Neural Networks for gravitational wave detection

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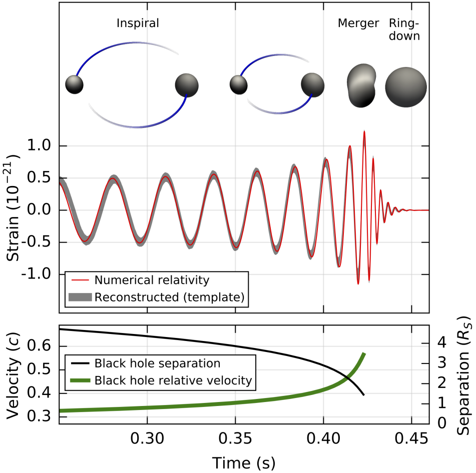
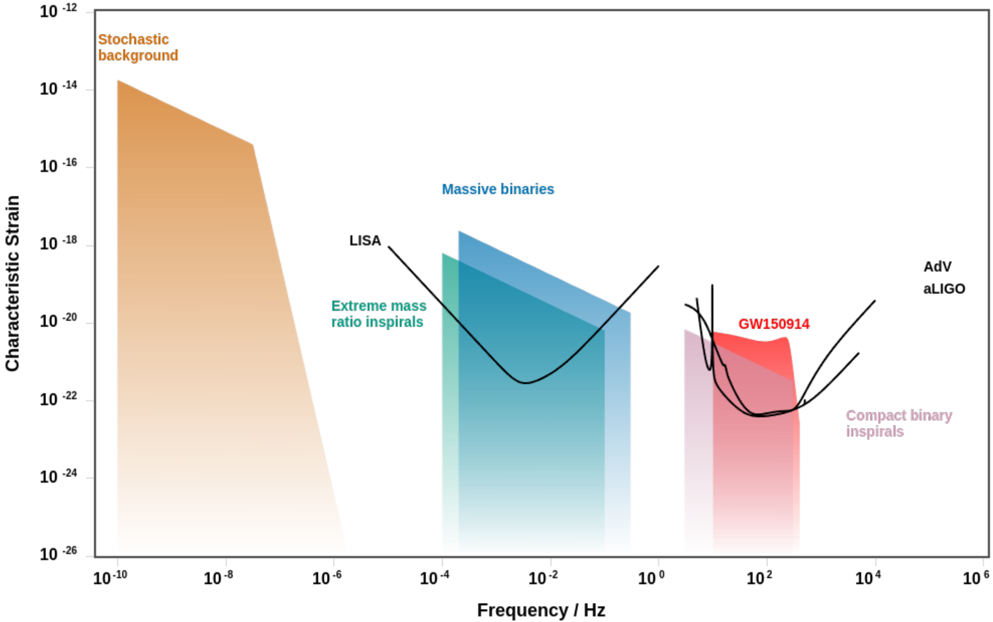
Gravitational waves

- disturbances in spacetime geometry
- sources: accelerating massive objects
- most frequent: BBH mergers
- crucial for cosmology, SMBH/AGN formation etc.



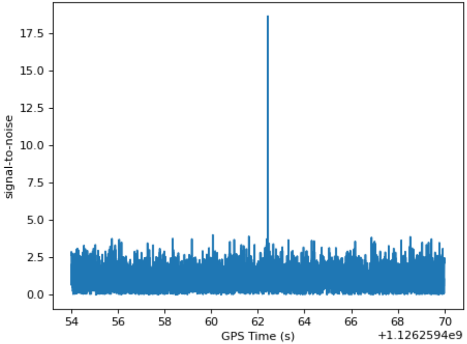
source: [A+16]



source: gwplotter.com

Gravitational wave searches

- binary black holes
- standard: matched filtering
  - dense template bank
  - slide templates over signal
  - non-optimal
  - computationally demanding
- complicated noise characteristic, glitches



source: PyCBC

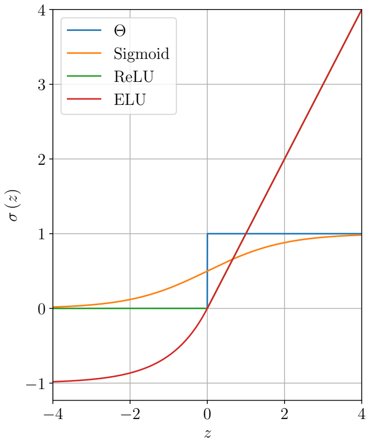
Neural Networks

artificial neurons

$$f(\mathbf{x}) = \sigma\left(\sum_j w_j x_j + b\right)$$

activation function

$$\mathrm{ELU}(z) = \begin{cases} \exp(z) - 1 & \text{if } z < 0 \\ z & \text{if } z \geq 0 \end{cases}$$



Neural Networks

organized in layers:

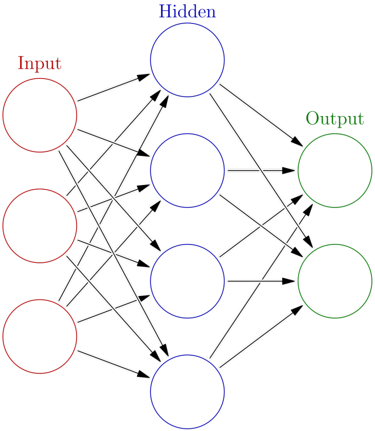
- matrix multiplication
- element-wise non-linear functions

training:

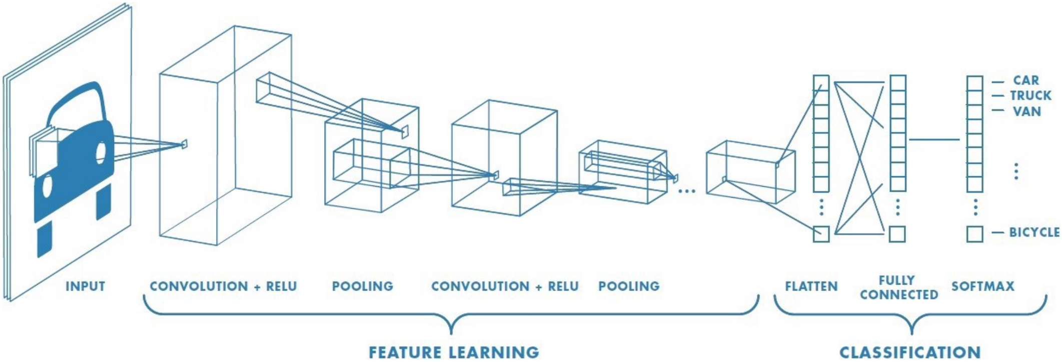
- dataset
- loss function (BCE)

$$\mathrm{BCE}\left(\bar{\mathbf{Y}}, \mathbf{Y}\right) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{2}\log\left(\bar{Y}_{ij}\right) Y_{ij}$$

- GD-based optimizer



Convolutional Neural Networks



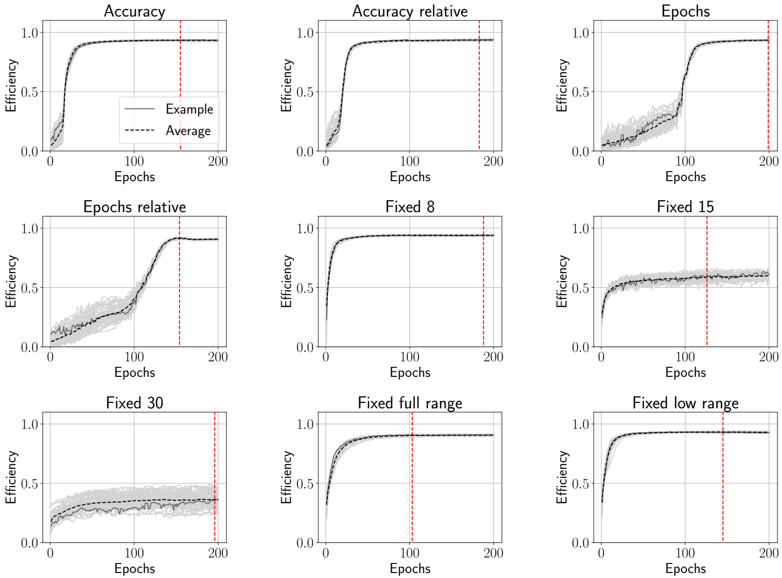
source: MathWorks

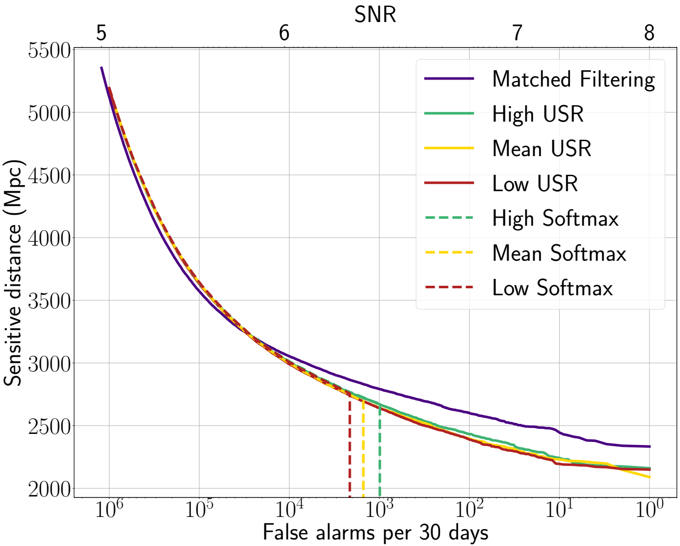
Single-detector searches

- [SZN+22, SZN+21]
- 1 second at 2048 $\mathrm{Hz} \to [0, 1]^2$
- dataset
  - Gaussian noise
  - EOB injections
  - 50% with injection $\mapsto (1, 0)$
  - 50% pure noise $\mapsto (0, 1)$

layer type	output shape
BatchNorm	1×2048
2× Convolution + ELU	32×2034
MaxPool	32×508
2× Convolution + ELU	16×478
MaxPool	16×159
2× Convolution + ELU	16×97
MaxPool	16×48
Flatten	768
Dense + Dropout + ELU	64
Dense + Dropout + ELU	64
Dense + Softmax	2

Training strategies




SNR
5
6
7
8
5500
5000
4500
4000
3500
3000
2500
2000
Sensitive distance (Mpc)
10^6
10^5
10^4
10^3
10^2
10^1
10^0
False alarms per 30 days
Matched Filtering
High USR
Mean USR
Low USR
High Softmax
Mean Softmax
Low Softmax

MLGWSC-1

- mock data challenge [SZN+23, SZ21]
- BBH signals in long segments from 2 detectors
- 4 test datasets, progressive complexity
- 4 ML + 2 traditional contributions

Test data

- 1-month strain in H1 and L1
- `IMRPhenomXPHM` injections

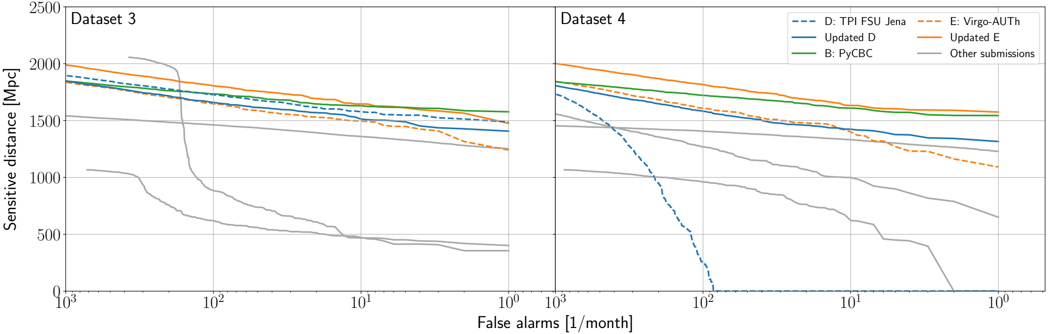
DS	injections			noise	
	spins	modes	masses	noise	PSD
1	zero	$l = 2,\ m = \pm 2$	$10 - 50 M_\odot$	Gaussian	fixed
2	aligned	$l = 2,\ m = \pm 2$	$7 - 50 M_\odot$	Gaussian	O3a
3	generic	all implemented[1]	$7 - 50 M_\odot$	Gaussian	O3a
4	generic	all implemented	$7 - 50 M_\odot$	real O3a noise	

[1] (2, 2), (2, -2), (2, 1), (2, -1), (3, 3), (3, -3), (3, 2), (3, -2), (4, 4), (4, -4)

TPI FSU Jena submission

- [ZBO24, SZN+22, Zel23]
- 1 second segments at 2048 Hz
- real noise from O3a
- waveforms of DS 3 and 4

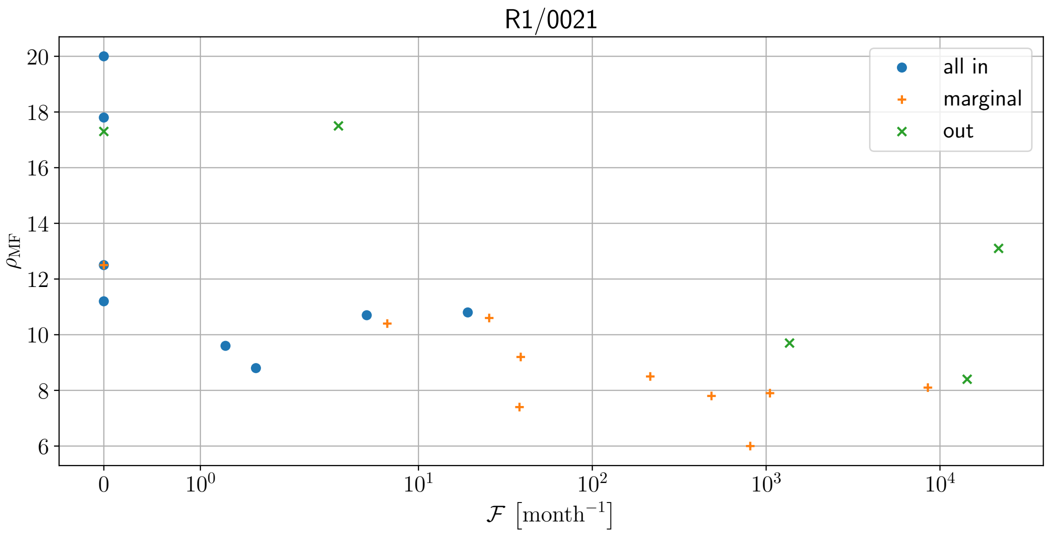
layer type	output shape
Input	2×2048
$4\times$ (Convolution + ELU)	16×1954
MaxPool	16×488
$4\times$ (Convolution + ELU)	32×442
MaxPool	32×147
$4\times$ (Convolution + ELU)	64×117
MaxPool	64×58
Flatten	3712
Dense + Dropout + ELU	128
Dense + Dropout + ELU	128
Dense + (Softmax)	2



Dataset 3
Dataset 4
D: TPI FSU Jena
Updated D
B: PyCBC
E: Virgo-AUTh
Updated E
Other submissions
Sensitive distance [Mpc]
False alarms [1/month]
2500
2000
1500
1000
500
0
10^3
10^2
10^1
10^0

Application to O3b data

- 1 November 2019 - 27 March 2020: $\sim$ 147 days
- high data quality in both L1 and H1: $\sim$ 95 days
- cropped GWTC-3 [A^+21]: 31 confident events
- 90% intervals: $m_i \in [10M_\odot, 50M_\odot]$?
  - all in: found 8/9
  - marginal: found 10/11
  - out: found 5/11


R1/0021
all in
marginal
out
ρ_{MF}
20
18
16
14
12
10
8
6
0
10^0
10^1
10^2
10^3
10^4
$\mathcal{F}$ [month^{-1}]

Conclusions

- ML-based searches competitive on Gaussian noise
- handling real noise not fully understood
- speed

Outlook for Earth-based searches

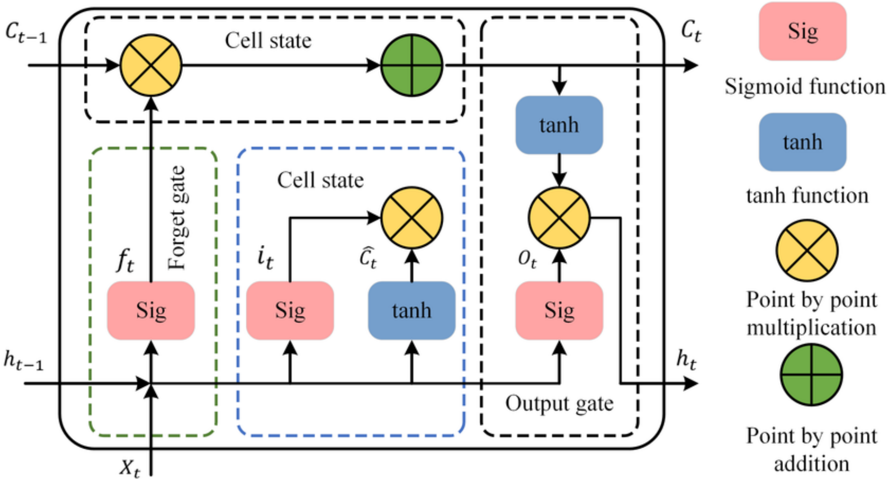
- hybrid ML/MF pipelines
- curriculum learning
- longer signals (BNS...)

Extension to LISA data

Problems:

- longer signals
    - computational complexity
    - motion of detector $\rightarrow$ larger effective parameter space
- overlap
    - need for full separation of signals

Recurrent architecture: LSTM



source: [RXH+24]

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