GWPopulation: Hardware agnostic population inference for compact binaries and beyond

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Software

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Summary

Since the first direct detection of gravitational waves by the LIGO–Virgo collaboration in 2015 (B. P. Abbott et al., 2016), the size of the gravitational-wave transient catalog has grown to nearly 100 events (R. Abbott et al., 2023), with the ongoing fourth observing run more than doubling the total number. Extracting astrophysical/cosmological information from these observations is a hierarchical Bayesian inference problem. `GWPopulation` is designed to provide simple-to-use, robust, and extensible tools for hierarchical inference in gravitational-wave astronomy/cosmology. It has been widely adopted for gravitational-wave astrnomy, including producing flagship results for the LIGO-Virgo-KAGRA collaborations (Abac et al., 2024; R. Abbott et al., 2023) [1]. While designed to work with observations of compact binary coalescences, `GWPopulation` may be available to a wider range of hierarchical Bayesian inference problems.

Building on `Bilby` (Ashton et al., 2019), `GWPopulation` can easily be used with a range of stochastic samplers through a standard interface. By providing access to a range of array backends (`numpy` (Harris et al., 2020), `JAX` (Bradbury et al., 2018), and cupy (Okuta et al., 2017) are currently supported), `GWPopulation` is hardware agnostic and can leverage hardware acceleration to meet the growing computational needs of these analyses. Included in the package are:

- implementations of the most commonly used likelihood functions in the field.
- commonly used models for describing the astrophysical population of merging compact binaries. Including the "PowerLaw+Peak" and "PowerLaw+Spline" mass models, "Default" spin model, and "PowerLaw" redshift models used in the latest LIGO-Virgo-KAGRA collaboration analysis of the compact binary population[2].
- functionality to simultaneously infer the astrophysical distribution of sources and cosmic expansion history using the "spectral siren" method (Ezquiaga & Holz, 2022).
- a standard specification allowing users to define additional models.

[1]For a full listing of papers using `GWPopulation`, see the citations for the previous publication.

[2]See R. Abbott, Abbott, Acernese, Ackley, Adams, Adhikari, Adhikari, Adya, Affeldt, Agarwal, Agathos, Agatsuma, Aggarwal, Aguiar, Aiello, Ain, Ajith, Akutsu, et al. (2023) for details of these models.

Statement of need

Hierarchical Bayesian inference is the standard method for inferring parameters describing the astrophysical population of compact binaries and the cosmic expansion history (e.g., Thrane & Talbot (2019), Vitale et al. (2022)). The first step in the hierarchical inference process is drawing samples from the posterior distributions for the source parameters of each event under a fiducial prior distribution along with a set of simulated signals used to quantify the sensitivity of gravitational-wave searches. Next, these samples are used to estimate the population likelihood using Monte Carlo integration with a computational cost that grows quadratically with the size of the observed population. Since evaluating these Monte Carlo integrals is embarrassingly parallel, this is a prime candidate for hardware acceleration using graphics/tensor processing units. `GWPopulation` provides functionality needed to perform this second step and is extensively used by members of the gravitational-wave astronomy community including the LIGO-Virgo-KAGRA collaborations.

Maximizing the information we can extract from the gravitational-wave transient catalog requires a framework where potential population models can be quickly constrained with the observed data with minimal boilerplate code. Additionally, the availability of a standard open-source implementation improves the reliability and reproducibility of published results. `GWPopulation` addresses all of these points by providing an open-source implementation of the functionality needed to perform population analyses while enabling user-defined models to be provided by a `Python` function/class definition. The flexible backend system means hardware acceleration can be used with minimal coding effort. Using `GWPopulation` on Google Colab, it is possible to perform an exploratory analysis with a new population model in minutes and produce production-quality results without needing high-performance/throughput computing clusters. With access to high throughput computing resources, a wide range of potential models can be easily explored using the associated `gwpopulation_pipe` (Talbot, 2021) package.

Related packages

Several other packages are actively used and maintained in the community that can be used for population inference that operate in complementary ways to `GWPopulation`.

- `GWInferno` (Edelman et al., 2023) is a package for hierarchical inference with gravitational-wave sources intended for use with `numpyro` (Phan et al., 2019) targeting high-dimensional models. `GWInferno` includes many population models initially adapted from `GWPopulation`.
- There are a wide range of packages designed for joint astrophyical and cosmological inference with gravitational-wave transients including `icarogw` (Mastrogiovanni et al., 2024), `gwcosmo` (Gray et al., 2023), `MGCosmoPop` (Mancarella & Genoud-Prachex, 2022), and `CHIMERA` (Borghi et al., 2024). `icarogw` supports some harware acceleration using `cupy` but some cosmological calculations are limited to CPU support only. `chimera` is `JAX`-compatible and supports flat Lambda-CDM cosmologies along with analysis using galaxy catalogs.
- `vamana` (Tiwari, 2021) models the compact binary distribution as a mixture of Gaussians and power-law distributions, and `popmodels` (Wysocki & O'Shaughnessy, 2017--) implements a range of parametric models for the compact binary distribution and supports sampling via `emcee` (Foreman-Mackey et al., 2013). However, neither supports hardware acceleration at the time of writing.

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