

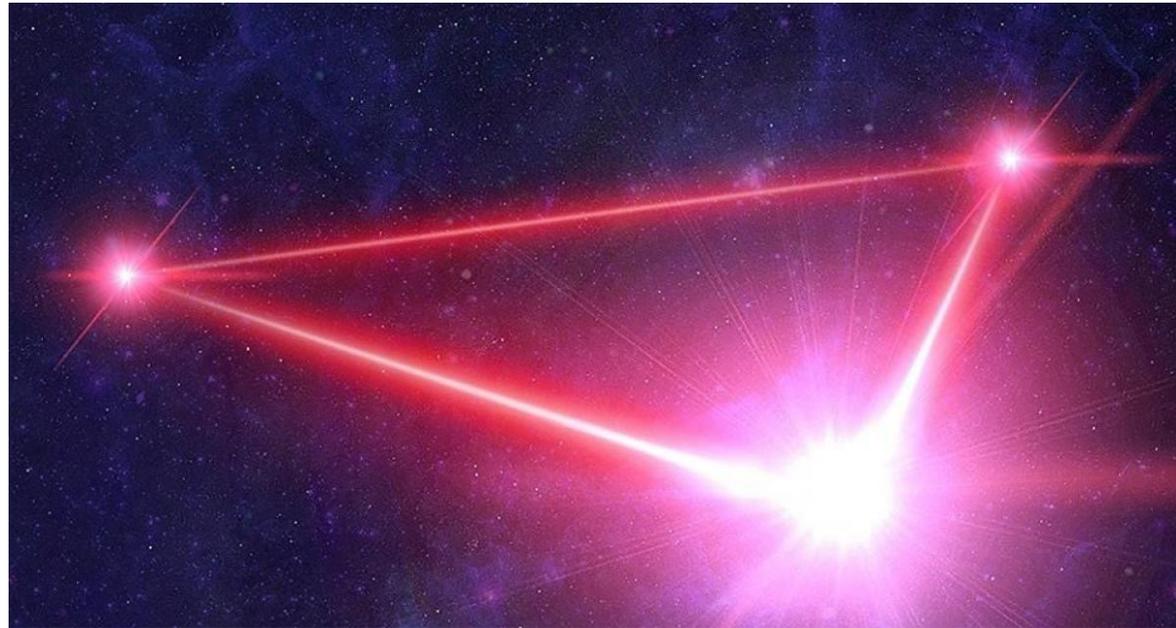
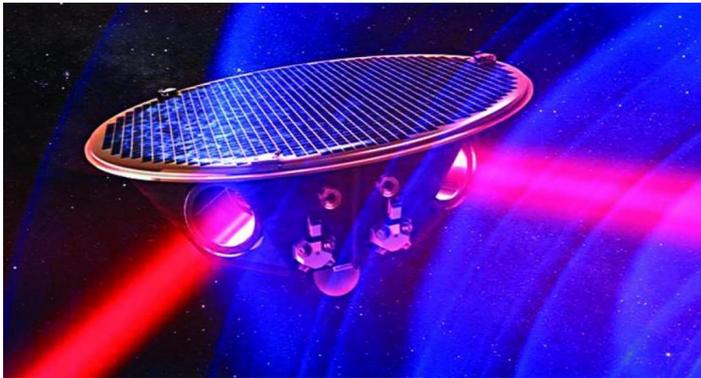


INSTITUTE OF
SPACE SCIENCE



www.spacescience.ro

LISA Mission: General Presentation and Romanian Contributions



LISA
CONSORTIUM

<https://www.elisascience.org/>

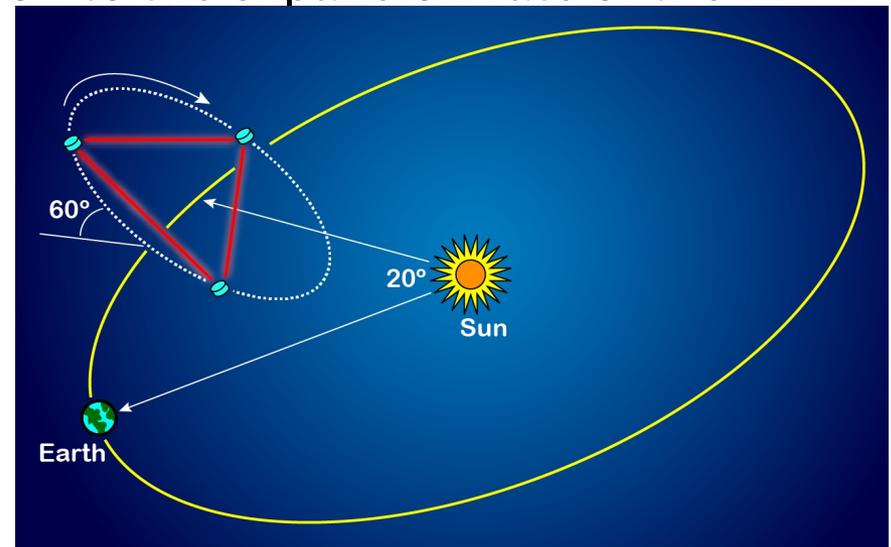
Institute of Space Science (ISS) in Bucharest-Magurele, Romania

LISA Mission



Scan me for a
LISA movie!

- The LISA (Laser Interferometer Space Antenna) mission will be one of the first space-based gravitational wave observatories.
- The observatory will consist of three satellites connected via laser signals and will be capable of in-depth studies related to various physics phenomena (from black hole formation to the expansion rate of the Universe).
- Most importantly, LISA, with the help of gravitational waves, will “listen” to different evolution stages of the Universe.

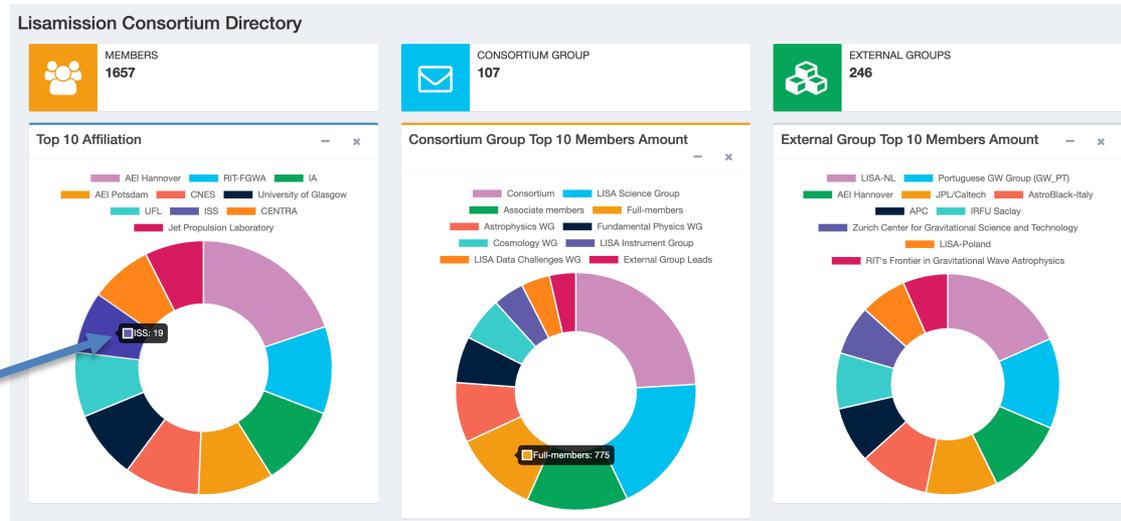


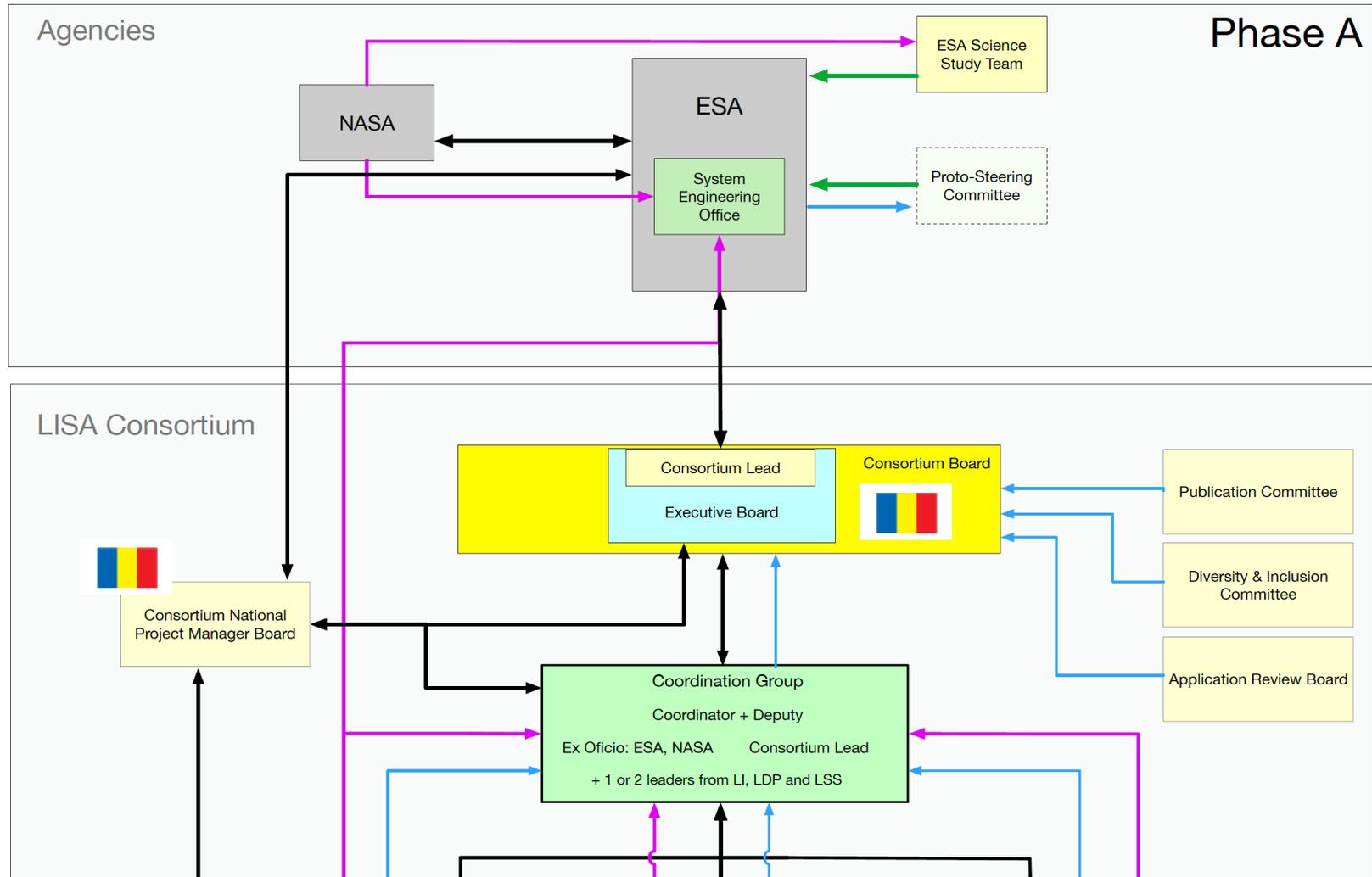
LISA Members

- 1657 members; ~ 353 groups and departments
- 16 countries with direct contributions:
- +10 associate countries:

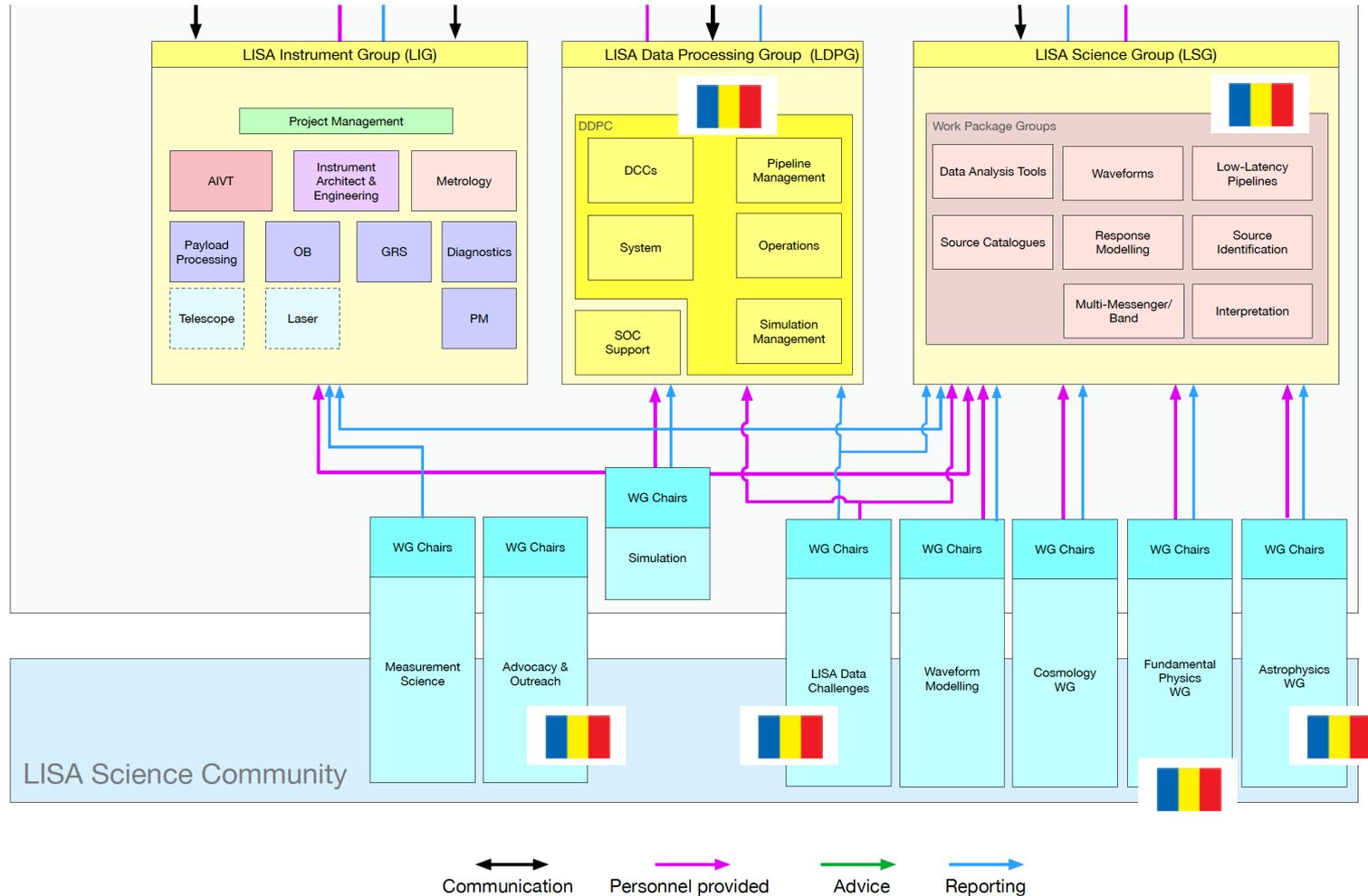


- Institute of Space Science (ISS) contributes with 19 full members on 3 directions





LISA Management



- Management Structure for PHASE B1

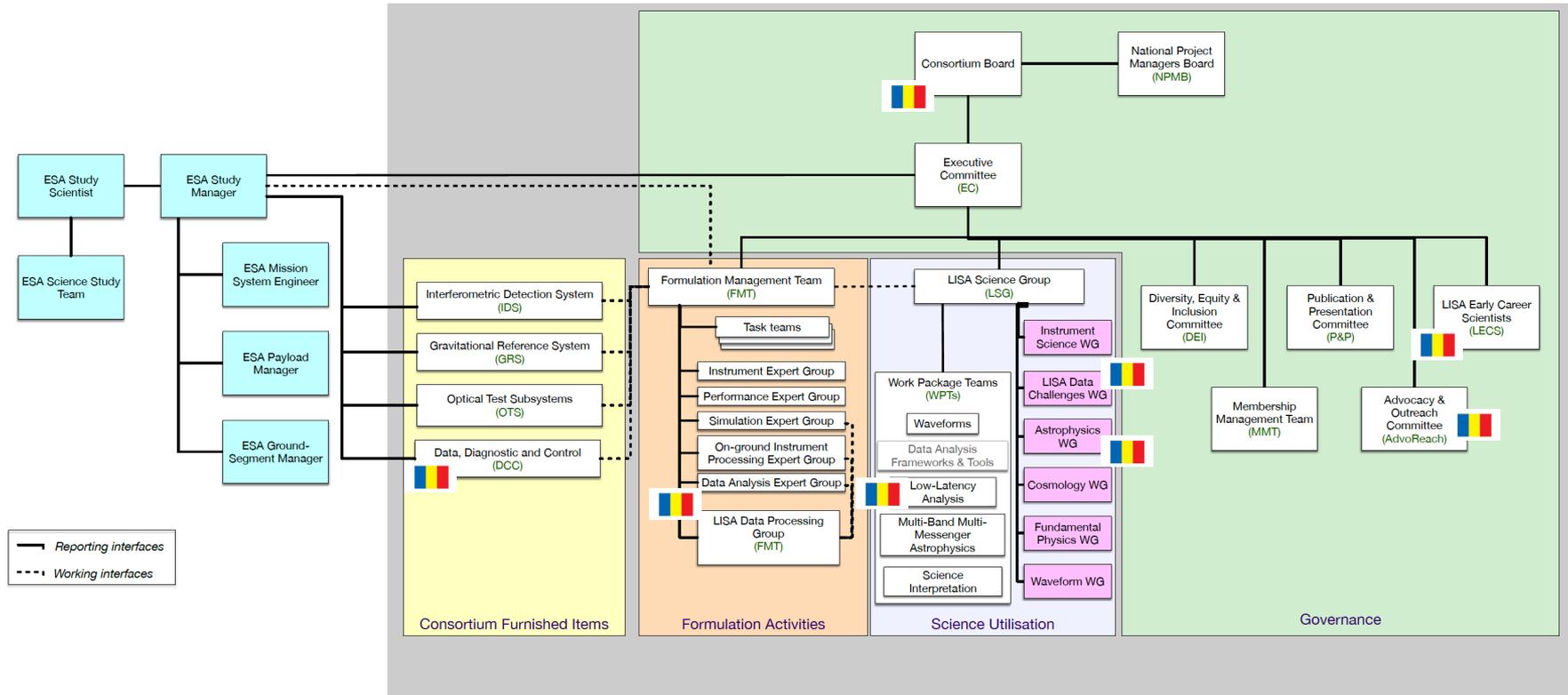


Figure 1 Organisation chart of the primary groups within the LISA Consortium, showing formal lines of reporting.



lisa

<https://signup.lisamission.org/signup>

LISA Consortium online application form

Name

e.g. Albert Einstein

E-Mail

e.g. user@example.com

Affiliation

e.g. AEI Hannover

Application type

- Group
 Associate

Attachments

Choose files No file chosen

(Spreadsheet format preferred, PDF will also be accepted.)

Comments

(optional)

Step by step

1. Download and fill out the [application spreadsheet template](#).
2. Consult the [Consortium Application Process Document](#), or [sample application one](#), or [sample application two](#) as references.
3. Fill out this application web-form and attach the completed application spreadsheet.
4. Submit the application by clicking the "Send application" button.

Help

LISA Consortium membership is handled by the LISA Membership Management Team (MMT). Additional information about membership and membership management will be available on the [LISA Consortium User Guide](#). If you run into issues or have questions with regards to your LISA consortium application please [contact us](#).

Additional Documents

The following documents are available for reference when indicating areas of commitment:

- [Consortium Management Plan](#)
- [Consortium Application Description](#)
- [Description of LSG Work Packages](#)

Code of Conduct and Privacy Policy

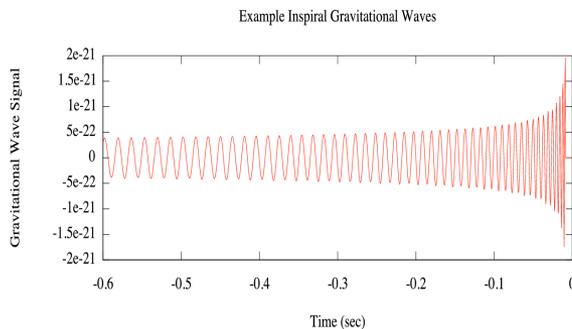
All members are required to abide by the LISA Consortium [Code of Conduct](#).

To join the consortium, all members must also agree to the [Privacy Policy](#).

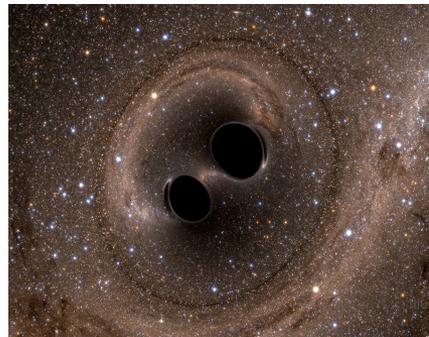
ISS-Science Group (ISS-Sci)

- Low-Latency Pipelines will be responsible for delivering the fastest responses related to gravitational wave detections and also for alerting other observatories (anticipating electromagnetic follow-ups).
- Data analysis using neuronal networks running on CPUs but also on space qualified FPGA and quantum computers
- Waveform analysis: we will provide wave- form simulation software and also a data-base for multiple type waveform solutions.
- Source catalogs: Catalogs of GW sources, their masses and also predictions for merger rates.
- Multimessenger science: Complex analysis of astrophysical sources using several messenger's, photons, gravitational waves, neutrinos, cosmic rays

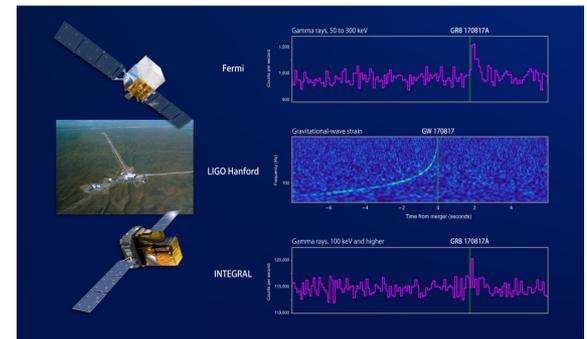
Waveform analysis



Source catalogs



Multimessenger science



ISS-Computing Group (ISS-Comp)

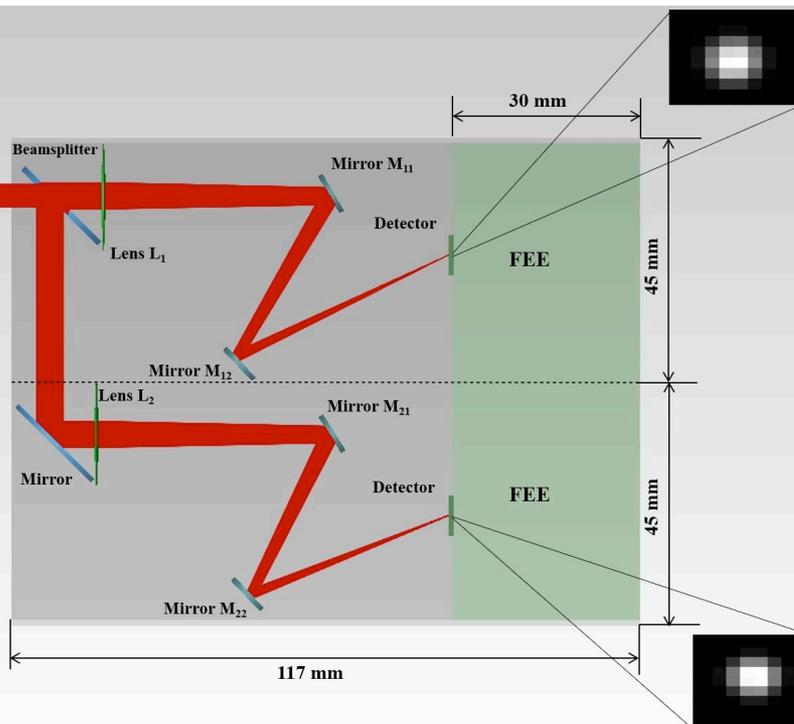
ISS will design and build a dedicated computing centre (DCC) that will perform data analysis, simulations and provide data storage for the LISA Collaboration.

First server already acquired and integrated, OS installed and used for prototyping: Server AMD single socket A+ Server, Nvidia Tesla T4, more to follow.

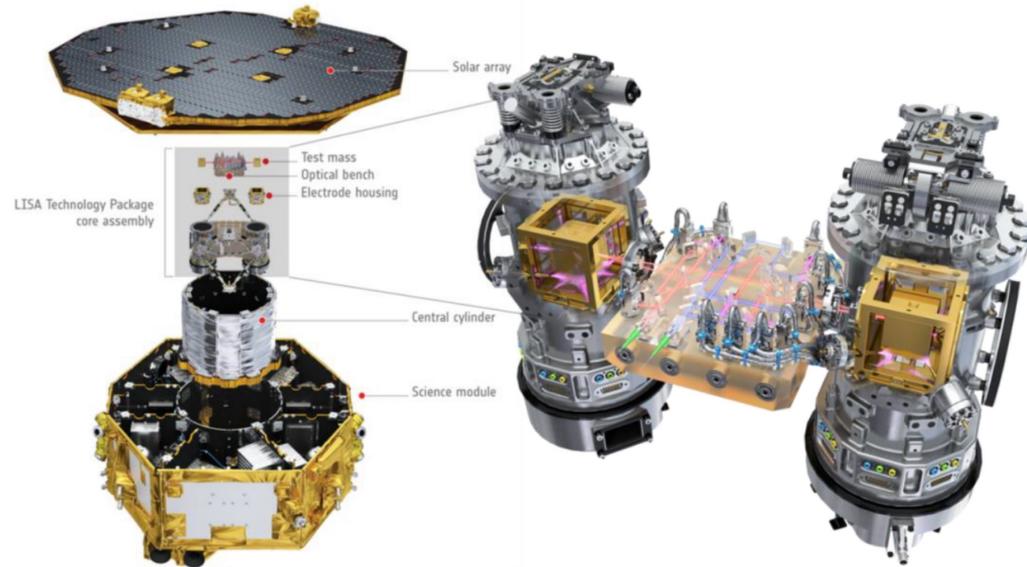


ISS-Hardware Group (ISS HW)

ISS committed to participate in the development of a precise positioning system for the three satellites – the CAS system (Constellation Acquisition Sensor), an essential component for correct observations. The positioning will be done with a laser system, each satellite sending a laser beam to each other. The received signal will determine the reorientation of the satellites in the right position.



Schematics of the CAS system



Schematics of the LISA satellite (left) and the placement of the test masses and the optical bench (Schleicher, A., et al., In-Orbit Performance of the LISA Pathfinder Drag Free and Attitude Control System, Proceedings of the 10th International ESA Conference on Guidance Navigation & Control Systems, 29 May – 2 June 2017, Salzburg, Austria, 2017).

- Management Structure for PHASE B1

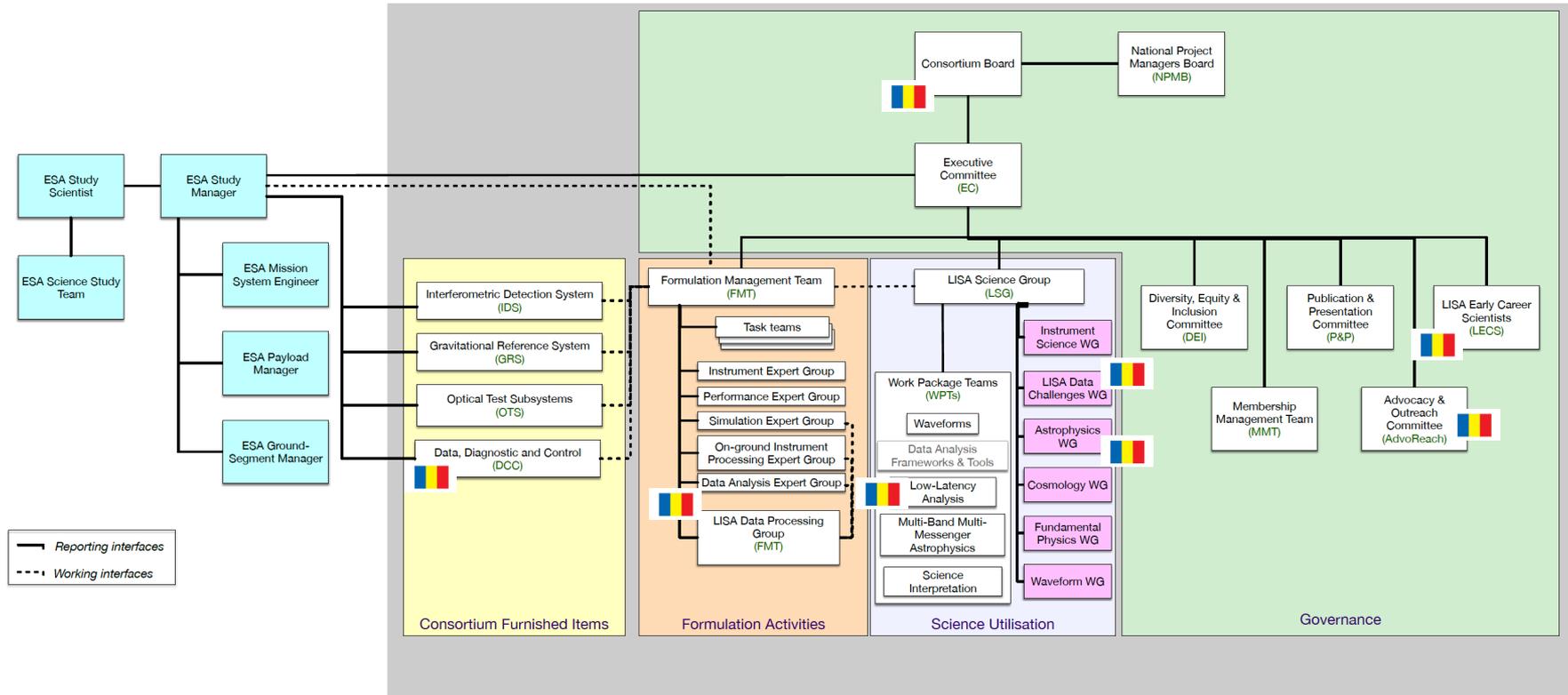


Figure 1 Organisation chart of the primary groups within the LISA Consortium, showing formal lines of reporting.

ISS-Science Group (ISS-Sci): Low-latency pipelines

- We need the capability to rapidly identify source candidates in the instrument data so that alerts can be sent out to partners for follow-up observations.
- A mechanism must be in place to trigger protected observing periods in advance, to ensure the existence of good quality data for the science analysis.
- Understanding the performance of the instrument in real time is also important, so that the general quality of data can be checked and any problems on the satellite identified quickly.
- The tools in this work package are designed to generate and distribute alerts by monitoring the LISA data in real time, as well as monitoring the instantaneous data

WP	Description	Priority
4.1	Create low latency pipeline to run on `realistic' data	3
4.2	Alert generation for EM observatories	3
4.3	Trigger generation from GW signals	2
4.4	Generation of data quality metrics and flags	2
4.5	Source-based observatory diagnostics	2
4.6	Search and classification of unmodelled signals	2
4.7	Assessment and triggering of protected periods	1

1: end of phase A; 2: demonstration of capabilities at TRL6; 3: development of sci ops

Low-latency pipelines

4.1 Create low latency pipeline to run on `realistic` data

The LISA instrument will produce an evolving data set, and the data analysis will likewise need to produce an evolving set for the many signals in the data. The goal is to build, run and test several different pipelines in order to explore as many options as possible.

Working steps	Deliverables
<ul style="list-style-type: none">• Combine pipelines for different sources• Test the performance of the pipeline on the realistic data in the presence of realistic noise• Test alert generation• Low-latency noise characterisation and diagnostic of the observatory	<ul style="list-style-type: none">• Pipeline for source identification. Initial solution for the global fit• Refined localization of black hole mergers• Rapid identification of transient signals• Continuous updates on the noise characterisation
Timeframe and human resources requirements	List of projects
<ul style="list-style-type: none">• End of Phase A: requirements document and preliminary versions of pipeline components• Mission adoption: working version of the pipeline• Closed to the launch of the mission: Fully functional pipeline	<ul style="list-style-type: none">• Noise characterisation in the presence of signals• Prototype the pipeline

Low-latency pipelines

4.2 Alert generation for EM observatories

To maximize collaboration with the wider astronomy community new and updated LISA sources must be rapidly and predictably communicated with EM observers. Low-latency source characterization and localization tools to get EM observers on source with minimal delay are of paramount importance.

Working steps	Deliverables
<ul style="list-style-type: none">• Collect all relevant details of the experiments, by elaborating a database of experiments• Providing procedures to generate alerts and distribute them to the observatories• Study the alert stages• Veto procedure(s) and procedures for calculate/estimate the false alarm rate.• Develop a phone application based on the state-of-the-art smart technologies that can take alerts from the Cloud.	<ul style="list-style-type: none">• Database of potential follow-up experiments and their classification• Framework for the alert generation for the observatories• Procedure to generate alerts;• Studies related to the role, description, content, classification and the stages/lifetime of alerts• Requirements document and software for alert generation for EM observatories.
Possible subpackages	List of projects
<ul style="list-style-type: none">• Collecting and maintaining the database of relevant EM observatories• Tools for alert distribution	<ul style="list-style-type: none">• Database of potential follow-up experiments and their classification based on the time lapse for their signal to pick up• Web and phone app for the alert generation

Low-latency pipelines

4.3 Trigger generation from GW signals

We will need to develop data analysis tools, which can perform fast parameter estimation of the gravitational wave signals. Especially important are sky localisation and time of coalescence for MBHBs.

Working steps	Deliverables
<ul style="list-style-type: none">• Develop the tool for the rapid parameter estimation for the MBHBs, especially concerning the sky localisation• Tools for low-latency updates to MBHB source localization in the late stages of the merge• Tools for rapid LISA source localization software for short-lived transients. The procedure might be different from the long lived MBHBs	<ul style="list-style-type: none">• Algorithms and implementations for rapid LISA source localization software for short-lived transients• Tools for fast parameter estimation• Tools for low-latency updates to MBHB source localization in the late stages of the merger• Scientific publications describing the method
Dependencies	Possible subpackages
<ul style="list-style-type: none">• This is the critical deliverable for the multimessenger follow-ups and setting of the protected periods• Requires fast waveforms• Requires accurate current noise estimates	<ul style="list-style-type: none">• Fast waveform database• Tools for rapid LISA source localization software for short-lived transients• Tools for low-latency updates to MBHB source localization in the late stages of the merger

Low-latency pipelines

4.4 Generation of data quality metrics and flags

For the different levels of data quality we will need to identify data quality flags. Data quality flags will be used to provide an indication as to the quality of the data for specific periods of time, and to explain what are the problems.

Working steps	Deliverables
<ul style="list-style-type: none">• Develop the tool for the rapid parameter estimation for the MBHBs, especially concerning the sky localisation• Tools for low-latency updates to MBHB source localization in the late stages of the merge• Tools for rapid LISA source localization software for short-lived transients. The procedure might be different from the long lived MBHBs	<ul style="list-style-type: none">• Procedure to estimate instrument's noise;• Catalog of the noise sources (transient and continuous);• A record of the data quality as a function of time;• Data quality flags describing the severity of noise problems;• A daily page containing data quality indicators
Timeframe and human resources requirements	Possible subpackages
<ul style="list-style-type: none">• Many data quality metrics will likely not converge until the completion of the assembly, integration, verification and testing phase of the satellites.	<ul style="list-style-type: none">• Estimates of noise power spectral densities;• Glitches in TDI channel and appropriate auxiliary channels: a low latency pipeline to identify correlations.

Low-latency pipelines

4.5 Source-based observatory diagnostics

General idea is to use verification binaries (VB) as a tool understand the instrument.

Working steps	Deliverables
<ul style="list-style-type: none">• The objective is to determine how verification binaries be used to improve upon the TDI ranging that uses pseudo random noise (PRN) modelling, how do the (expected) presence and absence of these binaries in various TDI observables complement the PRN-based TDI ranging• Also, how can VBs be used to validate the calibration of the amplitude and phase of the signals from LISA	<ul style="list-style-type: none">• Pipeline that uses VBs as prior in an optimal estimation method to determine whether adding information from the VBs' signals changes TDI ranging• Pipeline for amplitude and phase calibration for a strain and uncertainty of the VB
Dependencies	List of projects
<ul style="list-style-type: none">• WP 1.4 Provide GB waveforms	<ul style="list-style-type: none">• As a first study to do is to look at what ranging errors can be derived from VBs alone;• Then try to combine PRN and VBs;• Determine if VBs can be used to calibrate the amplitude and phase of the signal.

Low-latency pipelines

4.6 Search and classification of unmodelled signals

The past research has shown that new unexpected sources are revealed whenever a new detection/observation capability becomes available. Therefore, it is very important to have methods to detect gravitational waves from unmodelled sources.

Working steps	Deliverables
<ul style="list-style-type: none">• Developing techniques that can distinguish unmodelled GW signals from instrumental artifacts• Developing techniques to characterize unmodelled GW signals• Developing the necessary LLP software to extract transients• Concurrently using of multiple methods to enhance the unmodelled GW transients detection.	<ul style="list-style-type: none">• Phenomenological models for the unmodelled GW transients and methods to characterize them• Algorithms that can be used to extract unmodelled GW signals• Software implementation of the algorithms to extract unmodelled GW signals, which will run as part of the low-latency pipeline• Databases with identified unmodelled GW signals
Timeframe and human resources requirements	List of projects
<ul style="list-style-type: none">• This is largely uncharted territory. Good to explore multiple approaches over the next several years.	<ul style="list-style-type: none">• Study the coherent WaveBurst (cWB) algorithm which has been applied to LIGO / Virgo for using in the case of LISA

Low-latency pipelines

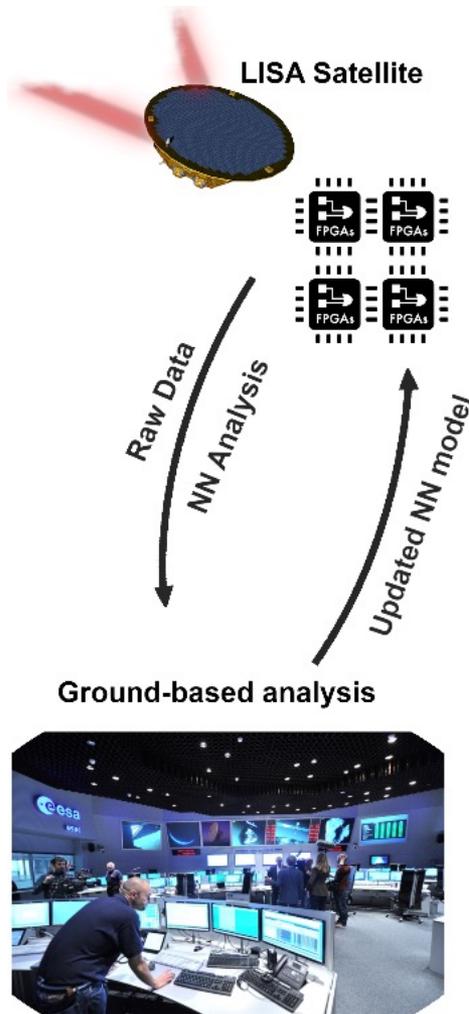
4.7 Assessment and triggering of protected periods

The goal here is to identify the mechanisms and decisions involved in triggering a protected period on the observatory. We also need to look at the constraints coming from the operations and the instrument itself.

Working steps	Deliverables
<ul style="list-style-type: none">• We have to identify the routine which will combine the information on the scheduled antenna repointing with the triggers of the coalescence time from the MBHBs and ensure that LISA is operational during the merger and ringdown• Moreover we need to ensure that routine interruptions are scheduled in such a way as to allow them to be rescheduled to avoid the protected period	<ul style="list-style-type: none">• Technical note, which identifies the loss of science due to the gap in data close to the merger of MBHB• Procedure that monitors: the schedule of the antenna repointing; triggers of the MBHB events and based on this information defines protected periods within the allowed range• Tools to communicate protected periods to SOC/MOC
Timeframe and human resources requirements	List of projects
<ul style="list-style-type: none">• The limitations on how much in advance we can trigger the protected periods and what does it imply for the detection, parameter estimation and multimessenger observations have to be identified by the end of Phase A.	<ul style="list-style-type: none">• Routine to combine predictions for the coalescence time and ringdown length with the schedule restrictions in order to find the optimal adjustment scheme.

ISS-Science Group (ISS-Sci): Low-latency pipelines

Using AI techniques, the pipeline will detect and characterize GW events and deliver alerts related to gravitational wave detections to other observatories.



NEURAL NETWORKS
DEPLOYMENT AND EXECUTION

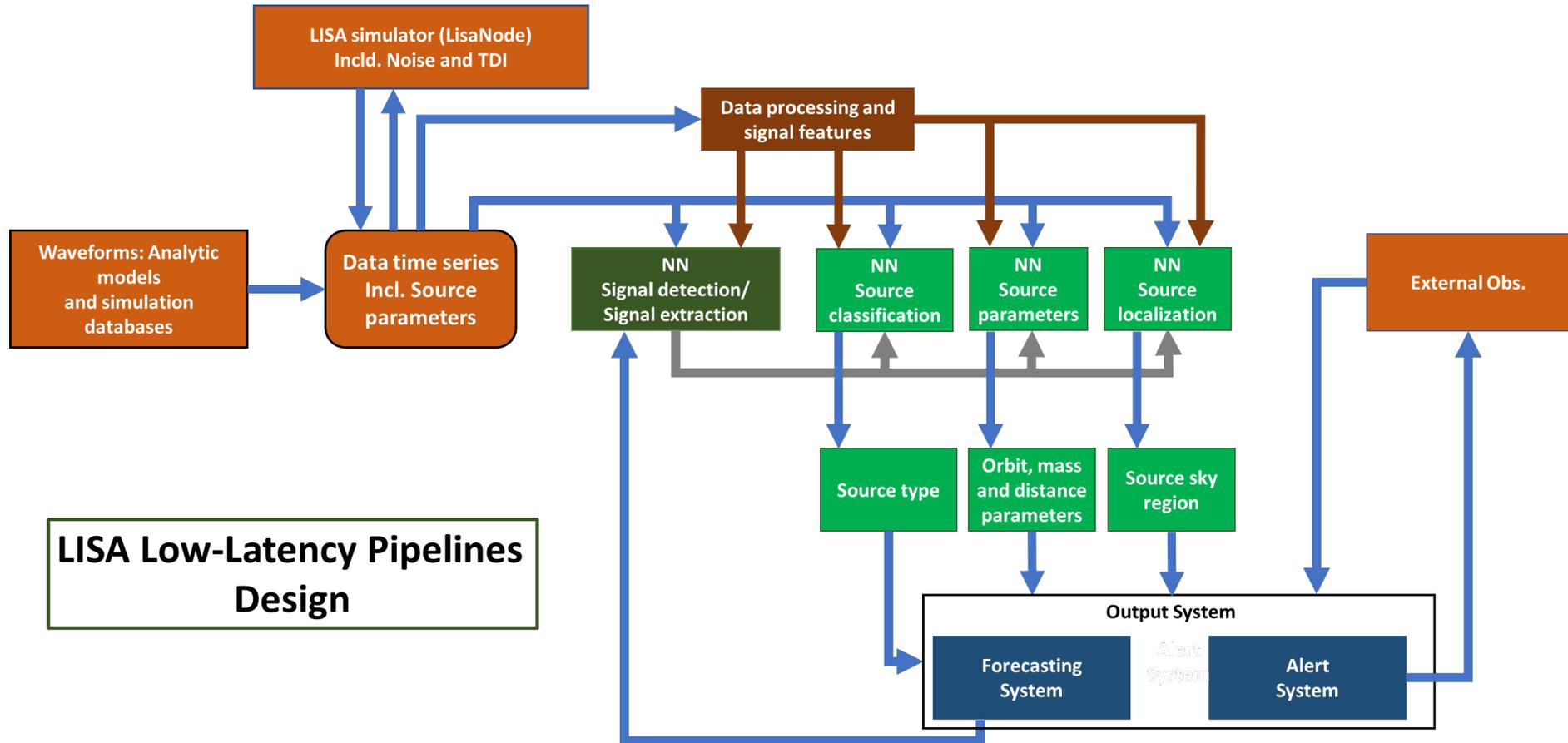
ISS HPC Data Center
(Server Cluster for Machine Learning)



Refined Data

New NN prediction

ISS-Science Group (ISS-Sci)



ISS-Science Group (ISS-Sci)

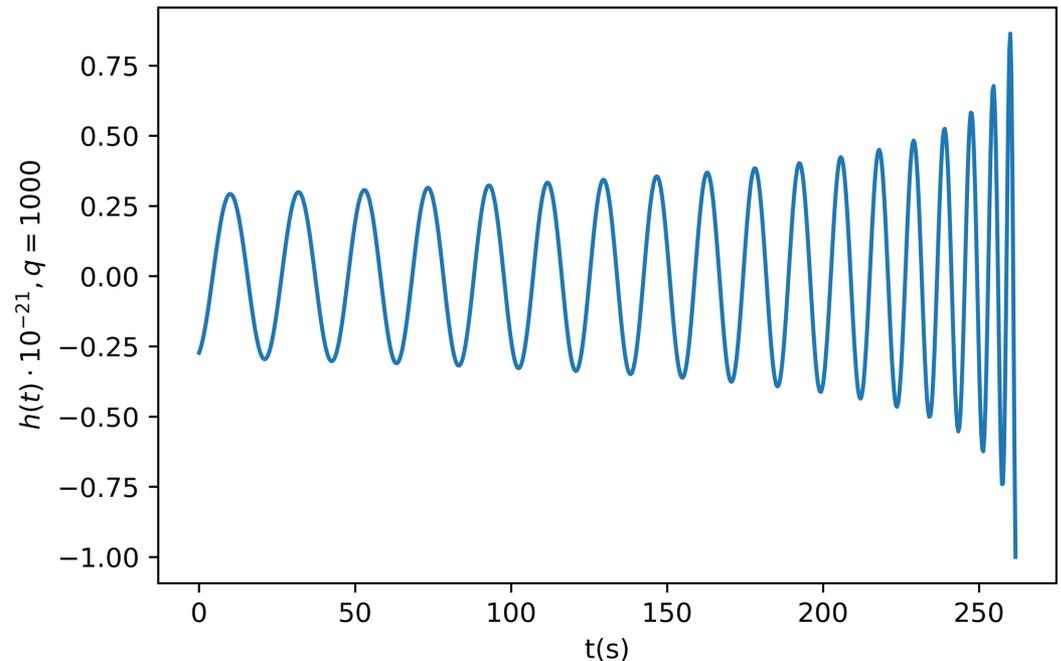
(<https://www.mathworks.com/matlabcentral/fileexchange/>)

Quick Gravitational Wave Data Generation

This code is a basic computer implementation of the quadrupole formalism of general relativity applied to point-mass binary systems in circular orbits.

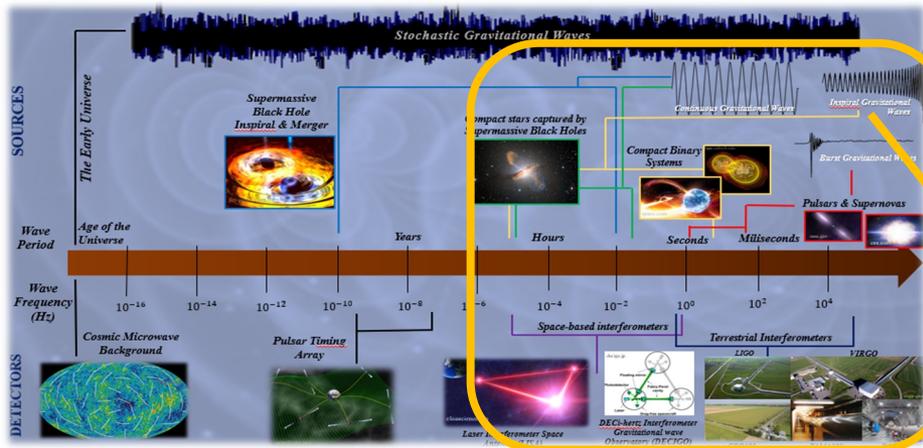
The code was written with the aim to efficiently generate large amounts of parameter-dependent gravitational waveform time-series used for the incipient development of neural networks dedicated to the detection and classification of gravitational waves.

The variable source parameters considered are the binary mass ratio, orbital inclination, distance to source and antenna pattern coefficients. The generated gravitational waveforms are either "clean" or distorted with adjustable additive random noise.

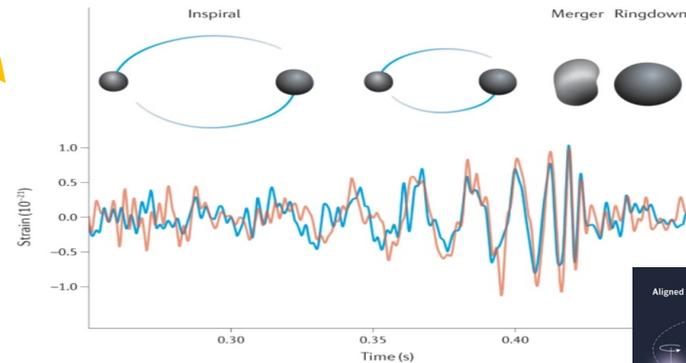


Besides gravitational waveforms, the code also computes the parameter-dependent time-evolution of the main physical quantities in the quadrupole formalism (orbital separation, gravitational waves frequency, amplitude and phase).

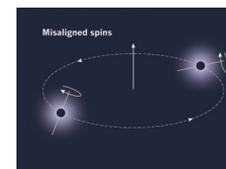
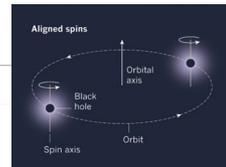
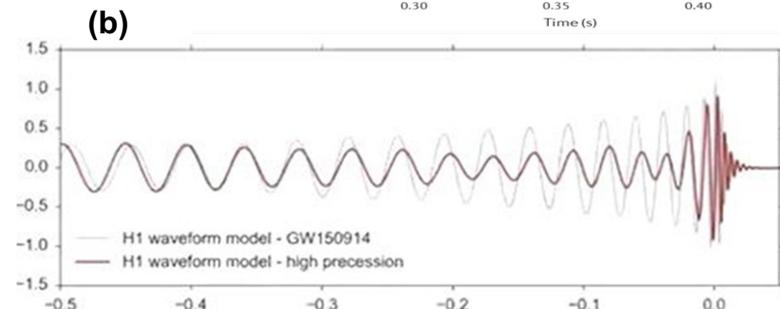
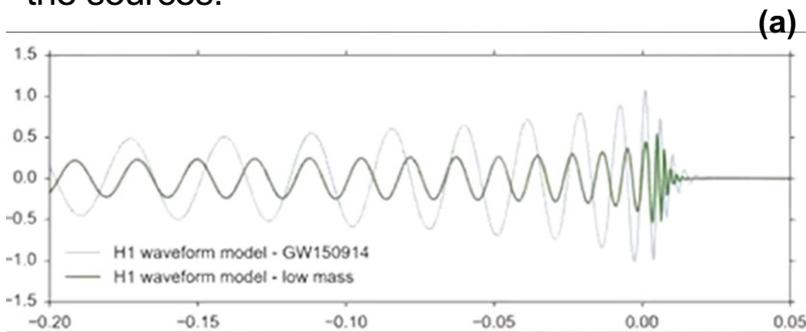
Interpretation of gravitational wave signals based on the parameters of the sources



When it comes to the Gravitational Wave (GW) sources, Massive and Supermassive Black Hole Binaries (MBHB) present certain parameters with great effect on the aspect of the waveform. Thus, by analyzing the shape of the signal, we can determine the type of event that causes the space-time ripples and vice-versa. We are of course interested in the LISA frequency range, but the LIGO/VIRGO data is a great way to practice and validate the algorithm.



Such parameters are the masses (a) and the spins (b) of the sources:

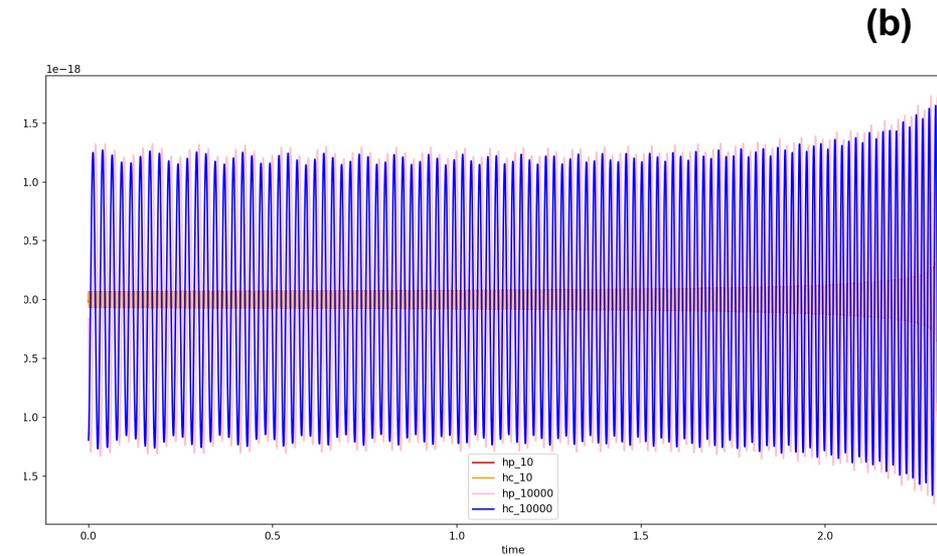
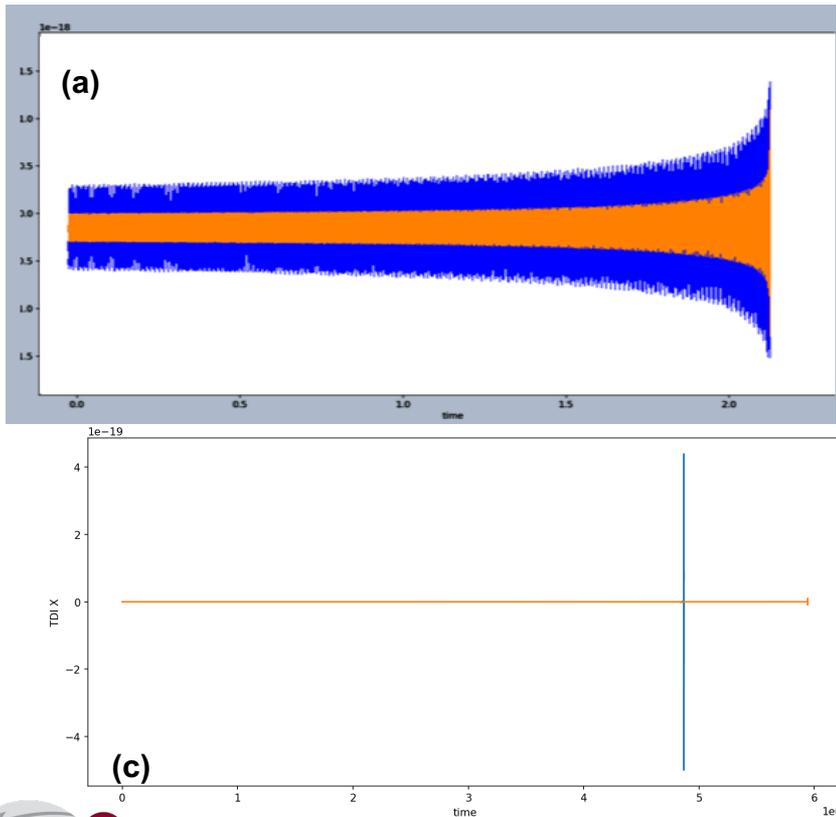


*representations realized based on the LIGO/VIRGO collaboration data as a study model, using the LIGO/VIRGO analysis tools



ISS-Science Group (ISS-Sci)

⇒ With the LDC tools (*LISA constants, LISA instrument, LISA GW response*), we can simulate our own waveforms in the LISA frequency range in order to train neural networks meant to differentiate GWs produced by MBHB sources



Simulations realized with the LDC tools in order to emphasize the effect of the mass ratio (a), the signal-to-noise ratio (b) and the moment of coalescence (c) upon the waveform of a GW



ISS-Science Group (ISS-Sci)

Previous activities:

- A software platform and a database containing present and future experiments capable to detect EM and non-photonic (e.g., cosmic rays, neutrino, etc.) GW counterpart signals. The source parameters inferred from the GW event (Low Latency Pipeline) are to be used by the LISA alerting system
- A software platform and a database which can accommodate with simulated GW waveforms from different types of sources, aimed to support rapid data analysis procedures required by the LLP to decide on setting the instrument in a protected state and/or alerting potential observers of the astronomical counterpart signals

Current activities:

Developing of a CNN in order to detect a GW signal from EMRI, implying a number of steps, like:

- Installing and configuring the appropriate software frameworks to: Simulate EMWI waveforms using both analytical (very fast but missing some waveform details) and numerically (accurate but at least one order of magnitude slower); Simulate Galactic Binaries stochastic signal, this being the most important noise that poses major problems in the analysis of the gravitational signal of interest; Generate the LISA response to the detected gravitational wave (it depends on the orbit and the orientation of the satellites constellation relative to the GW source)
 - Conducting a number of studies to determine the optimal NN configuration and the optimal form of the input data (data series, spectra, spectrograms). The spectrogram seems to be the best choice since it reconcile the other two options: the time series which contains all the information but is a very big data and the spectrum which is much more smaller data but are missing the time information
 - Developing a CNN to analyse the GW spectrograms, the purpose being to detect the presence of an EMRI regardless of the time series content (such as the simultaneous presence of other GW signals from GB, MBHB, SMBHB)
-

ISS-Science Group (ISS-Sci)

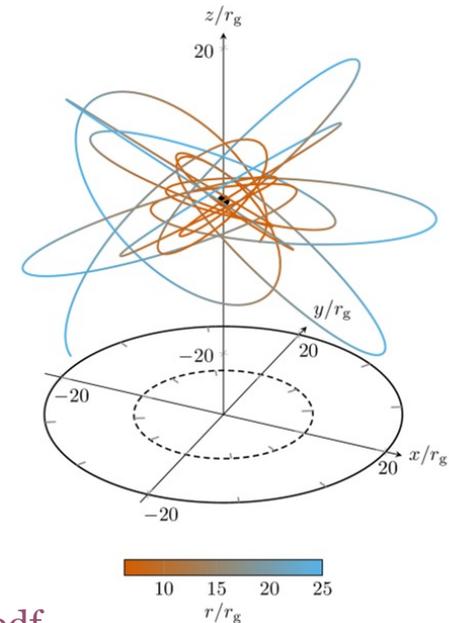
Some aspects regarding the detection of EMRI signals by LISA:

A SMBH with $10^6 M_\odot$ will capture an CO end may generate an EMRI GW signal once in $10^6 \div 10^8$ years

LISA can detect such signals from cosmological distances; some studies (Babak et al. , Phys. Rev. D 95, 2017) suggest that in one year, LISA will detect from few to few thousand EMRI signals

The study of the EMRI events detected by LISA will contribute to the testing of GR in strong field regime, permitting the direct study of the geometry of the Black Holes (Kerr or Schwarzschild metrics).

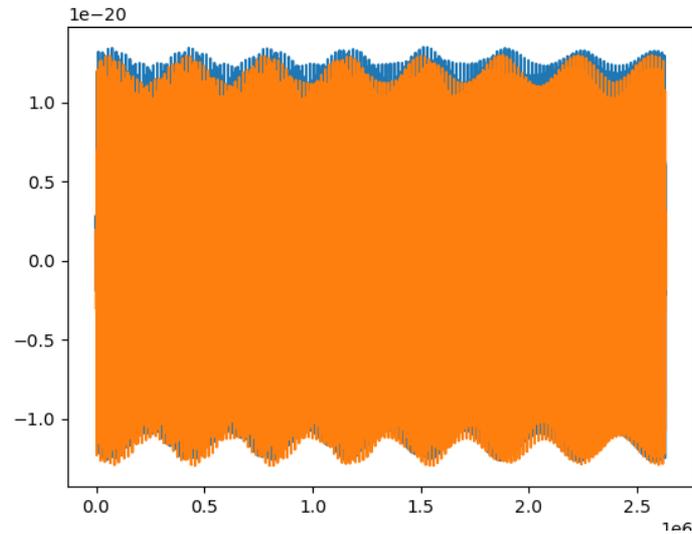
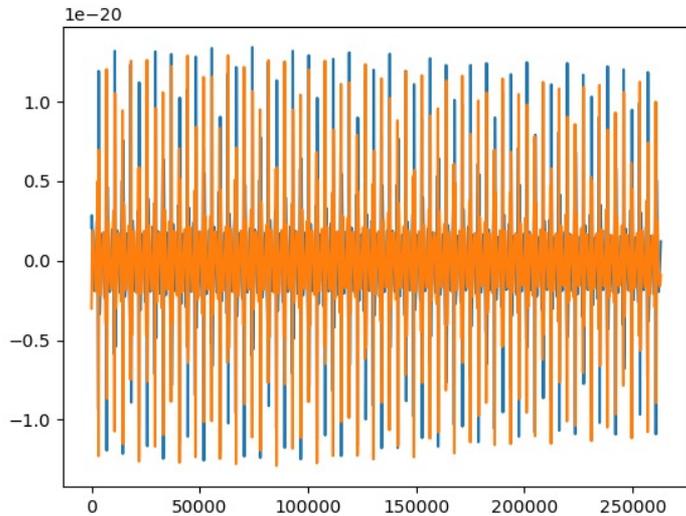
Illustration of an EMRI orbit in Kerr spacetime, appropriate for a short portion of an EMRI around a spinning MBH. The central black hole has a mass $M = 10^6 M_\odot$ and a dimensionless spin of 0.9. Distances are measured in units of the gravitational radius $r_g = GM/c^2$. The innermost stable circular orbit for this MBH would be at $r \cong 2.3r_g$. The coordinates have been mapped into Euclidean space to visualise the orbit.



Credit:

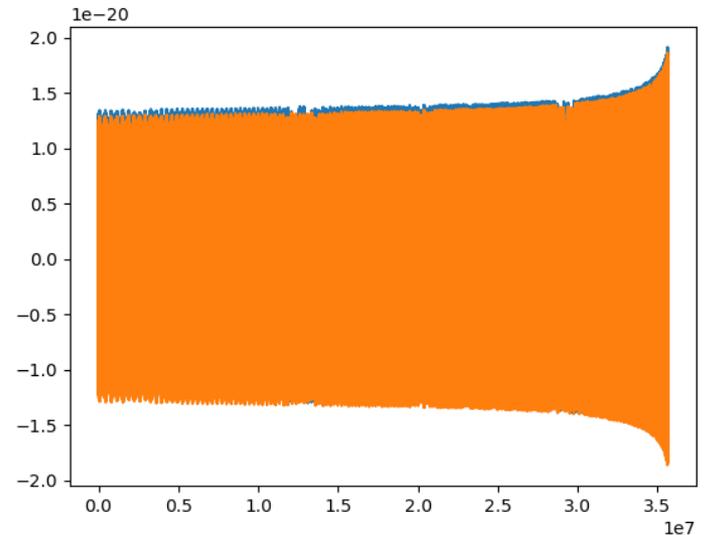
<https://arxiv.org/pdf/1903.03686.pdf>

ISS-Science Group (ISS-Sci)



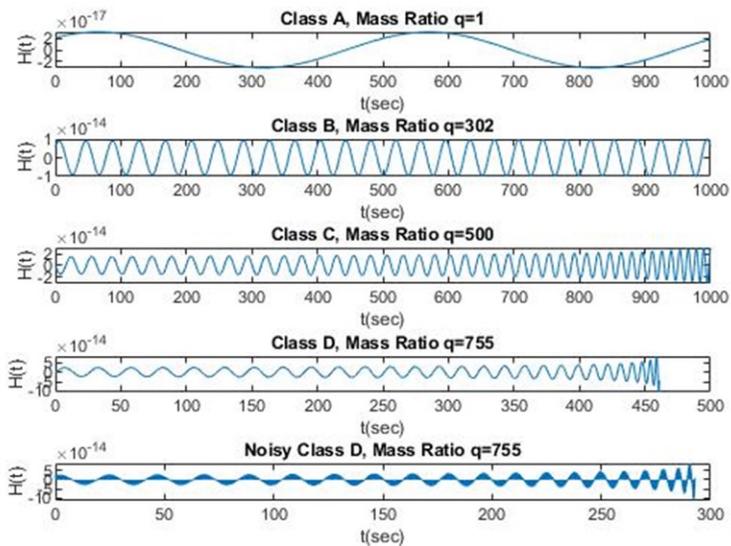
The “plus” (orange) and “cross” (blue) components of the GW from an EMRI, in 3 days (left), 1 month (central) and 2 years (right).

The data were obtained with the FEW software (FastEMRIWaveforms), with the following source parameters: $M = 1e6$ (Mass of MBH in MSun); $m = 1e2$ (Mass of CO in MSun); $a = 0.2$ (MBH spin); $p_0 = 14.0$ (Initial semi-latus rectum); $e_0 = 0.6$ (initial eccentricity; $dist = 1.0$ (distance in Gpc)

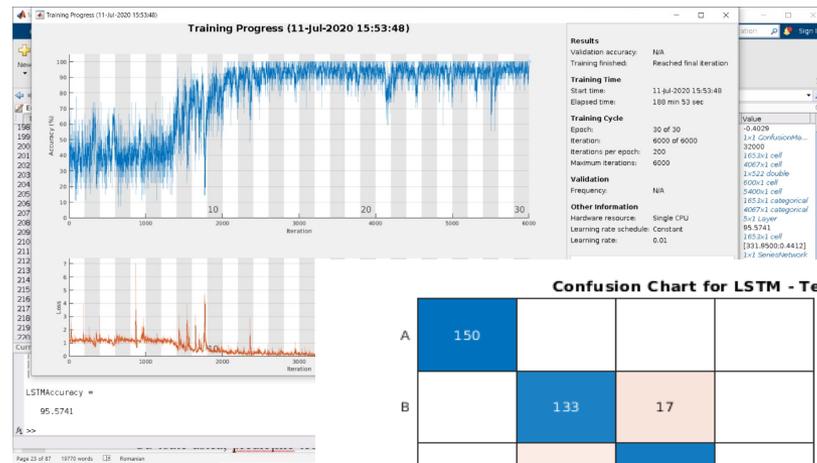


ISS-Science Group (ISS-Sci)

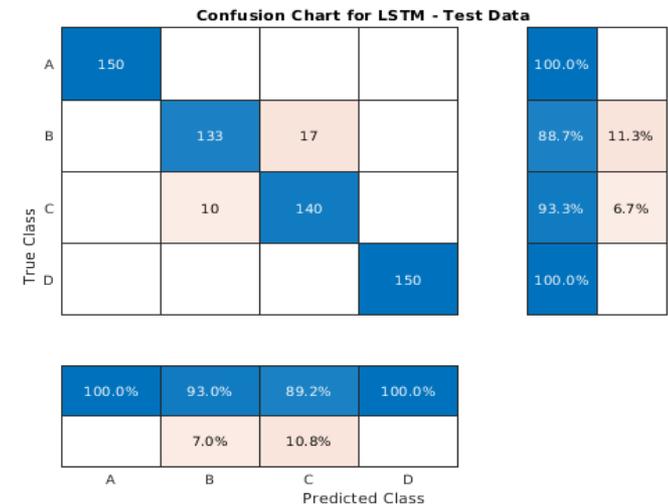
- Low-Latency Bi-LSTM Neural Network Classifier (LL-BiLSTM) implementat in Matlab
- Deep Learning programs for classifying GW waveforms with Python (DL MLP)



Multiple waveform classes with and without noise

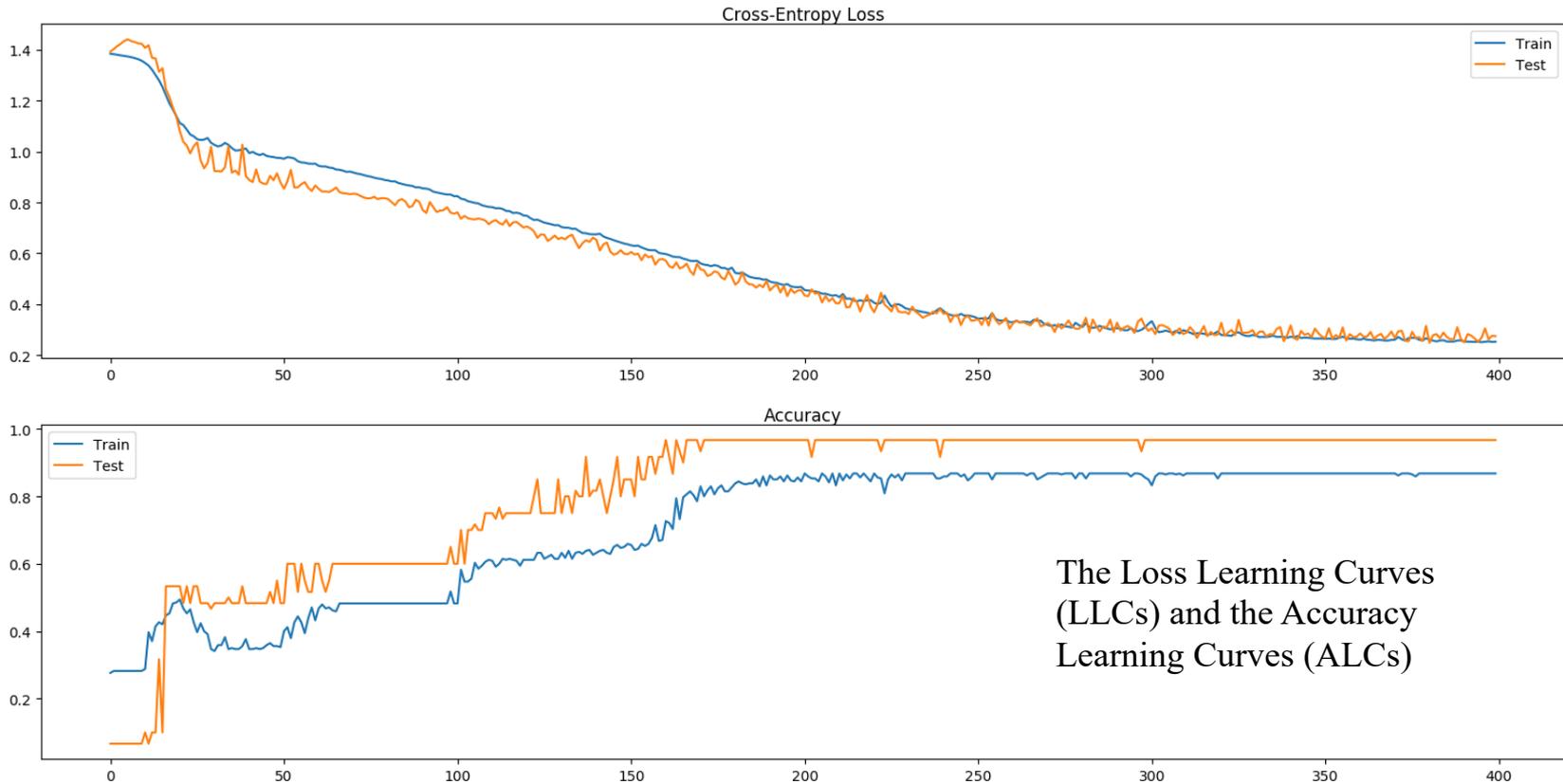


The algorithm works good for any number of classes and it's a viable candidate classifier



ISS-Science Group (ISS-Sci)

- Deep Learning programs for classifying GW waveforms with Python (DL MLP)



Activities and results

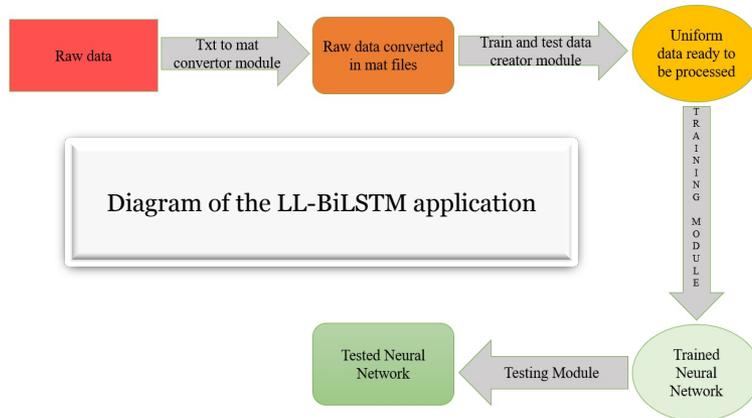
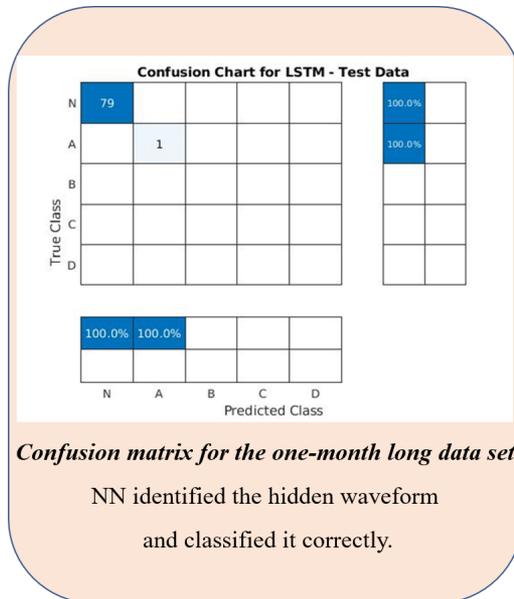
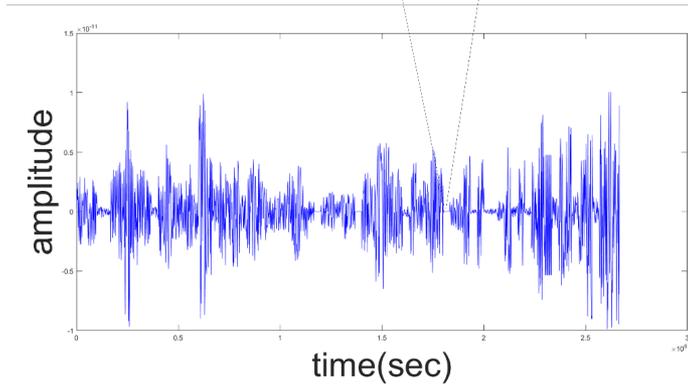
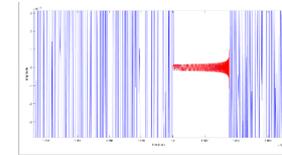


Diagram of the LL-BiLSTM application

Input data: one month of GW waveforms



Identification and classification of a gravitational wave signal from a batch of data (noise and hidden signal).

NN: trained with gravitational wave signals and noise data files (16,000 gravitational waveforms (“clean” and “noisy”) and 4000 noise data files).

Environment: Matlab Categories: five (A, B, C, D, N)

Training accuracy: 98.71 Training time: ~308 minutes

Testing accuracy: 98.55% Testing time: < 1 minute



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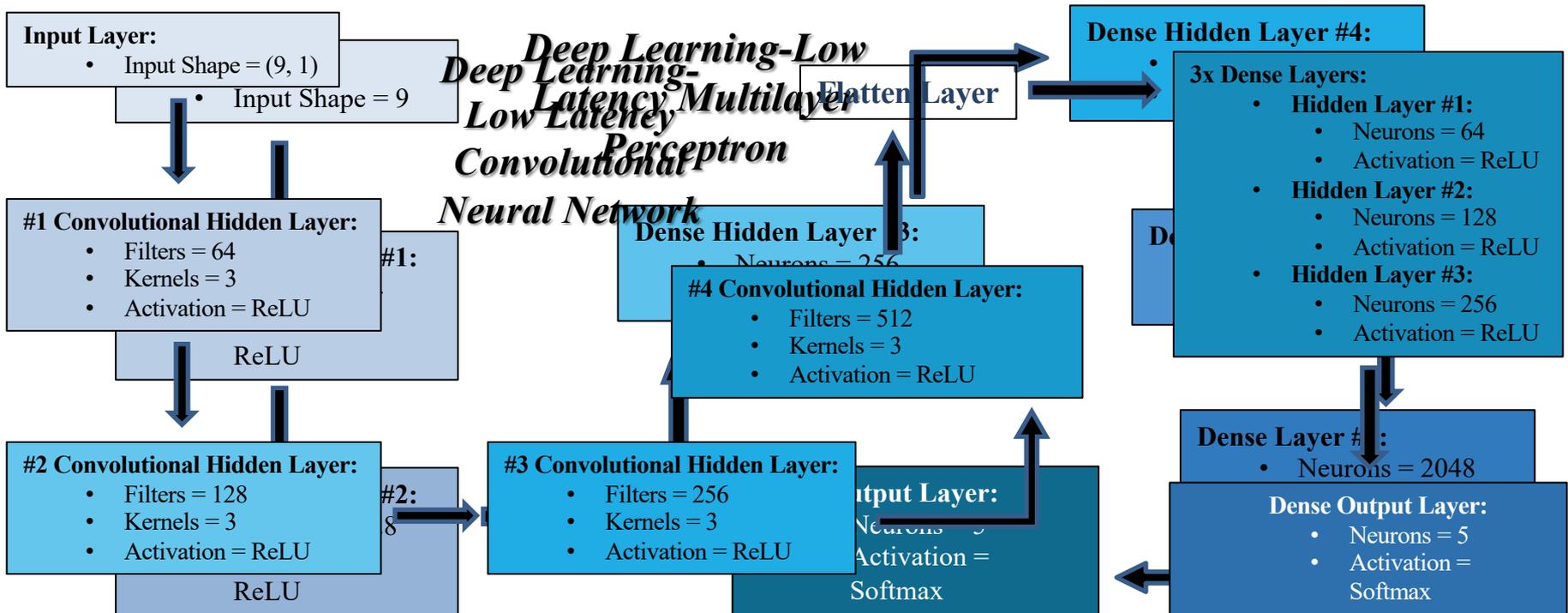


*A **Deep** Learning Toolkit for Gravitational **Waves** Analysis (**GWEEP**)*

Deep Learning Models

1. DL-LL MLP Architecture

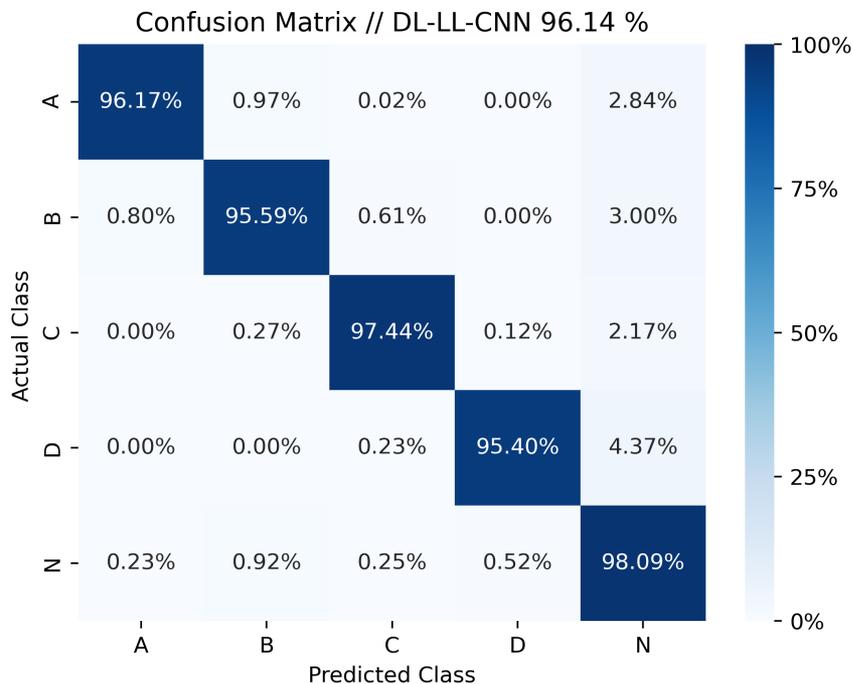
2. DL-LL CNN Architecture



Inference DL-LL MLP Inference DL-LL GNN Inference Confusion Matrix



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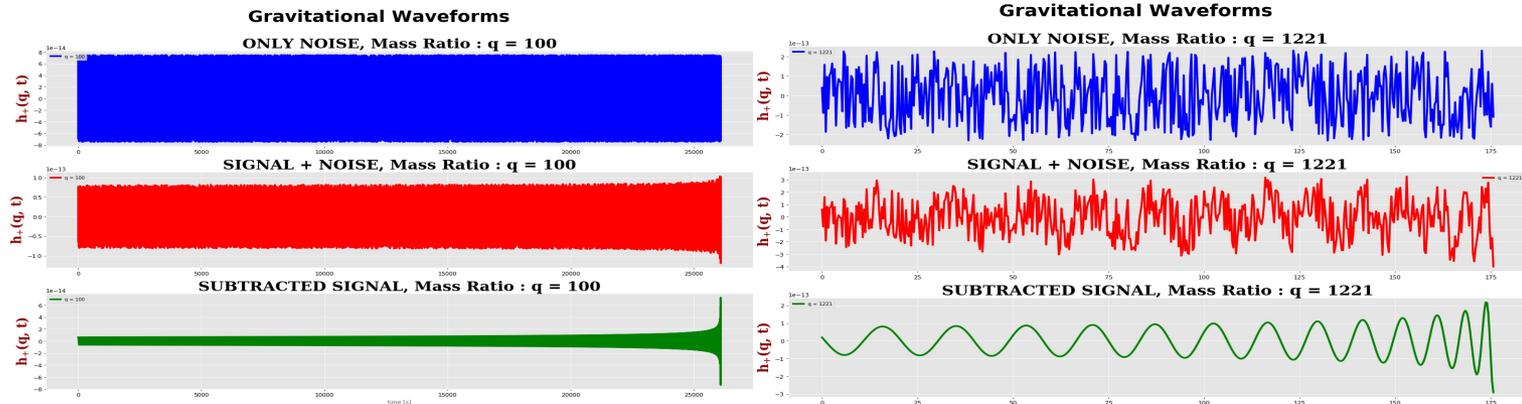
Training & Validation:

- Training Acc. = 99.78%
- Validation Acc. = 99.75%
- Training loss = $1.22 \cdot 10^{-2}$
- Validation loss = $8.91 \cdot 10^{-2}$
- Training time = 37 min 29 s 515 ms

Inference:

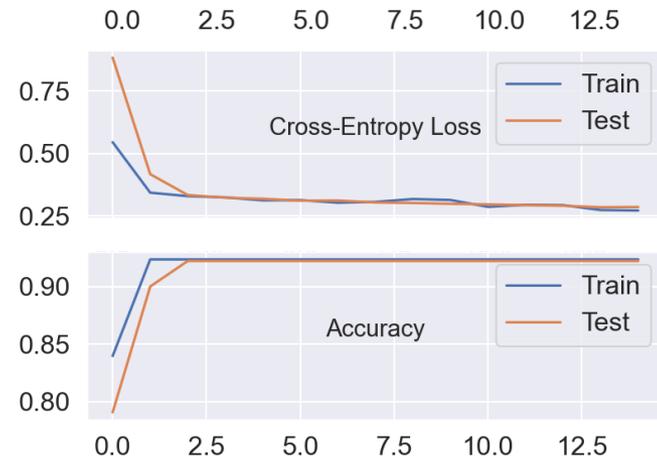
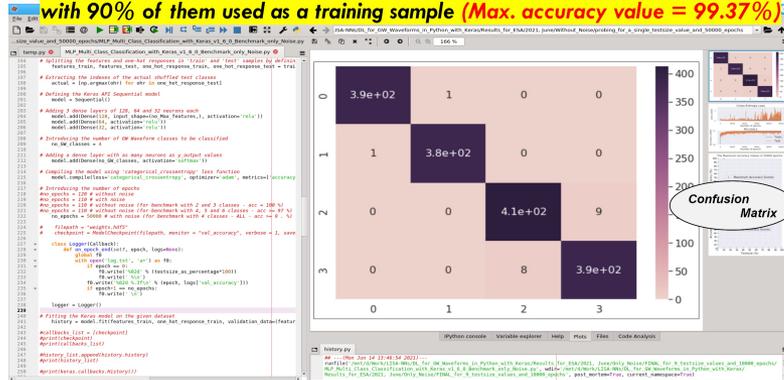
- Inference Acc. = 98.76%
- Inference time = 2 min 45.92 sec

Activities and results



Sample of Data Used, Gravitational waves waveforms with and without noise

for 15,886 simulated GW waveform signals, divided into 4 mass ratio classes, with 90% of them used as a training sample (Max. accuracy value = 99.37%)



Building and training a MultiLayer Perceptron (MLP) Multi Class Classification Deep Learning NN in Python using Keras wrapper on top of TensorFlow 2 DL framework backend

Architecture of the DL MLP

Python software design

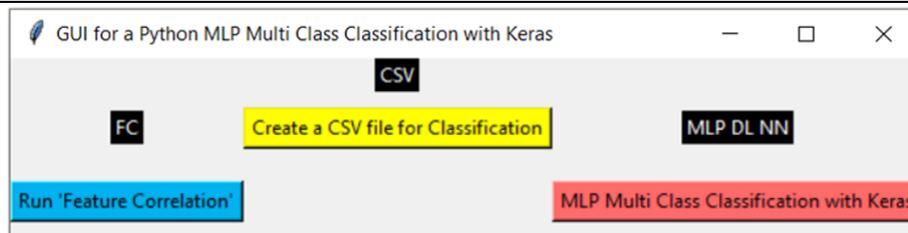


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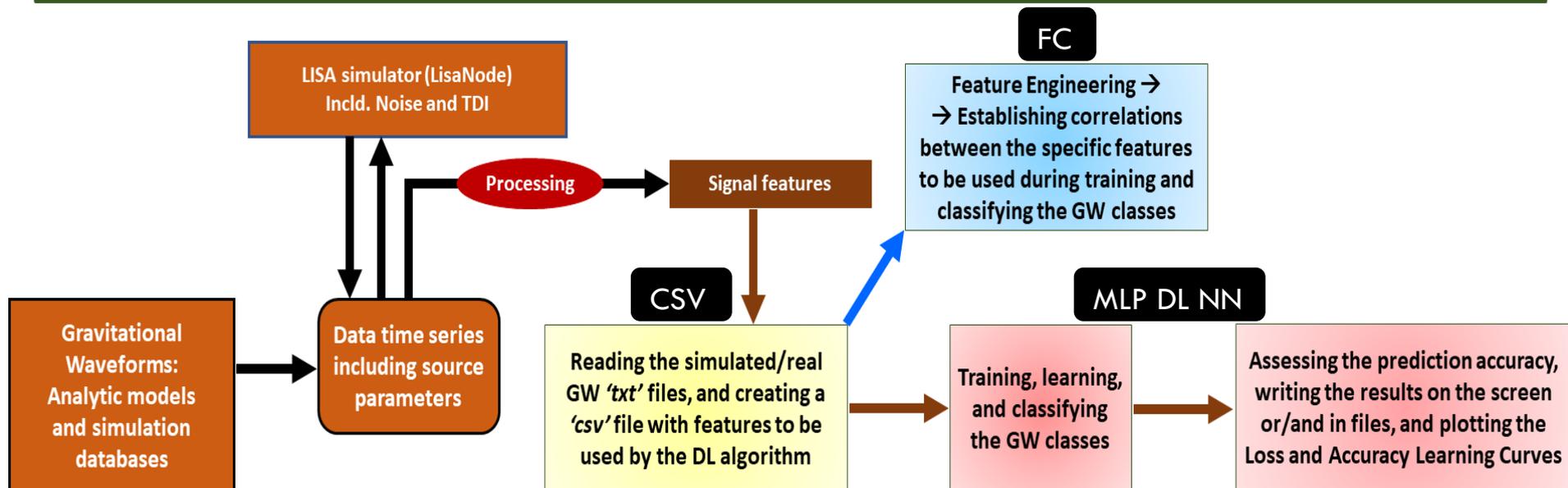
Components of the DL MLP Python Software

The *architecture of the DL MLP software is currently divided* in *four steps*:



**Current
version**

LISA Low-Latency Pipelines - Deep Learning Multilayer Perceptron Python Software Design



Data Used and Accuracy Values :

Using:

- 1. Full available data (generated by Traian) : 708,544 GW waveforms**
= 266,544 (without noise, pure signal) + 442,000 (with noise).

Operations needed :

- Creating the CSV files (**6 classes**).
- Training and classifying the GW waveforms.

- **Maximum accuracy values for test percentage values (10% ÷ 90 %) and for 100 MLP epochs : 95.49% ÷ 85.83% (figure 1) – for 6 classes**

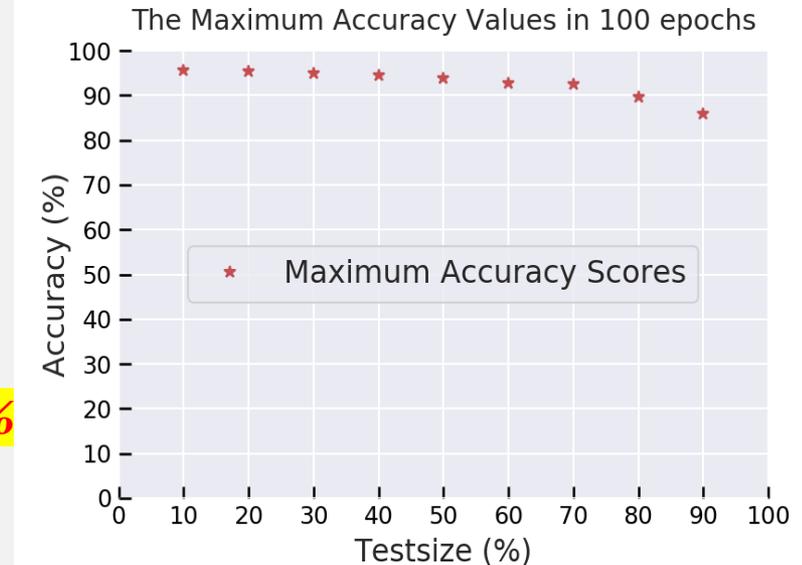


Fig.

1

Plotting the Accuracy values versus the

Data Used and Accuracy Values :

Using:

- 1. Full available data (generated by Traian) : 708,544 GW waveforms** = 266,544 (without noise, pure signal) + 442,000 (with noise), *but the noise was subtracted to obtain a pristine signal* : $S = [(S+Z) - Z]$.

Operations needed :

- Generating the files with a pure GW signal by extracting the additive noise from the files using the signal mixed with noise and those containing only the generated noise. **(figures 2 and 3)**
 - Creating the CSV files **(6 classes)**.
 - Training and classifying the GW waveforms.
- **Maximum accuracy values for test percentage values (10% ÷ 90 %) and for 100 MLP epochs : 99.65% ÷ 99.43% (figure 2)**
 - **Maximum accuracy value for a single test percentage value (10%) and 1,000 MLP epochs : 99.87% ! (figure 3)**



Building and training a **MultiLayer Perceptron (MLP) Multi-Class Classification** Deep Learning NN in Python - using Keras wrapper on top of TensorFlow 2 DL framework backend

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A Python DL MLP Multi-Class Classification Code

Plotting the Accuracy values versus the

for 708,544 simulated GW waveform signals,
divided into 6 mass ratio classes,
with 90% of them used as a training sample

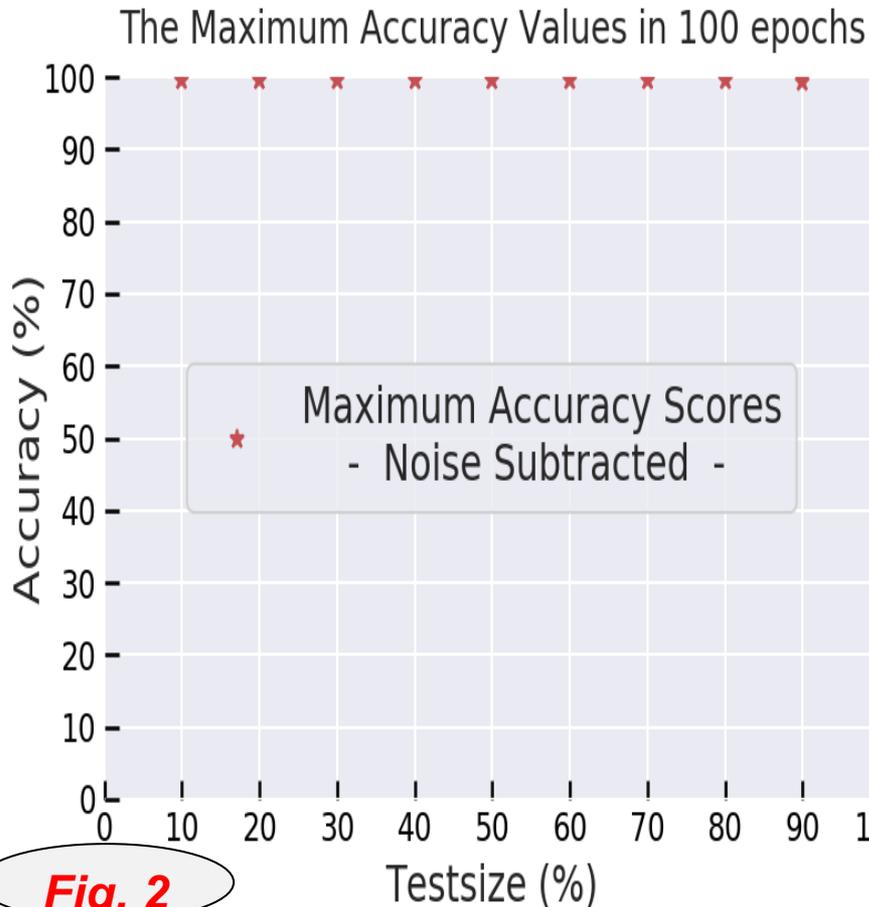


Fig. 2

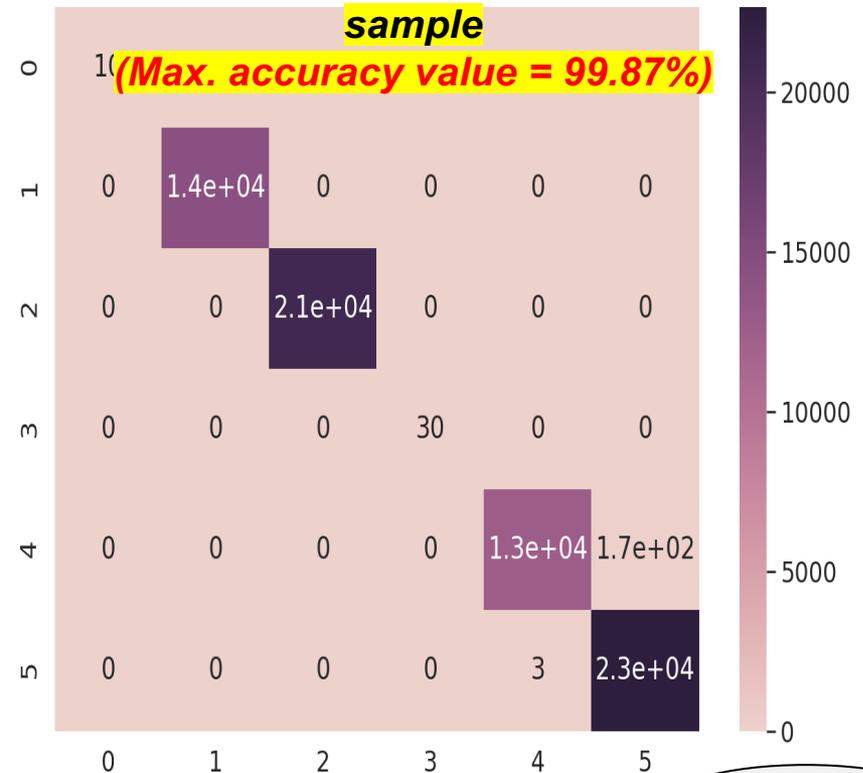


Fig. 3

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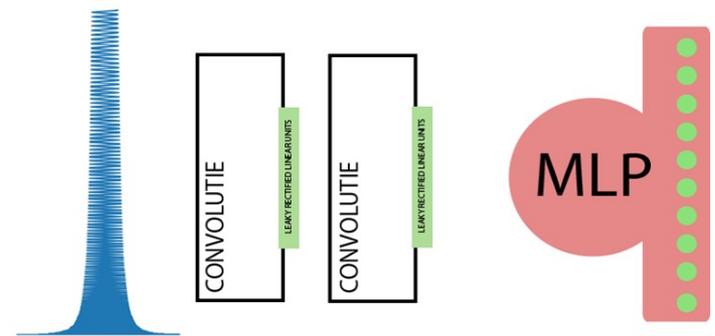
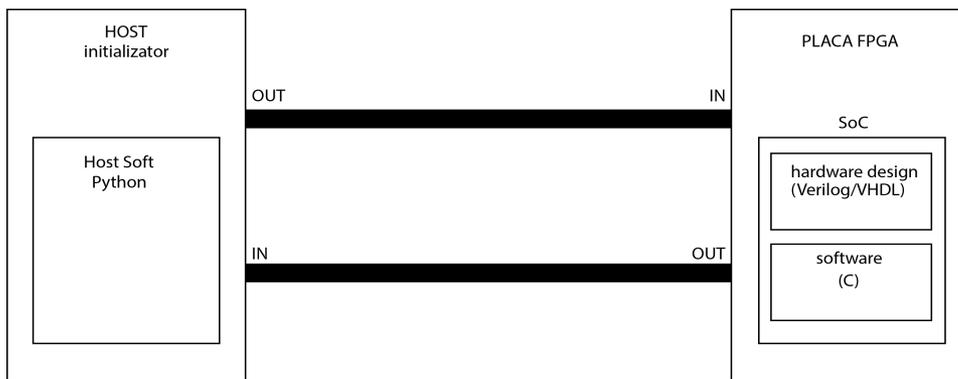
- Artificial Intelligence Inference Acceleration System



Deep Learning Convolutional Neural Network for Characterization and Classification of Gravitational Waves, inferred on Xilinx Spartan®-7 XC7S100 FPGA.

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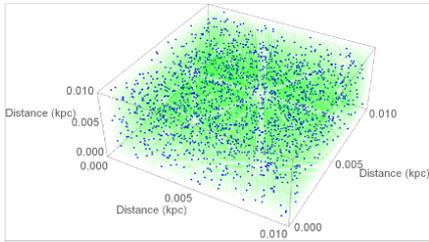
- FPGA setup for LISA low latency implementation using Neuronal Networks.
- Developed in Python and translated into C to be embedded into an FPGA.
- The hardware design is developed in Verilog/VHDL. The host program is developed in Python and it is responsible for transferring the data into the FPGA board, receiving the results and running the prediction algorithm.
- The algorithm has 4 layers: Input Layer: feeds discrete signal, Convolution Layer I: Morlet, Shannon and B-spline frequency wavelet, Convolution Layer II: Shannon ver. 1, Shannon ver. 2 and B-spline frequency, Convolution Layer III (MLP): 2 completely connected sub-layers and one output sub-layer.



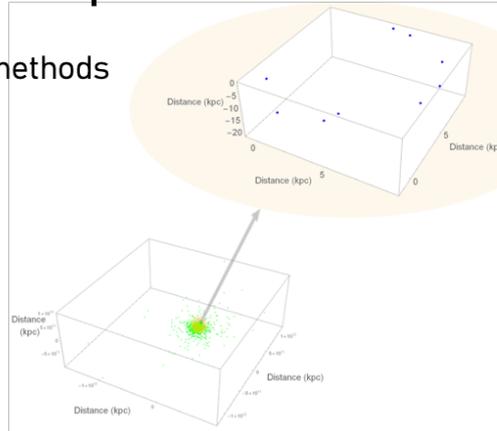
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LISA Astrophysics Working Group

Evolution of MBH populations and growth methods

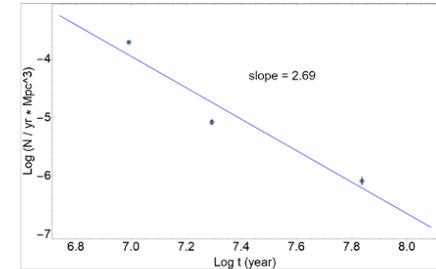


Initial conditions for MBH populations
(green - 166375 gas particles ; blue - 2004 BHs)



Final distributions after 13 Gyrs
(green - 135661 gas particles ; blue - 9 BHs)

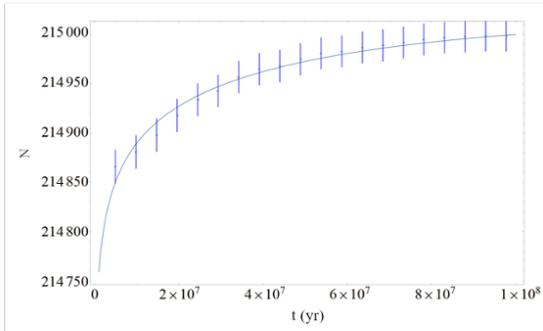
Merging Rates



Merging Rates per year per cubic Mega-parsec over time

We anticipate detection values somewhere between a few tens and little over a thousand yr^{-1} .

Exotic growth method (Star Gulping)



SG rate (Number of gulped stars over time)

Fit function: $y = a + b \cdot x + c \cdot \log_{10} x$

In accordance to previous results (Kesden, 2012)

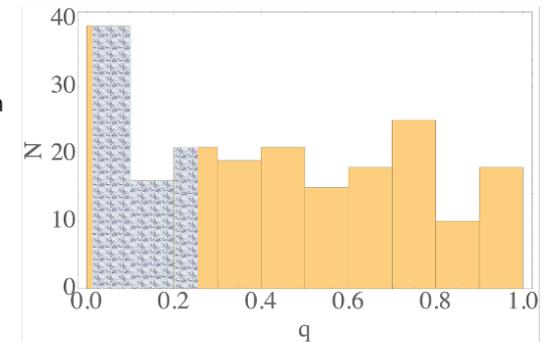
Poses as an argument for further study, especially because it might represent a very interesting case for the LISA Extreme Mass Ratio Inspirals (EMRIs) candidates.

Merging MBH binaries with mass ratios (q) values between

$$1/30 < q < 1/3$$

generate a 36% chance of spin-flip.

MBH Spin-Flip



Merging rates over mass ratios
(shaded area gives the highest spin-flip probability)

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LISA Astrophysics Working Group (continued)

White Paper contribution

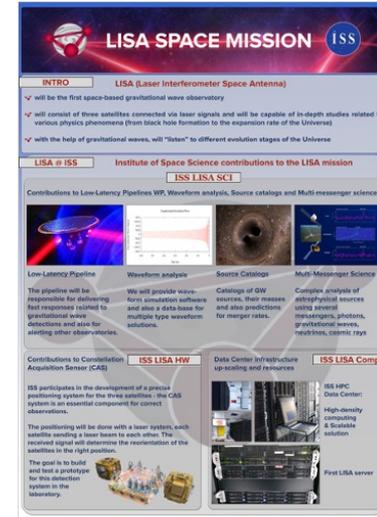
Section 2 - "MBH origin and growth across the cosmic time" & "MBH spin-flip"

Submitted for *Living Reviews*

 Laser Interferometer Space Antenna	Ref : LISA-
	Issue : 0 Revision : 1
	Date : 2021/05/19 Page : 1/ 113
LISA Astrophysics White Paper	
N/Ref :	LISA-
Title :	LISA Astrophysics White Paper
Abstract :	Here comes the abstract.

LISA Outreach Group

Posters



LECS – LISA EARLY CAREER SCIENTISTS

Organizing Job Fairs & Workshops



Co-chairing the LECS WG for a mandate

LECS chairs

Thomas Kupfer tkupfer@ttu.edu
 Valeriya Korol korol@star.srbham.ac.uk
 Răzvan Balașov rabalasov@spacescience.ro

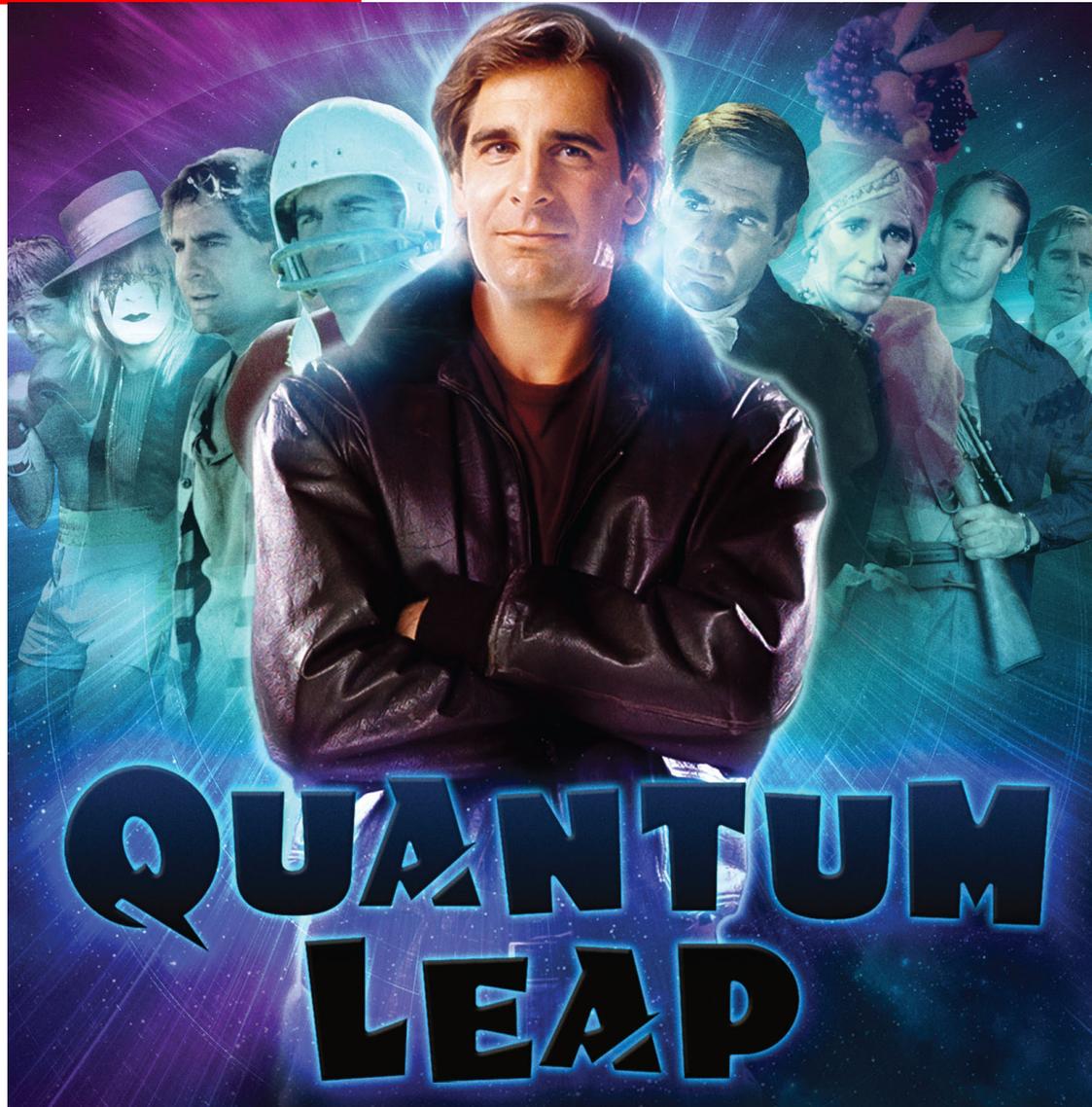


GWAECs Workshop @Lorentz Center, NL

Brochures



ISS-Science Group (ISS-Sci)



Quantum Neural Networks For The LISA Space Mission

Motivation

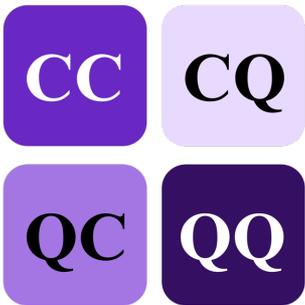
- The large amount of information which can be manipulated and the low computational costs of quantum computers allow us to process and analyze fastly a great quantity of space mission data.
- Complex data space requires a quantum leap in data analysis

With just 275 qubits, we can represent more states than the number of atoms in the observable universe: 2^{275} !

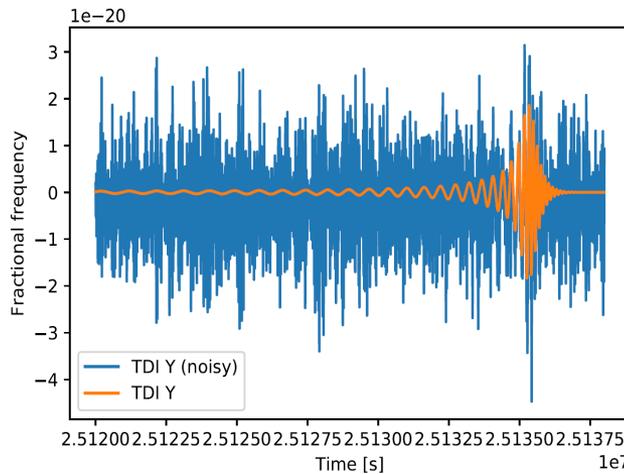


Data processing device

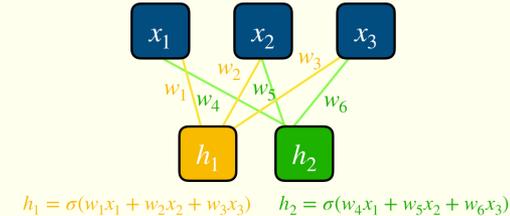
Data generating system



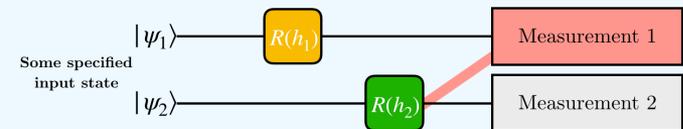
C – classical, Q - quantum



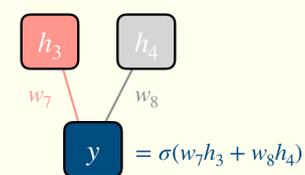
Classical



Quantum



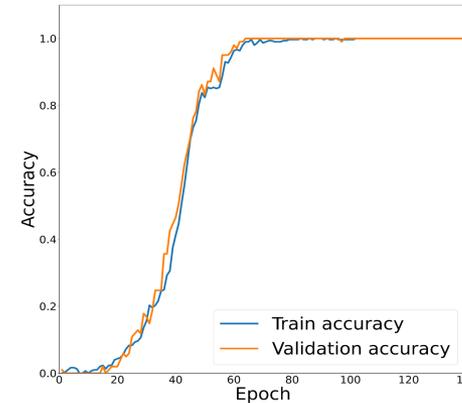
Classical



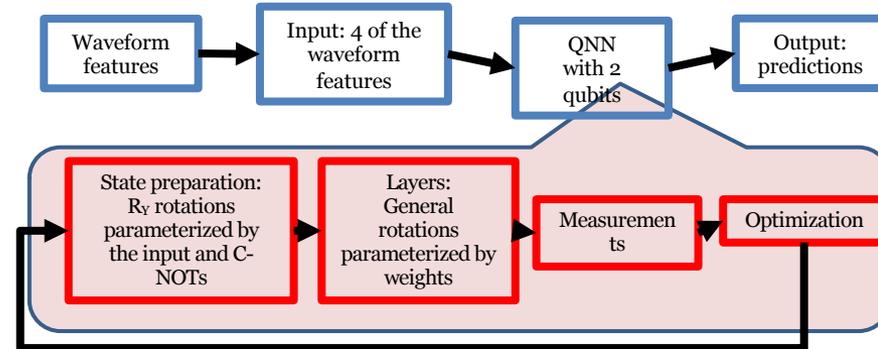
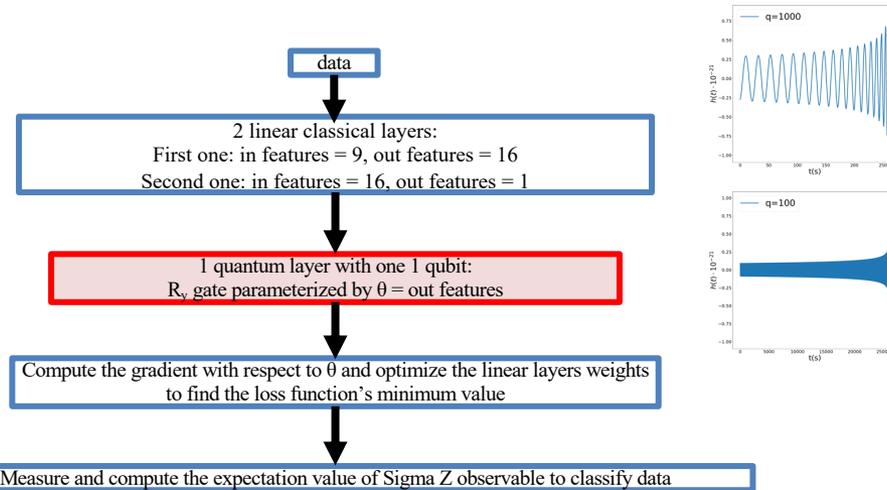
Quantum Neural Networks For The LISA Space Mission

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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■ Scientific output:

- Many talks and posters at LISA Symposium, LISA Conference, at COSPAR Scientific Assembly and more
- Papers:
 - *Simulations and analysis of the first black hole populations*; Balasov, R., Caramete, L.; **Rom. Rep. Phys.** 72, 114 (2020)
 - *Prospects for fundamental physics with LISA*; Barausse, Enrico, ..., Mircea Rusu; **General Relativity and Gravitation**, Volume 52, Issue 8, article id.81, 2020
 - *Characterization of Gravitational Waves Signals Using Neural Networks*; Caramete A. et al.; to be submitted; ArXiv, 2009.06109, 2020
 - *LLP-Deep Learning programs for classifying Gravitational Waveforms*, Felea, D. et Al.; to be submitted 2022
 - *Study of the first populations of black holes in the context of gravitational wave observations*; Caramete, L., Balasov, R.; published in **Advances in Space Research** (ASR), Volume (69) Issue1 Page438-447 (2022)

ISS-Science Group (ISS-Sci)

- Scientific output:

- Papers:

- *Data analysis for gravitational waves using neural networks on quantum computers*, Maria-Catalina Isfan, Laurentiu-Ioan Caramete, Ana Caramete, Vlad-Andrei Basceanu, Traian Popescu, accepted for publication in **Rom. Rep. Phys**, 2022
- *Massive black hole growth using the Star Gulpig mechanism*, L. I. Caramete, R. A. Balasov, A.M. Paun, accepted for publication in **Rom. Rep. Phys**, 2022
- *Tabletop gravitational waves waveform simulator*, Laurentiu-Ioan Caramete, Vlad-Andrei Basceanu, Ana Caramete, Maria-Catalina Isfan, Florentina-Crenguta Pislau, Traian Popescu, Florin-Adrian Popescu, in prep.
- *Astrophysics with the Laser Interferometer Space Antenna*, Pau Amaro-Seoane, Jeff Andrews, ... R.A. Balasov, L. Caramete, et al., *accepted for publication in Living Reviews in Relativity*, 2022, arXiv:2203.06016

Thank you!

Activities and results

Our activities concentrated on the task of using the LISA data generated by the consortium to improve our pipelines.

LISA Data Challenge 2a, Sangria:

includes two main datasets: each contains *Gaussian instrumental noise* and simulated waveforms from 30 million *Galactic white dwarf binaries*, from 17 *verification Galactic binaries*, and from merging *massive black-hole binaries* with parameters derived from an astrophysical model.

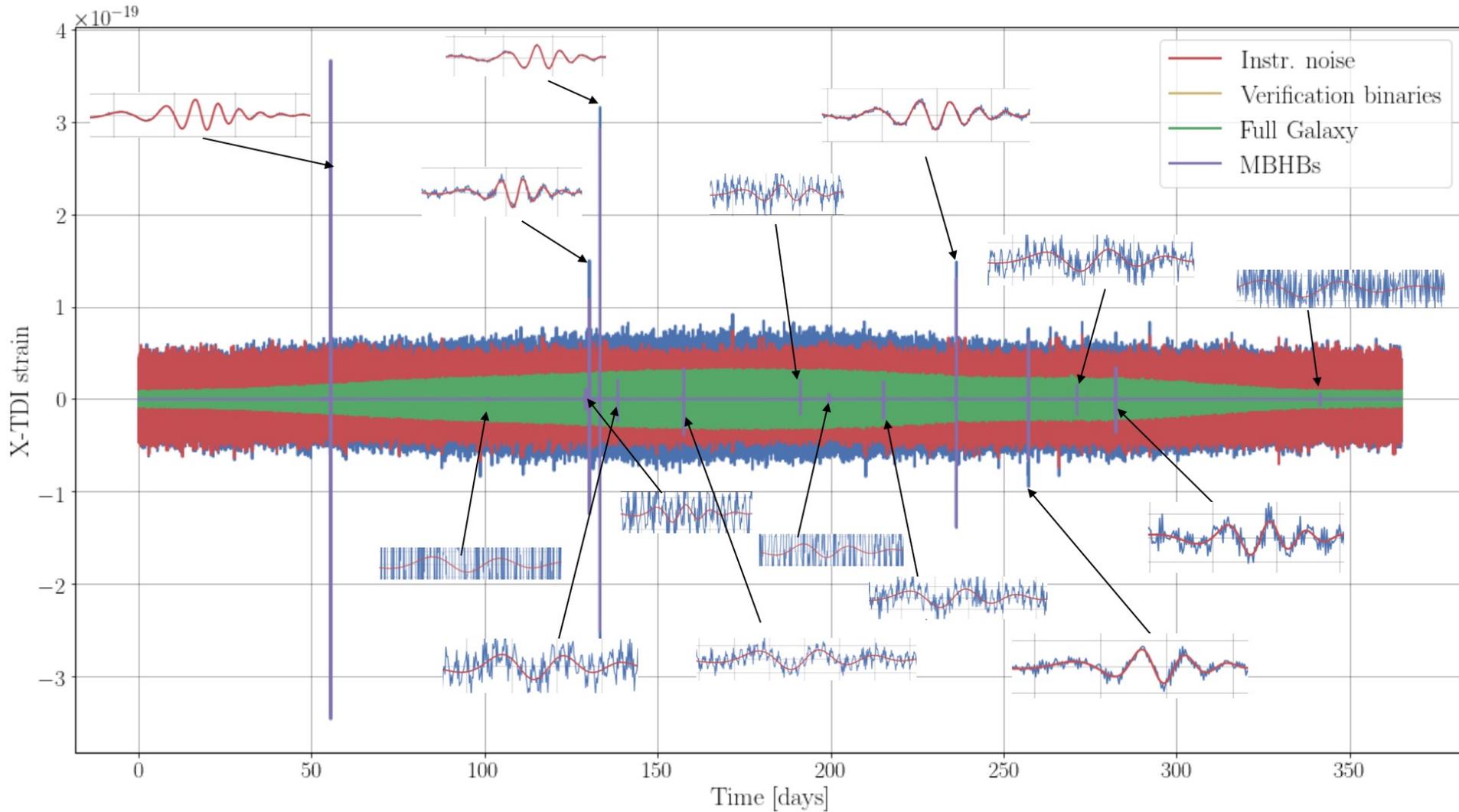
LDC2a-v1.Training dataset

The dataset includes the full specification used to generate it: source parameters, a description of instrumental noise with the corresponding power spectral density, LISA's orbit, etc. We also release noiseless data for each type of source, for waveform validation purposes.

LDC2a. Blind data challenge

The dataset is blinded: the level of instrumental noise and number of sources of each type are not disclosed (except for the known parameters of the verification binaries).

Activities and results



LDC2a-v1.Training dataset, LISA collaboration, <https://lisa-ldc.lal.in2p3.fr/challenge2>

Activities and results



LDC2a. Blind data challenge, LISA collaboration, <https://lisa-ldc.lal.in2p3.fr/challenge2>

Activities and results

Direct Training

Use the training data set provided by the LISA consortium to train the NN and then apply the network to the blind data set and try to find the waveforms and characterize them.

The training set must be sliced in suitable bunch of data and prepared before use. The blind data set must also be sliced with a moving search window.

Pros: it has all the characteristics of LISA data generated by the consortium.

Cons: it is limited to the few waveforms provided by the consortium.

External training

Use the in-house generated waveforms and the noise provided by the LISA consortium to train the NN and then to apply the network to the blind data set and try to find the waveforms and characterize them.

The training set is used to validate the NN and then the blind set is analysed to complete the challenge. Both searches use a moving window.

Pros: it can find and characterize a large interval of waveforms.

Cons: the waveform data base has to be constantly checked and improved with the new input from the collaboration.