

gwsnr: A python package for efficient signal-to-noise calculation of gravitational-waves

Hemantakumar Phurailatpam¹ and Otto Akseli HANNUKSELA¹

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) ↗
- [Repository](#) ↗
- [Archive](#) ↗

Editor: Pending Editor ↗

Reviewers:

- [@Pending Reviewer](#)
- @

Submitted: 13th Dec 2024

Published:

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](https://creativecommons.org/licenses/by/4.0/)).

¹ Department of Physics, The Chinese University of Hong Kong, Shatin, New Territories, Hong Kong

Summary

Gravitational waves (GWs), ripples in spacetime predicted by Einstein's theory of General Relativity, have revolutionized astrophysics since their first detection in 2015 (Abbott, B.P. et al. (2016a), B. P. Abbott et al. (2016)). These waves are emitted by cataclysmic events like the merging of binary black holes (BBHs), binary neutron stars (BNSs) and BH-NS pairs, providing a unique window into the cosmos. A critical aspect of GW analysis is the Signal-to-Noise Ratio (SNR). SNR quantifies the strength of a GW signal relative to the background noise in a detector, like LIGO (The LIGO Scientific Collaboration et al. (2015), B. P. Abbott et al. (2020), Buikema et al. (2020)), Virgo (F. Acernese et al. (2014), F. Acernese et al. (2019)) or KAGRA (Akutsu et al. (2020), Aso et al. (2013)). This ratio is pivotal in confirming the detection of GWs and extracting astrophysical information from them (Abbott, B.P. et al. (2016b)). However, specific scenarios in GW research, particularly in simulations of detectable GW events (B. P. Abbott et al. (2016)) and in hierarchical Bayesian analysis (Thrane and Talbot (2019)) where selection effects are considered, demand extensive and efficient computation of SNR. This requirement presents a significant challenge, as conventional computational approaches, such as noise-weighted inner product, are typically time-consuming and impractical for such specialized and large-scale analyses (Taylor and Gerosa (2018), Gerosa et al. (2020)).

Statement of Need

The *gwsnr* Python package addresses the need for efficient SNR computation in GW research. It provides a flexible and user-friendly interface, allowing users to combine various detector noise models, waveform models, detector configurations, and signal parameters. *gwsnr* enhances SNR calculations through several key features. Firstly, it utilizes an innovative interpolation method, employing a partial-scaling approach for accurately interpolating the SNR of GWs from spin-less and spin-aligned binary systems. Secondly, the package features a noise-weighted inner product method, similar to that in the *bilby* package (Ashton et al. (2019), Ashton, Gregory et al. (2022)), but enhanced with multiprocessing capabilities. This parallel processing is crucial for handling large datasets and computationally intensive analyses. Thirdly, a trained Artificial Neural Network (ANN) model is incorporated for rapid 'probability of detection' (Pdet) estimation for BBH systems with spin precession. Lastly, *gwsnr* leverages *numpy* (NumPy Community (2022)) vectorization, and *numba*'s (Lam, Pitrou, and Seibert (2022)) and *JAX*'s (James Bradbury and others (2018)) Just-In-Time compiler (*numbba.njit* and *jax.jit*), which optimizes performance by compiling Python code into machine code at runtime, drastically reducing execution times. This combination of advanced techniques and user-friendly design makes *gwsnr* a valuable tool for GW data analysis, particularly in simulating detectable compact binary mergers, determining rates of both lensed and unlensed GW events (as demonstrated by its use in the *ler* package; Phurailatpam et al. (2024), Ng et al. (2024), More and Phurailatpam (2025), Janquart et al. (2023), R. Abbott et al. (2021), Collaboration et al. (2023), Wierda et al. (2021), Wempe et al. (2022)), and will help in the analysis of selection effects within hierarchical Bayesian frameworks (Thrane and Talbot (2019)).

Mathematical Formulation

The `gwsnr` package provides two efficient methods for computing the optimal SNR in GW data analysis: the Noise-Weighted Inner Product Method with Multiprocessing and the Partial Scaling Interpolation Method. In addition, there are two approaches for estimating P_{det} for preprocessing systems: ANN-based P_{det} Estimation and the Partial Scaling Interpolation Method with SNR recalculation. Extensive details of these methods can be found in the package documentation (Phurailatpam and Hannuksela (2025)).

Noise-Weighted Inner Product Method with Multiprocessing

The noise-weighted inner product is a robust and widely used technique, suitable for any frequency-domain gravitational waveform, including complex models with spin precession and higher-order harmonics available in `lalsimulation` (LIGO Scientific Collaboration, Virgo Collaboration, and KAGRA Collaboration (2018)). Following (Allen et al. (2012)), the inner product between two frequency-domain signals, $\tilde{a}(f)$ and $\tilde{b}(f)$, is defined as:

$$\langle a|b \rangle = 4\Re \int_{f_{\min}}^{f_{\max}} \frac{\tilde{a}(f)\tilde{b}^*(f)}{S_n(f)} df$$

Here, $S_n(f)$ is the one-sided power spectral density of the detector noise, and (f_{\min}, f_{\max}) is the analysis frequency band. The optimal SNR ρ , is the norm of the inner-product for the given signal h : $\rho = \sqrt{\langle h|h \rangle}$. For a gravitational wave signal composed of plus (h_+) and cross (h_\times) polarizations, and assuming orthogonality between them, the SNR can be expressed in terms of the detector's antenna patterns, F_+ and F_\times :

$$\rho = \sqrt{F_+^2 \langle \tilde{h}_+|\tilde{h}_+ \rangle + F_\times^2 \langle \tilde{h}_\times|\tilde{h}_\times \rangle}$$

While this approach is versatile, it can be computationally intensive, with waveform generation representing the primary bottleneck. The `gwsnr` package addresses this challenge by parallelizing waveform generation across multiple CPU cores and accelerating the antenna pattern and inner product calculations using `numba.njit` compilation. Additionally, `gwsnr` provides optional support for JAX-based waveform generation and acceleration via the `ripple` waveform library (Edwards et al. 2024), utilizing `jax.jit` for just-in-time compilation and `jax.vmap` for efficient batched operations.

Partial Scaling Interpolation Method

For non-spinning or aligned-spin binary systems restricted to the dominant harmonic mode, `gwsnr` implements a highly efficient interpolation-based technique called the Partial Scaling method. This approach, adapted from the FINDCHIRP algorithm (Allen et al. (2012)), decouples the computationally expensive parts of the SNR calculation from the extrinsic source parameters. It achieves this by defining a “partial-scaled SNR” $\rho_{1/2}$, which isolates the dependence on the intrinsic parameters (masses and spins). For a given full IMR waveform SNR, ρ_{full} , the partial SNR is defined as:

$$\rho_{1/2} = \left(\frac{D_{\text{eff}}}{1 \text{ Mpc}} \right) \left(\frac{\mathcal{M}}{M_\odot} \right)^{-5/6} \times \rho_{\text{full}}$$

Here, \mathcal{M} is the chirp mass and D_{eff} is the effective distance, which encapsulates the luminosity distance, sky location, and detector orientation wrt the binary. Since $\rho_{1/2}$ depends only on the intrinsic properties of the binary, its value can be pre-computed on a grid and stored. For non-spinning systems, this is a two-dimensional grid of total mass (M) and mass ratio

(q), while for aligned-spin systems, it is a four-dimensional grid that also includes the two spin magnitudes. To find the SNR for a new binary, `gwsnr` performs a rapid cubic spline interpolation on the pre-computed grid to find the corresponding $\rho_{1/2}$ value. The final SNR is then recovered almost instantaneously by applying the scaling transformation:

$$\rho = \rho_{1/2} \times \left(\frac{\mathcal{M}}{M_{\odot}} \right)^{5/6} \times \left(\frac{1 \text{ Mpc}}{D_{\text{eff}}} \right)$$

This procedure transforms a computationally intensive integration into a simple, JIT-compiled table lookup and multiplication, enabling massive performance gains for large-scale population studies.

ANN-based Pdet Estimation

The `gwsnr` package now incorporates an artificial neural network (ANN) model, developed using TensorFlow (Abadi et al. (2015)) and scikit-learn (Pedregosa et al. (2011)), to rapidly estimate P_{det} in binary black hole (BBH) systems using the IMRPhenomXPHM waveform approximant. This complex IMR waveform model accounts for spin-precessing systems with subdominant harmonics. The ANN model is especially useful when precise signal-to-noise ratio (SNR) calculations are not critical, providing a quick and effective means of estimating P_{det} . This value indicates detectability under Gaussian noise by determining if the SNR exceeds a certain threshold (e.g., $\rho_{\text{th}} = 8$). Trained on a large dataset from the `1er` package, the ANN model uses 'partial scaled SNR' values as a primary input, reducing input dimensionality from 15 to 5 and enhancing accuracy. This approach offers a practical solution for assessing detectability under specified conditions. Other similar efforts with ANN models are detailed in (Chapman-Bird et al. (2023), Gerosa et al. (2020), Callister et al. (2024)).

In addition to providing trained ANN models for specific configurations, `gwsnr` offers users the flexibility to develop and train custom models tailored to their unique requirements. This adaptability allows for optimization based on variations in detector sensitivity, gravitational-wave properties, and other research-specific factors, ensuring maximum model effectiveness across different scenarios.

Partial Scaling Interpolation Method with SNR Recalculation for Pdet Estimation

While the Partial Scaling method is highly efficient for aligned-spin systems, its utility can be further enhanced by recalculating the SNR for precessing systems within a predefined small range of generated SNRs. This is done by first obtaining optimal SNRs with the Partial Scaling method, selecting the SNRs near ρ_{th} , and then recalculating the SNRs for these systems using the Noise-Weighted Inner Product Method. This approach allows us to leverage the speed of the Partial Scaling method while ensuring accurate SNR values for systems close to the detection threshold. The recalculated SNRs can then be used to estimate P_{det} , providing a balance between computational efficiency and accuracy.

Acknowledgements

The author gratefully acknowledges the substantial contributions from all who supported this research. Special thanks go to my academic advisors for their invaluable guidance and unwavering support. The interactions with my research colleagues have greatly enriched this work. The Department of Physics at The Chinese University of Hong Kong is acknowledged for the Postgraduate Studentship that made this research possible. Thanks are also due to the LIGO Laboratory for the computational resources, supported by National Science Foundation Grants No. PHY-0757058 and No. PHY-0823459.

- [ref-tensorflow:2015 Abadi, Martín, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, et al. 2015. "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems." <https://www.tensorflow.org/>.
- Abbott, B. P., R. Abbott, T. D. Abbott, M. R. Abernathy, F. Acernese, K. Ackley, C. Adams, et al. 2016. "ASTROPHYSICAL IMPLICATIONS OF THE BINARY BLACK HOLE MERGER GW150914." *The Astrophysical Journal Letters* 818 (2): L22. <https://doi.org/10.3847/2041-8205/818/2/L22>.
- Abbott, B.P., R. Abbott, T.D. Abbott, M.R. Abernathy, F. Acernese, K. Ackley, C. Adams, et al. 2016a. "Observation of Gravitational Waves from a Binary Black Hole Merger." *Physical Review Letters* 116 (6). <https://doi.org/10.1103/physrevlett.116.061102>.
- Abbott, B.P., R. Abbott, T.D. Abbott, M.R. Abernathy, F. Acernese, K. Ackley, C. Adams, et al. 2016b. "GW150914: First Results from the Search for Binary Black Hole Coalescence with Advanced LIGO." *Physical Review D* 93 (12). <https://doi.org/10.1103/physrevd.93.122003>.
- Abbott, B.P., R. Abbott, T.D. Abbott, M.R. Abernathy, F. Acernese, K. Ackley, C. Adams, et al. 2016. "Properties of the Binary Black Hole Merger GW150914." *Physical Review Letters* 116 (24). <https://doi.org/10.1103/physrevlett.116.241102>.
- Abbott, B. P., R. Abbott, T. D. Abbott, S. Abraham, F. Acernese, K. Ackley, C. Adams, et al. 2020. "Prospects for Observing and Localizing Gravitational-Wave Transients with Advanced LIGO, Advanced Virgo and KAGRA." *Living Reviews in Relativity* 23 (1). <https://doi.org/10.1007/s41114-020-00026-9>.
- Abbott, R., T. D. Abbott, S. Abraham, F. Acernese, K. Ackley, A. Adams, C. Adams, et al. 2021. "Search for Lensing Signatures in the Gravitational-Wave Observations from the First Half of LIGO–Virgo's Third Observing Run." *The Astrophysical Journal* 923 (1): 14. <https://doi.org/10.3847/1538-4357/ac23db>.
- Acernese, F., M. Agathos, L. Aiello, A. Allocca, A. Amato, S. Ansoldi, S. Antier, et al. 2019. "Increasing the Astrophysical Reach of the Advanced Virgo Detector via the Application of Squeezed Vacuum States of Light." *Phys. Rev. Lett.* 123 (December): 231108. <https://doi.org/10.1103/PhysRevLett.123.231108>.
- Acernese, F, M Agathos, K Agatsuma, D Aisa, N Allemandou, A Allocca, J Amarni, et al. 2014. "Advanced Virgo: A Second-Generation Interferometric Gravitational Wave Detector." *Classical and Quantum Gravity* 32 (2): 024001. <https://doi.org/10.1088/0264-9381/32/2/024001>.
- Akutsu, T., M. Ando, K. Arai, Y. Arai, S. Araki, A. Araya, N. Aritomi, et al. 2020. "Overview of KAGRA: Detector Design and Construction History." <https://arxiv.org/abs/2005.05574>.
- Allen, Bruce, Warren G. Anderson, Patrick R. Brady, Duncan A. Brown, and Jolien D. E. Creighton. 2012. "FINDCHIRP: An Algorithm for Detection of Gravitational Waves from Inspiring Compact Binaries." *Physical Review D* 85 (12). <https://doi.org/10.1103/physrevd.85.122006>.
- Ashton, Gregory, Sylvia Biscoveanu, Neil Cornish, Isaac Dal Canto, Prayush Kumar, Duncan Meacher, Hannah Middleton, Divyansh Mistry, Rory Smith, and Tom Stevenson. 2022. "bilby: a user-friendly Bayesian inference library." *GitHub Repository*. GitHub. <https://github.com/GregoryAshton/Bilby>.
- Ashton, Gregory, Moritz Hübner, Paul D. Lasky, Colm Talbot, Kendall Ackley, Sylvia Biscoveanu, Qi Chu, et al. 2019. "Bilby: A User-Friendly Bayesian Inference Library for Gravitational-Wave Astronomy." *The Astrophysical Journal Supplement Series* 241 (2): 27. <https://doi.org/10.3847/1538-4365/ab06fc>.
- Aso, Yoichi, Yuta Michimura, Kentaro Somiya, Masaki Ando, Osamu Miyakawa, Takanori Sekiguchi, Daisuke Tatsumi, and Hiroaki Yamamoto. 2013. "Interferometer Design of the

- KAGRA Gravitational Wave Detector.” *Phys. Rev. D* 88 (August): 043007. <https://doi.org/10.1103/PhysRevD.88.043007>.
- Buikema, A., C. Cahillane, G. L. Mansell, C. D. Blair, R. Abbott, C. Adams, R. X. Adhikari, et al. 2020. “Sensitivity and Performance of the Advanced LIGO Detectors in the Third Observing Run.” *Phys. Rev. D* 102 (September): 062003. <https://doi.org/10.1103/PhysRevD.102.062003>.
- Callister, Thomas A. et al. 2024. “Neural Network Emulator of the Advanced LIGO and Advanced Virgo Selection Function.” *Physical Review D* 110 (12). <https://doi.org/10.1103/physrevd.110.123041>.
- Chapman-Bird, Christian E A et al. 2023. “Rapid Determination of LISA Sensitivity to Extreme Mass Ratio Inspirals with Machine Learning.” *Monthly Notices of the Royal Astronomical Society* 522 (4): 6043–54. <https://doi.org/10.1093/mnras/stad1397>.
- Collaboration, The LIGO Scientific, the Virgo Collaboration, the KAGRA Collaboration, R. Abbott, H. Abe, F. Acernese, K. Ackley, et al. 2023. “Search for Gravitational-Lensing Signatures in the Full Third Observing Run of the LIGO-Virgo Network.” <https://arxiv.org/abs/2304.08393>.
- Edwards, Thomas D. P., Kaze W. K. Wong, Kelvin K. H. Lam, Adam Coogan, Daniel Foreman-Mackey, Maximiliano Isi, and Aaron Zimmerman. 2024. “Differentiable and hardware-accelerated waveforms for gravitational wave data analysis.” *Phys. Rev. D* 110 (6): 064028. <https://doi.org/10.1103/PhysRevD.110.064028>.
- Gerosa, Davide et al. 2020. “Gravitational-Wave Selection Effects Using Neural-Network Classifiers.” *Physical Review D* 102 (10). <https://doi.org/10.1103/physrevd.102.103020>.
- James Bradbury, Peter Hawkins, Roy Frostig, and Various others. 2018. “JAX: Composable Transformations of Python+NumPy Programs.” GitHub. <https://github.com/google/jax>.
- Janquart, J, M Wright, S Goyal, J C L Chan, A Ganguly, Á Garrón, D Keitel, et al. 2023. “Follow-up analyses to the O3 LIGO–Virgo–KAGRA lensing searches.” *Monthly Notices of the Royal Astronomical Society* 526 (3): 3832–60. <https://doi.org/10.1093/mnras/stad2909>.
- Lam, Stan, Stéphane Pitrou, and Mark Seibert. 2022. “Numba: A High Performance Python Compiler.” *Numba Documentation*. Anaconda, Inc. <https://numba.pydata.org/>.
- LIGO Scientific Collaboration, Virgo Collaboration, and KAGRA Collaboration. 2018. “LVK Algorithm Library - LALSuite.” Free software (GPL). <https://doi.org/10.7935/GT1W-FZ16>.
- More, Anupreeta, and Hemantakumar Phurailatpam. 2025. “Gravitational Lensing: Towards Combining the Multi-Messengers.” <https://arxiv.org/abs/2502.02536>.
- Ng, Leo C. Y., Justin Janquart, Hemantakumar Phurailatpam, Harsh Narola, Jason S. C. Poon, Chris Van Den Broeck, and Otto A. Hannuksela. 2024. “Uncovering Faint Lensed Gravitational-Wave Signals and Reprioritizing Their Follow-up Analysis Using Galaxy Lensing Forecasts with Detected Counterparts.” <https://arxiv.org/abs/2403.16532>.
- NumPy Community. 2022. “NumPy: A Fundamental Package for Scientific Computing with Python.” *NumPy Website*. NumPy. <https://numpy.org/>.
- Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, et al. 2011. “Scikit-Learn: Machine Learning in Python.” *Journal of Machine Learning Research* 12: 2825–30.
- Phurailatpam, Hemantakumar, and Otto Akseli Hannuksela. 2025. “Gwsnr: Gravitational Wave Signal-to-Noise Ratio Computation Package Documentation.” <https://gwsnr.readthedocs.io/en/latest/>.
- Phurailatpam, Hemantakumar, Anupreeta More, Harsh Narola, Ng Chung Yin, Justin Janquart, Chris Van Den Broeck, Otto Akseli Hannuksela, Neha Singh, and David Keitel. 2024. “Ler :

LVK (LIGO-Virgo-KAGRA Collaboration) Event (Compact-Binary Mergers) Rate Calculator and Simulator." <https://arxiv.org/abs/2407.07526>.

Taylor, Stephen R., and Davide Gerosa. 2018. "Mining Gravitational-Wave Catalogs to Understand Binary Stellar Evolution: A New Hierarchical Bayesian Framework." *Physical Review D* 98 (8). <https://doi.org/10.1103/physrevd.98.083017>.

The LIGO Scientific Collaboration, J Aasi, B P Abbott, R Abbott, T Abbott, M R Abernathy, K Ackley, et al. 2015. "Advanced LIGO." *Classical and Quantum Gravity* 32 (7): 074001. <https://doi.org/10.1088/0264-9381/32/7/074001>.

Thrane, Eric, and Colm Talbot. 2019. "An Introduction to Bayesian Inference in Gravitational-Wave Astronomy: Parameter Estimation, Model Selection, and Hierarchical Models." *Publications of the Astronomical Society of Australia* 36. <https://doi.org/10.1017/pasa.2019.2>.

Wempe, Ewoud, Léon V. E. Koopmans, A. Renske A. C. Wierda, Otto Akseli Hannuksela, Alberto Agnello, Cyril Bonvin, Bendetta Bucciarelli, et al. 2022. "A Lensing Multi-Messenger Channel: Combining LIGO-Virgo-Kagra Lensed Gravitational-Wave Measurements with Euclid Observations." <https://arxiv.org/abs/2204.08732>.

Wierda, A. Renske A. C., Ewoud Wempe, Otto A. Hannuksela, Léon V. E. Koopmans, Alberto Agnello, Cyril Bonvin, Bendetta Bucciarelli, et al. 2021. "Beyond the Detector Horizon: Forecasting Gravitational-Wave Strong Lensing." *The Astrophysical Journal* 921 (1): 154. <https://doi.org/10.3847/1538-4357/ac1bb4>.