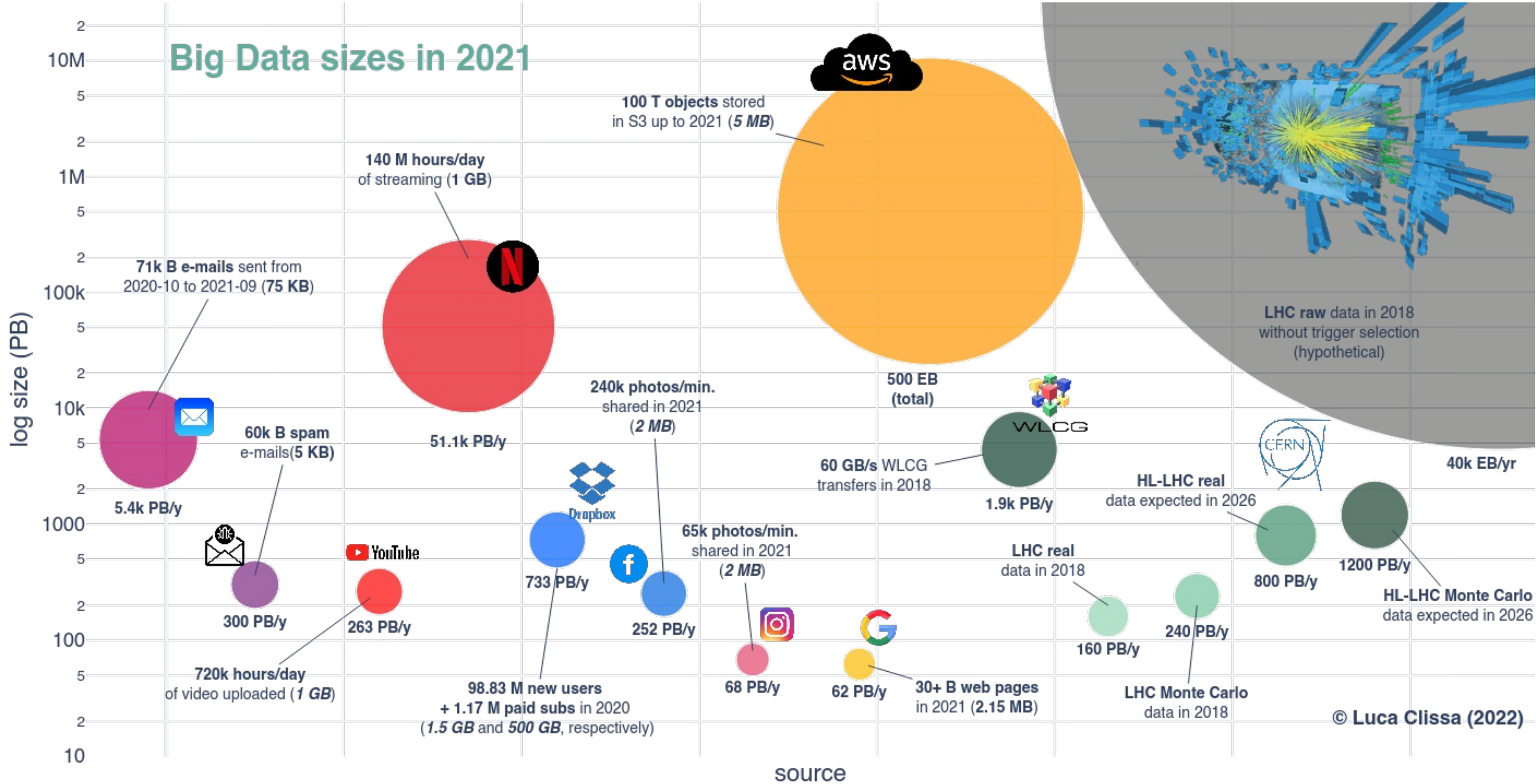
Machine Learning for Gravitational Waves (and some extras on pulsars)

Massimiliano Razzano[1,2]
[1]University of Pisa [2]INFN-Pisa

Virgo Pisa Internal Workshop
22-23 May 2024

Big Data in Science



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

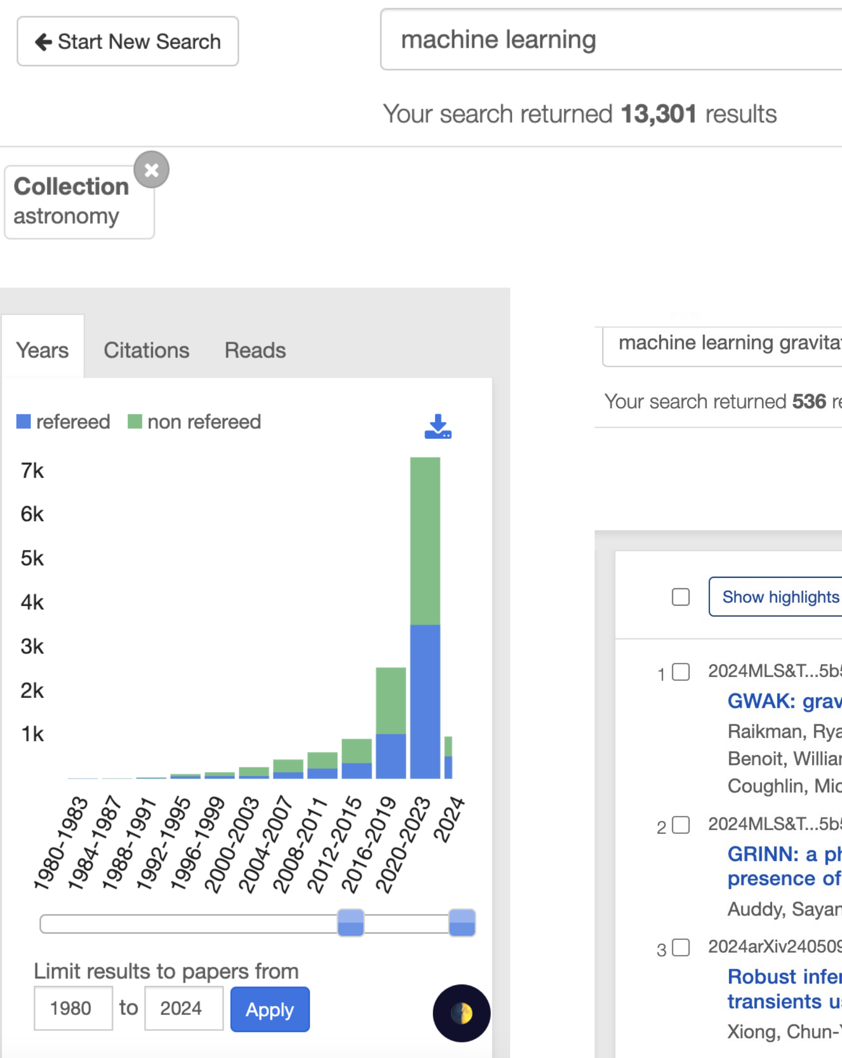
Notes:
The column Volume refers to raw data produced at the end of the experiment.
Values regarding Pan-STARRS, LSST, and SKA surveys refer to expected Volume and Velocity values.

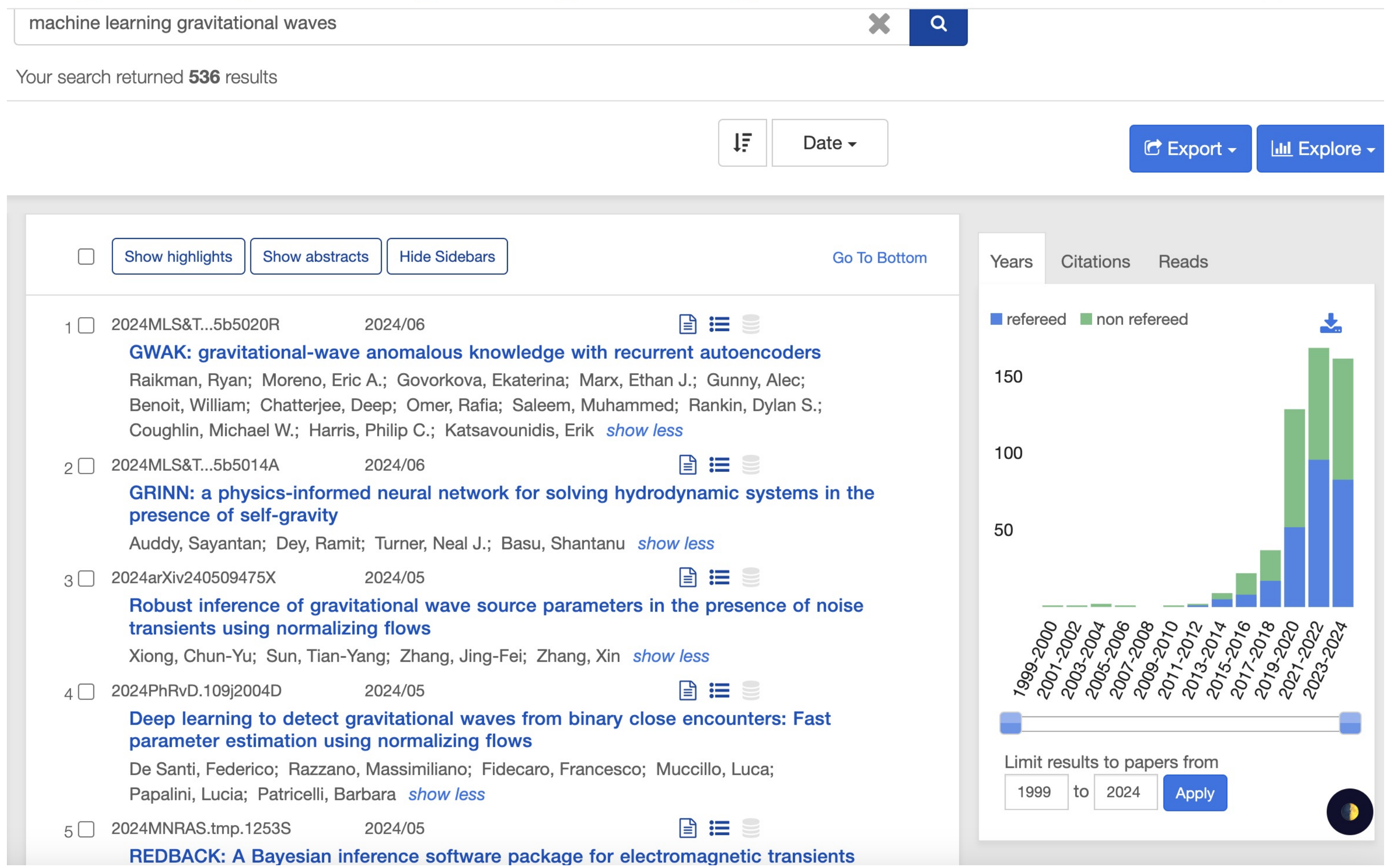
Virgo Data
Order of ~50 MB/s → about 0.5 TB/day from all channels

*

Machine Learning and GW

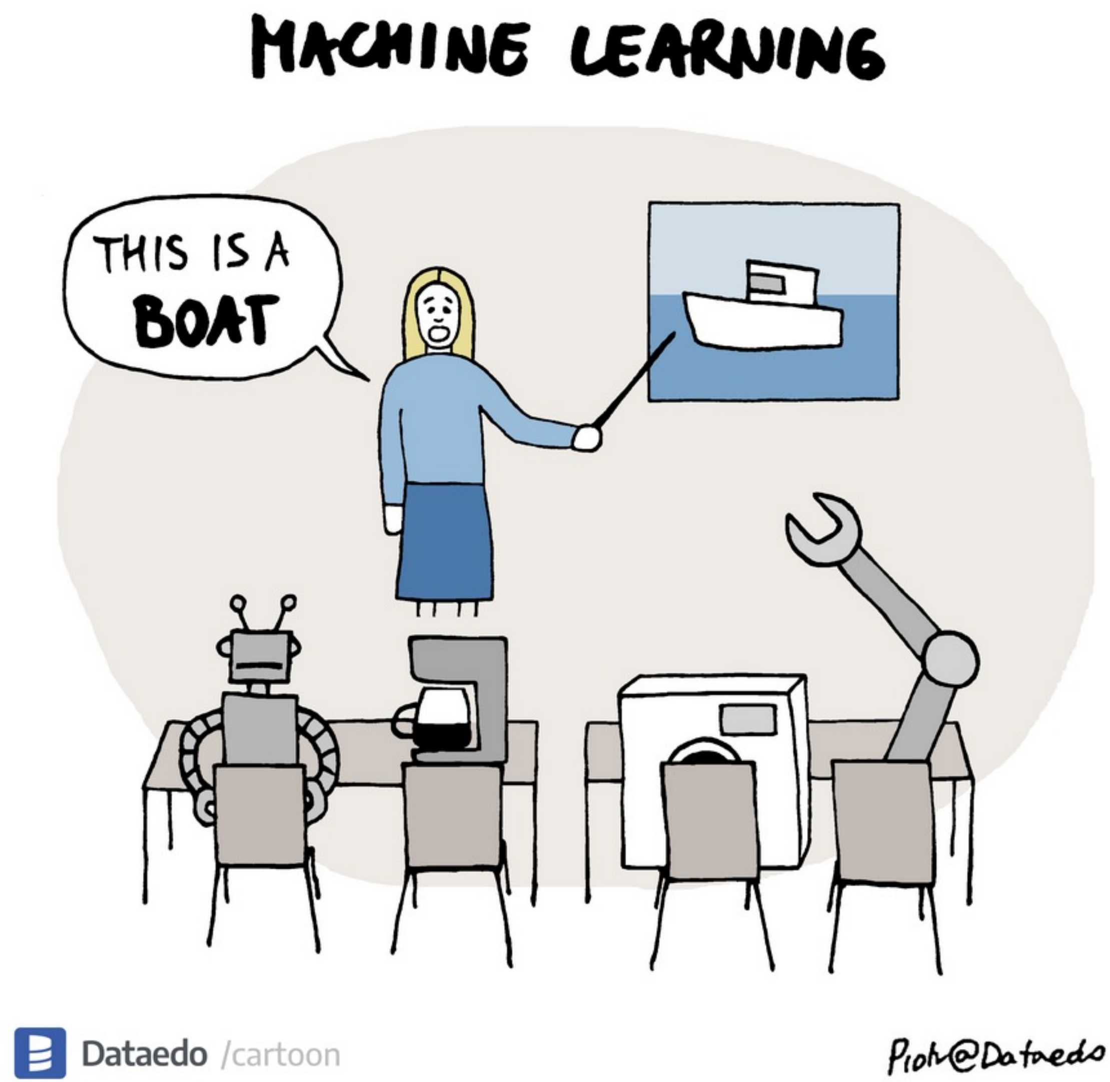
A simple ADS search…





Context of Machine Learning

«A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E» (T. Mitchell)

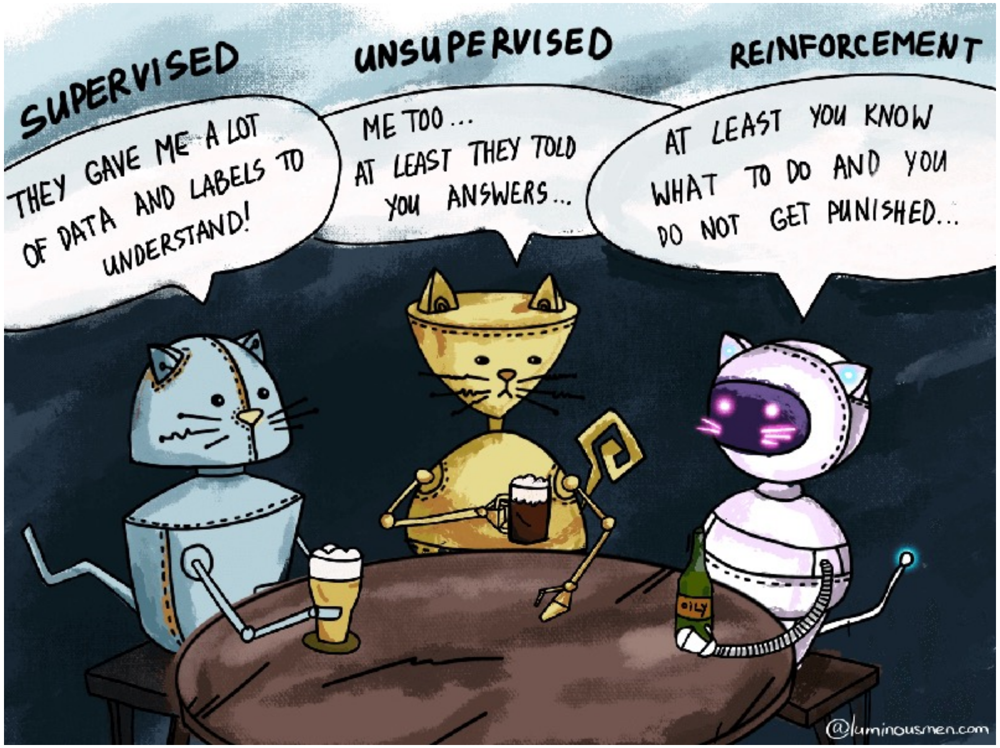


Approaches to Machine Learning

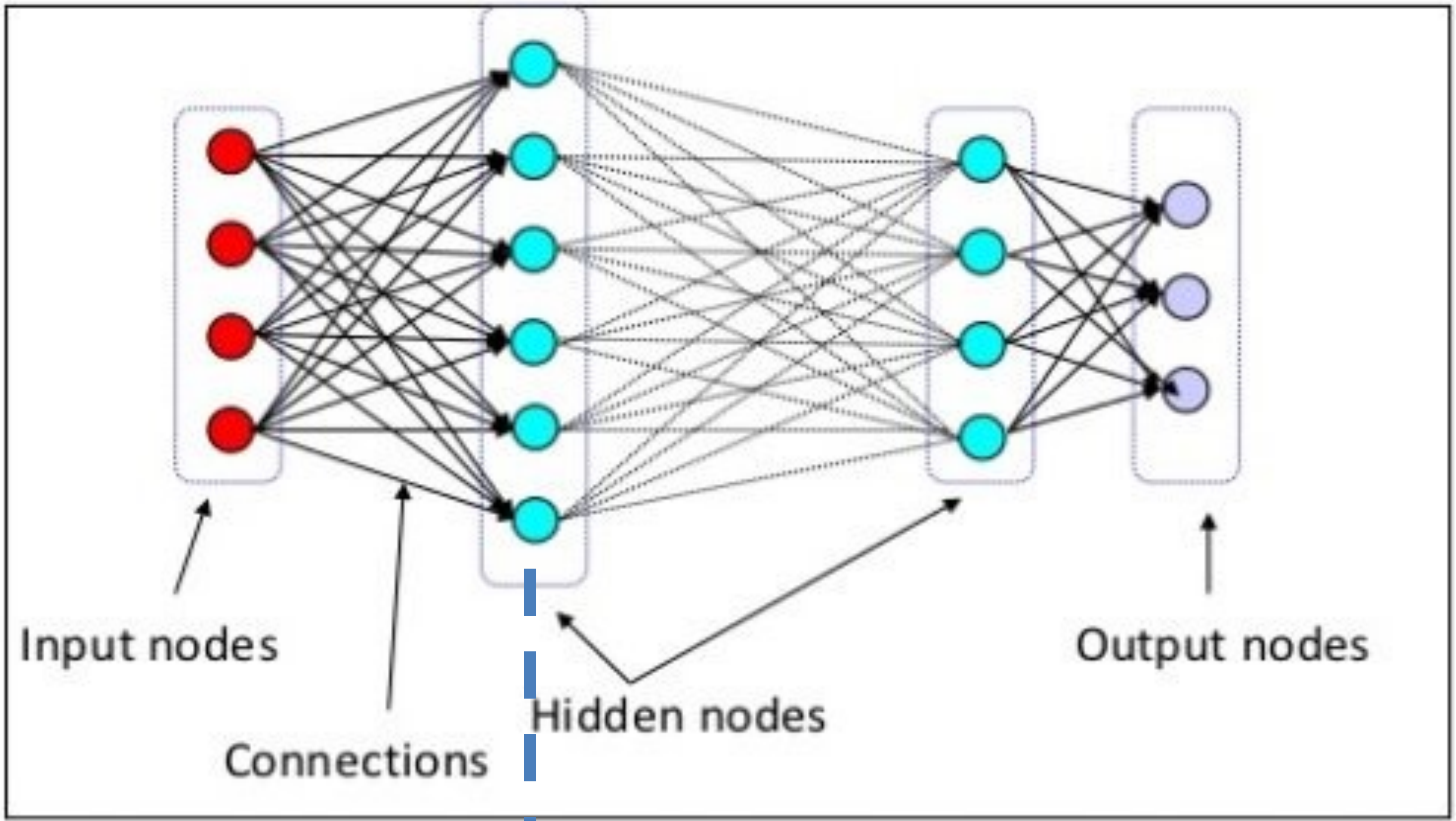
- Supervised: the algorithm is fed with labeled data, and learn the features that are best linked to each label (task driven)
  - Classification
  - Regression

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

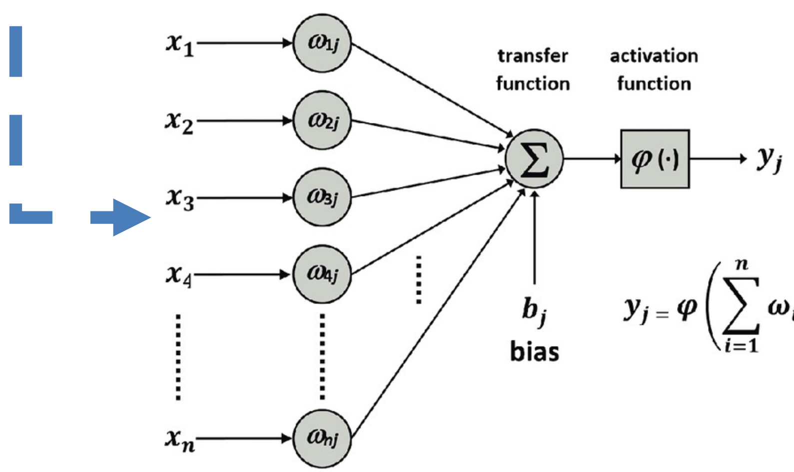
- Reinforcement learning: trial and error strategy (experience driven)



What is a Neural Network?



Each node is a (nonlinear) processing unit
(perceptron model)



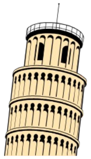
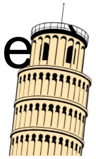
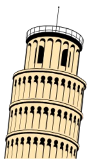
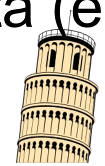
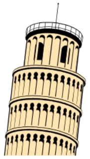
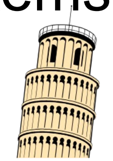
$$y_j = \varphi\left(\sum_{i=1}^{n} \omega_{ij} x_i + b_j\right)$$

Weights updating depending on data

Machine Learning and GW

- **Instrument characterization examples**
  - Study and characterize noise (glitches)
  - Coupling among channels
  - Denoising algorithms
- **Detection and PE**
  - Fast detection for transients
  - Search large amount of data (e.g. continuous waves)
  - Fast Parameter Estimation
- **Detector R&D**
  - Simulate complex systems (e.g. digital twins)
  - Active control systems

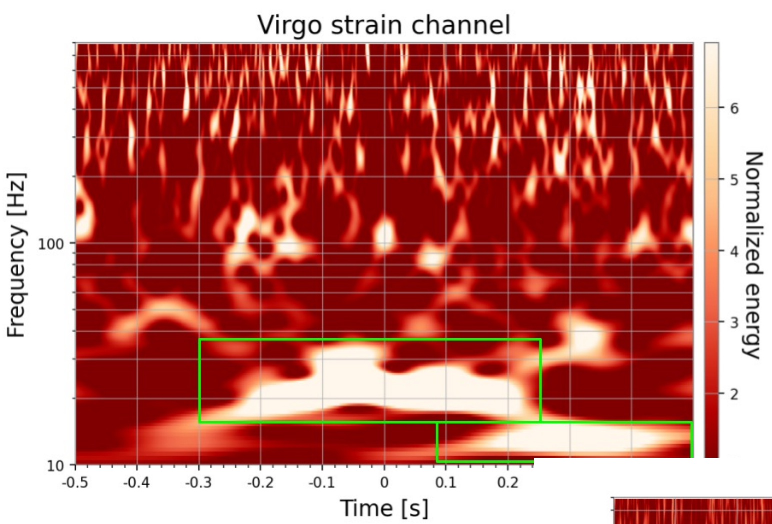
Machine Learning and GW

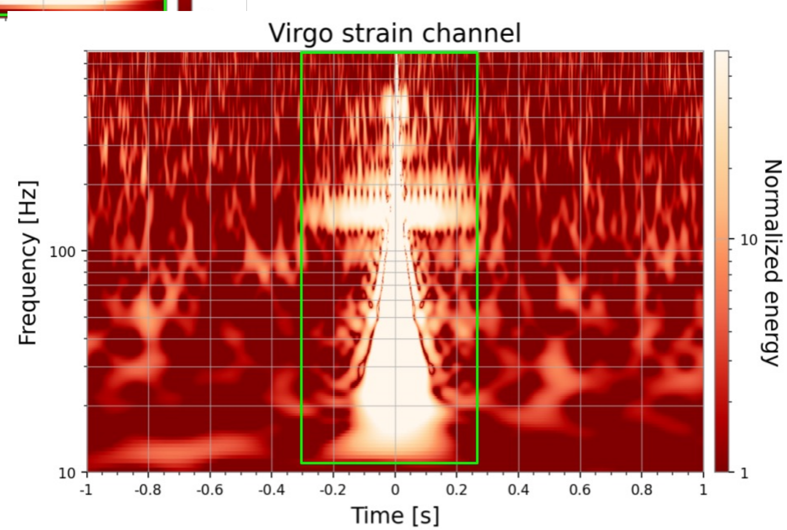
- **Instrument characterization examples** 
  - Study and characterize noise (glitche 
  - Coupling among channels
  - Denoising algorithms
- **Detection and PE** 
  - Fast detection for transients
  - Search large amount of data (e.g. continuous waves)
  - Fast Parameter Estimation 
- **Detector R&D**
  - Simulate complex systems (e.g. digital twins) 
  - Active control systems 

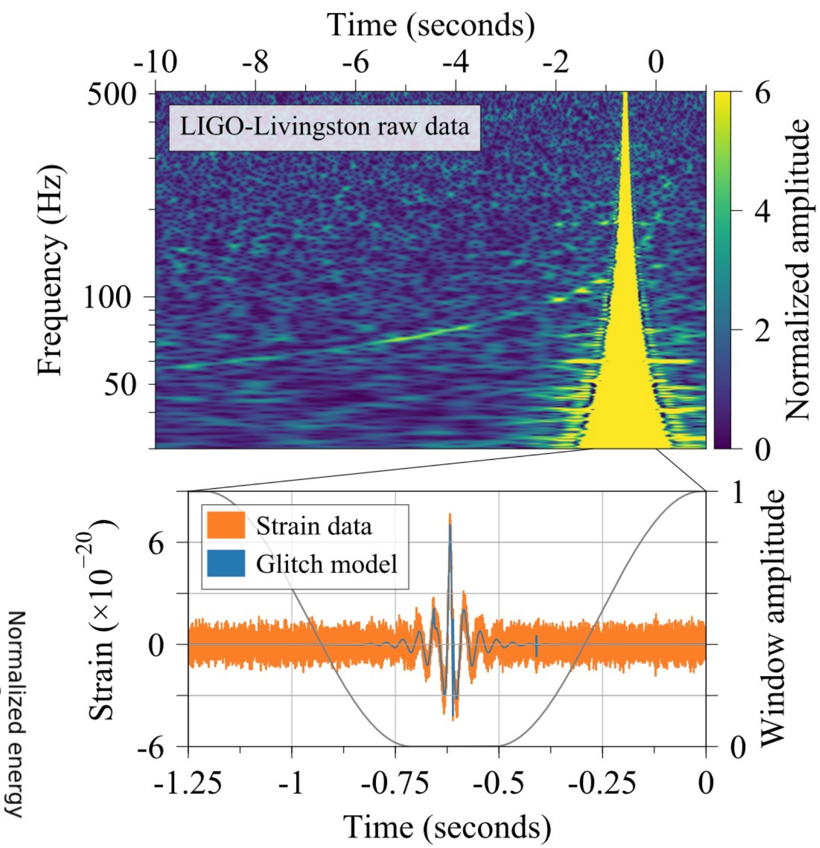
Credits: Wannapic studios (https://www.wannapik.com/)

Glitch characterization

- Classification and characterization of transient noise events (“glitches)
- Glitches can affect data quality and duty cycle
- Glitch morphologies can be complex
- Deep learning promising tools



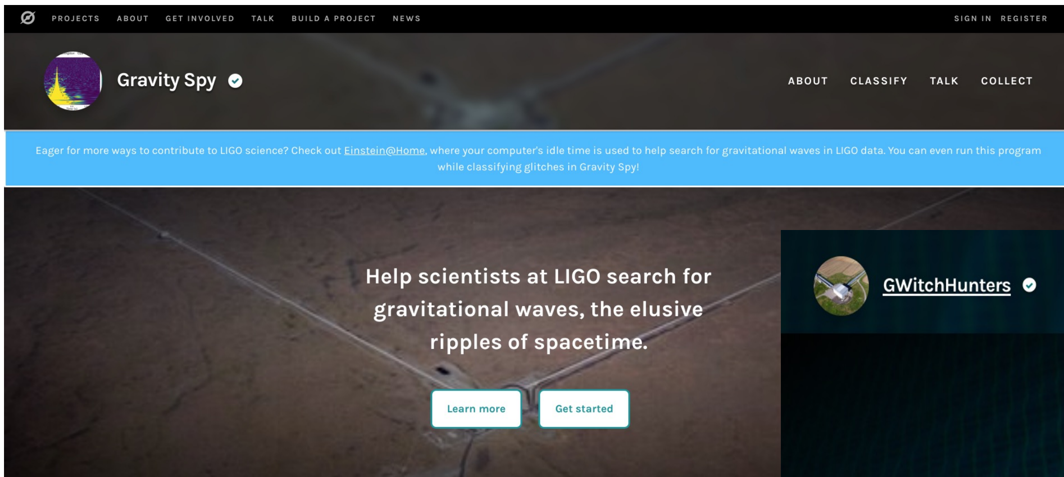


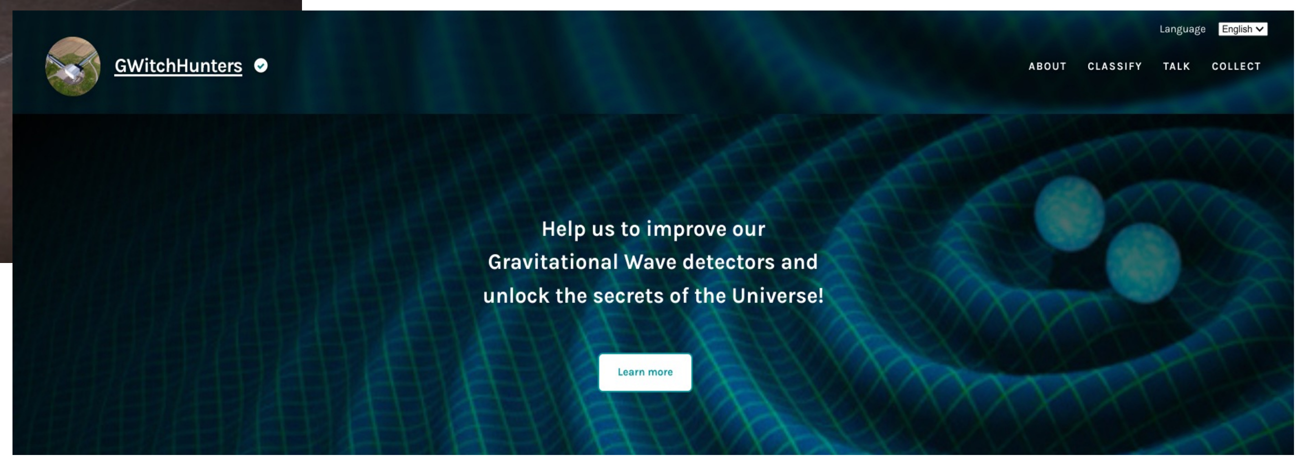


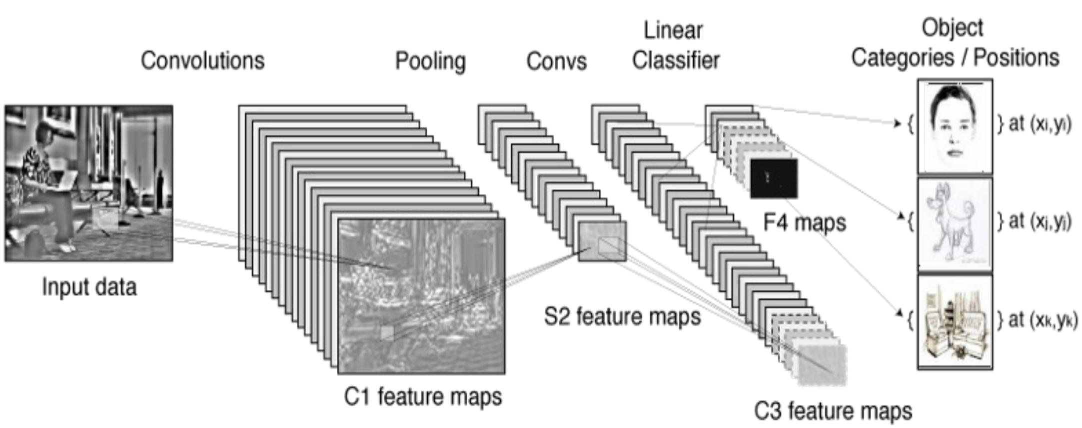
Abbott et al 2017

Glitch classification & Citizen Science

- Supervised approach requiring labeled datasets
- Labels can be acquired via Citizen Science projects (GravitySpy@LIGO ,GWitchHunters @Virgo)
- Goal: Infrastructure for glitch classification in real time





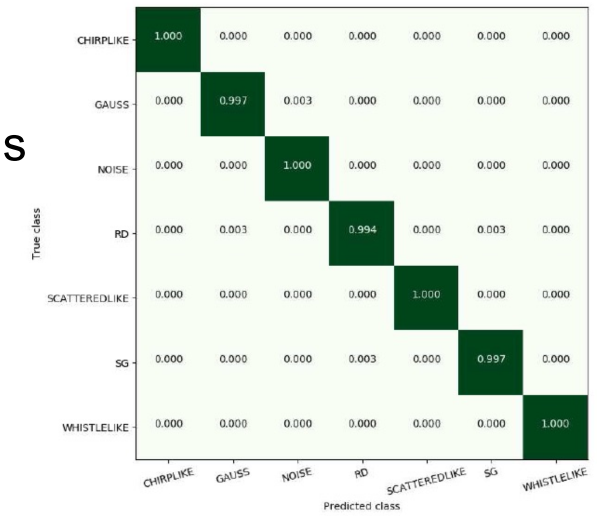


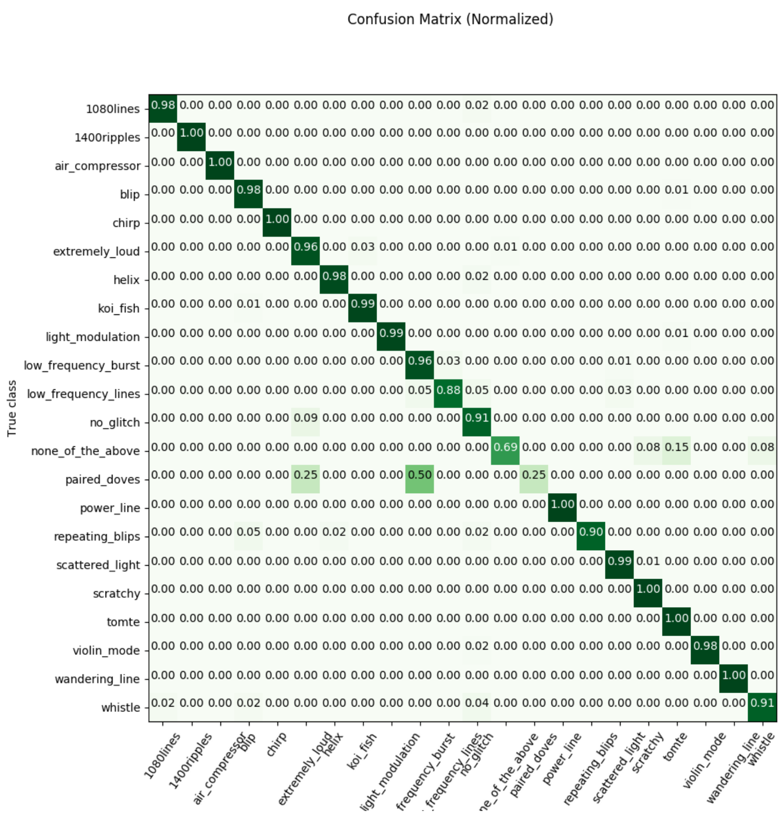
Based on Convolutional Neural Networks

Steps of glitch classifications in Pisa

- First pipeline and tests on simulations (e.g. Razzano&Cuoco 2018)
- Tests on real data (O1+O2) using 2D CNN
- Explored 1D CNN (e.g Talpini&Razzano 2020)

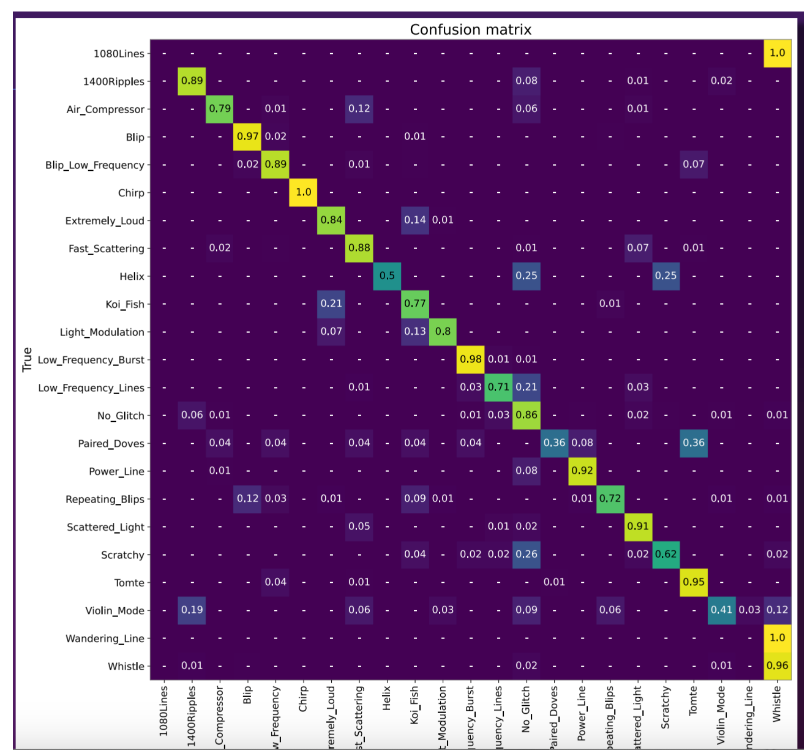
Simulations





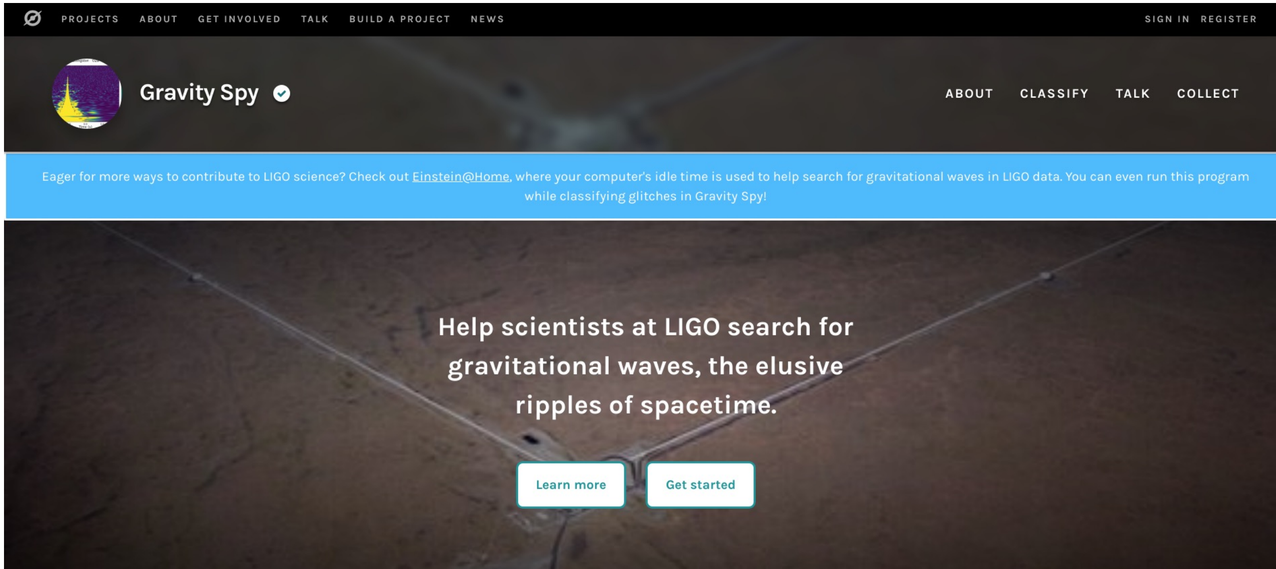
O1+O2

O3



- Check with GravitySpy and citizen science project
- Tests on O3 data (custom pipeline vs gravitySpy)+ comprehensive analysis of O3 glitches (work with M. Vacatello)

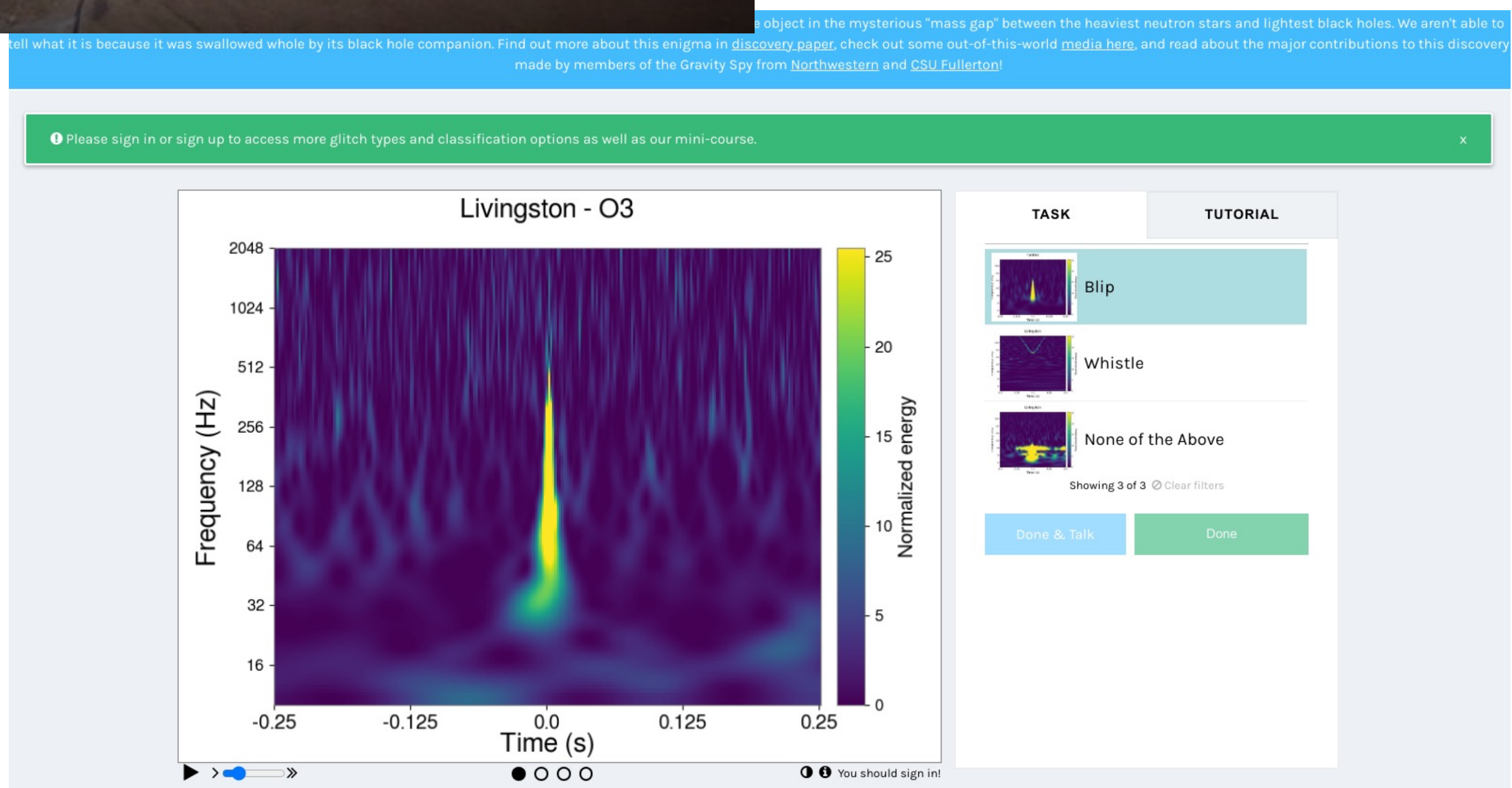
Detector characterization & citizen science



GravitySpy:

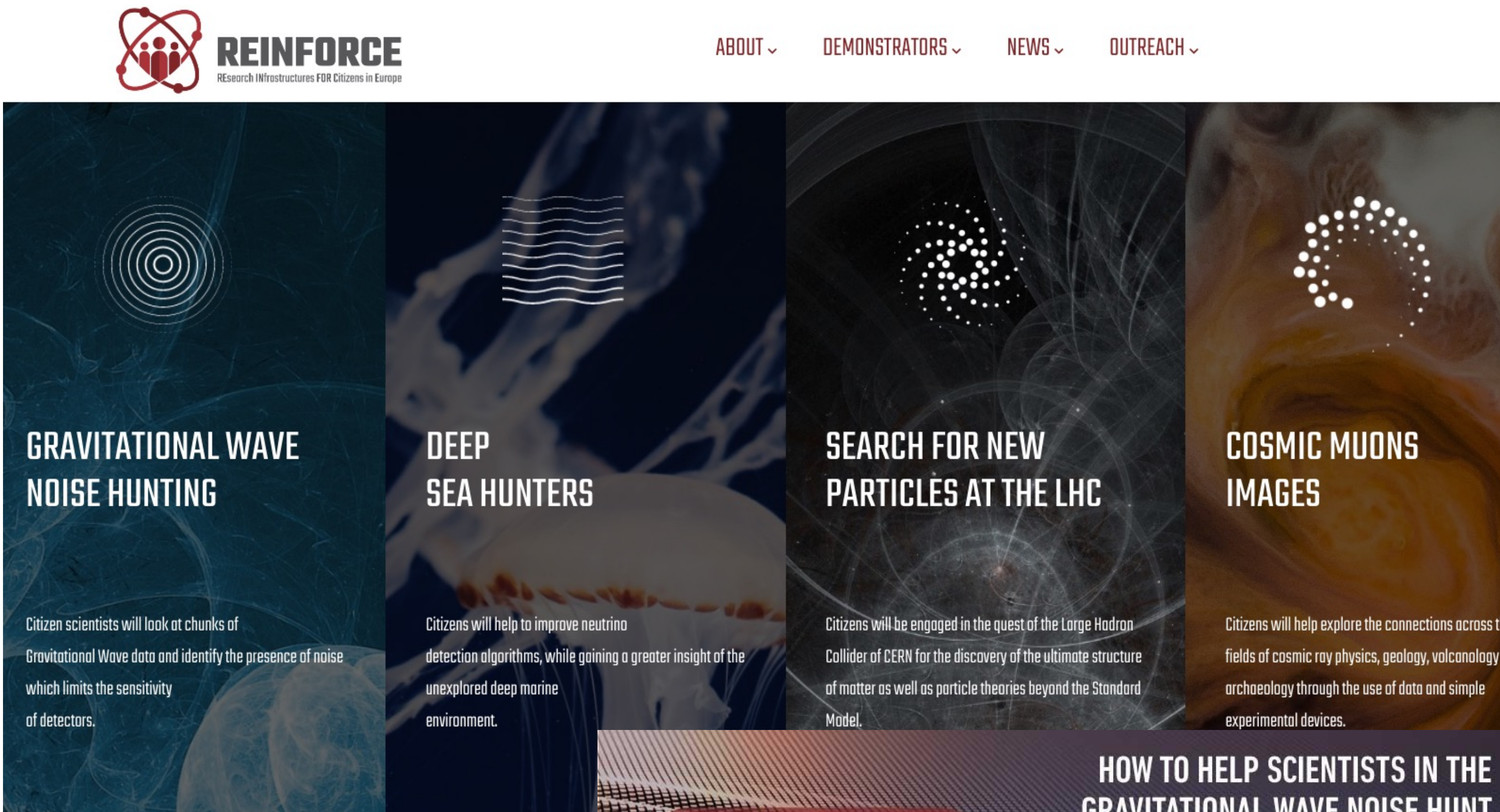
Citizen science + Machine Learning

Zevin et al. 2017, CQG,34,6



Classifications made by citizen scientists
Used to train ML

The REINFORCE project

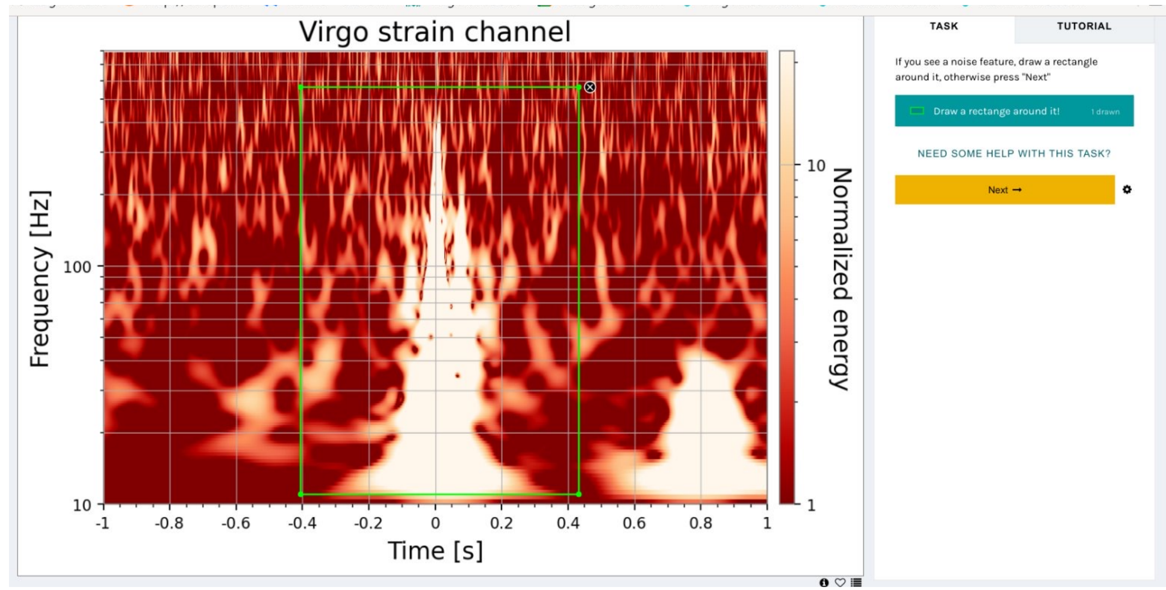


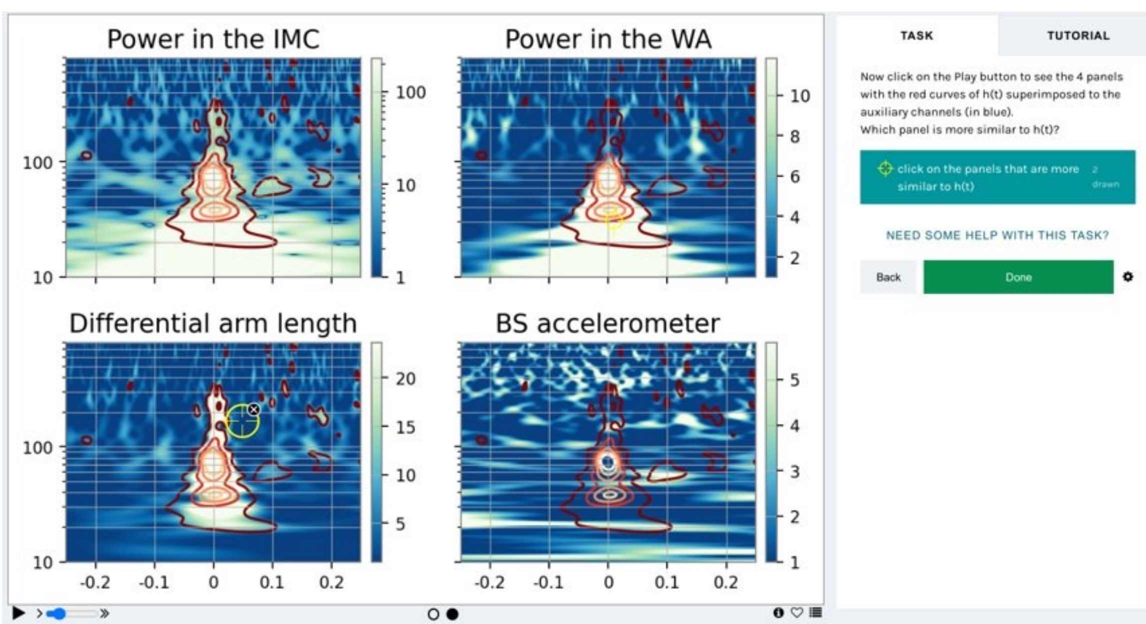
https://www.reinforceeu.eu/

Horizon 2020
EU-funded project on multimessenger approach to citizen science

Overview of GwitchHunters

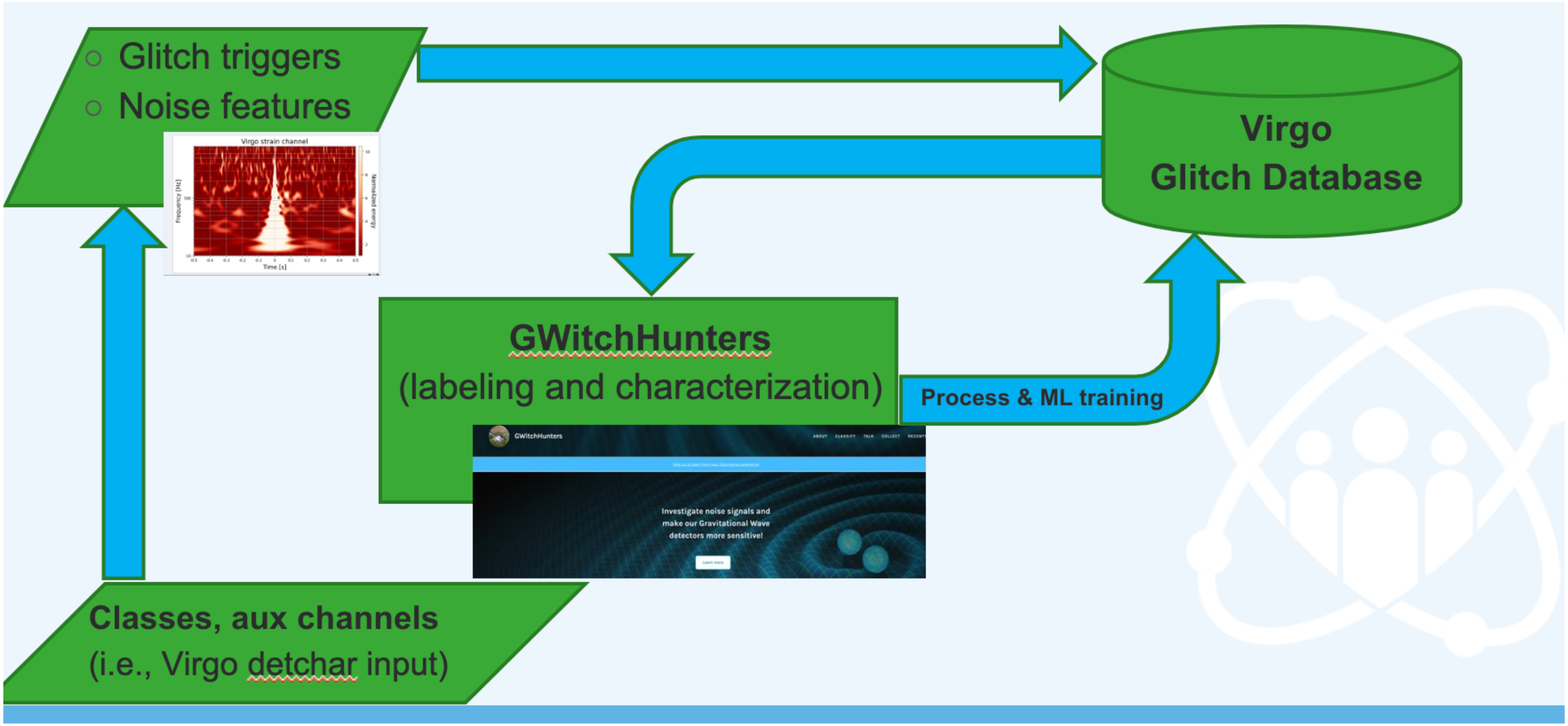
- **3 Levels (desktop + mobile)**
  - Classifications only
  - Classification + localization
  - Classification + localization
  + comparison with Aux channels





- Collaboration UNIPI (coordination), EGO, Ellinogermaniki Agogi, Uni Valencia, Oxford
- Organized engagement activities
- Italian and English Versions
- Spanish and Greek in progress

Overview of GwitchHunters



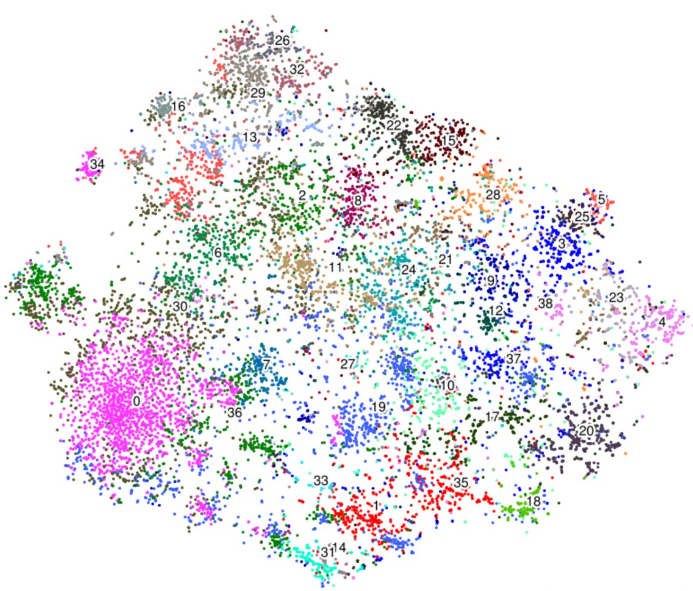
92% Complete

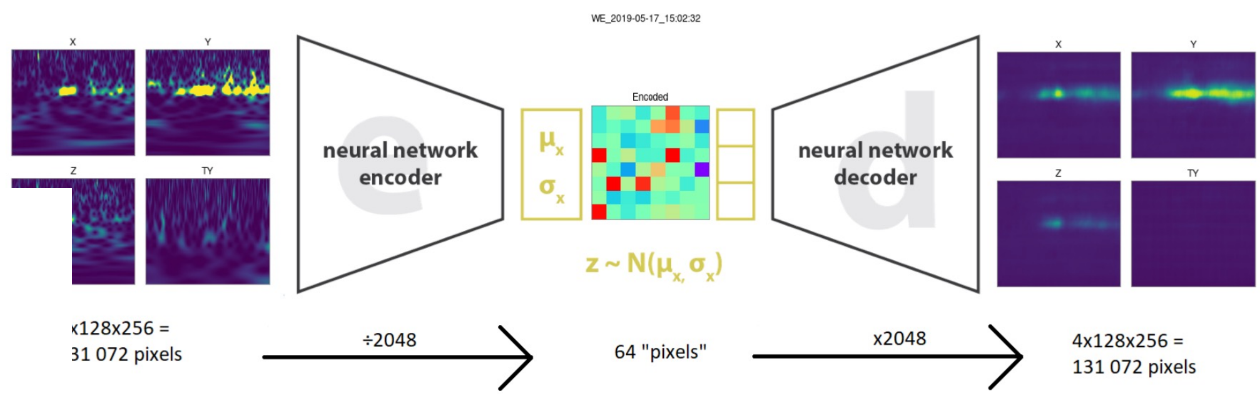
5.028	739.422	41.620	38.296
Volunteers	Classifications	Subjects	Completed Subjects

Next Steps: we are no longer supported by REINFORCE
→ However, efforts to continue and put O4 data

Work using Auxiliary Channels

- Auxiliary channels are a rich data source
- Apply ML to auxiliary channels data (work with L. Negri, A. Gennai, V. Boschi)
- Using Variational Autoencoders to cluster data related to seismic activity (using channels from SA)
- GMM + VAE to cluster data in low dim space
- Transformers for anomaly detection (paper in prep)

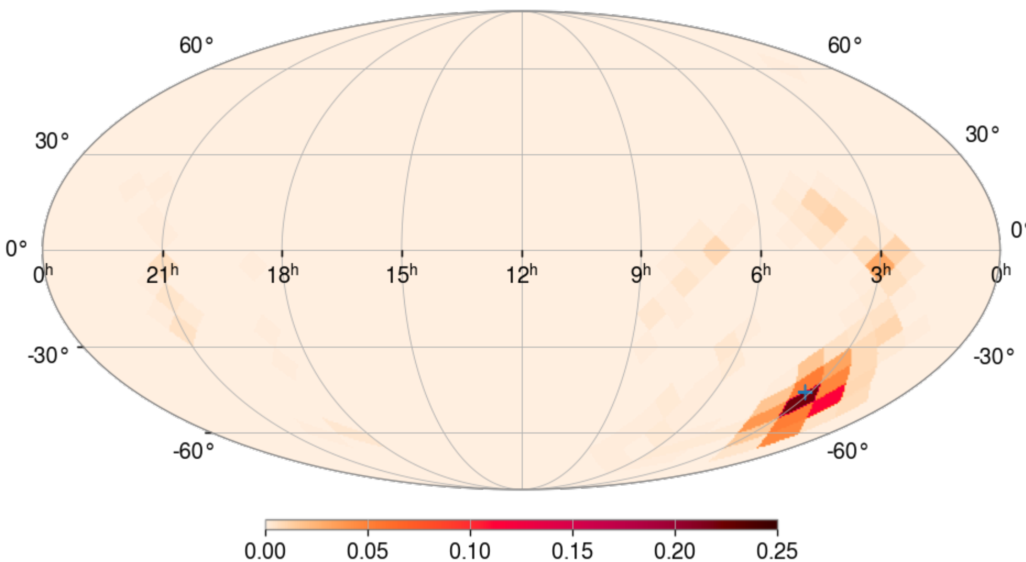


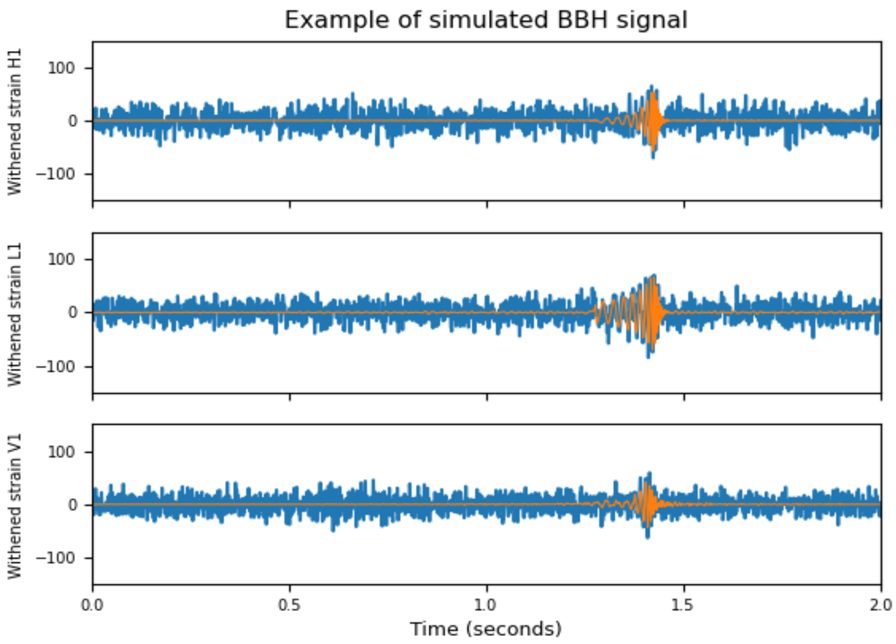


- Application to digital twins? (EU project InterTwin
- Data release in progress on GWOSC

Signal detection: Localization and Early Warning

- Fast detection and localization essential to trigger EM follow-up
- Deep Learning provides fast detection (classification) and localization (regression)
- Tests on simulated data for BBHs, BNSs and eccentric Close Encounters
- Can we provide fast pre-alert (early warning)?





Localization

Work with S. Randino, thesis 2020

2 approaches

- Localization as a classification problem
- Localization as a regression problem

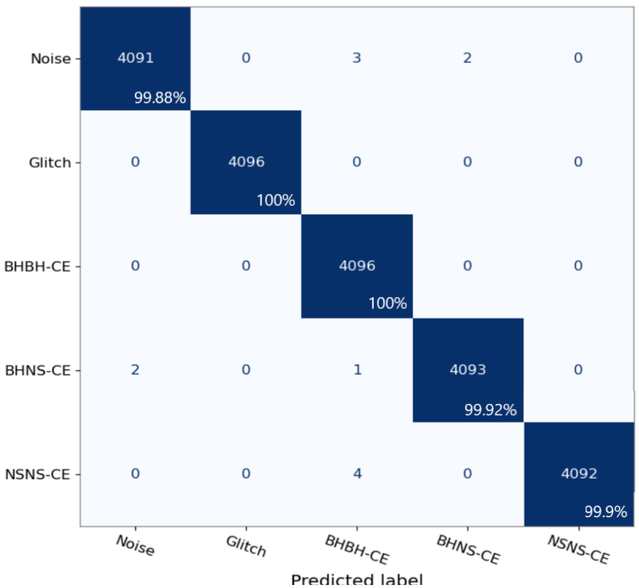
Early Warning

Work with L. Papalini, thesis 2022

- CNN on timeseries
- Sliding window approach
- Test on simulations

Machine Learning for Close Encounters

- CNN-based architectures have been extensively tested
- New architectures have been developed, can be used for GW analysis
- Eccentric close encounters: short, burst-like signals: can we detect and perform fast PE on them?

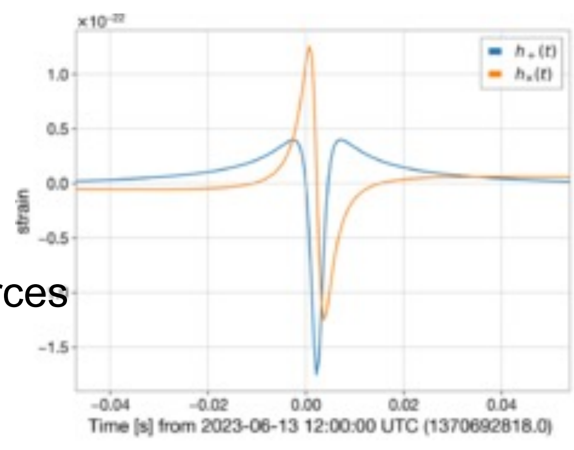


- Firsts tests using CNN-based classification (work with N. Sorrentino, PhD thesis 2023)

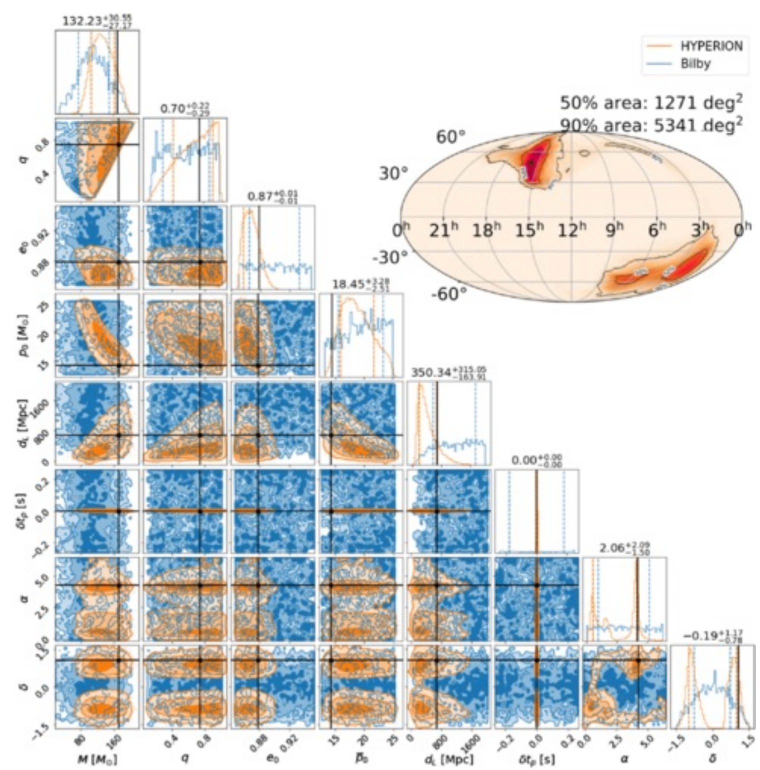
- Next steps:
Using Normalizing flows and run on real data
(De Santi et al 2024 , see talk by F. De Santi)

- Not only Normalizing Flows
Transformers are quite promising

Dedicated pipeline for transient sources
Tested on ET MDC
(See talk by L. Papalini)

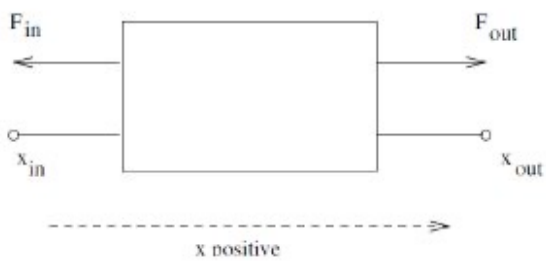


(a) $10\,M_\odot + 10\,M_\odot$

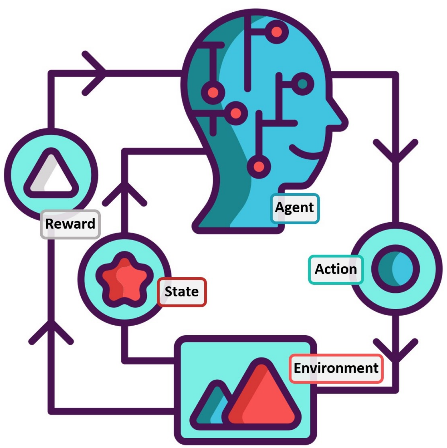


ML for optimal control

- We are exploring Reinforcement Learning to control real systems
- Aim to application to Pendulum Inverted Pendulum (and/or other systems)
- Work in two directions: simulations/algorithms + tests on prototype
- Approach Policy Based Gradients (Actor-critic mechanism, G. Bartoli thesis)
- Connected to development of new position sensors

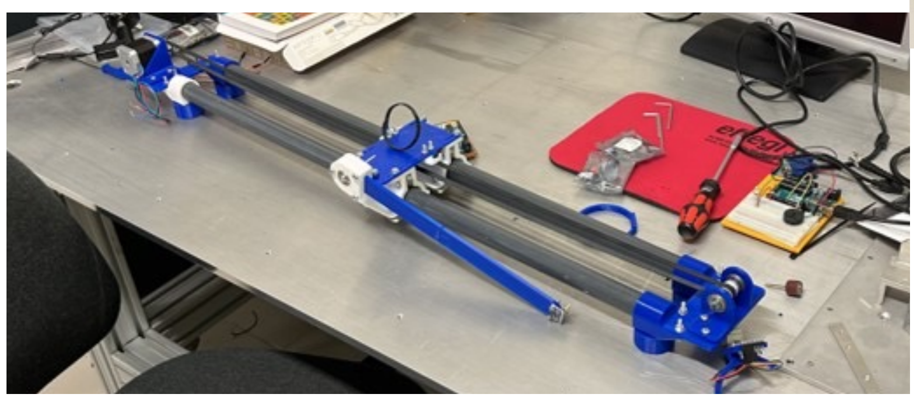


F-domain simulations (OctoPyus)



Reinforcement Learning algorithms

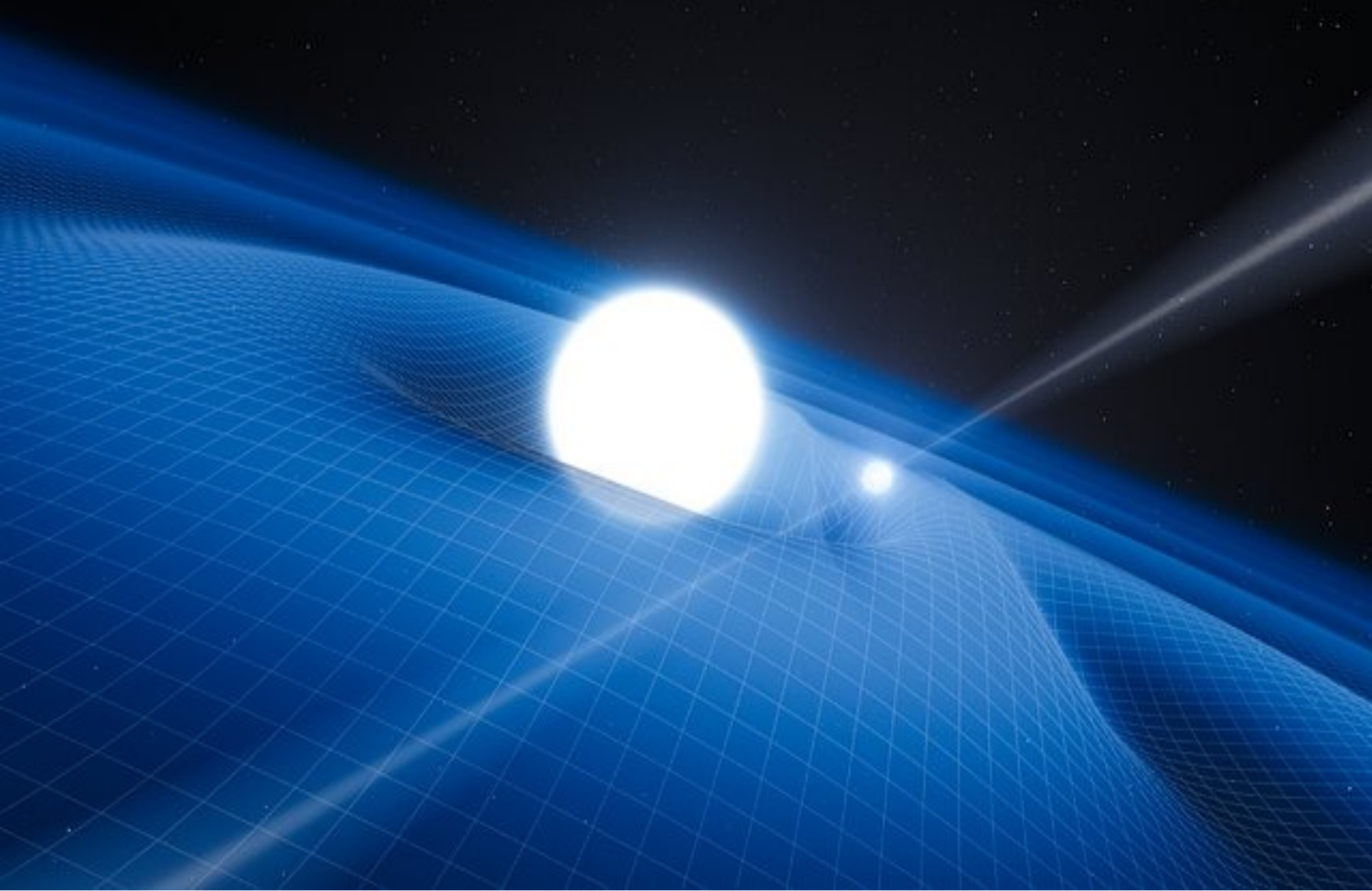
PIP



Basic testbench

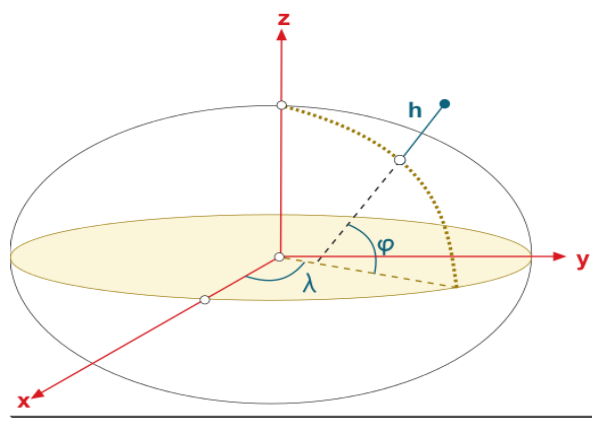
See M.A. Palaia talk

Gravitational Waves from pulsars



Searching for GW pulsars

- Constraints on ellipticity
- Equation of State
- Stellar Evolution
- Magnetic Field Geometry



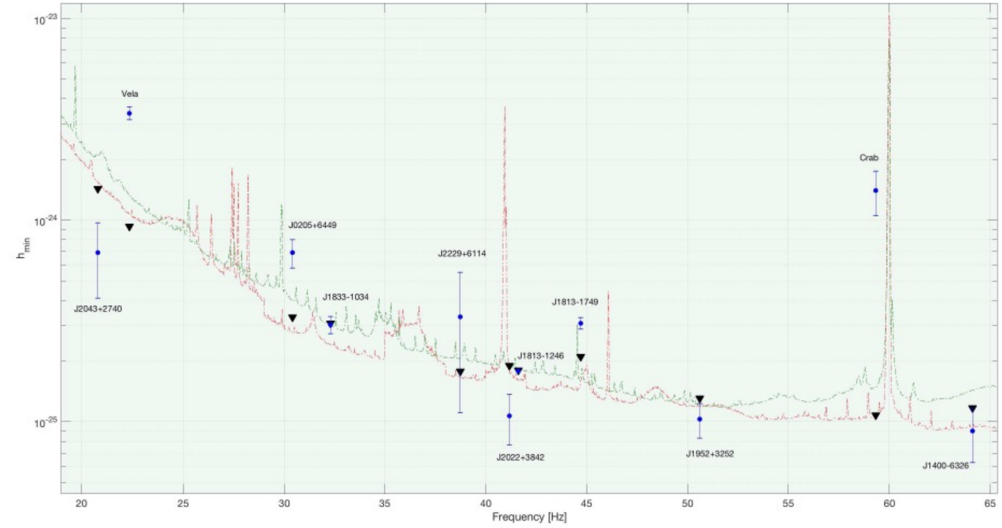
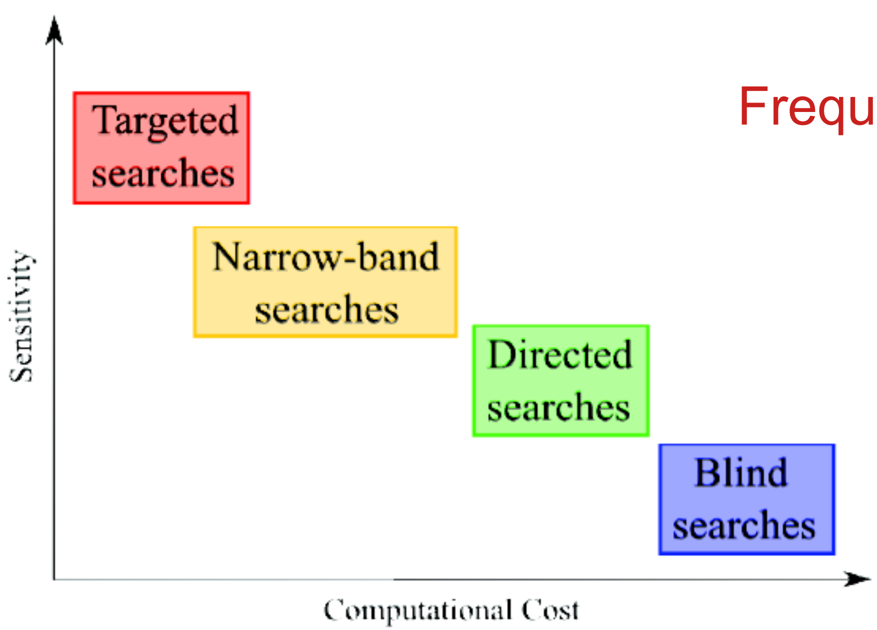


FIG. 2. Blue points: Value of the theoretical spin-down limit computed for the 11 known pulsars in our analysis, corresponding to Tab. I, error bars correspond to 1σ confidence level. Black triangles: median over the analysed frequency band of the upper-limits on the GW amplitude, corresponding to Tab. IV. Red dashed line: Estimated sensitivity at 95% confidence level of a narrow-band search using data from LIGO H. Green dashed line: Estimated sensitivity at 95% confidence level of a narrow-band search using data from LIGO L.



Frequency evolution+sky location

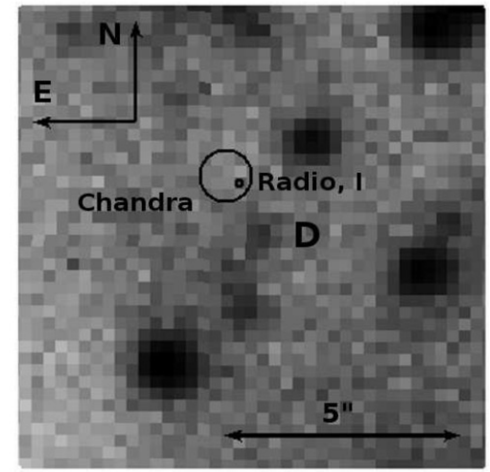
Sky location, NO frequency evolution

NO sky location, NO frequency evolution

Sieniawska & Bejger (2016)

From multiwavelength to multimessenger

- Pulsars still undetected in GWs
- What can we learn from EM observations?
- Exploiting on EM observations to estimate observing scenarios, find candidates for CM searches
- What about transient (e.g. glitches) emission?



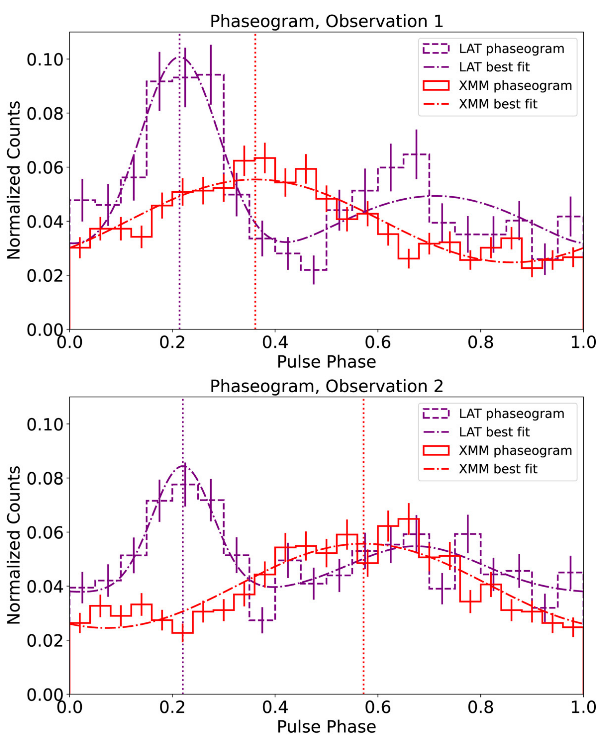
Razzano et al 2012

Radio

Good channel for discoveries
Very good localization
e.g. Parkes, GBT, FAST

Optical

Super faint, ULs
Very good localization
e.g. VLT, GranTecan



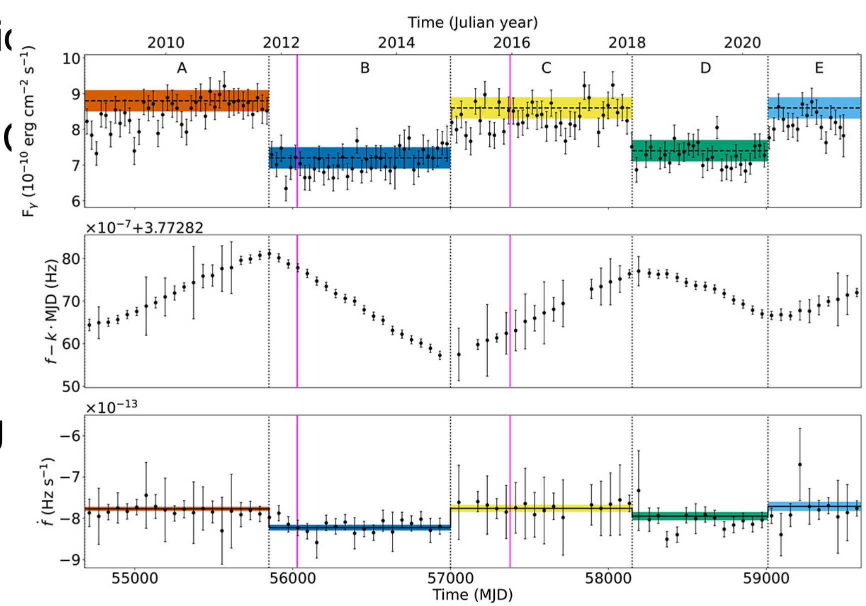
Razzano et al 2024

X-rays

Thermal and nonthermal emissi
MM high-energy modeling
e.g. Chandra, XMM-Newton, NI(

Gamma rays

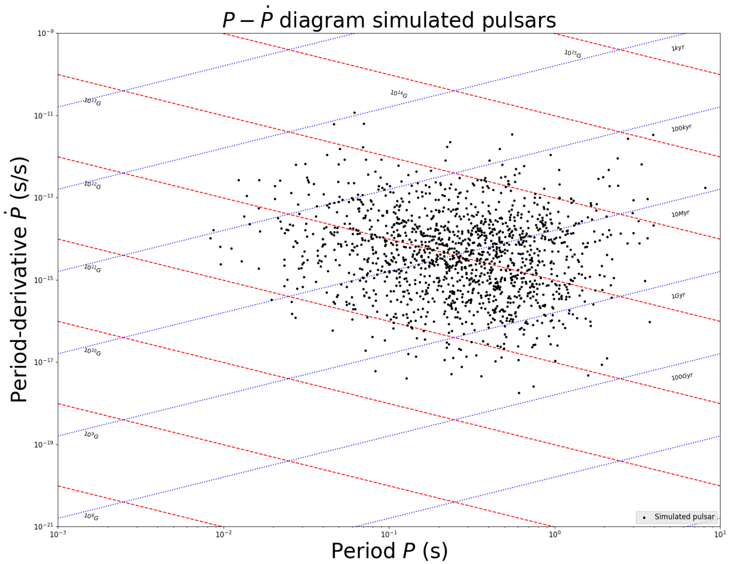
Nonthermal emission
High-energy modeling
e.g. Fermi-LAT

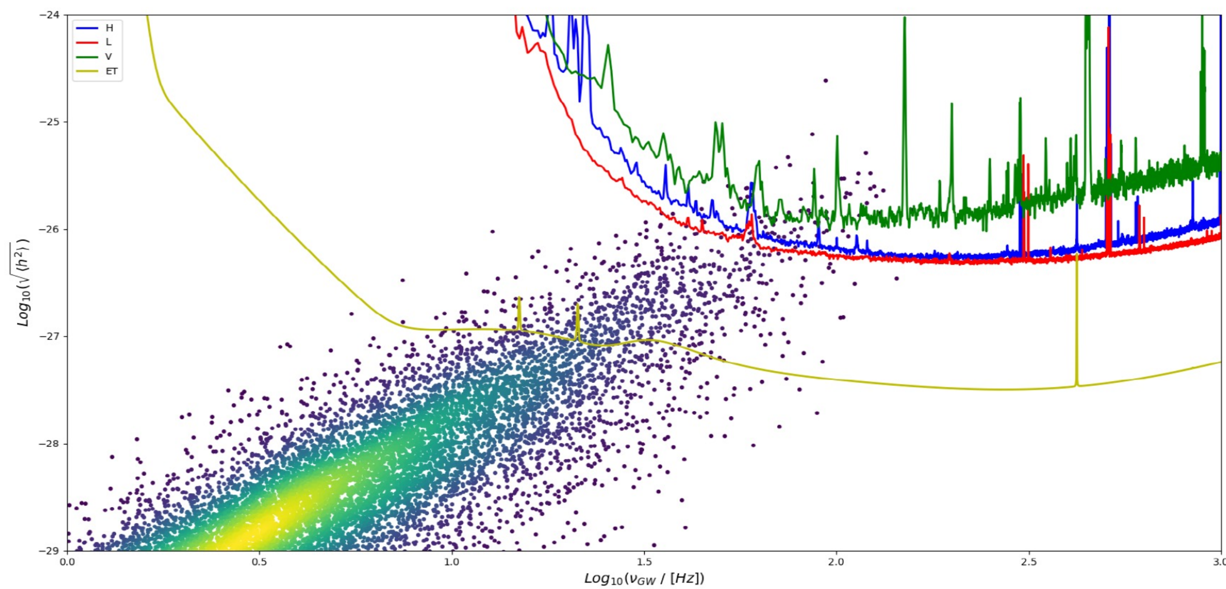


Fiori et al 2024

Population Studies

- Simulating realistic populations of neutron stars in the Galaxy
- Propagate synthetic NSs in the Milky Way
- Derive Multiwavelength and GW emission properties
- Observing scenarios for Current and future detectors

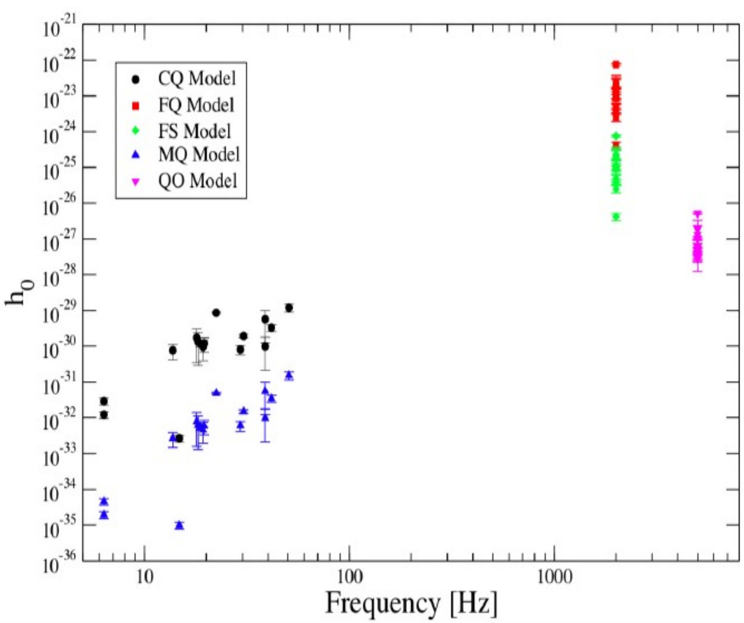


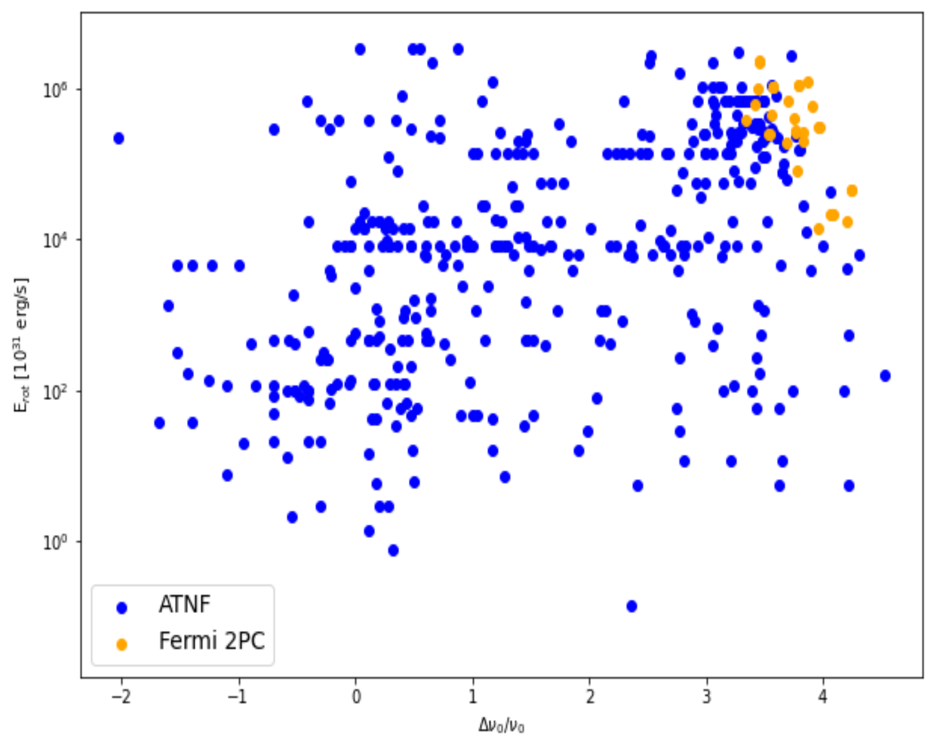


Work with A. Lipovanu thesis

Pulsar glitches: from gamma-ray to GW

- Pulsar Glitches are sudden changes in spindown properties of pulsars
- Can be seen in EM radiation What can we say on GW emission?
- Starquakes?
- Glitch monitoring fundamental for CW searches
- Multimessenger link with high-energy, gamma-ray pulsars
- Collaboration with UC Santa Cruz (NASA Fermi GI funded project, 2023)
- Phenomenological study with A. Fiori, L. Papalini, G. Cozzolongo (Erlangen Center for Astroparticle Physics)





* Stopnitzky & Profumo 2014, ApJ 787, 114

NASA Fermi GI, 2023

Conclusions

- **Pisa very active in Machine Learning applications to GW**
  - Noise characterization
  - Superattenuator-related studies
  - Detection, Early Warning and Parameter Estimation for GW signals

- **Among first groups to work on ML, various collaborations**
  - EGO
  - Ellinogermaniki Agogi
  - Univ of Glasgow
  - Univ of Valencia
  - Univ. of Turin
  - Univ of Erlangen
  - Univ of Hamburg
  - Univ of California, Santa Cruz
  - Univ of Missouri
  - INGV and Dept Earth Science, Univ of Pisa

- **Future developments**
  - Finalize online pipeline for glitch classification
  - Further develop ML for Superattenuators
  - Finalize pipeline for detection and parameter estimation for burst signals (real data and ET MDC)
  - Explore models for seismic and geophysical applications
  - Implement ML-based controls to PIP and other seismic attenuation systems