Improving future searches for gravitational wave transients on multi-detector data

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Framework

Compact Binary Coalescences
All sky transient GW
Continuous GW
Electromagnetic triggered
Stochastic Background
...

Framework

- Compact Binary Coalescences
- **All sky transient GW**
- Continuous GW
- Electromagnetic triggered
- Stochastic Background
- ...

Search for generic short-duration GW transients, without any assumptions on incoming signal direction, polarization or morphology.

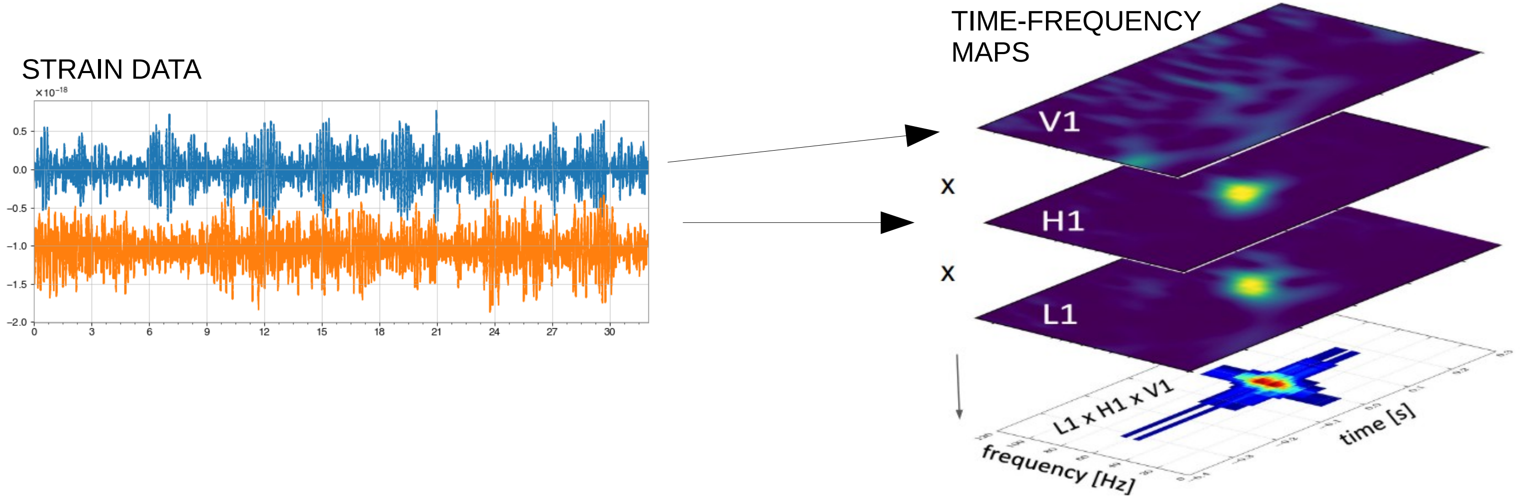
Possible sources are:

- Compact binary coalescences
- core-collapse supernovae
- neutron star excitations
- cosmic strings
- ...

[Abbott, R., et al. "All-sky search for short gravitational-wave bursts in the third Advanced LIGO and Advanced Virgo run." (2021)]

Coherent WaveBurst (cWB)

Algorithm based on the all-sky maximum-likelihood-ratio statistic, applied to excesses of signal power in the time–frequency representation from the network of detectors



https://gwburst.gitlab.io/

[Klimenko, S., et al. "Method for detection and reconstruction of gravitational wave transients with networks of advanced detectors." (2016)]

Multi-detector analysis

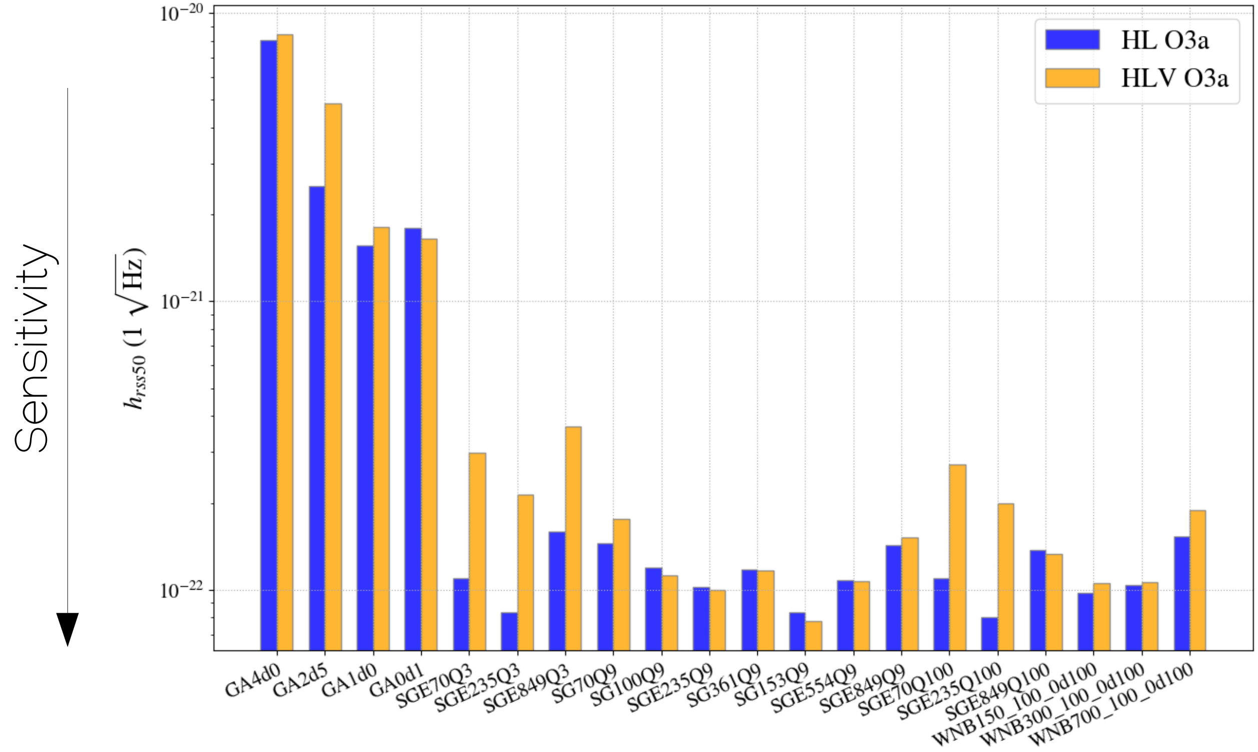
- Broad detector network enhance both waveform reconstruction and sky localization
- The contribution of the Virgo detector has not been fully exploited due to its lower sensivity and favorable co-alignment of LIGO detectors
- The advantages of including Virgo are offset by the overall increase of background noise.

[Abbott, R., et al. "All-sky search for short gravitational-wave bursts in the third Advanced LIGO and Advanced Virgo run." (2021)]

Multi-detector analysis

Comparison between HL and HLV search sensitivity on ad-hoc waveforms (Gaussian pulses (GA), Sine Gaussian (SG) and White Noise Burst (WNB))

IFAR = 100



Multi-detector analysis

In order to increase the search sensitivity of HLV network we are:

- Implementing a new post production criteria[1,2] that improves the signal-noise classification (as done for HL)
- Studying the impact of some internal parameters on the sensitivity of the three-detector network (preliminary)

1Mishra, Tanmaya, et al. "Optimization of model independent gravitational wave search for binary black hole mergers using machine learning." (2021)
2 Mishra, T., et al. "Search for binary black hole mergers in the third observing run of Advanced LIGO-Virgo using coherent WaveBurst enhanced with machine learning." (2022).
3 ex: https://ldas-jobs.ligo.caltech.edu/~waveburst/waveburst/WWW/doc/cwb/man/faq.html?highlight=regulators#the-cwb-2g-regulators]

New post-production

Motivations

- So far, the signal-noise discrimination is based on hard thresholds chosen by data-analysts, according to certain benchmarks
- This procedure is complex, person-power consuming and lead to the creation of multiple bins

Methods

- A decision tree based learning algorithm (eXtreme Gradient Boost[1]) is able to look at several features at the same time and identify correlations.
- XGBoost has been implemented to automate signal-noise classification in cWB, to improve BBH searches[2,3]

[1.Chen, Tianqi, and Carlos Guestrin. "Xgboost: A scalable tree boosting system.", 2016.
2. Mishra, Tanmaya, et al. "Optimization of model independent gravitational wave search for binary black hole mergers using machine learning." (2021)
3. Mishra, T., et al. "Search for binary black hole mergers in the third observing run of Advanced LIGO-Virgo using coherent WaveBurst enhanced with machine learning." (2022)]

XGBoost

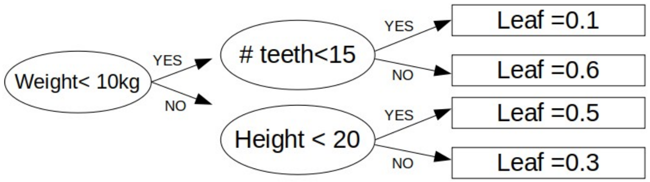
Goal: distinguish between cats and dogs

Training

Class	Height [cm]	Weight [kg]	#hour of sleep	..
dog	30	15	9	
dog	..	..	..	..
cat	20	10	16	..
cat	..	..	..	..

→ algorithm →

Builds the tree



Testing

?	22	7	12	..

→ algorithm →

Answer

XGBoost in cWB

The model learns a binary classification (signal or noise) using a subset of summary statistics generated from the cWB reconstructed events

h(t) → WB → List of triggers (with time-frequency maps and properties)

↓

Subset of the statistics (ex: coherence among detectors, quality of the likelihood fit)

Class	netcc	Qa	Qp	..
signal	0.94	3	13	
signal	..	..	..	..
noise	0.6	0.1	3	

→ **XGBoost**
Output [0,1], acts as penalization

→ NEW RANKING

XGBoost in cWB

Training dataset:

Noise

- We use 50% of the available background data (obtained through time-shifting) for training and the remaining 50% for testing

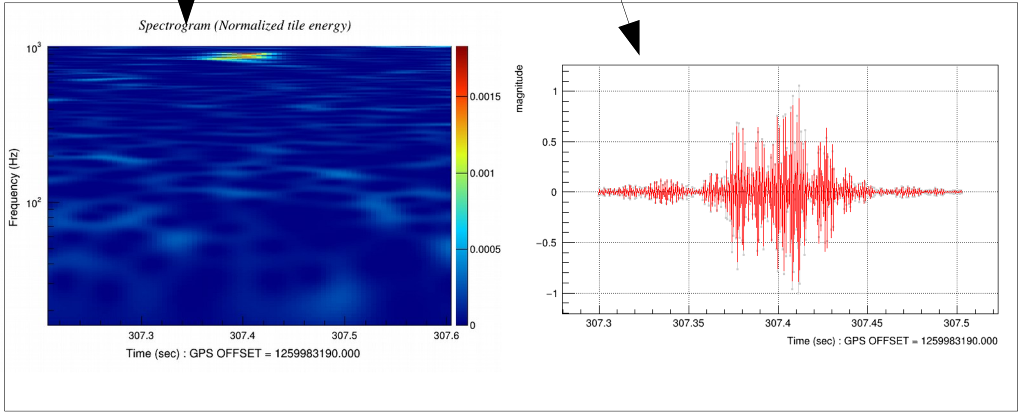
Signal

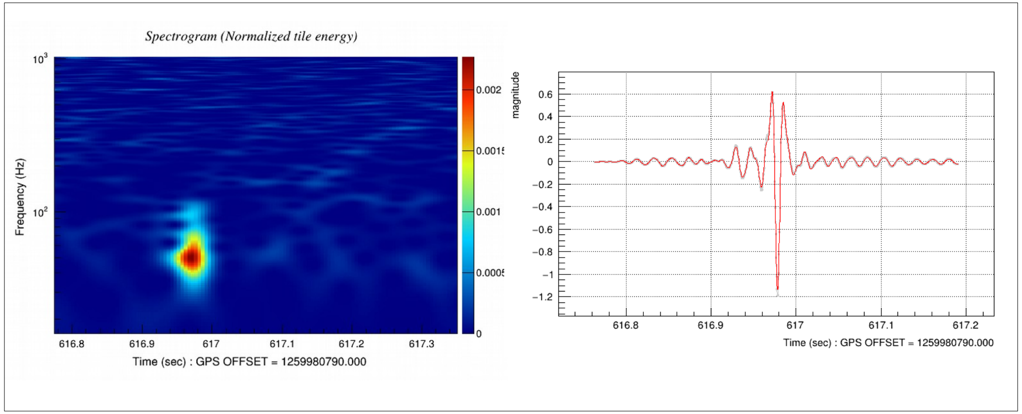
- We do not use targeted simulations that follow specific astrophysical population distributions
- Instead, we train the models on White-Noise-Bursts (WNB) with randomly chosen peak frequency, duration and bandwidth that populate different region of the time-frequency map

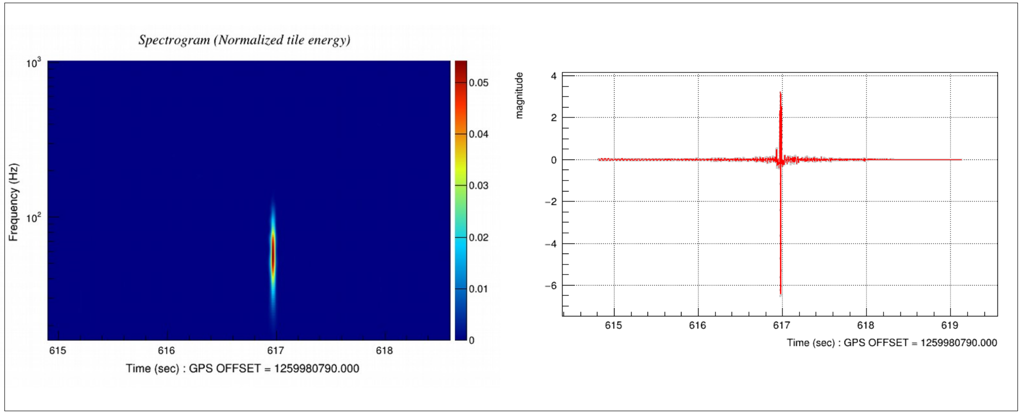
Examples of WNB injections

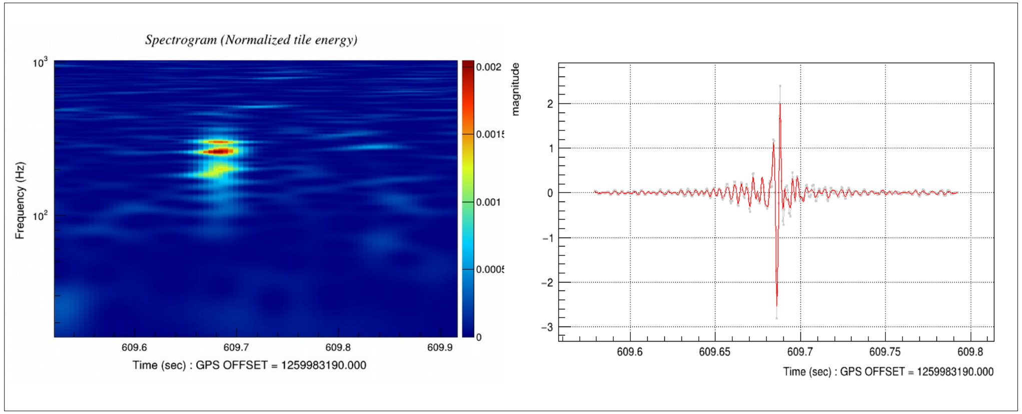
Time-frequency (L)

Recontructed response







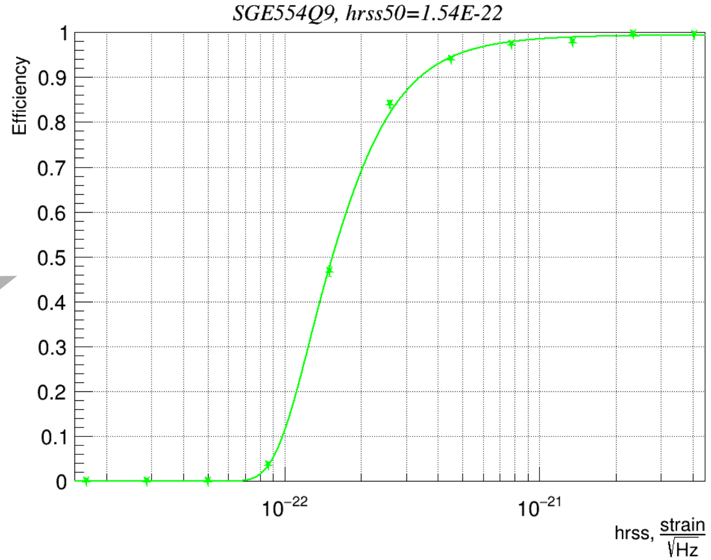


Sensitivity volume

- Check robustness of the method on several waveforms (not included in the training dataset)
- Search metric: **sensitivity volume**[1,2]

computed from the detection efficiency measured by the simulations, assuming a population of standard-candles sources at distance r_0 and average GW amplitude at Earth h_0

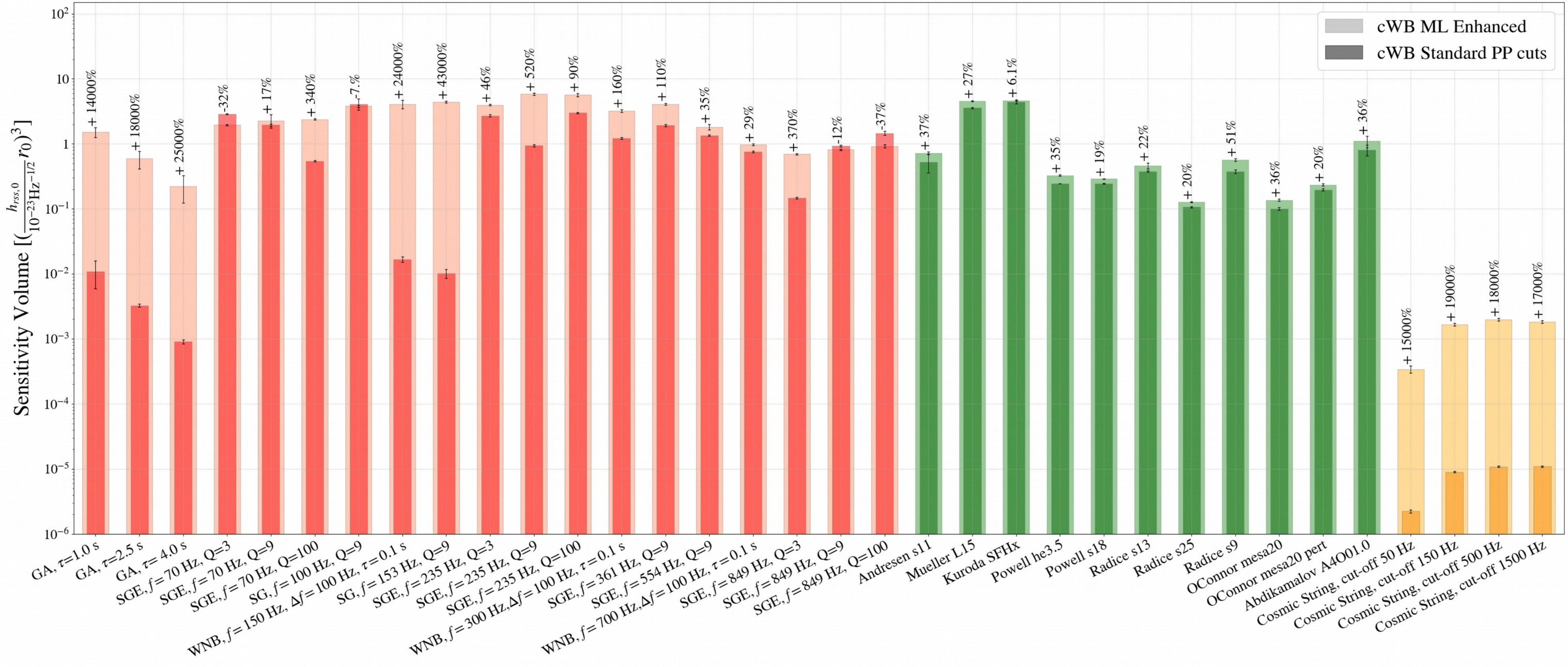
$$V = 4\pi (h_0 r_0)^3 \int_0^\infty dh \frac{\text{efficiency}(h)}{h^4}$$



[1.Abbott, B. P., et al. "All-sky search for short gravitational-wave bursts in the second Advanced LIGO and Advanced Virgo run."(2019)
2. https://dcc.ligo.org/DocDB/0179/G2102171/001/AllSky_burst_20211012.pdf]

Search sensitivity

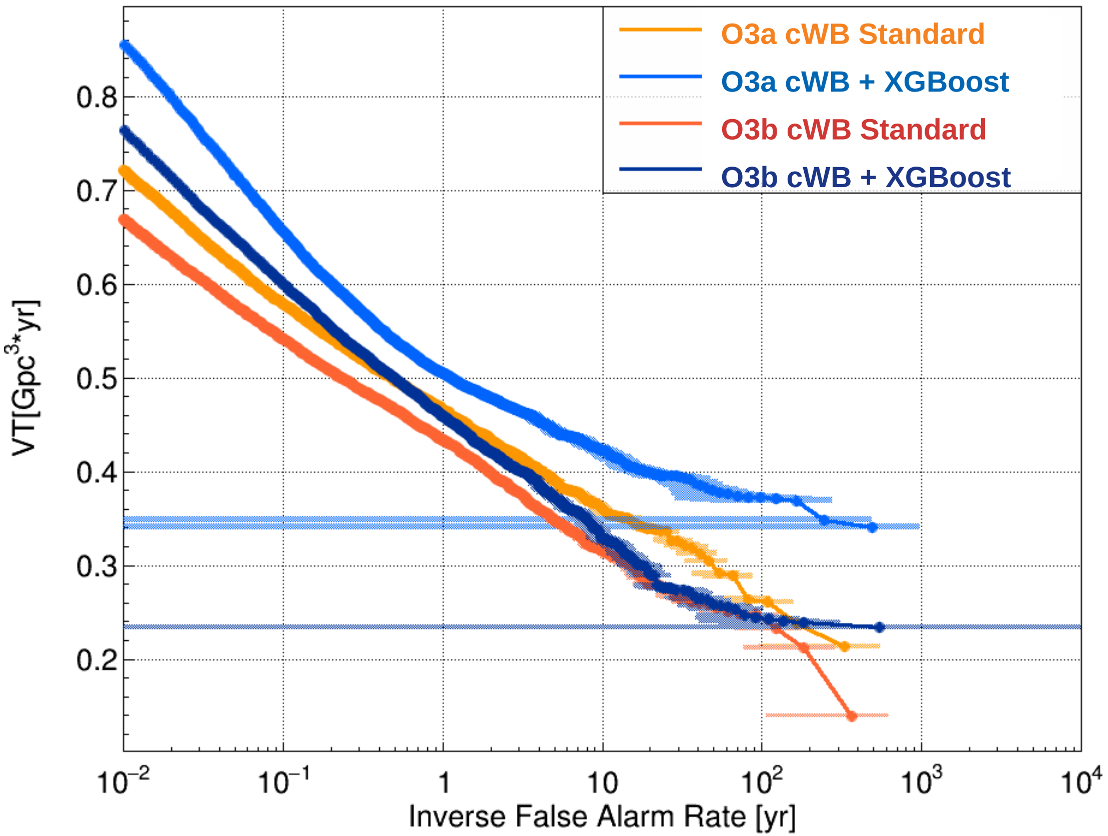
LHV, IFAR = 100, full O3 run



Ad-hoc waveform supernovae cosmic strings

Search sensitivity

LHV, Black hole – black hole mergers injections



Conclusions

- Broad detector networks are crucial to enhance the detection and the characterization of GWs
- We are investigating the thee-detector network (HLV) performance with cWB and implementing a machine-learning based methodology to improve the signal - noise classification
- The HLV sensitivity search is enhanced by using this XGBoost methodology for most of the waveforms tested.
- The results on HLV be considered a further proof of robustness of the methodology

(short author list paper is in preparation)

Extra slides

Detection statistic

(1) cWB detection statistic: $$\rho_0 = \sqrt{E_c/\max(1,\chi^2)}$$

(2) CWB+XGBoost enhanced statistic: $$\rho_{XGB} = \sqrt{\frac{E_c}{1+\chi^2(\max(1,\chi^2)-1)}}W_{XGB}$$

where E_c = coherent energy,

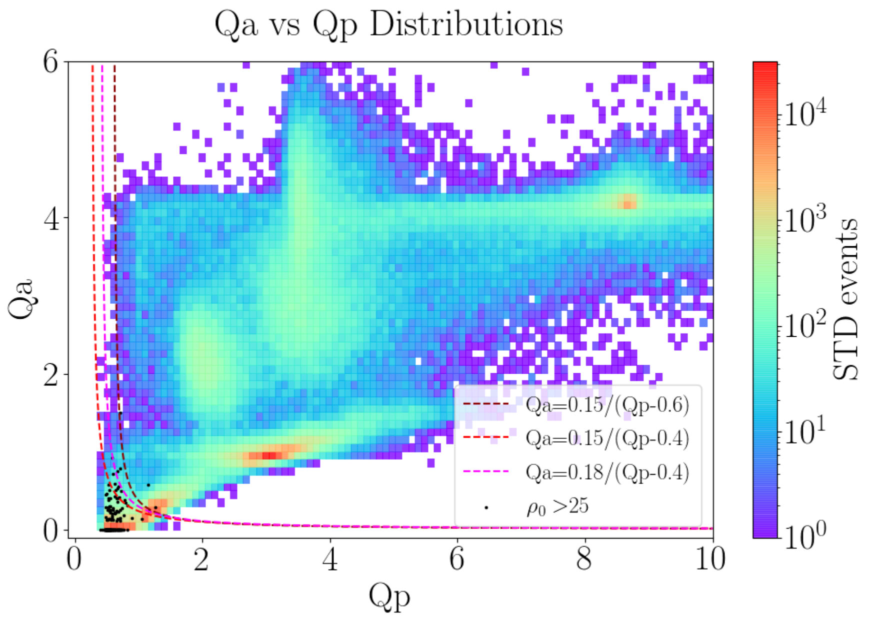
$$\chi^2 = \frac{\text{residual energy}}{\text{number of independent wavelets}}$$

W_{XGB} function of the XGBoost output

Qa-Qp penalization

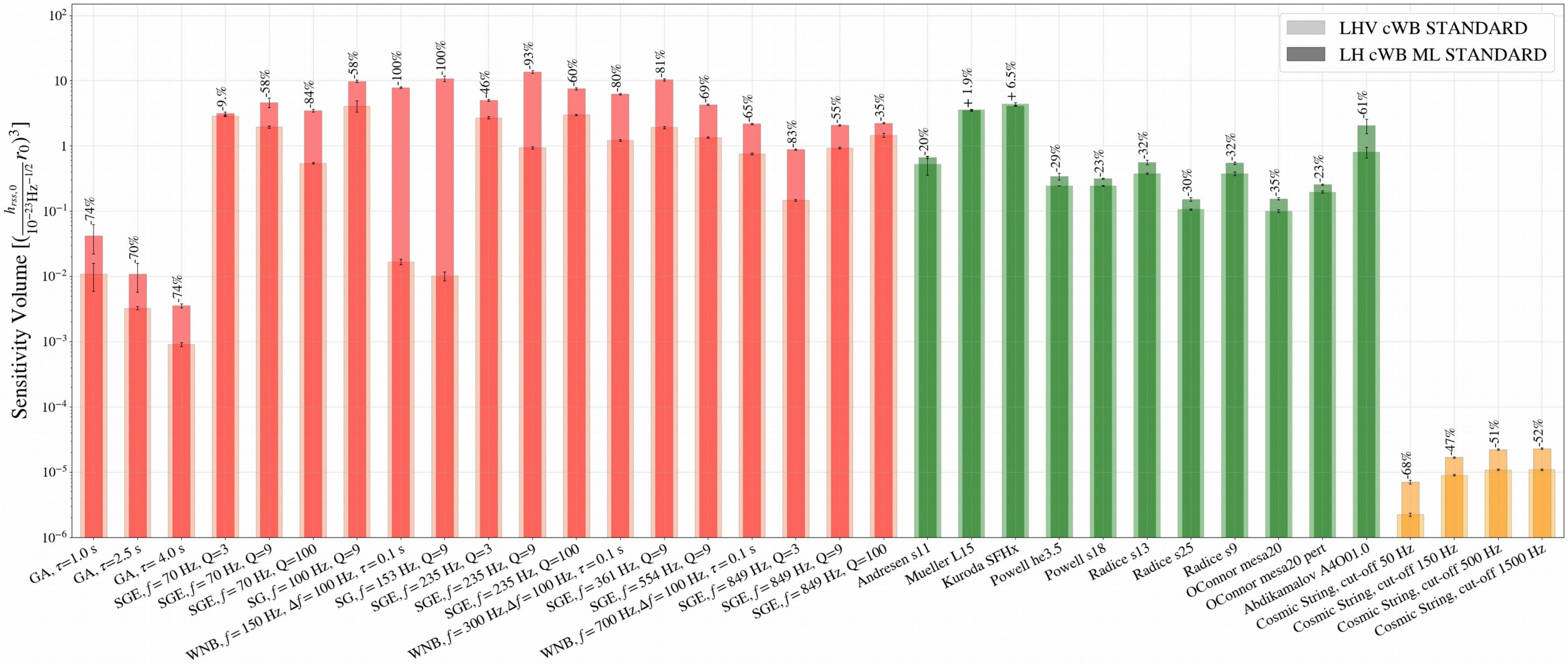
- XGBoost output p_{XGB} is penalized with Q_a and Q_p to mitigate glitches

$$\hat{p}_{XGB} = \begin{cases} p_{XGB} - (0.15 - Q_a * (Qp - 0.6)), & \text{if } Q_a * (Q_p - 0.6) \leq 0.15 \\ p_{XGB}, & \text{if } Q_a * (Q_p - 0.6) > 0.15 \end{cases} .$$



Comparison LH - LHV (standard PP cuts)

LH better than LHV for all waveforms



Comparison LH – LHV (ML-enhanced)

LH still better than LHV for most of the waveforms