AI for GW

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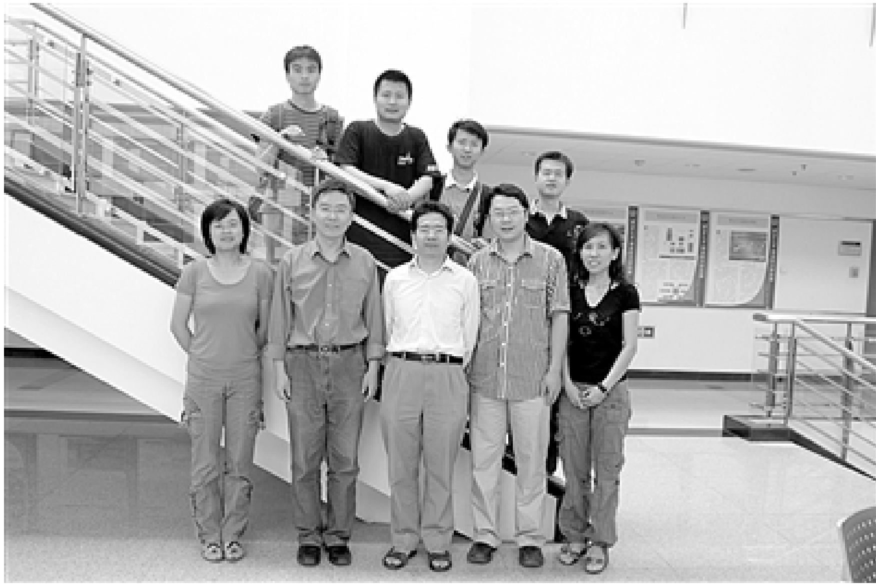
Outline

- Introduction to Tsinghua group
- Real-time / low-latency GW search
  - » Machine learning for burst search
  - » Deep neural networks for CBC search
- Future Work – Entering the era of GW astronomy and Multi-messenger astronomy

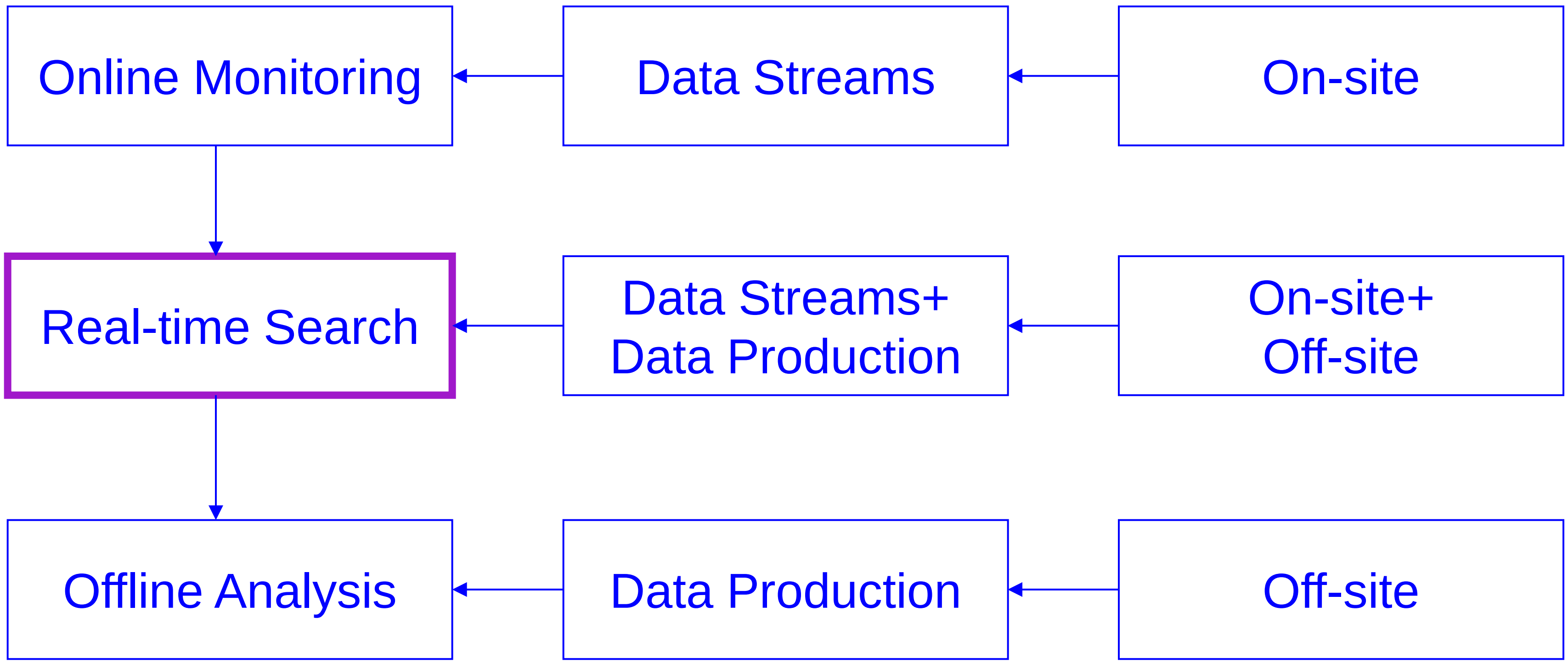
Our Group

- The only LSC member group in mainland China, including 2 faculty members
- GW data analysis and computing infrastructure
- Also involved in KAGRA, AIGO
- With close collaboration with MIT, Caltech, UWA, UGlasgow …



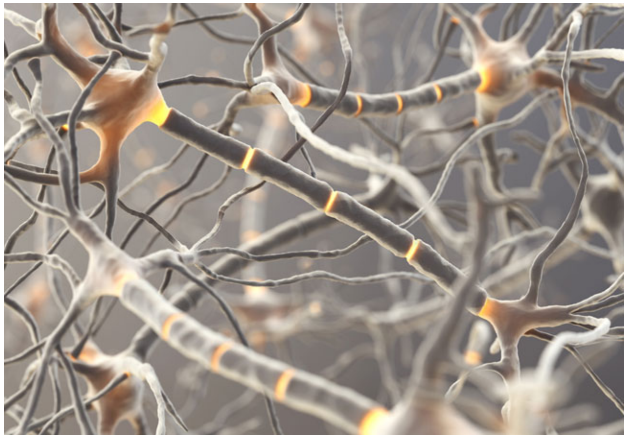
Real-time Search

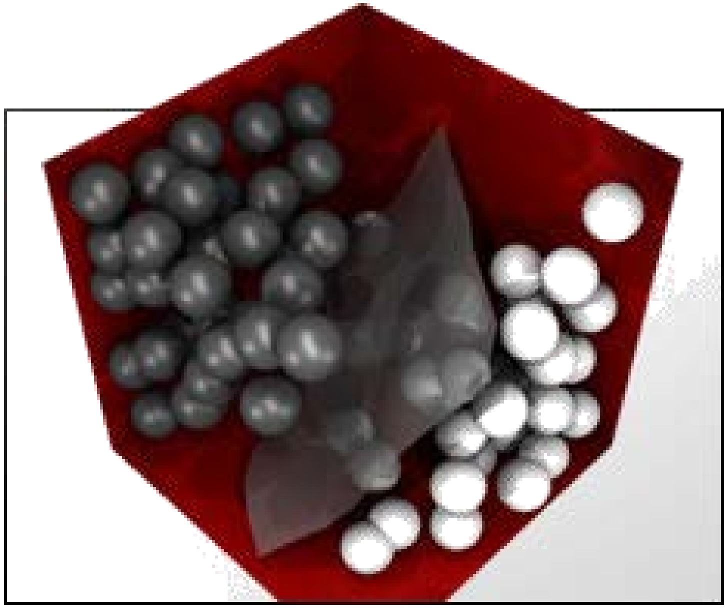
- Real-time: between online and offline mode for large-scale data analysis



Some "Classic" Classifiers from Machine Learning

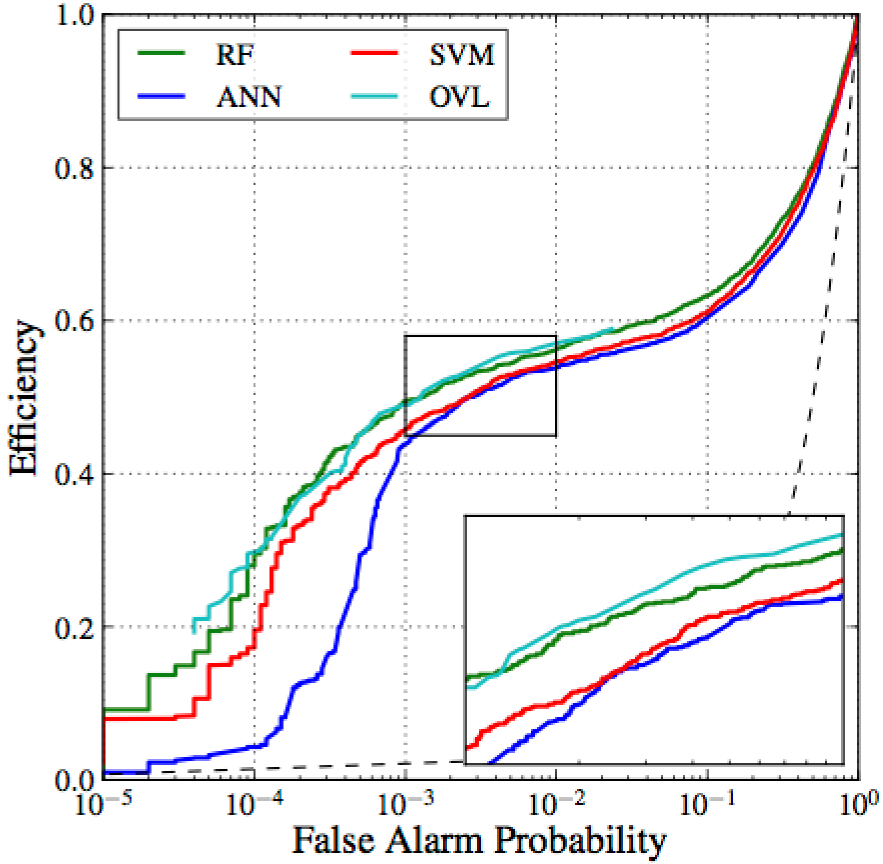
1. Artificial neural networks
2. Random forests
3. Support Vector Machines (SVM)





Machine Learning for Burst Search

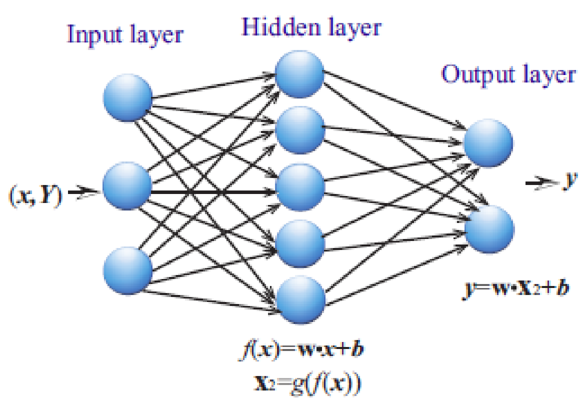
- Performance of machine learning (ANN, RF, SVM): as good as the performance of the best designed algorithm…
- … but machine learning gives an automatic GW search algorithm!

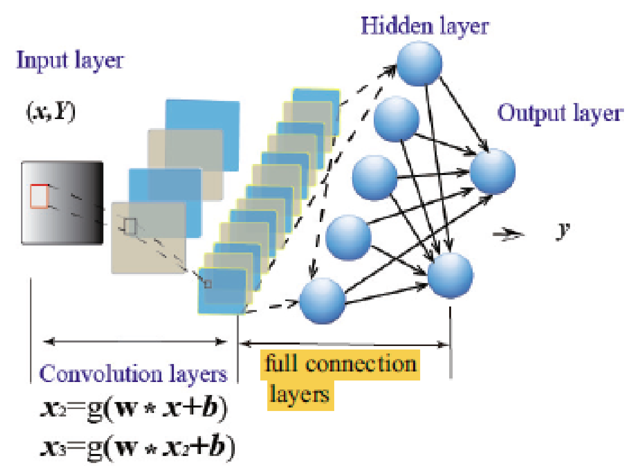


DNN for CBC search

Comparing DNN with matched-filtering used widely in Advanced LIGO-Virgo's pipelines indicates the performing speed of DNN can be accelerated greatly due to its powerful feature extraction.

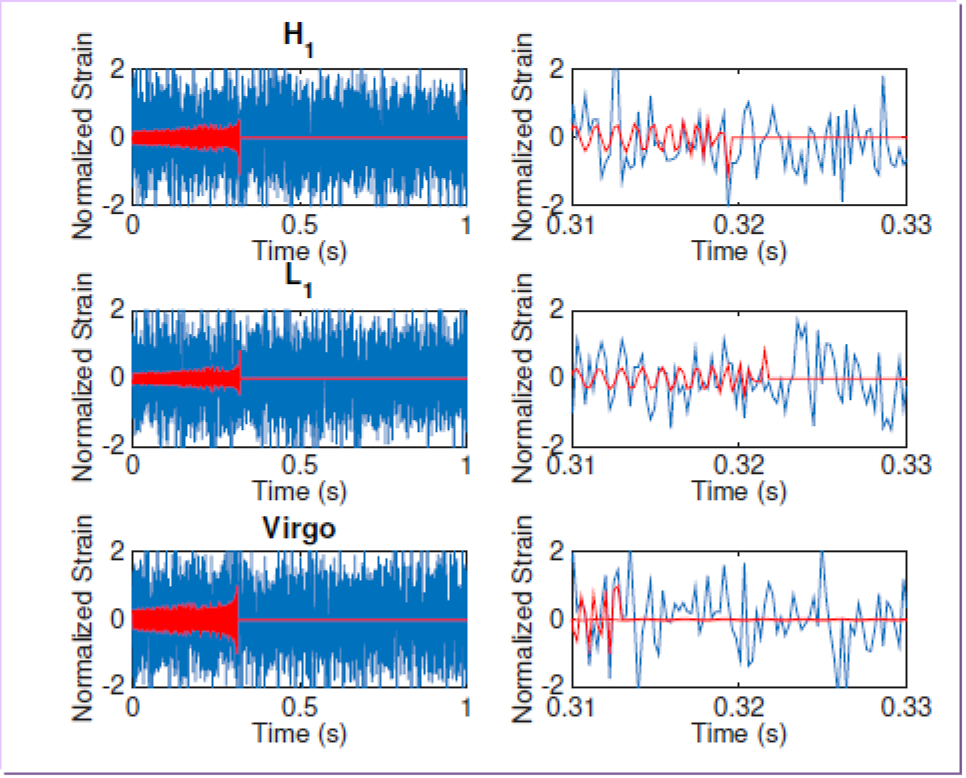
- Firstly, we will train the DNN as a classier to distinguish the signal from noise.
- Secondly the DNN structure will be adjusted and trained as a predictor to estimate the source's parameters.





Training Data

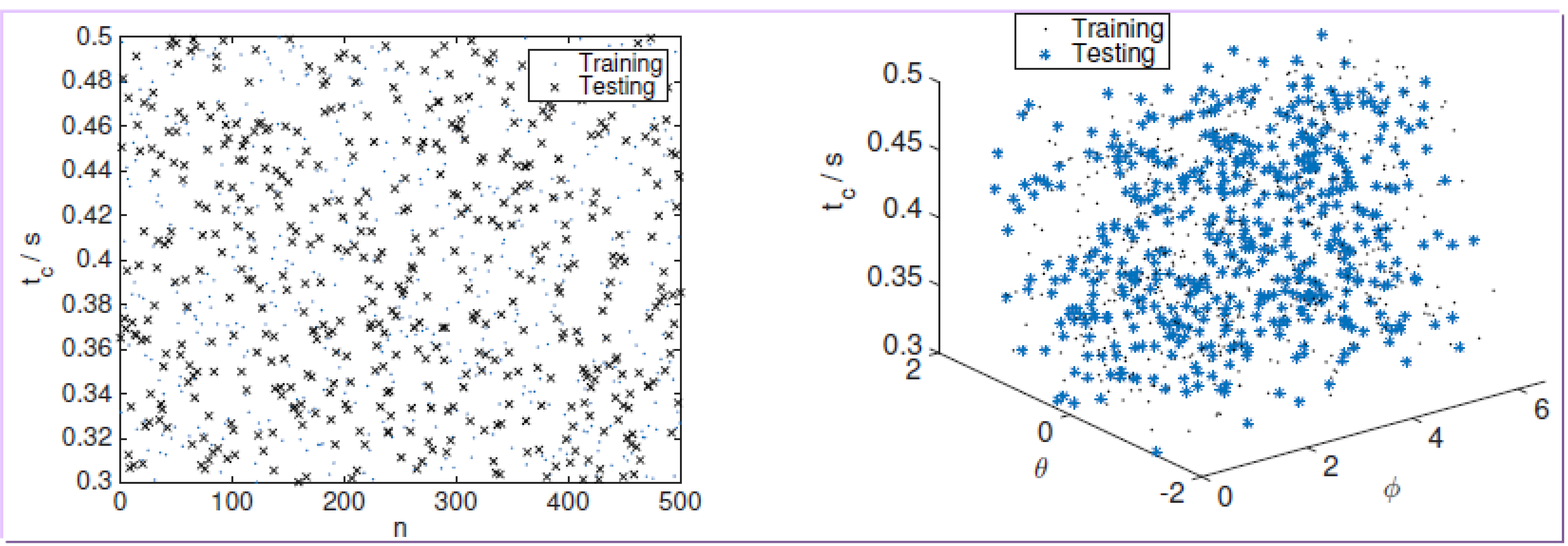
- Left panel: The blue curves are sample time-series in H1, L1 and Virgo detectors respectively, which correspond to a same GW event and will be input to our DNN together.
- Right panel: The zoom plots correspond to the left plots around injection time, which varies in different detectors.



Training Data

The plots show how the injection time t_c and source's space angle (ϕ,θ) of compact binary star were chosen for our training and testing data sets.

- Left panel: t_c distribution for the single parameter estimation;
- Right panel: t_c and (ϕ,θ) together for the multiply parameters estimation.



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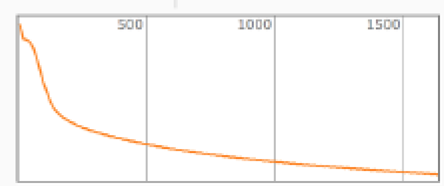
DNN Structure

- Left panel: modified version of the DNN that we used for classification, which is also used for prediction simply replacing the 15th layer with a ramp function, and changing the size of layer 14 according to the dimension of predicted parameters;
- Right panel: a snapshot of one training process for classification.

	Input	matrix (size: 3 × 3596)
1	ReshapeLayer	tensor (size: 1 × 3 × 3596)
2	ConvolutionLayer	tensor (size: 8 × 1 × 3581)
3	PoolingLayer	tensor (size: 8 × 1 × 3482)
4	ElementwiseLayer	tensor (size: 8 × 1 × 3482)
5	ConvolutionLayer	tensor (size: 16 × 1 × 3467)
6	PoolingLayer	tensor (size: 16 × 1 × 3368)
7	ElementwiseLayer	tensor (size: 16 × 1 × 3368)
8	ConvolutionLayer	tensor (size: 32 × 1 × 3353)
9	PoolingLayer	tensor (size: 32 × 1 × 3254)
10	ElementwiseLayer	tensor (size: 32 × 1 × 3254)
11	FlattenLayer	vector (size: 104128)
12	DotPlusLayer	vector (size: 64)
13	ElementwiseLayer	vector (size: 64)
14	DotPlusLayer	vector (size: 2)
15	SoftmaxLayer	vector (size: 2)
	Output	decoded vector (size: 2)

Training Progress

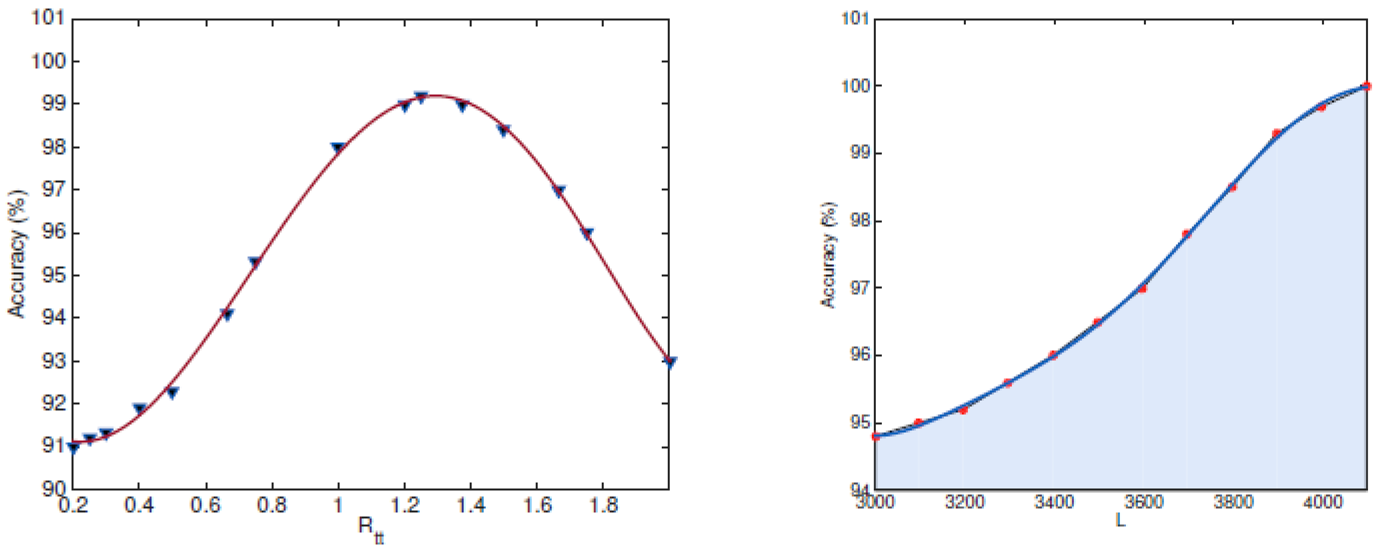
round	822 / 1000
batch	2 / 2
inputs/second	10
time elapsed	2h42m01s
time remaining	35m05s
batch loss	0.0000274
round loss	0.0000207



Stop

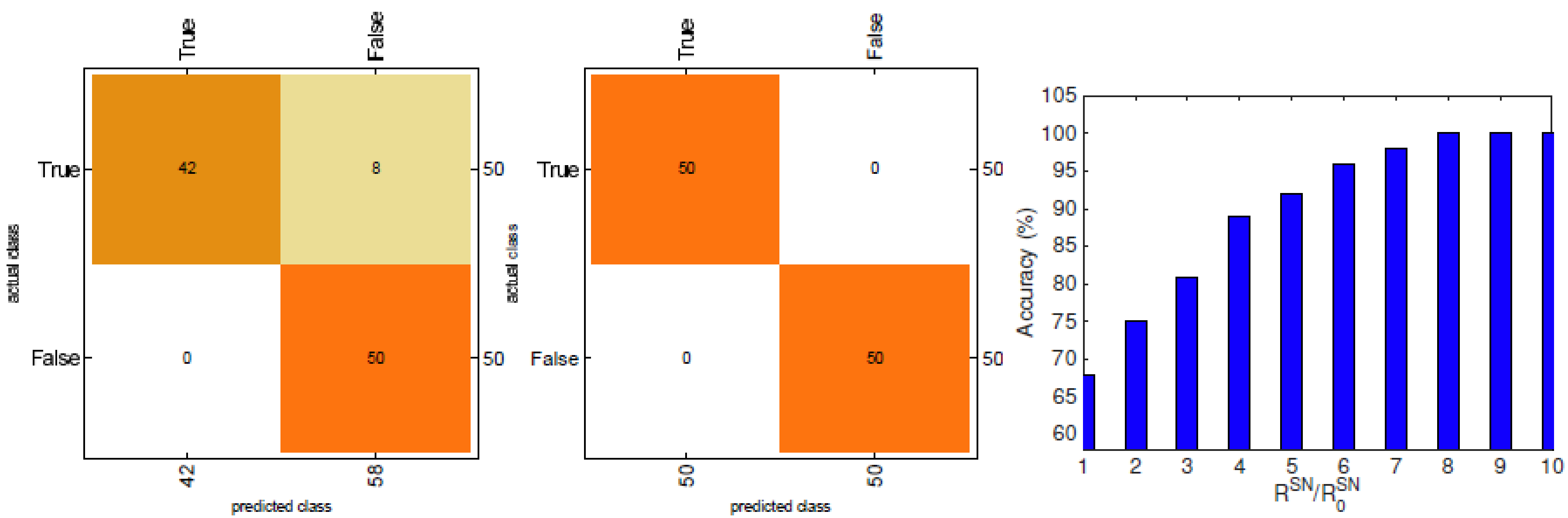
Classifier Accuracy

- Left panel: accuracy of classifier varying with the ratio of training and testing data sets.
- Right panel: accuracy of classifier varying with the length of each time-series.



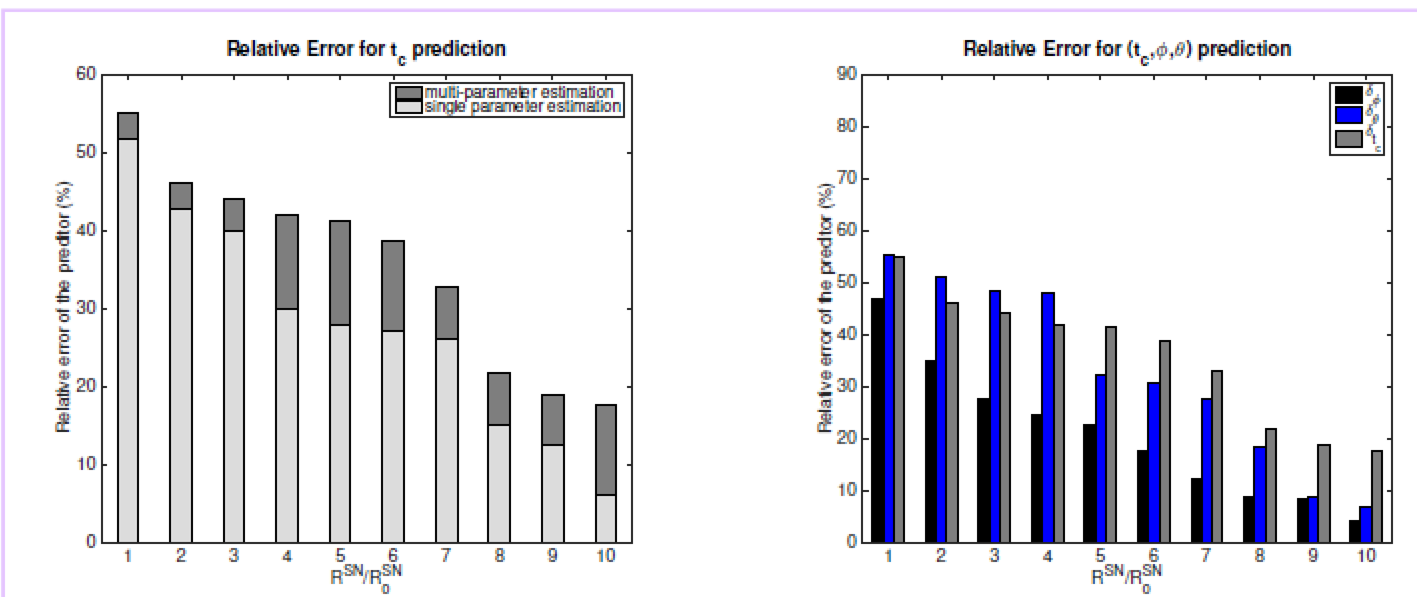
Classifier Accuracy

- Left panel: confusion matrix of classifier on a test set with $R^{SN} = 2.5$ (the accuracy is 92%).
- Middle panel: confusion matrix of classifier on a test set with $R^{SN} = 4.4$ (the accuracy is 100% for all signals with higher R^{SN}.).
- Right panel: accuracy of classifier varying with R^{SN}.



Predictor Accuracy

- Left panel: Comparison of the relative errors in single parameter predictor and in multi-parameter predictor.
- Right panel: The relative error of the predictor estimating (t_c,ϕ,θ).



Conclusions

The main superiority of adding DNN to GW searches is that, retraining a DNN is time saving once trained well at a given power spectral density of Advanced LIGO and Virgo. Therefore the realization of real-time coincident detection is hopeful.

Applying deep neural networks to the detection of binary neutron star mergers with a network of gravitational wave detectors

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(Dated: October 7, 2017)

We study an application of deep learning to the LIGO-Virgo coincident detection of gravitational waves (GW) from binary neutron star (BNS) mergers. Based on deep neural networks (DNN), some simulated coincident time-series data sets in Advanced LIGO (H1, L1) and Virgo detectors are analyzed. From the raw noisy time-series data sets, our DNN as a classifier can effectively recognize the presence of GW signals when the ratio between the maximum amplitude of the waveform and the white Gaussian noise standard deviation ($h_{\mathrm{max}}(t)/\sigma_{\mathrm{noise}}$) arrives more than 2.75; and as a predictor it can accurately estimate the corresponding source parameters, including the time of the GW signal arriving at the center of Earth and the sky locations of the binary neutron star mergers, when the $h_{\mathrm{max}}(t)/\sigma_{\mathrm{noise}}$ is increased to be 4.4. From our results, it can be found that the DNN algorithm is efficient for processing raw noisy time-series, even the coincident time-series. On the other hand, the data quality also impacts on the performance of DNN algorithm. So that we have discussed the accuracy of our DNN varying with $h_{\mathrm{max}}(t)/\sigma_{\mathrm{noise}}$, length of time-series, ratio between training and testing sets, number of estimated parameters. Due to the high efficiency of retraining a DNN, it makes real-time GW coincident detection possible. And from the real-time GW multiple parameters estimation, the search of their electromagnetic counterparts would be realized easily.

Keywords: deep neural networks; LIGO-Virgo coincident detection of gravitational waves; multiple parameters estimation

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I. INTRODUCTION

As the authority of gravitational wave (GW) detection, the Advanced Interferometer Gravitational-wave Observatory (Advanced LIGO and Virgo) recently has realized the first three-detector detection of GW signal from a binary black hole (BBH) merger[1], which is the fourth direct GW detection of Advanced LIGO[1–4]. As other promising astrophysical GW sources in the frequency range of these detectors, the mergers of binary neutron star (BNS) and neutron star-black hole are highly possible to be observed in the near future. With the continuous improvement of Advanced LIGO and Virgo[5, 6], there will be numerous GW triggers appearing in the time-series. Since the current data analysis of Advanced LIGO and Virgo is computationally expensive for spotting the matched GW signals in noisy data and distinguishing signals and glitches, some new methodologies of signal processing that can process data rapidly with high accuracy are required. In recent years, the application of machine learning on GW detection has been proposed widely[7–11]. The key point that makes machine learning useful is the learning algorithms, which en-

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