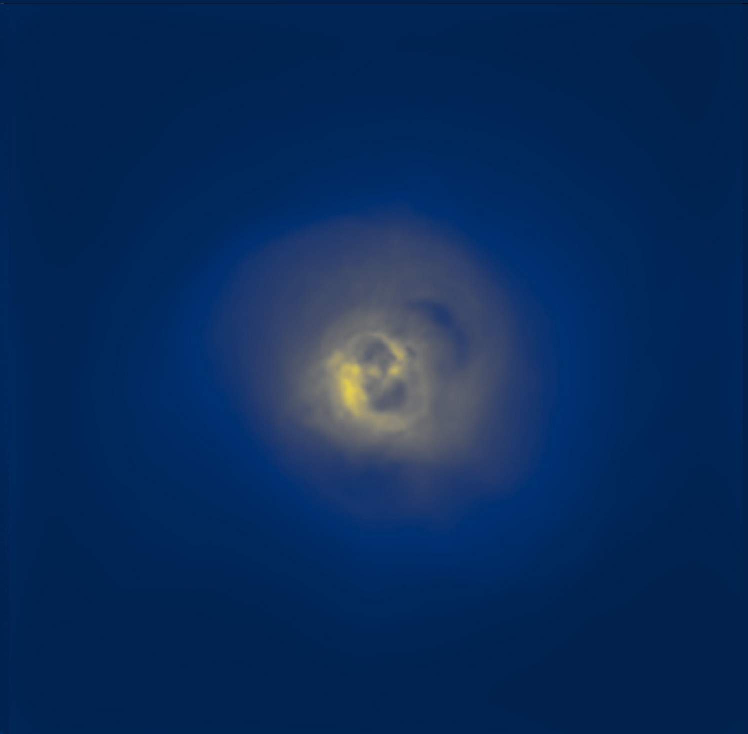
More data? No Problem!

Observations: 11713-11716, 3209, 4289, 4948, 4952

Sky Reconstruction

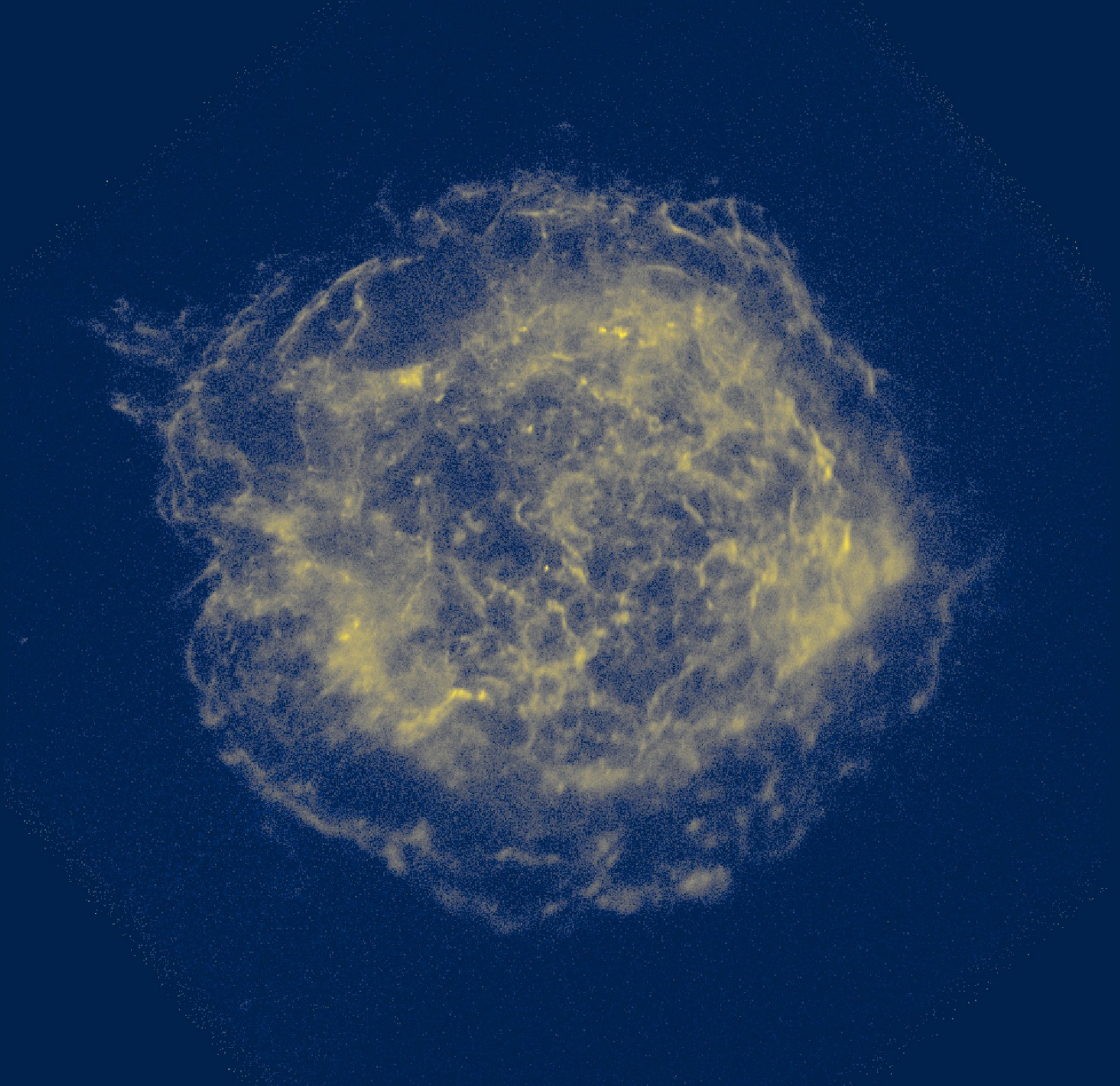


diffuse / correlated

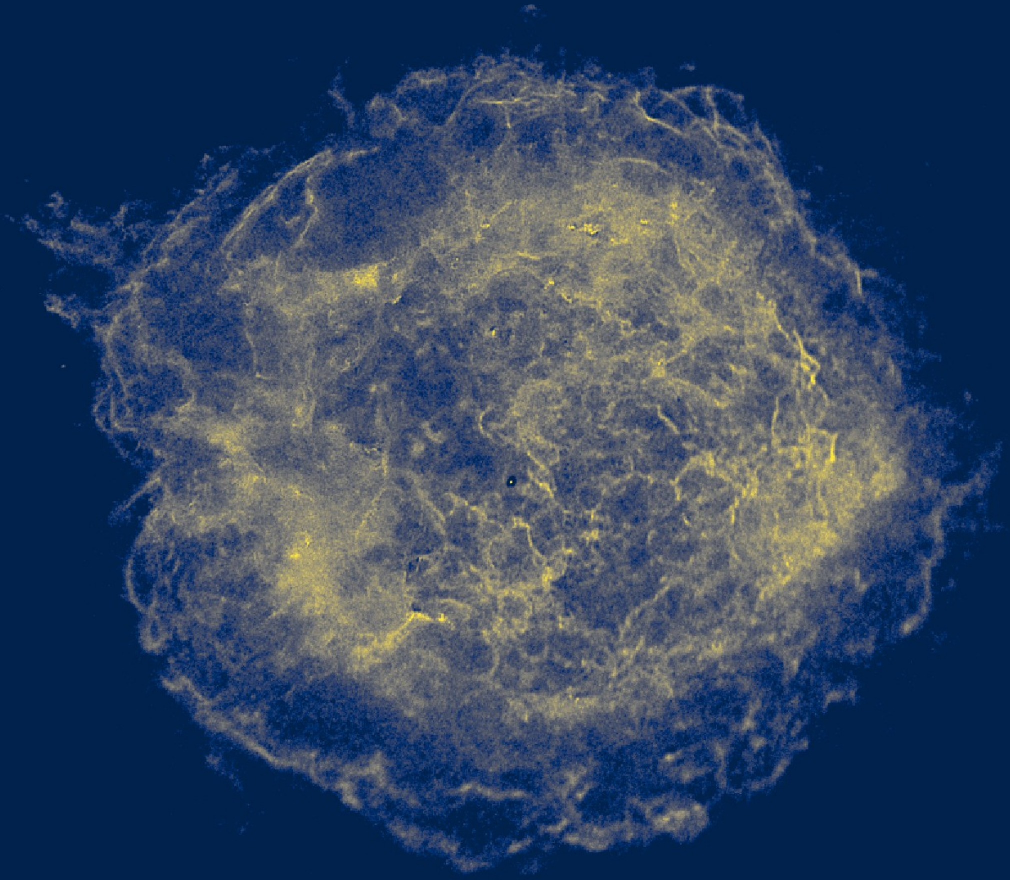


point source-like

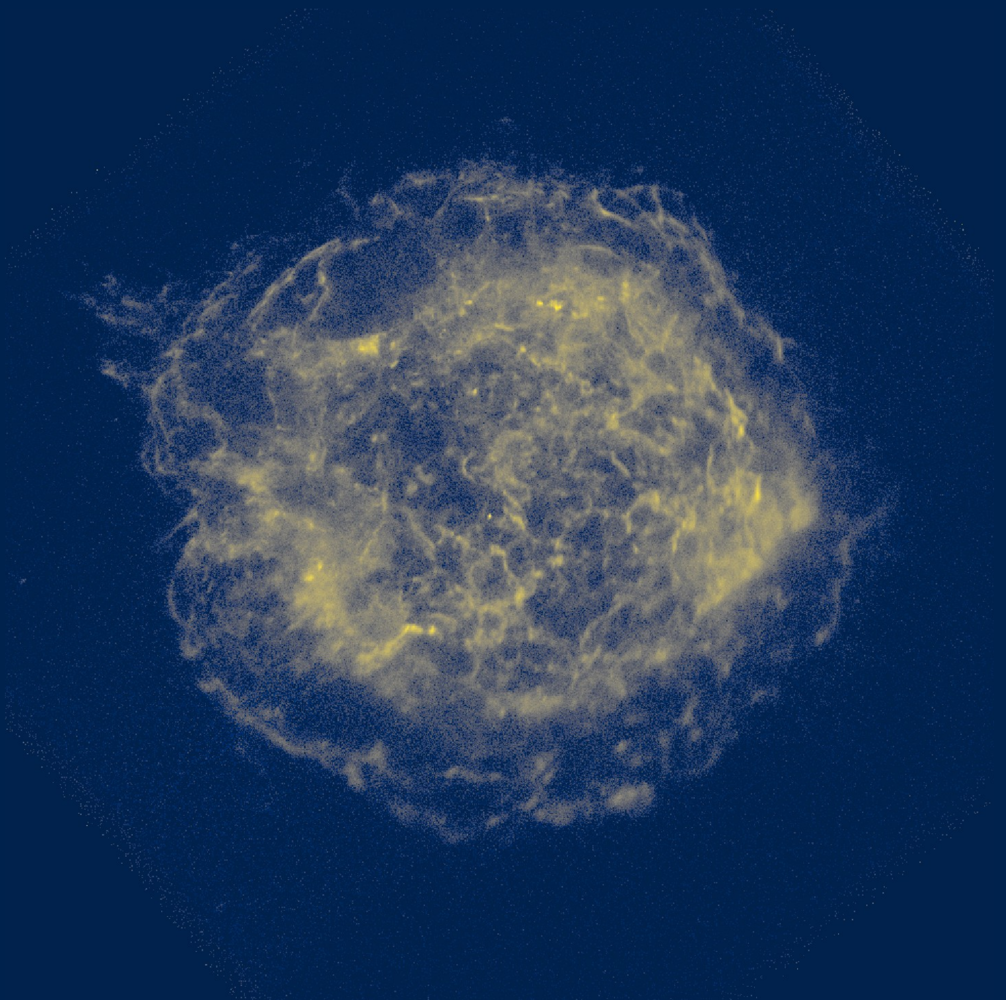
Cassiopeia A

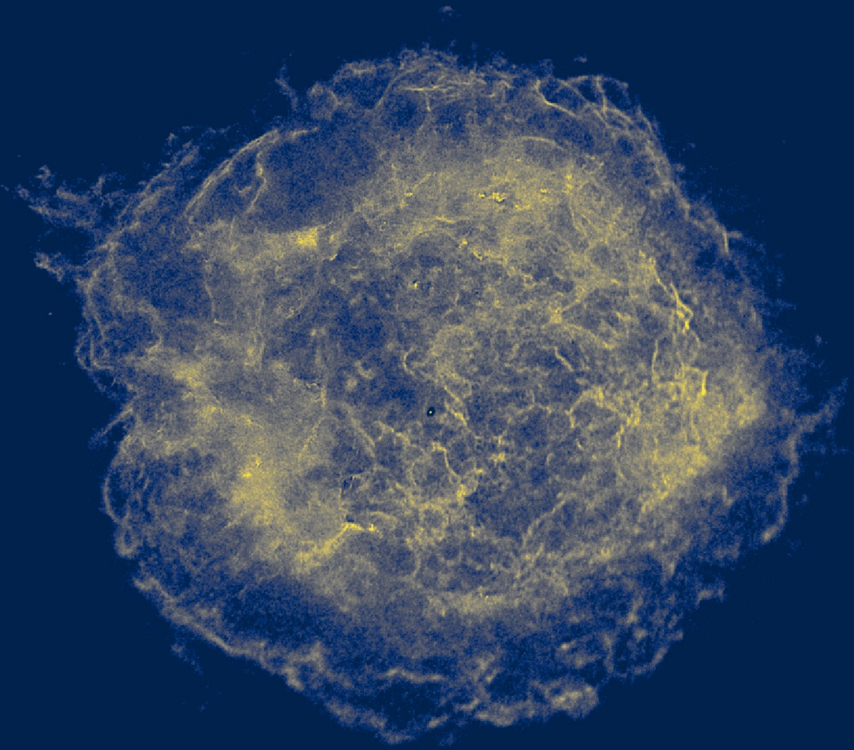


Cassiopeia A

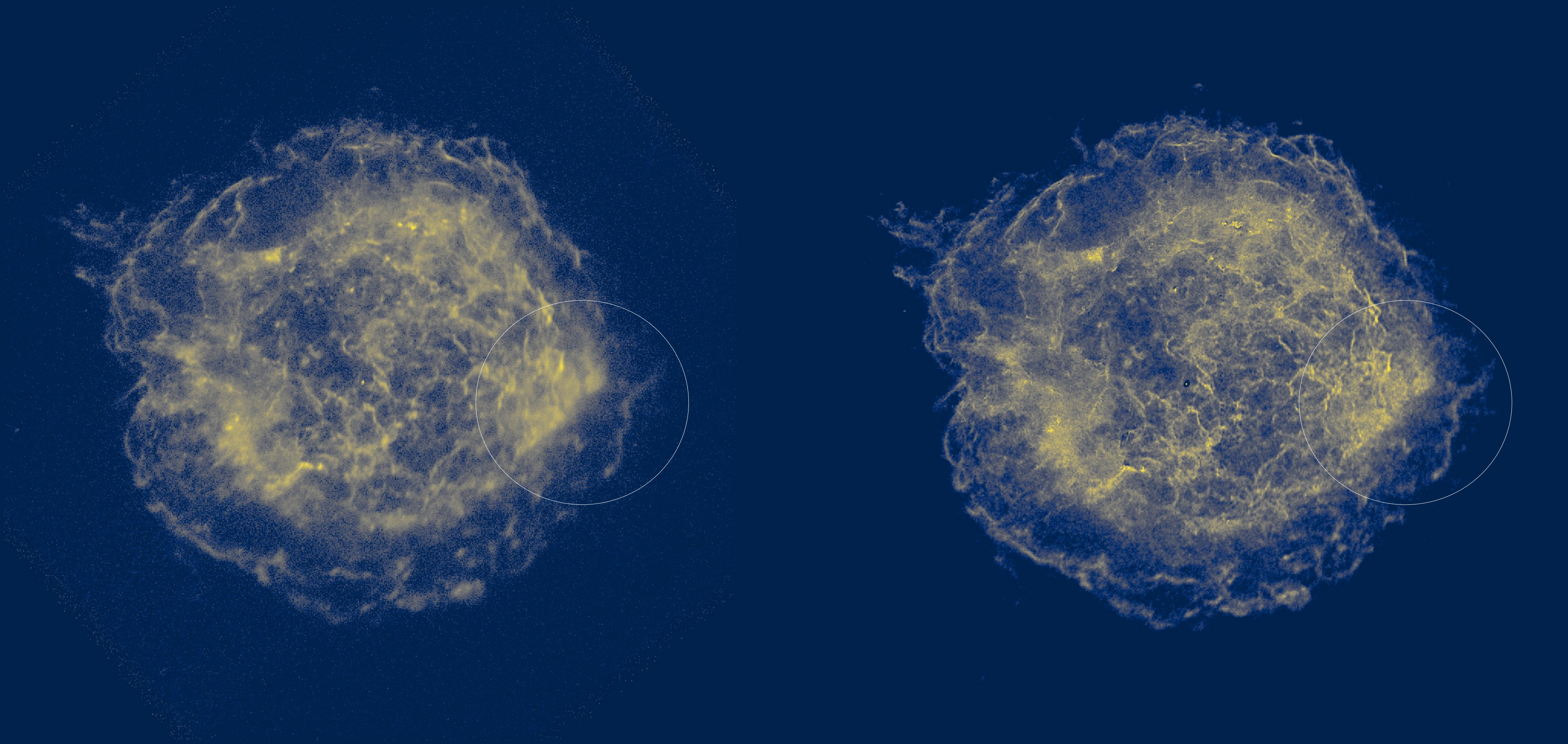


Cassiopeia A

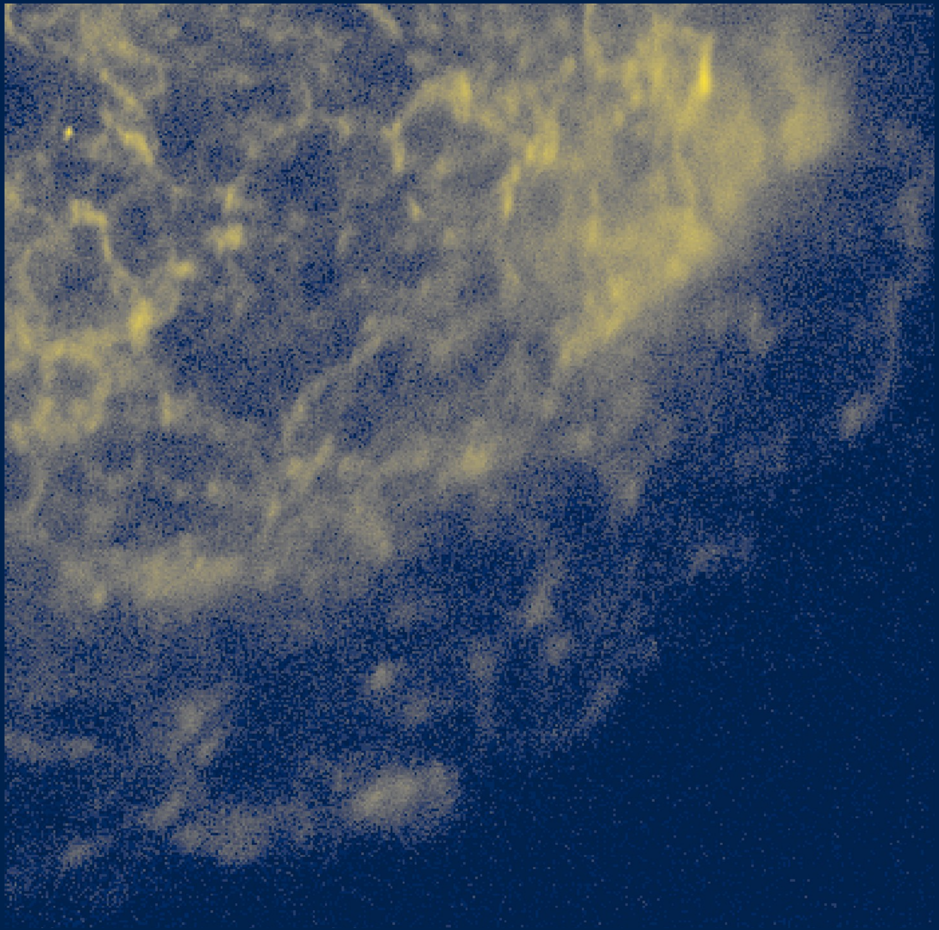


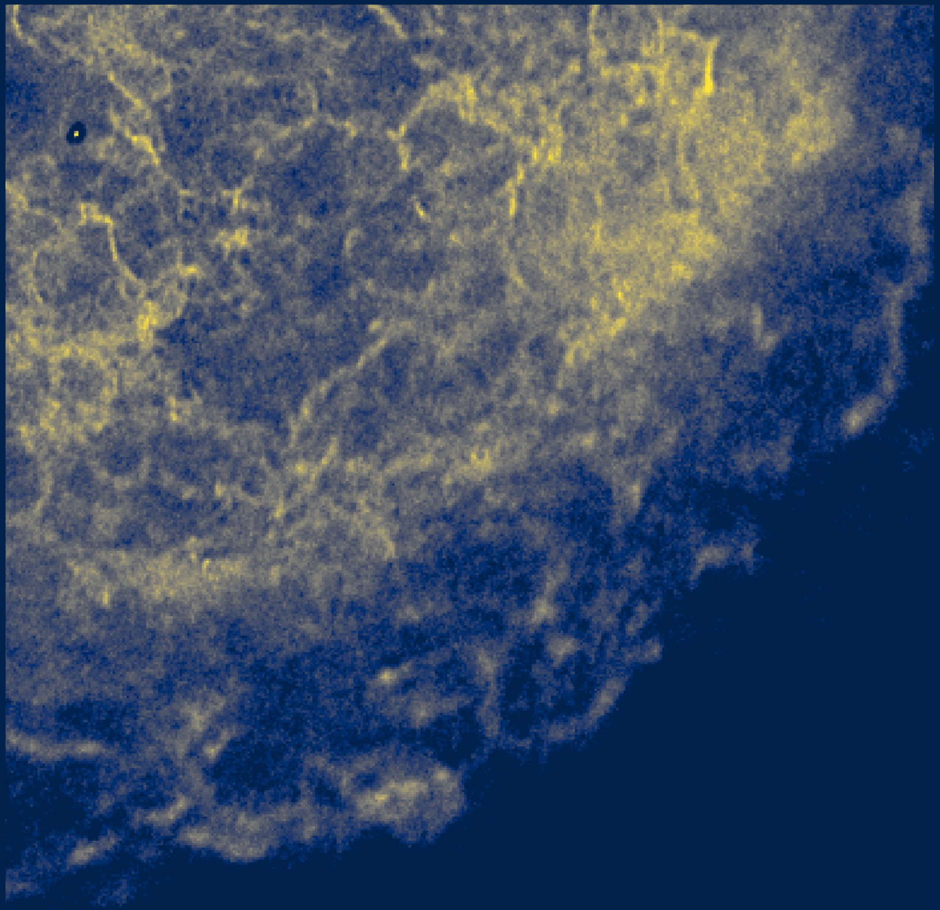


Cassiopeia A

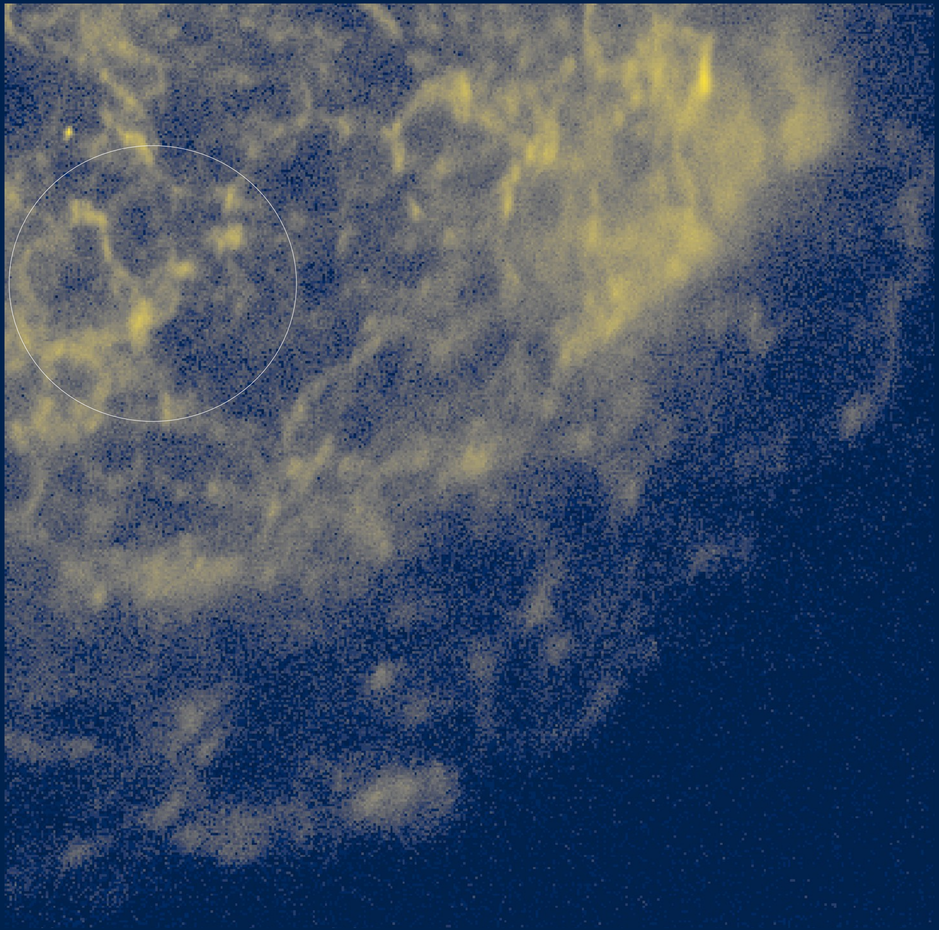


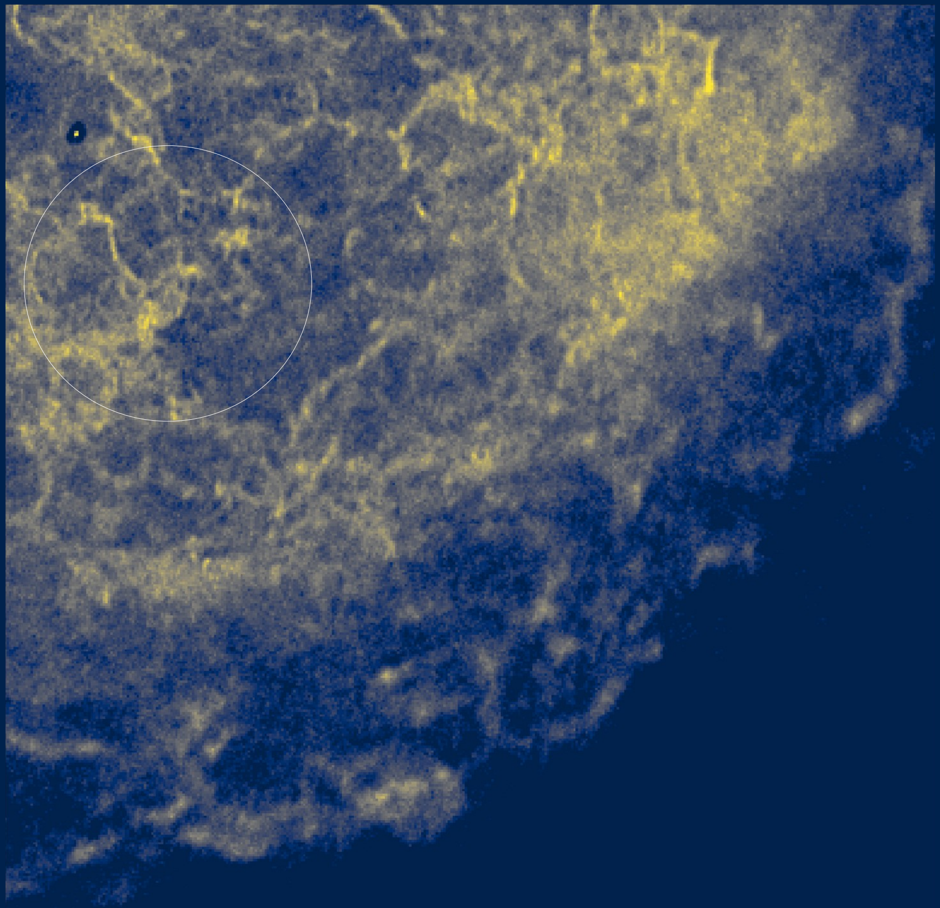
Cassiopeia A



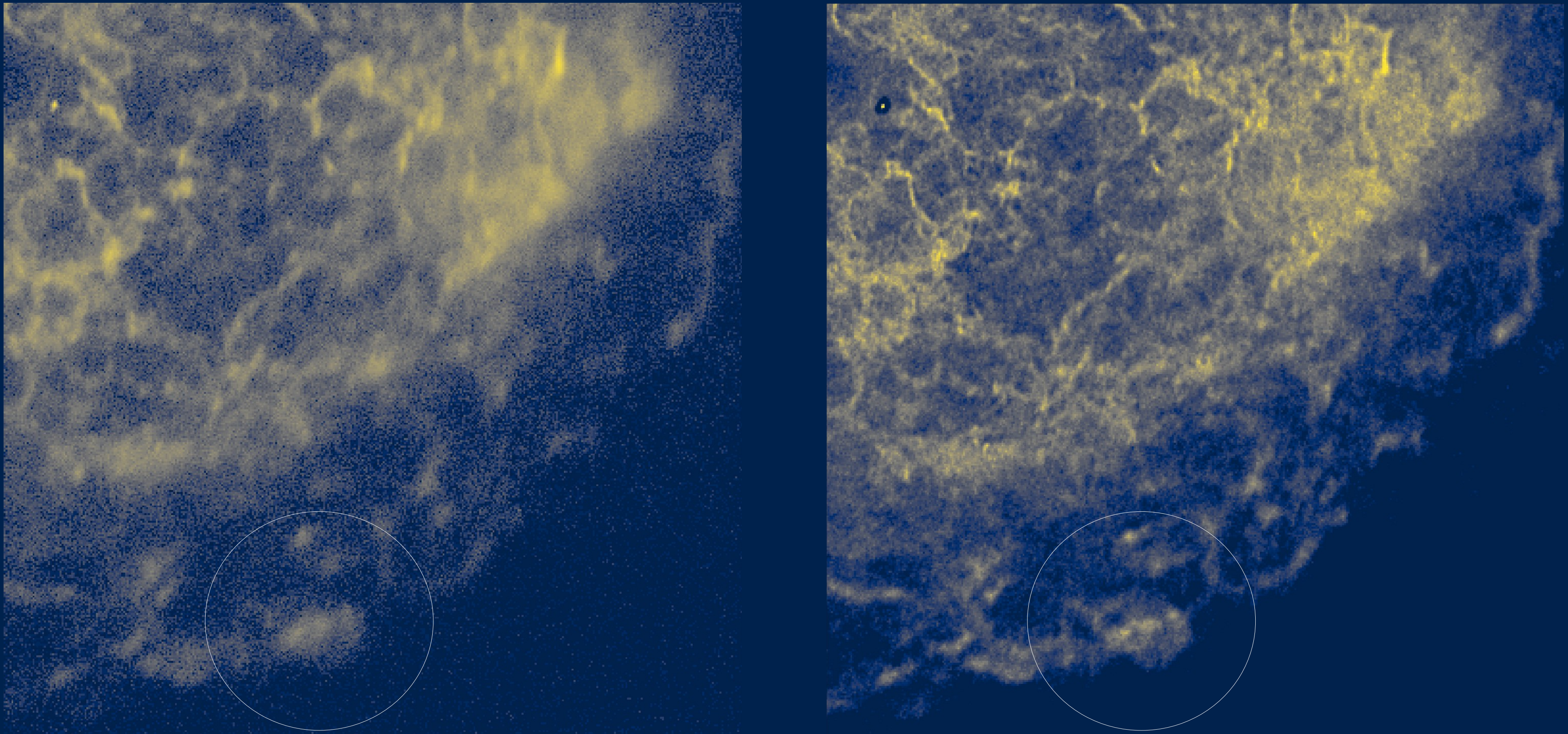


Cassiopeia A



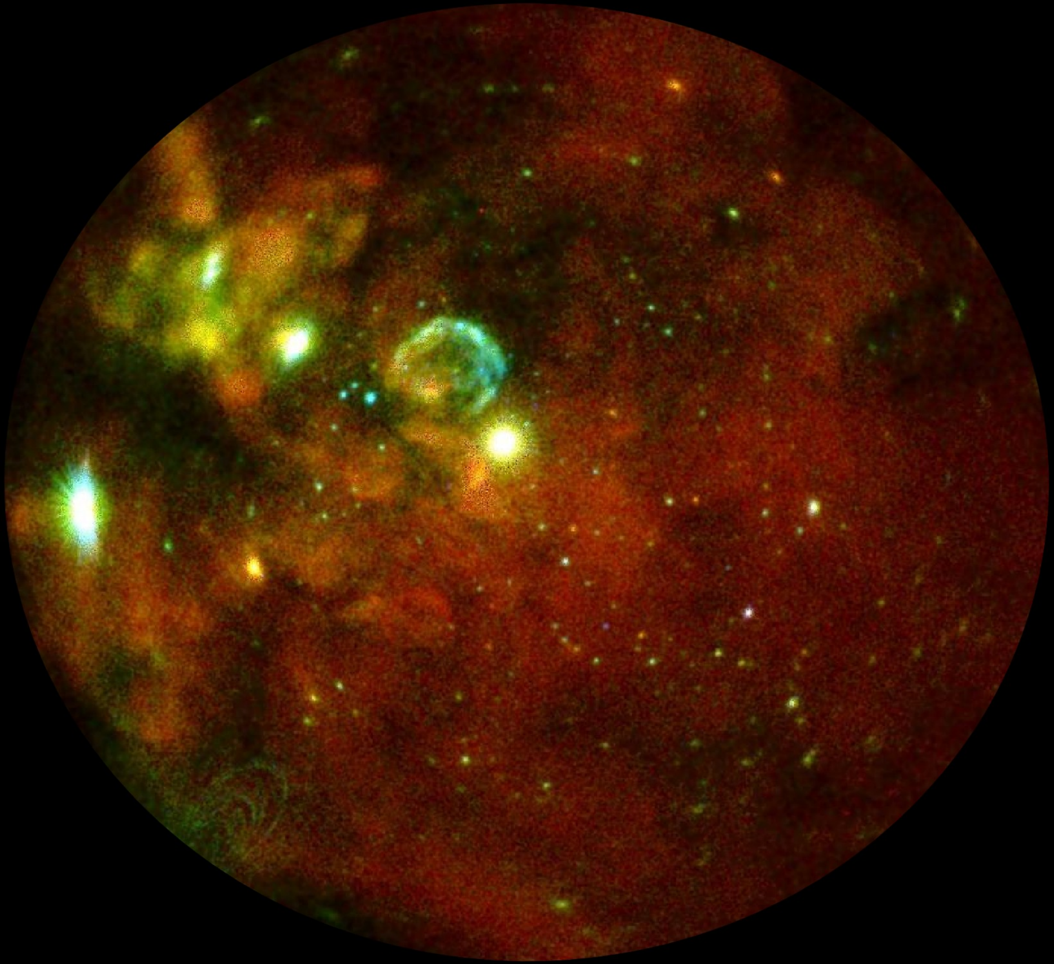


Cassiopeia A



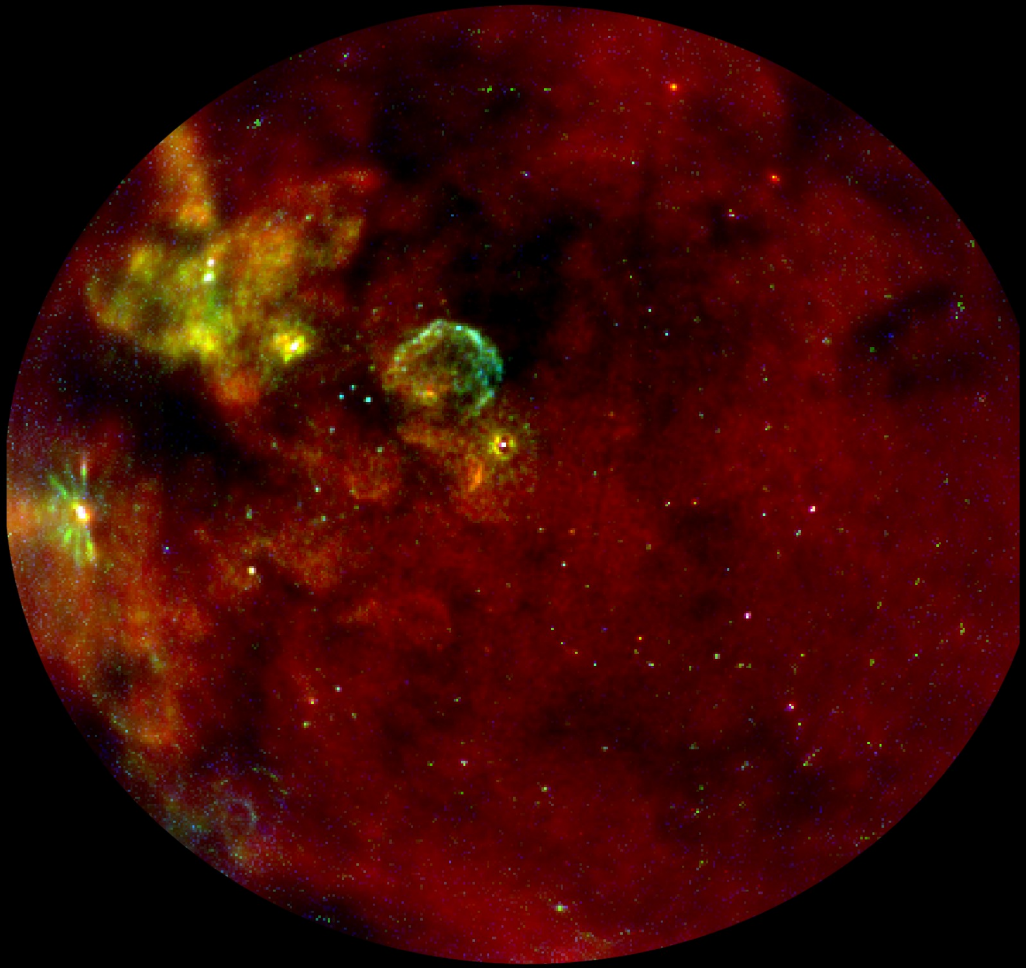
eROSITA

LMC 1987A



eROSITA

LMC 1987A



Summary

Summary

- Removal of spatially variant PSF is possible, despite Poisson noise

Summary

- Removal of spatially variant PSF is possible, despite Poisson noise
- Enables us to use also far off-axis observations

Summary

- Removal of spatially variant PSF is possible, despite Poisson noise
- Enables us to use also far off-axis observations
- Stabilizes point source detection

Summary

- Removal of spatially variant PSF is possible, despite Poisson noise
- Enables us to use also far off-axis observations
- Stabilizes point source detection

Future:

Summary

- Removal of spatially variant PSF is possible, despite Poisson noise
- Enables us to use also far off-axis observations
- Stabilizes point source detection

Future:

- Search for even faster and more precise representations

Summary

- Removal of spatially variant PSF is possible, despite Poisson noise
- Enables us to use also far off-axis observations
- Stabilizes point source detection

Future:

- Search for even faster and more precise representations
- Infer PSF and other detector effects (pileup etc.) from redundancy in data

You want to know more about IFT, NIFTy or PSF Representation?

Get in contact direct or via mail:

veberle@mpa-garching.mpg.de