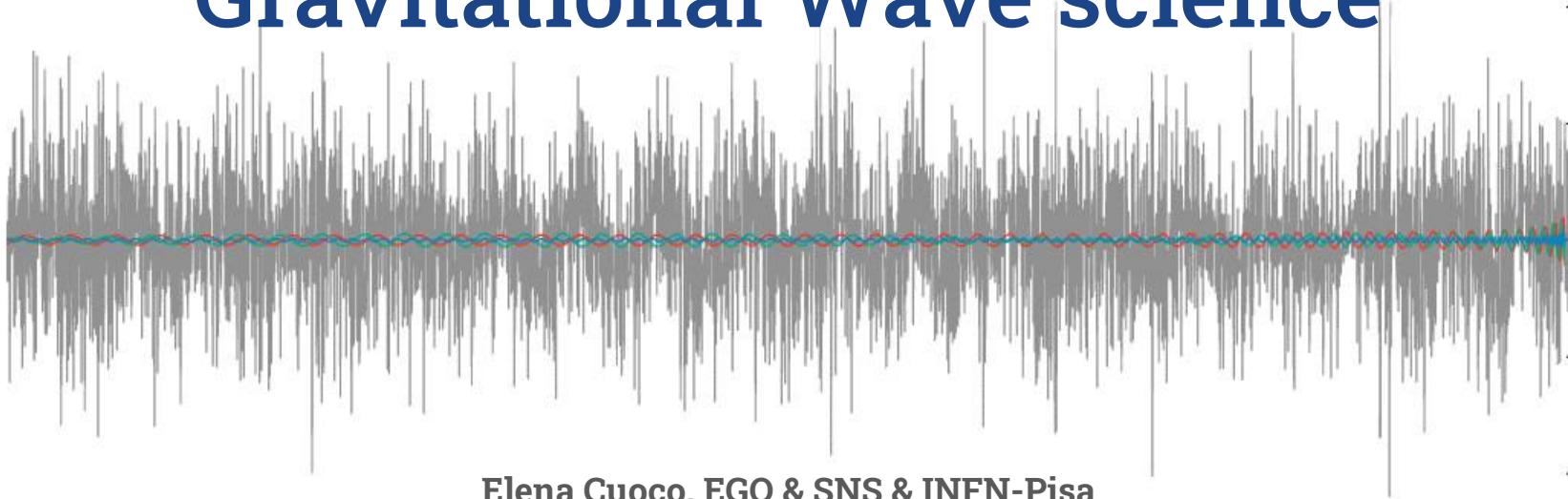


Machine Learning Application for Gravitational Wave science

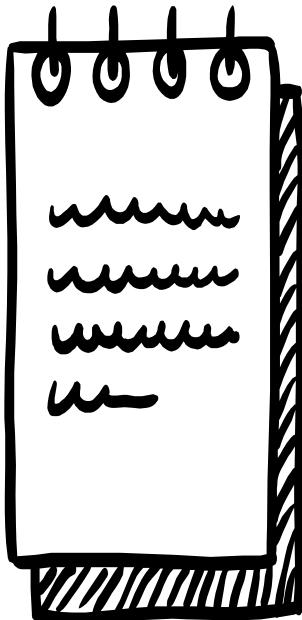
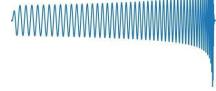


Elena Cuoco, EGO & SNS & INFN-Pisa

"Big Data within Science and Industry" September 22, 2023 , University of Milano-Bicocca



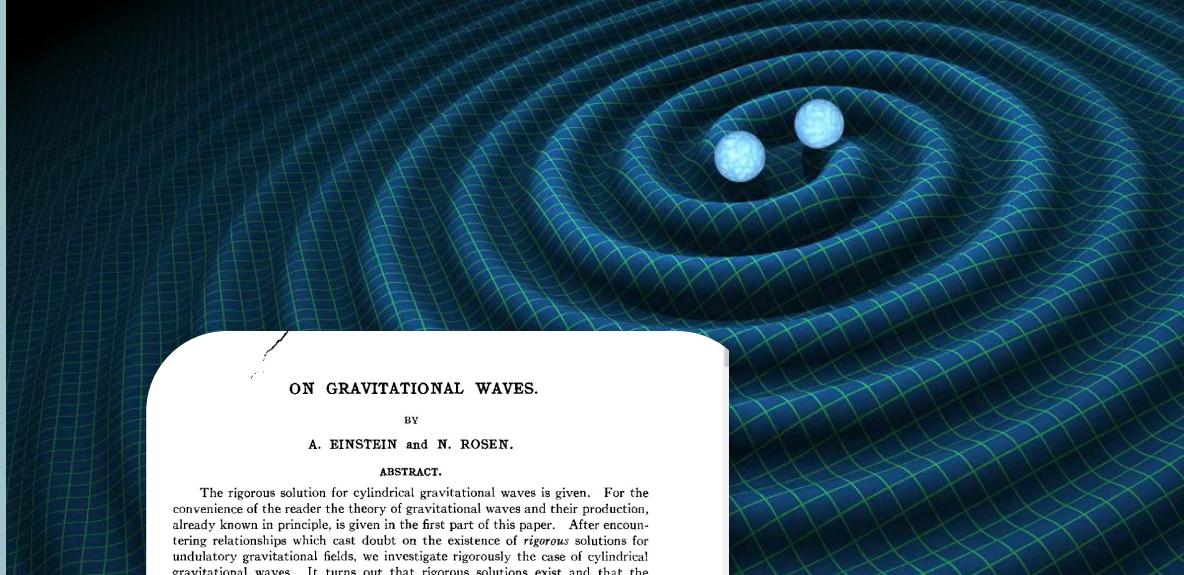
Outline



- Short overview of GW detector and data
- Data transformation and GW real data
- A roundup of use cases and applications of Machine Learning in Gravitational Wave science



What are gravitational waves



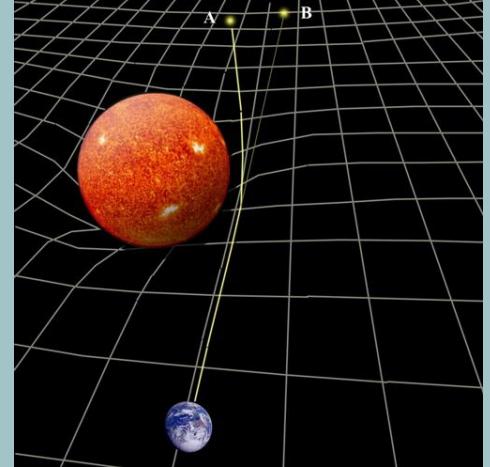
I. APPROXIMATE SOLUTION OF THE PROBLEM OF PLANE WAVES AND THE PRODUCTION OF GRAVITATIONAL WAVES.

It is well known that the approximate method of integration of the gravitational equations of the general relativity theory leads to the existence of gravitational waves. The method used is as follows: We start with the equations

$$R_{\mu\nu} - \frac{1}{2}g_{\mu\nu}R = -T_{\mu\nu}. \quad (1)$$

We consider that the $g_{\mu\nu}$ are replaced by the expressions

$$g_{\mu\nu} = \delta_{\mu\nu} + \gamma_{\mu\nu}, \quad (2)$$



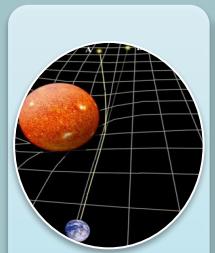
$$G_{\mu\nu} = \frac{8\pi G}{c^4} T_{\mu\nu}$$

Gravitational Waves (1916)

General Relativity (1915)



The GW search: a long history...



1915

- General Relativity



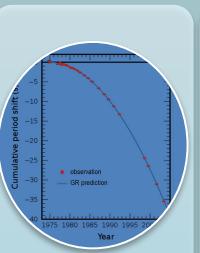
1916

- Gravitational Waves



1966

- Weber and Resonant Bars



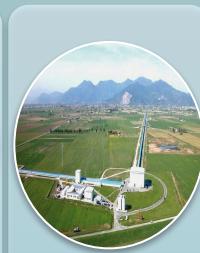
1974

- Hulse-Taylor Observing the pulsar binary PSR B1913+16



1980-1990

- Cryogenic Resonant Bars



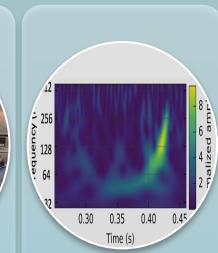
1993

- The approval of Virgo Experiment



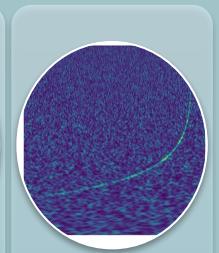
1999+

- Data taking from LIGO and Virgo



2015

- GW BHB detection



2017

- BNS detection: Multi-messenger Astronomy

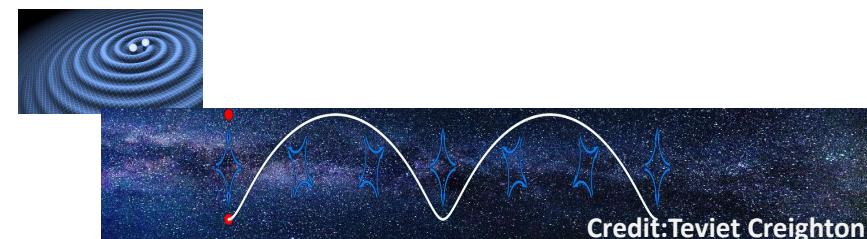
~100 years



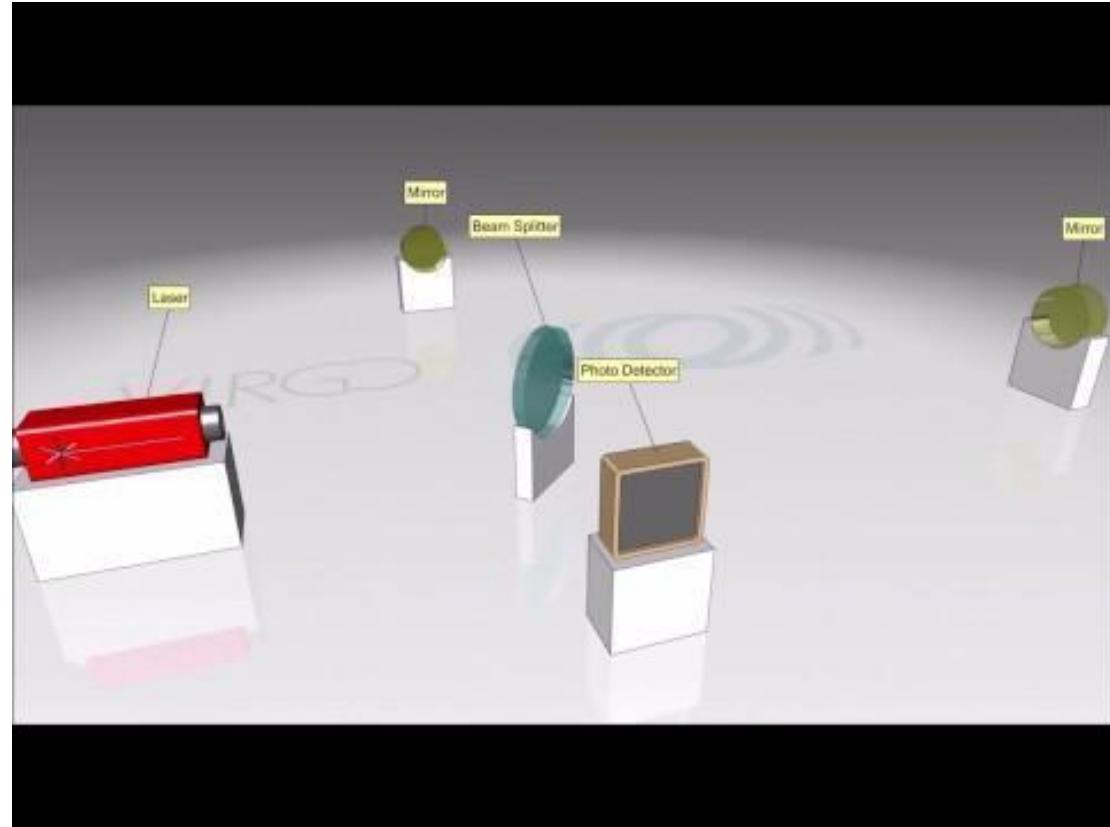
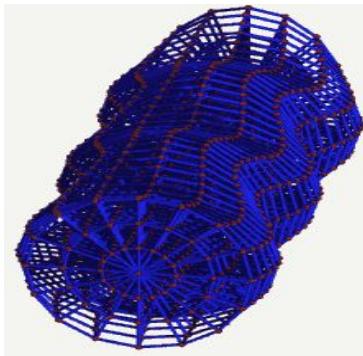
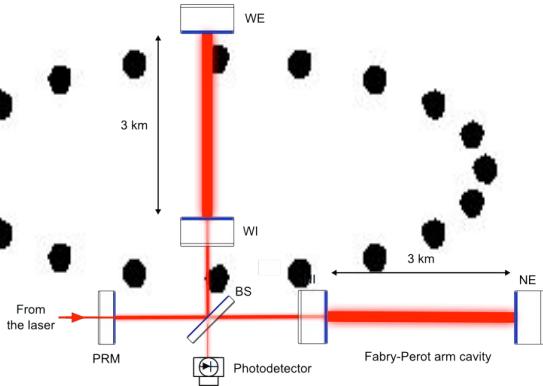
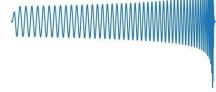
2017 Nobel Prize in Physics



The Gravitational Wave detectors



GW detection



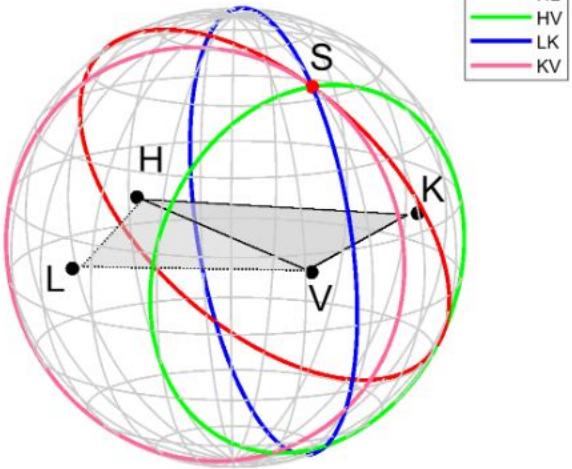
International Collaboration: ground based detectors





Why more than 1 detector?

- Source localization using only timing for a two-site network yields an annulus on the sky.
- For three detectors, the time delays restrict the source to two sky regions which are mirror images with respect to the plane passing through the three sites.
- With four or more detectors, timing information alone is sufficient to localize to a single sky region, and the additional baselines help to limit the region to under 10 deg² for some signals.

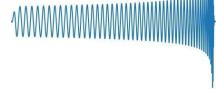


arXiv:1304.0670

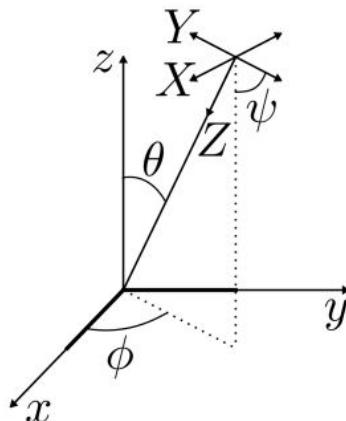
- 2 detector → 100 - 1000 deg²
- 3 detector → 10 - 100 deg²
- 4 detector → < 10 deg²



Detector response and Antenna Patterns



The detector response can be written



$$F_+ = \frac{1}{2} (1 + \cos^2 \theta) \cos 2\phi \cos 2\psi + \cos \theta \sin 2\phi \sin 2\psi$$

$$F_\times = \frac{1}{2} (1 + \cos^2 \theta) \cos 2\phi \sin 2\psi + \cos \theta \sin 2\phi \cos 2\psi$$



This let us have the localization of the source

$$h(t) = h_+ F_+ + h_\times F_\times$$

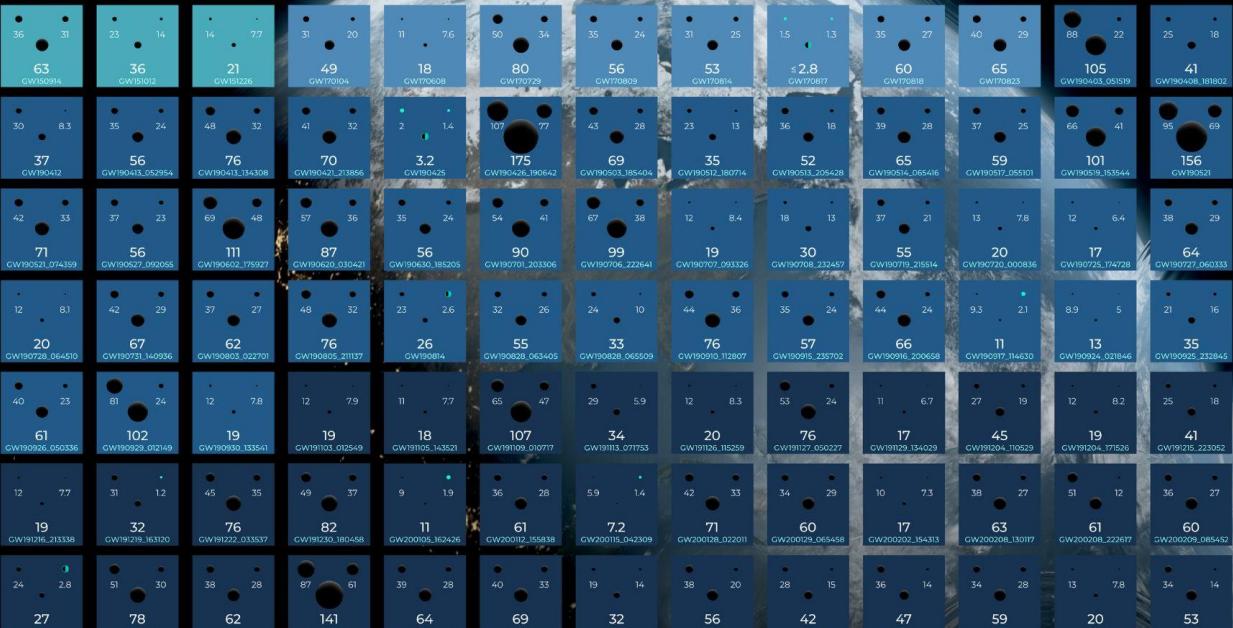


91 events!!!

OBSERVING
01
RUN
2015 - 2016

02
2016 - 2017

03a+b
2019 - 2020



GRAVITATIONAL WAVE MERGER DETECTIONS SINCE 2015

OzGrav

ARC Centre of Excellence for Gravitational Wave Discovery

UNITS ARE SOLAR MASSES

1 SOLAR MASS = 1.988×10^{30} kg

Note that the mass estimates shown here do not include uncertainties, which is why this final mass is often very different from the total mass of the two individual objects. In reality, the final mass is probably less than the primary plus secondary mass.

These detections were made by LIGO, Virgo and KAGRA. They are also being used to search for pulsars and other astronomical phenomena.

For more information, see the OzGrav website or our papers.

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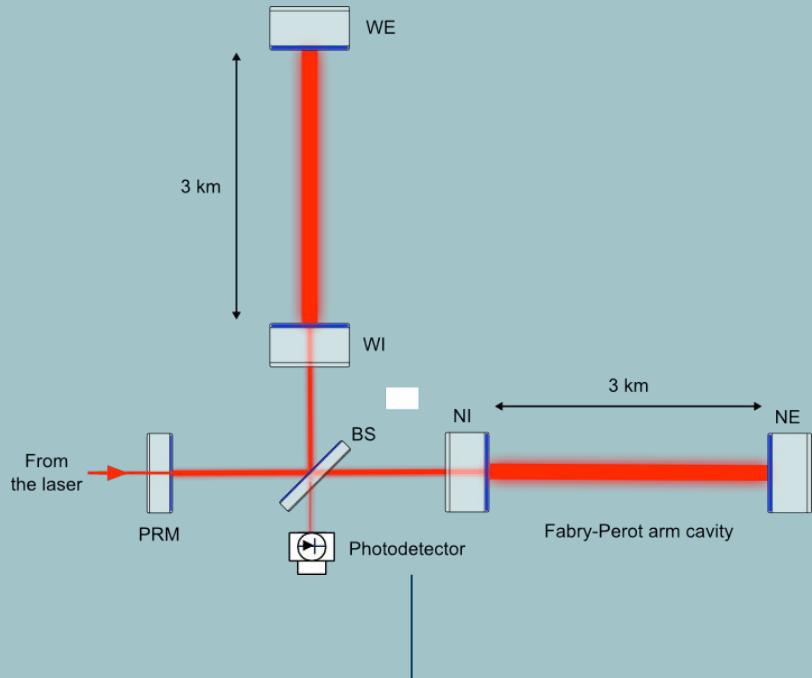
CC-BY-NC-SA 4.0 International License

www.gw-openscience.org

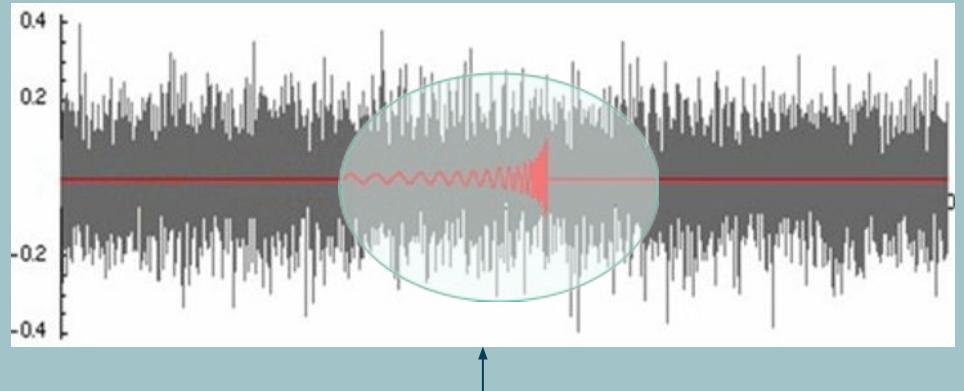
Credit: Carl Knox (OzGrav,
Swinburne University of
Technology).



Gravitational Wave (GW) detector data

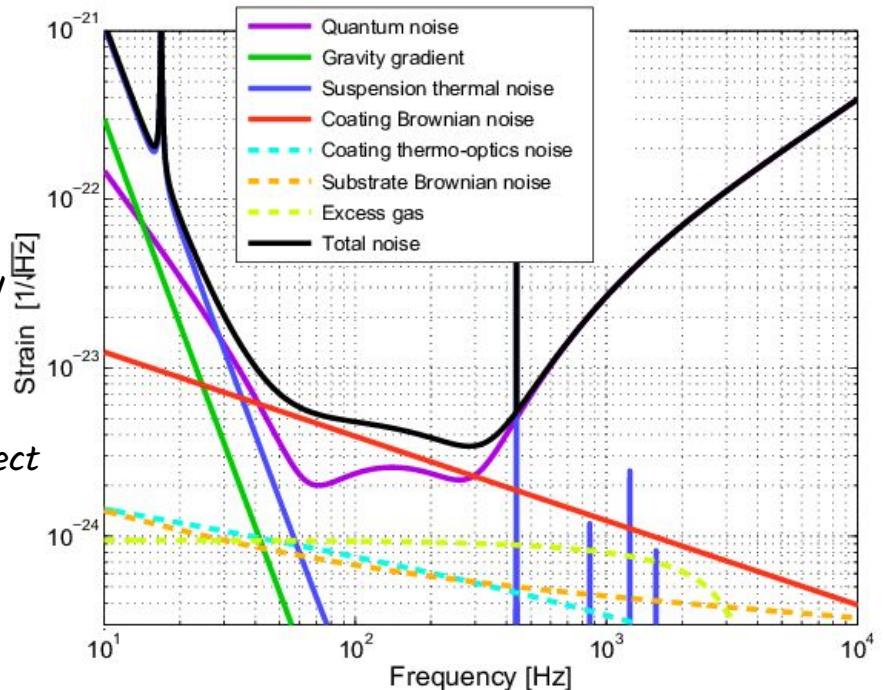


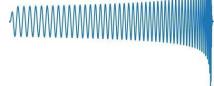
- **Time series sequences...** noisy time series with low amplitude GW signal buried in



Theoretical Detector sensitivity

- Noise at the output of the detector is the superimposition of different contribution
- If we consider the noise as a stationary stochastic process we can identify it with its Covariance and so Power Spectral density
- The sensitivity curve define the minimum value of amplitude signal we are able to detect



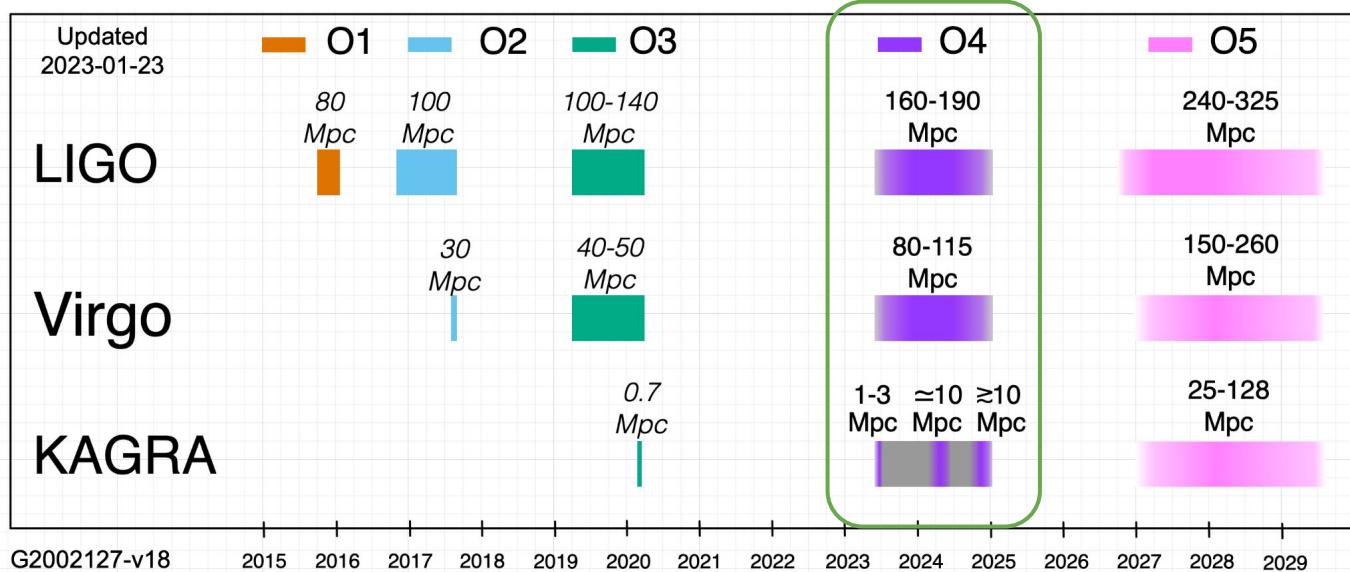


The O-run timeline

The detector strain sensitivity is the minimum *detectable* value of the strain produced by an incoming GW:

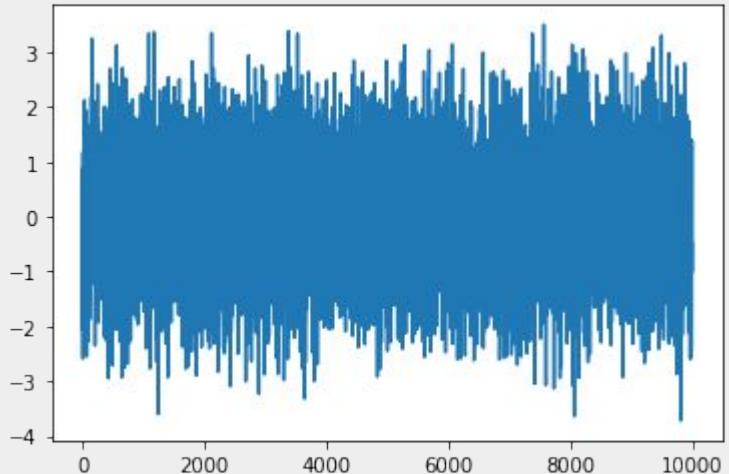
⇒ It is determined by the detector noise.

BNS inspiral range: the distance, averaged over GW polarizations and directions in the sky, at which a single detector can observe with matched-filter Signal-to-noise Ratio (SNR) of 8 the inspiral of two neutron stars.



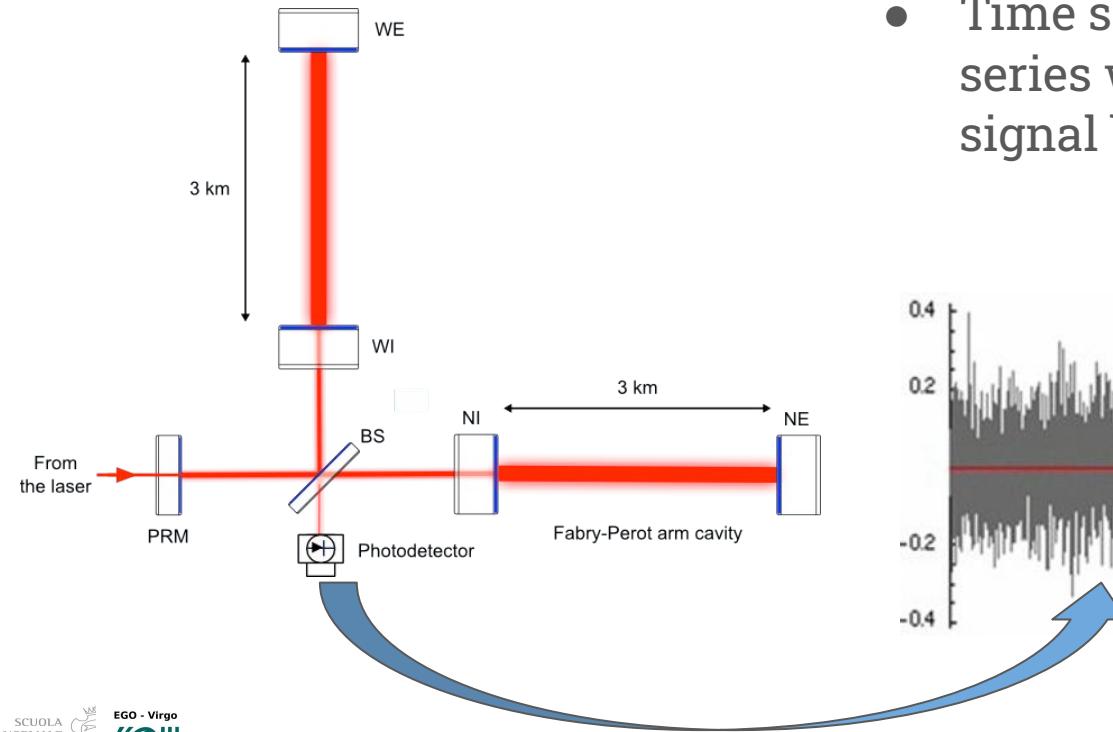
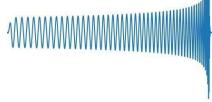


The GW Data

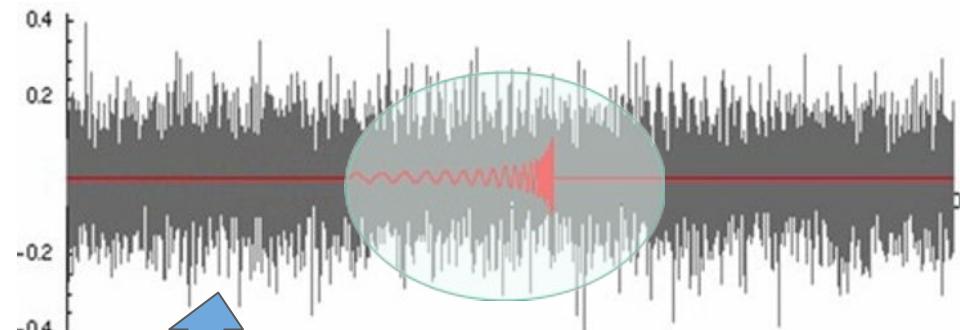




GW detector data

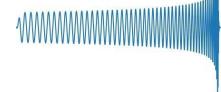


- Time series sequences... noisy time series with low amplitude GW signal buried in

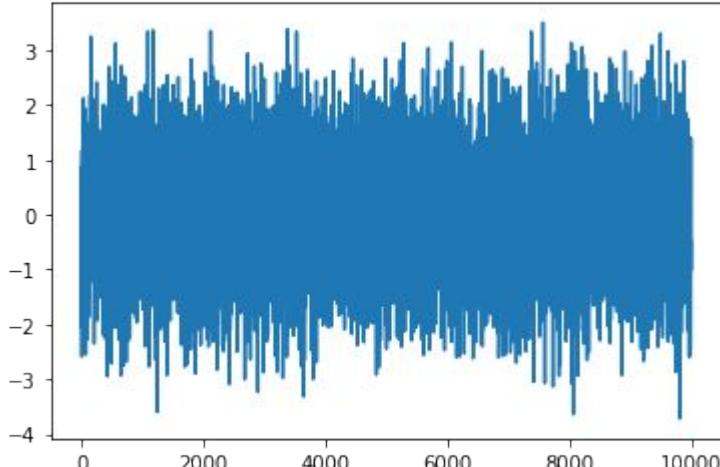
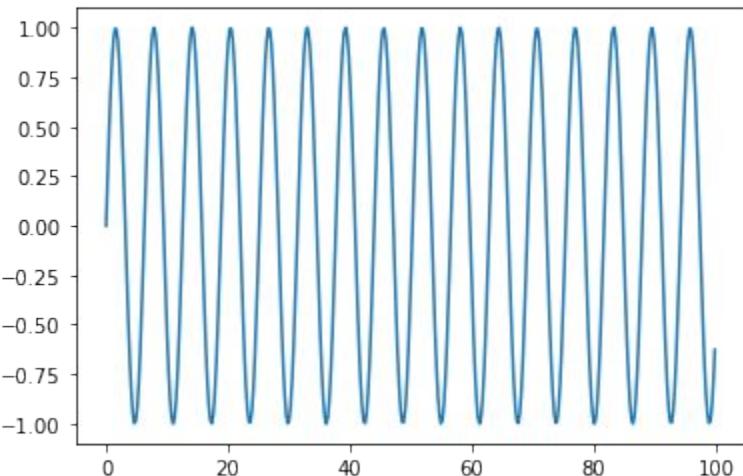




Time series

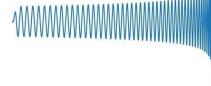


- A time series $x[n]$ is a sequence of data points measuring a physical quantity at successive times spaced at uniform time intervals.
- We say that $x[n]$ is a stationary process, if its statistical description does not depend on n .





Data mapping, preserving the info



01

Time-domain

- Time-series at the output of the detector (be careful with the sampling theorem)

02

Frequency-domain

- Fourier transform
 - Useful for stationary data
 - Useful for persistent signals
 - It captures the global frequency information

03

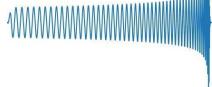
Time-frequency domain

- Short Fourier Transform
 - Useful for not stationary data
 - Useful for transient signals

04

Others

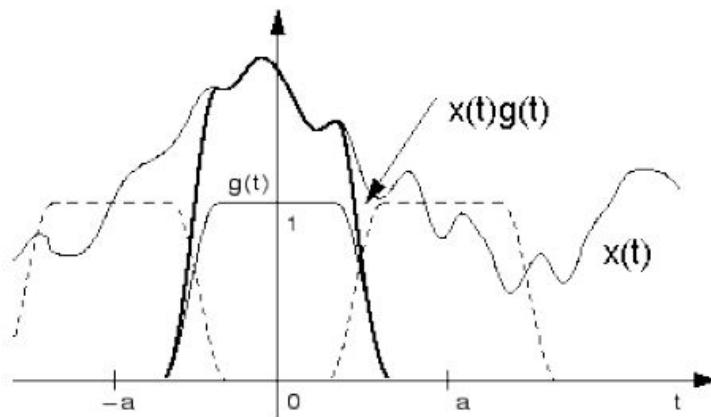
- Wavelet decomposition (useful for multiresolution analysis)
- Q-Transform (useful for transient)
- Hough-transform (useful for lines)



Time-Frequency domain: STFT

The short time Fourier transform (STFT) function is simply the Fourier transform operating on a small section of the data. Here a moving window is applied to the signal and the fourier transform is applied to the signal within the window as the window is moved.

$$STFT\{x(t)\} = X(\tau, f) = \int_{-\infty}^{\infty} x(t)g(t-\tau) \exp(-2i\pi ft) dt$$





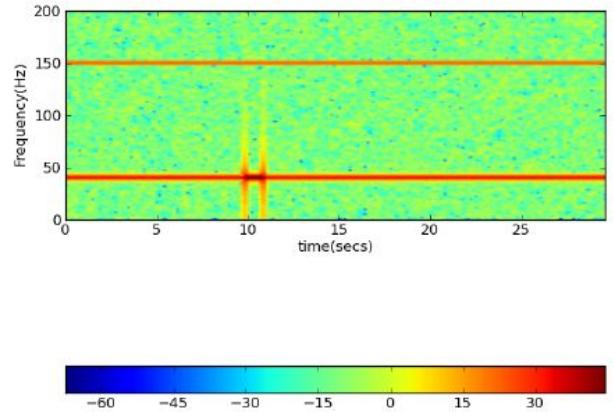
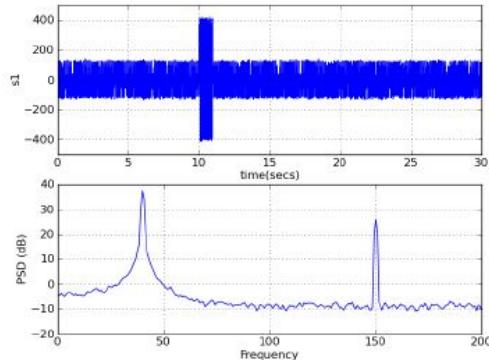
Spectrogram

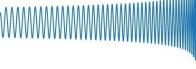


To have easy access to the information of the STFT we can plot the spectrogram.
It is defined as

$$\text{Spectrogram}(\tau, f) = |X(\tau, f)|^2$$

So we will have a bidimensional plot where on x-axis usually is plotted the time, on y-axis the frequency, while the color of the map is the the amplitude of a particular frequency at a particular time.

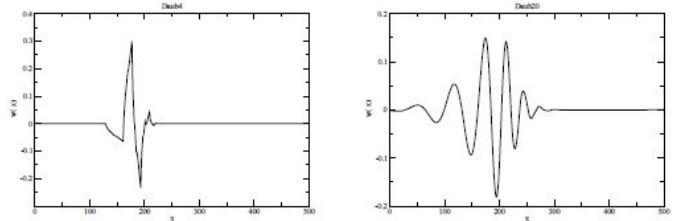




Wavelet decomposition of time series

The wavelet transform replaces the Fourier transform sinusoidal waves by a family generated by translations and dilations of a window called a wavelet.

$$Wf(a, b) = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{b}} \psi^*\left(\frac{t-a}{b}\right) dt$$



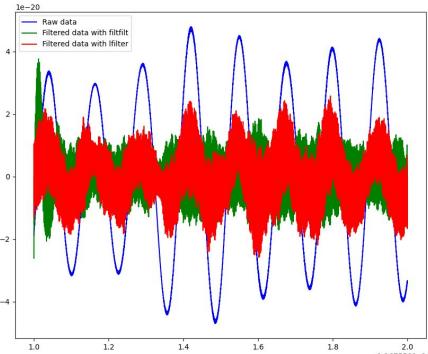
The scale of the wavelet is determined by the parameter **b**.

- When **b** is decreased, the wavelet appears more compressed, allowing it to capture high-frequency information.
- Increasing the value of **b** elongates the wavelet, enabling it to capture low-frequency information.

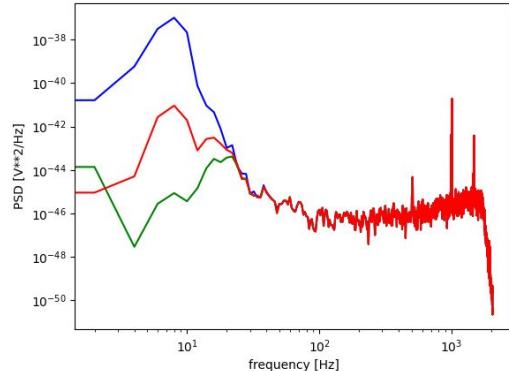
The location of the wavelet is determined by the parameter **a**.

- If we decrease the value of **a**, the wavelet will be shifted to the left, whereas an increase in **a** will shift it to the right.
- Note that the location of the wavelet is crucial because, unlike waves, wavelets are only non-zero within a short interval.

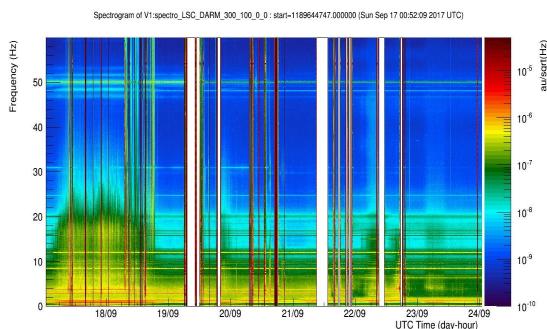
Data representations



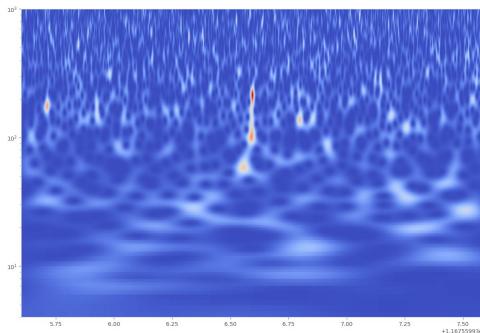
Time-domain



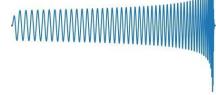
Frequency-domain



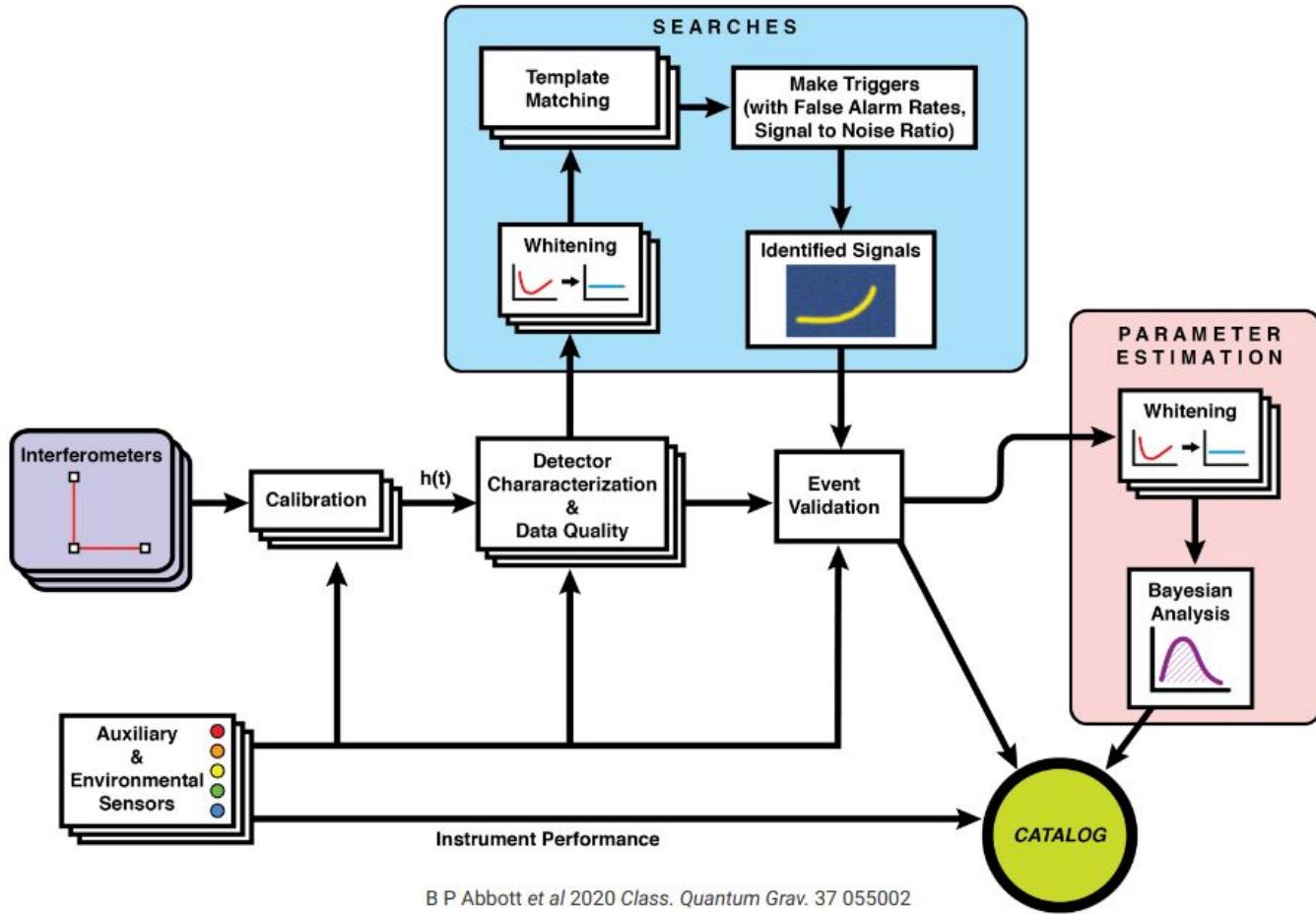
Time-frequency-domain



Wavelet-domain

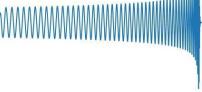


The data analysis workflow



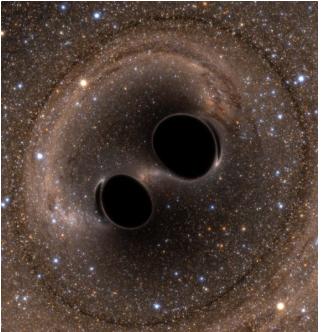


GW astrophysical sources



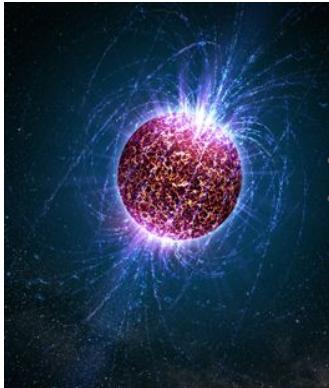
Short long

Known unknown form



Coalescing Binary Systems CBC

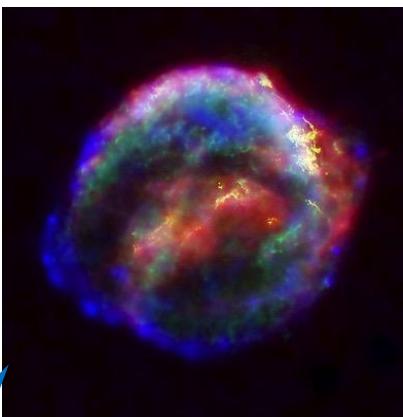
- Black hole – black hole (BBH)
- Neutron star – neutron star (BNS)
- BH-NS
- Analytical waveform



Continuous Sources

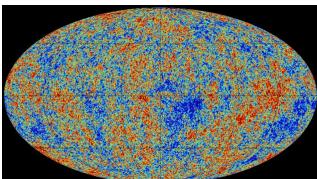
- Spinning neutron stars
- Monotone waveform

What else?



Transient Burst Sources

- Core Collapse Supernovae (CCSN)
- cosmic strings
- unmodeled waveform



Cosmic GW Background

- residue of the Big Bang,
- stochastic, incoherent background

Do we know their Waveforms?



GW Signal Detection and Matched Filter for known waveforms

- Defining the problem
- The Neyman Pearson Criteria
- The Matched Filter

[Switch to pdf slides...:\)](#)



Optimal Filter is Matched Filter, if the noise is gaussian distributed

Maximizing the likelihood

$$\rho(t) = 4 \int_0^{\infty} \frac{\tilde{x}(f) \tilde{h}^*(f)}{S_n(f)} e^{2\pi i f t} df$$

↑
Noise power spectral density

Annotations: "Data" points to the $\tilde{x}(f)$ term; "Template" points to the $\tilde{h}^*(f)$ term.

Look for maxima of $|\rho(t)|$ above some threshold → trigger



- pyCBC (Usman et al, 2015)
- MBTA (Adams et al. 2015)
- gstdl-SVD (Cannon et al. 2012)

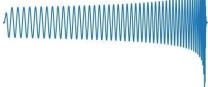
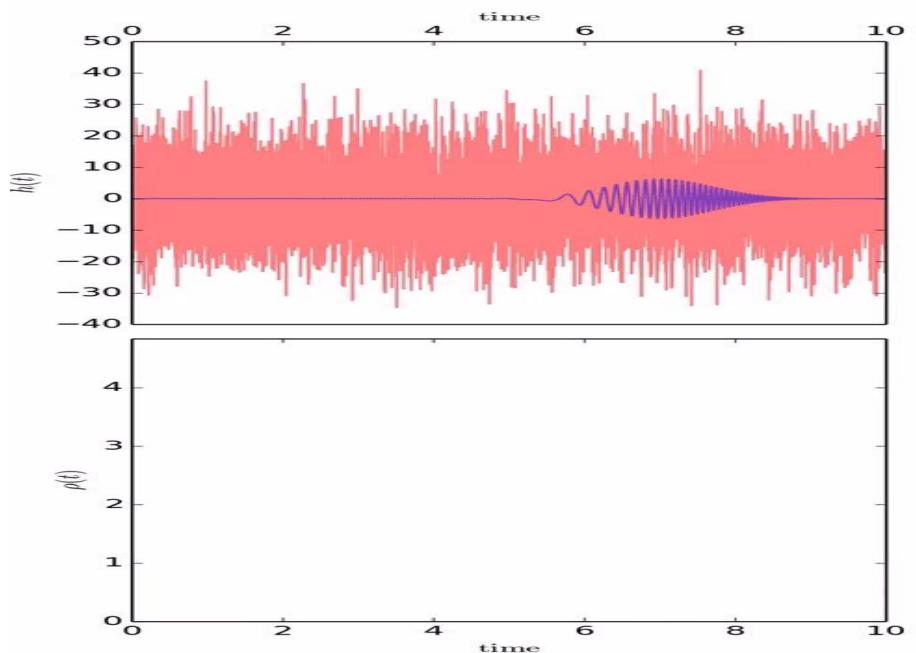
Matched-filter

Data Template

$$\rho(t) = 4 \int_0^{\infty} \frac{\tilde{x}(f) \tilde{h}^*(f)}{S_n(f)} e^{2\pi f t} df$$

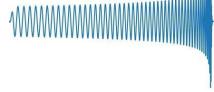
Noise power spectral density

How we detect transient signals: modeled search





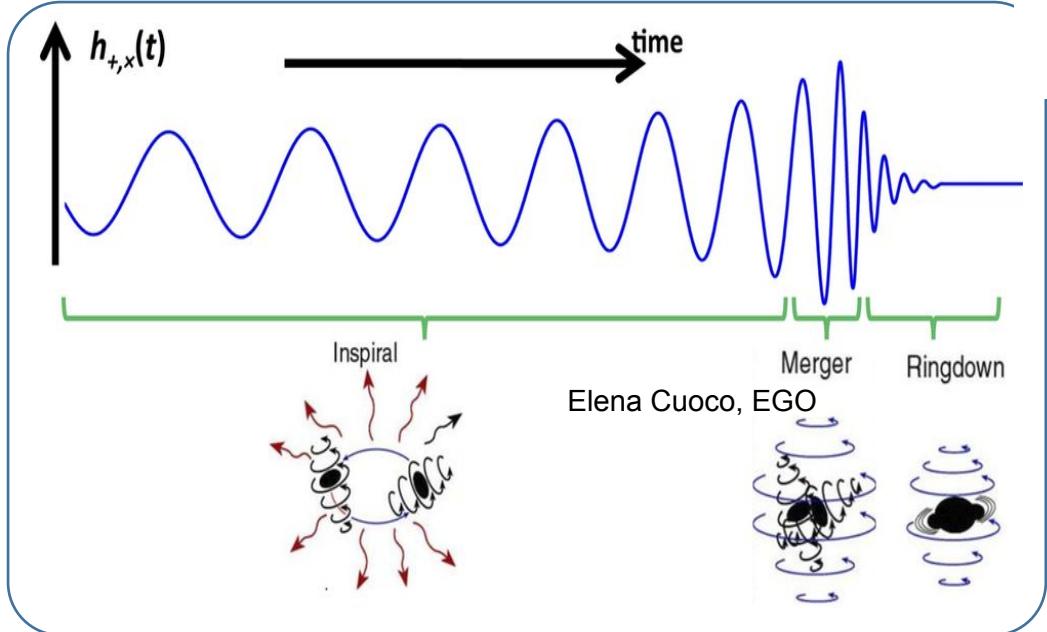
CBC template generation



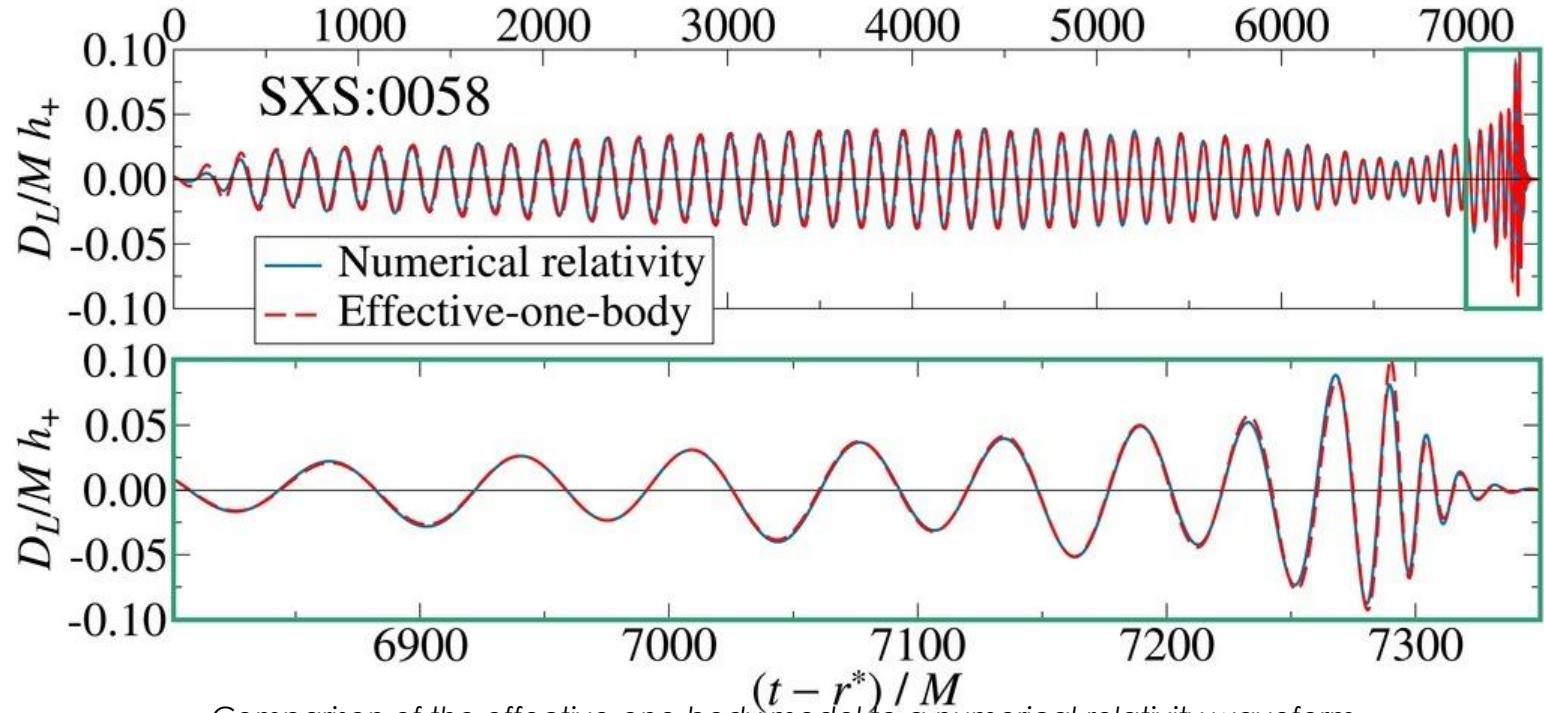
$$h(f) = A(f)e^{i\Phi(f)}$$

$$\Phi(f) = \sum_{k=1}^7 (\varphi_k + \varphi_k^l \log(f)) f^{(5-k)/3} + \sum_{i \neq k} \varphi_i f^i$$

$$\varphi_j \equiv \varphi_j(m_1, m_2, \vec{s}_1, \vec{s}_2) \quad \forall j = k, i$$



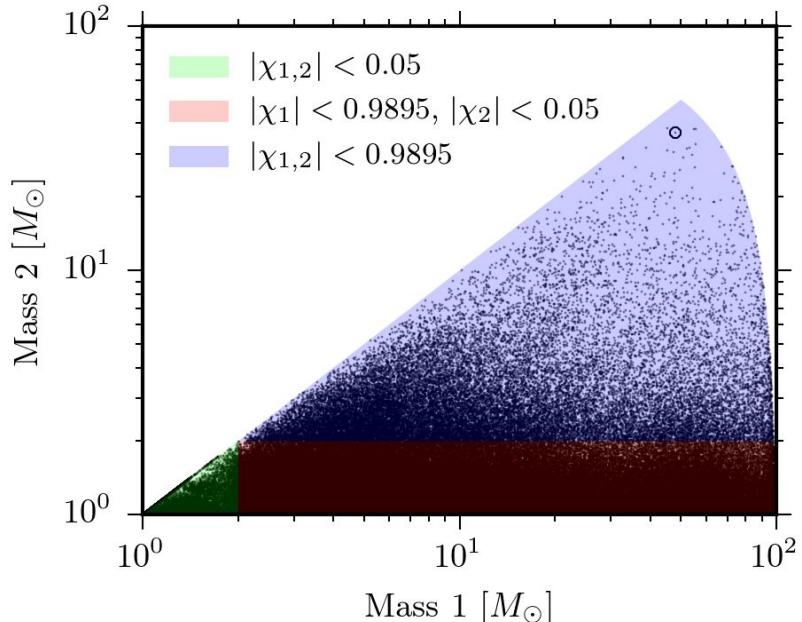
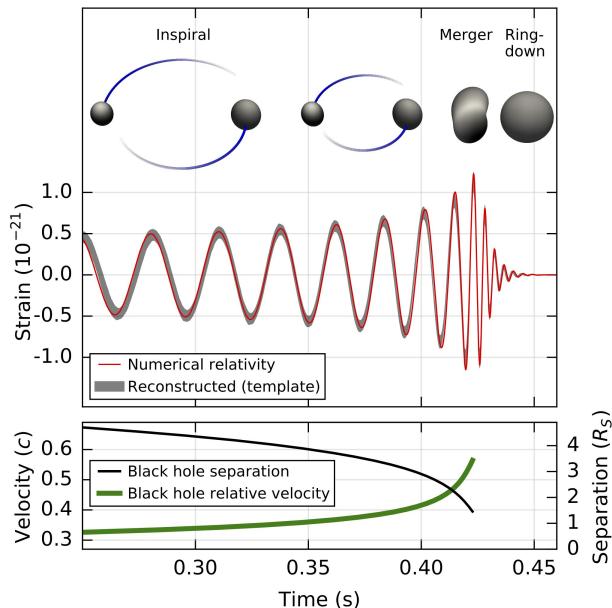
CBC template generation



Comparison of the effective-one-body model to a numerical-relativity waveform of a precessing black-hole binary. © A. Taracchini/AEI

How many templates?

To cover in efficient way the parameters space, we build a templates bank requiring that the signal can be detected with a maximum loss of 3% of its SNR



~250000 waveforms used for GW150914



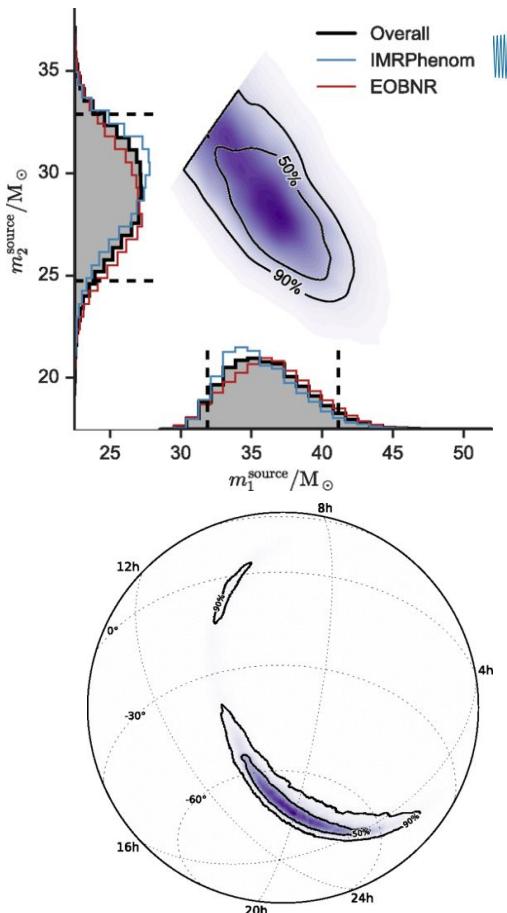
Parameter estimation

$$p(\theta|d, H) = \frac{p(\theta|H)p(d|\theta, H)}{p(d|H)}.$$

- MCMC and Nested Sampling
 - MCMC Random steps are taken in parameter space, according to a proposal distribution, and accepted or rejected according to the Metropolis-Hastings algorithm.
 - Nested sampling can also compute evidences for model selection.

Parameter estimation for compact binaries with ground-based gravitational-wave observations using the LALInference software library

J. Veitch et al. Phys. Rev. D 91, 042003

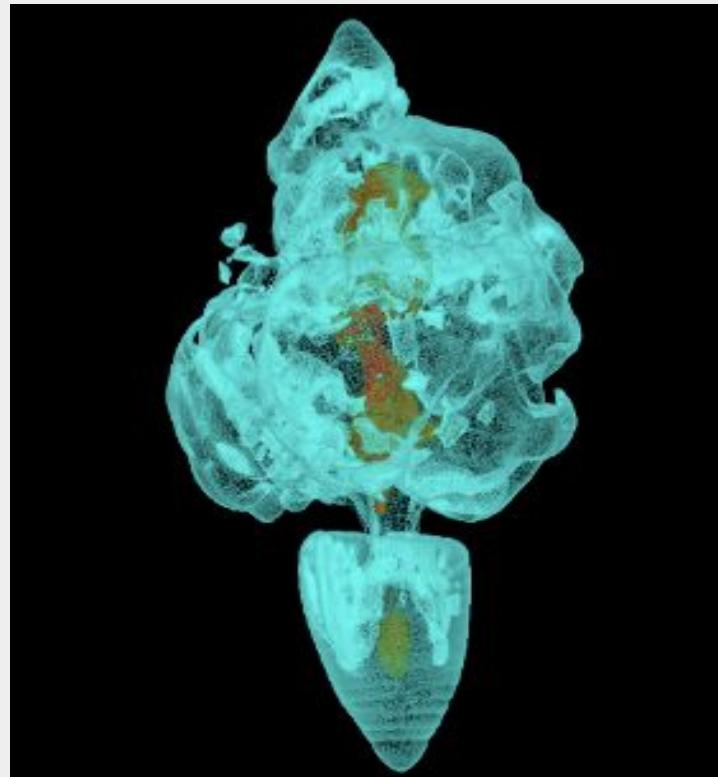


LVC (PRL:116, 241102)



Searches for unmodeled signals

What we do for signals with
unknown waveforms



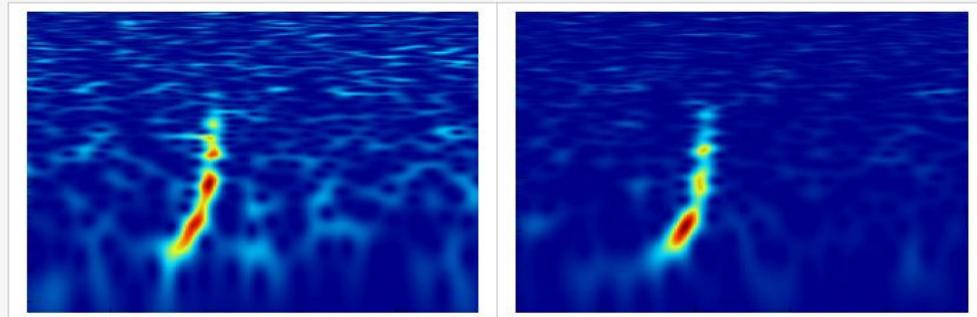
Computer simulation of gravitational waves emitted
by a supernova. Credit: J Powell / B Mueller



How we detect transient signals: un-modeled search

- Strategy: look for excess power in single detector or coherent/coincident in network data
- Example cWB
 - <https://gwburst.gitlab.io/>
 - Time-domain data preprocessed
 - Wavelet decomposition
 - Event reconstruction

Coherent WaveBurst was used in the [first direct detection](#) of gravitational waves (GW150914) by LIGO and is used in the ongoing analyses on LIGO and Virgo data.



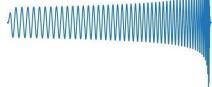
Time-Frequency maps of GW150914: Livingston data (left), Hanford data (right)
First screenshot of GW150914 event

Burst search

Phys. Rev. D 93, 042004 (2016)
Class.Quant.Grav.25:114029,2008



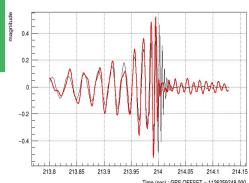
Coherent WaveBurst



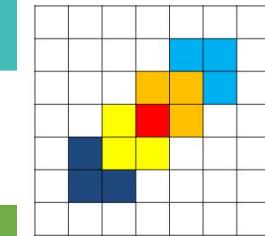
Excess power are selected from
a set of wavelet
time-frequency maps
Data from both detector are
combined together

Triggers are analyzed
coherently to estimate signal
waveform, wave polarization,
source location, using the
constrained likelihood method

Selects the best fit waveform
which corresponds to the
maximum likelihood statistic
over a 200000 sky positions

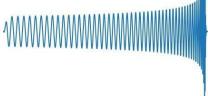


The event are ranked using a
variable η_c
 $E_c \rightarrow$ Normalized coherent energy
between the two detectors
 $E_n \rightarrow$ normalized noise energy
derived by subtracting the
reconstructed signal from the
data

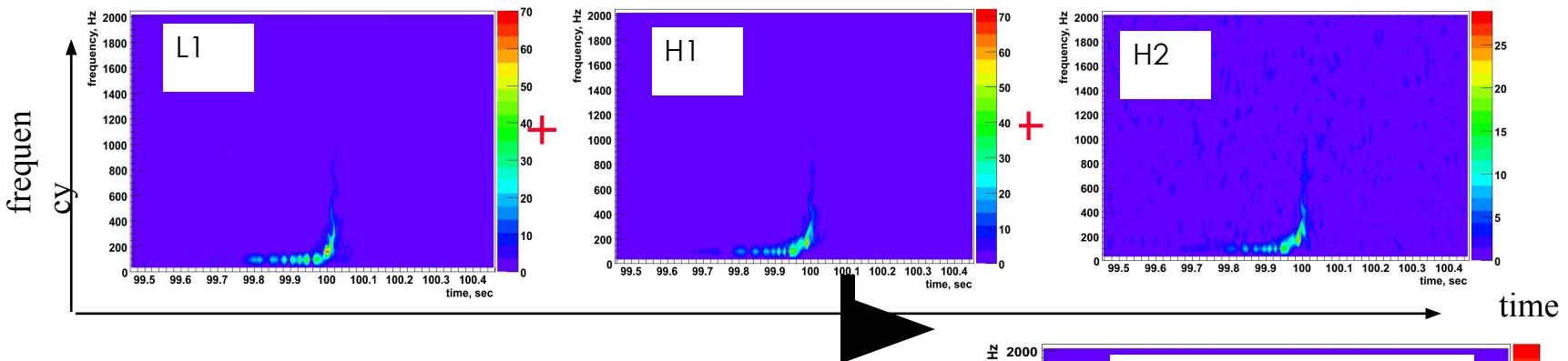


$$\eta_c = \sqrt{\frac{2E_c}{(1 + E_n/E_c)}}$$

Coherent WaveBurst

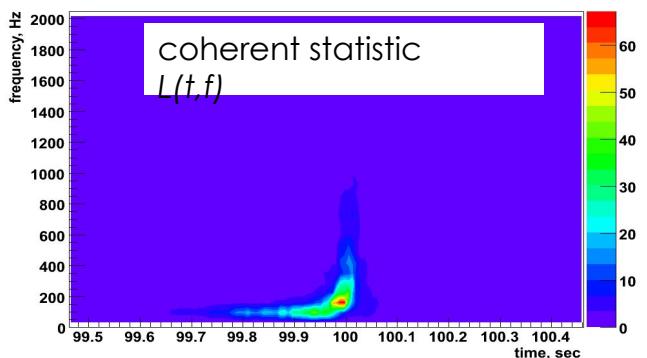


- End-to-end multi-detector coherent pipeline
 - construct coherent statistics for detection and rejection of artifacts
 - performs search over the entire sky
 - estimates background with time shifts



$$\xi_k = h_+ F_{+k} + h_x F_{xk}$$

$$L(t, f) = \max_{h_+ h_x \theta \varphi} \sum_k \frac{x_k^2[t, f] - (x_k[t, f] - \xi_k[t, f])^2}{\sigma_k^2(f)}$$

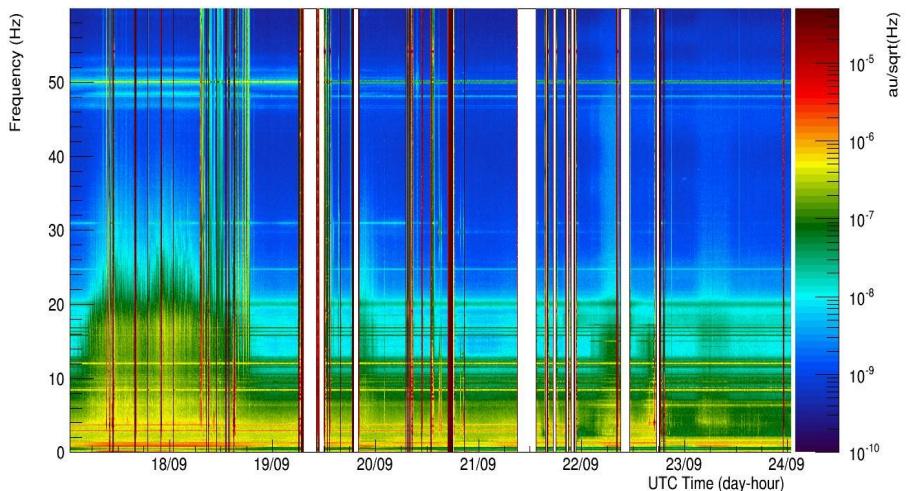




The Real Data

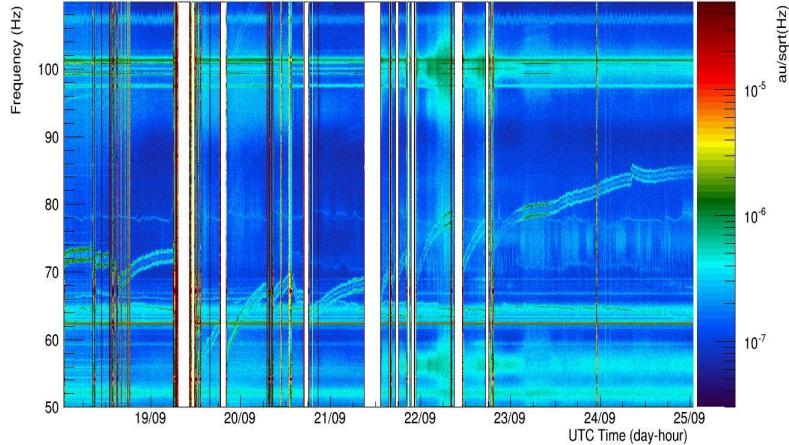
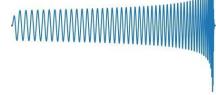
The noise it not at all ideal...

Spectrogram of V1:spectro_LSC_DARM_300_100_0_0 : start=1189644747.000000 (Sun Sep 17 00:52:09 2017 UTC)

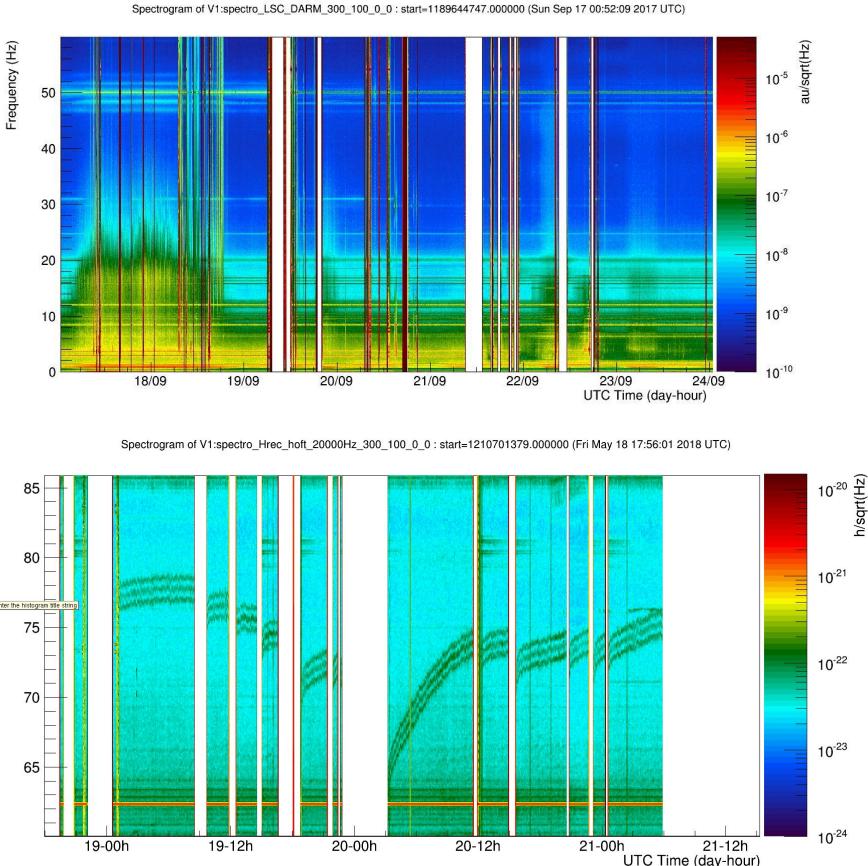




Not linear and not stationary noise

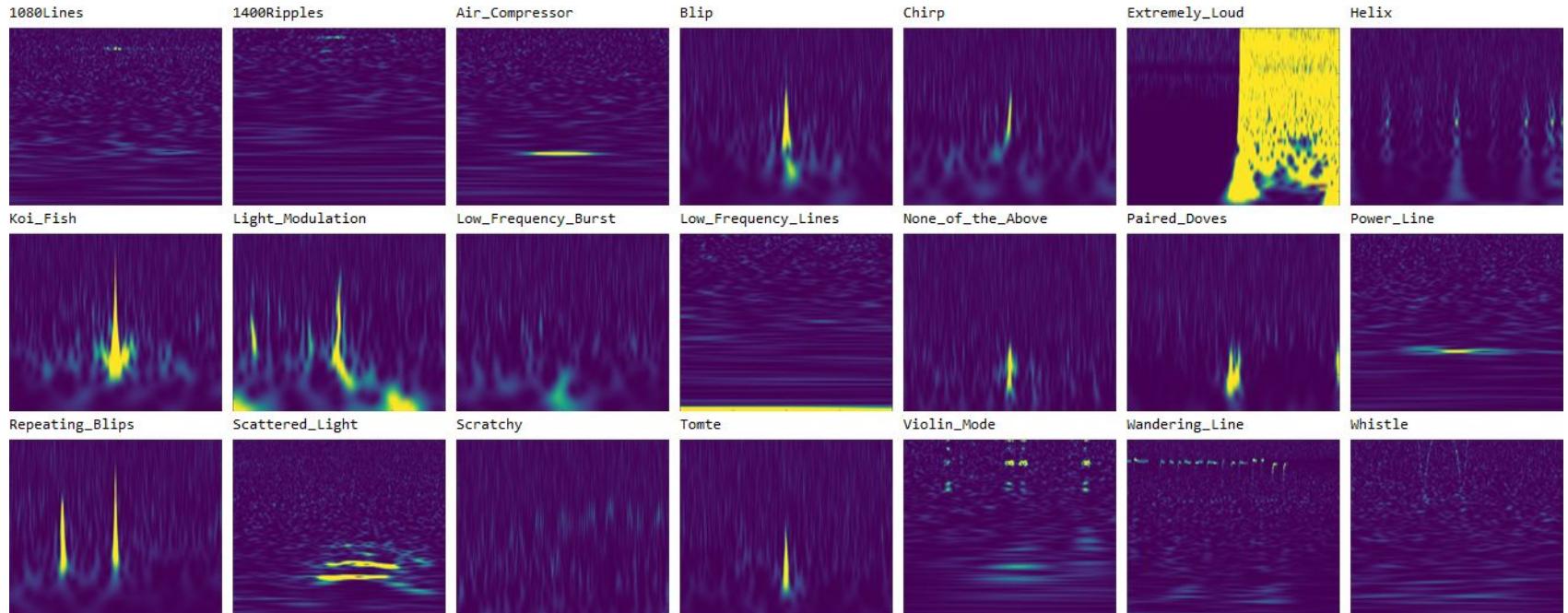
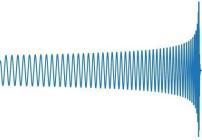


I. Fiori courtesy





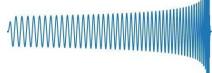
Transient noise signals: Glitches



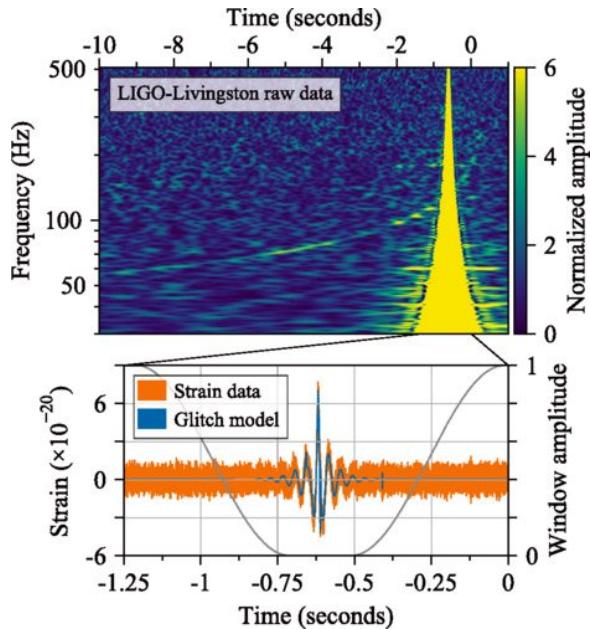
<https://www.zooniverse.org/projects/zooniverse/gravity-spy>

Gravity Spy, Zevin et al (2017)

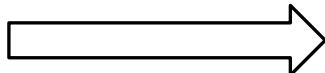
The importance of glitch analysis



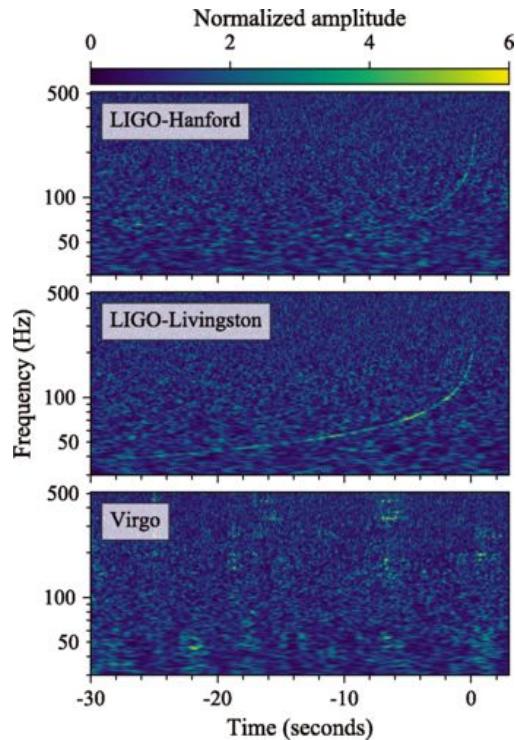
Ligo Livingston



Glitch mitigation



GW 170817

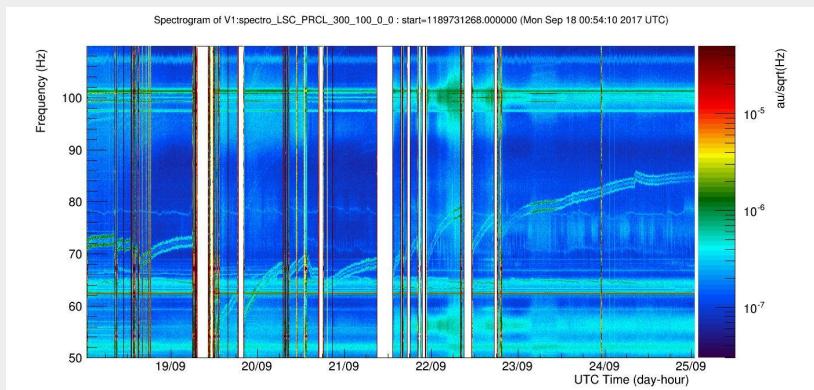
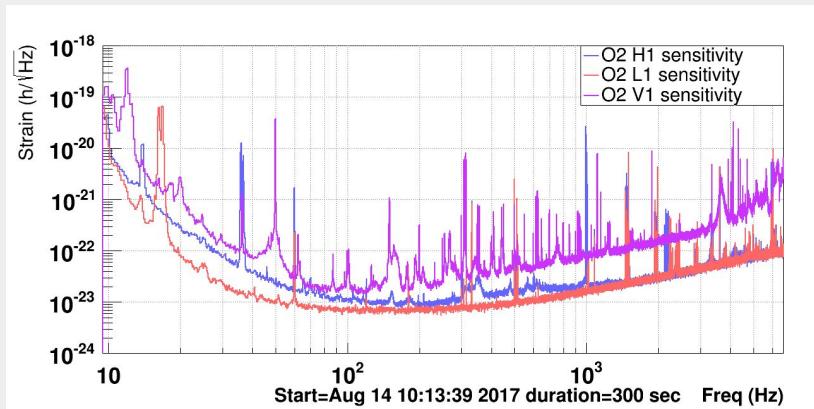


[Abbott et al. \(2017\)](#)

<https://arxiv.org/pdf/2002.11668.pdf>

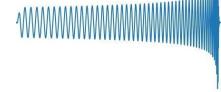


Data preprocessing

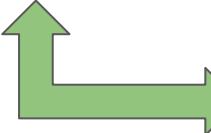




Whitening

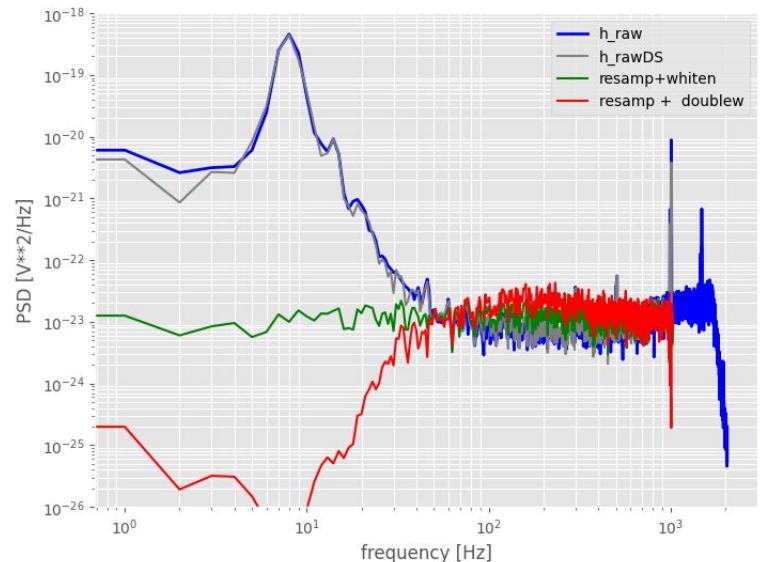


$$\rho(t) = 4 \int_0^{\infty} \frac{\tilde{x}(f) \tilde{h}^*(f)}{S_n(f)} e^{2\pi i f t} df$$



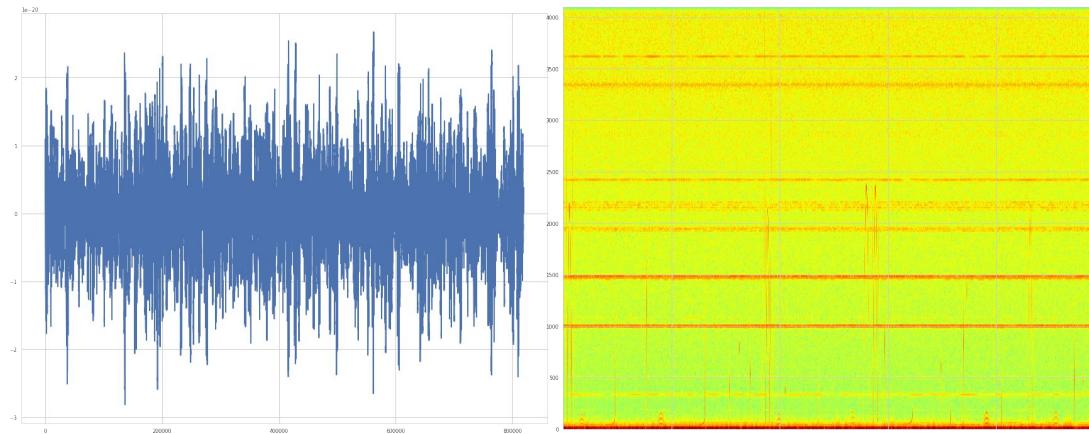
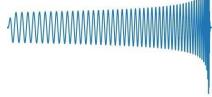
Whitening

We can do in frequency domain
estimating the PSD

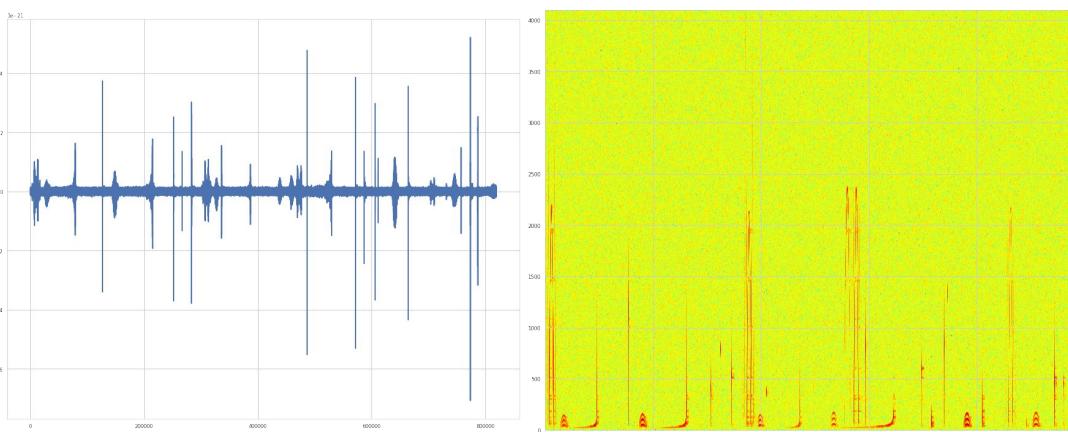




Signals in whitened data



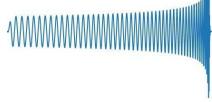
Not Whitened



Whitened



Whitening in time domain

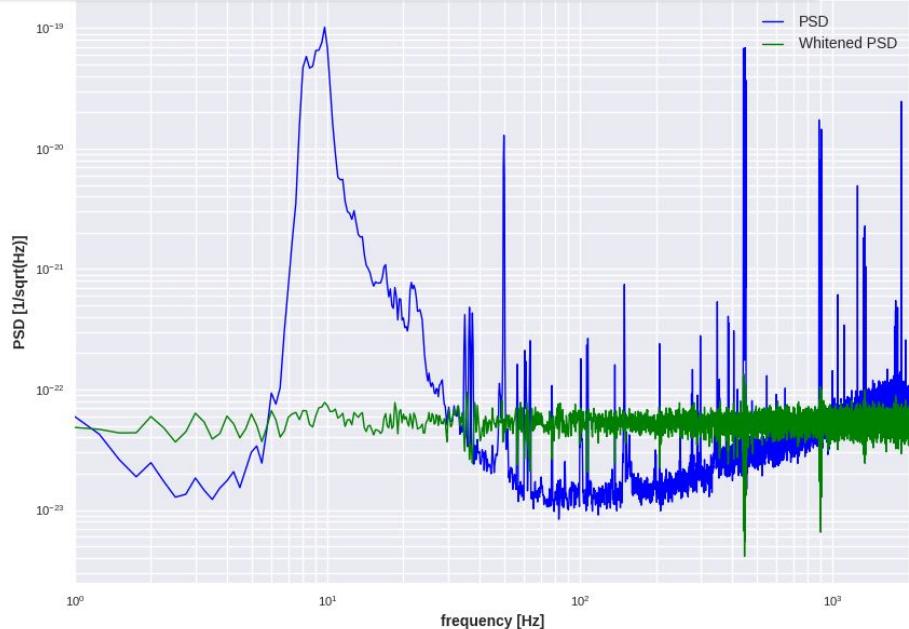


We need parametric modeling

It can be useful for
on-line application

It can be implemented
for non stationary noise

It can catch the
autocorrelation function
to larger lags





AR parametric modeling



An AutoRegressive process is governed by this relation

$$x[n] = - \sum_{k=1}^P a[k]x[n-k] + w[n],$$

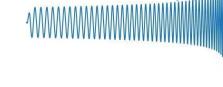
and its PSD for a process of order P is given by

$$P_{AR}(f) = \frac{\sigma^2}{|1 + \sum_{k=1}^P a_k \exp(-i2\pi kf)|^2}$$

Kay S 1988 Modern spectral estimation: Theory and Application Prentice Hall Englewood Cliffs



Advantages of AR modeling



- Stable and causal filter: same solution of **linear predictor filter**

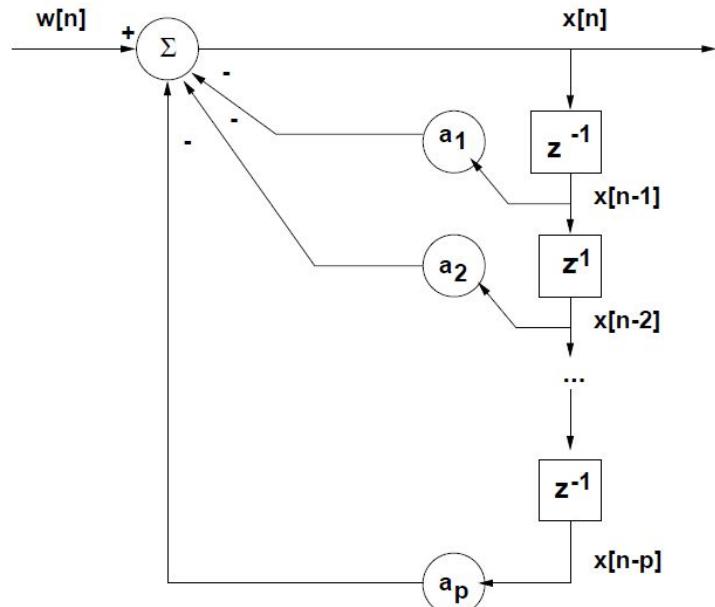
$$\hat{x}[n] = \sum_{k=1}^P w_k x[n-k].$$

$$e[n] = x[n] - \hat{x}[n]$$

$$\varepsilon_{min} = r_{xx}[0] - \sum_{k=1}^P w_k r_{xx}[-k],$$

$$w_k = -a_k$$

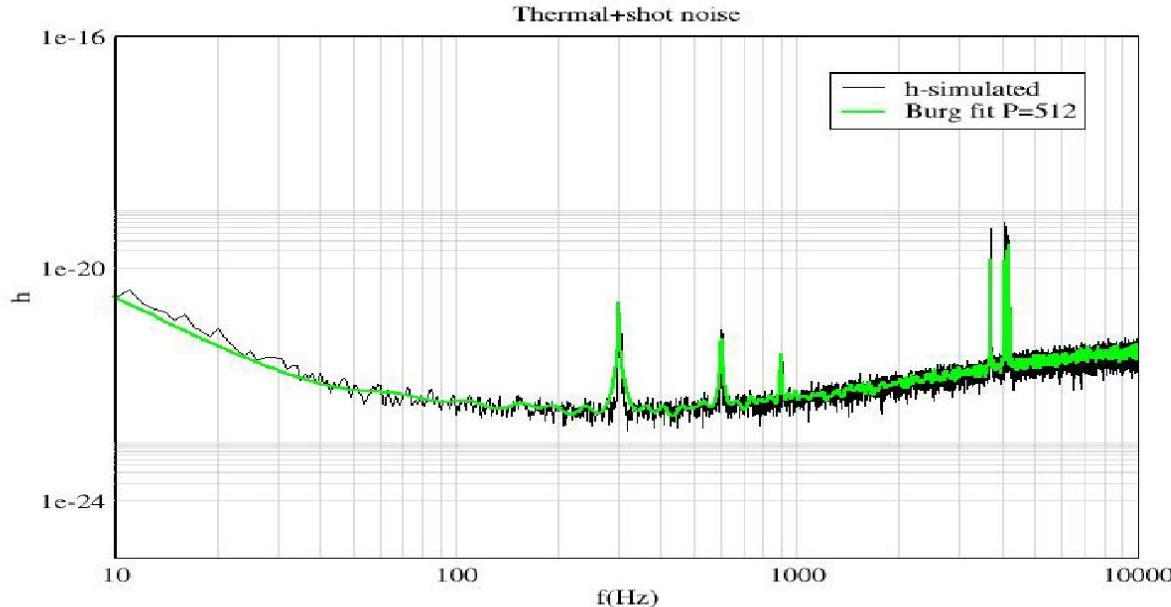
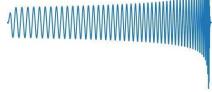
$$\varepsilon_{min} = \sigma^2$$



Wiener-Hopf equations



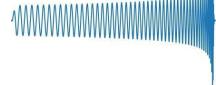
PSD AR(P) Fit



Cuoco et al. Class.Quant.Grav.18 (2001) 1727-1752 and
Cuoco et al.Phys.Rev.D64:122002,2001



Lattice Filter



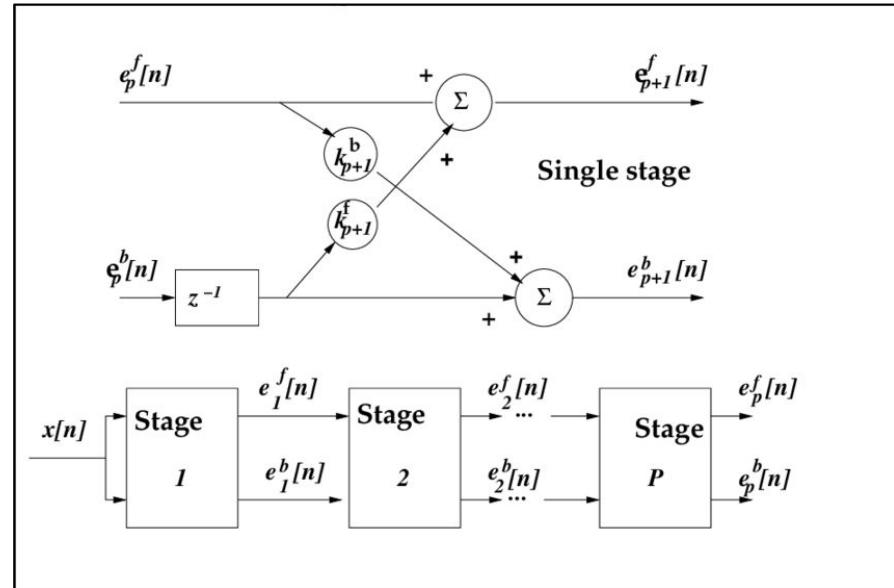
The Least Squares based methods build their cost function using all the information contained in the error function at each step, writing it as the sum of the error at each step up to the iteration n

$$\epsilon[n] = \sum_1^n \lambda^{n-1} e^2(i|n)$$

Forgetting factor

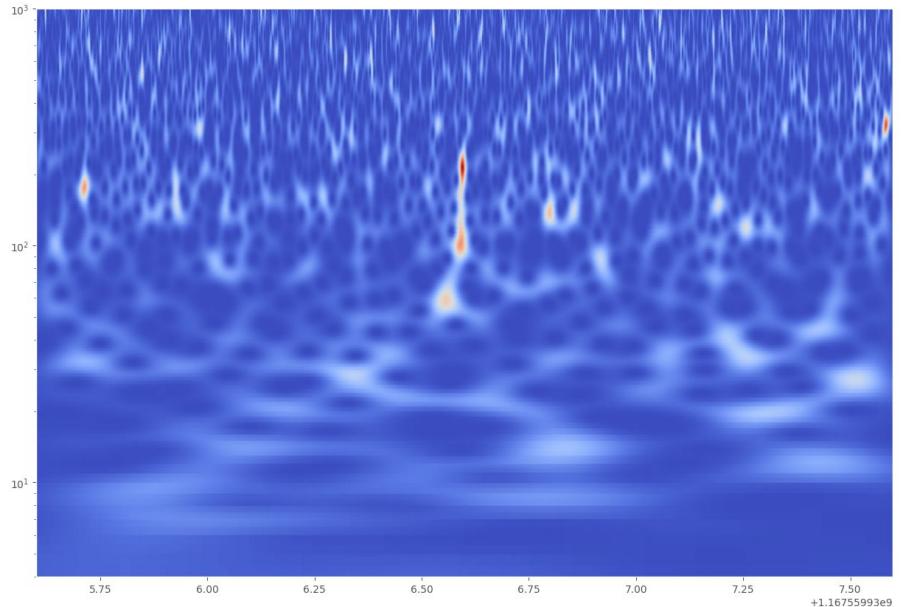
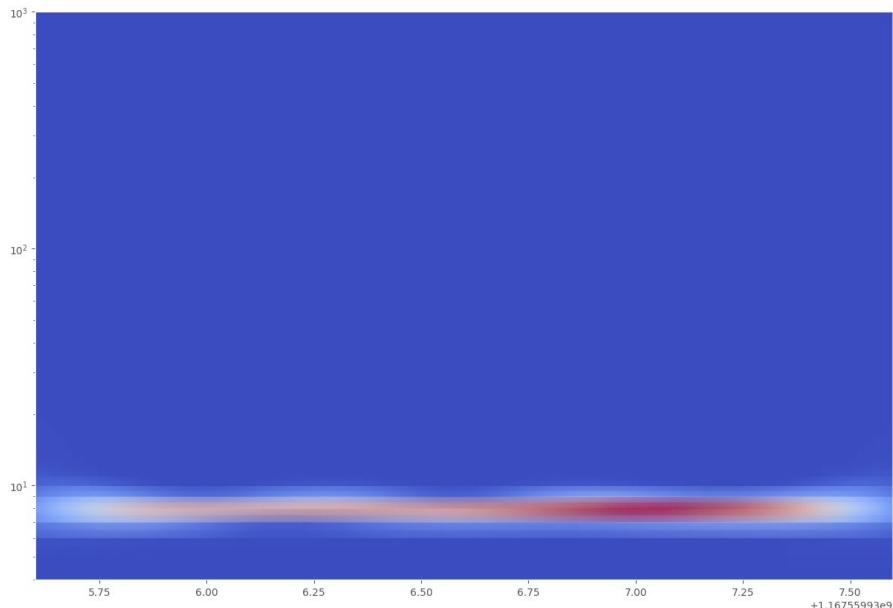
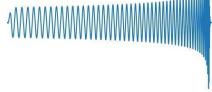
$$e(i|n) = d[i] - \sum_{k=1}^N x_{i-k} w_k[n],$$

Desired signal



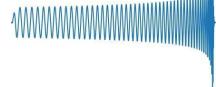


The effect of whitening





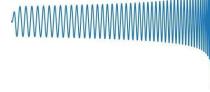
Why artificial Intelligence for GW data?



- Our data: a lot of noise and few GW signals (soon will be many)
- Low SNR signals (overlapping signals)
- Many transient noise disturbances (glitches)
- Not stationary/not linear noise (strange noise coupling)
- Many monitoring auxiliary channels ("big" data)
- Computational and timing efficiency (Fast alert system)

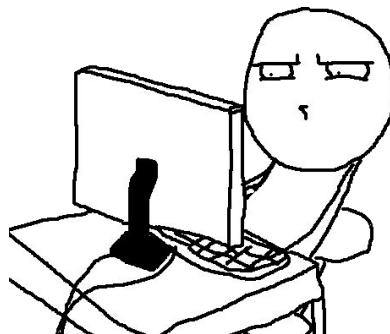


How Machine Learning can help



Data conditioning

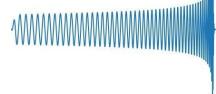
- Identify Non linear noise coupling
- Use Deep Learning to remove noise
- Extract useful features to clean data



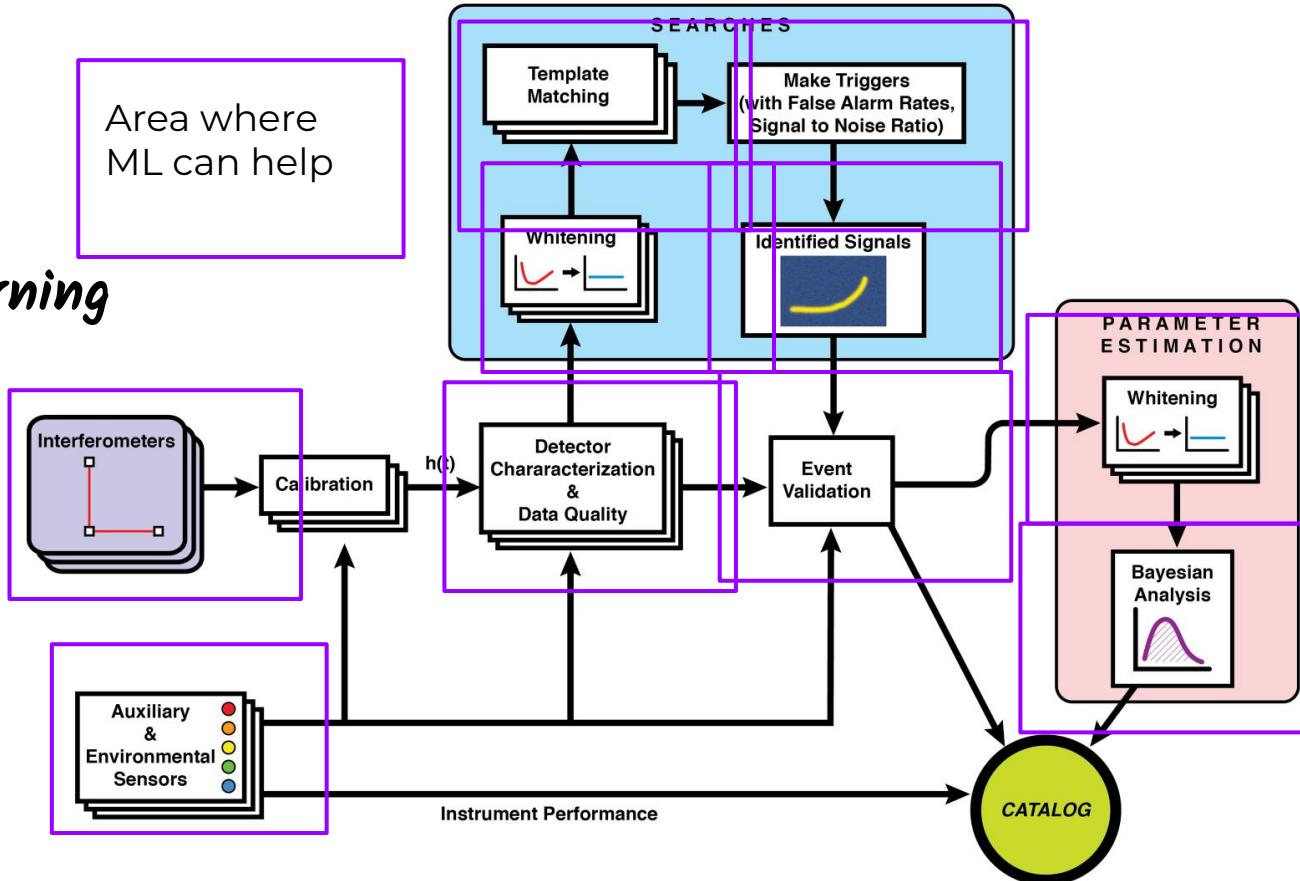
Signal Detection/Classification/PE

- A lot of fake signals due to noise
- Fast alert system
- Manage parameter estimation

The data analysis workflow and ML

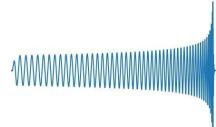


Machine Learning
everywhere





An outdated overview



IOP Publishing

Mach. Learn.: Sci. Technol. 2 (2021) 011002

<https://doi.org/10.1088/2632-2153/abb93a>

MACHINE
LEARNING
Science and Technology



TOPICAL REVIEW

Enhancing gravitational-wave science with machine learning

OPEN ACCESS

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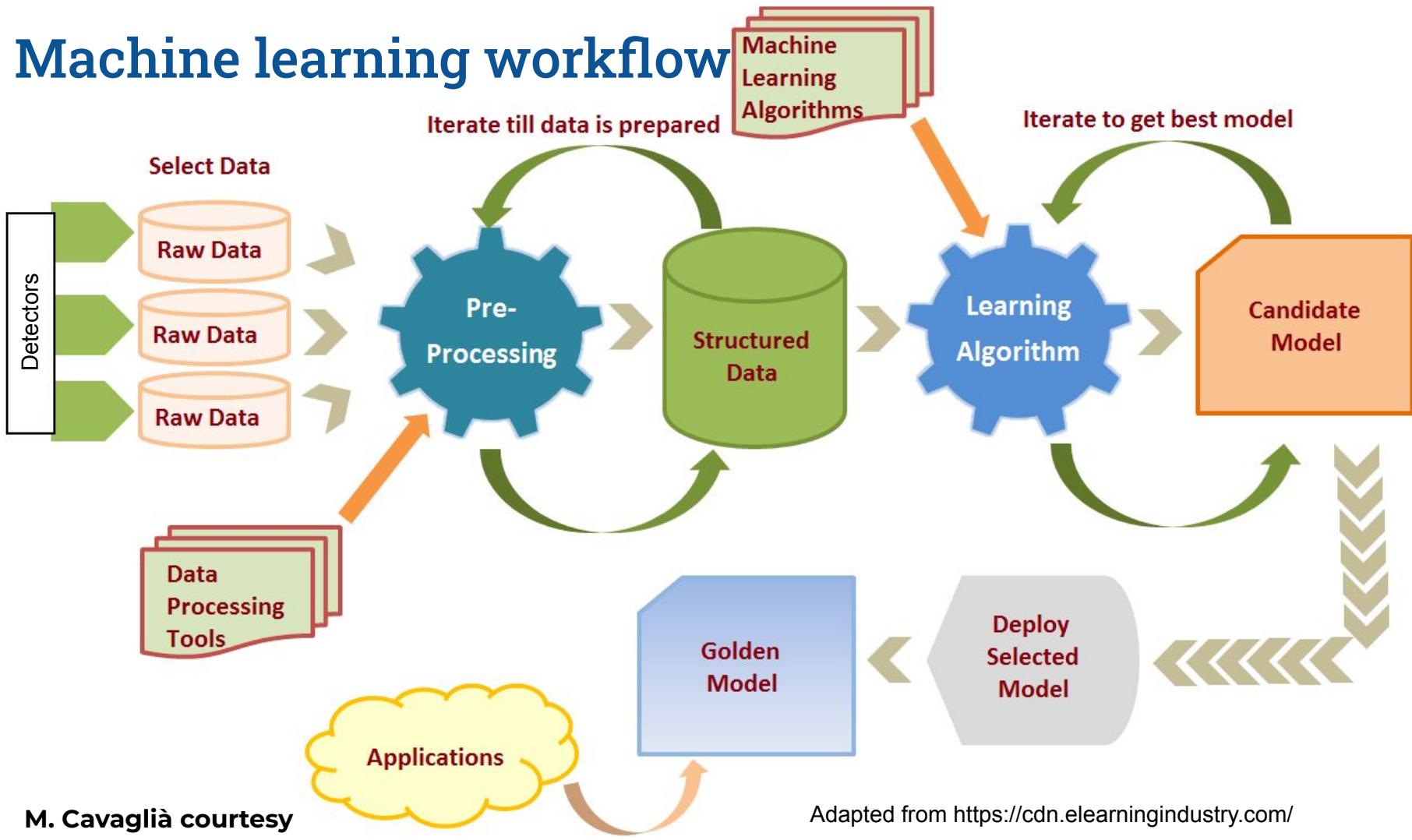
Elena Cuoco^{1,2,3} , Jade Powell⁴ , Marco Cavaglià⁵ , Kendall Ackley^{6,7}, Michał Bejger⁸, Chayan Chatterjee^{7,9}, Michael Coughlin^{10,11}, Scott Coughlin¹², Paul Easter^{6,7}, Reed Essick¹³ , Hunter Gabbard¹⁴, Timothy Gebhard^{15,16}, Shaon Ghosh¹⁷, Leila Haegel¹⁸, Alberto Iess^{19,20} , David Keitel²¹ , Zsuzsa Márka²², Szabolcs Márka²³, Filip Morawski⁸ , Tri Nguyen²⁴, Rich Ormiston²⁵, Michael Pürrer²⁶, Massimiliano Razzano^{3,27} , Kai Staats¹², Gabriele Vajente¹⁰ and Daniel Williams¹⁴

¹ European Gravitational Observatory (EGO), I-56021 Cascina, Pisa, Italy.

² Scuola Normale Superiore (SNS), Piazza dei Cavalieri, 7 - 56126 Pisa, Italy.

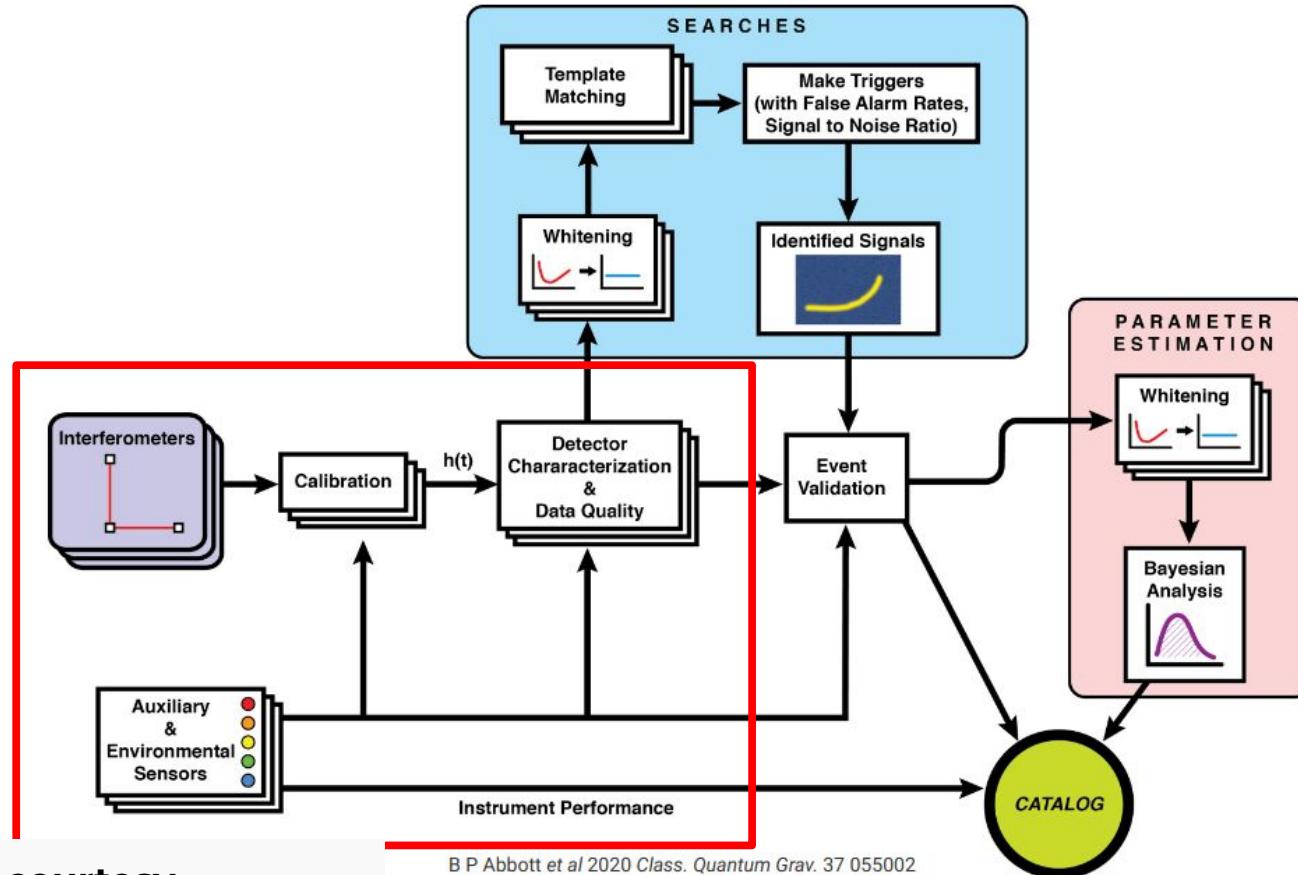
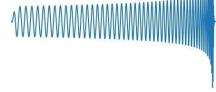
³ Istituto Nazionale di Fisica Nucleare, Sezione di Pisa, Pisa, I-56127, Italy.

Machine learning workflow



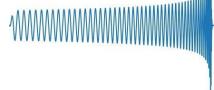


ML for GW data quality

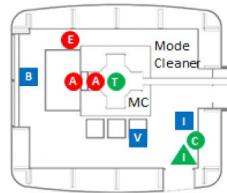




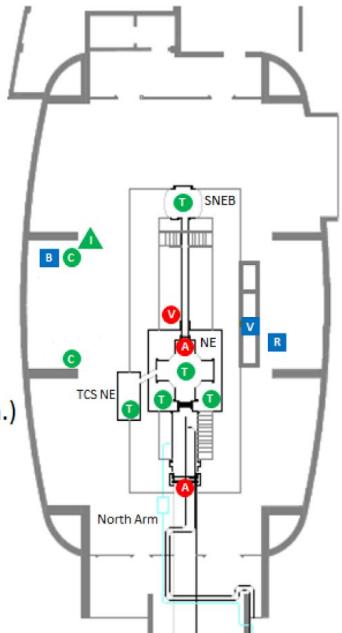
Algorithms for GW Data Quality improvement



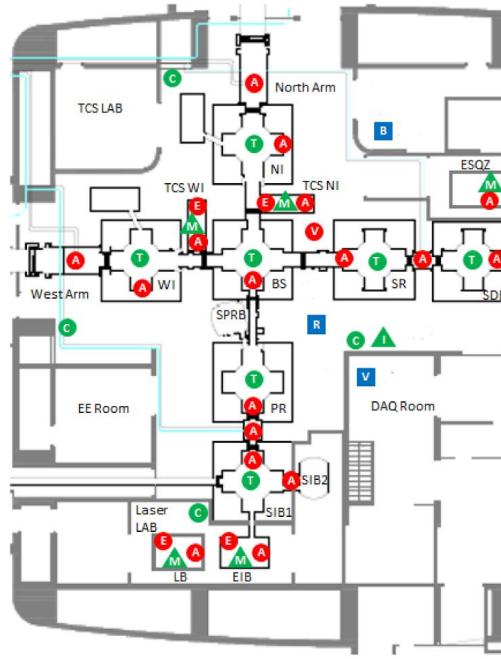
MCB



NEB (WEB)



CEB



● Accelerometer

● Episensor

● Velocimeter

● Thermometer

● Comb. (temp.+press.+hum.)

● Microphone

● Infrasound microphone

● Magnetometer

● Voltage probe

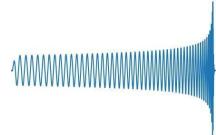
● Current probe

● Radio frequency antenna

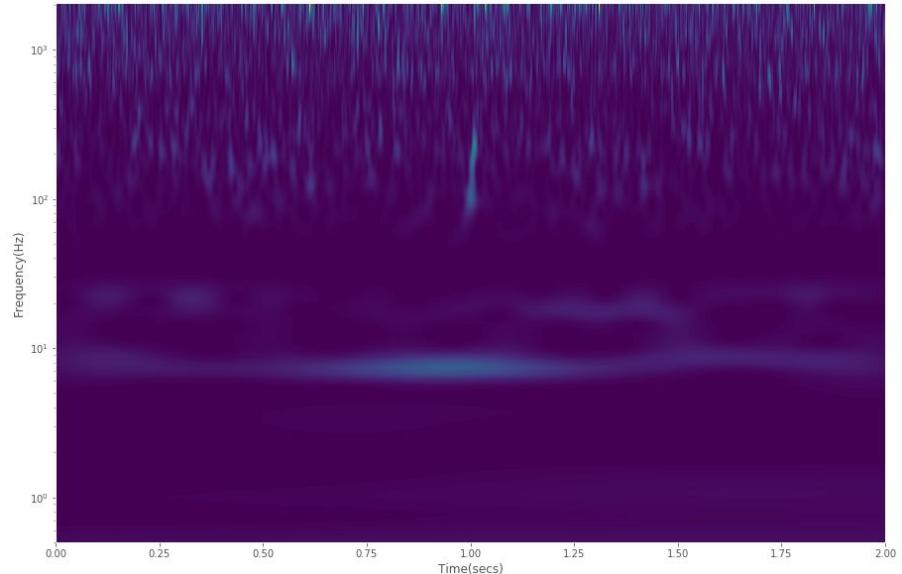
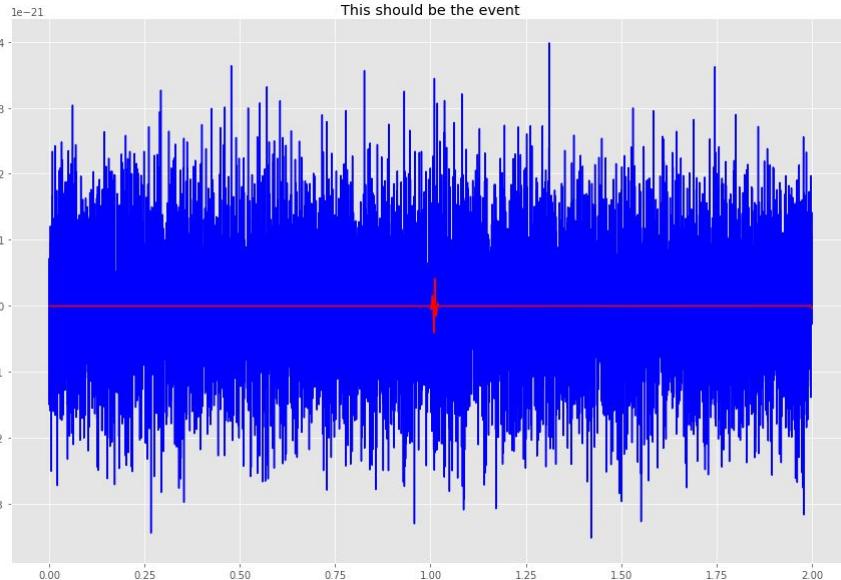
- Sensors continuously monitor the behavior of the detectors and their environment.
- Sensor data are used to characterize noise that may negatively impact searches and signal estimation.
- Information is in the form of time series.
- Invalid data due to detector malfunctions, calibration errors, data acquisition are removed from analyses.
- Flags are created according to different levels of data quality.



How to deal with data: Time series or Images?

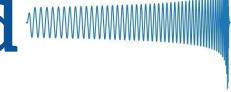


- Pre-processing analysis (whitening, band pass filtering)
- Change of domain space: Time-Frequency projections





Noise transient classification, time series based



OPEN ACCESS

IOP Publishing

Class. Quantum Grav. 32 (2015) 215012 (20pp)

Classical and Quantum Gravity

doi:10.1088/0264-9381/32/21/215012

Classification methods for noise transients in advanced gravitational-wave detectors

Jade Powell¹, Daniele Trifirò^{2,3}, Elena Cuoco^{4,5},
Ik Siong Heng¹ and Marco Cavaglià³

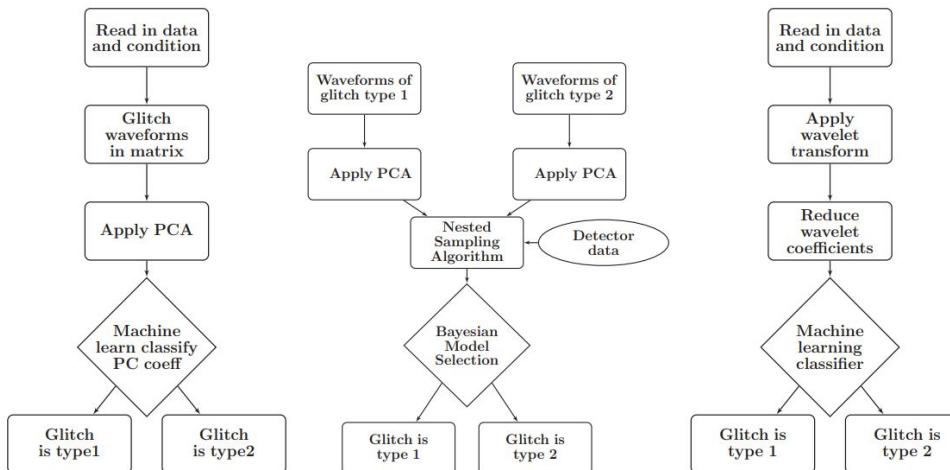
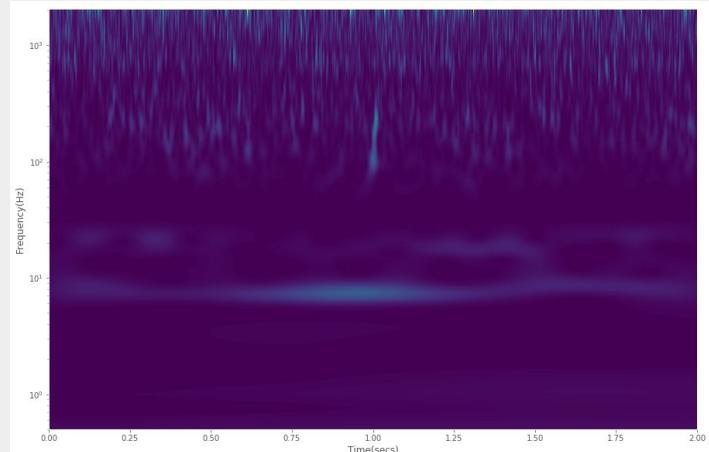




Image-based classification

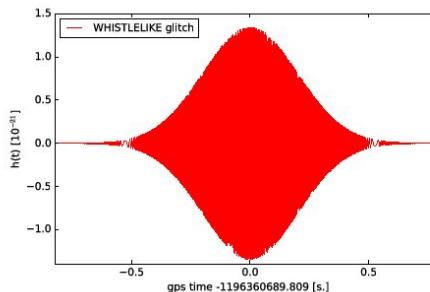
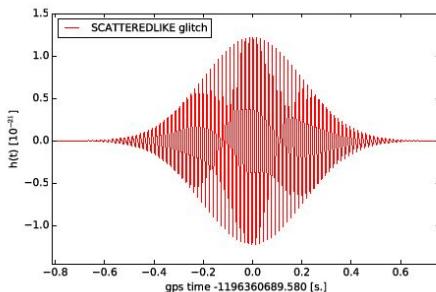
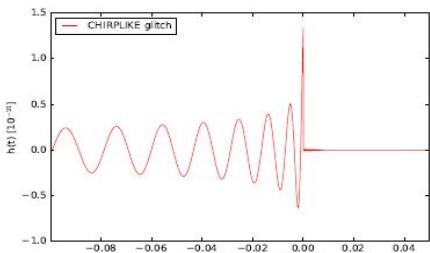
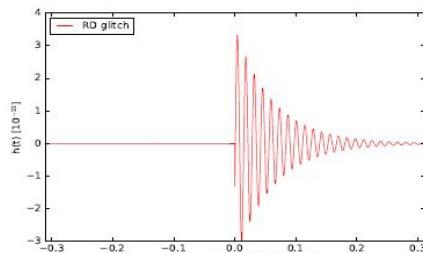
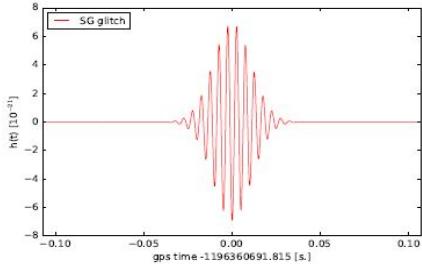
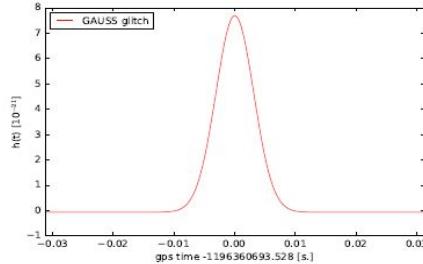
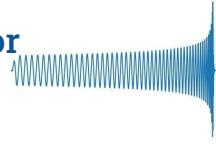
Simulated and real data

- ❖ Transient Noise classification and Images as input data



2018

How we started: Data simulation (transient signal families + Detector colored Noise)



Waveform

Gaussian

Sine-Gaussian

Ring-Down

Chirp-like

Scattered-like

Whistle-like

NOISE (random)

To show the glitch time-series here we don't show the noise contribution





Building the images

Spectrogram for each image

2-seconds time window to highlight features in long glitches

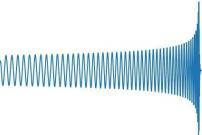
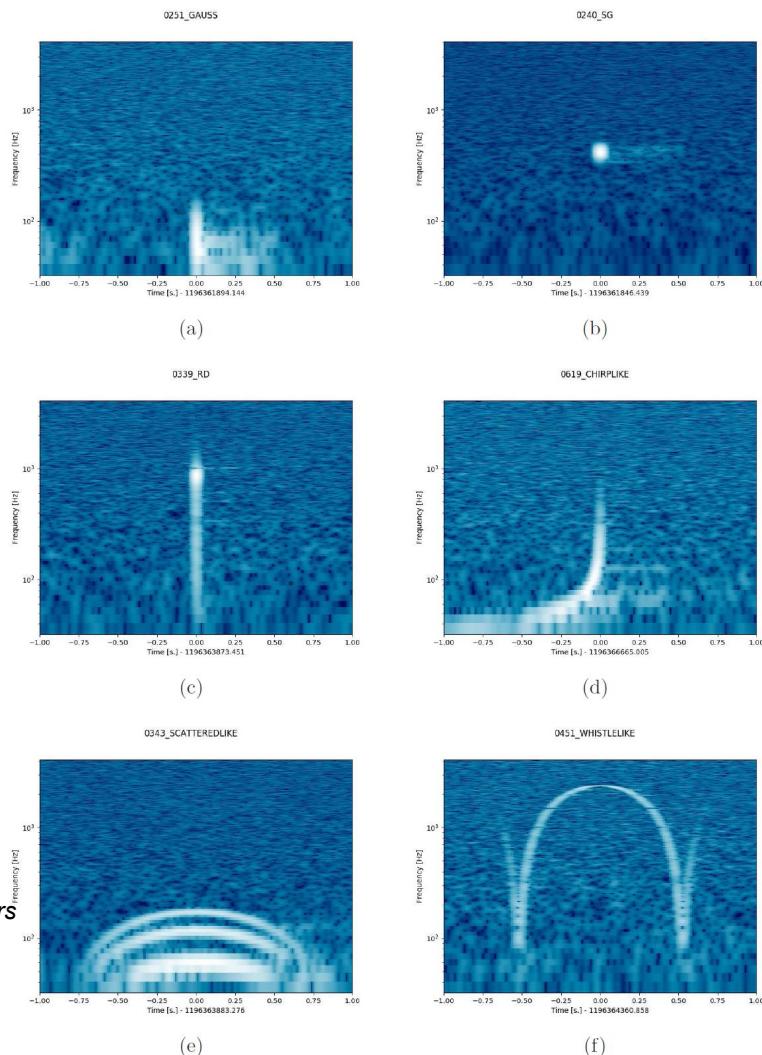
Data is whitened

Optional contrast stretch

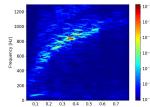
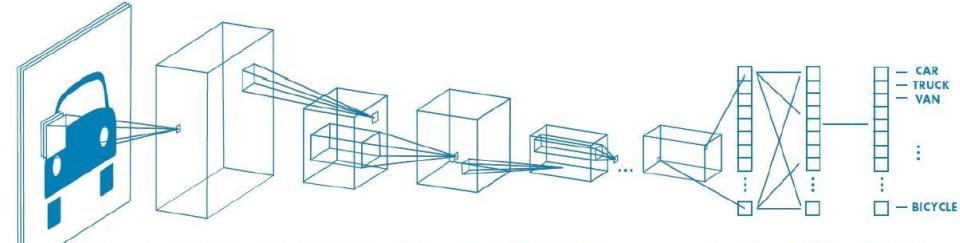
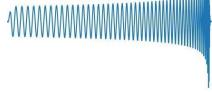
Simulations now available on FigShare

Razzano, Massimiliano; Cuoco, Elena (2018): Simulated image data for testing machine learning classification of noise transients in gravitational wave detectors (Razzano & Cuoco 2018). figshare. Collection.

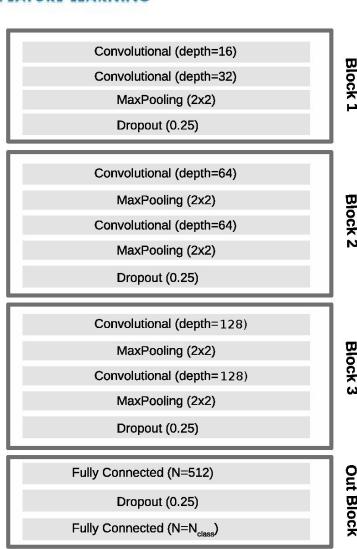
<https://doi.org/10.6084/m9.figshare.c.4254017.v1>



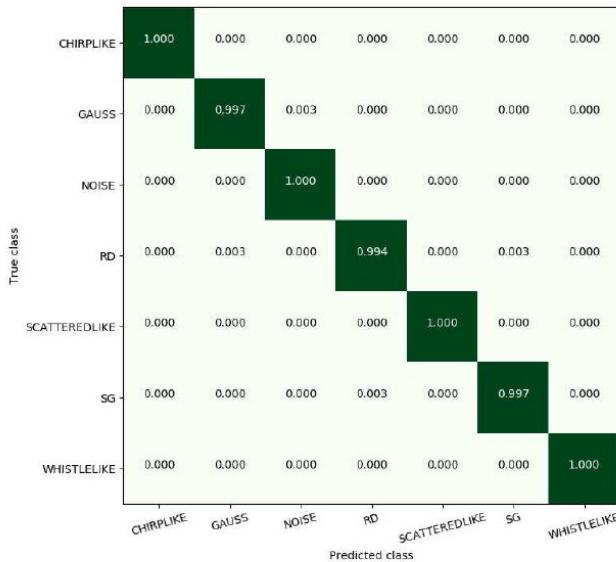
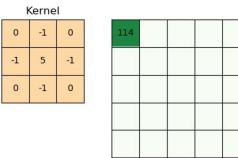
Deep learning. Convolutional Neural Network



Spectrogram images



0	0	0	0	0	0	0
0	60	113	56	139	85	0
0	73	121	54	84	128	0
0	131	99	70	129	127	0
0	80	57	115	69	134	0
0	104	126	123	95	130	0
0	0	0	0	0	0	0



Normalized Confusion Matrix

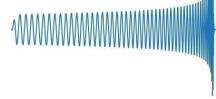
Razzano M., Cuoco E.

CQG-104381.R3

EGO - Virgo



Application Test on Real data: O1 run



Glitch name	# in H1	# in L1	Dataset from <u>GravitySpy</u> images		
Air compressor	55	3			
Blip	1495	374	Paired doves	27	-
Chirp	34	32	Power_line	274	179
Extremely Loud	266	188	Repeating blips	249	36
Helix	3	276	Scattered_light	393	66
Koi fish	580	250	Scratchy	95	259
Light Modulation	568	5	Tomte	70	46
Low_frequency_burst	184	473	Violin_mode	179	-
Low_frequency_lines	82	371	Wandering_line	44	-
No_Glitch	117	64	Whistle	2	303
None_of_the_above	57	31			



Results

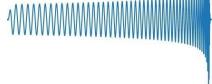
Confusion Matrix (Normalized)

True class	1080lines	1400ripples	air_compressor	blip	chirp	extremely_loud	helix	koi_fish	light_modulation	low_frequency_burst	low_frequency_lines	no_glitch	none_of_the_above	paired_doves	power_line	repeating_bumps	scattered_light	scratchy	tome	violin_mode	wandering_line	whistle
1080lines	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
1400ripples	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
air_compressor	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
blip	0.00	0.00	0.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	
chirp	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
extremely_loud	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
helix	0.00	0.00	0.00	0.00	0.00	0.98	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
koi_fish	0.00	0.00	0.00	0.01	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
light_modulation	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	
low_frequency_burst	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	
low_frequency_lines	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.88	0.05	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
no_glitch	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
none_of_the_above	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.69	0.00	0.00	0.00	0.08	0.15	0.00	0.00	0.08	0.00	0.00	0.00	
paired_doves	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.50	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
power_line	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
repeating_bumps	0.00	0.00	0.00	0.05	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
scattered_light	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.01	0.00	0.00	0.00	0.00	0.00	0.00	
scratchy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
tome	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	
violin_mode	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.00	0.00	0.00	0.00	
wandering_line	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	
whistle	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.91	0.00	

O1-Gravity Spy data set

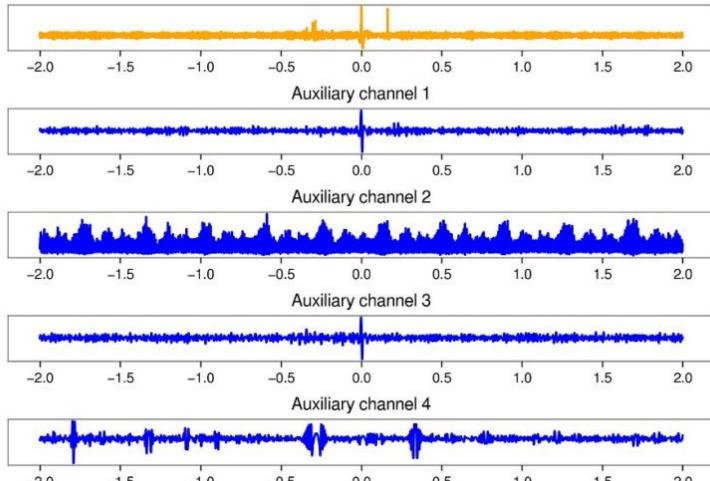
Full CNN stack

Consistent with Zevin+2017





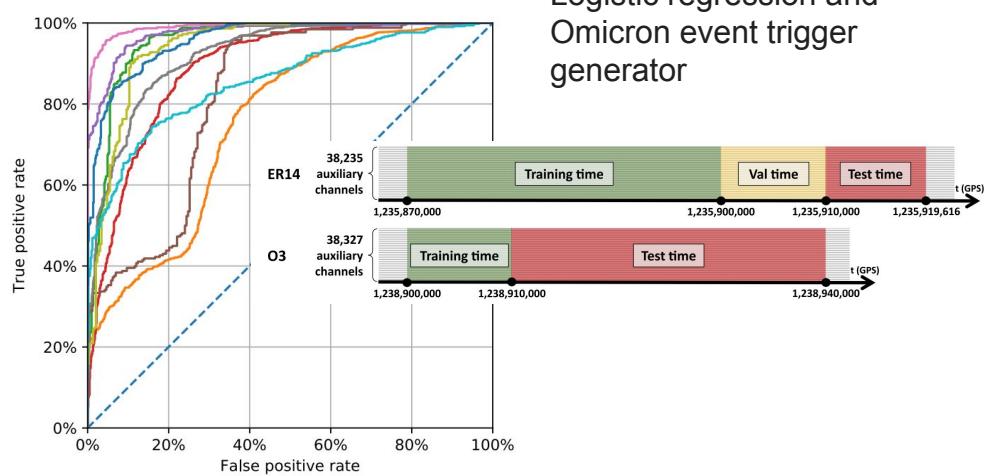
Noise transient classification on auxiliary channels



PHYSICAL REVIEW D 88, 062003 (2013)

**Application of machine learning algorithms to the study of noise artifacts
in gravitational-wave data**

Rahul Biswas,¹ Lindy Blackburn,² Junwei Cao,³ Reed Essick,⁴ Kari Alison Hodge,⁵ Erotokritos Katsavounidis,⁴ Kyungmin Kim,^{6,7} Young-Min Kim,^{8,7} Eric-Olivier Le Bigot,³ Chang-Hwan Lee,⁸ John J. Oh,⁷ Sang Hoon Oh,⁷ Edwin J. Son,⁷ Ye Tao,⁹ Ruslan Vaulin,^{4,*} and Xiaoge Wang⁹



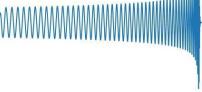
PHYSICAL REVIEW D 101, 102003 (2020)

**Efficient gravitational-wave glitch identification from environmental data
through machine learning**

Robert E. Colgan^{1,2} K. Rainer Corley,^{3,4} Yenson Lau^{2,5} Imre Bartos,⁶
John N. Wright,^{2,5} Zsuzsa Márka^{2,4}, and Szabolcs Márka³



Deep Clean

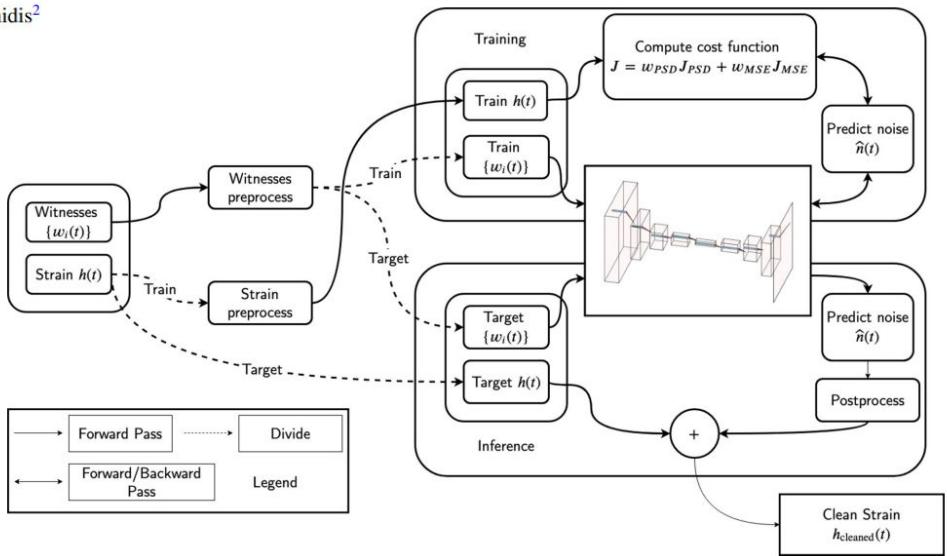
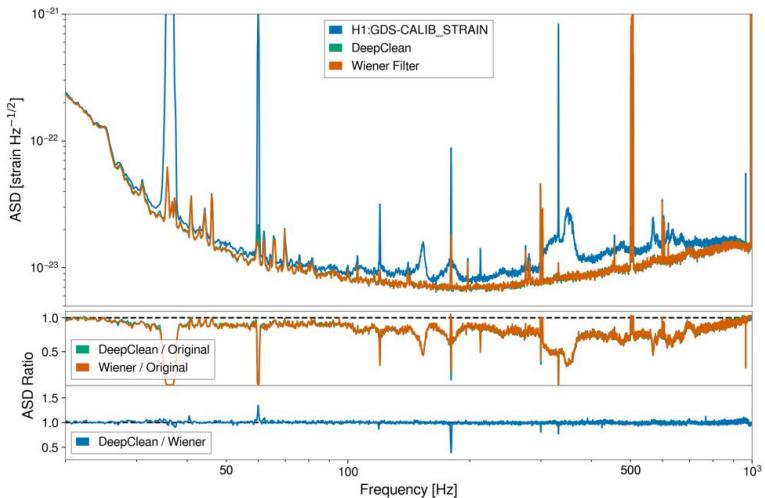


PHYSICAL REVIEW RESEARCH 2, 033066 (2020)

One-dimensional Convolutional Neural Network which takes a specified set of witness channels and subsequently outputs the predicted noise in strain.

Noise reduction in gravitational-wave data via deep learning

Rich Ormiston,¹ Tri Nguyen^{1,2}, Michael Coughlin^{1,3}, Rana X. Adhikari^{1,3}, and Erik Katsavounidis²



Citizen science for GW-AI

GWitchHunters



Gravity Spy

Help scientists at LIGO search for gravitational waves, the elusive ripples of spacetime.

Learn more Get started

Join in

Citizen scientists contribute to classify glitches

More details in Zevin+17
[10.1088/1361-6382/aa5cea](https://doi.org/10.1088/1361-6382/aa5cea)

<https://doi.org/10.1016/j.ins.2018.02.068>

Get started

This project is organized in increasing order of difficulty. We suggest starting in this playground to get familiar with our data and practice with some basic "noise hunting", then progress to the next levels in increasing order of difficulty. At each level, you will discover new challenging tasks. And, if it is not enough for you, we have some bonus challenges that you can unlock by reaching the top percentile!

Learn more

Task Tutorial

If you see a noise feature, draw a rectangle around it, otherwise press "Next".

Draw a rectangle

Next

NE

Power in the IMC

Power in the WA

Differential arm length

BS accelerometer

Normalised energy

Frequency [Hz]

Time [s]

Team: M. Razzano, F. Di Renzo, F. Fidecaro (@Unipi), G. Hemming, S. Katsanevas (@EGO)

Launched @ Nov 2019 - REINFORCE Project H2020-SWAWS (2019-2022)

Machine learning for control system

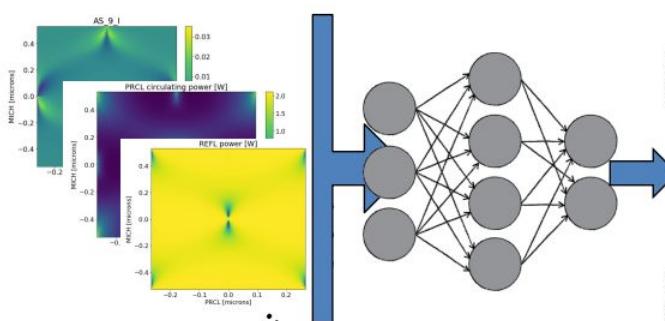


Machine Learning for Lock Acquisition

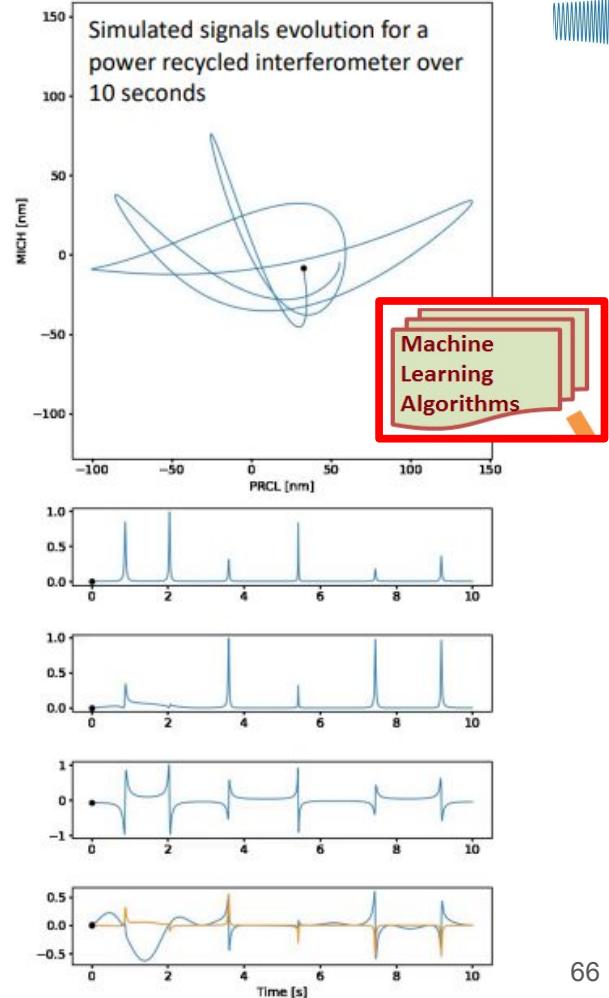
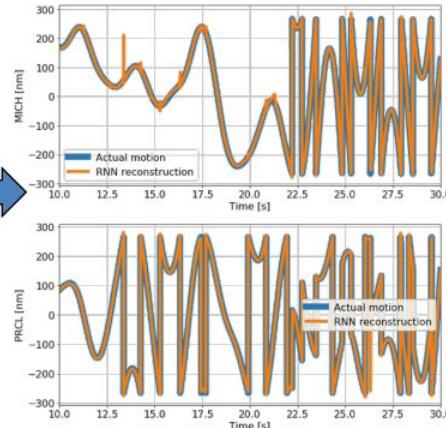


Non-linear control problem: drive the system into a narrow region of the 5d phase space, where linear control is possible

- Construct a **non-linear state estimator**: use all available signals as input, build an estimate of the degree of freedom positions that works (almost) everywhere

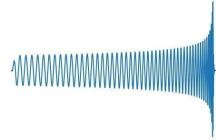


In simulation we have both **input signals** and **target coordinates**: supervised learning

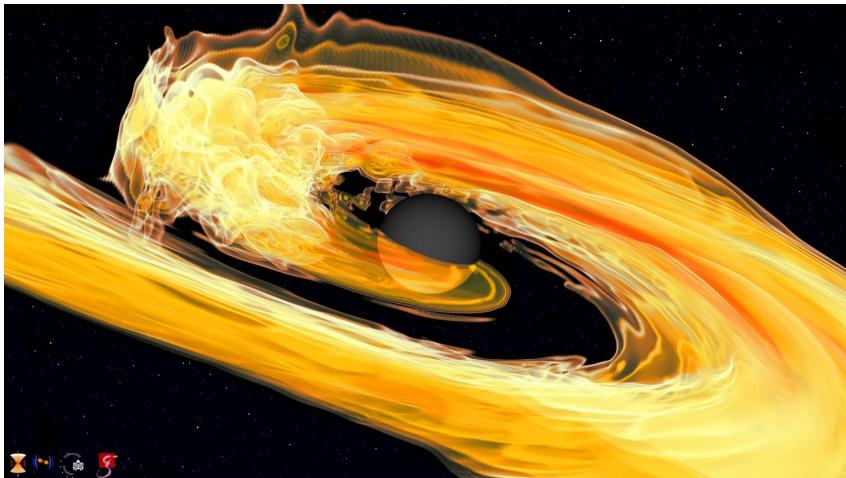




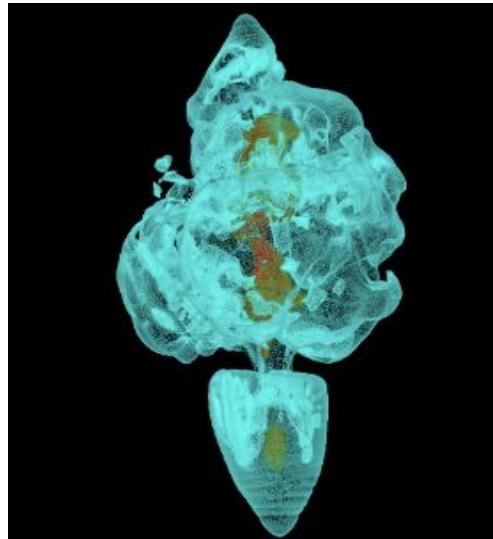
Astrophysical GW source and ML



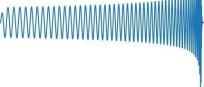
Compact Binary Coalescences
Matched filter modeled searches



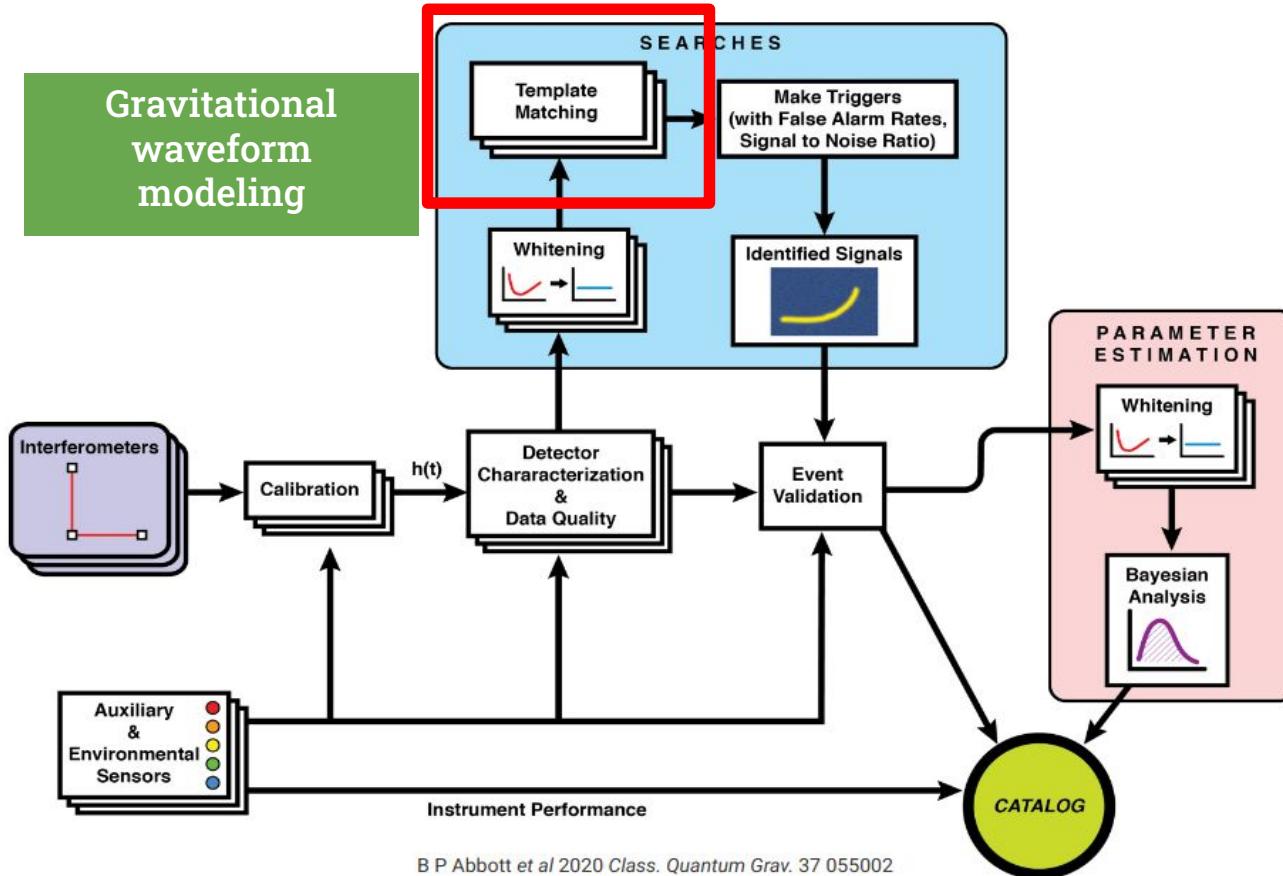
Core Collapse Supernovae
Unmodeled searches



Computer simulation of gravitational waves emitted by a supernova. Credit: J Powell / B Mueller

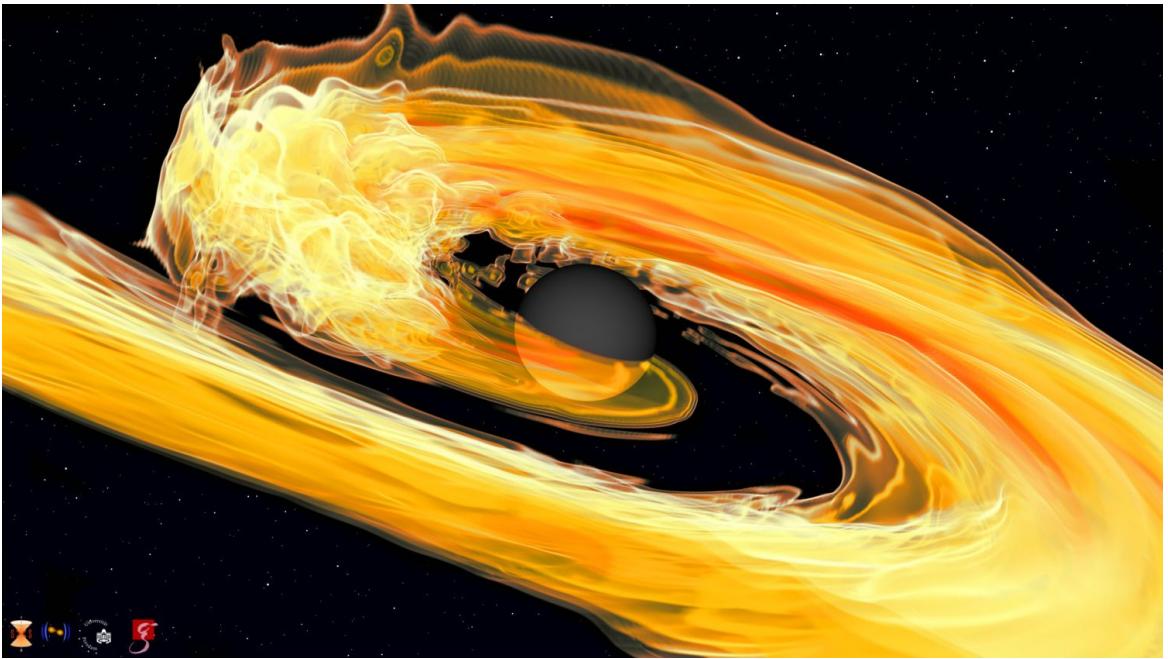
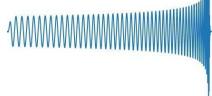


Template matching





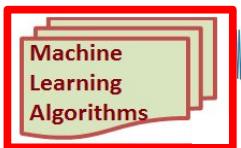
Gravitational wave modeling



- GW detection of binary systems relies on matched-filter analysis. Template accuracy is crucial!
- Accurate solutions of the Einstein equations for binary sources can be obtained with Numerical Relativity (NR) simulations.
- High computational cost prevent the production of NR waveforms catalogs spanning the full parameter space.
- LIGO and Virgo rely on approximate solutions that are traditionally obtained through the effective-one-body or phenomenological modeling approaches.
- How can machine learn



Waveform Building



Gaussian process regression to compute the waveform at points of the parameter space not covered by numerical relativity.

GPR has been used to build surrogate models of both non-precessing and precessing BBH systems.

PHYSICAL REVIEW D 101, 063011 (2020)

Precessing numerical relativity waveform surrogate model for binary black holes: A Gaussian process regression approach

D. Williams^{*} and I. S. Heng[†]

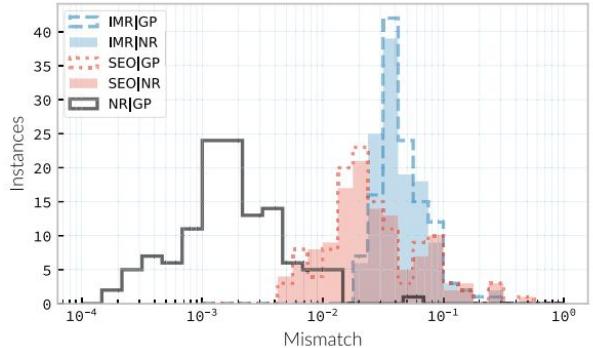
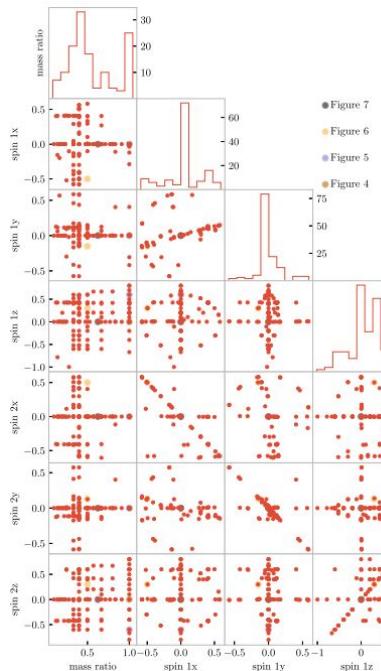
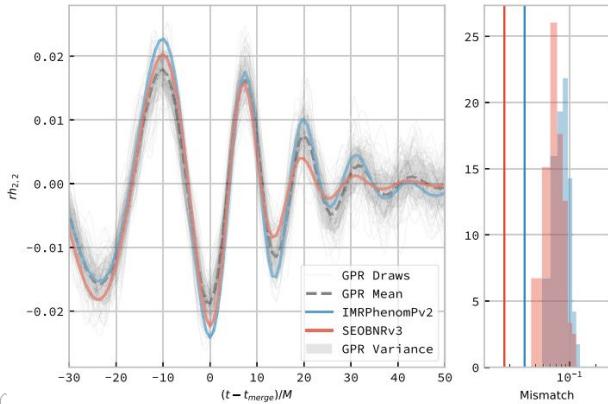
SUPA, University of Glasgow, Glasgow G12 8QQ, United Kingdom

J. Gair

Max Planck Institute for Gravitational Physics,
Potsdam Science Park, Am Mühlenberg 1, D-14476 Potsdam, Germany

J. A. Clark and B. Khamesra

Center for Relativistic Astrophysics and School of Physics,
Georgia Institute of Technology, Atlanta, Georgia 30332, USA



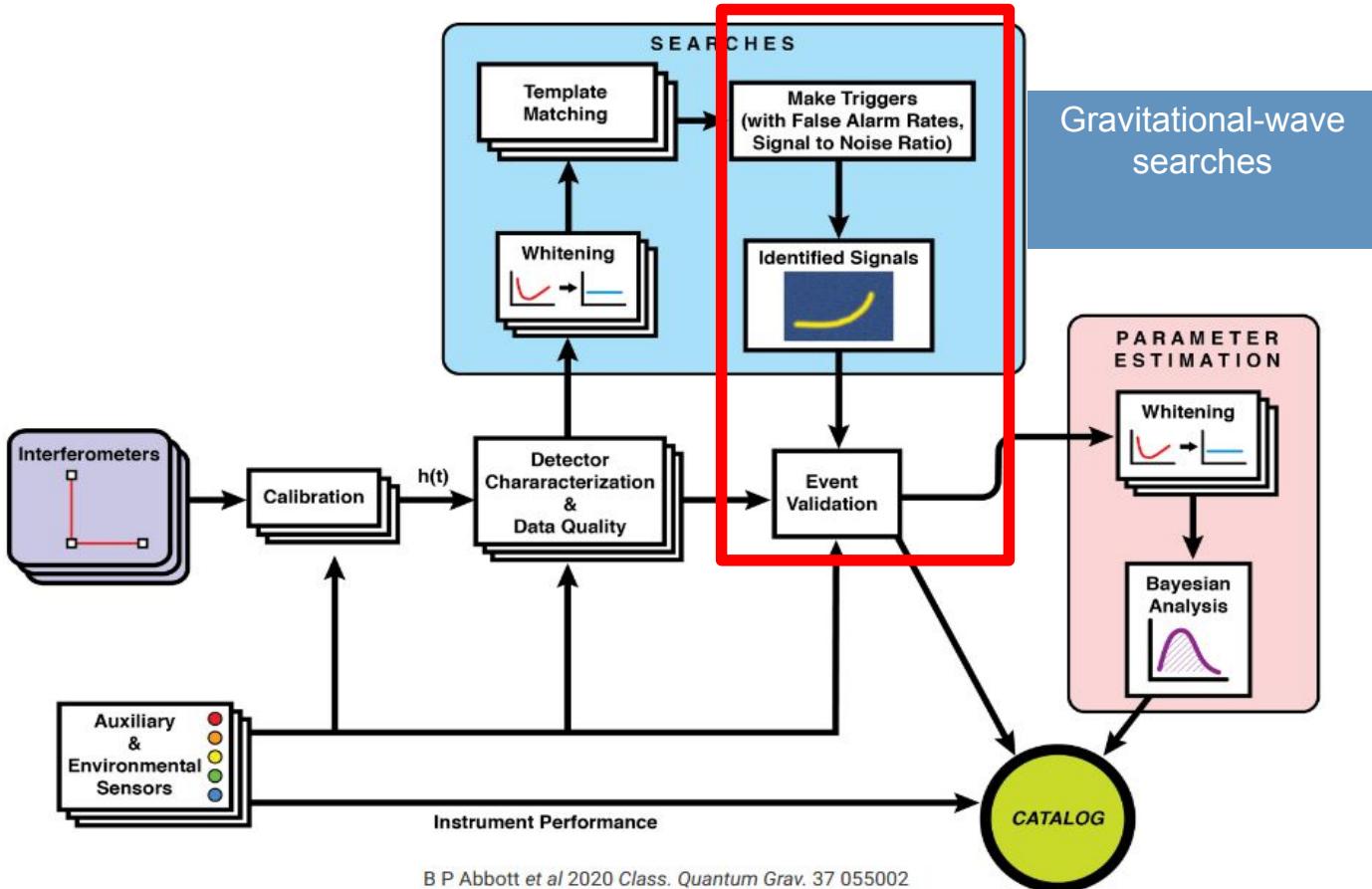
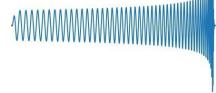
See also:

Z. Doctor et al, "Statistical gravitational waveform models: What to simulate next?"

Phys. Rev. D 96, 123011 (2017)

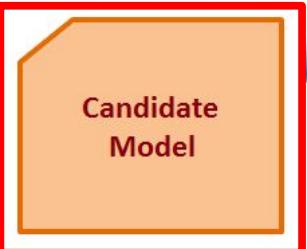


Gravitational wave signal detection





CBC detection



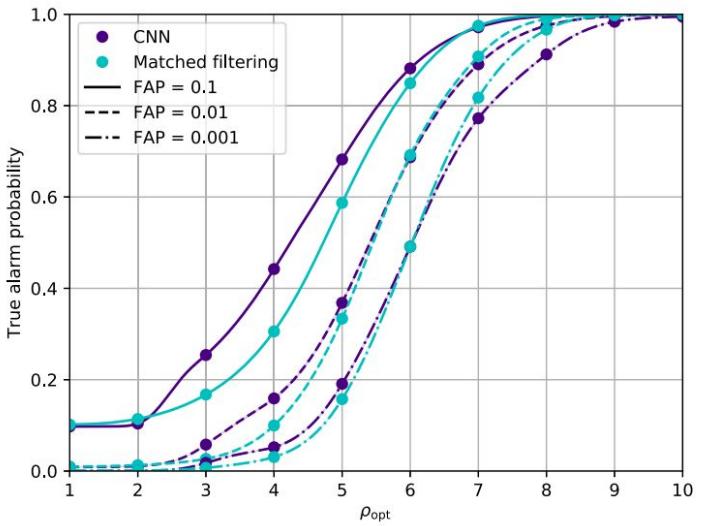
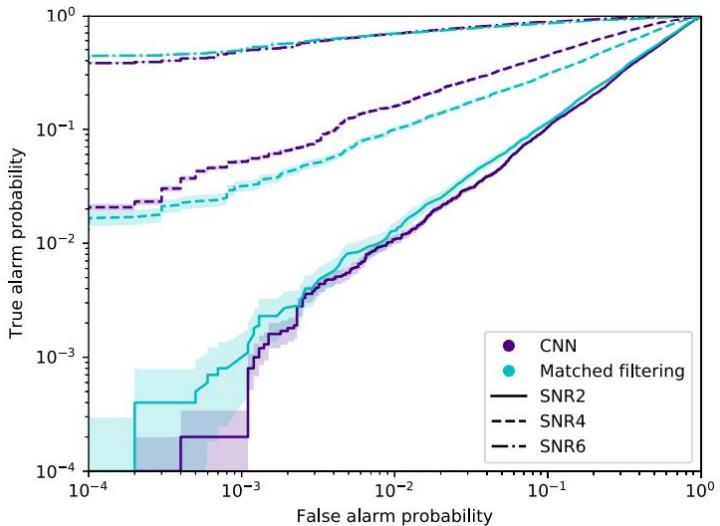
PHYSICAL REVIEW LETTERS 120, 141103 (2018)

Editors' Suggestion

Matching Matched Filtering with Deep Networks for Gravitational-Wave Astronomy

Hunter Gabbard,^{*} Michael Williams, Fergus Hayes, and Chris Messenger
SUPA, School of Physics and Astronomy, University of Glasgow, Glasgow G12 8QQ, United Kingdom

- Deep convolutional neural network to search for binary black hole gravitational-wave signals.
- Input is the whitened time series of measured gravitational-wave strain in Gaussian noise.
- Sensitivity comparable to match filtering.



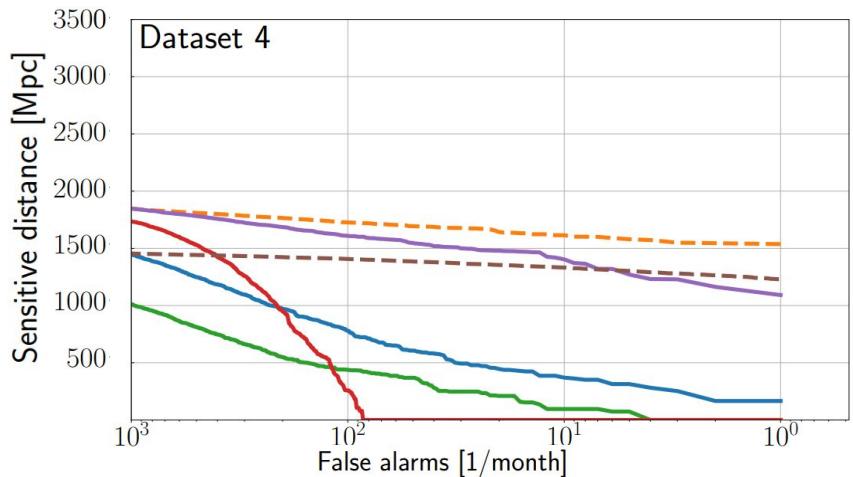
See also:
D. George and E.A. Huerta
Phys. Lett. B 778 64–70
(2018)

CBC detection



MLGWSC-1: The first Machine Learning Gravitational-Wave Search Mock Data Challenge

Marlin B. Schäfer^{1,2}, Ondřej Zelenka^{3,4}, Alexander H. Nitz^{1,2}, He Wang⁵, Shichao Wu^{1,2}, Zong-Kuan Guo⁵, Zhoujian Cao⁶, Zhixiang Ren⁷, Paraskevi Nousi⁸, Nikolaos Stergioulas⁹, Panagiotis Iosif^{10,9}, Alexandra E. Koloniar⁹, Anastasios Tefas⁸, Nikolaos Passalis⁸, Francesco Salemi^{11,12}, Gabriele Vedovato¹³, Sergey Klimenko¹⁴, Tamaya Mishra¹⁴, Bernd Brügmann^{3,4}, Elena Cuoco^{15,16,17}, E. A. Huerta^{18,19}, Chris Messenger²⁰, Frank Ohme^{1,2}

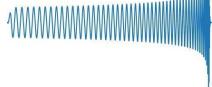


Candidate Model

- Comparison of 6 algorithms for binary black hole searches.
- Four different data sets of different complexity (from Gaussian noise to varying real detector PSD)
- Benchmark data set for algorithm testing.

A few excerpts from the paper conclusions:

- Machine learning search algorithms are competitive in sensitivity compared to state-of-the-art searches on simulated data and the limited parameter space explored in this challenge.
- Most of the tested machine learning algorithms struggle to effectively handle real noise, which is contaminated with non-Gaussian noise artifacts.
- Traditional search algorithms are capable of detecting signals at lower FARs, thus making detections more confident.
- The tested machine learning searches struggle to identify long duration signals.



Anomaly Detection in Gravitational Waves data using Convolutional AutoEncoders for CBC signals

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre, <https://doi.org/10.1088/2632-2153/abf3d0>



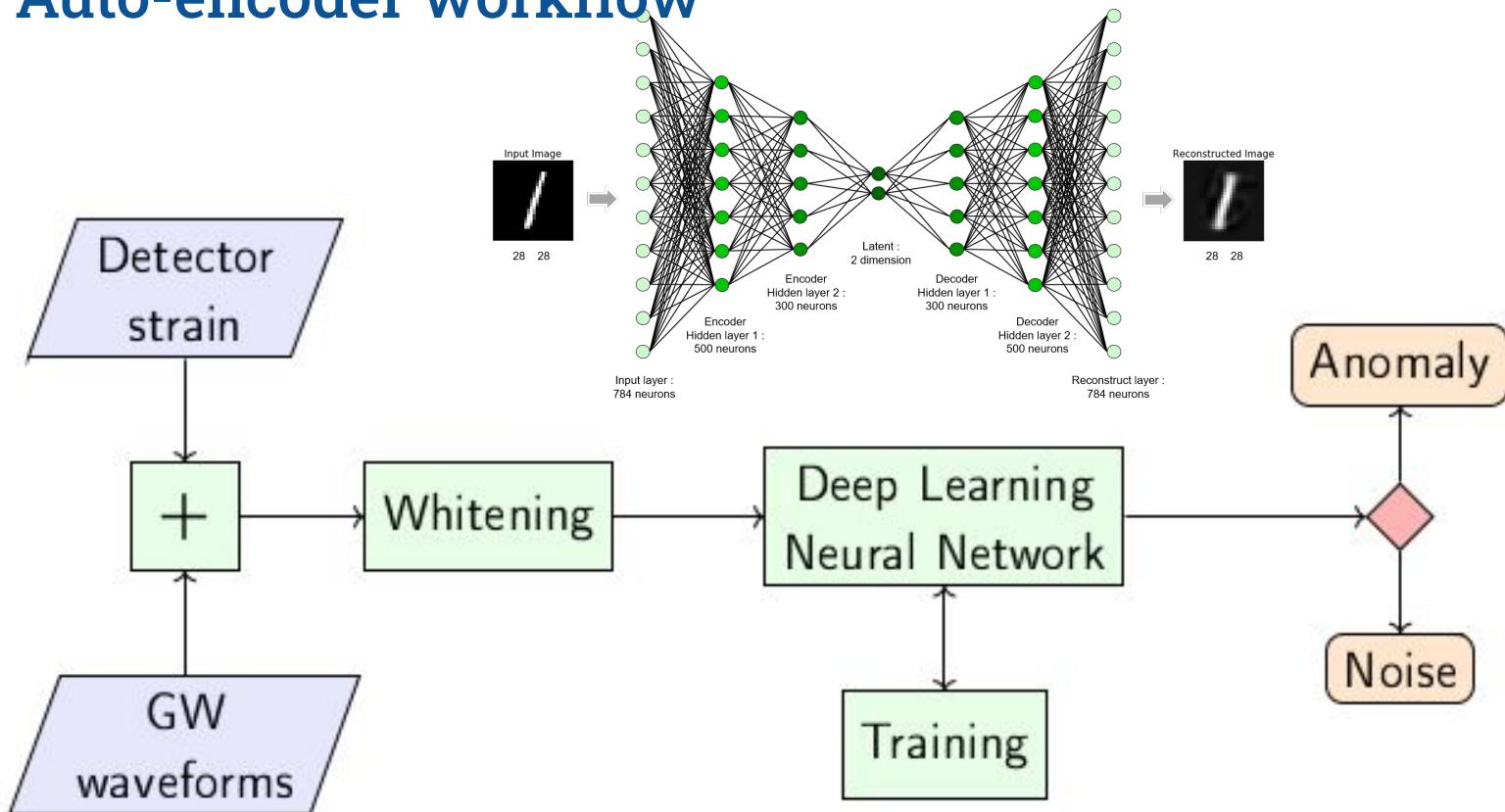
Example for detection/classification for CBC signals

Create a deep learning pipeline allowing detection of anomalies defined in terms of **transient signals**: gravitational waves as well as glitches.

Additionally: Consider **reconstruction of the signal** for the found anomalies.

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre, <https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0>

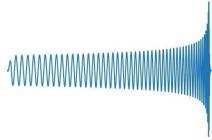
Auto-encoder workflow



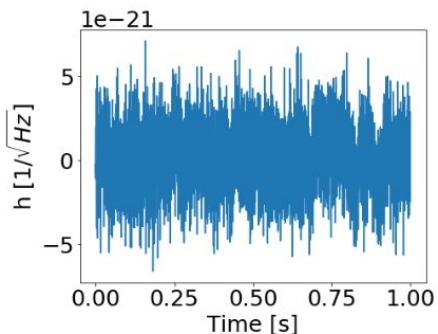
Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre, <https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0>



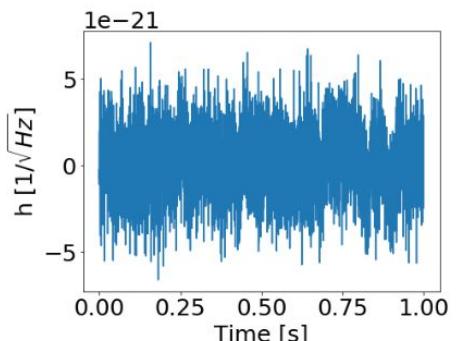
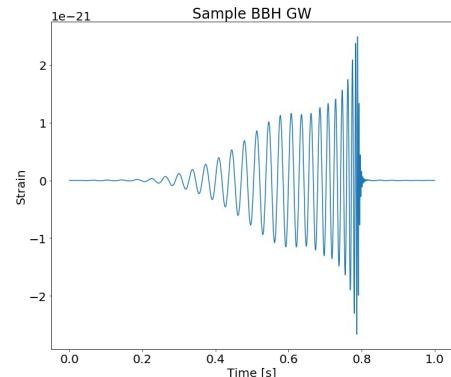
Auto-encoder workflow



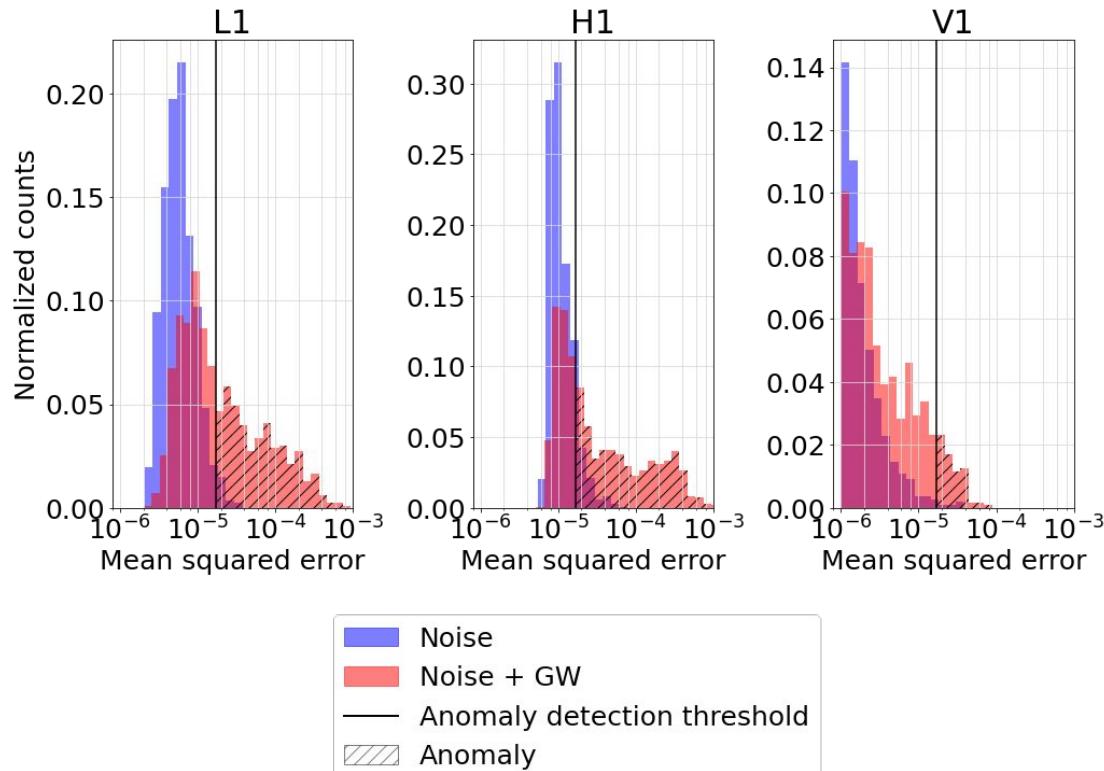
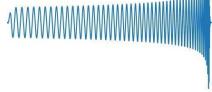
Model
input



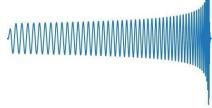
Model
prediction



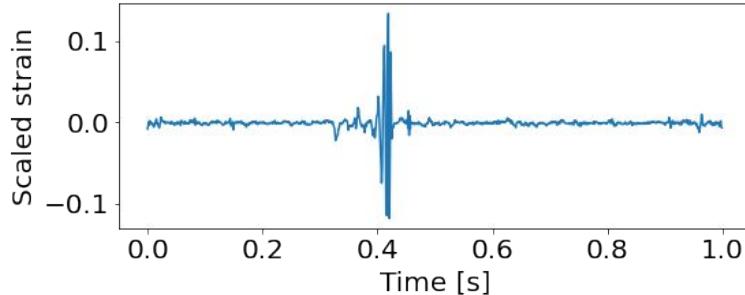
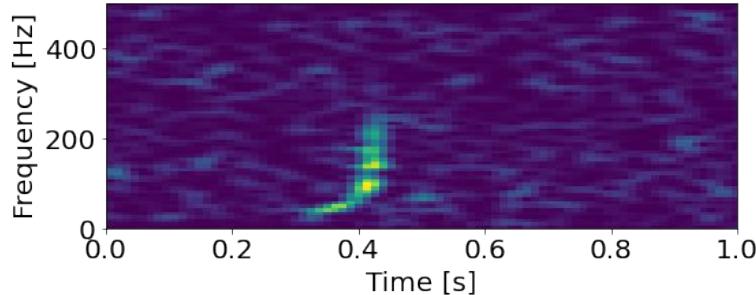
O2 data - MSE Distributions



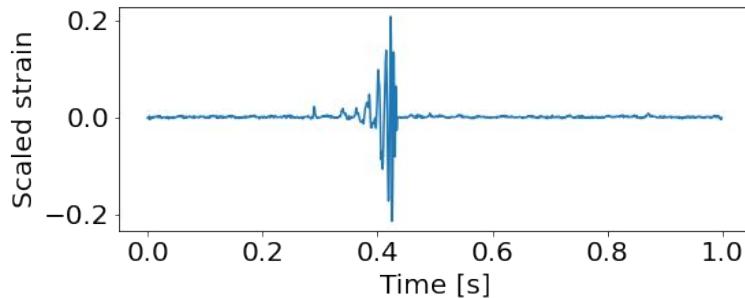
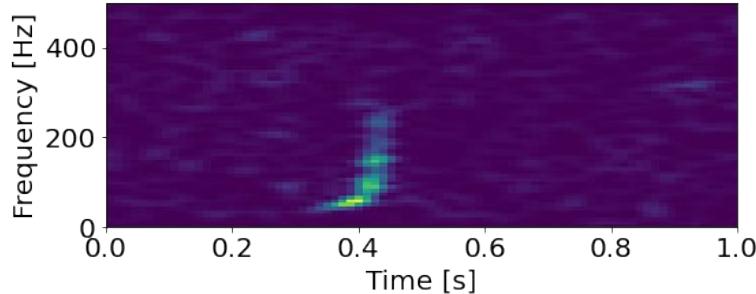
GW150914



LIGO Livingston



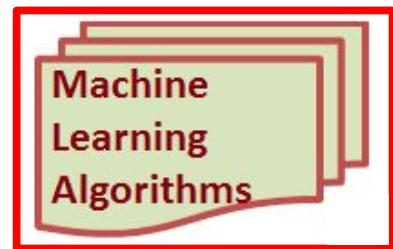
LIGO Hanford



Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
<https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0>



Rapid localization of sources



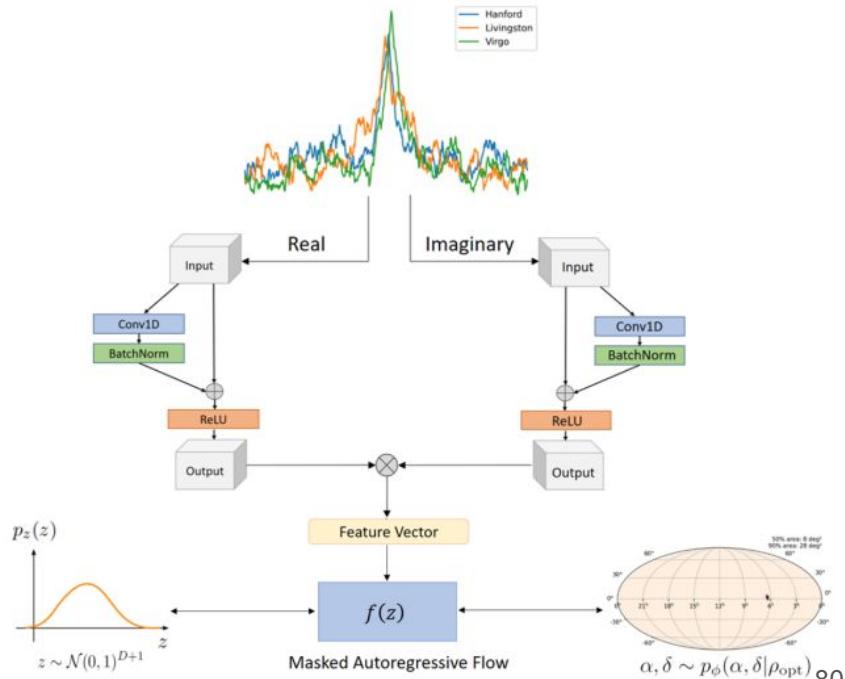
Rapid localization of gravitational wave sources from compact binary coalescences
using deep learning

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*Department of Physics, OzGrav-UWA, The University of Western Australia,
35 Stirling Hwy, Crawley, Western Australia 6009, Australia*

Foivos Diakogiannis[§]
*The Commonwealth Scientific and Industrial Research Organisation
7 Conlon St, Waterford, WA, Australia*

Kevin Vinsen[¶]
*International Centre for Radio Astronomy Research, The University of Western Australia
M468, 35 Stirling Hwy, Crawley, WA, Australia*
(Dated: August 1, 2022)

- Deep learning-based approach for sky localization of binary coalescences
- Train and test a normalizing flow model on matched-filtering output from GW searches.
- Fast sky localizations.

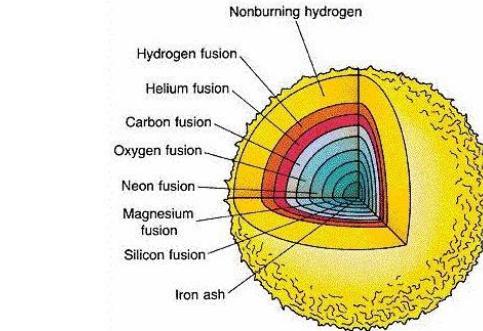


GWs from Core Collapse Supernovae

- Waveform depends on progenitor star
- Different emission mechanisms (Proto-neutron star oscillation, Standing Accretion Shock Instability (SASI),..)
- Largely Stochastic
- Best waveform models from computationally expensive 3D simulations
- Different simulation models
- Rare (~100 yrs in Milky Way)



Need an alternative to matched filter approach

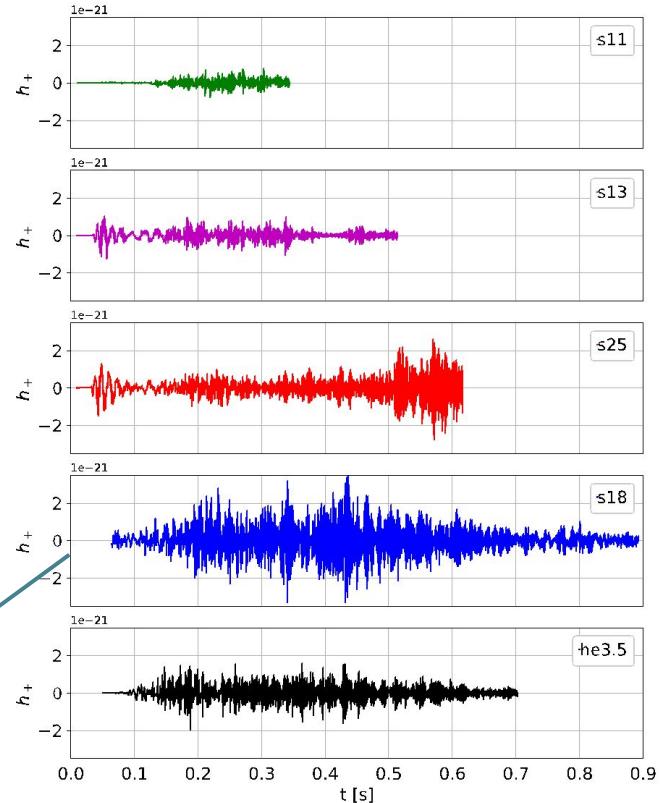
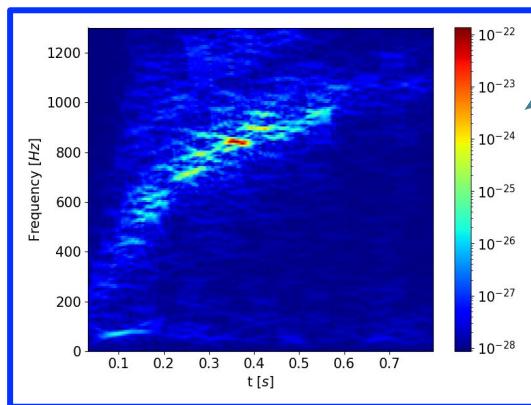
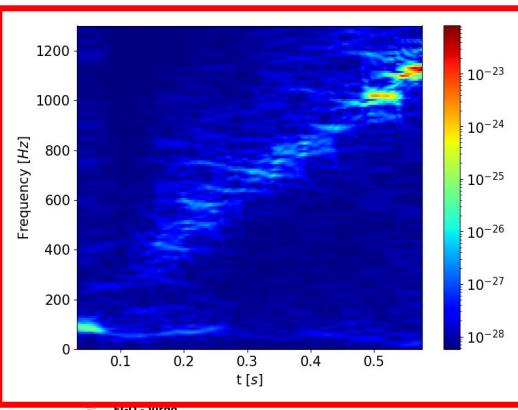


GW emission Process	MHD mechanism (rapid rotation)	Neutrino mechanism (slow/no rotation)	Acoustic mechanism (slow/no rotation)
Rotating collapse and Bounce	Strong	None/weak	None/weak
3D rotational instabilities	Strong	None	None
Convection & SASI	None/weak	Weak	Weak
PNS g -modes	None/weak	None/weak	Strong

Ott et al. (2017)

Core-Collapse Supernovae models

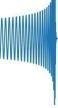
- Andresen s11: Low amplitude, non-exploding, peak emission at lower frequencies
- Radice s13: Non-exploding, lower amplitudes
- Radice s25: Late explosion time, standing accretion shock instability (SASI), high peak frequency
- Powell s18: High peak frequency, exploding model
- Powell He3.5: ultra-stripped helium star, high peak frequency, exploding model



less, Cuoco, Morawski, Powell,
<https://doi.org/10.1088/2632-2153/ab7d31>

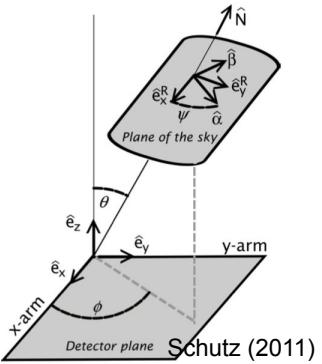


MDC and CCSN GW simulations



$$h(t) = F_+ h_+(t) + F_\times h_\times(t)$$

- Distances:
VO3 0.01 kpc to 10 kpc
ET 0.1 kpc to 1000 kpc
- Random sky localization
- Large SNR range

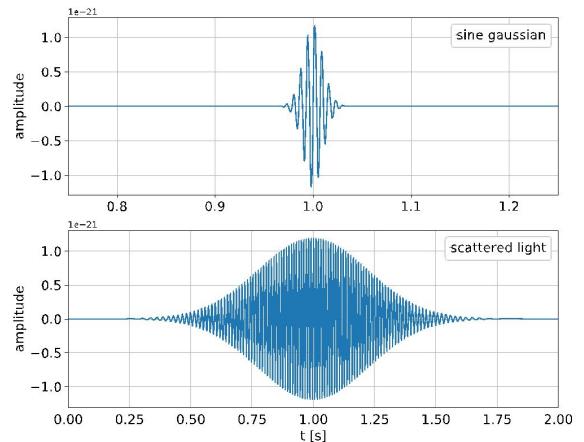
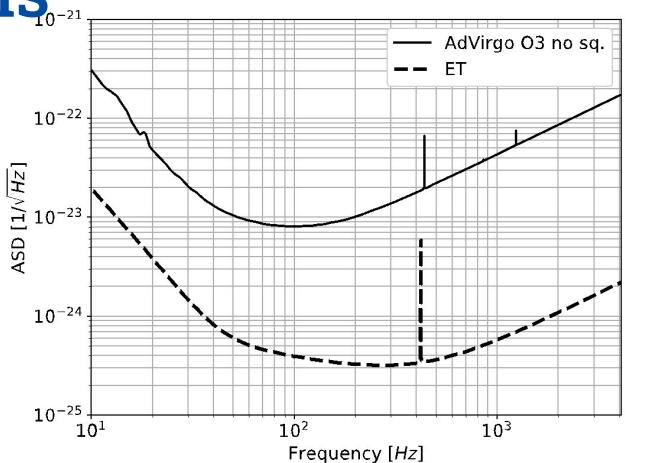


SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

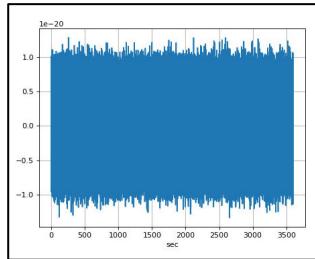
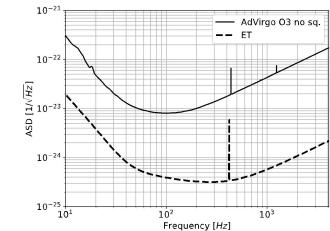
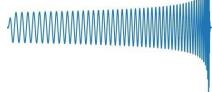
$$h_{SG}(t) = h_0 \sin(2\pi f_0(t - t_0)) e^{-\frac{(t-t_0)^2}{2\tau^2}}$$

$$h_{SL}(t) = h_0 \sin(\phi_{SL}) e^{-\frac{(t-t_0)^2}{2\tau}} \quad \phi_{SL} = 2\pi f_0(t - t_0)[1 - K(t - t_0)^2]$$

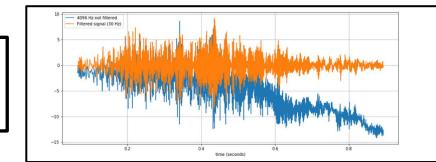
BACKGROUND STRAIN : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities



Pipeline Workflow



RESAMPLING,
FILTERING



WHITENING & TRIGGER
GENERATION
(WDF)

MACHINE-LEARNING
CLASSIFIER

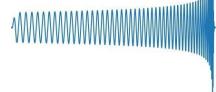
TRAINING

GW SIGNAL TYPE

GLITCH NOISE TYPE



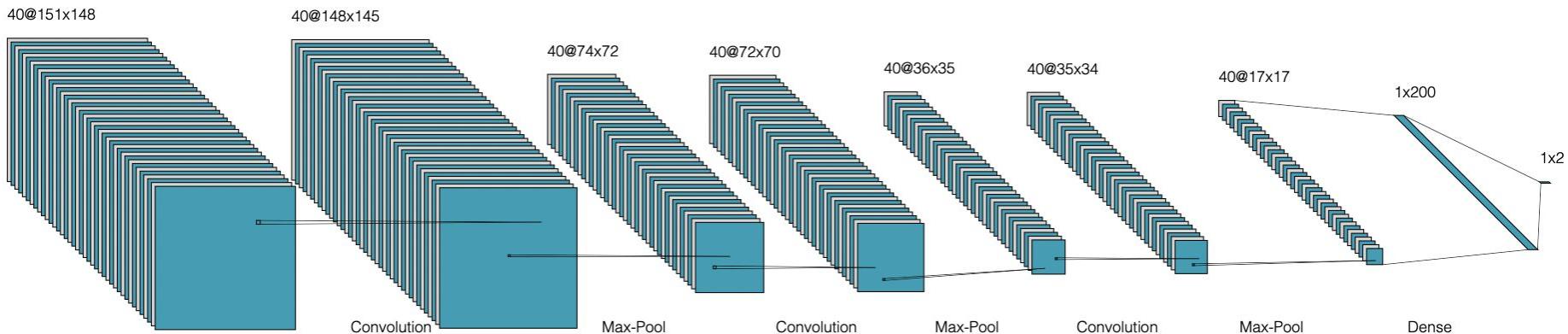
Neural Network architecture



- **Train, Validation, Test sets: 60%, 10%, 30%**
- 3 or 4 Convolutional layers
- Activation function f : ReLU
- Adam optimizer, learning rate $\alpha = 0.001$, decay rate of 0.066667
- Early stopping
- Batch Size: 64 or 128
- Loss function: Categorical-cross entropy

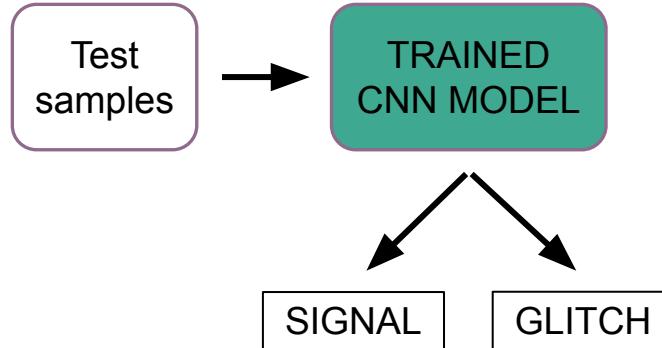
Dataset: chunks of 3 hr data with 1000 injections/h

GPU: Tesla k40



Binary Classification

- Train on all CCSNe waveforms and glitches.
- Test on all.

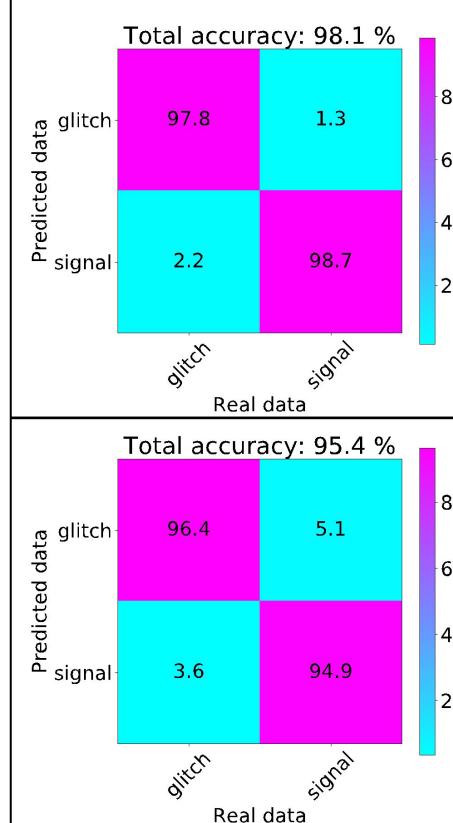


- Training time: ~ 30 min

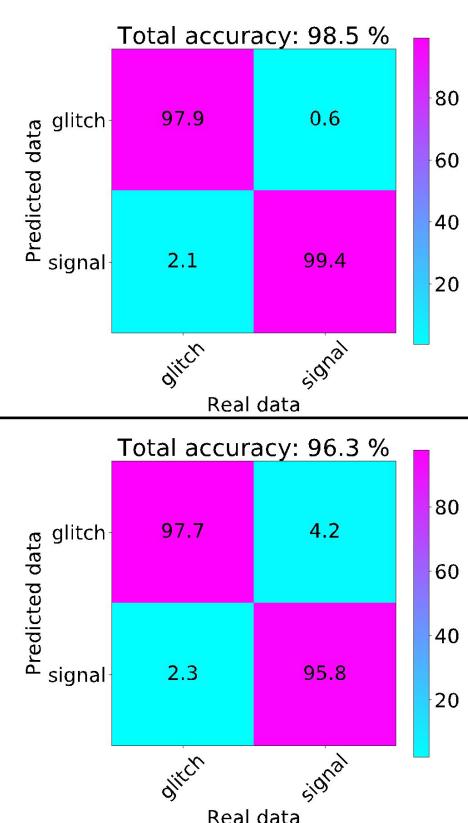
ET

VO3

1D CNN

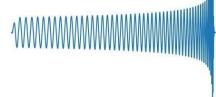


2D CNN

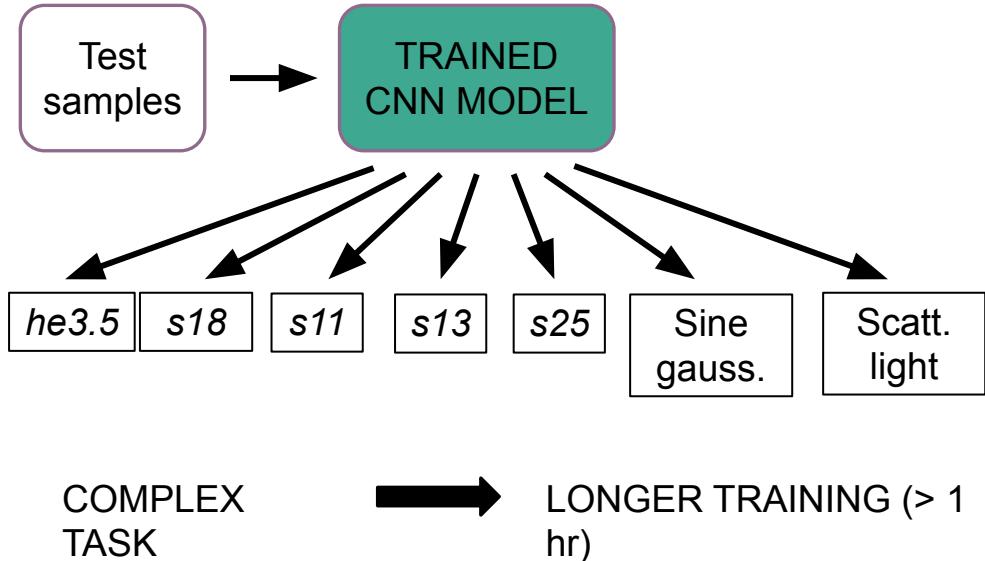




MultILabel classification

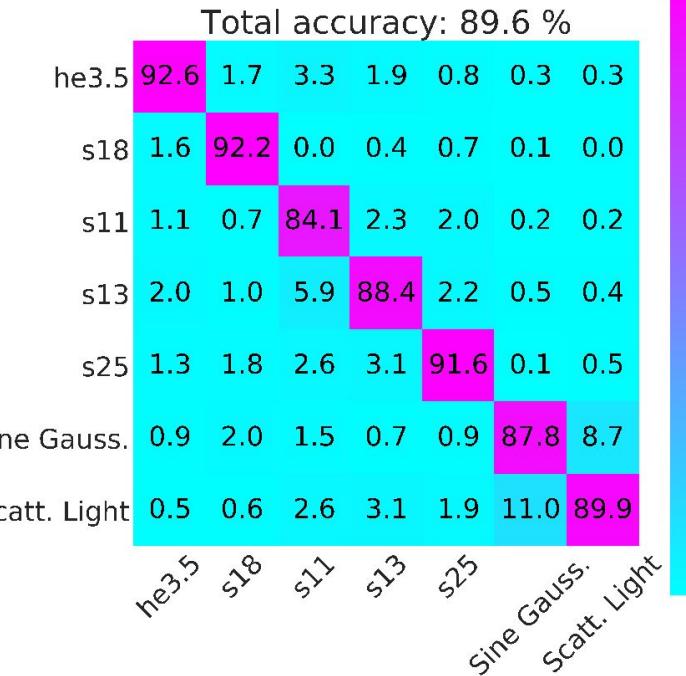


- Train on all (4 CCSNe waveform models + glitches).
- Test on all.



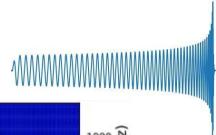
Predicted data

ET, MERGED 1D & 2D CNN

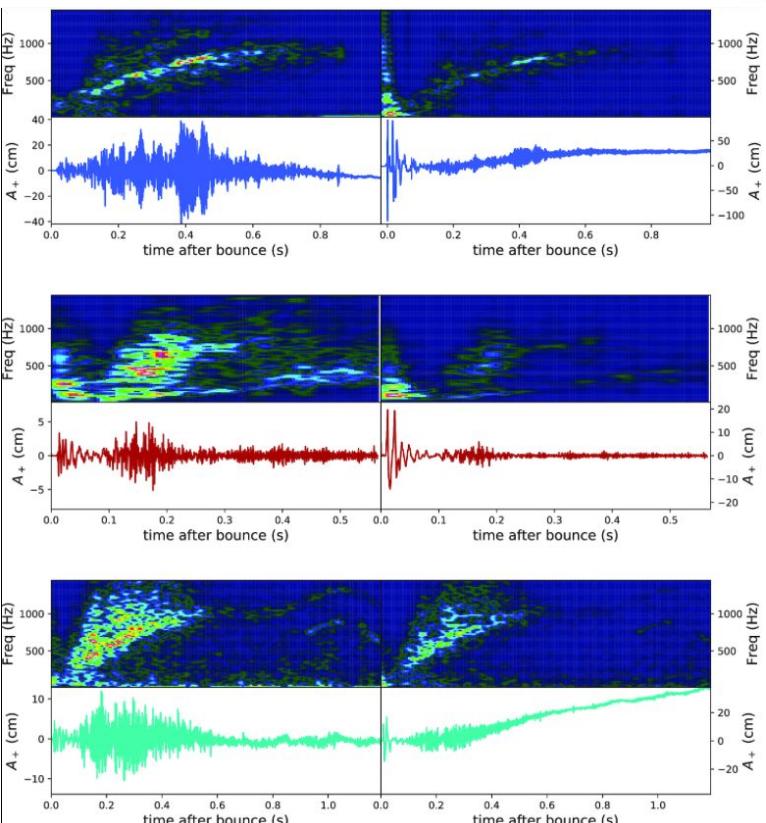




Test on O2 real Data

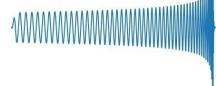


- 44 segments (4096s per segment) from O2 science run.
 - Added m39, y20, s18np models (Powell, Mueller 2020).
 - **Fixed distance of 1 kpc.**
 - Added LSTM Networks, suited for timeseries data.
 - **Added Three ITF classification.**
-
- *Powell s18np*: differs from s18 since simulation does not include perturbations from the convective oxygen shell. As a result, this model develops strong SASI after collapse.
 - *Powell y20*: non-rotating, 20 solar mass Wolf-Rayet star with solar metallicity.
 - *Powell m39*: rapidly rotating Wolf-Rayet star with an initial helium star mass of 39 solar masses



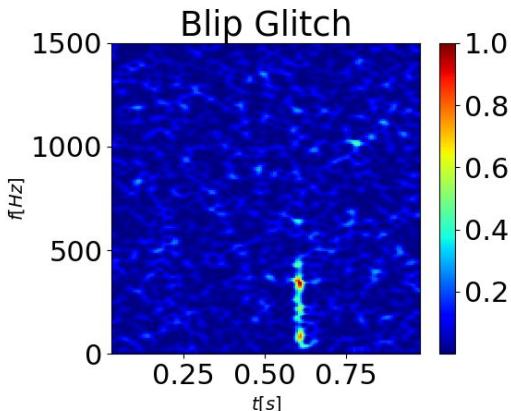
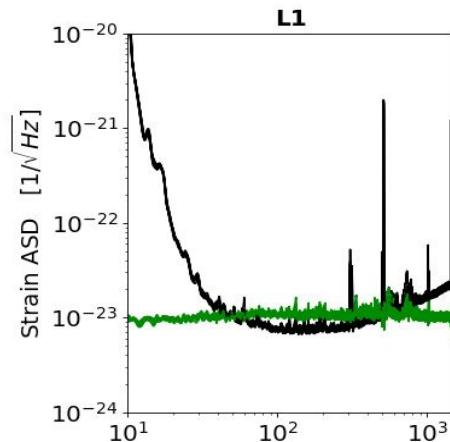


Real noise from O2 science run



- Noise PSD is non stationary.
- Multiple Glitch Families.
- SNR distribution is affected by ITF antenna pattern.
- Dataset: ~15000 samples.
- Imbalanced Dataset due to different model amplitudes.

Detector	Triggers		
	Signal	Noise	Total
Virgo V1	9273	47901	57174
Ligo L1	10480	3810	14290
Ligo H1	10984	4103	15087
L1, H1, V1	5647	675	6322

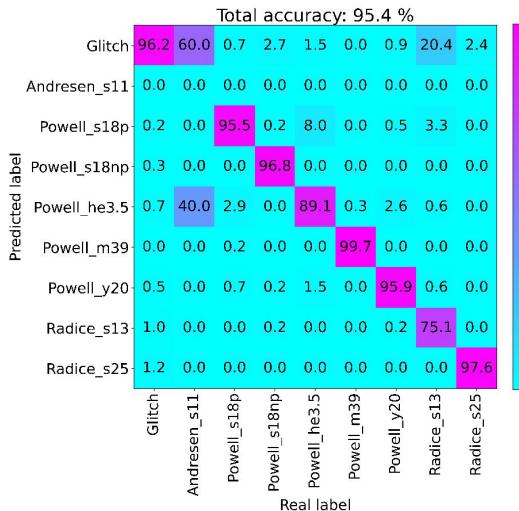


CCSN Classification on Simulated and Real O2 Data with CNNs and LSTMs
A. Iess, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, accepted for A&A

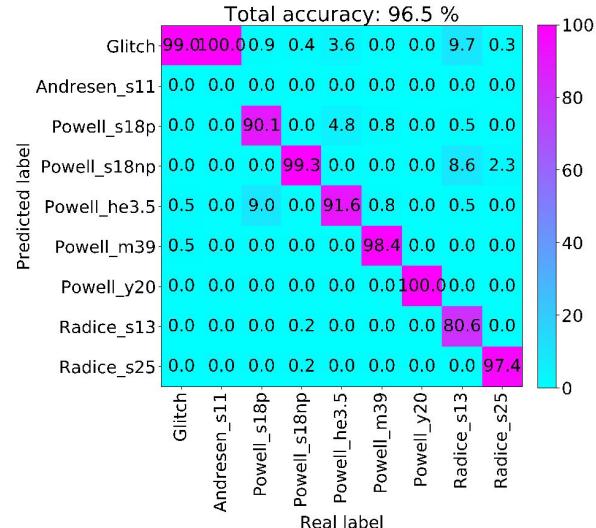
Multi-label task

MULTILABEL CLASSIFICATION ON REAL O2 NOISE (SINGLE ITF, LIGO H1, DIFFERENT MODELS)

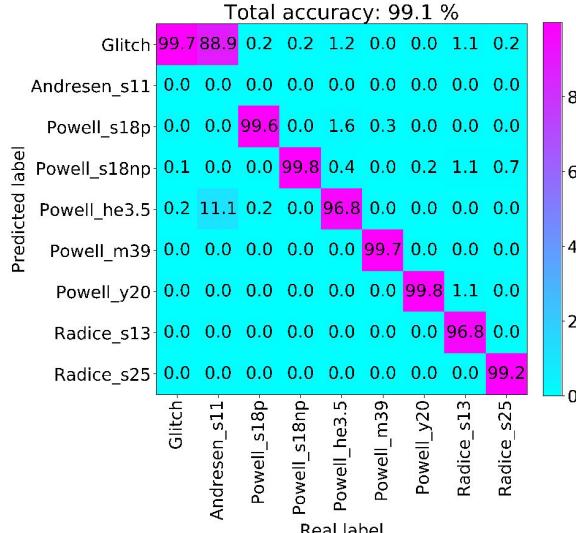
- **Bi-LSTM**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs



- **1D-CNN**, 4 convolutional layers
- ~2 ms/sample
- Best weights over 20 epochs

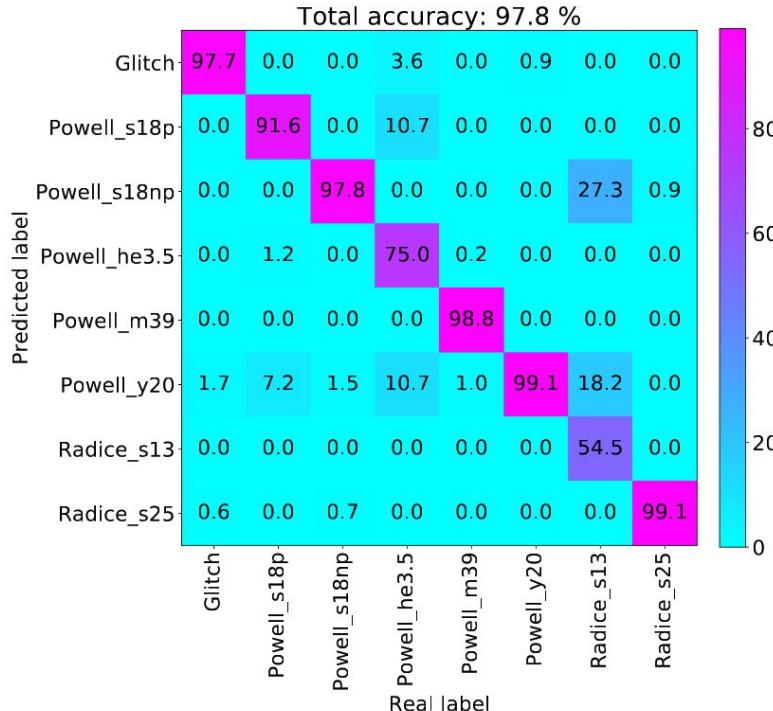
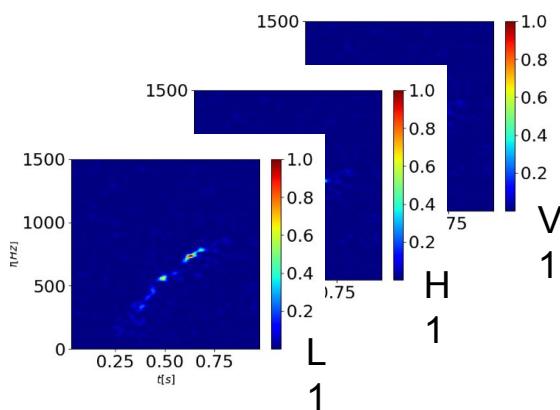


- **2D-CNN**, 4 convolutional layers
- ~3 ms/sample
- Best weights over 20 epochs



Analysis on 3 detectors and merged models on O2 data

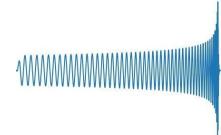
- Dataset breakdown:
675 noise, 329 s18p, 491 s18np, 115 he3.5,
1940 m39, 1139 y20, 76 s13, 1557 s25.
- Input to NNs have additional dimension (ITF)



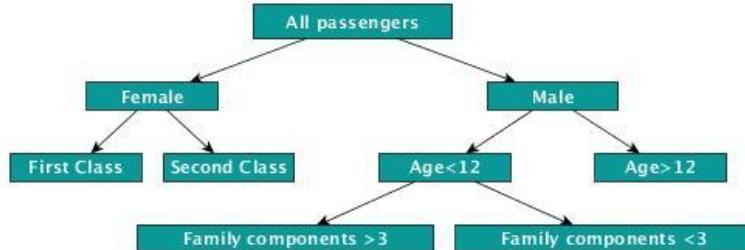
A. Iess, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, accepted in A&A



Supervised Classification: eXtreme Gradient Boosting



- <https://github.com/dmlc/xgboost>
- Tianqi Chen and Carlos Guestrin. XGBoost: A Scalable Tree Boosting System. In 22nd SIGKDD Conference on Knowledge Discovery and Data Mining, 2016
- XGBoost originates from research project at University of Washington, see also the Project Page at UW.



Tree Ensemble

dmlc
XGBoost

$$y_n = \sum_{k=1}^K f_k(x_n)$$

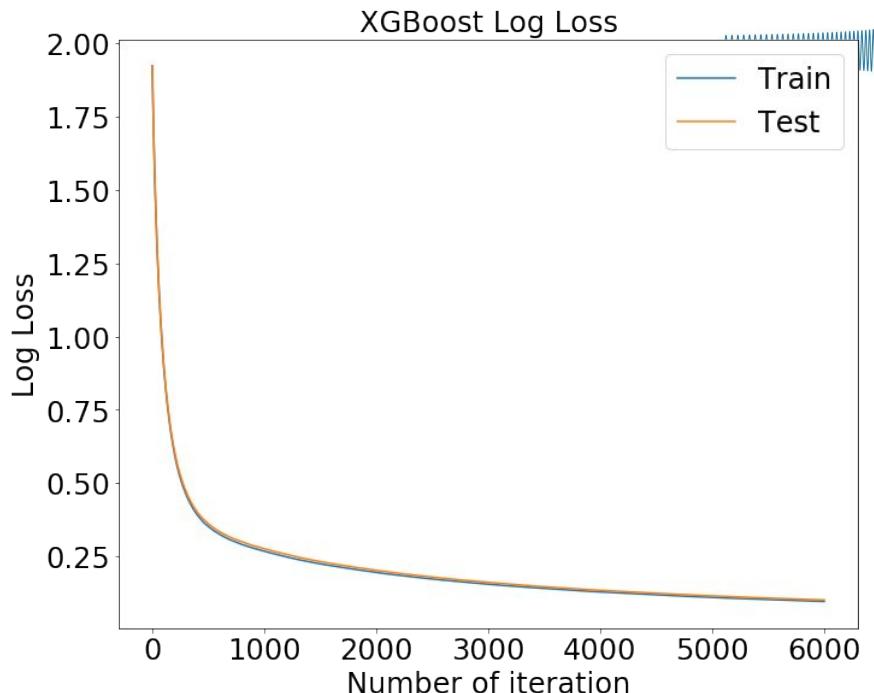


Xgboost performance

$$L = -\frac{1}{N} \sum_1^N ((y_i \log(p_i)) + (1 - y_i)(\log(1 - p_i))) + \Omega$$

Cost function

Train/validation/test set: 70/15/15

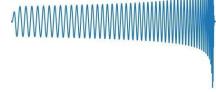


Data set Features: Wavelet coefficients

task	Classes	Learning-rate	Max_depth	estimators
Binary	2	0.01	7	5000
Multi-label	7	0.01	10	6000



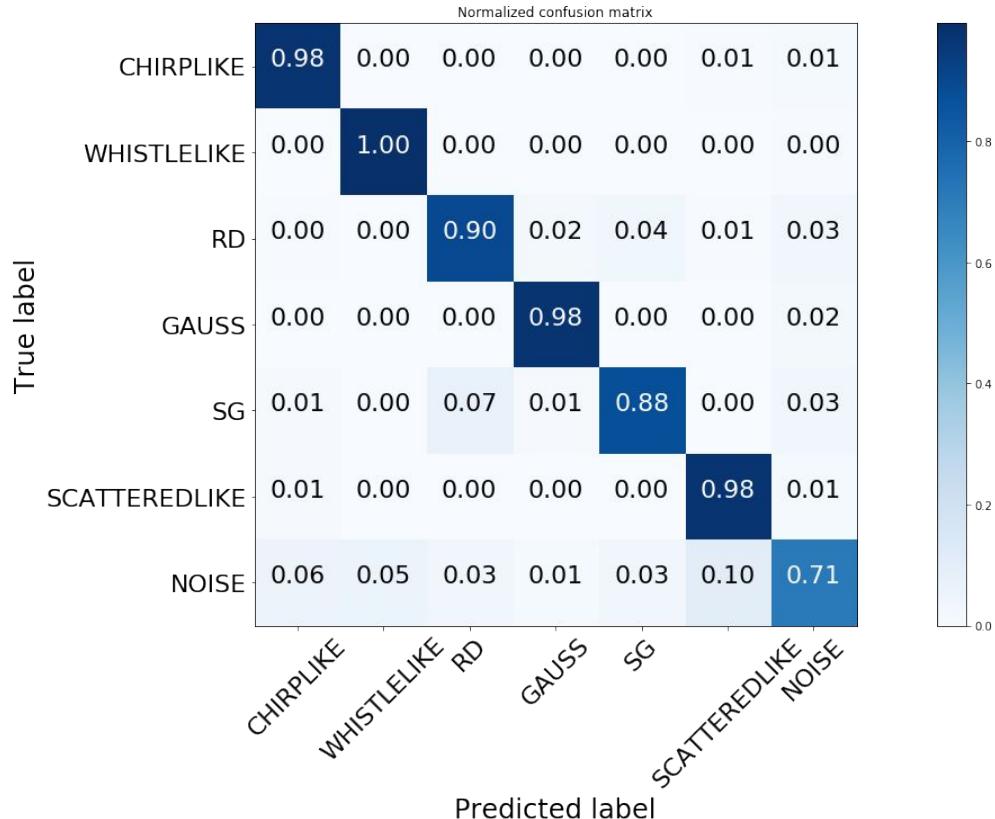
WDFX Results: Multi-Label Classification



Overall accuracy
>>93%

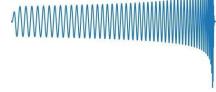
Cuoco et al.

[10.23919/EUSIPCO.2018.8553393](https://doi.org/10.23919/EUSIPCO.2018.8553393)
2018 26th European Signal Processing Conference (EUSIPCO)





WDFX: Binary Classification Results



Chirp-like signals

OR

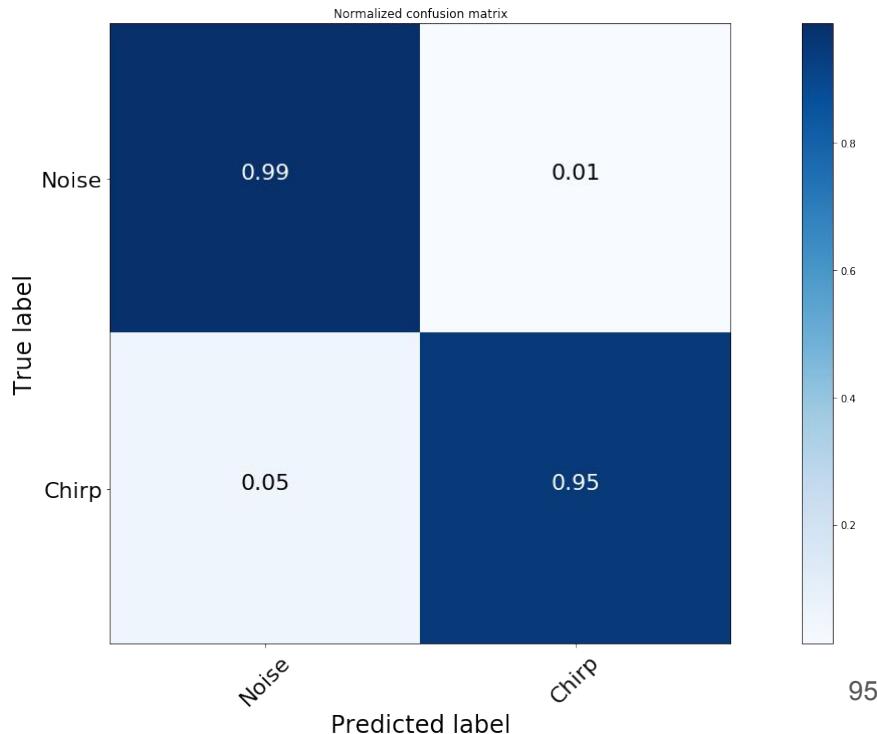
Noise

Cuoco et al.

[10.23919/EUSIPCO.2018.8553393](https://doi.org/10.23919/EUSIPCO.2018.8553393)

[2018 26th European Signal Processing Conference \(EUSIPCO\)](#)

Overall accuracy
>98%





Burst search

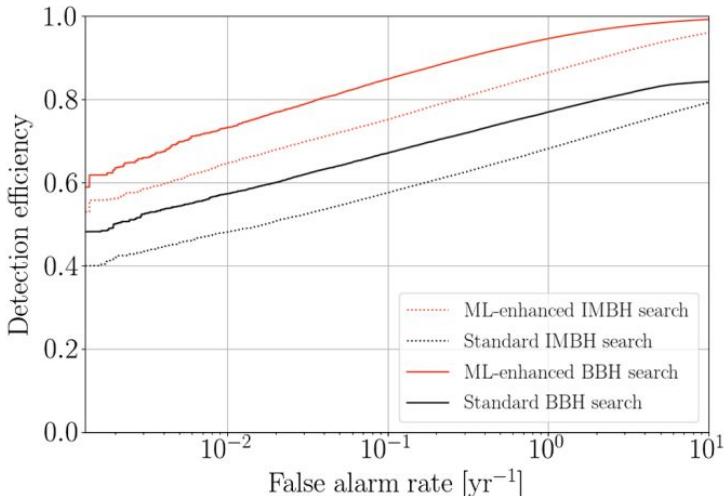
- Decision tree-based machine learning algorithm (eXtreme-Gradient Boost) to automate signal vs. noise classification in coherent WaveBurst searches for binary black hole mergers.
- Post-processing application replacing standard veto techniques.

Deploy
Selected
Model

PHYSICAL REVIEW D 105, 083018 (2022)

Search for binary black hole mergers in the third observing run of Advanced LIGO-Virgo using coherent WaveBurst enhanced with machine learning

T. Mishra,¹ B. O'Brien,¹ M. Szczepańczyk,¹ G. Védrovato,² S. Bhaumik,¹ V. Gayathri,¹ G. Prodi,^{3,4} F. Salemi,^{5,4} E. Milotti,^{6,7} I. Bartos,¹ and S. Klimenko¹



Event	Standard cWB	ML-enhanced cWB	SNR	P_{astro}
	FAR (yr ⁻¹)	FAR (yr ⁻¹)		
GW190408_181802	$<9.5 \times 10^{-4}$	$<1.0 \times 10^{-3}$	14.8	0.999
GW190412	$<9.5 \times 10^{-4}$	$<1.0 \times 10^{-3}$	19.7	0.999
GW190421_213856	3.0×10^{-1}	1.8×10^{-2}	9.3	0.997
GW190503_185404	1.8×10^{-3}	$<9.9 \times 10^{-4}$	11.5	0.999
GW190512_180714	3.0×10^{-1}	1.8×10^{-1}	10.7	0.941
GW190513_205428	...	$1.0 \times 10^{+0}$	11.5	0.703
GW190517_055101	6.5×10^{-3}	6.2×10^{-4}	10.7	0.999
GW190519_153544	3.1×10^{-4}	$<1.0 \times 10^{-4}$	14.0	1.000
GW190521	2.0×10^{-4}	$<1.0 \times 10^{-4}$	14.4	1.000
GW190521_074359	$<1.0 \times 10^{-4}$	$<1.0 \times 10^{-4}$	24.7	0.999
GW190602_175927	1.5×10^{-2}	$<8.8 \times 10^{-4}$	11.1	0.999
GW190701_203306	5.5×10^{-1}	1.1×10^{-2}	10.2	0.997
GW190706_222641	$<1.0 \times 10^{-3}$	$<1.1 \times 10^{-3}$	12.7	0.999
GW190707_093326	...	1.1×10^{-1}	11.2	0.976
GW190727_060333	8.8×10^{-2}	3.4×10^{-3}	11.4	0.998
GW190728_064510	...	2.6×10^{-2}	10.5	0.999
GW190828_063405	$<9.6 \times 10^{-4}$	$<1.1 \times 10^{-3}$	16.6	0.999



Supernova searches



Mach. Learn.: Sci. Technol. 1 (2020) 015005

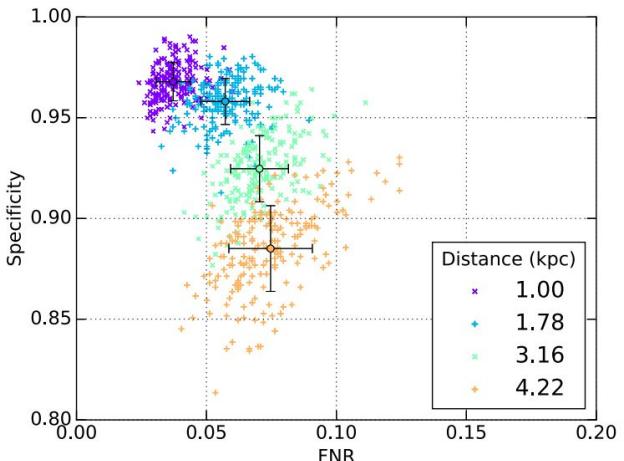
<https://doi.org/10.1088/2632-2153/ab527d>

MACHINE
LEARNING
Science and Technology

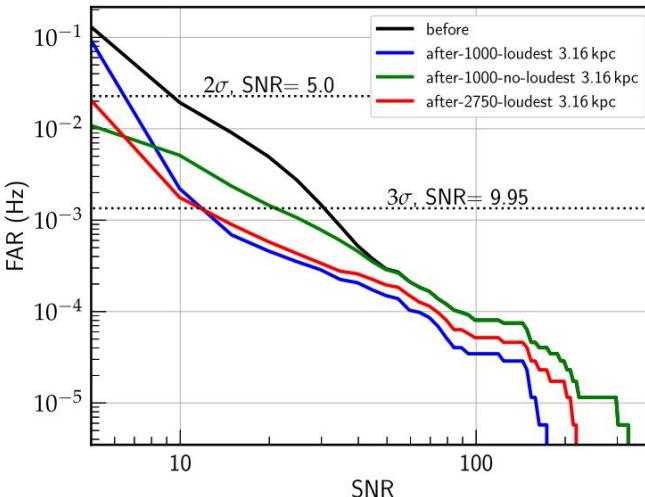
PAPER

Improving the background of gravitational-wave searches for core collapse supernovae: a machine learning approach

M Cavaglia^{a,1}, S Gaudio^a, T Hansen^b, K Staats^c, M Szczepańczyk^d and M Zanolini^b



- Genetic evolutionary algorithm to perform single-interferometer supernova searches.
- Post-processing method on top of cWB.

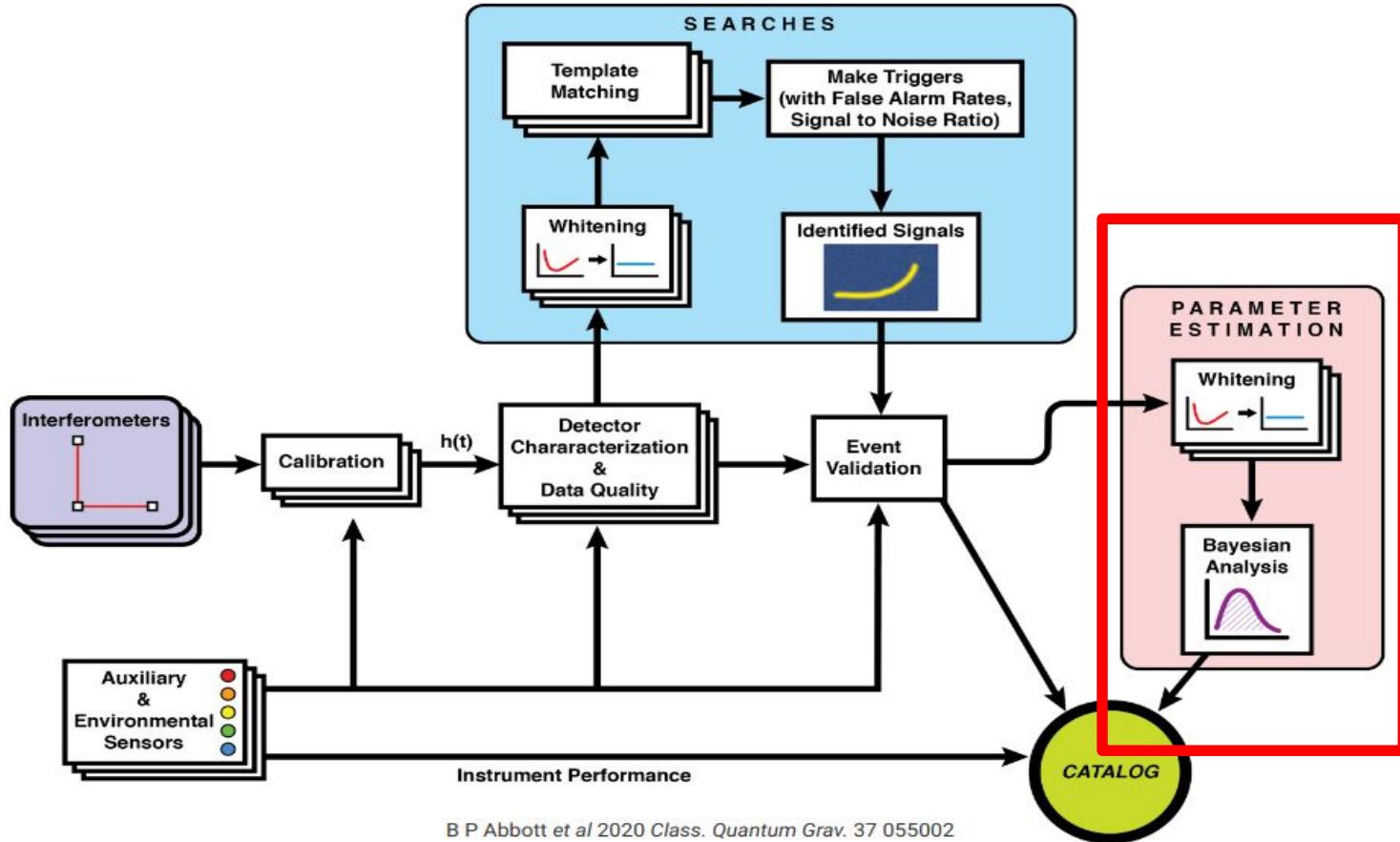


Trigger time	n_+	$P(s n_+)$	Actual
1137221362.849899	0	0.03	BKG
1137221296.450439	12	0.35	BKG
1137221270.478584	7	0.26	BKG
1137221315765	0	0.03	BKG
1137221256.461151	0	0.03	BKG
1137221254.992889	0	0.03	BKG
1137221206.790939	0	0.03	BKG
1137221187.891924	0	0.03	BKG
1137088411.819580	0	0.03	BKG
1137088400.326843	91	0.50	BKG
1137123606.447540	146	0.50	SIG (Yak, 3.16 kpc)
1137234559.739685	188	0.65	SIG (Yak, 3.16 kpc)
1137250081.748009	167	0.52	SIG (Yak, 3.16 kpc)
1137215815.308205	188	0.65	SIG (Yak, 1 kpc)
1137240747.519287	188	0.65	SIG (Yak, 1 kpc)
1137251495.131439	188	0.65	SIG(Yak, 1 kpc)
1137232392.167053	188	0.65	SIG (Yak, 1 kpc)
1137237558.365189	186	0.62	SIG (Yak, 1 kpc)

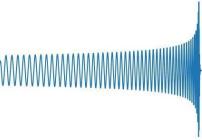
Currently extending to multi-detector and applying to O3 data



Astrophysical interpretation of GW sources



Astrophysical interpretation of GW sources



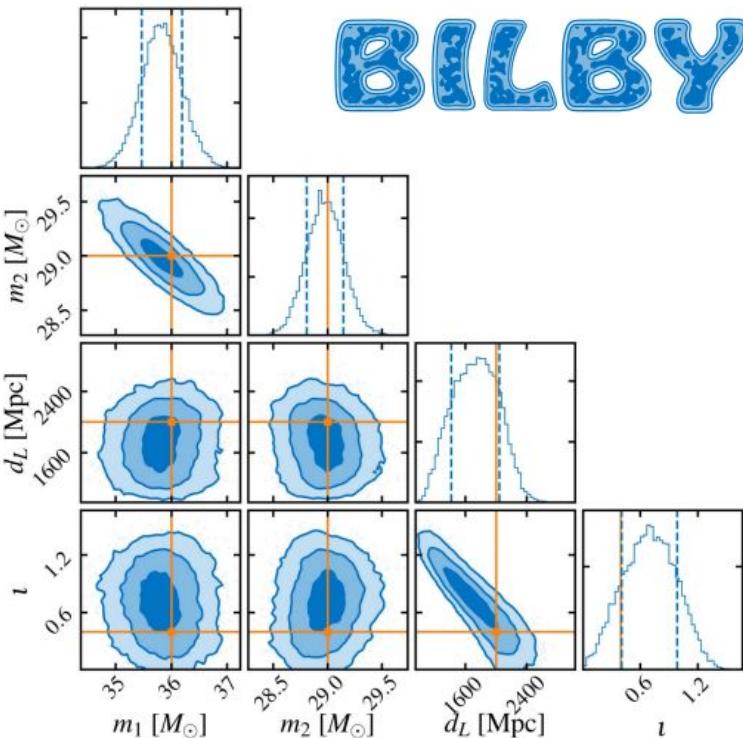
THE ASTROPHYSICAL JOURNAL SUPPLEMENT SERIES, 241:27 (13pp), 2019 April
© 2019. The American Astronomical Society. All rights reserved.

<https://doi.org/10.3847/1538-4365/ab06fc>



BILBY: A User-friendly Bayesian Inference Library for Gravitational-wave Astronomy

Gregory Ashton^{1,2}, Moritz Hübner^{1,2}, Paul D. Lasky^{1,2}, Colm Talbot^{1,2}, Kendall Ackley^{1,2}, Sylvia Biscoveanu^{1,2,3}, Qi Chu^{4,5}, Atish Divakarla^{1,2,6}, Paul J. Ester^{1,2}, Boris Goncharov^{1,2}, Francisco Hernandez Vivanco^{1,2}, Jan Harms^{7,8}, Marcus E. Lower^{9,10}, Grant D. Meadors^{1,2}, Denyz Melchor^{1,2,11}, Ethan Payne^{1,2}, Matthew D. Pitkin^{1,2}, Jade Powell^{9,10}, Nikhil Sarin^{1,2}, Rory J. E. Smith^{1,2}, and Eric Thrane^{1,2}



PHYSICAL REVIEW D 91, 042003 (2015)

Parameter estimation for compact binaries with ground-based gravitational-wave observations using the LALInference software library

J. Veitch,^{1,2,*} V. Raymond,³ B. Farr,^{4,5} W. Farr,¹ P. Graff,⁶ S. Vitale,⁷ B. Aylott,¹ K. Blackburn,³ N. Christensen,⁸ M. Coughlin,⁹ W. Del Pozzo,¹ F. Feroz,¹⁰ J. Gair,¹¹ C.-J. Haster,¹ V. Kalogera,⁵ T. Littenberg,⁵ I. Mandel,¹ R. O’Shaughnessy,^{12,13} M. Pitkin,¹⁴ C. Rodriguez,⁵ C. Röver,^{15,16} T. Sidery,¹ R. Smith,³ M. Van Der Sluys,¹⁷ A. Vecchio,¹ W. Vossen,¹ and L. Wade¹²

Publications of the Astronomical Society of the Pacific, 131:024503 (16pp), 2019 February
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<https://doi.org/10.1088/1538-3873/aaf0b>



PyCBC Inference: A Python-based Parameter Estimation Toolkit for Compact Binary Coalescence Signals

C. M. Biwer^{1,2}, Collin D. Capano³, Soumi De², Miriam Cabero³, Duncan A. Brown², Alexander H. Nitz³, and V. Raymond^{4,5}

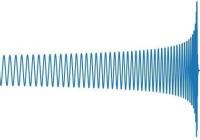
Rapid and accurate parameter inference for coalescing, precessing compact binaries

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¹Center for Computational Relativity and Gravitation, Rochester Institute of Technology, Rochester, New York 14623, USA

- Current parameter estimation techniques for compact binary coalescence signals rely on Bayesian analysis (posteriors + evidence).
- Computationally costly!
- Need to dramatically speed up the process!
- How can machine learning help?

Rapid inference of source parameters



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<https://doi.org/10.3847/1538-4357/ab8dbe>



A Machine Learning-based Source Property Inference for Compact Binary Mergers

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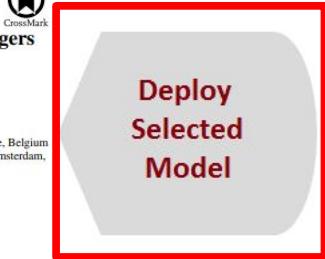
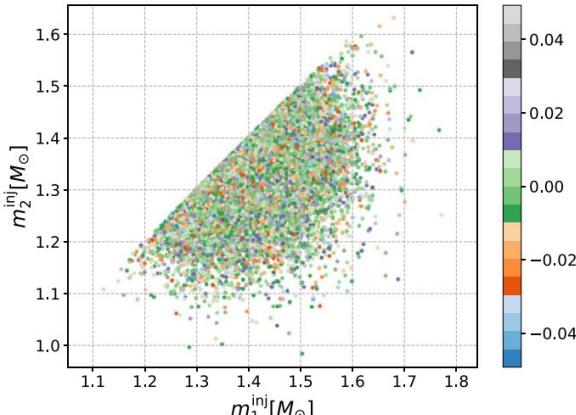
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⁵ GRAPPA, Anton Pannekoek Institute for Astronomy and Institute of High-Energy Physics, University of Amsterdam, Science Park 904, 1098 XH Amsterdam, The Netherlands

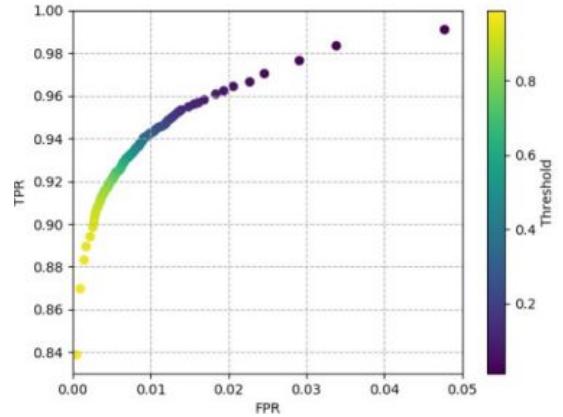
⁶ Dipartimento di Fisica, Università di Roma "Sapienza", Piazzale A. Moro 5, I-00185 Roma, Italy

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- Classifiers (Kneighbors, genetic, random forests) for HasNS and HasRemnant properties of sources in low-latency
- Train and test on LIGO-Virgo online MDC
- Integrate in the LVK low-latency infrastructure and run in O4

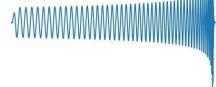


See also:
S. Sharma Chaudhary, MC, D.
Chatterjee, S. Ghosh, in preparation

100



Parameter estimation



Classical and Quantum Gravity

PAPER

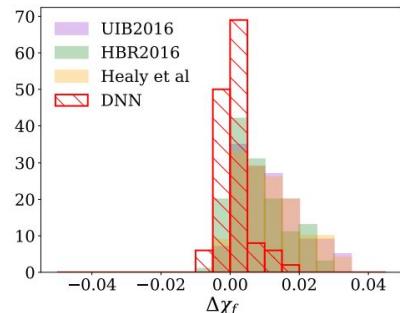
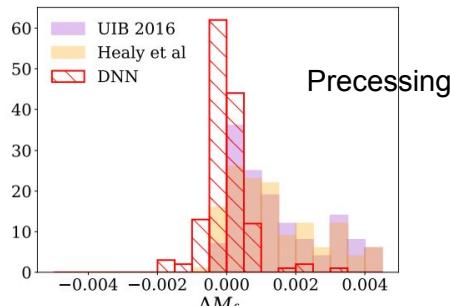
Predicting the properties of black-hole merger remnants with deep neural networks

L Haegel^{3,1,2} and S Husa¹

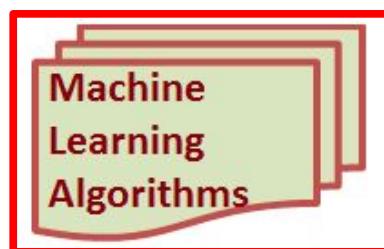
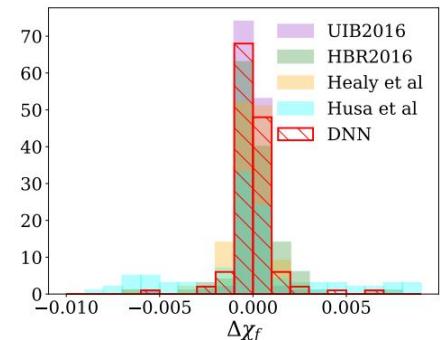
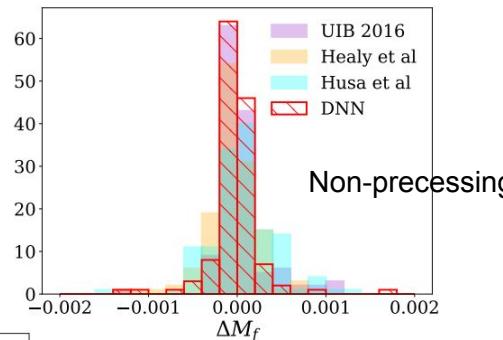
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Classical and Quantum Gravity, Volume 37, Number 13

Citation L Haegel and S Husa 2020 *Class. Quantum Grav.* **37** 135005

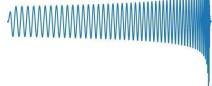


- Deep neural networks to infer the relationship between the initial BBHs parameters and the remnant final mass and final spin of a binary black hole merger.
- Trained with publicly available NR catalogs.





Parameter estimation

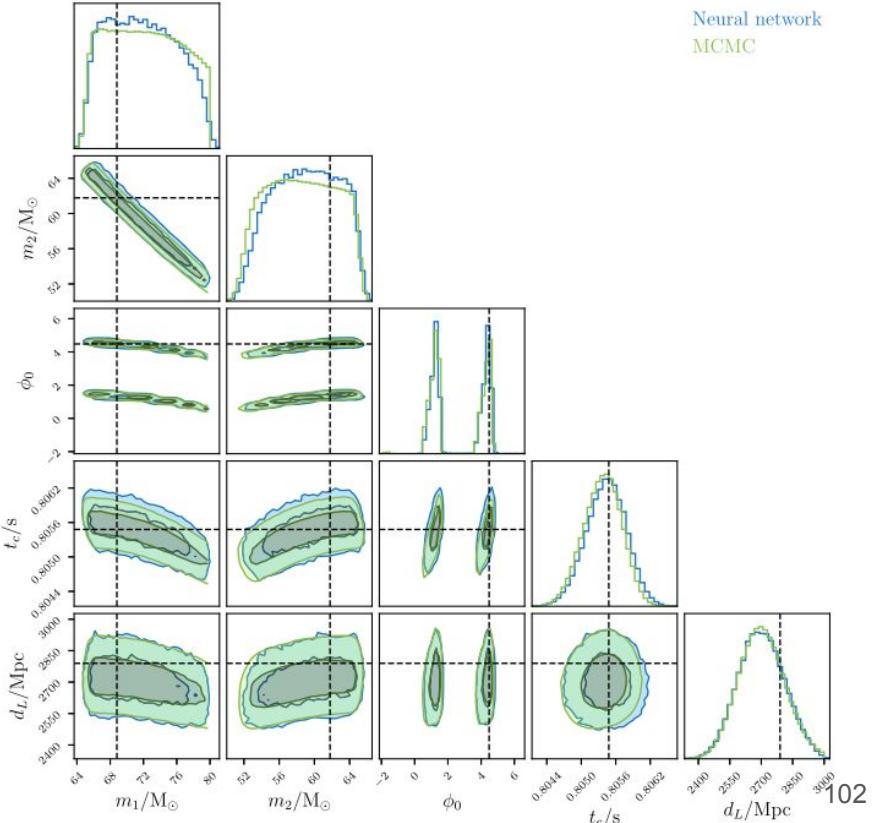


PHYSICAL REVIEW D **102**, 104057 (2020)

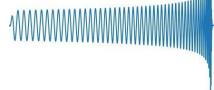
Gravitational-wave parameter estimation with autoregressive neural network flows

Stephen R. Green^{1,*} Christine Simpson^{2,†} and Jonathan Gair^{1,‡}

- Autoregressive normalizing flows for rapid likelihood-free inference of binary black hole system parameters.
- Maps a **multivariate standard normal distribution** into the **posterior distribution of system parameters**.
- Performance comparable to Markov chain Monte Carlo.



Parameter estimation



Bayesian parameter estimation using conditional variational autoencoders for gravitational-wave astronomy

Hunter Gabbard^{1,2}, Chris Messenger³, Ik Siong Heng¹, Francesco Tonolini² and Roderick Murray-Smith^{4,2}

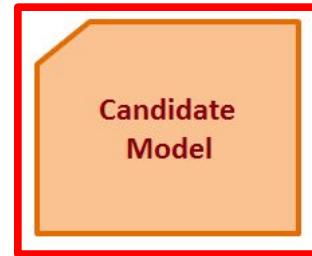
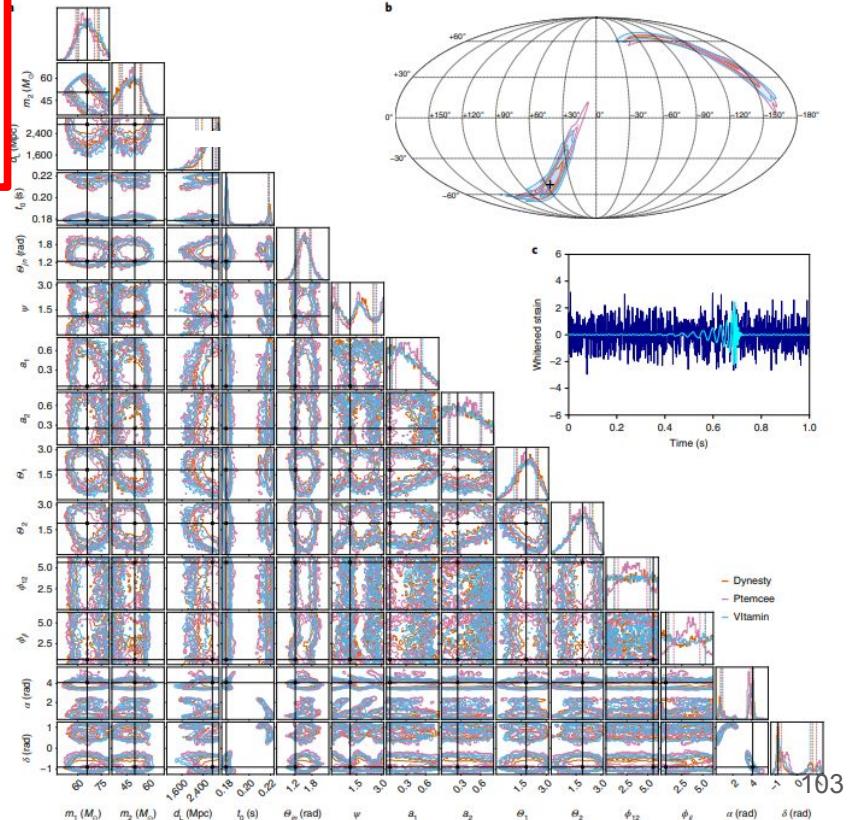


Table 2 | Durations required to produce samples from each of the sampling approaches

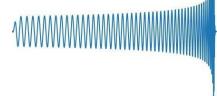
Sampler	Run time (s)			Ratio $\frac{t_{\text{Vitamin}}}{t_x}$
	Min.	Max.	Median	
Dynesty ^a	21,564	261,268	45,607 ^b	2.2×10^{-6}
emcee ⁸	16,712	39,930	19,821	5.1×10^{-6}
ptemcee ⁹	2,392	501,632	41,151.0	2.4×10^{-6}
CPNest ⁶	10,309	437,008	83,807	1.2×10^{-6}
Vitamin ^c	1 × 10⁻¹		1	

- Pre-trained conditional variational autoencoder
- Standard advanced detector power spectral density.
- Full-parameter estimation ~ 1 s.





Machine learning applications in LVK: a long list



Glitches
classification

GW signal
detection

Parameter
estimation

Sky
localization

Easy access
information

Data quality

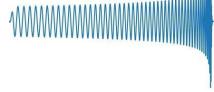
Waveform
modelling

...

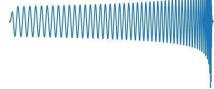
Review paper: Enhancing gravitational-wave science with machine learning Elena Cuoco *et al*
2021 *Mach. Learn.: Sci. Technol.* 2 011002...We are preparing the updated version



Hands-on session



- ❑ GW Data reading and plotting
- ❑ Whitening procedure
- ❑ CNN-1D classification for CCSN signals
- ❑ CNN-2D classification for CCSN signals
- ❑ Code repo: <https://github.com/elenacuoco/GWML-masterclass>
 - ❑ please download the code and try to run CCN-1D on your pc, to setup the data sets.



Thank you

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elena.cuoco@ego-gw.it



SCUOLA
NORMALE
SUPERIORE

