Detection and parameter estimation for GW-burst signal with machine learning

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Abstract

In recent years, machine learning(ML) has begun to be used to find out small signal of gravitational wave(GW) from noisy data and to estimate physical parameters of it. The approach is an alternative to using templates, by which the parameters are estimated by matching with theoretical models. George and Huerta (2018) demonstrated the ML method for GW from binary black holes. It is important to explore the possibility of detection and estimation for different types of GW signals. We consider the possibility of detection and parameter estimation for GW burst by ML. Since the wave forms, e. g., driven by magnetar giant flares, are uncertain at present, we model them and explore the ability of the ML approach. We use the same algorithms based by convolution neural network used in binary black hole merger by George and Huerta (2018). In this poster, we discuss accuracy of detection and how much error we can estimate parameters.

Content and Summary

0 Introduction

I GW signal from binary black holes

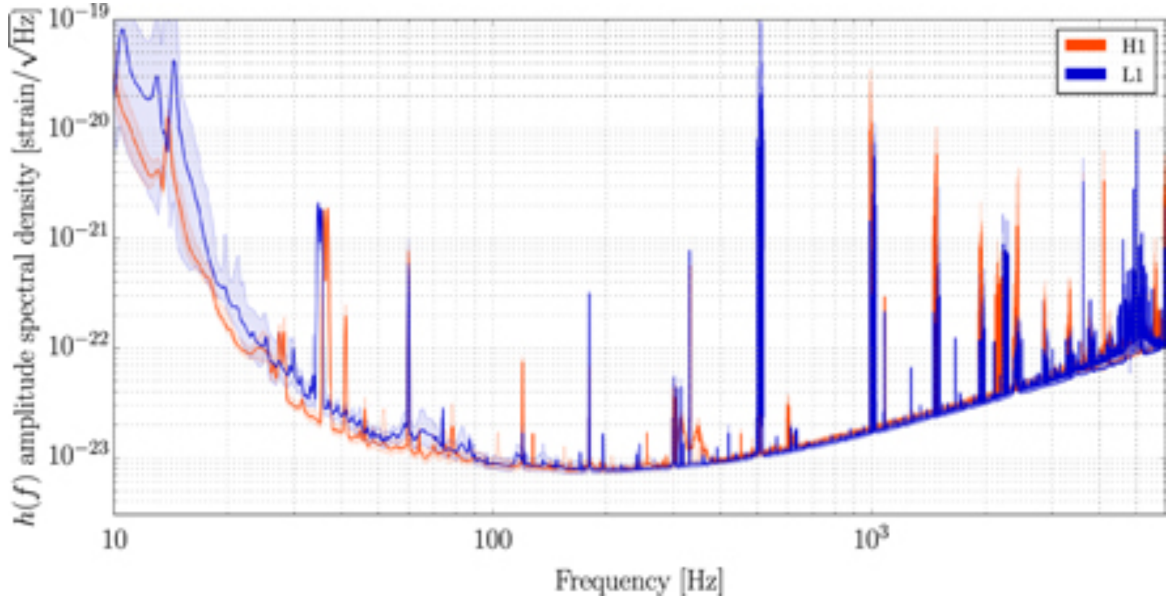
- Testing our ML program
- Successful results

II GW signal from burst

- Finding exponentially damped burst signal
- Our ML program is sensitive to burst time.
- Resultant decay time is not reliable (at present).
- We further improve our program.

0 Introduction

Sensitivity curve of LIGO



B P Abbott *et al.* 2016 Class. Quantum Grav. **33** 134001

Previous works

ex.

- George & Huerta (2018)

  Detection of GW from binary black hole(BBH)

  Parameter estimation for masses of two black holes

- Fan *et al.* (2018)

  Detection of GW from BBH

  Parameter estimation for luminosity distance and position on the celestial sphere

The GW data contain a lot of noise, and we have to find out small signals from it.

In recent years, ML has begun to be used for detection and parameter estimation.

I GW signal from binary black hole

By Newtonian approximation

Amplitude $$h(t) = \frac{1}{D}\frac{(G\mathcal{M})^{5/3}}{c^4}\{\pi f(t)\}^{2/3}\cos\{2\pi f(t)t\}$$

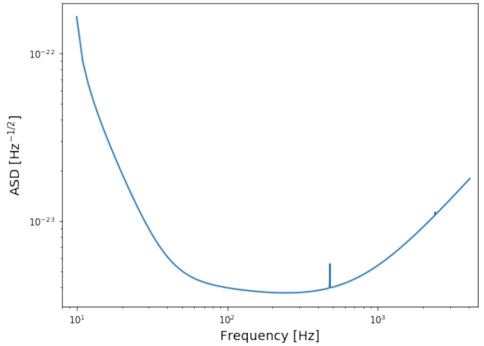
Chirp mass $\mathcal{M}$ is unique parameter $$\mathcal{M} = \frac{(m_1 m_2)^{3/5}}{(m_1+m_2)^{1/5}}$$

Frequency $f(t)$ grows with time,
but is truncated at $f_{\rm cutoff}$.

$$f(t) = f_0\left[1-\frac{t}{\tau}\right]^{-3/8} \qquad f_{\rm cutoff} = \frac{1}{6\sqrt{6}(2\pi)}\frac{c^3}{G(M_1+M_2)}$$

Time to merger $$\tau^{-1} \equiv \frac{256}{5}(\pi f_0)^{8/3}\left(\frac{G\mathcal{M}}{c^3}\right)^{5/3}$$

Numerical data constructed with whitening



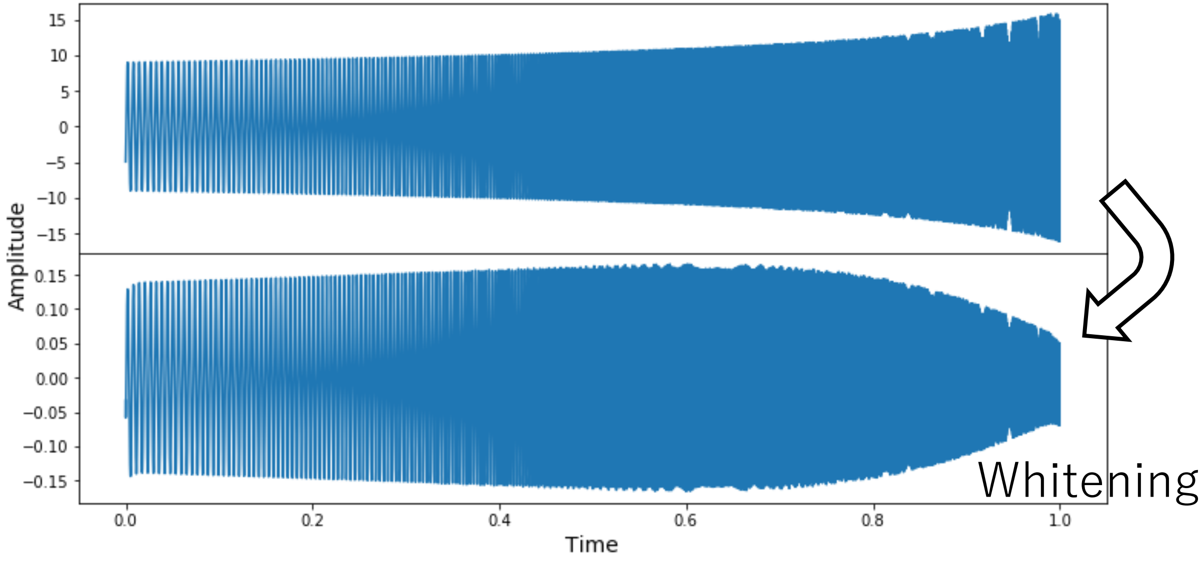
Sensitivity of detector

(Amplitude Spectrum Density (ASD))

https://dcc.ligo.org/LIGO-T0900288/public

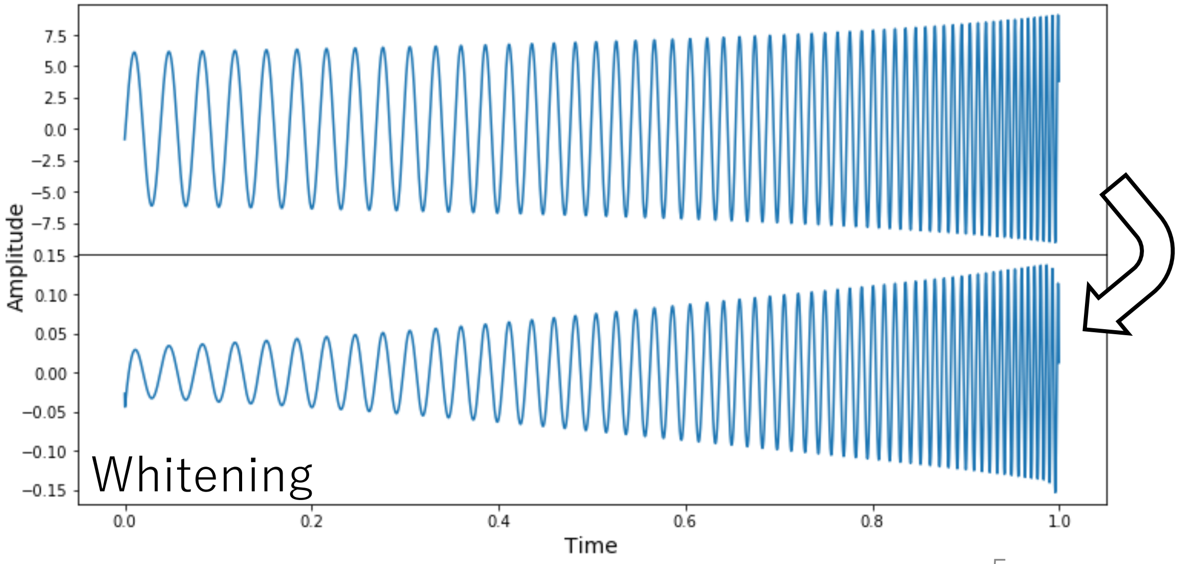
Two examples of GW signal

$17M_\odot$ & $17M_\odot$



Whitening

$40M_\odot$ & $40M_\odot$



Whitening

Simulation data

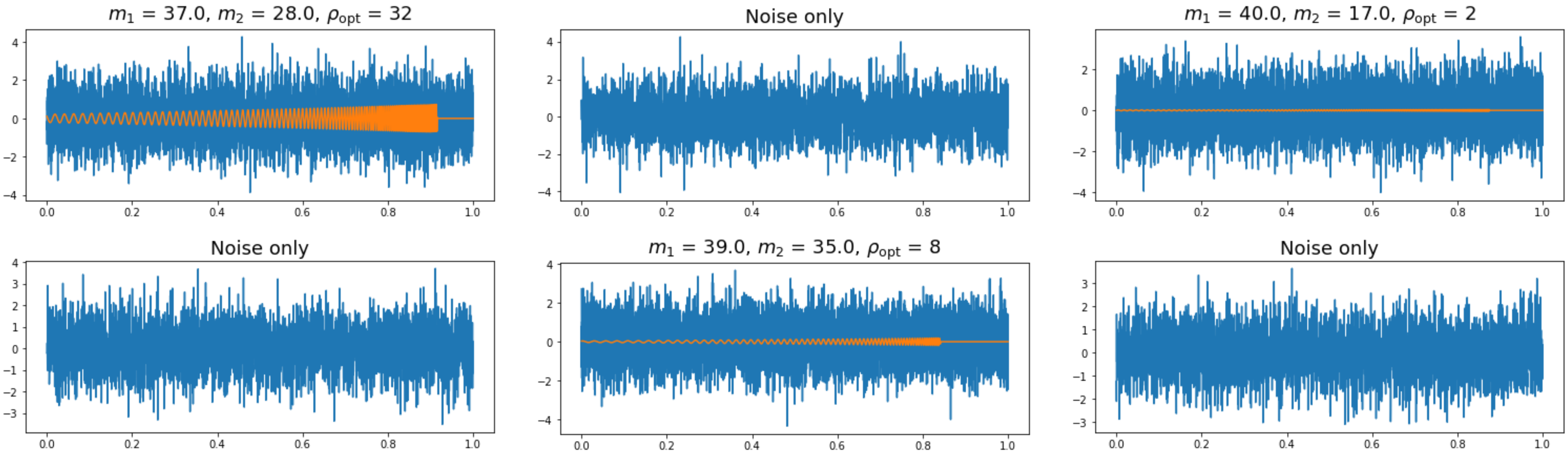
Two types of data sets for training and test

- “GW + Noise”
- “Noise only”

Six examples of data sets with/without signal are shown.

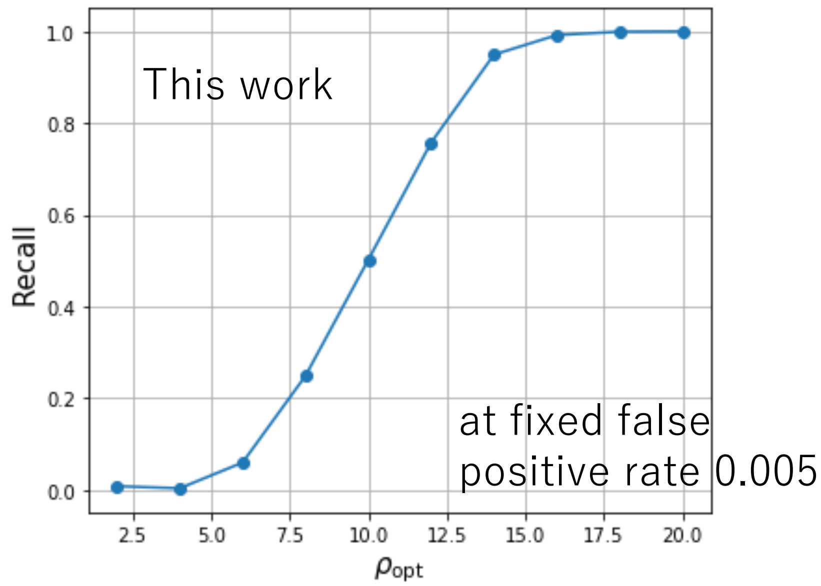
Definition of signal to noise ratio(SNR)

$$\rho_{\mathrm{opt}}^2 = 4\int_0^\infty \frac{|\tilde{h}(f)|^2}{S_n(f)}df \qquad S_n(f) = \mathrm{ASD}^2$$



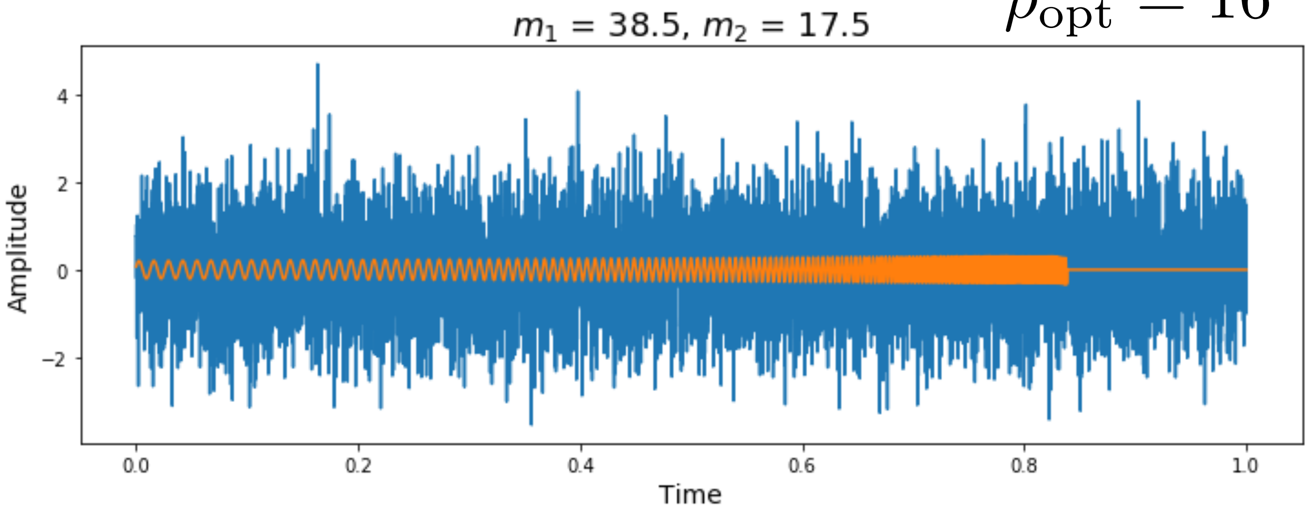
At what level of SNR ρ_{opt} can the machine detect the signal and estimate masses of BHs?

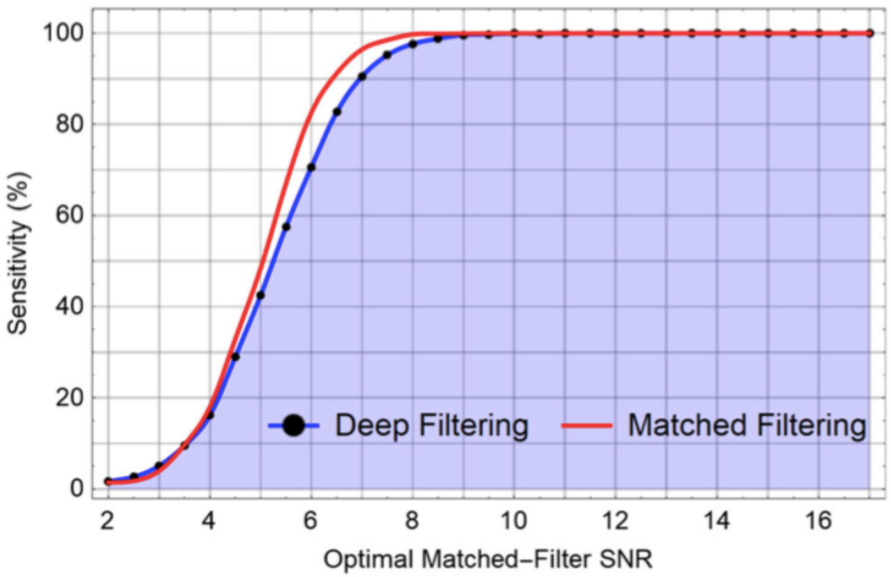
Results of detection for BBH



An example of successful detection

$\rho_{opt} = 16$





George & Huerta (2018)

We confirmed our method.

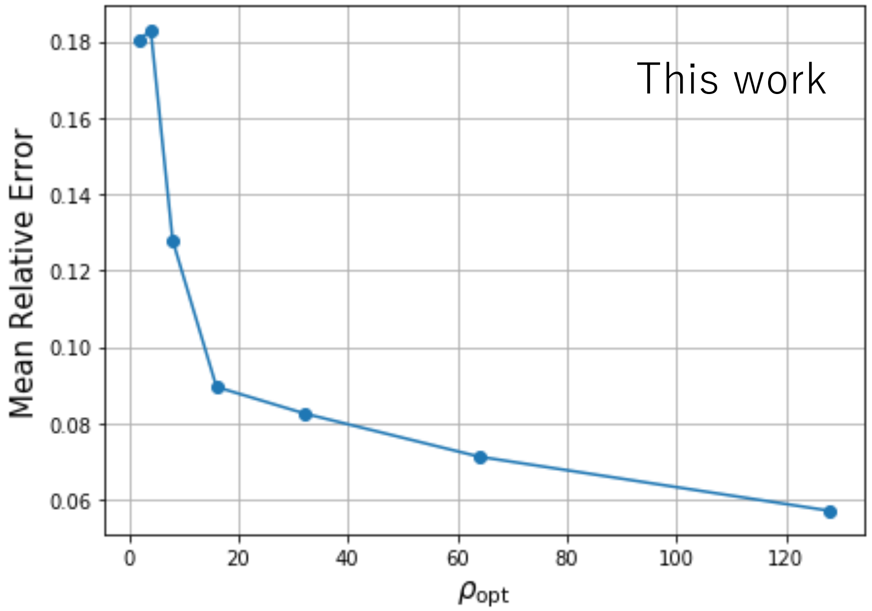
Similar behavior to previous work

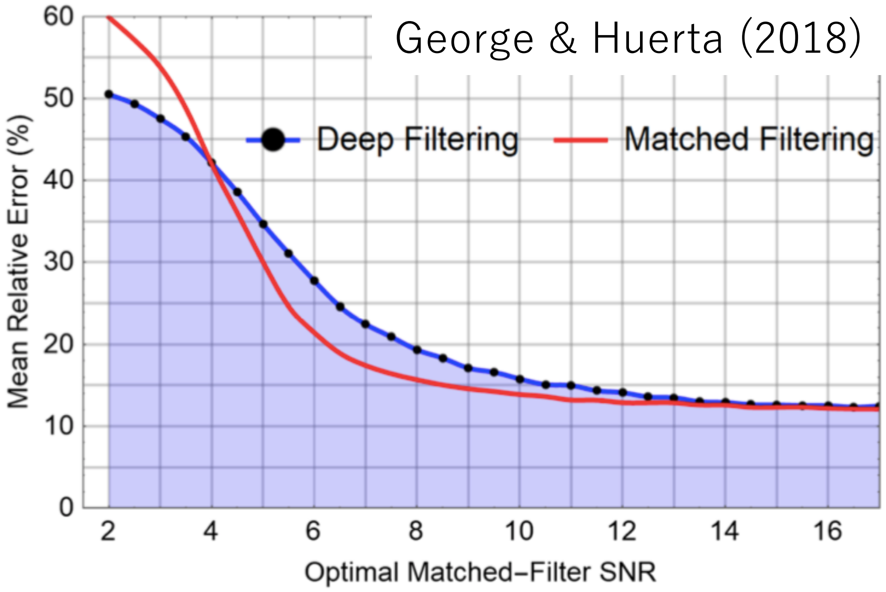
Possible detection

$$\rho_{opt} \gtrsim 16 \quad h_{strain} \gtrsim 1.0 \times 10^{-22}\ [\mathrm{Hz}^{-1/2}]$$

cf. GW150914 $\quad h \sim 10^{-21}\ [\mathrm{Hz}^{-1/2}]$

Results of parameter estimation for BBH

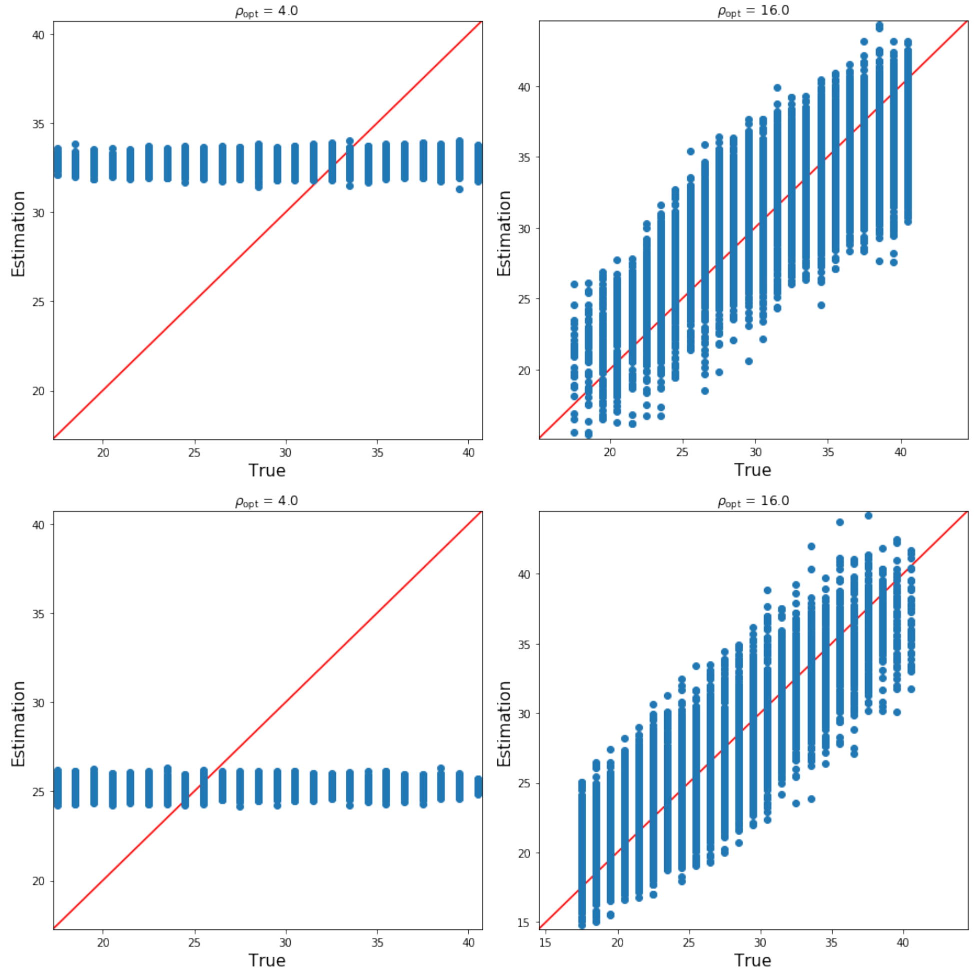




$\rho_{\rm opt} = 4$ $\rho_{\rm opt} = 16$

m_1

m_2



Our parameter estimator is bad.

One reason is different wave-form models, but is still explored.

Difficult estimation below $\rho_{\rm opt} \sim 4$

II GW signal from burst

Detailed wave-form is uncertain at present.

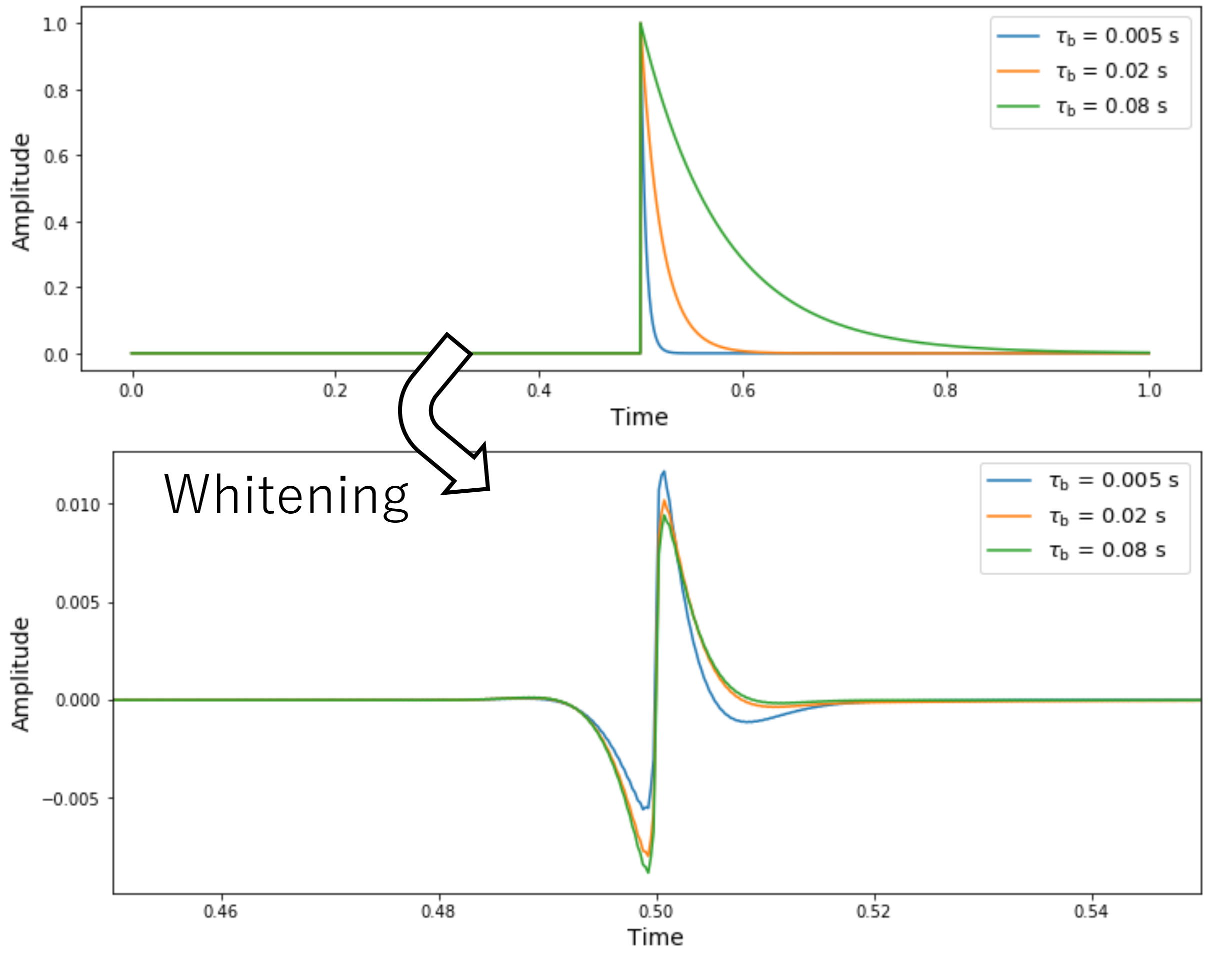
Exponential form is assumed.

$$h(t) = \exp\left[-\frac{1}{\tau_{\mathrm{b}}}(t - t_{\mathrm{b}})\right]$$

Three types of data sets distributed in range.

1. $\tau_{\mathrm{b}} \sim \mathcal{N}\left(0.005\ [\mathrm{s}], 0.001\ [\mathrm{s}]\right)$
2. $\tau_{\mathrm{b}} \sim \mathcal{N}\left(0.02\ [\mathrm{s}], 0.004\ [\mathrm{s}]\right)$
3. $\tau_{\mathrm{b}} \sim \mathcal{N}\left(0.08\ [\mathrm{s}], 0.016\ [\mathrm{s}]\right)$

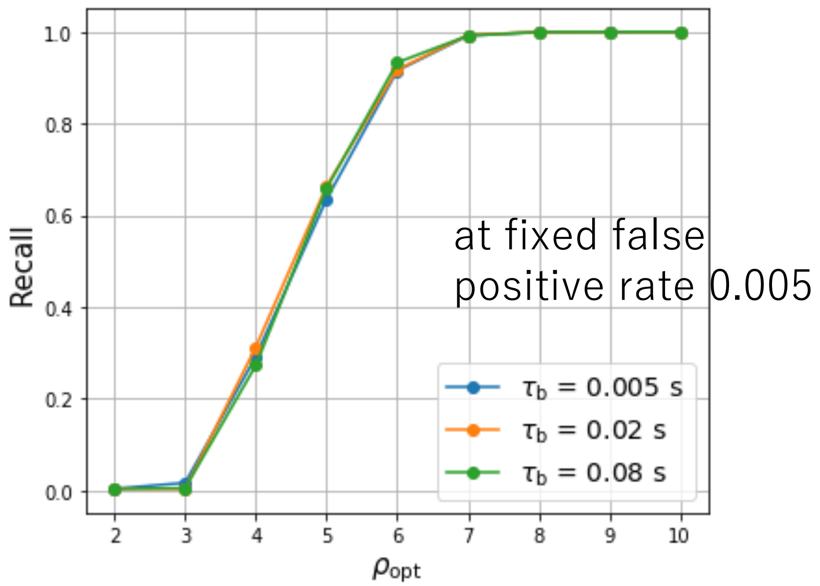
$$0.2 \leq t_{\mathrm{b}} < 0.8$$



Parameters

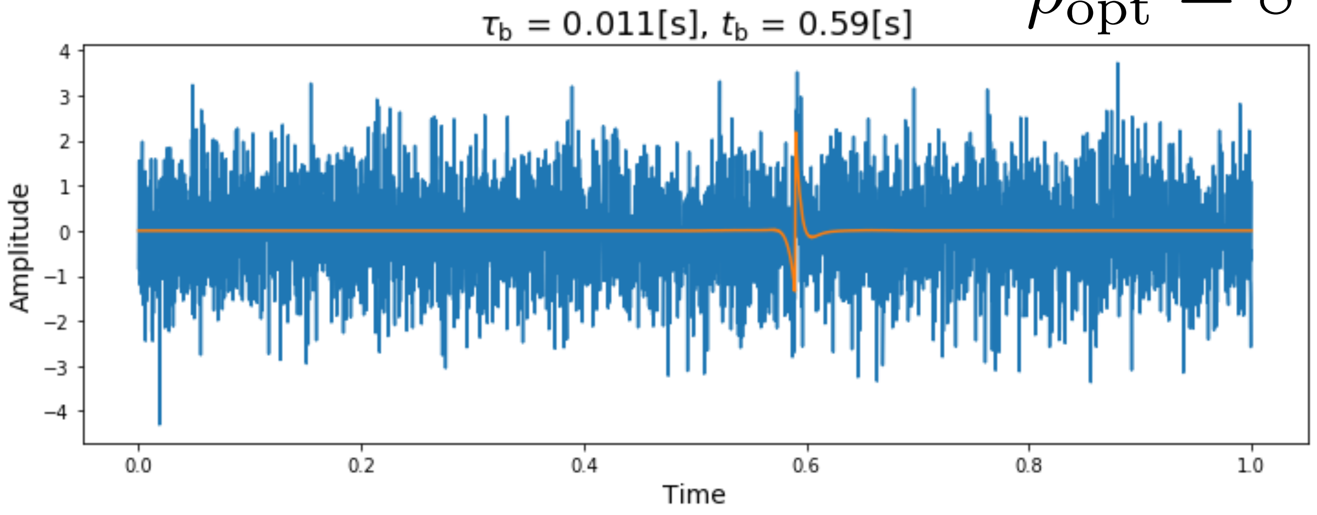
τ_{b} : Damping time t_{b} : Burst time

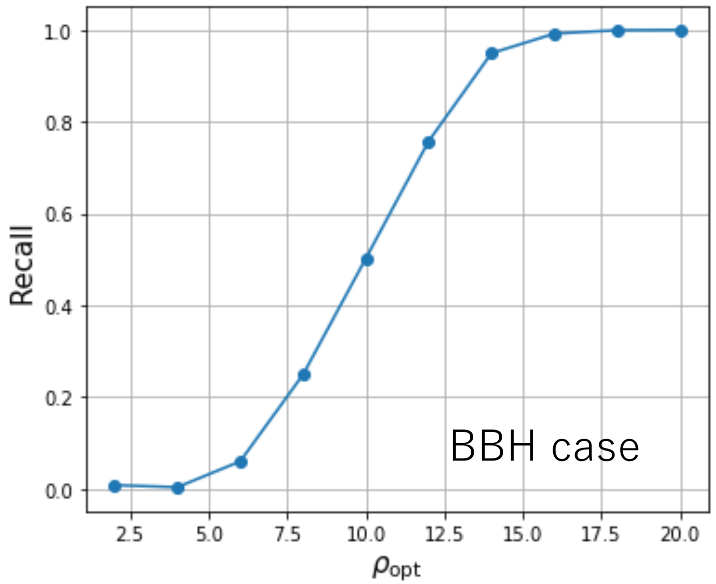
Results of detection for GW-burst signal



An example of successful detection

$$\rho_{opt} = 8$$





Equivalent detection performance independent of τ_b

Possible detection

$$\rho_{opt} \gtrsim 8 \qquad h_{strain} \gtrsim 3.1 \times 10^{-23} \ [\mathrm{Hz}^{-1/2}]$$

BBH $\quad \rho_{opt} \gtrsim 16 \quad h_{strain} \gtrsim 1.0 \times 10^{-22} \ [\mathrm{Hz}^{-1/2}]$

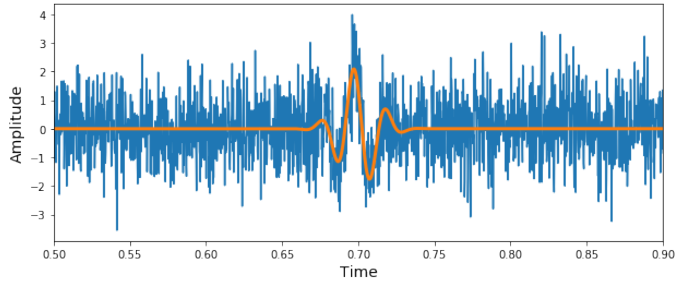
We include new types of signal at test, which are not included in training data. How does ML respond?

Three types of test data sets

① ・“GW + noise” ・“Noise only”

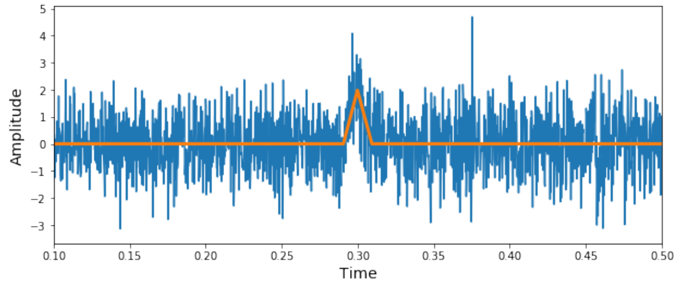
② ・“GW + noise” ・“Noise only”

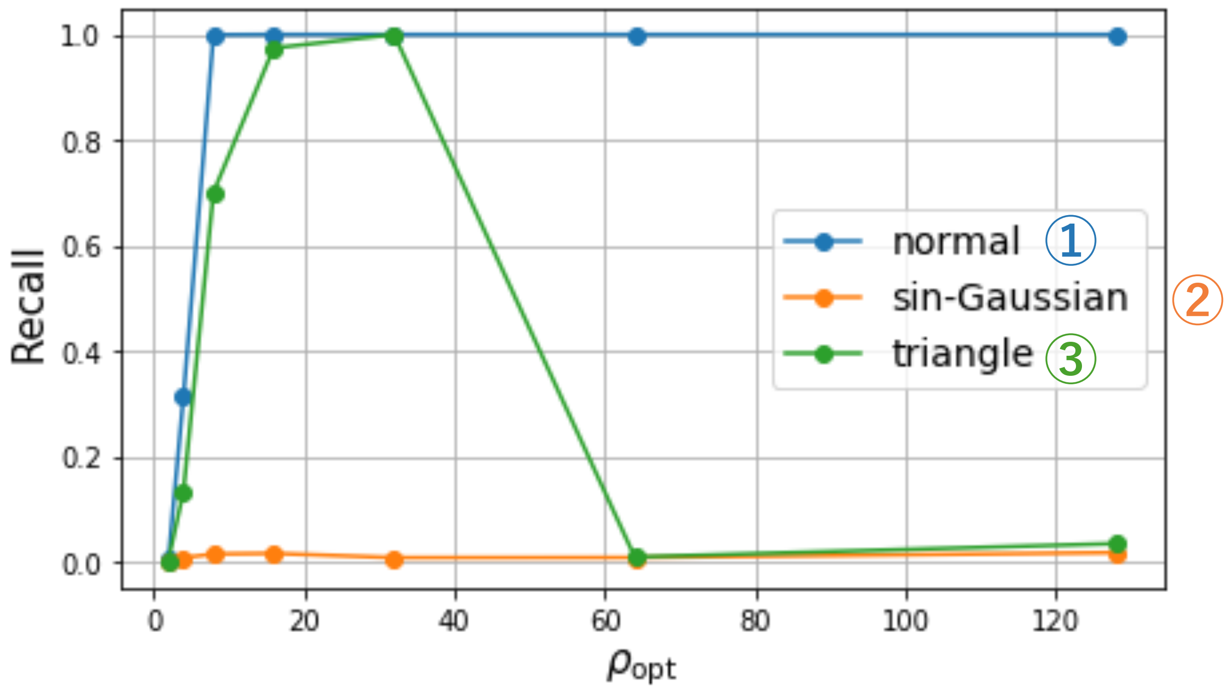
・“sin-Gaussian(sG)” as “Noise only”



③ ・“GW + noise” ・“Noise only”

・“triangle wave(tri)” as “Noise only”



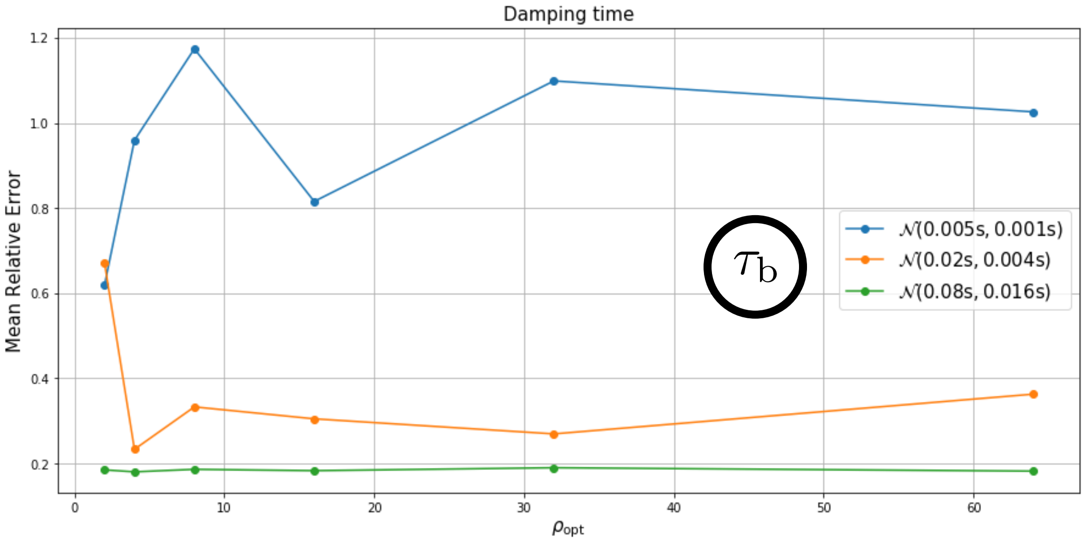


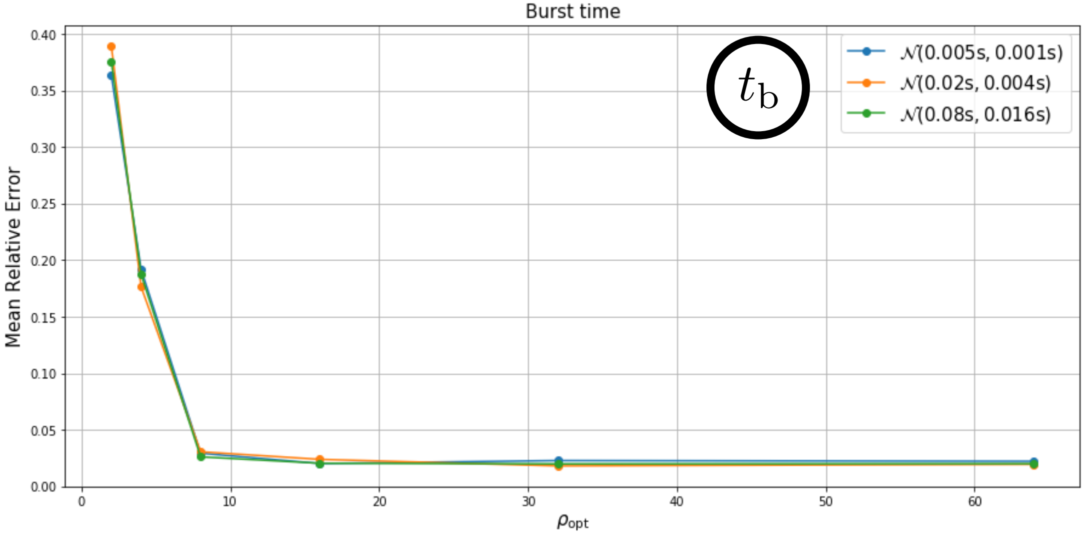
Machine identifies “sG” and “tri” as true signals.

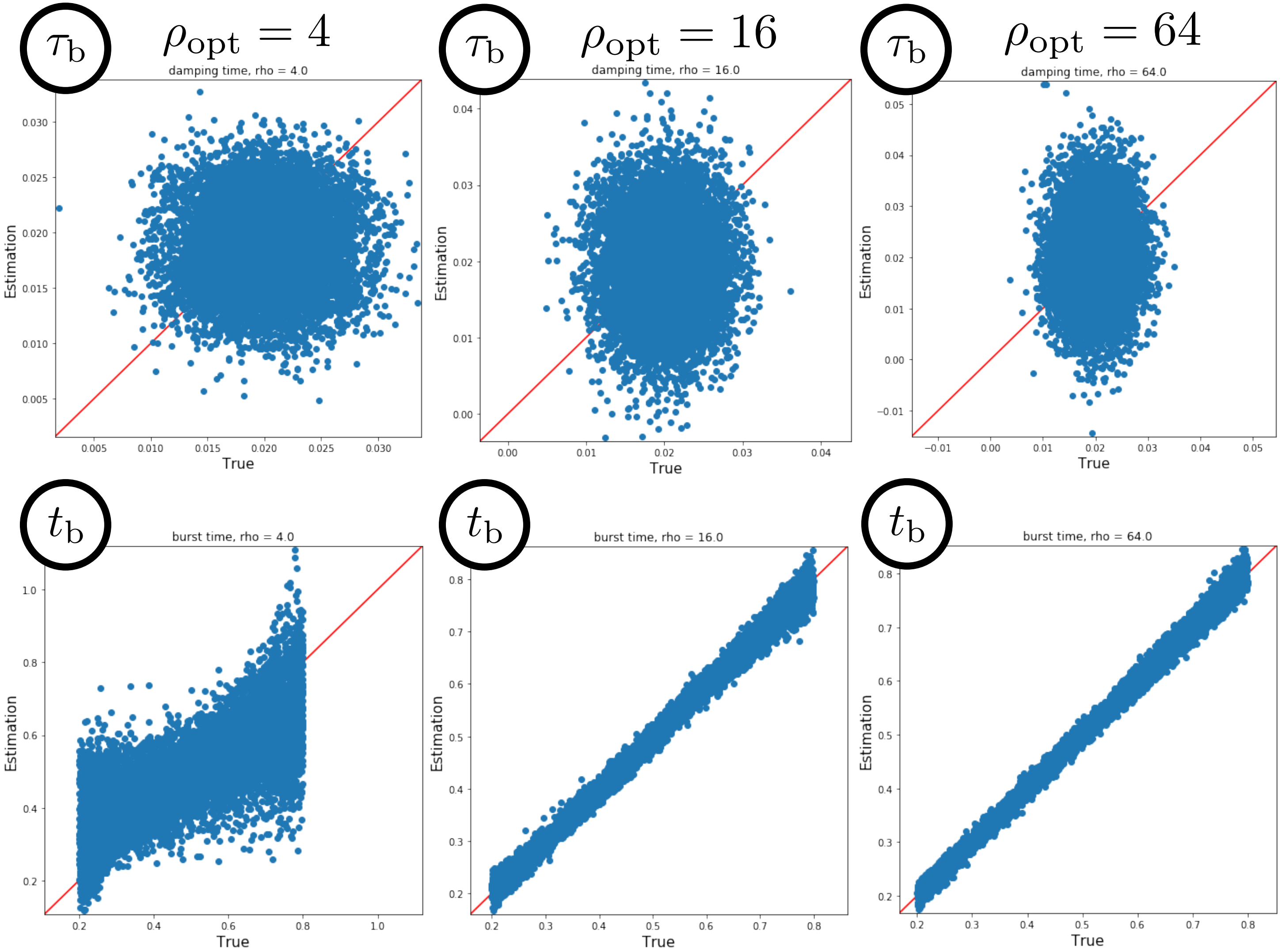
Recall decreased by confusing “sG” or “tri” signal.

Results of parameter estimation for GW-burst signal

$\tau_\mathrm{b} = 0.02$ s







Difficult to estimate damping time τ_b for any ρ_opt

Similar behavior to the case of BBH for burst time t_b

Summary

We used machine learning to detect signal of GW and estimate the parameters.

GW from Binary Black Hole

We confirmed the behavior to be similar to that of George & Huerta (2018).

GW signal from burst

There is possibility to detect signal with signal to noise ratio $\rho_{\rm opt} \gtrsim 8$.

Machine's response to unexpected coherent data-train such as sin-Gaussian and triangle wave was "signal".
It is important to prepare training data to extract true signal we look for.

There may be a way to label that would reduce the mean relative errors of both damping time $\tau_{\rm b}$ and burst time $t_{\rm b}$.

Appendix: Test procedure of detection

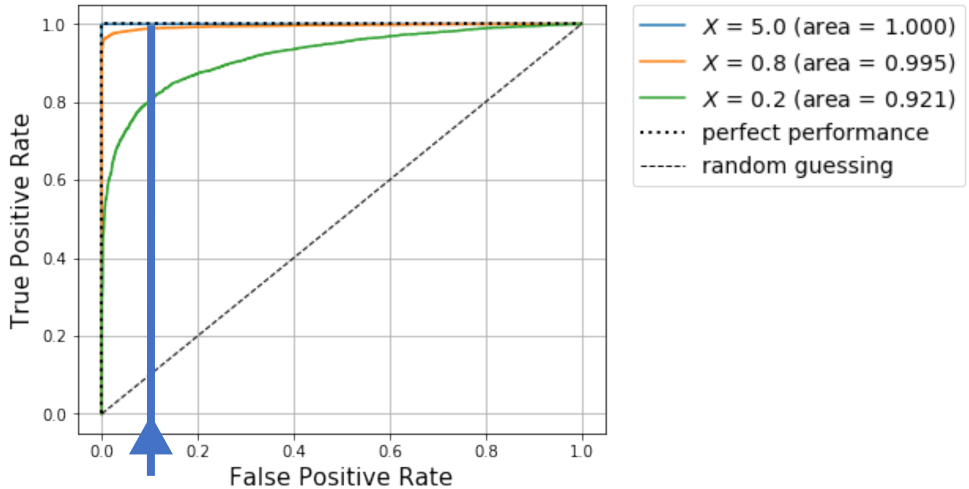
1. Classification results

Test data	Class	Score	TPR	FPR
1	"A"	0.9	0.3	0.0
2	"B"	0.4	1.0	1.0
…	…	…	…	…
N	"A"	0.7	0.7	0.8

"A" : "GW + Noise"

"B" : "Noise only"

3. Receiver operating characteristic curve



fixed FPR

2. Calculating TPR & FPR with confusion matrix

True \ Prediction	"A"	"B"
"A"	TP	FN
"B"	FP	TN

True Positive Rate, (Recall, Sensitivity)

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

False Positive Rate

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}}$$

4. Drawing TPR (recall) graph with fixed FPR