Artificial Intelligence for Gravitational Wave science

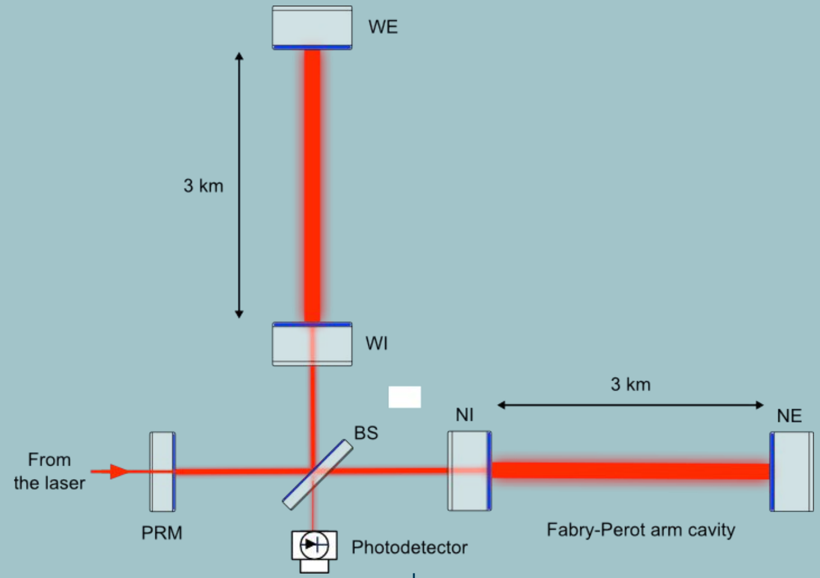
AI@INFN - Artificial Intelligence at INFN 2-3 May 2022

Elena Cuoco, EGO & SNS & INFN Pisa

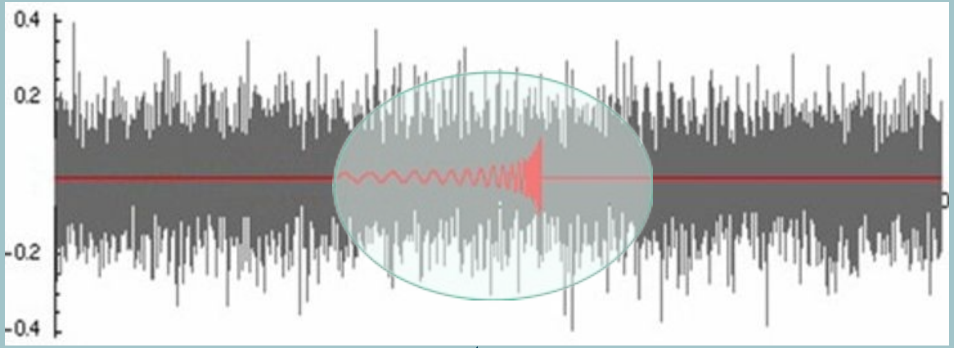
EGO European Gravitational Observatory
SCUOLA NORMALE SUPERIORE
INFN

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

Gravitational Wave (GW) detector data



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



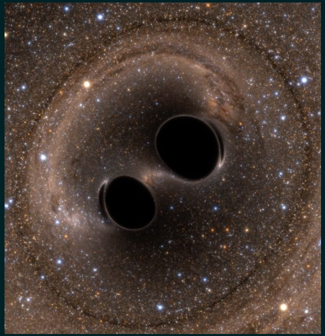
Why Artificial Intelligence for GW data?

- Our data: <u>a lot of noise and few GW signals (soon will be many)</u>
- 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)

GW astrophysical sources

Short□ long

Known □ unknown form



Coalescing Binary Systems CBC

Black hole – black hole (BBH)

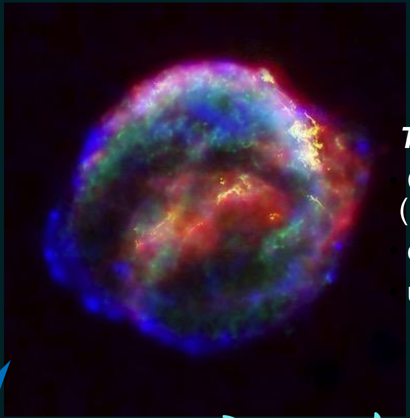
Neutron star – neutron star (BNS)

BH-NS

- Analytical waveform

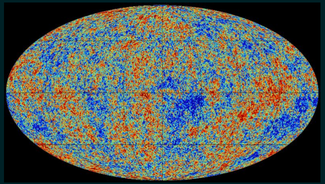
Continuous Sources

- Spinning neutron stars
- Monotone waveform



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?

How we detect transient signals: modeled search

Matched-filter

Data

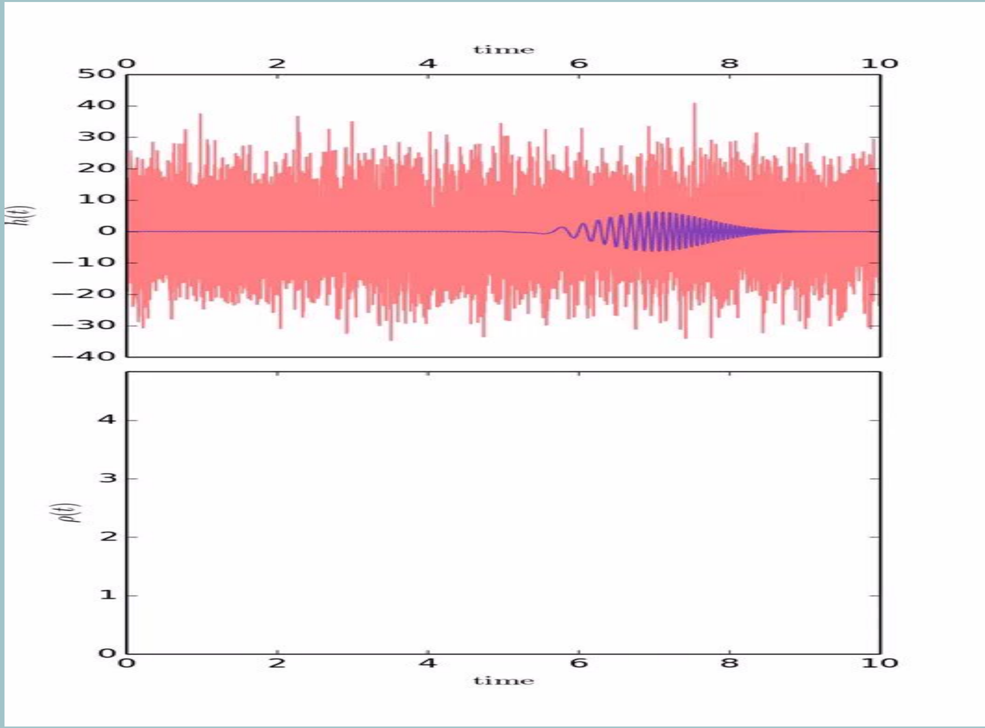
Template

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

Noise power spectral density

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

CBC search

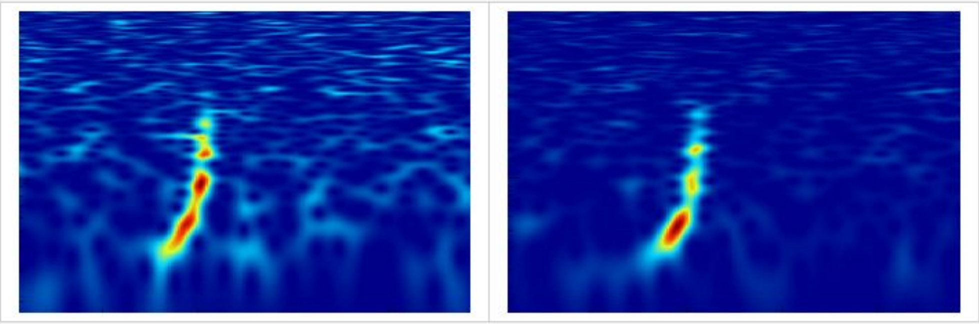


How we detect transient signals: un-modeled search

- *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*

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.

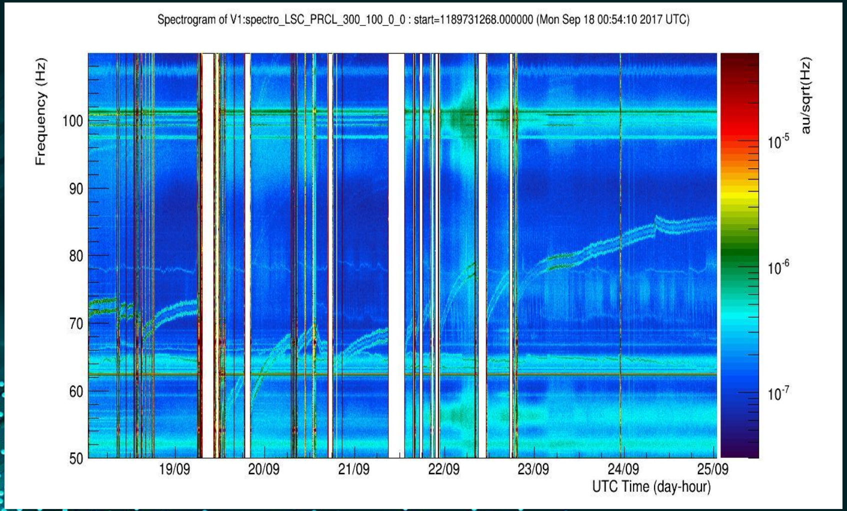


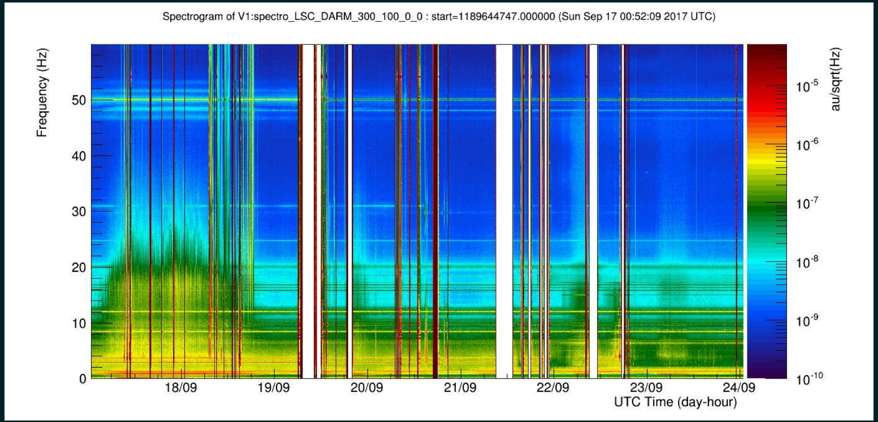
Time-Frequency maps of GW150914: Livingston data (left), Hanford data (right)
First screenshot of GW150914 event

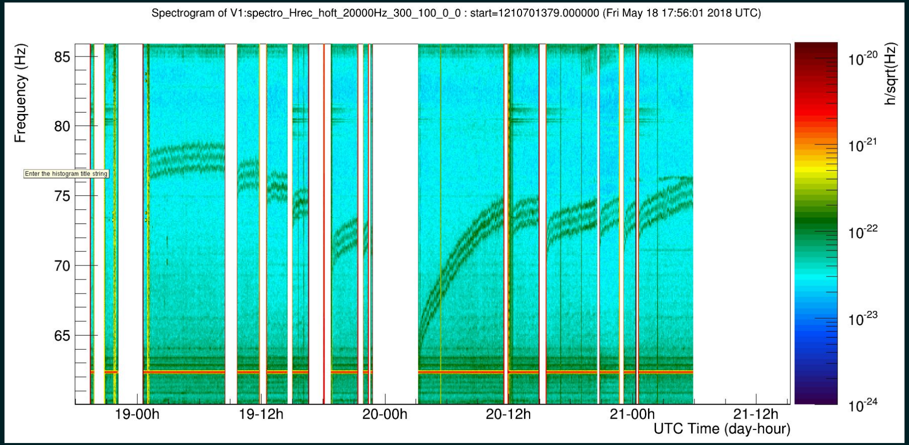
Burst search

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

Non linear, not stationary noise

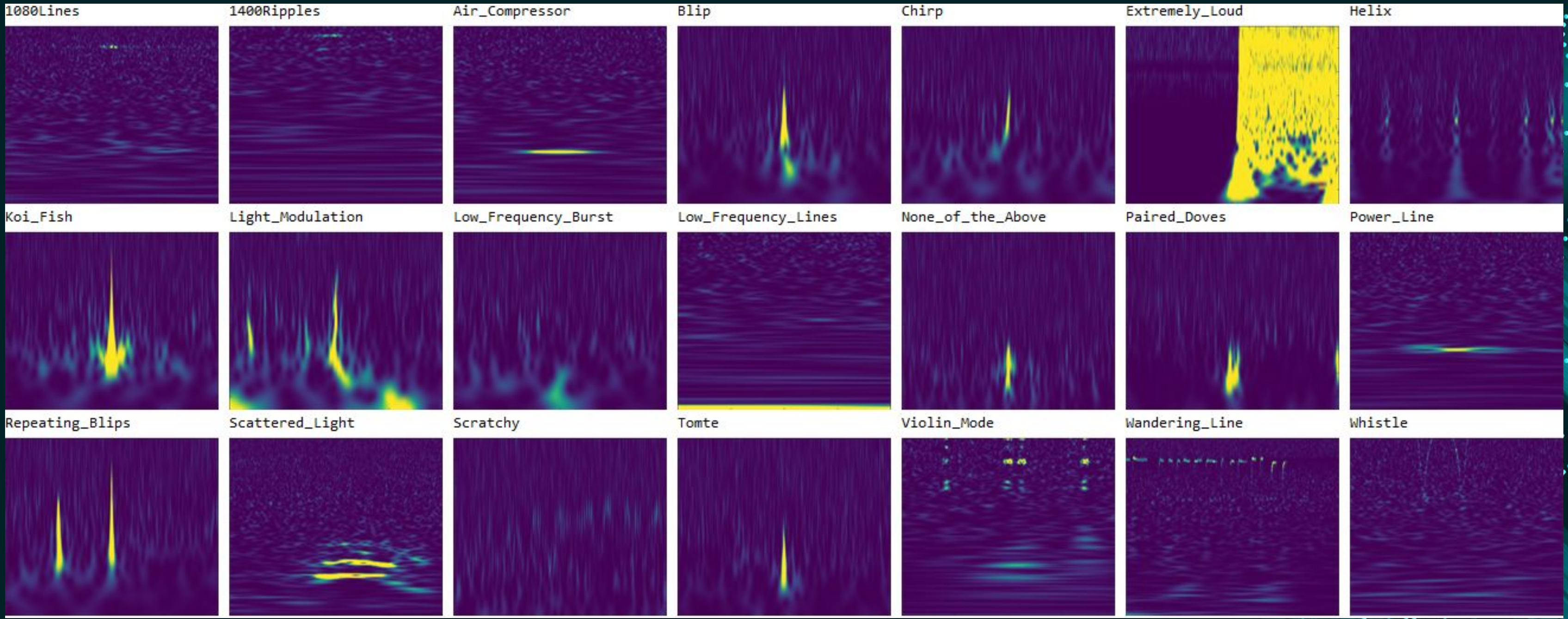






I. Fiori courtesy

Transient noise signals: glitches



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

How Artificial Intelligence could help

Data conditioning

Data preprocessing and cleaning

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

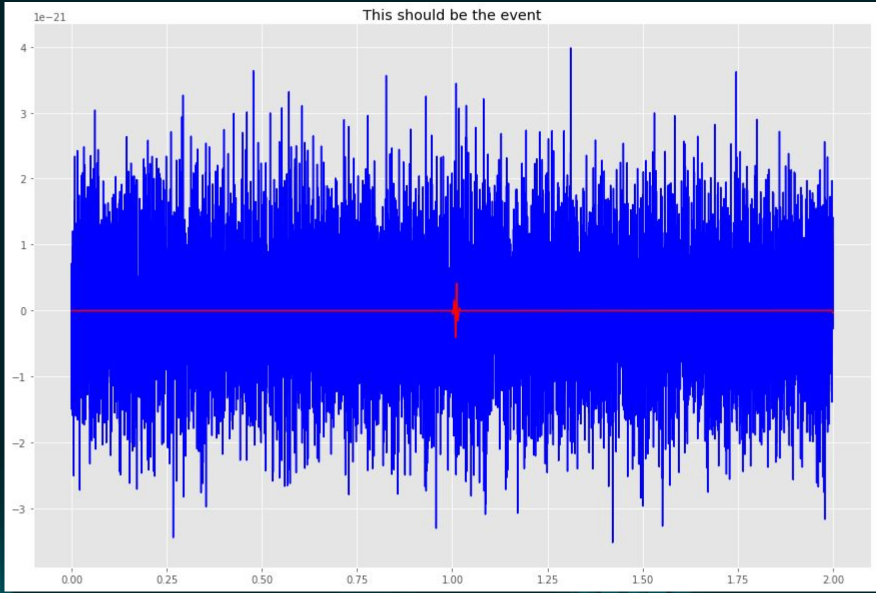
Signal detection / classification / parameter estimation

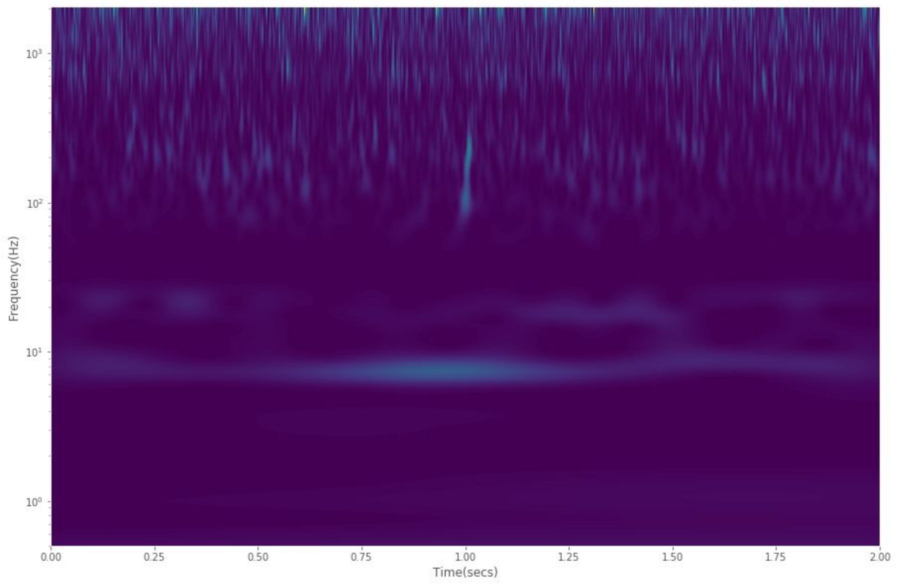
Detect signals, identify, estimate parameters for waveform

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

How to deal with data: Time series or Images?

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





Few examples developed in my team, but many more in LVK collaboration...

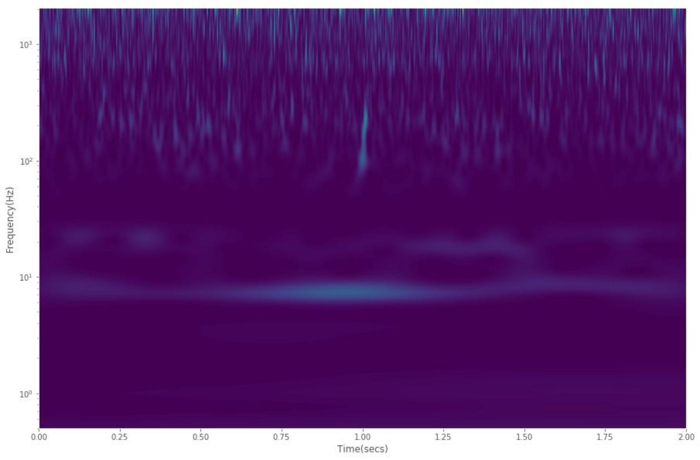
Review paper: Enhancing gravitational-wave science with machine learning Elena Cuoco *et al* 2021 *Mach. Learn.: Sci. Technol.* 2 011002

AI GW application

- Noise Transient signal classification
- GW signal classification (CBC or CCSN)
- Stochastic background detection (in extra slides)

A.Iess, F. Morawski, B. Patricelli and g2net members

❖ Transient Noise classification and Images as input data

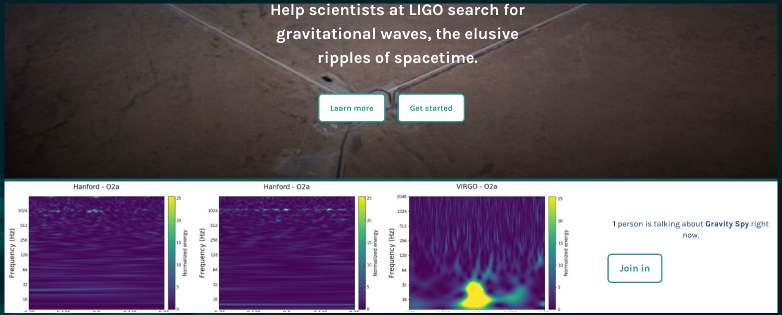


Why Image-based classification

Simulated and real data

Citizen science for GW-AI

Gravity Spy



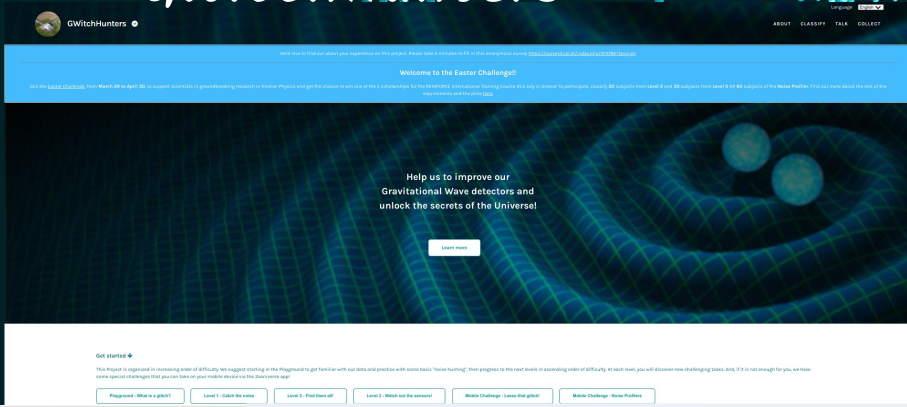
http://www.gravityspy.org/

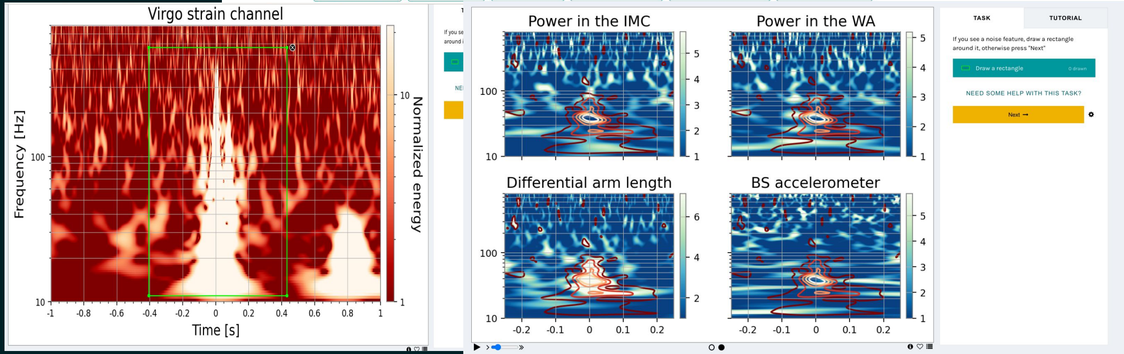
Citizen scientists contribute to classify glitches

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

GWitchHunters



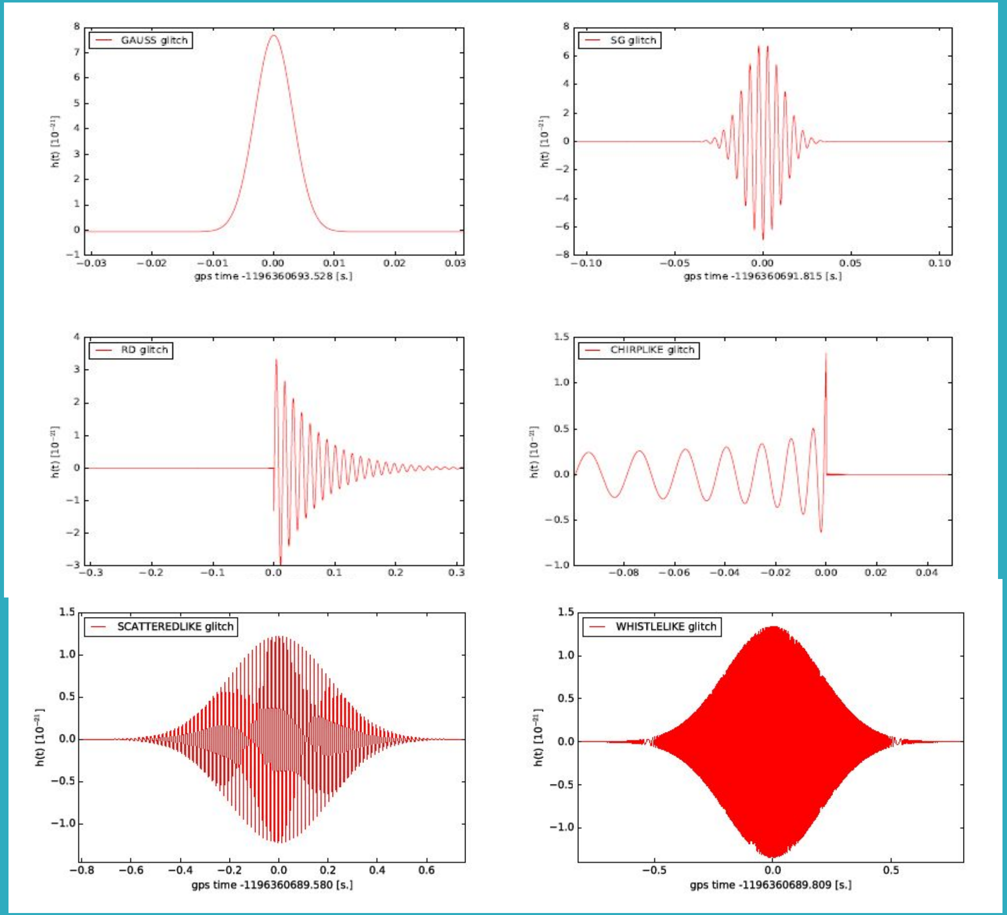


REINFORCE
REsearch INfrastructures FOR Citizens in Europe

- *Team: M. Razzano, F. Di Renzo, F. Fidecaro (@Unipi), G. Hemming, S. Katsanevas (@EGO)*
- *Launched @ Nov 2019 - REINFORCE Project H2020-SWAFS (2019-2022)*

https://www.zooniverse.org/projects/reinforce/gwitchhunters

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

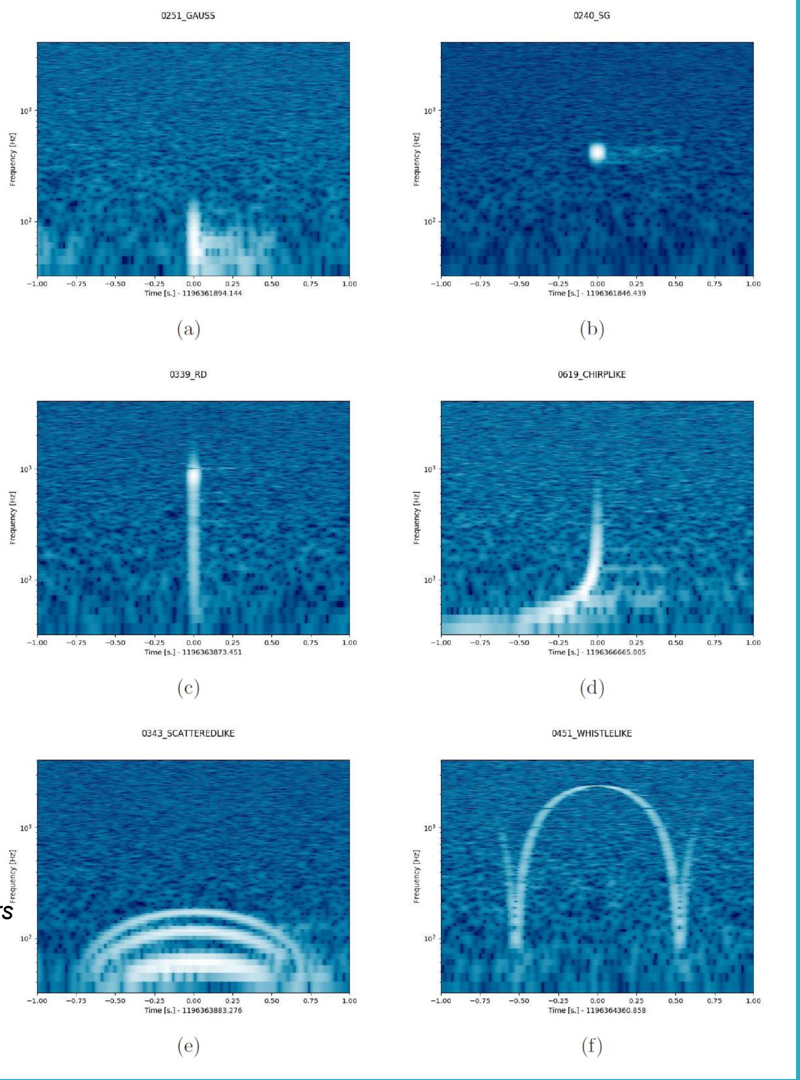
Razzano M., Cuoco E. CQG-104381.R3

Building the images

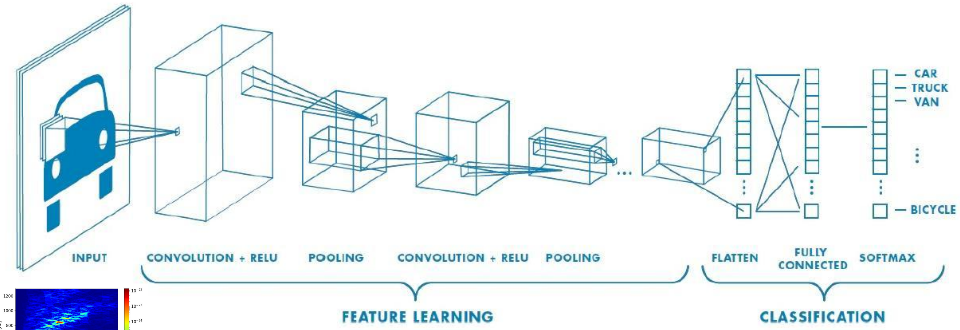
- Spectrogram for each image
- 2-seconds time window to highlight features in long glitches
- Data is whitened
- Optional contrast stretch

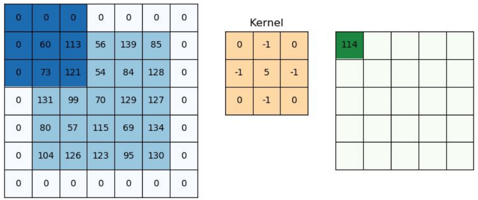
Simulations now available on FigShare

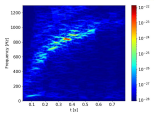
Razzano, Massimiliano; Cuoco, Elena (2018): Simulated image data for testing machine learning classification of noise transients in gravitational wave detectors (Razzano & Cuoco 2018). figshare. Collection. https://doi.org/10.6084/m9.figshare.c.4254017.v1



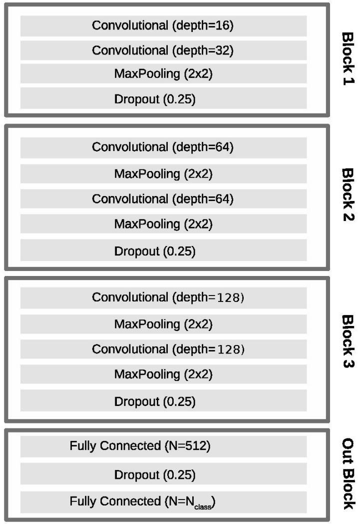
Deep learning. Convolutional Neural Network

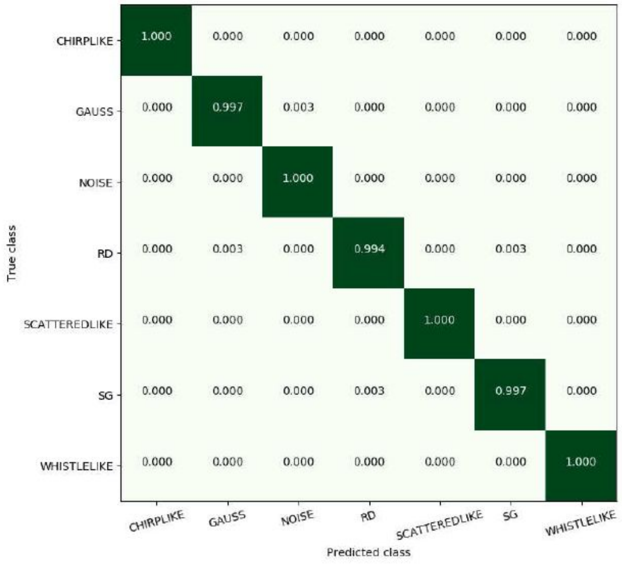






Spectrogram images





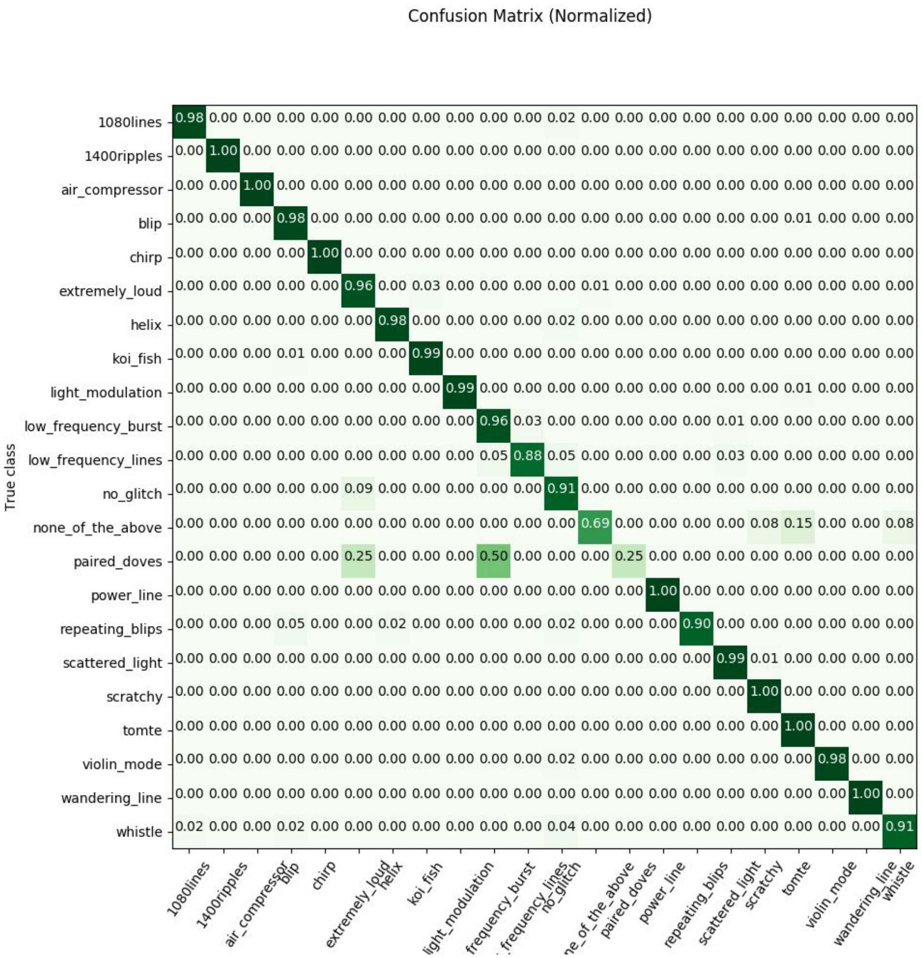
Normalized Confusion Matrix

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

Application Test on Real data: O1 run

Dataset from GravitySpy images

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
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

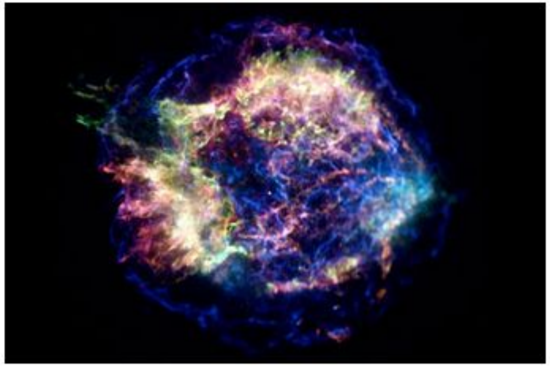
GW Astrophysical signal classification

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.

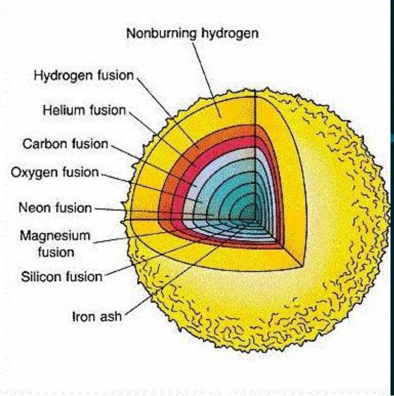
NASA/CXC/UNAM/IOFFE/D. PAGE, P. SHTERNIN ET AL

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

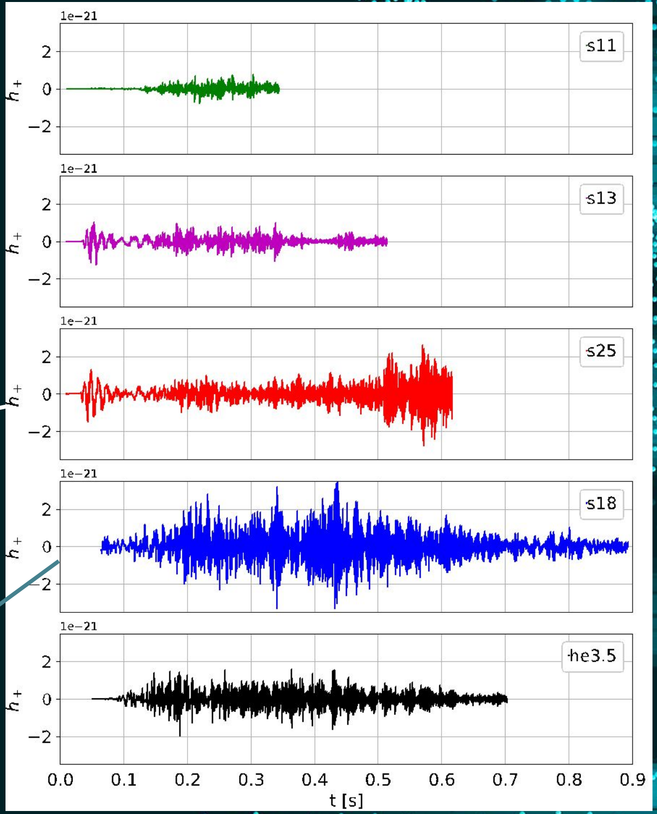


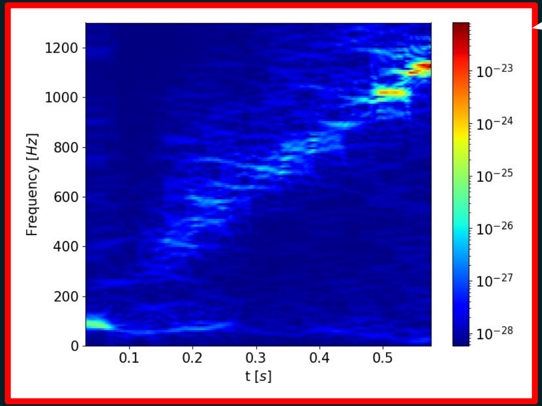
GW emission Process	Potential explosion mechanism: MHD mechanism (rapid rotation)	Neutrino mechanism (slow/no rotation)	Acoustic mechanism (slow/no rotation)
Rotating collapse and Bounce	Strong	None/weak	None/weak
3D rotational instabilities	Strong	None	None
Convection & SASI	None/weak	Weak	Weak
PNS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

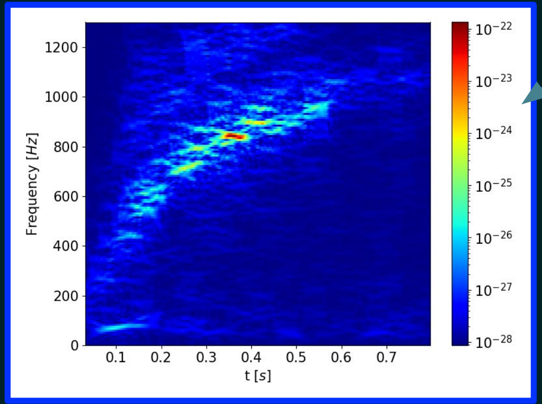
Ott et al. (2017)

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*





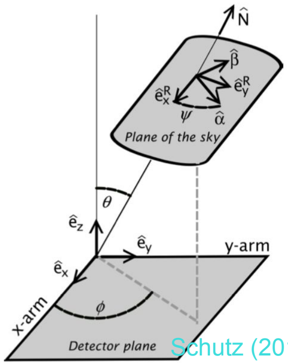


Iess, Cuoco, Morawski, Powell,
https://doi.org/10.1088/2632-2153/ab7d31

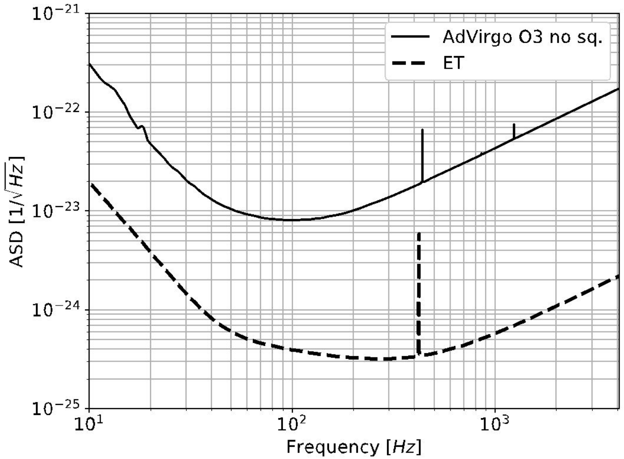
MDC and CCSN GW simulations

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

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



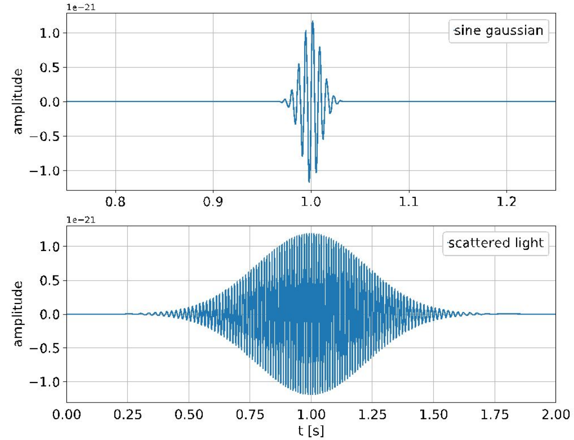
Schutz (2011)



SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

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

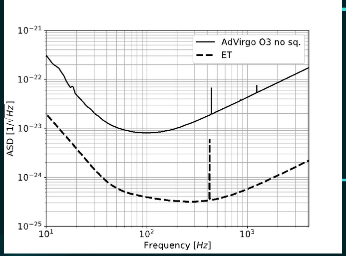
$$h_{SL}(t) = h_0 \sin(\phi_{SL}) e^{-\frac{(t-t_0)^2}{2\tau}} \quad \phi_{SL} = 2\pi f_0 (t - t_0)[1 - K(t - t_0)^2]$$

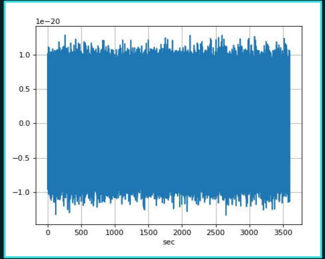


BACKGROUND STRAIN : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

Pipeline Workflow

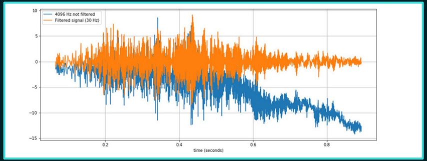
STRAIN





WAVEFORMS

RESAMPLING, FILTERING



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WHITENING & TRIGGER GENERATION (WDF)

TRAINING

MACHINE-LEARNING CLASSIFIER

GW SIGNAL TYPE

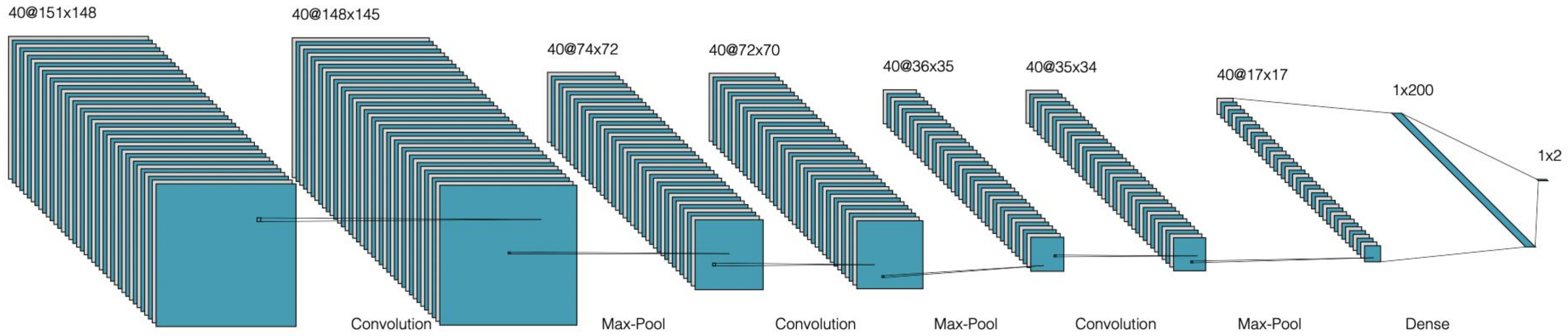
GLITCH NOISE TYPE

Neural Network architecture

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



Binary Classification

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

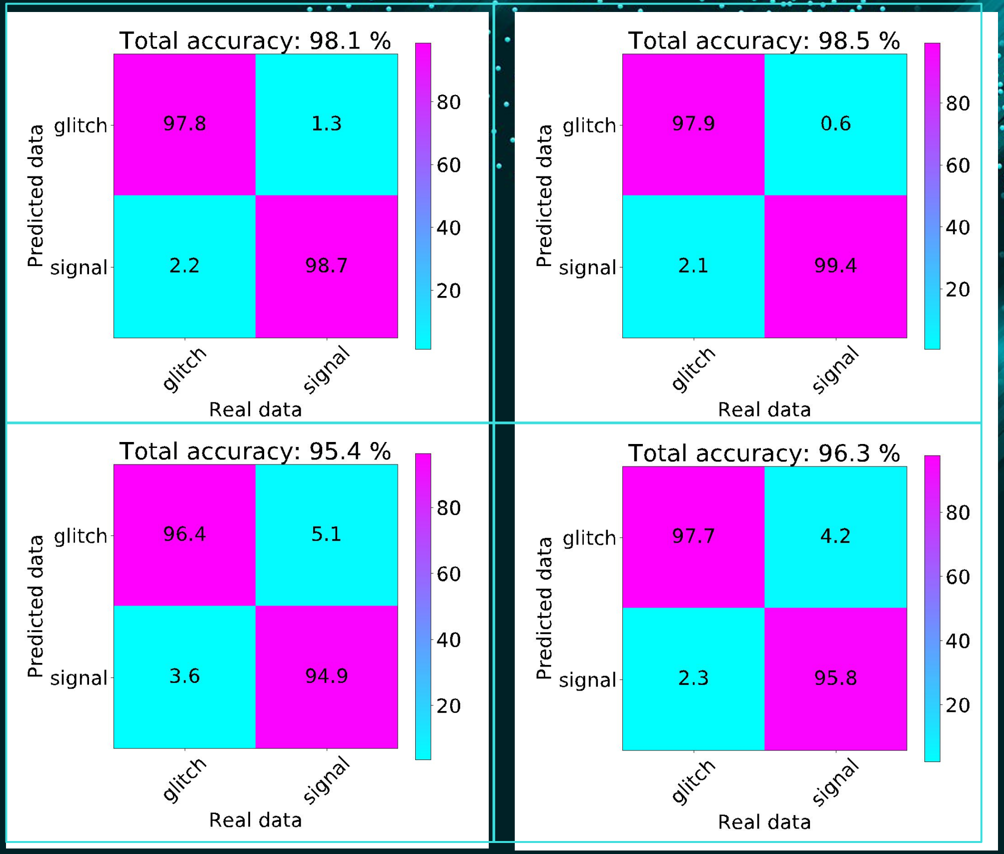
Test samples → TRAINED CNN MODEL → SIGNAL / GLITCH

- Training time: ~ 30 min

1D CNN | 2D CNN

ET

VO3

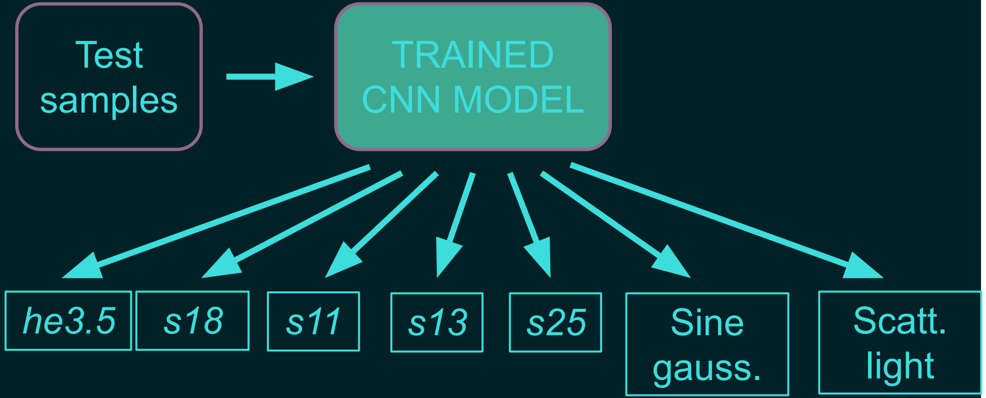


Alberto Iess *et al* 2020 *Mach. Learn.: Sci. Technol.* **1** 025014

COST EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY

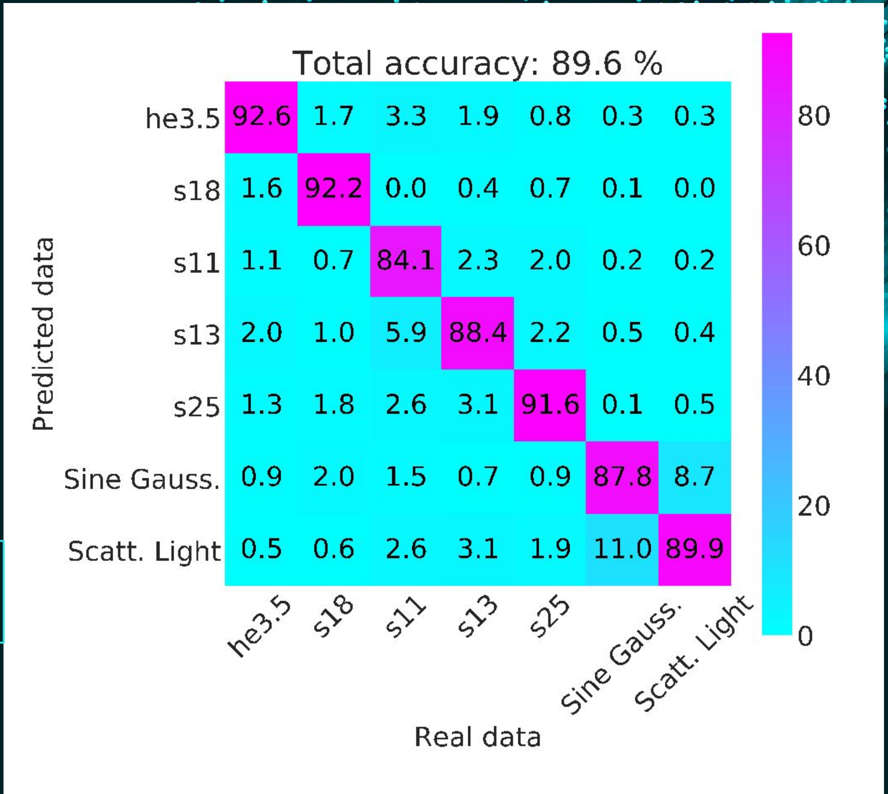
MultiLabel classification

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



COMPLEX TASK → LONGER TRAINING (> 1 hr)

ET, MERGED 1D & 2D CNN



Test on O2 real Data

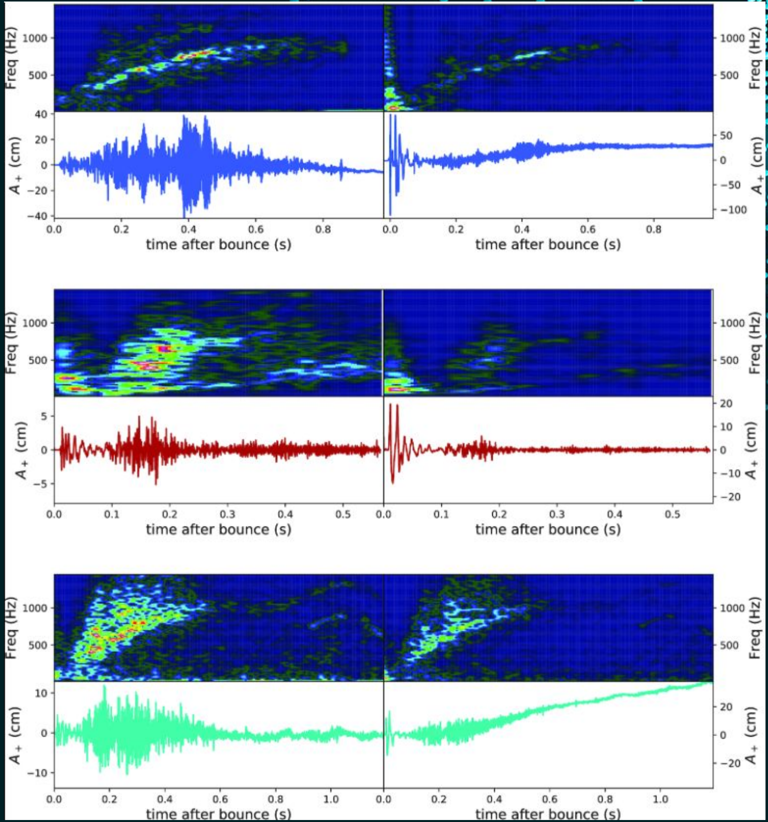
- 44 segments (4096s per segment) from O2 science run.
- Added m39, y20, s18np models (Powell, Mueller 2020).
- **<u>Fixed distance of 1 kpc</u>.**
- Added LSTM Networks, suited for timeseries data.
- **Added Three ITF classification.**

- *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

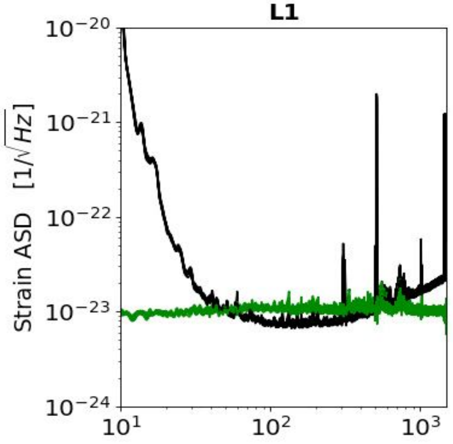


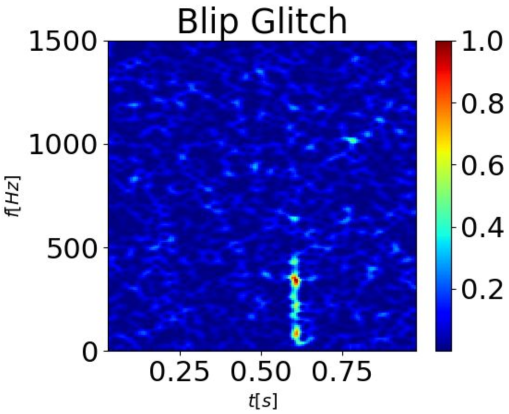
Powell and Müller (2020)

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





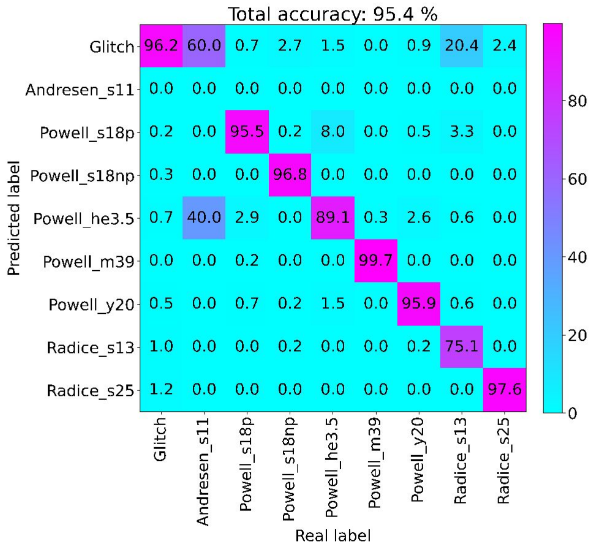
CCSN Classification on Simulated and Real O2 Data with CNNs and LSTMs
***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, accepted for A&A*

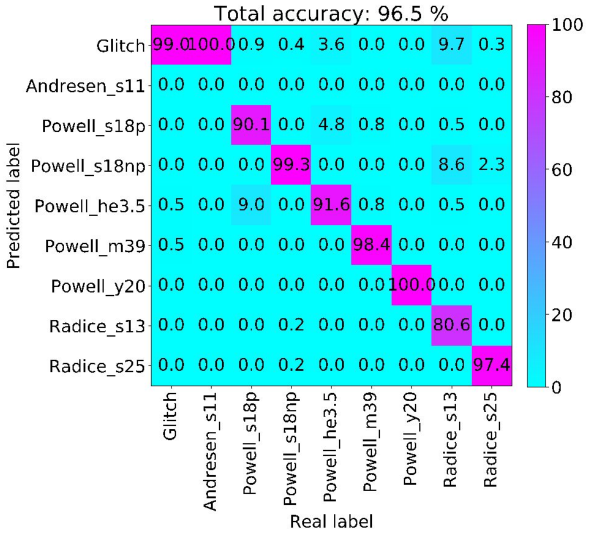
MULTILABEL CLASSIFICATION ON REAL O2 NOISE (SINGLE ITF, LIGO H1, DIFFERENT MODELS)

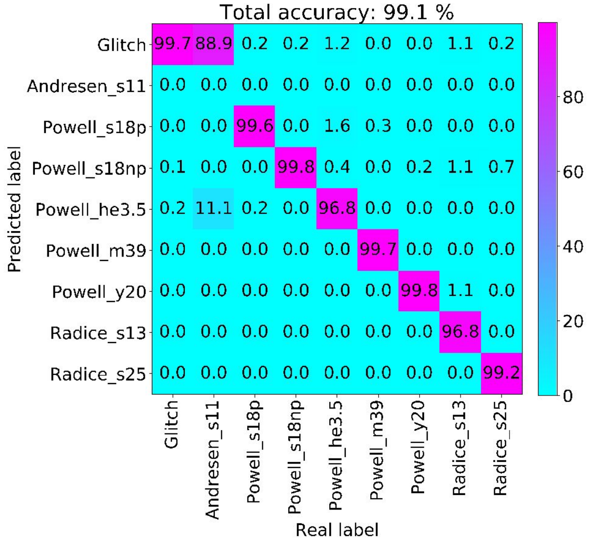
- **Bi-LSTM**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs

- **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



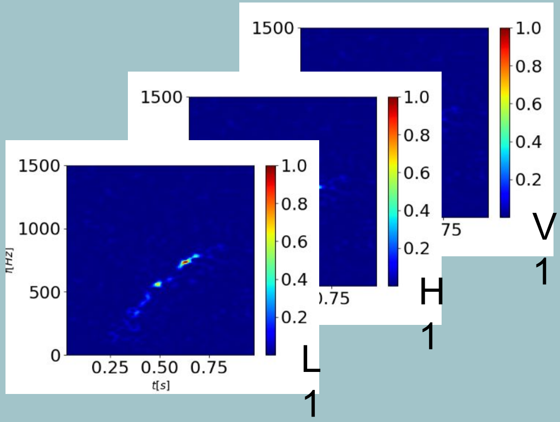


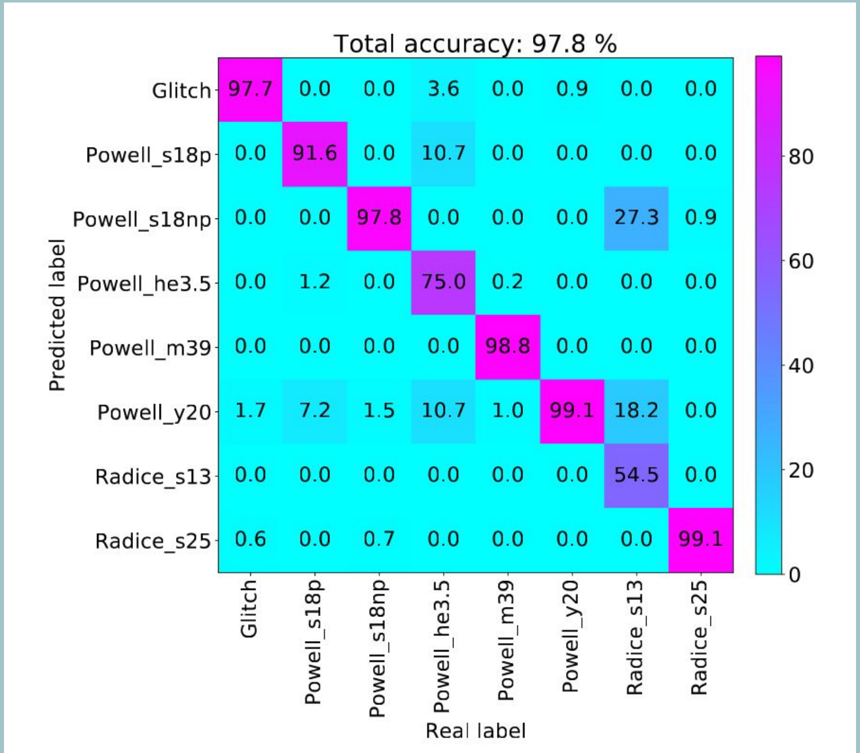


***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, 2022*

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, 2022 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

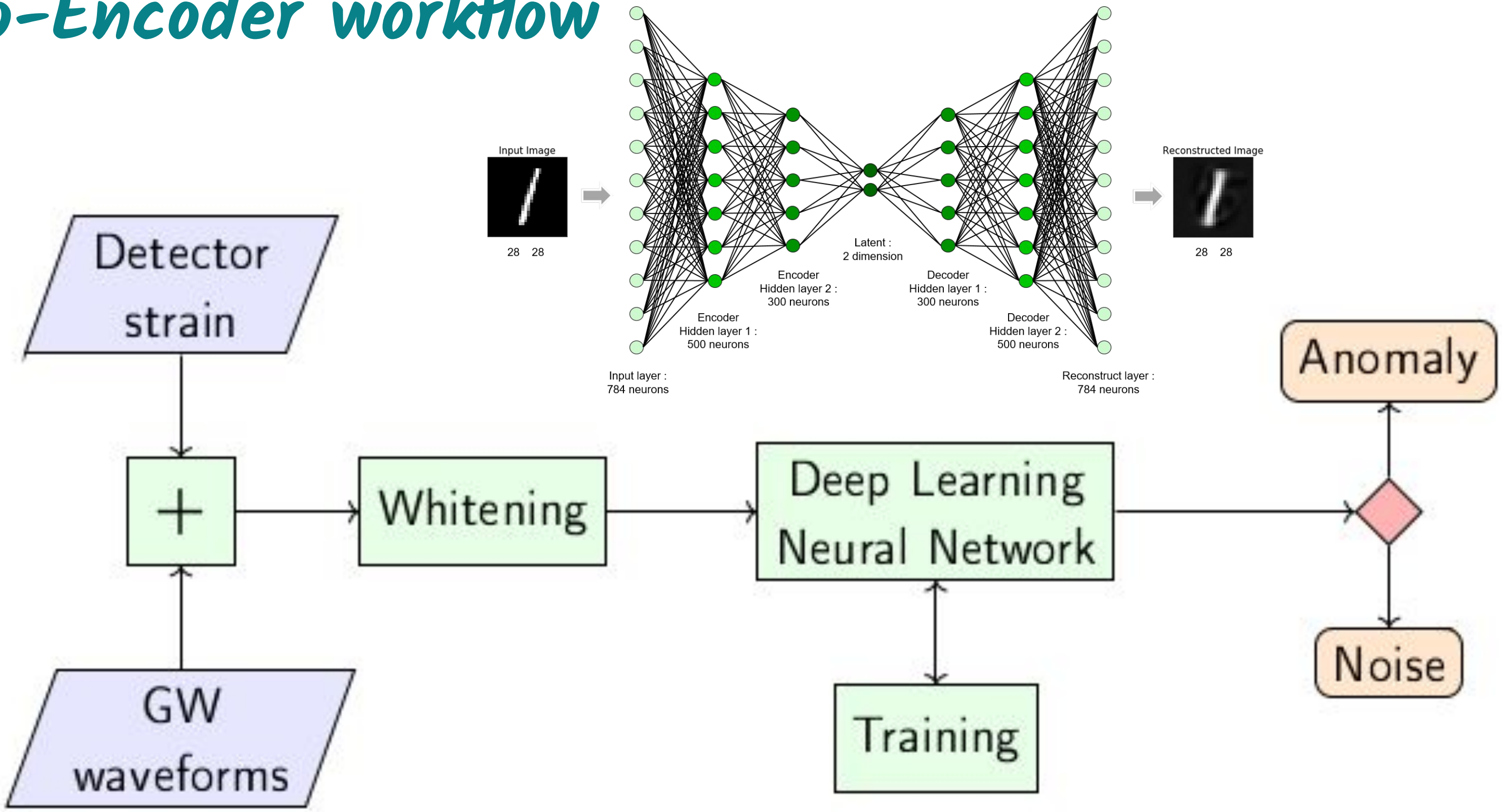
Example for detection/classification for CBC signals

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

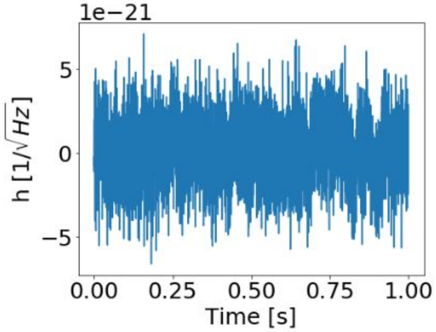


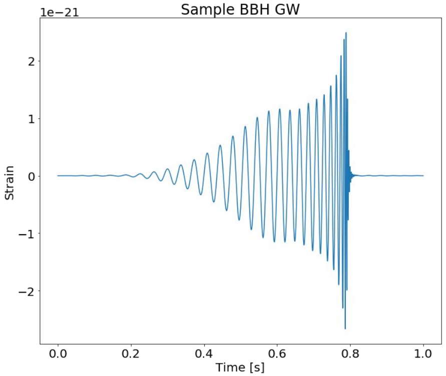
Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre, https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0*

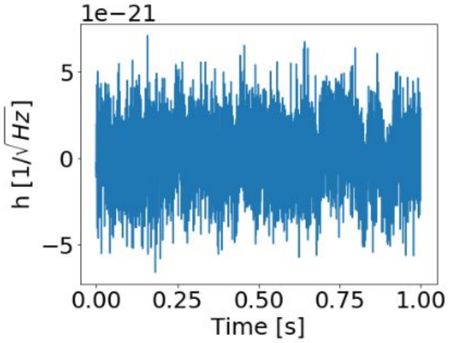
Auto-Encoder workflow

Model input

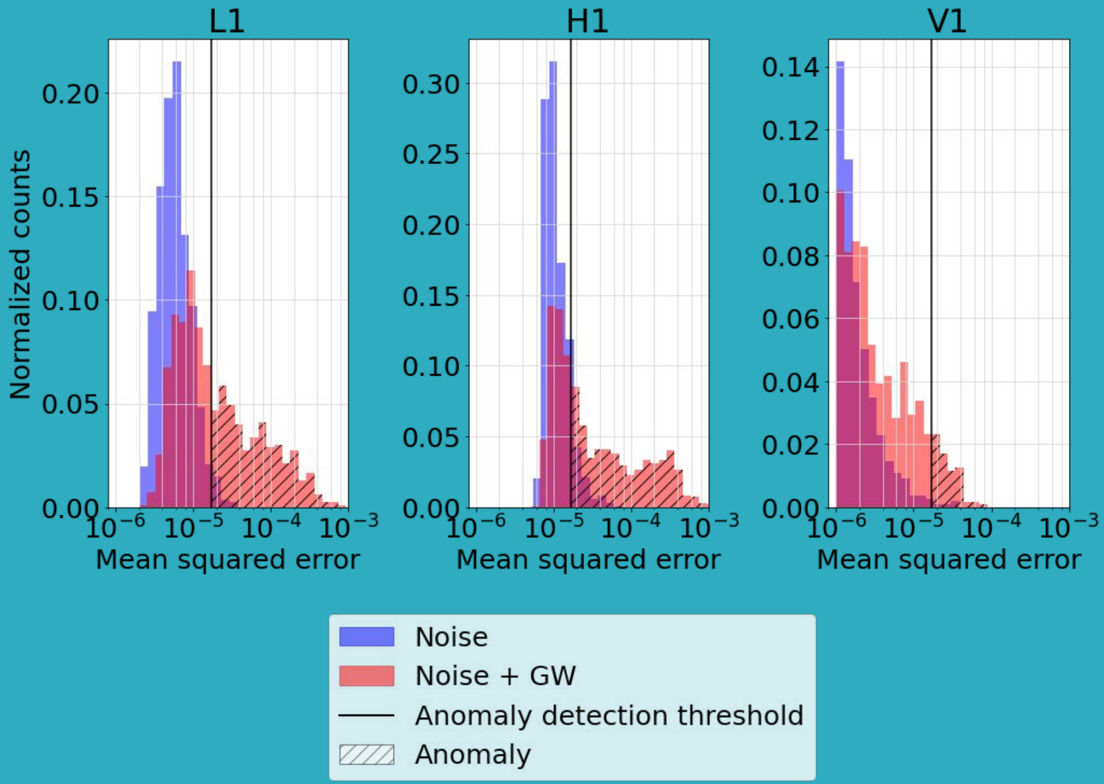
Model prediction



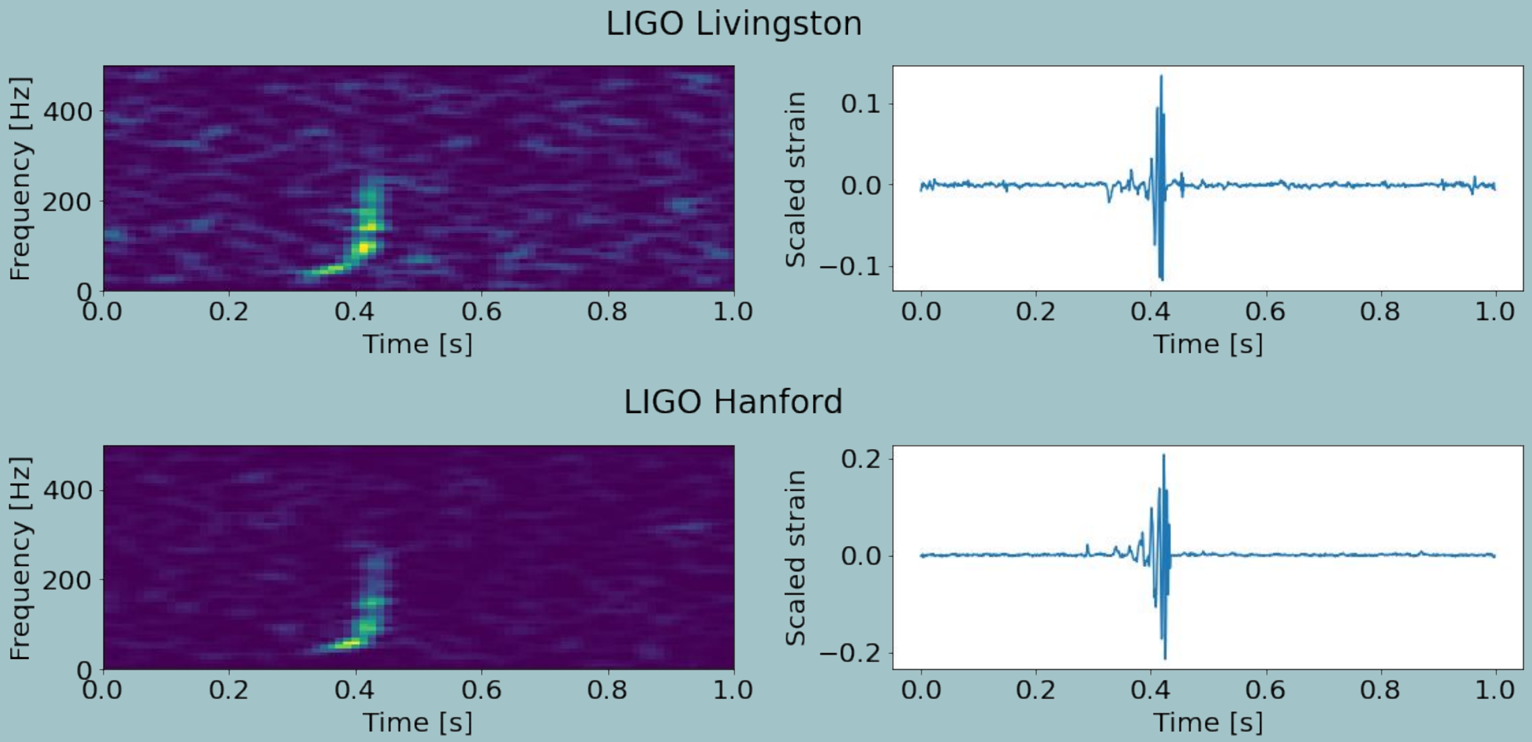




O2 data - MSE Distributions



GW150914



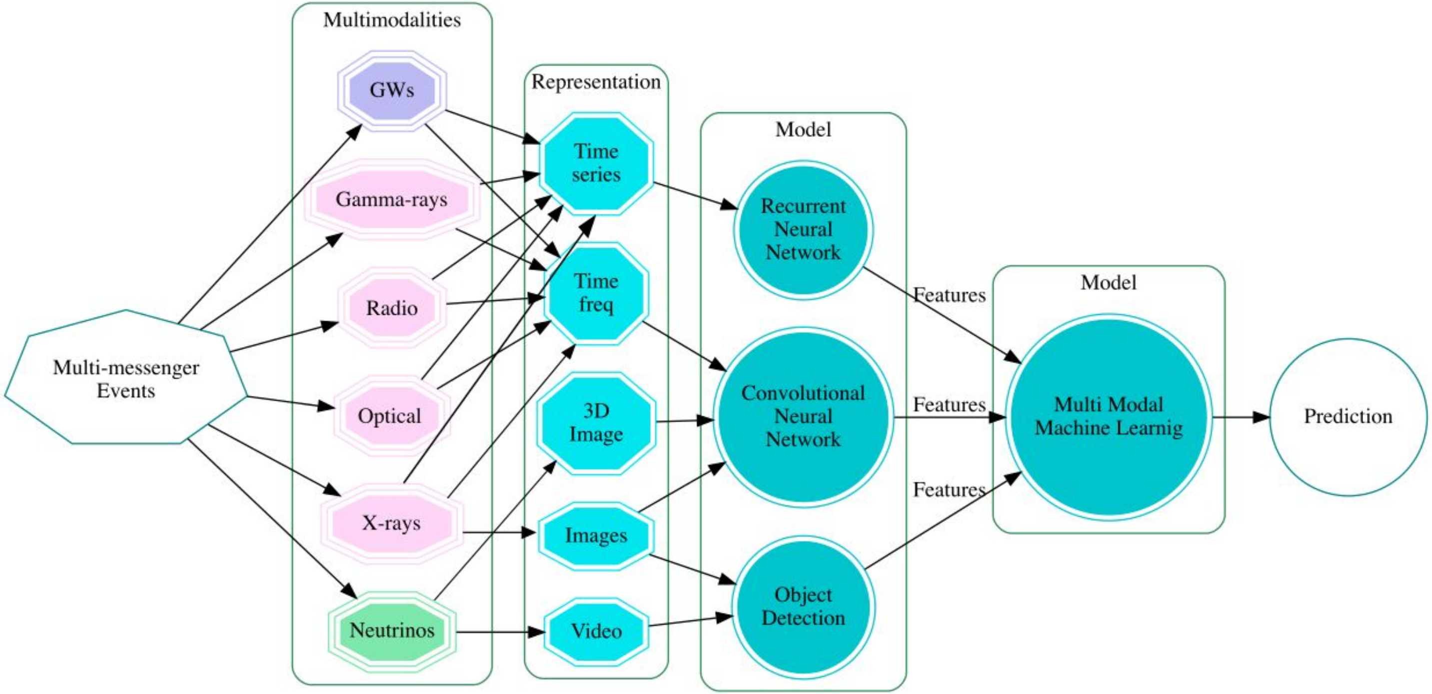
Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre,*
https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0

What's next?

Multimodal Machine Learning in Astrophysics

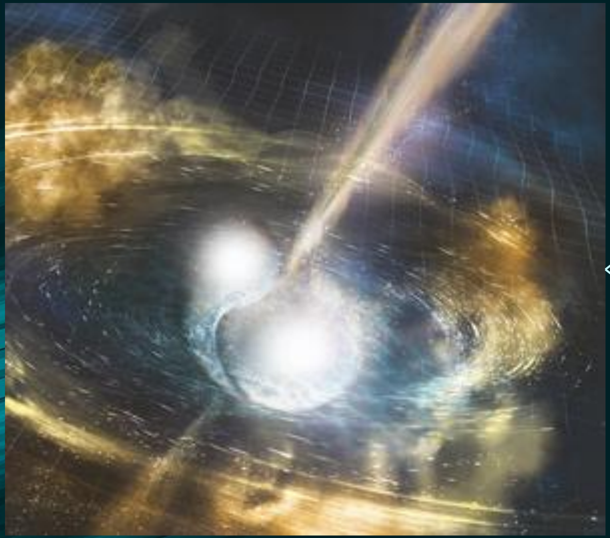
Why?

MMML for Astrophysics

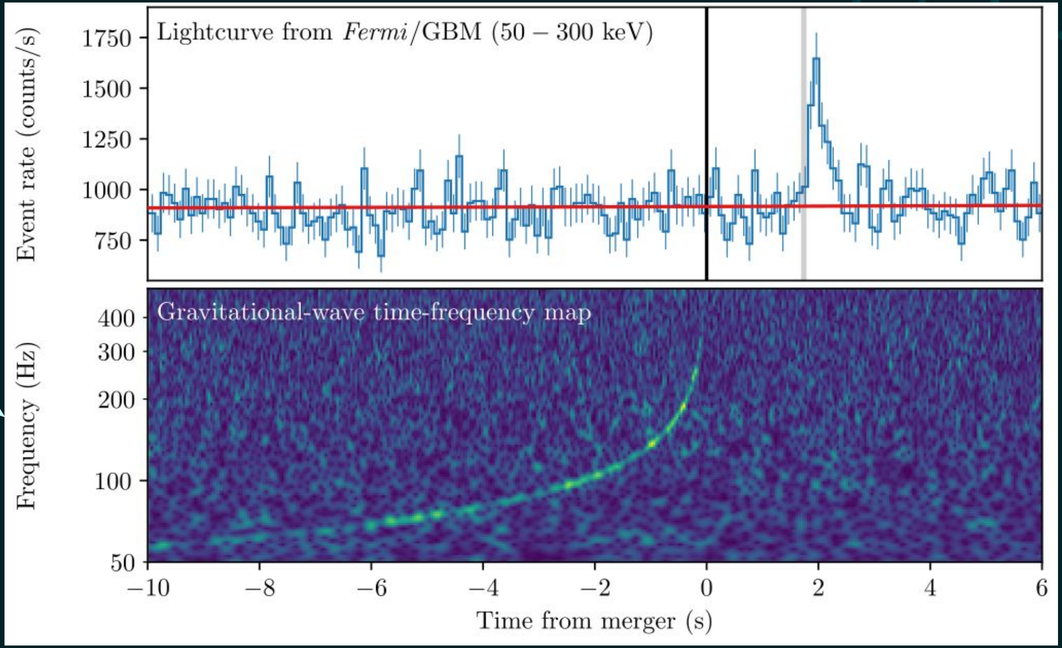


We are working on a multimodal real time analysis

Case study: Application to GW-GRB signals



[Credit: NSF/LIGO/Sonoma State University/A. Simonnet]

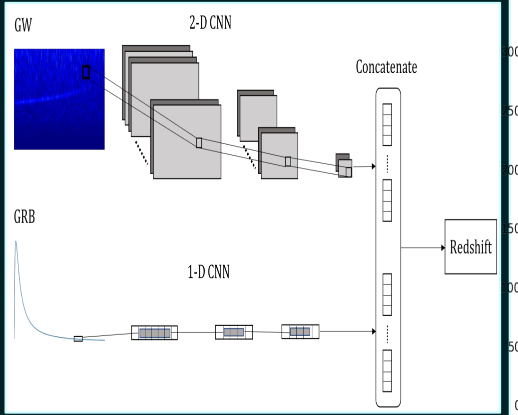


credits: LIGO/VIRGO collaboration; Abbott et al. 2017, ApJ, 848, 13

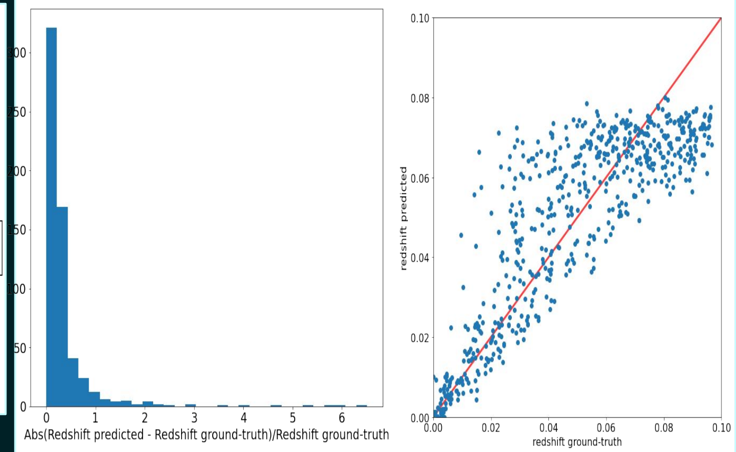
Goal of the project: estimate the redshift (z) of GRBs associated with BNS mergers

GRB+GW simulation → Training → Prediction

- *Generation of a population of BNS merging systems*
- *Simulation of the associated GW signals and GW data for a detector such as the Einstein Telescope*
- *Simulation of the associated short GRB light curve as observed by a Fermi-like detector (we knew the redshift only for few of them)*



Multimodal chain



We predict z using joint GRB and GW analysis

Cuoco, E.; Patricelli, B.; Iess, A.; Morawski, F. Multimodal Analysis of Gravitational Wave Signals and Gamma-Ray Bursts from Binary Neutron Star Mergers. Universe 2021, 7, 394. **https://doi.org/10.3390/universe7110394**

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