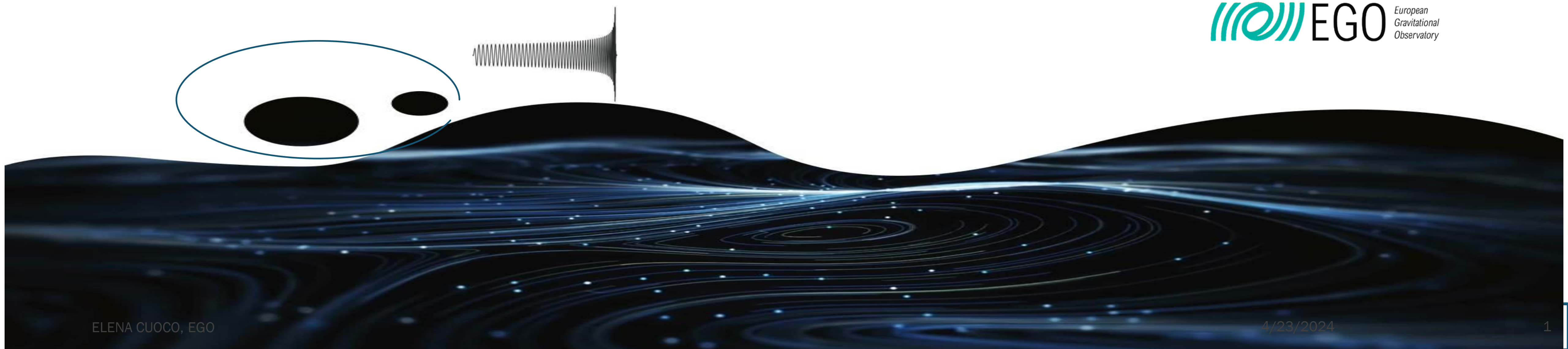
# GRAVITATIONAL WAVE PHYSICS AND ARTIFICIAL INTELLIGENCE

1st EuCAIF Conference, Amsterdam 30 April- 3May

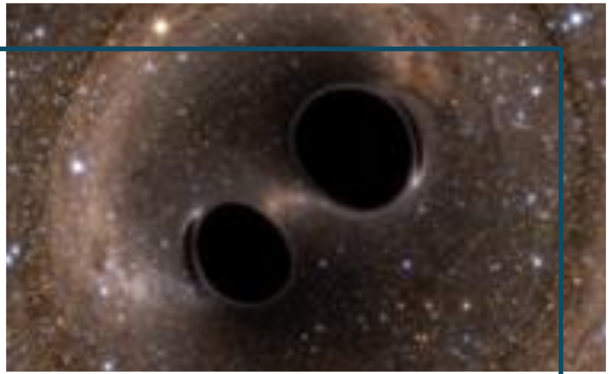
ELENA CUOCO
EGO European Gravitational Observatory



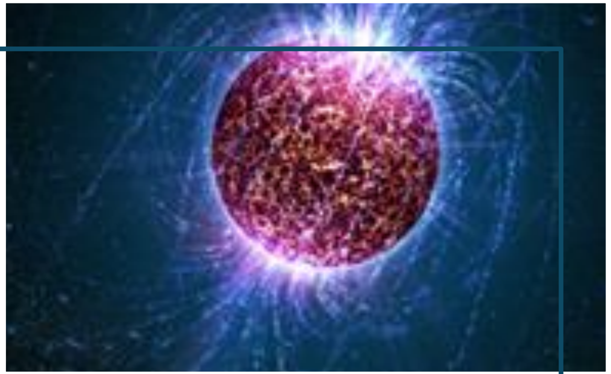
# GW ASTROPHYSICAL SOURCES

Short → Long

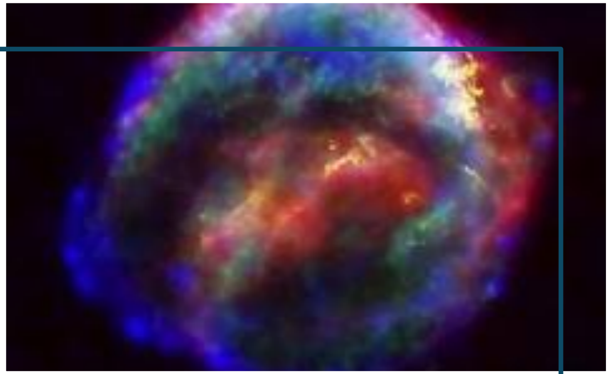
Known → Unknown



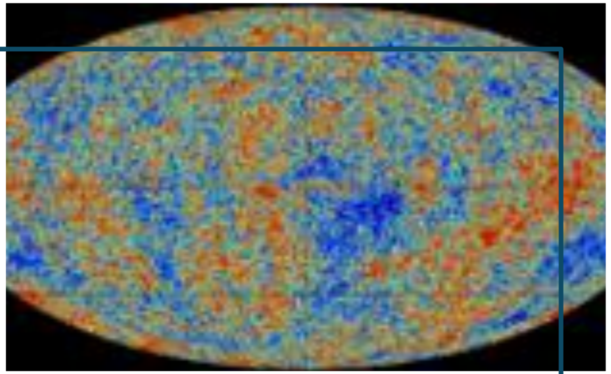
CBCs (BBH, BHNS, BNS)



Pulsars



CCSNe

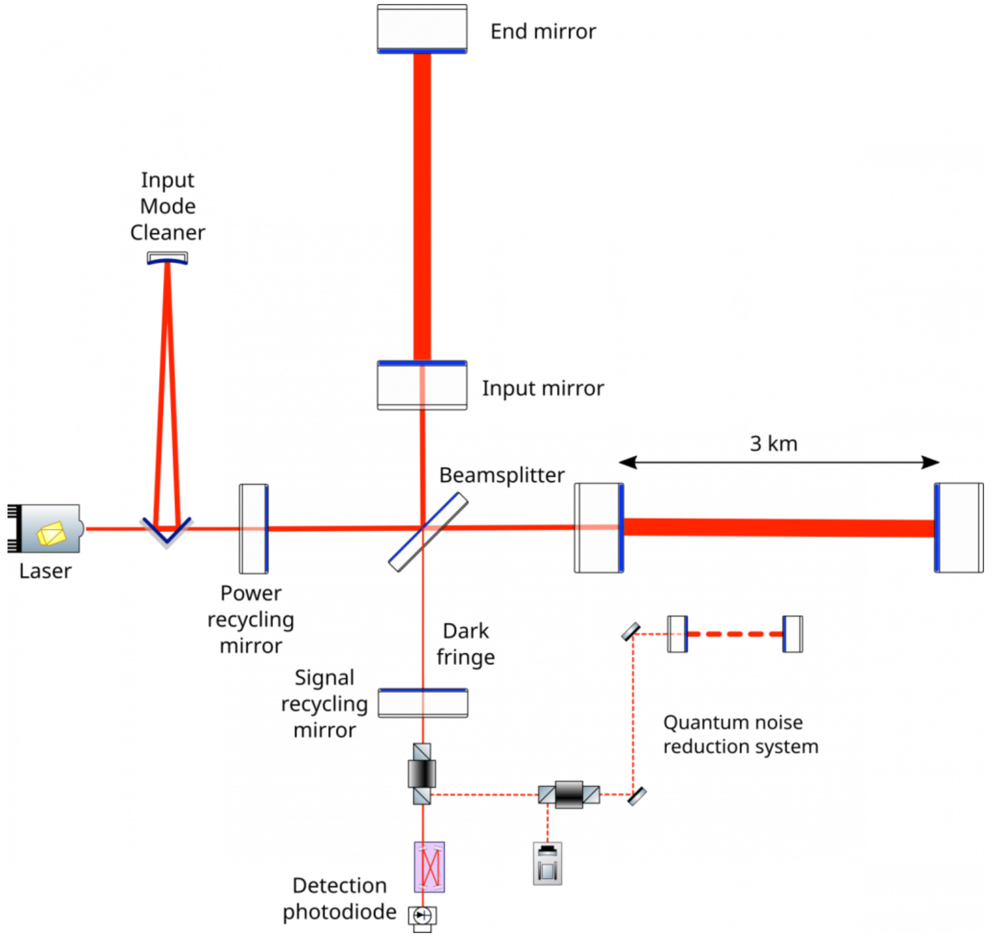


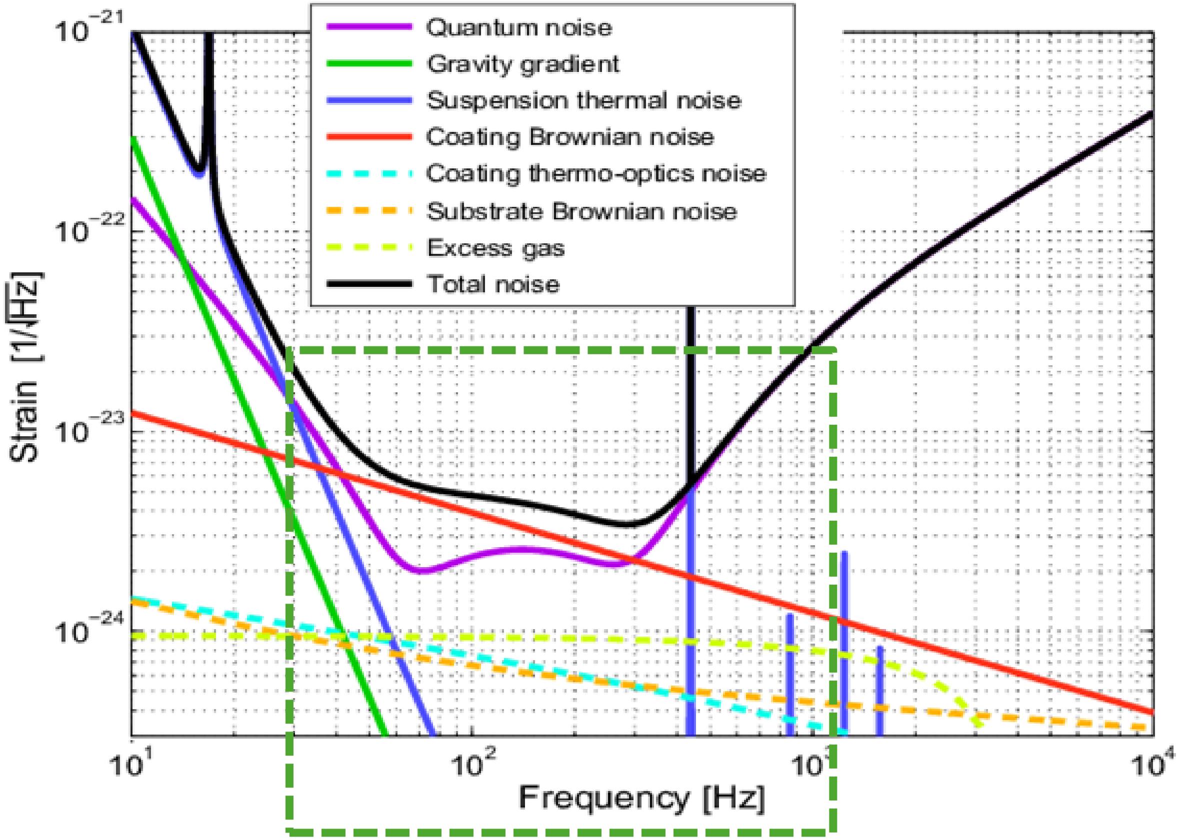
GW Background

Do we know their Waveforms?

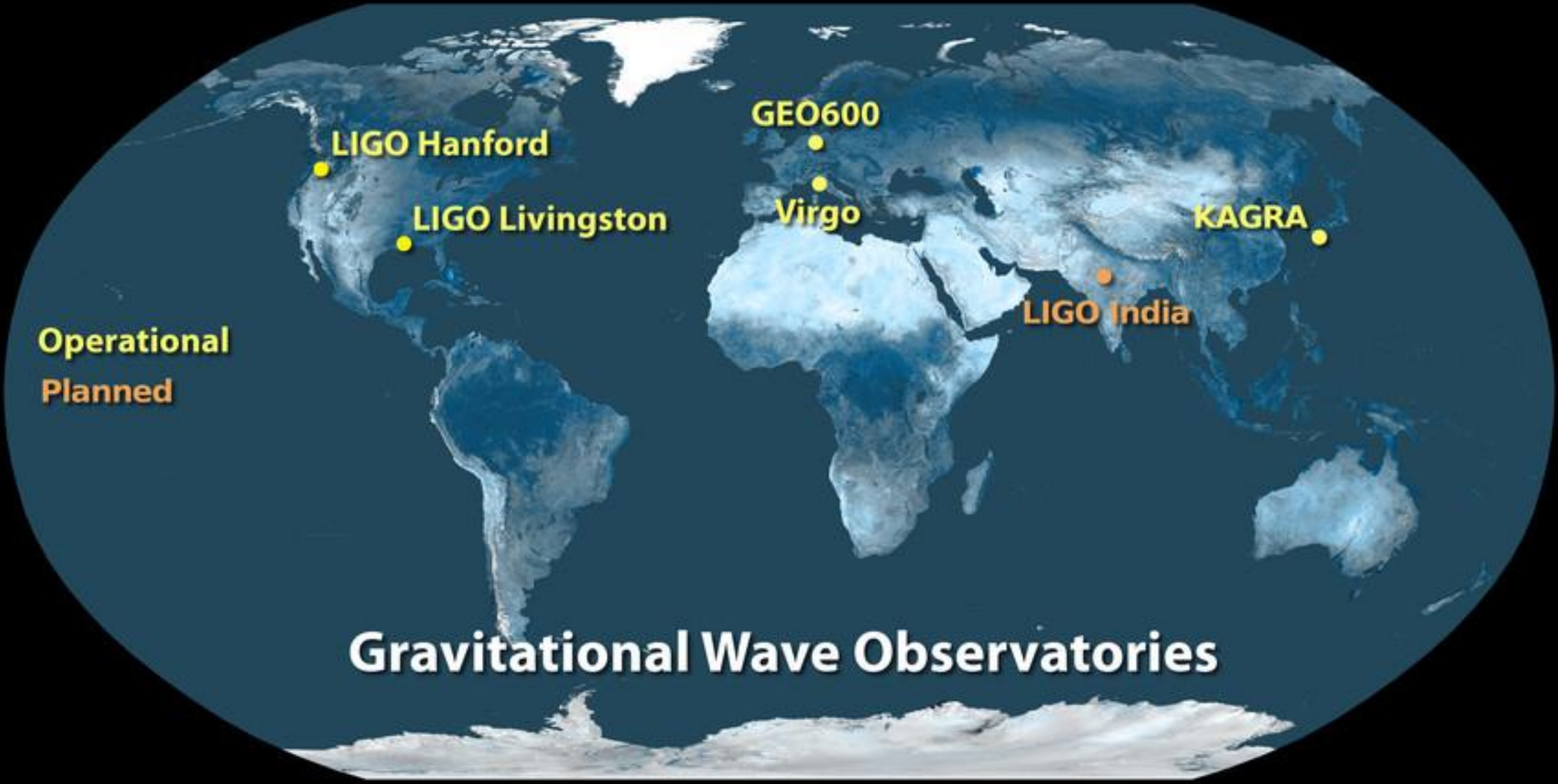
Which is the signal duration?

# ITF DETECTORS AND THEIR SENSITIVITY



# 2ND GENERATION GROUND BASED DETECTORS

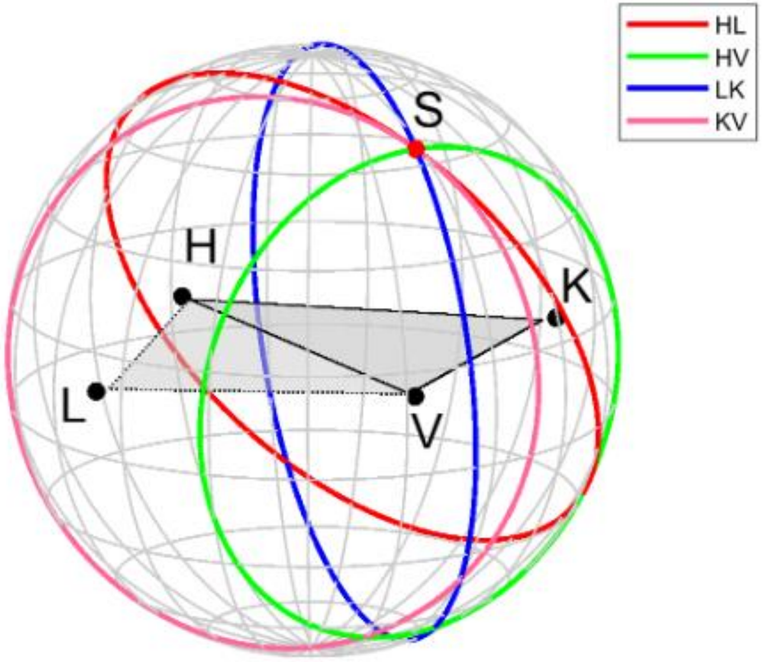


# WHY MORE THAN 1 DETECTOR?

Source localization using only timing for a two-site network yields an **annulus** on the sky.

For three detectors, the time delays restrict the source to **two sky regions** which are mirror images with respect to the plane passing through the three sites.

With four or more detectors, timing information alone is sufficient to localize to a single sky region, <10 deg$^2$ for some signals.




arXiv:1304.0670

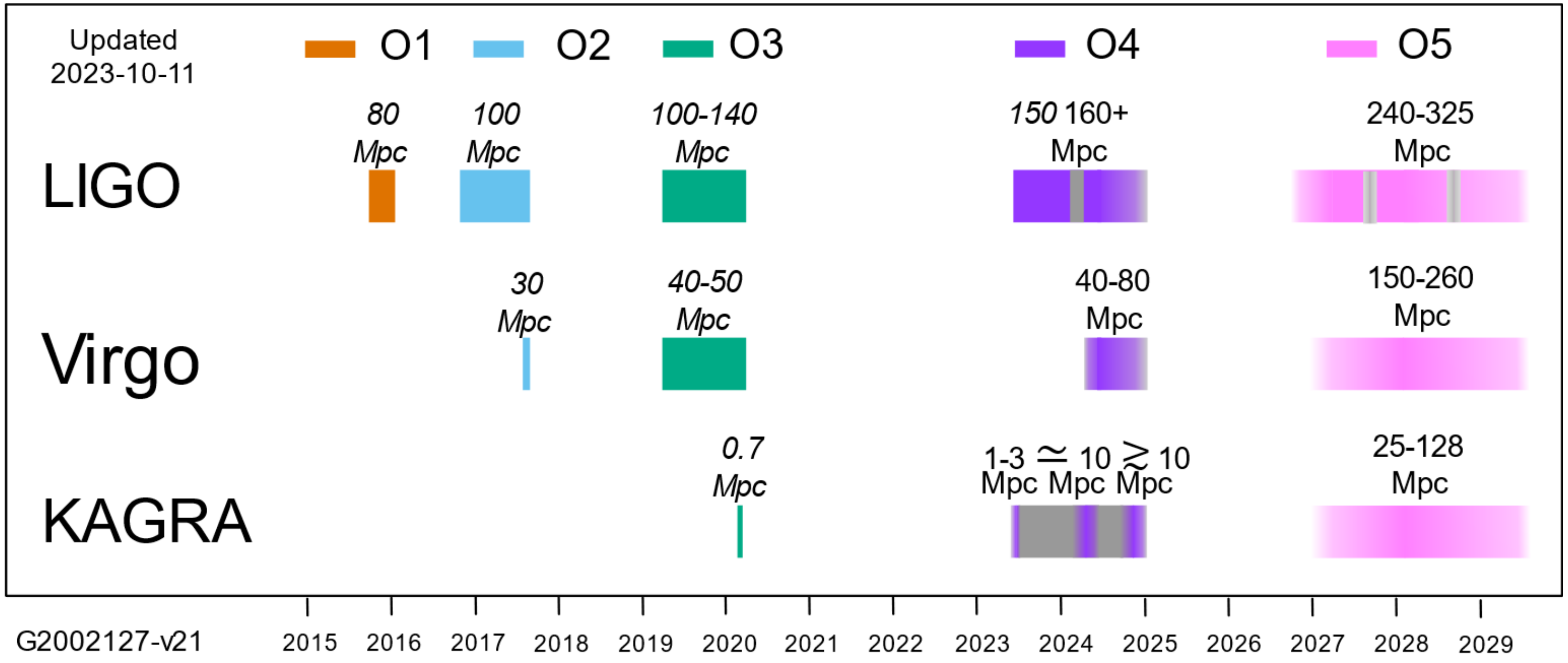
- 2 detector → 100 -1000 deg$^2$
- 3 detector → 10 - 100 deg$^2$
- 4 detector → < 10 deg$^2$

# THE O-RUN TIMELINE

The detector **strain sensitivity** is the minimum *detectable* value of the strain produced by an incoming GW:

⇒ It is determined by the **detector noise**.

**BNS inspiral range**: the distance, averaged over GW polarizations and directions in the sky, at which a single detector can observe with matched-filter Signal-to-noise Ratio (SNR) of 8 the inspiral of two neutron stars.




https://observing.docs.ligo.org/plan/

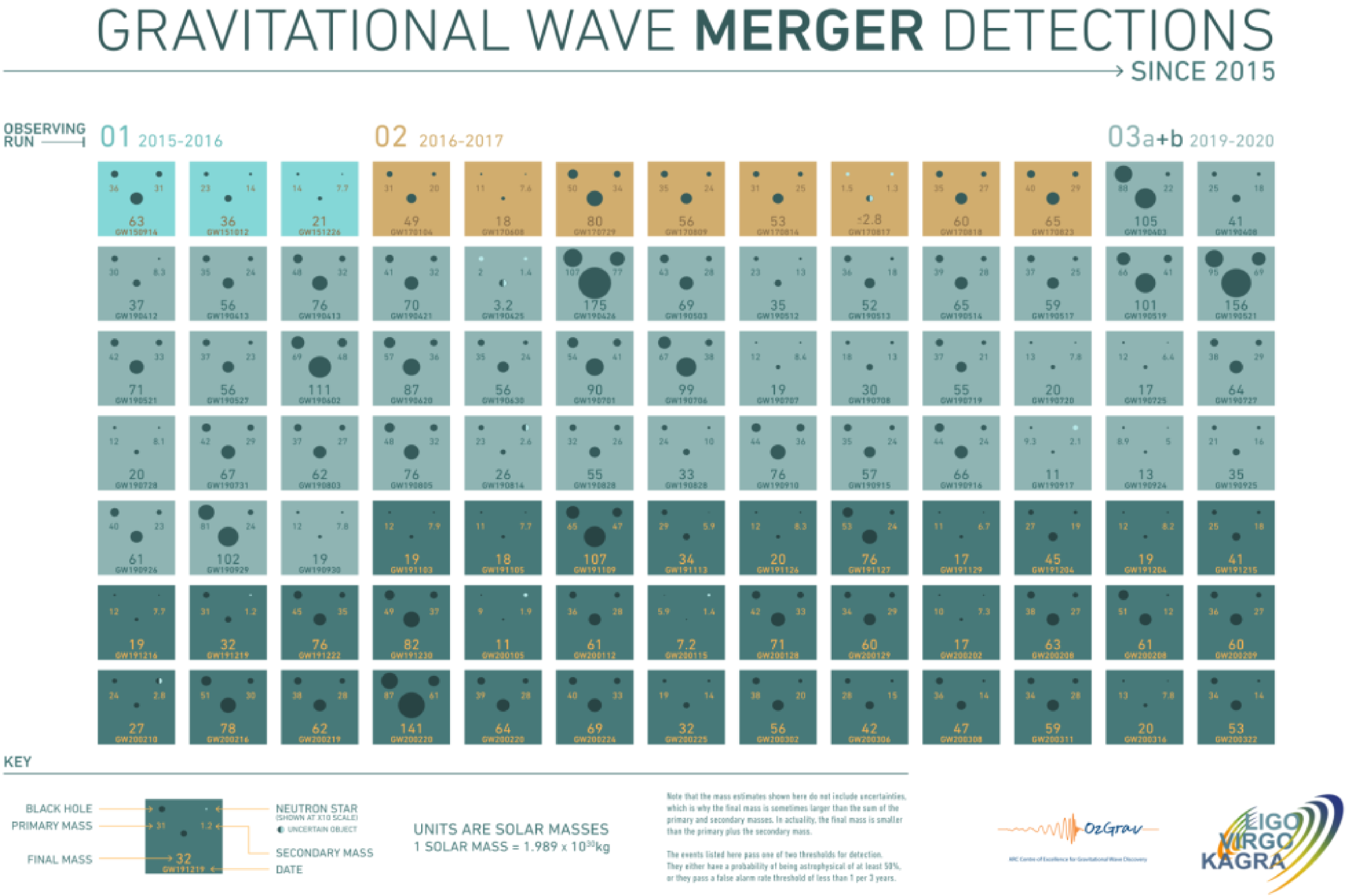
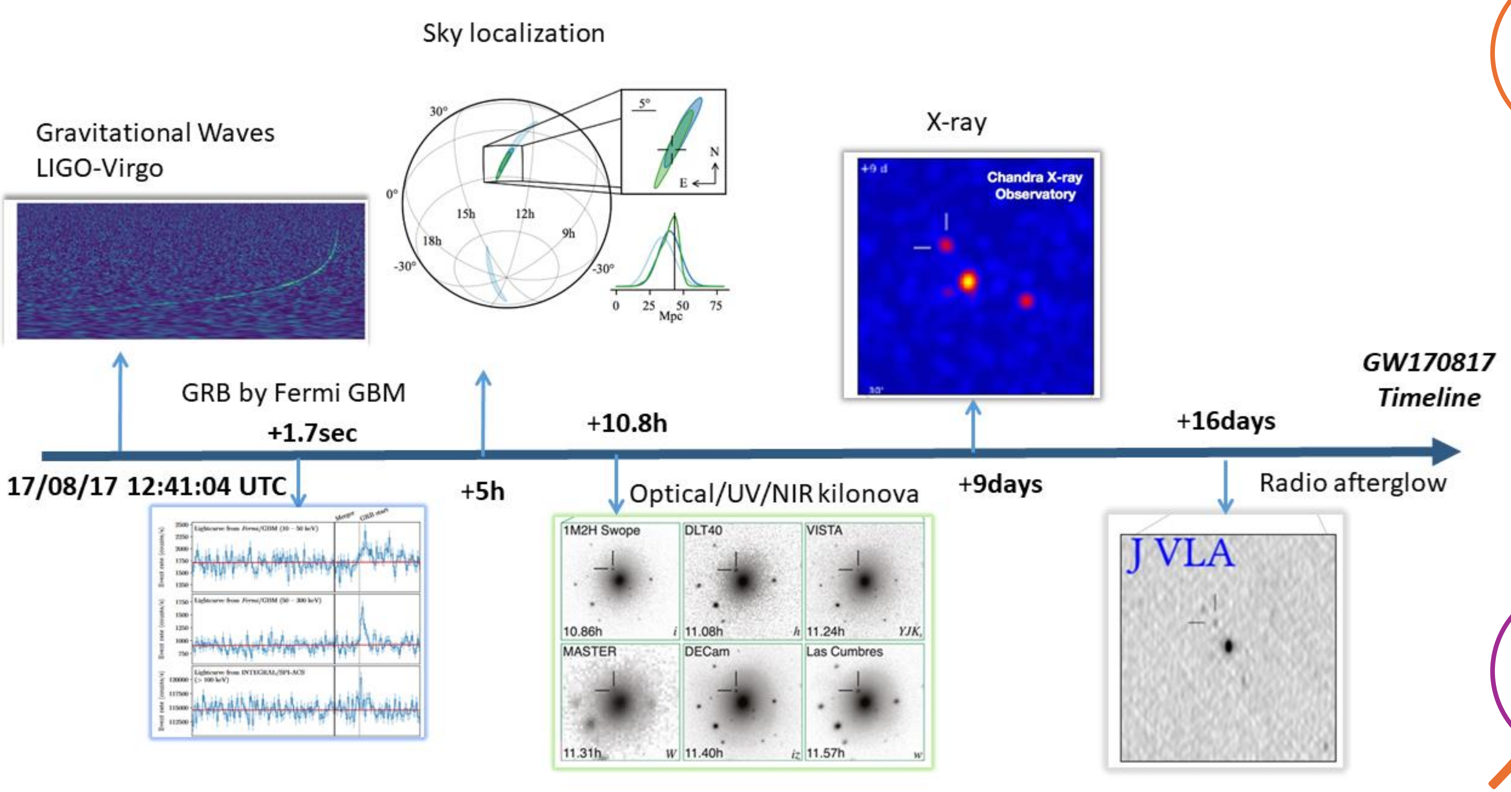



Image credit: Carl Knox,Hannah Middleton, Federica Grigoletto, LVK

# GW170817: THE FIRST MULTI-MESSENGER GW EVENT




Abbott et al. 2017 and refs. therein

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

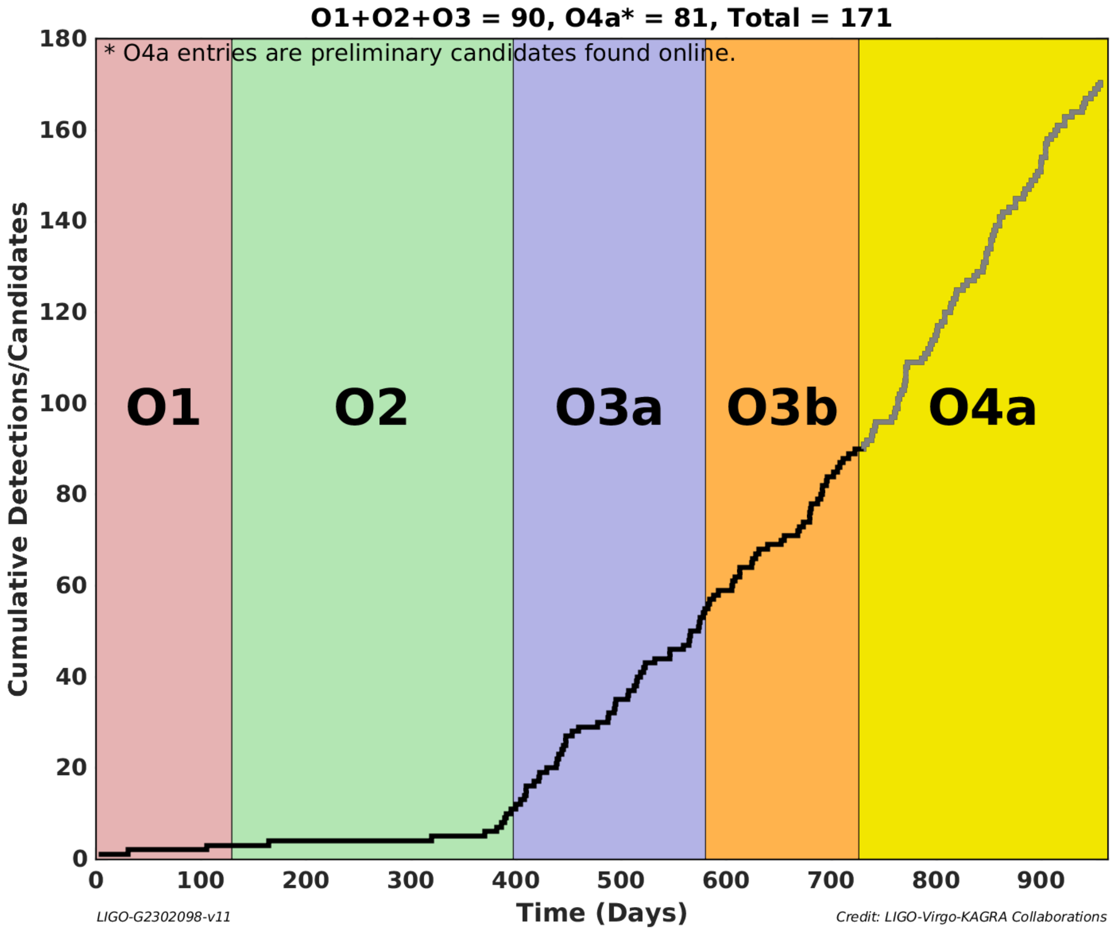
An X-ray and a radio counterparts have been identified

- off-axis afterglow from a structured jet

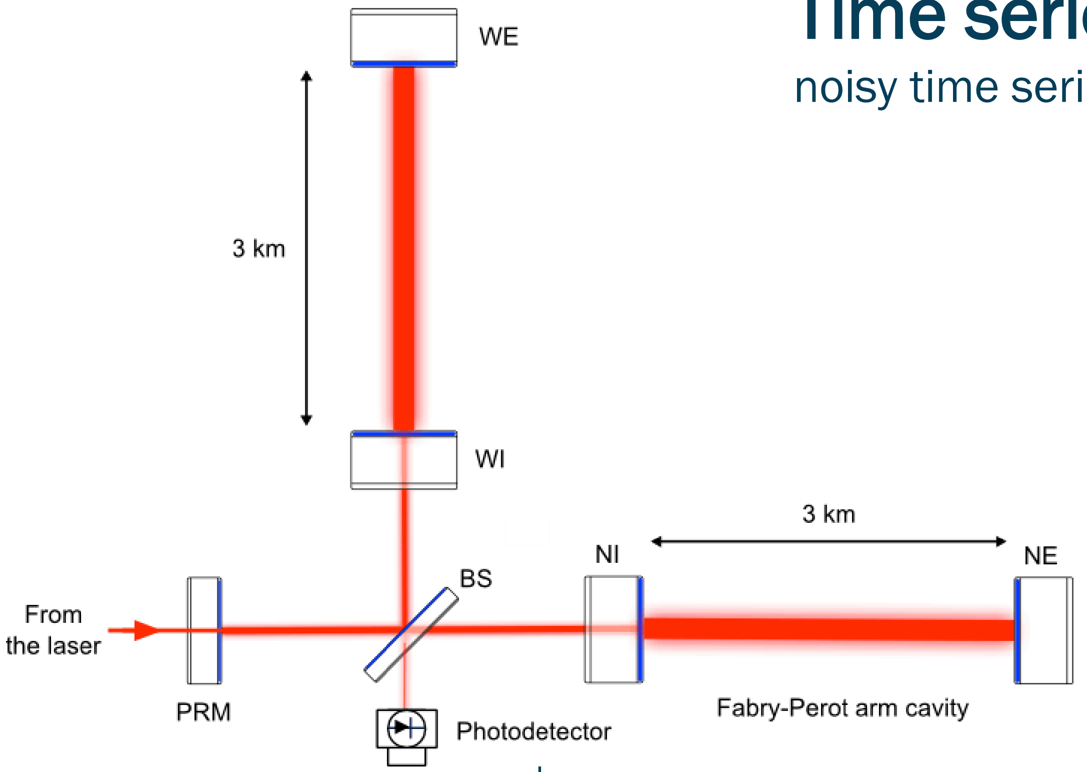
# DETECTION SUMMARY UP TO O4A

O4 Significant Detection Candidates: **81** (92 Total - 11 Retracted)
O4 Low Significance Detection Candidates: **1610** (Total)

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

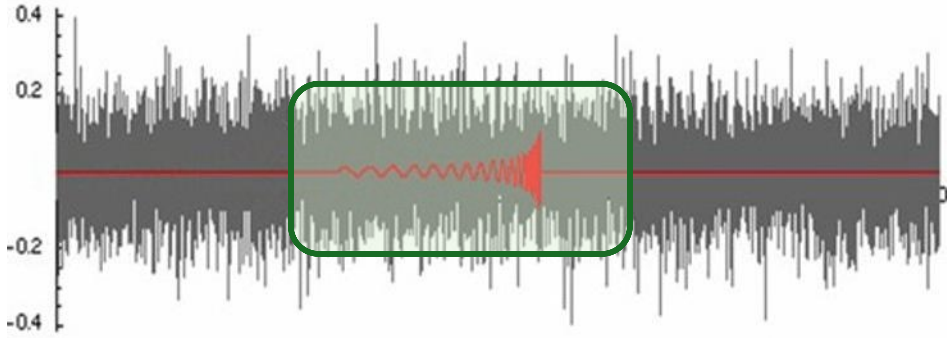


# GRAVITATIONAL WAVE DETECTOR DATA

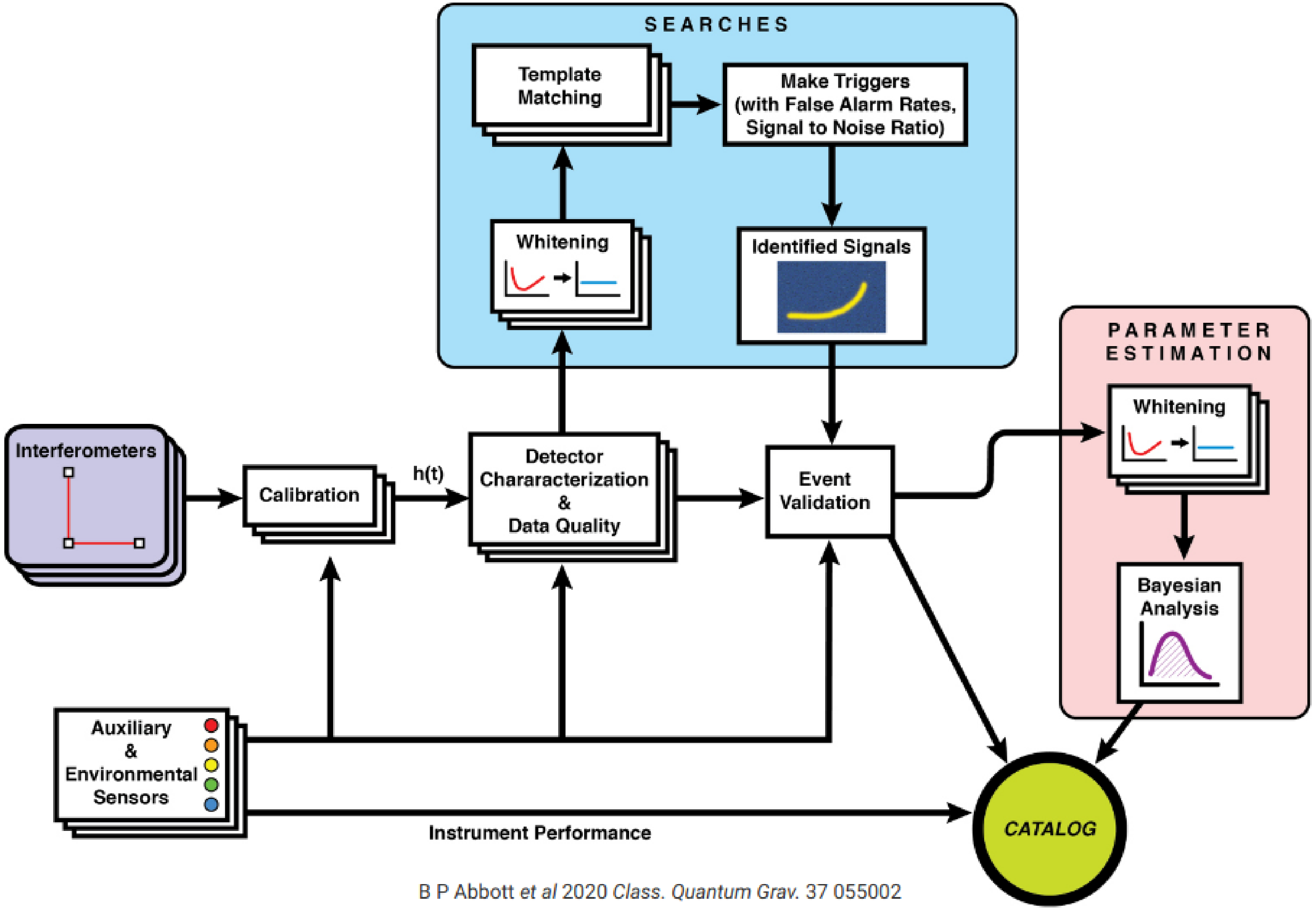



## Time series sequences:

noisy time series with low amplitude GW signal buried in

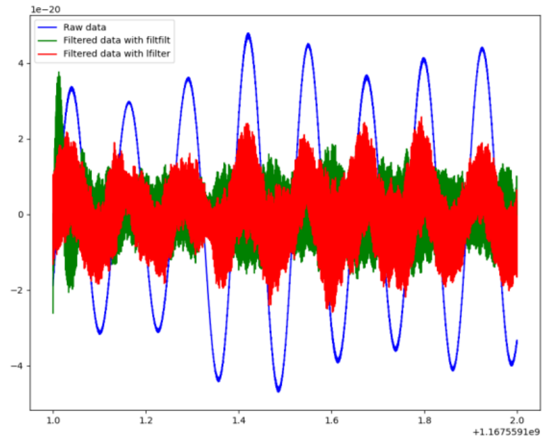


# THE DATA ANALYSIS WORKFLOW

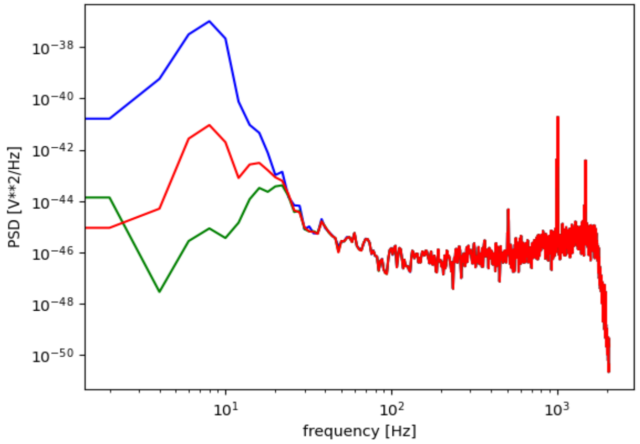



B P Abbott *et al* 2020 *Class. Quantum Grav.* 37 055002

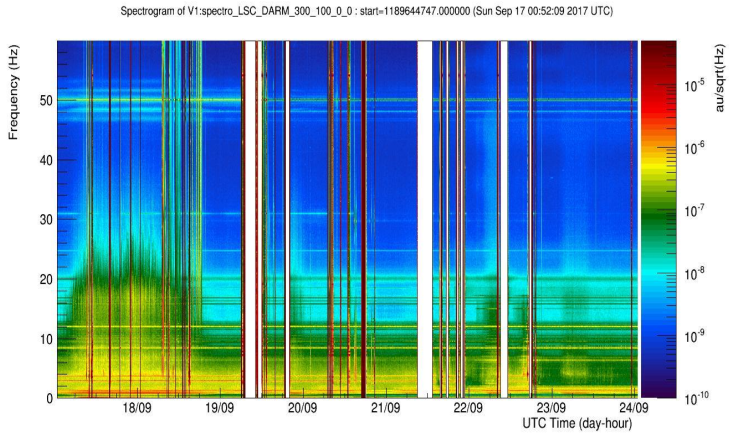
# DATA REPRESENTATIONS



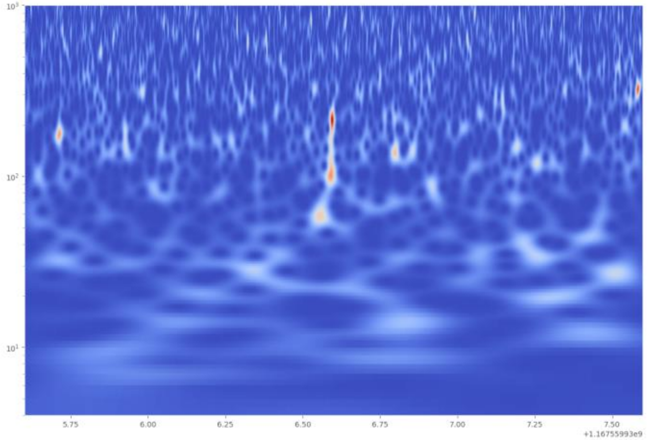

*Time-domain*




*Frequency-domain*




*Time-frequency-domain*



*Wavelet-domain*

# GRAVITATIONAL WAVE **TRANSIENT** SIGNAL SOURCES

## Compact binary coalescences

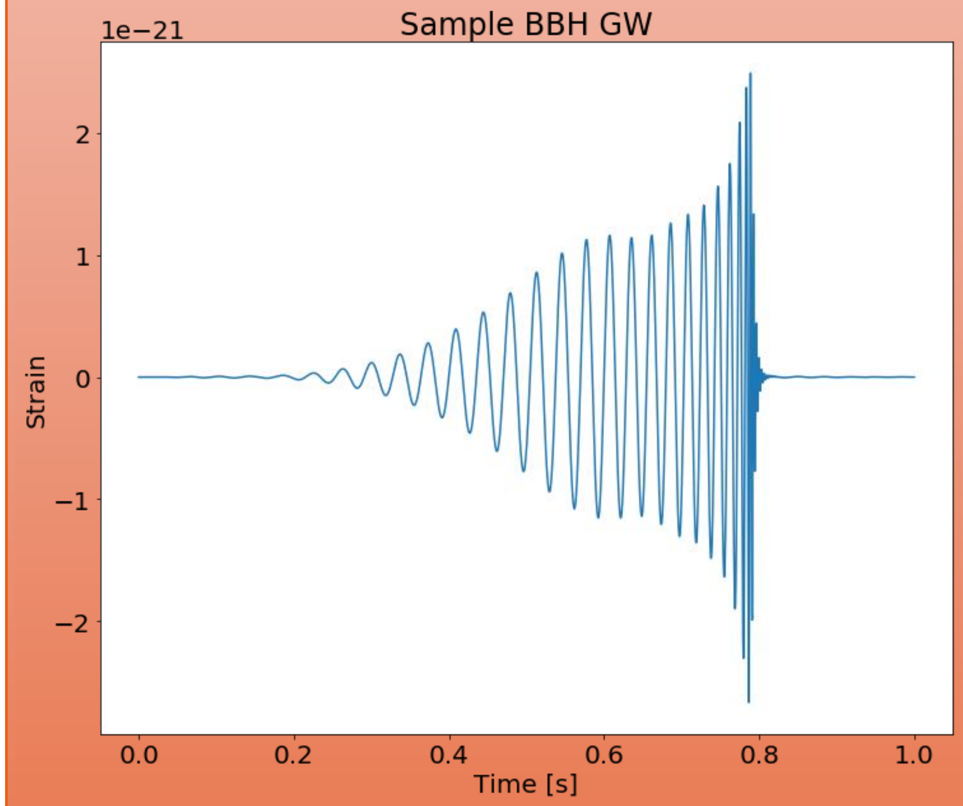
Credit
LIGO/Caltech/MIT/R. Hurt (IPAC)

## Core collapse Supernovae

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

# GRAVITATIONAL WAVE TRANSIENT SIGNALS

CBC signals




CCSN signals

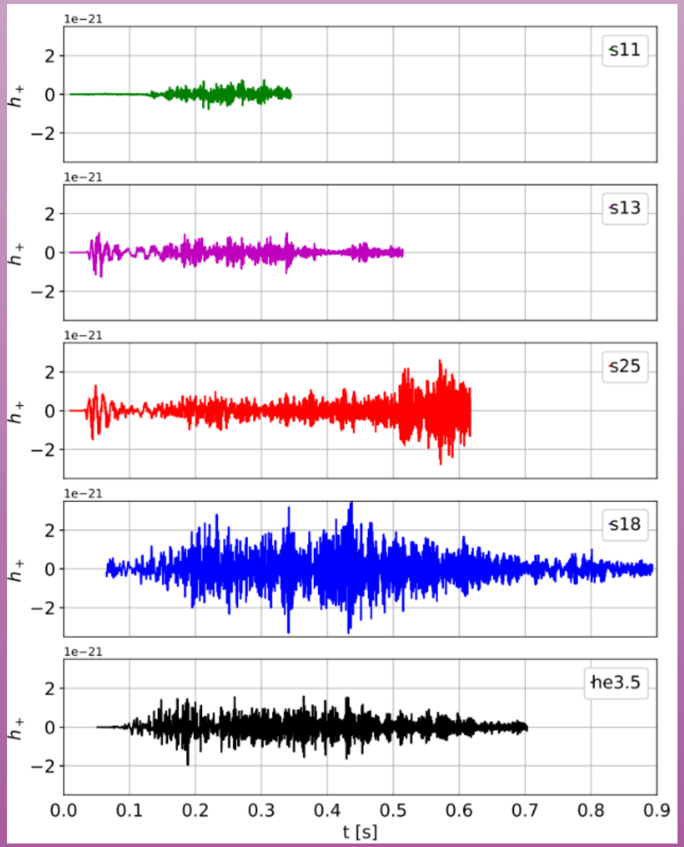



Image from Iess, Cuoco, Morawski, Powell (2020)

# HOW WE DETECT TRANSIENT SIGNALS: MODELED SEARCH

Matched-filter

Data

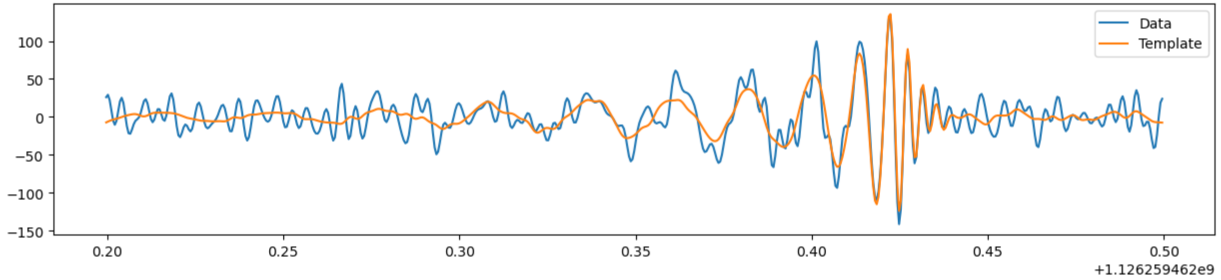
Template

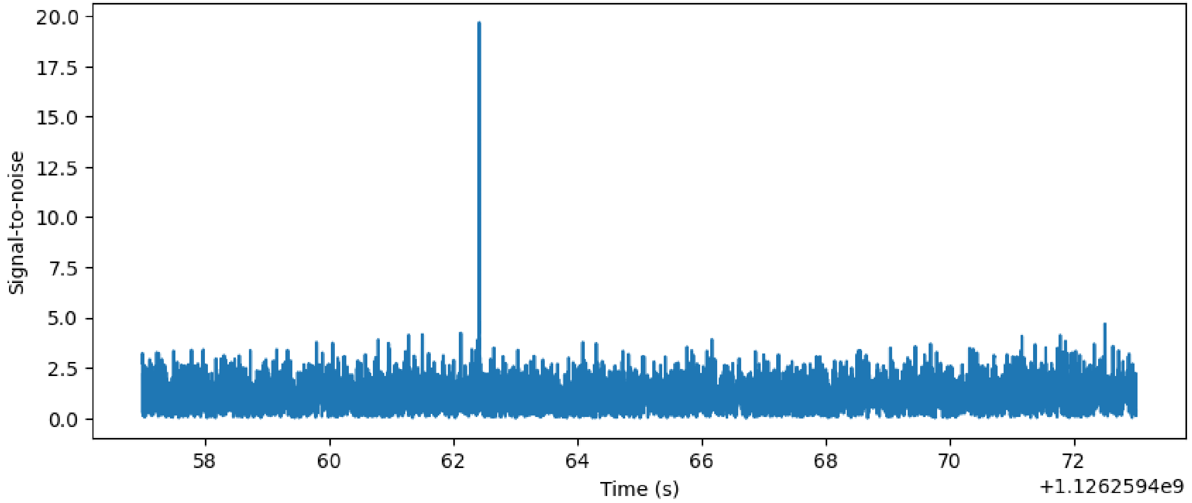
$$\rho(t) = 4 \int_0^\infty \frac{\tilde{x}(f)\, \tilde{h}^*(f)}{S_n(f)}\, e^{2\pi i f t}\, df$$

Noise power spectral density

## CBC search

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

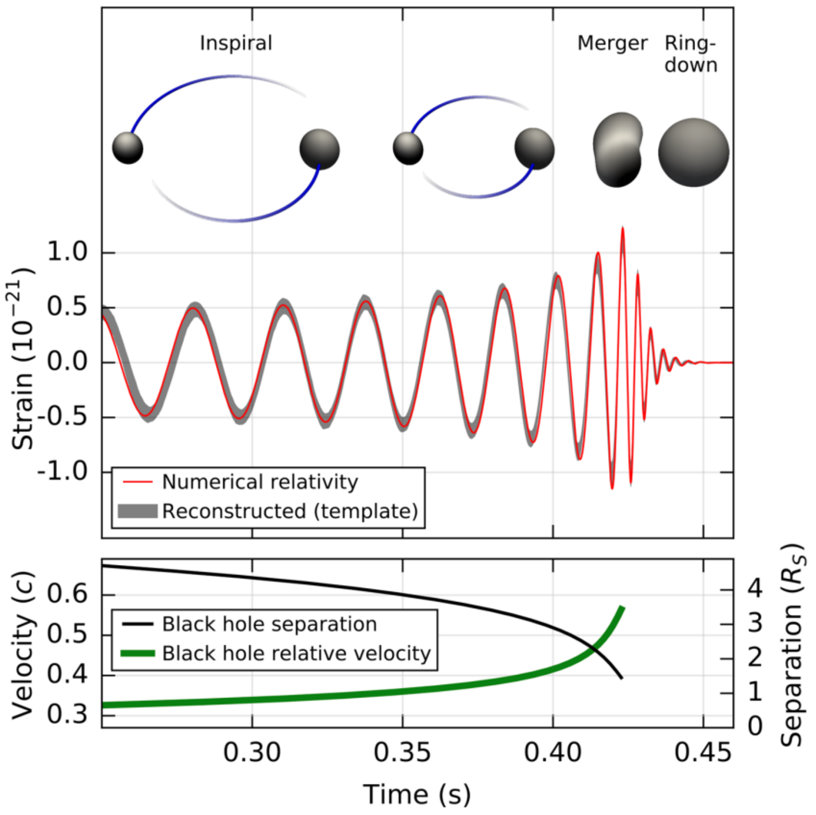


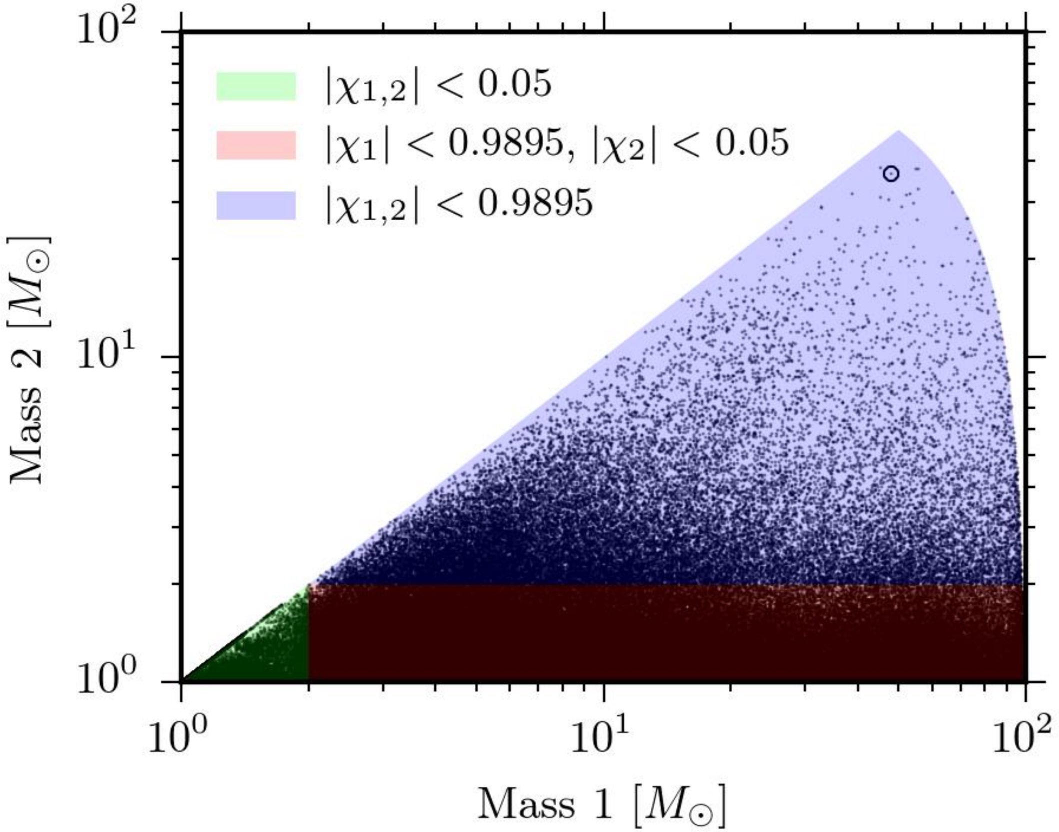

https://github.com/gw-odw/odw-2023/

# HOW MANY TEMPLATES?

To cover in efficient way the parameters space, we build a templates bank requiring that the signal can be detected with a maximum loss of 3% of its SNR

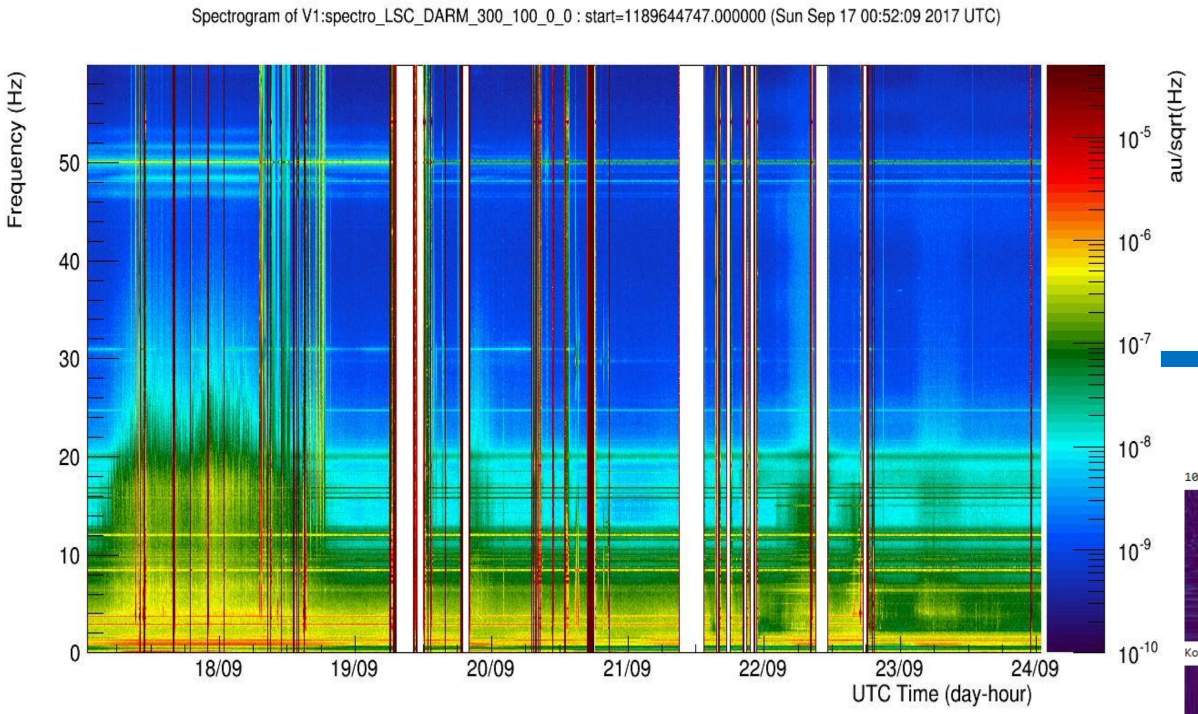



~250000 waveforms used for GW150914




LVC Phys. Rev. X 6 (2016)

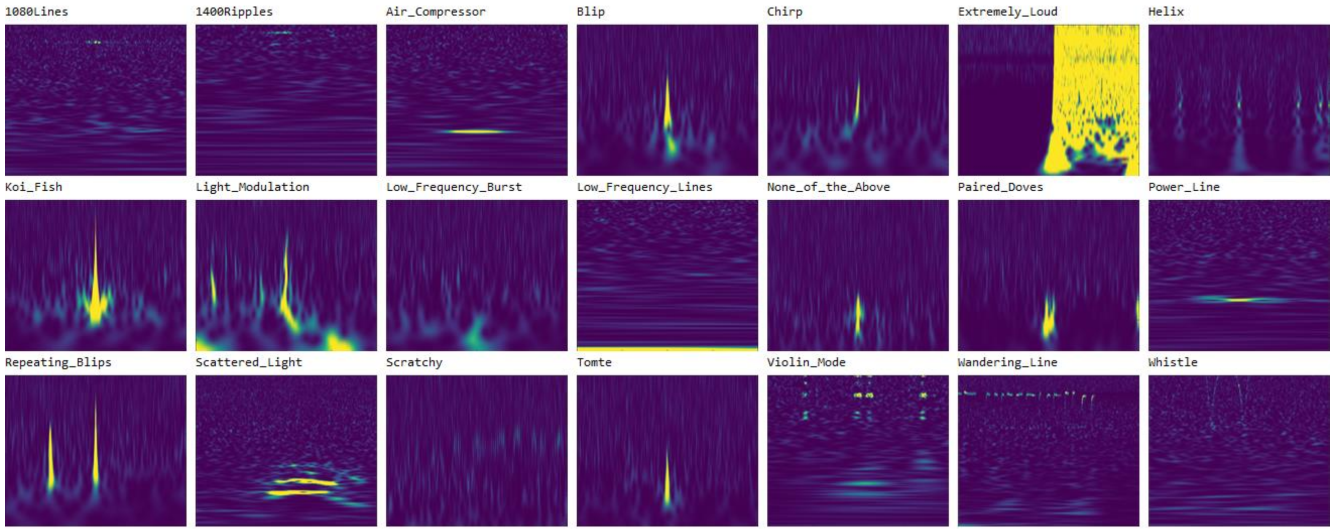
# DETECTOR NOISE: IS IT IDEAL?




Broadband

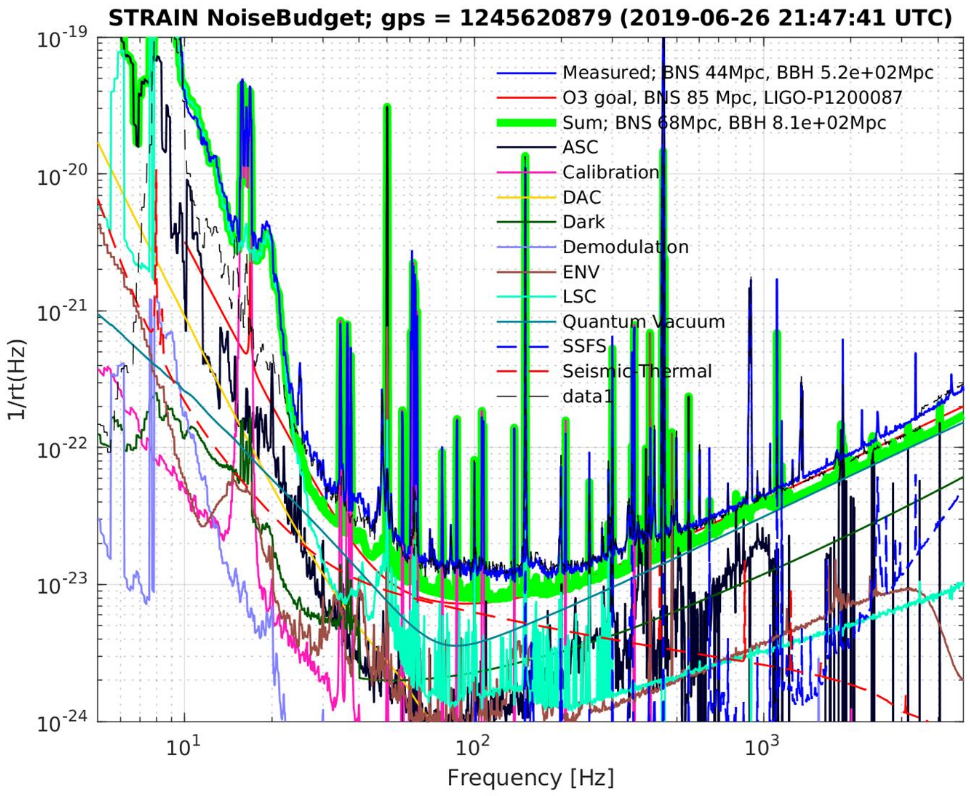
Gravity Spy, Zevin et al (2017)

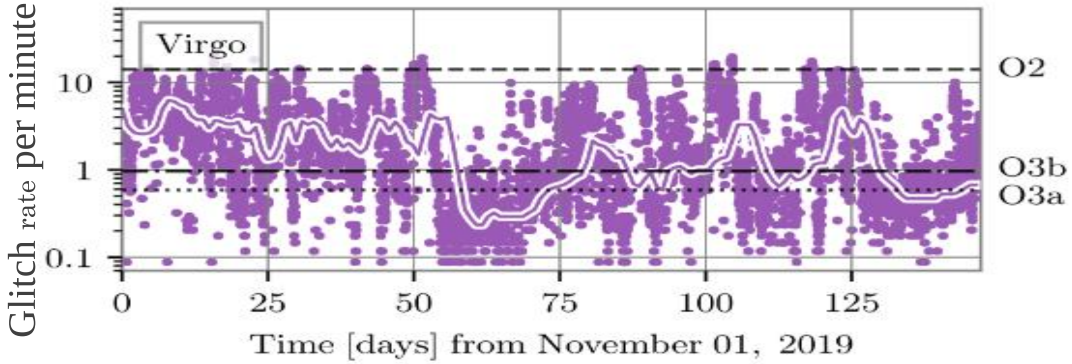
https://www.zooniverse.org/projects/zooniverse/gravity-spy



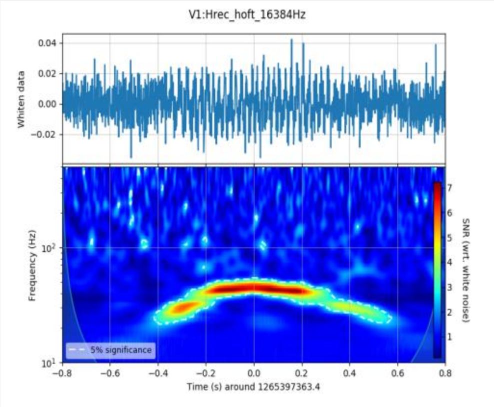

Transient noise signals: Glitches

# NON-STATIONARY AND TRANSIENT NOISE

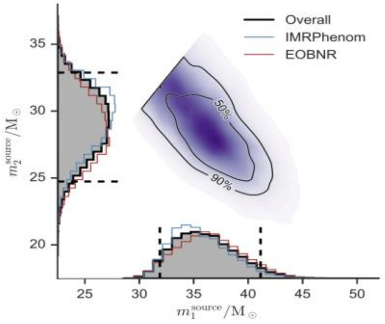



**Example of Scattered light glitch**



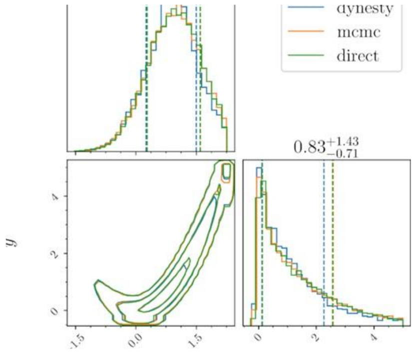
# PARAMETER ESTIMATION



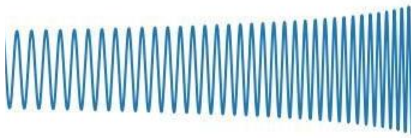

Estimation of physical quantities that describe a detected GW signal

$$P(h|s) = \frac{P(s|h)P(h)}{P(s)}$$

Bayesian framework allows to perform a quantitative analysis of GW signals and to calculate statistical significance of the physical parameters that best match a detected signal




MCMC for GW parameter estimation.



GW waveforms and priors needed for parameter estimation

# HOW WE DETECT TRANSIENT SIGNALS: UN-MODELED SEARCH

## Burst search

**Strategy: look for excess power in single detector or coherent/coincident in network data**

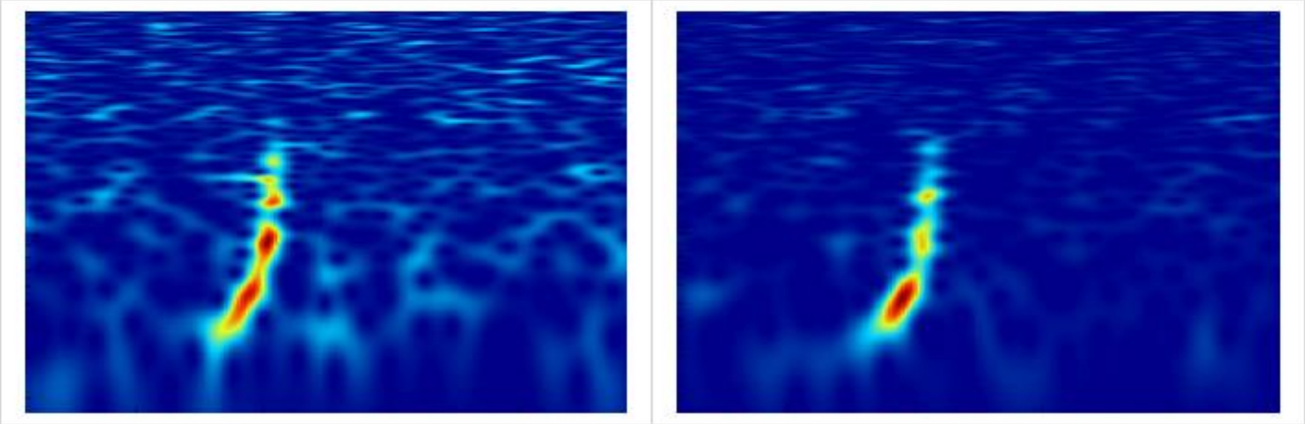
**Example cWB ([https://gwburst.gitlab.io/](https://gwburst.gitlab.io/))**

Time-domain data preprocessed

Wavelet decomposition

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

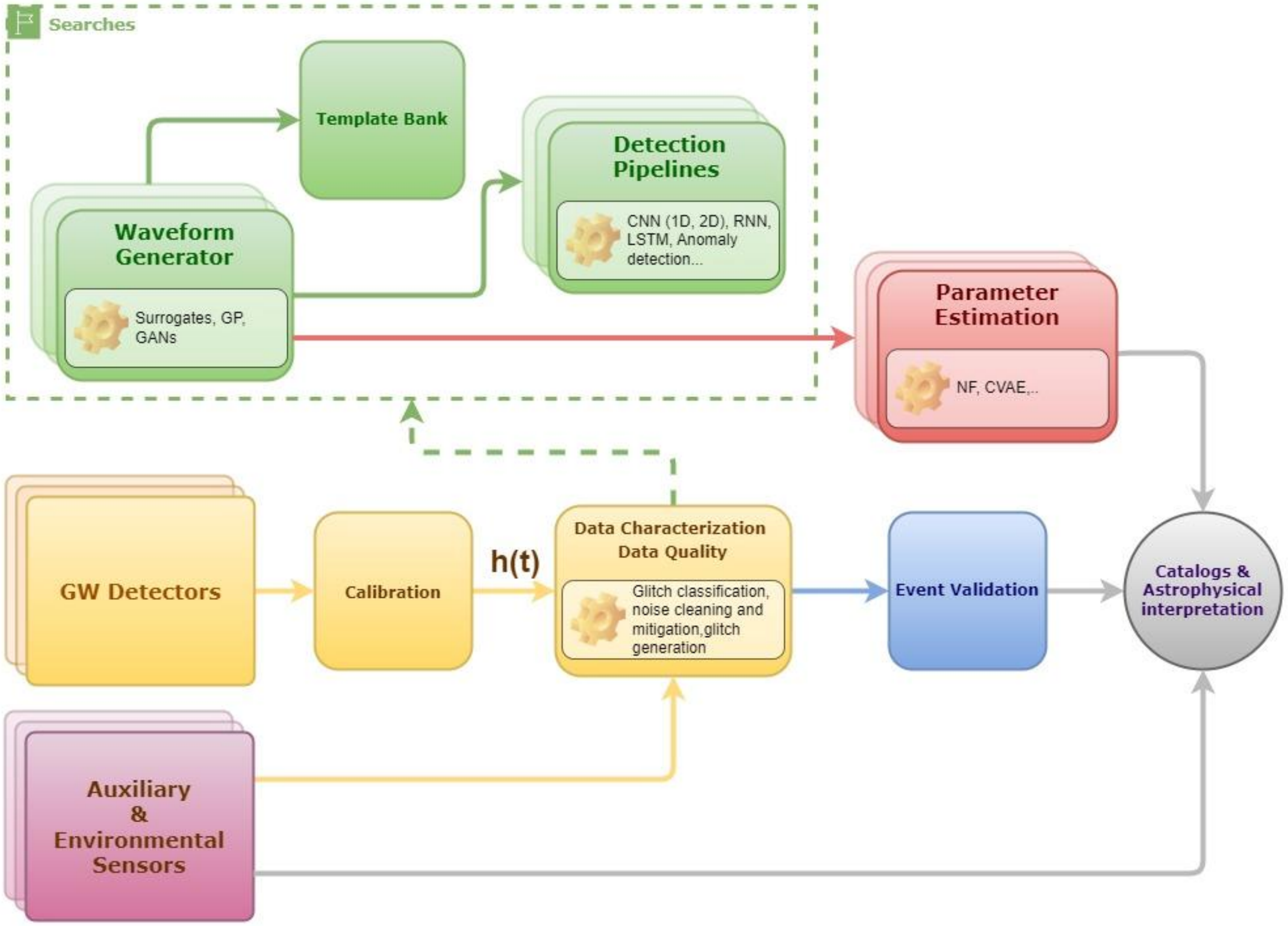
Phys. Rev. D 93, 042004 (2016)
Class.Quant.Grav.25:114029,2008

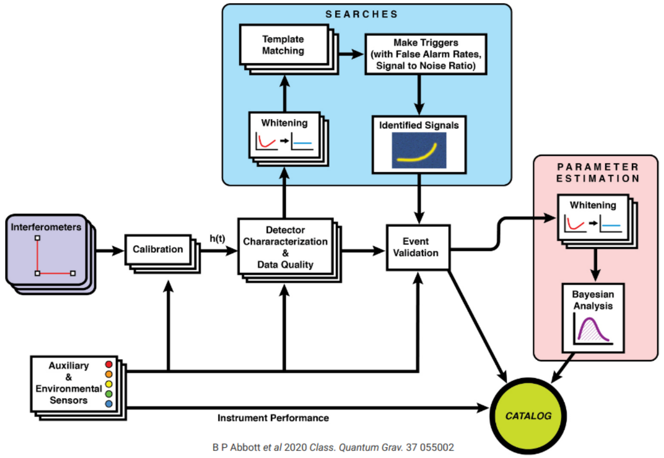
# AI APPLICATIONS FOR GW

## LIMITED EXAMPLES

Read more…
E. Cuoco *et al* 2021 *Mach. Learn.: Sci. Technol.* **2** 011002
E. Cuoco *et al* *Living Review in Relativity*, submitted

# THE DATA ANALYSIS WORKFLOW AND AI




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

E. Cuoco, M. Cavaglià, Ik. S. Heng, D. Keitel. C. Messenger, Living Review in Relativity, submitted

# GRAVITATIONAL WAVE SCIENCE AND AI

### NOISE

- Data cleaning
- Glitch classification
- Nonlinear noise
- ITF anomaly detection
- Glitch simulation

### BURST

- ML-based method for detection
- CCSN waveform classification

### CBC

- Detection
- Early warning
- Anomaly detection

### CW

- Clustering in the parameter space
- Computing efficiency

### SWBG

- Noise correlation

### PARAMETER ESTIMATION

- Faster and efficient methods

### ALERT SYSTEM

- Ad hoc hardware/software solution?

E. Cuoco, M. Cavaglià, Ik. S. Heng, D. Keitel. C. Messenger, Living Review in Relativity, submitted

# GWS FROM CORE COLLAPSE SUPERNOVAE

Waveform depends on progenitor star

Rare (~100 yrs in Milky Way)

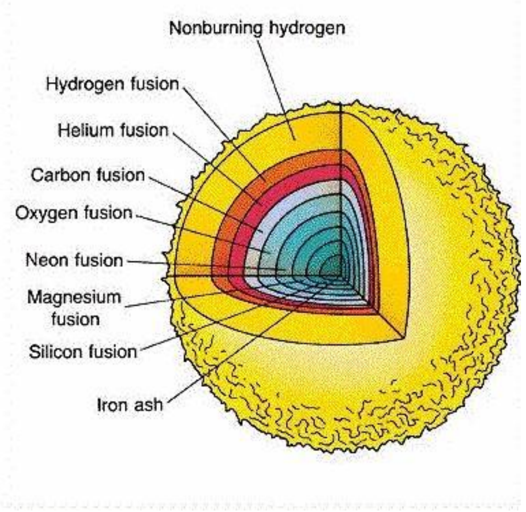
Different emission mechanisms (Proto-neutron star oscillation, Standing Accretion Shock Instability (SASI),..)

Largely Stochastic

Different simulation models

Best waveform models from computationally expensive 3D simulations

**Need an alternative to matched filter approach**

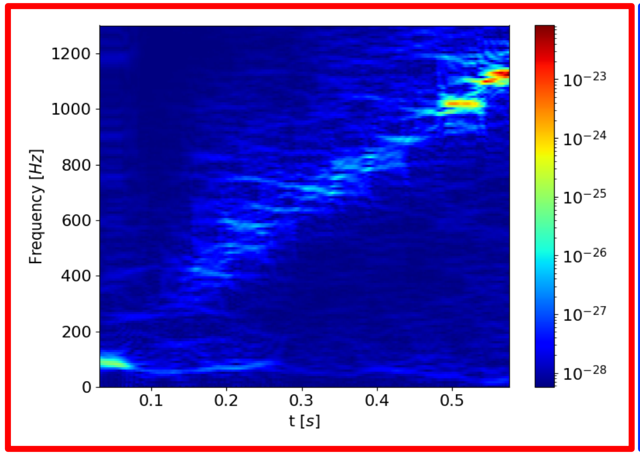


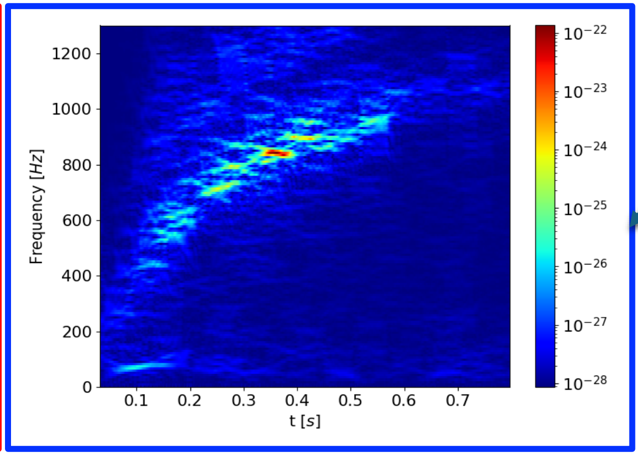

Ott et al. (2017)

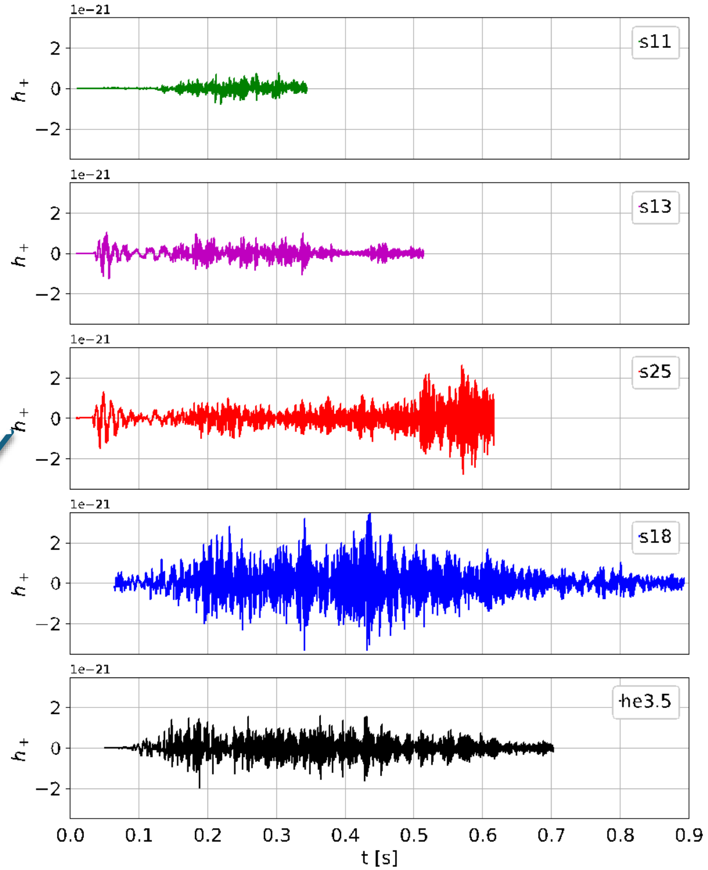
| GW emission Process | Potential explosion mechanism: MHD mechanism (rapid rotation) | Neutrino mechanism (slow/no rotation) | Acoustic mechanism (slow/no rotation) |
|---|---|---|---|
| Rotating collapse and Bounce | Strong | None/weak | None/weak |
| 3D rotational instabilities | Strong | None | None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

# 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

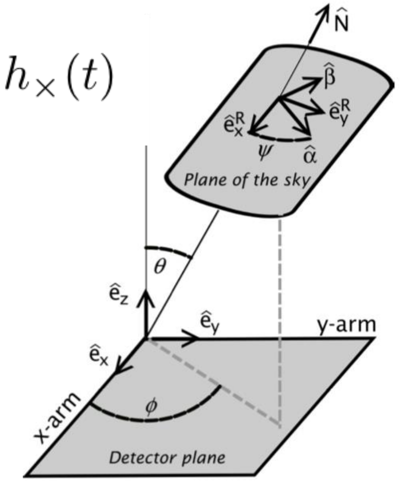
# MDC AND CCSN GW SIMULATIONS

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

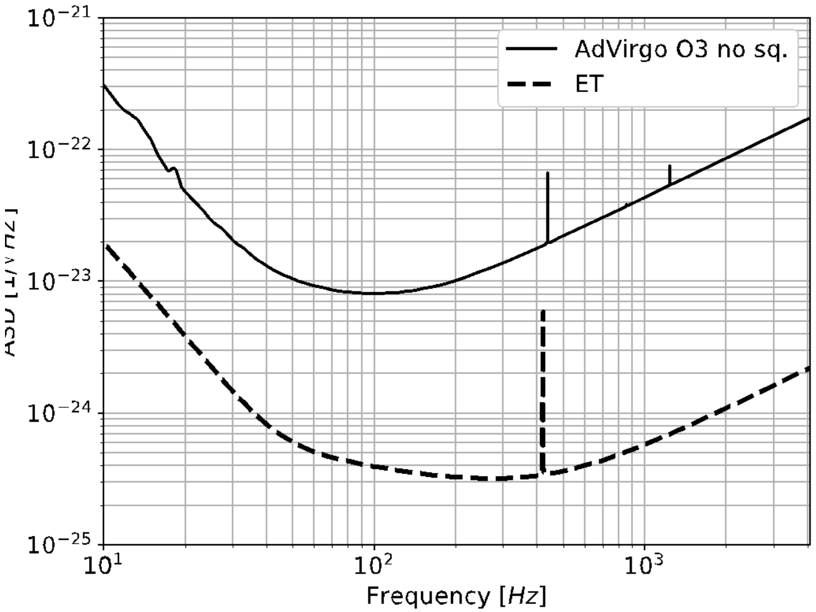
Distances:
**VO3** 0.01 kpc to 10 kpc
**ET** 0.1 kpc to 1000 kpc

Random sky localization

Large SNR range



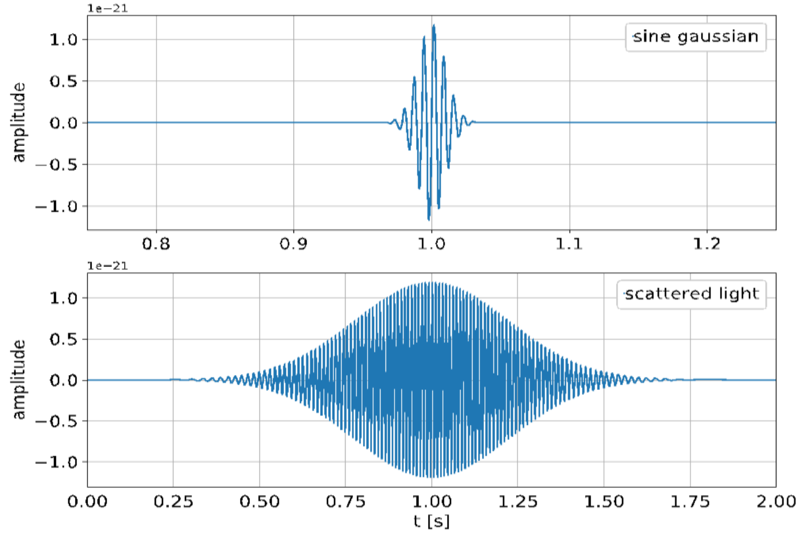

Schutz (2011)




## SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

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

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

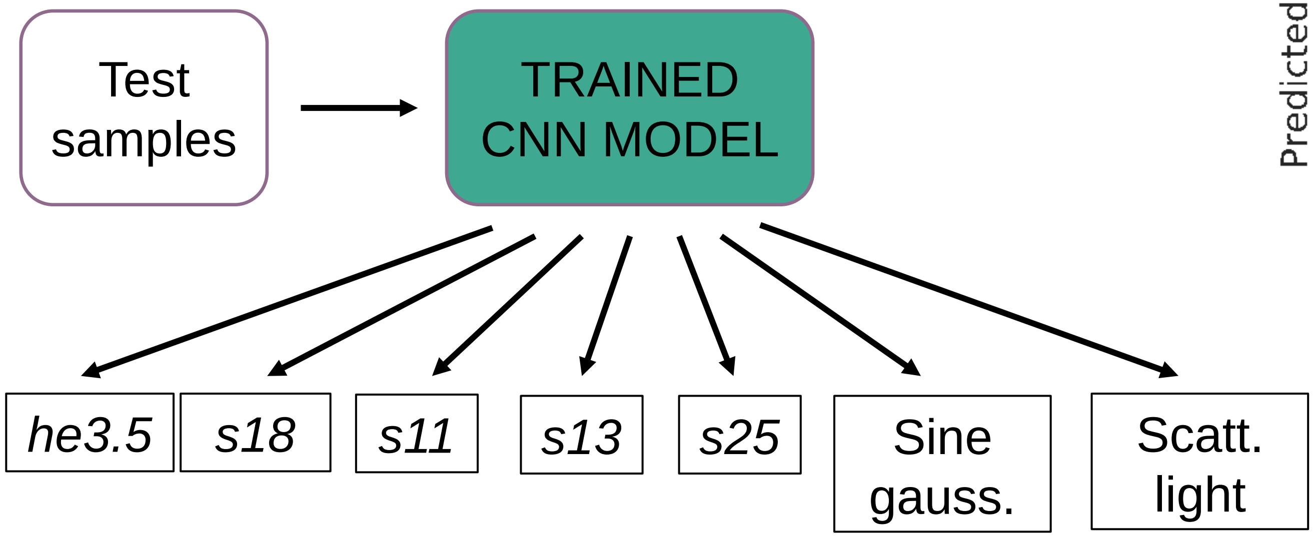



**BACKGROUND STRAIN** : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

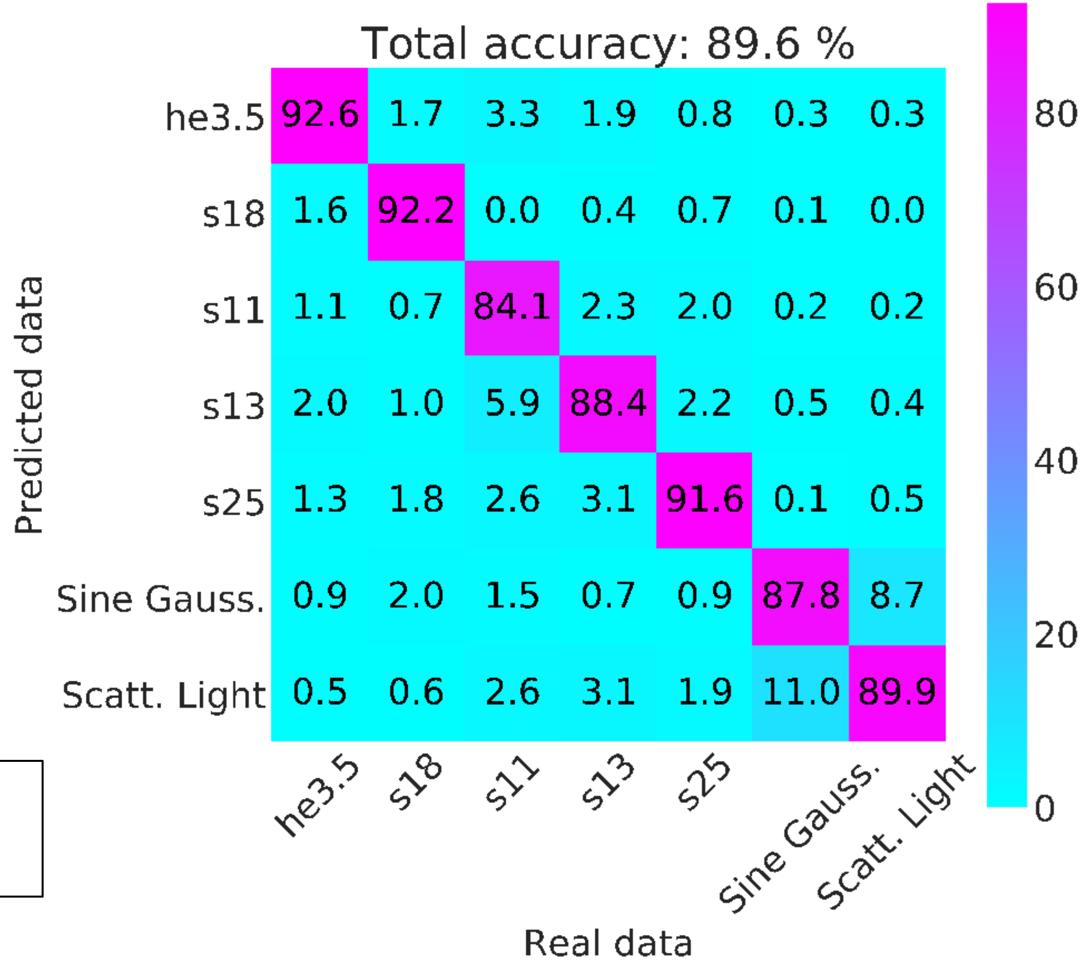
# MULTILABEL CLASSIFICATION

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.

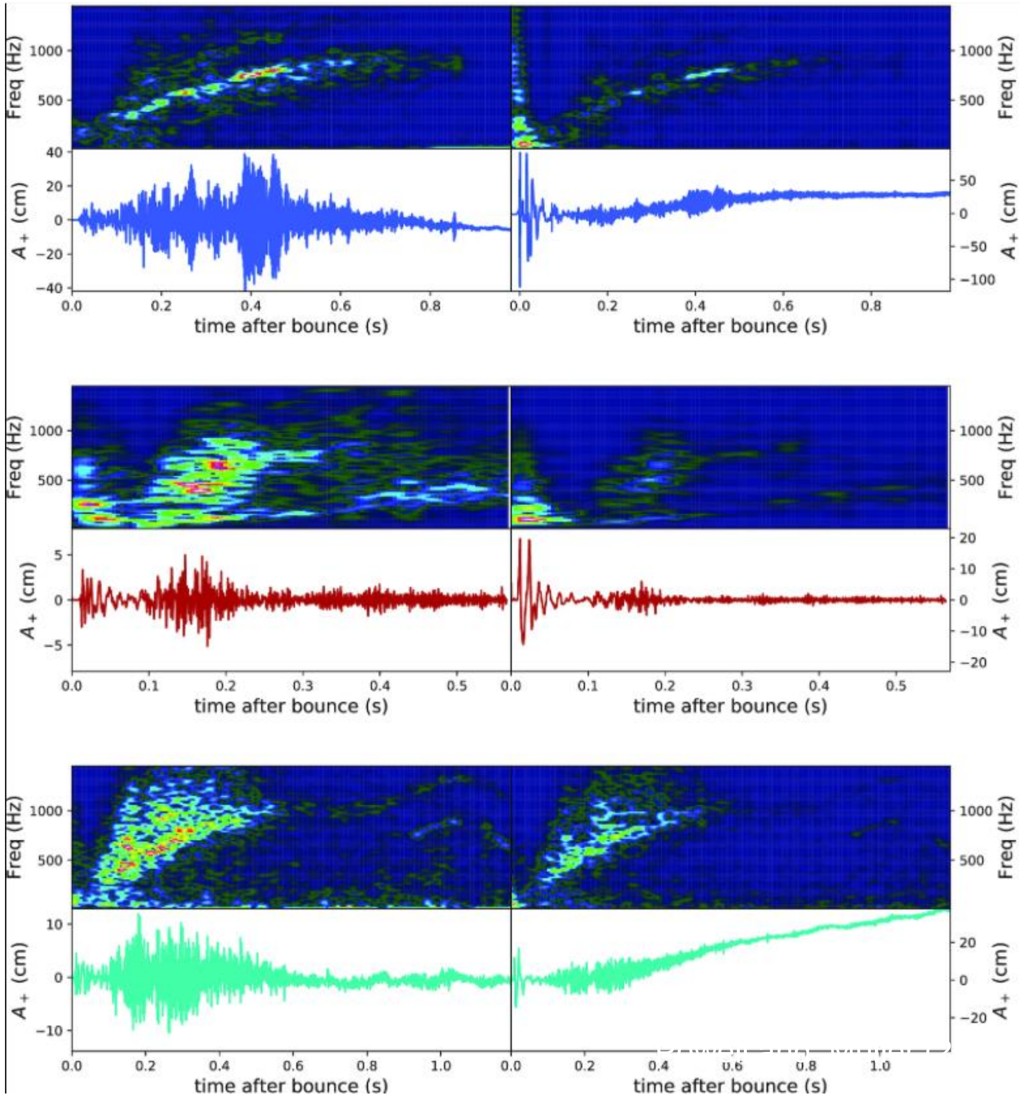
Added LSTM Networks, suited for time series data.

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.

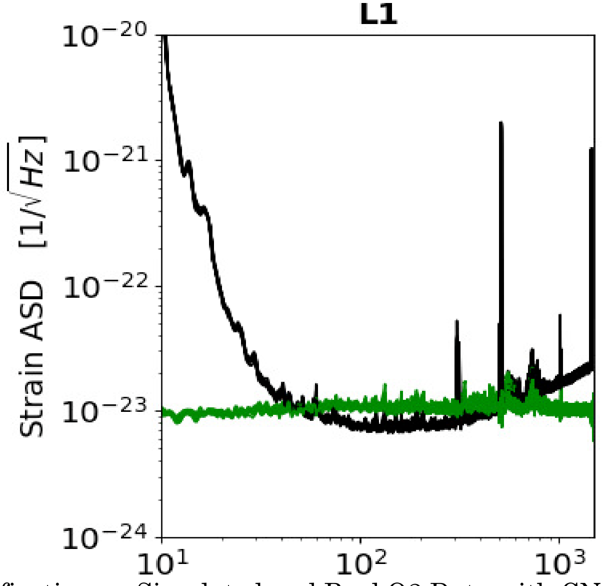
*Powell m39*: rapidly rotating Wolf-Rayet star with an initial helium star mass of 39 solar masses

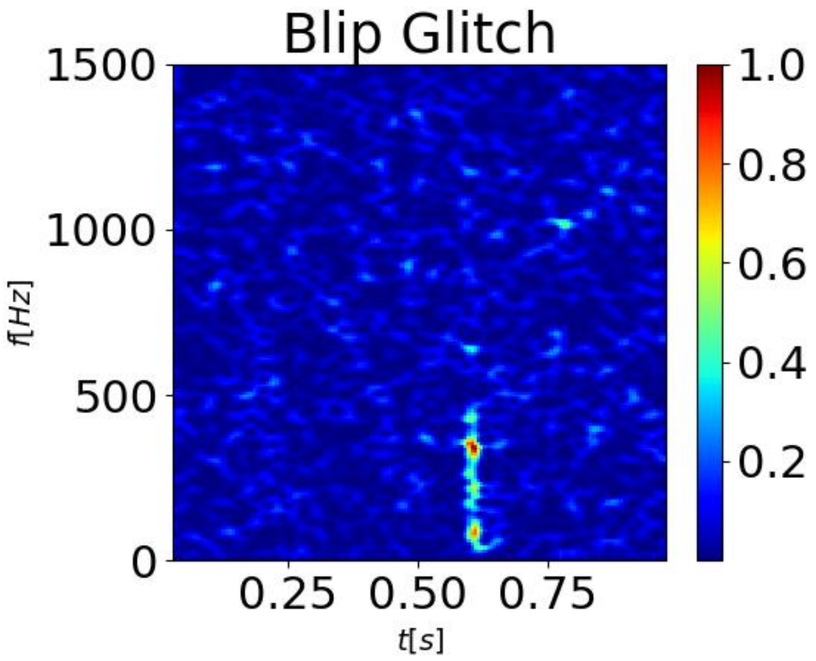


# REAL NOISE FROM O2 SCIENCE RUN

- 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 |

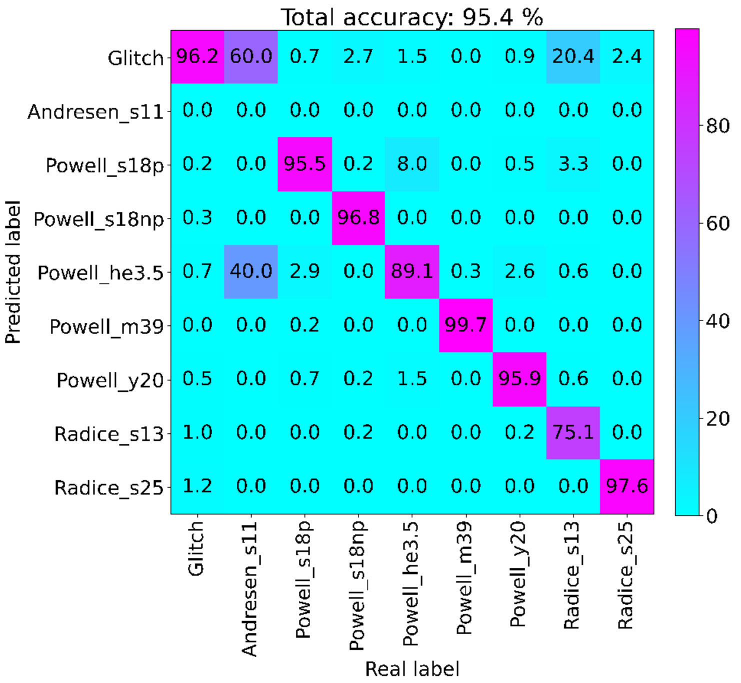


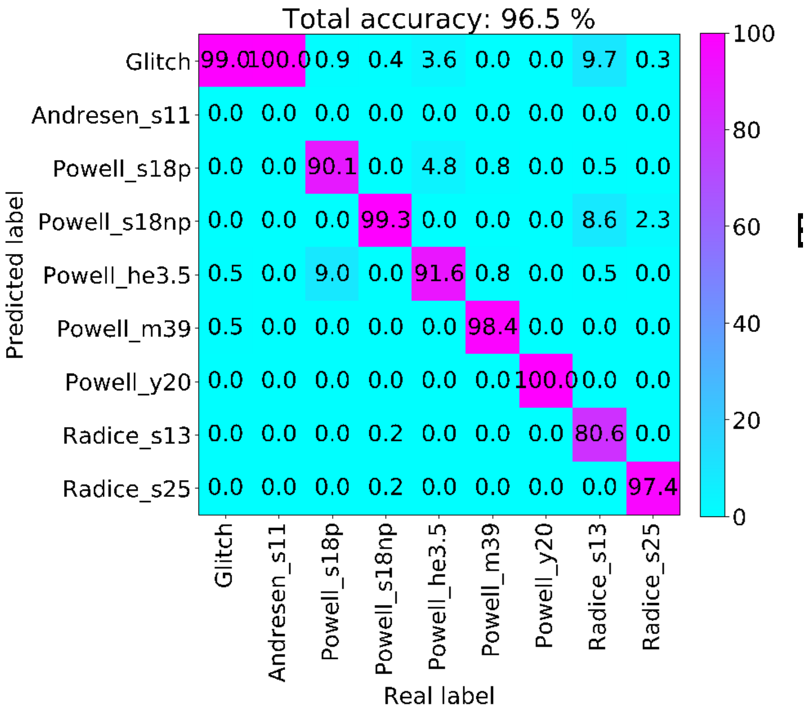

CCSN Classification on Simulated and Real O2 Data with CNNs and LSTMs
***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)*

# MULTI-LABEL TASK

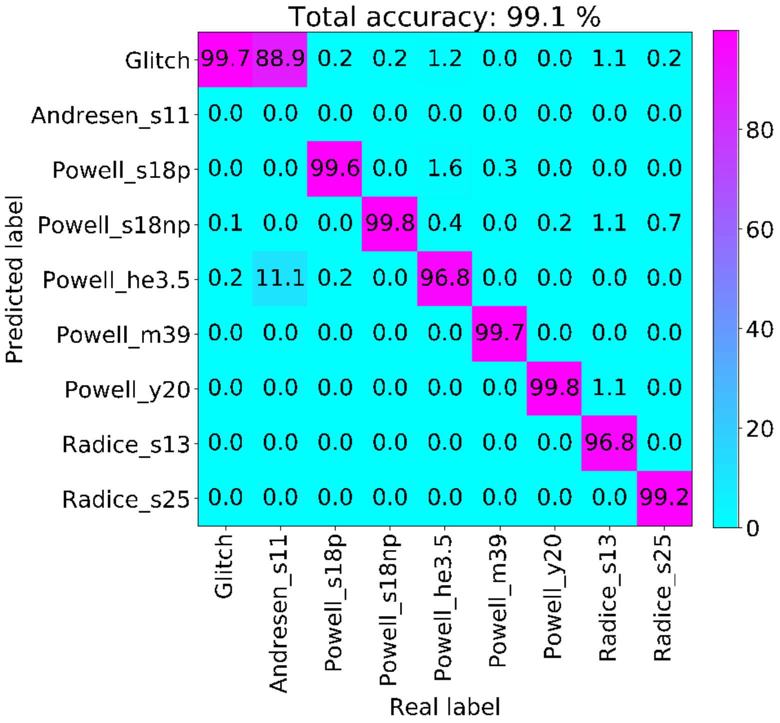
- **Bi-LSTM**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs




- **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

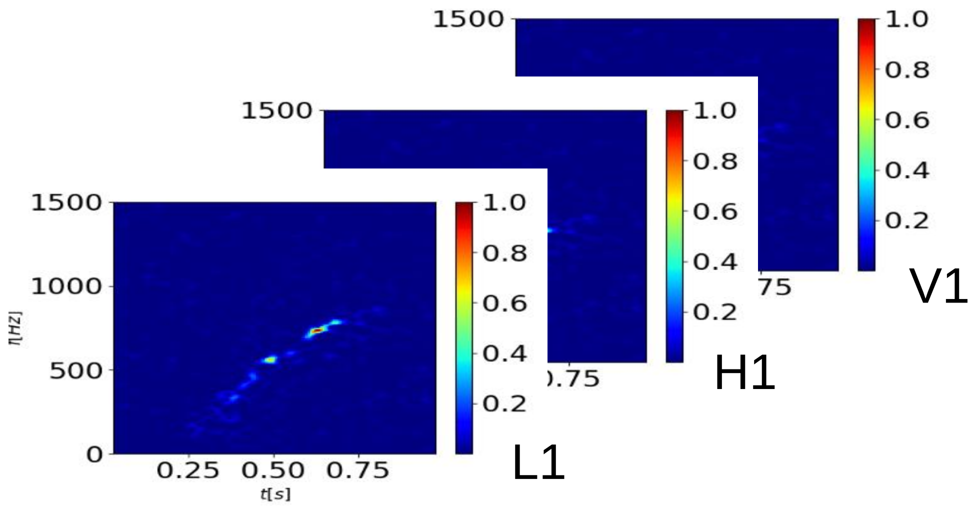


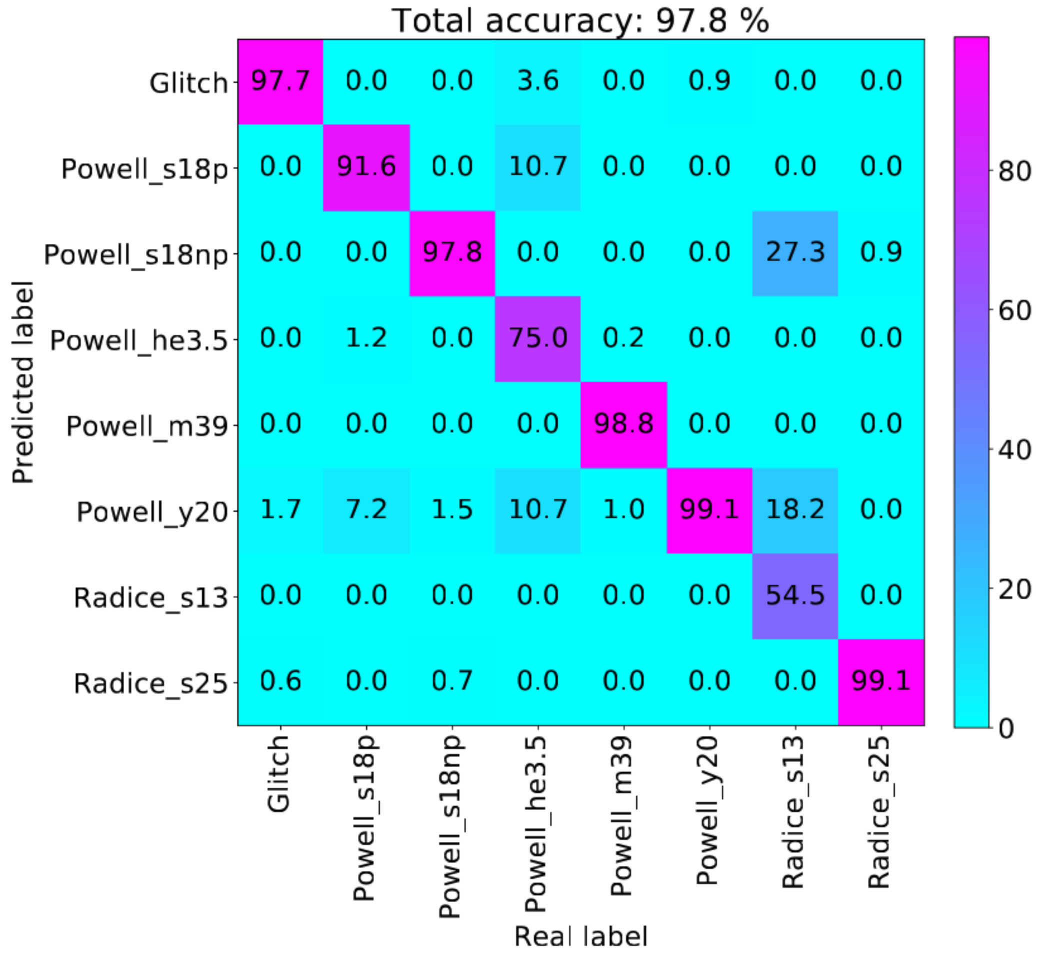

A. Iess, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)

# 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.

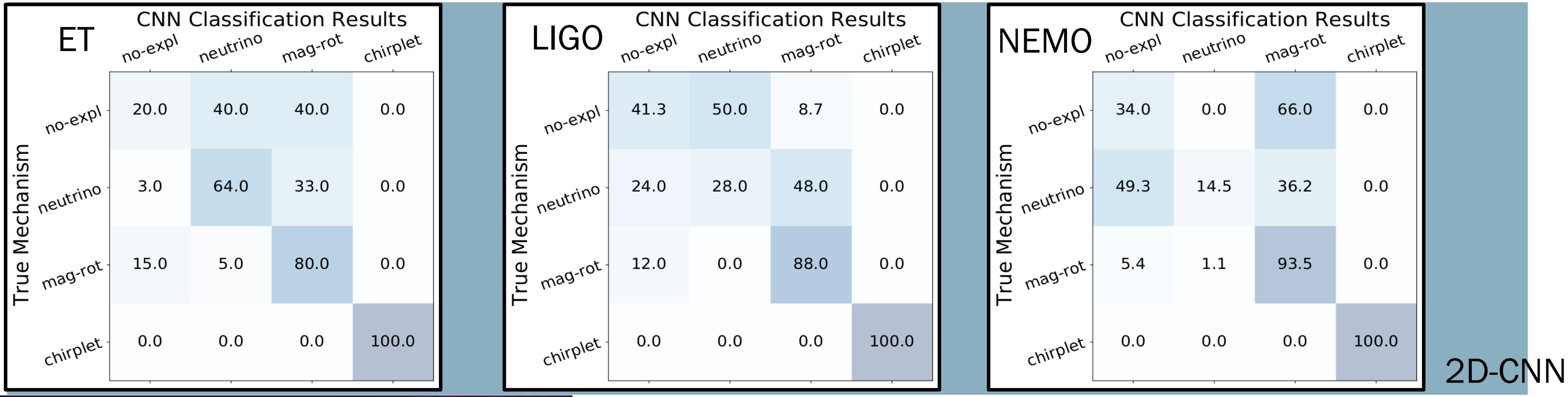
Input to NNs have additional dimension (ITF)

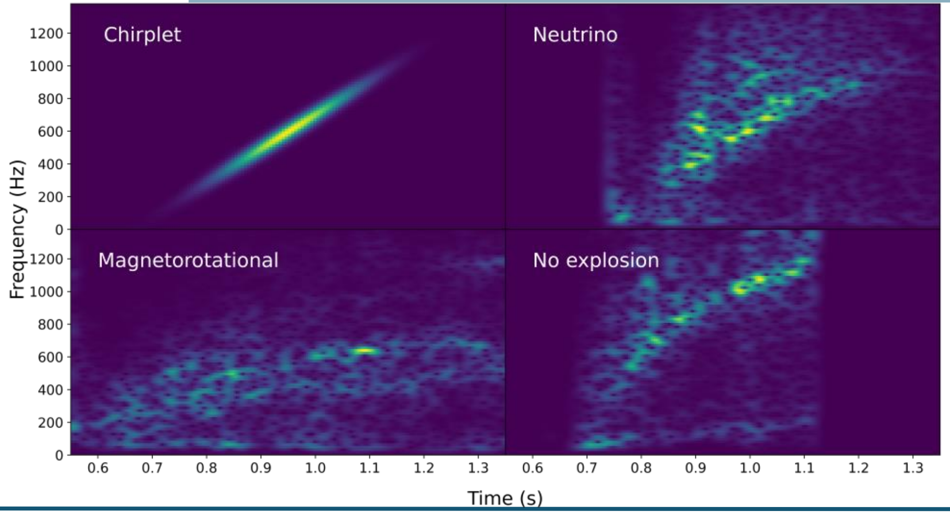



**A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)

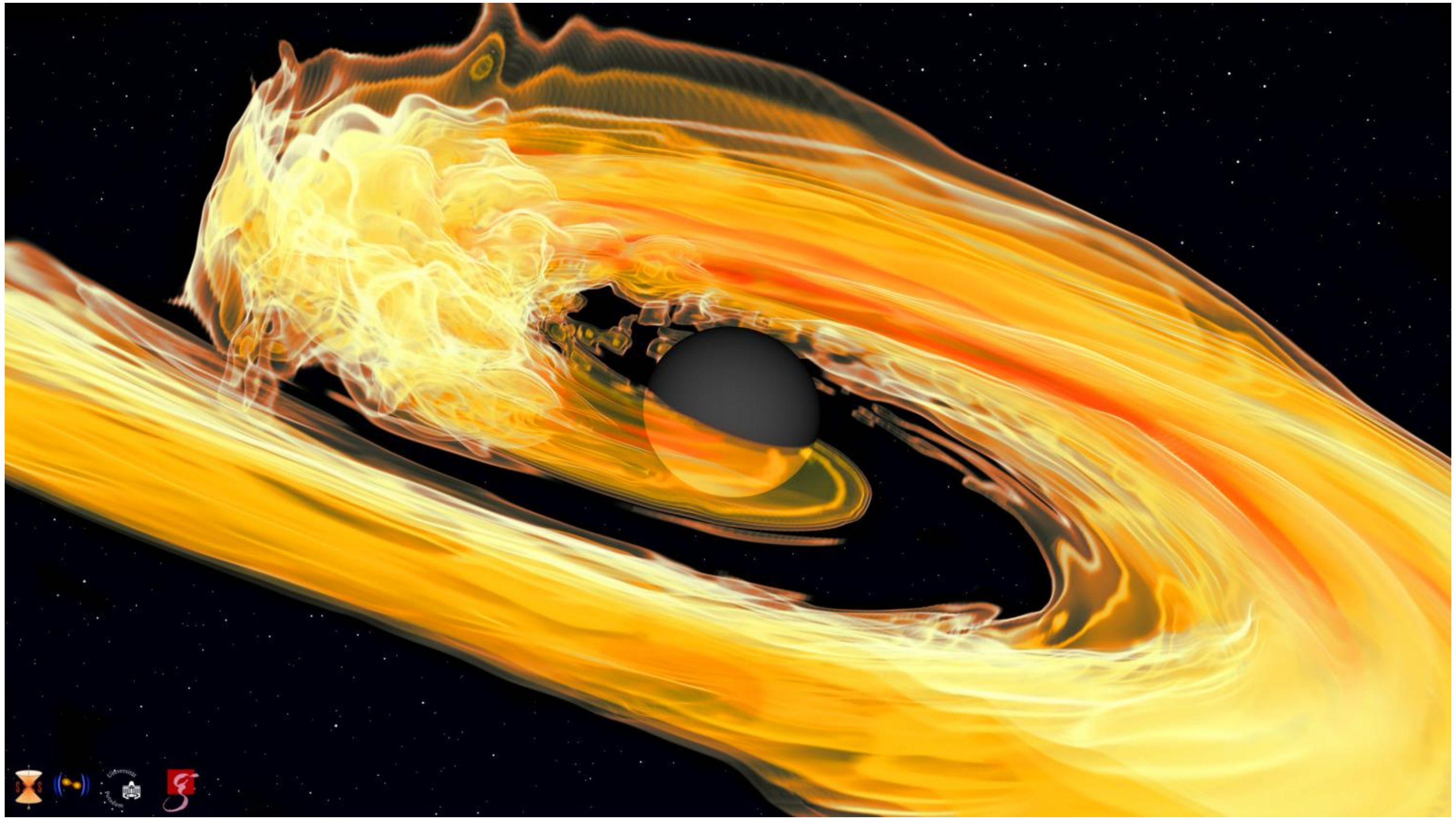
# DETERMINING THE CORE-COLLAPSE SUPERNOVA EXPLOSION MECHANISM




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.* 11 2023, 2311.18221, accepted for publication on PRD

# 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?

# WAVEFORM BUILDING

- Gaussian process regression 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.

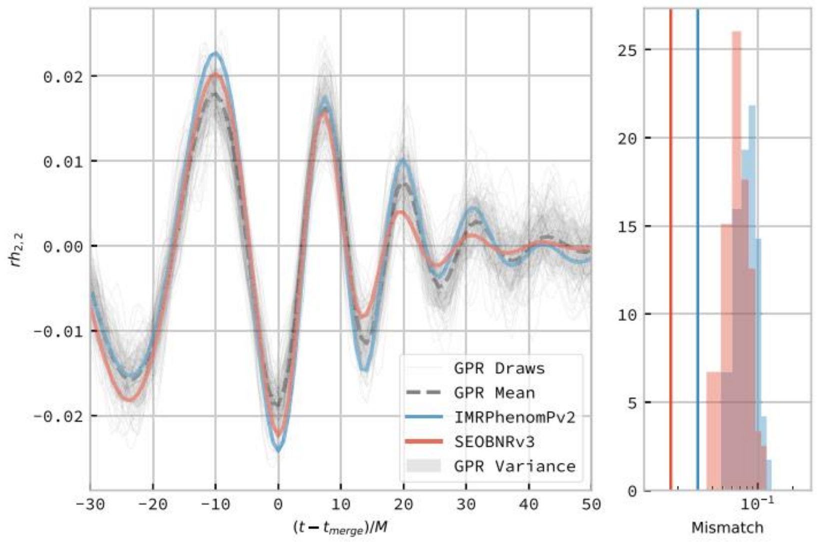
PHYSICAL REVIEW D **101,** 063011 (2020)

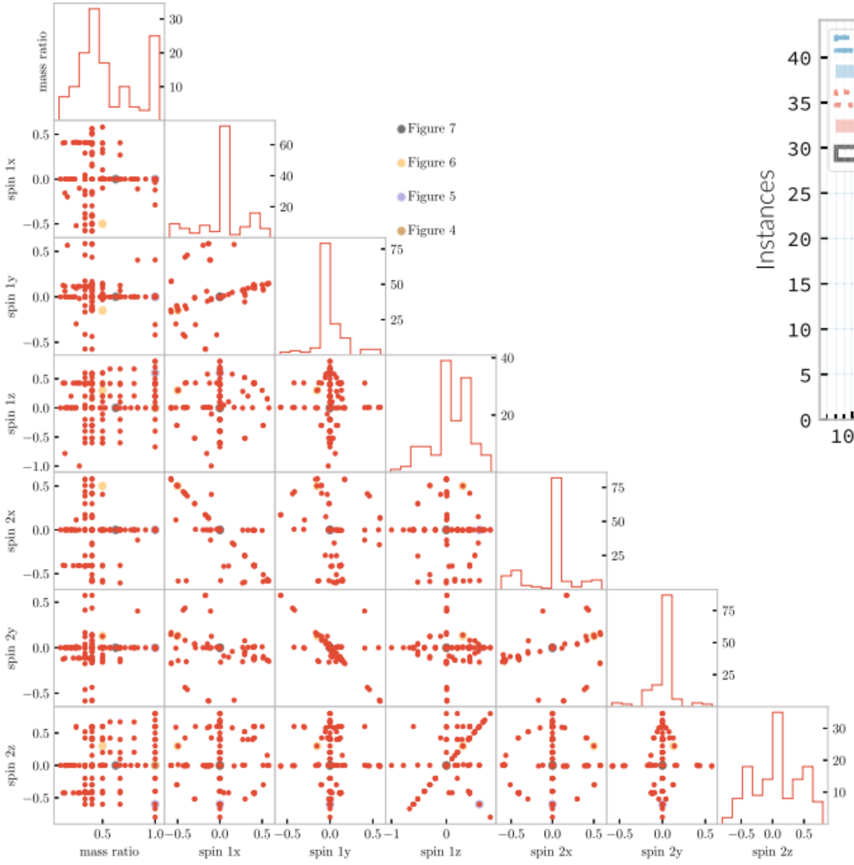
**Precessing numerical relativity waveform surrogate model for binary black holes: A Gaussian process regression approach**

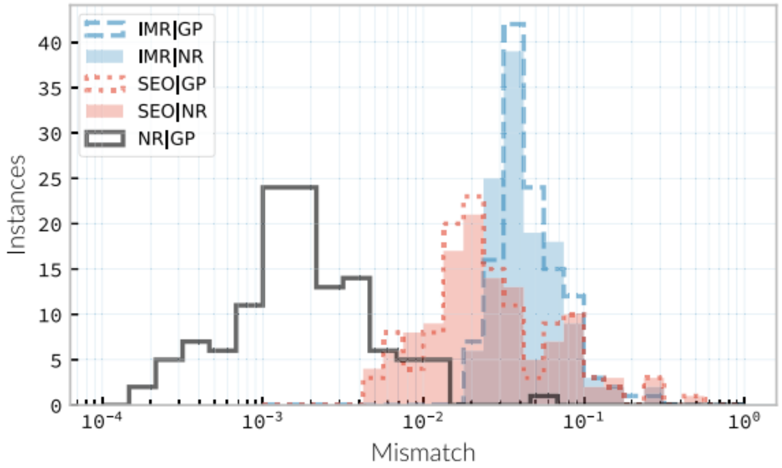
D. Williams* and I. S. Heng
*SUPA, University of Glasgow, Glasgow G12 8QQ, United Kingdom*

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)

# CBC DETECTION

Deep convolutional neural network to search for binary black hole gravitational-wave signals.

Input is the whitened time series of measured gravitational-wave strain in Gaussian noise.

Sensitivity comparable to match filtering.

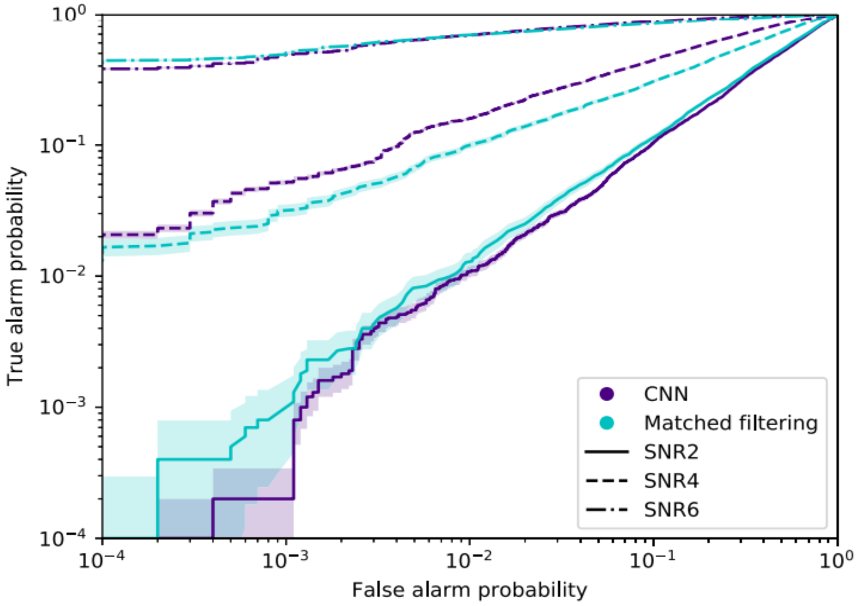
PHYSICAL REVIEW LETTERS 120, 141103 (2018)

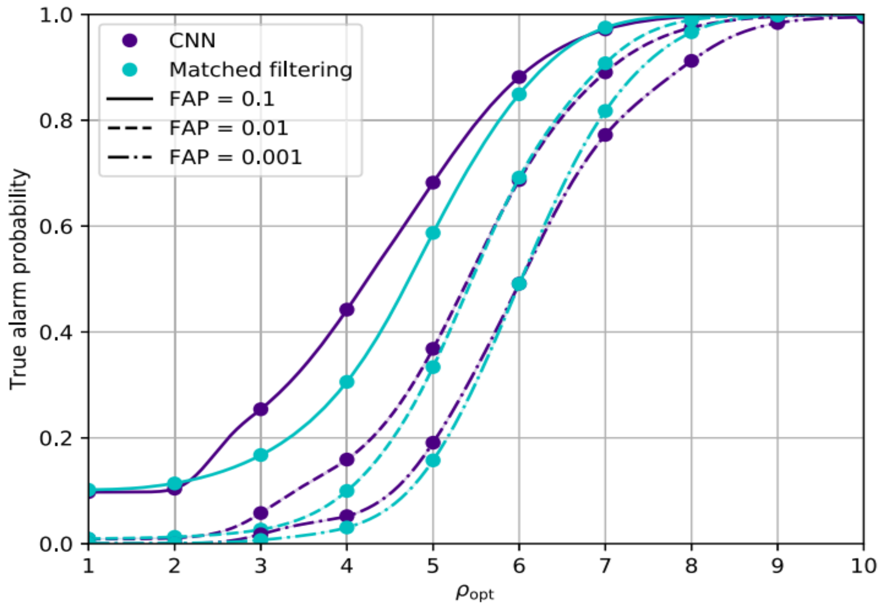
Editors' Suggestion

**Matching Matched Filtering with Deep Networks for Gravitational-Wave Astronomy**

Hunter Gabbard,[*] Michael Williams, Fergus Hayes, and Chris Messenger

*SUPA, School of Physics and Astronomy, University of Glasgow, Glasgow G12 8QQ, United Kingdom*



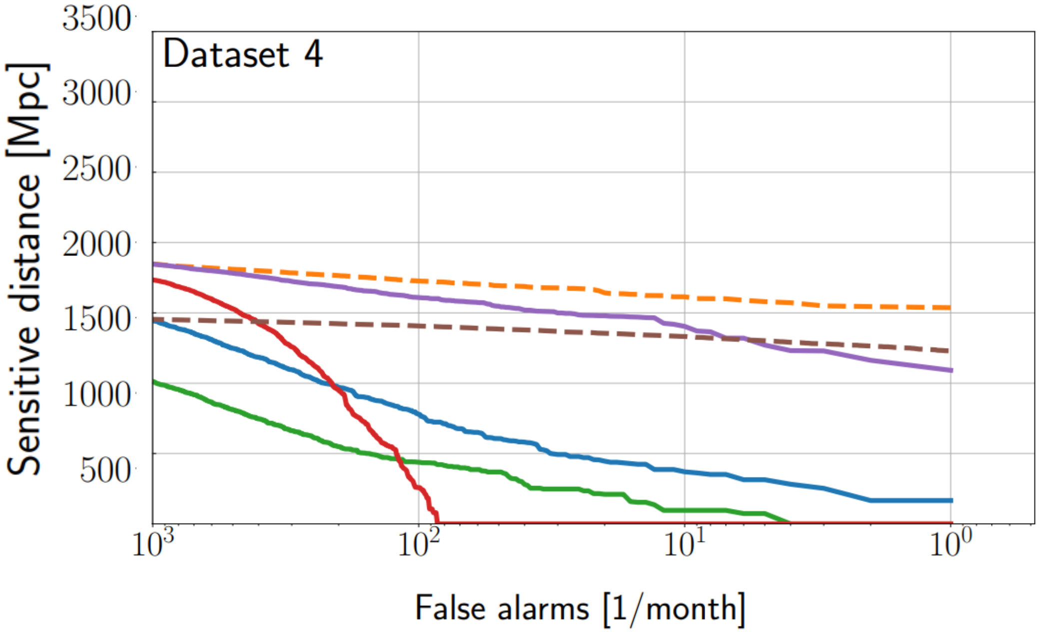

See also:

D. George and E.A. Huerta Phys. Lett. B 778 64–70 (2018)

# CBC DETECTION

**MLGWSC-1: The first Machine Learning Gravitational-Wave Search Mock Data Challenge**

Marlin B. Schäfer[1,2], Ondřej Zelenka[3,4], Alexander H. Nitz[1,2], He Wang[5], Shichao Wu[1,2], Zong-Kuan Guo[5], Zhoujian Cao[6], Zhixiang Ren[7], Paraskevi Nousi[8], Nikolaos Stergioulas[9], Panagiotis Iosif[10,9], Alexandra E. Koloniari[9], Anastasios Tefas[8], Nikolaos Passalis[8], Francesco Salemi[11,12], Gabriele Vedovato[13], Sergey Klimenko[14], Tanmaya Mishra[14], Bernd Brügmann[3,4], Elena Cuoco[15,16,17], E. A. Huerta[18,19], Chris Messenger[20], Frank Ohme[1,2]




- Comparison of 6 algorithms for binary black hole searches.
- Four different data sets of different complexity (from Gaussian noise to varying real detector PSD)
- Benchmark data set for algorithm testing.

A few excerpts from the paper conclusions:

- Machine learning search algorithms are competitive in sensitivity compared to state-of-the-art searches on simulated data and the limited parameter space explored in this challenge.
- Most of the tested machine learning algorithms struggle to effectively handle real noise, which is contaminated with non-Gaussian noise artifacts.
- Traditional search algorithms are capable of detecting signals at lower FARs, thus making detections more confident.
- The tested machine learning searches struggle to identify long duration signals.

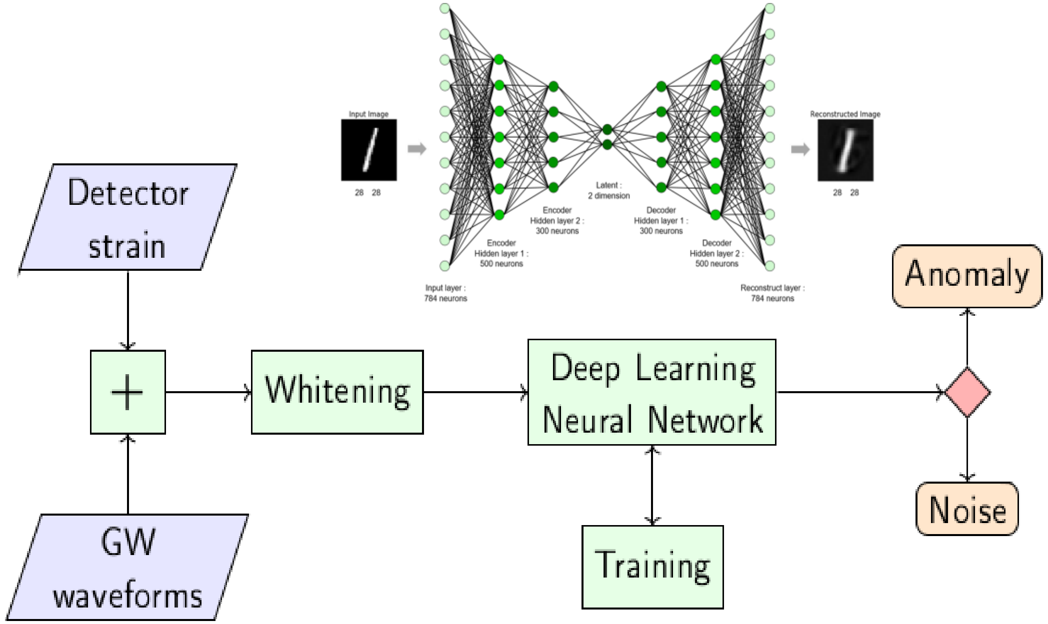
# EXAMPLE FOR DETECTION/CLASSIFICATION FOR CBC SIGNALS: ANOMALY DETECTION

## AUTO-ENCODER WORKFLOW

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

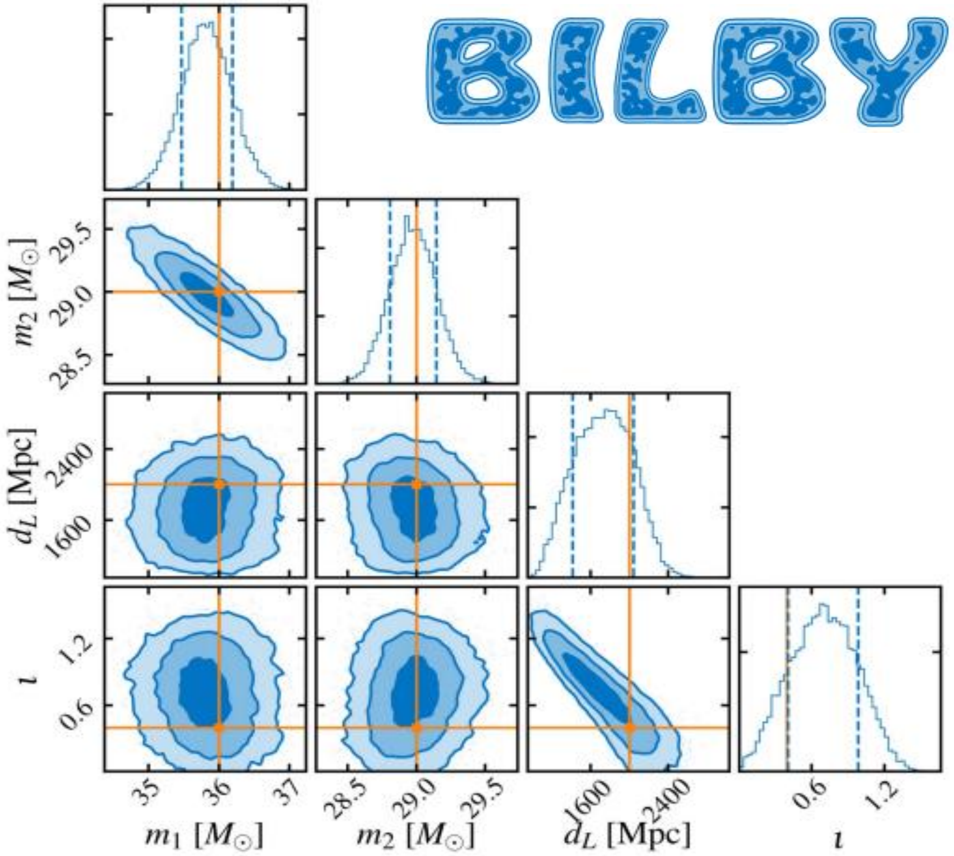


# ASTROPHYSICAL INTERPRETATION OF GW SOURCES

The Astrophysical Journal Supplement Series, 241:27 (13pp), 2019 April https://doi.org/10.3847/1538-4365/ab06fc


**BILBY: A User-friendly Bayesian Inference Library for Gravitational-wave Astronomy**

Gregory Ashton[1,2], Moritz Hübner[1,2], Paul D. Lasky[1,2], Colm Talbot[1,2], Kendall Ackley[1,2], Sylvia Biscoveanu[1,2,3], Qi Chu[4,5], Atul Divakarla[1,2,6], Paul J. Easter[1,2], Boris Goncharov[1,2], Francisco Hernandez Vivanco[1,2], Jan Harms[7,8], Marcus E. Lower[1,9,10], Grant D. Meadors[1,2], Denyz Melchor[1,2,11], Ethan Payne[1,2], Matthew D. Pitkin[12], Jade Powell[9,10], Nikhil Sarin[1,2], Rory J. E. Smith[1,2], and Eric Thrane[1,2]




PHYSICAL REVIEW D 91, 042003 (2015)

**Parameter estimation for compact binaries with ground-based gravitational-wave observations using the LALInference software library**

J. Veitch,[1,2,*] V. Raymond,[3] B. Farr,[4,5] W. Farr,[1] P. Graff,[6] S. Vitale,[7] B. Aylott,[1] K. Blackburn,[3] N. Christensen,[8] M. Coughlin,[9] W. Del Pozzo,[1] F. Feroz,[10] J. Gair,[11] C.-J. Haster,[1] V. Kalogera,[5] T. Littenberg,[5] I. Mandel,[1] R. O'Shaughnessy,[12,13] M. Pitkin,[14] C. Rodriguez,[5] C. Röver,[15,16] T. Sidery,[1] R. Smith,[3] M. Van Der Sluys,[17] A. Vecchio,[1] W. Vousden,[1] and L. Wade[12]

Publications of the Astronomical Society of the Pacific, 131:024503 (16pp), 2019 February https://doi.org/10.1088/1538-3873/aaef0b


**PyCBC Inference: A Python-based Parameter Estimation Toolkit for Compact Binary Coalescence Signals**

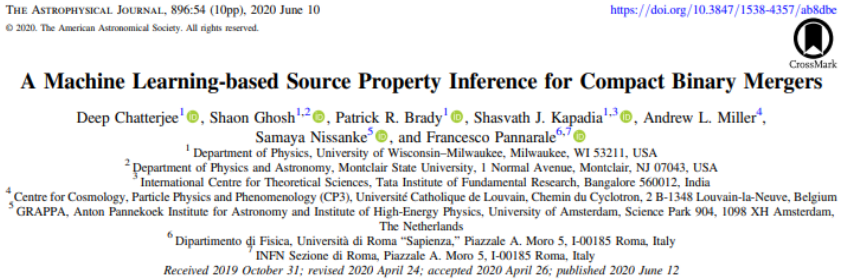
C. M. Biwer[1,2], Collin D. Capano[3], Soumi De[2], Miriam Cabero[3], Duncan A. Brown[2], Alexander H. Nitz[3], and V. Raymond[4,5]

**Rapid and accurate parameter inference for coalescing, precessing compact binaries**

J. Lange,[1] R. O'Shaughnessy,[1] and M. Rizzo[1]
[1]*Center for Computational Relativity and Gravitation, Rochester Institute of Technology, Rochester, New York 14623, USA*

- Current parameter estimation techniques for compact binary coalesce signals rely on Bayesian analysis (posteriors + evidence).
- Computationally costly!
- Need to dramatically speed up the process!
- How can machine learning help?

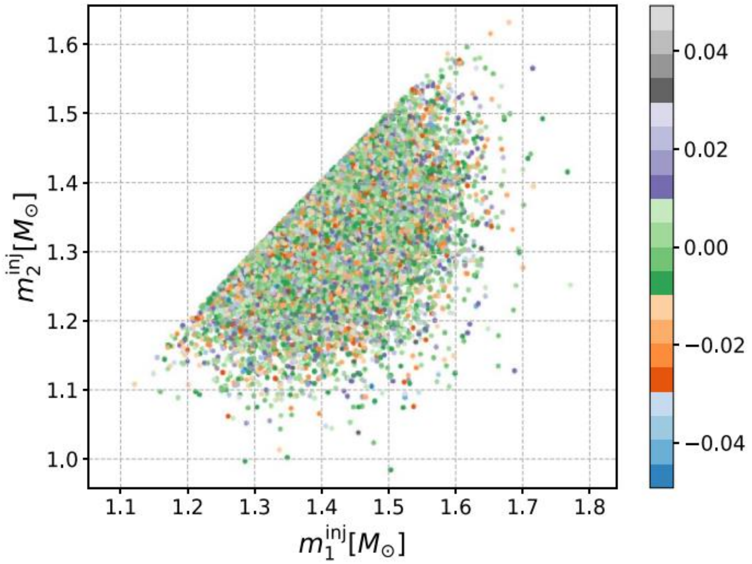
# RAPID INFERENCE OF SOURCE PARAMETERS


THE ASTROPHYSICAL JOURNAL, 896:54 (10pp), 2020 June 10 https://doi.org/10.3847/1538-4357/ab8dbe

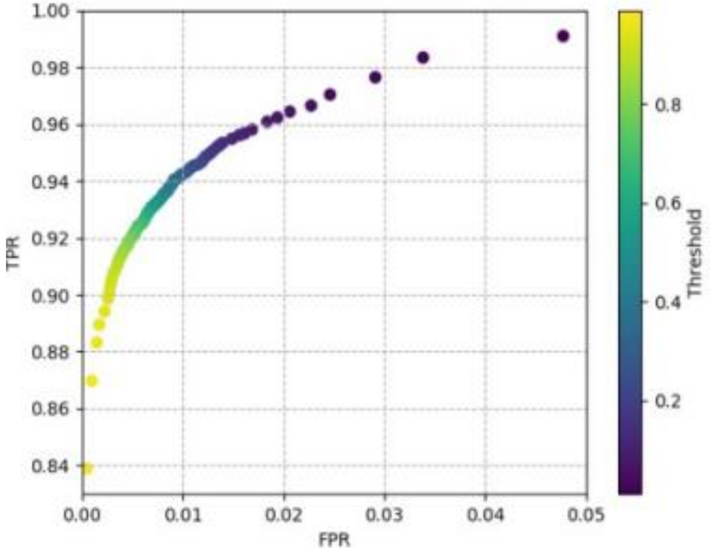

**A Machine Learning-based Source Property Inference for Compact Binary Mergers**

Deep Chatterjee[1], Shaon Ghosh[1,2], Patrick R. Brady[1], Shasvath J. Kapadia[1,3], Andrew L. Miller[4], Samaya Nissanke[5], and Francesco Pannarale[6,7]
[1] Department of Physics, University of Wisconsin–Milwaukee, Milwaukee, WI 53211, USA
[2] Department of Physics and Astronomy, Montclair State University, 1 Normal Avenue, Montclair, NJ 07043, USA
[3] International Centre for Theoretical Sciences, Tata Institute of Fundamental Research, Bangalore 560012, India
[4] Centre for Cosmology, Particle Physics and Phenomenology (CP3), Université Catholique de Louvain, Chemin du Cyclotron, 2 B-1348 Louvain-la-Neuve, Belgium
[5] GRAPPA, Anton Pannekoek Institute for Astronomy and Institute of High-Energy Physics, University of Amsterdam, Science Park 904, 1098 XH Amsterdam, The Netherlands
[6] Dipartimento di Fisica, Università di Roma "Sapienza," Piazzale A. Moro 5, I-00185 Roma, Italy
[7] INFN Sezione di Roma, Piazzale A. Moro 5, I-00185 Roma, Italy
*Received 2019 October 31; revised 2020 April 24; accepted 2020 April 26; published 2020 June 12*

- Classifiers (Kneighbors, genetic, random forests) for HasNS and HasRemnant properties of sources in low-latency
- Train and test on LIGO-Virgo online MDC
- Integrate in the LVK low-latency infrastructure and run in O4




| O3 event | p(HasNS) | p(HasRemnant) |
|---|---|---|
| GW190425 | 0.999 | 0.9959 |
| GW190426 | 0.9676 | 0.0029 |
| GW190421 | 0.0057 | 0.0012 |
| GW190915 | 0.0057 | 0.0012 |
| GW200115 | 0.967 | 0.0029 |
| GW20012 | 0.0057 | 0.0012 |



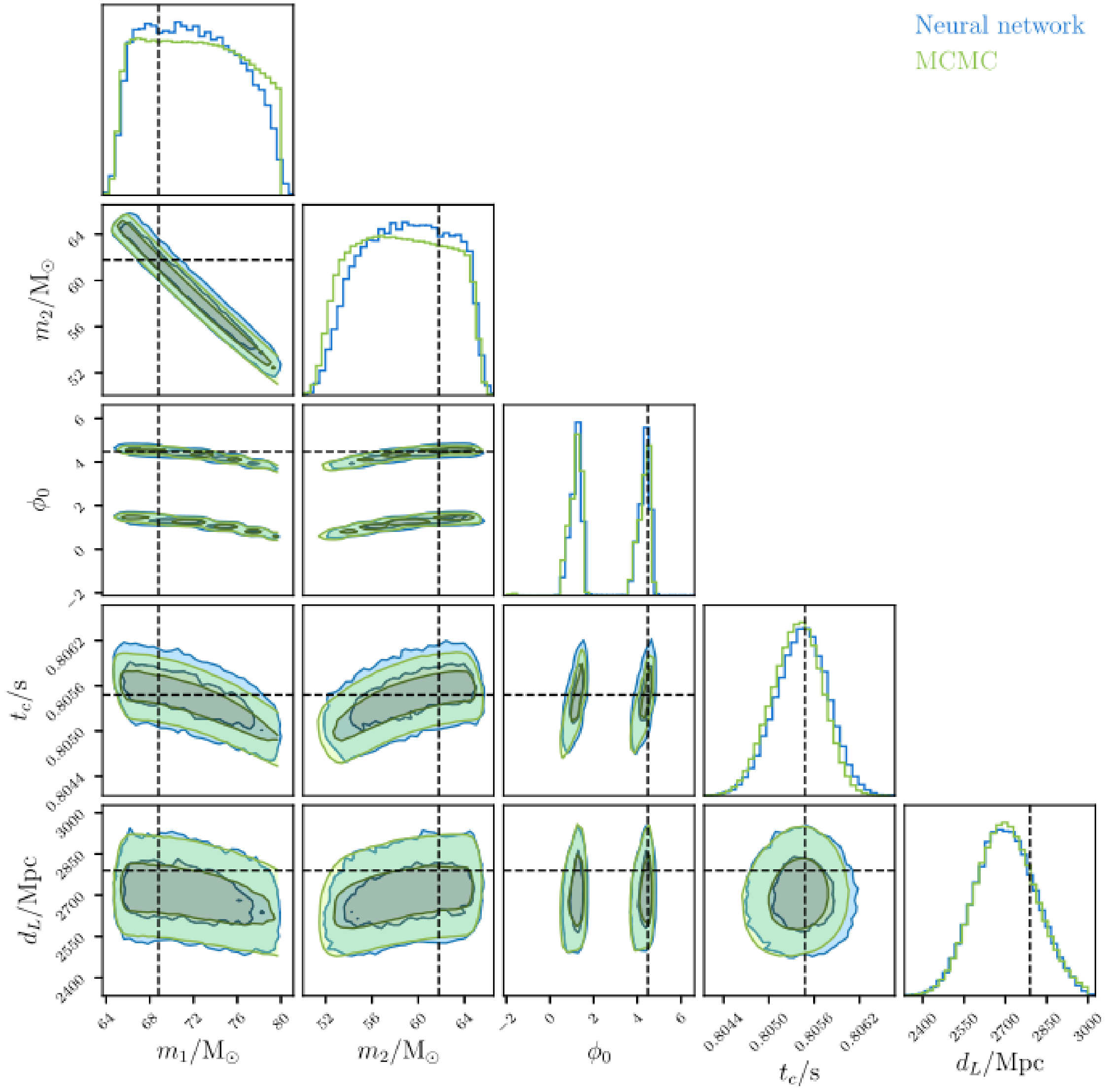
# PARAMETER ESTIMATION

PHYSICAL REVIEW D **102,** 104057 (2020)

**Gravitational-wave parameter estimation with autoregressive neural network flows**

Stephen R. Green,[1,*] Christine Simpson,[2,†] and Jonathan Gair[1,‡]

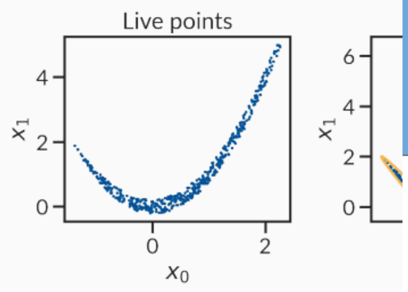
- Autoregressive normalizing flows for rapid likelihood-free inference of binary black hole system parameters.
- Maps a multivariate standard normal distribution into the posterior distribution of system parameters.
- Performance comparable to Markov chain Monte Carlo.



## nessai

**nessai:** Nested Sampling with Artificial Intelligence

**Core idea:** train a normalising flow to learn likelihood contou
sample directly from those contours to produce new sample




M. J. Williams - LVK September 2022

## Deep Learning for LIGO's Lock Acquisition

Machine Learning for non-linear dynamic controls.

Peter Ma | Supervisor: Dr. Gabriele Vajente

## Rapid localization of gravitational wave sources from compact binary coalescences using deep learning


Chayan Chatterjee,* Linqing Wen,† and Damon Beveridge‡
Department of Physics, OzGrav-UWA, The University of Western Australia, 35 Stirling Hwy, Crawley, Western Australia 6009, Australia

Foivos Diakogiannis§
The Commonwealth Scientific and Industrial Research Organisation 7 Conlon St, Waterford, WA, Australia

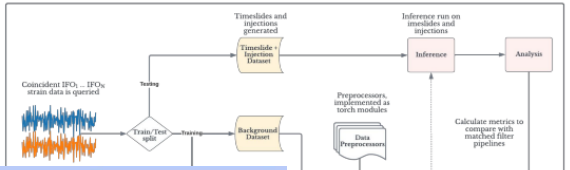
Kevin Vinsen¶
International Centre for Radio Astronomy Research, The University of Western Australia M468, 35 Stirling Hwy, Crawley, WA, Australia

(Dated: July 21, 2022)

## A Machine Learning Software Infrastructure for Gravitational Wave Signal Discovery


Ethan Marx


**How can ML detection algorithms achieve results comparable to matched filter**




## A convolutional neural network to distinguish glitches from minute-long gravitational wave bursts


Vincent Boudart

PhD student
University of Liège, Belgium


## GRITS: Genetic Rapid Inference for Trigger Sources

A machine learning algorithm to identify GW signals with EM counterpart


Sushant Sharma Chaudhary[1], Marco Cavaglia[1], Deep Chatterjee[2], Shaon Ghosh[3]
[1]Missouri University of Science and Technology,
[2]Center for AstroPhysical Surveys, NCSA, University of Illinois Urbana-Champaign, [3]Montclair State University


IFAE EGO

## Searches for Compact Binary Coalescence Events using Neural Networks in LIGO/Virgo Third Observation Period


M. Andrés-Carcasona[1], A. Menéndez-Vázquez[1], M. Martínez[1,2], Ll. M. Mir[1]
[1] Institut de Física d'Altes Energies (IFAE), Barcelona Institute of Science and Technology, E-08193 Barcelona, Spain
[2] Catalan Institution for Research and Advanced Studies (ICREA), E-08010 Barcelona, Spain


## MLy-Pipeline , a new transient search pipeline for O4


Cardiff University / Prifysgol Caerdydd
Vasileios Skliris[1,2], Patrick Sutton[1], Michael Norman[1],
Kyle Willetts[1], Wasim Javed[1], Amin Be...
1. Gravity Exploration Institute, Cardiff Univ...
2. Data Innovation Institute, Cardiff Unive...


### Overview

MLy-pipeline is an exclusively machine learning pipeline that is used to quickly identify generic transient signals from detector noise. Its function is provided by a combination of a residual CNN and a simple CNN model classifier. [1] For a given positive classification,

MLy-pipelir
To measur
minimum F
which mea

## All-sky search for gravitational-wave bursts in the third Advanced LIGO-Virgo run with coherent WaveBurst enhanced by Machine Learning


Marek J. Szczepańczyk [1] Francesco Salemi [2,3,a] Sophie Bini [2,3] Tanmaya Mishra [1] Gabriele Vedovato [4] V. Gayathri [1] Imre Bartos [1] Shubhagata Bhaumik [1] Marco Drago [5,6] Odysse Halim [7,8] Claudia Lazzaro [9,10] Andrea Miani [2,3] Edoardo Milotti [7,8] Giovanni A. Prodi [11,3] Shubhanshu Tiwari [12] and Sergey Klimenko [1]
[1] Department of Physics, University of Florida, PO Box 118440, Gainesville, FL 32611-8440, USA
[2] Università di Trento, Dipartimento di Fisica, I-38123 Povo, Trento, Italy

# AN OUTDATED OVERVIEW

IOP Publishing Mach. Learn.: Sci. Technol. 2 (2021) 011002 https://doi.org/10.1088/2632-2153/abb93a

MACHINE LEARNING
Science and Technology

TOPICAL REVIEW

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RECEIVED
7 May 2020

REVISED
31 July 2020

ACCEPTED FOR PUBLICATION
16 September 2020

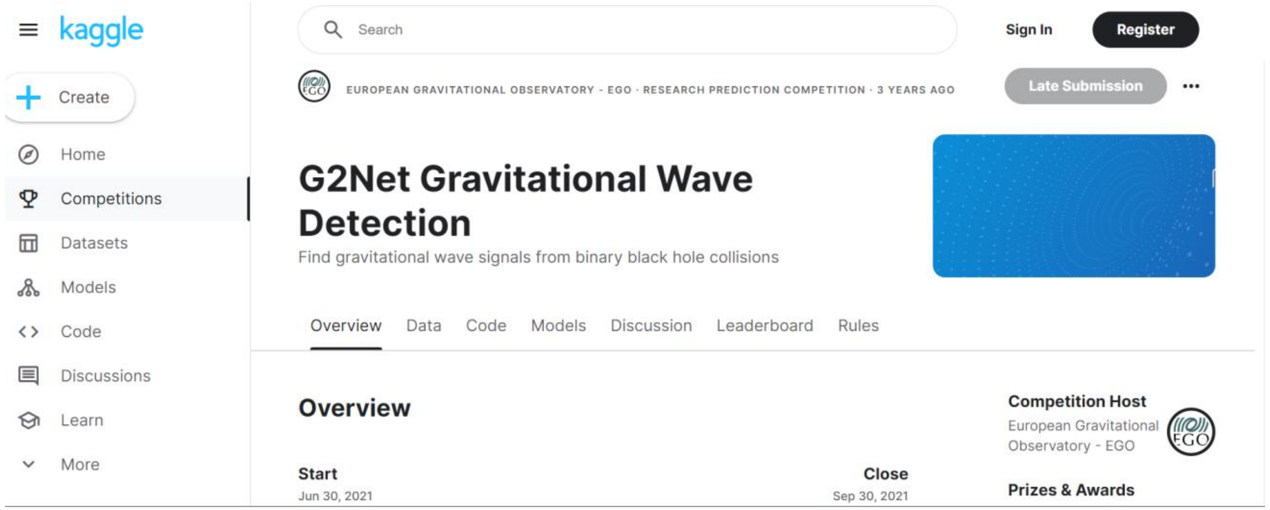
PUBLISHED
1 December 2020

## Enhancing gravitational-wave science with machine learning

Elena Cuoco[1,2,3], Jade Powell[4], Marco Cavaglià[5], Kendall Ackley[6,7], Michał Bejger[8], Chayan Chatterjee[7,9], Michael Coughlin[10,11], Scott Coughlin[12], Paul Easter[6,7], Reed Essick[13], Hunter Gabbard[14], Timothy Gebhard[15,16], Shaon Ghosh[17], Leïla Haegel[18], Alberto Iess[19,20], David Keitel[21], Zsuzsa Márka[22], Szabolcs Márka[23], Filip Morawski[8], Tri Nguyen[24], Rich Ormiston[25], Michael Pürrer[26], Massimiliano Razzano[3,27], Kai Staats[12], Gabriele Vajente[10] and Daniel Williams[14]

1 European Gravitational Observatory (EGO), I-56021 Cascina, Pisa, Italy.
2 Scuola Normale Superiore (SNS), Piazza dei Cavalieri, 7 - 56126 Pisa, Italy.
3 Istituto Nazionale di Fisica Nucleare, Sezione di Pisa, Pisa, I-56127, Italy.

# G2NET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Late Submission
G2Net Gravitational Wave Detection
Find gravitational wave signals from binary black hole collisions
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Rules
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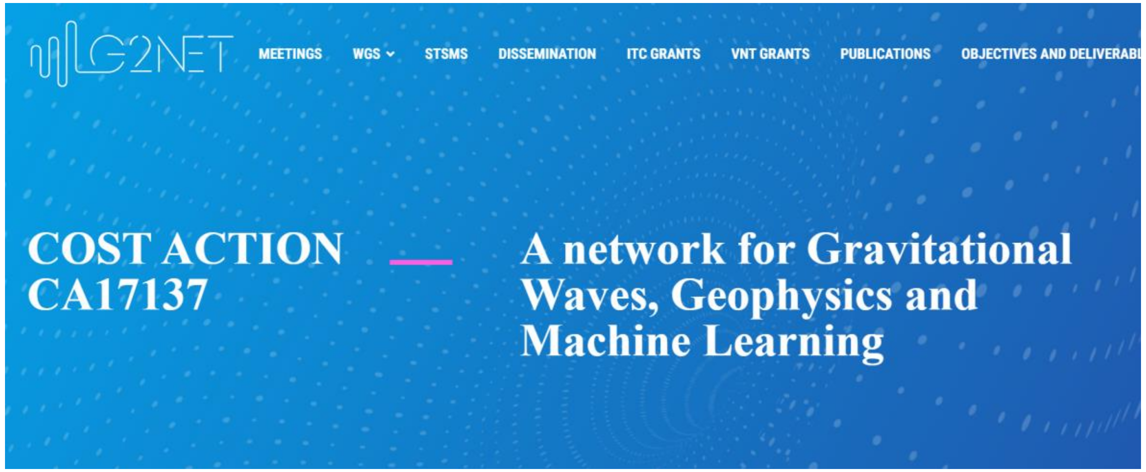
Prizes & Awards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WGS
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PUBLICATIONS
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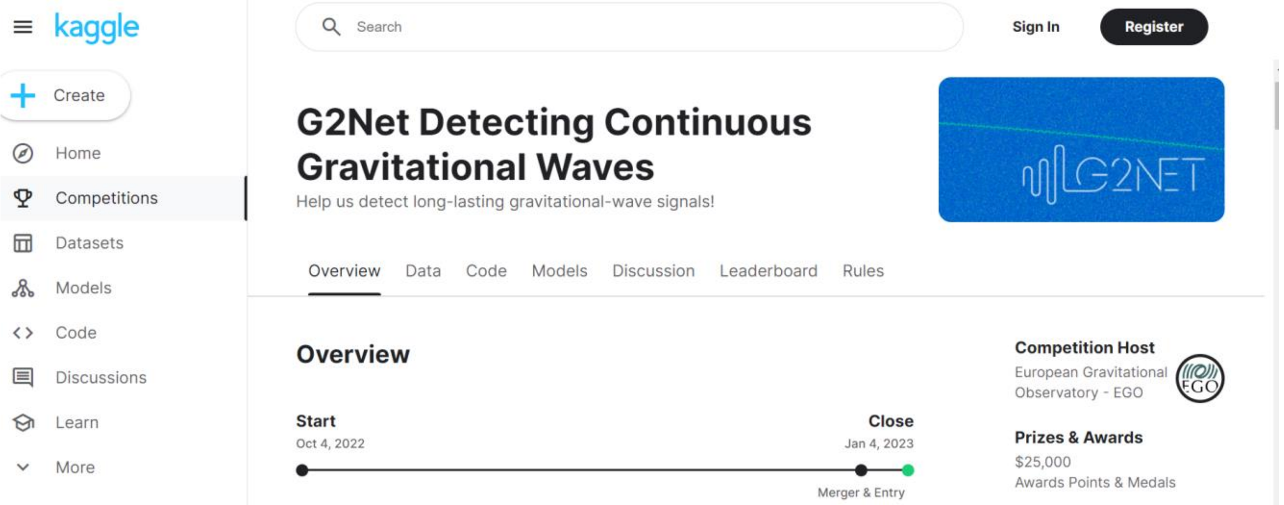
COST ACTION CA17137
A network for Gravitational Waves, Geophysics and Machine Learning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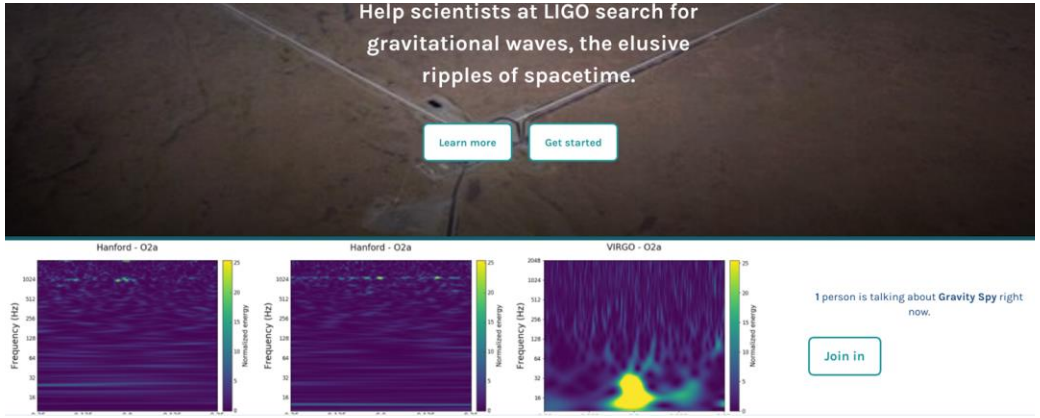
Awards Points & Medals

# CITIZEN SCIENCE

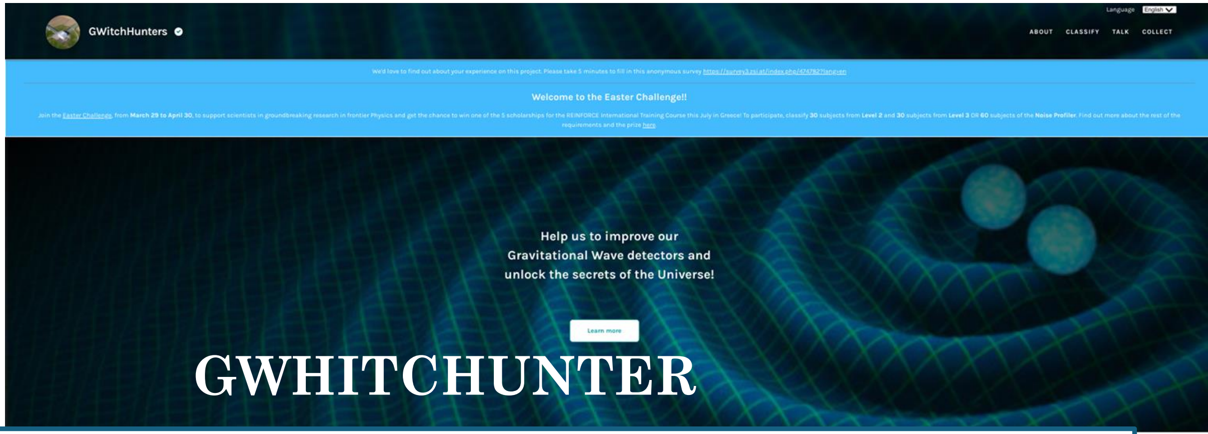
## GRAVITY SPY




Citizen scientists contribute to classify glitches

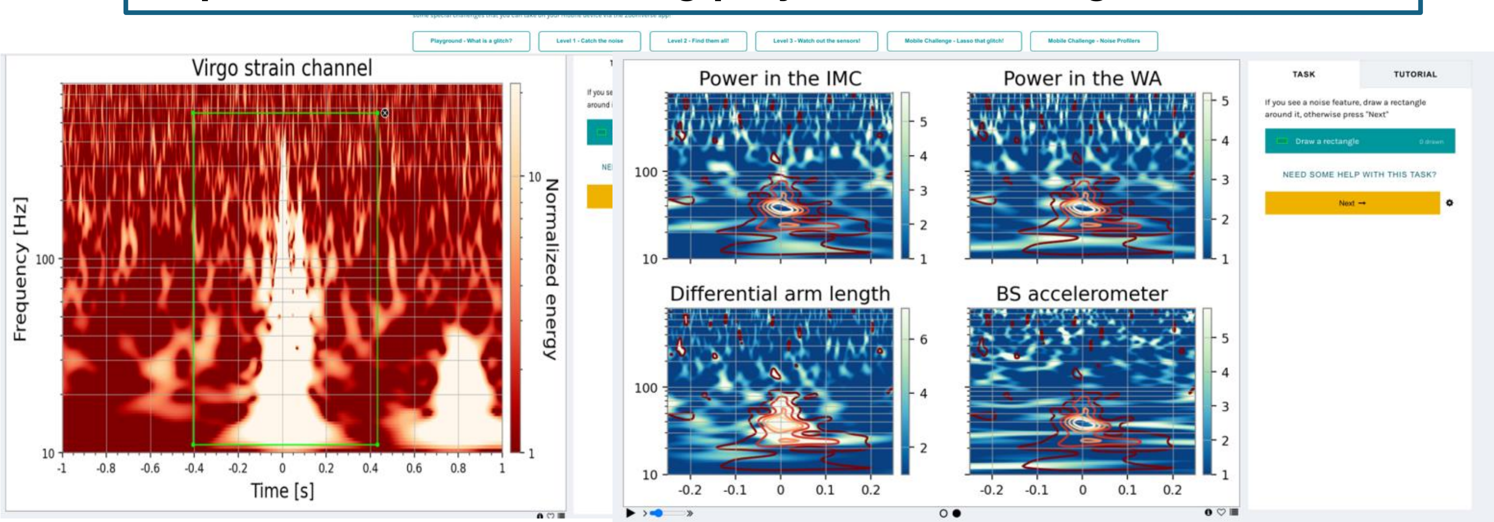
More details in Zevin+17 [10.1088/1361-6382/aa5cea](https://doi.org/10.1088/1361-6382/aa5cea)

https://doi.org/10.1016/j.ins.2018.02.068




## GWHITCHUNTER

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




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

# WHAT'S NEXT?

Use of ML pipeline for ITF instrumental studies (from lock-loss to data cleaning)

ML pipeline in production: MLy-Pipeline (Emily), was added to the unmodelled burst searches as standalone machine learning GW detection pipeline

On-line parameter estimation for Fast alert system

Multi-messenger analysis through AI applications

# THANK YOU

TWITTER: @ELENACUOCO

ELENA.CUOCO@EGO-GW.IT

credits for the slides to: M. Cavaglià, F. Di Renzo, A. Iess, F. Morawski

- **ACKNOWLEDGEMENTS:** this material is based upon work supported by NSF's LIGO Laboratory which is a major facility fully funded by the National Science Foundation. The authors gratefully acknowledge the Italian Istituto Nazionale di Fisica Nucleare (INFN), the French Centre National de la Recherche Scientifique (CNRS) and the Netherlands Organization for Scientific Research (NWO), for the construction and operation of the Virgo detector and the creation and support of the EGO consortium.