



Using Random Forest To Rank-Order Potential Gravitational-Wave Events

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Compact Binary Coalescences



» Second order Post-Newtonian templates





Detectors



• Large Michelson interferometers

- » H1: 4 km
- » H2: 2 km
- » L1:4 km



http://www.ligo.caltech.edu/LIGO_web/PR/scripts/facts.html





- Data from the detectors is broken into segments of time, which are compared to a bank of waveform templates
 - » When a segment from a detector triggers a template, parameters that describe the event (mass, SNR, etc.) are produced
- Gravitational-wave candidate event: triggers from more than one detector are similar in time and mass
 - » The pipeline produces the values of the parameters for each detector it was seen in
- Follow up on the candidates
 - » None of the candidates has yet proven to be a gravitational-wave!



Matched Filtering





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- Any large glitch in the data can caused the matched filter to have a large SNR output
- Signal based vetoes check that the matched filter output is consistent with a signal

$$\chi^2(t) = \ p \sum_{i=1}^p |
ho_i(t) -
ho(t)/p|^2$$

• Require that:

$$\frac{\chi^2}{p + \delta^2 \rho^2} < \text{threshold}$$

 r² veto duration is a measure of the time that chi² is above threshold



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- Glitches can still be a problem, even with signal based vetoes (particularly in higher mass searches)
- A lot of work in the LSC is devoted to finding, identifying and eliminating glitches
- Loud glitches reduce our range (and hence rate) by hiding signals
 - » Reduces the volume of the sky we can see by (reduction in rate)³
- Even if a template has excellent overlap with signals, if it picks up lots of glitches we have a problem



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- Follow-ups are necessary because of the glitches that ring up triggers and pass the signal based vetoes
- Currently, the candidates are ranked according to the sum of squares of effective SNR for each detector

$$\rho_{eff}^2 = \frac{\rho^2}{\sqrt{\left(\frac{\chi^2}{2p-2}\right)\left(1+\frac{\rho^2}{250}\right)}}$$

• The top-ranking candidates on this list are subjected to rigorous examination



Slide + Injection Statistic





- Random forest technology can take into account the correlations between the many parameters that describe a candidate event and create a more robust rank-ordering statistic
- I use simulated gravitational waves "injected" into the data as the signal for my analysis
 I have 9,569
 - » From the LSC's 1st year S5 Low-Mass Compact Binary Coalescence Analysis*
 - » I am only using H1-L1 coincidences for the moment since they are harder to classify as signal than triply coincident events

see: Drew Keppel's GWDAW talk LIGO-G070820-00-Z

injections



Background



- Noise in the detectors:
 - » Seismic motion, thermal disturbances, quantum fluctuations (shot noise)
- Time slides estimate the background:
 - » The data streams from two detectors are slid integer multiples of 5 seconds from each other and run through the Inspiral Pipeline
 - » These accidental coincidences can't be gravitational waves
 - » I use time slides from one month of the S5 playground







• Single detector parameters

- » SNR
- » chi²
- » r² veto duration

»
$$\operatorname{SNR}_{eff}^2 \quad \rho_{eff}^2 = \frac{\rho^2}{\sqrt{\left(\frac{\chi^2}{2p-2}\right)\left(1+\frac{\rho^2}{250}\right)}}$$

Coincidence parameters

- » Difference in coalescence time
- » Relative difference in chirp mass





Single Detector Parameters







Single Detector Parameters







Single Detector Parameters







Coincidence Parameters







Two Dimensions







Two Dimensions







- I use SprBaggerDecisionTree to train a random forest of bagged trees
 - » This algorithm creates many decision trees, each a bootstrap replica of the training sample. If you start with N training events, then each tree will also have N events, but these events are chosen with replacement
- The random forest technology will sample up to 4 out of 10 of the variables for each split on the tree
- I build 100 trees
 - » Specify each has a minimum of 5 events per leaf
- ~300,000 time slides and ~10,000 injections
 - » 1/2 for training
 - » 1/4 for validation
 - » 1/4 for testing



Criteria for Optimization

- The goal of each tree is to optimize a certain criterion
- SprBaggerDecisionTree gives the option of 9 different criteria
 - » The results for the best of these, as compared to the sum of squares of effective SNR, are summarized on the next plot





Criterion Performance







Cross-Entropy

If you want to live in the region where your false alarm fraction is between 1/1000 and 1/100, then Cross-Entropy gives the best results

Variable	Splits	Delta FOM
dt	1680	193.15895
H1 SNR	2287	255.79869
L1 SNR	2185	254.86952
H1 chi ²	2159	206.18350
L1 chi ²	2499	289.57461
H1 r ²	41	5.58936
L1 r ²	51	8.59637
(dM) _{rell}	2360	216.16415
H1 SNR _{eff} ²	2625	264.50807
L1 SNR _{eff} ²	2594	270.51128



Improvement in Region of Weak Signal





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Conclusion



- The random forest separates injected signals from accidental coincidences more effectively than the current ranking statistic
- More optimization of the leaf size, number of sampled parameters, etc. will lead to improved results