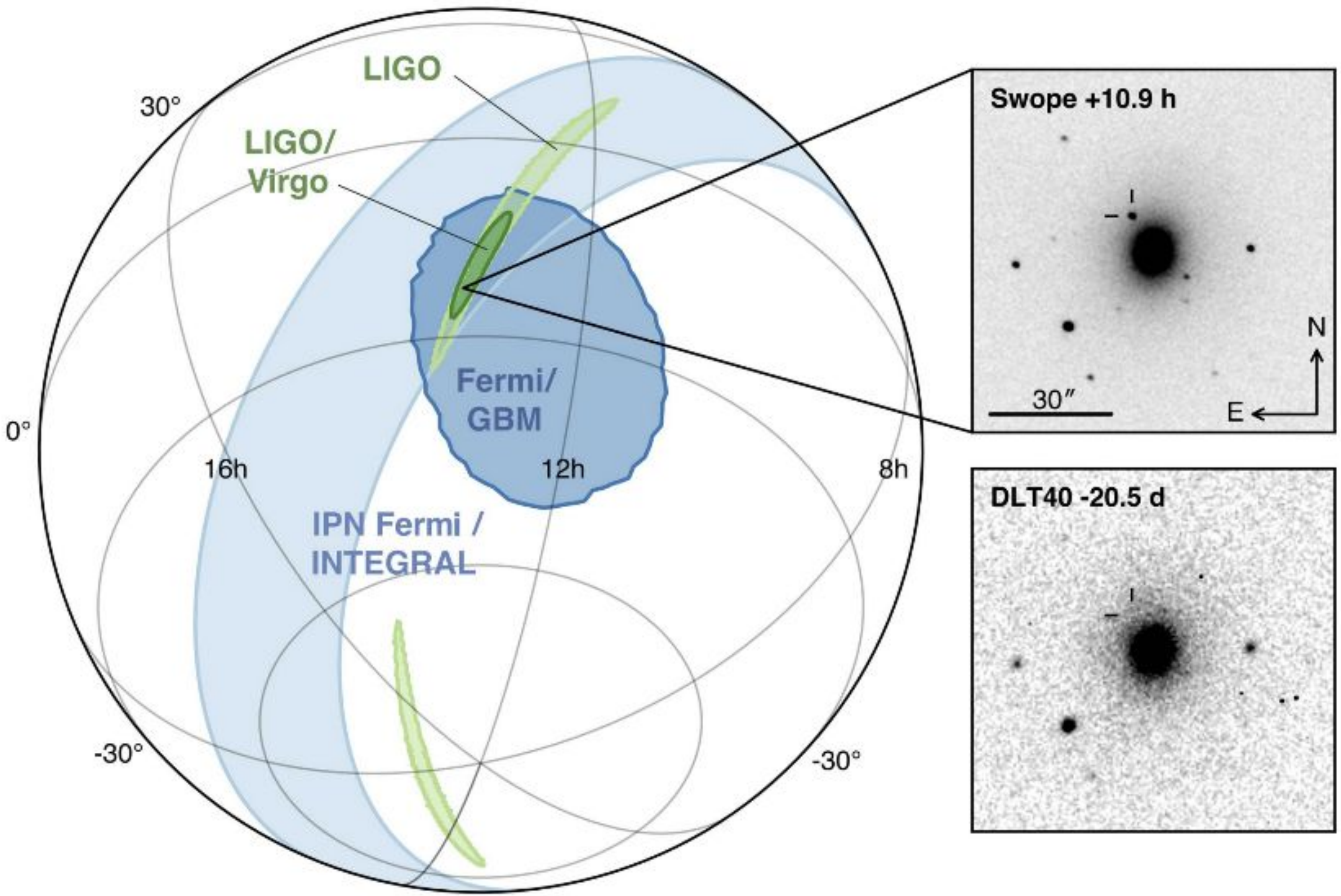
Inferring Gravitational Wave Source Properties with Machine Learning

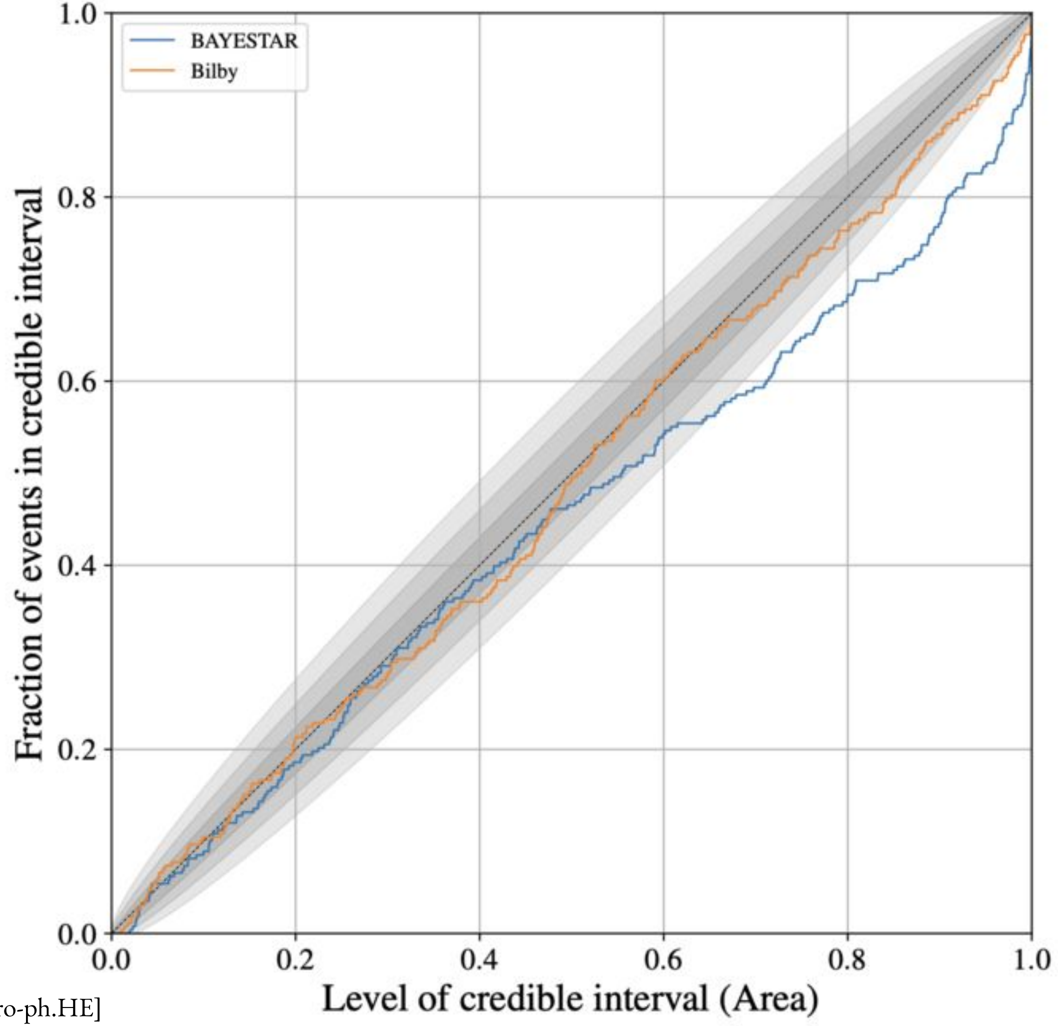
Jules Levanti & Ryan Magee

Presentation Navigator

1. Motivation: Current Sky Map Algorithms and Performance
2. Main Project Goal and Techniques
3. Intermediate Pipeline Data Products: Singular Value Decomposition
4. Parameter Estimation: Simulation Based Inference and Convolutional Neural Networks
5. Results and Conclusion



GW170817 - The Astrophysical Journal Letters 848: (59pp) from LSC, Virgo, Fermi, et al.

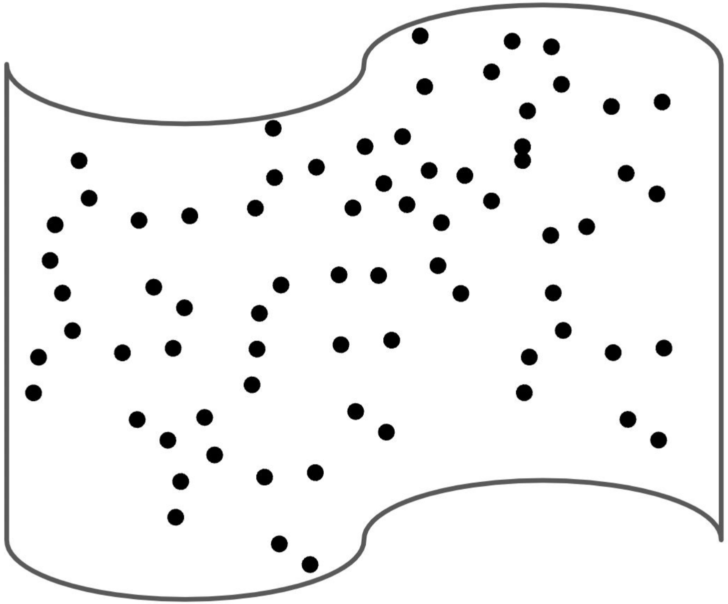


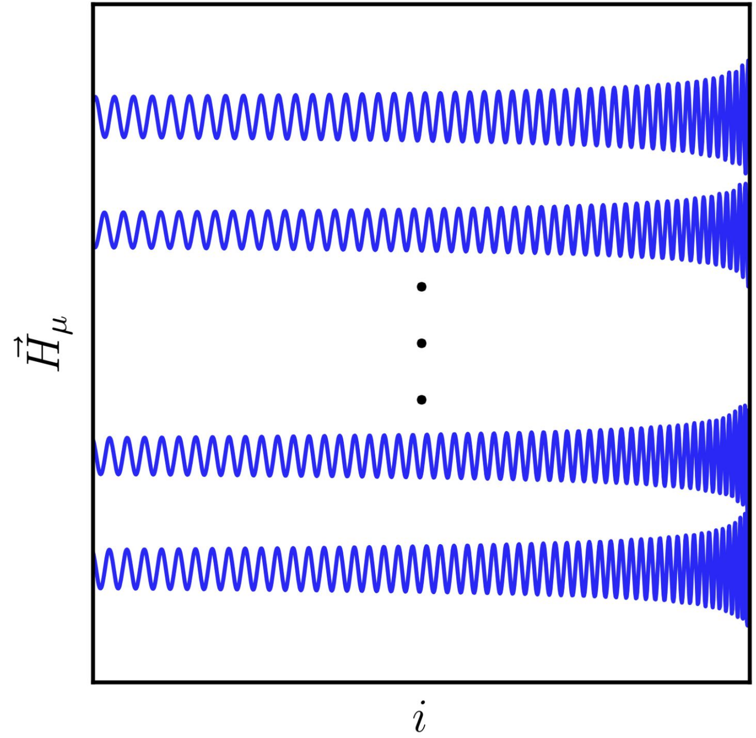
Chaudhary et al arXiv:2308.04545 [astro-ph.HE]

Find ways to produce skymaps <u>quickly</u> and <u>accurately</u> with two techniques:

1. Using intermediate pipeline data products

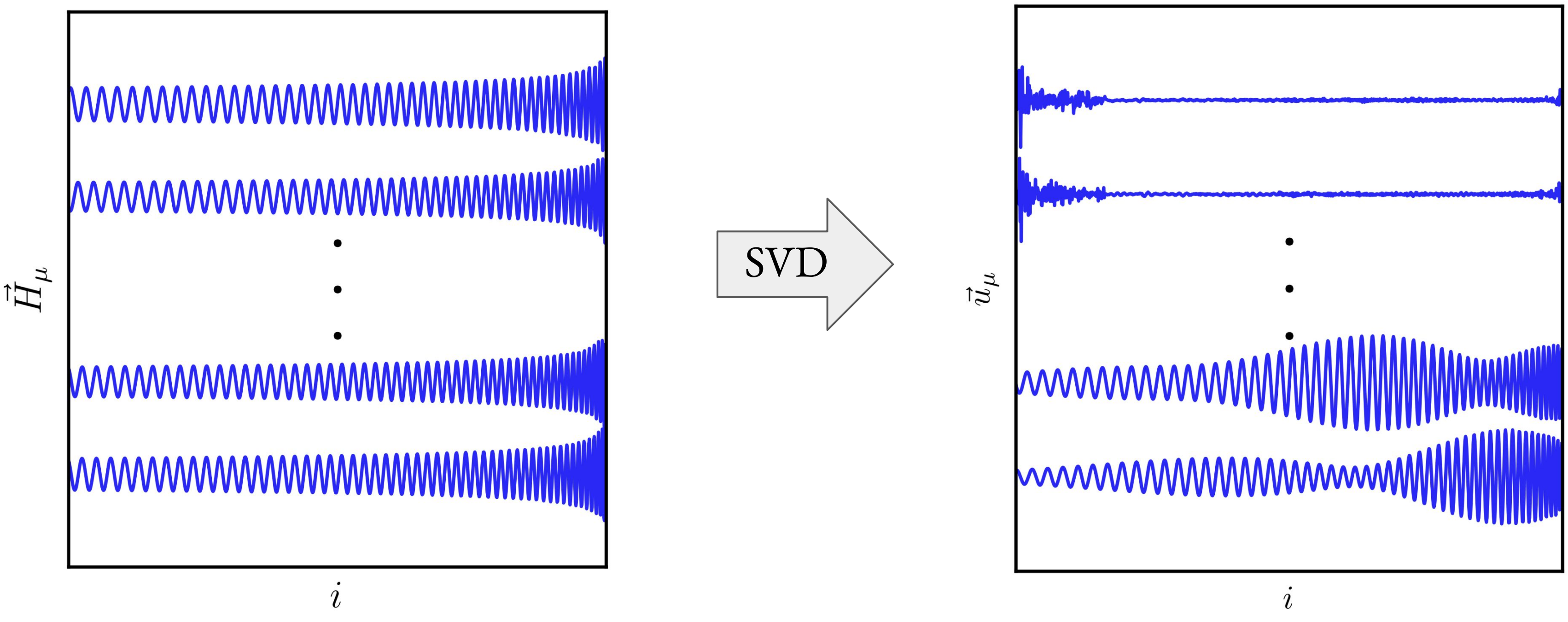
2. Implement machine learning techniques such as simulation based inference





Magee, 2020

Singular Value Decomposition



Magee, 2020

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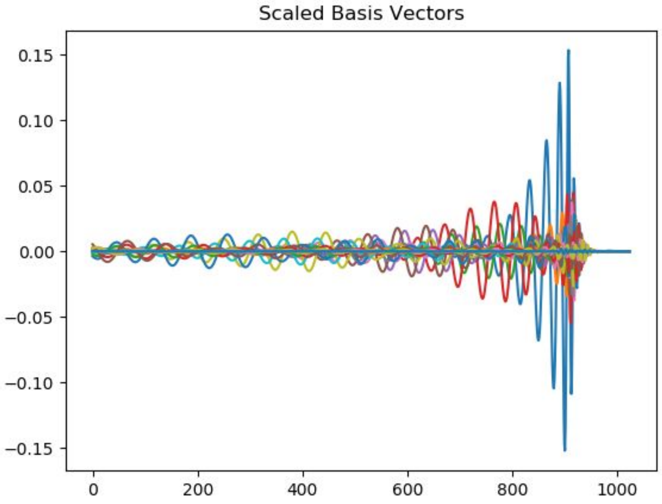
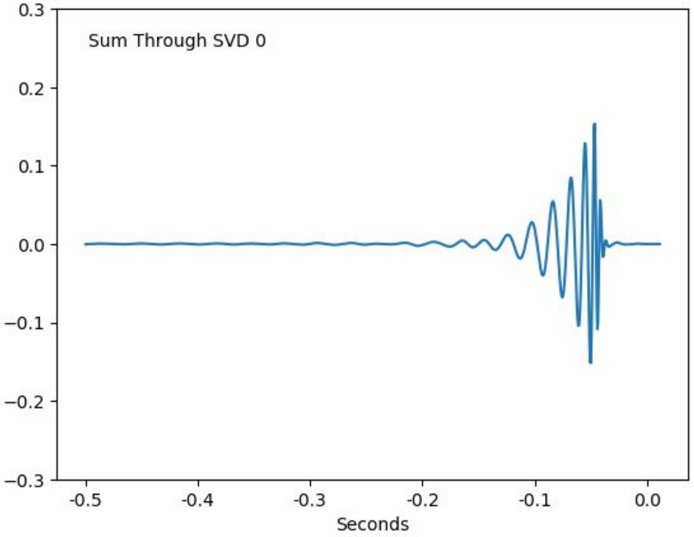
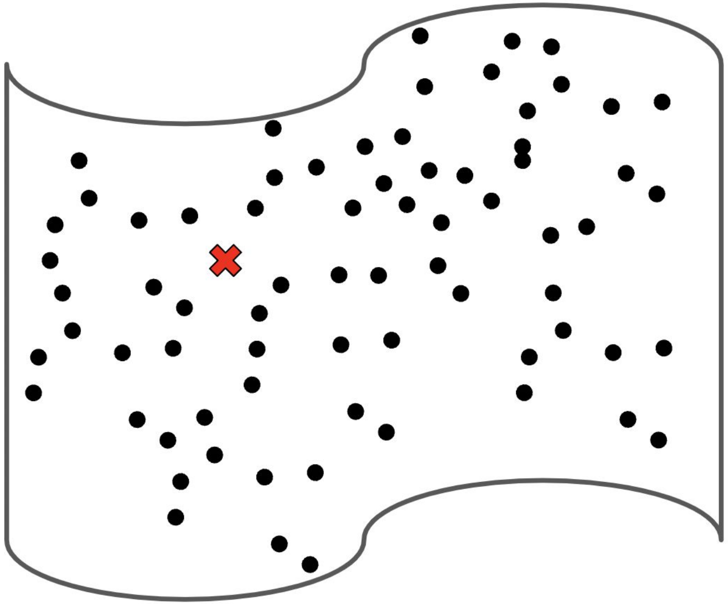
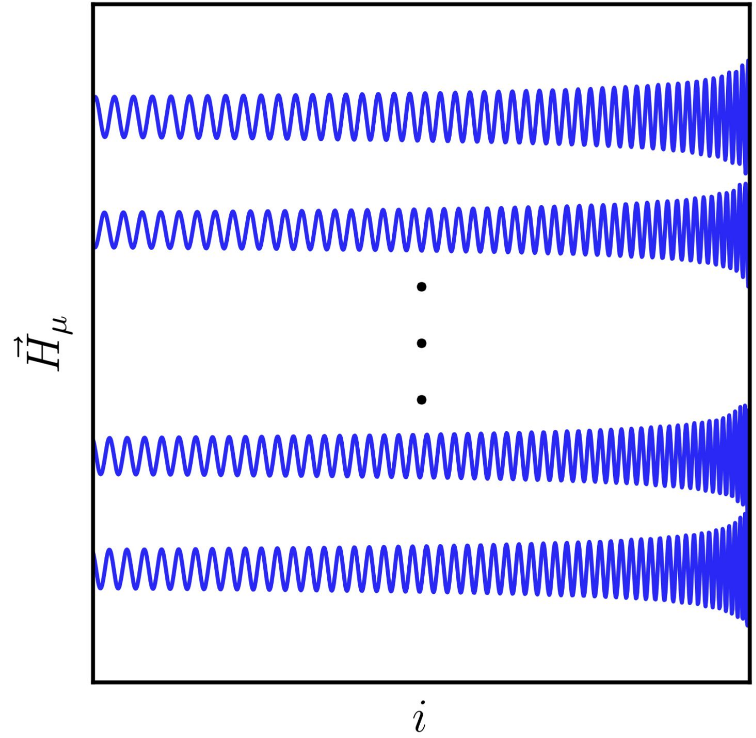


$$h = \Sigma a_{\mu} u^{\mu}$$







Magee, 2020

Template break-down into SVD basis vectors:

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SNR:

$$\rho = < h|d >$$

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...which relies on Bayes' Theorem...

$$P(\theta|\{x\}_i) \propto P(\{x\}_i|\theta)P(\theta)$$

For parameter estimation, we perform inferences on parameters (θ) given observation x...

...and the likelihood function

(very expensive to compute)

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Instead, we can generate a parameter estimation using simulated observations to compute an inference.

Simulation Based Inference

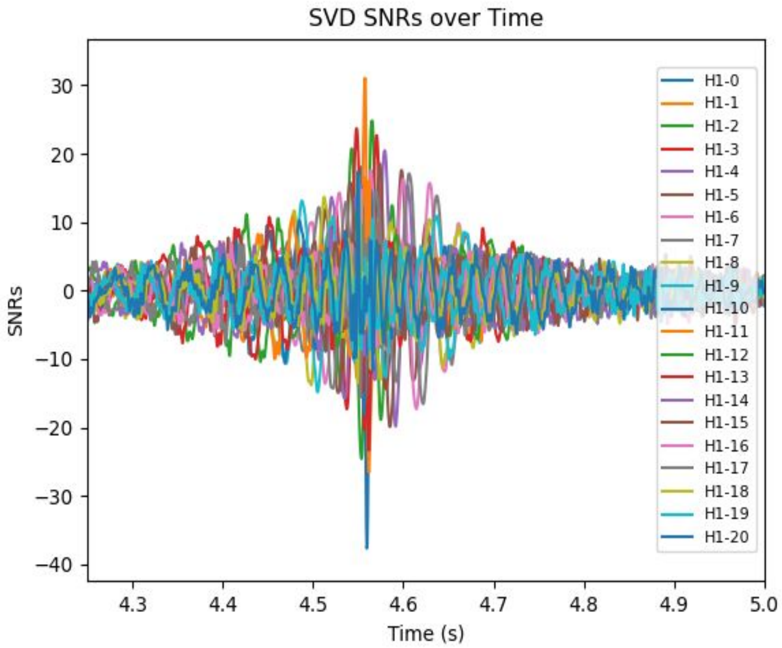
A likelihood free inference algorithm

1. We have an array of time-series, looking at parameters $\theta_1, \theta_2, \ldots$

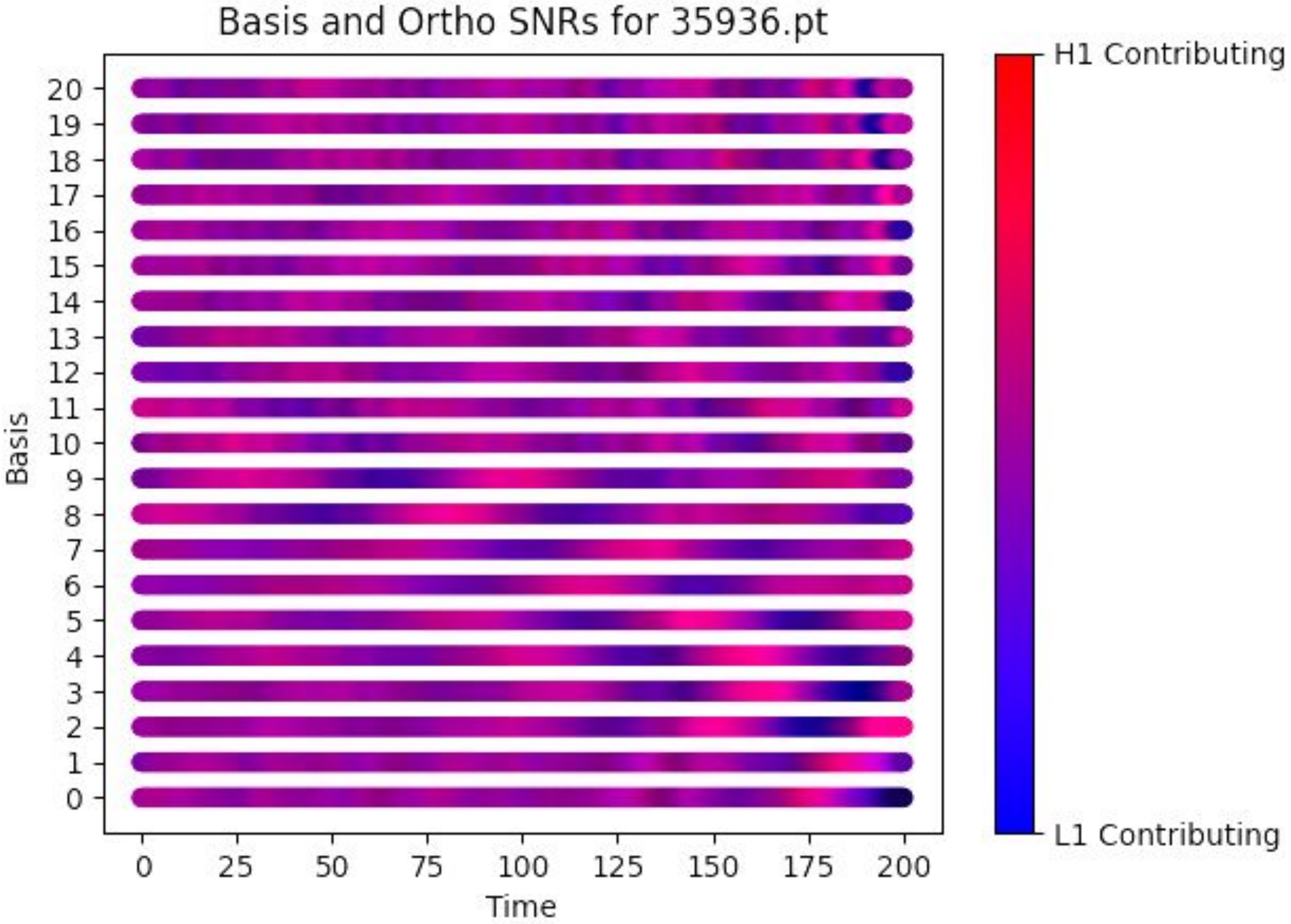
2. Draw samples from prior distribution

3. Simulate response to that sample

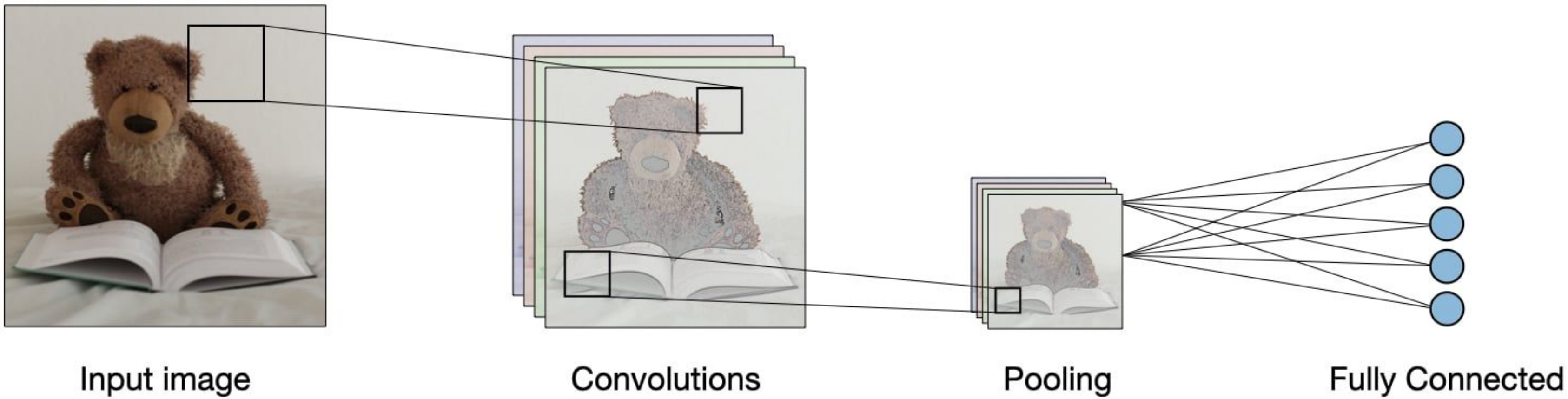
4. Use responses and the sample to train the NN

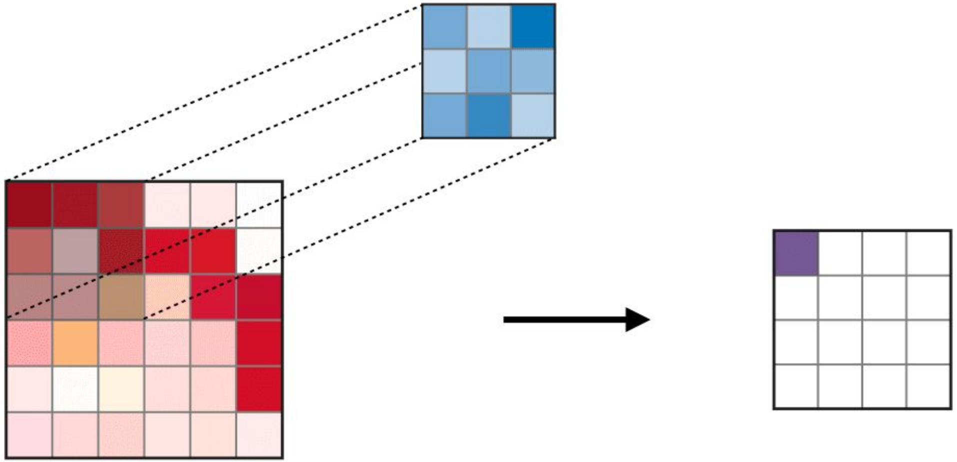


$$\rho = \sum a_\mu Q^\mu$$

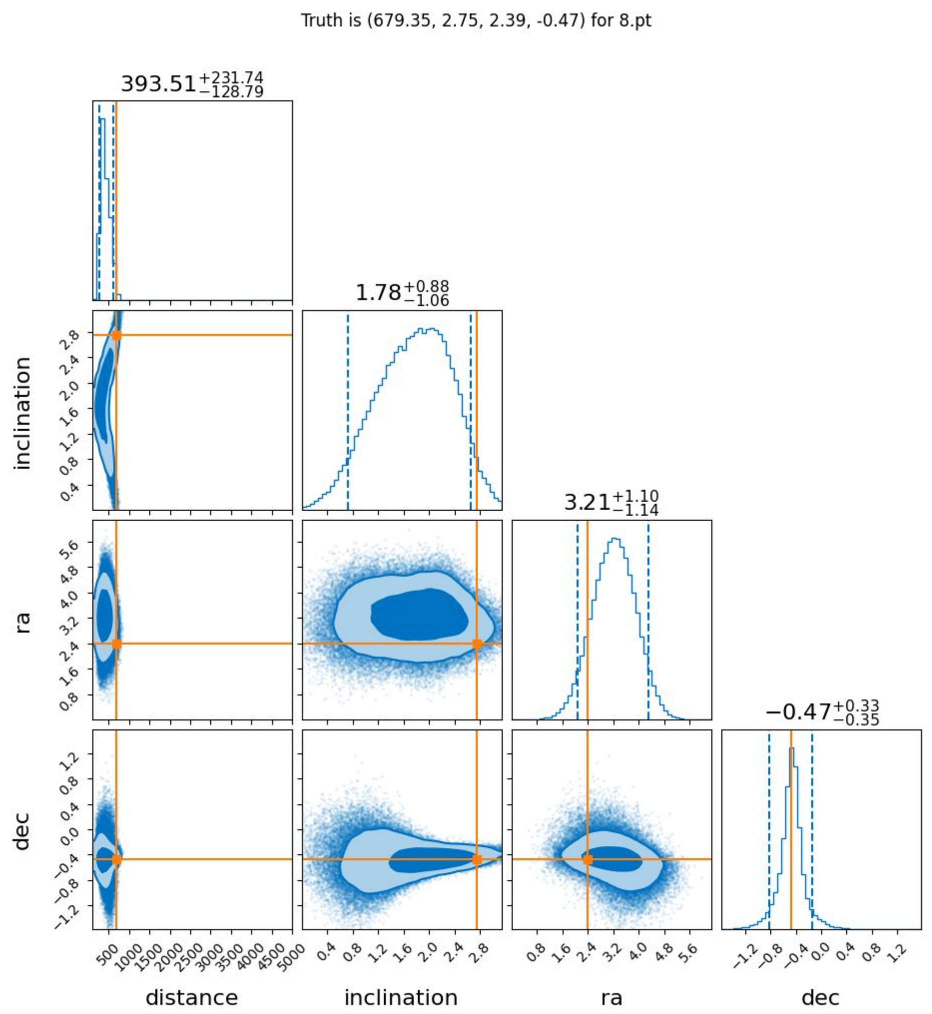


samples on y-axis taken at 2048 Hz





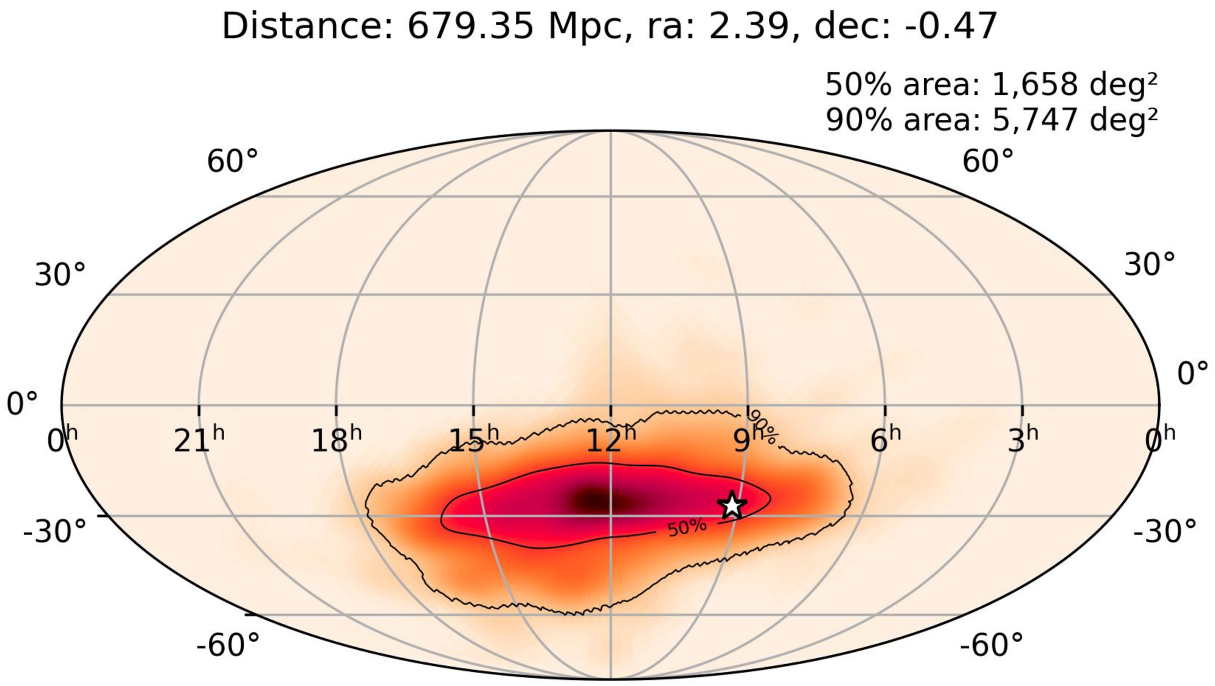
A. Amidi at Stanford University and S. Amidi at MIT



4D posterior distribution

distance, inclination, right ascension, declination

- 50,000 injections
- 15000 samples
- Distributions are fairly precise
- Right ascension and declination

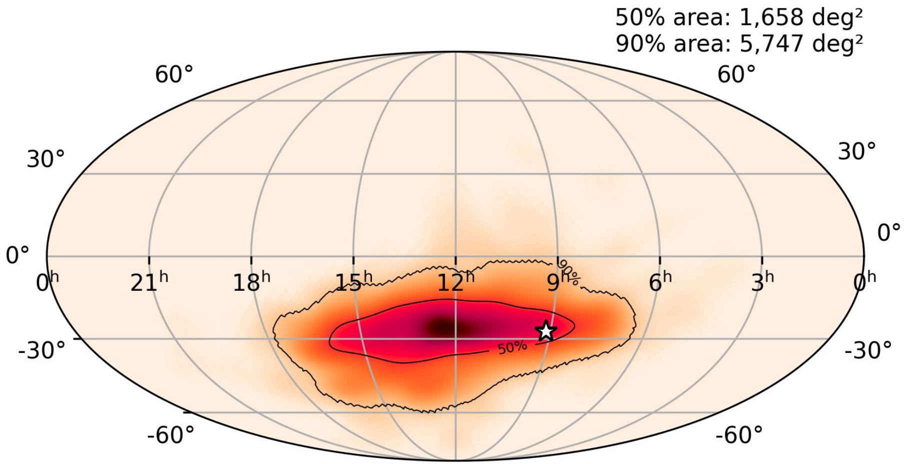


SKymaps **I**n**F**ferred **F**rom **S**vds (SKIFFS)

Time to sample and plot:
SKIFFS = .5 seconds
BAYESTAR = 1 second

Sky Map Comparison

SKIFFS



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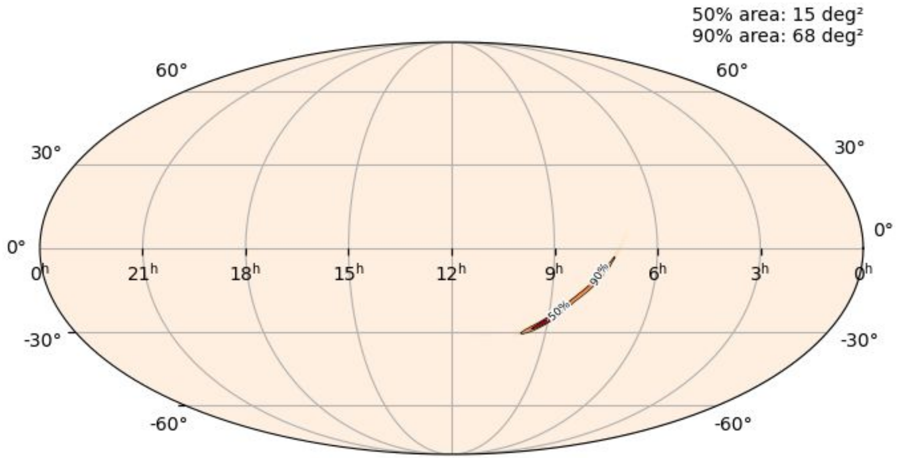

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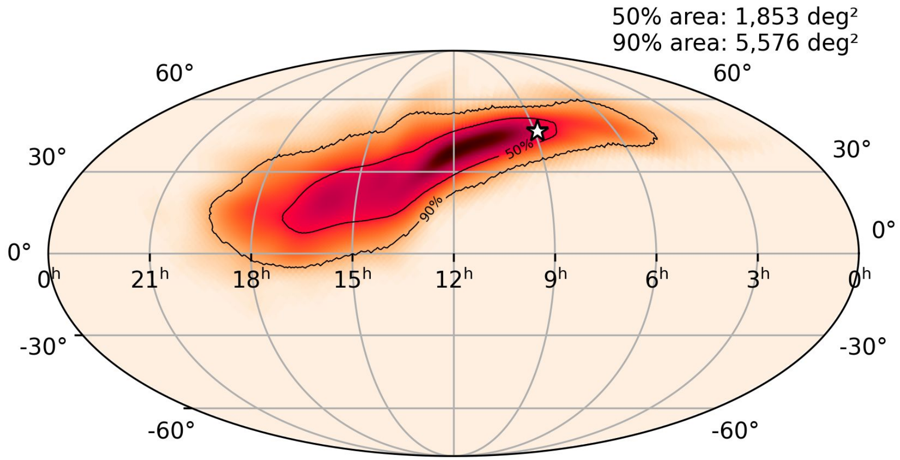

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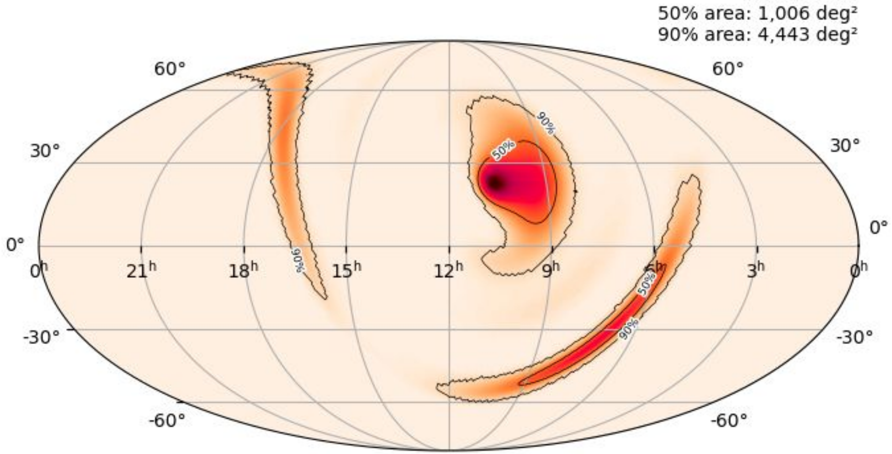

Conclusions

WE KNOW

Model does a good job locating the true value

More efforts towards concealing the confidence areas

Different area structure

WHY?

Possible poor neural network architecture

Noise realization

Ridding of information on timing and phases

The importance in connecting GWs to EM

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Thank you!