Search for Inspiral GW Signals Associated with Short GRBs using Artificial Neural Networks

Kyungmin Kim and Hyun Kyu Lee
Hanyang Univ.

In collaboration with
Y.-M. Kim, C.-H. Lee (PNU), J.J. Oh, S.H. Oh, E.J. Son (NIMS),
I.W. Harry (Syracuse Univ.), and K.A. Hodge (Caltech)

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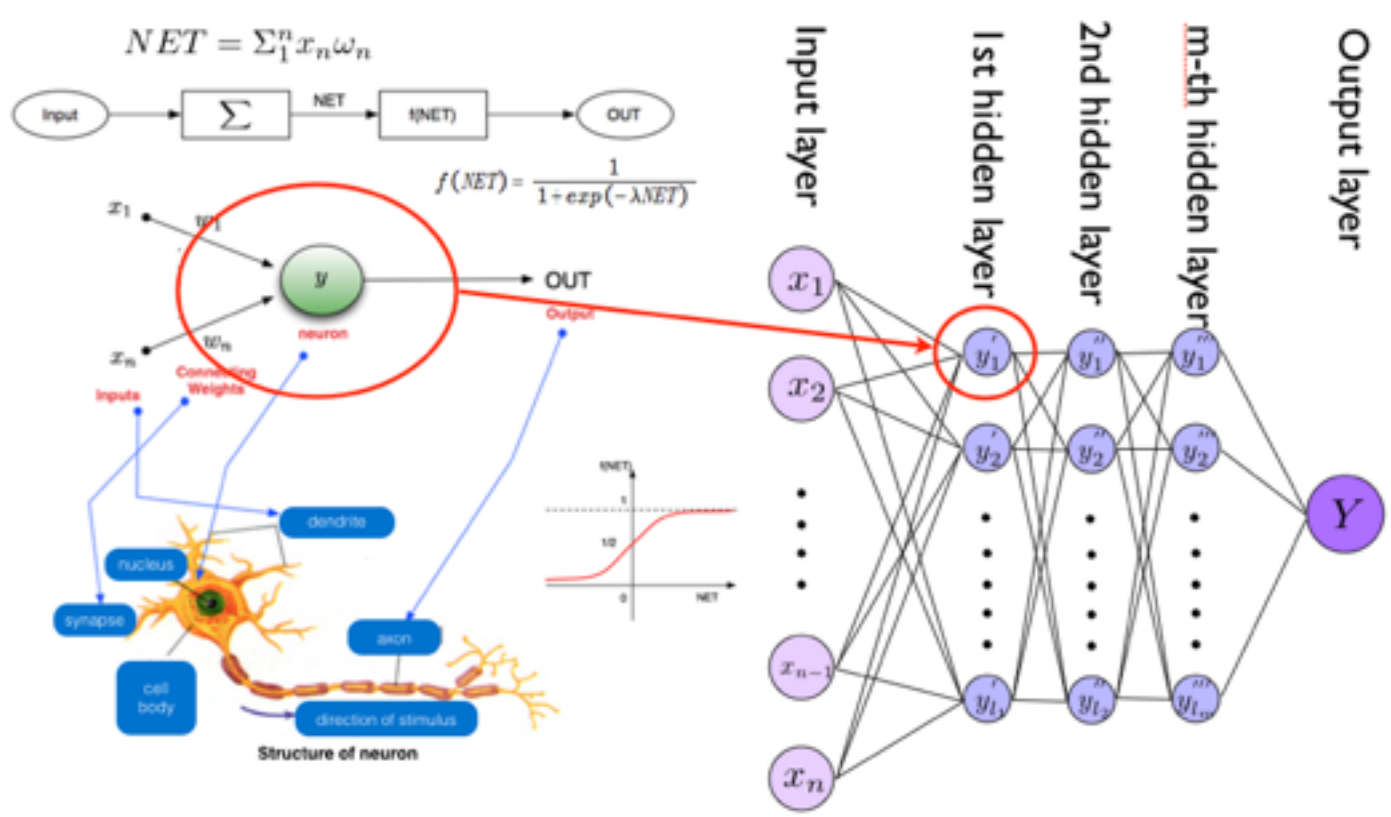
Introduction

- GRBs are the most energetic and very frequent (more or less once a day) astrophysical events in our Universe.
  - Short GRBs (< 2 sec): merger of NS-NS or NS-BH binaries
  - Long GRBs (> 2 sec): stellar collapse of massive star
- In particular, the progenitors of short GRBs are also considered as one of the most promising source of gravitational-waves (GWs).
- We consider application of a machine learning algorithm (MLA), the Artificial Neural Networks (ANN) to improve the performance on data classification in the CBC-GRB search.

Artificial Neural Networks

- Mimicking the biological neural system in order to make a decision based on a complex combination between neurons (nodes), their network structures (node topology), and some environmental conditions (data) from outside.

  - In this study, we use the Fast Artificial Neural Network (FANN) library (http://leenissen.dk/fann/wp)



Test Short GRB

TABLE I. A table of the observed information of selected GRB. RA and DEC indicate right ascension and declination, respectively. The duration time T_{90} given in second. The values of of duration time and redshift are read out from Ref. [3].

GRB	Observation				
	UTC Time	RA	DEC	Duration, T_{90} (sec)	Redshift
070714B	2007-07-14 T04:59:29	57.85°	28.29°	2.0	0.923

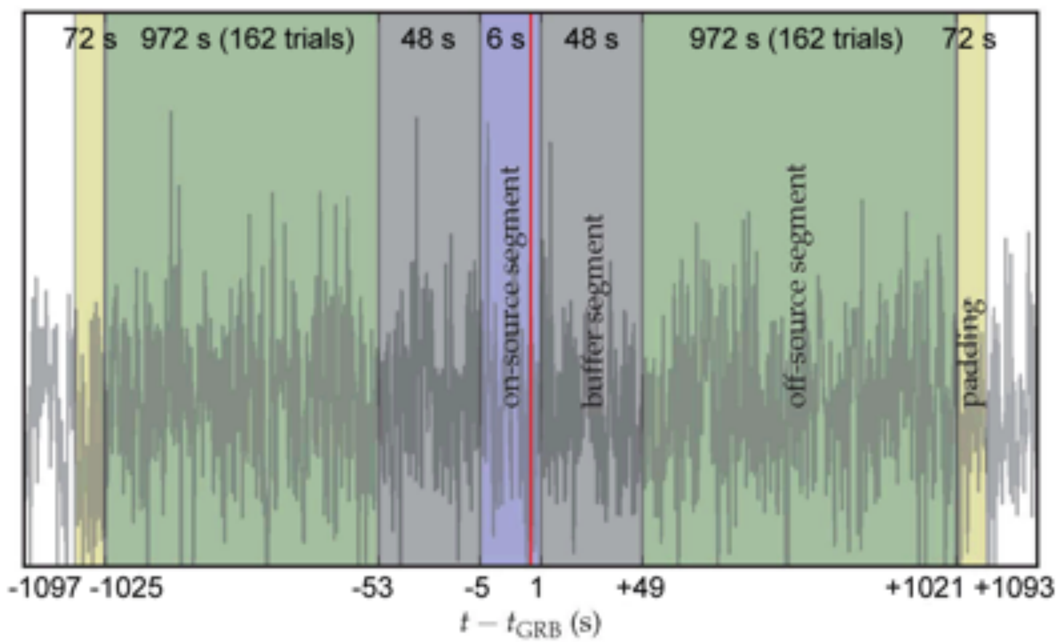
TABLE II. A table of the characteristics of GW detectors related to selected GRBs in Table I. The second column is showing the list of GW detectors which were in fully operation for given GRBs. From the third to fifth column we summarize the antenna factors [20, 21] of each detector for '+' and '×' polarizations of expected GWs with pairing them in a parenthesis such as $(F_+, F_\times)$. We present each detector's antenna response, $\mathcal{F}$, given by Eq. (A1), in the last three columns, respectively.

GRB	GW detectors	Antenna Factor, $F_{+,\times}$			Antenna Response, $\mathcal{F}$		
		H1	L1	V1	H1	L1	V1
070714B	H1, L1, V1	(-0.25, -0.07)	(0.27, 0.26)	(-0.83, -0.03)	0.26	0.37	0.83

$$\left(F_+^2 + F_\times^2\right)^{1/2} = \mathcal{F}$$

Trigger Generation

- The coherent search pipeline generates following triggers
  - On-source triggers, Off-source triggers, and Software injection triggers (NS-BH & NS-NS)



- We use the off-source triggers as background samples (class 0) and the software injection triggers as signal samples (class 1) for training ANN.

Features

- Triggers generated by the coherent search pipeline contain physical quantities tabulated in following table.

TABLE III. Brief description of each of considered features. One can find more detailed descriptions and forms of listed features from Ref. [10].

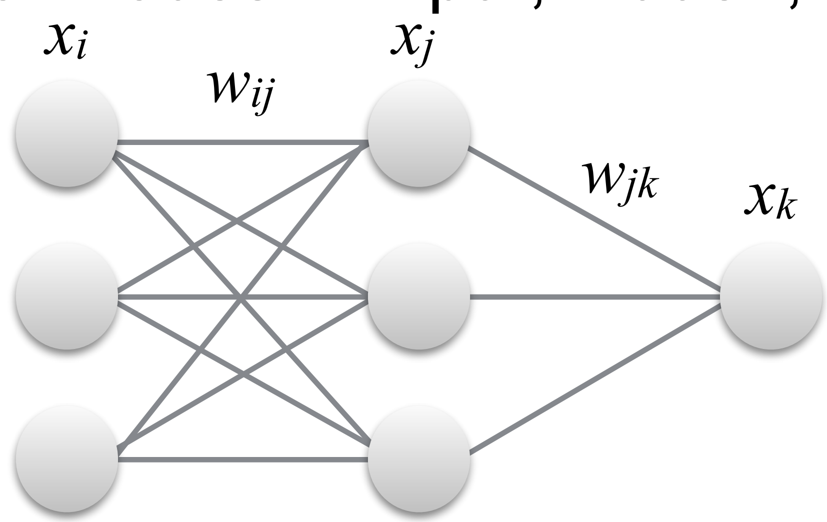
Feature	Description
Single detector's SNR, $\rho_{\rm IFO}$	Signal-to-noise ratio (SNR) value gotten from each of detectors' data where IFO = H1, L1, or V1. In this work, we have $\rho_{\rm H1}$, $\rho_{\rm L1}$, and $\rho_{\rm V1}$
Coherent SNR, $\rho_{\rm coh}$	Coherent combination of the complex single detector's SNRs with each detector's antenna factor
Coherent χ^2-tested value	Mitigating non-Gaussian noises' contribution by testing the differences between template waveforms and instrumental/environmental noises
New SNR, $\rho_{\rm new}$	Filtered $\rho_{\rm coh}$ by checking whether the χ^2-test value is larger or smaller than the number of degrees-of-freedom of χ^2 statistic
Coherent bank χ^2-tested value	Testing the consistency of the observed $\rho_{\rm coh}$ over different template waveforms in the template bank at the time of signal candidate trigger
Coherent auto-correlation χ^2-tested value	Filtering a template waveform against to the data which generates a peak in the $\rho_{\rm coh}$
Physical quantities related to mass	Component masses, m_1 and m_2 chirp mass, $\mathcal{M} = (m_1 m_2)^{3/5}(m_1 + m_2)^{-1/5}$ symmetric mass ratio, $(m_1 m_2)(m_1 + m_2)^{-2}$

For details, refer Harry & Fairhurst, PRD **83**, 084002 (2011)

- We take them as features for ANN.

Training & Evaluation

- Training ANN with training samples of 12 features
  - determines a set of connection weights, w_{ij} and w_{ik}, between each nodes in input, hidden, and output layers.



- Evaluating test samples using determined connection weights
  - gives ranks on each test sample.
  - $0 \leq \text{rank} \leq 1$

Training & Evaluation

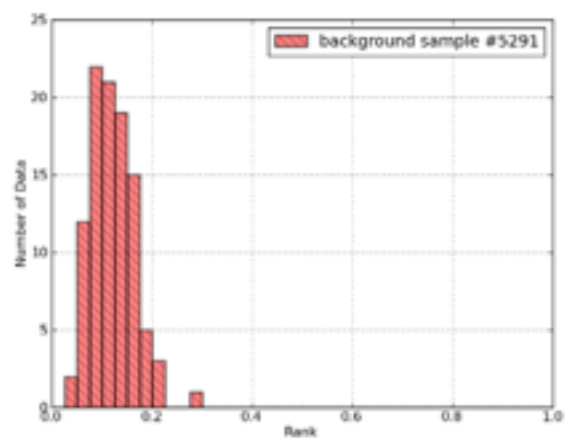
- Procedure: We take 9/10 of whole available samples as training samples and 1/10 of them as test samples.
- We repeat above procedure 100 times.
  - Training
    - MSE (Mean Squared Error) for the training is not sufficiently small: observed MSE ~= 0.06-0.08.

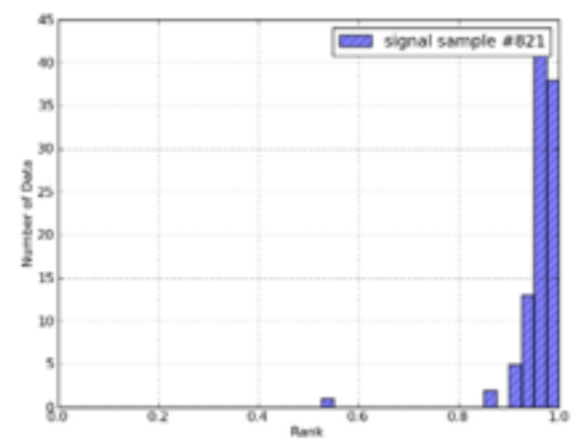
$$\mathrm{MSE} = \frac{1}{N}\sum_{i}^{N} |t_i - o_i|^2$$

    - Training limit of ANN for the data of a test GRB
    - Each run results in a different set of connection weights: noticeable variance in 100 runs.

Training & Evaluation

- Evaluation
  - Using the connection weights determined in the training procedure, we evaluate ranks of test samples.
  - The evaluated ranks are found to have noticeable variance in 100 runs.

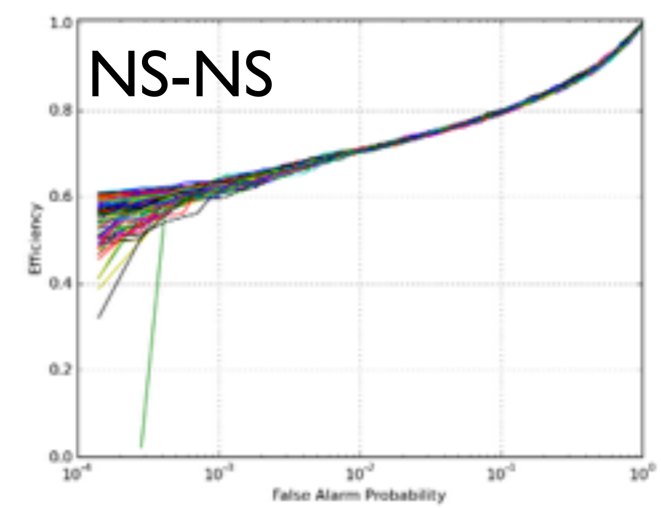




  - The variance in ranks is attributed to the variance in connection weights.

Reduction of Variance: Trial I. Averaged Ranks

- We average ranks scored on a sample from 100 runs and draw ROC curves with calculating the efficiency and false alarm probability (FAP).

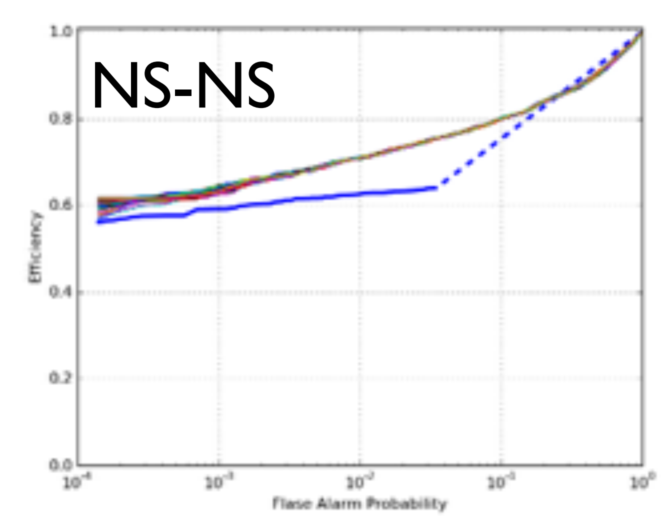


$$\text{Efficiency} \equiv \frac{N_S(R)}{N_S},$$

$$\text{FAP} \equiv \frac{N_B(R)}{N_B},$$

$$N_S(R) \equiv \{x_S^i(r); r \geq R, i = 1, 2, \ldots, N_S\},$$
$$N_B(R) \equiv \{x_B^j(r); r \geq R, j = 1, 2, \ldots, N_B\}$$

- With averaged ranks, the variance in ranks is significantly reduced and it is represented in the ROC curves!



Reduction of Variance: Trial II. Maximum Likelihood Ratio

- Likelihood ratio is the ratio between the probability of correctly finding a signal given existence of signal and the probability of incorrectly finding a signal given that only noise exists in the data.

- We calculate the likelihood ratios for each sample of each run and take the maximum of them as a representative value. Then we use it as a new rank of each sample. (Biswas et al., PRD **88**, 062003 (2013) and Biswas et al., PRD **85**, 122009 (2012))

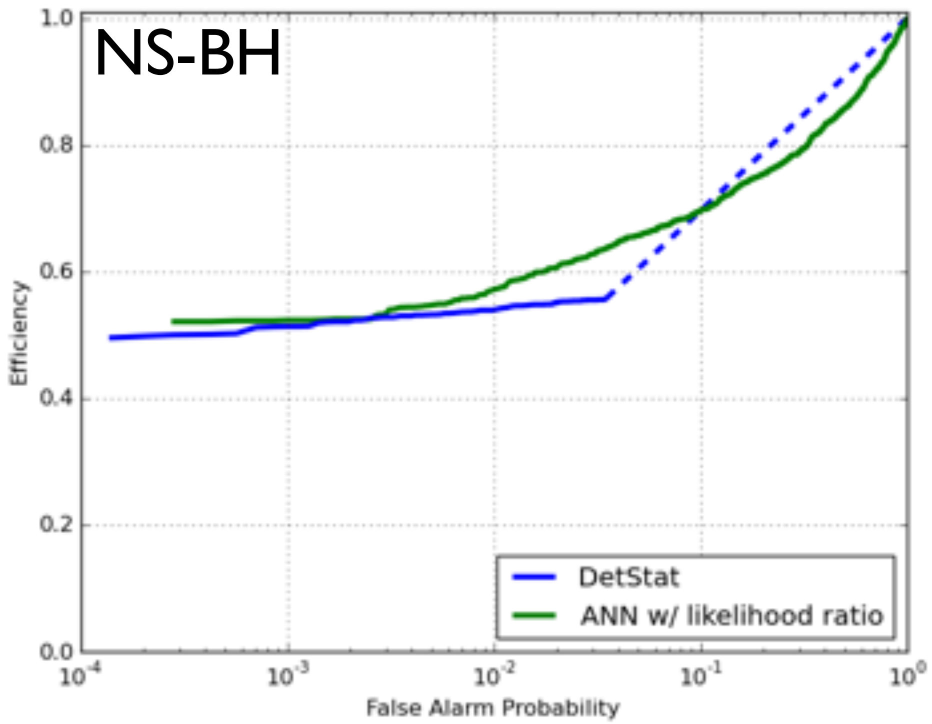
$$L_i^{\#} = \frac{\mathrm{Efficiency}(R_i^{\#})}{\mathrm{FAP}(R_i^{\#})},$$

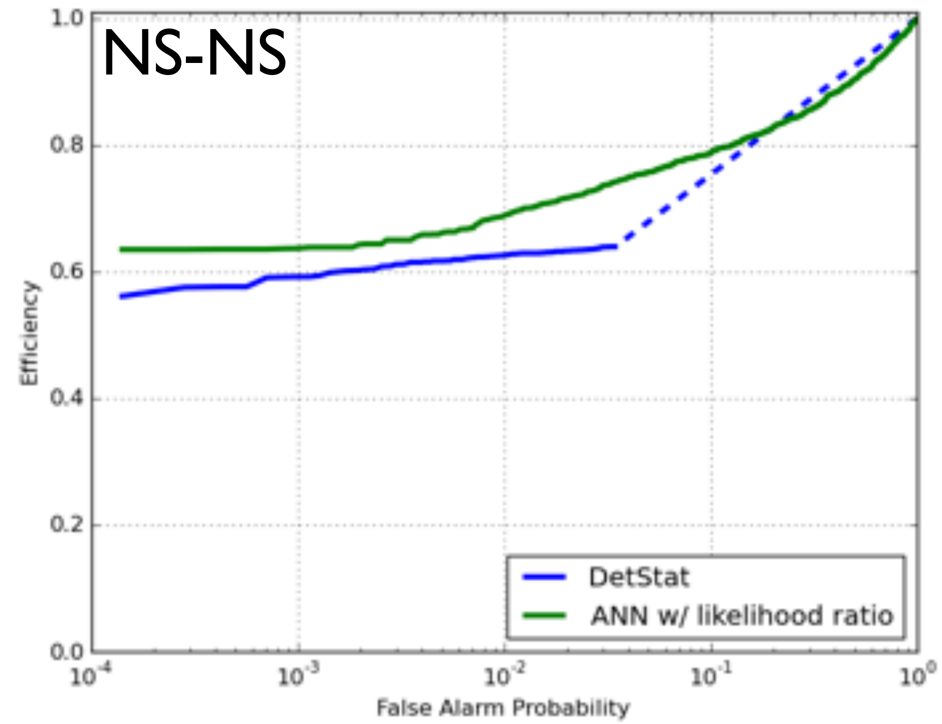
where $i = 1, 2, ..., (N_S + N_B)$

$\# = 1, 2, ..., \#$ of runs

ROC Curves with Maximum Likelihood Ratios

$$\text{Efficiency} \equiv \frac{N_S(L)}{N_S}, \quad \text{FAP} \equiv \frac{N_B(L)}{N_B}$$

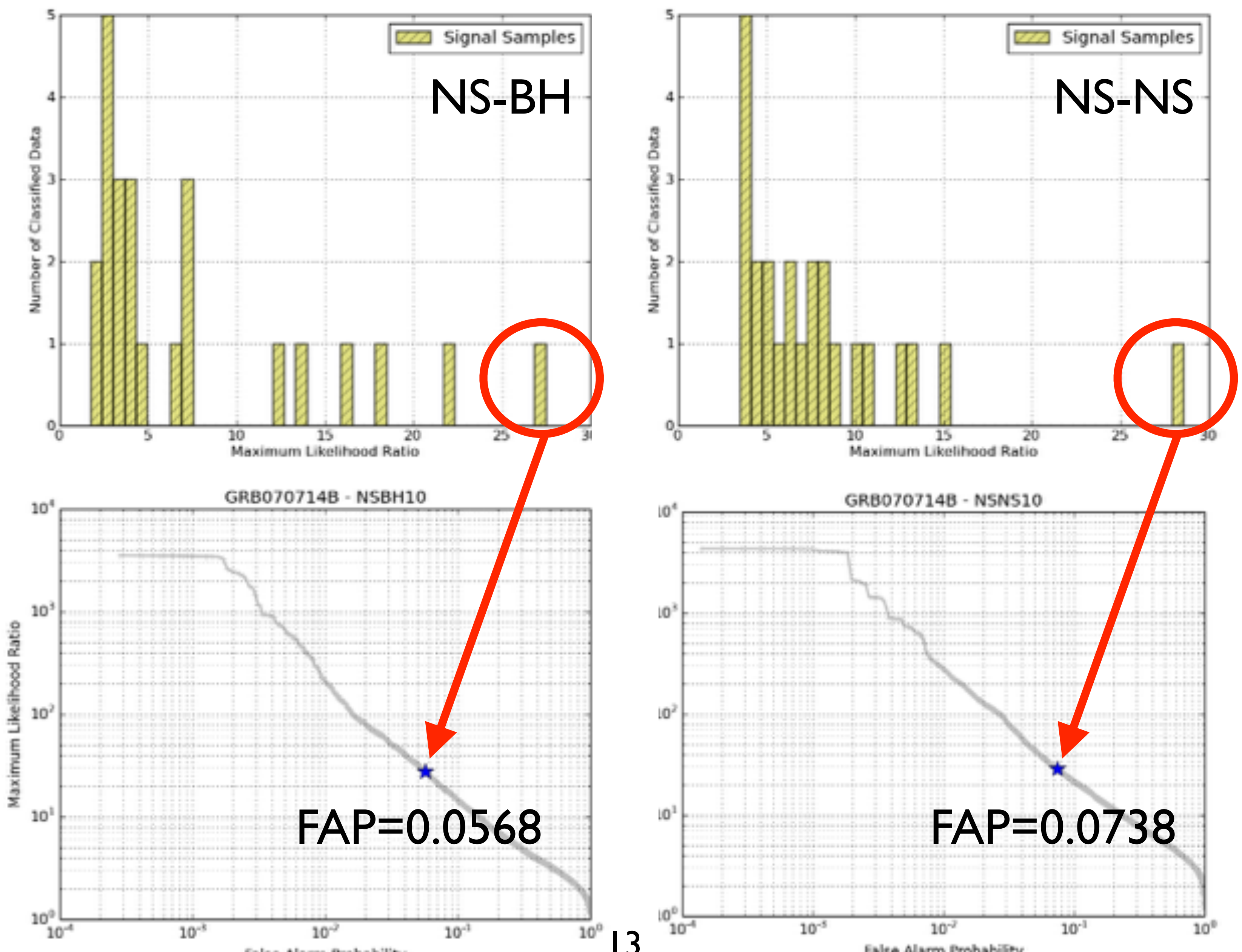




- With the maximum likelihood ratios, we can get comparable performance against the conventional method!

Evaluation of On-Source Triggers with Maximum Likelihood Ratio

- With 24 on-source triggers



Conclusion

- We demonstrate a search for inspiral GW signals related to a short GRB by using the ANNs.
    - For the input data for the MLAs, we use triggers generated by applying the coherent search pipeline to S5/VSR1 data, in specific, related to a short GRB, 070714B.
- We used the maximum likelihood ratio or averaged rank-value methods for each sample in order to reduce the statistical variance.
    - With averaged ranks, we could see clearly reduced variance.
    - With the maximum likelihood ratio, we could see comparable performance in data classification against the conventional method.

Conclusion

- We evaluated on-source triggers and calculated their FAPs based on the maximum likelihood ratios of background samples.
    - The FAP of the loudest on-source trigger (the largest likelihood ratio) is consistent with background noise (no GW signal).
    - We get consistent result comparing with the previous S5/VSR1 CBC-GRB search.
- In order to improve search performance, we may consider feature selection methods.

Thank you for
your attention!