Searching in the Dark: Finding the Electromagnetic Components of Gravitational Wave Events

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Abstract

1 Introduction

The detection of gravitational waves (GW) in Feburary(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:

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

Figure 1 is the full data set in terms of chirp mass. The electromagnetic counterparts events are seperated from the other events by color. 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 **2012ApJ...759...52D** or in parenthesis with a page number (**2012ApJ...759...52D**).

2 Chirp Mass Distribution

2.1 Weighted Histogram

2.2 The Likelihood of Fitting Parameters

The likelihood of each fitting parameter is:

$$P(\{d\}|\lambda) = \frac{p_{smooth}^{-1}}{n!} \prod_k E(x) r(x_k) \exp\left\{ - \int E(x) r(x_k) dx \right\} \tag{2}$$

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

$$p_{smooth} = \exp\left\{ - \int \left[\frac{\mathrm{d}^n(r)}{\mathrm{d}(x)^n} \right]^2 dx \right\} \tag{3}$$

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:

$$\ln P(\{d\}|\lambda) \tag{4}$$

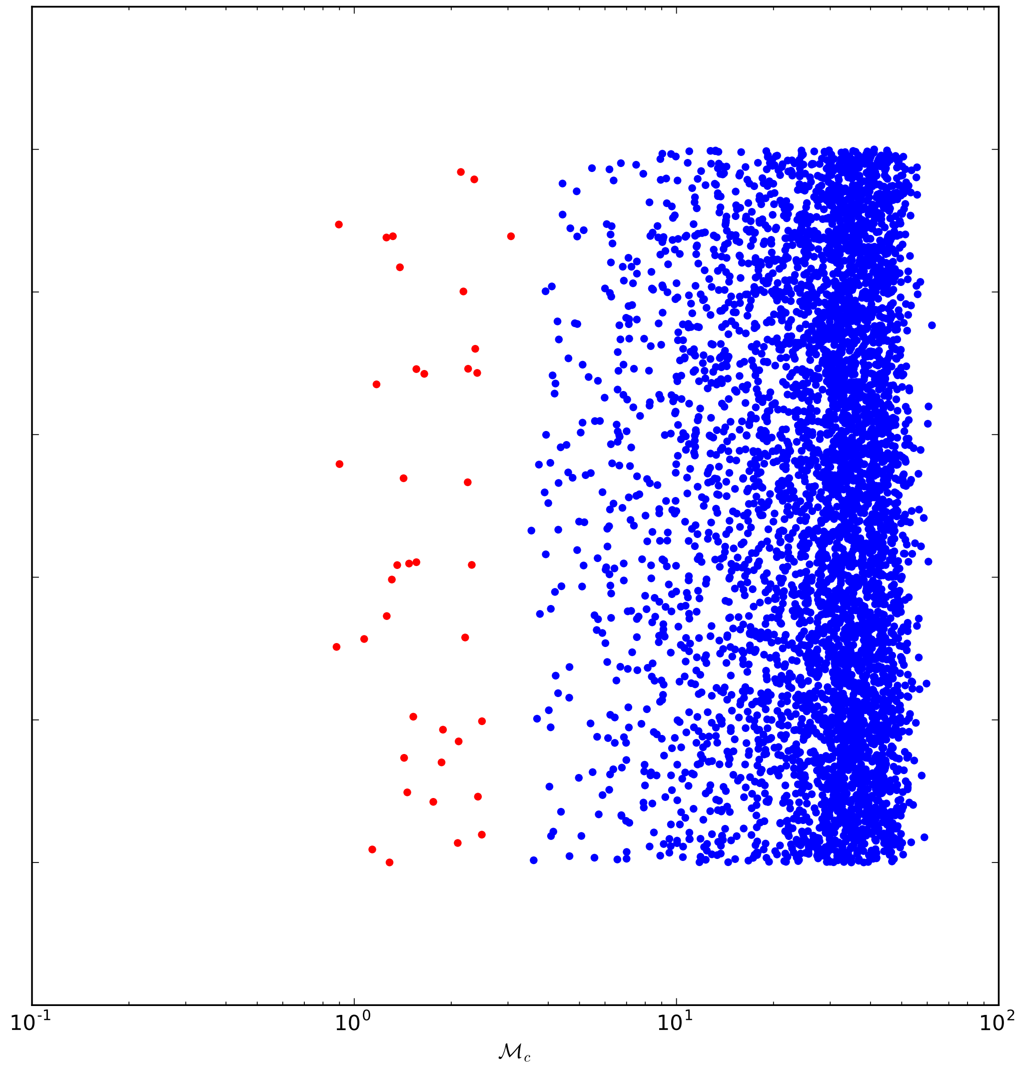

Figure 1: This figure shows all the 5000 events' chirp mass. Here the y-axis is a uniform random number between zero and one. The events that have an electromagnetic counterpart are in red, and the events without a electromagnetic counterpart are in blue.

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 other group. This is shown in Figure 2. This was then used on the whole dataset as shown in Figure 3.

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 distance between those two events. This trained for the first half of the dataset. The result can be seen in Figure 2; the vertical line represents half the distance between the maximum chirp mass of the electromagnetic counterpart group and the other group.

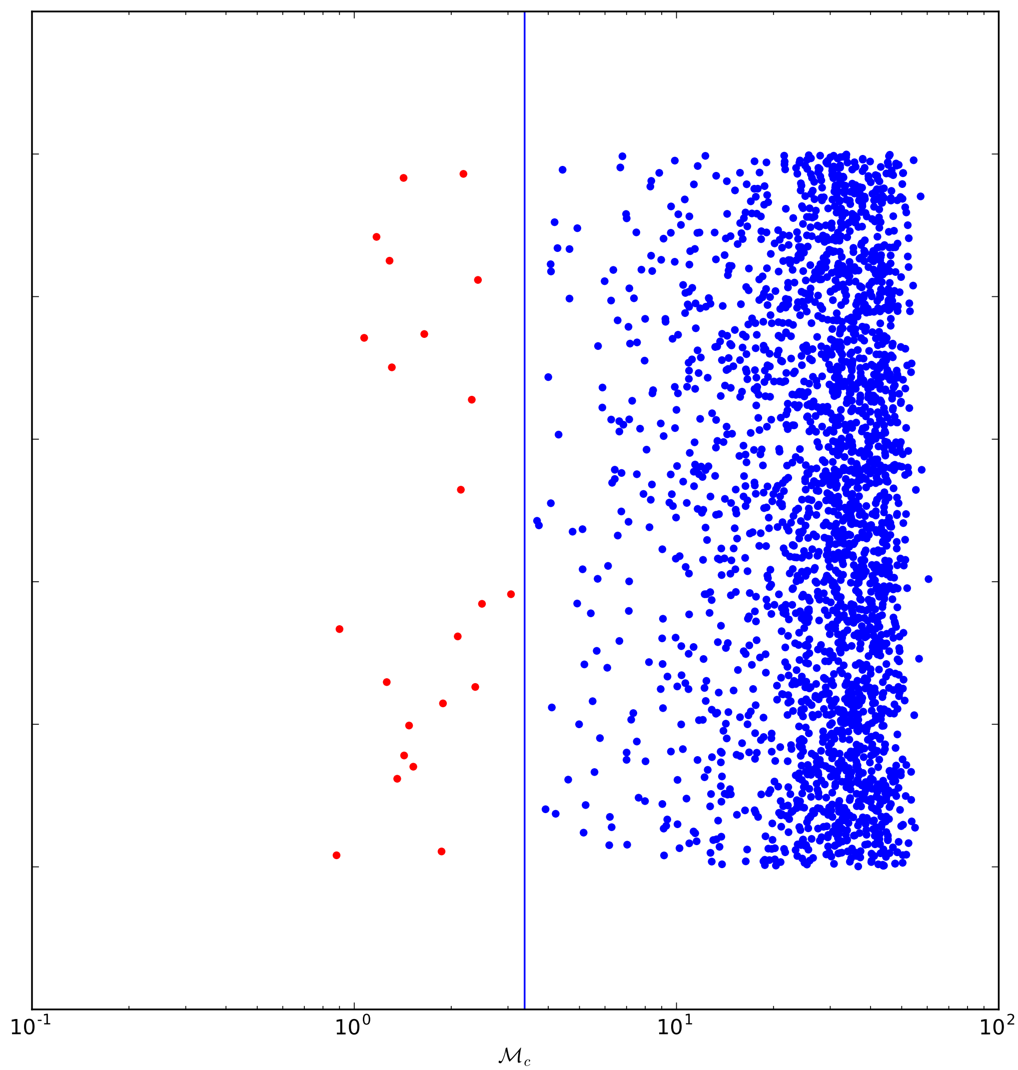

Figure 2: This shows the first half of the data with the same two groups as before. The vertical line indicates the division between the two groups.

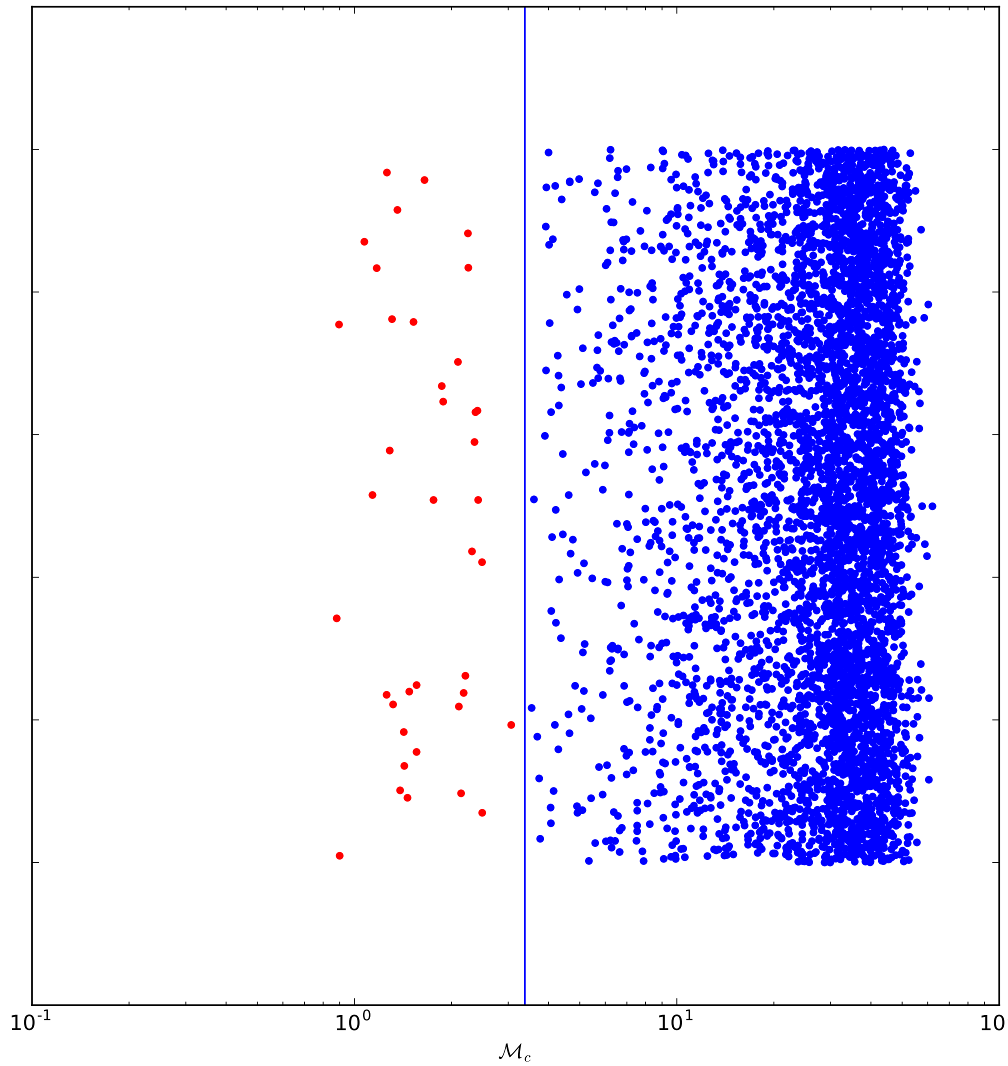

Figure 3: This shows the full set of the data with the dividing line trained by half the data.

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 3, the classifier correctly classified the two groups without any contamination.

4 Conclusions

Appendices

A Example