# Evaluation of GAN architectures for the characterization of transient noise in the Virgo interferometer

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Master’s Degree in Physics of Complex Systems

A.Y. 2022/2023

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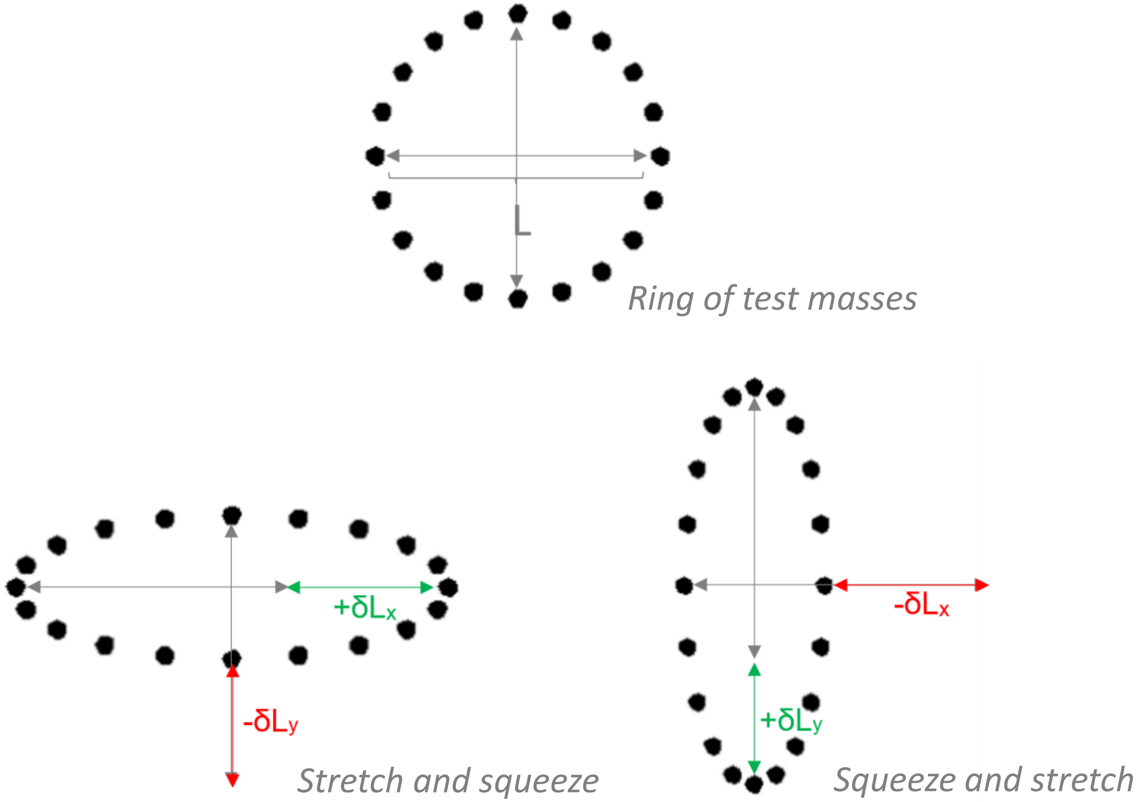
# What are gravitational waves?

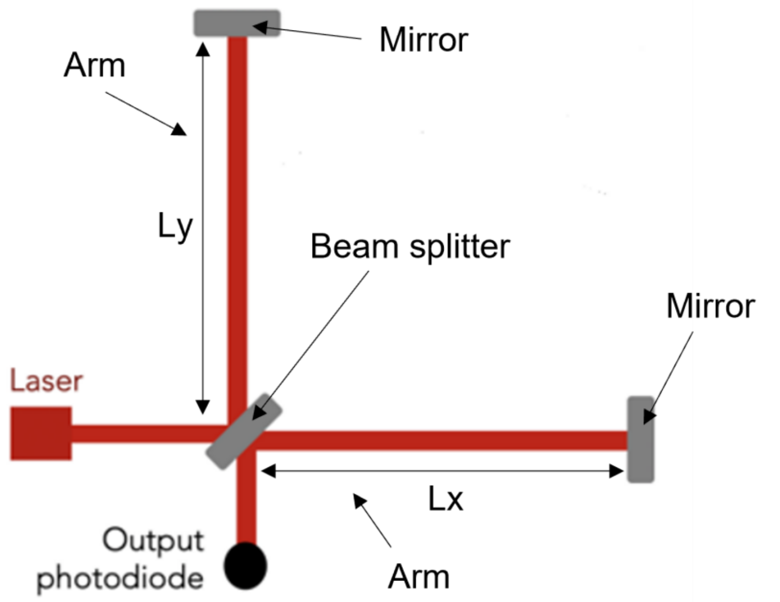
- According to General Relativity, **gravity is a local property of the space occupied by a test mass**, which is curved by another source mass
- Information about changing gravitational fields is carried by **gravitational waves** (GW), which manifest as **ripples of curvature in the fabric of spacetime**, transverse to the propagation direction
- Their effect is to **stretch and squeeze the space** between test masses
- We measure the effect of a GW in the form of a variable called **strain** $(h)$




$$\boxed{h = \frac{\Delta L}{L} = \frac{\delta L_x - \delta L_y}{L} \sim 10^{-21}}$$

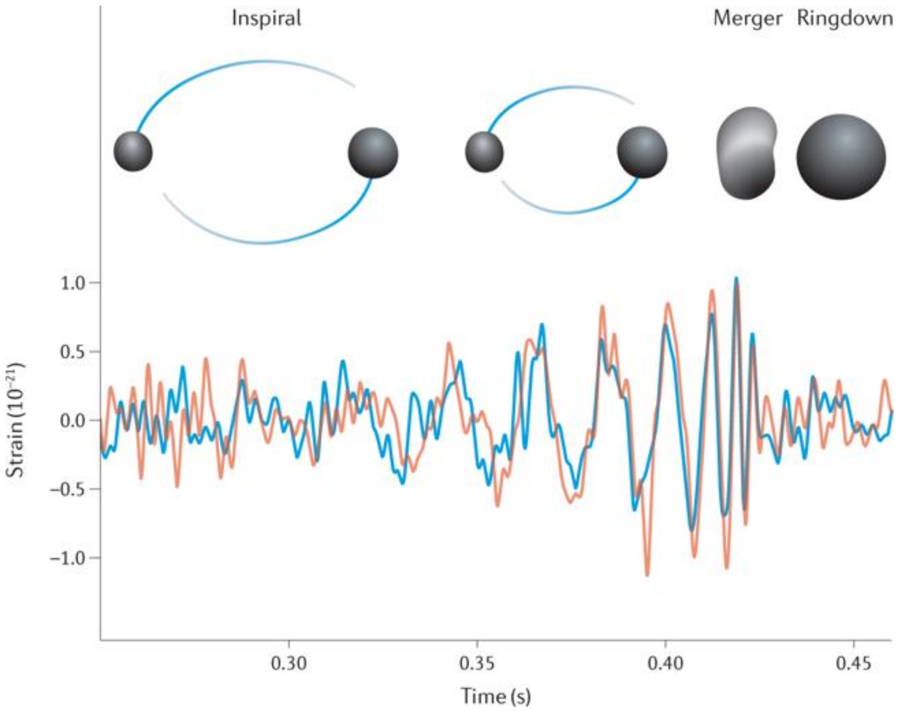
# GW detector: The Interferometer

- A GW detector is a modified Michelson interferometer, it measures the strain as a difference in length of its orthogonal arms
- Each arm in the Virgo interferometer has a length of $L_x = L_y = 3\ Km$, and ends with a suspended mirror that reflects light and acts as test mass
- A GW effectively alters the arm lengths such that the measured difference is $\Delta L = \delta L_x - \delta L_y = hL$
- This $\Delta L$ alters the phase difference between the two light fields returning to the beam splitter, transmitting an optical signal proportional to the GW strain to the output photodiode




*Simplified diagram of an interferometer*
*Note that to achieve sufficient sensitivity to measure gravitational waves, the detectors include several enhancements to the basic Michelson interferometer*

# A real GW signal




*The first GW signal ever revealed by the Advanced LIGO interferometer, which is composed of two detectors, the orange and blue curves show the matching of the signal registered by the two detectors*

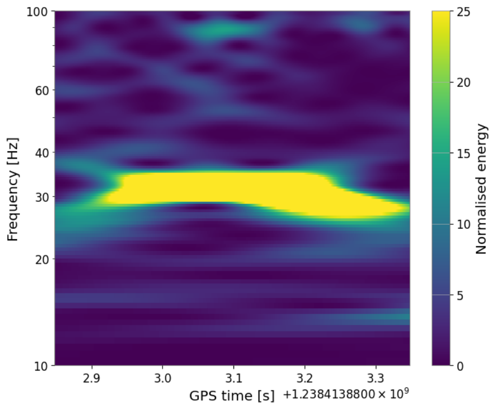
- On the left is shown a real strain signal in the form of a time series, coming from a compact binary coalescence, i.e., the merging of two compact objects like black holes or neutron stars
- During the evolution of the system, the signal changes in amplitude and in frequency, breaking the detectable barrier of $h = 10^{-21}$ for a brief amount of time just before the merger (transient signal)
- The interferometer collects data also from a variety of instrumental and environmental sensors (e.g., photodetectors, seismometers) which are available in the so-called auxiliary channels
- Data collected by auxiliary channels can help determine the non-astrophysical nature of triggers

# Noise sources in the interferometer

**Continuous noise:** reduce the sensitivity of the interferometer by adding background noise

**Transient noise:** if it has a duration comparable to a typical GW signal, we refer to it as "glitch"

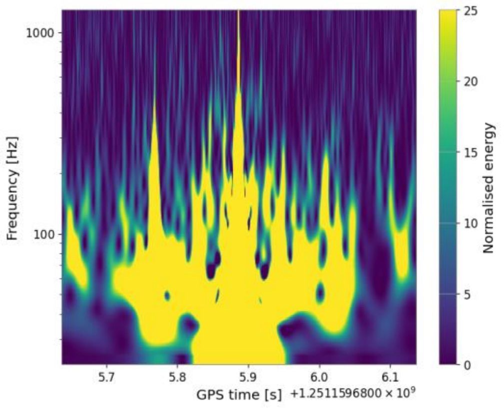
Starting from a time series, we can get a time-frequency representation of a glitch, called spectrogram, which shows a characteristic shape containing information on the physical origin of the glitch




*Scattered Light glitch*

***Some auxiliary channels are sensitive to this kind of glitches***

Classification based on the shape seen in the spectrogram




*Koi Fish glitch*

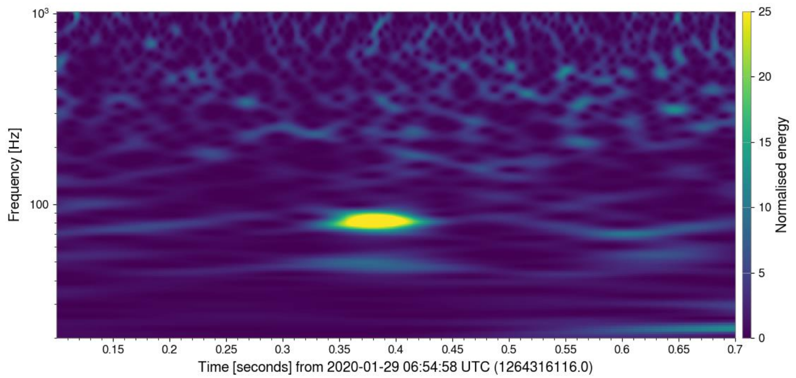
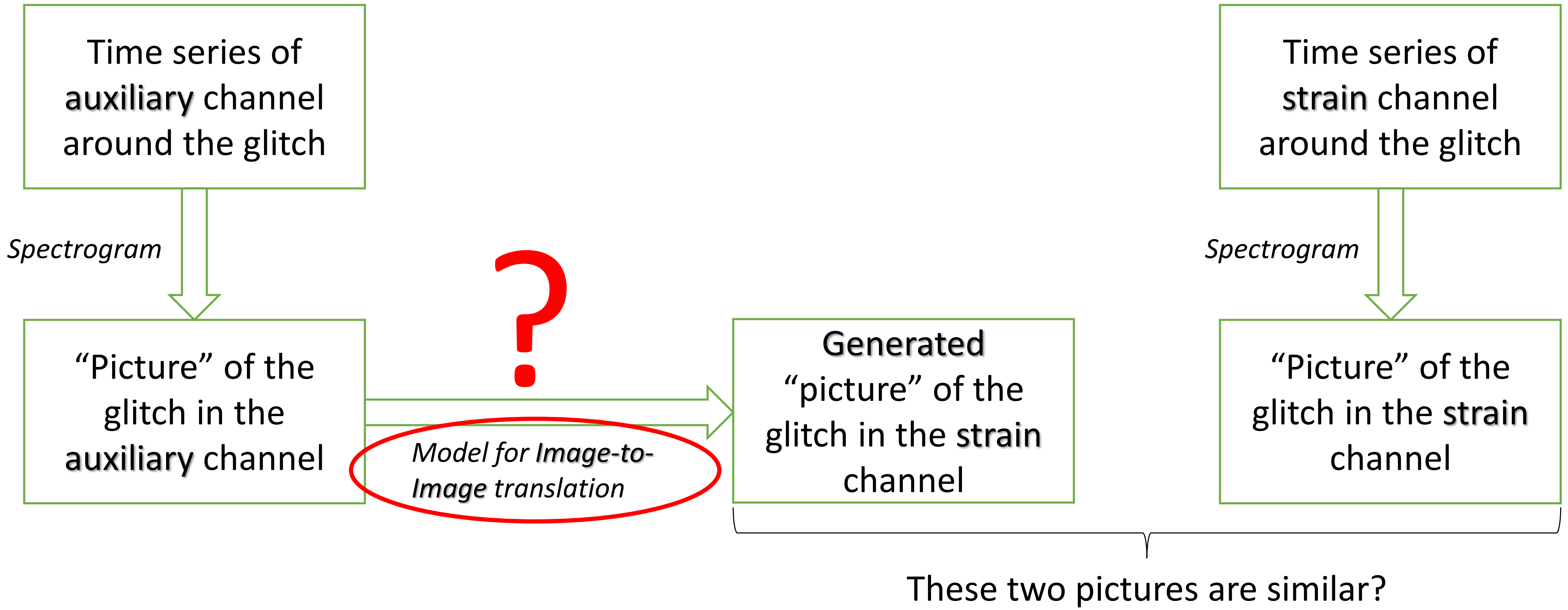



*Image of a real GW signal observed by Virgo*

***This signal will not show in auxiliary channels!***

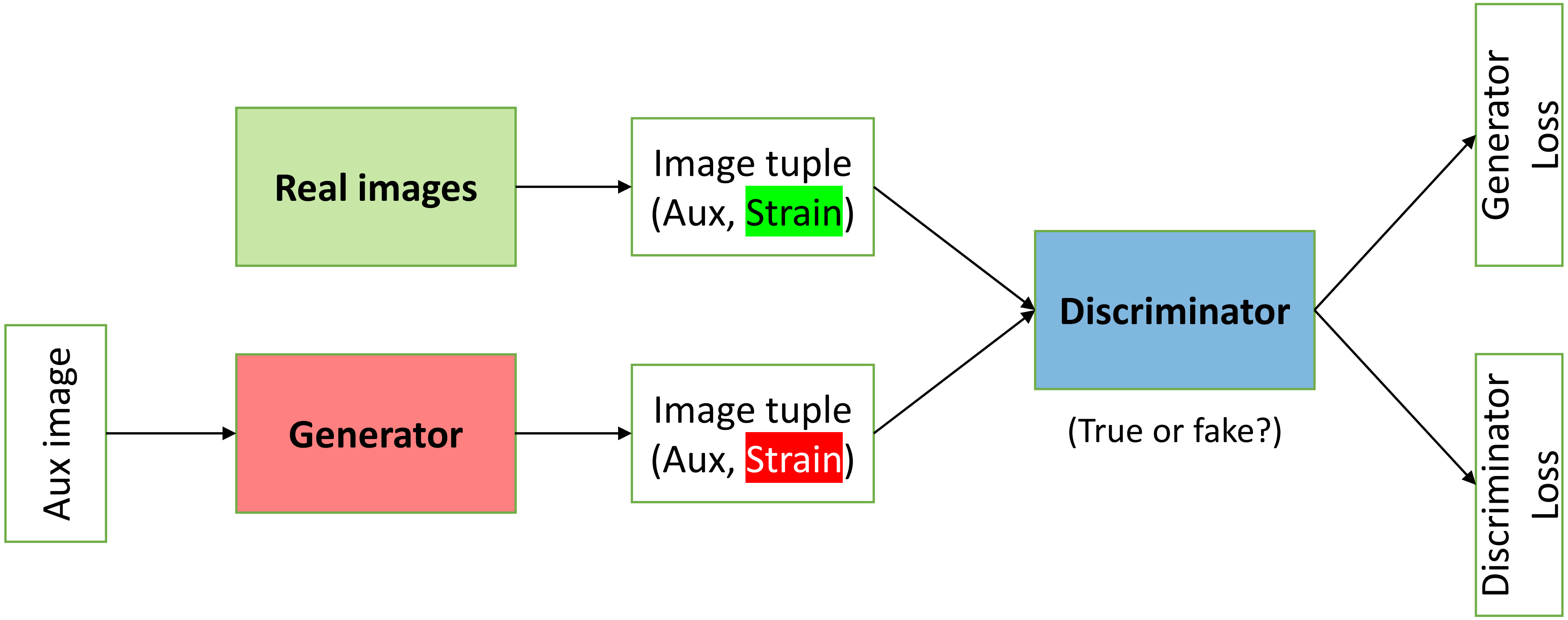
# My thesis goal: find the mapping between glitch in auxiliary and strain channel




➡ **Finding the mapping between the auxiliary channel and the strain allows us to better discriminate the GW signal with respect to transient noise**

# Generative Adversarial Networks

- Generative Adversarial Networks (GANs) are a class of **deep-learning** models, used for generative tasks like text and image generation, and **Image-to-Image translation**.
- The training is achieved through an adversarial process in which two architectures: the **Generator** and the **Discriminator**, compete against each other.

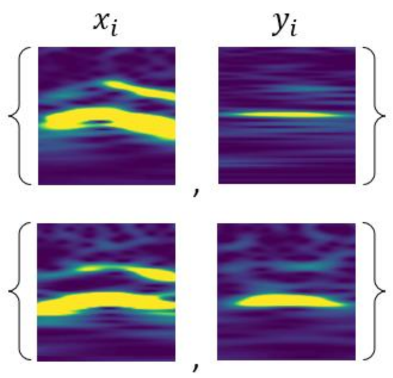


# Implemented architectures

The two GAN architectures that I implemented are the **Pix2Pix** and the **CycleGAN**

**Pix2Pix:** **Best Results**

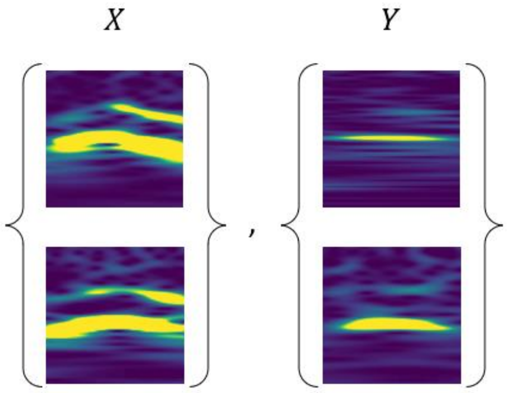
- Requires training images to be paired:




- Relatively fast training

**CycleGAN:**

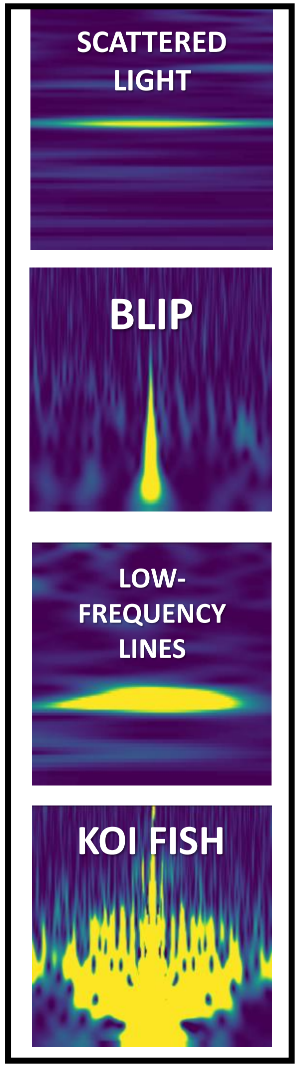
- Training images can be unpaired:




- Consists of two generators and two discriminators → Relatively slow training

# My working data

- 4 glitch classes:
  - Scattered Light, 855 samples → 755 in the training set / 100 in the testing set
  - Blip, 370 samples
  - Low-Frequency Lines, 335 samples
  - Koi Fish, 389 samples
- For each glitch sample I had available 8 time series lasting 16 seconds each
  - One for the strain channel
  - Seven for the auxiliary channels

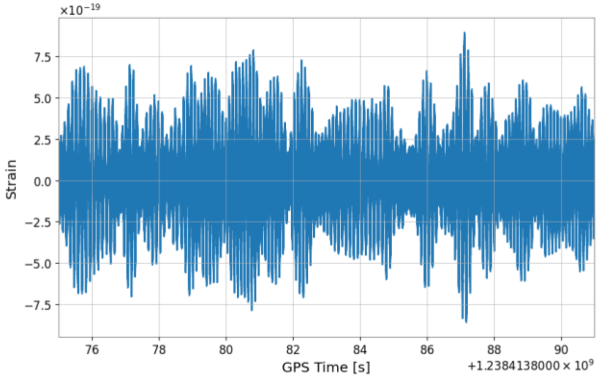



I focused the analysis on **two auxiliary channels**, which I will refer to as:

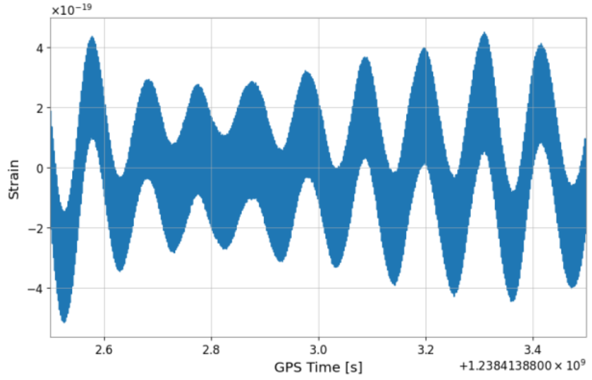
- **Correlated**: Monitors the deviation in the differential interferometer's arms length measurement → Directly correlated to the strain channel
- **Uncorrelated**: Monitors the deviation in the length of the Power-Recycling Cavity, a component of the interferometers that enhances the sensitivity by recycling and amplifying the laser power → Not sensitive to GW signal

# Preprocessing

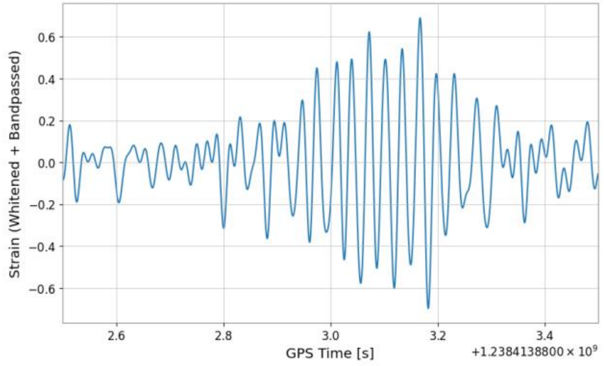
*Time series – 16 seconds long*




*Time series – **Centered** on the glitch*

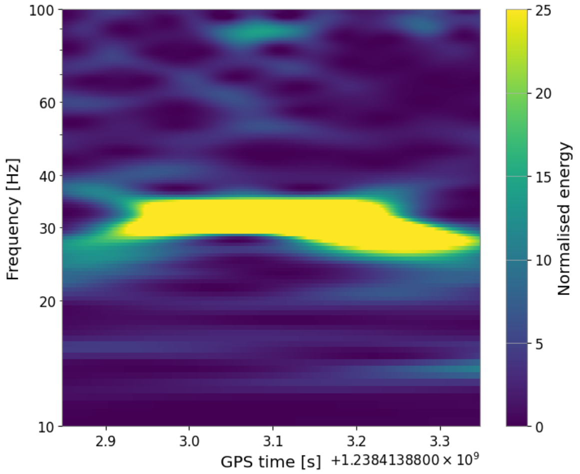



*Time series – **Denoised and bandpassed***

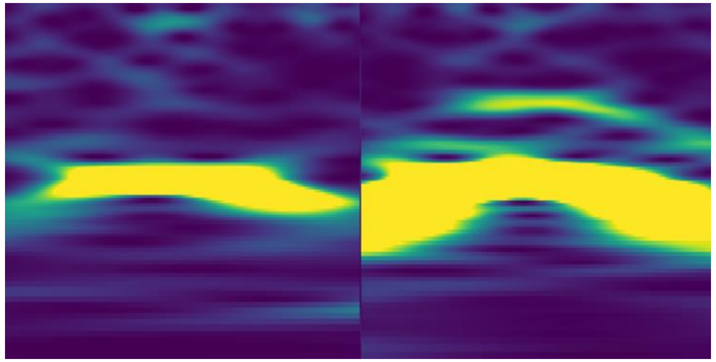



**~0.5s long glitch**

## Spectrogram of this region:

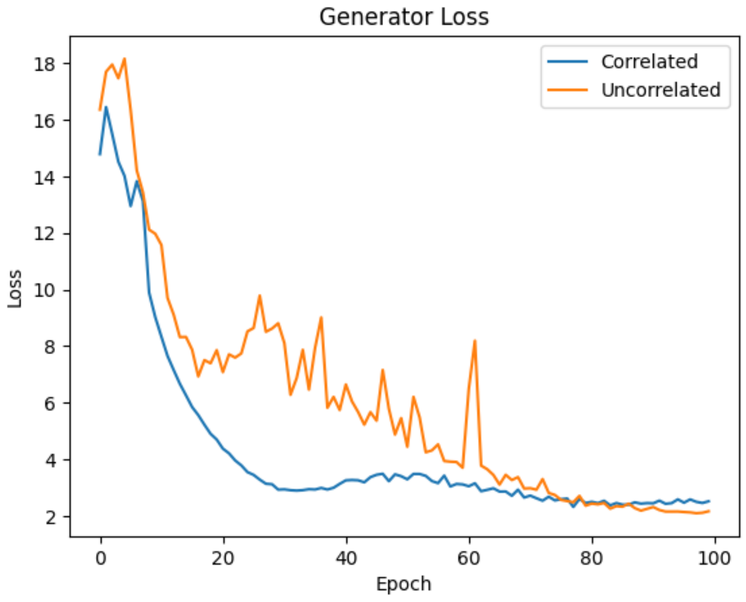



- Apply the same preprocessing to the auxiliary channels' time series
- Turn the plots into images



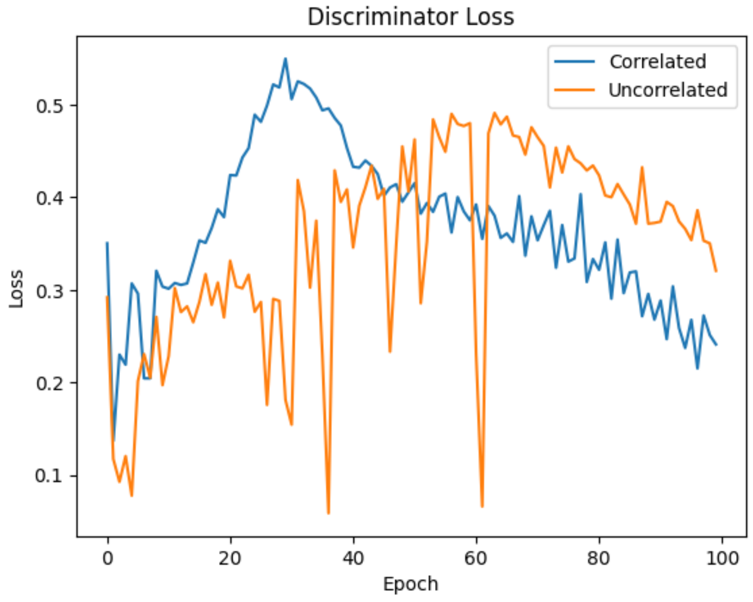
*Example of image sample in the **training and testing set of Pix2Pix**. On the left is the glitch in the strain channel, on the right is its counterpart in the correlated auxiliary channel*

# Model training




Expected behavior:

- The generator loss should **decrease smoothly**
- The discriminator loss should **approach 0.5**, indicating that it is no longer able to discern real from generated images




These trends are useful to understand whether the training went well or not, but the value of the losses is **not directly related to the quality of the generated images**

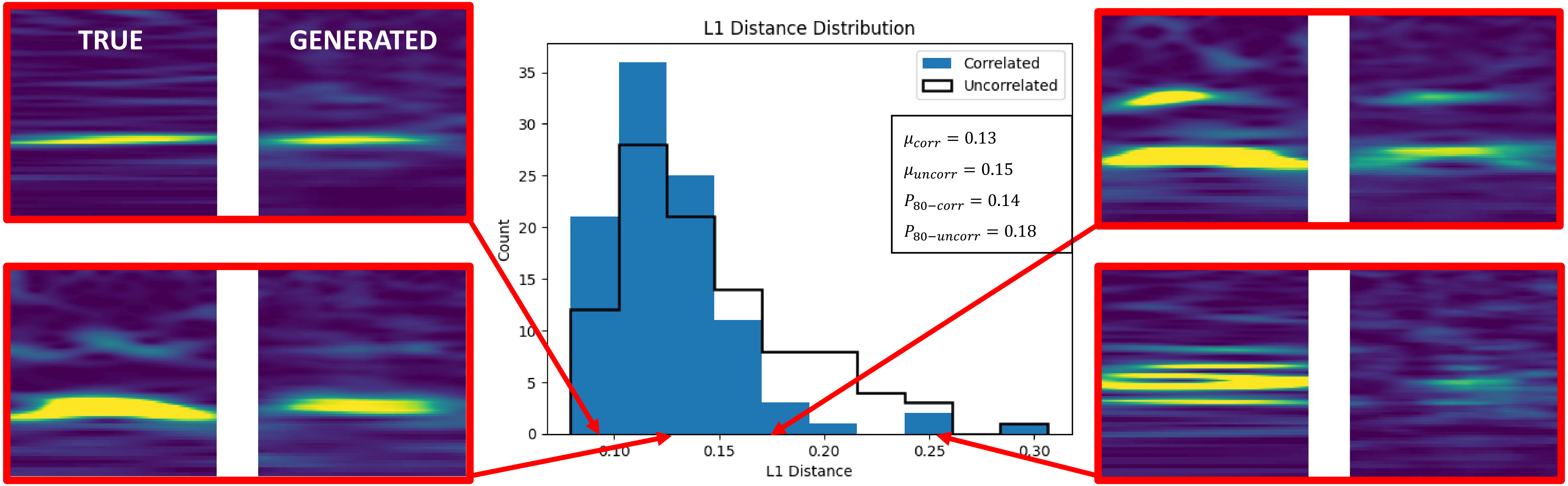
Define an evaluation metric

$$\boxed{L_1(\hat{y}, y) = \frac{1}{N}\sum_{i=1}^{N} |\hat{y}_i - y_i|}$$

*$\hat{y}$: Generated image*
*$y$: Corresponding true image*
*$N$: Number of pixels of the images*
*$\hat{y}_i, y_i$: i-th pixel value of the images*

# Model testing

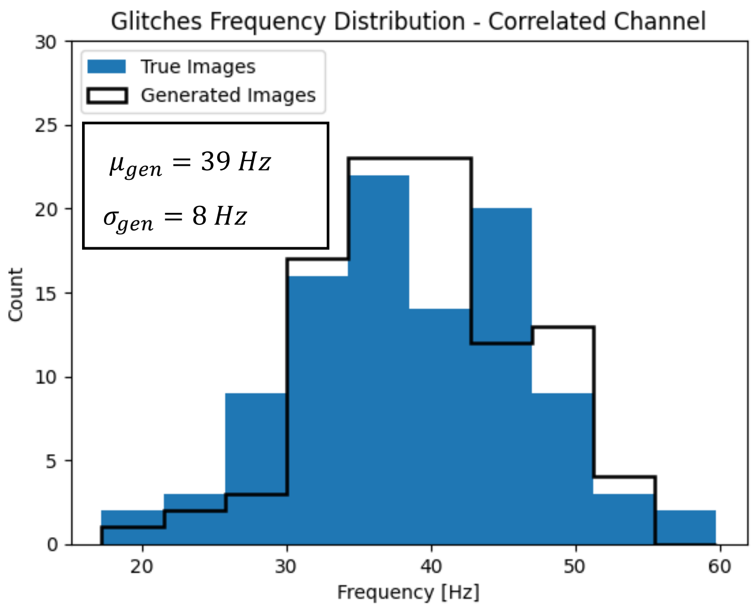
For each sample in the testing set, I calculated the $L_1$ **Distance** and placed the value in the following distribution, this **gives an idea of the quality of generated images**




*The examples shown are for the uncorrelated channel*

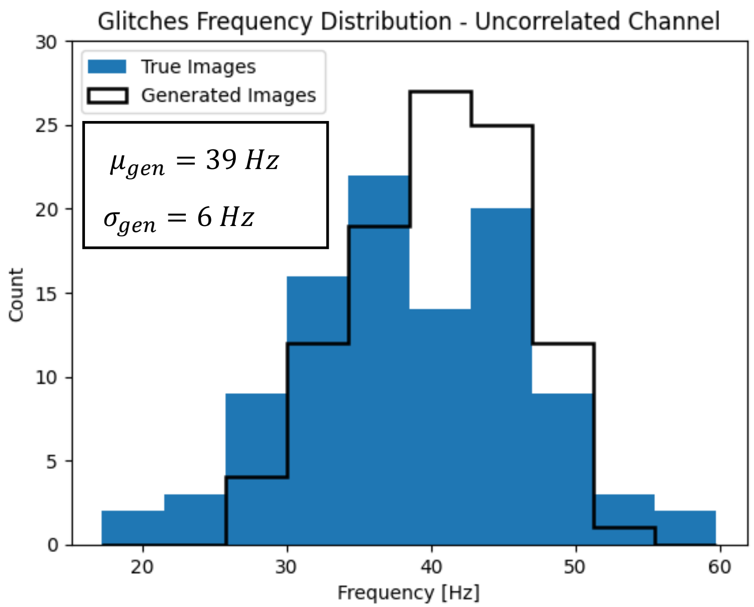
# Glitch frequency distribution

Scattered Light glitches are approximately lines, the **height** at which the line is drawn is a **fundamental property**, being related to the **frequency content** of the glitch




$\mu_{true} = 38\ Hz$

$\sigma_{true} = 8\ Hz$




The **mean absolute error** in the frequency of generated glitches is:

- $\delta_{f-corr} = 5\ Hz$
- $\delta_{f-uncorr} = 6\ Hz$

**The network understands the importance of placing the glitch at the right frequency**

# Conclusions

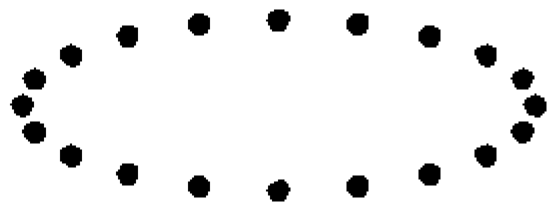
- Once these models are trained, they can help us **distinguish real GW events from glitches** or also **understand better the physical origin of glitches**, as well as **classify new events in the appropriate glitch classes** by looking for the auxiliary channels for which the translation succeeded
- The results indicate that using GANs to translate glitches from an auxiliary channel to the strain channel is an **effective method**. With Pix2Pix, on Scattered Light glitches, I obtained the following:

| | $\mathbf{L_1 - \mu}$ | $\mathbf{L_1 - P_{80}}$ | $\boldsymbol{\delta_f}$ |
|---|---|---|---|
| **Correlated Channel** | $0.13 \sim 9.0\%$ | $0.14 \sim 9.6\%$ | 5.2 Hz |
| **Uncorrelated Channel** | $0.15 \sim 10.3\%$ | $0.18 \sim 12.4\%$ | 6.0 Hz |

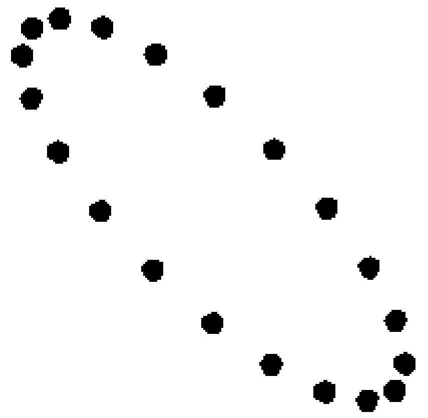
- **Future works** should consider a more **thorough exploration of the hyperparameters space** of the models, **gather more data** from many glitch classes, and integrate the model in Virgo online processing for veto and denoising

# Thanks for the attention

# Backup 1 – Plus and Cross polarization



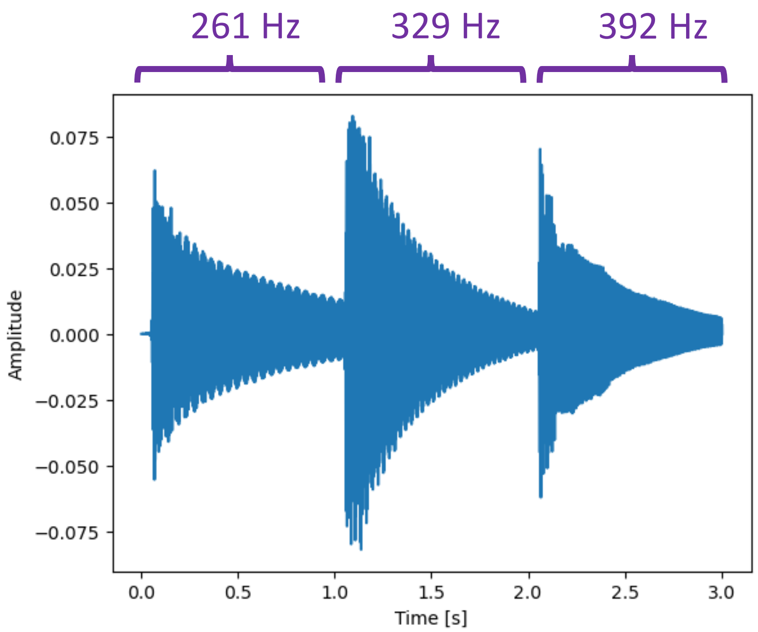
**PLUS**



**CROSS**

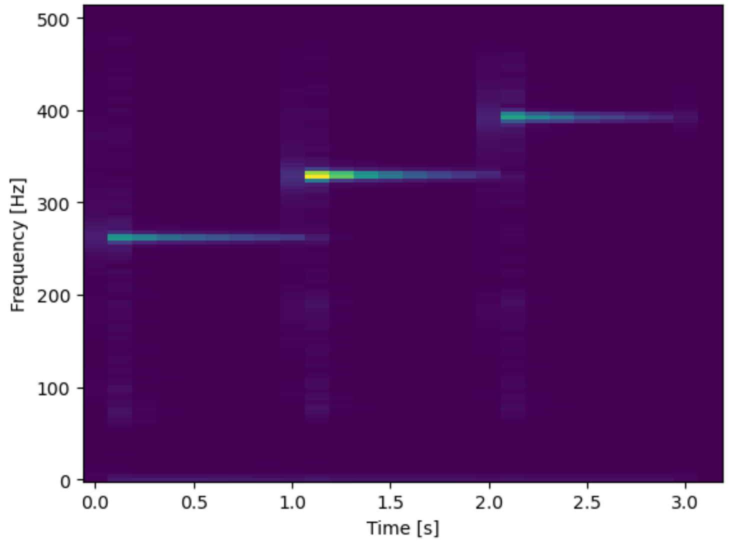
# Backup 2 – Spectrograms

*A spectrogram is a visual representation of the spectrum of frequencies of a signal* ***as it varies with time***




*Audio signal of a grand piano playing a C major chord arpeggio*

**Spectrogram calculation algorithm**

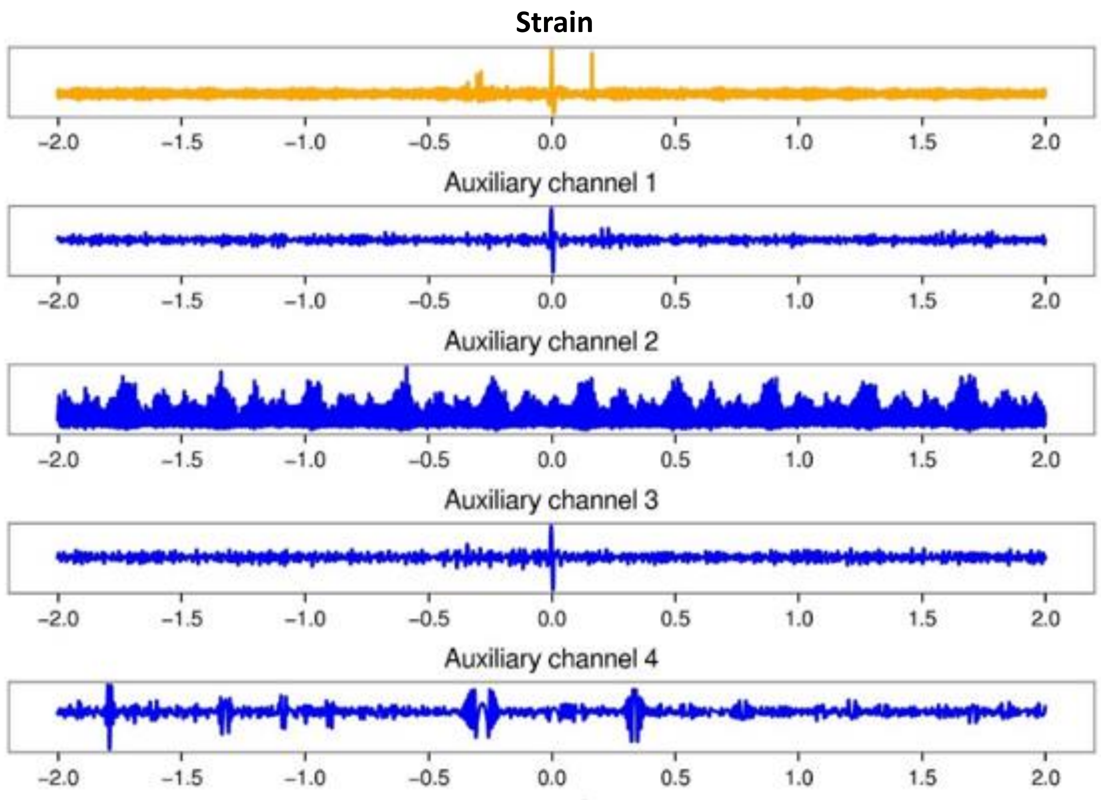



*Spectrogram of the audio signal*

**Q transform**: Provides **good time resolution** at high frequencies and **good frequency resolution** at low frequencies

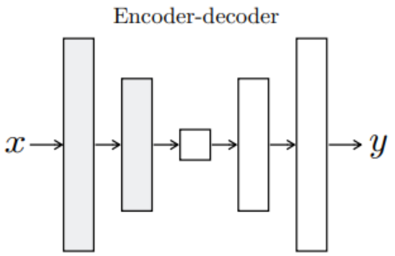
# Backup 3 – Auxiliary Channels

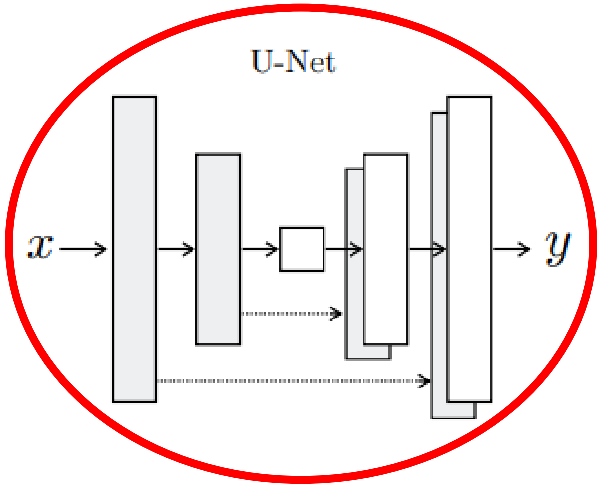
- Collect data from a variety of **instrumental and environmental sensors** (i.e. photodetectors, seismometers)
- Several tens of thousand channels
- Can help **determine the non astrophysical nature of triggers**:
    - The spike in the strain time series (right plot) at t=0 occurs also in auxiliary channel 1 and 3, so it is not a GW
- Some auxiliary channels are directly correlated to the strain



# Backup 4 – Pix2Pix Generator

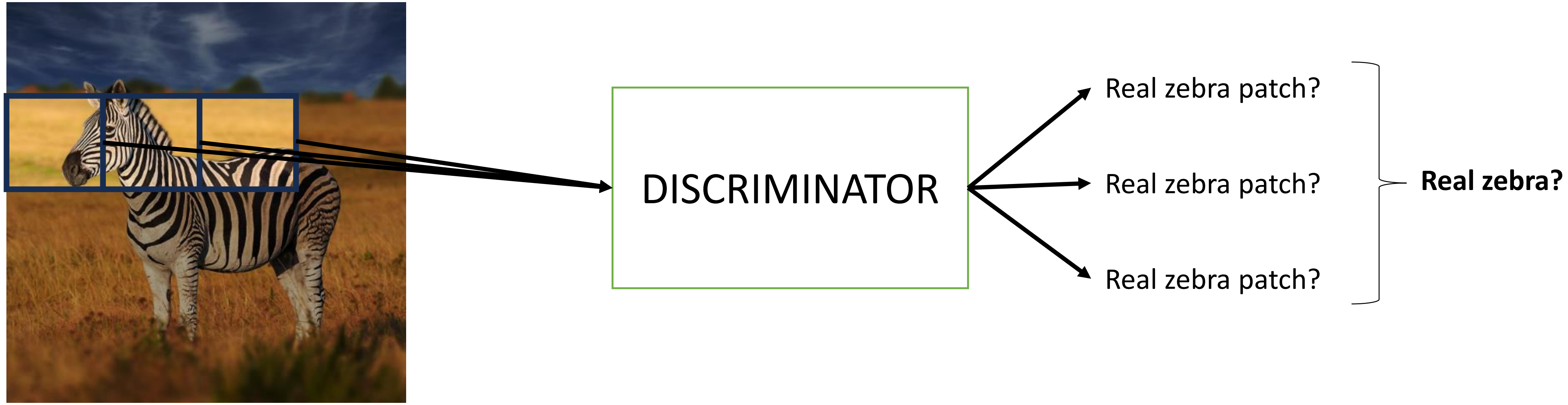
- The input is passed through a series of layers that progressively downsample, until a bottleneck layer
- Then the process is reversed → All the information passes through all the layers
- In most tasks, a great amount of information is shared by the input and output image → We shuttle this information directly across the net



# Backup 5 – Pix2Pix Discriminator

- The discriminator architecture is called **PatchGAN**, it's a convolutional classifier that classifies the images patch by patch



# Backup 6 – Pix2Pix Examples

# Backup 7 – CycleGAN Examples