Glitch noise classification in KAGRA O3GK observing data using unsupervised machine learning

the 2nd “AI + HEP in East Asia” Workshop

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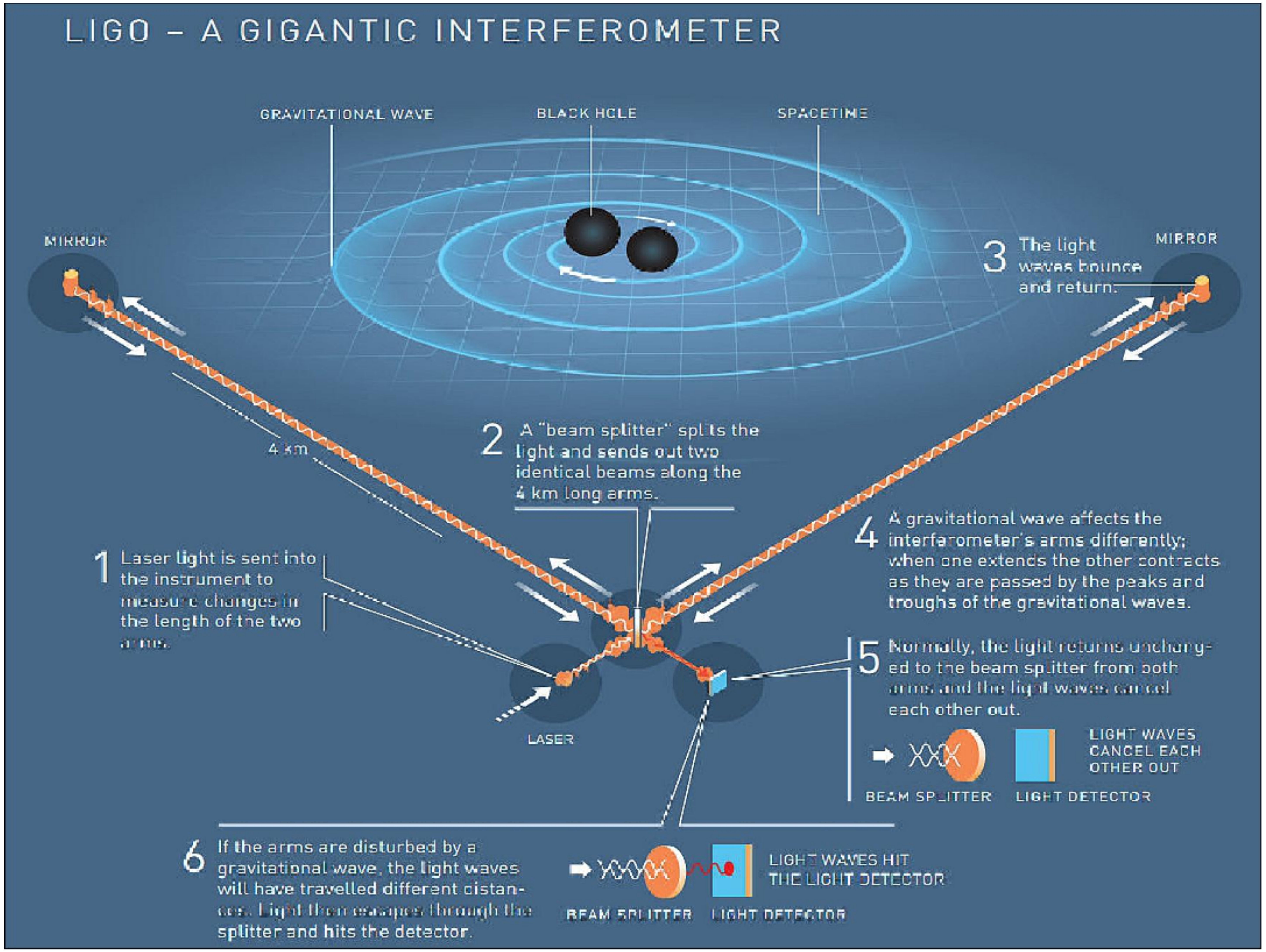
Motivation

- Glitch noises are short-lived, non-Gaussian transients that contaminate the gravitational wave data, degrade search pipelines, and may mimic or mask astrophysical signals if left uncharacterized
- LIGO has prepared large-scale training data with the cooperation of citizen scientists and has successfully used it to perform classification using machine learning
- However, KAGRA does not have such training data, so a similar approach cannot be used
- Therefore, in this study, we investigated whether it is possible to classify glitch noise contained in KAGRA's observational data using **unsupervised learning techniques**

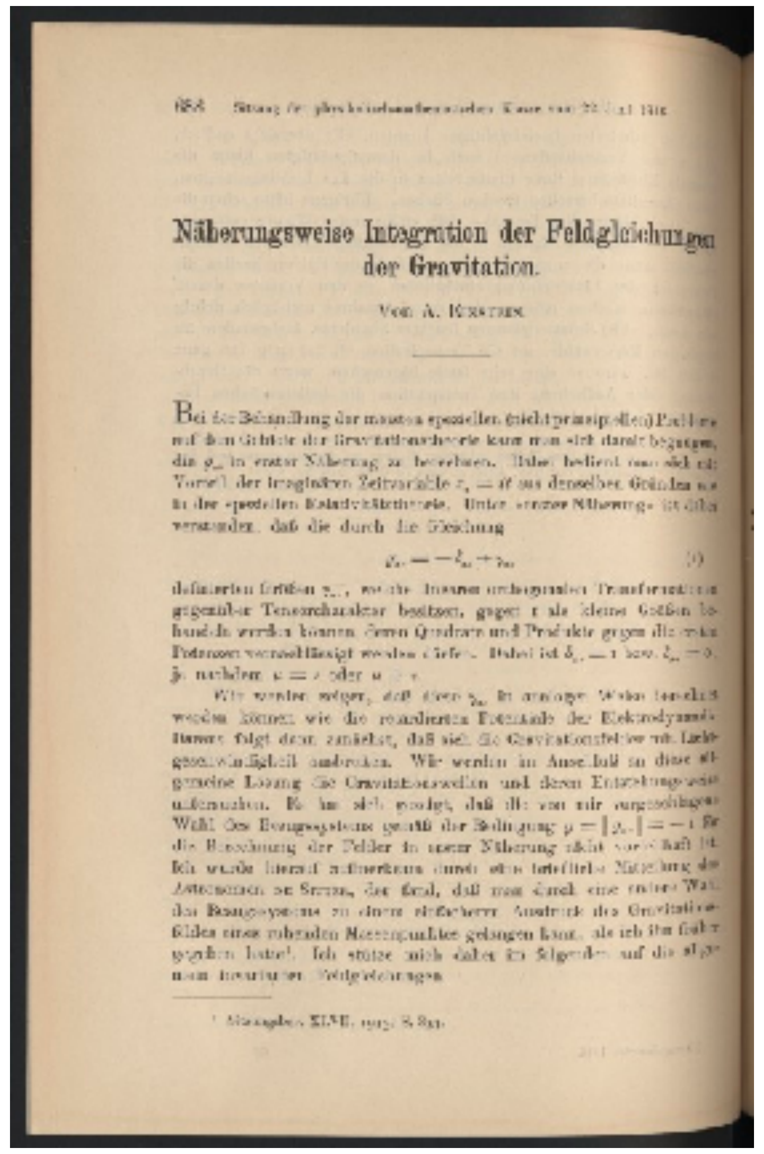
Gravitational wave detector



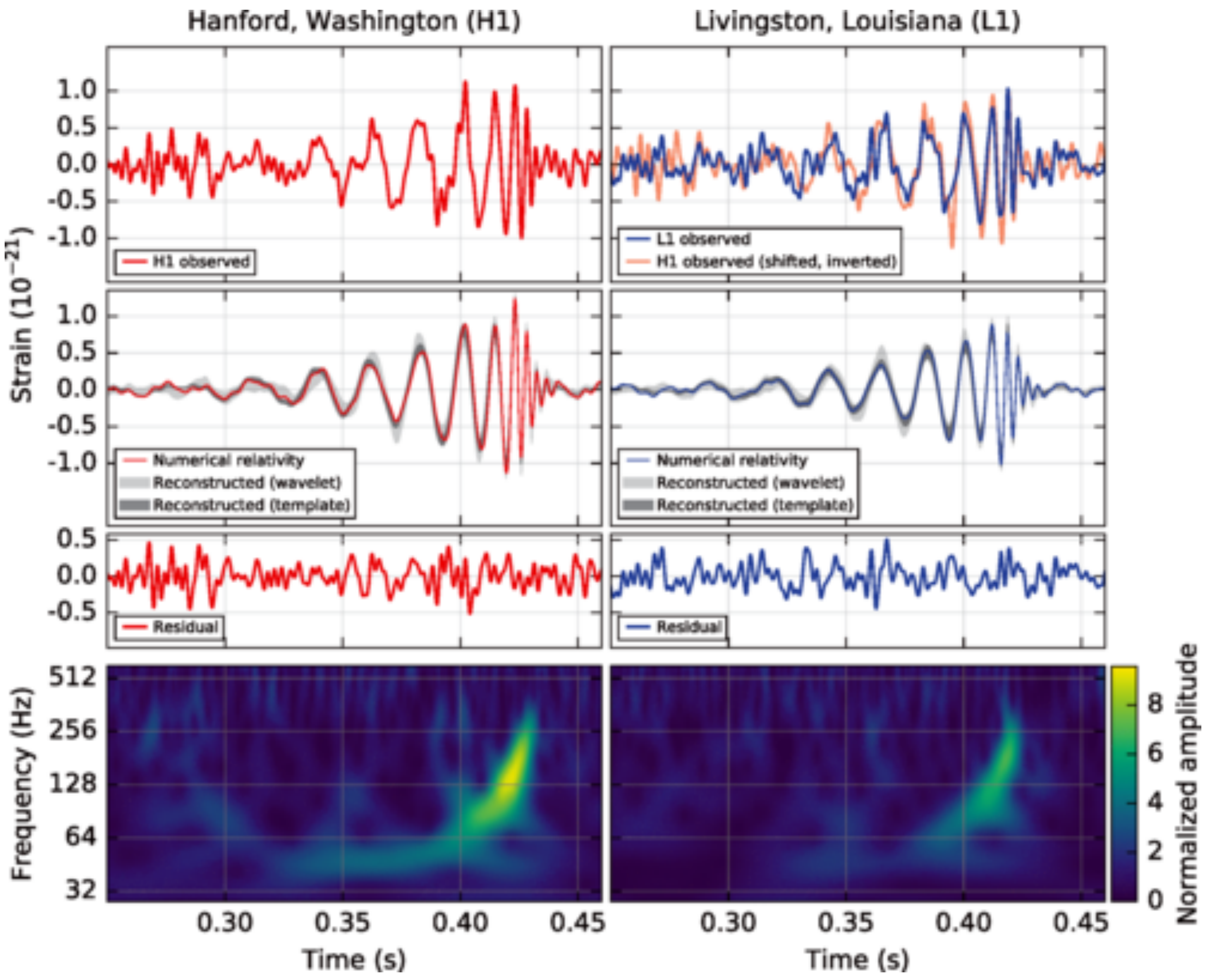
Credit: LIGO

- In 1916, Albert Einstein predicted the phenomenon of space-time distortion propagating as waves

- When an extremely heavy object accelerates, space-time is violently shaken, and the distortion travels at the speed of light


Näherungsweise Integration der Feldgleichungen der Gravitation.

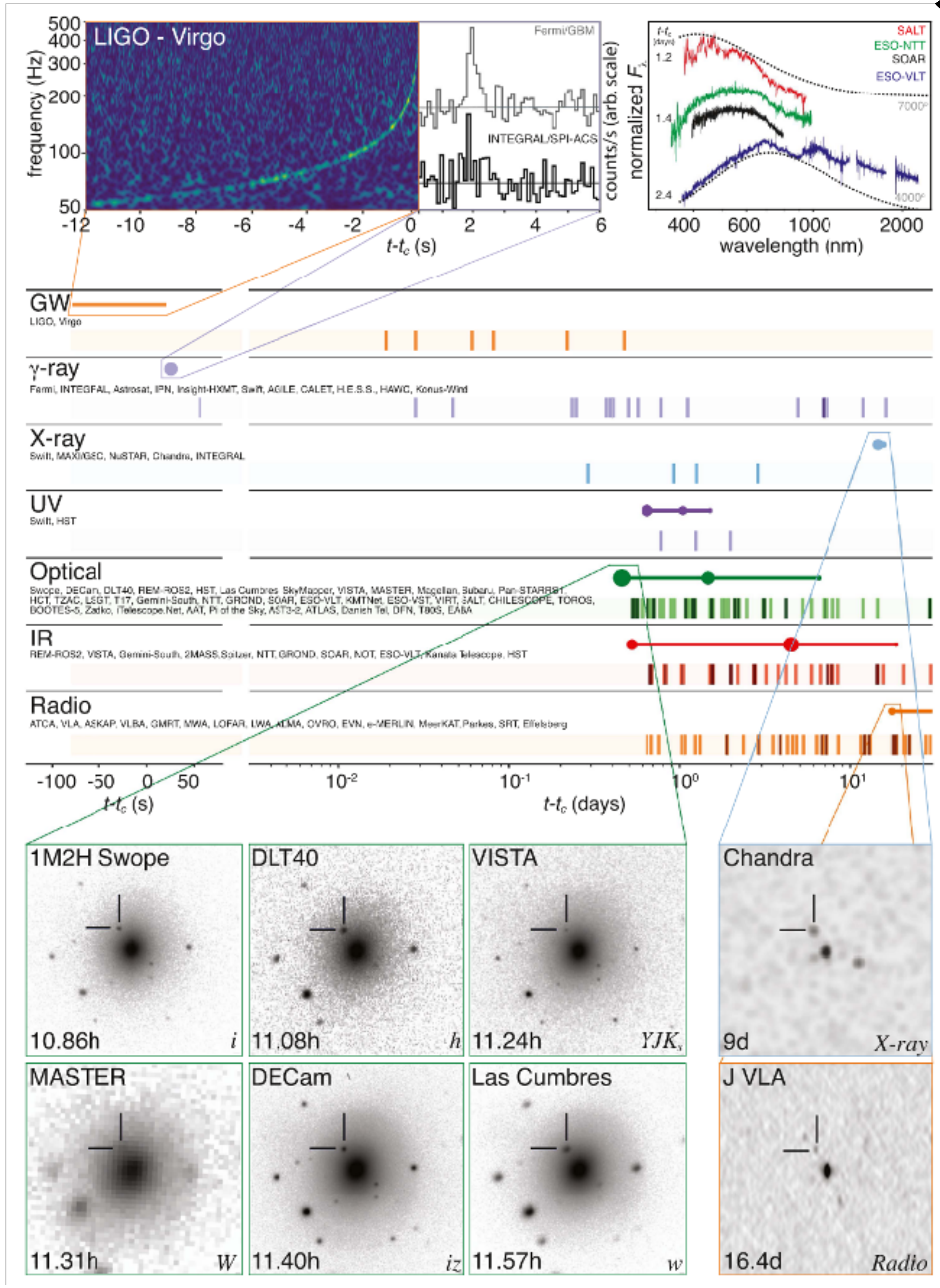
First detection of gravitational waves by LIGO



Phys. Rev. Lett. 116, 061102

- September 14, 2015
- Detection of gravitational waves from the merger of two black holes (announced February 11, 2016)
- First direct detection of gravitational waves
- BH masses before merger: approximately 36 and 29 times the mass of the Sun
- → Post-merger mass: approximately 62 solar masses

Multi messenger Astronomy

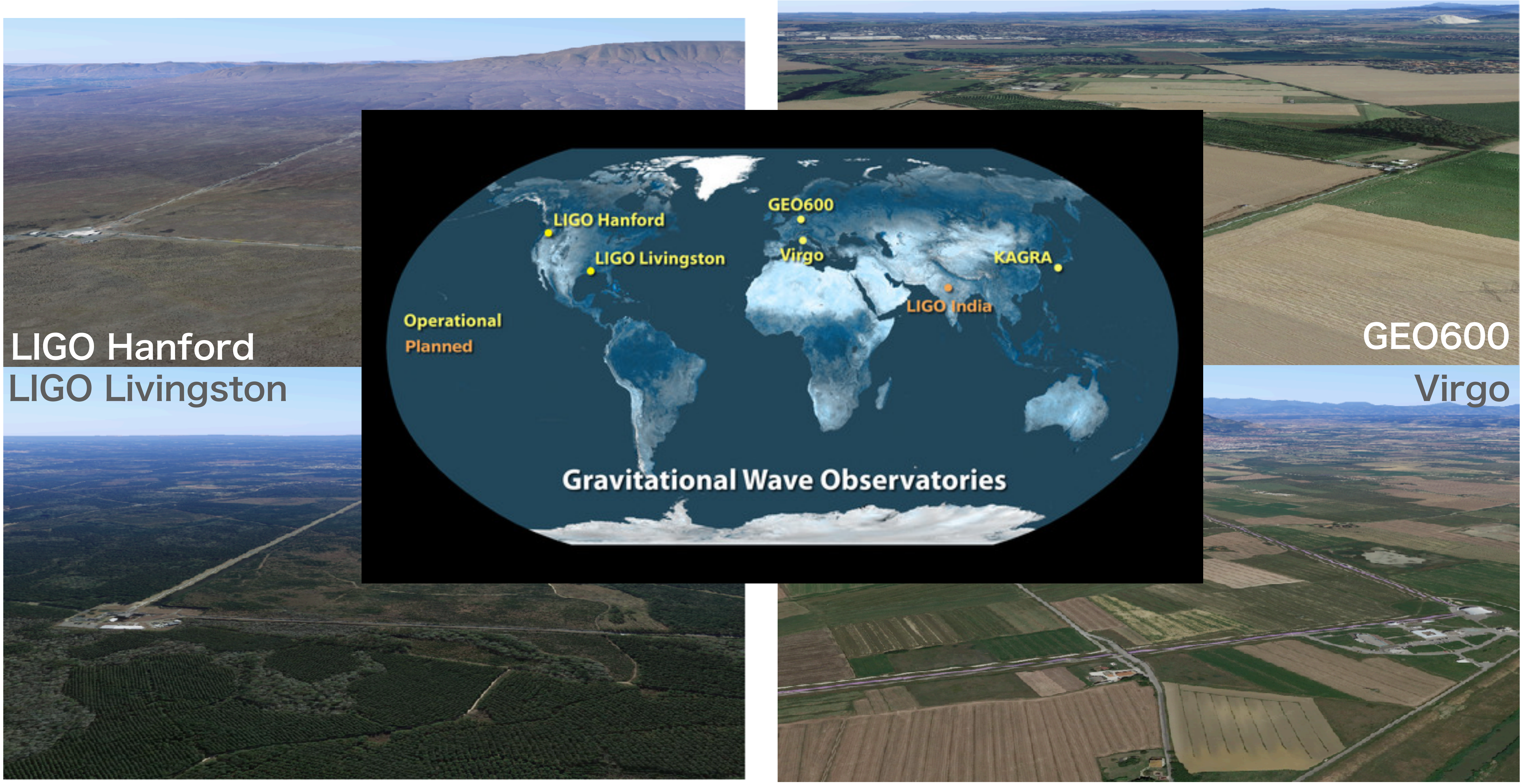


- Electromagnetic wave observations over a wide frequency range were conducted on the neutron star binary merger event GW170817

- It has become possible to elucidate astronomical phenomena by combining optical observations of multiple wavelengths, observations of cosmic rays such as neutrinos, and observations of gravitational waves

Astrophys. J. Lett. 848:L12 (2017), arXiv:1710.05833

International Gravitational-Wave Observatory Network



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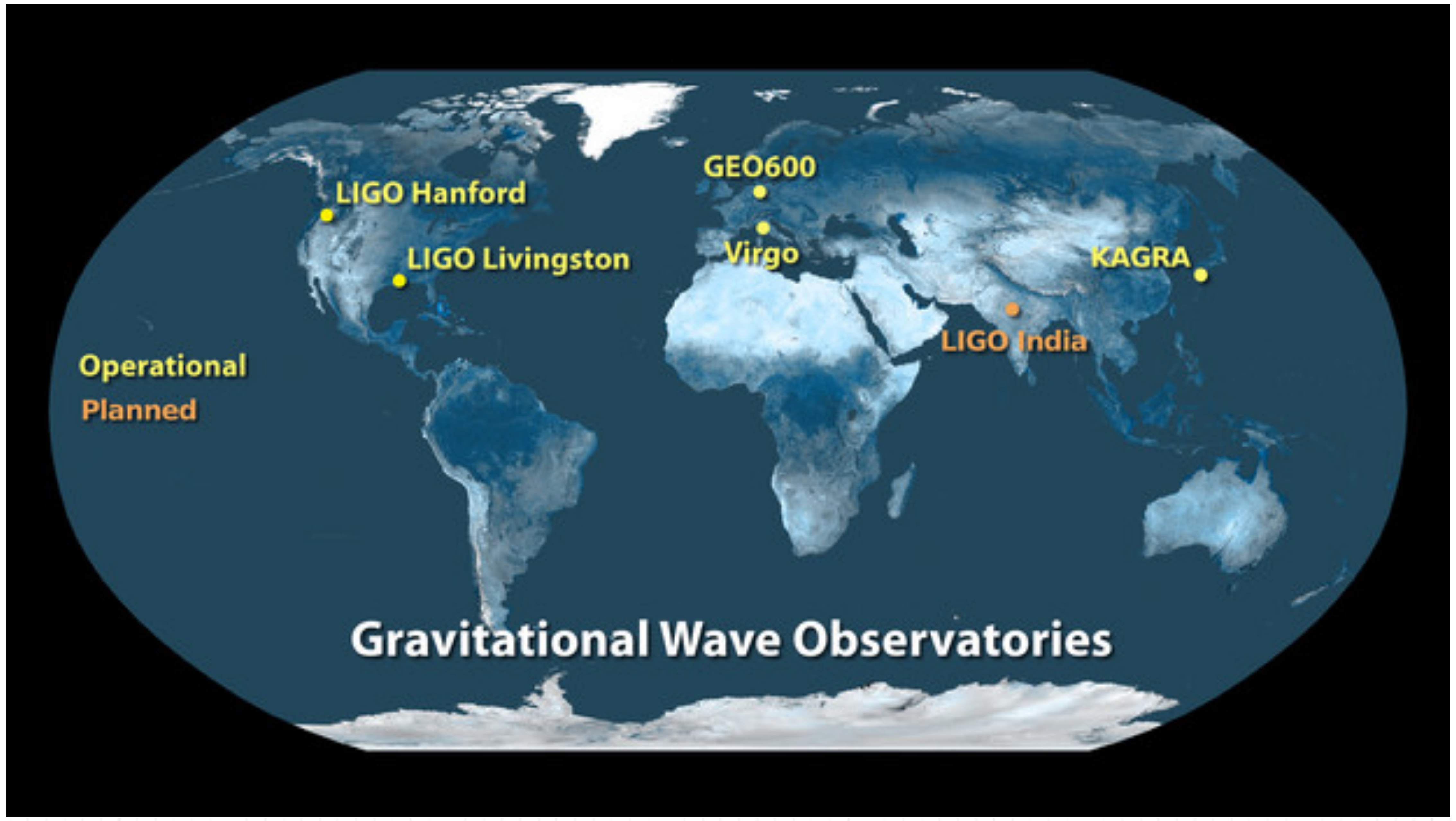
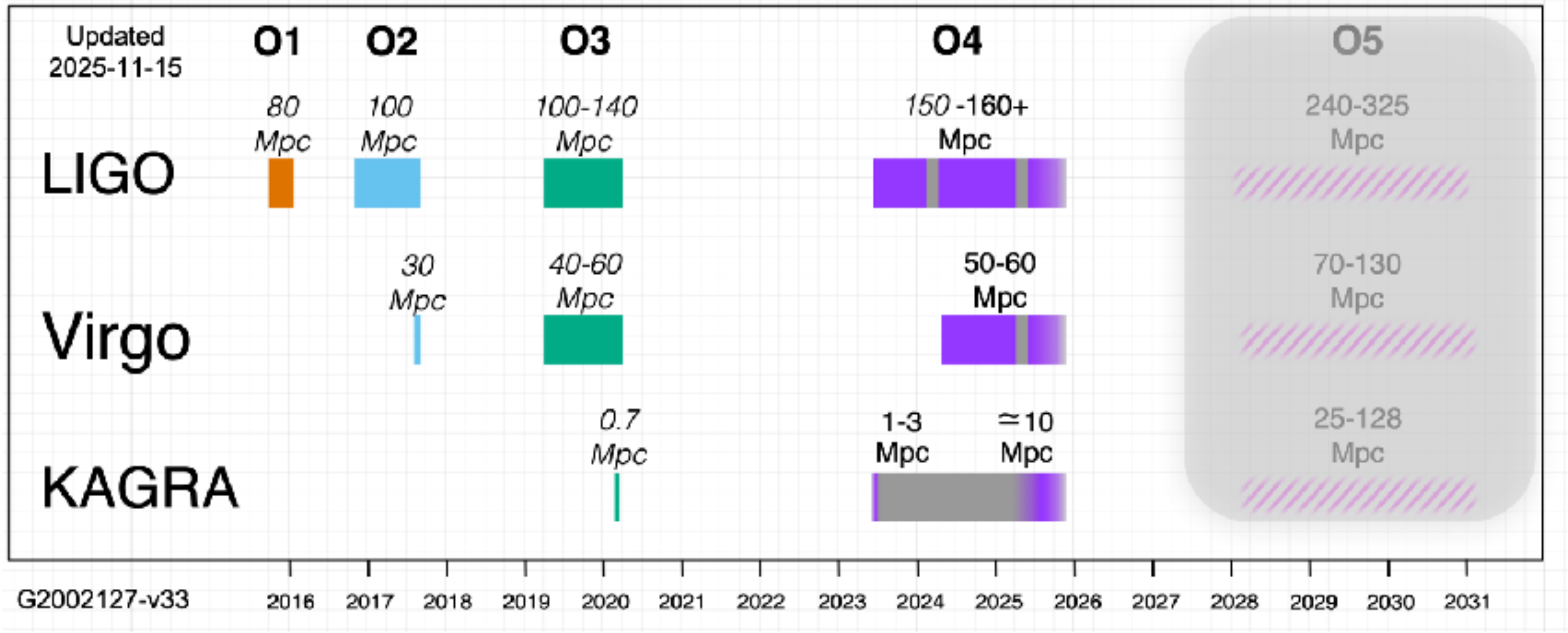




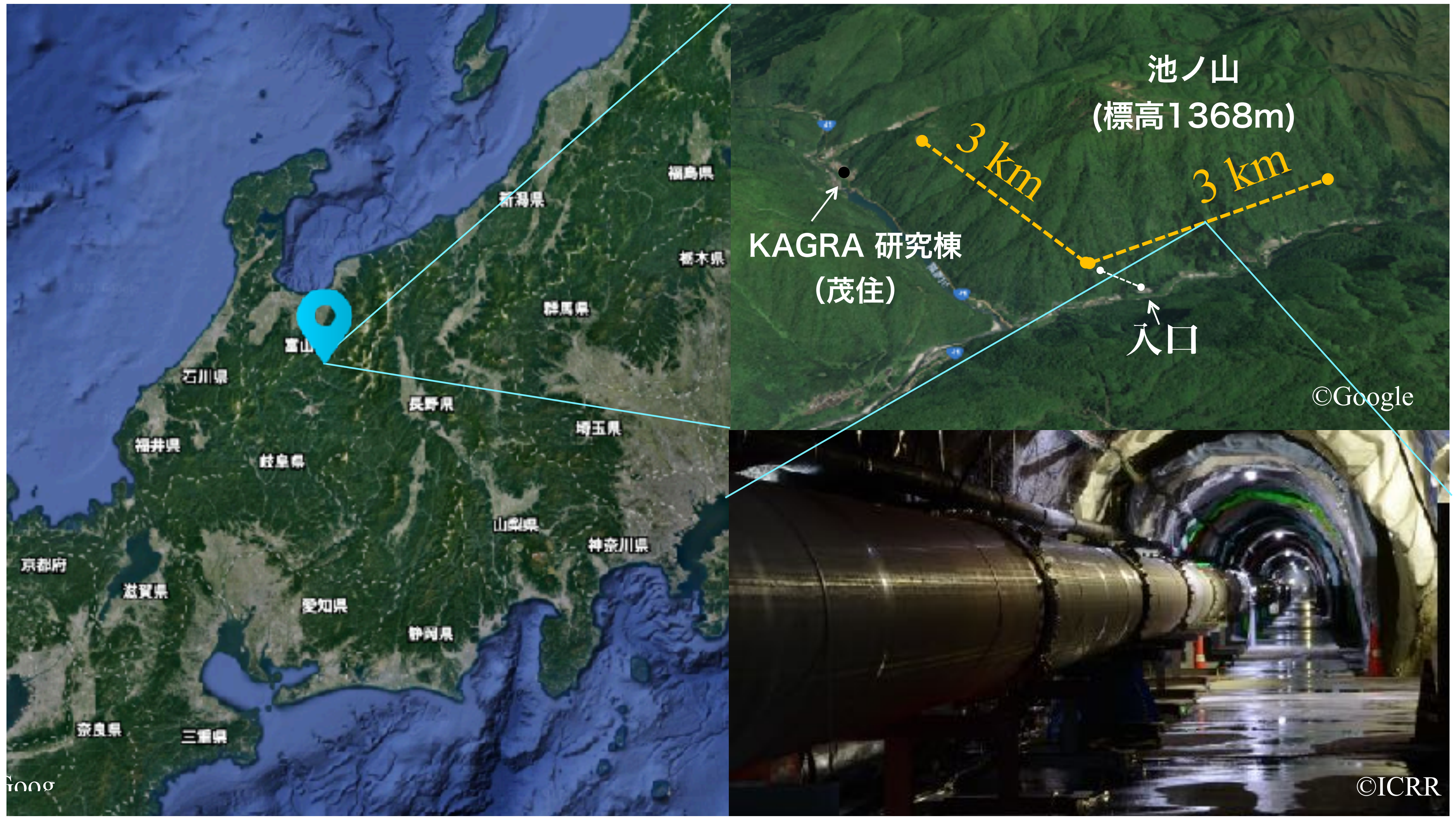
https://observing.docs.ligo.org/plan/

- Advantages of Multiple Observations
  - Improved accuracy in determining the direction of gravitational wave sources
  - Improved accuracy in estimating parameters such as optical distance, orbital inclination, and gravitational wave polarization (resolving degeneracy)
  - Increased probability of simultaneous observations with three or more detectors
- International collaborative observations by LIGO-Virgo-KAGRA and collaborative research (data analysis and publication)

Credit: LIGO/Caltech/MIT/R. Hurt (IPAC)

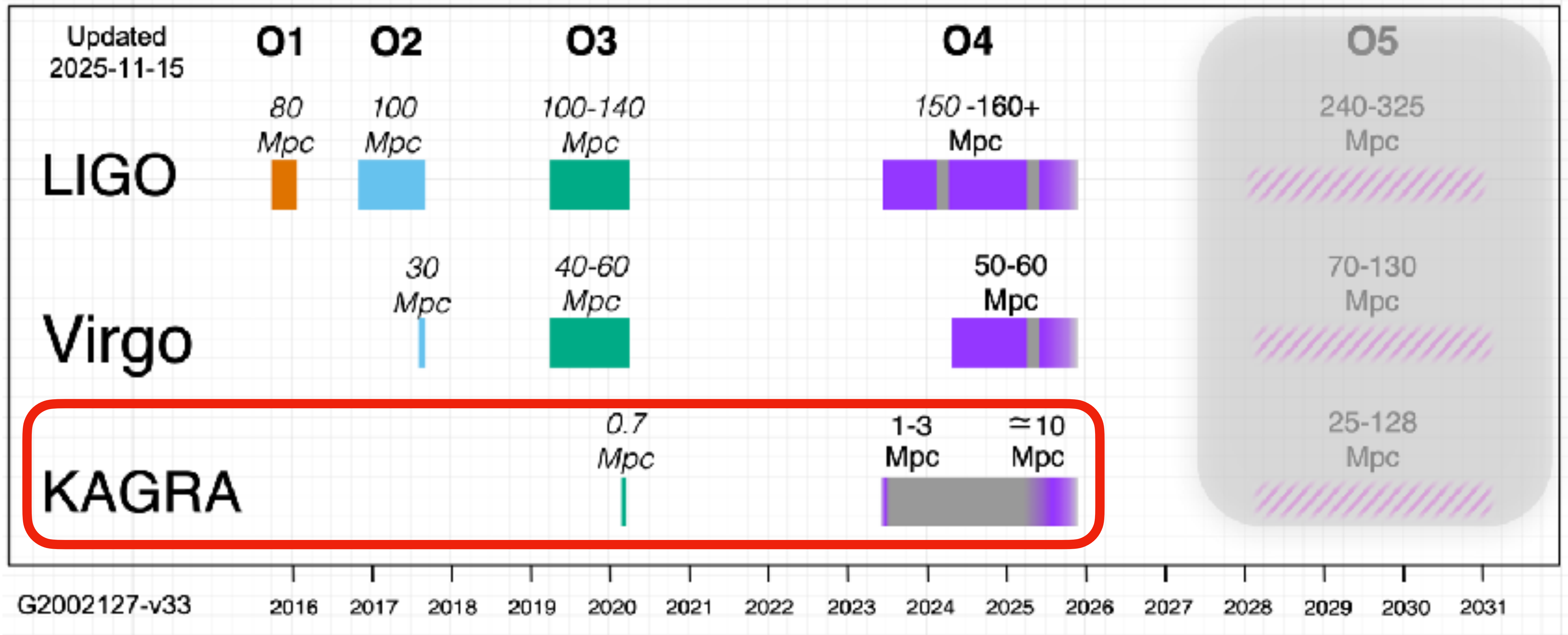
Large-scale Cryogenic Gravitational wave Telescope KAGRA

- A laser interferometer-type gravitational wave detector constructed underground at Ikenoyama in Hida City, Gifu Prefecture
  - It is a 3km-long interferometer
  - The current configuration of the interferometer is PRFPMI
  - Underground structure and a cryogenic mirror
  - The mirror is made of sapphire and cooled to approximately 40K



International collaborative observations with KAGRA

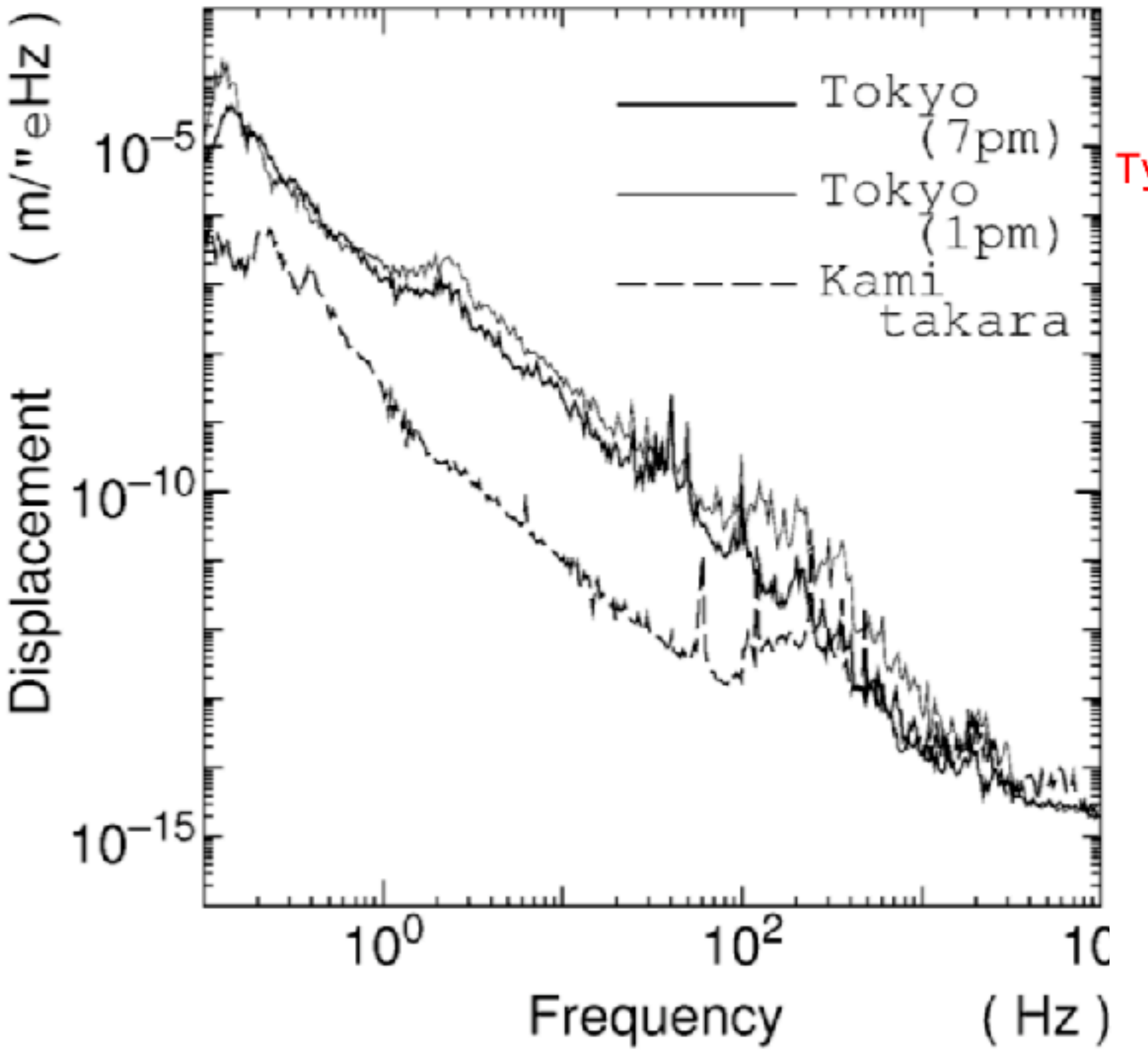
- O3GK: Two-week joint observation with GEO600 in April 2020
- O4a: Four-week joint observation with LIGO and Virgo in May 2023
- O4c: LVK joint observation from Jun 2025 to Nov

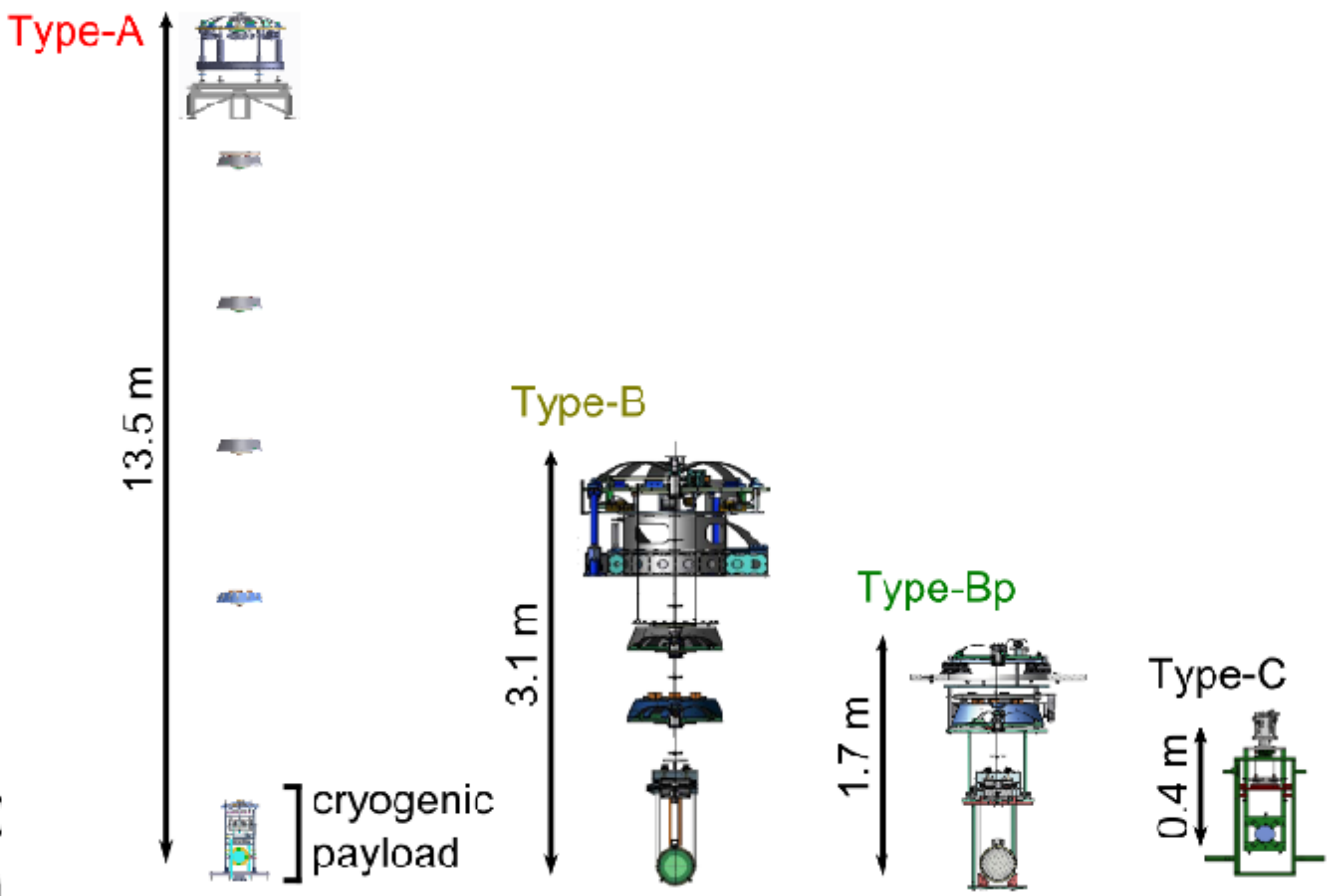


Large-scale Cryogenic Gravitational wave Telescope KAGRA

Underground experiment : Low ground vibration

- Ground vibration is strongly disturb when observing gravitational wave
- Ground vibration in Kamioka underground is about 1/100 of ground in Tokyo

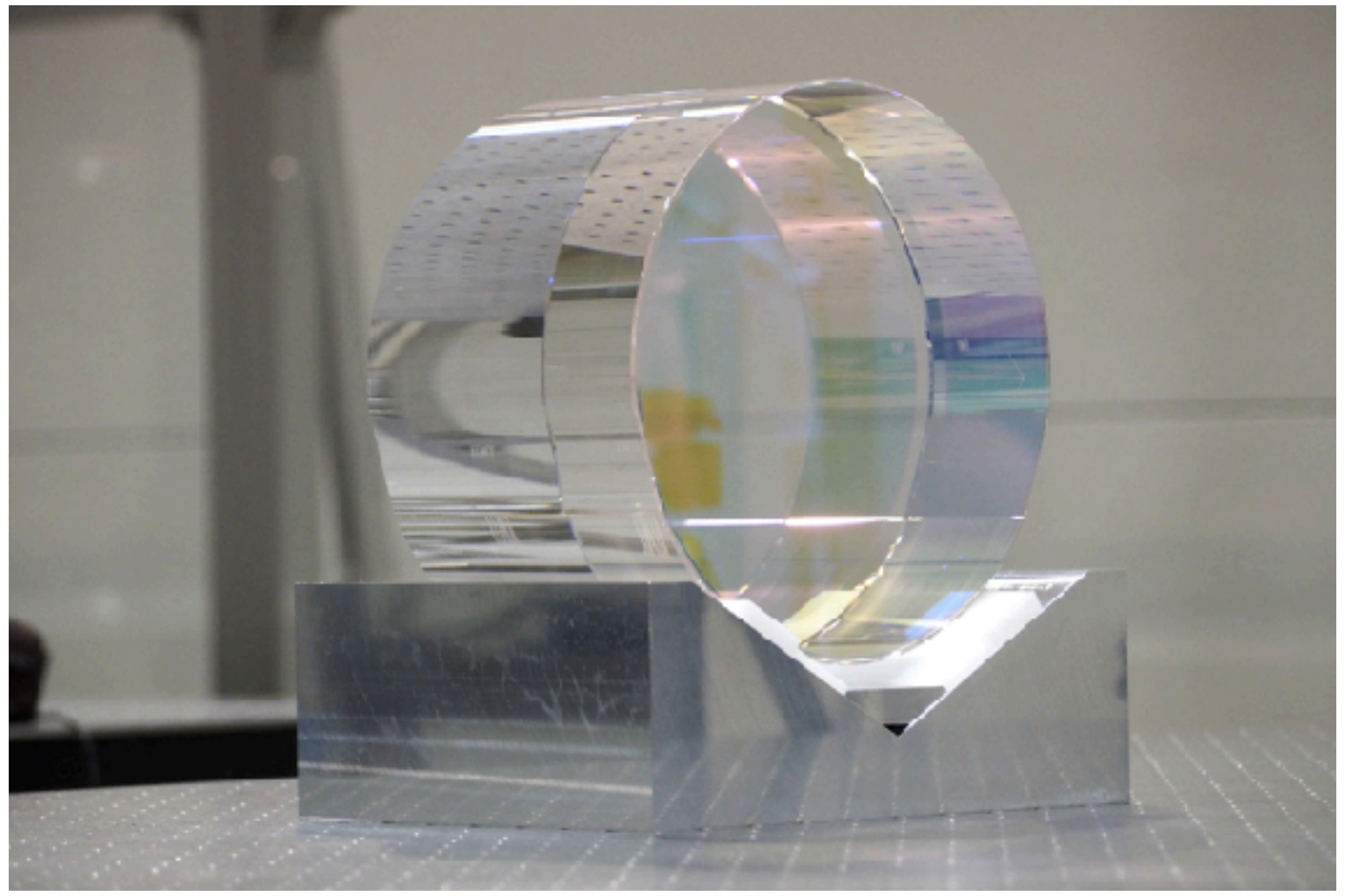


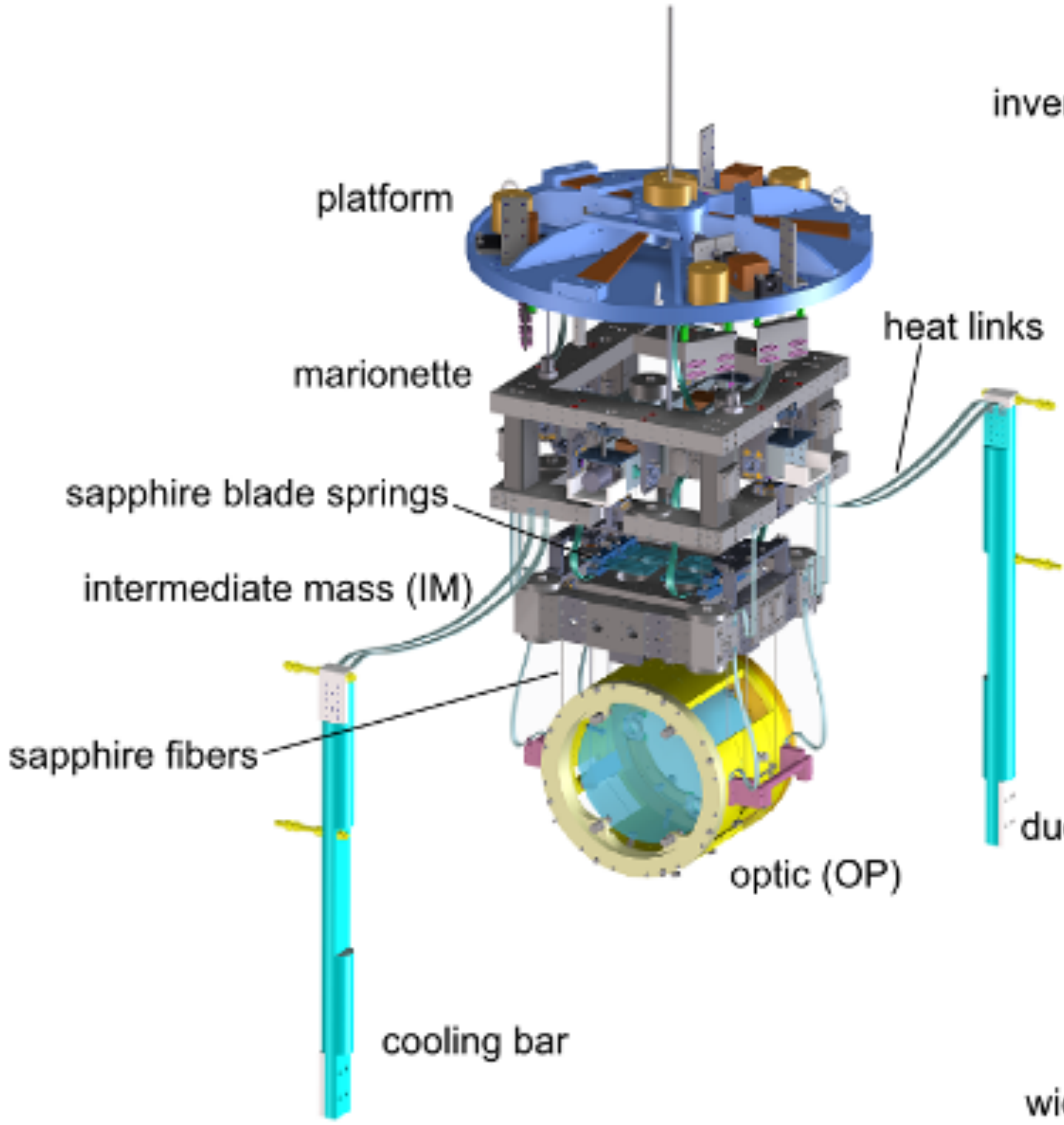


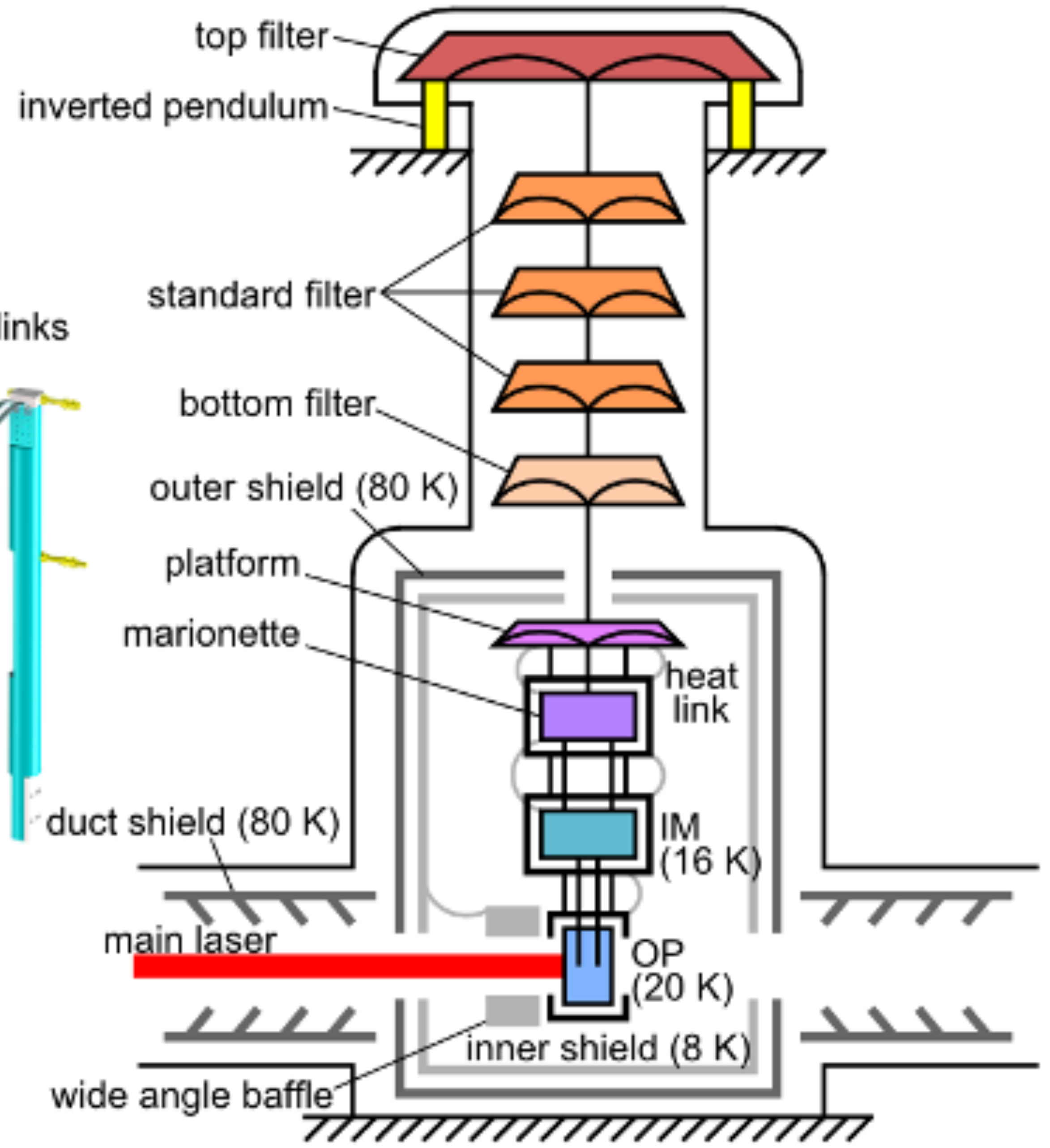
Large-scale Cryogenic Gravitational wave Telescope KAGRA

Cryogenic temperature : Low thermal noise

- Cooling the mirror reduces the thermal noise that affects laser reflection
- Using **sapphire** substrate for mirrors(Aluminium oxide, Al_2O_3)
  - Good thermal conductivity in lower temperature
  - Highly transparent across a wide range of wavelengths from ultraviolet to infrared



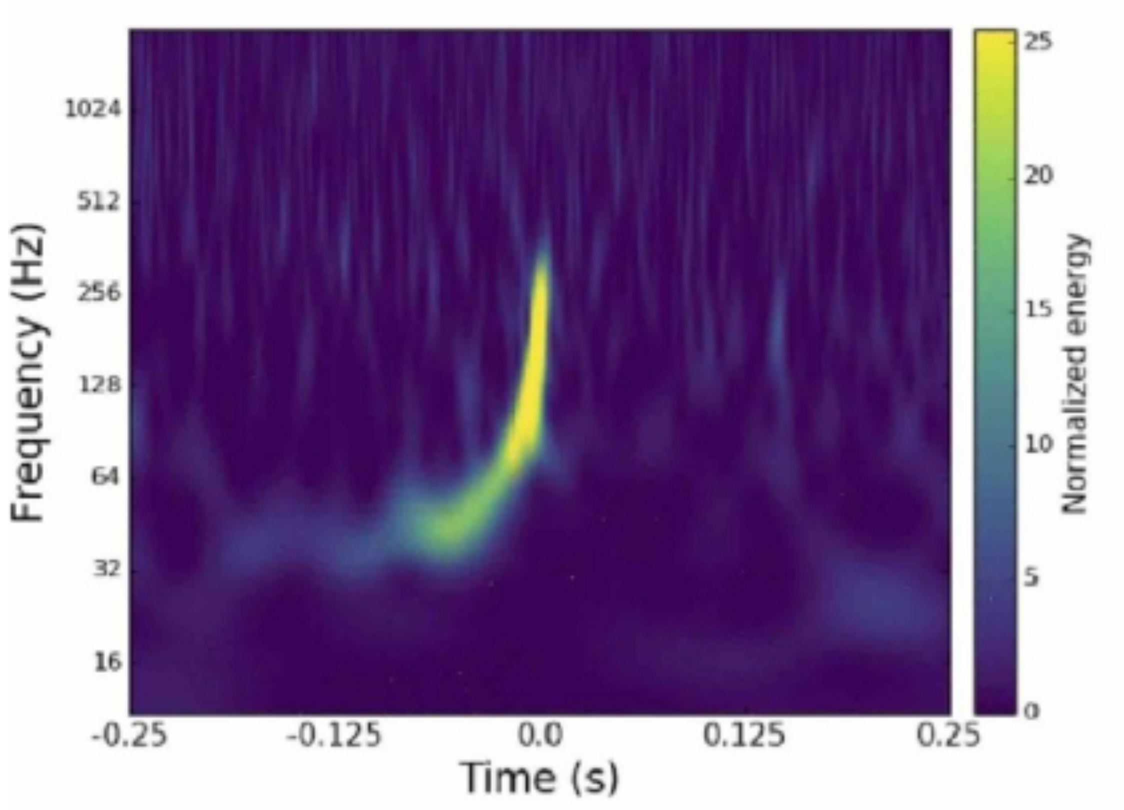




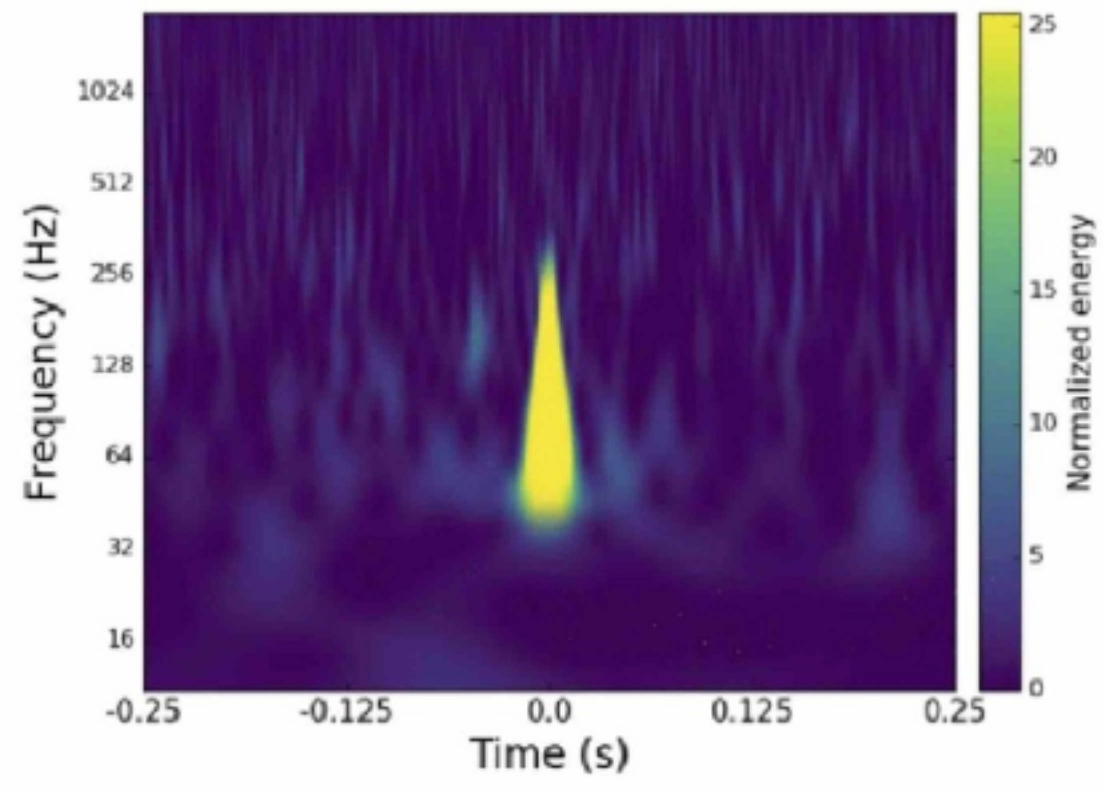
Importance for classification of Glitch noises

Transient noise(Glitch noise)：Non-stationary, non-Gaussian noise that appears in gravitational wave detectors

Chirp

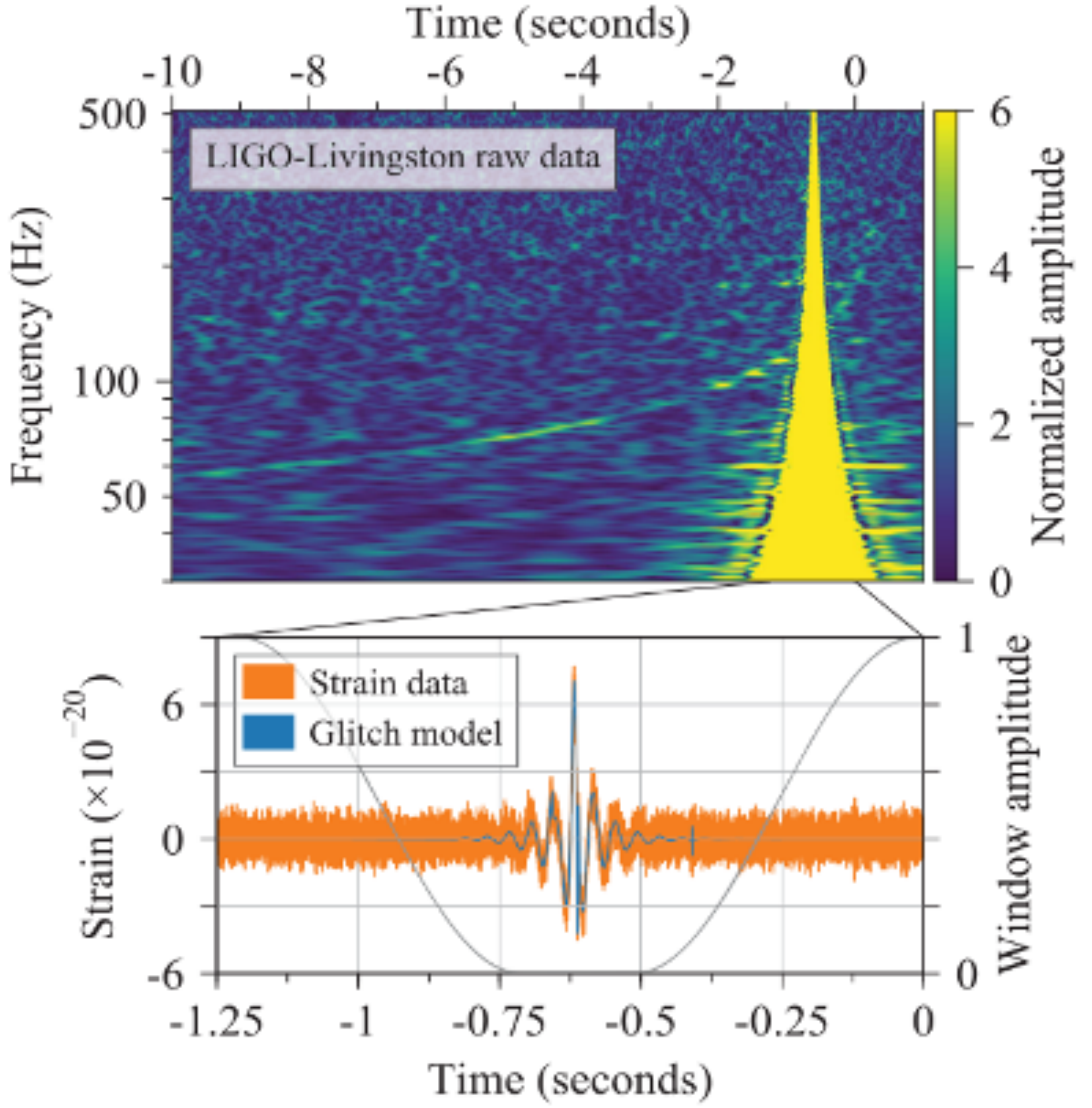


Blip



[Zevin+ 2017]

GW170817

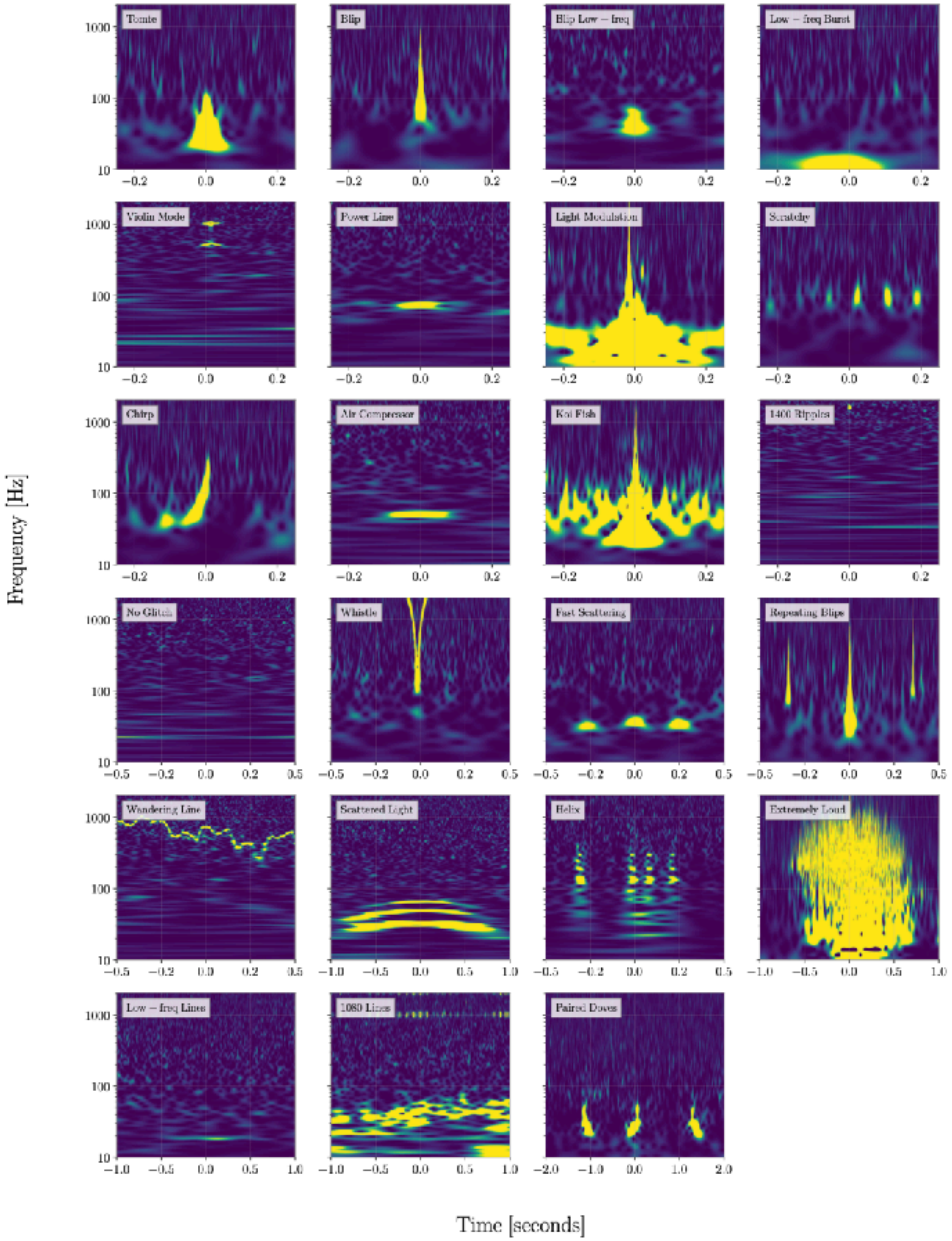


[Abbott+ 2017]

- Confirm that the gravitational waves are from an astronomical sources
  - Distinguishing gravitational wave signals from binary star mergers from noise originating from the environment, equipment, etc.
- Identify the cause of the glitch noise and make improvements such as removing the noise source to improve sensitivity

Classifying glitch noise can provide important information for improvement

Previous study : Gravity Spy



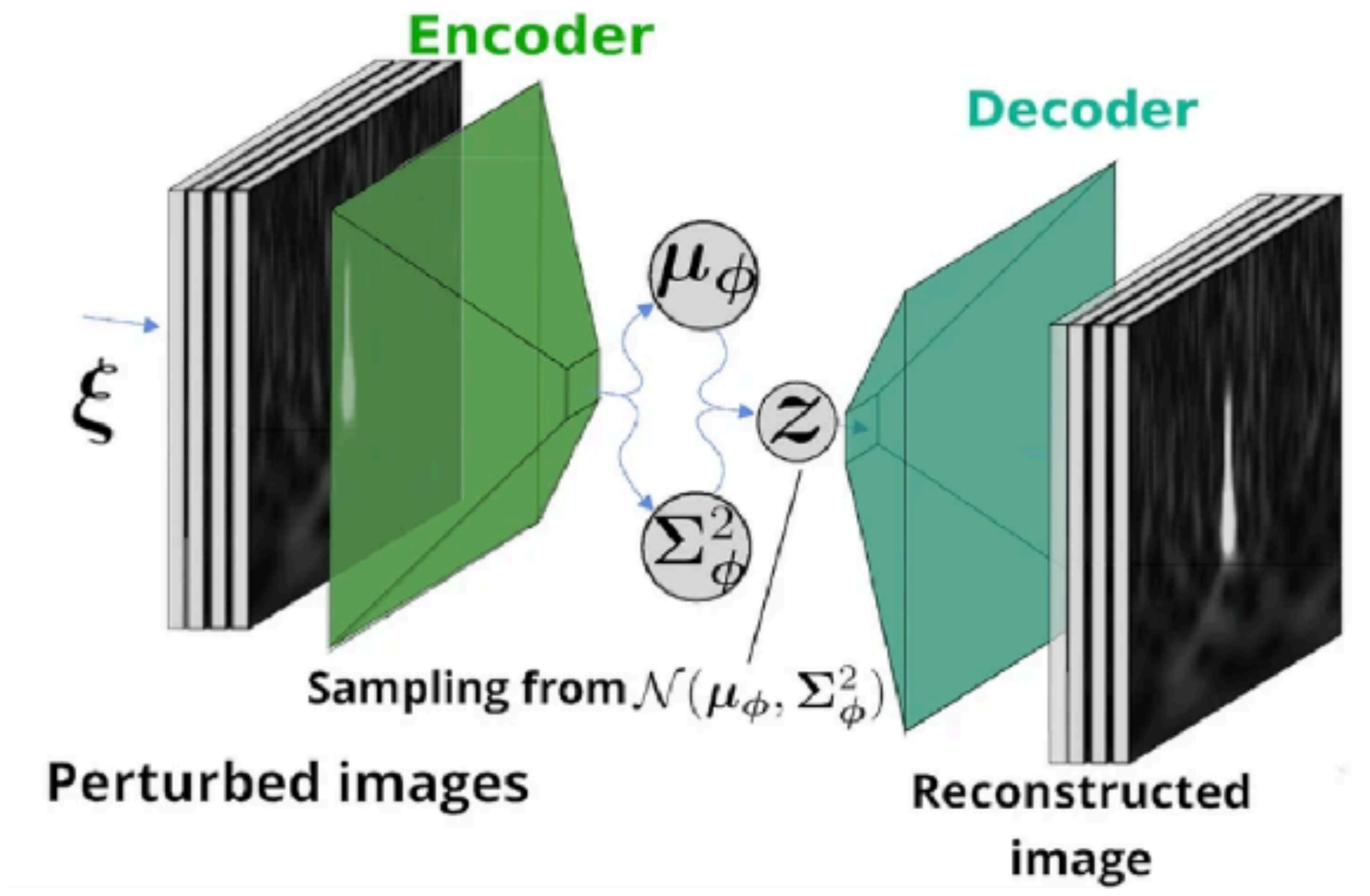
- Gravity Spy [Zevin+ 2017, Bahaadini+ 2018, Glanzer+2023]
- The Gravity Spy project collaborated with citizen science to classify LIGO glitches and create a labeled training dataset
  - The LIGO O1/O2 data are classified into 22 types of glitches, and the O3 data are classified into 23 types of glitches
- It also successfully used the dataset to build machine learning models with high classification accuracy (97.1%)
- The model is incorporated into a pipeline that analyzes observational data and is used to determine whether detected signals are gravitational waves or glitch noise

Previous study : Unsupervised Learning on Gravity Spy

[Sakai+ 2022, 2024]

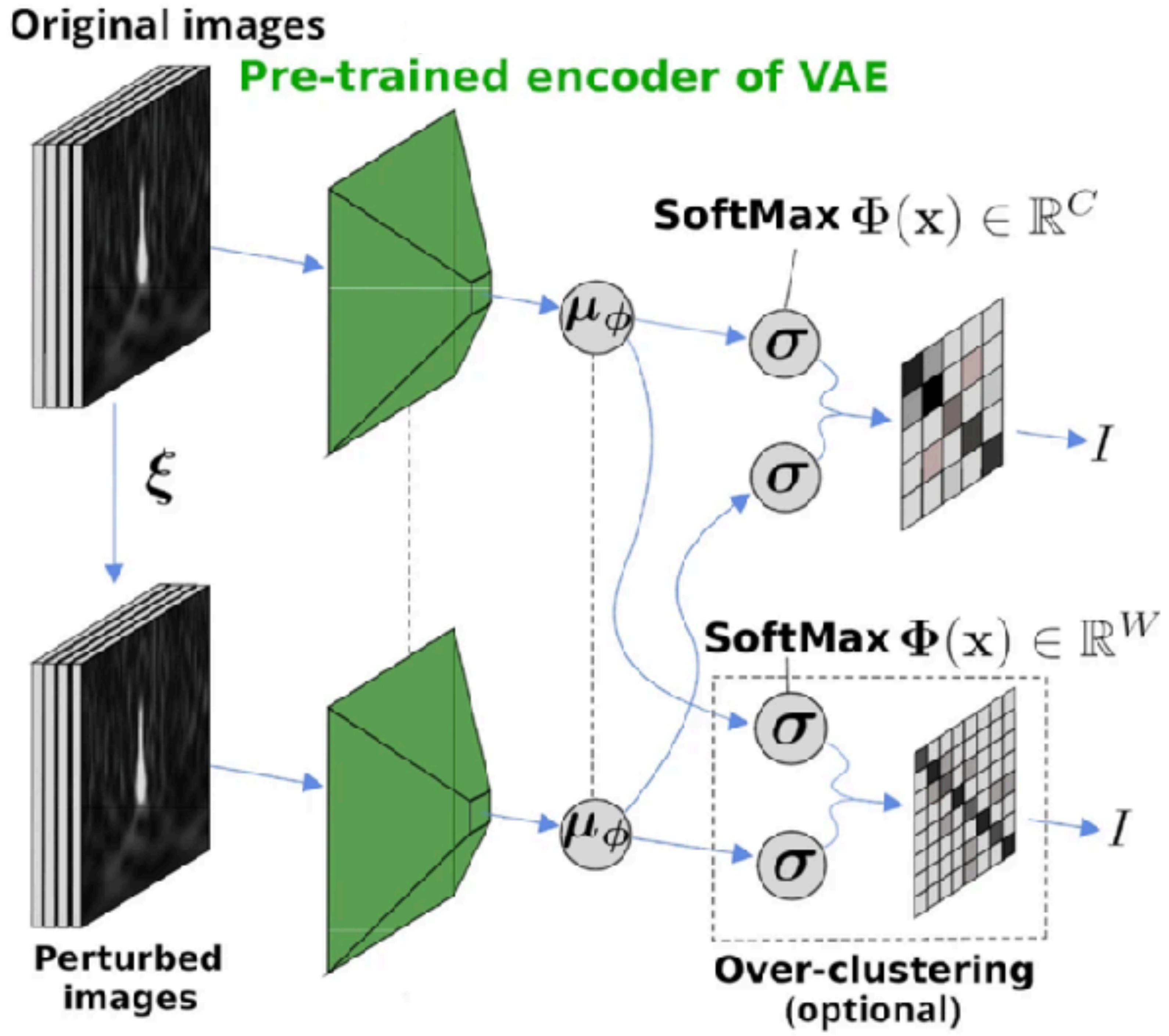
The Gravity Spy dataset was classified using unsupervised learning and showed comparable classification accuracy

1. Variational Auto Encoder : VAE



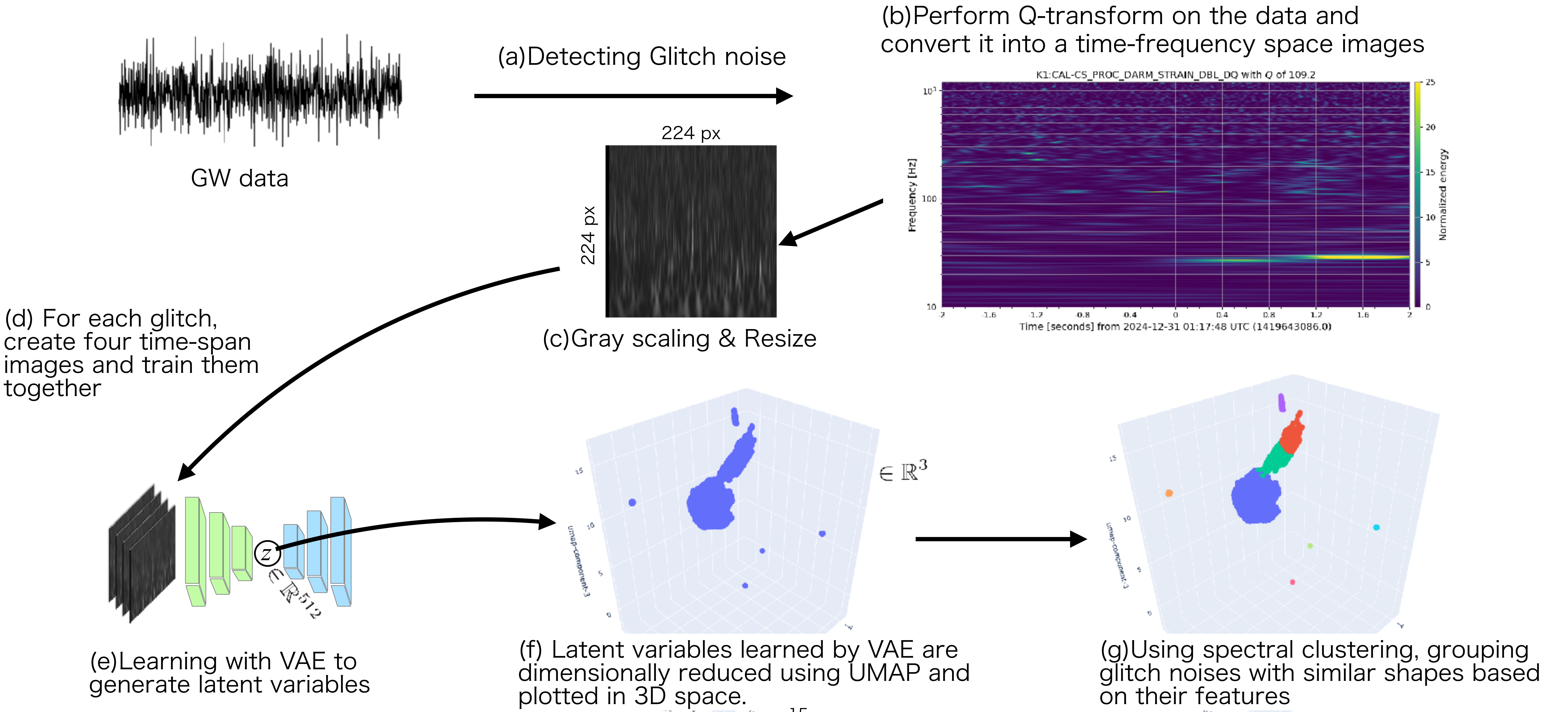
A generative encoder–decoder that learns a compact latent vector by reconstructing time–frequency glitch images

2. Invariant Information Clustering : IIC

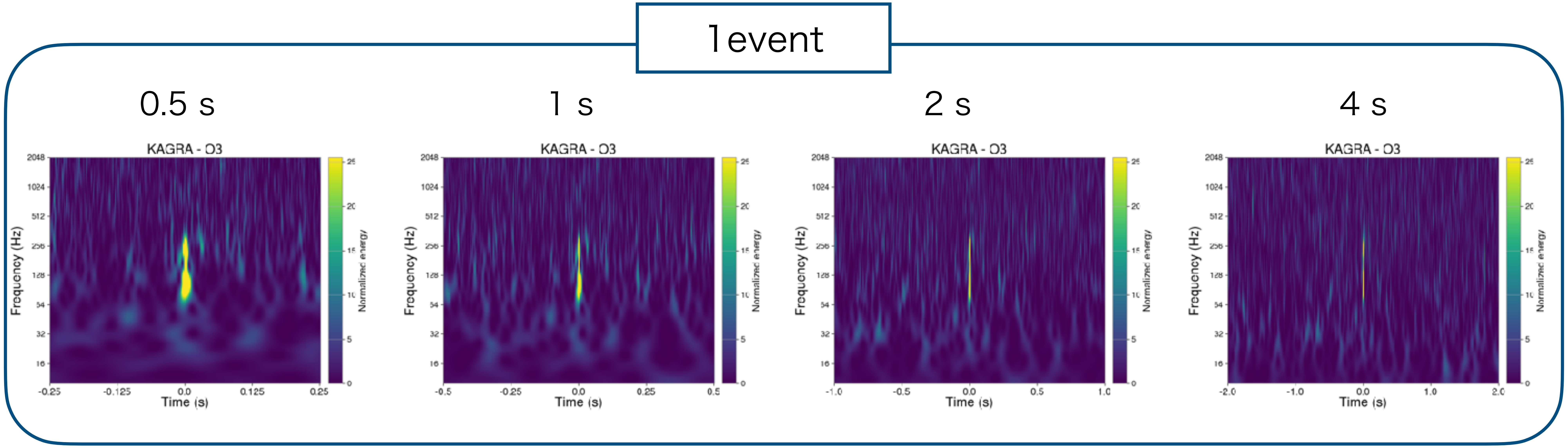


An unsupervised learning that maximizes mutual information between predictions for paired/augmented views of the same input

The glitch noise classification process in this study

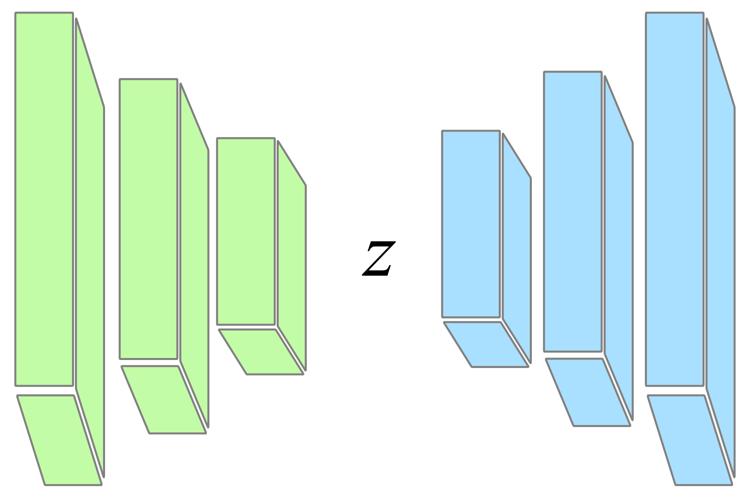


KAGRA O3GK data

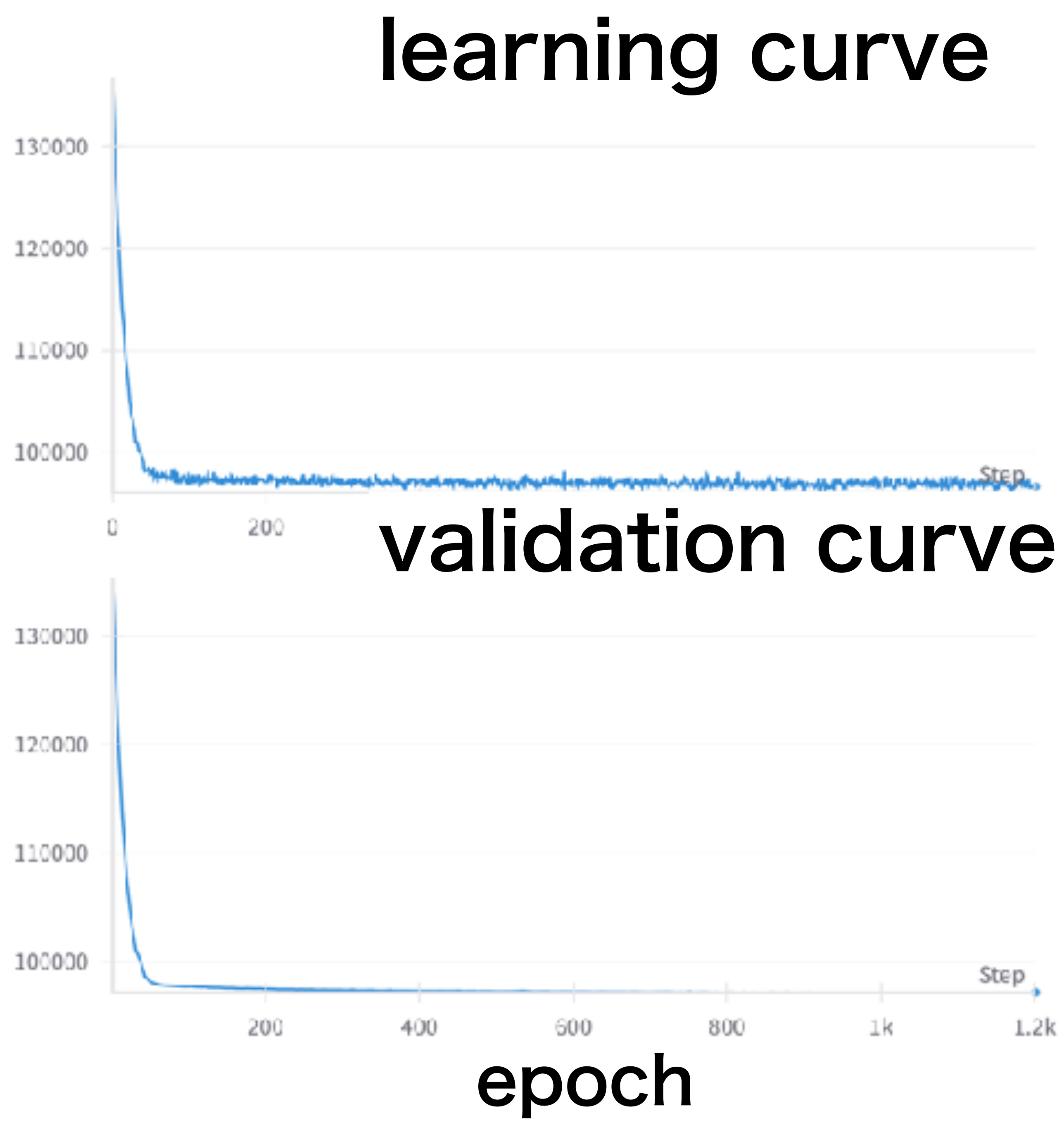


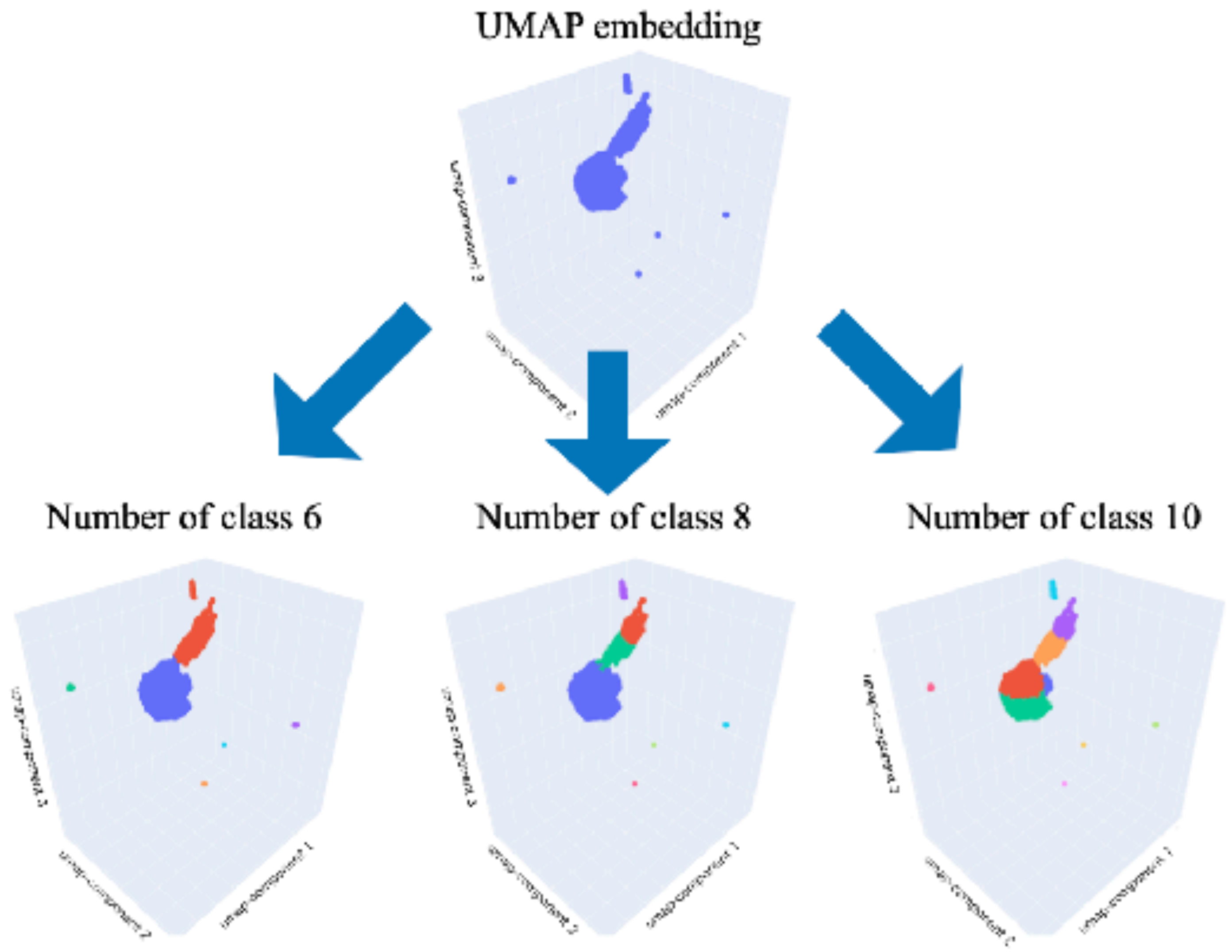
- **Input data**: KAGRA Strain channel from the O3GK period
- **Event detection**: The glitch detection pipeline Omicron (Robinet+ 2020) was used to identify the time of sudden noise occurrence
  - SNR > 7.5, 10-2048 Hz (peak frequency)
  - 4.63 events/min
- **Imaging**: Time-frequency space image creation (Q transform)
  - Four images were created for each event, at 0.5, 1, 2, and 4 seconds.
- Gray scaled + 224x224 pixel size
- **Data size**: 45,345 events

Conditions of Unsupervised learning in this study



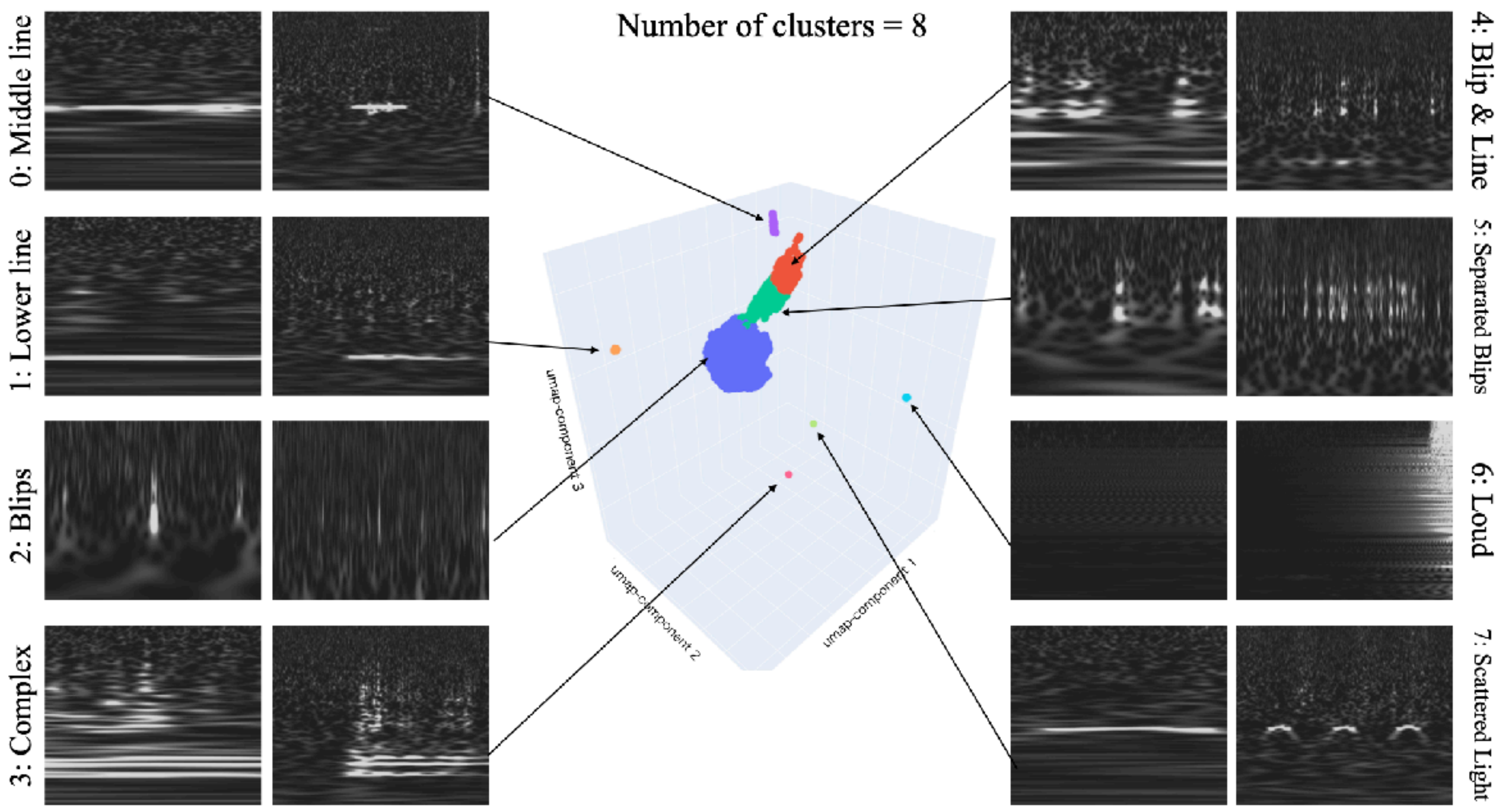
VAE (based on Sakai 2022/2024 CNN configuration)
Latent dimension z∈{32, 64, 128, 256, 512}
Minibatch {32, 64, 96, 128}
Epoch 100
Learning rate: 5e-4
Training data:Test data = 80%:20%





- We changed the VAE hyperparameters to check the difference in the learning curve
- Since there was no significant difference within the range we checked, we adopted z=512 and minibatch=96 parameters
- UMAP was used to compress the learned latent variables (512 dimensions) to 3 dimensions
- Spectral clustering was used to visually check how the features were divided when the number of classes was 4 to 12

Glitch Noise Shapes and Classification



Classification into 8 classes where shape differences are considered to be clear

- Visually check the glitch noise shapes contained in the clusters (4 to 12) divided by spectral clustering
  - When the number of classes is small, different shapes (blips and lines) are grouped together in the same cluster
  - When the number of classes is large, blips are separated into different clusters

Glitch Noise Shapes and Classification

Shape of glitch noise	Number of glitch noise	Percentage
Middle line	621	1.4%
Lower line	294	0.6%
Blips	35925	79.2%
Complex	44	0.1%
Blips & Line	4016	8.9%
Separated Blips	4358	9.6%
Loud	60	1.3%
Scattered Light	27	0.6%

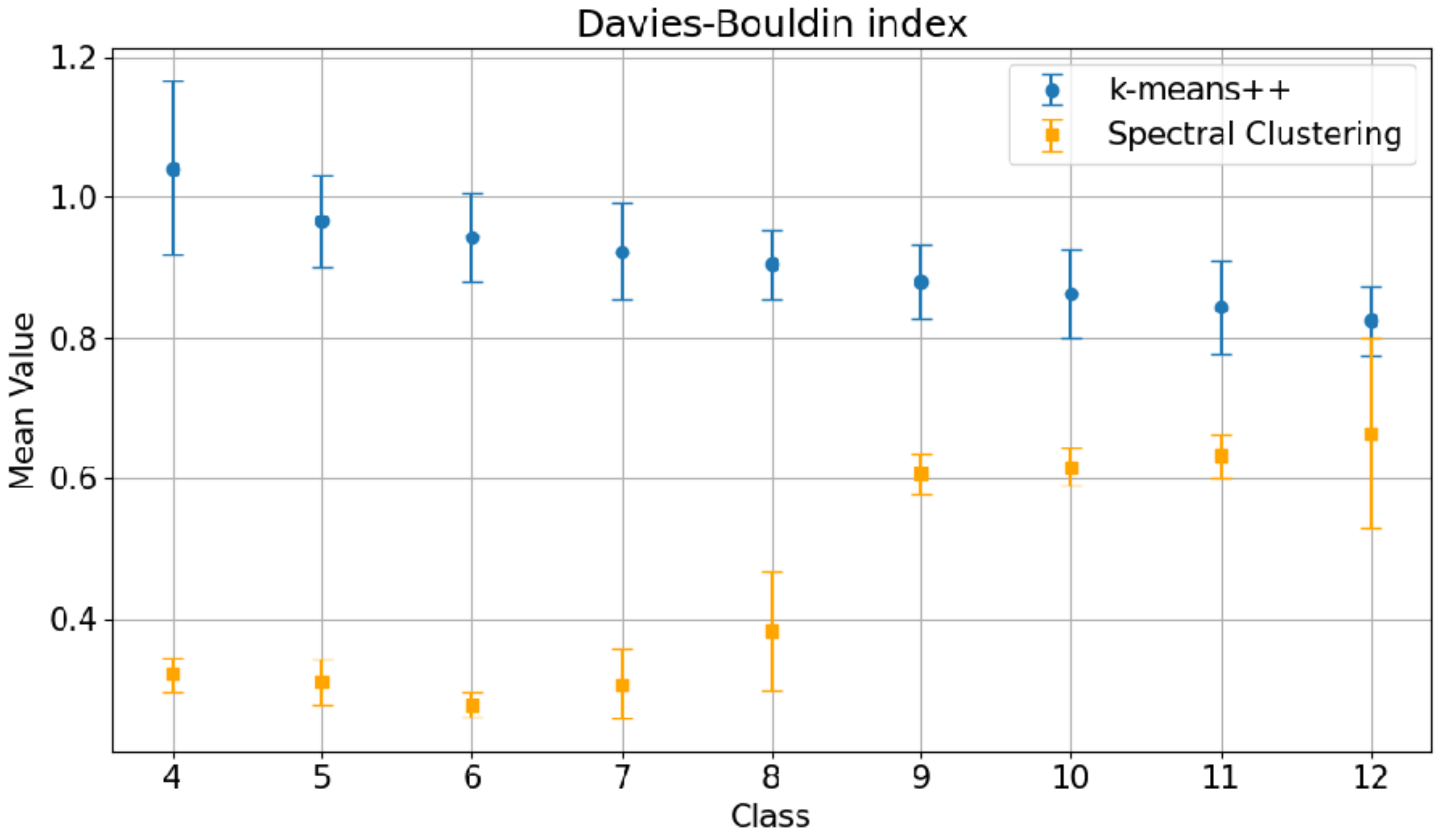
- Blips account for approximately 80% of the total
  - LIGO O1/O2 also has many blips
- The cause of glitches other than Scattered Light is unknown
  - The scattered light is caused by the vibration of the Power Recycling mirror

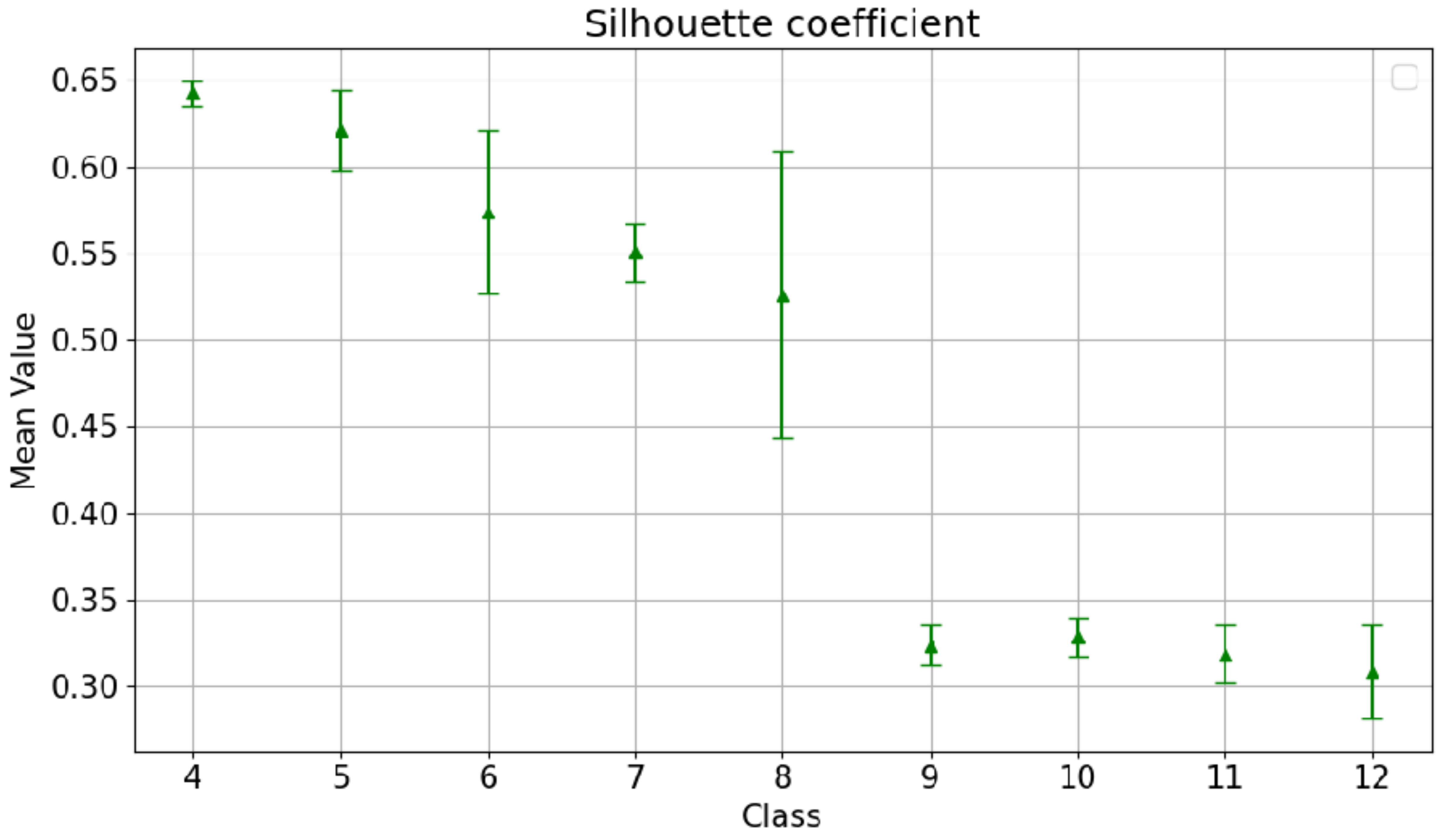
[Yamamura+, 2024, CQG, 41, 205008]

Evaluation of the number of clusters

- In this study, we classified O3GK glitches into eight types. To verify the validity of these results, we used the following two methods:
  - **Davies-Bouldin Index (DBI)**: Evaluates the degree of separation and dispersion between clusters
  - **Silhouette Coefficient**: Quantifies the degree to which each sample conforms to its assigned cluster

Evaluation of the number of clusters





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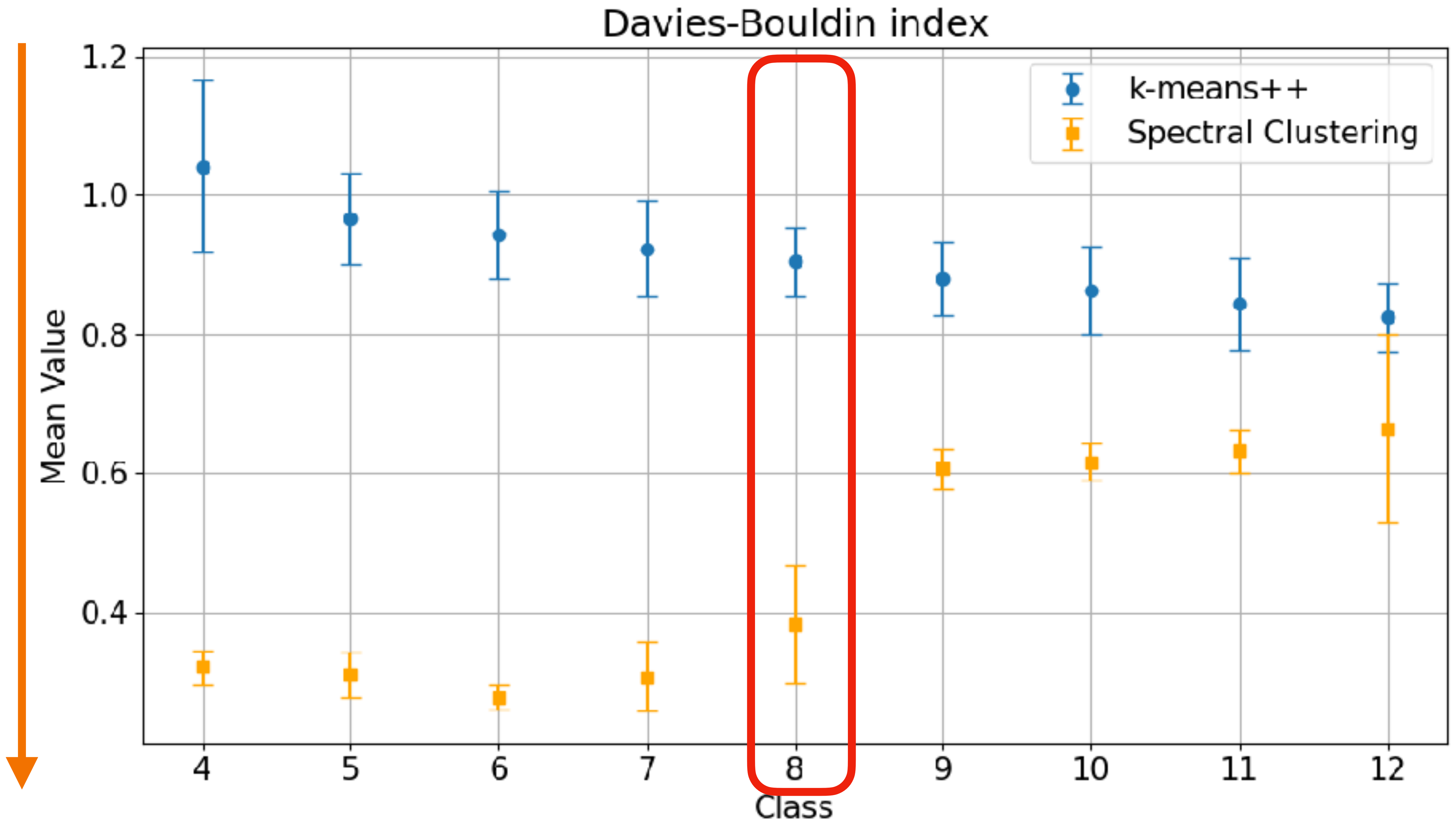
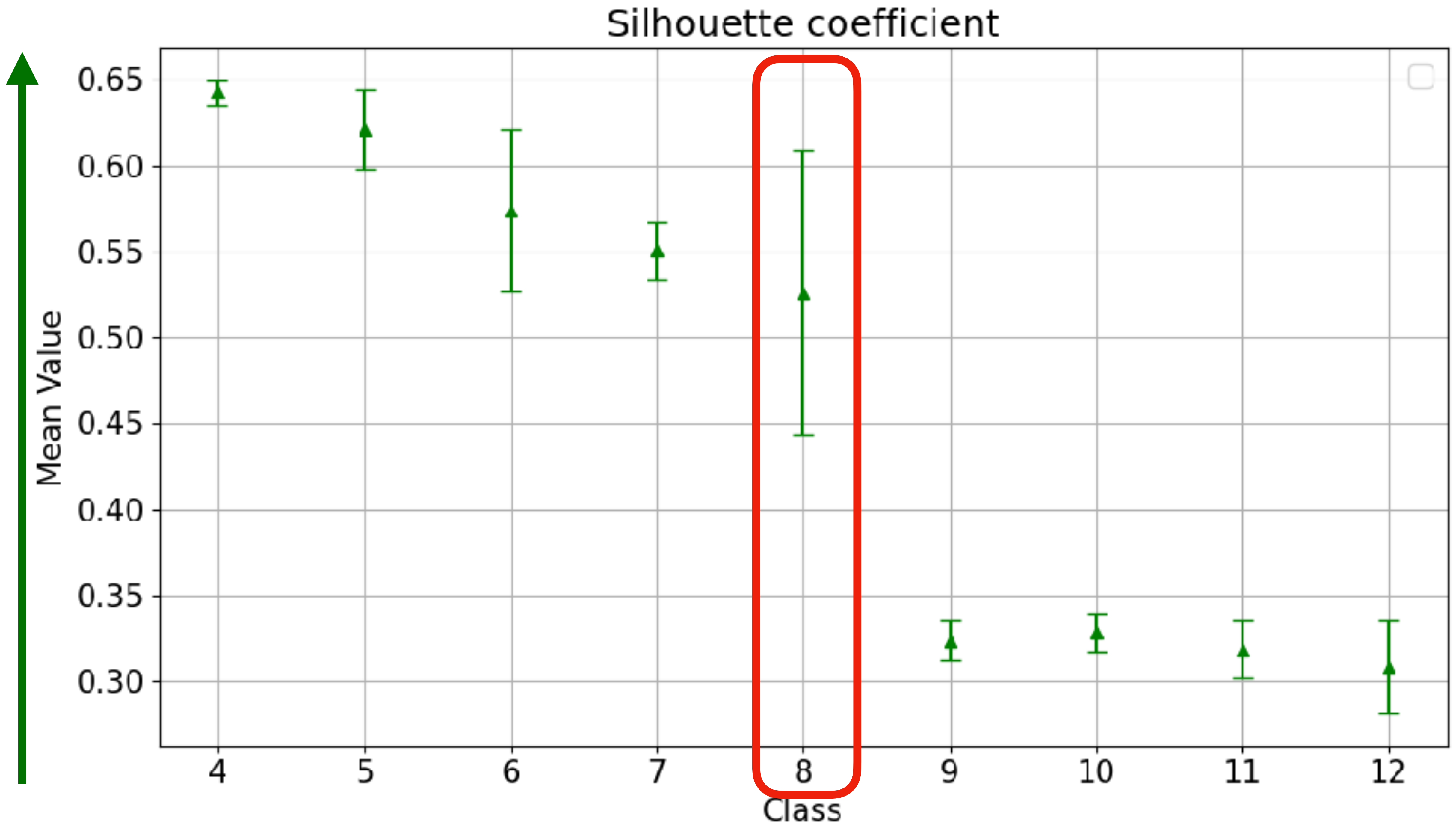


Smaller values are better



The closer to 1 the better

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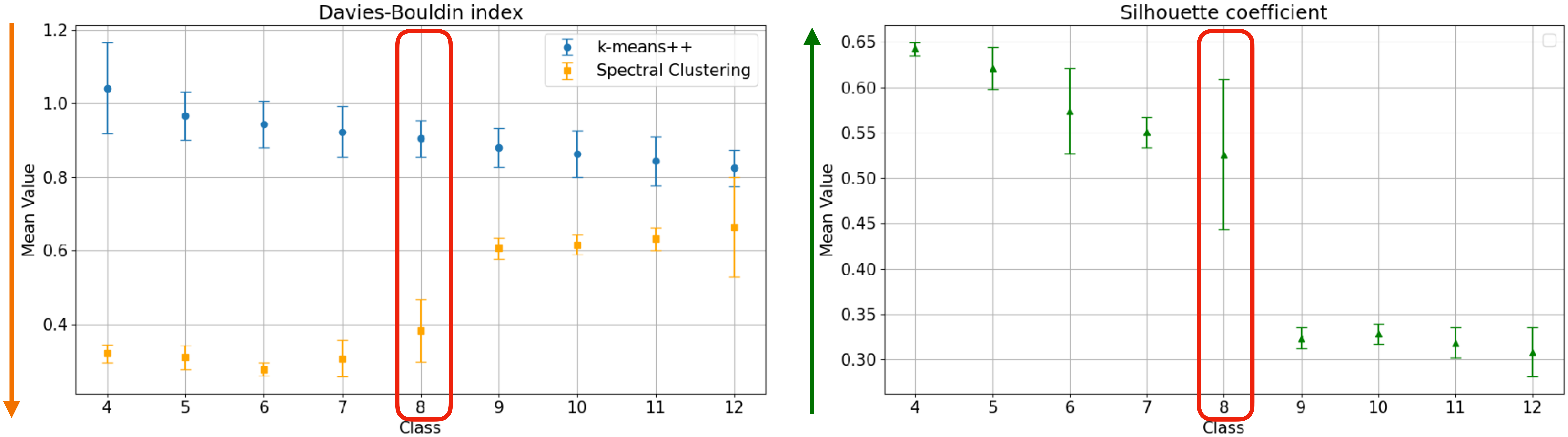

Smaller values are better

The closer to 1 the better

- From visual confirmation + DBI and silhouette coefficient comparison, it is considered that there are eight types of glitch shapes included in the O3GK data
- The results are consistent with the results of analyzing O3GK data with Hveto and visually distinguishing the shapes (6 types) [KAGRA collaboration, 2025, PTEP, 8, 083]

Summary

- We performed unsupervised machine learning tequnique to characterize O3GK glitches into eight classes by sequentially applying a VAE for representation learning, UMAP for dimensionality reduction, and Spectral Clustering for partitioning
- The certainty of the number of clusters was confirmed by the Davies–Bouldin Index (DBI), silhouette coefficients, and complementary expert visual inspection
- The number of classes of glitches observed in KAGRA O3GK appears reduced relative to that reported for LIGO O1/O2
- One possible reason is the higher noise floor in KAGRA, which may hide additional glitch shapes that could otherwise be detected

Summary

Future Work:

- Apply this method to O4 observation data to investigate whether previously unavailable glitch types appear under improved detector sensitivity
- Develop a system similar to GSpyNetTree that can automatically respond to gravitational-wave alerts, perform rapid glitch identification, and support low-latency data quality assessment