LISA Data Analysis
A Deep Learning Approach

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ISS-Science Group (ISS-Sci)

- Data analysis using NNs implemented on different hardware platforms
- Estimating the merging rate of BHs
- Waveform generation
- Building of GW source catalogues
- Multi messenger analysis of astrophysical sources
- Deep learning based low-latency alert pipeline for the detection and characterisation of GW from LISA data

- Develop and test different types of neural network models, configurations and pre-processing approaches.

OUR APPROACH (so far):

Multilayer Perceptron (MLP)

Convolutional (CNN)

- Develop and test different types of neural network models, configurations and pre-processing approaches.
  - Generate simplified data set

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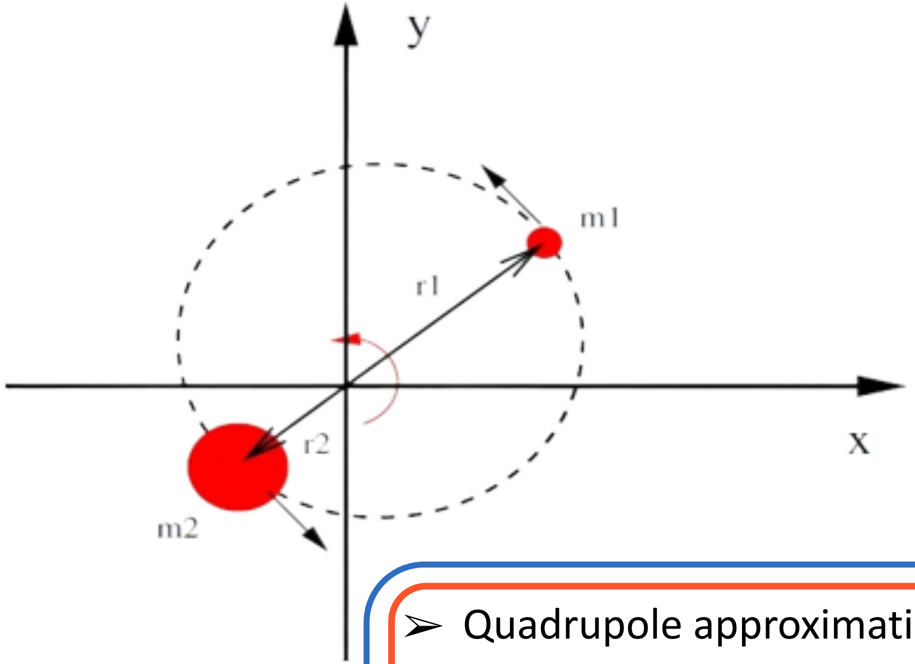
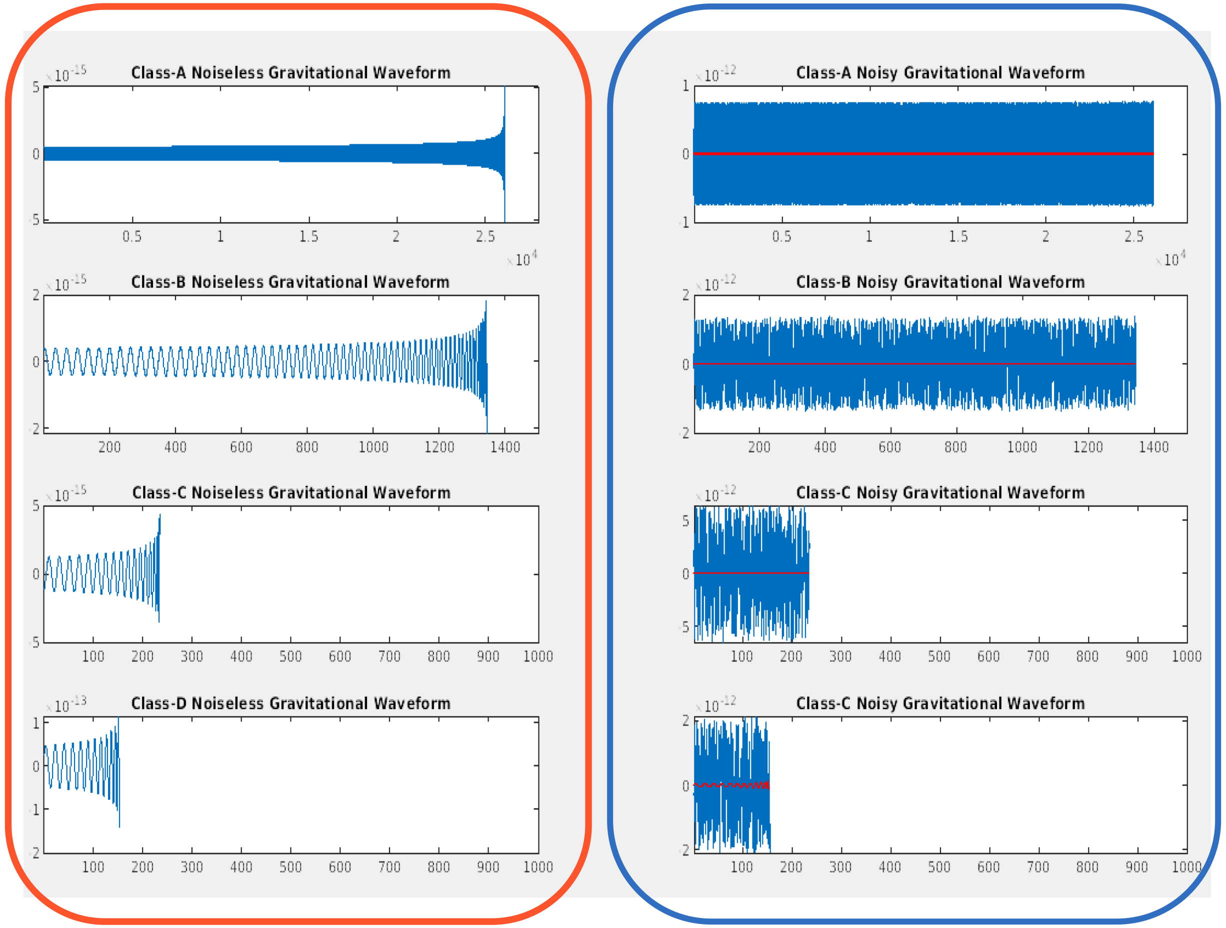


- Quadrupole approximation
- Non-spinning point-masses
- Circular orbits

- **Additive Gaussian Random Noise**



https://www.mathworks.com/matlabcentral/fileexchange/116105-quick-gravitational-wave-data-generation

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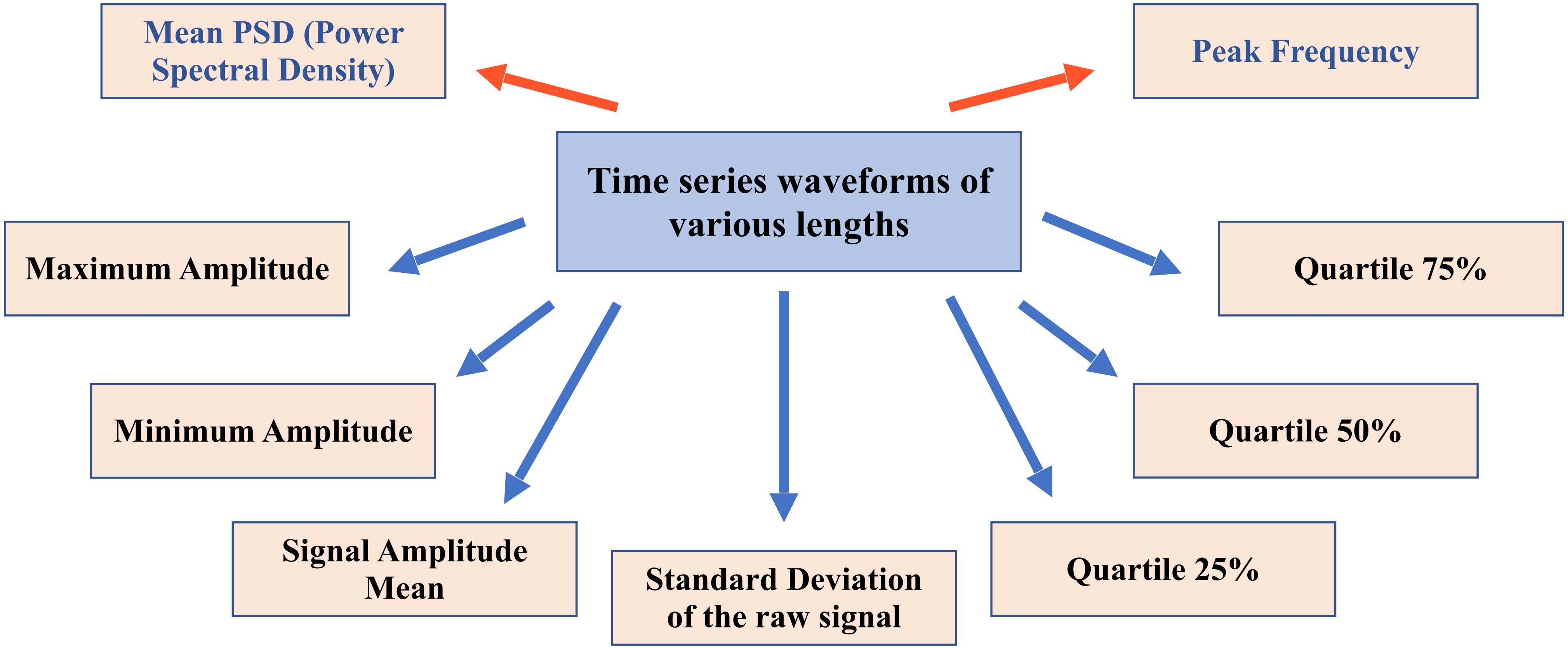
- Test the models with the simplified data set.

Multilayer Perceptron (MLP)

Convolutional (CNN)



Multilayer Perceptron (MLP)

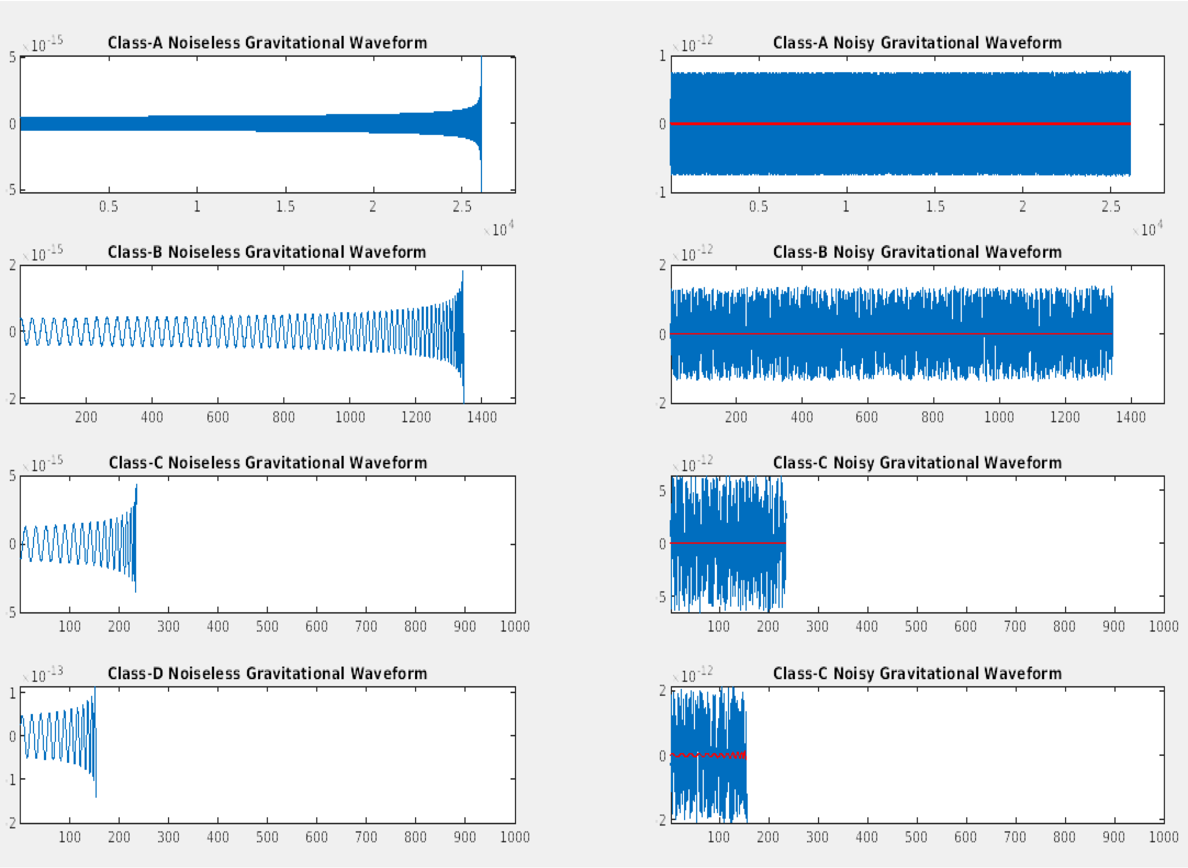
Convolutional (CNN)

The GW Dataset
1.960.959 total samples

out of which:

800.000 (40%): **train**

1.160.959 (60%): **inference**



5 x Classes of adjecent mass ratios:

A (q = 1 – 300)

B (q = 301 – 749)

C (q = 750 – 1200)

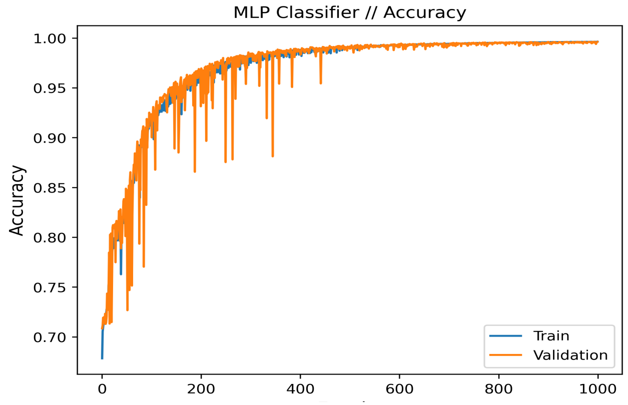
D (q = 1201 – 1501)

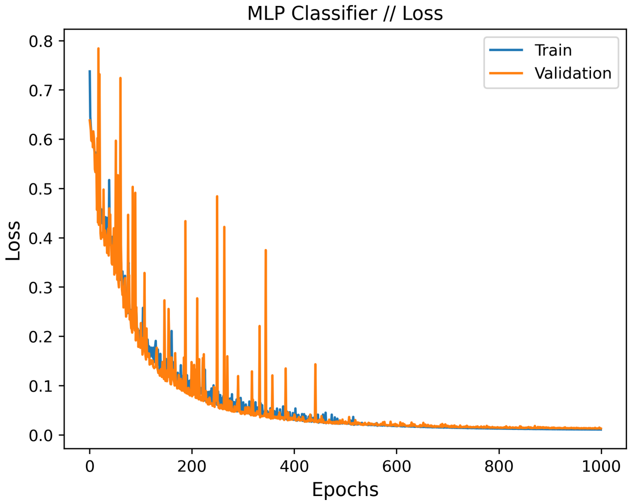
N (Noise)

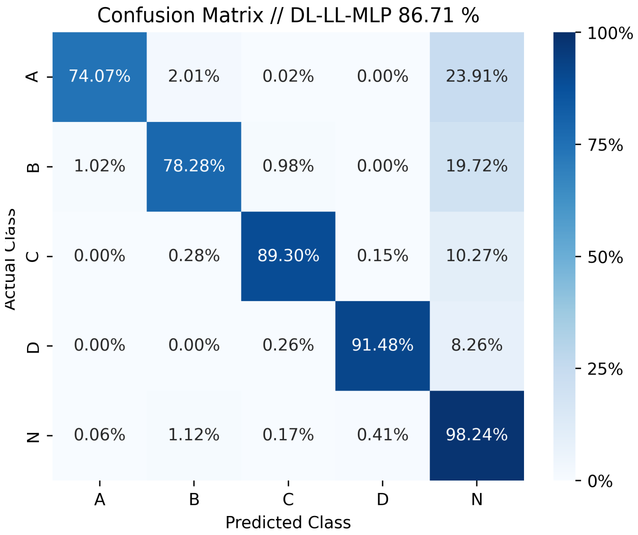
Min-Max Feature Standardization:

$$X = \frac{features - min}{max - min}$$

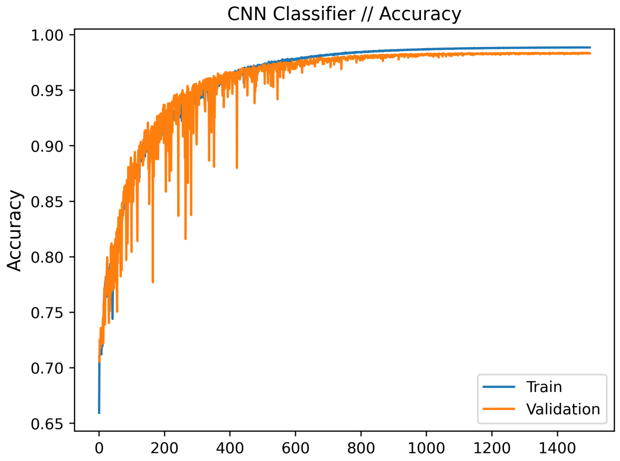
Multilayer Perceptron (MLP)

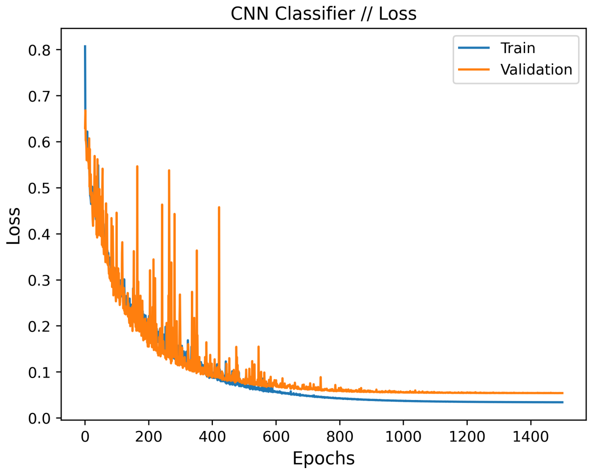


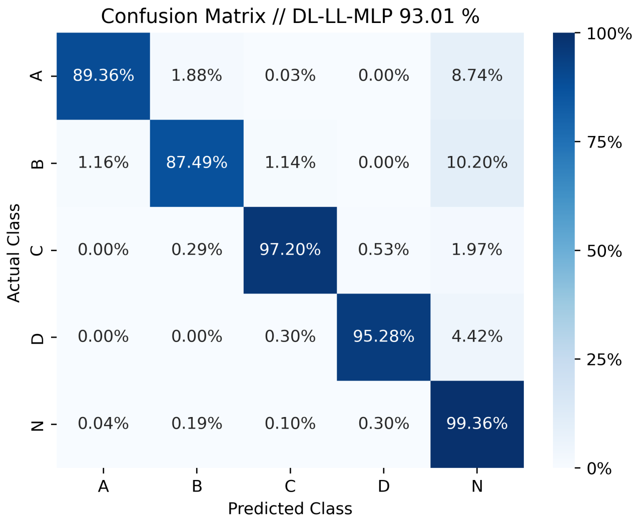




Convolutional (CNN)







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- ➢ Develop and test different types of neural network models, configurations and pre-processing approaches.
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- ➢ Test the models with the simplified data set.

- ➢ Perform a benchmarking on different platforms (assuming the same configuration).

Multilayer Perceptron (MLP)

Convolutional (CNN)

Credits: V.A. Bâsceanu

Models	Platform	Memory	Cores	FP32	Lib	Training Time	Inference Time	Inference Accuracy
DL-LL CNN	Nvidia RTX 3050 Ti	GDDR6/ 4Gb	RT 20/ Tensor 80	5.299 TFLOPS	Keras/ Tensorflow	87 min 10.15 sec	2 min 45.92 sec	96.16 %
DL-LL CNN	Nvidia Tesla T4	GDDR6/ 16Gb	RT 40/ Tensor 320	8.141 TFLOPS	Keras/ Tensorflow	*379 min 15 sec	1 min 29.4 sec	96.40 %
DL-LL CNN	Apple M1 Neural Engine	LPDDR4X/ 16Gb	Neural Engine 16 Cores	2.6 TFLOPS	Keras/ Tensorflow	1099 min 10.20 sec	2 min 55.15 sec	95.27 %
DL-LL CNN	AMD EPYC 7551P	DDR4/ 128Gb	32 Cores/ 64 Threads	---	Keras/ Tensorflow	680 min 20.40 sec	1 min 51.2 sec	95.61 %
DL-LL MLP	Nvidia RTX 3050 Ti	GDDR6/ 4Gb	RT 20/ Tensor 80	5.299 TFLOPS	Keras/ Tensorflow	57 min 29.51 sec	2 min 25.77 sec	83.76%
DL-LL MLP	Nvidia Tesla T4	GDDR6/ 16Gb	RT 40/ Tensor 320	8.141 TFLOPS	Keras/ Tensorflow	*369 min 45.03 sec	42.03 sec	84.27 %
DL-LL MLP	Apple M1 Neural Engine	LPDDR4X/ 16Gb	Neural Engine 16 Cores	2.6 TFLOPS	Keras/ Tensorflow	239 min 49.85 sec	1 min 31.34 sec	84.61 %
DL-LL MLP	AMD EPYC 7551P	DDR4/ 128Gb	32 Cores/ 64 Threads	---	Keras/ Tensorflow	381 min 21.59 sec	2 min 34.22 sec	82.54 %

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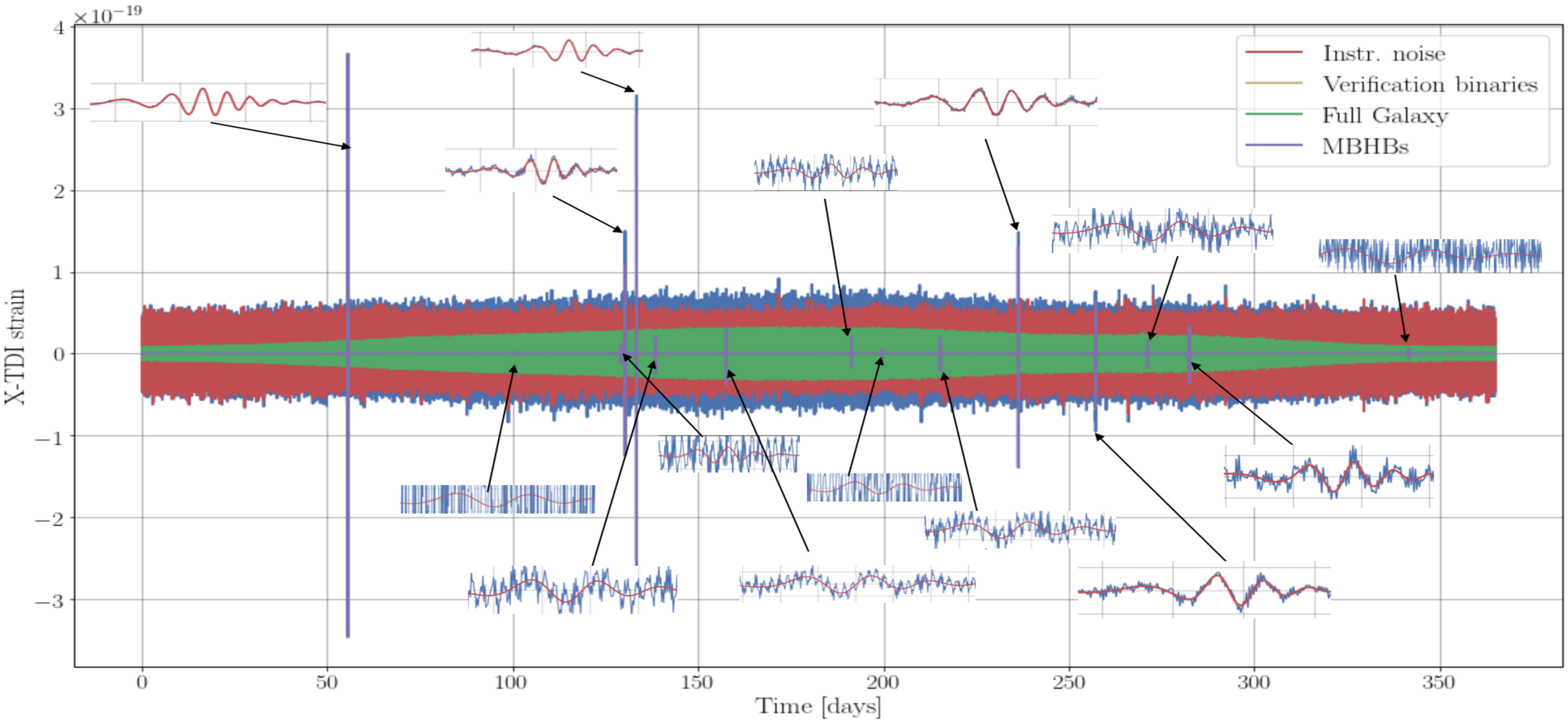
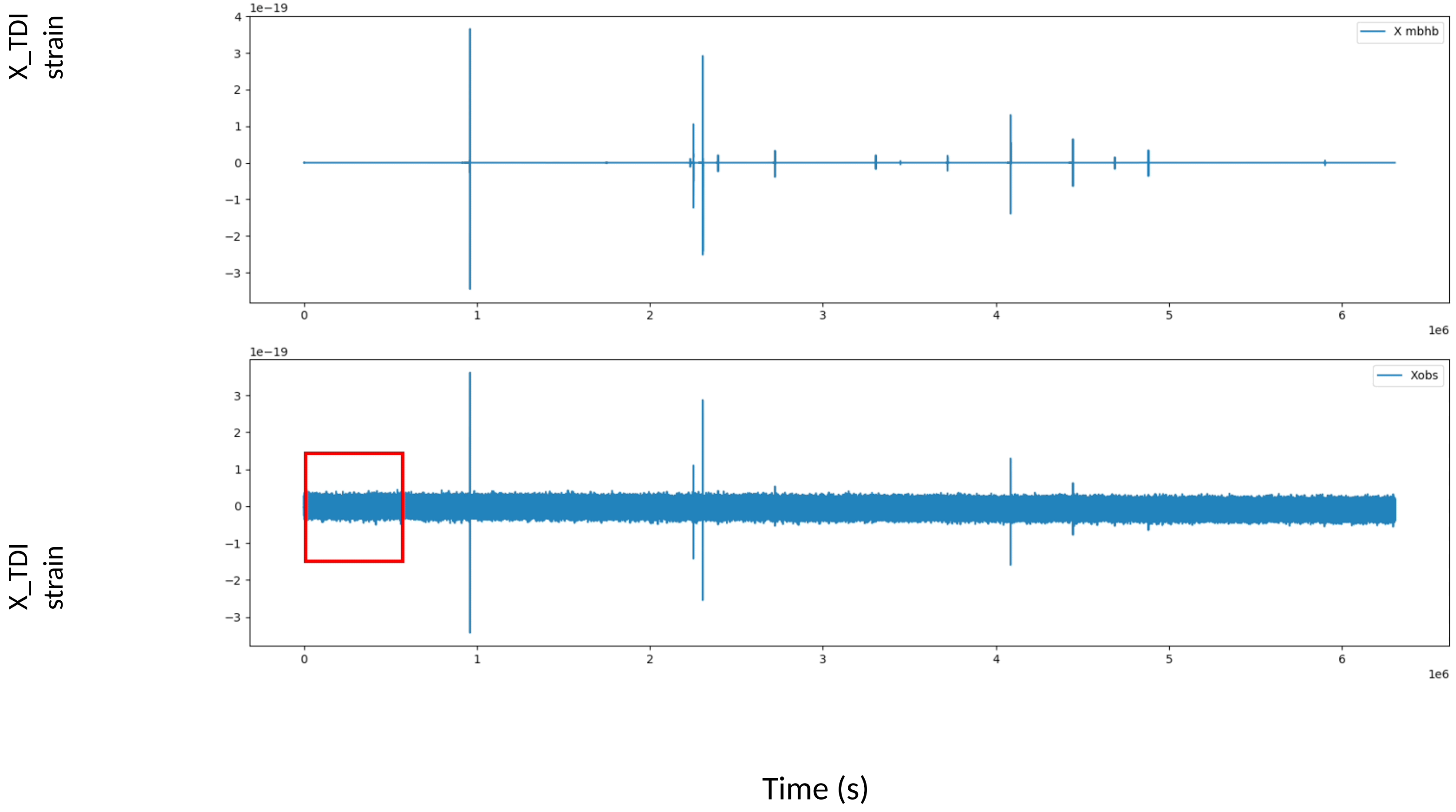
- Test on (much) more realistic data

SANGRIA DATA CHALLENGE

https://lisa-ldc.lal.in2p3.fr/challenge2a

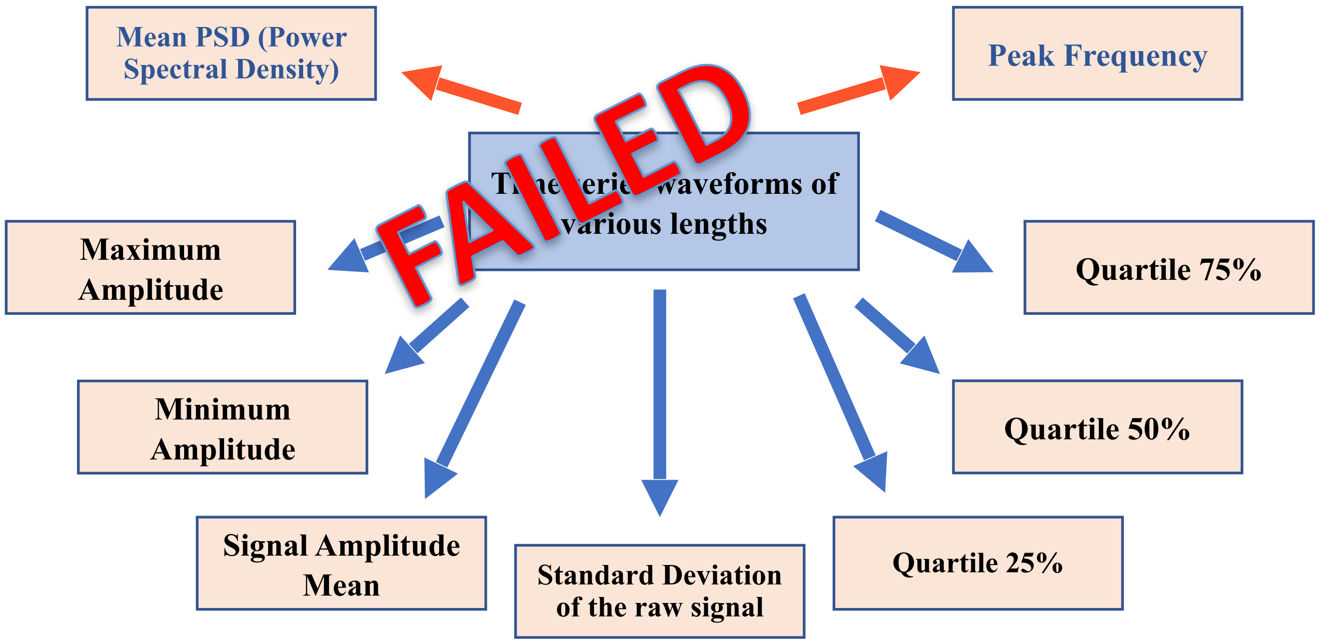


SANGRIA TRAIN DATA



We use overlapping moving window to generate multiple sequences.

Multilayer Perceptron (MLP)	***Convolutional (CNN)***	***Recurrent (RNN)***



10 features into the input layer:

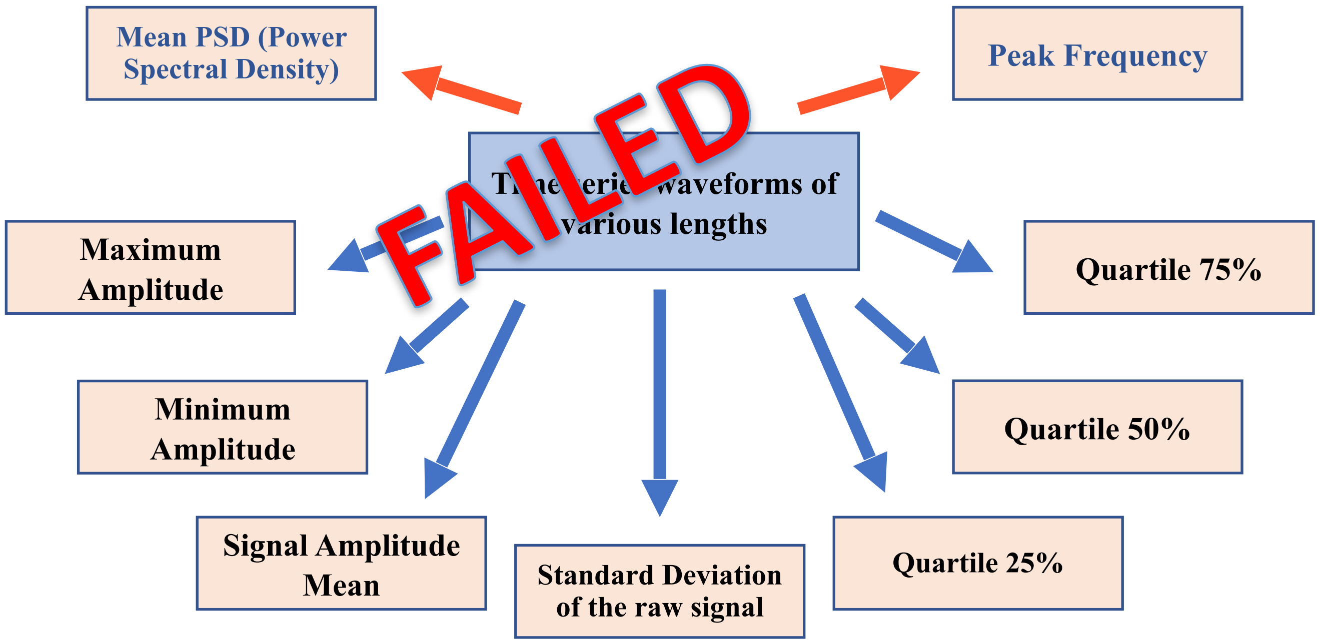
X, Y, Z, A, E projections + spectral entropies of those above

Labels: 0 or 1. Each data point is "manually" labeled in the beginning.

Multilayer Perceptron (MLP)

Convolutional (CNN)

Recurrent (RNN)



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Recurrent (RNN)

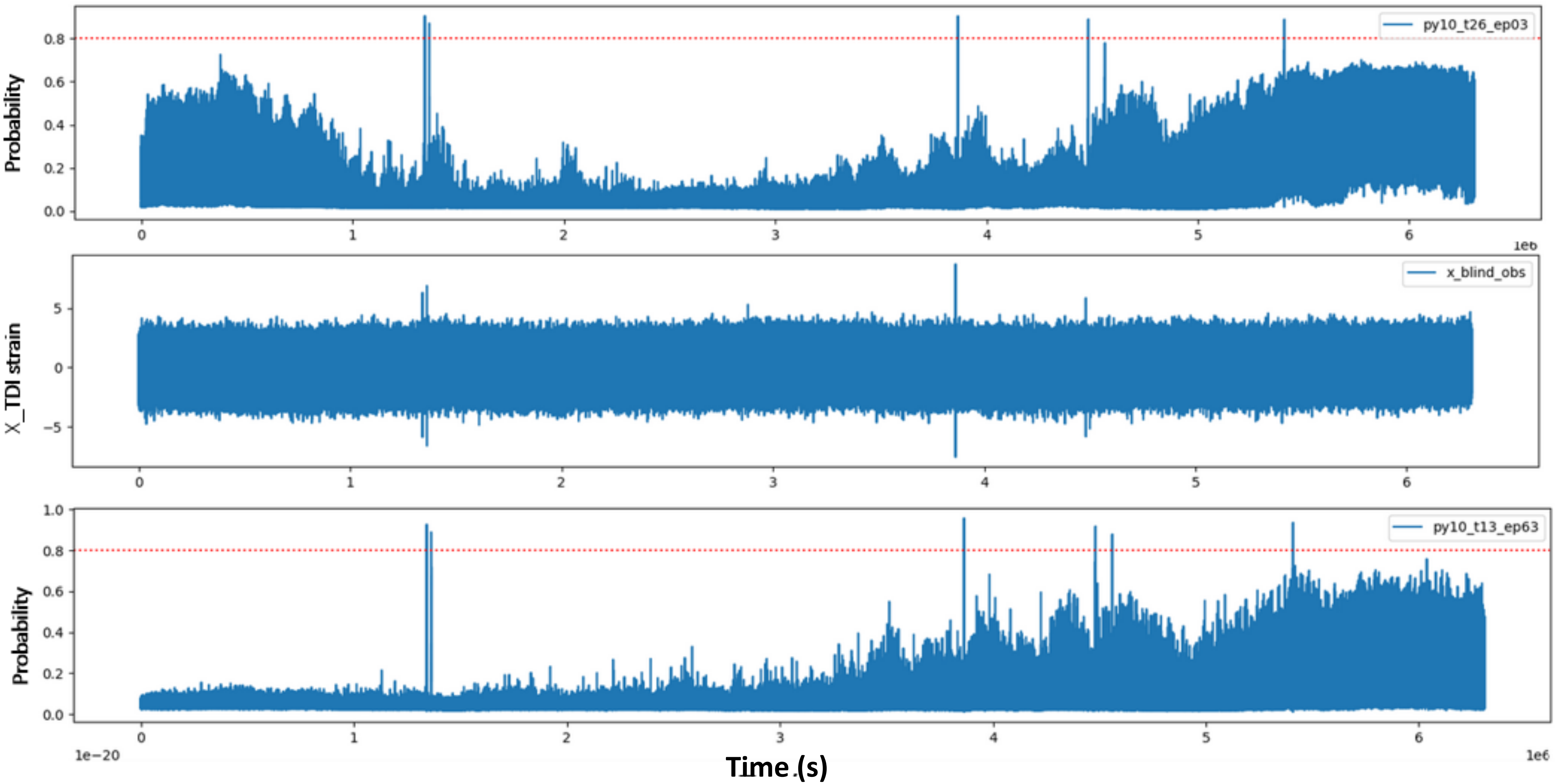
Input feature DF split into train (68%) and test datasets (32%)

Loss function: Binary Crossentropy

Optimizer: ADAM

Layers: LSTM, BiLSTM, GRU, SimpleRNN

	MODEL 1	MODEL 2	MODEL 3
Hidden Cells	10	30	10
No. of feature dimensions	10	10	10
Learning rate	10^{-4}	10^{-5}	10^{-4}
Layers	1xLSTM + 1xDense	2xLSTM + GlobalMaxPooling1D + 1xDense	1xLSTM + 1xDense



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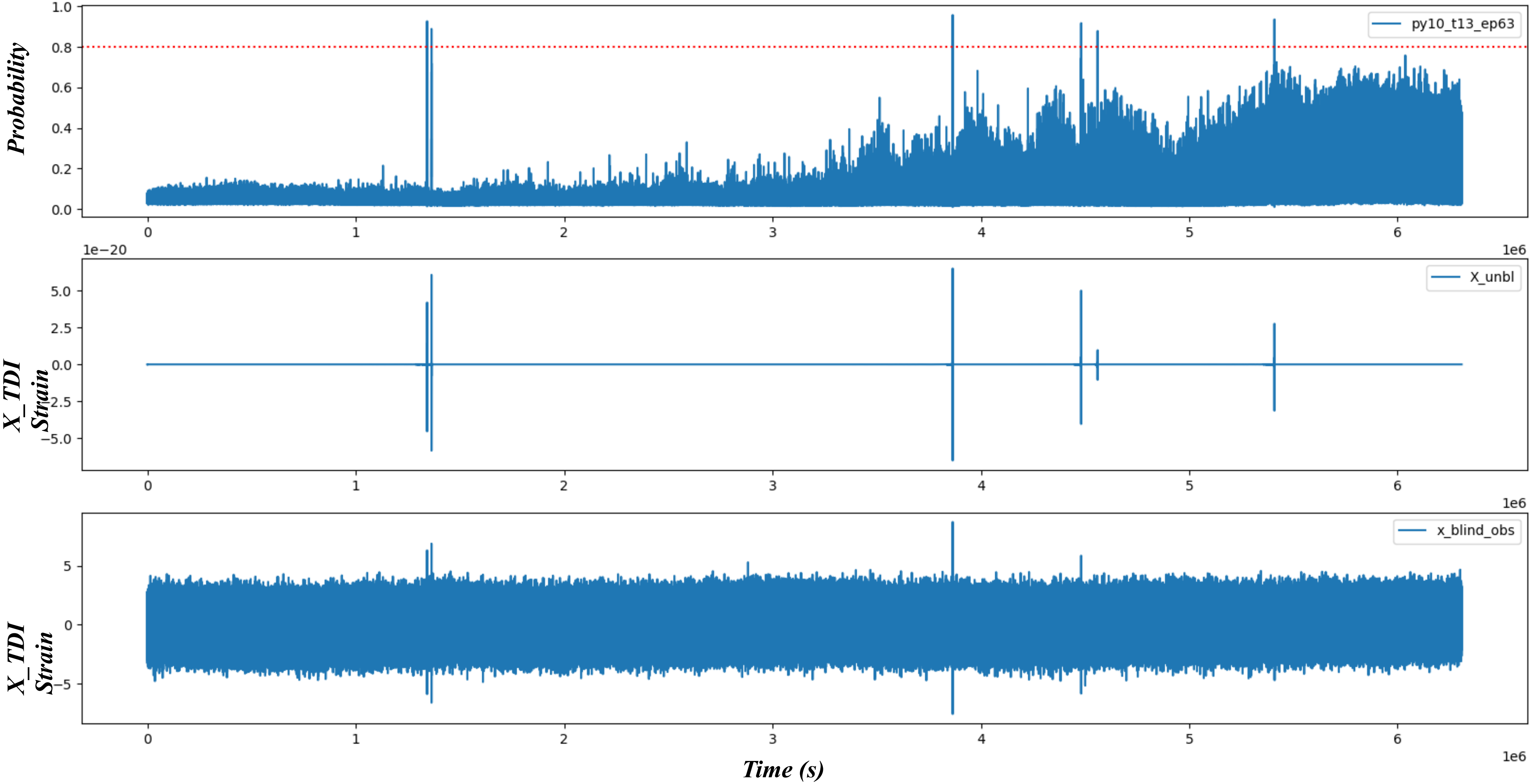
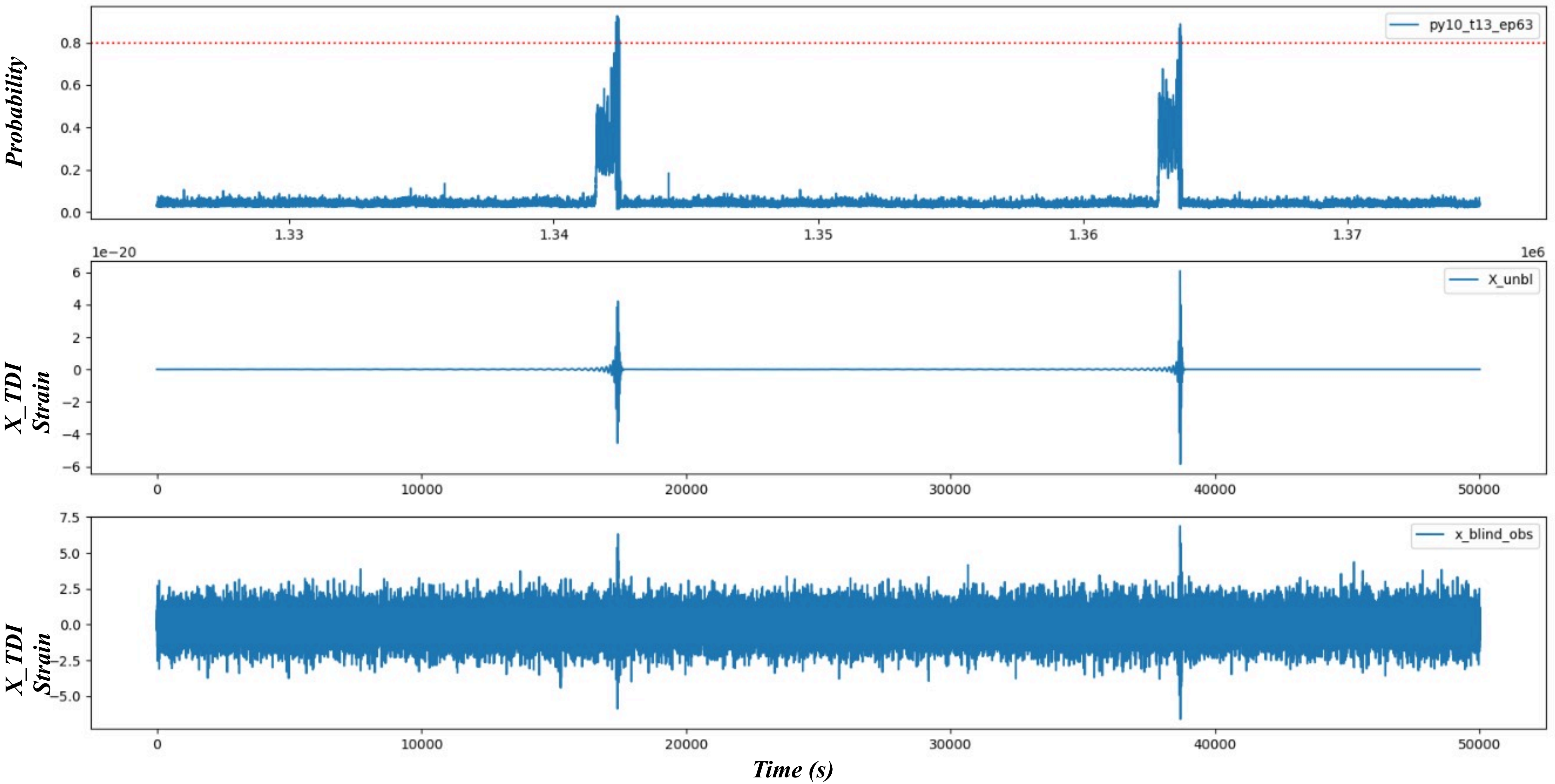

Probability
py10_t13_ep63
1.0
0.8
0.6
0.4
0.2
0.0
0
1
2
3
4
5
6
1e6
1e−20
X_unbl
5.0
2.5
0.0
−2.5
−5.0
X_TDI Strain
1e6
x_blind_obs
5
0
−5
X_TDI Strain
1e6
Time (s)



Probability
py10_t13_ep63
1.33
1.34
1.35
1.36
1.37
1e6
1e−20
X_unbl
X_TDI Strain
0
10000
20000
30000
40000
50000
x_blind_obs
X_TDI Strain
Time (s)

Results:

- ✓ All peaks are detected if the threshold is above 0.8 (80%)
- ✓ We proved that the development of a low latency pipeline which can detect MBHB events is feasible
- ✓ We intend to further develop our tools, to increase our models detection accuracy
- ✓ Prediction time on Sangria blind: seconds
- ✓ Training time: 12-24h depending on model architecture and hardware (PC) resources

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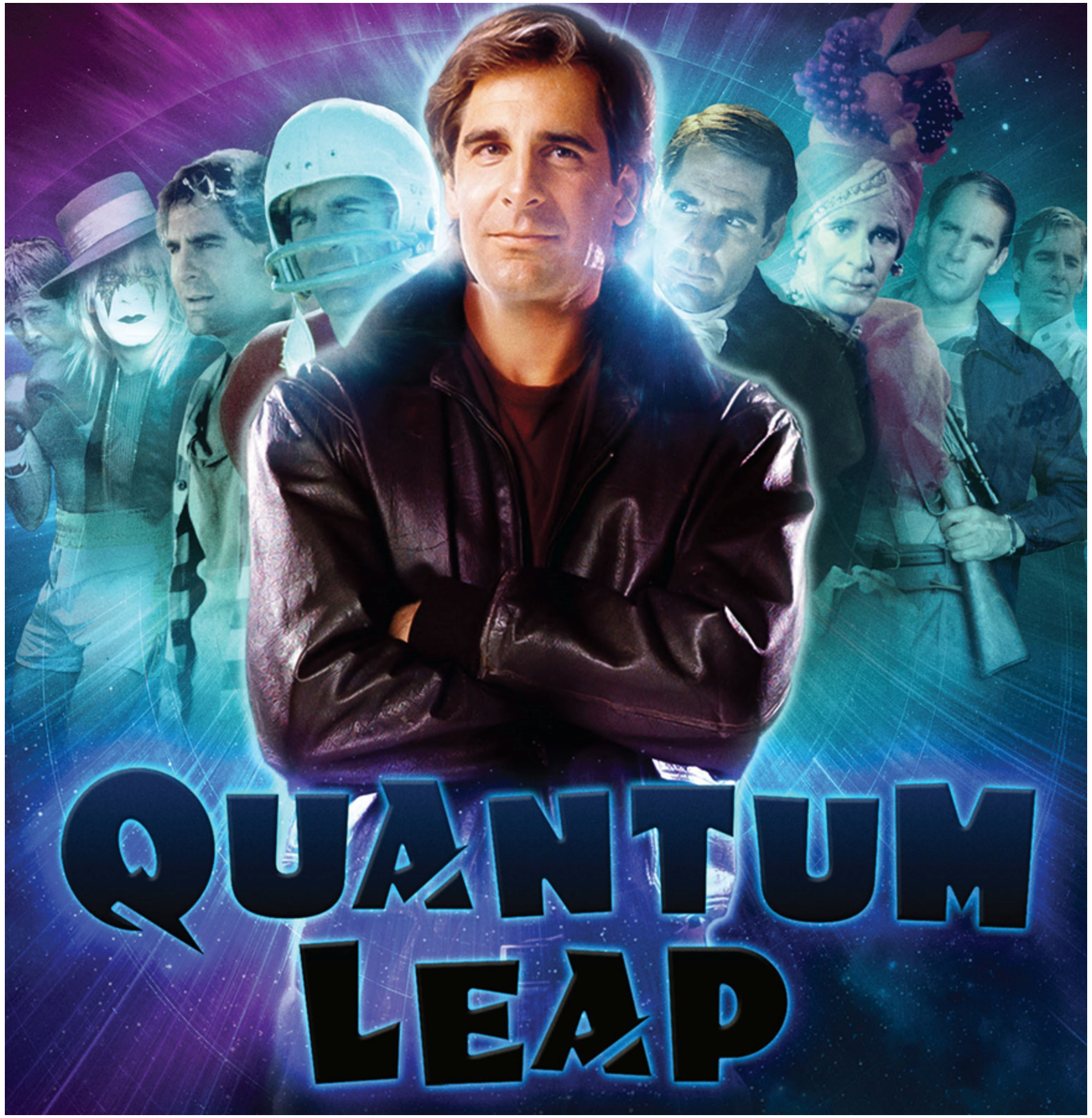
- Perform a benchmarking on different platforms (assuming the same configuration).
- Test on (much) more realistic data

- Take the quantum leap

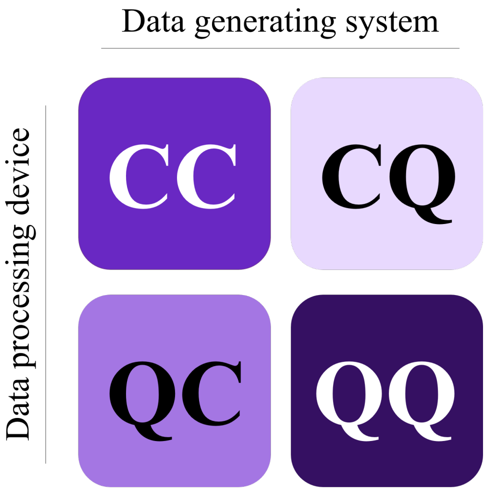

QUANTUM
LEAP

Quantum Neural Networks For The LISA Space Mission

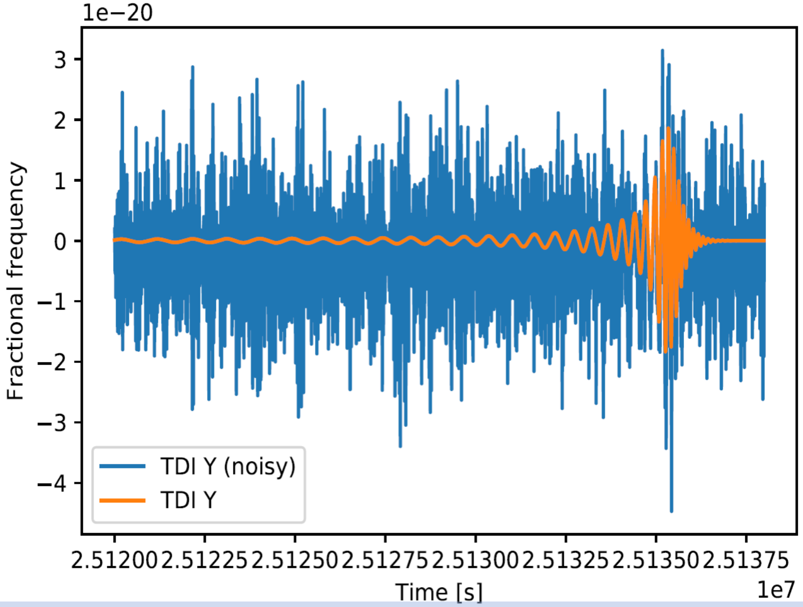
http://www.rrp.infim.ro/IP/AP653.pdf

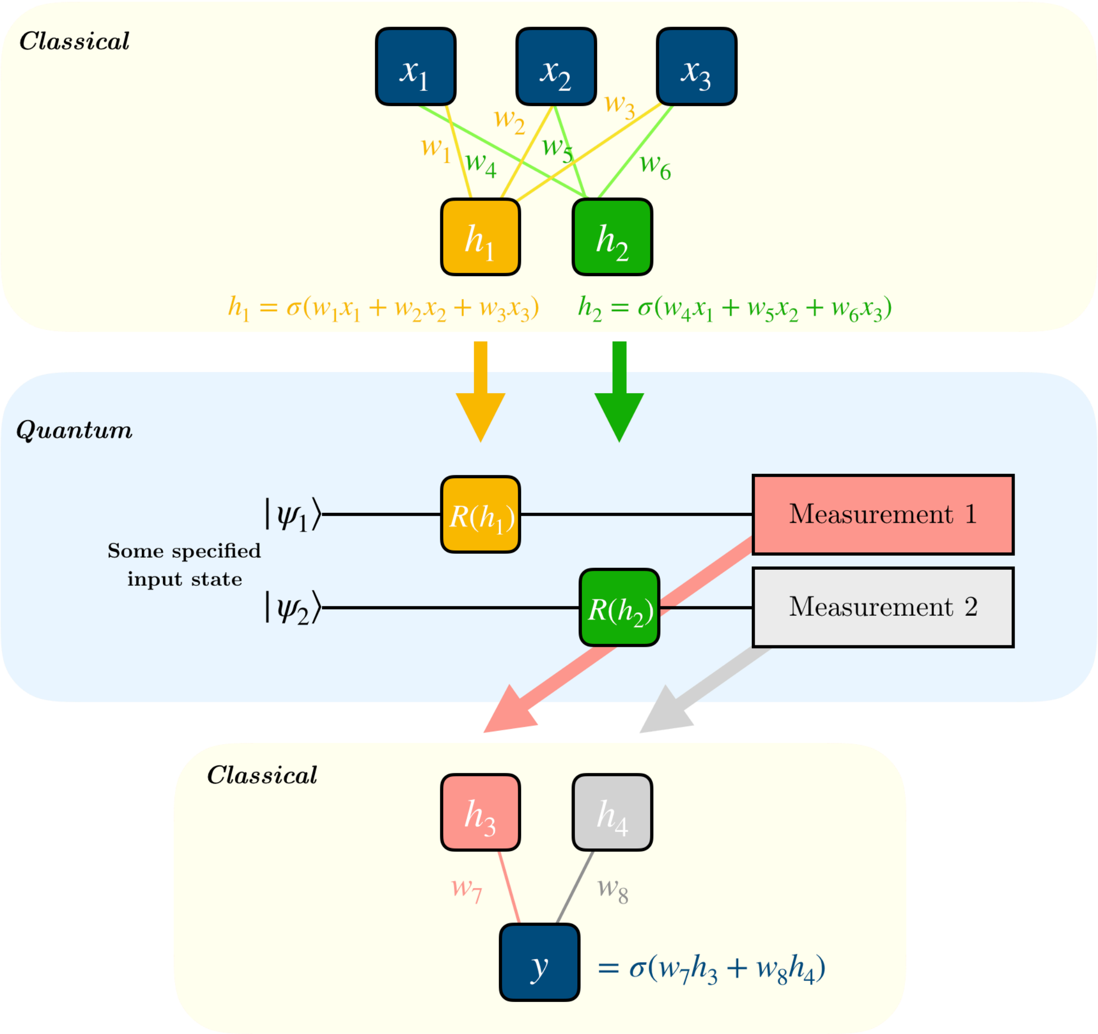
Motivation

- The large amount of information which can be manipulated and the low computational costs of quantum computers allow us to process and analyze fastly a great quantity of space mission data.
- Complex data space requires a quantum leap in data analysis



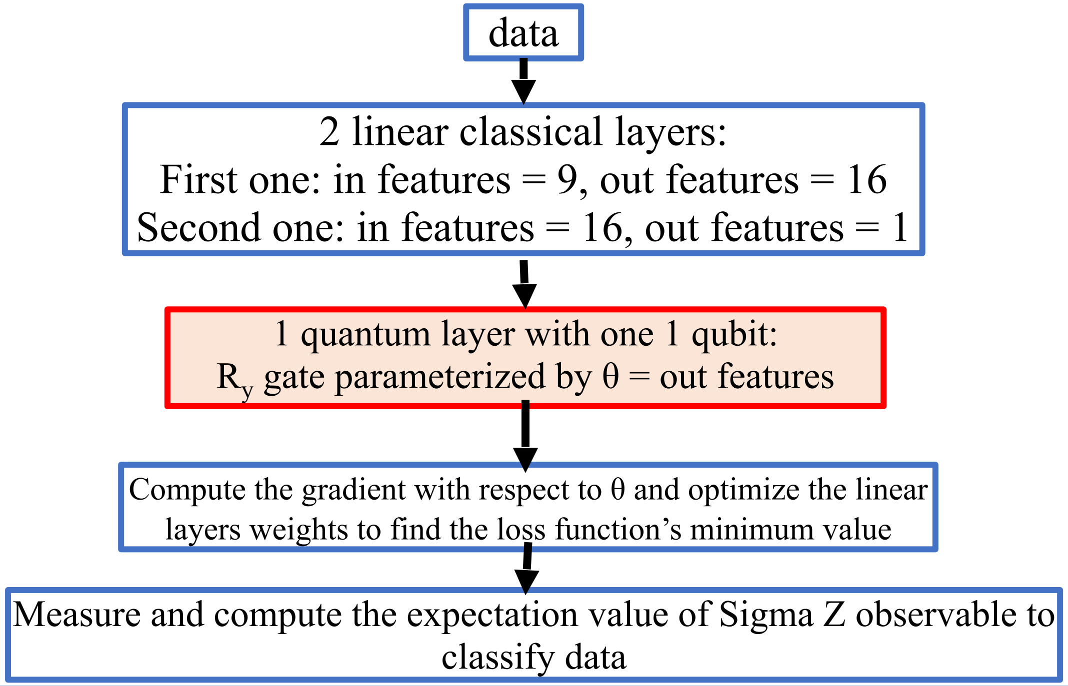
C – classical, Q - quantum

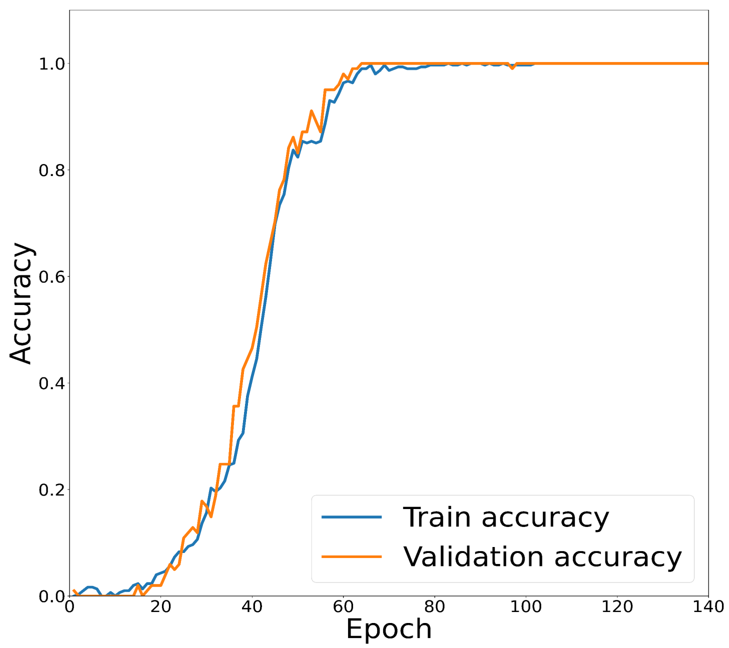




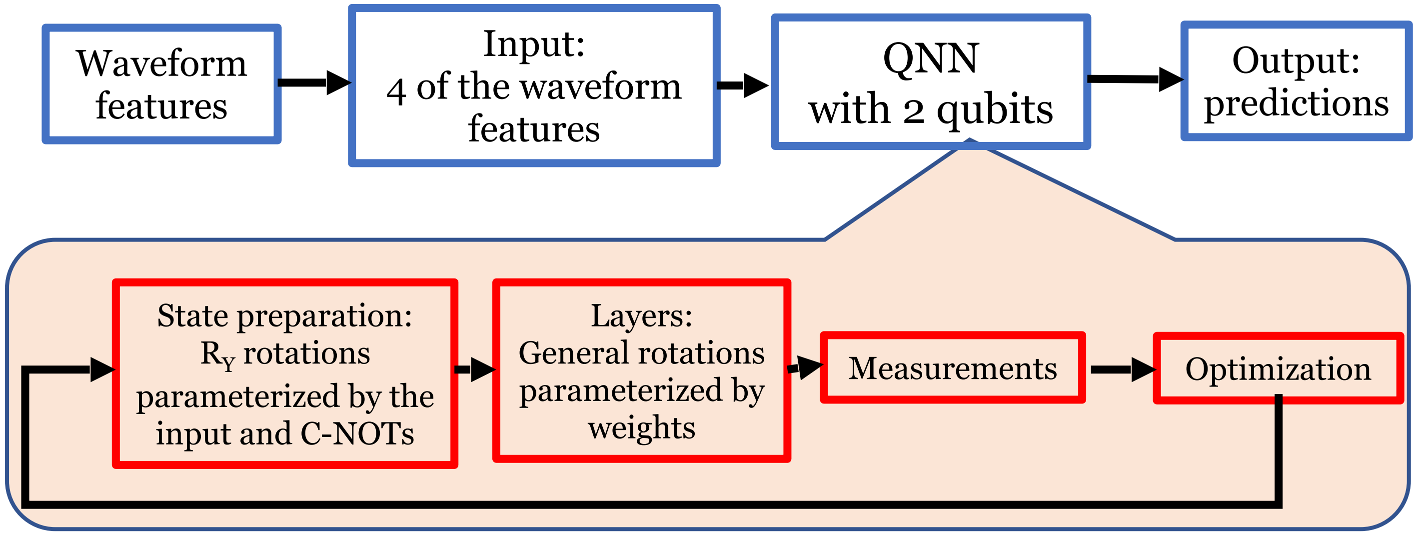
Our first results

- We successfully adapted two quantum neural network tutorials for binary classification of simulated noiseless gravitational waveforms, with respect to source mass ratio
- A quantum neural network can extract meaningful information and perform classification of a dataset with less parameters
- Adding a quantum layer to an underperforming classical neural network leads to dramatic accuracy improvements





Name of the quantum computer	Testing accuracy
ibm_nairobi	53,5%
ibm_oslo	70,3%
ibmq_belem	31,7%
ibmq_manila	49,5%
ibmq_quito	71,3%
ibmq_lima	48,5%
ibmq_armonk	67,3%



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Conclusions and Future Work

- We implemented several NN models, both on simple “in-house” generated GW data and on LISA-like data;
- We tested the NN models on different hardware configurations, including QC;
- We successfully detected the peaks in the Sangria blind data set;
- We intend to further develop our tools in order to increase the detection accuracy of our models and to decrease the training time;
- We plan on training our MLP and CNN models with a different feature set;
- We plan on correctly identifying the rest of the GW sources’ parameters;
- We plan on also implementing our quantum neural networks on LISA-like data .

Thank you!

Multilayer Perceptron (MLP)

Convolutional (CNN)

Nvidia RTX 3050 Ti

Technology = 8 nm

RT Cores = 20

Tensor Cores = 80

Core Clock = 1035 MHz

VRAM = GDDR6

VRAM size = 4 Gb

Bandwidth = 192 Gb/s

Mem. Clock = 1500 MHz

FP32 = 5.299 TFLOPS

Nvidia Tesla T4

Technology = 12 nm

RT Cores = 40

Tensor Cores = 320

Core Clock = 1590 MHz

VRAM = GDDR6

VRAM Size = 16 Gb

Bandwidth = 320 Gb/s

Mem. Clock = 1250 Mhz

FP32 = 8.141 TFLOPS

Apple M1 Neural Engine

Technology = 5 nm

CPU Cores = 8

GPU Cores = 8

GPU Clock = 1278 MHz

CPU Clock = 3200 MHz

Neural Engine = 16 Cores

Unified Memory = 16 Gb

Memory = LPDDR4X

FP32 = 2.6 TFLOPS

AMD EPYC 7551P

Technology = 14 nm

Cores = 32

Threads = 64

Core Clock = 2000 MHz

Boost Clock = 3000 MHz

RAM = DDR4

RAM Size = 128 Gb

RAM Clock = 2666 Mhz