

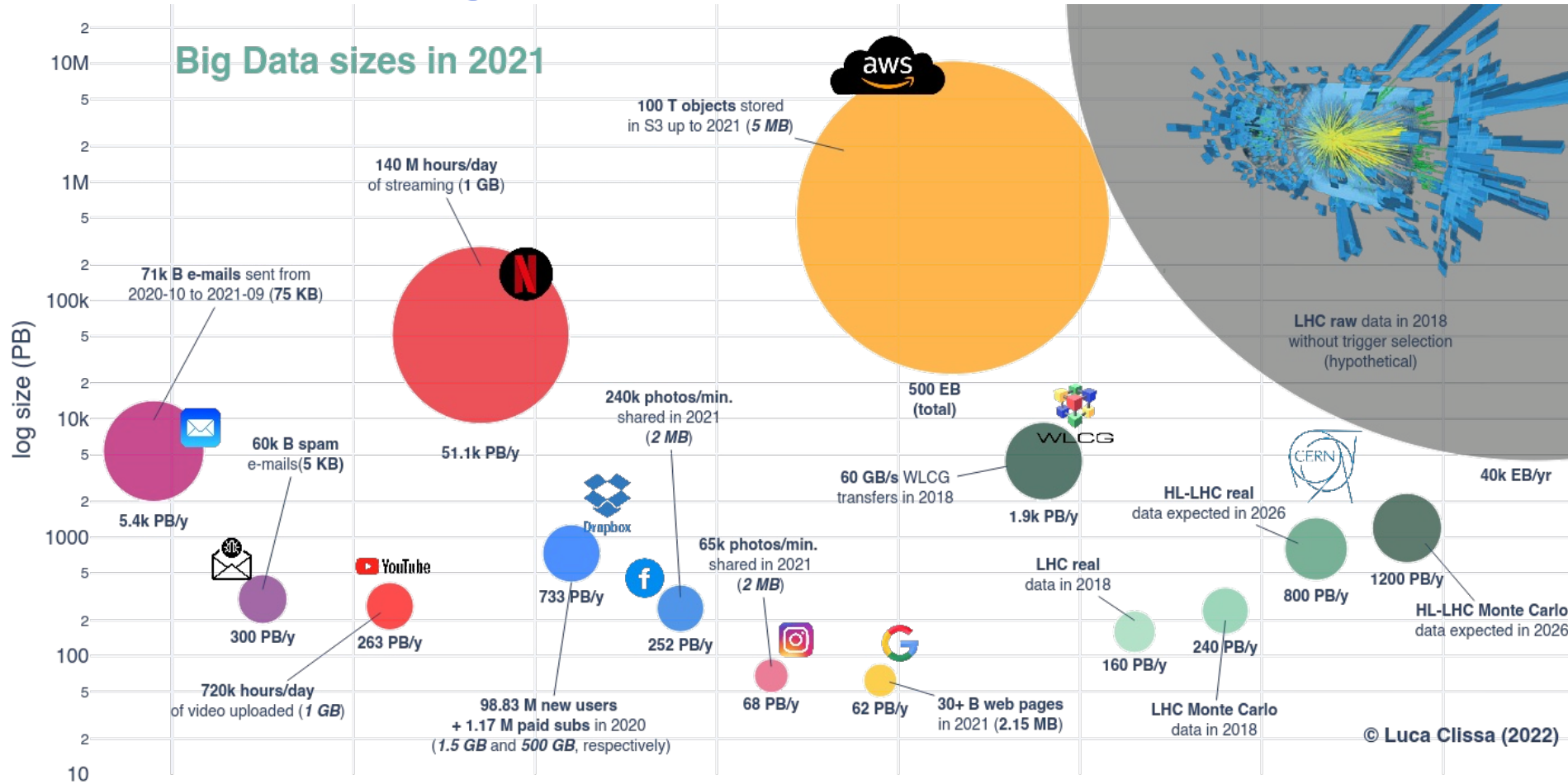
Machine Learning for Gravitational Waves (and some extras on pulsars)

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Virgo Pisa Internal Workshop
22-23 May 2024

Big Data in Science



© Luca Clissa (2022)

Virgo Data

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

Source	Volume	Velocity	Variety
SDSS <i>Sloan Digital Sky Survey</i>	50 TB	200 GB per day	images, catalogs, redshifts
GAIA	100 TB	40 GB per day	more than 100 parameters
Pan-STARRS <i>Panoramic Survey Telescope and Rapid Response System</i>	5 PB	5 TB per day	images, catalogs
LSST <i>Large Synoptic Survey Telescope</i>	60 PB	10 TB per day	images, catalogs
SKA <i>Square Kilometer Array</i>	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.

Machine Learning and GW

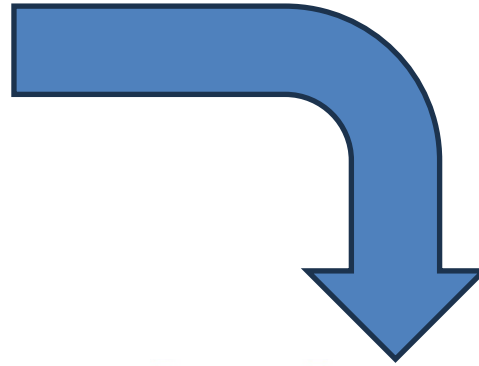
A simple ADS search...

← Start New Search

machine learning

Your search returned **13,301** results

Collection ×
astronomy

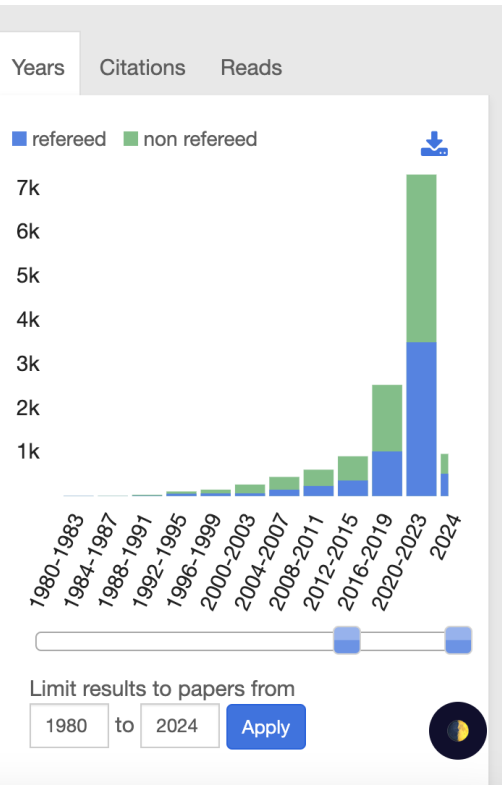


machine learning gravitational waves

Your search returned **536** results

↓ ↑ Date ▾

Export ▾ Explore ▾



Show highlights Show abstracts Hide Sidebars Go To Bottom

- 2024MLS&T...5b5020R 2024/06
GWAK: gravitational-wave anomalous knowledge with recurrent autoencoders
Raikman, Ryan; Moreno, Eric A.; Govorkova, Ekaterina; Marx, Ethan J.; Gunny, Alec; Benoit, William; Chatterjee, Deep; Omer, Rafia; Saleem, Muhammed; Rankin, Dylan S.; Coughlin, Michael W.; Harris, Philip C.; Katsavounidis, Erik [show less](#)
- 2024MLS&T...5b5014A 2024/06
GRINN: a physics-informed neural network for solving hydrodynamic systems in the presence of self-gravity
Auddy, Sayantan; Dey, Ramit; Turner, Neal J.; Basu, Shantanu [show less](#)
- 2024arXiv240509475X 2024/05
Robust inference of gravitational wave source parameters in the presence of noise transients using normalizing flows
Xiong, Chun-Yu; Sun, Tian-Yang; Zhang, Jing-Fei; Zhang, Xin [show less](#)
- 2024PhRvD.109j2004D 2024/05
Deep learning to detect gravitational waves from binary close encounters: Fast parameter estimation using normalizing flows
De Santi, Federico; Razzano, Massimiliano; Fidecaro, Francesco; Muccillo, Luca; Papalini, Lucia; Patricelli, Barbara [show less](#)
- 2024MNRAS.tmp.1253S 2024/05
REDBACK: A Bayesian inference software package for electromagnetic transients

Years Citations Reads

■ refereed ■ non refereed

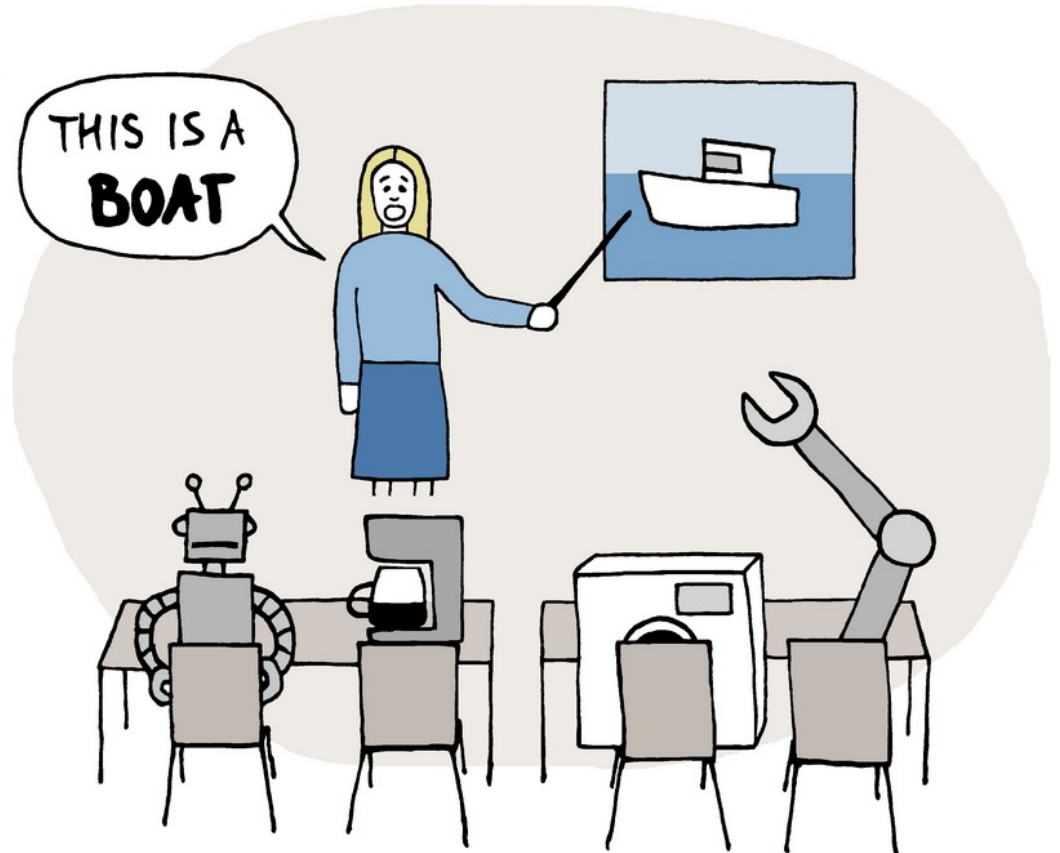
Year	Refereed	Non-refereed
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2001-2002	0	0
2003-2004	0	0
2005-2006	0	0
2007-2008	0	0
2009-2010	0	0
2011-2012	0	0
2013-2014	0	0
2015-2016	~10	~10
2017-2018	~20	~20
2019-2020	~50	~50
2021-2022	~100	~100
2023-2024	~100	~100

Limit results to papers from 1999 to 2024 Apply

Context of Machine Learning

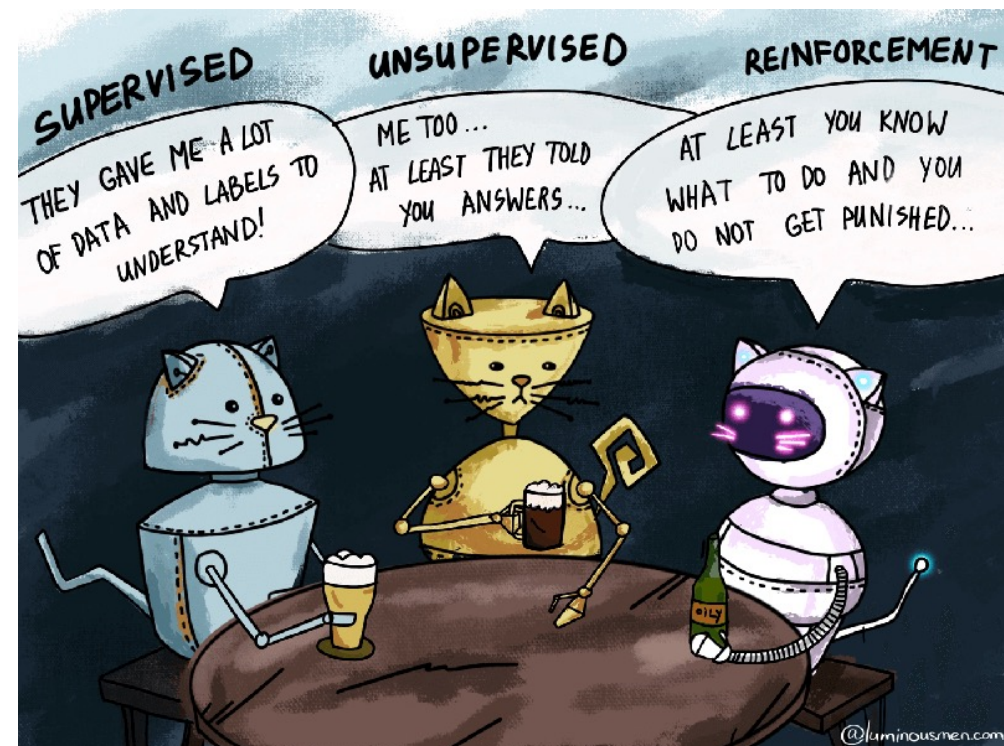
«A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E » (T. Mitchell)

MACHINE LEARNING

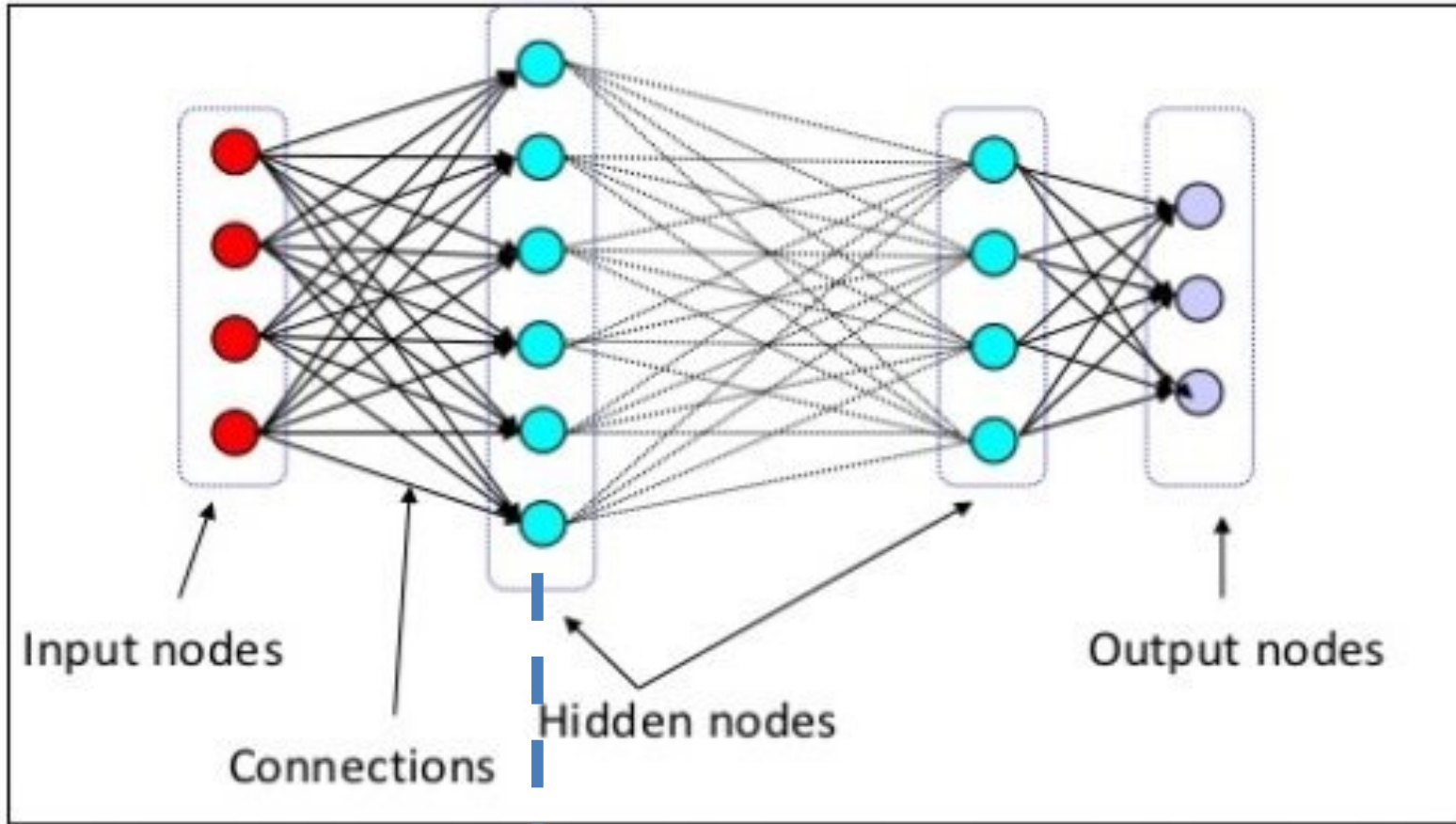


Approaches to Machine Learning

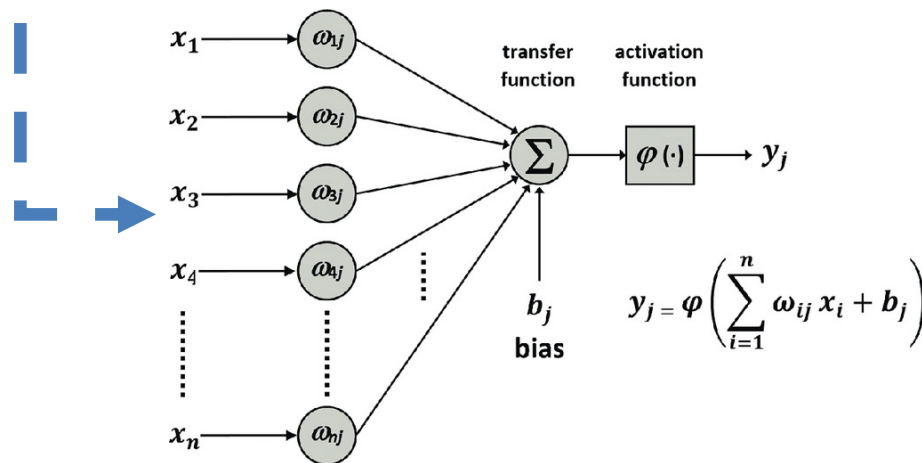
- **Supervised**: the algorithm is fed with labeled data, and learn the features that are best linked to each label (task driven)
 - Classification
 - Regression
- **Unsupervised**: No labels, features are extracted (data driven)
 - Clustering
 - Dimensionality reduction
- **Reinforcement learning**: trial and error strategy (experience driven)



What is a Neural Network?



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



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

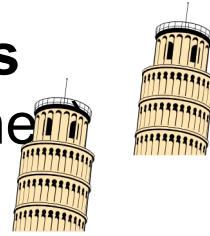
● Detector R&D

- Simulate complex systems (e.g. digital twins)
- Active control systems

Machine Learning and GW

● Instrument characterization examples

- Study and characterize noise (glitches)
- Coupling among channels
- Denoising algorithms



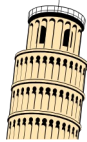
● Detection and PE

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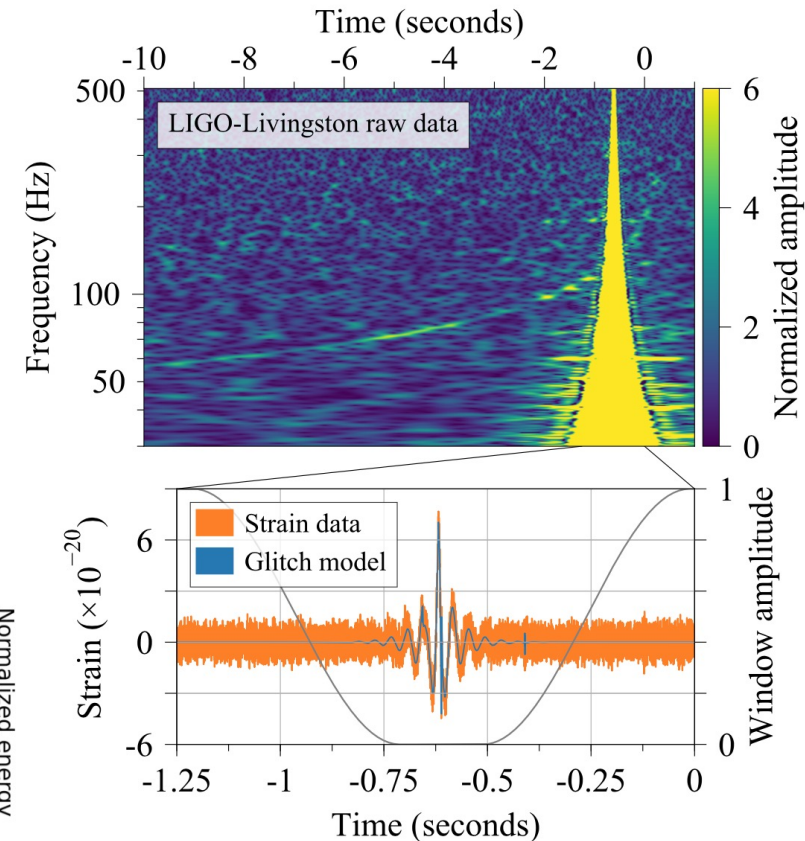
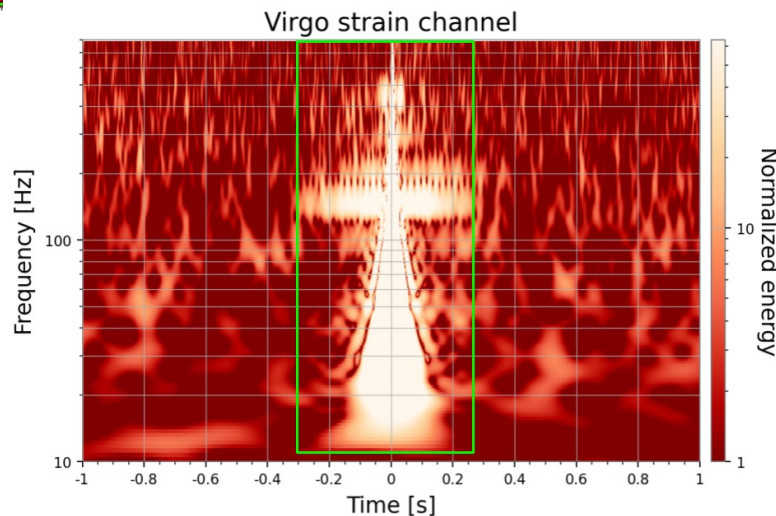
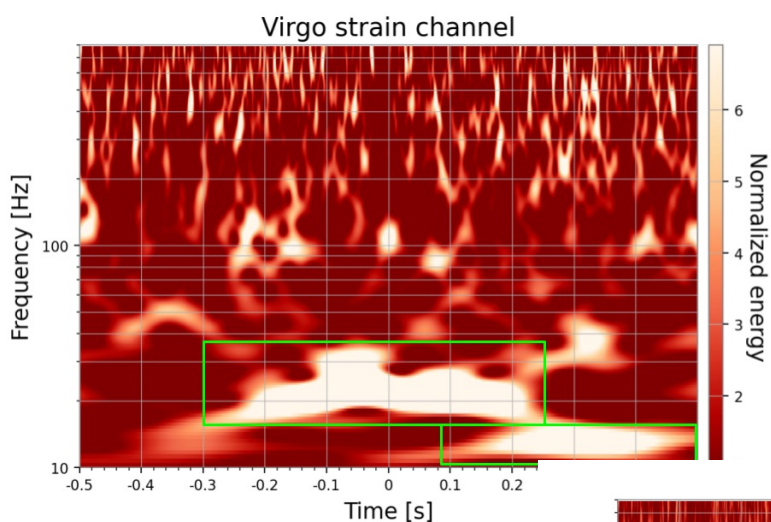
● Detector R&D

- Simulate complex systems (e.g. digital twins)
- Active control systems



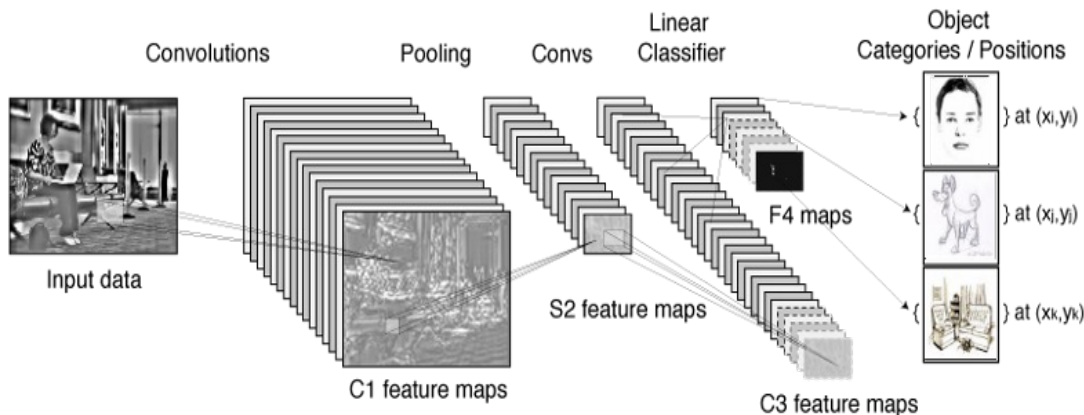
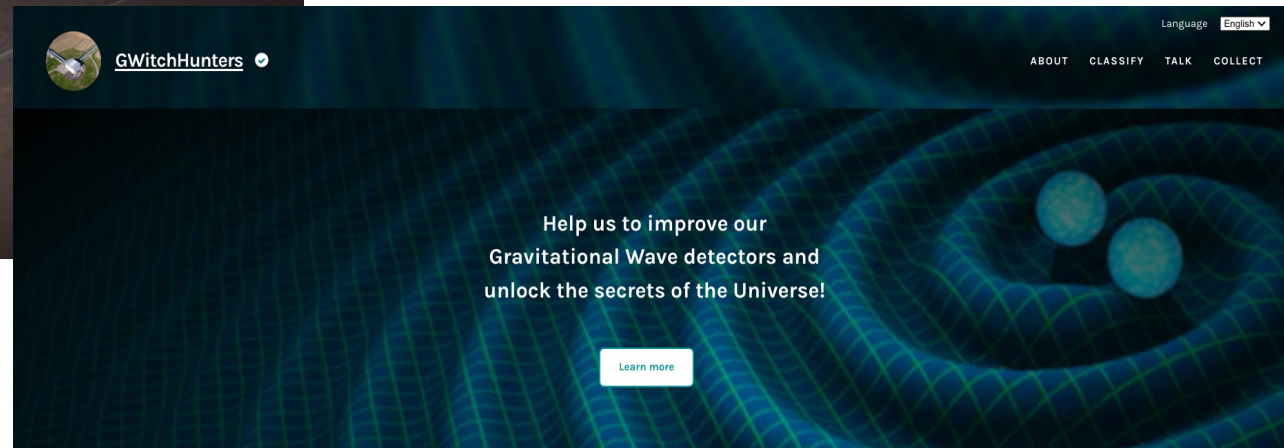
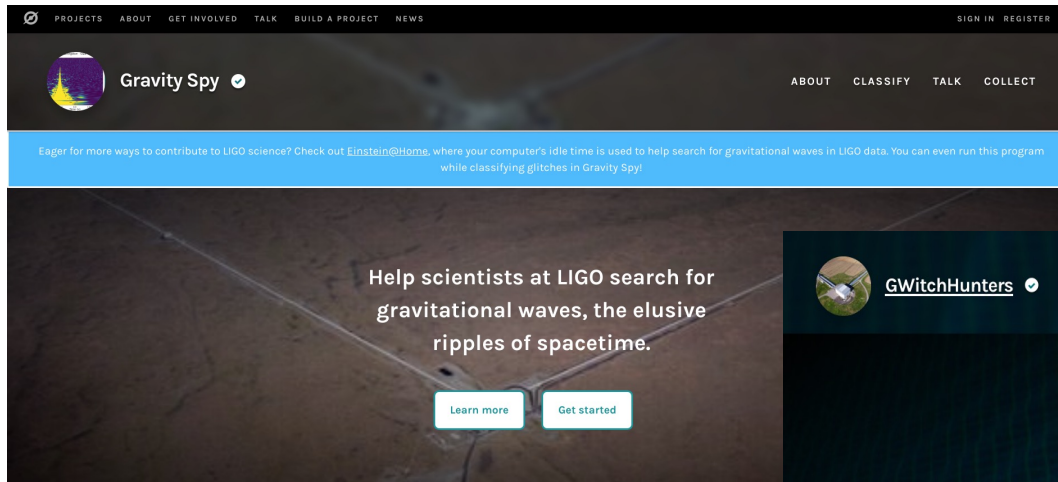
Glitch characterization

- 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



Glitch classification & Citizen Science

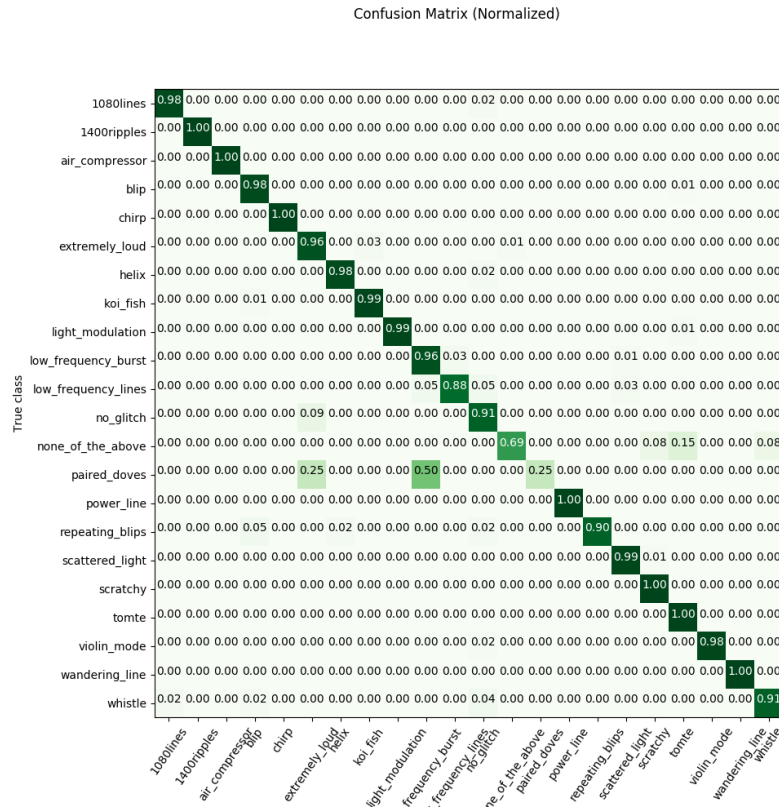
- Supervised approach requiring labeled datasets
- Labels can be acquired via Citizen Science projects (GravitySpy@LIGO, GWitchHunters @Virgo)
- Goal: Infrastructure for glitch classification in real time



Based on Convolutional Neural Networks

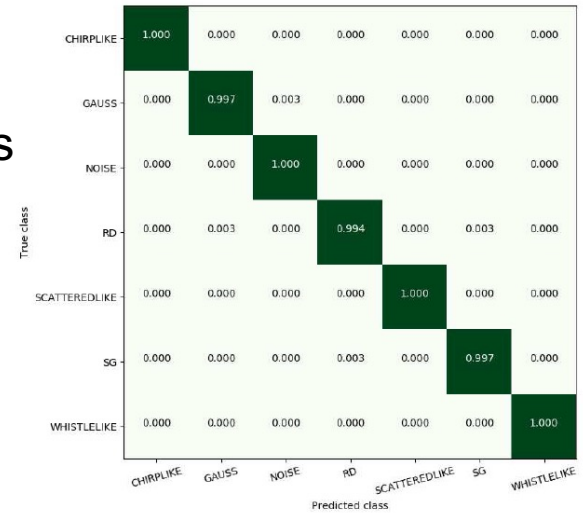
Steps of glitch classifications in Pisa

- 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)

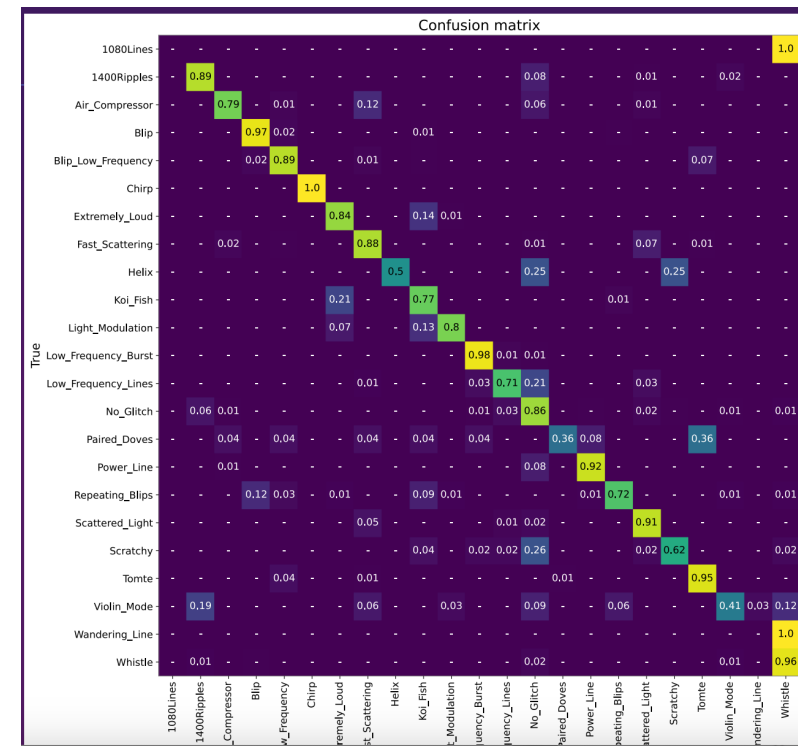


O1+O2

Simulations



O3



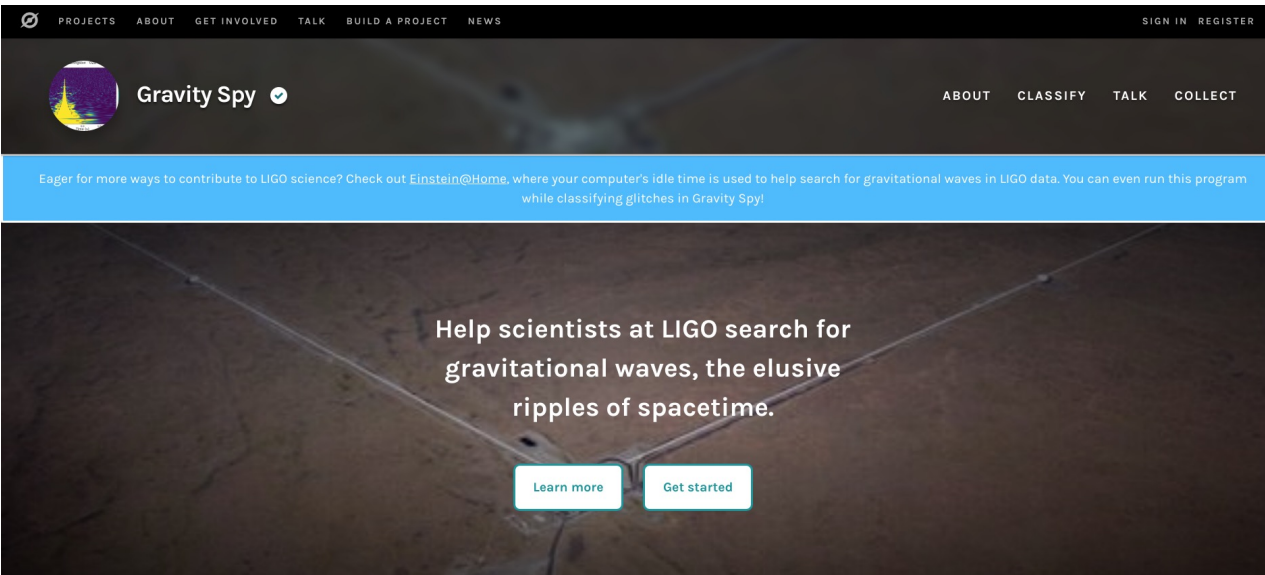
- Check with GravitySpy and citizen science project
- Tests on O3 data (custom pipeline vs gravitySpy)+ comprehensive analysis of O3 glitches (work with M. Vacatello)

Detector characterization & citizen science

GravitySpy:

Citizen science + Machine Learning

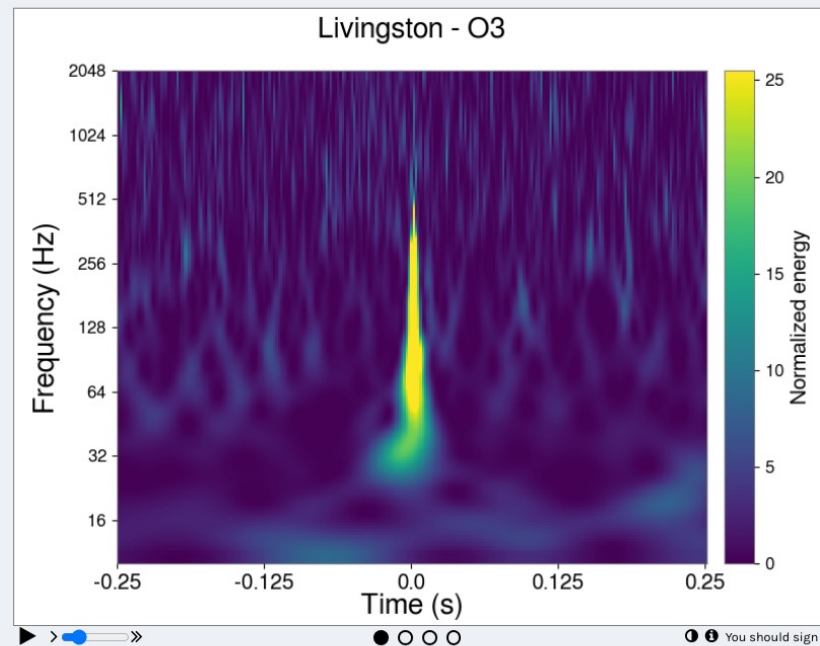
Zevin et al. 2017, CQG,34,6



... object in the mysterious "mass gap" between the heaviest neutron stars and lightest black holes. We aren't able to tell what it is because it was swallowed whole by its black hole companion. Find out more about this enigma in [discovery paper](#), check out some out-of-this-world [media](#) here, and read about the major contributions to this discovery made by members of the Gravity Spy from [Northwestern](#) and [CSU Fullerton](#)!

Please sign in or sign up to access more glitch types and classification options as well as our mini-course.

Classifications
made by
citizen scientists
Used to train ML



The interface shows a classification task. At the top, there are two tabs: "TASK" and "TUTORIAL". Below the tabs, there are three classification options, each with a small spectrogram icon and a text label: "Blip", "Whistle", and "None of the Above". Below these options, it says "Showing 3 of 3" and "Clear filters". At the bottom, there are two buttons: "Done & Talk" and "Done".

You should sign in!

The REINFORCE project



ABOUT ▾

DEMONSTRATORS ▾

NEWS ▾

OUTREACH ▾

GRAVITATIONAL WAVE NOISE HUNTING

Citizen scientists will look at chunks of Gravitational Wave data and identify the presence of noise which limits the sensitivity of detectors.

DEEP SEA HUNTERS

Citizens will help to improve neutrino detection algorithms, while gaining a greater insight of the unexplored deep marine environment.

SEARCH FOR NEW PARTICLES AT THE LHC

Citizens will be engaged in the quest of the Large Hadron Collider of CERN for the discovery of the ultimate structure of matter as well as particle theories beyond the Standard Model.

COSMIC MUONS IMAGES

Citizens will help explore the connections across the fields of cosmic ray physics, geology, volcanology and archaeology through the use of data and simple experimental devices.

HOW TO HELP SCIENTISTS IN THE GRAVITATIONAL WAVE NOISE HUNT

16 OCTOBER
15:00 - 16:15 CEST

WEBINAR



SPEAKERS

Chris Lintott - Zooniverse

Stavros Katsanevas - EGO

Massimiliano Razzano - University of Pisa

Beatriz Garcia - CONICET

Julia Casanueva - Virgo

Francesca Spagnuolo - EGO



REINFORCE
Research Infrastructures FOR Citizens in Europe

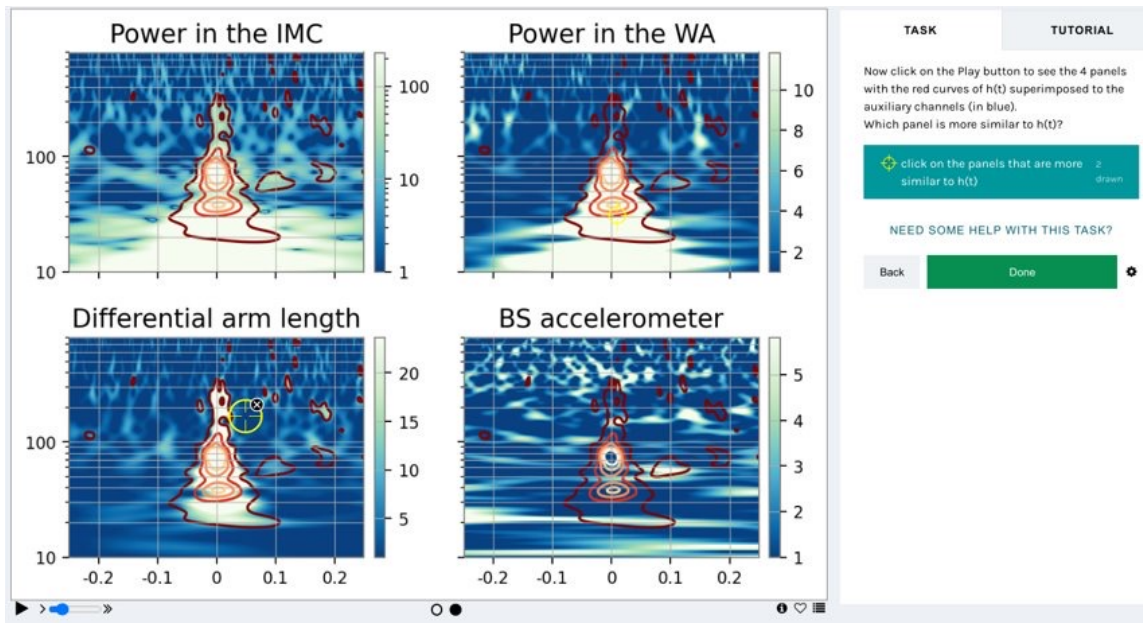
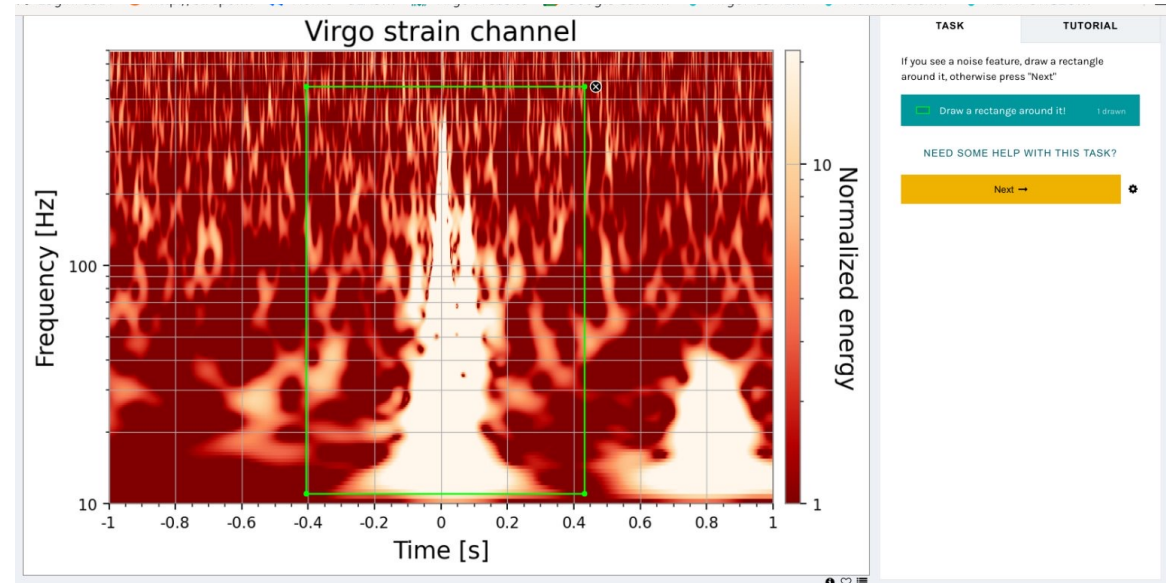


<https://www.reinforceeu.eu/>

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

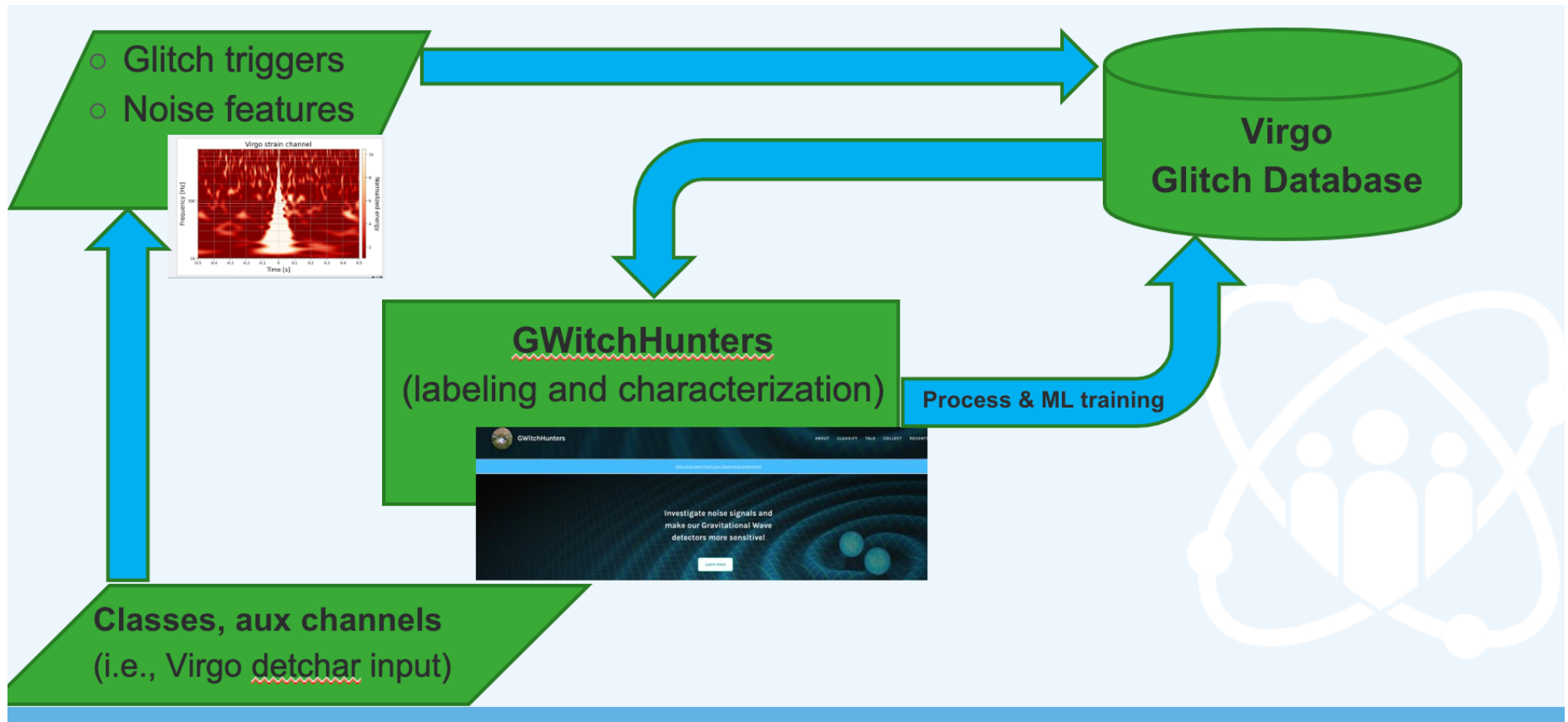
Overview of GwitchHunters

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



- Collaboration UNIFI (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

Volunteers

739.422

Classifications

41.620

Subjects

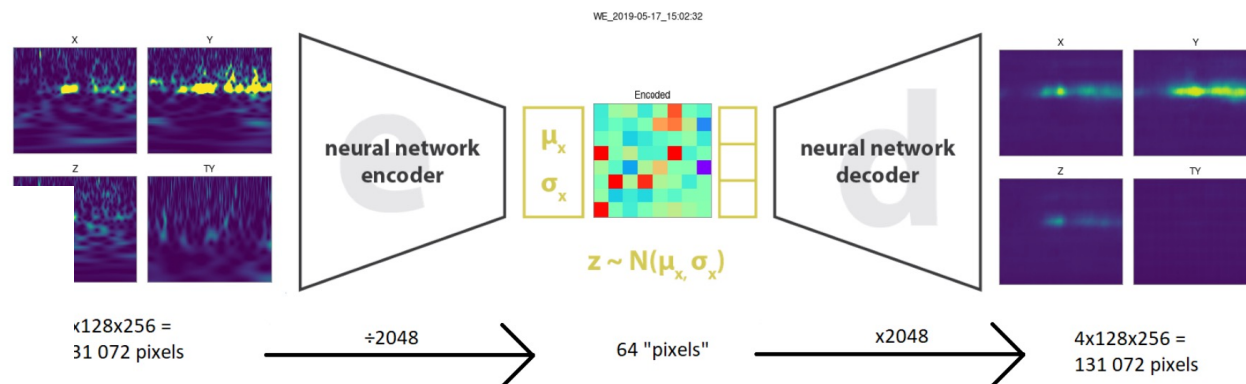
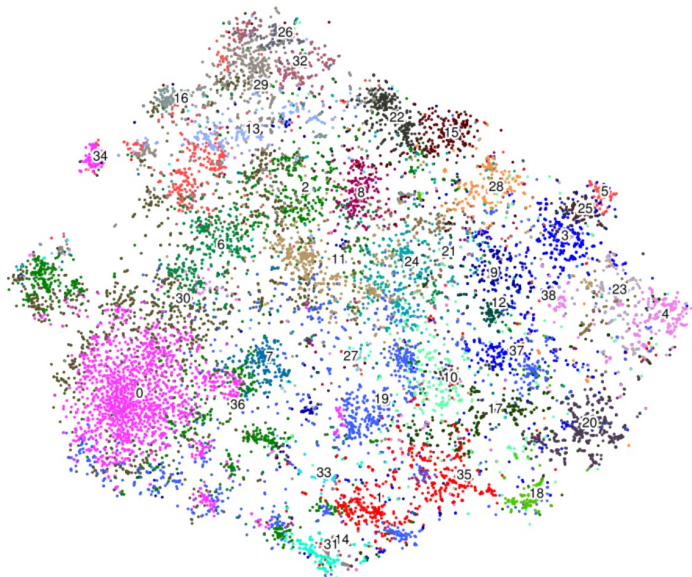
38.296

Completed Subjects

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

Work using Auxiliary Channels

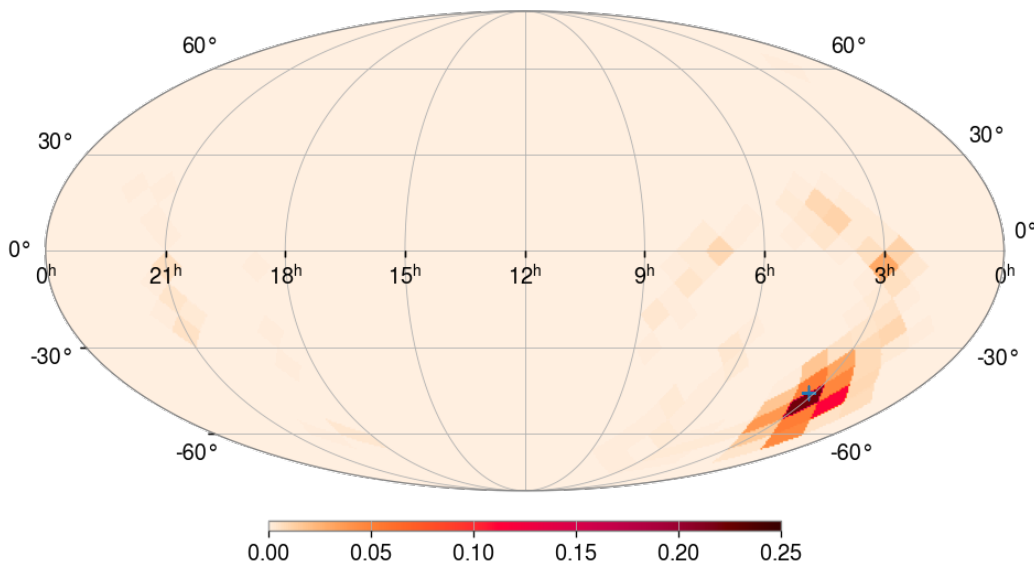
- Auxiliary channels are a rich data source
- Apply ML to auxiliary channels data (work with L. Negri, A. Gennai, V. Boschi)
- Using Variational Autoencoders to cluster data related to seismic activity (using channels from SA)
- GMM + VAE to cluster data in low dim space
- Transformers for anomaly detection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

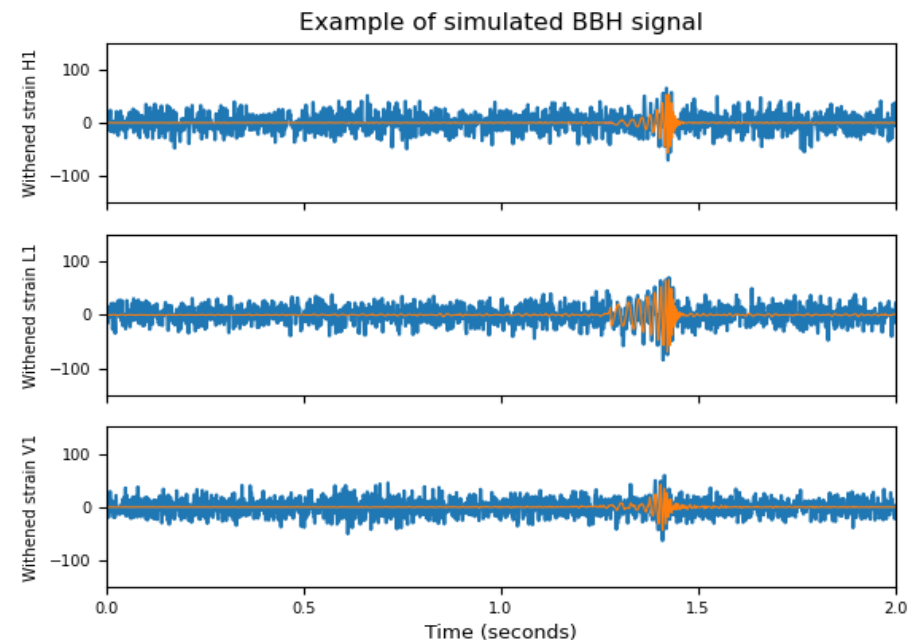


Localization

Work with S. Randino, thesis 2020

2 approaches

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



Early Warning

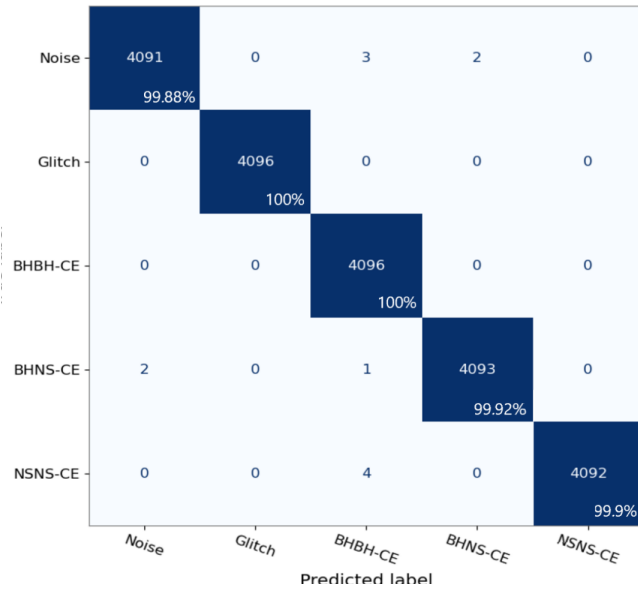
Work with L. Papalini, thesis 2022

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

Machine Learning for Close Encounters

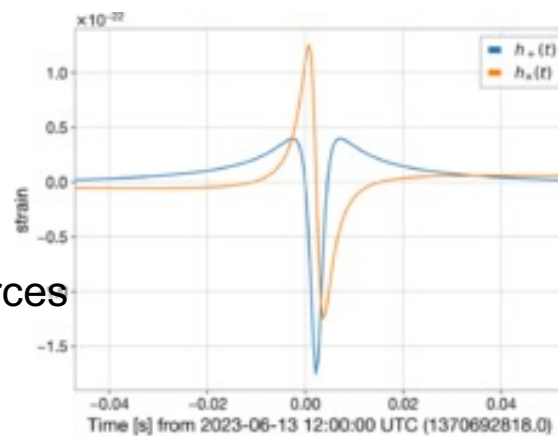
- CNN-based architectures have been extensively tested
- New architectures have been developed, can be used for GW analysis
- Eccentric close encounters: short, burst-like signals: can we detect and perform fast PE on them?

- 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)

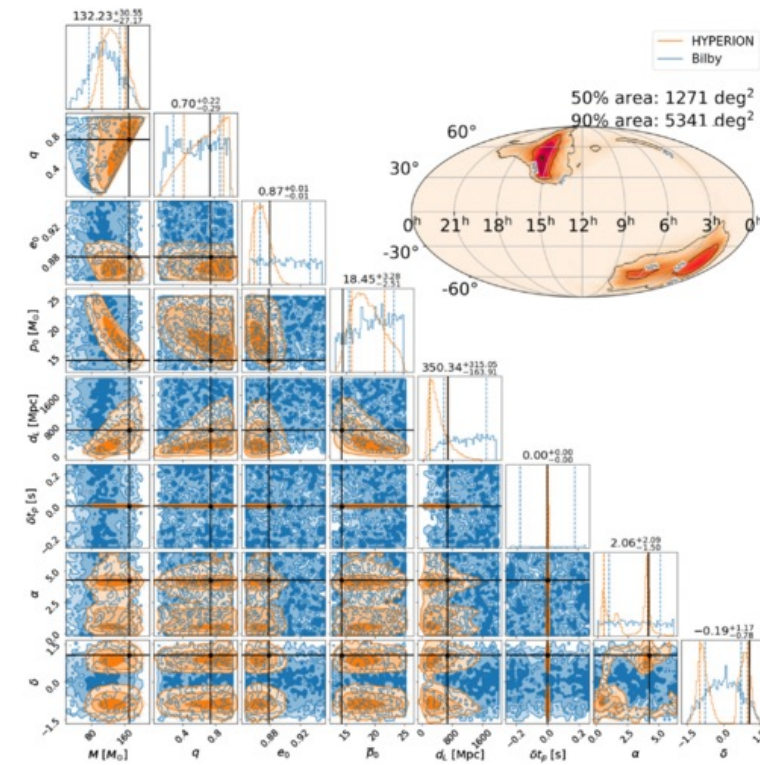


- Not only Normalizing Flows
Transformers are quite promising

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

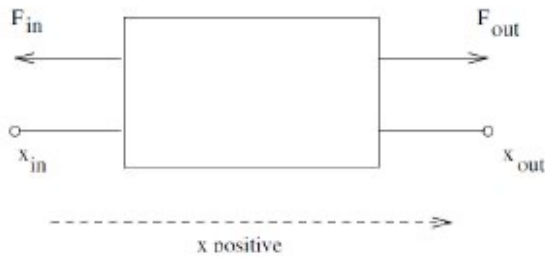


(a) $10 M_{\odot} + 10 M_{\odot}$

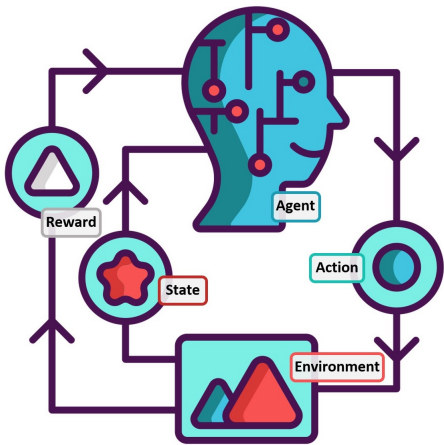


ML for optimal control

- 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

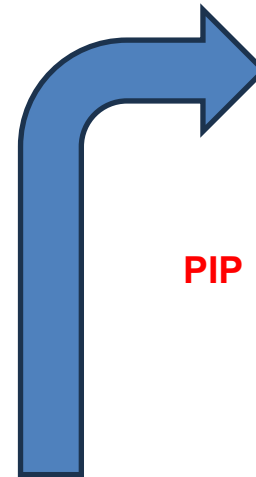


F-domain simulations (OctoPyus)



Reinforcement Learning algorithms

Basic testbench

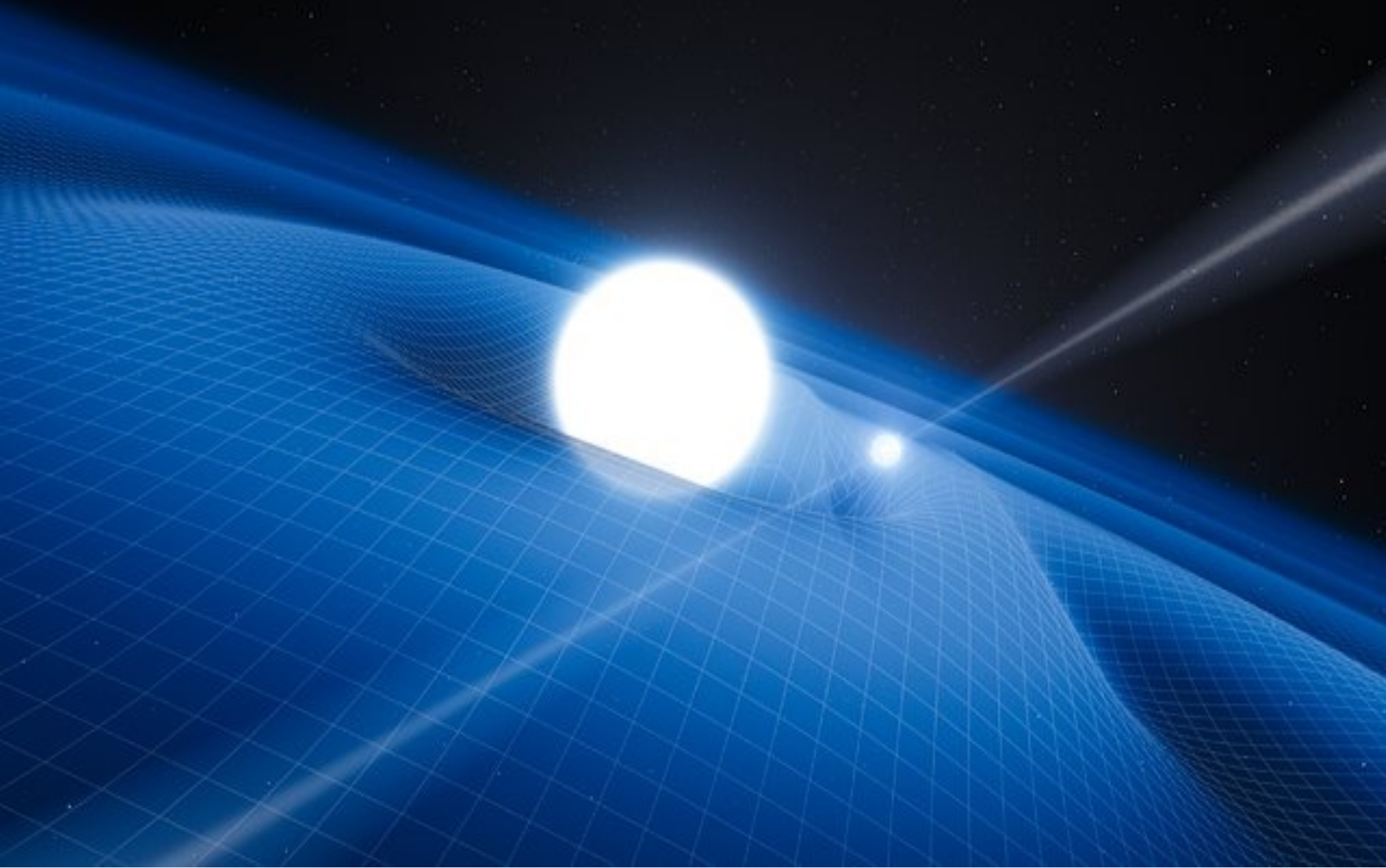


PIP



See M.A. Palaia talk

Gravitational Waves from pulsars



Searching for GW pulsars

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

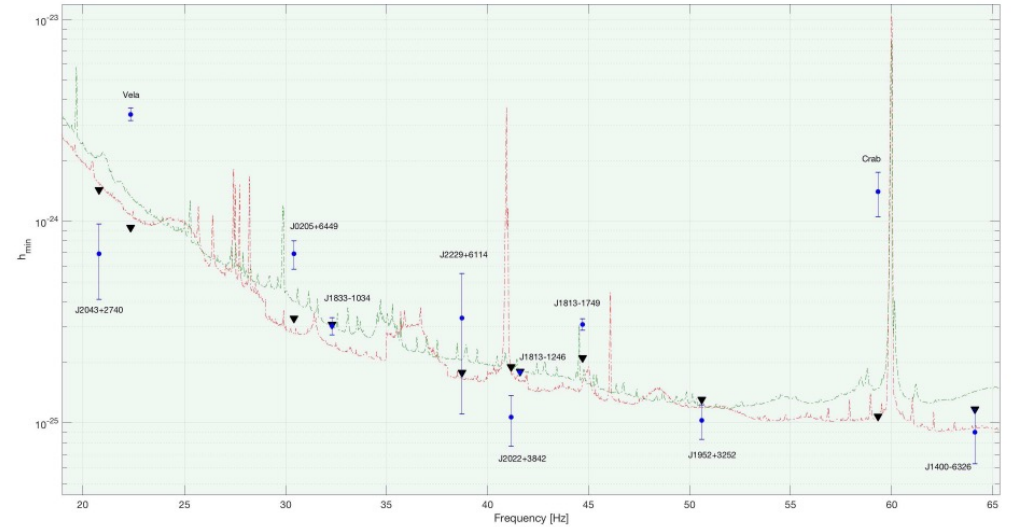
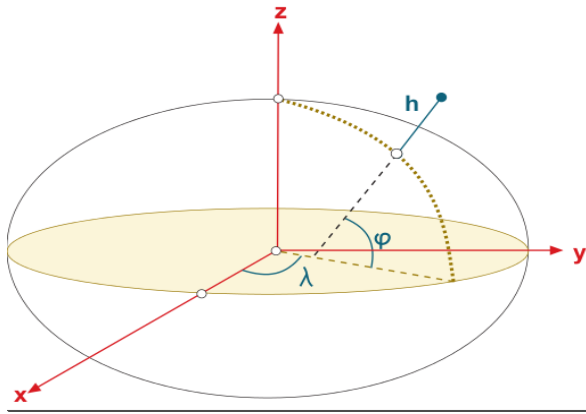
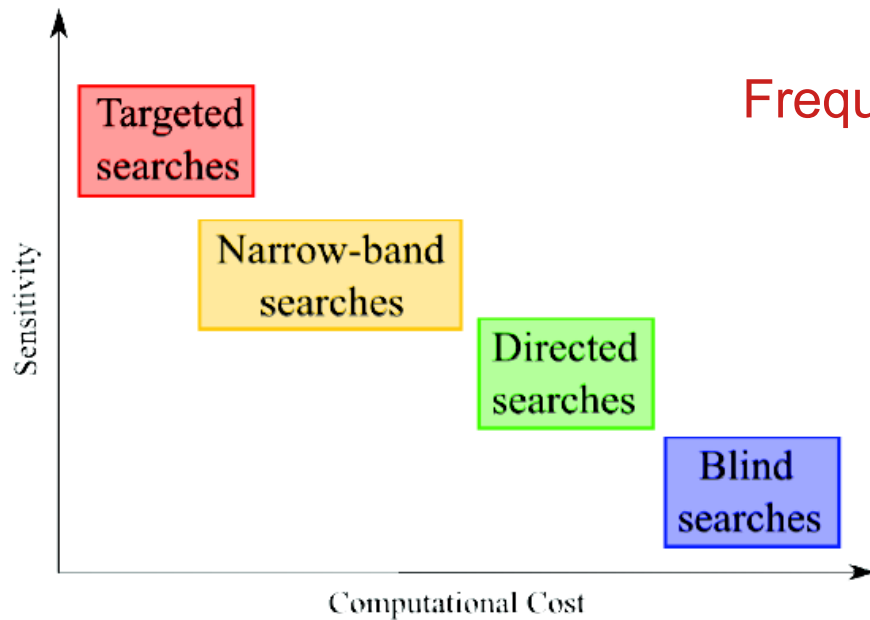


FIG. 2. Blue points: Value of the theoretical spin-down limit computed for the 11 known pulsars in our analysis, corresponding to Tab. I, error bars correspond to 1σ confidence level. Black triangles: median over the analysed frequency band of the upper-limits on the GW amplitude, corresponding to Tab. 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

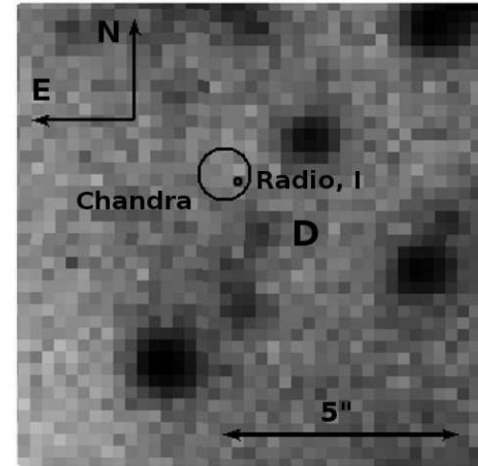
- Pulsars still undetected in GWs
- What can we learn from EM observations?
- Exploiting on EM observations to estimate observing scenarios, find candidates for CM searches
- What about transient (e.g. glitches) emission?

Radio

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

Optical

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



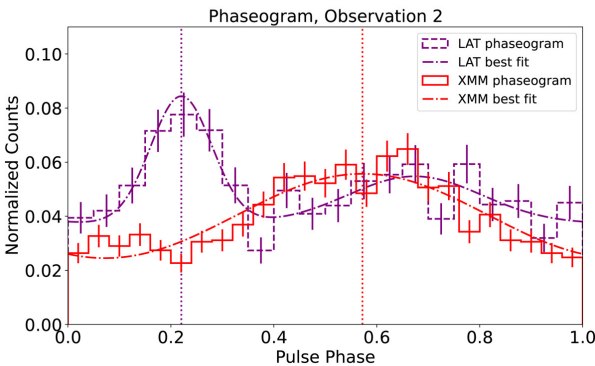
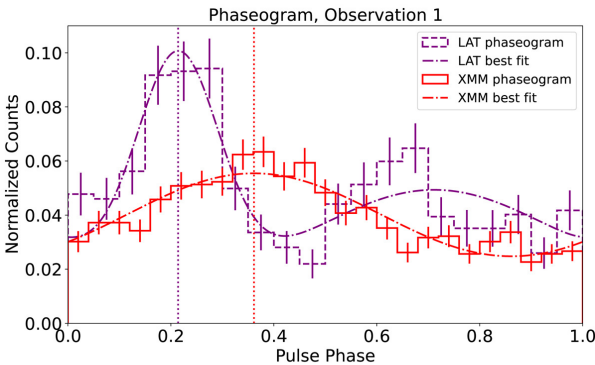
Razzano et al 2012

X-rays

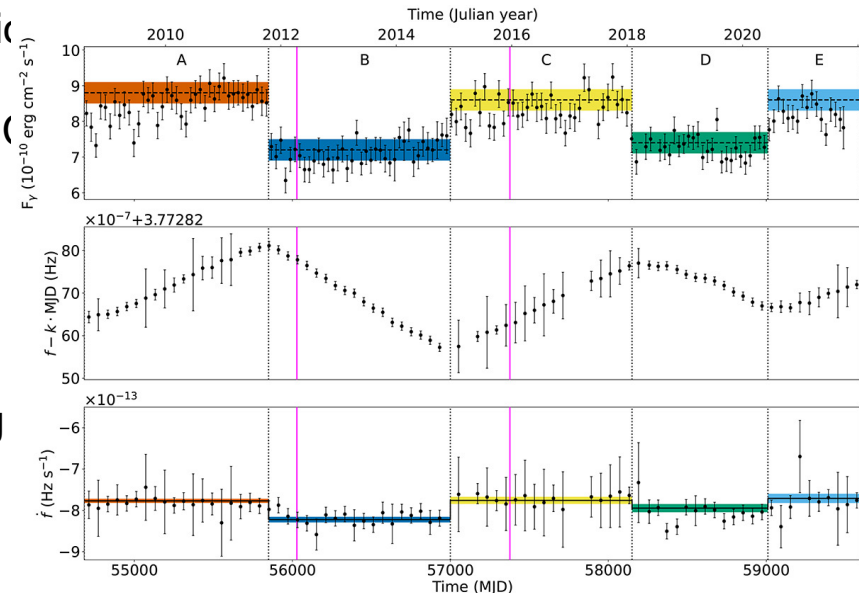
Thermal and nonthermal emission
 MM high-energy modeling
 e.g. Chandra, XMM-Newton, NIC

Gamma rays

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



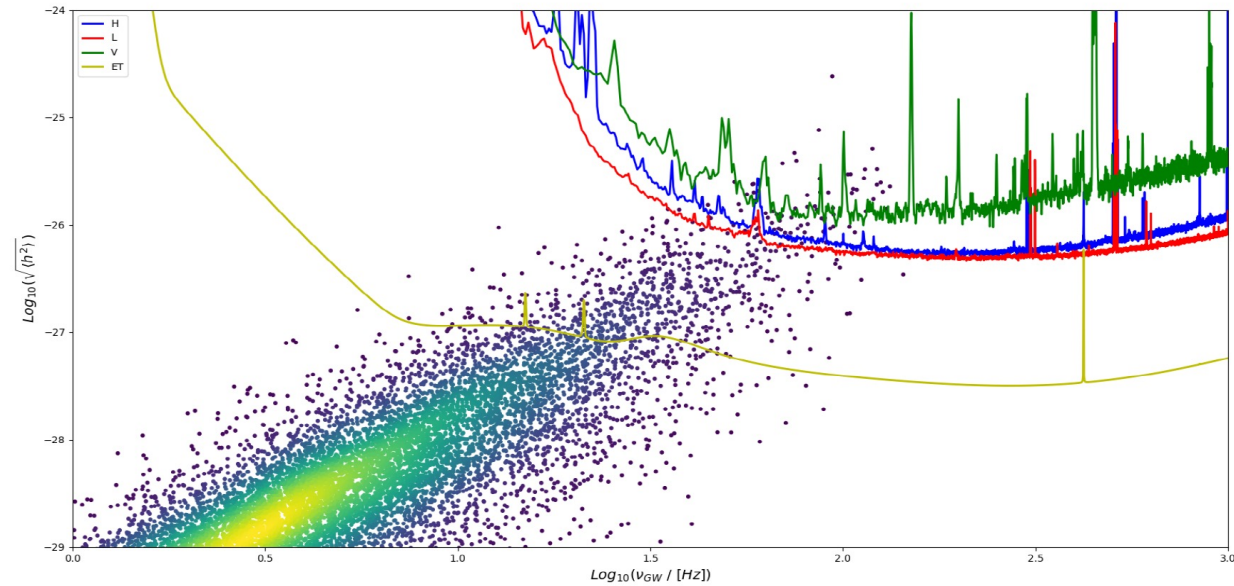
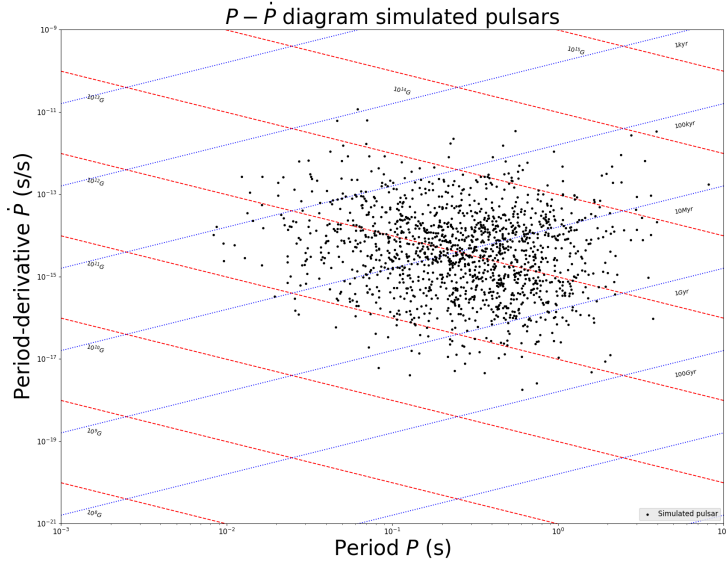
Razzano et al 2024



Fiori et al 2024

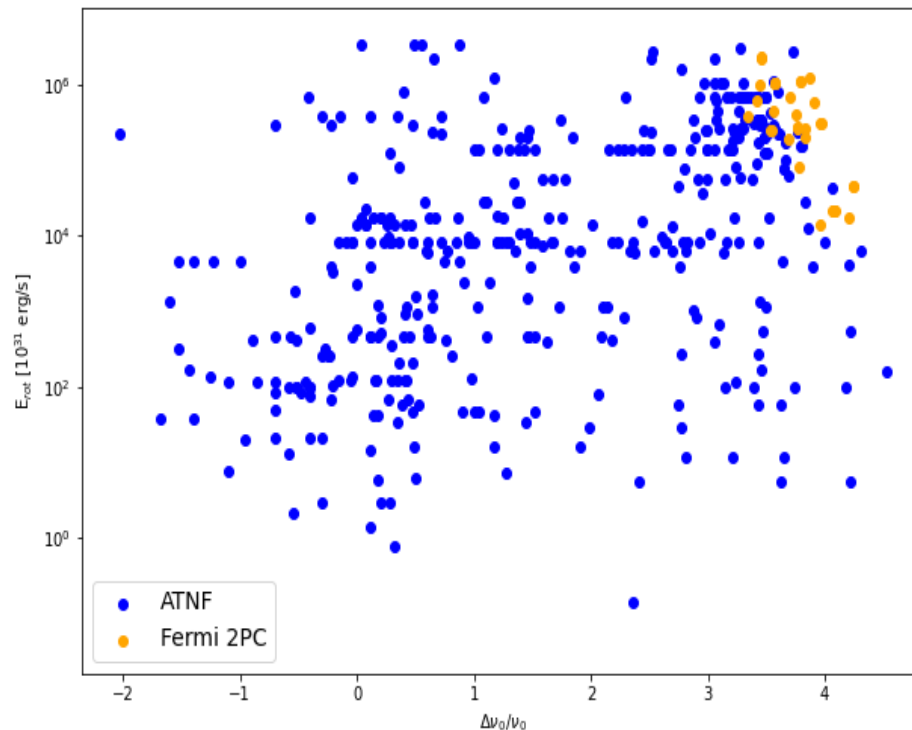
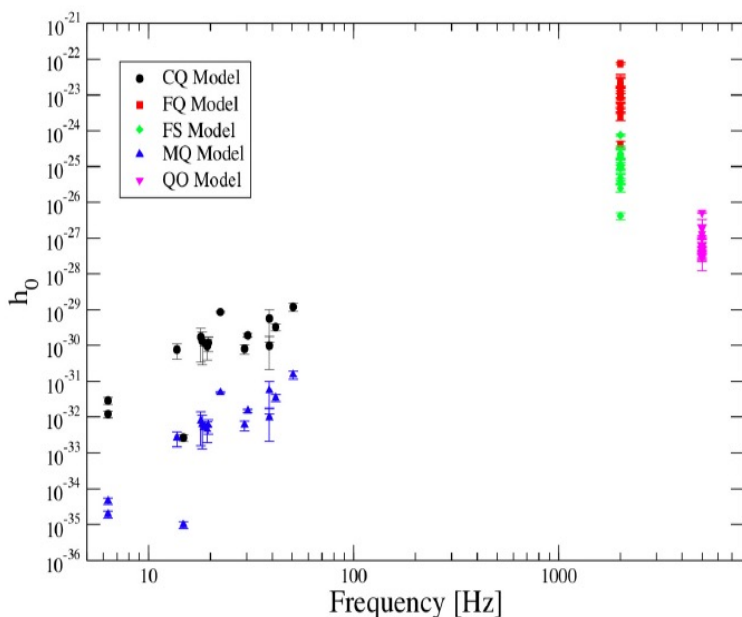
Population Studies

- 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



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)



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