Glitch Reweighting by Glitch Parameter Simulation

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A. Abstract

Transient, non-Gaussian noise artifacts, or detector "glitches" challenge gravitational-wave parameter inference. When left unmitigated, or mitigated incorrectly, glitches lead to bias in parameter estimation since underlying noise assumptions do not match the collected data. The current method for mitigating glitches in gravitational-wave detectors is to fit the glitch as well as a compact binary in the detector, subtract a point realization of that glitch model, and pass the residuals on for downstream analysis. This process leaves much to be desired as the uncertainty in the glitch model is not propagated into later analyses. A solution could be to fit for both a glitch and a compact-binary in the data while doing parameter estimation but there are two main problems. Firstly, a more computationally expensive model is more costly to simulate and a larger parameter space is more difficult to sample. Secondly, there is no existing analysis that can account for both glitches and the full nuances of current gravitational waveforms, notably precession. Here we explore a method that combines outputs of various LIGO data analysis schemes via reweighting. We find that such methods were ineffective at constructing accurate compact binary parameter estimation while accounting for the uncertainty introduced by the glitch model.

I. INTRODUCTION

Gravitational waves are ripples in space-time caused by the acceleration of high mass objects. They were first observed by LIGO (Laser Interferometer Gravitational-wave Observatory) in 2015 [1]. LIGO utilizes highly precise instrumentation to detect the differences in length of its perpendicular, 4 kilometer "arms" when a gravitational wave passes through. LIGO is able to detect the inspiral and merger of orbiting black holes and neutron stars. The resulting waveform is dependent on the physics of the system, like mass and angular momentum. After accounting for the noise in the detectors, the waveform can be matched to a model and the parameters of the system that produced the signal can be estimated.

In addition to gravitational waveforms, also present in the data are transient noise artifacts, or "glitches". These such glitches differ from typical detector noise in that they are non-Gaussian. Glitches vary in sources, frequency, time, duration and strength. The presence of this non-Gaussian noise changes the noise background. When most analyses assume that a signal is present in only Gaussian noise, their presence can bias the estimation.

BayesWave is a Bayesian algorithm that can produce a posterior distribution accounting for various glitch models, but it cannot construct a CBC (compact binary coalescence) waveform model that includes precession. Bilby is another Bayesian algorithm that can construct CBC models which include precession parameters, but cannot account for glitches. Our objective was to reweight a set of posterior samples from a BayesWave CBC+Glitch run and obtain a posterior distribution with both the glitch model and a fully precessing waveform. We obtained this posterior distribution by constructing an approximate distribution using two distinct methods, both of which relied upon multiplying parameter spaces together to create the approximate distribution. After constructing the approximate we applied weights to samples to estimate the target distribution. The first method was by simulating glitch parameters, using the Bilby precessing CBC waveform and attaching samples from BayesWave glitch models. We revised this method to take draws from specific BayesWave glitch models instead of from all of them. The alternate method was simulating precession parameters, where we began with a BayesWave CBC and glitch subtracted run and attached random samples from the Bilby spin precession priors.

This study focuses on the parameters describing spin precession of binary systems. The parameters $\chi_{\rm eff}$ and $\chi_{\rm p}$ measure the amount of spin angular momentum aligned and perpendicular to the orbital angular momentum respectively. Higher precession means the axes are more misaligned. In precessing binaries, the orbital plane shifts and therefore LIGO's viewing angle changes as well. This manifests as a cyclical increase and decrease of the amplitude of the waveform. Effective detection of spin precession requires a waveform model unimpeded by glitches. As concluded in [2],

> any evidence for spin-precession in GW200129 depends sensitively on the glitch model and priors employed.

An unambiguous measurement of spin precession is important because it can provide hints to how the binary was formed. High mass binaries either form together as stars and remain in orbit with each other throughout their lives, or through dynamical capture where they form independently and later fall into orbit with each other. When binaries are born from the same stellar nursery, the stars evolve together and their angular momentum axes are aligned. This is not always the case for binaries formed through dynamical capture because the stars form independently. Their axes are aligned with their local stellar nursery. When dynamical capture occurs when they fall into highly eccentric and precessing orbits. By accurately identifying spin precession in signals, we can begin to ascertain what part of the high mass binary population was formed through dynamical capture.

BayesWave is a Bayesian algorithm that can produce a posterior distribution accounting for various glitch models, but it cannot construct a CBC (compact binary coalescence) waveform model that includes precession. It uses the waveform model 'IMRPhenomD'. Bilby is another Bayeseian algorithm that can construct CBC models which include precession parameters, but cannot account for glitches. It uses an 'NSur' waveform model.

Our objective is to create a posterior that accounts for both the CBC in the waveform as well as the glitch. To do so we reweight a set of posterior samples from a BayesWave run for a compact binary coalescence signal impacted by a glitch (for short a CBC+Glitch run). Then obtain a posterior distribution with both the glitch model and a fully precessing waveform. In other words, a more complete CBC (including precession) and glitch parameter space.

II. GW200129

The research that preceded and inspired this project, [2], reexamined evidence for spin precession of a the black hole binary [3], GW200129. The Livingston detector experienced a glitch that overlapped with the time-frequency path of the CBC. Parameter estimation of the LIGO Hanford data shows a lack of evidence for spin precession. The paper concludes

> that the difference between a spin-precessing and a non-precessing interpretation for GW200129 is smaller than the statistical and systematic uncertainty of the glitch subtraction, finding that the support for spin-precession depends sensitively on the glitch modeling.

III. ANALYSIS PIPELINES

A. bayeswave

BayesWave constructs a glitch model using sine-Gaussian wavelets. This noise model has variable dimension and is parameterized. It is meant to account for non-Gaussian data. The amount and location of wavelets are determined by a Markov Chain Monte Carlo algorithm [4]. The algorithm analyzes the data for excess power that does not fit the clusters of power expected from gravitational wave signals in a time-frequency representation. We utilize BayesWave for parameter estimation, specifically to produce a posterior distribution that accounts for different possible glitches. BayesWave is limited by its inability to include spin precession parameters as it creates the waveform.

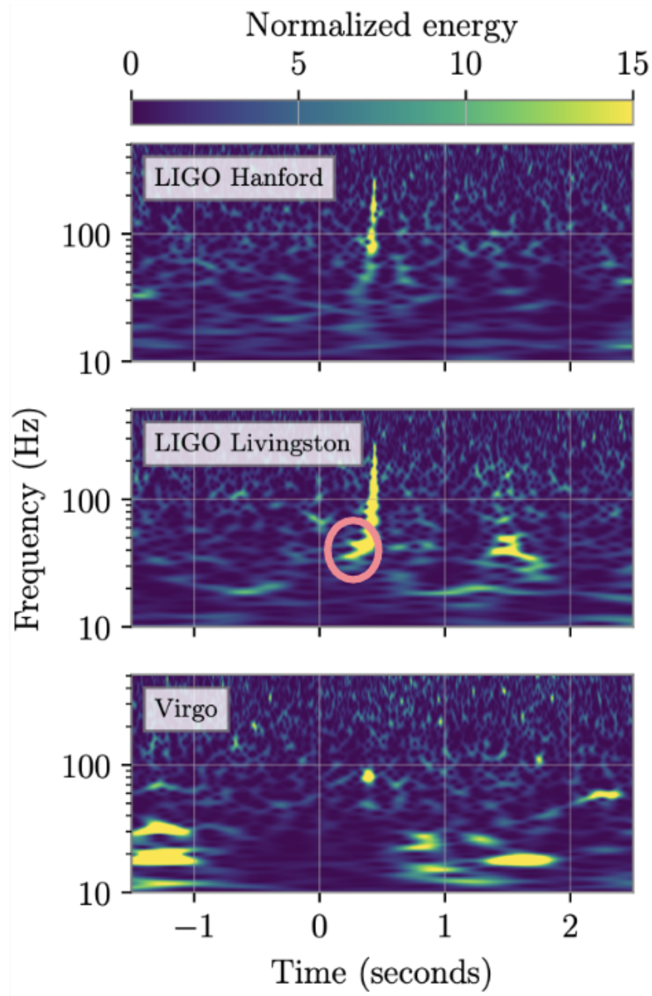

FIG. 1. Signal data of event GW200129 across the three detectors, glitch in Livingston detector circled in pink

B. bilby

Bilby is a Bayesian inference library used to perform parameter estimation. It is designed for interferometric data recorded from CBC events. The CBC models that bilby constructs include spin precession parameters. However, bilby is meant for signal data without the presence of glitches. It cannot detect and account for them like BayesWave.

IV. BAYES' THEOREM

Bayes' Theorem is made up of the likelihood term ($\mathcal{L}$), the prior term (π) and the evidence term (Z). The likelihood evaluates how well the model fits the signal, or the probability of the data given the waveform. The

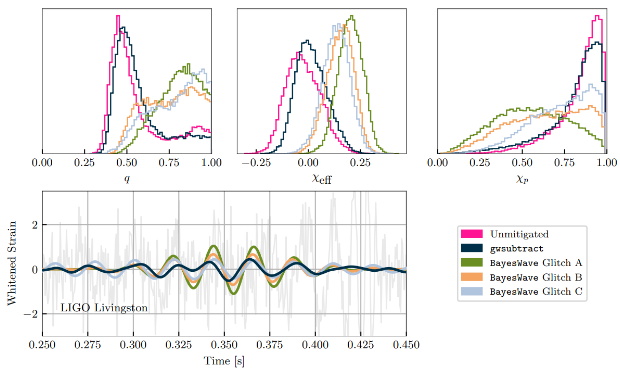

FIG. 2. The bottom left graph shows the different glitch models used for the glitch mitigation, the histogram shows probability distributions for the precession parameter [2]

prior term is a probability distribution that uses prior knowledge to include how likely we believe each parameter value is. The evidence term is a normalization factor.

Bayesian algorithms utilize Bayes' Theorem in order to produce a posterior, a probability distribution conditioned on both the prior knowledge as well as its realization in data. Here we write the posterior that we are interested, the posterior including both precessing CBC parameters θ_p with precessing waveform model $W_{\nearrow}$ as well as glitch parameters g described by glitch model G.

$$p(\theta_p, g|d, W_{\nearrow}, G) = \frac{\mathcal{L}(d|\theta_p, g, G, W_{\nearrow})\pi(\theta_p, g|G, W_{\nearrow})}{Z(d|W_{\nearrow}, G)} \tag{1}$$

V. SAMPLING AND REWEIGHTING

The output of bayesian samplers are posteriors, or sets of parameters distributed according to some posterior distribution. If we have a probability distribution we want to sample (a target distribution) that is similar to another distribution that we have already sampled (an approximate distribution), then instead of sampling the target distribution directly, we can instead "reweight" the approximate distributions.

Before obtaining a posterior on a complete CBC and glitch parameter space, we needed to know how to add additional parameters to create a higher dimensional probability distribution. This can be achieved by creating a probability distribution with the parameter we want to attach, $\Phi(\phi)$, and multiplying it by the original distribution that lacks the parameter, $p(\theta)$

$$\mathcal{P}(\theta, \phi) = p(\theta)\Phi(\phi) \tag{2}$$

When starting from one probability distribution of posteriors the process of reweighting requires dividing the target probability density by the approximate probability density to obtain "weights". This process can be applied to acquire weights for the probability distributions, likelihoods and priors. Weights are useful because multiplying the original probability density by the weights results in a new probability density that can be used to estimate the target distribution. For example, using p the "approximate" distribution and $\tilde{p}$ the "target" distribution. We can write:

$$\begin{aligned}\tilde{p}(\theta) &= \frac{p(\theta)}{p(\theta)}\tilde{p}(\theta) \\ &= \frac{\tilde{p}(\theta)}{p(\theta)}p(\theta) \\ &= w(\theta)p(\theta)\end{aligned} \tag{3}$$

where we have defined.

$$w(\theta) = \frac{\tilde{p}(\theta)}{p(\theta)} \tag{4}$$

These are our "weights". Essentially, what we have done is applied a weight to each location in parameter space. Now, we can draw from samples $\{\theta_i\}$, but *weighing* each sample by the corresponding $w(\theta_i)$. Now we have a set, $\{\tilde{\theta_i}\}$ that is statistically distributed by $\tilde{p}$. This is how reweighting works.

After reweighting we have samples distributed according to a target distribution. To quantify how well these samples describe that distribution we use "effective number of samples", $n_{\rm eff}$ and efficiency, ε using

$$n_{eff} \approx \frac{[\Sigma w]^2}{\Sigma[w^2]} \tag{5}$$

$$\varepsilon = \frac{n_{eff}}{Ns} \tag{6}$$

where N_s is the number of samples originally from the aprroximate distribution. Calculating $n_{\rm eff}$ is important for quantifying sampling errors. If we were to estimate the integral of the target distribution using the reweighted samples, the effective number of samples represents how many samples from the target distribution would yield the same level of accuracy. The efficiency is simply a rescaling of the effective number of samples to gain a percent value.

VI. SIMULATING GLITCH PARAMETERS

The first method we tried for constructing our approximate distribution $\mathcal{P}(\theta_p, g)$ was utilizing the Bilby precessing CBC waveform $p\left(\theta_p|d, g_A, W_{\nearrow}\right)$ and attaching samples from the BayesWave glitch space $\mathcal{G}(g)$ to draws from the bilby posterior.

$$\mathcal{P}(\theta_p, g) = p\left(\theta_p|d, g_A, W_{\nearrow}\right)\mathcal{G}(g) \tag{7}$$

Now for each $\{\theta_p^i, g^i\}$ sample, both the likelihood $\mathcal{L}(\theta_p, g|d, W_{\nearrow}, G)$ and the prior $\pi(\theta_p, g|W_{\nearrow}, G)$ are calculable.

We can rewrite Eq (1) almost in terms of entirely known quantities,

$$p(\theta_p, g|d, G, W_{\nearrow}) = w_{\mathcal{L}}(\theta_p, g) w_{\pi}(\theta_p, g) \mathcal{P}(\theta_p, g) \frac{Z(d|W_{\nearrow}, g_A)}{Z(d|W_{\nearrow}, G)} \quad (8)$$

$w_{\mathcal{L}}$ being the likelihood weight and w_{π} being the prior weight.

$$w_{\mathcal{L}}(\theta_p, g) = \frac{\mathcal{L}(d|\theta_p, g, W_{\nearrow}, G)}{\mathcal{L}(d|\theta_p, g_A, W_{\nearrow})} \quad (9)$$

$$w_{\pi}(\theta_p, g) = \frac{\pi(\theta_p, g|W_{\nearrow}, G)}{\pi(\theta_p|W_{\nearrow}, g_A)\mathcal{G}(g)}. \quad (10)$$

Finally, using the property

$$x \sim p(x) \rightarrow \int f(x)p(x)dx \approx \frac{1}{N}\Sigma_i^N f(x_i) \quad (11)$$

where $\sim$ means distributed by and $p(x)$ is a normalized probability distribution, and x_i are discrete samples of N total samples. We can estimate the evidence term

$$Z(d|W_{\nearrow}, G) \approx \frac{Z(d|g_A, W_{\nearrow})}{N}\Sigma_i^N w_{\mathcal{L}}(\theta_p^i, g^i) w_{\pi}(\theta_p^i, g^i) = Z(d|g_A, W_{\nearrow})\bar{w}, \quad (12)$$

where $\{i\}$ is indexed over our samples drawn from $\mathcal{P}$ and $\bar{w}$ is the average weight over all samples.

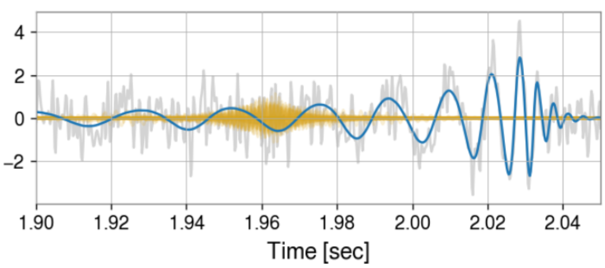

FIG. 3. Bilby precessing waveform in blue lies on top of the signal data in gray and various possible glitch models in 'goldenrod' that coincide with the time of the glitch in the L1 detector

Efficiency for this method was $< 1\%$. The reweighted distributions in Fig. 4 have no continuous shape, indicative of the low efficiency. We decided to revise this method. Previously, to construct our approximate distribution we drew a unique glitch sample for each CBC parameter sample.

VII. SINGLE GLITCH REALIZATION REWEIGHTING

Instead, we used a single glitch realization across all CBC parameter samples in hopes that this method would

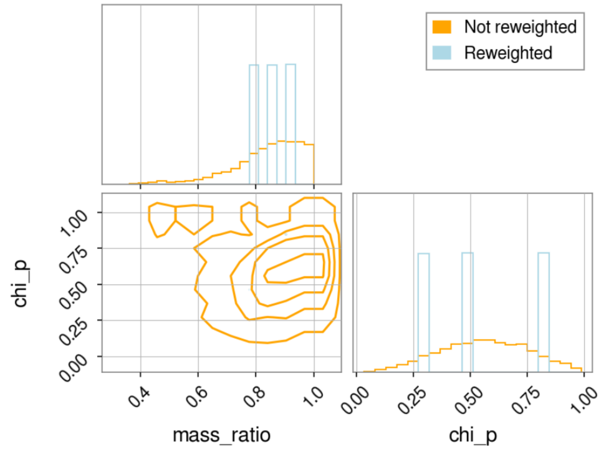

FIG. 4. Corner plot, Chi-p (precession parameter) vs. Mass ratio

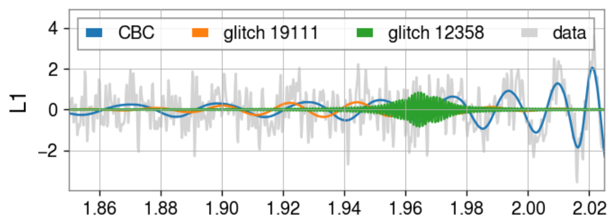

FIG. 5. Bilby precessing waveform in blue lies on top of the signal data in gray with two example glitch models in orange and green

increase efficiency. We attached these draws to samples from the bilby precessing waveform as we had before.

Two example glitch models are shown on Fig. 7. The orange glitch model Fig. 6 contained fewer wavelets but a longer glitch duration thank the green glitch model Fig. 7. It yielded an efficiency of 5.6% which was a small improvement from before. The reweighted probability distributions are continuous but not very distinct from the approximate distributions. The green glitch model Fig. 7 contained many wavelets with a shorter duration. It yielded an unusually high efficiency of 99.99%. The reweighted distribution is identical to the approximate, which implies the glitch model had no effect on the parameter estimation. This lends credence to the conclusions of Payne et al about the posteriors being sensitive to choice of glitch model.

VIII. SIMULATING PRECESSION PARAMETERS

The alternate method for constructing an approximate distribution was starting with a BayesWaveCBC+Glitch run posterior $p(\theta, g|d, W_{\uparrow})$ and drawing random samples from the spin parameters priors $\pi(\theta_+)$. With $W_{\uparrow}$ being the BayesWave run waveform model, θ representing the

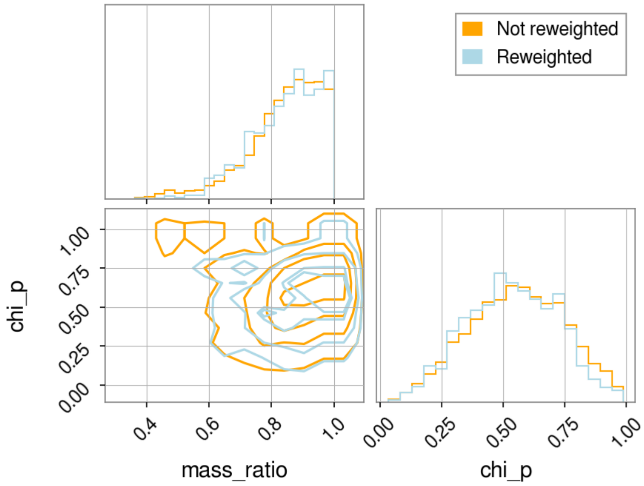

FIG. 6. Corner plot, Chi-p (precession parameter) vs. Mass ratio

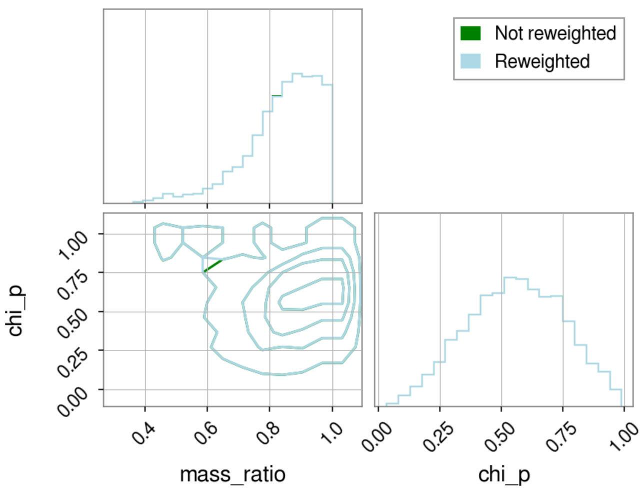

FIG. 7. Corner plot, Chi-p (precession parameter) vs. Mass ratio

non-spinning parameters and $\theta_=$ being the spin precession parameters we begin with.

$$p(\theta, g|d, W_{\uparrow})\pi(\theta_+) = \frac{\mathcal{L}(d|\theta, g, W_{\uparrow})\pi(\theta, g)\pi(\theta_+)}{\mathcal{Z}(d|W_{\uparrow})} \Rightarrow \quad (13)$$

$$p(\theta, g, \theta_+|d, W_{\uparrow}) = \frac{\mathcal{L}(d|\theta, \theta_+, g, W_{\uparrow})\pi(\theta, g, \theta_+)}{\mathcal{Z}(d|W_{\uparrow})} . \quad (14)$$

and want to end up with

$$p(\theta_p, g|d, W_{\nearrow}) = \frac{\mathcal{L}(d|\theta_p, g, W_{\nearrow})\pi(\theta_p, g)}{\mathcal{Z}(d|W_{\nearrow})} , \quad (15)$$

Equation (15) then becomes

$$\begin{aligned} p(\theta_p, g|d, W_{\nearrow}) &= \frac{\mathcal{L}(d|\theta_p, g, W_{\nearrow})\pi(\theta_p, g)}{\mathcal{Z}(d|W_{\nearrow})} \\ &= \frac{\mathcal{L}(d|\theta, \theta_+, g, W_{\uparrow})}{\mathcal{L}(d|\theta, \theta_+, g, W_{\uparrow})} \frac{\mathcal{L}(d|\theta_p, g, W_{\nearrow})\pi(\theta_p, g)}{\mathcal{Z}(d|W_{\nearrow})} , \\ &= \frac{\mathcal{L}(d|\theta_p, g, W_{\nearrow})}{\mathcal{L}(d|\theta, \theta_+, g, W_{\uparrow})} \frac{\mathcal{L}(d|\theta, \theta_+, g, W_{\uparrow})\pi(\theta_p, g)}{\mathcal{Z}(d|W_{\nearrow})} , \end{aligned} \quad (16)$$

Simplifying $\mathcal{L}(d|\theta, \theta_+, g, W_{\uparrow}) = \mathcal{L}(d|\theta, g, W_{\uparrow})$ we end up with

$$p(\theta_p, g|d, W_{\nearrow}) = \frac{\mathcal{L}(d|\theta_p, g, W_{\nearrow})}{\mathcal{L}(d|\theta, g, W_{\uparrow})} \frac{\mathcal{L}(d|\theta, g, W_{\uparrow})\pi(\theta_p, g)}{\mathcal{Z}(d|W_{\nearrow})} . \quad (17)$$

Starting with the samples from the BayesWave posterior that have been augmented with precession parameters drawn from the prior $p(\theta, g, \theta_+|d, W_{\uparrow}) \sim \mathcal{L}(d|\theta, g, W_{\uparrow})\pi(\theta_p, g)$ we re-weight them with weights

$$w_L = \frac{\mathcal{L}(d|\theta_p, g, W_{\nearrow})}{\mathcal{L}(d|\theta, g, W_{\uparrow})} . \quad (18)$$

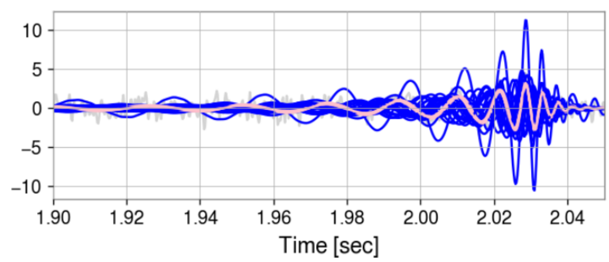

FIG. 8. BayesWaveCBC+Glitch waveform in in pink, different precessing waveforms in blue, signal data in gray

Most of the precessing waveforms do not match well in frequency against the BayesWaveCBC+Glitch waveform , Fig. 8, or the signal data. The efficiency from this method was $< 1\%$. The approximate distributions were much smaller than those constructed in the previous method. The reweighted probability distributions do not share this trait, they feature tall spikes at very specific values Fig. 9.

IX. CONCLUSION

Our goal was to create a posterior that accounts for both the CBC in the waveform as well as the glitch. We attempted three different methods: simulating glitch parameters, reweighting with single glitch realization, simulating precession parameters.

For the simulating glitch parameters method we calculated a very low efficiency while marginalizing over many

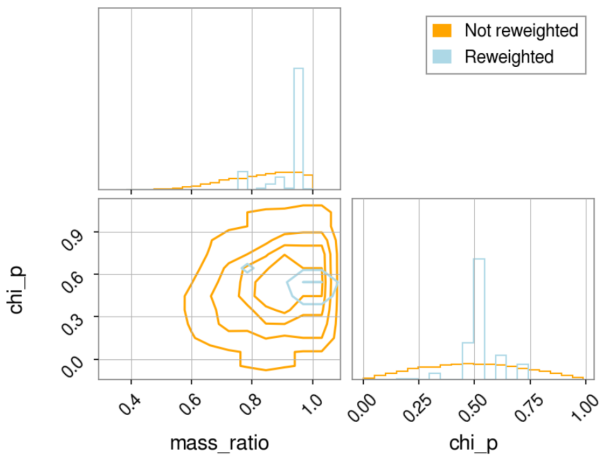

FIG. 9. Corner plot, Chi-p (precession parameter) vs. Mass ratio

different glitch models. We attribute this low efficiency to an ineffective BayesWave run. BayesWave could not confidently identify the characteristics of the glitch within the Livingston detector, and therefore the glitch models provided were not accurate to the actual glitch in the data. Alternately for the revised method of drawing samples from single glitch realizations, we encountered unusually high efficiencies. After examining the signal and the glitch model on the frequency domain we conclude that most glitch models from the BayesWave run do not intersect with the signal and therefore have no impact on the probability distributions. These issues could be resolved with a more confident BayesWave run where the glitch can be more accurately identified, or working with simulated data in order to test the effectiveness of the method. Another potential method is drawing from the glitch prior as we drew from the precession prior, instead of from specific glitch models. Our method of simulating precession parameters yielded low efficiency and waveform models that did not fit the data well. We theorize the problem with this method lies in the difference of waveform models employed by BayesWave and Bilby. BayesWave utilizes the waveform model 'IMRPhenomD' while Bilby uses an 'NRSur' waveform. Parameter spaces from the two distinct waveform models do not translate well between each other, which impacted the effectiveness of the method.

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