This work is part of the following group publication to evaluate the sensitivity of the **AresGW code** in detecting gravitational waves in real noise data.

New Gravitational Wave Discoveries Enabled by Machine Learning

Alexandra E. Koloniari, **Evdokia C. Koursoumpa**, Paraskevi Nousi, Paraskevas Lampropoulos, Nikolaos Passalis, Anastasios Tefas, Nikolaos Stergioulas

Published: **Mach. Learn.: Sci. Technol. 6(1), 015054 (2025)**

Importance of Noise Filtering for Improving the False Alarm Rate in Gravitational Wave Events

Evdokia C. Koursoumpa

Physics Graduate - Aristotle University of Thessaloniki

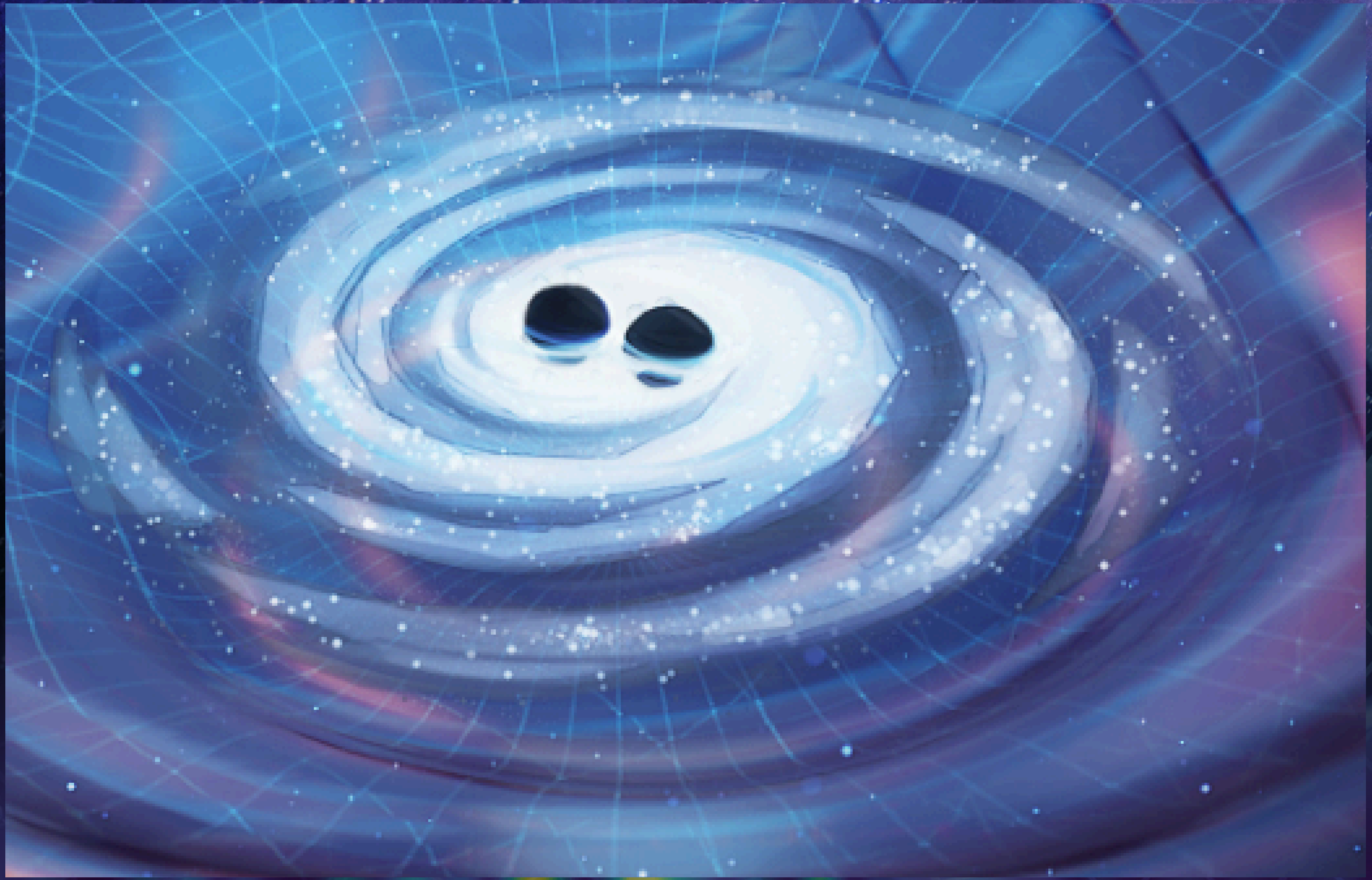
21st conference in the series "Recent Developments in Gravity" (NEB)

IN A GALAXY FAR...FAR AWAY

Evdokia C. Koursoumpa

21st conference in the series "Recent Developments in Gravity" (NEB)

Importance of Noise Filtering for Improving the False Alarm Rate in Gravitational Wave Events



Evdokia C. Koursoumpa

21st conference in the series "Recent Developments in Gravity" (NEB)

Importance of Noise Filtering for Improving the False Alarm Rate in Gravitational Wave Events

Importance of Noise Filtering for Improving the False Alarm Rate in Gravitational Wave Events

"Gravitational Wave Observation"

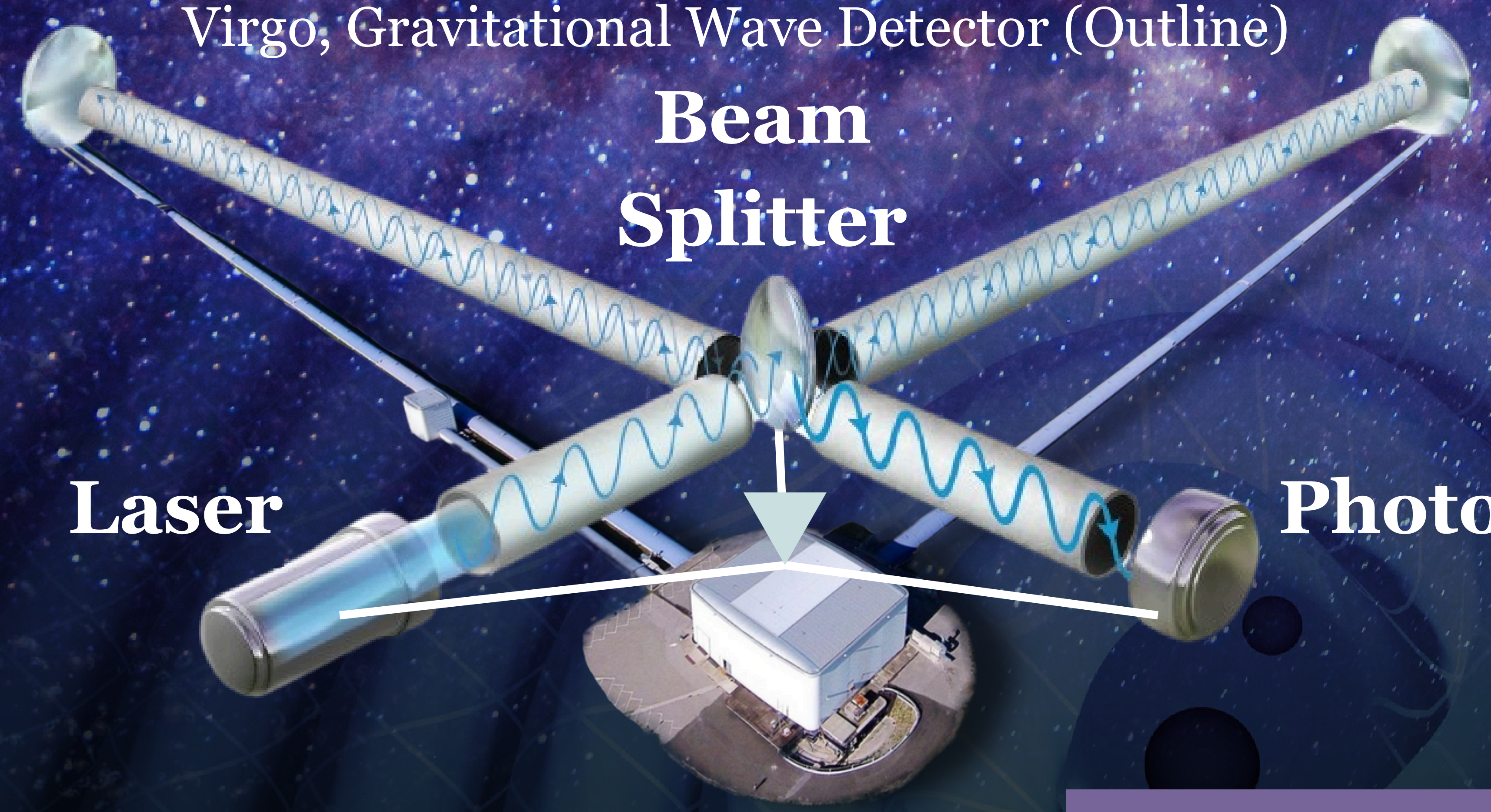
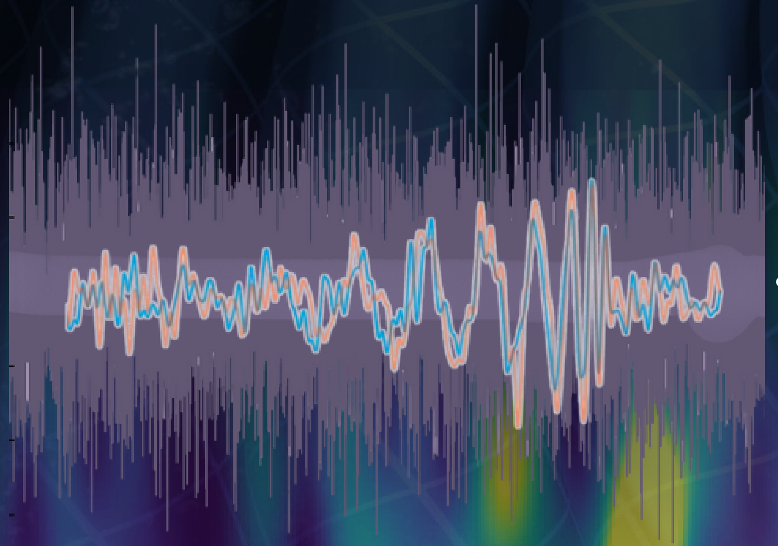


Image Credit: Nicolle Rager Fuller

Strain Channel:

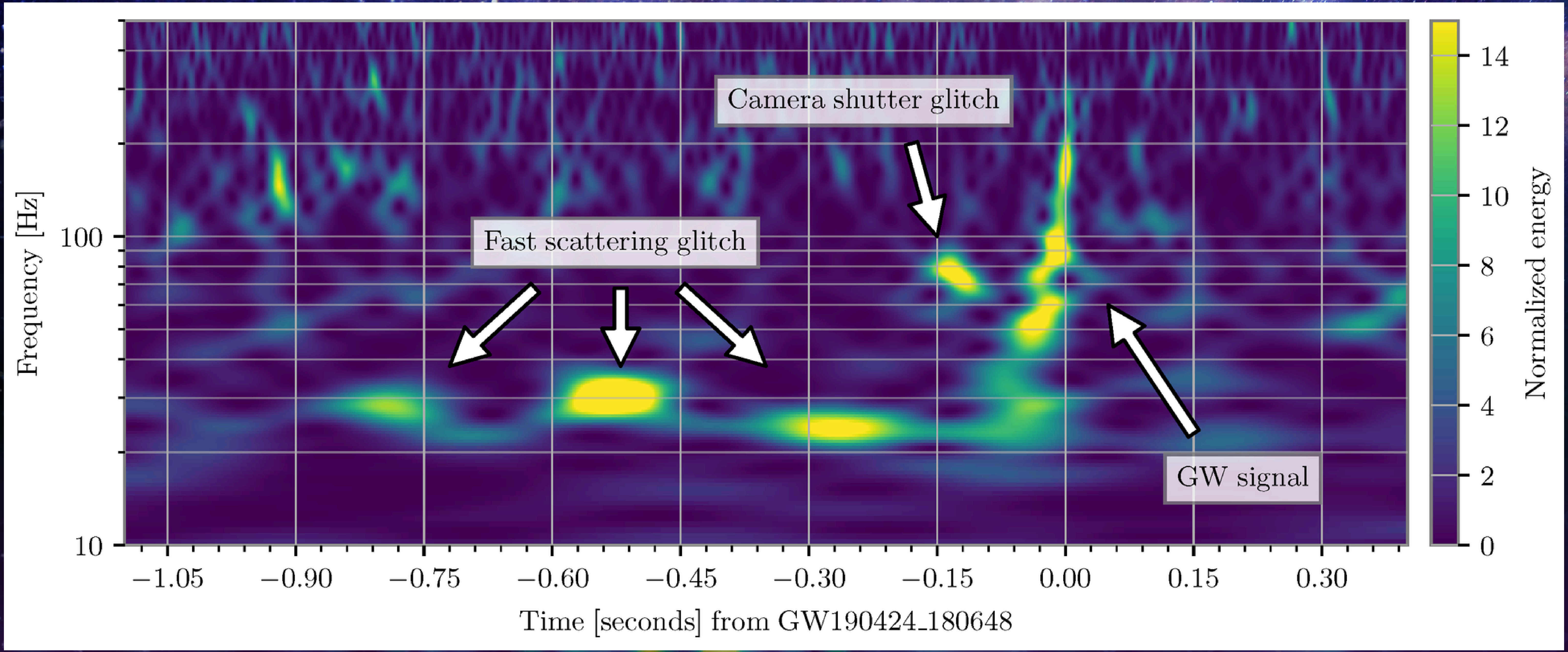


Noise

Astrophysical Information (BBH, BNS, NSBH)

Glitches

Glitches are short-duration noise transients observed in the gravitational-wave strain data that are not of astrophysical origin and can reduce the sensitivity of searches for gravitational waves.



Davis et al. 2022

"Outline of the work"

1 — Objective

Identification of **BBH** with ANN **AresGW**

2 — Challenge

Noise causes **false alarms** and **hides real signals**

3 — Approach

Filter noise to **improve detection confidence**

4 — Goal

Lower false alarms, improve detection confidence

EXTRA BONUS

Detection of **New GW Events**

"MAKE THE DATA - QUALITY AGAIN!"

Machine Learning Pipelines

AresGW

model 2

Network Type:

Deep Residual Network (**ResNet**) enhanced with Deep Adaptive Input Normalization (**DAIN**) and curriculum learning.

Input:

Time - Series

GravitySpy

Network Type:

Convolutional Neural Network (**CNN**), a deep learning model specialized for **image recognition** tasks.

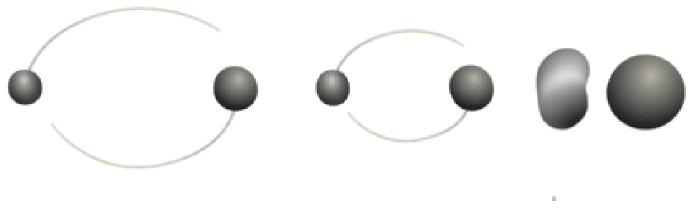
Input:

Spectrograms
(Time - Frequency)

AresGW Training Set

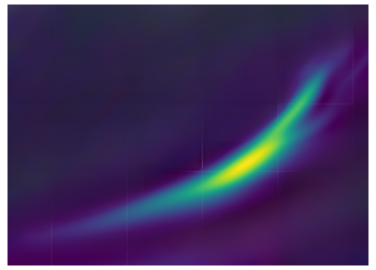
In this work, AresGW is trained on **real raw strain time series data** where each instance is labeled according to whether it contains a gravitational wave event or not.

Astrophysical Source



Binary Black Hole Systems

Chirp Mass Range



10 - 40 Solar Masses

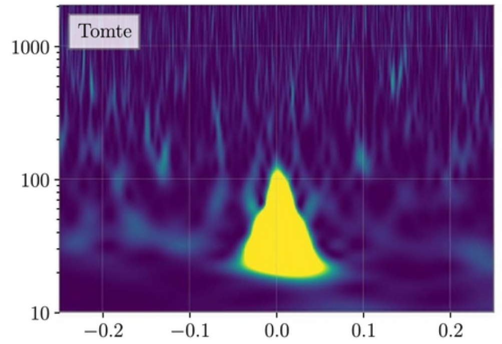
https://github.com/vivinousi/gw-detection-deep-learning.git

GravitySpy Training Set

Gravity Spy is trained on transient noise instances, known as **glitches**, which have characteristic frequency–time representations through their power spectra (spectrograms). The training data comes from the **O3 run of the LIGO detectors at Livingston (LLO) and Hanford (LHO)**.

Input

Glitch Spectrograms



Shown at 4 durations:
0.5 s, 1 s, 2 s, 4 s

Output

Multi-class classification

Glitches

23 Classes

Blip, Tomte, Scattered Light, Fast Scattering, etc

Training Labels

Labels from…

Detector experts

+

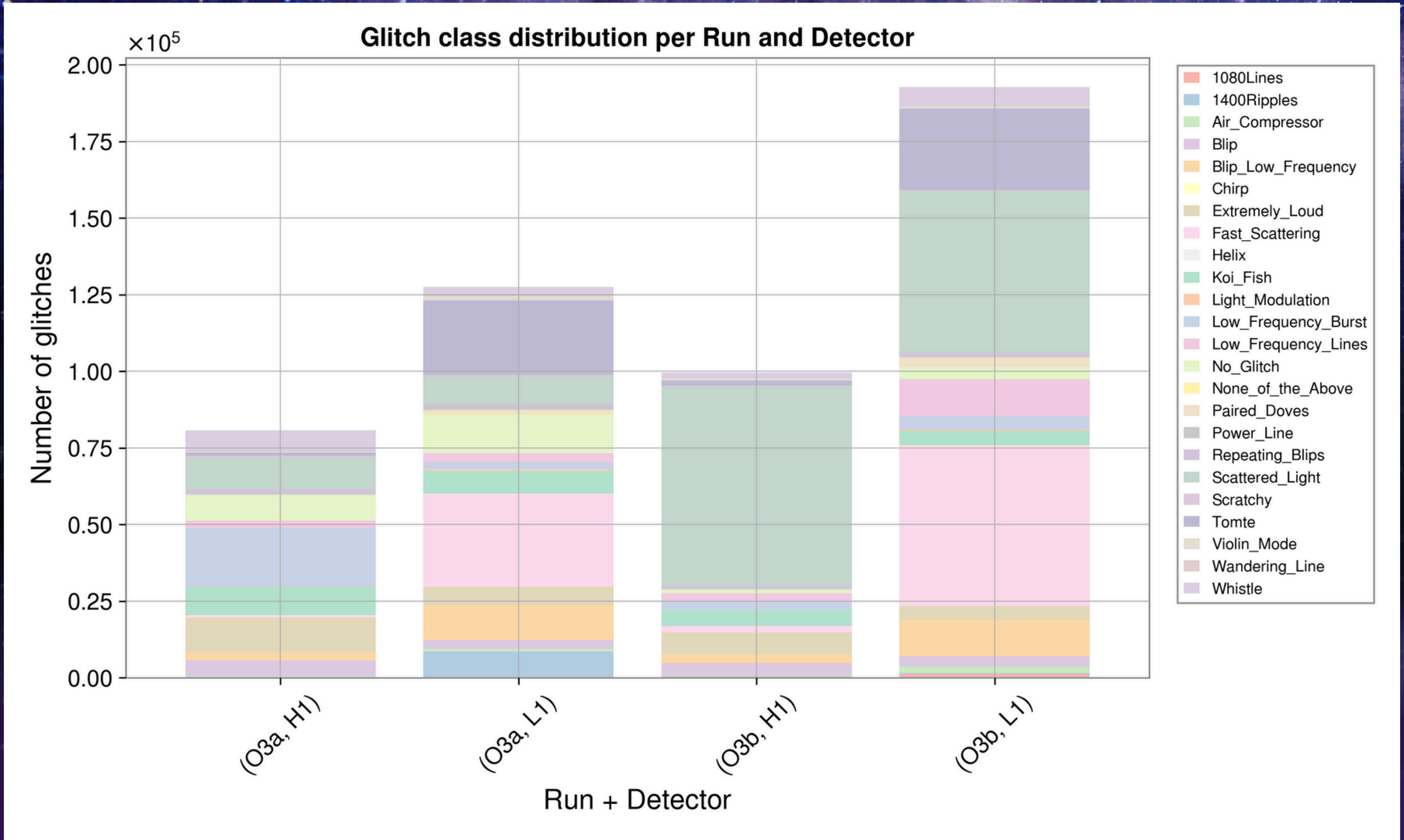
Citizen scientists

(Zooniverse)

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

GravitySpy Classification

Noise events flagged by the **Omicron trigger** pipeline and classified by Gravity Spy



Machine Learning Pipelines

AresGW

model 2

Main Goal

Detect **astrophysical gravitational-wave signals** directly from raw strain time-series.

GravitySpy

Main Goal

Identify and classify non-astrophysical **noise transients (glitches)**

Collective Goal

Lower false-alarm rates and improve sensitivity of GW searches

AresGW Dataset Analysis

Observing Period

O3 Run

O3a : 1 Apr 2019 → 1 Oct 2019 (6 m)

O3b: 1 Nov 2019 → 27 Mar 2020 (5 m)

GW Detectors

LLO

LIGO Livingston Observatory

LHO

LIGO Hanford Observatory

AresGW Dataset Analysis

1. Trigger Times

Represent instances where the neural network identified a potential event of interest.

2. Logarithmic Ranking Statistic

Relative importance of different elements within a dataset (0.5 to 16)

$$\mathcal{R}_s = -\log_{10}\left(1 - \mathcal{R} + 10^{-16}\right)$$

Ranking Statistic

0 to 1

(0.9999 → 4)

$\mathcal{R}$ $\mathcal{R}_s$

Filtering Methods

Iteratively counted triggers exceeding a Ranking Statistic (step size 0.5)

Key Steps
of
Custom Developed Code

Filtering Methods

Key Steps
of
Costum Developed Code

Iteratively counted triggers exceeding a Ranking Statistic (step size 0.5)

Ranking Statistic	Number of Triggers
16.00	0
15.49	3
15.01	3
14.51	4
14.00	4
13.50	4
13.00	4
12.50	4
12.00	4
11.50	4
11.00	5
10.50	5
10.00	6
9.50	6
9.00	7
8.50	7
8.00	7
7.50	7
7.00	7
6.50	7
6.00	7
5.50	8
5.00	8
4.50	10
4.00	11
3.50	20
3.00	44
2.50	165
2.00	642
1.50	2936
1.00	16549
0.50	218273

Filtering Methods

Key Steps
of
Costum Developed Code

- Iteratively counted triggers exceeding a Ranking Statistic (step size 0.5)
- Focusing on triggers with a **Rs > 3.5**

Filtering Methods

Key Steps
of
Costum Developed Code

Iteratively counted triggers exceeding a Ranking Statistic (step size 0.5)

Focusing on triggers with a **Rs > 3.5**

Ranking Statistic	Number of Triggers
16.00	0
15.49	3
15.01	3
14.51	4
14.00	4
13.50	4
13.00	4
12.50	4
12.00	4
11.50	4
11.00	5
10.50	5
10.00	6
9.50	6
9.00	7
8.50	7
8.00	7
7.50	7
7.00	7
6.50	7
6.00	7
5.50	8
5.00	8
4.50	10
4.00	11
3.50	20
3.00	44
2.50	165
2.00	642
1.50	2936
1.00	16549
0.50	218273

Costum Code

Key Steps
of
Costum Developed Code

- Iteratively counted triggers exceeding a Ranking Statistic (step size 0.5)
- Focusing on triggers with a **Rs > 3.5**
- Automatically applied **three filtering methods**

Filtering Methods

1. **Confident Events Removal Filter**

2. **Empirical Filter**
   Developed by Alexandra E. Koloniari

3. **Gravity Spy Glitches Removal Filter**

Filtering Methods

1. Confident Events Removal Filter

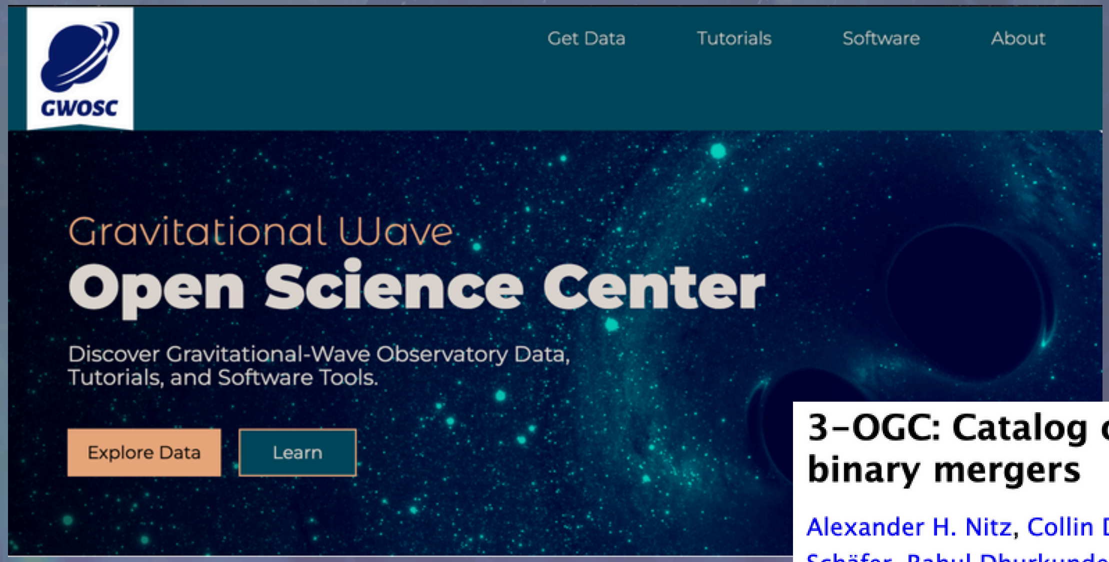
Trigger Times

Instances where AresGW identified a potential GW event.

Coincident Times

If these triggers coincide with real GW events already reported in **other catalogs***, they are removed from further analysis.

*GWTC-2.1 , GWTC-2, GWTC-3



https://gwosc.org/

3-OGC: Catalog of gravitational waves from compact-binary mergers

Alexander H. Nitz, Collin D. Capano, Sumit Kumar, Yi-Fan Wang, Shilpa Kastha, Marlin Schäfer, Rahul Dhurkunde, Miriam Cabero

*IAS Catalog + OGC Catalog

Olsen et al. 2022

Mehta et al. 2023

4-OGC: Catalog of gravitational waves from compact-binary mergers

Alexander H. Nitz, Sumit Kumar, Yi-Fan Wang, Shilpa Kastha, Shichao Wu, Marlin Schäfer, Rahul Dhurkunde, Collin D. Capano

Filtering Methods

2.

Empirical Filter

Developed by Alexandra E. Koloniari

1

2

Selective Noise Rejection

“Signals that survive strict noise checks”

- It doesn’t pass the strict “Selective Passband” conditions.
- It can’t be explained away by nearby noise triggers either

Selective Pass Band

“High-confidence signals”

- Higher cut-off frequencies
- Ranking statistic (Rs) stays consistently high
- No nearby noise triggers with high Rs

3. Gravity Spy Glitches Removal Filter

Gravity Spy Dataset

- start time
- duration
- ml label
- event time
- ml confidence

3. Gravity Spy Glitches Removal Filter

Filter Condition - Glitch Removal

$ARESGW_{trigger\_time}$

$Glitch_{start\_time} - 1$

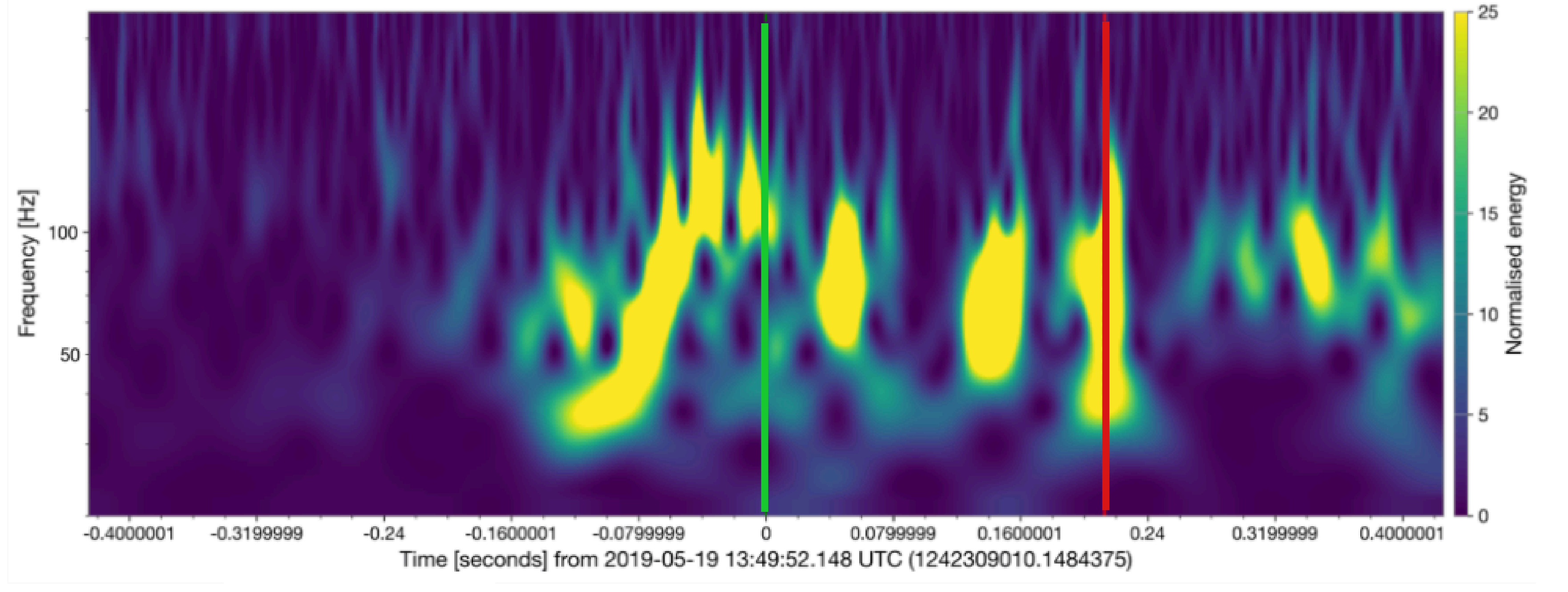
$Glitch_{start_{time}+Duration} + 1$

Coincidence Triggers Among AresGW & GravitySpy

G-Spy

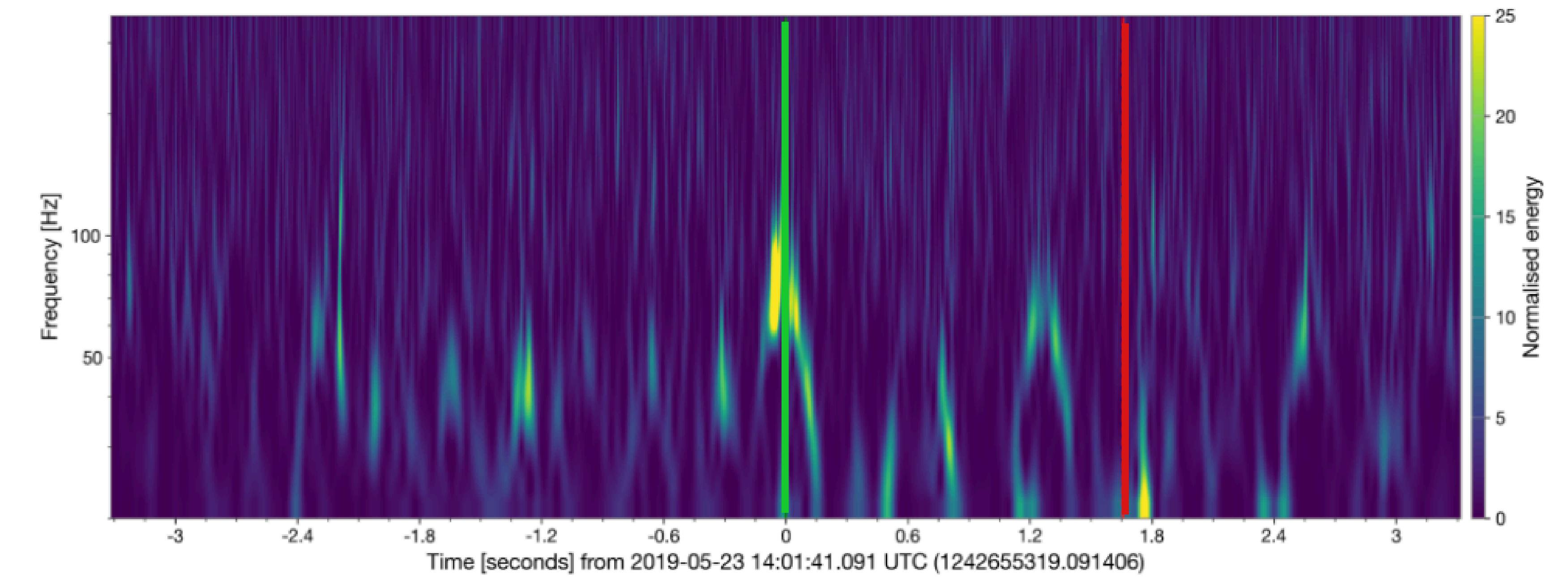
AresGW

Scratchy



Source: Light scattering from Swiss-cheese baffles in the interferometer

Light Modulation



Source: Likely due to unintended modulation of the laser light inside the interferometer

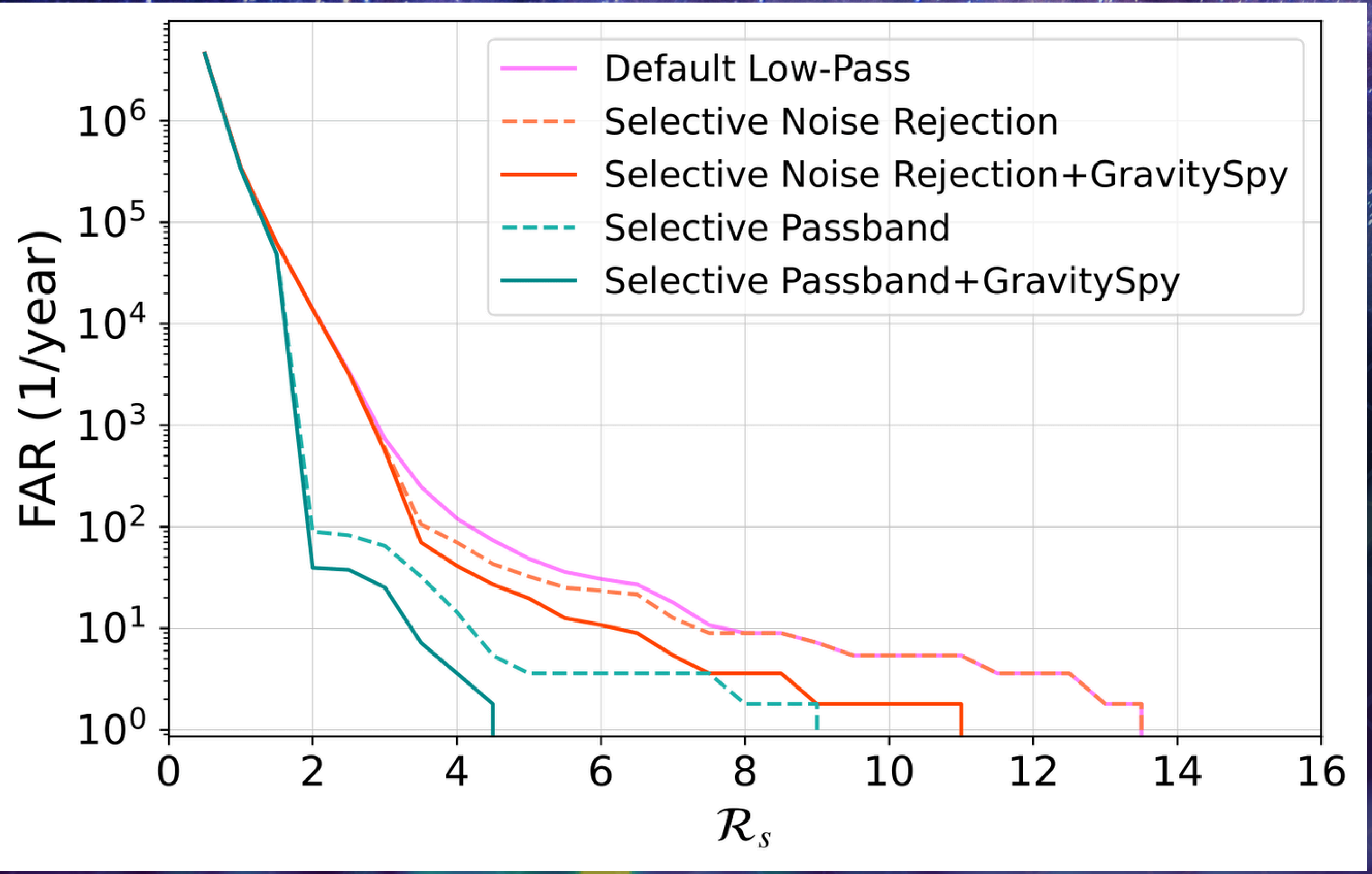
O3 Run
O3a period + O3b period

What's the False Alarm Rate from the real O3 data duration?

$$FAR(> R_s) = \frac{\text{Number of noise triggers with } R'_s \geq R_s}{\text{Total analyzed live time (6.7 months)}}$$

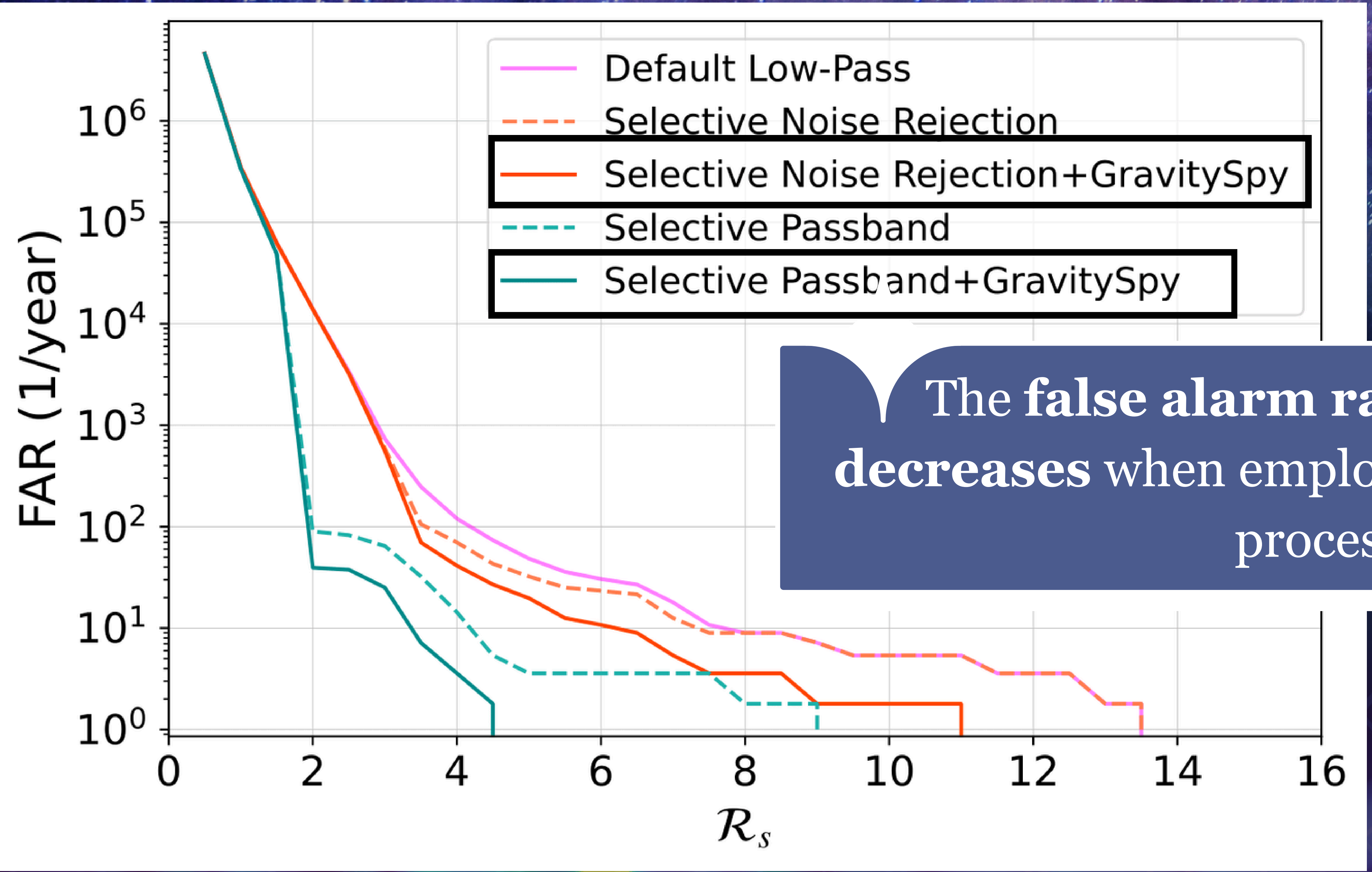
Results

False Alarm Rate vs Logarithmic Ranking Statistic



Results

False Alarm Rate vs Logarithmic Ranking Statistic



The **false alarm rate significantly decreases** when employing all three filtering processes.

Applying noise filters also improves background in p_astro calculation

pastro > 0.5

Increased Astrophysical Probability

Candidate Event

$$p_{\mathrm{astro}}(\langle R_s \rangle) = \frac{f(\langle R_s \rangle)}{f(\langle R_s \rangle) + b(\langle R_s \rangle)}$$

Applying noise filters also improves background in p_astro calculation

pastro > 0.5

Increased Astrophysical Probability

Candidate Event

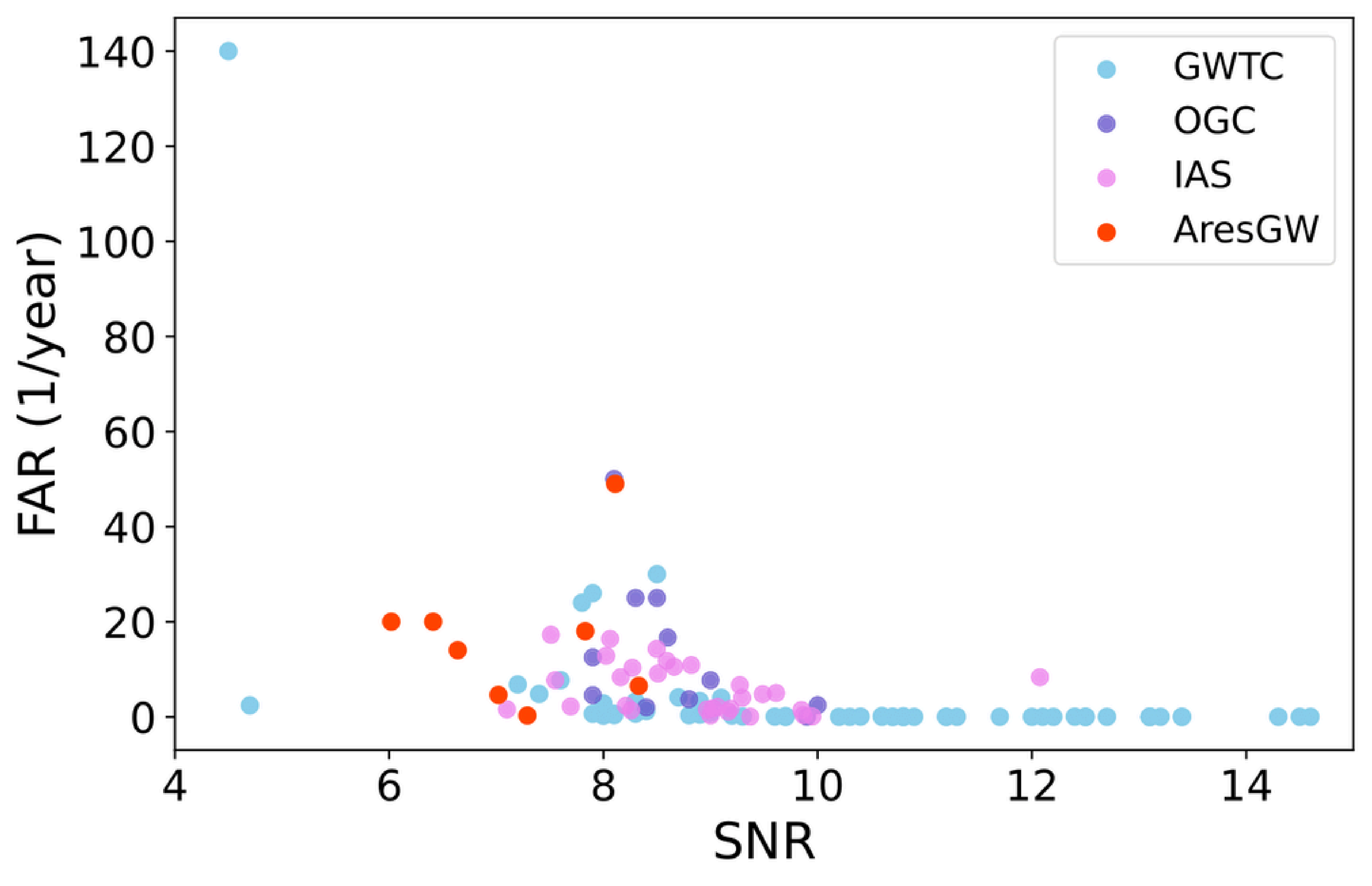
Foreground distribution (signals from injections)

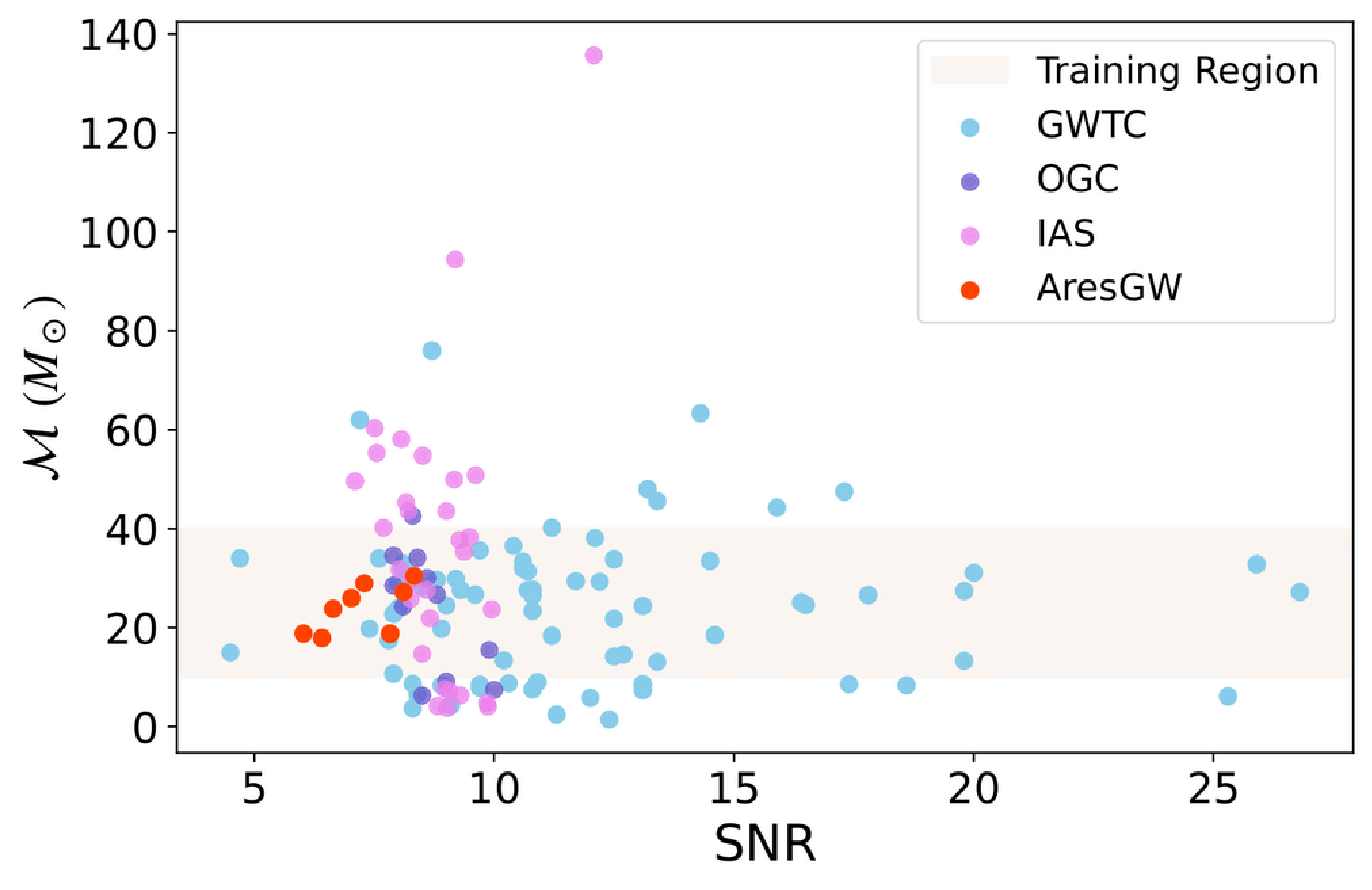
$$p_{\mathrm{astro}}(\langle R_s \rangle) = \frac{f(\langle R_s \rangle)}{f(\langle R_s \rangle) + b(\langle R_s \rangle)}$$

Background distribution (false alarms from real O3 noise)

Results

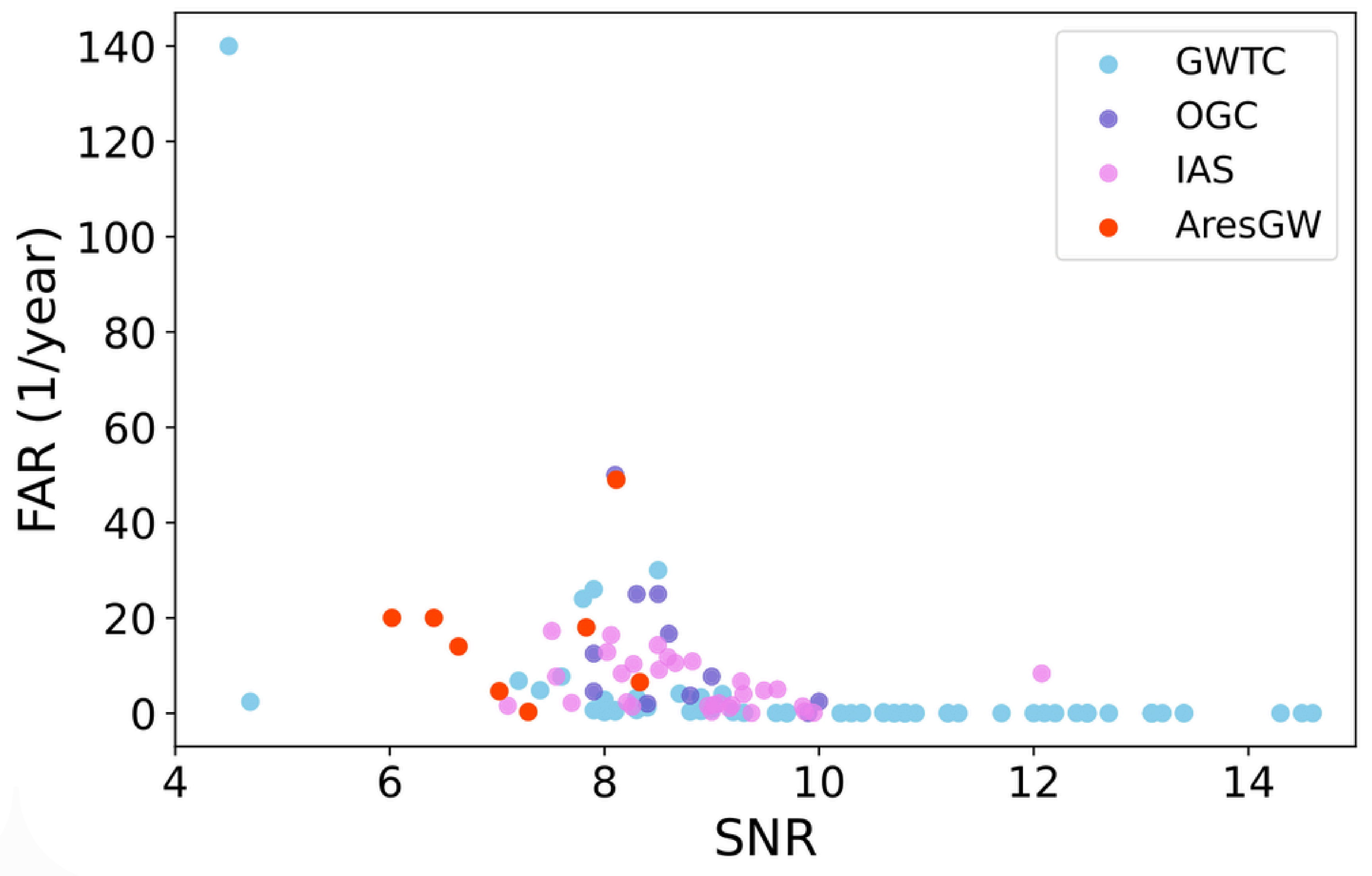
Population Properties of the 8 NEW GW candidate events

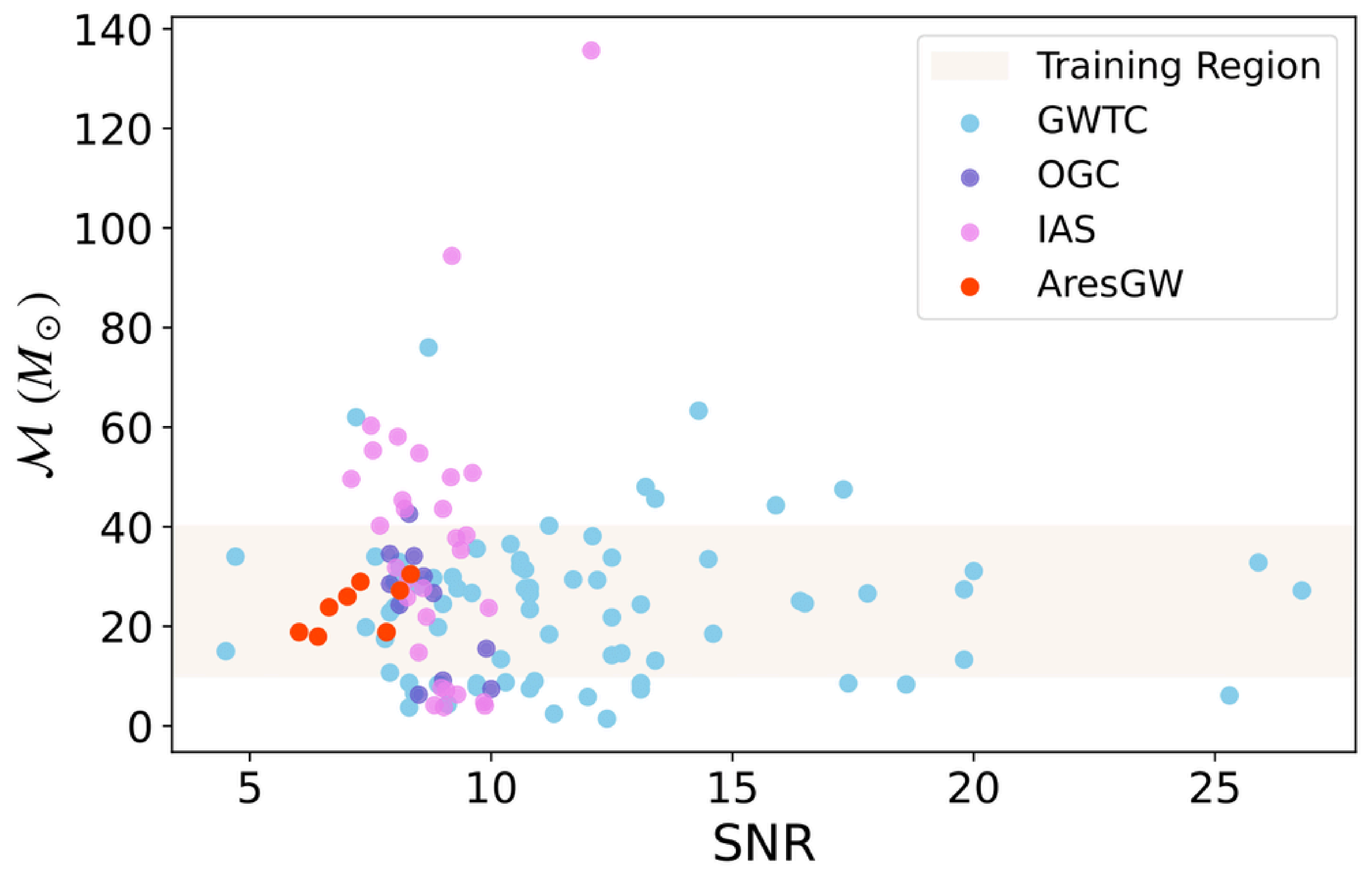




Results

Population Properties of the 8 NEW GW candidate events





AresGW detects gravitational waves with high confidence, **outperforming traditional pipelines**.

8 new low-SNR gravitational wave events[5] were identified - **the first to be detected** solely by a **machine learning** pipeline.

Thank You! Questions?

01

Three Filtering Process

Significant decrease in the FAR.

02

Outperforming Traditional Pipelines

AreGW detects the majority of the events with high confidence.

03

Discovery of 8 new GW events

First to be detected solely by a machine learning pipeline.

Contact: ekoursou@auth.gr