Deep learning classification of the gravitational-wave signal candidates from the time-domain *F*-statistic search

Filip Morawski, Michał Bejger, Paweł Ciecieląg
Nicolaus Copernicus Astronomical Center, ul. Bartycka 18, 00-716 Warsaw, Poland

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Context

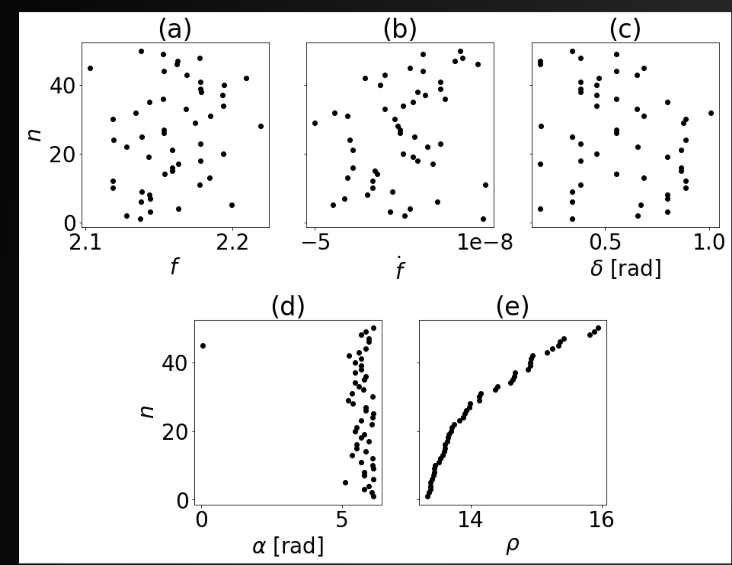
Development of interferometers will open new opportunities for the detection of gravitational waves (GW) originating from other sources than mergers of binary systems. Among many promising signal models, one in particular is very interesting: persistent continuous radiation from rotating, non-axisymmetric neutron stars (P. D. Lasky, PASA.2015.35). The search for such long-lived, periodic GW signals of unknown parameters and unknown position in the sky is particularly computationally intensive. This is because the GW signal is very weak and one needs to analyze long stretches of data in order to extract the signal "buried" in the noise of the detector.

The goal of our work is to show that the deep learning is a powerful tool for the classification of distributions of the candidate GW signals. We study three different ways the candidate GW signal may cross the *F*-statistic threshold. It may either be a:

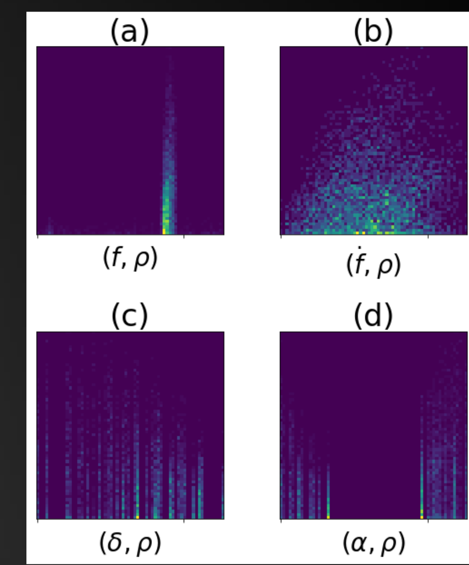
- **true GW signal** – modeled here by injecting a signal that matches the TD-Fstat GW filter, corresponding to the spinning triaxial ellipsoid
- **stationary "line"** – monochromatic signal representing an artifact disturbance caused locally in the detector,
- **Gaussian noise** – pure coincidence of the noise.

F-statistic signal candidates

F-statistic (P. Jaranowski et al. 1998, Phys. Rev. D58, 063001) is a data analysis method based on matched filtering by maximizing the likelihood function with respect to the set of unknown parameters. It reduces the parameter space to 4-dimensions: GW frequency, frequency derivative (also called spindown), right ascension and declination. To generate data we used TD-Fstat pipeline (https://github.com/mbejger/polgraw-allsky), incorporating this method (table below contains the parameters of the search). It returns clusters of candidate GW signals that crossed the pre-set threshold of the signal-to-noise – ρ (it corresponds to the reconstruction of the signal, not injection): $\rho=\sqrt{2(F-2)}$ where F is the value of *F*-statistic.



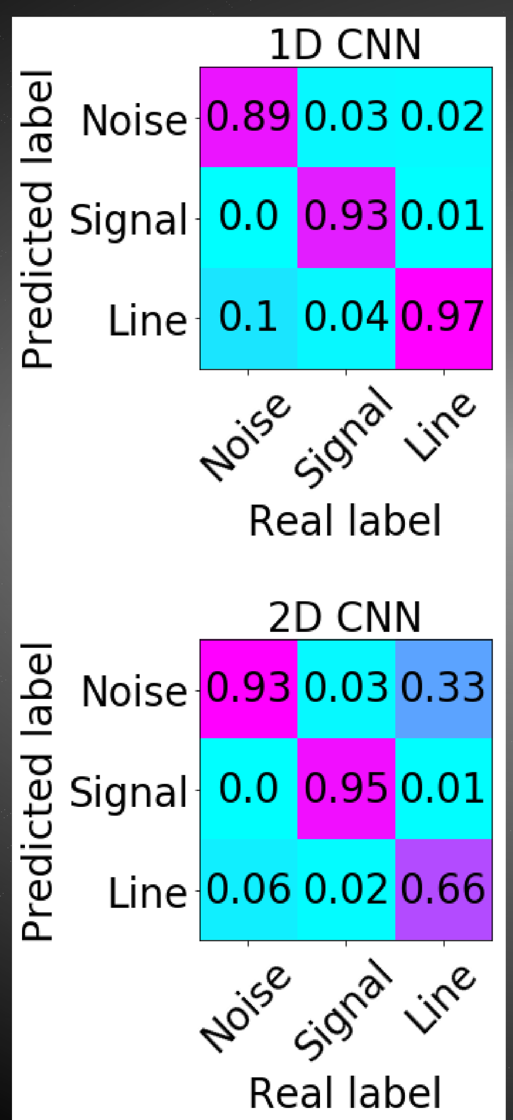
Reference frequency	50, 100, 200, 300, 500, 1000 Hz
Segment length	2 days
Bandwidth	0.25 Hz
Sampling time	2 seconds
Grid range	± 5 points
F-statistics threshold	14.5 (ρ = 5)
Signal to noise of injections	From 8 to 20

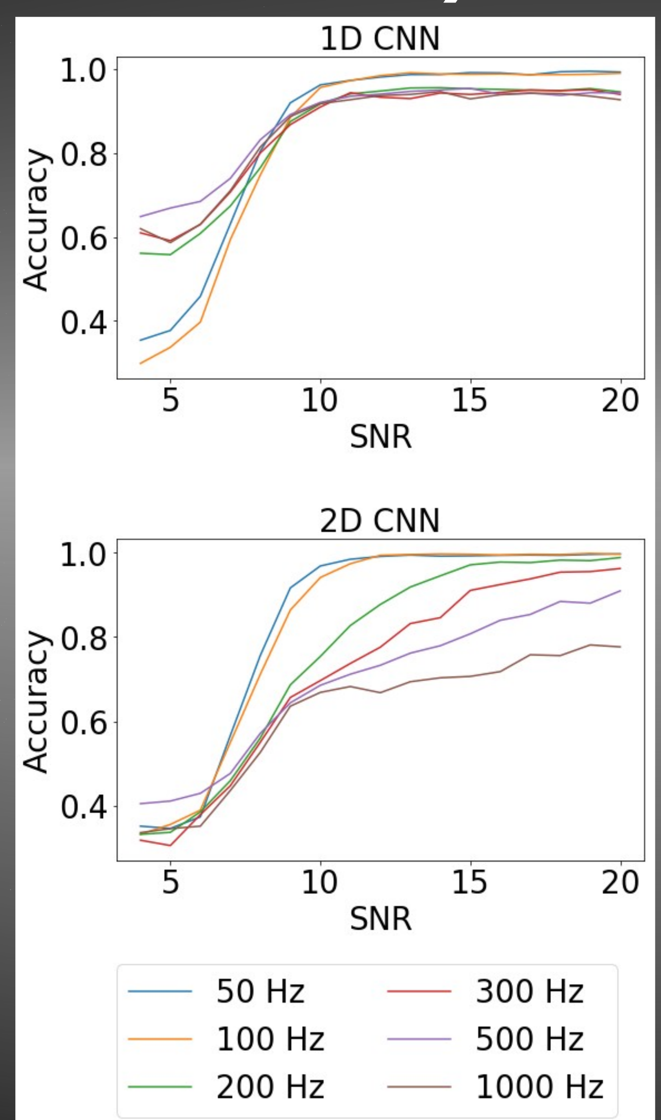


The 1D representation of TD-Fstat search. The plots present five parameters of *F*-statistic describing single signal candidate limited to the 50 maximum values of ρ: (a) frequency, (b) spin-down, (c) declination, (d) right ascension and (e) ρ.

The 2D representation of TD-Fstat search. Images have size equal to 64x64 pixels. They represent relations: (a) frequency – ρ, (b) spin-down – ρ, (c) declination – ρ, (d) right-ascension – ρ.

Convolutional neural networks (all *F*-statistic parameters)



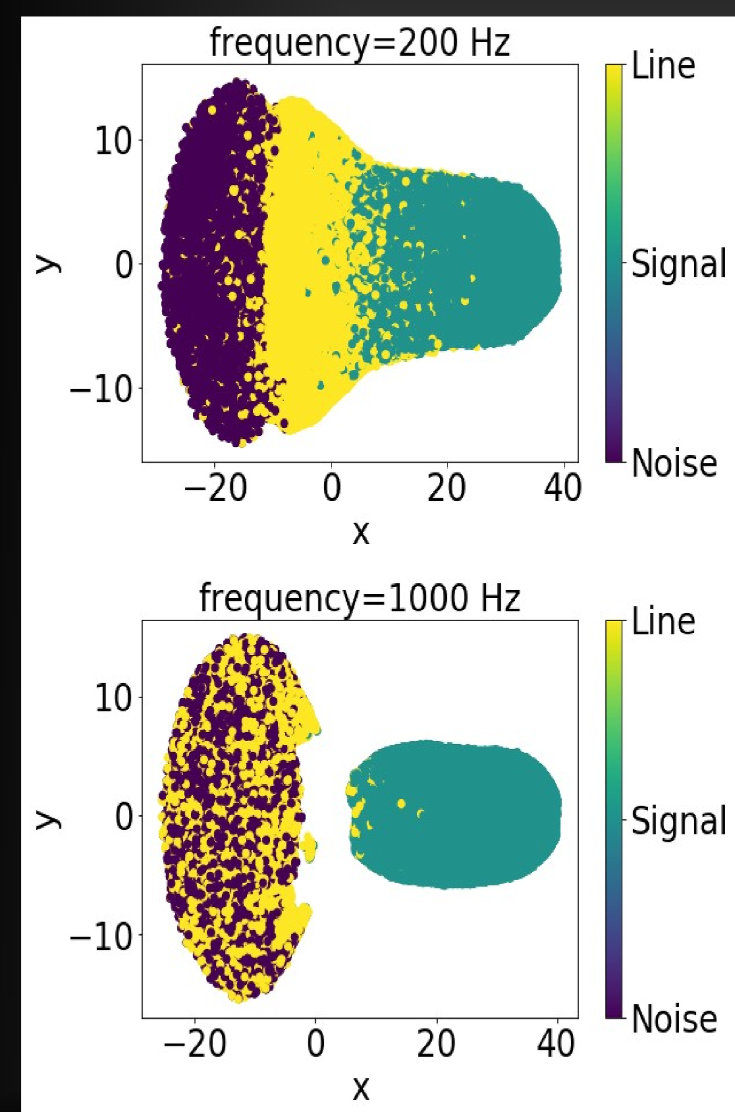


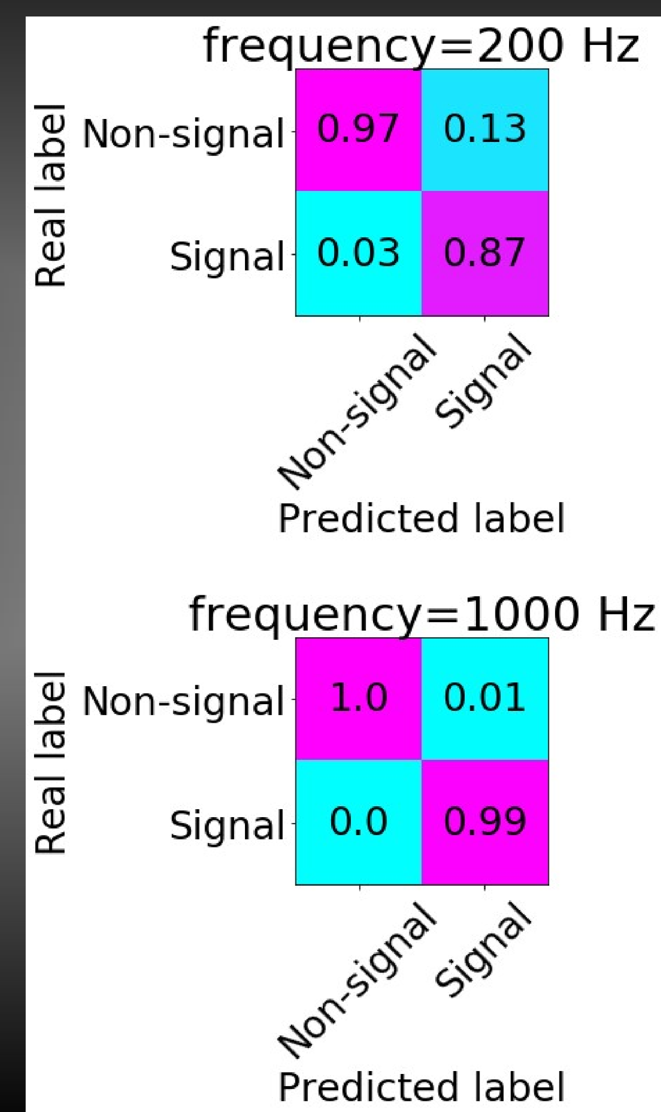
Both models were trained on the mixture of signals varying in frequencies and signal-to-noise ratios (SNRs). Later on they were tested against unknown during training samples from broader range of SNR (below 8).

The 1D CNN achieved much higher accuracy than 2D model (93% with respect to 84%) over candidate signals generated for broad range of frequencies and SNR. For majority of signals (SNR≥10) 1D CNN maintained more than 90% of accuracy.

The 2D model varied significantly with respect to the frequency. Although overall accuracy was worse, this CNN seemed to be more suited for the binary classification (between the noise and the GW signal).

t-SNE and AGNES hierarchical clustering (frequency, spin-down, ρ, SNR: 12-20)





In contrast to supervised approach, this unsupervised method was more suited to the directed searches (for signals of fixed frequency). Since the stationary line was indistinguishable from the noise, we introduced new class based on both – **non-signal** class.

The unsupervised pipeline allowed to reach very high accuracy (nearly 99%) for the biggest values of considered frequencies. Our analysis was in particular suited for the GW signals emitted by milisecond pulsars.

Conclusion

We showed that both, supervised and unsupervised learning, can be used to reach satisfactory results in the classification of *F*-statistic signal candidates. The CNNs process large number of candidates in a fast and accurate way. Whereas clustering allows for more detailed analysis of high frequency signals.

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