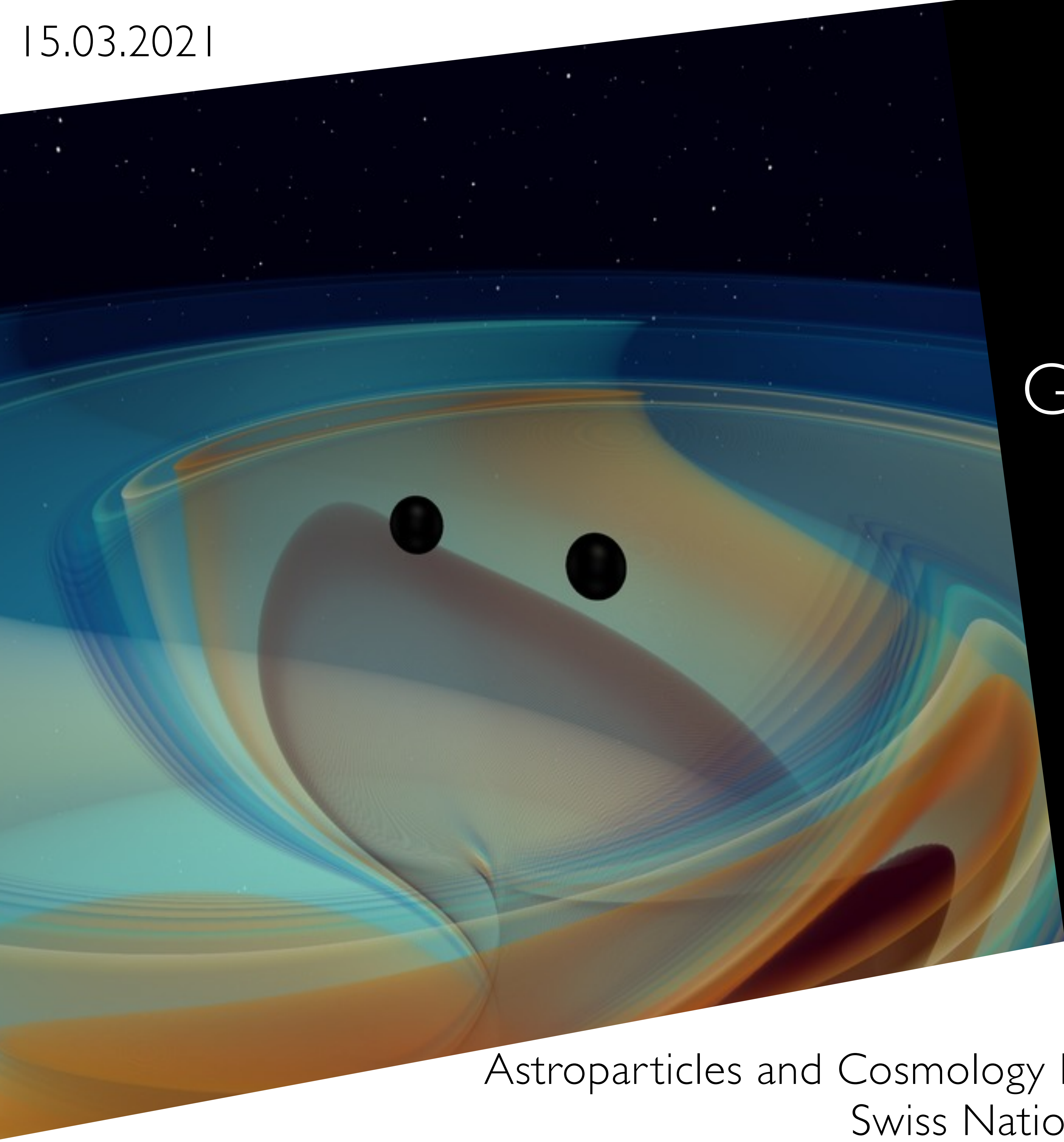
King's College London - EPAP Seminar

15.03.2021



Enhancing Gravitational-Wave Science with Machine Learning

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Swiss National Science Foundation fellow

Overview

- **GW physics**
  - A primer on GW astrophysics
  - Ground-based interferometers
  - Detection and analysis
  - Examples of physics results

- **Machine learning applications**
  - Why ML?
  - Characterisation of detector noise
  - Detection of astrophysical signals
  - GW modelling
  - Estimation of the GW sources parameters

GW physics

- **A primer on GW astrophysics**
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Gravitational waves primer 1/2

- **A prediction from GR:** linearised Einstein Equation for accelerating masses:

$$G_{\mu\nu} = 8\pi T_{\mu\nu} \quad \longrightarrow \quad \left(\nabla^2 - \frac{1}{c^2}\frac{\partial^2}{\partial t^2}\right) T_{\mu\nu} = 0$$

- **Propagation:** GW modify the spacetime according to:

$$ds^2 = -\,c\ dt^2 + \boxed{[1 - h(z \pm ct)]}\ dx^2 + \boxed{[1 - h(z \pm ct)]}\ dy^2 + dz^2$$

propagate at speed of light *GW deformation* *transverse waves*

- **Radiation mode:** GW are tensor perturbation, the spacetime stretch is quadrupolar

Energy conservation ↔ no monopole radiation
Momentum conservation ↔ no dipole radiation

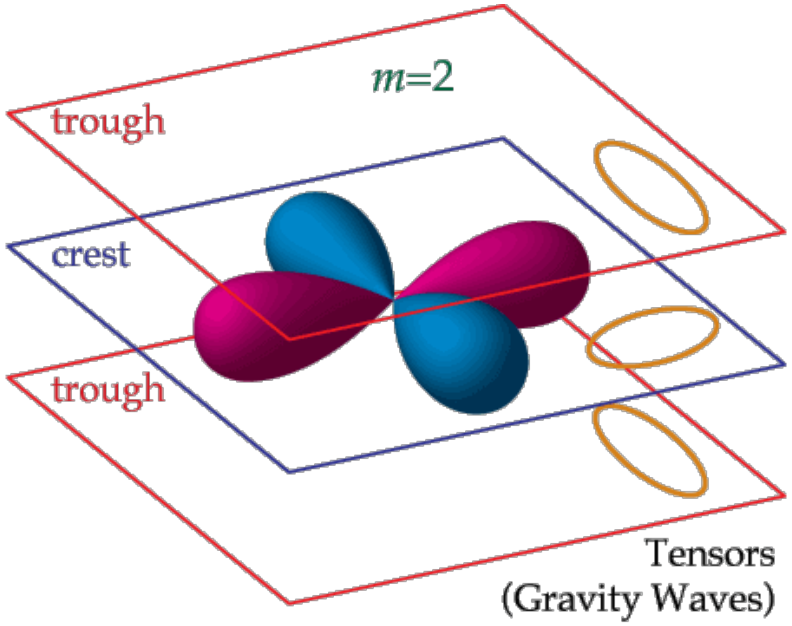


Image by Wayne Hu

Gravitational waves primer 2/2

- **Polarisations:** GW have 2 polarisations, h_+ and $h_\times$
- **Strain:** is the fractional change in distance between two points when a GW passes through: $$\frac{\Delta L}{L} = \frac{1}{2} h_{xx}(0, ct)$$
- **Deformation:**

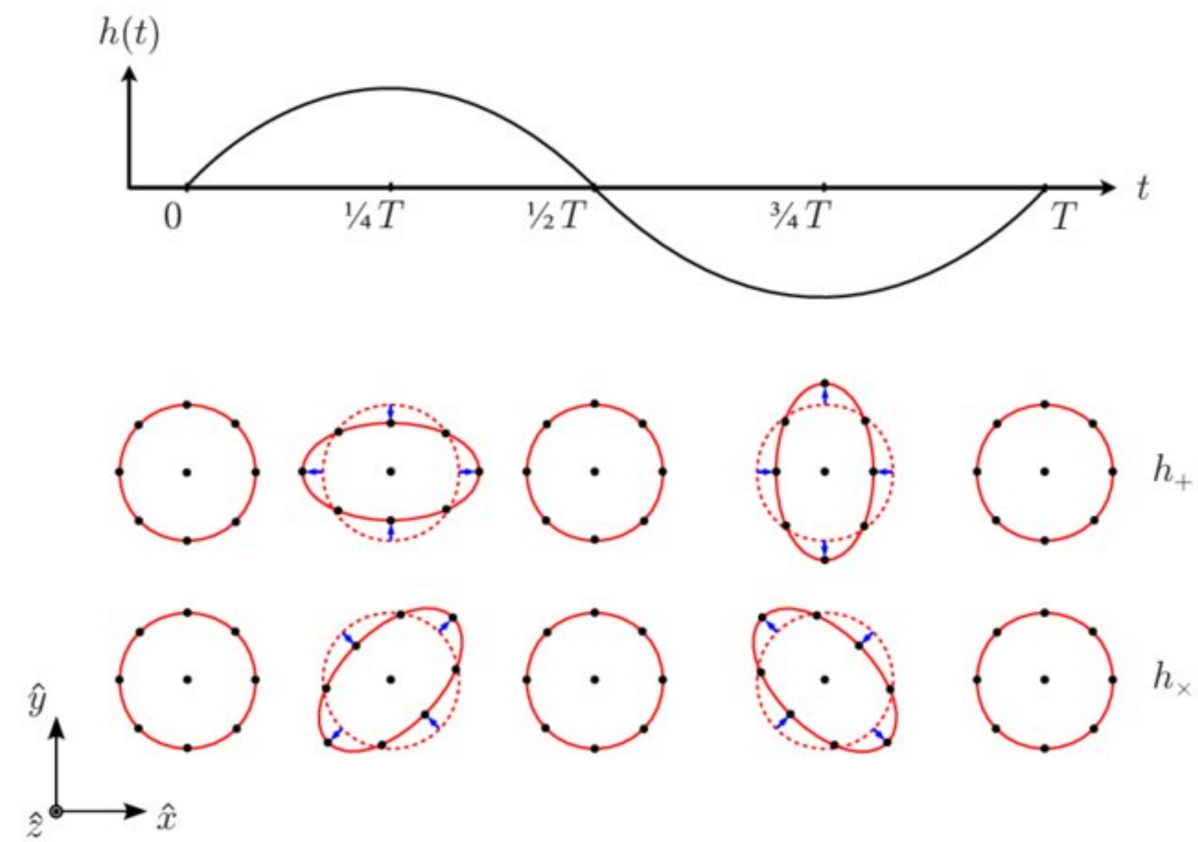


Figure by Alexandre Le Tiec

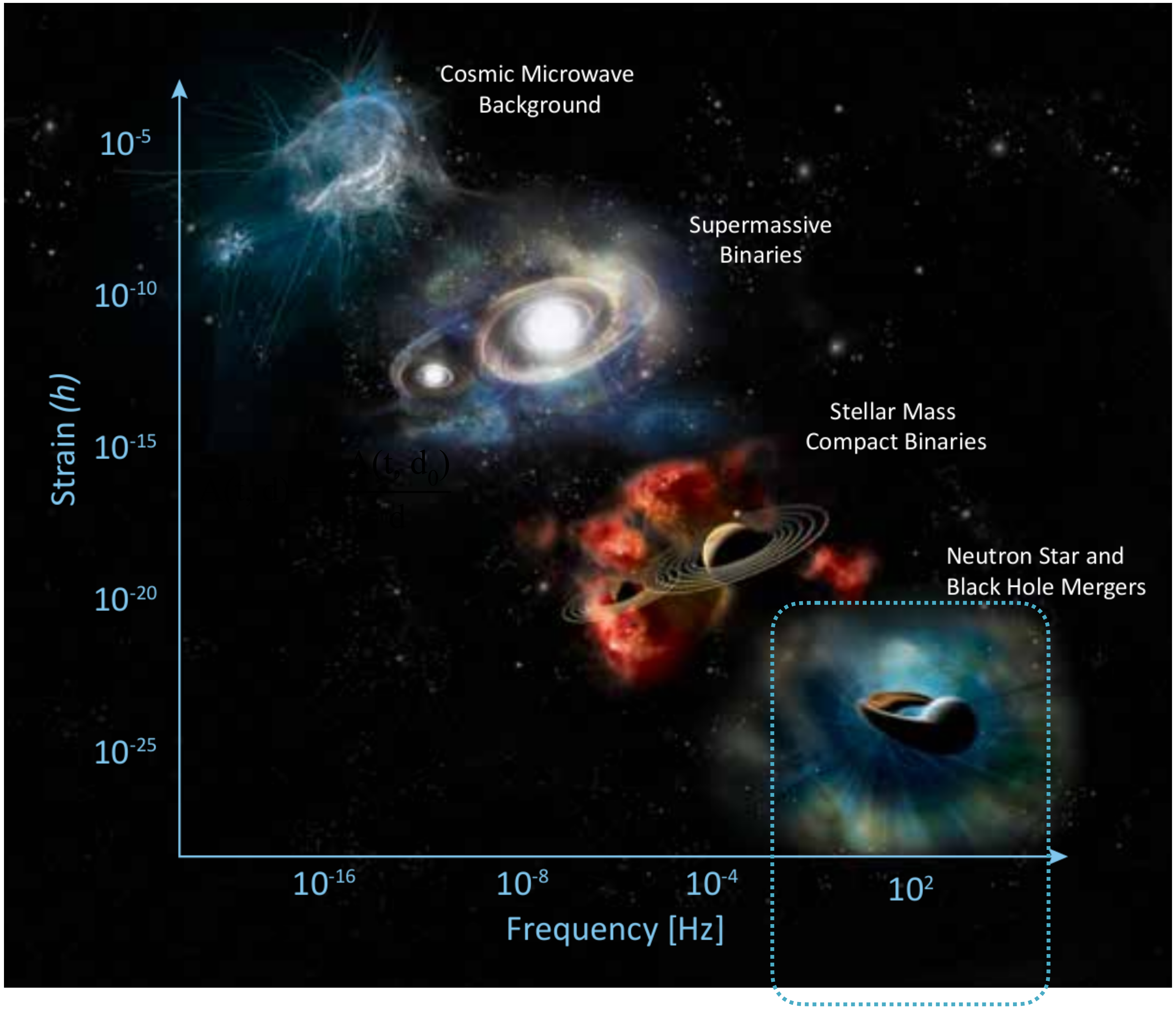
Gravitational waves sources

- **Strain:** follows a wave equation:

$$h(t) = A(t)\ \sin(\omega(t)\ t)$$

- **Amplitude:** decreases from the source as the GW propagates in spacetime

Credit: SSU EPO/Aurore Simonnet



LIGO-Virgo-KAGRA

GW physics

- A primer on GW astrophysics
- **Ground-based interferometers**
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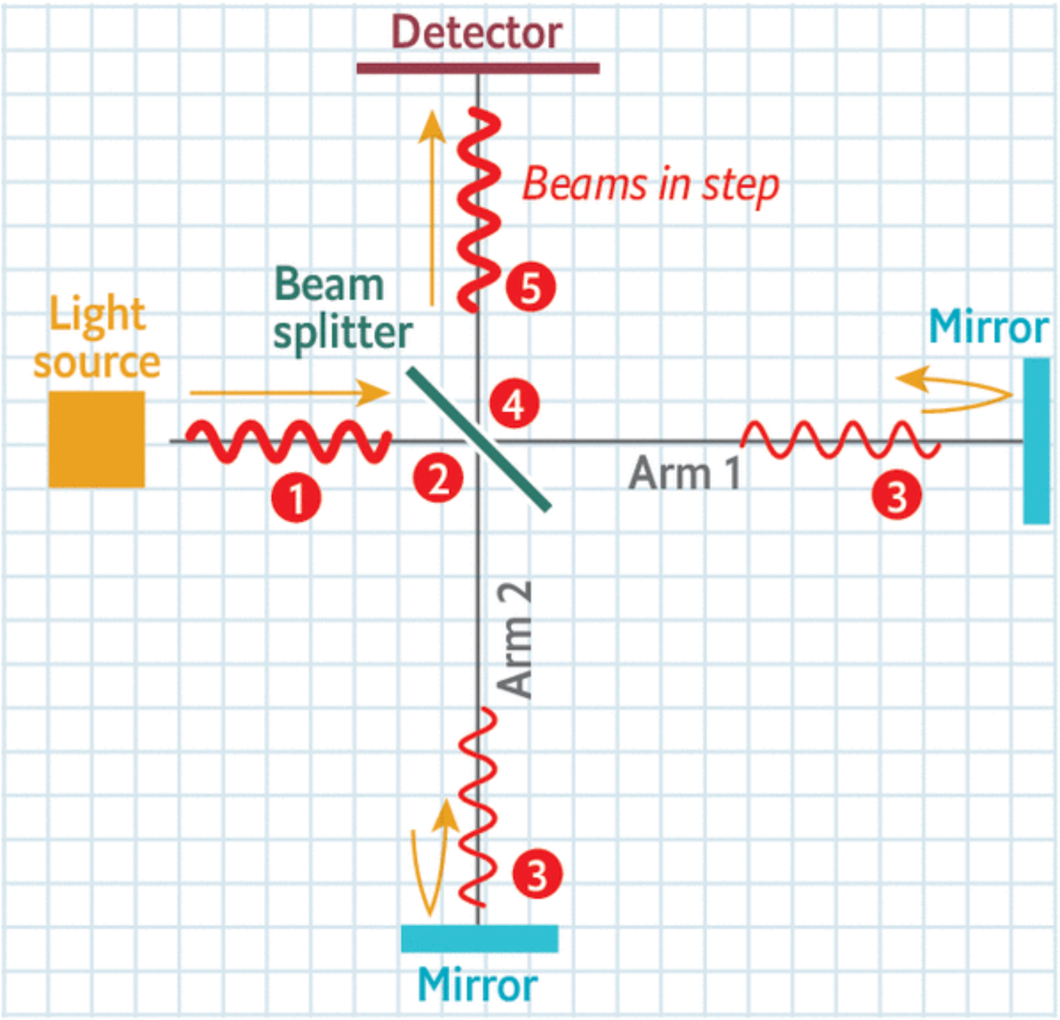
- Examples of physics results

Gravitational waves detection

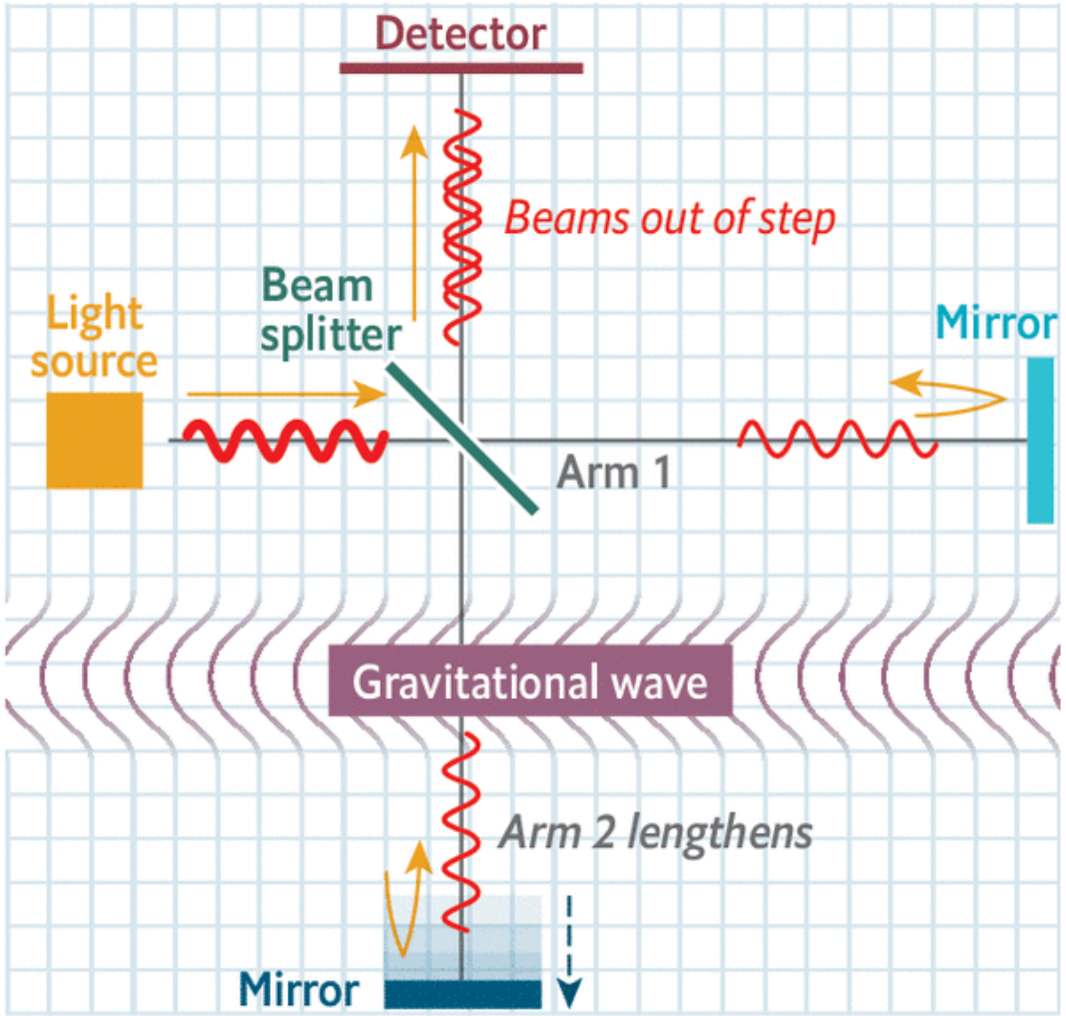
- The variation of space-time interval is measured with **light interferometry**.
- A light beam is divided in **two beams** travelling along orthogonal arms.
- Mirrors in the end of the arms reflect the beams back to a **photodetector**.
- If no gravitational wave passes through, the arm length remains the same and **the interference pattern is the sum of the splitted electromagnetic waves**.



Source: The Economist

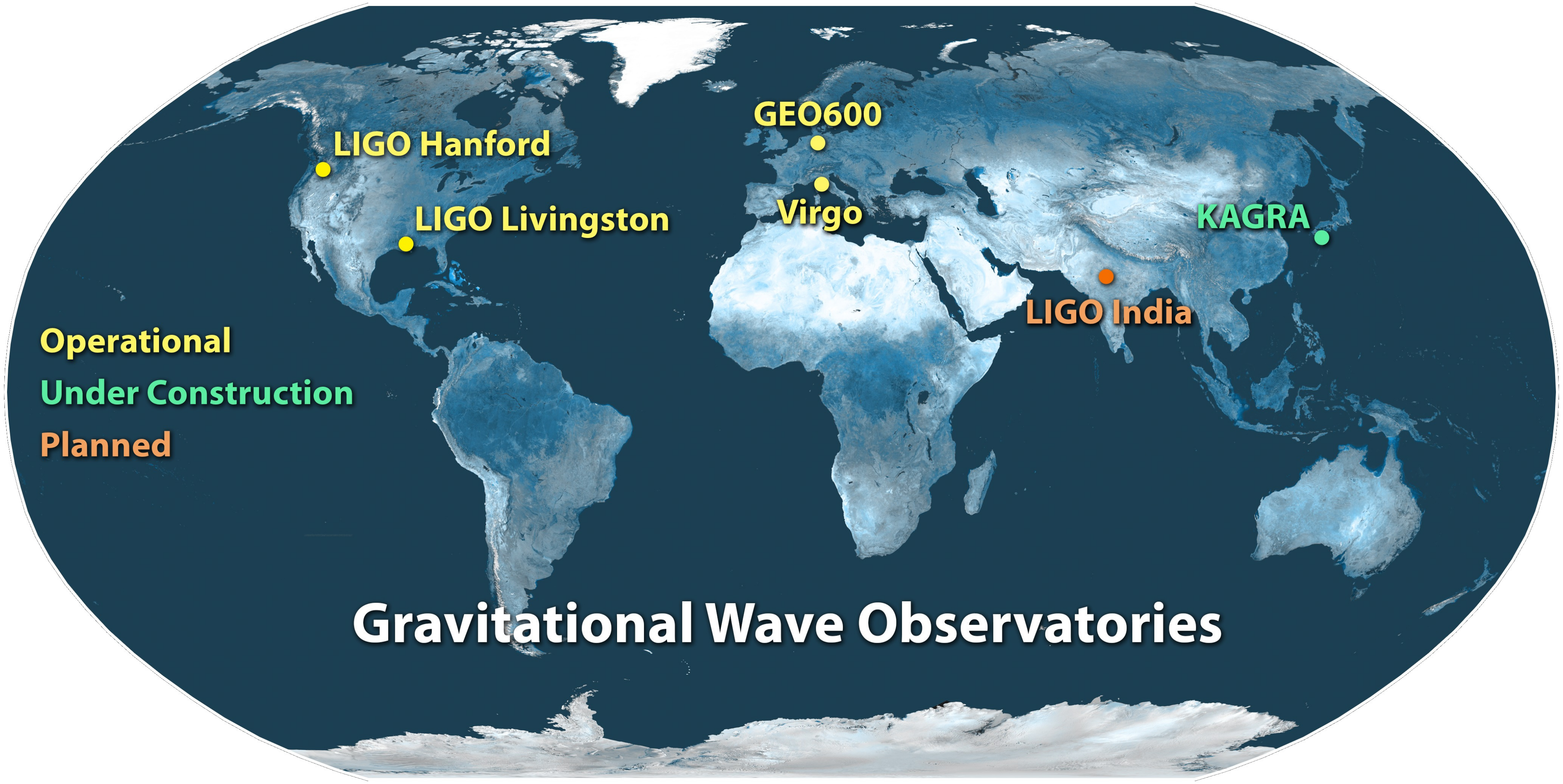
Gravitational waves detection

- The variation of space-time interval is measured with **light interferometry**.
- A light beam is divided in **two beams** travelling along orthogonal arms.
- Mirrors in the end of the arms reflect the beams back to a **photodetector**.
- If a gravitational wave passes through, the arm length is different and **the interference pattern is distorted**.

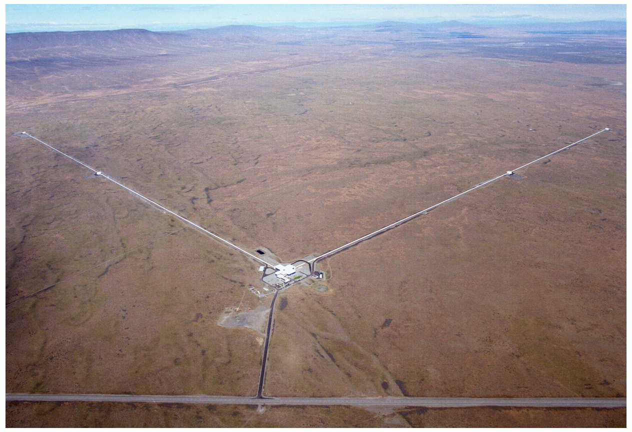


Source: The Economist

Gravitational waves observatories



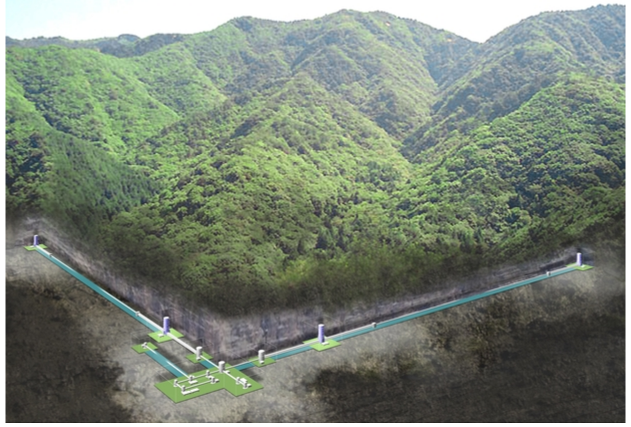
LIGO Hanford



LIGO Livingston

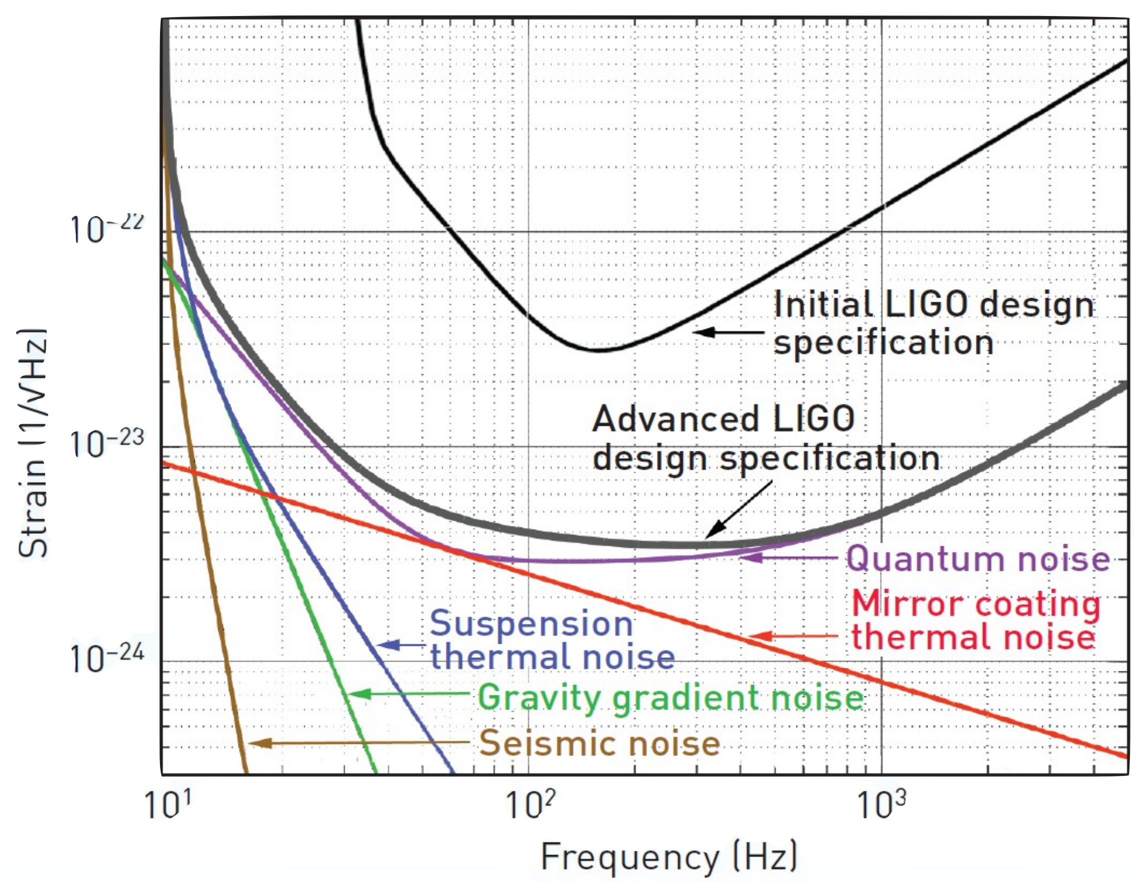
Virgo

KAGRA

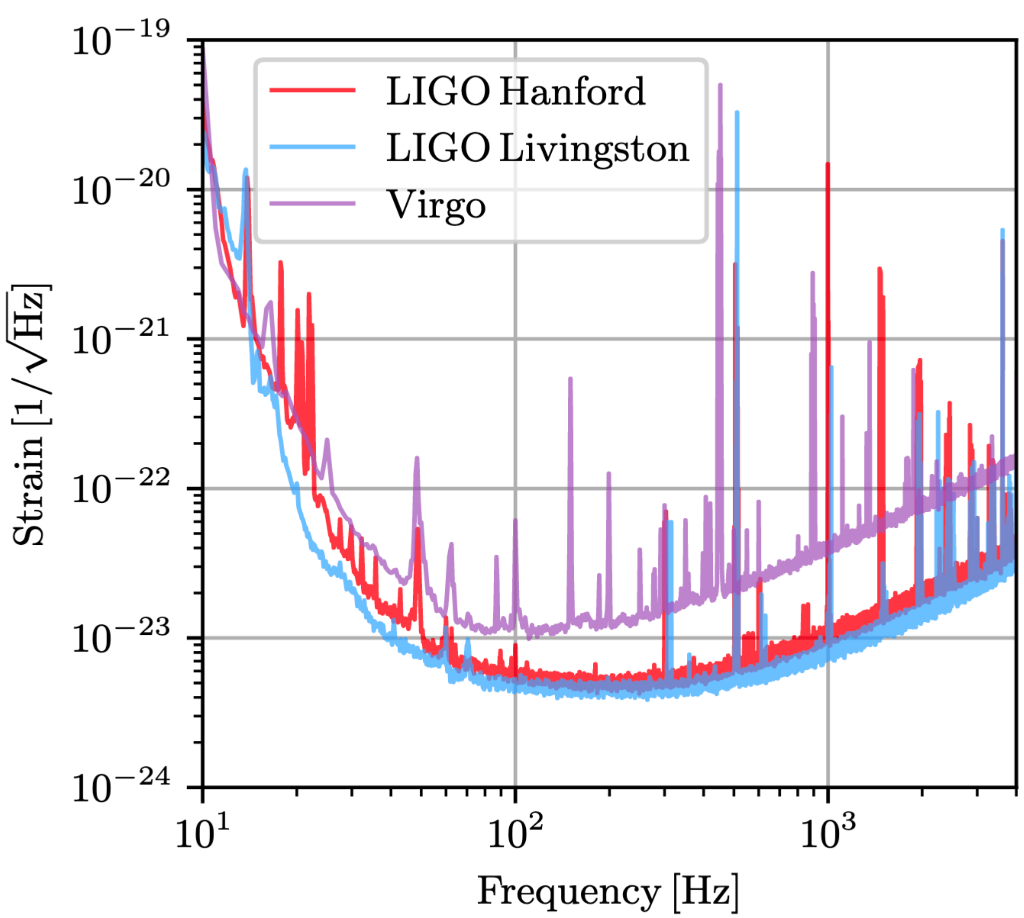


LIGO-Virgo sensitivities

- Ground-based light interferometers are sensitive to the **frequency range 10 - 10^3 Hz**
- Signals entering the detection range are **coalescence of compact binaries** (stellar-mass black holes or neutron stars) and possibly pulsars

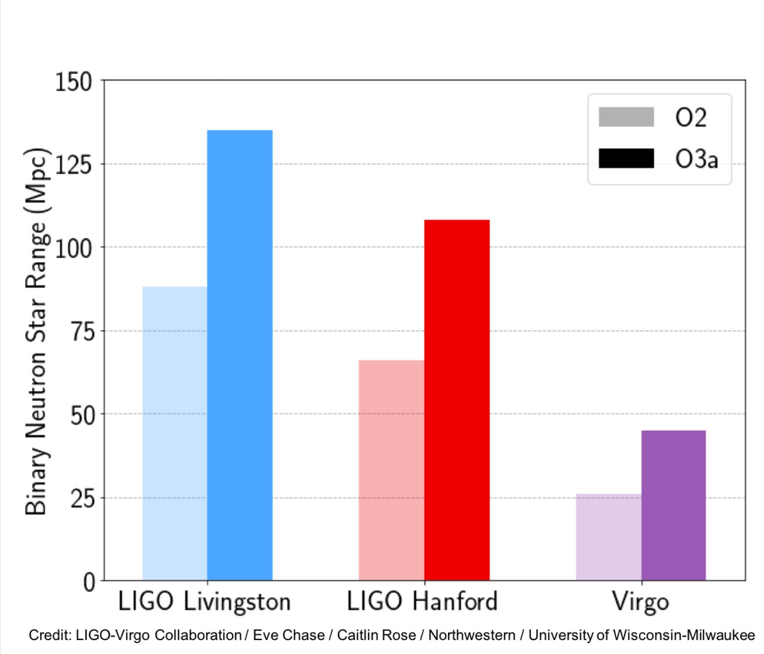


O3a sensitivity

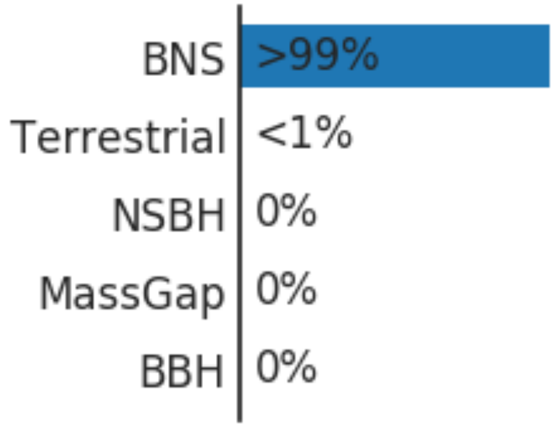


GW physics

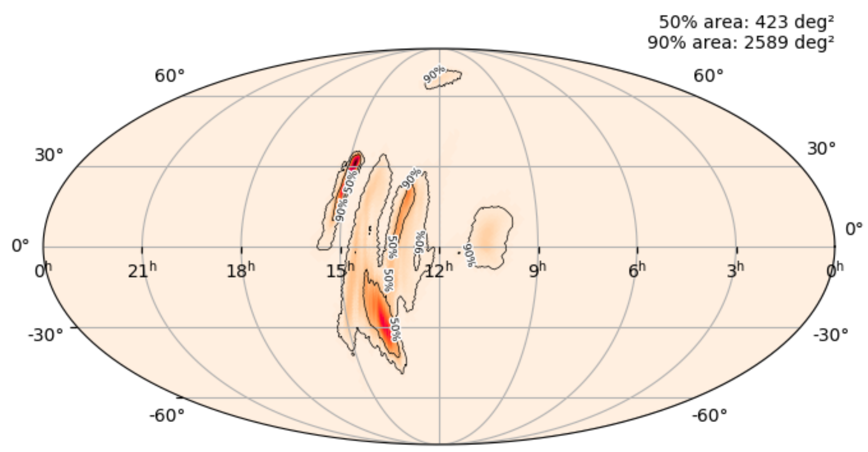
- A primer on GW astrophysics
- Ground-based interferometers
- **Detection and analysis**
- Examples of physics results



- **Detection range:** during O3 run
- **Different type of searches:**
  - 4 modelled searches pipelines
  - 2 unmodelled searches pipelines



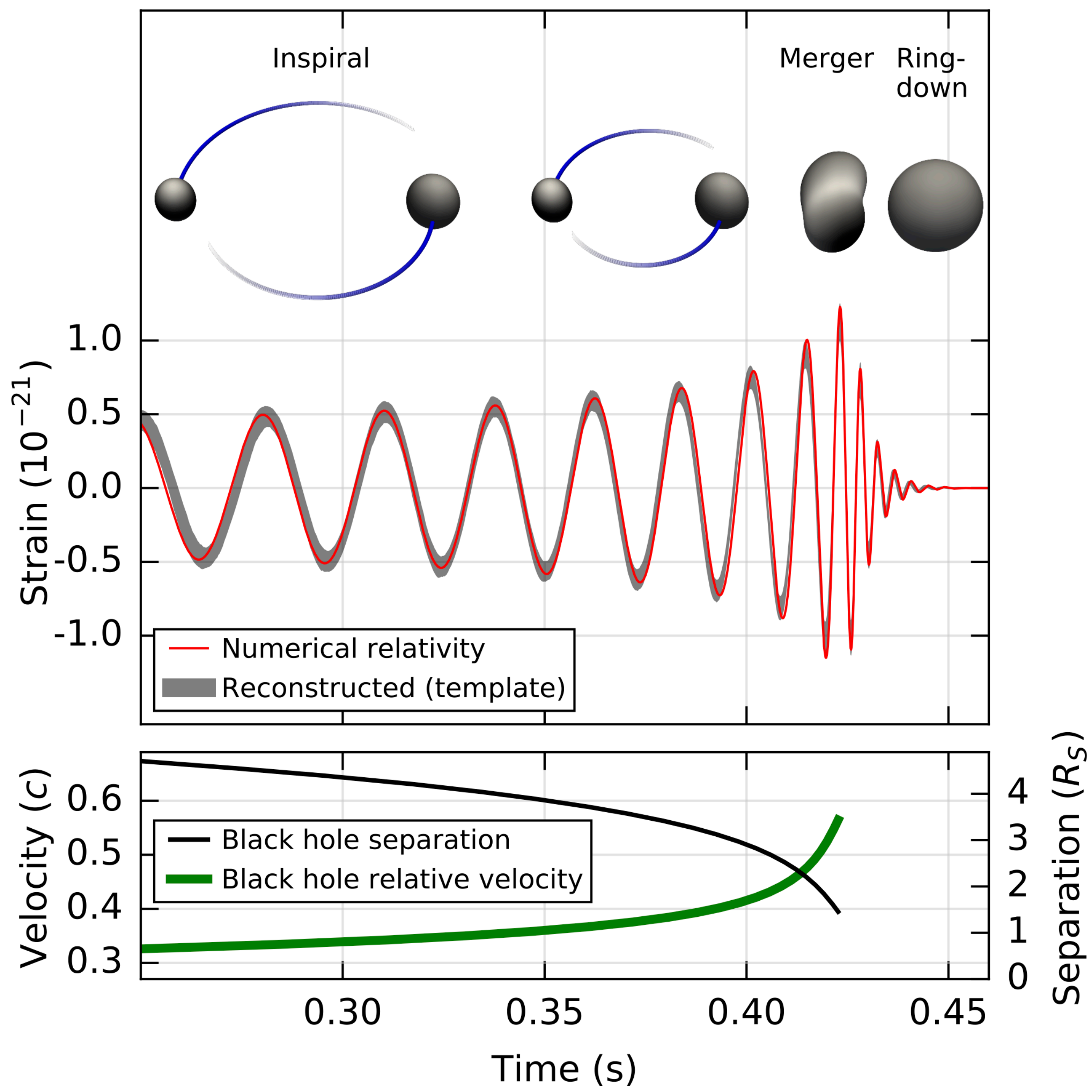
- **Database automatically updated:**
  - GraceDB contains low-latency information about the event
  - In case of possible neutron star, alert sent to satellites and telescopes to search for electromagnetic counterpart



GW signals from binary systems of compact objects

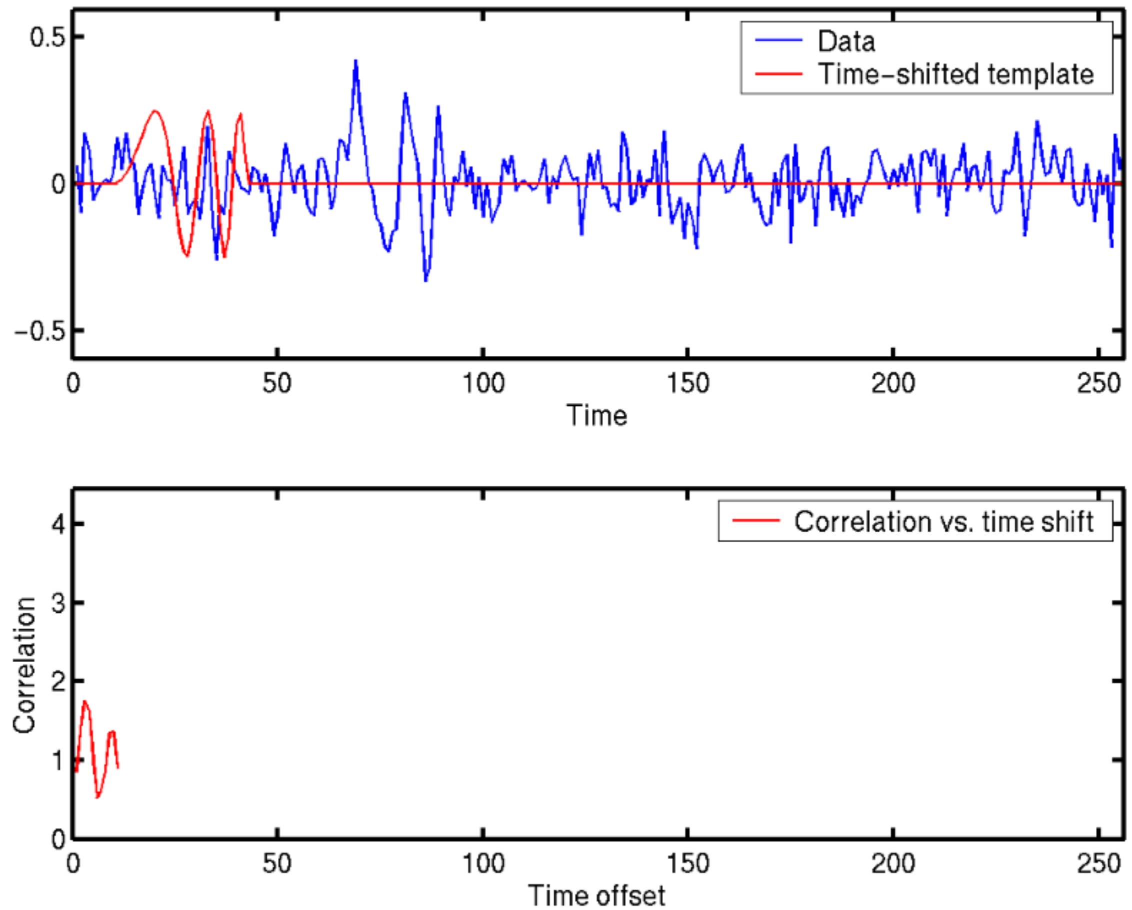
- **Black holes / neutron stars** orbiting in binaries emit gravitational waves.
- When the distance between the objects is large, the **inspiral waveform has a low frequency**, low amplitude.
- While they get closer, **frequency and amplitude increase up to the merging**.
- The final **remnant relax during ringdown**, when the wave is dumped.

LVC, arXiv:1602.03837



GW analysis with matched filtering

- Due to the low amplitude of the signal from binary systems, the analysis of the GW rely on **matched filtering** to evaluate the correlation between the signal template h and the data s



Source: L. Candonati

$$z(t) = 4 \int h^*(f)\ s(f)\ \exp(2\pi i f t)\ df$$

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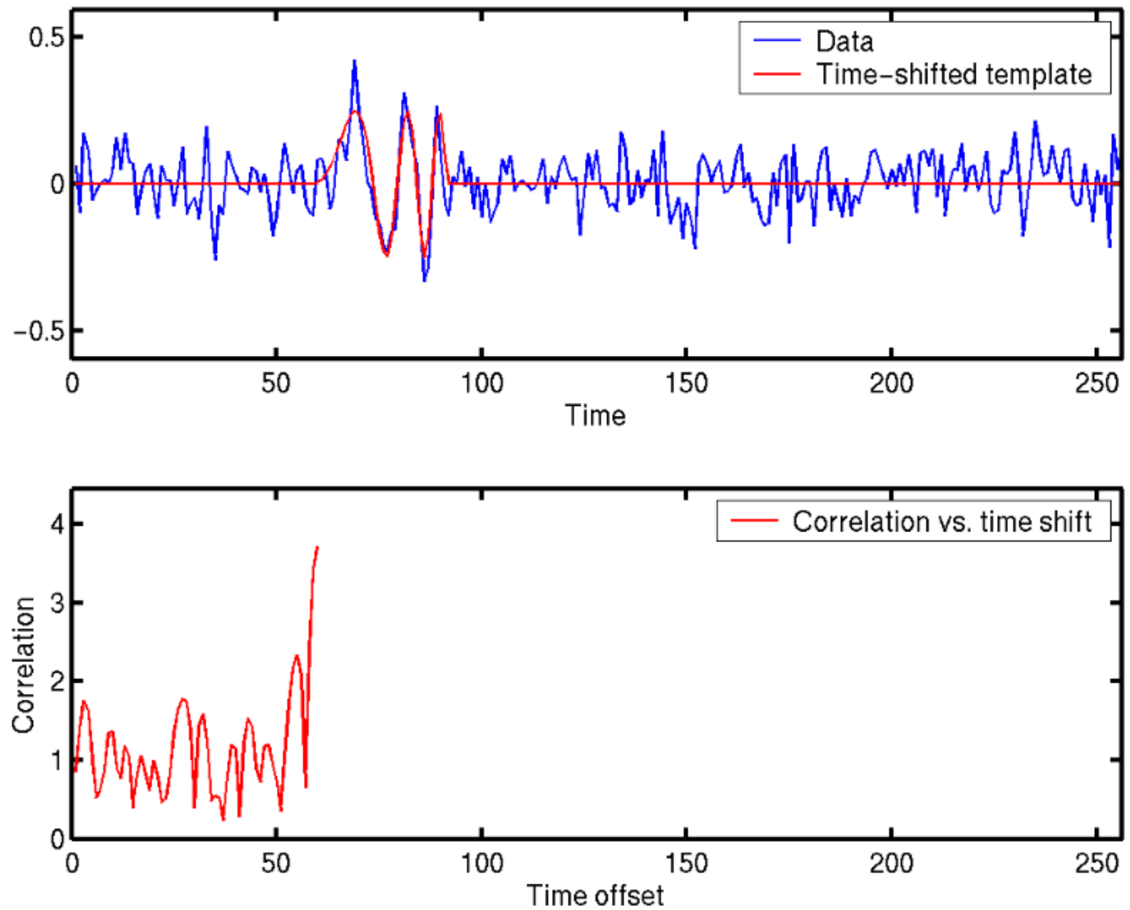

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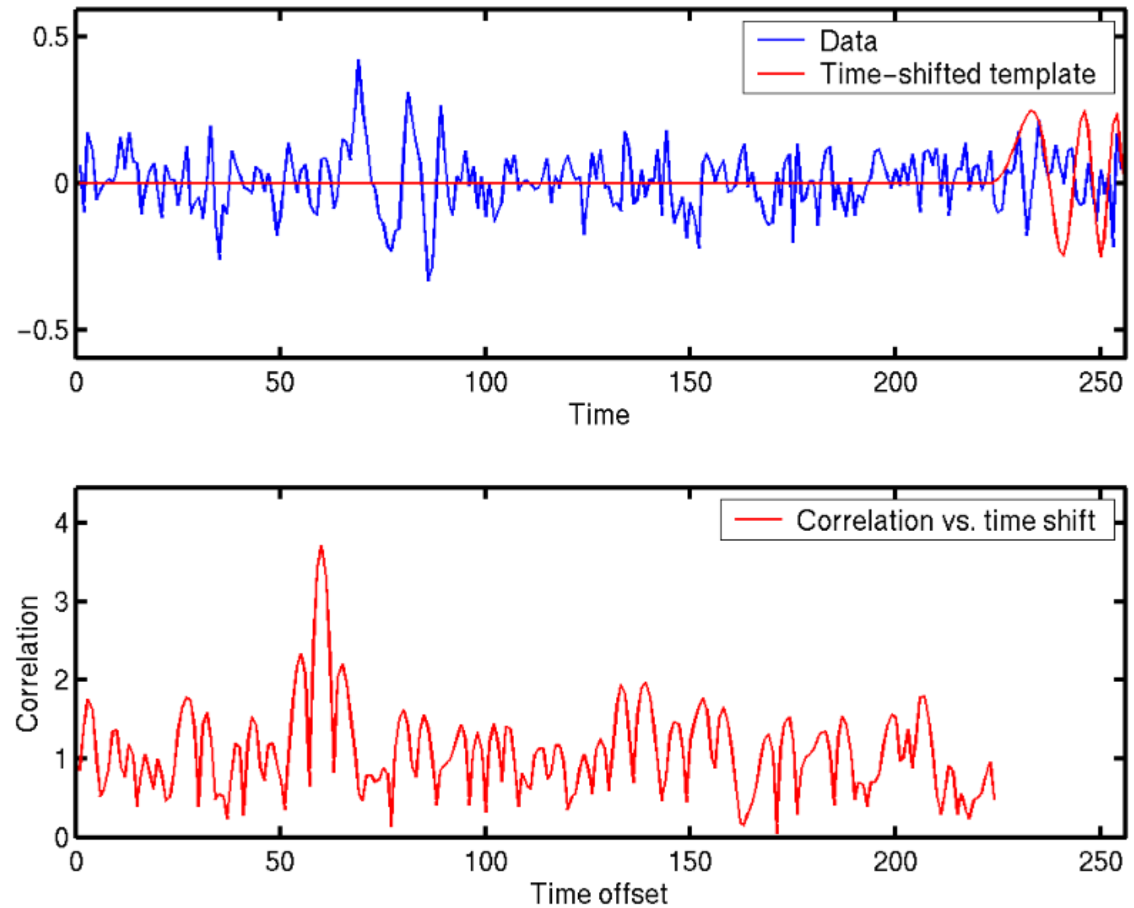


Source: L. Candonati

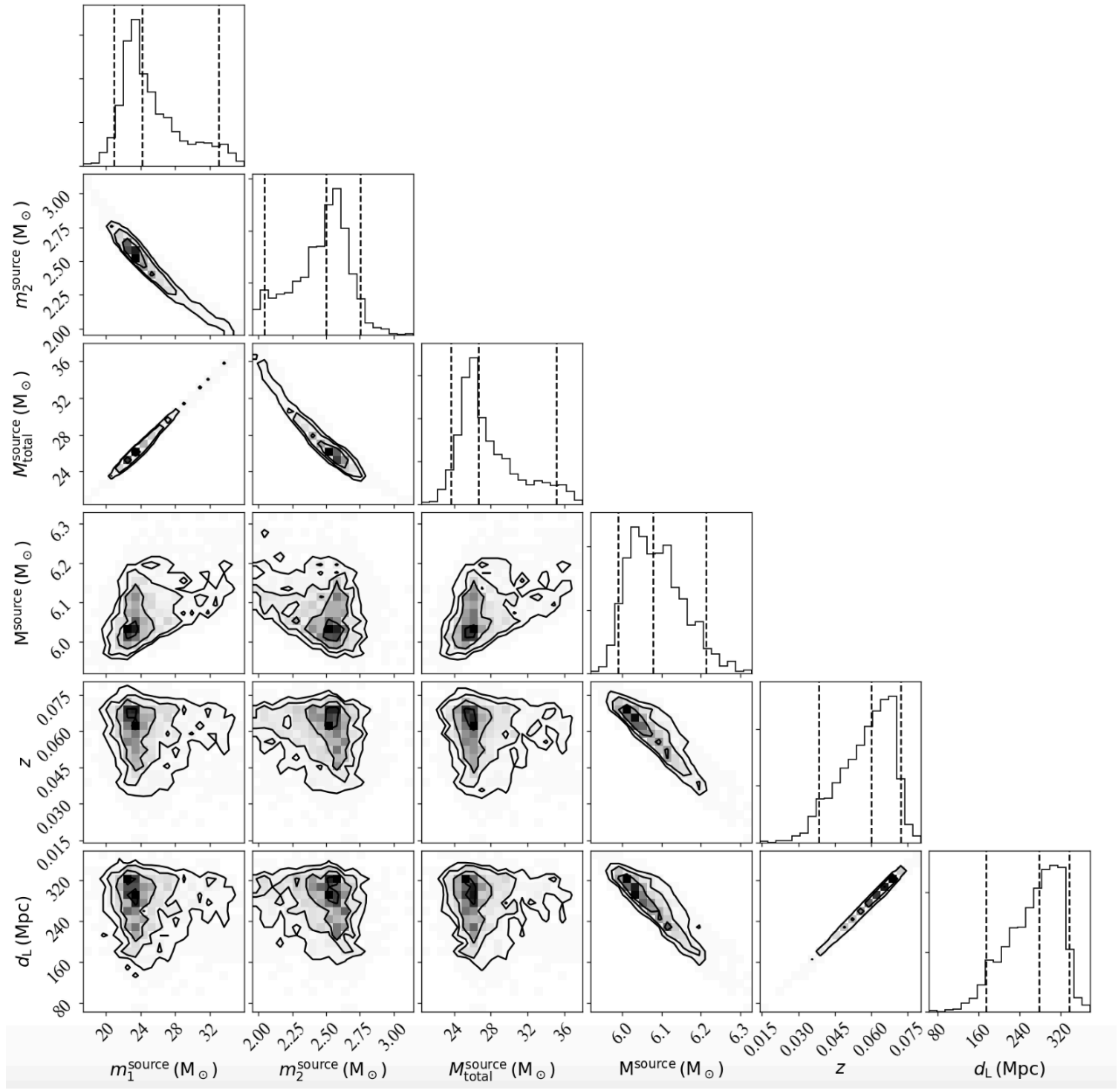
$$z(t) = 4 \int h^*(f)\ s(f)\ \exp(2\pi i f t)\ df$$

GW parameter estimation

- The posterior probabilities of the parameters of the source are estimated with **Markov chains sampling methods** (Nested sampling, MCMC).

- **15 parameters minimum** to describe a binary system:

  - 2 masses
  - 2 spin magnitudes
  - 2 angles for each spin
  - Reference time
  - Orbital phase at reference time
  - Luminosity distance
  - Right ascension & declination
  - Inclination angle
  - Polarisation angle



GW physics

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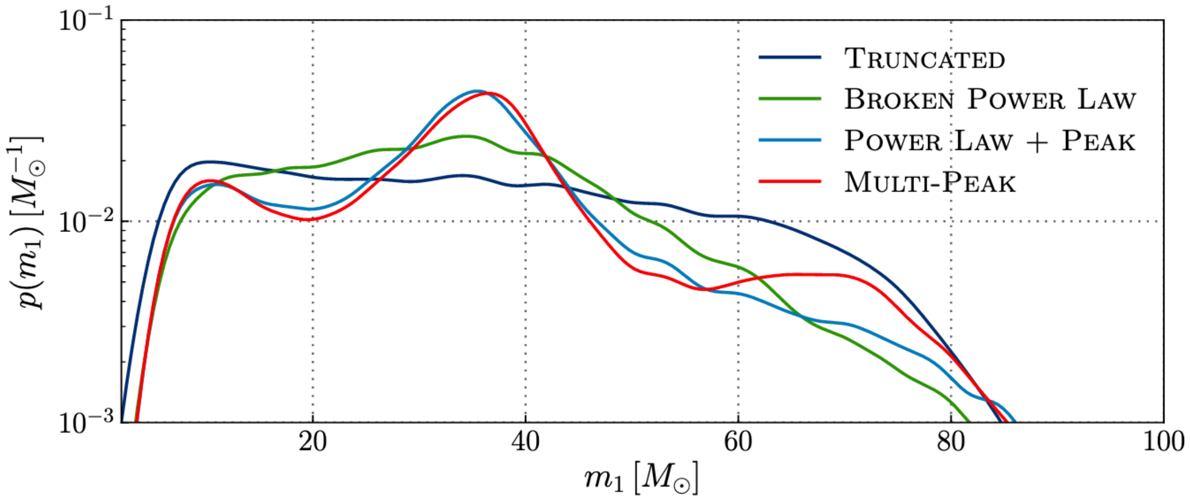
- **Examples of physics results**

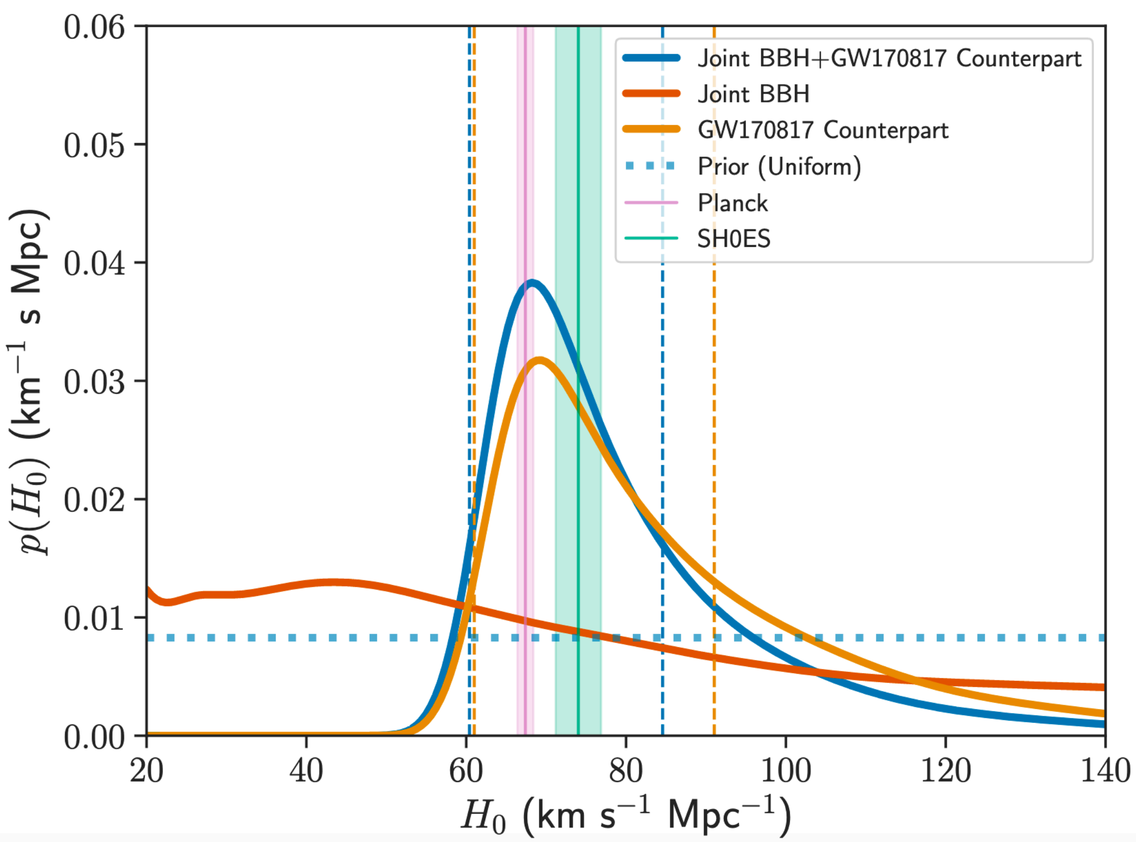
GW astrophysics

- **Astrophysical distribution**: presence of features compare to the star power-law distribution

LVC, arXiv:2010.14533

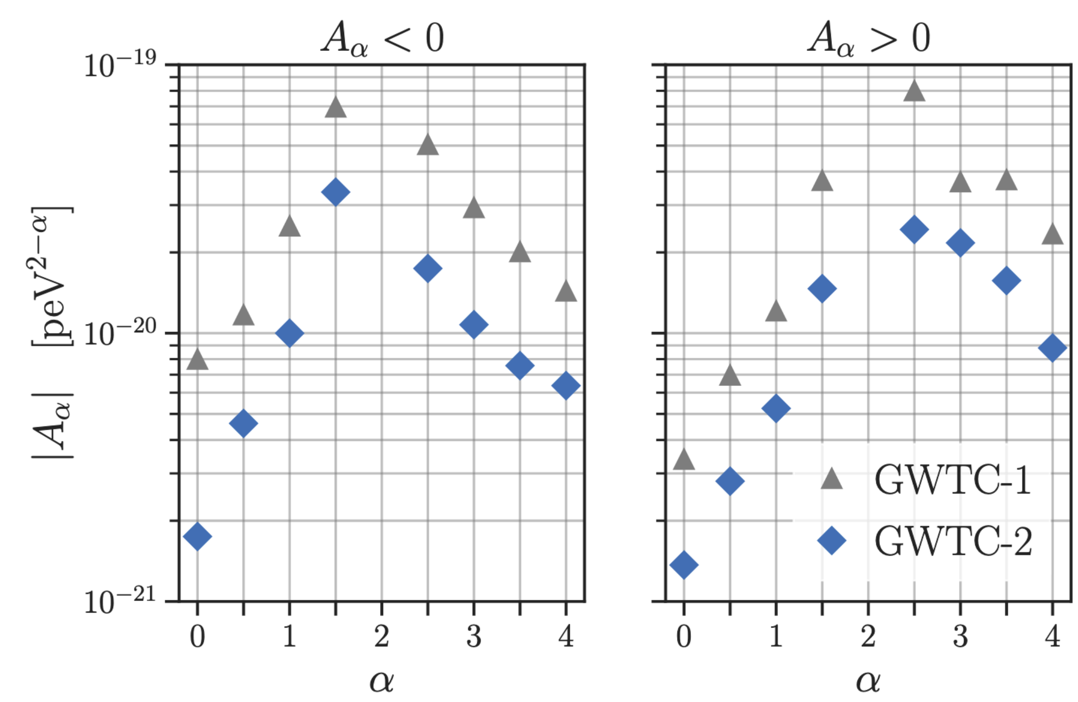


LVC, arXiv:1908.06060



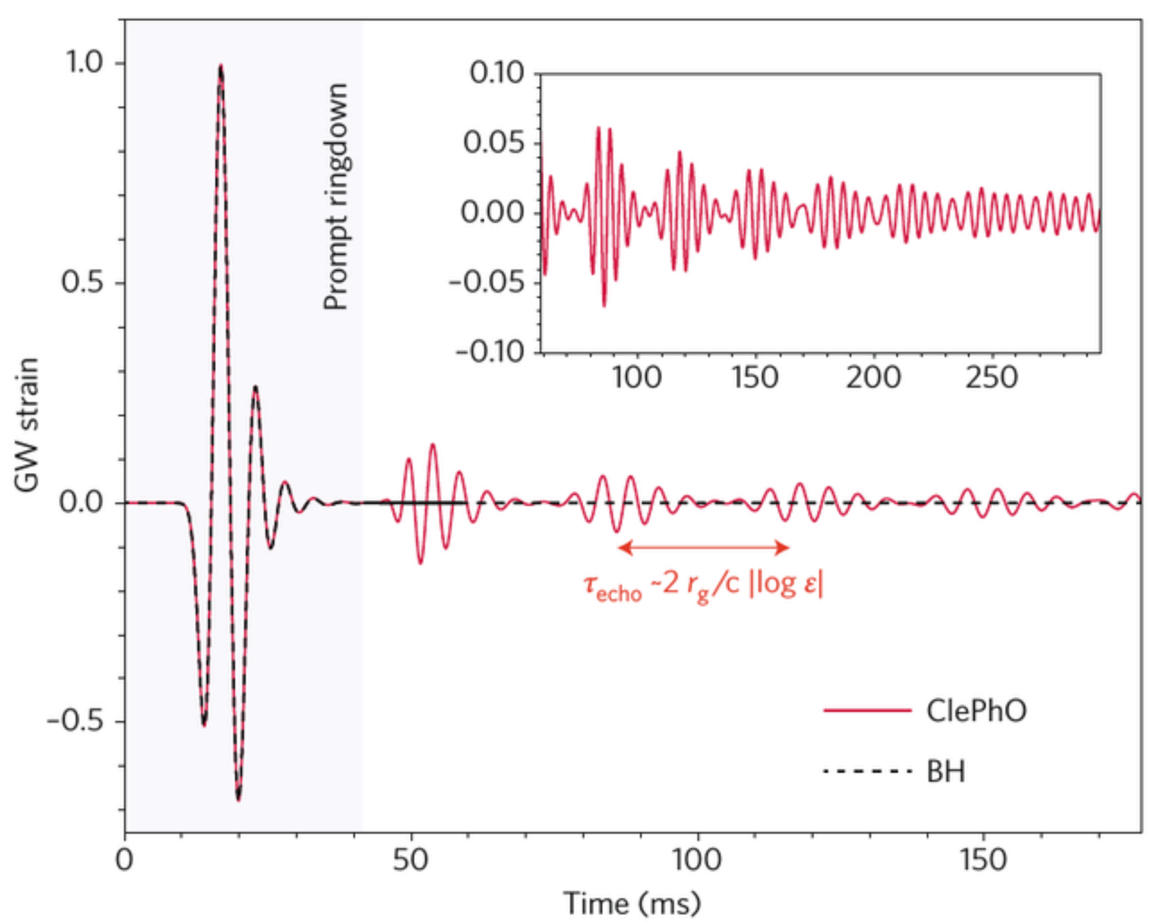
- **Neutron stars binary**: the presence of an electromagnetic counterpart enables to measure the Hubble constant

LVC, arXiv:2010.14529



- **GW propagation**: constraints on the mass of the graviton and other alternative theories of gravitation

Cardoso & Pani, arxiv:1709.01525



- **GW ringdown (end of signal)**: the presence of higher harmonics or echoes can help testing the nature of the black holes as sources of GW

Machine learning applications

- **Why ML?**
- Characterisation of detector noise
- Detection of astrophysical signals
- GW modelling
- Estimation of the GW sources parameters

Machine learning usefulness

- **Small signals**: the amplitude of the signal is ~ the amplitude of the noise
- **Complex system**: the Einstein Equations are non-linear and the physics of the strong-field regime is highly complex
- **High dimensionality**: from the detectors channels to the binary characterisation, the systems need many parameters to be described
- **Computationally intensive**: solving Einstein Equations require numerical relativity simulations on superclusters, sampling the source parameters probabilities can take weeks with distributed computing
- **Review article**: Enhancing Gravitational-Wave Science with Machine Learning, Machine Learning: Science and Technology, arXiv:2005.03745

Machine learning applications

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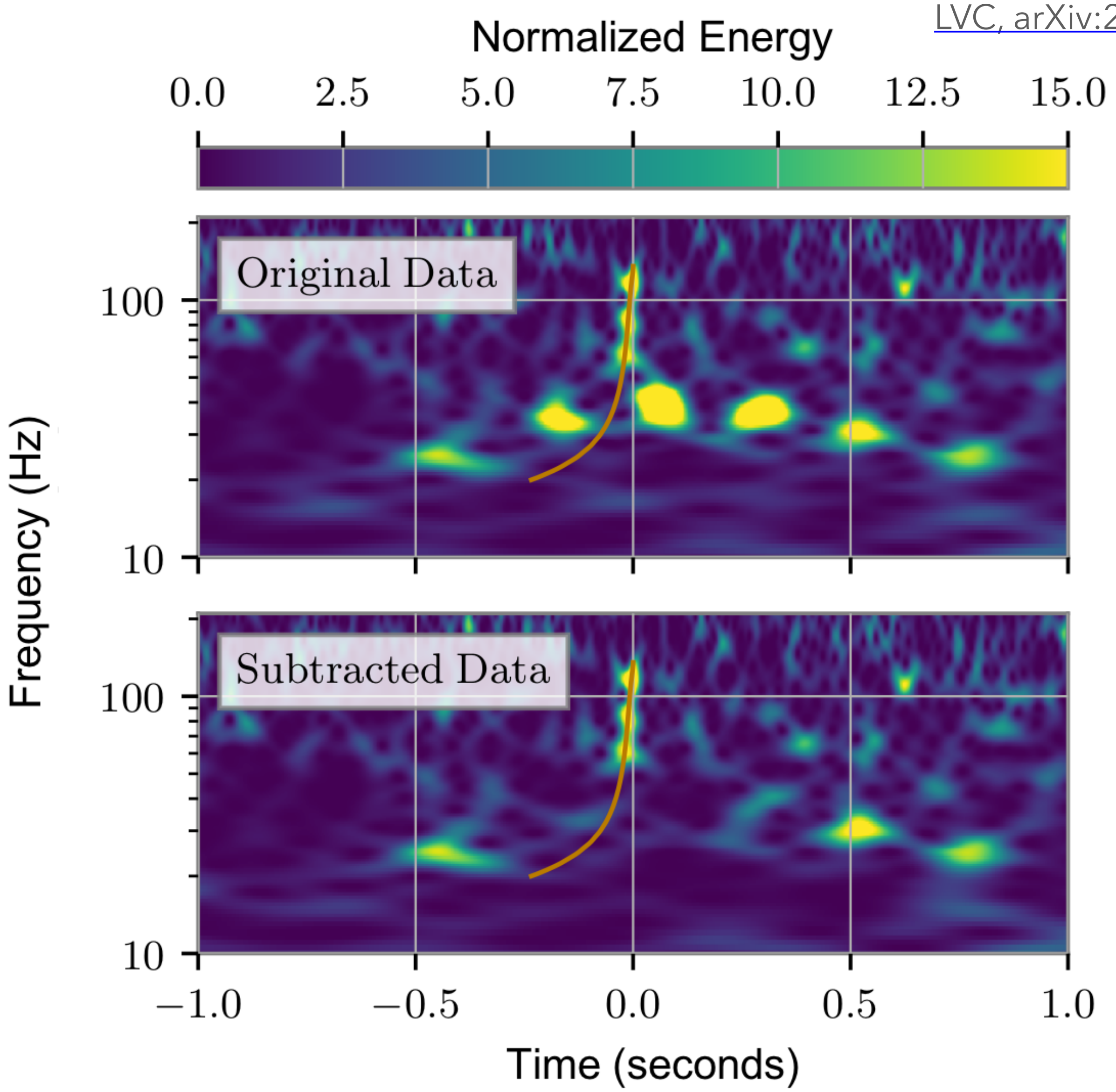
Detector glitches

- **Glitches**: Short-lived non-stationary and nonlinear transients signals of environmental / instrumental origin

- **Characterisation**:
  - Origin needs to be understood to understand the noise of the detectors
  - Glitches can occur at the same time than signals and need to be subtracted
  - Several different morphologies

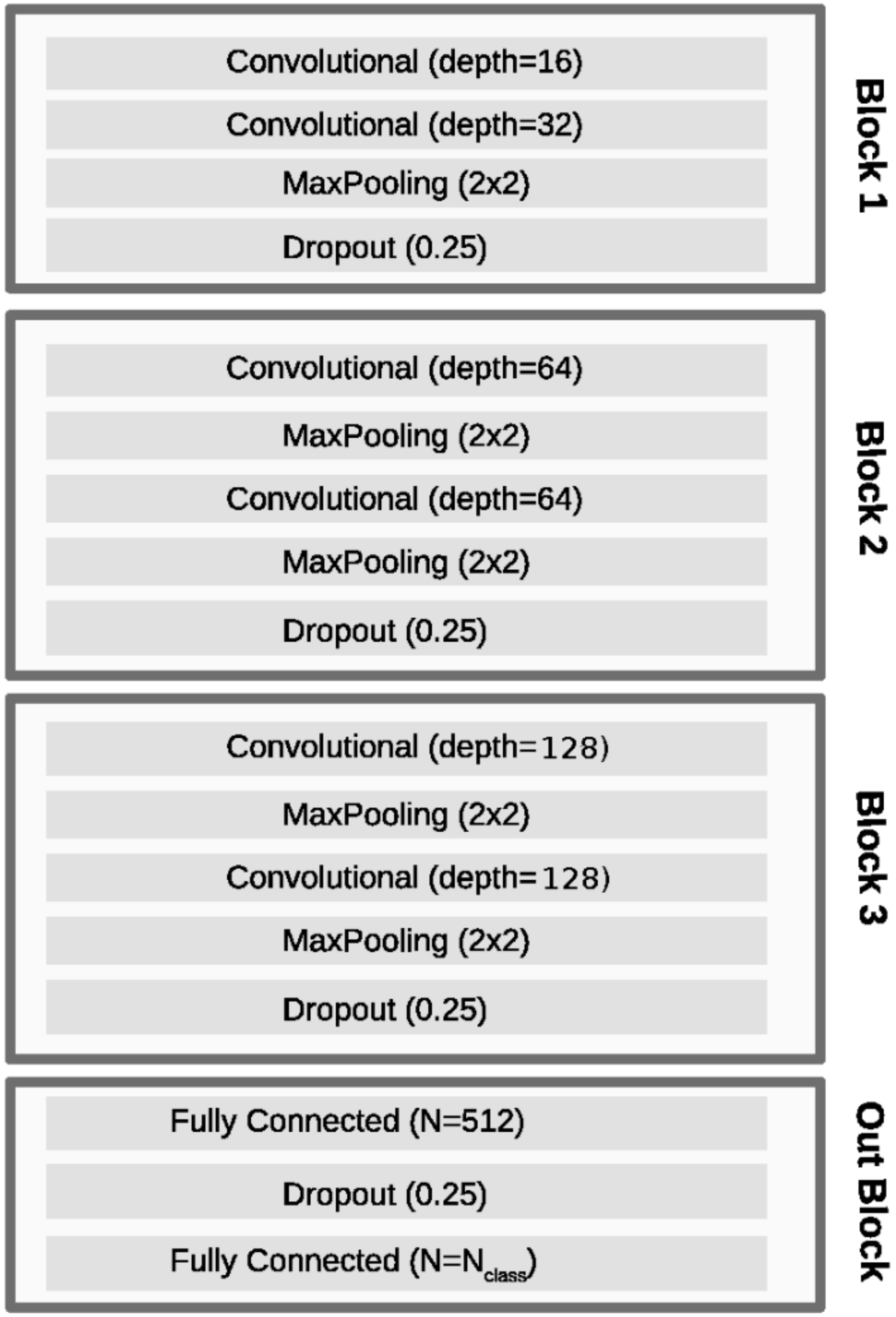
LVC, arXiv:2010.14529



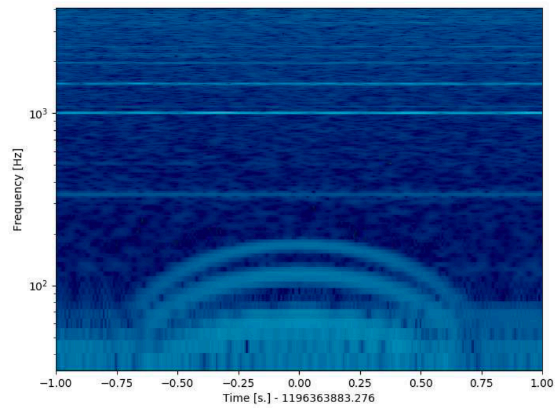
Characterisation of glitches with CNN

- **Spectrograms**: time/frequency maps provides 2D representation of glitches analogous to images

- **Convoluted Neural Networks**:
  - CNN on simulated glitches offer 99% classification efficiency
  - Supervised learning where categories are based on morphological features



[Razzano & Cuoco, arXiv:1803.09933]



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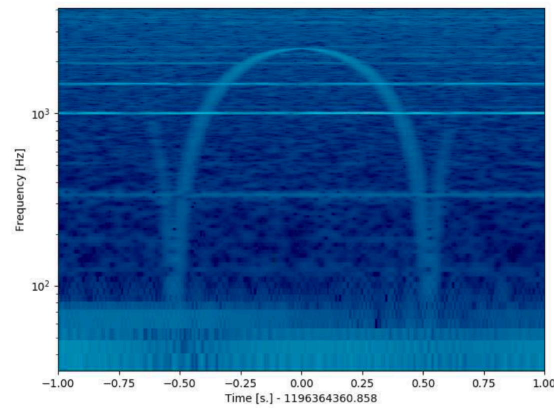

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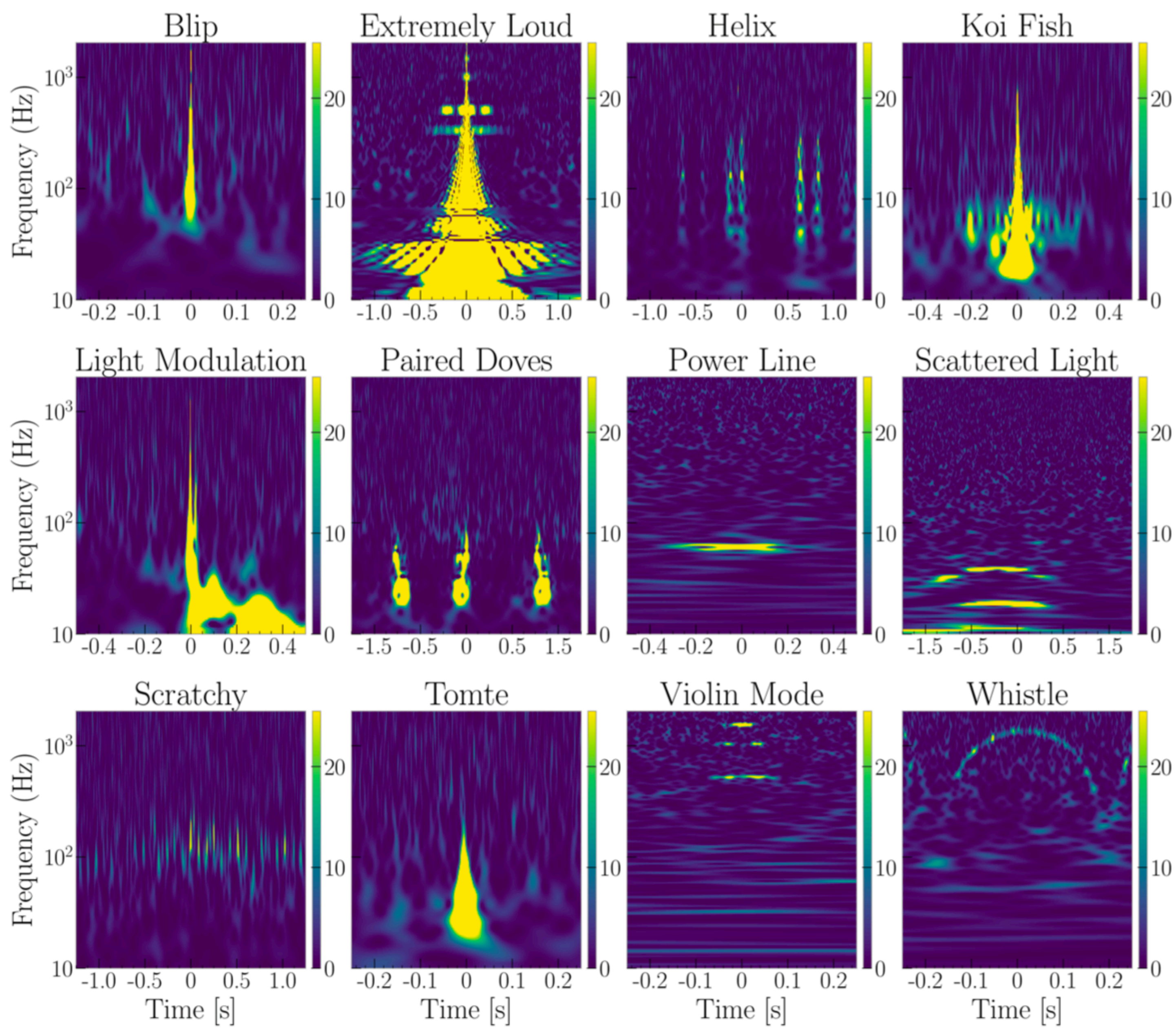
Human-based glitch tagging

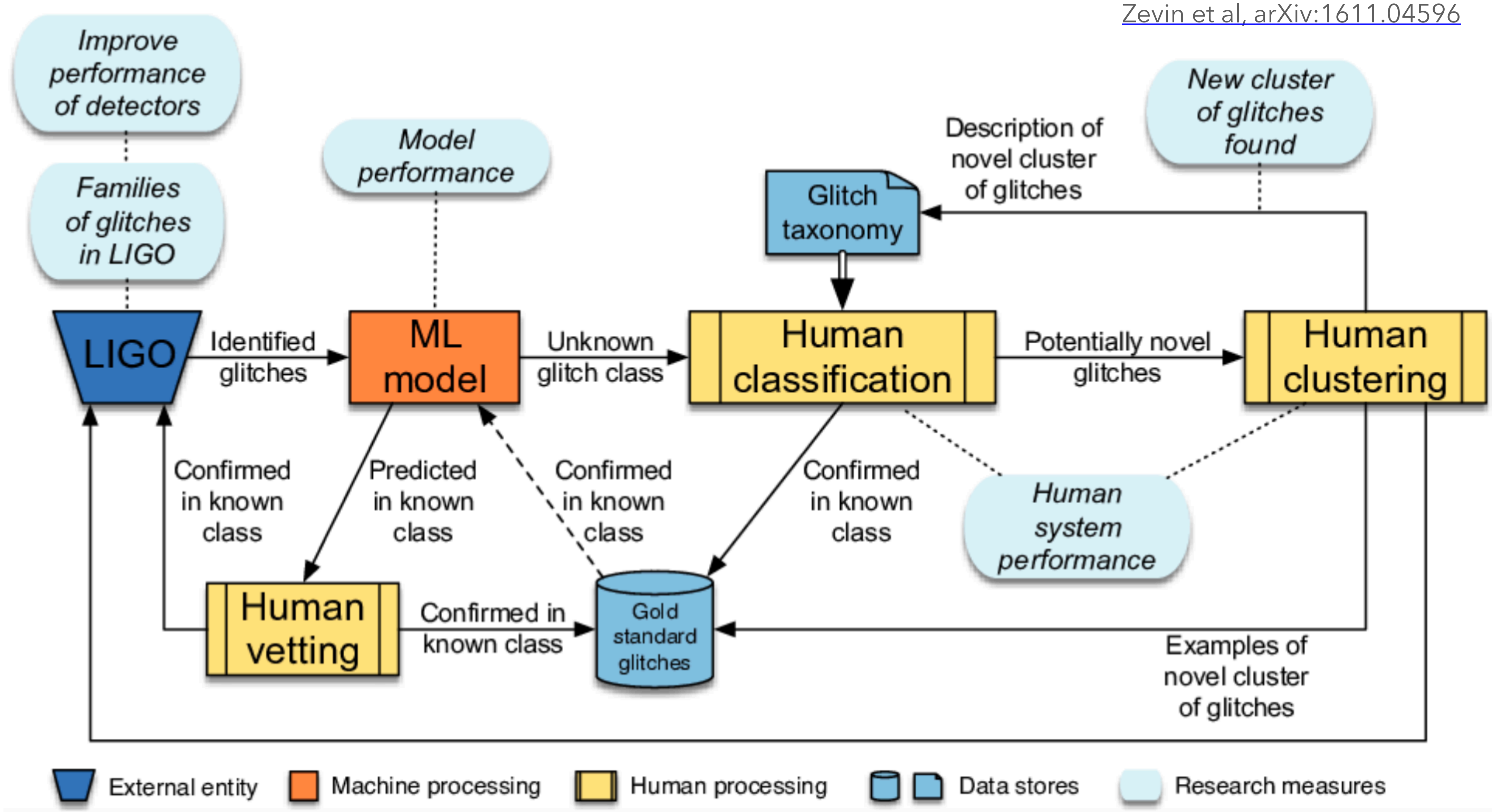
- **<u>GravitySpy</u>:** citizen science projet where anybody can tag glitches from LIGO and Virgo. Create a dataset for next ML application of glitch characterisation.



GravitySpy and machine learning

- **CNN efficiency**: training on citizen-tagged events show >0.9 correct tagging except for “Paired Doves” and “Wandering Lines” categories.

Zevin et al, arXiv:1611.04596



Machine learning applications

- Why ML?
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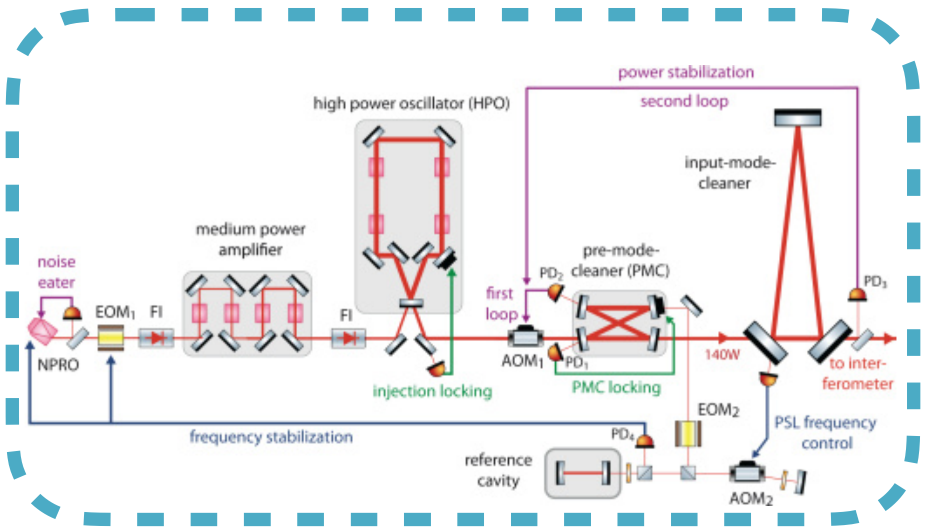
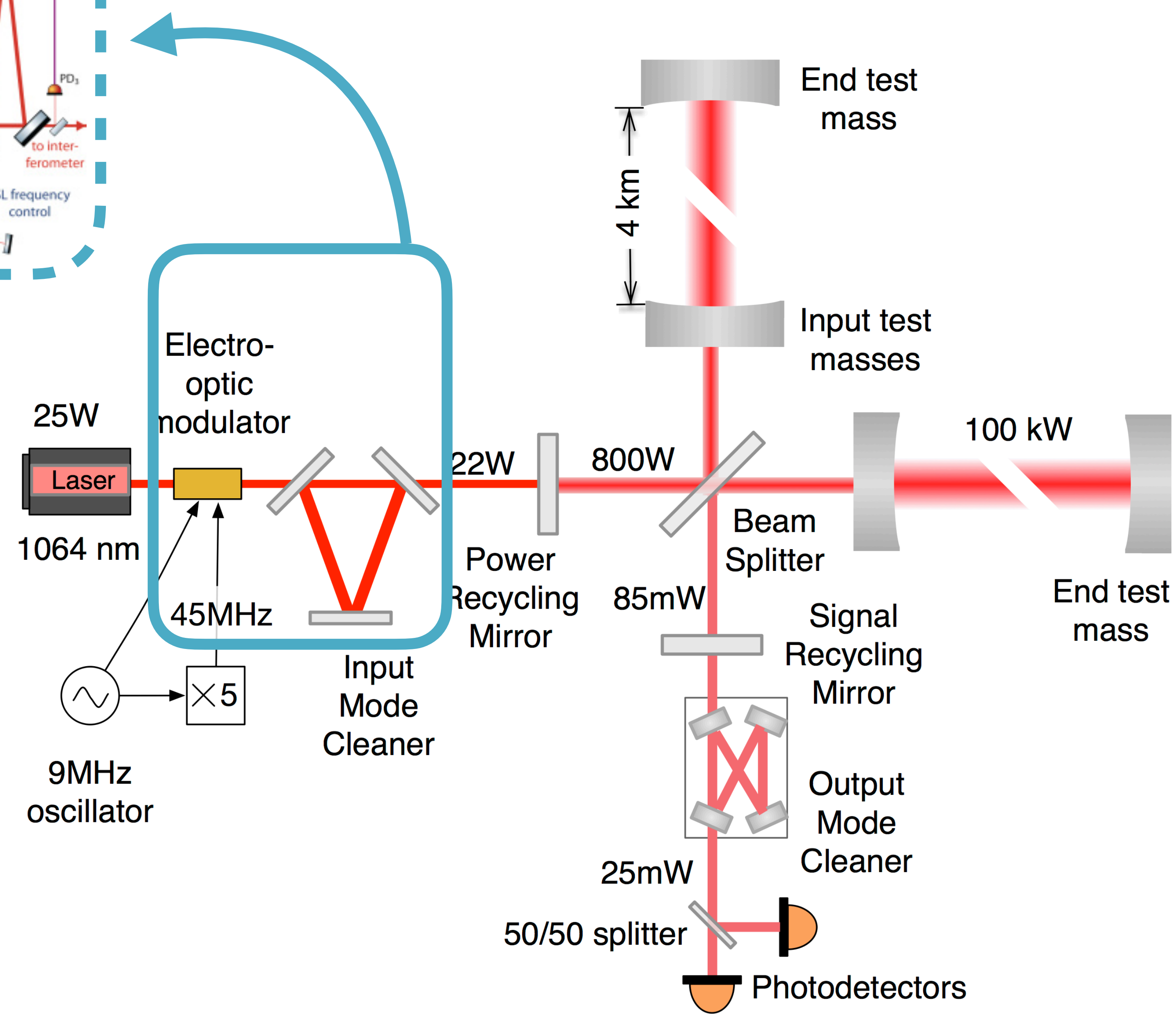
LIGO-Virgo auxiliary channels

- **Auxiliary channels**: a plethora of additional detectors monitoring the interferometers





Kwee et al, Optics Express Vol. 20, Issue 10, pp. 10617-10634 (2012)

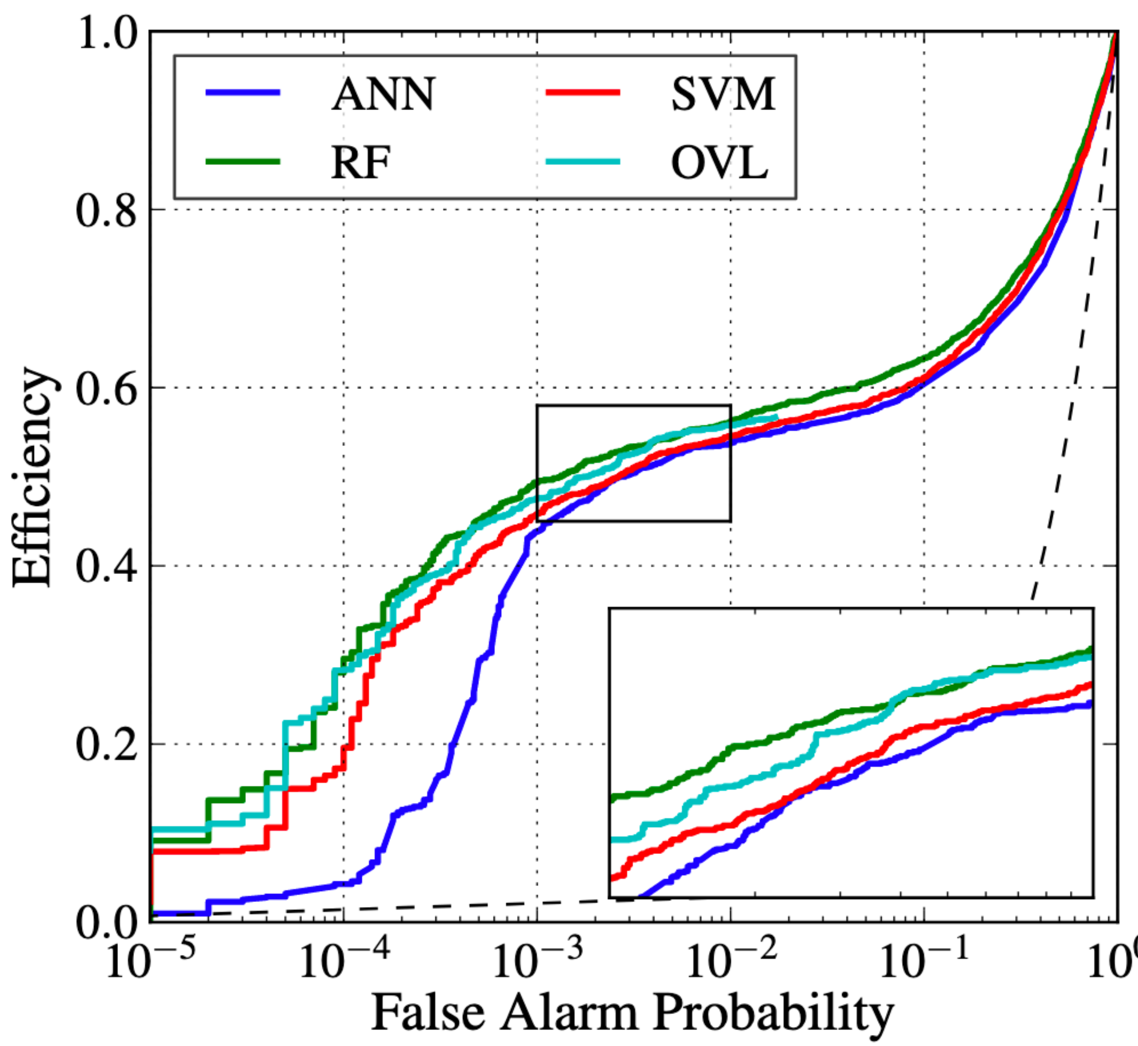
Martynov et al, arXiv:1604.00439

Identify astrophysical signals from noise

- **Glitches**: can be identified from astrophysical signals with the auxiliary channels

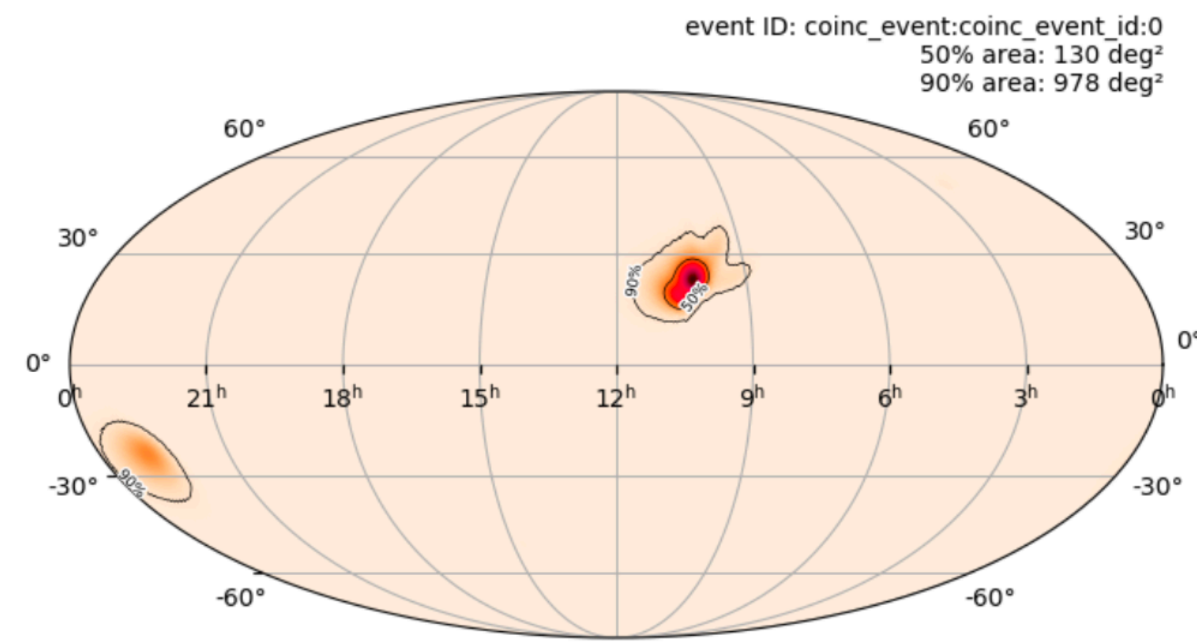
- **Comparison of ML algorithms**:
  - Artificial Neural Network
  - Support Vector Machines
  - Random Forest
  - Ordered Veto List (correlation of glitches in GW / auxiliary channel with hierarchical ordering)

Biswas et al, arXiv:1303.6984

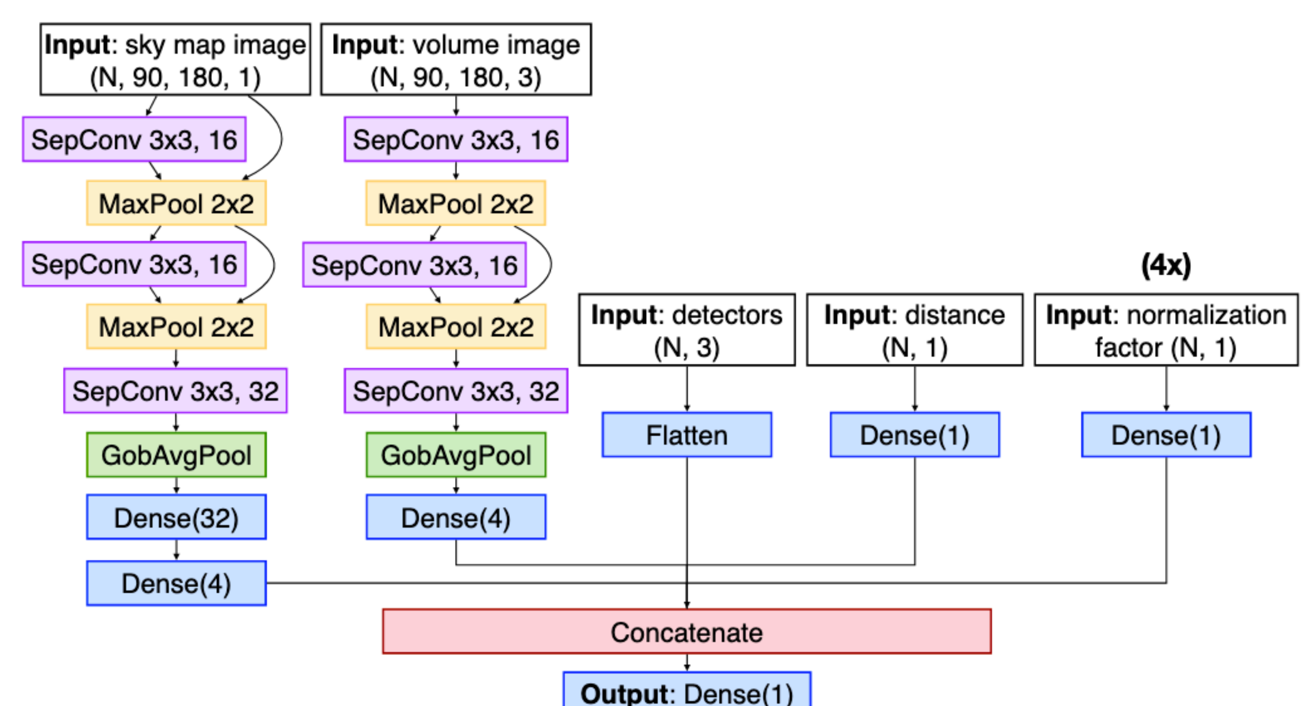


Using public data for electromagnetic alerts

- **Alerts**: are sent to multimessenger facilities when event false alarm rate is large. Can be retracted after further studies if the event is noise.



- **CNN classifiers:**
  - Use public data only as inputs (sky localisation, distance, detector network)
  - Correctly classify events from noise is 93% of cases
  - Support the decision to follow GW events with telescopes



Cabero et al, 2010.11829

Machine learning applications

- Why ML?
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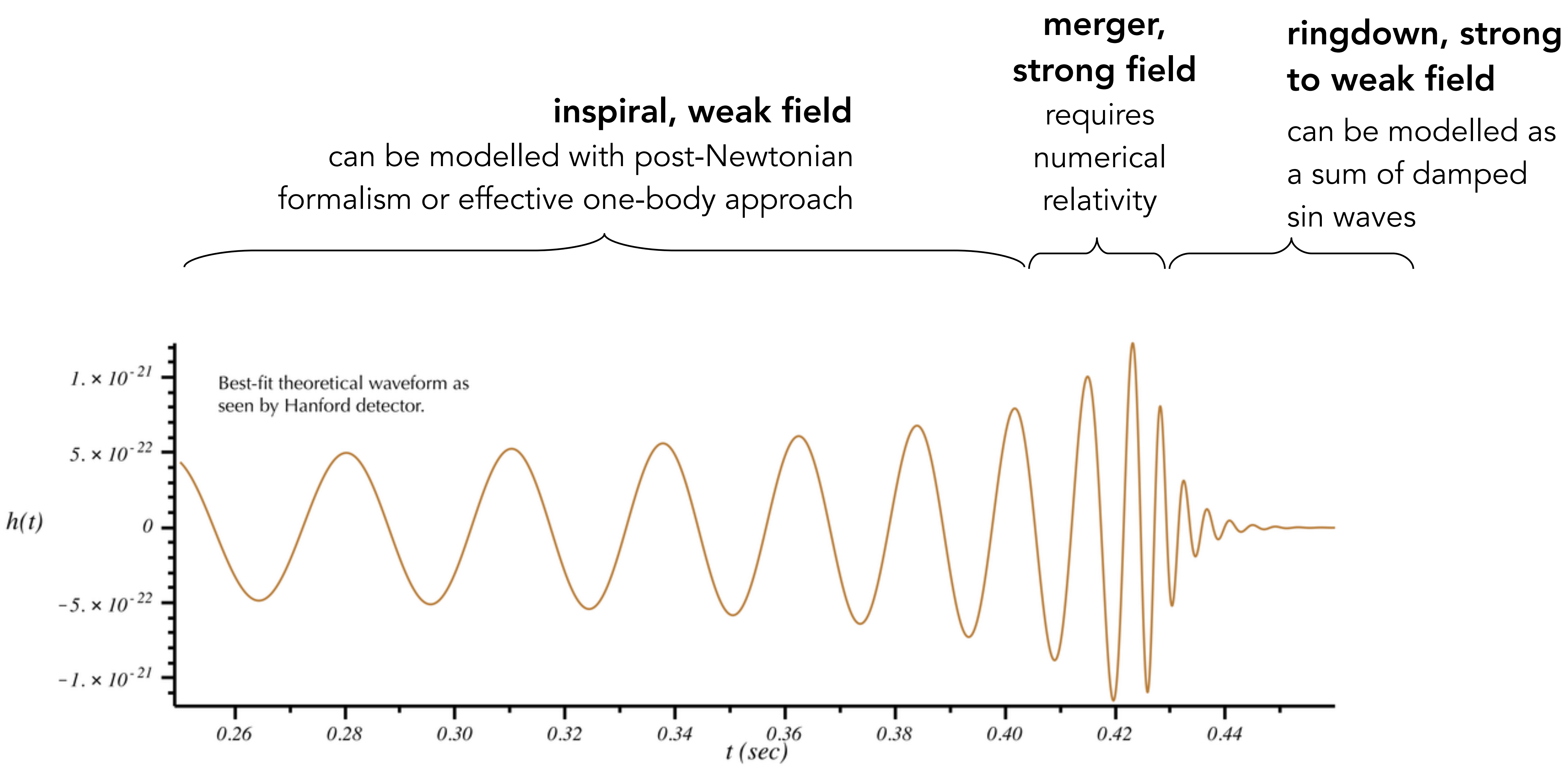
The necessity of GW modelling

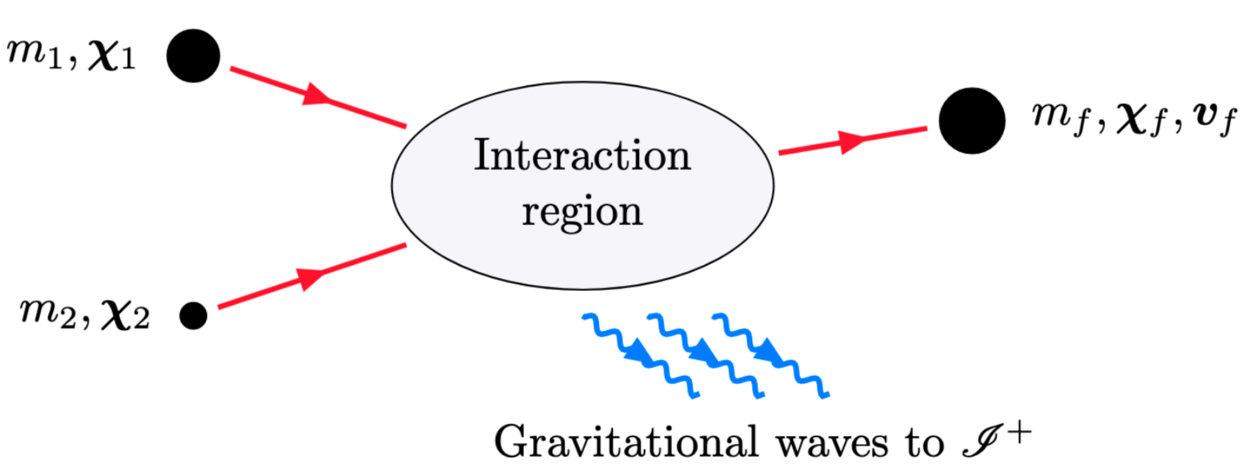
- **Necessity of a template bank of GW signals**: matched filtering algorithms and modelled search need to compare the data stream to templates
- **GW modelling**: approximate signals as numerical relativity simulations are too computationally intensive



Source: Sound of Spacetime

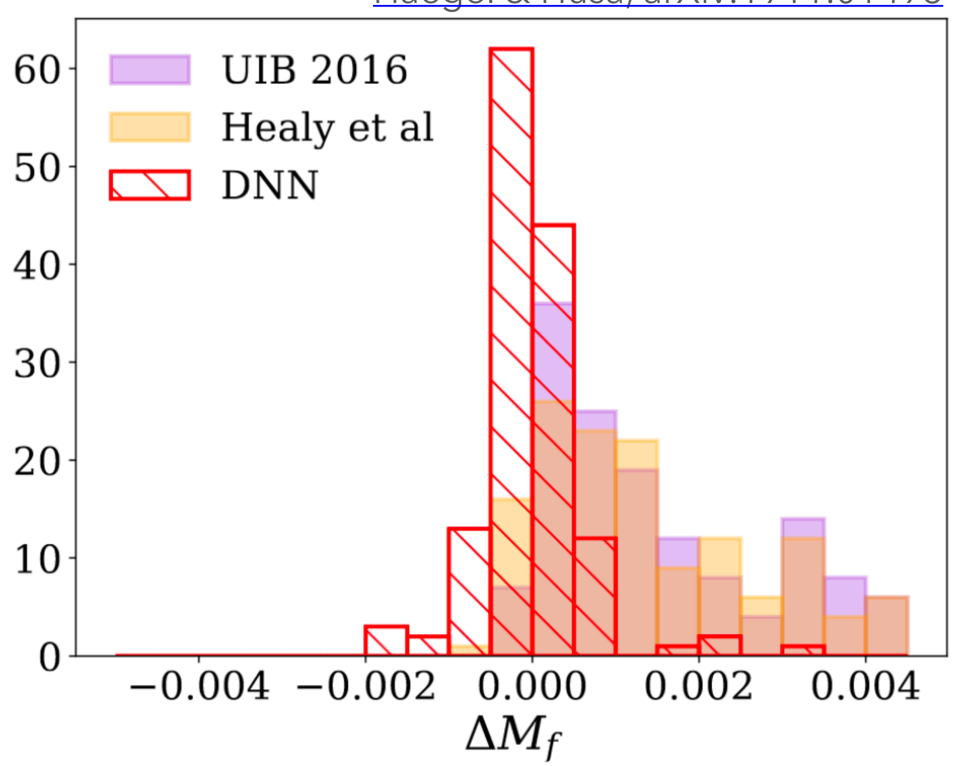
Predicting the remnant parameters

- **Final black holes properties**: are important for GW modelling (final mass, spin)
- **Spinning black holes**: induce precession in the binary, high-dimensional (7 parameters) system to model, traditionally approximated
- **ML applications**: neural networks and GP can fully take into account the spin effects and correct biases in the prediction



Varma et al, arXiv:1809.09125

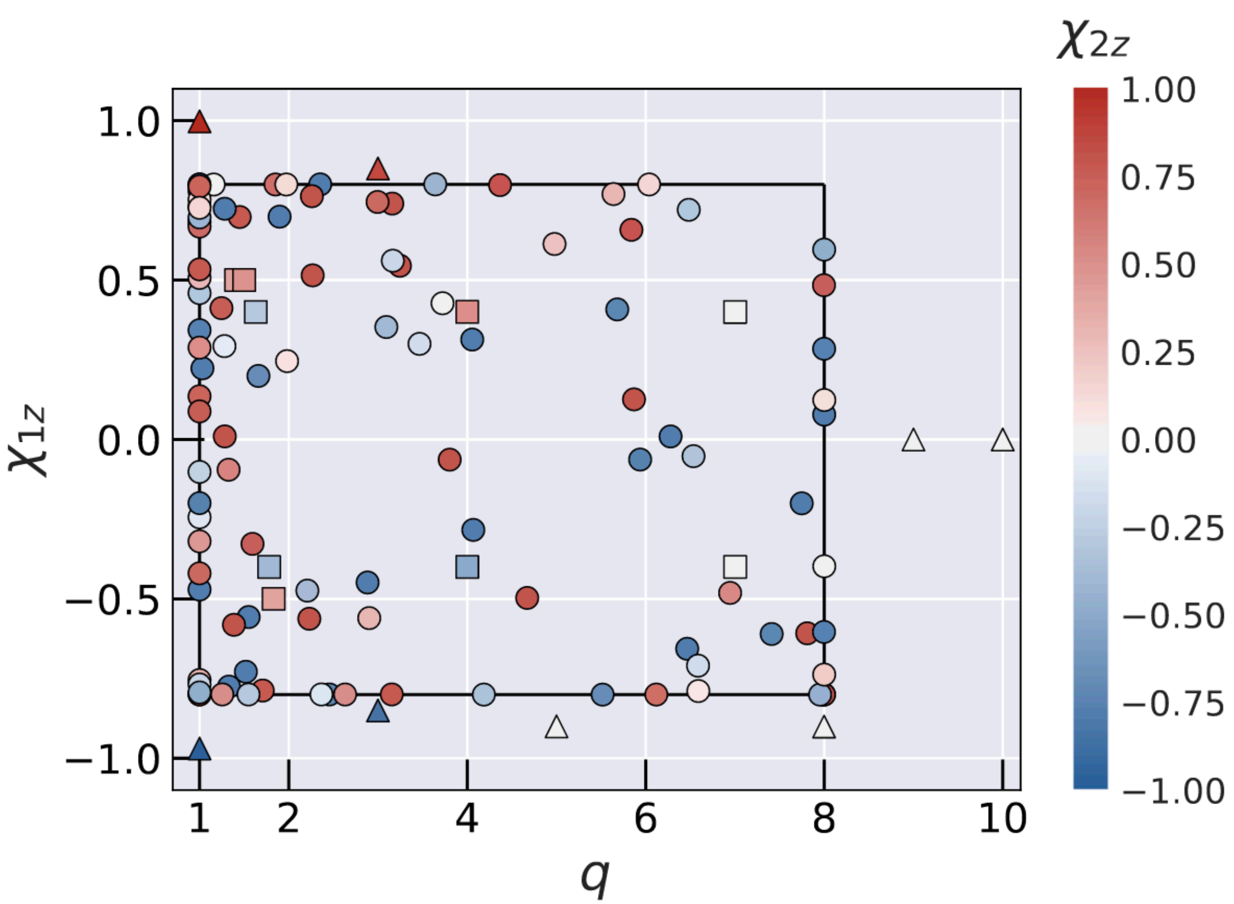
Haegel & Husa, arXiv:1911.01496

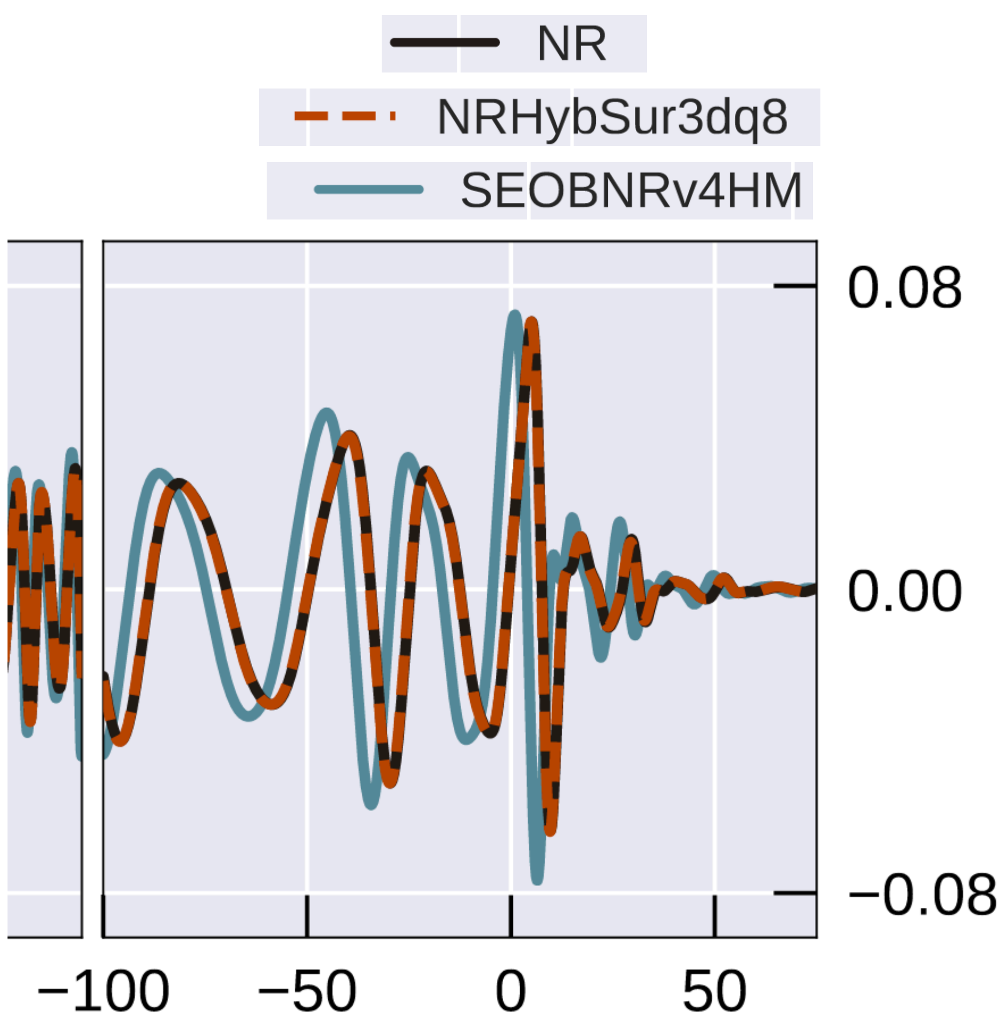


Interpolating numerical relativity simulations

- **Gaussian Process**: can be trained on numerical simulations to generate GW template
- **Interpolation**: in the parameter space of the simulations
- **Errors**: of the GP training can be naturally propagated into parameter inference

Varma et al, arXiv:1809.09125





Machine learning applications

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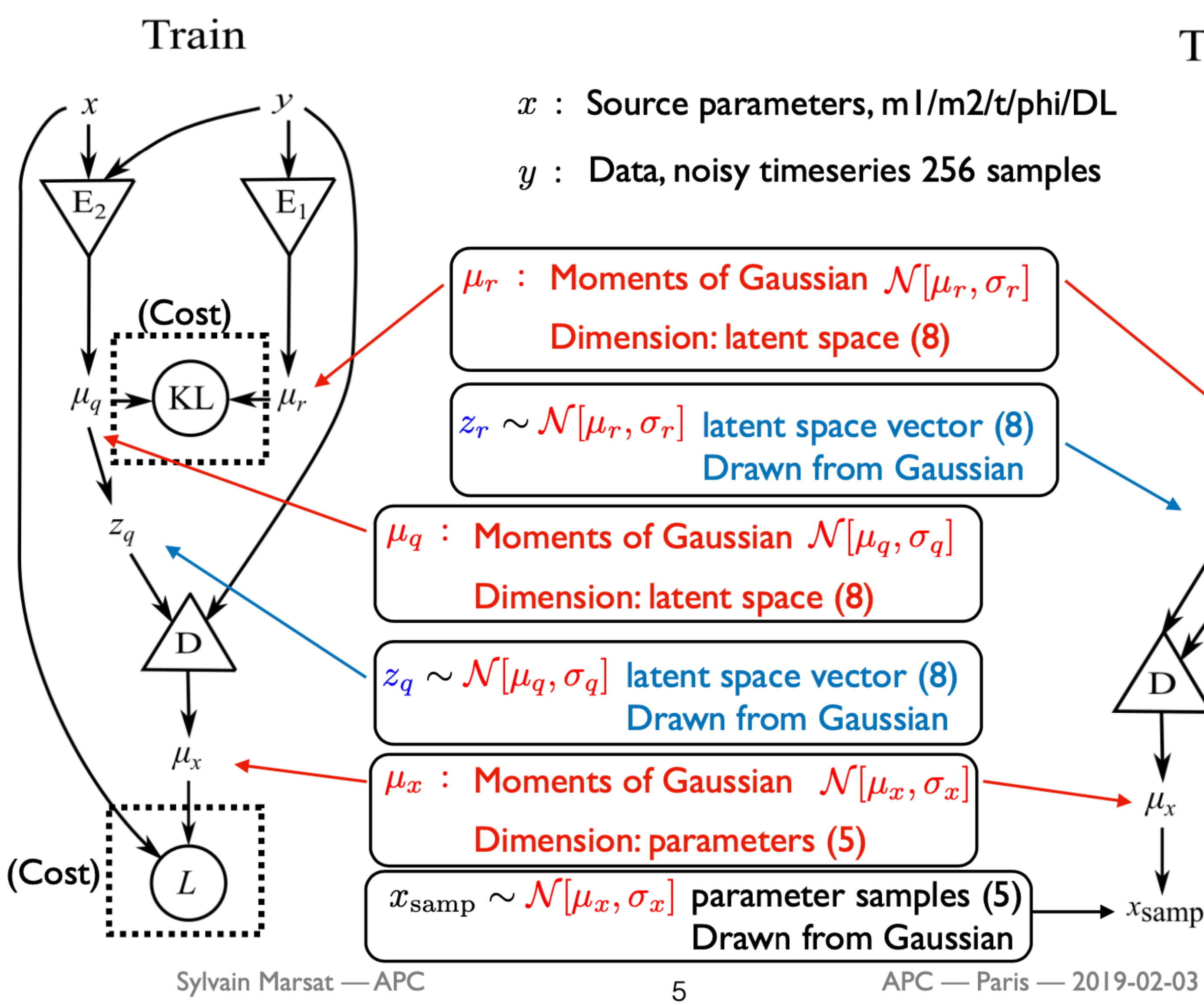
- **Estimation of the GW sources parameters**

Estimation of GW source parameters

- **Markov chain sampling**: slow process (up to weeks)
- **Conditional variational auto-encoder (CVAE):** minimize the cross-entropy between the true Bayesian posterior and an approximate Bayesian posterior produced by the neural network

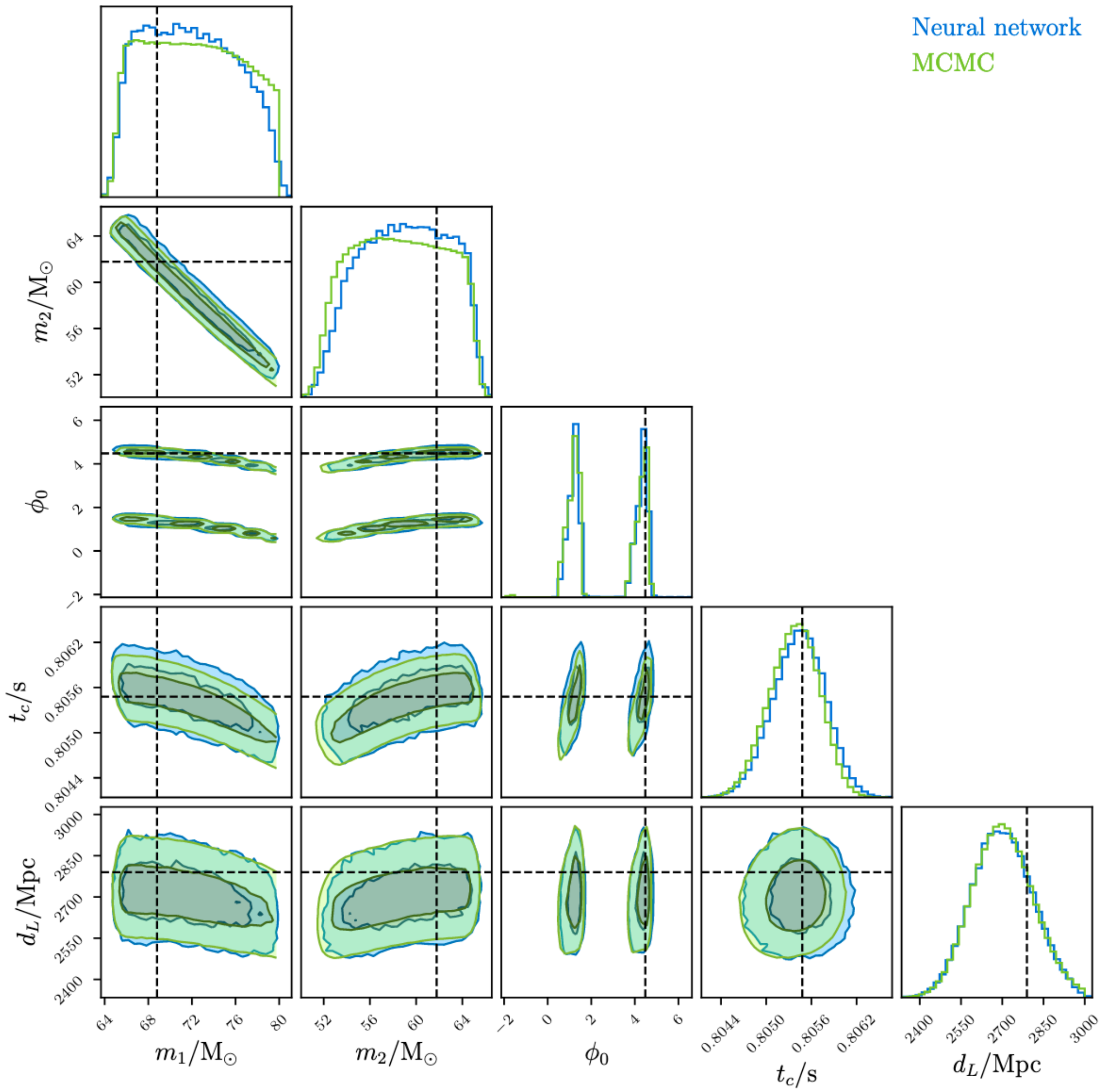


Gabbard et al, arXiv:1909.06296

Estimation of GW source parameters

- **Normalizing flow**: invertible transformations to transform a simple initial distribution (multivariate Gaussian) into a more complex target distribution (posterior probability density of source parameters)

- **Quick estimate**: both methods provide estimates consistent with MCMC in a much reduced time (~1 mn)



(c) CVAE+

Green et al, arXiv:2002.07656

Thank you for your attention

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