Automatic Point Source Detection through Model Stress

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

First Results from the SRG/eROSITA All-Sky Survey: From Stars to Cosmology, September 19th 2024, TUM Campus, Garching, Germany



MAX PLANCK INSTITUTE FOR ASTROPHYSICS





The problem

SRG/eROSITA







X-ray Imaging with IFT





Information field theory **Bayes' Theorem**

$P(s \mid d) = \frac{P(d \mid s) P(s)}{P(d)}$



The prior

































$P\left(\xi\right) = \mathcal{N}\left(\mathbf{0},\mathbb{I}\right)$

30

20

10

0 -

-10

-20

FOV [arcmin]





$P(s) = P\left(\xi\right) \quad \frac{\partial\xi}{\partial s}$

10 FOV [arcmin] 0 --10 -20 -30+-30

30

20





FOV [arcmin] 0

30

20

10

-10

-20





$P(s) = \mathcal{N}(\mathbf{0}, \mathbb{I}) \star A(x, y)$

-30 -30

30

20

10

-10

-20





$\frac{P(s)}{\partial s} = \mathcal{N}(0, \mathbb{I}) \quad \frac{\partial \xi}{\partial s}$ FOV [arcmin] 0

30

20

10

-10

-20







Point sources





Point sources

Diffuse emission





Point sources

Diffuse emission



Sky signal





Point sources

Diffuse emission



Sky signal









The Likelihood Instrument response



Sky signal



The Likelihood Instrument response



Sky signal



eROSITA on SRG



The Likelihood Instrument response



Sky signal



Sky data on earth

Credits @ Roscosmos

The Likelihood **Point-spread function**

• R = PSF

 $10 \cdot$

30

20 -

FOV [arcmin] 0 -

-10

-20





The Likelihood Exposure

• R = E

-20

30

20

10

0 -

-10

FOV [arcmin]



eROSITA TM1 exposure



The Likelihood Signal

S

FOV [arcmin]





The Likelihood Signal response







The Likelihood Signal response

$RS = E\left(PSF(S)\right)$





The Likelihood Signal response



FOV [arcmin]





The Likelihood **Poissonian noise**

 $P(d \mid \lambda) = \prod_{i=1}^{N} \frac{\lambda_i^{d_i} e^{-\lambda_i}}{d_i!}$

⁼OV [arcmin]





The Likelihood Poissonian noise

 $P(d \mid \lambda) = \prod_{i=1}^{N} \frac{\lambda_i^{d_i} e^{-\lambda_i}}{d_i!}$ i=1

-OV [arcmin]





The Data



eROSITA TM1 SN1987A data







Inference geometric Variational Inference



Credits @ Frank, P.; Leike, R.; Enßlin, T.A. Geometric Variational Inference. Entropy 2021, 23, 853.





The Data



Simulated eROSITA TM1 data






























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Posterior mean reconstructed sky

- 10⁻¹

 $= 10^{-2}$

10^{-3}

10⁻⁴





 -10^{-1} - 10-2 - 10⁻³ - 10-4

44





Posterior mean sky reconstruction





Point source detection



Point source detection Component separation



Posterior mean sky reconstruction



Point source detection Component separation



Posterior mean diffuse reconstruction

 -10^{-1}

- 10⁻²



Point source detection Component separation



Posterior mean point source reconstruction

 -10^{-1} - 10-2 - 10⁻³

 10^{-4} - 10⁻⁵



Point source detection Detection thresholds from synthetic data









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Prior driven







- Prior driven
- A point source in every pixel







- Prior driven
- A point source in every pixel
- Hard optimization





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Automatic point source detection



Let's use a different model...











Point sources

Diffuse emission

Sky signal







Posterior mean diffuse-only reconstruction

-10^{-4}

 -10^{-1}

- 10⁻²

- 10⁻⁵

- 10⁻³





Posterior mean diffuse-only reconstruction

Spatially correlated

10-1

 -10^{-2}

- 10⁻³

 -10^{-4}

- 10⁻⁵





Posterior mean diffuse-only reconstruction

Spatially correlated

 10^{-1}

- 10⁻²

- 10⁻³

 -10^{-4}

- 10⁻⁵

Spectrally dependent from the background





Posterior mean diffuse-only reconstruction

Spatially correlated

 10^{-1}

- 10⁻²

- 10⁻³

- 10-4

- 10⁻⁵

- Spectrally dependent from the background
- Live on a grid



Point source detection Diffuse prior model

$P(s) = \mathcal{N}(\mathbf{0}, \mathbb{I}) \star A(x, y)$

-20 ·

-10

20

10



Signal space prior sample

63

Point source detection Model stress? 30 ·

$P\left(\xi ight) = \mathcal{N}\left(\mathbf{0},\mathbb{I} ight)$

-10

FOV [arcmin]

20

10

0 ·

-20





64

Point source detection Model stress?

$P\left(\boldsymbol{\xi} \mid \mathbf{d}\right) \neq \mathcal{N}\left(\mathbf{0}, \mathbb{I}\right)$

-10

30

20

 10^{-1}

0 -

FOV [arcmin]

-20

-30 + -30



Point source detection Model stress, yessir!







Point source detection Model stress, yessir!







Point source detection Automatic detection



Posterior mean diffuse-only reconstruction





Point source detection Automatic detection



Diffuse-only reconstruction + point source model





Point source detection Relax excitations!



Latent ξ excitations



Point source detection Relax excitations! 30



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Point source detection Relaxed excitations

-) | -30

20 -

10

-10

20 ·



Relaxed latent ξ excitations


Point source model







Spatially uncorrelated



- Spatially uncorrelated
- Spectrally independent from background



- Spatially uncorrelated
- Spectrally independent from background
- Does not live on a grid



- Spatially uncorrelated
- Spectrally independent from background
- Does not live on a grid







Real data



Point source detection Single-frequency information











Point source detection Multi-frequency information



0.2 - 1.0 keV





2.0 - 4.5 keV



Point source detection Multi-frequency information



0.2 - 1.0 keV





2.0 - 4.5 keV



Point source detection Multi-frequency model









Point source detection Multi-frequency model







Point source detection Multi-frequency model







Point source detection Multi-frequency model latent excitations

Latent space excitations





Point source detection Multi-frequency model latent excitations

Latent space excitations



- 0



Point source detection Generalizable to extended sources!



- 0

Latent space excitations



- - - -----











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TM1

4

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91













94



Model stress can rescue component separation!



Model stress can rescue component separation!







- Model stress can rescue component separation!
- Point sources sub-pixel positions can be learned!

ent separation! can be learned!







- Model stress can rescue component separation!
- Point sources sub-pixel positions can be learned!
- Diffuse emission can be clearly separated!





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- Model stress can rescue component separation!
- Point sources sub-pixel positions can be learned!
- Diffuse emission can be clearly separated!
- Model has many applications! (spectral lines, exoplanets, ...)





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- Model stress can rescue component separation!
- Point sources sub-pixel positions can be learned!
- Diffuse emission can be clearly separated!
- Model has many applications! (spectral lines, exoplanets, ...)
- Soon public in J-UBIK!





- Model stress can rescue component separation!
- Point sources sub-pixel positions can be learned!
- Diffuse emission can be clearly separated!
- Model has many applications! (spectral lines, exoplanets, ...)
- Soon public in J-UBIK!
- Soon preprint on arxiv!





matteani@mpa-garching.mpg.de



matteani@mpa-garching.mpg.de

Looking for PostDocs!



Thank your

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