

¹ Argus: JAX state-space filtering for gravitational wave detection with a pulsar timing array

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⁹ Summary

¹⁰ Argus is a high-performance Python package for detecting and characterizing nanohertz²¹ gravitational waves in pulsar timing array (PTA) data. The package provides a complete¹² Bayesian inference framework based on state-space models, using Kalman filtering for efficient¹³ likelihood evaluation. Argus leverages the JAX library ([Bradbury et al., 2018](#)) for just-in-time¹⁴ (JIT) compilation, GPU acceleration, and end-to-end automatic differentiation, facilitating¹⁵ rapid Bayesian inference with gradient-based samplers. The state-space approach provides a¹⁶ computationally efficient alternative to traditional frequency-domain methods, offering linear¹⁷ scaling with the number of pulse times-of-arrival, and natural handling of non-stationary¹⁸ processes.

Statement of Need

²⁰ PTAs monitor the precise arrival times of radio pulses from a collection of millisecond pulsars²¹ distributed across the sky. By measuring the correlated variations in these pulse arrival times,²² PTAs are sensitive to gravitational waves in a frequency band inaccessible to ground-based²³ interferometers. The possible discovery of a nanohertz stochastic gravitational-wave background²⁴ (GWB) by PTA collaborations ([EPTA Collaboration et al., 2023; NANOGrav Collaboration, 2023; Reardon et al., 2023](#)) through measuring the Hellings-Downs spatial correlation ([Hellings & Downs, 1983](#)) represents a landmark achievement in gravitational-wave astronomy.²⁵

²⁷ State-space methods provide a powerful and complementary framework for PTA data analysis,²⁸ offering an alternative computational structure to traditional frequency-domain modeling.²⁹ Instead of relying on full covariance matrix inversions, state-space methods model the temporal³⁰ evolution of hidden states (such as pulsar spin fluctuations and gravitational-wave effects) using³¹ Kalman filtering ([Kalman, 1960](#)) for recursive state estimation. This approach exhibits linear³² scaling $\mathcal{O}(N)$ with the number of observations N , naturally accommodates non-stationary³³ processes, tracks the actual time-ordered realization of intrinsic timing noise in each pulsar³⁴ rather than averaging over ensemble realizations, and can readily handle non-Gaussian statistics³⁵ ([Uhlmann & Julian, 2024](#)).

³⁶ Despite these theoretical advantages, state-space methods have seen limited adoption in PTA³⁷ research, partly due to their recency, and partly due to the lack of accessible, high-performance³⁸ implementations. Argus addresses this gap, providing a modern, science-ready implementation³⁹ of state-space methods for gravitational-wave detection in PTA data. The package leverages⁴⁰ JAX's just-in-time compilation, automatic differentiation, and GPU acceleration to handle the⁴¹ computational demands of Bayesian inference at PTA scales, consolidating and formalising the

42 methodology developed in prior work (Kimpson et al., 2024a, 2024b, 2025).

43 State of the Field

44 Traditional PTA data-analysis methods operate in the frequency domain, treating noise processes
45 as Gaussian stationary signals characterized by their power spectral densities. Noise sources
46 generally fall into two categories: uncorrelated white noise (measurement noise from telescope
47 receivers) and time-correlated red noise (pulsar spin noise, dispersion measure variations from
48 electron density fluctuations in the interstellar medium). The GWB signal is modeled as a red
49 noise process with a characteristic power-law spectrum (Goncharov et al., 2021), distinguished
50 by its Hellings-Downs spatial correlation. This frequency-domain framework is the foundation
51 for widely used packages such as ENTERPRISE (Ellis et al., 2020) and TempoNest (Lentati et
52 al., 2014), typically combined with Bayesian inference methods such as Markov Chain Monte
53 Carlo for parameter estimation (van Haasteren et al., 2009).

54 While these tools have been central to recent GWB discoveries, they carry inherent limitations.
55 They assume stationary Gaussian processes, require $\mathcal{O}(N^3)$ covariance matrix inversions, and
56 characterize timing noise by fitting a power spectral density – effectively averaging over an
57 ensemble of admissible noise realizations rather than tracking the specific noise realization
58 in the data (e.g., Goncharov et al. (2021)). They also lack built-in support for automatic
59 differentiation and hardware acceleration via GPU/TPU. Prior PTA state-space prototypes
60 established feasibility on mock datasets (Kimpson et al., 2024a, 2024b), but no production-ready
61 implementation was available.

62 Argus fills this gap as the first production-ready, time-domain state-space PTA package
63 built on JAX. It is complementary to ENTERPRISE and TempoNest: the package offers
64 an independent cross-check of GWB analyses with fundamentally different numerical and
65 systematic properties, while retaining parity in astrophysical content (white and red noise,
66 dispersion measure variations, and a GWB with Hellings-Downs correlations).

67 Software Design

68 Argus is built on JAX, providing a JAX-jittable log-likelihood for PTA datasets that is directly
69 suitable for gradient-based Bayesian inference on CPUs, GPUs, and TPUs. The software design
70 reflects several deliberate architectural choices.

71 **JAX as computational backend.** JAX was chosen over alternatives (e.g. PyTorch, pure NumPy)
72 for its functional programming paradigm, which naturally matches the Kalman filter's recursive
73 structure. JAX's composable transformations – jit for compilation, vmap for vectorization,
74 and grad for automatic differentiation – enable efficient likelihood evaluation and gradient
75 computation. The XLA compiler provides transparent hardware acceleration across CPU, GPU,
76 and TPU backends.

77 **Kalman filter as core algorithm.** The Kalman filter (Kalman, 1960) evaluates the likelihood
78 with $\mathcal{O}(N)$ complexity, avoiding the $\mathcal{O}(N^3)$ cost of full covariance matrix inversions. It
79 tracks the actual, measured, time-ordered realization of timing noise, enabling separation of
80 gravitational-wave-induced perturbations from intrinsic noise.

81 **SDE-based process specification.** Stochastic processes – pulsar-intrinsic red noise (modeled as
82 an Ornstein-Uhlenbeck process), dispersion measure variations, and the GWB – are specified
83 as linear stochastic differential equations in continuous time, discretized at observation times.
84 This formulation naturally handles irregular sampling cadences and allows new physics to be
85 incorporated by augmenting the state vector, providing a modular framework for extending the
86 model. Hellings-Downs spatial correlations are implemented through the covariance structure
87 coupling processes across pulsars.

88 **Sampler-agnostic likelihood.** The log-likelihood is a pure JAX function exposing gradients
 89 via autodiff, compatible with any JAX-native sampler such as numpyro (Phan et al., 2019) or
 90 blackjax (Cabezas & others, 2024). This enables efficient gradient-based algorithms like the
 91 No-U-Turn Sampler (NUTS) (Hoffman & Gelman, 2014).
 92 Argus ingests pulsar timing data through libstempo (Vallisneri, 2020), ensuring compatibility
 93 with standard PTA data formats.

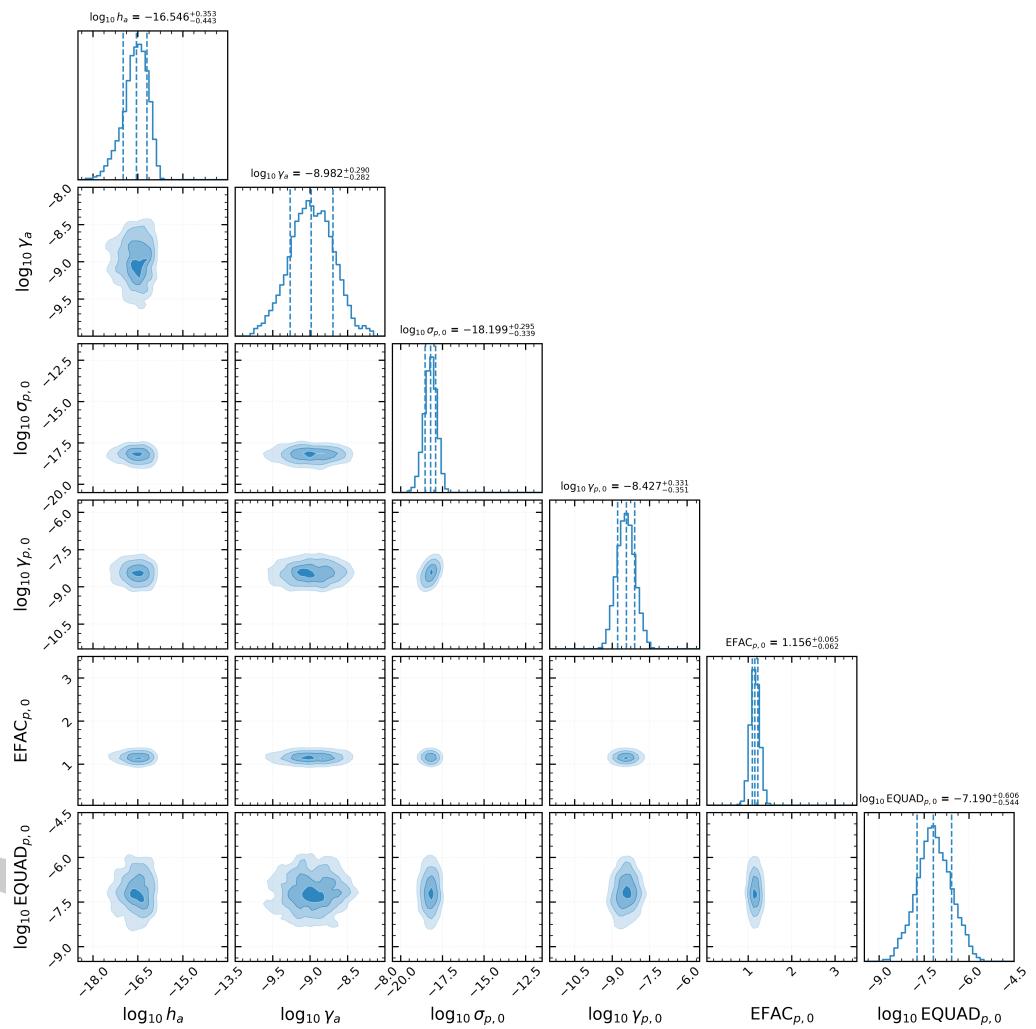


Figure 1: Corner plot showing posterior distributions from Bayesian parameter estimation using Argus on the second IPTA mock data challenge (Hazboun et al., 2018). The first two parameters h_a , γ_a describe the amplitude and turnover frequency of the GWB. The middle two parameters $\sigma_{p,0}$, $\gamma_{p,0}$ 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.

94 Research Impact Statement

95 The state-space methodology implemented in Argus has been developed and validated through
 96 three peer-reviewed publications in Monthly Notices of the Royal Astronomical Society: Kimpson

et al. (2024a) established the Kalman filtering framework for continuous gravitational-wave tracking with a PTA; Kimpson et al. (2024b) extended this to include pulsar-term contributions; and Kimpson et al. (2025) developed the algorithm for detecting the stochastic gravitational-wave background, including Hellings-Downs correlations. Argus has been successfully validated on the second International Pulsar Timing Array (IPTA) mock data challenge (Hazboun et al., 2018), an internationally recognized community benchmark.

PTA collaborations worldwide – NANOGrav, the European PTA (EPTA), the Parkes PTA (PPTA), and the MeerKAT PTA (Miles et al., 2025) – are actively seeking independent analysis pipelines for cross-validation of GWB detection claims. Argus provides a fundamentally different methodology (time-domain state-space vs. frequency-domain) for this critical cross-check, with different numerical and systematic failure modes. Next-generation PTA datasets from the Square Kilometre Array will particularly benefit from the $\mathcal{O}(N)$ scaling.

Argus has been developed across the University of Melbourne/OzGrav and the California Institute of Technology, with professional software engineering support from the Astronomy Data and Computing Services (ADACS). The package includes comprehensive documentation, an automated test suite, and compatibility with standard PTA data formats, supporting community adoption and contribution.

AI Usage Disclosure

Generative AI tools were used during the development of Argus to assist with software infrastructure tasks, including setting up the documentation website, configuring automated CI/CD workflow testing, and scaffolding boilerplate configuration files. All scientific methodology, algorithm design, core implementation, and numerical validation were carried out by the authors. We affirm that human team members thoroughly reviewed, modified, and validated all AI-generated content while making primary architectural and design decisions.

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