Searching for long-duration transient gravitational waves from glitching pulsars using Convolutional Neural Networks

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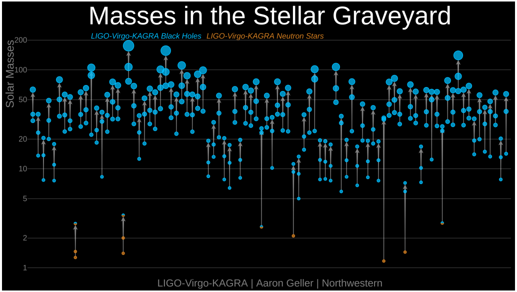
G2Net meeting (Valencia), 11-13 April 2022

Universitat de les Illes Balears

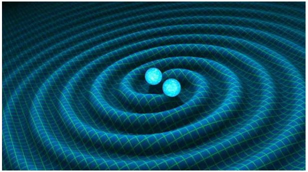
12 April 2022

Gravitational waves sources

So far the LVK has detected 90 compact binary coalescence events.



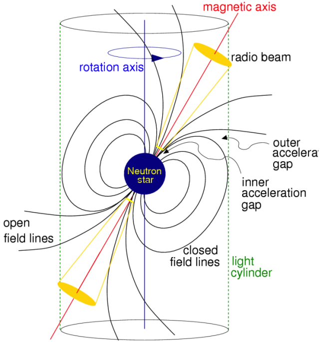
Credit: LIGO-Virgo/Aaron Geller/Northwestern



Credit: NASA

Another possible source of gravitational waves (GWs) could be **rotating neutron stars** (not yet detected).

Introduction to pulsars

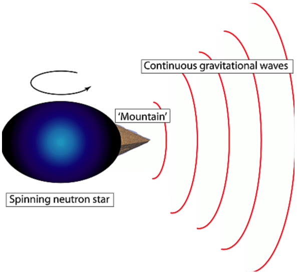


Credit: Lorimer & Kramer, Handbook of Pulsar Astronomy

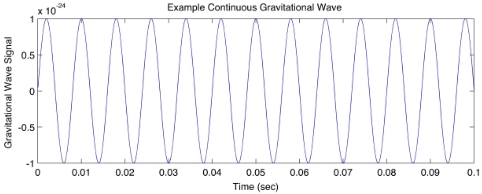
- Rotating neutron stars emitting an electromagnetic (EM) beam.
- Detectable if the EM beam swipes Earth's line of view ("lighthouse" effect).
- Over 3000 known pulsars.
- EM observations can't probe the inner composition of these extreme objects $\rightarrow$ GWs *could!*

Continuous waves (CWs)

Asymmetries in the rotating neutron star are possible sources for GW emission.



Credit: Australian National University. Center for Gravitational Astrophysics

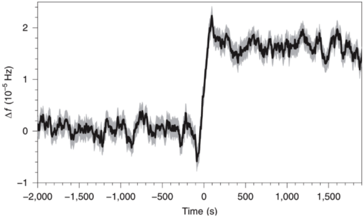


$h(t; \lambda, \mathcal{A})$ CW signal with parameters:

$\lambda = \{\alpha, \beta, f, \dot{f}, \ddot{f} ...\}$ Doppler modulation due to Earth's motion, source frequency, spindown...

$\mathcal{A} = \{h_0, \cos\iota, \psi, \phi_0\}$ signal amplitude, source orientation.

Glitching pulsars

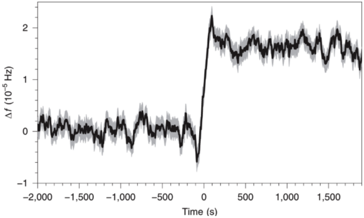


Credit: Ashton et al. 2019

Rotational frequency suddenly increases!

- Pulsars **lose energy** due to EM and GW emission.
- Some young pulsars undergo "glitches", i.e. a **spin-up** event.

Glitching pulsars



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- Energy not created out of nothing, rather need to look into the depths of the neutron star $\rightarrow$ mostly unknown!

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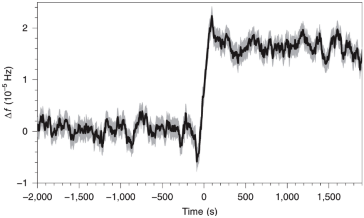

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Rotational frequency suddenly increases!

- Pulsars **lose energy** due to EM and GW emission.
- Some young pulsars undergo "glitches", i.e. a **spin-up** event.
- Energy not created out of nothing, rather need to look into the depths of the neutron star → mostly unknown!
- Two-fluid model: anomaly could be due to angular momentum transfer from an interior superfluid component, and GWs could be produced from the freed energy.

Transient continuous waves

Similar to CW standard model, but in addition to the phase and amplitude parameters:

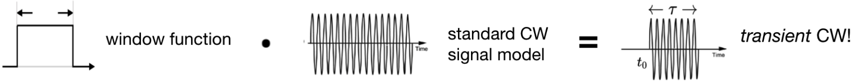
$$\lambda = \{\alpha, \beta, f, \dot{f}, \ddot{f} ...\}$$
$$\mathcal{A} = \{h_0, \cos\iota, \psi, \phi_0\}$$

we consider a set of **transient** parameters:

$$\mathcal{T} = \{\tau, t_0\}$$

Transient continuous wave model (Prix et al. 2011)

$$h(t; \lambda, \mathcal{A}, \mathcal{T}) = \omega(t; \mathcal{T}) h(t; \lambda, \mathcal{A})$$



How do we detect these signals?

1. Signal vs noise hypotheses framework (Prix et al. 2011)

$$\begin{cases} \mathcal{H}_{\mathrm{G}} : x(t) = n(t) & \text{data } x \text{ contains only Gaussian noise} \\ \mathcal{H}_{\mathrm{tS}} : x(t) = n(t) + h(t; \lambda, \mathcal{A}, \mathcal{T}) & \text{data } x \text{ contains tCW signal too!} \end{cases}$$

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$$\frac{P(x|\mathcal{H}_{\mathrm{tS}};\lambda,\mathcal{A},\mathcal{T})}{P(x|\mathcal{H}_{\mathrm{G}})}$$

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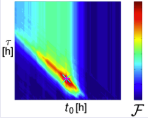
3. $\mathcal{F}$-stat map

maximize the likelihood ratio over $\mathcal{A}$ and obtain:
$\mathcal{F}_{mn} = \mathcal{F}(\lambda, t_{0m}, \tau_m)$



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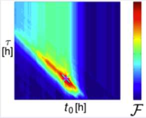


4. Detection statistic for tCWs

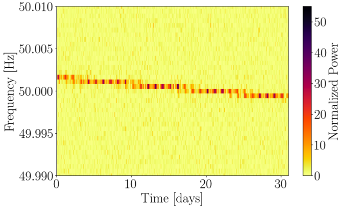
For each λ, either:

- *maximize* over $\mathcal{T}$ $\rightarrow \max_{\mathcal{T}} \mathcal{F}(x; \lambda, \mathcal{T})$
- *marginalize* over $\mathcal{T}$ $\rightarrow \log_{10} \mathcal{B}_{\mathrm{tS/G}}$

$\mathcal{F}$-stat atoms

In this framework, the detection statistic for tCWs comes from the $\mathcal{F}$-stat. Using **Short Fourier Transforms** (SFTs) as the building blocks of $x(t)$, $\mathcal{F}$-stat coherently sums up the power along the correctly Doppler-demodulated track with the antenna-pattern weights.

The inputs to its practical implementation are called $\mathcal{F}$-stat "atoms":



$\mathcal{F}$-stat atoms

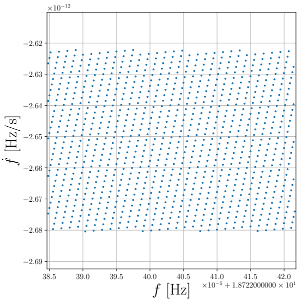
$$F_{\mathrm{a,b}}^{X\alpha}, \langle a_{X\alpha}^2 \rangle_t, \langle b_{X\alpha}^2 \rangle_t, \langle a_{X\alpha} b_{X\alpha} \rangle_t$$

7 numbers for each SFT (typically 1800s).

where $X\alpha$ denotes an SFT of detector X, $\langle a_{X\alpha}^2 \rangle_t, \langle b_{X\alpha}^2 \rangle_t$, are the noise-weighted antenna-pattern functions and $F_{\mathrm{a,b}}^{X\alpha}$ are the projections of the normalized data on the complex basis $\{\mathrm{a,b}\}$.

Search methods: matched filtering

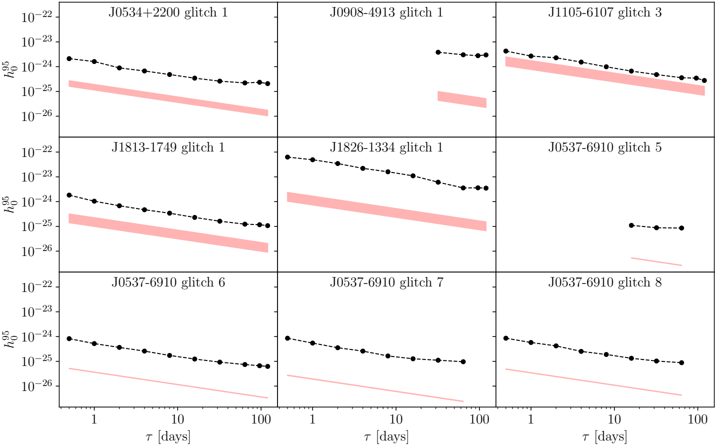
1. Set up a template grid λ_i covering parameter space of interest.
2. Evaluate a statistic ($\max \mathcal{F}$ or $\log_{10} \mathcal{B}_{\mathrm{tS/G}}$) on each template.
3. Highest statistic over templates $\rightarrow$ possible candidates of tCWs.



Previous searches have covered a parameter space λ, as given by ephemerides uncertainties, and $\mathcal{T}$ limited to (Modafferi et al. 2021):

$$\begin{cases} \tau \in [3600 \text{ s}, 120 \text{ days}] \\ t_0 \in [T_{\text{glitch}} \pm 1 \text{ day}] \\ \omega(t; \mathcal{T}) = \text{rectangular} \end{cases}$$

- Searches limited in $\mathcal{T}$ because of the computation of partial sums corresponding to different combinations of $\mathcal{T} = \{t_0, \tau\} \rightarrow$ very expensive!
- Machine learning could help us.

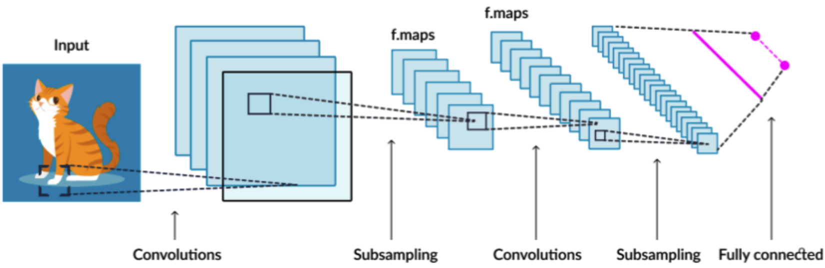


The LIGO Collaboration, the Virgo Collaboration and the KAGRA Collaboration, arXiv:2112.10990

Indirect energy upper limits (red line): $h_0 \leq \frac{1}{d}\sqrt{\frac{5G}{2c^3}\frac{I_z}{\tau}\frac{|\Delta f|}{f}}$

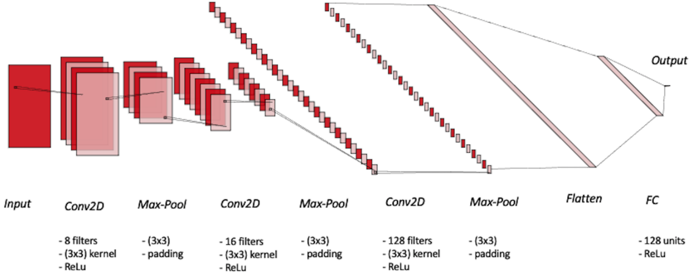
Convolutional Neural Networks (CNNs)

- Deep learning algorithm that can pick up **patterns** from an input.
- Great for image recognition.
- Make use of convolution kernels or **filters** that slide along input features and provide translation equivariant responses known as feature maps.



$\mathcal{F}$-stat atoms as inputs of CNN

- If the 7 per-timestamp $\mathcal{F}$-stat atom vectors $\sim$ pixels of an image, we can feed them as input to a CNN!
- Output: probability of belonging to signal/noise category.
- Threshold set on output probability by fixing false-alarm probability p_{FA}.



First model: simple design made up of 3 stacks of convolutional + MaxPooling layer, we then flatten the output and add 2 fully-connected layers, where the last outputs the detection statistic.

Exploring different outputs: regression vs classification

- The output of a classification algorithm is usually an ad-hoc created **detection statistic** $d \in [0, 1]$.
- A threshold is set on d to distinguish between noise/signal output.
- A different approach: use regression to predict a **continuous target**, e.g **signal-to-noise ratio** (SNR).
- SNR would label how strong the signal in the input is.
- Set a threshold on SNR, e.g. fixing p_{FA}.

For our first setup[1] we use:

Testing set:

- 10^5 Noise samples
- 10^4 Signal samples

Training set:

- 2×10^4 Noise samples
- 2×10^4 Signal samples

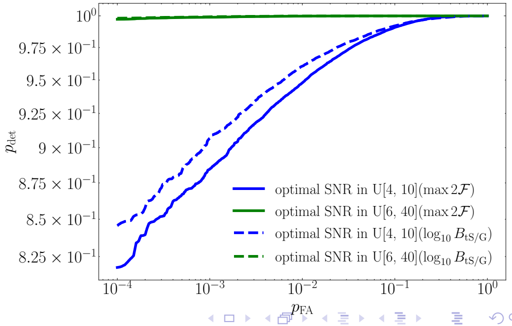
[1] Special thanks to Artemisa, computing resources located here in Valencia!

How do we characterize the performance of the CNN?

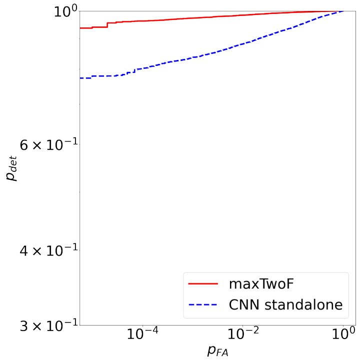
1. First **define the search setup** (parameter space size, noise/signal distributions...).
2. **Compare** the CNN to matched filtering performances of previous searches → test set of the CNN close to real search outputs.
3. The CNN model gets as good as its training set: will be defined based on the data we want to target.

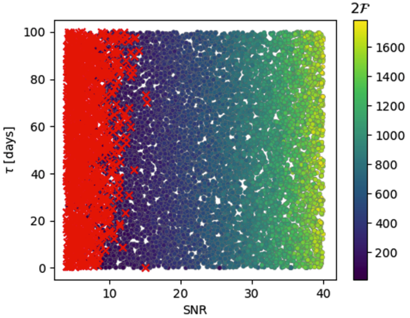
Testing set:

- Noise samples → determines how deep p_{FA} can go.
- Signal samples → determines resolution of p_{det}.



Early results





Duration of injected signal τ as a function of SNR. Red crosses are the signals that haven't been found by the CNN.

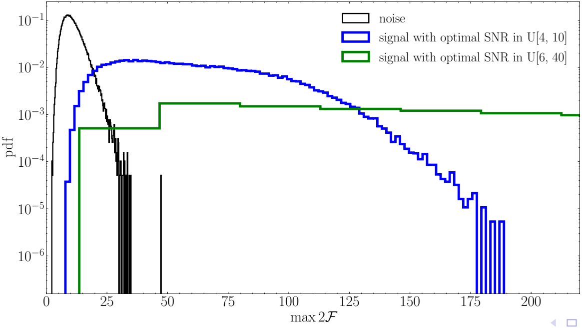
- Using only Gaussian noise + simulated injections.
- Performance holds when testing different sky positions and data with realistic gaps.
- False dismissal rate $\sim 12\%$ at $p_{FA} = 0.01$.

Not the best we can do...

Let's try a different training strategy.

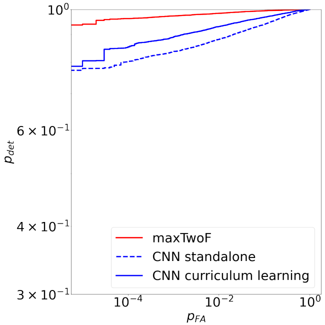
Curriculum learning (CL)

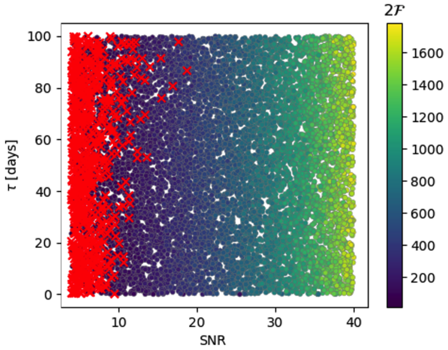
- CL is a training strategy consisting of training on datasets of gradually increasing difficulty (Bengio et al. 2009).
- Previous studies have used CL on GW data (López et al. 2021, Baltus et al. 2021).
- Difficulty criterion: SNR $\rightarrow$ first train on high SNR, then on low SNR training data.



The green distribution goes up to $\max 2\mathcal{F} \sim 1750$

Early results - with curriculum learning





False dismissal rate at $p_{\mathrm{FA}} = 0.01$: from 12% (standalone model) $\rightarrow$ 7% (curriculum learning).

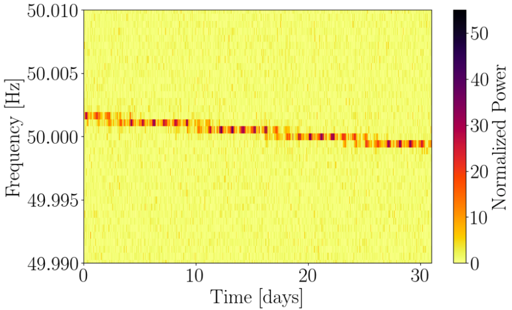
Next steps

- Fine-tune hyperparameters to minimize loss.
- Use real data.

Conclusions

- Machine learning represents a complementary tool for traditional matched filtering techniques.
- Will test on exponential window function, which was prohibitive in traditional searches.
- Our model currently allows for flexible amplitude evolution.

- We here do not allow for f variation beyond standard spin-down model.
- $\rightarrow$ future project would use directly detector SFT data as input to allow for more flexible f variation.



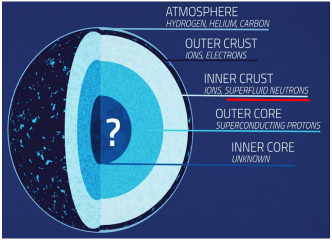
Acknowledgements

Thank you for listening!

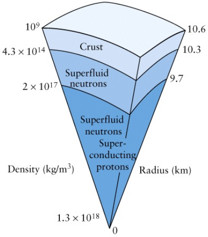
L.M.M. is supported by the Universitat de les Illes Balears. D.K. is supported by the Spanish Ministerio de Ciencia, Innovación y Universidades (ref. BEAGAL 18/00148) and cofinanced by the Universitat de les Illes Balears. This work is supported by the European Union FEDER funds; the Spanish Ministry of Science and Innovation and the Spanish Agencia Estatal de Investigación grants PID2019-106416GB-I00/MCIN/AEI/10.13039/501100011033, RED2018-102661-T, RED2018-102573-E; the European Union NextGenerationEU (PRTR-C17.I1); the Comunitat Autonoma de les Illes Balears through the Conselleria de Fons Europeus, Universitat i Cultura and the Direcció General de Política Universitaria i Recerca with funds from the Tourist Stay Tax Law ITS 2017-006 (PRD2018/24, PRD2020/11); the Vicepresidència i Conselleria d'Innovació, Recerca i Turisme del Govern de les Illes Balears; the Generalitat Valenciana (PROMETEO/2019/071); and EU COST Actions CA18108, CA17137, CA16214, and CA16104. The authors gratefully acknowledge the computer resources at Artemisa, funded by the European Union ERDF and Comunitat Valenciana as well as the technical support provided by the Instituto de Física Corpuscular, IFIC (CSIC-UV).
Credit background title slide: Wallpaper Access

Bonus slides

Theory of pulsar glitches: two-fluid model



Credit: NASA's Goddard Space Flight Center/Conceptual Image Lab



- Observed pulses with angular velocity Ω, associated to NS magnetic field and which gradually decreases.
- Interior neutrons are superfluid, forming an independent component that rotates at angular velocity Ω_S.
- Weak coupling between the two components $\rightarrow$ growing "lag" $\Delta\Omega = \Omega_S - \Omega$.
- When lag reaches a critical value, some sort of instability occurs.
- Transfer of angular momentum from superfluid to normal fluid $\rightarrow$ spin-up.
- Change in quadrupole moment can cause GW emission.

Exponential vs Rectangular windows