First search for a remnant of GW170817 using convolutional neural networks

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Outline

Gravitational waves from isolated neutron stars

- Small deformation on the star → gravitational waves (GWs) are radiated [11]
- For older neutron stars, search spindowns/spinups -1×10^{-8} to 2×10^{-9} Hz/s- "continuous waves" [3]
- Model is generally Taylor series expansion of frequency
- For younger neutron stars, $O(10^{-3} - 10^{-1})$ Hz/s, so-called "long duration transients", $O(hours - days)$
- Result of binary neutron star merger or supernova

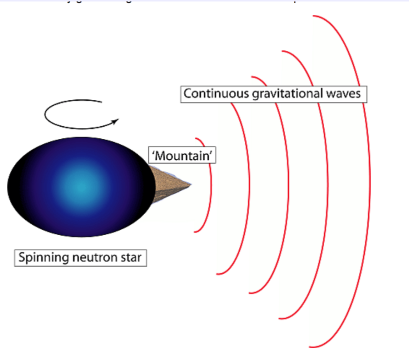


Image courtesy of ANU

The signal model for long duration transients

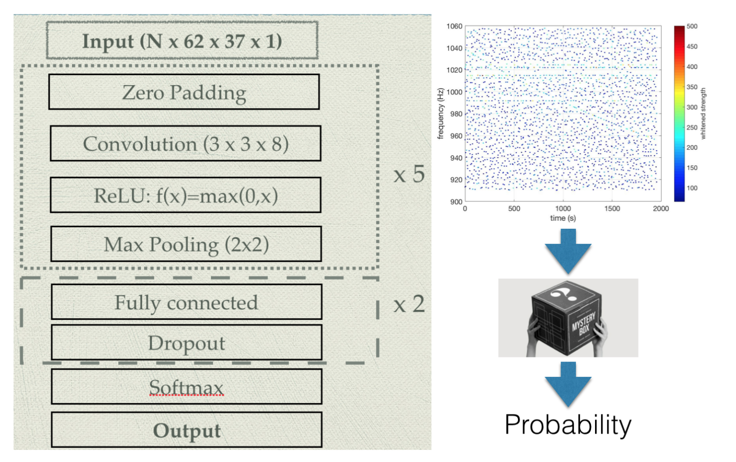
$$\dot{f} = -kf^n \tag{1}$$

$$f(t) = f_0\left(1 + (n-1)kf_0^{n-1}(t - t_0)\right)^{-1/(n-1)} \tag{2}$$

- $f, \dot{f}$: frequency, spindown
- n: braking index
- k: proportionality constant, some physics is here
- t_0: reference time
- f_0: frequency at t_0
- n indicates emission mechanism [18]:
  - $n = 3 \rightarrow$ rotating magnetic dipole [10]
  - $n = 5 \rightarrow$ GWs due to deformation (ellipticity) [16]
  - $n = 7 \rightarrow$ GWs due to r-modes [15]

Why machine learning?

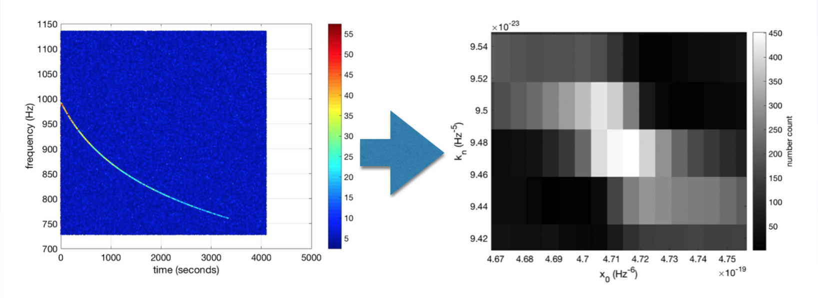
- Unmodeled approach to detecting GWs
- Modeled searches are slow, computationally expensive, and not ideal if the model cannot be fully trusted
- Can see signals with time-varying braking indices
- Lots of applications already in GW physics, e.g. [14, 9]



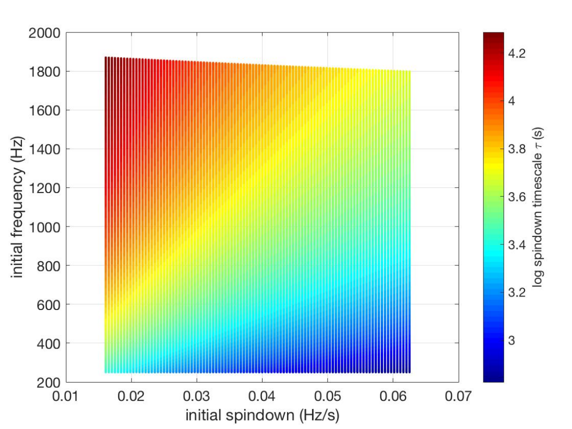
- Input: time/frequency map
- Output: probability of signal p_{out}, apply threshold $p_{thr} = 0.9$ to control false alarm probability (FAP)
- Architecture used in [5, 13]

Search design

- Start with Short Fast Fourier Transform Database (SFDB) [7]
- Choose T_{FFT}, construct 2000 s x 150 Hz time/frequency maps, give to CNNs
- Look for coincident maps in H/L when $p_{out} > p_{thr}$
- For triggered maps, perform follow-up using Generalized FrequencyHough Transform [12] to estimate parameters



Parameter space explored

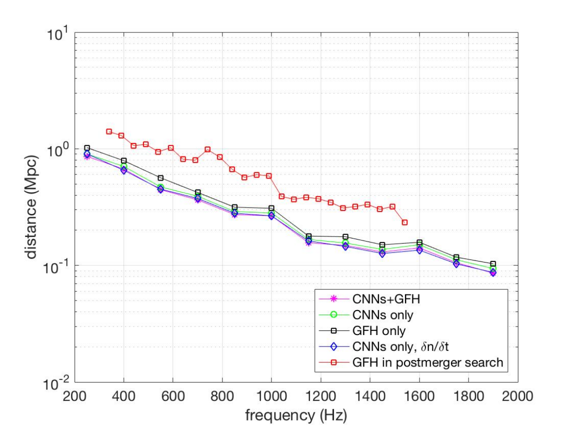


- Searched the 1 week of data after GW170817 in 2000 s chunks
- Made a network for each detector, then performed coincidences in time between maps with output > 0.9

Search results

- 50 coincident time/frequency maps with $p > p_{thr}$ returned by CNNs
- For a grid in $n = [2.5, 7]$, the Hough returned 431 coincident candidates
- After requiring $FAP < 0.02\%$, only 1 candidate remained, which was subsequently vetoed after a few iterations of increasing T_{FFT}, running the Hough again and looking at the time/frequency maps

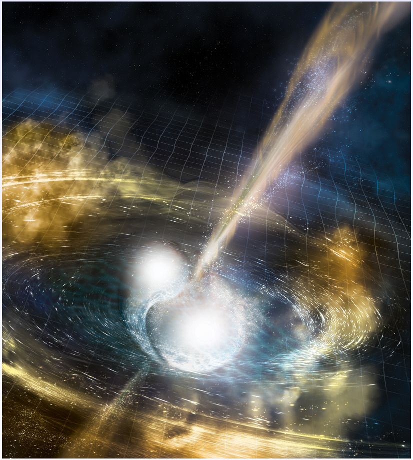
Upper limits at 50% confidence



- 250 injections per amplitude, with parameters uniformly distributed in search volume [13]
- Variation in n, $\frac{\delta n}{\delta t} = [-10^{-4}, 10^{-4}]/\mathrm{s}$

Backup slides

- Kilanova model (r-process) cannot fully explain the spectra: hybrid models considered [19]
- Searches for $O(s)$-$O(days)$ signals done already [1, 2].
- Parameter space explored for long-lived remnant- could be produced with stiff equation of state (EoS) [4]
- Constrain pre/post merger EoS [8]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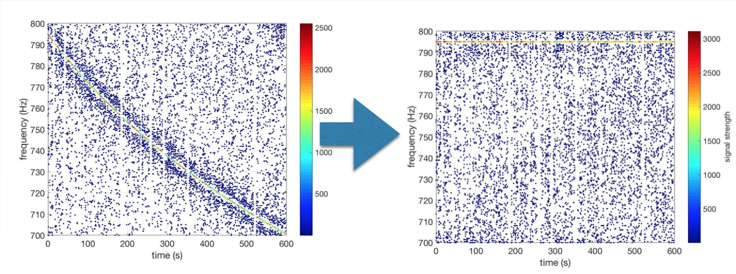
Networks constructed for this search

- Trained on ~ 22 days of science data (~ 2000 noise maps), with ~ 20000 injections at different amplitudes in $[600, 750]$ Hz band
- Comparable sensitivity to previous method [12], though higher FAP

Search design part 2: Follow-up

- Do coincidences between parameters of returned candidates
- Require false alarm probability $< 0.02\%$ to perform next follow-up
- Correct for phase evolution of the signal [17], run original FrequencyHough [6]



Future work

- Expanding classification of neural networks to include separate categories for glitches and time-varying braking indices
- Parameter estimation of GW signal using machine learning; low-latency search
- Currently running a search on O3 data

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