Glitch Reweighting by Glitch Parameter Simulation

Julien Kearns
(Dated: May 2023)

I. INTRODUCTION/BACKGROUND

Gravitational waves are ripples in space-time caused by the acceleration of high mass objects. General relativity predicts their existence and they were first observed by LIGO (Laser Interferometer Gravitational-wave Observatory) in 2015. 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 dependant on the parameters of the system. After accounting for the noise in the detectors the waveform can be matched to a model and parameters can be found.

However, glitches in the data can occur which vary in sources, frequency, time, duration and strength. These glitches can interfere with how we account for noise before parameter estimation and lead to biased parameters. To account for glitches we can cut them out or subtract them from the data using the program BayesWave, but BayesWave cannot construct a waveform model for CBC (compact binary coalescence) that includes precession. As concluded in my mentors' paper on GW200129 [1] "any evidence for spin-precession in GW200129 depends sensitively on the glitch model and priors employed".

II. OBJECTIVE

My objective is 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.[1] In other words, a complete CBC (including precession) and glitch parameter space.

Reweighting is the process of starting with one probability distribution of posteriors and calculating new likelihoods on the same samples. Then computing the ratio of likelihoods between both, which become the new weights for the posteriors.

III. METHOD

The first step is understanding the process of reweighting probability distributions in the same parameter space in order to change an "approximate" distribution to a "target" distribution. Then doing the same for a target on a different parameter space by constructing a new approximate distribution that includes both parameter spaces. This can be done by multiplying both probability distributions together.

Starting with a set of posterior samples from a BayesWave CBC+Glitch run

$$p(\theta, g|d, W_{\uparrow}, G) = \frac{\mathcal{L}(d|\theta, g, G, W_{\uparrow})\pi(\theta, g|G, W_{\uparrow})}{Z(d|W_{\uparrow}, G)} \quad (1)$$

where θ are our (non-precessing) CBC parameters, g are our glitch parameters, d is our data, $W_{\uparrow}$ is a non-precessing waveform model, and G is our glitch model (sine-Gaussian wavelets). We want to end up with a posterior distribution that includes the glitch model as well as a fully precessing waveform.

$$p(\theta_p, g|d, W_{\nearrow}, G) = \frac{\mathcal{L}(d|\theta_p, g, G, W_{\nearrow})\pi(\theta_p, g|G, W_{\nearrow})}{Z(d|W_{\nearrow}, G)} \quad (2)$$

where $W_{\nearrow}$ is a precessing waveform model, $\mathcal{L}$ is our likelihood function and π is our prior. We include G and $W_{\nearrow}$ in our priors to differentiate between models with and without precession and/or glitches since priors are not compelled to be the same between models.

To get here we first we draw the glitch model, g_A, evenly from our glitch samples while ignoring CBC samples. Then we subtract g_A from the original data and run the inference library, Bilby, including precession parameters which gives us the posterior

$$p\left(\theta_p|d, g_A, W_{\nearrow}\right) = \frac{\mathcal{L}(d|\theta_p, g_A, W_{\nearrow})\pi(\theta_p|g_A, W_{\nearrow})}{Z(d|W_{\nearrow}, g_A)}, \quad (3)$$

Now we have $\theta_p \sim p\left(\theta_p|d, g_A, W_{\nearrow}\right)$, that is, the CBC precession parameter posterior posterior over a *single* glitch realization (essentially, Fig. 11 in [1]). However we want this posterior over a full g parameter space.

A. Approach: Simulate Glitch Parameters

We will use Eq (3) as an approximate distribution. First we need to increase its dimensions to include the glitch parameter space, which creates a new approximate distribution.

$$\mathcal{P}(\theta_p, g) = p\left(\theta_p|d, g_A, W_{\nearrow}\right)\mathcal{G}(g) \quad (4)$$

Then we can rewrite Eq (2) almost in terms of entirely

[1] the same, or a similar procedure could be used to include something like an eccentric parameter or even higher order modes

known quantities.

$$p(\theta_p, g|d, G, W_{\nearrow}) = w_{\mathcal{L}}(\theta_p, g) w_\pi(\theta_p, g) \mathcal{P}(\theta_p, g) \frac{Z(d|W_{\nearrow}, g_A)}{Z(d|W_{\nearrow}, G)} \quad (5)$$

Finally, using the property

$$x \sim p(x) \to \int f(x)p(x)dx \approx \frac{1}{N} \Sigma_i^N f(x_i) \quad (6)$$

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

$$\begin{aligned} Z(d|W_{\nearrow}, G) &\approx \frac{Z(d|g_A, W_{\nearrow})}{N} \Sigma_i^N w_{\mathcal{L}}(\theta_p^i, g^i) w_\pi(\theta_p^i, g^i) \\ &= Z(d|g_A, W_{\nearrow})\bar{w}, \end{aligned} \quad (7)$$

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

[1] E. Payne, S. Hourihane, J. Golomb, R. Udall, R. Udall, D. Davis, and K. Chatziioannou, Phys. Rev. D **106**, 104017 (2022), arXiv:2206.11932 [gr-qc].