ASTROMETRIC CONSTRAINTS ON STOCHASTIC GRAVITATIONAL WAVE BACKGROUND WITH NEURAL NETWORKS

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AI goes MAD²
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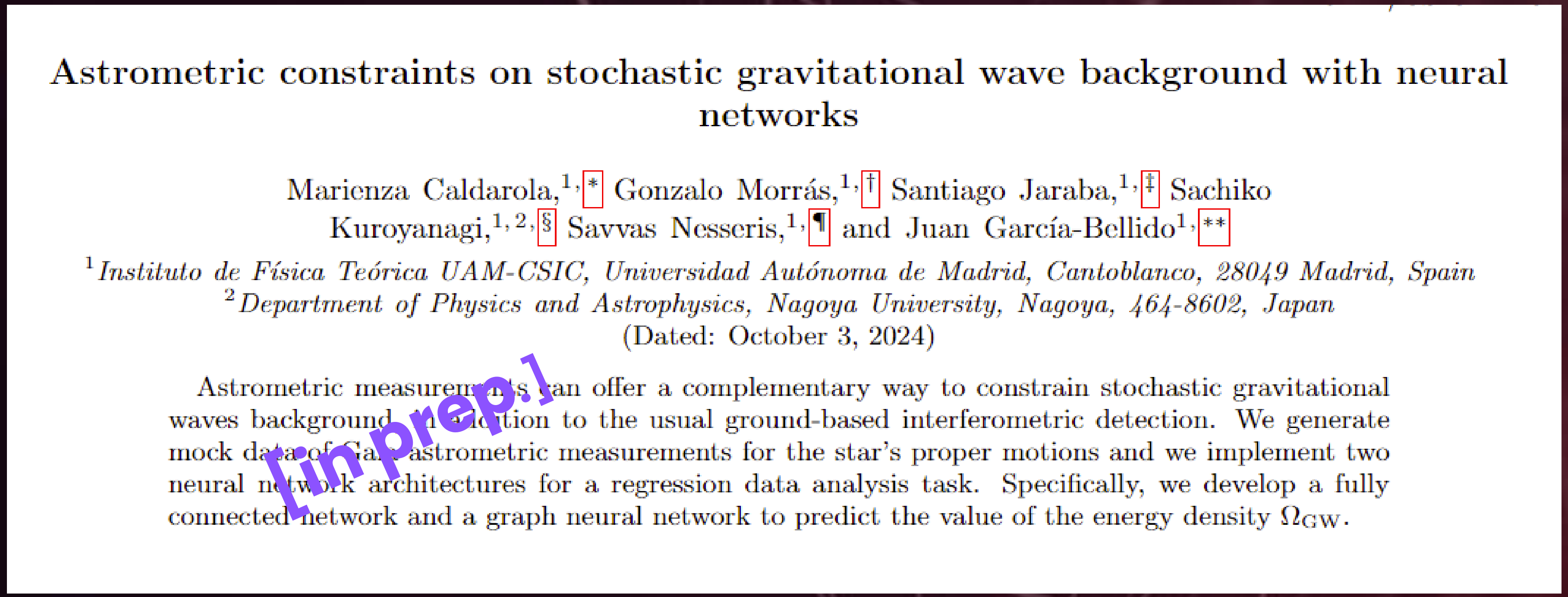

Astrometric constraints on stochastic gravitational wave background with neural networks

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Astrometric measurements can offer a complementary way to constrain stochastic gravitational waves background in addition to the usual ground-based interferometric detection. We generate mock data of Gaia astrometric measurements for the star's proper motions and we implement two neural network architectures for a regression data analysis task. Specifically, we develop a fully connected network and a graph neural network to predict the value of the energy density Ω_{GW}.

[in prep.]

About the Project

Possibility of constraining the energy density of the stochastic gravitational waves background (SGWB) at very low frequencies thanks to astrometric surveys.

We explore the application of two neural networks.

Fully Connected Network, one of the simplest and most flexible machine learning architecture.

Graph Neural Network, given the nature of our dataset and its natural conformity to a graph representation.

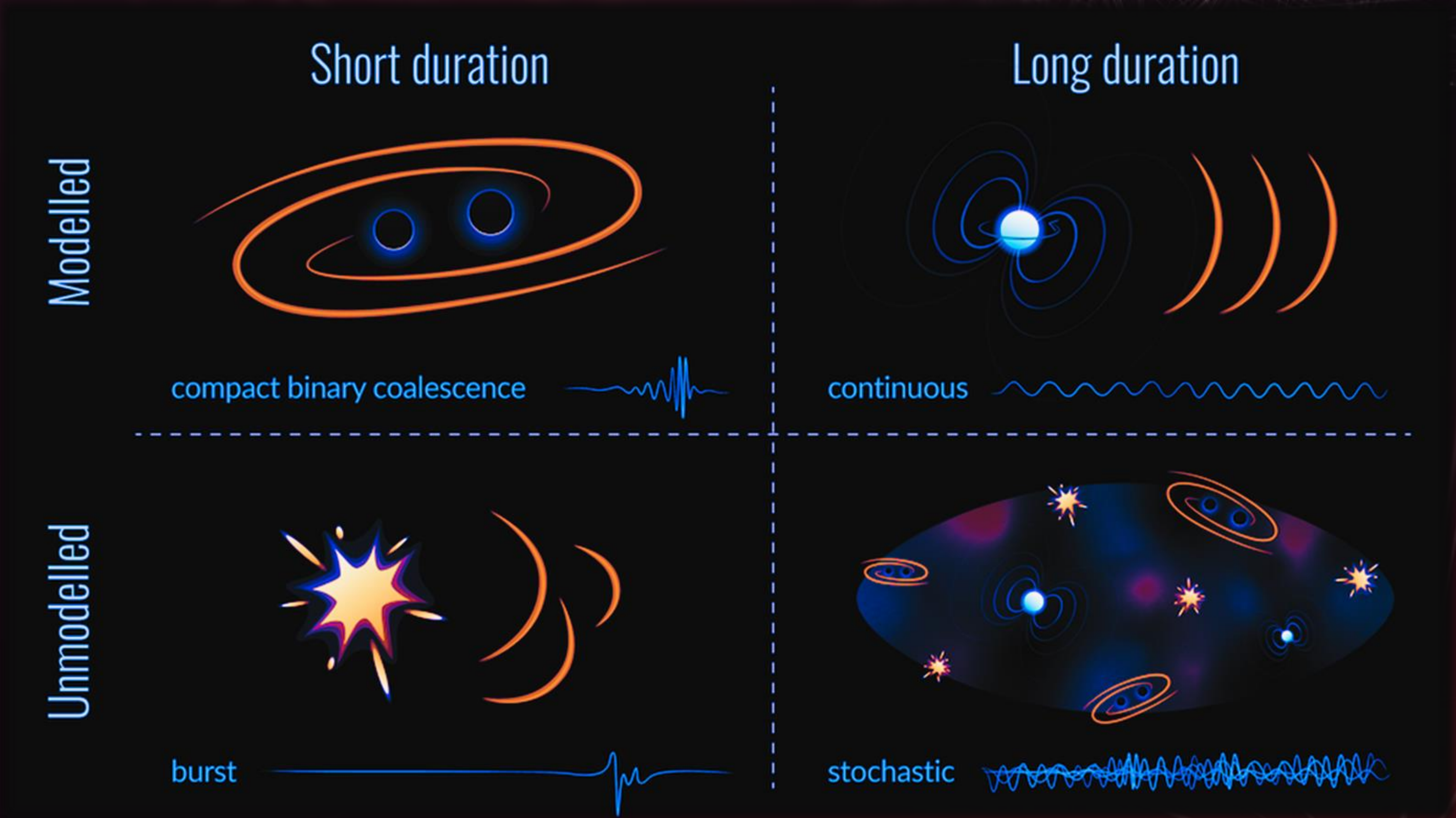
Why ML is important for GWs field

- GW signal detection
- Glitches classification
- Waveform modelling
- Overlapping signals
- Computational and timing efficiency
- etc...

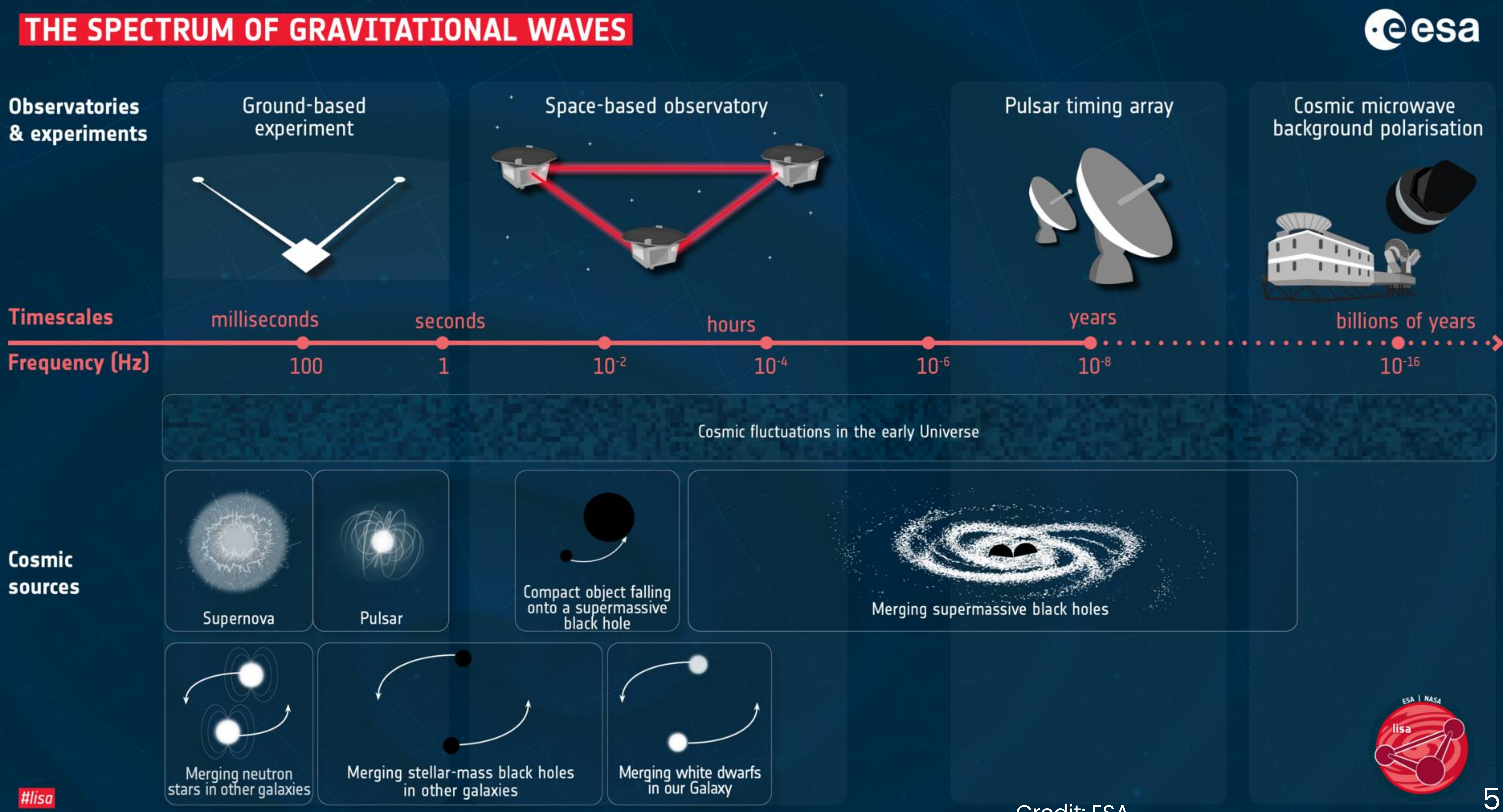
- Noise reduction
- Parameters estimation
- Improving sensitivity

Review paper: *Enhancing gravitational-wave science with machine learning*
Elena Cuoco et al
2021 Mach. Learn.: Sci. Technol. 2 011002

Different types of gravitational-wave sources

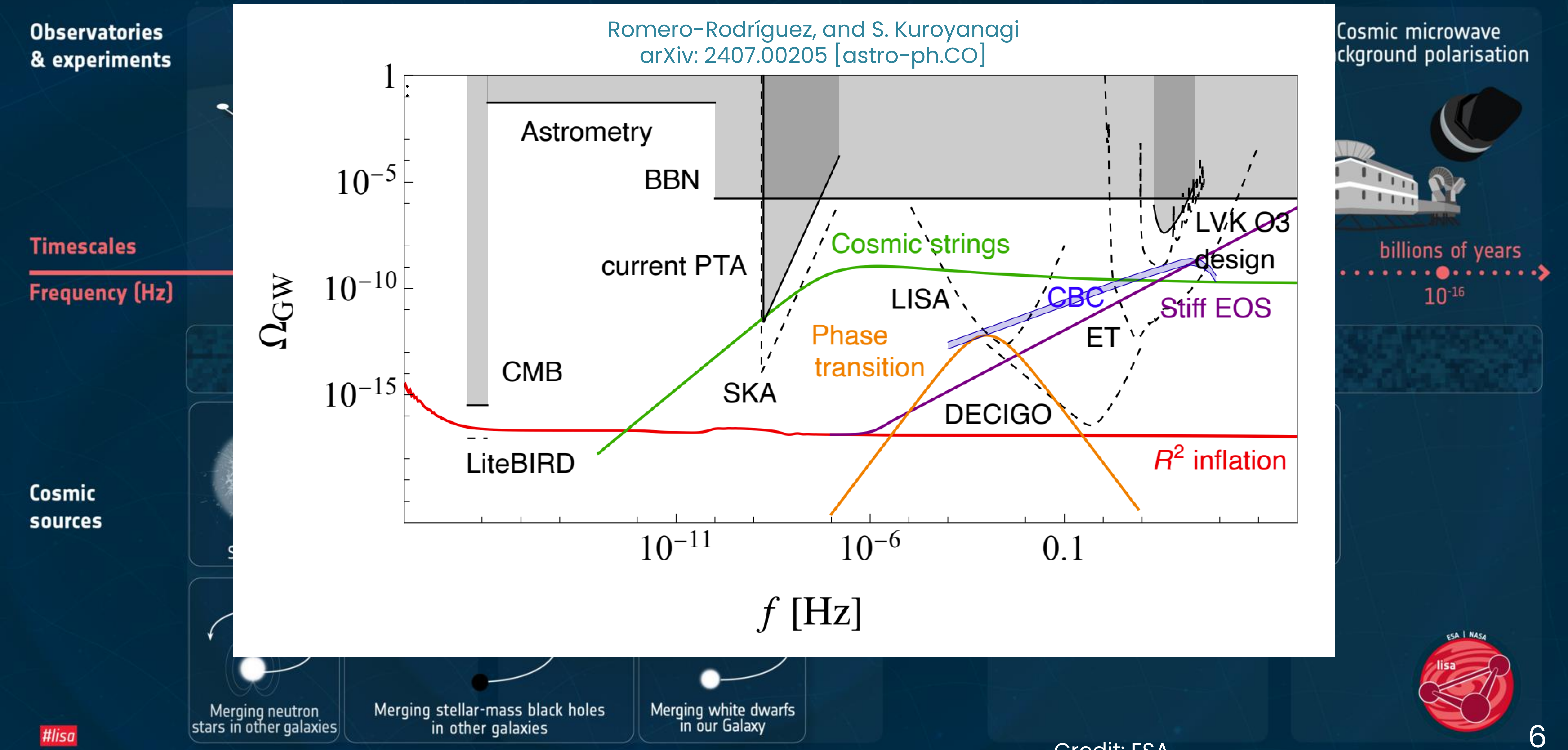


Credit: Shanika Galaudage


THE SPECTRUM OF GRAVITATIONAL WAVES
Observatories & experiments
Ground-based experiment
Space-based observatory
Pulsar timing array
Cosmic microwave background polarisation
Timescales
milliseconds
seconds
hours
years
billions of years
Frequency (Hz)
100
1
10^{-2}
10^{-4}
10^{-6}
10^{-8}
10^{-16}
Cosmic fluctuations in the early Universe
Cosmic sources
Supernova
Pulsar
Compact object falling onto a supermassive black hole
Merging supermassive black holes
Merging neutron stars in other galaxies
Merging stellar-mass black holes in other galaxies
Merging white dwarfs in our Galaxy
#lisa
ESA | NASA
lisa

Credit: ESA

THE SPECTRUM OF GRAVITATIONAL WAVES



Credit: ESA

Astrometry for GWs

- Astrometric measurements can offer a complementary way to constrain SGWB, in addition to the usual ground-based interferometric detection.

- Precise astrometric measurements offer a novel approach for detecting SGWB, because GWs cause fluctuations in the positions and proper motions of stars with a characteristic pattern in the sky.

- Future surveys will gather data on billions of stars, increasing precision but also complexity (e.g., inhomogeneity by mask).

- E.g., Gaia is a very precise three-dimensional map of our Galaxy by surveying more than billion objects. It is precisely charting their positions, distances, movements, and changes in brightness.

  Launched on 19 December 2013 (still in operation).

https://www.esa.int/Science_Exploration/Space_Science/Gaia_overview

- The amplitude of the SGWB is usually defined as

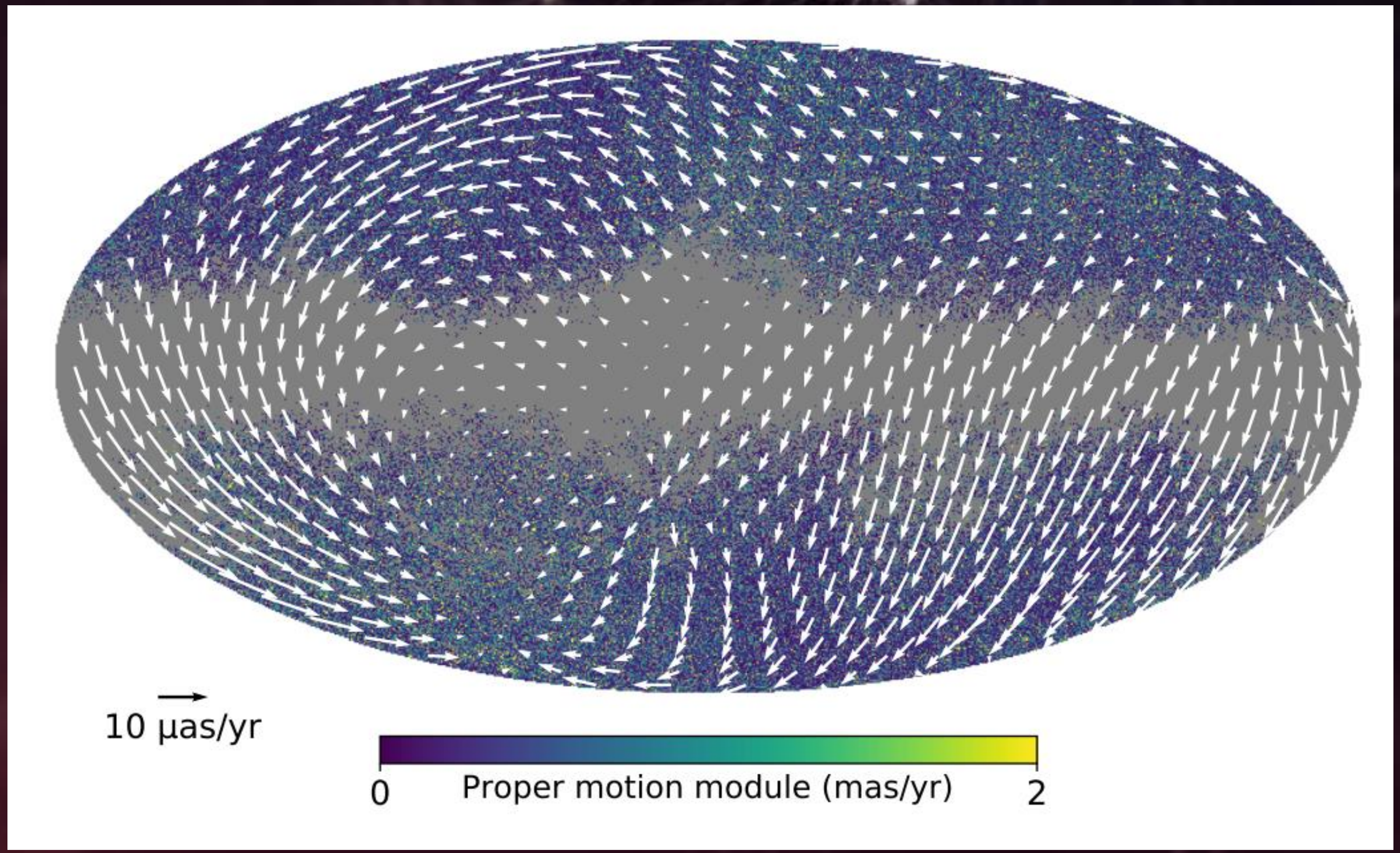
$$\Omega_{\mathrm{GW}}(f) = \frac{1}{\rho_c}\frac{d\rho_{\mathrm{GW}}}{d(\ln f)} \qquad \rho_c = \frac{3H_0^2}{8\pi G}$$

- We generate mock data of Gaia astrometric measurements for the star's proper motions to fit a generic quadrupole field typical of GWs. The sky averaged proper motion uncertainties are taken from Gaia DR3.

- The expected SGWB constraints from astrometry within a certain mission is

$$\Omega_{\mathrm{GW}} \lesssim \frac{\Delta\theta^2}{NT^2H_0^2}.$$

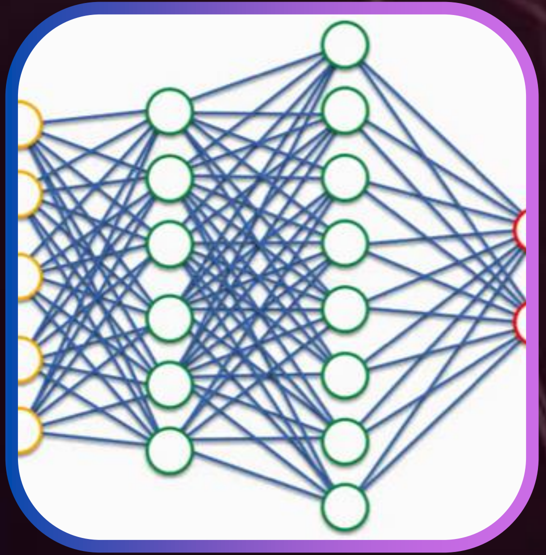
- Our goal is to extract physical information about Ω_{GW} from data.



Santiago Jaraba, et al.
arXiv: 2304.06350 [astro-ph.CO]

$$h_{70}^2\Omega_{\mathrm{GW}} \lesssim 0.087 \text{ for } 4.2\times10^{-18}\text{ Hz} \lesssim f \lesssim 1.1\times10^{-8}\text{ Hz}$$
$$h_{70}^2\Omega_{\mathrm{GW}} \lesssim 0.024 \text{ for } 5.8\times10^{-18}\text{ Hz} \lesssim f \lesssim 1.4\times10^{-9}\text{ Hz}$$

Neural network architectures



Fully Connected Network (FCN)

Regression task

Graph Neural Network (GNN)

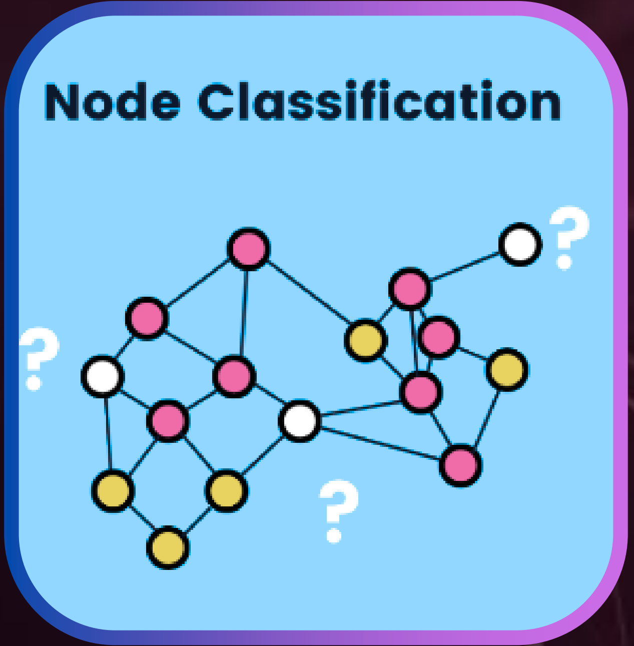
Each neuron of each layer is connected to every neuron of the subsequent layer, without regard for any underlying structure between data points.

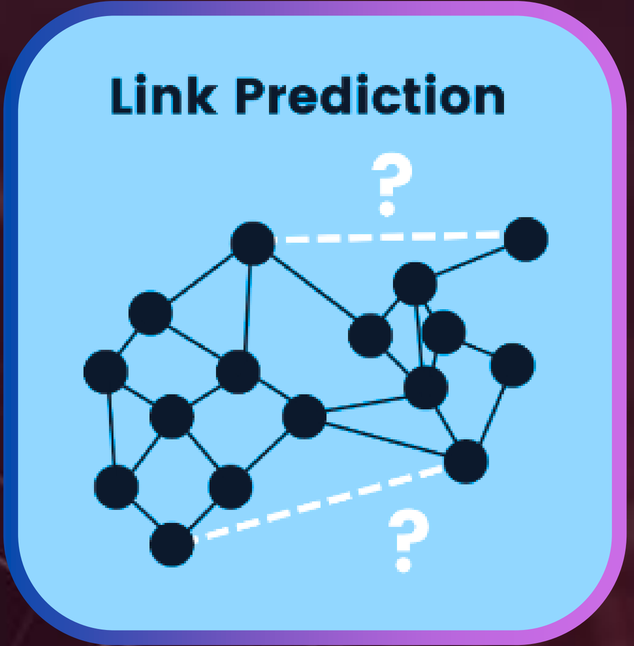
Typically simpler in design, with fewer computational complexity for training on large-scale data.

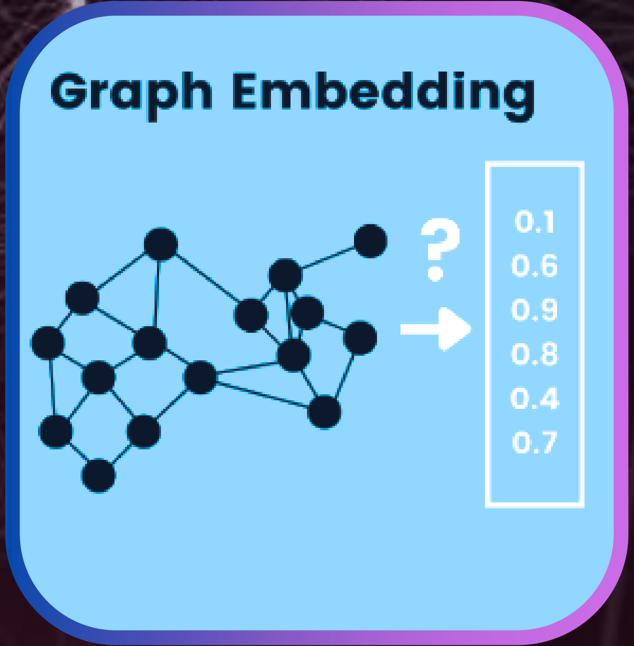
Operates directly on graph structures, where nodes are connected based on the graph's structure, preserving relationships.

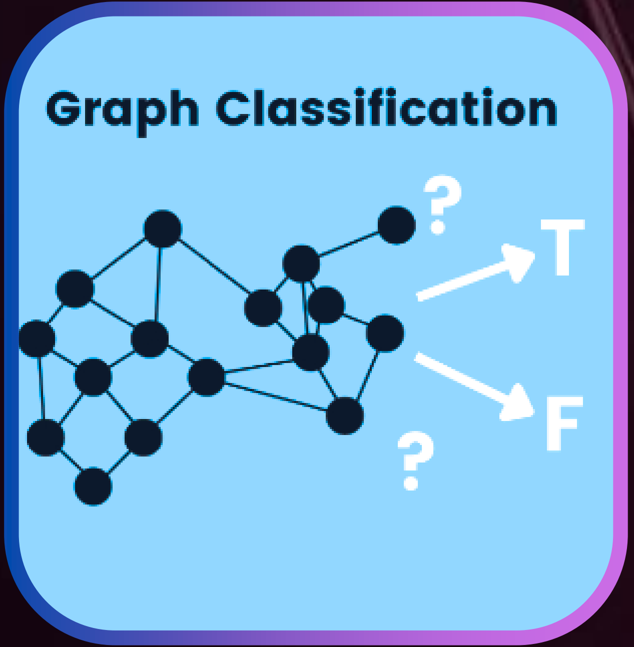
More complex, both computationally and in terms of architecture, as it requires handling graph structures and neighborhood aggregation.

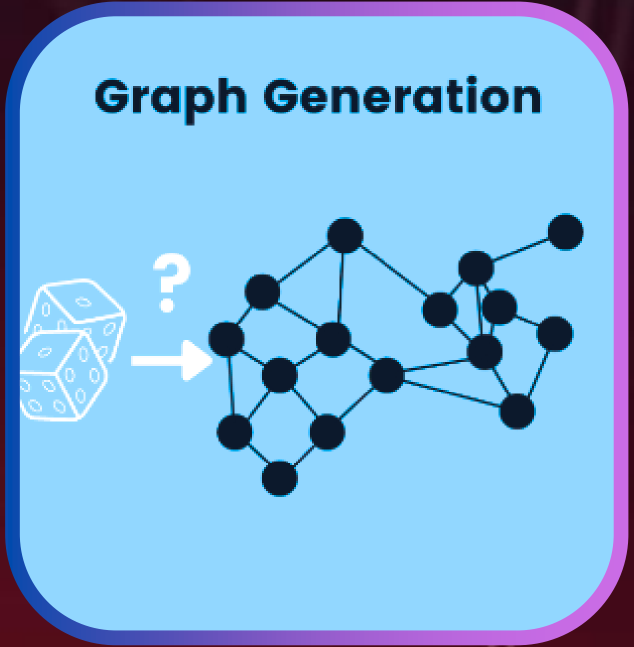
Credit: datacamp.com/comprehensive-introduction-graph-neural-networks-gnns-tutorial







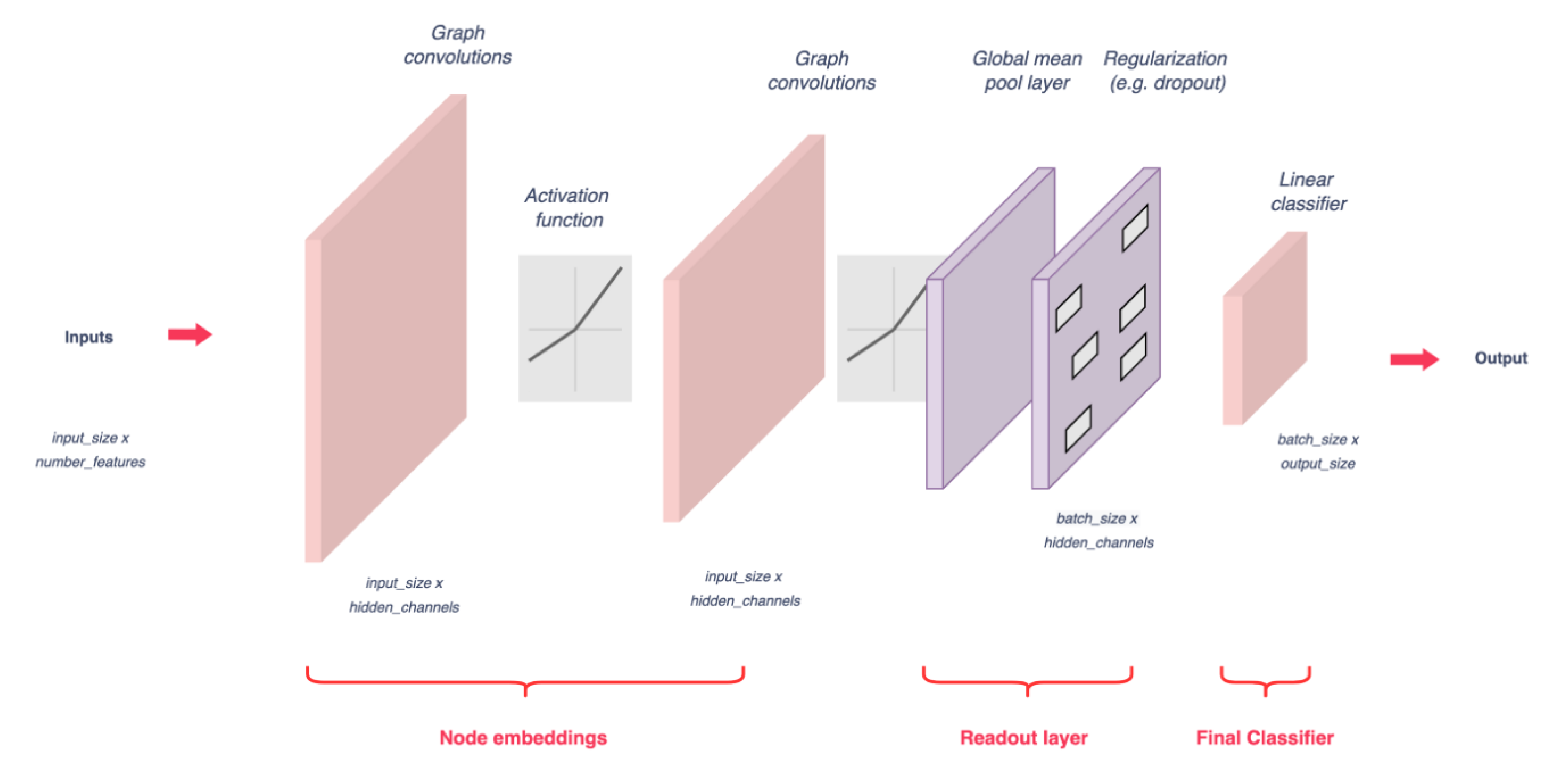




Types of GNN

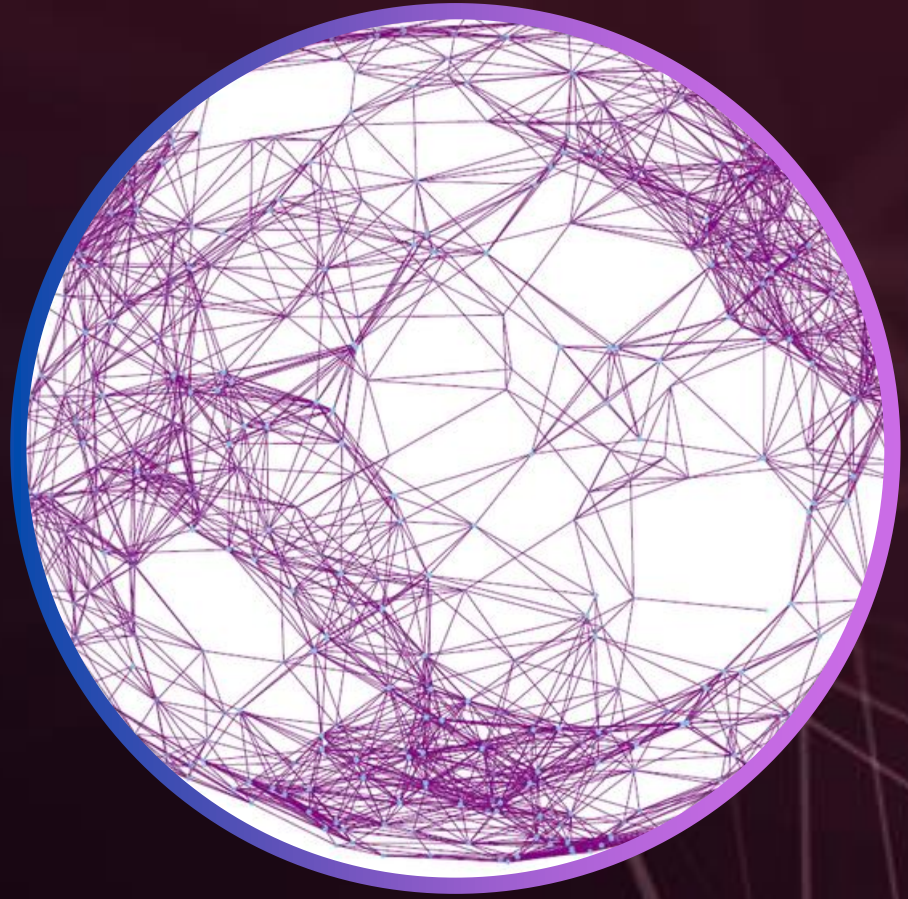
- **Graph Classification:** classify graphs into various categories.
- **Node Classification:** predict missing node labels in a graph.
- **Link Prediction:** predicts the link between a pair of nodes in a graph with an incomplete adjacency matrix.
- **Community Detection:** divides nodes into various clusters based on edge structure.
- **Graph Embedding:** maps graphs into vectors.
- **Graph Generation:** generate a new but similar graph structure.

GNN model architecture for Graph Classification



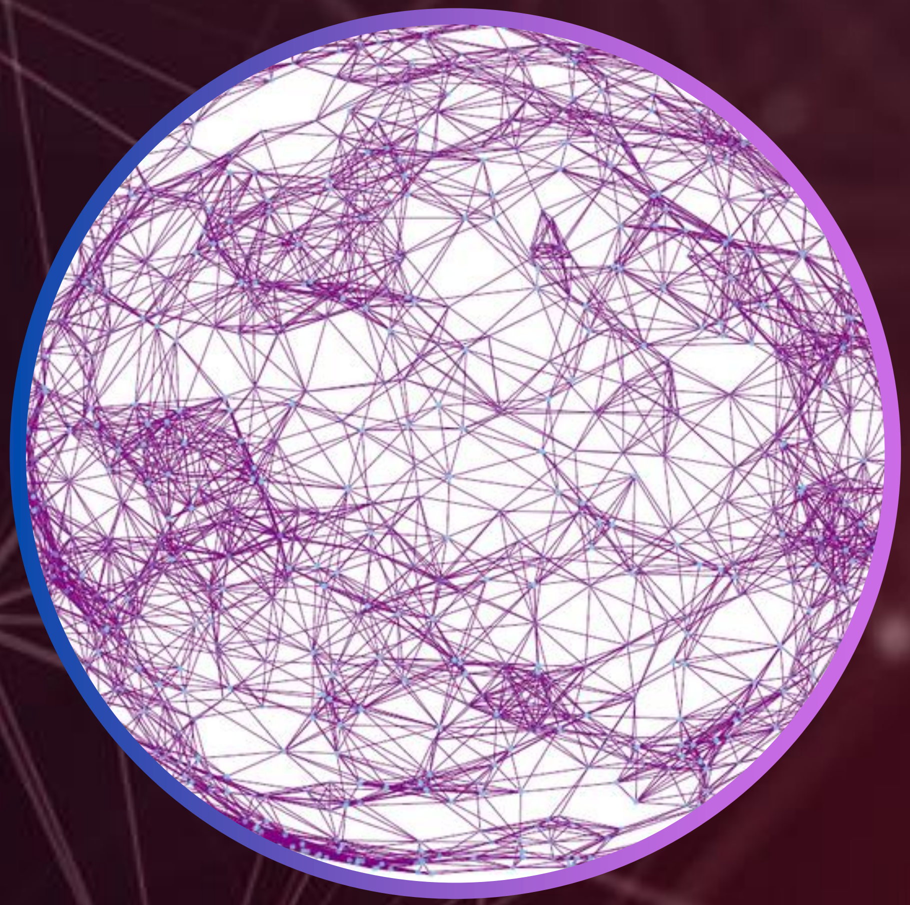
Credit: Lina Faik

Graphs



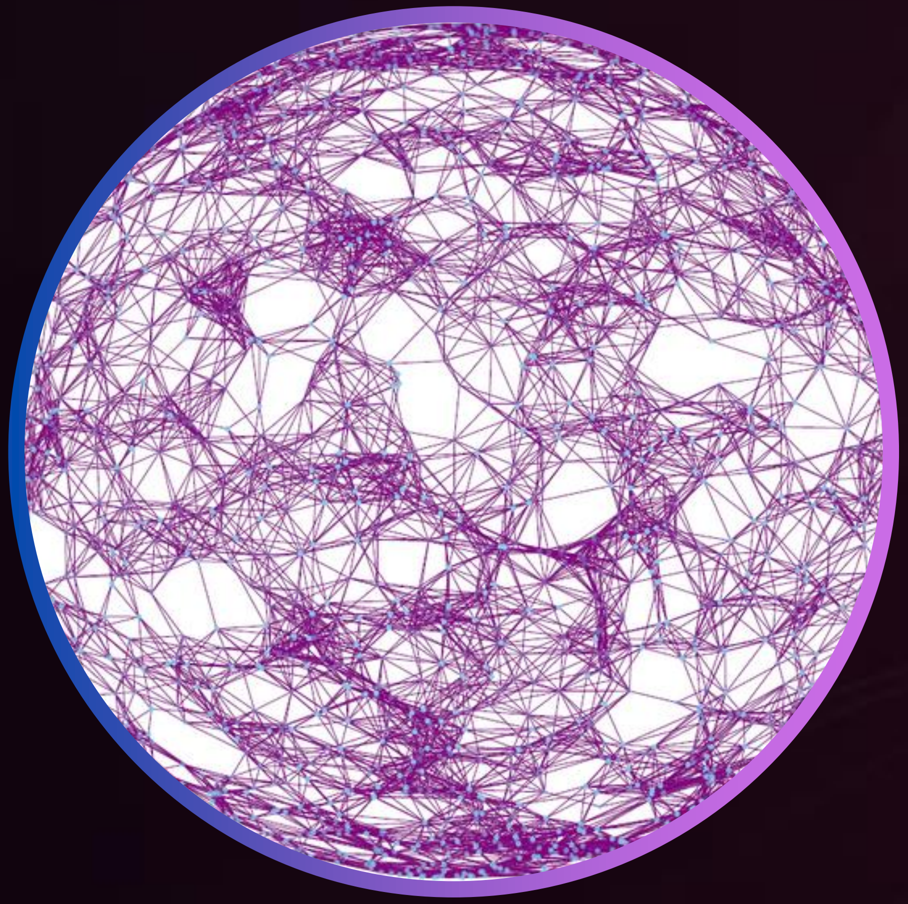
Num. stars = 500

Distance threshold = 0.317 rad



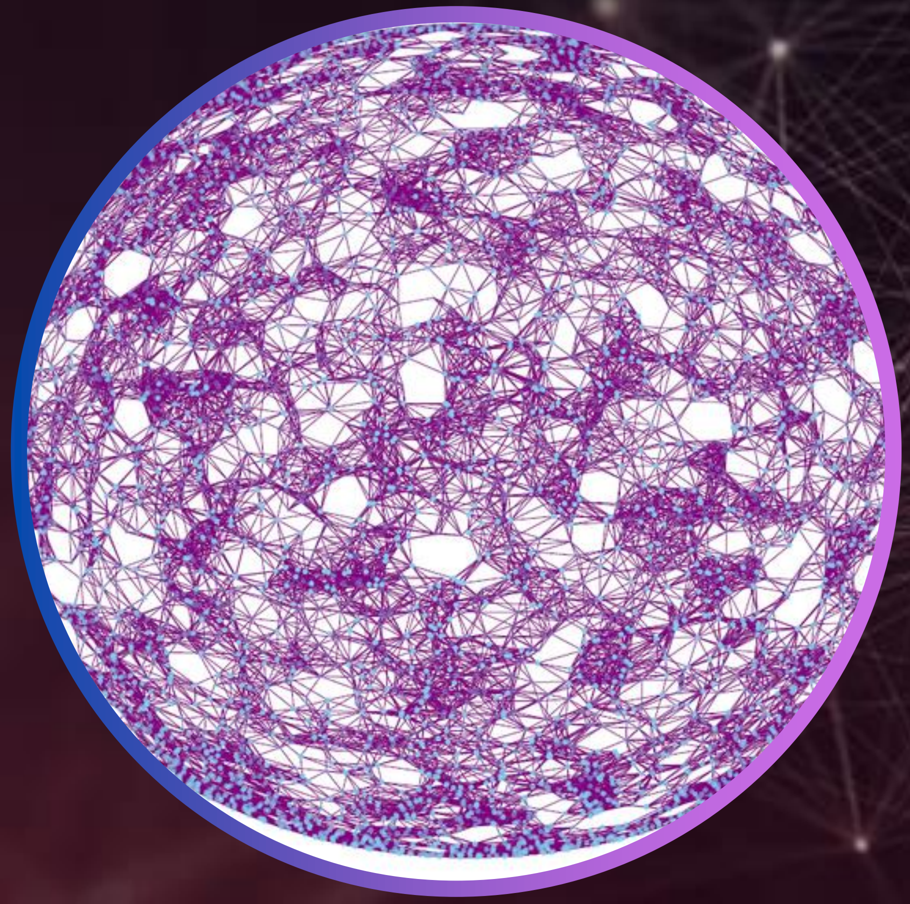
Num. stars = 1000

Distance threshold = 0.224 rad



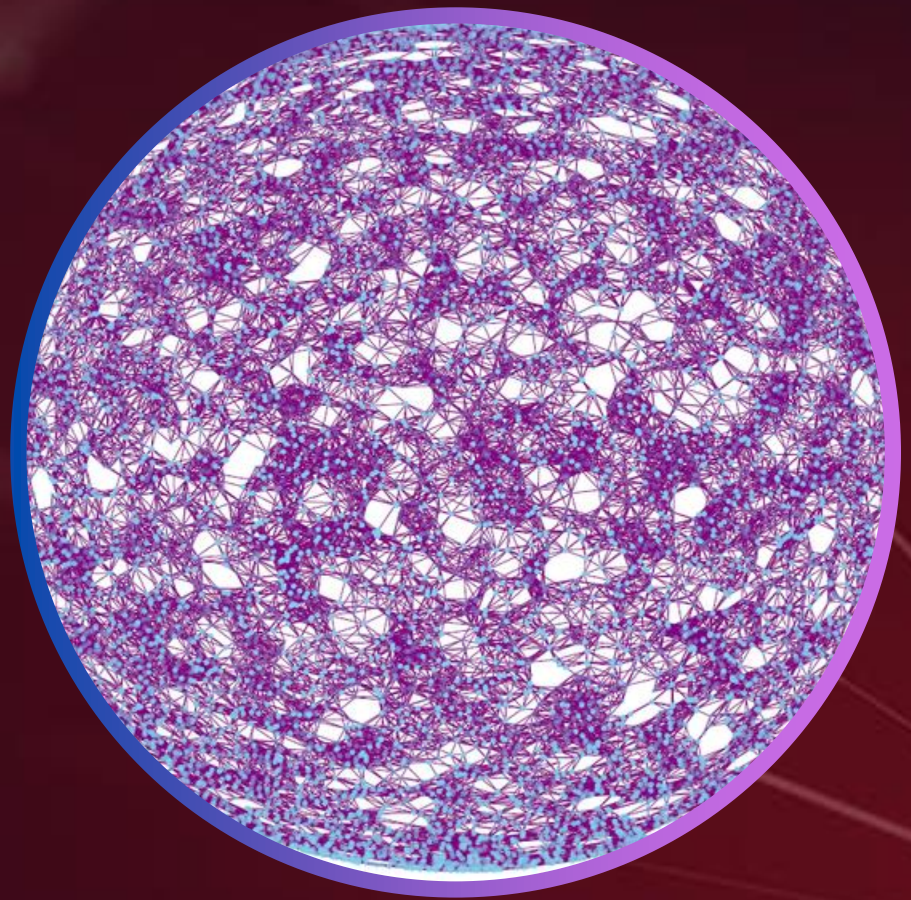
Num. stars = 2000

Distance threshold = 0.159 rad



Num. stars = 6000

Distance threshold = 0.091 rad



Num. stars = 12000

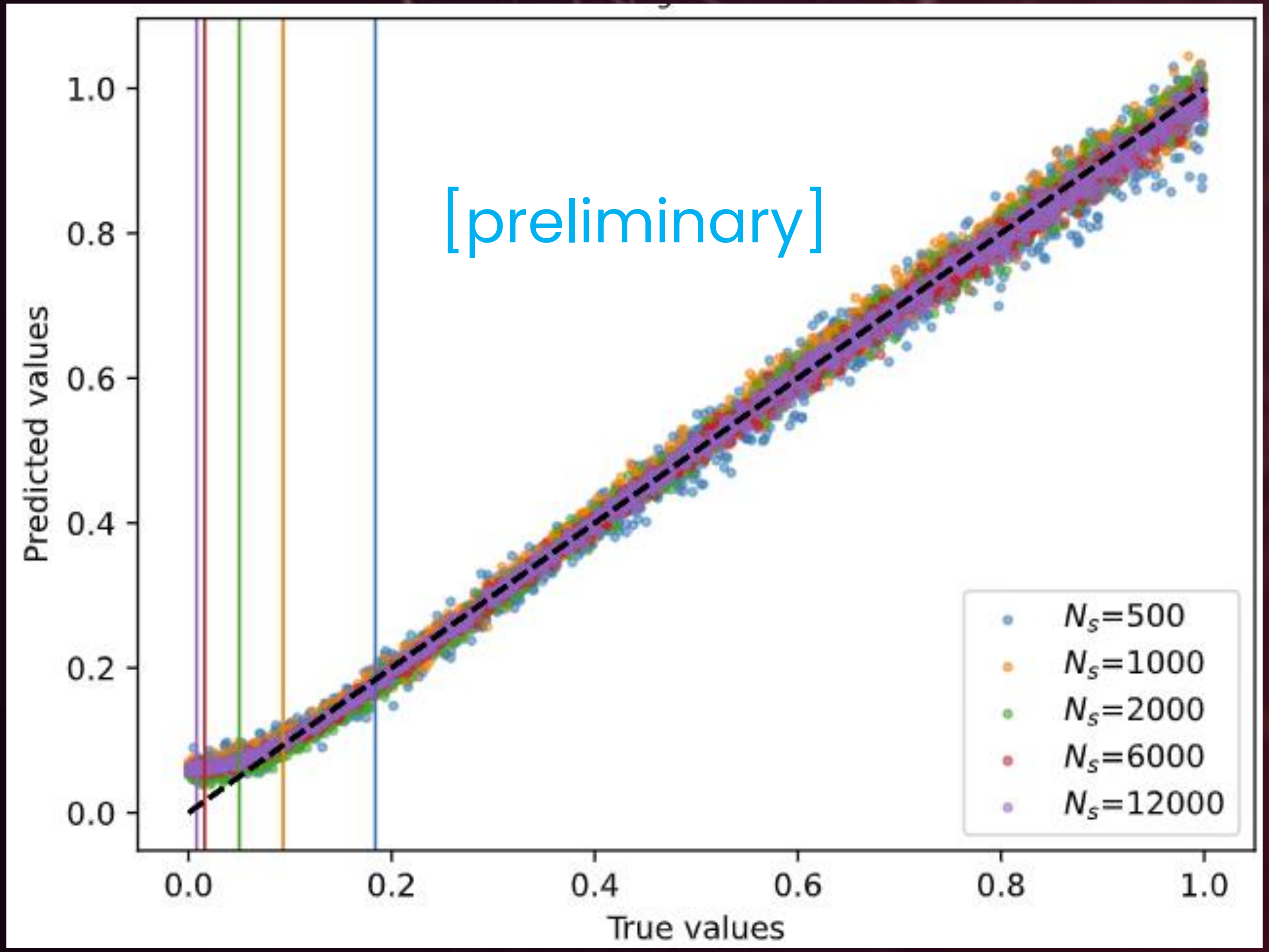
Distance threshold = 0.065 rad

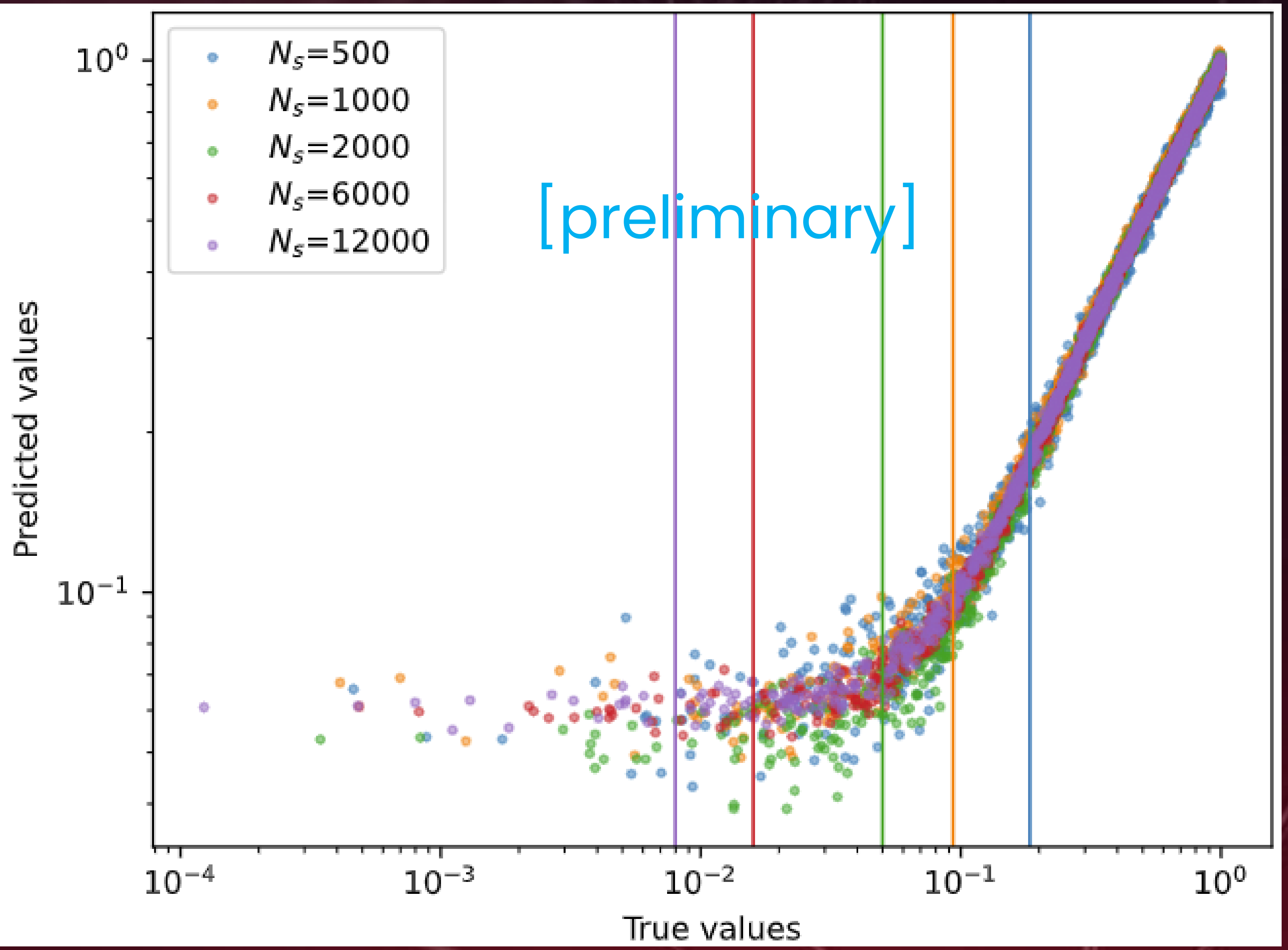
Data object

- Different configurations of number of stars, made up by 500, 1000,2000, 6000, 12000 stars.
- 8000 realizations for fixed number of stars.
- Six features for each star (right ascension and declination, corresponding uncertainties, and proper motion components).
- For GNN, graph connectivity is constructed if distance between two nodes is less than a specific distance threshold.

Results

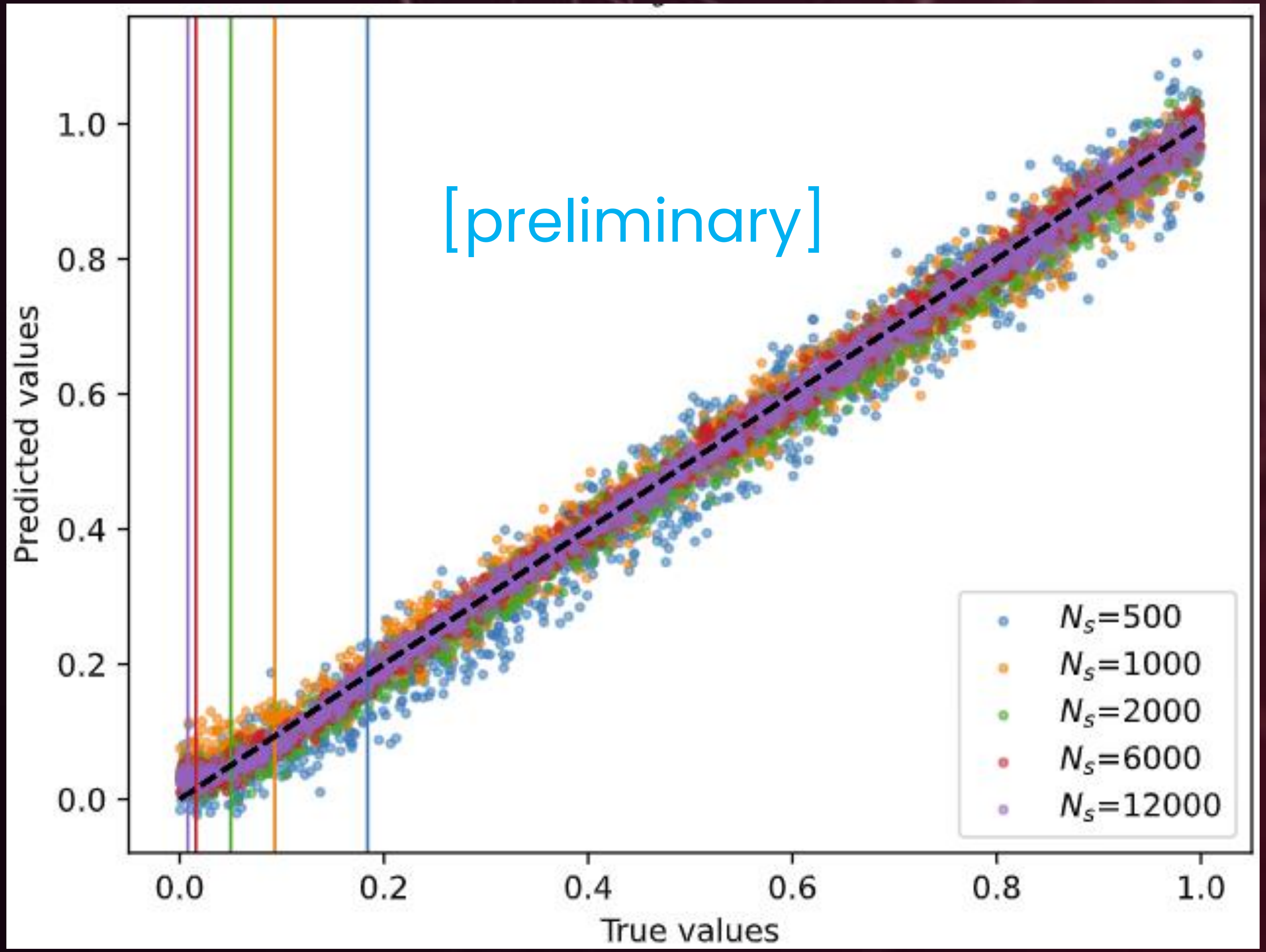
Predictions on Ω_{GW} from FCN, on the right-side in log scale

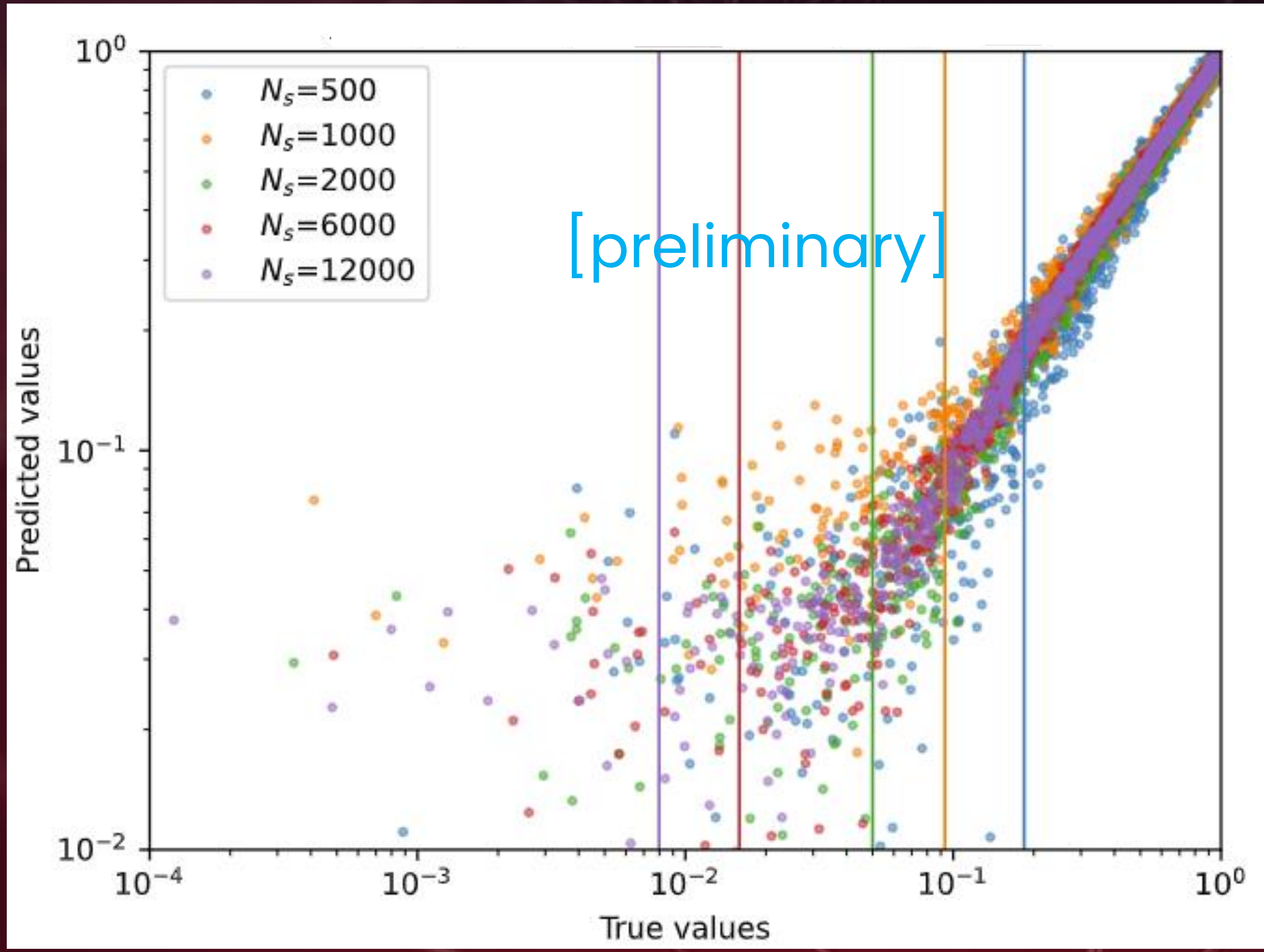




Results

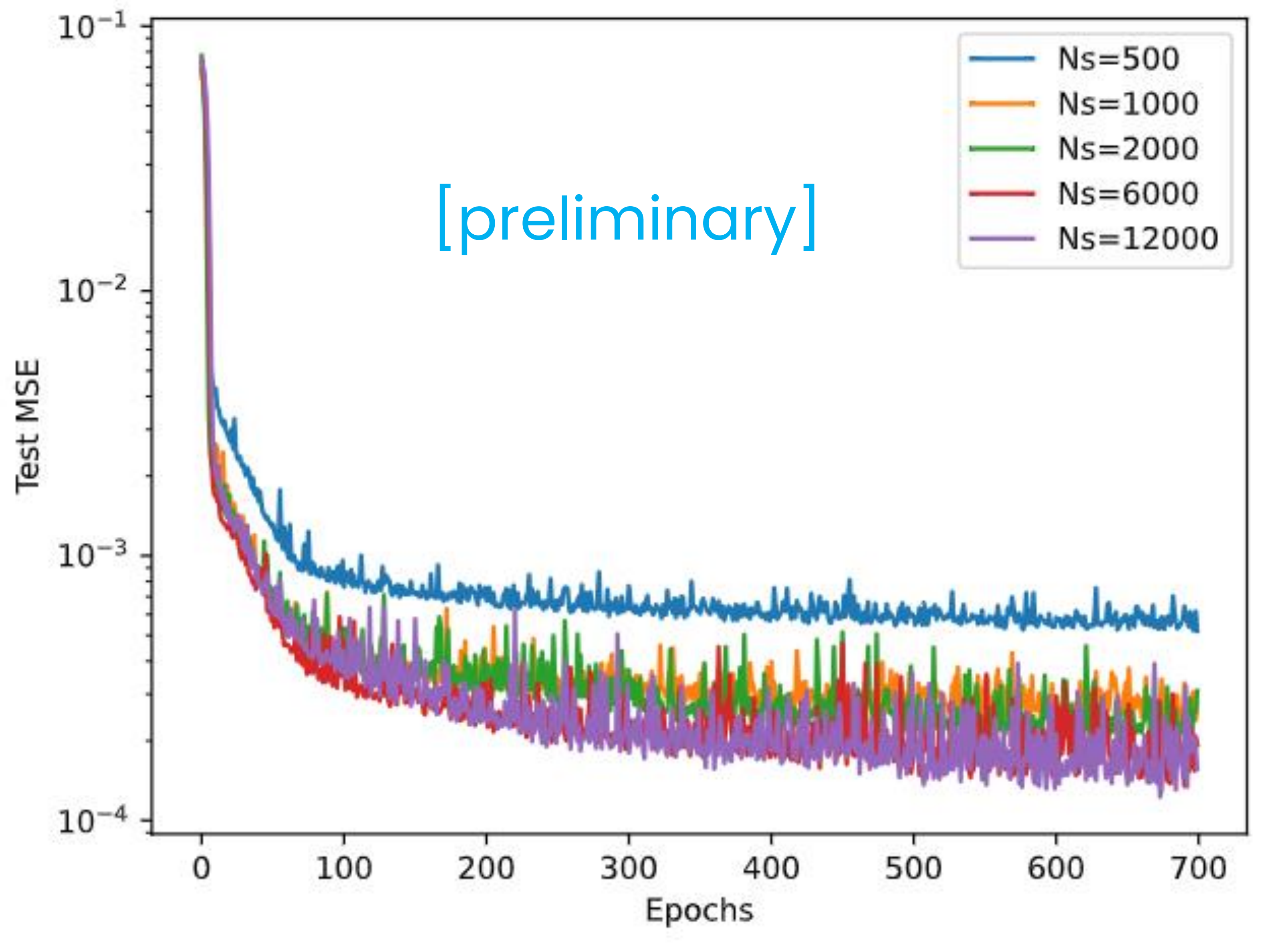
Predictions on Ω_{GW} from GNN, on the right-side in log scale



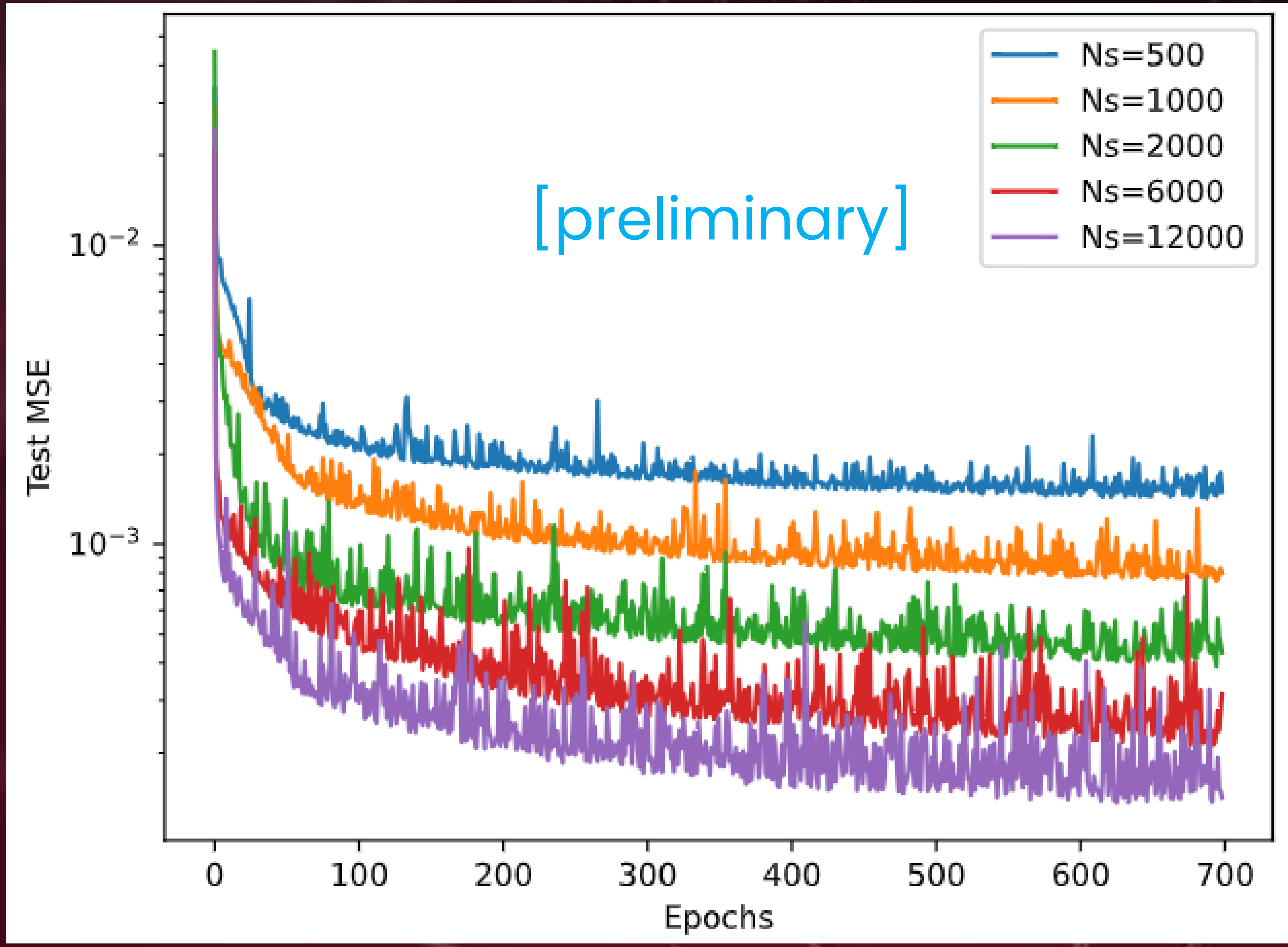


Results

Loss functions trend



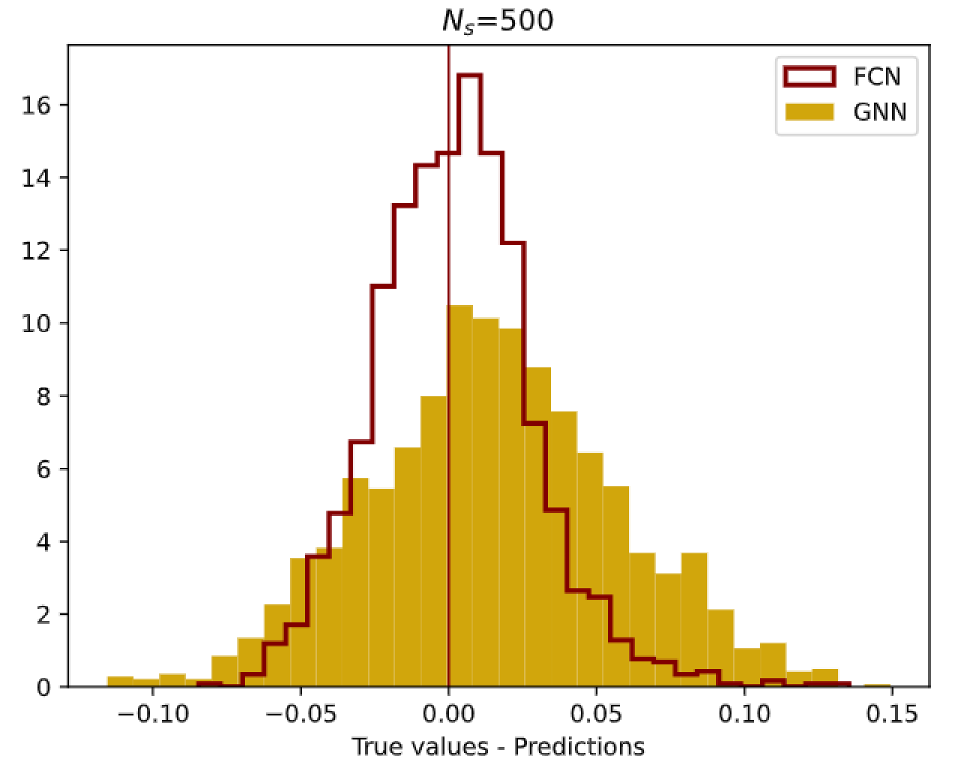
FCN

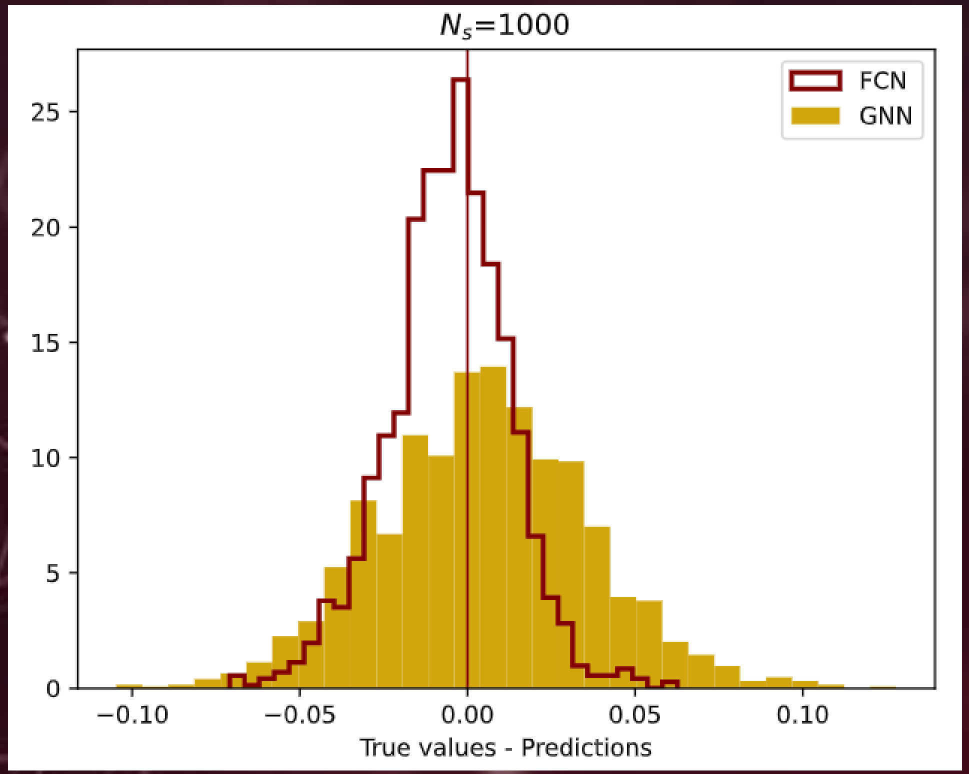


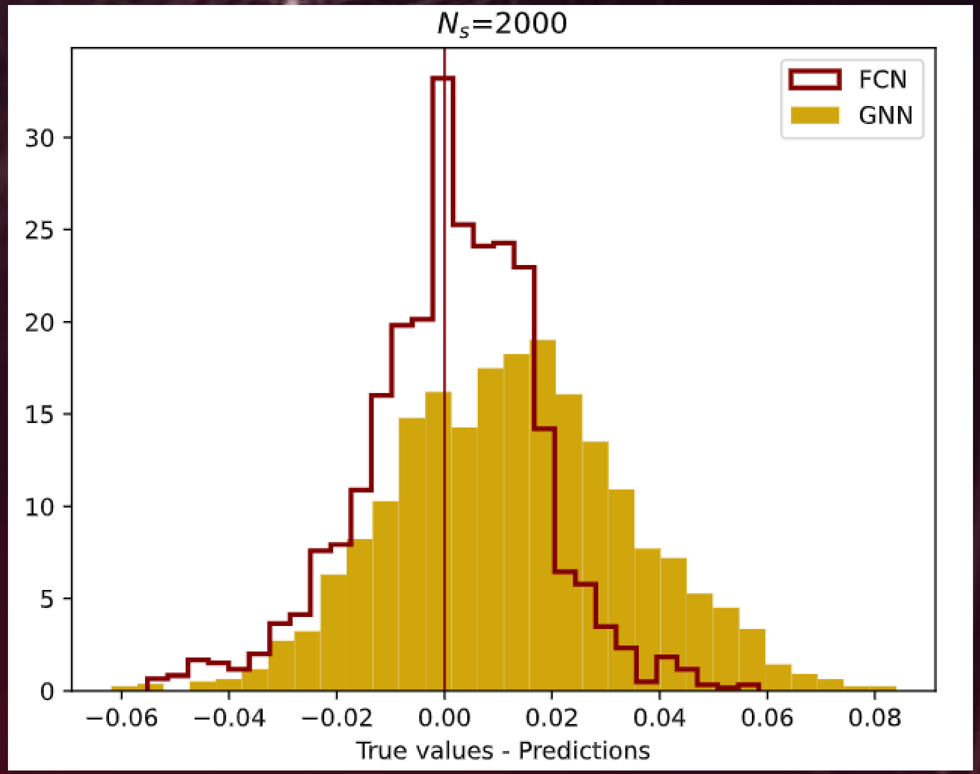
GNN

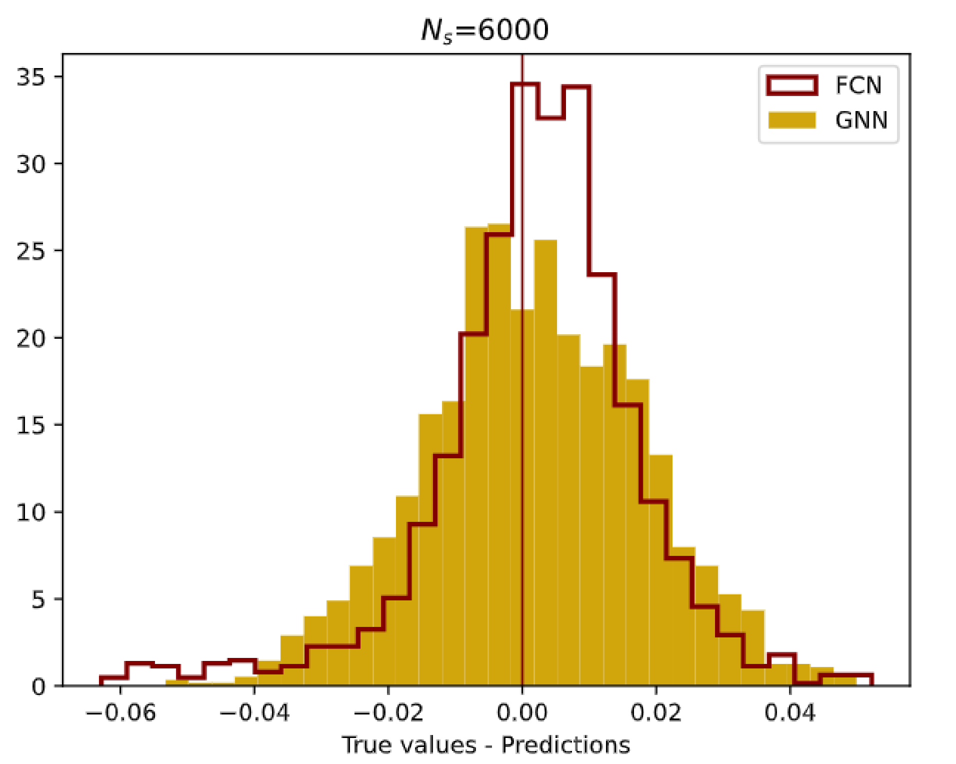
Results [preliminary]

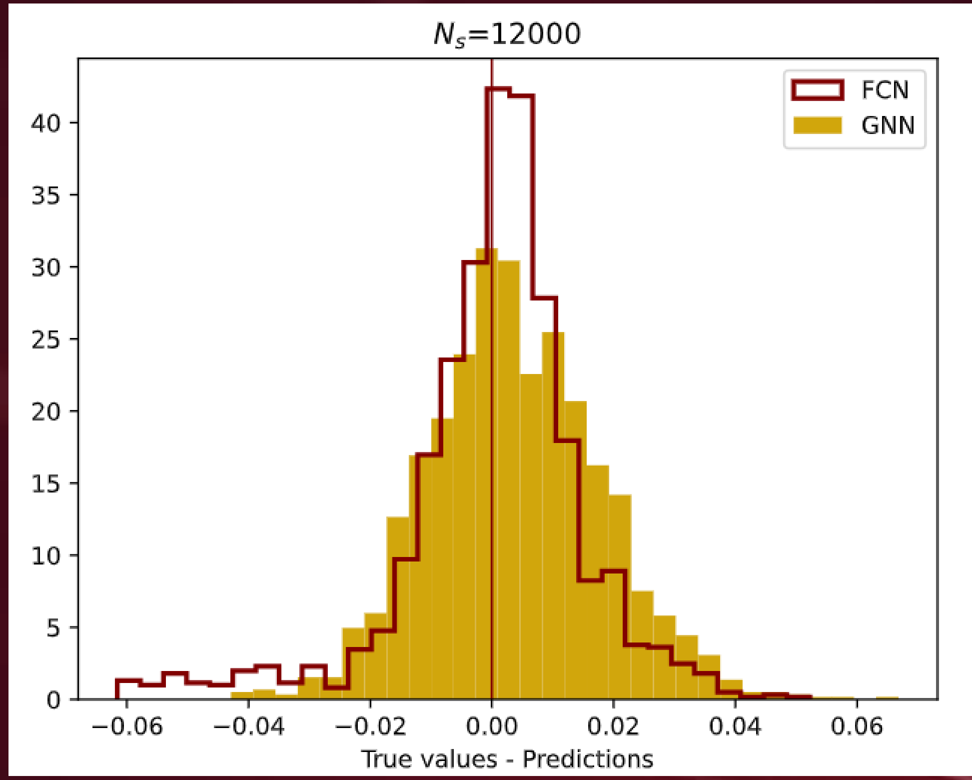
Distribution comparison between predictions and true values for FNN and GNN











Conclusions

- The importance of SGWB research is underscored by its potential to address fundamental questions in cosmology and astrophysics, making it a key area of focus in gravitational wave astronomy.

- FCNs are simpler, scalable, and easier to optimize, but can lose structural information.

- GNNs are designed for graph-structured data, capturing relationships between nodes (e.g., suitable for social networks, molecular structures, etc.).

- GNNs also come with their own challenges, such as higher computational complexity, due to deeper or more complex structure of the graph-data input, and the need for specialized architectures.

- In the future, due to the increasing amount of astrometric data, ML applications would be a useful tool to treat data and put constraints on SGWB.

THANK YOU

For Your Attention