



Neutron star gravitational waves emission

Fundamental physics and searches

Francesca Attadio, 17th April, 2024

Presentation outline

- **Gravitational waves** (GWs) and standard categorization of GWs signals with a focus on modeled signals
- **Neutron stars** (NSs), pulsars and magnetars,
- **GWs emitted by NSs**, amplitude and relevant parameters
- Different kind of **searches** and time frequency maps
- **Machine learning** approach
- **Conclusions**

Gravitational waves

Gravitational-Waves (GW) are **ripples in the space-time fabric** produced by **huge astrophysical catastrophes**, such as the coalescence of compact binary (two black holes and/or neutron stars).

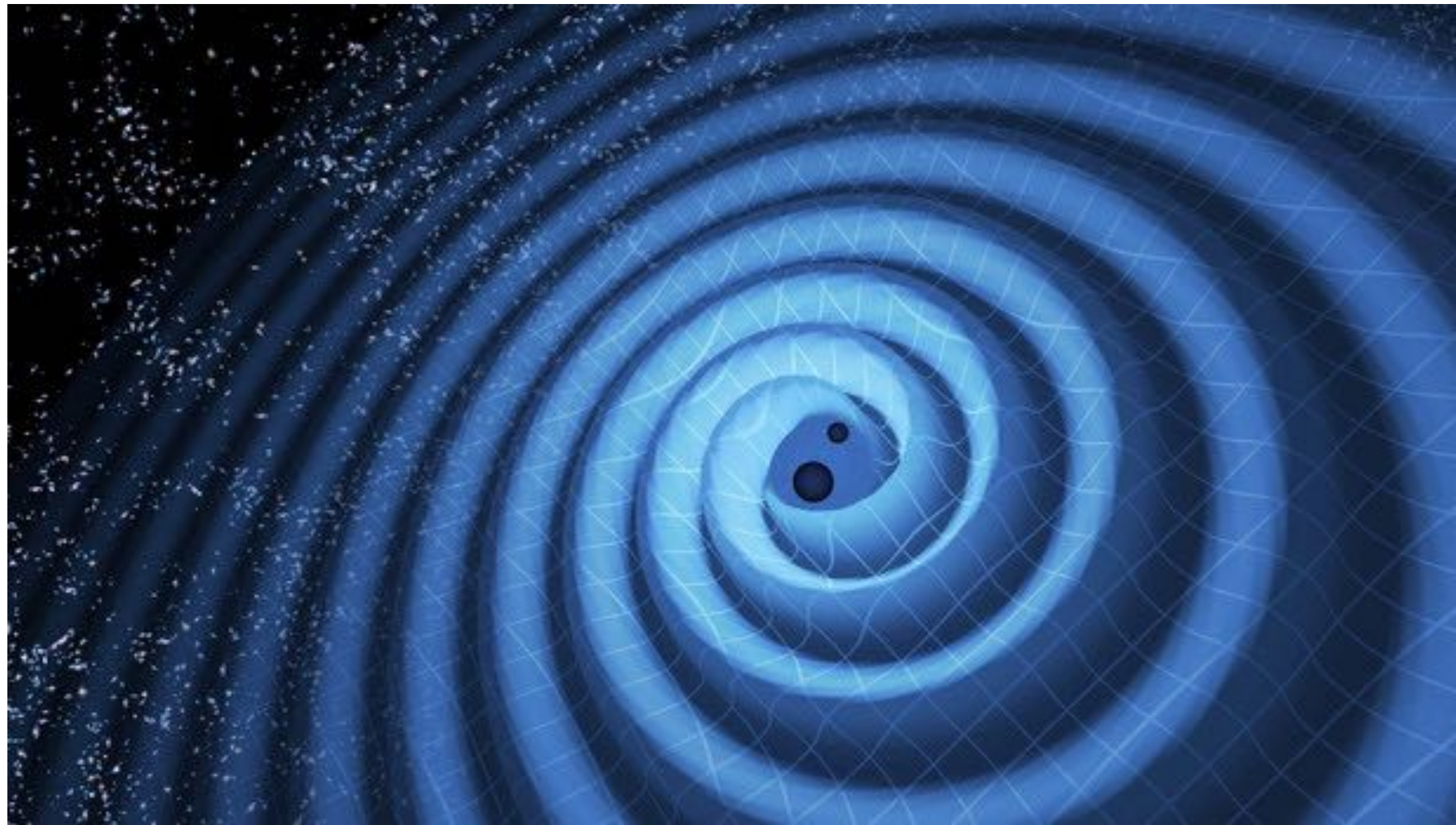


Image credit: LIGO/T. Pyle

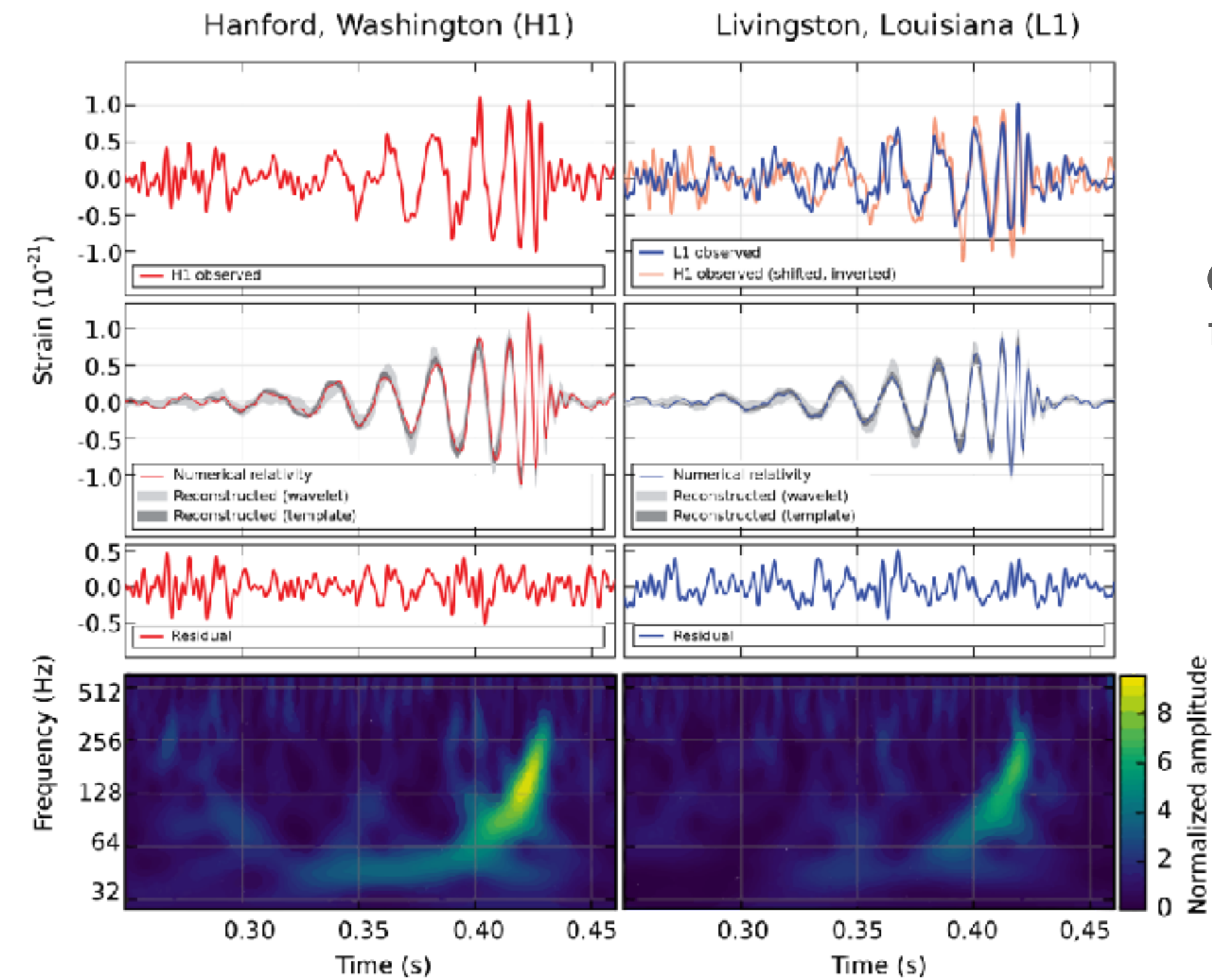


Image credit:
**Observation of
Gravitational Waves
from a Binary Black
Hole Merger**
LIGO collaboration,
Virgo collaboration

The **first direct detection is dated 14th September 2015**, a century after their prediction by Einstein (1916), within the General Relativity framework.

Standard categorization of GWs signals

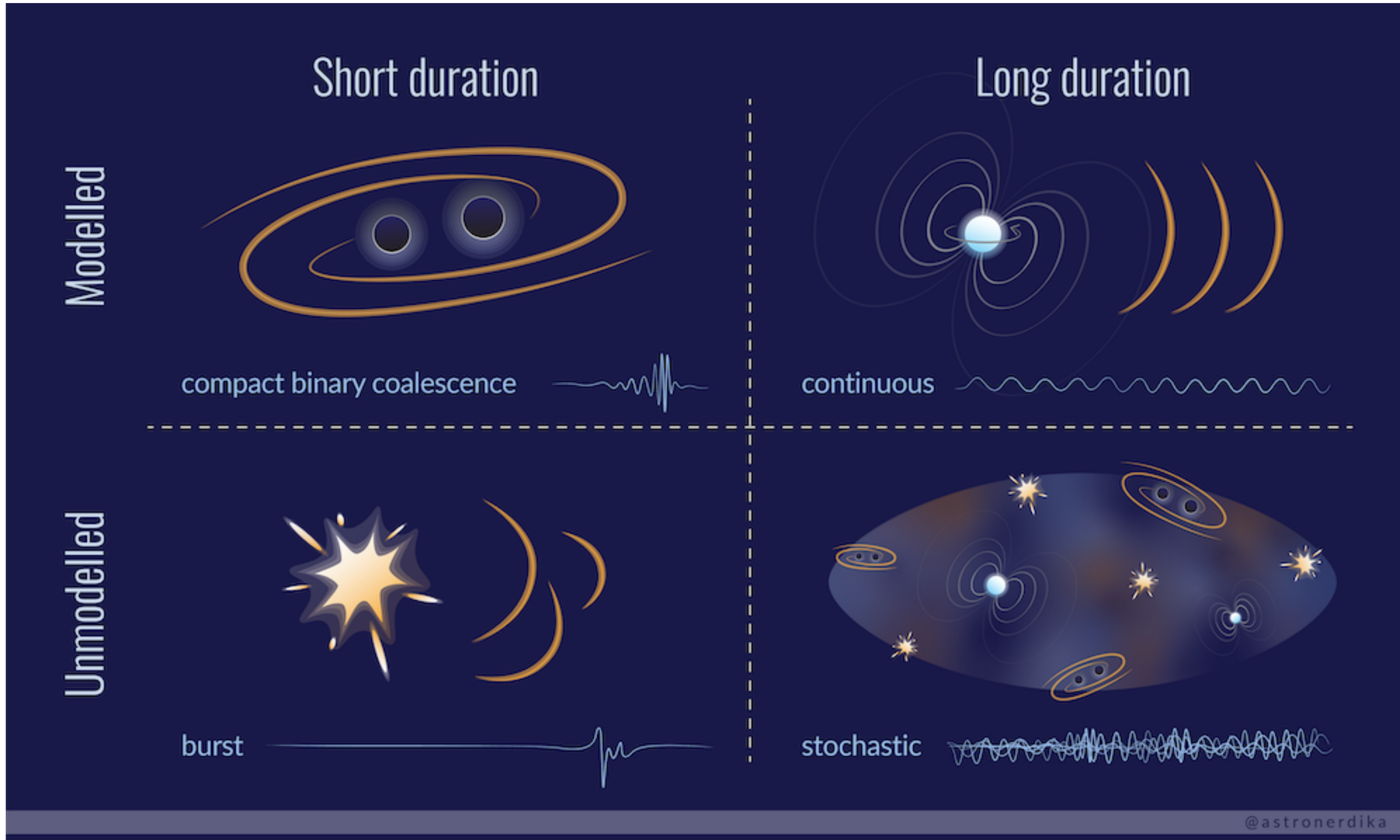
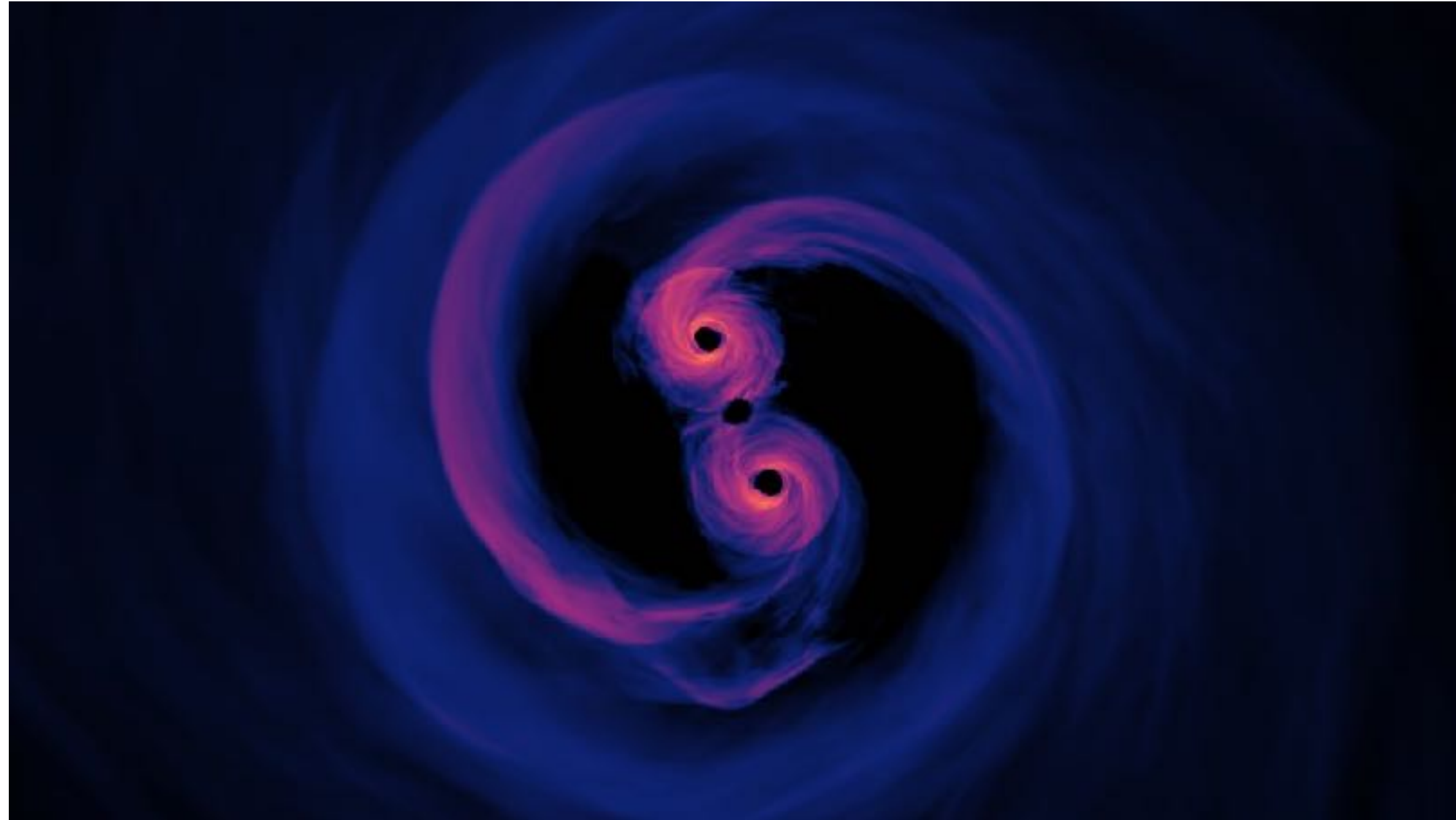


Image credit: Shanika Galaudage

Modeled signals

Transient signals



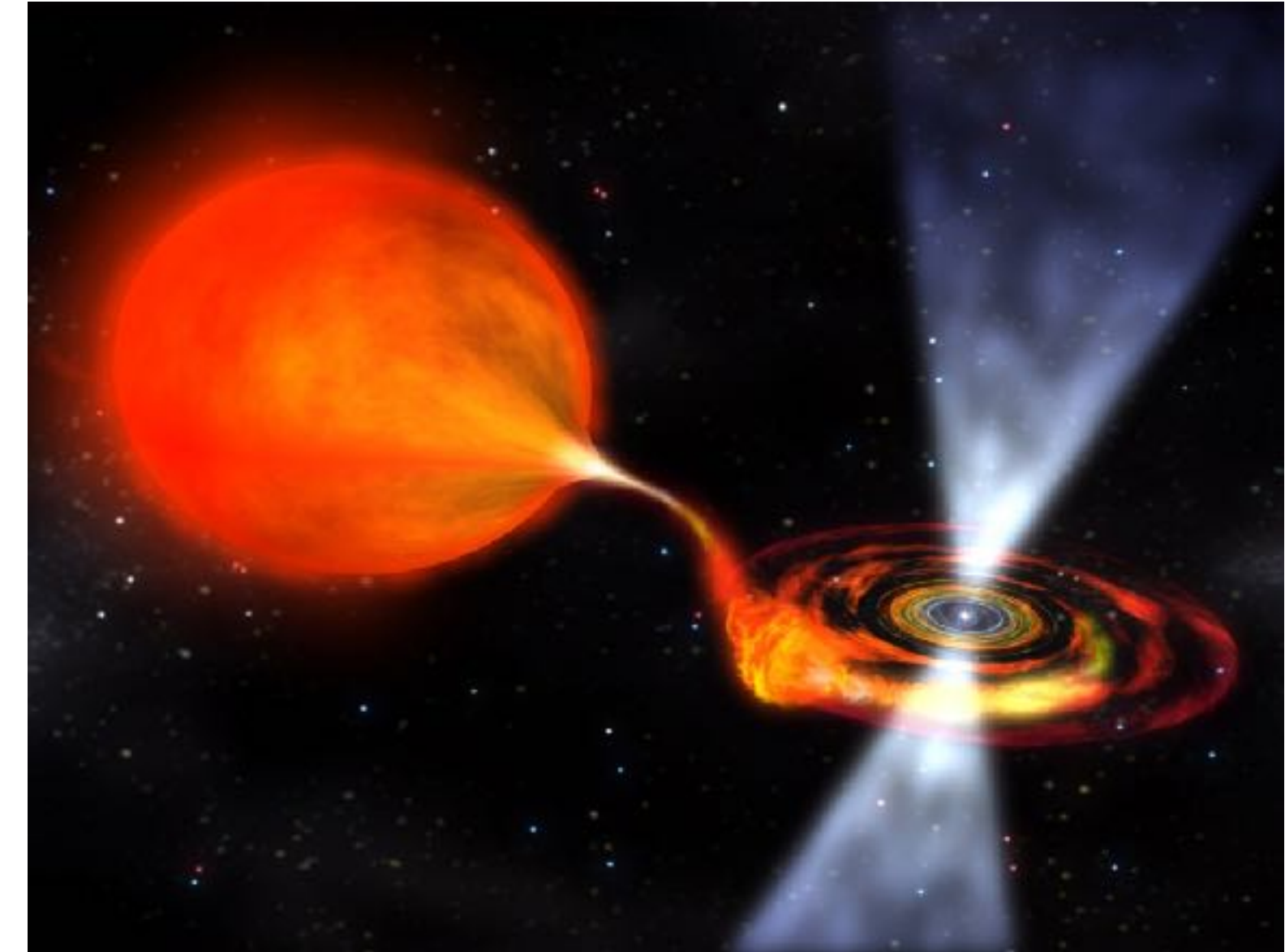
Duration: 0.1 to 100 seconds

Image credit: NASA's
Goddard Space Flight
Center/Scott Noble

Sources: Compact binary coalescence
(CBC)

→ Detected

Continuous waves



Duration: hours to years

Image credit: NASA,
Dana Berry

Sources: Isolated neutron stars,
low mass x ray binary

→ Not detected

Neutron stars (NSs)

Final stage of stars with an initial mass between 8 and 30 solar masses.

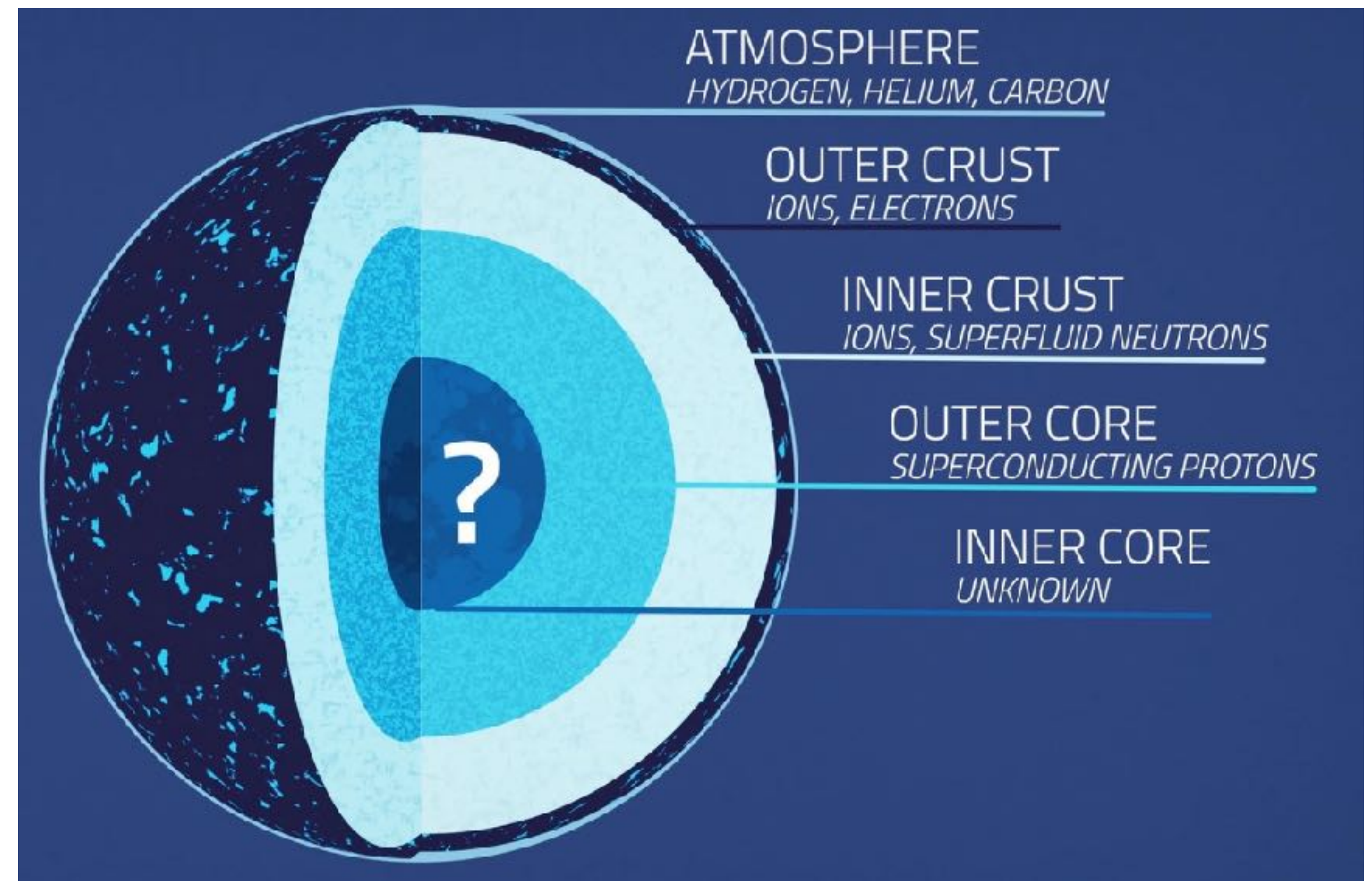
Main characteristics:

- Mass: 1.25-2.15 solar masses
- Radius: 10-12 km
- Density: $\rho \leq 10^{15} \frac{\text{g}}{\text{cm}^3}$

(From the crust to the core)

It is impossible to reach on earth this kind of densities

- NSs are cosmic laboratory



Credit: NASA's Goddard Space Flight Center/Conceptual Image Lab

Gravitational waves

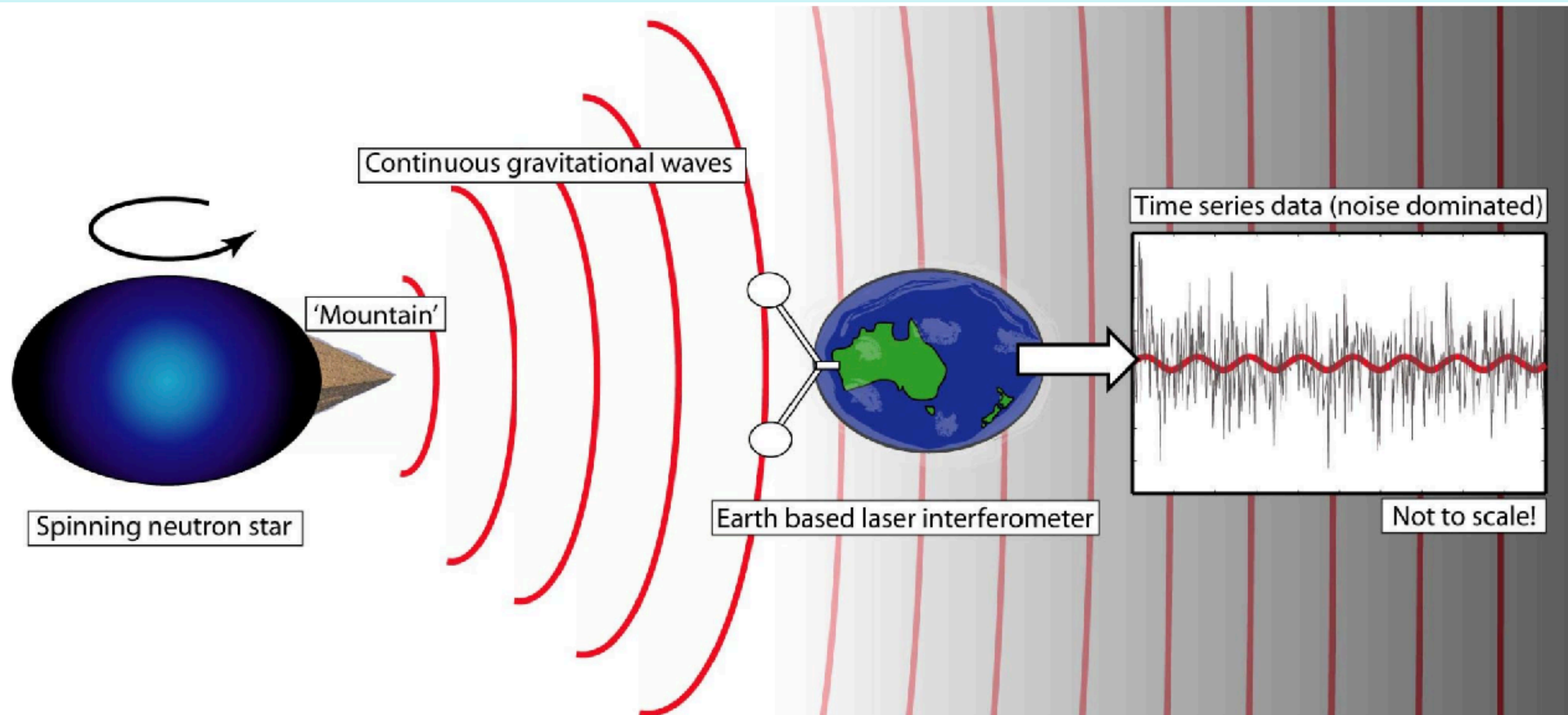


Image credit: Graham Woan

Isolated NSs spinning with a non axis-symmetric asymmetry emit GWs

GW amplitude

$$h_0(t) = \frac{4\pi^2 G}{c^4} \frac{I f(t)^2}{d} \epsilon$$

Distance of the source

GW frequency

Ellipticity

Spin down equation

The rotational energy of the star is used to emit GWs and electromagnetic radiation

$$\dot{f}_{\text{rot}} = -k f_{\text{rot}}^n$$

n: Braking index

k: Constant

They depend on the kind of emission

$$f_{\text{GW}} = 2f_{\text{rot}} \equiv f$$

Star rotational parameters $\rightarrow \mathbf{f}, \dot{\mathbf{f}}, \dots$

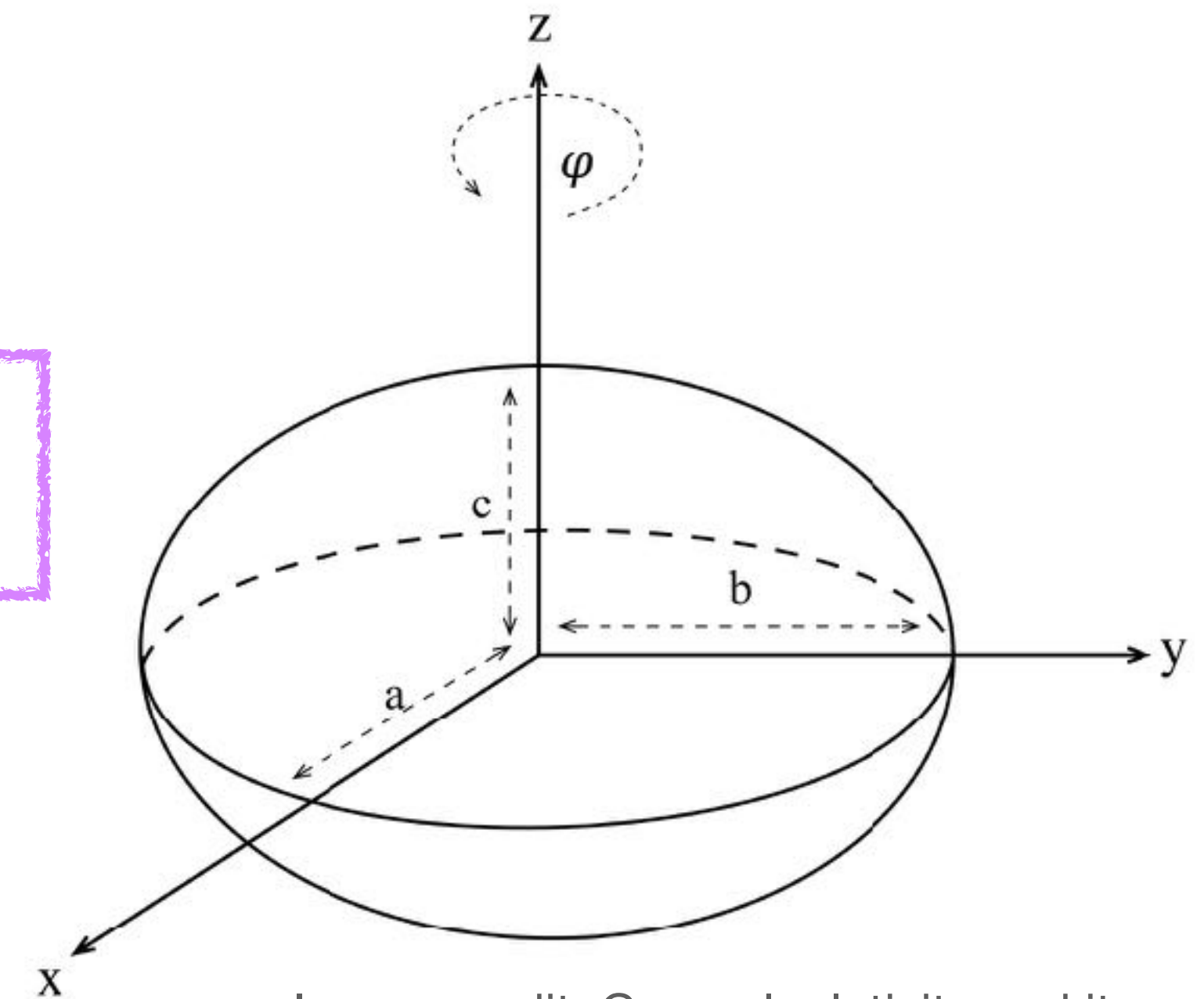


Image credit: General relativity and its application, Ferrari, Gualtieri, Pani

Ellipticity (Oblateness)

The measure of the asymmetry is the ellipticity (ϵ)

$$\epsilon \sim 10^{-5} - 10^{-3} \rightarrow 0.1 - 10 \text{ m}$$

Possible cause of **asymmetry**:

- Mountains
- R-modes
- Magnetic field

We do not have a measure of ellipticity for known NSs

Different kind of NSs

Pulsar

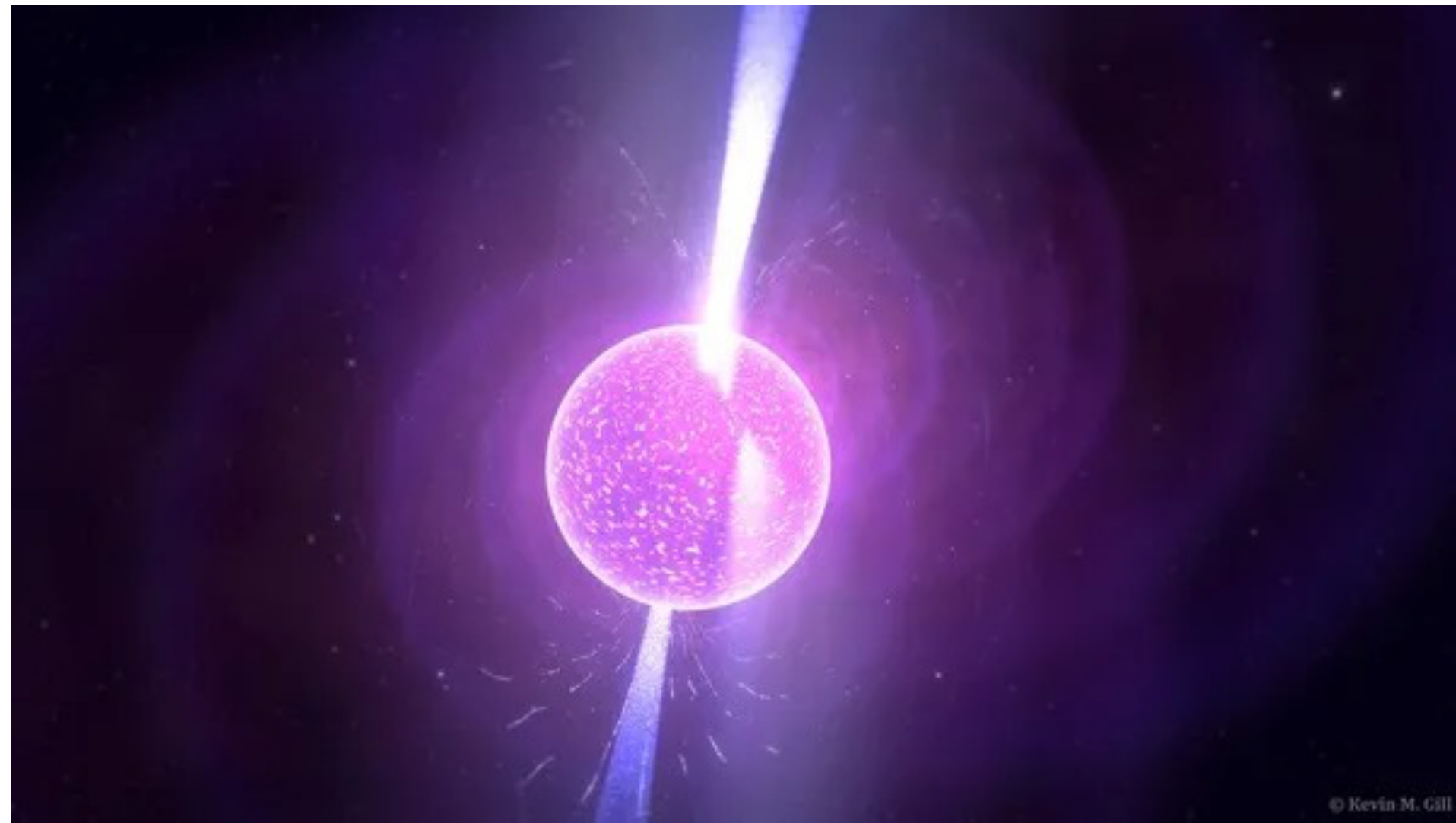


Image credit: Kevin Gill

- $B \sim 10^9 - 10^{14}$ G
- $f_{rot} \sim 0.1 - 740$ Hz
- $\epsilon < 10^{-5}$

Newly born Magnetars

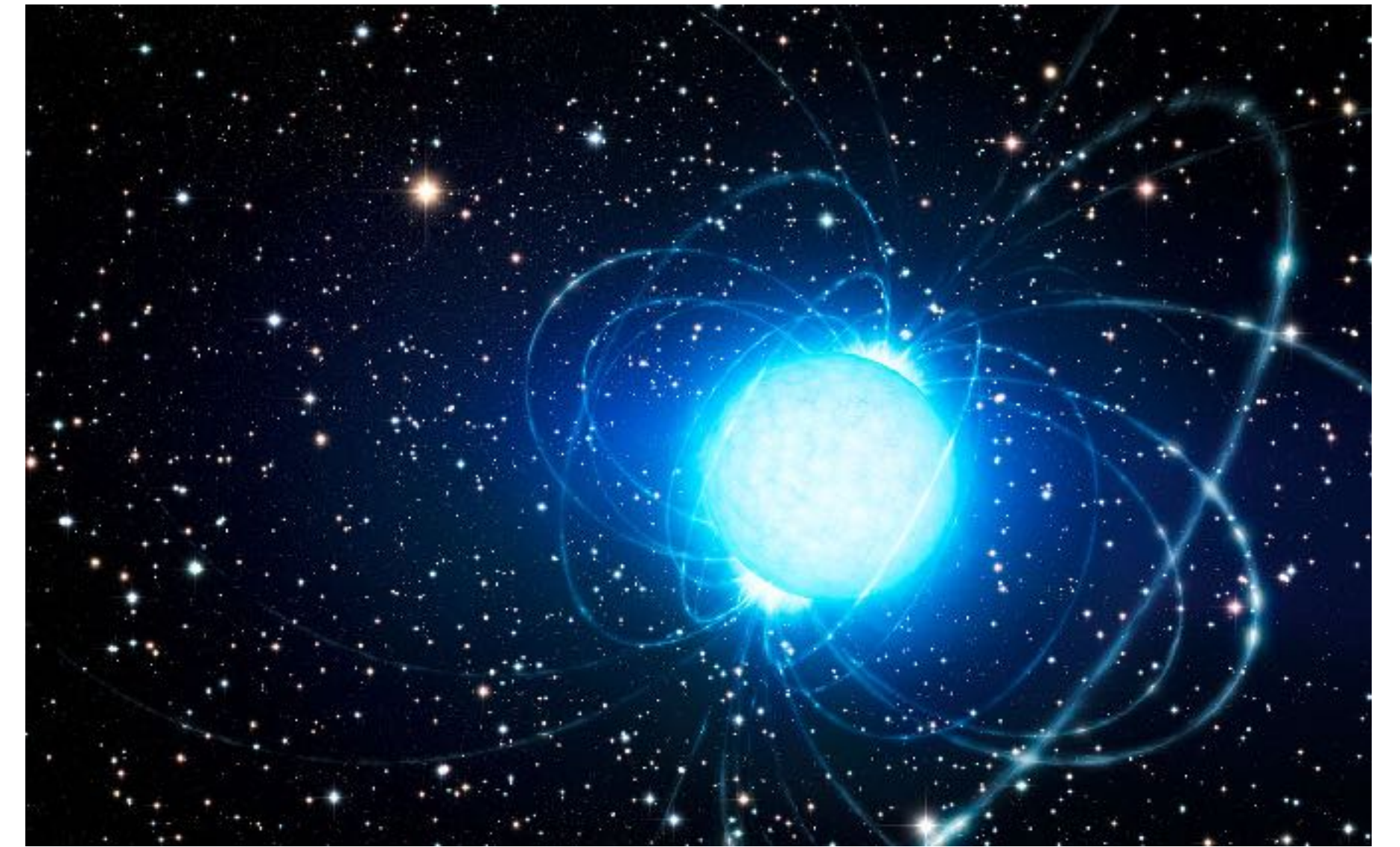


Image credit: ESO/L. Calçada

- $B \sim 10^{15} - 10^{16}$ G
- $f_{rot} \sim 250 - 1000$ Hz
- $\epsilon \sim 10^{-5} - 10^{-3}$

Different kind of searches

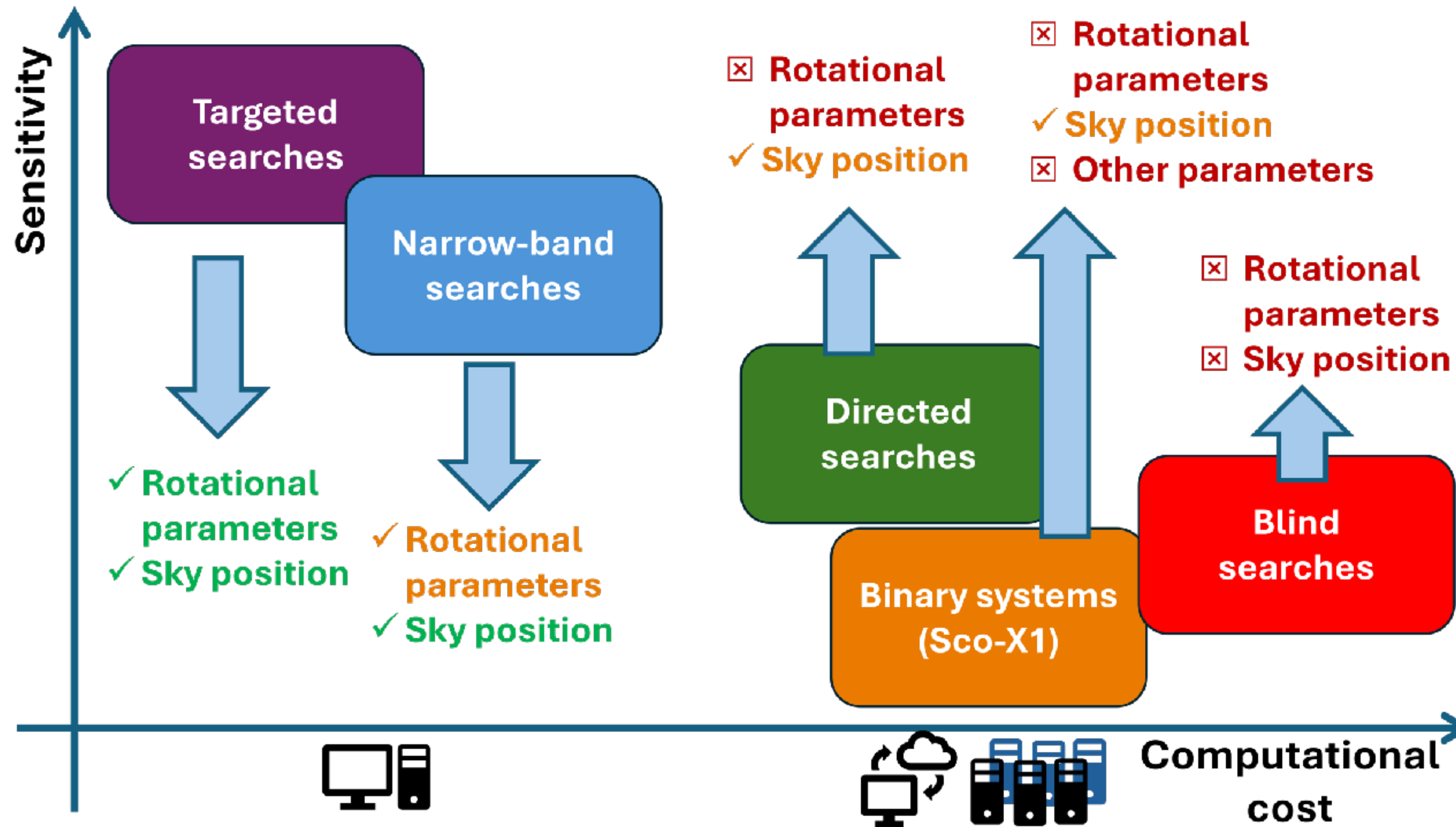


Image credit: Cristiano Palomba

Time-frequency maps

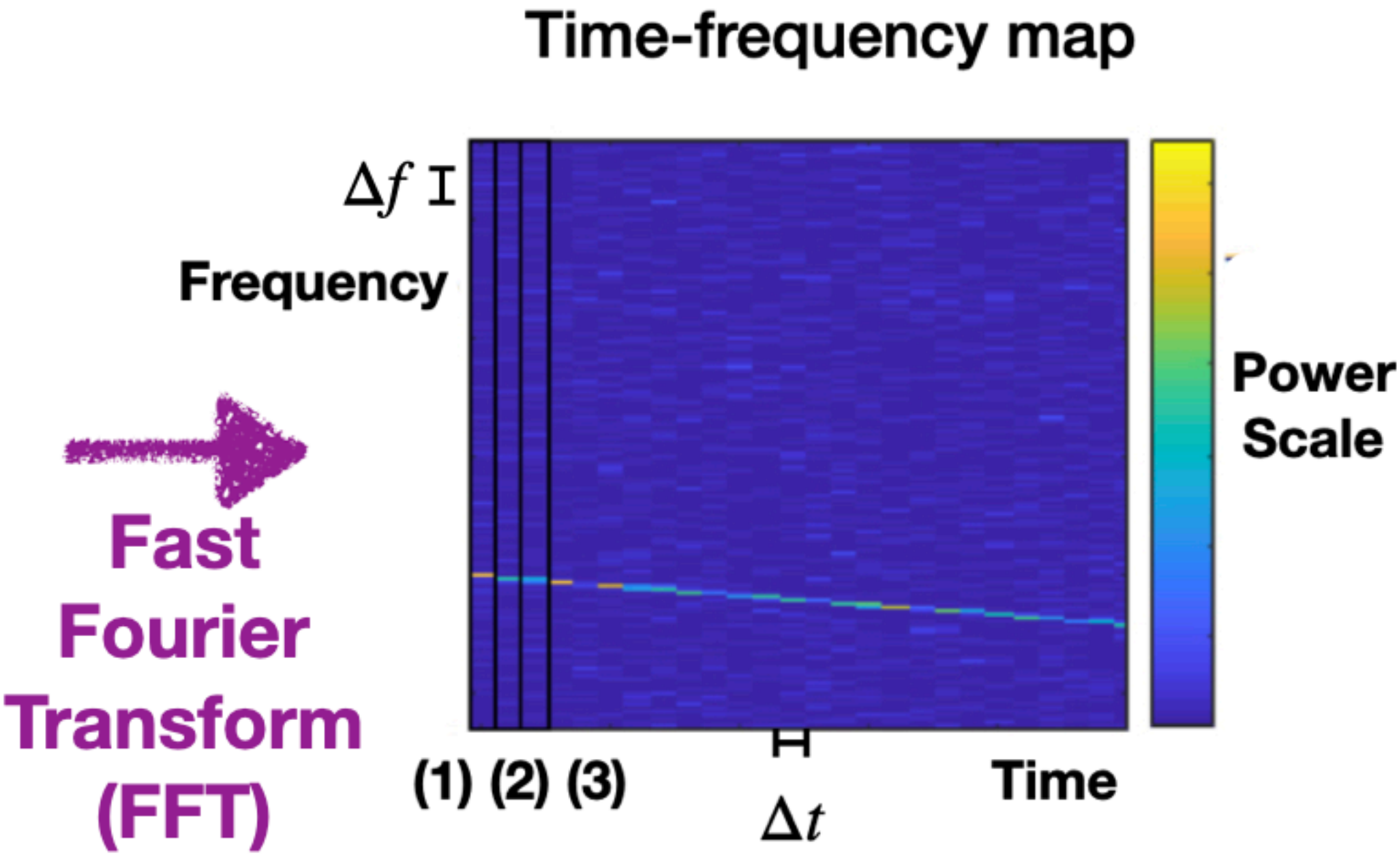
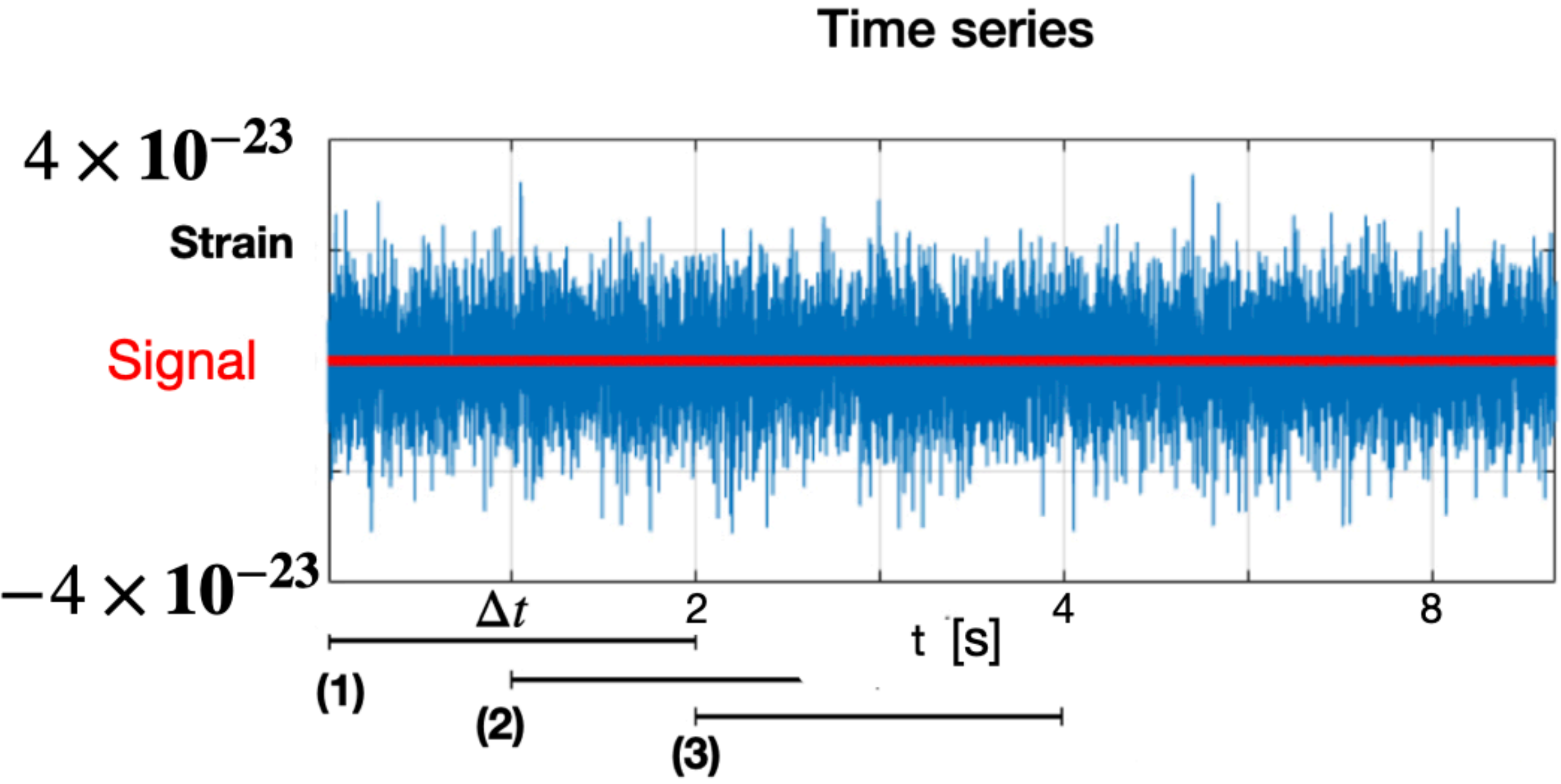


Image credit: Lorenzo Pierini

Machine learning

Dataset

- * Training set
- * Validation set
- * Test set

Loss function

→ It estimates the distance from the current output and the desired output

→ Our goal during the training is to minimize this function

→ The choice of the loss function depends on the choice of the ML model

Dataset preparation

Definition of the model structure

Training

Testing

Machine learning

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- * Training set
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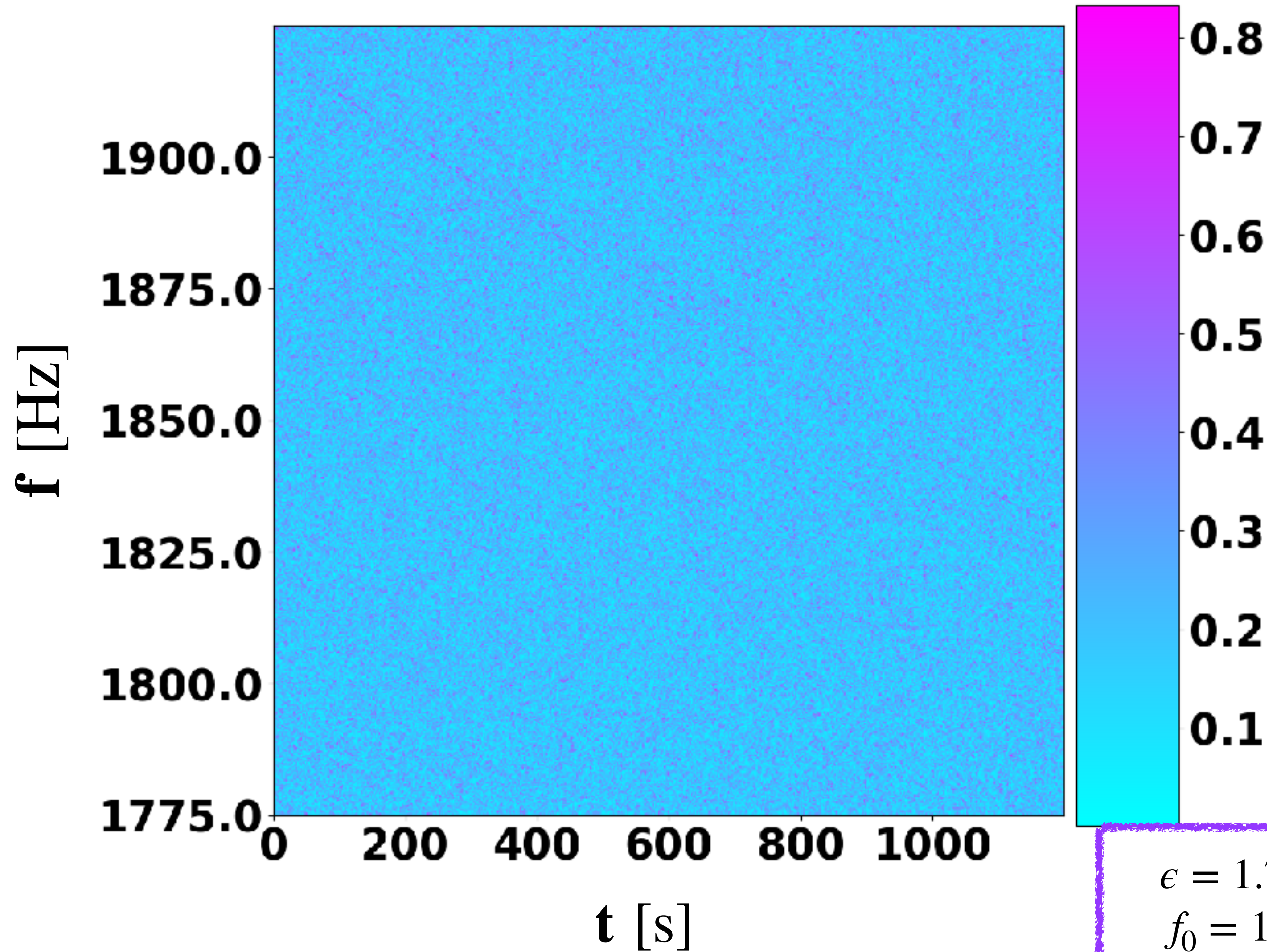
Testing

I have developed two ML models, a **denoiser** and a **classifier**

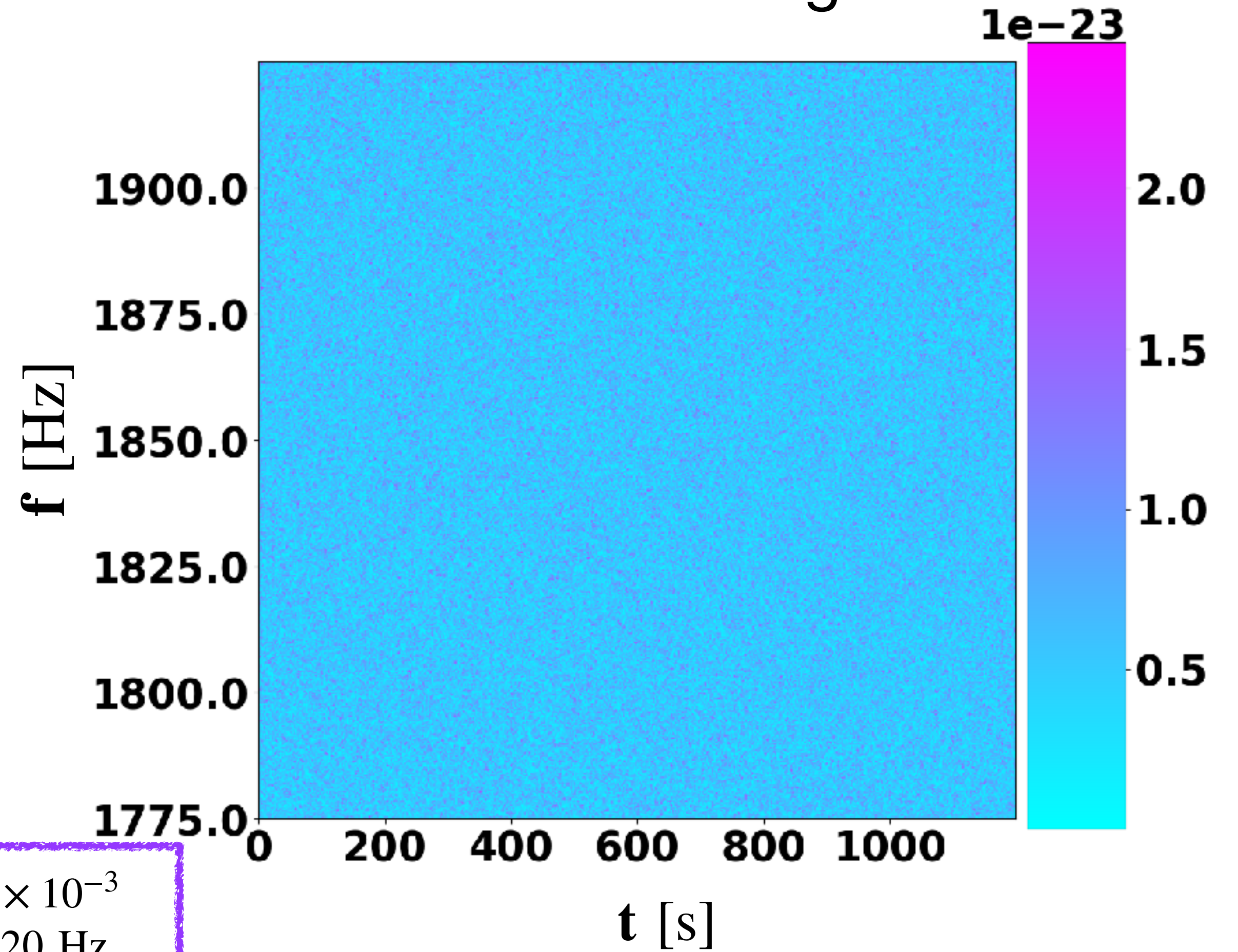
Classifier

Classification of time-frequency maps

Presence of signal



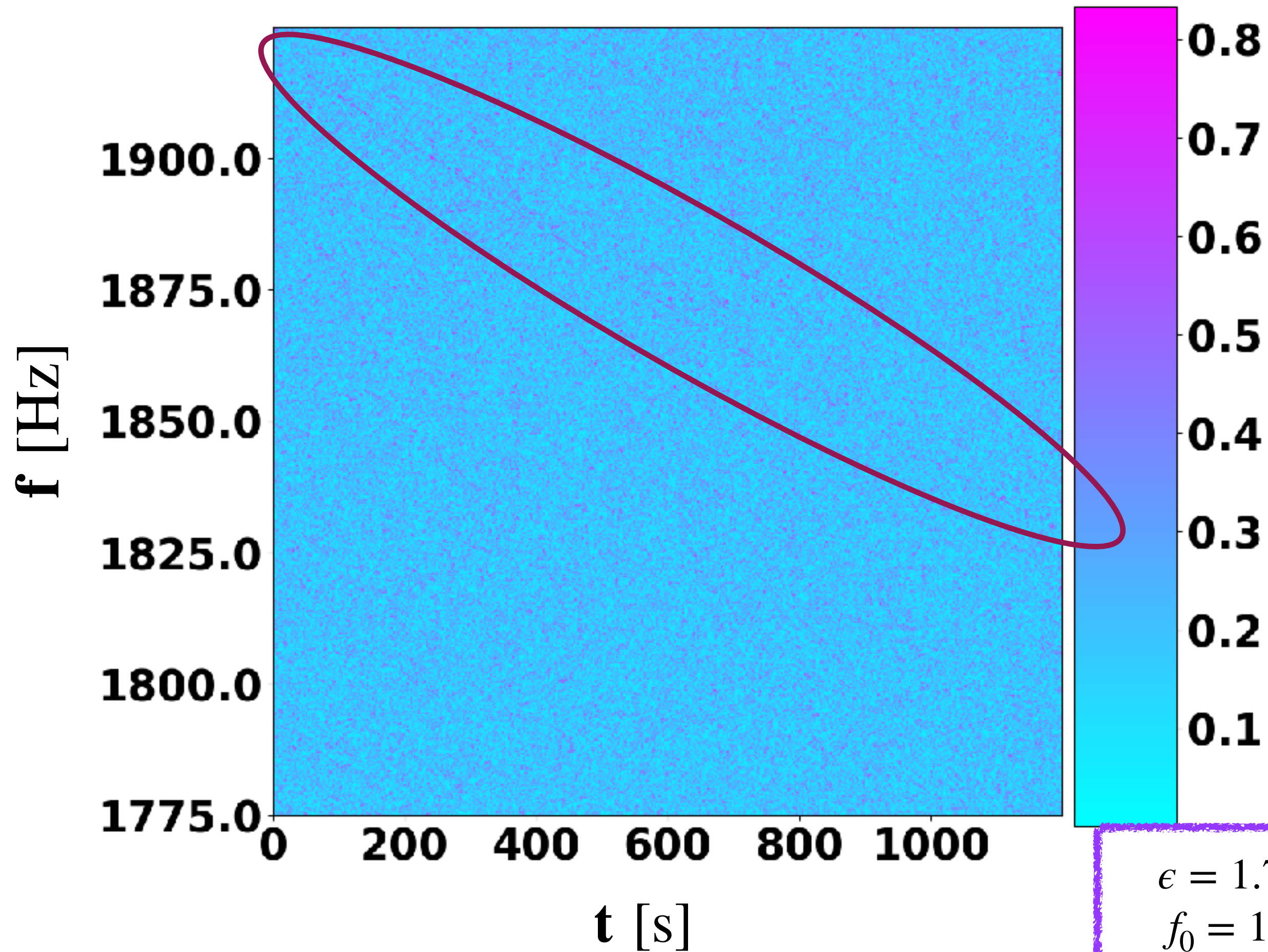
Absence of signal



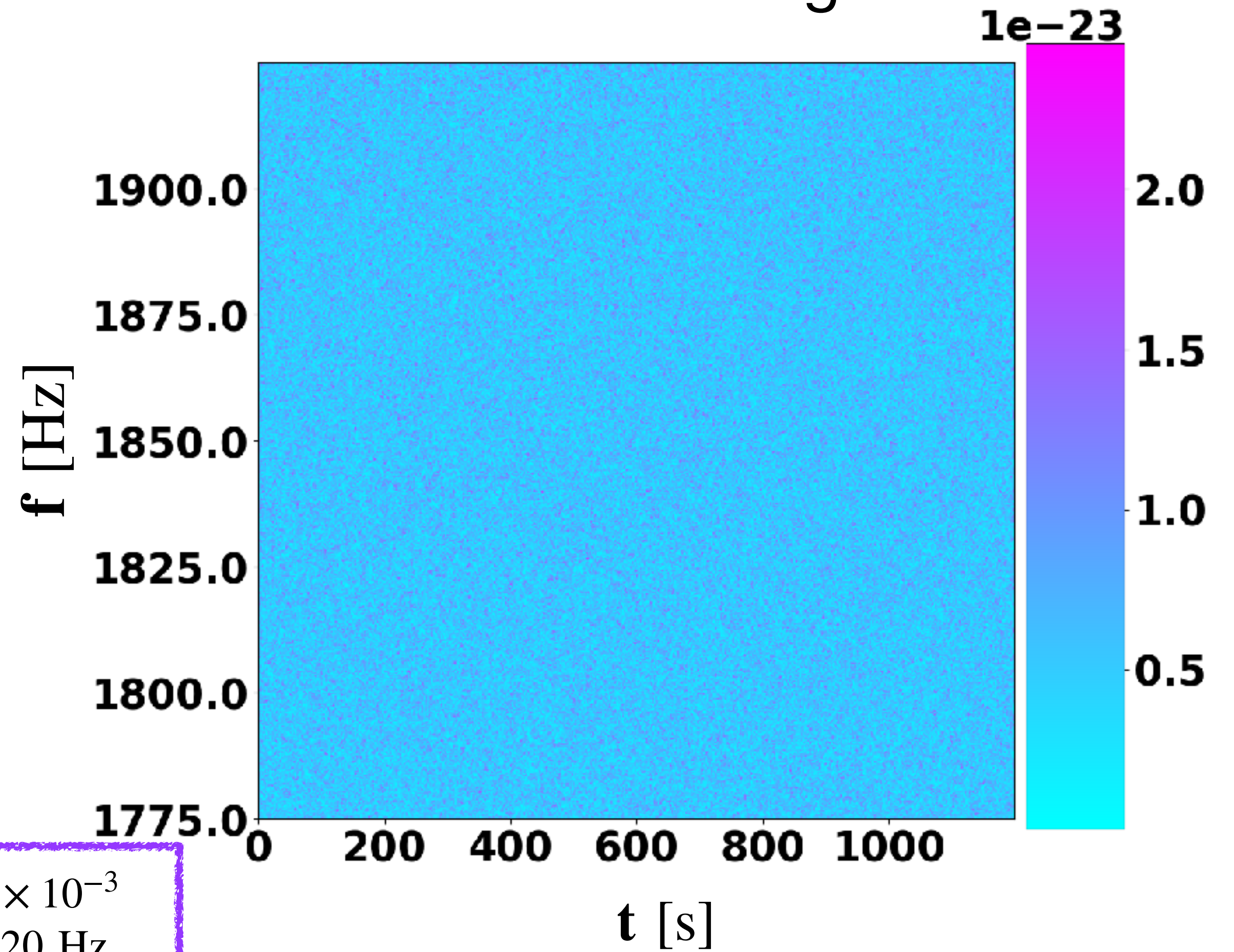
Classifier

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Absence of signal

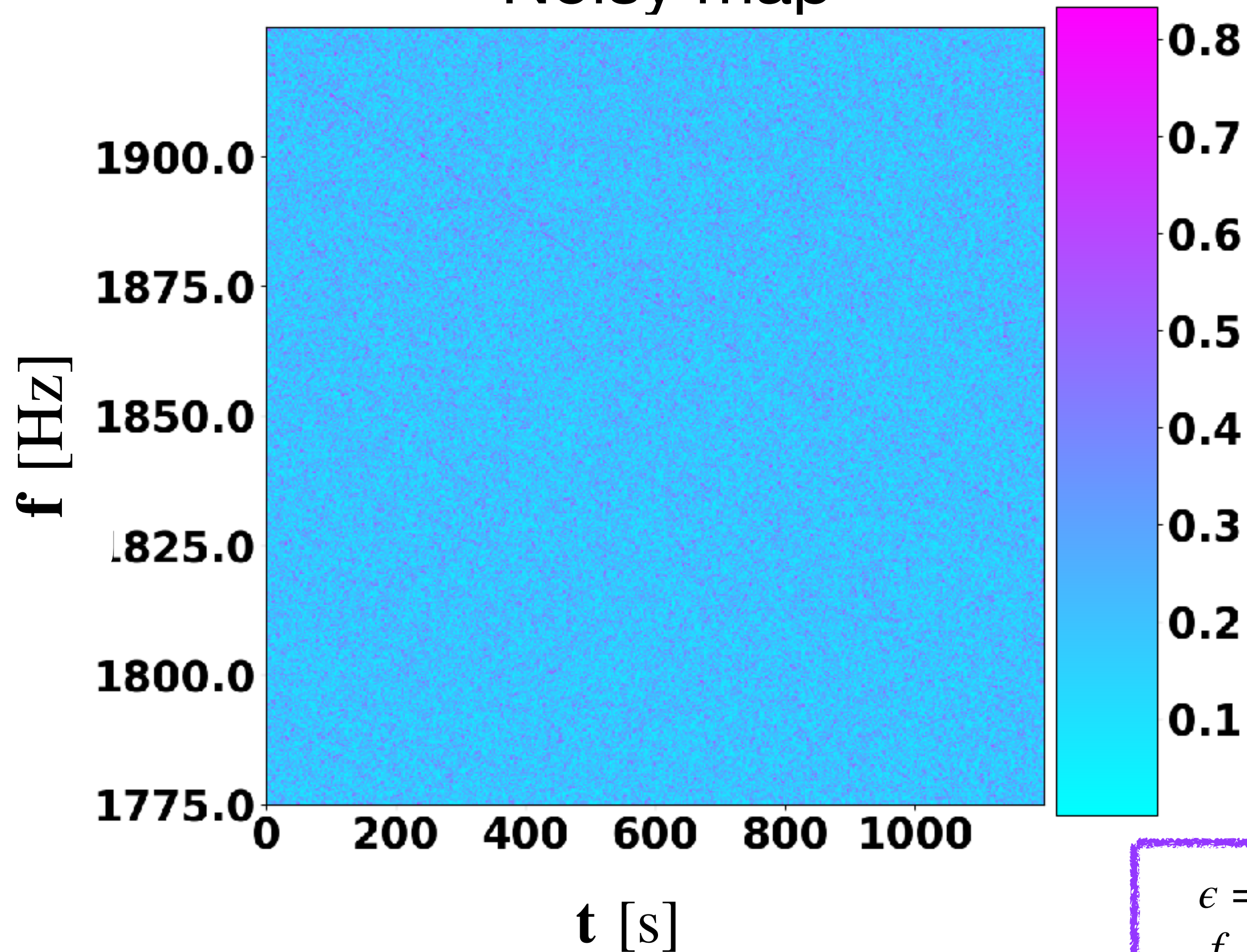


$$\epsilon = 1.7 \times 10^{-3}$$
$$f_0 = 1920 \text{ Hz}$$

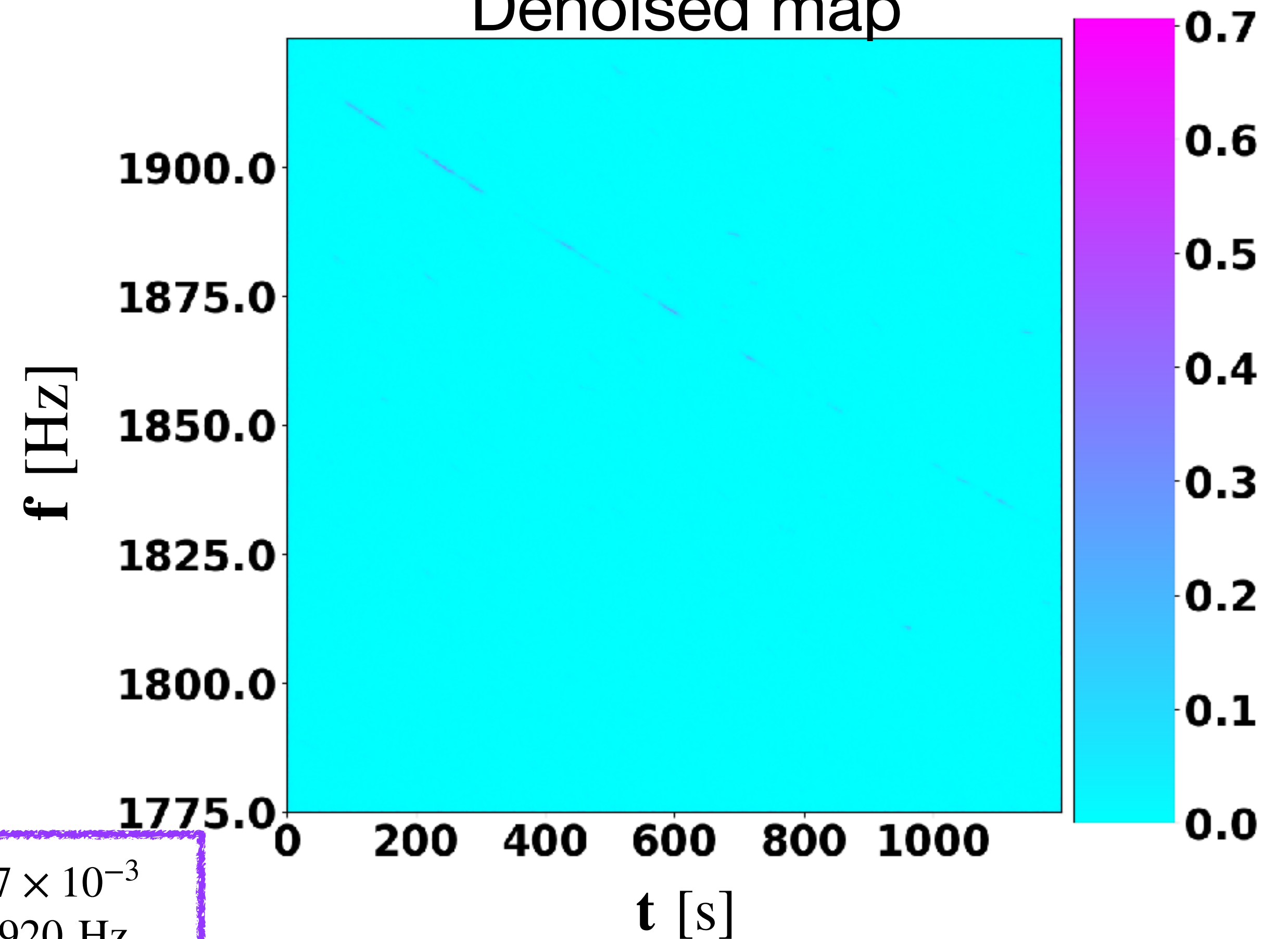
Denoiser

It reduces the noise level of the image while preserving a significant fraction of the signal

Noisy map

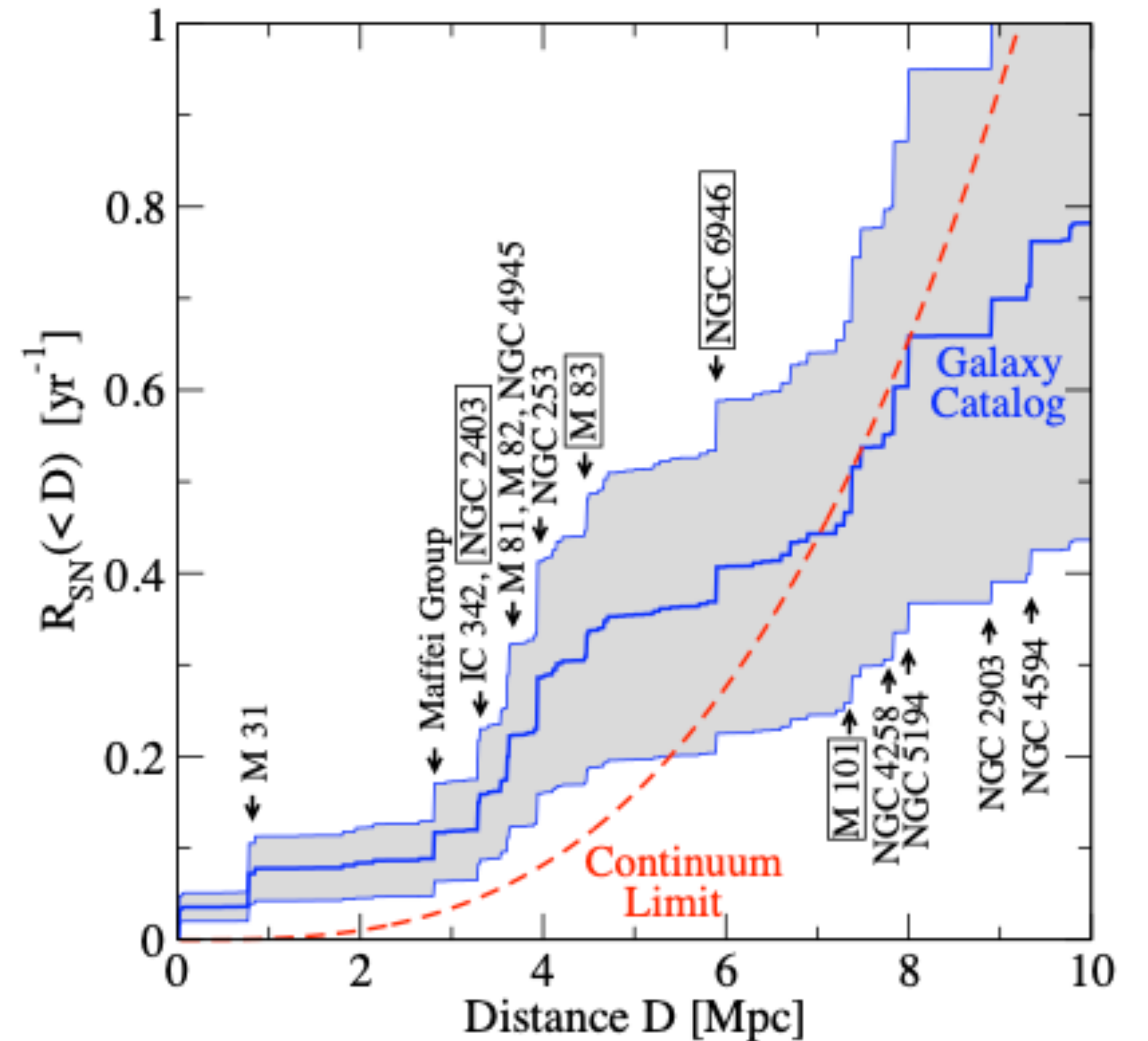
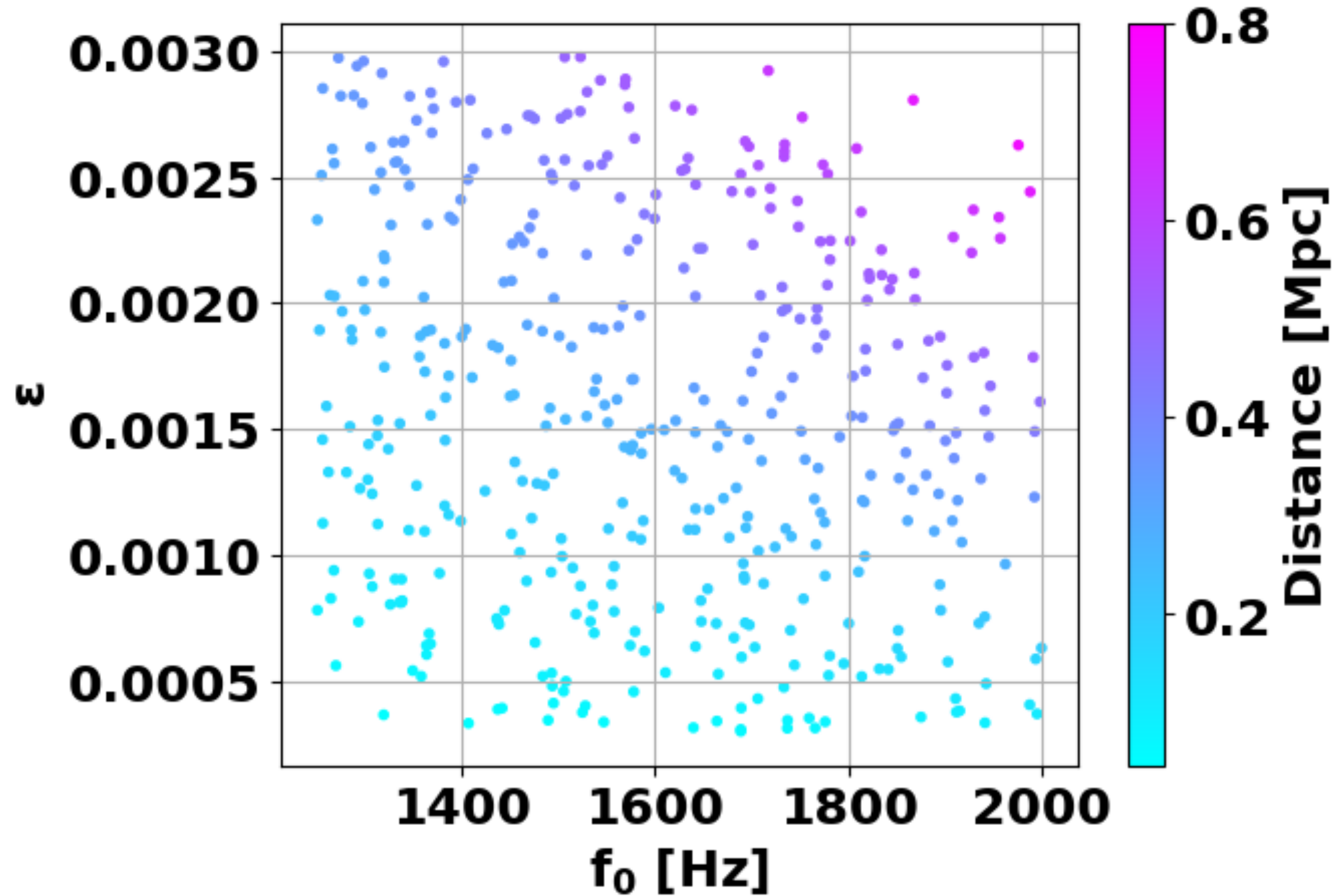


Denoised map



$$\epsilon = 1.7 \times 10^{-3}$$
$$f_0 = 1920 \text{ Hz}$$

Preliminary conclusions



We need to reach higher distances to increase the probability to see an event

Hyper-Kamiokande Proto-Collaboration et al. Hyper-Kamiokande
Design Report

Conclusions

It is important to detect GWs emitted by NSs in order to understand how matter behaves in such extreme conditions

→ It is an open research field

→ We are studying frontier physics

What is next?

→ Improve the already existing data analysis techniques

→ Develop new techniques

→ New generation interferometers

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It is important to detect GWs emitted by NSs in order to understand how matter behaves in such extreme conditions

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**THANK YOU
FOR YOUR
ATTENTION**

Backup slides

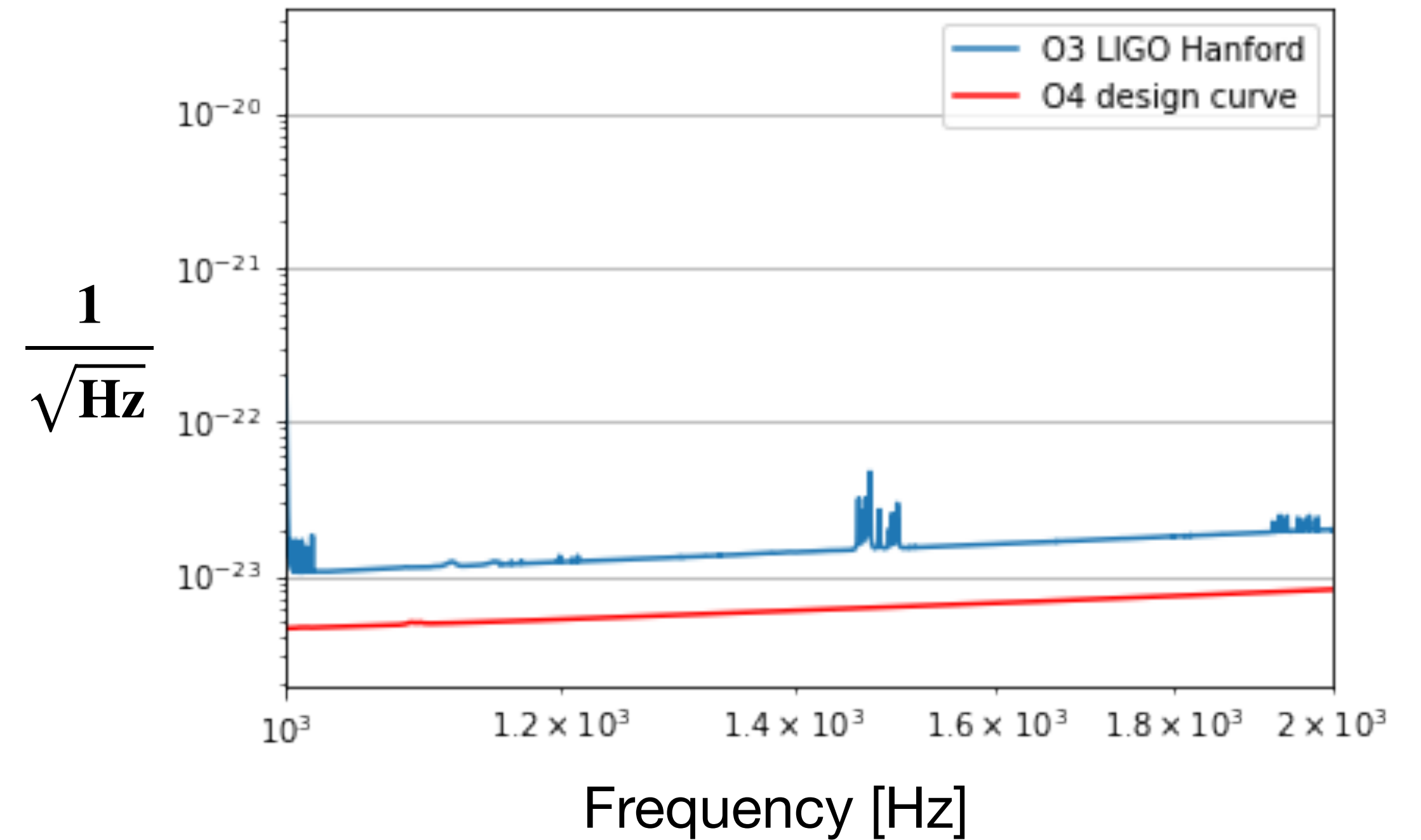
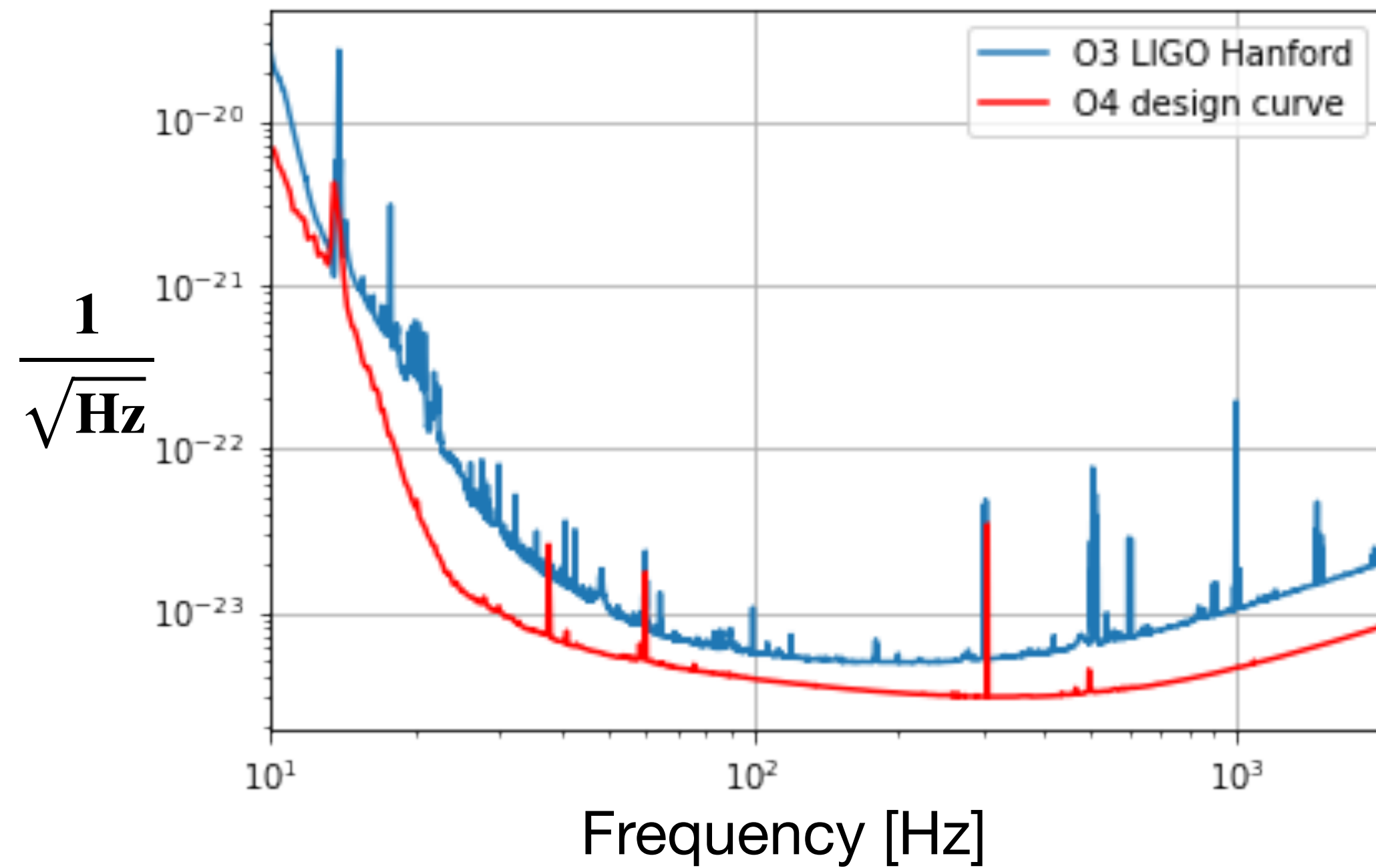
Noise

Simulated data:



Simulated noise according to the noise curve

Gaussian frequency dependent noise



Signal

**GW
amplitude**

$$h_0(t) = \frac{4\pi^2 G I f(t)^2}{c^4 d} \epsilon$$

Distance of the source

Frequency variation

$$\dot{f}(t) \sim -\epsilon^2 f(t)^5 \quad \rightarrow \quad f(t) = f_0 \left(1 + \frac{t \epsilon^2 f_0}{const} \right)^{-\frac{1}{4}}$$



Fixed initial amplitude : 2×10^{-23}

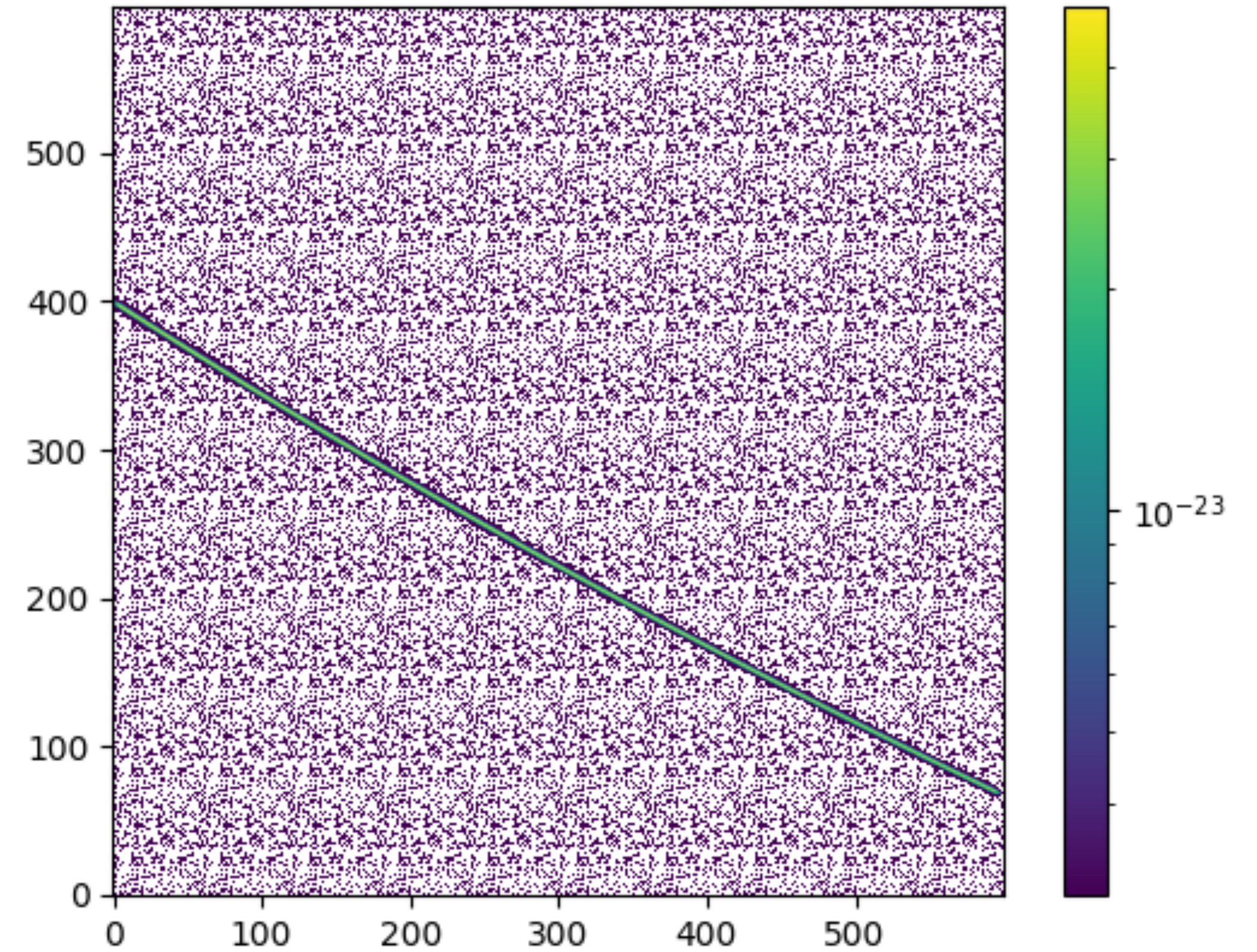
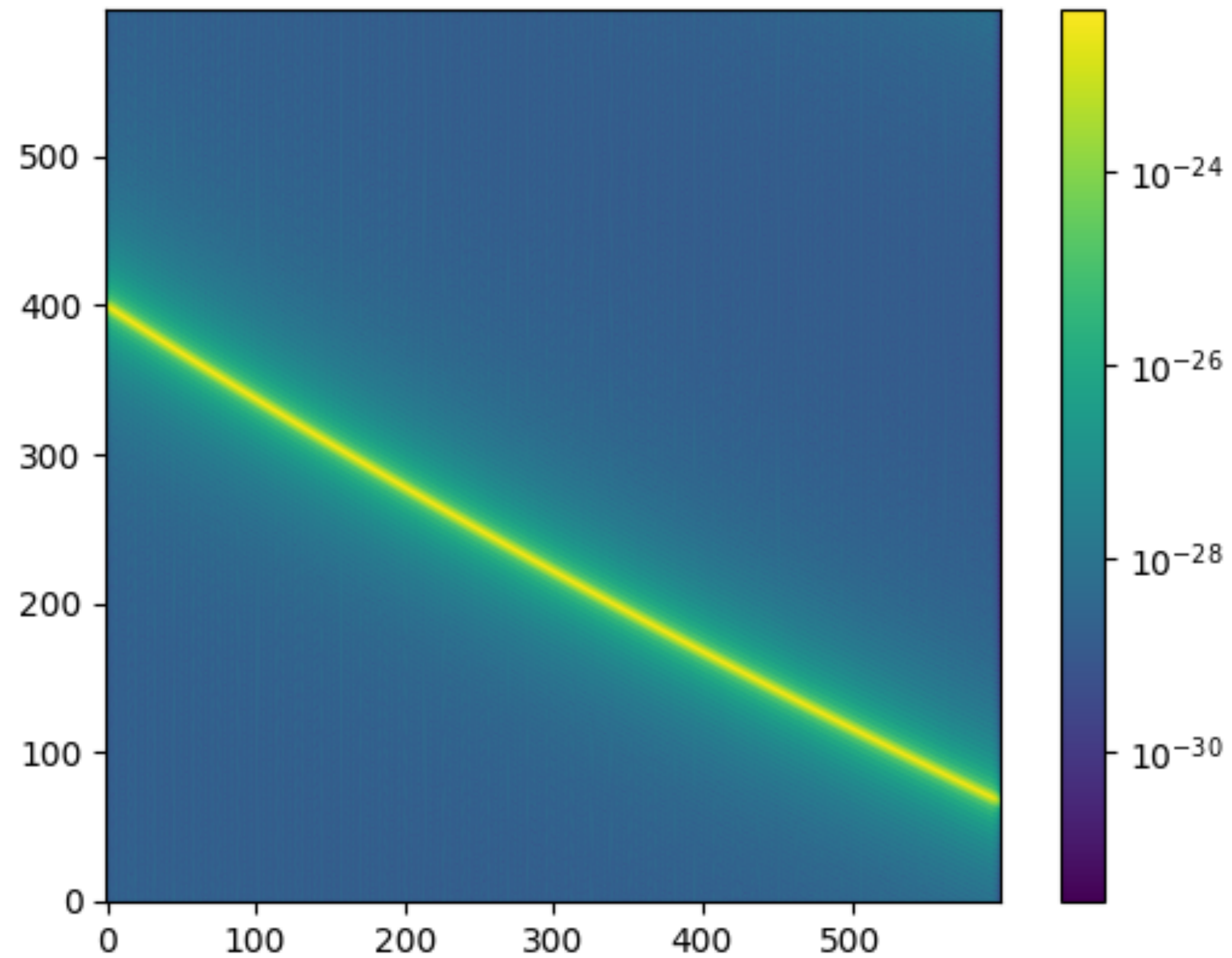


Fixed inclination angle: $\iota \sim 56^\circ$

Parameters range: $\epsilon \in [3,30] \times 10^{-4}$ $f_0 \in [1.25,2.00]$ kHz

We are not focusing on continuous signals

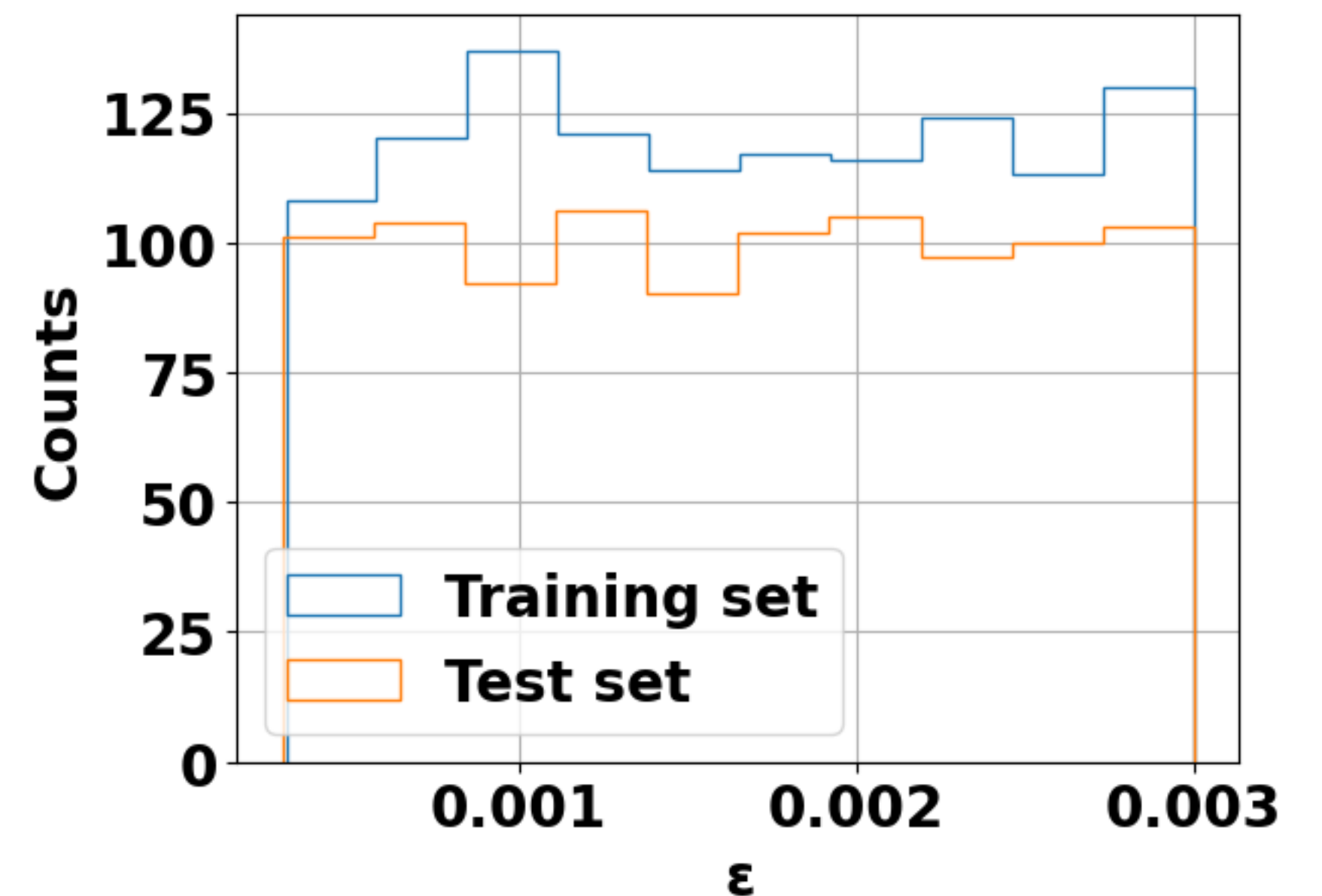
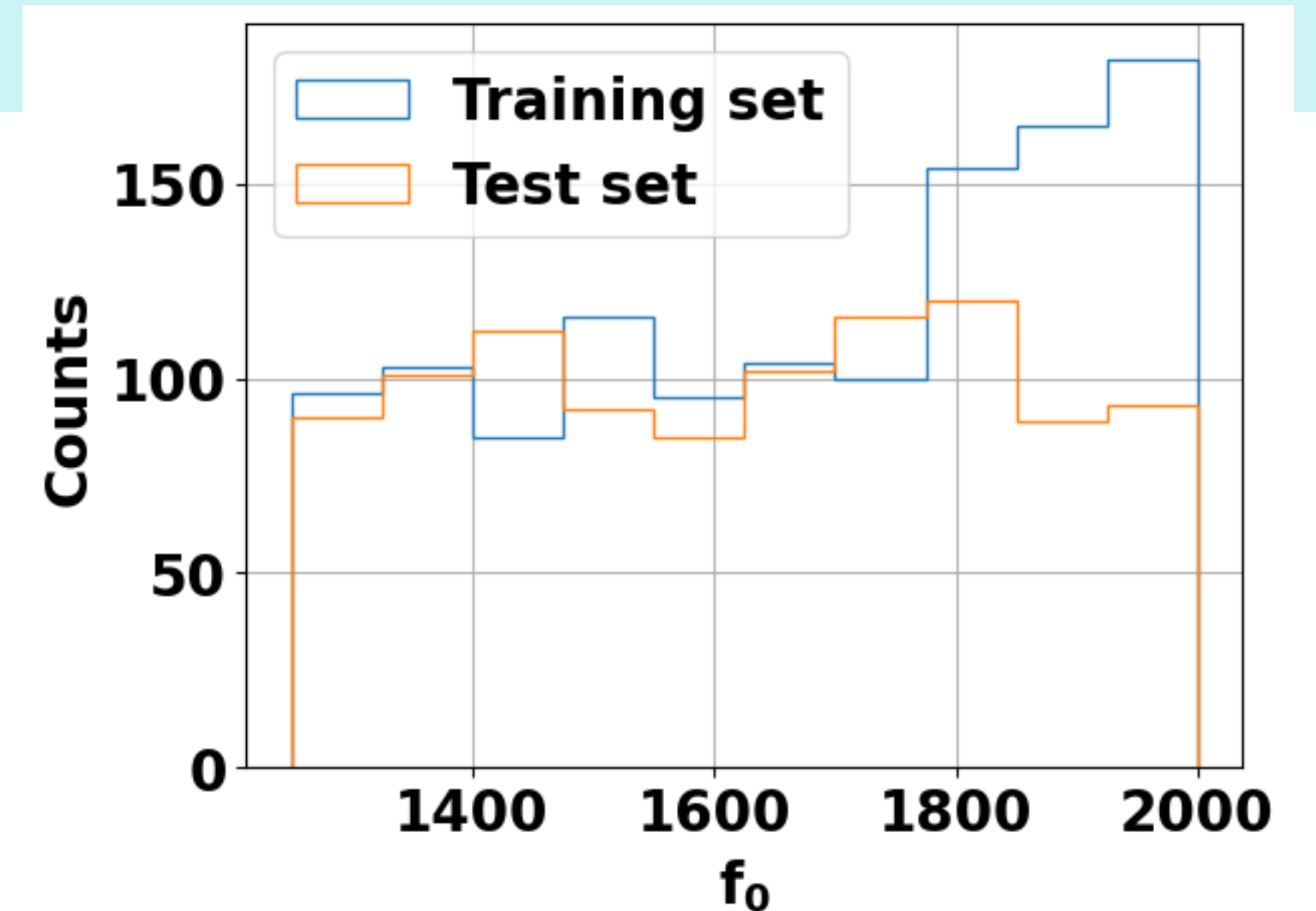
Artefacts



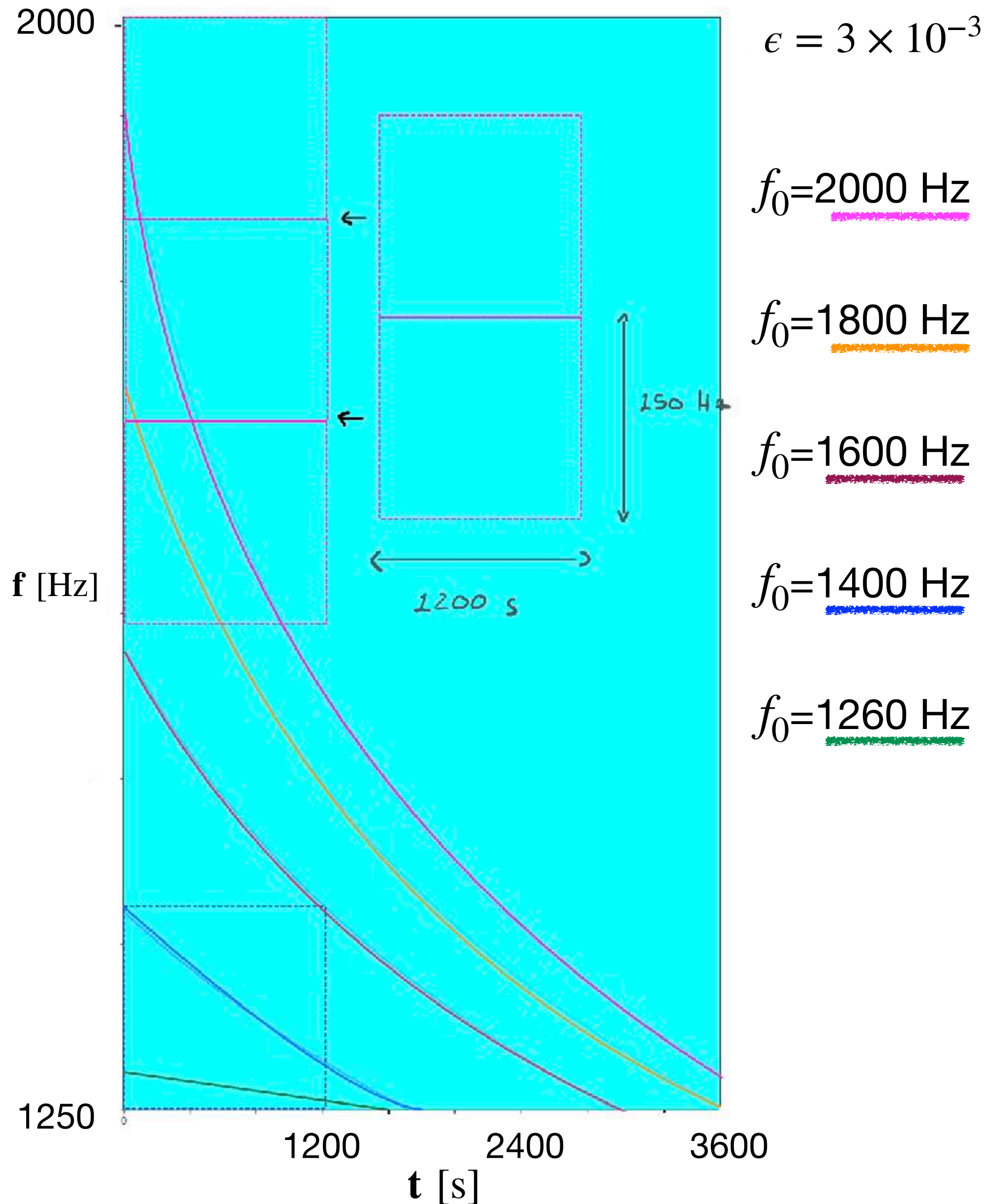
Dataset

Number of signals:
1200 training, 1200 testing

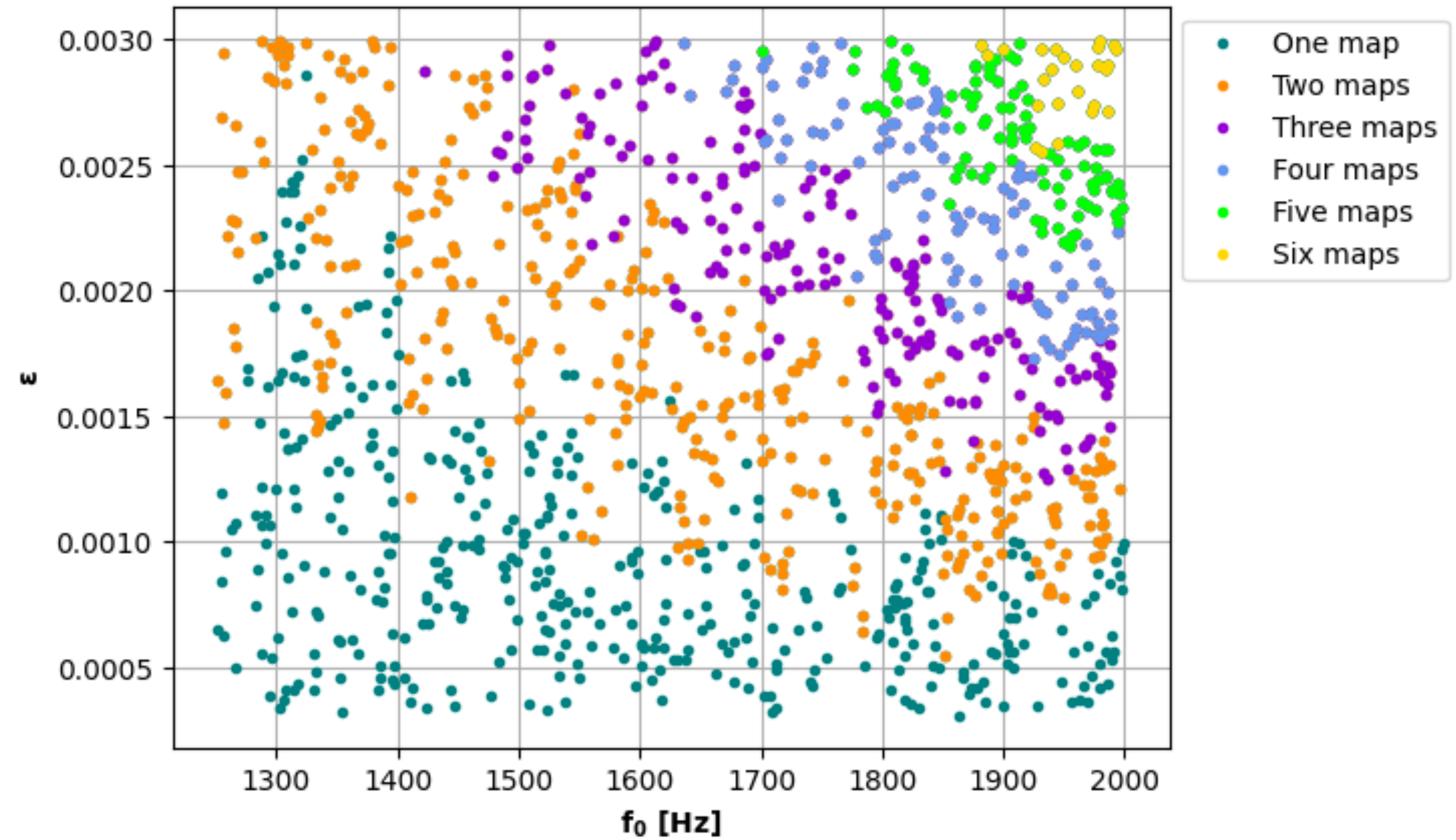
- * **Training set:** 2226
- * **Validation set:** 556
- * **Test set:** 2177
- * **Threshold 10^{-23} :** 5×10^{-25}
- * **Normalization:** maximum of noise and signal maps group



Maps construction



Number of maps crossed by a signal

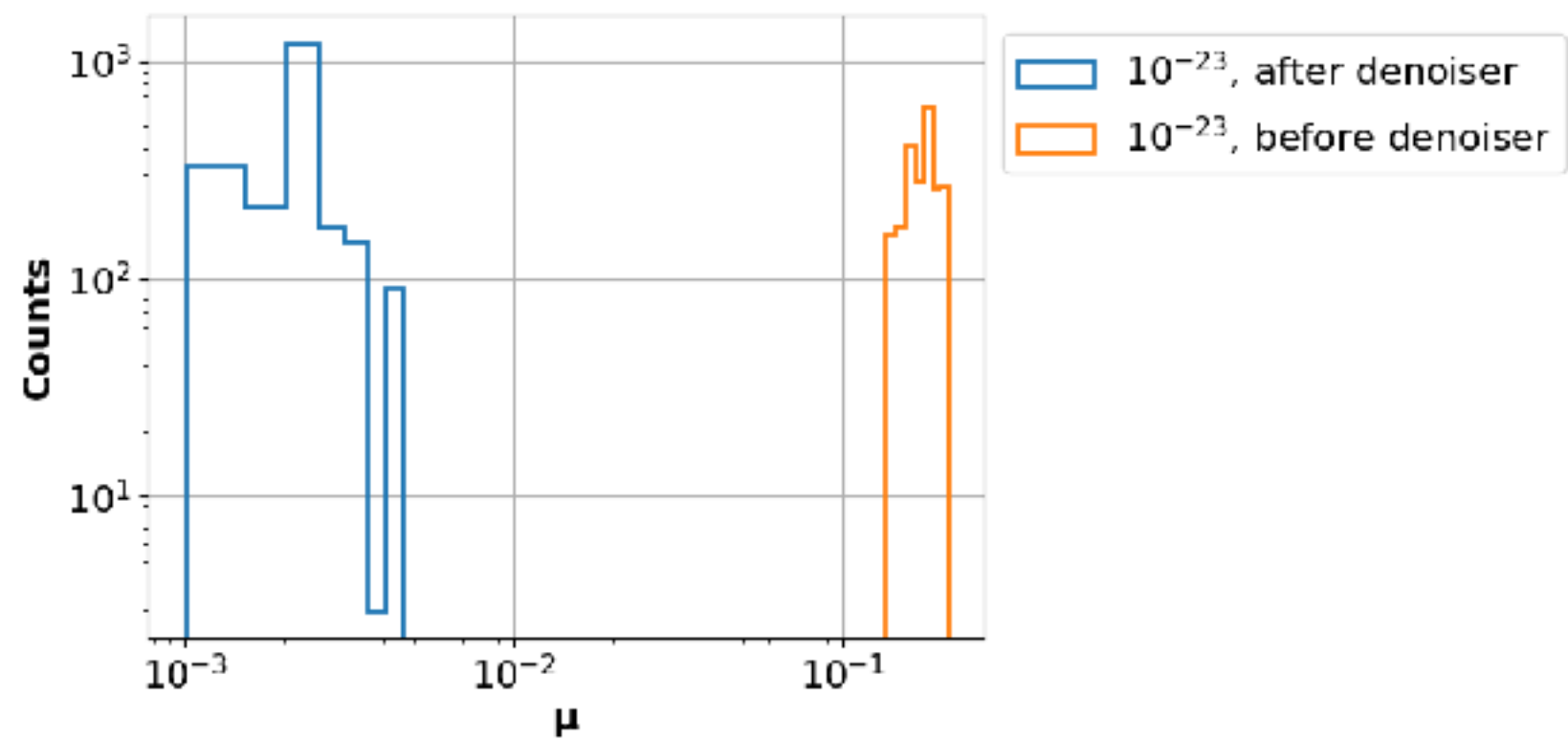


The number of maps per signal depends on the parameters

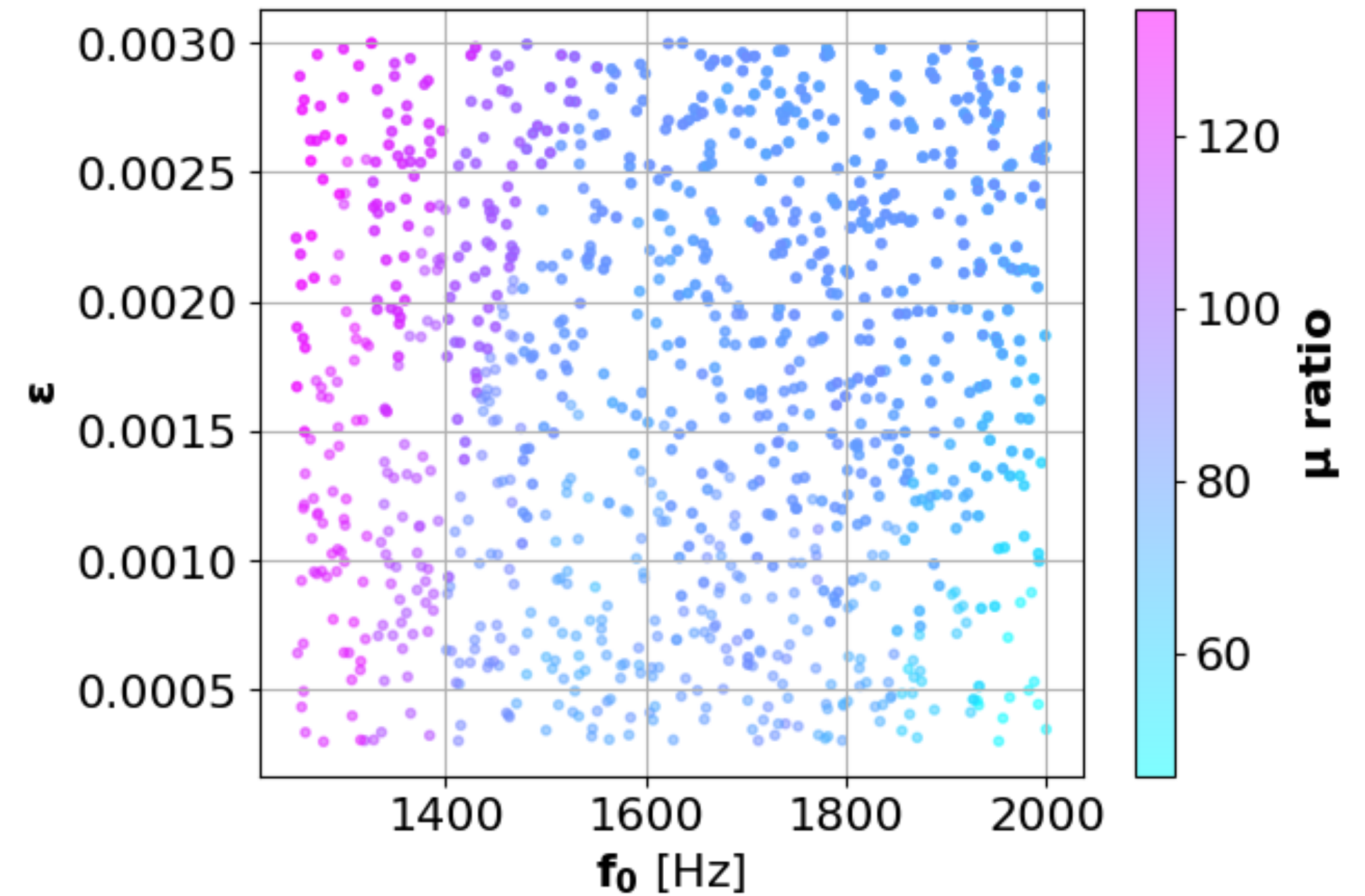
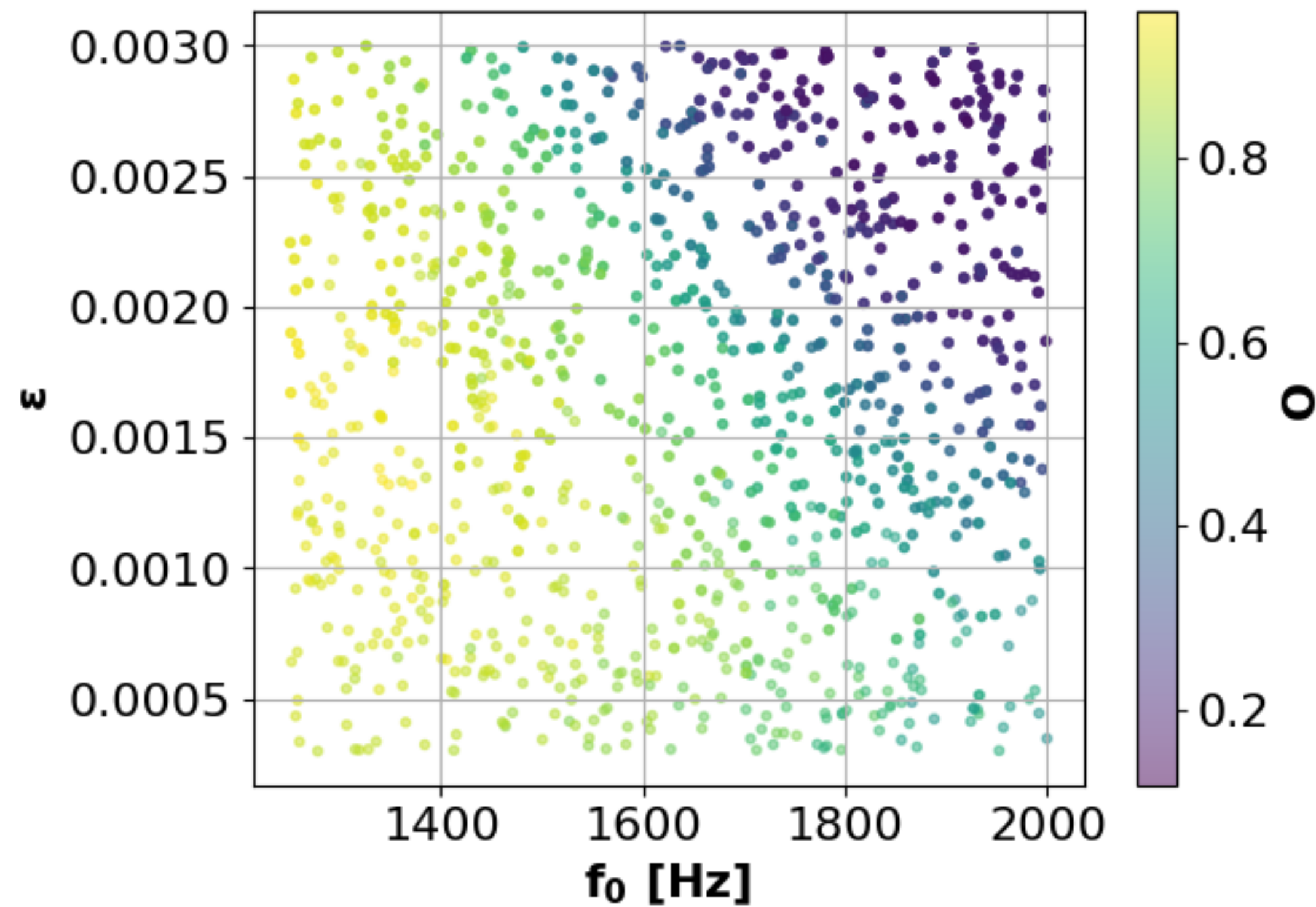


It is enough to tag right one map to have a trigger

Denoiser



Removing noise

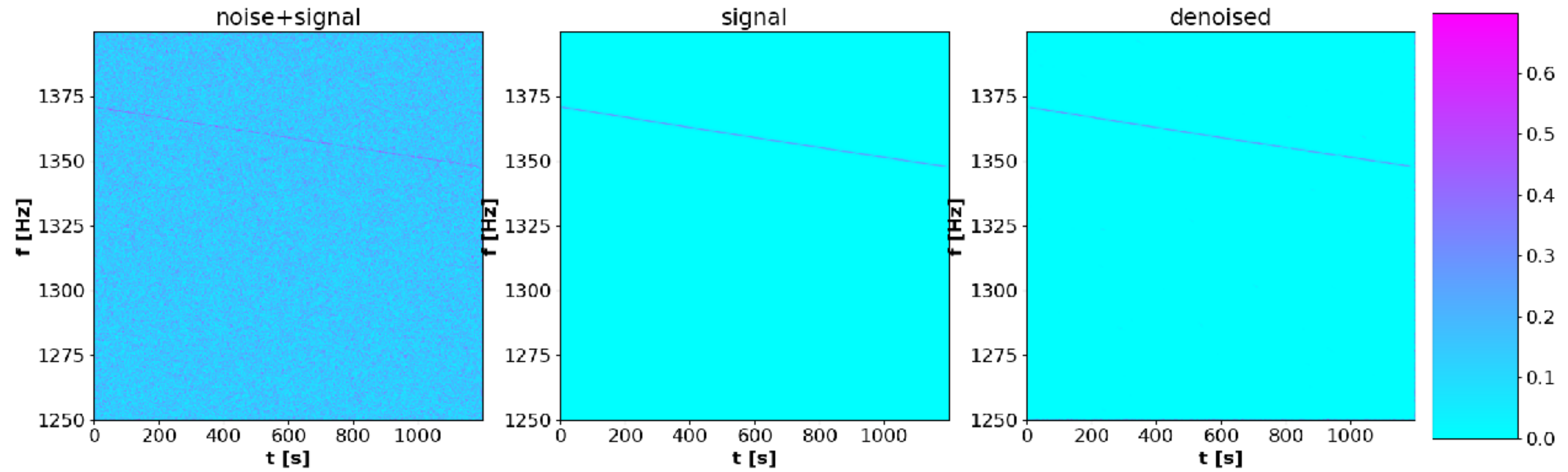


Preserving the signal

Overlap

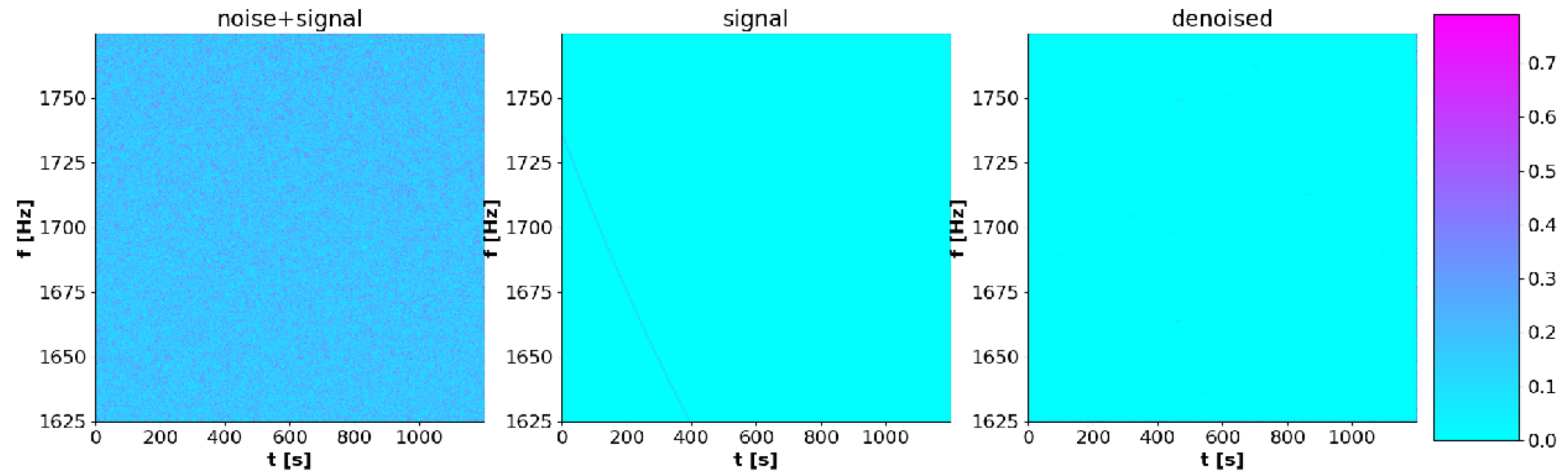
$$\epsilon = 1.3 \times 10^{-3}$$
$$f_0 = 1370 \text{ Hz}$$

$$\mathcal{O} = 0.96$$

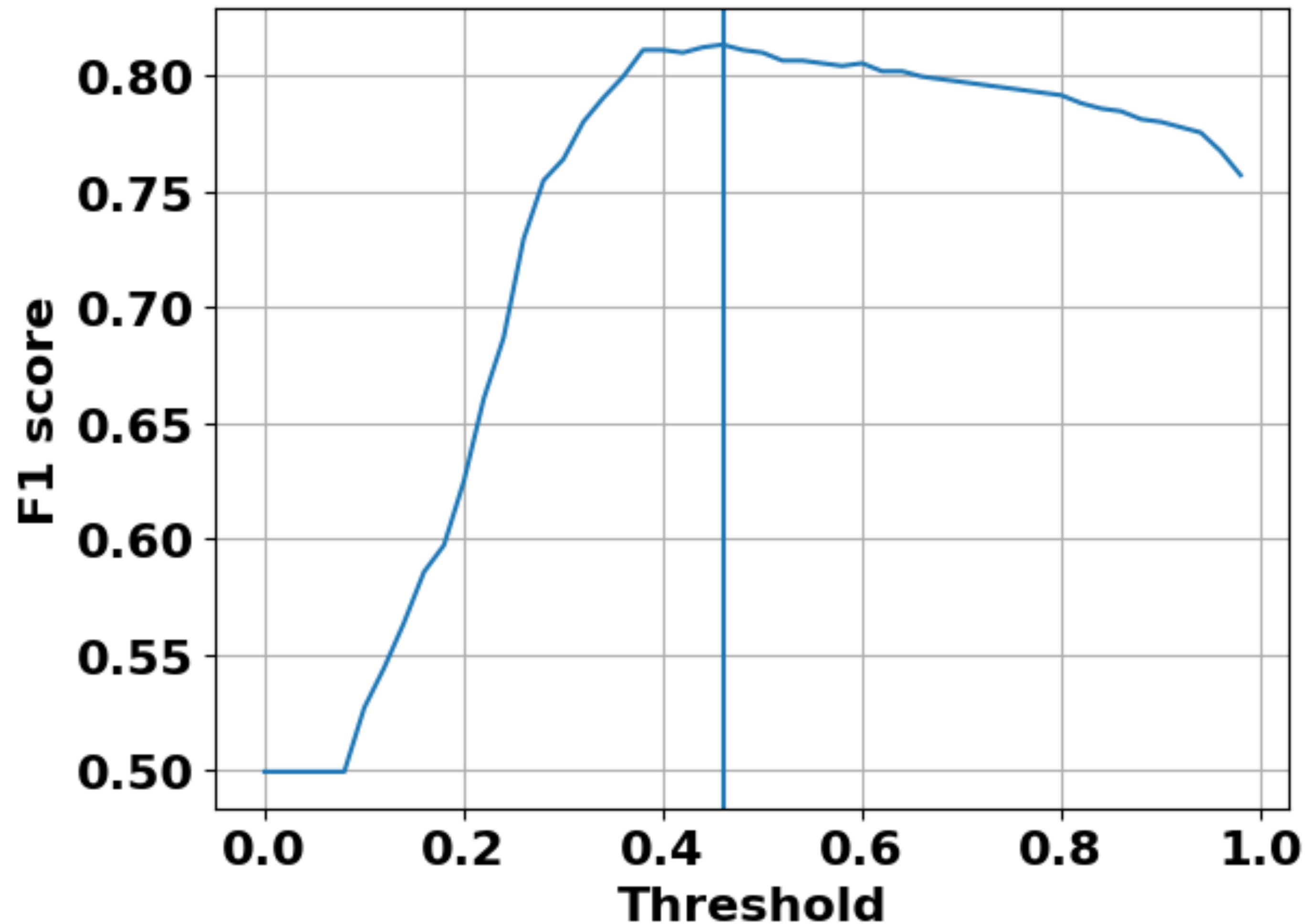


$$\epsilon = 3 \times 10^{-3}$$
$$f_0 = 1737 \text{ Hz}$$

$$\mathcal{O} = 0.11$$



F1 score

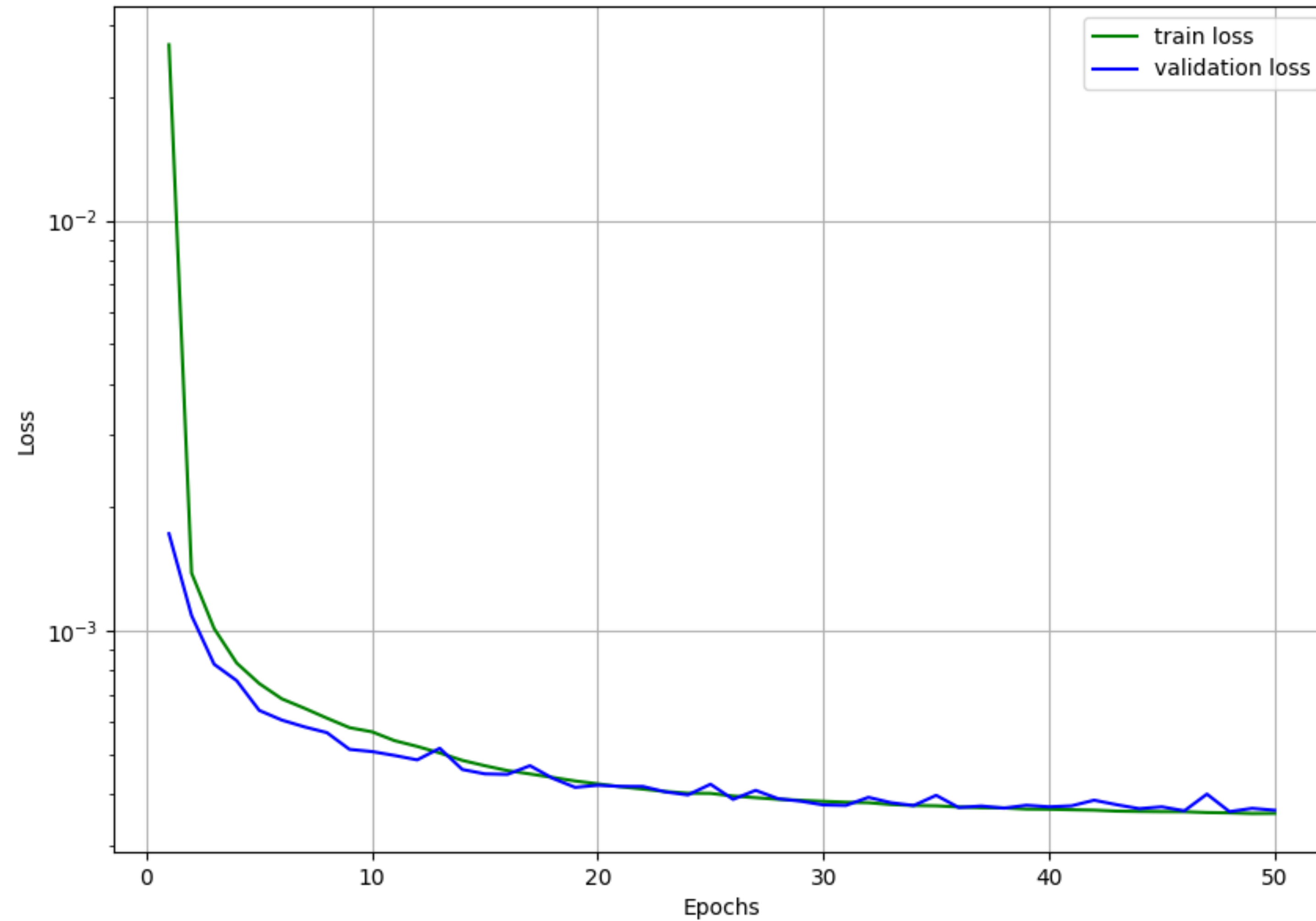


$$p = \frac{\text{true positive}}{\text{predicted positive}}$$

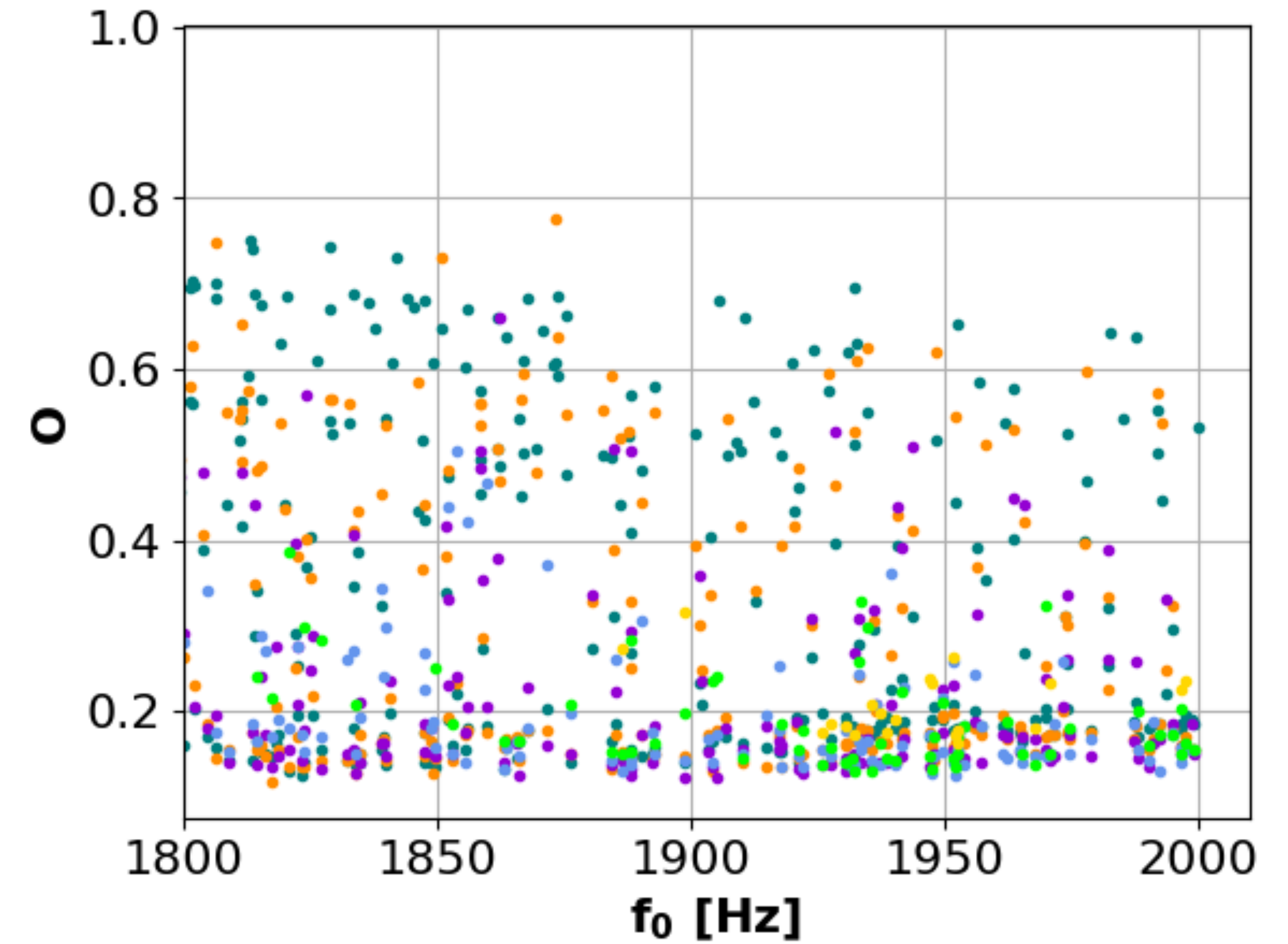
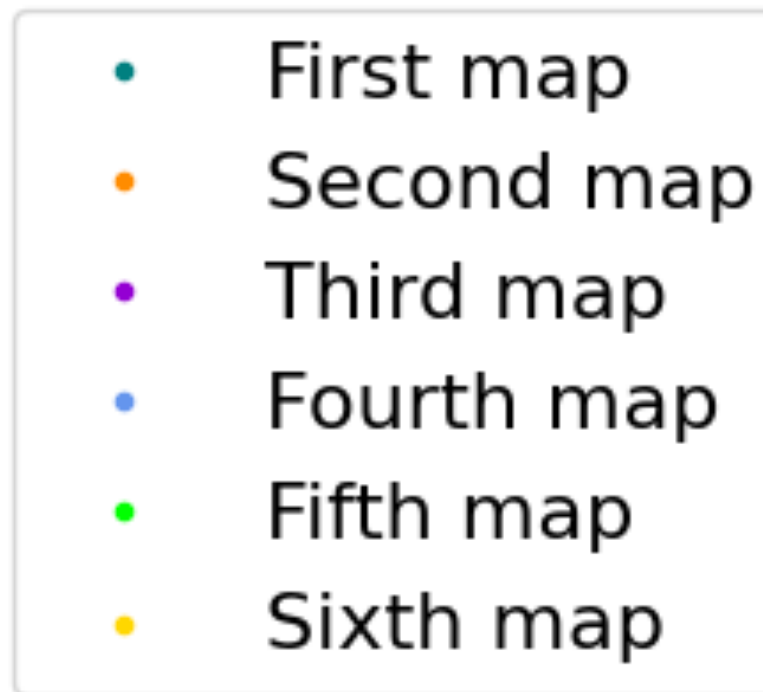
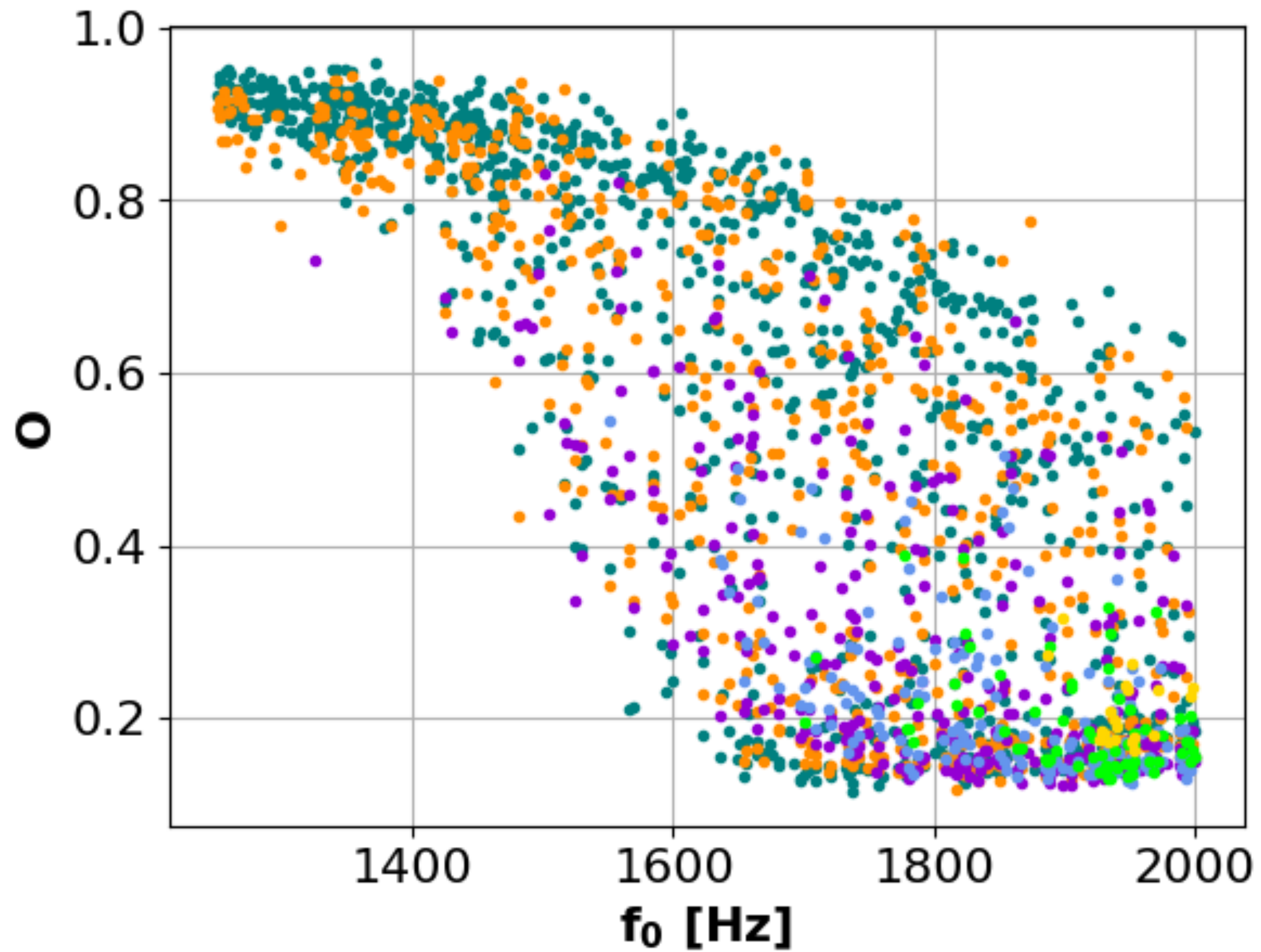
$$r = \frac{\text{true positive}}{\text{true positive} + \text{false negative}}$$

$$F_1 = 2 \frac{p \cdot r}{p + r}$$

Loss function, denoiser



Overlap vs #maps



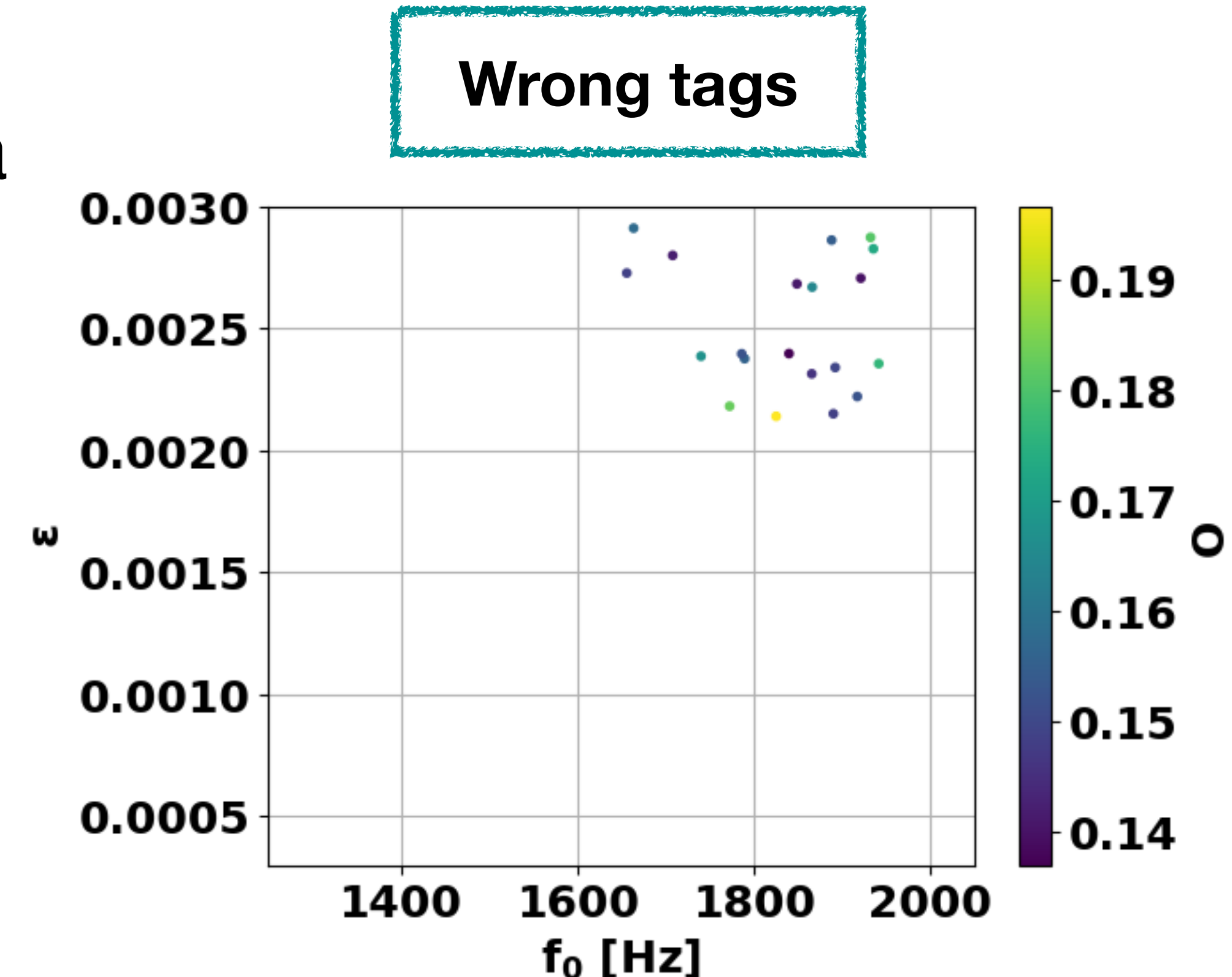
Efficiency and wrong tags

→ The frequency can vary rapidly in time and the signal can cross more maps

→ It is enough to tag right one map to have a trigger

The efficiency of our method is 90%

→ **Right tags:** 182 signals over a sample of 202



Comparison with other methods for long-transient signals

Collaboration paper: *Search for Gravitational Waves from a Long-lived Remnant of the Binary Neutron Star Merger GW170817*, Abbott et al. 2019

**Generalized
FrequencyHough**

$$\epsilon = 1.44 \times 10^{-3} \quad f_0 = 1740 \text{ kHz} \quad \Delta t = 2 \text{ s} \quad \underline{I = 4.34 \times 10^{38} \text{ kg m}^2} \quad \longrightarrow \quad d_{FrH} = 0.242 \text{ Mpc}$$

This method

Computational cost: 1 GPU for ~ 3 hours, smaller than GFh

$$\epsilon = 1.77 \times 10^{-3} \quad f_0 = 1753 \text{ kHz} \quad \Delta t = 2 \text{ s} \quad \underline{I = 1.4 \times 10^{38} \text{ kg m}^2} \quad \longrightarrow \quad d = 0.402 \text{ Mpc}$$

\longrightarrow Detector sensitivity improved by a factor of 3 in the [1700, 1800] frequency band

We gained a factor of ~ 2 in distance