Discovering the mass gap: Analyzing mass-gap black hole objects through gravitational waves

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Abstract

Mass gap objects have eluded researchers for many years, as they occupy the space between the lightest black holes and the heaviest neutron stars. The purpose of this study was to use gravitational wave analysis emitted by the process of forming these objects to gain a deeper understanding of their properties and general trends. We hypothesized that mass-gap mergers differed from other black hole mergers primarily by their chirp-mass distribution, spin, and effective spin distributions, which was partially proven correct when the chirp mass of mass gap mergers was estimated to be very different from black hole mergers. However, nested sampling and kernel density estimation revealed that the spin and effective spins of mass gap objects do not differ significantly from those of black holes, which is a fascinating result that will help further research in the future.

Introduction

Black holes and neutron stars are both results of stellar evolution [1], depending on how massive the star was. However, there is a "mass gap" between the heaviest neutron stars discovered at ~2.5 solar masses and the lightest black holes found at ~5 solar masses. There weren't any objects that we believed would form in this mass gap until 2017, when an event happened that could greatly alter our understanding of cosmological objects. Gravitational wave astronomy became a reality for the first time in 2015, when the Laser Interferometer Gravitational Observatory (LIGO) detected gravitational waves in a black hole merger [2]. Since then, gravitational wave detectors like LIGO, Virgo, and KAGRA have detected a multitude of events involving objects of different masses and properties colliding, with the most notable of these occurring in 2017. On August 17, 2017, LIGO detected gravitational waves emitted from a neutron star merger for the first time, with the result appearing to be an object with a mass belonging to the "mass gap" previously hypothesized [3]. In this study, we analyze all of the future events that produced an object in this mass gap to try to discover trends in the properties of these mysterious objects. To do this, we used Bayesian statistics, which allows us to use prior knowledge to better estimate the properties of objects in the mass gap. In this way, we can obtain full posterior distributions of properties such as masses, spins, and redshift. For a given parameter set θ and data D, the posterior is computed as

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)} \qquad (1)$$

Where $P(D|\theta)$ is the likelihood derived from gravitational-wave strain data, $P(\theta)$ is the prior distribution, and $P(D)$ is the likelihood of the data [4]. Additionally, chirp mass and effective spin of mass gap merger events detected by LIGO were compared with other events that produced “normal-sized” black holes, with a similar statistical distribution regarding effective spin.

Results

To find spin values of black holes, parameter estimation was done using the dynesty sampler in Python [3]. Figure 1 shows a sample posterior estimation of the first gravitational wave event GW150914, which reports the highest probability of chirp mass, mass ratio, phase, and geocent time to be 31.44(±0.33), 0.92(±0.07), 4.72(+0.46,-2.82), and 1126259462.41(±0), respectively.

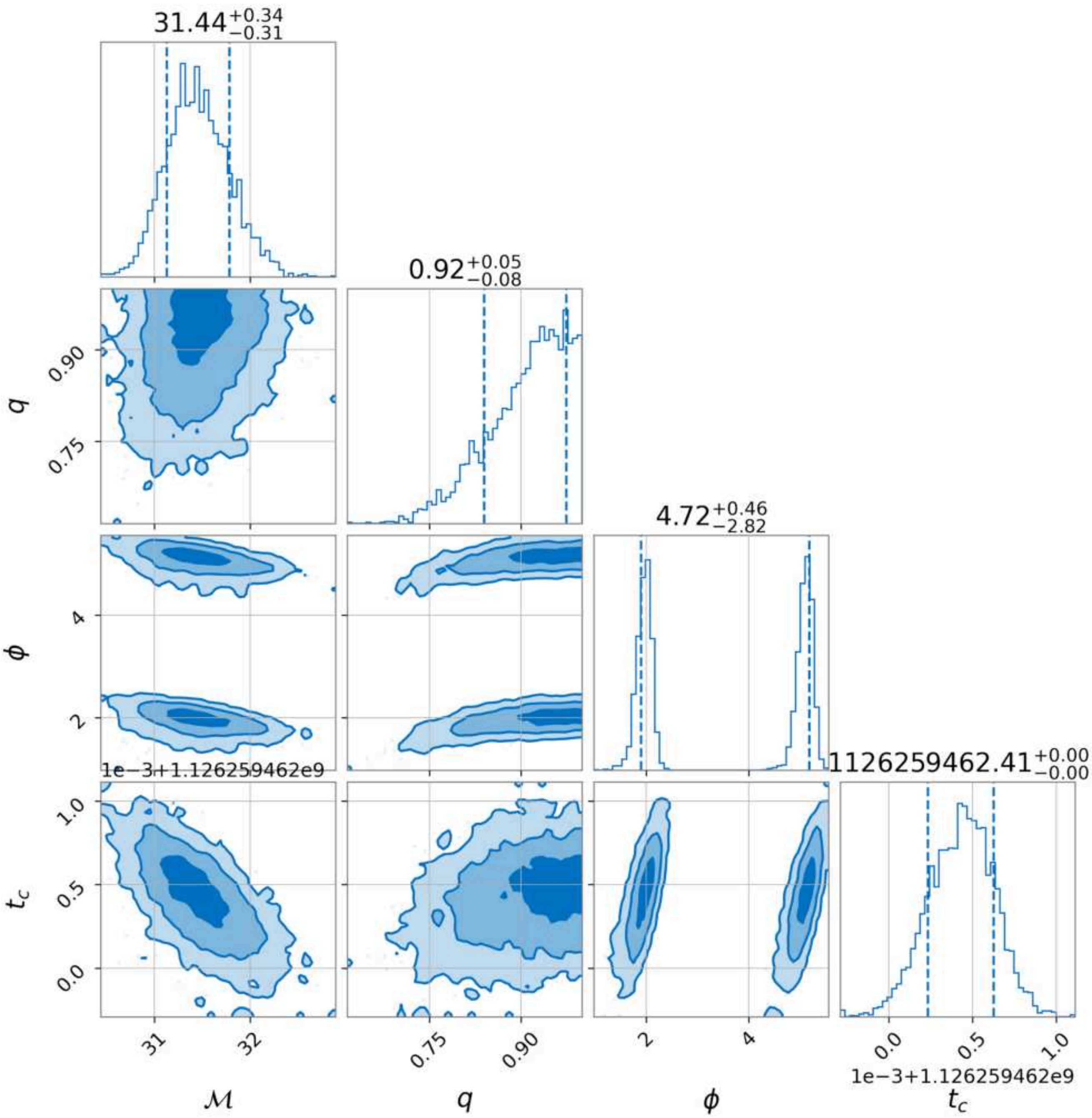

Figure 1: Posterior distributions for GW150914, estimating Mass ratio, chirp mass, phase, and geocentric time. Mass ratio is estimated at 31.44 ±0.33, chirp mass is estimated at 0.92 ± 0.07,

phase is estimated at 4.72(+0.46/-2.82), and geocentric time is estimated at 1126259462 ±0. The distributions containing phase appear to be bimodal, while the rest are all unimodal. Applying the same method for the estimation of other parameters, mainly viewing angles for a recent mass gap merger, GW230529, results in Figure 2, showing many concentrated spots of probability.

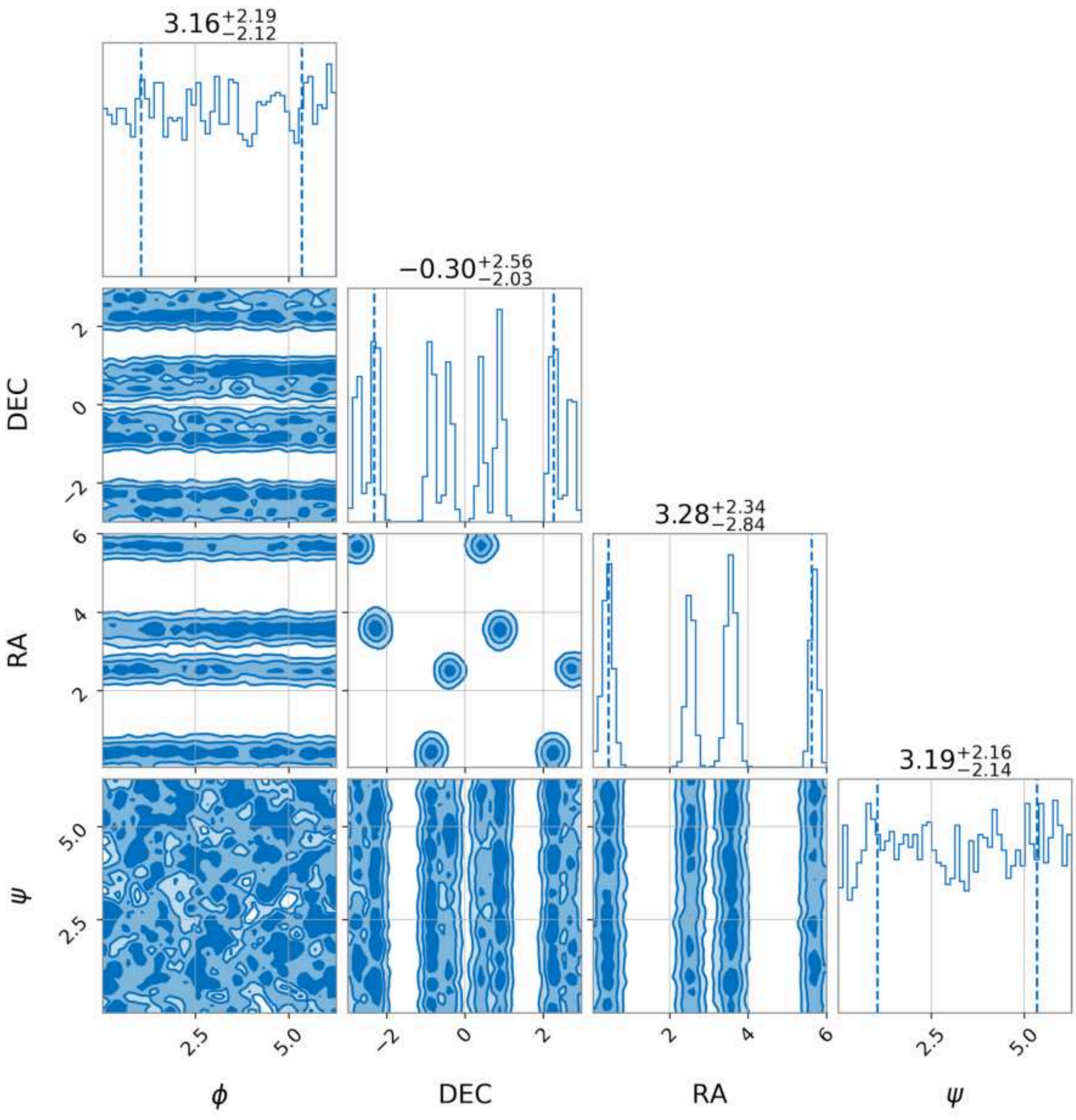

Figure 2: Parameter estimations of GW230529, estimating phase, declination, right ascension, and phi, the last three of which are viewing angles. Right ascension and declination have well-defined points, while the other two do not.

Two additional estimations were done on spin values for GW170817 (Figure 3) and GW190425 (Figure 4), which led to narrow distributions for the former but broad distributions for the latter.

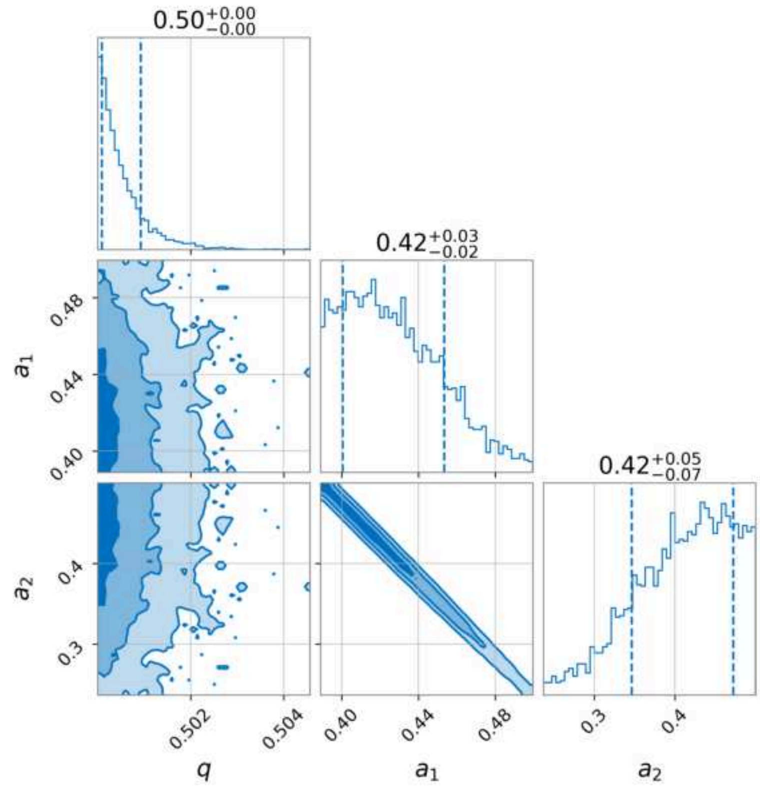

Figure 3: Spin and chirp mass estimations for GW170817. Spins concentrate around 0.42, chirp mass at around 0.5.

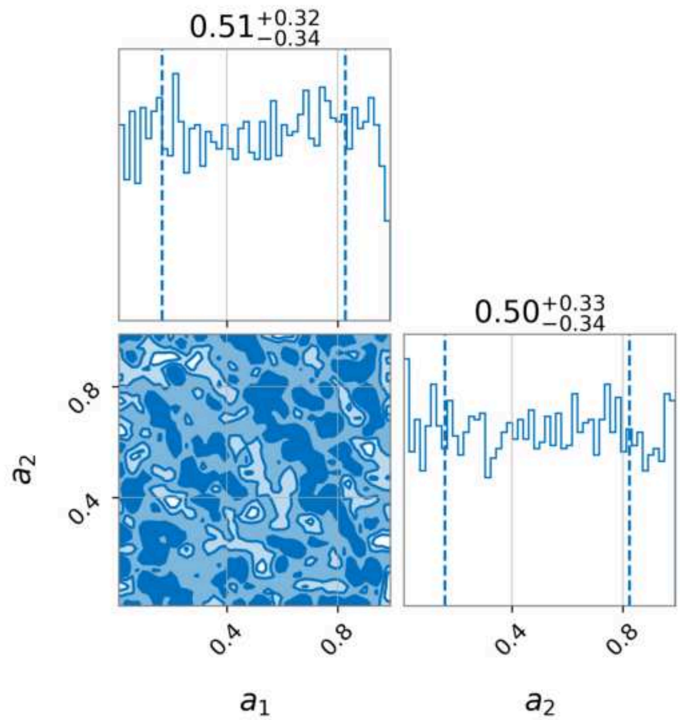

Figure 4: Unclear parameter estimation for GW190425 spins. Lots of areas with high and low probability

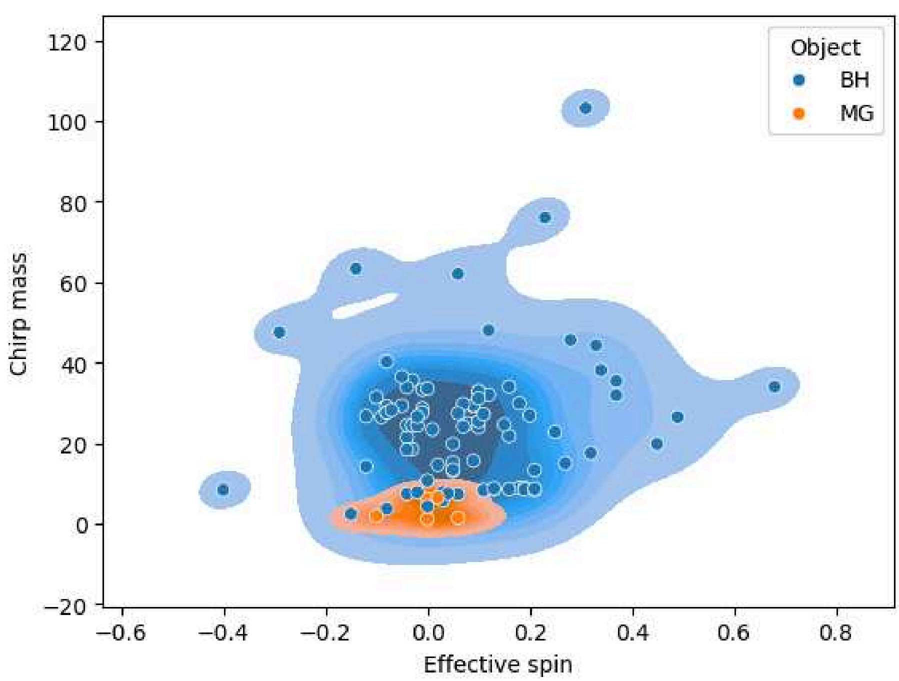

Figure 5: The effective spin compared to chirp mass for mass gap objects and other black holes detected through gravitational waves.
Kernel density estimation for most black holes detected by LIGO. Concentrations of both black holes and mass gap objects are at around 0 spin and ~5 chirp mass for mass gap objects and ~30 chirp mass for black holes.

Kernel estimation and Kolmogorov–Smirnov(KS) tests were performed[5], with the KS test comparing mass gap object properties with other black holes, reporting p-values of 0.95 for effective spin and 5.21e-6 for chirp mass. The kernel density estimation is also shown, with the majority of mass gap objects centering around 0 effective spin and chirp mass of ~5.

Discussions of Results

The more well-defined parameter estimations for GW150914 and 170817 show that when the signal-to-noise ratio(SNR) is high enough, dynesty sampling is effective at estimating posterior distributions. However, as mass gap objects tend to emit lower amounts of energy due to having smaller chirp masses, it is harder to assess their properties, as demonstrated in the broad posterior distribution of GW190425, with an SNR of 11.3[6]. Estimates of spin for three mass-gap gravitational events(GW170817, GW190425, and GW230529) were able to estimate primary spins all within the range of 0.4-0.5, which could imply most mass gap systems have at least one object with a spin of ~0.45 before merging. Since most of these systems have an effective spin of around zero after they merge, that would imply the other object also has a moderate spin, and the spin values cancel out. This provides valuable insight into how these systems form, as spin values for both objects will usually have more similar or aligned spin values [7]. This means the neutron stars that merged into this mass-gap object only merged through long-distance attraction and not from a binary star system.

When comparing the effective spin and chirp mass of mass gap objects to other black holes, the KS test outputted a p-value that was notably high when comparing the effective spin. This means we cannot reject the null hypothesis, showing that the distributions for effective spin do not seem to be dependent on the object's mass.

However, this has a lot of limitations that need to be addressed. The variety of high-probability angles for GW230529 demonstrate a major limitation today in gravitational astronomy: the inconsistency and low number of gravitational detectors. Particularly for this event, the only detector that was able to be used for data collection was LIGO-Livingston [8]; all other detectors were either offline or unable to detect the signal due to not having enough sensitivity. Current detectors are also prone to environmental noise from many factors, which makes it harder to detect gravitational waves and creates broad posteriors, increasing the difficulty of estimation. Also, there have only been a handful of mass-gap objects detected using LIGO, so any trend observed may just be a coincidence and isn't concrete evidence supporting the properties of mass gap objects.

In the near future, many of these limitations could be overcome. With more advanced technology and improved tuning of detectors, scientists may be able to reduce noise significantly and detect gravitational waves at even lower amplitudes. This especially benefits mass gap detections, as these events typically have smaller chirp masses and produce weaker signals than black hole systems as large as 100 solar masses. More mass gap detections will help confirm the trends observed in this study and provide additional insights into the true nature of these mysterious objects. Additionally, there is a planned gravitational detector to be located in space, which will eliminate a lot of seismic noise and detect many more gravitational waves coming from both black hole mergers and neutron star mergers [9].

Materials and Methods

All gravitational wave data from LIGO is free and can be accessed by importing the "gwpy" library in Python [10]. This data gave us the strain data from the interferometer, but it contained a lot of statistical noise, both from its environment and the detector itself. Since LIGO is based on the ground, the interferometer frequently picks up seismic vibrations from inside the Earth that disrupt the data. LIGO's own instruments also cause noise due to imperfect electromagnetic shielding and the location of mirrors [11].

We used a bandpass filter and notched frequencies to remove noise from the data. Bandpass filters are filters designed to filter out specific frequencies when detecting noise, usually done by combining low-pass filters and high-pass filters to get the desired range of frequencies [12]. By combining multiple of these filters, we can create a bandstop filter, otherwise known as a notch filter [13]. This allows us to leave out specific frequencies of energy in the data that are known to cause noise. For example, low-frequency seismic noise is known to occur at the frequency of 60 Hz and its harmonics at 120 and 180 Hz [11], so we can notch those frequencies to reduce the noise in our data. This helps us obtain a more filtered plot of the strain data to better determine the strain caused by the gravitational wave, as shown in Figure 6.

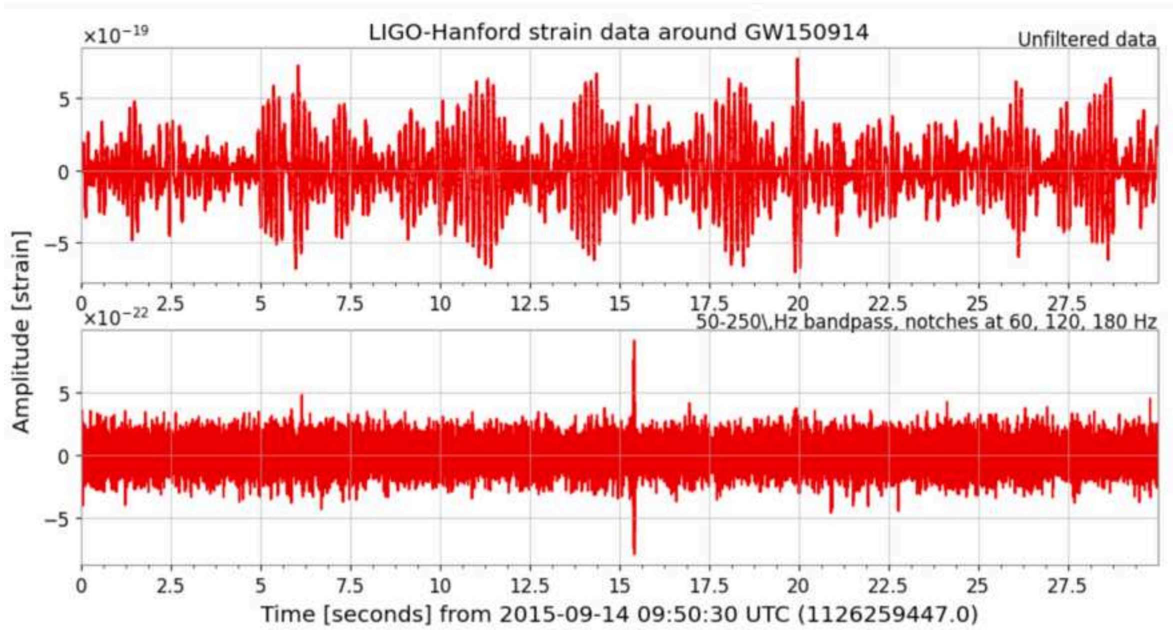

Figure 6: Unfiltered and filtered data from LIGO-Hanford. The first image is unfiltered data, with the gravitational wave not discernible and lots of noise. The second image shows the gravitational wave clearly at 15 seconds.

Often, there are glitches in the detector that produce a result similar to a very strong gravitational wave that simple bandpass filtering can't filter out. In this case, we use a Q-transform, in Figure 7.

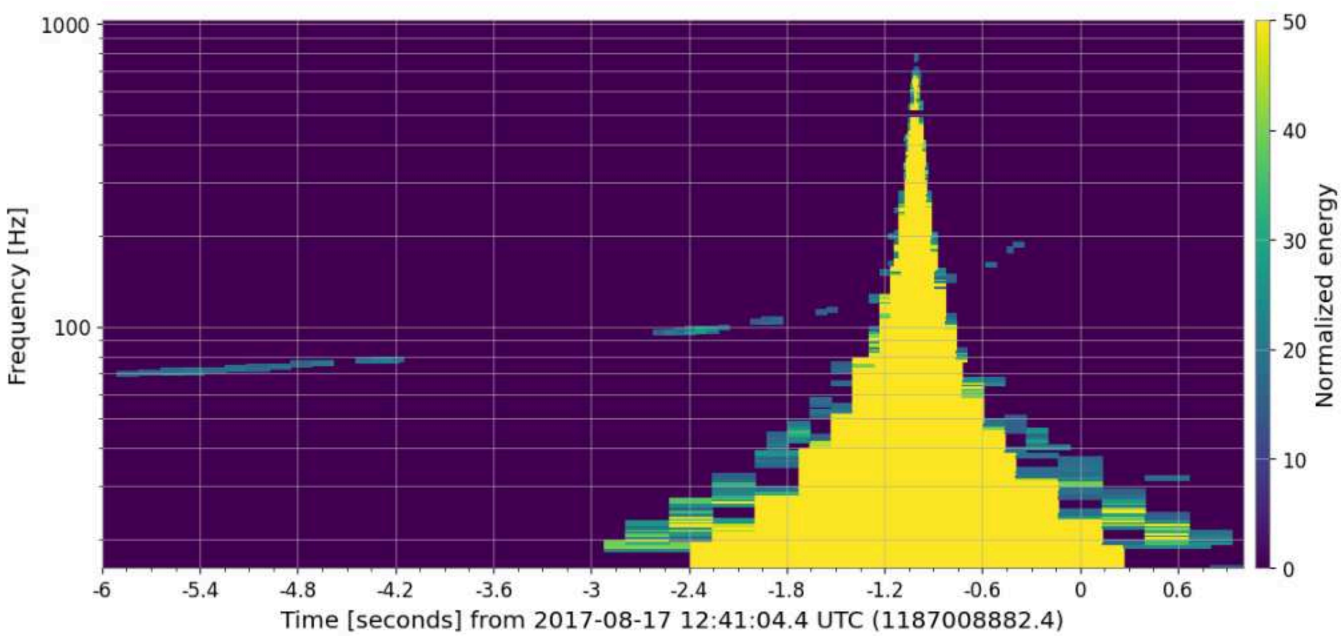

Figure 7: Q-transform of GW170817. Large glitch in the data from -2.4 to 0.3 seconds, with a slight curve in the background showing the gravitational wave.

A Q-transform displays the amount of energy detected at various frequencies over time[14], and we see that there is a huge spike of energy at all frequencies at around -1.2 seconds. However, we also see a faint curve of energy increasing in frequency behind the glitch, which is the gravitational wave that LIGO detected at that time, letting us see past the glitch and reveal what actually happened.

Markov Chain Monte Carlo and Nested Sampling

To explore the posterior space, we use nested sampling, a variation of the Markov Chain Monte Carlo (MCMC) method. The MCMC method employs many walkers in the posterior distribution, each exploring the distribution by moving toward points with higher probability computed with Bayes' theorem[15]. The walkers also have a chance to move toward regions with lower probability to find more high-probability areas. However, the MCMC method is not as efficient as nested sampling when dealing with complex distributions, which can often occur in black hole parameter estimation [16]. Nested sampling works by first selecting multiple points, then computing the point with the least probability, P_{min}. Next, it replaces that point with a new point, provided the new point has a probability P greater than P_{min}, and shrinks the boundaries of the probability it is computing. As the likelihood floor rises, the prior mass shrinks exponentially, until another iteration doesn't meaningfully contribute to P, then the algorithm is stopped[16]. To use this method, we use the Dynesty sampler [17] in Python, along with bilby [18], which helped run the sampler and set priors, numpy[19], which provides numerical values for pi, Pandas [20], which helps load the posterior samples, matplotlib [21], which helps plot data, LALinference[22], which gives likelihoods for parameters, and gwosc [23] and gwpy [10] for obtaining the data.

Priors and Statistical Analysis

Priors were chosen based on data from the original LIGO detection papers[2][3][6][8], including mass ratio, chirp mass, luminosity distance, and geocentric time. Other non-mentioned priors, such as viewing angles and phase, were separately calculated using nested sampling in Python, as shown in Figure 2. Parameters to be estimated were set as uniform between two fixed values.

The plot and kernel density estimation were run using seaborn [24], scipy [25] to run the KS test, and Pandas [20] to interpret the dataset. Data from most early events came from the stellar graveyard plot[26] which provided the spin values and chirp masses that were needed. Additionally, later events, such as GW231123 and GW230529, had their properties extracted from their respective discovery papers [27][7].

Conclusions and Future Works

Overall, this study used techniques such as parameter estimation, kernel density estimation, and KS tests to analyze the similarities and trends of mass-gap objects through their gravitational wave data. The results indicate that the spin distributions of mass-gap objects are similar and resemble a more concentrated distribution of larger black holes, in addition to mass-gap objects having similar chirp masses. This research has enhanced our understanding of the distinguishing properties of black holes and will be valuable in the future as more mass-gap objects are detected.

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