Detection of Gravitational Waves from Repetitive Magnetar Bursts Using Autoencoder-Based Denoising and Stacking

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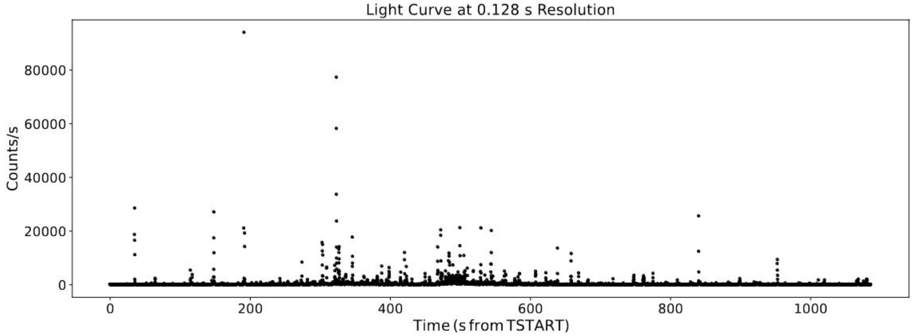
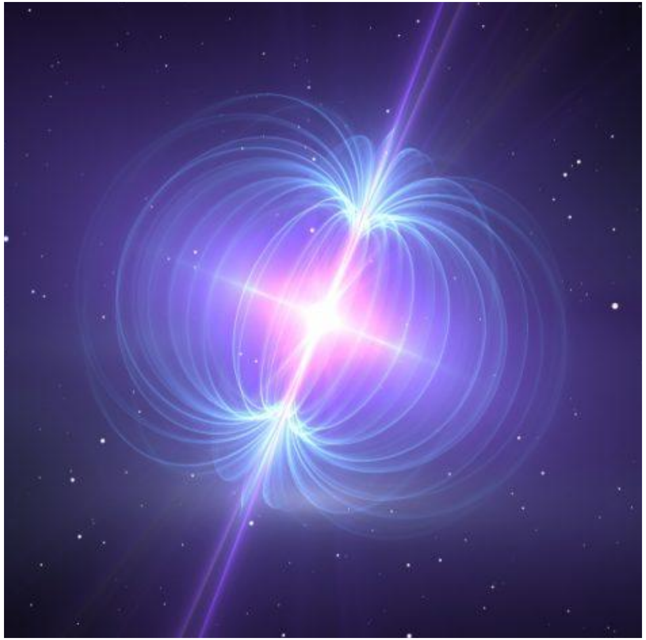
Magnetars and bursting activity

- **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** $L_{\mathrm{peak}} \approx 10^{41} - 10^{43}\,\mathrm{erg/s}$

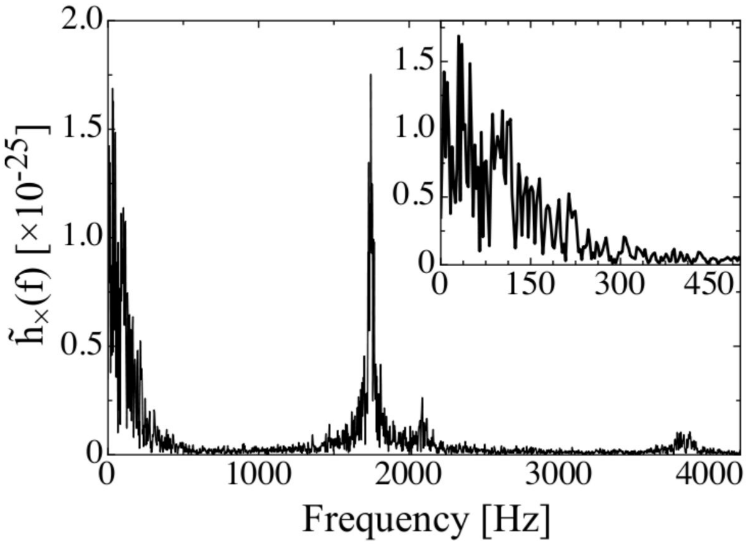


(SGR1935 bust storm light curve, 1120s taken on 2020 April 28 00:40:58: arXiv:2009.07886)

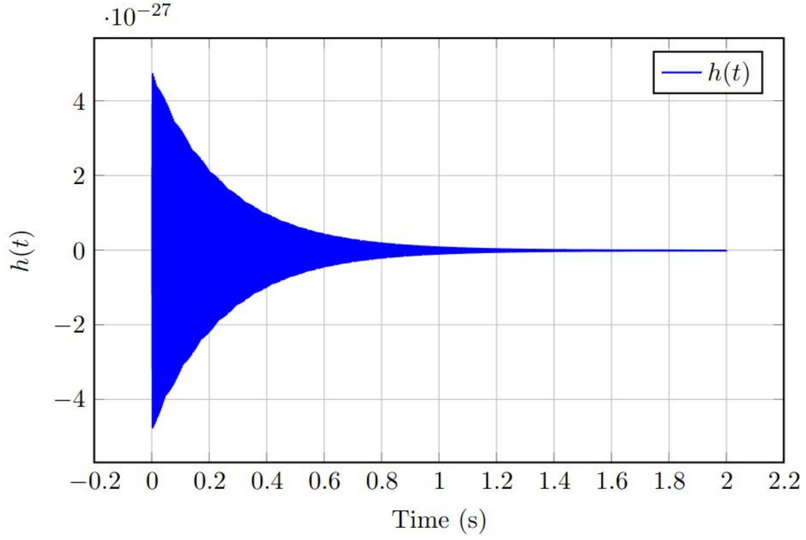


(Artistic representation of a magnetar)

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)

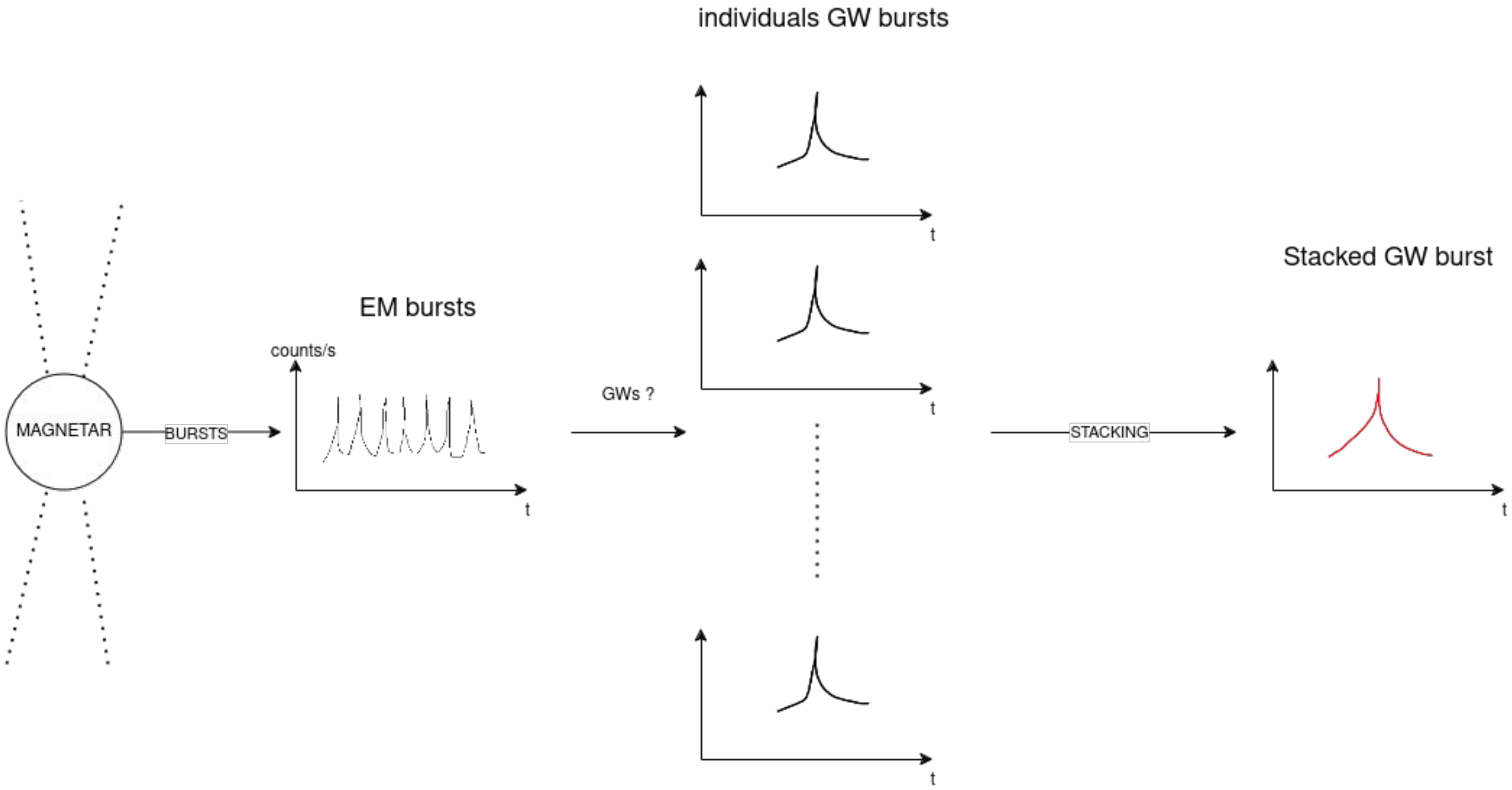


(strain modelized for an f-mode GW emission)

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

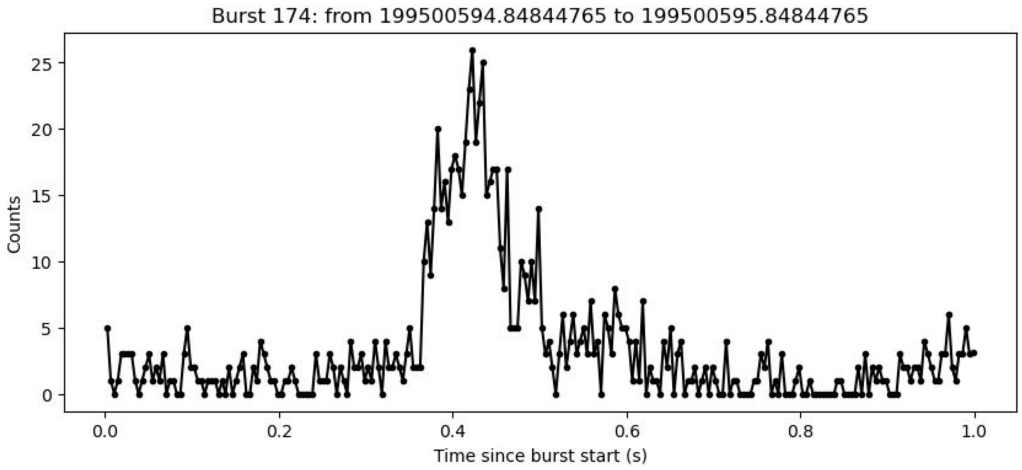
$$h_{max} = 8.5\times10^{-28}\times\frac{10kpc}{d}\left(\frac{R}{10km}\right)^{4.8}\left(\frac{M}{M_\odot}\right)^{1.8}\left(\frac{B_{pole}}{10^{15}G}\right)^{2.9}$$

Stacking bursts



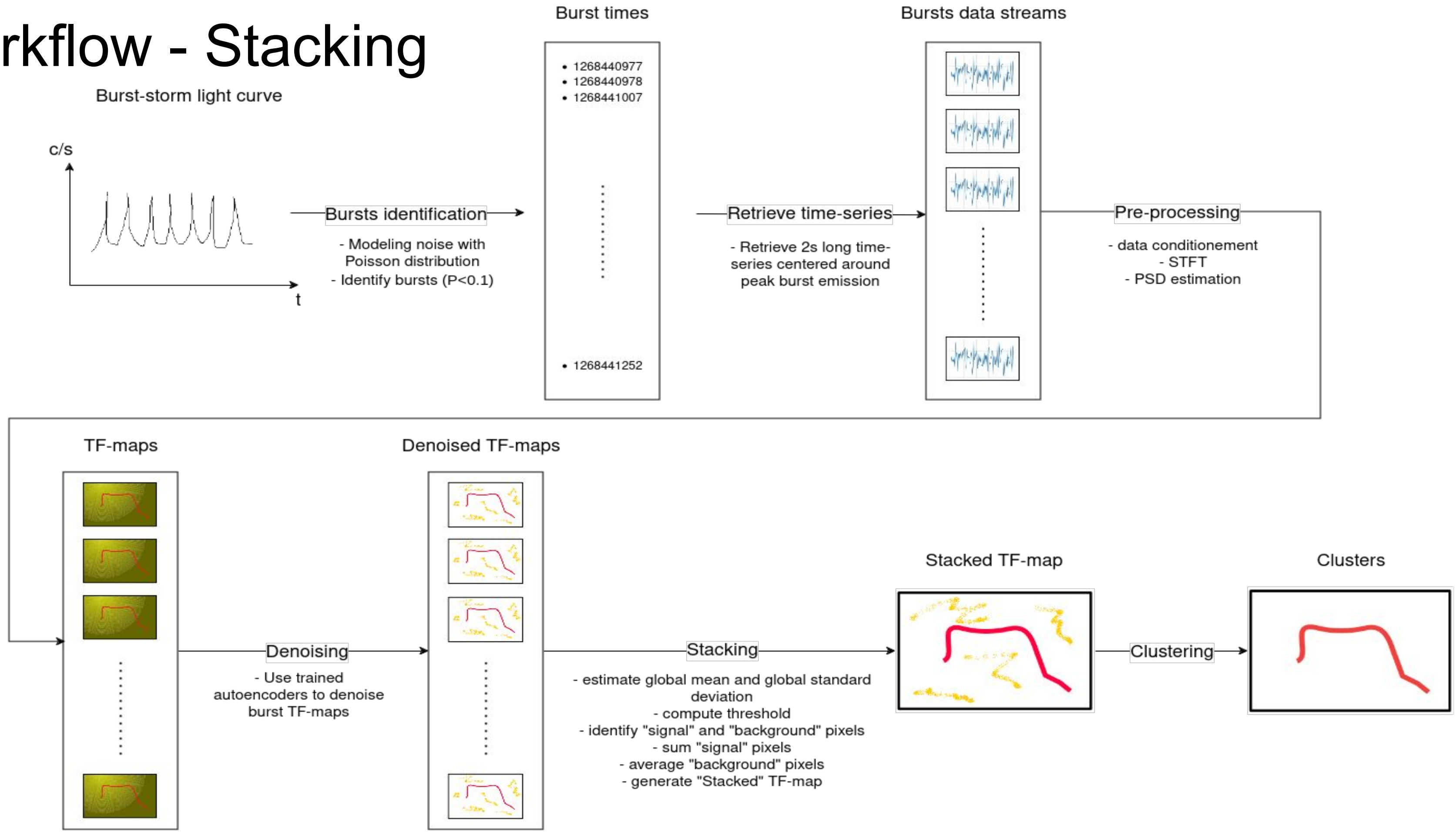
Burst identification

- NICER data (1120s, 1–10 keV energy range)
- Detected by comparison to background modeled by poisson noise (P<0.1)
- 153 bursts detected :
- 1s<
- Total time considered for study : 6358s
- Bursts times = “on-source segments”
- “Off-source segments” = (Total time) - (Bursts times)

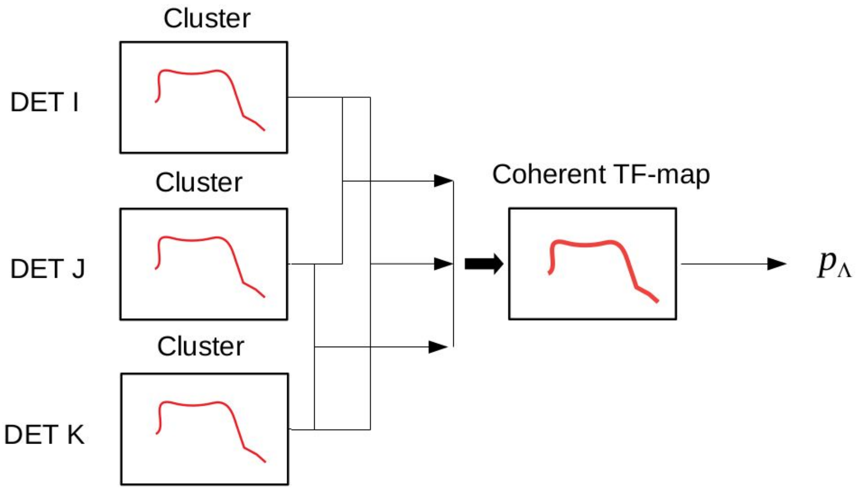


(A single burst isolated from SGR1935 2020 burst storm centered around peak emission, April 28 00:40:58: arXiv:2009.07886)

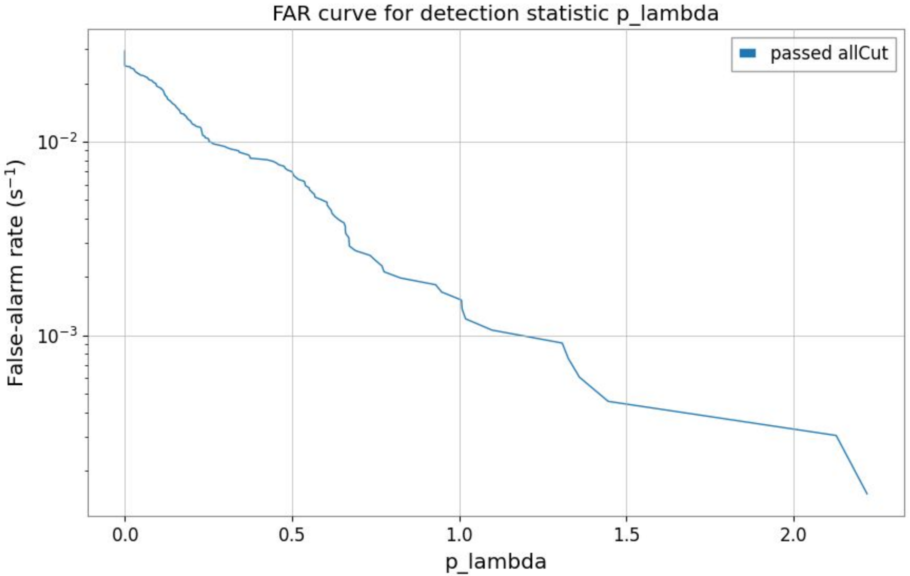
Workflow - Stacking



Workflow - statistics 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)



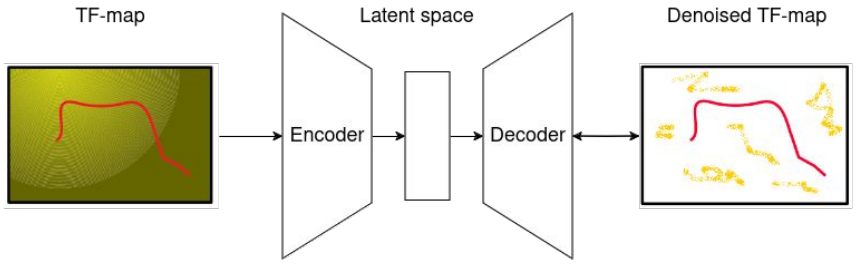
(Example of ranked P_lambda values as a function of the false alarm rate estimated on off-source segments)

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

Denoising - Autoencoders

Denoising made using autoencoder architecture for deep neural networks with 4 millions parameters :

- Encoder :
    - Convolutional block with MaxPooling2D and Dropout
- Decoder :
    - Convolutional block with attention gate



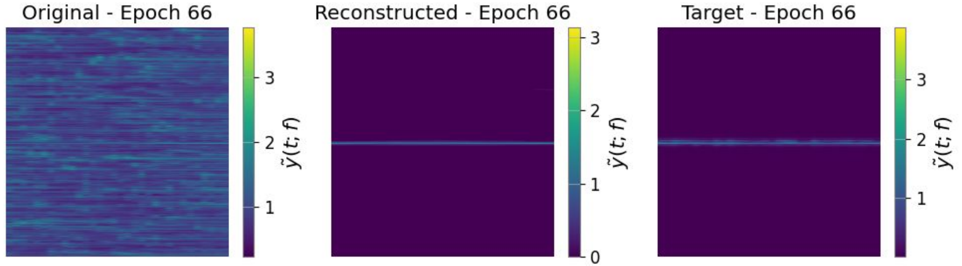
(Schematic representation of the structure of an autoencoder for TF-map denoising)

Training data : off-source segments in between bursts on different types of waveforms to not overfit on morphology or frequency.

- Training input : signal + noise
- Training target : signal only

Loss function : Mean Square error

Curriculum learning : From loud to faint target



(Example of testing TF-map used to measure the testing loss value during training)

Stacking procedure

Set of denoised TF-maps outputted from autoencoders :
(“w” stands for “window”)

$$W = \{w^1, w^2, \ldots, w^n\}$$

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

$$\bar{w} = \frac{1}{N} \sum_{k=1}^{L} \sum_{i=1}^{M} \sum_{j=1}^{N} w_{ij}^k \quad \sigma_w = \sqrt{\frac{1}{N} \sum_{k=1}^{L} \sum_{i=1}^{M} \sum_{j=1}^{N} (w_{ij}^k - \bar{w})^2}$$

Threshold computation (Theta) :

$$\theta = \bar{w} + \alpha \cdot \sigma_w$$

Compute “Signal” mask S_k and “Background” mask B^k, w^k is the k-tk TF-map of the list and p_ij is the pixel at position ij on the k-th TF-map :

$$S^k = \{p_{ij} \in w^k : p_{ij} > \theta\}$$

$$B^k = \{p_{ij} \in w^k : p_{ij} \leq \theta\}$$

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 :

$$A^s = \sum_{i=1}^{n} w^i \cdot S^i \quad A^b = \sum_{i=1}^{n} w^i \cdot B^i$$

Compute the average “background” :

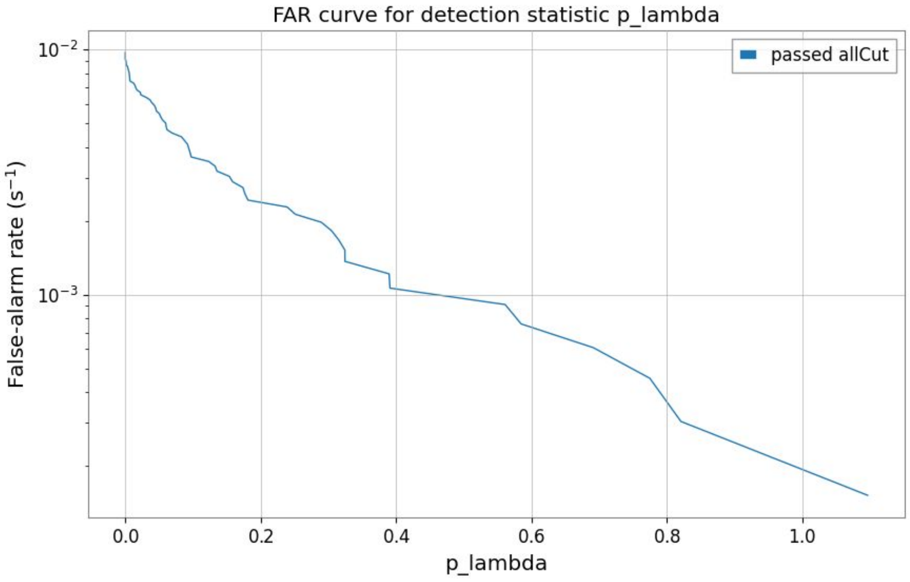
$$\overline{B} = \frac{A^b}{n}$$

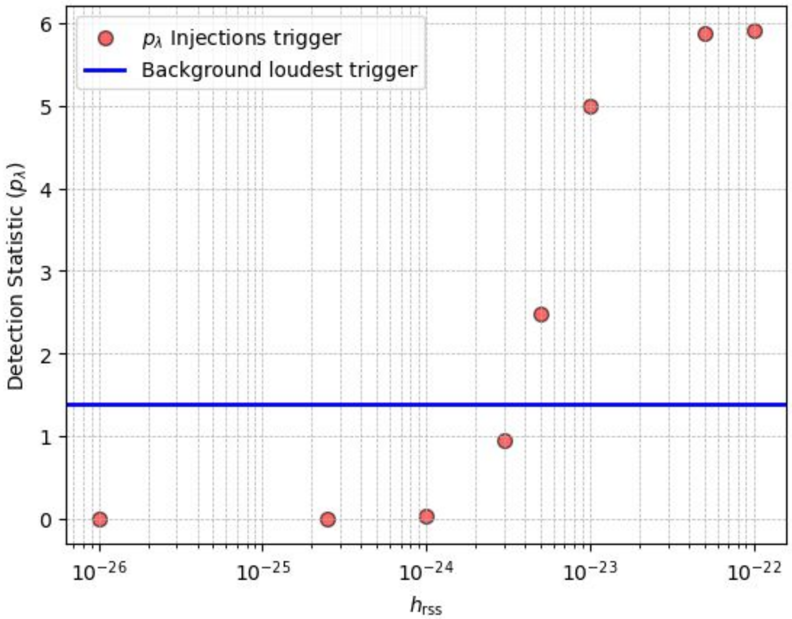
Compute the combined “stacked” TF-map with accumulated “signal” and average “background”:

$$C = A^s + \overline{B}$$

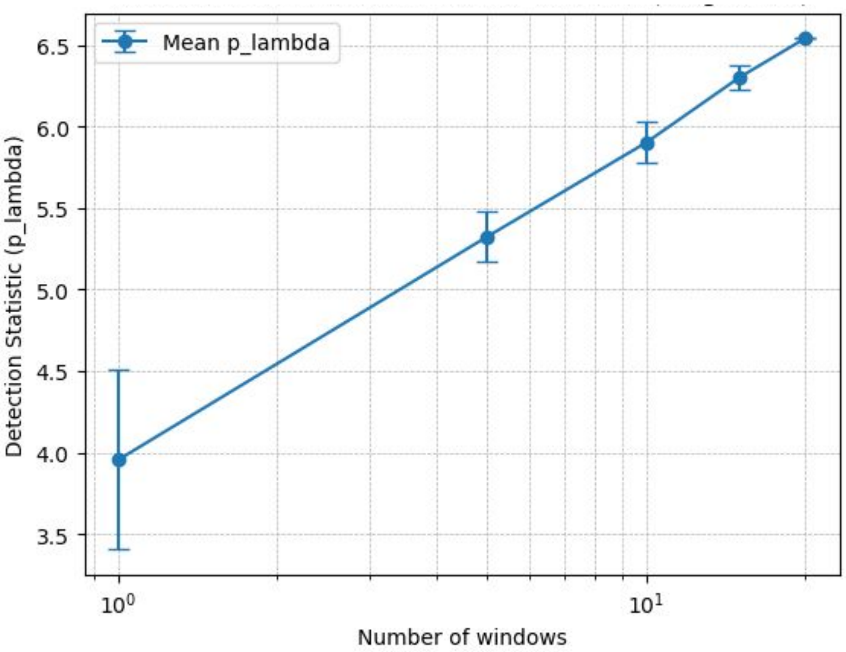
Results - Background and injections (Monte-Carlo data)

- 2s long FTmaps
- Autoencoder trained on 11 waveforms :
- Background estimated on ~6000s of “off-source” data
- 20 “on-source” windows for injections
- Injection of a magnetar waveforms (not in the training set)



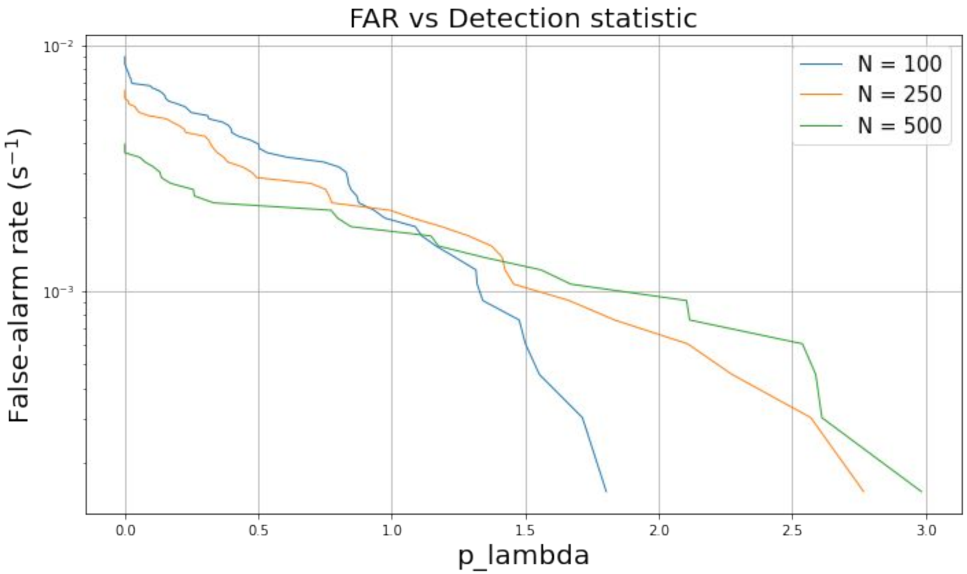


Results - Injection statistic vs Number of windows (Monte-Carlo data)

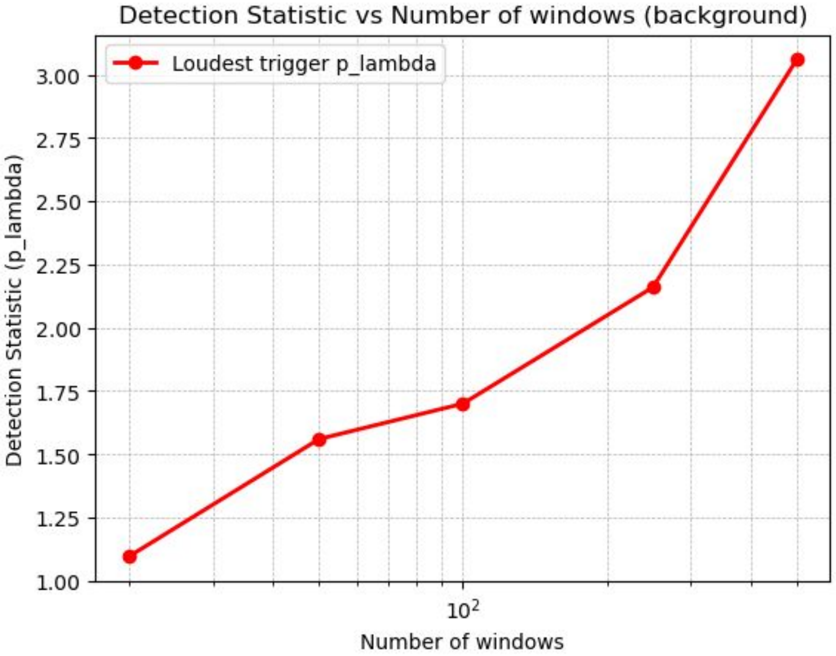


Evolution of detection statistic for a set of injections (magnetarF, hrss = 1e-22) as a function of the number of windows stacked (1, 5, 10, 15 and 20 windows)

Results - Background FAR vs Number of windows (Monte-Carlo data)



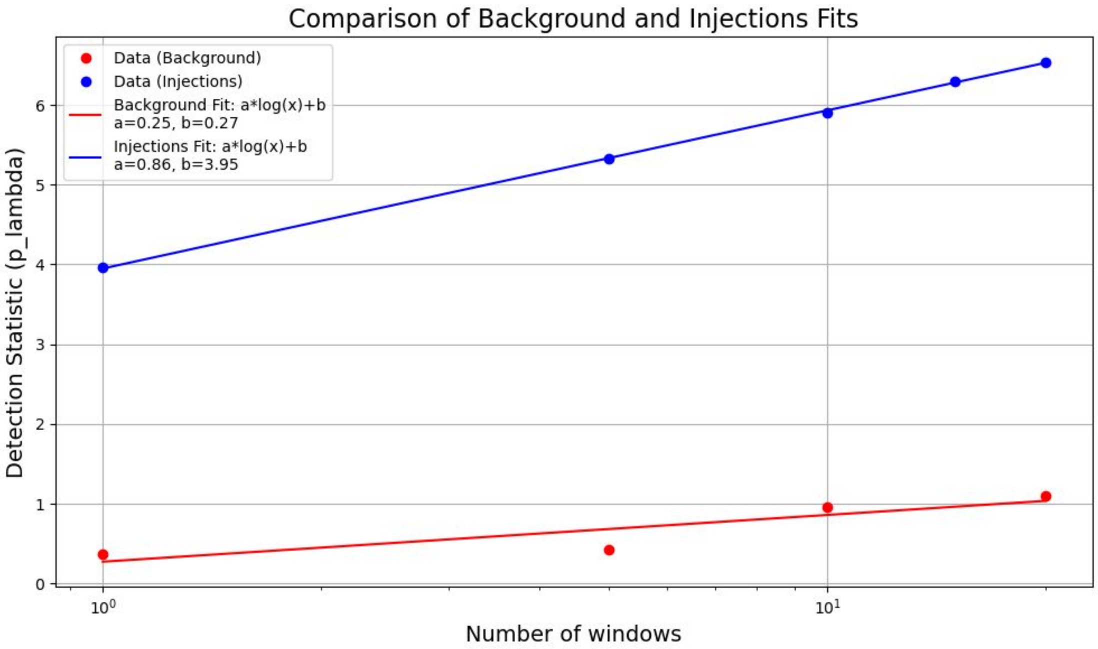
FAR curves estimated for increasing number of windows stacked to account for the evolution of the loudest trigger's detection statistic as a function of the number of windows.



Loudest background FAR trigger detection statistic a a function of the number of windows stacked

Results - Background FAR vs Number of windows (Monte-Carlo data)

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 - Background and injections (real data)

- O3 data (GWOSC)
- 2s long FTmaps
- Autoencoder trained on 11 waveforms :
- Background estimated on ~6000s of “off-source” data
- 20 “on-source” windows for injections
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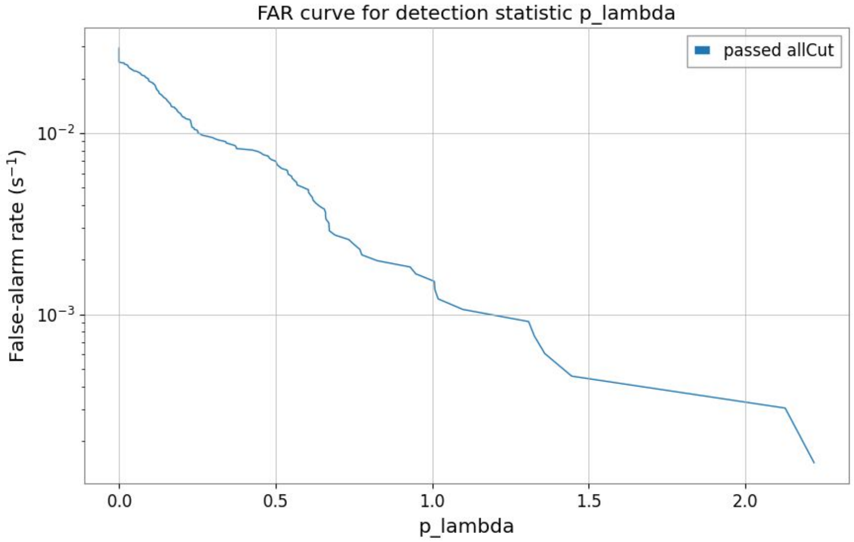
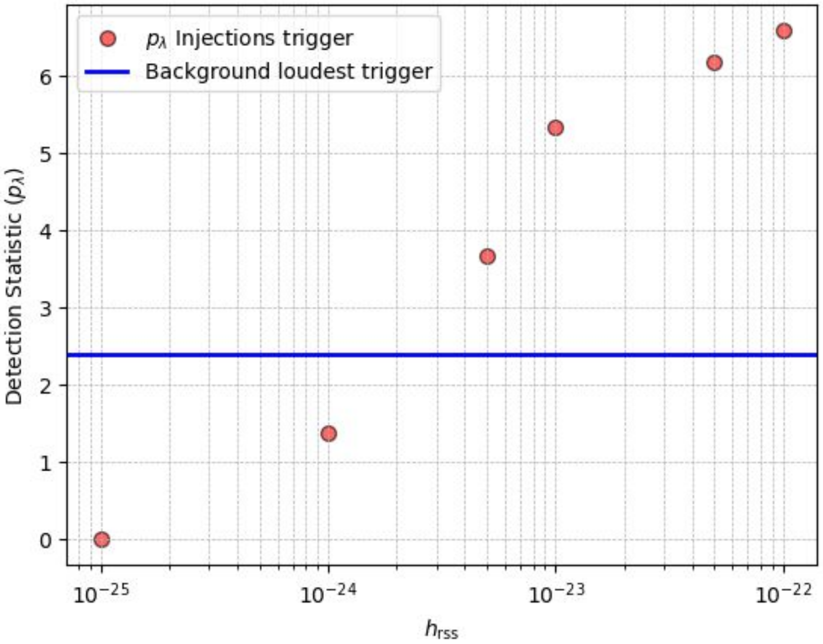
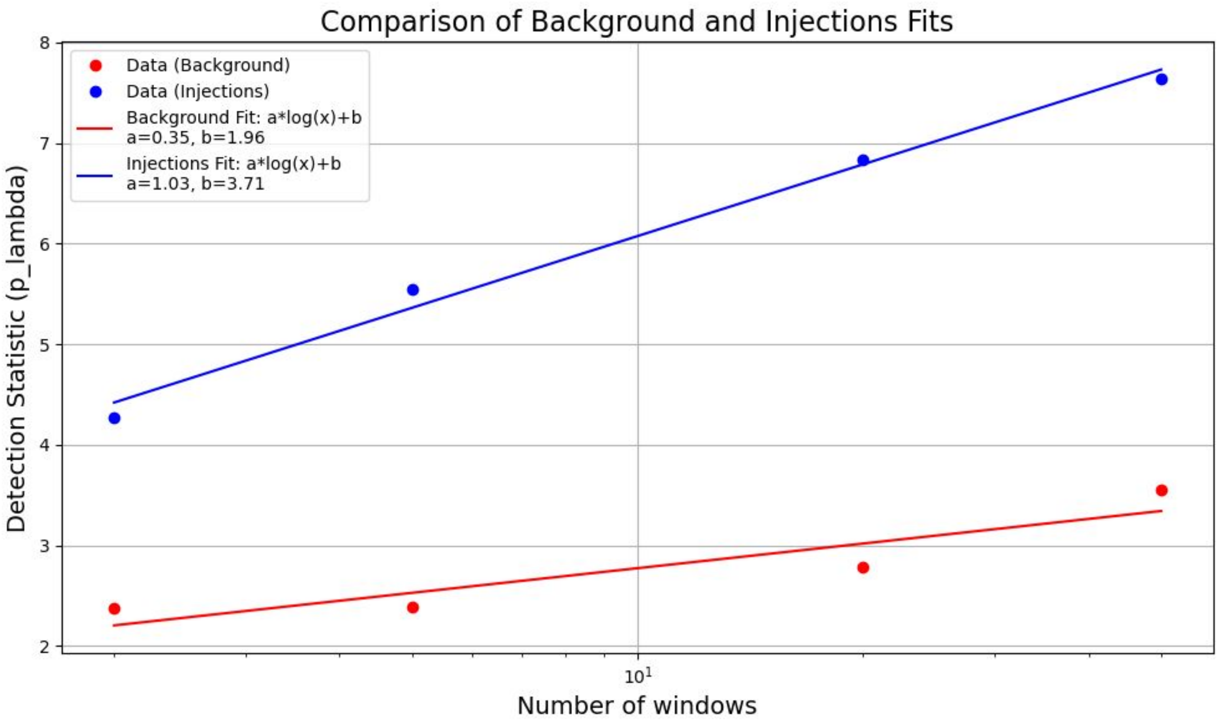




Results - Background FAR vs Number of windows (real data)



$$\text{Ratio} = \frac{a_{\text{injections}}}{a_{\text{background}}} = \frac{1.03}{0.35} \approx 2.94$$

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 !