A search for intermediate mass black holes mergers in the second LIGO–Virgo observing run with the Bayes Coherence Ratio

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The detection of an intermediate-mass black hole population (10^2-10^6 M$_\odot$) will provide clues to their formation environments (e.g., disks of active galactic nuclei, globular clusters) and illuminate a potential pathway to produce supermassive black holes. Ground-based gravitational-wave detectors are in principle sensitive to such mergers and have been used to detect one 142^{+28}_{-16} M$_\odot$ intermediate-mass black hole formation event. Ground-based detector data contain numerous short-duration noise transients that can mimic the gravitational-wave signals from merging intermediate-mass black holes, limiting the sensitivity of searches. Here we demonstrate a Bayesian-inspired ranking statistic to detect binary black hole mergers with a total mass $\gtrsim 55$ M$_\odot$. We use this statistic to identify candidate events with total masses > 55 M$_\odot$ using data from LIGO's second observing run. Our analysis does not yield evidence for new intermediate-mass black holes. However, we find support for some stellar-mass binary black holes not reported in the first LIGO–Virgo gravitational-wave transient catalog, GWTC-1.

I. INTRODUCTION

Since the 1970s, there has been a steady accumulation of evidence for stellar mass ($M_{\rm BH} < 10^2$ M$_\odot$) and supermassive black holes ($M_{\rm BH} > 10^6$ M$_\odot$) [1–7]. However, there is a deficiency of observational evidence for black holes in the intermediate-mass range $10^2 - 10^6$ M$_\odot$. The discovery of an intermediate-mass black hole population will bridge this observational gap, probe intermediate-mass formation environments (e.g. accretion disks of active galactic nuclei [8–20], the centers of dense stellar clusters [21–31], Population-III stars [32–36]), and illuminate our understanding of supermassive black hole formation [37–40].

A variety of techniques have been employed to search for $10^4 - 10^6$ M$_\odot$ intermediate mass candidates including reverberation mapping [41], direct kinematic measurements [42, 43], applying macroscopic galaxy to black hole mass scaling relations (M_{BH}-σ and M_{BH}-L relations) [44, 45], studying X-ray luminosity and spectra [46, 47], gravitational lensing of gamma-ray burst light curves [48], and others [49–51]). However, these observational techniques are challenging to use for intermediate mass black holes due to their small sphere of influence compared to super-massive black holes [51]. Additionally, some IMBH candidates can be attributed to sources other than intermediate-mass black holes (e.g., clusters of stellar-mass black holes [52, 53], anisotropic emission from neutron stars [54, 55]), while others have high uncertainties intrinsic to the observational techniques [49]. [ET: Consider replacing previous sentence that says none of the current IMBH candidates are widely accepted within the astronomical community as unambiguous.]

Compact binary coalescences (CBCs) can provide unambiguous gravitational-wave signals for intermediate-mass candidates (e.g., the 142^{+28}_{-16} M$_\odot$ remnant observed from the gravitational wave event GW190521 [56]). As a binary's total mass M$_T$ is associated with its gravitational-wave merger frequency, $f \sim$ M$_T^{-1}$, ground-based gravitational-wave detectors ($f \sim 10^1 - 10^3$ Hz) are sensitive to the last milliseconds of merging systems with 100M$_\odot$ $<$ M$_T$ $<$ 400M$_\odot$ [57–59], while space-based detectors ($f \sim 10^{-2} - 10^1$ Hz) can study the full signals of merging systems with 10^4M$_\odot$ $<$ M$_T$ $< 10^7$M$_\odot$ [59, 60]. Because of the short-duration of intermediate-mass gravitational-wave signals in ground-based detectors, data quality is critical for their detection. Gravitational-wave data is characterized by numerous non-stationary terrestrial artifacts called *glitches* [61–63]. Like signals from intermediate mass mergers, most glitches last for a fraction of a second, making them difficult to distinguish from astrophysical signals. These glitches can decrease the sensitivity of searches for binary black hole mergers with total masses > 55 M$_\odot$ [61].

Although a significant fraction of the glitches can be identified by testing them for coherence amongst two or more detectors and performing matched-filtering, these methods are insufficient to identify all glitches [61–63]. One method to discriminate more glitches while searching for CBC is the Bayesian odds [64–69]. [ET: Need sentence here saying we are inspired by the Bayesian odds to develop a ranking statistic that incorporates some of the ideas used in the odds.] In this paper, we rank O2's candidate gravitational-wave signals from $55-500$ M$_\odot$ ([ET: lab frame]) total mass systems using a ranking statistic called the Bayesian Coherence Ratio ρ_{BCR} [66]. [ET: I deleted some text here going into detail about the BCR; save for method section.] For each candidate, we calculate the probability of astrophysical origin, $p_{\mathrm{astro}}^{\mathrm{BCR}}$ and compare to candidate events reported by other authors including the LIGO-Virgo-KAGRA (LVK) collaboration in GWTC-1 [70], the PyCBC-team [71–80], by the Institute of Advanced study's team (IAS) [81–83], or by Pratten and Vecchio [69]. [ET: Deleted several sentences here about innovations that I think are in the weeds.]

We find that (a) high-mass events reported in the GWTC-1, including GW170729 (the heaviest event in GWTC-1) are very statistically significant $p_{\mathrm{astro}}^{\mathrm{BCR}} > 0.9$; (b) three out of the eight IAS events and candidates have $p_{\mathrm{astro}}^{\mathrm{BCR}} > 0.5$, corroborating IAS's detection claims for GW170304, GW170727, and GW170817A; and that (c) our ranking statistic does not identify any new intermediate-mass black holes, but does identify an unreported marginal stellar-mass binary black hole candidate, 170222 with $p_{\mathrm{astro}}^{\mathrm{BCR}} \sim 0.5$.

The remainder of this paper is structured as follows. We outline our methods, including details of our ranking statistic and the retrieval of our candidates in Section II. We present details on the implementation of our analysis in Section III. Finally, we present our results in Section IV, and discuss these results in the context of the significance of gravitational-wave candidates in Section V.

II. METHOD

The standard framework to identify CBC gravitational-wave signals in data is to quantify the significance of candidates with null-hypothesis significance testing [70, 84]. In this framework, the candidates' ranking statistic is compared against a background distribution. The independent matched-filter searches, e.g., PyCBC [76], SPIIR [85] and GstLAL [86], and Coherent WaveBurst [87] used by LVK to search for signals in gravitational-wave data all use ranking statistics in such a manner [70]. Both PyCBC and GstLAL's ranking statistic incorporate information about the relative likelihood that the data contains a coherent signal versus noise. In contrast, cWB's ranking statistic uses the information of coherent energy present in the network of detectors [70].

Bayesian inference offers an alternative means to rank the significance of candidate events by computing the odds that the data contain a transient gravitational-wave signal versus instrumental glitches [66]. This method relies on accurate models for the signal and glitch morphologies [66]. In principle, Bayesian odds is the optimal method for hypothesis testing [67]. Much of its power comes from the Bayesian evidence, the likelihood of the data given a hypothesis. However, the evidence is not used in current matched filter searches. Here, we explore a hybrid frequentist/Bayesian ranking statistic that makes use of the Bayesian evidence. We compute the Bayesian evidence under the assumption that they either contain a coherent gravitational-wave signal, noise, or a glitch. However, instead of computing true Bayesian odds, we use the evidences as a ranking statistic. We form a bootstrapped distribution of the evidence for simulated foreground and background events in order to form a frequentist ranking statistic.

A. Formalism

Bayes' theorem states that the posterior probability distribution $p(\vec{\theta}|d,\mathcal{H})$ for data d and a vector of parameters $\vec{\theta}$ that describe a model which quantifies a hypothesis $\mathcal{H}$, is given by

$$p(\vec{\theta}|d,\mathcal{H}) = \frac{\mathcal{L}(d|\vec{\theta},\mathcal{H})\ \pi(\vec{\theta}|\mathcal{H})}{\mathcal{Z}(d|\mathcal{H})}\ , \tag{1}$$

where $\mathcal{L}(d|\vec{\theta},\mathcal{H})$ is the likelihood of the data given the parameters $\vec{\theta}$ and the hypothesis, $\pi(\vec{\theta}|\mathcal{H})$ is the prior probability of the parameters, and finally,

$$\mathcal{Z}(d|\mathcal{H}) = \int_{\vec{\theta}} \mathcal{L}(d|\vec{\theta},\mathcal{H})\ \pi(\vec{\theta}|\mathcal{H})\ d\vec{\theta}\ , \tag{2}$$

is the likelihood after marginalizing over the parameters $\vec{\theta}$. To compare two hypotheses $\mathcal{H}_A$ and $\mathcal{H}_B$ through Bayes' theorem one can calculate an odds-ratio

$$\mathcal{O}_B^A = \frac{\mathcal{Z}^A\ \pi^A}{\mathcal{Z}^B\ \pi^B}\ , \tag{3}$$

where $\{\pi^A, \pi^B\}$ are the prior-odds for each hypothesis and $\{\mathcal{Z}^A, \mathcal{Z}^B\}$ are shorthand for the evidences $\{\mathcal{Z}(d|\mathcal{H}_A), \mathcal{Z}(d|\mathcal{H}_B)\}$. The odds-ratio can quantify which of the two hypotheses is more likely. For example, if $\mathcal{O}_B^A >> 1$, then the odds are in favor of the $\mathcal{H}_A$ hypotheses.

The $\mathcal{O}_{\mathrm{BCR}}$ quantity is a Bayesian odds-ratio like the above, of a coherent signal hypotheses $\mathcal{H}_S$ and an incoherent instrumental feature hypothesis $\mathcal{H}_I$ (the null-hypotheses) for a network of D detectors. $\mathcal{H}_{\mathcal{I}}$ states that each detector i has either pure stationary Gaussian noise $\mathcal{H}_N$ or Gaussian noise and an incoherent noise transient (glitch) $\mathcal{H}_G$. Taking Z^S, Z_i^G and Z_i^N as the Bayesian evidences (defined in Appendix A) for $\mathcal{H}_S$, $\mathcal{H}_N$, and $\mathcal{H}_G$, $\mathcal{O}_{\mathrm{BCR}}$ is given by

$$\mathcal{O}_{\mathrm{BCR}} = \frac{\pi^S Z^S}{\prod_{i=1}^{D}\left[\pi^G Z_i^G + (1-\pi^G) Z_i^N\right]}\ , \tag{4}$$

where π^S and π^G are the prior-odds of obtaining a signal or a glitch from a stretch of data. The prior-odds can be defined more explicitly as

- $\pi^S = \pi(\mathcal{H}_S)/\pi(\mathcal{H}_I)$, the prior-odds for obtaining a coherent signal versus an incoherent instrumental feature.
- $\pi^G = \pi(\mathcal{H}_G|\mathcal{H}_I)$, the probability of obtaining a glitch assuming there is an incoherent instrumental feature.

When $\mathcal{H}_S$ and $\mathcal{H}_I$ are precisely described and the prior-odds represent our true beliefs, the $\mathcal{O}_{\rm BCR}$ is a Bayesian odds-ratio. As an odds-ratio, the $\mathcal{O}_{\rm BCR}$ is the optimal discriminator between coherent signals and incoherent instrumental features. However, as the priors-odds are unknown, we *tune* values for prior-odds, $\hat{\pi}^S$ and $\hat{\pi}^G$, to estimate $\mathcal{O}_{\rm BCR}$ with a ranking statistic, $\rho_{\rm BCR}$, given by [ET: I would remove everything in this subsection before this point. Save it for your dissertation if you want, but I don't think we need to review Bayesian basics here. Instead, just begin by saying that we implement the BCR, which is given by Eq. 5 with suitable references to the previous BCR papers. The motivation for the BCR can be summarised in a single sentence.]

$$\rho_{\rm BCR} = \frac{\hat{\pi}^S Z^S}{\prod_{i=1}^{D} \left[\hat{\pi}^G Z_i^G + (1-\hat{\pi}^G) Z_i^N\right]} \ . \tag{5}$$

[ET: Rewrite the remaining paragraphs to explain that how the BCR relates to the odds with just a few sentences, avoiding equations.] In the limit where the estimated prior-odds equal the true prior-odds, $\rho_{\rm BCR} \to \mathcal{O}_{\rm BCR}$. However, as we are uncertain what the true prior-odds are, it is invalid to use the $\rho_{\rm BCR}$ as an odds-ratio to make an informed decision about whether a candidate is from an astrophysical or terrestrial source. Instead of interpreting the $\rho_{\rm BCR}$ as a Bayesian odds-ratio, it can be used as a ranking statistic. Using the $\rho_{\rm BCR}$ as a ranking statistic we can obtain a frequentist significance of a candidate $\rho_{\rm BCR}$-value measured against a background $\rho_{\rm BCR}$ distribution.

When using the $\rho_{\rm BCR}$ as a detection statistic, the prior-odds are empirically tuned to maximize the separation between the $\rho_{\rm BCR}$ distribution of the background (expected to favor the $\mathcal{H}_I$ hypothesis) and the $\rho_{\rm BCR}$ distribution of artificially manufactured simulated signals (expected to favor the $\mathcal{H}_S$ hypothesis). Increasing the separation between the two distributions can improve ability of the $\rho_{\rm BCR}$ to discriminate candidate events as coherent signals or incoherent instrumental features. The tuning process is further described in Appendix B.

B. Estimation of astrophysical signal probability

[ET: Above, I propose to cut the previous subsection way back. I think this subsection can be cut way back too and combined with the previous subsection. Once we have finished talking about $\rho_{\rm BCR}$, we can just state that we use time-shifted data to generate distributions of $\rho_{\rm BCR}$ for noise, which we use to calculate a single-event false alarm probability = the fraction of triggers with a $\rho_{\rm BCR}$ at least that big. (The thing we are currently calling f is a single-event false alarm probability, so we should call it that and give it a better variable name like p_1.) Then comment that we consider N triggers so we also calculate a false-alarm probability with trial factors, which is given by the current Eq. 6. (I suggest you call the false alarm probability with trial factors p_N to avoid confusion.) The text should say how N is determined. I agree that $p_{\rm astro} = 1 - p_N$ is too sloppy to do in a paper. (The reason we are using FAP is because there was not appetite to calculate the distribution of $\rho_{\rm BCR}$ for a plausible signal distribution, which is necessary to get an actual $p_{\rm astro}$.) At this late stage, I think the best thing to do is just say that we are going to report $1 - p_N$ alongside $p_{\rm astro}$ values even though they are apples and oranges. While it's sloppy to compare them directly, they *are* both indicators of significance. Moreover, different groups make different assumptions about the signal distribution, and so the different $p_{\rm astro}$ values are sort of already different fruit; see Shanika's paper. We can explain all this and say we're going to put everything into one table anyway. However, the least bad thing to do is to report p_N without calling it $p_{\rm astro}$. I think most referees can live with that.] Candidate $\rho_{\rm BCR}$-values are either statistically insignificant compared to the background $\rho_{\rm BCR}$ distribution, implying the candidate is more probable to be an incoherent instrumental feature (the $\mathcal{H}_I$ null-hypothesis), or statistically significant relative to the background distribution, indicating the possible presence of an astrophysical signal (the $\mathcal{H}_S$ hypothesis). A false alarm probability with trial factors, FAP, for the candidate $\rho_{\rm BCR}$-value can quantify the significance. The FAP for a $\rho_{\rm BCR}$-value is the probability that a candidate originating from a non-astrophysical source can be falsely identified as a signal once in N trials, and is given by

$$\text{FAP} = 1 - (1-f)^N \ , \tag{6}$$

where f is the probability of observing a background ${\rho_{\rm BCR}}'$ greater than or equal to the candidate $\rho_{\rm BCR}$,

$$f = \frac{\text{Count of } {\rho_{\rm BCR}}' \leq \rho_{\rm BCR}}{\text{Count of } {\rho_{\rm BCR}}'} \ . \tag{7}$$

Finally, the FAP can be used to construct a $p_{\rm astro}$, the probability that a signal is of astrophysical origin [88–90]

$$p_{\rm astro} = 1 - \text{FAP} \ . \tag{8}$$

[AV: Eric, can you take a look at this section about the FAP p-astro?] [AV: The pastro calculation may need some more discussion. Taking pastro = 1-FAP as identifying a real signal can be hugely problematic: `https://en.wikipedia.org/wiki/Misuse_of_p-values`, even though its ok in this case. Maybe the following papers have something that can help motivate this [91–93]]

C. Background estimation

To rank candidate event $\rho_{\rm BCR}$ values we compute a background $\rho_{\rm BCR}$ distribution. We use time-shifted background data from PyCBC [76]. [ET: Add sentence here explaining what time-shifting is and why it is used.] The output of PyCBC's search is a list of times and their corresponding PyCBC ranking statistic $\rho_{\rm PC}$ values. Whenever a local maximum of $\rho_{\rm PC} > \rho_{\rm T}$, where $\rho_{\rm T}$ is some predetermined threshold value, the PyCBC search pipeline produces a single-detector *trigger* associated with the detector and time t_c where the apparent signal in the data has its merger [78]. For each PyCBC background trigger, we calculate $\rho_{\rm BCR}$. [ET: I think this section can be cut way back too. (I've deleted a bunch of stuff w track changes.) I don't think we need to get into the three types of triggers; just focus on background triggers. I would move this discussion into a single subsection along with IIA and IIB. I would cover this stuff *before*getting into FAP calculation. That way, we already have introduced the distribution of $\rho_{\rm BCR}$; it will be more clear what we are talking about.]

III. ANALYSIS

A. Acquisition of triggers

Advanced LIGO's second observing run O2 lasted 38 weeks [94]. The software package, PyCBC [71], was used by LVK to process the O2 data in 22 time-frames (approximately 2 weeks per frame) and found several gravitational-wave events and numerous gravitational-wave candidates [72–78]. Some candidate events were vetoed to be glitches, while others were rejected due to their low significance. The data are divided into these time-frames because the detector's sensitivity does not stay constant throughout the eight-month-long observing period.

In addition to finding candidate events, PyCBC also identified several million background triggers for each time-frame, by searching background data manufactured by time-sliding data within that time-frame. The background triggers help quantify the candidate events' significance for the respective time-frames. Finally, to test the search's sensitivity, PyCBC produced and searched for thousands of simulated signals.

For our study, we filter the PyCBC background, simulated and candidate triggers to include only triggers in the ranges of the parameters presented in Table I. Filtering triggers to this region focuses our analysis to binary black hole mergers with total masses above $> 55{\rm M}_\odot$. This corresponds to binary systems with signal durations $<$ 454 ms, signals which may be mistaken for short-duration glitches. A plot of the PyCBC triggers from one time-frame, during April 23 - May 8, 2017, is presented in Fig. 1. This figure also depicts the gravitational-wave templates used by PyCBC's search through this time-frame of data.

TABLE I. Trigger-selection parameter space (parameters correspond to signals with durations $<$ 454 ms).

	Minimum	Maximum
Component Mass 1 [${\rm M}_\odot$]	31.54	491.68
Component Mass 2 [${\rm M}_\odot$]	1.32	121.01
Total Mass [${\rm M}_\odot$]	56.93	496.72
Chirp Mass [${\rm M}_\odot$]	8.00	174.56
Mass Ratio	0.01	0.98

B. Calculating the BCR for triggers

To evaluate Z^S, Z_i^G and Z_i^N and calculate the $\rho_{\rm BCR}$ Eq. 4 for triggers, we carry out Bayesian inference with Bilby [95, 96], employing dynesty [97] as our nested sampler. Nested sampling, an algorithm introduced by Skilling [98, 99], provides an estimate of the Bayesian evidence and is often utilized for parameter estimation within the LIGO collaboration [95, 100, 101].

The most computationally intensive step during Bayesian inference is evaluating the likelihood $\mathcal{L}(d_i|\mu(\vec{\theta}))$. To accelerate our analysis, we use a likelihood that explicitly marginalizes over coalescence time, phase at coalescence, and luminosity distance (Eq. 80 from Thrane and Talbot [102]). [ET: I think that IIIa and IIb should probably be shrunken and merged so that Section III does not have any subsections (IIC can be deleted; see below). The way to cut these sections down is to stick to just *describing what was done* rather than trying to add a lot of explanation. (Explaining what PyCBC does and why is particularly excessive, IMO.) Just cut out anything that is not part of a recipe to reproduce the analysis.]

We set the priors $\pi(\vec{\theta}|\mathcal{H}_S)$ and $\pi(\vec{\theta}|\mathcal{H}_G)$ to be identical which reflects our ignorance of the distribution of the population properties of signals and signal-like glitches. These priors restrict signals with mass parameters in the ranges presented in Table I. The spins are aligned over a uniform range for the dimensionless spin magnitude from $[0, 1]$. The luminosity distance prior assigns probability uniformly in comoving volume, with an upper cutoff of 5 Gpc. The full list of the priors, along with their shapes, limits and boundary conditions are documented in Table II.

The waveform template we utilize is `IMRPhenomPv2`, a phenomenological waveform template constructed in the frequency domain that models the in-spiral, merger, and ring-down (IMR) of a compact binary coalescence [104]. Although there exist gravitational-wave templates such as `IMRPhenomXPHM` [105], `NRSur7dq4` [106] and `SEOBNRv4PHM` [107] which incorporate more physics, such as information on higher-order modes, we use `IMRPhenomPv2` as it is computationally inexpensive compared to others.

To generate the PSD, we take 31 neighboring off-source non-overlapping 4-second segments of time-series data

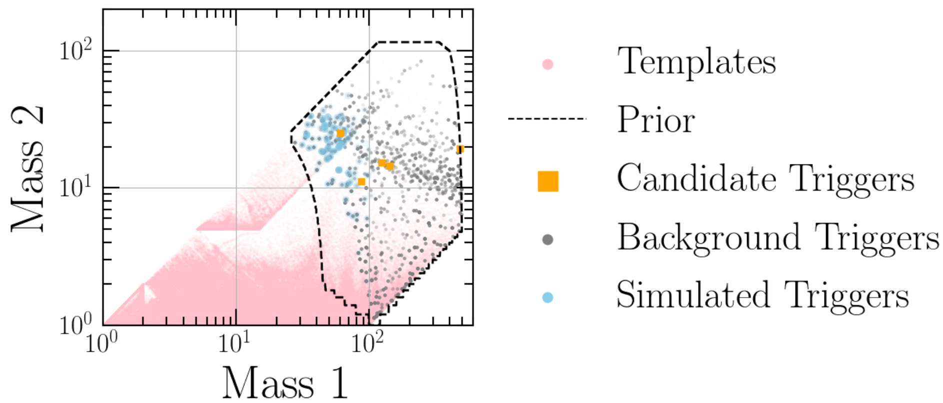

FIG. 1. The templates (pink) used by PyCBC to search a section of O2 data from April 23 - May 8, 2017. Our search is constrained to the parameter space enclosed by the dashed line. The candidate, background and simulated triggers detected in this region of the parameter space during this period are plotted in orange, gray and blue respectively.

TABLE II. Prior settings for the parameters used during our parameter estimation. The definitions of the parameters are documented in Romero-Shaw *et al.* [103] Table E1. The trigger time t_c is obtained from the data products of PyCBC's O2 search.

Parameter	Shape	Limits
$\mathcal{M}/\mathrm{M}_\odot$	Uniform	7–180
q	Uniform	0.1–1
$M/\mathrm{M}_\odot$	Constraint	50–500
$d_\mathrm{L}/\mathrm{Mpc}$	Comoving	100–5000
a_1, a_2	Uniform	0–1
θ_{JN}	Sinusoidal	0–π
ψ	Uniform	0–π
ϕ	Uniform	0–2π
ra	Uniform	0–2π
dec	Cosine	0–2π
t_c/s	Uniform	$t_c \pm 0.1$

before the analysis data segment d_i. To suppress spectral leakage, a Tukey window with a 0.2-second roll-off is applied to each data segment . After this the segments are fast-Fourier transformed and median-averaged to create a PSD [108]. Like other PSD estimation methods, this method adds statistical uncertainties to the PSD [109–111]. To marginalize over the statistical uncertainty, we use the median-likelihood presented by Talbot and Thrane [109] as a post-processing step. We find that this post-processing step improves the search efficiency by 49.26% the details of this calculation are presented in the Appendix C.

Finally, we acquire the foreground, background and data in which we inject simulated signals into, from from the gravitational-wave Open Science Center [94]. The data we use are the publicly accessible O2 strain data from the Hanford and Livingston detectors, recorded while the detectors are in "Science Mode". We obtain the data using GWpy [112].

C. Assigning p_astro to candidate events

After calculating the ρ_BCR for the entire set of background and simulated triggers, we calculate the background and simulated ρ_BCR probability distributions for each 2-week time-frame of O2 data. These distributions are used to 'tune' prior-odd $\hat{\pi}^S$ and $\hat{\pi}^G$ values as described in Appendix B. [ET: This subsection discusses formalism (how the analysis works) and so it feels out of place in Section III, which is about the details of the implementation. I would delete this subsection entirely and just add a sentence or two to the formalism section explaining that the π's are tuned emprically; see Appendix B.]

Using the tuned prior-odds the ρ_BCR for the candidate events can be calculated. Fig. 2 shows the ρ_BCR distributions for the background triggers, simulated triggers and candidate events. The bulk of the background and simulated trigger distributions are separate but slightly overlap due to some of the simulated signal's being very faint. The separation suggests that the ρ_BCR can successfully distinguish signals from noise or glitches. The vertical lines in Fig. 2 displays the ρ_BCR for gravitational-wave candidate events. On comparing the candidate event ρ_BCR values with the background distribution, we can estimate p_astro values for the candidate events.

IV. RESULTS

We analyze the 60,996 background, 5,146 simulated, and 25 candidate triggers reported by PyCBC's search on the data from LIGO's second observing run, restricting our analysis to the triggers that fall within our mass-space as described in Section II. We also analyze events and candidate events reported by GWTC-1 and the IAS group (note: some of these were identified as candidates

TABLE III. The $p_{\rm astro}$ of gravitational wave events from various detection pipelines, along with the event candidates with $p_{\rm astro}^{\rm BCR} > 0.3$. Only the candidates and events within our prior space are displayed. The various pipeline $p_{\rm astro}$ represented in this table, $p_{\rm astro}^{\rm ext}$, are from the following pipelines: GstLAL $^{\heartsuit}$ [70], PyCBC $^{\spadesuit}$ [70], PyCBC OGC-2 $^{\clubsuit}$ [80], PyCBC 'single-search' $^{\diamondsuit}$ [79], IAS * [82, 83], and Pratten and Vecchio [69]'s significances $^{\blacktriangle}$. The catalogs labelled IAS-1 and IAS-2 correspond to the candidates published in Venumadhav *et al.* [82] and Zackay *et al.* [83].

Event	Catalog	$p_{\rm astro}^{\rm BCR}$	$p_{\rm astro}^{\rm ext}$	t_c
GW170104	GWTC-1	0.94	$1.00^{\heartsuit}; 1.00^{\spadesuit}; 1.0^{\blacktriangle}$	1167559934.60
GW170121	IAS-1	0.76	$1.00^{\clubsuit}; 1.00^{\star}; 0.53^{\blacktriangle}$	1169069152.57
170222	-	0.49	-	1171814476.97
170302	IAS-1	0.64	$0.45^{\star}; 0.0^{\blacktriangle}$	1172487815.48
GW170304	IAS-1	0.83	$0.70^{\clubsuit}; 0.99^{\star}; 0.03^{\blacktriangle}$	1172680689.36
GWC170402	IAS-2	0.38	$0.68^{\star}; 0.03^{\diamondsuit}; 0.0^{\blacktriangle}$	1175205126.57
GW170403	IAS-1	0.33	$0.03^{\clubsuit}; 0.56^{\star}; 0.27^{\blacktriangle}$	1175295987.22
GW170425	IAS-1	0.10	$0.21^{\clubsuit}; 0.77^{\star}; 0.74^{\blacktriangle}$	1177134830.18
GW170608	GWTC-1	0.95	$0.92^{\heartsuit}; 1.00^{\spadesuit}; 1.0^{\blacktriangle}$	1180922492.50
GW170727	IAS-1	0.92	$0.99^{\clubsuit}; 0.98^{\star}; 0.66^{\blacktriangle}$	1185152686.02
GW170729	GWTC-1	0.96	$0.98^{\heartsuit}; 0.52^{\spadesuit}; 1.0^{\blacktriangle}$	1185389805.30
GW170809	GWTC-1	0.98	$0.99^{\heartsuit}; 1.00^{\spadesuit}; 1.0^{\blacktriangle}$	1186302517.75
GW170814	GWTC-1	1.00	$1.00^{\heartsuit}; 1.00^{\spadesuit}; 1.0^{\blacktriangle}$	1186741859.53
GW170817A	IAS-2	0.83	$0.86^{\star}; 0.36^{\diamondsuit}; 0.02^{\blacktriangle}$	1186974182.72

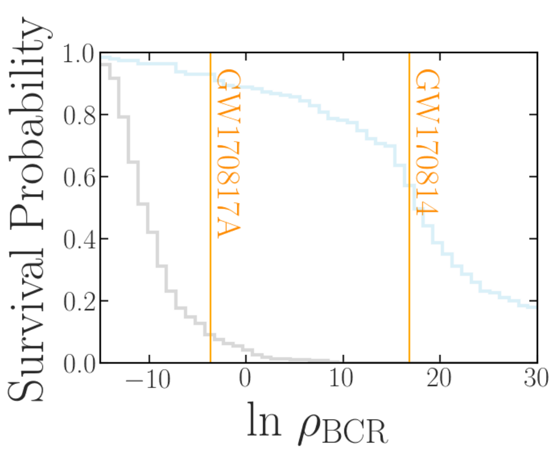

FIG. 2. Histograms represent the survival function (1-CDF) from our selection of background triggers (gray) and simulated signals (blue) triggers obtained from PyCBC's search of data from August 13 - 21, 2017. Vertical lines mark the ln $\rho_{\rm BCR}$ of IAS's GW170817A and GWTC-1's GW170814.

by the PyCBC search). Table III summaries the $p_{\rm astro}^{\rm BCR}$, along with the $p_{\rm astro}$ of other pipelines for comparison. [ET: The previous text about what we analysed should go in Section III. This section is just for reporting the results.]

[ET: Rewrite the following text w better explanation of FAP vs p-value.] Although the various pipeline $p_{\rm astro}$ are not mathematically equivalent, by comparing pipeline $p_{\rm astro}$ values for a given candidate, we can compare how significant each pipeline deems various candidates. The $\hat{\pi}^S$ and $\hat{\pi}^G$ values utilized for each time-frame are reported in Appendix D.

A. GWTC-1 Events

All the confirmed gravitational-wave events from binary black hole mergers reported in GWTC-1 and within our prior space, (specifically GW170104, GW170608, GW170729, GW170809 and GW170814), have $p_{\rm astro}^{\rm BCR} > 0.9$, indicating a high probability of an astrophysical signal.

In addition to the above confirmed gravitational-wave events from GWTC-1, we have also analyzed several candidate events from GWTC-1, most of which have low $p_{\rm astro}^{\rm BCR}$. For example, consider the candidate event 170412, assigned a $p_{\rm astro}$ of 0.06 by GstLAL and has a $p_{\rm astro}^{\rm BCR}$ of 0.01. This candidate was reported to be excess power caused due noise appearing non-stationary between 60-200 Hz [70]. This candidate acts as an example of how $p_{\rm astro}^{\rm BCR}$ may be utilized to eliminate candidates originating from terrestrial noise sources.

B. IAS Events

Our analysis of the IAS events and candidates with $M_T > 55$ M$_\odot$ in O2 has resulted in three events with disfavored $p_{\rm astro}^{\rm BCR} < 0.5$ (GWC170402, GW170403, GW170425), and four events and one candidate with $p_{\rm astro}^{\rm BCR} \geq 0.5$ (GW170121, 170302, GW170304, GW170727, GW170817A). While GW170727 and GW170817A's $p_{\rm astro}^{\rm BCR}$ are similar to the $p_{\rm astro}$ reported from IAS (the differences between the $p_{\rm astro}$ from $\rho_{\rm BCR}$ and IAS is $|\Delta p_{\rm astro}| < 0.1$), the remaining candidates have opposing $p_{\rm astro}$ values (with $|\Delta p_{\rm astro}| > 0.15$).

GWC170402, detected by Zackay *et al.* [83], is reported to originate from a binary with non-zero eccentricity [83]. Hence, we might have computed a low $p_{\rm astro}^{\rm BCR}$ due to our usage of IMRPhenomPv2, a waveform that does not account for eccentricity. Additionally, the search conducted by Zackay *et al.* [83] was a single-detector search. Our ranking statistic relies on the signal to appear coherent, even if just faintly coherent, amongst the various detectors to have a high $p_{\rm astro}^{\rm BCR}$. The lack of coherence and the non-eccentric waveform may be the leading factors for a low $p_{\rm astro}$. GW170403 and GW170425 which have $p_{\rm astro}^{\rm BCR} < 0.35$ also have low $p_{\rm astro}$ reported by Nitz *et al.* [80], suggesting that these events may have been false alarms.

From the candidates with $p_{\rm astro}^{\rm BCR} > 0.5$, GW170727 and 170302 are of particular interest, with $p_{\rm astro}^{\rm BCR}$ of 0.92 and 0.63. GW170727 was emitted from a black hole binary system with a source frame total mass ≈ 70 $\rm M_{\odot}$. In addition to the high $p_{\rm astro}^{\rm BCR}$ reported by our study, Venumadhav *et al.* [82] and Nitz *et al.* [80] have also reported high $p_{\rm astro}$ values of 0.98 and 0.99, making it a viable gravitational-wave event candidate. Similarly, the sub-marginal-candidate 170302 reported by [82] with a $p_{\rm astro}$ of 0.45 appears to have a higher significance from our analysis, resulting in a $p_{\rm astro}^{\rm BCR}$ of 0.63.

C. New Candidate Events

Although no clear detections are made with the $\rho_{\rm BCR}$, a marginal-candidate 170222 has been discovered with a $p_{\rm astro}^{\rm BCR} \sim 0.5$. This candidate has an SNR$\sim$ 7.7, low spin magnitudes and source-frame component masses of $(47.16^{+8.00}_{-5.77}, 35.50^{+5.79}_{-6.35})\rm M_{\odot}$, making it one of the heavier black-hole mergers from O2 and GWTC-1. This candidate may be of interest as one component black hole may lie in the pair-instability mass gap $(55^{+10}_{-10} - 148^{+13}_{-12}\rm M_{\odot})$ [113, 114]. More details on the candidate are presented in Appendix E. The remaining coherent trigger candidates all have $p_{\rm astro}^{\rm BCR} \ll 0.5$ making them unlikely to originate from astrophysical sources.

V. CONCLUSION

In this paper, we demonstrate that the Bayesian Coherence Odds-Ratio $\rho_{\rm BCR}$ [66] can be used as a ranking statistic to provide a measure of significance for gravitational wave signals originating from CBCs with total masses between $55\rm M_{\odot}$ and $400\rm M_{\odot}$, a range that includes intermediate-mass black holes. To compute the $\rho_{\rm BCR}$ for candidates, we utilize Bayesian inference to explicitly calculate the probability of data under various hypotheses (the hypotheses that the data contains a coherent signal, just noise, or an incoherent glitch). This Bayesian ranking method takes a step towards building a unified Bayesian framework that provides a search-pipeline agnostic measure of significance for candidates and estimates their parameters, utilizing the same level of physical information incorporated during detected parameter estimation studies.

In our study, we analyze O2 binary-black hole events and candidates with $M_T > 55\rm M_{\odot}$ reported by the PyCBC search [80], the IAS-team [82, 83] and those reported in GWTC-1 [70]. Using $p_{\rm astro}^{\rm BCR}$, we find that the GWTC-1 events have high probabilities of originating from an astrophysical source. We also find that some of the GWTC-1 marginal triggers that have corroborated terrestrial sources (for example, candidate 170412) have low $p_{\rm astro}^{\rm BCR}$, indicating this method's ability to discriminate between terrestrial artifacts and astrophysical signals. Our analysis of the IAS events demonstrates that GW170121, GW170727, and GW170817A are likely to originate from astrophysical sources, while GWC170402, GW170402, and GW170425 are not. Finally, we do not identify any new gravitational-wave events, but we find a new marginal binary-black hole merger candidate, 170222.

Although our analysis targets triggers with $M_T > 55\rm M_{\odot}$, this method can be extended to include the entire range of LIGO-detectable gravitational-wave sources. Additionally, to further improve the method's infrastructure, we can use more robust gravitational-wave templates (such as templates that incorporate higher-order modes and orbital precession) and sophisticated glitch models. Future analysis can also incorporate data from all available detectors in a network to increase the sensitivity of $p_{\rm astro}^{\rm BCR}$.

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Appendix A: Bayesian Evidence Evaluation

1. Noise Model

We assume that each detector's noise is Gaussian and stationary over the period being analyzed [108]. In practice, we assume that the noise has a mean of zero that the noise variance σ^2 is proportional to the noise power spectral density (PSD) $P(f)$ of the data. Using the $P(f)$, for each frequency-domain data segment d_i in each of the i detectors in a network of D detectors, we can write

$$Z_i^N = \mathcal{N}(d_i|\mu = 0, \sigma^2 = P(f)), \tag{A1}$$

where $\mathcal{N}$ is a normal distribution.

2. Coherent Signal Model

We model coherent signals using a binary black hole waveform template $\mu(\vec{\theta})$, where the vector $\vec{\theta}$ contains a point in the 12 dimensional space describing aligned-spin binary-black hole mergers. For the signal to be coherent, $\vec{\theta}$ must be consistent in each 4-second data segment d_i for a network of D detectors. Hence, the coherent signal evidence is calculated as

$$Z^S = \int\limits_{\vec{\theta}} \prod_{i=1}^{D} \left[\mathcal{L}(d_i|\mu(\vec{\theta}))\right] \pi(\vec{\theta}|\mathcal{H}_S)\ \mathrm{d}\vec{\theta}\ , \tag{A2}$$

where $\pi(\vec{\theta}|\mathcal{H}_S)$ is the prior for the parameters in the coherent signal hypothesis, and $\mathcal{L}(d_i|\mu(\vec{\theta}))$ is the likelihood for the coherent signal hypothesis that depends on the gravitational-wave template $\mu(\vec{\theta})$ and its parameters $\vec{\theta}$.

3. Incoherent Glitch Model

Finally, as glitches are challenging to model and poorly understood, we follow Veitch and Vecchio [64] and utilize a surrogate model for glitches: the glitches are modeled using gravitational-wave templates $\mu(\vec{\theta})$ with uncorrelated parameters amongst the different detectors such that $\vec{\theta}_i \neq \vec{\theta}_j$ for two detectors i and j [64]. Modeling glitches with $\mu(\vec{\theta})$ captures the worst case scenario: when glitches are identical to gravitational-wave signals (excluding coherent signals). Thus, we can write Z_i^G as

$$Z_i^G = \int\limits_{\vec{\theta}} \mathcal{L}(d_i|\mu(\vec{\theta}))\ \pi(\vec{\theta}|\mathcal{H}_G)\ \mathrm{d}\vec{\theta}\ , \tag{A3}$$

where $\pi(\theta|\mathcal{H}_G)$ is the prior for the parameters in the incoherent glitch hypothesis.

Appendix B: Tuning the prior-odds

After calculating the ρ_{BCR} for a set of background triggers and simulated triggers from as stretch of detector-data (a data chunk), we can compute probability distributions for the background and simulated triggers, $p_b(\rho_{\mathrm{BCR}})$ and $p_s(\rho_{\mathrm{BCR}})$. We expect the background trigger and simulated signal ρ_{BCR} values to favor the incoherent glitch and the coherent signal hypothesis, respectively. Ideally, these distributions representing two unique populations should be distinctly separate and have no overlap in their ρ_{BCR} values. The prior odds parameters $\hat{\pi}^S$ and $\hat{\pi}^G$ from Eq. 4 help separate the two distributions. Altering $\hat{\pi}^S$ translates the ρ_{BCR} probability distributions while adjusting $\hat{\pi}^G$ spreads the distributions (refer to Appendix A of Isi *et al.* [66]). Although Bayesian hyper-parameter estimation can determine the optimal values for $\hat{\pi}^S$ and $\hat{\pi}^G$, an easier approach is to adjust the parameters for each data chunk's ρ_{BCR} distribution. In this study, we tune $\hat{\pi}^S$ and $\hat{\pi}^G$ to maximally separate the ρ_{BCR} distributions for the background and simulated triggers.

To calculate the separation between $p_b(\rho_{\mathrm{BCR}})$ and $p_s(\rho_{\mathrm{BCR}})$, we use the Kullback–Leibler divergence (KL divergence) D_{KL}, given by

$$D_{KL}(p_b|p_s) = \sum_{x\in\rho_{\mathrm{BCR}}} p_b(x) \log\left(\frac{p_b(x)}{p_a(x)}\right)\ . \tag{B1}$$

The $D_{KL} = 0$ when the distributions are identical and increases as the asymmetry between the distributions increases.

We limit our search for the maximum KL-divergence in the $\hat{\pi}^S$ and $\hat{\pi}^G$ ranges of $[10^{-10}, 10^0]$. We set our values for $\hat{\pi}^S$ and $\hat{\pi}^G$ to those which provide the highest KL-divergence and calculate the ρ_{BCR} for candidate events present in this data chunk. Note that we conduct the analysis in data chunks of a few days rather than an entire data set of a few months as the background may be different at different points of the entire data set.

Appendix C: Marginalizing over PSD statistical uncertainties

To generate the results in Fig. 2, we applied a post-processing step to marginalize the uncertainty in the PSD. In Fig. 3, we show the results if this post-processing step is not applied. Clearly, marginalizing over uncertainty in the PSD yields an improvement in the separation of the noise and signal distributions. Quantitatively, at a threshold ${\rho_{\rm BCR}}^T = 0$ the post-processing step results in a reduction in the number of background $\rho_{\rm BCR} > {\rho_{\rm BCR}}^T$ from 60.7% to 25.28% in the August 13 - 21, 2017 time-frame of data. For the entirety of O2 PSD marginalization resulted in a 49.26% improvement in search efficiency.

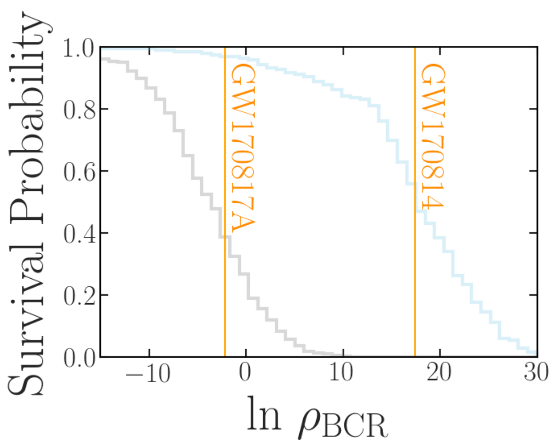

FIG. 3. This plot is analogous to Fig. 2, but without using the post-processing step to marginalize over PSD statistical uncertainties. Without the post-processing step, there is a greater overlap between the background (gray) and foreground (blue) survival functions. For more details about this plot, refer to the caption of Fig. 2.

Appendix D: Tuned prior odds

O2 lasted several months over which the detector's sensitivity varied. Hence, a part of our analysis entailed tuning the prior odds for obtaining a signal and a glitch, $\hat{\pi}^S$ and $\hat{\pi}^G$, as described in Section II. Table IV presents the signal and glitch prior odds utilized for each time-frame of O2 data.

Tuning the prior odds can dramatically affect the $p_{\rm astro}^{\rm BCR}$. For example, consider Table V, which reports tuned $p_{\rm astro}^{\rm BCR}$ and un-tuned $p_{\rm astro}^{\rm BCR\prime}$ (where $\hat{\pi}^S = 1$ and $\hat{\pi}^G = 1$) for various events and candidates. By tuning the prior odds, the $p_{\rm astro}^{\rm BCR}$ for some IAS events (for example, GW170403 and GW170817A) can change by more than 0.5, resulting in the promotion/demotion of a candidate's significance.

Appendix E: A closer look at 170222

PyCBC found the candidate 170222 with $\mathcal{M}_c = 49.46$ and $q = 0.68$, values that fall within our uncertainty limits. Some of the posteriors that were produced as a by-product of our $\rho_{\rm BCR}$ calculation can be viewed in Fig. 4.

TABLE IV. The prior odds used for each time-frame of data from O2. Each time frame commences at the start date and concludes at the following time-frame's start date.

Start Date	$\hat{\pi}^S$	$\hat{\pi}^G$
2016-11-15	-	-
2016-11-30	-	-
2016-12-23	1.00E+00	6.25E-01
2017-01-22	1.00E+00	2.33E-02
2017-02-03	1.00E-10	2.44E-01
2017-02-12	1.76E-08	5.96E-02
2017-02-20	6.55E-10	2.22E-03
2017-02-28	1.00E-10	5.96E-02
2017-03-10	2.56E-10	3.91E-01
2017-03-18	1.60E-10	1.00E+00
2017-03-27	1.10E-08	5.96E-02
2017-04-04	3.73E-02	2.33E-02
2017-04-14	1.05E-09	2.44E-01
2017-04-23	2.68E-09	1.46E-02
2017-05-08	1.00E+00	2.44E-01
2017-06-18	6.55E-10	3.39E-04
2017-06-30	2.02E-05	5.69E-03
2017-07-15	1.05E-09	9.54E-02
2017-07-27	1.00E+00	2.12E-04
2017-08-05	2.12E-04	3.73E-02
2017-08-13	2.68E-09	8.69E-04
2017-08-21	-	-

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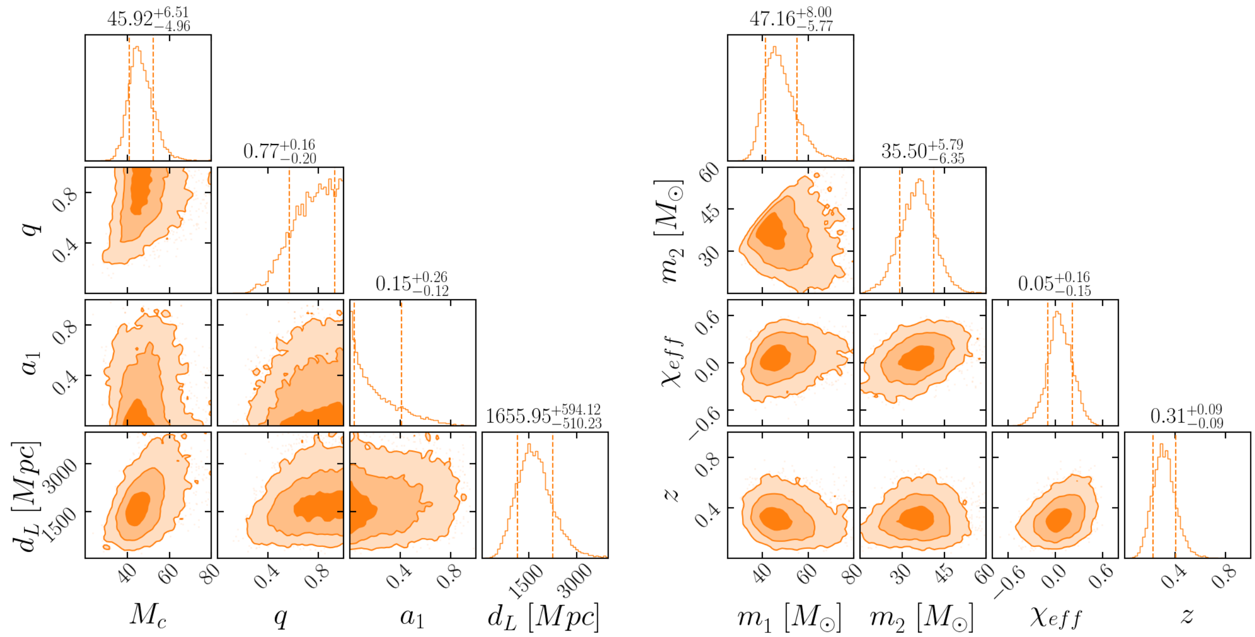

FIG. 4. Posterior distributions for 8 parameters of 170222. Left: Posterior probability distributions for 4 of the 12 search parameters. Right: Posterior probability distributions for 4 derived parameters.

TABLE V. The BCR p-astro after tuning the prior odds, $p_{\rm astro}^{\rm BCR}$, and without tuning the prior odds, $p_{\rm astro}^{\rm BCR\prime}$ (where $\hat{\pi}^S = 1$ and $\hat{\pi}^G = 1$).

Event	Catalog	$p_{\rm astro}^{\rm BCR}$	$p_{\rm astro}^{\rm BCR\prime}$
161202	-	0.09	0.41
GW170104	GWTC-1	0.94	0.93
GW170121	IAS-1	0.76	0.72
170206	-	0.11	0.52
170222	-	0.49	0.49
170302	IAS-1	0.64	0.54
GW170304	IAS-1	0.83	0.81
GWC170402	IAS-2	0.38	0.01
GW170403	IAS-1	0.33	0.89
GW170425	IAS-1	0.10	0.22
GW170608	GWTC-1	0.95	0.95
GW170727	IAS-1	0.92	0.96
GW170729	GWTC-1	0.96	0.94
GW170809	GWTC-1	0.98	0.99
GW170814	GWTC-1	1.00	1.00
GW170817A	IAS-2	0.83	0.36

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