

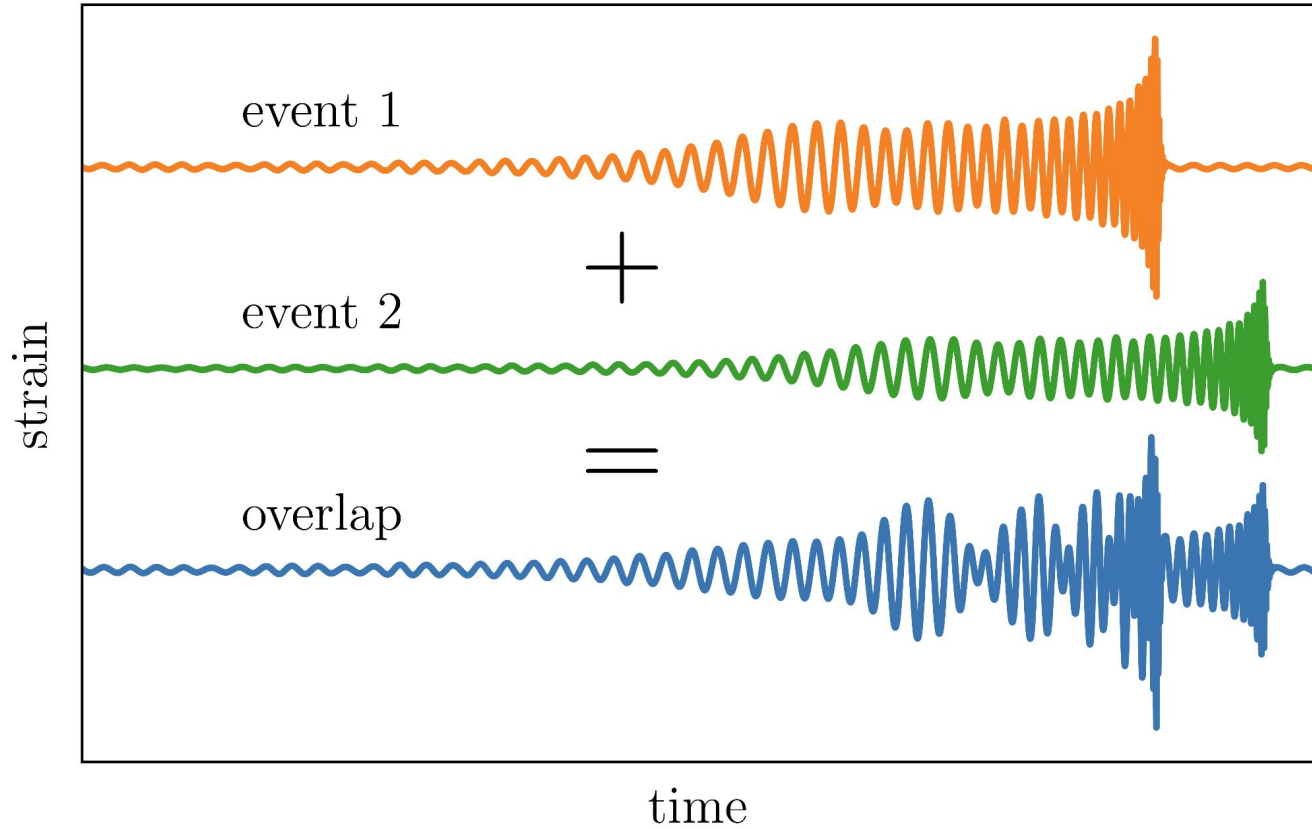
# Overlapping signals in Einstein Telescope

J. Janquart, based on work done in collaboration with  
T. Baka, T. Dietrich, A. Kolmus, J. Langendorff, H.  
Narola, A. Samajdar, C. Van Den Broeck



# Overlapping signals?

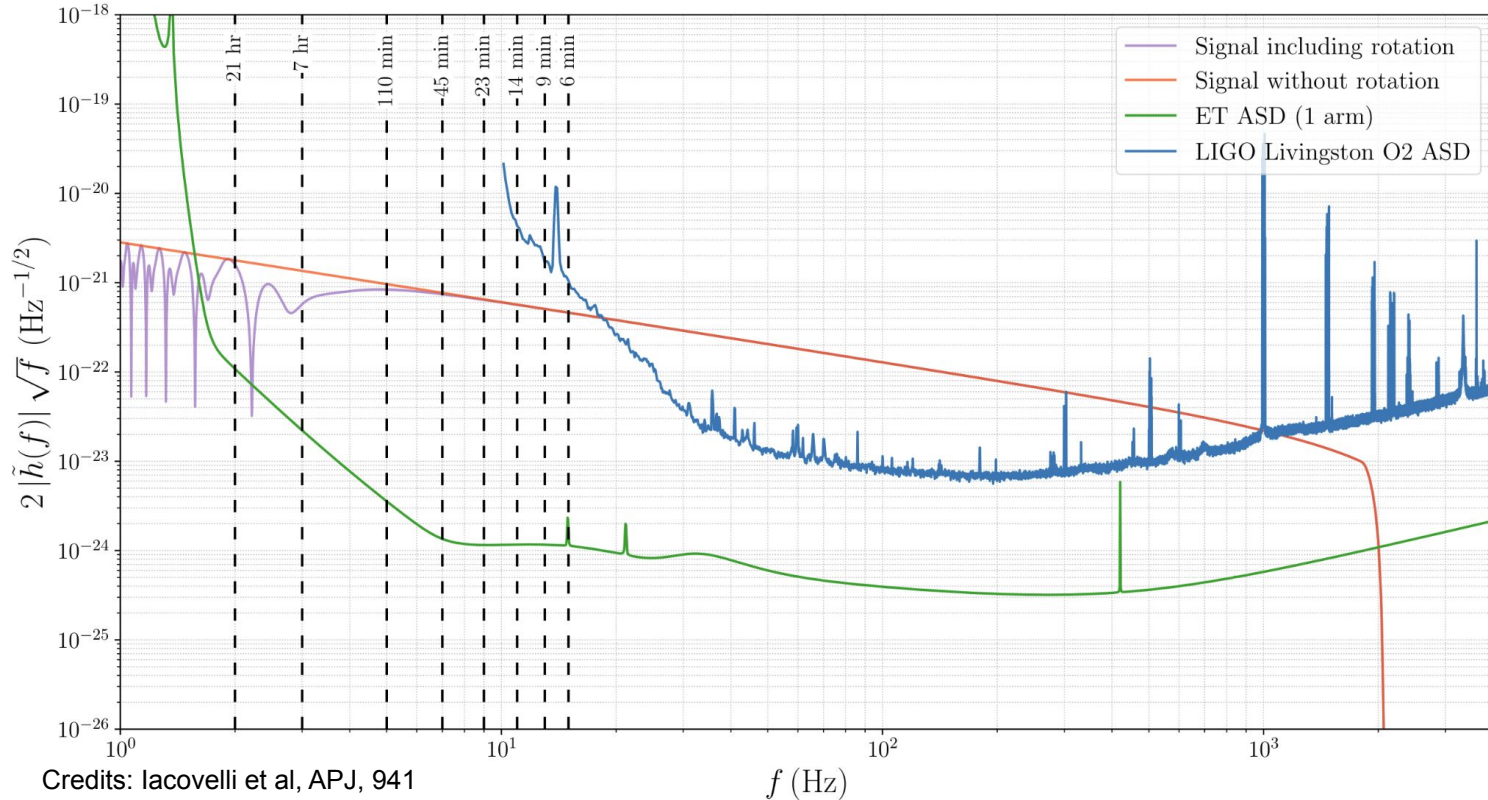
= Detectable signals which are in-band at the same time



# Overlapping signals, really?

Probability of overlapping signals increase as the detector gets upgraded because:

## a) Longer duration signals



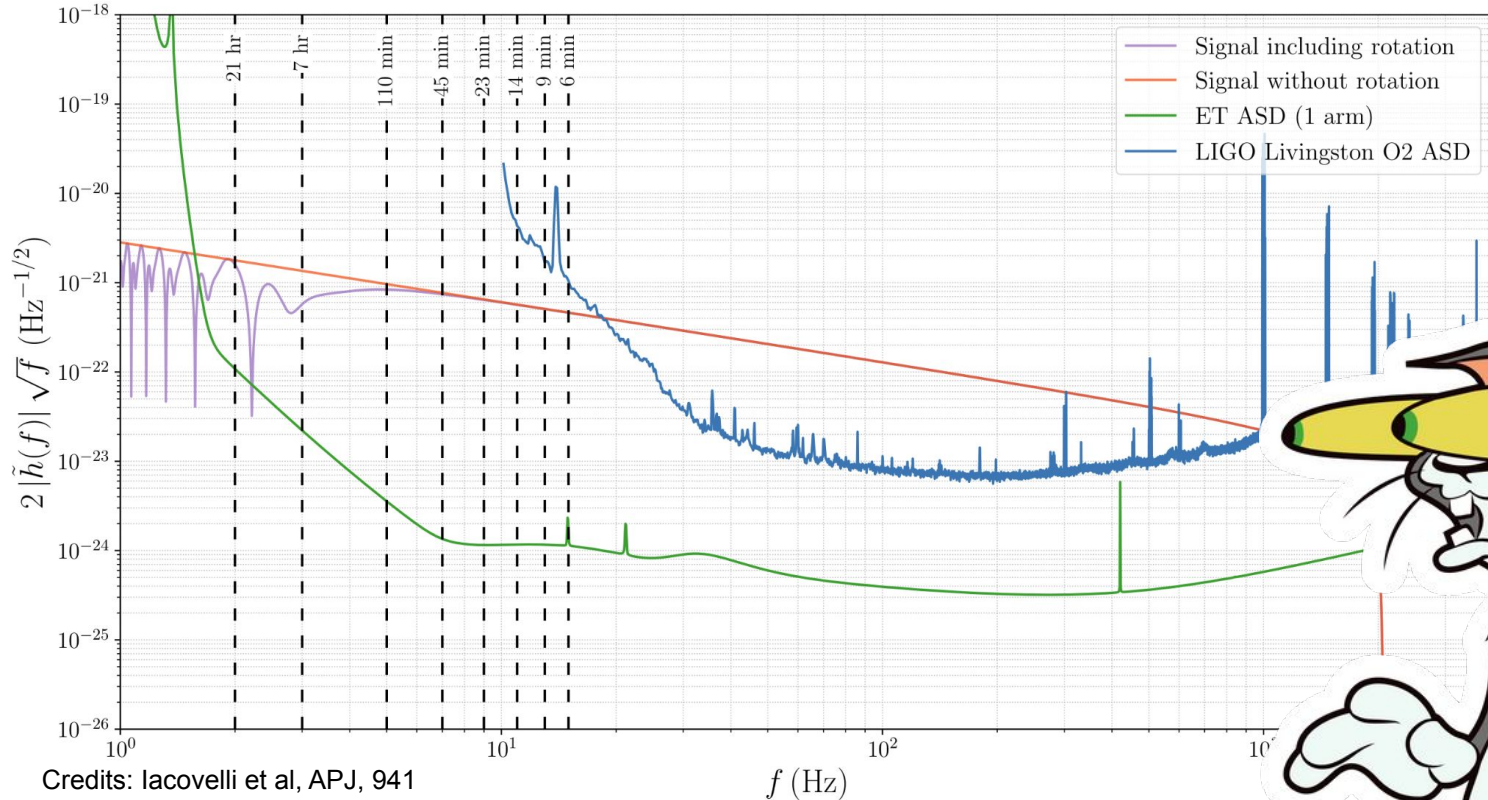
For a GW170817-like signal:

- ~ 3 min for O2
- ~ 1 day for ET

# Overlapping signals, really?

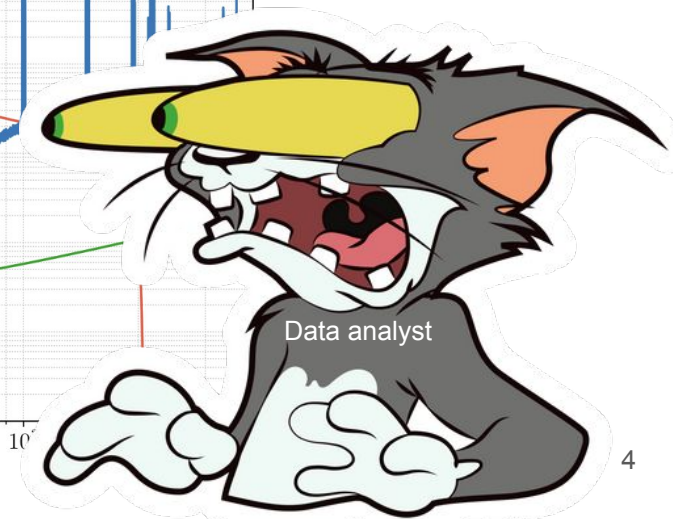
Probability of overlapping signals increase as the detector gets upgraded because:

## a) Longer duration signals



For a GW170817-like signal:

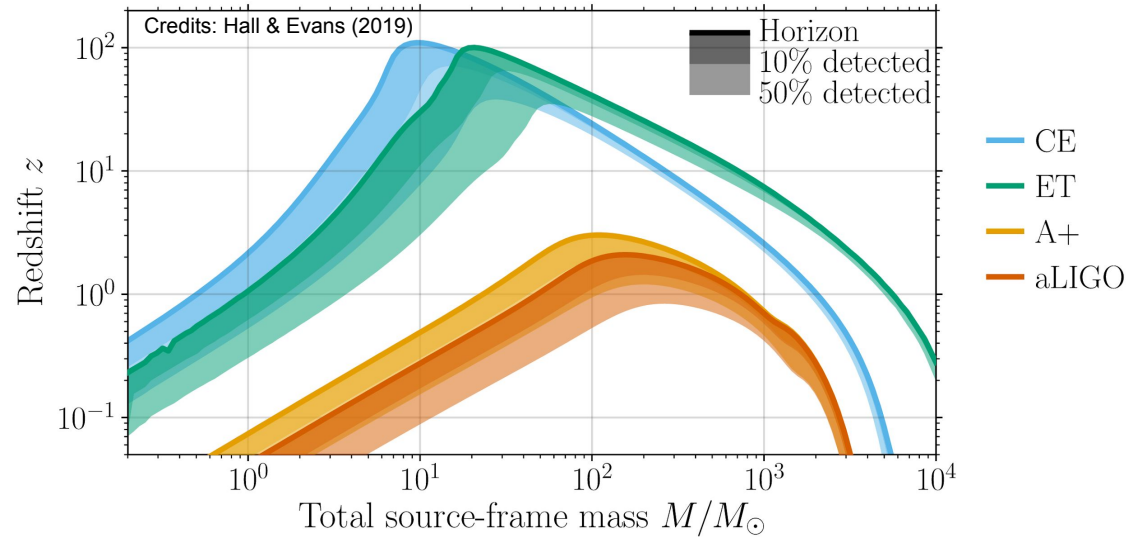
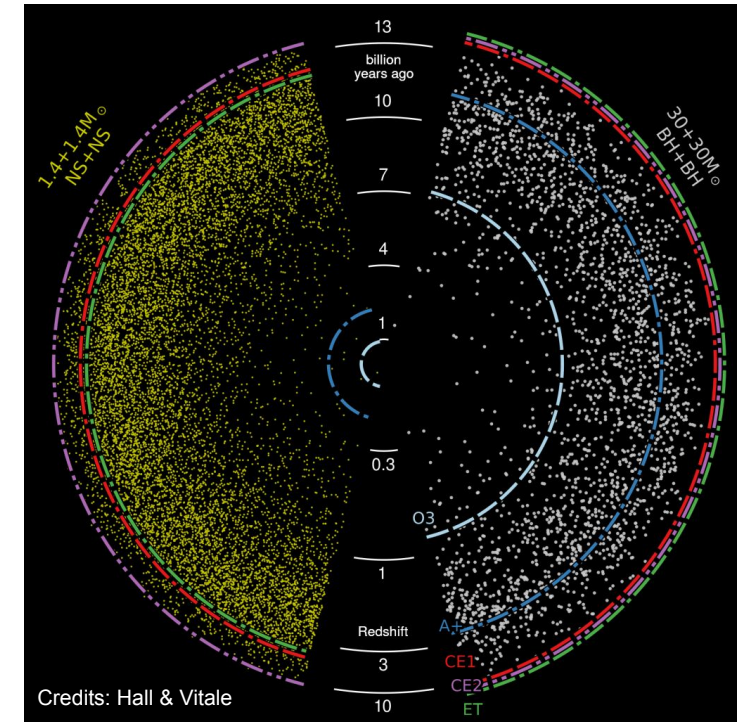
- ~ 3 min for O2
- ~ 1 day for ET



# Overlapping signals, really?

Chances of overlapping signals increase as the detector gets upgraded because:

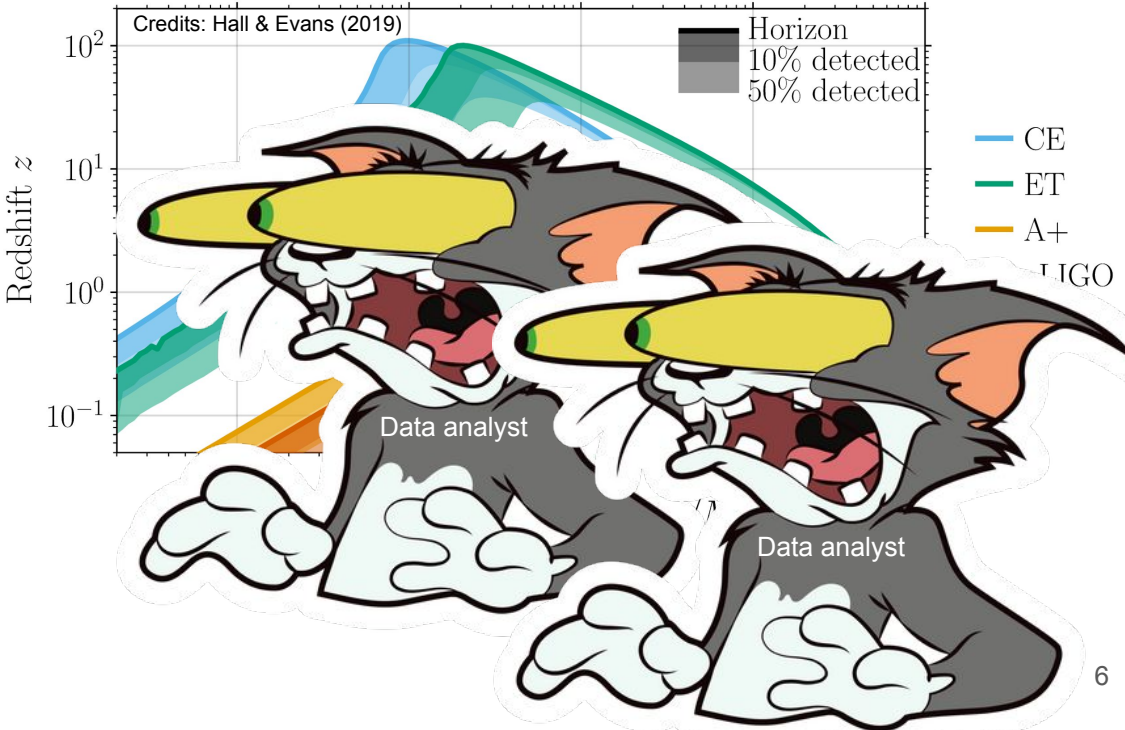
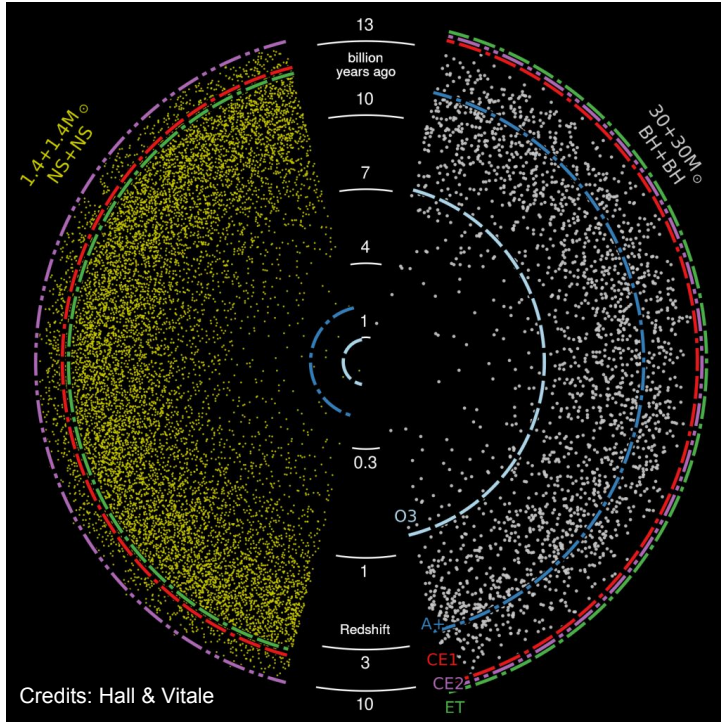
- Longer duration signals
- More signals



# Overlapping signals, really?

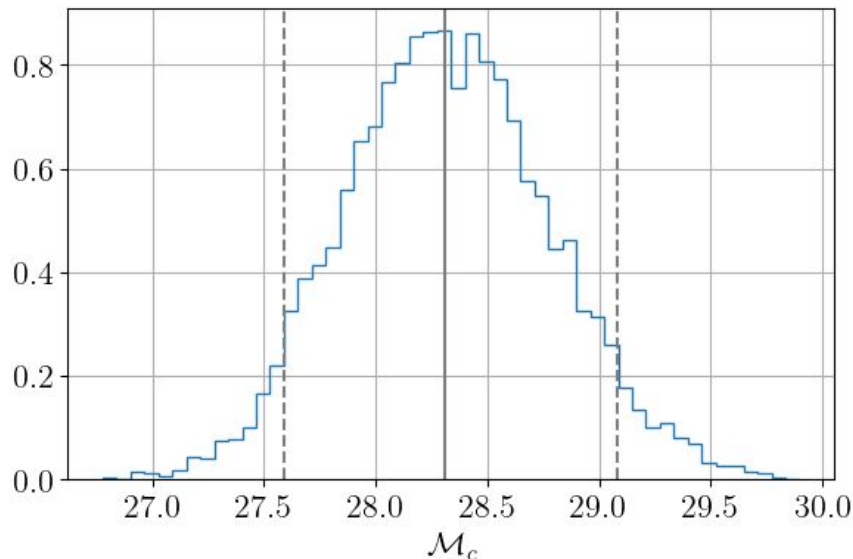
Chances of overlapping signals increase as the detector gets upgraded because:

- a) Longer duration signals
- b) More signals



# A very basic sketch of GW parameter estimation

The goal is to find the values of the parameters at the origin of the observed signal. Instead of a single value, we build a *posterior* describing the probability distribution of the signals

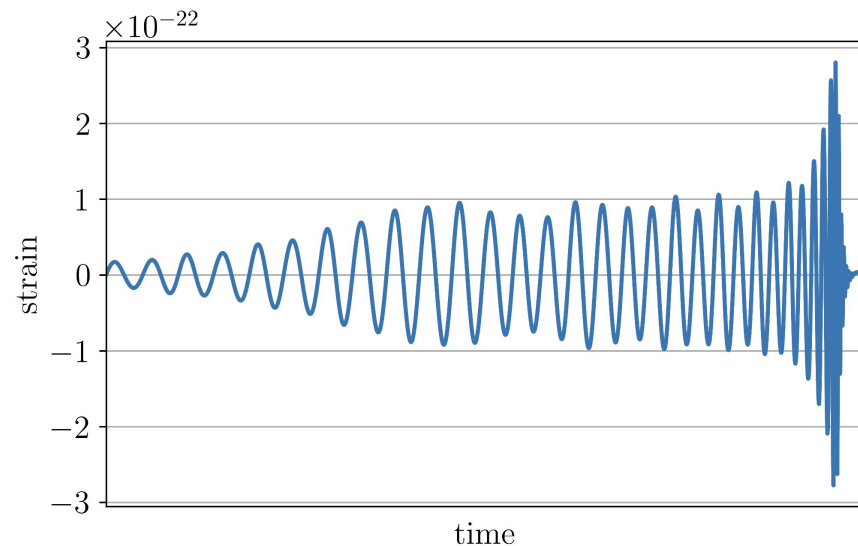
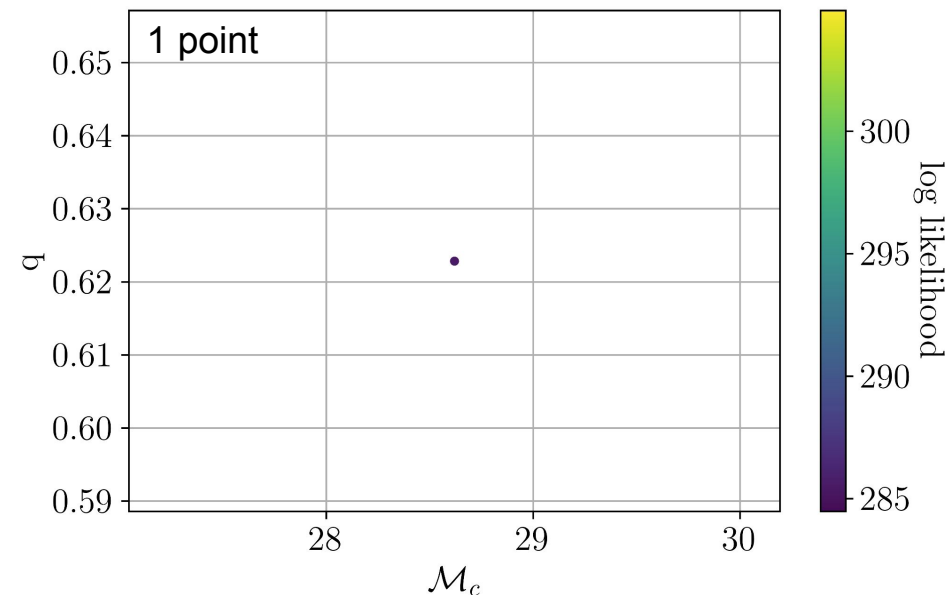


Generally done using Monte Carlo methods or Nested Sampling

# A very basic sketch of GW parameter estimation

The goal is to find probability distributions (*posteriors*) for the event parameters based on the data.

**Nested Sampling** → Find points in parameter space with increasing point of likelihood

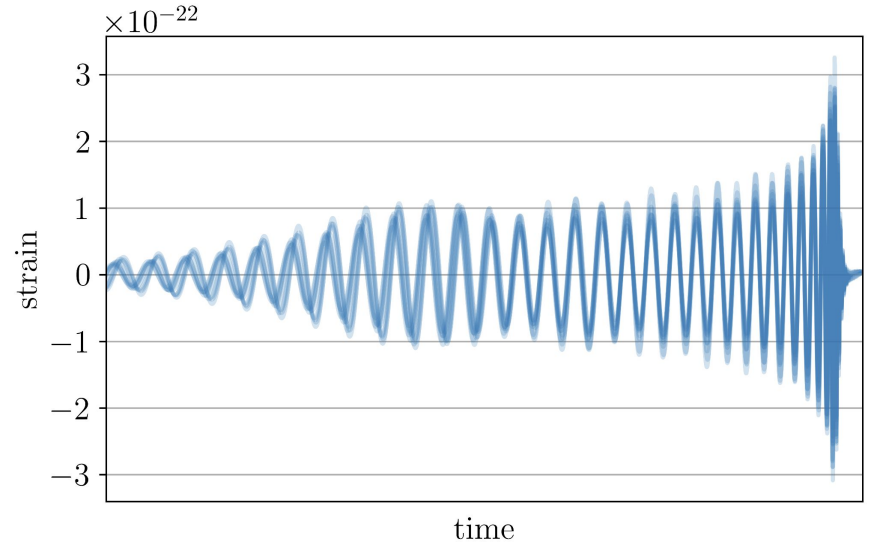
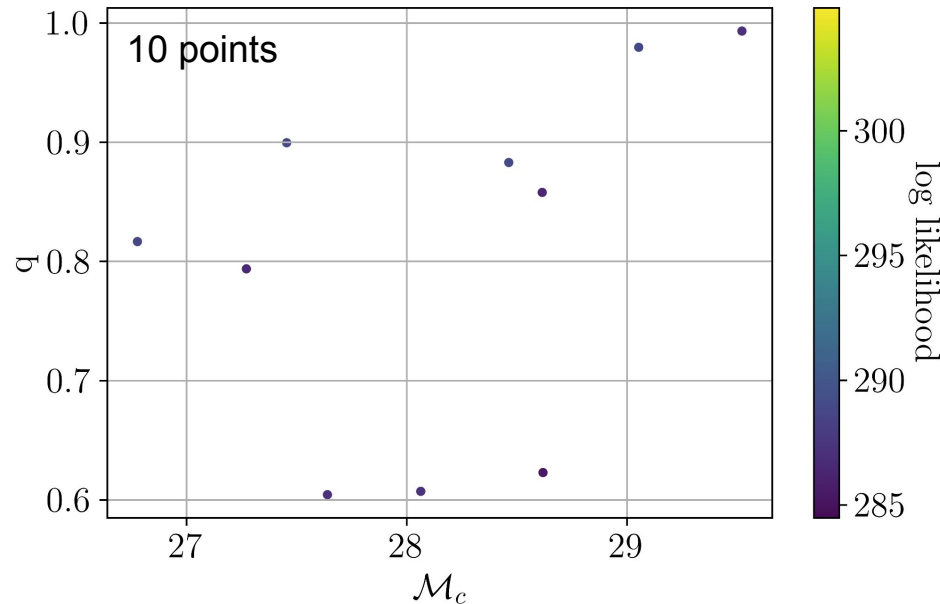




# A very basic sketch of GW parameter estimation

The goal is to find probability distributions (*posteriors*) for the event parameters based on the data.

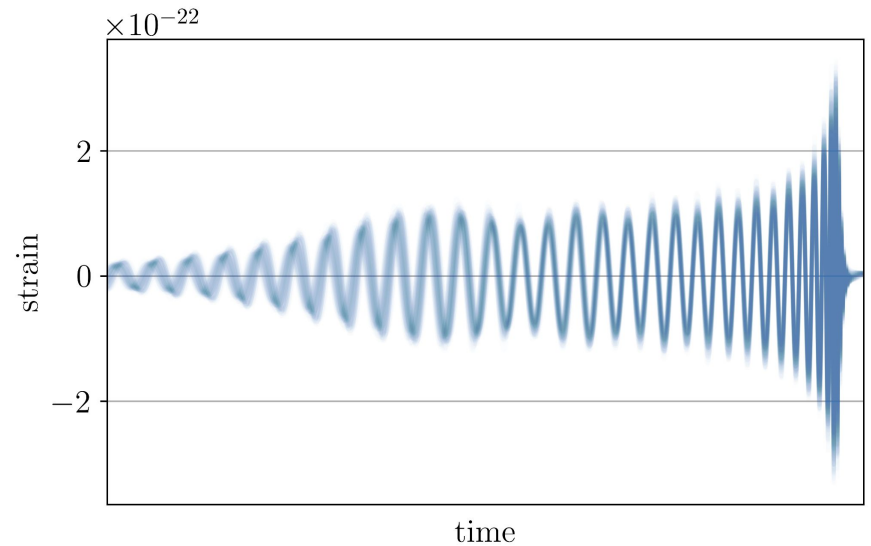
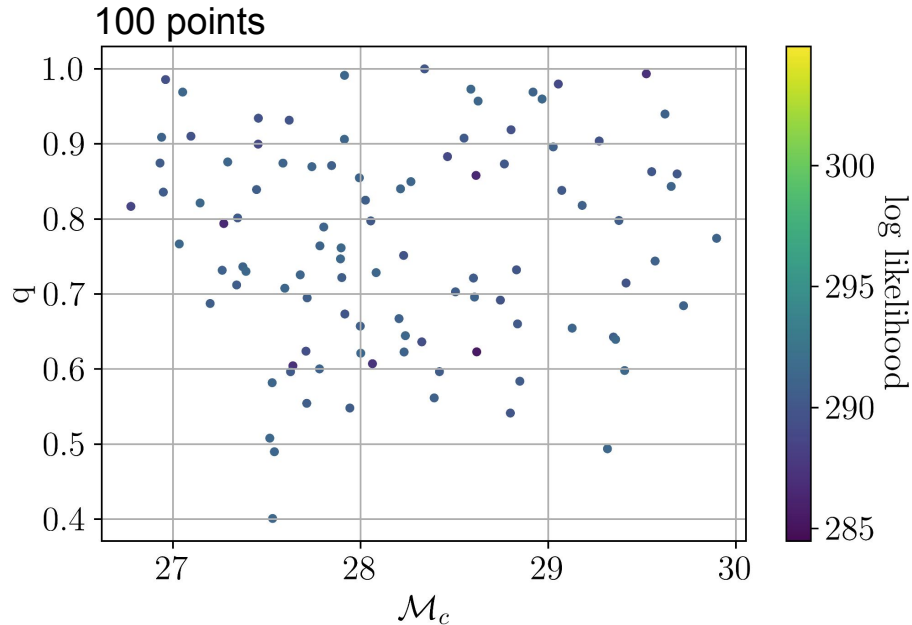
**Nested Sampling** → Find points in parameter space with increasing point of likelihood



# A very basic sketch of GW parameter estimation

The goal is to find probability distributions (*posteriors*) for the event parameters based on the data.

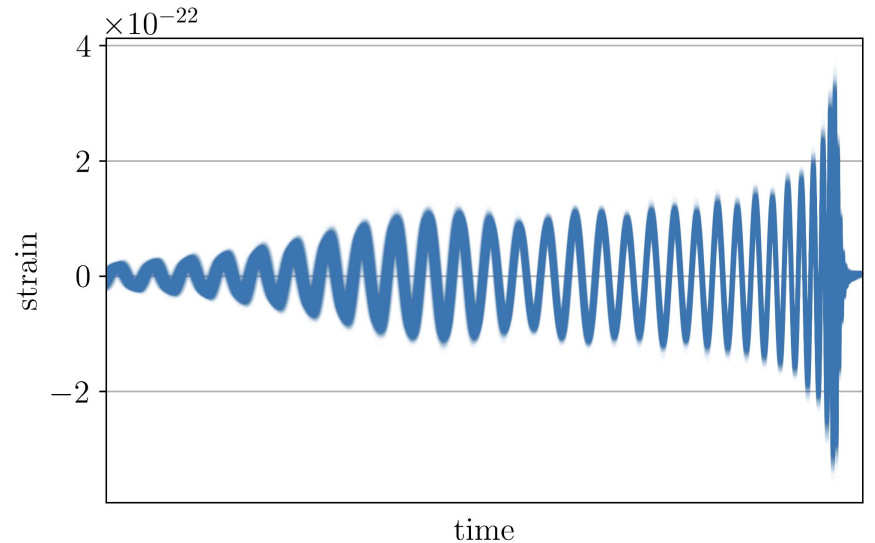
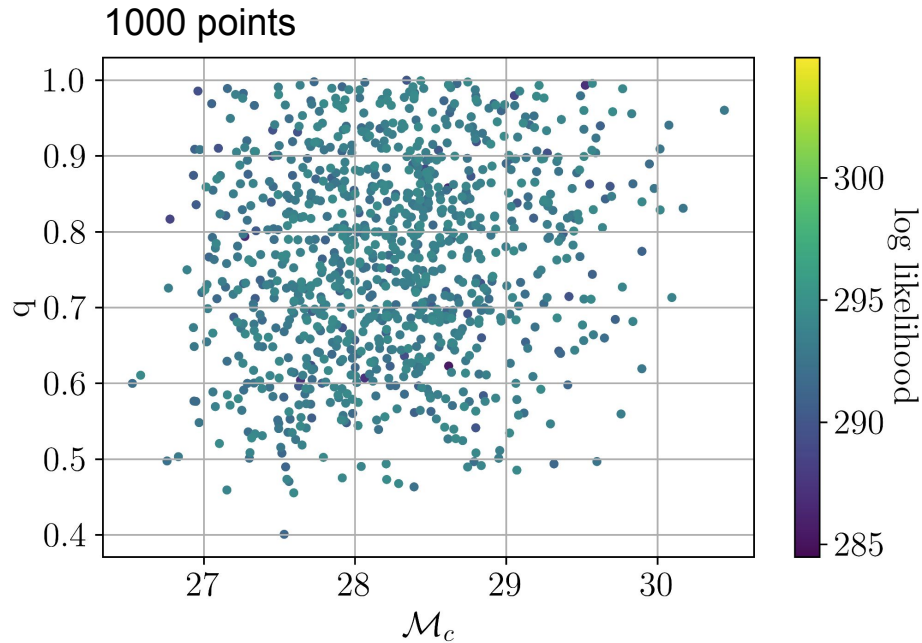
**Nested Sampling** → Find points in parameter space with increasing point of likelihood



# A very basic sketch of GW parameter estimation

The goal is to find probability distributions (*posteriors*) for the event parameters based on the data.

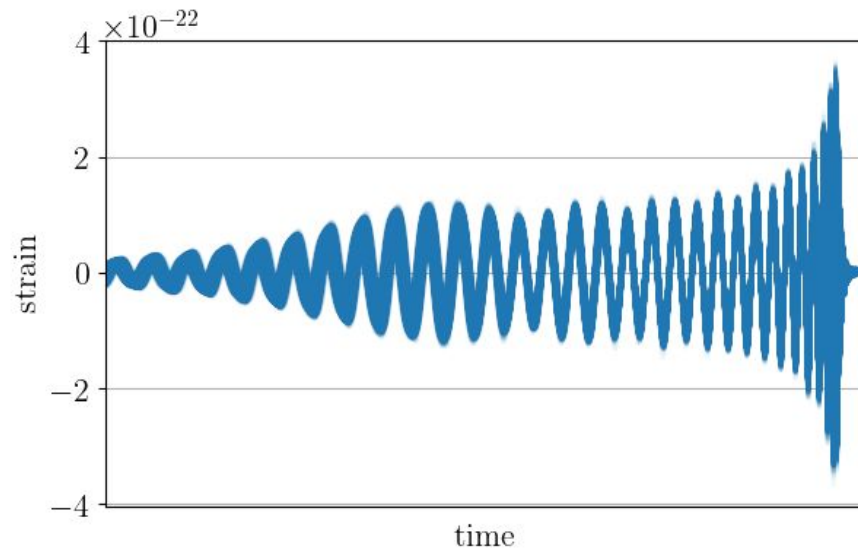
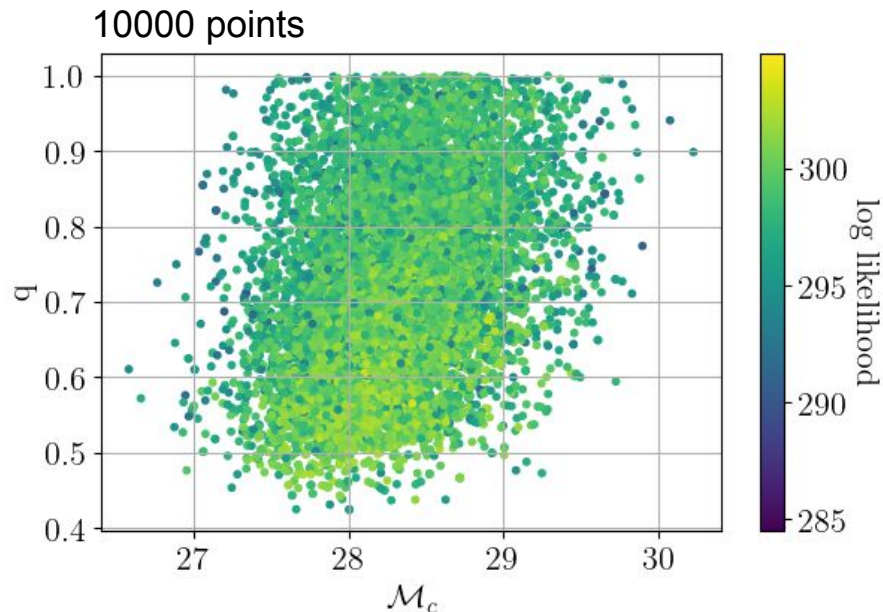
**Nested Sampling** → Find points in parameter space with increasing point of likelihood



# A very basic sketch of GW parameter estimation

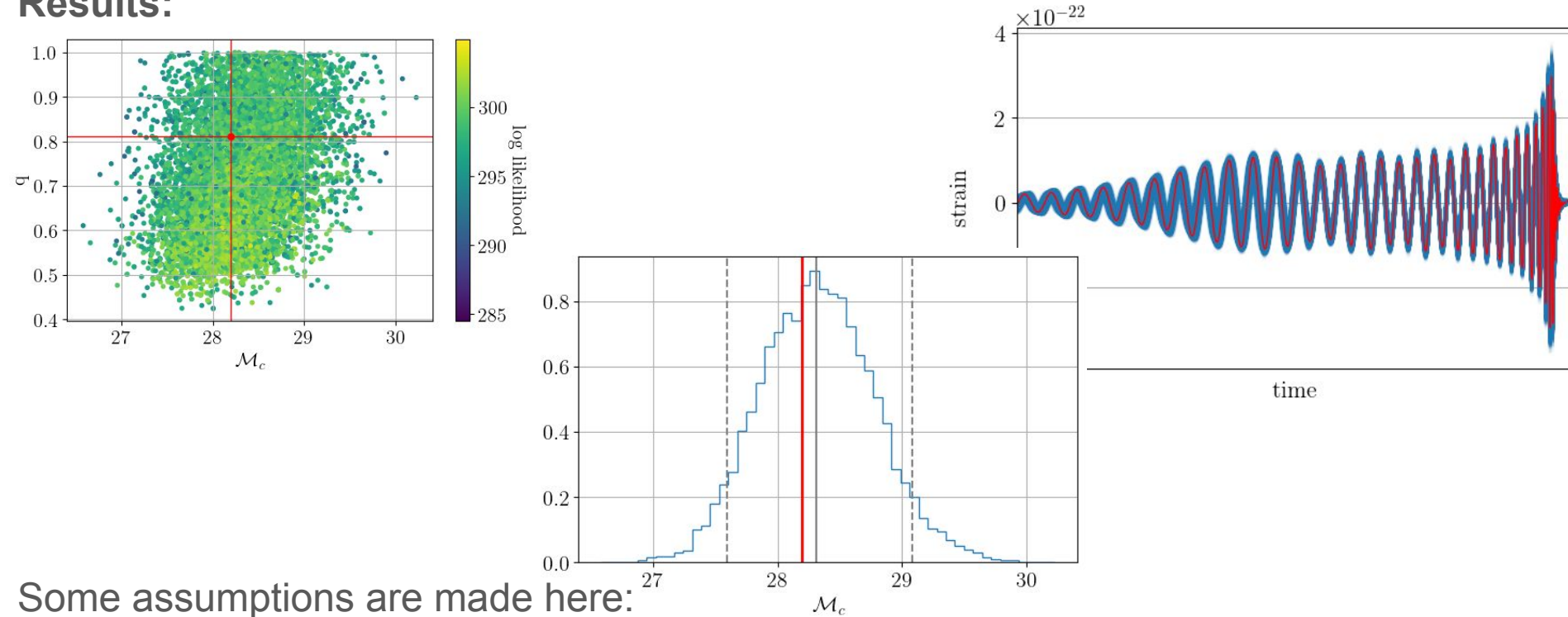
The goal is to find probability distributions (*posteriors*) for the event parameters based on the data.

**Nested Sampling** → Find points in parameter space with increasing point of likelihood



# A very basic sketch of GW parameter estimation

Results:

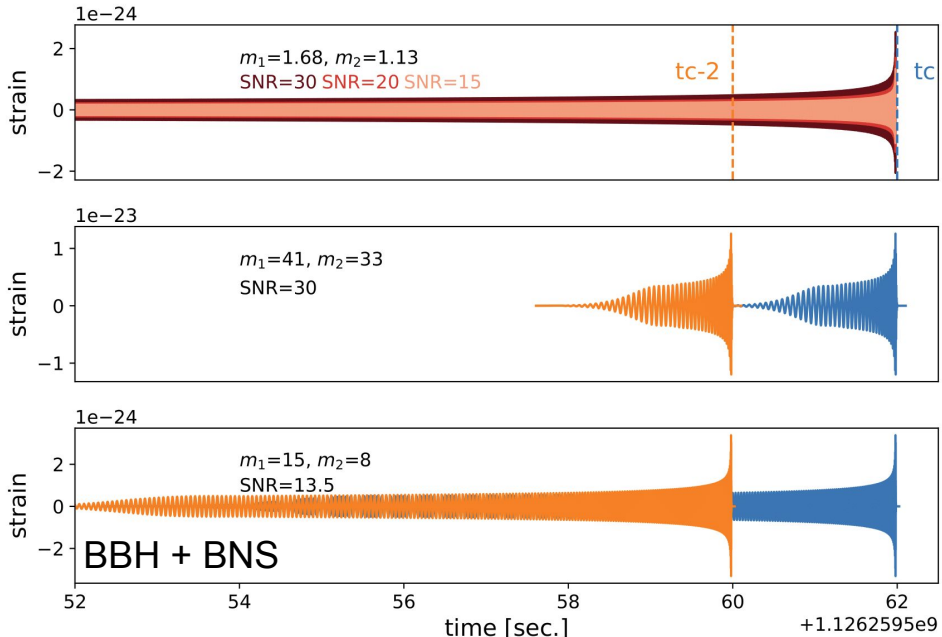
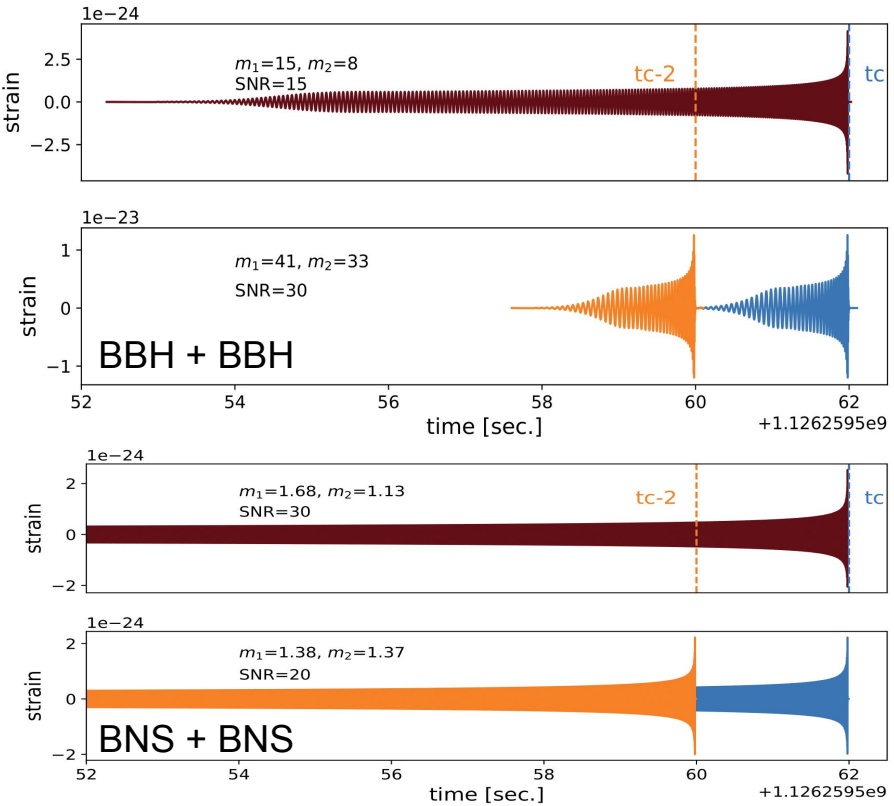


Some assumptions are made here:

- Stationary Gaussian noise
- One detectable signal is present in the data

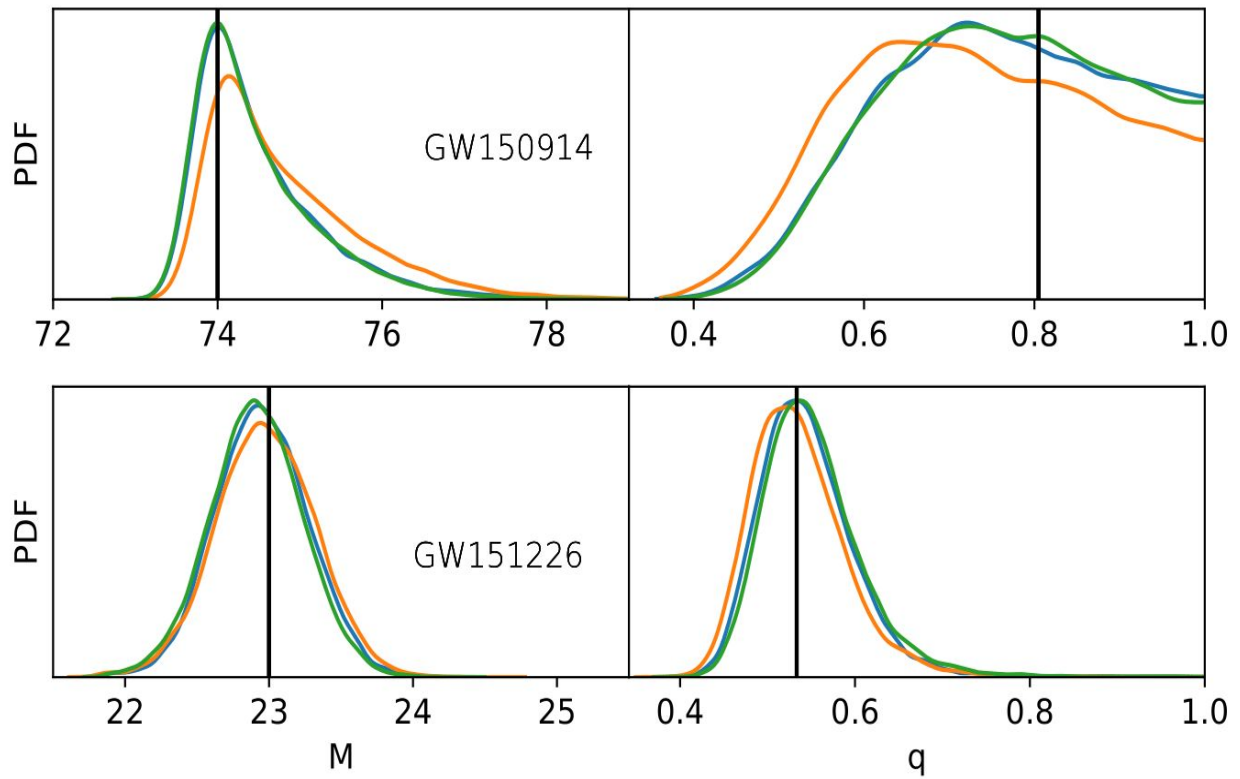
# Can we just pretend overlaps do not occur?

Results from [Samajdar et al, 2021](#):



# Overlapping BBHs:

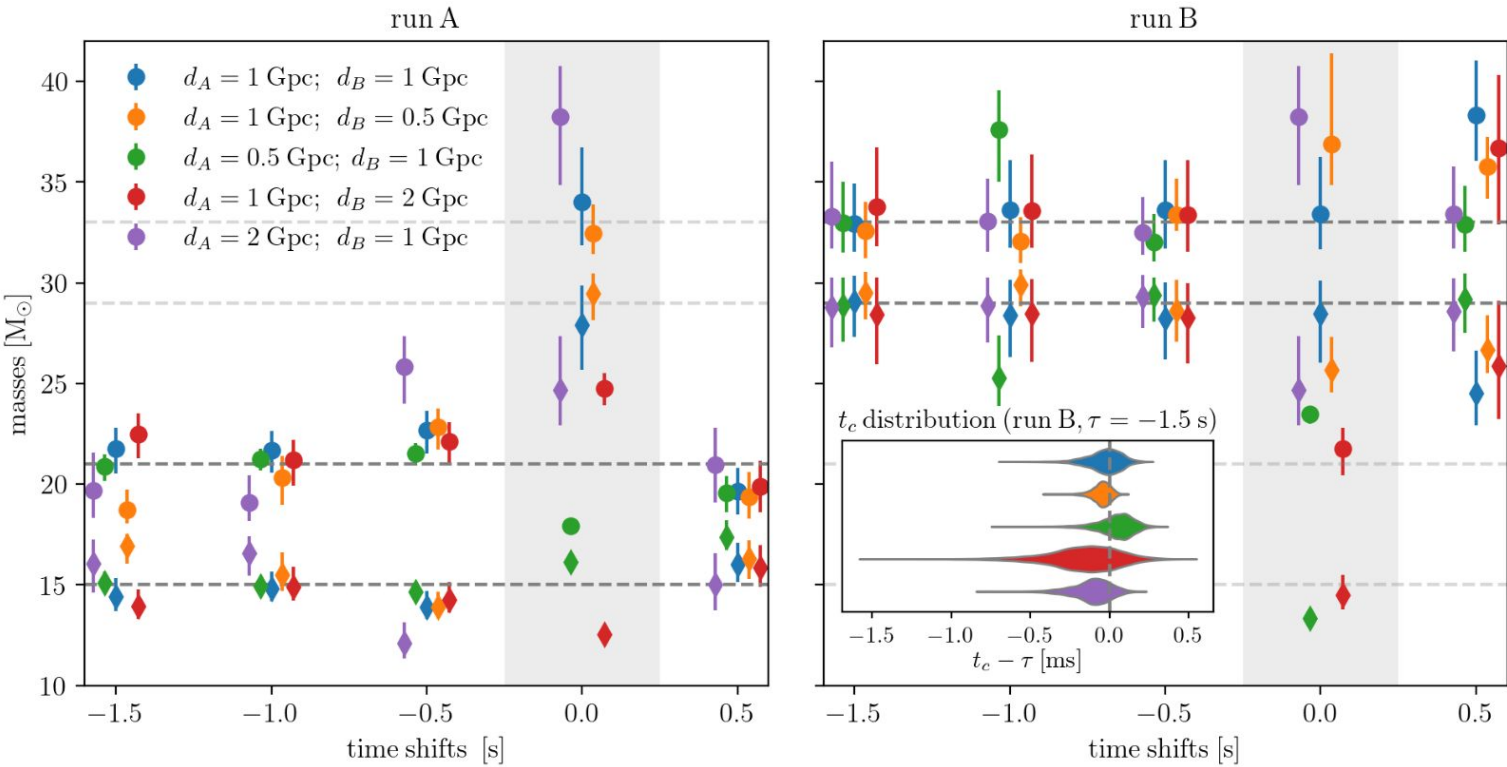
SNR(GW150914-like) = 30  
SNR(GW151226-like) = 15



**No bias observed**, regardless of the difference in time. Probably **due to the very different characteristics** and **duration** of the signals

# Overlapping BBHs, other scenarios:

E.g [Pizzati et al, 2021](#)



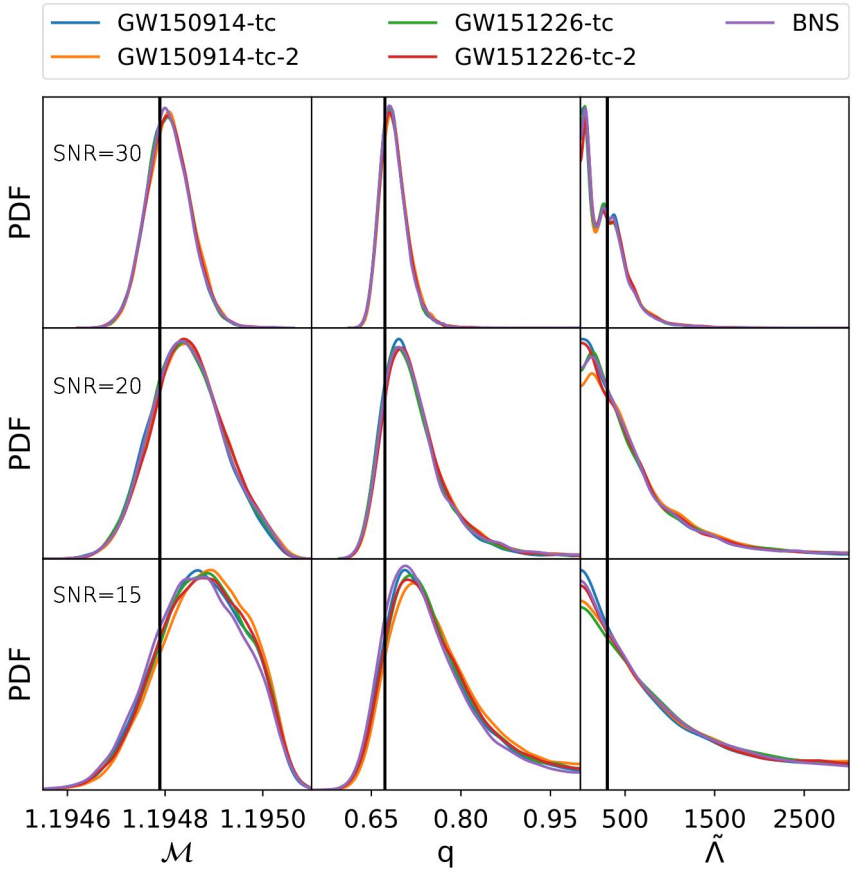
When the signal characteristics are close, bias can happen when BBHs merge within 0.1s

→ The exact effect of the overlap **depends on the exact signals involved** (also confirmed by [Relton et al, 2022](#))



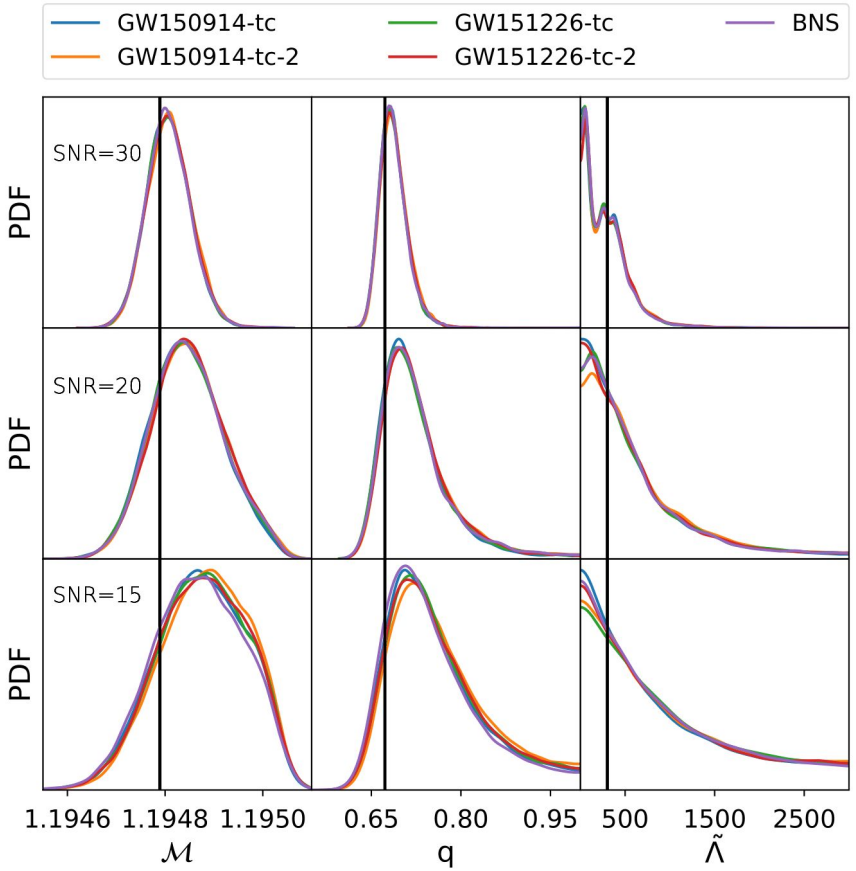
# BBH overlapping with a BNS

For the BNS recovery: **No bias** observed



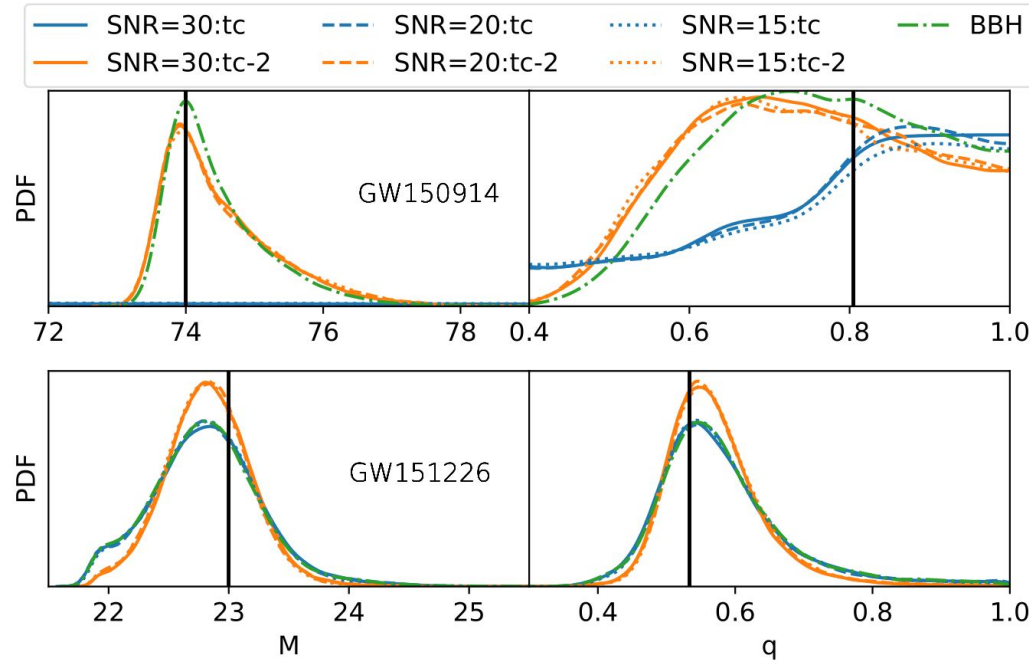
# BBH overlapping with a BNS

For the BNS recovery: No bias observed

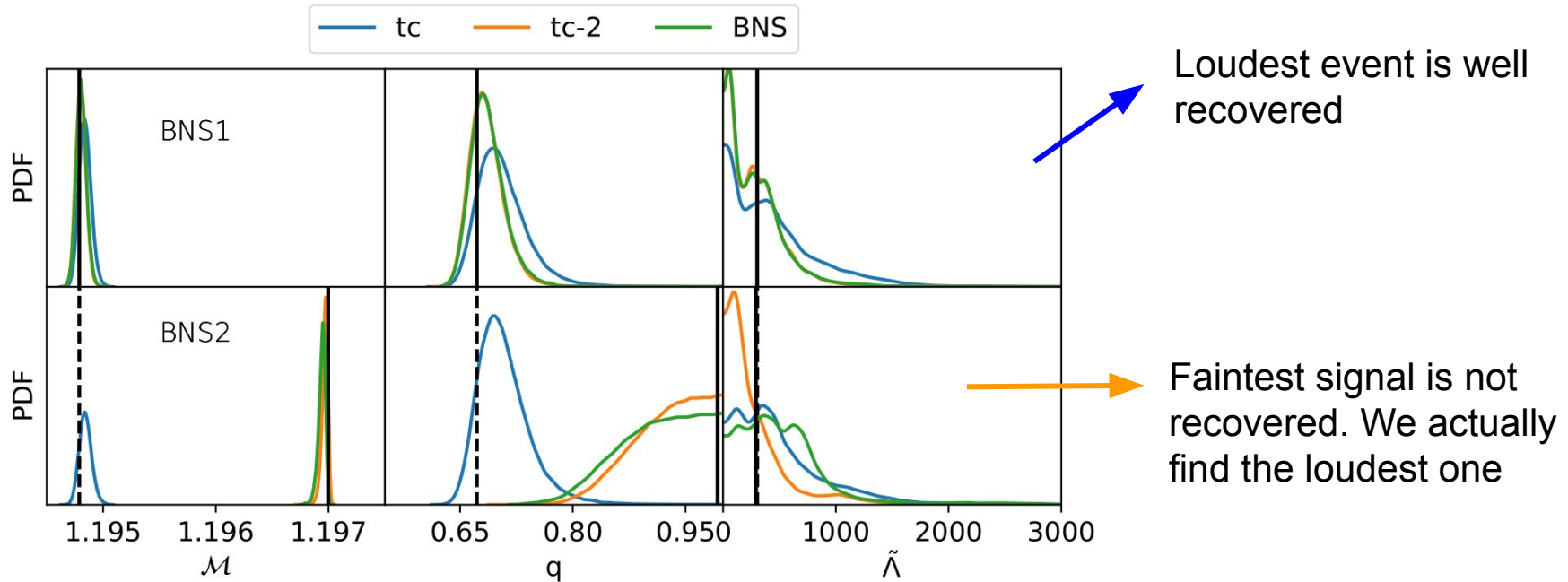


For the BBH recovery:

- High-mass BBH **not recovered**
- Low-mass BBH **recovered with larger uncertainty**



# Overlapping BNS signals



→ The Bias could be due to the closely related properties of the signals, generally not so much bias expected

# Final takeaway for biases due to overlapping signals

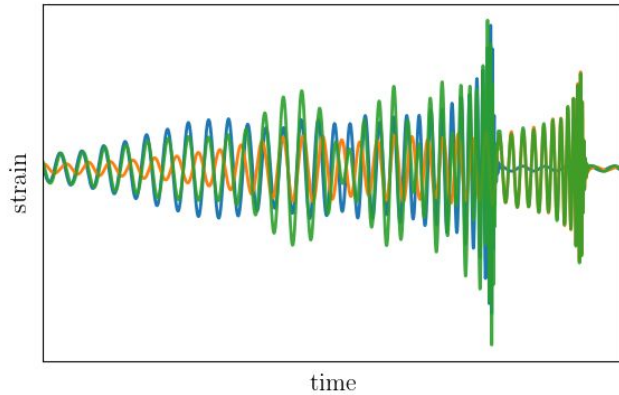
Different studies (e.g. [Regimbau & Hughes, 2009](#); [Samajdar et al, 2021](#); [Pizzati et al, 2021](#); [Himemoto et al, 2021](#); [Relton et al, 2022](#); [Antonelli et al, 2022](#)) have been undertaken with different approaches, all conclude that **bias can occur in some cases, especially when events have close merger times.**

It is very hard to determine the detailed situations where bias will occur but it certainly is a risk

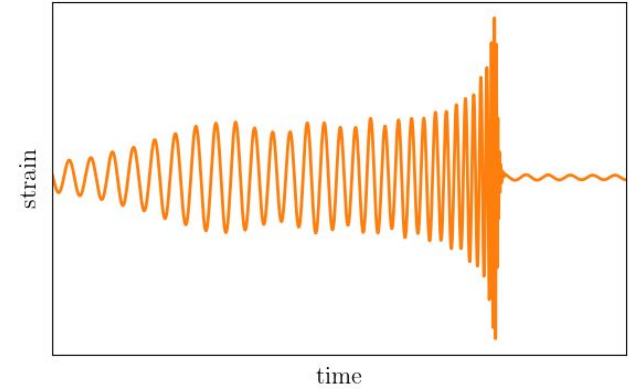
# Can we do better?

We can try to better account for the presence of two signals in two ways:

- 1) Assuming the bias is generally not too strong: hierarchical subtraction



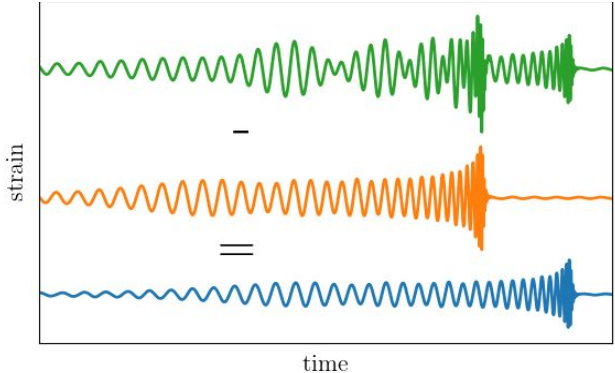
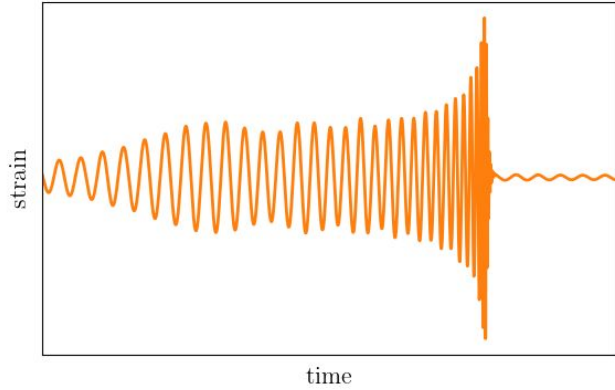
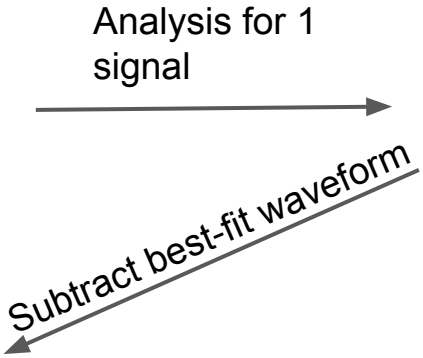
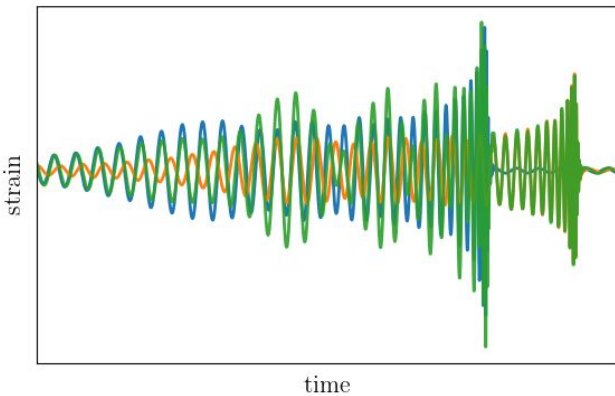
Analysis for 1  
signal



# Can we do better?

We can try to better account for the presence of two signals in two ways:

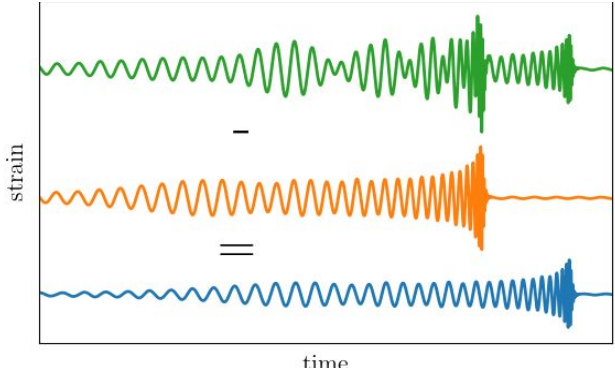
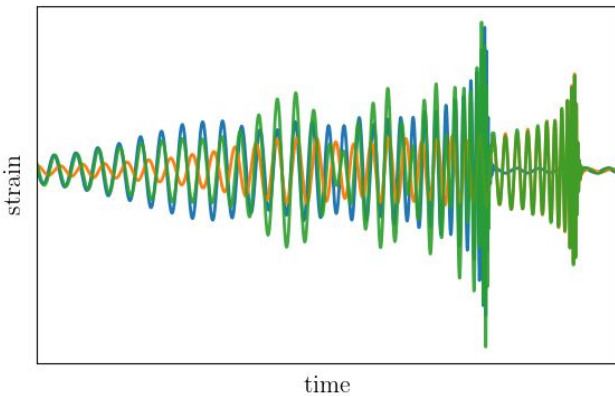
- 1) Assuming the bias is generally not too strong: hierarchical subtraction



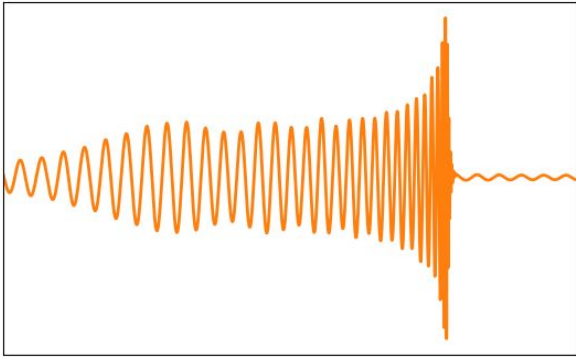
# Can we do better?

We can try to better account for the presence of two signals in two ways:

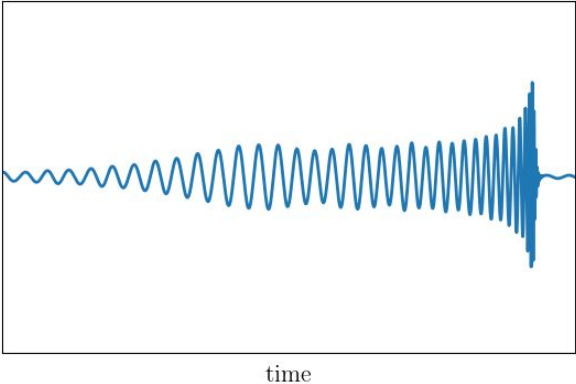
1) Assuming the bias is generally not too strong: hierarchical subtraction



Analysis for 1 signal  
→  
Subtract best-fit waveform  
↙



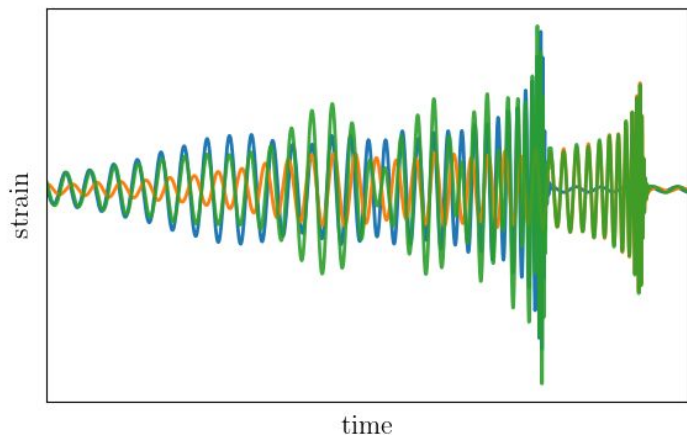
Analysis of the residuals  
→



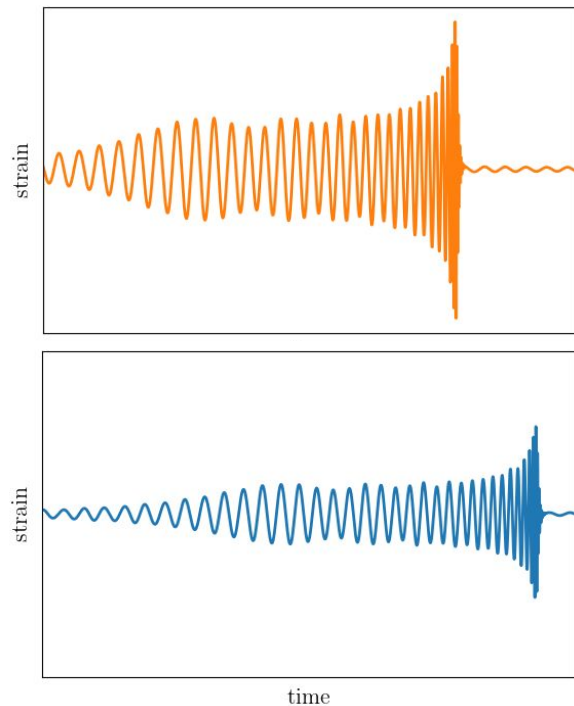
# Can we do better?

We can try to better account for the presence of two signals in two ways:

- 1) Assuming the bias is generally not too strong: hierarchical subtraction
- 2) Analyze the two signals jointly: Adapt the framework to account for two signals



Joint analysis





# Still some caveats...

We can try to better account for the presence of two signals in two ways:

- 1) Assuming the bias is generally not too strong: hierarchical subtraction
- 2) Analyze the two signals jointly: Adapt the framework to account for two signals

→ Methods tested in [Janquart et al, 2022](#)

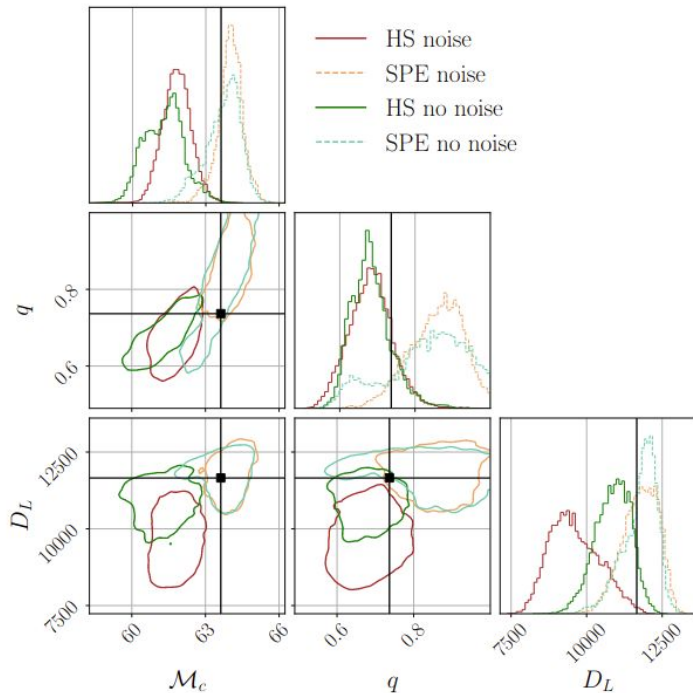
However, **restricted to overlapping BBHs with a lower frequency of 20Hz due to restricted computational resources...**

Before having the possibility to go to lower masses and frequencies, **improvements need to be made on the individual signal analysis** too (ASK about it in the discussion session)

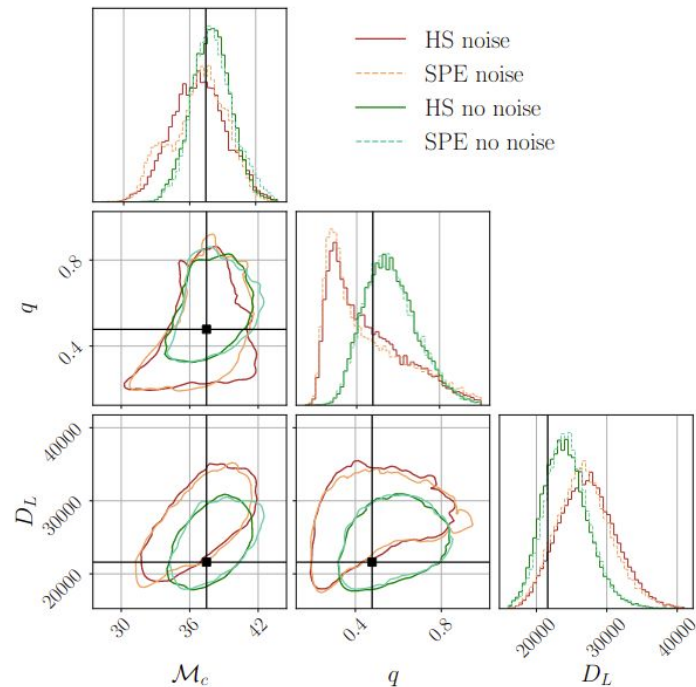
# Hierarchical subtraction

2 main situations:

HS is biased w.r.t SPE



HS is comparable to SPE

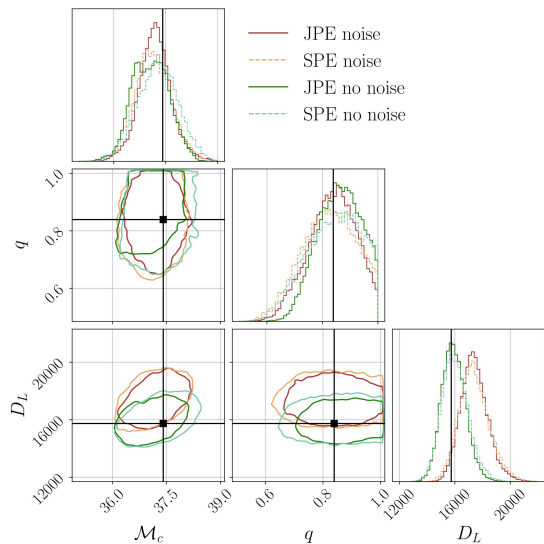


On average, hierarchical subtraction is less precise and more prone to bias than without overlap

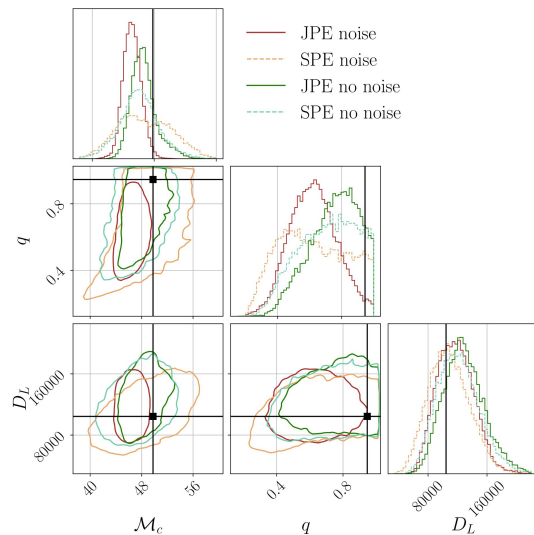
→ Expected since imperfect noise realization

# Joint parameter estimation

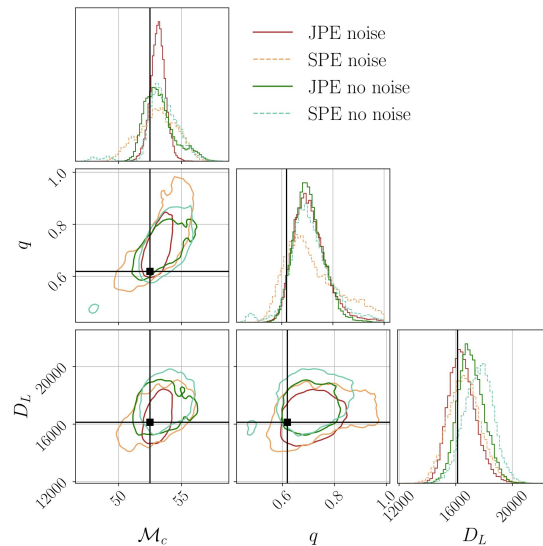
## JPE and SPE are equivalent



## JPE is biased w.r.t SPE



## JPE is better than SPE



More diversity in the recoveries are observed, probably due to the cross term in the joint likelihood.  
More extended studies are needed to fully grasp the behavior

→ Joint parameter estimation is **more accurate** than hierarchical subtraction, but slightly **less precise** than without overlap

# Overview Bayesian analysis methods

Joint posterior overlap is **better suited** than hierarchical subtraction for close-by mergers

Joint parameter estimation has **larger uncertainty** than without overlap

→ It is possible to use Bayesian frameworks to analyze two overlapped signals

# Overview Bayesian analysis methods

Joint posterior overlap is **better suited** than hierarchical subtraction for close-by mergers

Joint parameter estimation has **larger uncertainty** than without overlap

→ It is possible to use Bayesian frameworks to analyze two overlapped signals

BUT

- Not optimal yet → Some degeneracies need to be accounted for
- Not yet tested on more types of signals due to heavy analyses
- Would not be able to keep up the pace with predicted detection rate
- We have not accounted for the difficulties in noise modeling or many overlapping mergers

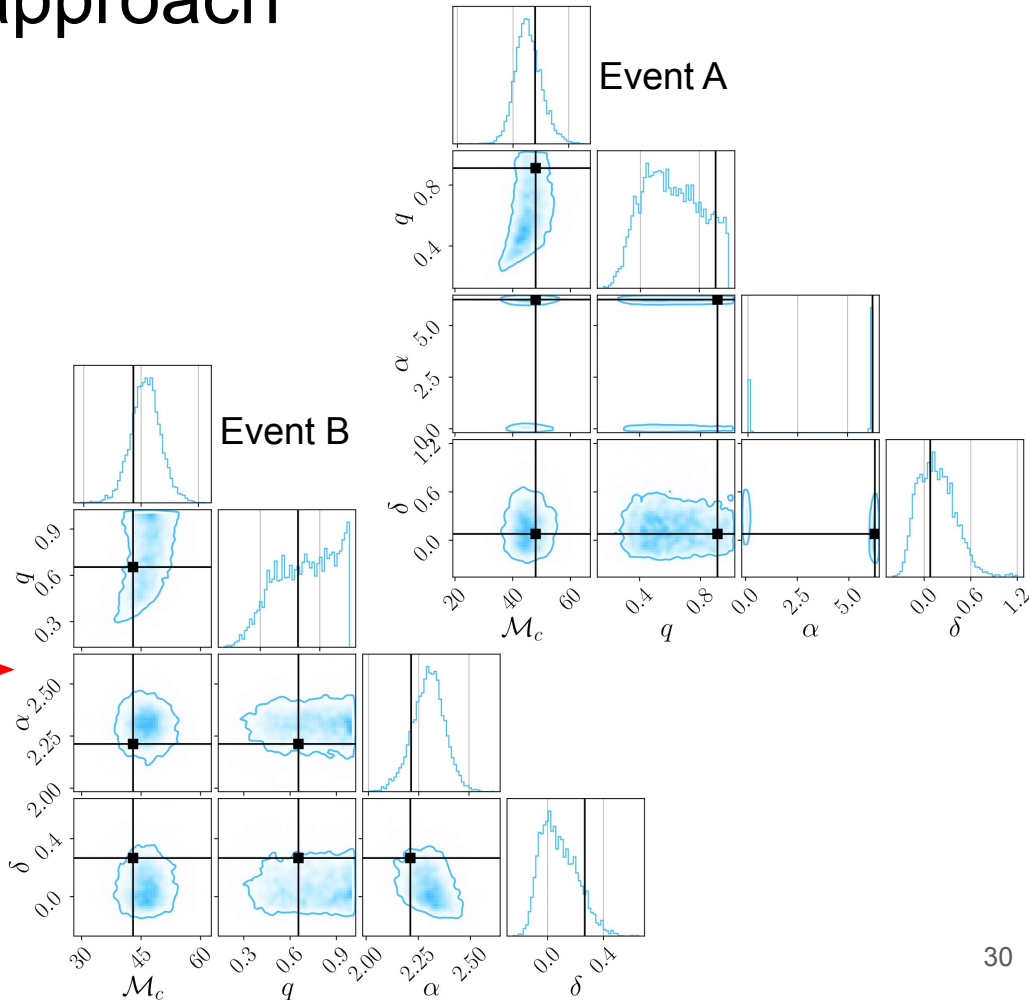
Can we try something else?

# Machine learning based approach

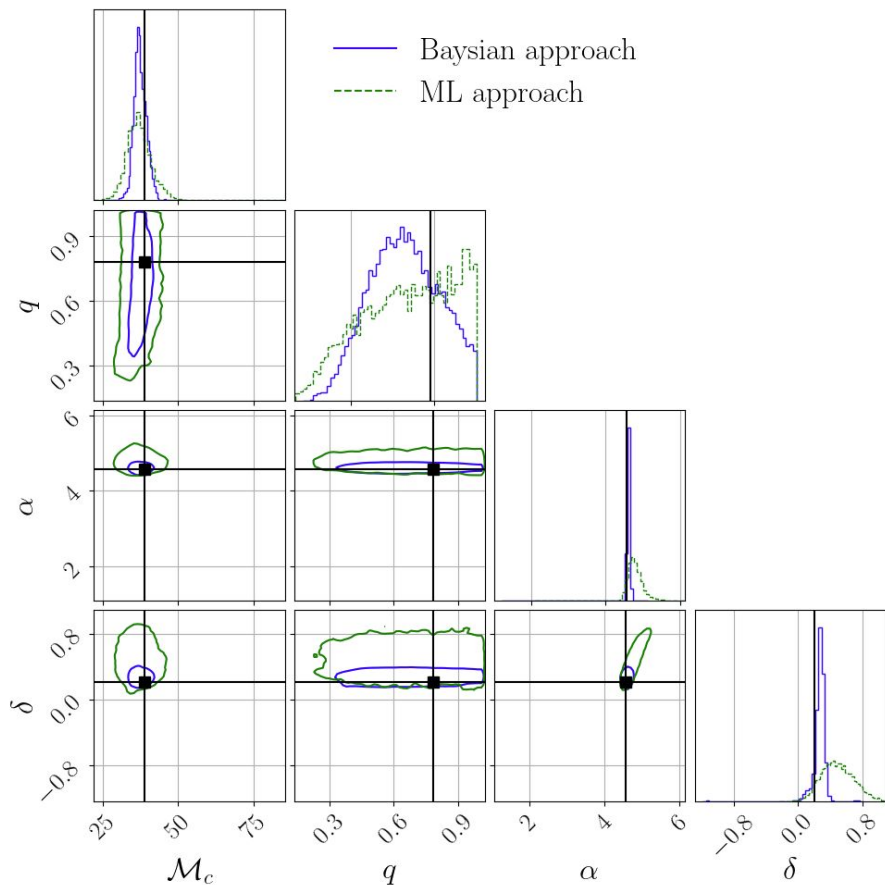
Results based on [Langendorff et al., 2022](#)



1 second



# Machine learning vs Bayesian



Machine learning is **less prone to bias** but has regularly **larger posteriors** than Bayesian joint parameter estimation

Possible cause: **small network** compared to other

Possible solutions:

Make the network **bigger**

Use **importance sampling** in the output

# Conclusions and Outlook

In the 3G era, **overlaps will happen** and be **quite common** ([Samajdar et al, 2021](#))

Overlaps raise **several issues** and can lead to biased posteriors, negatively impacting science studies

In our works, we have presented **several avenues to tackle the issue**:

- Hierarchical subtraction ([Janquart et al, 2022](#))
- Joint parameter estimation ([Janquart et al, 2022](#))
- Machine learning based joint parameter estimation ([Langendorff et al, 2022](#))

Up to now, these techniques have been **limited** to overlapping BBHs due to computational restrictions

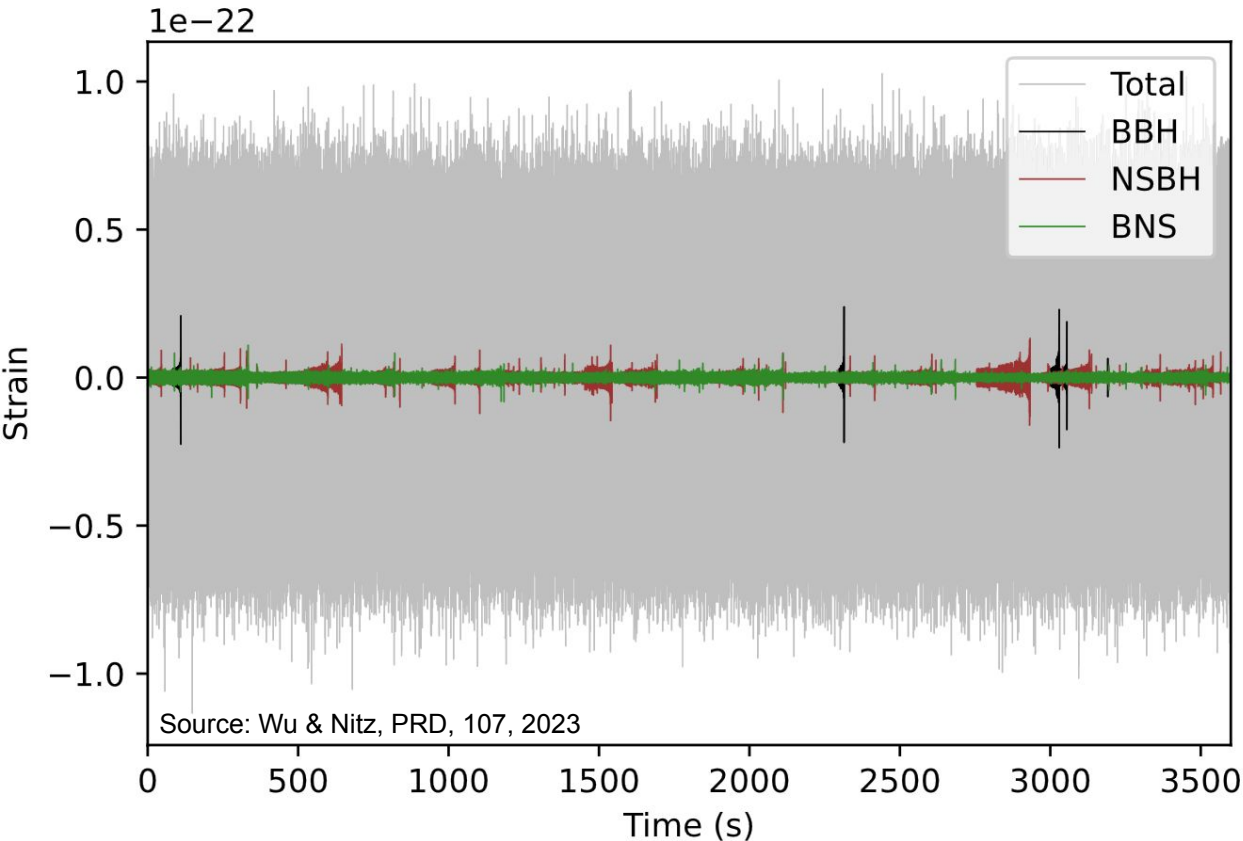
They are **not optimal yet but can be improved**

In the future:

Work to **more realistic scenarios** with more background signals, more signal types and higher SNRs



# A more realistic picture of what will need to be analyzed



Some issues needing to be tackled (and key word solutions):

- Longer duration signals
- Characterization of the noise (null-stream vs correlated noise)
- Multi-signal analysis
- Detection rate vs algorithmic speed

Back of the envelope: we would need more than a year run-time to analyze all the signals in this frame

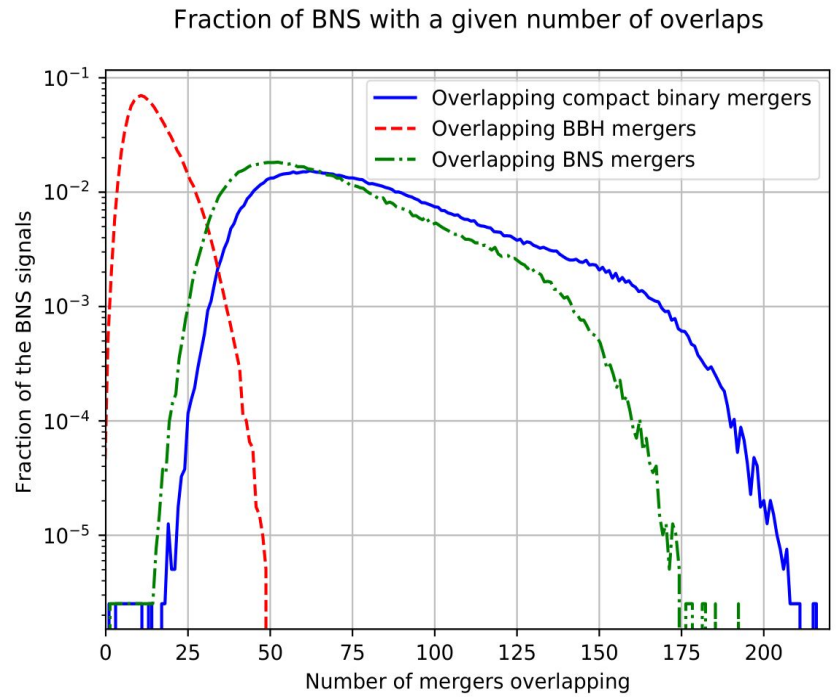
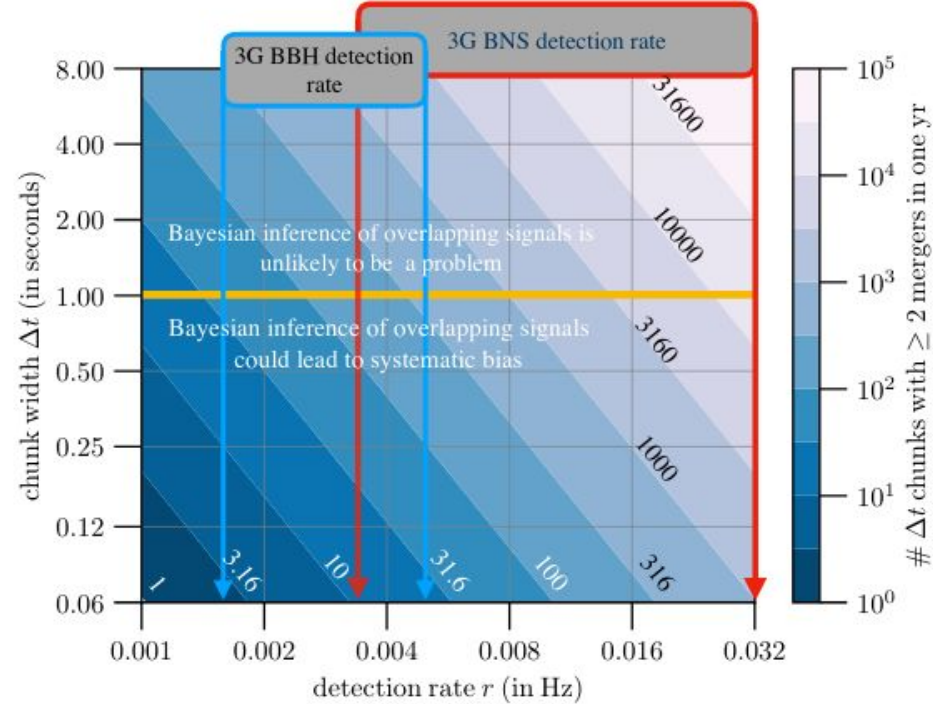
**More detailed slides**

# More details on rate of overlapping signals

Several independent studies have looked at the probability to have overlapping signals:

- [Regimbau & Hughes, 2009](#): Based on vanilla events, check the noise regime
- [Samajdar et al, 2021](#): Simulate one year of data and look at the observed overlaps
- [Pizzati et al, 2021](#): Assuming a Poisson process, look at the overlap rate

→ All agree: **overlaps will be quite common in the 3G detector era**



# More details on close-by mergers

Different studies (e.g. [Regimbau & Hughes, 2009](#); [Samajdar et al, 2021](#); [Pizzati et al, 2021](#); [Himemoto et al, 2021](#); [Relton et al, 2022](#); [Antonelli et al, 2022](#)) have been undertaken with different approaches, all conclude that **bias can occur in some cases, especially when events have close merger times.**

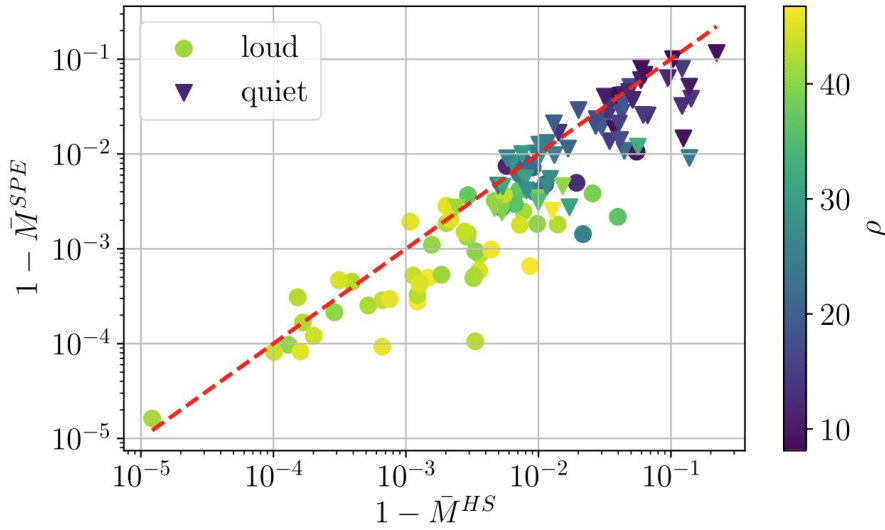
Number of seconds in the year with at least 2 mergers occurring

Rate \ case	$N_{\text{sec}} > 2$ BBH	$N_{\text{sec}} > 2$ BNS	$N_{\text{sec}} > 2$ Events
Lowest	48	155	374
Median	127	2412	3663
Highest	303	15581	20149

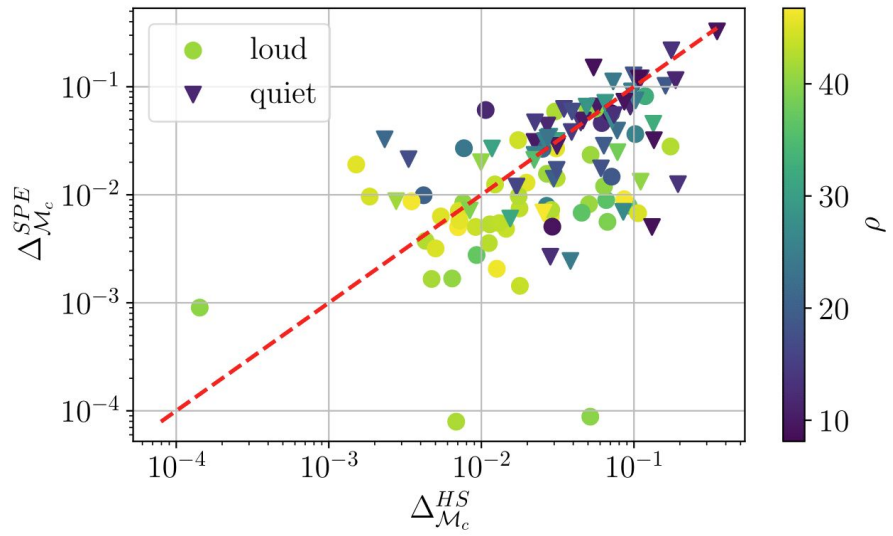
Depending on the exact rate, it can go from a few on a year to many of them.

# Hierarchical subtraction, comparison with no overlap

Mismatch for the maximum likelihood recovery



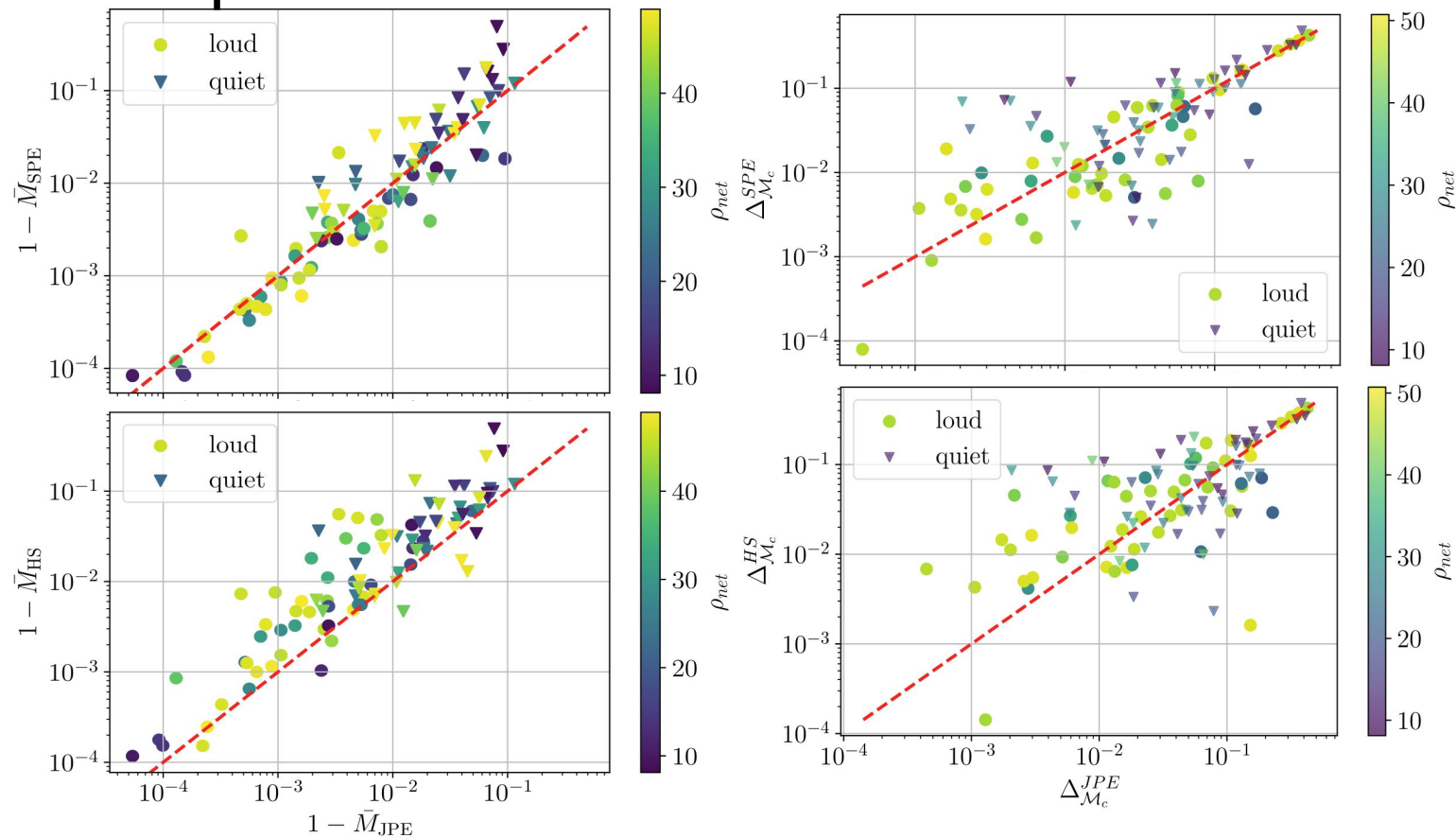
Measure of the bias (normalized distance between the median and injected value)



On average, hierarchical subtraction is less precise and more prone to bias than without overlap

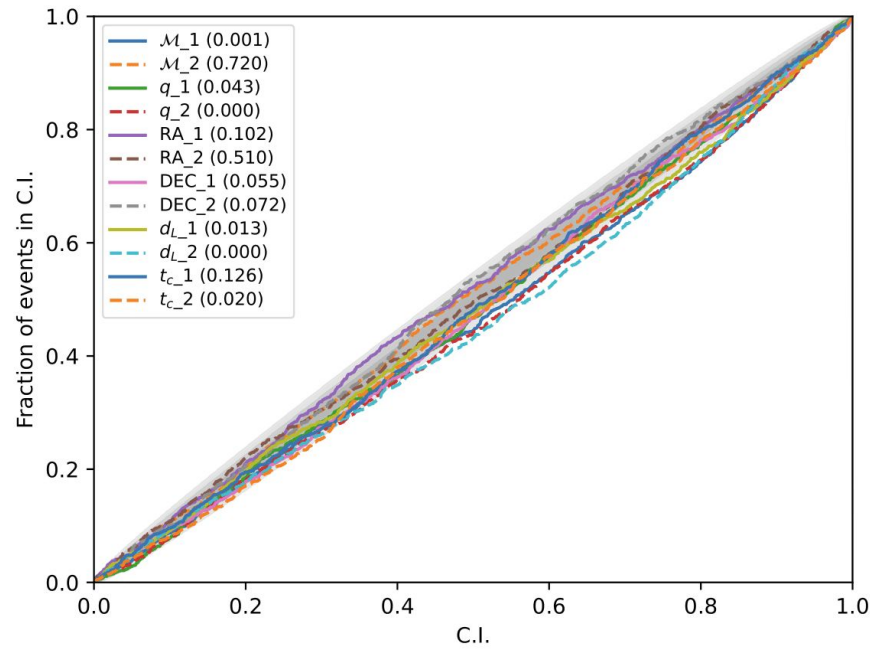
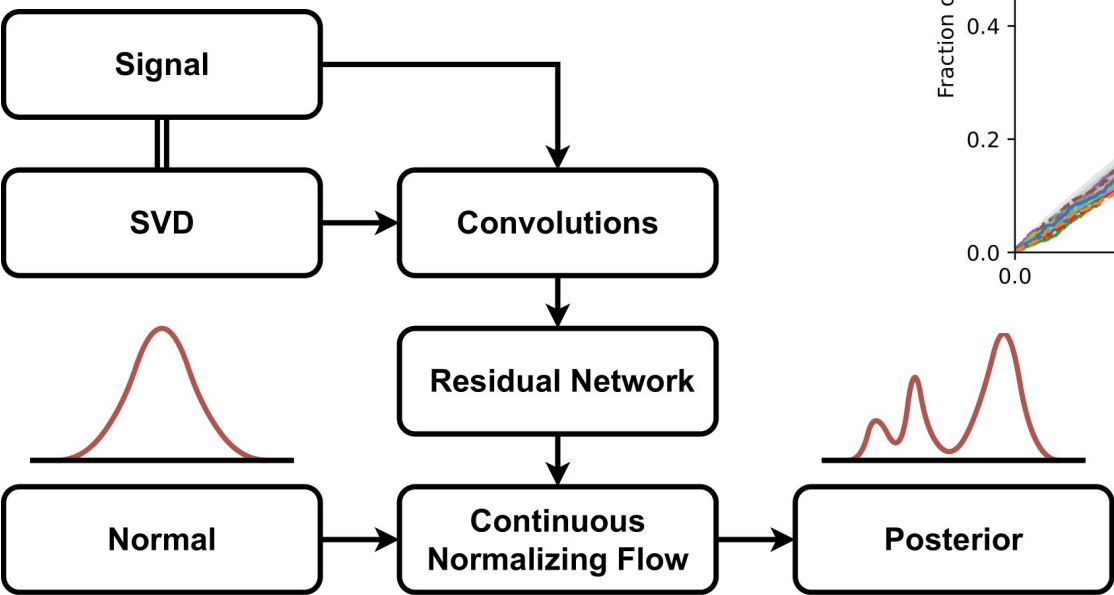
→ Expected since imperfect noise realization

# Comparison with hierarchical subtraction and without overlap



Joint parameter estimation is more accurate than hierarchical subtraction, but slightly less precise than without overlap

# Machine learning based performance



Stable results throughout the parameter space, with a good speed