

Searching Core-Collapse Supernovae with ML

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Summary

- Core-Collapse Supernova (CCSN)
- Search and classification of CCSN signals in simulated datasets with CNNs
- Search and classification of CCSN signals in simulated datasets with CNNs and LSTMs
- Classification of CCSN explosion mechanisms with ML models

Matched Filtering

The usual approach in GW data analysis for extraction of a signal from a signal+noise data-stream $s(t) = n(t) + h(t)$ is to implement **matched filtering** (see Allen et al 2012, Abbott et al. 2016):

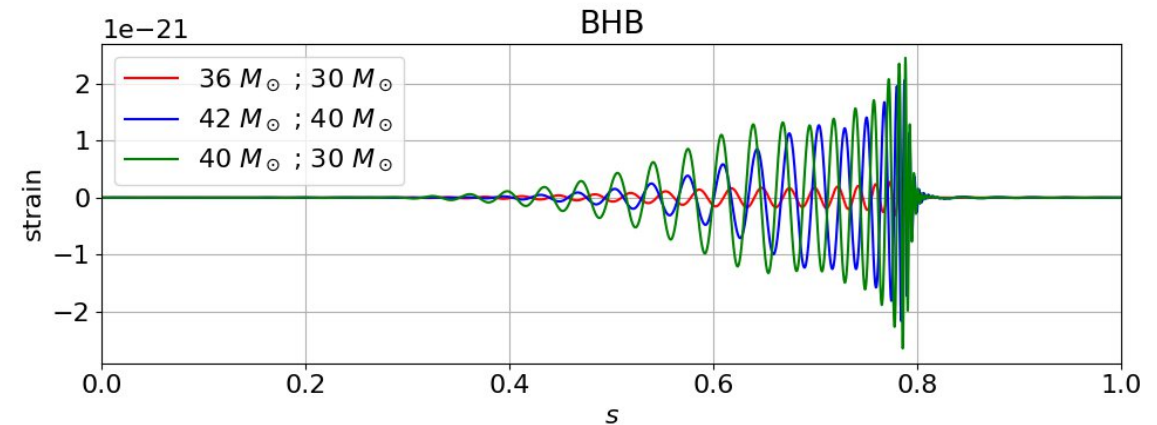
$$\rho^2(t) \equiv \frac{1}{\langle h|h \rangle} |\langle s|h \rangle(t)|^2$$

Matched filter SNR
time-series

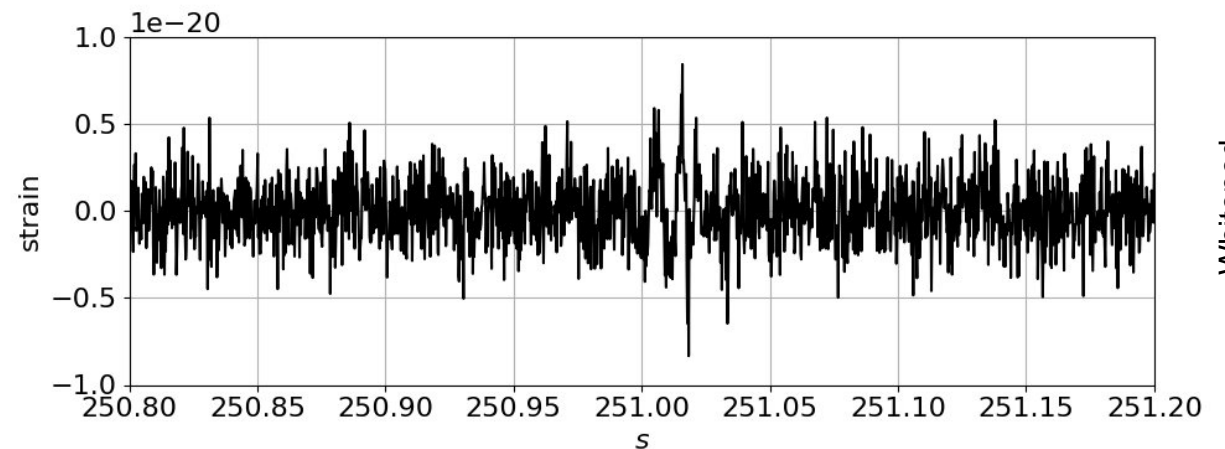
$$\langle s|h \rangle(t) = 4 \int_0^\infty \frac{\tilde{s}(f)\tilde{h}^*(f)}{S_n(f)} e^{2\pi i f t} df$$

Matched filter
correlation

- Large template bank to cover the parameter space $(M_c, \phi_c, t_c, \iota, D, \theta, \varphi)$.
- Requires perfect modeling of phase evolution of the signal.
- Optimal for stationary gaussian background.
- Computationally expensive.



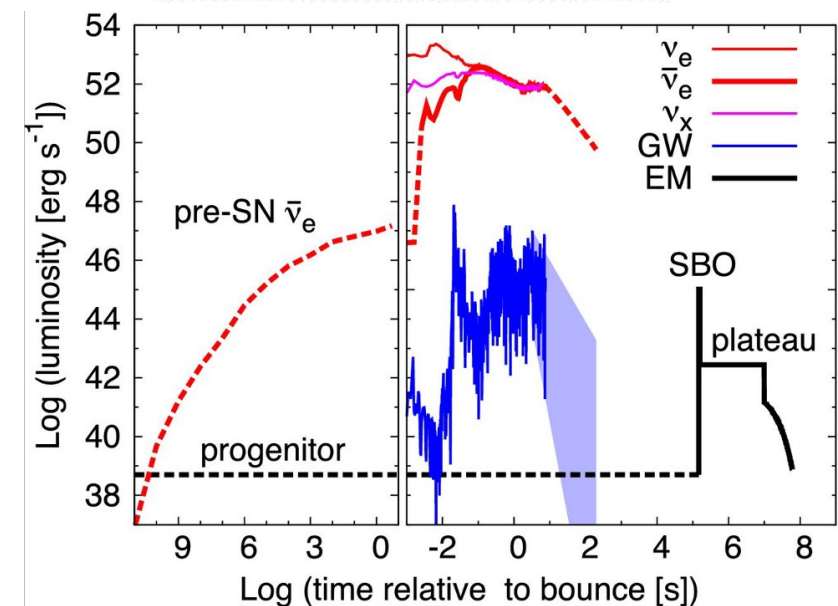
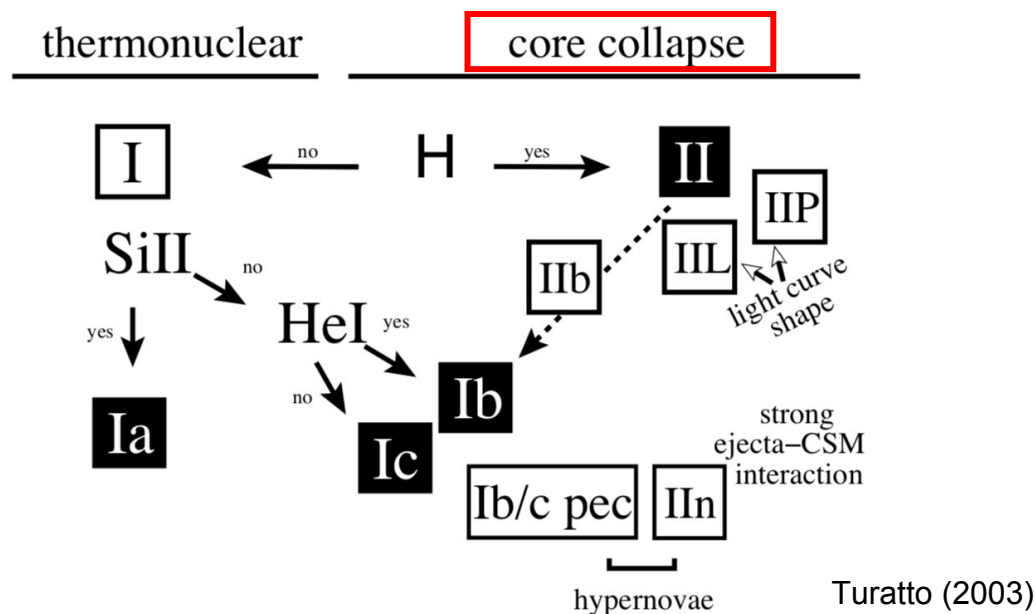
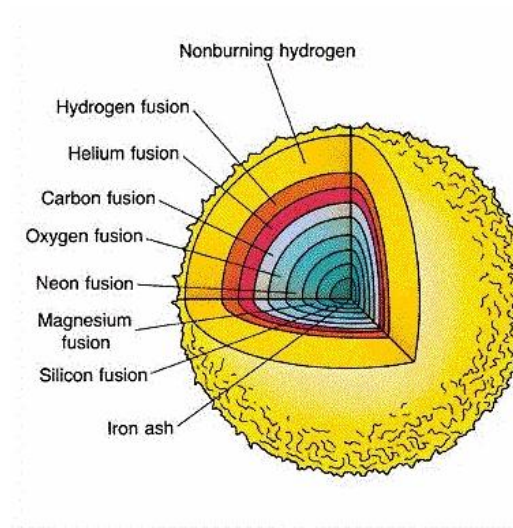
Waveform template



Whitened
interferometer data

Core-Collapse Supernovae (CCSNe)

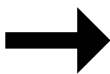
- Final evolutionary stages of **massive stars**, ($\gtrsim 8-9 M_{\odot}$), after nuclear burning accumulates iron core mass greater than Chandrasekhar mass limit.
- **Multi-messenger** emission, 99% energy in **neutrinos**.
- Rare, optimistically ($\sim 50 \div 100$ yrs in **Milky Way**).
- Prompt neutrino emission at ~ 10 MeV.
- Weak prompt GW signals, expected less than 0.0001% supernova energy, h.
- Late EM emission.



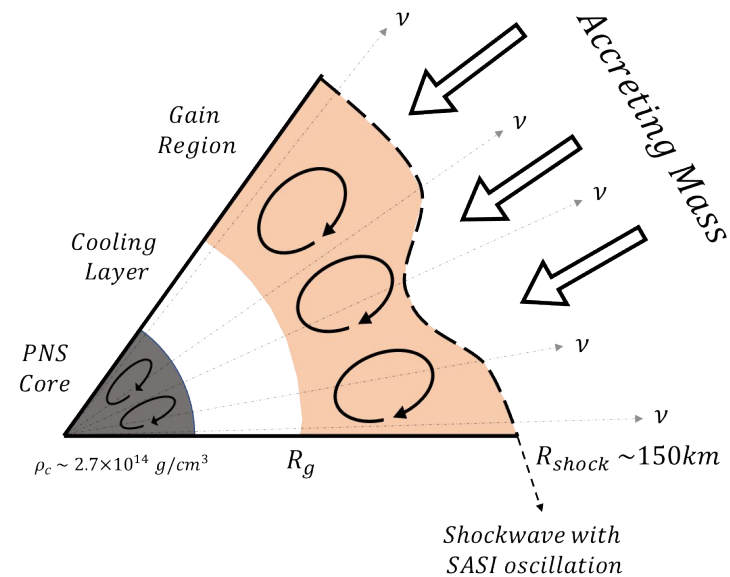
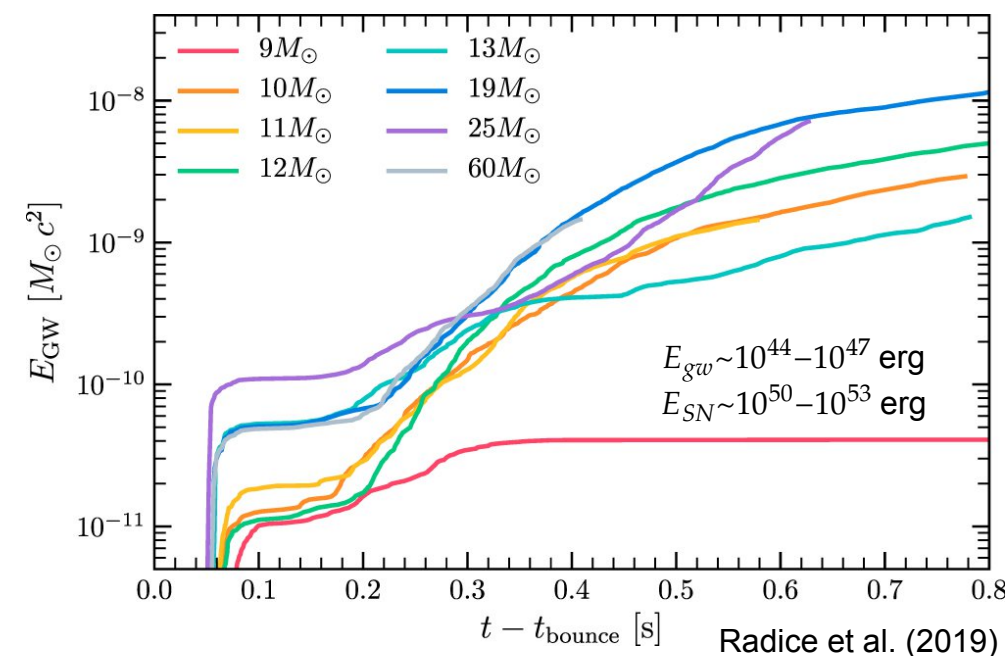
Nakamura et al. (2016)

Core-Collapse Supernovae (CCSNe)

- Waveform depends on progenitor star.
- Different emission mechanisms.
- **Highly stochastic** waveform.
- Broadband emission.
- Best waveform models from computationally expensive 3D simulations.



Matched filter
not feasible!

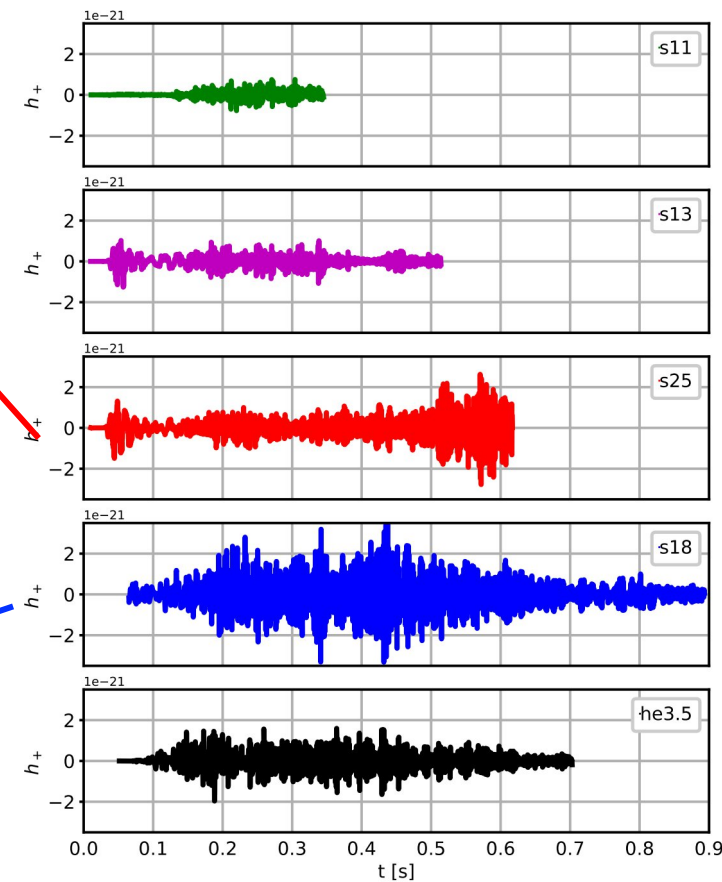
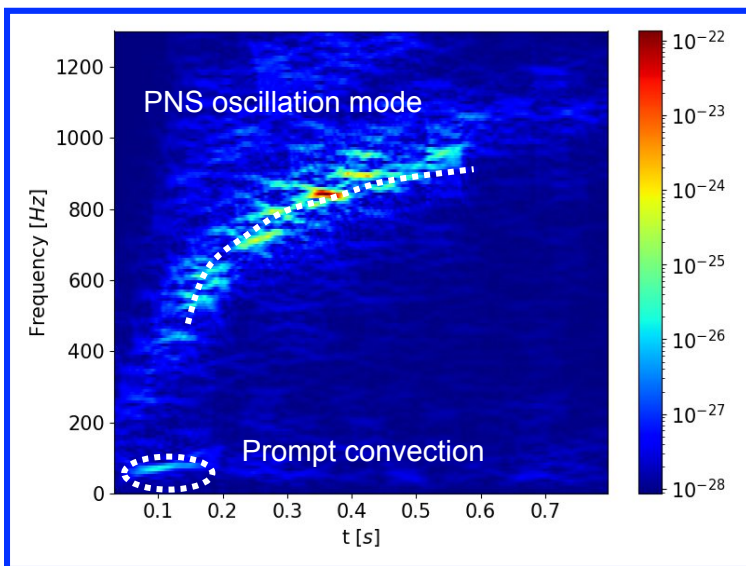
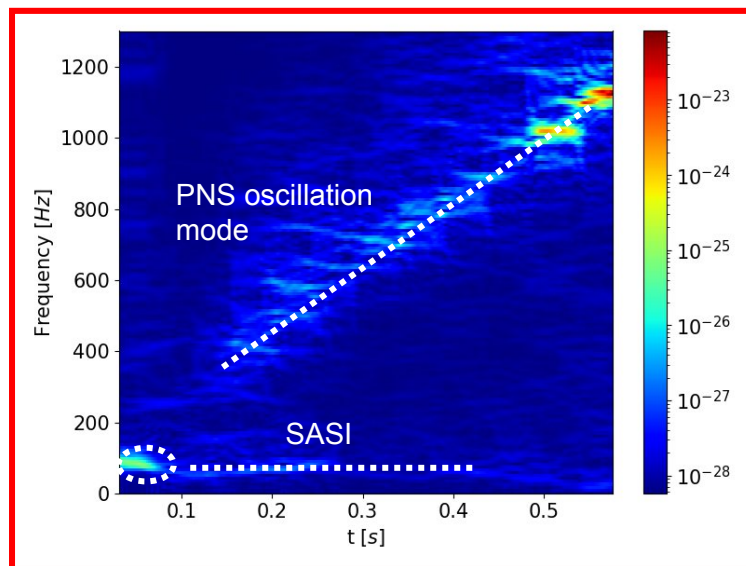


GW emission Process	Potential explosion mechanism		
	MHD mechanism (rapid rotation)	Neutrino mechanism (slow/no rotation)	Acoustic mechanism (slow/no rotation)
Rotating collapse and Bounce	Strong	None/weak	None/weak
3D rotational instabilities	Strong	None	None
Convection & SASI	None/weak	Weak	Weak
PNS g-modes	None/weak	None/weak	Strong

Ott et al. (2017)

CCSN emission

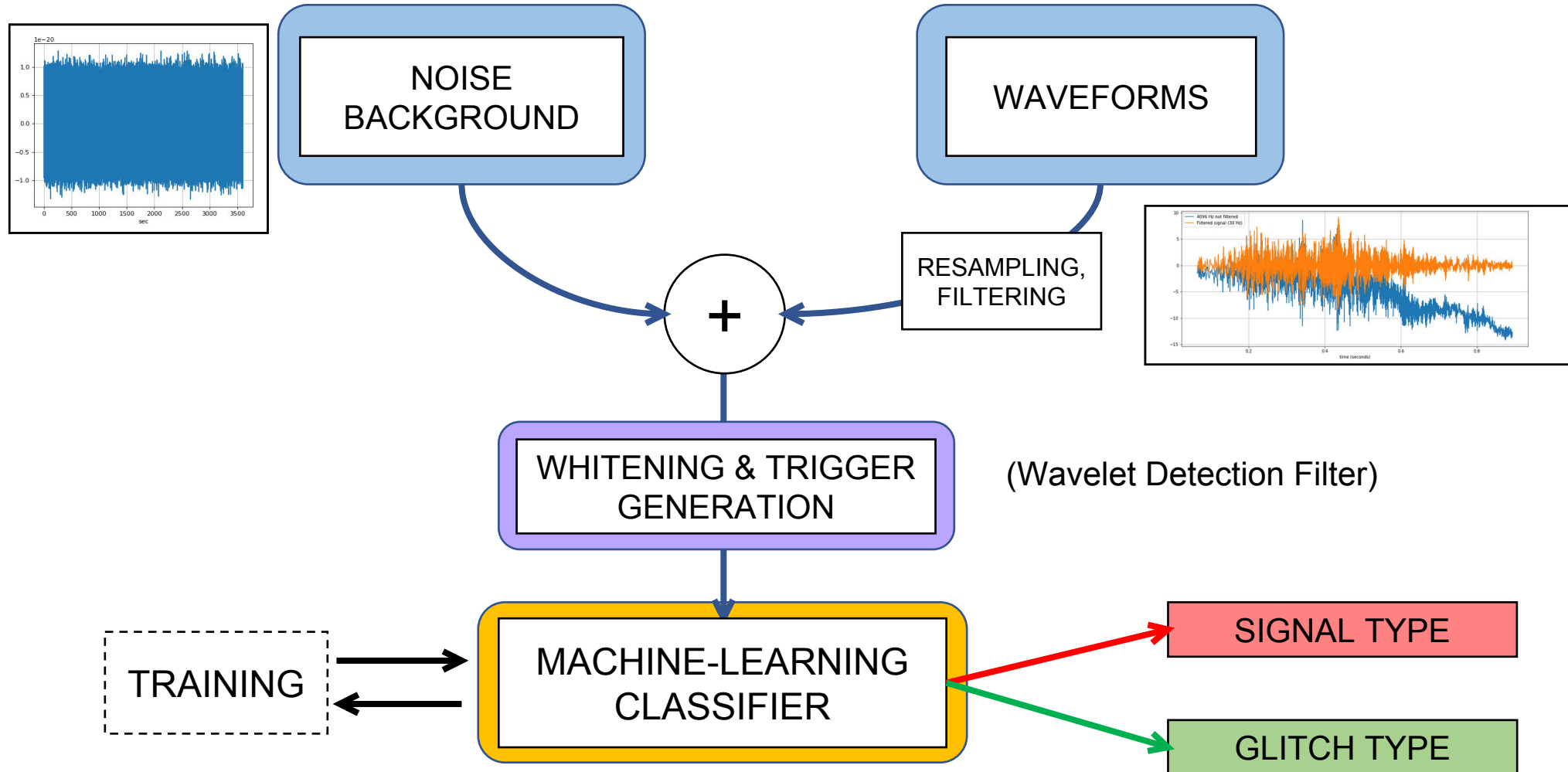
- Final evolutionary stages of **massive stars**, ($\gtrsim 8-9 M_{\odot}$), nuclear burning accumulates iron core mass greater than Chandrasekhar mass limit.
- Multi-messenger emission, **99% energy in neutrinos**, weak GW.
- Rare, optimistically ($\sim 50 \div 100$ yrs in Milky Way).
- Largely stochastic GW emission, candidate for **unmodeled searches**.



less, Cuoco, Morawski, Powell (2020)

Searching CCSNe with ML – The Search And Classification Pipeline

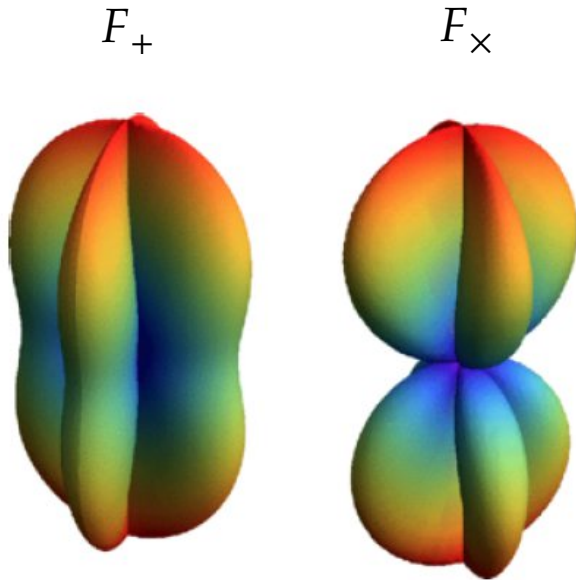
Workflow



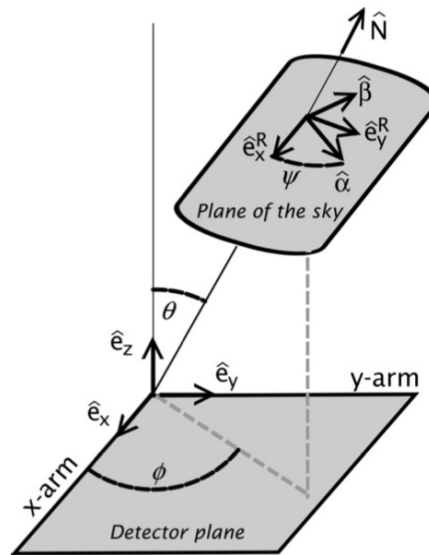
Antenna Pattern

- Short duration, no need to take into account Earth's rotation

$$h(t) = F_+(\alpha, \delta, \lambda, \beta, \chi, \eta) h_+(t) + F_\times(\alpha, \delta, \lambda, \beta, \chi, \eta) h_\times(t)$$



Adhikari (2014)



Schutz (2011)

Virgo



LIGO Hanford



LIGO Livingston



The Wavelet Detection Filter (WDF)

- Python Library for signal processing and transient detection based on wavelet transform.
- Dockers implementation for lightweight use on any platform, including HPC clusters.
- Website: [WDF](#)

References

- E. Cuoco, The Wavelet Detection Filter: a real-time unmodelled search for gravitational wave transients, ranking coincidences with a graph neural network, (2026), in preparation. VIR-0605A-26
- E. Cuoco, M. Razzano, A. Utina, Wavelet-based classification of transient signals for gravitational wave detectors, 26th European Signal Processing Conference (EUSIPCO), 2648–2652 (2018)

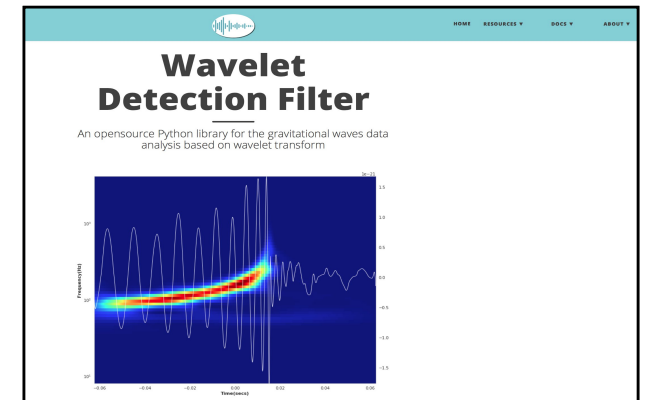
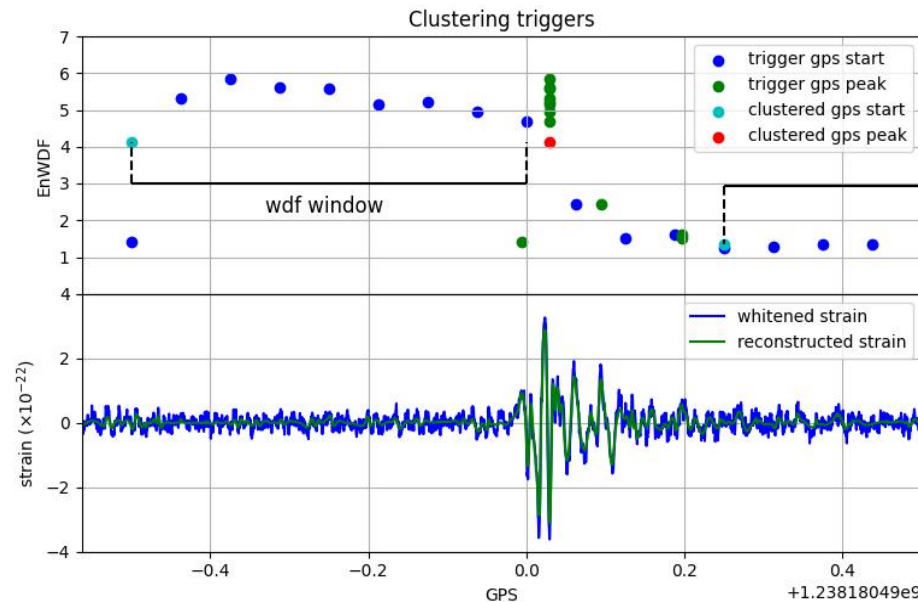
Data (.gwf, .h5 file)

↓
DOWNSAMPLING

↓
WHITENING

↓
WAVELET TRANSFORM

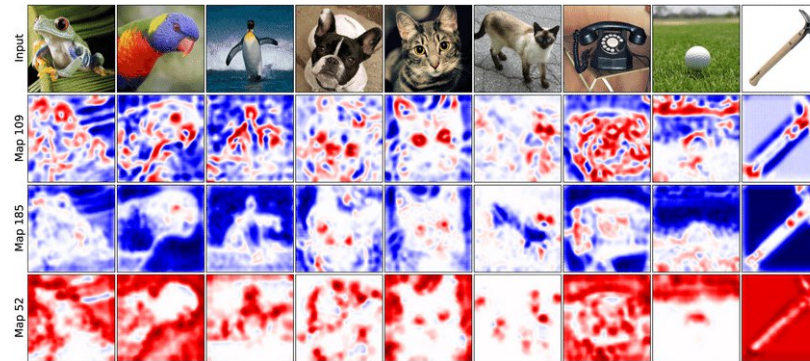
↓
Event trigger (.csv file)



Searching CCSNe with ML - Machine Learning Models

CNNs

- Local pattern recognition
- Automatic feature learning
- Robust to shifts in time/frequency
- Efficient for high-dimensional time-series / spectrogram inputs



0	0	0	0	0	0	0	0
0	60	113	56	139	85	0	
0	73	121	54	84	128	0	
0	131	99	70	129	127	0	
0	80	57	115	69	134	0	
0	104	126	123	95	130	0	
0	0	0	0	0	0	0	

Kernel		
0	-1	0
-1	5	-1
0	-1	0

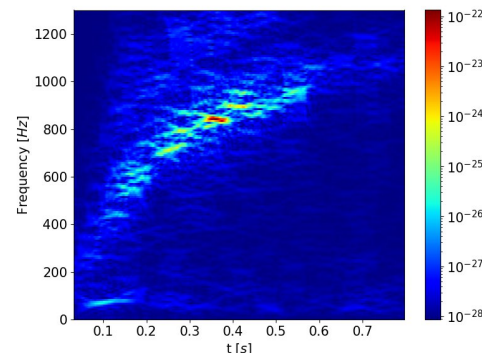
114				

Zintgraf et al. (2017)

We will consider two types of inputs:

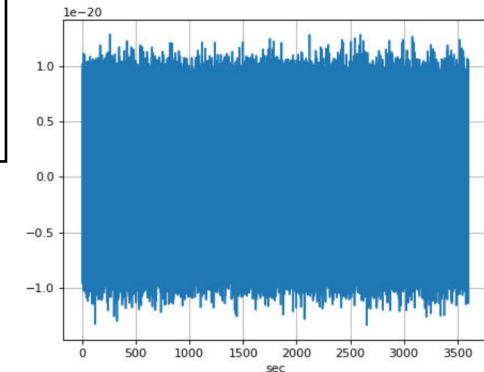
2-D CNN

Time-frequency images



1-D CNN

Whitened time series



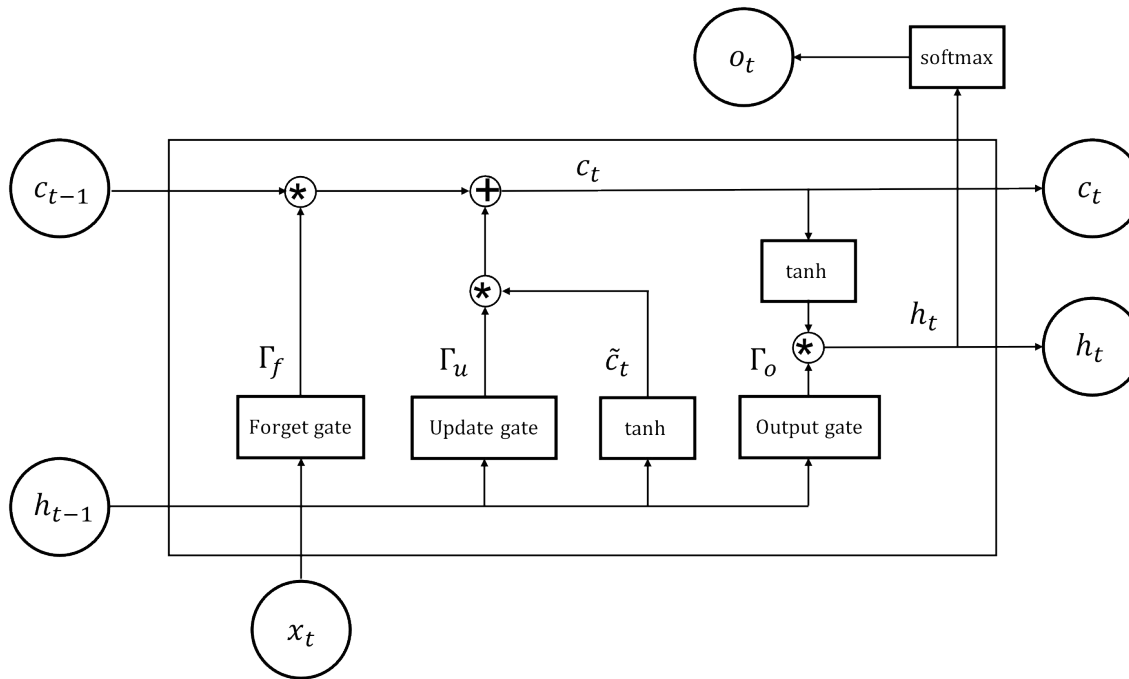
Long Short Term Memory Network (LSTM)

PROS

- **Keeps track of dependencies in time-series** with internal loop updating a “state” cell (Hochreiter and Schmidhuber 1997).
- Avoids the *Vanishing Gradient* problem.

CONS

- Long training times.
- Hyperparameter tuning can be challenging.
- **Decreased performances for long sequences** (above $O(1000)$).



LSTM EQUATIONS

$$\tilde{c}_t = \tanh(W_{ch}h_{t-1} + W_{cx}x_t + b_c)$$

$$\Gamma_f = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f)$$

$$\Gamma_u = \sigma(W_{uh}h_{t-1} + W_{ux}x_t + b_u)$$

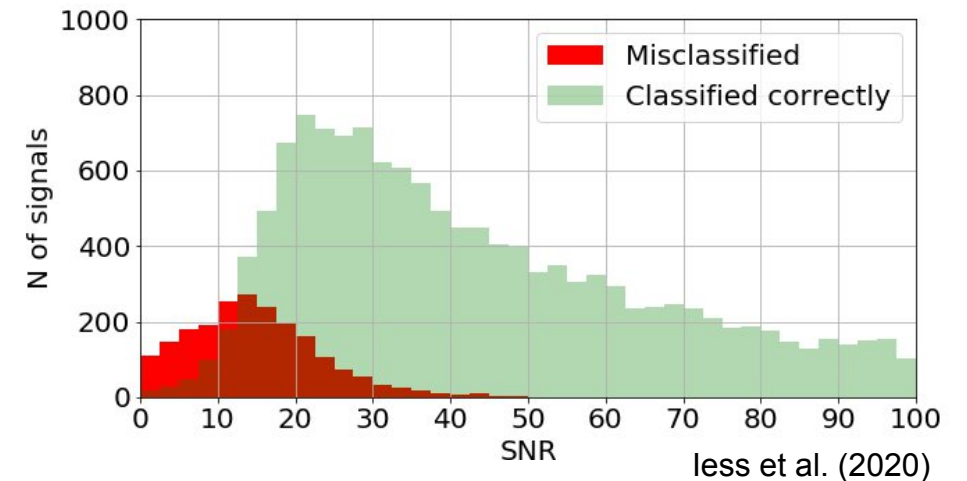
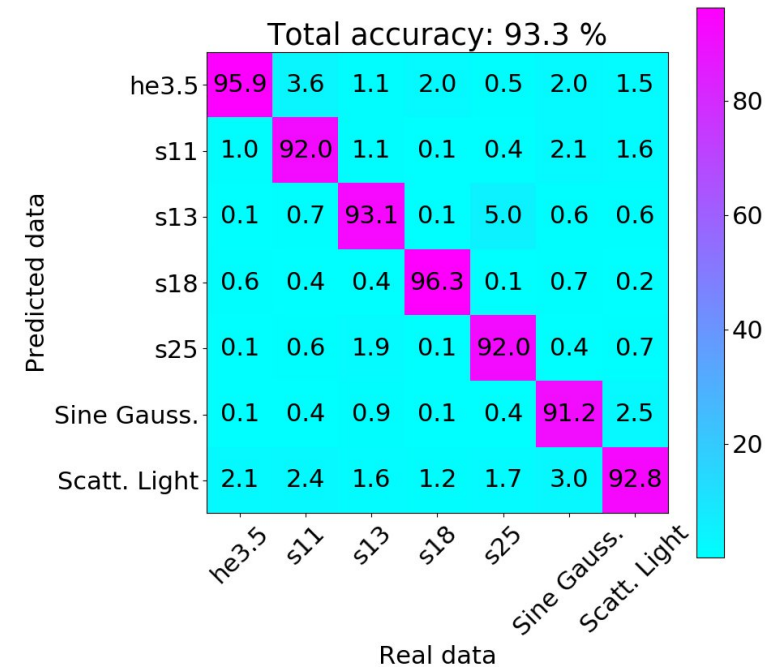
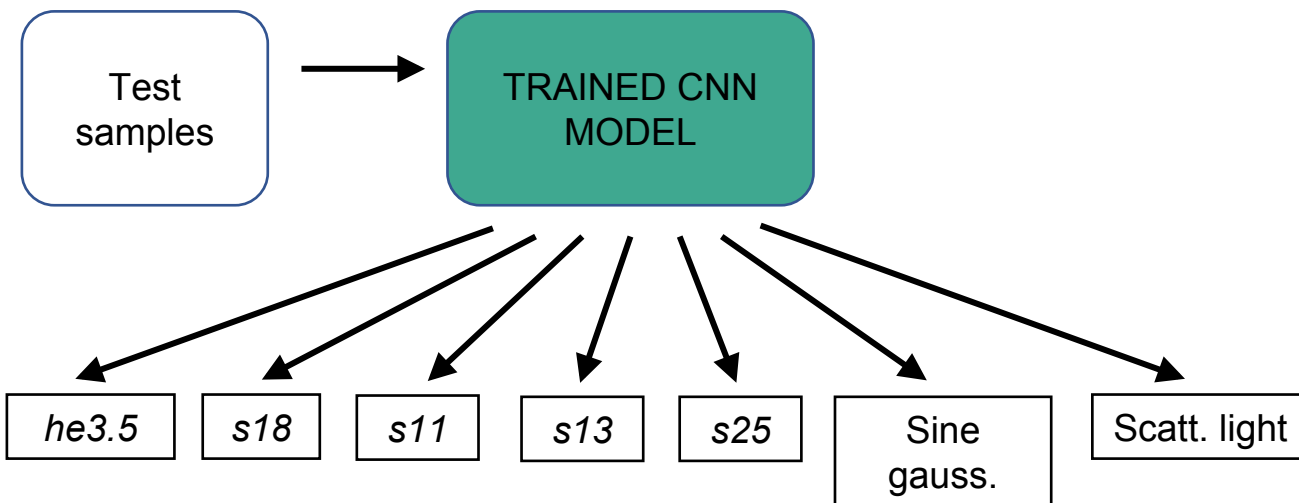
$$\Gamma_o = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o)$$

$$c_t = \Gamma_u * \tilde{c}_t + \Gamma_f * c_{t-1}$$

$$h_t = \Gamma_o * \tanh(c_t)$$

CNN classification on simulated noise

- 5 Neutrino-driven explosion mechanism models
- Simulated sine gaussian and scattered light glitches
- Simulated Virgo and ET background (single ITF)
- ML models: 1-D CNN (timeseries), 2-D CNN (time-frequency)
- Classification: binary, multi-class

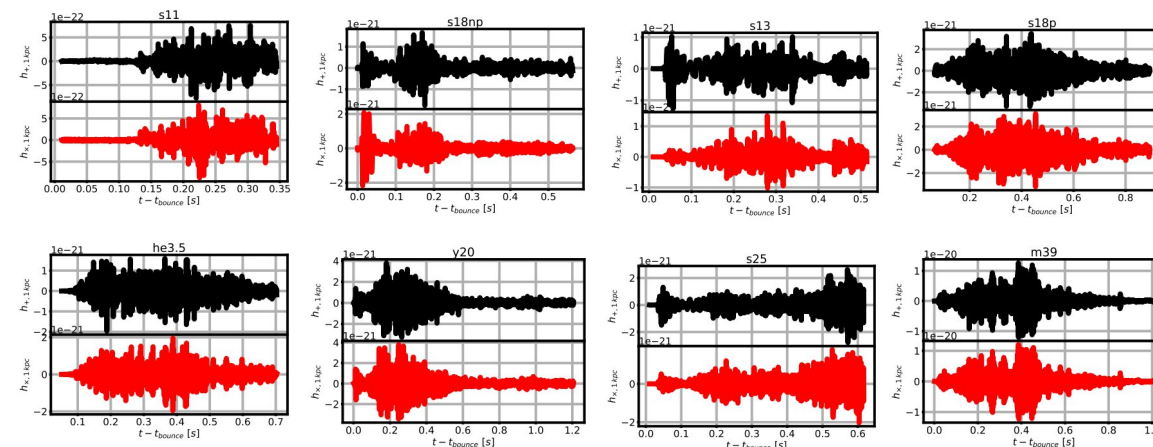
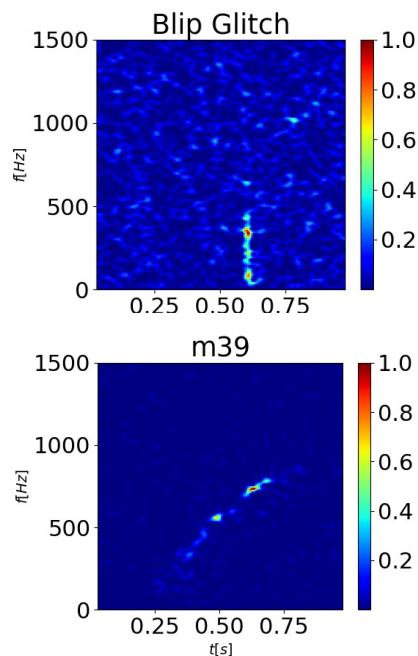
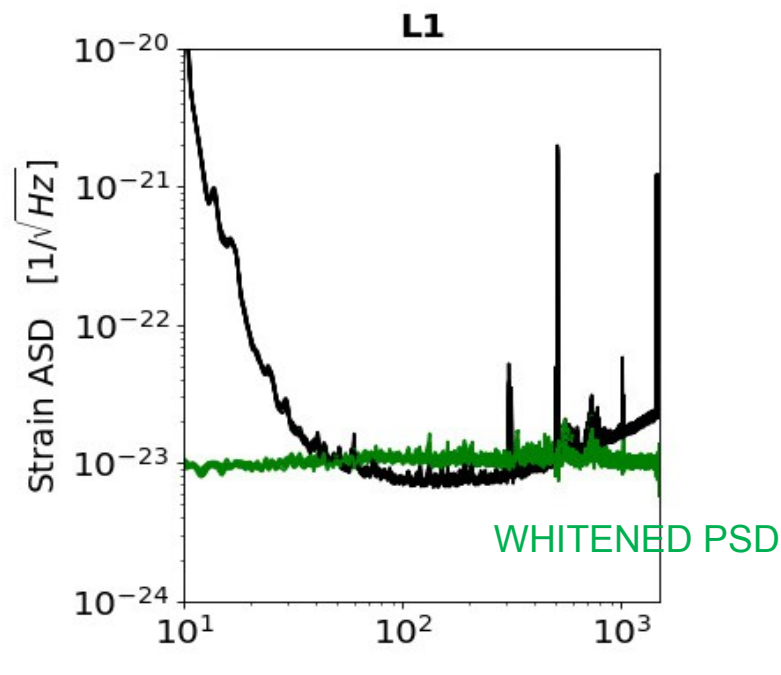


Searching CCSNe with ML – An Analysis on Real Noise

How does a dataset look like?

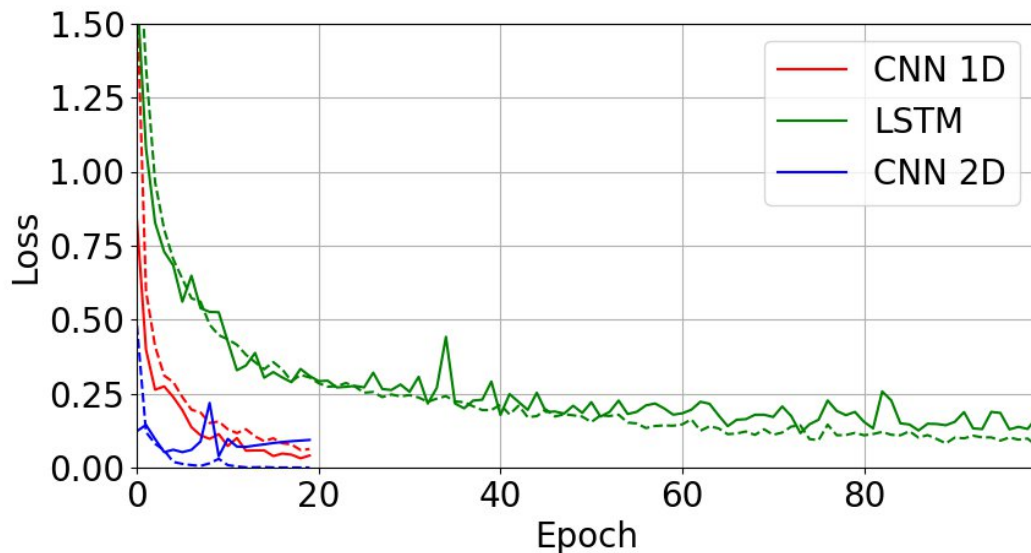
- 44 segments (4096s per segment) from O2 science run
- CCSN Dataset: ~15000 samples at 1 kpc.
- Multiple real glitch families.
- **After WDF, Imbalanced Dataset** due to different model amplitudes.

	Triggers		
Detector	Signal	Noise	Total
Virgo V1	9273	47901	57174
Ligo L1	10480	3810	14290
Ligo H1	10984	4103	15087
L1, H1, V1	5647	675	6322



Comparison of ML model Accuracy (*Single interferometer, V1,H1,L1*)

- **Bi-LSTM**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs
- **1D-CNN**, 4 convolutional layers
- ~2 ms/sample
- Best weights over 20 epochs
- **2D-CNN**, 4 convolutional layers
- ~3 ms/sample
- Best weights over 20 epochs



ITF	ML Model	Waveform Model									Total
		Noise	s11	s18p	s18np	He3.5	m39	y20	s13	s25	
V1	LSTM	49.2	*	3.6	58.4	0.0	89.5	69.9	0.0	89.8	73.7
	CNN 1-D	44.6	*	8.4	10.9	0.0	84.3	73.1	0.0	87.4	68.3
	CNN 2-D	48.6	*	9.6	39.4	3.6	92.3	72.5	0.0	94.6	75.2
L1	LSTM	90.1	0.0	98.2	92.8	85.4	98.7	96.0	87.1	94.8	93.6
	CNN 1-D	99.4	0.0	89.5	95.3	82.2	99.2	98.2	75.5	98.8	95.9
	CNN 2-D	99.8	0.0	99.1	99.3	97.4	100.0	99.7	91.6	99.8	99.3
H1	LSTM	96.2	0.0	95.5	96.8	89.1	99.7	95.9	75.1	97.6	95.4
	CNN 1-D	99.0	0.0	90.1	99.3	91.6	98.4	100.0	80.6	97.4	96.5
	CNN 2-D	99.7	0.0	99.6	99.8	96.8	99.7	99.8	96.8	99.2	99.1

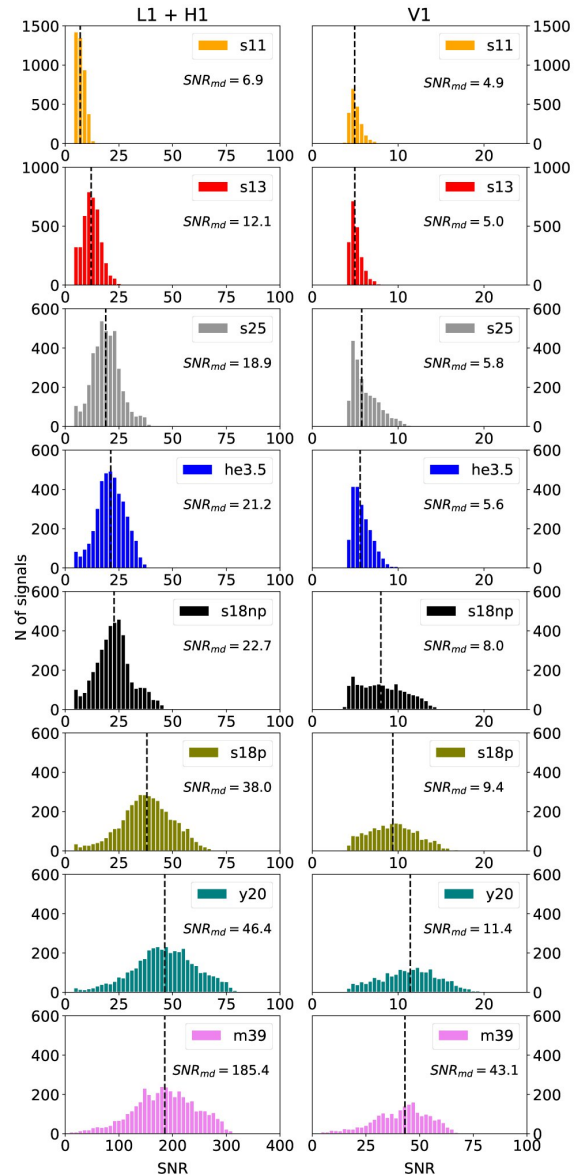
TRUE POSITIVE
RATE

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

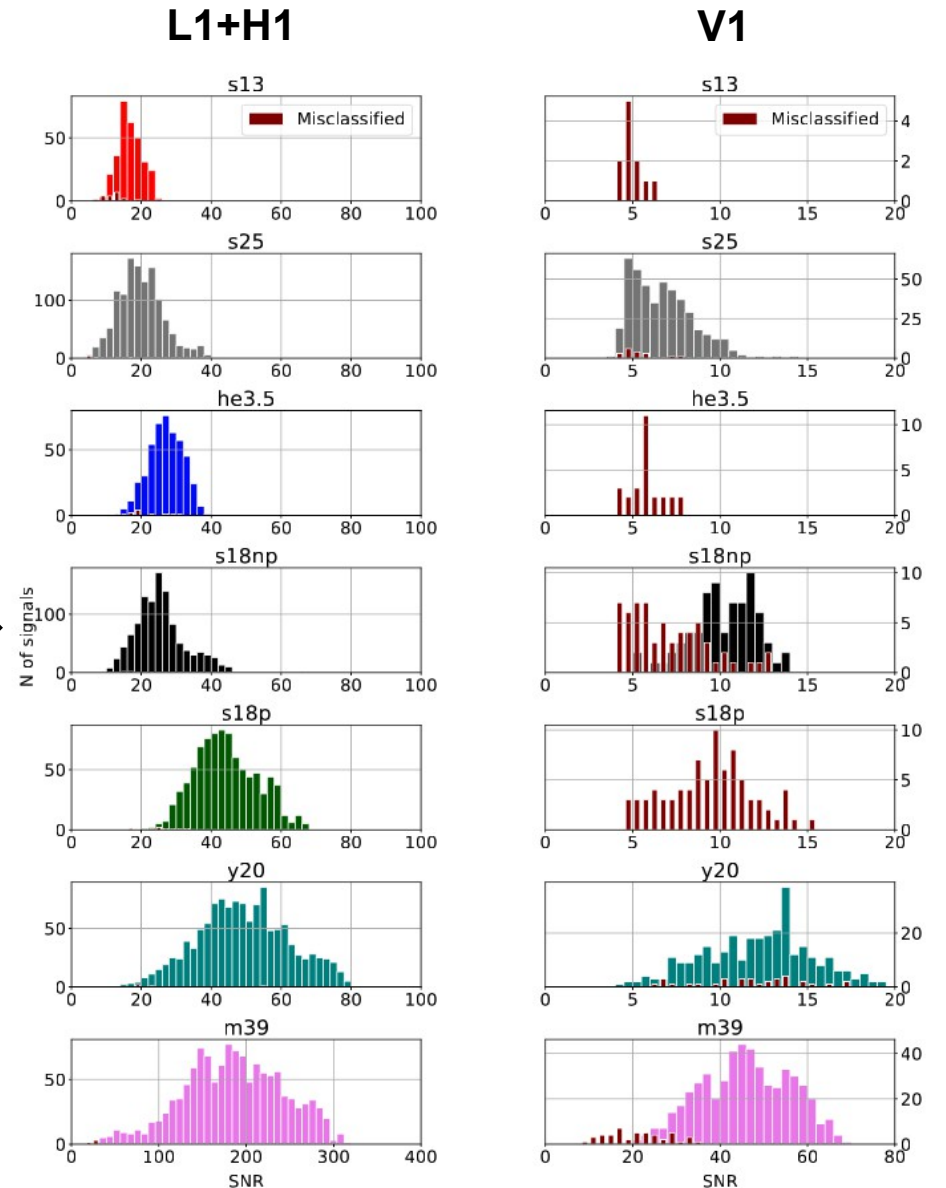
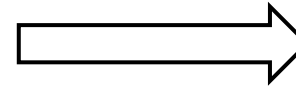
Searching CCSNe with ML - An Analysis on Real Noise

Search and classification for various CCSN models

less, Cuoco, Morawski, Nicolaou, Lahav (2022)

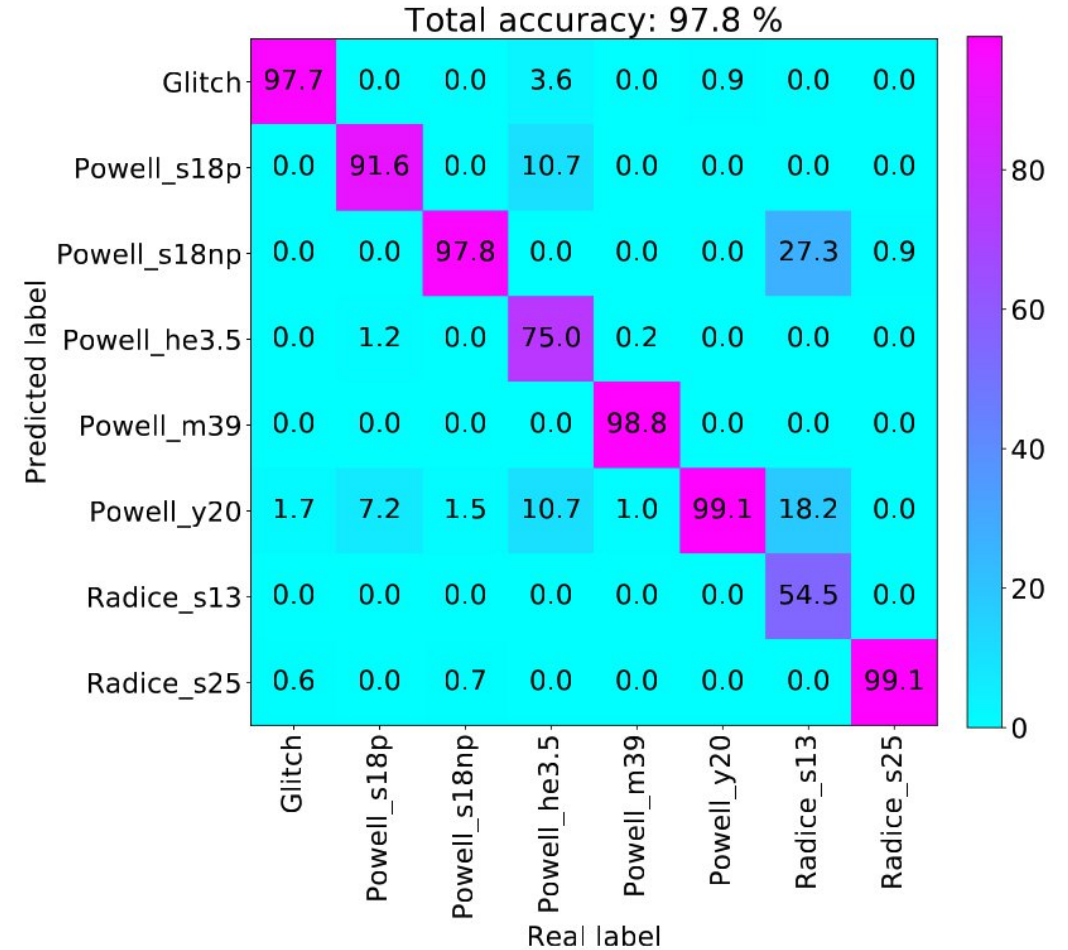
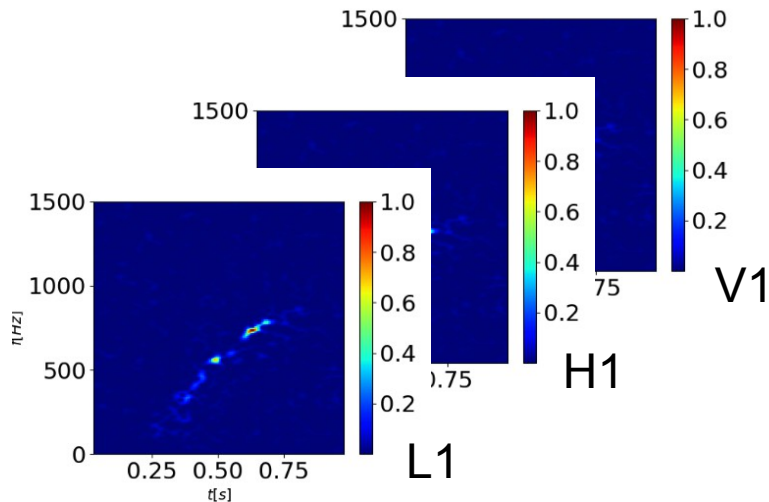


Multi-model
classification



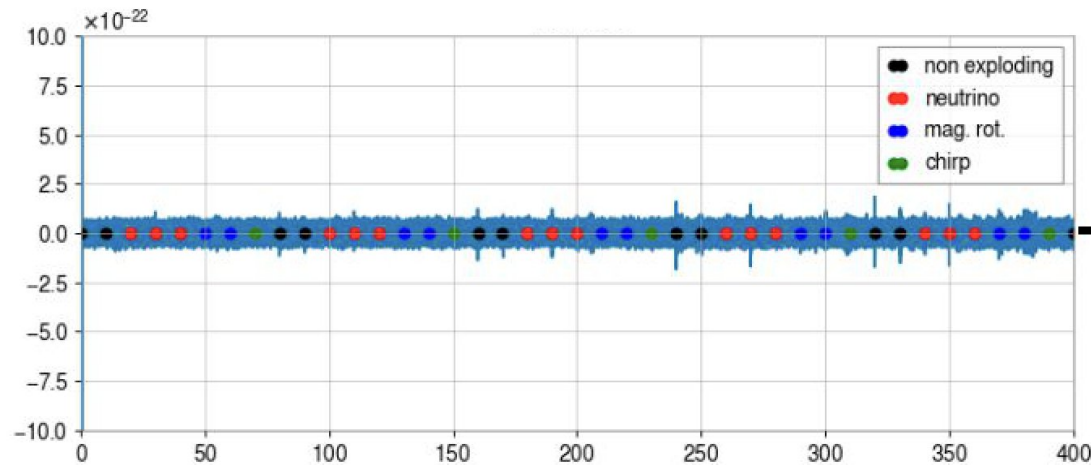
Classification with 3 ITF input

- Using triple coincident triggers you can classify signals based on 3 ITF inputs
- Merged-model by averaging 1-D CNN, 2-D CNN and LSTM.



less, Cuoco, Morawski, Nicolaou, Lahav (2022)

Classifying the CCSN explosion mechanism



CLASSIFIER

NON EXPLODING

NEUTRINO

MAGNETOROTATIONAL

OTHER BURST SIGNAL

*TIME
SERIES*

*RECURRENT, 1-D CNN, TCNN,
state of the art adaptations*

*TIME
FREQUENCY*

*2-D CNN and modern state of
the art adaptations*

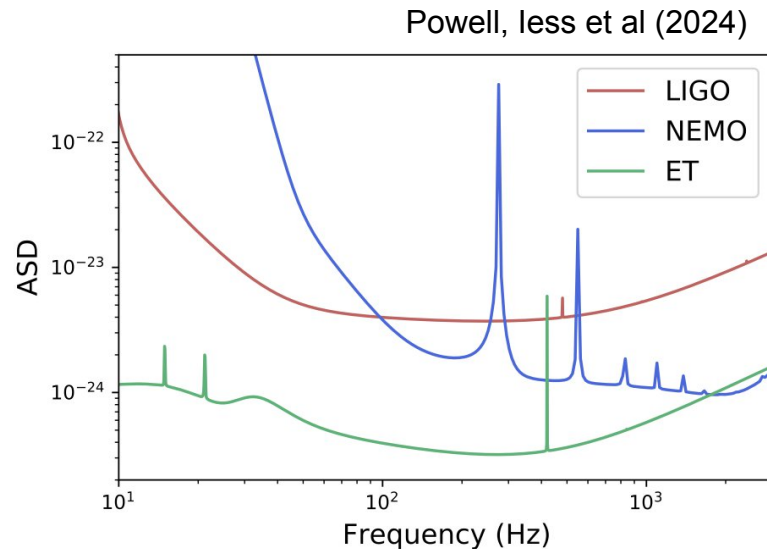
*DERIVED PHYSICAL
QUANTITIES
(duration, peak frequency,
peak amplitude)*

*Genetic Programming, Decision
Trees, etc*

Searching CCSNe with ML - Classifying the Explosion Mechanisms

Explosion mechanism?

- Tested different ML models: **2-D CNN**, Dictionary Learning, PCA+Bayesian Model selection
- 3 different ITF backgrounds
- Good accuracy in classifying CCSN
- Not straightforward to determine the explosion mechanism



LIGO

SMEE Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	58.0	31.2	8.0	2.8
neutrino	18.5	75.4	3.0	3.1
mag-rot	7.7	16.0	76.3	0.0
chirplet	0.0	0.0	0.0	100.0

DL Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	88.0	12.0	0.0	0.0
neutrino	24.0	72.0	2.0	1.0
mag-rot	8.0	8.0	52.0	33.0
chirplet	0.0	0.0	0.0	100.0

CNN Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	41.3	50.0	8.7	0.0
neutrino	24.0	28.0	48.0	0.0
mag-rot	12.0	0.0	88.0	0.0
chirplet	0.0	0.0	0.0	100.0

ET

SMEE Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	60.2	31.3	7.4	1.1
neutrino	17.5	75.8	4.3	2.4
mag-rot	3.8	10.7	80.0	5.7
chirplet	0.0	0.0	0.0	100.0

DL Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	99.0	0.0	1.0	0.0
neutrino	8.0	61.0	26.0	5.0
mag-rot	9.0	49.0	42.0	0.0
chirplet	0.0	41.0	0.0	59.0

CNN Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	20.0	40.0	40.0	0.0
neutrino	3.0	64.0	33.0	0.0
mag-rot	15.0	5.0	80.0	0.0
chirplet	0.0	0.0	0.0	100.0

NEMO

SMEE Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	51.0	33.7	13.0	2.3
neutrino	20.3	73.2	3.6	2.9
mag-rot	4.5	13.6	77.4	4.5
chirplet	0.0	0.0	0.0	100.0

DL Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	84.0	4.0	12.0	0.0
neutrino	1.0	73.0	12.0	13.0
mag-rot	3.0	4.0	47.0	46.0
chirplet	0.0	26.0	0.0	74.0

CNN Classification Results

	no-expl	neutrino	mag-rot	chirplet
no-expl	34.0	0.0	66.0	0.0
neutrino	49.3	14.5	36.2	0.0
mag-rot	5.4	1.1	93.5	0.0
chirplet	0.0	0.0	0.0	100.0

ML methods used in literature for CCSN detection and classification

At the moment, unmodelled coherent excess-power searches (e.g. cWB, X-pipeline..) are the state-of-the-art pipelines for CCSN detection, but a large number of ML methods have been tested:

- **Dictionary learning / sparse coding** - Llorens-Monteagudo et al. 2022
- **PCA + Bayesian model selection** - Powell et al. 2024
- **DNN & classical ML regression** - Moreno et al. 2023; Franco-Hernández et al. 2025
- **Autoencoders & anomaly detection** - Raikman et al. 2024
- **Self-supervised learning** - PRD 111, 063520 (2025)
- **Contrastive learning** - Wang et al. 2026; Sun et al. 2026

Interesting to investigate for 3rd generation ITFs!

Thank You!