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Gravity-Gradient Noise Mitigation via Deep Learning for the Einstein Telescope

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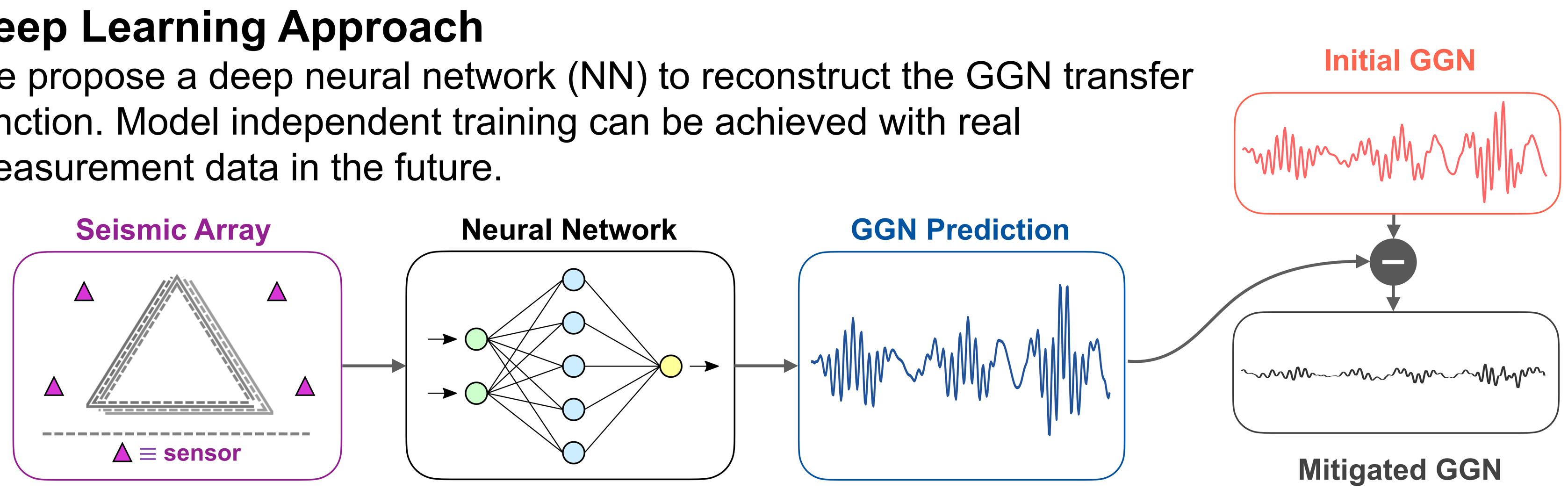
Background & Methodology

Gravity-Gradient Noise (GGN) Cancellation

GGN caused by seismic perturbations is anticipated to be the limiting factor for the sensitivity of third-generation gravitational wave detectors at frequencies below 10 Hz. For the Einstein Telescope, the underground construction alone will not provide sufficient shielding, and additional cancellation will be critical to achieve the design sensitivity. The associated challenge is a precise reconstruction of GGN based on the seismic activity recorded by an array of auxiliary sensors.

Deep Learning Approach

We propose a deep neural network (NN) to reconstruct the GGN transfer function. Model independent training can be achieved with real measurement data in the future.



Simulation

An idealized simulation of the signals in the seismic sensor array and the corresponding GGN strain is used to develop a suited network architecture and perform a first proof of concept.

i. Seismic Field Simulation

- **Fast analytical Monte-Carlo approach:** construct the seismic field through sampling of multiple wave equations
- **Wave modes:** gaussian wave packets of body p- and s-waves
- **Distant sources:** propagating wavefronts modeled as plane waves
- **Dispersion & scattering:** simulate homogenous half space

Seismic Displacement

Density Perturbation

ii. Sensor Array

- **Positioning:** regular 8x8 grid in ET plane at 250m depth
- **Instrumental noise:** use noise ASD measurements[1] of state-of-the art seismometer to generate colored noise
- **Noise level:** $\mathrm{SNR} = \mathcal{O}\left(10^3\right)$ is realistic, additional scenario with $\mathrm{SNR} = \mathcal{O}(10)$ implemented to test noise robustness of the network

iii. GGN Strain

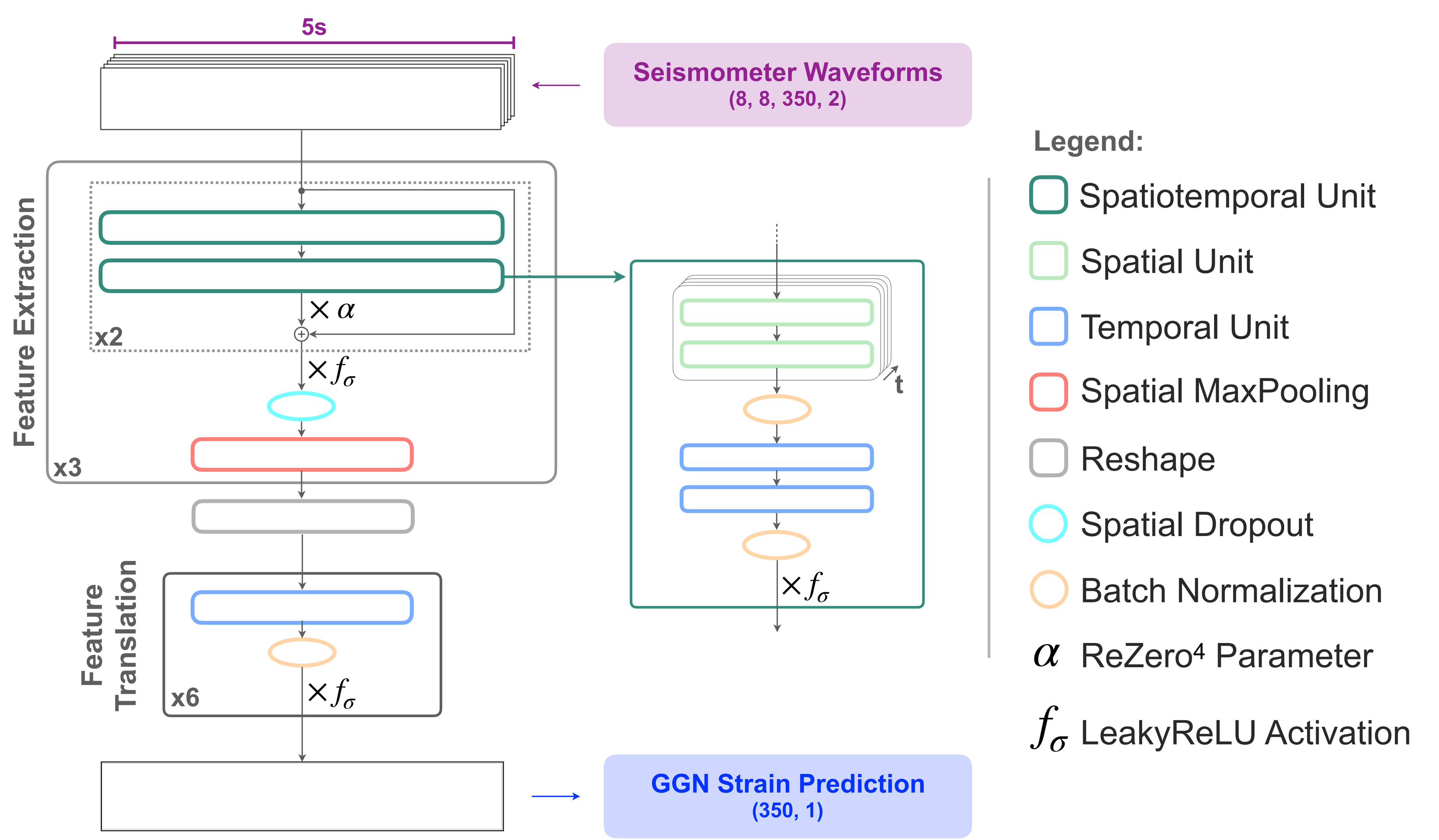
Steps to model the transfer function between the seismic field and the GGN strain present in the interferometer:

1. **Test-mass acceleration:** analytical solution for spherical cavities[2]
2. **Test-mass displacement:** pendulum to approximate suspension system
3. **Strain:** combine test-masses and ET geometry

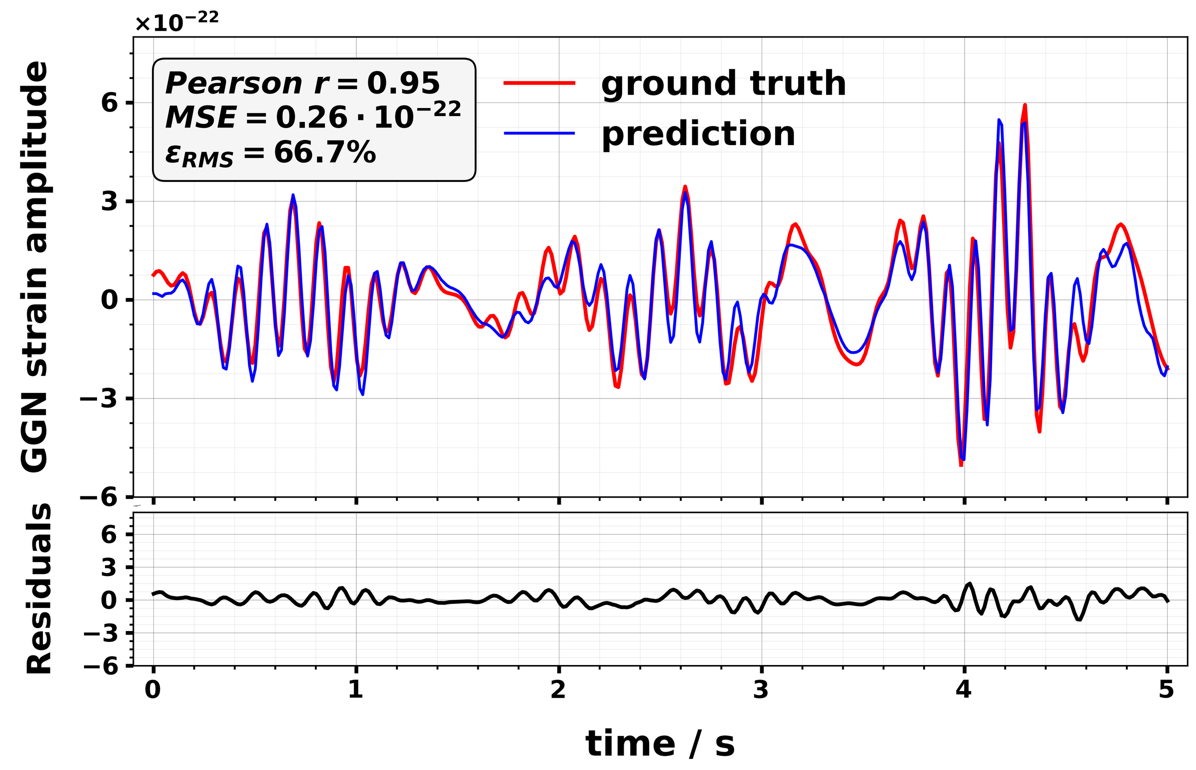
Spatiotemporal ResNet Architecture

The underlying concept is to extract increasingly abstract spatial and temporal features from the data recorded by the seismic array. Subsequently, the network learns to translate the features into the corresponding GGN strain.

- **Spatial Unit:** Time-distributed 2D Convolutions applied to the spatial axis. The modular approach allows potential adaptation to Graph convolution layers.
- **Temporal Unit:** WaveNet[3] inspired dilated 1D Convolutions. The receptive field grows exponentially with the dilation factor.
- **Spatial MaxPooling:** Reduce spatial dimensions for better latent feature abstraction.



Noise Mitigation Performance



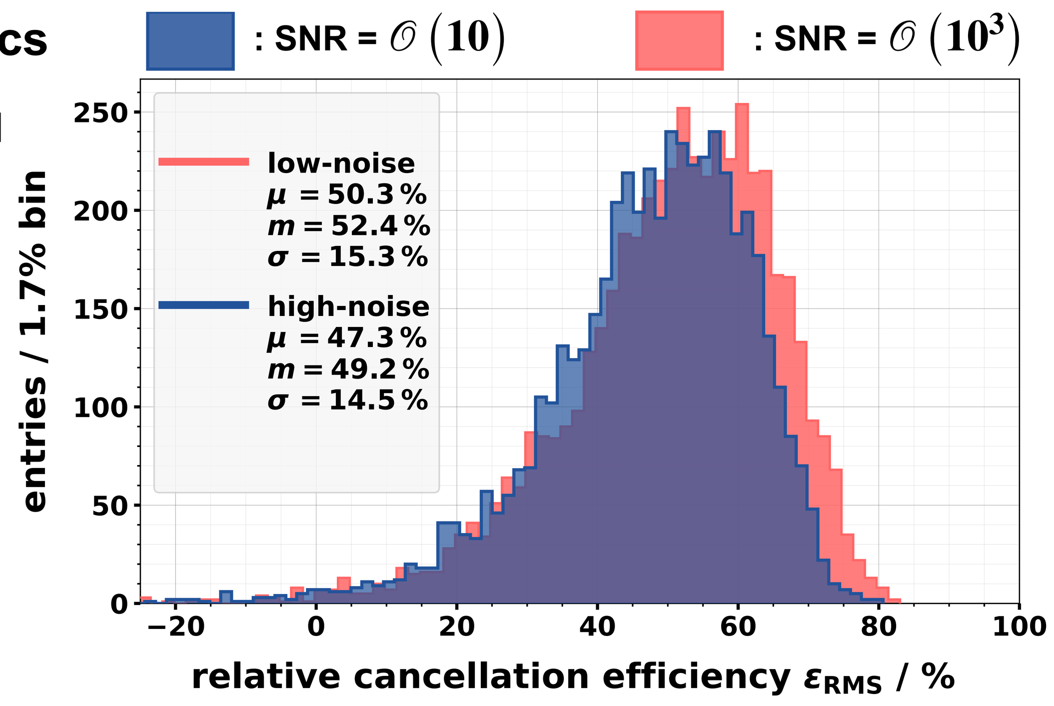
- Train NN to predict GGN from 40k seismic events
- Test on 5k independent events
- Evaluate quantitative performance metrics and compare the two instrumental noise scenarios

Quantitative Performance Metrics

- Strong linear correlation of 0.85 and factor two cancellation on average
- Histogramm shows relative RMS cancellation efficiency:

$$\varepsilon_{\mathrm{RMS}} \equiv \frac{\mathrm{RMS}_{\mathrm{true}} - \mathrm{RMS}_{\mathrm{pred}}}{\mathrm{RMS}_{\mathrm{true}}}$$

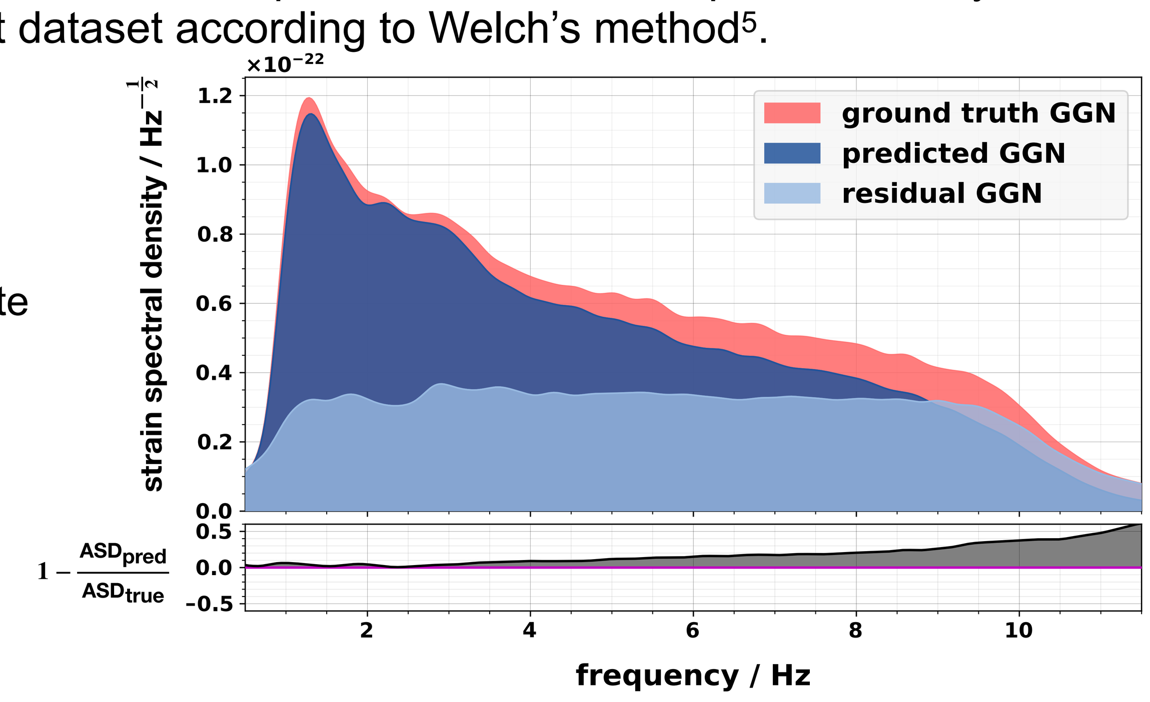
- Indicates good instrumental noise robustness



Strain Spectral Density

To investigate any spectral performance dependence, the strain spectral density is estimated over the whole test dataset according to Welch's method[5].

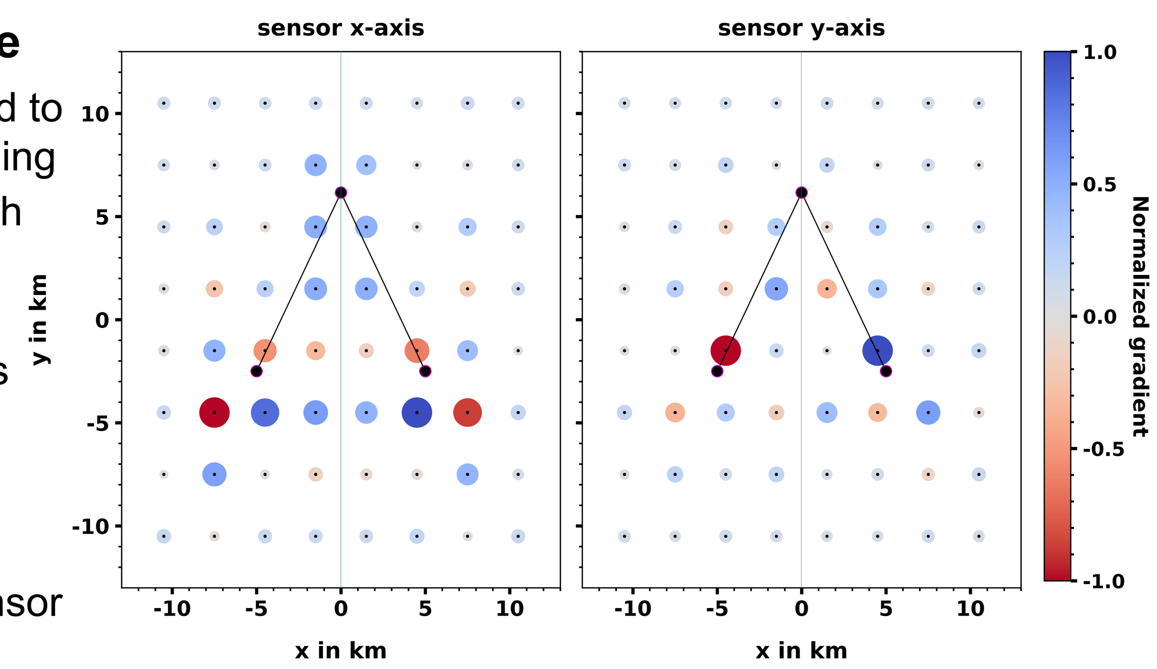
- NN learns bias from data → challenging in case of strongly unbalanced training datasets
- Residual GGN follows white noise spectrum
- No artificial noise through potential over-prediction
- Sensor spacing influences high-frequency resolution



Towards Optimized Sensor Arrangements

Relative Sensor Importance

- **Motivation**: NN can be utilized to optimize sensor array positioning → reduce total borehole length while increasing the GGN correlation
- **Technique:** important sensors have large gradients ('*Saliency maps*[5]')
- **Result:** insights in exploitable symmetries and important sensor positions



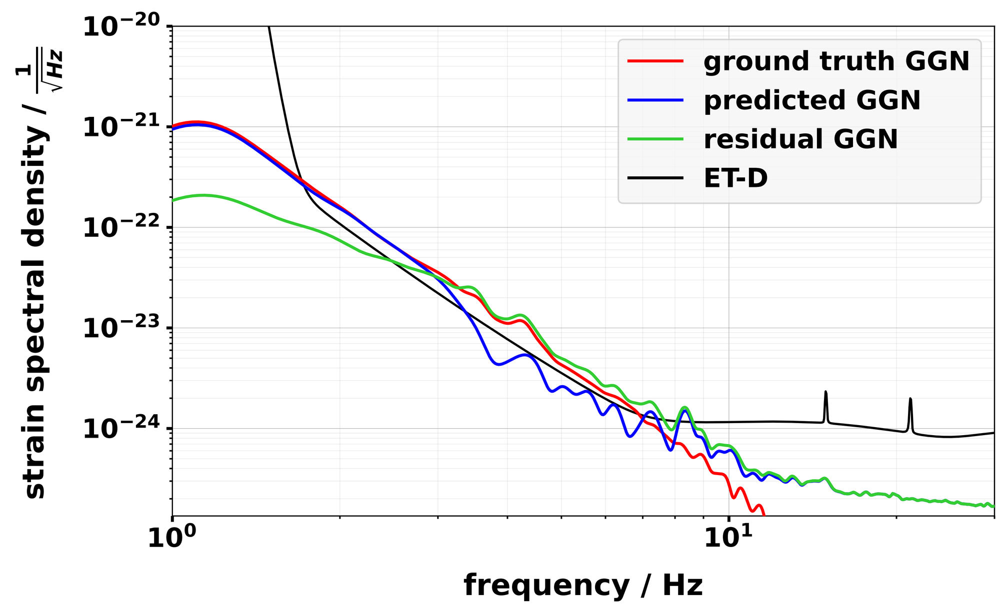
Conclusion

Summary

- Successful proof-of-concept study for GGN cancellation using deep learning techniques
- Test scenario with **factor two cancellation** and **good instrumental noise robustness**

Outlook

- Adapt NN to optimize irregular sensor arrays using a Graph NN
- Explore techniques for training on unbalanced datasets
- Investigate potential for online or forecasting applications (Multi Messenger Astronomy)



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