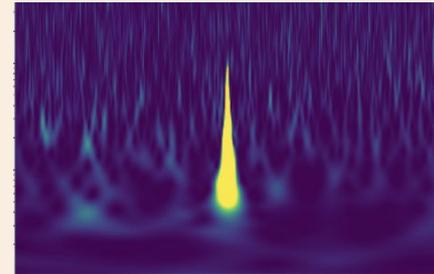


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# Glitch Characterization and Statistical Analyses - II

Tabata Aira Ferreira, INPE  
IUCAA - DetChar Workshop



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December 18, 2025

# Outline

- Omicron
- Unclustered vs. Clustered Omicron information
- Effects of Q-value on the signal morphology
- Analysis Using Omicron
  - Examples
- Analysis Using Gravity Spy
  - Examples

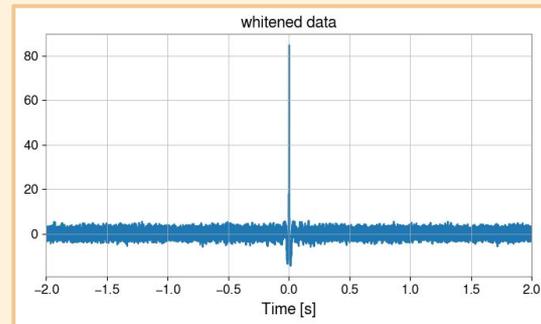
# Omicron

# Glitch studies rely on Omicron

Omicron looks for excess power in the data using the Q-transform

$$X(\tau, \phi, Q) = \int_{-\infty}^{+\infty} x(t)w(t - \tau, \phi, Q)e^{-2i\pi\phi t} dt.$$

$$Q \propto \frac{f_0}{\Delta f_0}$$

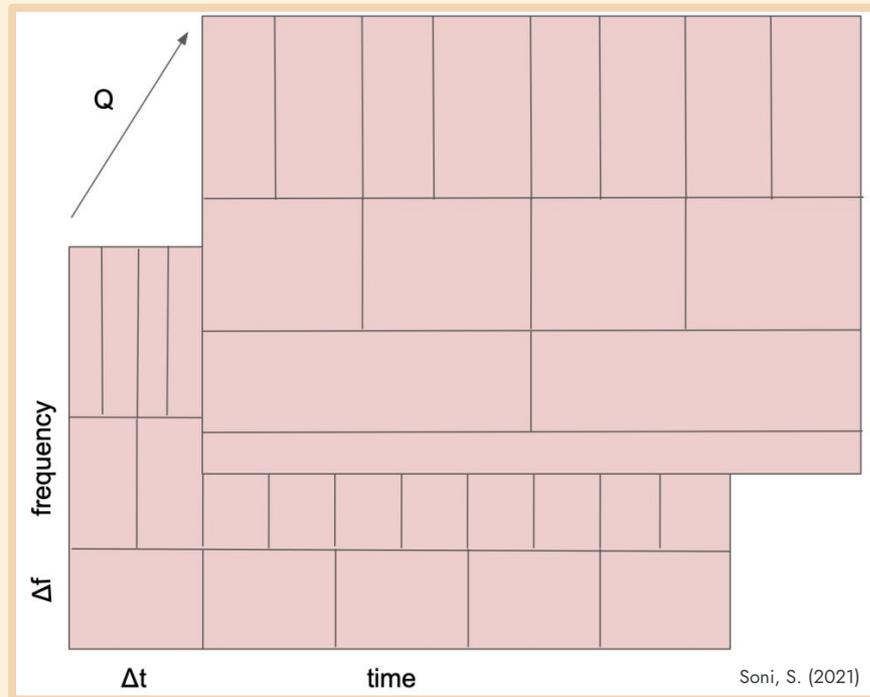


# Glitch studies rely on Omicron

$$X(\tau, \phi, Q) = \int_{-\infty}^{+\infty} x(t)w(t - \tau, \phi, Q)e^{-2i\pi\phi t} dt.$$

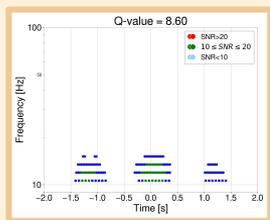
$$Q \propto \frac{f_0}{\Delta f_0}$$

All this information is saved in **.root** files.



# Unclustered Omicron

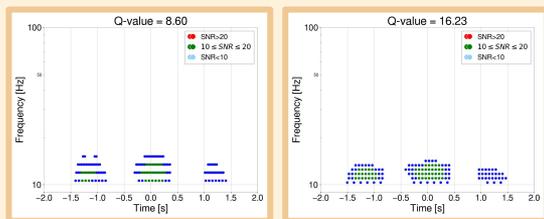
The same glitch can generate multiple Omicron triggers at different Q-values



Ferreira, T.A. & Gonzalez, G.  
(2025)

# Unclustered Omicron

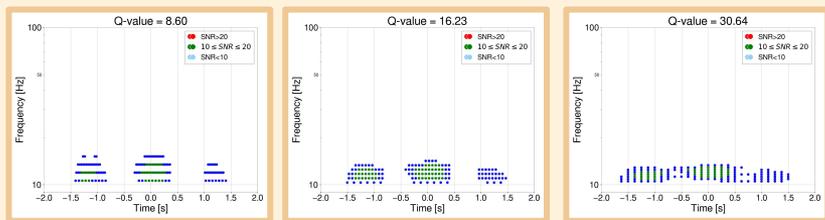
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Ferreira, T.A. & Gonzalez, G.  
(2025)

# Unclustered Omicron

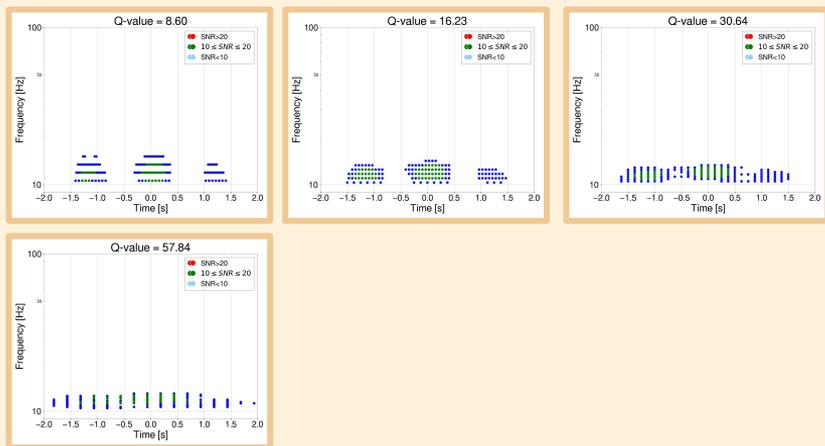
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Ferreira, T.A. & Gonzalez, G.  
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# Unclustered Omicron

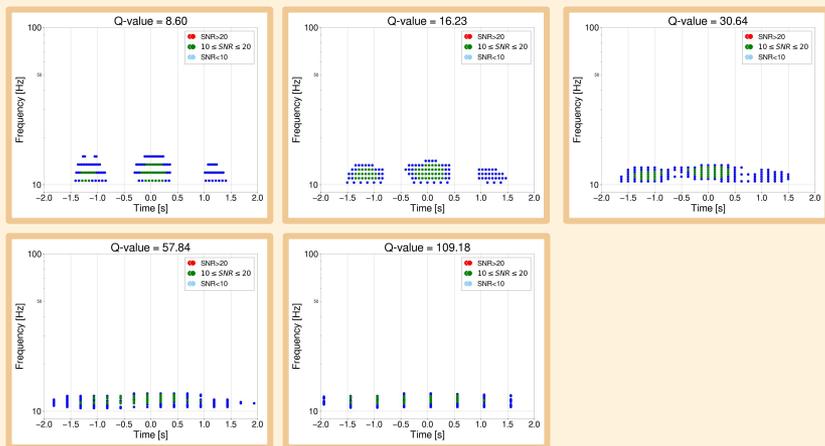
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Ferreira, T.A. & Gonzalez, G.  
(2025)

# Unclustered Omicron

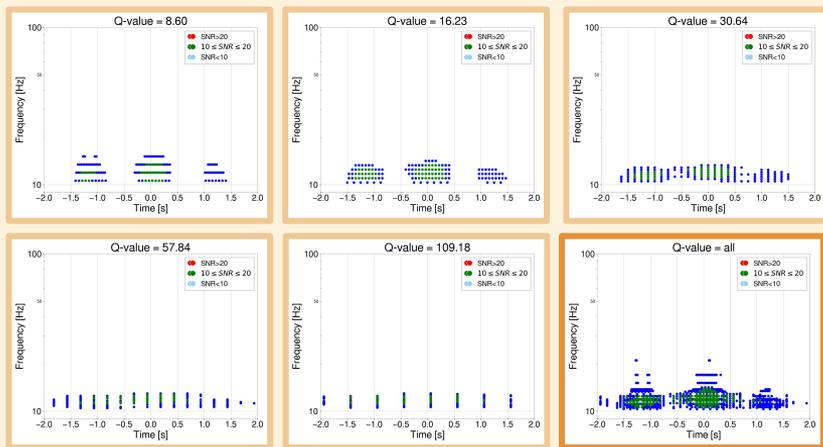
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Ferreira, T.A. & Gonzalez, G.  
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# Unclustered Omicron

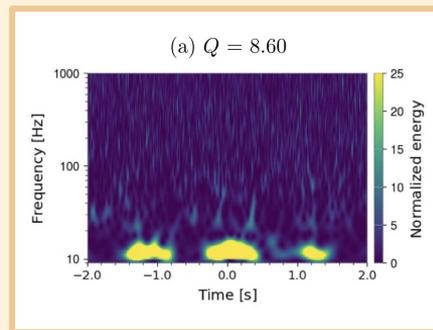
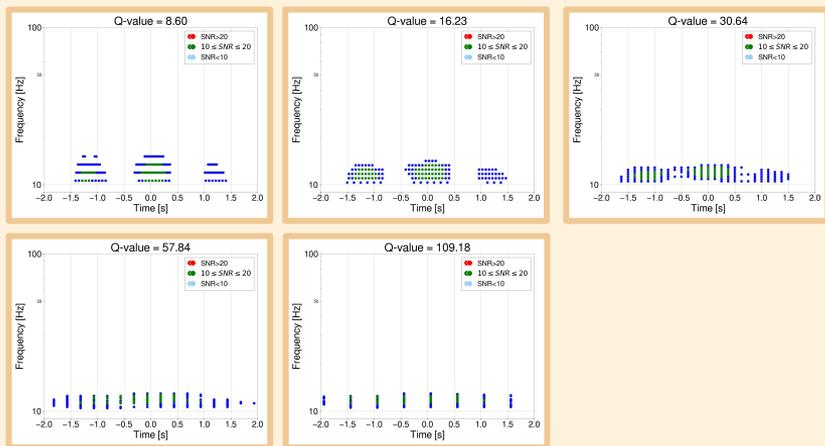
The same glitch can generate multiple Omicron triggers at different Q-values



Ferreira, T.A. & Gonzalez, G.  
(2025)

# Unclustered Omicron

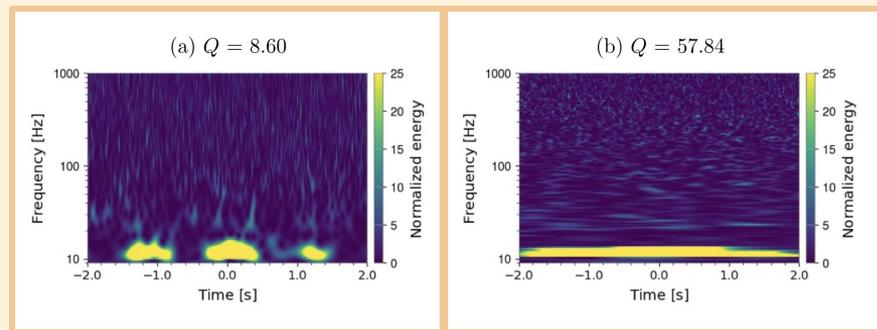
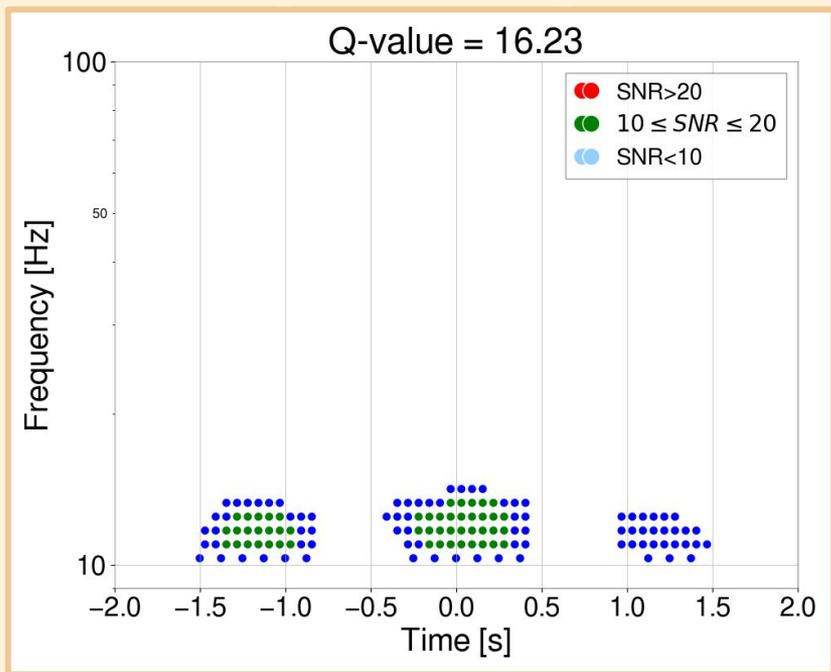
The same glitch can generate multiple Omicron triggers at different Q-values



Ferreira, T.A. & Gonzalez, G.  
(2025)

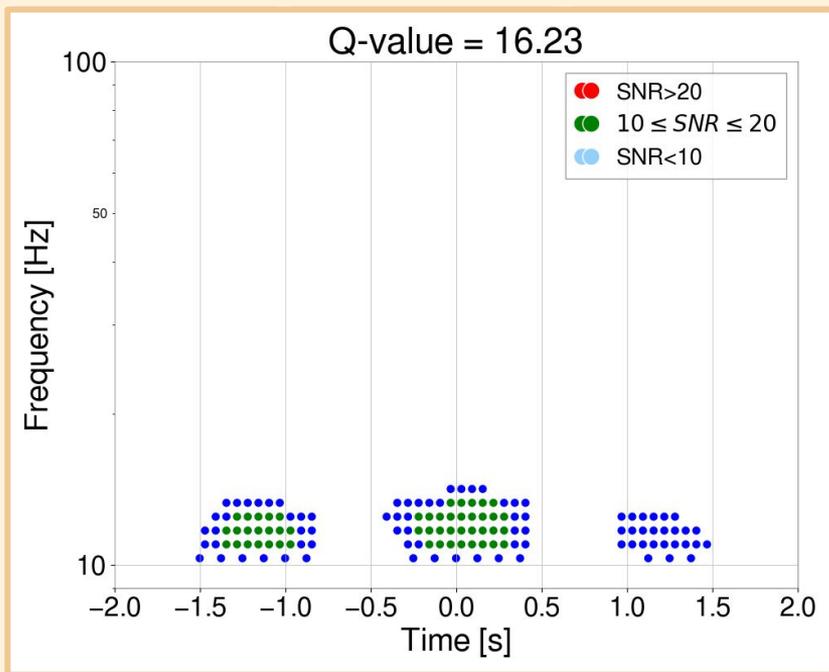
# Unclustered Omicron

The same glitch can generate multiple Omicron triggers at different Q-values



# Clustered Omicron

One representative Q-plane will be chosen for each glitch

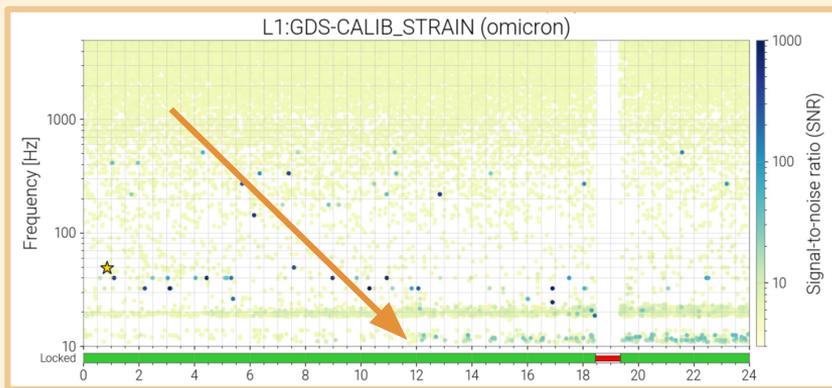


## Parameters

GPS time  
Duration  
Peak Frequency  
SNR  
...

# Clustered Omicron

One representative Q-plane will be chosen for each glitch



## Parameters

GPS time  
Duration  
Peak Frequency  
SNR  
...

All this information is  
saved in **.h5** files.

# Difference in file size: **.root** vs **.h5** files (same time period)

Using **10 hours** of  
data, from  
**December 23, 2023,**  
**13:00 to 23:00.**

There are **3906843** triggers  
from unclustered Omicron

There are **34510** glitches from  
clustered Omicron

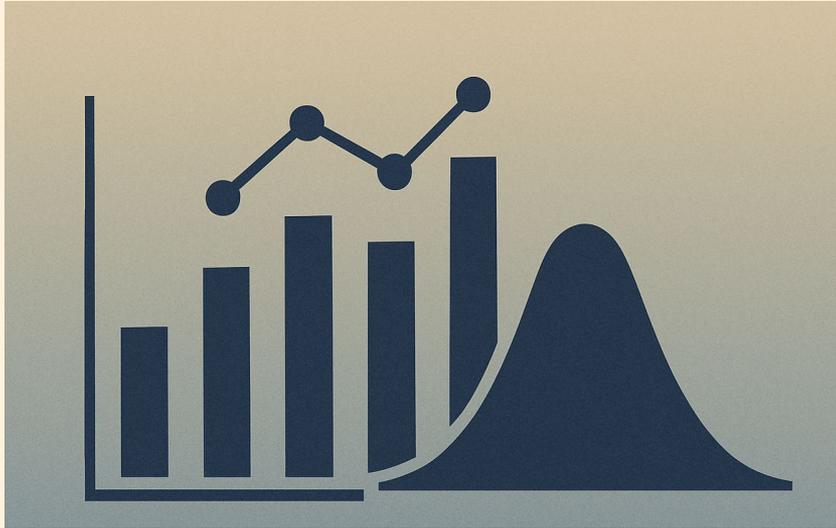
# Difference in file size: **.root** vs **.h5** files (same time period)

Using 10 hours of  
data, from  
December 20  
13-0

3906843 triggers  
unclustered Omicron

There are 34510 glitches from  
clustered Omicron

These numbers will vary depending on the  
size of the data and the type of glitch



Statistical analyses can be performed on both clustered and unclustered Omicron triggers, although the clustered information is more commonly used



Statistical analyses can be performed on both clustered and unclustered Omicron triggers, although the clustered information is more commonly used

**What can we learn statistically once glitches are properly represented (especially clustered)?**

# Examples and Some Applications

# Using clustered information

It is very common to focus on frequency regions with glitches above a minimum SNR.

```
len(o4a_l1)
```

```
14931958
```

```
len(o4a_l1[(o4a_l1['frequency']>=10) & (o4a_l1['frequency']<=2048)])
```

```
1672247
```

```
len(o4a_l1[o4a_l1['snr']>=7.5])
```

```
673284
```

```
len(o4a_l1.loc[(o4a_l1['frequency'] >= 10) & (o4a_l1['frequency'] <= 2048) & (o4a_l1['snr'] >= 7.5)])
```

```
166139
```

# Using clustered information

It is very common to

```
len(o4a_l1)
```

```
14931958
```

```
len(o4a_l1[(o4a_l1['frequency'] > 10)])
```

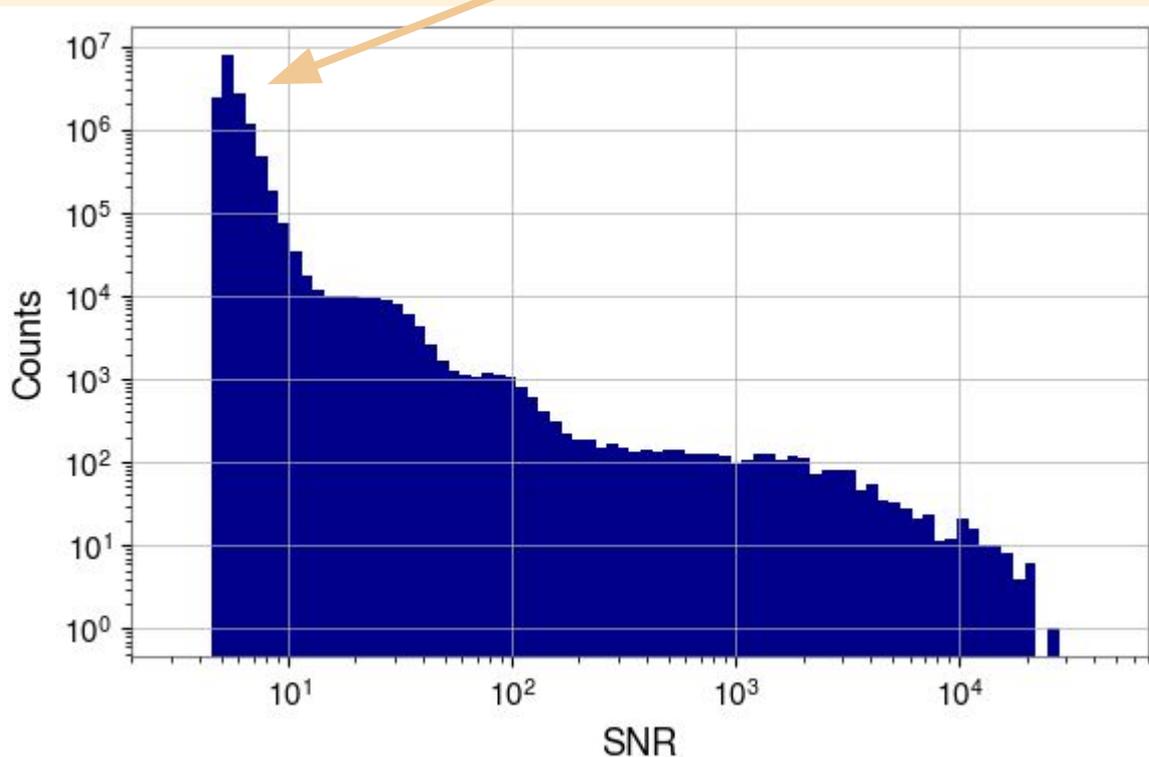
```
1672247
```

```
len(o4a_l1[o4a_l1['snr'] >= 7.5])
```

```
673284
```

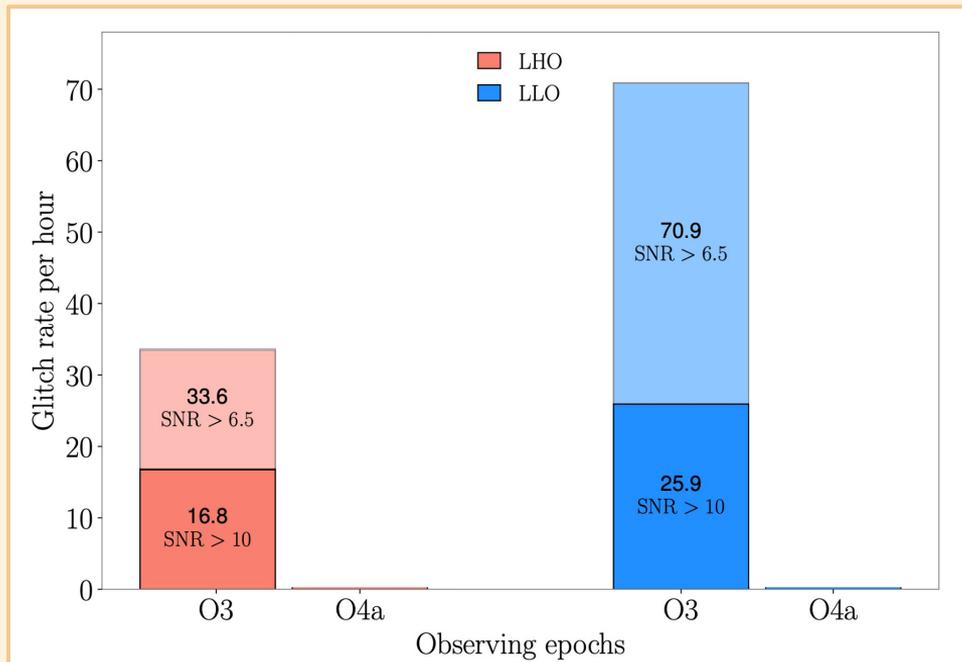
```
len(o4a_l1.loc[(o4a_l1['frequency'] > 10) & (o4a_l1['snr'] >= 7.5)])
```

```
166139
```



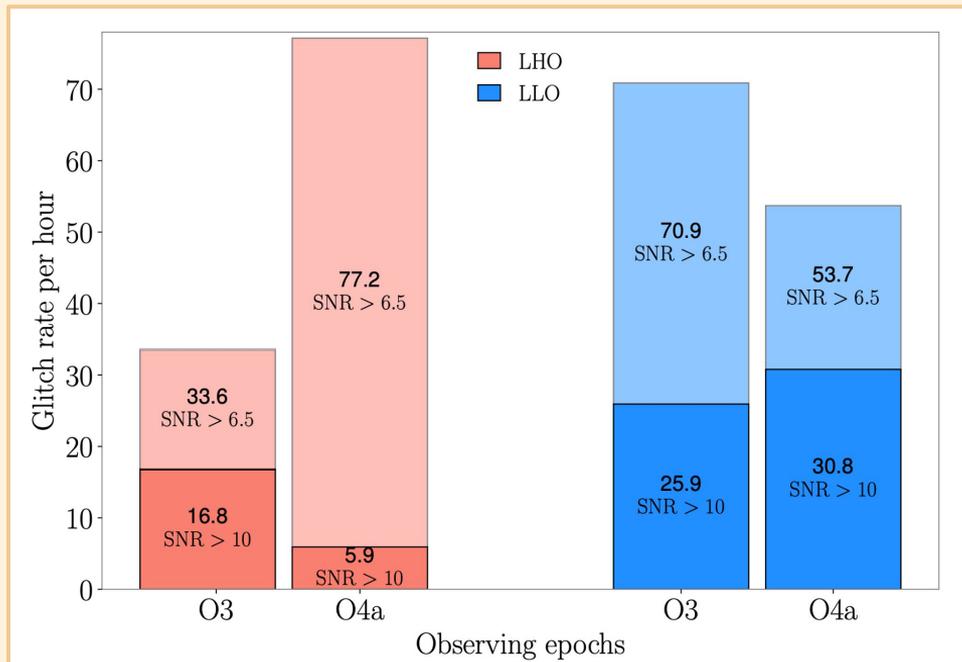
# Using clustered information

Comparison between different observing epochs



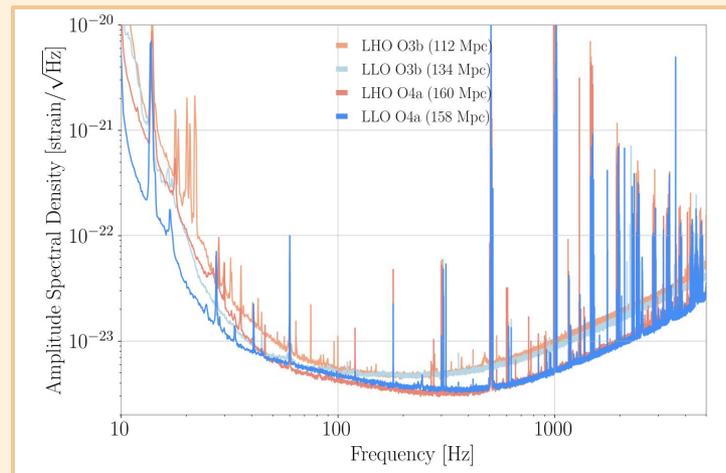
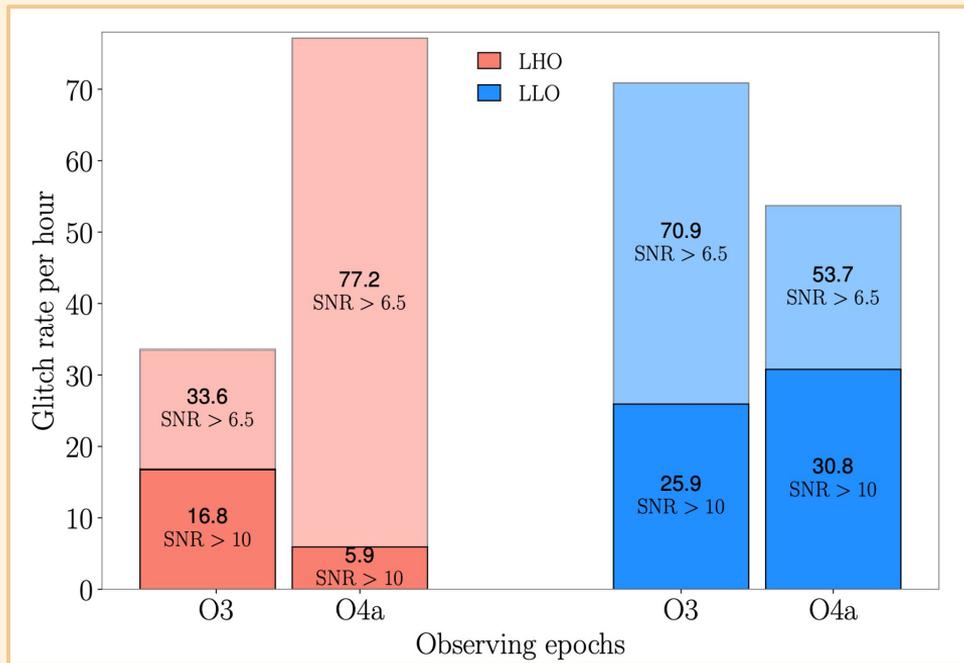
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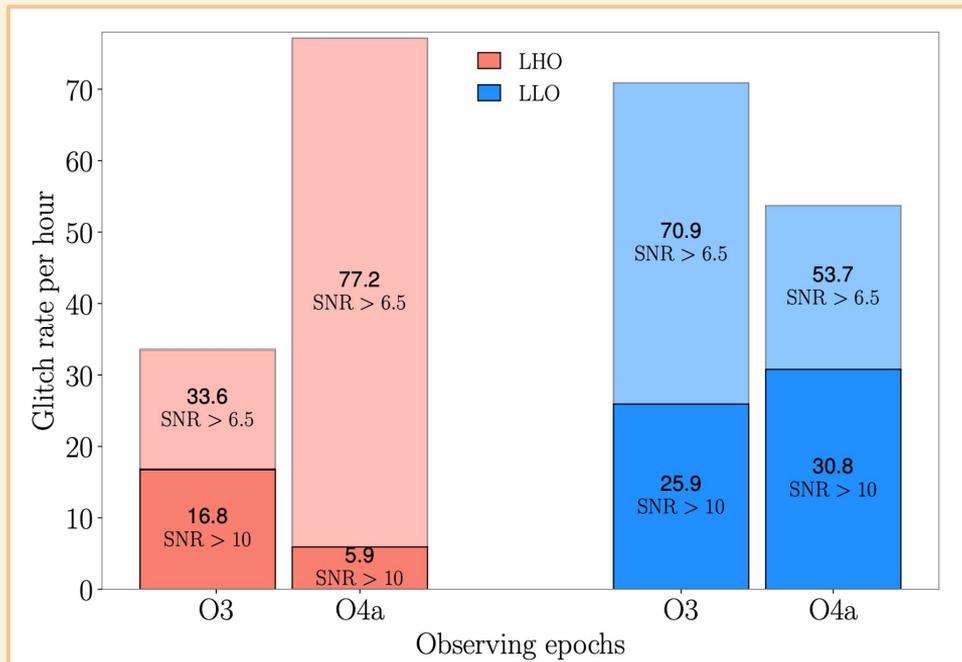
# Using clustered information

Comparison between different observing epochs



# Using clustered information

Comparison between different observing epochs



Soni et al. (2025)

**Questions we can try to answer:**

Why did the glitch rate increase or decrease?

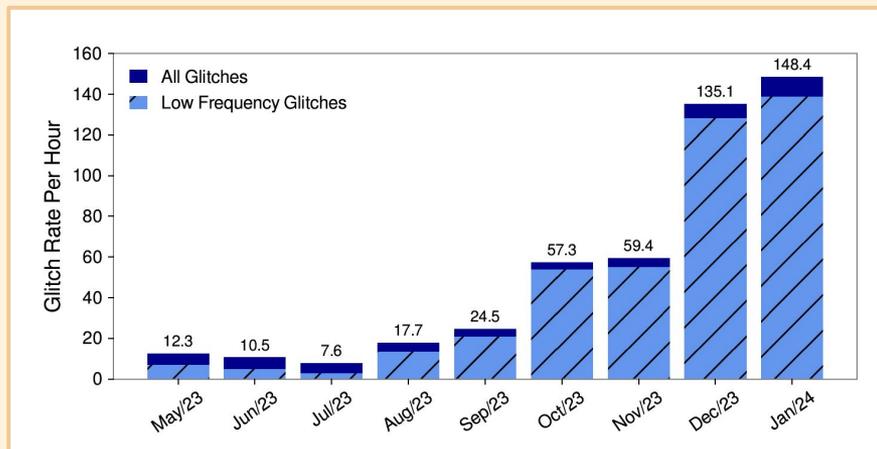
Which detector was more affected, and why?

Were the glitches evenly distributed over time, or were there periods of higher dominance? If so, what happened during those periods?

# Using clustered information

Comparison between different months in a same observing run (O4a)

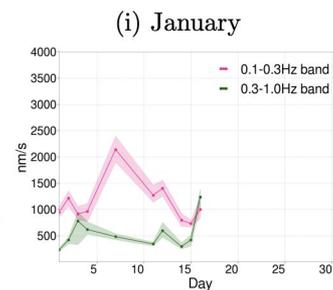
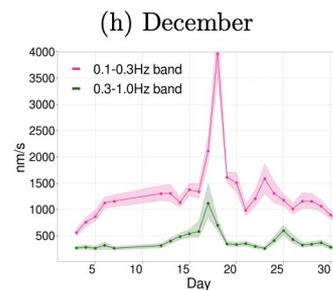
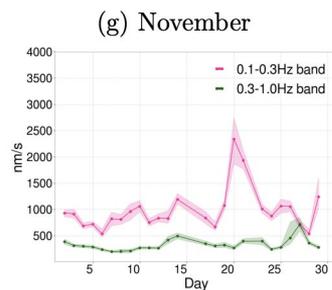
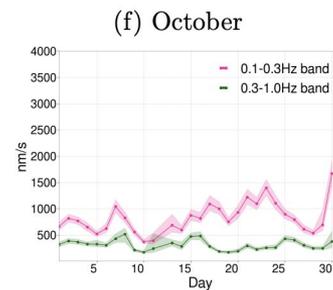
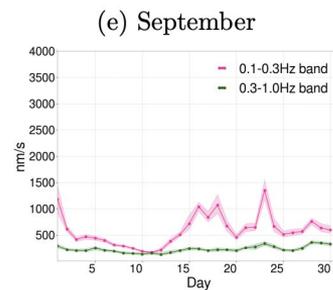
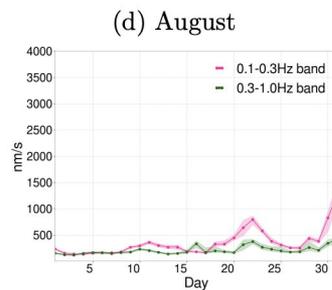
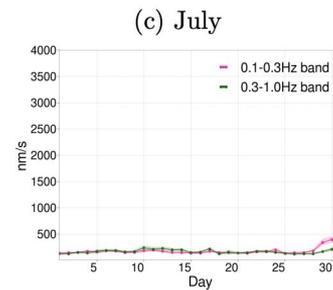
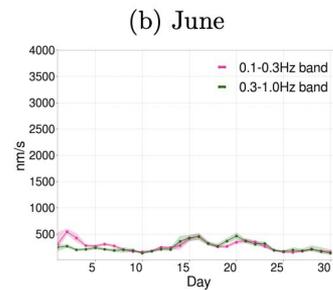
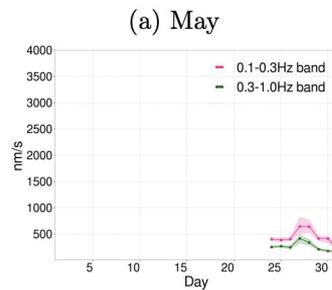
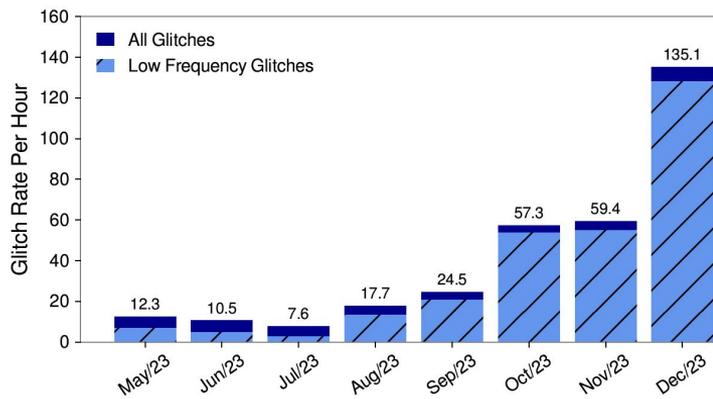
LLO



Ferreira, T.A. et al. (2025)

# Using clustered in

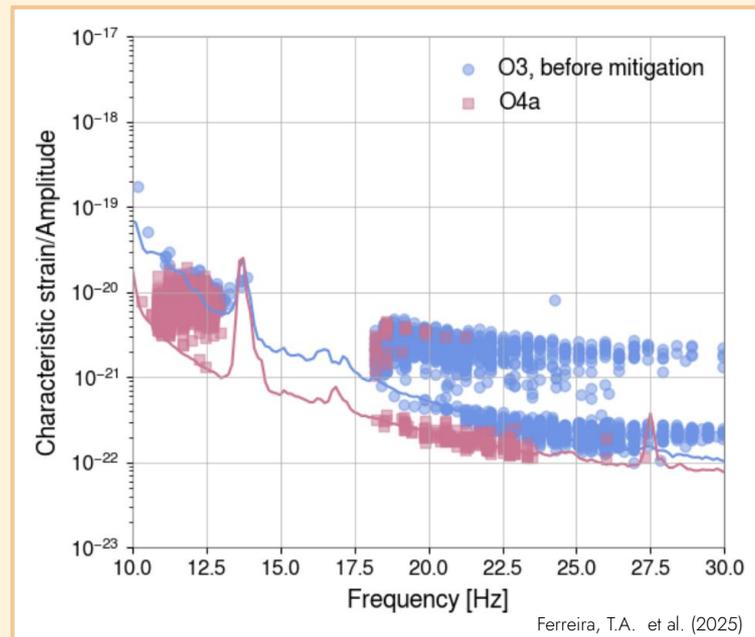
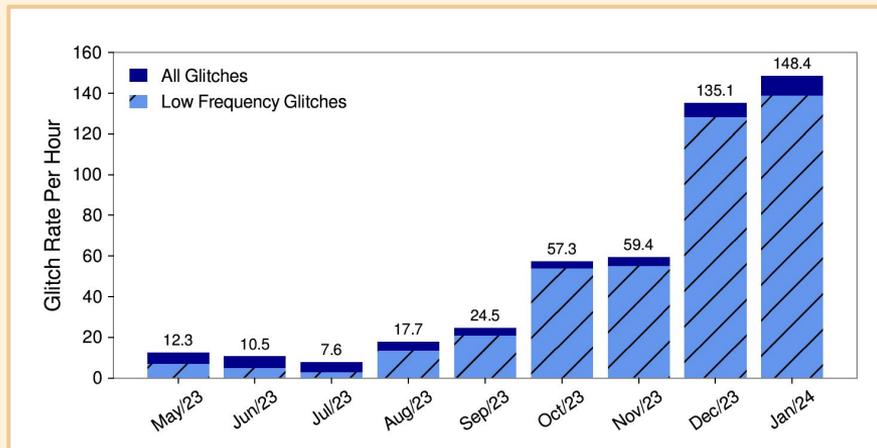
## LLO



# Using clustered information

Comparison between different months in a same observing run (O4a)

LLO



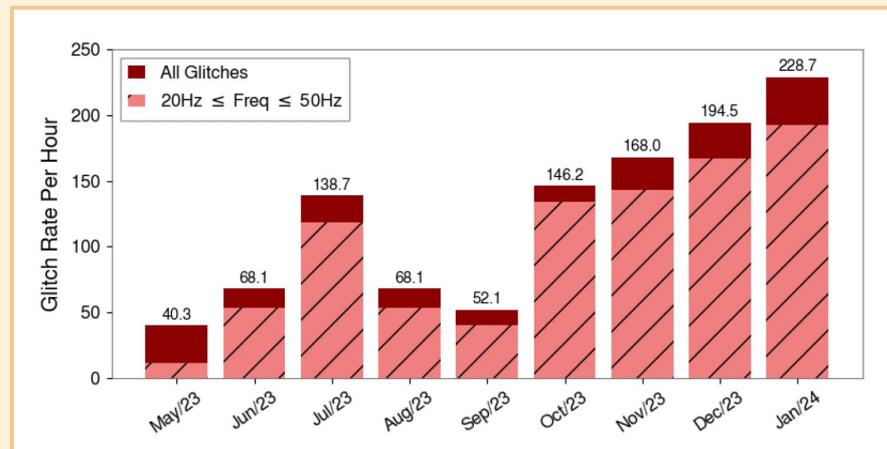
# Using clustered information

Comparison between different months in a same observing run (O4a)

## LLO



## LHO

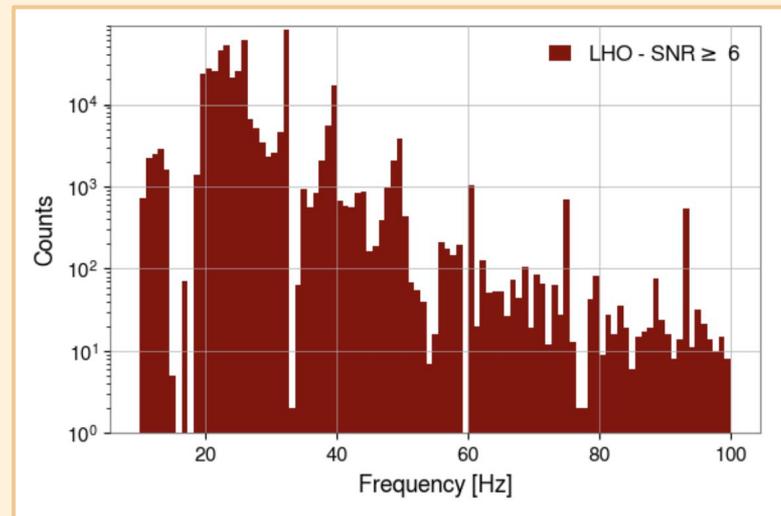
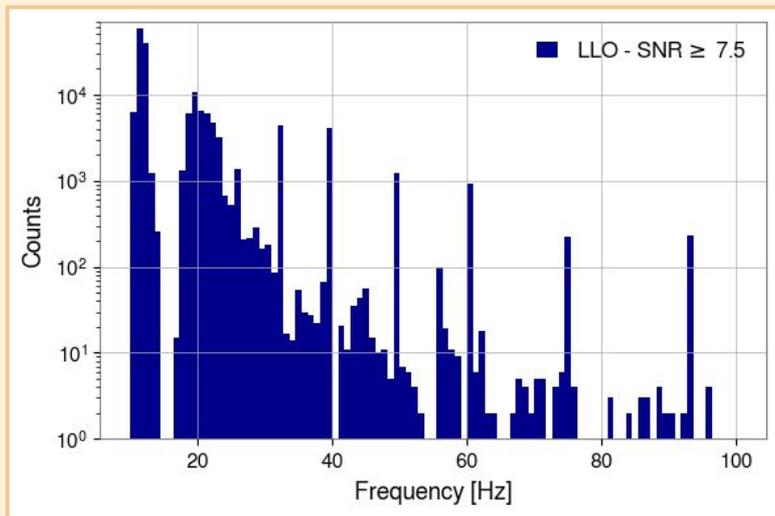


Ferreira, T.A. et al. (2025)

# Parameter characteristics

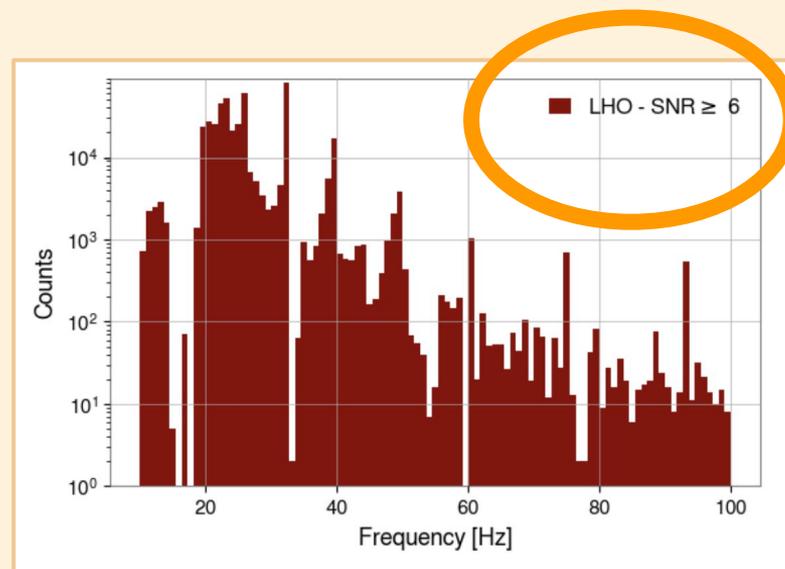
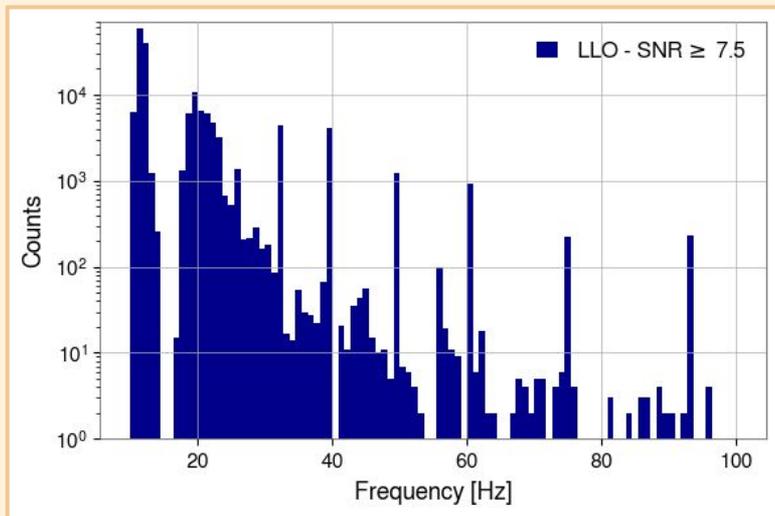
# Using clustered information

## Parameter distributions



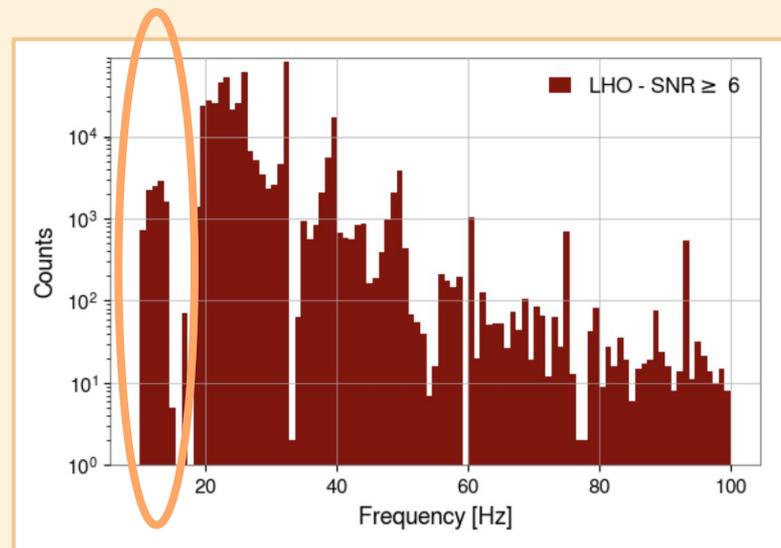
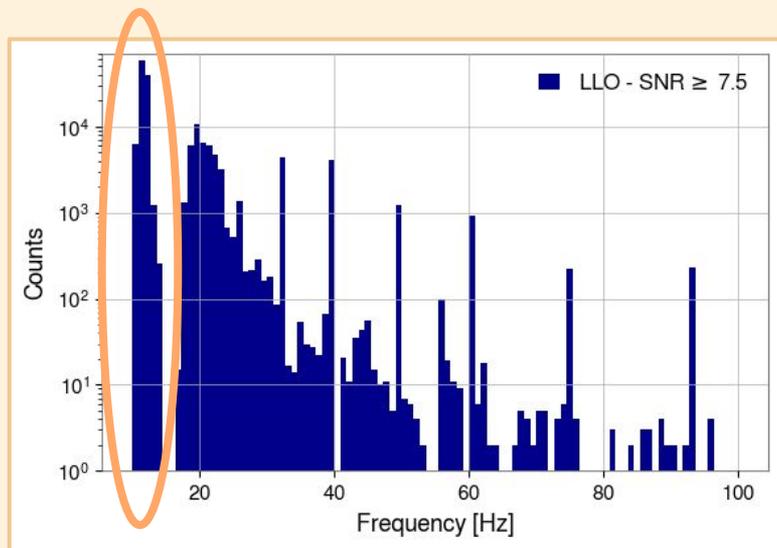
# Using clustered information

## Parameter distributions



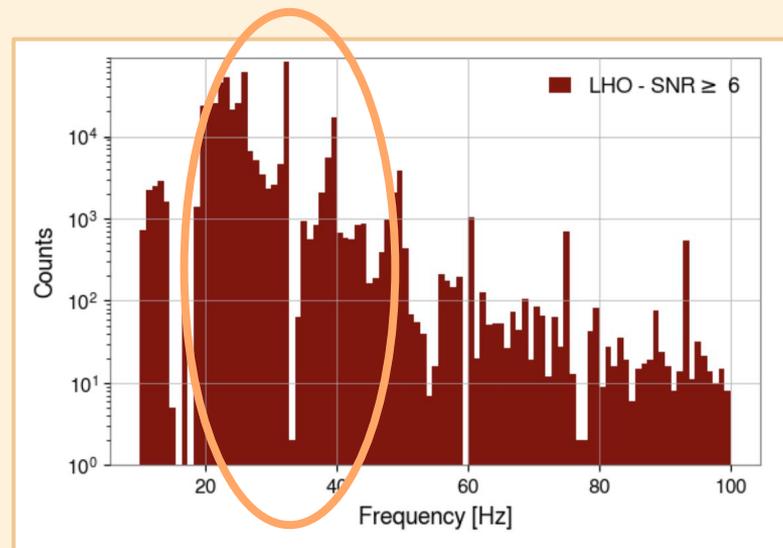
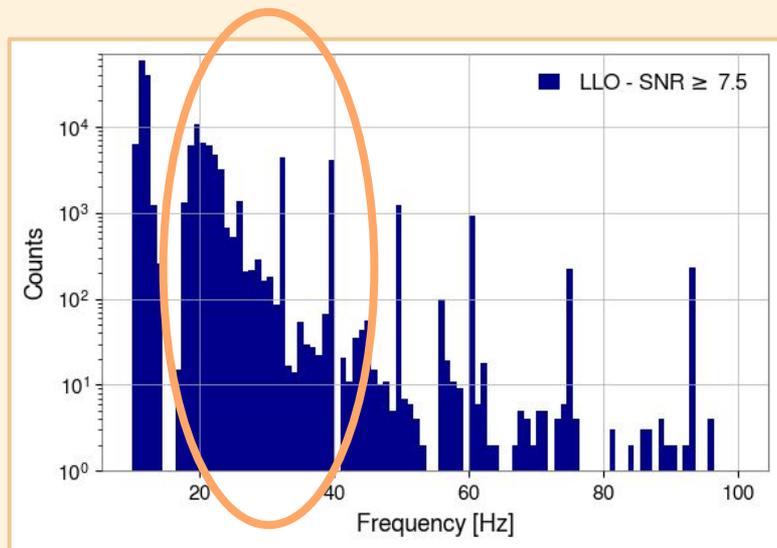
# Using clustered information

## Parameter distributions



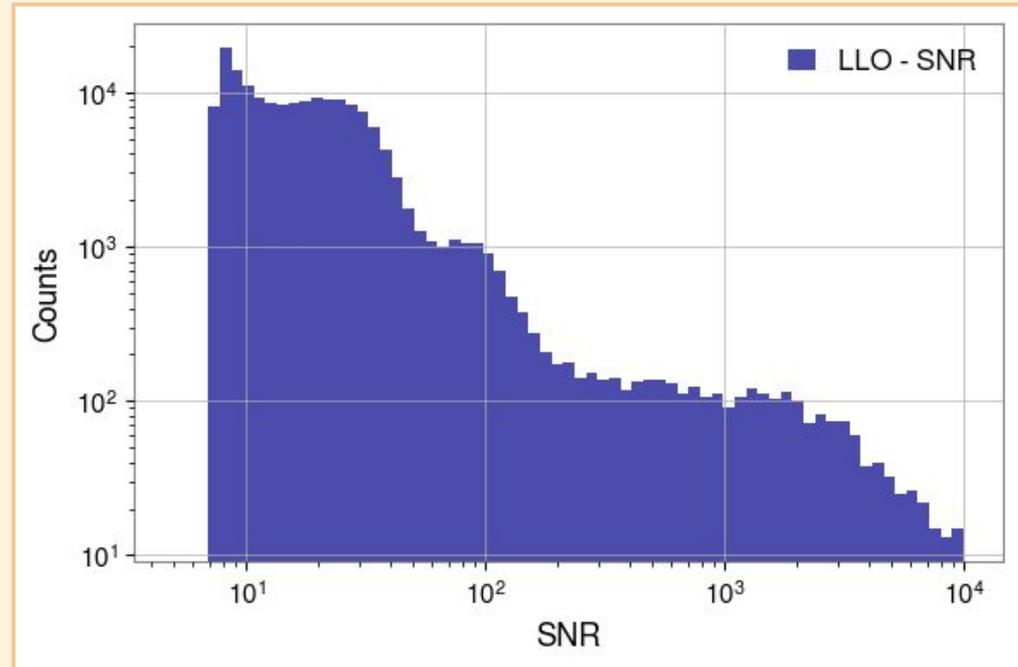
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## Parameter distributions



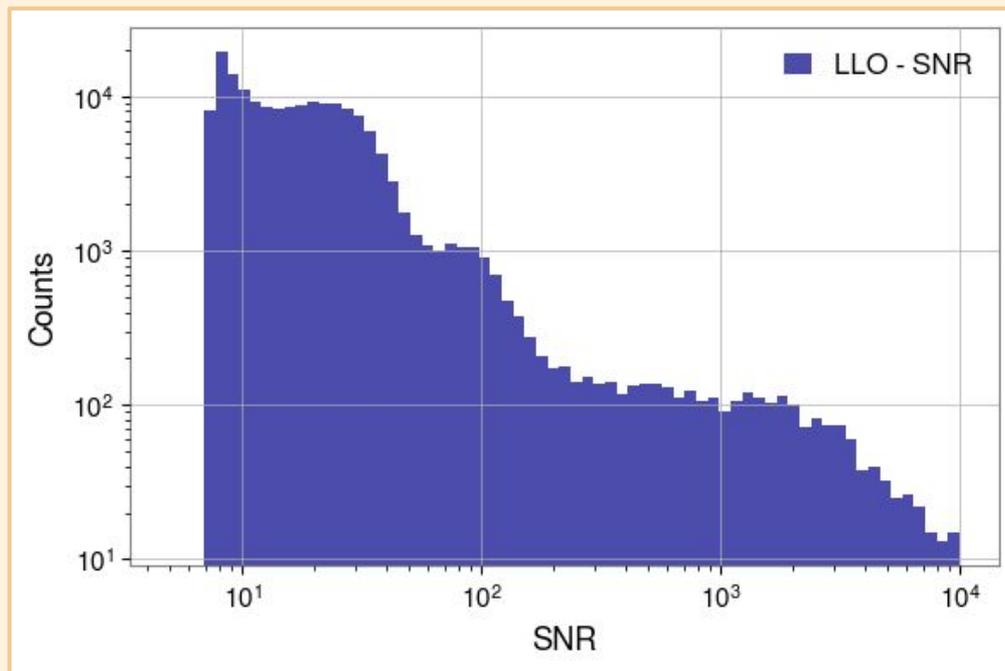
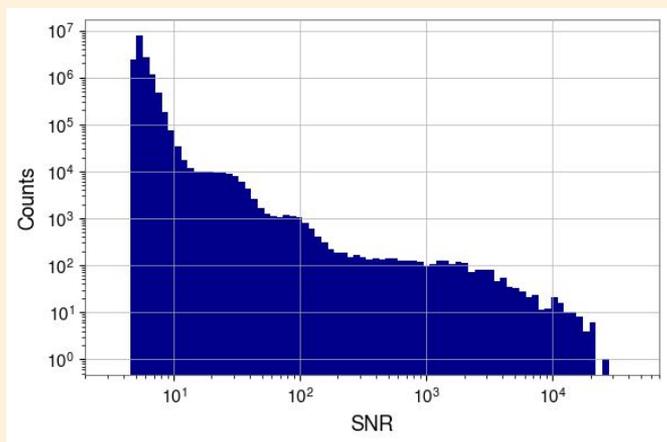
# Using clustered information

## Parameter distributions



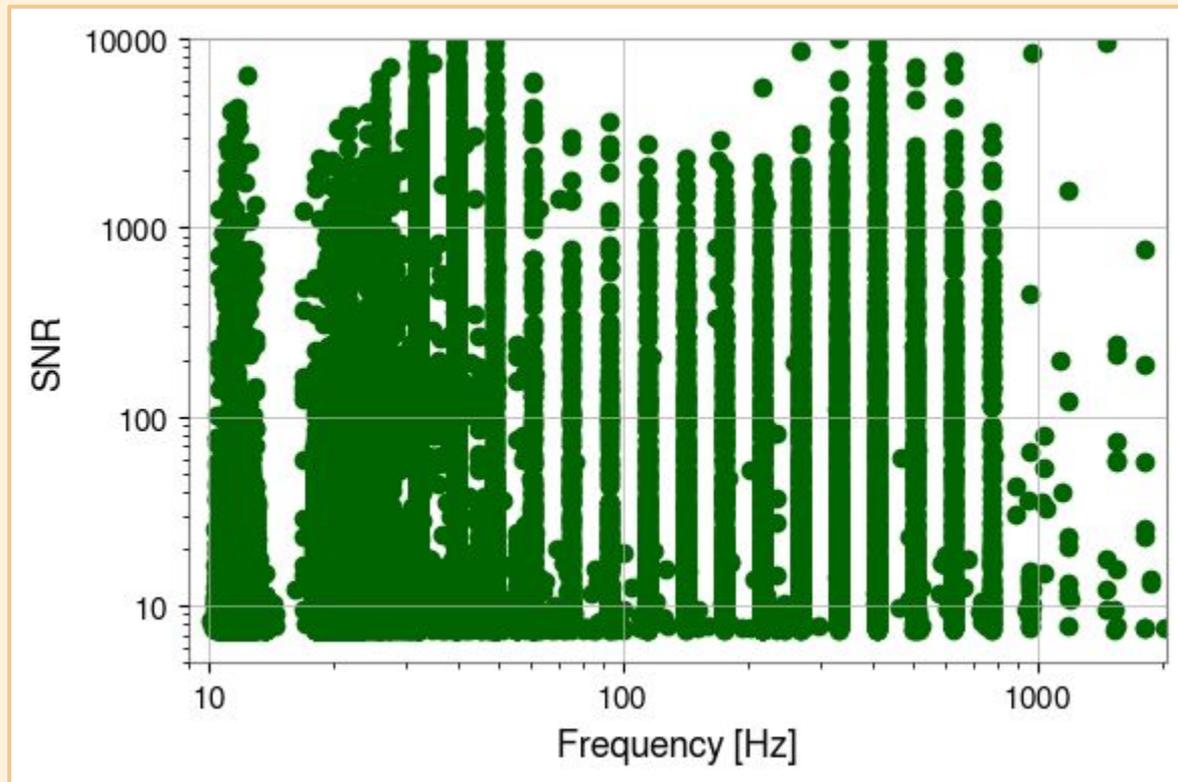
# Using clustered information

## Parameter distributions



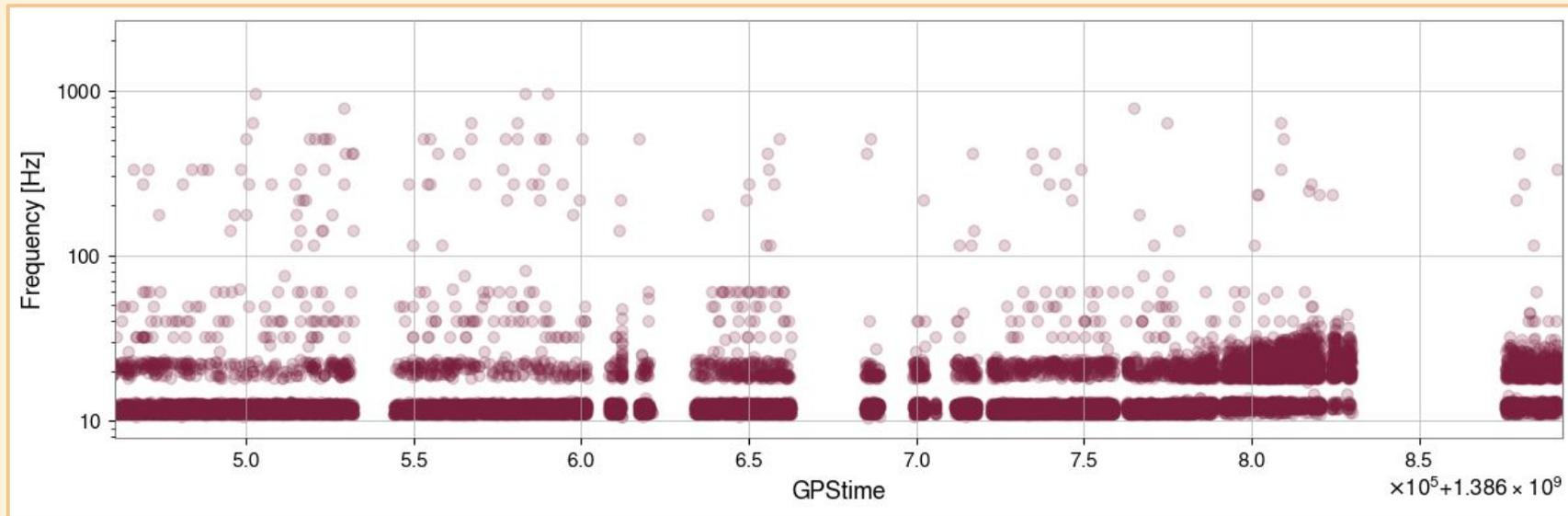
# Using clustered information

Scatter plot



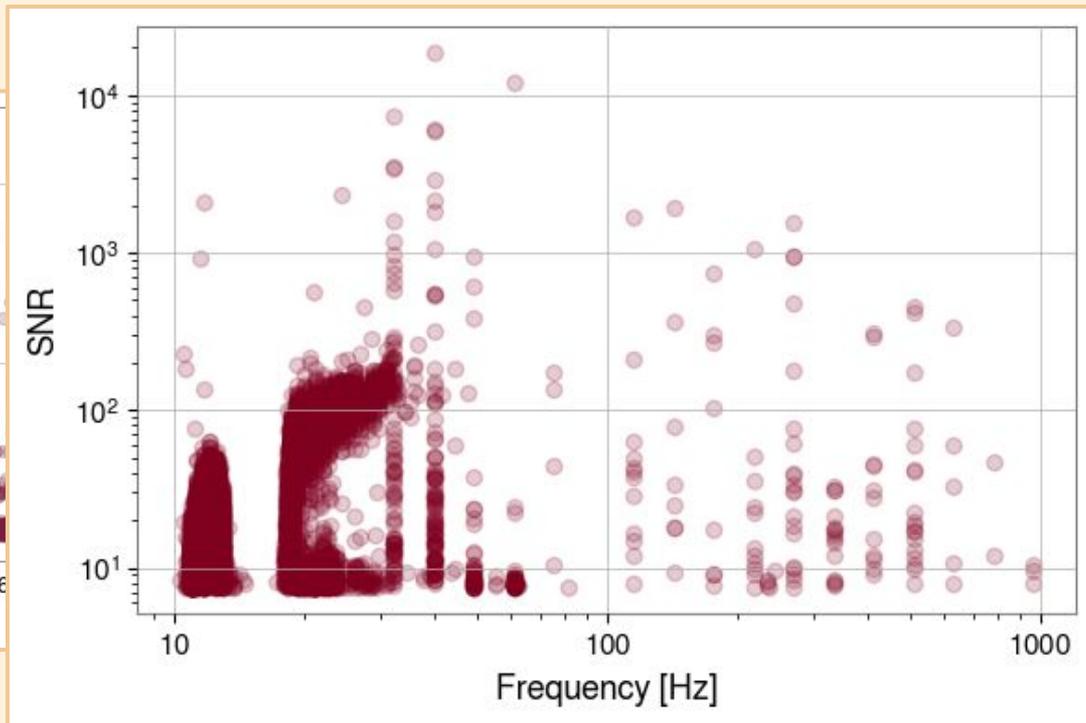
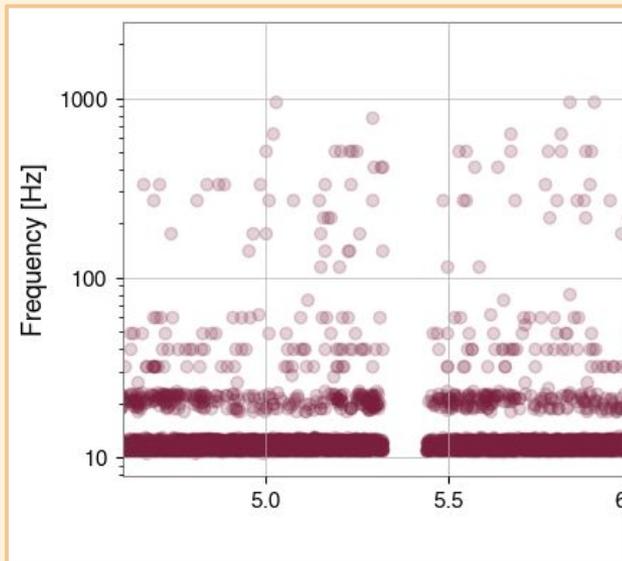
# Using clustered information

Glitches over time (short time period, in this case)



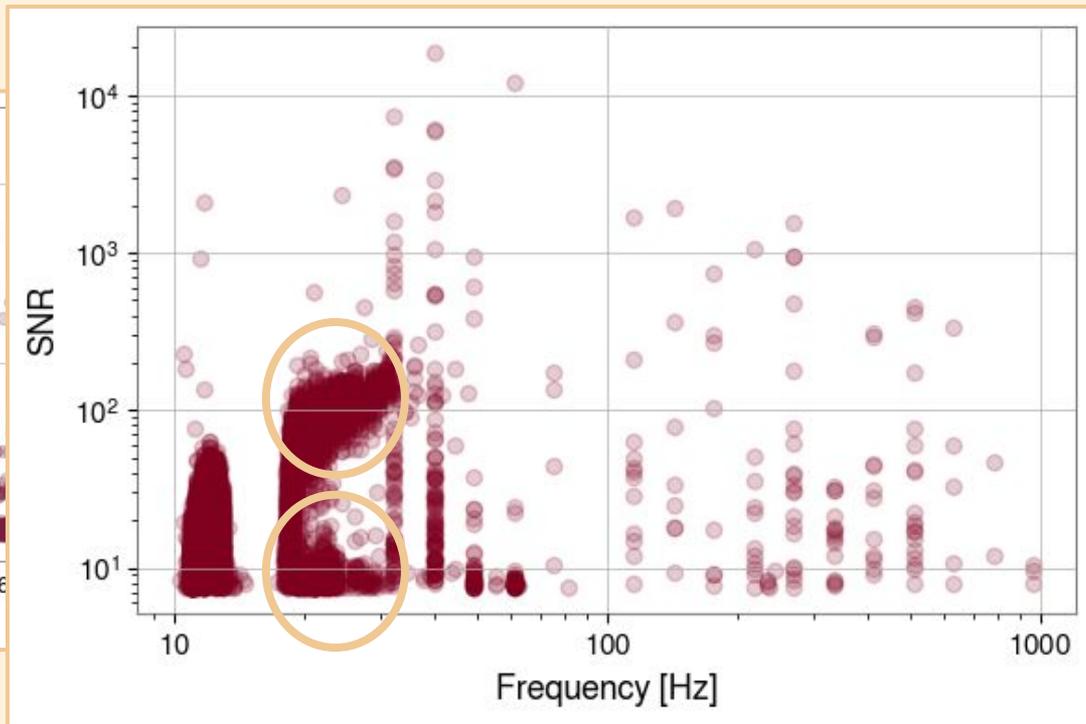
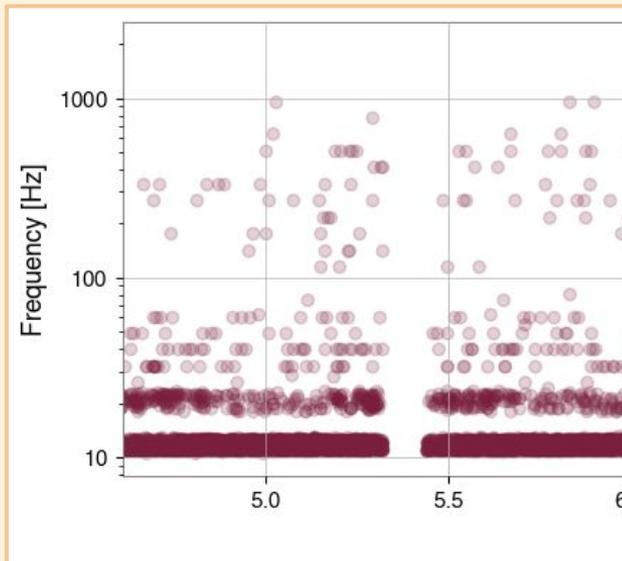
# Using clustered information

Glitches over time (short time period, in this case)

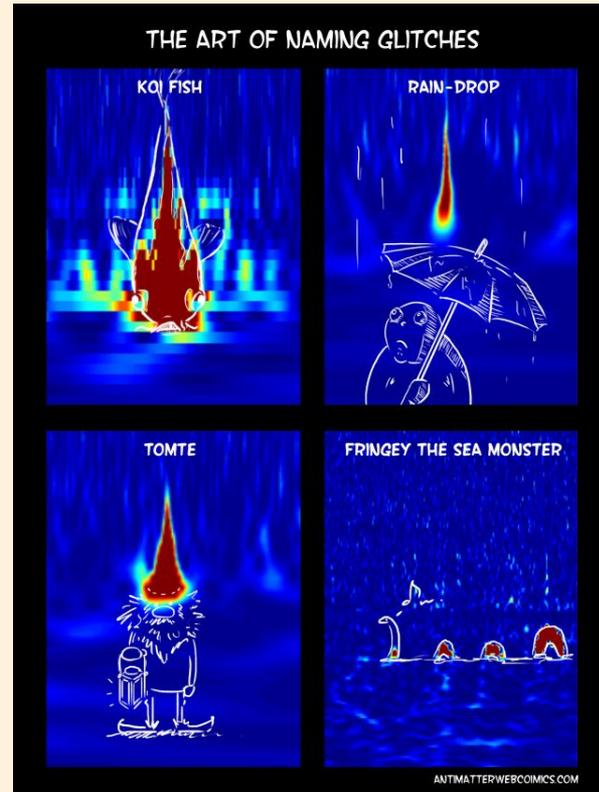


# Using clustered information

Glitches over time (short time period, in this case)



# Glitch Classes



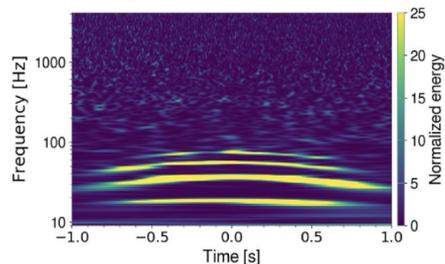
<https://cqplus.wordpress.com/2016/06/06/how-do-we-know-ligo-detected-gravitational-waves/>

# Class names

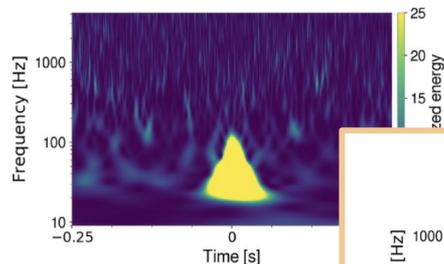
```
print(gs_o4['label'].unique())
```

```
['Extremely_Loud' 'Koi_Fish' 'Tomte' 'Low_Frequency_Burst'  
'Low_Frequency_Lines' 'Blip_Low_Frequency' 'Fast_Scattering'  
'Scattered_Light' 'Light_Modulation' 'Whistle' 'Blip'  
'Repeating_Blips' 'Scratchy' 'Power_Line' 'Air_Compressor'  
'Violin_Mode' 'Paired_Doves' 'Wandering_Line' 'No_Glitch'  
'Helix' '1080Lines' 'Chirp' '1400Ripples']
```

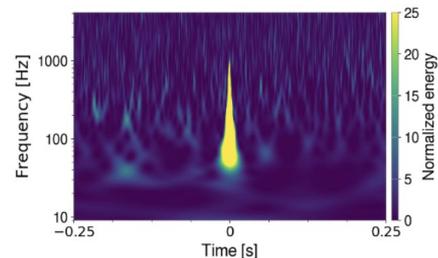
(a) *Scattered Light*



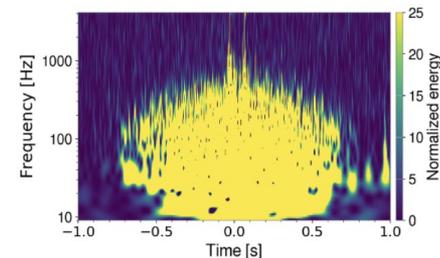
(b) *Tomte*



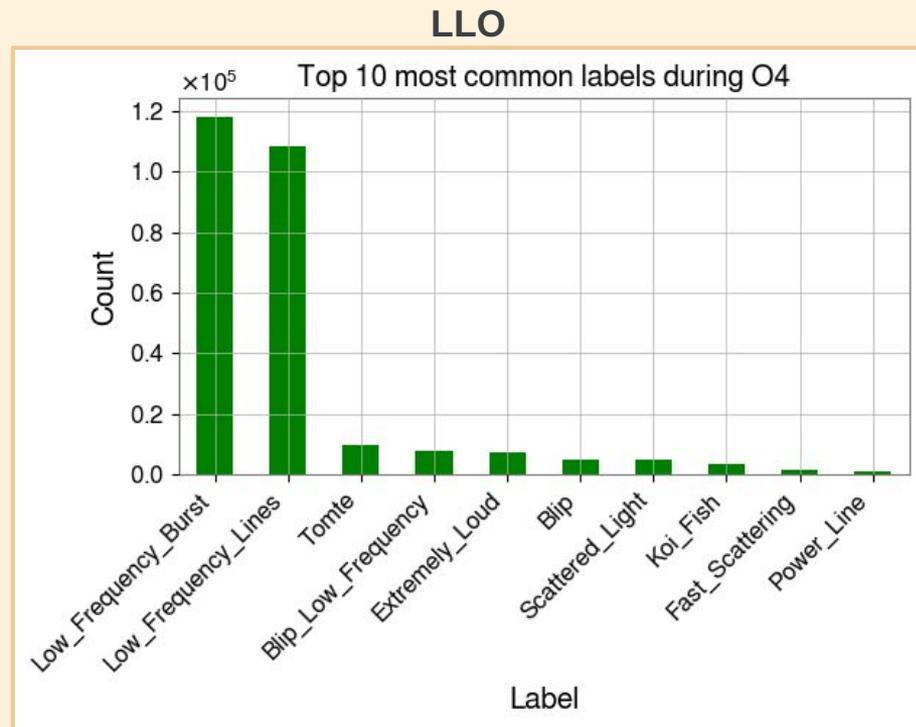
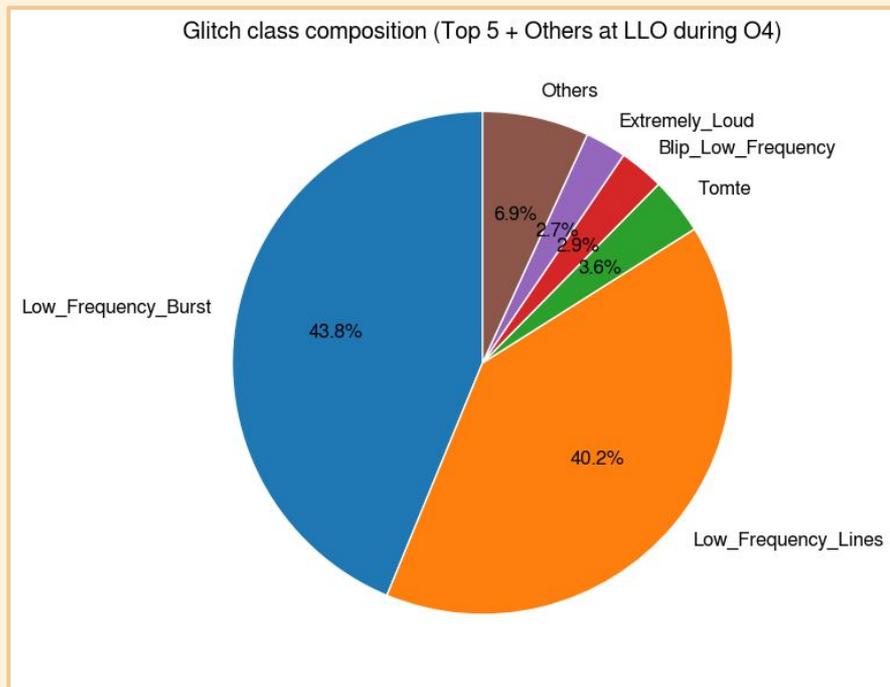
(c) *Blip*



(d) *Extremely Loud*

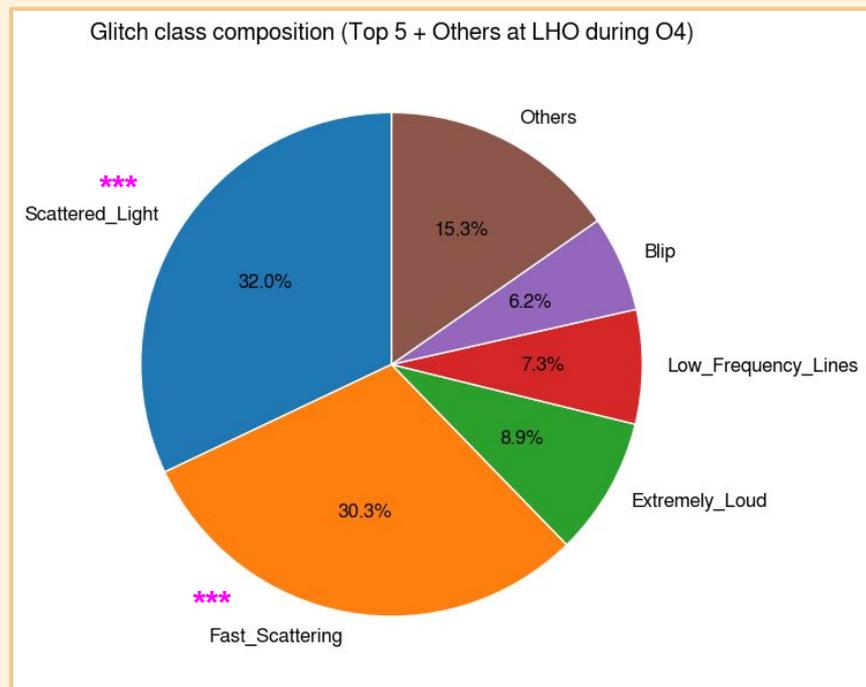
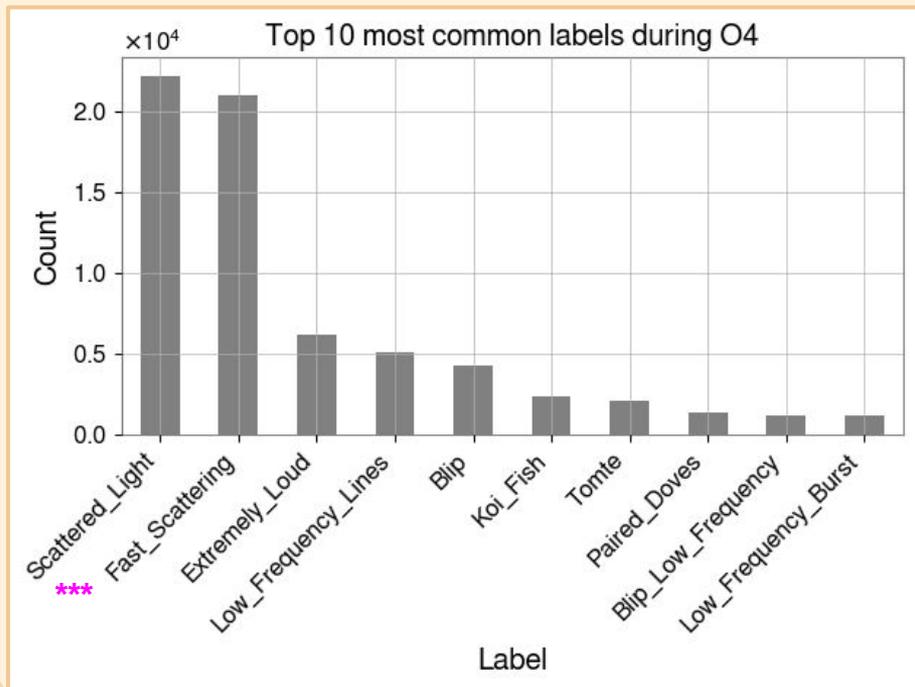


# The most common classes and comparisons between interferometers



# The most common classes and comparisons between interferometers

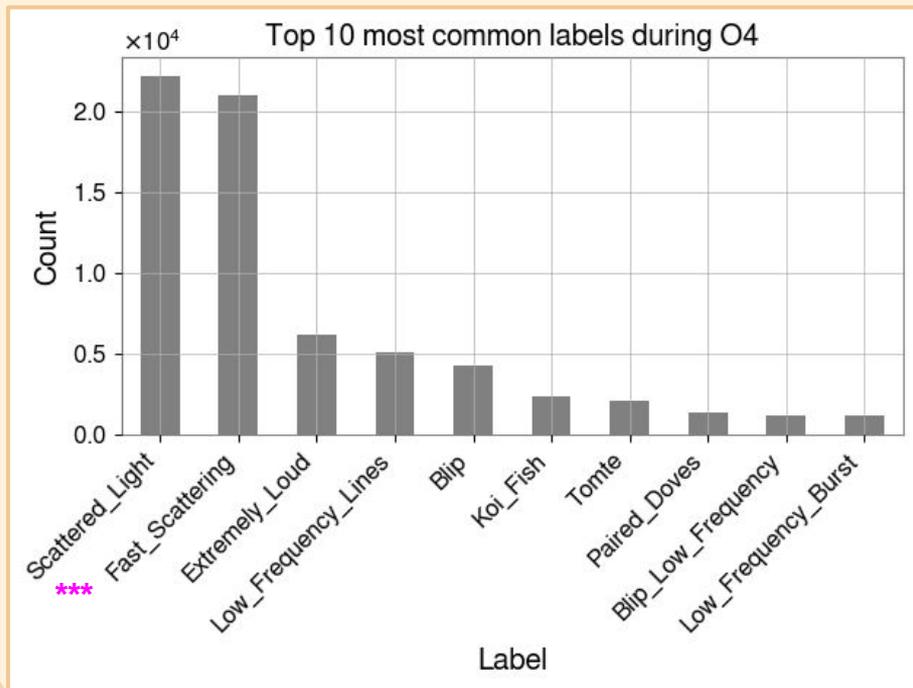
LHO



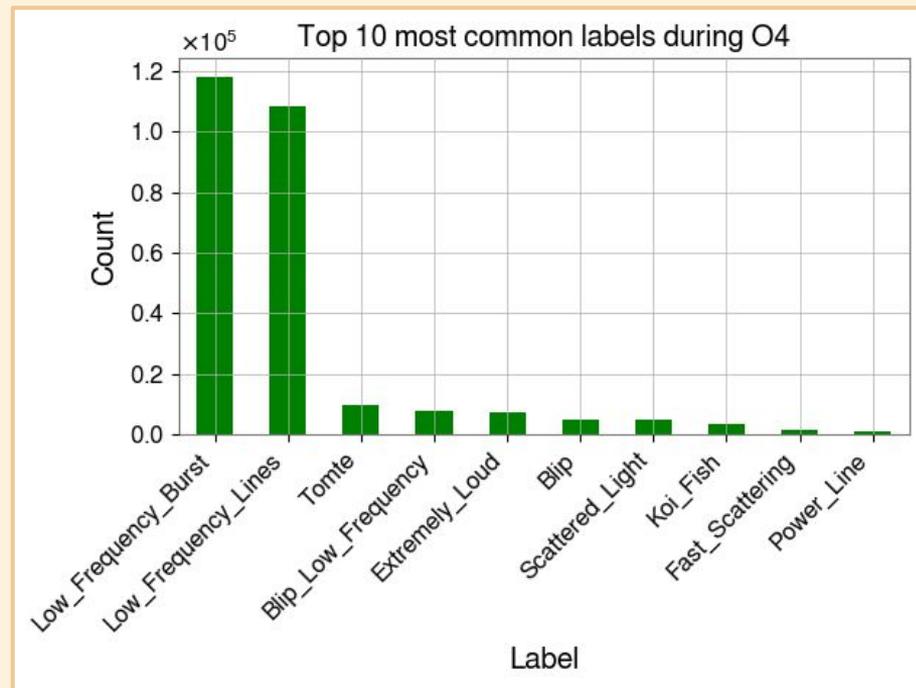
\*\*\* Broadband glitches

# The most common classes and comparisons between interferometers

LHO



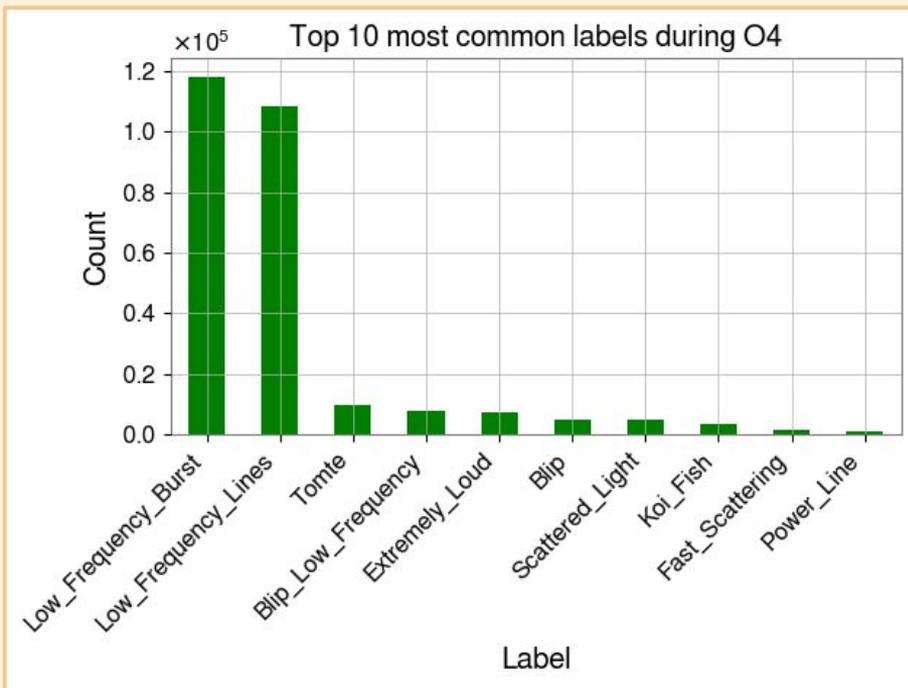
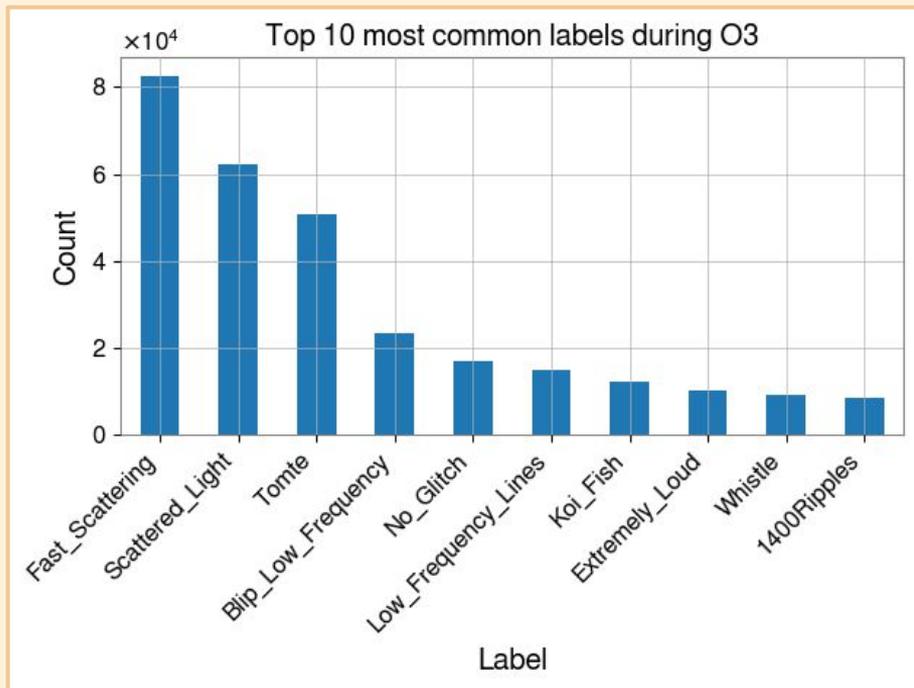
LLO



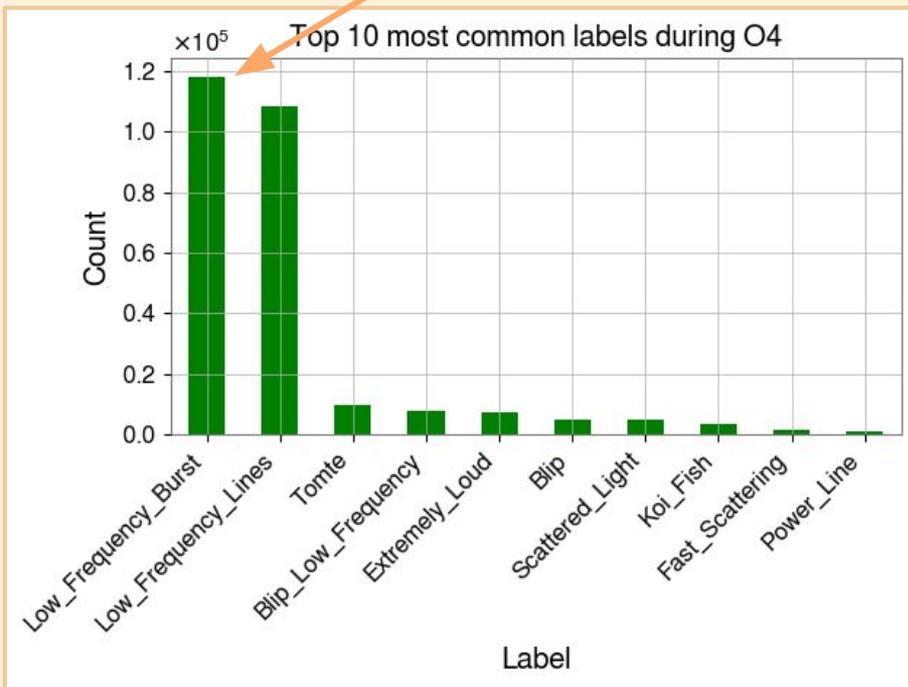
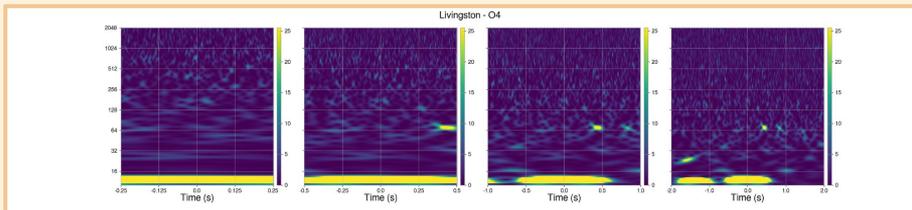
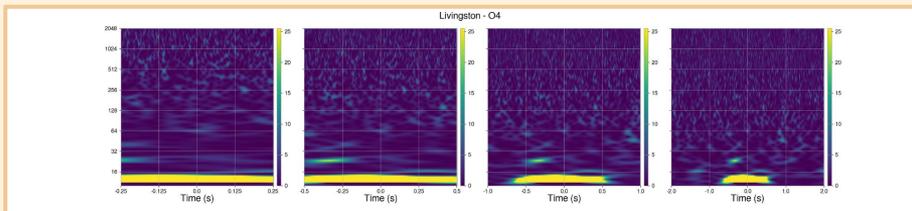
\*\*\* Broadband glitches

# **Comparison between different observing runs**

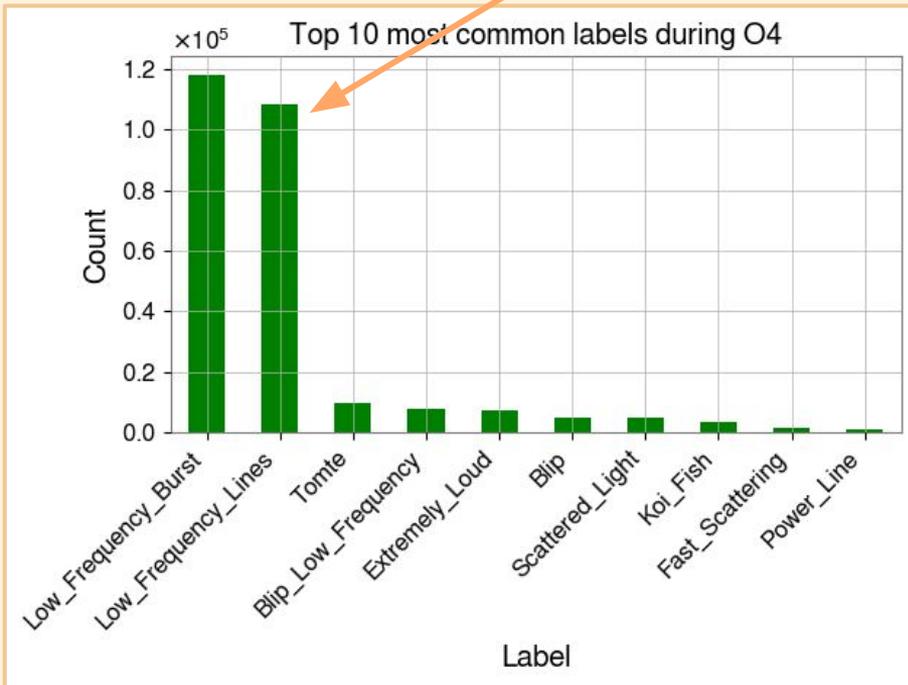
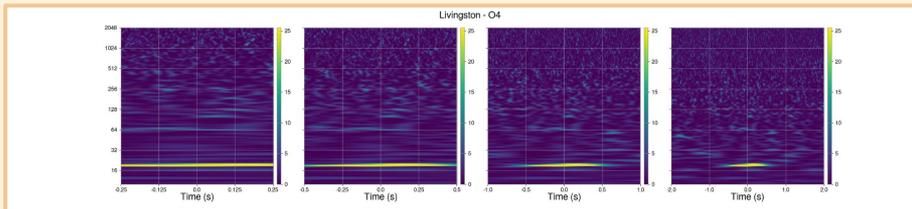
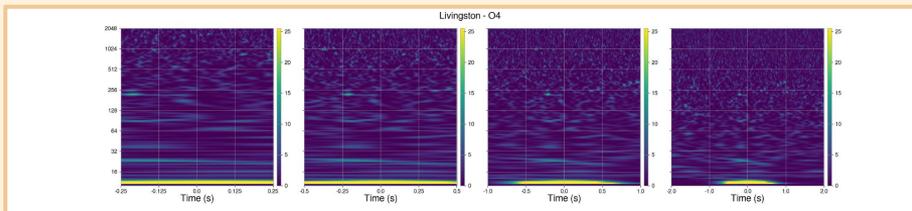
# The most common classes and comparisons between different runs (LLO)



# The most common classes and comparisons (LLO)

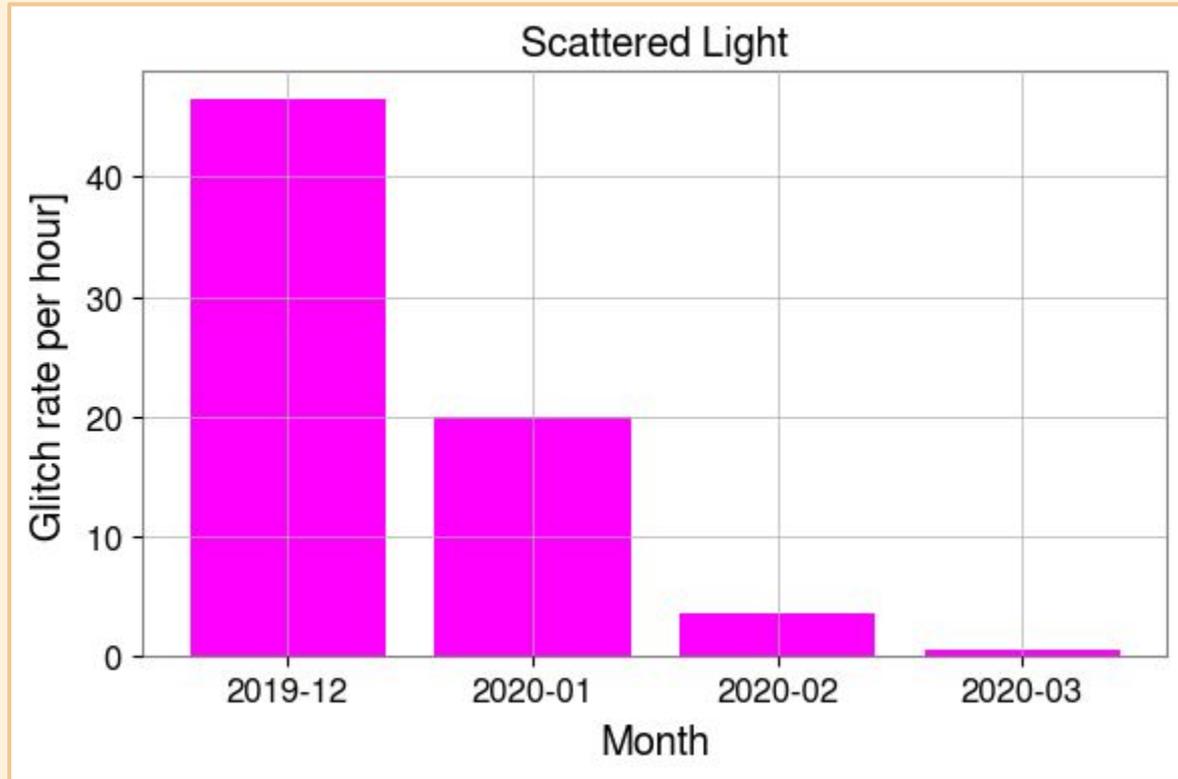


# The most common classes and comparisons (LLO)



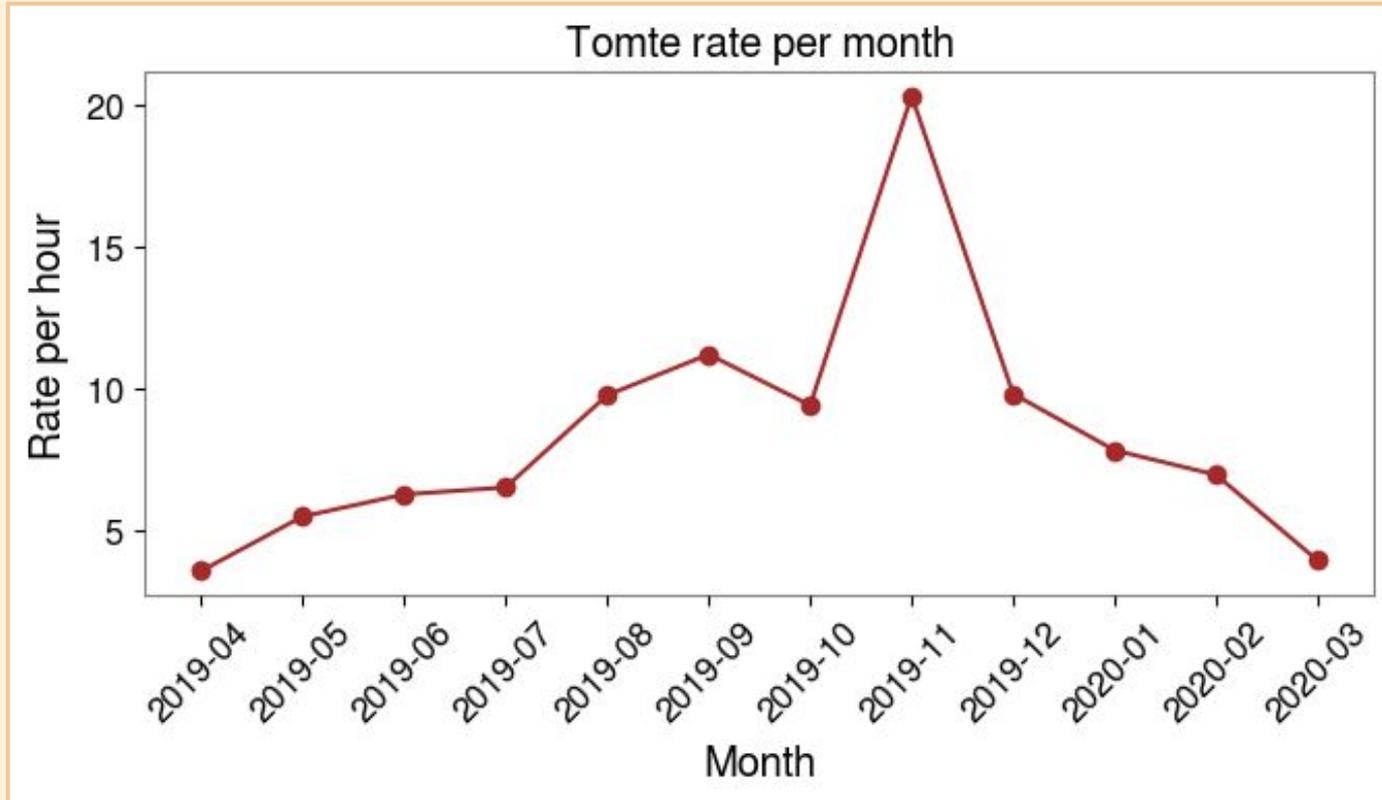
# Class rate over time

# Class rate over time (LLO - 03)



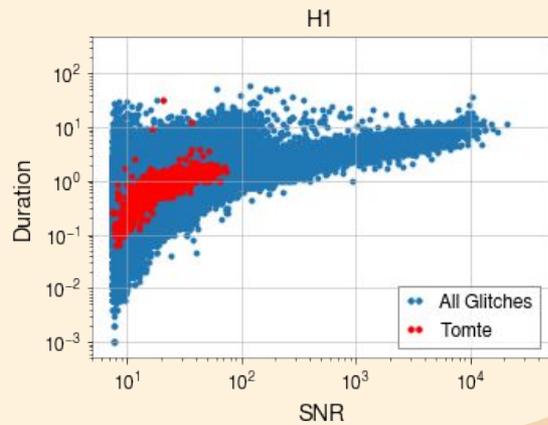
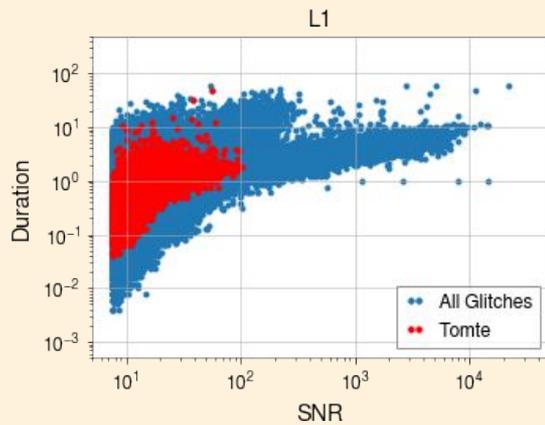
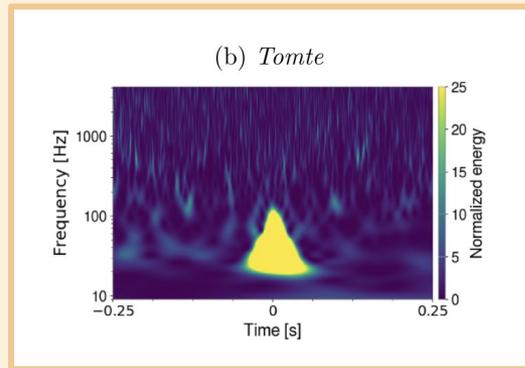
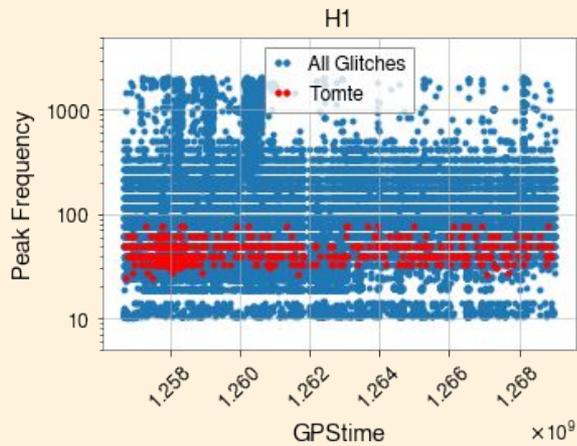
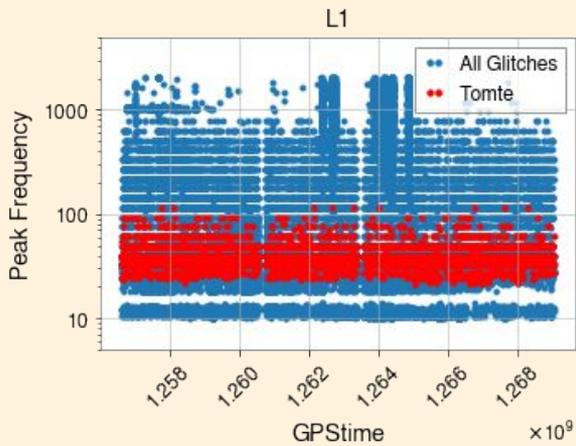
# Class rate over time

What happened in November?

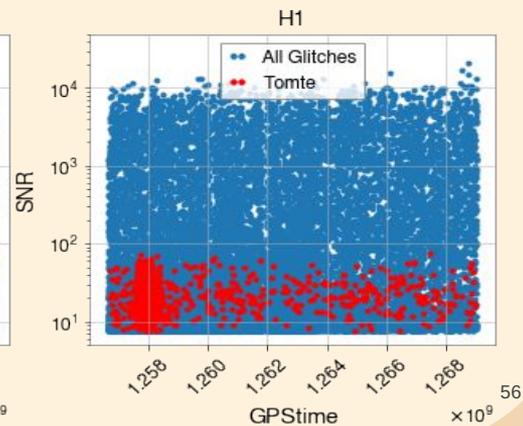
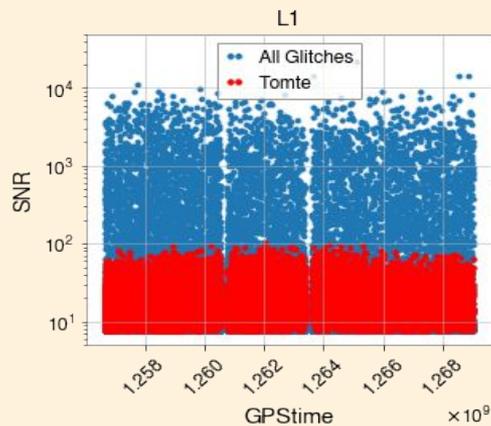
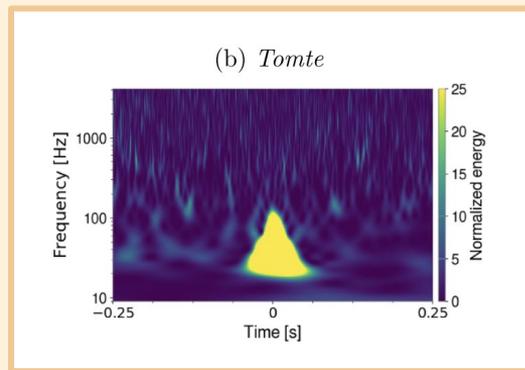
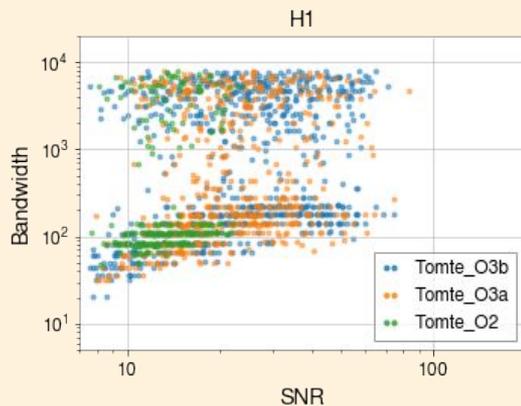
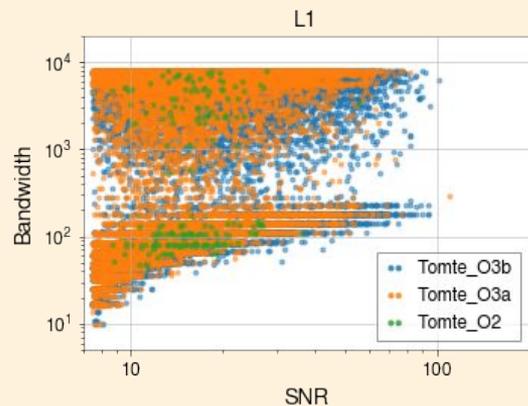


# Comparisons

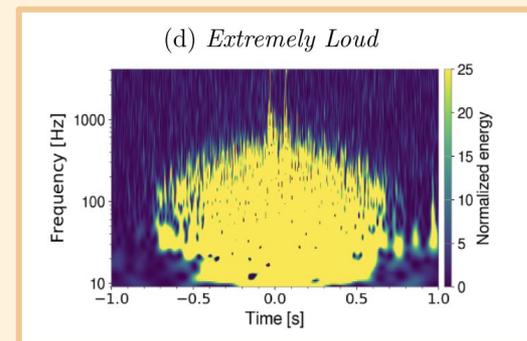
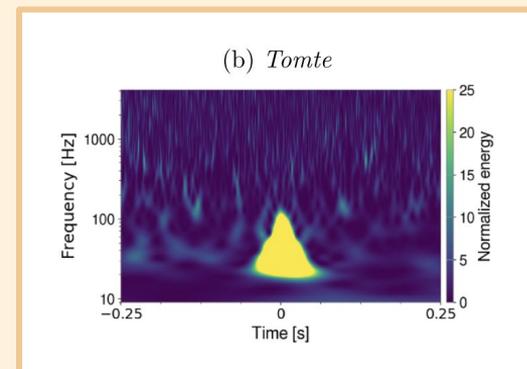
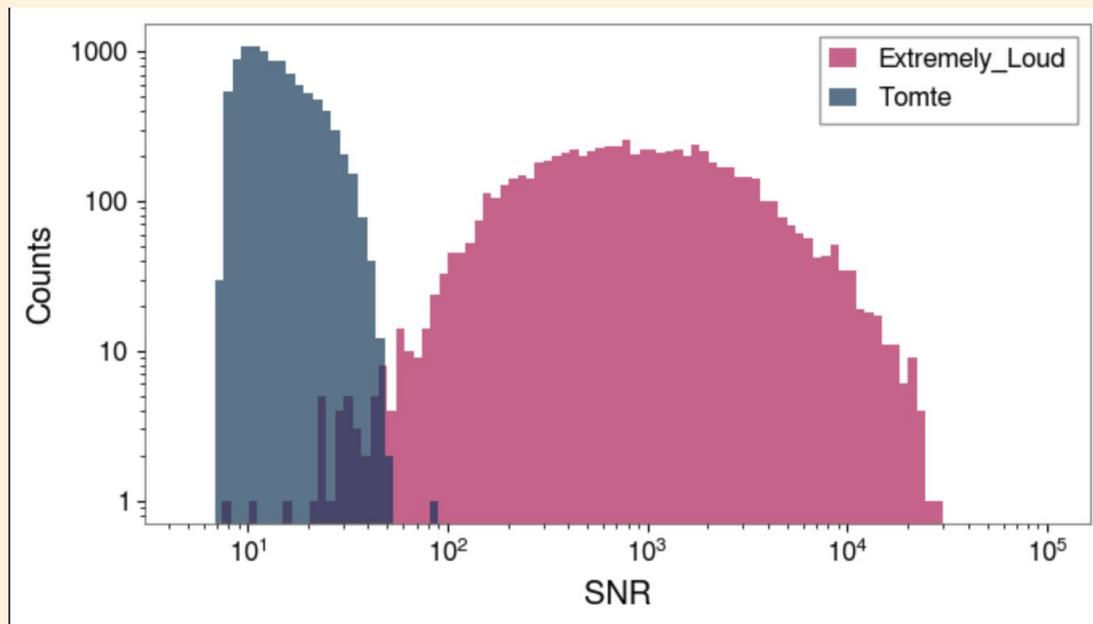
# Tomte



# Tomte



# Tomte vs. Extremely Loud

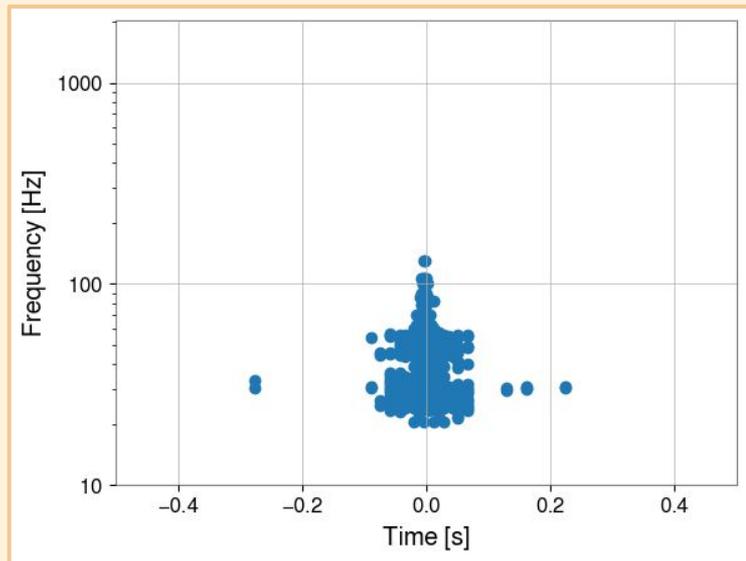


# Using unclustered information

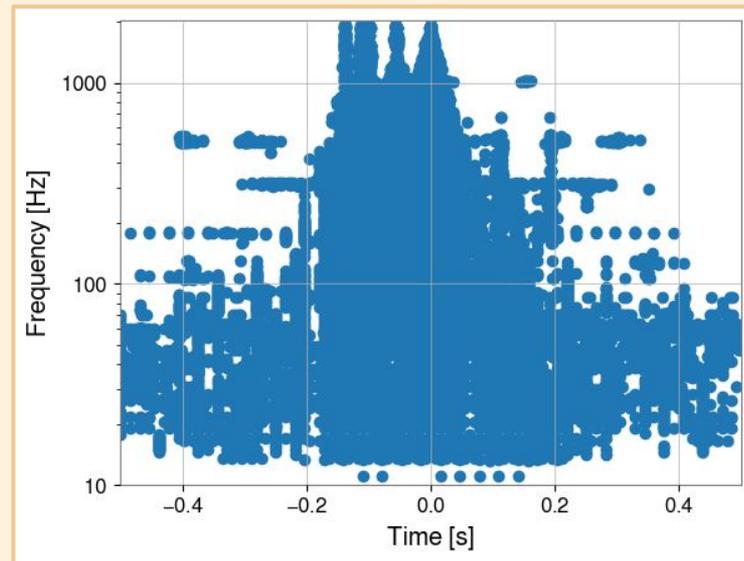
# Using **unclustered** information

Comparison between the number of unclustered triggers for two different classes

Tomte (308 triggers)

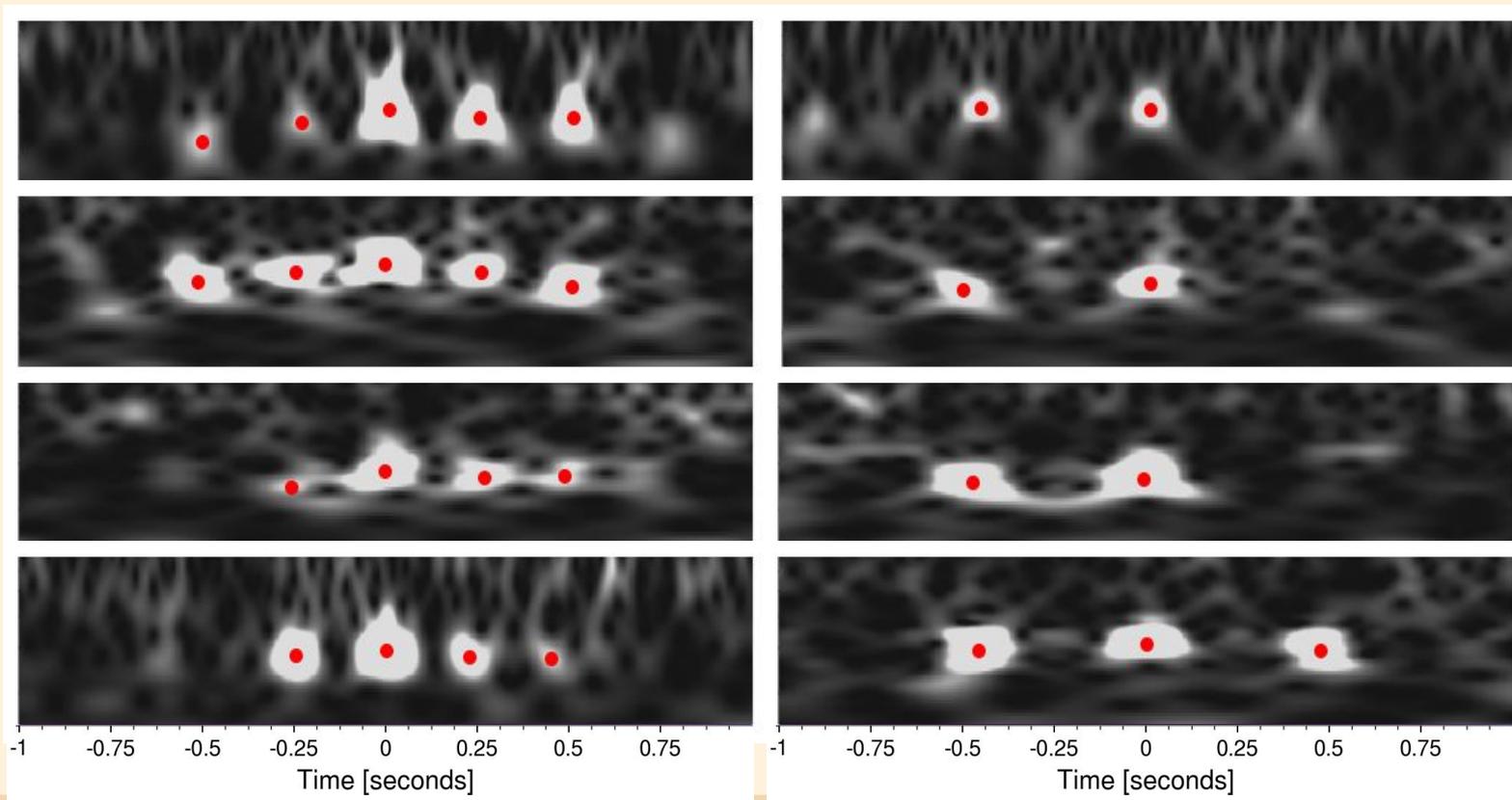


Extremely Loud (21202 triggers)

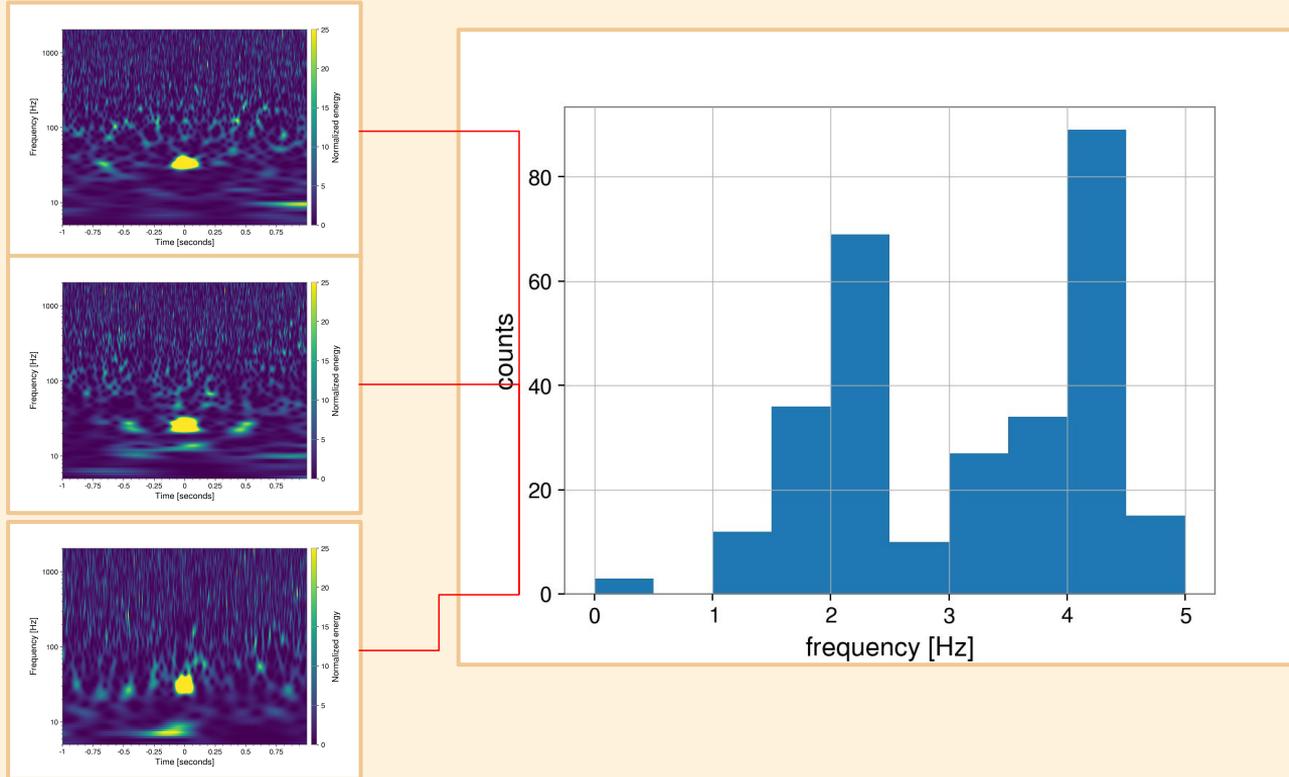


# Subclasses

# Finding subclasses within a specific class (Fast Scattering, O3: 2–4 Hz)



# Finding subclasses within a specific class (Fast Scattering, O3: 2–4 Hz)



# **Statistics from Omega Scan**

# Omega scan for a class

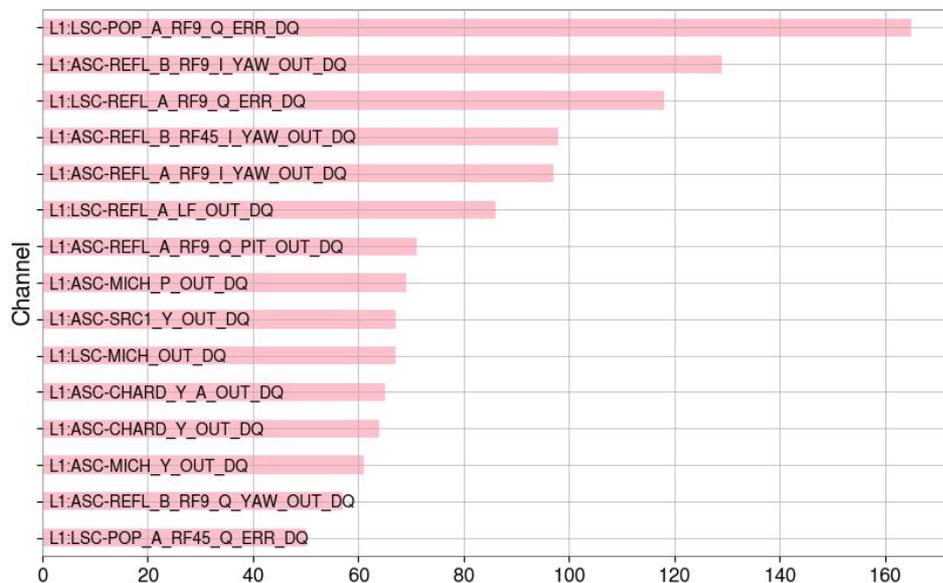
After selecting GPS times for a given glitch class:

How often do auxiliary channels exceed a minimum correlation threshold?

Do any channels appear consistently?

Can such channels be used as witnesses?

What can we infer about the underlying noise coupling?



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# Summary and conclusions

- Statistical studies of glitches are essential for understanding detector behavior and identifying underlying noise sources.
  - Omicron information enables a wide range of statistical analyses, including comparisons between interferometers, studies of glitch parameters and their distributions, and tracking glitch populations over time.
  - The same analyses can be performed by focusing on a single glitch class, allowing for more targeted studies that reveal class-specific characteristics and help uncover potential noise coupling mechanisms.
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**Thank you!**

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