Searching in the Dark

Chasing Magnum Opus

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Statistical Methods for Astrophysical Sciences (ASTP-611)
Spring 2016

1 Introduction

The detection of gravitational waves (GW) in September(ref) opened a new era of astronomy; however, it is only in sync with electromagnetic astronomy that the most physics can be discovered. Electromagnetic counterparts are expected from binary sources involving matter i.e. neutron star-neutron star and neutron star-black hole. Because of this, GW detectors will work in conjunction with electromagnetic telescopes to observe a GW source. Some of these will yield weak, nearly isotropic electromagnetic counterparts and others will not. GW detectors will identify sources characterized by its chirp mass:

$$\mathcal{M}_c = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}} \tag{1}$$

This report is organized as follows. Section 2 describes the developement of the chirp mass distribution, Section 3 descibes a electromagnetic followup classifier based on the data, and Section 4 will state our conclusions.

See Section **??** and Appendix A. Example text citation is Dominik et al. (2012), or in parenthesis with a page number (Dominik et al. 2012, pg 2).

2 Chirp Mass Distribution

2.1 Density Estimation

We use a histogram to estimate the merger rate as a function of $\mathcal{M}_c$ (See Figure 1). Since we are interested in the intrinsic rate, not just those that we detect, we weigh each point by the inverse of the spacetime volume in which we are sensitive to it, $w = 1/VT$. Binaries with a higher chirp mass are easier detect, so we do not want to count them as heavily. For a given chirp mass, we are sensitive out to a distance of

$$D(\mathcal{M}_c) = 200\,\mathrm{Mpc}\big(\mathcal{M}_c/1.2\,\mathrm{M}_\odot\big)^{5/6} \tag{2}$$

which corresponds to a volume of

$$V(\mathcal{M}_c) = \frac{4}{3}\pi D(\mathcal{M}_c). \tag{3}$$

Multiplying this by the time spent observing, $T = 0.6\,\mathrm{yr}$, gives us the spacetime volume $(VT)(\mathcal{M}_c)$.

2.2 The Likelihood of Fitting Parameters

The likelihood of each fitting parameter is:

$$\ln\left[P(\{d\}|\lambda)\right] = \frac{-1}{2}\sum_k \frac{(r(x_k) - r_{model}(x_k))^2}{\sigma_r^2}\exp\left\{-\int E(x)r(x_k)dx\right\} \tag{4}$$

where p_{smooth} is the smoothing prior, defined to be:

$$p_{smooth} = \exp\left\{-\int\left[\frac{\mathrm{d}^n(r)}{\mathrm{d}(x)^n}\right]^2 dx\right\} \tag{5}$$

In theory, p_{smooth} can be any n^{th} derivative. To make our code robust, we define a function that takes n as an argument. The function then calls numpy.polynomial.polyder() to find the n^{th} derivative. Next, we square the n^{th} derivative and integrate it between the minimum and maximum of x. Here we choose $n = 3$.

The likelihood estimator is:

$$\ln P(\{d\}|\lambda) \tag{6}$$

2.3 Model fitting

We employed a Markov Chain Monte Carlo (MCMC) script to fit the coefficients of a polynomial model for $r(M_c)$. The MCMC uses the smoothing prior as defined in section 2.2. We performed a least square fit first in order to obtain the initial guess for the coefficients of the model.

3 Classifying GW Events that have Electromagnetic Countparts

3.1 Overview

The GW observatory, the Laser Interferometer Gravitational Wave Observatory (LIGO), can provide very rapid mass estimates of candidate GW events. Since most of these detections are mostly binary black holes and electromagnetic followup is extremely expensive, only a few events can be followed up. We have therefore trained a classifier to determine if an event will have a electromagnetic followup. We trained this classifier on the first half of the data; we simply took the mid-way point betweewn the maximum chirp mass for the electromagnetic counterpart group and the nonelectromagnetic counterpart group. This can be seen in Figure 2.

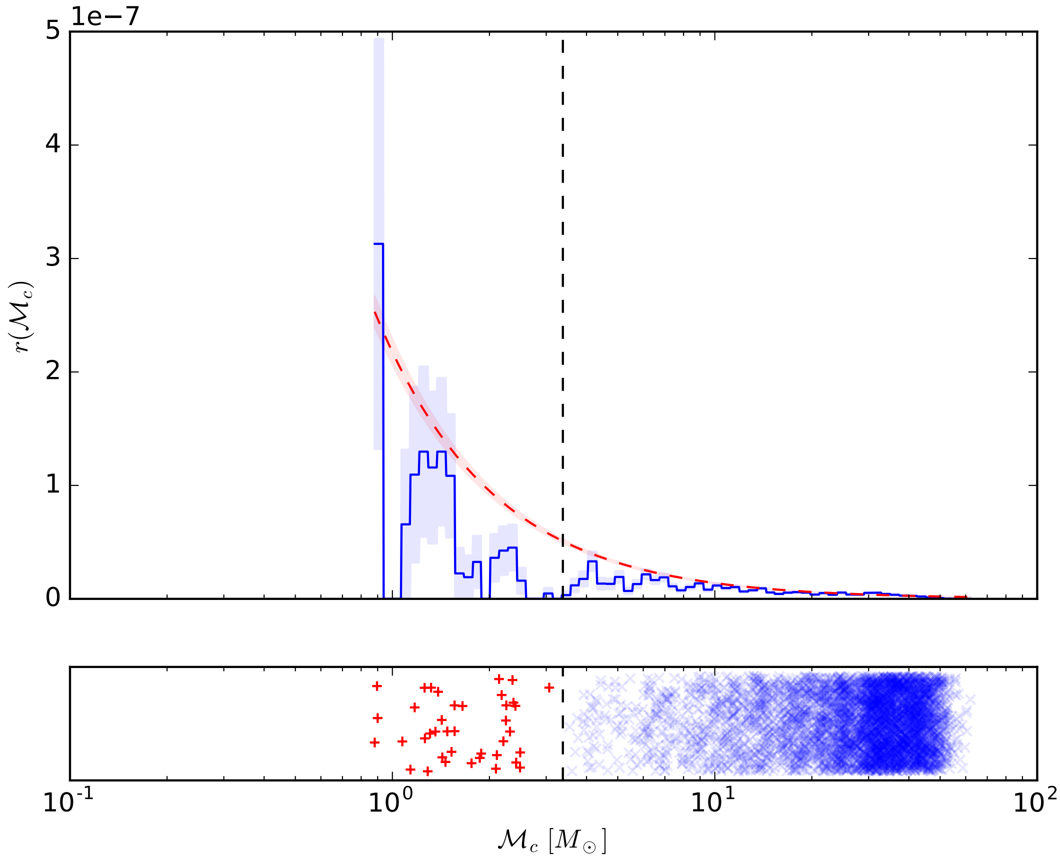

Figure 1: Estimated rate of compact binary mergers, based on 5000 synthetic observations. Blue line is weighted histogram fit. Red curve is power law fit. Shaded regions are 1-σ error bars. Vertical dashed line is boundary between events with counterparts and without.

3.2 Method

The classifier was constructed simply by taking the minimum chirp mass event of the other group (no electromagnetic counterparts) and the maximum chirp mass event of the electromagnetic counterpart group and finding the mid-point between those two events. This classifier was trained from the first half of the dataset. This is visiualized by the filled points in FIgure 2.

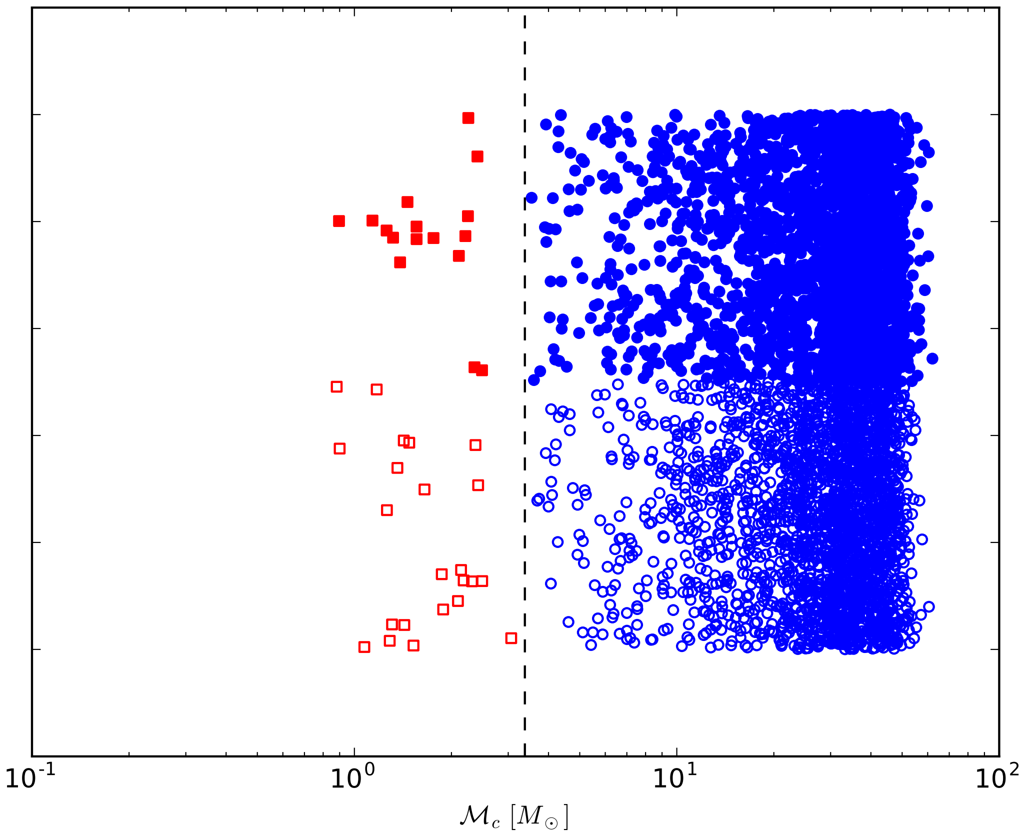

Figure 2: This shows a selected set of the data. The red points represent the events with electromagnetic counterparts, and the blue points represent the events without electromagnetic counterparts. The filled points represent represent the train dataset, and the open points represent the rest of the data. The vertical line indicates the division between the two groups indicated by the classifier.

3.3 Results

The classifier correctly classified the two groups without any contamination. More importantly this was also the case when classifying the full data set. As you can see in Figure **??**, the classifier correctly classified the two groups without any contamination. In the Table **??** You can see the chirp mass for the maximum electromagnetic counterpart event and the minimum of the other group along with the chirp mass of the line that divides the group. This shows a clear distinction between the two group.

Figure 1 shows the rate vs the chirp mass with the dividing line from the classifier

Table 1: Chirp masses of the maximum event from the electromagnetic counterpart group, the minimum event from nonelectromagnetic counterpart group, and the vertical dividing line.

3.545980	3.065123	3.378711

overplotted. This correlates to the two hump structure in the graph that represents the two groups (electromagnetic counterparts and others). Figure ... shows a similar correlation. The dividing clearly separates the two groups in m_1-m_2 parameter space.

4 Conclusions

We created a classifier to distinguish between GW events with and without electromagnetic counterparts. This classifier was trained using half of the data. The classifier correctly classified both groups completely without any contamination for both the training set and the full dataset. Figure ... and ... shows the correlation between 1D and 2D mass distributions and the classification of the two groups.

References

[1]M. Dominik, K. Belczynski, C. Fryer, D. E. Holz, E. Berti, T. Bulik, I. Mandel, and R. O'Shaughnessy, "Double Compact Objects. I. The Significance of the Common Envelope on Merger Rates", ApJ **759**, 52, 52 (2012).

Appendices

A Example