Artificial Intelligence for Gravitational Wave Data Analysis

Applications of AI to gravitational wave science

March 18, 2022 Université de Genève

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European Gravitational Observatory

SCUOLA NORMALE SUPERIORE

EOSC Future

ESCAPE
European Science Cluster of Astronomy & Particle physics ESFRI research infrastructures

cost
EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY

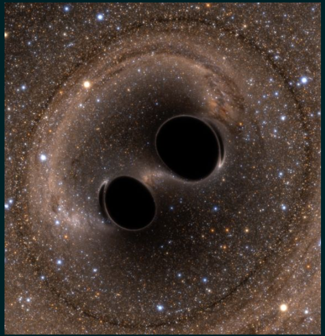
G2NET

COST ACTION CA17137
A NETWORK FOR GRAVITATIONAL WAVES, GEOPHYSICS AND MACHINE LEARNING

GW astrophysical sources

Short□ long

Known □ unknown form

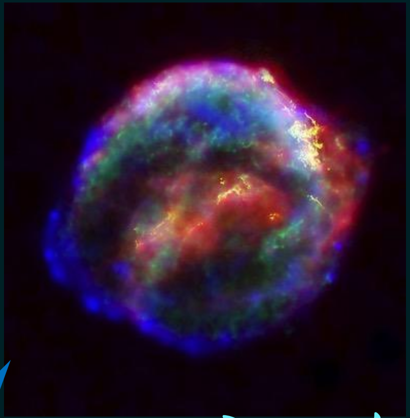


Coalescing Binary Systems CBC

- ✔ Black hole – black hole
- ✔ Neutron star – neutron star
- BH-NS
- Analytical waveform

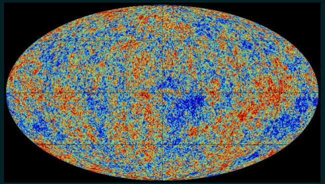
Continuous Sources

- Spinning neutron stars
- monotone waveform



Transient'Burst'Sources

- core collapse supernovae
- cosmic strings
- unmodeled waveform

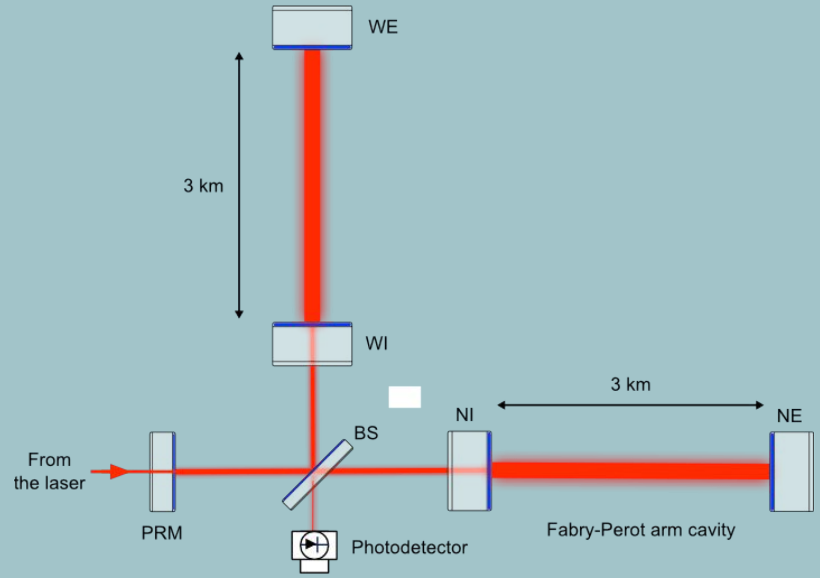


Cosmic GW Background

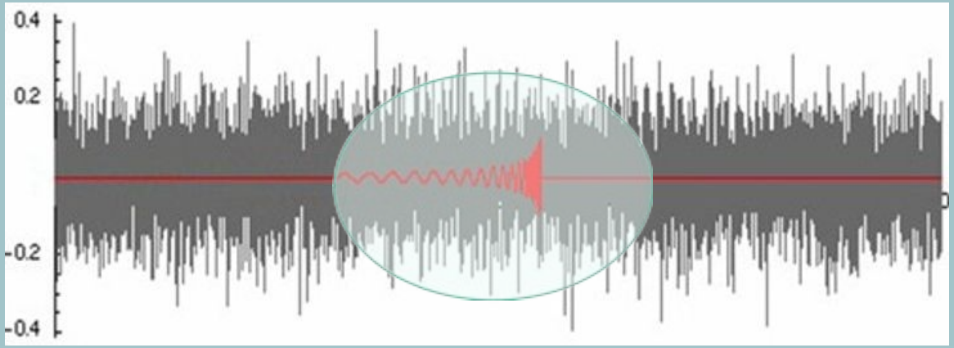
- residue of the Big Bang,
- stochastic, incoherent background

Do we know their Waveforms?

GW detector data



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



How we detect transient signals: modeled search

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

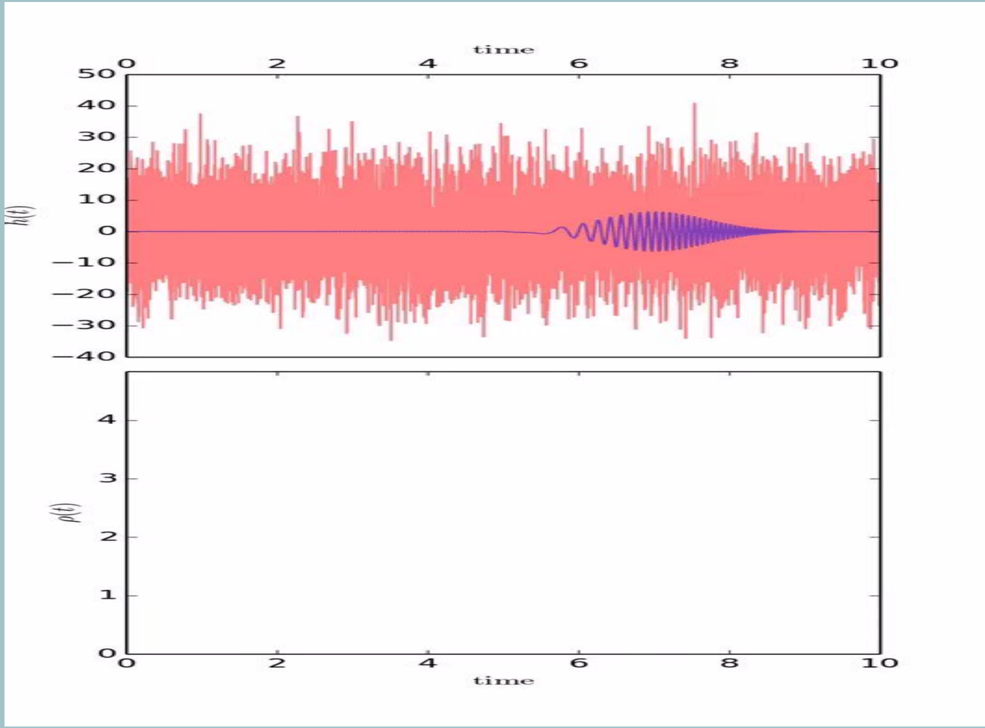
Matched-filter

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

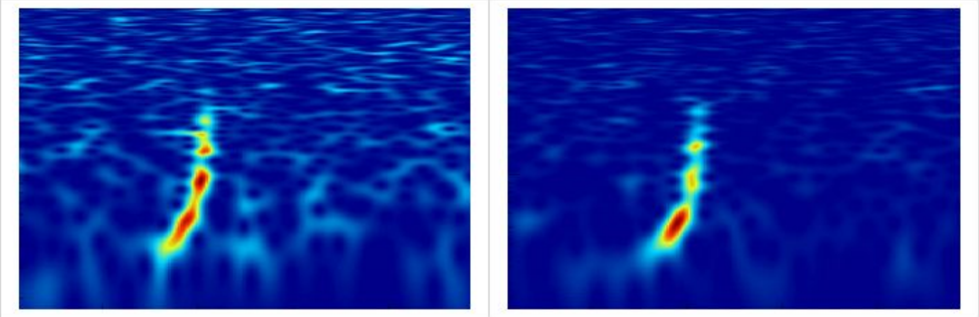
How we detect transient signals: un-modeled search

- *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 decompostion*
  - *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.



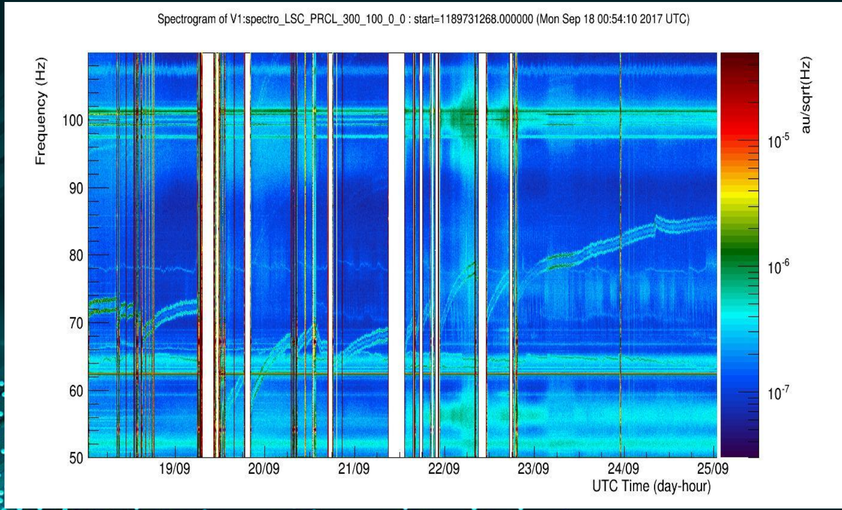
Time-Frequency maps of GW150914: Livingston data (left), Hanford data (right)
First screenshot of GW150914 event

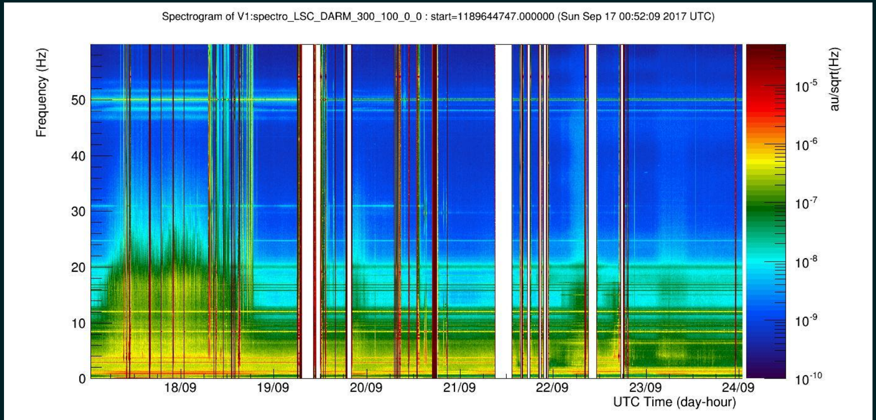
Phys. Rev. D 93, 042004 (2016)
Class.Quant.Grav.25:114029,2008

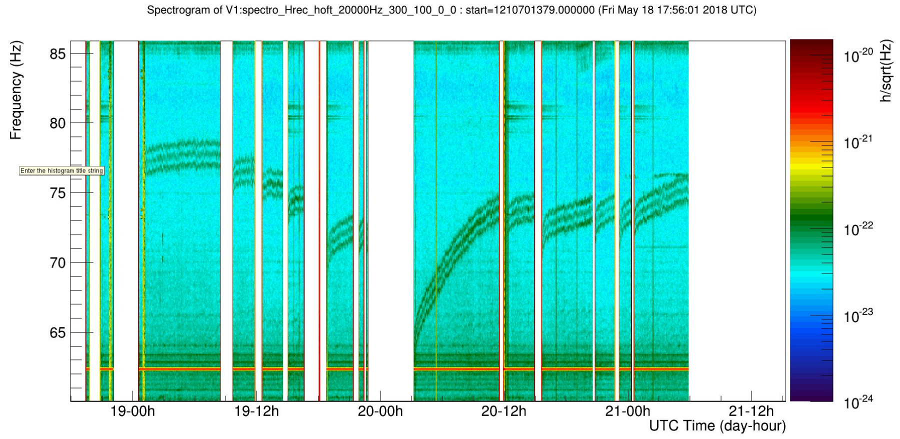
Why AI for Gravitational Wave data?

- A lot of noise and few GW signals
- Low SNR signals
- Many transient noise disturbances
- Not stationary/non linear noise
- Many monitoring auxiliary channels
- Computational and timing efficiency

Non linear, not stationary noise

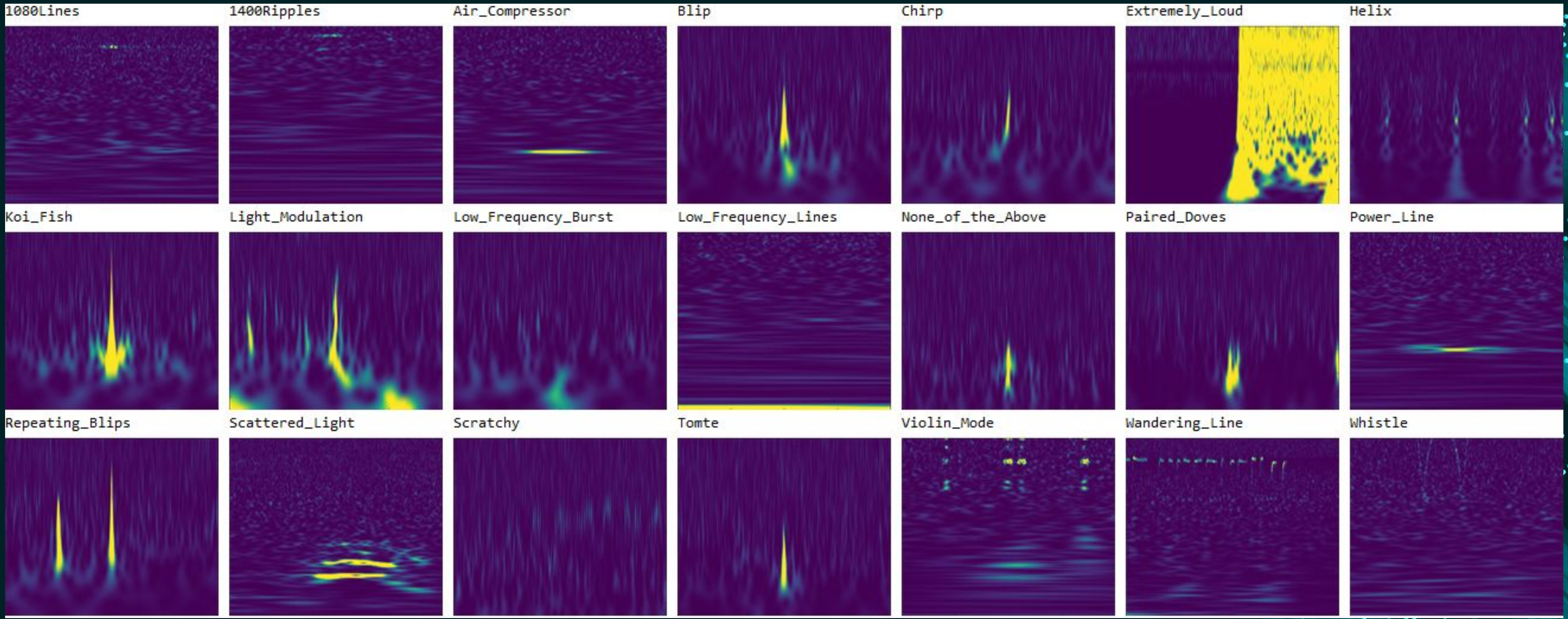






I. Fiori courtesy

Glitches



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

How machine learning can help

Data conditioning

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

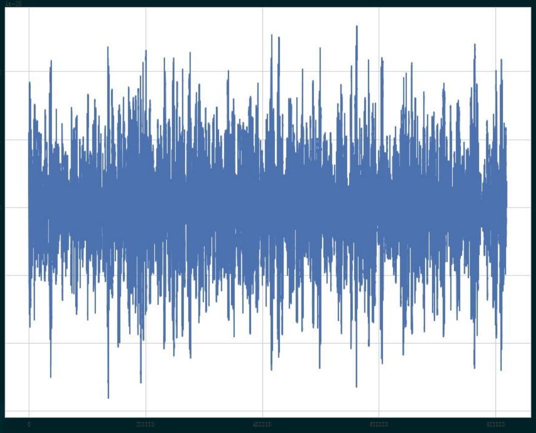
Signal Detection/Classification/PE

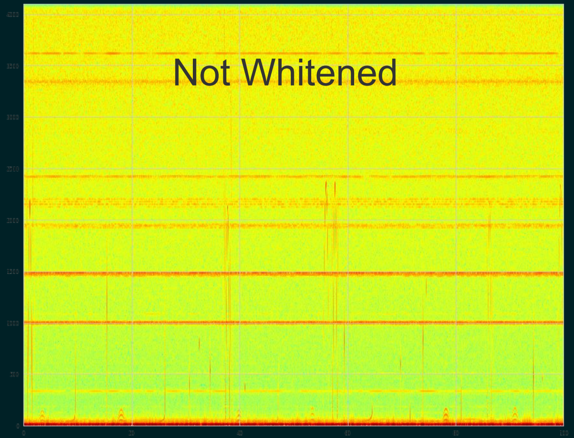
- A lot of fake signals due to noise
- Fast alert system
- Manage parameter estimation (See following talks)

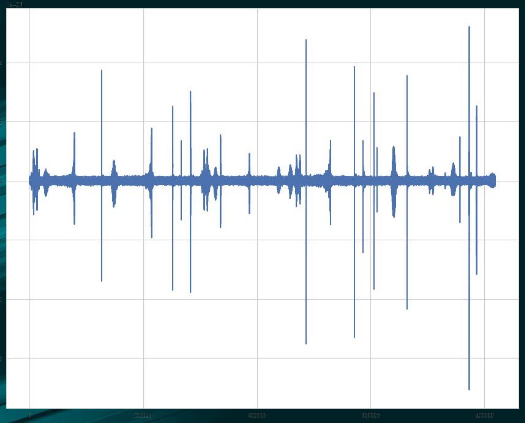
How to deal with data?

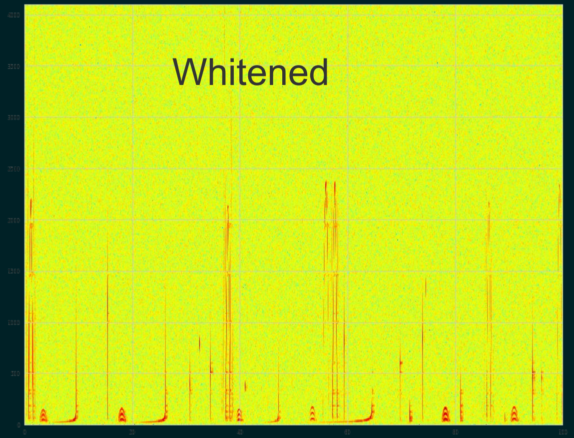
- Input: Time series
- Pre-processing analysis
- Change of domain space: Time-Frequency projections
- Different Machine Learning models

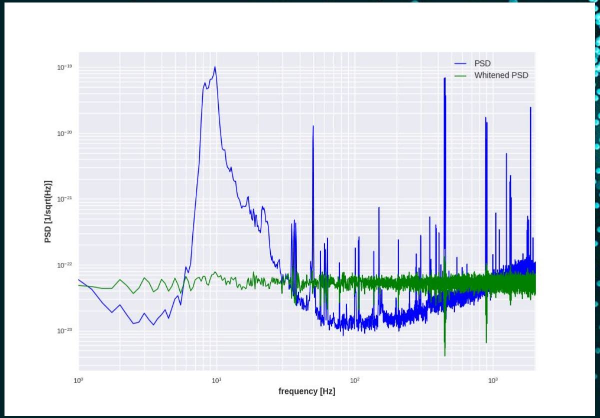
Preprocessing-Whitening











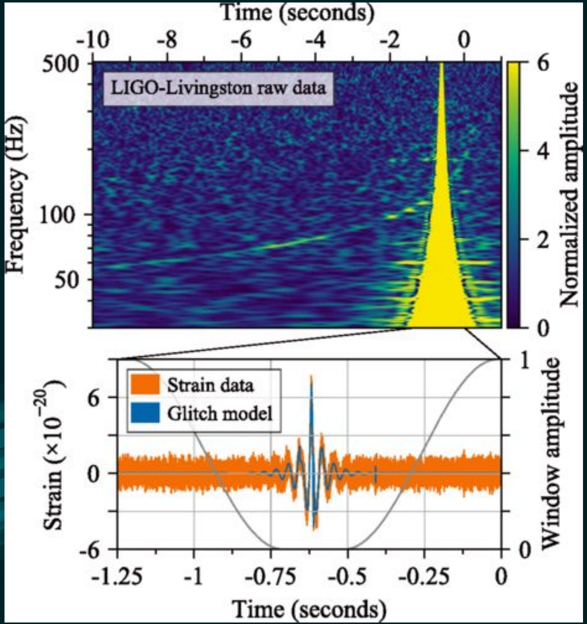
On-line power spectra identification and whitening for the noise in interferometric gravitational wave detectors

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

Classical and Quantum Gravity

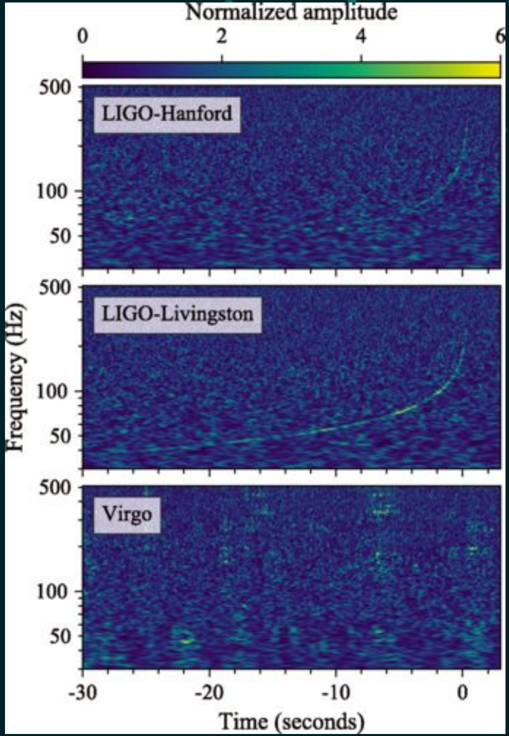
Are we able to clean data from glitch?

Ligo Livingston



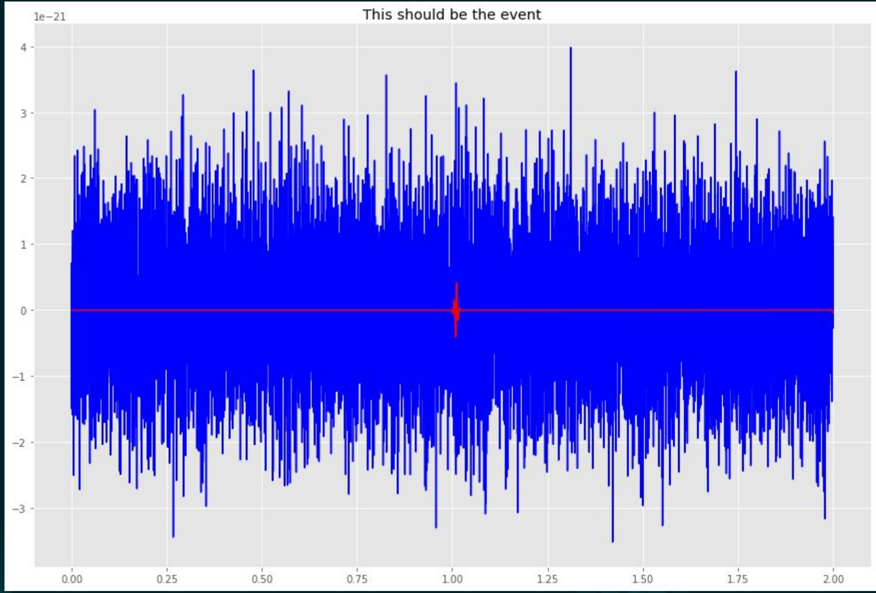
Glitch mitigation

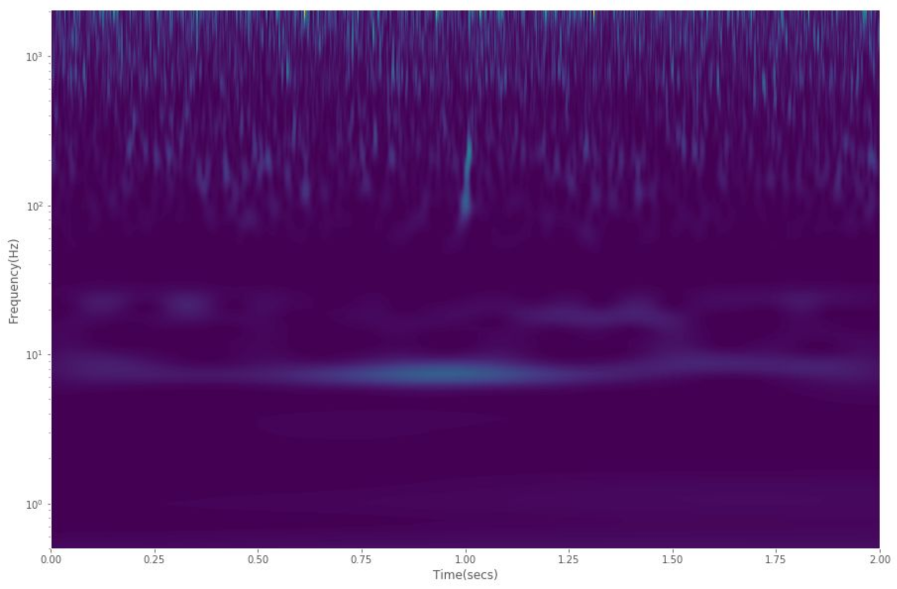
GW 170817



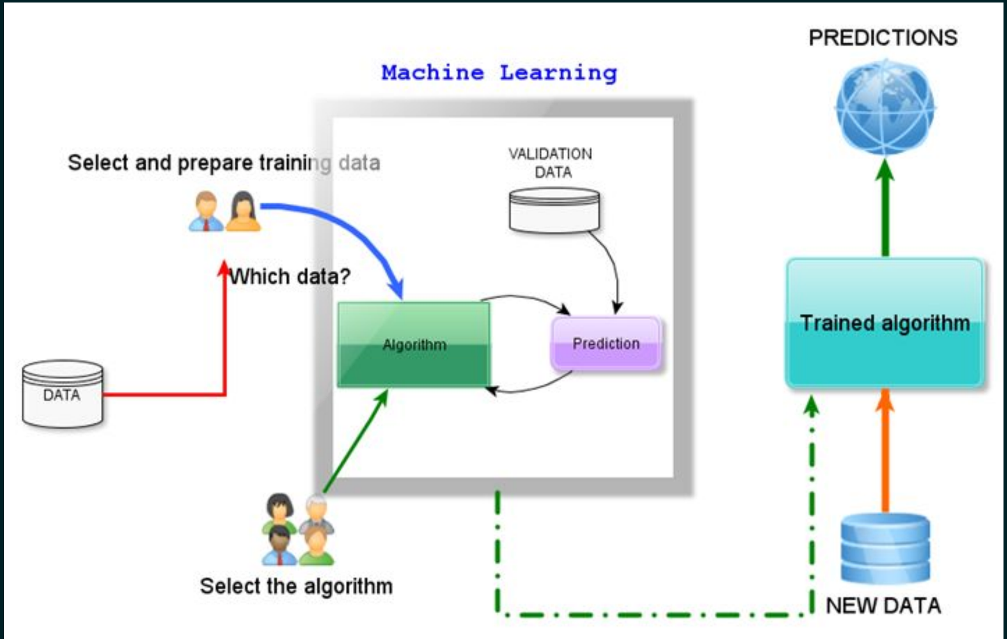
Abbott et al. (2017)

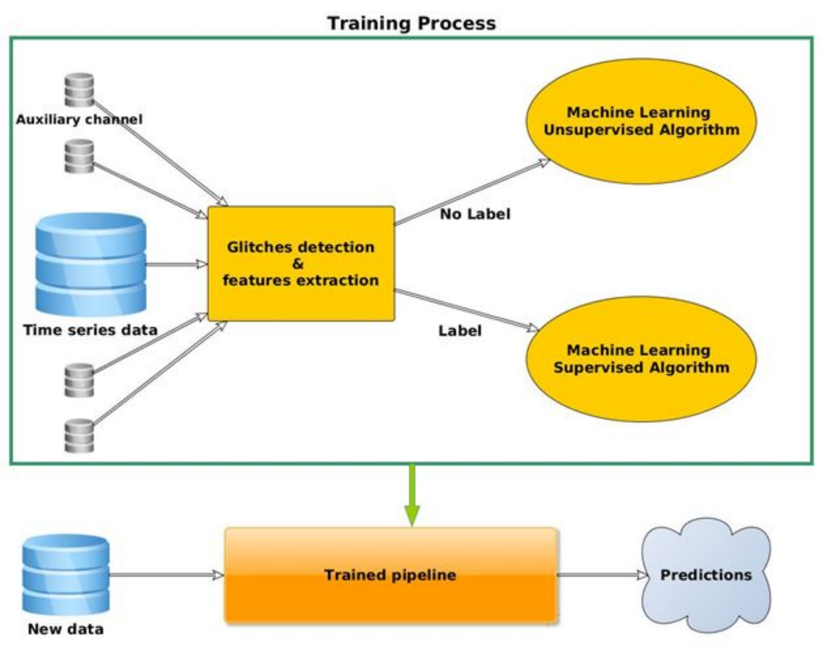
Time series or Images?





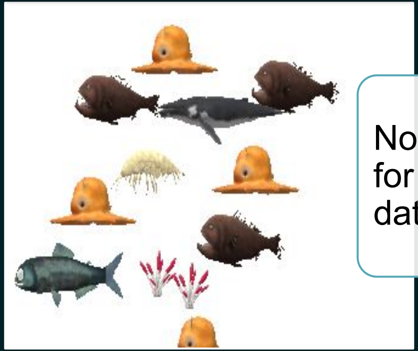
Machine learning workflow





Machine learning models. Which one ??

Unsupervised



No label for the data

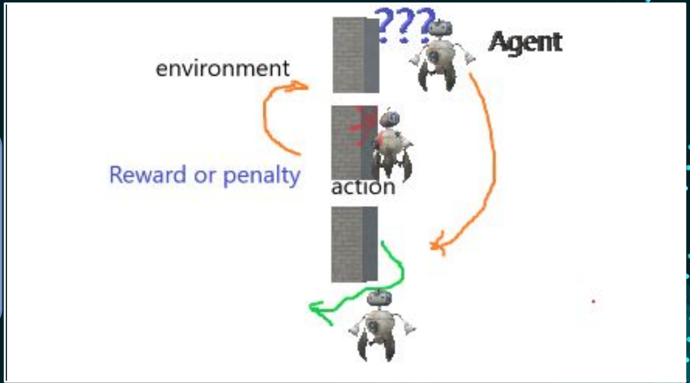
Semi-supervised

Few labeled data

Supervised

Labeled training data

Reinforcement learning



Some examples from my group, but many more in LVK callaboration...

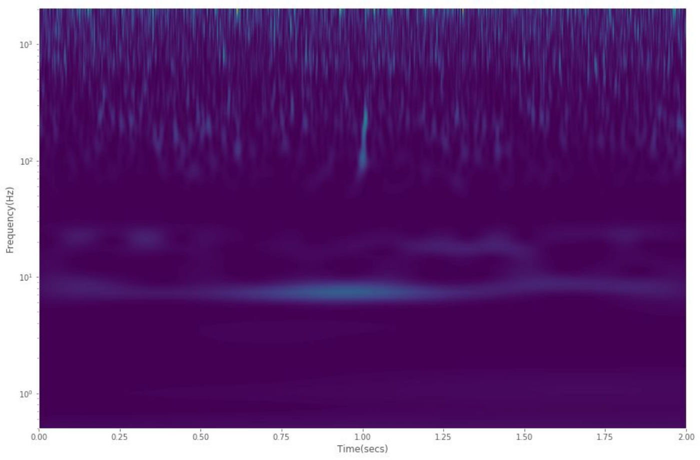
AI GW application

Noise Transient signal classification

GW signal classification (CBC or CCSN)

Stochastic background detection

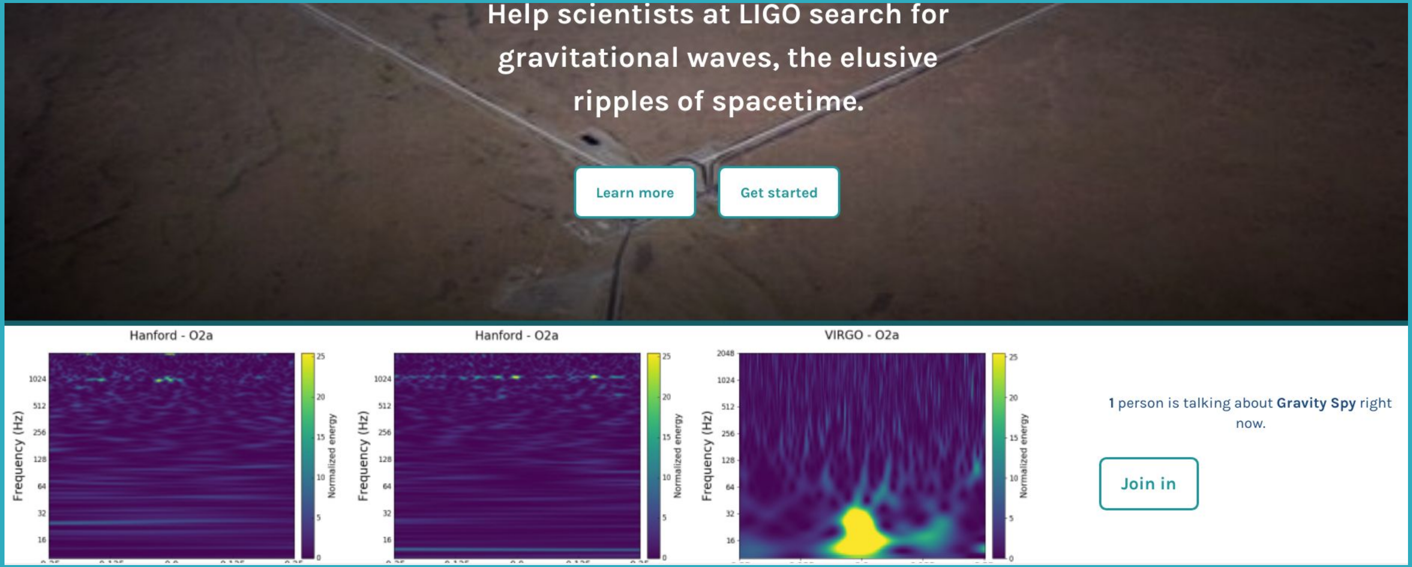
❖ Transient Noise classification and Images as input data



Why Image-based classification

Simulated and real data

Glitch & Citizen science: GravitySpy



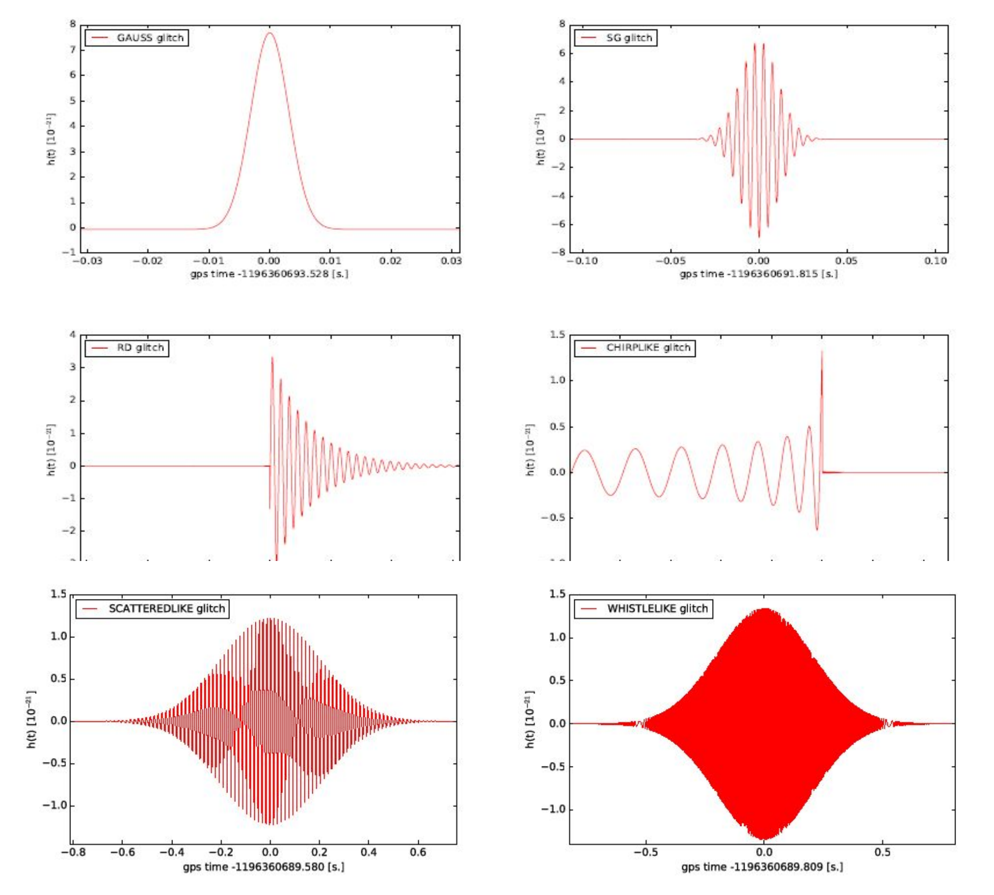
www.gravityspy.org

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

Elen Cuoco

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

Building the images

Spectrogram for each image

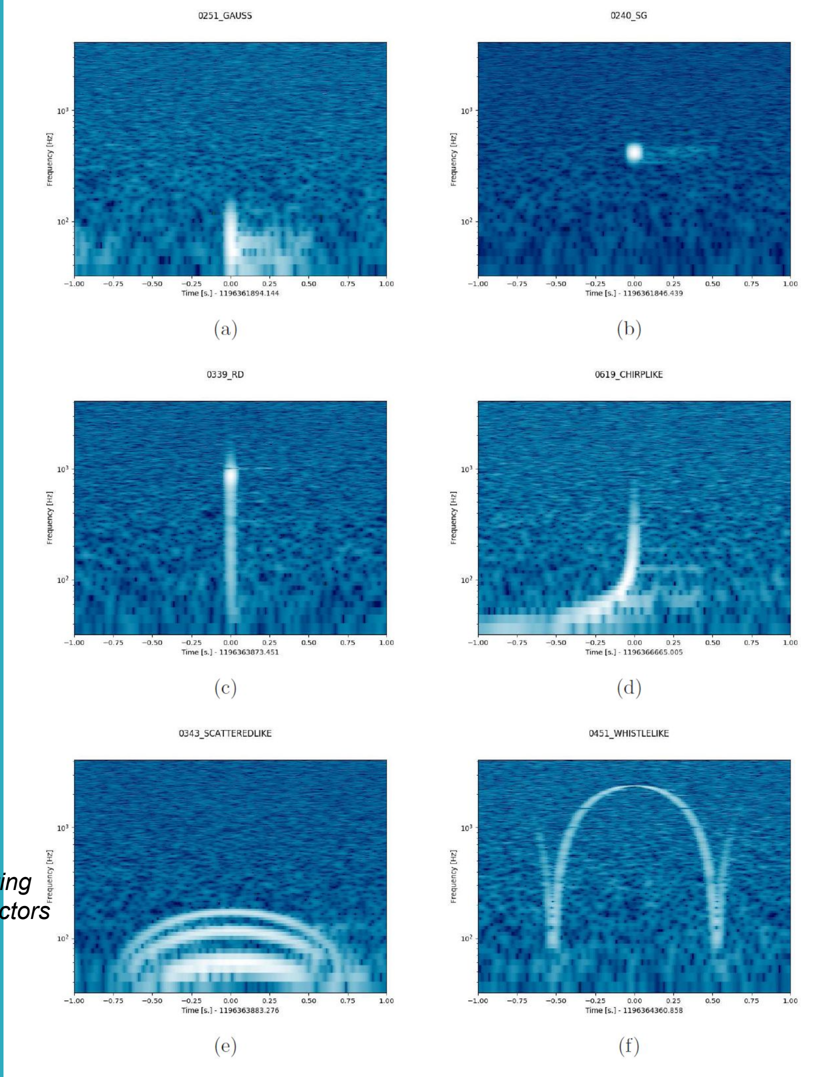
2-seconds time window to highlight fatures in long glitches

Data is whitened

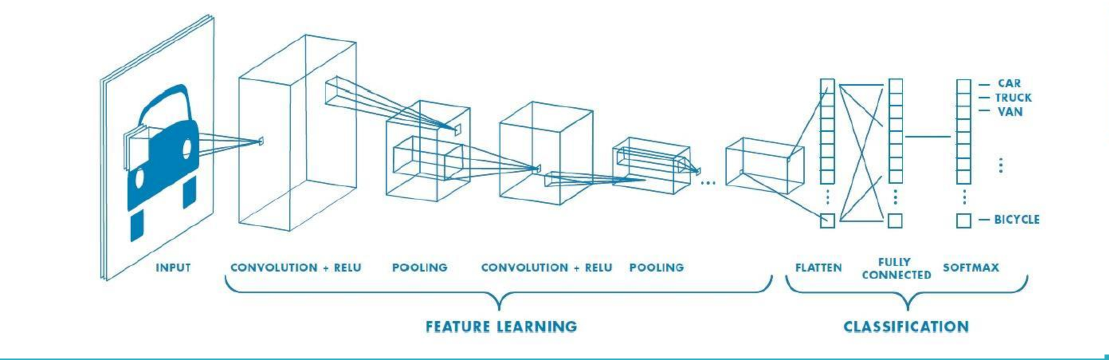
Optional contrast stretch

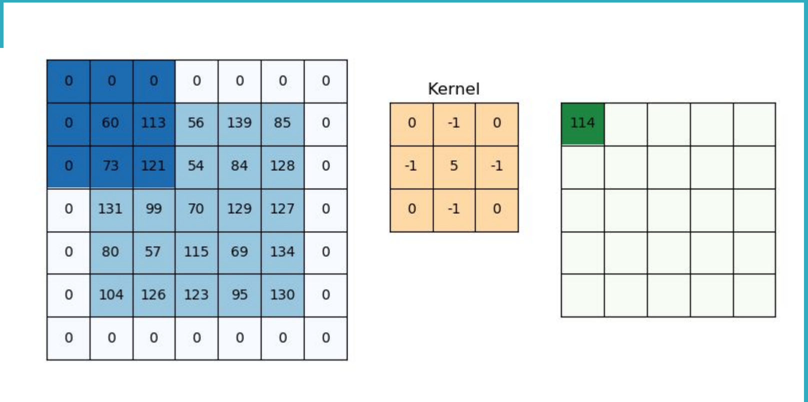
Simulations now available on FigShare

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*](https://doi.org/10.6084/m9.figshare.c.4254017.v1)



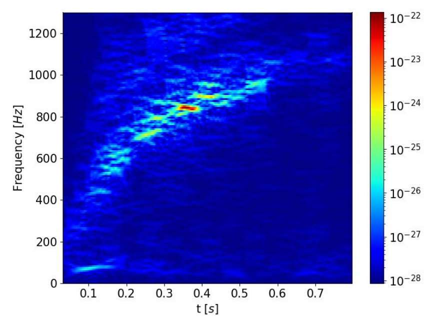
Deep learning: Convolutional Neural Network





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

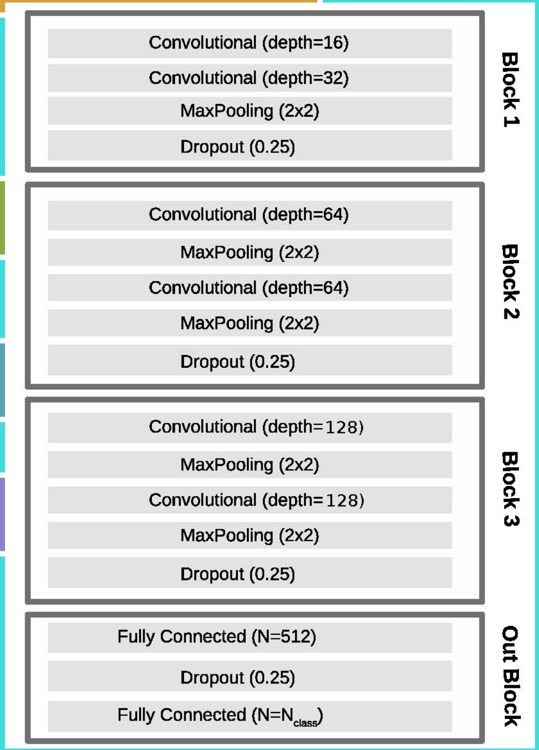
- A probability for each class, take the max
- Add a NOISE class to crosscheck glitch detection

Network layout

- Tested various networks, including a 4-block layers

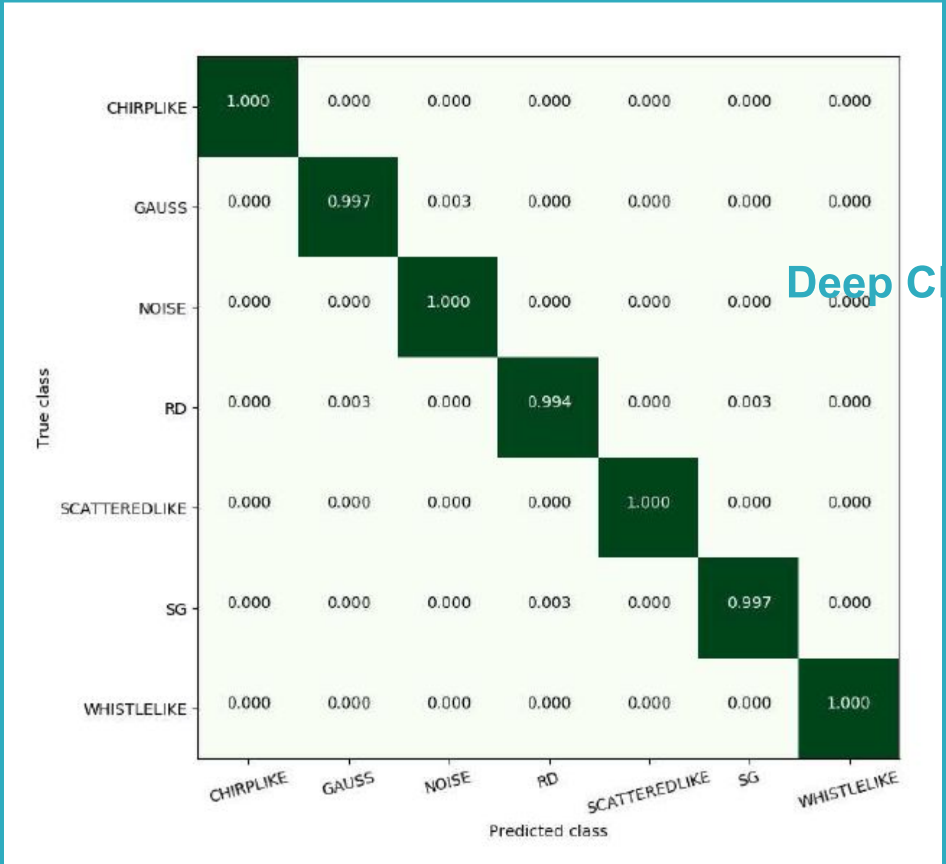
Run on GPU Nvidia GeForce GTX 780

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



M. Razzano courtesy

Classification accuracy



Normalized Confusion Matrix

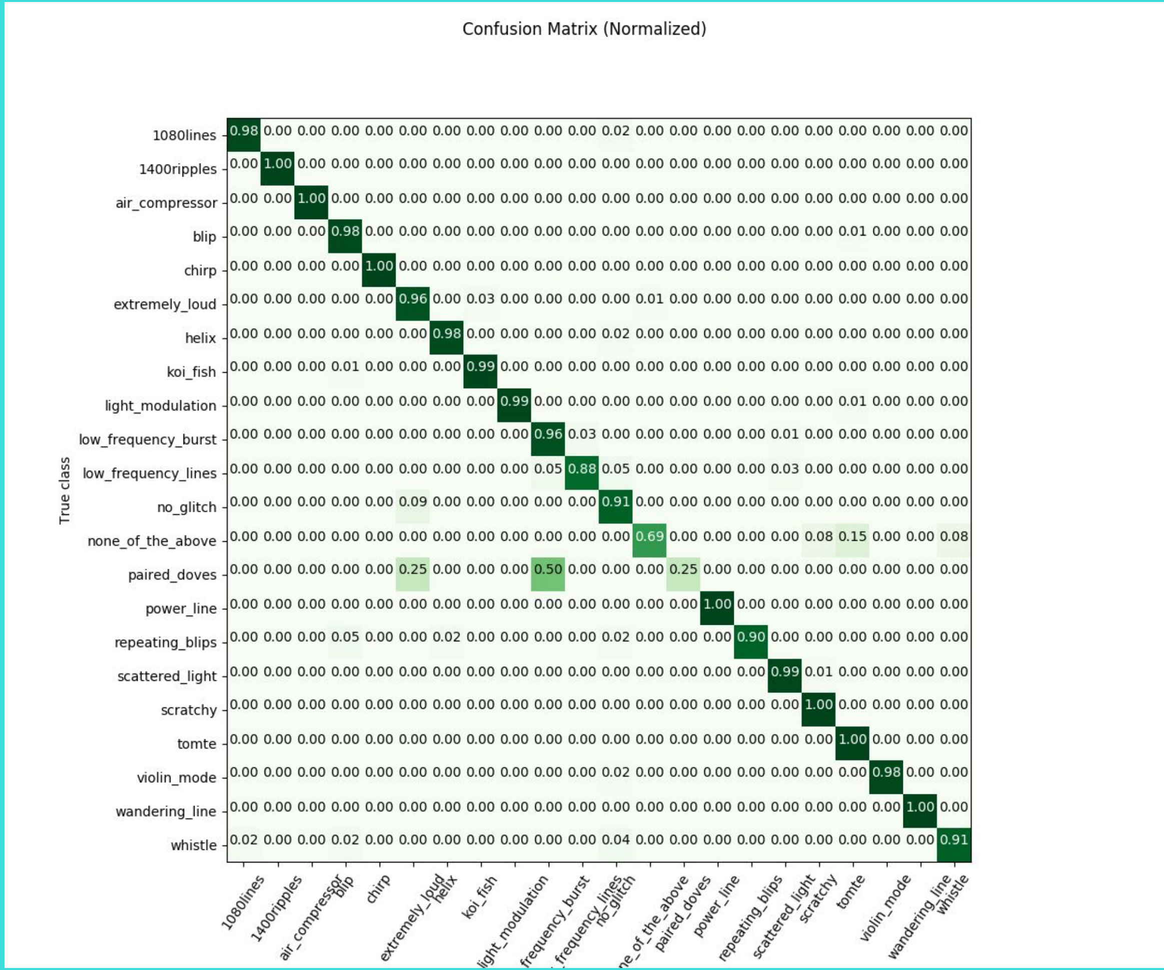
Razzano M., Cuoco E. CQG-104381.R3

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



Full CNN stack

Consistent with Zevin+2017

Elena Cuoco

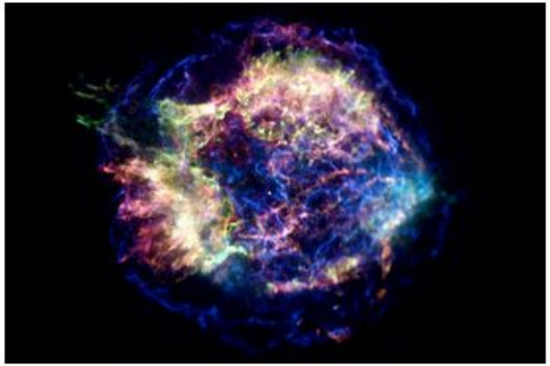
GW Astrophysical signal classification

Compact Binary Coalescences

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

Matched filter modeled searches

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.

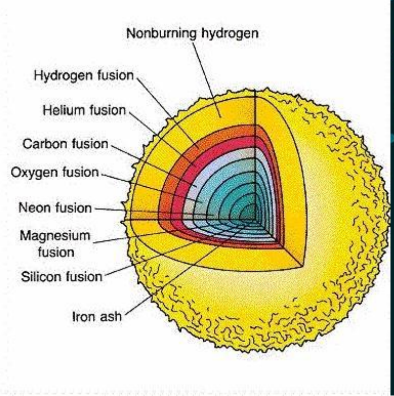
NASA/CXC/UNAM/IOFFE/D. PAGE, P. SHTERNIN ET AL

Unmodeled searches

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

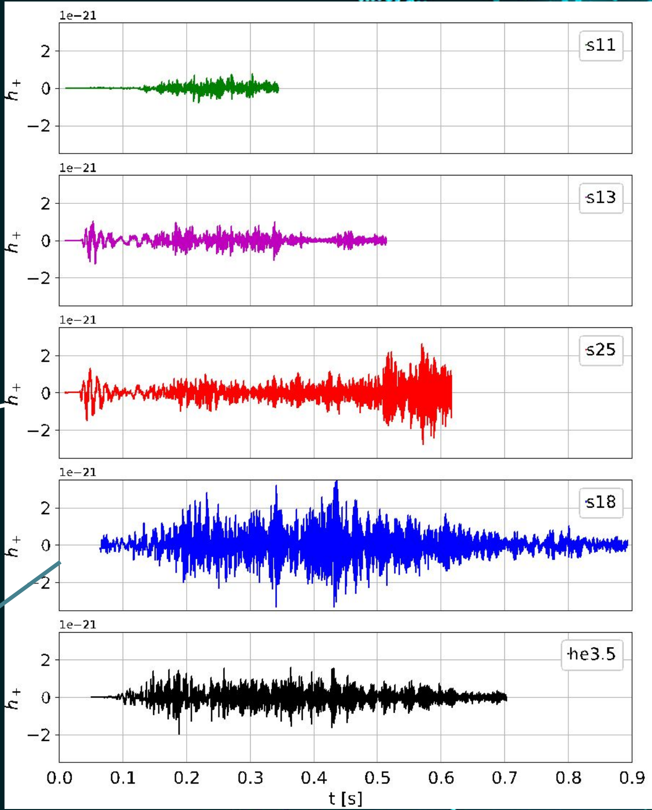


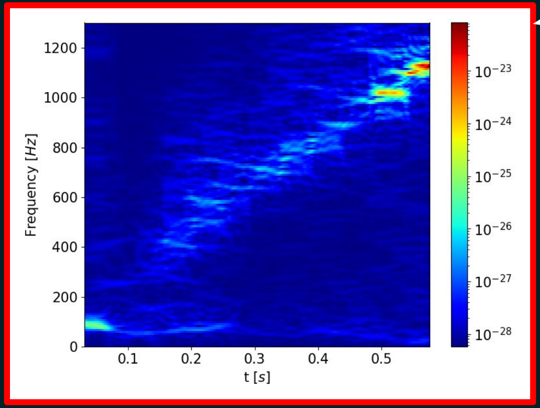
GW emission Process	Potential explosion mechanism: MHD mechanism (rapid rotation)	Neutrino mechanism (slow/no rotation)	Acoustic mechanism (slow/no rotation)
Rotating collapse and Bounce	Strong	None/weak	None/weak
3D rotational instabilities	Strong	None	None
Convection & SASI	None/weak	Weak	Weak
PNS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

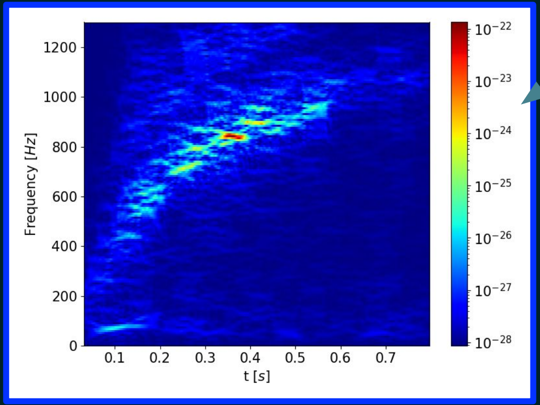
Ott et al. (2017)

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*





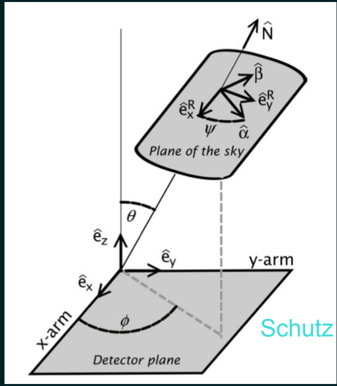


Iess, Cuoco, Morawski, Powell, https://doi.org/10.1088/2632-2153/ab7d31

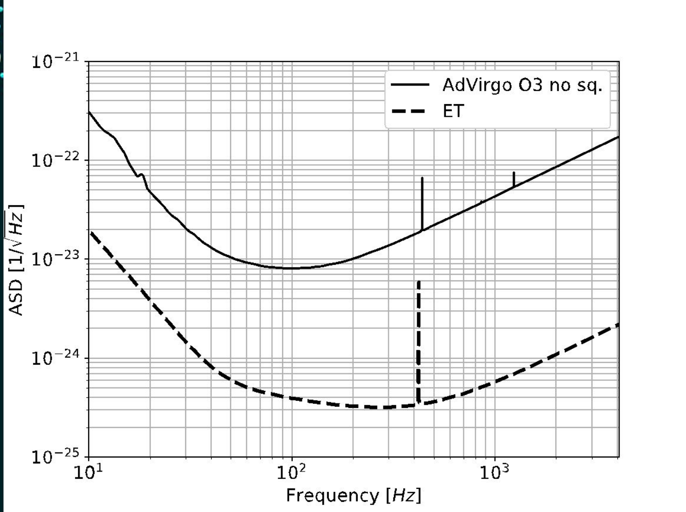
MDC and CCSN GW simulation

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

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



Schutz (2011)

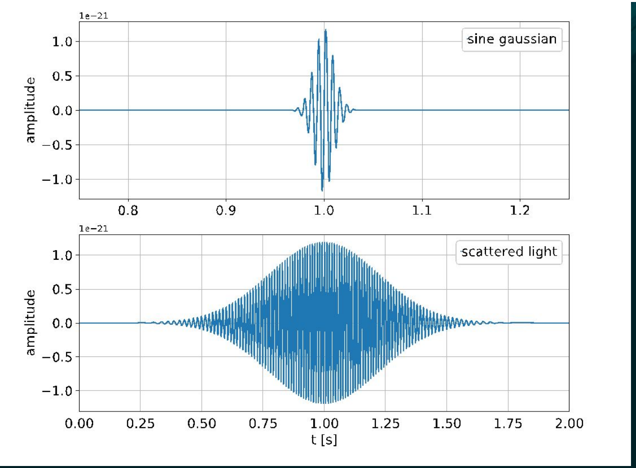


SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

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

$$h_{SL}(t) = h_0 \sin(\phi_{SL}) e^{-\frac{(t-t_0)^2}{2\tau}}$$

$$\phi_{SL} = 2\pi f_0 (t - t_0)[1 - K(t - t_0)^2]$$

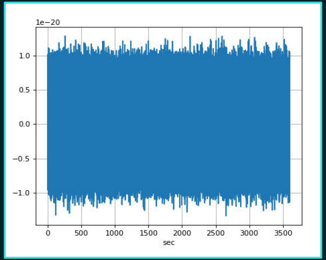


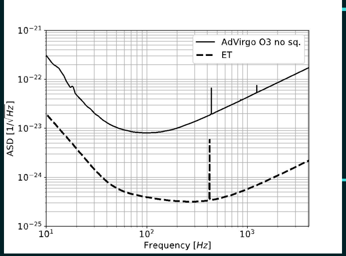
BACKGROUND STRAIN : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

Alberto Iess courtesy

Pipeline Workflow

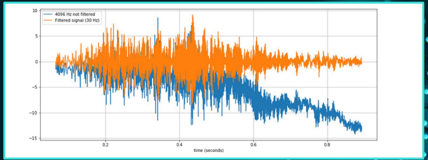
STRAIN





WAVEFORMS

RESAMPLING, FILTERING



+

WHITENING & TRIGGER GENERATION (WDF)

TRAINING

MACHINE-LEARNING CLASSIFIER

GW SIGNAL TYPE

GLITCH NOISE 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)

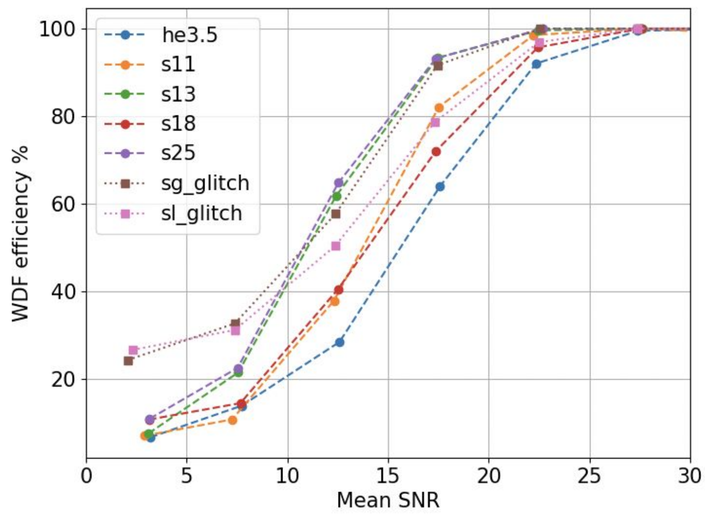
- Trigger generation based on threshold (tunable). WDF signal-to-noise ratio:

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

- Window 0.25 s, overlap 0.0625 s

GPS TIMES OF TRIGGERS

WDF efficiency vs. injection SNR

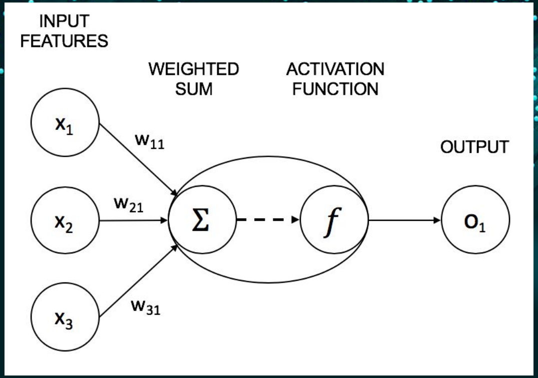


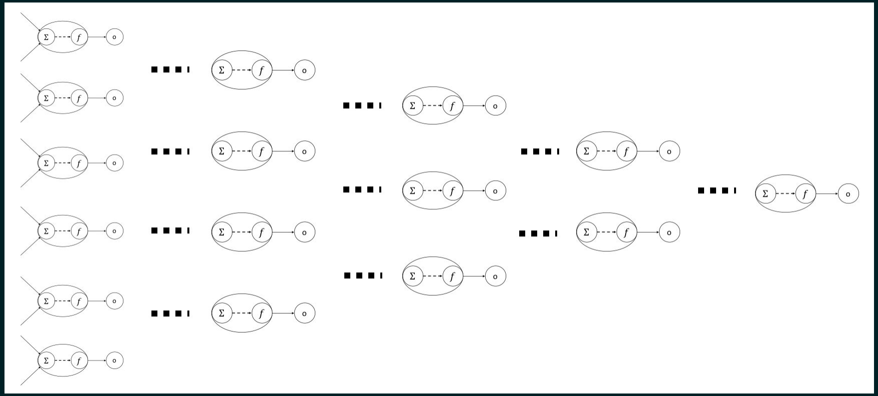
Iess, Cuoco, Morawski, Powell (preprint 2020)

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





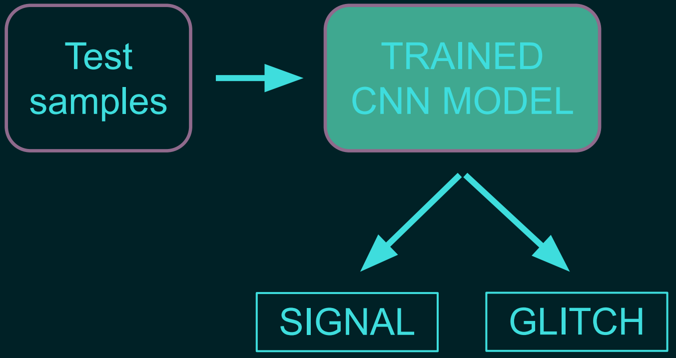
Dataset: chunks of 3 hr data with 1000 injections/h

GPU: Tesla k40

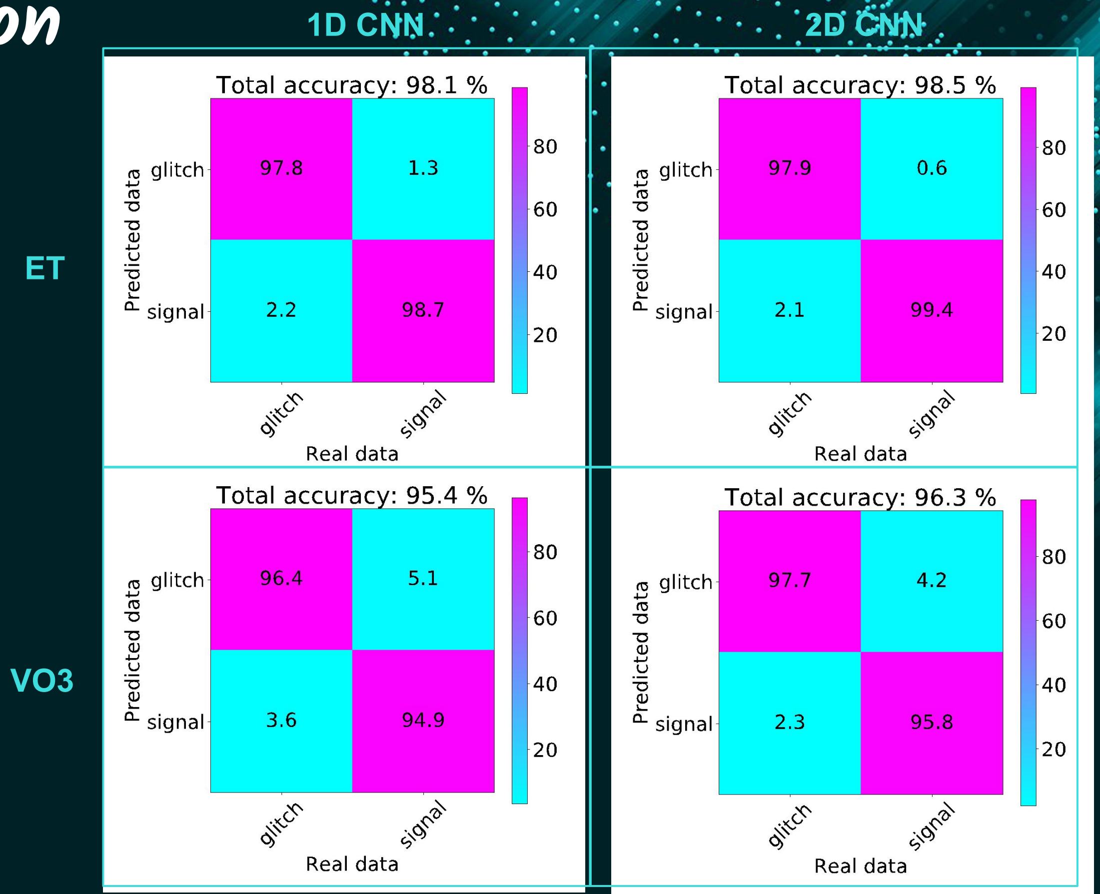
Alberto Iess courtesy

Binary Classification

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



- Training time: ~ 30 min

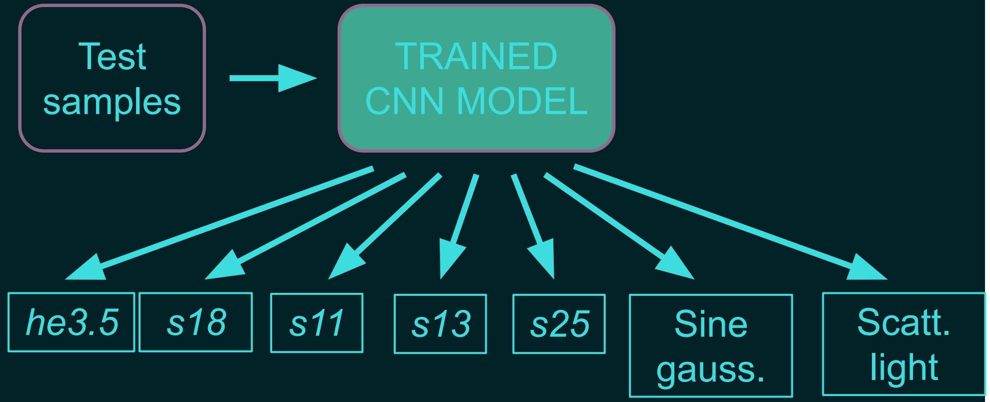


Iess, Cuoco, Morawski, Powell (preprint 2020)

Alberto Iess courtesy

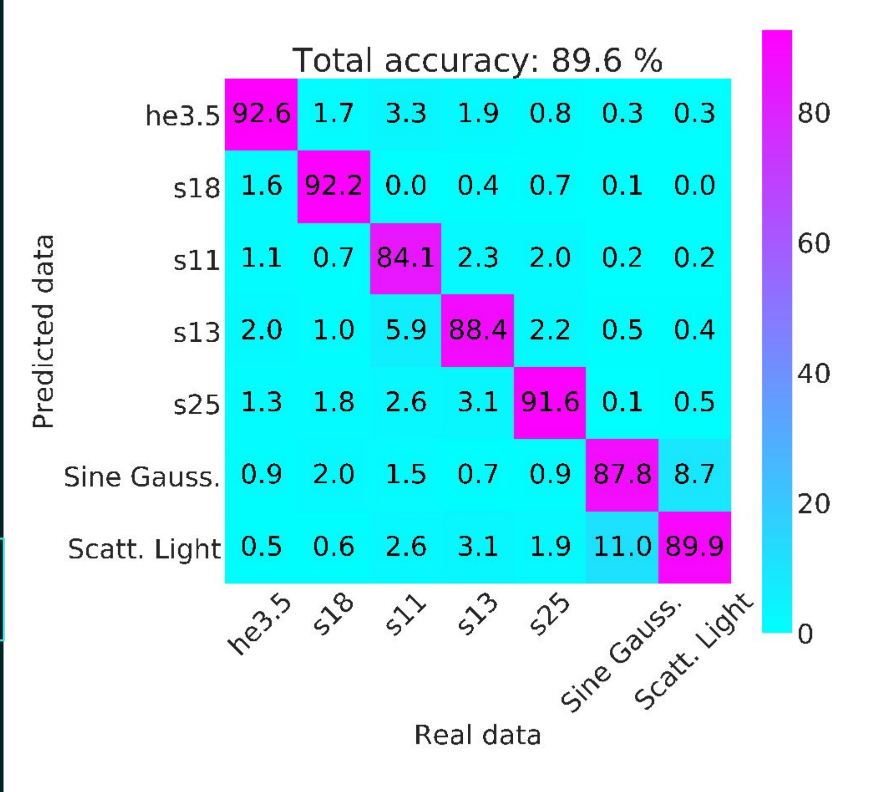
MultiLabel classification

- Train on **<u>all</u>** (4 CCSNe waveform models + glitches).
- Test on **<u>all.</u>**



COMPLEX TASK → LONGER TRAINING (> 1 hr)

ET, MERGED 1D & 2D CNN



Alberto Iess courtesy

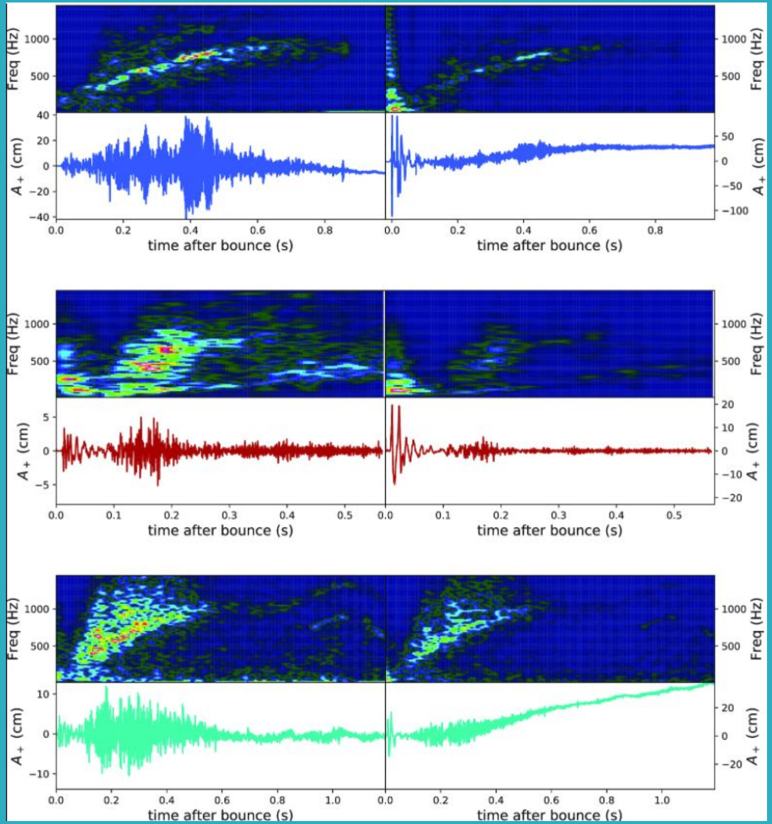
REAL NOISE FROM O2 SCIENCE RUN

- 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



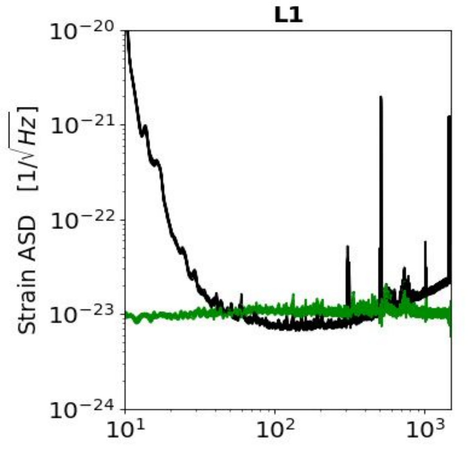
Powell and Müller (2020)

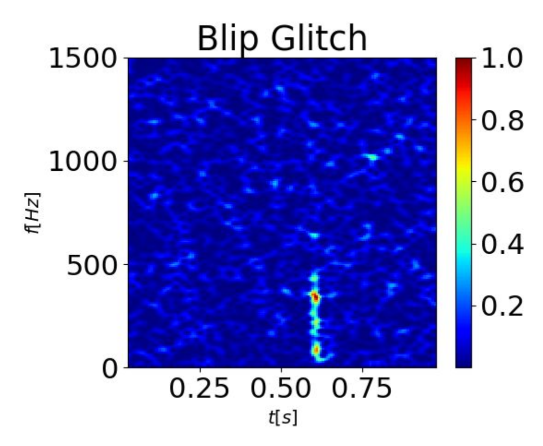
Alberto Iess courtesy

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, accepted for A&A*

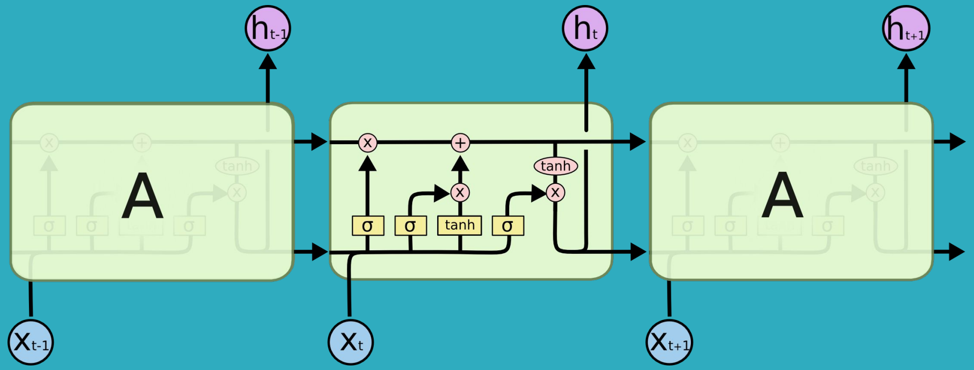
LONG SHORT TERM MEMORY (LSTM) NETWORK

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

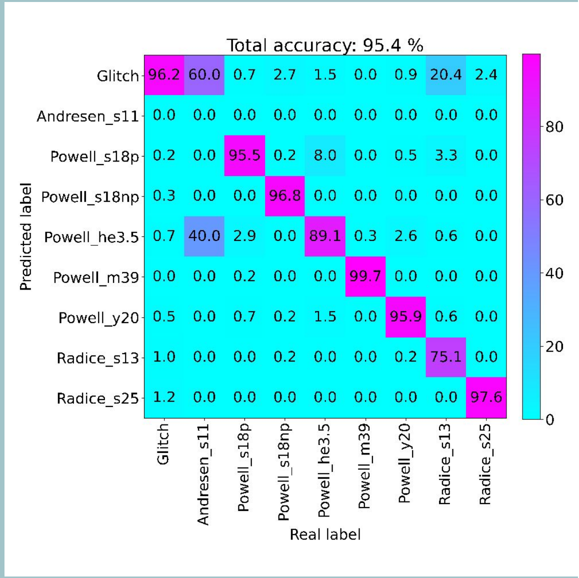
$$o_t = \sigma\left(W_o\,[h_{t-1}, x_t] + b_o\right)$$

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

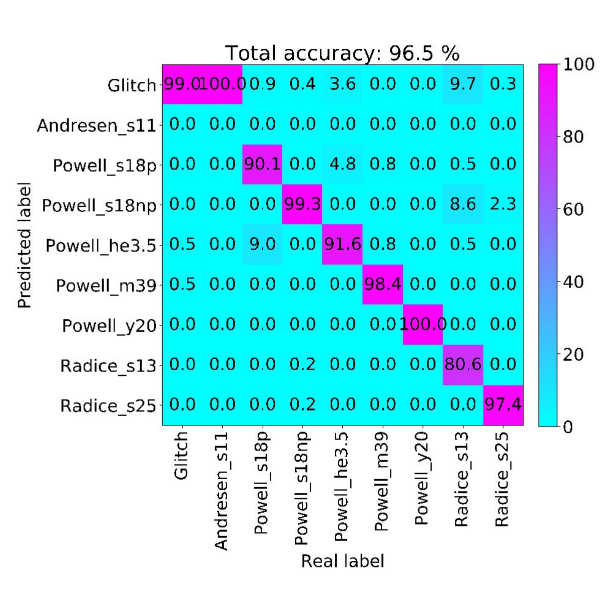
***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, 2022*

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

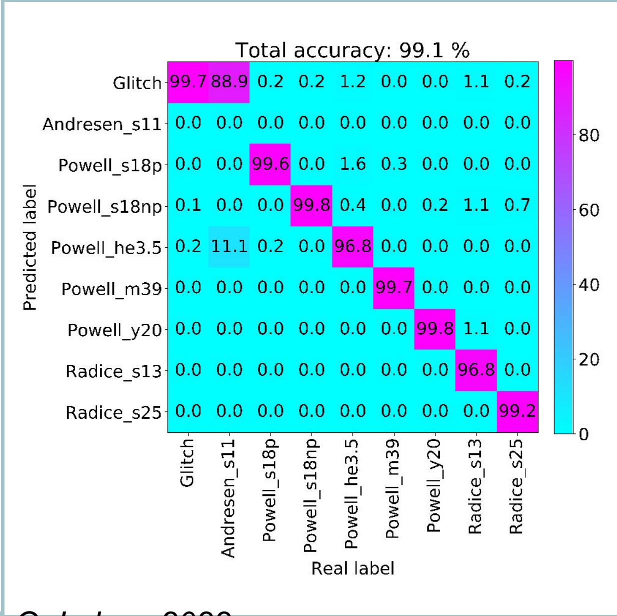
- **<u>Bi-LSTM</u>**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs



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



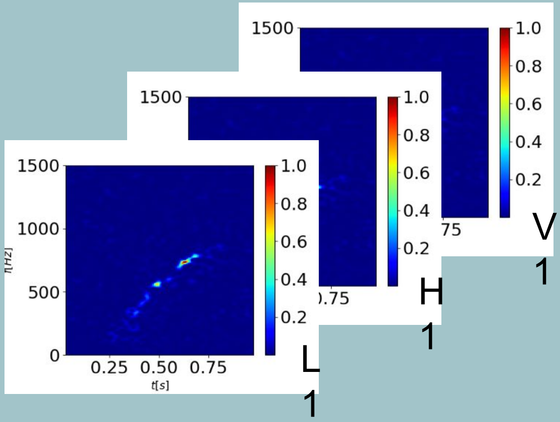
- **<u>2D-CNN</u>**, 4 convolutional layers
- ~3 ms/sample
- Best weights over 20 epochs

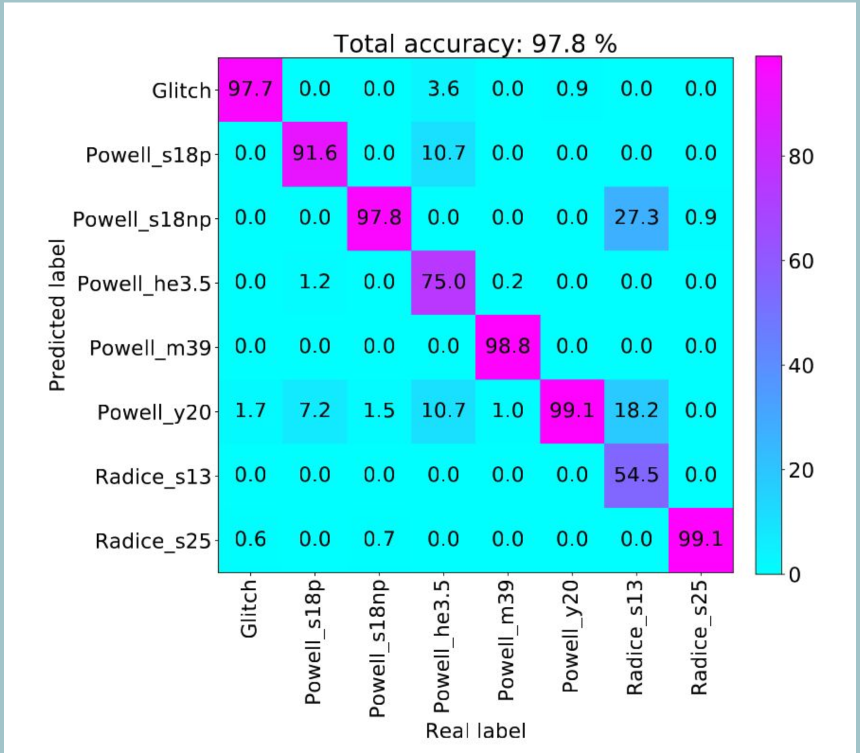


***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, 2022*

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*

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

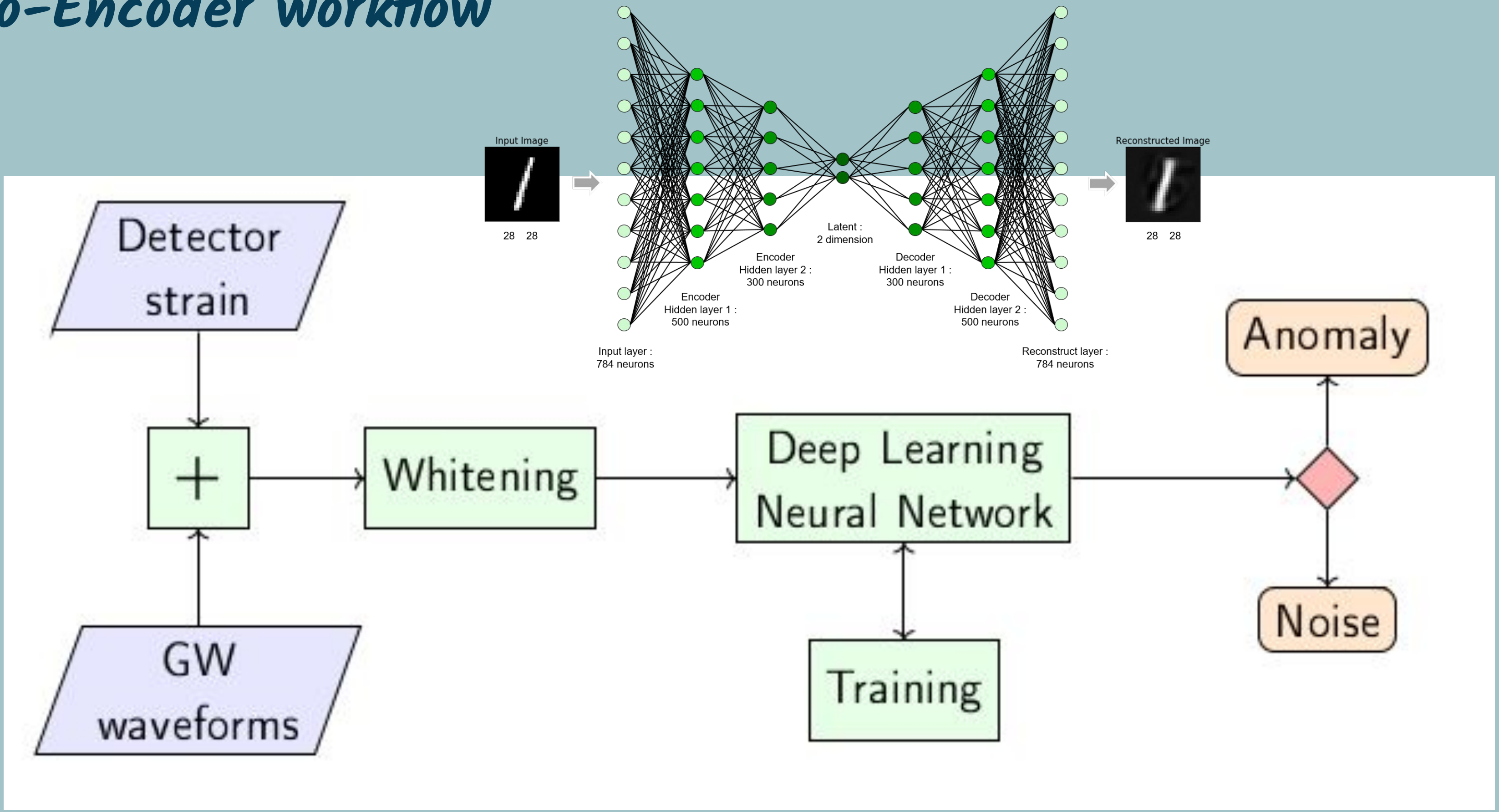
Example for detection/classification for CBC signals

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

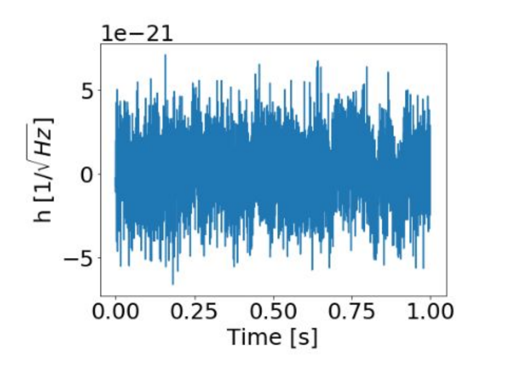


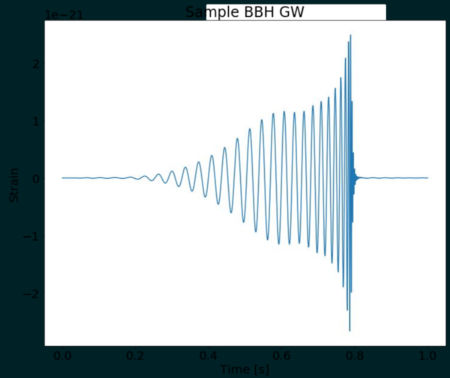
Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre, https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0*

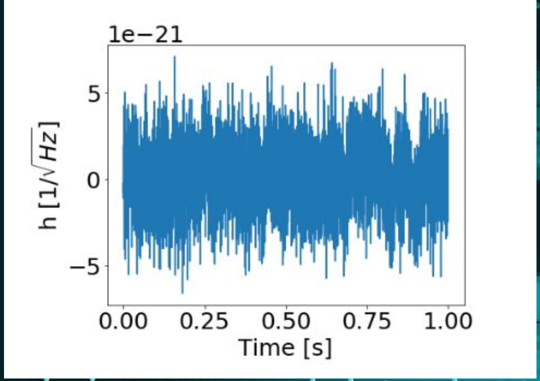
Filip Morawski courtesy

Pipeline concept

Model input — Model prediction

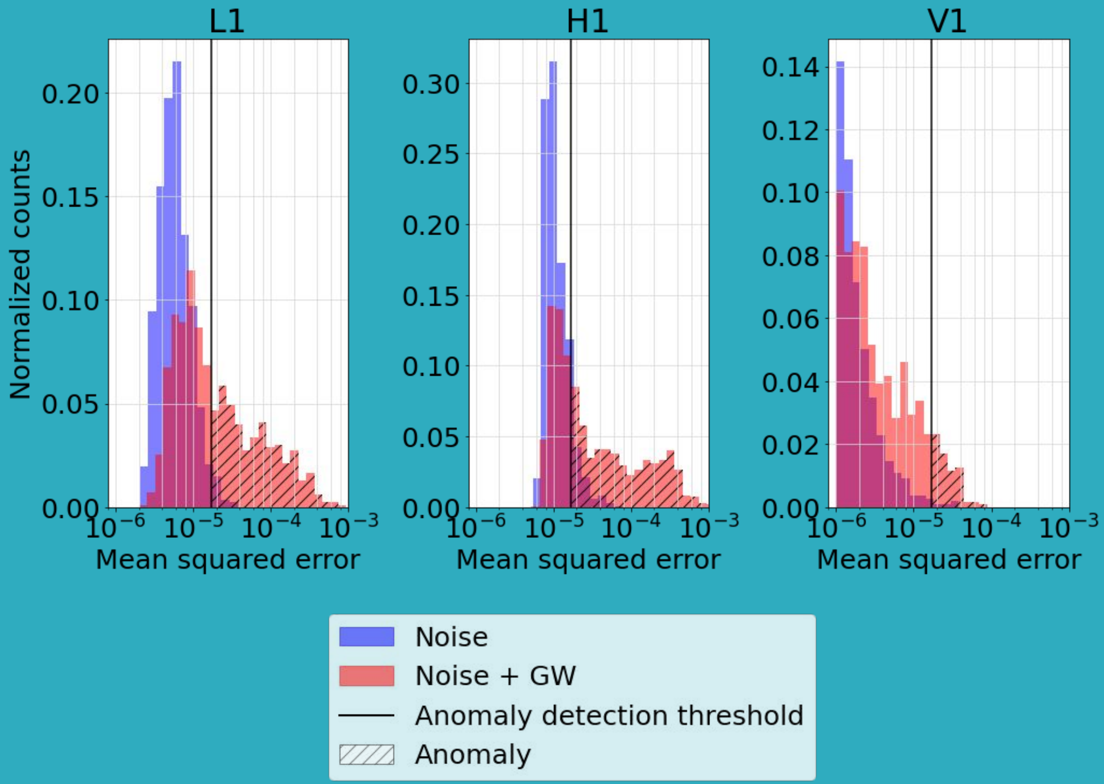




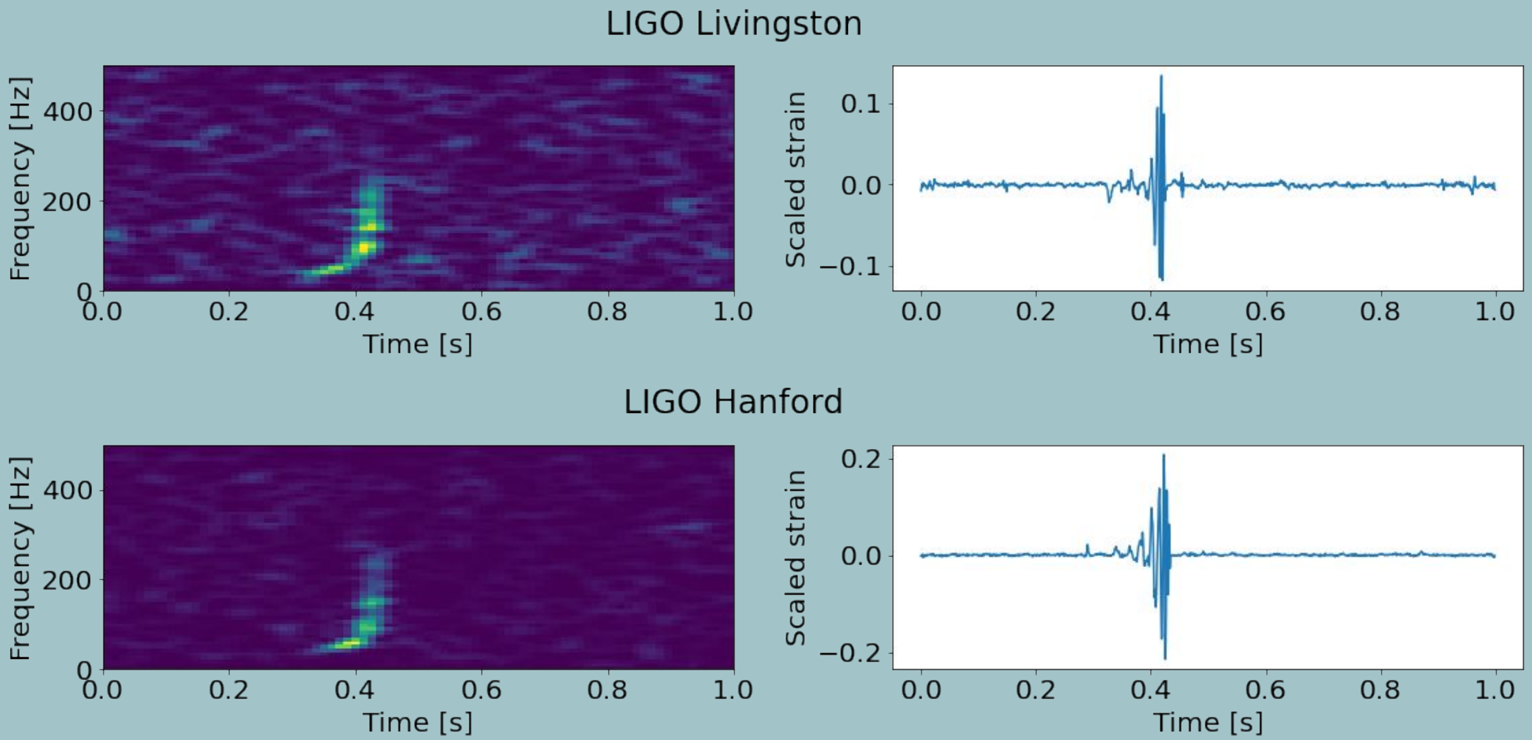


Filip Morawski courtesy

O2 data - MSE Distributions

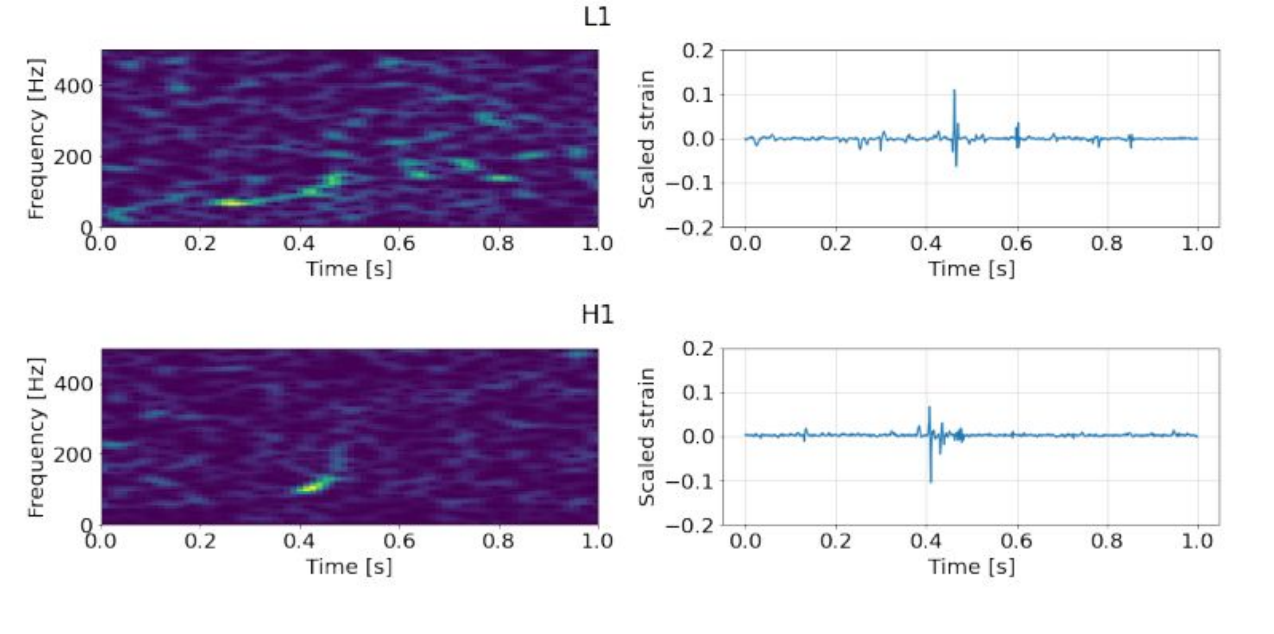


GW150914



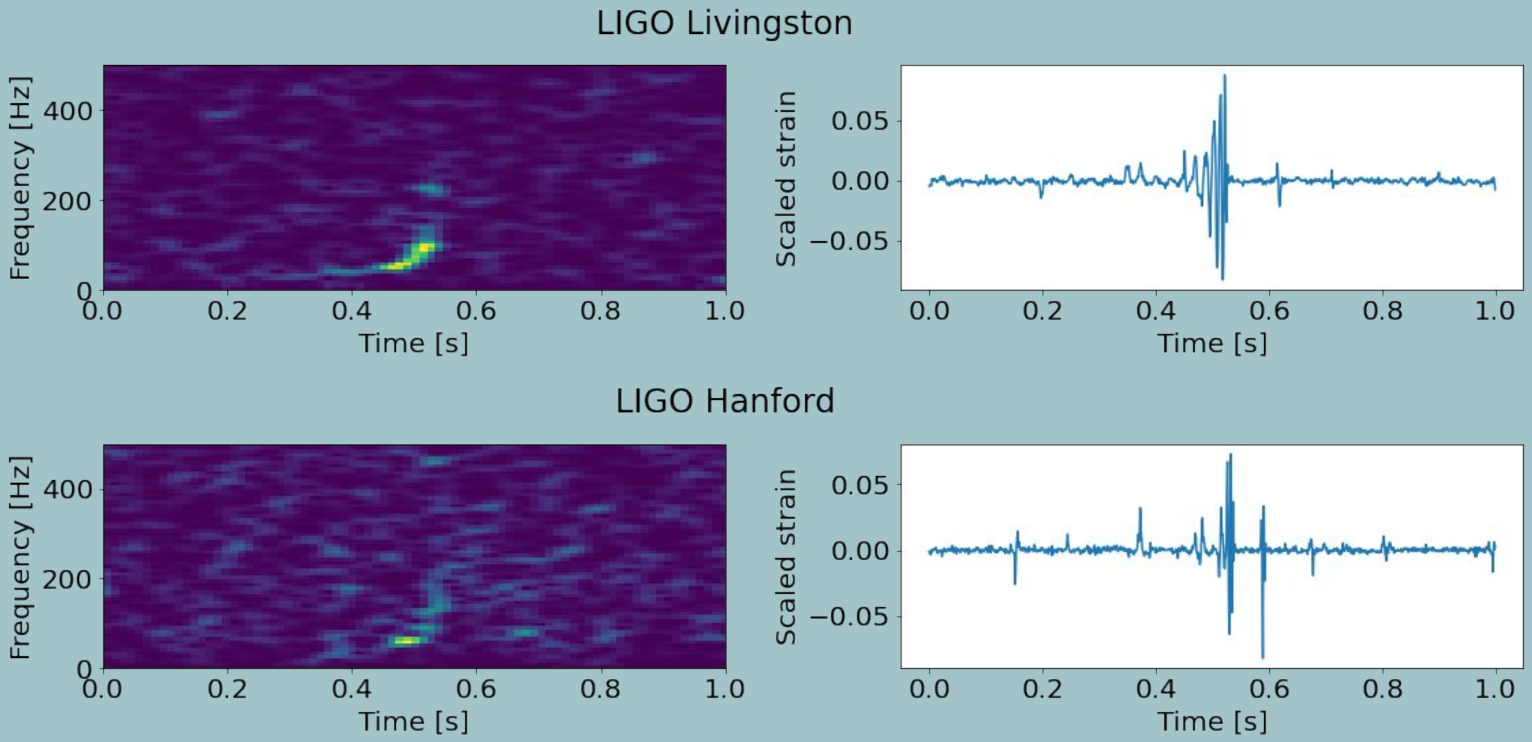
Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre,*
https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0

GW170806



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

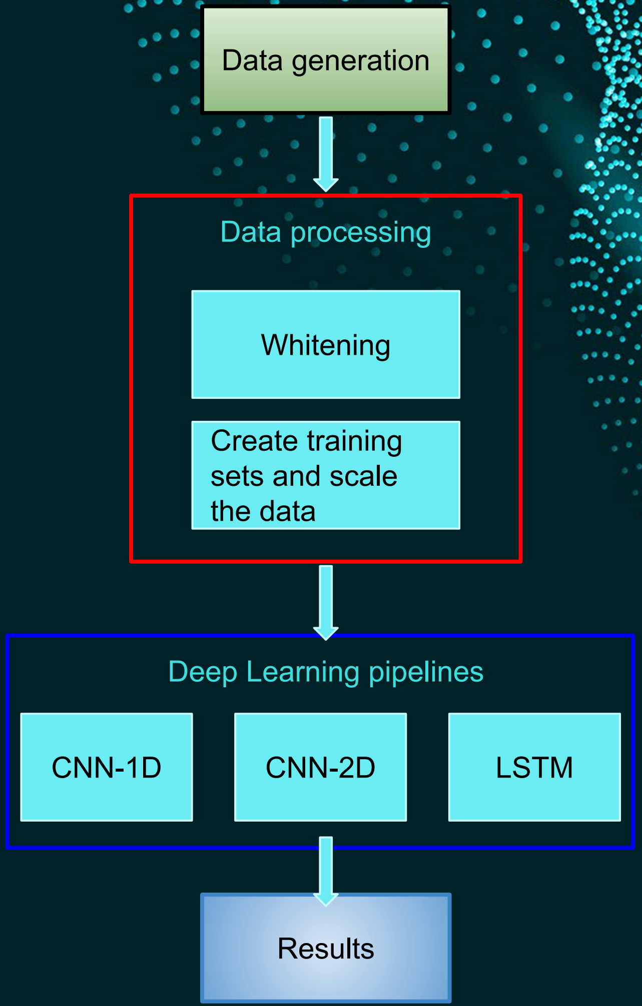
GW170814



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

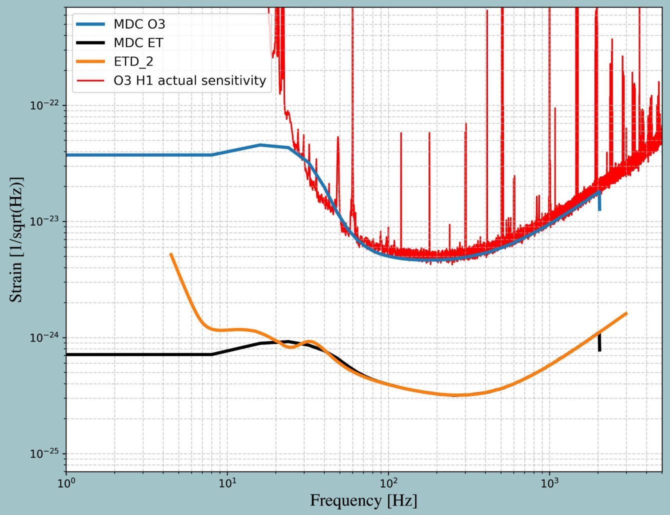
Deep learning searches for gravitational waves stochastic backgrounds

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*

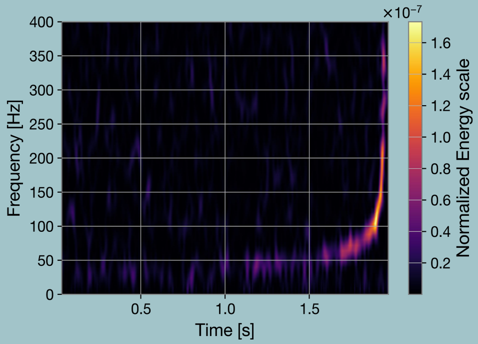


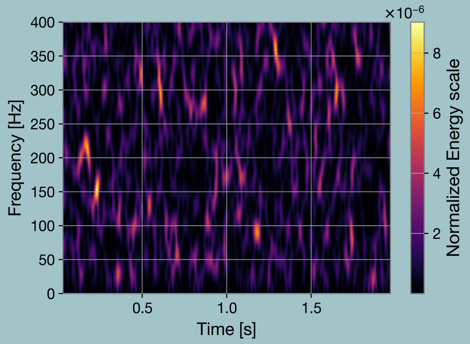
Recovered signals from a Welch method are shown by the blue and black curves above. For reference, ET-D design sensitivity is shown by the orange curve and the H1 O3 measured strain on Sep 05 2019 at 36.6 W input power and 2 dB of squeezing.

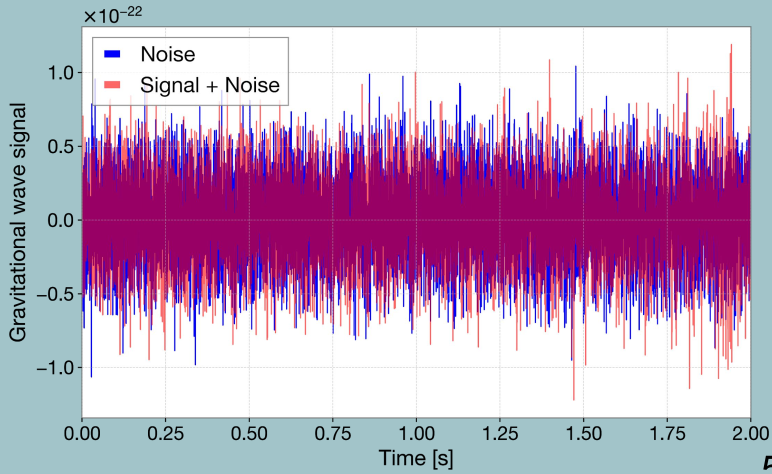
Andrei Utina courtesy

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

- 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.





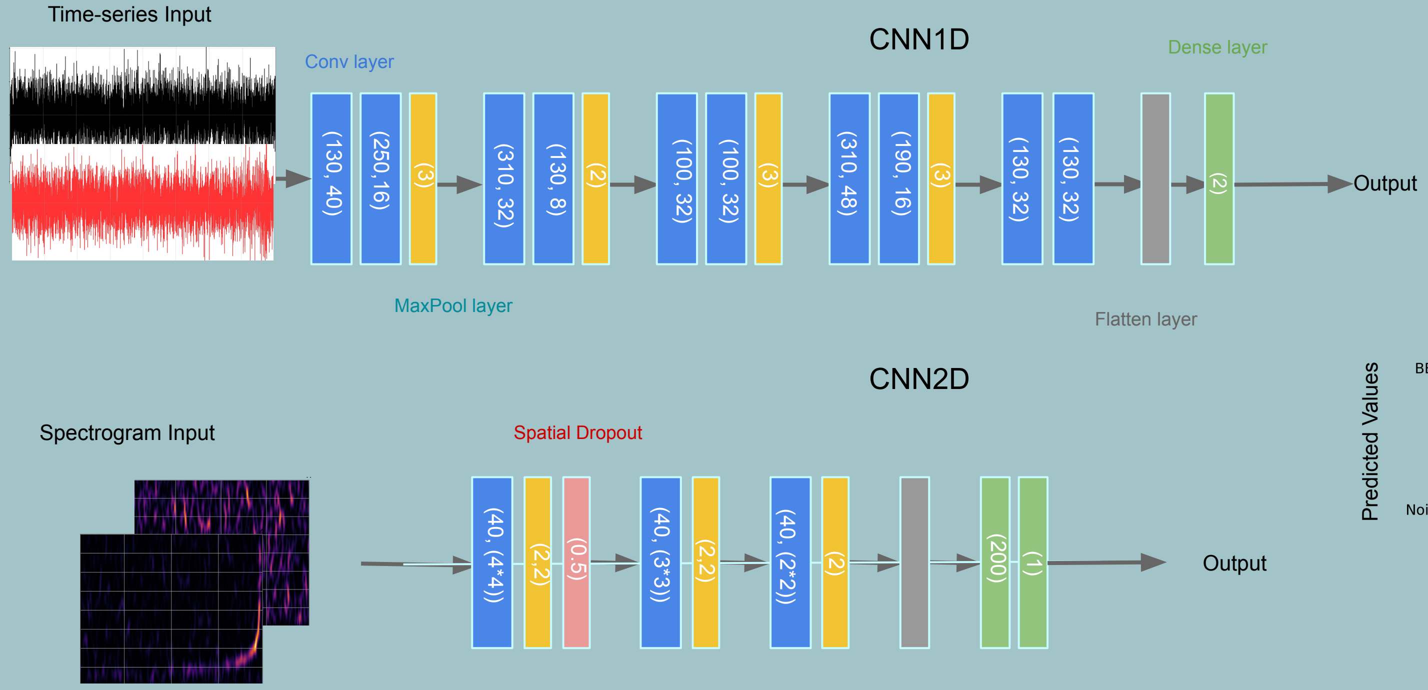


Andrei Utina courtesy

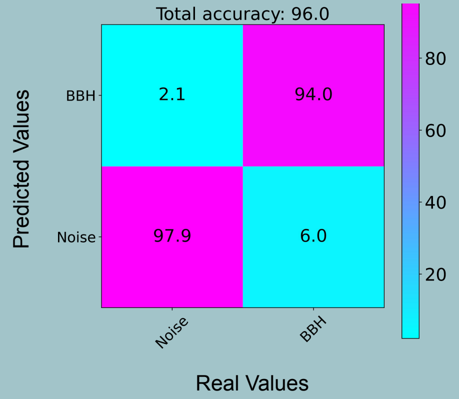
Deep Learning setup

- 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.

CNN architectures

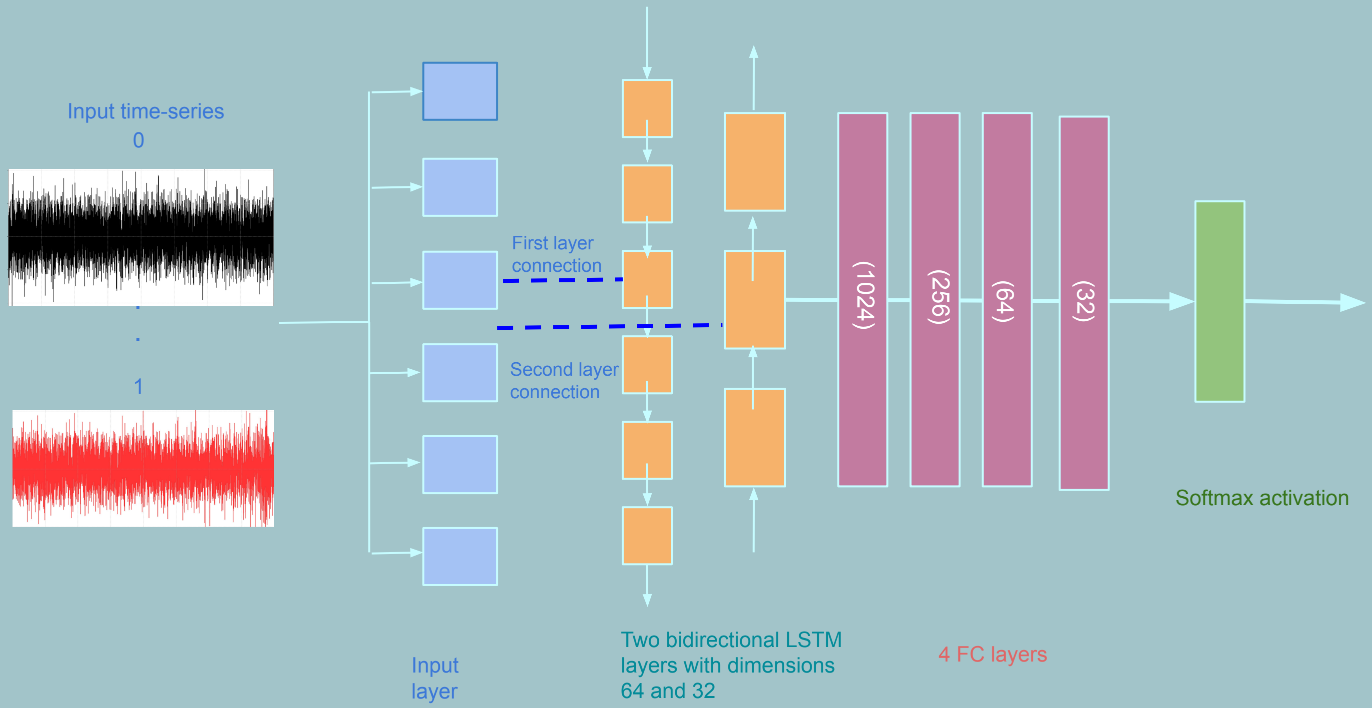


Output example: The confusion matrix from the classification



Andrei Utina courtesy

LSTM architecture



Output, similar performance metric as in the CNN architectures

Andrei Utina courtesy

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

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

Thank you