Argus: JAX state-space filtering for gravitational wave detection with a pulsar timing array

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DOI: 10.xxxxxx/draft

Software

- Review
- Repository
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Editor:

Submitted: 10 October 2025
Published: unpublished

Summary

Argus is a high-performance Python package for detecting and characterizing nanohertz gravitational waves in pulsar timing array (PTA) data. The package provides a complete Bayesian inference framework based on state-space models, using Kalman filtering for efficient likelihood evaluation. Argus leverages the JAX library (Bradbury et al., 2018) for just-in-time (JIT) compilation, GPU acceleration, and end-to-end automatic differentiation, facilitating rapid Bayesian inference with gradient-based samplers. The state-space approach provides a computationally efficient alternative to traditional frequency-domain methods, offering linear scaling with the number of pulse times-of-arrival, and natural handling of non-stationary processes.

Statement of Need

PTAs monitor the precise arrival times of radio pulses from a collection of millisecond pulsars distributed across the sky. By measuring the correlated variations in these pulse arrival times PTAs are senstive to gravitational-waves in a frequency band inaccessible to ground-based interferometers. The possible discovery of a nanohertz stochastic gravitational-wave background (GWB) by PTA collaborations (NANOGrav Collaboration, 2023) (EPTA Collaboration et al., 2023) (Reardon et al., 2023) through measuring the spatial correlation of the variations between different pulsars - the characteristic Hellings-Downs curve (Hellings & Downs, 1983) - represents a landmark achievement in gravitational wave astronomy.

Traditional PTA data-analysis methods operate in the frequency domain. The various noise processes are treated as Gaussian stationary processes, characterised by their power spectral densities (PSDs). These noise sources generally fall into two categories: uncorrelated white noise and time-correlated red noise. White noise sources include measurement noise from telescope receivers, while red noise components include pulsar spin noise (intrinsic to the neutron star) and dispersion measure (DM) variations (from electron density fluctuations in the interstellar medium). The GWB signal itself is also modeled as a red noise process with a characteristic power-law PSD (Goncharov et al., 2021), distinguished from the other noise components by its specific spatial correlation, the Hellings-Downs correlation. Frequency domain modelling is the foundation for widely used packages such as ENTERPRISE (Ellis et al., 2020) and TempoNest (Lentati et al., 2014) and is typically combined with standard Bayesian inference methods (van Haasteren et al., 2009), such Markov Chain Monte Carlo (MCMC) algorithms for parameter estimation and model selection.

State-space methods provide a novel, powerful and complementary framework for PTA data analysis. The approach features a time-domain version of the Gaussian processes framework, offering an alternative computational structure to traditional frequency-domain modeling. Instead of relying on full matrix inversions of the covariance matrix, state-space methods model the temporal evolution of hidden states (such as pulsar spin fluctuations and gravitational-wave effects) using Kalman filtering (Kalman, 1960) for recursive state estimation. This approach exhibits linear scaling $\mathcal{O}(N)$ with the number of observations N. State-space methods can easily incorporate physical knowledge about how different stochastic processes evolve over time directly into the model structure, naturally accommodating non-stationary processes. Additionally, the method tracks the actual, measured, time-ordered realization of intrinsic timing noise in each pulsar, rather than averaging over ensemble realizations, and can readily handle non-Gaussian statistics (Uhlmann & Julier, 2024).

Despite their theoretical advantages, state-space methods have seen limited adoption in PTA research, partly due to their recency, and partly due to the lack of accessible, high-performance implementations. `Argus` provides a modern, science-ready implementation of state-space methods for gravitational-wave detection in PTA data. Argus leverages JAX's just-in-time compilation, automatic differentiation, and GPU acceleration capabilities to handle the computational demands of Bayesian inference at PTA scales. Argus consolidates and formalises the state-space methodology applied in prior work (Kimpson et al., 2024a, 2024b, 2025), transforming proof-of-concept implementations into a tool ready for scientific analysis.

Relation to Existing Work

Frequency-domain PTA packages such as ENTERPRISE (Ellis et al., 2020) and TempoNest (Lentati et al., 2014) represent timing noise and GW signals as Gaussian processes specified by power spectra. In contrast, `Argus` adopts a time-domain, state-space formulation in which latent variables describe the pulsar rotational states and other stochastic processes (e.g., DM variations), and the likelihood is evaluated via a Kalman filter, with $\mathcal{O}(N)$ complexity (Kalman, 1960). The Kalman filter tracks the actual, measured, time-ordered realization of intrinsic, achromatic timing noise in each pulsar, effectively following the specific random draw of noise present in the data, which allows the method to separate and identify GW-induced timing perturbations from this intrinsic noise. This differs from frequency-domain approaches that characterise timing noise statistically by fitting a power spectral density, effectively averaging over an ensemble of admissible noise realizations through a PSD fit (e.g., Goncharov et al. (2021)). Prior PTA state-space prototypes established feasibility on mock datasets (Kimpson et al., 2024a, 2024b). `Argus` consolidates this methodology into a production-ready JAX implementation with JIT/GPU acceleration and end-to-end automatic differentiation, which enables gradient-based samplers. As such, the package is complementary to ENTERPRISE/TempoNest: it offers an independent cross-check with different numerical/systematic failure modes, while retaining parity in astrophysical content (white/red noise, DM, and a GWB with Hellings–Downs correlations). While `Argus` currently focuses on the stochastic GWB, the same state-space machinery naturally extends to deterministic sources such as individual supermassive black hole binaries (see Future Directions).

Functionality

`Argus` is built on JAX, enabling high-throughput computation on CPUs/GPUs/TPUs with JIT compilation and end-to-end automatic differentiation. Its core deliverable is a JAX-jittable log-likelihood for PTA datasets, making it directly suitable for gradient-based Bayesian inference.

Core functionality

- **State-space model construction:** Stochastic processes like pulsar-intrinsic red noise (modeled as an Ornstein-Uhlenbeck process) and the stochastic GWB are specified in the time domain as linear stochastic differential equations (SDEs). The package compiles these into a single state-space model, which naturally separates process noise (e.g., physical spin wandering and GWB fluctuations) from measurement noise (EFAC, EQUAD). Hellings-Downs spatial correlations are implemented through the covariance structure that couples the stochastic processes across pulsars.

Kalman filter likelihood evaluation: The core of the package is an optimised Kalman filter (Kalman, 1960). The filter evaluates the likelihood of the time-of-arrival data in the time domain and achieves a computational complexity that scales linearly with the number of observations, $\mathcal{O}(N)$.

- **Sampler Integration:** The likelihood and its gradients (provided by JAX's autodiff capabilities) integrate directly with JAX-native samplers such as those in `numpyro` (Phan et al., 2019) or `blackjax`(Cabezas & others, 2024). This enables the use of efficient gradient-based algorithms like Hamiltonian Monte Carlo (HMC).
- **Standardized Data Input:** `Argus` ingests pulsar timing data through an interface with `libstempo` (Vallisneri, 2020), ensuring compatibility with standard PTA data formats.

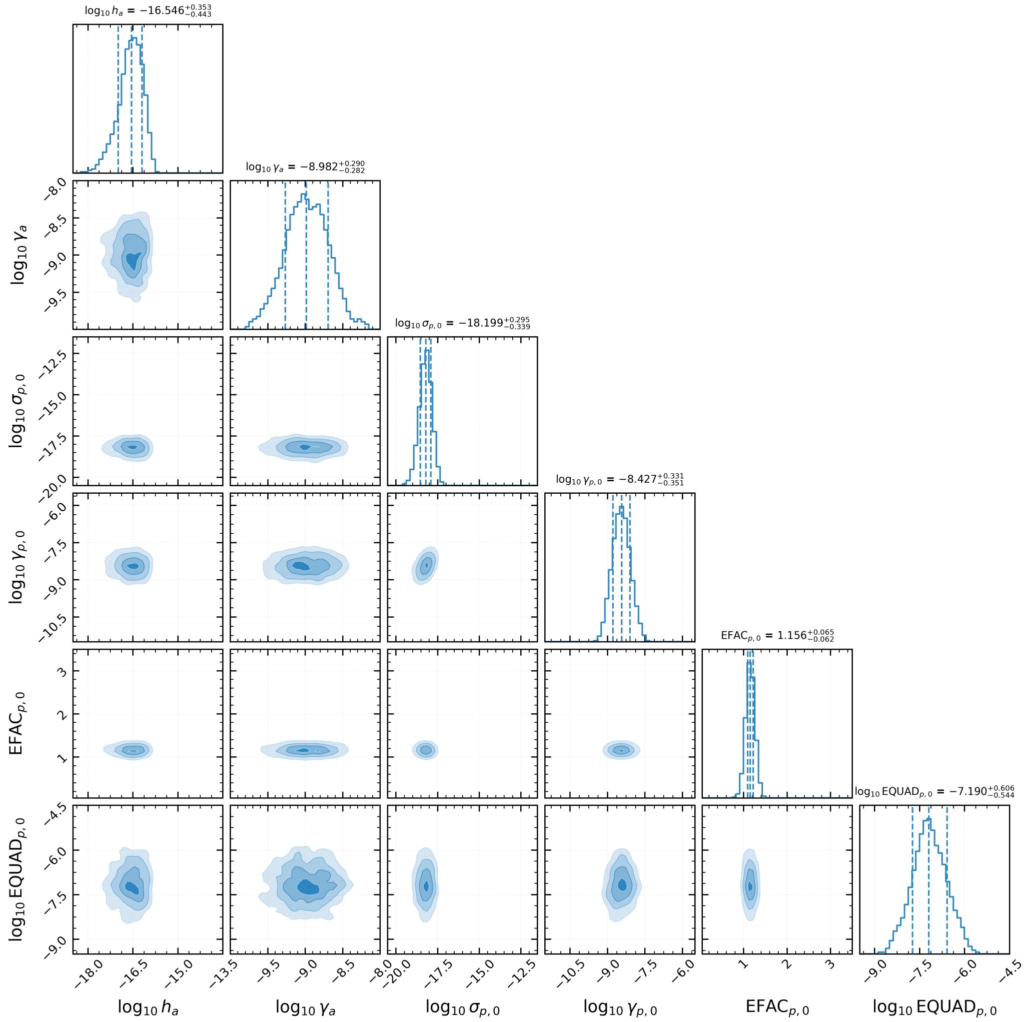

Figure 1: Corner plot showing posterior distributions from Bayesian parameter estimation using Argus on the second IPTA mock data challenge (Hazboun et al., 2018). The first two parameters h_{a}, γ_{a} describe the amplitude and turnover frequency of the GWB. The middle two parameters $\sigma_{\mathrm{p},0}$, $\gamma_{\mathrm{p},0}$ characterise the red timing noise for an arbitrary pulsar in the array (indexed by 0). The final two parameters, EFAC, EQUAD are the standard white measurement noise parameters for the arbitrary pulsar. The posteriors were obtained using the No-U-Turn Sampler (NUTS) (Hoffman & Gelman, 2014) from `numpyro` (Phan et al., 2019), leveraging Argus's JAX-native log-likelihood and automatic differentiation for gradient-based sampling. The unimodal marginalised posteriors demonstrate the effectiveness of the state-space Kalman filtering approach for parameter estimation in pulsar timing array analysis.

Future Directions

Planned extensions to `Argus` include: model selection via Bayes factors, deterministic signals from continuous gravitational waves, advanced noise modeling (chromatic noise, non-Gaussian components), enhanced modularity for custom state-space models, performance optimization for next-generation PTAs like SKA, and integration with pipelines such as ENTERPRISE (Ellis et al., 2020). We release Argus in its current form as it successfully addresses the core challenge of Bayesian parameter estimation for PTA analysis using state-space methods, providing a well-tested, production-ready implementation. We encourage contributions from the PTA community to help implement these extensions.

Acknowledgements

We acknowledge support from the Australian Research Council Centre of Excellence for Gravitational Wave Discovery (OzGrav) under grant CE170100004. NJO is the recipient of a Melbourne Research Scholarship. This work was performed on the OzSTAR national facility at Swinburne University of Technology. The OzSTAR program receives funding in part from the Astronomy National Collaborative Research Infrastructure Strategy (NCRIS) allocation provided by the Australian Government, and from the Victorian Higher Education State Investment Fund (VHESIF) provided by the Victorian Government. This work was supported by software support resources awarded under the Astronomy Data and Computing Services (ADACS) Merit Allocation Program. ADACS is funded from the Astronomy National Collaborative Research Infrastructure Strategy (NCRIS) allocation provided by the Australian Government and managed by Astronomy Australia Limited (AAL). We thank the International Pulsar Timing Array collaboration for providing mock data challenges that aided in the development and validation of this software.

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