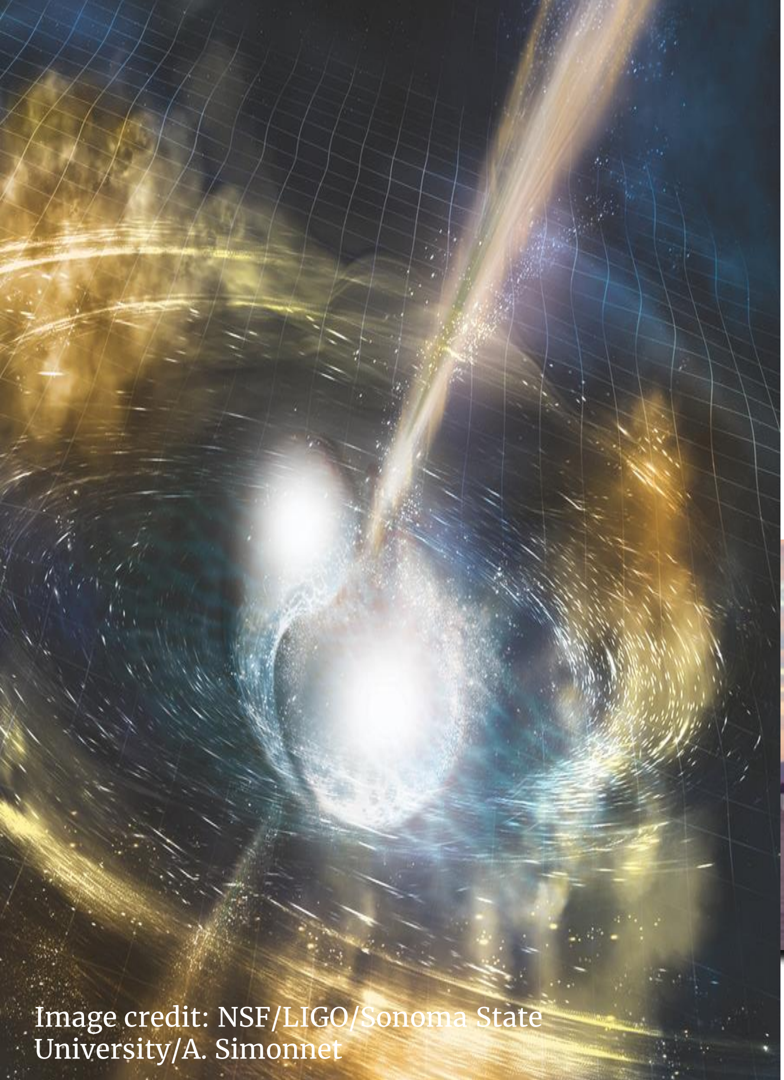


Image credit: NSF/LIGO/Sonoma State University/A. Simonnet

Machine Learning for Transient signal analysis in Gravitational Wave data

Elena Cuoco

European Gravitational Observatory and Scuola Normale Superiore, Pisa

June 9th -11th

11th Iberian Gravitational Waves Meeting

G2NET cost EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY ESCAPE EGO - Virgo SCUOLA NORMALE SUPERIORE

Outline

- Transient Gravitational Wave signals
- Gravitational Wave data and detection strategy
- GW alert system
- Machine learning and its application to
    - Transient noise
    - Core Collapse Supernovae
    - Compact Binary Coalescences
    - Astrophysical Stochastic Background

Gravitational Wave Transient signal sources

Compact binary coalescences

Credit
LIGO/Caltech/MIT/R. Hurt (IPAC)

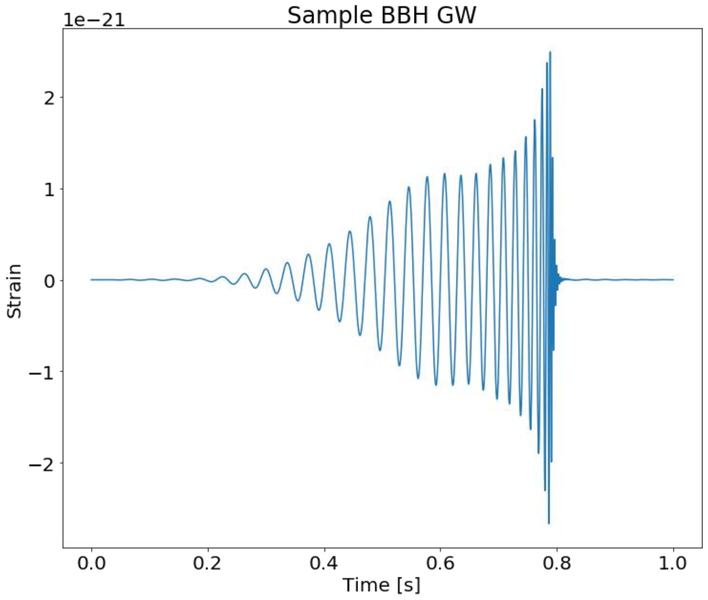
Core collapse Supernovae

ESA/XMM-Newton & NASA/Chandra (X-ray);
NASA/WISE/Spitzer (Infrared)

UNKNOWN SOURCES...

Gravitational Wave Transient signals

CBC signals



CCSN signals

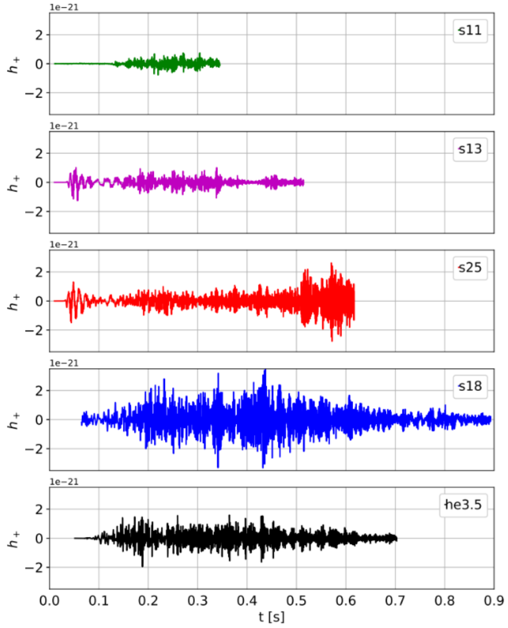
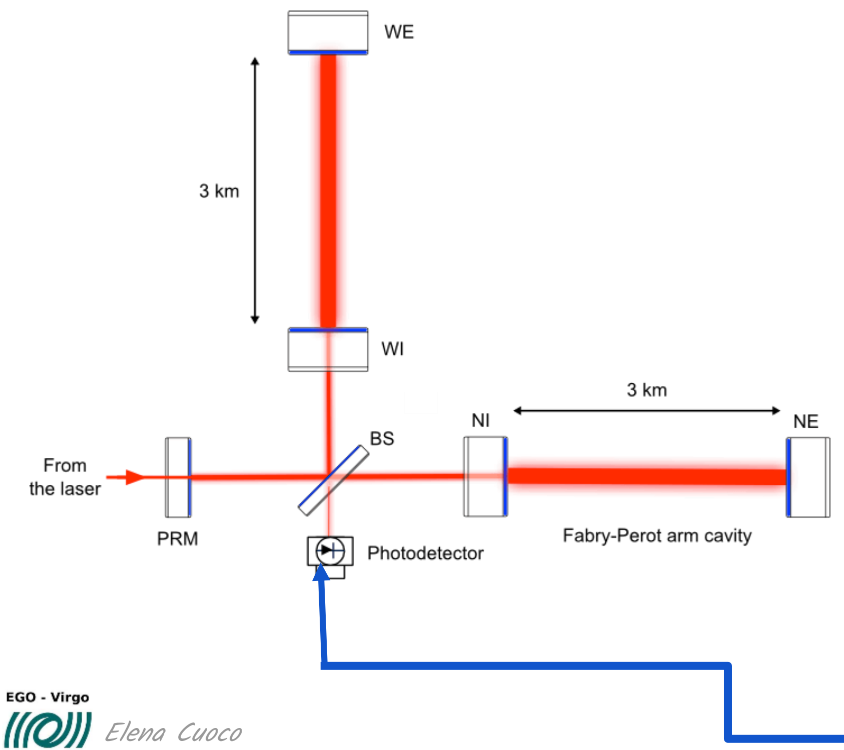
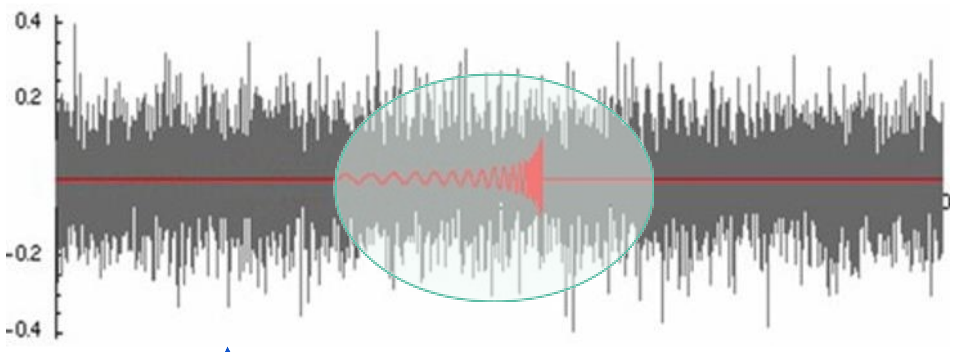


Image from Iess, Cuoco, Morawski, Powell (2020)

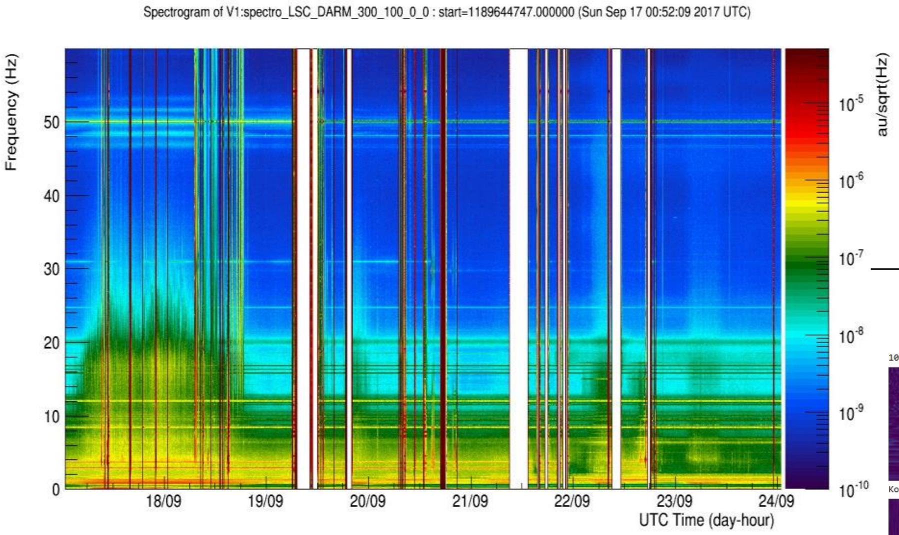
GW detector data



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

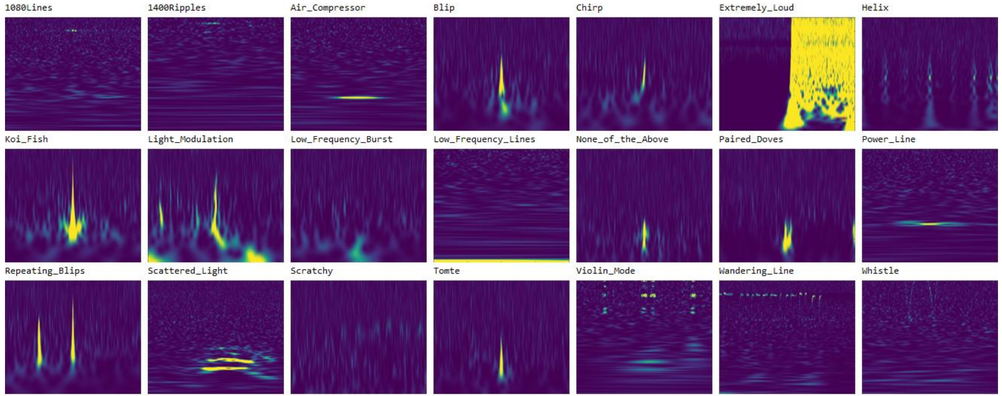


Detector Noise



Broadband

- *Thermal noise*
- *Seismic noise*
- *Electromagnetic noise*
- *Control noise*
- *Environmental noise*
- *Laser noise*
- ...



Glitches

Gravity Spy, Zevin et al (2017) https://www.zooniverse.org/projects/zooniverse/gravity-spy

How we detect transient signals: modeled search

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

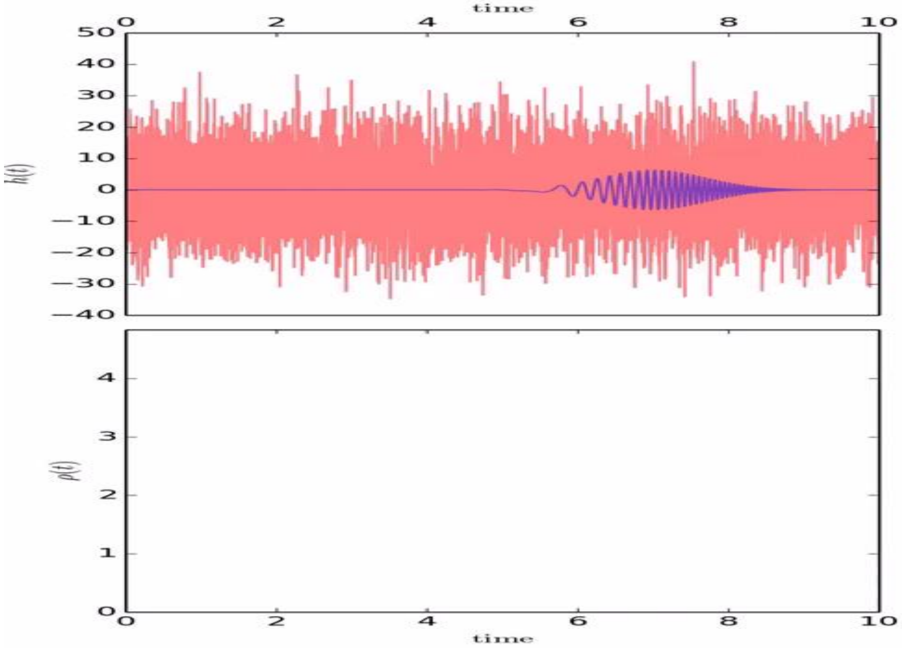
Matched-filter

Data

Template

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

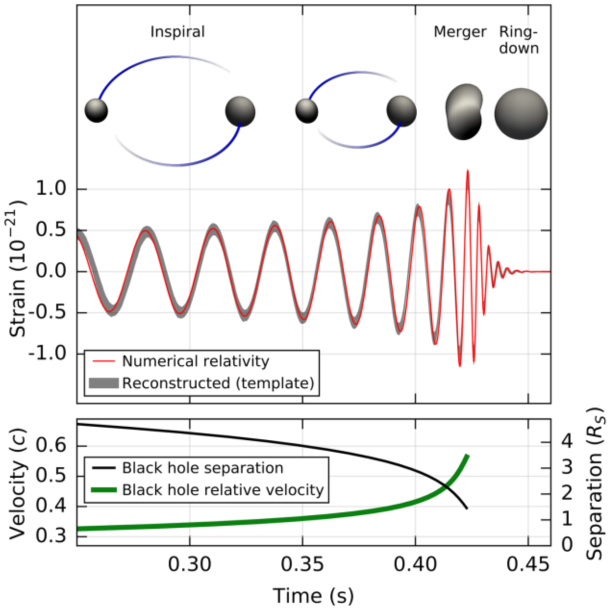
Noise power spectral density

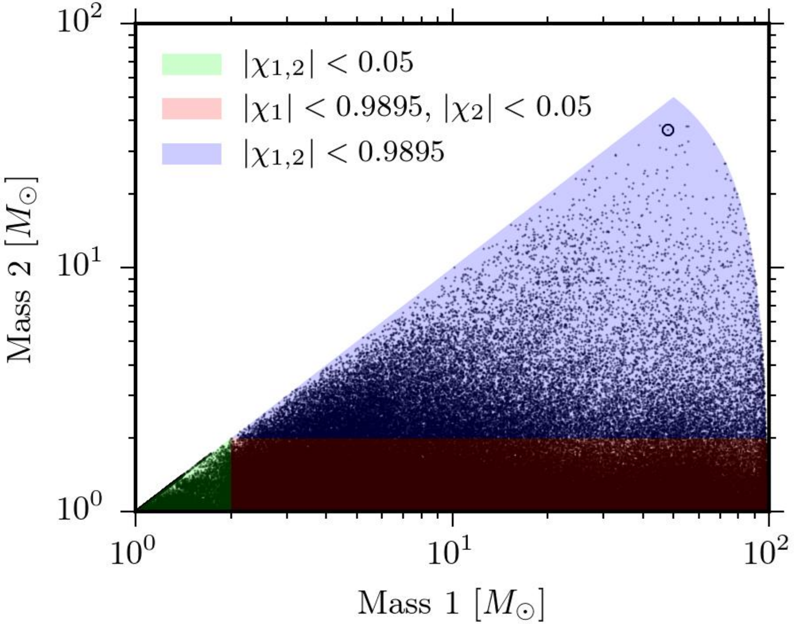


CBC search

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

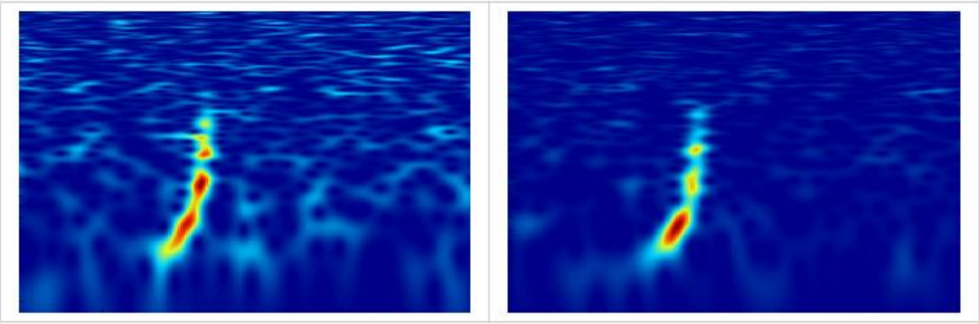
LVC Phys. Rev. X 6 (2016)

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*

Burst search

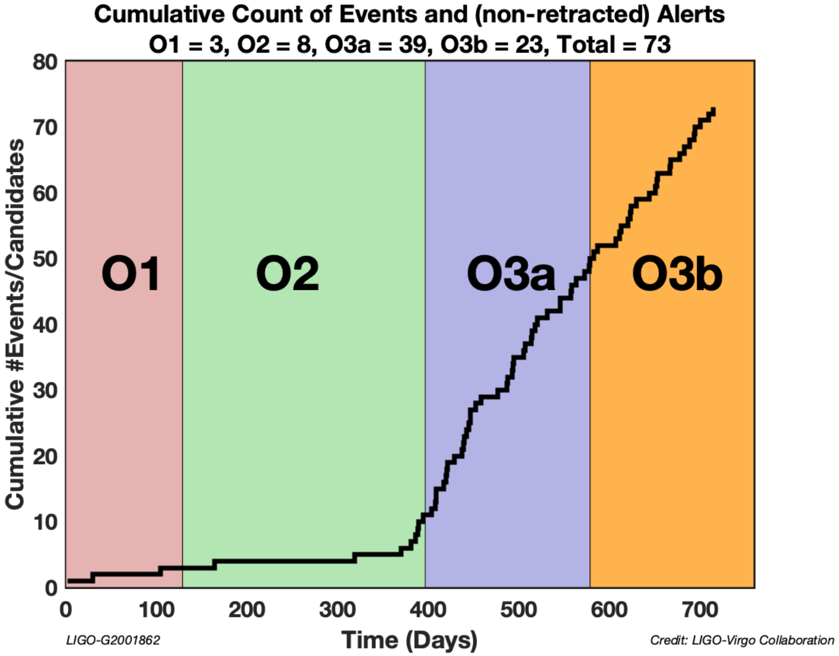
Coherent WaveBurst was used in the first direct detection of gravitational waves (GW150914) by LIGO and is used in the ongoing analyses on LIGO and Virgo data.



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

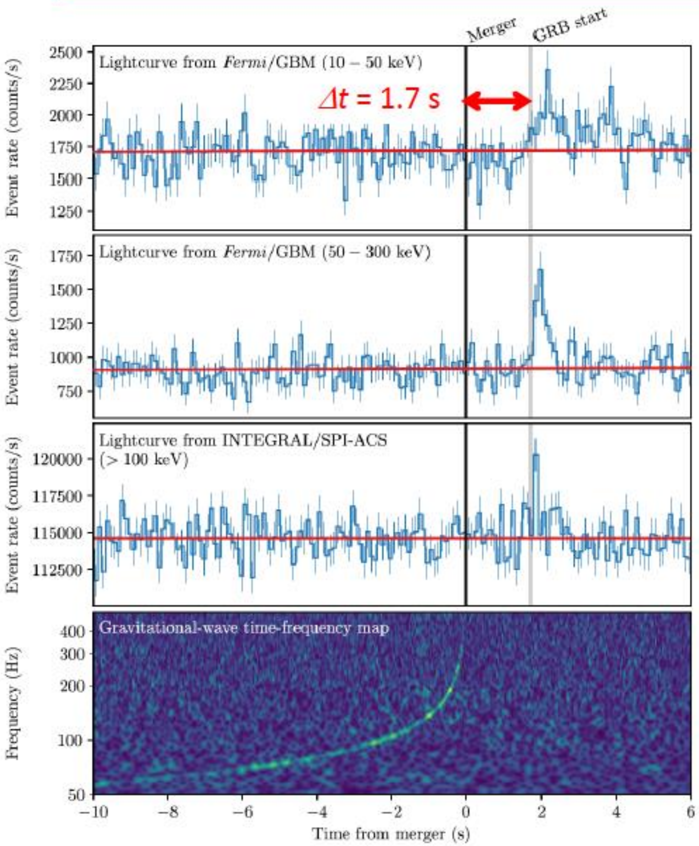
Phys. Rev. D 93, 042004 (2016)
Class.Quant.Grav.25:114029,2008

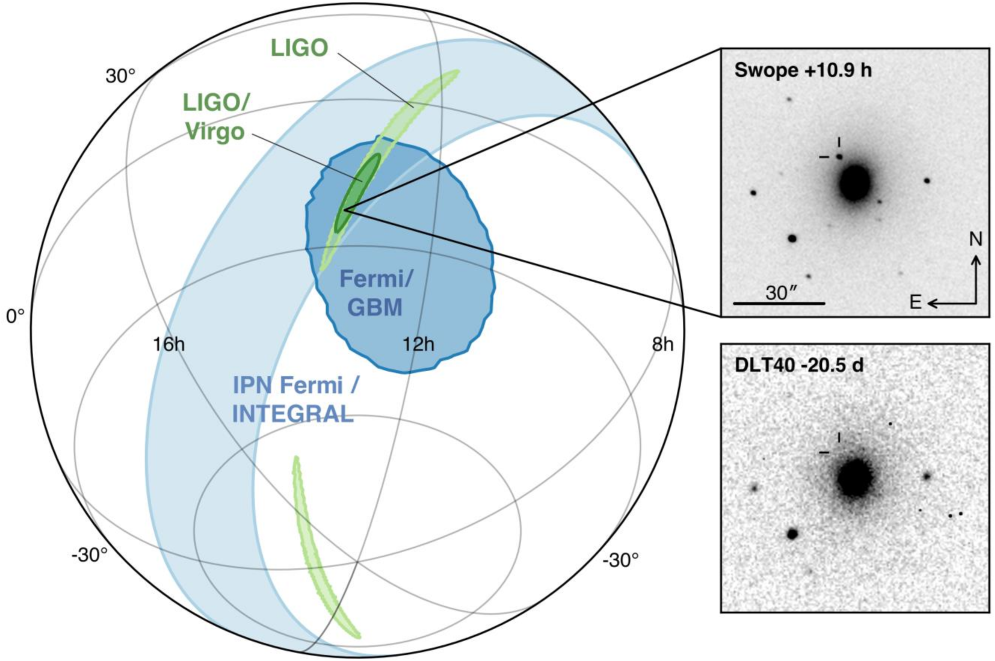
Detection to date



- O1 (~ 4 months): - 3 BBHs .
- O2 (~ 8 months) - 7 BBHs - 1 BNS .
- O3a (~ 6 months) - 1 BNS (GW190425) - 2 BH + lighter object (GW190814, GW190426 152155) - 36 BBHs
- Given the increased sensitivity, the detection of 39 candidate events during O3a is consistent with GWTC-1 (O1 + O2) LVC GWTC-2 paper; arXiv:2010.14527 7
- 23 public alerts released during O3b
- O3b Analysis still on going

GW170817: 17 August 2017, 12:41:04 UT: The Multi-Messenger Astronomy





B.P. Abbott *et al.* (LIGO Scientific Collaboration and Virgo Collaboration)
Phys. Rev. Lett. 119, 161101 – Published 16 October 2017

GW detection → GW candidates → Sky localization → Event validation GW alert → EM observatories

From few minutes to 30 minutes

Low latency analysis

Pipelines running real time	Pipelines assess the significance of candidate	Data Quality evaluated autonomously for initial alert	Initial alert released on order of 1 minute; Notice on order of 10 minutes

- 4 low-latency CBC search pipelines: GstLAL, MBTAOnline, PyCBC Live, and SPIIR
- 1 GW burst search pipeline: cWB (Coherent WaveBurst)

- False Alarm Rate (FAR) based on empirically measured noise properties
- The initial searches focus on detection, not on estimating the parameters of the source

GCN notice

Root		
IVORN	ivo://nasa.gsfc.gcn/LVC#[{T,M}]SYYMMDDabc-{1,2,3}-{Preliminary,Initial,Update,Preliminary-Retraction}	
Role	{observation,test}	
Who		
Date	Time sent (UTC, ISO-8601), e.g. 2018-11-01T22:34:49	
Author	LIGO Scientific Collaboration and Virgo Collaboration	
WhereWhen	Time of signal (UTC, ISO-8601), e.g. 2018-11-01T22:22:46.654437	
What		
GraceID	GraceDb ID: [{T,M}]SYYMMDDabc. Example: MS181101abc	
Packet Type	GCN Notice type: {Preliminary,Initial,Update}	
Notice Type	Numerical equivalent of GCN Notice type: {150,151,152}	
FAR	Estimated false alarm rate in Hz	
Sky Map	URL of HEALPix FITS localization file	
Group	CBC	Burst
Pipeline	{GstLal,MBTAOnline,PyCBC,SPIIR}	{cWB,oLIB}
CentralFreq	N/A	Central frequency in Hz
Duration		Duration of burst in s
Fluence		Gravitational-wave fluence in erg cm^{-2}
BNS, NSBH, BBH, Noise	Probability that the source is a BNS, NSBH, NSBH merger, or terrestrial (i.e., noise) respectively	N/A
HasNS, HasRemnant	Probability, under the assumption that the source is not noise, that at least one of the compact objects was a neutron star, and that the system ejected a nonzero amount of neutron star matter, respectively.	

Public Alert

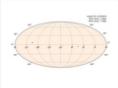
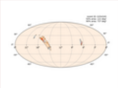
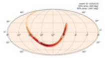
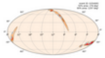
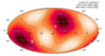
GraceDB — Gravitational-Wave Candidate Event Database

HOME | PUBLIC ALERTS | SEARCH | LATEST | DOCUMENTATION

LIGO/Virgo O3 Public Alerts

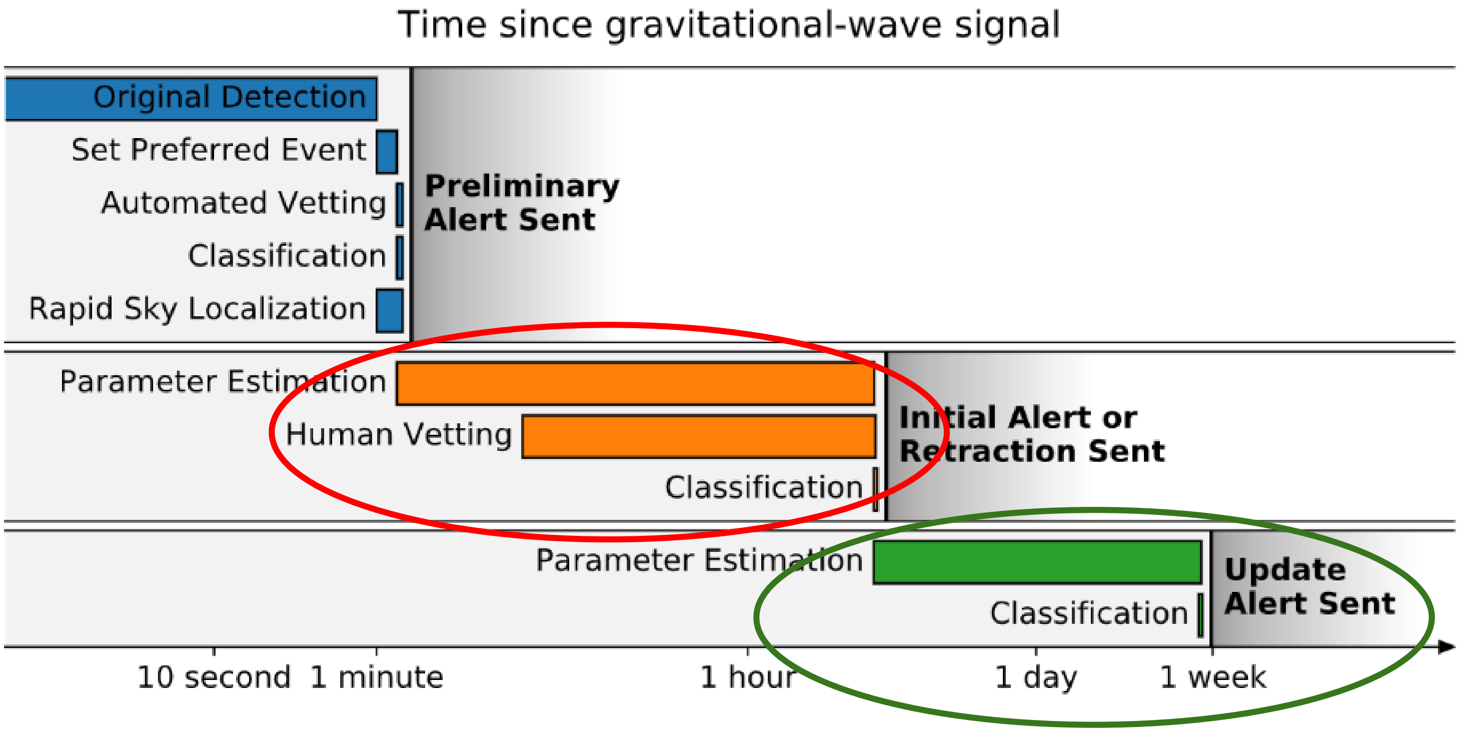
Detection candidates: 35

SORT: EVENT ID (A-Z)

Event ID	Possible Source (Probability)	UTC	GCN	Location	FAR	Comments
S191117j	NSBH (>99%)	Nov. 17, 2019 06:08:22 UTC	GCN Circulars Notices | VOE		1 per 2.8433e+10 years	RETRACTED
S191110af		Nov. 10, 2019 23:06:44 UTC	GCN Circulars Notices | VOE	No public skymap image found.	1 per 12.681 years	RETRACTED
S191110x	MassGap (>99%)	Nov. 10, 2019 18:08:42 UTC	GCN Circulars Notices | VOE		1 per 1081.7 years	RETRACTED
S191109d	BBH (>99%)	Nov. 9, 2019 01:07:17 UTC	GCN Circulars Notices | VOE		1 per 2.062e+05 years	
S191105e	BBH (95%), Terrestrial (5%)	Nov. 5, 2019 14:35:21 UTC	GCN Circulars Notices | VOE		1 per 1.3881 years	
S190930t	NSBH (74%), Terrestrial (26%)	Sept. 30, 2019 14:34:07 UTC	GCN Circulars Notices | VOE		1 per 2.0536 years	

https://gracedb.ligo.org/superevents/public/O3/

GW alert system

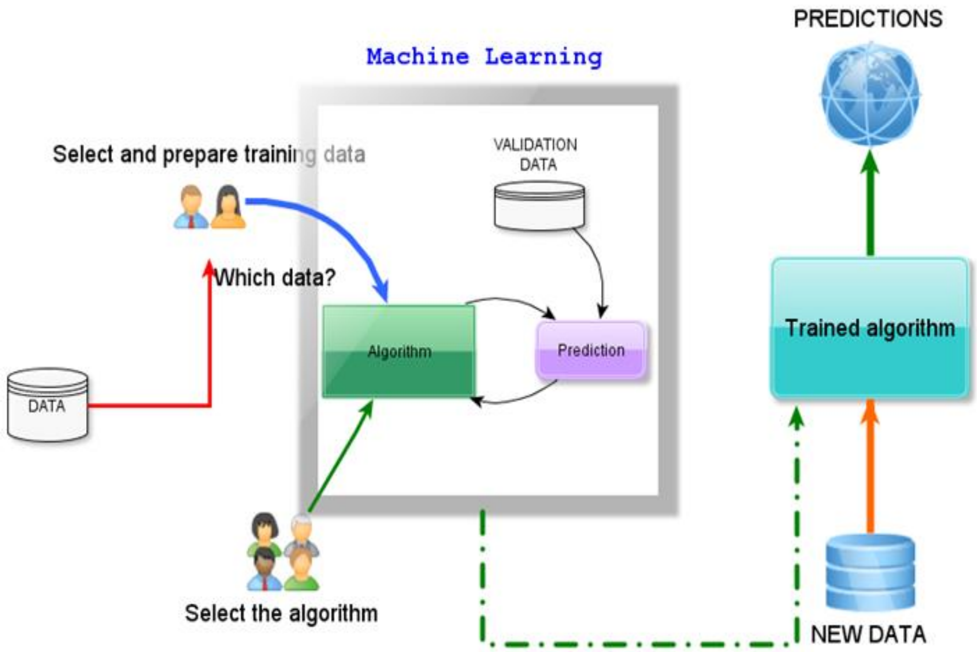


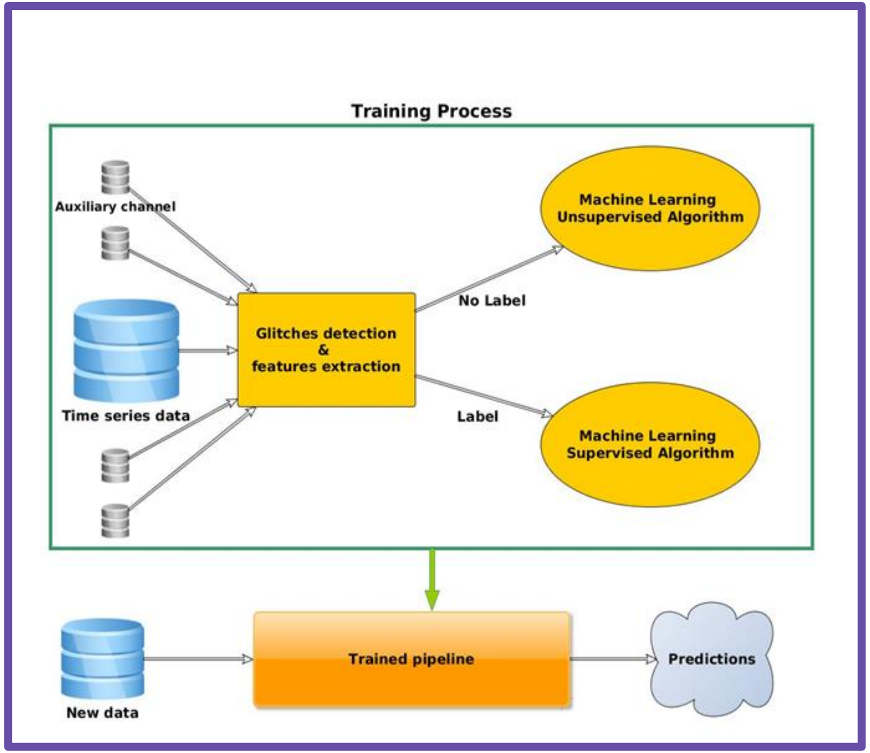
How Machine Learning can help

Data conditioning	Signal Detection/Classification/PE
• Identify Non linear noise coupling • Extract useful features to clean data	• A lot of fake signals due to noise • Fast alert system • Manage parameter estimation

You can find more here:
E.Cuoco, J.Powell, M. Cavaglià et al https://doi.org/10.1088/2632-2153/abb93a

Machine learning workflow for signal classification

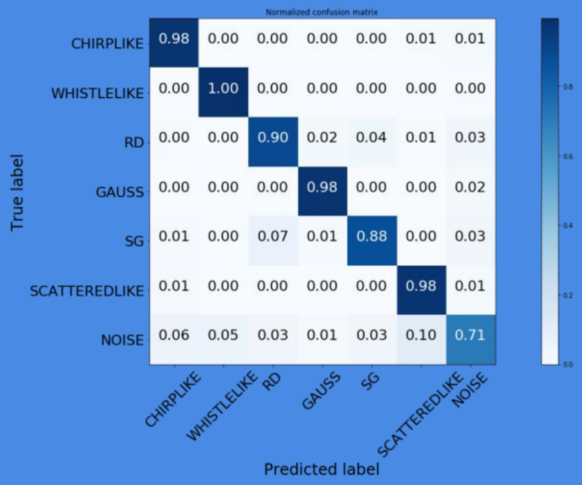




Outline

- Time-series based classification
- Image based classification with Deep Learning
- Application on Simulated data
- Application on Real Data

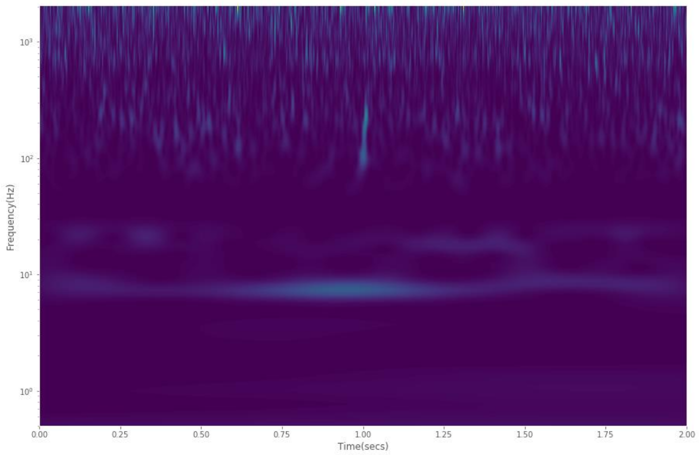
Transient noise (glitch) classification



	CHIRPLIKE	WHISTLELIKE	RD	GAUSS	SG	SCATTEREDLIKE	NOISE
CHIRPLIKE	0.98	0.00	0.00	0.00	0.00	0.01	0.01
WHISTLELIKE	0.00	1.00	0.00	0.00	0.00	0.00	0.00
RD	0.00	0.00	0.90	0.02	0.04	0.01	0.03
GAUSS	0.00	0.00	0.00	0.98	0.00	0.00	0.02
SG	0.01	0.00	0.07	0.01	0.88	0.00	0.03
SCATTEREDLIKE	0.01	0.00	0.00	0.00	0.00	0.98	0.01
NOISE	0.06	0.05	0.03	0.01	0.03	0.10	0.71

Two different approaches

- Images
- Time series



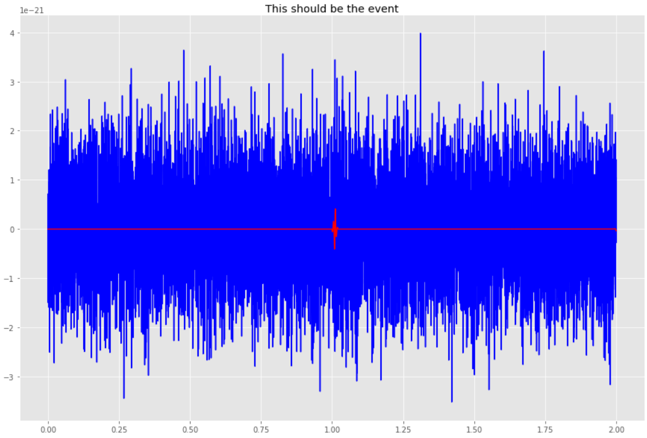
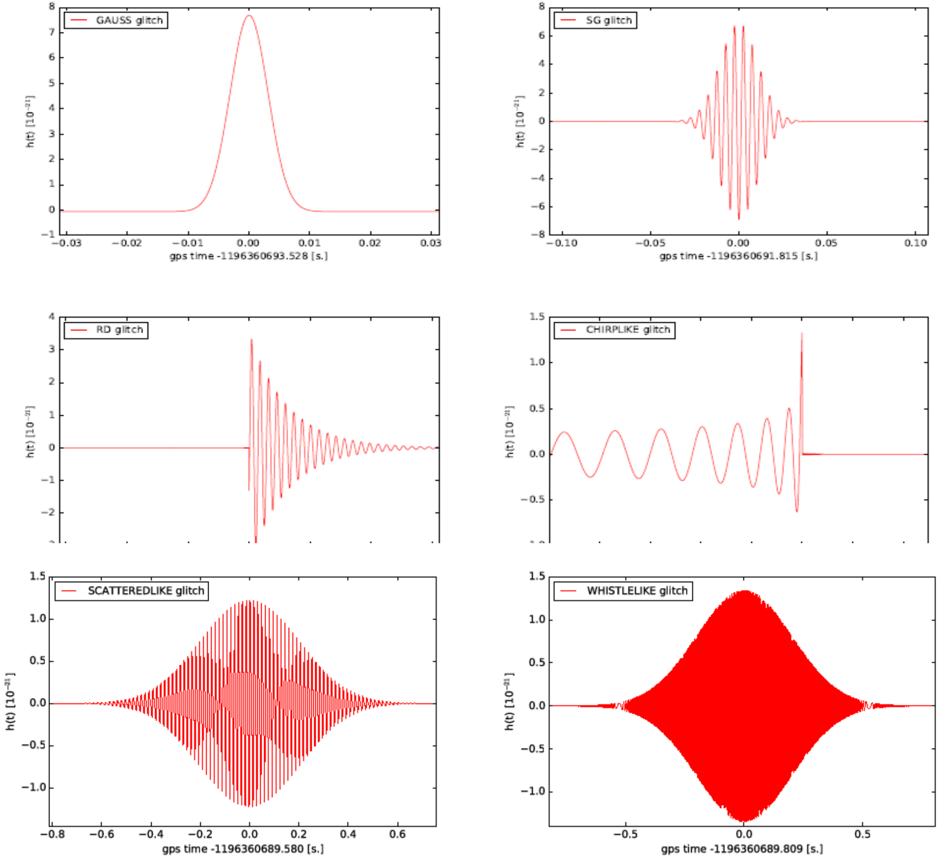


Image-based deep learning for classification of noise transients in gravitational wave detectors, Massimiliano Razzano, Elena Cuoco, Class.Quant.Grav. 35 (2018) no.9, 095016

Wavelet-based Classification of Transient Signals for Gravitational Wave Detectors, Elena Cuoco, Massimiliano Razzano and Andrei Utina, #1570436751 accepted reviewed paper at EUSIPCO2018

How we started...
Data simulation: signal families + Detector colored Noise



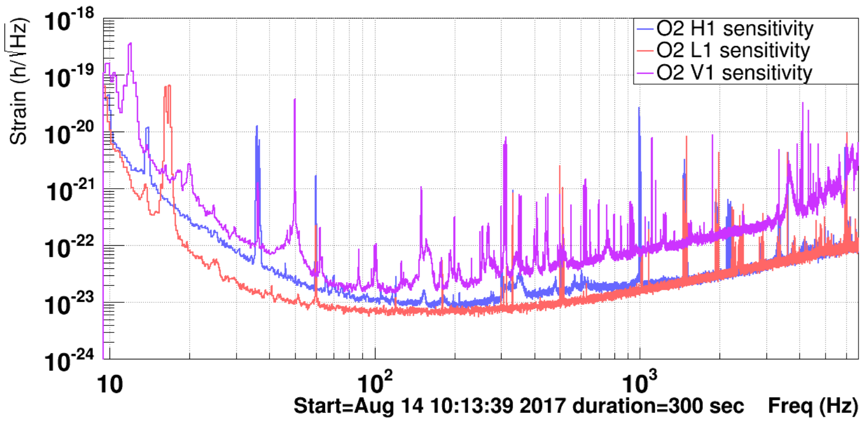
Waveform
Gaussian
Sine-Gaussian
Ring-Down
Chirp-like
Scattered-like
Whistle-like
NOISE (random)

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

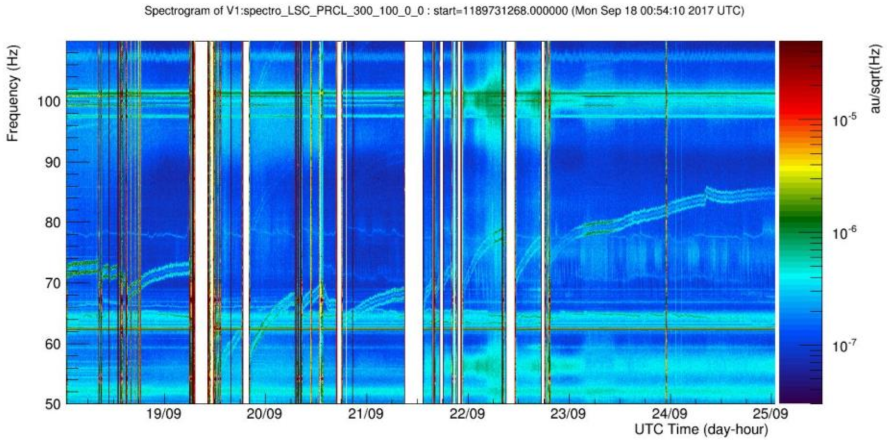
Razzano M., Cuoco E. CQG-104381.R3

Data preprocessing

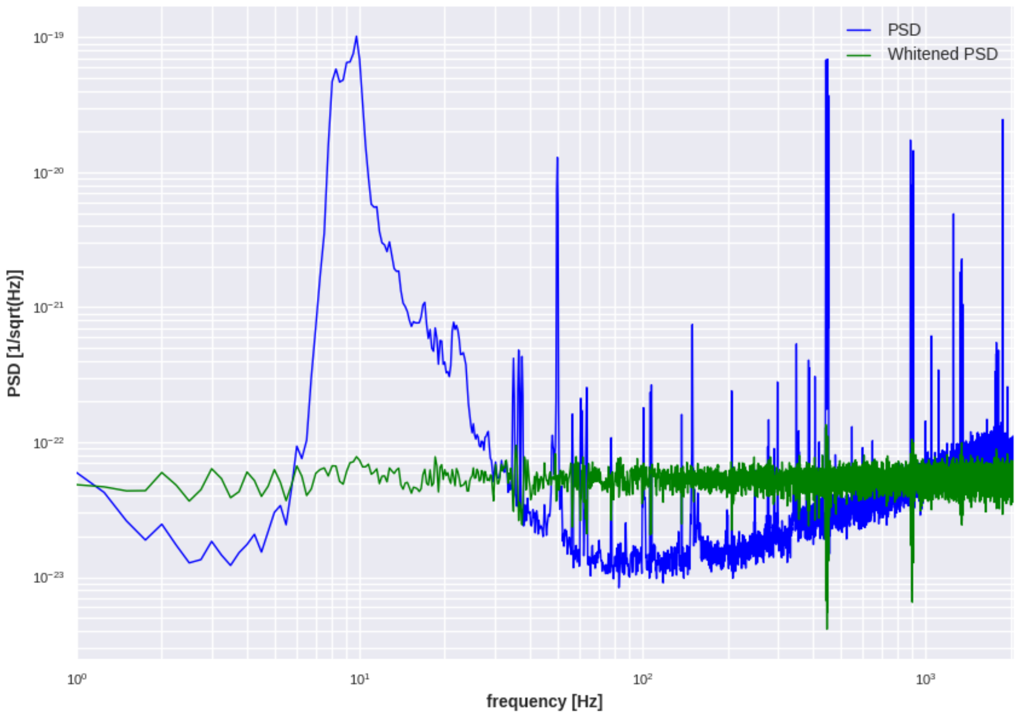
- Many spectral features



- Non stationary and non linear noise



Whitening process

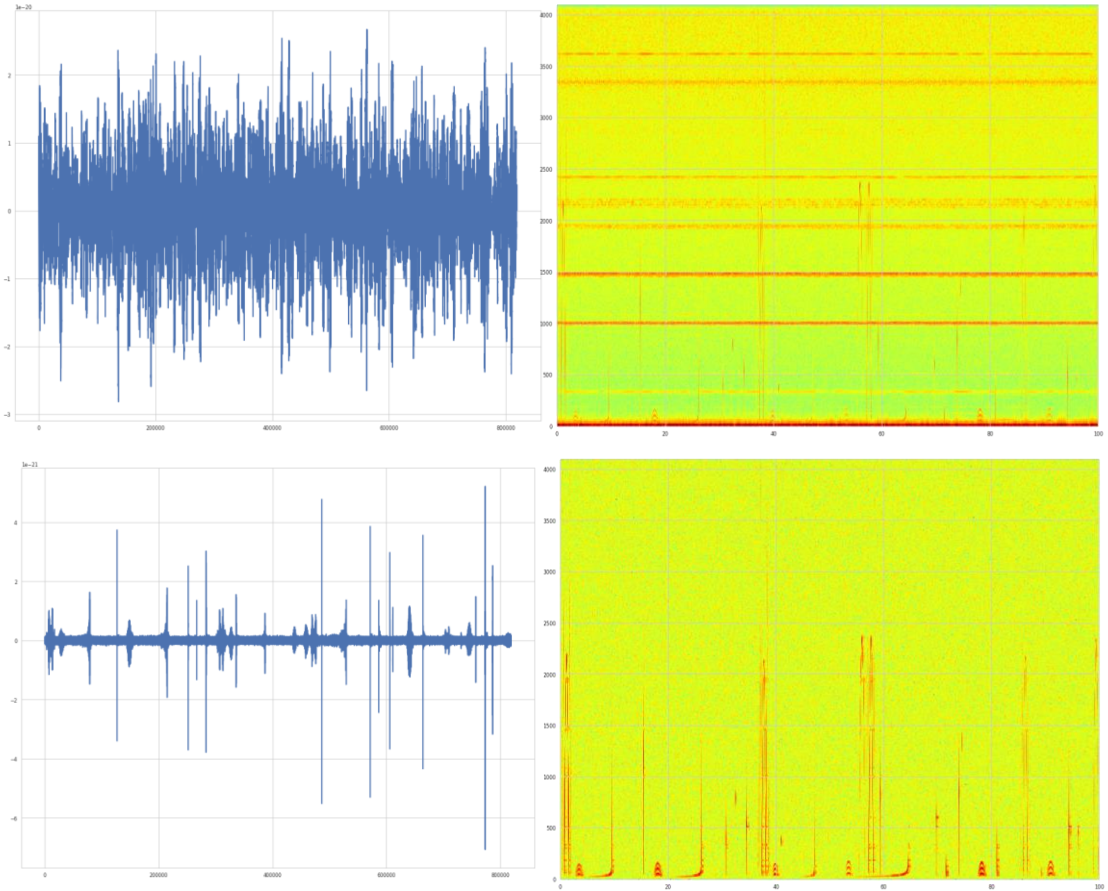


On-line power spectra identification and whitening for the noise in interferometric gravitational wave detectors

DOI 10.1088/0264-9381/18/9/309

Classical and Quantum Gravity

Signals in whitened data

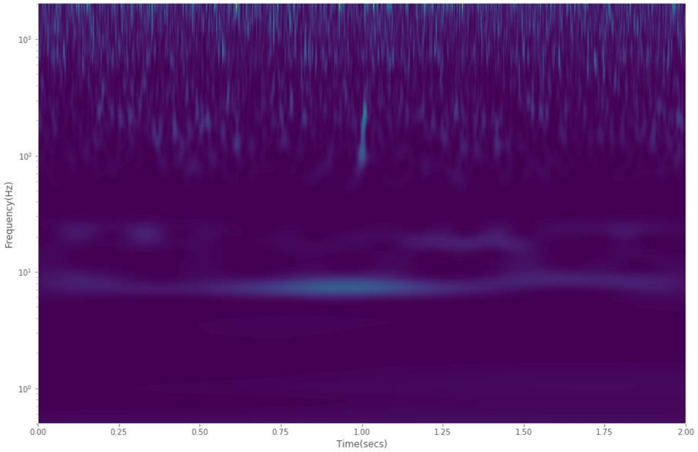


Not Whitened

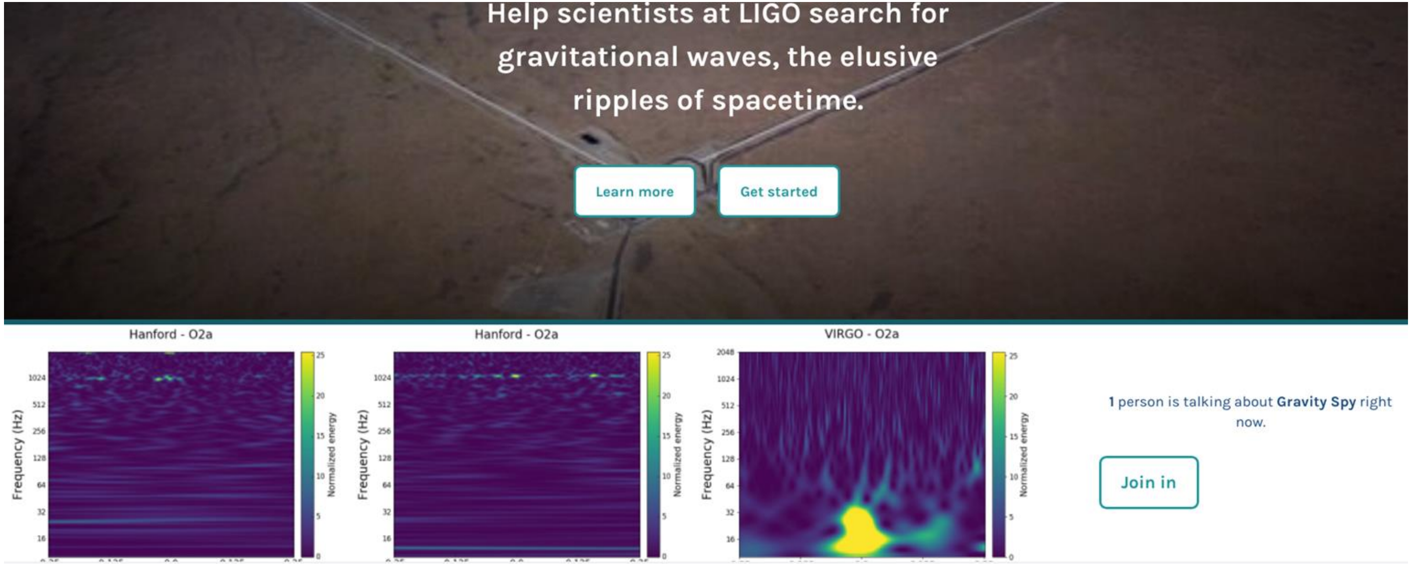
Whitened

Why Image-based classification

- Images as input data



Glitches and citizen science



www.gravityspy.org

Citizen scientists contribute to classify glitches

More details in Zevin+17 10.1088/1361-6382/aa5cea https://doi.org/10.1016/j.ins.2018.02.068

Building the images

Spectrogram for each image

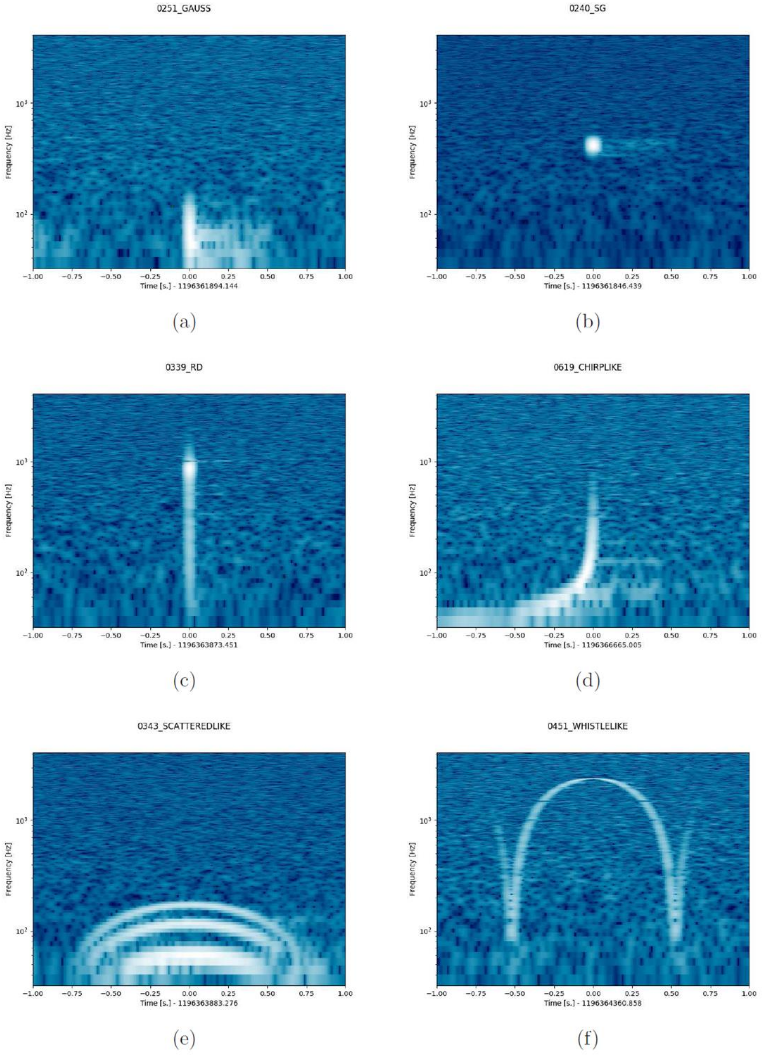
2-seconds time window to highlight fatures in long glitches

Data is whitened

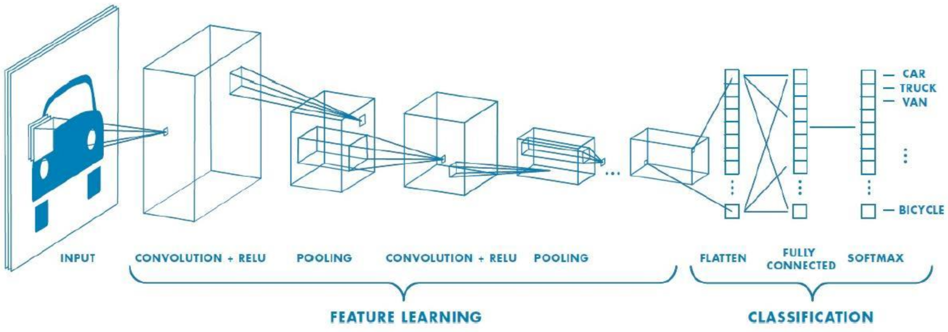
Optional contrast stretch

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



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

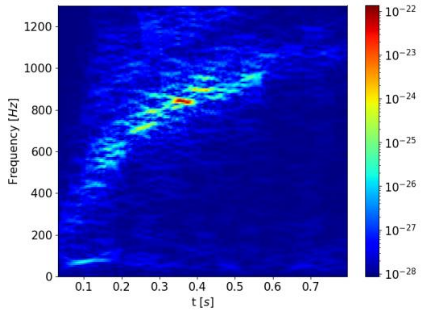
Kernel

0	-1	0
-1	5	-1
0	-1	0

114				

2-D CNN

Spectrogram images



Alberto Iess courtesy

Pipeline structure

Input GW data

- Image processing
- Time series whitening
- Image creation from time series (FFT spectrograms)
- Image equalization & contrast enhancement

Classification

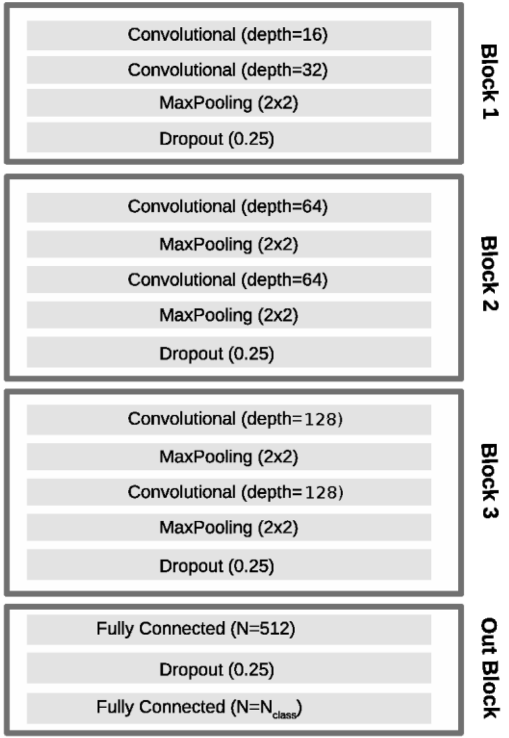
- A probability for each class, take the max
- Add a NOISE class to crosscheck glitch detection

Network layout

- Tested various networks, including a 4-block layers

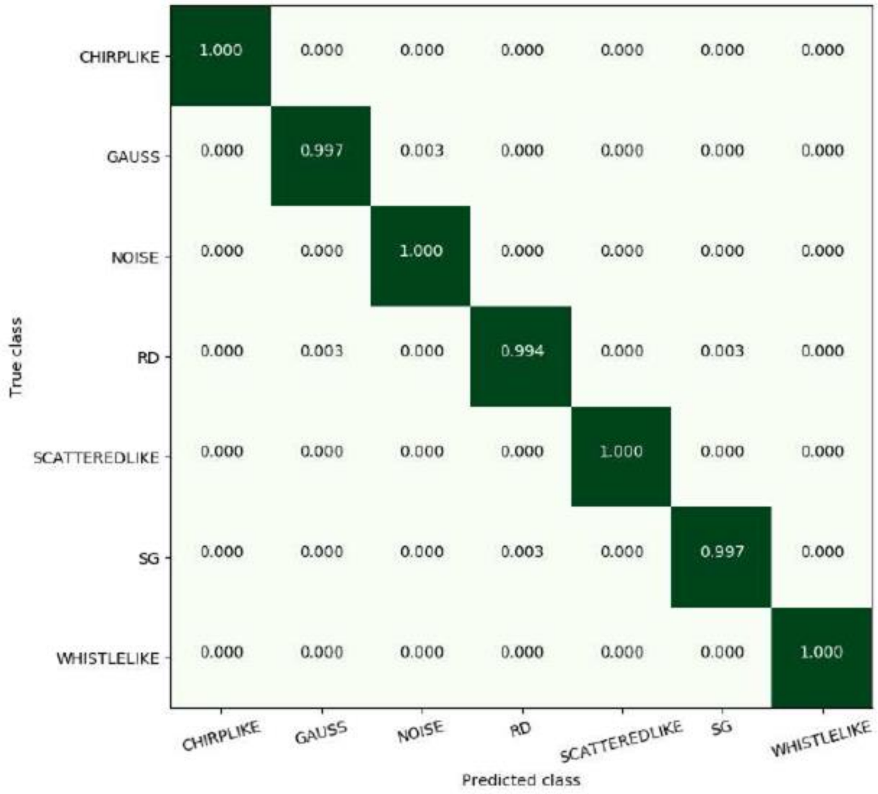
Run on GPU Nvidia GeForce GTX 780

- 2.8k cores, 3 Gb RAM)
- Developed in Python + CUDA-optimized libraries



M. Razzano courtesy

Classification accuracy



Deep CNN

Normalized Confusion Matrix

Razzano M., Cuoco E. CQG-104381.R3

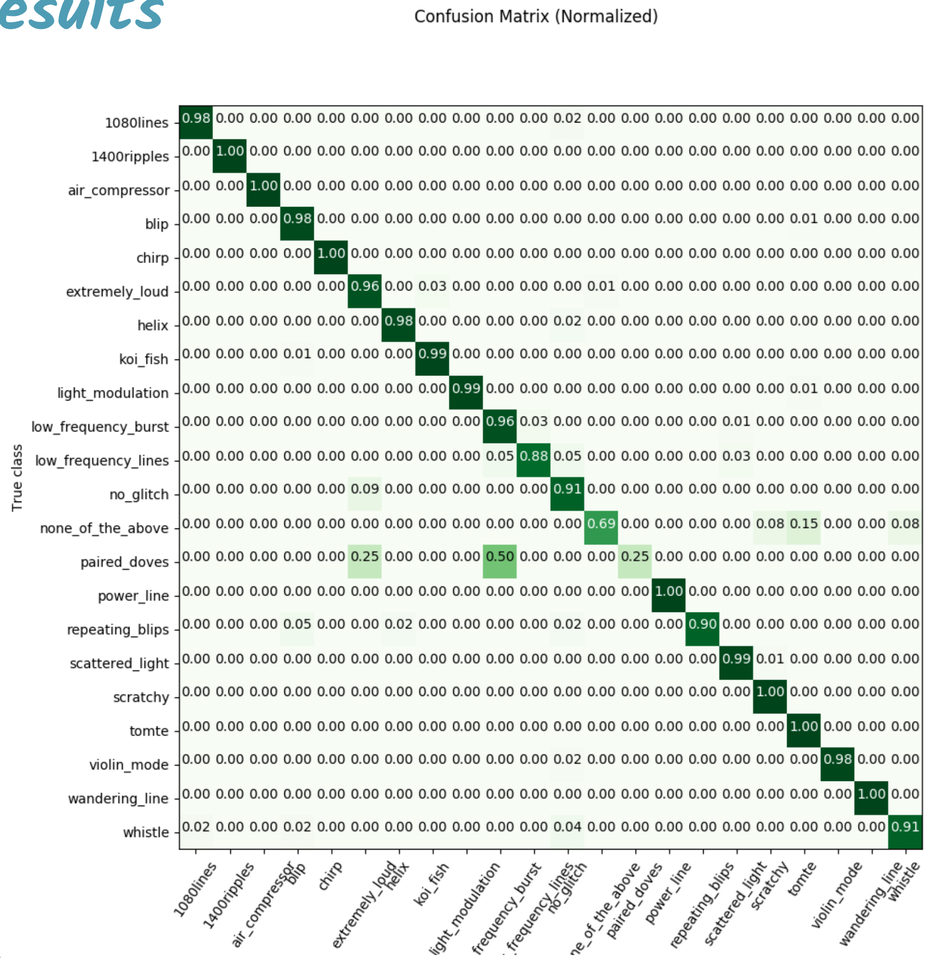
Application Test on Real data: O1 run

Glitch name	# in H1	# in L1
Air compressor	55	3
Blip	1495	374
Chirp	34	32
Extremely Loud	266	188
Helix	3	276
Koi fish	580	250
Light Modulation	568	5
Low_frequency_burst	184	473
Low_frequency_lines	82	371
No_Glitch	117	64
None_of_the_above	57	31

Dataset from GravitySpy images

Paired doves	27	-
Power_line	274	179
Repeating blips	249	36
Scattered_light	393	66
Scratchy	95	259
Tomte	70	46
Violin_mode	179	-
Wandering_line	44	-
Whistle	2	303

Results

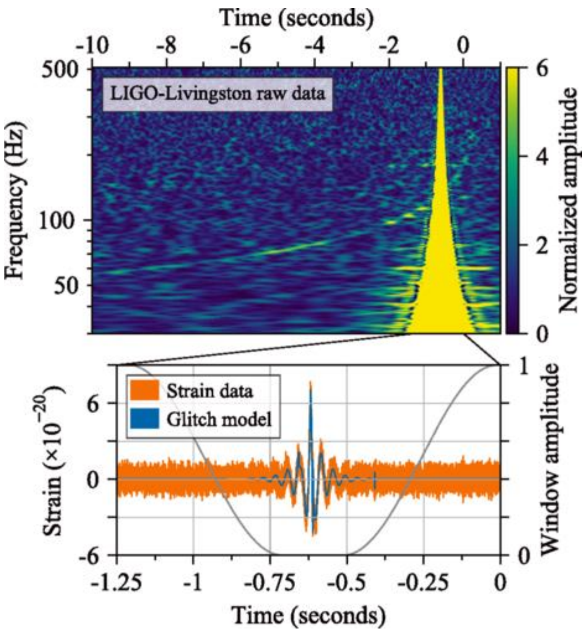


Full CNN stack

Consistent with Zevin+2017

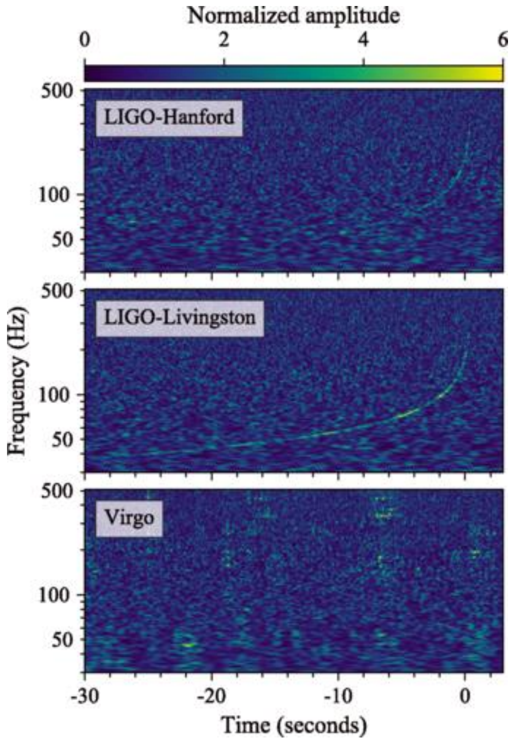
The importance of glitch analysis

Ligo Livingston



Glitch mitigation

GW 170817

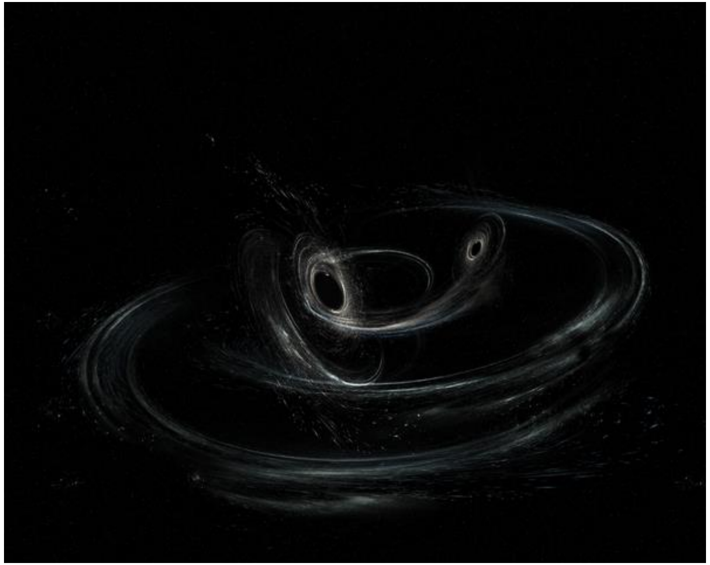


Abbott et al. (2017)

Alberto Iess courtesy

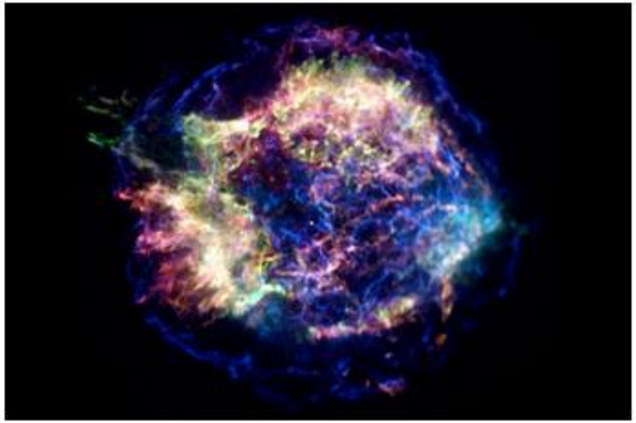
GW Astrophysical signal classification

Compact Binary Coalescences



Credit
LIGO/Caltech/MIT/Sonoma State (Aurore Simonnet)

Core Collapse Supernovae



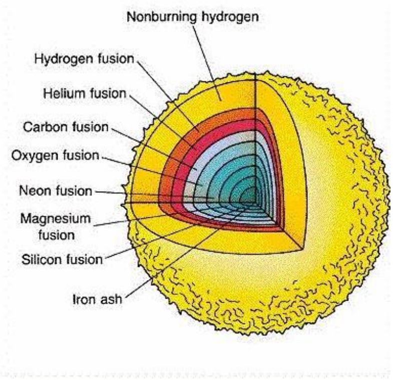
This is Cassiopeia A, a core collapse supernova remnant with a neutron star in its center. Located in the Milky Way only some 11,000 light-years away from Earth, it originally exploded about 330 years ago.

NASA/CXC/UNAM/IOFFE/D. PAGE, P. SHTERNIN ET AL

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



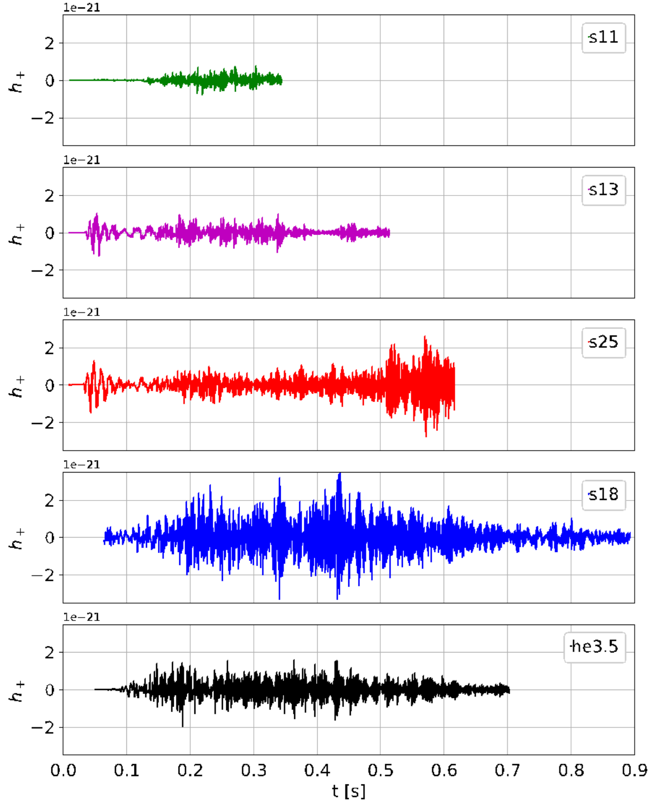
GW emission Process	Potential explosion mechanism: MHD mechanism (rapid rotation)	Neutrino mechanism (slow/no rotation)	Acoustic mechanism (slow/no rotation)
Rotating collapse and Bounce	Strong	None/weak	None/weak
3D rotational instabilities	Strong	None	None
Convection & SASI	None/weak	Weak	Weak
PNS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

Ott et al. (2017)

Alberto Iess courtesy

Core-Collapse Supernovae models

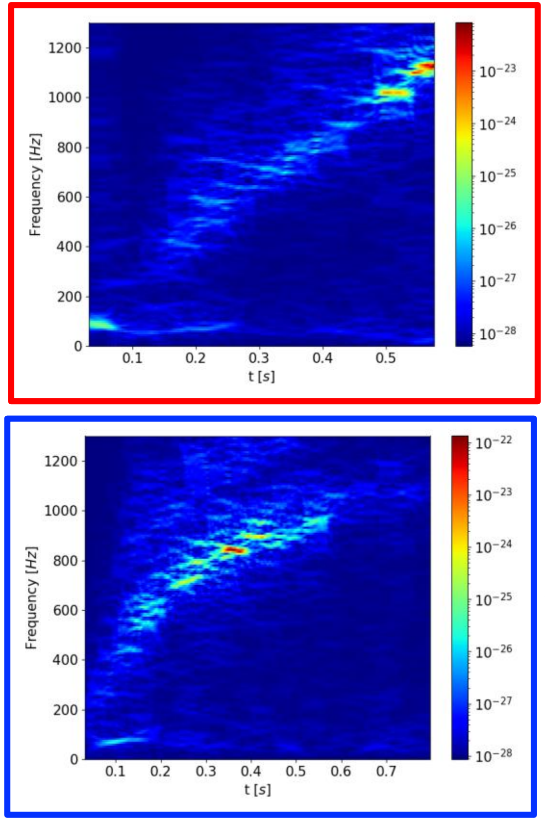
- *Andresen s11*: Low amplitude, non-exploding, peak emission at lower frequencies
- *Radice s13*: Non-exploding, lower amplitudes
- *Radice s25*: Late explosion time, standing accretion shock instability (SASI), high peak frequency
- *Powell s18*: High peak frequency, exploding model
- *Powell He3.5*: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

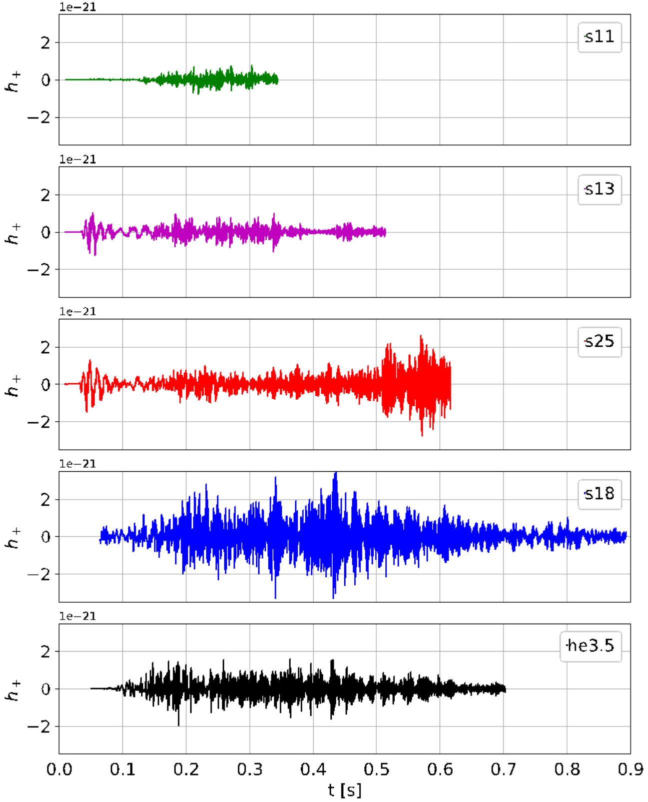


Iess, Cuoco, Morawski, Powell (preprint 2020)

Alberto Iess courtesy

Time frequency waveforms





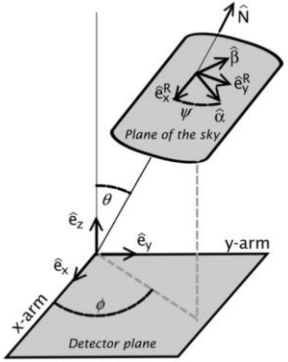
Alberto Iess courtesy

Iess, Cuoco, Morawski, Powell,
https://doi.org/10.1088/2632-2153/ab7d31

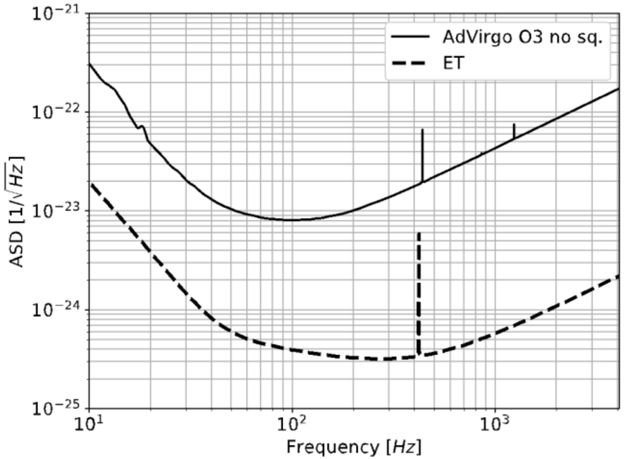
MDC and CCSN GW simulations

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

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



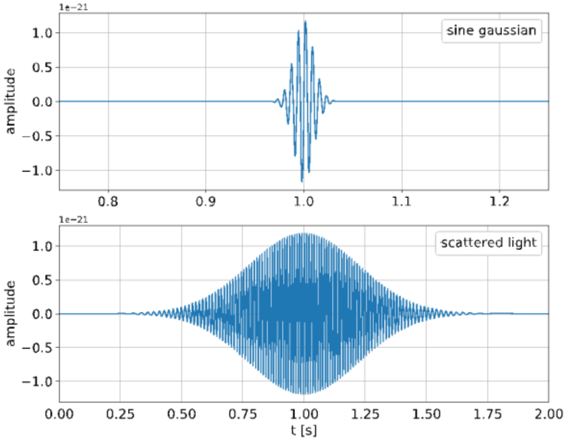
Schutz (2011)



SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

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

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

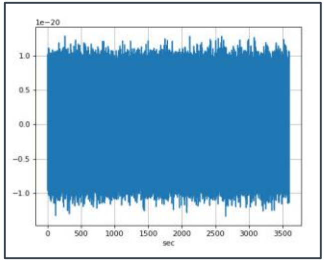


BACKGROUND STRAIN : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

Alberto Iess courtesy

Pipeline Workflow

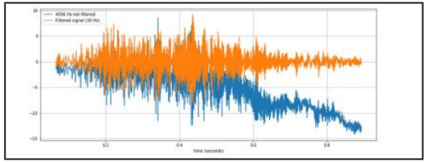
STRAIN



WAVEFORMS

+

RESAMPLING, FILTERING



WHITENING & TRIGGER GENERATION (WDF)

TRAINING

MACHINE-LEARNING CLASSIFIER

SIGNAL

GLITCH TYPE

Alberto Iess courtesy

Wavelet Detection Filter (WDF) as event trigger generator

WDF *(Cuoco et al. 2015)*

- Whitening
- Wavelet decomposition

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

$$t = \sqrt{2\log N}\hat{\sigma}$$ (Donoho, Johnstone 1994)

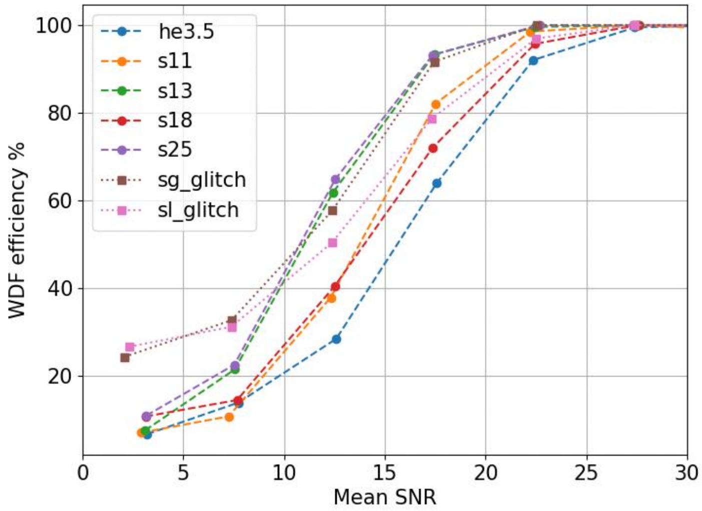
- Trigger generation based on threshold (tunable). WDF signal-to-noise ratio:

$$\mathrm{SNR}_w = \frac{\sum_i w_i^2}{\hat{\sigma}}$$

- Window 0.25 s, overlap 0.0625 s

GPS TIMES OF TRIGGERS

WDF efficiency vs. injection SNR

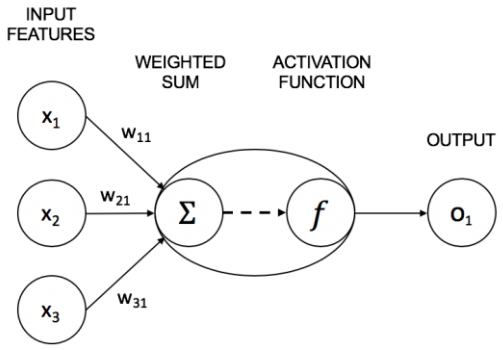


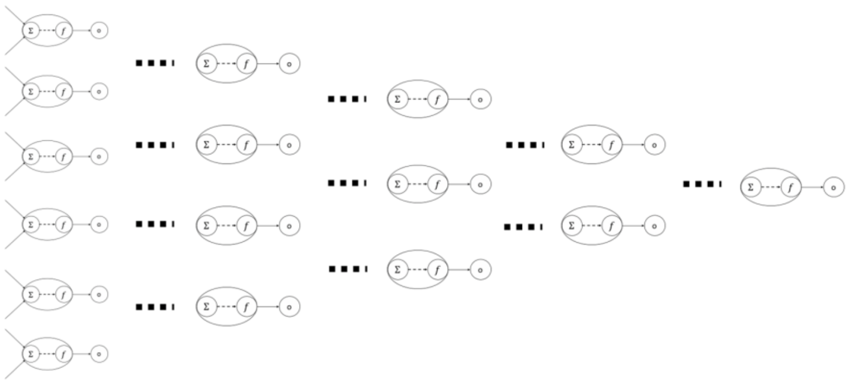
Iess, Cuoco, Morawski, Powell, https://doi.org/10.1088/2632-2153/ab7d31

Alberto Iess courtesy

Neural Network architecture

- ***Train, Validation, Test sets: 60%, 10%, 30%***
- 3 or 4 Convolutional layers
- Activation function *f:* ReLU
- Adam optimizer, learning rate α = 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

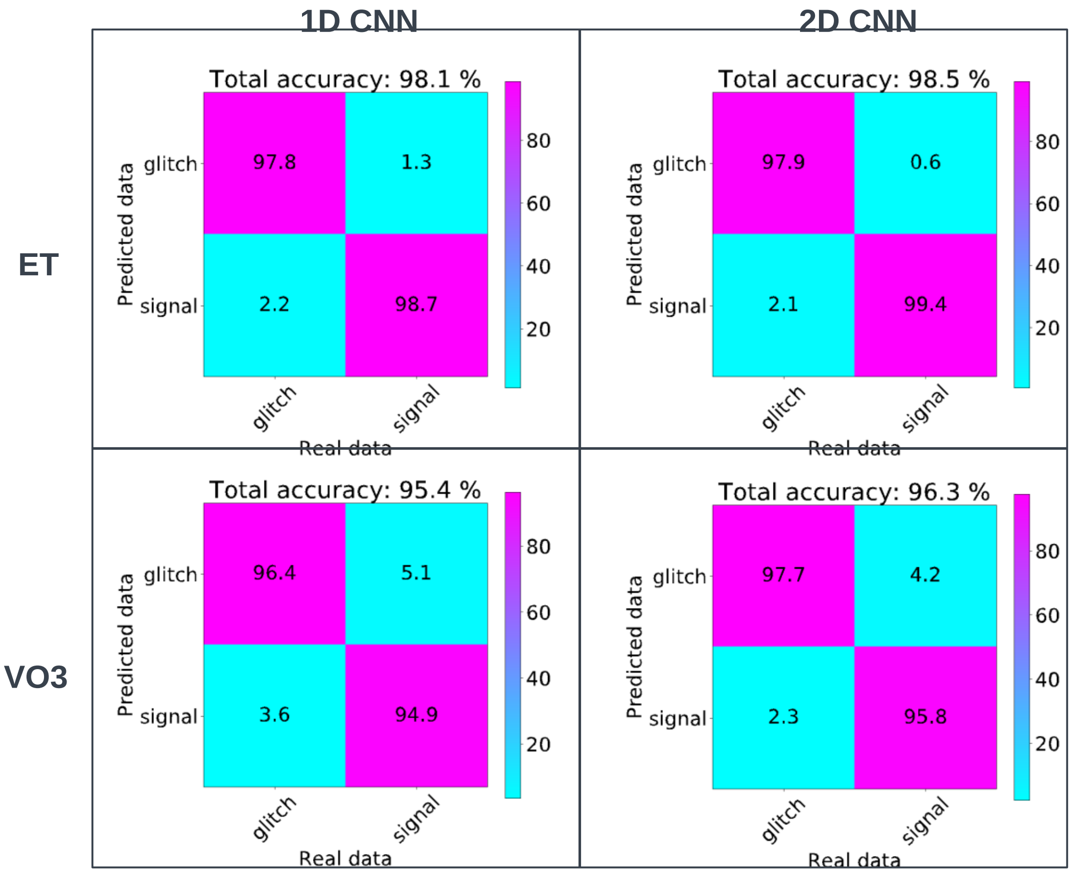
GPU: Tesla k40

Alberto Iess courtesy

Binary Classification

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

Test samples → TRAINED CNN MODEL → SIGNAL / GLITCH



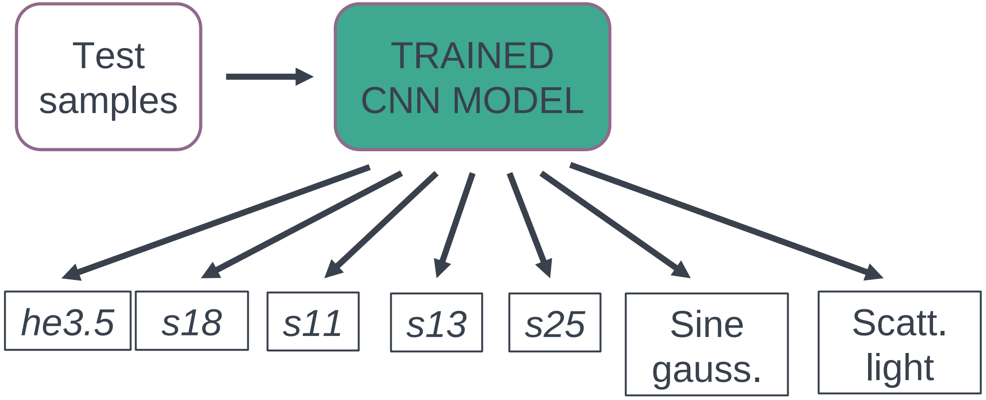
- Training time: ~ 30 min

Alberto Iess courtesy

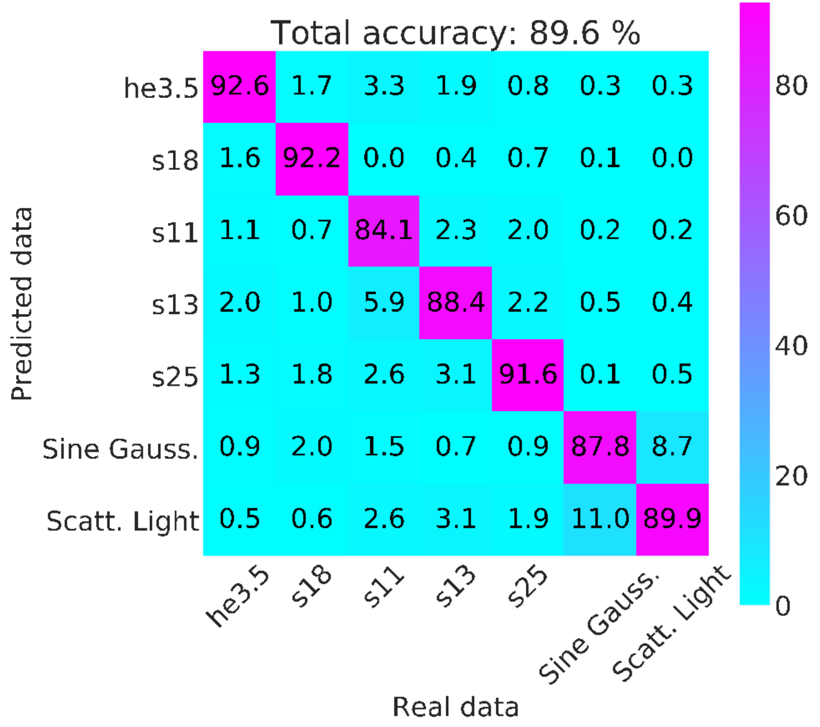
Iess, Cuoco, Morawski, Powell, https://doi.org/10.1088/2632-2153/ab7d31

MultiLabel classification

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



ET, MERGED 1D & 2D CNN



COMPLEX TASK → LONGER TRAINING (> 1 hr)

Alberto Iess courtesy

Iess, Cuoco, Morawski, Powell, https://doi.org/10.1088/2632-2153/ab7d31

REAL NOISE FROM O2 SCIENCE RUN

- 44 segments (4096s per segment) from O2 science run.
- Added m39, y20, s18np models (Powell, Mueller 2020).
- **<u>Fixed distance of 1 kpc</u>**.
- 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.

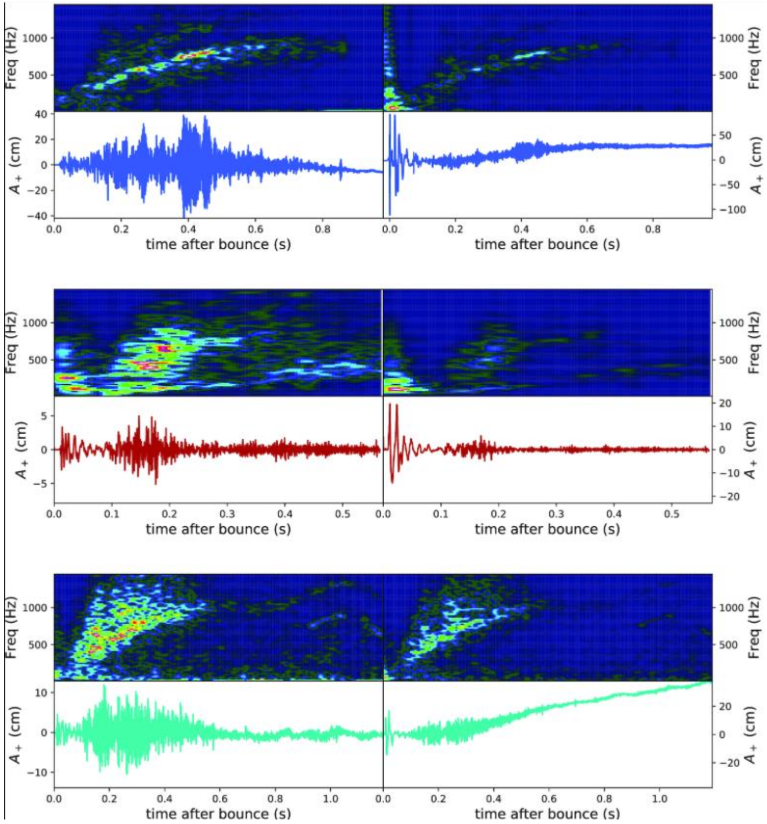
- *Powell y20*: non-rotating, 20 solar mass Wolf-Rayet star with solar metallicity.

- *Powell m39*: rapidly rotating Wolf-Rayet star with an initial helium star mass of 39 solar masses

m39

s18np

y20



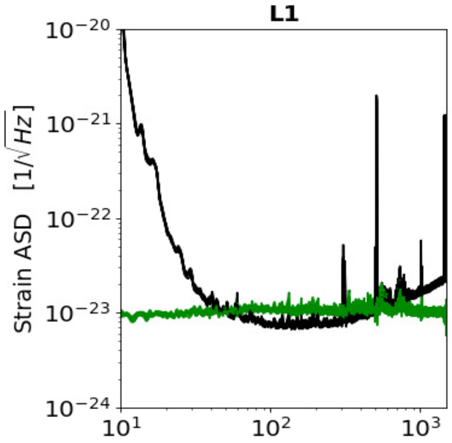
Powell and Müller (2020)

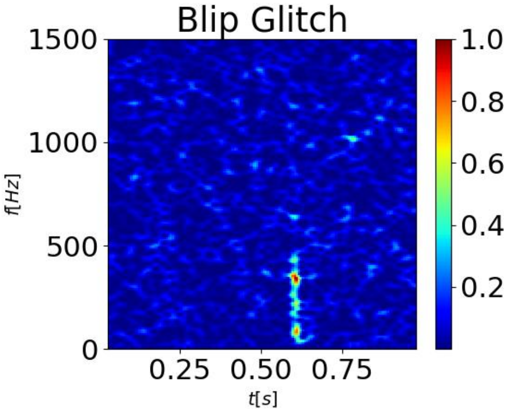
Alberto Iess courtesy

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.

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



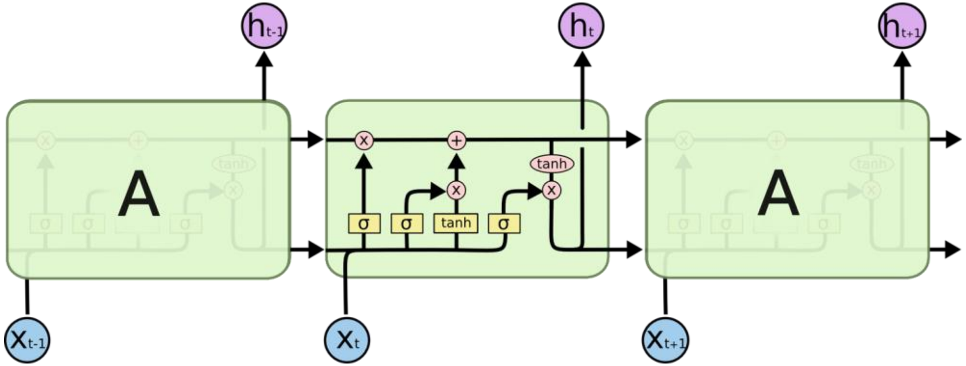


CCSN Classification on Simulated and Real O2 Data with CNNs and LSTMs
***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, submitted to MLST*

LONG SHORT TERM MEMORY (LSTM) NETWORK

Pros

- Keeps track of dependencies in time-series.
- Avoids the *Vanishing Gradient* problem.



Cons

- Many parameters to train, long training times.
- Hyperparameter tuning can be challenging.

Prediction

$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

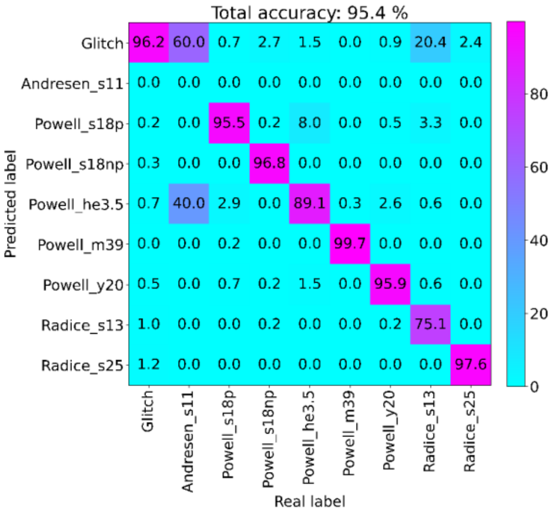
***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, submitted to MLST*

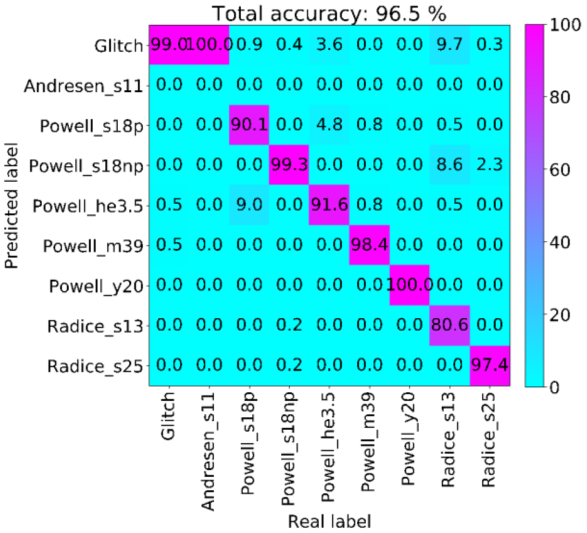
MULTILABEL CLASSIFICATION ON REAL O2 NOISE (SINGLE ITF, LIGO H1, DIFFERENT MODELS)

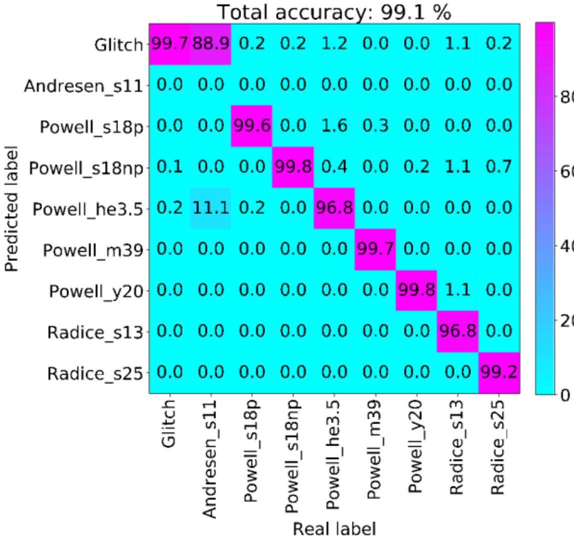
- **<u>Bi-LSTM</u>**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs

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

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



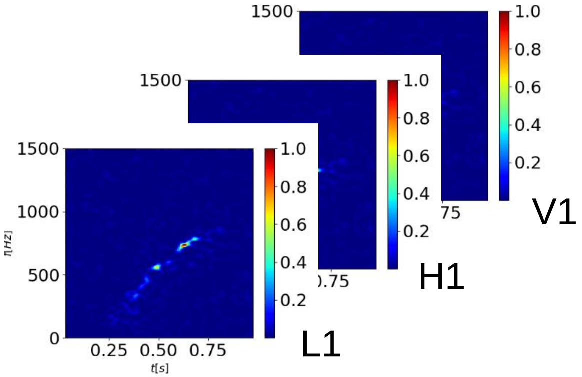


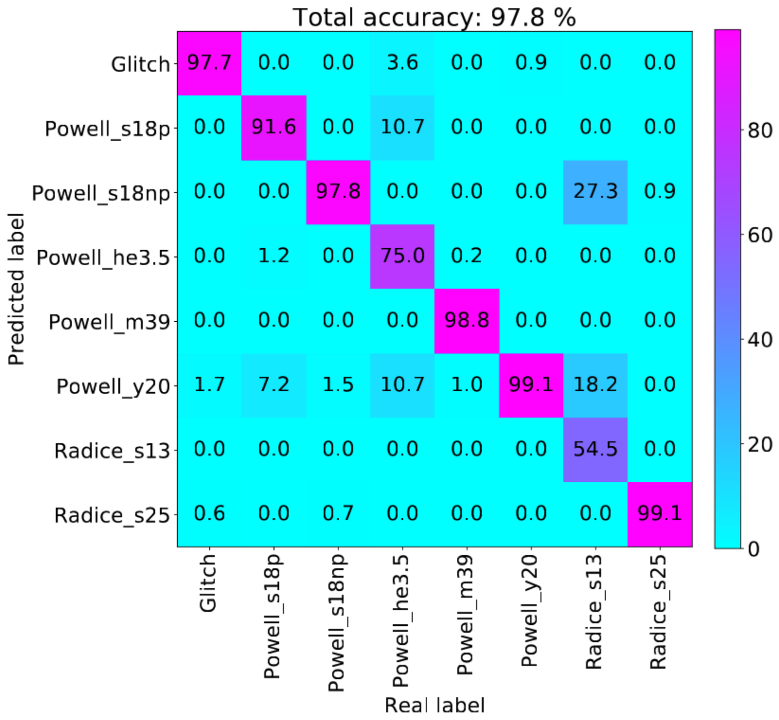


***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, submitted to MLST*

3 ITF MERGED MODEL MULTILABEL CLASSIFICATION ON REAL O2 NOISE

- 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, submitted to MLST*

Anomaly Detection in Gravitational Waves data using Convolutional AutoEncoders

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre, https://arxiv.org/abs/2103.07688

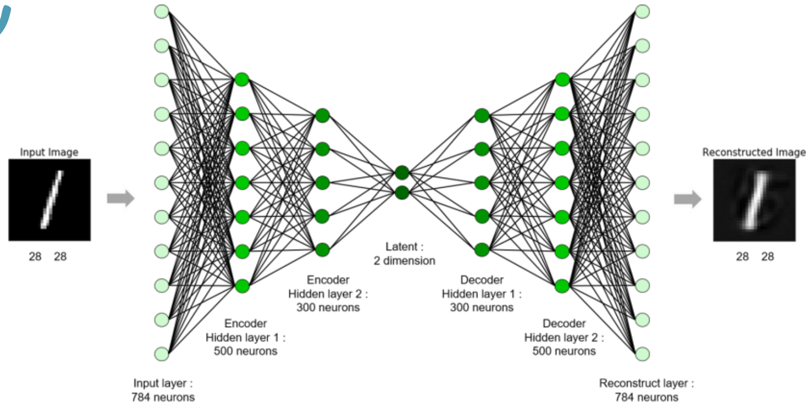
Example for detection/classification for CBC signals

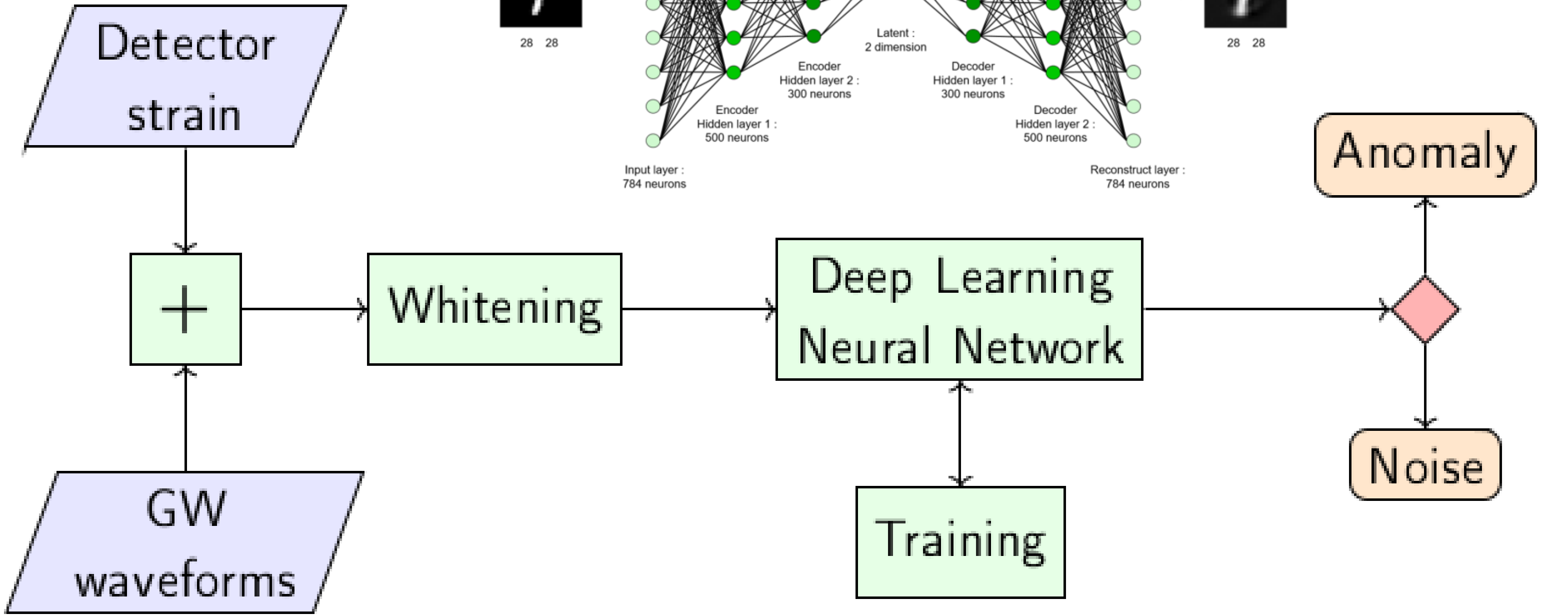
- Create a deep learning pipeline allowing detection of anomalies defined in terms of **transient signals**: gravitational waves as well as glitches.
- Additionally: Consider **reconstruction of the signal** for the found anomalies.

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre, https://arxiv.org/abs/2103.07688

Pipeline Workflow

Autoencoder





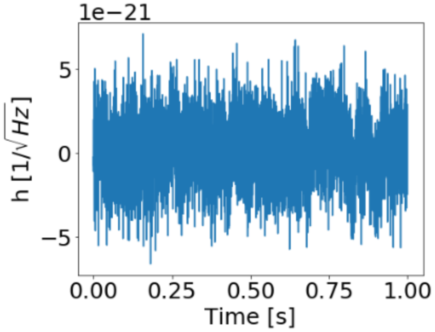
Filip Morawski courtesy

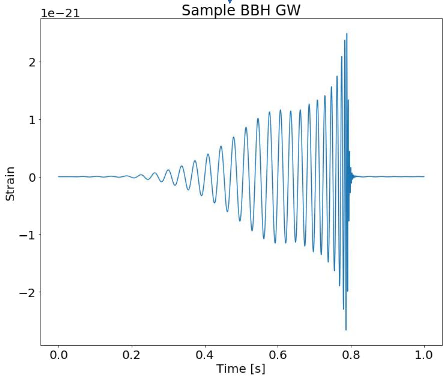
***Filip Morawski**, Michał Bejger, Elena Cuoco, Luigia Petre*, *https://arxiv.org/abs/2103.07688*

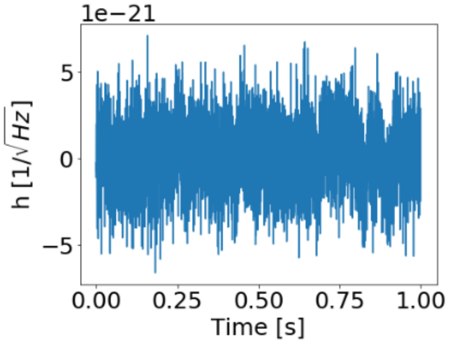
Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://arxiv.org/abs/2103.07688

Concept

Model input − Model prediction







Filip Morawski courtesy

Data

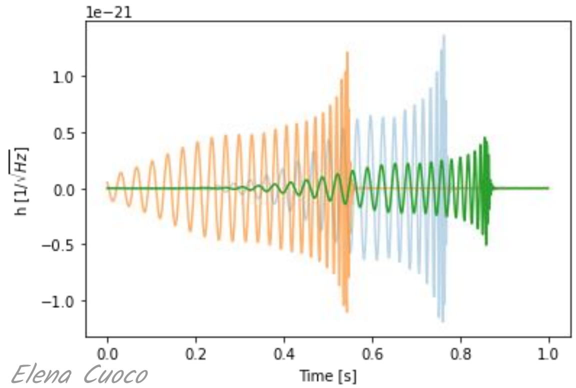
Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://arxiv.org/abs/2103.07688

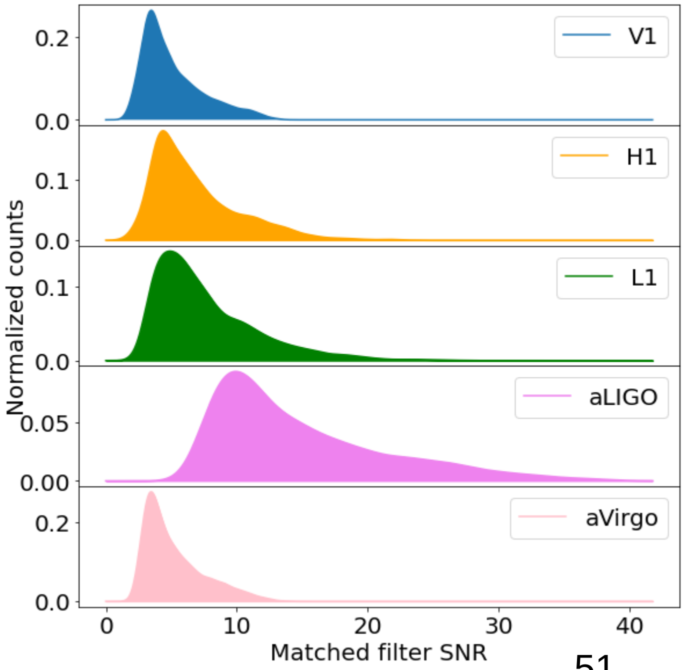
Real or simulated strain with injected anomalies - BBH GW.

Mass range: 26-40 $M_{\odot}$

Distance: 200-800 Mpc

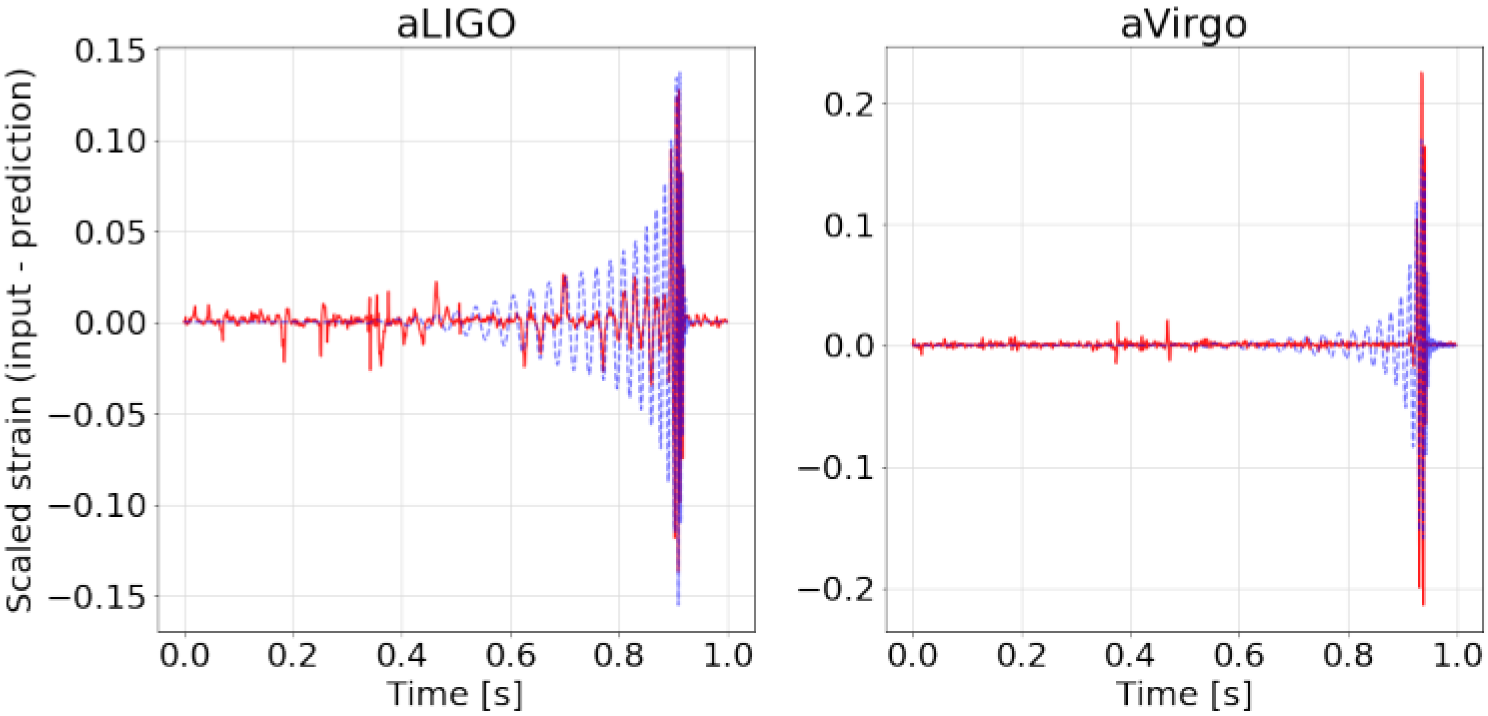
Sampling rate: 1024 Hz





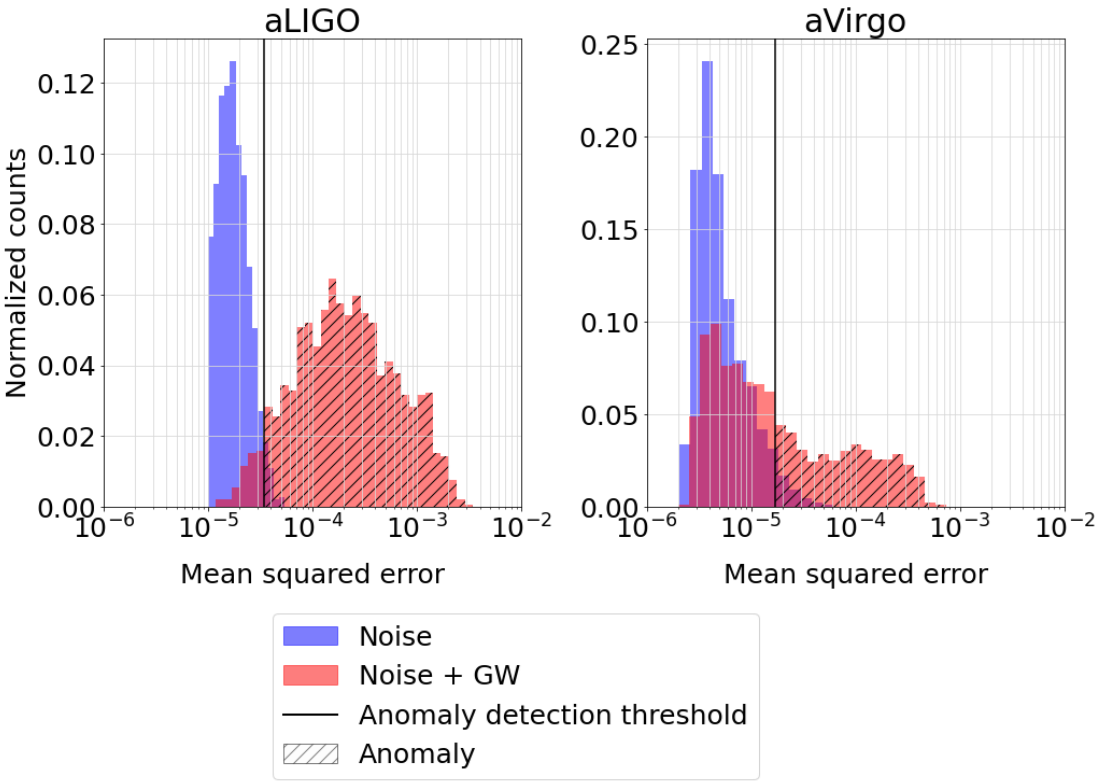
Simulations - reconstructed signal

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://arxiv.org/abs/2103.07688



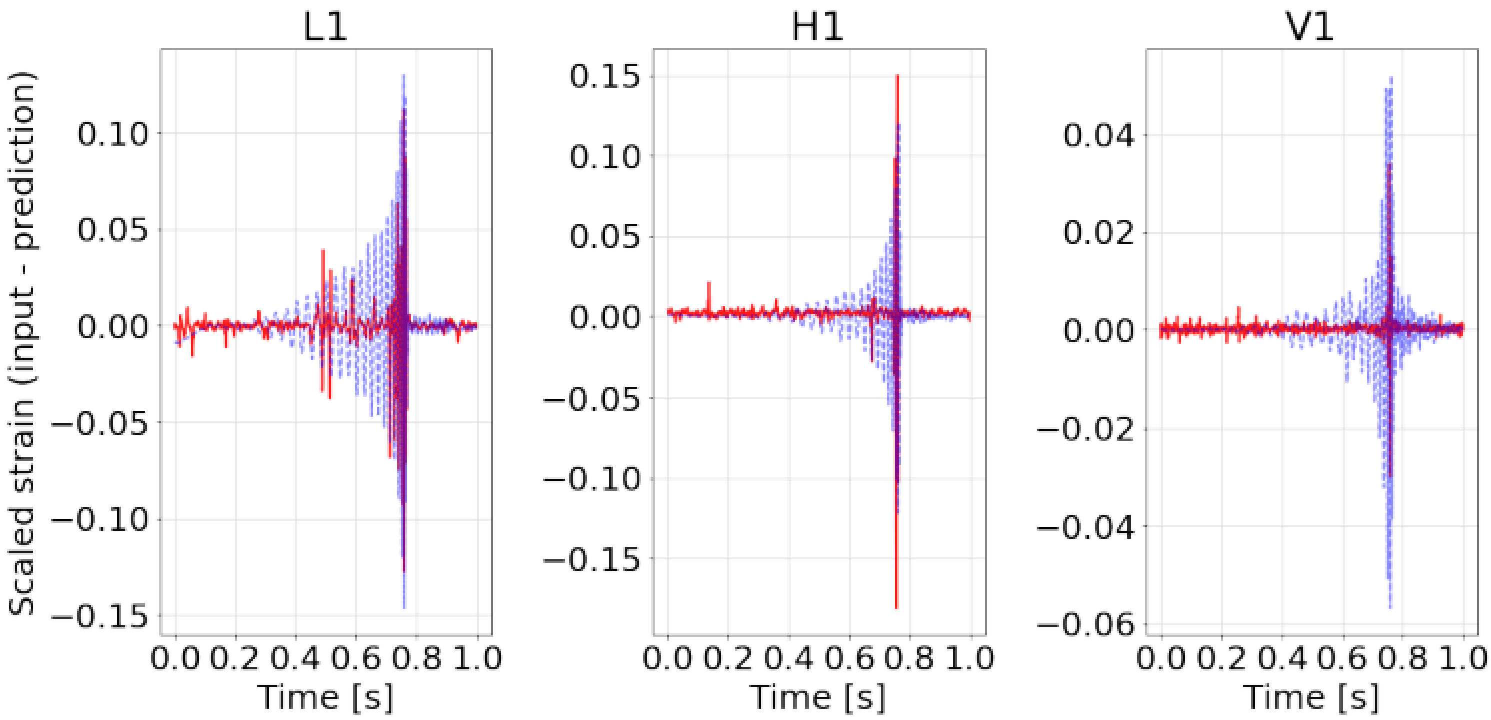
Simulations – Mean Squared Error Distributions

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://arxiv.org/abs/2103.07688



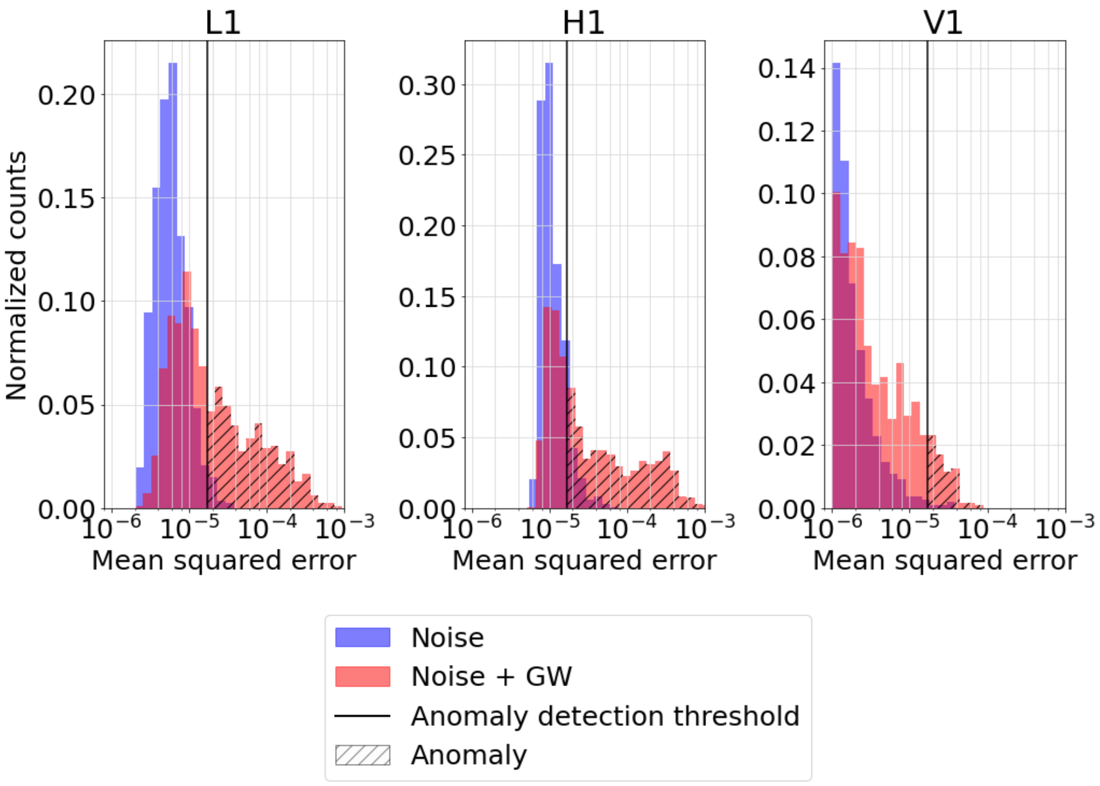
Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://arxiv.org/abs/2103.07688

O2 data - reconstructed signal



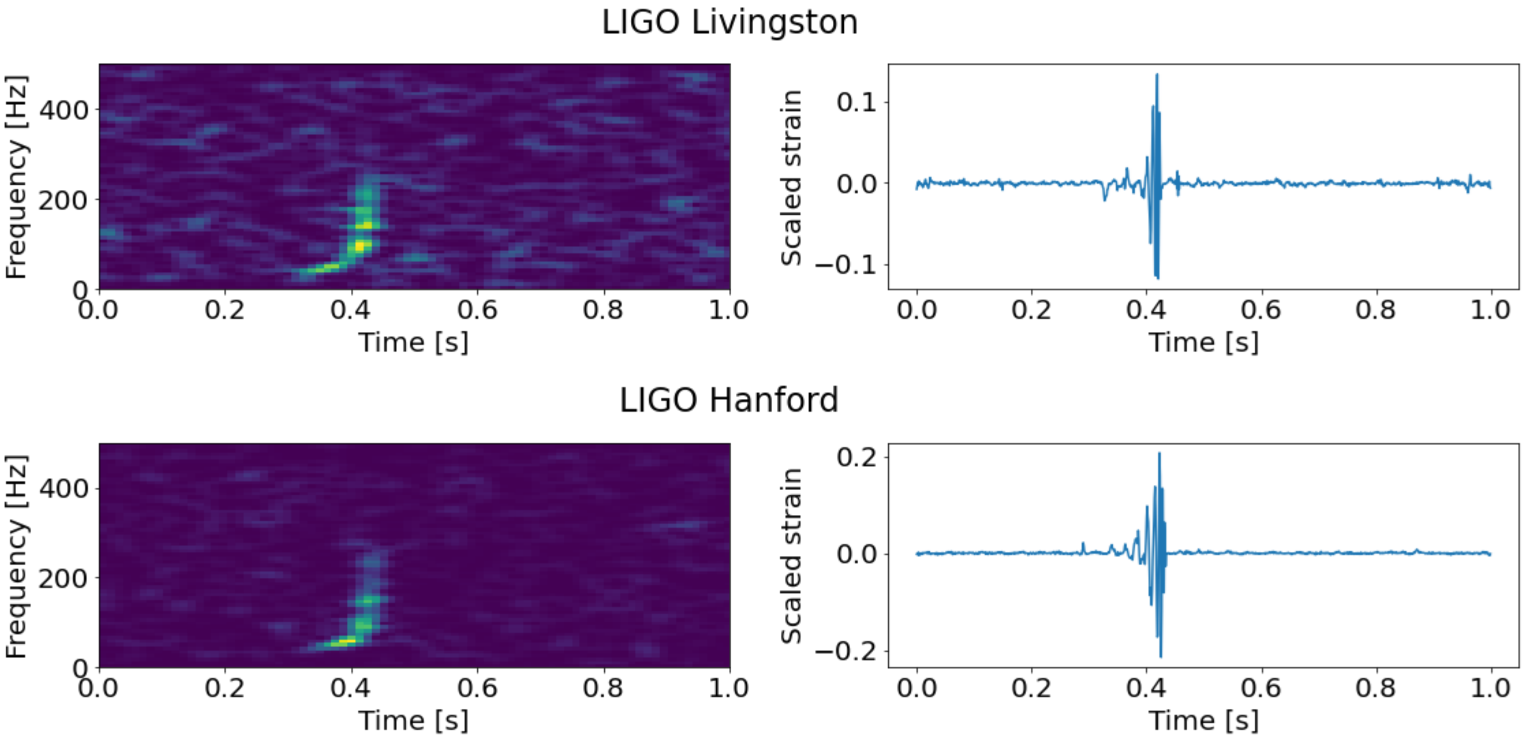
Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre,*
https://arxiv.org/abs/2103.07688

O2 data - MSE Distributions



Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://arxiv.org/abs/2103.07688

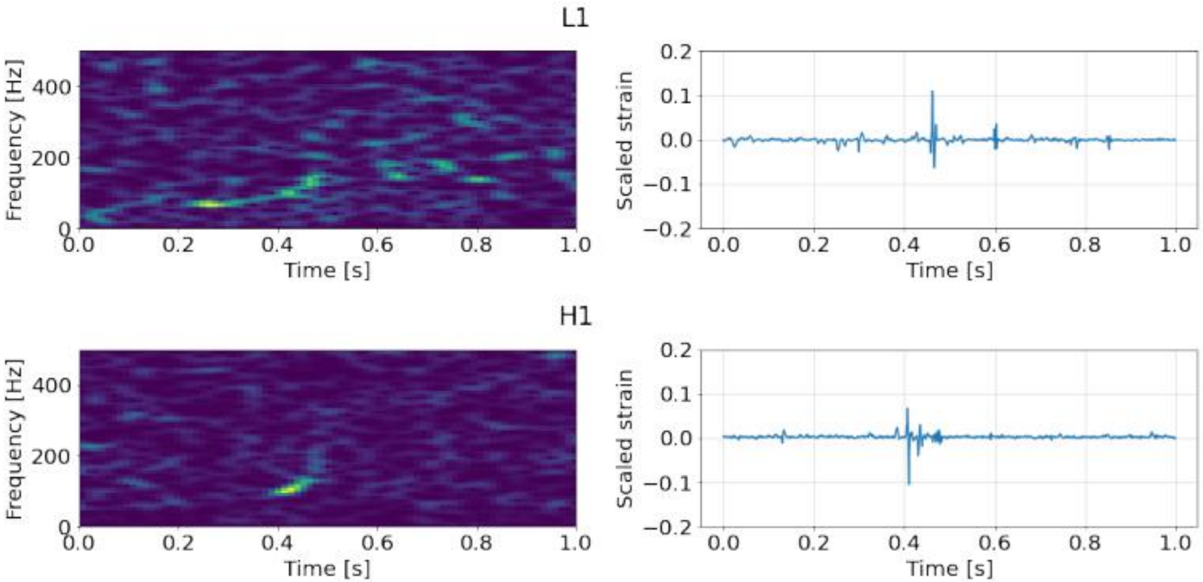
GW150914



Filip Morawski courtesy

Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre,*
https://arxiv.org/abs/2103.07688

GW170806

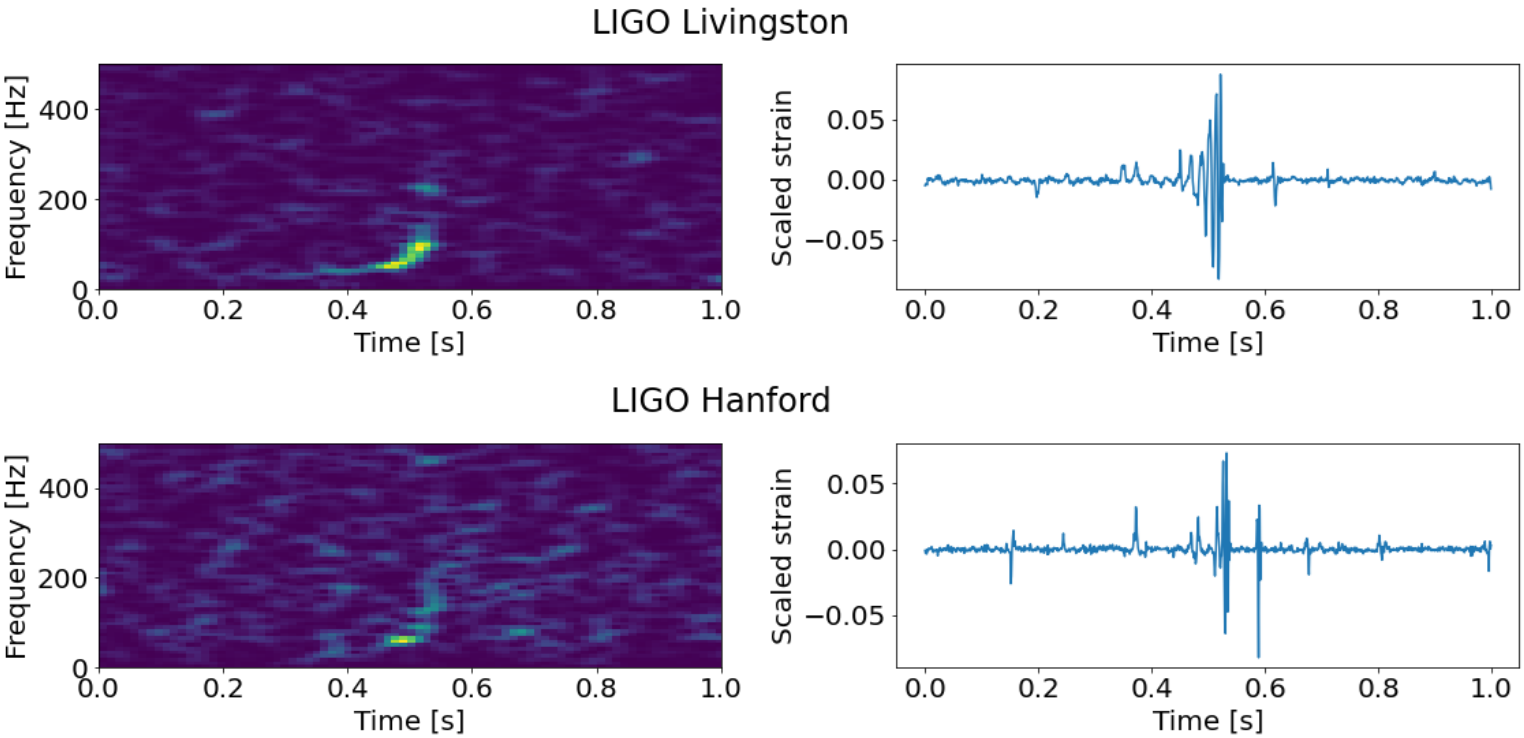


Filip Morawski courtesy

INTERESTING! GW170806 HAS MUCH LOWER MASSES!

Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre,*
https://arxiv.org/abs/2103.07688

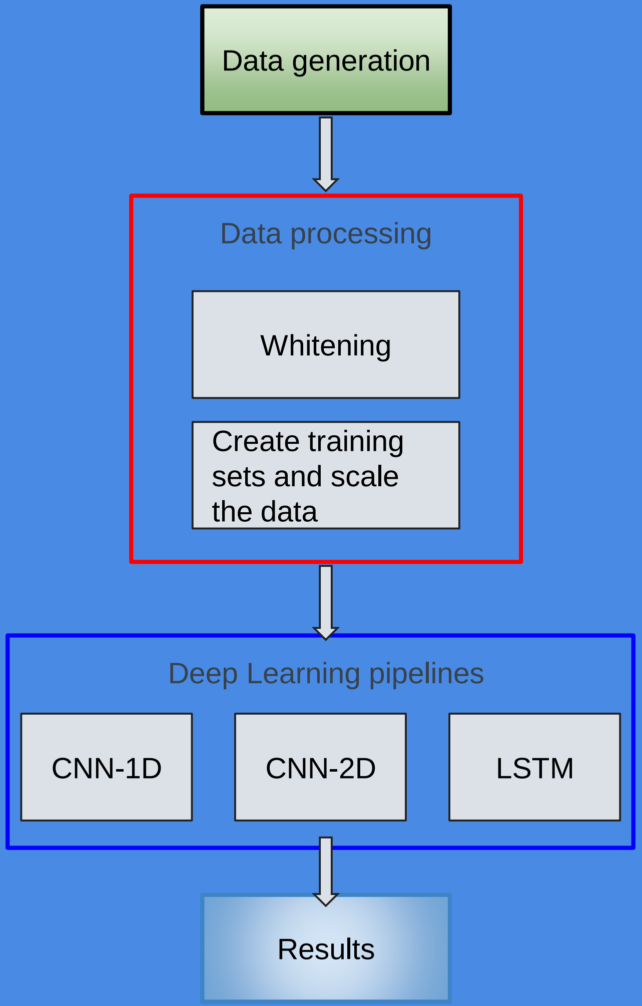
GW170814



Filip Morawski courtesy

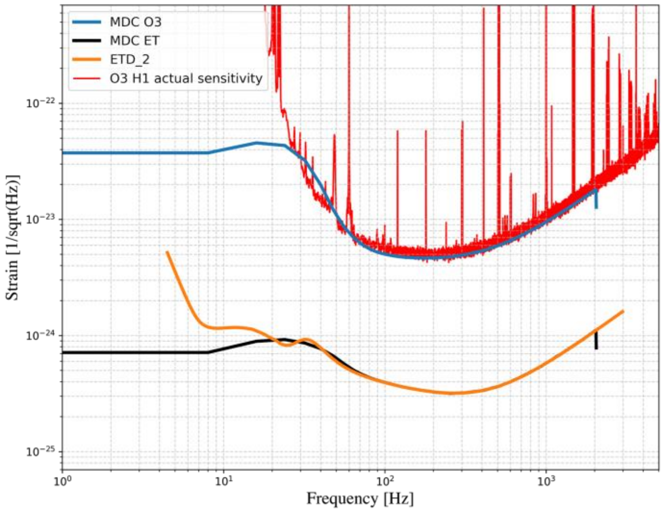
Deep learning searches for gravitational waves stochastic backgrounds

Andrei Utina, Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni



Data generation

- MDC package was used to generate time-series data of detector noise and BBH coalescences.
- Data was simulated for **Handford O3 sensitivity and ET-D design sensitivity** starting at 30 Hz.
- A full duration of a simulated dataset was 2048 seconds, sampled at 4096 Hz.
- The time interval between successive events defined three datasets:
  - BBH10s for a Poisson parameter of 0.1
  - BBH4s for a Poisson parameter of 0.25
  - BBH1s for a Poisson parameter of 1



Recovered signals from a Welch method are shown by the blue and black curves above. For reference, ET-D design sensitivity is shown by the orange curve and the H1 O3 measured strain on Sep 05 2019 at 36.6 W input power and 2 dB of squeezing.

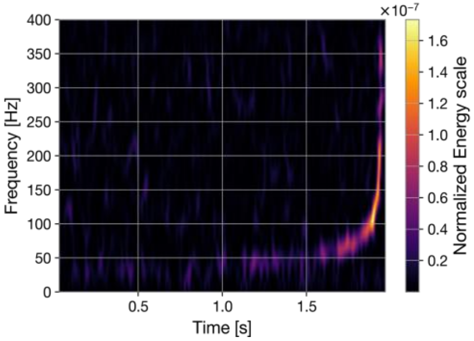
Andrei Utina courtesy

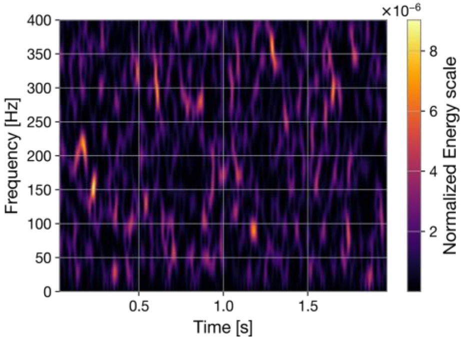
Andrei Utina, *Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni*

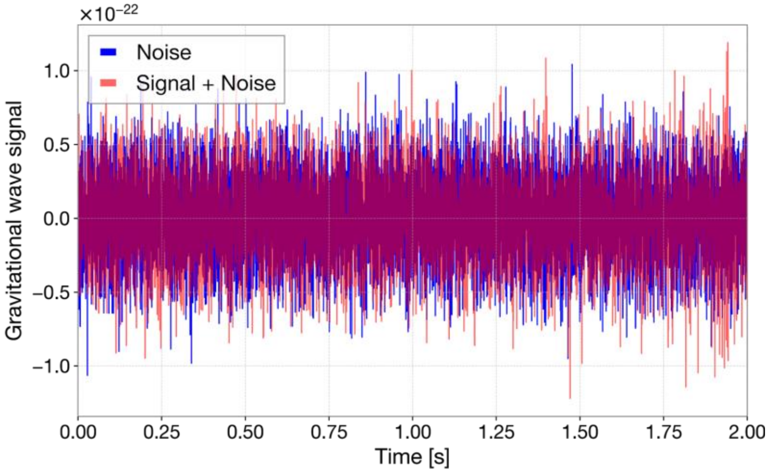
Andrei Utina, *Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni*

Generated datasets

- After processing, the library of feature and label vectors were created.
- The duration of each data instance was set to 2 seconds. For performance reasons, in the case of the LSTM algorithm, the length was set to 1 second.
- The 2-D space of the spectrogram representation gives the input for the CNN2D algorithm:
  - Top left shows a high SNR chirp signal for ET.
  - Top right shows a similar signal but for LIGO.
- The 1-D time-series representation is the input for the CNN1D algorithm and the LSTM algorithm.







Andrei Utina courtesy

Deep Learning setup

- We chose Convolutional Neural Networks (CNN) and Long-Short-Term Memory Networks (LSTM) as the test deep learning algorithms.
- The full sets were split into 70% training set, 10% validation set and 20% test set.
- The performance of the algorithms strongly relies on the tuning of the hyperparameters:
    - **We hypertuned over a multi-dimensional parameter** space including the number and type of perceptron layers, the filter numbers and sizes, the learning rate and the optimizers.
    - The tuning was performed using Hyperband, a random search algorithm that assigns resources adaptively.
    - The hypertuning was performed on the whitened 4s and 10s datasets.
- All the computations were performed on the **Marconi100 HPC cluster of CINECA.**

Andrei Utina courtesy

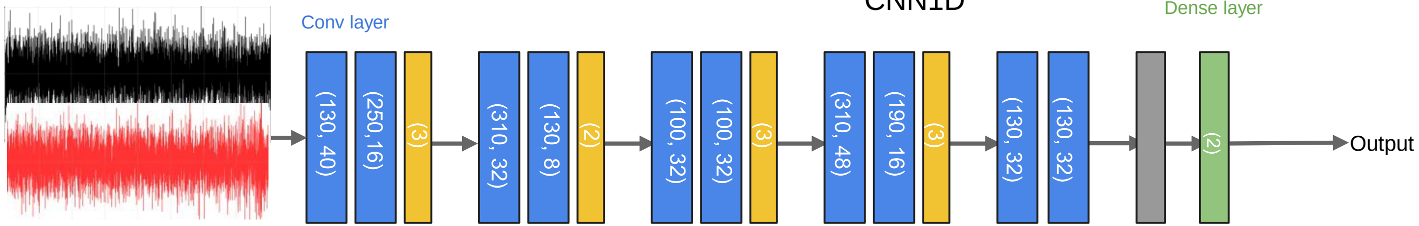
***Andrei Utina**, Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni*

Andrei Utina, Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni

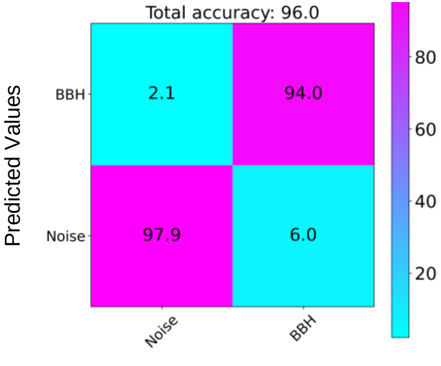
CNN Architectures

Time-series Input

CNN1D

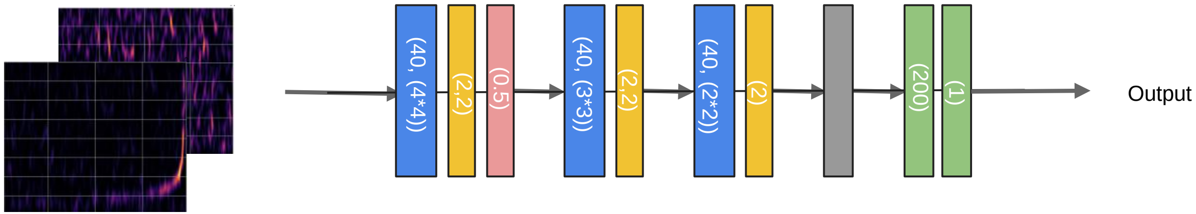


Output example: The confusion matrix from the classification



CNN2D

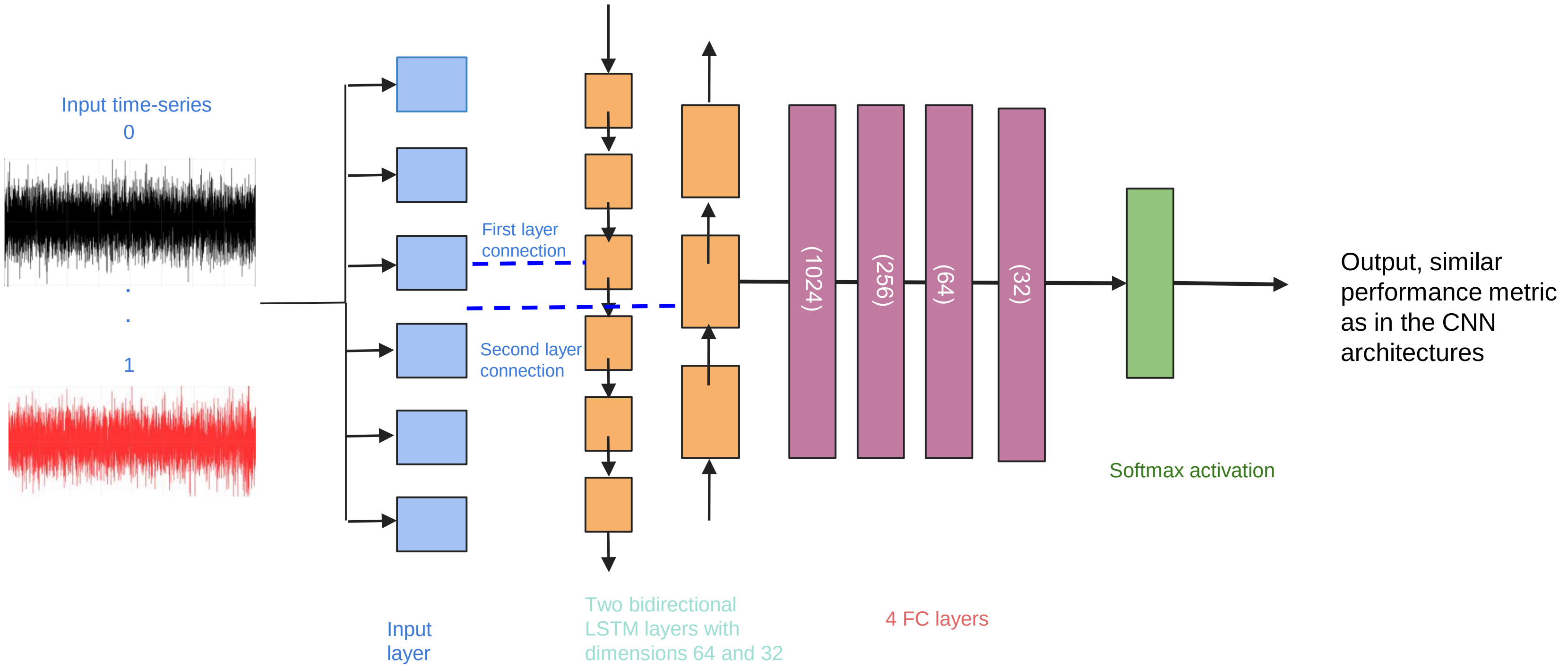
Spectrogram Input



Andrei Utina courtesy

Andrei Utina, Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni

LSTM Architecture



Andrei Utina courtesy

Andrei Utina, Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni

Results

LSTM Results

Chosen Detector	Whitened Data Results		
	Occurrence	*Noise*	*Signal*
ET	1s	99.0 %	91.3 %
	4s	94.5 %	62.4 %
	10s	94.5 %	48.7 %
LIGO H O3	1s	100 %	0 %
	4s	100 %	0 %
	10s	100 %	0 %

CNN2D Results

Chosen Detector	Whitened Data Results		
	Occurrence	*Noise*	*Signal*
ET	1s	97.9 %	95.3 %
	4s	89.2 %	79.2 %
	10s	88.3 %	69.2 %
LIGO H O3	1s	50 %	50 %
	4s	50 %	50 %
	10s	50 %	50 %

CNN1D Results

Chosen Detector	Whitened Data Results		
	Occurrence	*Noise*	*Signal*
ET	1s	97.9 %	95.3 %
	4s	87.5 %	75.7 %
	10s	90.2 %	67.3 %
LIGO H O3	1s	50 %	50 %
	4s	50 %	50 %
	10s	50 %	50 %

- We look at the percentages of the true rates for each Poisson intensity parameter. i.e the correct predictions given either noise or signal plus noise inputs.
- The H1 O3 detections are either 100% for noise (LSTM) or 50%-50% (not convergent) for both noise and signal with noise.
- With increasing the Poisson intensity parameter, the detection accuracy increases significantly for both noise and signal.
- All three algorithms showed similar results for the 1s dataset.
- The detection efficiencies of the CNNs were similar: 67%+ for 10s, 75%+ for the 4s and 95%+ for the 1s datasets.

Andrei Utina courtesy

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