

¹ J-UBIK: The JAX-accelerated Universal Bayesian Imaging Kit

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¹⁰ Summary

Many advances in astronomy and astrophysics originate from accurate images of the sky emission across multiple wavelengths. This often requires reconstructing spatially and spectrally correlated signals detected from multiple instruments. To facilitate the high-fidelity imaging of these signals, we introduce the universal Bayesian imaging kit (UBIK). Specifically, we present J-UBIK, a flexible and modular implementation leveraging the JAX-accelerated NIFTy.re (Edenhofer et al., 2024) software as its backend. J-UBIK streamlines the implementation of the key Bayesian inference components, providing for all the necessary steps of Bayesian imaging pipelines. First, it provides adaptable prior models for different sky realizations. Second, it includes likelihood models tailored to specific instruments. So far, the package includes three instruments: Chandra and eROSITA for X-ray observations, and the James Webb Space Telescope (JWST) for the near- and mid-infrared. The aim is to expand this set in the future. Third, these models can be integrated with various inference and optimization schemes, such as maximum a posteriori estimation and variational inference. Explicit demos show how to integrate the individual modules into a full analysis pipeline. Overall, J-UBIK enables efficient generation of high-fidelity images via Bayesian pipelines that can be tailored to specific research objectives.¹¹¹²¹³¹⁴¹⁵¹⁶¹⁷¹⁸¹⁹²⁰²¹²²²³²⁴²⁵²⁶

²⁷ Statement of Need

In astrophysical imaging, we often encounter high-dimensional signals that vary across space, time, and energy. The new generation of telescopes in astronomy offers exciting opportunities to capture these signals but also presents significant challenges in extracting the most information from the resulting data. These challenges include accurately modeling the instrument's response to the signal, accounting for complex noise structures, and separating overlapping signals of distinct physical origin.²⁸²⁹³⁰³¹³²³³

Here, we introduce J-UBIK, the JAX-accelerated Universal Bayesian Imaging Kit, which leverages Bayesian statistics to reconstruct complex signals. In particular, we envision its application in the context of multi-instrument data in astronomy and also other fields such as medical imaging. J-UBIK is built on information field theory (IFT, (Enßlin, 2013)) and the NIFTy.re software package (Edenhofer et al., 2024), a JAX-accelerated version of NIFTy [Selig:2013; Steininger:2019; Arras et al. (2019)].³⁴³⁵³⁶³⁷³⁸³⁹

Following the NIFTy paradigm, J-UBIK employs a generative prior model that encodes

41 assumptions about the signal before incorporating any data, and a likelihood model that
 42 describes the measurements, including the responses of multiple instruments and noise
 43 statistics. Built on NIFTy.re, J-UBIK supports adaptive and distributed representations
 44 of high-dimensional physical signal fields and accelerates their inference from observational
 45 data using advanced Bayesian algorithms. These include maximum a posteriori (MAP),
 46 Hamiltonian Monte Carlo (HMC), and two variational inference techniques: metric Gaussian
 47 variational inference (MGVI, ([Knollmüller & Enßlin, 2020](#))) and geometric variational inference
 48 (geoVI, ([Frank et al., 2021](#))). As NIFTy.re is fully implemented in JAX, J-UBIK benefits from
 49 accelerated inference through parallel computing on clusters or GPUs.

 50 Building generative models with NIFTy.re for specific instruments and applications can be very
 51 tedious and labor-intensive. Here, J-UBIK comes into play which addresses this challenge from
 52 two angles. First, it provides tools to simplify the creation of new likelihood and prior models
 53 and acts as a flexible toolbox. It implements a variety of generic response functions, such
 54 as spatially-varying point-spread functions (PSFs) ([Eberle et al., 2023](#)) and enables the user
 55 to define diverse correlation structures for various sky components. Second, J-UBIK includes
 56 implementations for several instruments.

 57 Currently, it supports Chandra, eROSITA pointings, and JWST observations, with plans to
 58 expand this list as the user base grows. This expansion will provide users with a diverse set of
 59 accessible inference algorithms for various instruments. Ultimately J-UBIK enables the user,
 60 through Bayesian statistics, not only to obtain posterior samples and hence measures of interest
 61 such as the posterior mean and uncertainty of the signal for a several data sets, but also to
 62 perform multi-instrument reconstructions.

 63 The software has already been applied by Westerkamp, M. et al. ([2024](#)), and publications
 64 on eROSITA pointings and JWST are currently in preparation. In the future, the set of
 65 instruments will be further expanded to include existing imaging pipelines from NIFTy
 66 and NIFTy.re such as those described in Scheel-Platz et al. ([2023](#)), Roth et al. ([2023](#)),
 67 Hutschenreuter et al. ([2022](#)), as well as new ones.

 68 Several existing tools, such as Jolideco ([Donath et al., 2024](#)) and LIRA ([Connors et al.,
 69 2011](#)), also address Bayesian deconvolution of low-count astronomical images. Jolideco
 70 employs a patch-based Gaussian mixture prior trained on external data to jointly deconvolve
 71 multi-instrument observations, achieving high-resolution reconstructions in the X-ray and γ-ray
 72 regimes. LIRA (also known through its Python implementation Pylira) uses hierarchical
 73 Poisson-image priors and posterior sampling, particularly for Chandra and Fermi-LAT data, to
 74 quantify uncertainty. J-UBIK complements these efforts by providing a modular and extensible
 75 Bayesian imaging framework integrated with the JAX-accelerated NIFTy.re ecosystem. It
 76 supports composable priors, multiple inference schemes, and native implementations for
 77 Chandra, eROSITA, and JWST, and natively enables deconvolution with spatially varying PSFs
 78 — a key capability for realistic instrument modeling and uncertainty quantification. These
 79 features enable users to construct flexible, end-to-end inference pipelines applicable to a broad
 80 range of scientific imaging tasks.

81 Bayesian Imaging with J-UBIK

82 At the core of the J-UBIK package is Bayes' theorem:

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

83 where the prior $\mathcal{P}(s)$ represents our knowledge about the signal s before observing the data d ,
 84 and the likelihood $\mathcal{P}(d|s)$ describes the measurement process. The posterior $\mathcal{P}(s|d)$ is the
 85 primary measure of interest in the inference process. J-UBIK's main role is to model the prior in
 86 a generative fashion and to facilitate the creation and use of instrument models to develop the
 87 likelihood model. The package includes demos for Chandra, eROSITA pointings, and JWST,

which illustrate how to use or build these models and how to construct an inference pipeline to obtain posterior estimates.

Prior models

The package includes a prior model for the sky's brightness distribution across different wavelengths, which can be customized to meet user needs in both spatial and spectral dimensions. This model allows for the generation of spatially uncorrelated point sources or spatially correlated extended sources, as described by the correlated field model in (Arras et al., 2022). In the spectral dimension, the model can be a power law, describe the correlation structure of the logarithmic flux using a Wiener process along the spectral axis or combine both of these models. The prior model's structure is designed to be flexible, allowing for modifications to accommodate additional dimensions and correlation structures. Figure 1 illustrates an example of a simulated X-ray sky in J-UBIK, sampled from a corresponding generative prior model with one energy bin. This example features two components: one representing spatially uncorrelated point sources and the other representing spatially correlated extended structures. Figure 1 shows from left to right the full sky and its components, the diffuse, extended structures and the point sources.

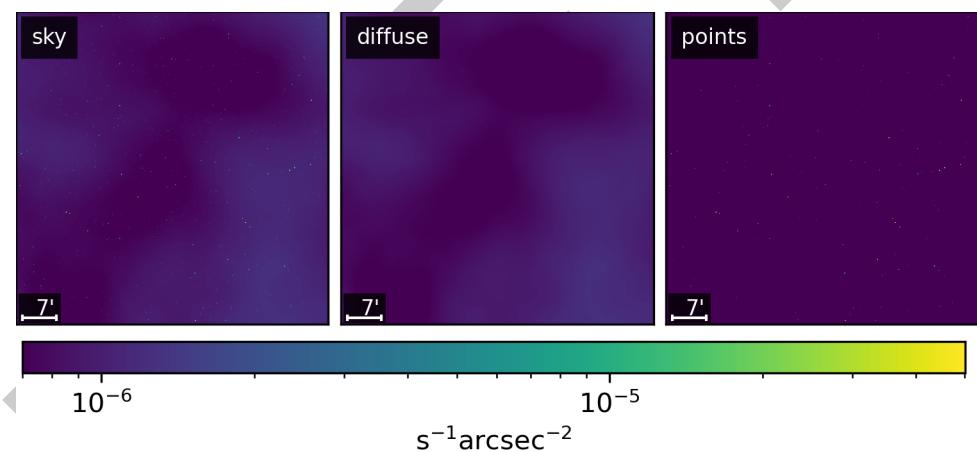


Figure 1: Simulated X-ray Sky

Likelihood models

J-UBIK implements several instrument models (Chandra, eROSITA, JWST) and their respective data- and response-loading functionalities, enabling their seamless integration into the inference pipeline. Due to its fully modular structure, we anticipate the inclusion of more instruments into the J-UBIK platform in the future. J-UBIK is not only capable of reconstructing signals from real data; since each instrument model acts as a digital twin of the corresponding instrument, it can also be used to generate simulated data by passing sky prior models through the instrument's response. This allows to test the consistency of the implemented models.

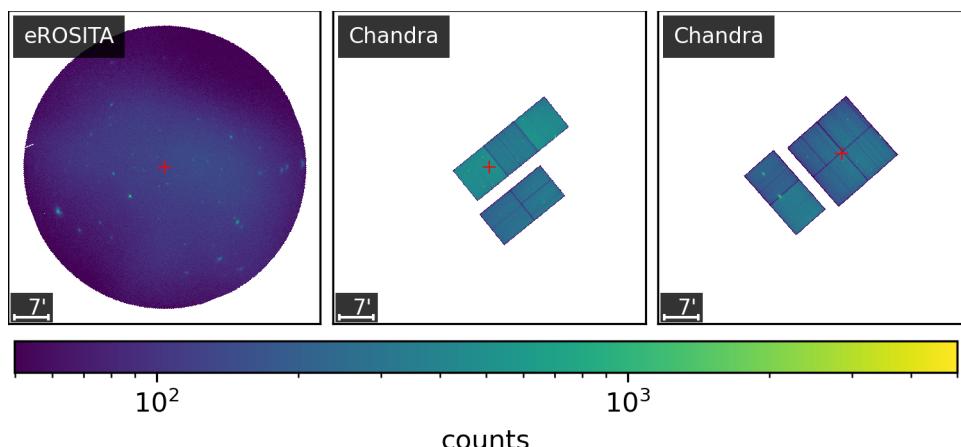


Figure 2: Simulated X-ray Data

112 Figure 2 shows the same simulated sky from Figure 1 seen by two different instruments,
 113 eROSITA and Chandra, with Poisson noise on the photon count data. The pointing center for
 114 each observation is marked in red. The two images on the right illustrate the same simulated
 115 sky seen by Chandra, but with different pointing centers, showing the impact of spatially
 116 varying PSFs (Eberle et al., 2023).

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