Deep learning methods
for the analysis of Gravitational Wave data

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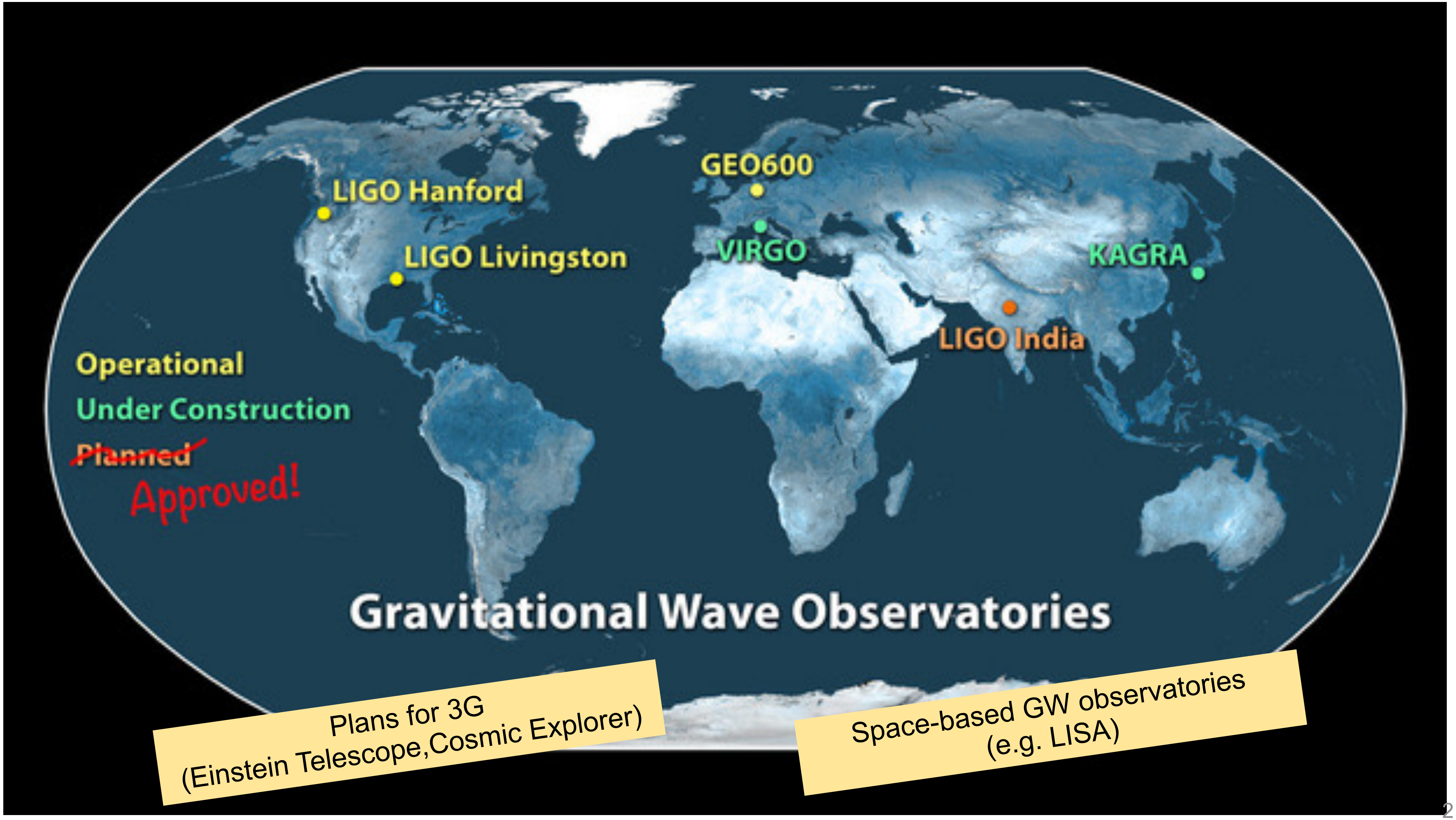
Gravitational waves, ElectroMagnetic and dark MAtter physics (GEMMA2) Workshop
Rome, 16-19 September 2024

Intro: The era of Advanced GW detectors

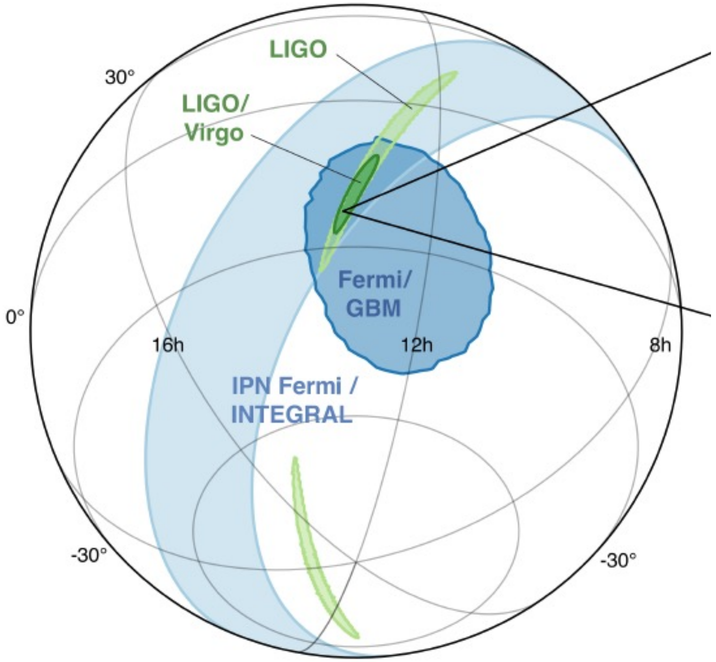


Plans for 3G
(Einstein Telescope,Cosmic Explorer)

Space-based GW observatories
(e.g. LISA)

Credits: Caltech/MIT/LIGO Lab

Some key challenges in GW data analysis



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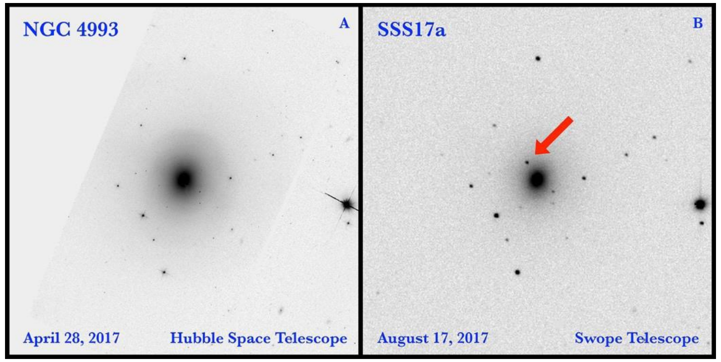
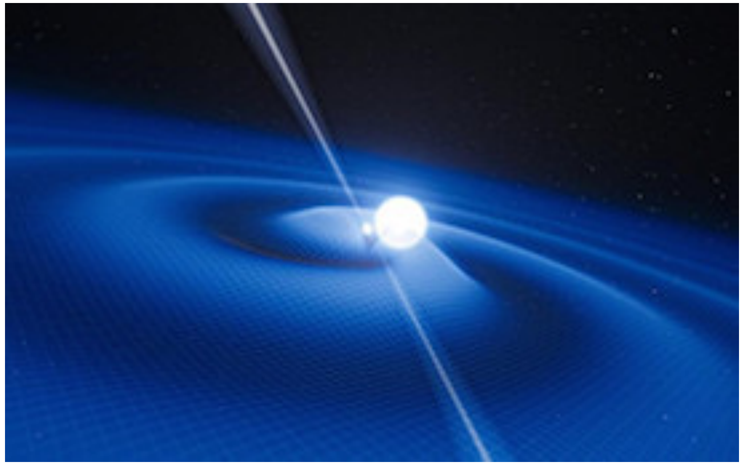


The need for speed
Low latency analysis for
EM follow-up observations

Large and complex datasets
(e.g. continuous waves, noise hunt,
stochastic background)



Credits: ESO/L. Calcada

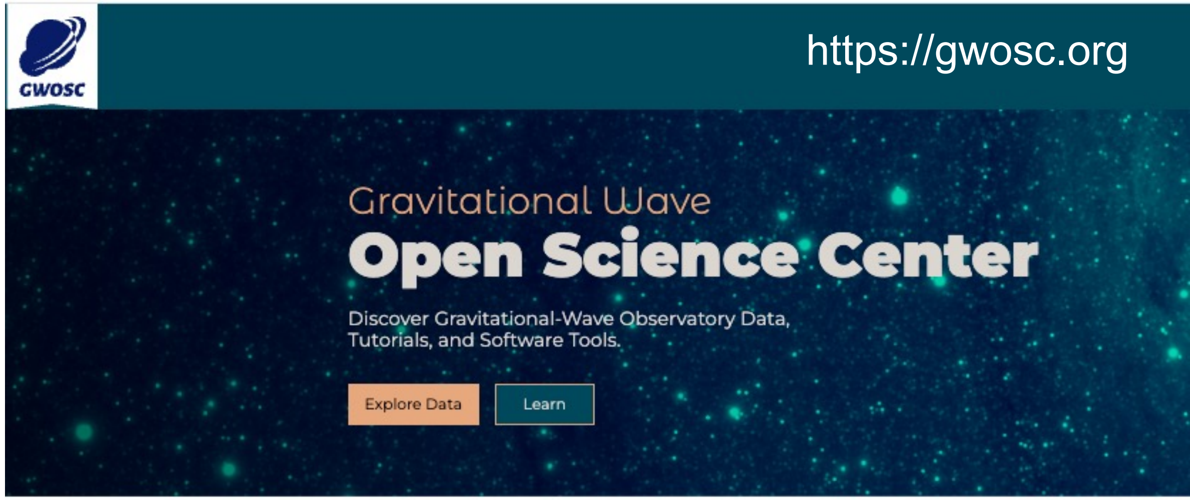
Credits: A. Simonnet/NANOGrav collab

Big Data is the key

Sky Survey	Volume	Velocity	Variety
SDSS *Sloan Digital Sky Survey*	50 TB	200 GB per day	images, catalogs, redshits
GAIA	100 TB	40 GB per day	more then 100 parameters
Pan-STARRS *Panoramic Survey Telescope and Rapid Response System*	5 PB	5 TB per day	images, catalogs
LSST *Large Synoptic Survey Telescope*	60 PB	10 TB per day	images, catalogs
SKA *Square Kilometer Array*	3 ZB	150 TB per day	images, catalog, redshifts

Notes:
The column Volume refers to raw data produced at the end of the experiment.
Values regarding Pan-STARRS, LSST, and SKA surveys refer to expected Volume and Velocity values.

Garofalo et al 2017



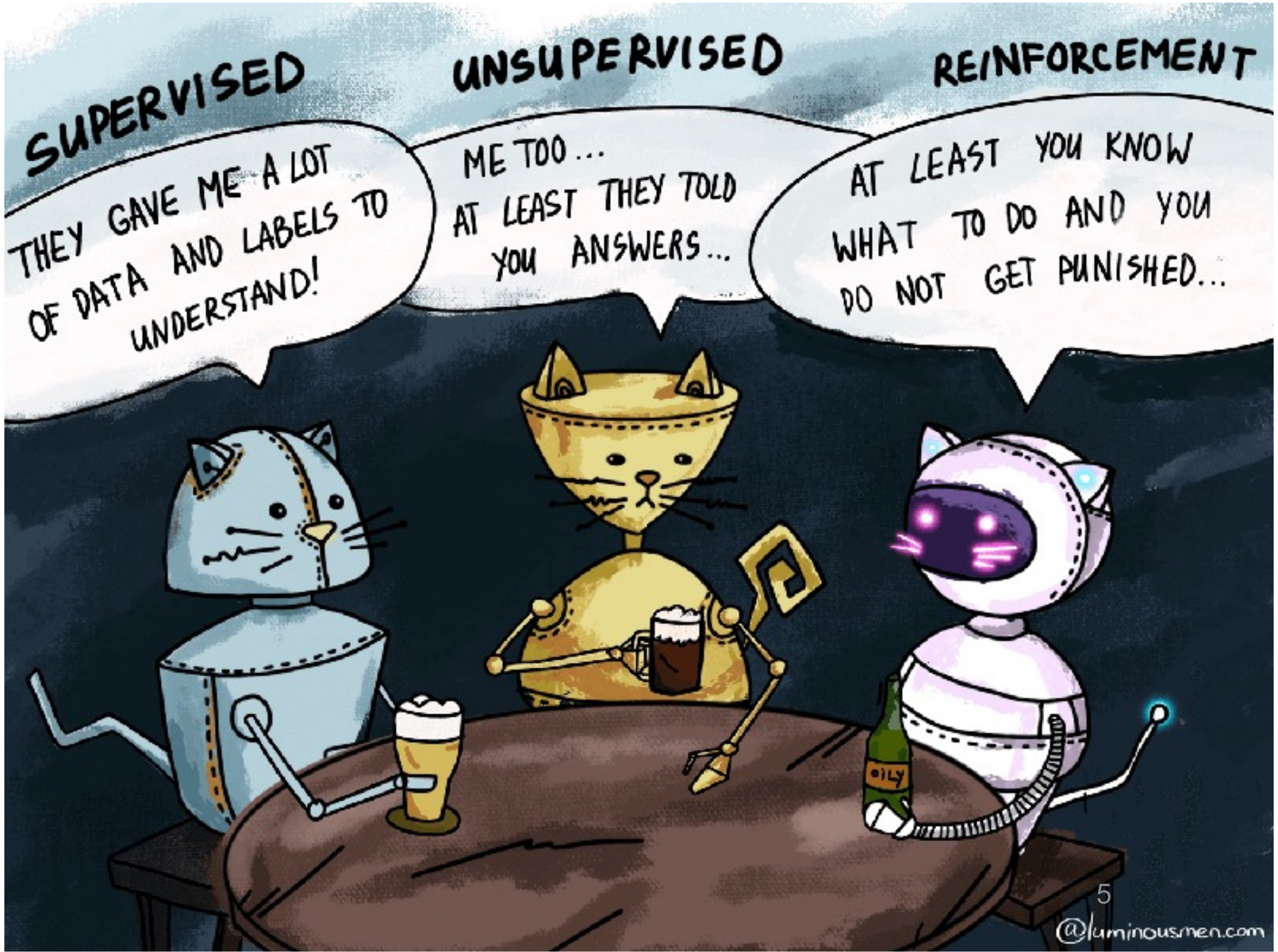
- Interferometers produce large amounts of data
- Order of ~ TB/day (depending on how many auxiliary channels)
- More than 30Tb of data from runs in the Gravitational Wave Open Science Center (GWOSC)
- Signals are buried in a high noise

Approaches to Machine Learning

- **Supervised**: the algorithm is fed with labeled data, and learn the features that are best linked to each label (task driven)
  - Classification
  - Regression

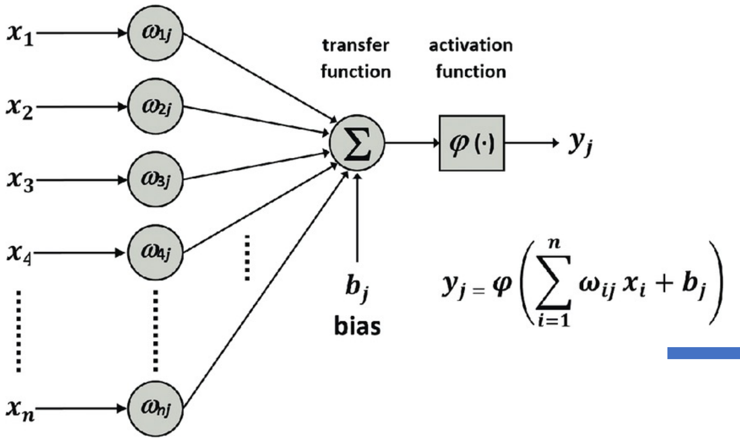
- **Unsupervised**: No labels, features are extracted (data driven)
  - Clustering
  - Dimensionality reduction

- **Reinforcement learning**: trial and error strategy (experience driven)

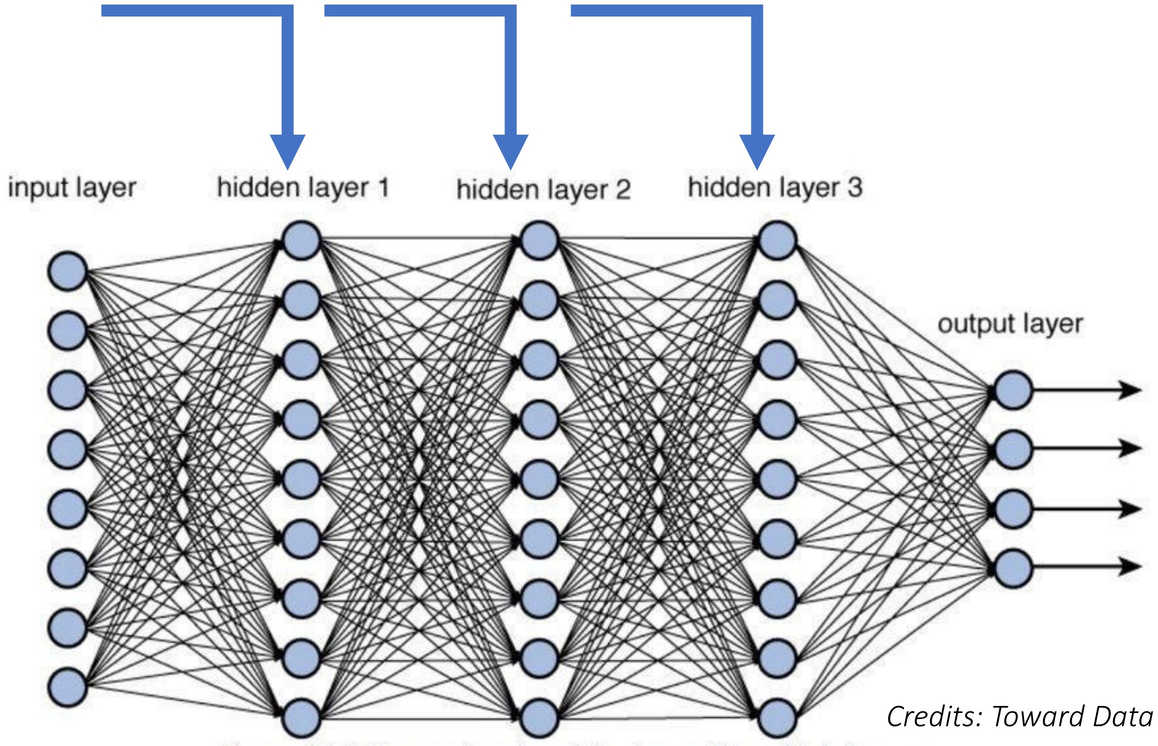


Neural Networks & Deep Learning

- Machine Learning is a vast area of computing science
- Neural Networks are very popular, but not the only approach to Machine Learning



Artificial neuron as processing unit (perceptron) with non linear activation function



- "Learning" is adjusting the weights w_{ij} and biases b_j during training
- More hidden layers make a network "deep" (deep learning)

Credits: Toward Data Science

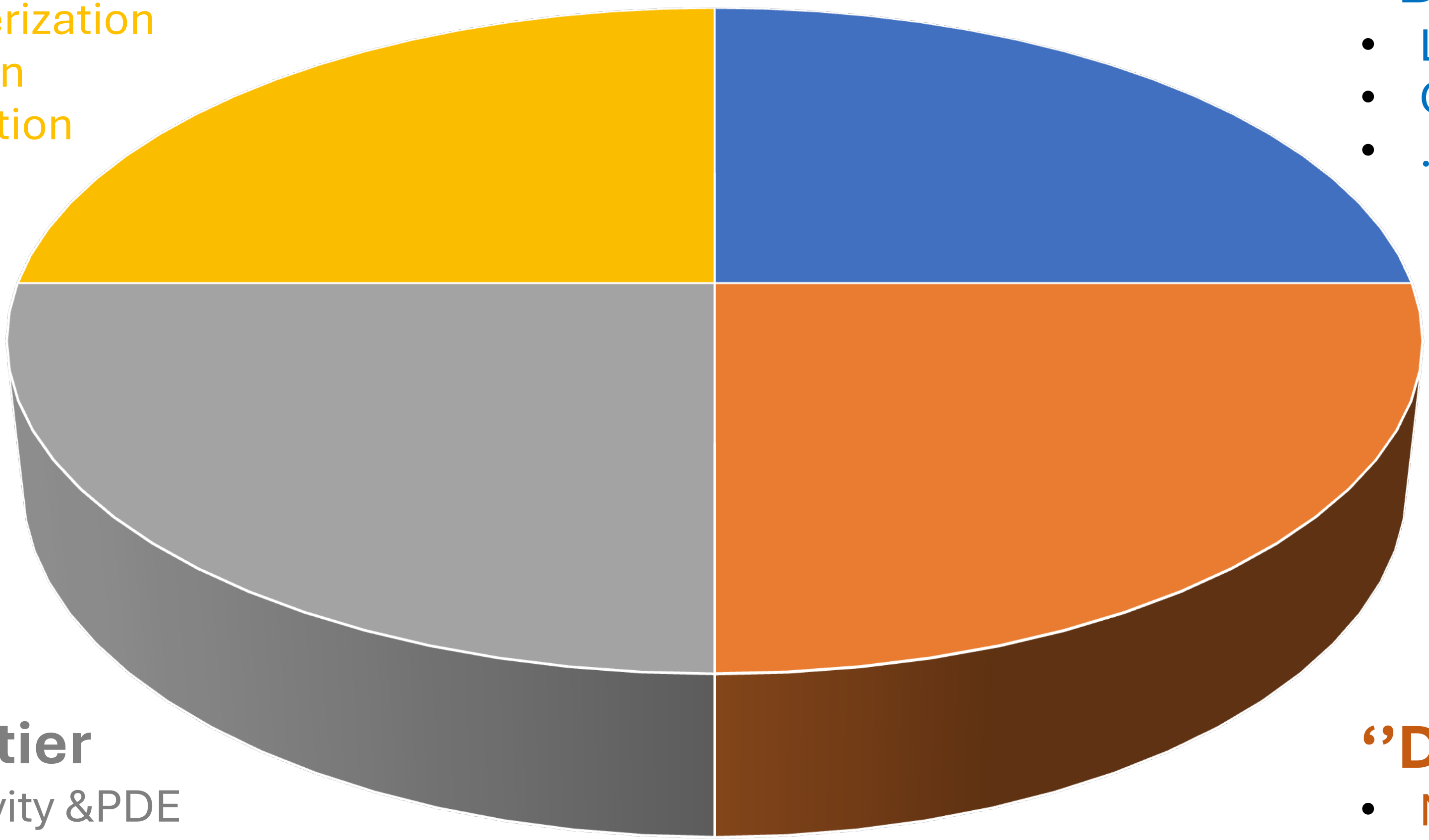
Deep Learning and Gravitational Waves

‘’Fast’’ Frontier

- Detector characterization
- Transient detection
- Parameter estimation
- …

‘’Big Data’’ Frontier

- Long datasets (CWs)
- Complex data (aux channels)
- …



‘’Theory’’ Frontier

- Numerical Relativity &PDE
- Simulations
- Waveforms
- …

‘’Detector’’ Frontier

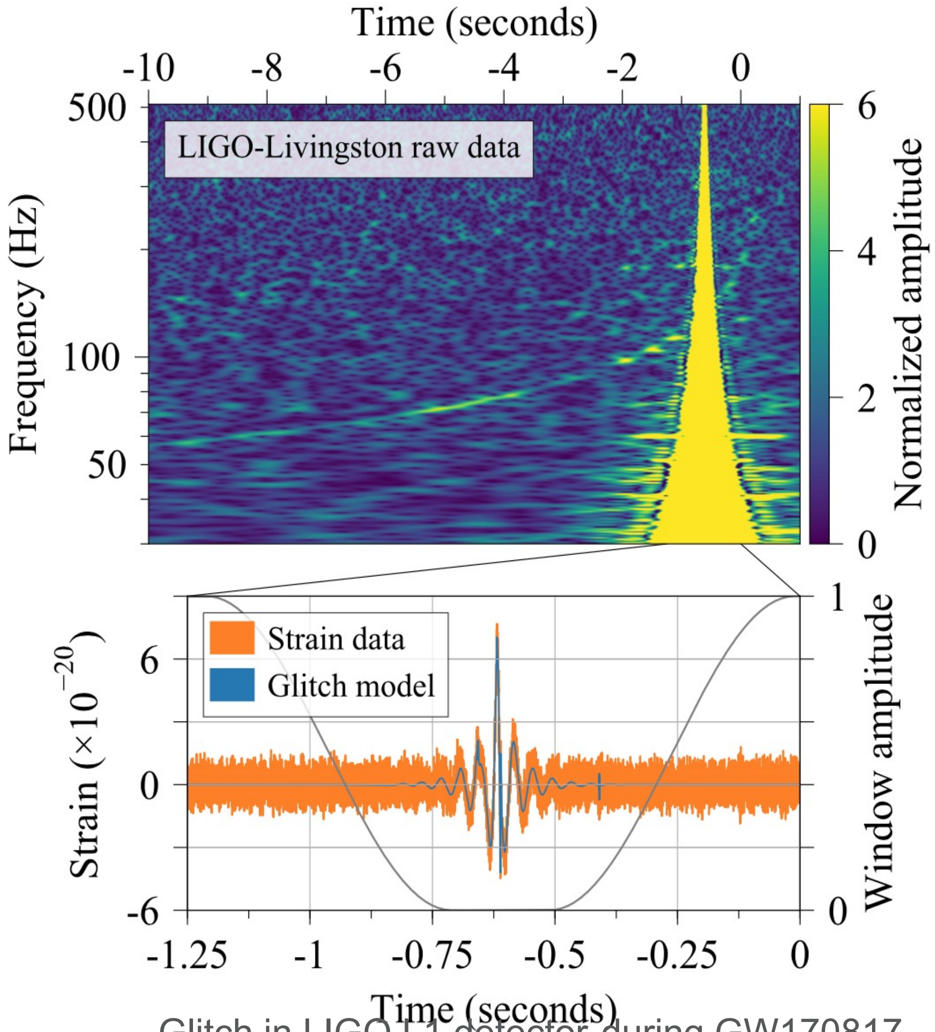
- Noise Hunting
- Controls
- …

Spoiler Alert: This list is not complete!

Detector characterization – Glitch studies

- **Noise in interferometers is not stationary**
  - Transient noise events can happen
  - Not related to astrophysical source, but local disturbances
  - Different timescales/frequency ranges
  - Affect data quality, stability and GW detection

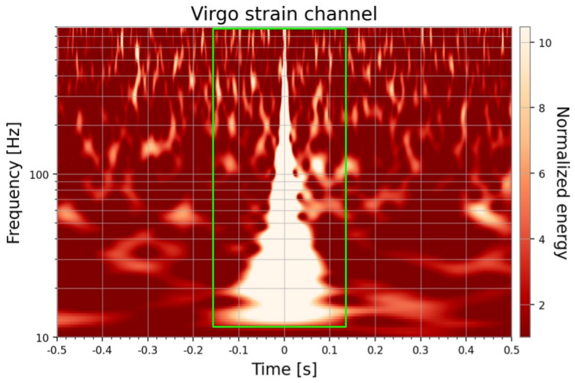
- **Noise hunting & characterization is critical**
  - Detect and classify glitches to find their origin and remove them
  - Hardware/software origin
  - Glitches have complex time-frequency morphologies
  - Data from auxiliary sensors important to understand glitch origin
  - Online detection & denoising
  - Machine learning offers promising approach (e.g. George&Huerta2017, Zevin et al 2017, MR&Cuoco 2018)



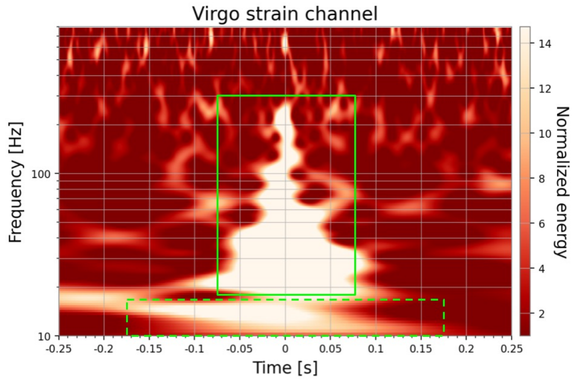
Glitch in LIGO L1 detector during GW170817
Abbott et al 2017

Glitch morphologies

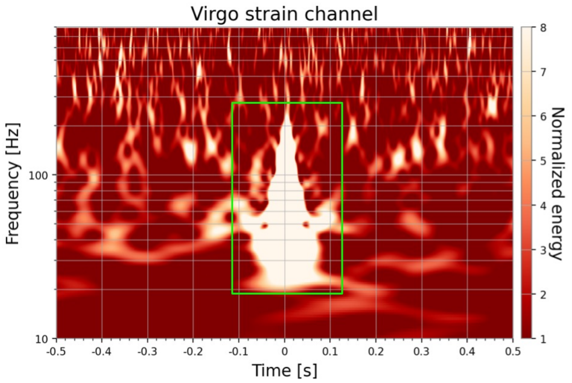
Build diagrams of frequency evolution vs time (spectrograms, Q-transform). Glitches can have very diverse morphologies



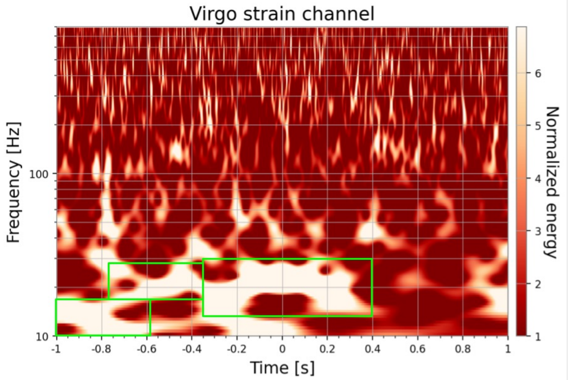
Blip



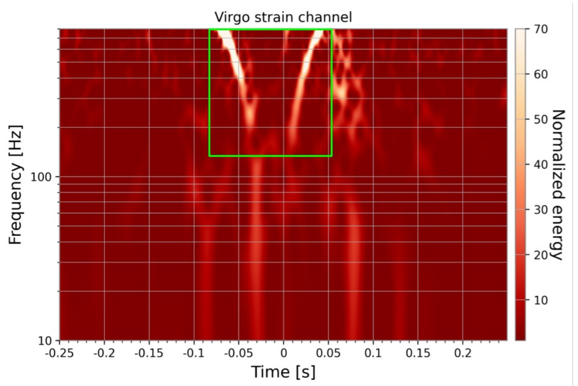
Helix



Koi Fish

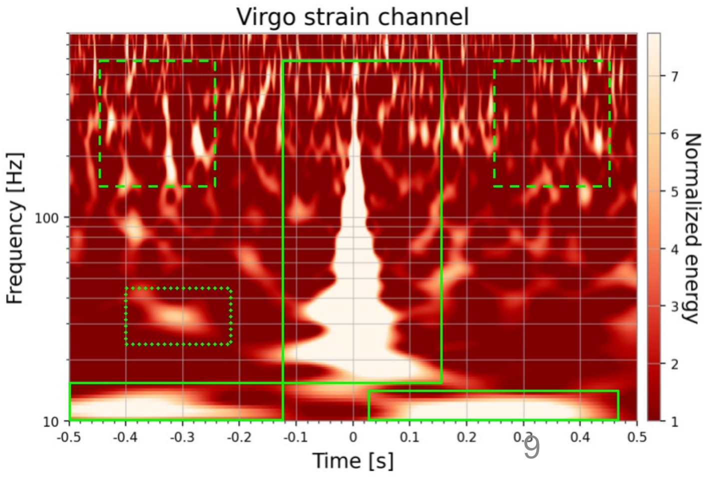


Scattered Light



Whistle

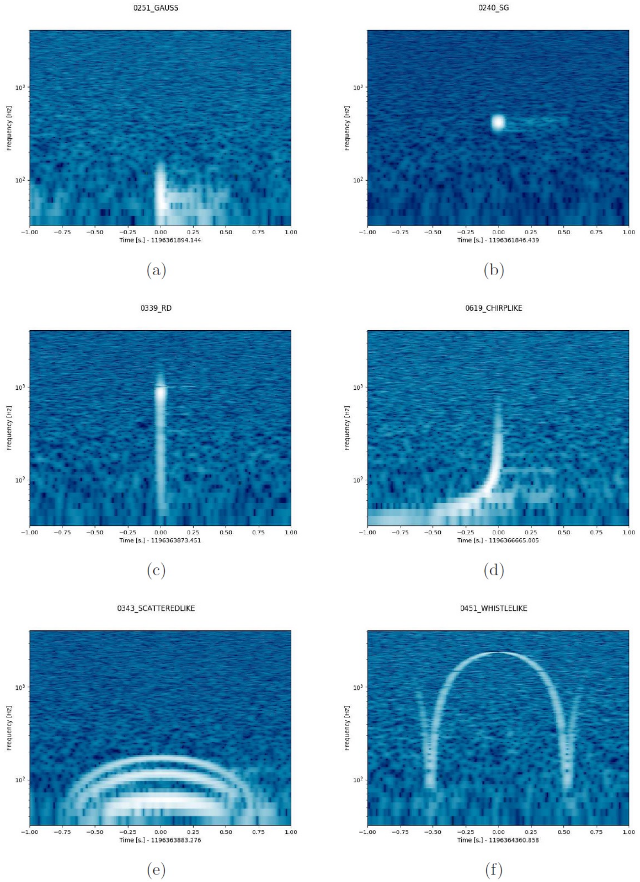
Many Glitches

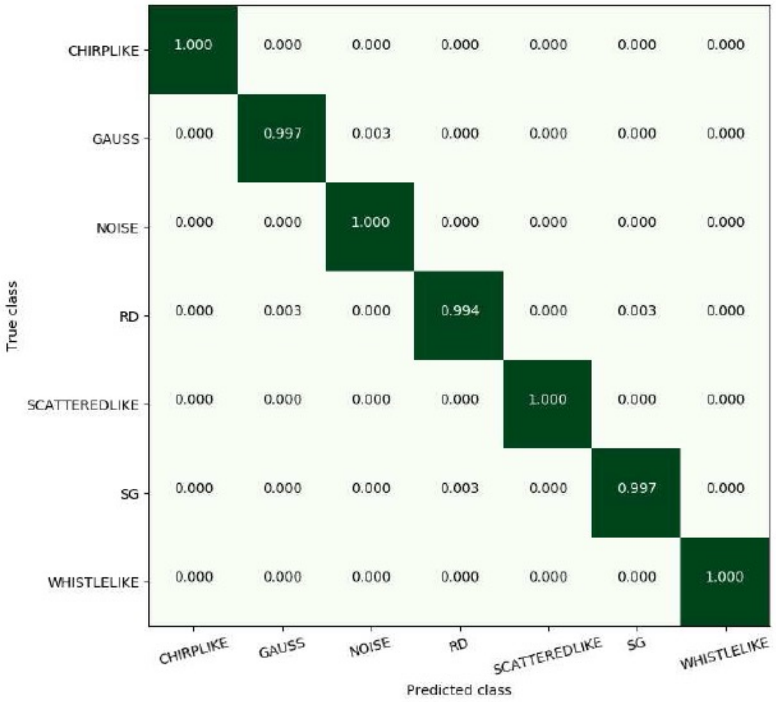


Credits: Zooniverse/GWitchHunters

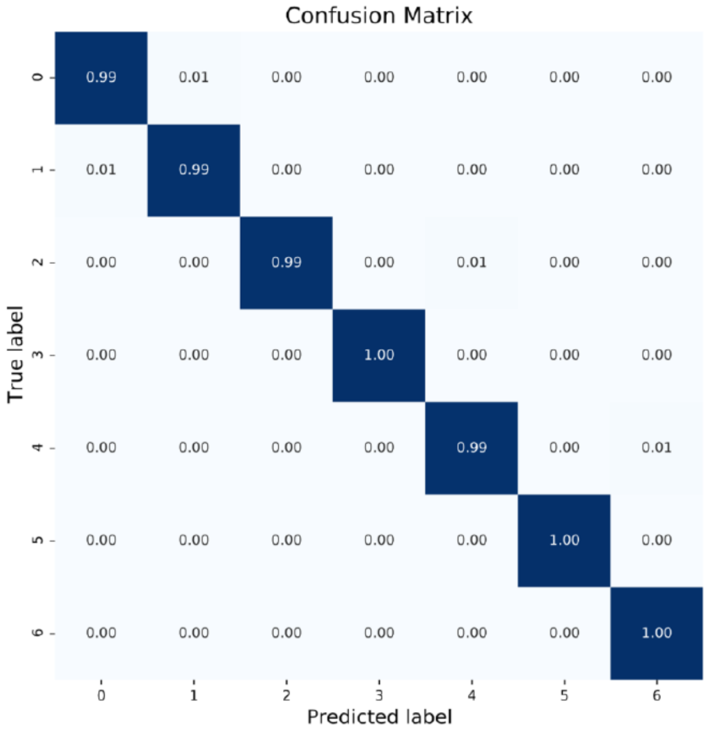
Glitch classification

- Supervised learning is the first and most accurate approach
- Need for large labeled datasets, so also unsupervised approach tested
- Convolutional Neural Networks (CNNs) best for extracting and recognizing features
- Runs with 2D (images) and 1D (time series) CNNs
- First on simulations, then real data
- Results very promising





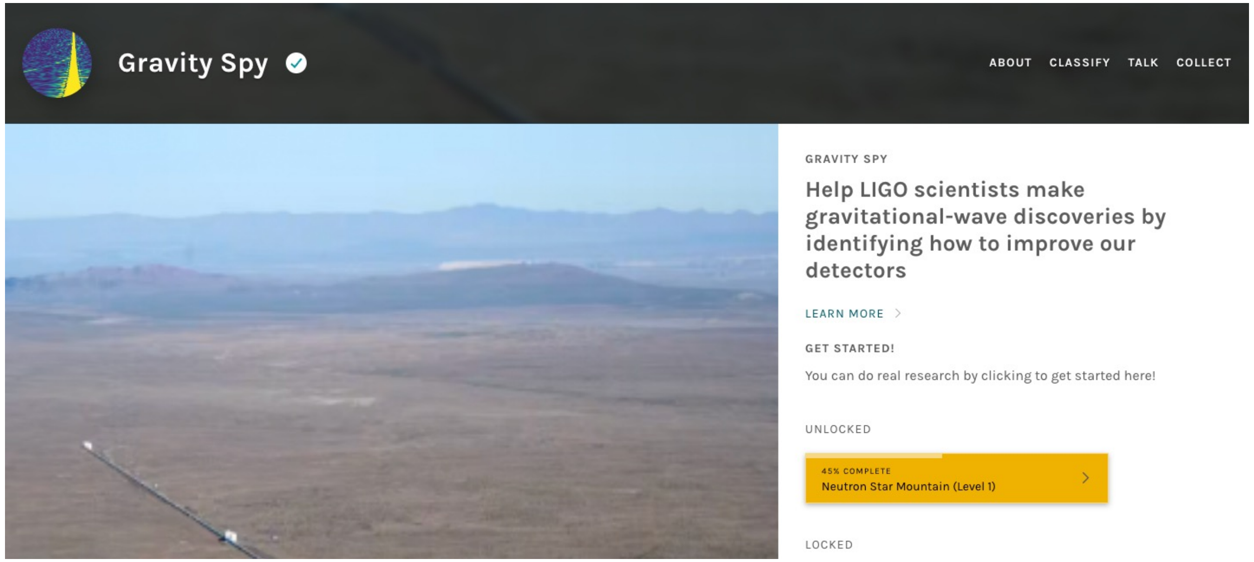
2D CNN on simulations
(MR & Cuoco 2018)

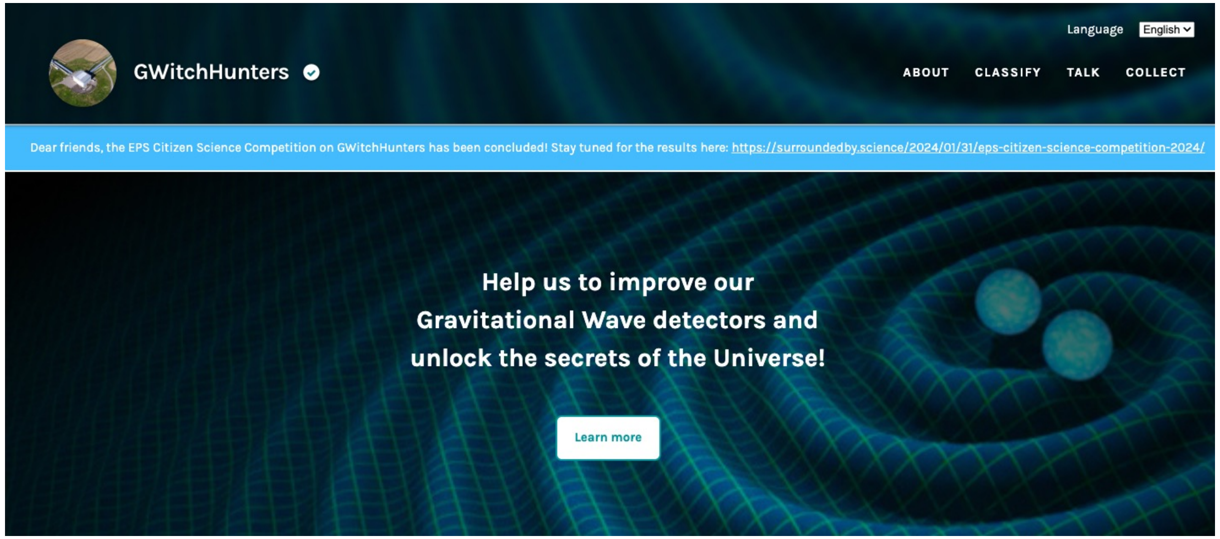


1D CNN on simulations
(Talpini & MR, 2021)

The problem of labeled data

- Supervised learning requires large datasets of labeled time series/images
- Citizen scientists can help!
- Two GW-based citizen science projects on Zooniverse platform:
  - GravitySpy
  - GwitchHunters





GravitySpy (2016)

- Managed by LIGO scientists (e.g. Zevin et al 2017)
- https://www.zooniverse.org/projects/reinforce/gwitchhunters
- Classification Tasks

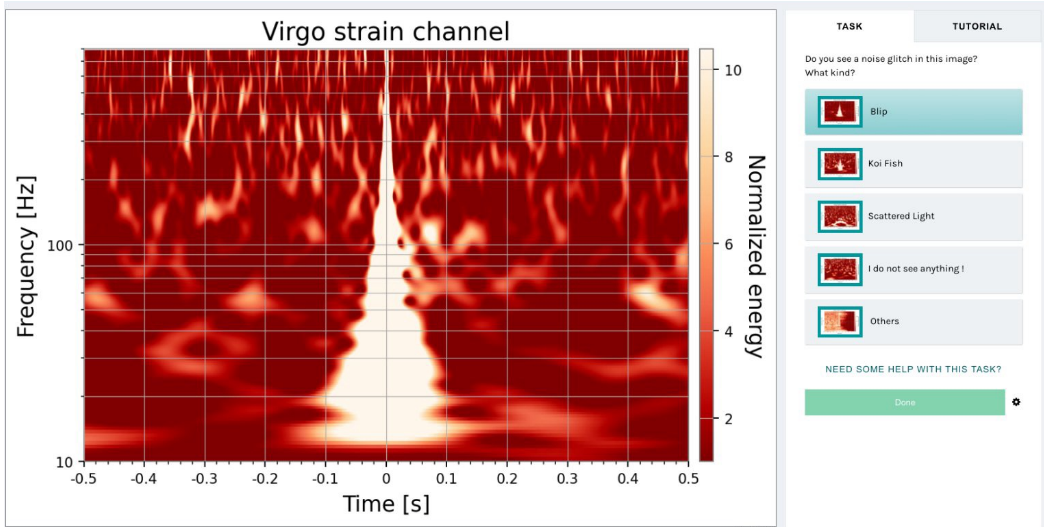
GwitchHunters (2019)

- Managed by Virgo scientists (e.g. MR et al 2024)
- https://www.zooniverse.org/projects/reinforce/gwitchhunters
- Classification, localization and aux channels tasks

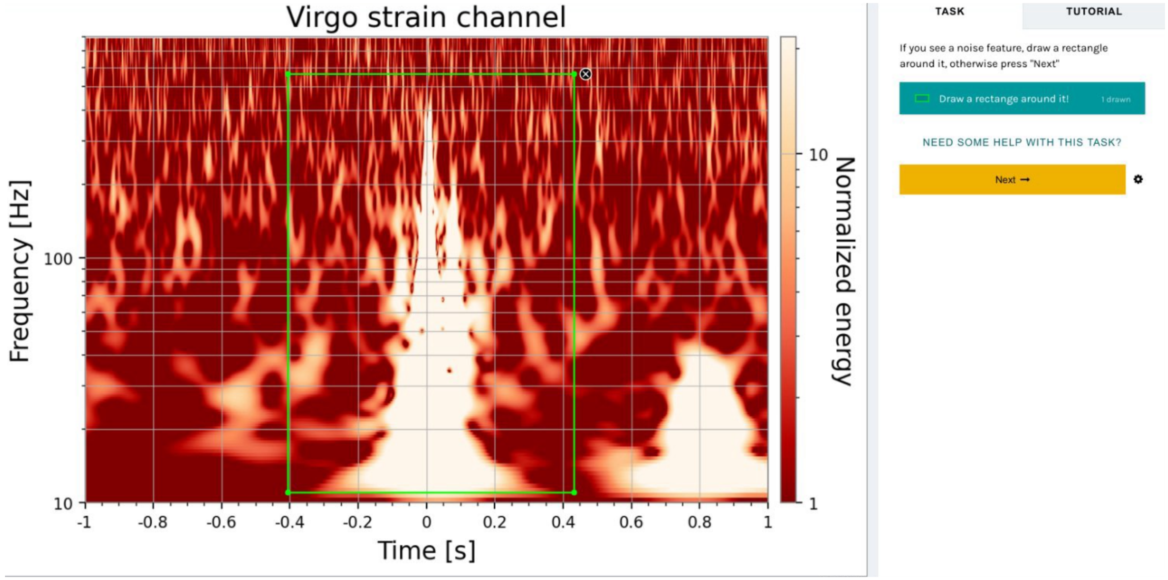
Glitches & Citizen Science

In GwitchHunters, citizens can help in different ways

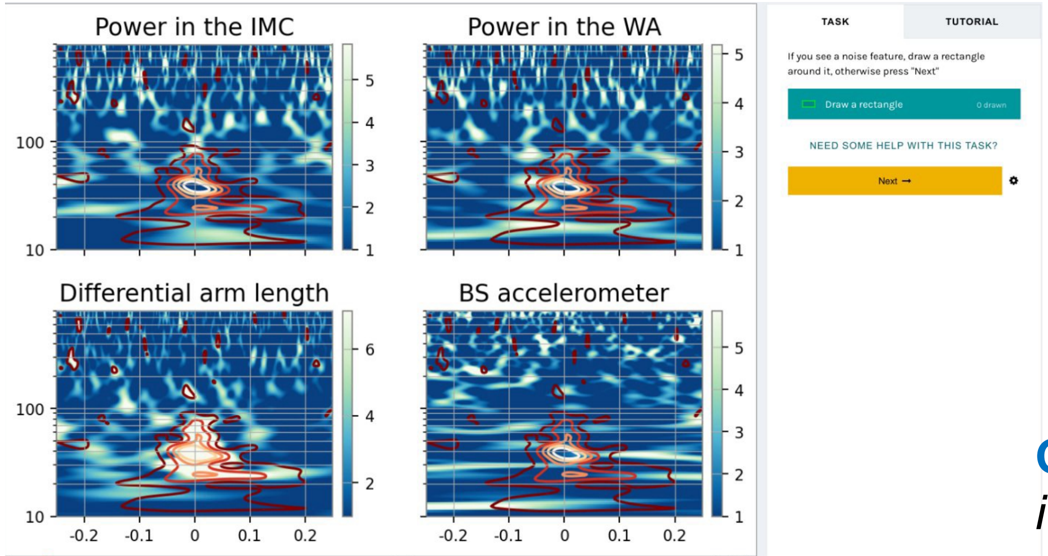
Update Sept 16, 2024
5.2k registered users
747k classifications



Classification
i.e. "what is the class of this glitch?"



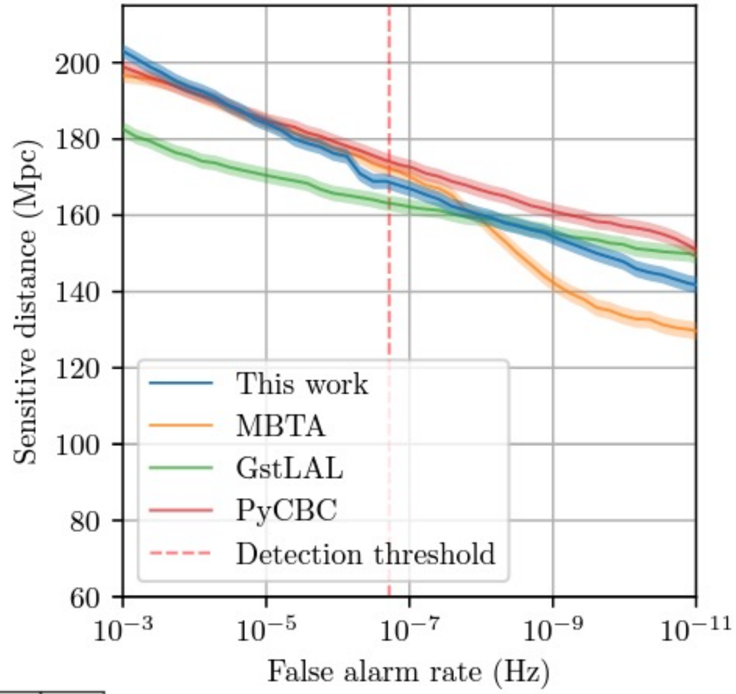
Localization/regression
i.e. "where is the glitch?"



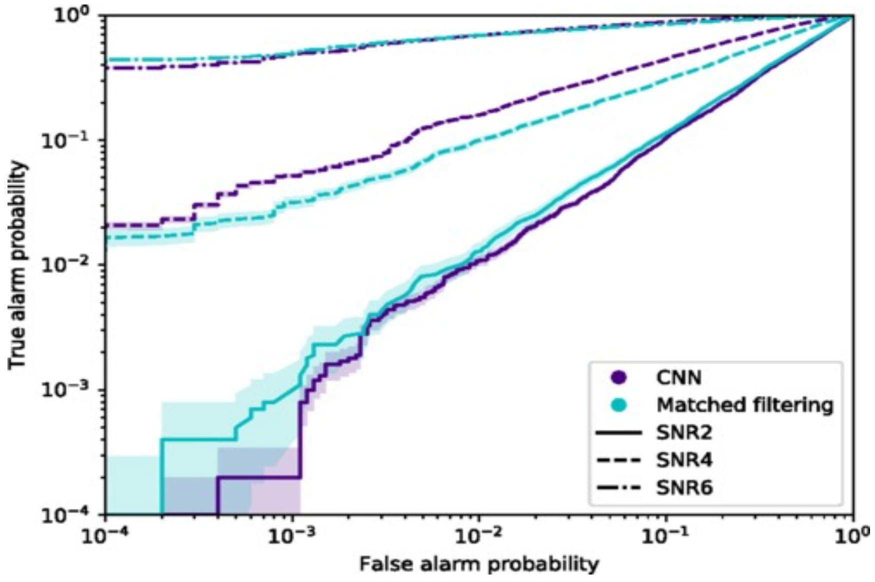
Glitch origin
i.e. "is there any similarity with aux channels?"

Fast detection of transients

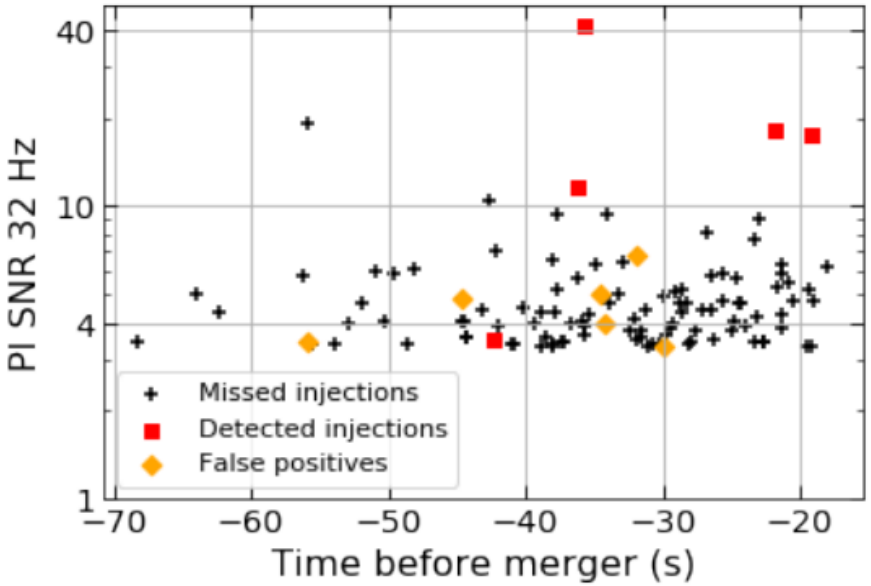
- Fast detection and Localization is crucial for low-latency alerts (multimessenger follow-up)
- Deep learning is promising method
- Computational load during training (many hours), then detection is very fast (<sec)
- Not many signals for training→ Use simulations
- Evolution from simulation-based studies to applications on real data
- Hot topic! Ca 200 papers in last 10 years



BNS detection
McLeod et al., 2024



Comparison with matched filter
Gabbard et al., 2018

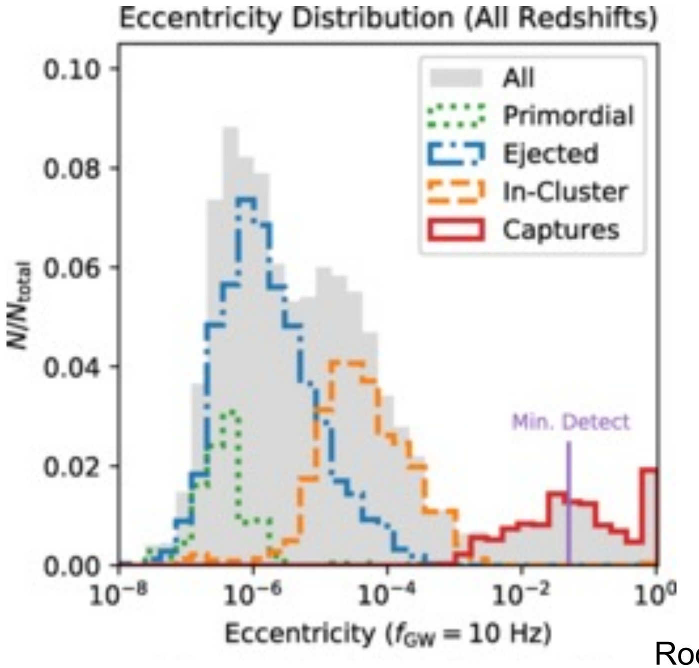


BNS early warning
Baltus et al, 2018

«Fast» Frontier

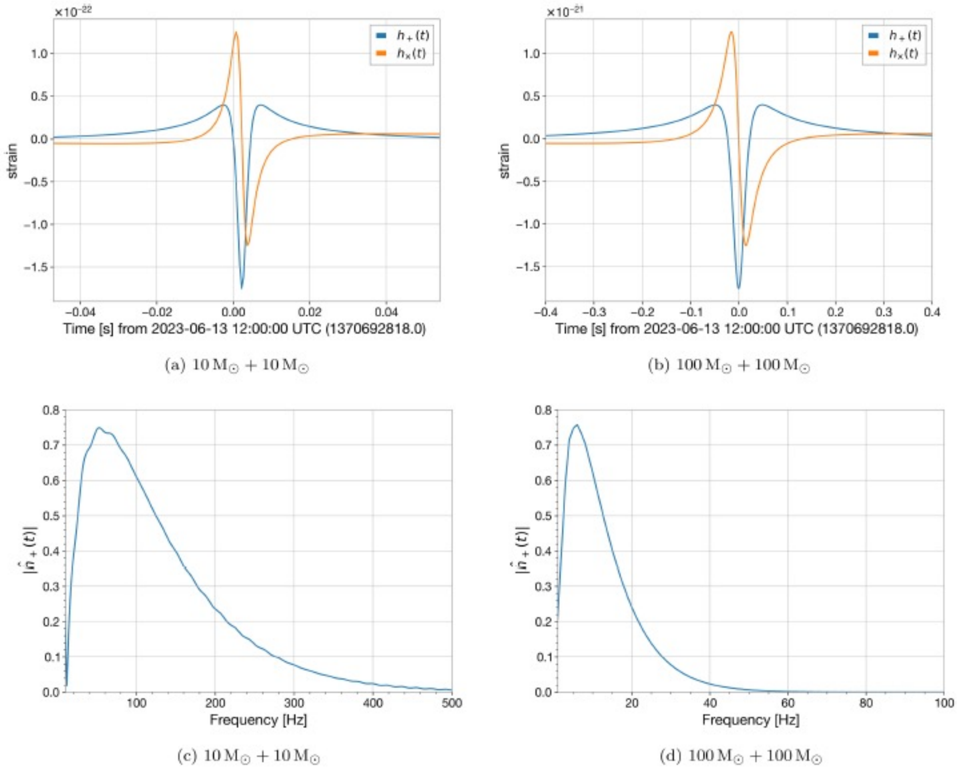
Deep learning for binary close encounters

- **Main Features**
  - High-mass BHs: Hints of a dynamical formation channel
  - N-body interactions
  - F-modes excitations in neutron stars: EoS studies
  - GW captures leading to subpopulation of eccentric binaries



Rodriguez et al, 2018

- **Close encounters**
  - Single-burst description
  - Multi-burst emission (multiple encounters)
  - GW emission at low frequencies



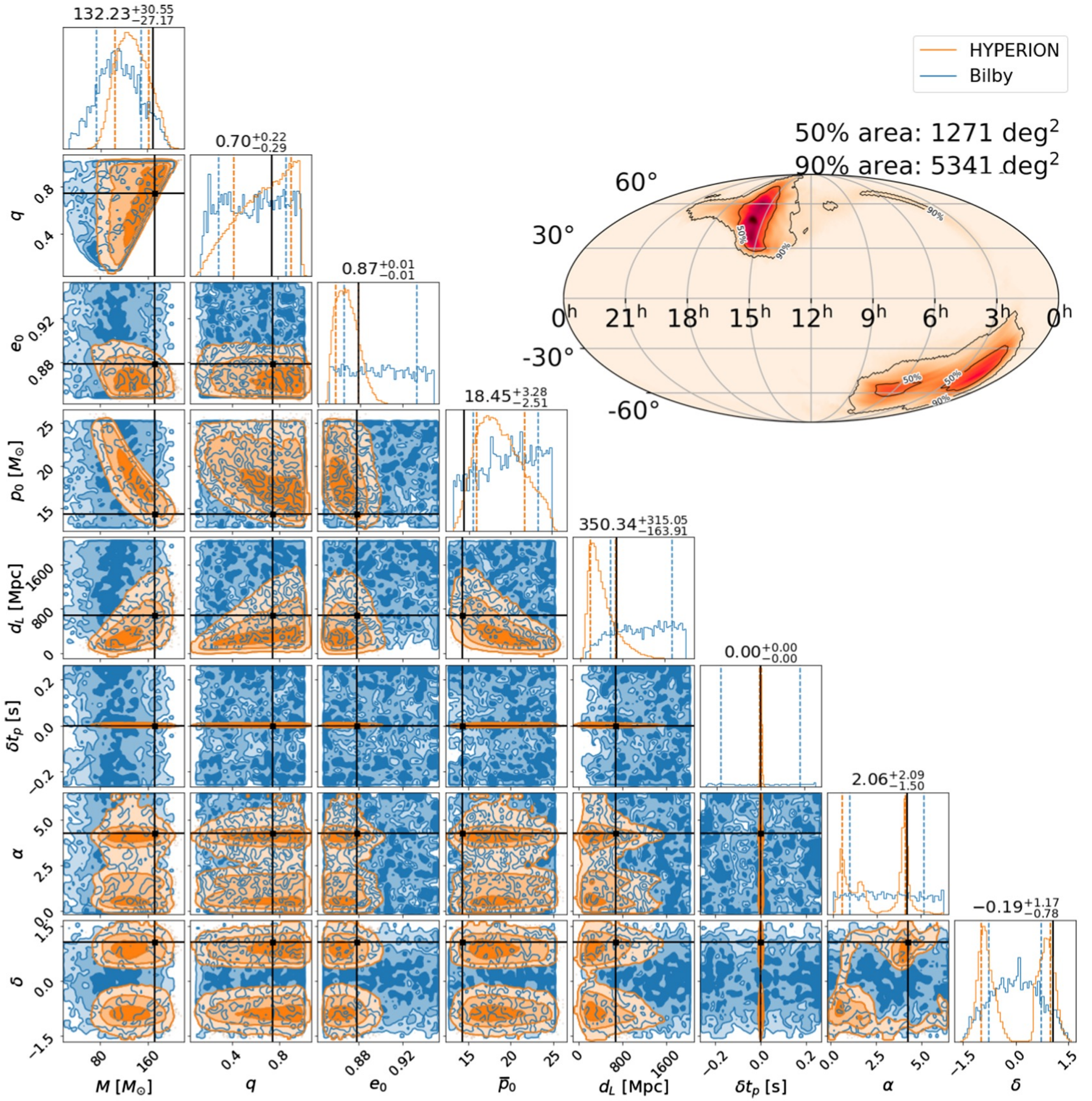
(a) $10\,M_\odot + 10\,M_\odot$ (b) $100\,M_\odot + 100\,M_\odot$ (c) $10\,M_\odot + 10\,M_\odot$ (d) $100\,M_\odot + 100\,M_\odot$

De Santi, MR et al 2024

Deep learning for binary close encounters

- **Challenging sources**
  - Very short burst-like emission
  - Low rates ($1 Gpc^{-3} yr^{-1}$)
  - Mostly at low frequencies

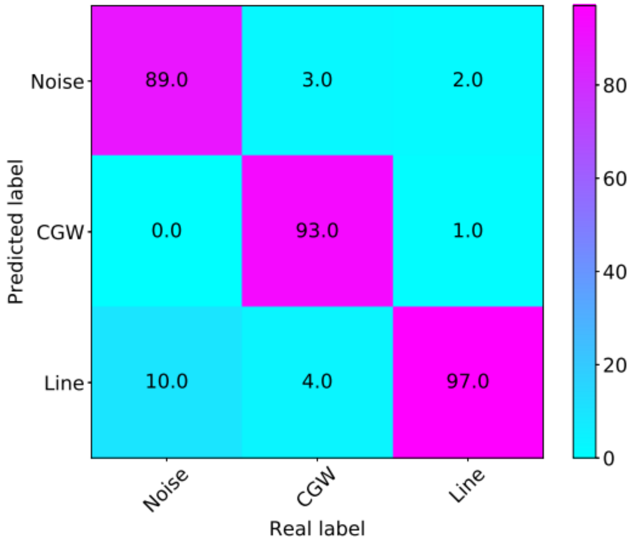
- **Deep-learning for CE**
  - Architecture based on Normalizing Flows
  - Very fast parameter estimation
  - From 10h ($5x10^3$ samples) to 0.5s ($5x10^4$ samples)



De Santi, MR et al 2024

Deep Learning for Continuous GW

- Continuous Waves from pulsars require searching over large datasets (O(yrs))
- Large parameter space (e.g. frequency, location)
- Noise (e.g. instrumental spectral lines)



Classification of Noise/Signal
Morawski et al 2020

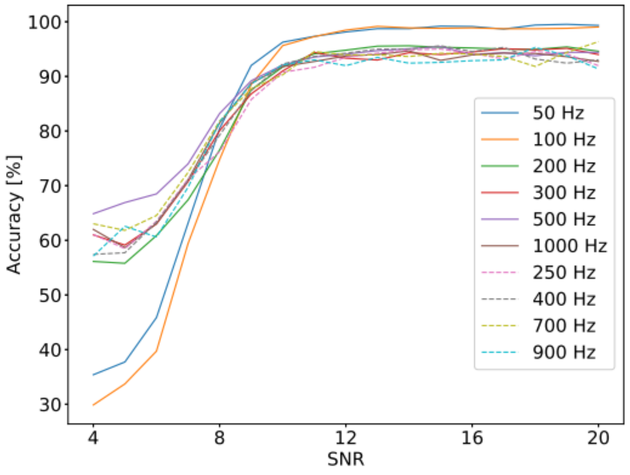
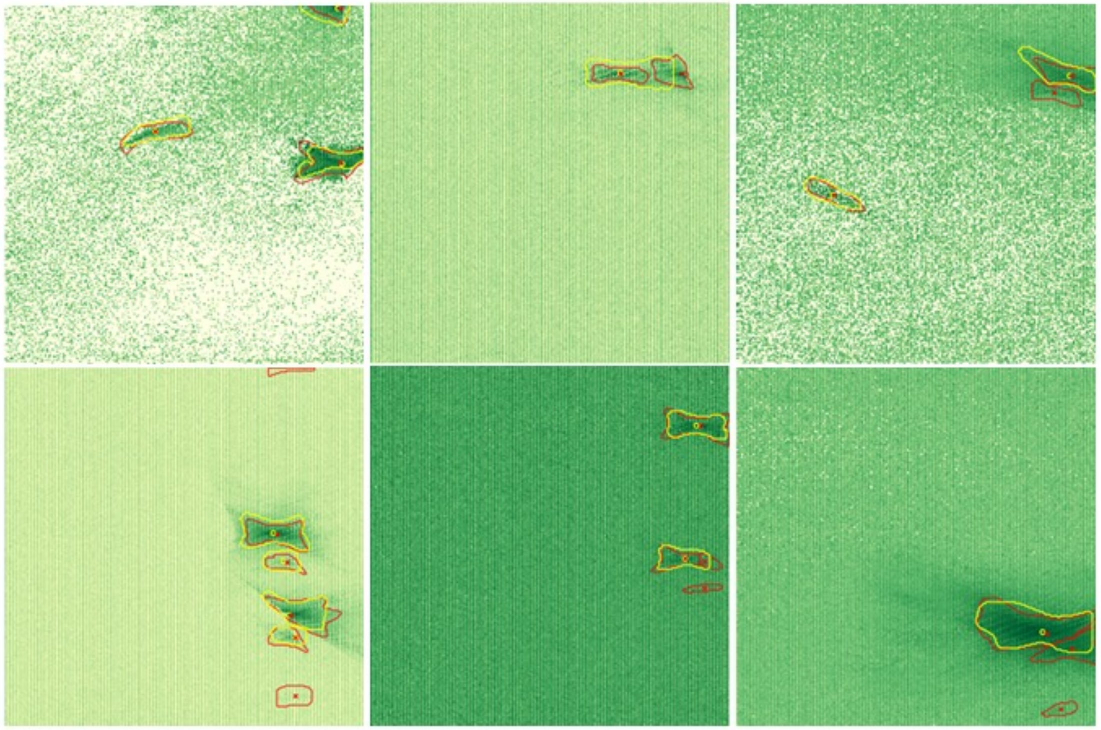


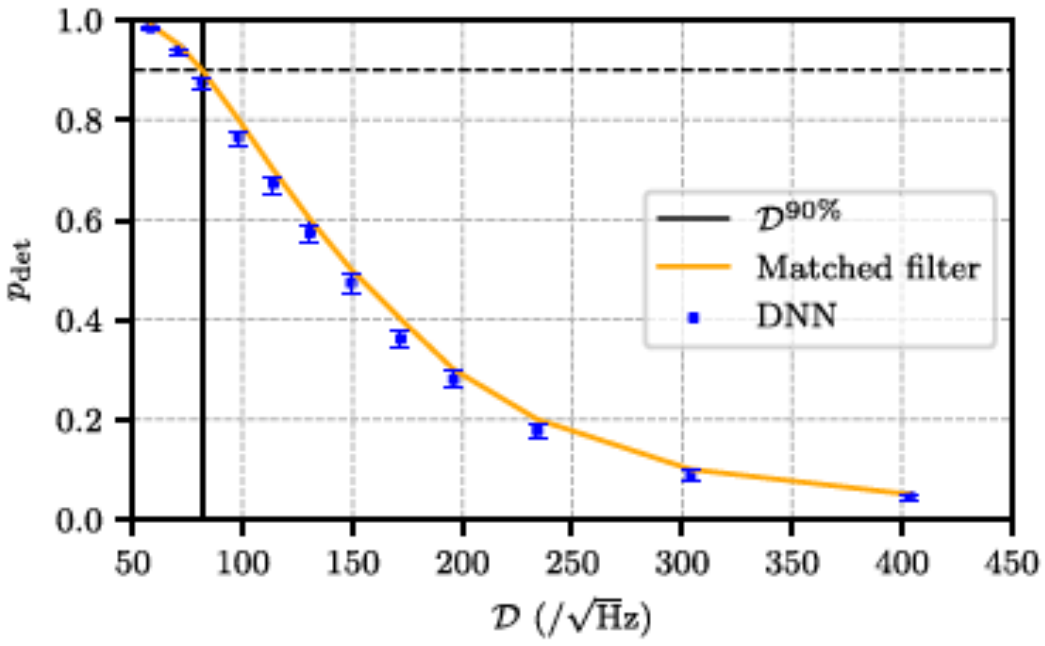
Fig. 4: The evolution of accuracy as the function of ρ for CNN over frequencies



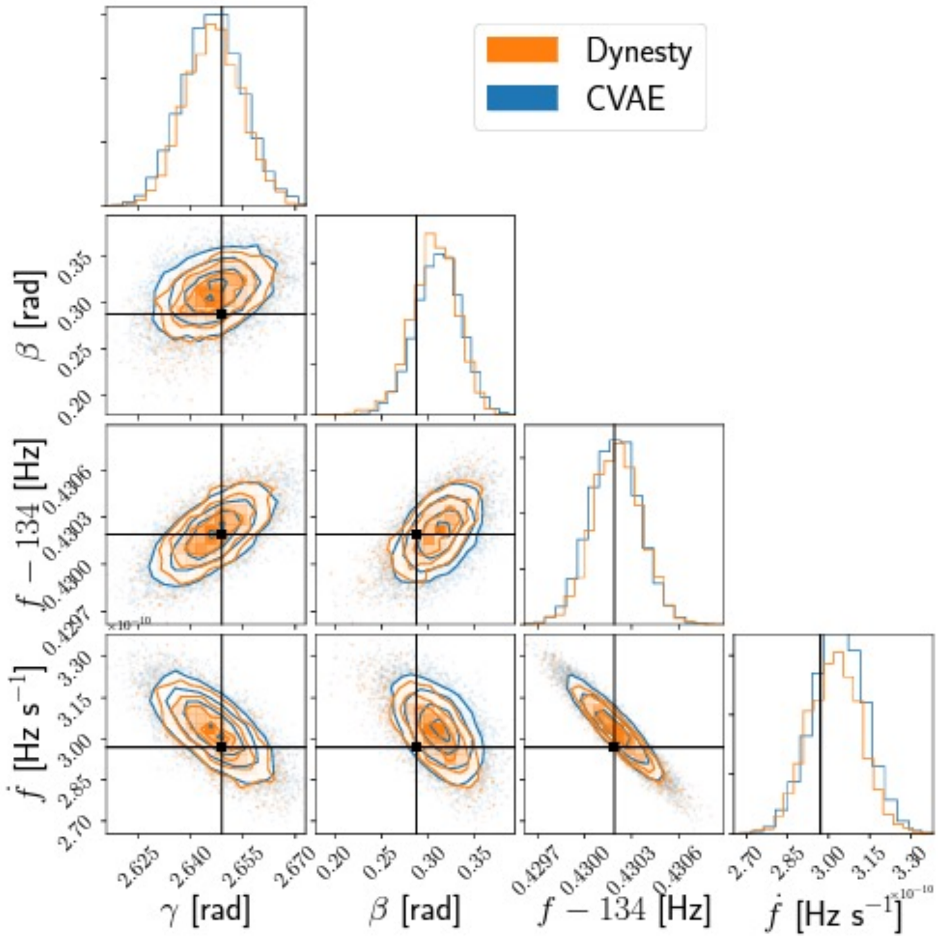
Clustering of pulsar candidates
(Beheshtipour & Papa, 2020)

Deep Learning for Continuous GW

- Continuous Waves from pulsars require searching over large datasets (O(year)
- Parameter estimation for continuous GW also explored (e.g. Variational Autoencoders)



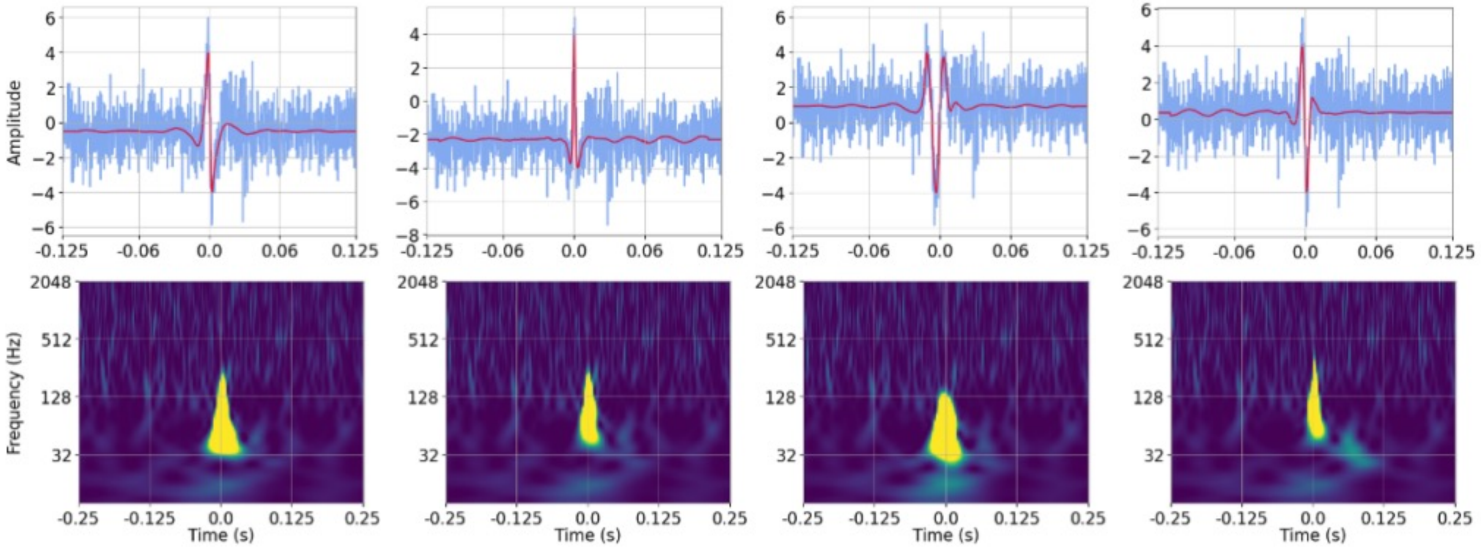
Joshi & Prix 2023



Bayley et al 2022

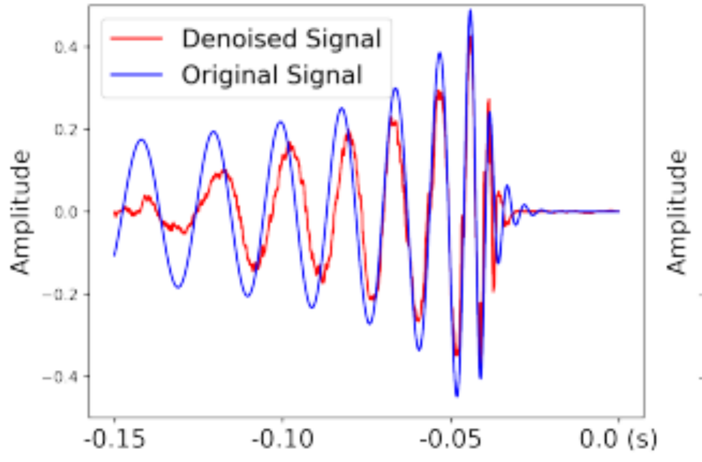
Deep Learning for Instrument Analysis

- Instrumental data can be highly complex (due to auxiliary channels from sensors)
- Deep learning algorithms can help in being fast and able to manage large datasets

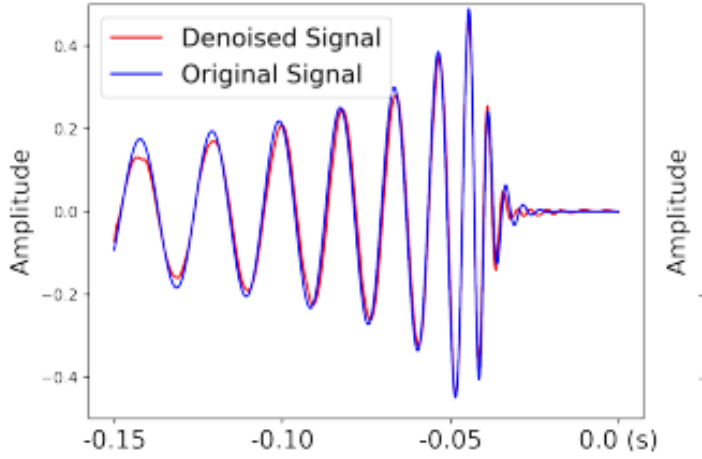


Data Augmentation via Generative Adversarial Networks (GANs)

e.g. Lopez et al 2022



(a) DRDAE: quasi-circular



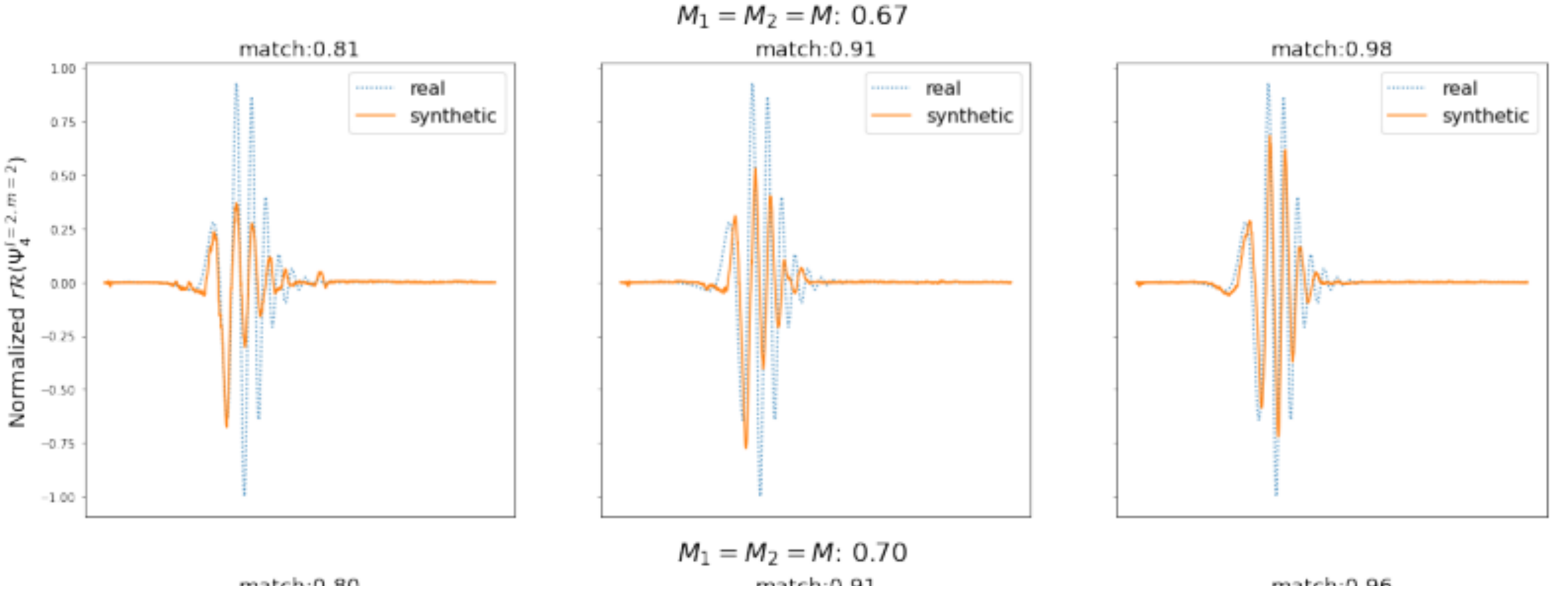
(d) EDRDAE: quasi-circular

Denoising using Autoencoders

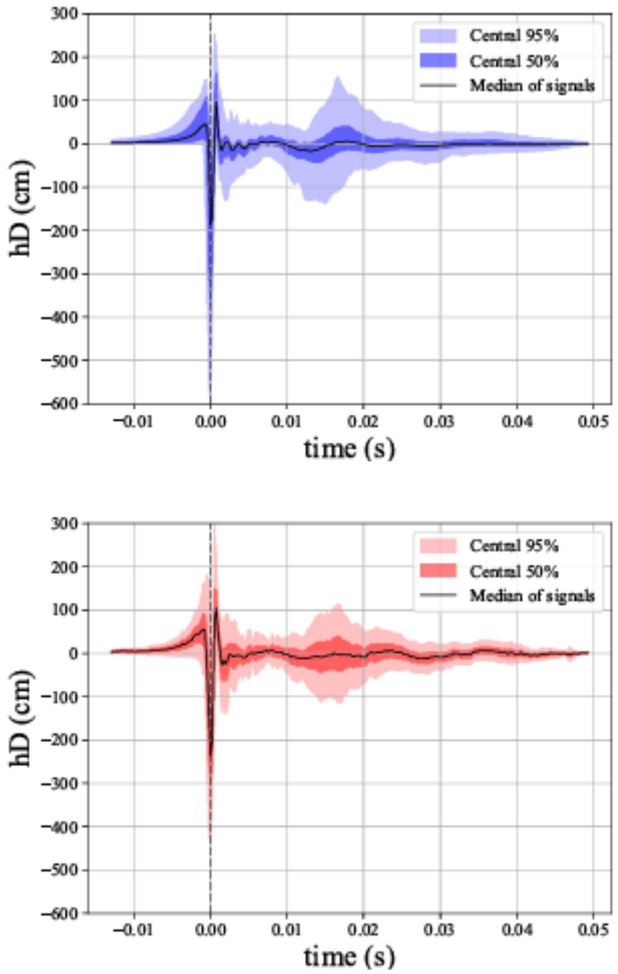
e.g. Shen et al. 2019

Deep Learning for GW theory

- ML to generate waveforms (e.g. postmergers)
- Various methods (GANs, VAEs)



Generative Adversarial Networks for GW waveforms
Freitas et al 2022



Generative Adversarial Networks for core-collapse GW
Eccleston et al 2024

Conclusions

- Machine and deep learning methods have grown fast in GW community
- Timeseries and Spectrograms good way to present datasets
- First works on simulations, now moved to analysis of real data
- New frontiers from instrument science to fast parameter estimation
- Offer a new, complementary method with respect to traditional analysis
- Field is growing very fast, hundreds of papers in last ~10 years
- What will be the next deep learning model/algorithm?


Thank you!