Machine-Learning investigation of Gravitational Wave SkyLocator with the application of Autoregressive Rational Quadratic-Spline flow

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With the growing population of gravitational-wave (GW) events, the electromagnetic (EM) follow-up observations have become important for multi-messenger astronomy. Since the EM afterglows of the compact binary coalescences (CBCs) decay rapidly, prompt and reliable GW localizations are essential for the EM counterpart identification. In this poster, we present the results of the Autoregressive Rational Quadratic Spline (ARQS) GW-Sky Locator, which provides fast GW localizations comparable to the conventional rapid sky localization BAYESTAR method. Auto-regressive normalizing flow was employed to compute the probability density of a GW location from an initial normal distribution. We then performed deep learning to infer the probability density in astronomical coordinate systems.

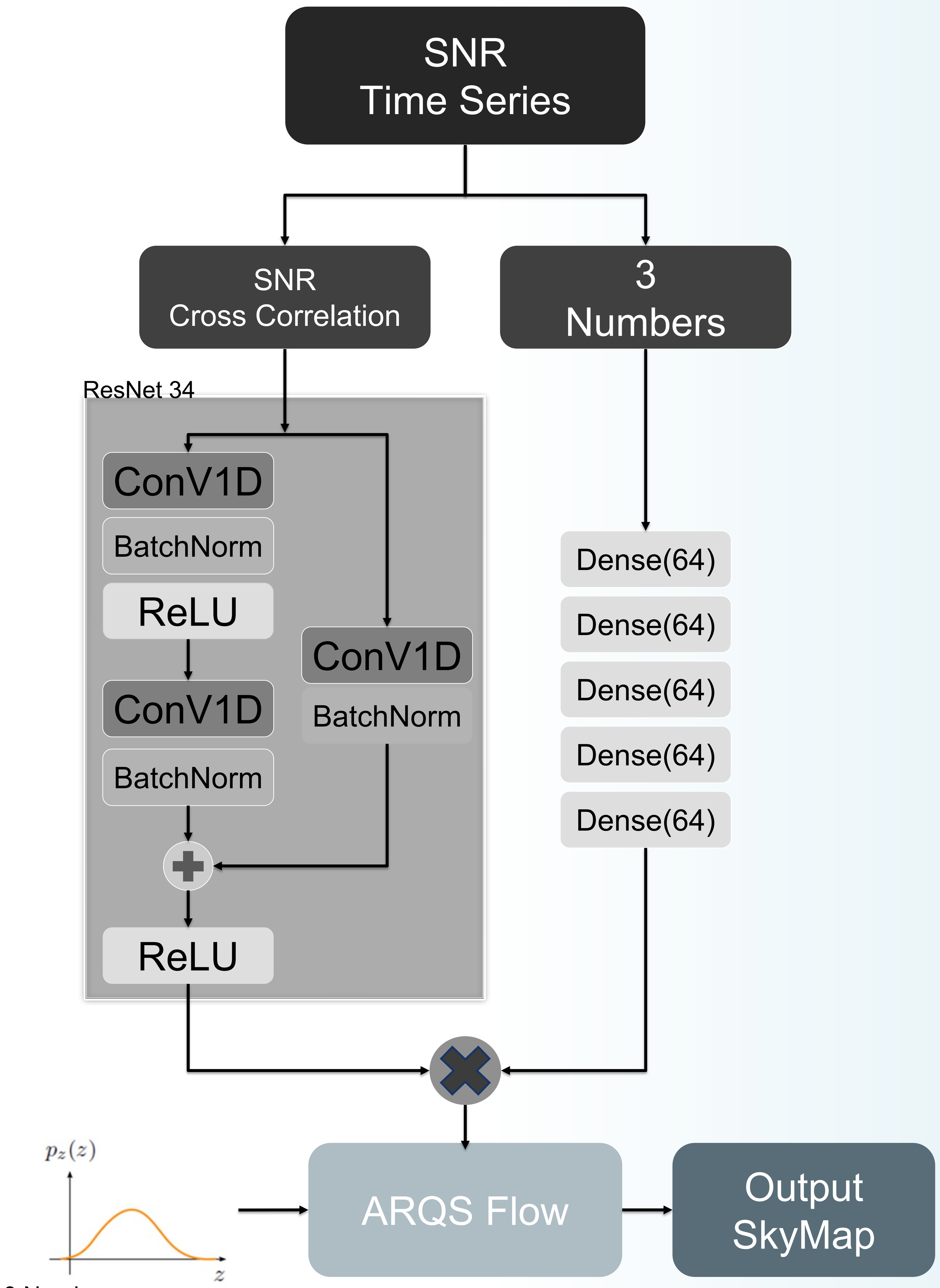
INTRODUCTION

Conventional rapid sky localization BAYESTAR provides the posterior of GW location without full parameter estimation, which requires massive computation time and resources. As a result, it provides a skymap right after detecting a GW event and maintains accuracy. Although BAYESTAR has been reasonably fast, it still needs seconds to minutes. We provide a machine learning method that gives us the probability distribution of GW location within seconds.

BAYESTAR

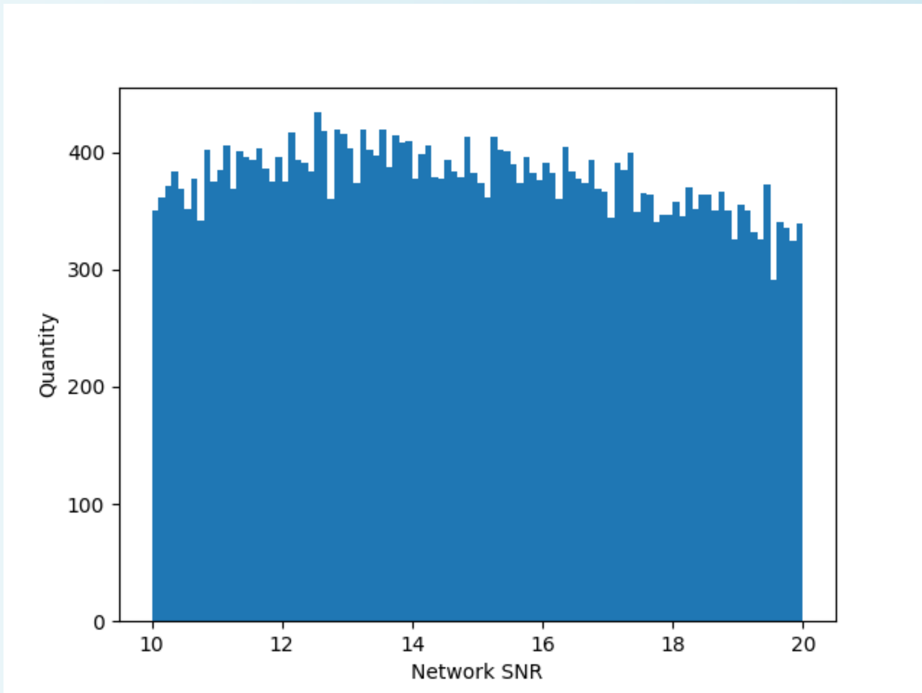
BAYESTAR is a Bayesian and non-Markov chain Monte Carlo (non-MCMC) sky localization algorithm to produce probability sky maps by analyzing the results from the matched-filter pipeline. It uses the triangulation from time delays and a fast Bayesian Inference method.

MACHINE LEARNING ARCHITECTURE (SKYLOCATOR)



3 Numbers:

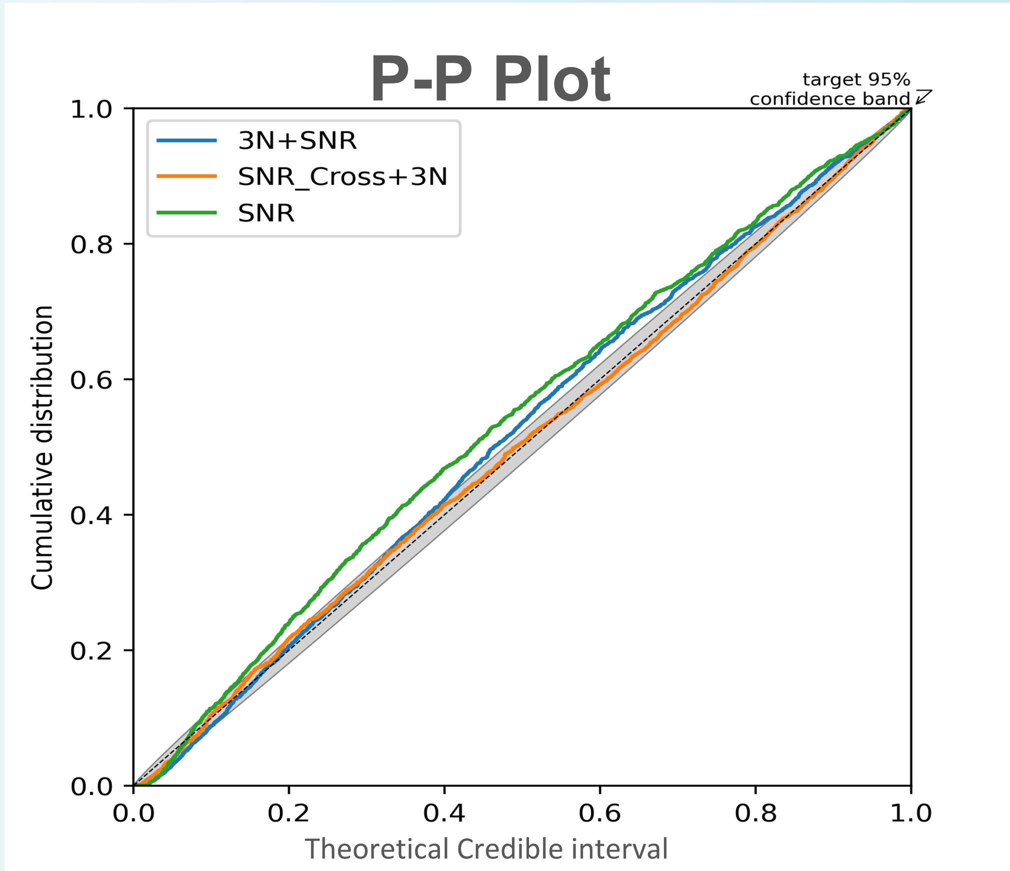
1. Amplitude Ratio: The ratio of maximum amplitude between 2 SNR series (Real part)
2. Phase Lag: The angle difference between 2 SNR series (Imaginary part)
3. Time difference: The time difference of merger time between 2 detectors



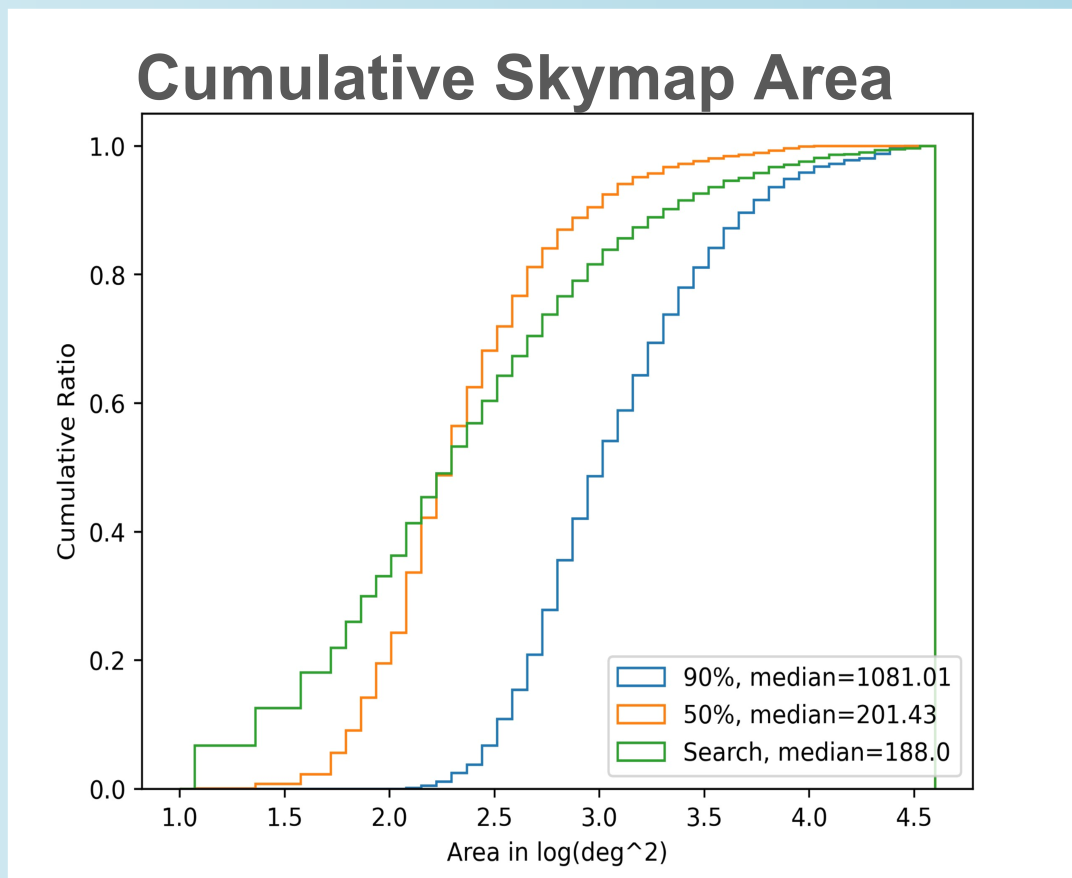
- The SNR distribution of training data: We use the template "SEOBNRv4_opt" to simulate the strain data and then determine the SNR time series by matched-filtering. and constrain the range between 10 and 20. The duration of the SNR data is 0.2 seconds sampling rate. Total amount of the training data used for training is 600k and the amount of validation data is 150k. We set the SNR range because the SNRs for most O3 event are between 10 and 20. Moreover, we generate the uniform distribution for the training data.

Here the $Network\ SNR = \sqrt{SNR_{H1}^2 + SNR_{L1}^2 + SNR_{V1}^2}$. H1 stands for the Hanford, L1 stands for the Livingston and V1 stands for the Virgo.

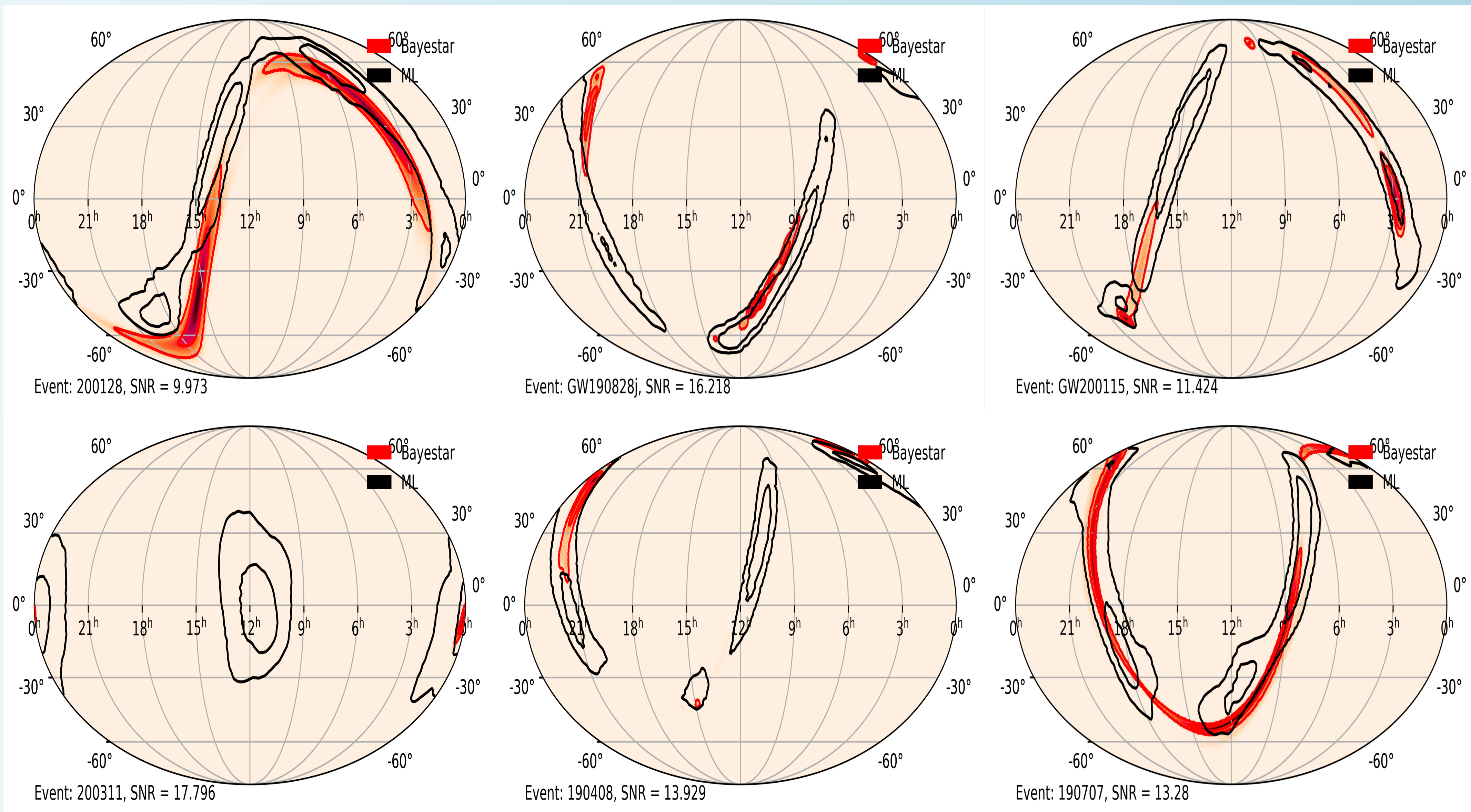
RESULTS



- The P-P plot to investigate the reliability of the models. The credible interval means the confidence level to find out the source in the specific given area. We test our model by three different inputs, including the full SNR time series only (labelled by green curve), the three numbers + cross-correlation of SNR time series (denoted by orange curve), and the three numbers + SNR time series (shown as blue curve).



- Cumulative ratio to find the simulated GW event in the given skymap area. We also compare the cumulative ratio to find the injected event in its 50% and 90% credible interval regions (denoted by blue and orange curves) determined by AI.



- Sky localization of O3 events. We compare the results determined by AI (SkyLocator) and BAYESTAR. Here the SNR indicates the network SNR.

CONCLUSION

According to our investigations of the P-P plot, the SNR time series does not give enough information for SkyLocator to locate the GW events. Moreover, adding the three numbers improves the test. Furthermore, we can obtain better results when the training network includes information from the cross-correlation SNR time series and three numbers. When locating an event, the time difference is important. The information gathered from three numbers and the cross-correlation SNR time series can emphasize the time information. The result indicates that the SkyLocator mainly requires learning the time information to locate a GW event. Comparing with the localizations determined by the AI (i.e., SkyLocator code) and BAYESTAR, we can still see the bias. To identify this problem, we must check whether it comes from the training data or other deeper reasons we have not figured out yet. In the future, we will review the quality of our training data and find the best way to process data that gives enough information to let SkyLocator correctly learn to locate the position without bias. Moreover, we will seek the best architecture and hyperparameters for the model of the SkyLocator.

REFERENCE

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