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Towards an implicit-likelihood future for gravitational wave data analysis

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An increasingly louder gravitational wave sky brings about a host of data analysis challenges especially when it comes to parameter inference. It is well understood that direct implementation of traditional, likelihood-based inference techniques such as *e.g.* `dynesty, MCMC` etc. for parameter inference of next-generation gravitational wave signals will not be feasible or even possible in certain cases where the likelihood function becomes mathematically intractable. In this article, I propose an implicit-likelihood technique called sequential simulation based inference packaged within the open-source pipeline `peregrine` and its applicability in dealing with upcoming data analysis challenges in gravitational wave physics. I highlight the simulation efficiency that `peregrine` exhibits whilst ensuring optimal precision in a statistically robust way. Ultimately, I emphasize the potential of implicit-likelihood techniques for parameter inference of multiple different types of signals in the current and upcoming era of gravitational wave physics.

The `peregrine` analysis and inference library is available here (`peregrine-gw/peregrine`).

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1. Introduction

Observational status. Since the initial gravitational wave (GW) detection in 2015 [1], the GW sky has become increasingly louder. The LIGO-Virgo-Kagra collaboration (LVKC) has reported 90 astrophysical events [2, 3], with additional sources present in extended catalogs[1]. These current source catalogs aid in exploring gravitational theory [8], cosmology [9–11], and astrophysical properties of black holes and neutron stars [12, 13].
The growth in the GW detection rate as evidenced by the cumulative distribution of detections in 1 (left panel) can be attributed to enhanced search pipelines [14–16] as well as an increased detector search volume. For instance, the ongoing fourth observing run (O4) predicts a search volume over 400% larger than the previous run (O3) [17, 18], marking a significant milestone for GW observatories. Moreover, with the next generation of gravitational wave observatories such as the Einstein Telescope (ET) [19], Cosmic Explorer (CE [20] and the Laser Interferometer Space Antenna (LISA) [21] starting operations in the near future, the rate of GW detections as well as the variety of GW sources is predicted to rise rapidly. These advancements however, presents a host of new computational challenges pertaining to GW data analysis.
GW Data Analysis. In general, data analysis efforts for gravitational waves are targeted towards two major avenues: detection and parameter inference. In this article, I highlight the host of data analysis challenges that current and future gravitational wave parameter inference efforts would need to tackle in order to ensure high precision follow-up studies in the context of data-driven gravitational physics as well as multi-messenger astronomy.
Simulation-based inference As a response to growing data analysis challenges in multiple physics scenarios combined with rapid development in machine learning algorithms, simulation-based inference (SBI) also known as implicit-likelihood inference has found widespread applications in parameter inference for various physics settings including gravitational waves. SBI methods facilitate Bayesian parameter inference using high fidelity simulations of signals (x) generated from a sample of source parameters (θ) without needing explicit likelihood evaluation, as evidenced in various studies (e.g., Refs. [22–32]). This approach is especially useful in GW analysis, offering advantages in simulation efficiency as well as allowing for amortized inference.

2. Sequential simulation based inference for gravitational waves: Peregrine

This article highlights the application of a specific SBI algorithm called TMNRE (Truncated Marginal Neural Ratio Estimation) [22] to GW data analysis [25, 34, 35]. Our open-source inference pipeline `peregrine` built on top of the `swyft` algorithm [22, 36] leverages the power of TMNRE to carry out targeted, sequential inference of parameters of interest by solving a binary classification task (see Refs. [22, 36] for more details.). The ability to target lower dimensional marginal posteriors in a sequential manner that composes well with marginalisation [22] makes this approach highly simulation efficient whilst allowing for the possibility to utilise simpler neural network architectures for training. The sequential SBI approach in `peregrine` is highlighted in the schematic shown in Fig. 2. An application to highly spinning, precessing binary black hole (BBH) signals [25] (evaluated with `SEOBNRv4PHM` [37]) has shown to provide posterior distributions with precision similar to likelihood-based approaches (see for e.g. Fig. 3) with only **2**% of

[1]See extended catalogs [4–7].

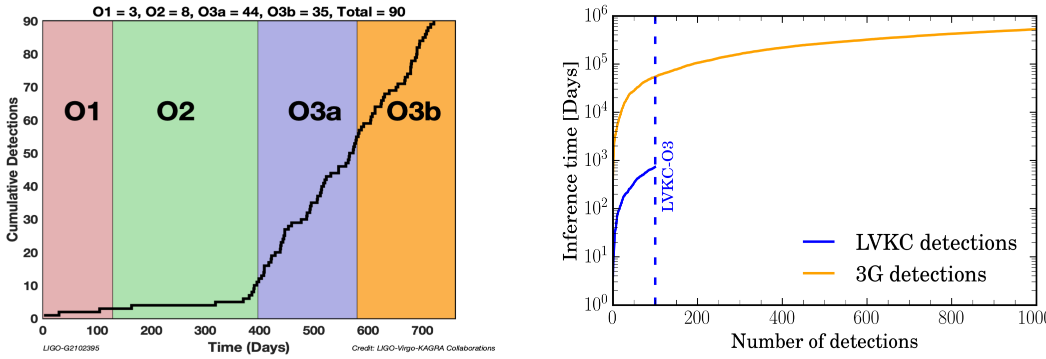

Figure 1: Left panel: Cumulative distribution of gravitational wave transient detections [33] by the LIGO-Virgo-Kagra collaboration (LVKC) upto the third observing run (O3) highlighting an increasing trend in the number of confident detections in each observing run. **Right panel:** Schematic representation of the cumulative time needed for parameter inference of gravitational wave detections from the LIGO-Virgo-Kagra collaboration (upto O3 shown in blue) and for a conservative number of next generation detections (in yellow) showing the unrealistic amount of computational time/resources necessary for current analysis techniques employed for analysing next generation detections.

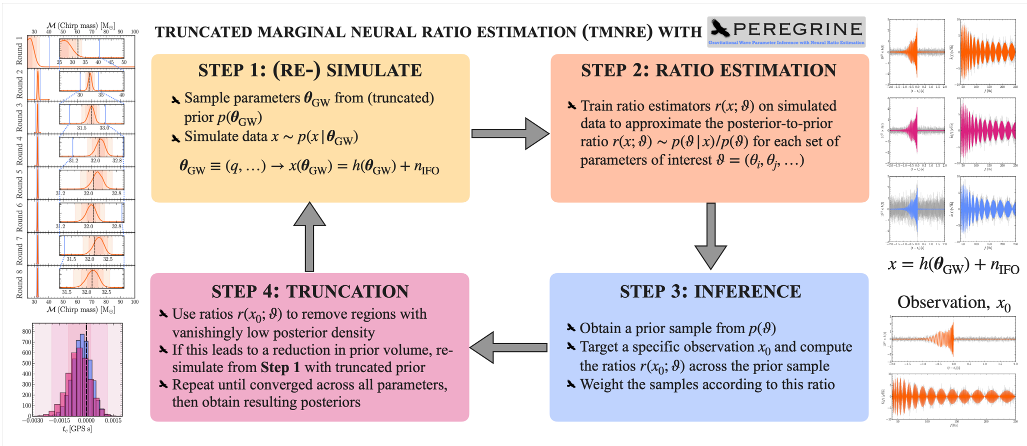

Figure 2: Illustration of the simulation based inference workflow of `peregrine` discussed in this paper. We use truncated marginal neural ratio estimation (TMNRE) to carry out sequential simulation based inference of gravitational wave signals [25].

waveform evaluations required for traditional likelihood-based methods such as nested sampling[2]. Additionally, applications to inference of overlapping gravitational wave signals [34] and stochastic gravitational wave background analysis [35] have also shown equally promising results in terms of simulation-efficiency as well as precision, thus, making a case of sequential SBI and other implicit-likelihood inference methods to have widespread utility throughout a host of GW data analysis challenges for current and next-generation GW astrophysics.

[2]Our sequential SBI approach required $\sim 7 \times 10^5$ waveform evaluations compared to $\sim 4 \times 10^7$ using nested sampling.

3. Results and Conclusions

Our results are represented in Figs. 3 and 4 wherein the level of agreement to traditional likelihood-based methods[3], as well as precision of posteriors obtained by analysing a BBH signal overlapping with another (similar SNR) BBH signal with merger time +0.05s are highlighted. The remarkably similar precision in the posteriors obtained from the overlapping analysis to that of the single signal analysis (in the absence of overlap) renders our approach the state of the art when it comes to analysing overlapping GW signals[4].

An important discussion regarding our analysis concerns computational efficiency. It has been explicitly shown that using traditional methods to carry out this type of joint inference is extremely costly, taking on average over 3 weeks to run (see Footnote 3 in Ref. [38]). In comparison, across 7 sequential rounds of inference using `peregrine` (see Ref. [34]), we require only a factor of 10 more than we required to perform analysis on a single signal in Ref. [25] for twice as many parameters (30) and convincingly break the expected scaling of traditional methods solving this joint inference problem, and is an order of magnitude fewer waveform evaluations than is typically required to analyse *even a single signal* with traditional methods such as MCMC.[5]

Conclusion. In conclusion, the scalability and simulation-efficiency of implicit-likelihood (SBI) approaches to parameter inference of current and future gravitational wave detections make a strong case for widespread applicability of this class of approaches to GW data analysis. With ever-increasing detection rates, overlapping signals etc. being major components of future GW detections, a foray towards such highly scalable and simulation-efficient methods promise a highly sustainable outlook for the future of GW data analysis. Furthermore, advancements in data compression, faster waveform evaluations, and more efficient neural network designs hold great promise for the future of implicit-likelihood inference.

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[3] Agreement of our (TMNRE) posteriors to those obtained using traditional likelihood-based approaches serve as validation of our results. Alternative validations of posterior calibration using coverage tests as shown in Refs. [25, 34, 35].

[4] Slightly broader posteriors of the overlapping signal analysis are expected due to reduction in the effective signal-to-noise ratio (in terms of confusion noise) due to the presence of the second signal in the data stream.

[5] In terms of time, we used an 18-core CPU cluster node to generate the 7×10^6 waveform evaluations using our infinitely parallelisable simulator, which took on average around 2-3 hours per round of 1 million examples. Training the network each round is currently the main time cost of the analysis, taking between 8 and 12 hours per round for 10^6 simulations. Overall, this means our analysis takes around 48 hours to complete, depending on the specific hardware choice.

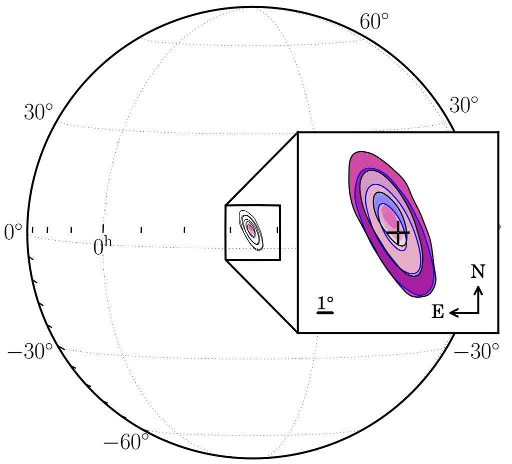

Figure 3: 2D skymap showing the localisation (post-inference) of a 20 signal-to-noise ratio spinning, precessing BBH merger using `dynesty` (in blue) and TMNRE via `peregrine` (in pink). This is representative of the agreement of our (TMNRE) posteriors with those obtained using traditional likelihood-based approaches.

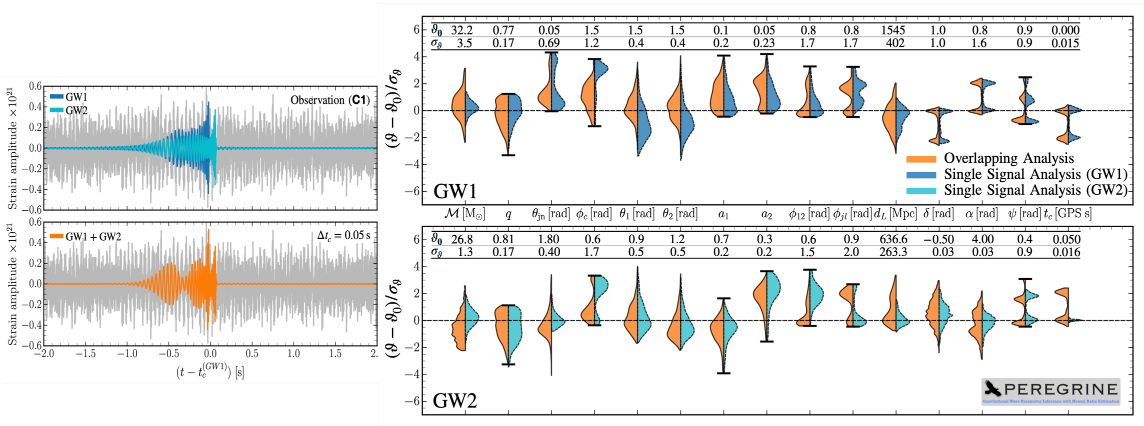

Figure 4: Right: Violin plots showing 1D marginal posterior distributions of all 30 parameters characterising an overlapping signal comprising two concurrent BBH signals with (merger time separation) $\Delta t_c = 0.05$ s (**left**). The left of each violin shows the 1D marginal posterior obtained from our overlapping signal analysis and the corresponding distributions on the right represent the posteriors obtained from a single signal analysis of each component signal in the absence of the other waveform. The top and bottom panels indicate parameters of the first (**GW1**) and second (**GW2**) signal respectively. For a detailed description see Ref. [34].

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