Gravitational Waves, Artificial Intelligence and a Multimodal Approach

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UNIVERSITÀ DI BOLOGNA

INFN BOLOGNA

AI&GW@CZ
Workshop on gravitational wave science and artificial intelligence in the Czech Republic
28 November 2025

Elena Cuoco

DIFA, Alma Mater Studiorum, Bologna University

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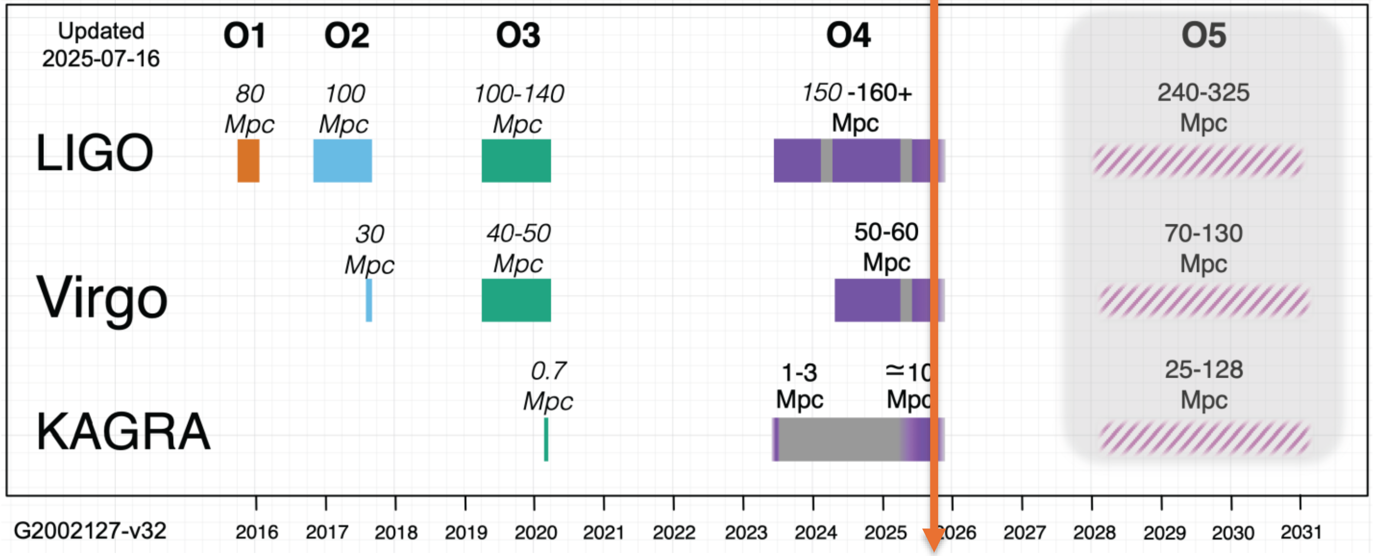
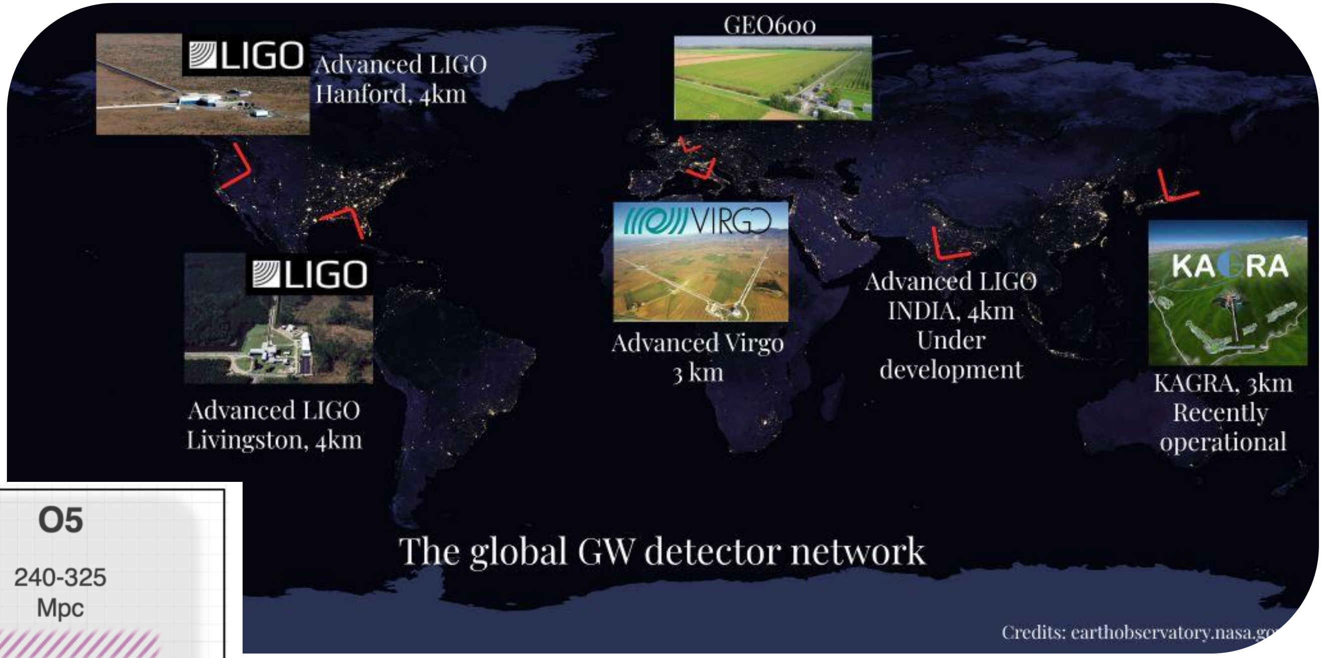
The LVK detector network

We are just completed O4 run





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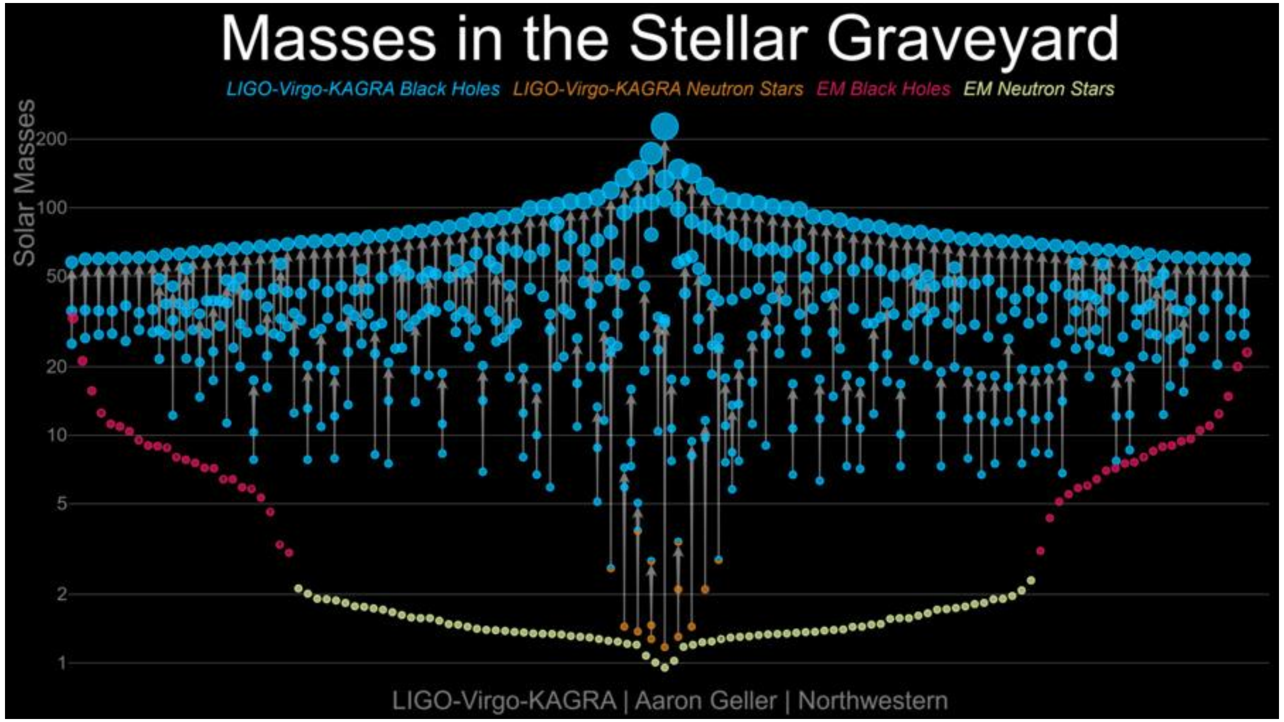
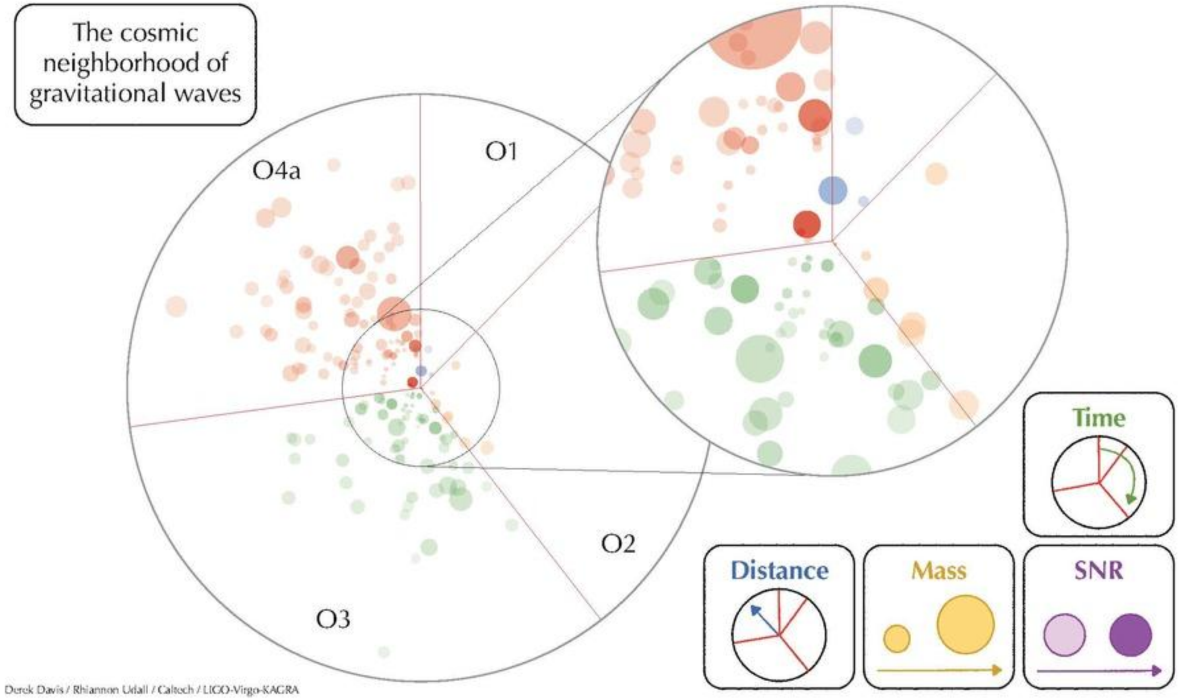
GWTC-04

https://arxiv.org/abs/2508.18082





The catalog now contains 218 candidates, 128 new compact binary coalescence candidates

Spoiler: I won’t cover the results

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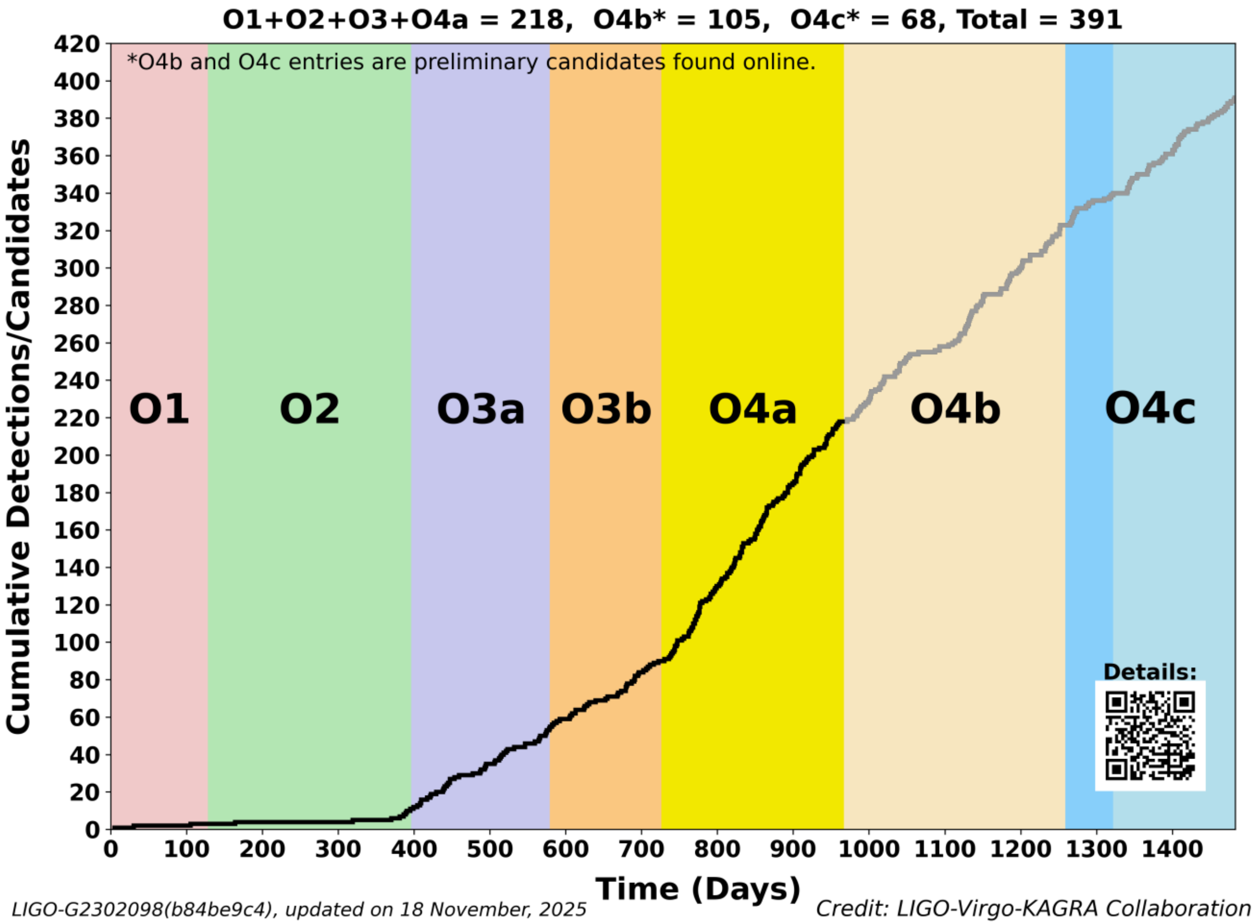
Detection summary up to O4c

O4 Significant Detection Candidates: 254 (283 Total - 29 Retracted)

O4 Low Significance Detection Candidates: 5136(Total)

https://gracedb.ligo.org/superevents/public/O4/



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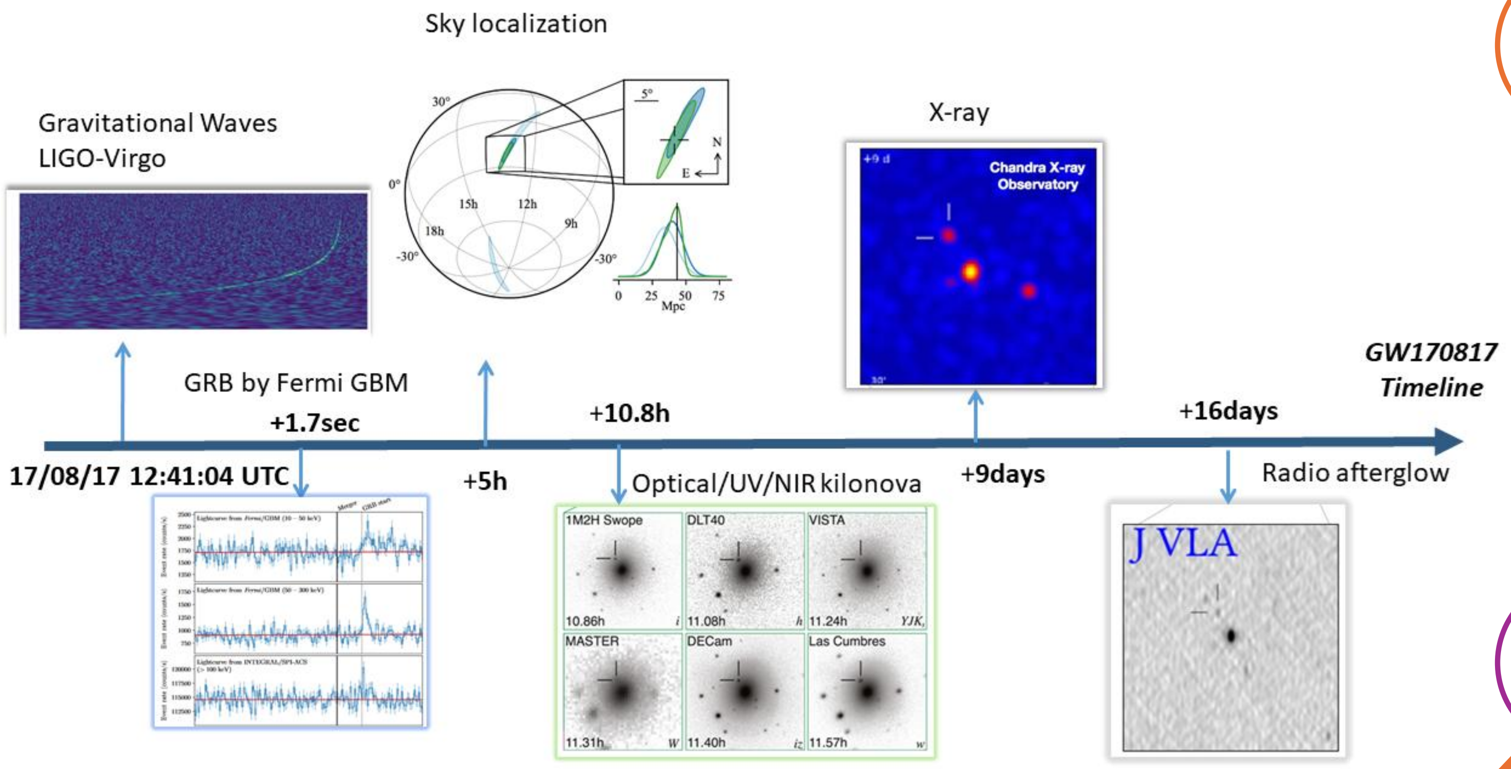
GW170817: the first Multi-messenger GW event



coincident short GRBs detected in **gamma rays**

- first direct evidence that at least some BNS mergers are progenitors of short GRBs

the host galaxy has been identified: NGC 4993

an **optical/infrared/UV** counterpart (AT2017gfo) has been detected

- first spectroscopic identification of a kilonova

An X-ray and a radio counterparts have been identified

- off-axis afterglow from a structured jet

Abbott et al. 2017 and refs. therein

See Samaya's talk

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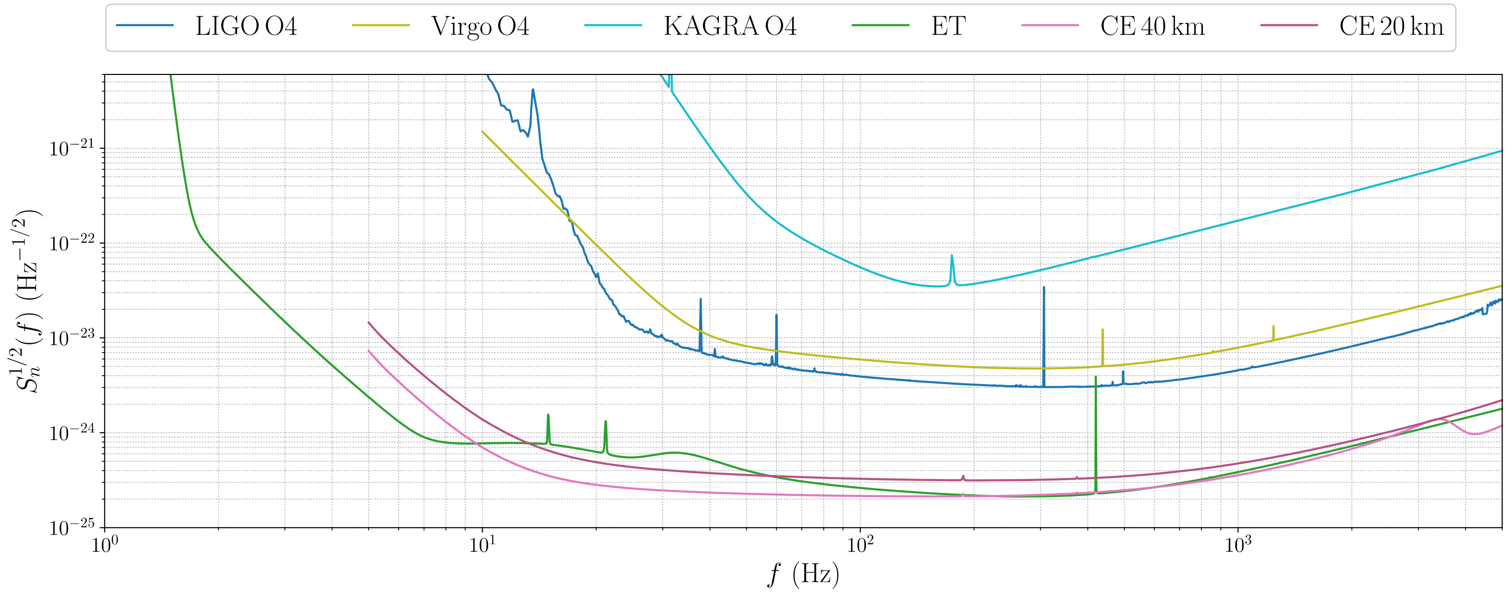
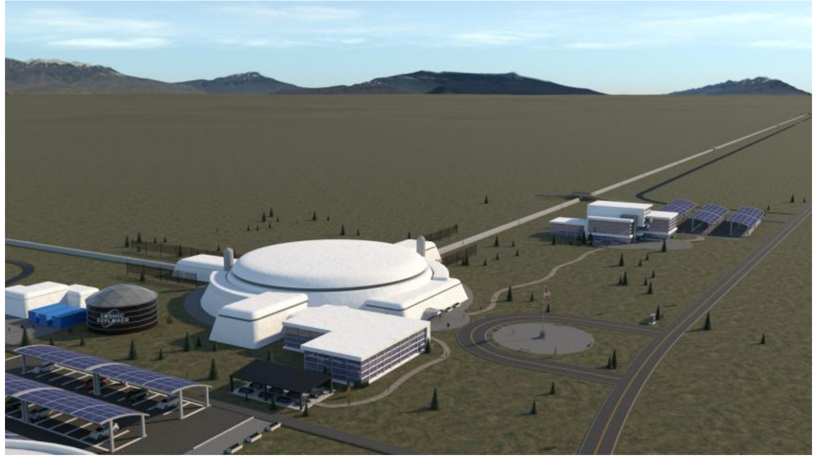
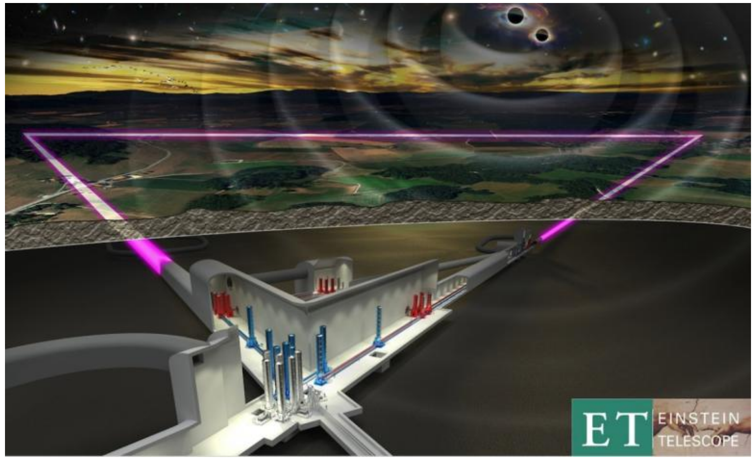
Next generation GW detectors

Gravitational wave detector of 3rd generation





Einstein Telescope
and
Cosmic Explorer



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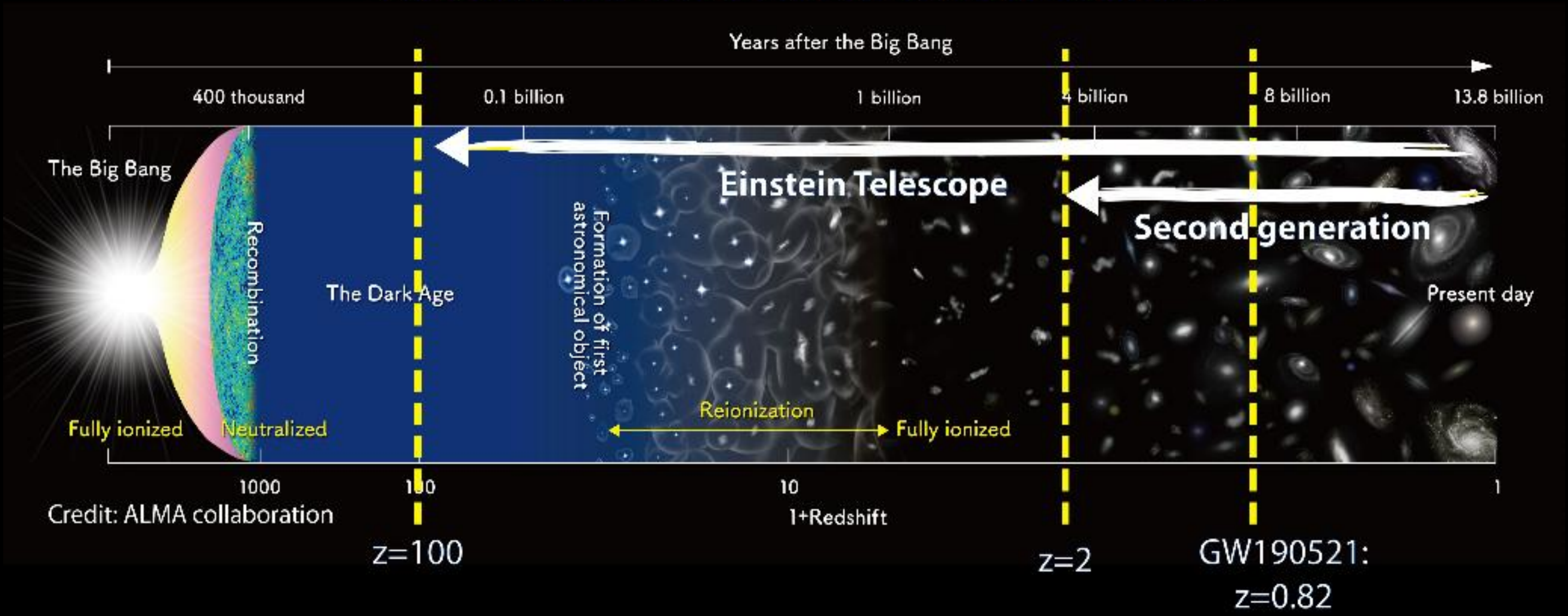
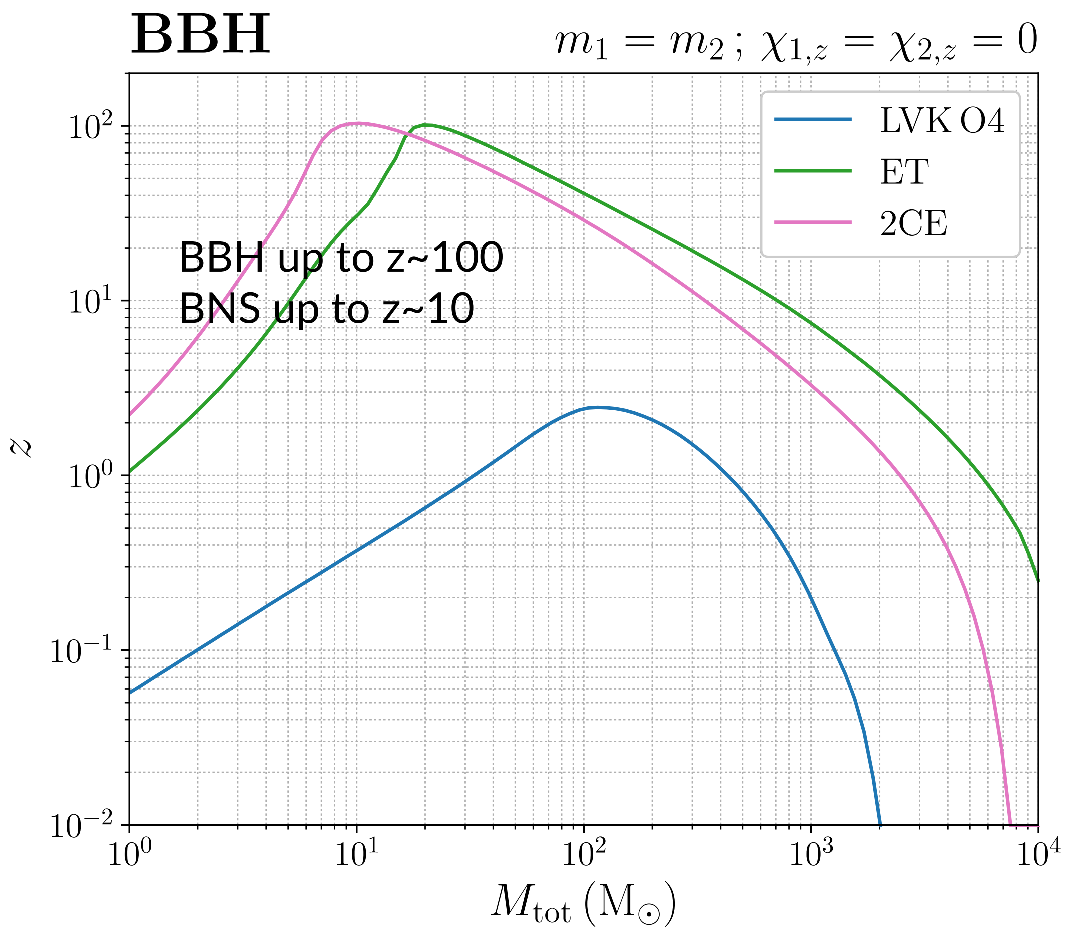
Detection horizon for black-hole binaries

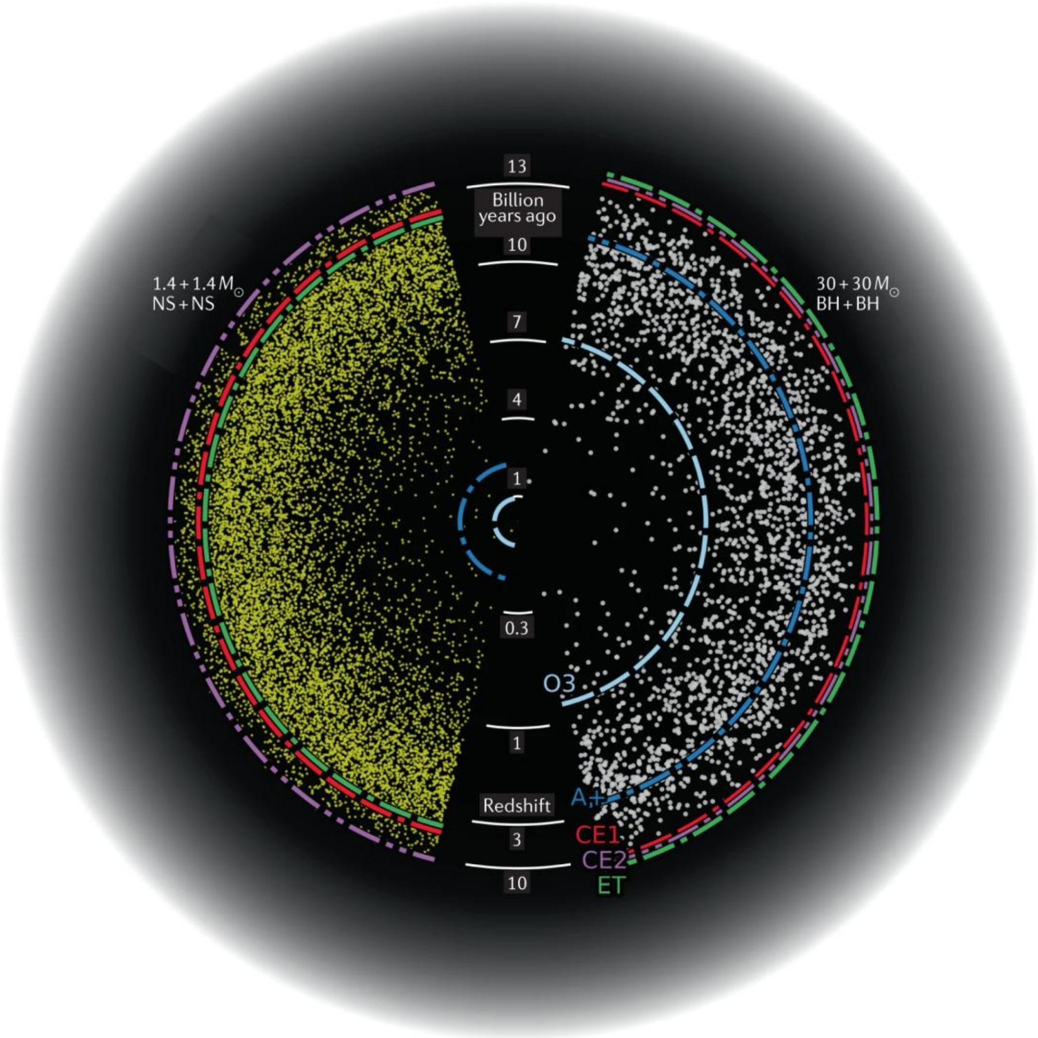


3G - Horizon



BBH up to z~100
BNS up to z~10

From Iacovelli et al, ApJ, 2022



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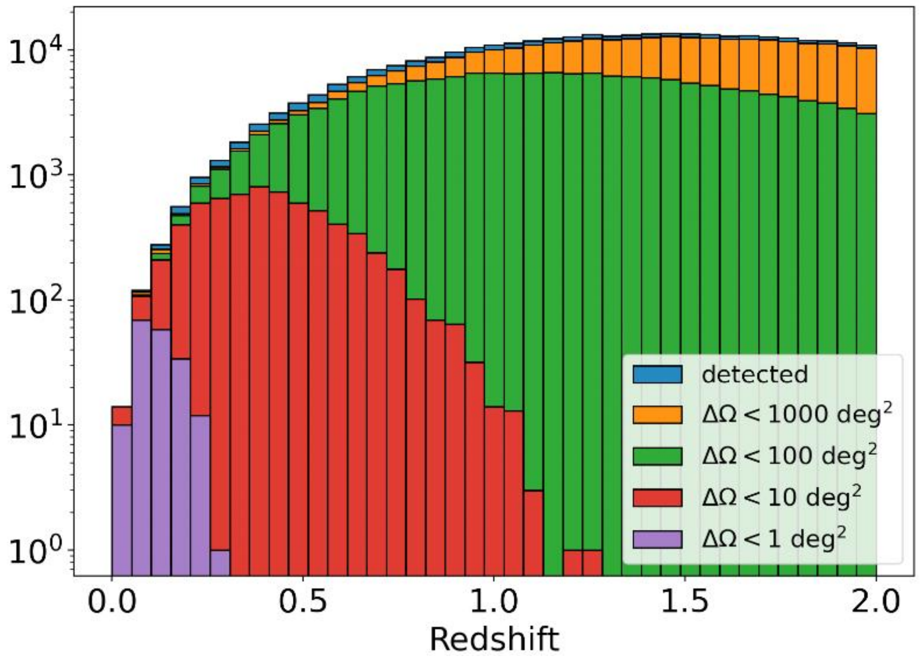
MULTIMESSENGER

We expect to detect thousand of MMA/year with ET



Dupletsa et al. 2022, Ronchini et al. 2022

Credit: M Branchesi

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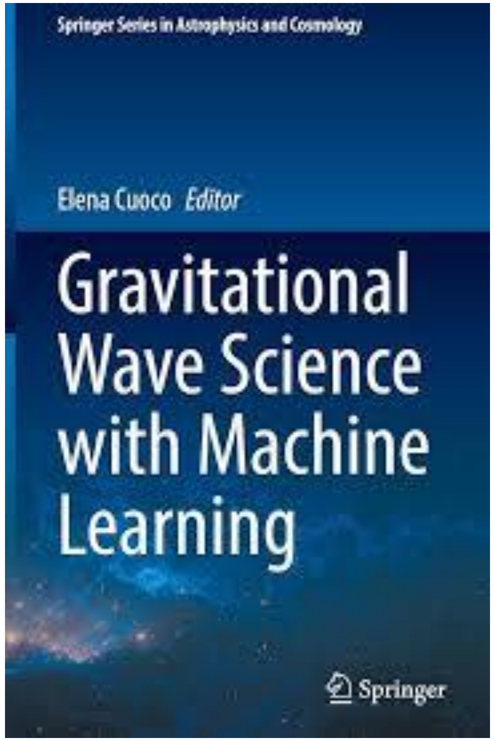
Should we panic now, or just enjoy the cosmic fireworks?

Artificial intelligence for GW science

Multimodal Machine Learning for Multimessenger physics

Machine learning for Gravitational wave science

A collection of research linked to COST Action CA17137, g2net, is presented in this book



Home › Living Reviews in Relativity › Article

Applications of machine learning in gravitational-wave research with current interferometric detectors

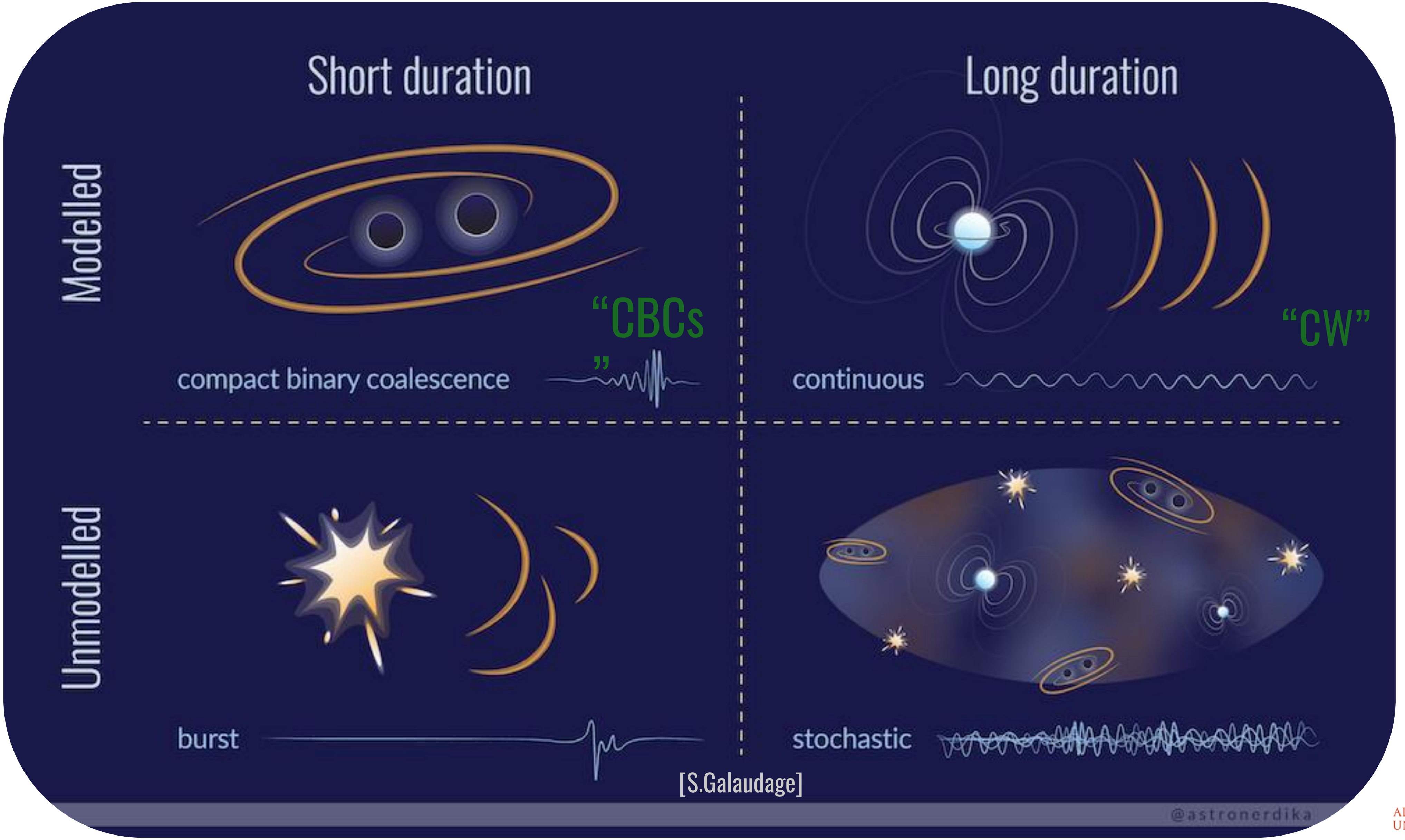
Review Article | Open access | Published: 27 February 2025

Volume 28, article number 2, (2025) Cite this article

Elena Cuoco, Marco Cavaglià, Ik Siong Heng, David Keitel & Christopher Messenger, doi:10.1007/s41114-024-00055-8

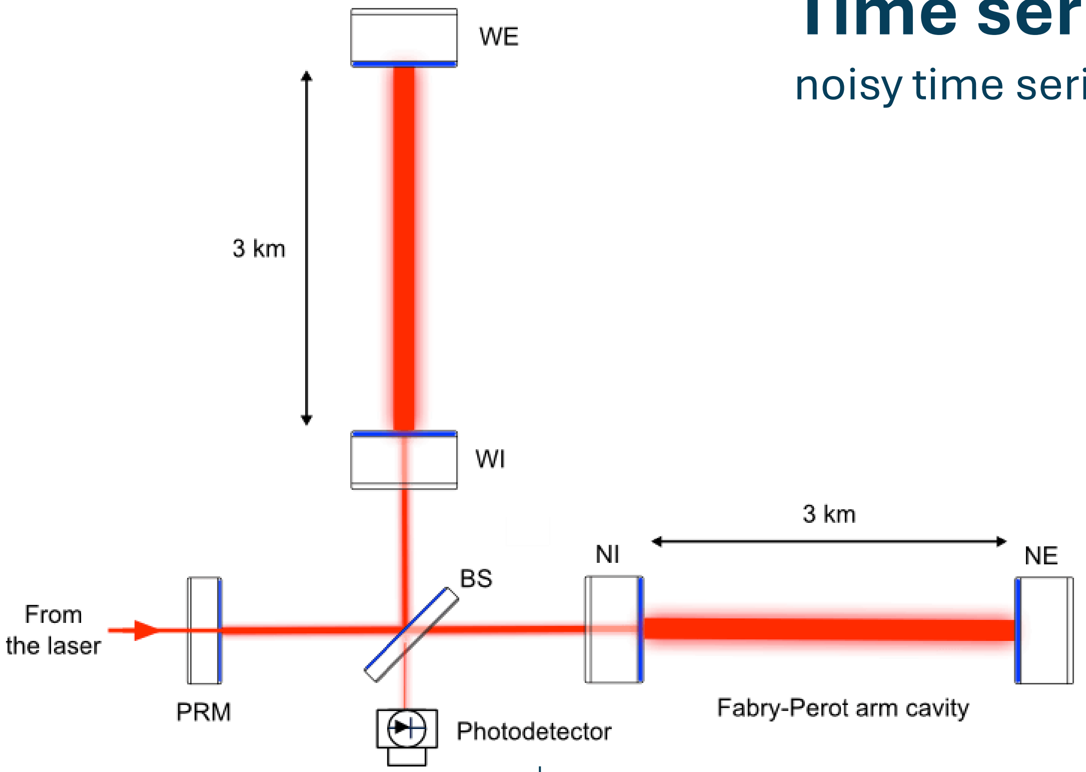
Most recent review paper

LVK search types



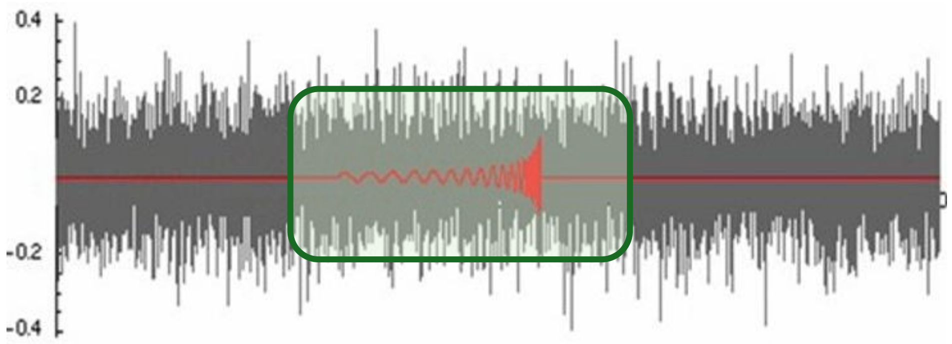
[S.Galaudage]

Gravitational Wave detector data

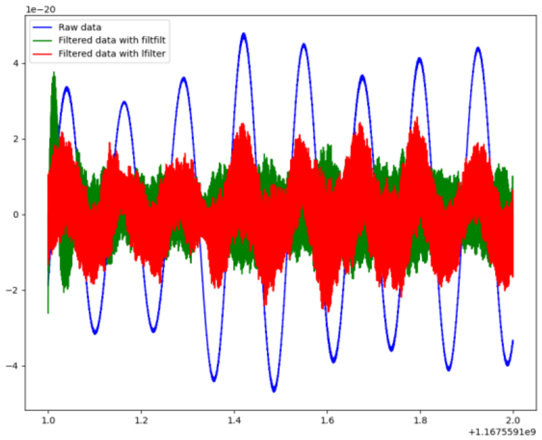


Time series sequences:

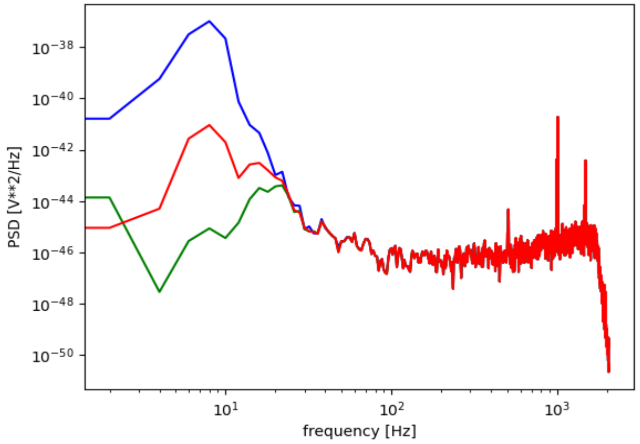
noisy time series with low amplitude GW signal buried in



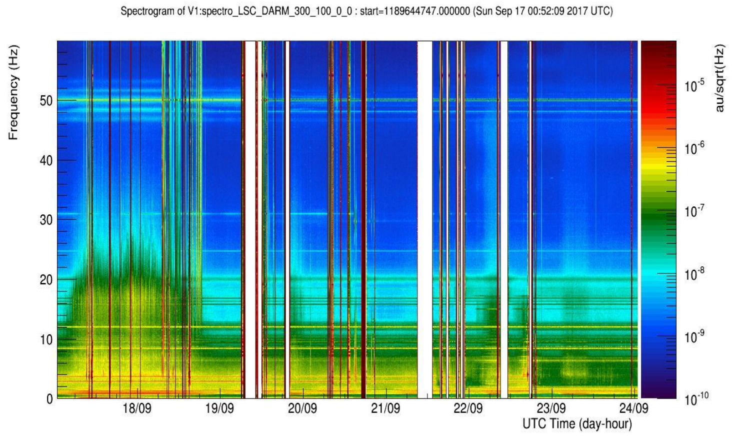
Data representations



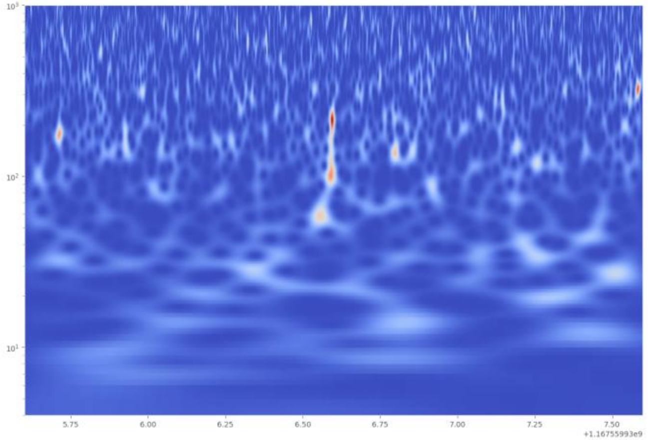
Time-domain



Frequency-domain



Time-frequency-domain



Wavelet-domain

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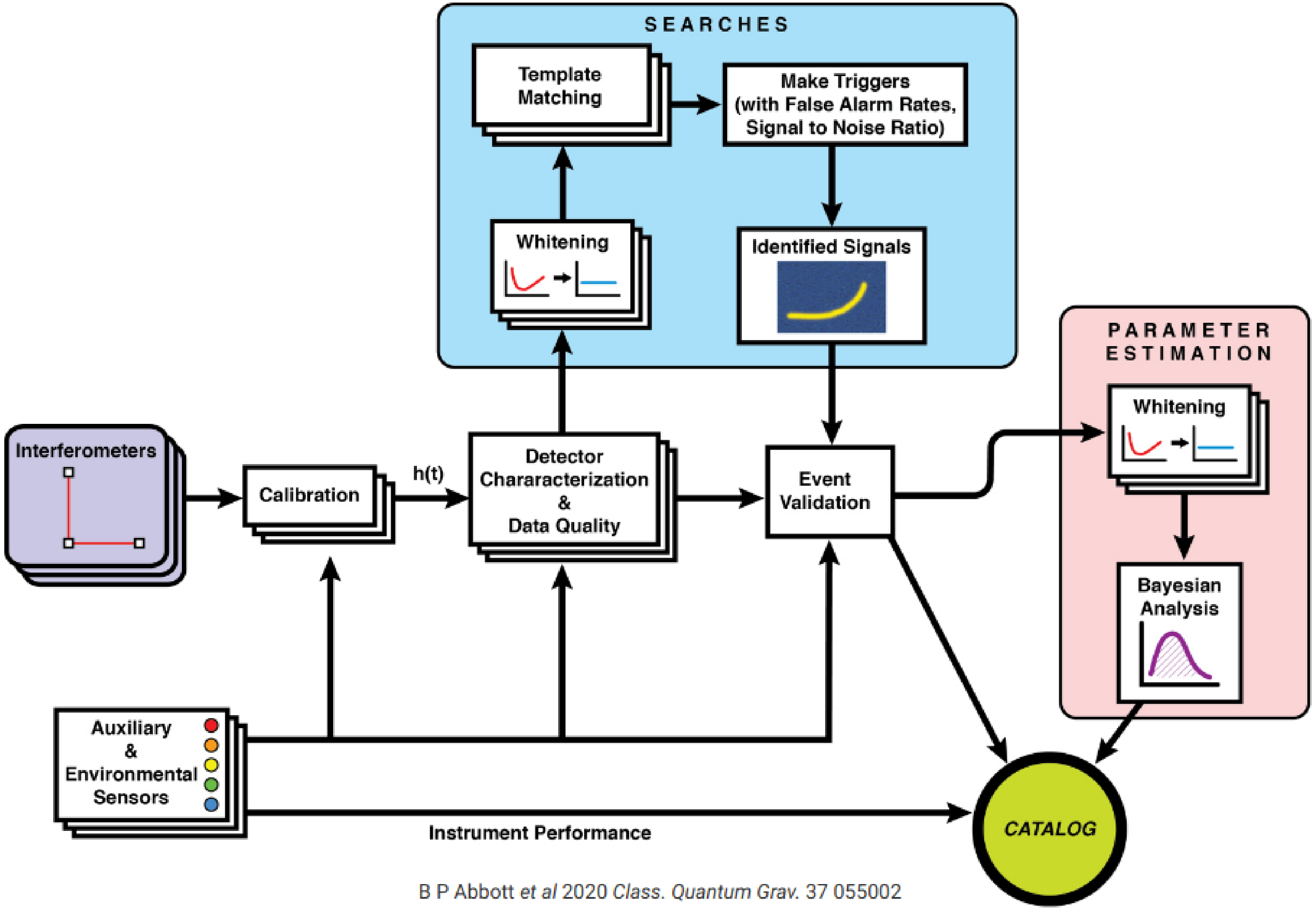
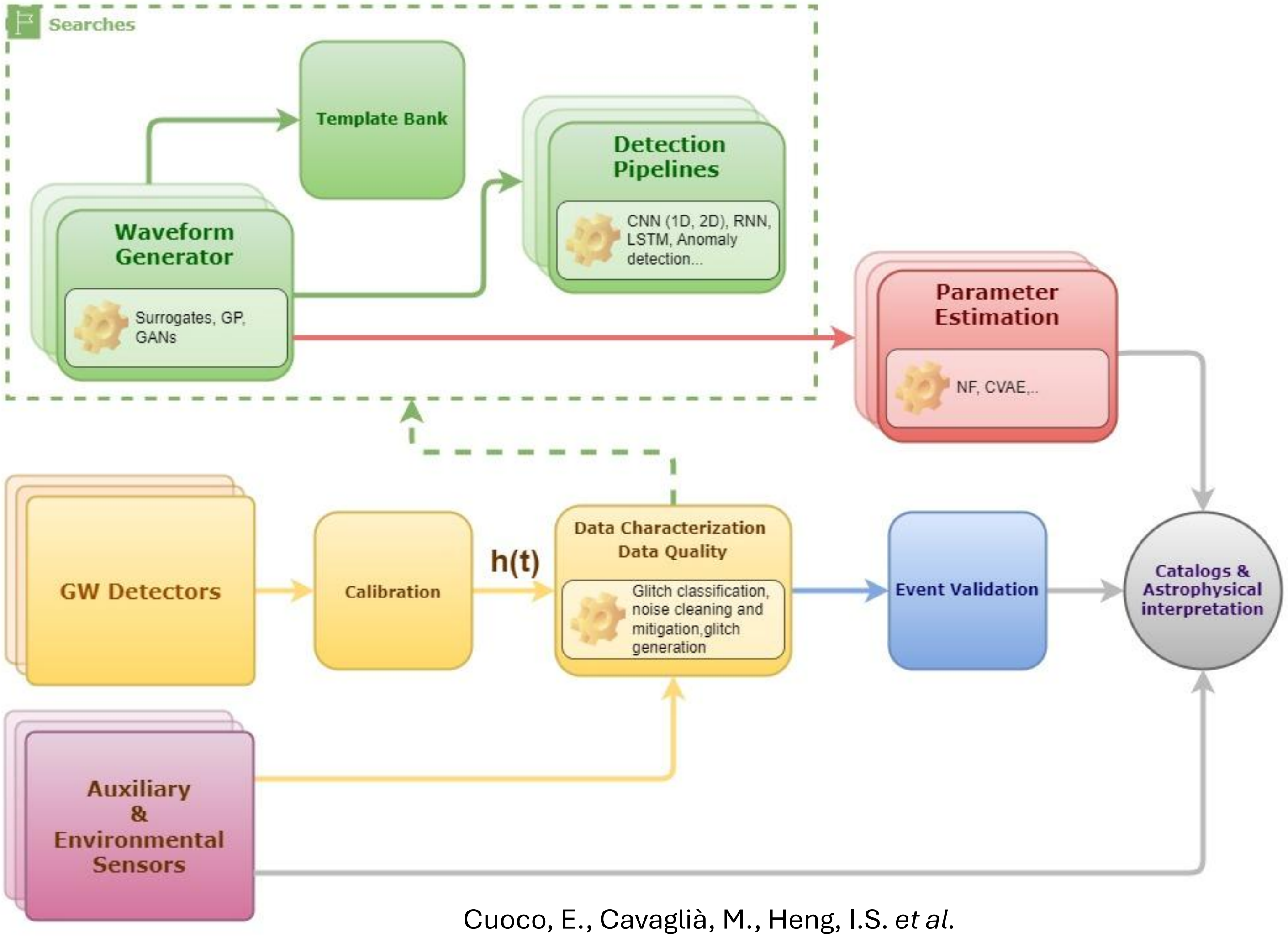
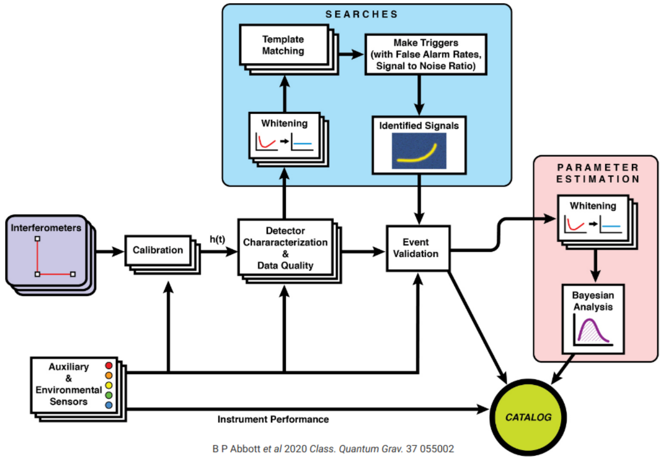
The data analysis workflow



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

The data analysis workflow and AI





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

Cuoco, E., Cavaglià, M., Heng, I.S. *et al.*
Applications of machine learning in gravitational-wave research with current interferometric detectors.
Living Rev Relativ **28**, 2 (2025). https://doi.org/10.1007/s41114-024-00055-8

"AI"/ML and gravitational waves

So, where ML help?

- For some signal types (e.g. CBCs, CWs) we know exactly what we're looking for, but might not be able to efficiently cover the full generic parameter space with "traditional algorithms".
- We also search for "unknown knowns" (waveforms that can't be fully predicted) and "unknown unknowns".

And why is it difficult?

- We are looking for extremely faint signals in our detector noise: only the loudest CBCs (peak strain ~10^{-21}) can be directly "seen" in the output timeseries.

Credit goes to D. Keitel for shaping, for EuCAIFCon 2025, Cagliari, 2025-06-16, most of the next 20 slide content you're about to see.

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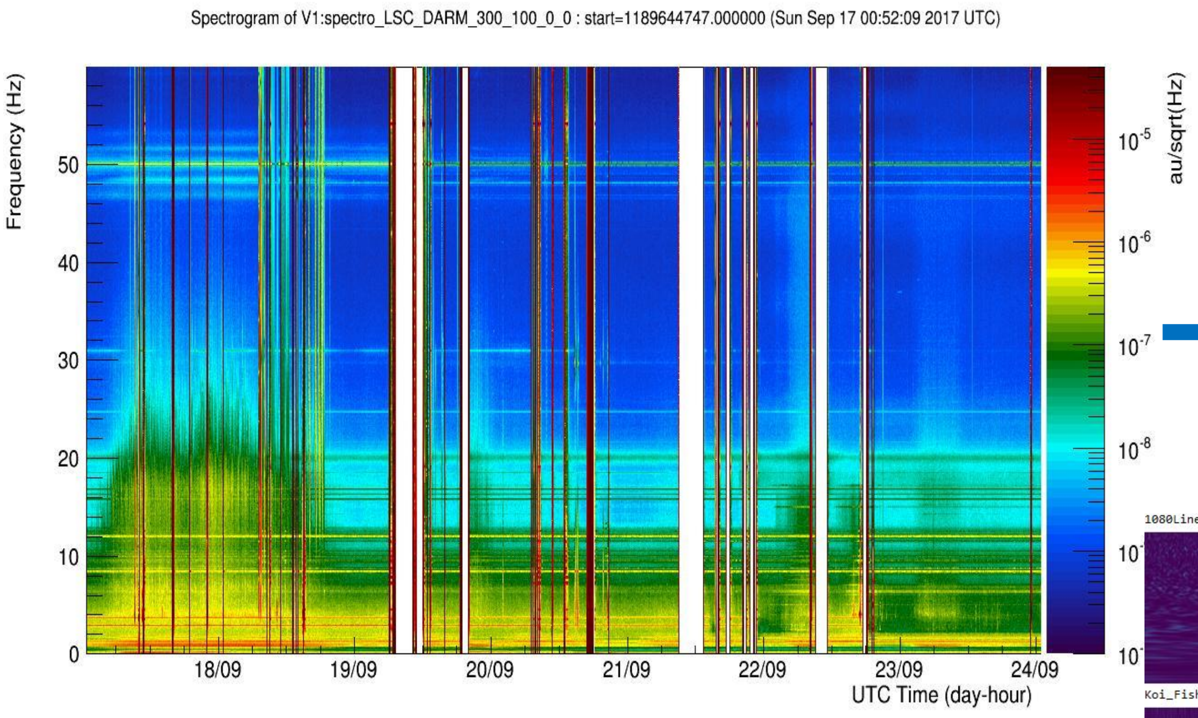
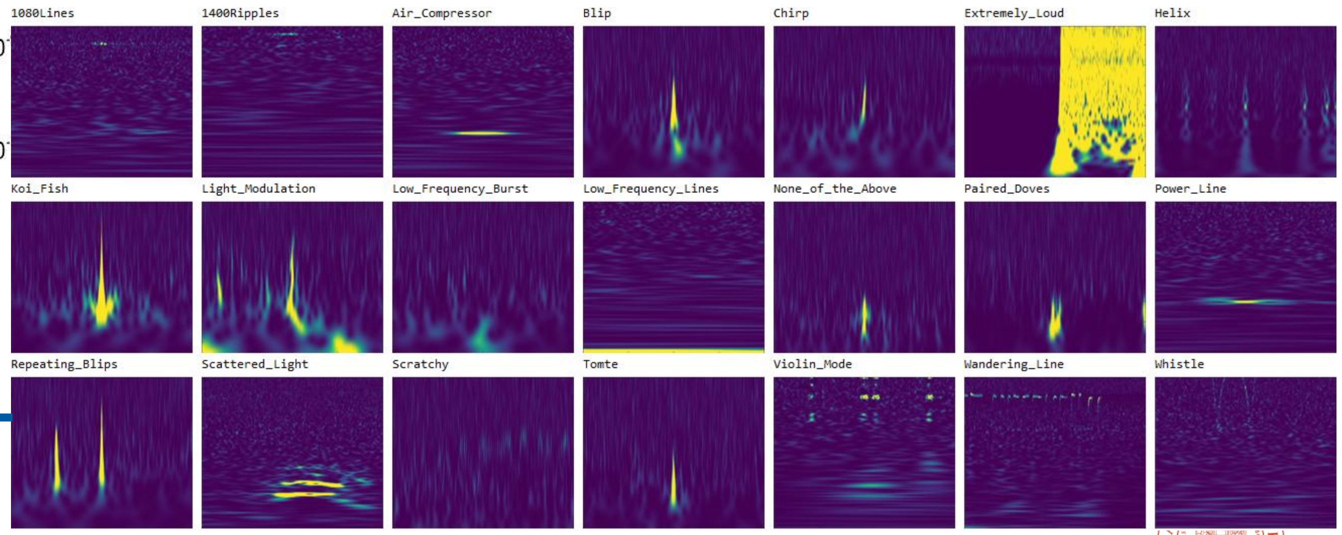
Detector noise: Is it ideal?



Broadband

Gravity Spy, Zevin et al (2017)

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



Transient noise signals: Glitches

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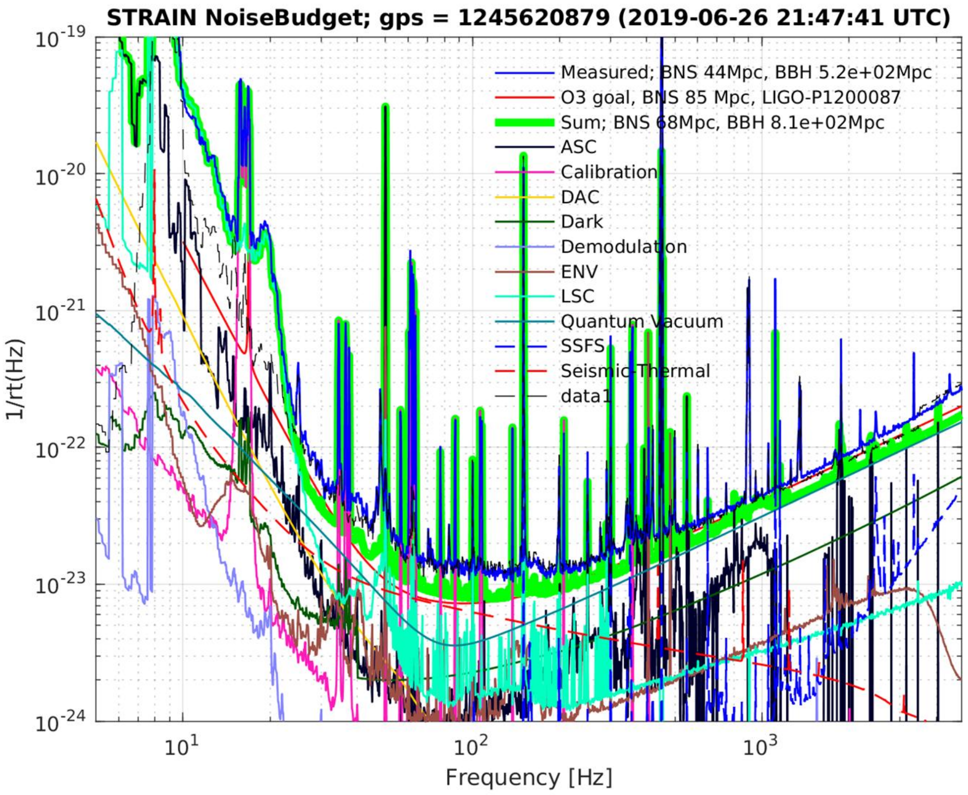
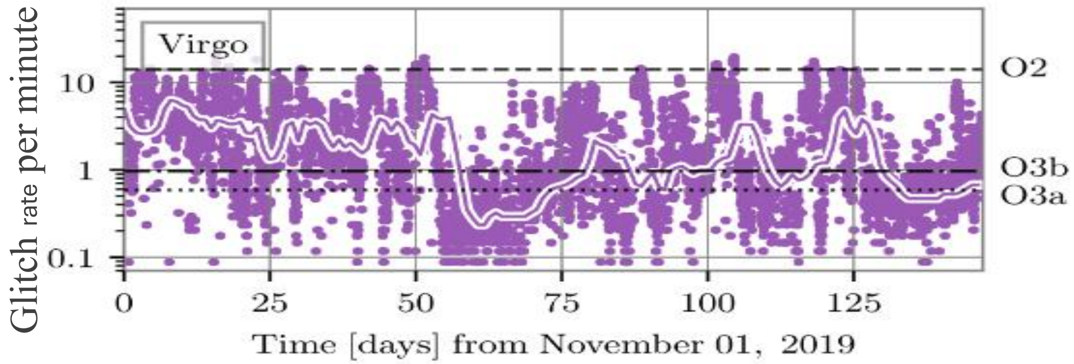
Non-stationary and transient noise

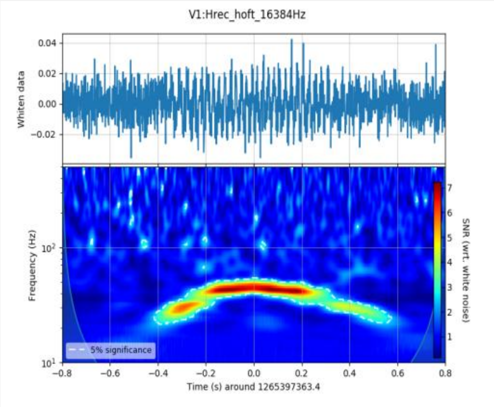


Virgo



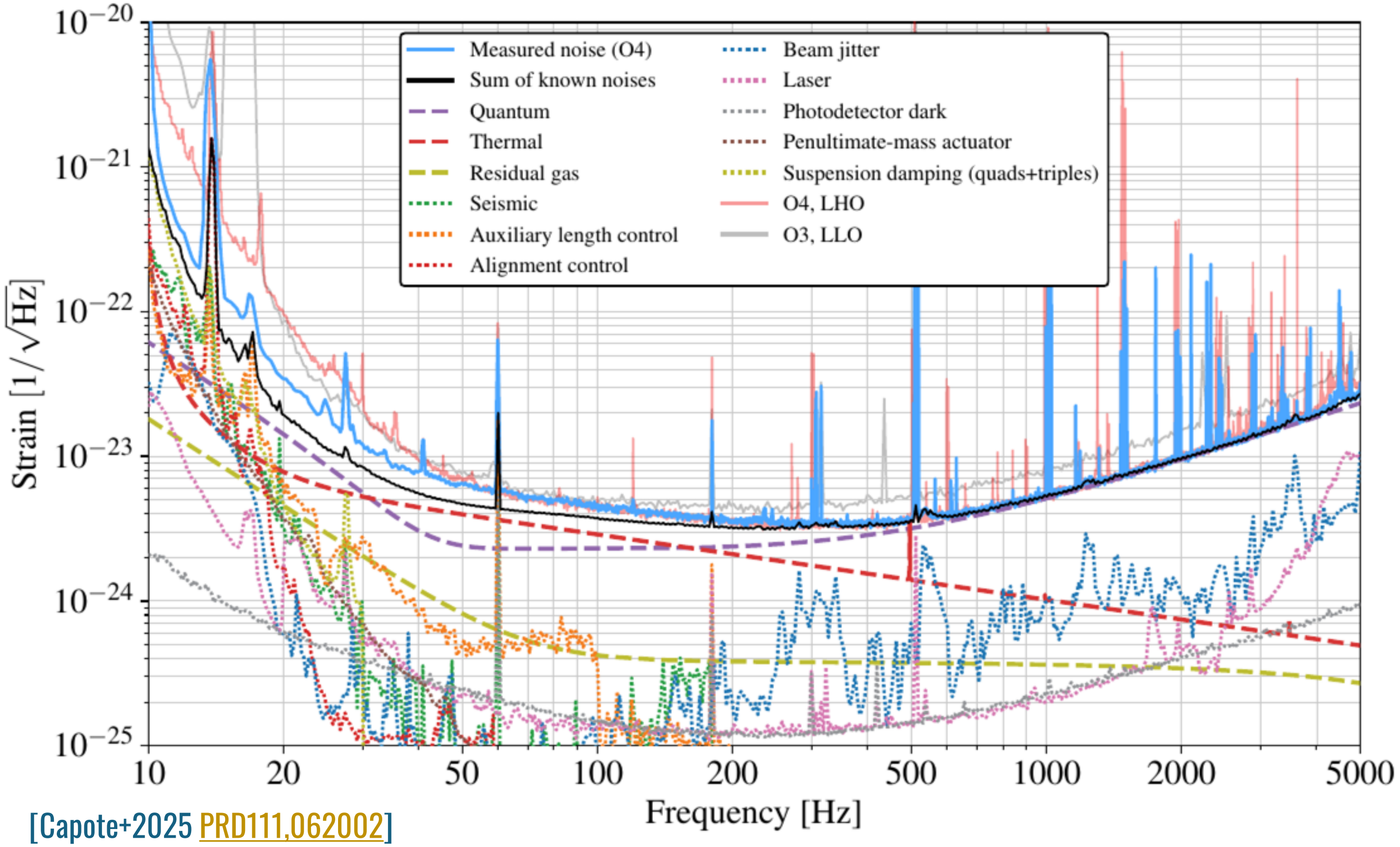
- GW detectors are extremely complex and intricate machines
- Near-Gaussian noise floor = superposition of instrumental and environmental noise sources
- Plus non-stationary and non-Gaussian components

Example of Scattered light glitch



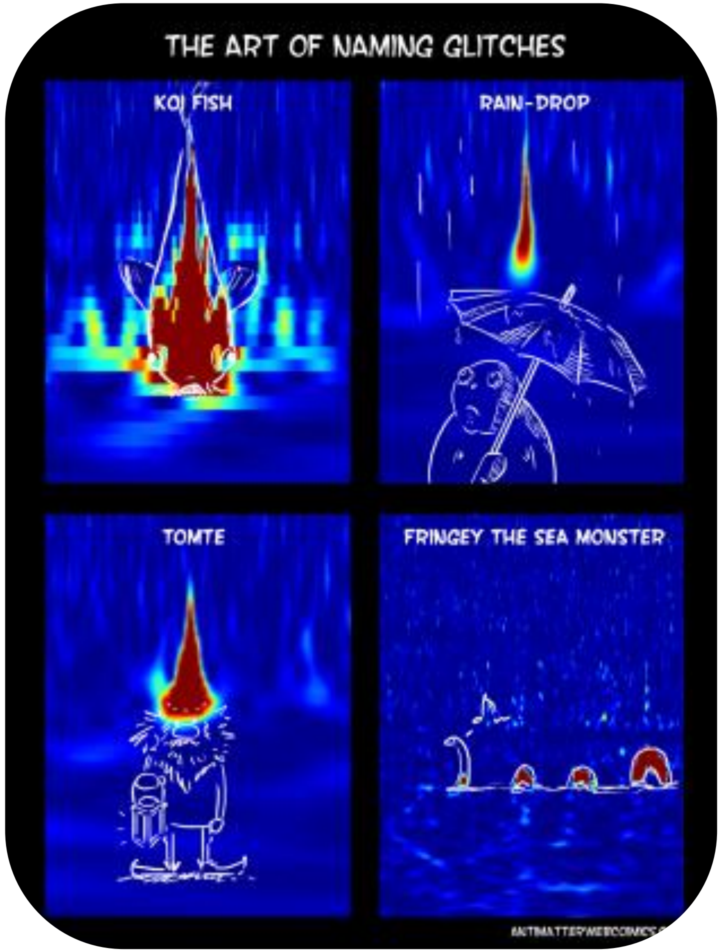
ML for Detector design, operation and characterisation

LIGO



[Capote+2025 PRD111,062002]

(b) Noise budget for the LIGO Livingston Observatory, as of October 2023.



[N. Kijbunchoo]

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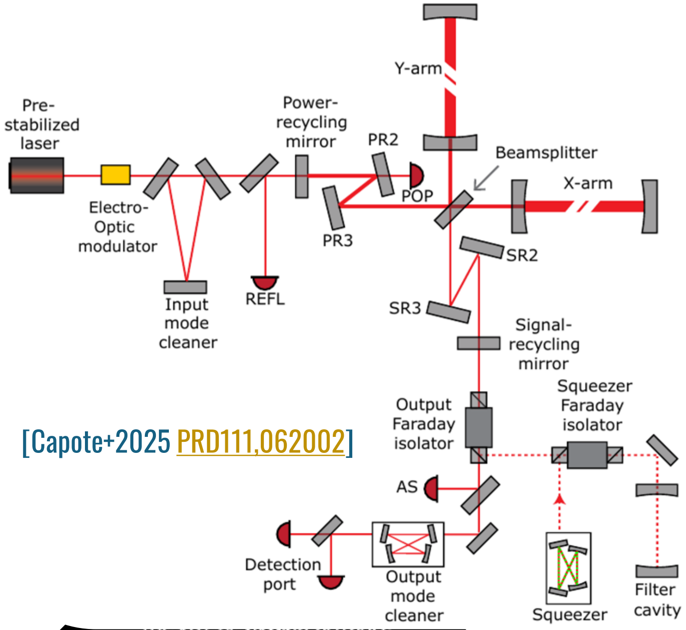
Detector design, operation and characterisation

ML could offer possibilities for:

- optimising detector design across an immensely-dimensional parameter space
- real-time optimization of detector parameters (augmenting the control loops)
- Real-time noise prediction and mitigation: correlations between environmental/instrumental monitors and the main GW strain channel
- Non-linear noise regression and subtraction after data-taking
- Glitch identification and removal (non-Gaussian transients)



[Capote+2025 PRD111,062002]

[N. Kijbunchoo]

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Detector design, operation and characterisation

Some noise components have secure “witness channels”:
auxiliary sensors that allow monitoring their time-varying strength and subtracting the effect from the GW strain channel

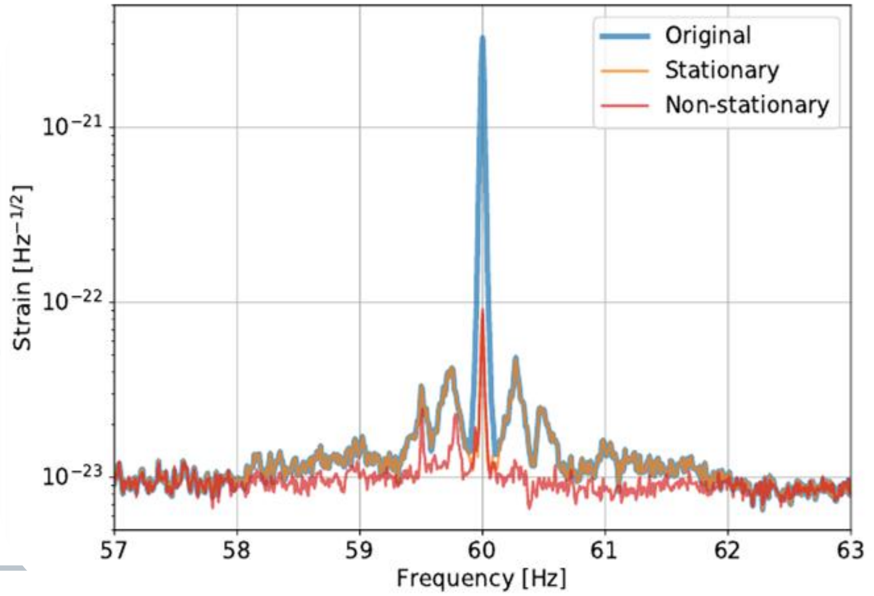
Vajente+2020 PRD101,042003: *“Machine-learning nonstationary noise out of gravitational-wave detectors”*
→ NonSENS: “Non-linear Noise Subtraction”

parameterised model for non-linear relations between channels

optimised with gradient descent model (ADAM)

O3: non-linear subtraction of narrowband instrumental lines, in particular 60 Hz power line

O4: mainly to remove beam jitter noise



[Vajente+2020 PRD101,042003]

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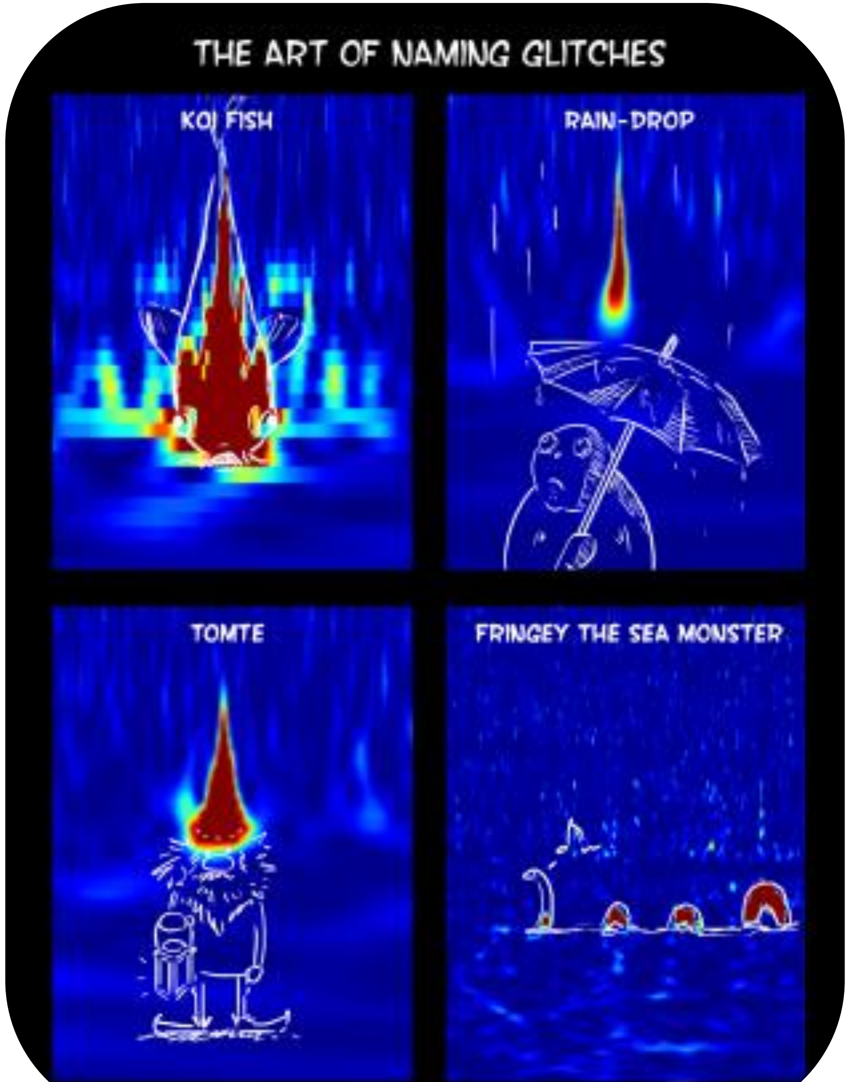
Detector design, operation and characterisation



[N. Kijbunchoo]

- Loud, short, broadband, complex-morphology *glitches* are among the most problematic noise artifacts.
- Gravity Spy: synergy of citizen science and machine learning
  - Zevin+ 2017 CQG34,064003, 2023 EPJP139,100
  - triggers flagged by excess power algorithm ("omicron")
  - basic data unit: time-frequency spectrograms
  - initial pre-labeled data to train a CNN for pre-classification
  - volunteers on Zooniverse* confirm/refine classification
  - feedback loop to retrain the network
- results used e.g. in rapid response to online alerts
- actual glitch removal mainly with BayesWave algorithm [Hourihane+2022 PRD106,042006]

[*] zooniverse.org/projects/zooniverse/gravity-spy

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CNN Glitch classification

Spectrogram for each image

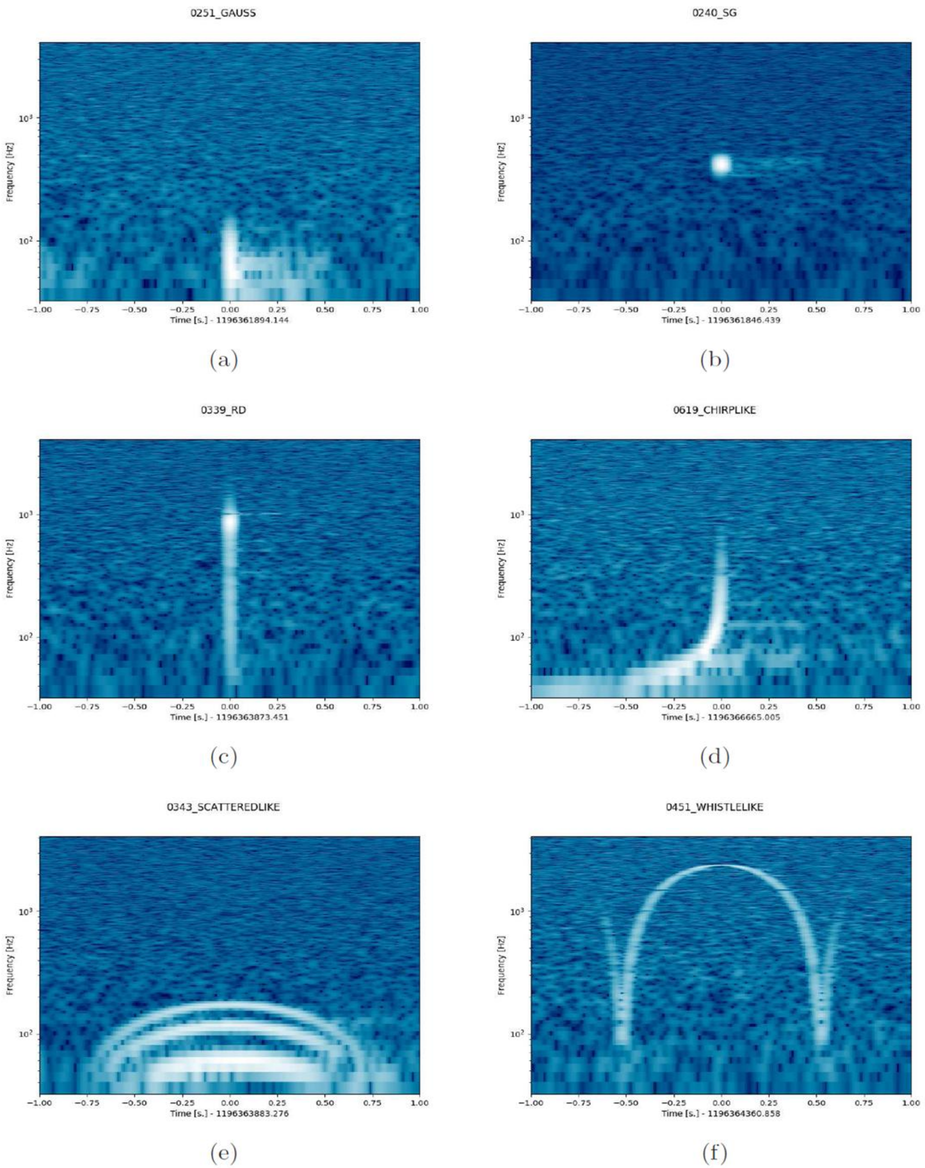
2-seconds time window to highlight features in long glitches

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



Detector design, operation and characterisation

Can we embed more ML/AI into the day-to-day detector operation?
(control loops, lock acquisition and loss prevention, ...) (→ e.g. YOLO point absorber detection, Goode+ 2411.16104)

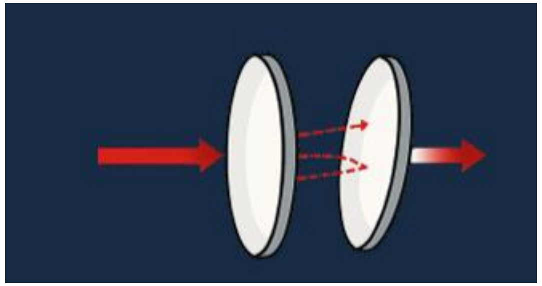
More production uses for improved noise subtraction and glitch mitigation?
(e.g. DeepClean [Saleem+2024 CQG41,195024], DeepExtractor [Dooney+ 2501.18423])

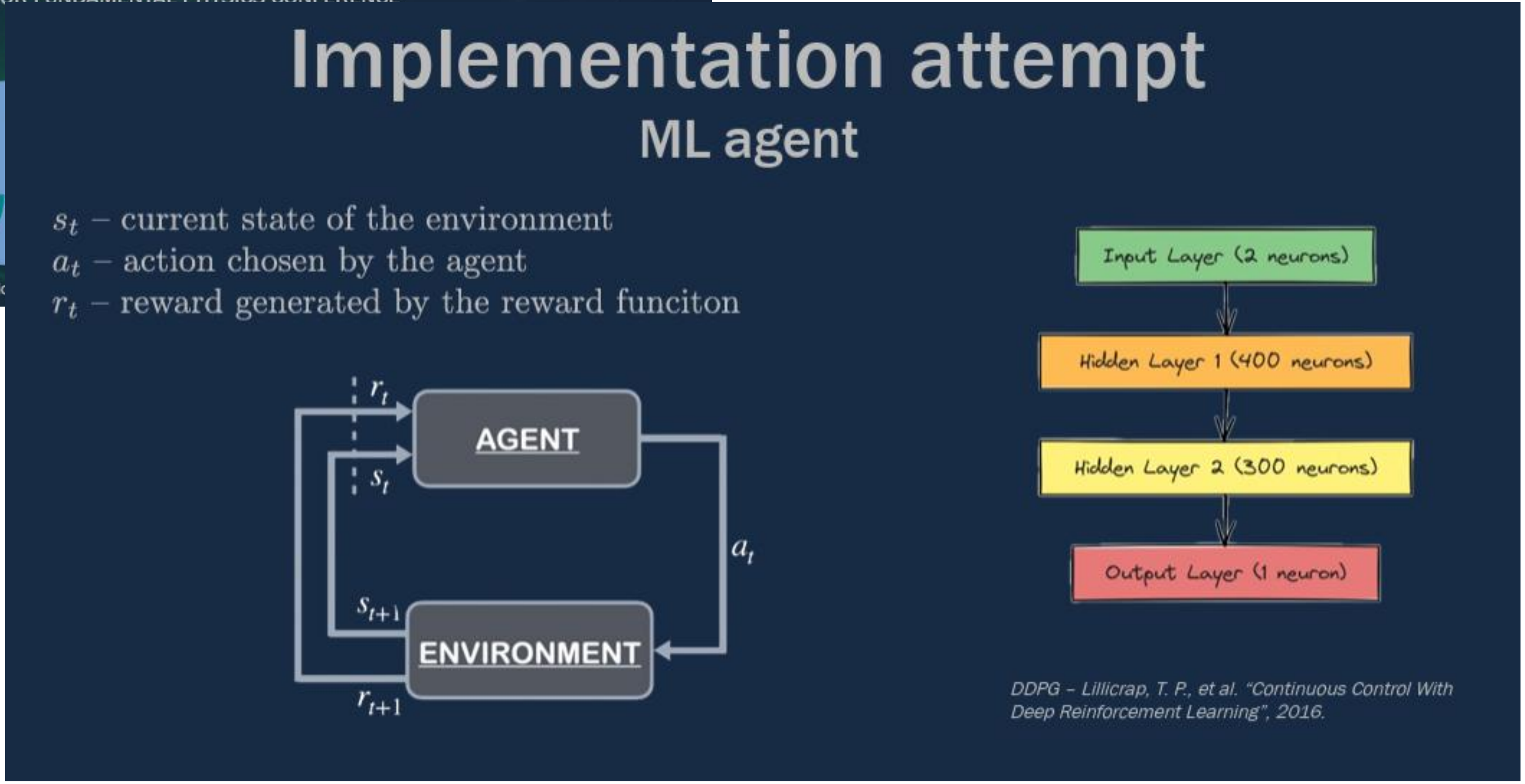
ML/AI for hunting narrow spectral lines, which especially affect long-duration signal searches?

Realistic noise simulation (e.g. Gengli glitch generator: Lopez+ 2205.09204)

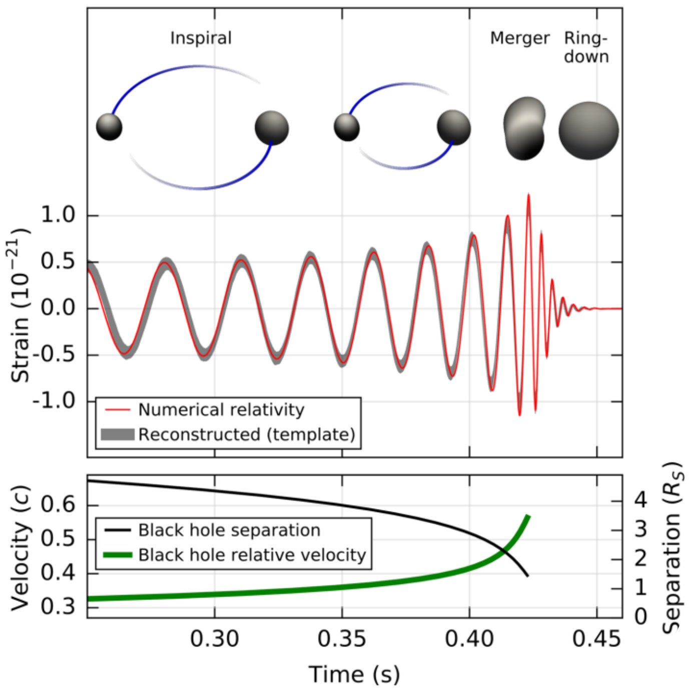
Improved automation of calibration and detector characterisation

Control system via Reinforcement learning

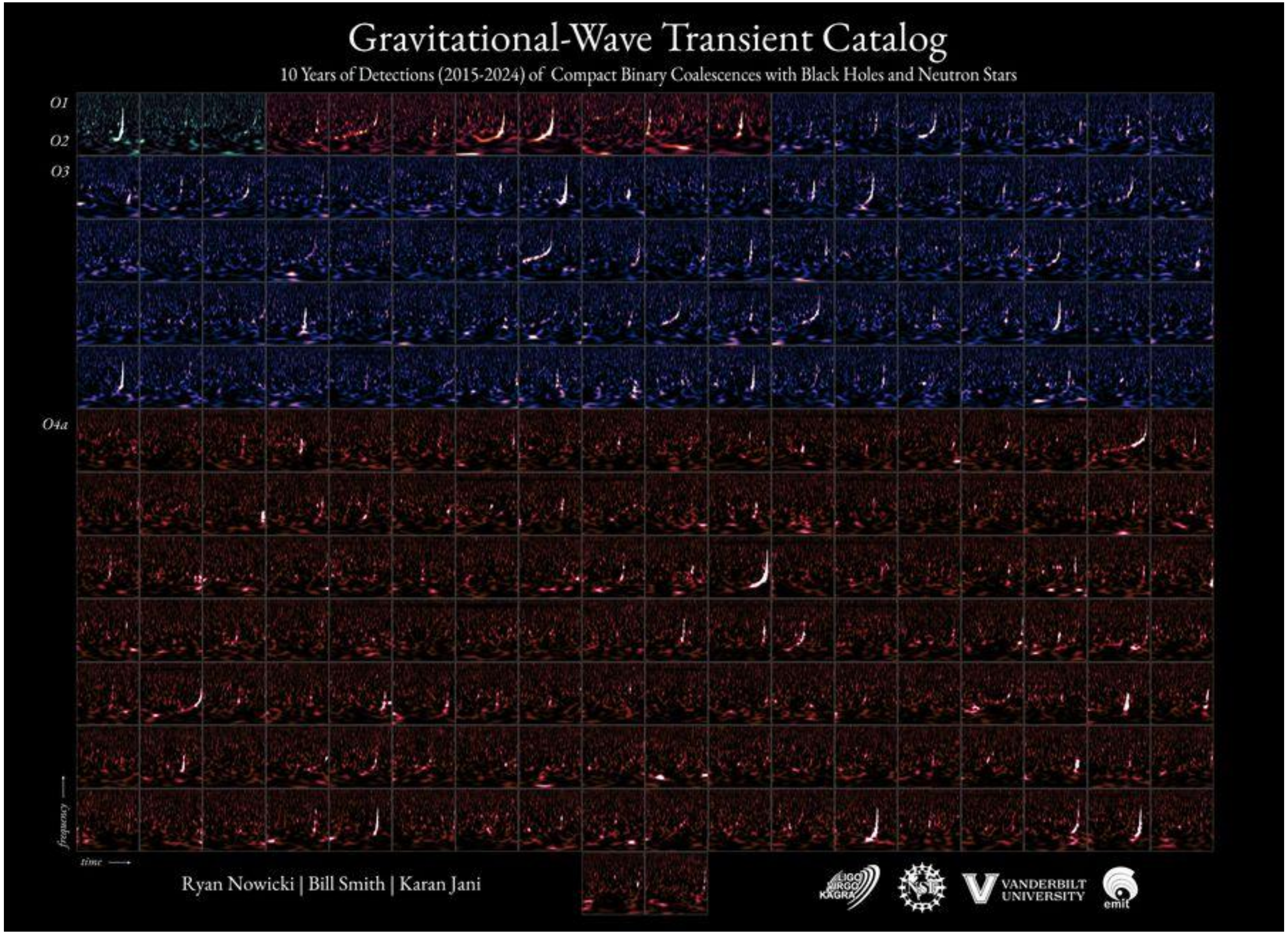




CBCs



[LVC2016 PRL116,061102 / PRL116,241102]



- evolution of compact objects
- tests of GR in strong-field regime
- “standard siren” cosmography
- nuclear matter at extreme densities

Compact binary coalescences

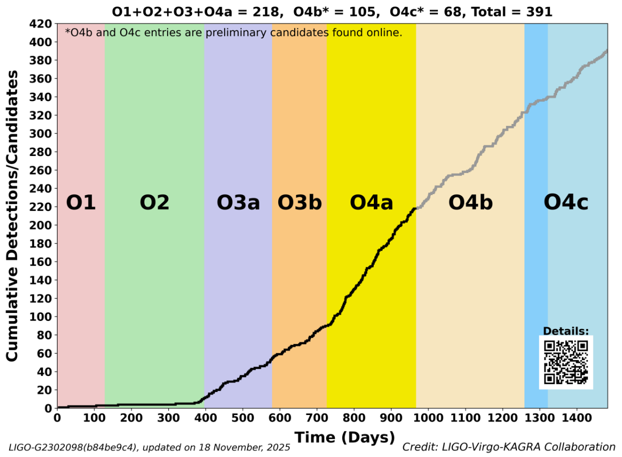
Signal waveforms can be predicted from General Relativity

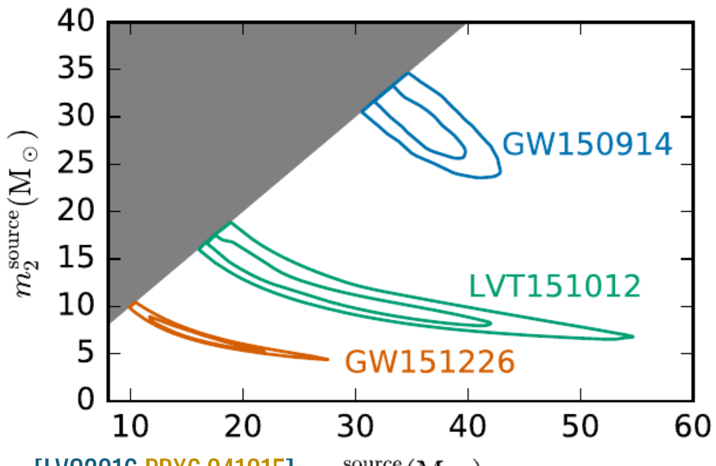
"Searches": find candidates and estimate their significance:

- multiple matched-filter pipelines (fixed template banks)
- weakly-modelled pipelines too

"Parameter estimation": Bayesian inference

Challenges:	
	Full generic parameter space coverage
	Search efficiency in periods affected by non-stationary noise
	Computational cost of full Bayesian inference
	Robustness of Bayesian inference in the presence of noise glitches
	Latency for public alerts (enabling telescope follow-up)





[LVC2016 PRX6,041015]

a review: Chatziioannou+ 2409.02037

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Compact binary coalescences – searches

- Main promise of ML: front-load computational cost to training phase, find candidates even faster
- GW g2net-Kaggle challenge[*] and MLGWSC-1 [Schäfer+2023 PRD107,023021]: standardised data sets to compare ML solutions to each other, and standard matched filter
- AresGW[**] [Nousi+2023 PRD108,024022, Kolonari+2025 MLST6,015054], based on ResNet: strong performance on MLGWSC-1, 8 new GW candidates reported from O3 data
- SAGE[***] [Nagarajan&Messenger 2501.13846], OSNet feature extractor + ResNet/CBAM classifier: further improvements on MLGWSC-1 over AresGW and matched filter
  - paper also highlights 11 types of *biases that challenge CBC detection with ML*: training set construction, spectral bias, etc
- Caveat: ML submissions often optimised to the specific parameter space of the challenge, which could also be done to improve performance of standard methods!
  (e.g. Kumar&Dent 2024 PRD110,043036)

[*] kaggle.com/c/g2net-gravitational-wave-detection (2021) | [**] github.com/vivinousi/gw-detection-deep-learning | [***] github.com/nnarenraju/sage

More examples:
Trovato+2024 CQG41,125003
Marx+ 2403.18661

Waveform building

- Gaussian process regression (GPR) to compute the waveform at points of the parameter space not covered by numerical relativity.
- GPR has been used to build surrogate models of both non-precessing and precessing BBH systems.

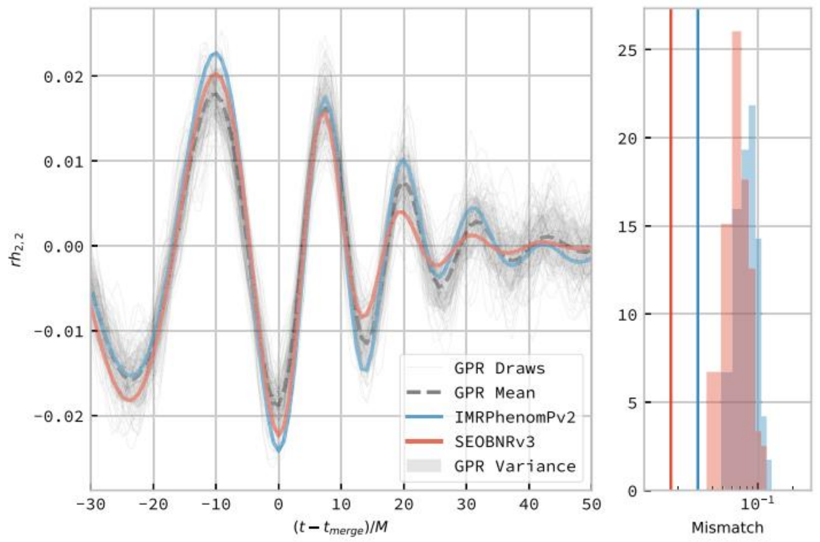
PHYSICAL REVIEW D **101,** 063011 (2020)

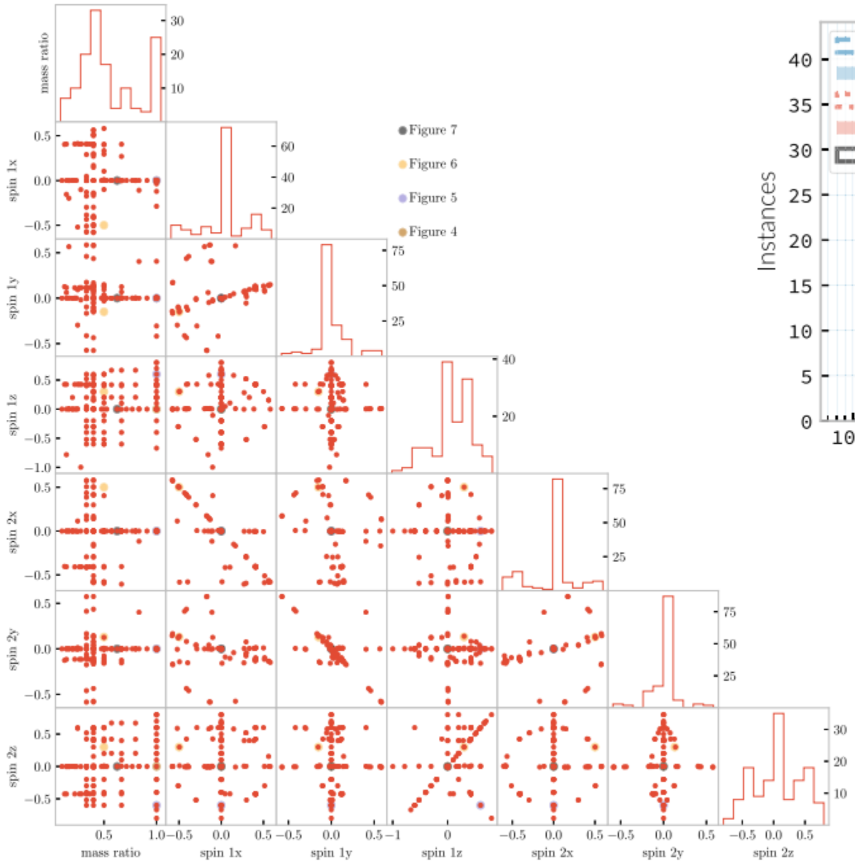
Precessing numerical relativity waveform surrogate model for binary black holes: A Gaussian process regression approach

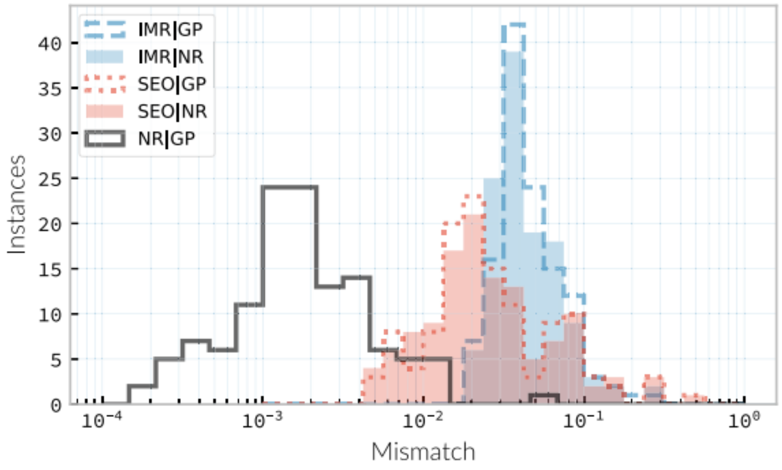
D. Williams* and I. S. Heng
SUPA, University of Glasgow, Glasgow G12 8QQ, United Kingdom

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

J. A. Clark and B. Khamesra
Center for Relativistic Astrophysics and School of Physics, Georgia Institute of Technology, Atlanta, Georgia 30332, USA







See also:
Z. Doctor et al, "Statistical gravitational waveform models: What to simulate next?"
Phys. Rev. D 96, 123011 (2017)

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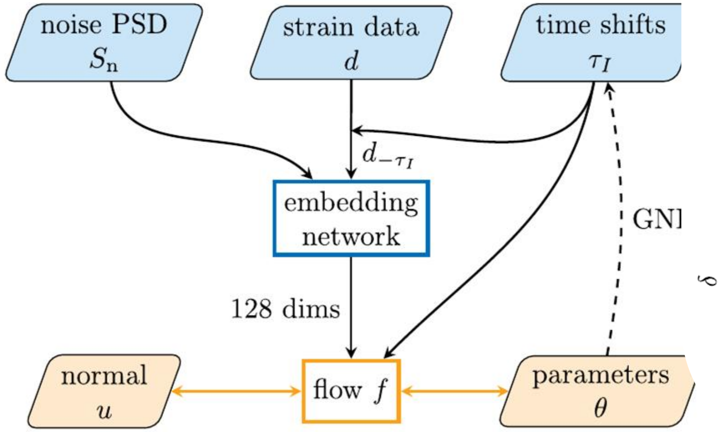
Compact binary coalescences – inference

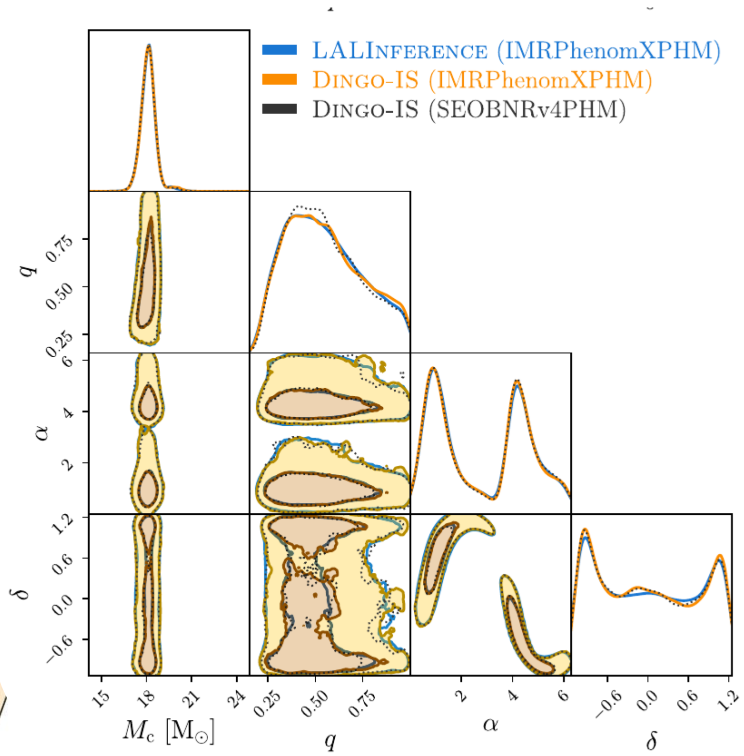
- DINGO [Dax+2021 PRL127,241103, 2023 PRL130,171403]: neural posterior estimation (with normalising flows)

in seconds–minutes instead of hours–days per event

[github.com/dingo-gw/dingo]



[Dax+2021 PRL127,241103]



[Dax+2023 PRL130,171403]

- initially working best for high-mass, short binary-black-hole signals, now also extended to binary neutron stars [Dax+2025 Nature 639,49-53]
- special promise for otherwise extremely expensive waveforms, e.g. including orbital eccentricity [Gupte+ 2404.14286]

Other examples:
Nessai: Williams+2021 PRD103,103006
Peregrine: Bhardwaj+2023 PRD108,042004
AMPLFI: Chatterjee+ 2407.19048

Compact binary coalescences

Optimal network architectures and training methods to deal with the typical kinds of biases identified by 2501.13846 and with the full complexities of real detector data

Fair comparisons between ML and “traditional” search algorithms, avoiding fine-tuning

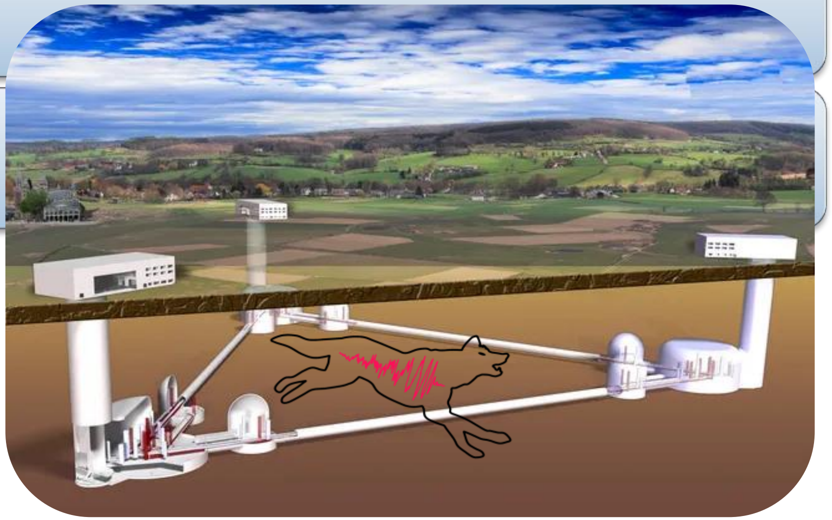
Finding the right mix for fruitful coexistence of fast neural and “full” Bayesian inference

Passing detailed LVK scientific&code review and operational stability criteria for production runs, including low-latency alerts (gracedb.ligo.org | emfollow.docs.ligo.org/userguide)

ML in waveform modeling itself

Future detectors:

- longer signal durations
  (e.g. Hu+2412.03454, Dax+2025 Nature 639,49-53)
- huge detection rates (→ overlapping signals!)
  (e.g. Langendorff+2023 PRL.130.171402, Alvey+ 2308.06318, Santoliquido+ 2504.21087)



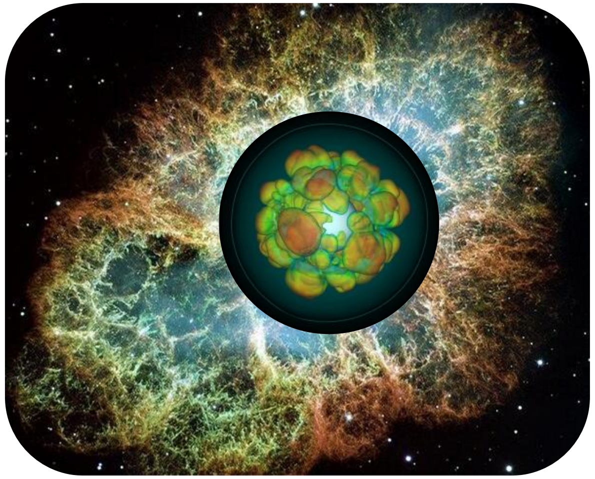
GW bursts

Less well-modeled GW transients: eccentric BBHs, supernovae, magnetars, cosmic strings

Search with more generic methods: excess power, pattern recognition, ...

No detections so far. (Besides BBHs!)

Non-detections can still yield physical constraints: nearby supernovae, glitching pulsars, ...



[NASA/ESA/ASU]

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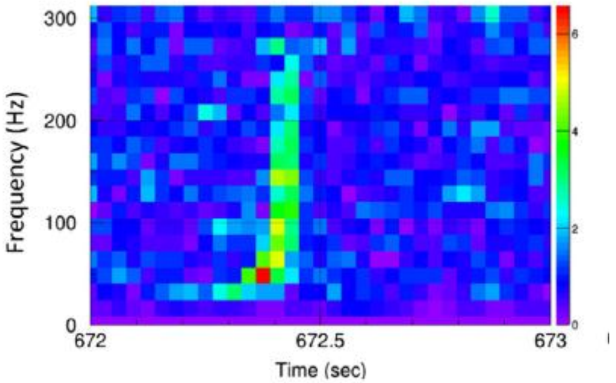
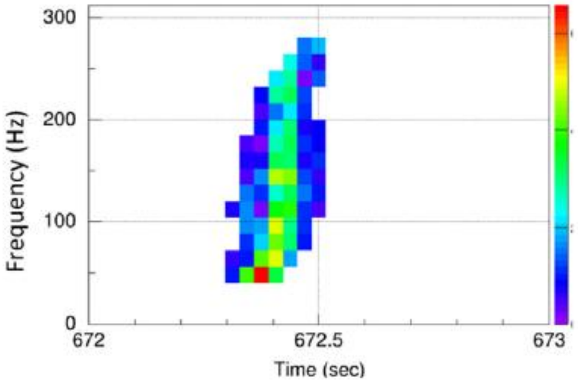
GW bursts

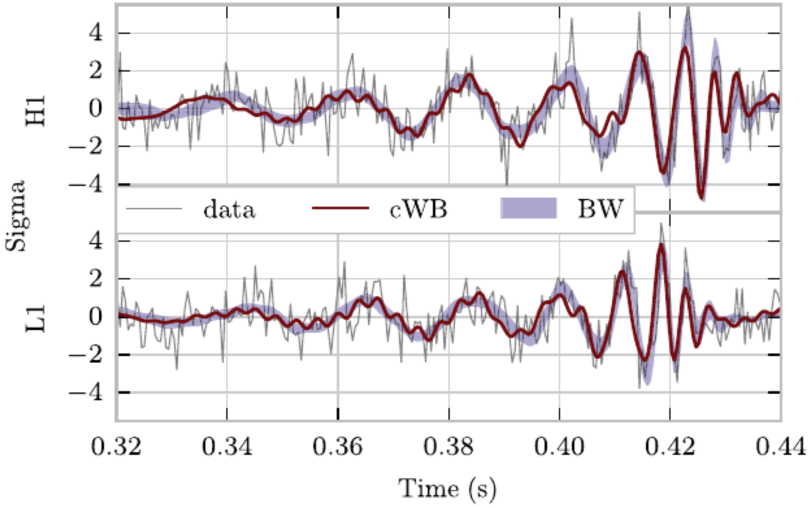
state of the art

- Less well-modeled GW transients: eccentric BBHs, supernovae, magnetars, cosmic strings,… and unknown unknowns!
- Most LVK algorithms based on some form of *excess power* and searches for correlated structures in time-frequency spectro
- Also possible *coherently* across multiple detectors
- Basically: anomaly detection and pattern recognition
- Weakly-modeled techniques, such as wavelet decomposition, also allow *signal reconstruction*





[Drago+2021 JsoftX14,100678]



[LVC2016 PRD93,122004]

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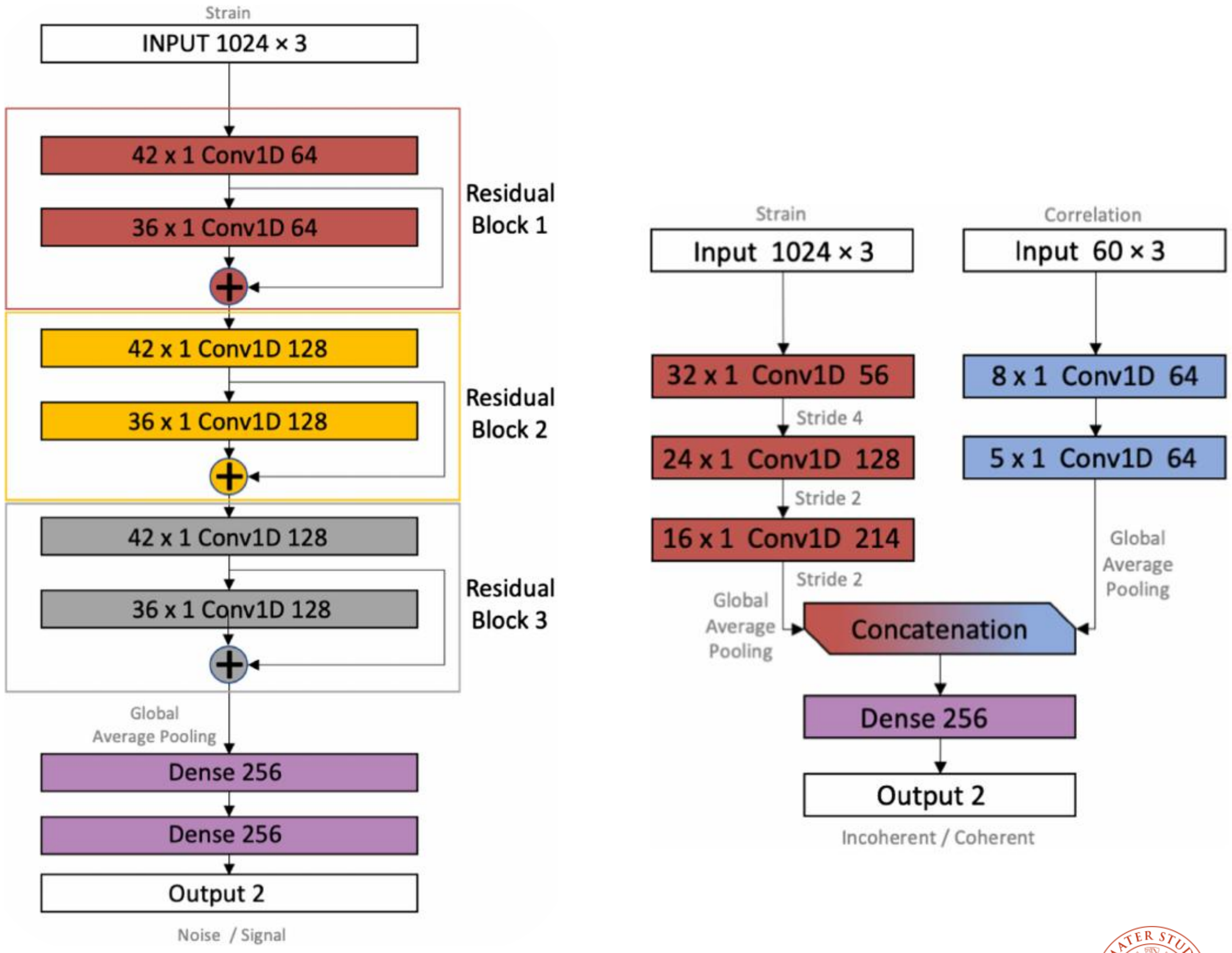
GW bursts. ML pipeline example

- MLy pipeline
  - Skliris+2024 PRD110,104034
  - git.ligo.org/mly/mly
- Dual architecture for coincidence and coherent modes across detectors
- First tested on LIGO-Virgo O2 data
- Now LVK-reviewed and running "in production" on O4 data [emfollow.docs.ligo.org/userguide/analysis/searches.html#unmodeled-search]



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GW bursts

open problems & future directions

Besides pure ML pipelines like MLy, also "traditional" ones getting enhanced with ML ingredients, e.g. XGBoost postprocessing for cWB [gwburst.gitlab.io] – Mishra+2021 PRD104,023014
→ used on O3 data in Szczepańczyk+2023 PRD107,062002, Mishra+2025 PRD111,023054

Bridging the gap between "modelled" and "unmodelled burst" analyses
for complicated sources like supernovae, with simulation-based inference etc.

Pure anomaly detection frameworks for the known unknowns
(e.g. GWAK, Raikman+2025 MLST5,025020 and 2412.19883)

Interpretable/explainable AI to understand what is being detected?

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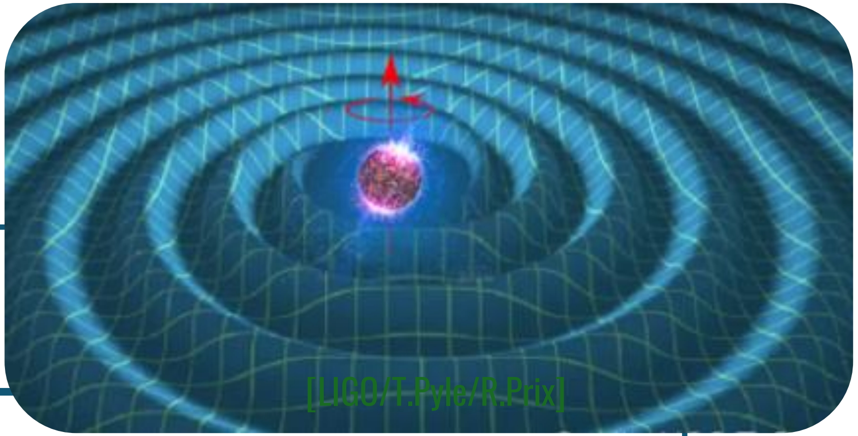
Continuous Waves



Simple signal model → matched filtering

Optimal fully-coherent analysis possible for known pulsars with full timing model from EM observations

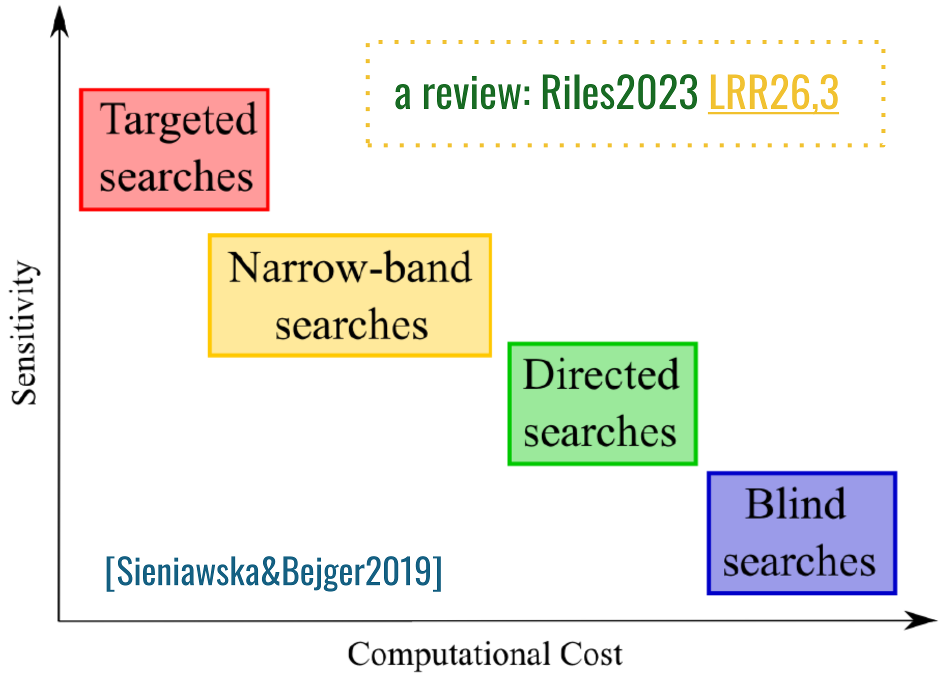
Computationally extremely challenging for *unknown* sources: large parameter space and extremely fine required grid resolution

Semi-coherent methods provide best tradeoff so far between sensitivity and computing cost

Similar issues for long-duration CW-like transients from glitching pulsars, BNS remnants, …

G2net-Kaggle challenge* mostly produced GPU-optimised variants of "traditional" semi-coherent methods

a review: Riles2023 LRR26,3



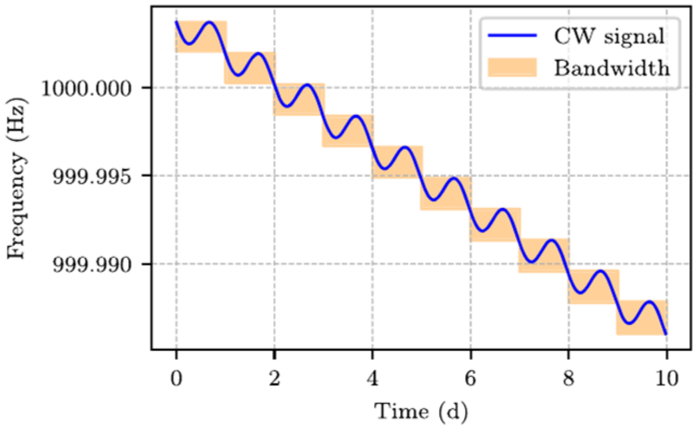
[*] kaggle.com/competitions/g2net-detecting-continuous-gravitational-waves (2023)

Continuous Waves

Joshi&Prix 2023: "*Novel neural-network architecture for continuous gravitational waves*" [PRD108,063021]

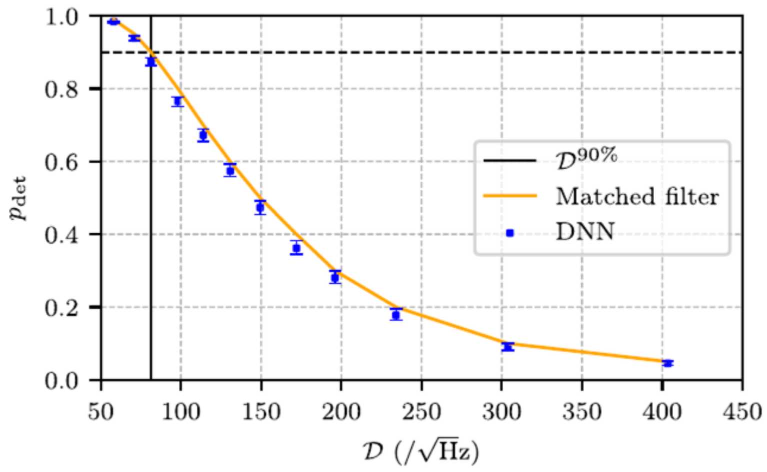
Identified the key challenges of neural networks applied to CWs:

- signals not only faint, but spread across long durations, with low local contrast and rich structure
- morphology changes across parameter space, Doppler shifts become more challenging at high frequencies



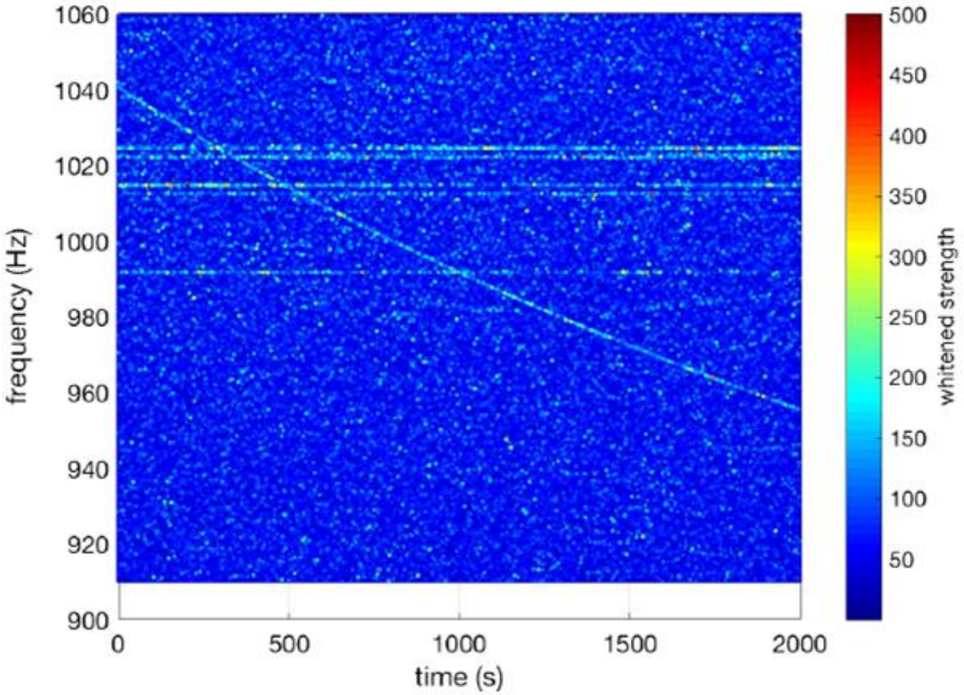
For durations up to 10 days, customised CNNs can almost reach matched-filter performance, but not yet quite.

Joshi&Prix 2024 [PRD110,124071]: can also generalise to a single network trained across 20–1000 Hz



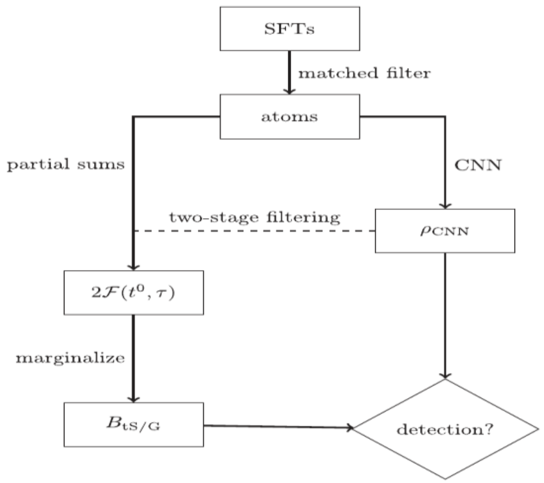
Continuous Waves(-like long transients)

BNS merger remnants: rapid spindown



- Miller+2019 PRD100,062005: *How effective is machine learning to detect long transient gravitational waves from neutron stars in a real search?*
- Using CNNs on spectrograms

- Pulsar glitches can trigger CW-like transients of unknown duration
- Modafferi+2023 PRD108,023005: *Convolutional neural network search for long-duration transient gravitational waves from glitching pulsars*
- Hybrid approach:CNN on matched-filter intermediate data products



Continuous Waves

Still working towards a "first detection" with *any* method ("traditional" or ML)

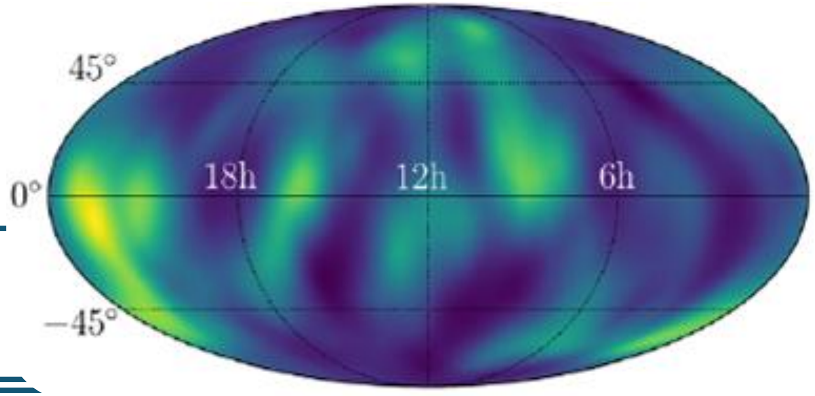
Immense sensitivity gap between optimal fully-coherent matched filter and what is computationally feasible over large parameter spaces (factors 5–50 in "depth" below the detector noise floor)

Neutron stars are known to be "messy" → make methods more robust to signal deviations?

Need to overcome the challenges identified by PRD108,063021 and others:

- very faint signals, with even fainter local contrast and complex morphologies, that vary strongly across parameter space

Stochastic signals and backgrounds

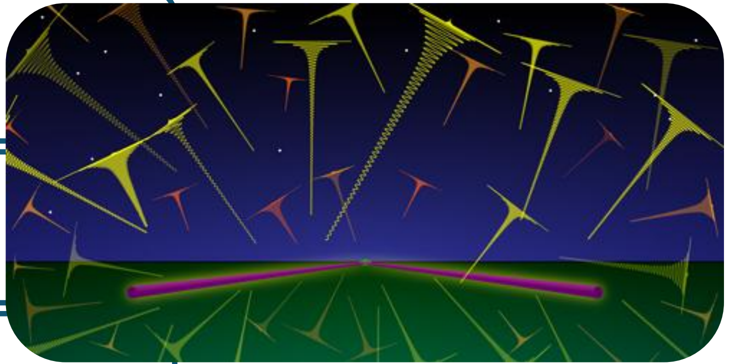


[LVK 2021 PRD104,022005]

Persistent signals without deterministic models

State of the art: primarily *cross-correlation* between 2+ detectors, already computationally very efficient

Key challenge: controlling correlated noise sources


[APS/A.Stonebraker]

Not many example applications of ML to this yet

Open problems & future directions:

- ML noise mitigation?
- Early-universe physics through simulation-based inference?
- Intermittent, non-Gaussian backgrounds: enabling optimal Bayesian-style search for stochastic background from faint CBC sources? [Smith&Thrane2018 PRX8,021019]
- Overlap with "burst" and CW-like searches for long-duration transients, with possibly rather complicated waveforms (newborn neutron stars, magnetars, ...)

a review: Remortel+2023 PPNP128,104003

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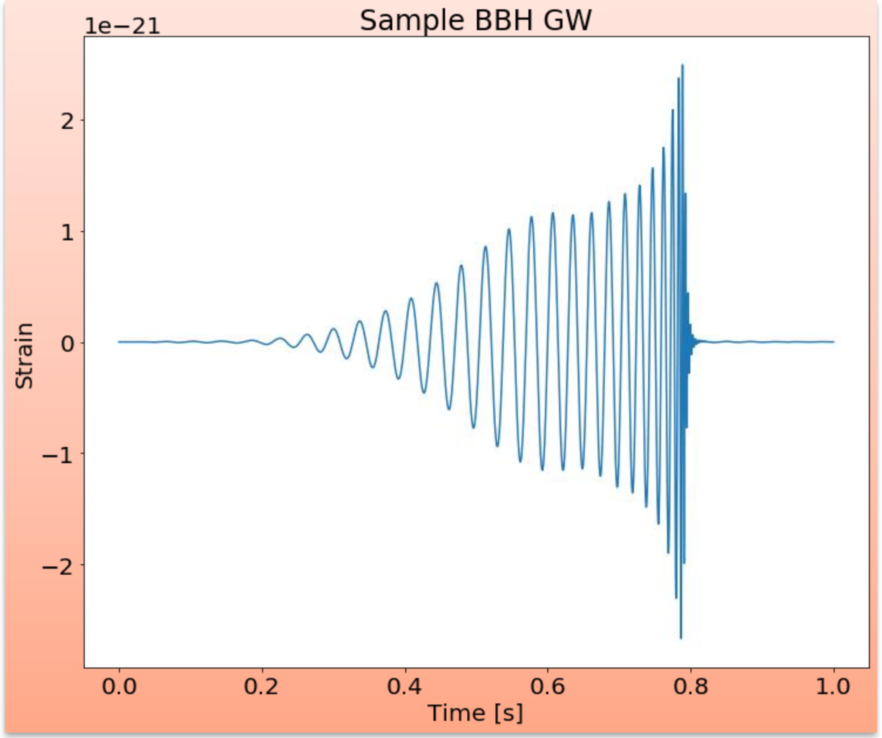
Examples of GW Transient signal ML approaches

CBC



CCSN

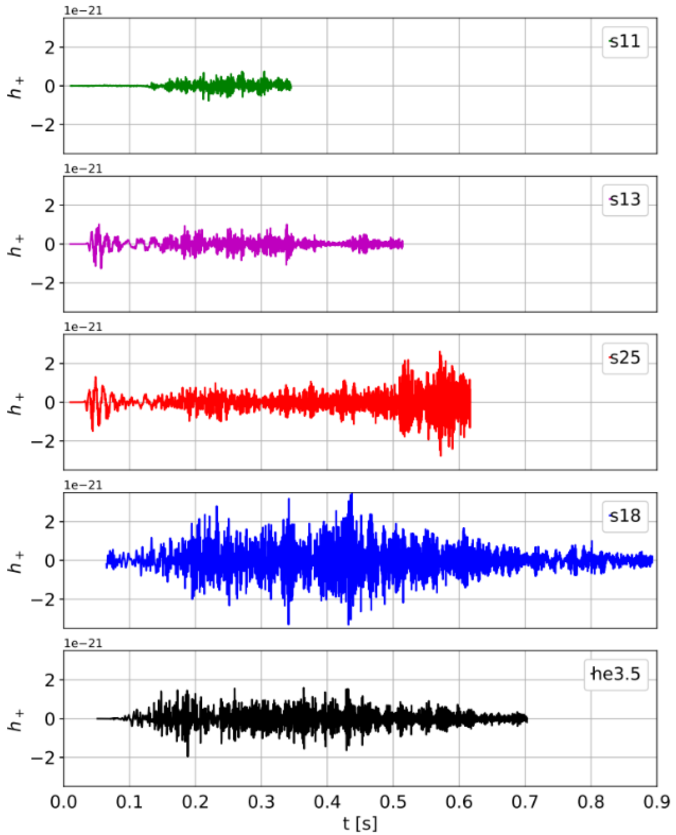


Image from Iess, Cuoco, Morawski, Powell (2020)

GWs from Core Collapse Supernovae

Waveform depends on progenitor star

Rare (~100 yrs in Milky Way)

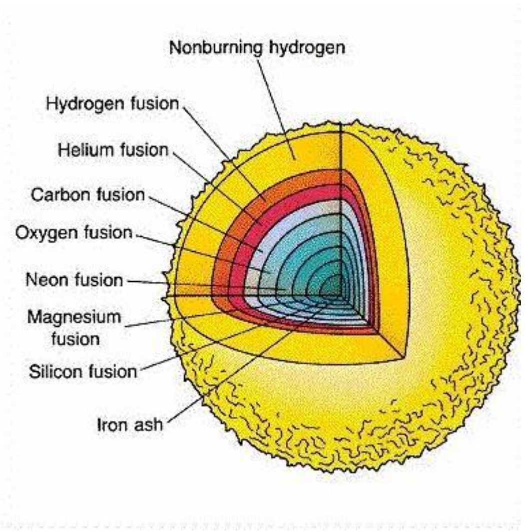
Different emission mechanisms (Proto-neutron star oscillation, Standing Accretion Shock Instability (SASI),..)

Different simulation models

Largely Stochastic

Best waveform models from computationally expensive 3D simulations

Need an alternative to matched filter approach



Ott et al. (2017)

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

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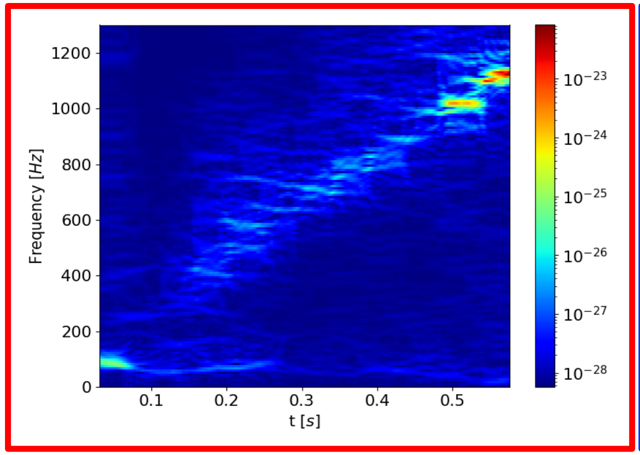
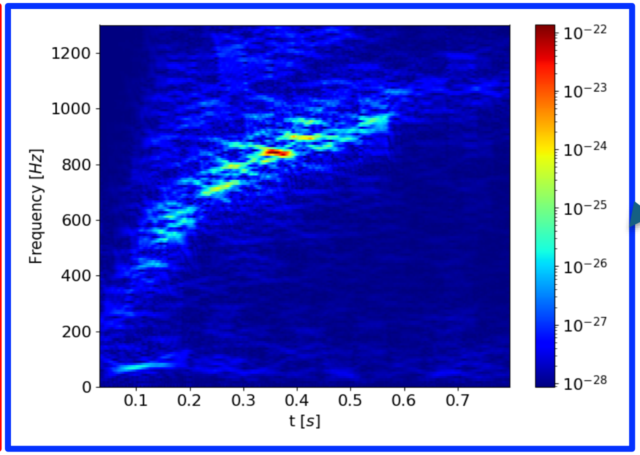
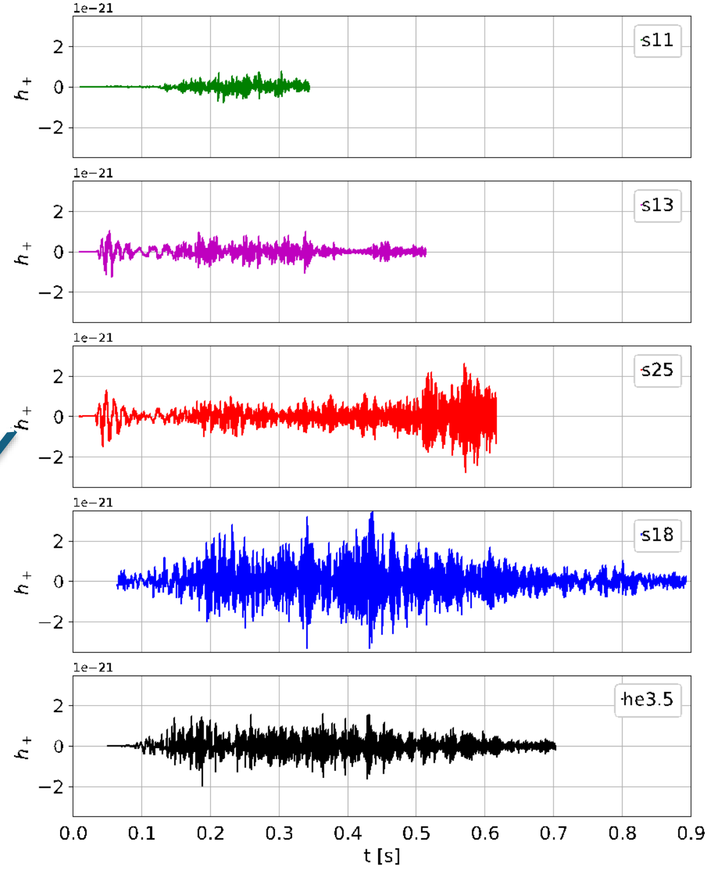
Core-Collapse Supernovae models

- 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

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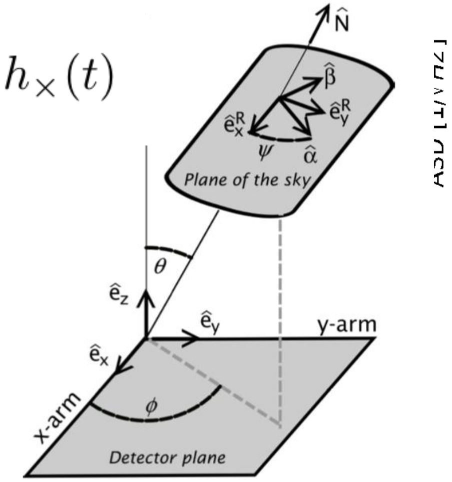
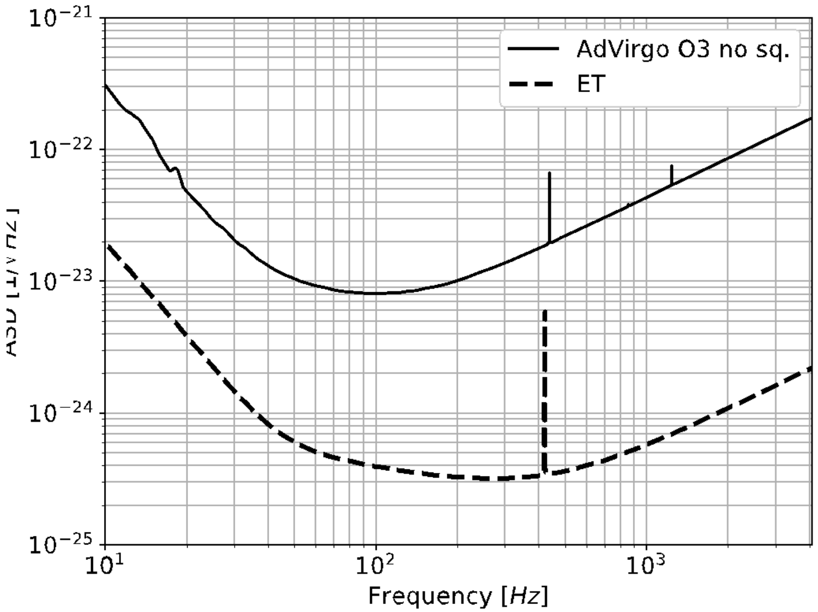
MDC and CCSN GW simulations

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



Schutz (2011)



Distances:
VO3 0.01 kpc to 10 kpc
ET 0.1 kpc to 1000 kpc

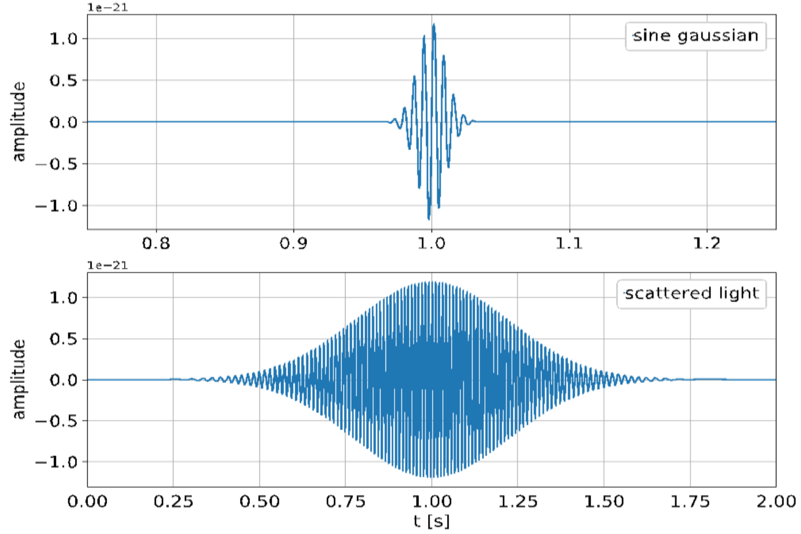
Random sky localization

Large SNR range

SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

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

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

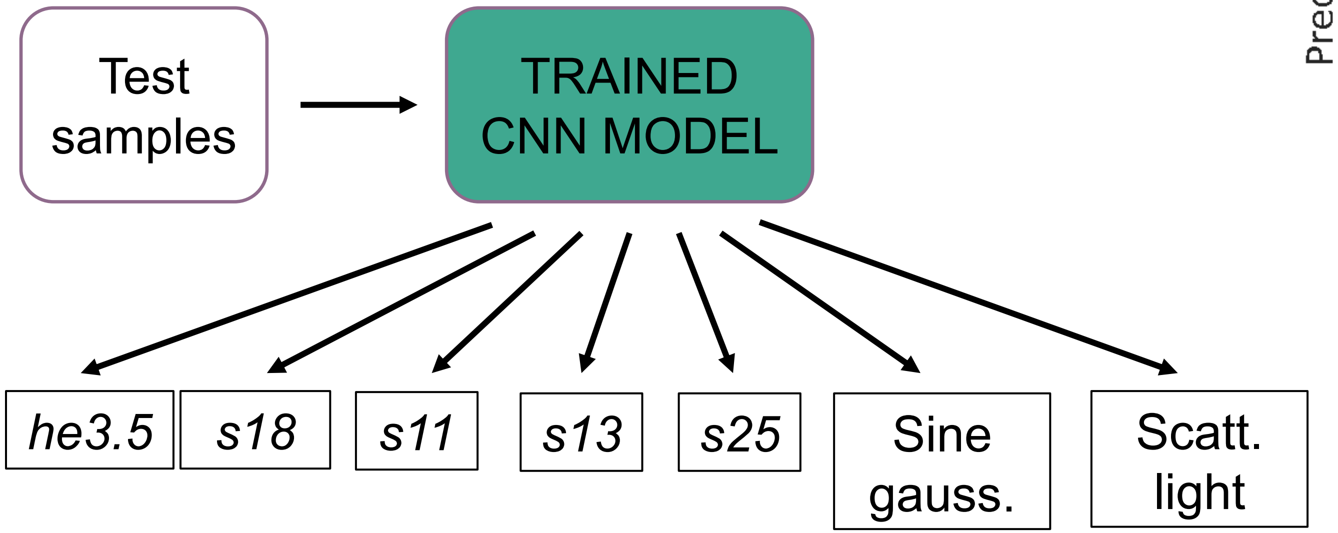


BACKGROUND STRAIN : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

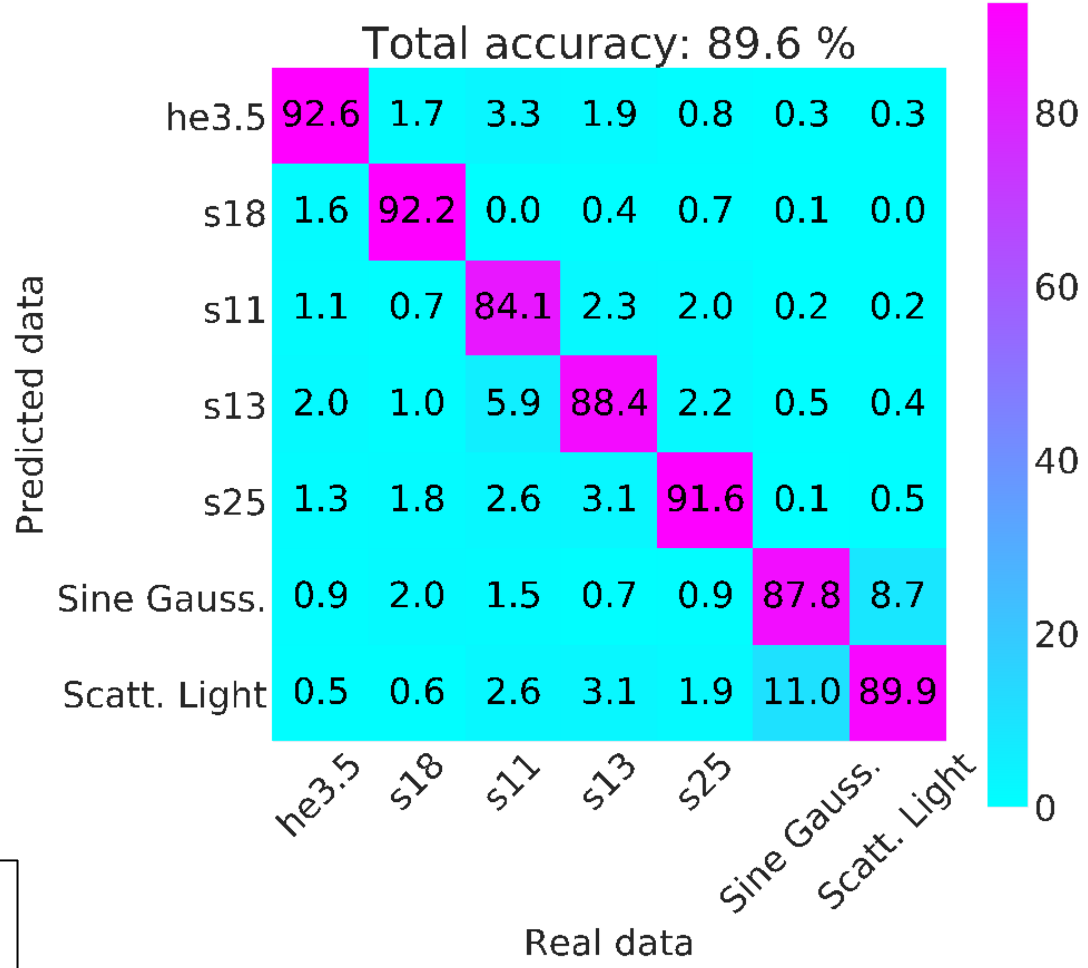
MultiLabel classification

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

Test on **all.**



ET, MERGED 1D & 2D CNN



COMPLEX TASK → LONGER TRAINING (> 1 hr)

Test on O2 real Data

44 segments (4096s per segment) from O2 science run.

Added m39, y20, s18np models (Powell, Mueller 2020).

Fixed distance of 1 kpc.

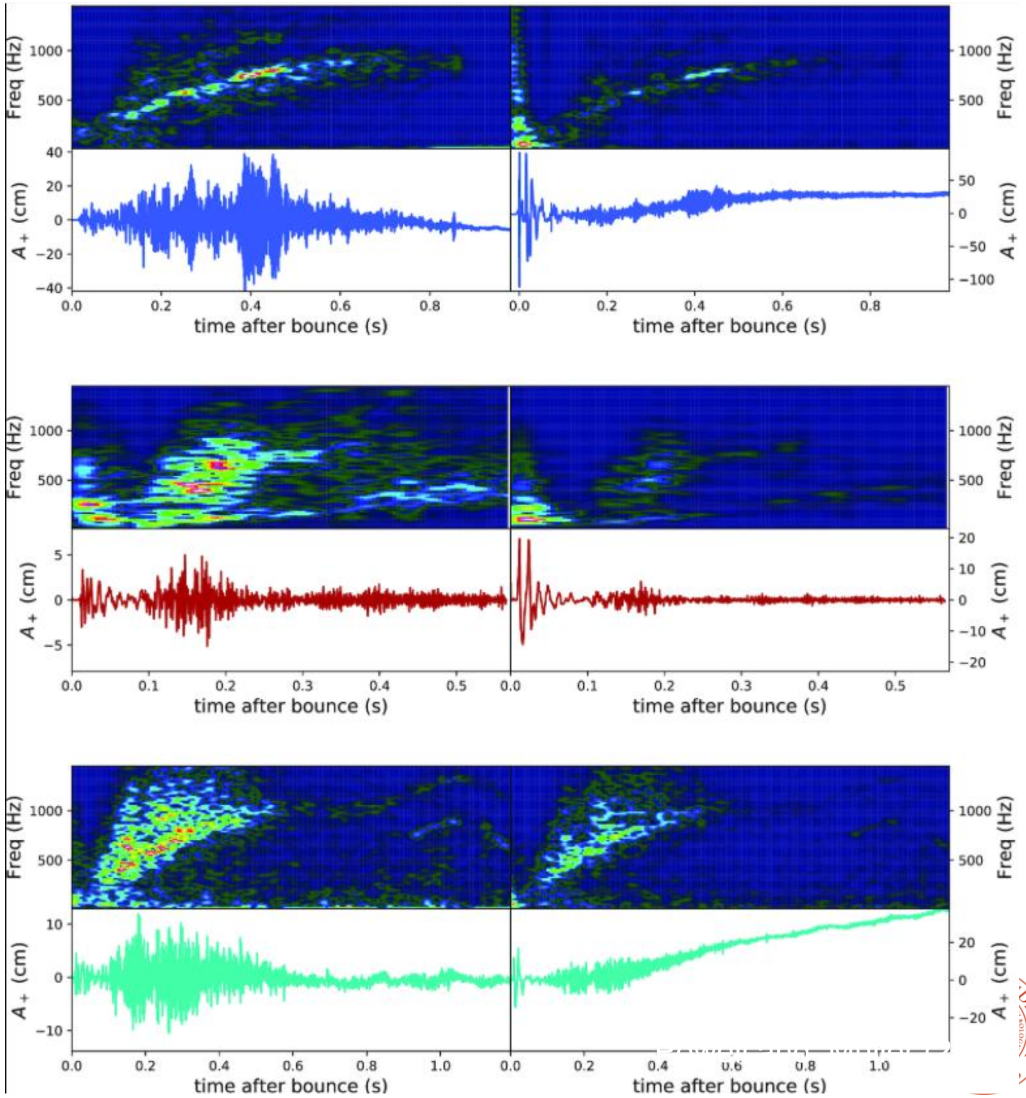
Added LSTM Networks, suited for time series data.

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.

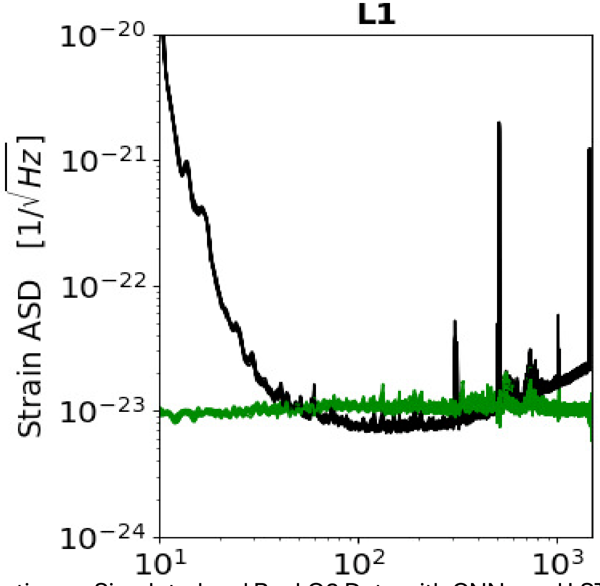
Powell m39: rapidly rotating Wolf-Rayet star with an initial helium star mass of 39 solar masses



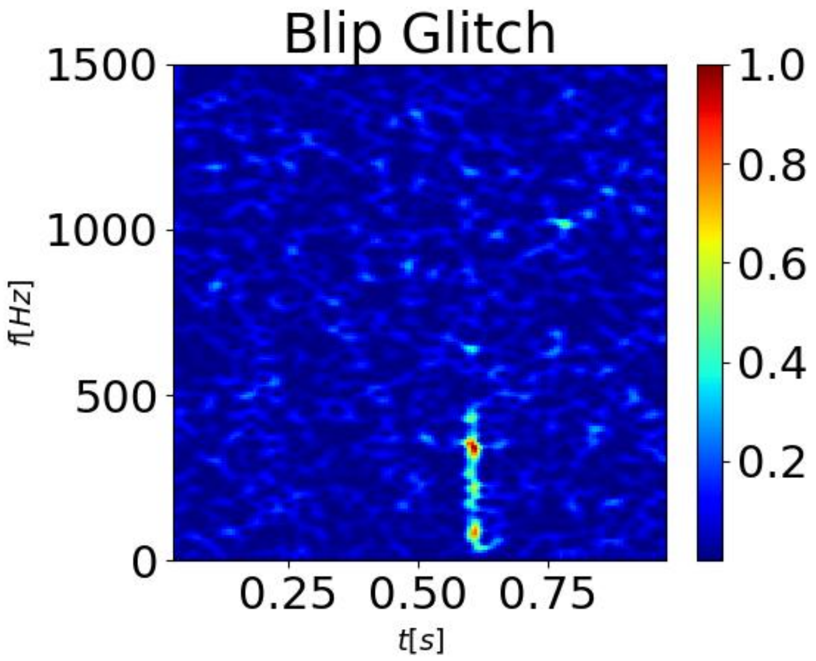
Real noise from O2 science run

- 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)*

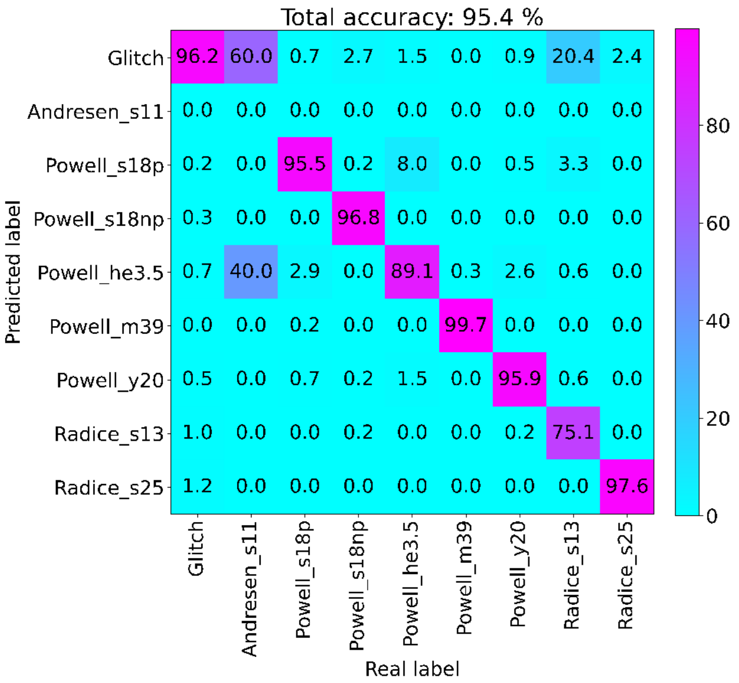


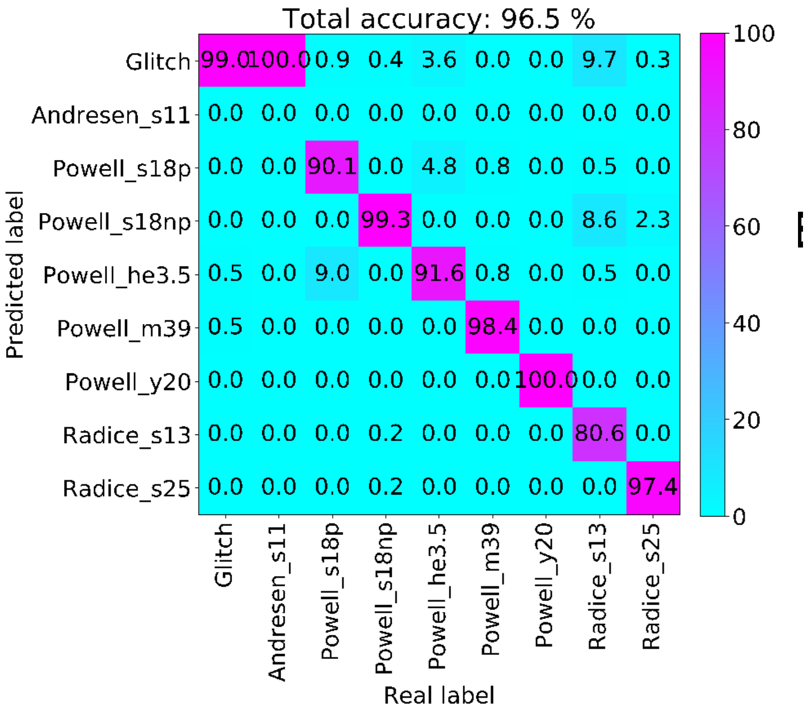
Multi-label task

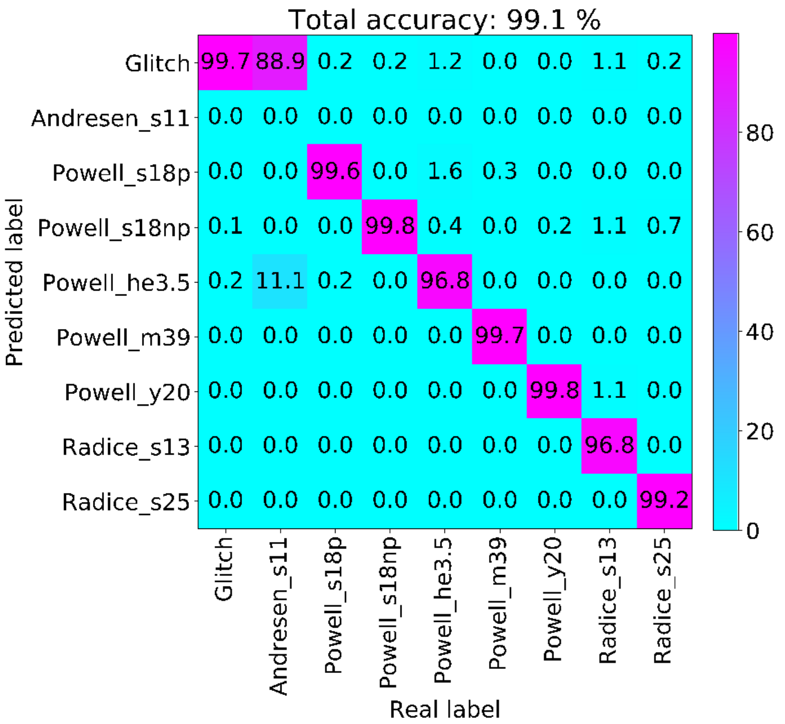
- **Bi-LSTM**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs

- **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





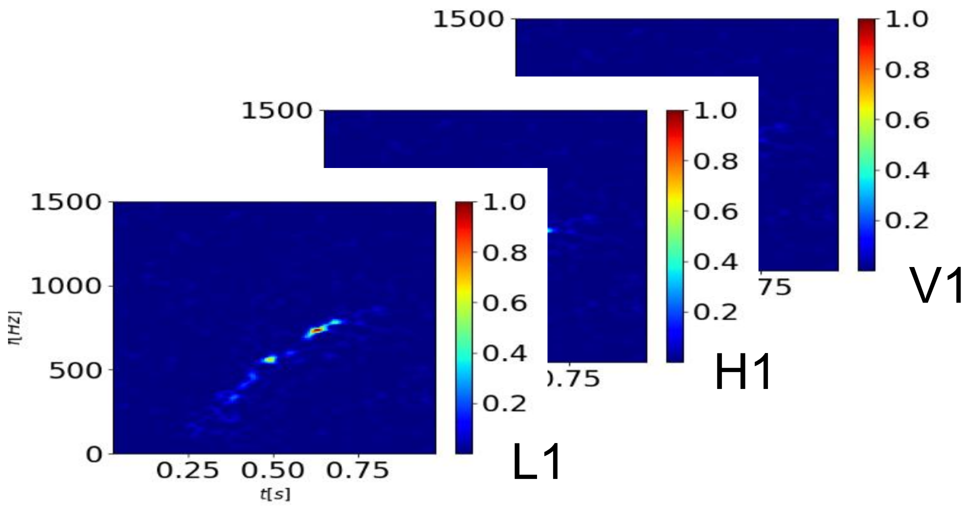


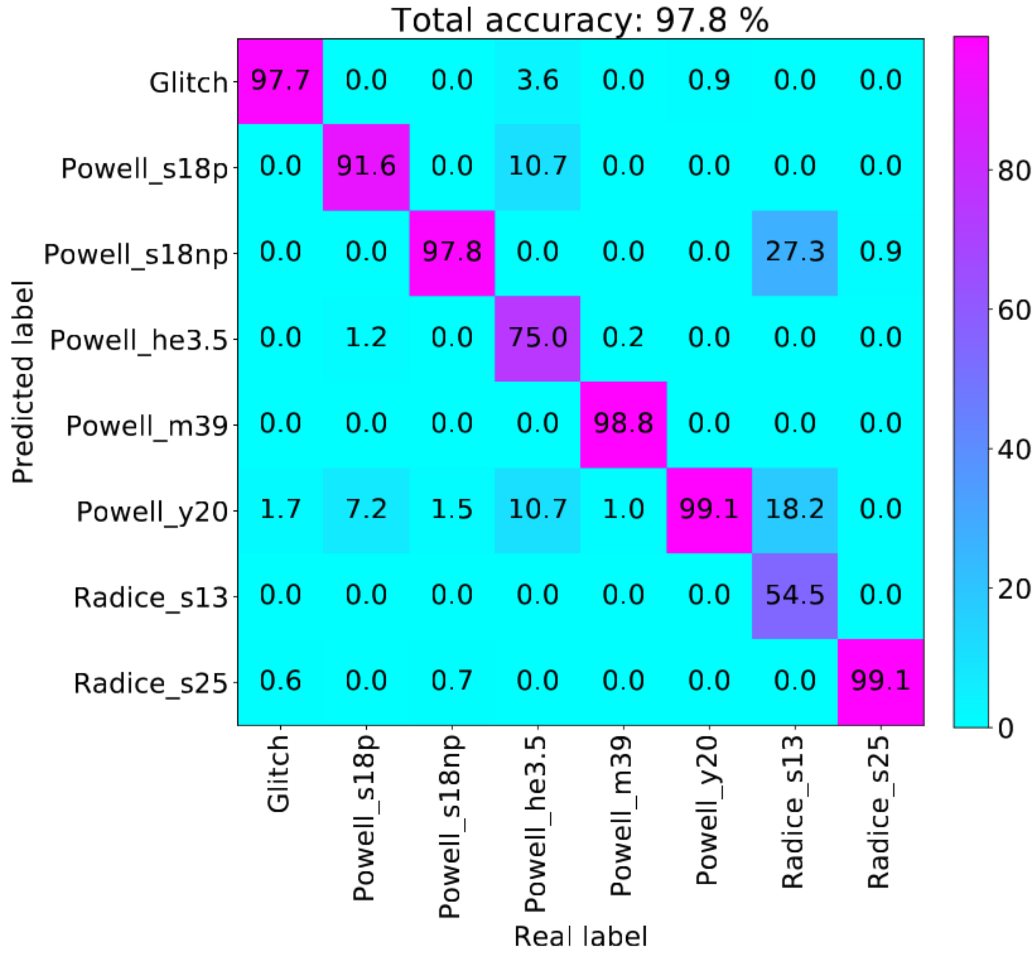
A. Iess, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)

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)

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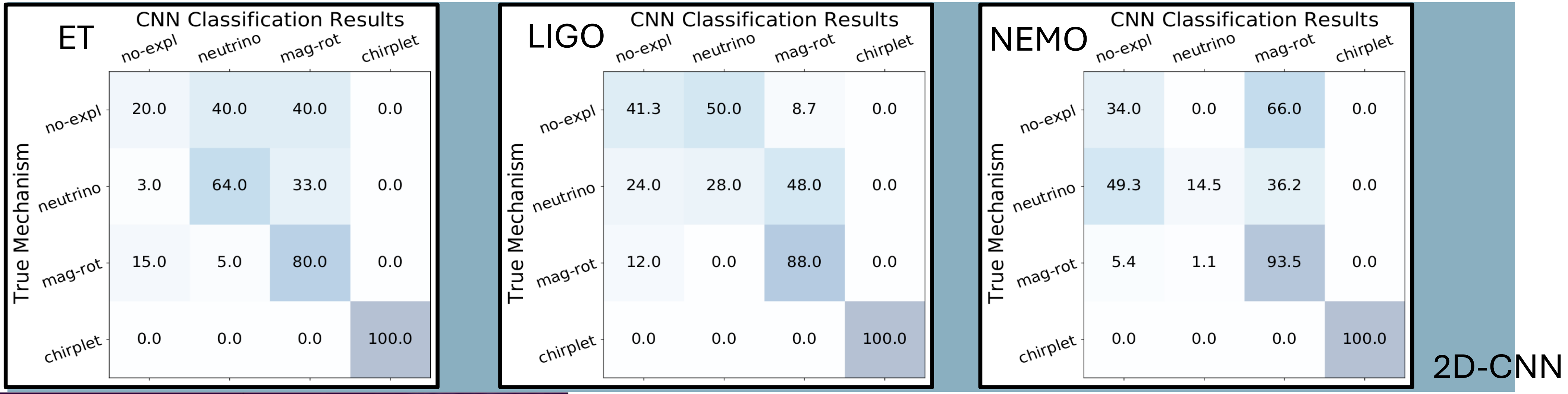
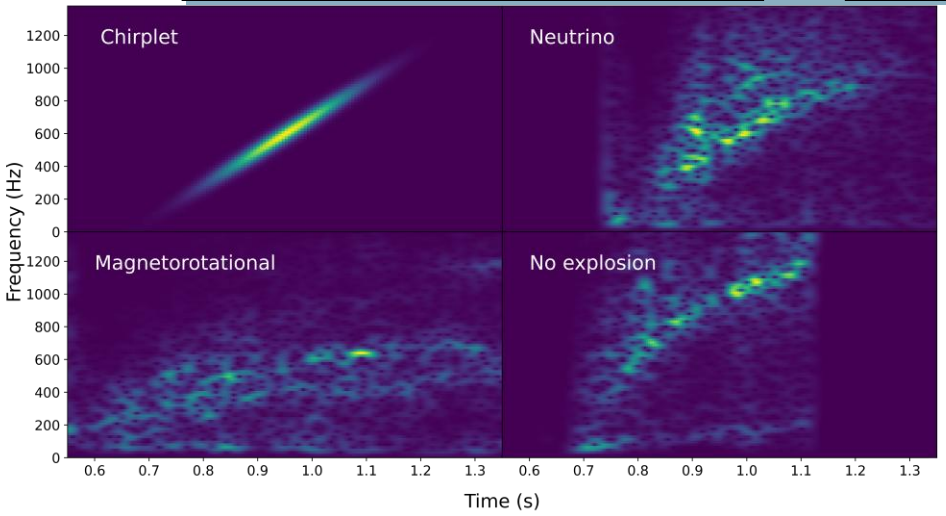
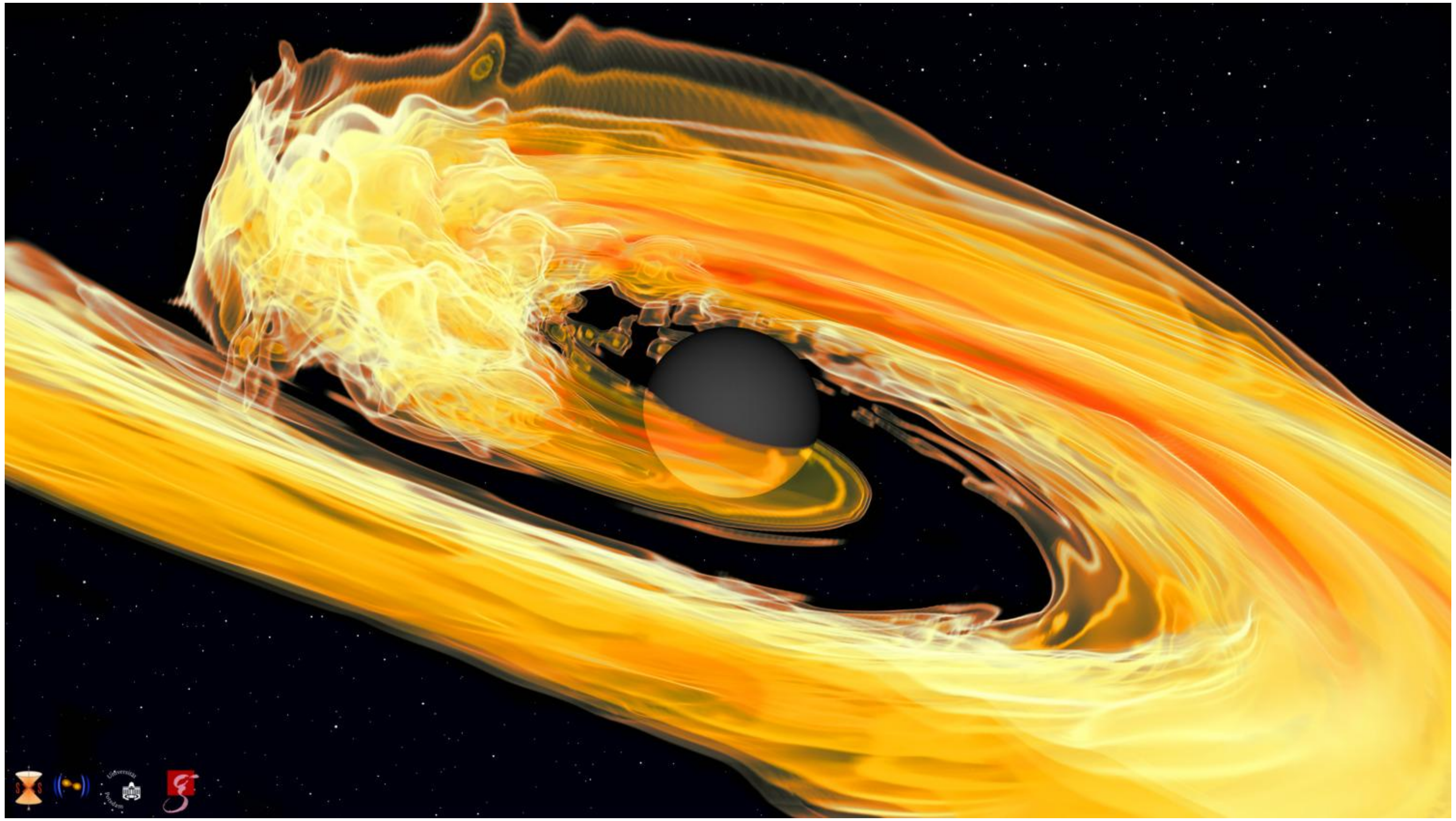
Determining the core-collapse supernova explosion mechanism





Jade Powell, Alberto Iess, Miquel Llorens-Monteagudo, Martin Obergaulinger, Bernhard Muller, Alejandro TorresFornè, Elena Cuoco, and Josè A. Font. *Determining the core-collapse supernova explosion mechanism with current and future gravitational-wave observatories*. Phys. Rev. D **109**, 063019

Gravitational wave modelling: template matching



GW detection of binary systems relies on matched-filter analysis. Template accuracy is crucial!

Accurate solutions of the Einstein equations for binary sources can be obtained with Numerical Relativity (NR) simulations.

High computational cost prevent the production of NR waveforms catalogs spanning the full parameter space.

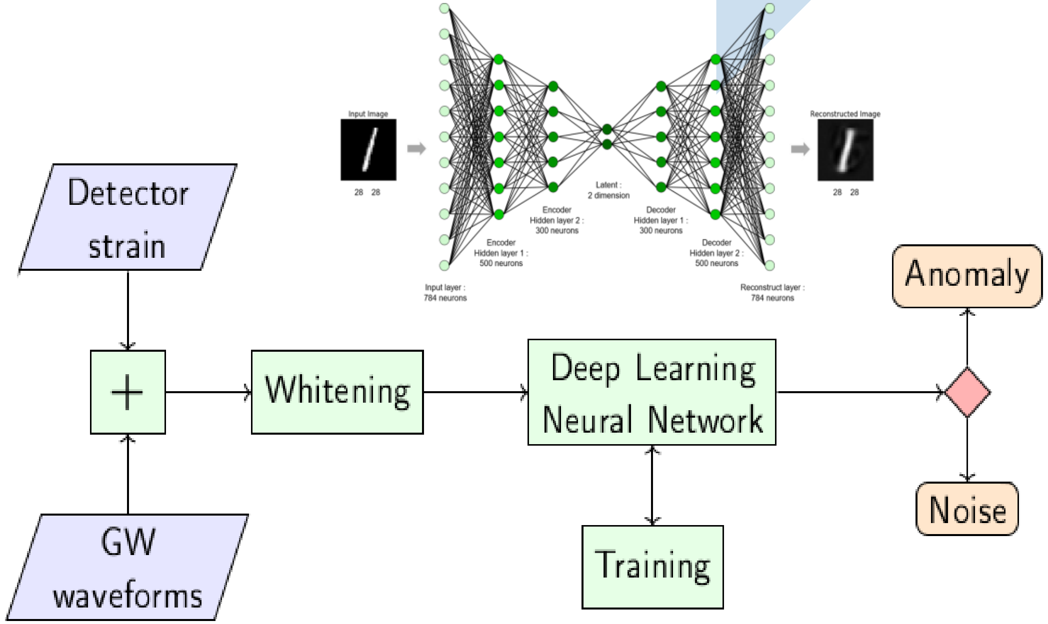
LIGO and Virgo rely on approximate solutions that are traditionally obtained through the effective-one-body or phenomenological modeling approaches.

How can machine learning help?

Example for detection/classification for CBC signals: Anomaly Detection

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, 2021 *Mach. Learn.: Sci. Technol.* **2** 045014

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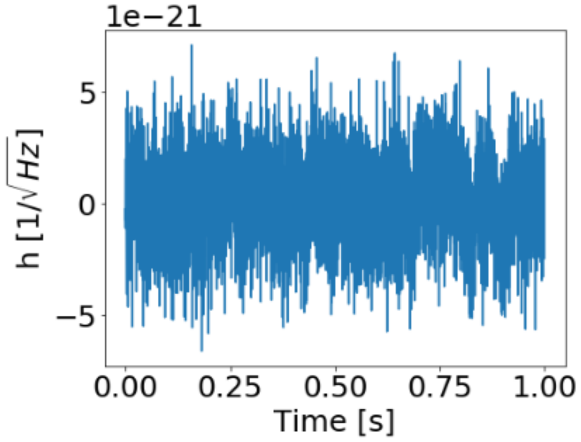
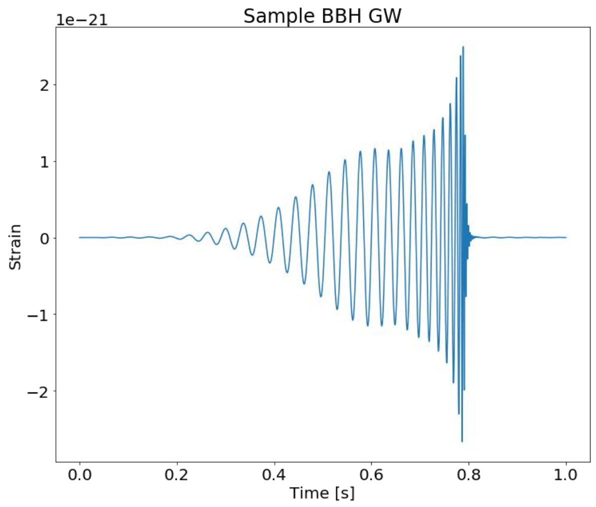
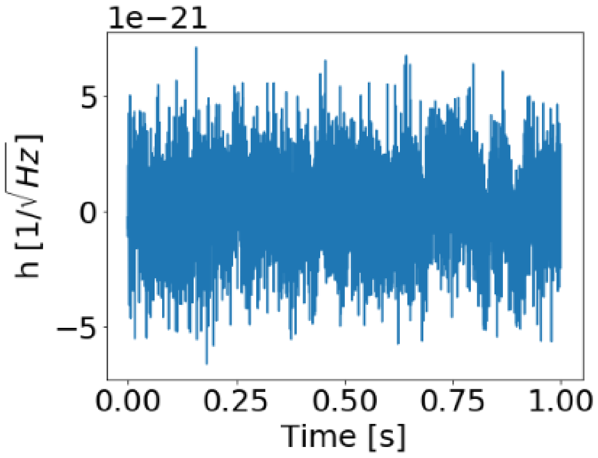
Autoencoder workflow

Model input

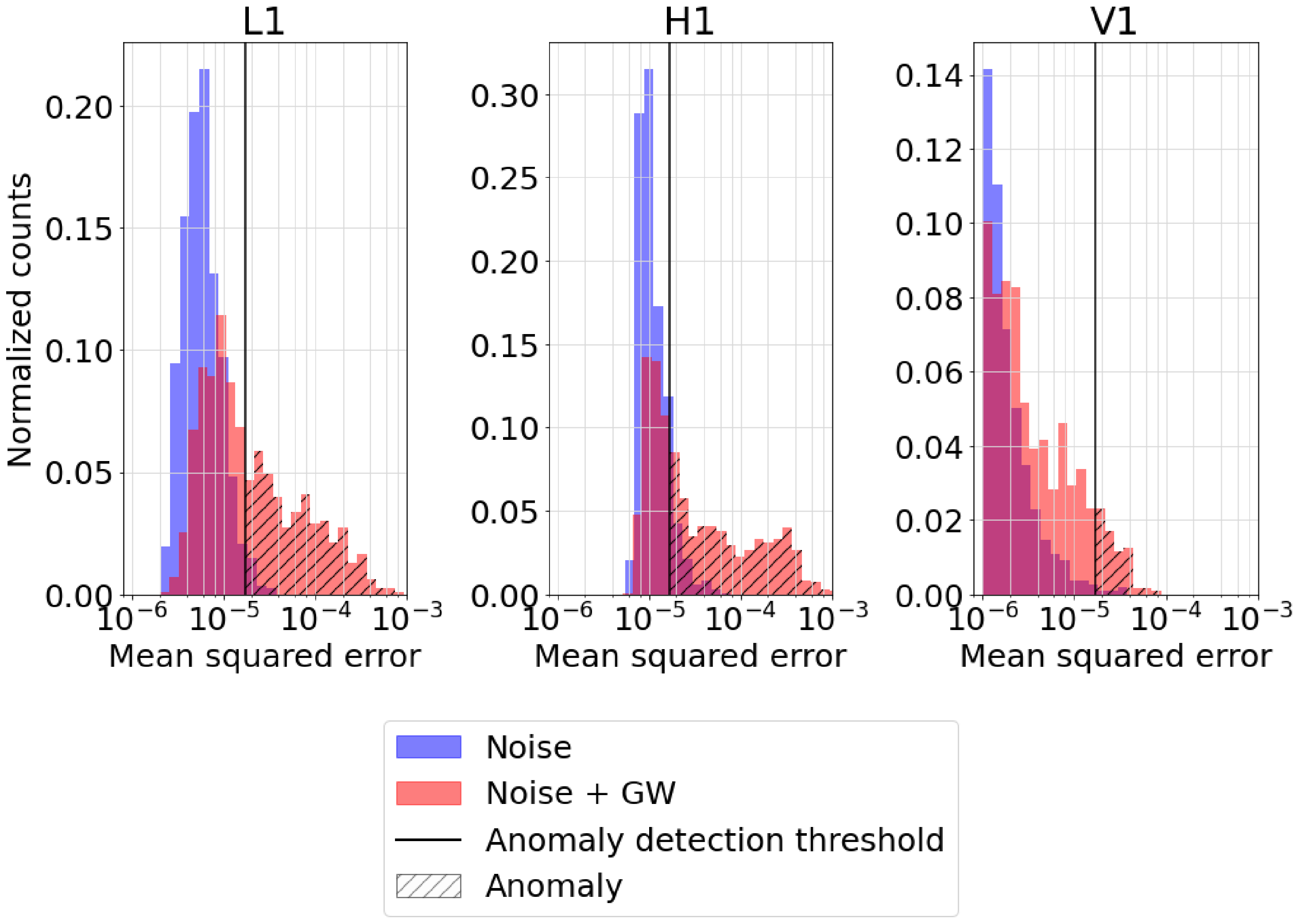
Model prediction







O2 data - MSE Distributions



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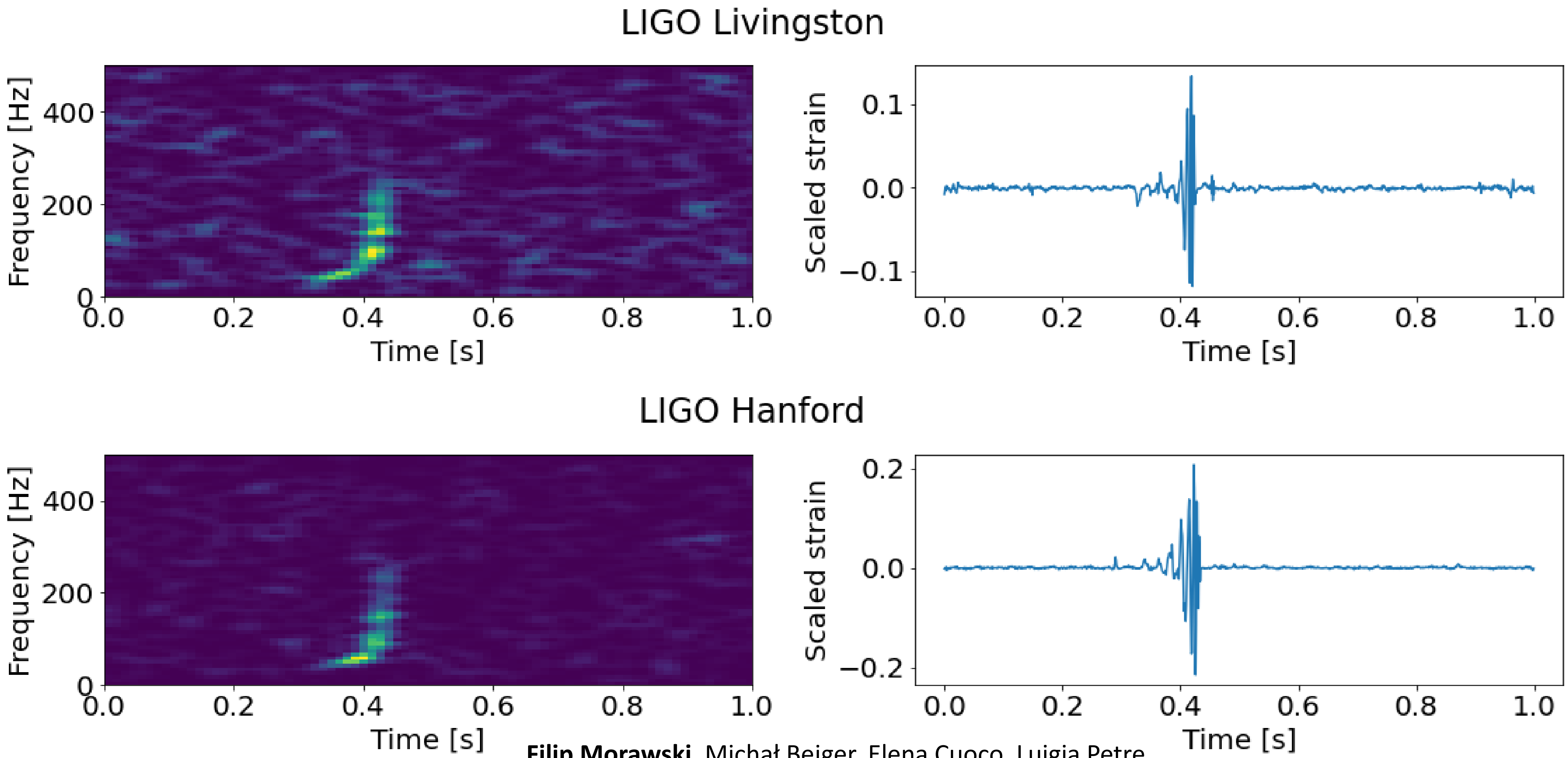
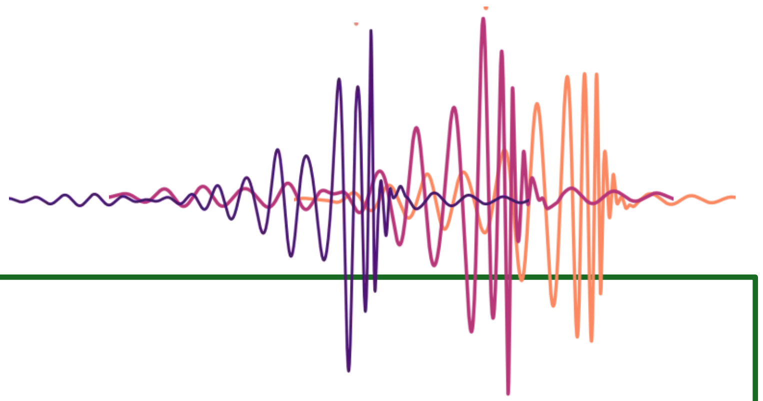
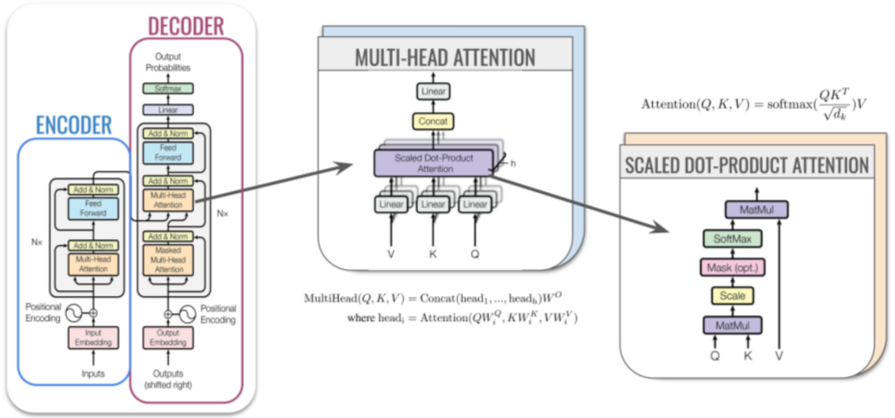
GW150914

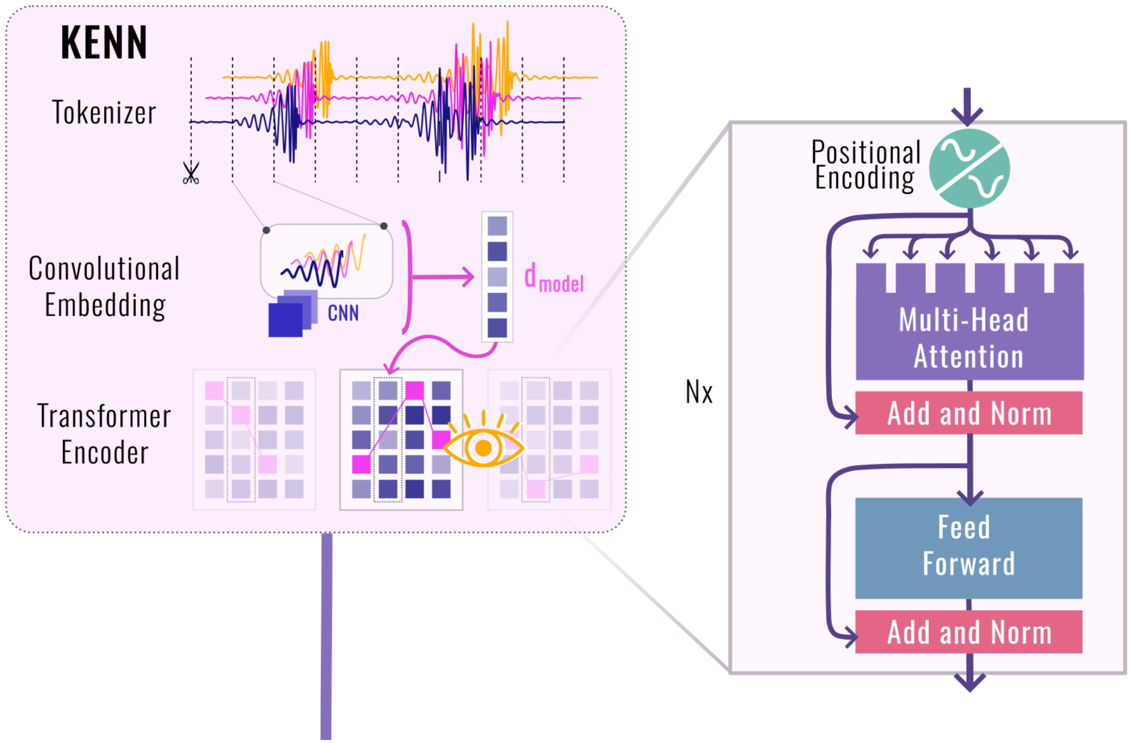


Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0

Overlapping signals in 3-G detectors: tansformer approach







Lucia Papalini , Federico De Santi, Massimiliano Razzano, Ik Siong Heng, Elena Cuoco,
arXiv:2505.02773 Accepted on CQG

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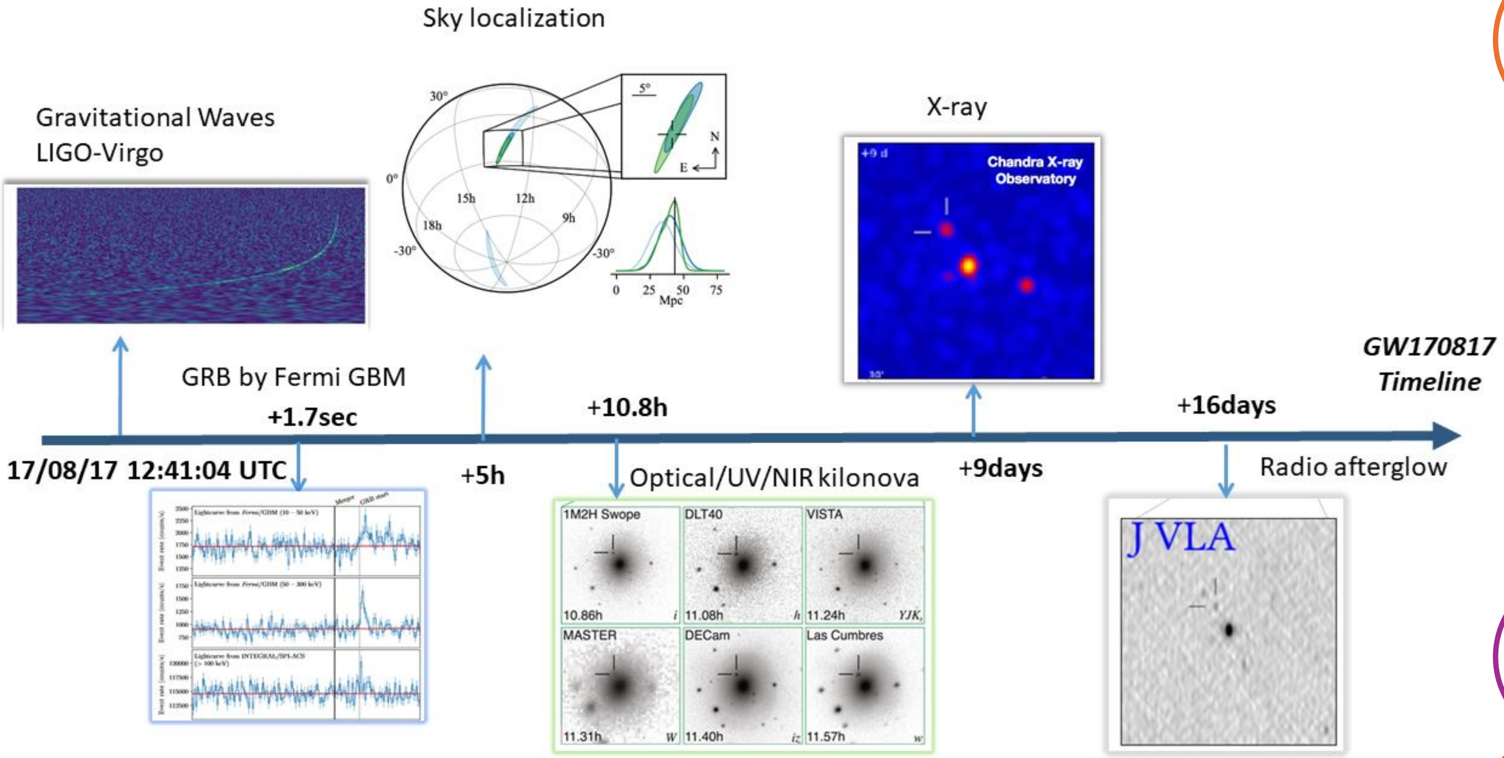
Multimodal Analysis for multi-messenger astrophysics

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

GW170817: the first Multi-messenger GW event



coincident short GRBs detected in **gamma rays**

- first direct evidence that at least some BNS mergers are progenitors of short GRBs

the host galaxy has been identified: NGC 4993

an **optical/infrared/UV** counterpart (AT2017gfo) has been detected

- first spectroscopic identification of a kilonova

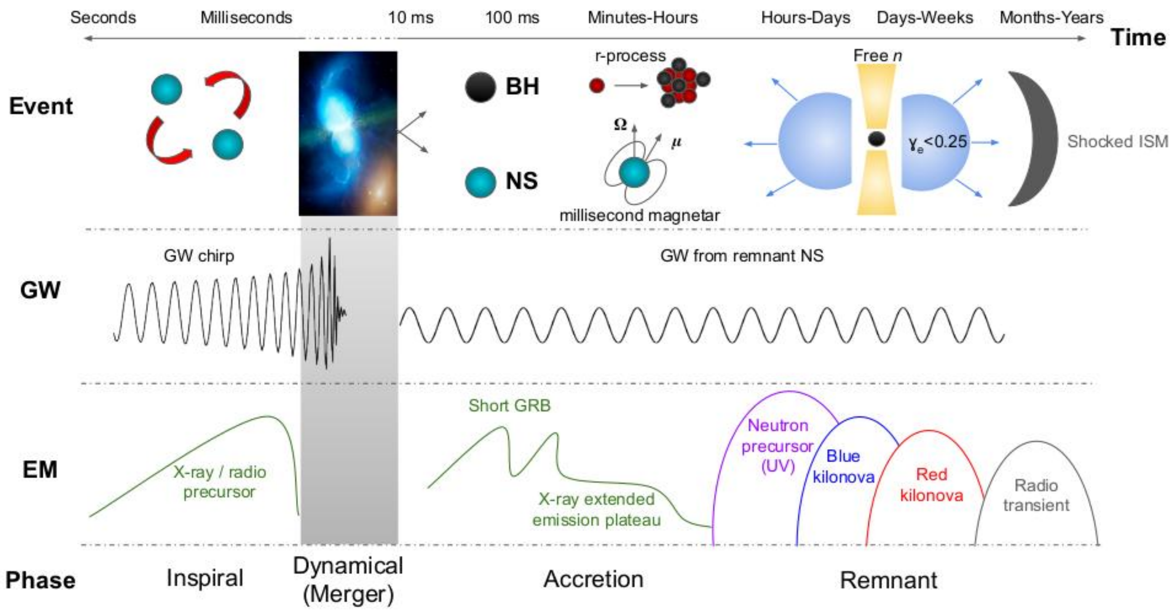
An X-ray and a radio counterparts have been identified

- off-axis afterglow from a structured jet

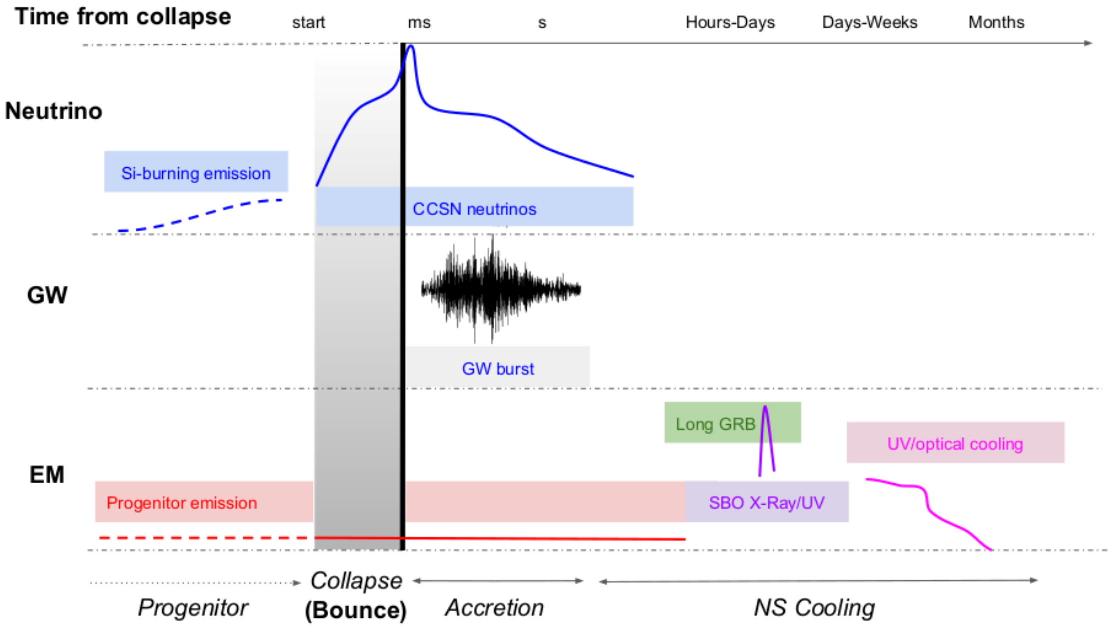
Abbott et al. 2017 and refs. therein

Multi-Messenger Astrophysical signals

CBC events



CCSN events



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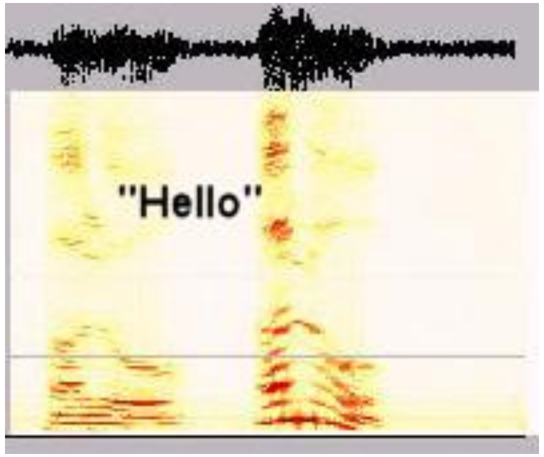
Multimodal inputs

The "world" communicates via different modalities

Visual:Images/videos	Text: Natural language processing	Speech/audio signal
	**Multimodal analysis of Gravitational Wave signals and Gamma-Ray Bursts from binary neutron star mergers** Elena Cuoco, Barbara Patricelli, Alberto Iess, Filip Morawski A major boost in the understanding of the universe was given by the revelation of the first coalescence event of two neutron stars (GW170817) and the observation of the same event across the entire electromagnetic spectrum. With 3rd Generation gravitational wave detectors and the new astronomical facilities, we expect many multi messenger events of the same type. We anticipate the need to analyse the data provided to us by such events, to fulfill the requirements of real-time analysis, but also in order to decipher the event in its entirety through the information emitted in the different messengers using Machine Learning. We propose a change in the paradigm in the way we will do multi-messenger astronomy, using simultaneously the complete information generated by violent phenomena in the Universe. What we propose is the application of a multimodal machine learning approach to characterize these events.	

How to combine different information?

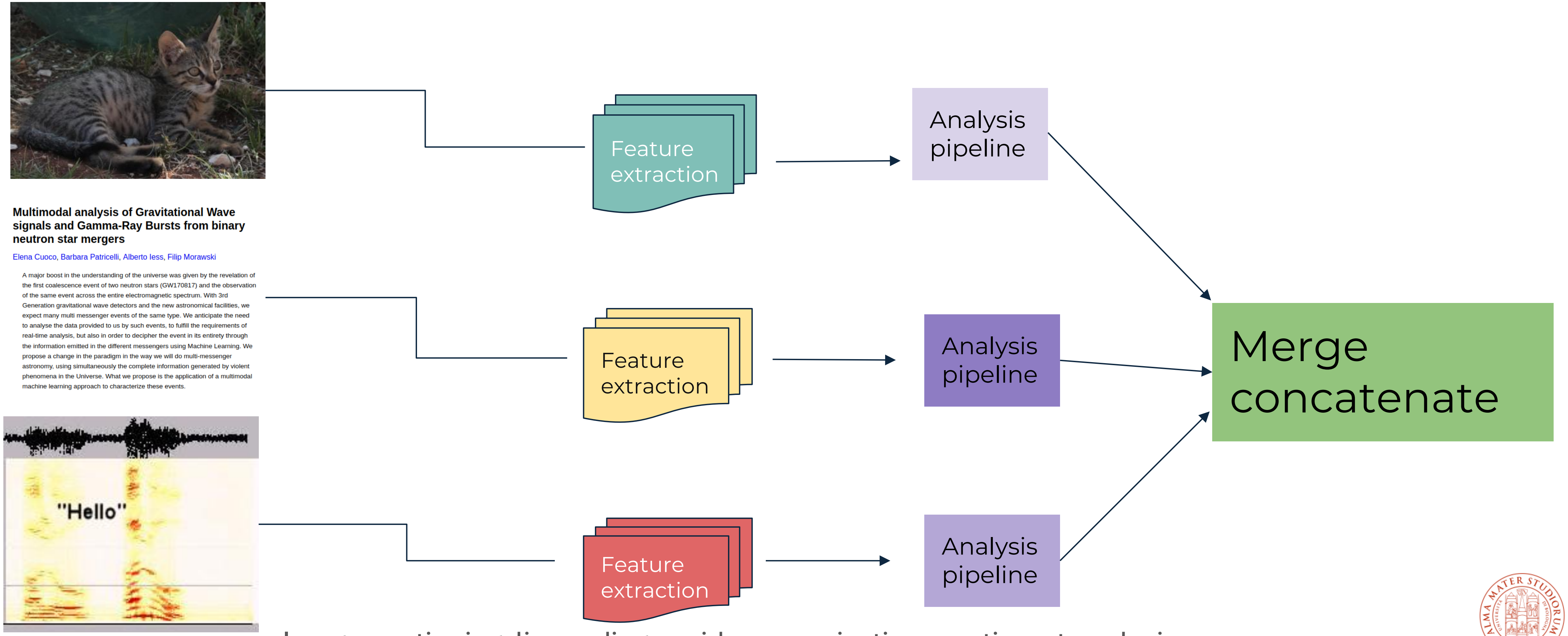
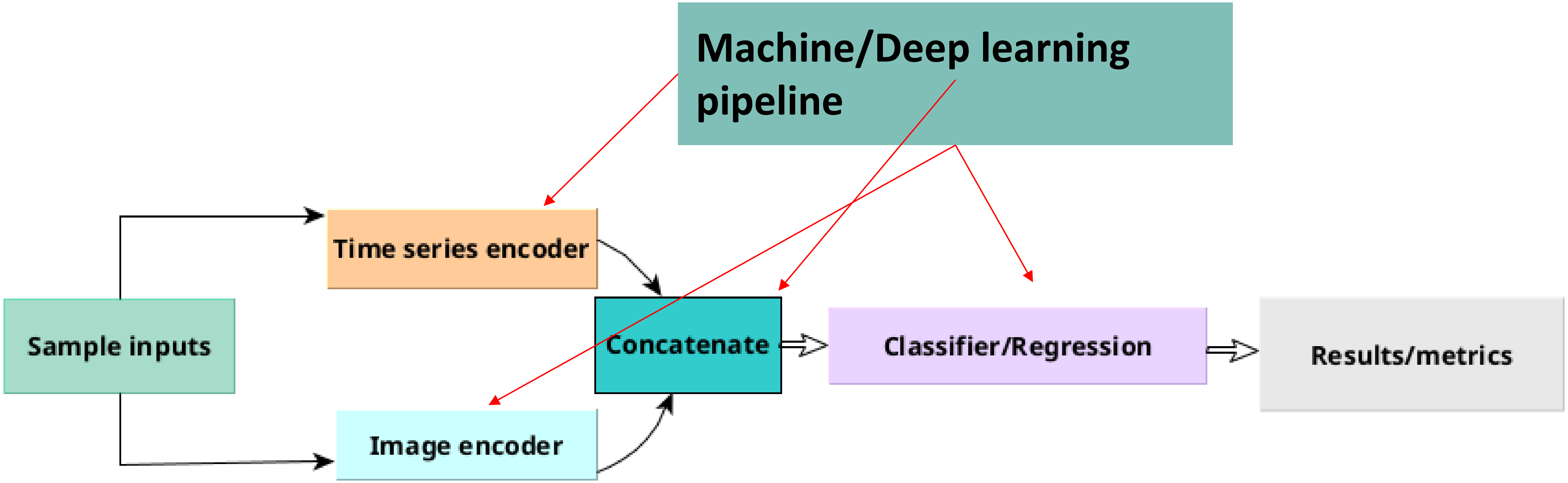


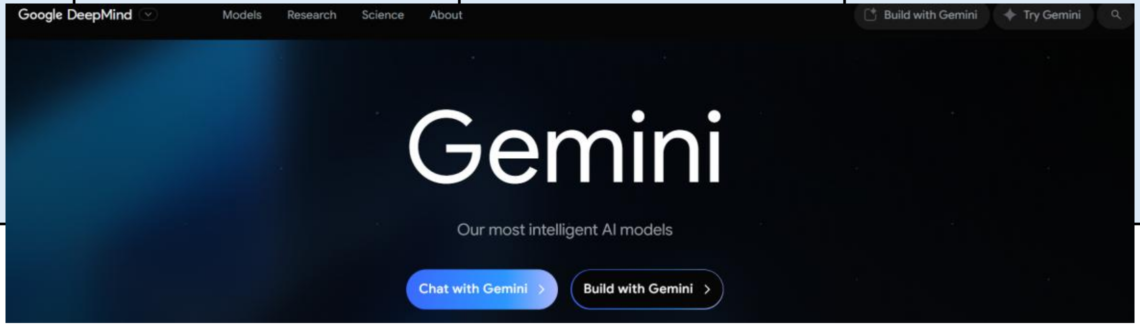
Image captioning, lip reading or video sonorization, sentiment analysis...

Multimodal Machine Learning (MMML)

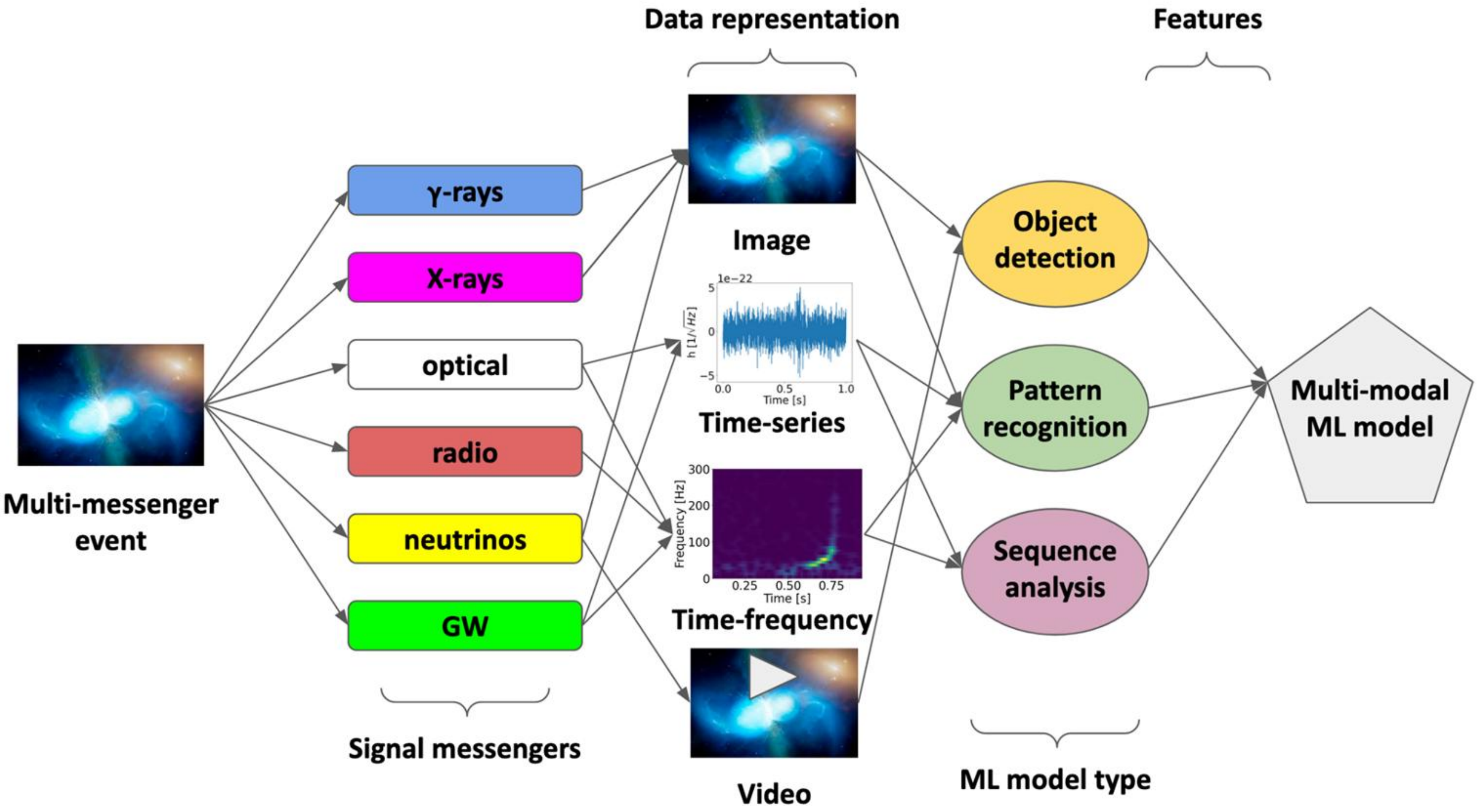


Example of MMML in other fields

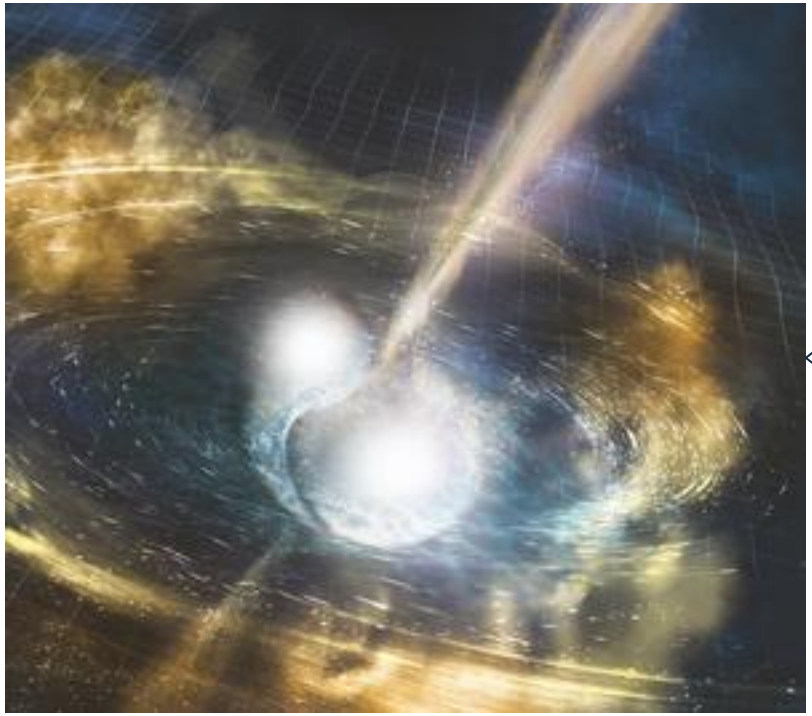
Medical applications	Speech recognition	Robotic	Fraudulent behaviours	Genetic	Sentiment analysis
Merge informations from images, symptoms, blood or other analysis,...	Images, videos, captions, labial,..	Spatial information, audio, multi-sensors,...	Biometrics, images, text, speech,...	histopathologic diagnosis, cytogenetic,...	Text, images, etc...



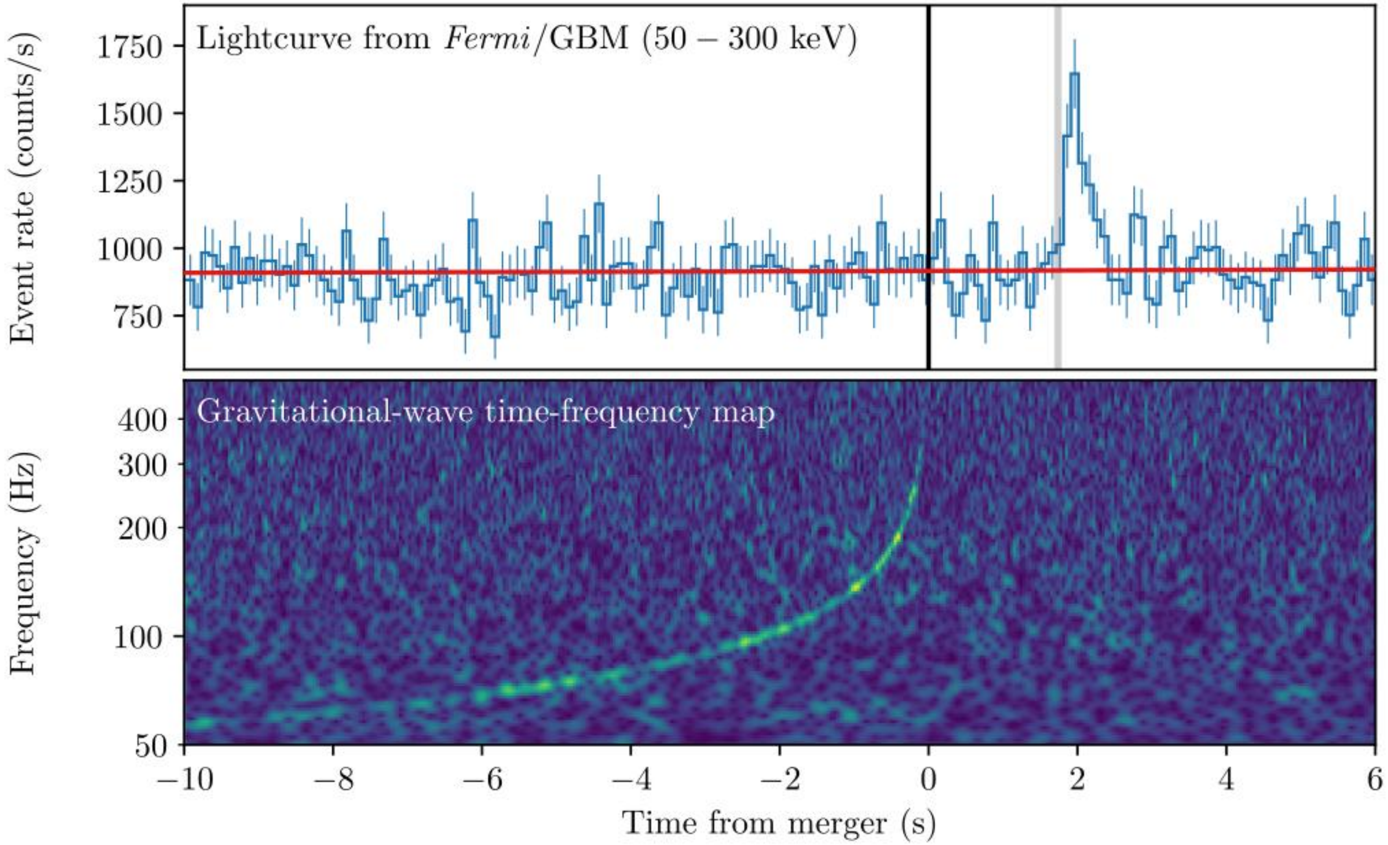
MMML for Astrophysics



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

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**

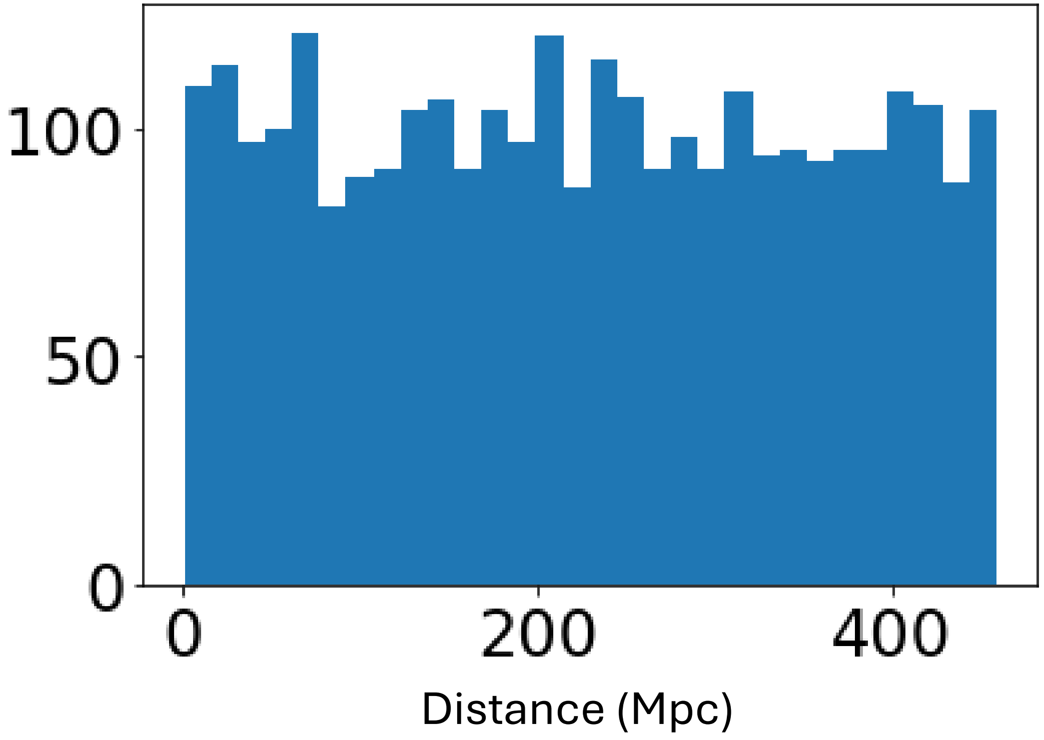
Simulations: what we simulated

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



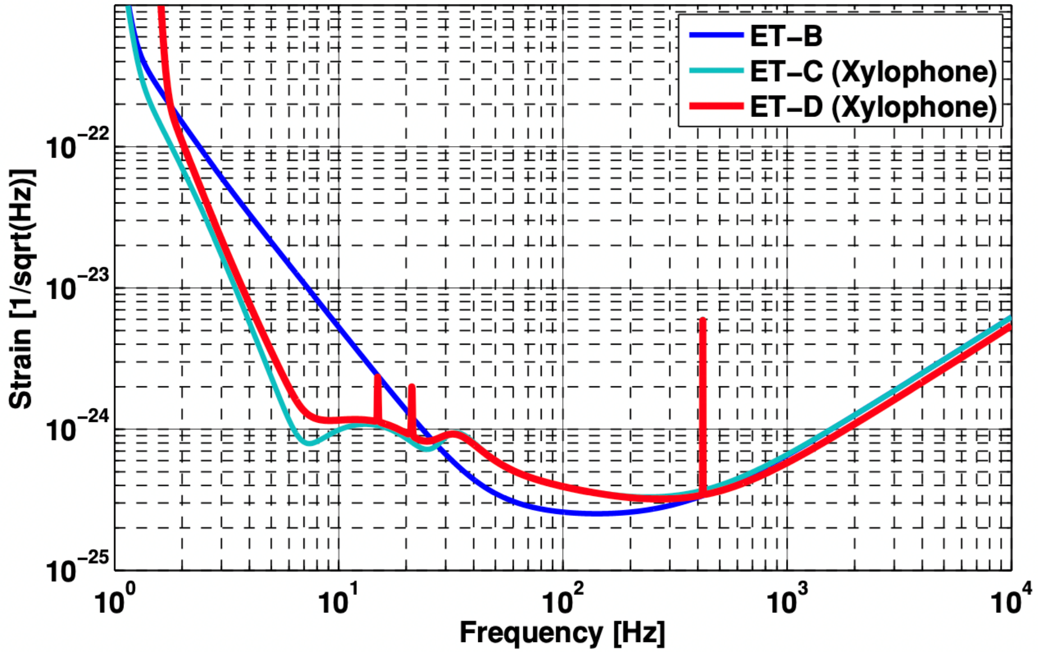
https://doi.org/10.3390/universe7110394

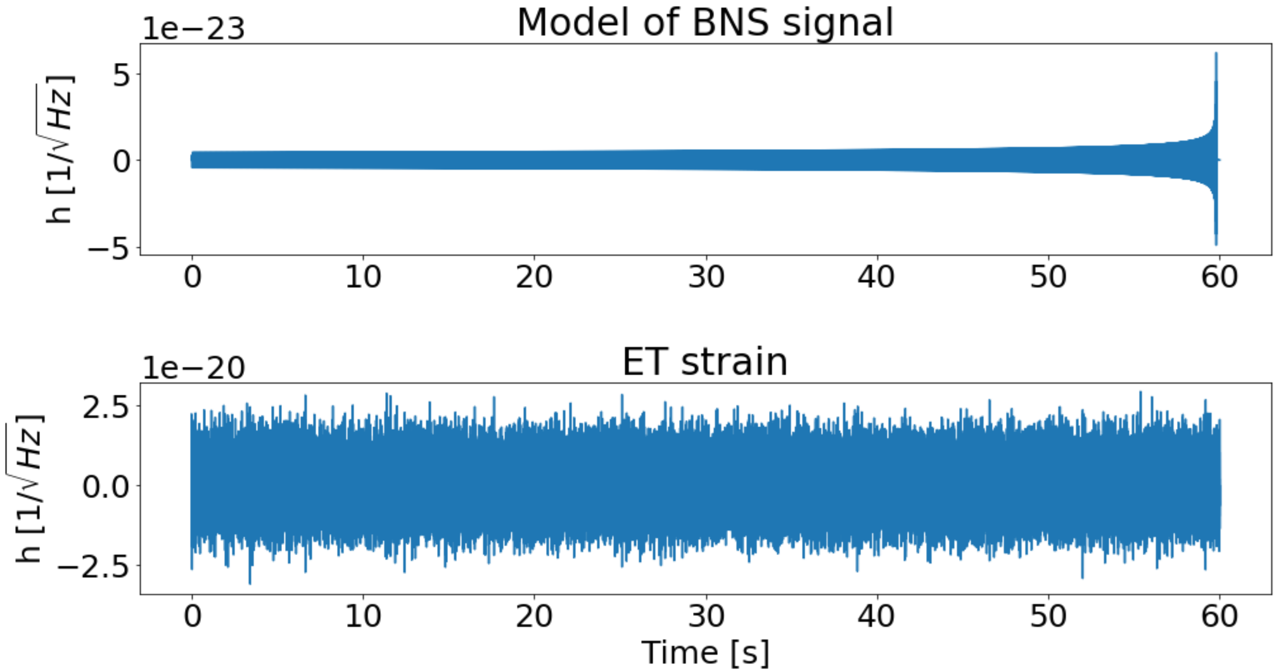
NS spins: aligned; maximum value: 0.05

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

GW detector noise: Einstein Telescope





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

https://doi.org/10.3390/universe7110394

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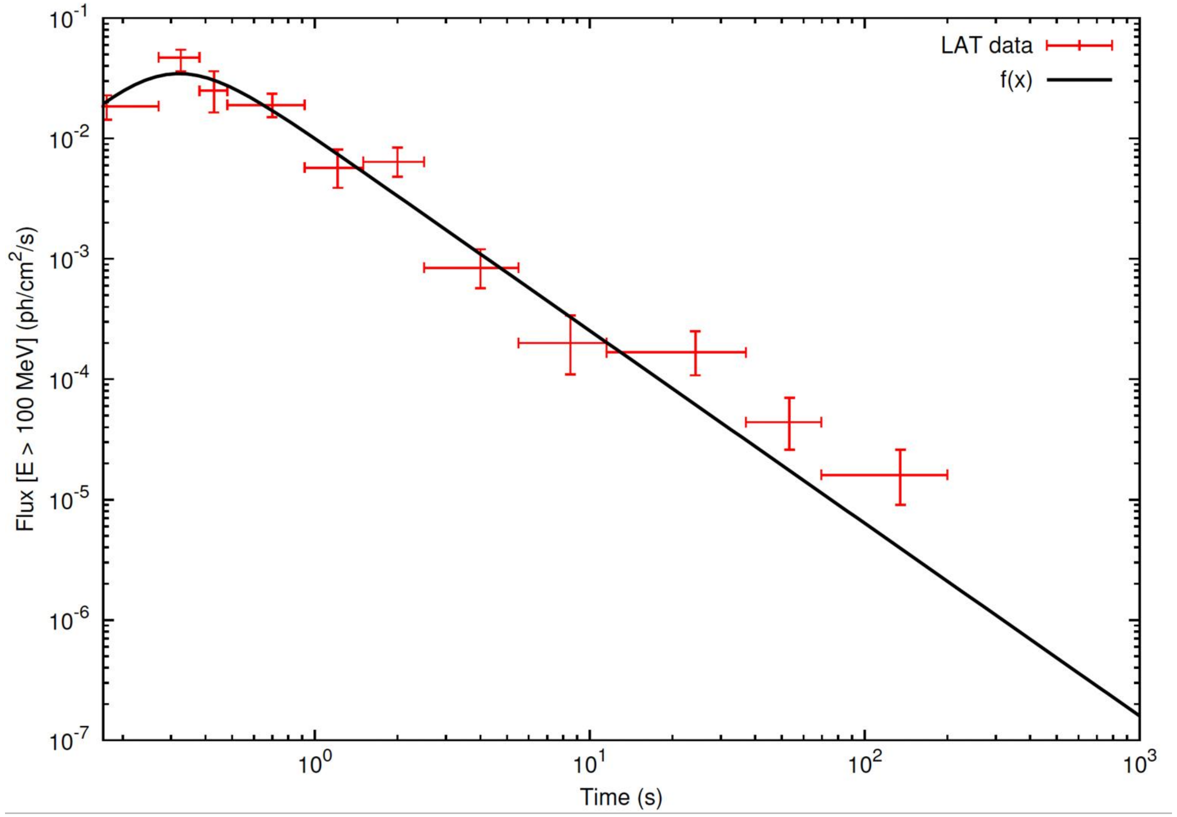
Electromagnetic simulations

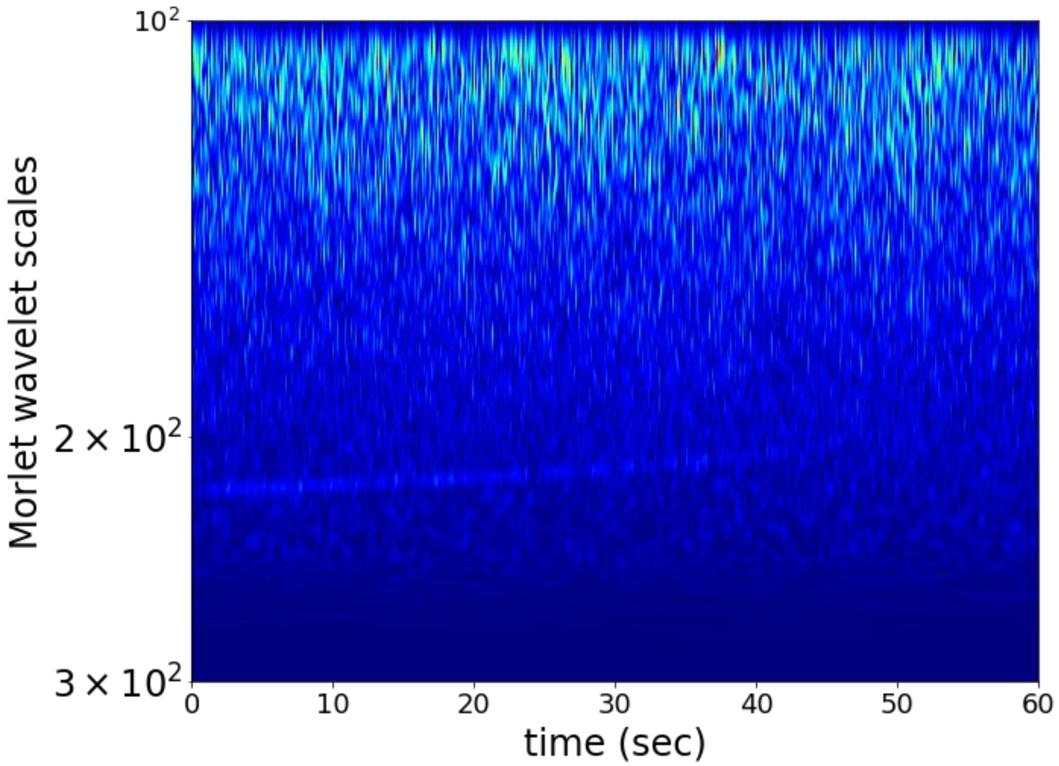
We assume that all BNS mergers are associated with a short GRB

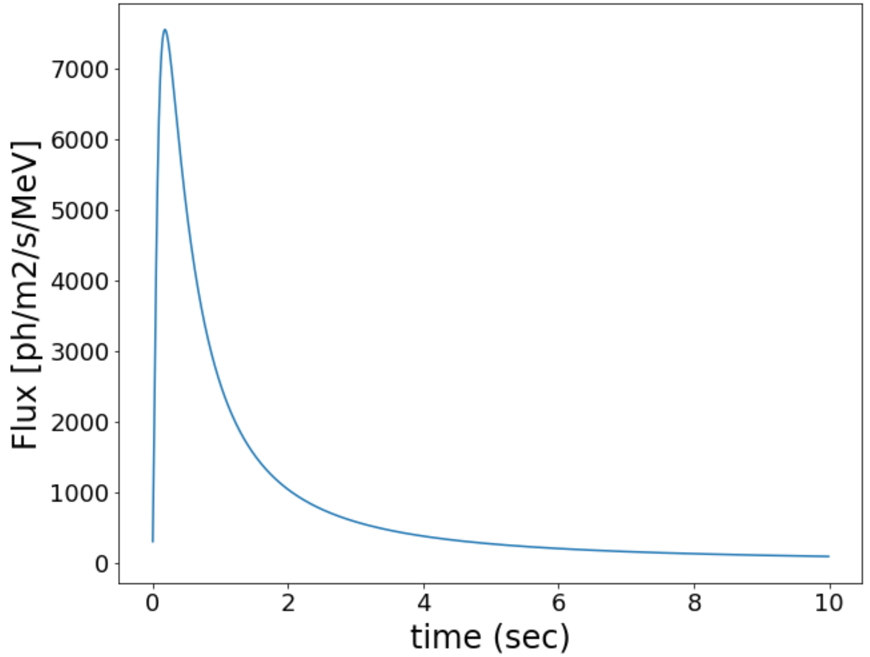
We simulate the **GRB afterglow gamma-ray light curves** following the approach in Patricelli et al. 2016:

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



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%

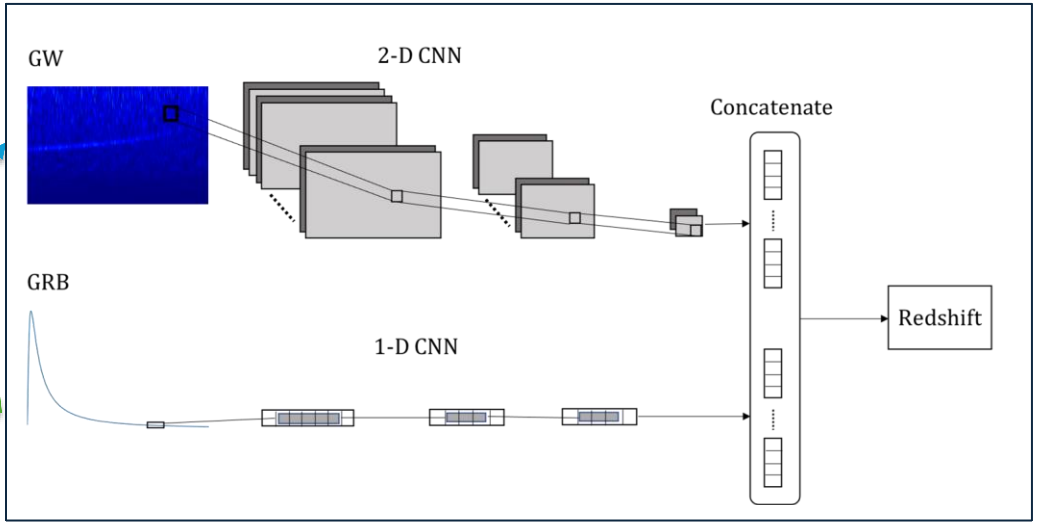
The deep network

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

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

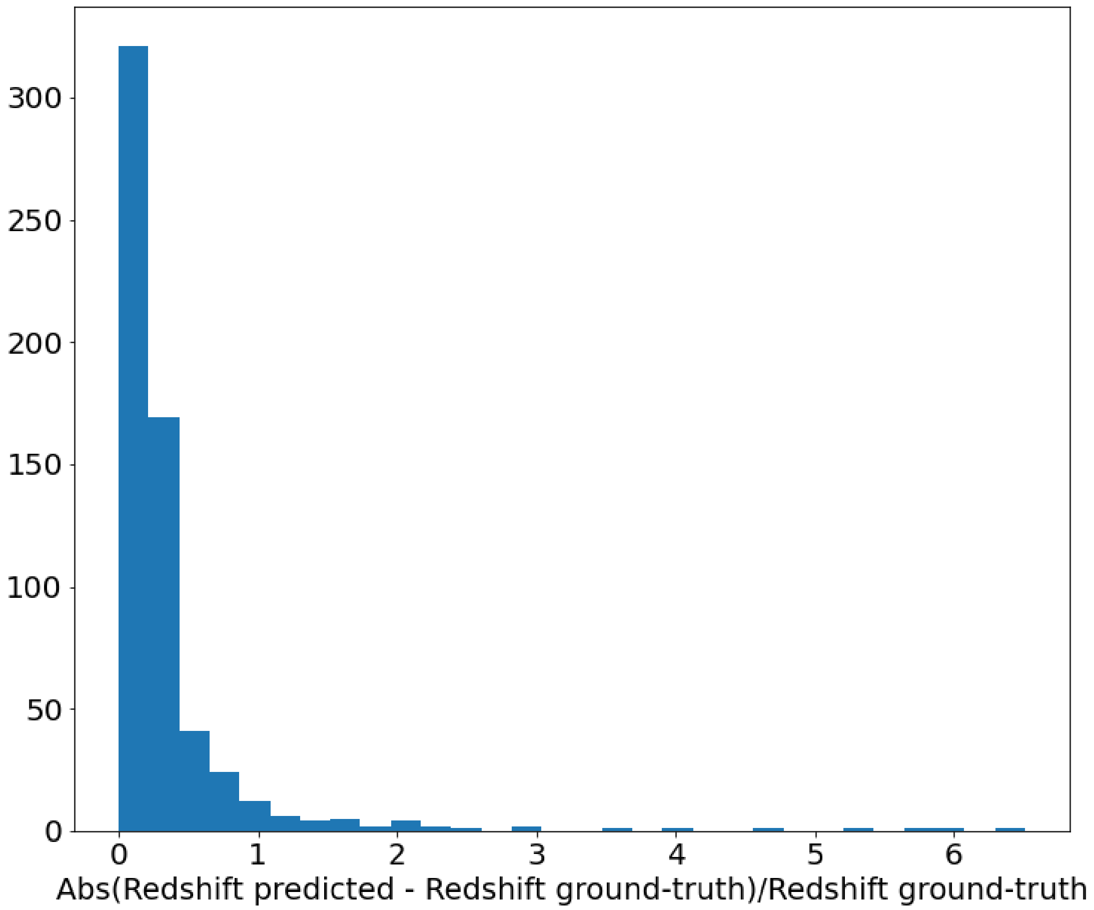


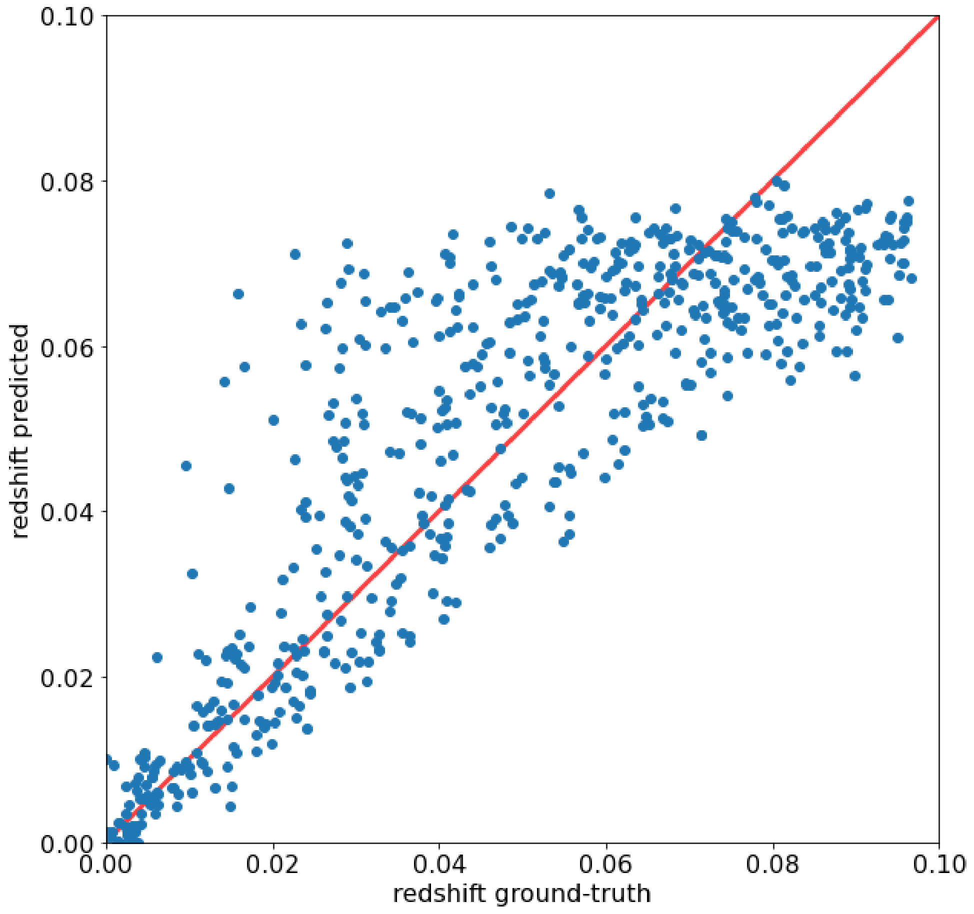
Flattening + Concatenation + FC layer with linear activation

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

https://doi.org/10.3390/universe7110394

MMML for GW-GRB results





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Wavefier: a framework for multi-messenger astrophysics

Elena Cuoco, Alberto Iess, Filip Morawski, Barbara Patricelli, sara vallero, Emanuel Marzini, Alessandro Petrocelli, Alessandro Staniscia.

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https://zenodo.org/records/3356656 https://wavefier.github.io/wavefier/

Wavefier: A framework for multi-messenger

WAVEFIER aims to set up a framework for analysis of different types of astrophysical data, paving the way to real-time Multi-Messenger astronomy studies. This is done leveraging the newest available software technologies.

KEY POINTS

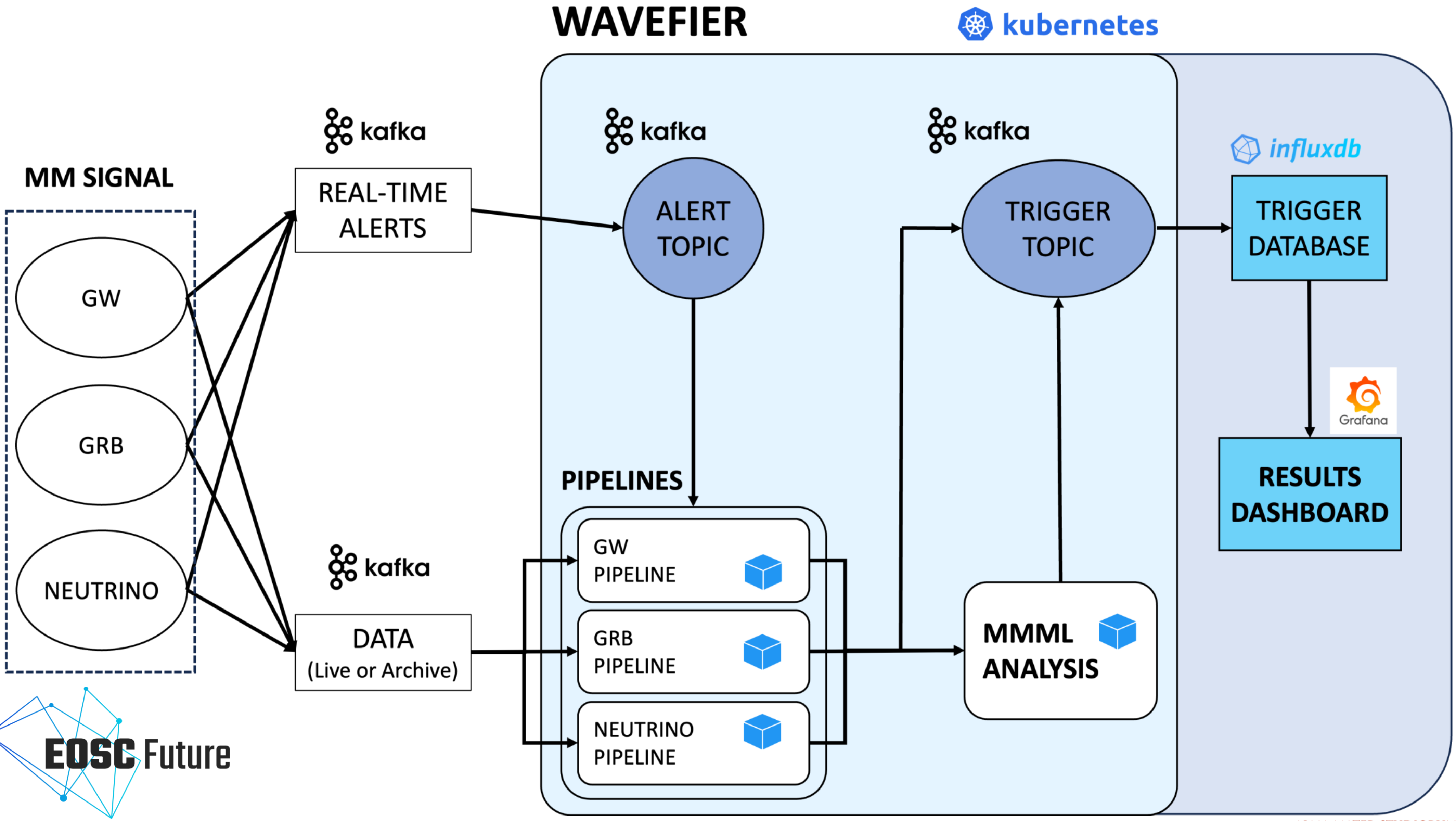
- Setup a prototype for a **real time** and offline pipeline for the detection and analysis of transient signals and their **automatic** classification.
- Best practice for **software management.**
- Software architecture solutions to prototype a **scalable** pipeline for **big data** analysis in GW context.
- **Interoperability** and access to data and services.
- **ICT services** supporting research infrastructures.
- Use of **data in network** infrastructures and service.

IN COLLABORATION WITH:

Trust-IT Services communicating to markets

Elena Cuoco, Emanuel Marzini, Filip Morawski, Alessandro Petrocelli, & Alessandro Staniscia. (2019). A prototype for a real time pipeline for the detection of transient signals and their automatic classification (1.0). Zenodo. https://doi.org/10.5281/zenodo.3356656

Wavefier GOAL



Alberto Iess

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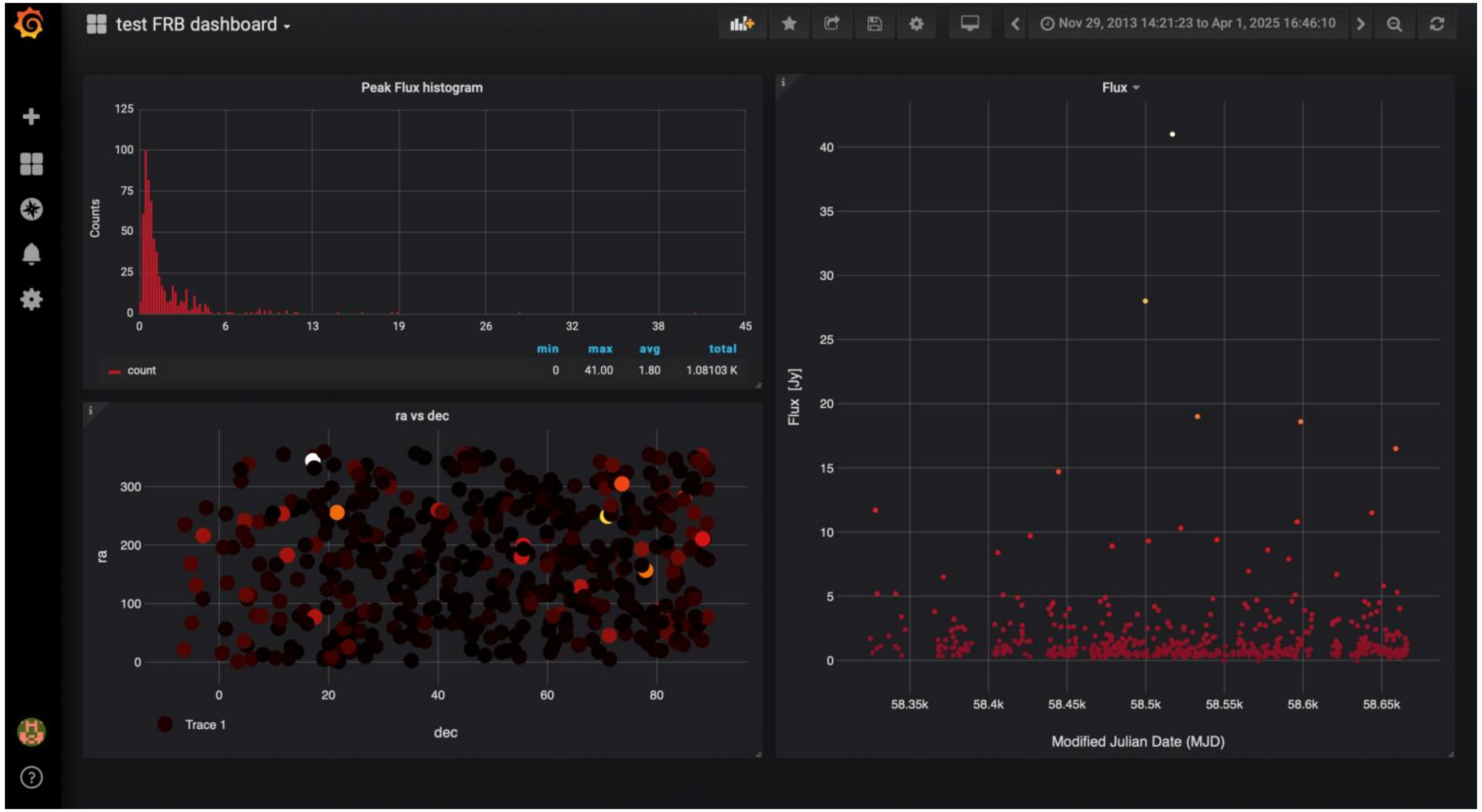
WAVEFIER: Fast Radio Burst and Gamma ray bursts

- Successfully tested attaching to NASA GCN notices alerts for GRB from Fermi and INTEGRAL via Kafka.
- Successfully imported FRB CHIME and Fermi LAT catalog data in .fits format.
- Grafana dashboard for FRB data visualization.

Alberto Iess

EOSC Future



A. Iess, G. Principe

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What's next?

ACME
Astrophysics Centre for Multimessenger studies in Europe

OSCARS
Open Science Clusters' Action for Research & Society

Wavefier in production (thanks to ACME and OSCARS project) on computing center	Test on new simulation data for ET	Merger of 3 and more messenger (open or simulated data)	Preparing more and more ML based pipeline for O5 or 3° generation detector

Thank you for your attention