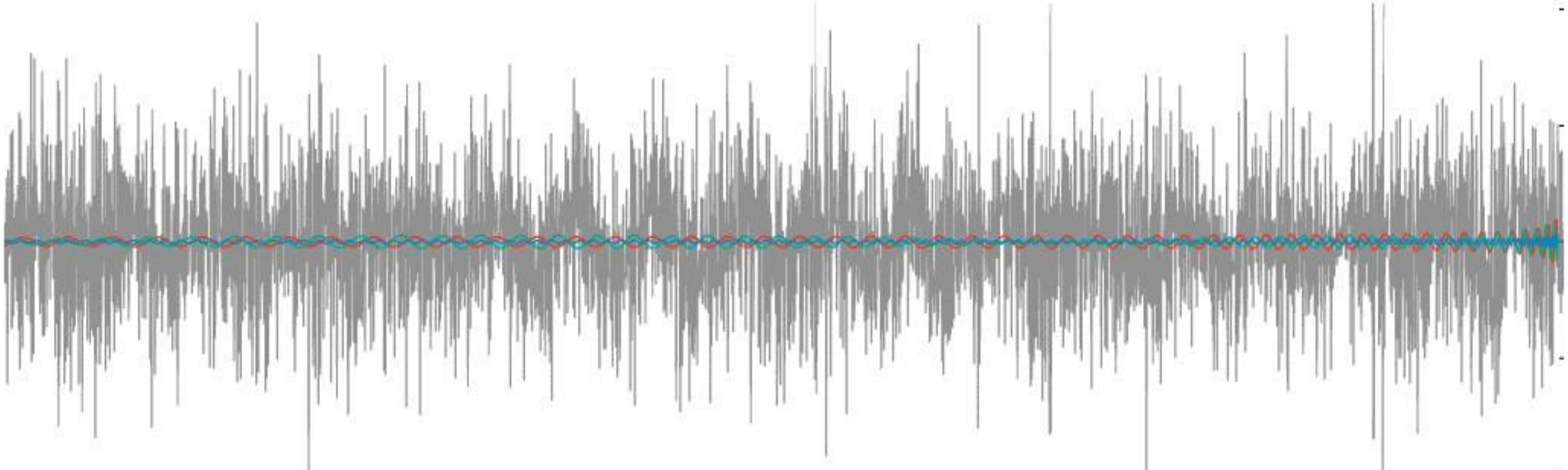
Machine Learning for Transient signal analysis in Gravitational Wave data



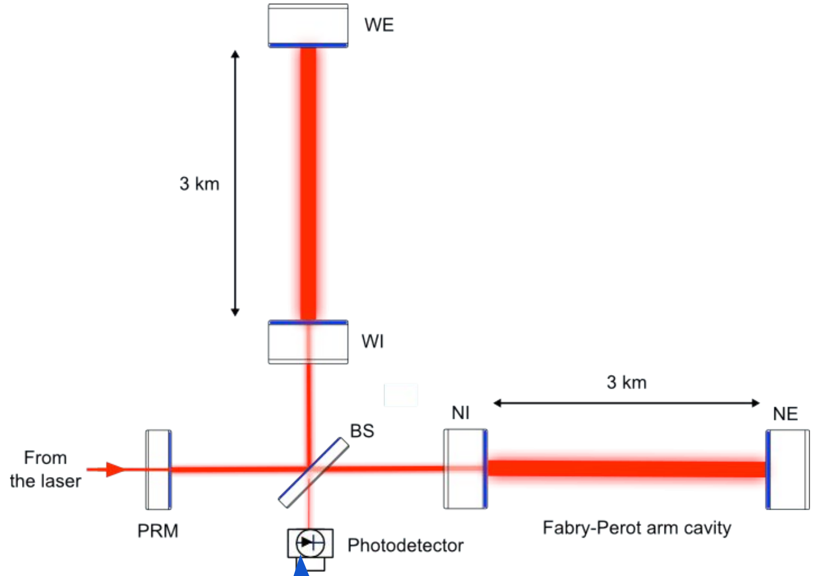
Elena Cuoco, EGO & SNS & INFN-Pisa

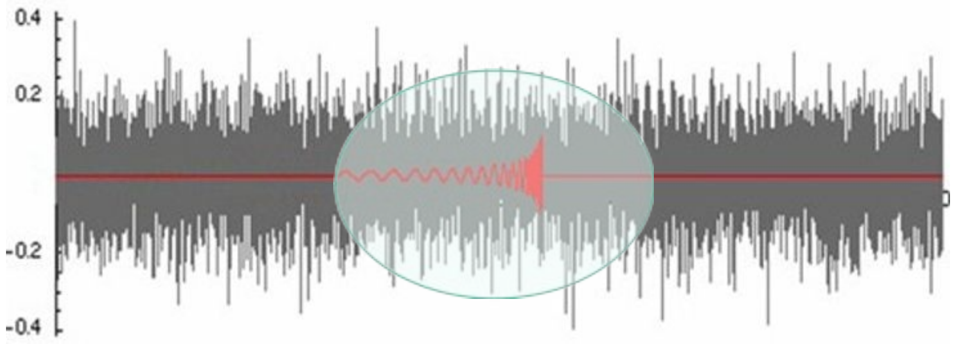
GravityShapePisa || Grasp 2023 October 24-27/2023 – University of Pisa

EGO - Virgo

GW detector data

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



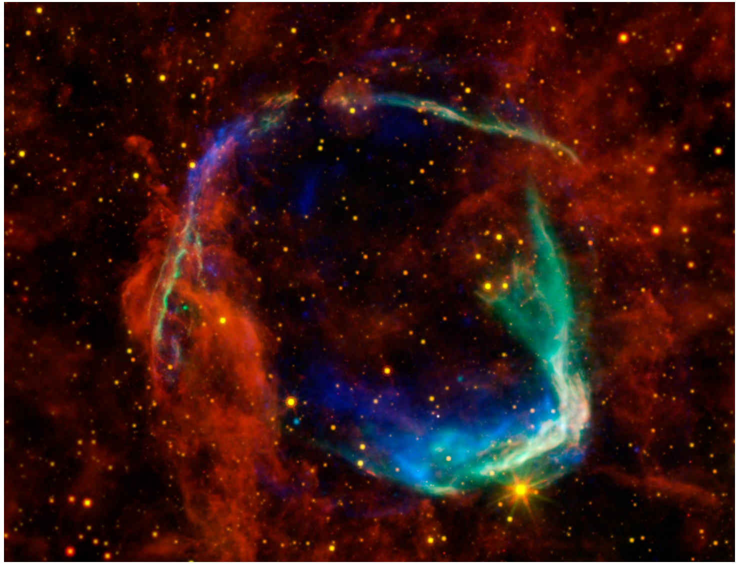


Gravitational Wave Transient signal sources

Compact binary coalescences

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

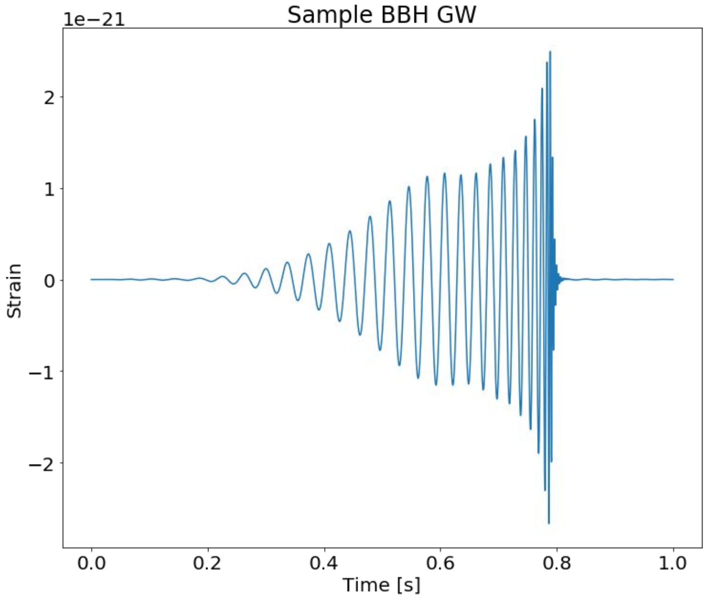
Core collapse Supernovae



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

Gravitational Wave Transient signals

CBC signals



CCSN signals

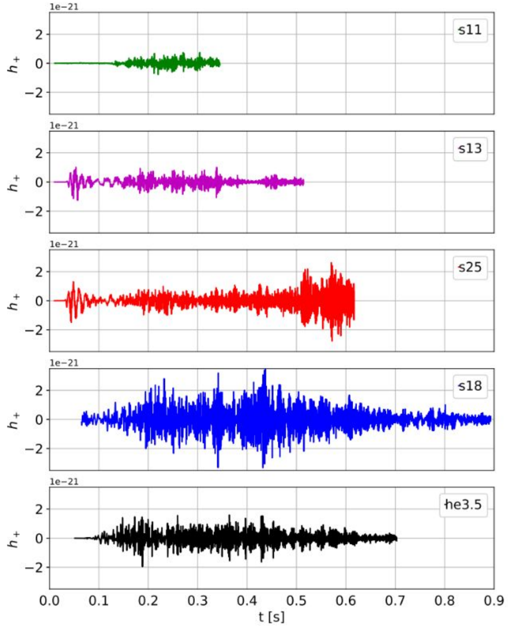
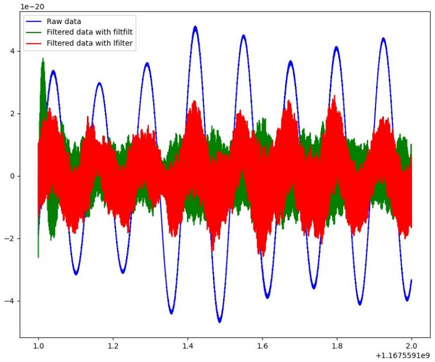


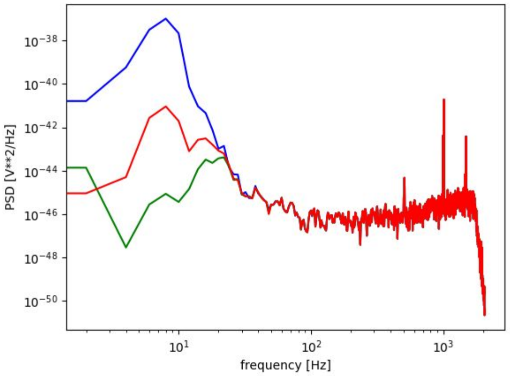
Image from Iess, Cuoco, Morawski, Powell (2020)

EGO - Virgo

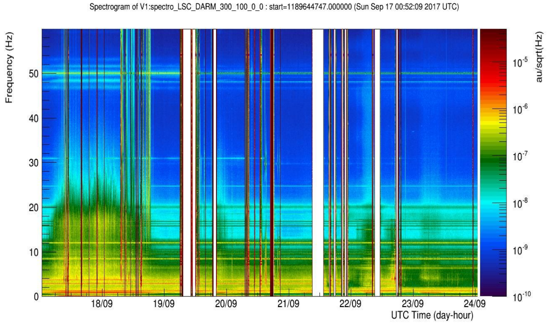
Data representations



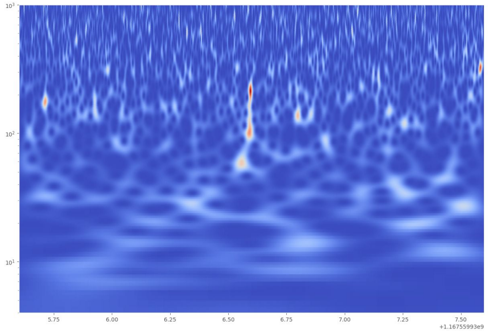
Time-domain



Frequency-domain

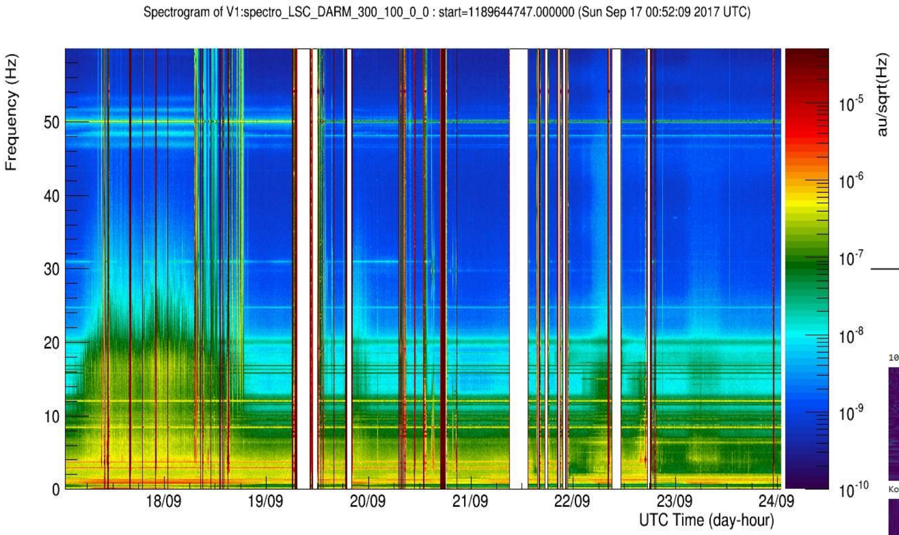


Time-frequency-domain



Wavelet-domain

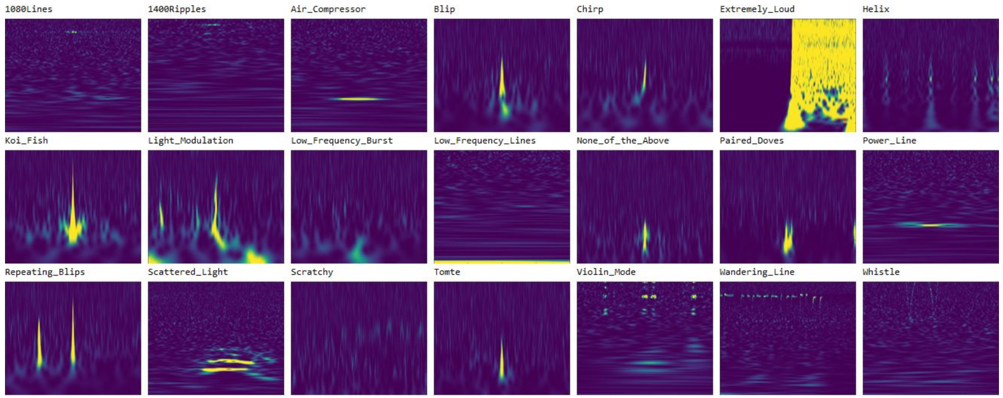
Detector Noise



Broadband

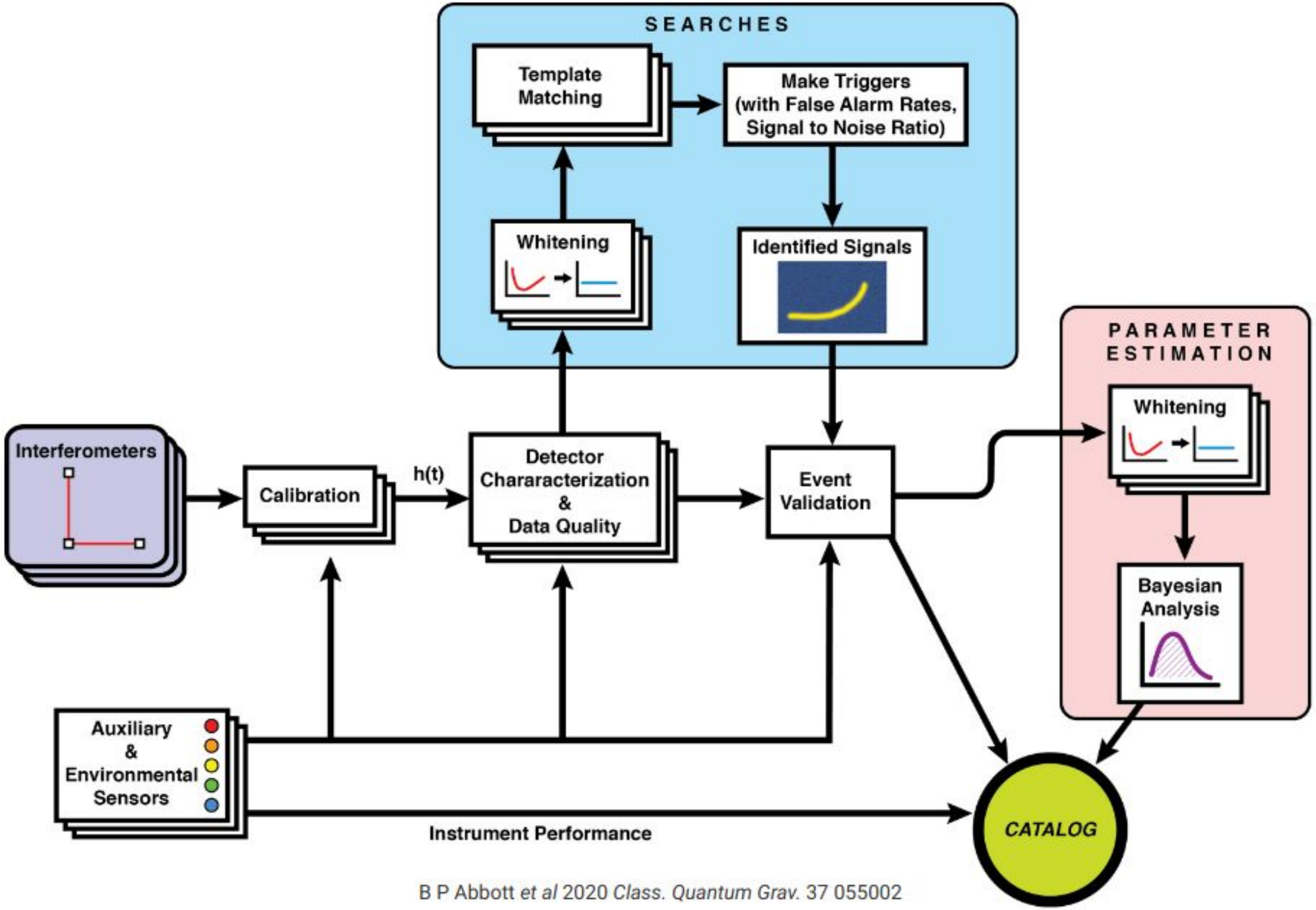
- *Thermal noise*
- *Seismic noise*
- *Electromagnetic noise*
- *Control noise*
- *Environmental noise*
- *Laser noise*
- *...*

Glitches



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

The data analysis workflow

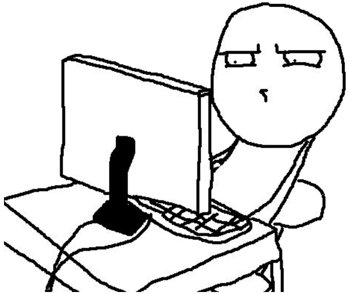


B P Abbott *et al* 2020 *Class. Quantum Grav.* 37 055002

How Machine Learning can help

Data conditioning

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



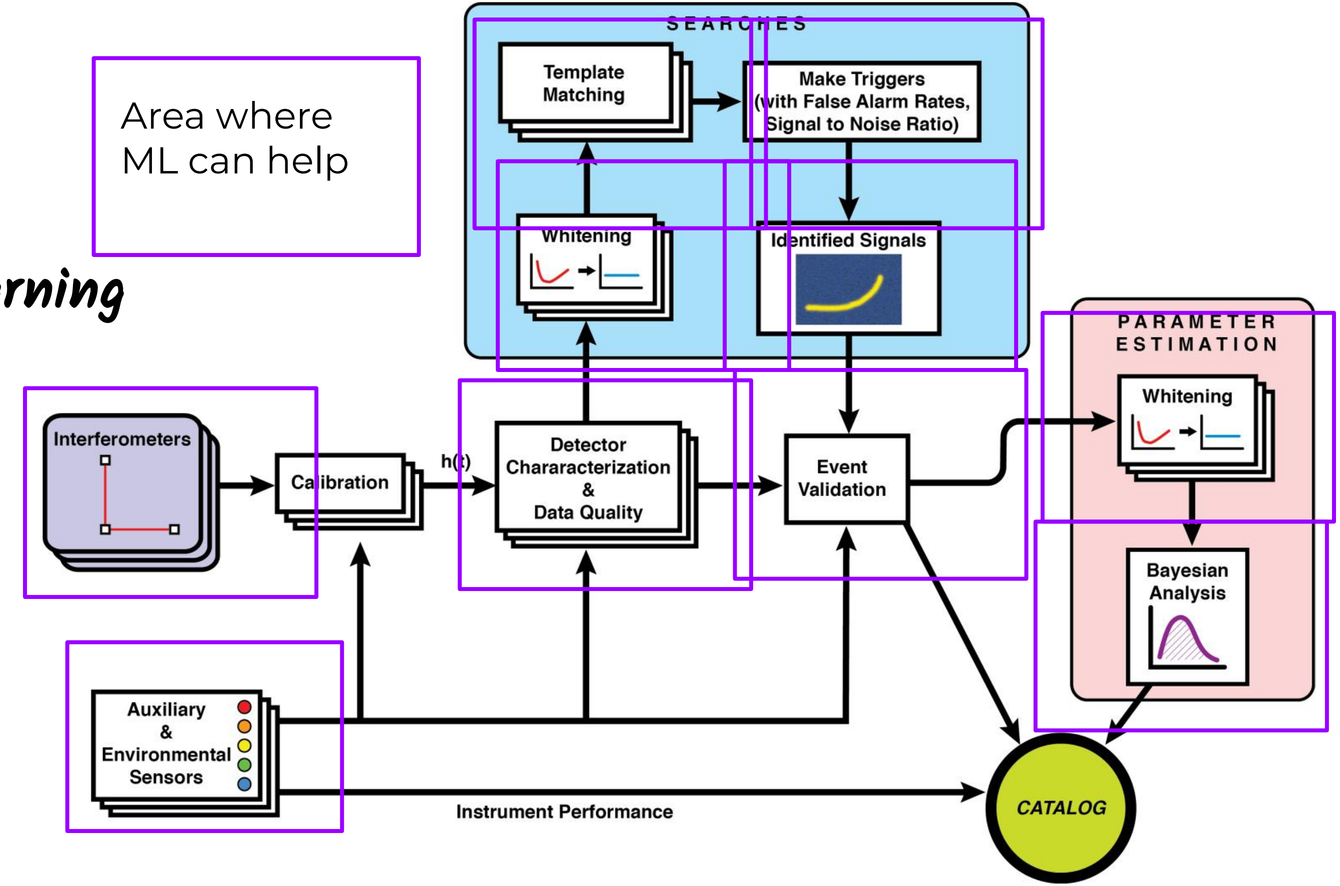
Signal Detection/Classification/PE

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

The data analysis workflow and ML

Area where ML can help

Machine Learning everywhere



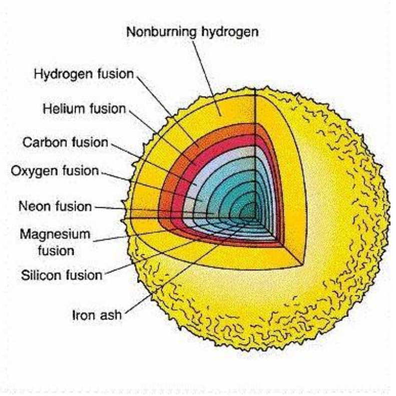
ML application to GW transient signals

CCSN and CBC

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

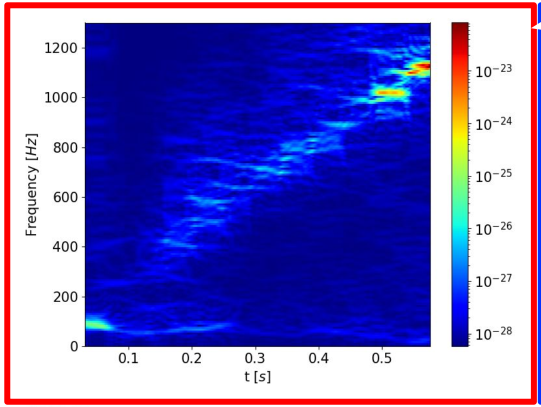


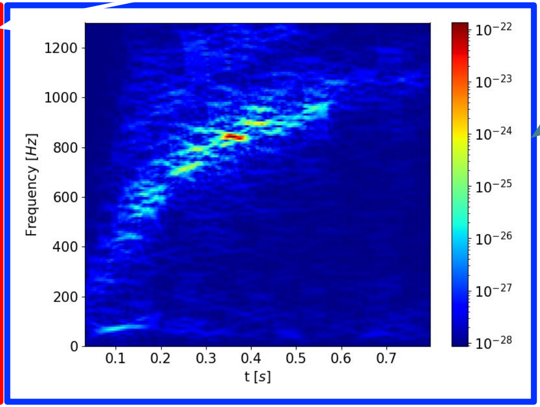
GW emission Process	Potential explosion mechanism: MHD mechanism (rapid rotation)	Neutrino mechanism (slow/no rotation)	Acoustic mechanism (slow/no rotation)
Rotating collapse and Bounce	Strong	None/weak	None/weak
3D rotational instabilities	Strong	None	None
Convection & SASI	None/weak	Weak	Weak
PNS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

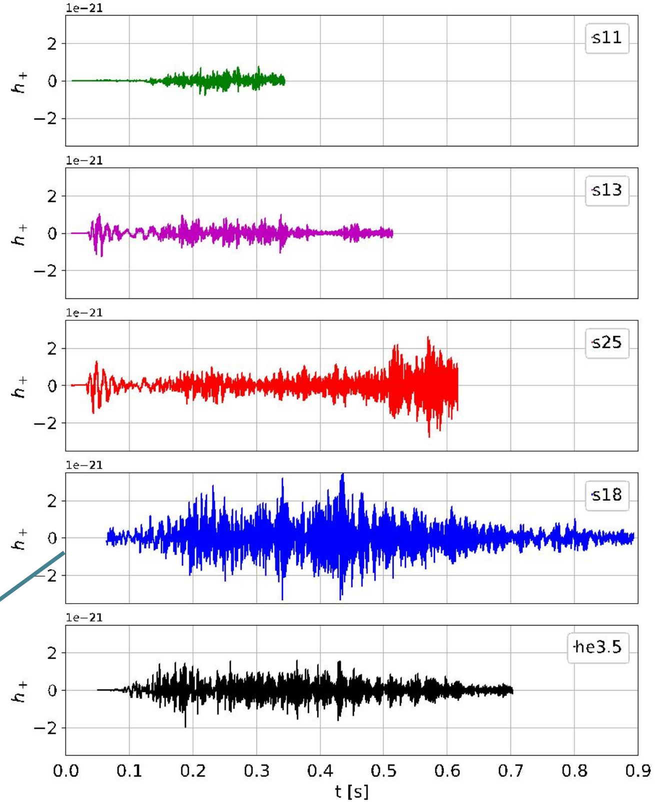
Ott et al. (2017)

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*





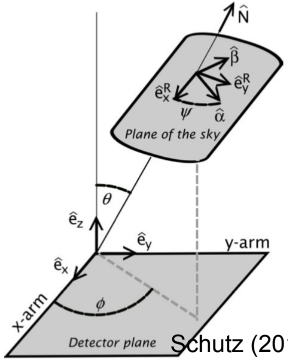


Iess, Cuoco, Morawski, Powell, https://doi.org/10.1088/2632-2153/ab7d31

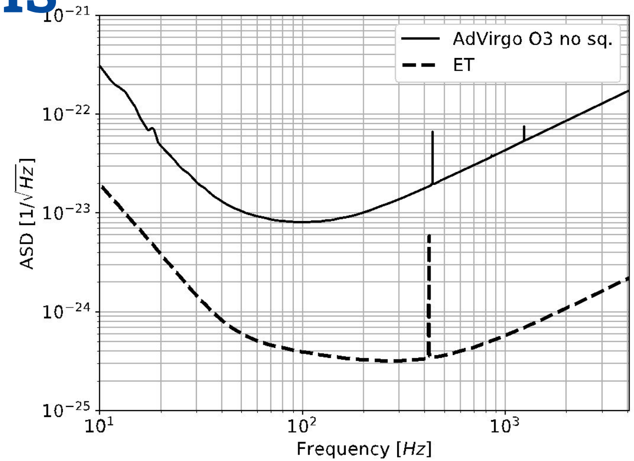
MDC and CCSN GW simulations

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

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



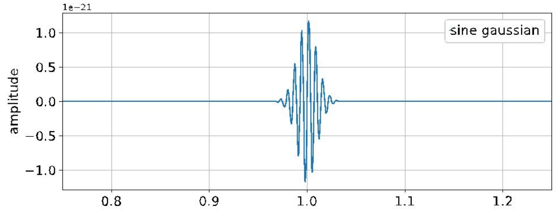
Schutz (2011)

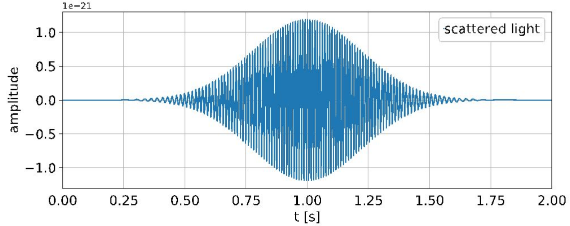


SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

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

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

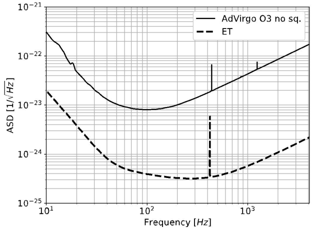


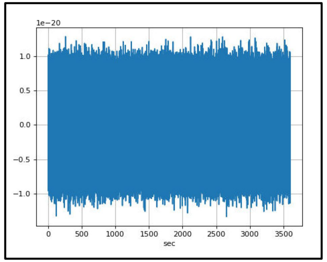


BACKGROUND STRAIN : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

Pipeline Workflow

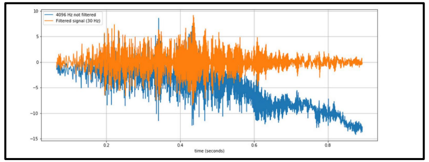
STRAIN





WAVEFORMS

RESAMPLING, FILTERING



+

WHITENING & TRIGGER GENERATION (WDF)

TRAINING

MACHINE-LEARNING CLASSIFIER

GW SIGNAL TYPE

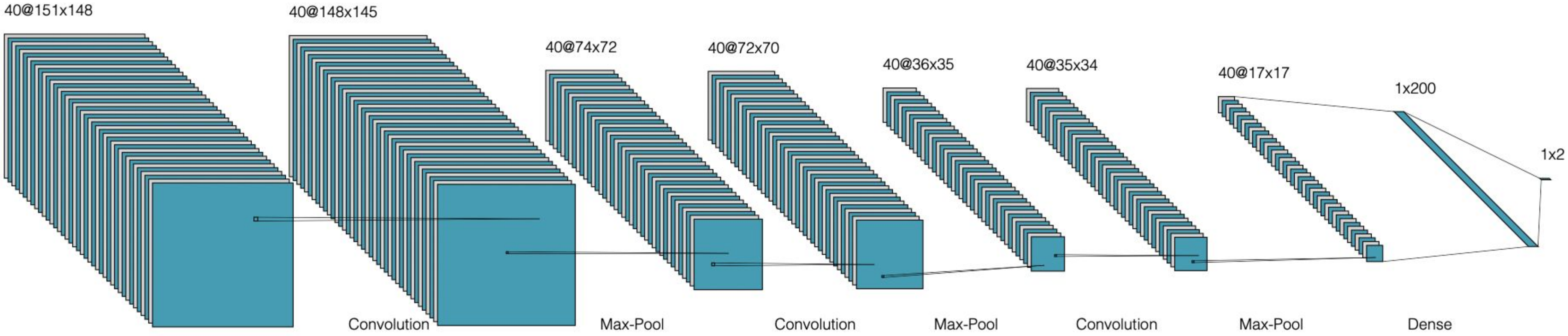
GLITCH NOISE TYPE

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

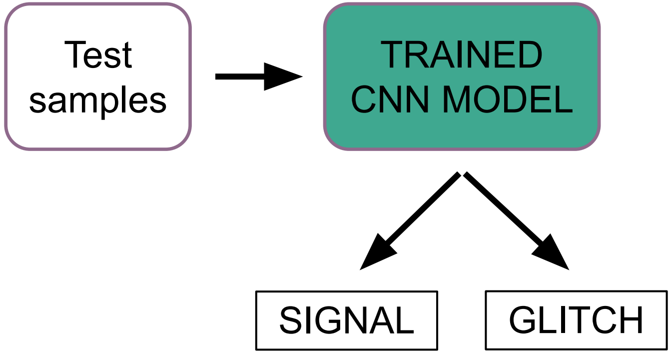
Dataset: chunks of 3 hr data with 1000 injections/h

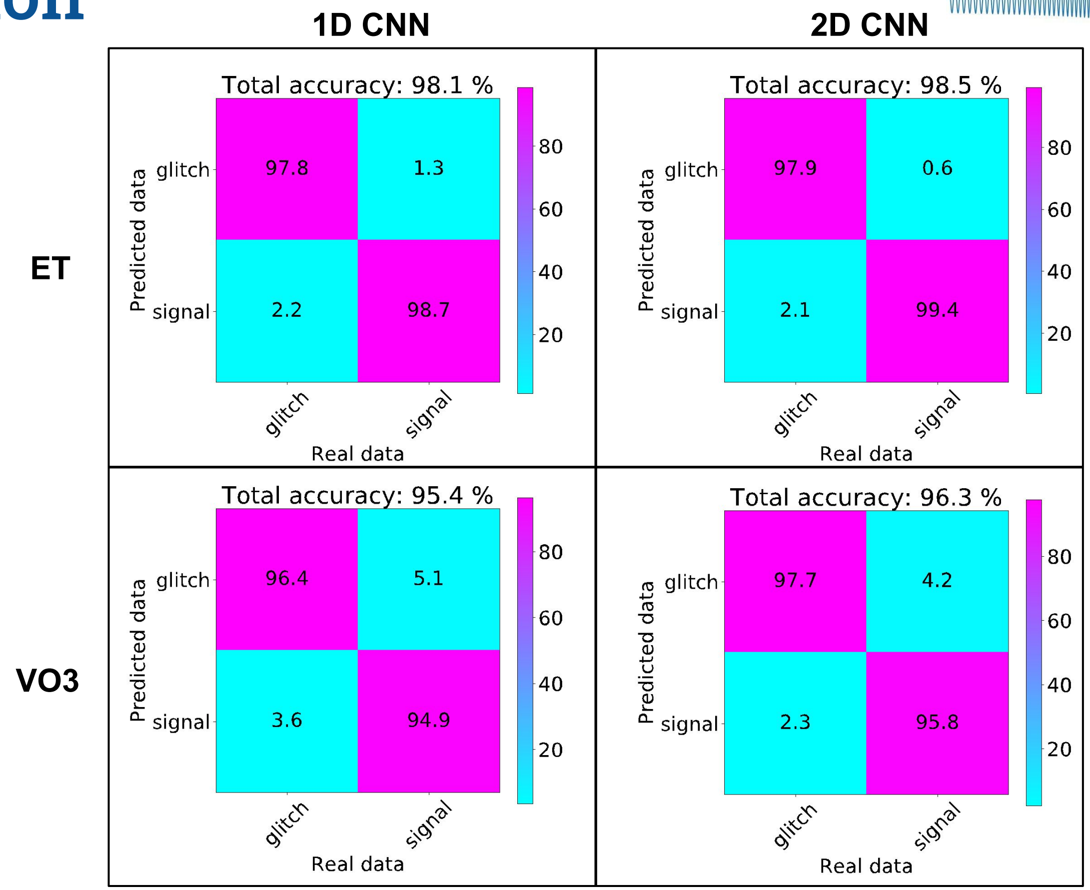
GPU: Tesla k40



Binary Classification

- Train on **<u>all</u>** CCSNe waveforms and glitches.
- Test on **<u>all</u>**.

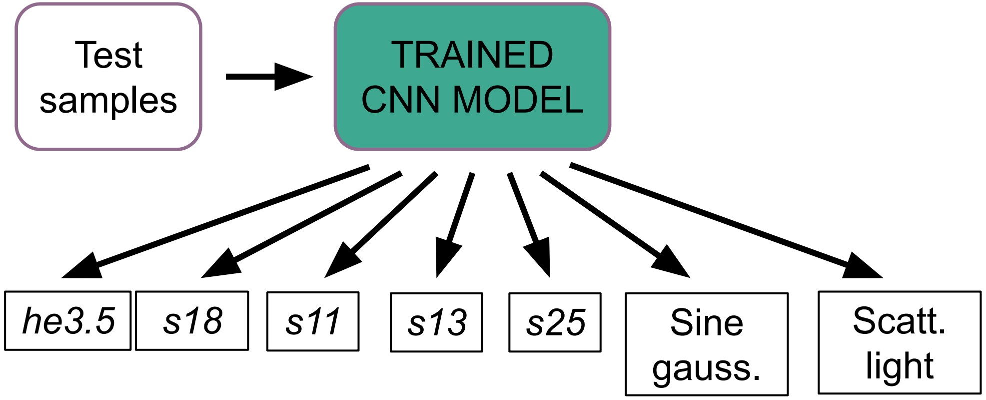




- Training time: ~ 30 min

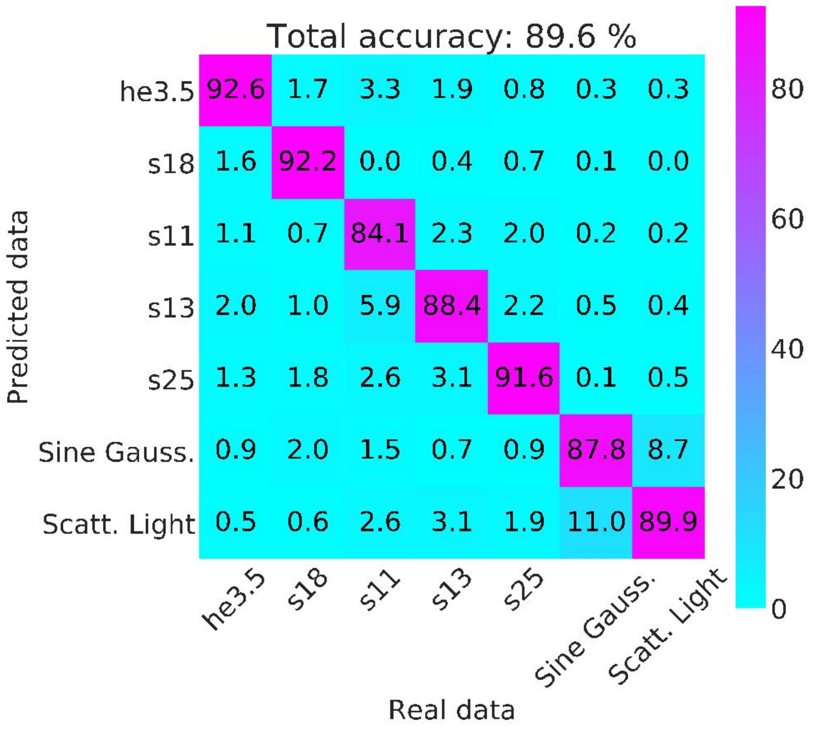
MultiLabel classification

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



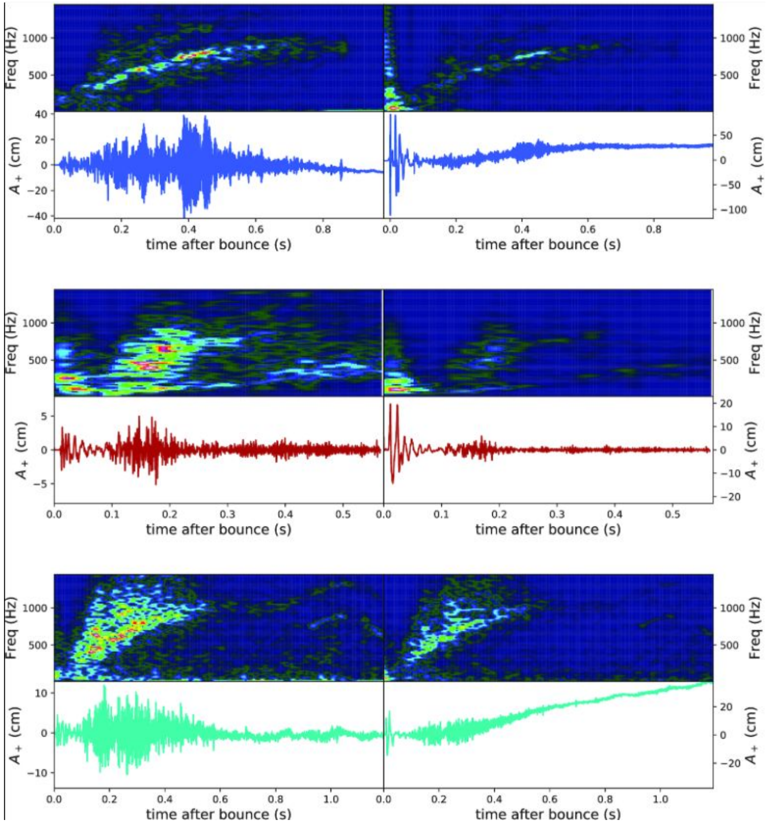
COMPLEX TASK → LONGER TRAINING (> 1 hr)

ET, MERGED 1D & 2D CNN



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 time series data.
- **Added Three ITF classification.**



- *Powell s18np*: differs from s18 since simulation does not include perturbations from the convective oxygen shell. As a result, this model develops strong SASI after collapse.

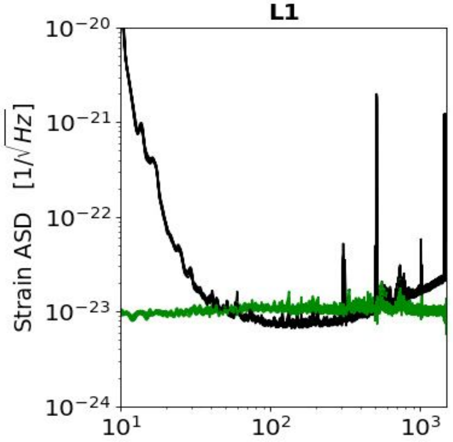
- *Powell y20*: non-rotating, 20 solar mass Wolf-Rayet star with solar metallicity.

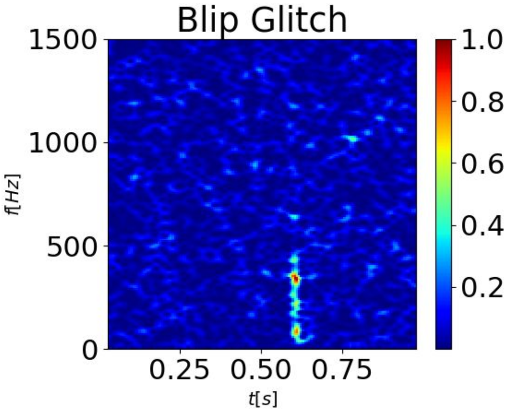
- *Powell m39*: rapidly rotating Wolf-Rayet star with an initial helium star mass of 39 solar masses

Real noise from O2 science run

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

	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

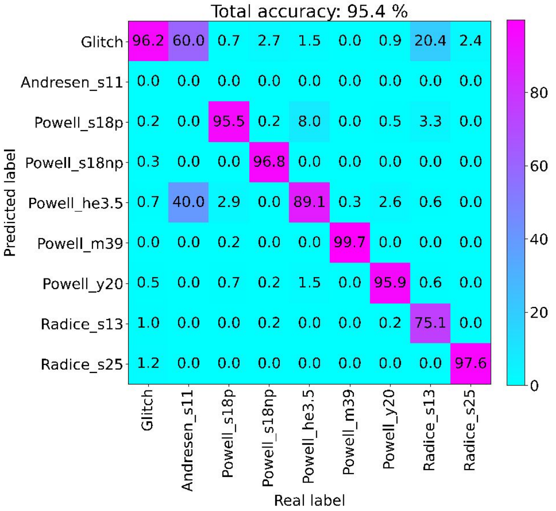
***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)*

EGO - Virgo

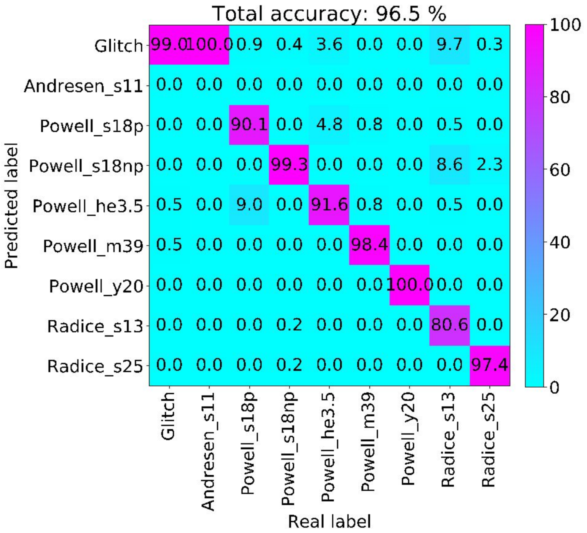
Multi-label task

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

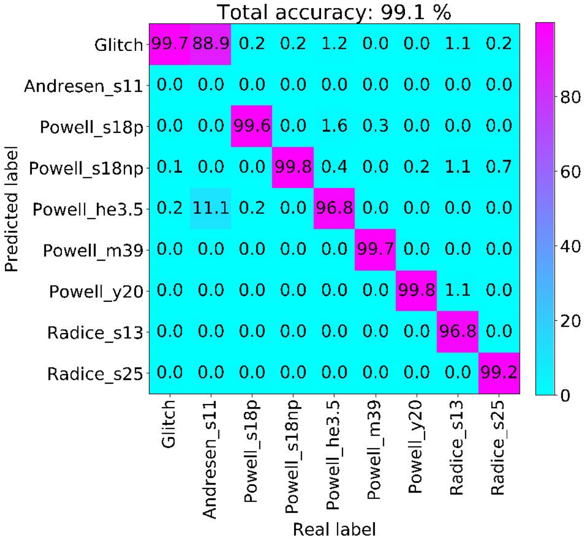
- **Bi-LSTM**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs



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



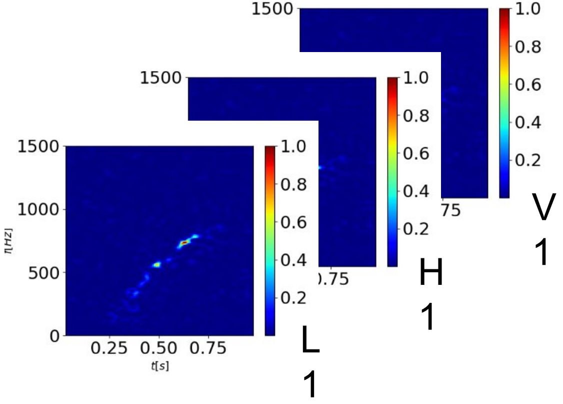
- **2D-CNN**, 4 convolutional layers
- ~3 ms/sample
- Best weights over 20 epochs

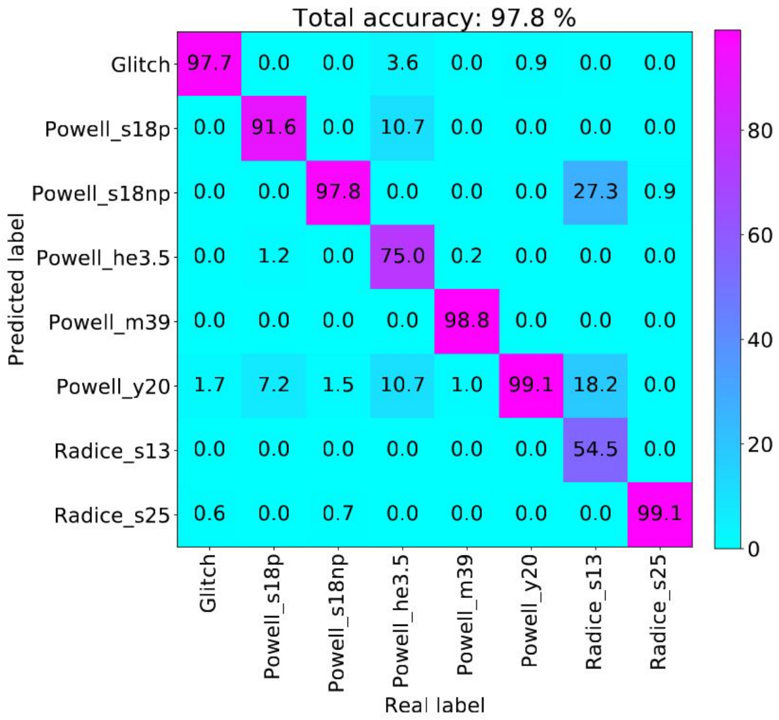


***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)*

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, A&A 669, A42 (2023)*

EGO - Virgo

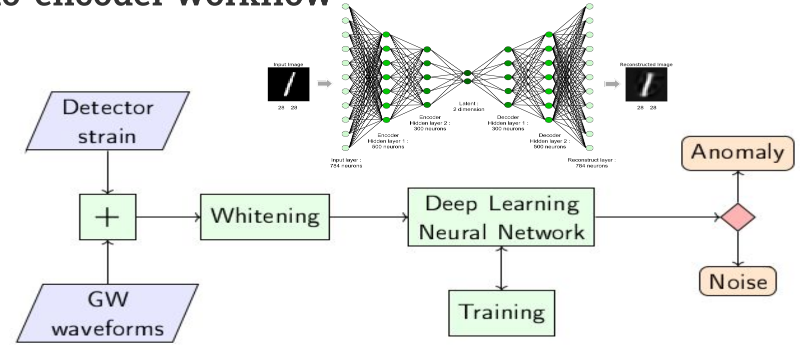
Anomaly Detection in Gravitational Waves data using Convolutional AutoEncoders for CBC signals

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.

Auto-encoder workflow

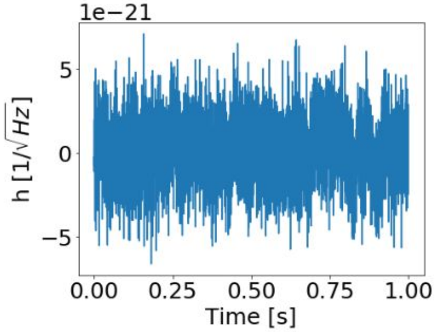


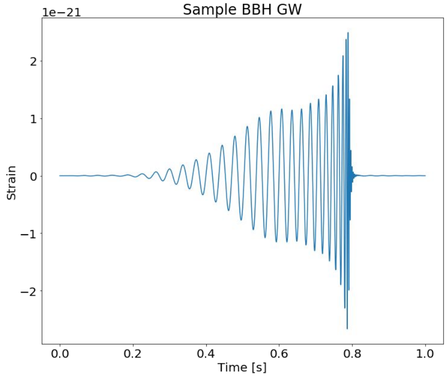
Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre,*
https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0

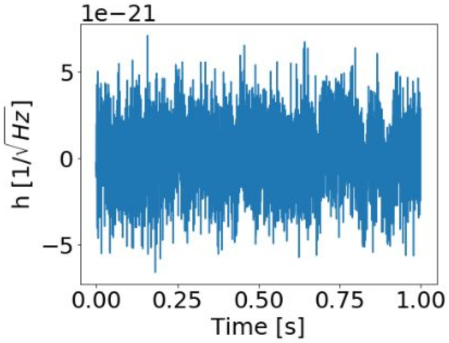
Auto-encoder workflow

Model input

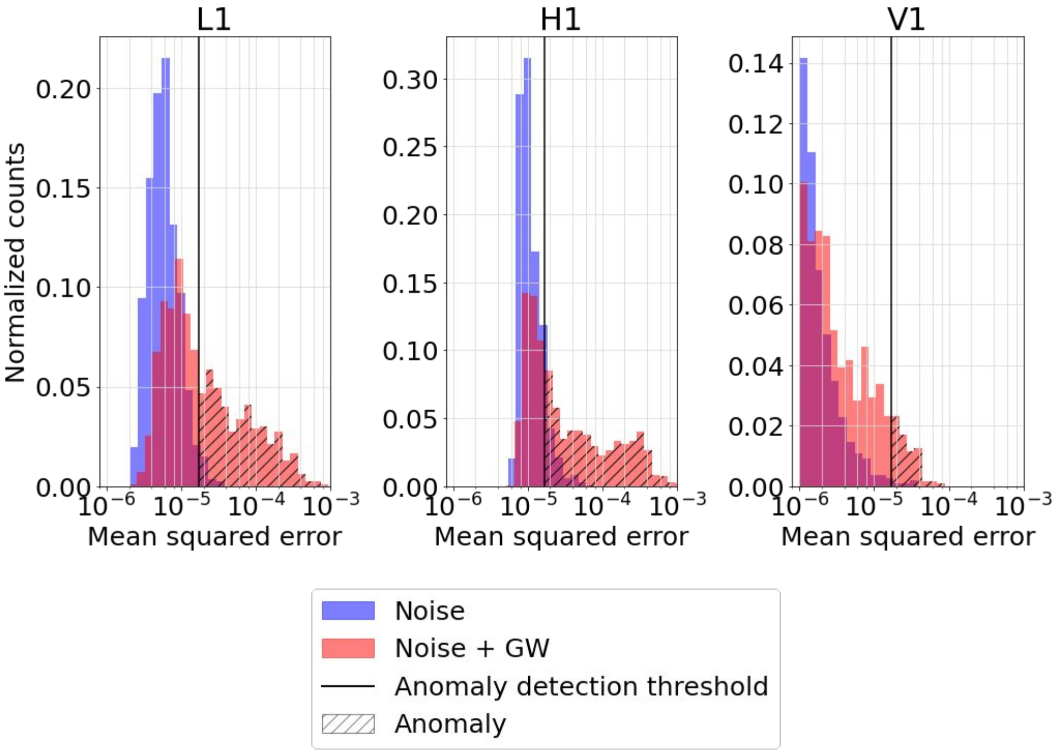
Model prediction



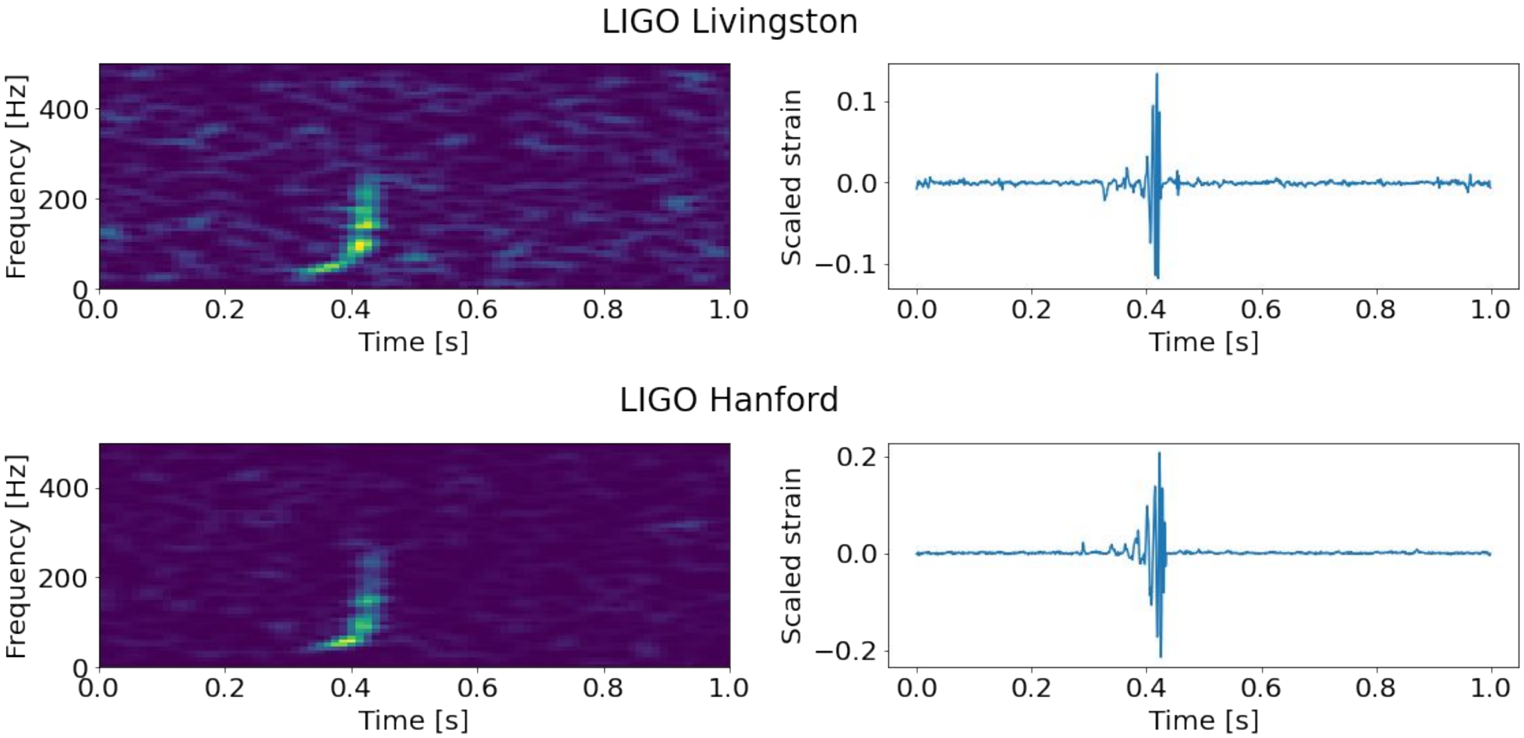




O2 data - MSE Distributions



GW150914



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

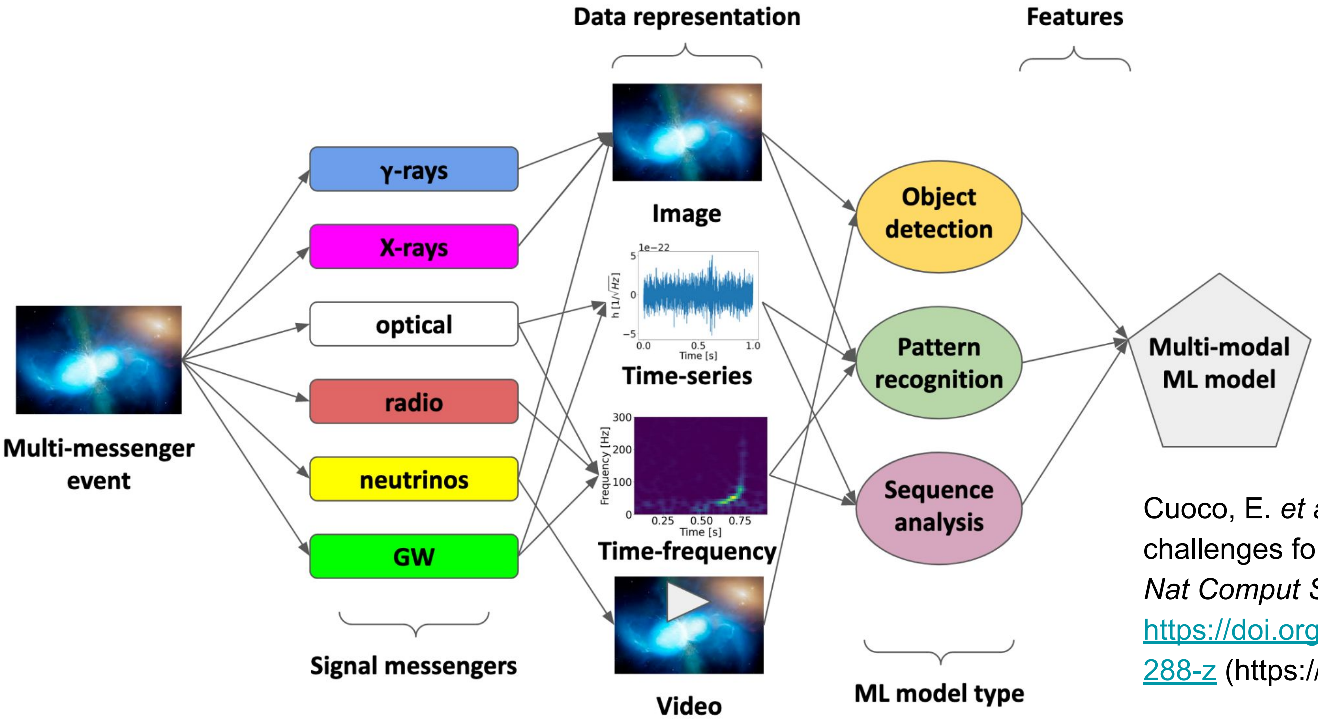
EGO - Virgo

Machine learning applications in LVK: a long list

Glitches classification	GW signal detection	Parameter estimation	Sky localization
Easy access information	Data quality	Waveform modelling	…

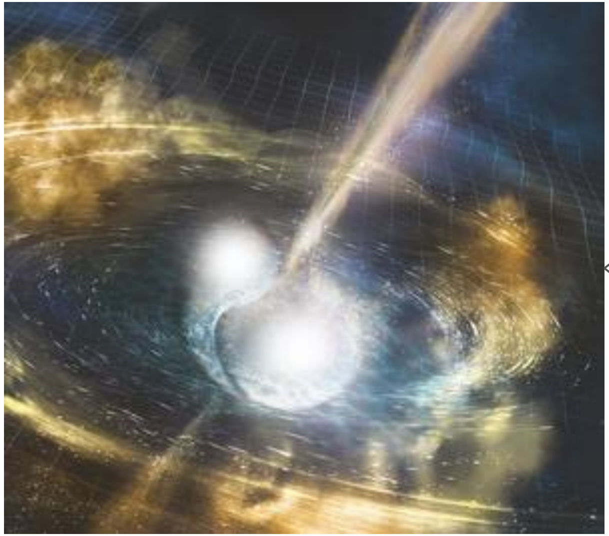
Review paper: Enhancing gravitational-wave science with machine learning Elena Cuoco *et al* 2021 *Mach. Learn.: Sci. Technol.* 2 011002…**We are preparing the updated version**

Multi Modal Machine Learning for Astrophysics

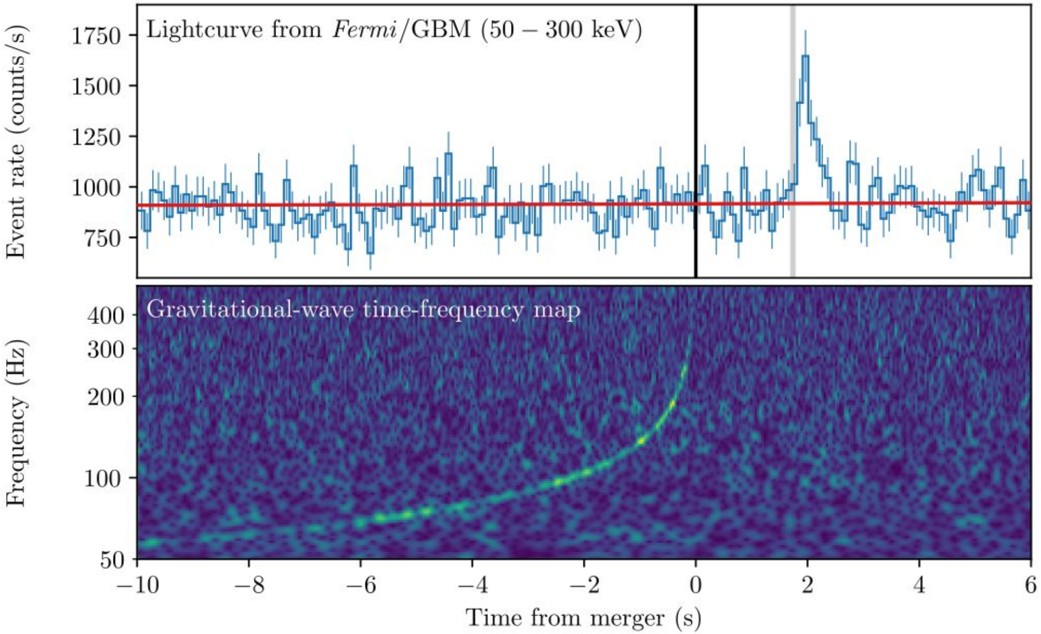


Cuoco, E. *et al.* Computational challenges for multimodal astrophysics. *Nat Comput Sci* **2**, 479–485 (2022). https://doi.org/10.1038/s43588-022-00288-z (https://rdcu.be/cT7OQ)

Case study: Application to GW-GRB signals



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



Goal of the project

We want to estimate the redshift (z) of GRBs associated with BNS mergers

- We have a bunch of simulated GRBs, and we assume that we know z only for a fraction of them;
- We train the pipeline on the GRBs with known z;
- We predict z using joint GRB and GW analysis

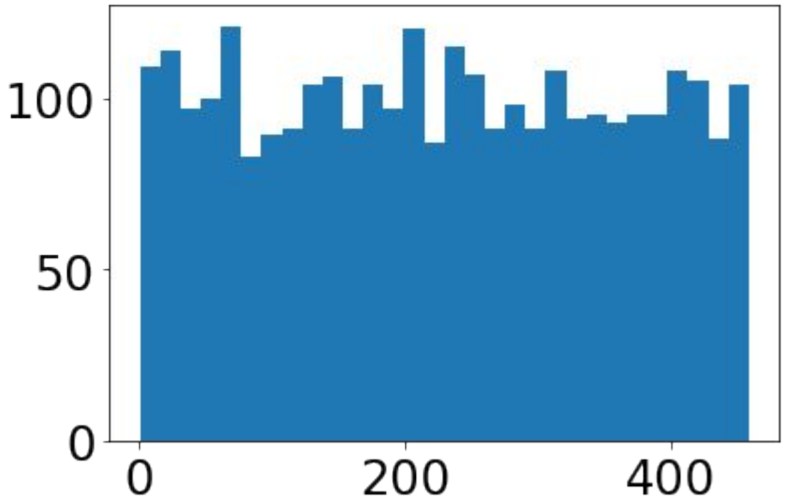
Simulations: what we simulated

Multi-messenger signals from BNS mergers in 3 steps:

- 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

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

Binary Neutron Star population

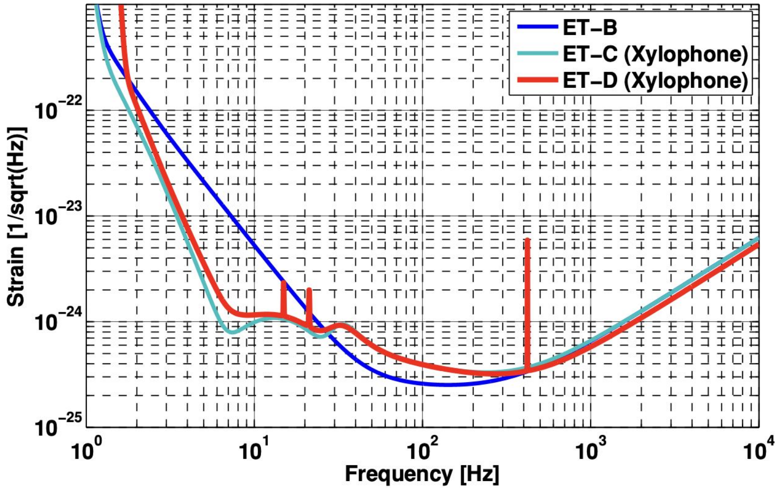


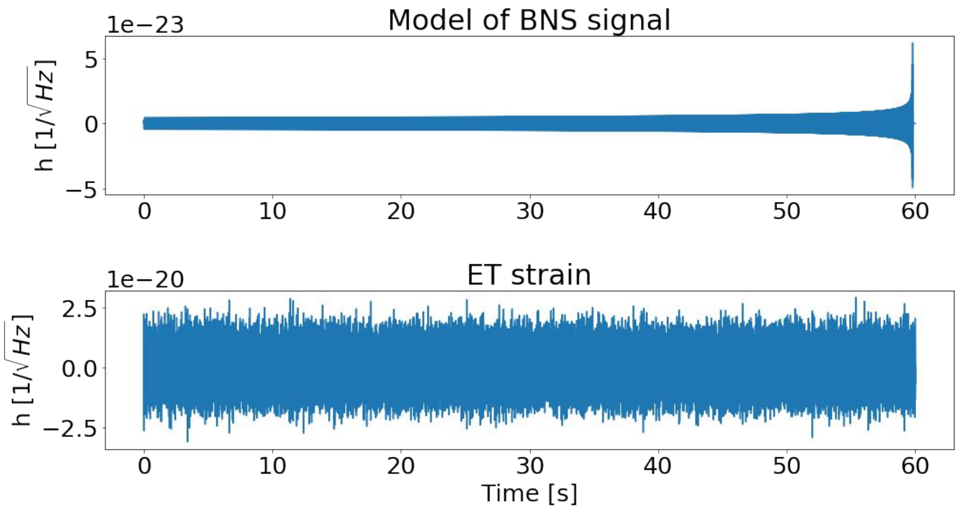
- NS spins: aligned; maximum value: 0.05
- Focus on sources giving rise to an on-axis GRB -> maximum inclination of the BNS system fixed to 8 deg NS masses: uniform distribution between 1 and 2.5 $M_\odot$
- BNS Distance: uniform distribution between 1 and 500 Mpc

https://doi.org/10.3390/universe7110394

EGO - Virgo

GW detector noise: Einstein Telescope





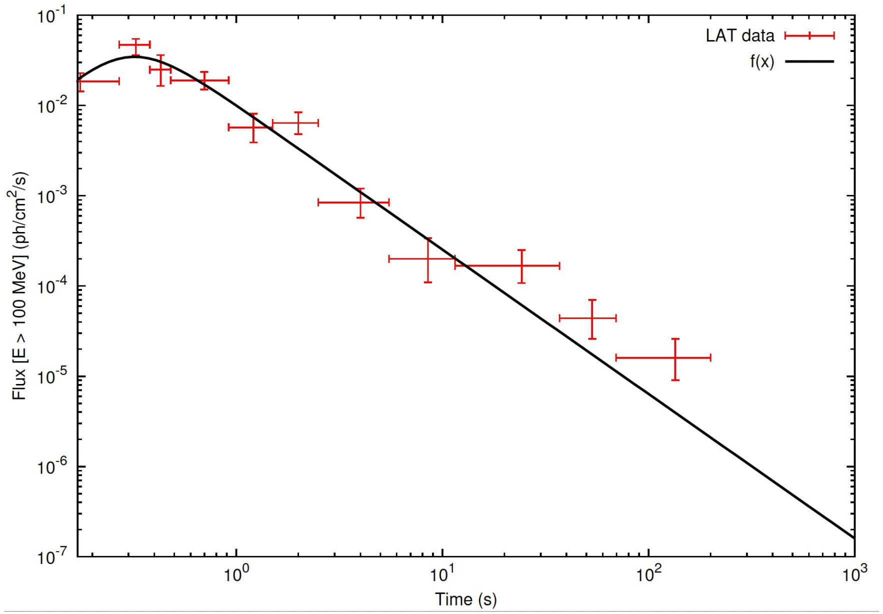
Hild et al. 2011, Class. Quantum Grav., 28 094013

https://doi.org/10.3390/universe7110394

Electromagnetic simulations

- We assume that all BNS mergers are associated with a short GRB

- We simulate the **GRB afterglow gamma-ray light curves** following the approach in **Patricelli et al. 2016:**
  - GRB 090510 as a prototype
  - light curve corrected to take into account
    - the distance of the sources with respect to GRB 090510
    - a range of possible GRB isotropic energies



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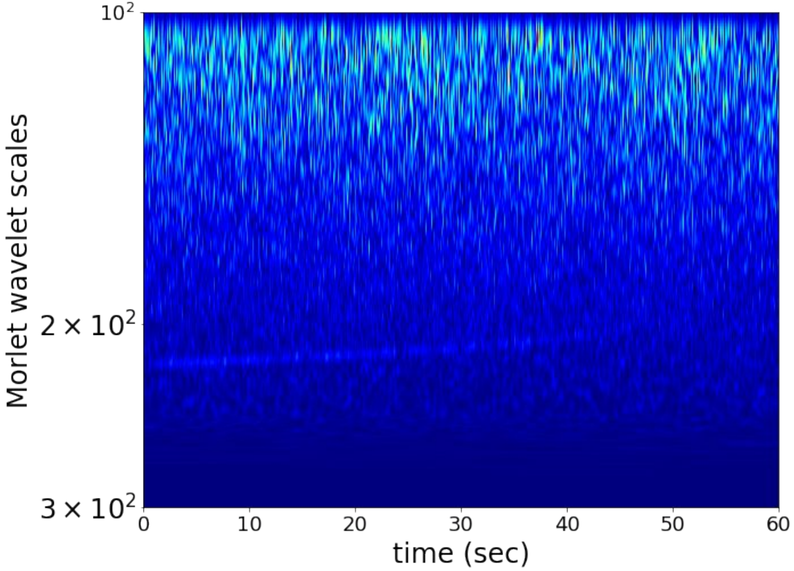
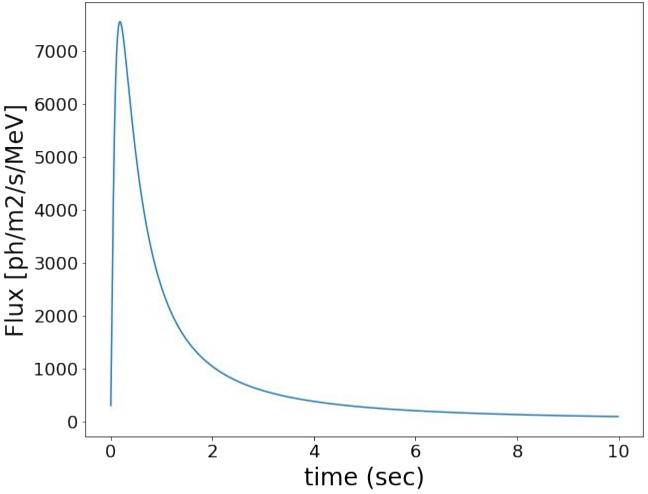
Data Transformation: Time-series or images

Simulated data set

- Sampling frequency: 2048 Hz
- Number of BNS-GRB events: 3000
- Train/Validation/Test set: 70%, 10%, 20%





Wavelet transform using: OverLordGoldDragon, ssqueezepy, 2020. GitHub repository, https://github.com/OverLordGoldDragon/ssqueezepy/. DOI: 10.5281/zenodo.5080514

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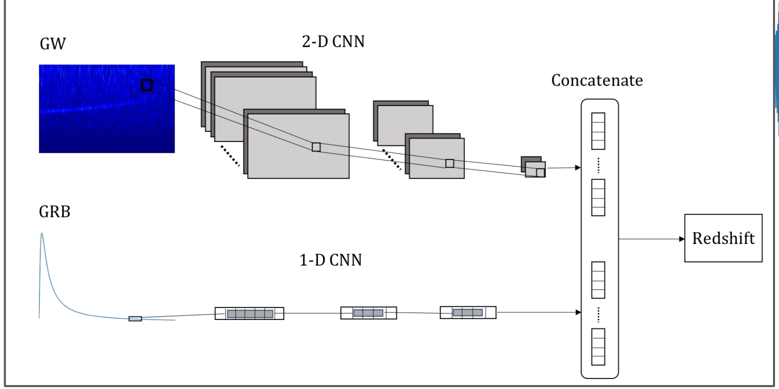
The deep network



2-D CNN for GW time-frequency:

- 5 convolutional layers with (3,3) kernels and 64, 32, 16, 16, 32 filters.
- Max pooling (2,2) after convolutional layer

Flattening + Concatenation + FC layer with linear activation

1-D CNN for GRB light curve:

- 3 convolutional layers with kernels 5, 3, 3 and 80, 40, 40 filters
- Max pooling of 2 after convolutional layer

- ReLU activation function in CNN
- Adam optimizer
- batch size: 16
- Number of training epochs: 100

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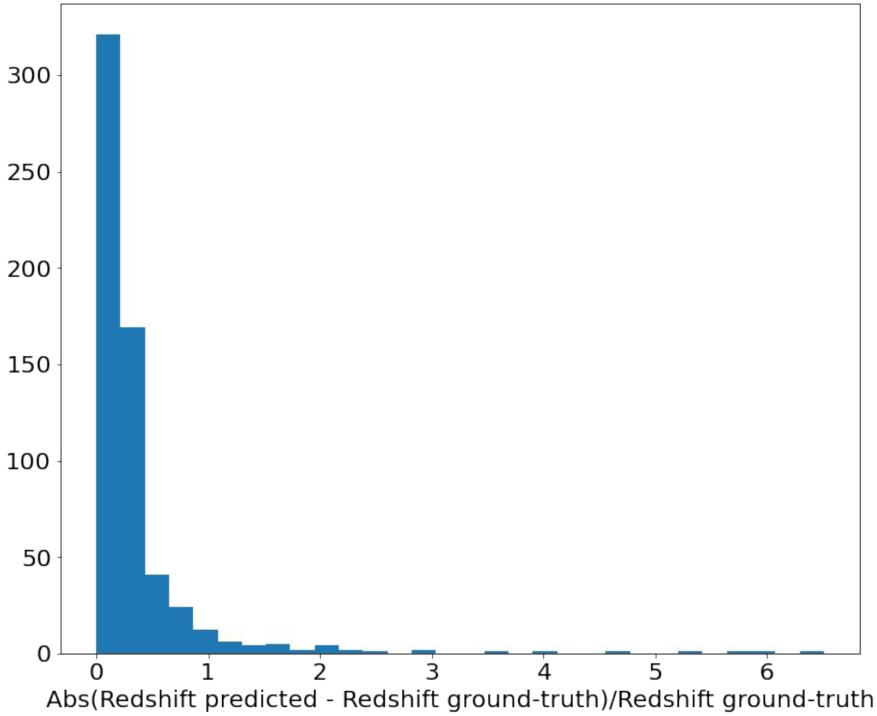
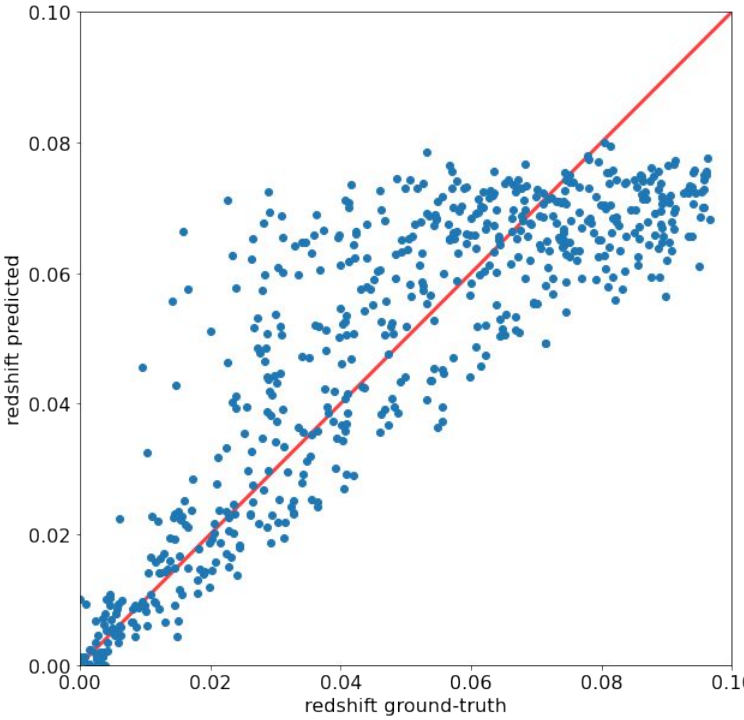
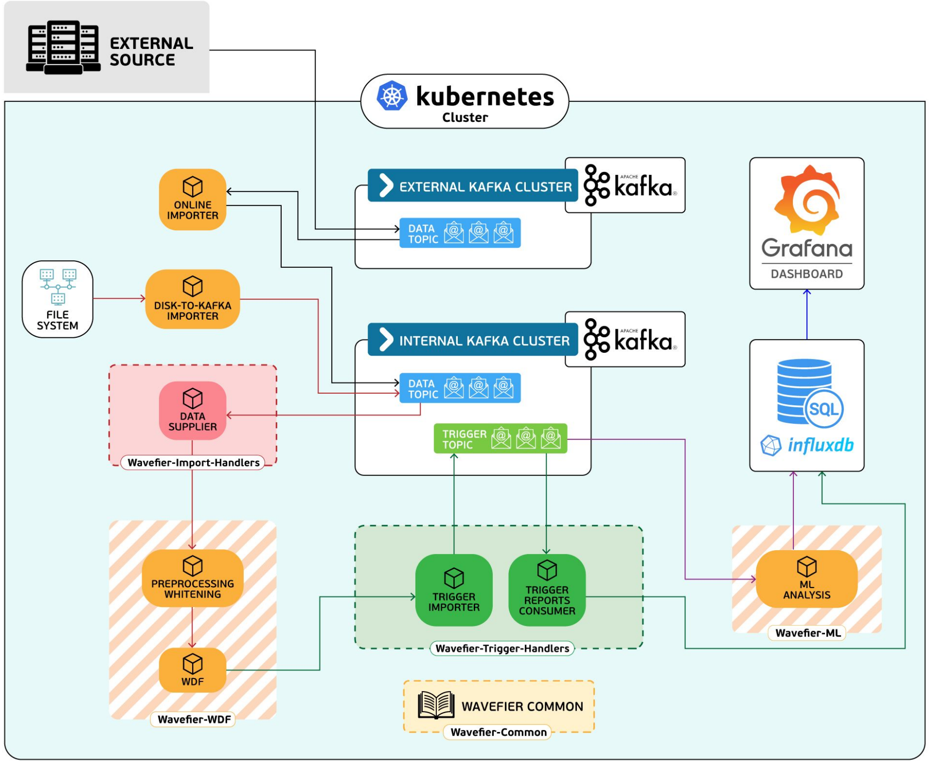
MMML for GW-GRB results





Wavefier: a prototype for real time transient classifier



- Setup a prototype for a **real time** pipeline for the detection of transient signals and their **automatic** classification
- European Open Science Cloud (EOSC) proof of concept

Wavefier

Real time Gravitational Wave transient signal classifier

https://wavefier.gitlab.io/

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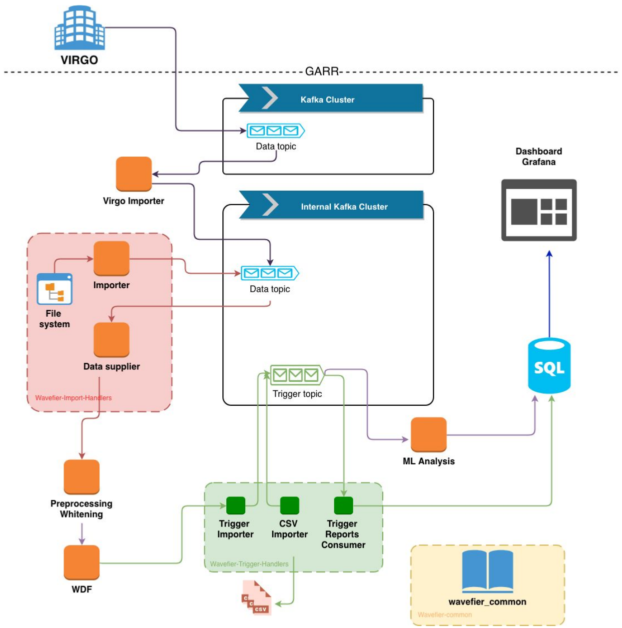
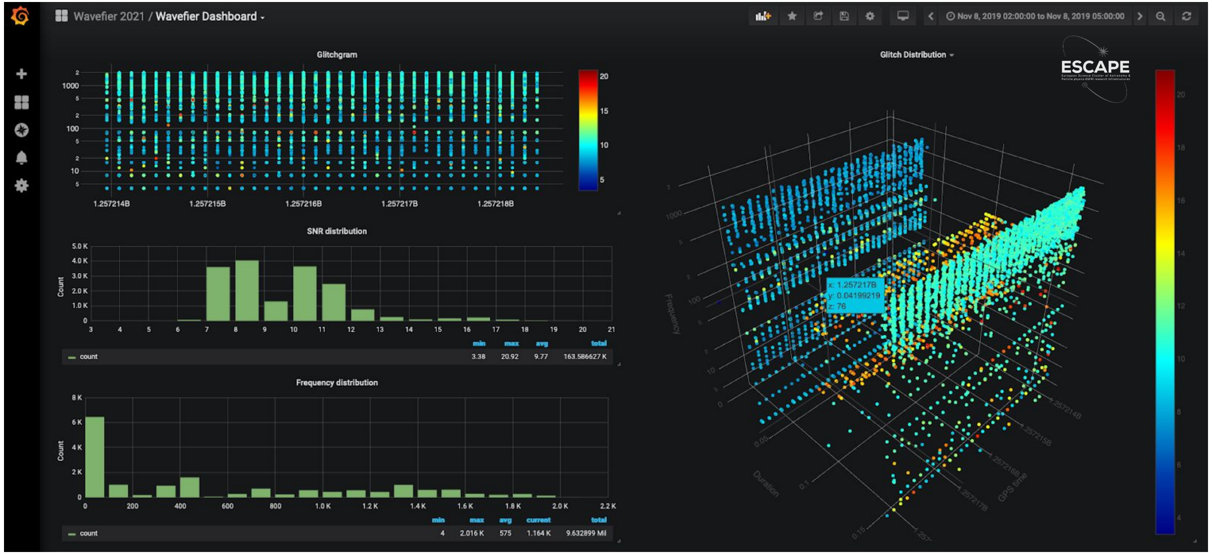
Wavefier Dashboard





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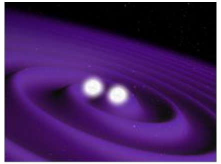
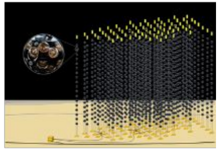
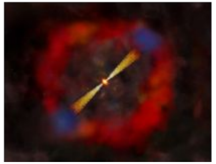
On-going Test Case: Multi-messenger Data

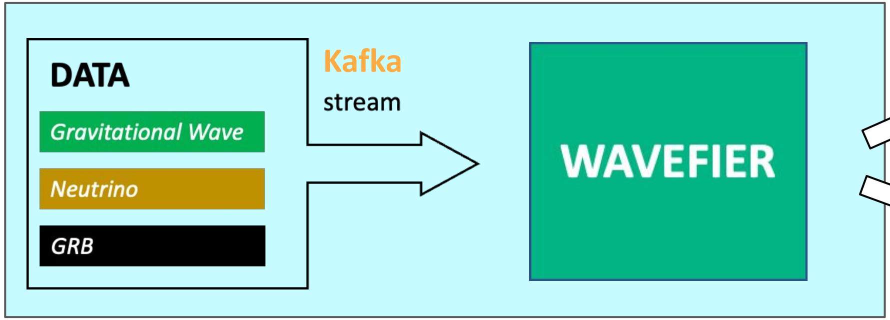
Separate Analysis Pipelines

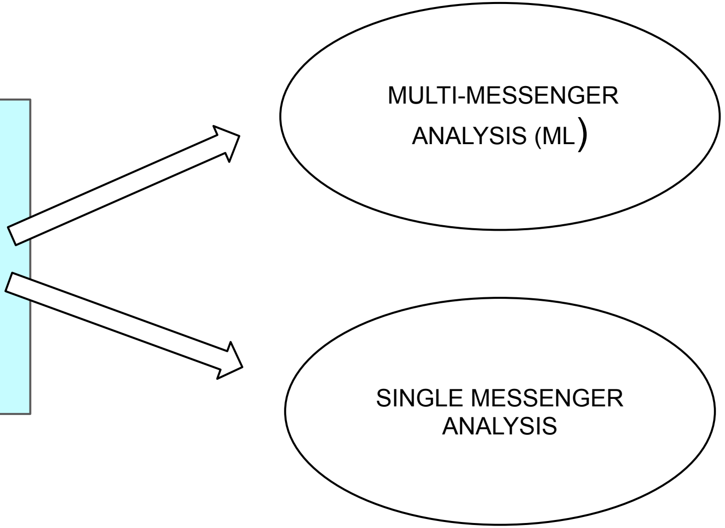
- Wavelet Detection Filter (GW) —> integration in ESCAPE VRE
- Analysis pipeline for Gamma ray
- Neutrino pipeline
- MM pipeline











Different Data Formats

- Gravitational waves (.gwf)
- Gamma ray bursts (.fits)
- Neutrino (.fits)

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Thank you

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