



A novel neural-network architecture for continuous-wave all-sky searches

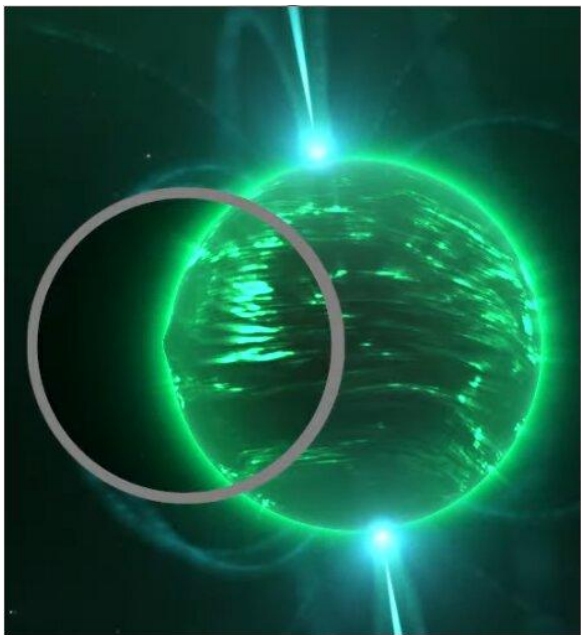
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Introduction



Coherent searches:

- Computationally infeasible
- Highly sensitive

Semi-coherent searches:

- Computationally expensive, yet feasible
- Less sensitive compared to coherent searches

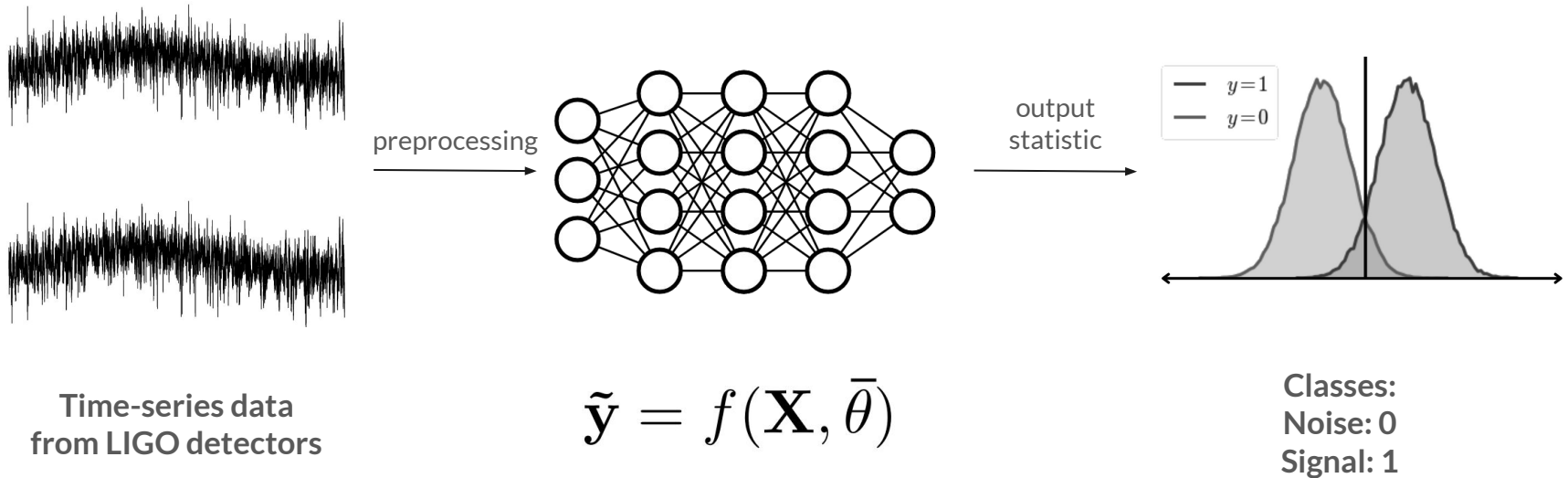
Semi-coherent searches have higher sensitivity at the same computational cost!

Deep Learning



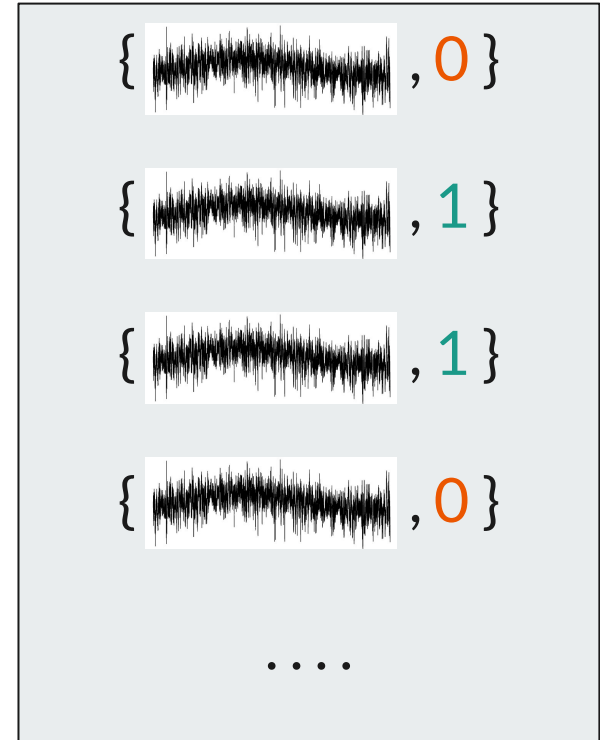
- **Reduction in search time**
 - Majority of computational cost is required for training
 - Training with a small number of templates
- **Improvement in sensitivity over semi-coherent searches**
 - Analyse the data coherently
- **Robustness against noise artifacts**
 - Training networks to distinguish between instrumental lines and true signals

CW Search as a classification problem



Labeled Dataset

- Large number of samples each for **noise** and **signal** cases
- **Noise** sample: simulated Gaussian noise; label **0**
- **Signal** sample: simulated Gaussian noise + CW signal with known parameters; label **1**
- Choice of parameters for injected signals based on the search.
- Noise generated dynamically at the time of training



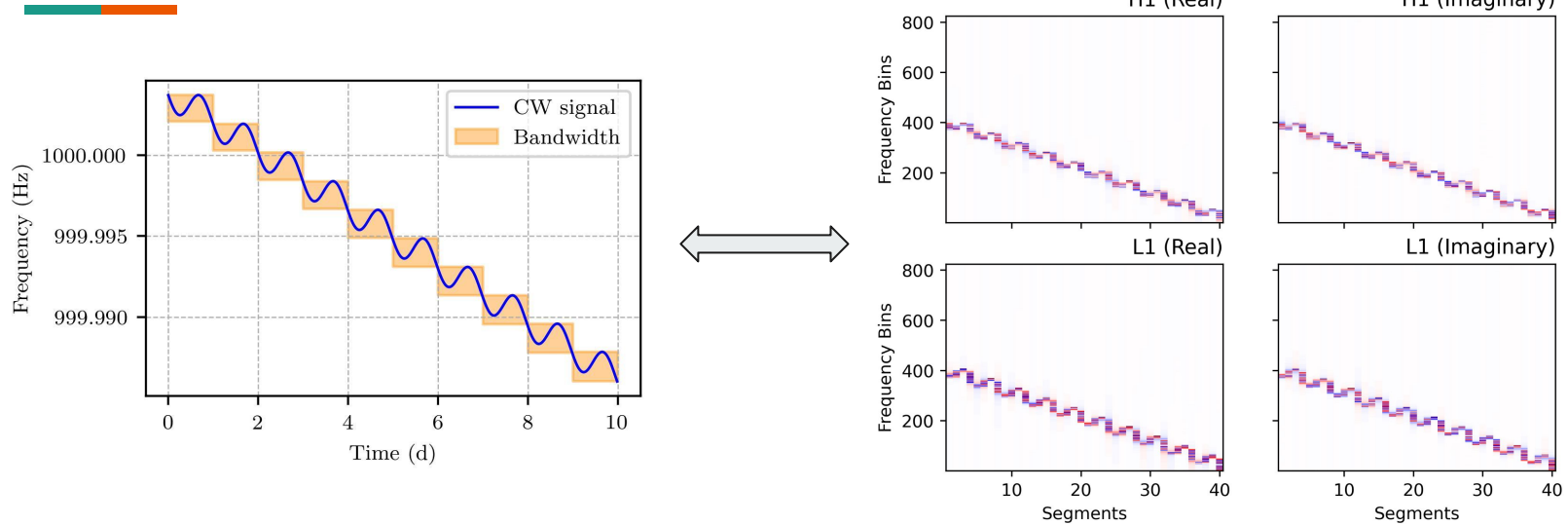
All-sky Dataset



- **32768** templates each for training and validation
- Sky-position sampled isotropically from all over the sky
- Spin-down sampled from the range $[-10^{-10}, 0]$ Hz/s

Dataset	Frequency band (Hz)	Sensitivity depth (\sqrt{h} Hz)
20 Hz	[20, 20.05]	39.04
100 Hz	[100, 100.05]	37.27
200 Hz	[200, 200.05]	36.62
500 Hz	[500, 500.05]	35.60
1000 Hz	[999.95, 1000]	33.37
20 - 1000 Hz	[20, 1000]	33.37

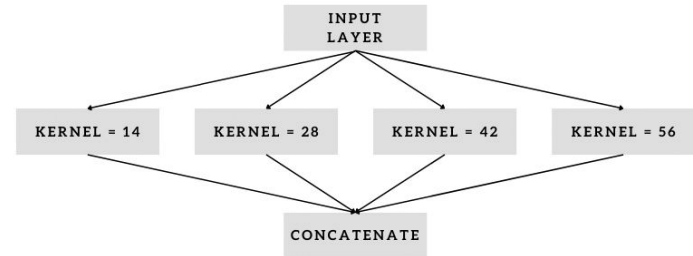
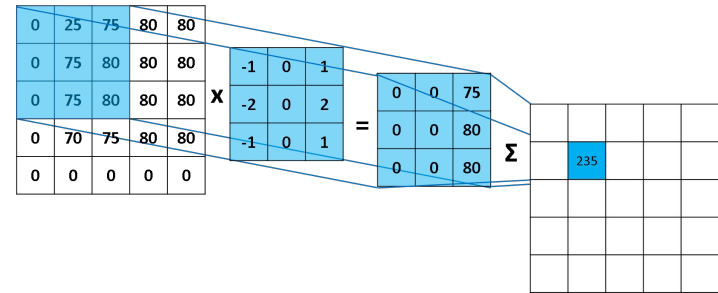
Preprocessing the input



- Make a **spectrogram** from the time-series data.
- Frequency bandwidth: twice the maximum signal bandwidth
- Repeating Doppler modulation → Repeating pattern in the spectrogram
- Learn using **convolutional neural networks!**

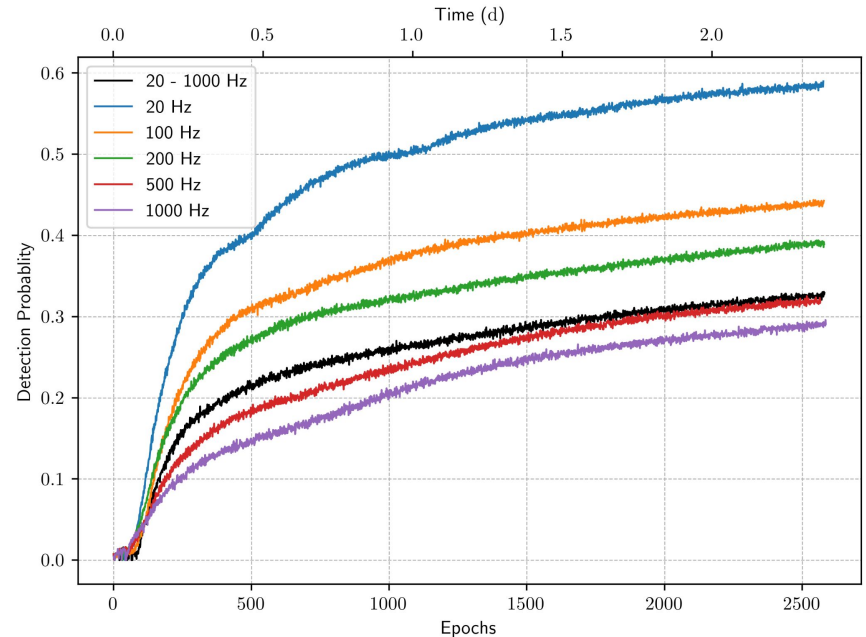
Network architecture

- Convolutional Neural Networks: search for the repeating pattern in different locations in the input
- **Kernel-size of convolutions:** wide enough to contain the widest possible signal
- **Power of signal is distributed in several bins:** difficulty to learn signal shape increases with increase in width of the signal
- Use convolutions of **different kernel-sizes** to learn signals with different widths



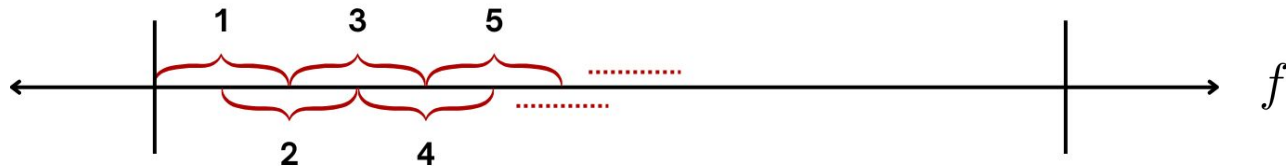
Network output and training

- Use linear output of the network for classification
- Loss function: **binary cross-entropy loss**
- Optimizer: **Adam**
- Training metric: detection probability calculated with a threshold corresponding to a value of false-alarm probability ($\sim 0.75\%$)



Estimation of network threshold

- **Comparison with WEAVE search:**
 - Coherent search
 - Template bank parameters: $N = 4 \times 10^{14}$, Mean SNR loss = 8%
 - Threshold set at $P_{FA} = 1\%$ per 50 MHz band.
- **Set threshold on network output at the same false-alarm probability as the above search for a fair comparison**
- Network placements with a half-overlap covers the entire search band.



$$\tilde{y} = \max(\tilde{y}_1, \tilde{y}_2, \tilde{y}_3, \tilde{y}_4, \tilde{y}_5, \dots)$$

Comparison of detection probability

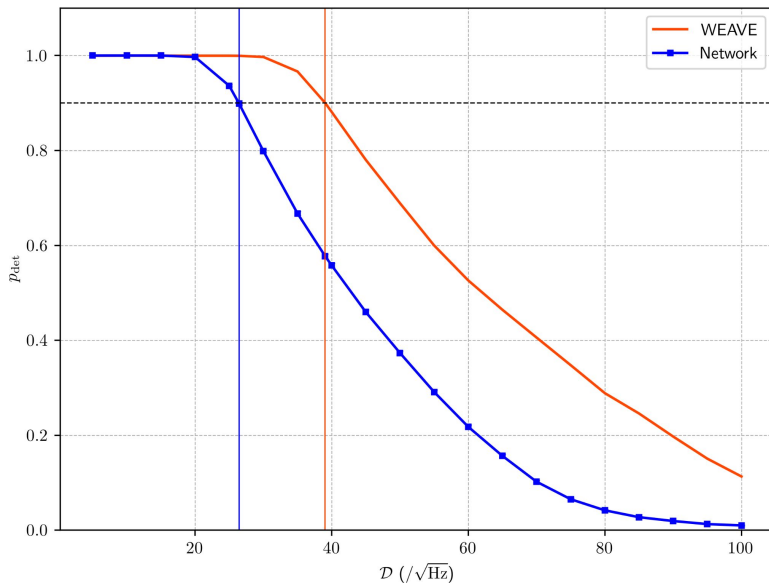
Dataset	This work			Earlier work [1] (%)
	Training (%)	Validation (%)	Testing (%)	
20 Hz	56.83	57.38	57.63	60.5
100 Hz	42.09	42.19	42.14	24.5
200 Hz	37.98	38.14	37.64	11.2
500 Hz	30.83	29.96	30.76	3.3
1000 Hz	27.88	28.16	28.35	0.7
20 - 1000 Hz	31.60	31.58	31.37	-

Network generalizes to CW signals with unknown parameters!

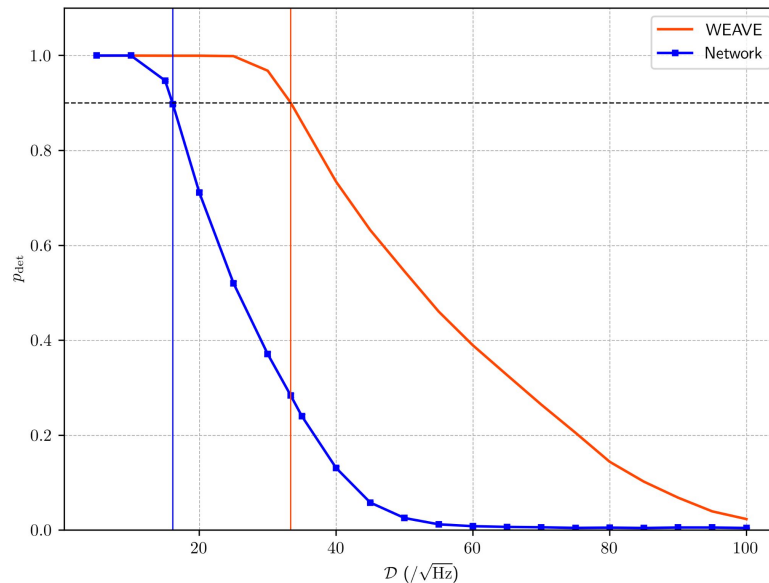
Comparison of 90% upper limits

Dataset	This work			Earlier work[1] ($1/\sqrt{\text{Hz}}$)
	Training ($1/\sqrt{\text{Hz}}$)	Validation ($1/\sqrt{\text{Hz}}$)	Testing ($1/\sqrt{\text{Hz}}$)	
20 Hz	26.29	26.33	26.45	29.6
100 Hz	21.22	21.21	21.34	17.5
200 Hz	19.77	19.79	19.82	13.9
500 Hz	17.71	17.62	17.65	9.7
1000 Hz	16.08	16.12	16.13	7.9
20 - 1000 Hz	16.70	16.70	16.70	-

Generalization in signal strength



Dataset: 20 Hz



Dataset: 1000 Hz

Network generalizes to CW signals with sensitivity depth different from training!

Summary



- We trained neural networks to perform all-sky searches with a better performance than previous networks
- We demonstrate network input and design properties that lead to efficient training and good performance
- We demonstrate the capability of the network to generalize to a wider set of CW signals, even after being trained on a small number of templates
- We show a method to compare the sensitivity of a neural network search to a matched filter search.
- The next steps in this work are to analyse longer time-spans of data and to perform parameter estimation.

Thank you!