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

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ABSTRACT

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 sensitive to a subset of such mergers and have been used to detect one $142^{+28}_{-16}\ M_\odot$ intermediate-mass black hole formation event. However, ground-based detector data contain numerous incoherent short duration noise transients that can mimic the gravitational-wave signals from merging intermediate-mass black holes, limiting the sensitivity of searches. Here we search for binary black hole mergers using a Bayesian-inspired ranking statistic which measures the coherence or incoherence of triggers in multiple-detector data. We use this statistic to identify candidate events with lab-frame total masses $\gtrsim 55\ M_\odot$ 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.

Key words: gravitational waves – transients: black hole mergers – stars: black holes – methods: statistical – methods: data analysis

1 INTRODUCTION

A variety of techniques have been employed to search for $10^4 - 10^6\ M_\odot$ intermediate-mass black hole (IMBH) candidates including reverberation mapping (Peterson 2014), direct kinematic measurements (Schödel et al. 2002; Kızıltan et al. 2017), applying macroscopic galaxy to black hole mass scaling relations, M_{BH}-σ and M_{BH}-L relations (Graham & Scott 2013; Wevers et al. 2017), studying X-ray luminosity and spectra (Greene & Ho 2004; Lin et al. 2020), gravitational lensing of gamma-ray burst light curves (Paynter et al. 2021), and others (see Greene et al. 2020; Koliopanos 2017; Mezcua 2017). However, because IMBH have smaller gravitational spheres of influence than those of supermassive black holes, it is much more challenging to observe them with these observational techniques (Mezcua 2017). Additionally, the numerous IMBH candidates discovered using these techniques are ambiguous as other sources can describe observations from the candidates (e.g., light sources orbiting clusters of stellar-mass black holes Ridolfi et al. 2016; Freire et al. 2017, anisotropic emission from neutron stars Israel et al. 2017; Rodríguez Castillo et al. 2020).

Stellar mass ($M_{\rm BH} < 10^2\ M_\odot$) and supermassive black holes ($M_{\rm BH} > 10^6\ M_\odot$) have been observed and well studied since the 1970s (Webster & Murdin 1972; Balick & Brown 1974; Ghez et al. 1998; Genzel et al. 2010; Abbott et al. 2019c; Event Horizon Telescope Collaboration et al. 2019; Abbott et al. 2020b). 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 IMBH population will bridge this observational gap, probe IMBH formation environments (e.g. accretion disks of active galactic nuclei Tagawa et al. 2021; Li et al. 2021; Samsing et al. 2020; Tagawa et al. 2020; Ishibashi & Gröbner 2020; Gröbner et al. 2020; Yang et al. 2019a; McKernan et al. 2019; Yang et al. 2019b; McKernan et al. 2018; Bellovary et al. 2016; McKernan et al. 2014, 2012, the centers of dense stellar clusters Banerjee 2021b; Zevin et al. 2021; Mapelli et al. 2021; Weatherford et al. 2021; Bouffanais et al. 2021; Ballone et al. 2021; Kumamoto et al. 2021; Banerjee 2021a; Martinez et al. 2020; Romero-Shaw et al. 2020b; Anagnostou et al. 2020, Population-III stars Toubiana et al. 2021; Farrell et al. 2021;

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Safarzadeh & Haiman 2020; Liu & Bromm 2020; Inayoshi et al. 2017), and illuminate our understanding of supermassive black hole formation (Askar et al. 2021; Arca Sedda & Mastrobuono-Battisti 2019; Amaro-Seoane et al. 2007; Gürkan et al. 2006).

Compact binary coalescences (CBCs) can provide unambiguous gravitational-wave signals for IMBH candidates e.g., the $142^{+28}_{-16}\,M_{\odot}$ (90% credible intervals) remnant observed from the gravitational-wave event GW190521 (Abbott et al. 2020d) and other candidates (Abbott et al. 2019a; The LIGO Scientific Collaboration et al. 2021; Chandra et al. 2021). As a binary's lab-frame total mass M is associated with its gravitational-wave merger frequency, $f \sim M^{-1}$, ground-based gravitational-wave detectors ($f \sim 10^1 - 10^3$ Hz) are sensitive to the last milliseconds of merging systems with $100\,M_{\odot} < M < 400\,M_{\odot}$ (LIGO Scientific Collaboration et al. 2015; Martynov et al. 2016; Moore et al. 2014; Acernese et al. 2015), while space-based detectors ($f \sim 10^{-2} - 10^1$ Hz) can study the full signals of merging systems with $10^4\,M_{\odot} < M < 10^7\,M_{\odot}$ (Moore et al. 2014; Lu et al. 2019). Because of the short duration of IMBH 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* (Nitz 2018; Powell 2018; Cabero et al. 2019). Like signals from IMBH 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 $M \gtrsim 55\,M_{\odot}$ (Nitz 2018).

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 (Nitz 2018; Powell 2018; Cabero et al. 2019). One method to discriminate more glitches while searching for CBCs is the Bayesian odds (Veitch & Vecchio 2010; Kanner et al. 2016; Isi et al. 2018; Ashton et al. 2019b; Ashton & Thrane 2020; Pratten & Vecchio 2020). The Bayesian Coherence Ratio $\rho_{\rm BCR}$ (Isi et al. 2018; Ashton et al. 2019b) is a Bayesian odds comparing the probability that the data contains coherent signals vs. incoherent glitches. In this paper, we use the $\rho_{\rm BCR}$ to rank O2's coincident CBC gravitational-wave candidates with lab-frame total masses in the range of $55 - 500\,M_{\odot}$. We present the candidates' $p_{\rm S}$, the probability that the candidate originates from a coherent gravitational-wave source. Additionally, for comparison, we provide the candidate's $p_{\rm astro}$ values reported by the LIGO-Virgo-KAGRA (LVK) collaboration in GWTC-1 (Abbott et al. 2019d), the PyCBC-team (Nitz et al. 2020a; Allen et al. 2012; Allen 2005; Nitz et al. 2017; Dal Canton et al. 2014; Usman et al. 2016; Nitz et al. 2018; Davies et al. 2020; Nitz et al. 2020c,b), by the Institute of Advanced study's team (IAS) (Venumadhav et al. 2019b; Venumadhav et al. 2019a; Zackay et al. 2019), and by Pratten & Vecchio (2020).

We find that (a) events reported in GWTC-1, including GW170729 (likely the most massive BBH system in GWTC-1) are statistically significant $p_{\rm S} > 0.9$; (b) three out of the eight IAS events and candidates have $p_{\rm S} > 0.9$, corroborating IAS's detection claims for GW170304, GW170727, and GW170817A; and that (c) our ranking statistic does not identify any new IMBH, but does identify an unreported marginal stellar-mass binary black hole candidate, 170222[1] with $p_{\rm S} \sim 0.6$.

[1] 170222 is a sub-threshold candidate detected by PyCBC ($t_c = 1171814476.97$) with a $p_{\rm S} \sim 0.6$. The prefix of GW is not utilized as this is a candidate event.

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 2. We present details on the implementation of our analysis in Section 3. Finally, we present our results in Section 4 and discuss these results in the context of the significance of gravitational-wave candidates in Section 5.

2 METHOD

2.1 A Bayesian Ranking Statistic

The standard framework to identify CBC gravitational-wave signals in data is to quantify the significance of candidates with null-hypothesis significance testing (Abbott et al. 2019d, 2020c). In this framework, the candidates' ranking statistic is compared against a background distribution. The independent matched-filter searches, e.g., PyCBC (Usman et al. 2016), SPIIR (Chu et al. 2020) and GstLAL (Sachdev et al. 2019), and Coherent WaveBurst (Klimenko et al. 2016) used by LVK to search for signals in gravitational-wave data all use ranking statistics in such a manner (Abbott et al. 2019d). 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 (Abbott et al. 2019d).

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 (Isi et al. 2018). This method relies on accurate models for the signal and glitch morphologies (Isi et al. 2018). In principle, Bayesian odds is the optimal method for hypothesis testing (Ashton et al. 2019b). 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 the data either contain a coherent gravitational-wave signal, noise, or a glitch (Z^S, Z^N, Z^G, defined in Appendix A). 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 to form a frequentist ranking statistic.

2.2 Formalism

Introduced by Isi et al. (2018), the Bayesian Coherence Ratio for a candidate signal in a network of D detectors is given by

$$\rho_{\rm BCR} = \frac{\hat{\pi}^S Z^S}{\prod_{i=1}^{D} [\hat{\pi}^G_i Z^G_i + \hat{\pi}^N_i Z^N_i]}\,, \tag{1}$$

where $\{\hat{\pi}^S, \hat{\pi}^N_i, \hat{\pi}^G_i\}$ are estimates of the astrophysical prior-odds that the data contain a coherent signal, incoherent noise or an incoherent glitch. We assume each detector has the same glitch and noise prior odds of $\{\hat{\pi}^N, \hat{\pi}^G\}$. In the limit where the estimated prior-odds equal the astrophysical prior-odds, the $\rho_{\rm BCR}$ becomes the optimal Bayesian odds described by Ashton et al. (2019b). However, as the astrophysical prior-odds are unknown, it is invalid to use the $\rho_{\rm BCR}$ as an odds-ratio to discriminate signals from glitches. Instead, we use the $\rho_{\rm BCR}$ as a ranking statistic to obtain a frequentist significance

Table 1. Trigger-selection lab-frame parameter space (parameters correspond to signals with durations $\leqslant$ 454 ms and $q \geqslant 0.1$).

	Minimum	Maximum
Component Mass 1, m_1 [$M_\odot$]	31.54	491.68
Component Mass 2, m_2 [$M_\odot$]	1.32	121.01
Total Mass, M [$M_\odot$]	56.93	496.72
Chirp Mass, $\mathcal{M}$ [$M_\odot$]	8.00	174.56
Mass Ratio, q	0.1	0.98

of a candidate $\rho_{\rm BCR}$-value, $\rho^c_{\rm BCR}$, measured against a background $\rho_{\rm BCR}$ distribution, $\rho^b_{\rm BCR}$.

Since it is impossible to shield ground-based gravitational-wave detectors from gravitational-wave signals, the LVK empirically estimates the background by repeatedly time-shifting strain data by amounts larger than the light-travel time between the two LIGO detectors (Abbott et al. 2019d). We use time-shifted data to generate $\rho^b_{\rm BCR}$. Following this, each candidate's single-event false alarm probability p_1 of being miss-classified as a glitch is given by

$$p_1 = \frac{\text{Count of } \rho^b_{\rm BCR} \leqslant \rho^c_{\rm BCR}}{\text{Count of } \rho^b_{\rm BCR}} \ . \tag{2}$$

Moreover, as we have several candidates (N candidates), each with a $\rho^c_{\rm BCR}$, we account for them by calculating a false-alarm probability with trial factors p_N given by

$$p_N = 1 - (1 - p_1)^N \ . \tag{3}$$

Finally, we can calculate the probability of the candidate signal event occurring from a gravitational-wave, $p_{\rm S}$ with

$$p_{\rm S} = 1 - p_N \ . \tag{4}$$

3 ANALYSIS

We acquire candidate signal triggers (times when the detector's data has a signal-to-noise ratio above a predetermined threshold) for $\rho_{\rm BCR}$ analysis from PyCBC's search in O2 (Nitz et al. 2020a; Allen et al. 2012; Allen 2005; Nitz et al. 2017; Dal Canton et al. 2014; Usman et al. 2016; Nitz et al. 2018; Davies et al. 2020; Abbott et al. 2020a). Some of the triggers are associated with gravitational-wave events and candidates while others are glitches. We also acquire background and simulated triggers from PyCBC's O2 search to calculate $\rho^b_{\rm BCR}$ and estimate values for $\{\hat{\pi}^S, \hat{\pi}^G\}$ (see Appendix B for details on the estimation process). The triggers are divided into two week time-frames because the detector's sensitivity does not stay constant throughout the eight-month-long observing period (Usman et al. 2016).

For our study, we filter PyCBC triggers to include only those in the parameter ranges presented in Table 1. This region focuses our analysis on binary black hole mergers with lab-frame total masses above $\gtrsim 55 M_\odot$, corresponding to binary systems with signal durations $<$ 454 ms and $q \geqslant 0.1$. The filtering process leaves us with 60, 996 background, 5, 146 simulated, and 25 candidate signal triggers. We additionally include events and candidate events reported by GWTC-1 and the IAS group in our list of candidate signal triggers. A plot of the lab-fame component mass space constrained by our search space is presented in Fig. 1.

To evaluate $\{Z^S, Z^G_i, Z^N_i\}$ and calculate the $\rho_{\rm BCR}$ (Eq. 1) for triggers, we carry out Bayesian inference with `bilby` (Ashton et al. 2019a; Ashton et al. 2020), employing `dynesty` (Speagle 2020) as our nested sampler. Nested sampling, an algorithm introduced by Skilling (2004, 2006), provides an estimate of the Bayesian evidence and is often utilized for parameter estimation within the LIGO collaboration (Ashton et al. 2019a,c; Smith et al. 2020).

We use a likelihood that marginalizes over coalescence time, the phase at coalescence, and luminosity distance (see Thrane & Talbot 2019, Eq. 80). We use identical parameter estimation priors for the glitch and signal models. We restrict the spin priors to aligned spins to reduce the number of parameters we sample. We define our mass priors to be uniform in chirp mass $\mathcal{M}$ and mass ratio q to avoid sampling issues that arise from sampling in thin regions of the component mass parameter space (Romero-Shaw et al. 2020a). As a post-processing step, we convert posterior samples calculated with uniform $\{\mathcal{M}, q\}$ priors to uniform component mass priors by re-sampling the posterior samples using the Jacobian given in Veitch et al. (2015, Eq. 21). The complete list of the priors is in Table 2.

Table 2. Prior settings for the lab-frame parameters used during our parameter estimation. The definitions of the parameters are documented in Romero-Shaw et al. (2020a, Table E1). The trigger time t_c is obtained from the data products of PyCBC's O2 search.

Parameter	Shape	Limits
$\mathcal{M}$ [$M_\odot$]	Uniform	7–180
q	Uniform	0.1–1
M [$M_\odot$]	Constraint	50–500
$d_{\rm L}$ [Mpc]	Comoving	100–5000
χ_1, χ_2	Uniform	-1–1
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	$t_c \pm 0.1$

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 (Khan et al. 2016). Although there exist gravitational-wave templates such as `IMRPhenomXPHM` (Pratten et al. 2020), `NRSur7dq4` (Blackman et al. 2017) and `SEOBNRv4PHM` (Ossokine et al. 2020) 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 before the analysis data segment d_i. A Tukey window with a 0.2-second roll-off is applied to each data segment to suppress spectral leakage. After this, we fast-Fourier transform and median-average the segments to create a PSD (Abbott et al. 2019b). Like other PSD estimation methods, this method adds statistical uncertainties to the PSD (Talbot & Thrane 2020; Chatziioannou et al. 2019; Biscoveanu et al. 2020). To marginalize over the statistical uncertainty, we use the median-likelihood presented by Talbot & Thrane (2020) 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 in the Appendix C.

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 from the gravitational-wave Open Science Center (Abbott et al. 2021) using `GWpy` (Macleod et al. 2020).

Finally, with the $\rho^c_{\rm BCR}$ and $\rho^b_{\rm BCR}$ for each time-frame of triggers, we calculate the candidate signal's $p_{\rm S}$.

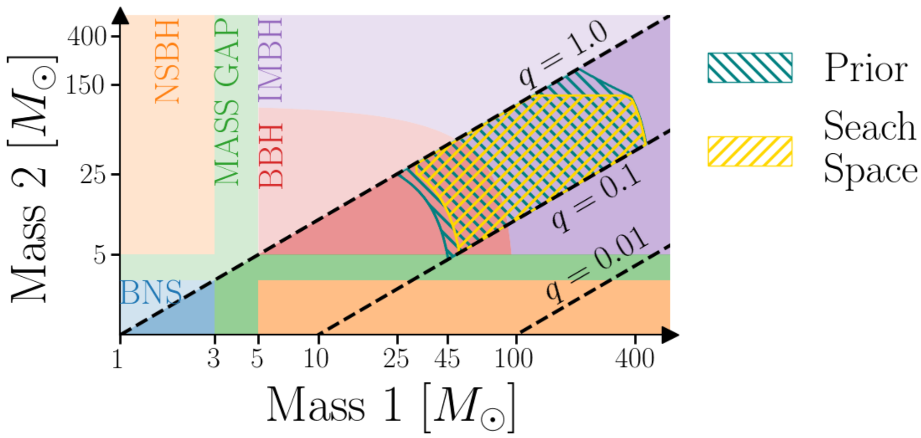

Figure 1. Lab-frame black hole component-mass boundaries for our search space and parameter estimation prior. Our search is constrained to the parameter space enclosed by the gold-colored hatches, while our prior is constrained to the slightly larger parameter space enclosed by the teal-colored hatches. The purple region labeled "IMBH" is the parameter space where merger remnants may be IMBHs.

4 RESULTS

We analyze the O2 candidates with $M > 55\ M_\odot$ and report candidates with $p_S \geqslant 0.2$ in Table 3. The $\hat{\pi}^S$ and $\hat{\pi}^G$ values utilized for each time-frame are reported in Appendix D. By imposing a p_S threshold of 0.5, we present 13 candidate gravitational wave events.

Various search pipeline $p_{\rm astro}$ are not mathematically equivalent (Galaudage et al. 2020). Moreover, $p_{\rm astro}$ is not equivalent to p_S. However, by comparing candidates' various $p_{\rm astro}$ values with p_S, we can compare how significant each pipeline deems the candidate. For comparison, in Table 3 we report $p_{\rm astro}$ values from GWTC-1 (Abbott et al. 2019d), PyCBC OGC-2 (Nitz et al. 2020b), PyCBC OGC-3 (Nitz et al. 2020b), PyCBC 'single-search' (Nitz et al. 2020c), IAS (Venumadhav et al. 2019a; Zackay et al. 2019), and Pratten & Vecchio (2020)'s analyses.

4.1 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 $p_S > 0.9$, 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_S. For example, consider the candidate event 170412 ($t_c = 1176047817$), assigned a $p_{\rm astro}$ of 0.06 by GstLAL and has a p_S of 0.01. This candidate was reported to be excess power caused due to noise appearing non-stationary between 60 − 200 Hz (Abbott et al. 2019d). This candidate demonstrates that p_S may be utilized to eliminate candidates originating from terrestrial noise sources.

4.2 IAS Events

Our analysis of the IAS events and candidates with $M \gtrsim 55\ M_\odot$ in O2 has resulted in one event with disfavored $p_S < 0.5$ (GW170425), and five events and two candidates with $p_S \geqslant 0.5$ (GW170121, GW170304, 170302, GWC170402, GW170403, GW170727, GW170817A). From this list, four events (GW170121, GW170304, GW170727, GW170817A) have $p_S > 0.8$ and $p_{\rm astro} > 0.9$ reported from other pipelines, making them viable gravitational-wave event candidates.

GWC170402, detected by Zackay et al. (2019), is reported to originate from a binary with non-zero eccentricity (Zackay et al. 2019). As we used a non-eccentric waveform during analysis, we may be under estimating this event's significance at $p_S \leqslant 0.6$. Finally, GW170425 which has $p_S < 0.25$ also has low $p_{\rm astro}$ reported in OGC-2 and OGC-3 (Nitz et al. 2020b, 2021), suggesting that GW170425 may have been false alarm.

4.3 New Candidate Events

Although no IMBH detections are made with the $\rho_{\rm BCR}$, a marginal stellar mass black hole merger candidate 170222 has been discovered with a $p_S \sim 0.6$. This candidate has a SNR ~ 7.7, low spin magnitudes, and source-frame component masses of $(47.16^{+8.00}_{-5.77}, 35.50^{+5.79}_{-6.35})M_\odot$ (90% credible intervals), 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 $(55^{+10}_{-10} - 148^{+13}_{-12})M_\odot$ (Woosley & Heger 2021; Heger & Woosley 2002). More details on the candidate are presented in Appendix E. The remaining coherent trigger candidates all have $p_S < 0.5$, making them unlikely to originate from astrophysical sources.

5 CONCLUSION

In this paper, we demonstrate that the Bayesian Coherence Odds-Ratio $\rho_{\rm BCR}$ (Isi et al. 2018) can be used as a ranking statistic to provide a measure of significance for gravitational-wave signals originating from CBCs with lab-frame total masses between 55 $M_\odot$ and 400 $M_\odot$, a range that includes IMBHs. To compute the $\rho_{\rm BCR}$ for candidates, we utilize Bayesian inference to calculate the probability of data under various hypotheses (the hypotheses that the data contains a coherent signal, just noise, or an incoherent glitch).

Table 3. $p_{\rm S}$ table for gravitational wave events and candidates in our search space with $p_{\rm S} > 0.2$, calculated using Hanford and Livingston observatory data. Displayed for comparison are significances of events taken from: GstLAL $p^{\rm GstLAL}_{\rm astro}$ (Abbott et al. 2019d), PyCBC $p^{\rm pyCBC}_{\rm astro}$ (Abbott et al. 2019d), IAS $p^{\rm IAS}_{\rm astro}$ (Venumadhav et al. 2019a; Zackay et al. 2019), $P(S|{\rm d})$ (Pratten & Vecchio 2020), PyCBC 'single-search' $p^{\rm S}_{\rm astro}$ (Nitz et al. 2020c), PyCBC OGC-2 $p^{\rm OGC2}_{\rm astro}$ (Nitz et al. 2020b) and PyCBC OGC-3 $p^{\rm OGC3}_{\rm astro}$ (Nitz et al. 2020b). The t_c column contains the 'GPS' coalescence-times of the gravitational wave events. The catalog column displays the first catalog reporting the event on each row (the catalogs labeled IAS-1 and IAS-2 correspond to the candidates published by Venumadhav et al. 2019a and Zackay et al. 2019).

Event	Catalog	$p_{\rm S}$	$p^{\rm pyCBC}_{\rm astro}$	$p^{\rm GstLAL}_{\rm astro}$	$p^{\rm IAS}_{\rm astro}$	$P(S\|{\rm d})$	$p^{\rm S}_{\rm astro}$	$p^{\rm OGC2}_{\rm astro}$	$p^{\rm OGC3}_{\rm astro}$	t_c
GW170104	GWTC-1	0.97	1.00	1.00		1.00		1.00		1167559936.60
GW170121	IAS-1	0.83			1.00	0.53		1.00	1.00	1169069154.57
170209	-	0.32								1170659643.47
170222	-	0.58								1171814476.97
170302	IAS-1	0.78			0.45					1172487817.48
GW170304	IAS-1	0.94			0.99	0.03		0.70	0.70	1172680691.36
GWC170402	IAS-2	0.60			0.68	0.00				1175205128.57
GW170403	IAS-1	0.54			0.56	0.27		0.03	0.71	1175295989.22
170421	-	0.27								1176789158.14
GW170425	IAS-1	0.22			0.77	0.74		0.21	0.41	1177134832.18
GW170608	GWTC-1	0.99	1.00	0.92		1.00				1180922494.50
GW170727	IAS-1	0.98			0.98	0.66		0.99	1.00	1185152688.02
GW170729	GWTC-1	0.98	0.52	0.98		1.00		1.00	0.99	1185389807.30
GW170809	GWTC-1	0.99	1.00	0.99		1.00		1.00	1.00	1186302519.75
GW170814	GWTC-1	1.00	1.00	1.00		1.00		1.00	1.00	1186741861.53
GW170817A	IAS-2	0.92			0.86	0.02				1186974184.72

This Bayesian ranking method takes a step towards building a unified Bayesian framework that provides a 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 $M > 55\,M_\odot$ reported by the PyCBC search (Nitz et al. 2020b), the IAS-team (Venumadhav et al. 2019a; Zackay et al. 2019) and those reported in GWTC-1 (Abbott et al. 2019d). Using a $p_{\rm S}$ threshold of 0.5, 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 $p_{\rm S}$, indicating this method's ability to discriminate between terrestrial artifacts and astrophysical signals. Our analysis of the IAS events demonstrates that GW170121, GW170304, GW170727, and GW170817A are likely to originate from astrophysical sources ($p_{\rm S} \geqslant 0.8$), while GW170425 is not ($p_{\rm S} < 0.25$). Finally, we report a new marginal binary-black hole merger candidate, 170222.

With the rapid rate of development in gravitational-wave Bayesian inference, we anticipate the ability to analyze longer-duration signals, utilize more advanced signal and glitch models, and incorporate data from the entire detector network. In a similar vein, with the accumulation of more gravitational wave events, future $\rho_{\rm BCR}$ work may utilize astrophysically informed priors during Bayesian inference and more accurate prior odds for each detector.

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All analyses (inclusive of test and failed analyses) performed for this study used 1.3M core-hours, amounting to a carbon footprint of ~ 167 t of CO_2 (using the U.S. average electricity source emissions of 0.429 kg/kWh (Carbonfund.org 2020) and 0.3 kWh for each CPU).

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DATA AVAILABILITY STATEMENT

We analyze publicly-available gravitational wave strain data from the LIGO-Virgo-KAGRA collaboration (Gravitational Wave Open Science Center 2019). The trigger times for analysis were provided by the PyCBC team (Nitz et al. 2020b). The derived data generated in this research will be shared on reasonable request to the corresponding author.

Software: `bilby` (Ashton et al. 2019a, v0.6.8), `bilby-pipe` (Ashton et al. 2020, v0.3.12), `dynesty` (Speagle 2020, v0.9.5.3), `GWpy` (Macleod et al. 2020, v1.0.1), `LALSimulation` (LIGO Scientific Collaboration 2018, v6.70), `matplotlib` (Hunter 2007, v3.2.0), `NumPy` (Harris et al. 2020, v1.8.1), `SciPy` (Virtanen et al. 2020, v1.4.1), `pandas` (pandas development team 2020, v1.0.2), `python` (Oliphant 2007; Millman & Aivazis 2011, v3.7).

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APPENDIX A: BAYESIAN EVIDENCE EVALUATION

A1 Noise Model

We assume that each detector's noise is Gaussian and stationary over the period being analyzed (Abbott et al. 2019b). 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 $P(f)$ of the data. Using $P(f)$, 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.

A2 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 11-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

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

where $\pi(\vec{\theta}|\mathcal{H}_S)$ is the prior for the parameters in the coherent signal hypothesis $\mathcal{H}_S$, 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 $\vec{\theta}$.

A3 Incoherent Glitch Model

Finally, as glitches are challenging to model and poorly understood, we follow Veitch & Vecchio (2010) 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 (Veitch & Vecchio 2010). 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

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

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

APPENDIX B: TUNING THE PRIOR-ODDS

After calculating the $\rho_{\rm BCR}$ 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, $p_b(\rho_{\rm BCR})$ and $p_s(\rho_{\rm BCR})$. We expect the background trigger and simulated signal $\rho_{\rm BCR}$ 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 $\rho_{\rm BCR}$ values. The prior odds parameters $\hat{\pi}^S$ and $\hat{\pi}^G$ from Eq. 1 help separate the two distributions. Altering $\hat{\pi}^S$ translates the $\rho_{\rm BCR}$ probability distributions while adjusting $\hat{\pi}^G$ spreads the distributions (see Isi et al. 2018, Appendix A). 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 $\rho_{\rm BCR}$ distribution. In this study, we tune $\hat{\pi}^S$ and $\hat{\pi}^G$ to maximally separate the $\rho_{\rm BCR}$ distributions for the background and simulated triggers.

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

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

The $D_{K.L.} = 0$ 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 $\rho_{\rm BCR}$ 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 presented in Table 3, we applied a post-processing step to marginalize the uncertainty in the PSD. In Fig. C1, we demonstrate the impact of the post-processing step. Marginalizing over uncertainty in the PSD yields an improvement in the separation of the noise and signal distributions (left plot). 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.

Table D1. 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	$\hat{\pi}^S$	$\hat{\pi}^G$
2016-12-23	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

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 2. Table D1 presents the signal and glitch prior odds utilized for each time-frame of O2 data.

Tuning the prior odds can dramatically affect the $p_{\rm S}$. For example, consider Table D2, which reports tuned $p_{\rm S}$ and un-tuned $p'_{\rm S}$ (where $\hat{\pi}^S = 1$ and $\hat{\pi}^G = 1$) for various events and candidates. By tuning the prior odds, the $p_{\rm S}$ 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 $\mathcal{M} = 49.46\ M_\odot$ and $q = 0.68$, values contained inside the 90% credible intervals of our posterior probability distributions for 170222. Some of the posteriors produced as a by-product of our $\rho_{\rm BCR}$ calculation can be viewed in Fig. E1.

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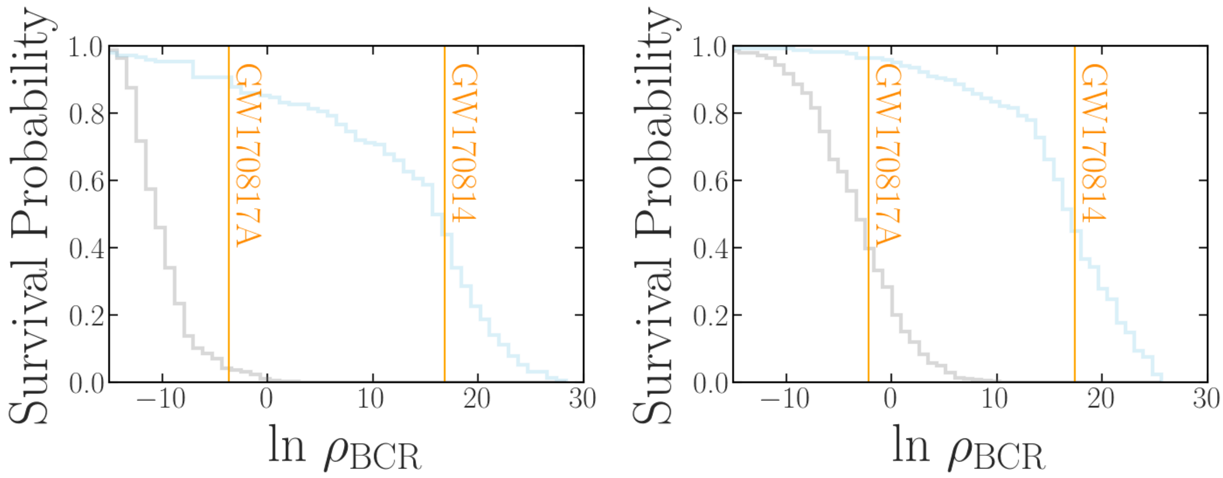

Figure C1. Histograms represent the survival function (1-CDF) from our selection of background triggers (gray) and simulated signals (blue) triggers obtained from PyCBC's search of data from August 13 - 21, 2017. Vertical lines mark the ln ρ_{BCR} of IAS's GW170817A and GWTC-1's GW170814. Left: Survival functions using the post-processing step to marginalize over PSD statistical uncertainties. Right: Survival functions without the post-processing step. Without the post-processing step, there is a greater overlap between the background (gray) and foreground (blue) survival functions.

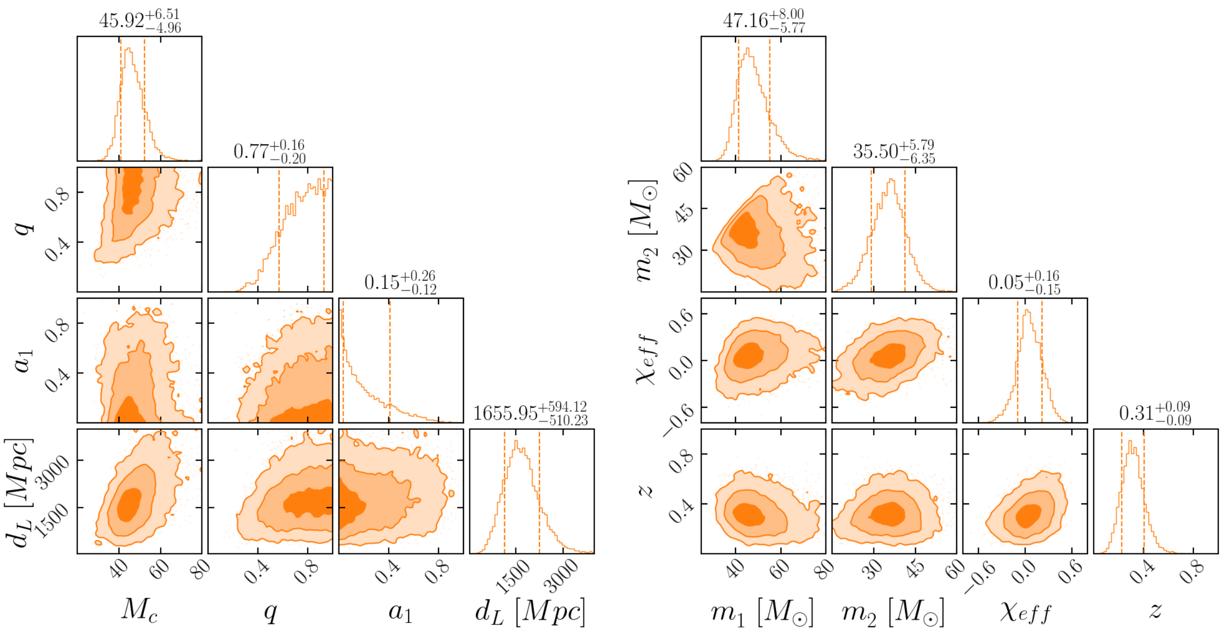

Figure E1. Posterior distributions for 8 parameters of 170222. Left: Posterior probability distributions for 4 of the 12 search parameters. Right: Posterior probability distributions for 4 derived parameters.

Table D2. Table of p_S using "tuned" prior odds and p_S using uninformed prior odds of $\hat{\pi}^S = 1$ and $\hat{\pi}^G = 1$ (represented by p'_S). Details of other columns provided in Table 3.

Event	Catalog	p_S	p'_S	t_c
GW170104	GWTC-1	0.97	0.95	1167559936.60
GW170121	IAS-1	0.83	0.68	1169069154.57
170209	-	0.32	0.00	1170659643.47
170222	-	0.58	0.50	1171814476.97
170302	IAS-1	0.78	0.54	1172487817.48
GW170304	IAS-1	0.94	0.80	1172680691.36
GWC170402	IAS-2	0.60	0.00	1175205128.57
GW170403	IAS-1	0.54	0.90	1175295989.22
170421	-	0.27	0.21	1176789158.14
GW170425	IAS-1	0.22	0.16	1177134832.18
GW170608	GWTC-1	0.99	0.99	1180922494.50
GW170727	IAS-1	0.98	0.99	1185152688.02
GW170729	GWTC-1	0.98	0.95	1185389807.30
GW170809	GWTC-1	0.99	0.99	1186302519.75
GW170814	GWTC-1	1.00	1.00	1186741861.53
GW170817A	IAS-2	0.92	0.30	1186974184.72