Assessing and marginalizing over CBC waveform systematics with RIFT

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Introduction

Parameter estimation of Gravitational Wave signals is a key part of Gravitational Wave Astronomy and Astrophysics. Unbiased and reliable parameter estimation help achieve a higher precision for tests of General Relativity [1]. However, waveforms used to perform parameter estimation produce systematic biases [2]. The goal here is to reassess and mitigate these biases using RIFT.

RIFT

Rapid parameter inference on Gravitational Wave sources via **I**terative **FiT**ing is a two-stage iterative process to interpret Gravitational Wave observations via comparison to predicted Gravitational Wave signals [3].

Stage 1: Compute marginal likelihood values for each point in parameter space (λ_α) from a "proposed grid".
Stage 2: Generate an approximation to likelihood values ($\mathcal{L}(\lambda)$) based on RIFT's accumulated archived knowledge of marginal likelihood evaluations ($\lambda_\alpha, \mathcal{L}_\alpha$) and from that approximation generate the (detector-frame) posterior distribution.

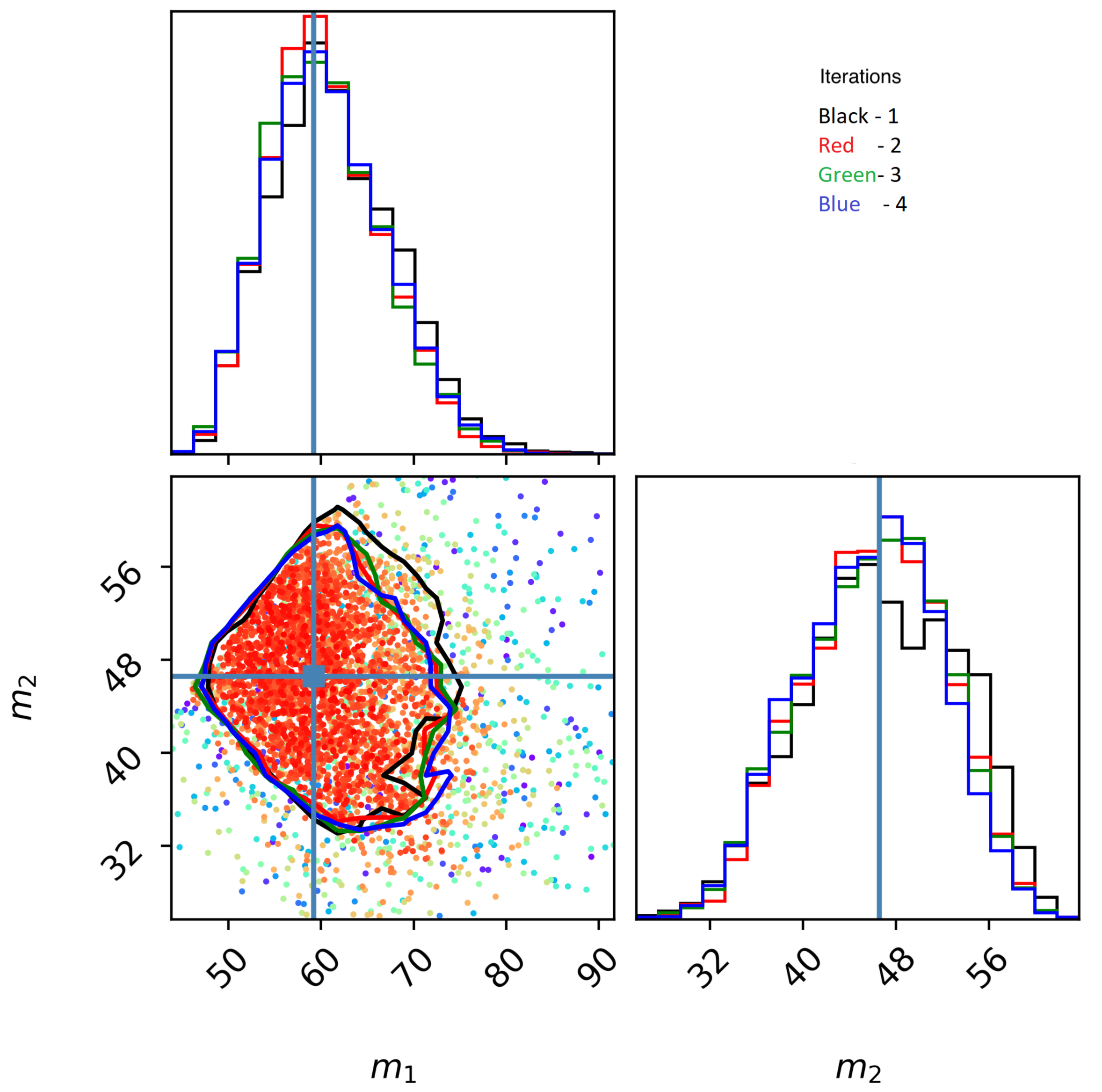
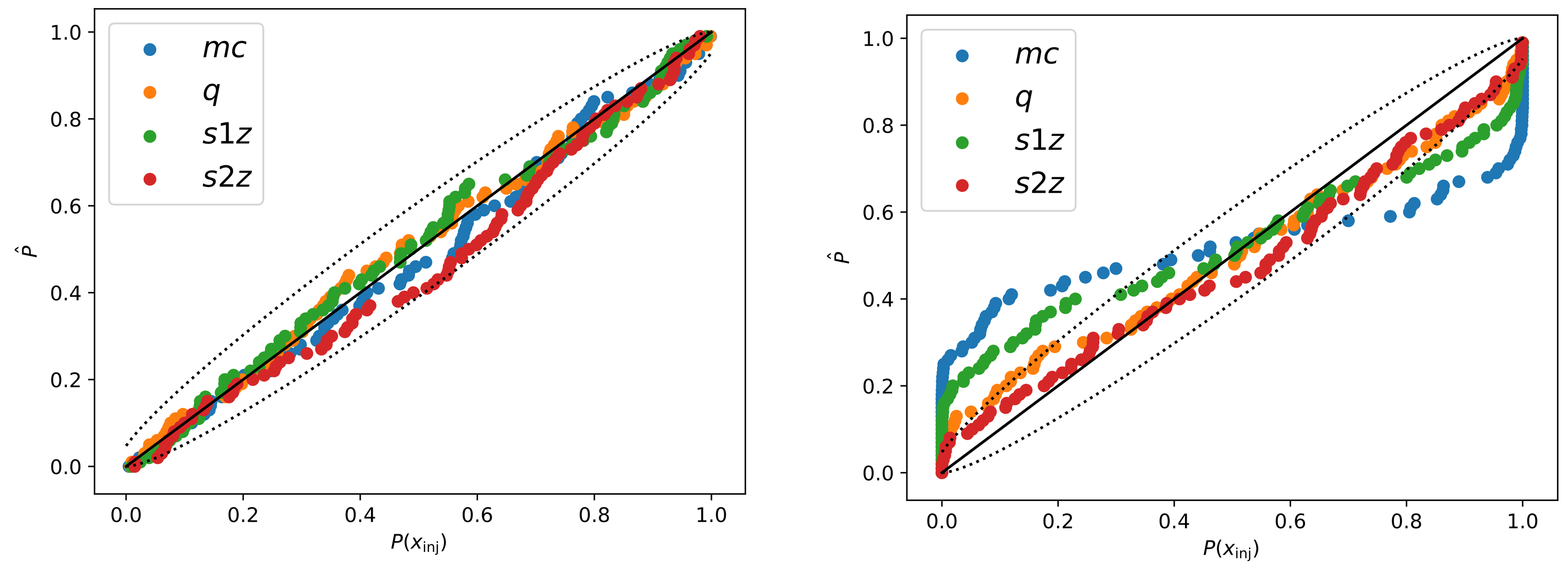


***Figure 1:** Likelihood and posteriors obtained using RIFT*

This figure shows inferred posterior parameter distributions for a non-precessing Binary Blackhole source using RIFT. The blue crosshairs indicate true parameter values and contours in two dimensional plots (bottom left) indicate the 90% credible region as estimated by each iteration. The colors correspond to different iterations.

Probability-Probability plots (P–P plots)

Basic Idea: x–axis shows the probability contained in a credible interval and y–axis shows the fraction of true values which lay inside that interval. They are used to quantify two or more data sets. When injection and recovery is performed using the same model, we expect the P–P plot to be a line of form $y = x$. However, if recovery is performed using a different waveform model, the P–P plot strays more from the expected $y = x$ behavior.



Injection: SEOBNRv4
Recovery: SEOBNRv4

Injection: SEOBNRv4
Recovery: IMRPhenomD

***Figure 2:** P–P plots for 100 non-precessing Binary Black Hole (BBH) events.*

In our runs, the waveform model used for injection was known allowing us to run parameter inference and recover unbiased posterior samples. However, such is not usually the case paving the need for model marginalization.

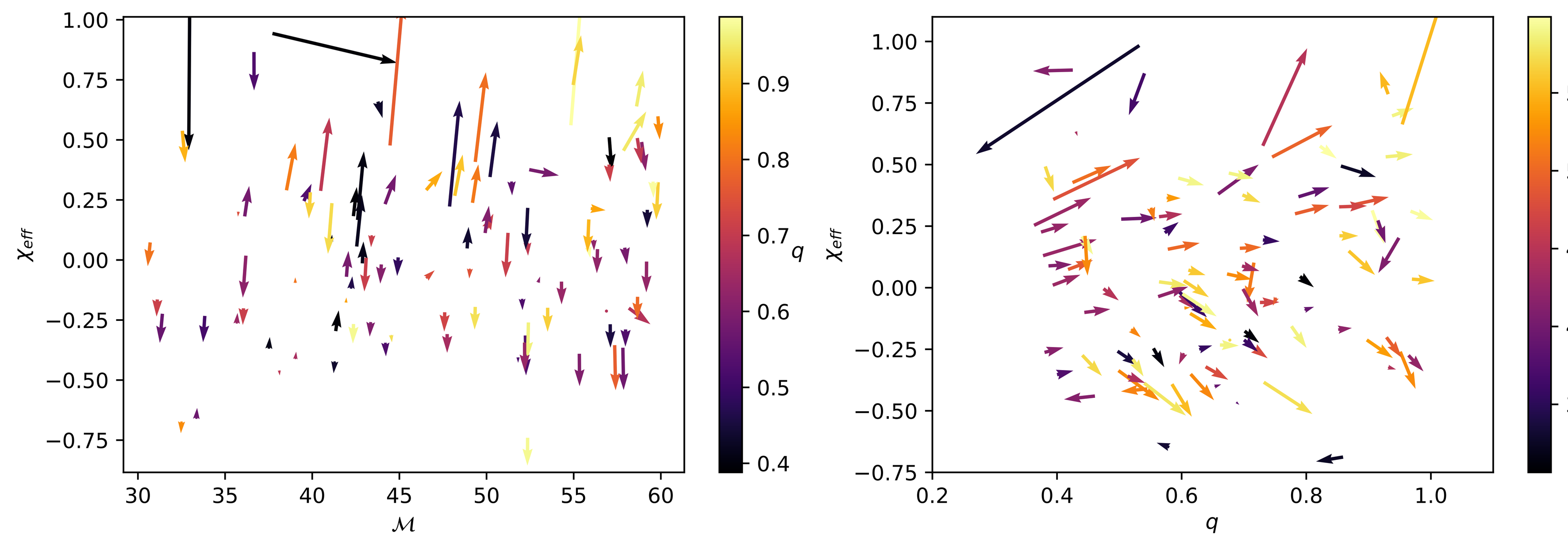


***Figure 3:** Systematic parameter biases*

The x and y axes on these vector plots are parameter values and length of the arrow denotes SNR-scaled offsets between parameters recovered by the two waveforms. The colormap is the value of the 3rd parameter($\mathcal{M}/q/\chi_{eff}$).

These plots were generated for zero-noise injections so we are seeing pure systematic differences between the two models. This plot shows that for a same event we will get different values from two different recovery models which might vary significantly.

Model Marginalization

Based on Ashton and Khan [4] description of marginalization between a discrete set of waveform models, we examine a waveform-marginalization technique. Operationally speaking, we construct model-averaged marginal likelihoods by the following procedure.

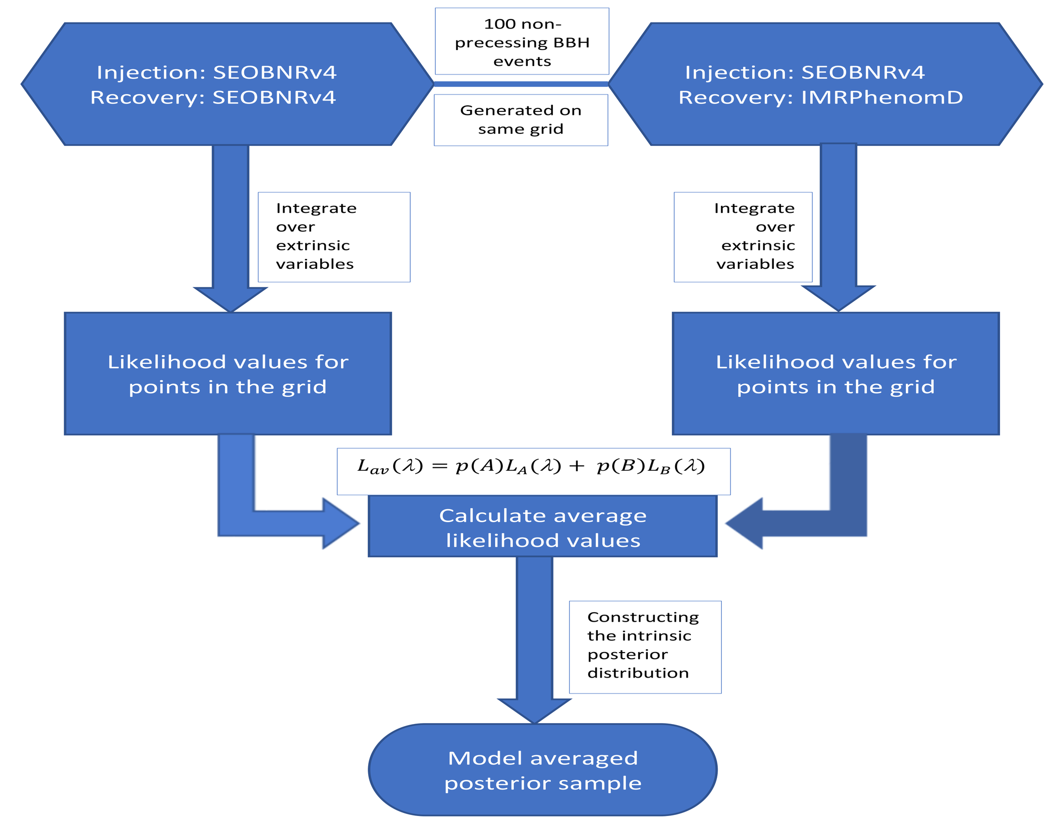


***Figure 4:** Model marginalization flowchart*

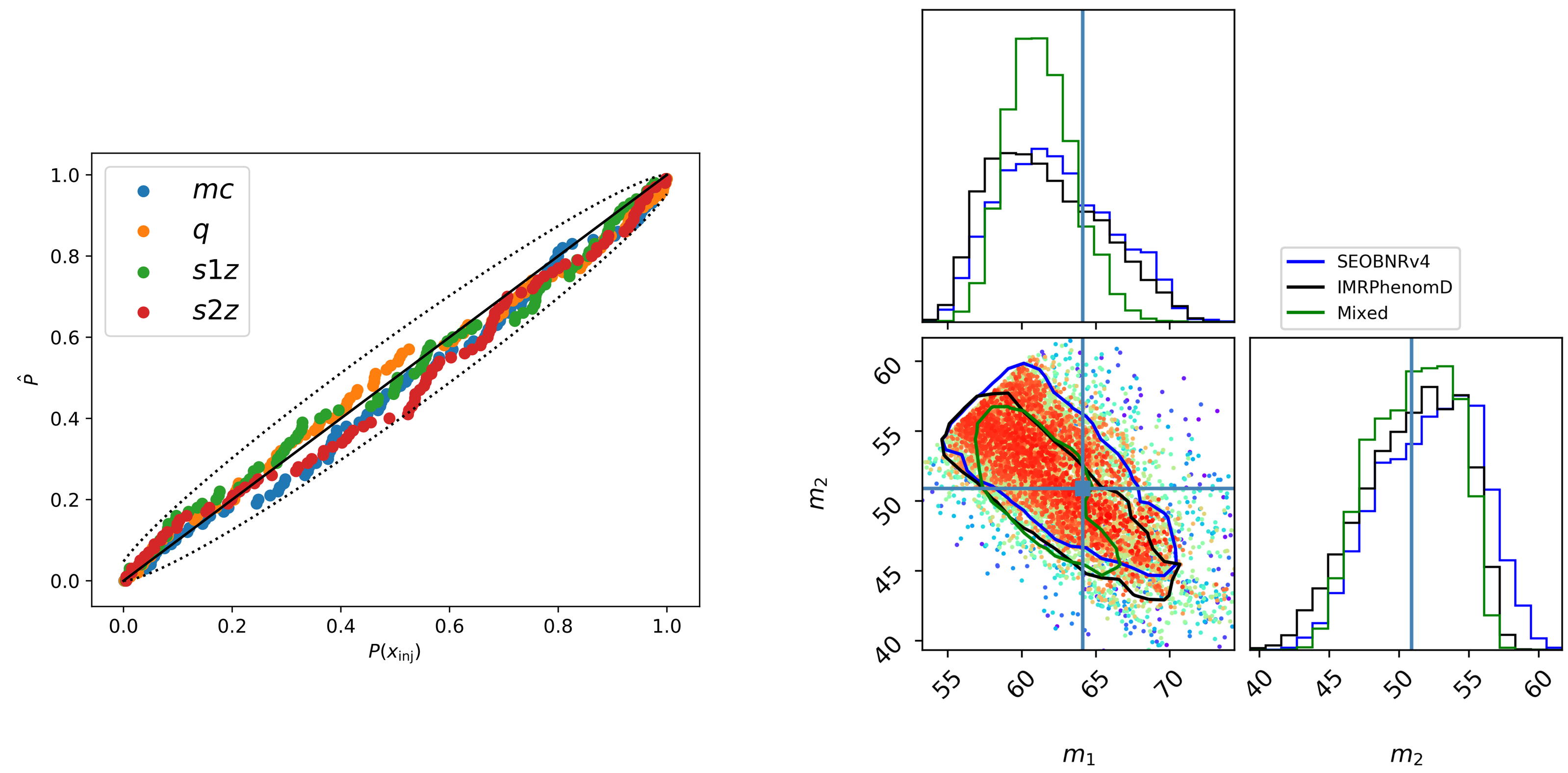


***Figure 5:** P–P plot and posteriors for model marginalized runs*

From the P–P plot and the posteriors, it appears if we used model averaging we get results which are less biased.

Conclusions

In situations where injections aren't known, we can perform model marginalization and get better results than randomly choosing a waveform as recovery. And since this is based on RIFT, a very efficient parameter inference engine, our technique can include any available model, including very accurate but computationally costly estimates.

References

[1] Feroz H. Shaik, Jacob Lange, Scott E. Field, Richard O'Shaughnessy, Vijay Varma, Lawrence E. Kidder, Harald P. Pfeiffer, and Daniel Wysocki. Impact of subdominant modes on the interpretation of gravitational-wave signals from heavy binary black hole systems. 11 2019.

[2] J. Veitch et al. Parameter estimation for compact binaries with ground-based gravitational-wave observations using the LALInference software library. *Phys. Rev. D*, 91(4):042003, 2015.

[3] J. Lange, R. O'Shaughnessy, and Monica Rizzo. Rapid and accurate parameter inference for coalescing, precessing compact binaries. *arXiv: General Relativity and Quantum Cosmology*, 2018.

[4] Gregory Ashton and Sebastian Khan. Multiwaveform inference of gravitational waves. *Phys. Rev. D*, 101(6):064037, 2020.