Detection of Gravitational Waves from Core-Collapse Supernovae Using Deep Learning

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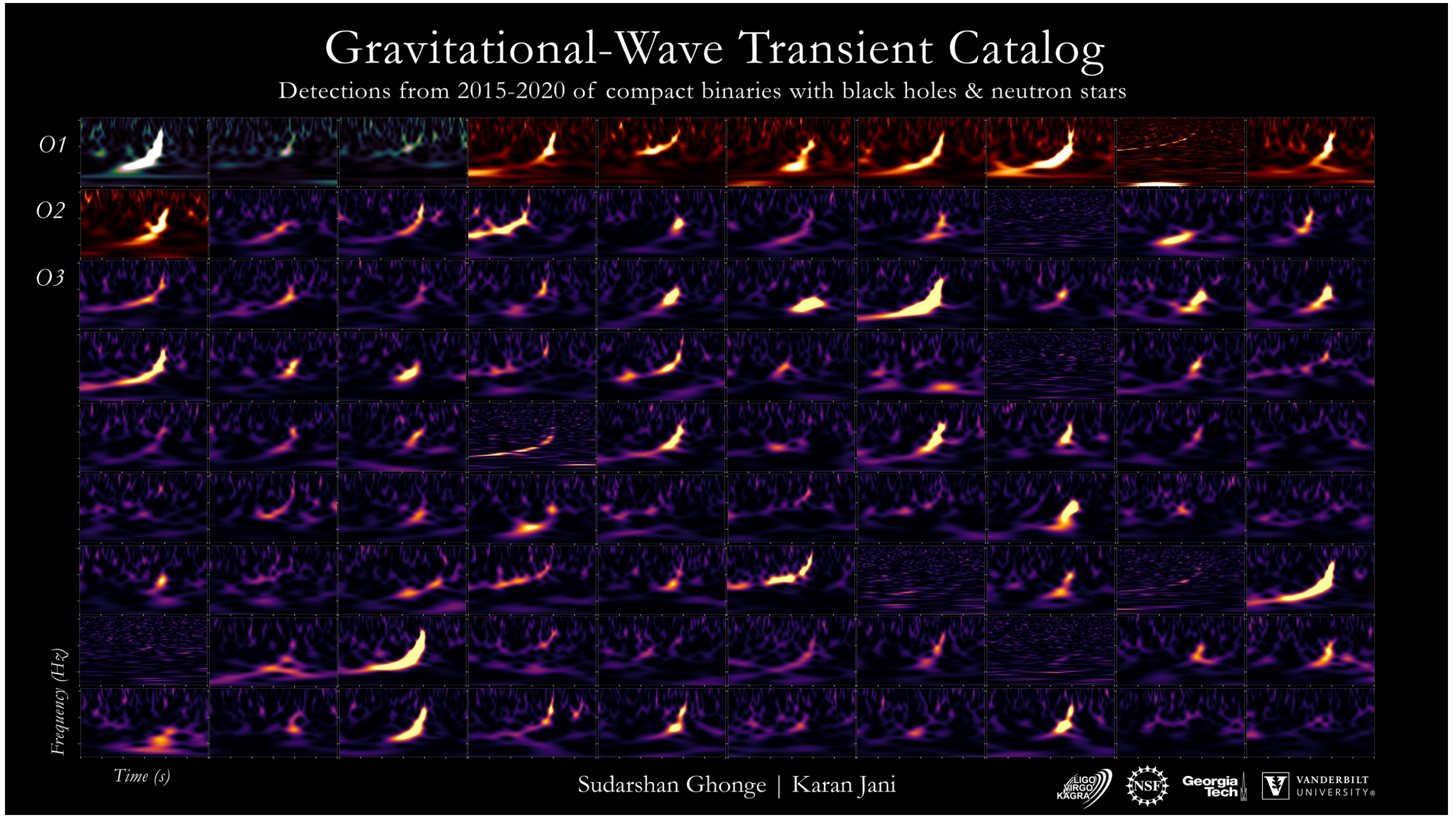
Gravitational Waves

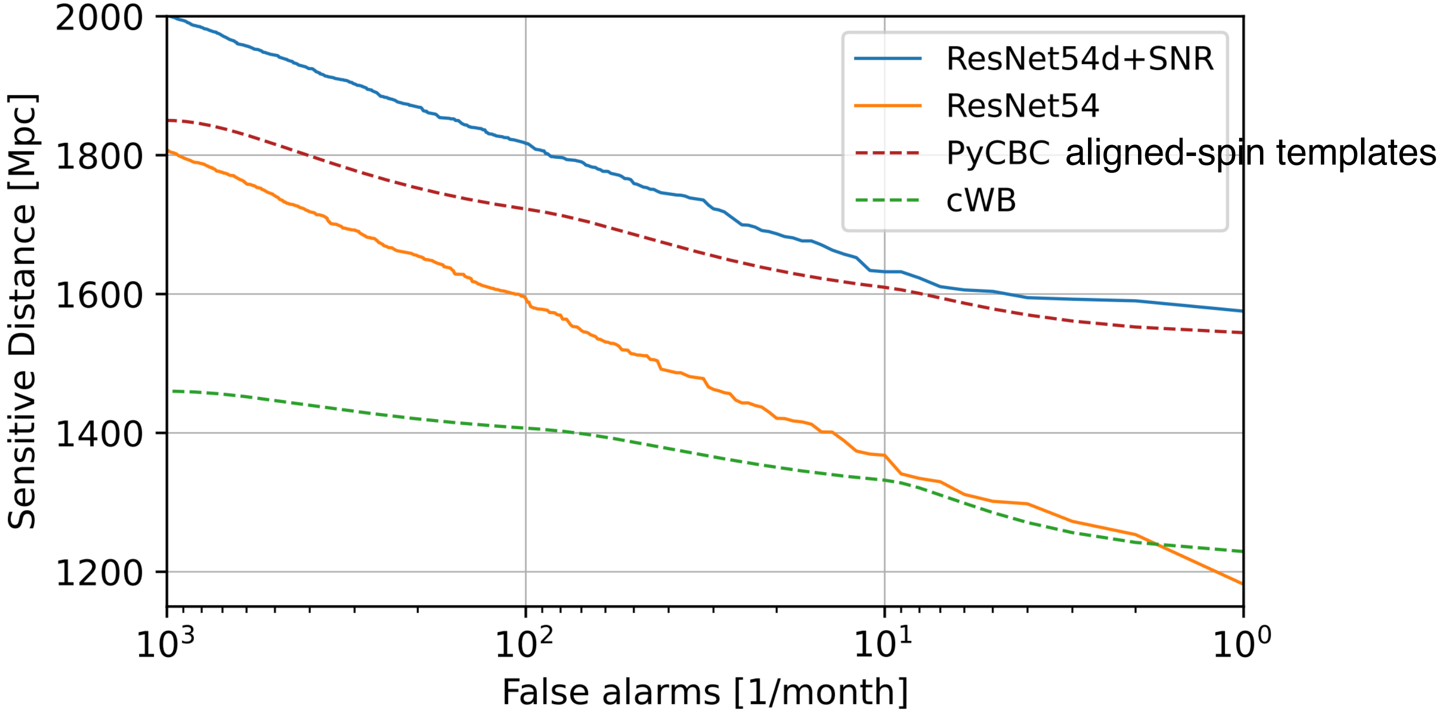
- 90 GW events from CBC have been detected.
- GWs from supernovae are expected to be detected in the near future.



https://dcc.ligo.org/LIGO-G2102338/public
Credit: LIGO/Virgo/KAGRA/S. Ghonge/K. Jani

Deep Learning for GWs from CBC

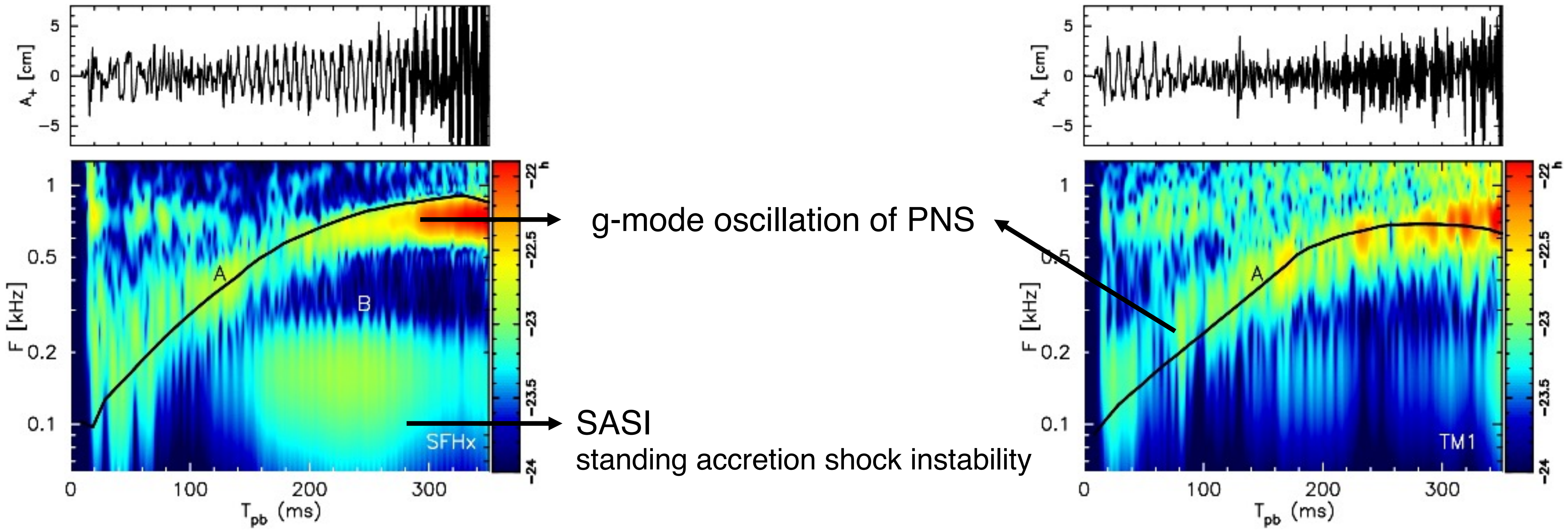
- Convolutional neural networks (CNNs) are effective for GWs from CBC because their waveforms are accurately predicted.
- A model from Nousi et al. (2022) shows better detection efficiency than matched filtering with aligned-spin templates.



Nousi+ 2022, arXiv:2211.01520

GW from CCSN

- Numerical simulations have revealed common features that the GWs from CCSNe have in time-frequency representation.



Kuroda et al., ApJL **829** L14 (2016)

Deep Learning for GWs from CCSNe

	Astone+ 2018	López+ 2021	Iess+ 2021	Chan+ 2020
Training and test data	phenomenological waveform with g-mode	train: phenomenological waveform with g-mode (updated from Astone) test: simulation data	simulation data and glitches	simulation data (magenetorotational and neutrino-driven)
Noise	Gaussian noise HLV	real noise in O2 HLV	Gaussian noise Virgo, ET (single detector)	Gaussian noise HLVK, LIGO A+&VK
CNN Model	2D-CNN binary classification: signal and noise	Mini Inception-Resnet (2D-CNN) binary classification: signal and noise	1D- and 2D-CNN binary classification: signal and glitch	1D-CNN three-class classification: magnetorotational neutrino-driven noise

→ We try to use phenomenological waveforms with g-mode and SASI to improve the detection efficiency

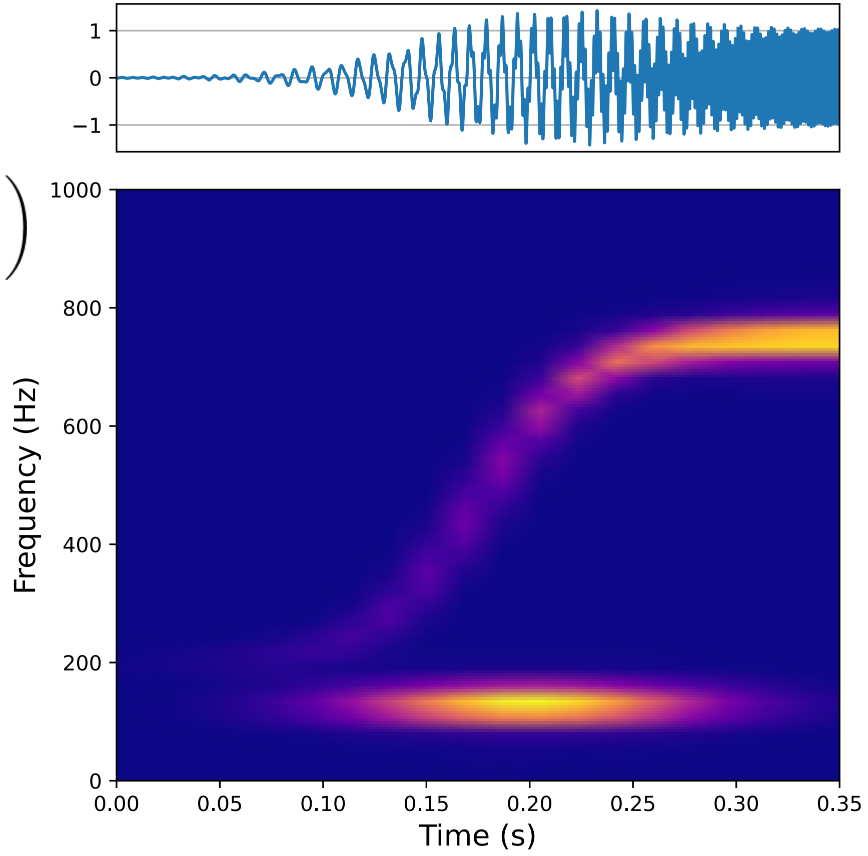
Phenomenological Waveform

$$h(t) = \underbrace{\exp\left[-\left(\frac{2\pi(t-t_g)}{\sigma_g^2}\right)^2\right]\cos\phi(t)}_{\text{g-mode}} + \underbrace{r\exp\left[-\left(\frac{2\pi(t-t_s)}{\sigma_s^2}\right)^2\right]\sin(2\pi f_s t)}_{\text{SASI}}$$

$$\phi(t) = 2\pi\left(\frac{f_{\max}+f_{\min}}{2}(t-t_g/2) + 0.05\frac{f_{\max}-f_{\min}}{2}\log\left(\cosh\left(\frac{t-t_g/2}{0.05}\right)\right)\right)$$

Range of parameters

		min	max
g-mode	t_g	0.2	0.6
	σ_g^2	0.8	1.3
	$f_{\min}$	150	500
	$f_{\max}$	500	2000
ratio	r	0	1
SASI	t_s	$t_g - 2$	$t_g + 2$
	σ_s^2	0.4	0.7
	f_s	100	150

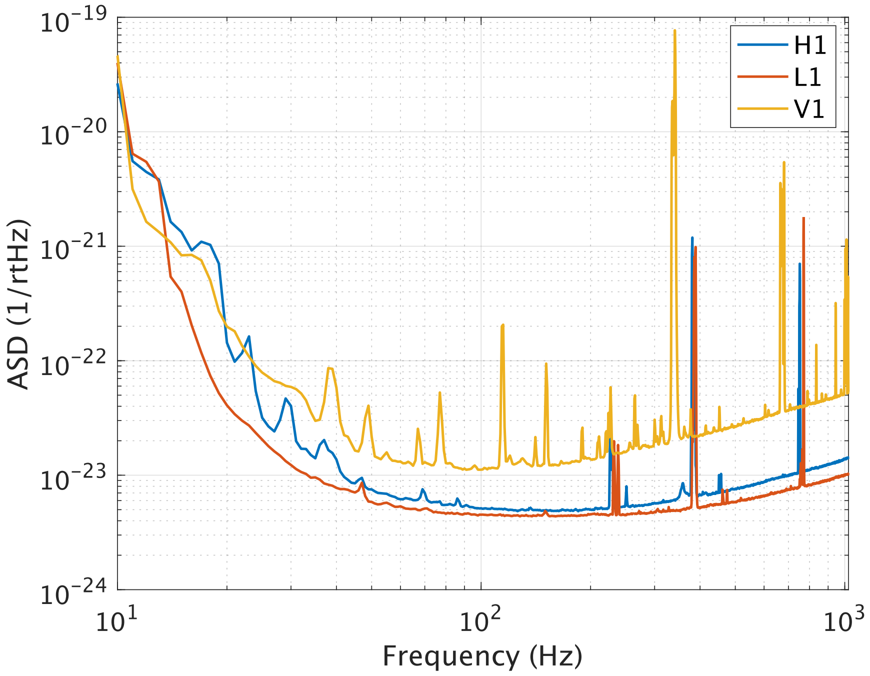


$t_g = 0.35, \sigma_g^2 = 1, f_{\min} = 200, f_{\max} = 750$
$r = 1, t = 0.2, \sigma_s^2 = 0.5, f_s = 130$

Training Data

- Noise
  - PSD: Estimate from O3 open data* using Welch's method
  - Gaussian noise

* GWOSC, The O3a Data Release, https://www.gw-openscience.org/O3/O3a/.



Estimated spectrums

- Signal
  - Phenomenological waveform
  - Sampling rate: 4096Hz
  - 1 second of data after core-bounce
  - Direction: randomly sampled
  - SNR: randomly sample from [5, 30]
  - Whitened

We generated 1,000,000 samples in total; 500,000 signal + noise samples & 500,000 pure-noise samples

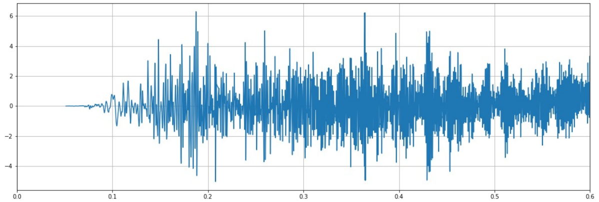
Test Data

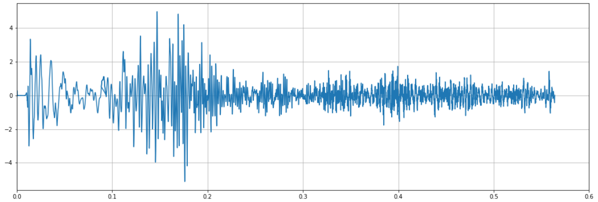
- Signal
  - Simulation data from Radice+2019, Powell+2019, Powell+2020 and Powell+2021

SASI did not occur

SASI occurred

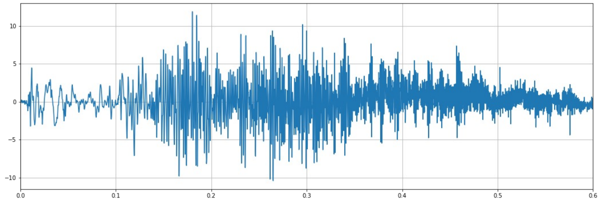
s3.5 in Powell2019

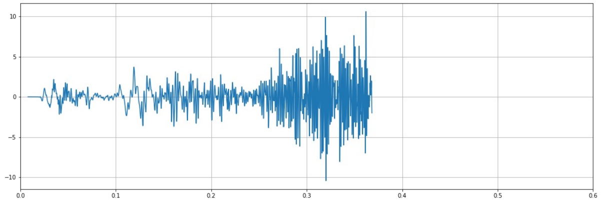




s18 in Powell2020

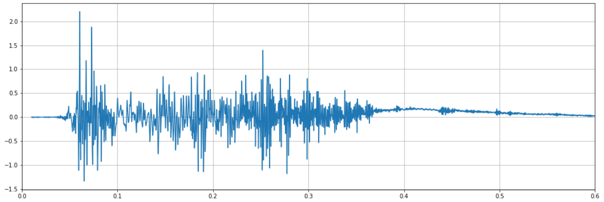
y20 in Powell2020

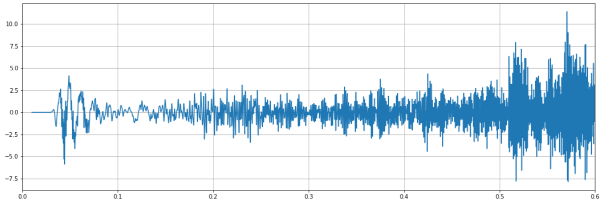




s25 in Radice2019

s9 in Radice2019





z100 in Powell2021

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Test Data

- Signal
  - Simulation data from Radice+2019, Powell+2019, Powell+2020 and Powell+2021
  - Preprocessing: resampling, highpass filtering, tukey window and zero padding
  - Distance: [1, 3, 5, 7, 9, 11, 13, 15, 17, 19] kpc

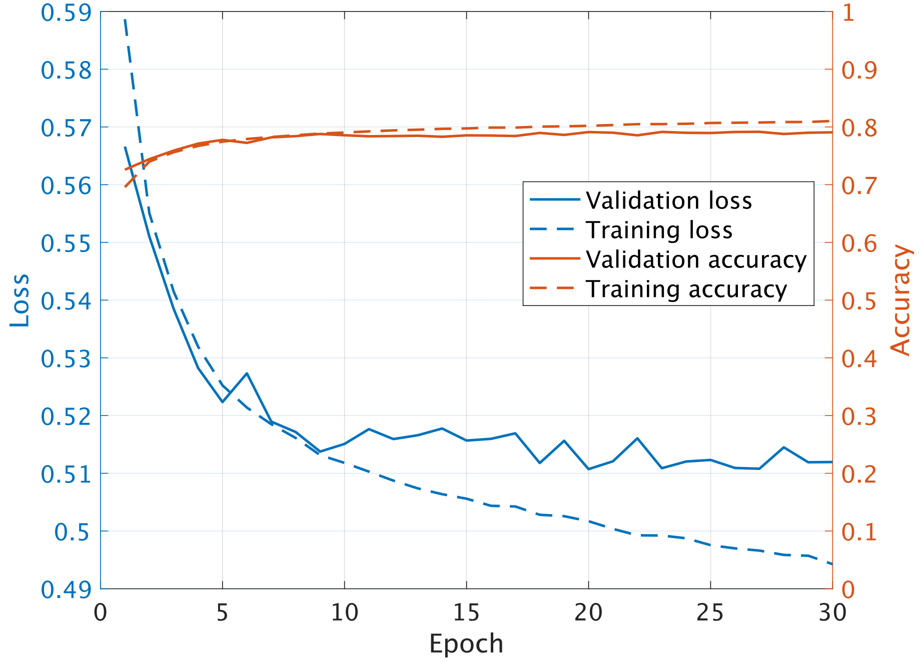
- Noise
  - Generated two test sets: signals in <u>Gaussian noise</u> and those in <u>real noise</u> of O3.

CNN Model

- 1D-CNN whose input are whitened strains

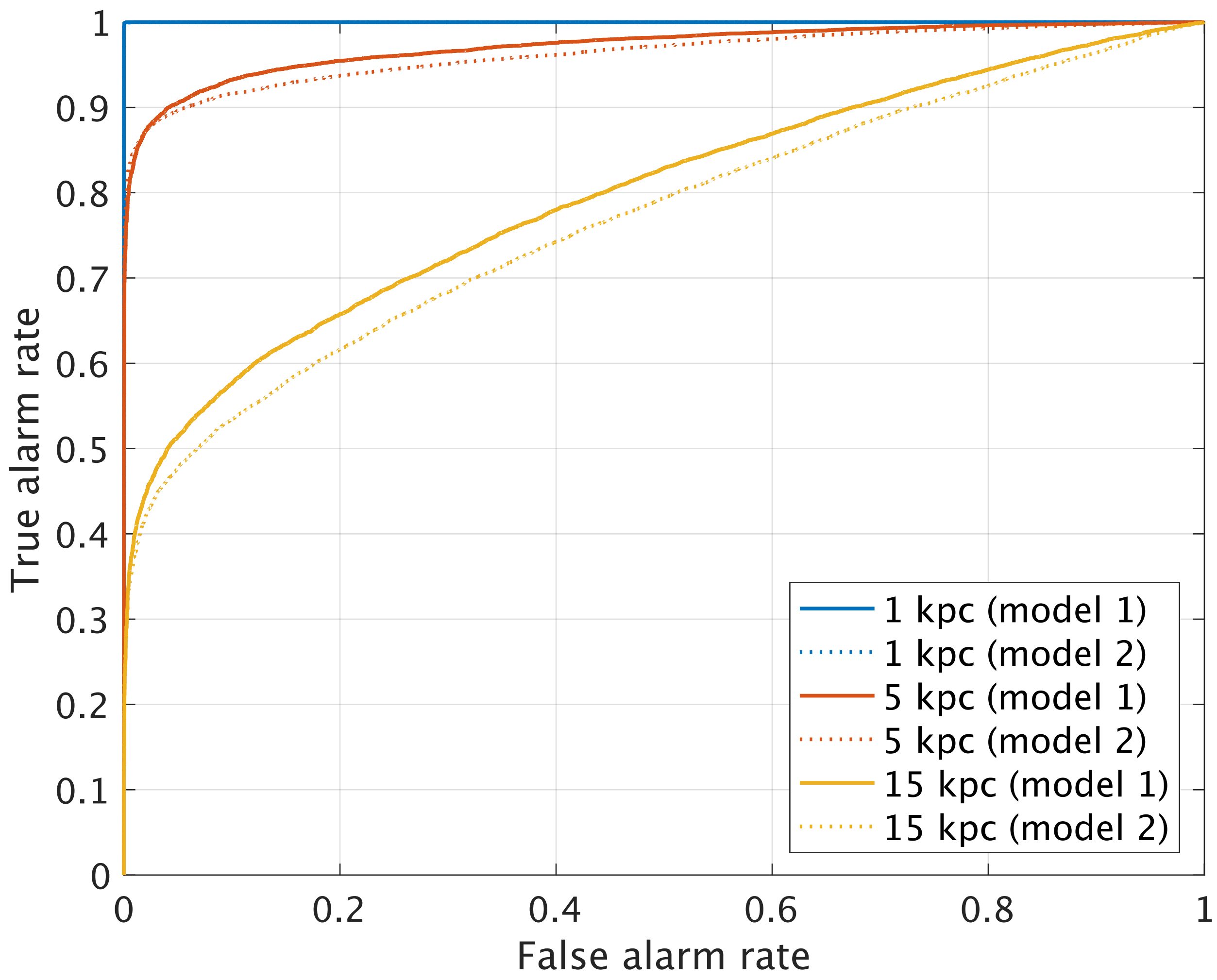
Layer	Input	1	2	3	4	5	6	7	8	9
Type		Conv	Conv	Conv	Conv	Conv	Conv	Linear	Linear	Linear
Size	(3,4096)	(16,4033)	(16,992)	(16,961)	(16,310)	(16,295)	(16,140)	64	64	2
Kernel size		64	64	32	32	16	16	-	-	-
Maxpool size		-	4	-	3	-	2	-	-	-
Dropout		0	0	0	0	0	0	0.25	0.25	0
Activation		SiLU	SiLU	SiLU	SiLU	SiLU	SiLU	SiLU	SiLU	Softmax

Number of parameters: 191,842



- We trained two models:
  - Model 1 is trained with phenomenological waveforms with g-mode and SASI
  - Model 2 is trained with phenomenological waveforms with <u>only g-mode</u>

ROC Curve



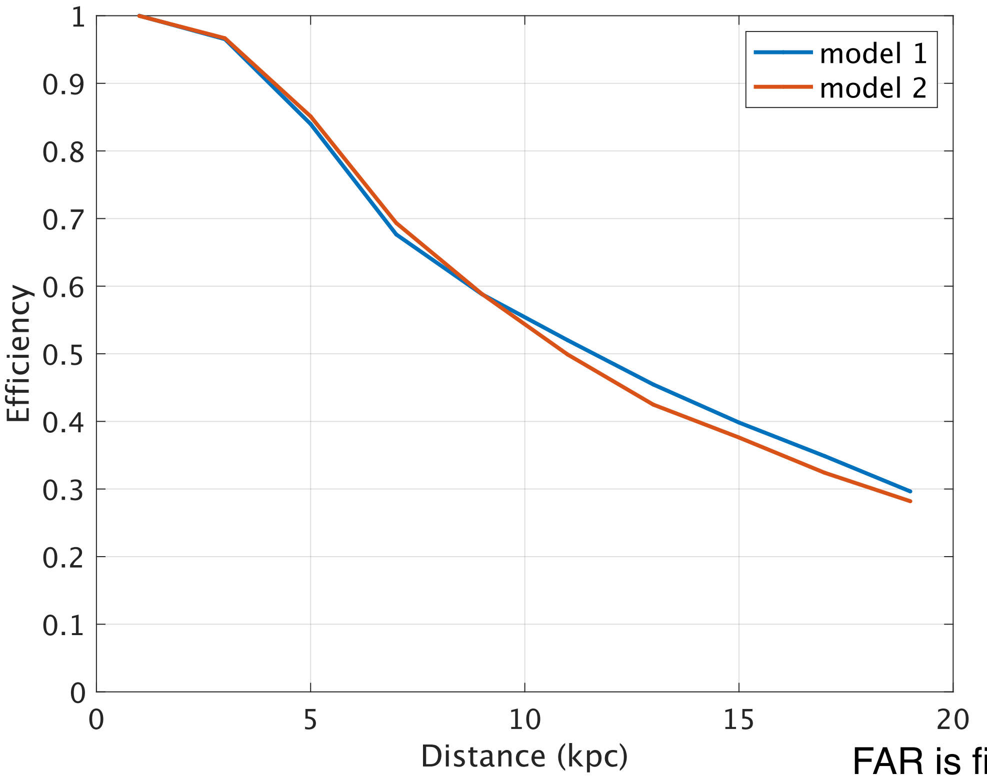
AUC (the area under the curve)

	1 kpc	5 kpc	15 kpc
model 1	1.00	0.97	0.80
model 2	1.00	0.96	0.77

Left figure: ROC curve for the signals that SASI occurred and injected in Gaussian noise.

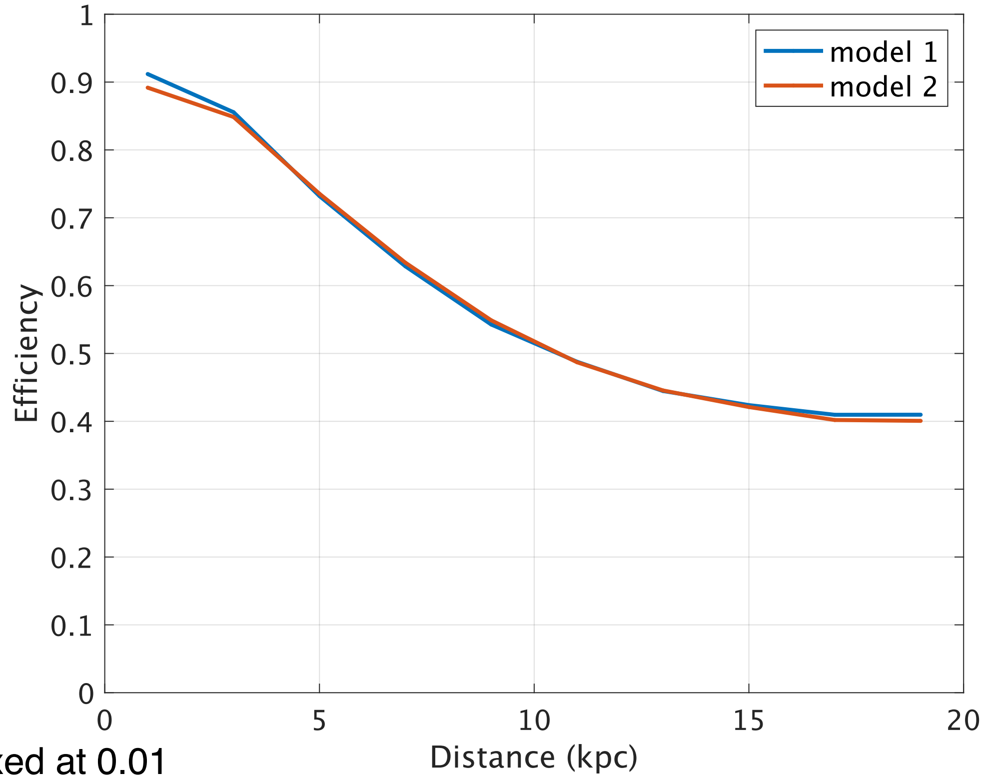
Model 1, trained using signals with SASI, shows better detection efficiency.

Detection efficiency vs. Distance



test with signals that SASI occurred

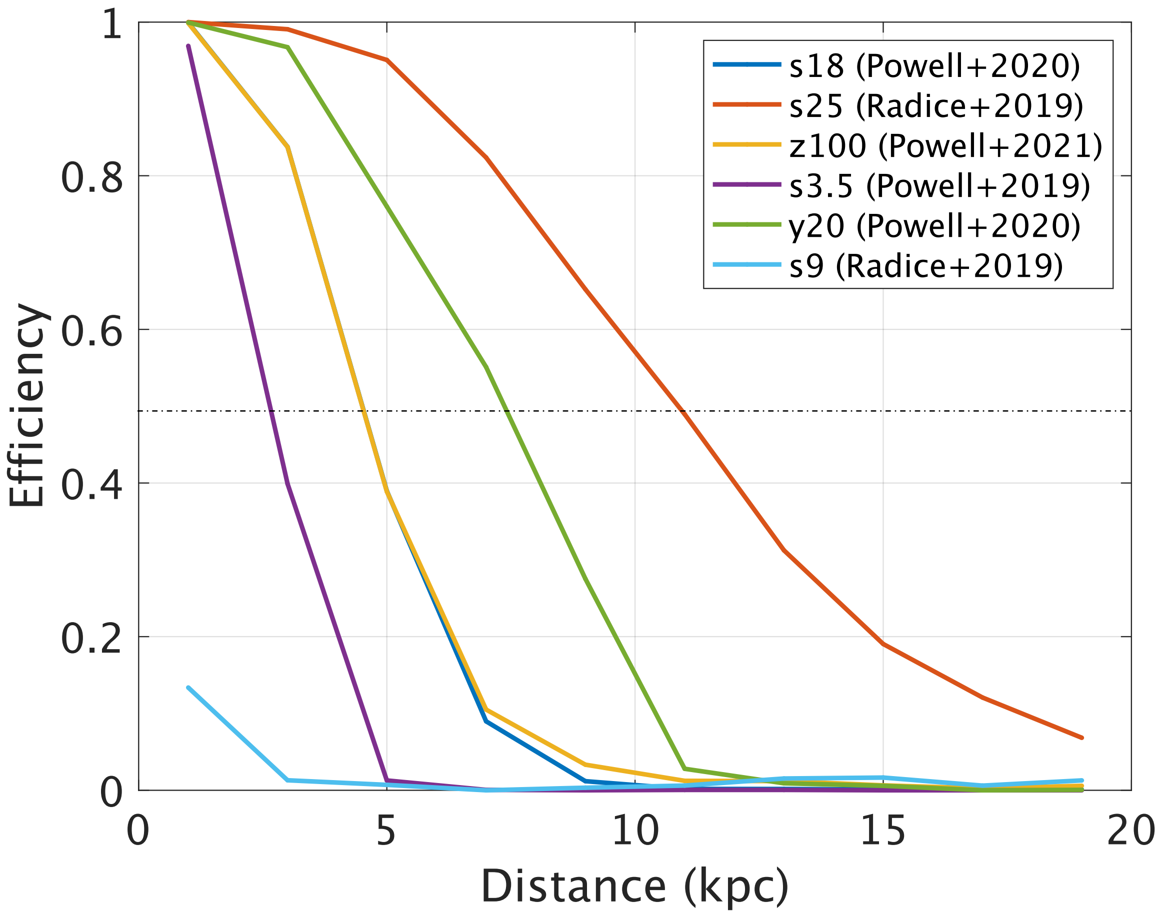
FAR is fixed at 0.01



test with signals that SASI did not occur

- Model 1, trained with signals with SASI performs better than model 2 for signal with SASI at large distances.
- For signals without SASI, there is no much difference between model 1 and 2 at any distance because the training set of model 1 also includes signals without SASI.

Detection Efficiency of Each Data

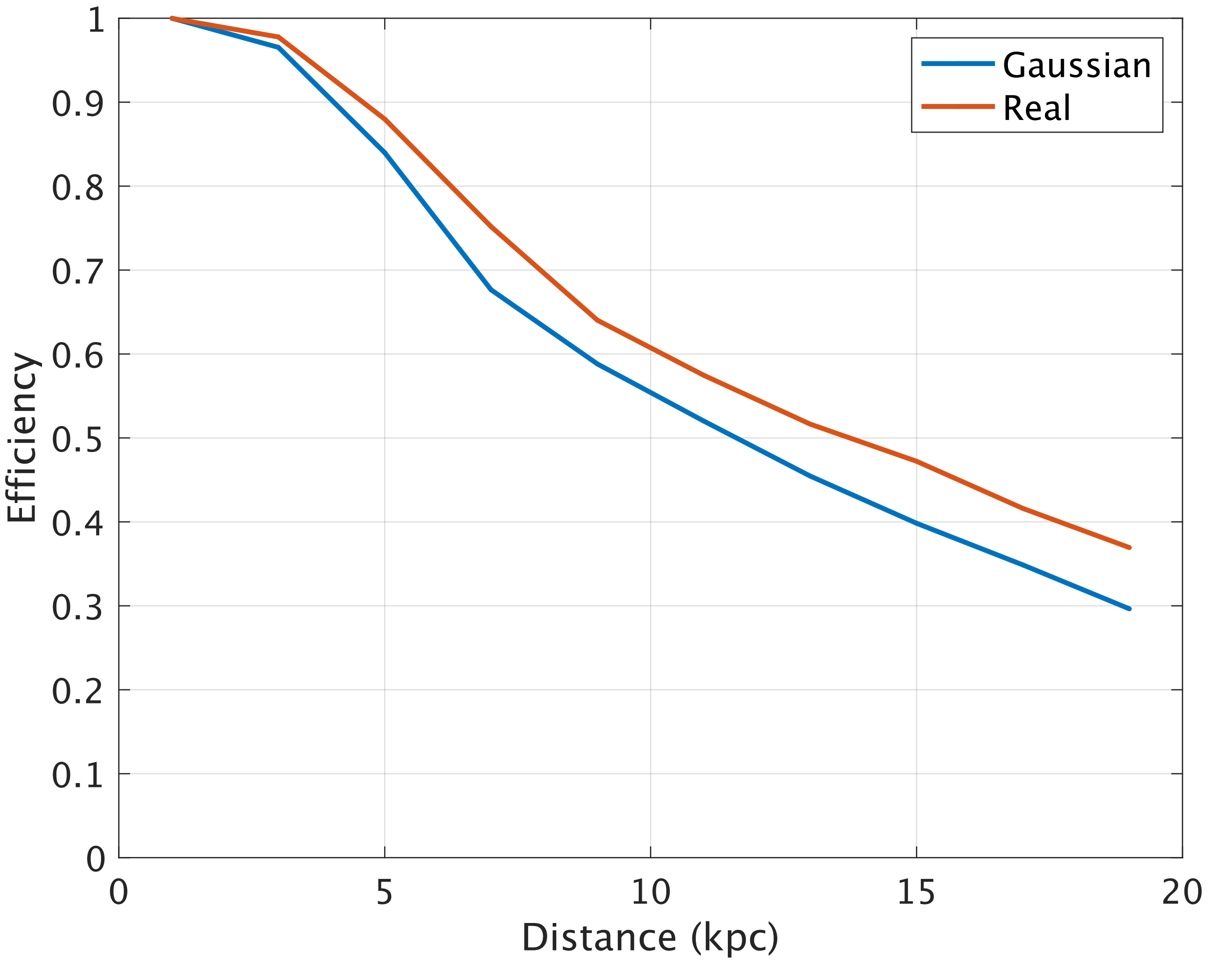


- The detection range is from a few kpc to 10 kpc.
- FAR is fixed at 0.01, which is larger than other pipelines, so we would like to improve the model to reduce the FAR.

Gaussian noise vs. Real noise

- The efficiency for signals in real noise was expected to be lower than those in Gaussian noise due to non-stationary or non-Gaussian noise

- The right figure shows the opposite, and we do not know the cause at the moment and would like to continue the investigation.



Conclusion

- Trained CNN using phenomenological waveforms with g-mode and SASI and improved the detection efficiency
- Somehow signals in real noise showed better efficiency than Gaussian noise

Future work

- Investigate the Gaussian vs. real noise issue
- Improve the efficiency by using 2D-CNN
- Compare the efficiency and speed with coherent WaveBurst