Search for LENSED GW events with MACHINE LEARNING

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Background: An artist's illustration of two black holes merging and creating ripples in spacetime known as gravitational waves. (Image credit: LIGO/T. Pyle)

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1. INTRODUCTION

- A **gravitational wave (GW)** is a disturbance in the fabric of spacetime, caused by the acceleration or movement of massive objects.

- Gravitational wave search promises to be an important part of the future of Physics, which makes necessary a way of analyzing the data in a fast and trustworthy way.

- We focus on GWs produced by Binary Black Holes.

1. INTRODUCTION

- One of the predictions of GR is that GW can suffer from **lensing**. Just as waves of light are lensed when interacting with a convex-shaped material, gravitational waves can experience a similar phenomenon.

- The search for **lensing** signatures within gravitational-wave signals is a challenging task that holds the potential to uncover fresh insights into fundamental physics, astrophysics, and cosmology.

1. INTRODUCTION
Machine Learning

- Tom Mitchell defines Machine Learning as the study of algorithms that improve their performance P at some task T based on experience E.

- In the context of gravitational waves, we can define these kind of problems in several ways.

- These last years, there has been active research on this way of studying the topic.

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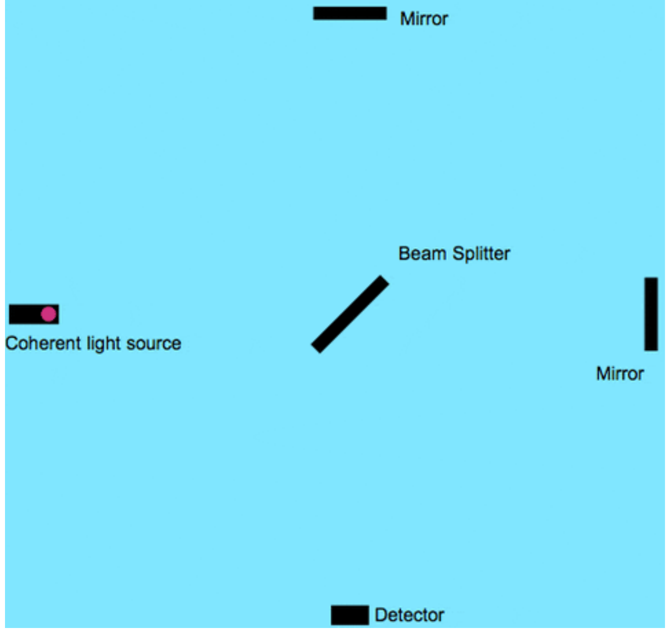
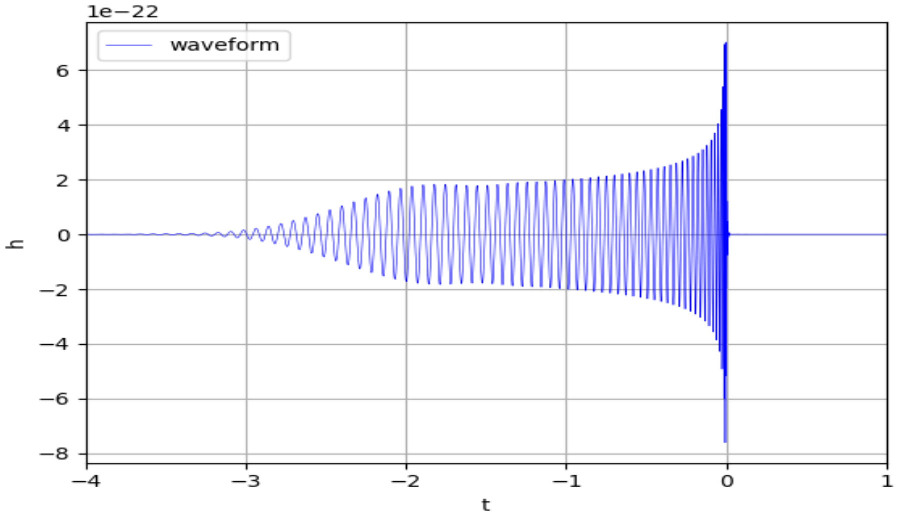
2. APPROACH
The Data

- GW interferometers measure the **differential change of length** of the arms of the detector, giving us a temporal series of the strain of the signal, *h(t)*.





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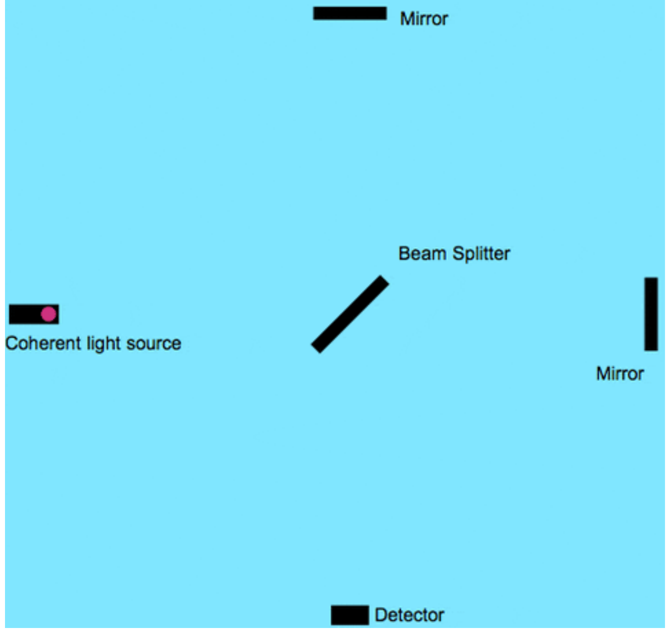

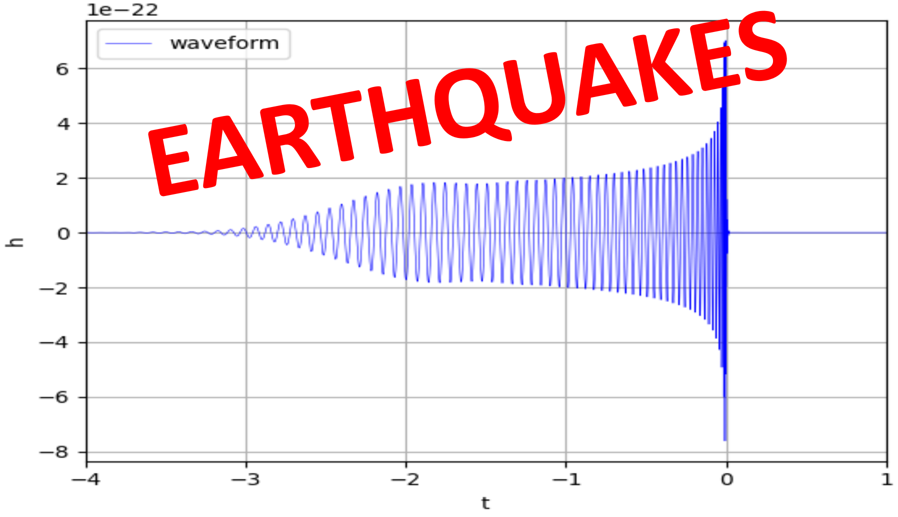

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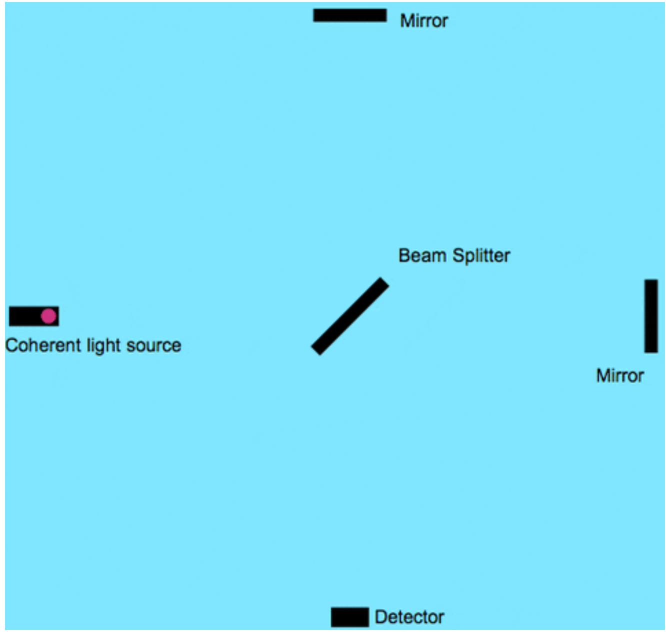

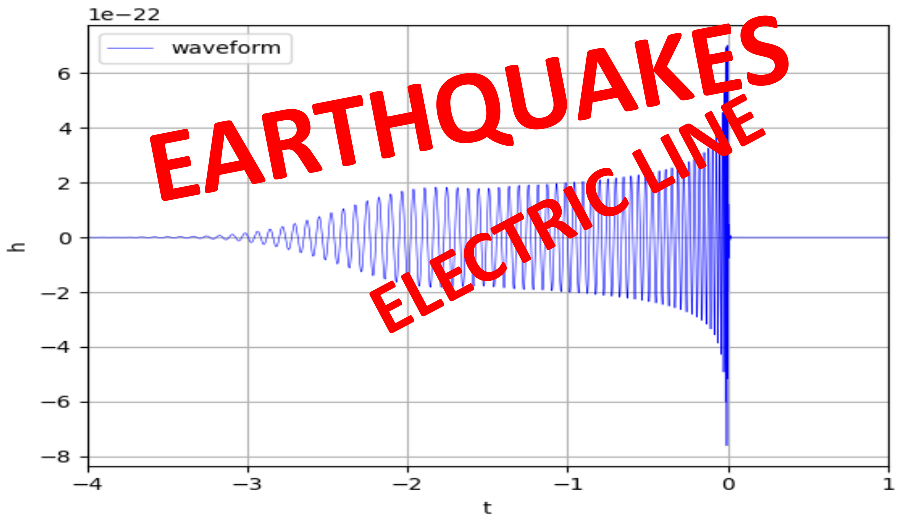

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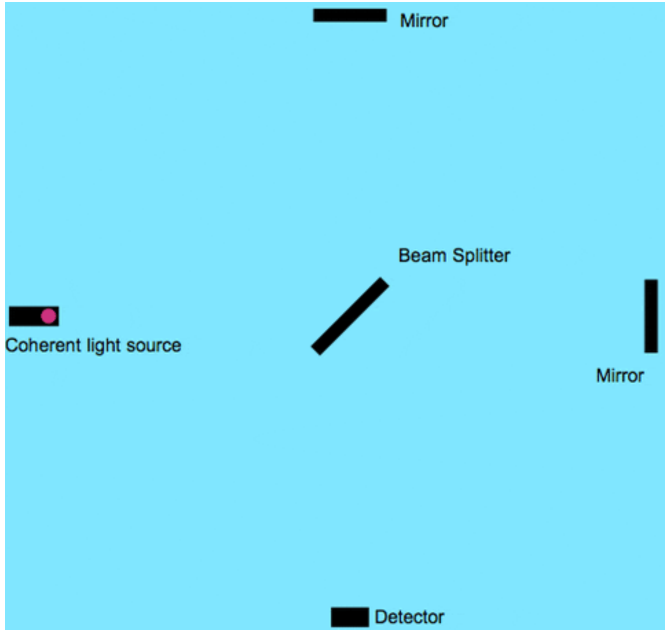

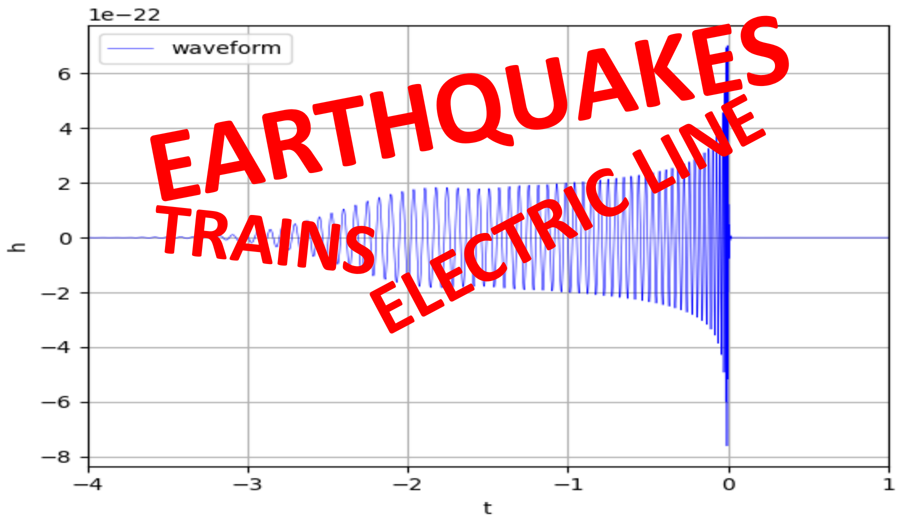

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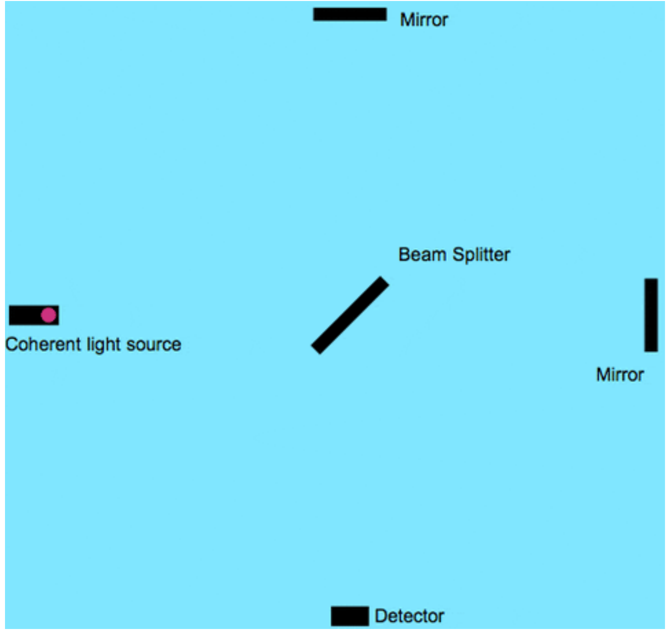

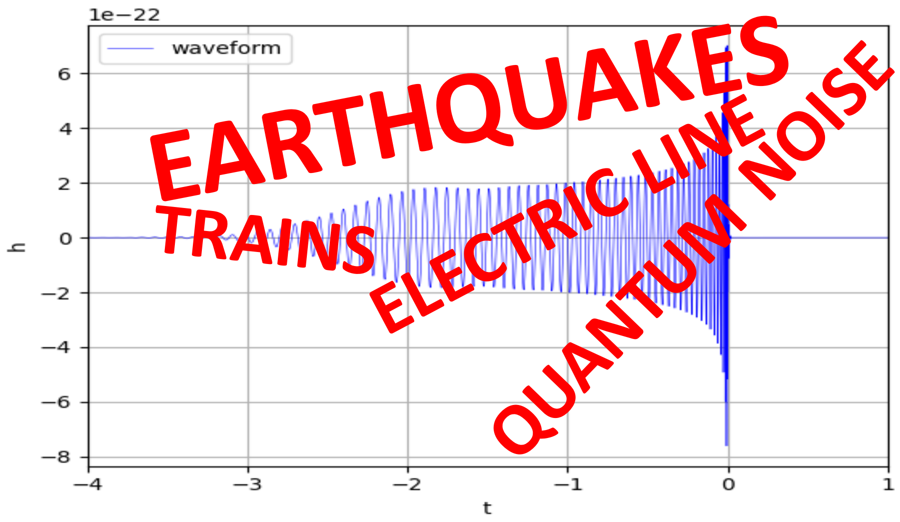

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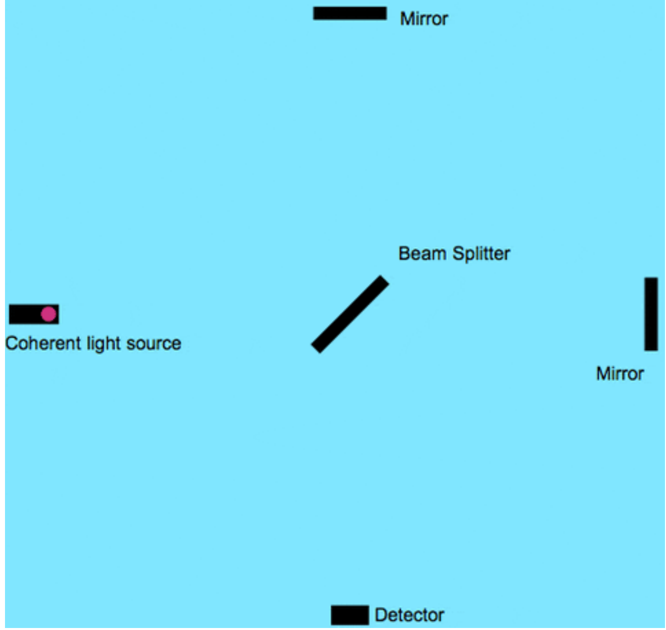

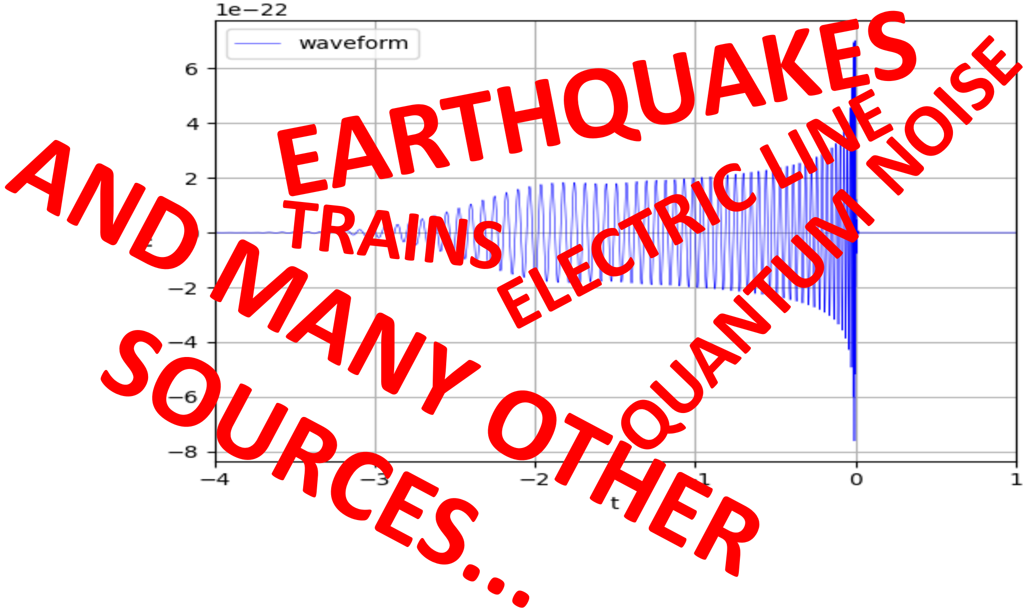

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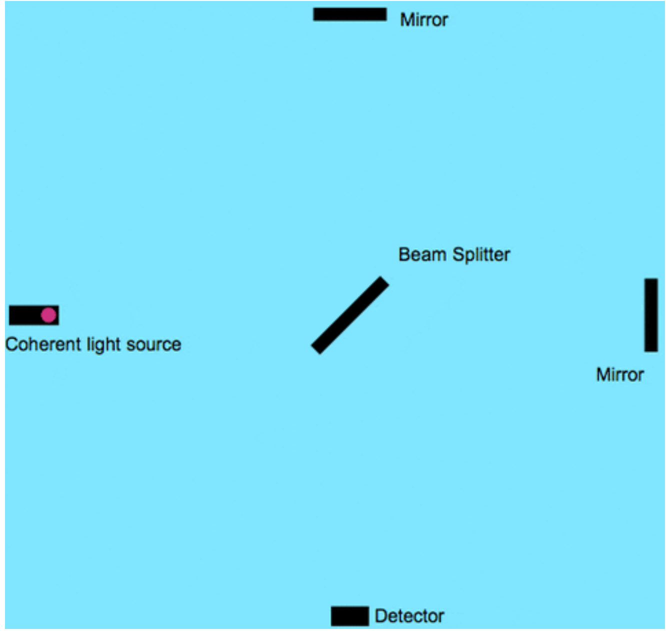
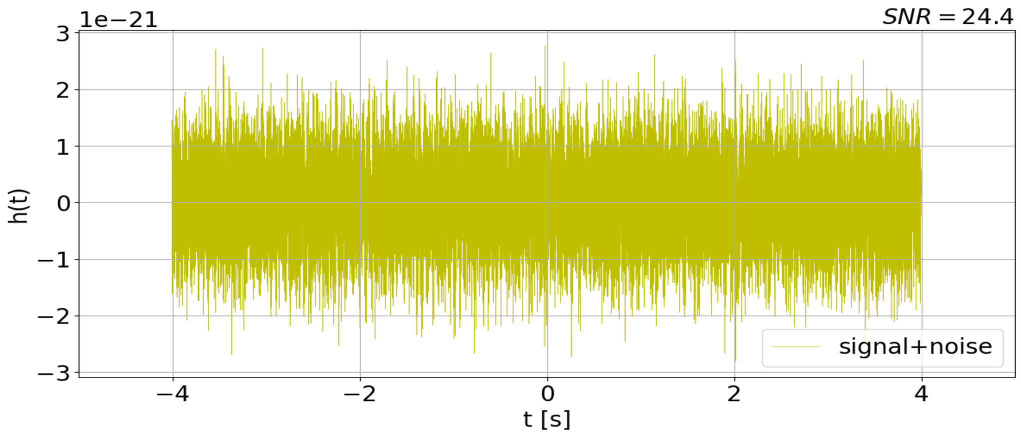
- The signal is always hidden in noise, and it is not visible to the plain eye.





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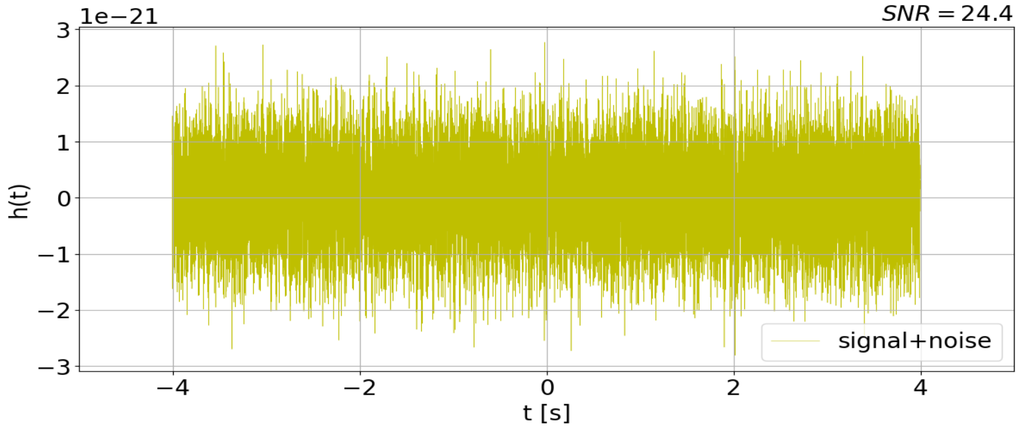
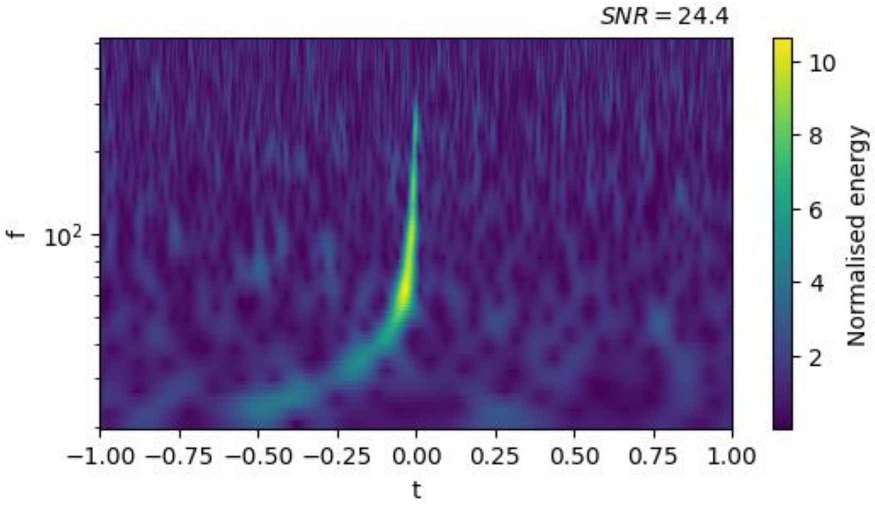
- There are different transforms that can help us visualizing the data. For example, by means of the so-called **Q-transform** [7]. This transform has proven to be a good way of studying GWs [8].





[7] J.C. Brown (1991). (DOI:10.1121/1.400476)

[8] S. Chatterji et al. (2004). (arXiv:gr-qc/0412119)

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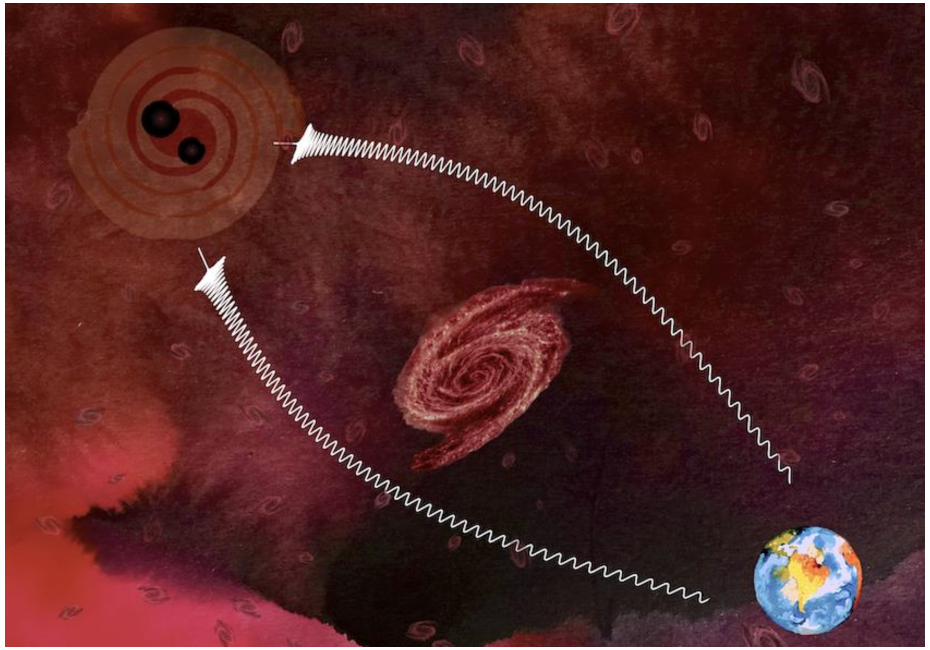

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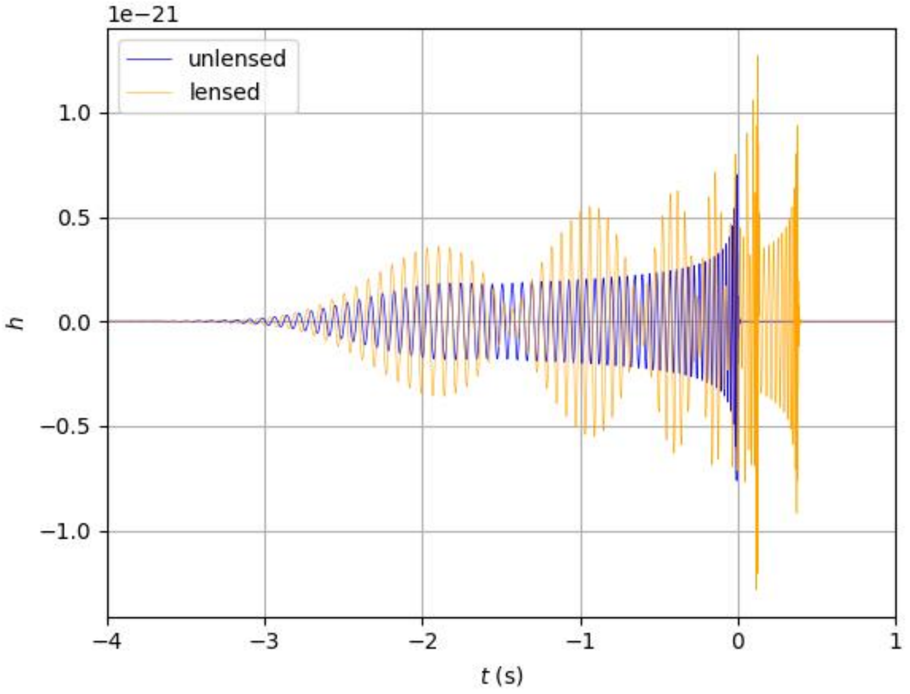

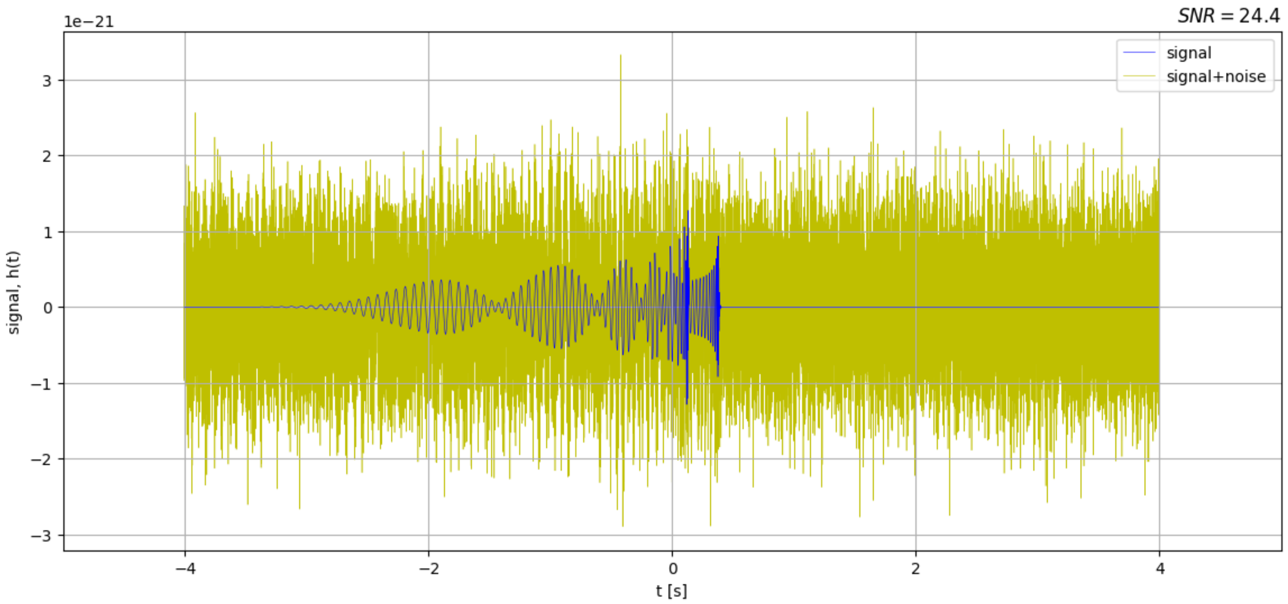

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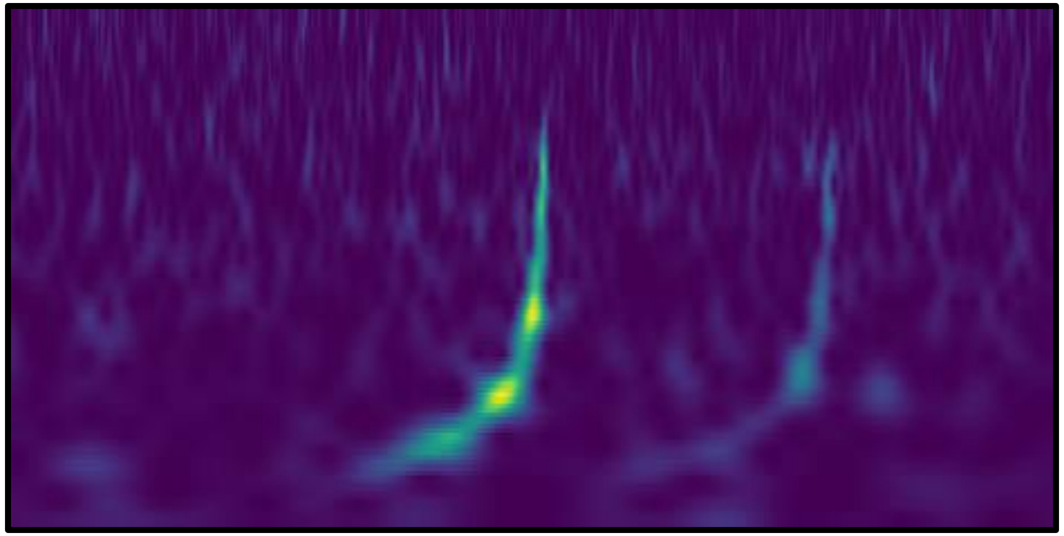

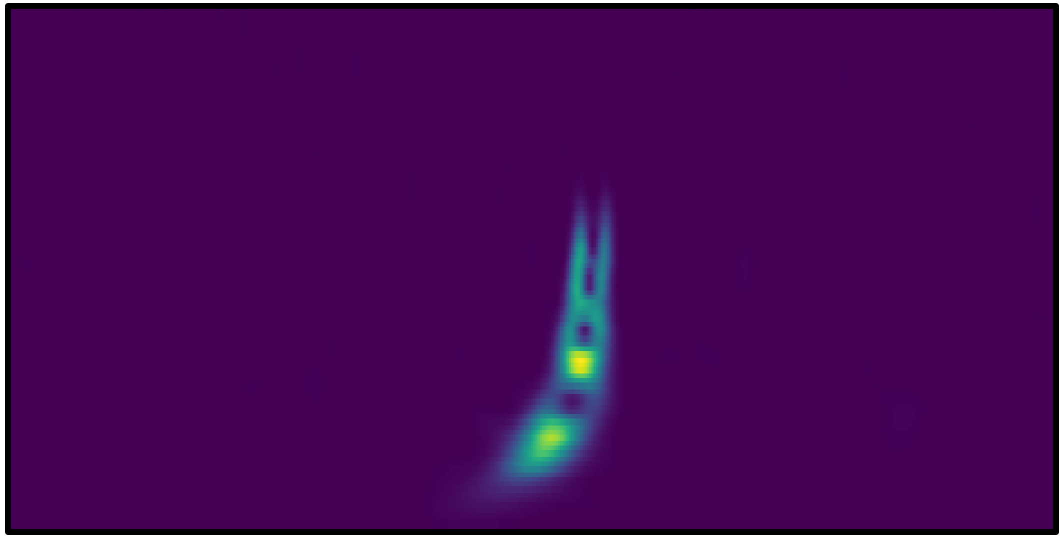

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- **Problem**: Small amount of data. The catalog released in October 2020 had 90 registered events. Currently, the detectors are collecting data, so this number is growing. Nevertheless, we do not have enough real data to train our models.

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- **Solution**: Simulated data. There are different Python libraries that give us tools to do so.

- We use this data for training ML models.

2. APPROACH
The Data

- We simulate different classes of data using the Python library **PyCBC** [10].
  - For generating the waveforms, we use the approximant **IMRPhenomenonPv2**.
  - For generating noise, we use the Power Spectral Density (PSD) of three detectors: the two LIGO detectors, in Hanford (H1) and Livingston (L1), and the Virgo detector, in Pisa (V1).
- We simulate the following data:

Type	Volume (approximate)	Datasets	Parameter Ranges and Distribution
Noise	20000	Training set: 20000 Validation set: 1000 Test set: 1000	PSD from H1, L1 and V1
Unlensed Signals	10000	Training set: 9000 Validation set: 500 Test set: 500	Masses: 10-80 solar masses, log-uniform Distances: 500, 750, 1000, 1250, 1500, 1750, 2000, 2500, 3000, 3500 (Mpc) Signal to Noise Ratio (SNR): 5-50
Lensed Signals	10000	Training set: 9000 Validation set: 500 Test set: 500	Same masses and distances. y: 0-1, uniform Δt: 0,.225ms-0.5s, uniform

[10] Nitz, A. et al. (2023). (https://doi.org/10.5281/zenodo.7885796)

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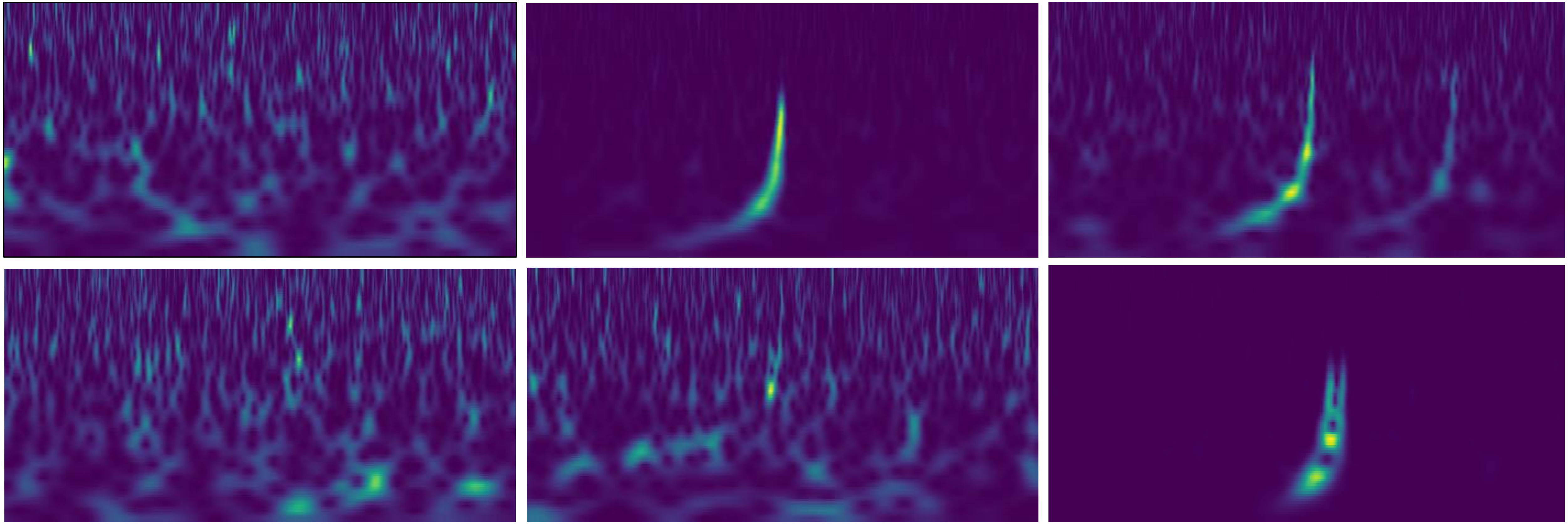
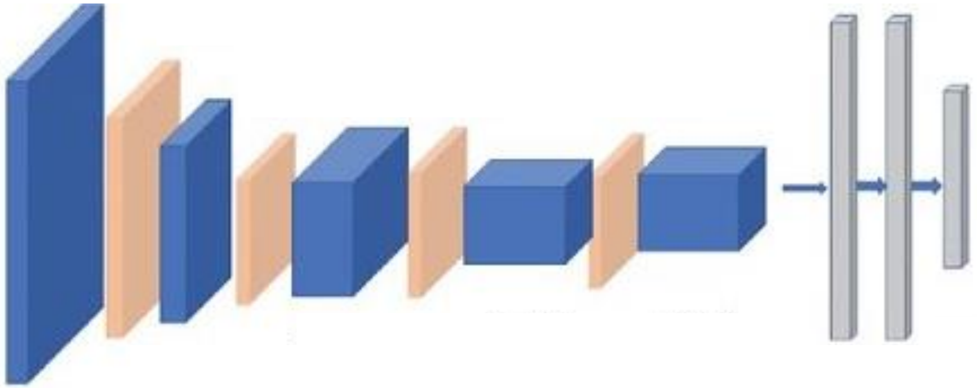
The Data

Noise | Unlensed signals | Lensed signals



2. APPROACH
The Models

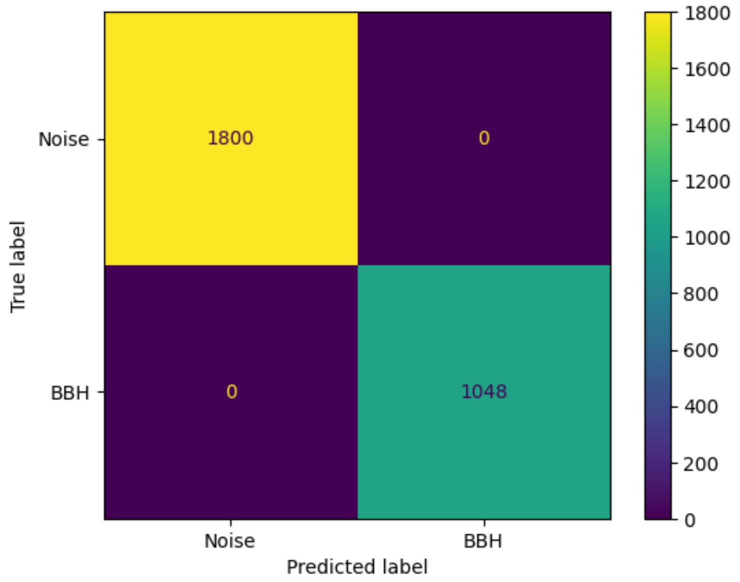
- We train two models based on **VGG19** [11] using two techniques:
  - **Transfer Learning**: VGG19 has been trained with a huge dataset. We take advantage of its knowledge for finding patterns.
  - **Fine Tuning**: Most of the network is unmodified while training. We just train the linear layers (after adding a fourth one) so that VGG19 specializes in GW search.
- These two models are:
  - **S-N (Signal-Noise):** Trained with around 18,000 noise spectrograms and 18,000 signal spectrograms (both lensed and unlensed signals). It classifies the image in “Noise” or “BBH”. 1,000 images per class for validation and testing.
  - **L-U (Lensed-Unlensed):** Trained with around 9,000 lensed signal spectrograms and 9,000 noise spectrograms. 500 images per class for validation and testing.



[11] Simonyan, K. et al. (2015).

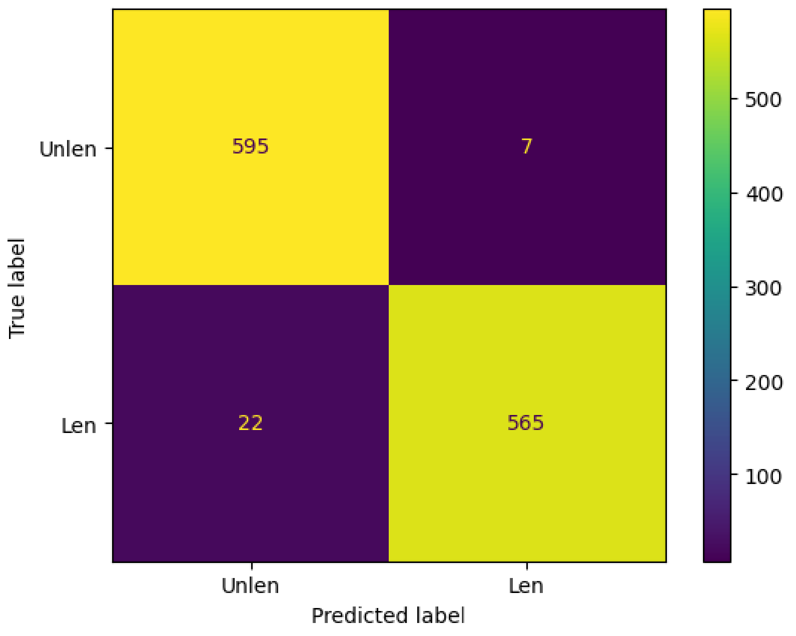
3. RESULTS
N-S Model

- In the testing phase, the N-S model classified every image with an accuracy of 100%. Observations:
  - The model had not seen these images before.
  - Some of the signal images had a SNR of less than 6. To this day, the detected event with lower SNR has an SNR of 6.



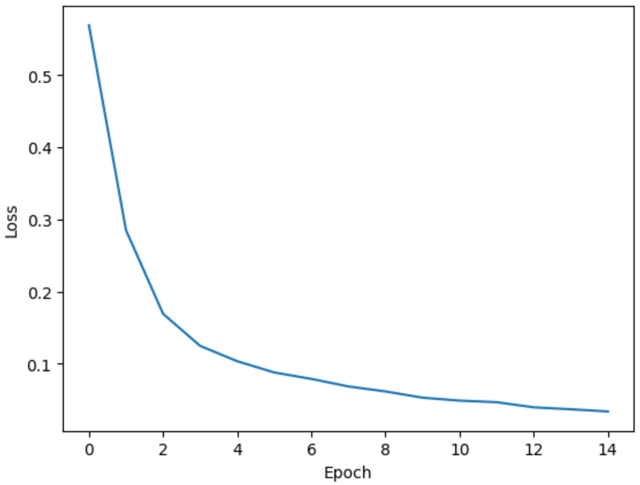
3. RESULTS
L-U Model

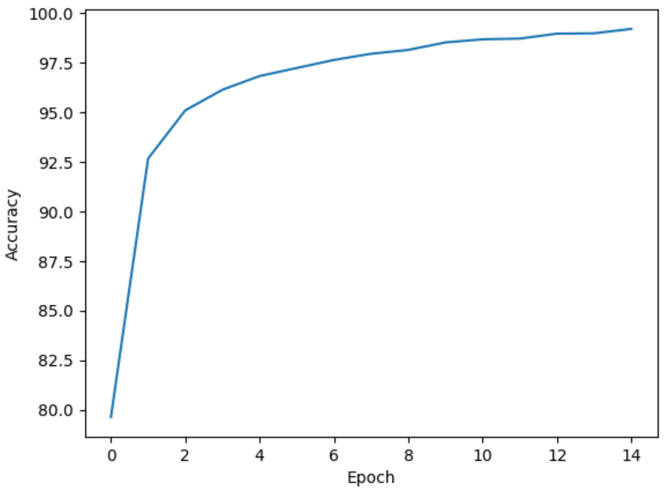
- In the testing phase, the N-S model classified every image with an accuracy of 98%.



3. RESULTS
Observations

- The training process took between 3 and 4 hours for both models.
- The test set classification was carried out in around 20 minutes. The test set for the N-S model has a total of 5696 seconds of data, while the test set for the L-U model consists of 2378 seconds of data. This is a clear advantage in front of traditional methods such as Matched Filtering [12].
- The evolution of the loss and the accuracy of the models during training show a smooth behavior.





[12] Sathyaprakash, B.S. et al. (1991). DOI:https://doi.org/10.1103/PhysRevD.44.3819

4. CONCLUSIONS

- ML methods can carry classification tasks in the context of GW search in a fast and accurate way.
- In the case of time-frequency spectrograms, we find that CNNs such as VGG19 perform specially well when differentiating between noise and simulated BBH signals with injected noise.
- Also in this context, VGG19 has proved to distinguish quite well (98% accuracy) between simulated lensed and unlensed signals.
- One of the main strengths about this type of models is how fast they prove to be in detection tasks. This characteristic makes them perfect for being combined with traditional GW search methods such as MF, which can be excruciatingly time-consuming.

5. FUTURE AND POSSIBILITIES

- **Different models:** U-Net (medical image), ResNet, more simple models...
- **Different types of data:** Time series, other type of frequency transforms...
- **Different tasks:** Noise reduction, dimensionality reduction, glitch detection, strong lensing...


THANK YOU