# ConvWave: Searching for Gravitational Waves with Fully Convolutional Neural Nets


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## ONE SENTENCE SUMMARY

We use fully convolutional neural nets to find gravitational waves in time series data of arbitrary length and propose metrics for evaluating the continuous predictions.


## BACKGROUND: GRAVITATIONAL WAVES & LIGO

- Prediction of Einstein's theory of General Relativity: Accelerating masses emit gravitational waves (GWs).
- GWs are perturbations in the metric of spacetime: They stretch and compress space as they pass through.
- First direct observation of a GW by LIGO in 2015 [1].
- LIGO idea: Measure length difference between arms of giant interferometer, look for chirp-like signal (▸ Fig. 3).
- Challenge: Signal incredibly small, only of $\mathcal{O}(10^{-21})$!

## STATUS QUO & OUR CONTRIBUTIONS

- Current pipeline uses matched filtering: Works well, but not computationally efficient, discards information.
- Obvious Idea: Use Deep Learning directly on strain data.
- First results with CNNs by George & Huerta, 2016 with fixed 1-second window and yes/no-classification [2].
- Their 2017 extension uses a sliding window approach → Works, but suboptimal efficiency and time resolution.
- Our idea: Use fully convolutional nets to directly process arbitrarily long input data (no window needed).
- Develop a sensible approach for the (training) labels and a metric for evaluating the net's performance.

## EXPERIMENTS & RESULTS

- Use real LIGO recordings as noise and add simulated GW signals to create training samples (▸ Fig. 2, 4, 7).
- Parameter range: $m_{1,2} = 1\text{–}50\,M_\odot$; $d = 100\text{–}1700$ Mpc
- Use a fully convolutional architecture without much finetuning or hyper-parameter optimization (▸ Fig. 5).
- Train and evaluate on 12 s stretches containing 0–2 injections; calculate detection and FA rates (▸ Fig. 6).
- Results: Detection rate 64.1–97.4%, FA rate 0.4–1.6%.
- Finally: Train net on GW151226 data and apply it to the real GW150914 event → Net successfully recovers it!

## NEXT STEPS & OUTLOOK

- Top priority: Better treatment of signal-to-noise ratio for comparison with other current methods.
- Optimize architecture and hyper-parameters.
- Potential complementary trigger generator for LIGO?

## REFERENCES


[1] Abbott, B.P. et al., 2016. *Observation of Gravitational Waves from a Binary Black Hole Merger*. Physical Review Letters, 116(6).

[2] George, D. and E. Huerta, 2016/2017: *Deep Neural Networks to Enable Real-time Multimessenger Astrophysics*. arXiv: 1701.00008.

[3] Van den Oord, A. et al., 2016. *WaveNet: A Generative Model for Raw Audio*. arXiv: 1609.03499.


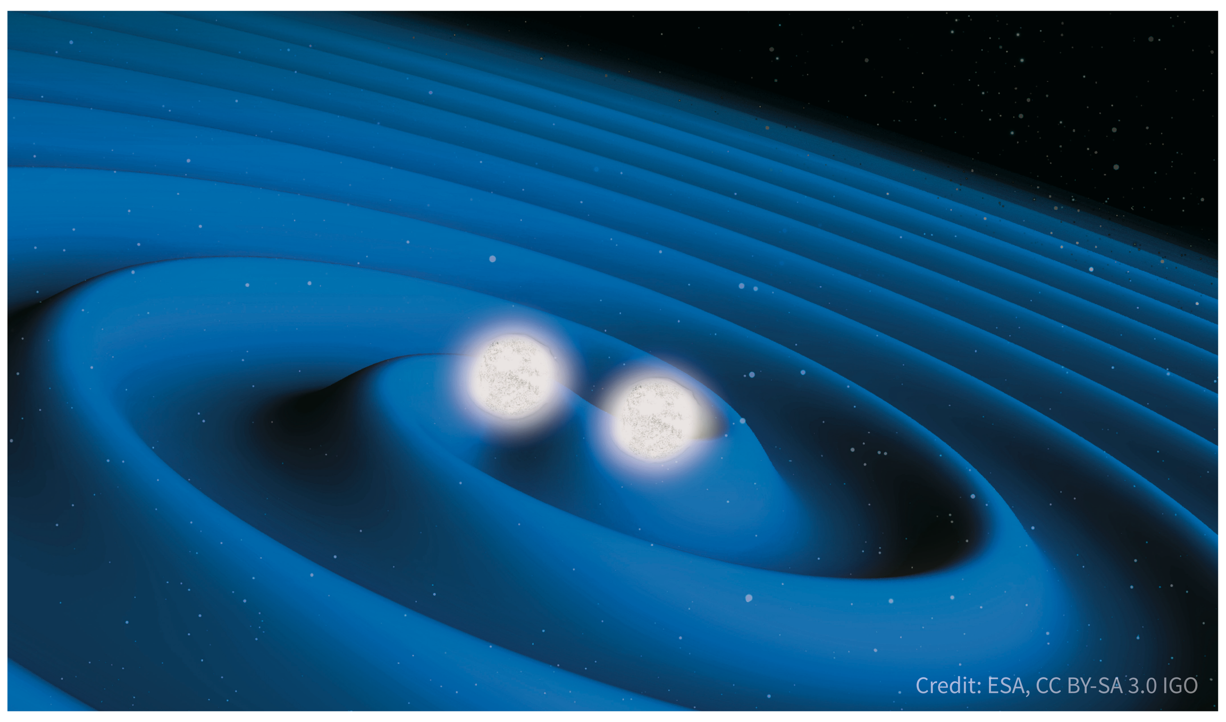


Fig. 1: Artist's impression of a BNS coalescence.

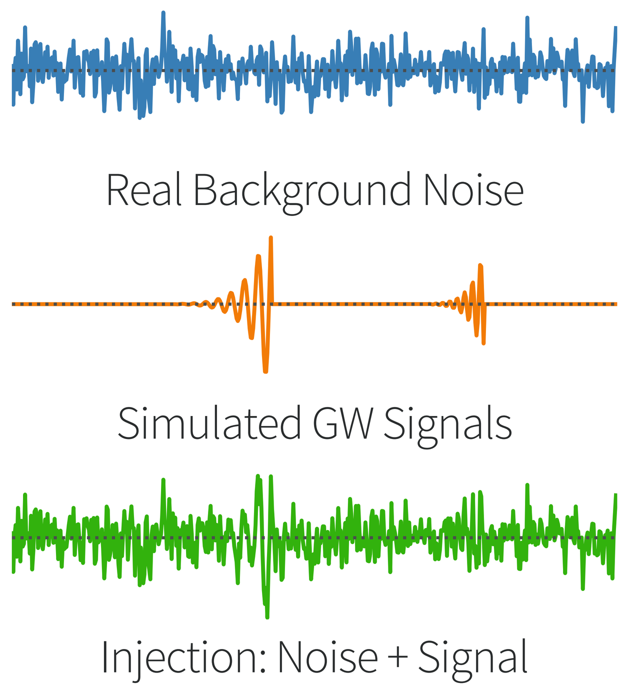


Fig. 2: Creating data.

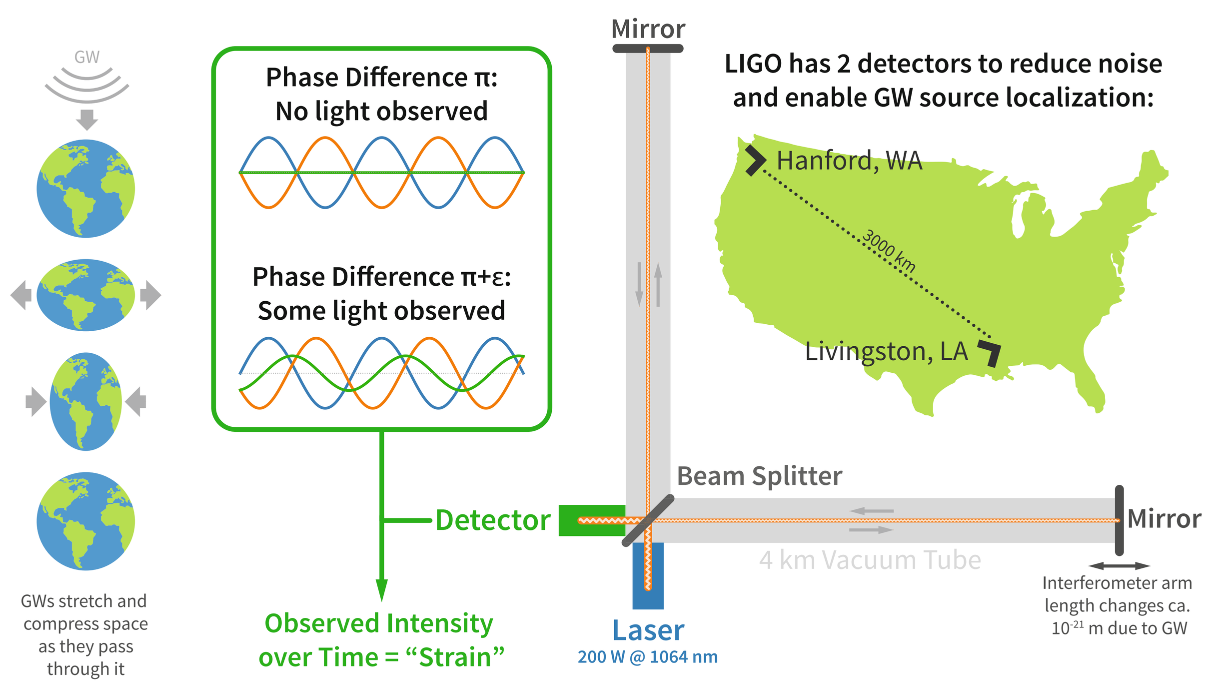


Fig. 3: Functional principle of the LIGO detectors.

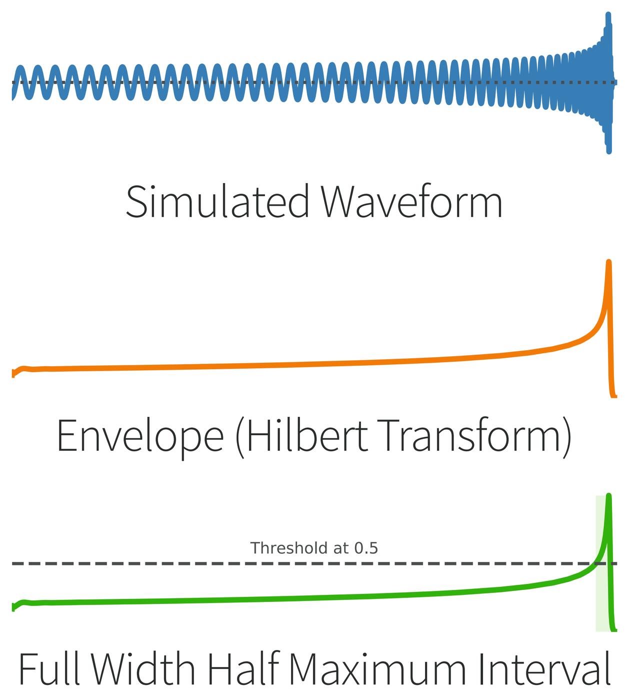


Fig. 4: Creating labels.

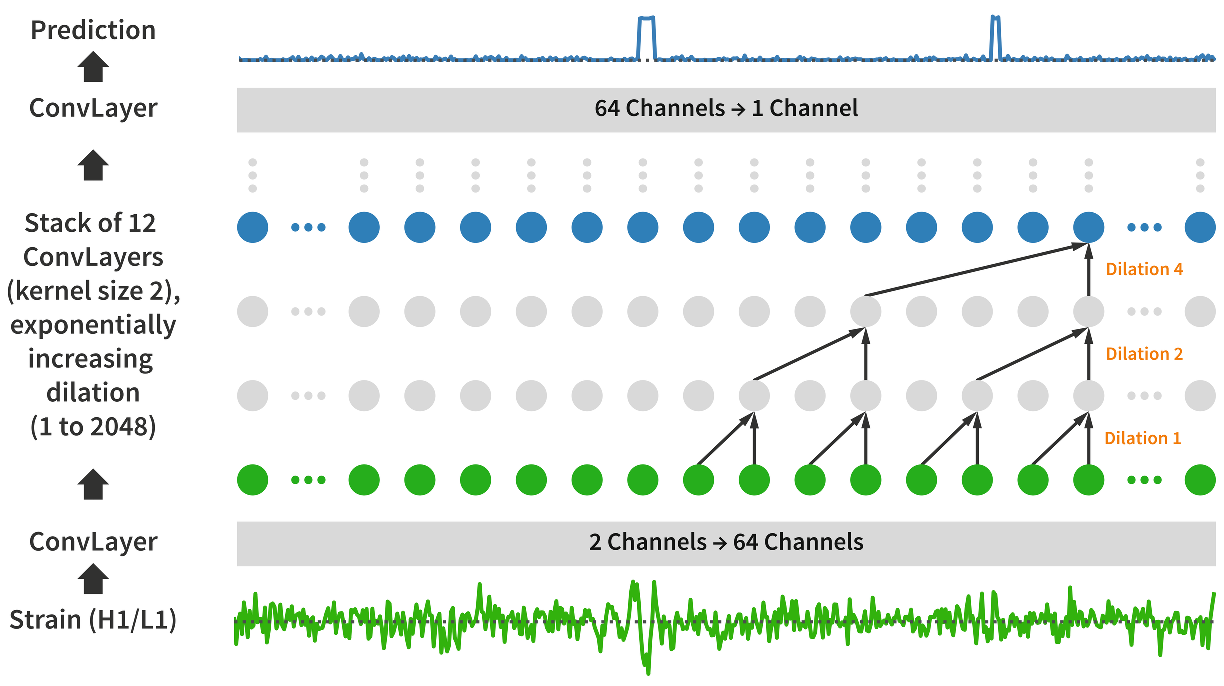


Fig. 5: Our *WaveNet*-inspired CNN architecture [3].

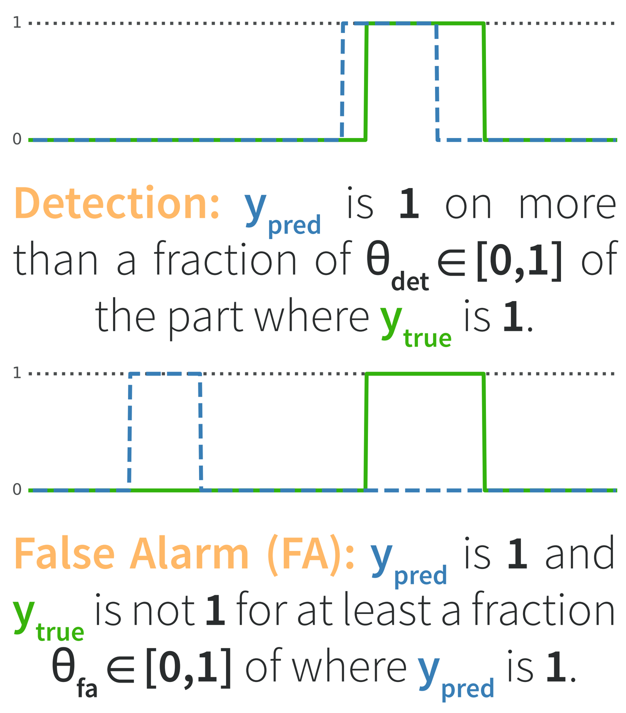


Fig. 6: Detections & FAs.

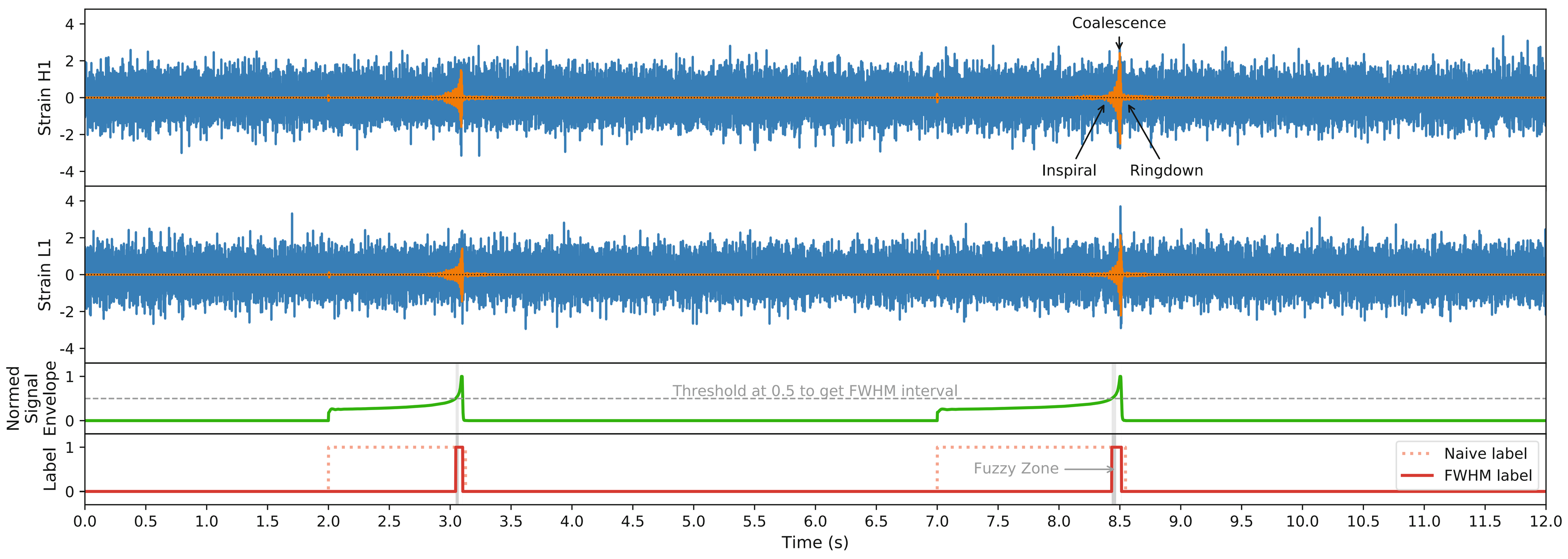


Fig. 7: Sample signal, corresponding (FWHM) label vectors and fuzzy zones.


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