Normalizing Flows As an Avenue to Study Overlapping Signals

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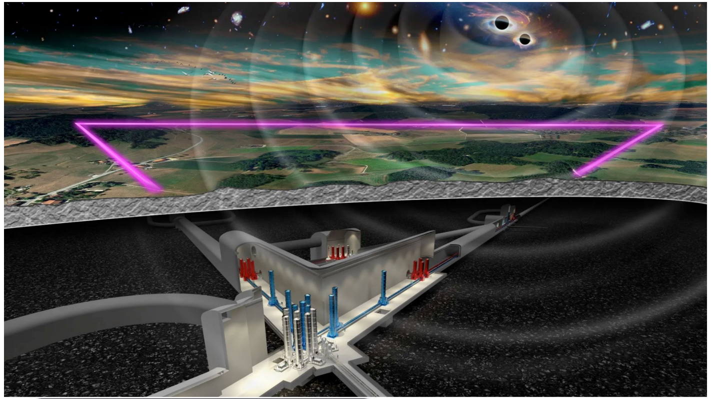
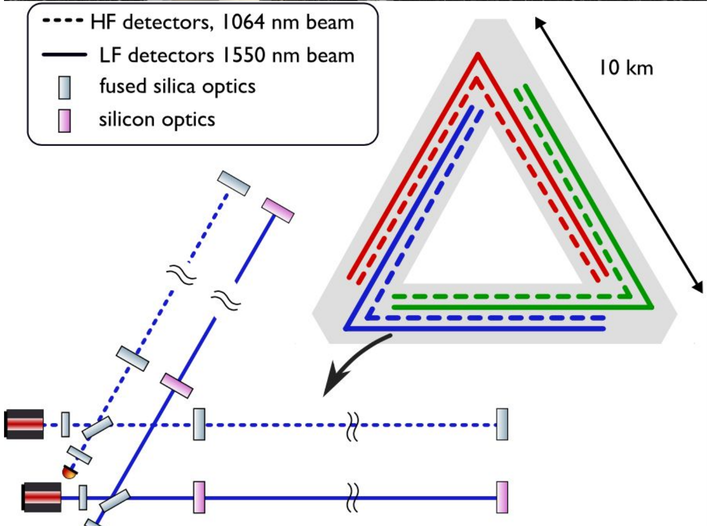
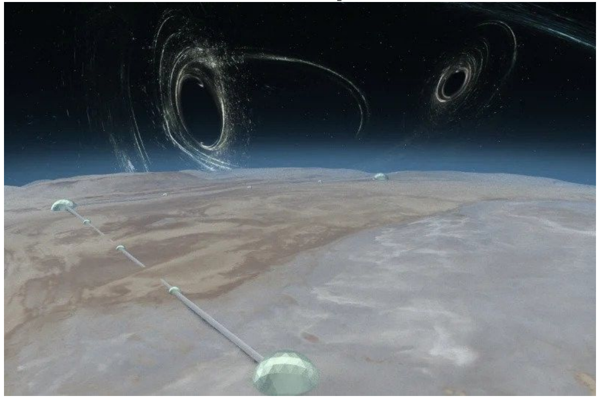
Next-generation detectors (1)

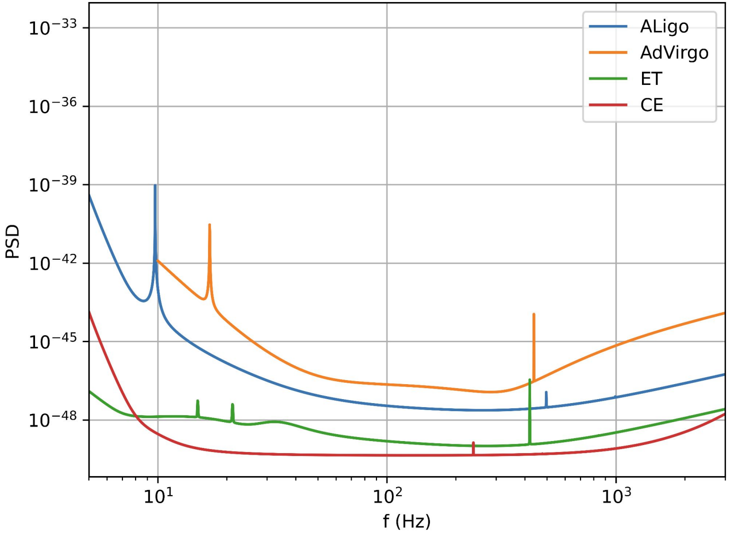
Einstein Telescope





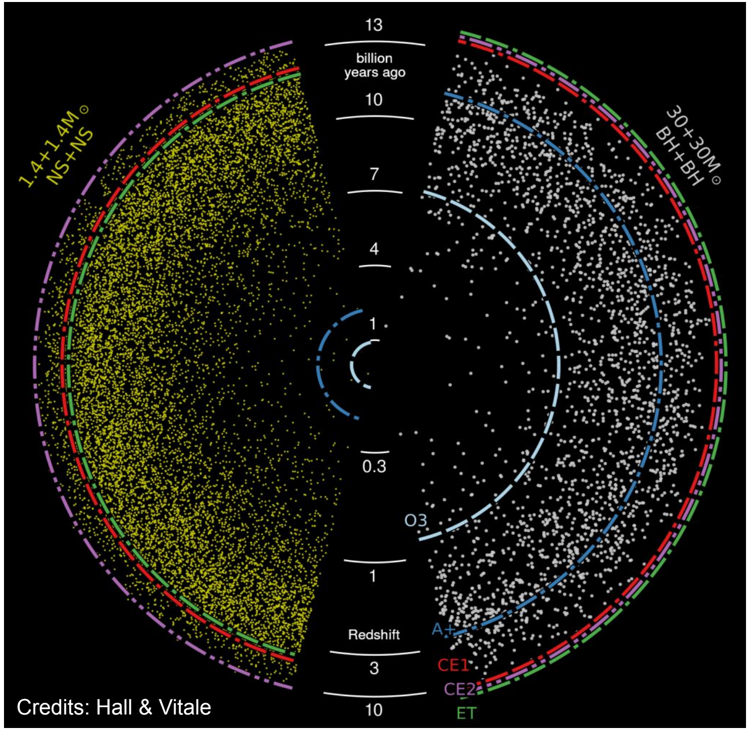
Cosmic Explorer

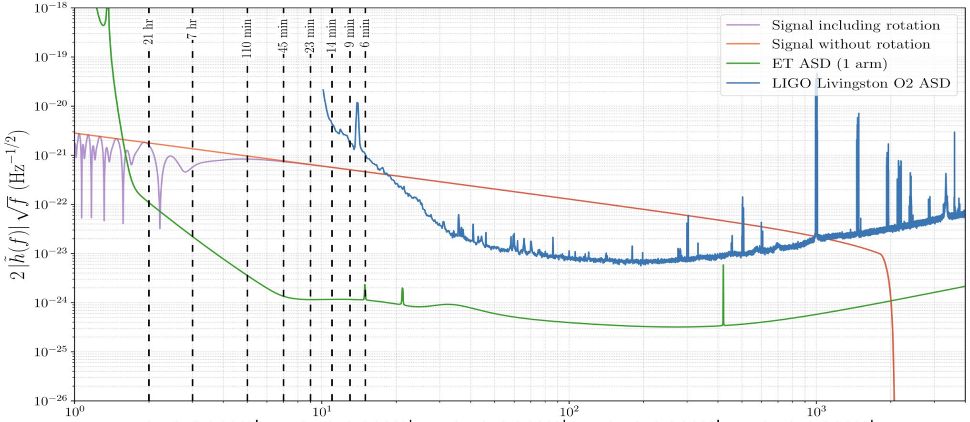


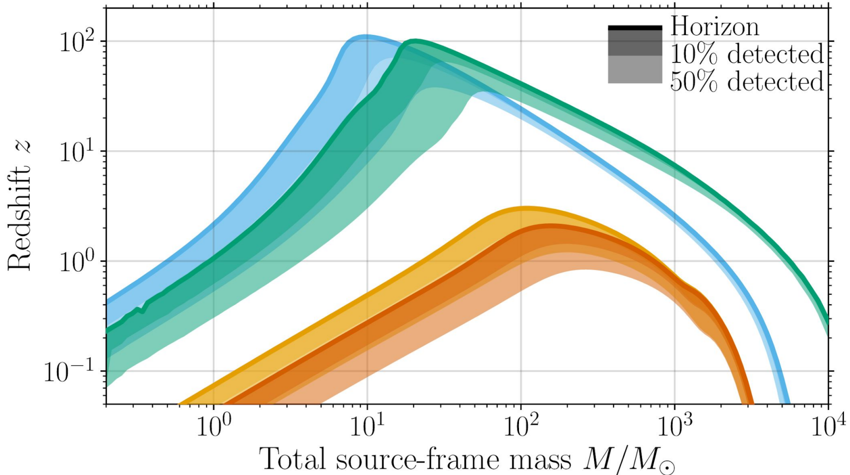


Next-generation detectors (2)

These detectors will have an extended sensitive frequency band and will see much further away







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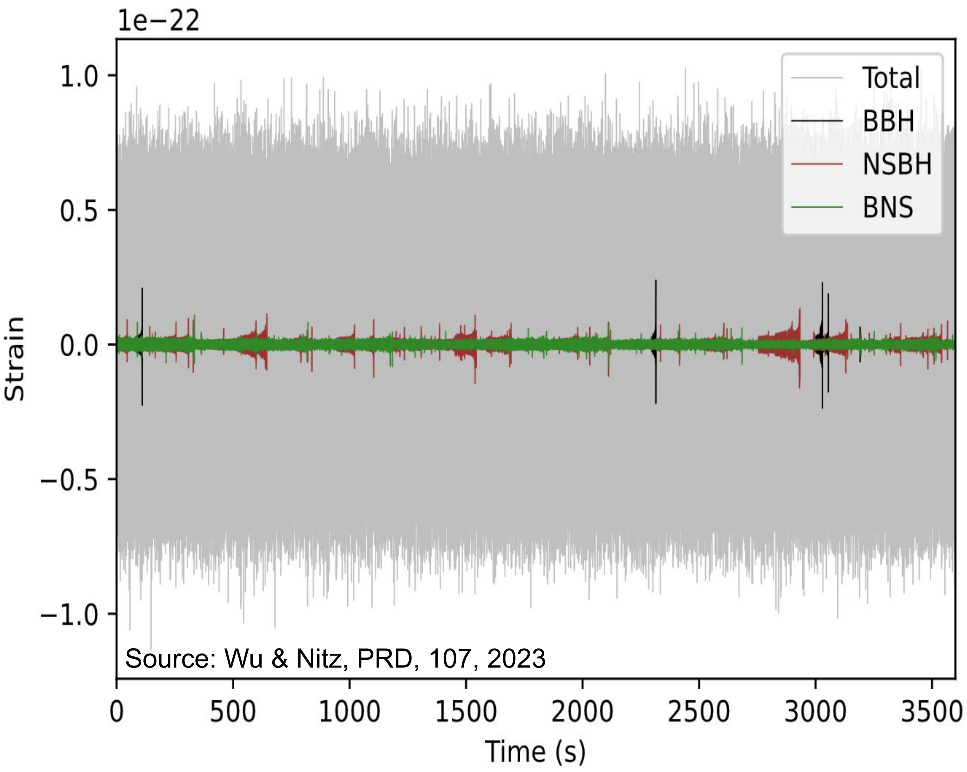

This will also lead to **some issues**. For example:

- Detectable mergers will start overlapping in the detectors’ sensitive band
- There will be problems evaluating the power-spectral density since there will be very little periods of time without ongoing mergers
- A large confusion background made of unresolved sources will bias the power-spectral density estimation
- Very loud events also challenge our current waveform models which are not accurate enough

These issues need to be addressed if we want to use future detectors optimally.

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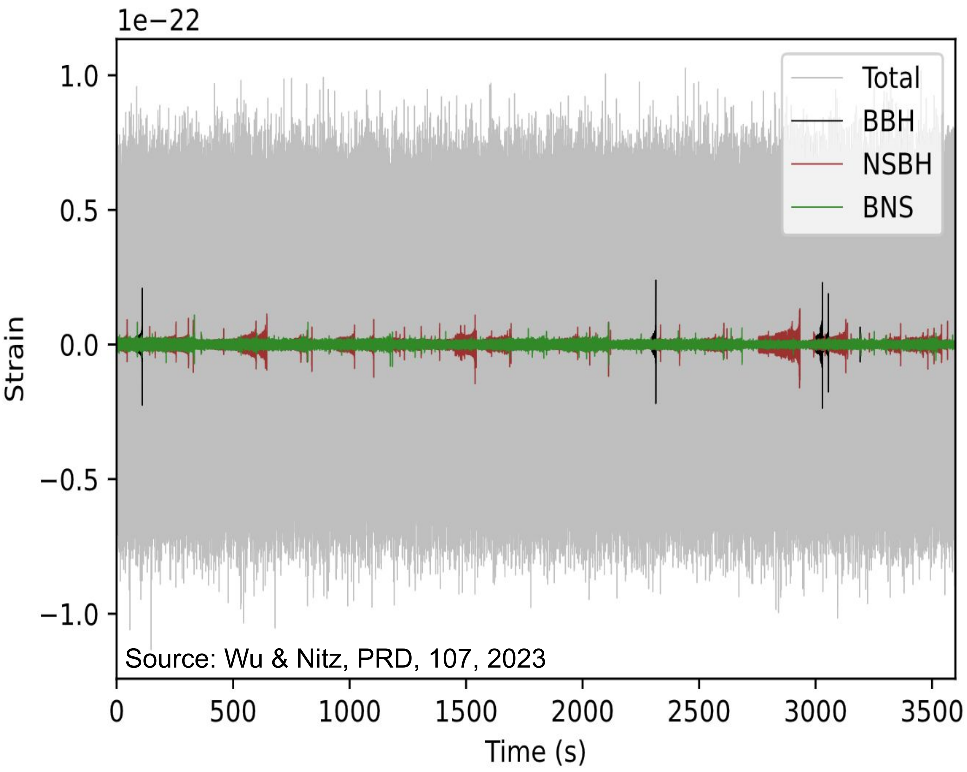

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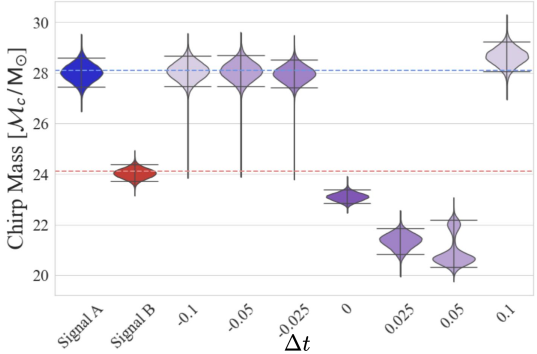
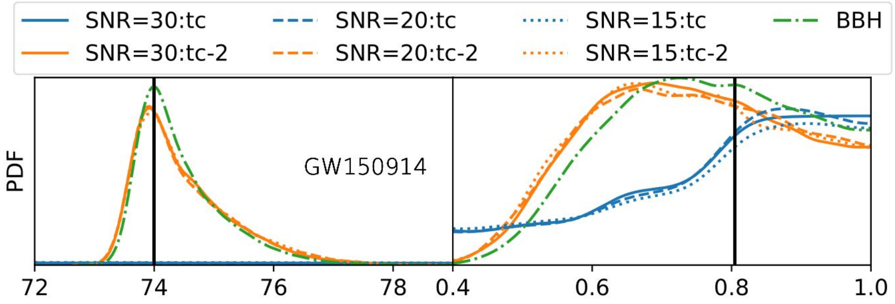
Is this a problem?

Most focus on overlapping pairs of signal. Depending on the scenario, neglecting overlap can lead to biases (Samajdar, Janquart et. al, 2021, Pizzati et. al, 2022, Relton & Raymond, 2022, Himemoto et. al, 2022)

BBH + BBH:



BBH + BNS:



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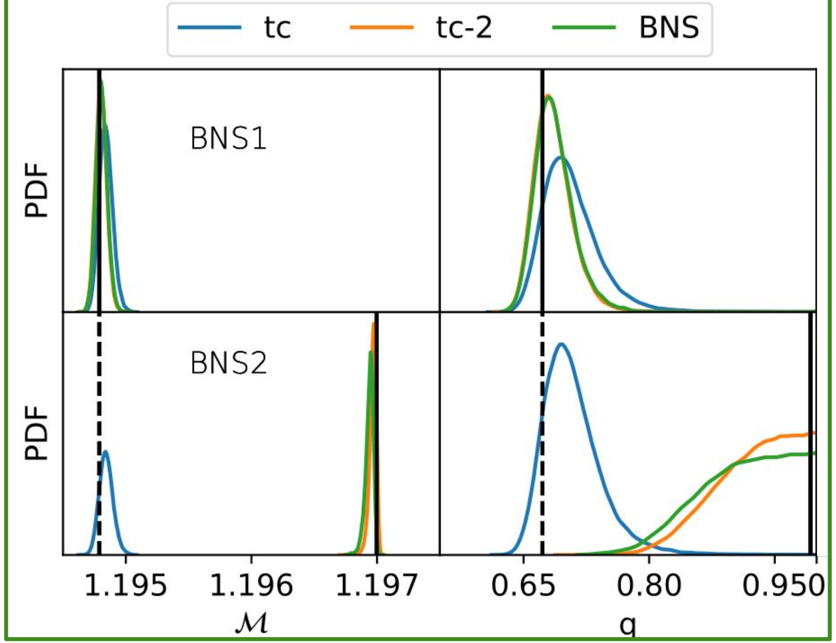

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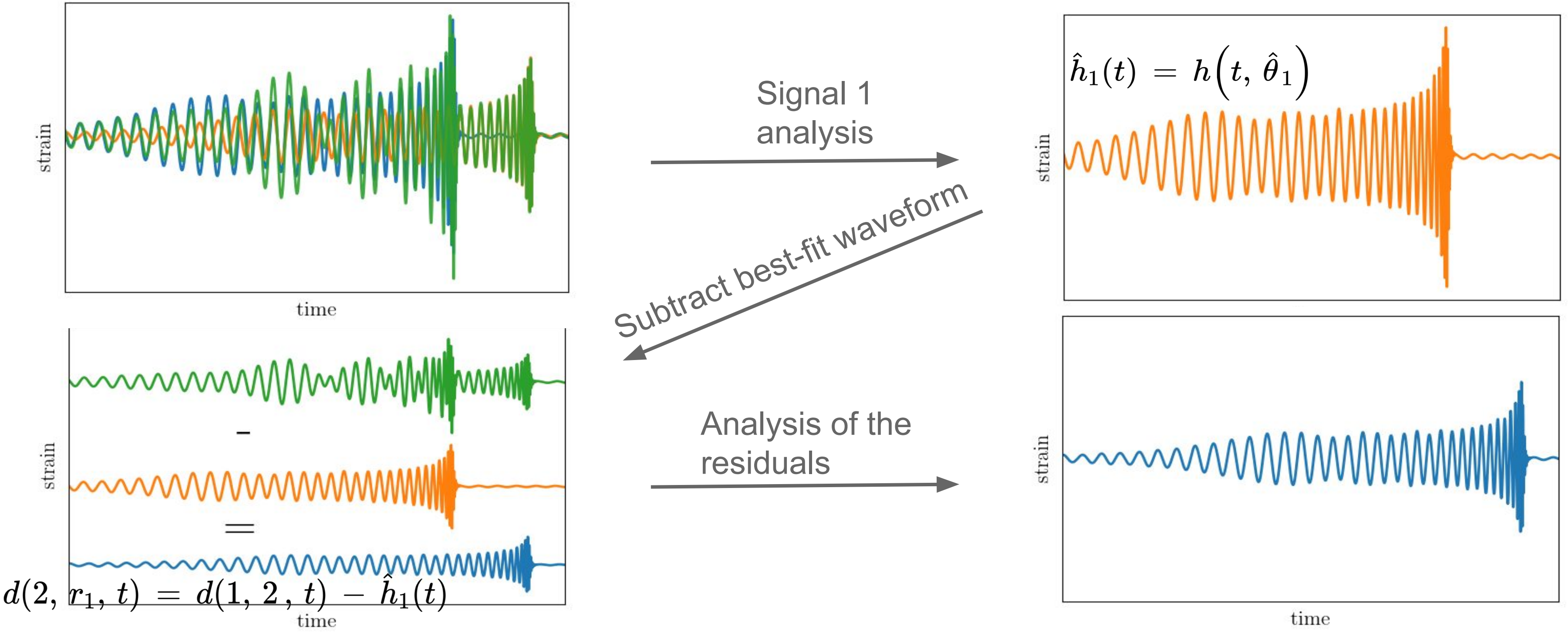

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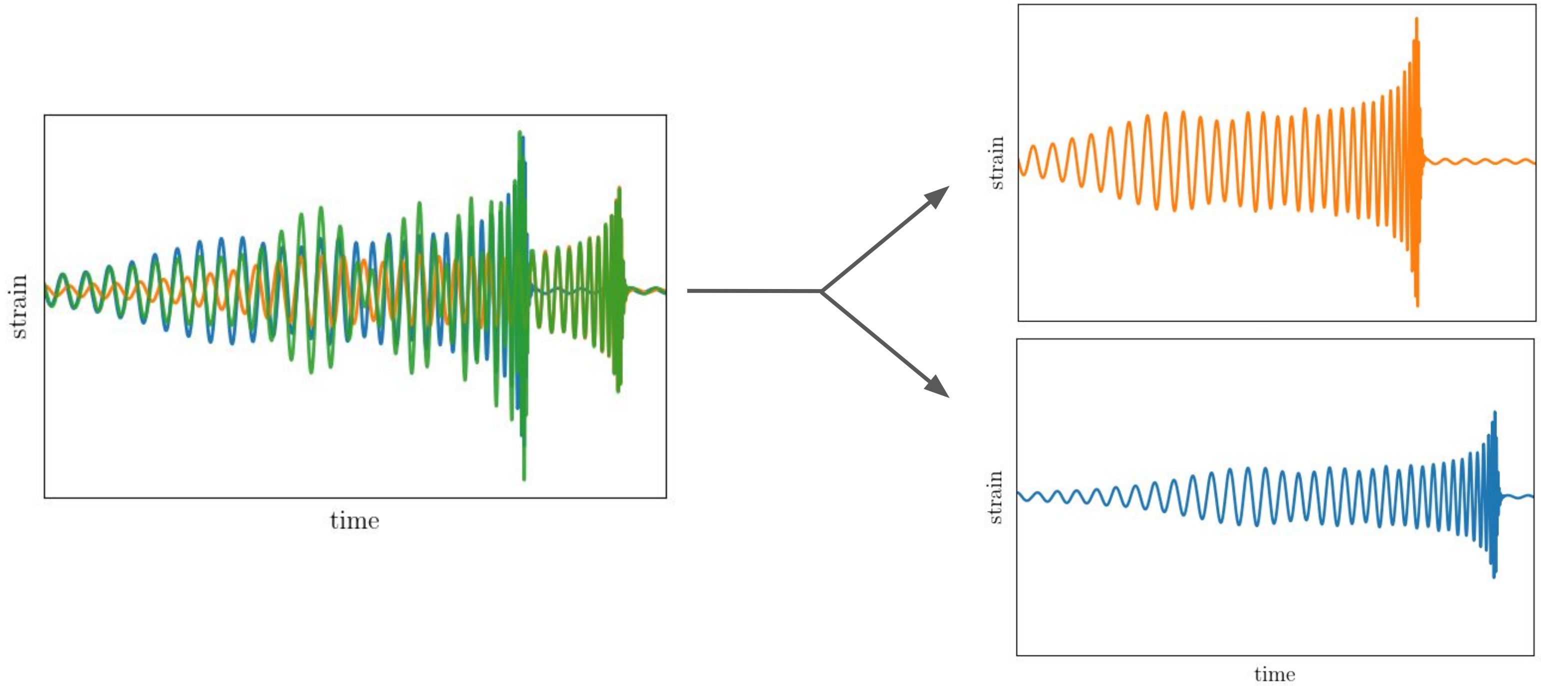
(b) **Joint parameter estimation**: joint analysis of the two signals, more accurate but slower



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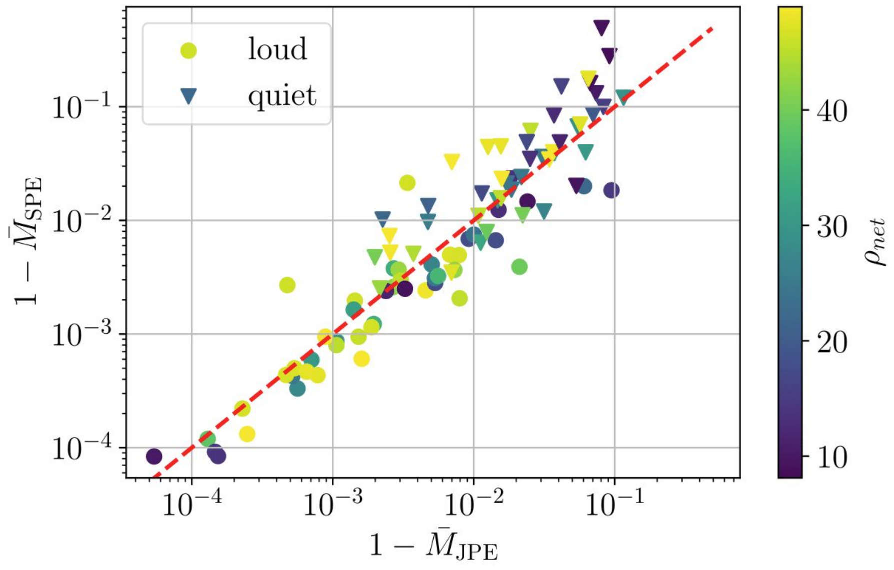
Comparison between JPE and SPE



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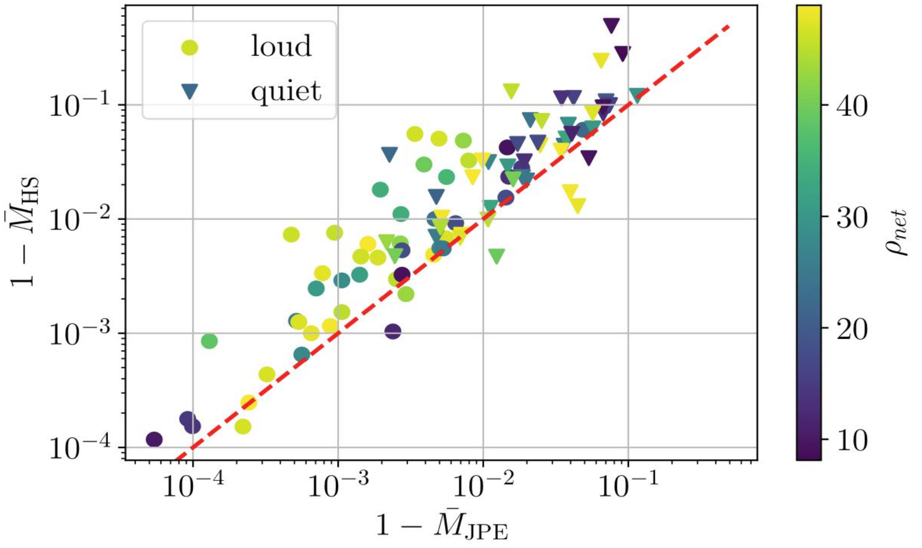

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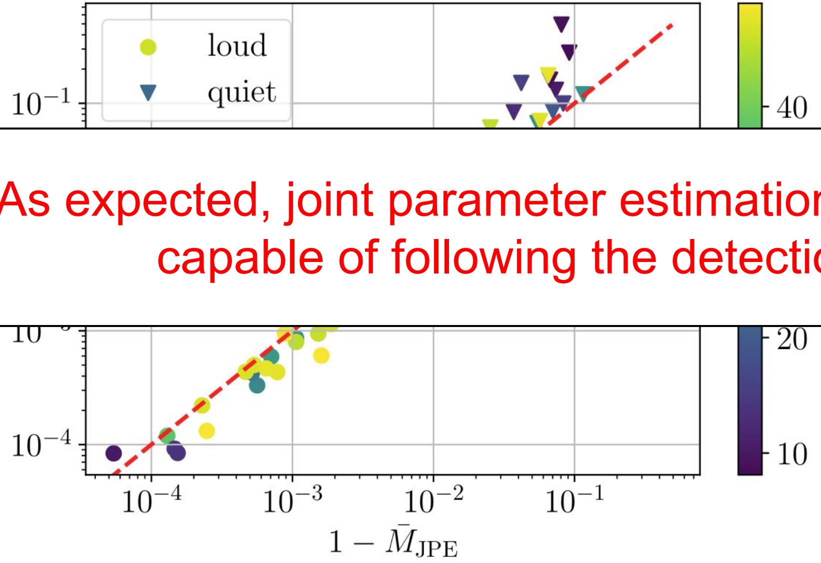

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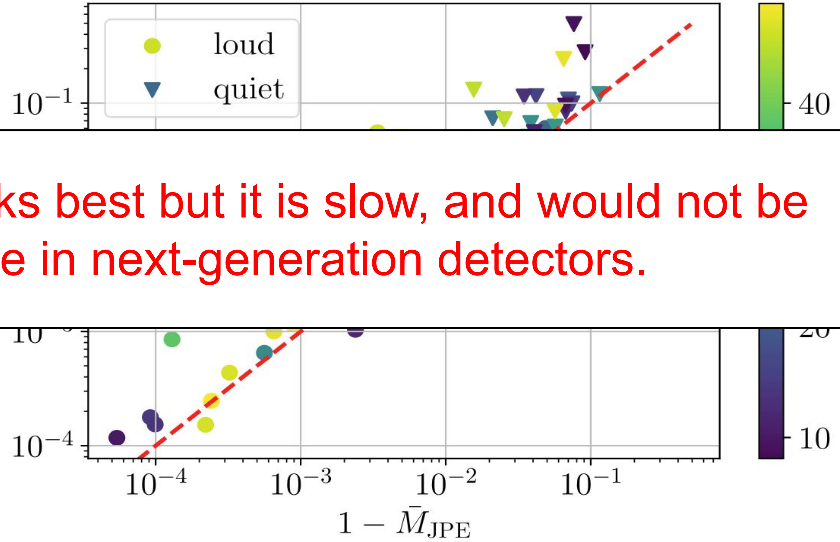

As expected, joint parameter estimation works best but it is slow, and would not be capable of following the detection rate in next-generation detectors.

Avenue to get equivalent results but (much) faster

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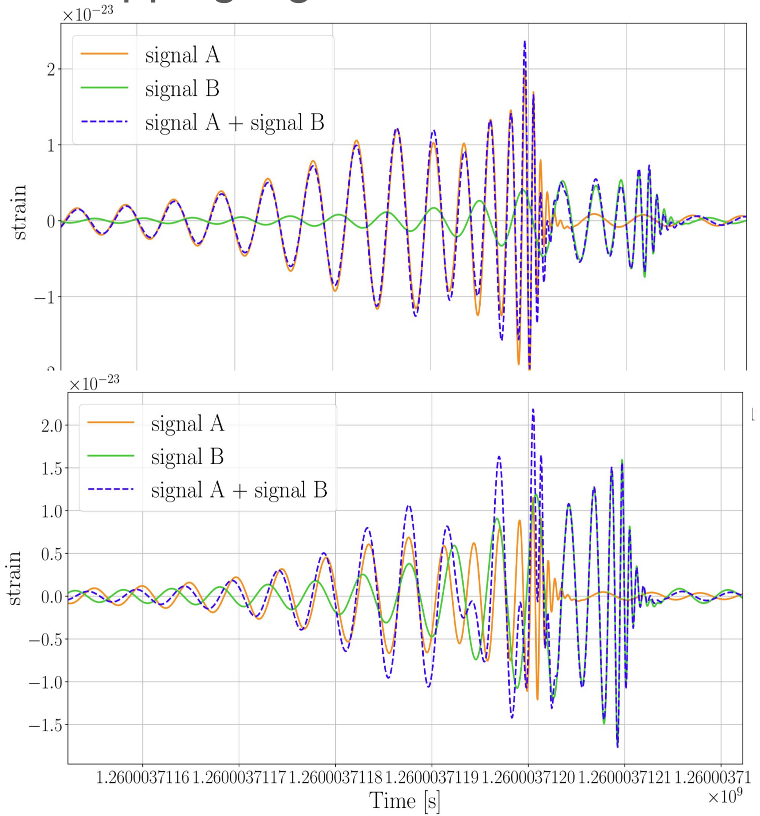

For this proof of concept, the setup is:

- **HLV** network at **design** sensitivity
- Focus on **binary black hole** signals
- Starting frequency is **20Hz**
- Signals overlap within **0.1s of each other**—corresponding to the high bias regime
- Masses are between 10 and 100 Solar Masses
- SNR is drawn from a beta distribution ranging from 8 to 50, with a peak around 12.

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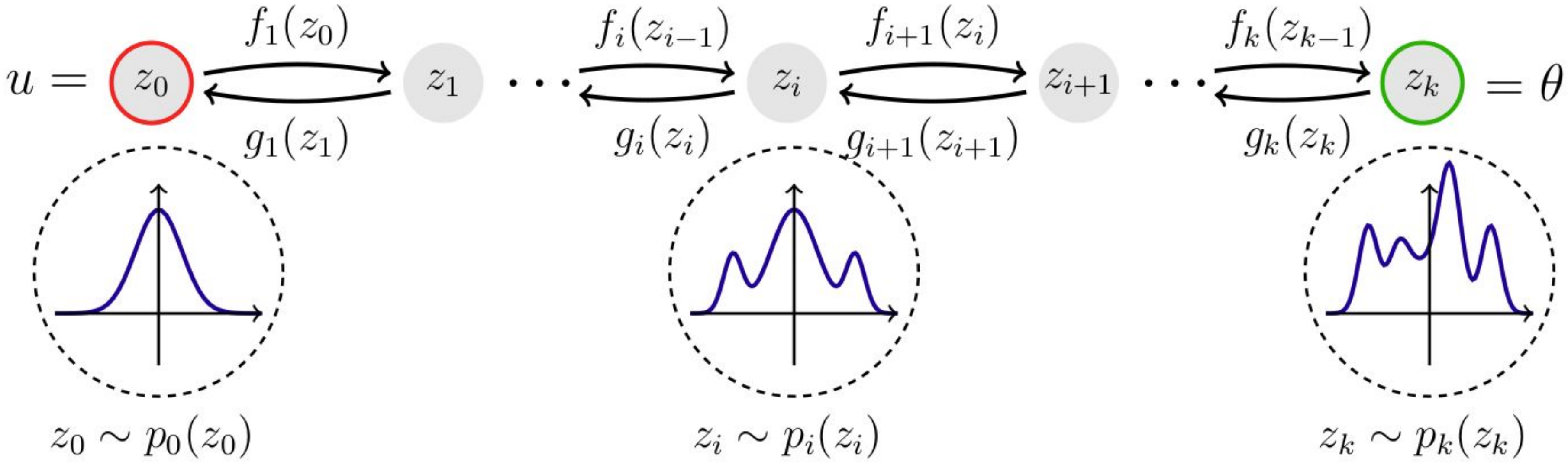
Classical normalizing flows:



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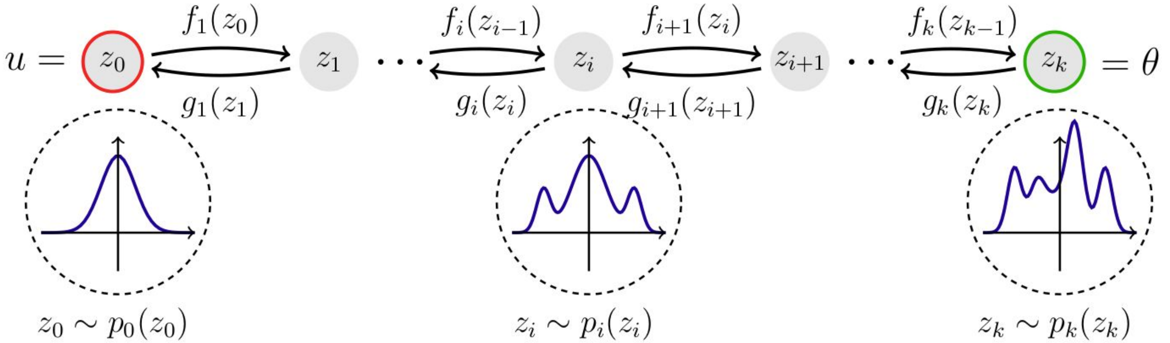
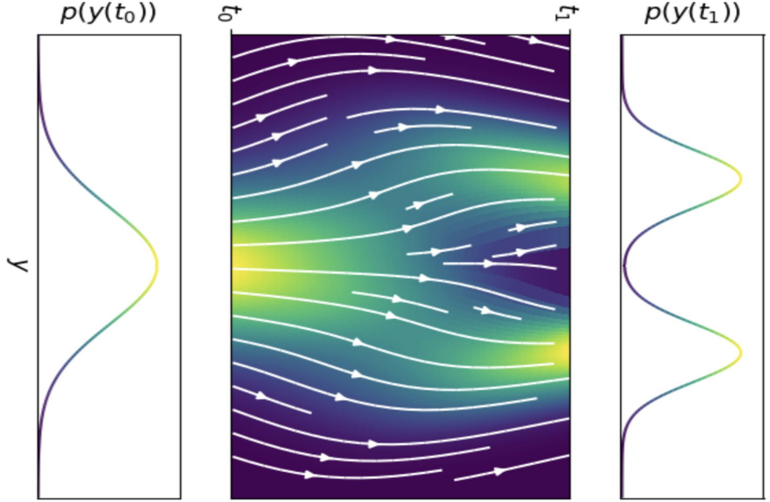
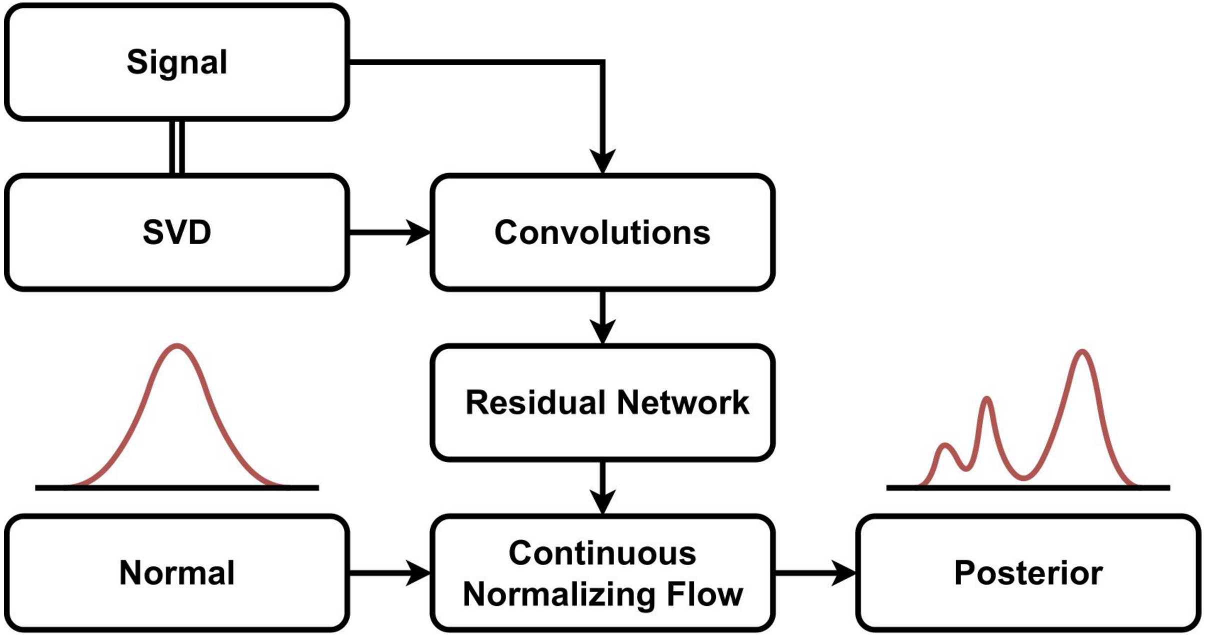


Actually, more like



We use a hypernetwork to represent the ordinary differential equation.
This is faster and lighter than a discrete normalizing flow network

Our full model

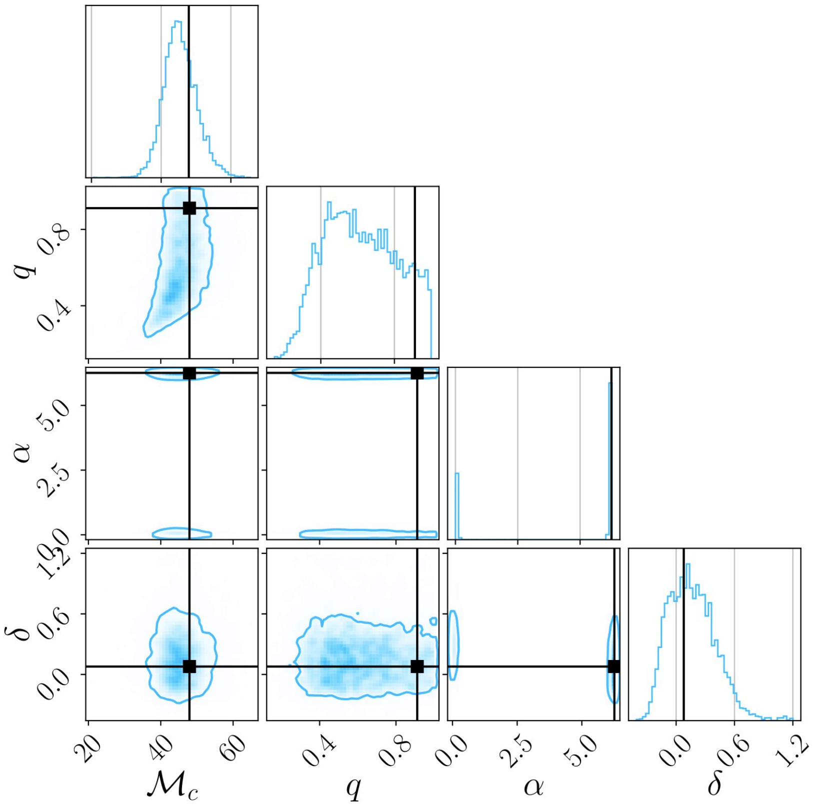


- SVD decomposition used to initialize the first convolution layer
- Residual network to summarize the GW data information passed to the continuous normalizing flow network
- Continuous normalizing flow network generates the posteriors for the overlapping BBH signals

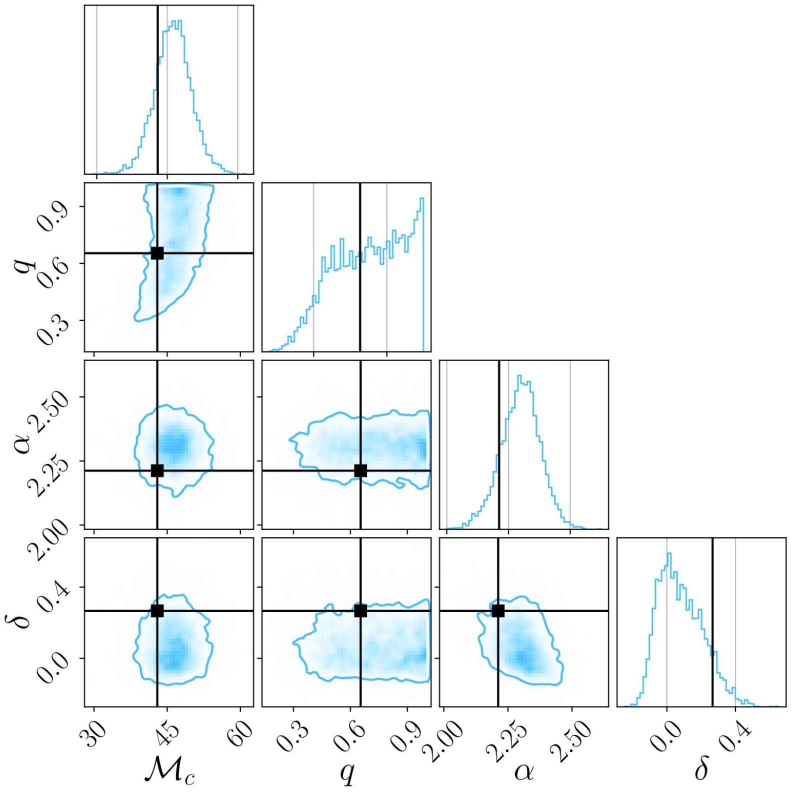
How does our network perform?

Our network can provide posteriors that look good

Event A

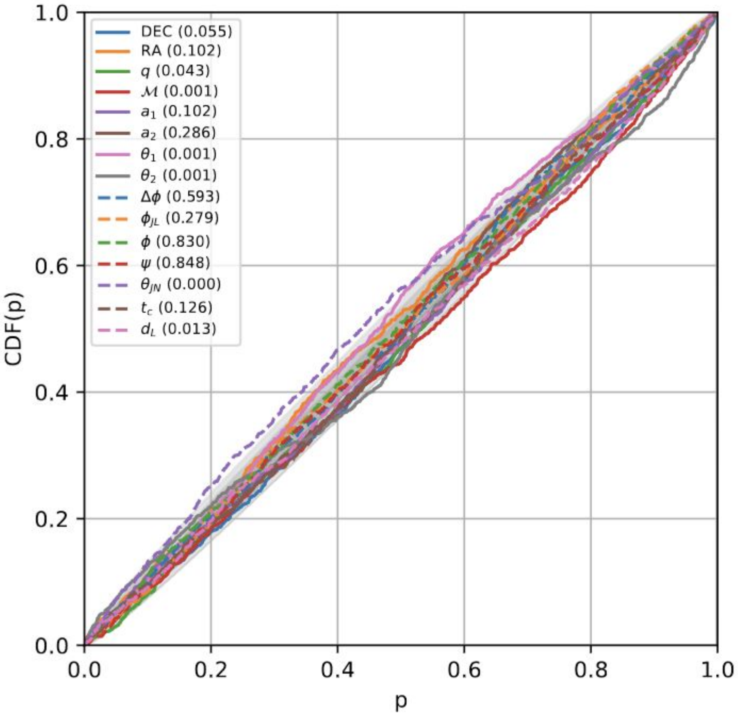


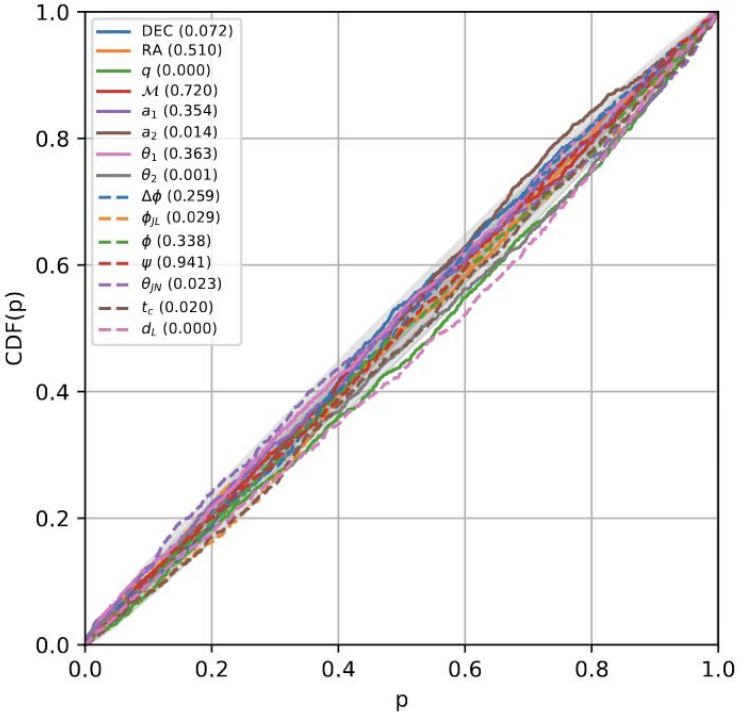
Event B



How does our network perform?

Our network does not show systematic bias (pp plots look fine)

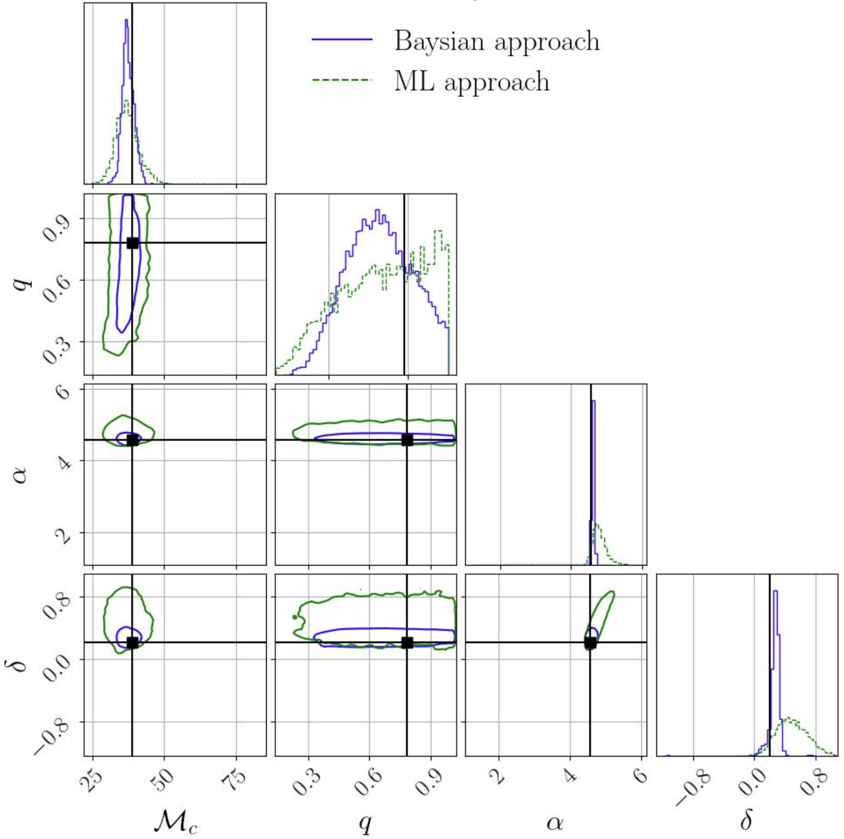




Note: this cannot be done with traditional methods as these are intractable on such a scale

How does our network perform?

However, our network tends to give broader posteriors when compared to Bayesian joint parameter estimation (test done on a reduced number of events)



Main expected reason: size of the network, which is pretty small when compared to those existing in literature for single parameter estimation.

Possible solutions:

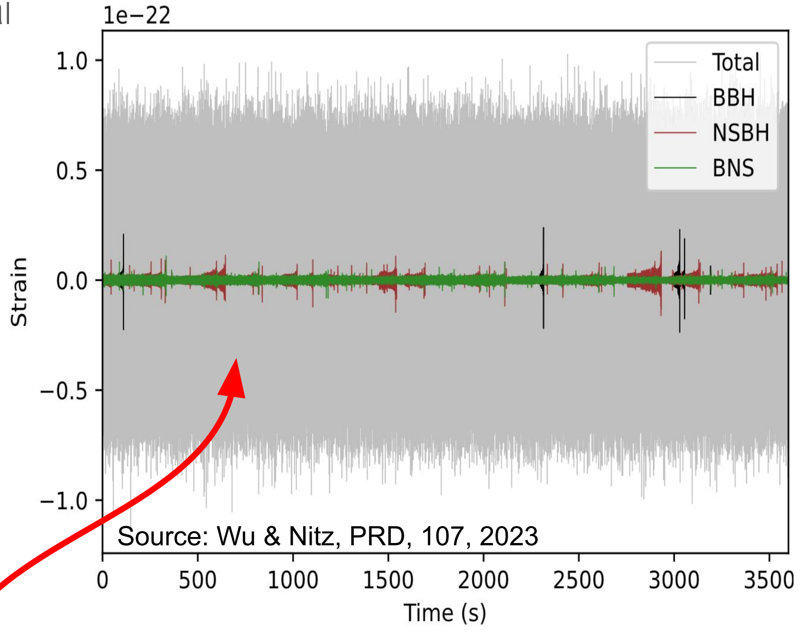
- **Increase size of the network** but would not work on low-end GPU anymore
- **Importance sampling** to improve the samples obtained from our model
- **Tuning the neural network during the training** to focus the network better on the parameter space region for the signals (see Alex’s talk on Friday)

Conclusions and Next Steps

In this work, we have shown it is possible to do joint parameter estimation for overlapping binary black hole signals using normalizing flows. Our results are unbiased but tend to be larger than expectations from usual Bayesian methods.

The next steps for this project:

- Adapt the framework to next generation detectors: change the network but also lower the minimum frequency, i.e. deal with longer duration signals (already non-trivial for single signal parameter estimation)
- Work with more signal types and different types of overlap (even longer signal…)
- Try flow matching
- Move towards more realistic data



Source: Wu & Nitz, PRD, 107, 2023