OBSERVATOIRE DE LA CÔTE D'AZUR
UNIVERSITÉ CÔTE D'AZUR

A new stacking pipeline to detect gravitational waves signals from repeaters

Huitième assemblée générale du GdR Ondes Gravitationnelles

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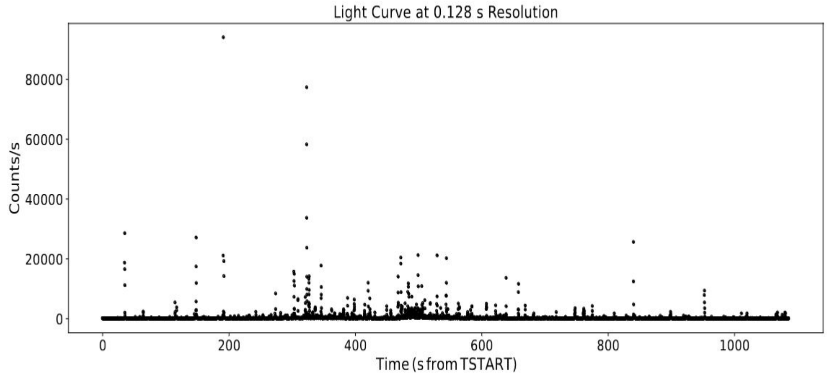
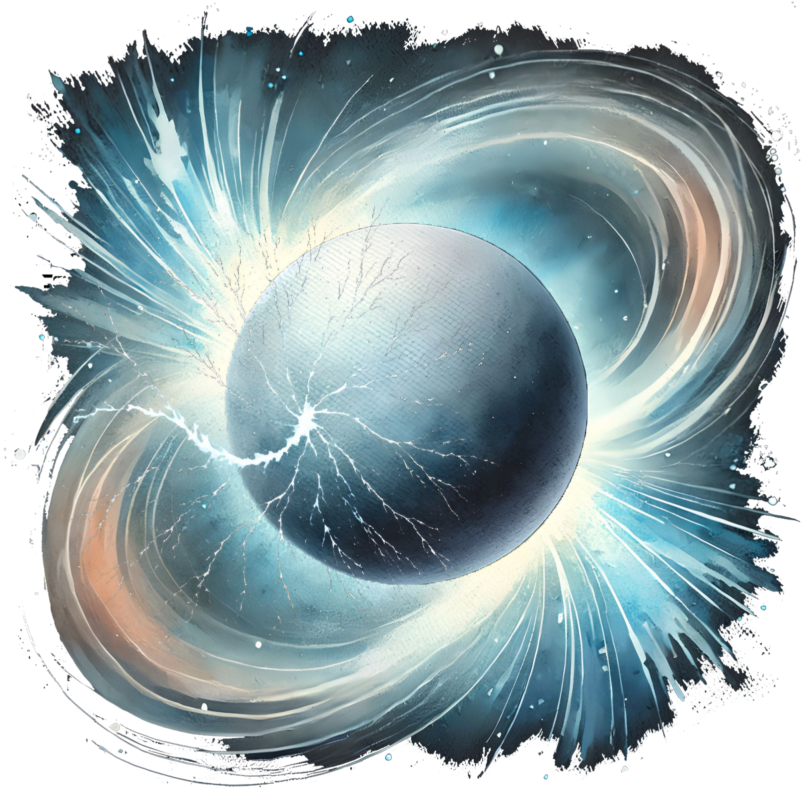
ARTEMIS

Magnetars and bursting activity

- Magnetic Field $B \approx 10^{14} - 10^{15}\,\mathrm{G}$
- Rotation Period $P \approx 0.3 - 12\,\mathrm{s}$
- Age $\tau \approx 10^{3} - 10^{5}$ years
- X-ray Luminosity $L_X \approx 10^{35} - 10^{36}\,\mathrm{erg/s}$
- Burst Energy $E \approx 10^{38} - 10^{41}\,\mathrm{erg}$
- Burst Duration $\Delta t \approx 0.1 - 1\,\mathrm{s}$
- Peak Luminosity $L_{\mathrm{peak}} \approx 10^{41} - 10^{43}\,\mathrm{erg/s}$

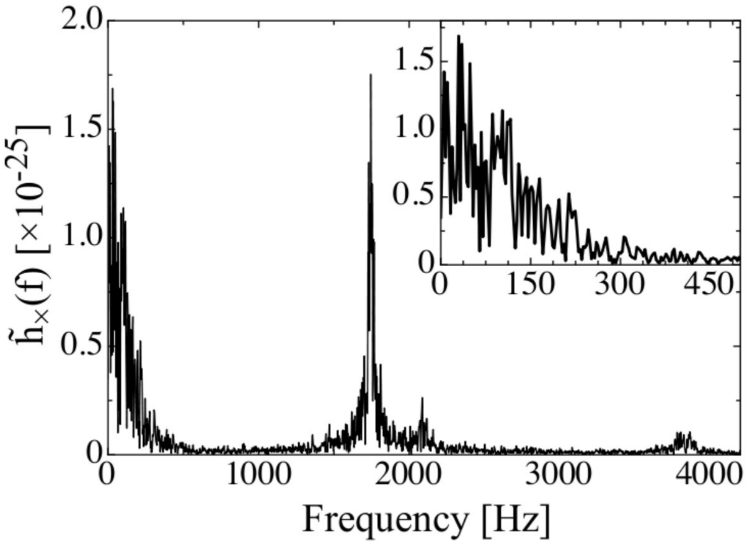


(SGR1935 bust storm light curve, 1120s taken on 2020 April 28 00:40:58: arXiv:2009.07886)

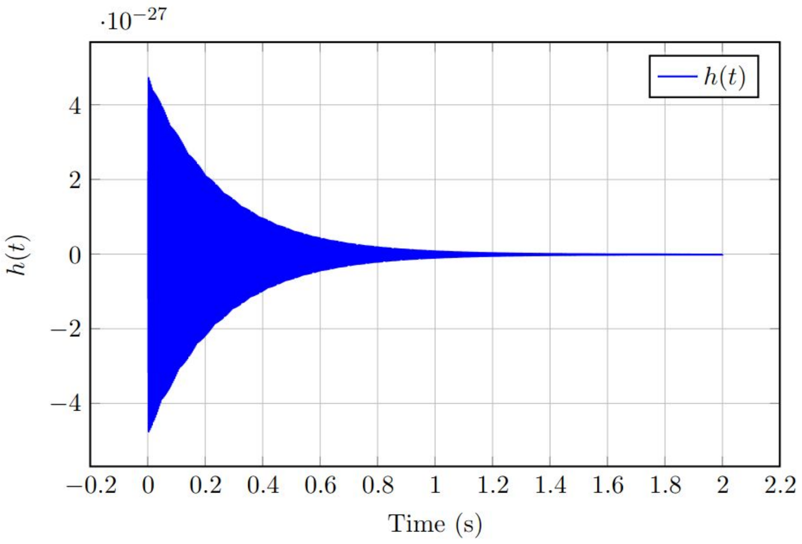


(Artistic representation of a magnetar flaring by me)

f-mode Gravitational Wave Emission Model



(Fundamental vibrational mode induced GW emission from Hydromagnetic Instabilities in Rotating Magnetized Neutron Stars, Paul D. Lasky : arXiv:1203.3590)

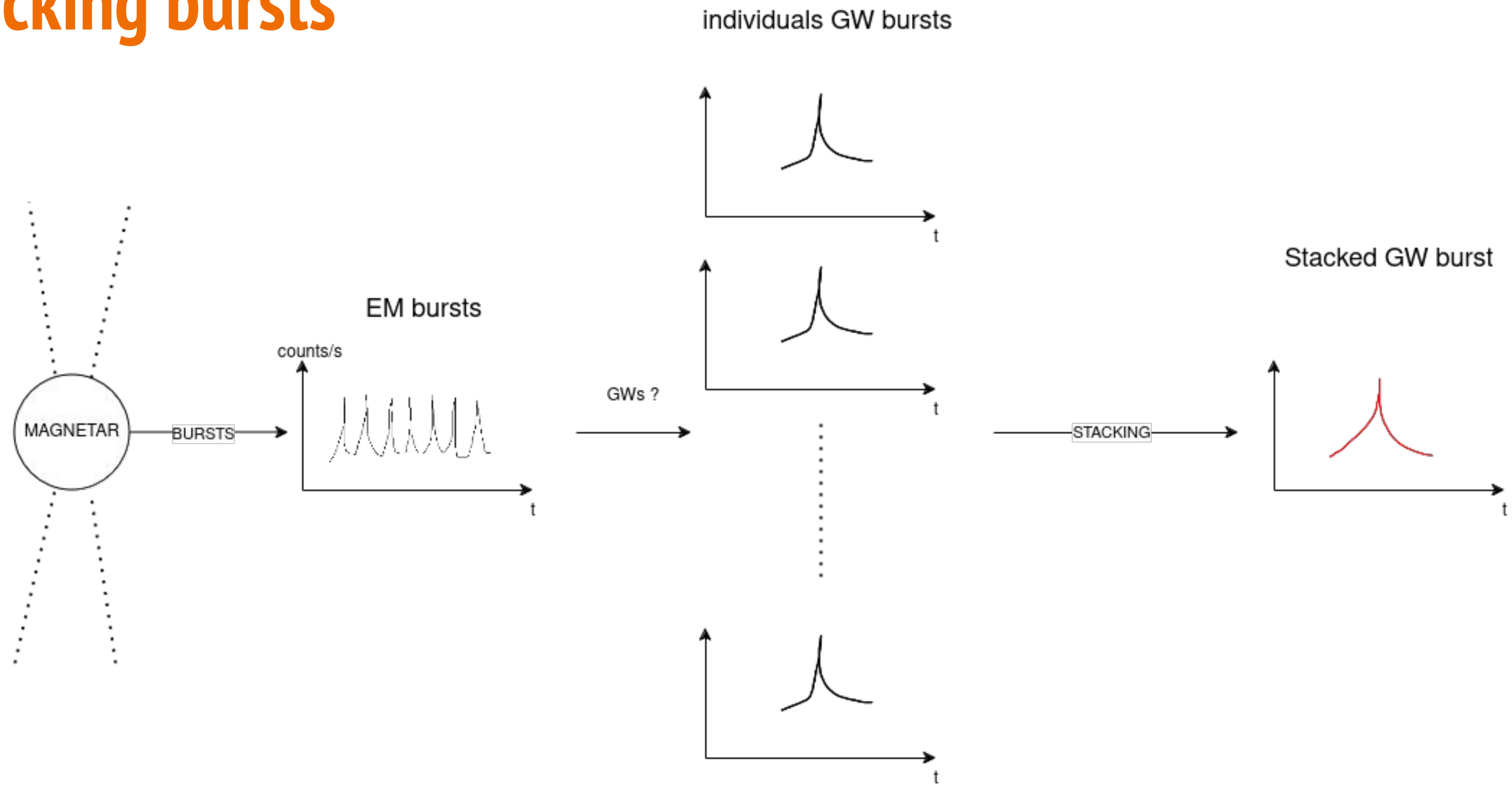


(strain modelized for an f-mode GW emission)

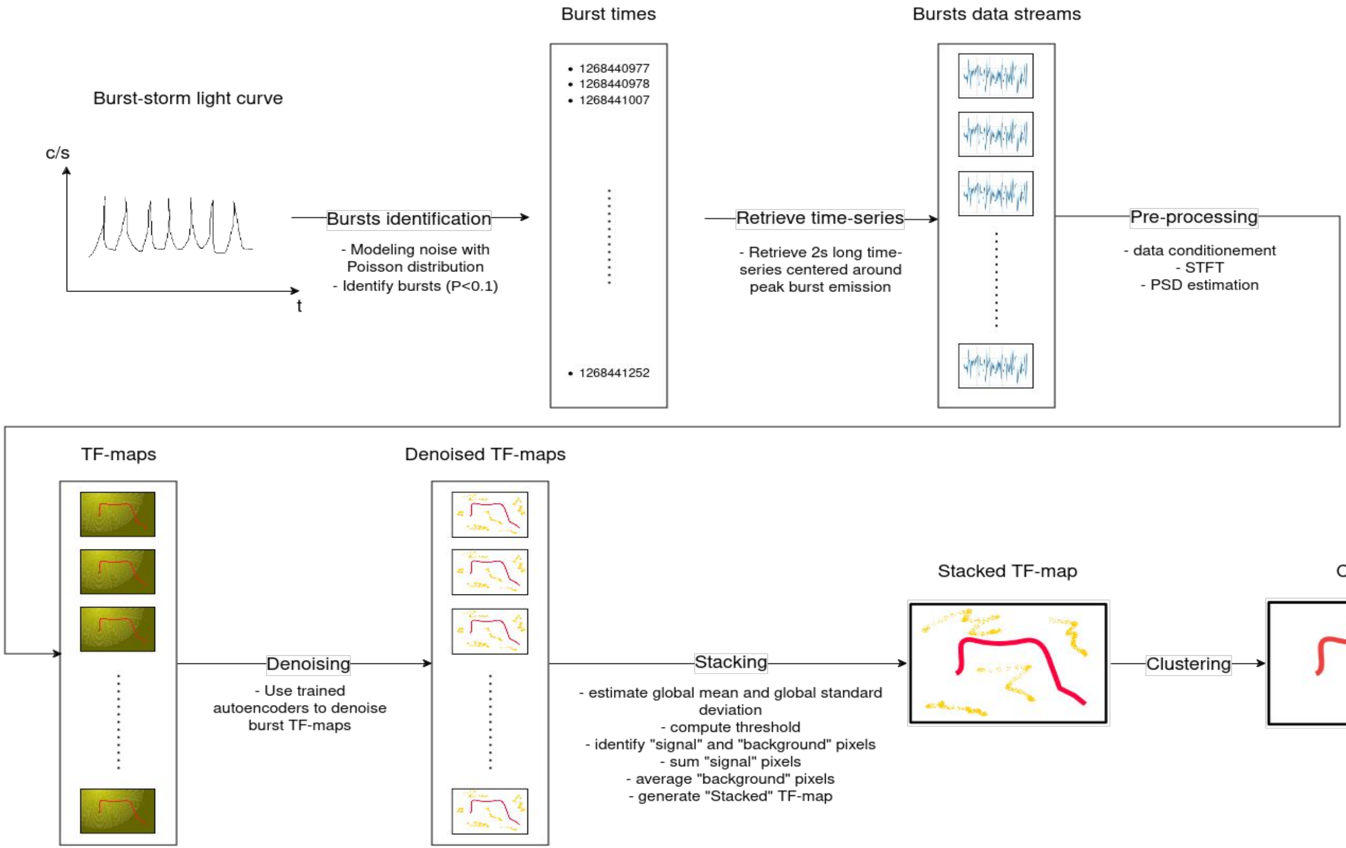
$$h = h_{max} sin(2\pi f_{mode} t) e^{\frac{-t}{\tau}}$$

$$h_{max} = 8.5 \times 10^{-28} \times \frac{10kpc}{d} \left(\frac{R}{10km}\right)^{4.8} \left(\frac{M}{M_{\odot}}\right)^{1.8} \left(\frac{B_{pole}}{10^{15}G}\right)^{2.9}$$

Stacking bursts



Workflow



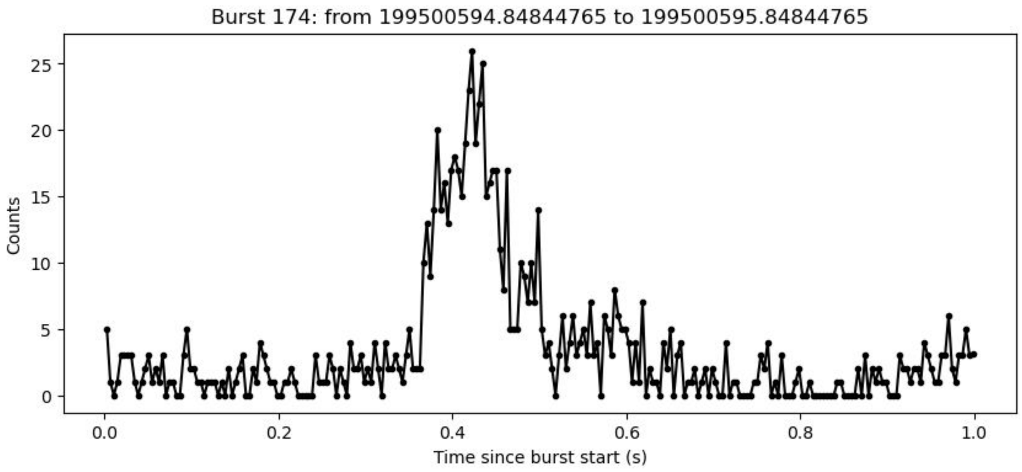
PySTAMPAS library !

Burst identification

- NICER data (1120s, 1–10 keV energy range)
- 214 bursts detected :
- 1s<
- Bursts times = “on-source segments”
- “Off-source segments” = (Total time) - (Bursts times)

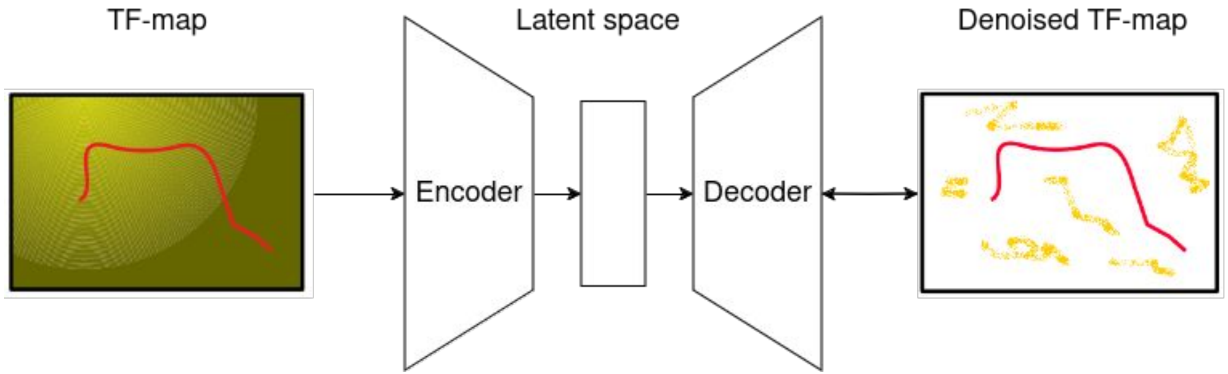
$$C^j_{\text{bins}} = \sum_i H(t_i - (t_1 + j\Delta t))H((t_1 + (j+1)\Delta t) - t_i)$$

$$\lambda = \frac{1}{\Delta T}\sum_{i=1}^{N_{\Delta T}} C^i_{\text{bins}} \qquad P_i = \frac{\lambda^{n_i} e^{-\lambda}}{n_i!} < \frac{0.01}{N_{\Delta T}}$$



(A single burst isolated from SGR1935 2020 burst storm centered around peak emission, April 28 00:40:58: arXiv:2009.07886)

Denoising with autoencoders



(Schematic representation of the structure of an autoencoder for TF-map denoising)

$$h = f(\tilde{x}) = \sigma_e(W_e\tilde{x} + b_e) \qquad r = g(h) = \sigma_d(W_d h + b_d)$$

Denoising with autoencoders - convolutional blocks

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} \end{bmatrix}$$

$$W = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix}$$

$$\text{Conv2D}(x, W)_{1,1} = w_{11}x_{11}+w_{12}x_{12}+w_{13}x_{13}+w_{21}x_{21}+w_{22}x_{22}+w_{23}x_{23}+w_{31}x_{31}+w_{32}x_{32}+w_{33}x_{33}$$

$$F_{i,j} = \sigma\left(\sum_{m=1}^{k_1}\sum_{n=1}^{k_1} W_{m,n} \cdot x_{i+m-1,j+n-1} + b\right)$$

$$F = [F_{i,j}] = \text{Conv2D}(x, f_1, k_1, \sigma) = \left[\sigma\left(\sum_{m=1}^{k_1}\sum_{n=1}^{k_1} W_{m,n} \cdot x_{i+m-1,j+n-1} + b\right)\right]$$

Denoising with autoencoders - attention gate

$$\theta_x = \text{Conv2D}(F, f, k) \qquad \phi_g = \text{Conv2D}(g, f, k)$$

$$\text{add}_x g = \theta_x + \phi_g$$

$$\psi = \sigma\left(\text{Conv2D}(\gamma(\text{add}_x g))\right)$$

$$y = F \odot \psi.$$

Denoising with autoencoders - curriculum learning

$$h(t) = s(t) + n(t) \longrightarrow \tilde{y}(t, f)$$

$$h_{\text{in}}^{(i)}(t) = \beta(e) \cdot \frac{s(t)}{\|s(t)\|} + n(t) \longrightarrow \tilde{y}_{\text{in}}$$

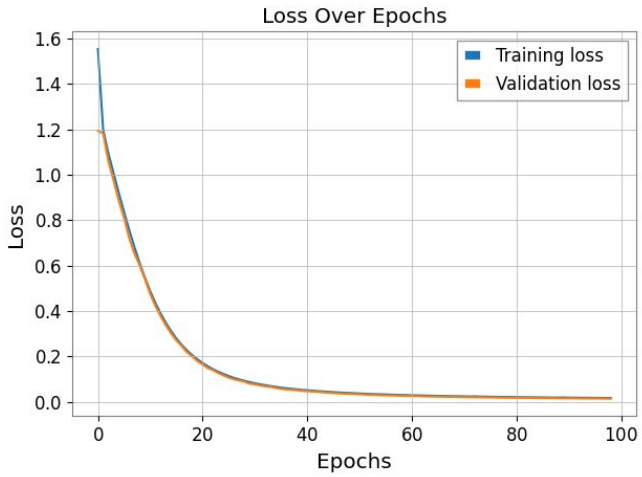
$$h_{\text{out}}^{(i)}(t) = \beta(e) \cdot \frac{s(t)}{\|s(t)\|} \longrightarrow \tilde{y}_{\text{out}}$$

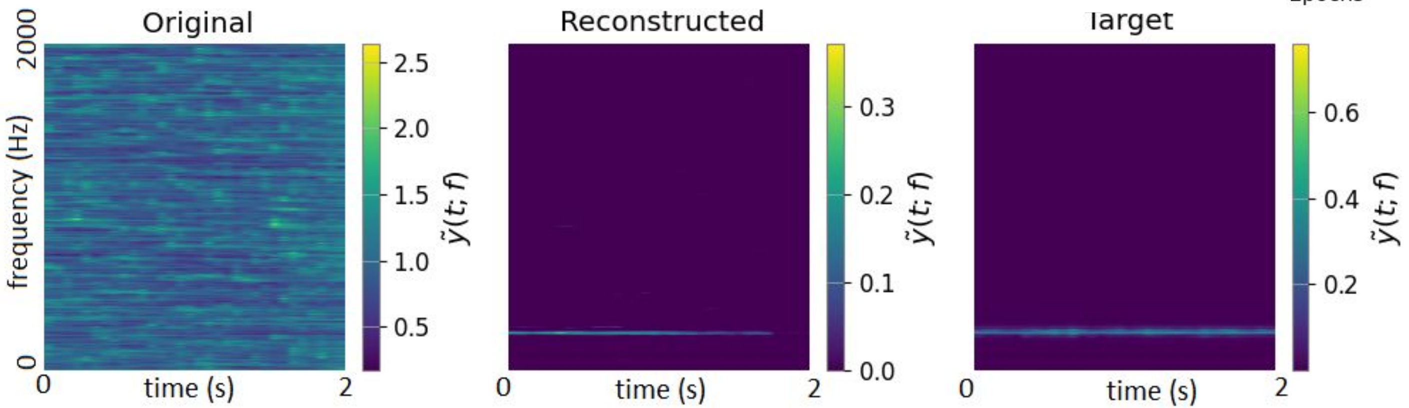
$$\beta(e) = \beta_{\text{start}} + \frac{e}{E}(\beta_{\text{end}} - \beta_{\text{start}})$$

$$L(\tilde{y}_{\text{out}}, \hat{\tilde{y}}_{\text{out}}) = \frac{1}{n} \sum_{i=1}^{n} \left(\tilde{y}_{\text{out}}^{(i)}(t, f) - \hat{\tilde{y}}_{\text{out}}^{(i)}(t, f) \right)^2$$

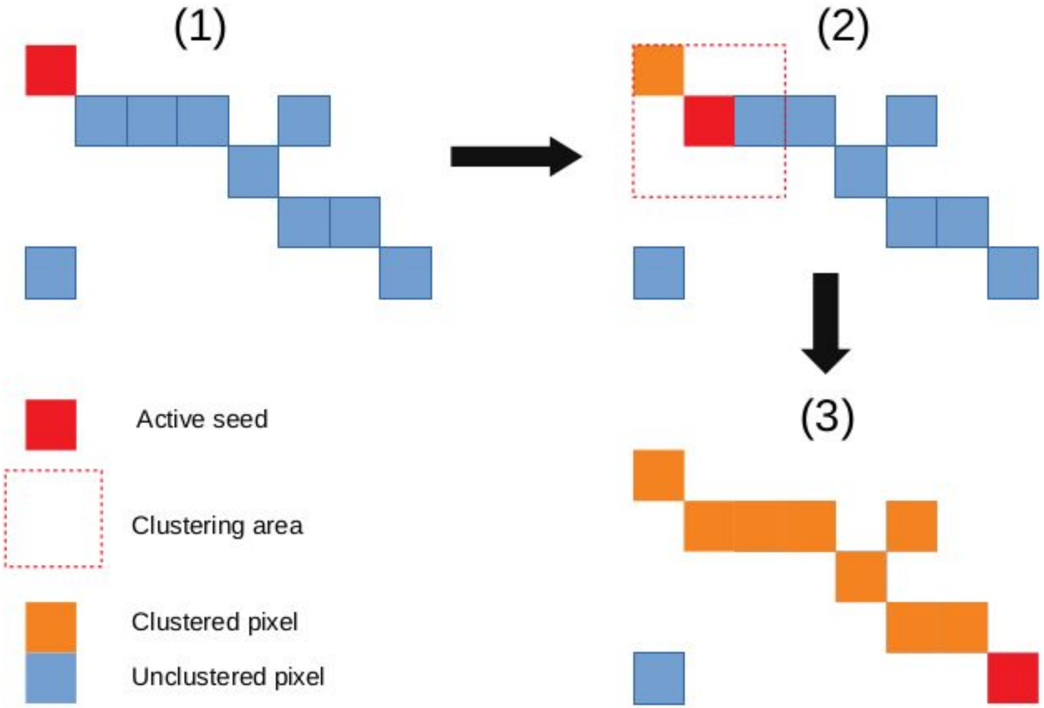
Denoising with autoencoders

Waveform	Distance (Mpc)	Duration (s)	Freq. Range (Hz)	Hrss
Bar Modes A	40	277.22	139 – 449	2.63×10^{-23}
Inspiral B	1.0	186.14	10 – 1570	2.09×10^{-20}
GRB Plateau Short	100	470.40	79 – 251	3.57×10^{-23}
ISCO Chirp A	100	238.62	1049 – 2048	3.40×10^{-23}
Magnetar D	1.0	400.0	1598 – 1900	7.06×10^{-22}
NCSACAM A	100	296.77	10 – 300	2.38×10^{-22}
PT B	1.0	196.90	800 – 1075	3.85×10^{-21}
Sine Damped (1600 Hz)	1.0	50.0	1595 – 1605	2.10×10^{-20}
Sine Damped (1050 Hz)	1.0	50.0	1045 – 1055	2.10×10^{-20}
Sine Damped (1300 Hz)	1.0	50.0	1295 – 1305	2.10×10^{-20}
ADI B	1.0	9.43	110 – 209	3.00×10^{-20}



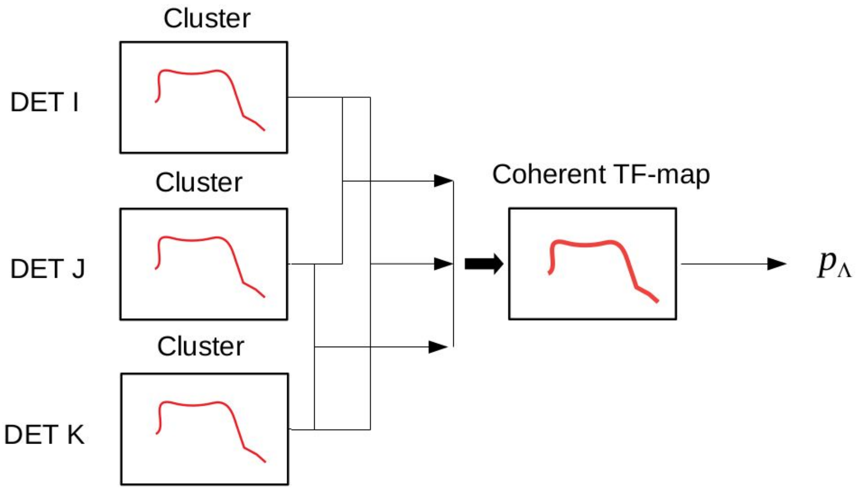


Clustering

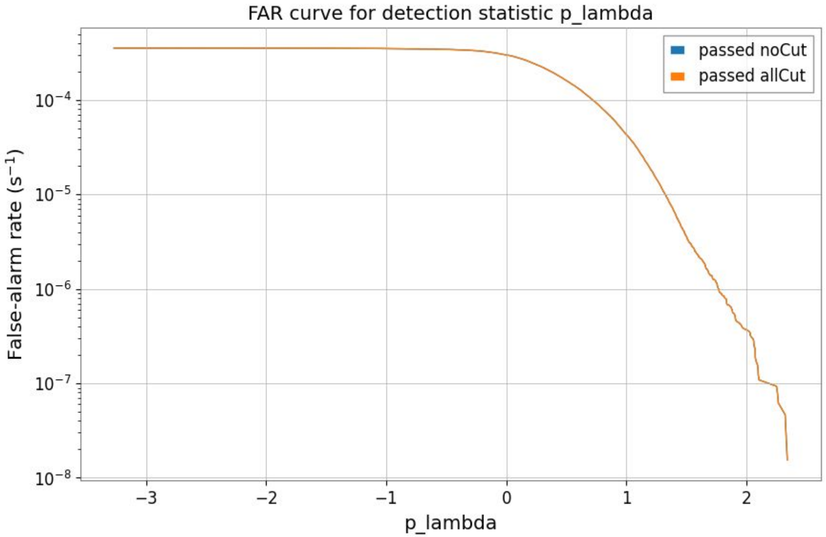


(1)
(2)
(3)
Active seed
Clustering area
Clustered pixel
Unclustered pixel

Detection statistic estimation



(clusters are cross-correlated between detectors to build a coherent detection statistic efficient at detecting coherent excess of energy in a network of GW detectors)



(Example of background triggers ranked by their P_lambda values as a function of the false alarm rate estimated on off-source segments)

False alarm rate (FAR) : how often a random noise fluctuation mimics a true signal.

Stacking procedure

Set of denoised TF-maps outputted from autoencoders :

$$Y = \{\tilde{y}^1, \tilde{y}^2, \ldots, \tilde{y}^L\} \qquad K = L \times M \times N$$

Compute global mean value and global standard deviation across all denoised TF-maps :

$$\mu = \frac{1}{K} \sum_{y \in \mathcal{P}} y$$

$$\sigma = \sqrt{\frac{1}{K} \sum_{y \in \mathcal{P}} (y - \mu)^2}$$

Threshold computation (Theta) :

$$\theta = \mu + \alpha \cdot \sigma$$

Compute the accumulated “background” A^b and “signals” A^s, by applying masks to the corresponding TF-maps, as the sum of all “signal” pixels on one hand and the sum of all “background” pixels on the other hand :

$$A^b(t,f) = \sum_{k=1}^{L} \tilde{y}^k(t,f) \cdot \mathbb{I}\left[\tilde{y}^k(t,f) \leq \theta\right]$$

$$A^s(t,f) = \sum_{k=1}^{L} \tilde{y}^k(t,f) \cdot \mathbb{I}\left[\tilde{y}^k(t,f) > \theta\right]$$

Compute the average “background” :

$$\overline{B(t,f)} = \frac{A^b(t,f)}{L}$$

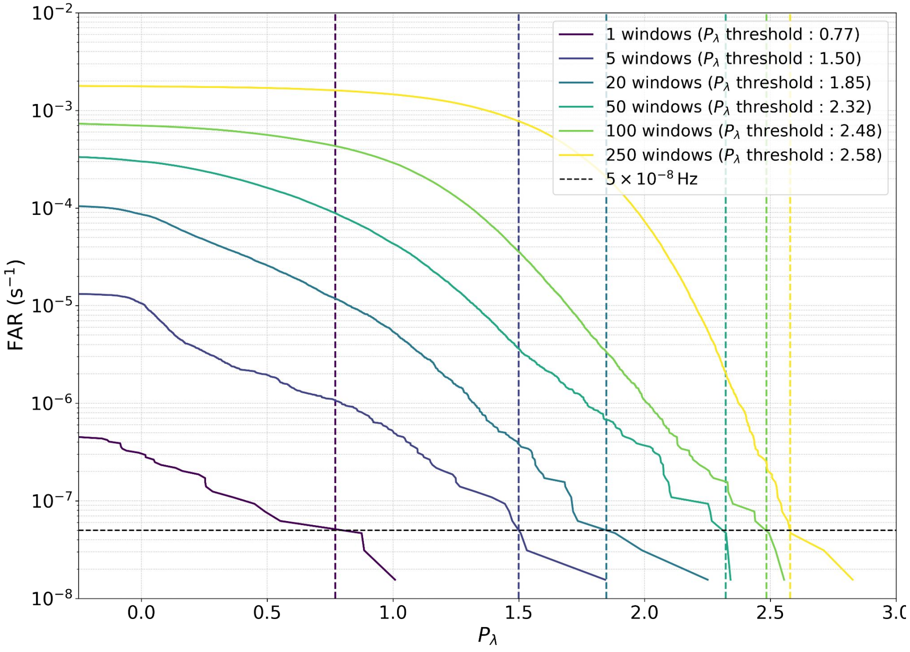
Compute the combined “stacked” TF-map with accumulated “signal” and average “background”:

$$\mathbf{Y}(t,f) = A^s(t,f) + \overline{B}(t,f)$$

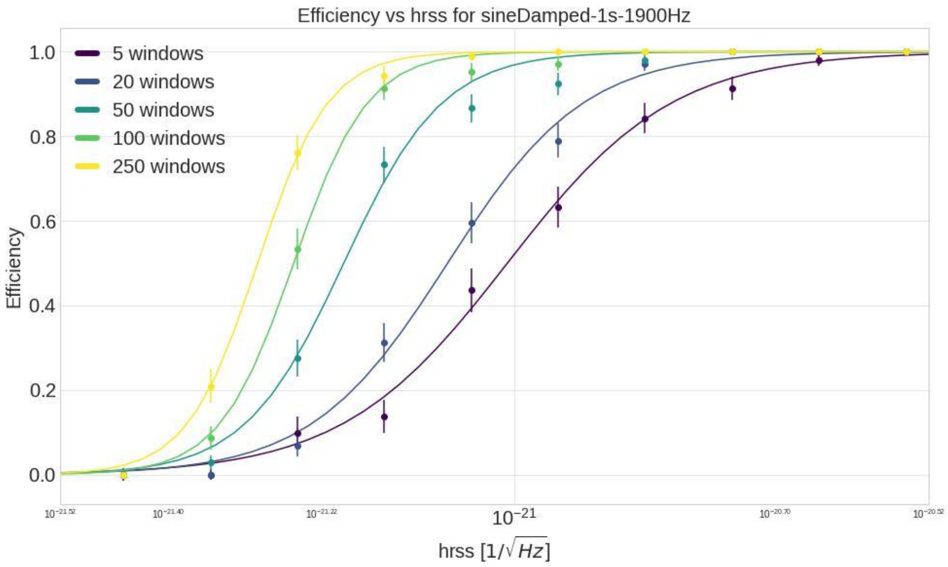
Results - Background and injection analysis

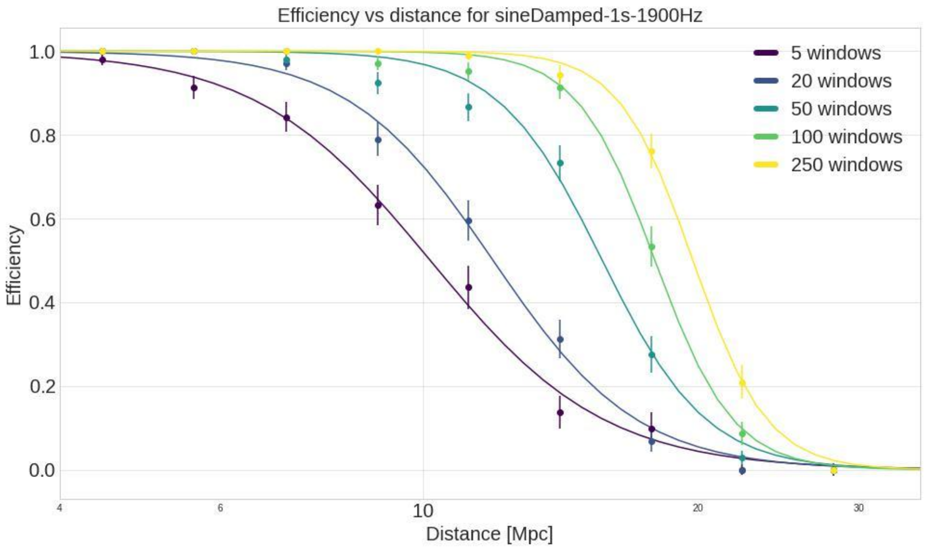
$$h(t) = h_0 \sin(2\pi f_0 t) e^{-t/\tau} \quad \begin{cases} h_0 = 1.0 \times 10^{-20} \\ \tau = 0.2 \end{cases}$$

Parameters	
TF-maps	
Duration	2s
Frequency range	22 – 2000 Hz
Time-frequency resolution	[1.0 s × 1.0 Hz – 0.5 s × 2.0 Hz] [0.25 s × 4.0 Hz – 0.125 s × 8.0 Hz] [0.0625 s × 16.0 Hz]
PSD estimation	full-median
GPS Start Time	1261870018
GPS End Time	1261877018
Run	O3
Detectors	H1, L1



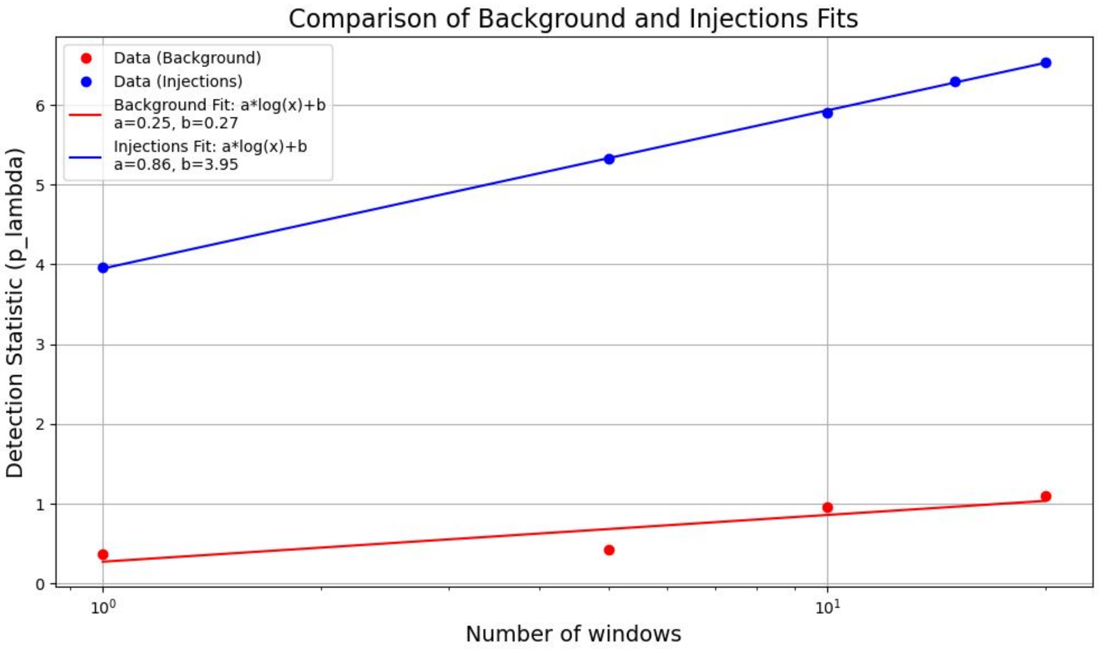
Results - injection analysis





Results - FAR loudest statistic vs Number of windows

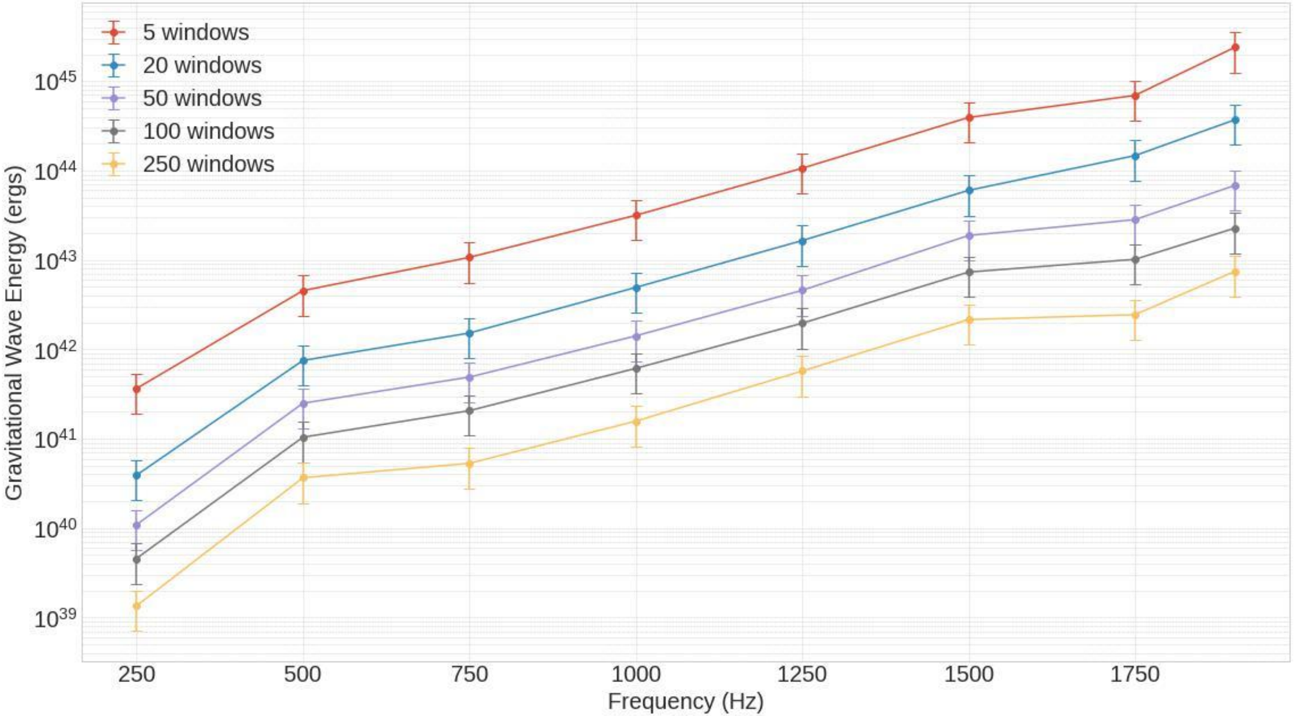
Both injections and background loudest trigger's detection statistic evolve logarithmically as a function of the number of windows, but which one evolves the fastest ?



(Loudest P_lambda value as a function of the number of windows, and magnetarF stacked trigger detection statistic for alpha = 500) with a logarithmic function with a linear scaling and an offset)

$$\text{Ratio} = \frac{a_{\text{injections}}}{a_{\text{background}}} = \frac{0.87}{0.25} \approx 3.44$$

Results - injection analysis



$$E_{\mathrm{GW}} = \frac{2}{5}\frac{\pi^2 c^3}{G} r^2 f_0^2 h_{\mathrm{rss}}^2$$

(arXiv:1304.0210v1)

Conclusion

- Denoising using autoencoders allows to effectively reduce background pixels while keeping excess of power from potential GW signals

- Stacking can help identifying repetitive and faint GW emission from magnetars

- The more burst there is in a storm, the more we are likely to identify a signal

Thank you for your attention !