First search for a remnant of GW170817 using convolutional neural networks

Andrew Miller
Pia Astone, Sabrina D'Antonio, Sergio Frasca, Giuseppe Intini, Iuri La Rosa, Paola Leaci, Simone Mastrogiavanni, Federico Muciaccia, Cristiano Palomba, Ornella J. Piccinni, Akshat Singhal and Bernard F. Whiting

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Gravitational waves from isolated neutron stars

- Small deformation on the star → gravitational waves (GWs) are radiated [11]
- For older neutron stars, search spindowns/spinups $-1 \times 10^{-8}$ to $2 \times 10^{-9}$ 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

\[ \dot{f} = -kf^n \quad (1) \]

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

- \(\hat{f}, \dot{f}\): 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]:
  - \(n = 3\) → rotating magnetic dipole [10]
  - \(n = 5\) → GWs due to deformation (ellipticity) [16]
  - \(n = 7\) → GWs due to r-modes [15]
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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]
Convolutional neural network (CNN) architecture

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]
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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 Frequency Hough 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 $> 0.9$
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 $n$, $\frac{\delta n}{\delta t} = [-10^{-4}, 10^{-4}]$/s
Backup slides
Why search for a remnant?

- 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]
Trained on \( \sim 22 \) days of science data (\( \sim 2000 \) noise maps), with \( \sim 20000 \) 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
References I

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