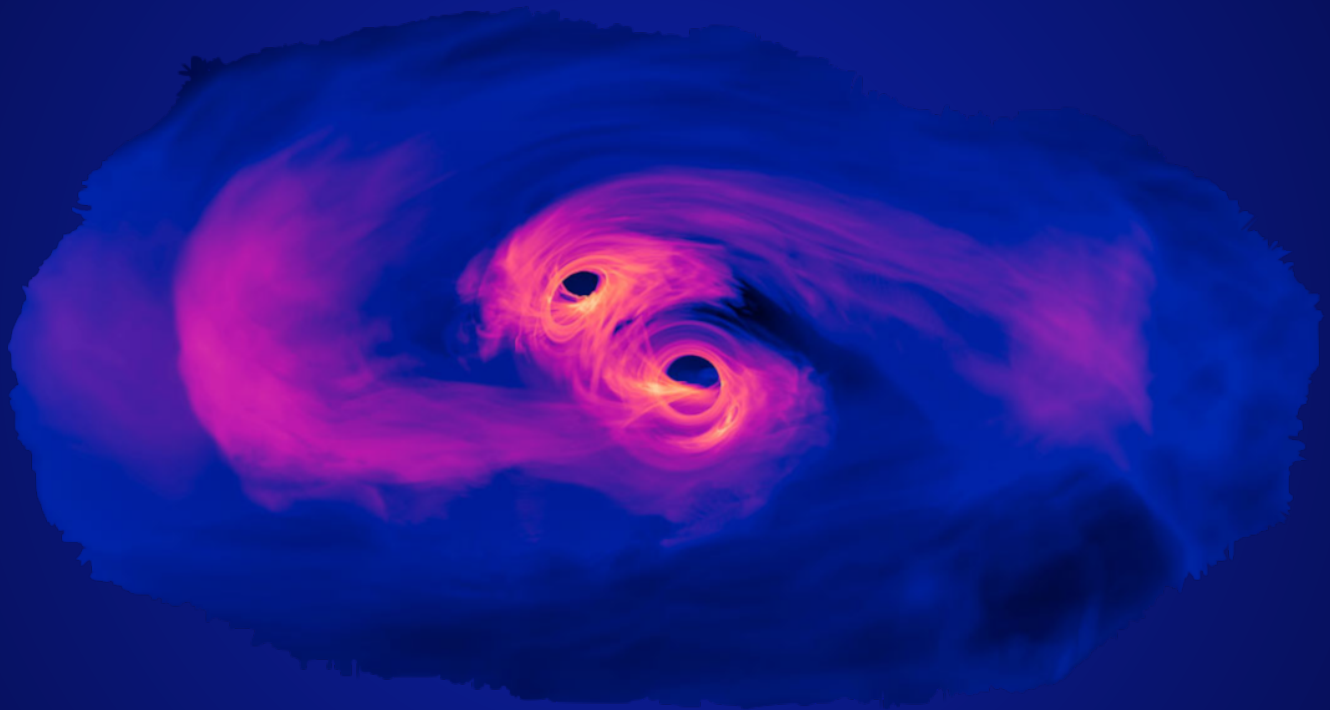
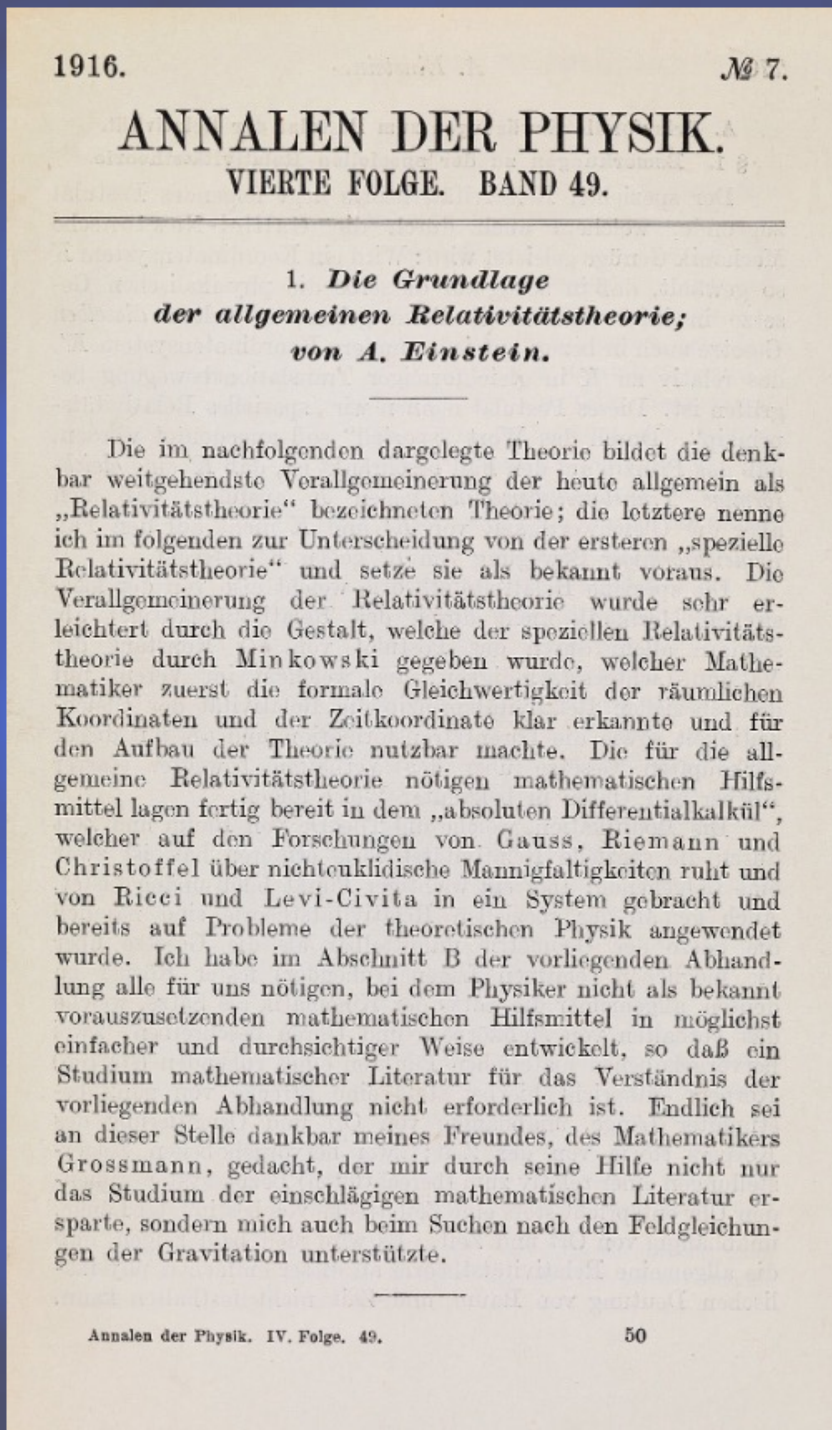


Real-time Gravitational Wave Data Analysis with Machine Learning

Eric A Moreno emoreno@mit.edu, Katya Govorkova, Ryan Raikman, Ethan J Marx, Alec Gunny, William Benoit, Deep Chatterjee, Rafia Omer, Andy Chen Muhammed Saleem, Dylan S Rankin, Michael W Coughlin, Philip C Harris, Erik Katsavounidis

A Little History



1916. № 7.

ANNALEN DER PHYSIK.
VIERTE FOLGE. BAND 49.

1. ***Die Grundlage der allgemeinen Relativitätstheorie;***
von A. Einstein.

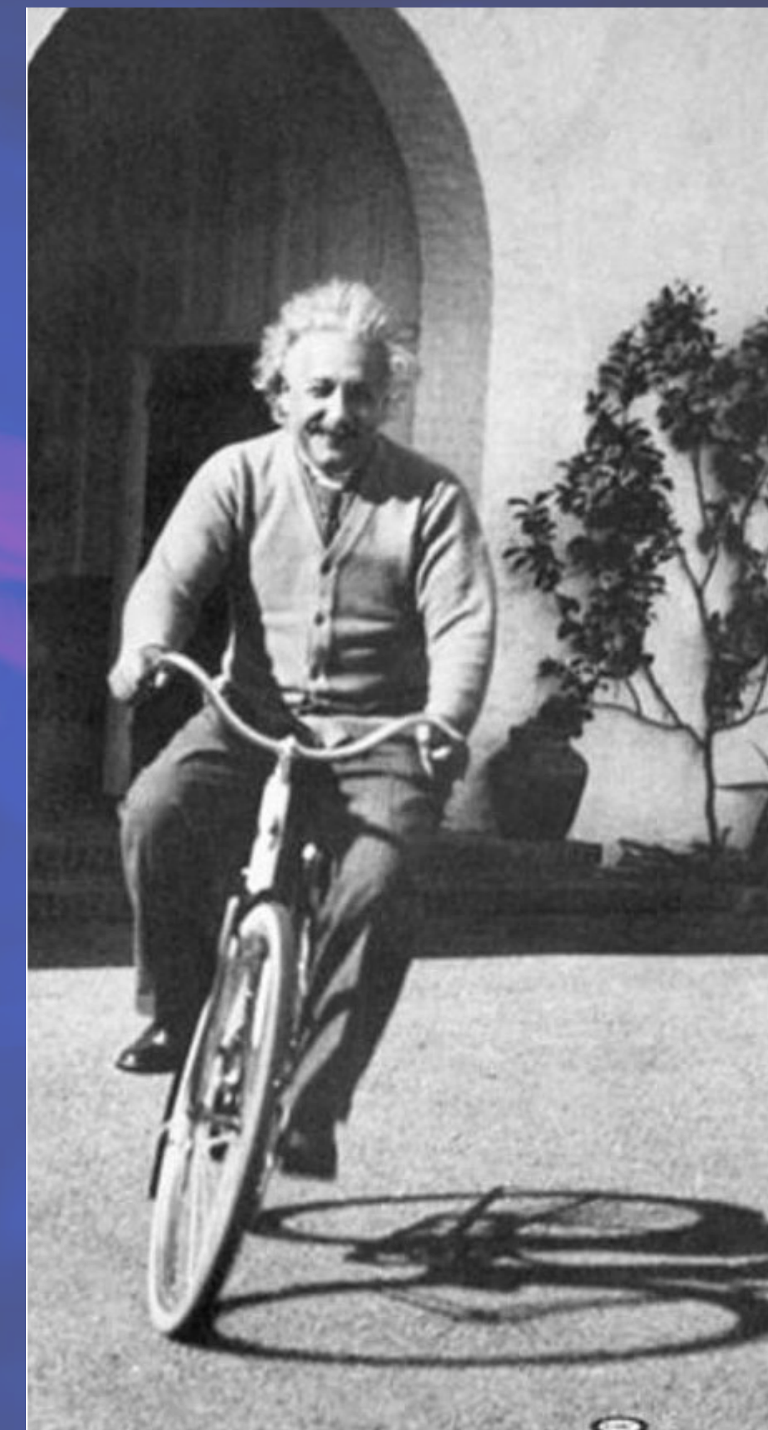
Die im nachfolgenden dargelegte Theorie bildet die denkbar weitgehendste Verallgemeinerung der heute allgemein als „Relativitätstheorie“ bezeichneten Theorie; die letztere nenne ich im folgenden zur Unterscheidung von der ersteren „spezielle Relativitätstheorie“ und setze sie als bekannt voraus. Die Verallgemeinerung der Relativitätstheorie wurde sehr erleichtert durch die Gestalt, welche der speziellen Relativitätstheorie durch Minkowski gegeben wurde, welcher Mathematiker zuerst die formale Gleichwertigkeit der räumlichen Koordinaten und der Zeitkoordinate klar erkannte und für den Aufbau der Theorie nutzbar machte. Die für die allgemeine Relativitätstheorie nötigen mathematischen Hilfsmittel lagen fertig bereit in dem „absoluten Differentialkalkül“, welcher auf den Forschungen von Gauss, Riemann und Christoffel über nichteuklidische Mannigfaltigkeiten ruht und von Ricci und Levi-Civita in ein System gebracht und bereits auf Probleme der theoretischen Physik angewendet wurde. Ich habe im Abschnitt B der vorliegenden Abhandlung alle für uns nötigen, bei dem Physiker nicht als bekannt vorauszusetzenden mathematischen Hilfsmittel in möglichst einfacher und durchsichtiger Weise entwickelt, so daß ein Studium mathematischer Literatur für das Verständnis der vorliegenden Abhandlung nicht erforderlich ist. Endlich sei an dieser Stelle dankbar meines Freundes, des Mathematikers Grossmann, gedacht, der mir durch seine Hilfe nicht nur das Studium der einschlägigen mathematischen Literatur ersparte, sondern mich auch beim Suchen nach den Feldgleichungen der Gravitation unterstützte.

Annalen der Physik. IV. Folge. 49. 50

It's been 9 years since the "happiest thought" of Albert Einstein's life sitting in the patent office in Bern.

World War I is raging on in Europe in 1916 and the newly famous Einstein publishes the General Theory of Relativity.

Included in GR is the concept of ripples in spacetime that should be induced by accelerating objects – Gravitational Waves (GW)!



A Sad Story!

Einstein predicted the existence of GWs but died before even evidence of GR could be realized.

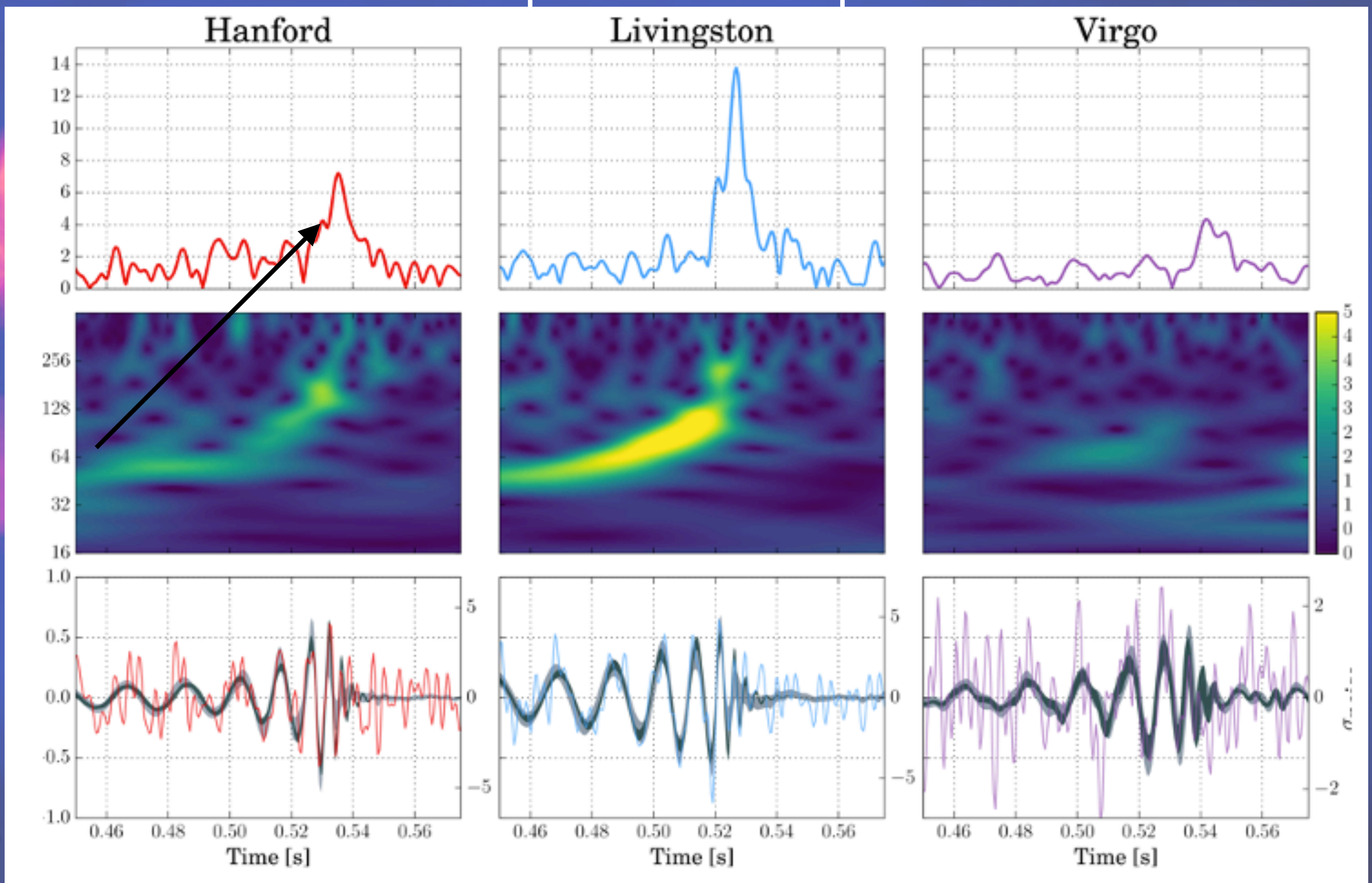
28 years after his death, astronomers at Arecibo Radio Observatory determined that a binary pulsar was inspiraling precisely predicted by GR and specifically GW emissions.

Despite even Einstein believing that an observation of GWs was impossible, the race was on...

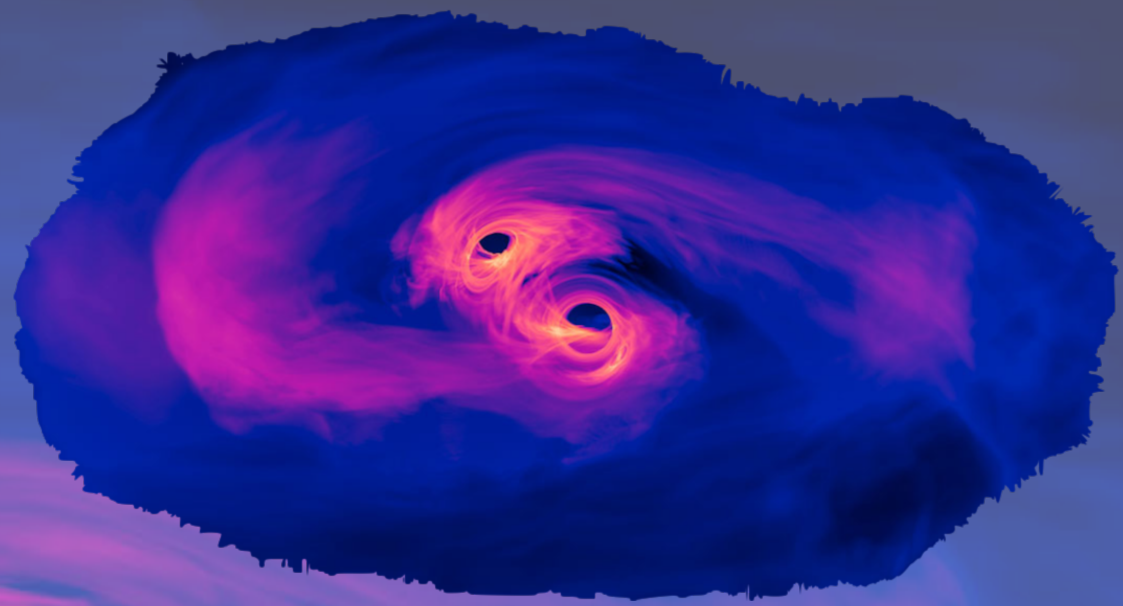
A Long Road For GWs

- 1980s – NSF Funds MIT and Caltech to research laser interferometers
- 1990s – Construction begins on LIGO, VIRGO, GEO600
- 1999-2003 – LIGO/VIRGO/GEO inauguration
- September 2015 – Advanced LIGO ready for first run
- September 14th, 2015 – aLIGO detects GWs from collision of two black holes
- 2017 - Multi-Messenger Astronomy (MMA) is realized (LIGO/VIRGO)
- 2020s+ – Golden era for GW astronomy! Detectors from all over the world are coming online

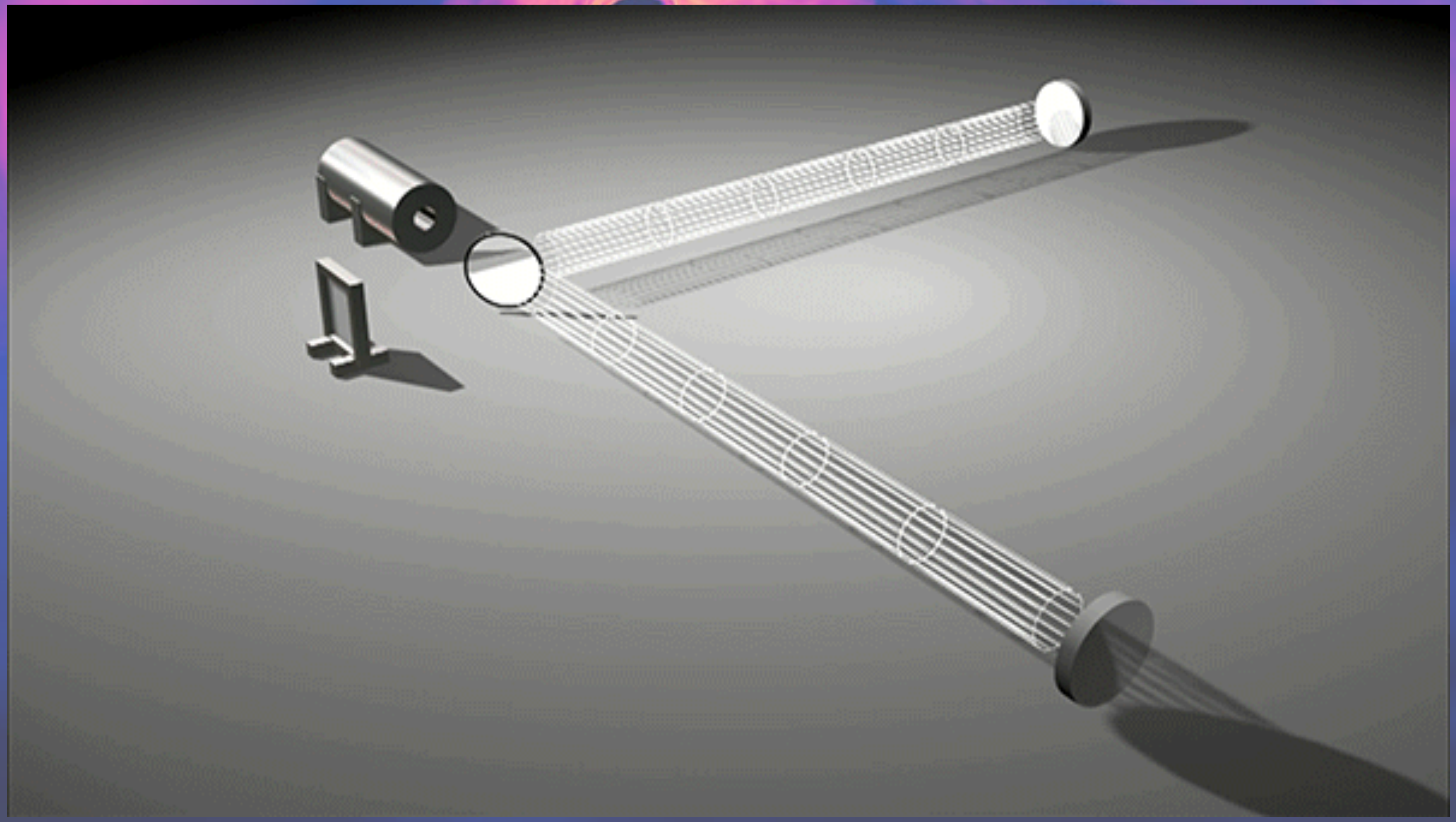
GW170817



Gravitational Waves and Their Detection

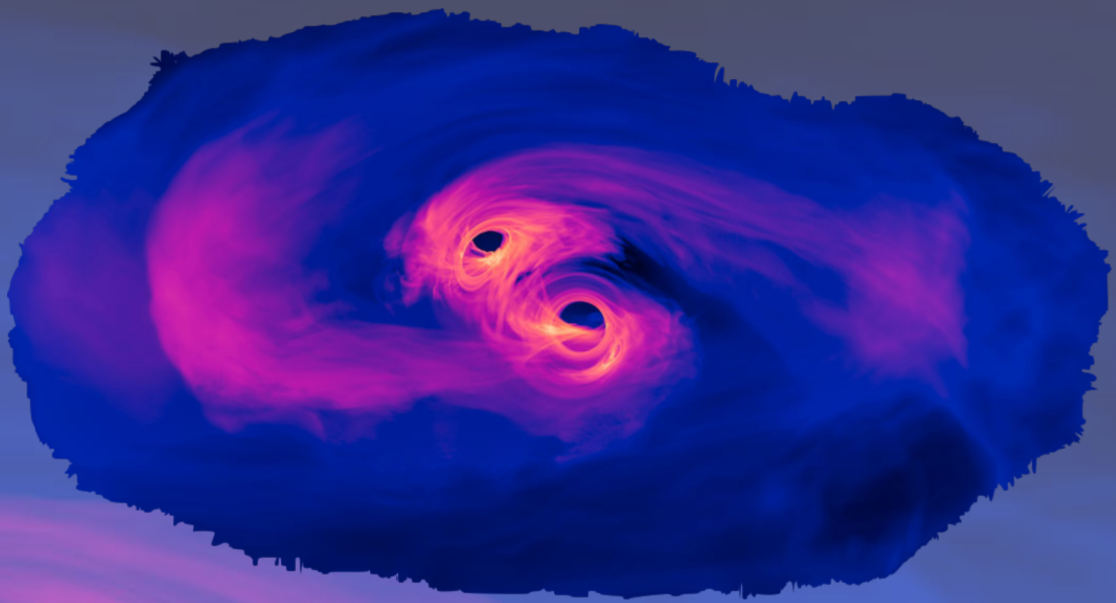


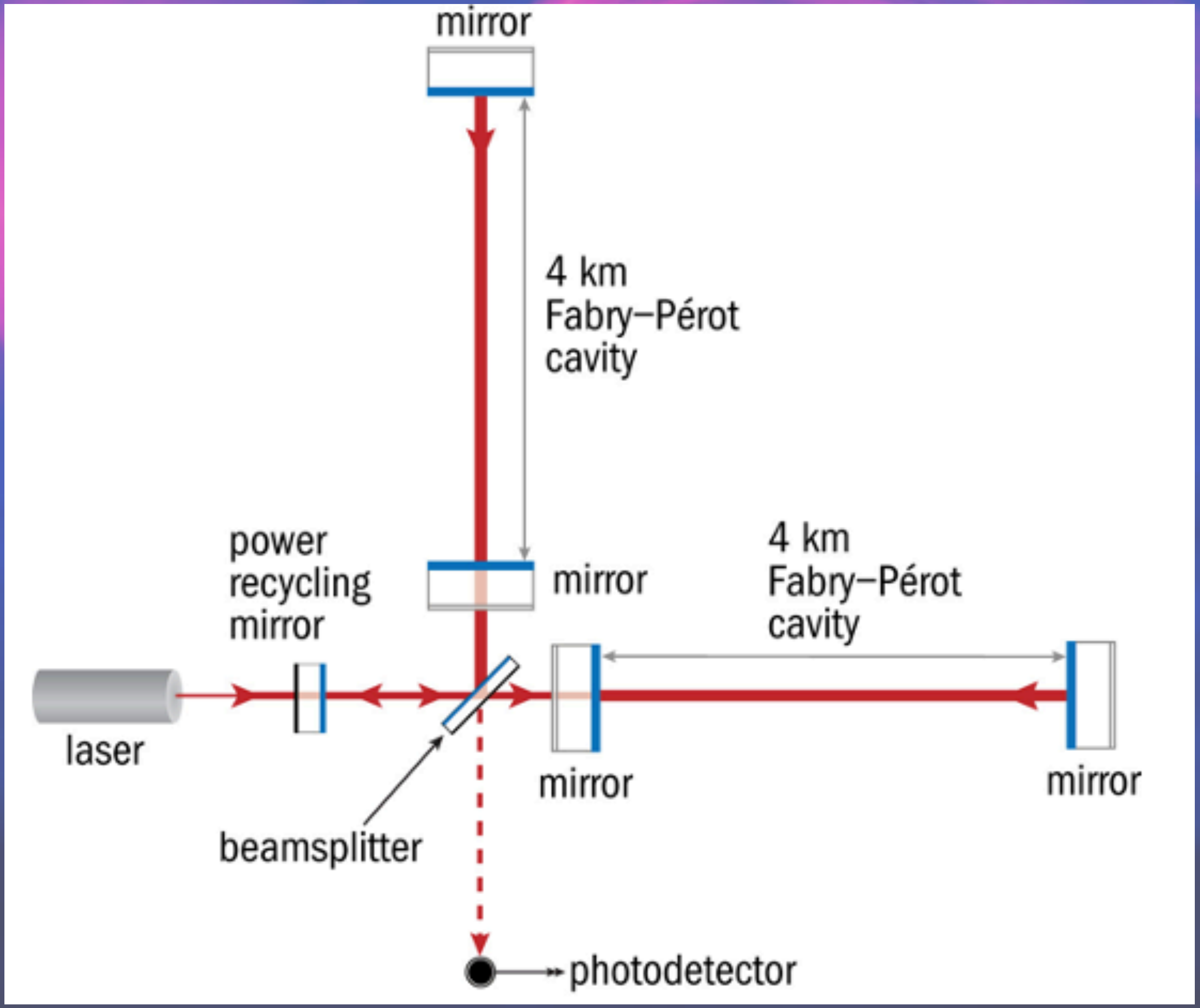
Accelerating masses produce deformations in space time that we can detect via interferometry



Gravitational Waves and Their Detection

Accelerating masses produce deformations in space time that we can detect via interferometry

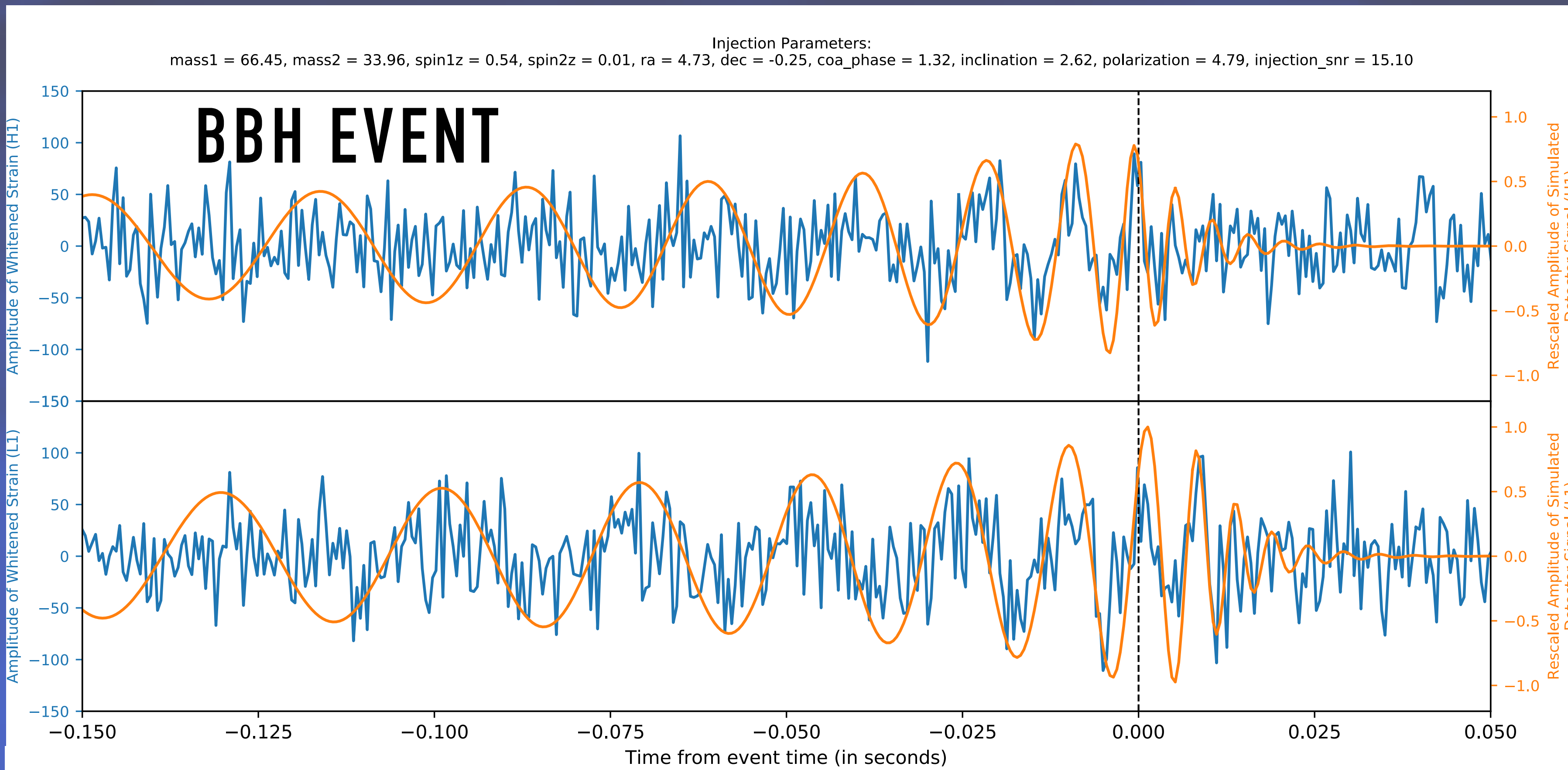


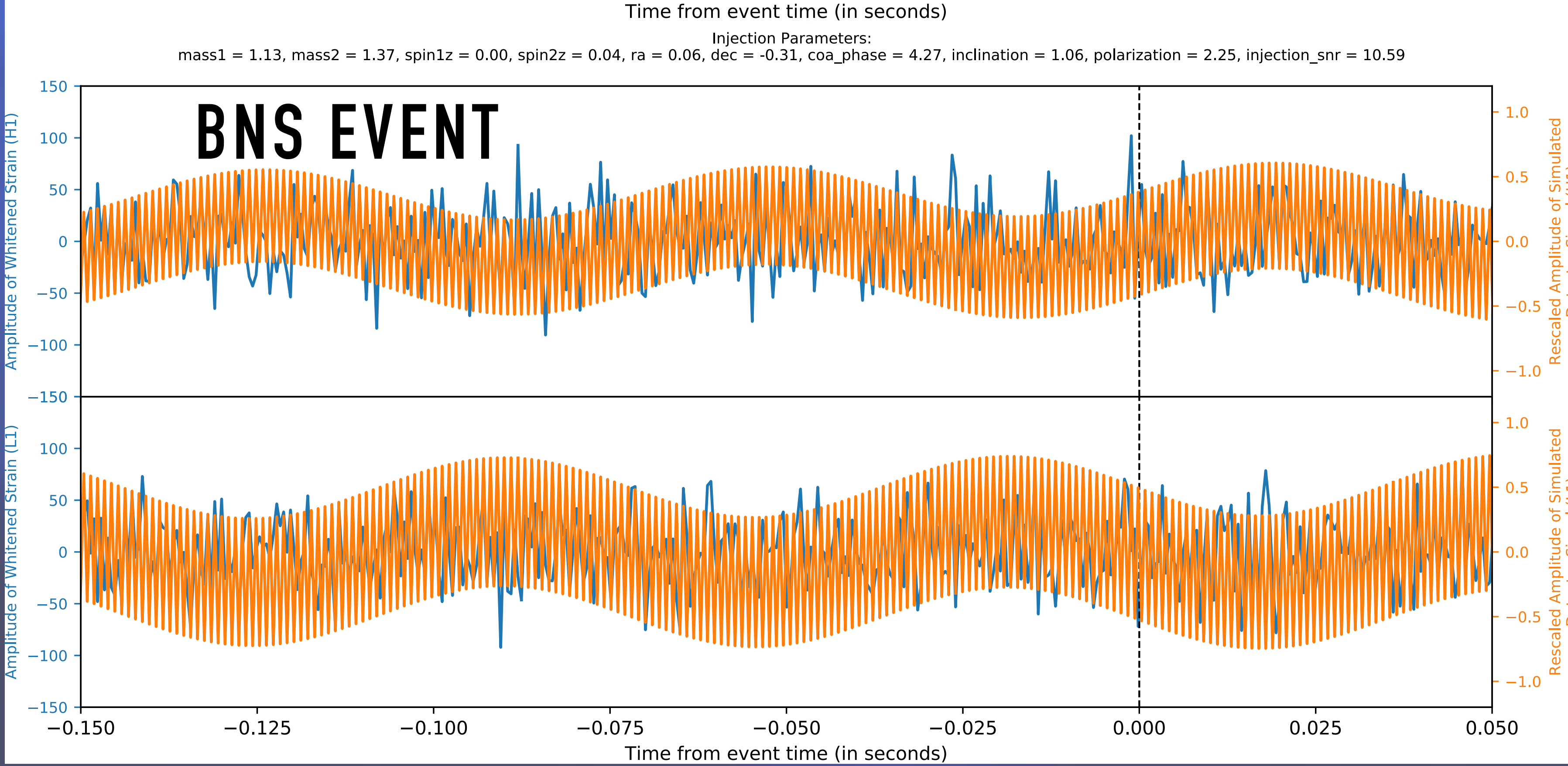


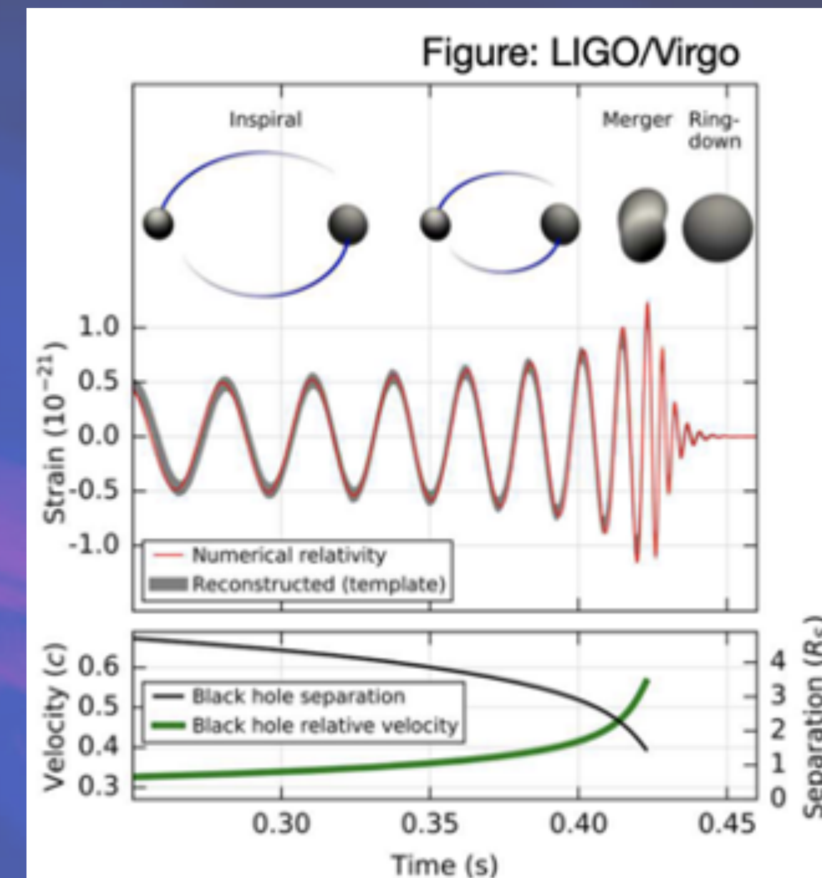
Produces: time-series [1-D strain + auxiliary channels]

A signal will appear in at least two interferometers, with the time delay because of the distance between the detectors

Sounds Trivial!



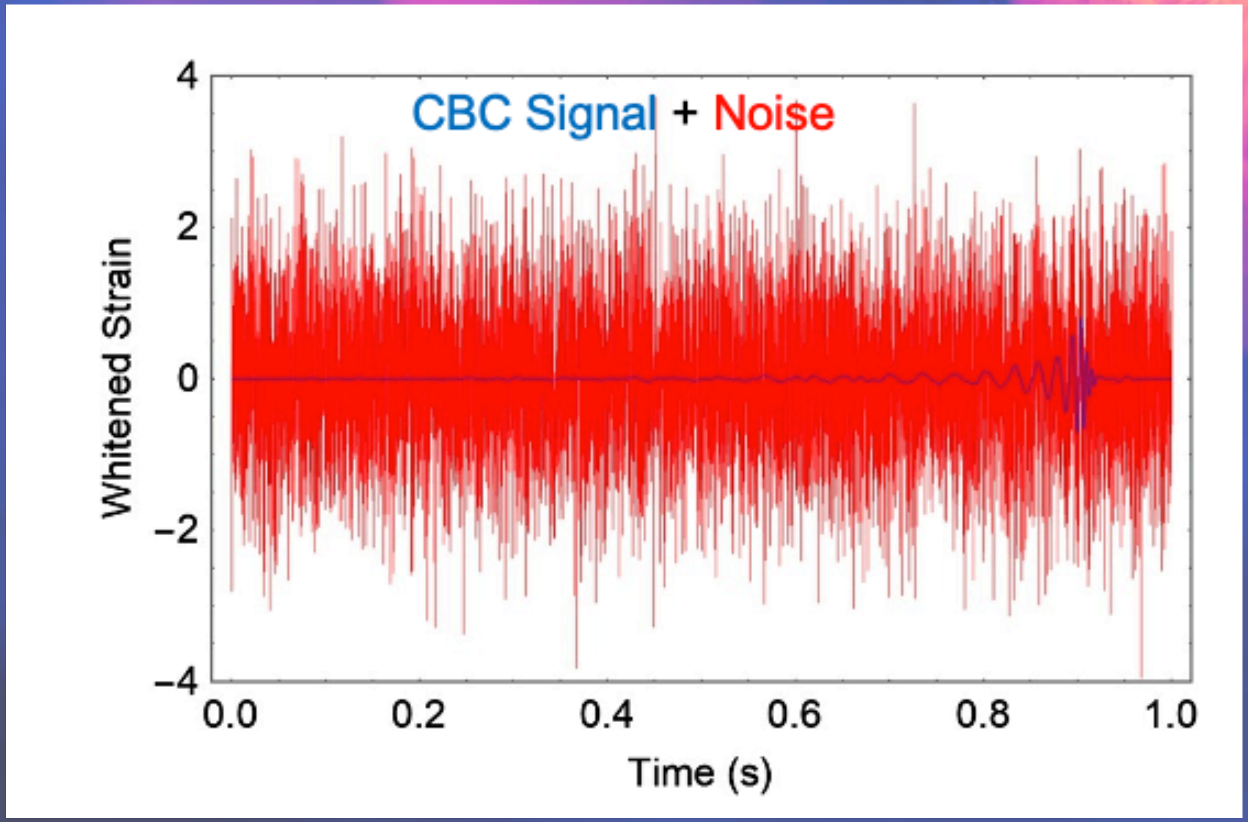




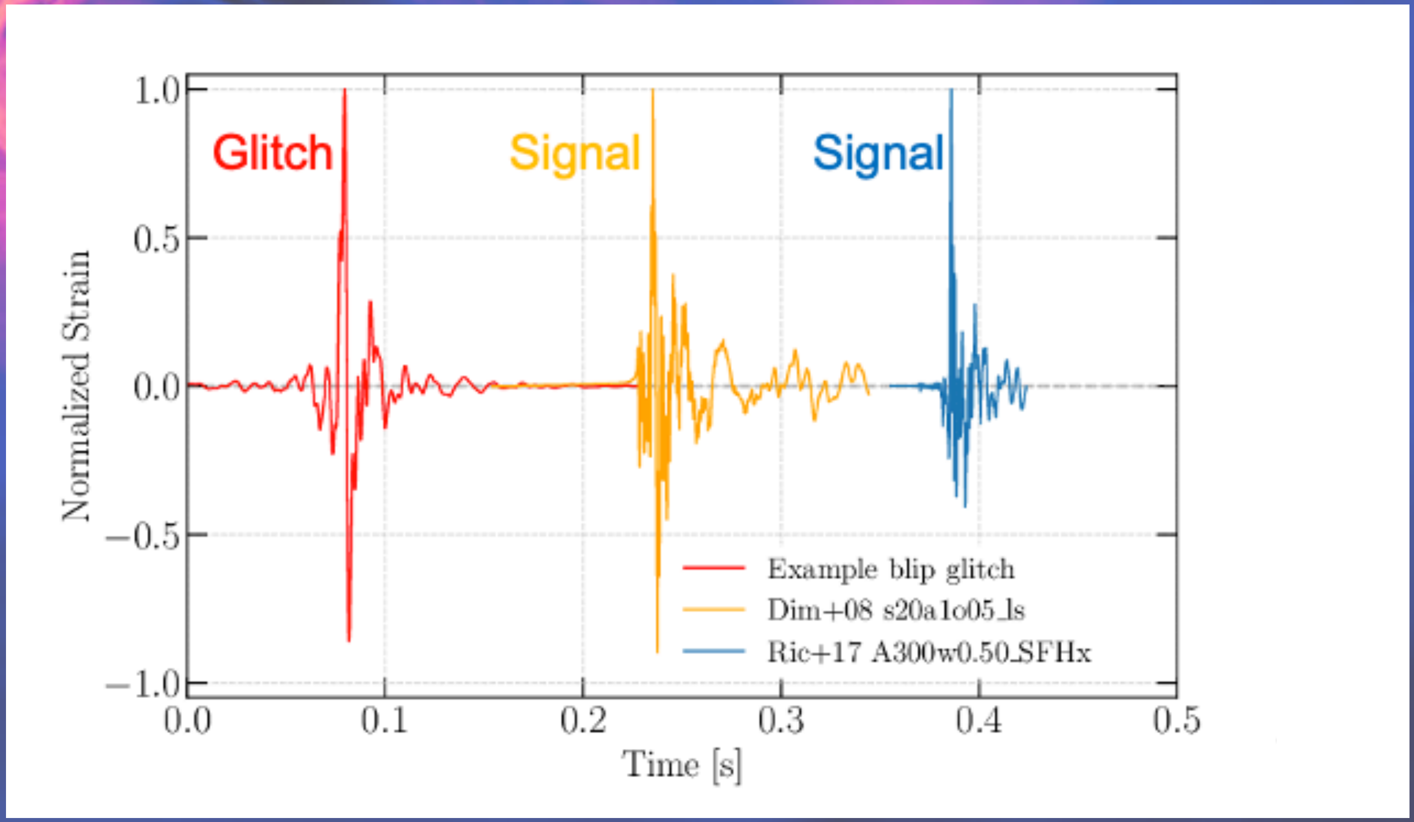
Produces: time-series [1-D strain + auxiliary channels]

GW Data Is Actually Nontrivial!

- Sounds trivial, but isn't – length measurements are ~ 10^(-22) m
- Constantly changing detector noise usually clouds signal
- Detector glitches occur every O(10 sec) – resembling GWs in excess power!



[George & Huerta (2017) (Phys.Lett.B)]



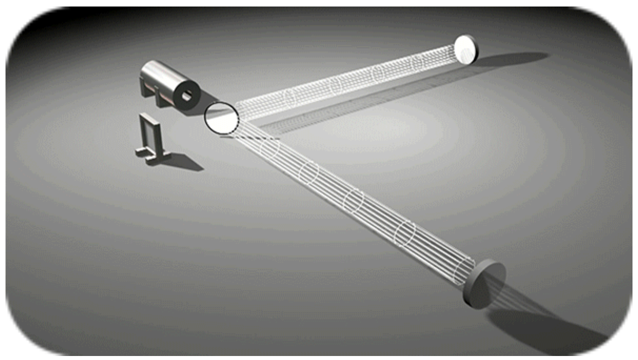
[Szczepanczyk et al. (2021) (Phys.Rev.D)]

Typical GW Data Workflow

Data 16kHz

~100k auxiliary channels

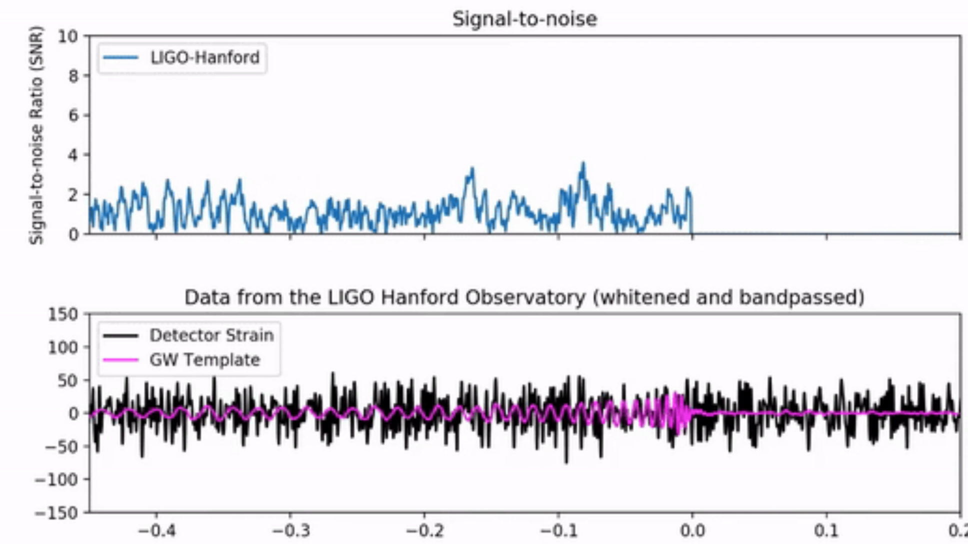
Detector characterisation



Use info from witness sensors to perform data de-noising

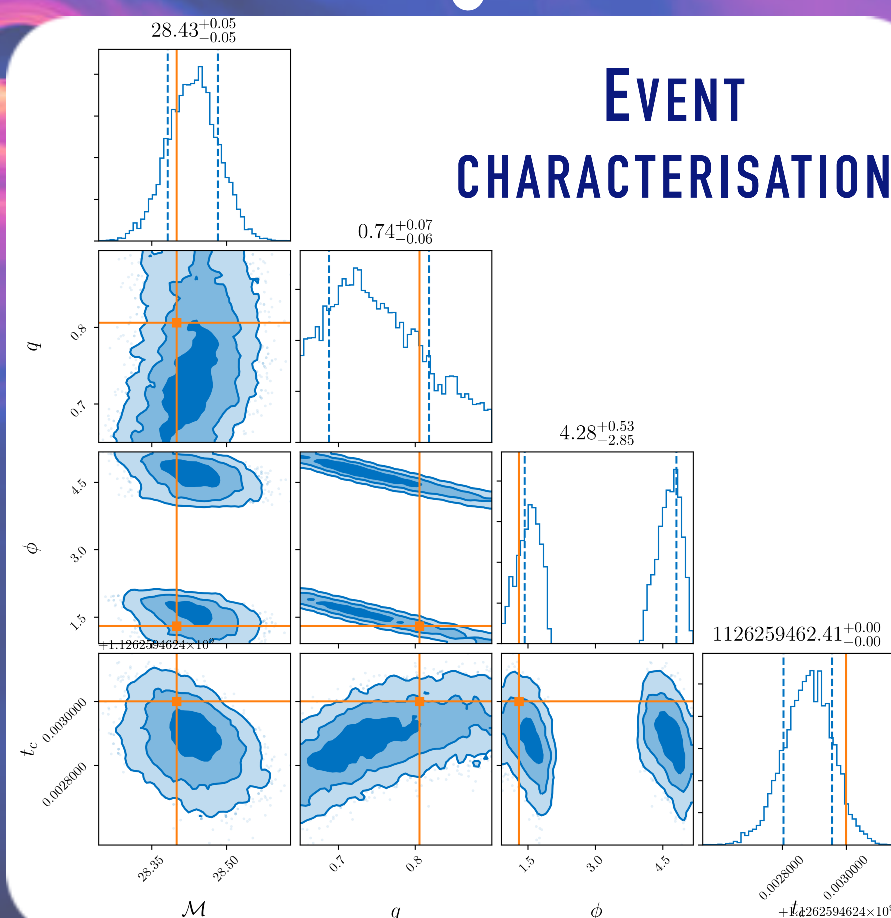
Cleaned Data

Event detection



Event

Event characterisation

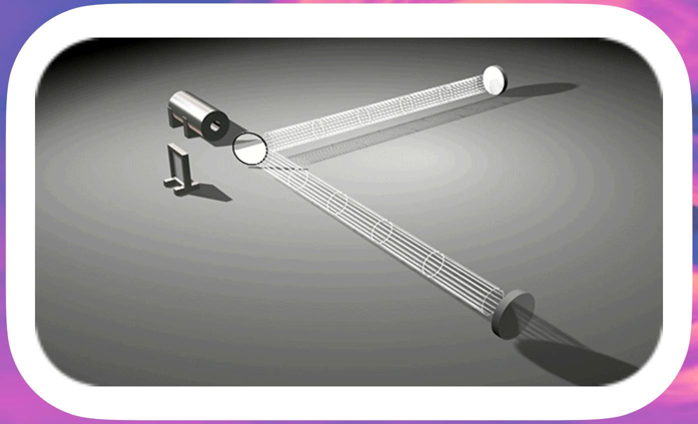


Alert

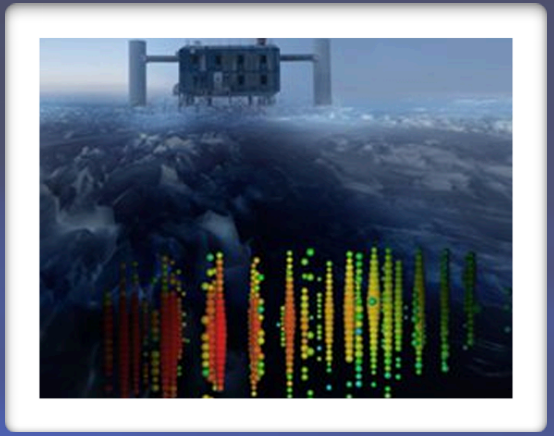
Current workflow uses CPU data grid with rule based algorithms
Challenge is to run this in real-time

Why ML?

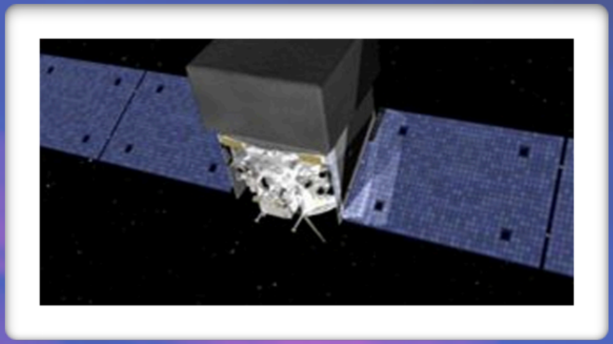
- Increasing detector sensitivity → more templates for matched filtering
- Makes ML advantageous in terms of computational cost and latency (and possibly sensitivity) – useful for Multi-messenger astrophysics efforts



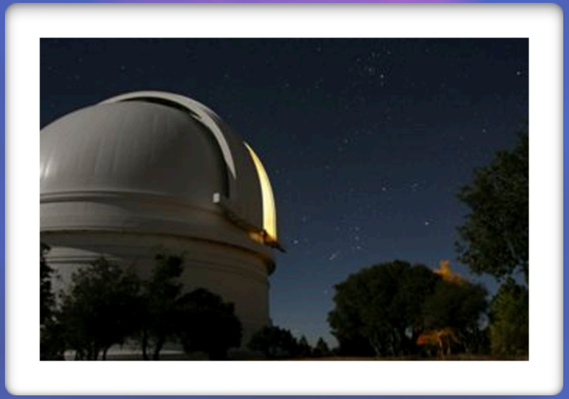
Alert



Neutrinos



X-rays/gamma-rays



Visible/infrared light

Radio waves

Why ML?

- Increasing detector sensitivity → more templates for matched filtering
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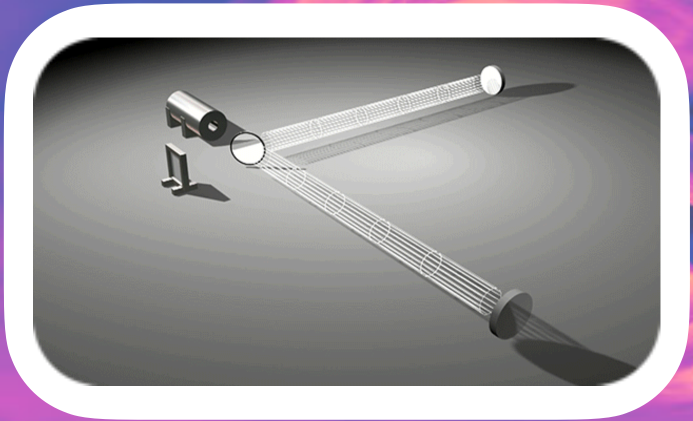
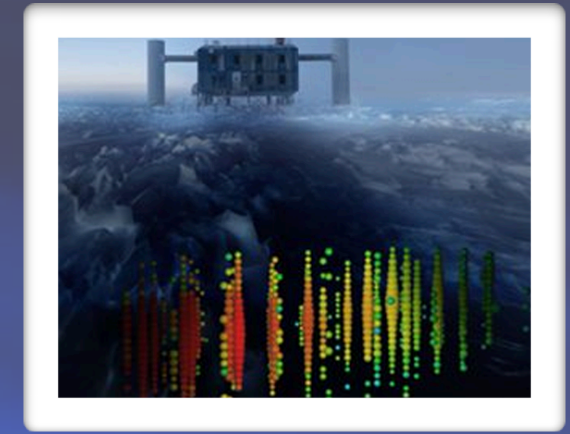
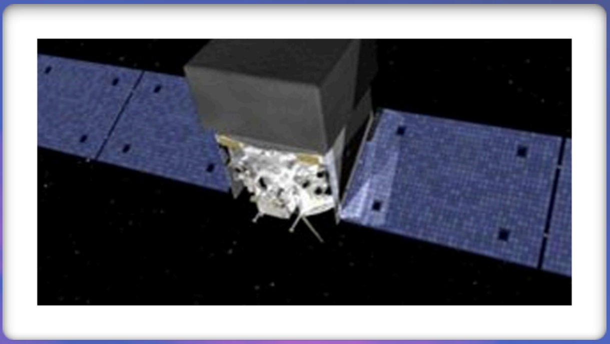
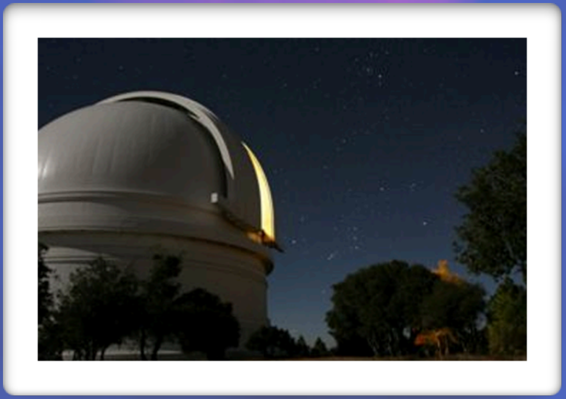




Neutrinos



X-rays/gamma-rays



Visible/infrared light

Radio waves

Noise subtraction and downstream algorithms need to work in real-time to capture as much data as possible and satisfy

- High throughput
- Low latency
- Robust to changing data distribution

Glitch cancellation / GW denosing

- Pending:
  - **[Cuoco et al. (2001) [68] (CQG)]** - On-line power spectra identification and whitening for the noise in interferometric gravitational wave detectors
  - **[Torres-Forné (2016) [69] (PRD)]** - Denoising of Gravitational Wave Signals Via Dictionary Learning Algorithms
  - **[Torres et al. (2014) [70] (PRD)]** - Total-Variation-Based Methods for Gravitational Wave Denoising
  - **[Torres-Forné (2018) [71] (PRD)]** - Total-variation methods for gravitational-wave denoising: Performance tests on Advanced LIGO data
  - **[Torres-Forné (2020) [72] (PRD)]** - Application of dictionary learning to denoise LIGO's blip noise transients
  - **[Shen et al. (2019) [73] (IEEE)]** - Denoising Gravitational Waves with Enhanced Deep Recurrent Denoising Auto-encoders
  - **[Wei & Huerta (2020) [74] (PLB)]** - Gravitational wave denoising of binary black hole mergers with deep learning
  - **[Vajente et al. (2020) [75] (PRD)]** - Machine-learning nonstationary noise out of gravitational-wave detectors
  - **[Alimohammadi et al. (2021) [76] (Scientific Reports)]** - A Template-Free Approach for Waveform Extraction of Gravitational Wave Events
  - **[Ormiston et al. (2020) [77] (PRR)]** - Noise Reduction in Gravitational-Wave Data via Deep Learning
  - **[Essick et al. (2020) [78] (Mach. learn.: sci. technol.)]** - iDQ: Statistical Inference of Non-gaussian Noise with Auxiliary Degrees of Freedom in Gravitational-wave Detectors
  - **[Mogushi et al. (2021) [79] (Mach. learn.: sci. technol.)]** - NNETFIX: an artificial neural network-based denoising engine for gravitational-wave signals
  - **[Chatterjee et al. (2021) [80] (PRD)]** - Extraction of Binary Black Hole Gravitational Wave Signals from Detector Data Using Deep Learning
  - **[Mogushi (2021) [81] (2105.10522)]** - Reduction of Transient Noise Artifacts in Gravitational-wave Data Using Deep Learning
  - **[Colgan et al. (2022) [82] (2203.05086)]** - Detecting and Diagnosing Terrestrial Gravitational-Wave Mimics Through Feature Learning
  - **[Lopez et al. (2022) [83] (2203.06494)]** - Simulating Transient Noise Bursts in LIGO with Generative Adversarial Networks
  - **[Yu & Adhikari (2022) [84] (Front. Artif. Intell.)]** - Nonlinear Noise Cleaning in Gravitational-Wave Detectors With Convolutional Neural Networks
  - **[Lopez et al. (2022) [85] (2205.09204)]** - Simulating Transient Noise Bursts in LIGO with Gengli
  - **[Vajente (2022) [@PhysRevD.105.102005] (PRD)]** - Data Mining and Machine Learning Improve Gravitational-Wave Detector Sensitivity
  - **[Bacon et al. (2022) [86] (2205.13513)]** - Denoising Gravitational-Wave Signals from Binary Black Holes with Dilated Convolutional Autoencoder
  - **[Kato et al. (2022) [87] (Astron. Comput.)]** - Validation of Denoising System Using Non-Harmonic Analysis and Denoising Convolutional Neural Network for Removal of Gaussian Noise from Gravitational Waves Observed by LIGO

- **[Staats & Cavaglià (2018) [38] (Commun. Comput. Phys.)]** - Finding the origin of noise transients in LIGO data with machine learning (**Karoo GP**)
- **[Mukund et al. (2017) [39] (PRD)]** - Transient classification in LIGO data using difference boosting neural network (**Wavelet-DBNN, India**)
- **[Llorens-Monteagudo et al. (2019) [40] (CQG)]** - Classification of gravitational-wave glitches via dictionary learning (**Dictionary learning**)
- Low latency transient detection and classification (I. Pinto, V. Pierro, L. Troiano, E. Mejuto-Villa, V. Matta, P. Addesso)
- **[George et al. (2018) [33] (PRD)]** - Classification and unsupervised clustering of LIGO data with Deep Transfer Learning (**Deep Transfer Learning**)
- **[Astone et al. (2018) [41] (PRD)]** - New method to observe gravitational waves emitted by core collapse supernovae (**RGB image SN CNN**)
- **[Colgan et al. (2020) [42] (PRD)]** - Efficient gravitational-wave glitch identification from environmental data through machine learning
- **[Bahaadini et al. (2017) [43] (IEEE)]** - Deep Multi-View Models for Glitch Classification
- **[Bahaadini et al. (2018) [44] (Info. Sci.)]** - Machine learning for Gravity Spy: Glitch classification and dataset
- **[Bahaadini et al. (2018) [45] (IEEE)]** - DIRECT: Deep Discriminative Embedding for Clustering of LIGO Data
- Young-Min Kim - Noise Identification in Gravitational wave search using Artificial Neural Networks (PDF) (4th K-J workshop on KAGRA @ Osaka Univ.)
- **[Biswas et al. (2020) [46] (CQG)]** - New Methods to Assess and Improve LIGO Detector Duty Cycle
- **[Morales-Alvarez et al. (2020) [47] (IEEE)]** - Scalable Variational Gaussian Processes for Crowdsourcing: Glitch Detection in LIGO
- **[Marianer et al. (2020) [48] (Mon. Not. Roy. Astron. Soc.)]** - A Semisupervised Machine Learning Search for Never-seen Gravitational-wave Sources
- **[Mesuga & Bayanay (2021) [49] (2107.01863)]** - On the Efficiency of Various Deep Transfer Learning Models in Glitch Waveform Detection in Gravitational-wave Data
- **[Sankarapandian & Kulis (2021) [50] (2107.10667)]** - β-Annealed Variational Autoencoder for Glitches
- **[Yu & Adhikari (2021) [51] (2111.03295)]** - Nonlinear Noise Regression in Gravitational-Wave Detectors with Convolutional Neural Networks
- **[Sakai et al. (2021) [52] (2111.10053)]** - Unsupervised Learning Architecture for Classifying the Transient Noise of Interferometric Gravitational-wave Detectors
- **[Merritt et al. (2021) [53] (PRD)]** - Transient Glitch Mitigation in Advanced LIGO Data
- **[Colgan et al. (2022) [54] (2202.13486)]** - Architectural Optimization and Feature Learning for High-Dimensional Time Series Datasets
- **[Davis et al. (2022) [55] (2204.03091)]** - Incorporating Information from LIGO Data Quality Streams into the PyCBC Search for Gravitational Waves
- **[Bahaadini et al. (2022) [56] (2205.13672)]** - Discriminative Dimensionality Reduction Using Deep Neural Networks for Clustering of LIGO Data

UH OH.....

Glitch cancellation / GW denosing

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  - **[Torres-Forné (2016)** [69] **(PRD)]** - Denoising of Gravitational Wave Signals Via Dictionary Learning Algorithms
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- Supernova Search

  Some burst searches are for targeted sources like supernovae. There is not enough supernova waveforms to match filter search but some supernova waveform features are known. The known features from supernova simulations can be incorporated into supernova searches using machine learning.

  - **[Astone et al. (2018)** [41] **(PRD)]** enhance the efficiency of cWB using a neural network. The network is trained on phenomenological waveforms that represent the g-mode emission in supernova waveforms. They use cWB to prepare images of the data. They use colours to determine which detectors find the signal. They find their method increases the sensitivity of traditional cWB.
  - **[Iess et al. (2020)** [321] **(Mach. learn.: sci. technol.)]** have a different approach that does not involve cWB. They use a trigger generator called WDF to find excess power in the detector. Then they do a neural network classification to decide if the trigger is a signal or noise. They train directly on supernova waveforms. They use both time series and images of data. They obtain high accuracies with both methods and include glitches.
  - **[Chan et al. (2019)** [322] **(PRD)]** also train directly on supernova waveforms. They use only the time series waveforms from different explosion mechanisms.
  - **[Cavaglia et al. (2020)** [323] **(Mach. learn.: sci. technol.)]** - Improving the background of gravitational-wave searches for core collapse supernovae: a machine learning approach
  - **[Stachie et al. (2020)** [324] **(Mon. Not. Roy. Astron. Soc.)]** - Using Machine Learning for Transient Classification in Searches for Gravitational-wave Counterparts
  - **[Marianer et al. (2020)** [48] **(Mon. Not. Roy. Astron. Soc.)]** - A Semisupervised Machine Learning Search for Never-Seen Gravitational-Wave Sources
  - **[Millhouse et al. (2020)** [325] **(PRD)]** - Search for Gravitational Waves from 12 Young Supernova Remnants with a Hidden Markov Model in Advanced LIGO's Second Observing Run
  - **[L'opez et al. (2021)** [326] **(PRD)]** - Deep Learning for Core-collapse Supernova Detection
  - **[L'operz et al. (2021)** [327] **(IEEE)]** - Deep Learning Algorithms for Gravitational Waves Core-collapse Supernova Detection
  - **[Antelis et al. (2021)** [328] **(PRD)]** - Using Supervised Learning Algorithms As a Follow-up Method in the Search of Gravitational Waves from Core-collapse Supernovae

- **[Xia et al. (2020)** [158] **(PRD)]** - Improved Deep Learning Techniques in Gravitational-wave Data Analysis
- **[Alvares et al. (2020)** [159] **(CQG)]** - Exploring Gravitational-wave Detection and Parameter Inference Using Deep Learning Methods
- **[Wang et al. (2019)** [130] **(New J. Phys.)]** - Identifying Extra High Frequency Gravitational Waves Generated from Oscillons with Cuspy Potentials Using Deep Neural Networks
- LIGO & Virgo provide two probabilities in low-latency. **[Chatterjee et al. (2020)** [160] **(ApJ)]** The probability that there is a neutron star in the CBC system, P(HasNS). The probability that there exists tidally disrupted matter outside the final coalesced object after the merger, P(HasRemnant). Matched filter searches give point estimates of mass and spin but they have large errors! To solve this a machine learning classification is used. (scikit learn K nearest neighbours, also tried random forest). A training set is created by injecting fake signals into gravitational wave data and performing a search. This then produces a map between true values and matched filter search point estimates which is learnt by the classifier.
- **[Wei et al. (2020)** [161] **(ApJ)]** - Deep Learning with Quantized Neural Networks for Gravitational Wave Forecasting of Eccentric Compact Binary Coalescence
- **[Menéndez-Vázquez et al. (2020)** [162] **(PRD)]** - Searches for Compact Binary Coalescence Events Using Neural Networks in the LIGO/Virgo Second Observation Period
- **[Krastev et al. (2020)** [163] **(PLB)]** - Detection and Parameter Estimation of Gravitational Waves from Binary Neutron-Star Mergers in Real LIGO Data Using Deep Learning
- **[Dodia (2021)** [164] **(2101.00195)]** - Detecting Residues of Cosmic Events Using Residual Neural Network
- **[Kulkarni et al. (2019)** [165] **(PRD)]** - Random Projections in Gravitational Wave Searches of Compact Binaries (**Random projections**)
- **[Rzeza et al. (2021)** [166] **(2101.03226)]** - Random Projections in Gravitational Wave Searches from Compact Binaries II: Efficient Reconstruction of Detection Statistic within LLOID Framework (**Random projections**)
- **[Zhan et al. (2021)** [167] **(2103.03557)]** - The Response of the Convolutional Neural Network to the Transient Noise in Gravitational Wave Detection
- **[Morawski et al. (2021)** [168] **(Mach. learn.: sci. technol.)]** - Anomaly Detection in Gravitational Waves Data Using Convolutional Autoencoders
- **[Baltus et al. (2021)** [169] **(PRD)]** - Convolutional Neural Networks for the Detection of the Early Inspiral of a Gravitational-wave Signal
- **[Yan et al. (2021)** [170] **(PRD)]** - Generalized Approach to Matched Filtering Using Neural Networks
- **[Yu et al. (2021)** [171] **(PRD)]** - Early Warning of Coalescing Neutron-star and Neutron-star-black-hole Binaries from Nonstationary Noise Background Using Neural Networks
- **[Fan et al. (2021)** [172] **(ICPR)]** - Improving Gravitational Wave Detection with 2d Convolutional Neural Networks
- **[Baltus et al. (2021)** [173] **(IEEE)]** - Detecting the Early Inspiral of a Gravitational-wave Signal with Convolutional Neural Networks
- **[Schäfer et al. (2021)** [174] **(2106.03741)]** - Training Strategies for Deep Learning Gravitational-wave Searches
- **[Goyal et al. (2021)** [175] **(PRD)]** - Rapid Identification of Strongly Lensed Gravitational-wave Events with Machine Learning
- **[Dodia et al. (2021)** [176] **(2107.03607)]** - Specgrav – Detection of Gravitational Waves Using Deep Learning
- **[Van Lieshout (2021)** [177] **(Master Thesis)]** - Sparse, Deep Neural Networks for the Early Detection of Gravitational Waves
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Where are all the online/offline algorithms/results?

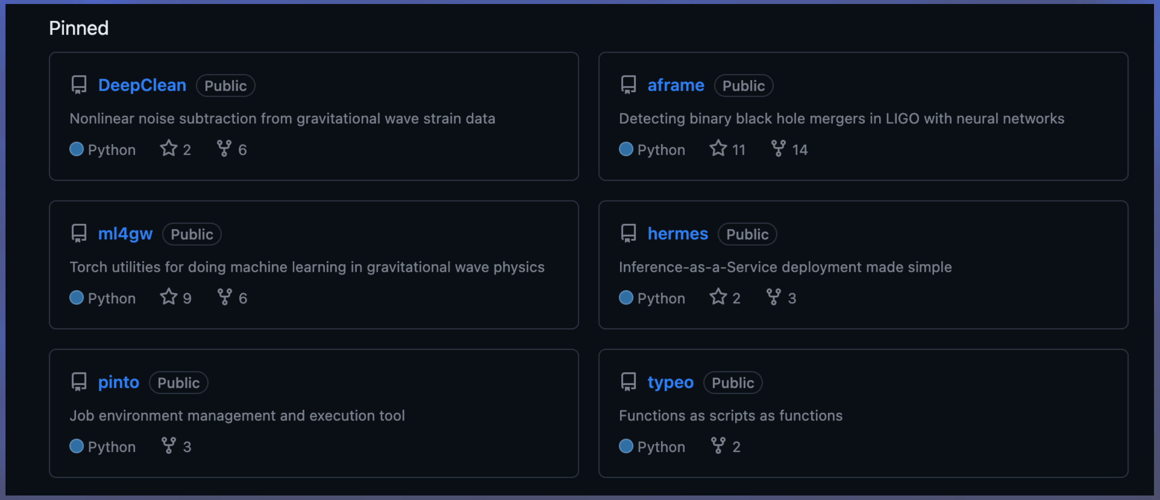
Multi-Messenger Astrophysics (MMA) requires low-latency alerts.

With LIGO Observing Run 4 running, GW signals are no longer "rare" – MMA collaborators require accurate alerts, parameter estimation, event probabilities.

GW-physics is not a high statistics field. Everything needs to be trained/validated on years – decades of detector data.

Online (real-time) ML for GW hasn't happened because there is was no team dedicated to making the GW-ecosystem ML-friendly. This leads to issues in data loading, simulation, inference, validation, optimization, etc.

Enter: ML4GW & Hermes



ml4gw — torch utilities for training neural networks in gravitational wave physics applications

Fast data loading

GPU-friendly implementations of common analysis operations

Allowing for more robust use of simulations

hermes — A set of APIs for assisting in the acceleration, export, serving, and requesting of models using Triton Inference Server

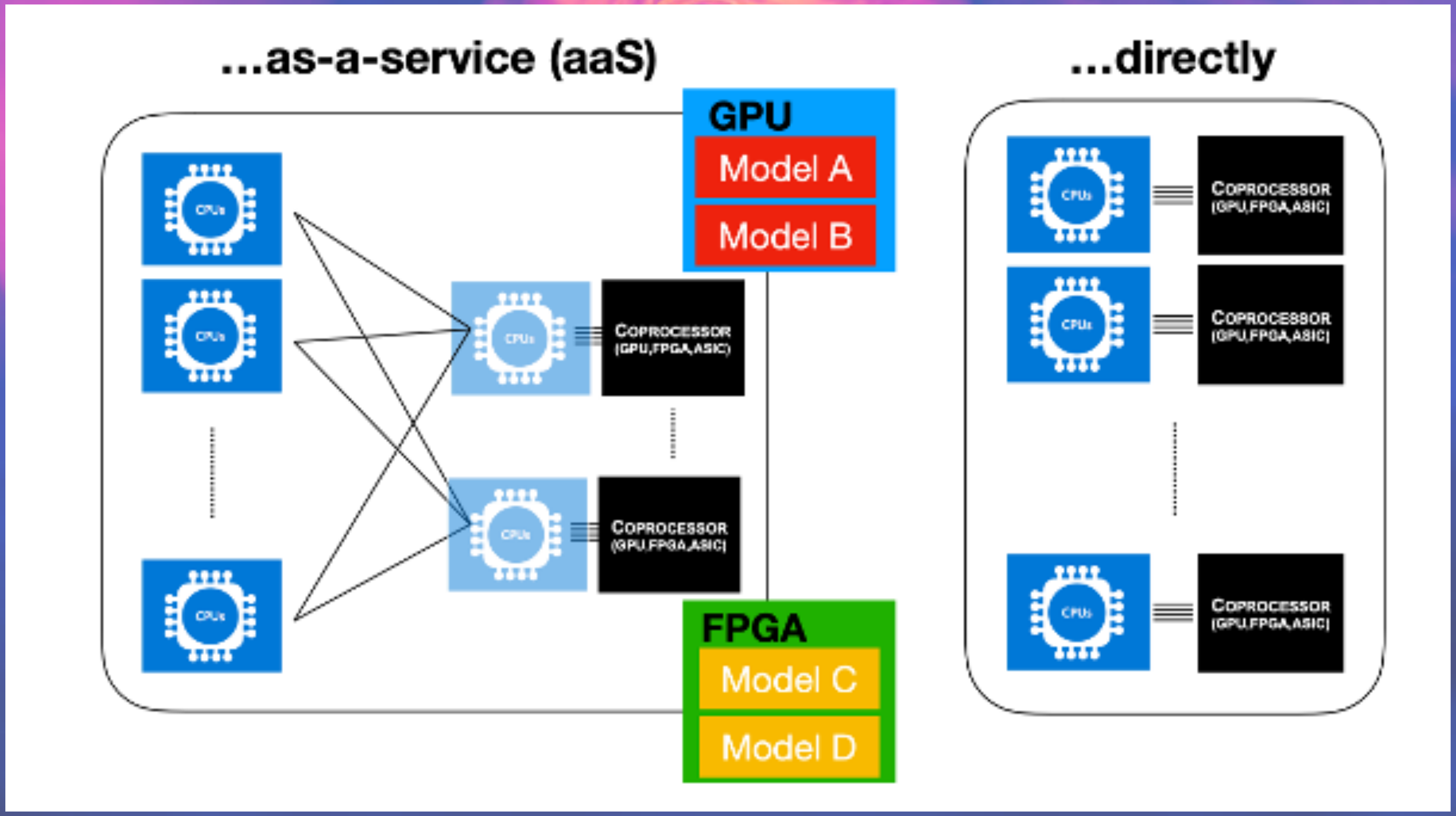
Distribute models using centralized repos

Perform inference with an off-the-shelf application - NVIDIA Triton

Users interact via lightweight client APIs, abstracting implementation details

Inference-as-a-Service (IaaS) Paradigm

- IaaS is becoming a common paradigm (also in HEP) to efficiently use compute resources
- Highly parallelizable
- Off-the-shelf solution: Triton inference server



Inference-as-a-Service (IaaS) + Timeseries Snapshotter

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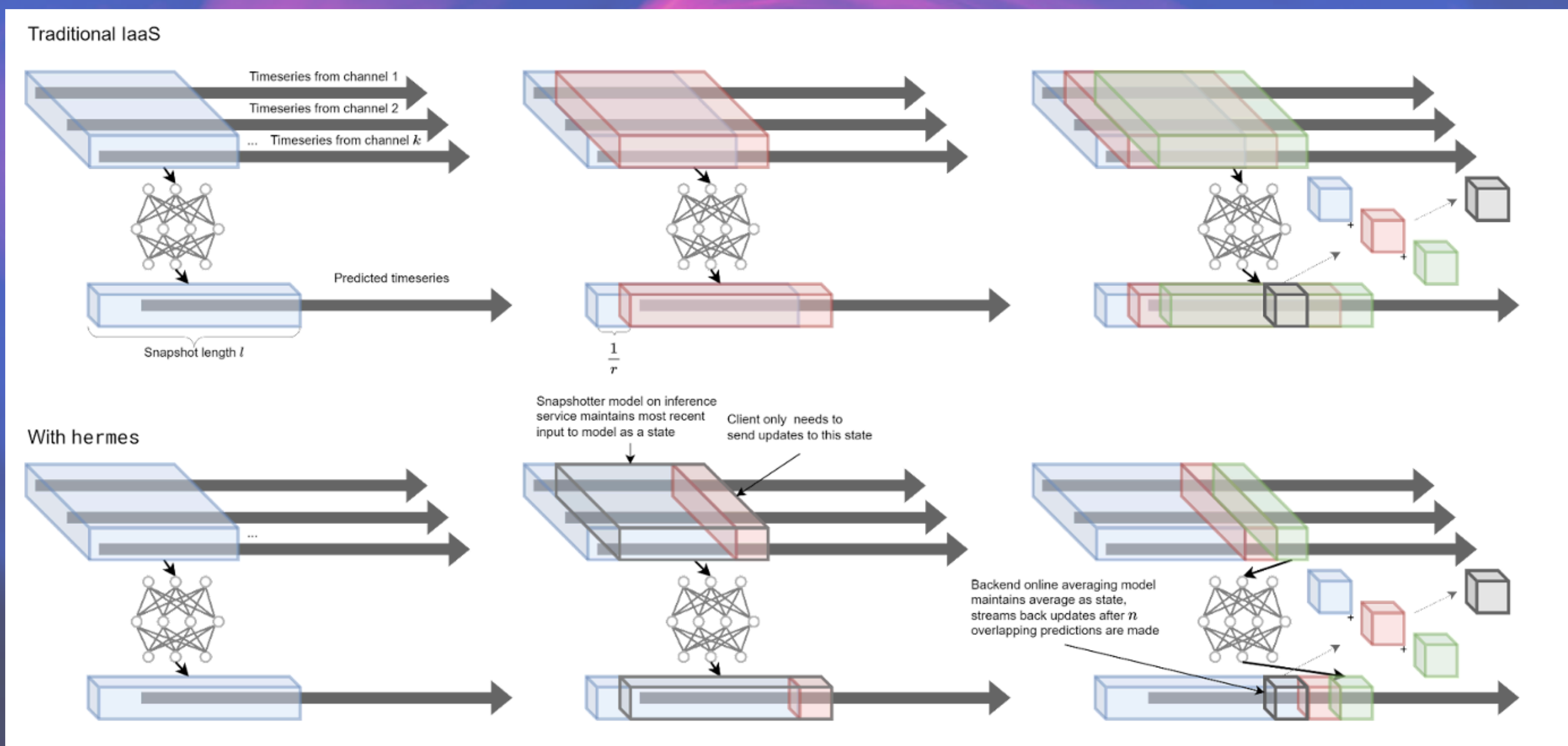
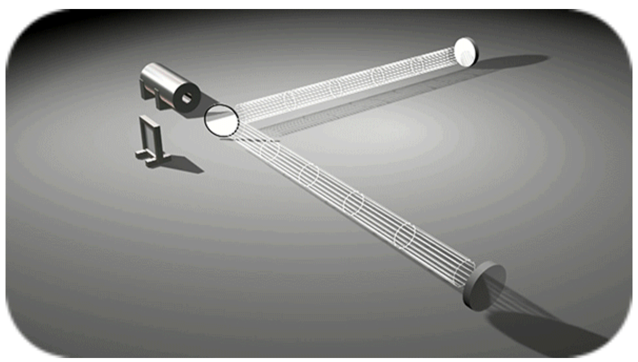


Future ML-based workflow

Data 16kHz

~100k auxiliary channels

Detector characterisation



DeepClean
NN based AE
noise subtraction

Cleaned Data

GW Strain content

The output reconstructed from an interferometer contains

$$h(t) = s(t) + n(t)$$

Possible GW signal

Detector noise

GW Strain content

The output reconstructed from an interferometer contains

$$h(t) = s(t) + n(t)$$

Possible GW signal

Detector noise

$$n(t) = n_{nw}(t) + n_w(t)$$

Non-removable (fundamental noise)
Eg: photon shot noise, thermal noise

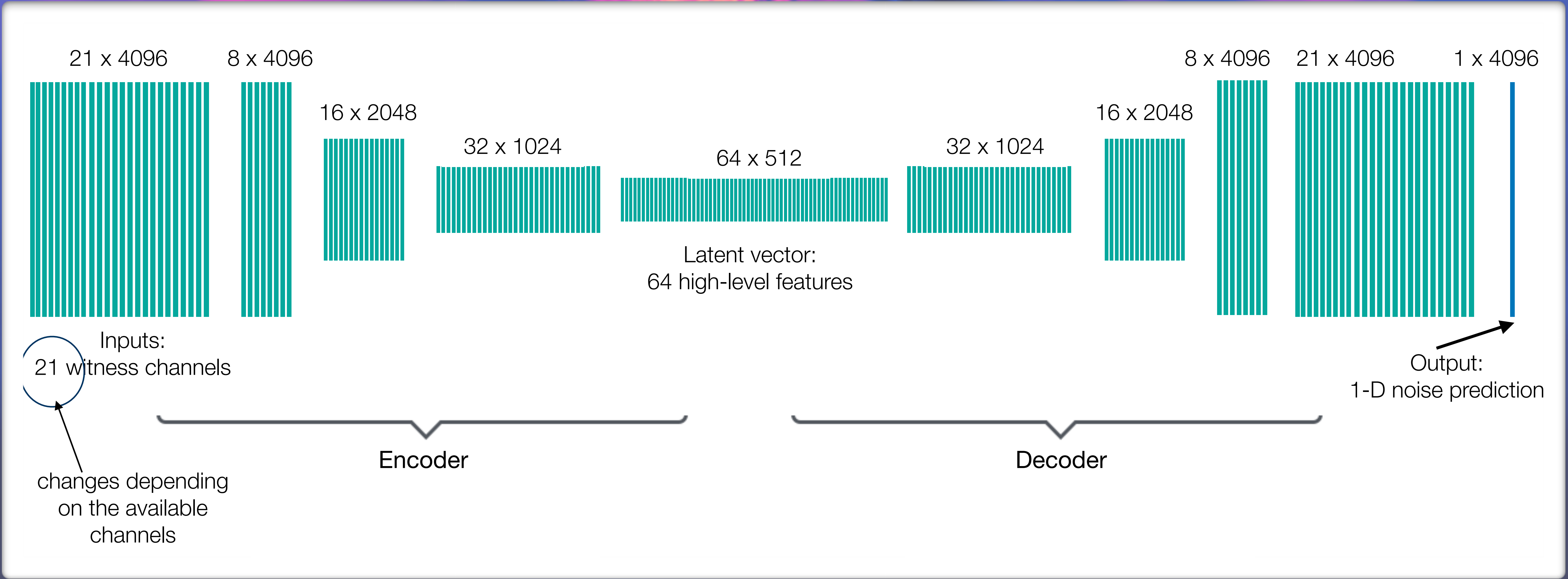
Can be reduced only with upgraded design and technology

Source of noise witnessed by dedicated system monitors (witness sensors)

Environmental contamination or technical noise eg: noise arising from the control of suspended optics

DeepClean Denoising

- CNN-based autoencoder to predict the noise using witness channels
- Active-learning: network is fine-tuned at fixed intervals and the new model is hosted alongside stable model on inference service
- DeepClean is capable of denoising the data at ~ 1 s latency – a promising prospect for electromagnetic follow-up of gravitational wave observations

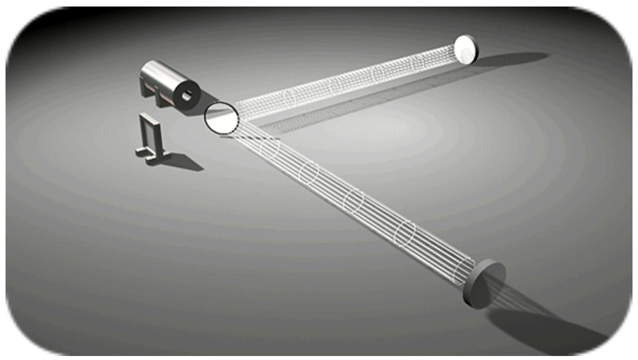


Future ML-based workflow

Data 16kHz

~100k auxiliary channels

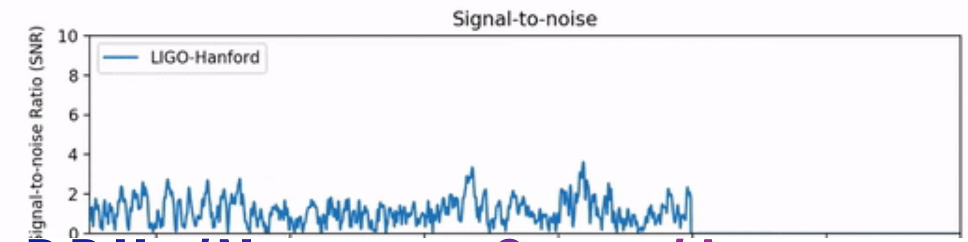
Detector characterisation



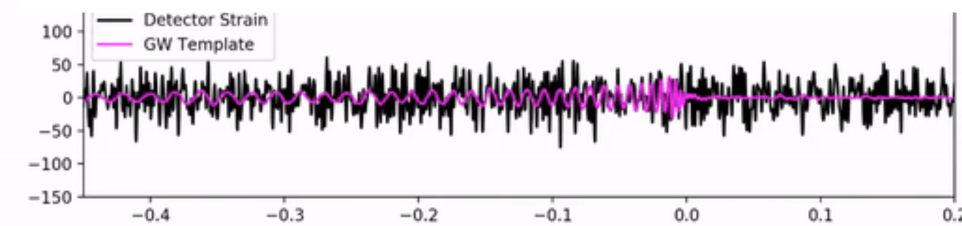
DeepClean
NN based AE
noise subtraction

Cleaned Data

NN-based algos for Event detection



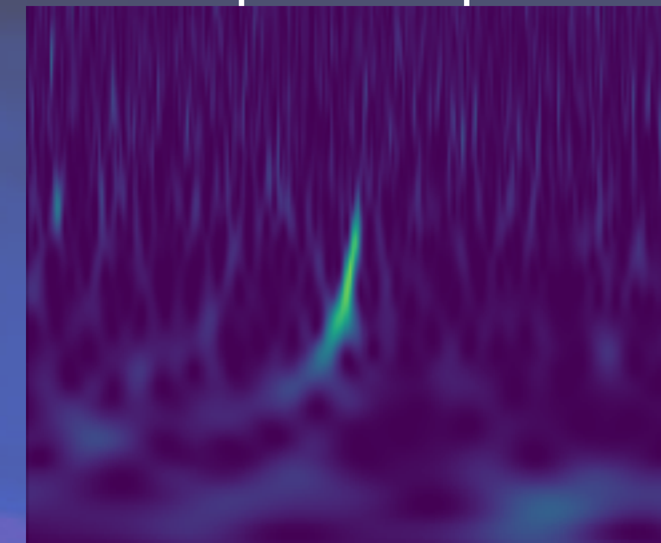
BBHs/Neutron Stars/Anomalies

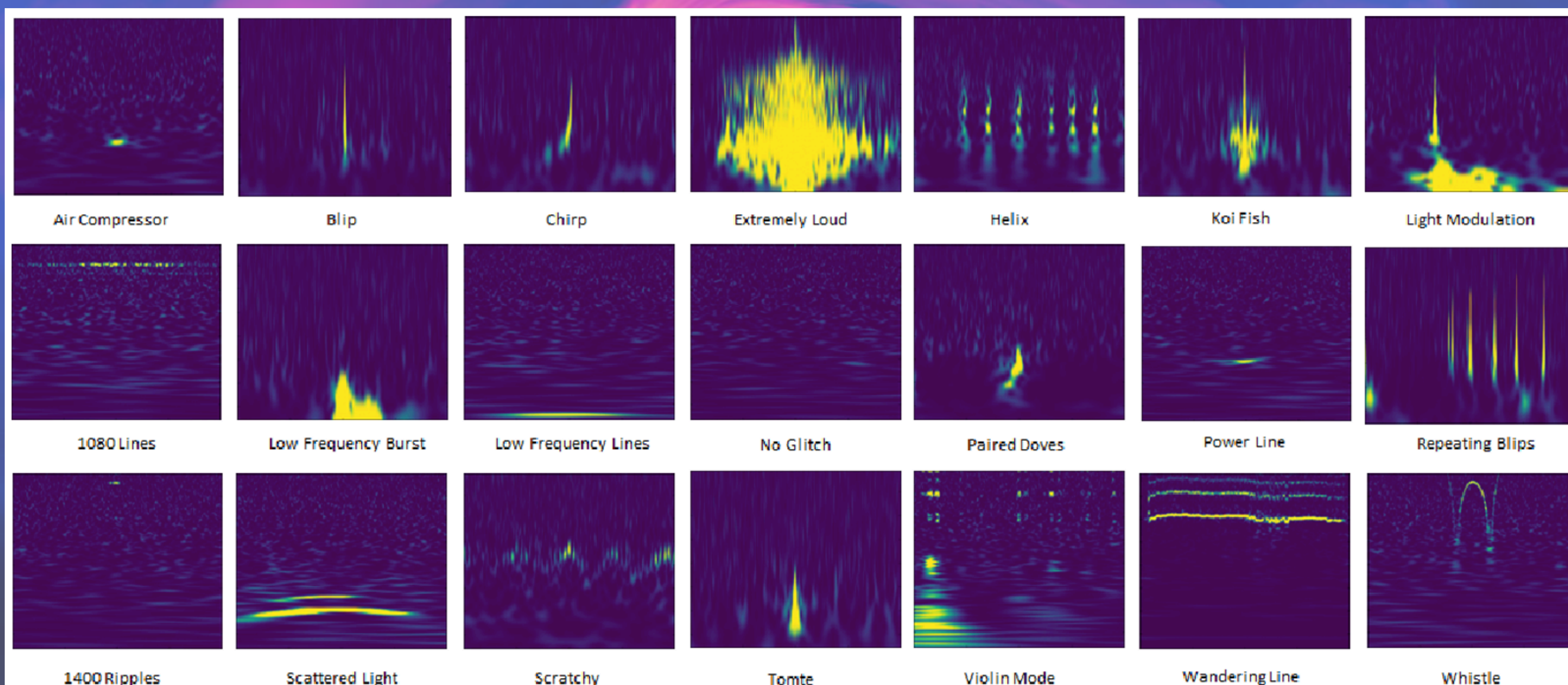


ML Applications in LIGO

- As opposed to detector noise subtracted by DeepClean, glitches are short duration non-Gaussian noise transients originated from instrumental or environmental couplings.
- Glitches are by far the culprit of most significant false alarms — excess power isn't enough!

Signal

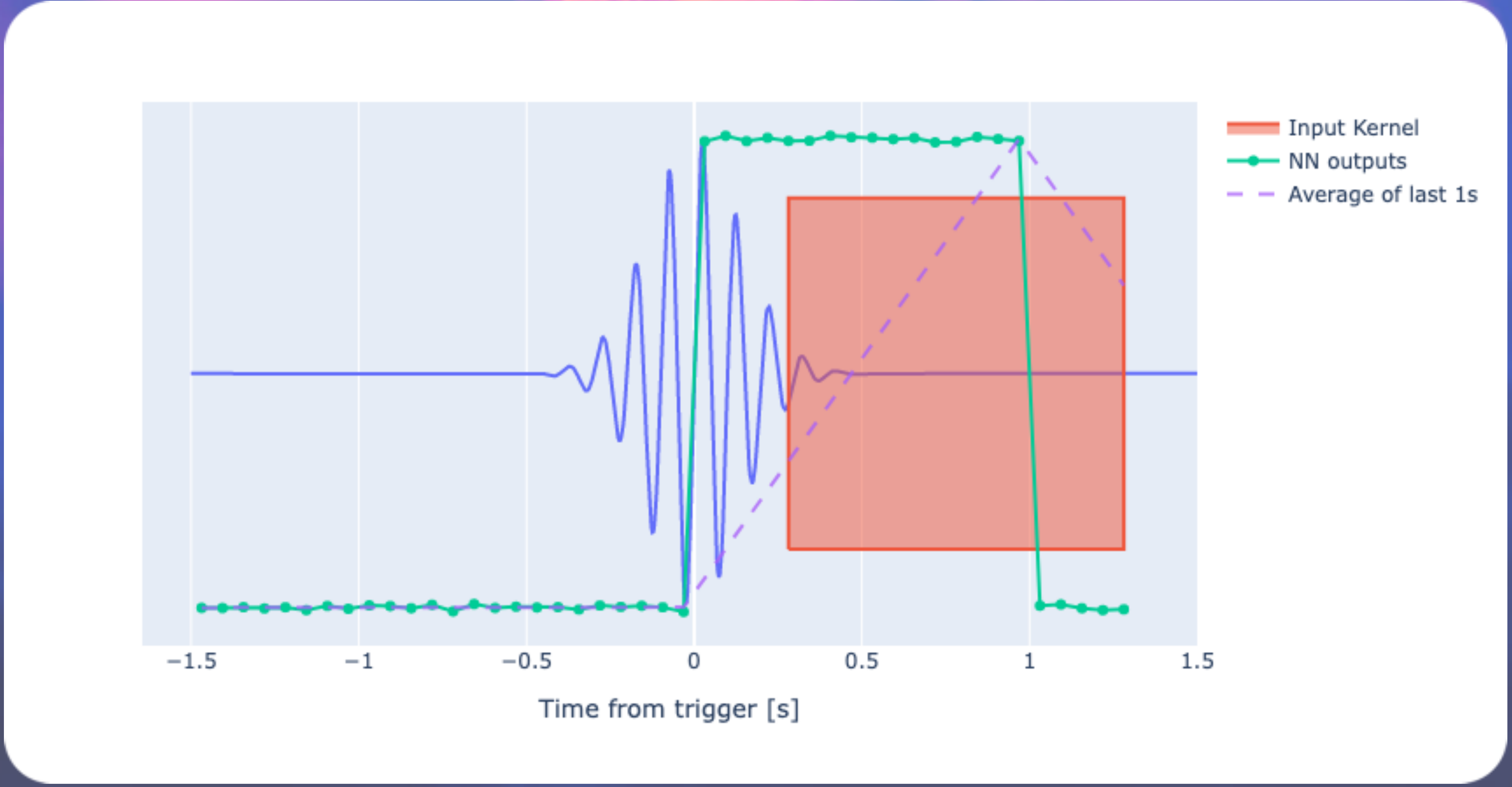




A-Frame

arXiv2403.18661

- Detecting compact binary coalescences in gravitational wave strain timeseries data using neural networks
- ResNet architecture, maps from detector strain from two interferometers to a scalar neural-network output
- 2-10 times faster than matched filtering CBC pipeline

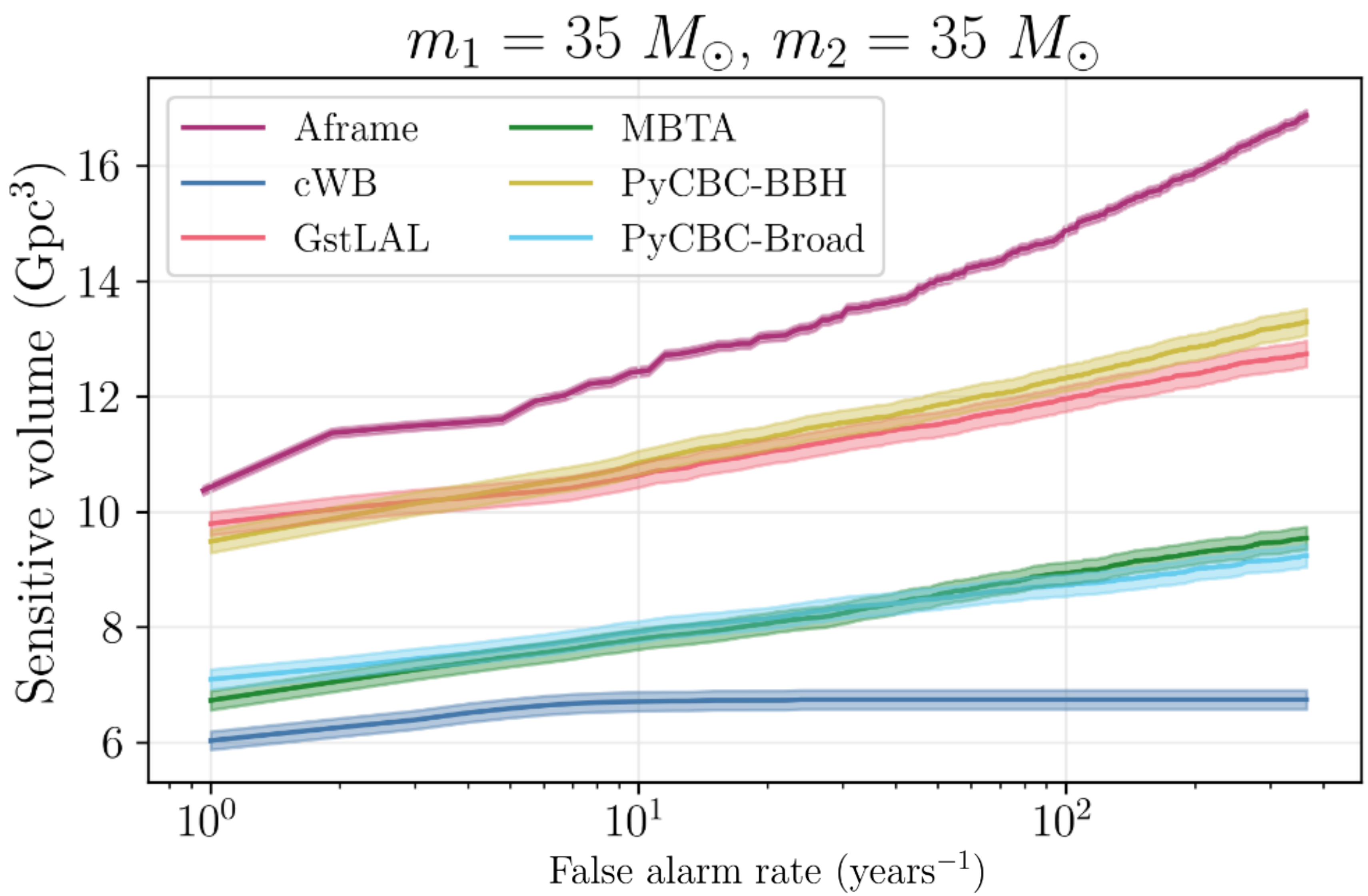


A-Frame performance comparison

arXiv2403.18661

Competitive performance on higher-mass catalog distributions

Work remains to be done for lower masses — alternative architectures or smarter training techniques



Future ML-based workflow

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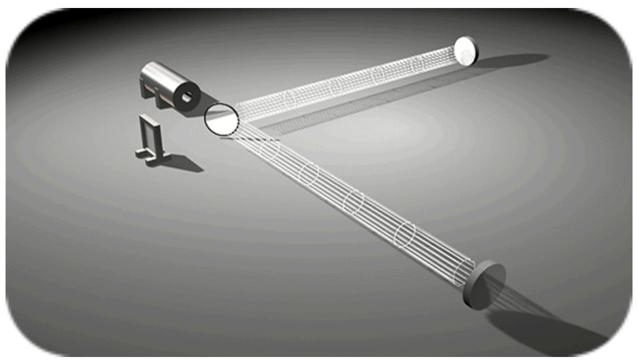
~100k auxiliary channels

Detector characterisation



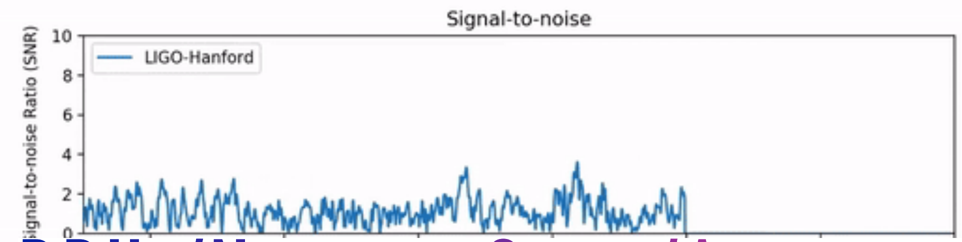
DeepClean

NN based AE

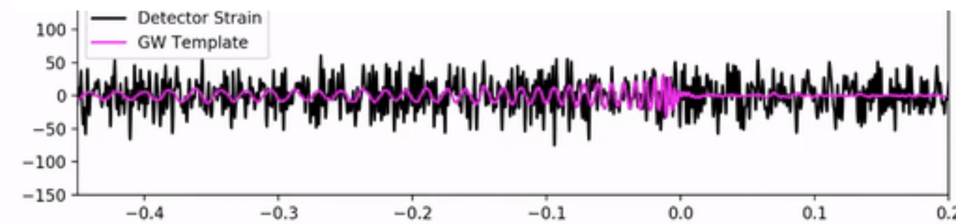
noise subtraction

Cleaned Data

NN-based algos for Event detection

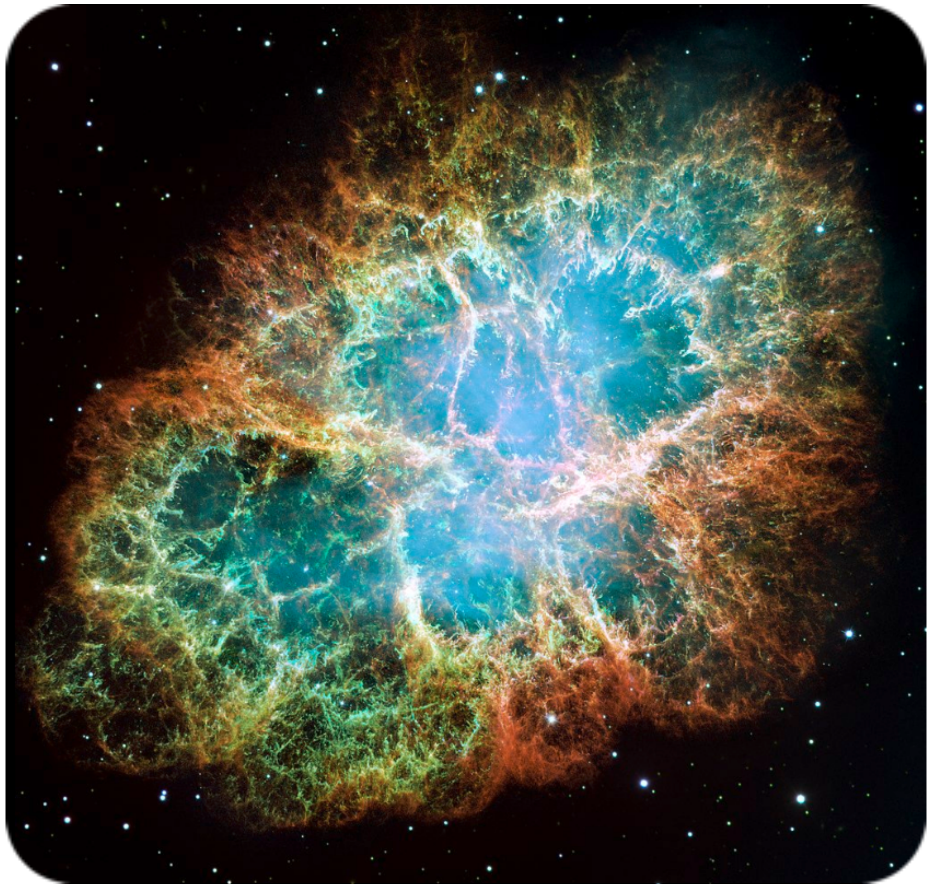


BBHs/Neutron Stars/Anomalies

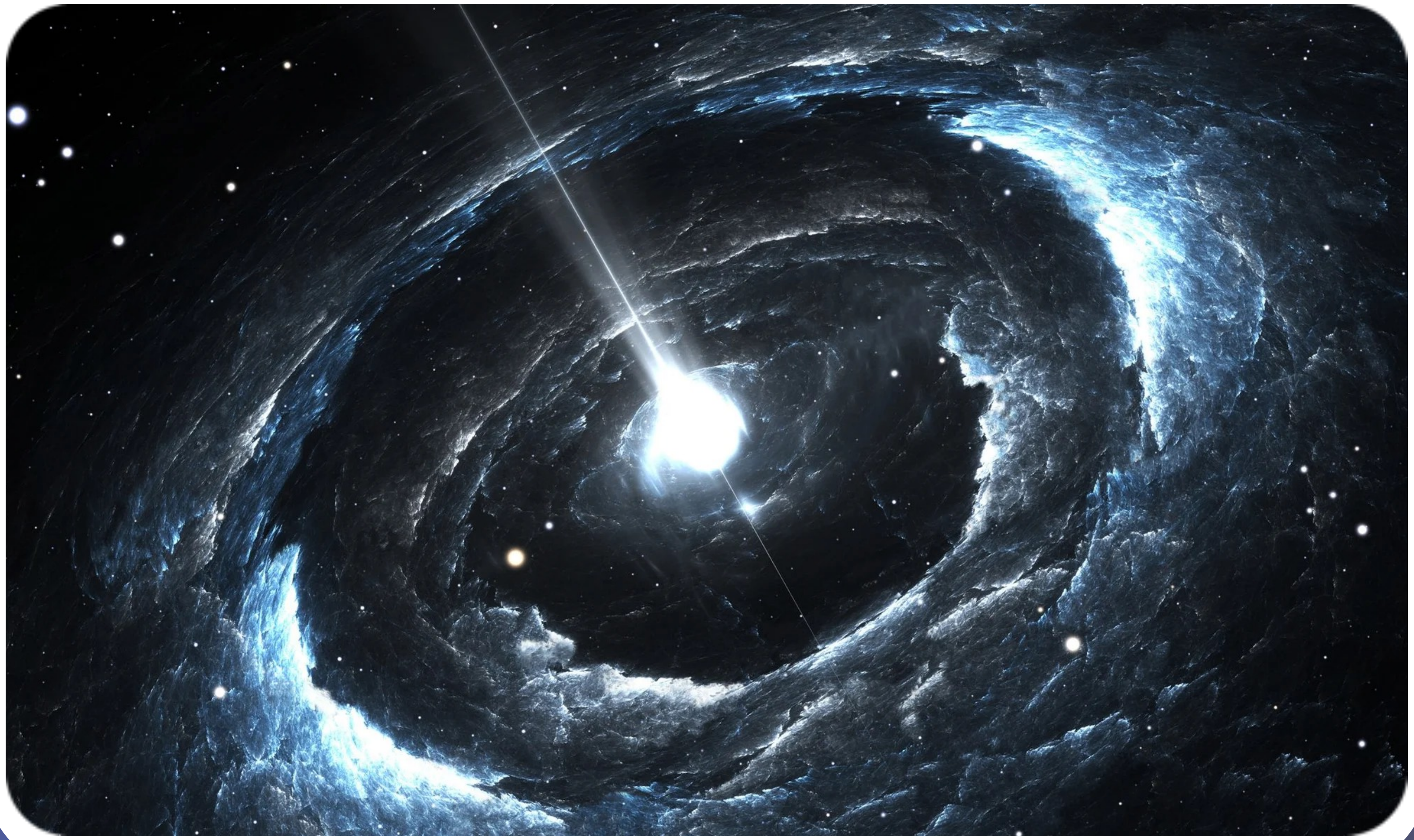


Known "Unknowns" possible signal sources that are poorly modelled and therefore cannot be easily detected using the match filtering pipeline

Core-collapse supernova (CCSN)



Neutron Star Glitches



Unknown "Unknowns" new, unexpected GW sources

We refer to them as anomalous and aim to develop a semi-supervised approach which would let us to discover anomalous signals without explicit modelling

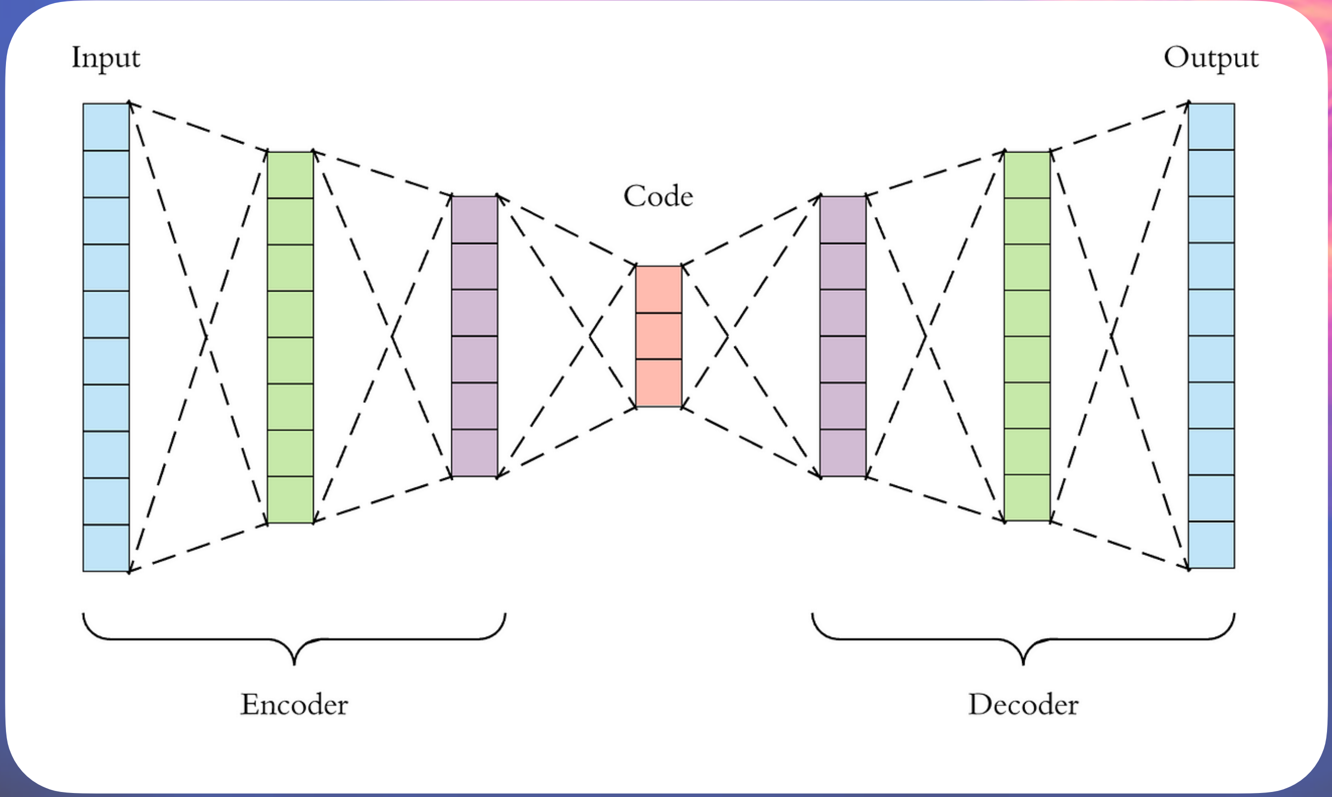
?

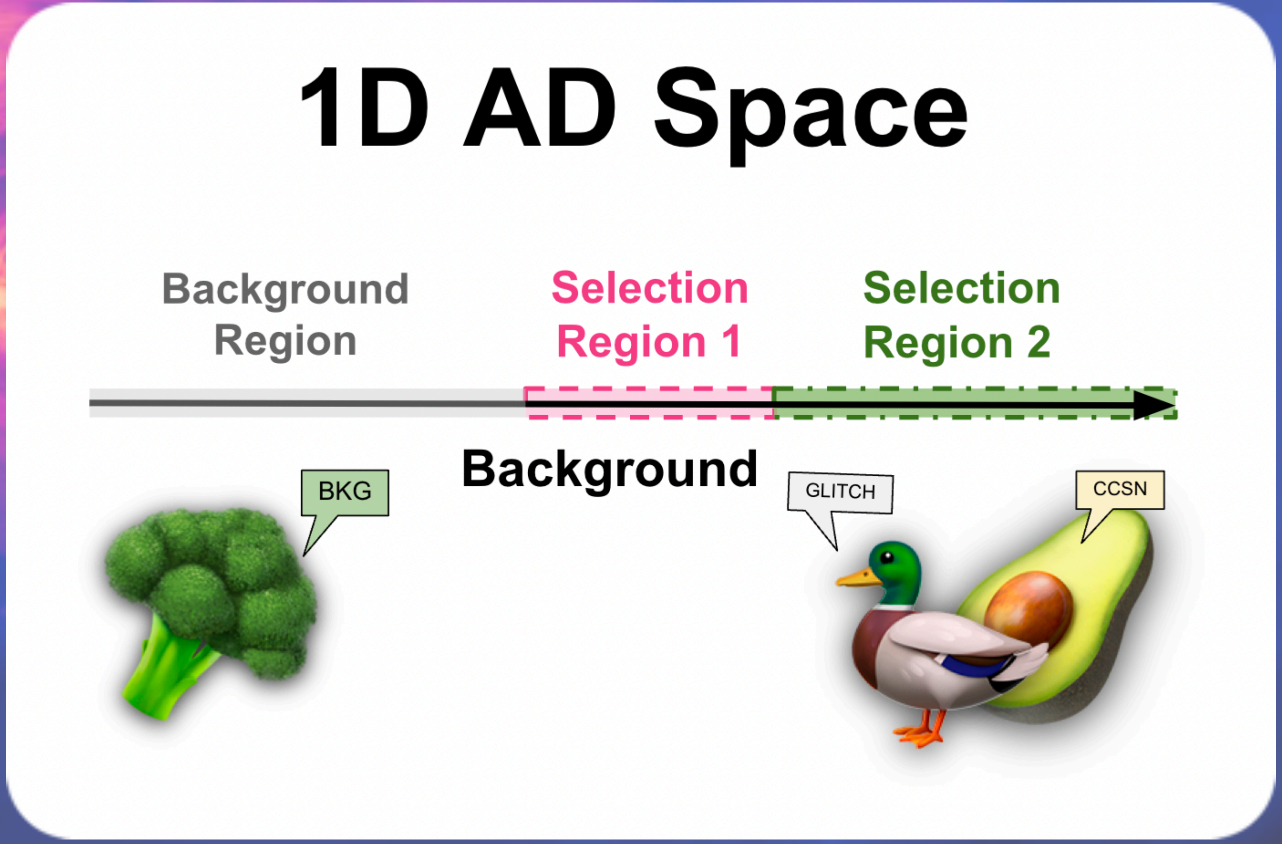
Vanilla Anomaly Detection

K.Govorkova et al MLST
10.1088/2632-2153/ad3a31

The algorithm is inspired by QUAK arXiv2011.03550 from LHC HEP

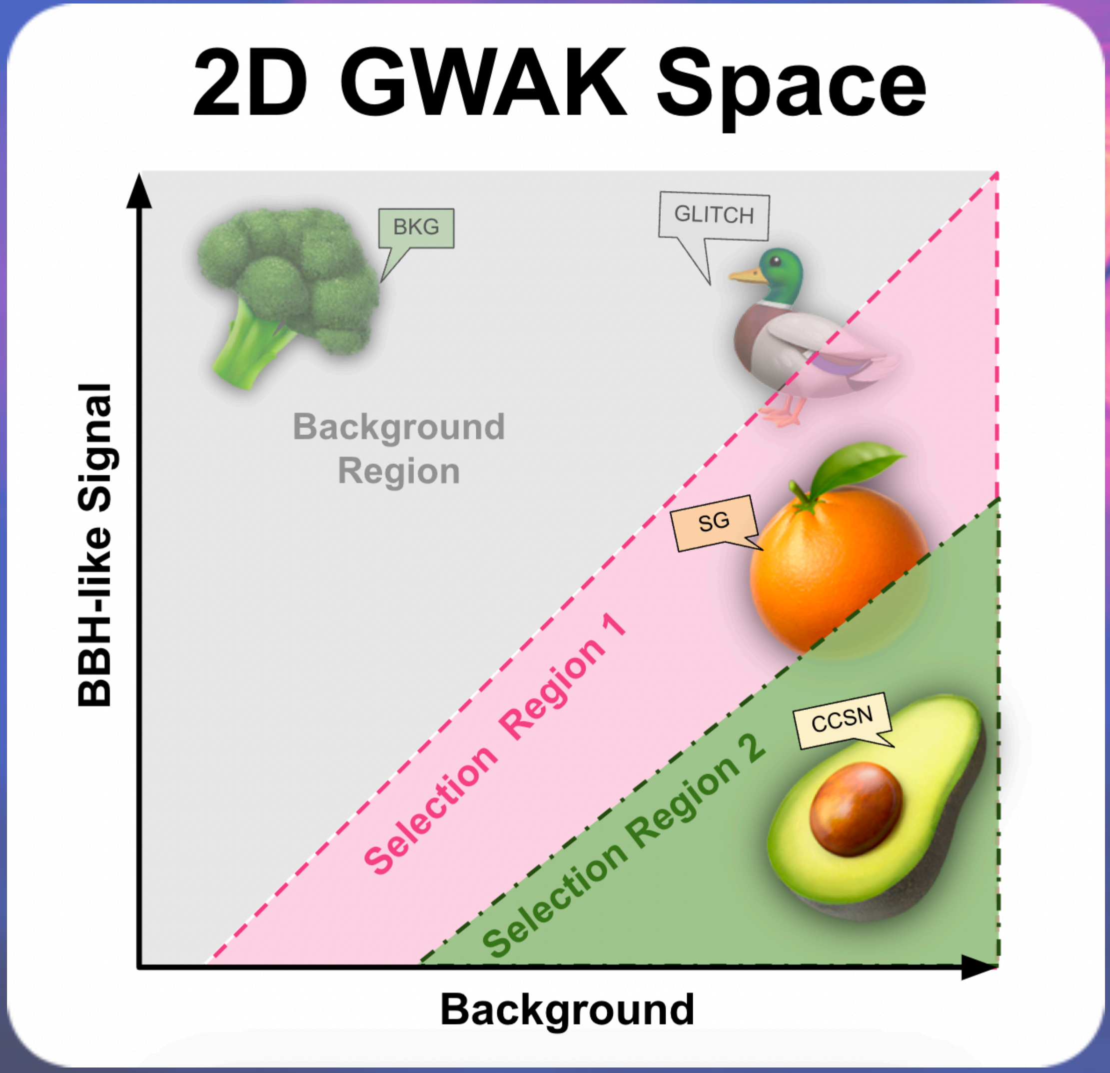
Use the distance between the input and output as a metric for anomaly detection





K.Govorkova et al MLST
10.1088/2632-2153/ad3a31

Including more axes, both signal and background, allows to more efficiently select a signal-like anomalies



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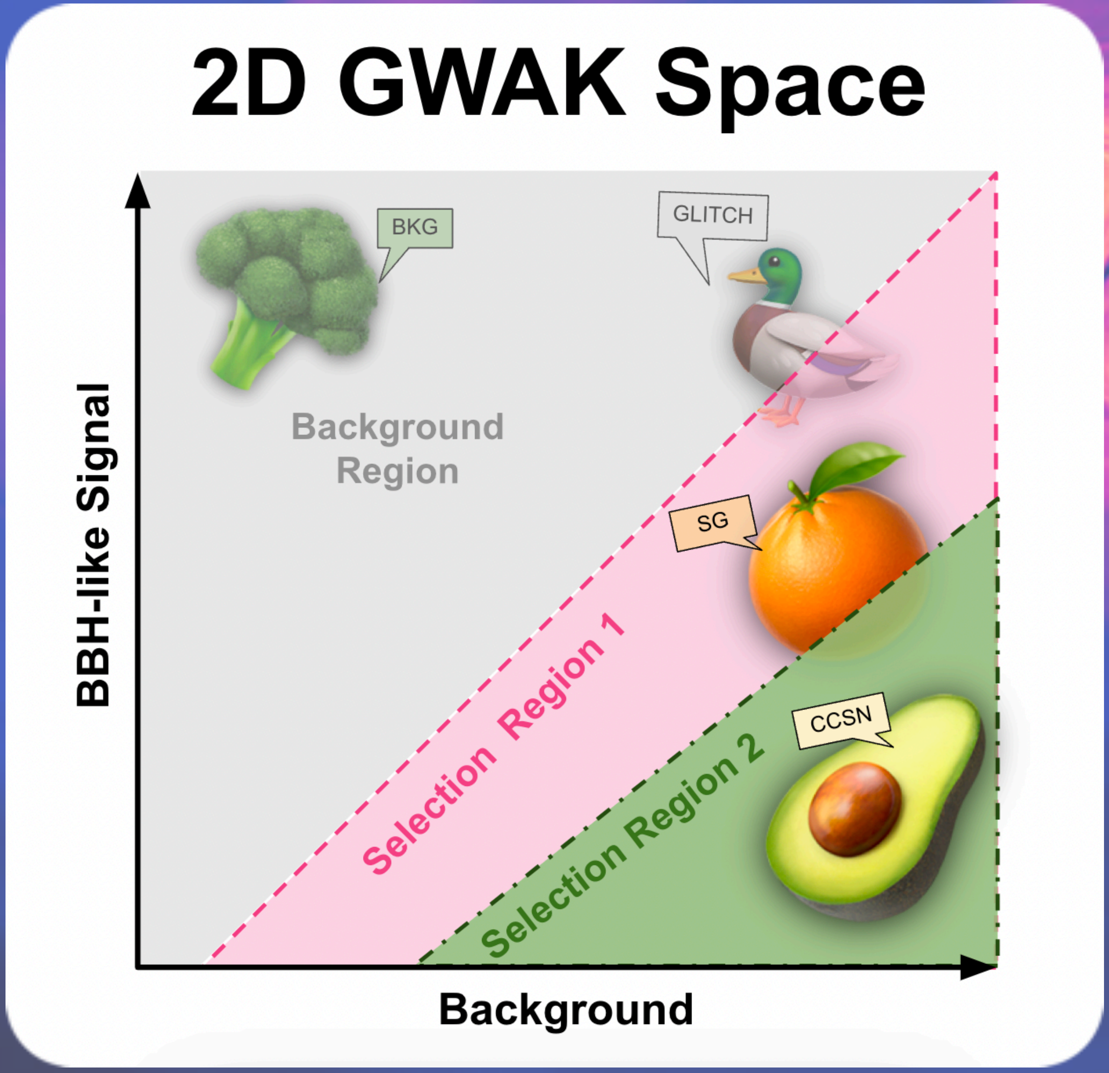
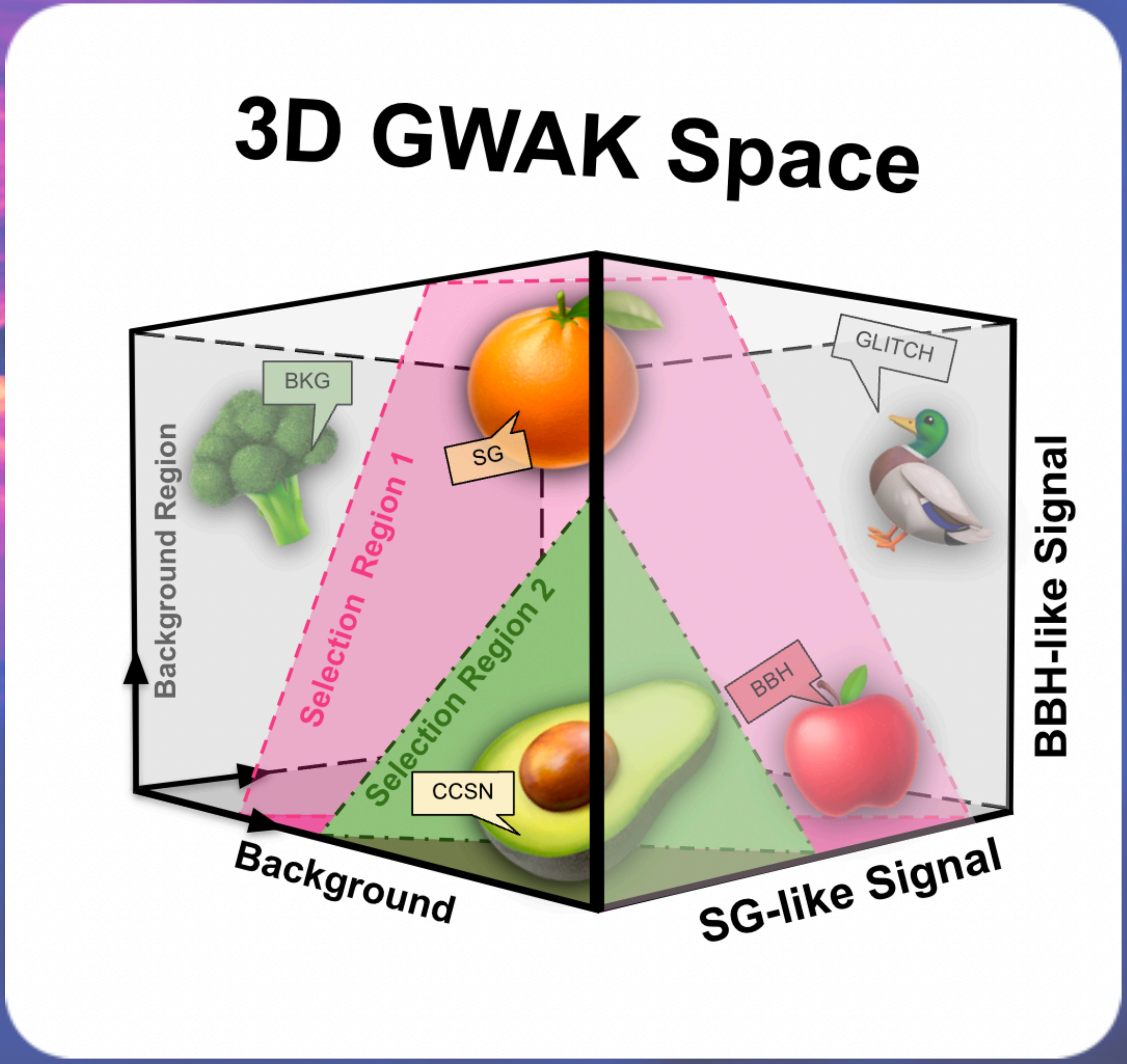
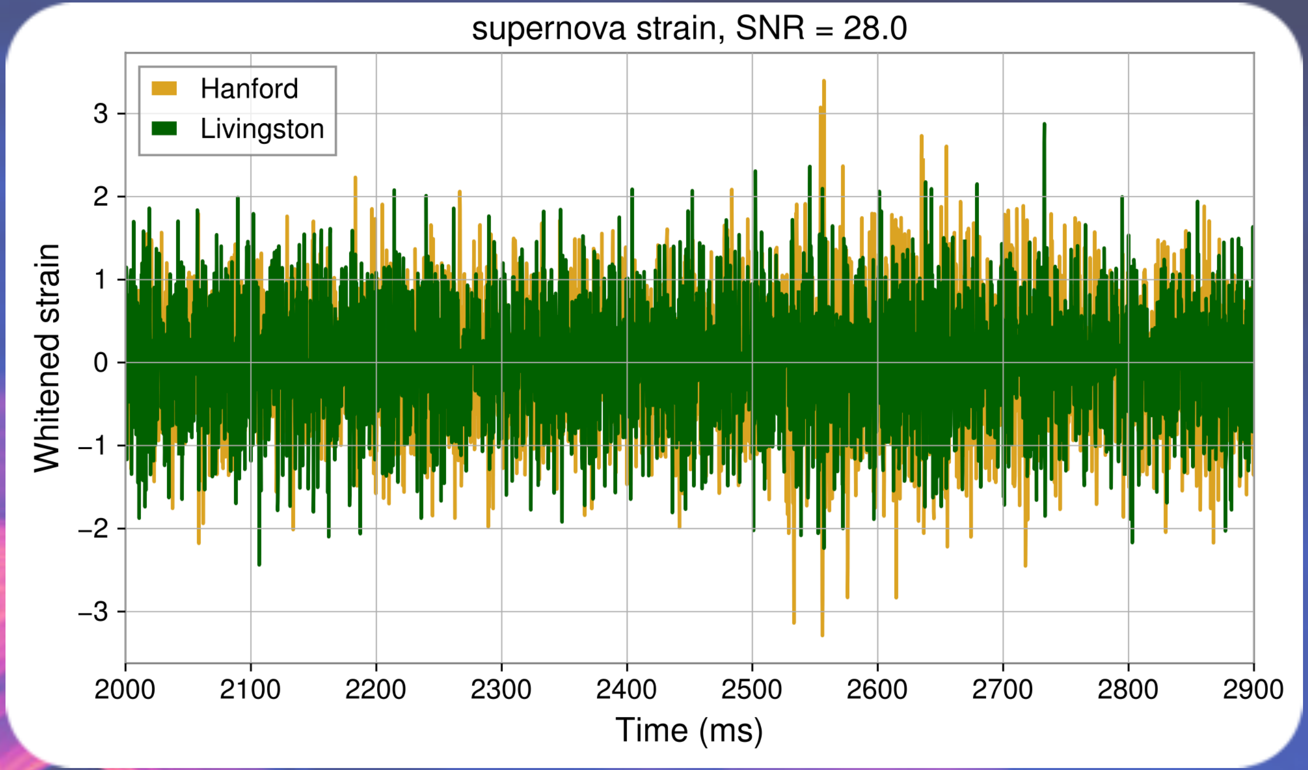


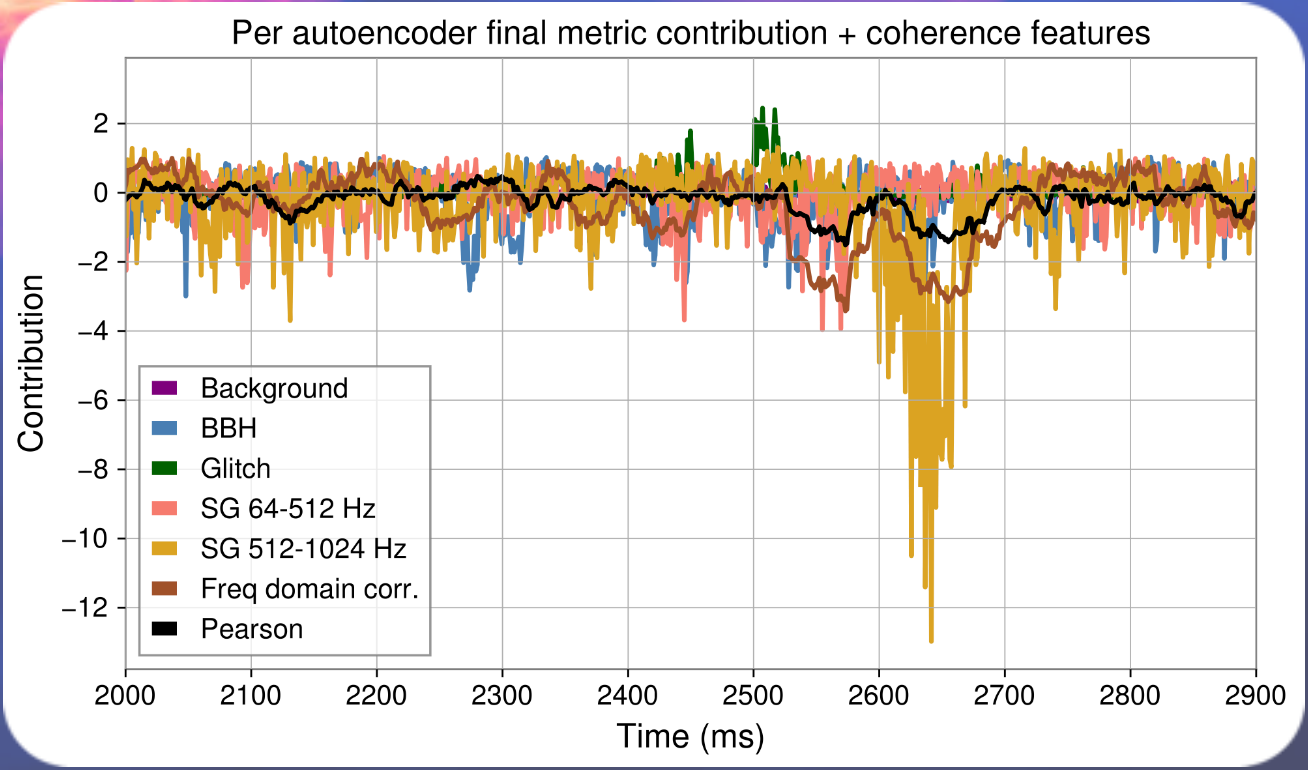


K.Govorkova et al MLST
10.1088/2632-2153/ad3a31

Strain, GWAK metric response and final metric response for Supernova simulated signal

The evaluation of GWAK axes and Pearson correlation with time and on the top right total metric value and FAR are shown as an example of the algorithm's ''reaction'' to an unseen signal





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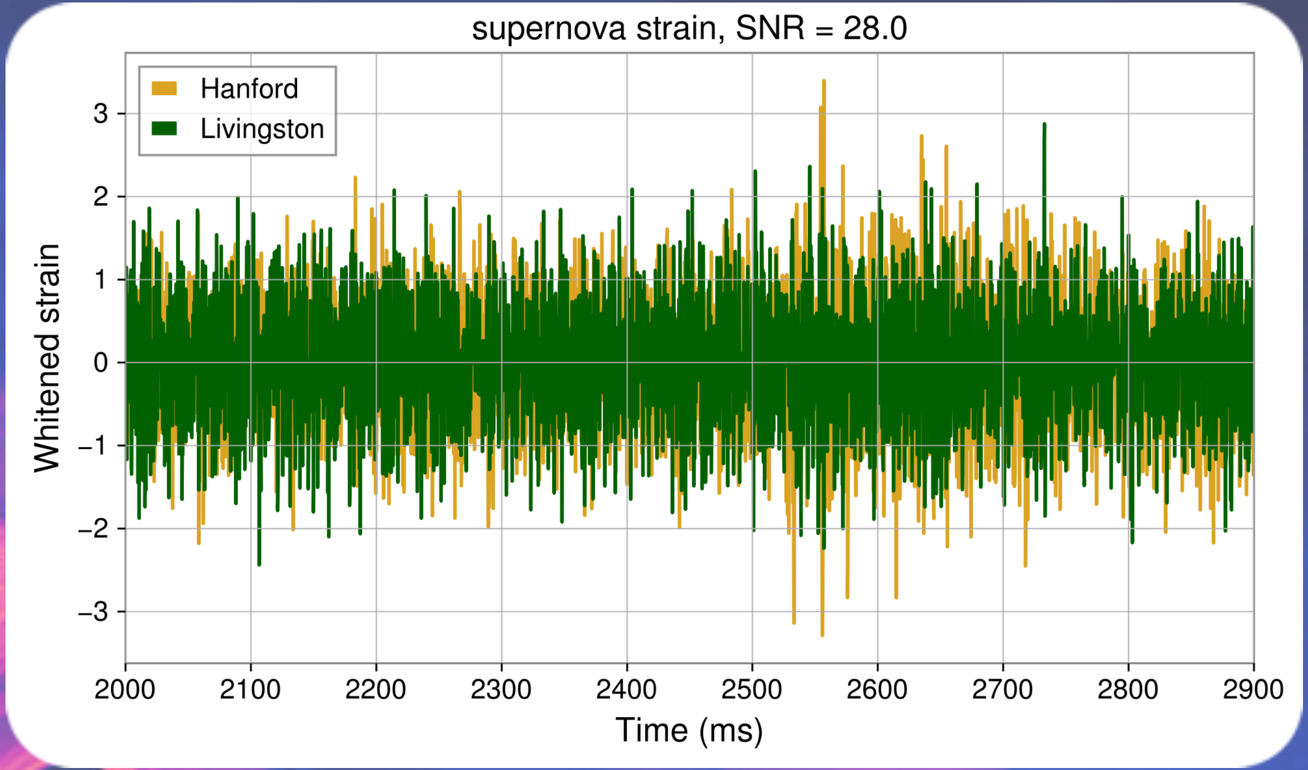
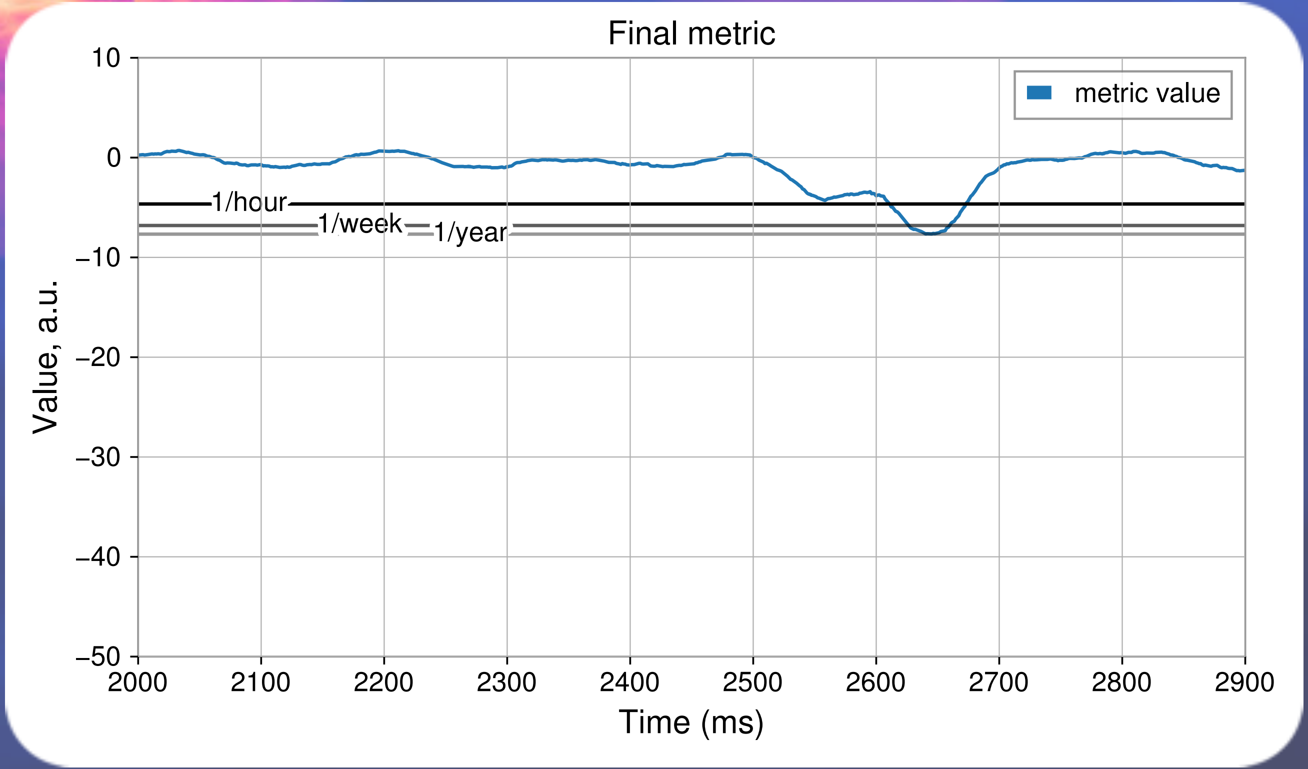


Strain, GWAK metric response and final metric response for Supernova simulated signal

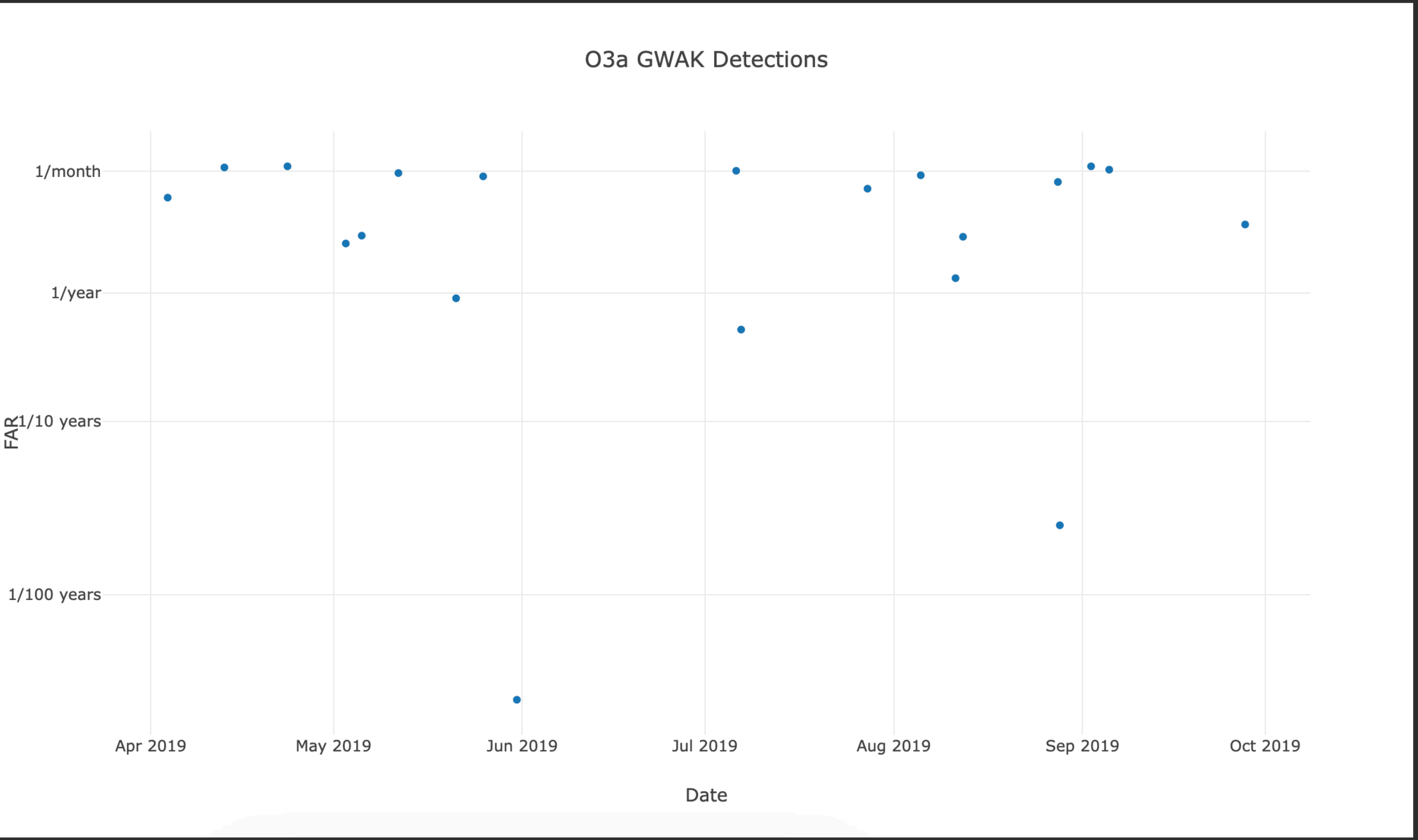


The evaluation of GWAK axes and Pearson correlation with time and on the top right total metric value and FAR are shown as an example of the algorithm's ''reaction'' to an unseen signal

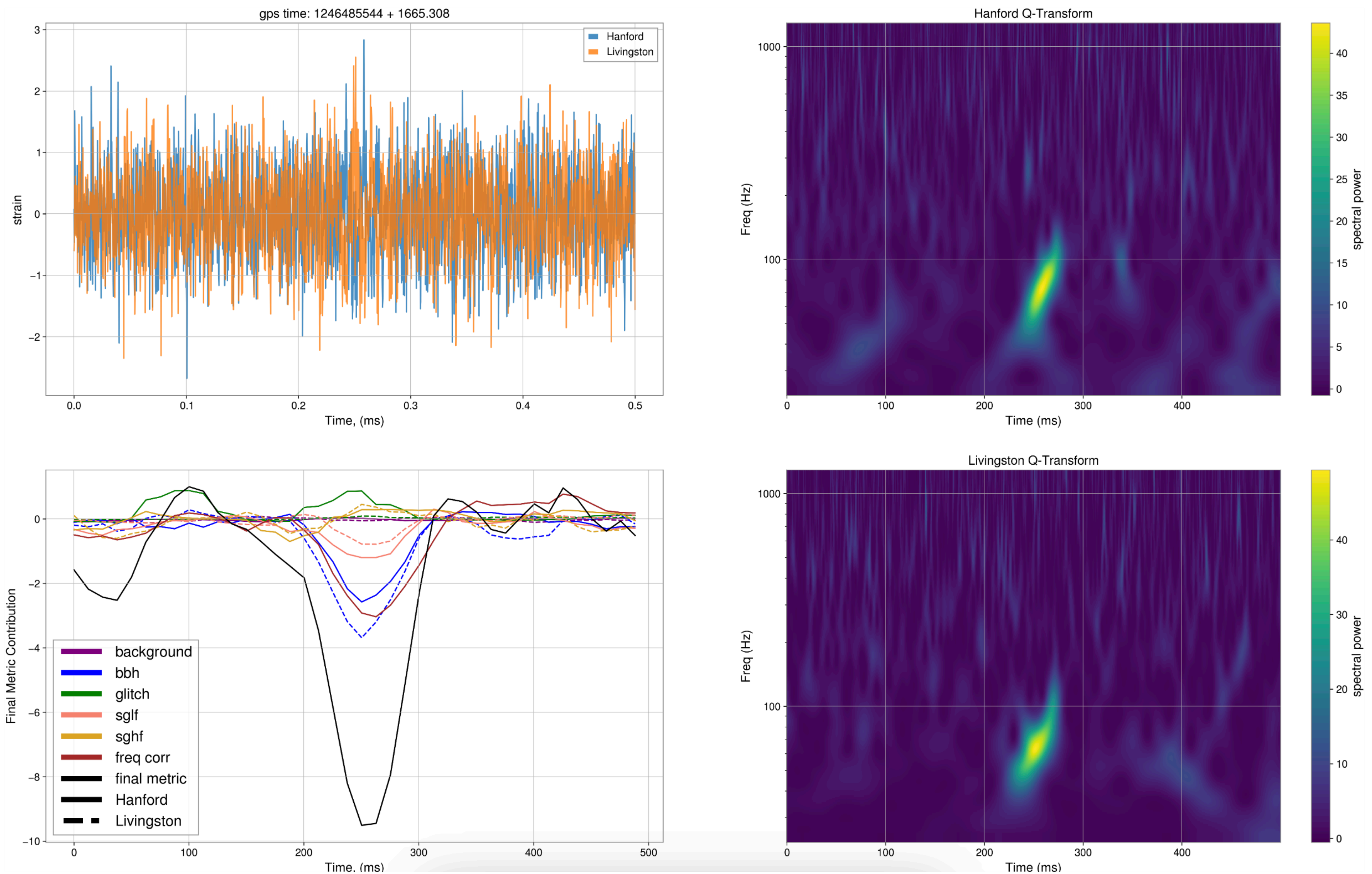
GWAK Detection

Welcome to the
Collection of Anomalies
Detected by the GWAK pipeline

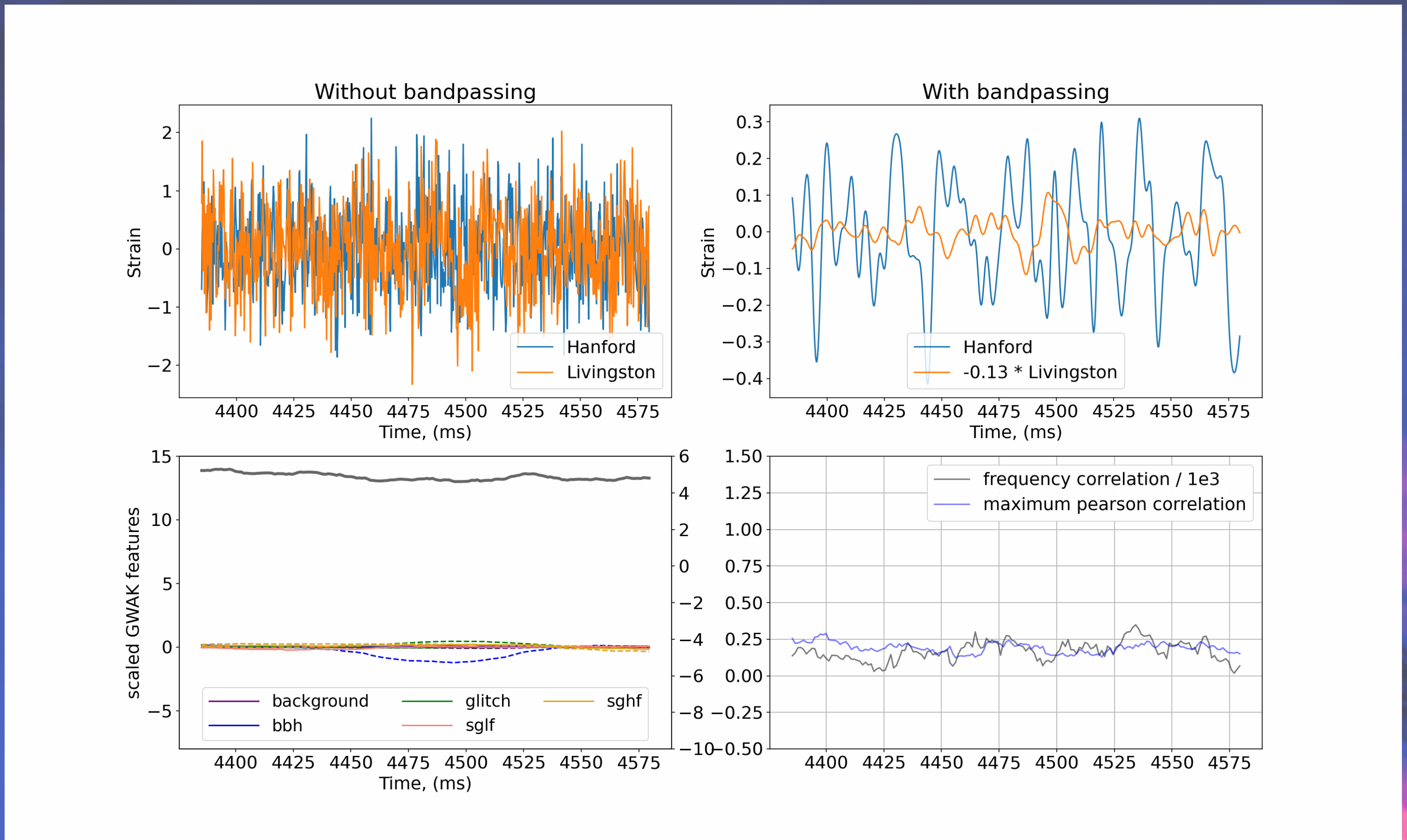
O3a analysis | O3b analysis | Burst O3a training | Burst O3b training

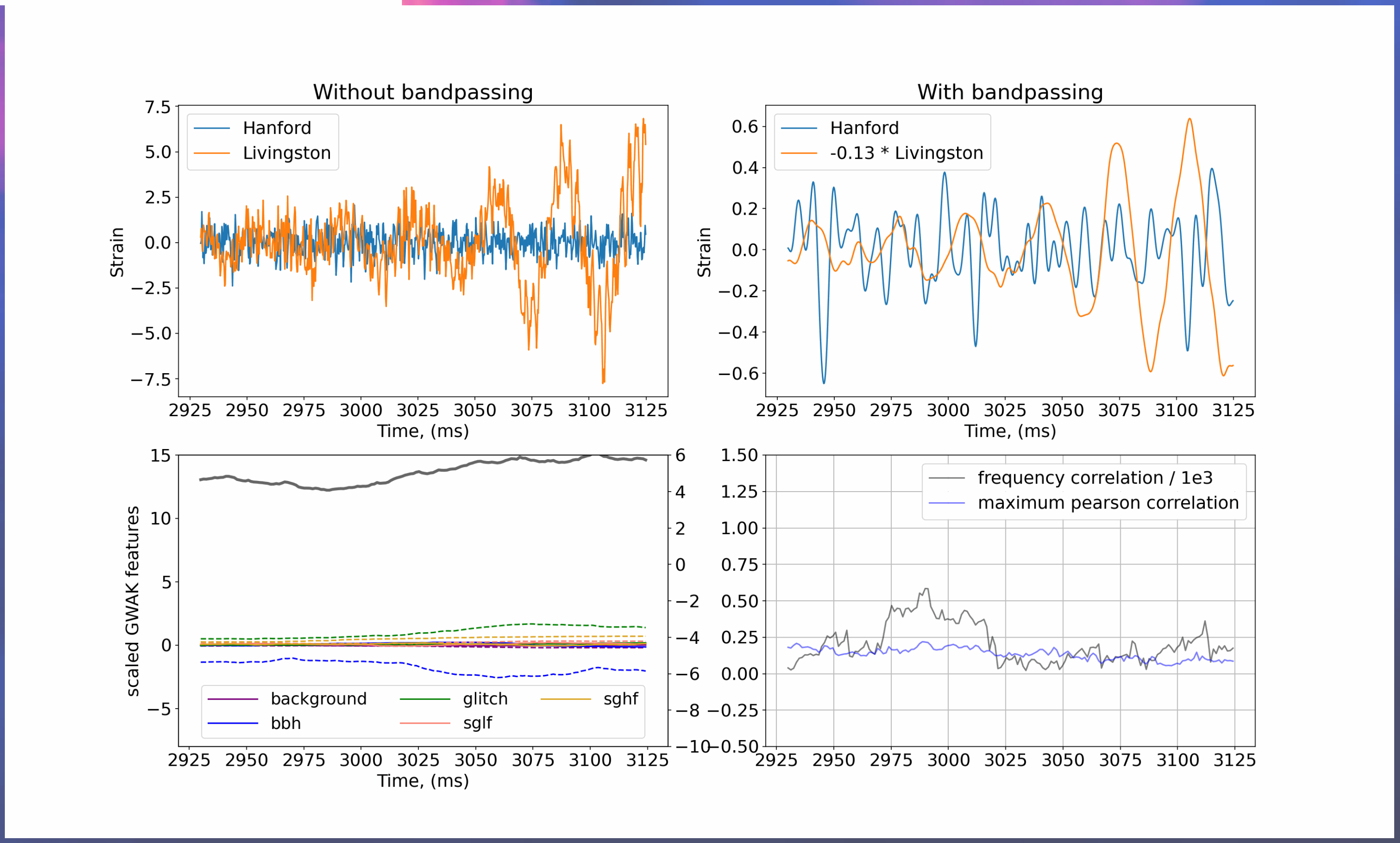


GWAK Detection

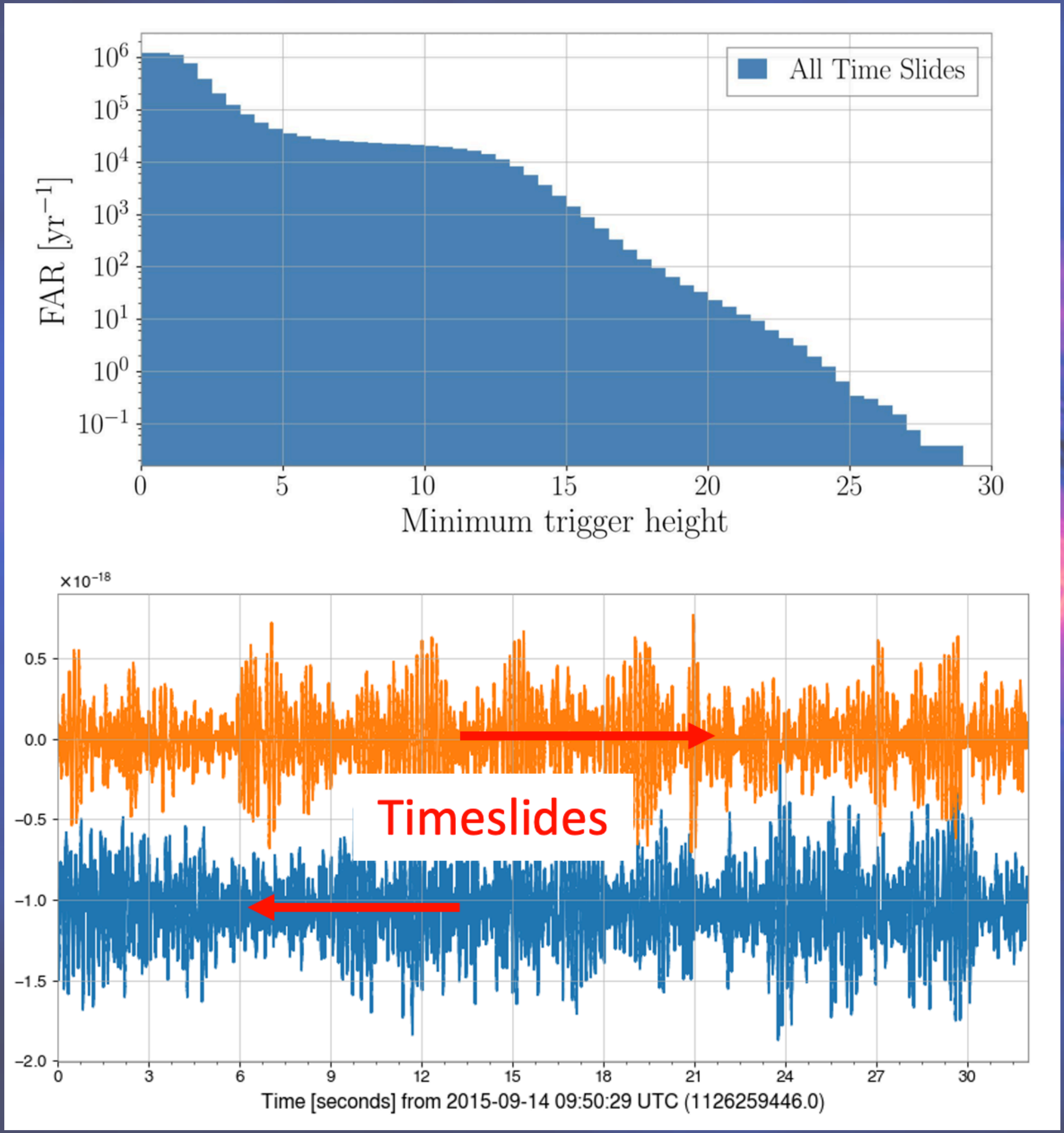


GWAK Detection





Statistically Sound Validation



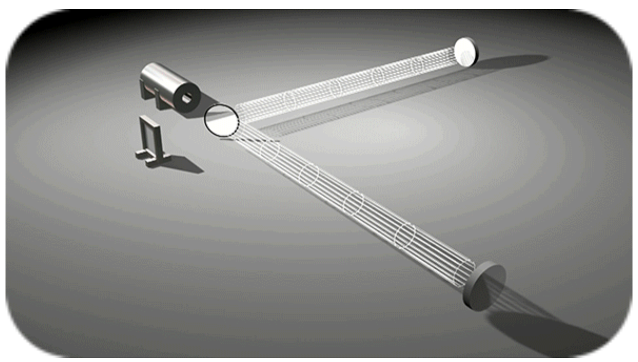
- GW search sensitivity evaluated by comparing to background events generated through "timeslides"
- Achieving high significance detections requires analyzing years of background
- This could mean O(1 years) to O(100k) of time slides run through algorithms for validation

Future ML-based workflow

Data 16kHz

~100k auxiliary channels

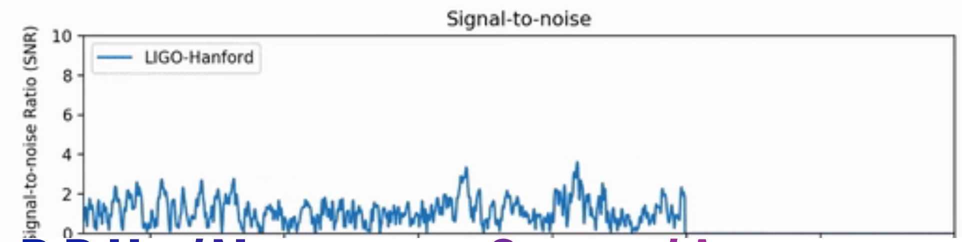
Detector characterisation



DeepClean
NN based AE
noise subtraction

Cleaned Data

NN-based algos for Event detection



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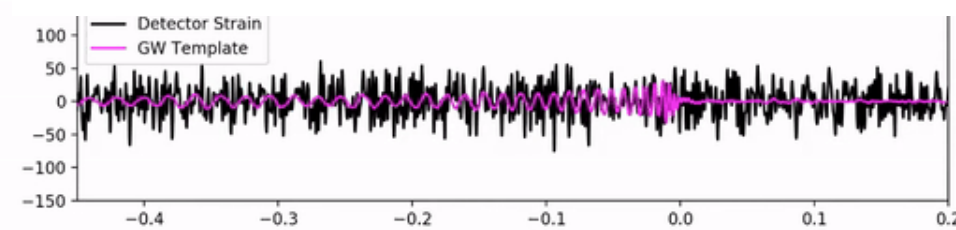
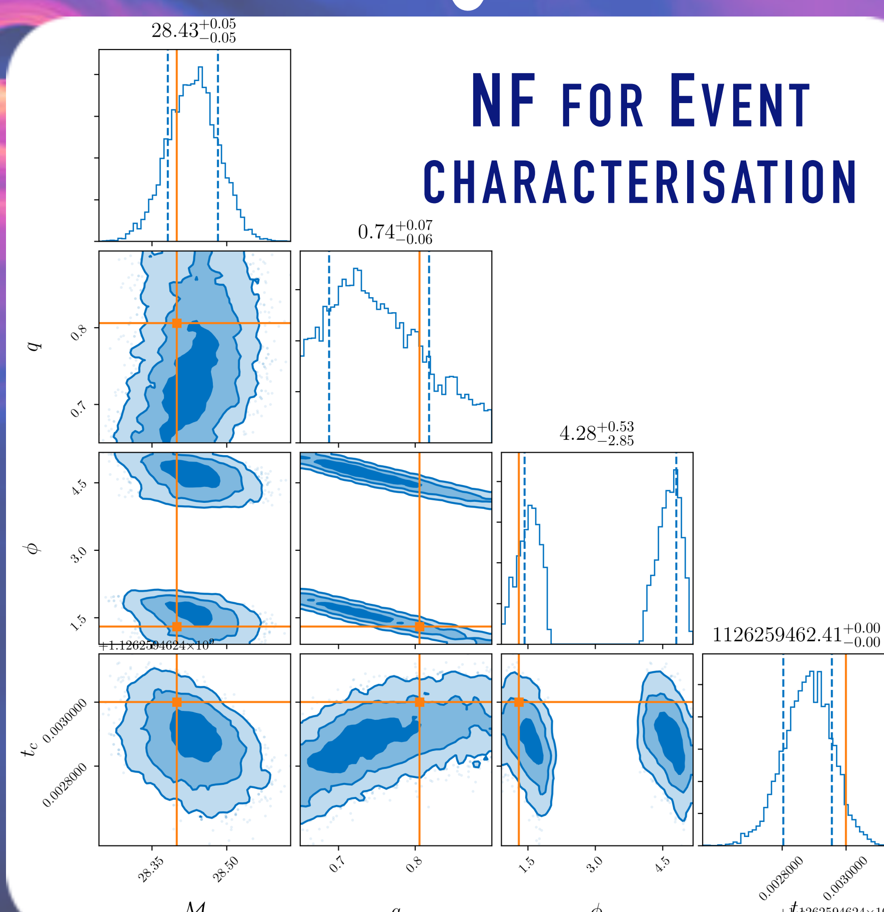


Event

NF for Event characterisation



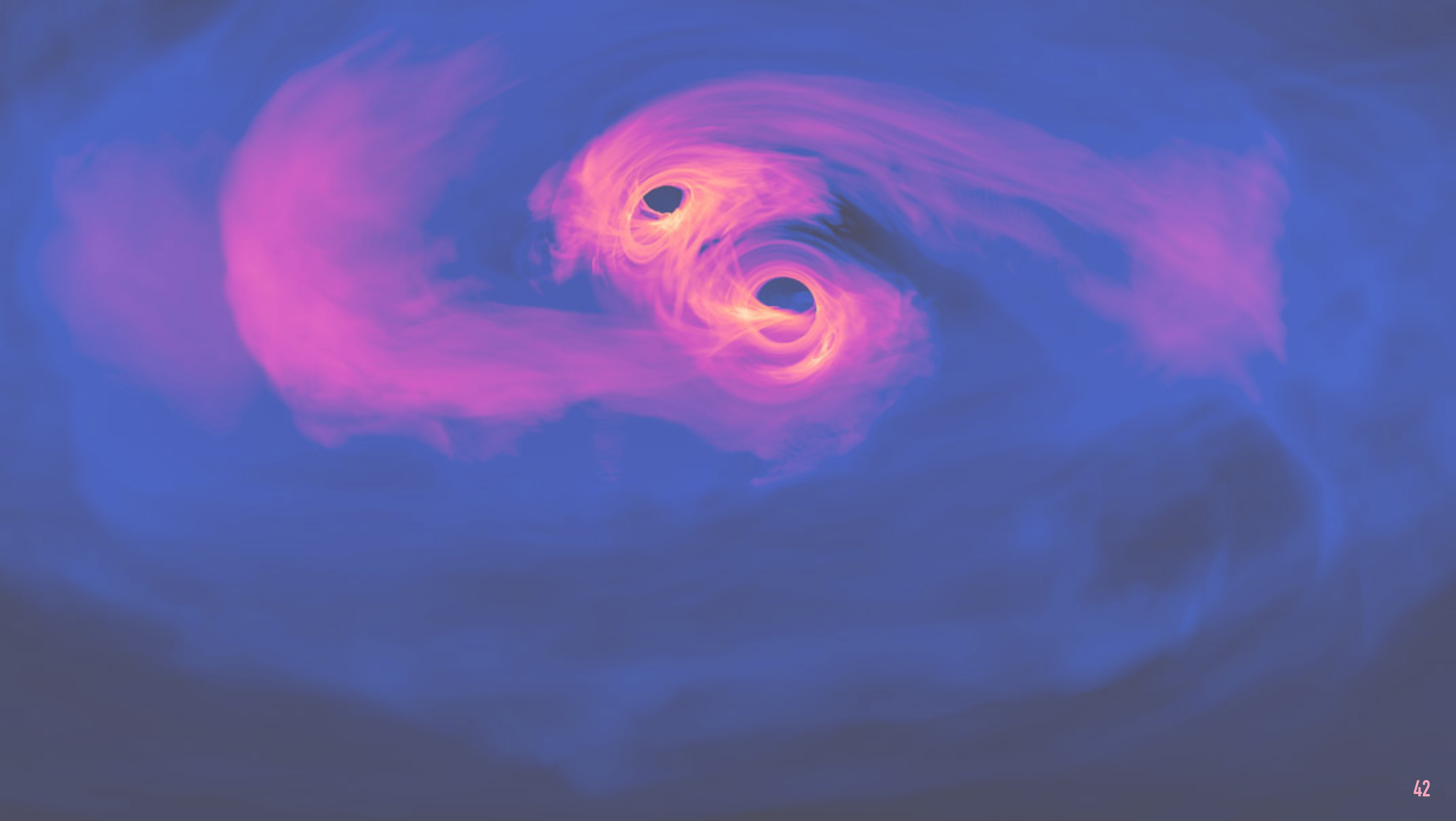
Alert

AMPLFI: Accelerated Multi-messenger Parameter estimation using Likelihood Free Inference

NeurIPS ML4PS 2023 69 PDF

Perform fast parameter estimation using simulation-based inference

- Simulate data from the likelihood, train neural network to approximate posterior
- Use self-supervision to marginalize symmetries



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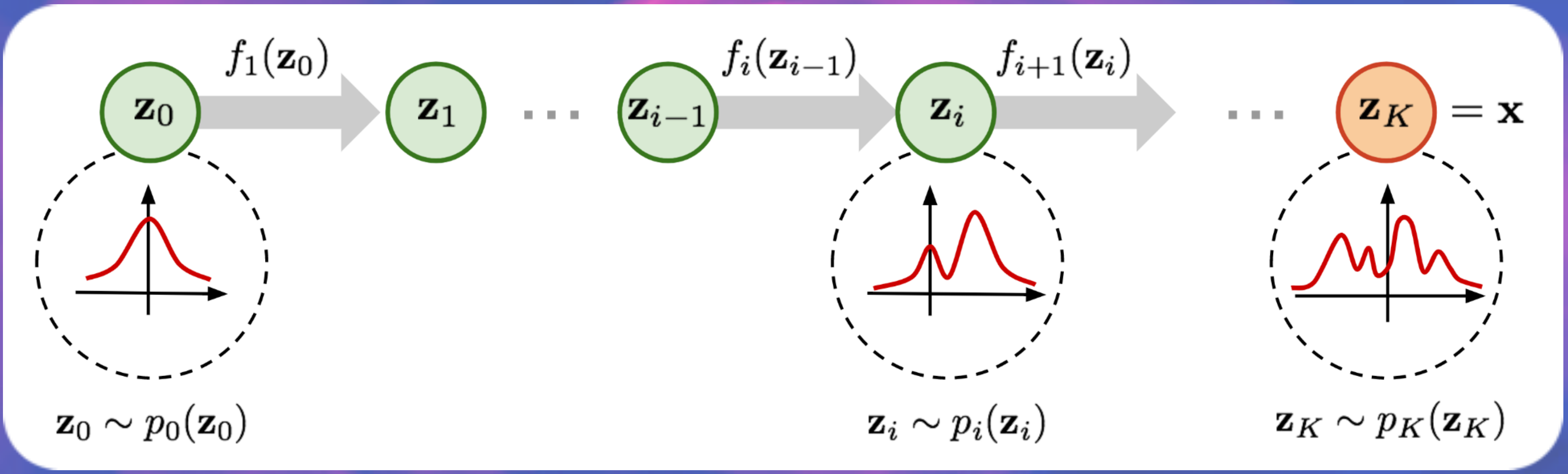
- Normalizing flows (invertible transforms map simple distribution to complex distribution) embed broad knowledge of waveforms



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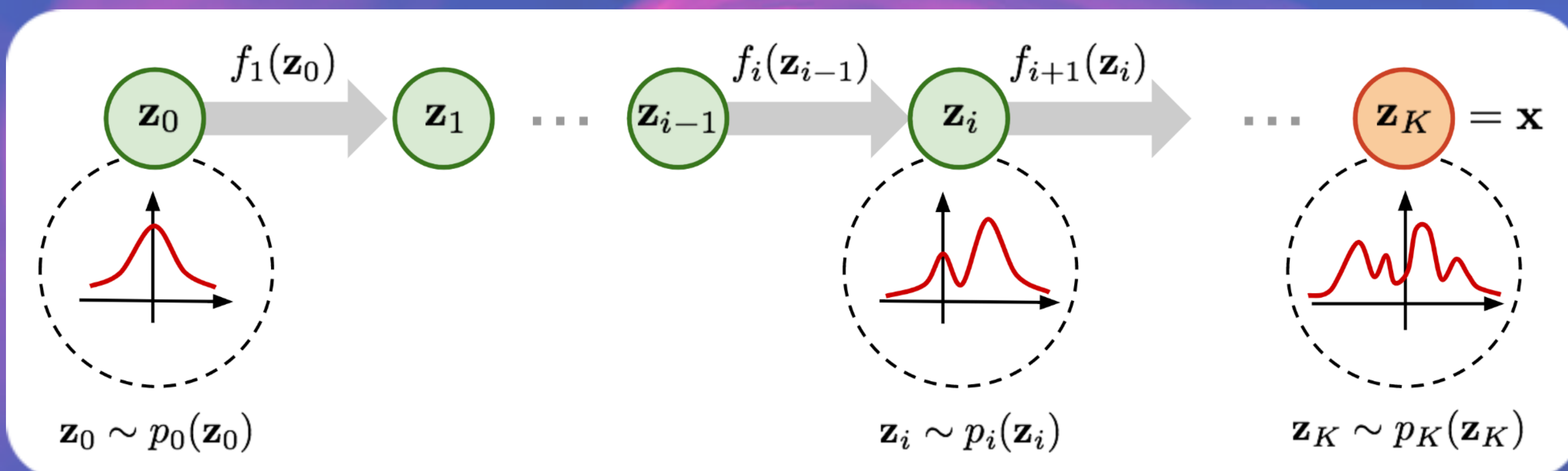
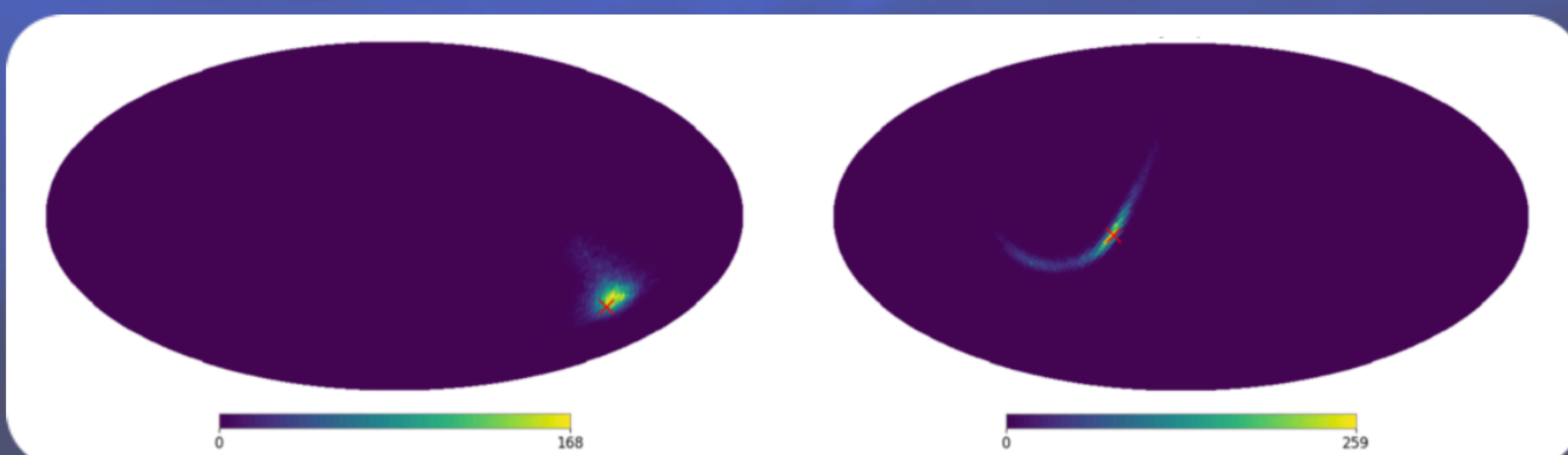


- PE done in seconds!



SMOOTH INTEGRATION INTO ONLINE!

GraceDB (USER TESTING) Public Alerts Latest Search Notifications Pipelines Documentation Logout

Authenticated as: Katya Govorkova

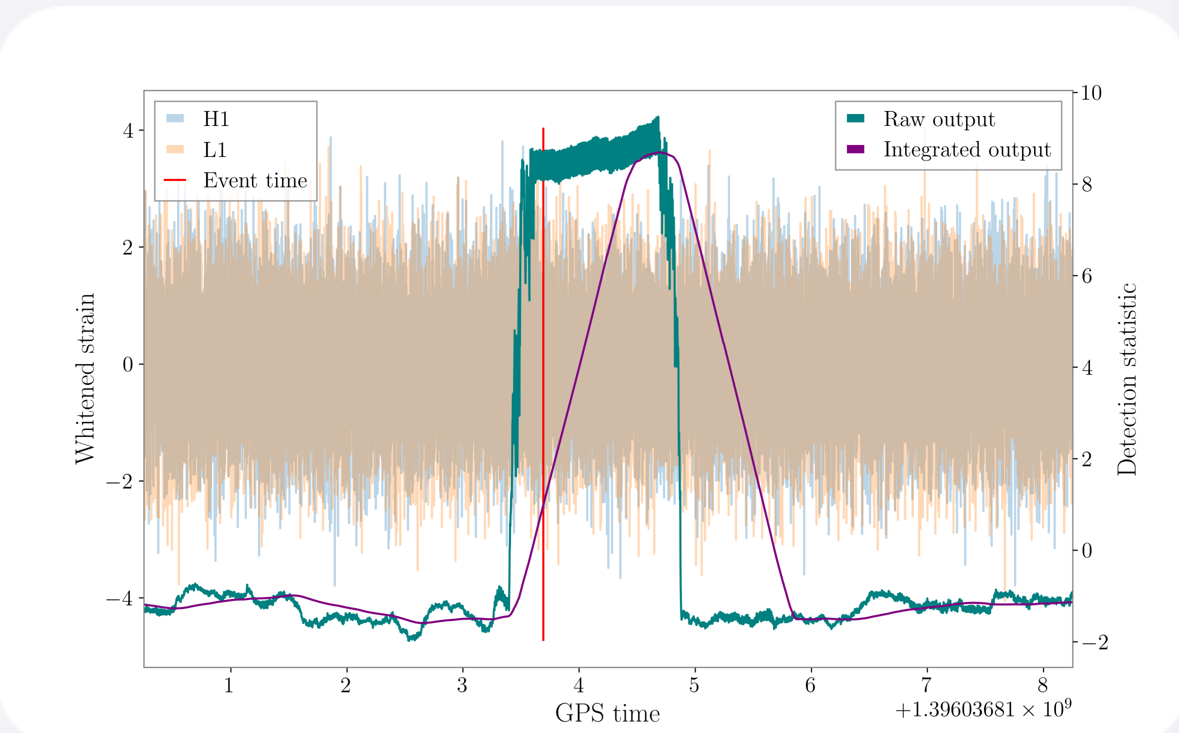
G1783271

Neighbors

Log Messages

Full Event Log

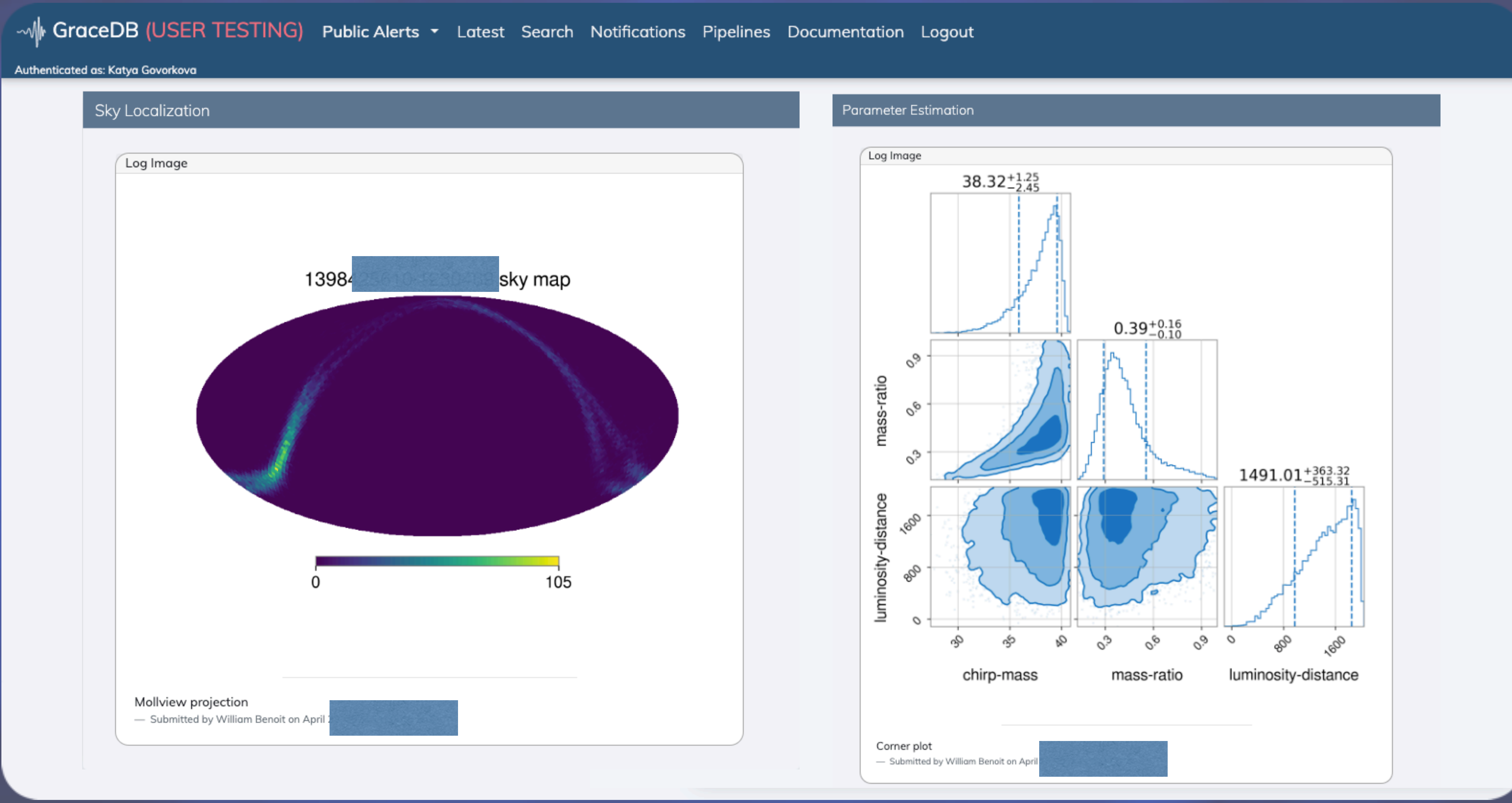
G1783271



Basic Event Information

UID	G1783271
Labels	
Group	CBC
Pipeline	aframe
Search	AllSky
Instruments	['H1', 'L1']
Event Time	139[redacted]
FAR (Hz)	3.087e-08
FAR (yr^{-1})	1 per 1.0264 years
Latency (s)	3.524
Links	Data
Submitted	2024[redacted] UTC

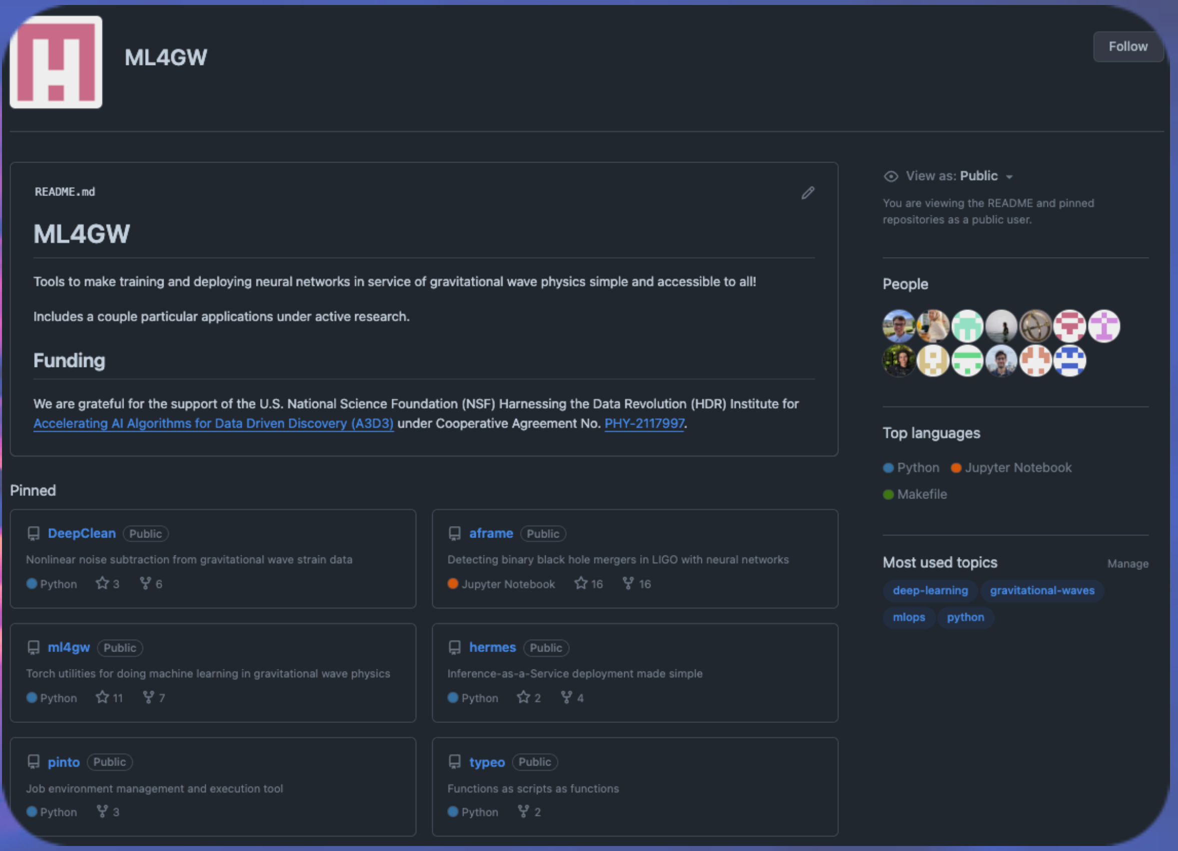
SMOOTH INTEGRATION INTO ONLINE!



Conclusions

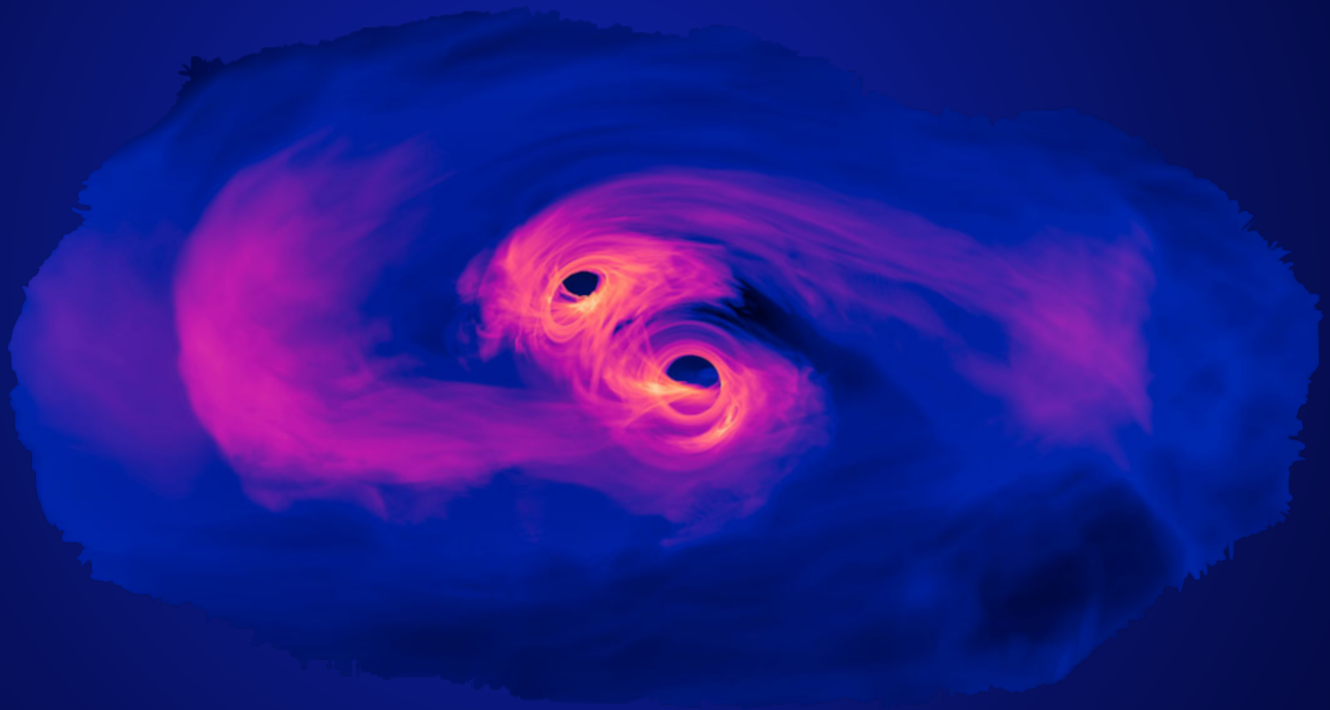
To enable a complete AI pipeline, we have developed github.com/ML4GW — a set of comprehensive tools for ML pipeline in GW physics which allows to perform

- Modelled and unmodelled searches
- Run efficiently Offline
- Run Online with low latency
- Seamless development and fast deployment of NN-based algorithms
- Small computation footprint and optimised heterogeneity



— Looking to invite many others to build on our work!

We run open weekly meetings and everyone is welcome to join



BACKUP

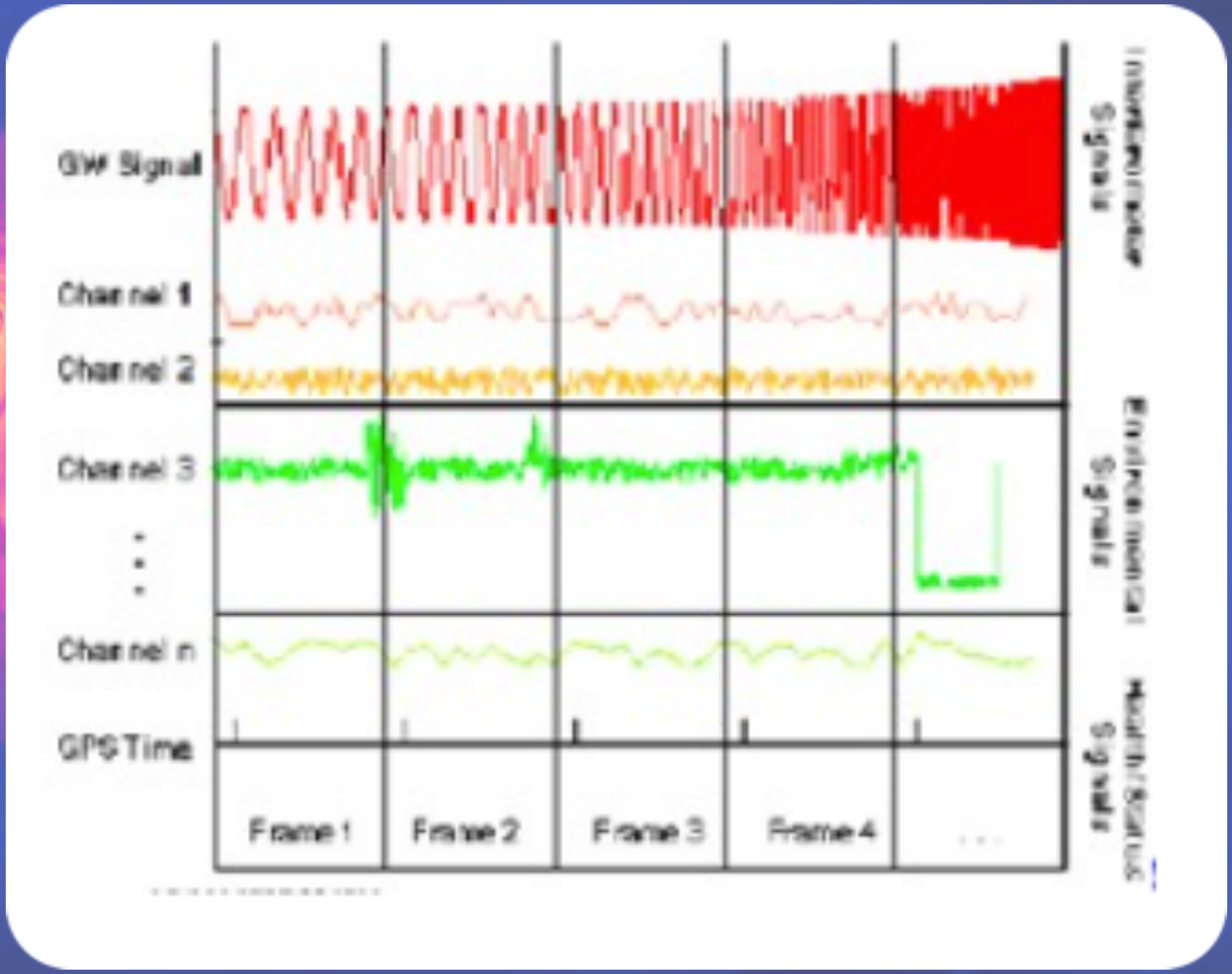
Gravitational-wave detector data

Continuous time series (1Hz, 128Hz ... 16kHz)

Gravitational Wave channel
~20GB/day (per instrument)

Physical Environment Monitors
(seismometers, accelerometers, magnetometers, microphones etc)

Internal Engineering Monitors
(sensing, housekeeping, status etc)



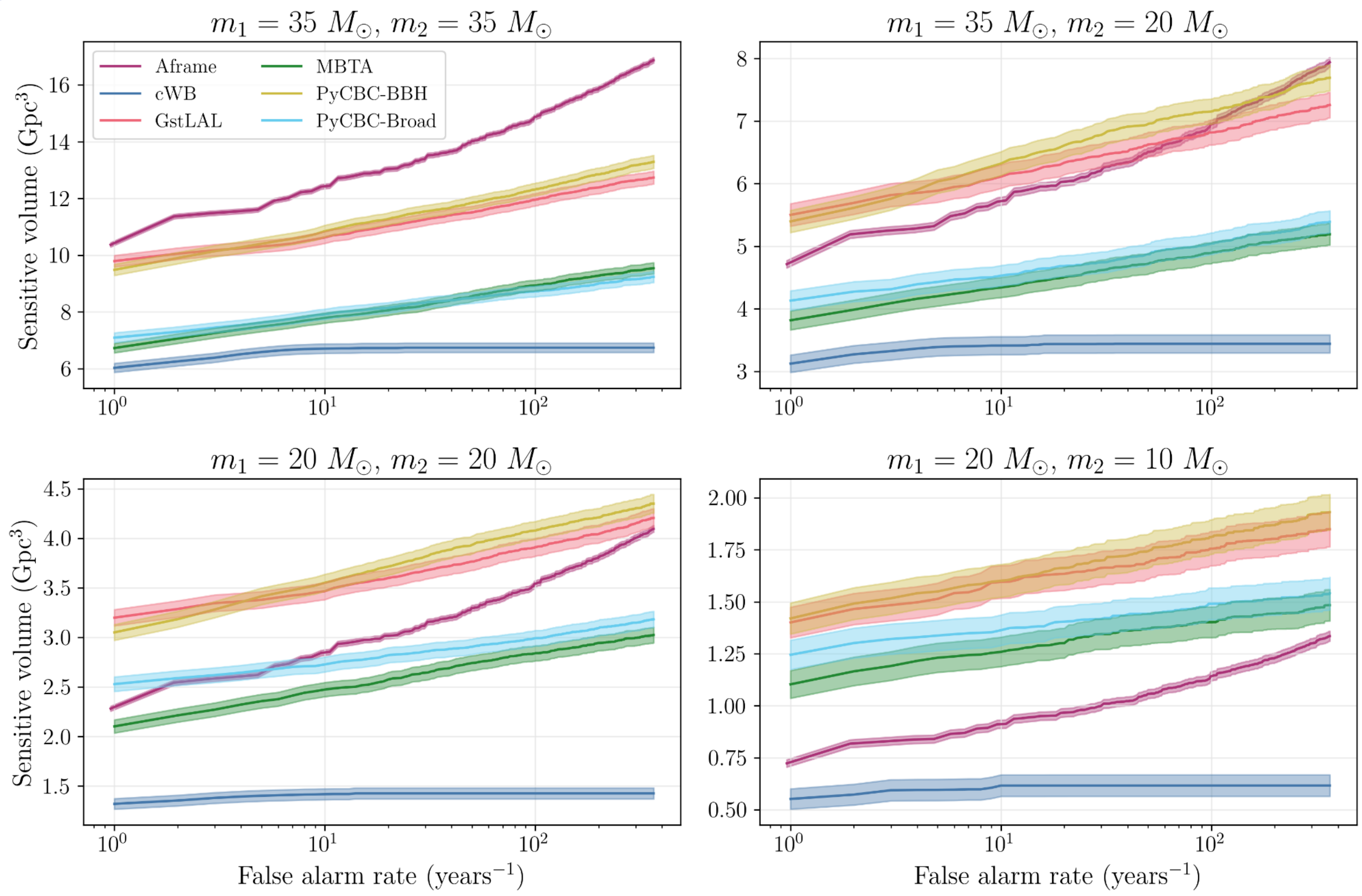
Together with various intermediate data products >2TB/day (per instrument)

A-Frame performance comparison

[Zenodo]

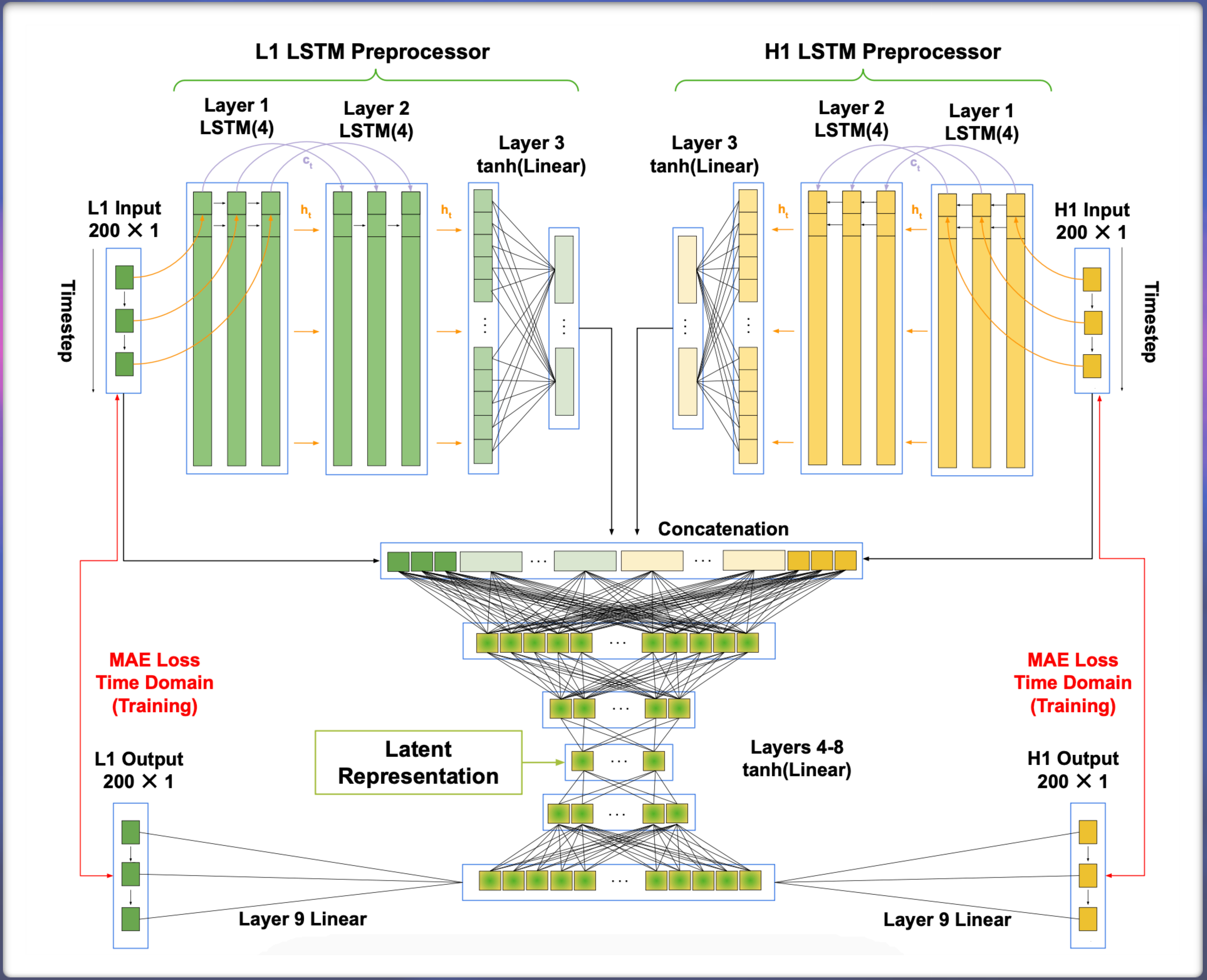
Competitive performance on higher-mass catalog distributions
Work remains to be done for lower masses — alternative architectures or smarter training techniques

$$V(\mathcal{F}) = \int \mathrm{d}\mathbf{x}\, \mathrm{d}\theta\, \epsilon(\mathcal{F}; \mathbf{x}, \theta)\phi(\mathbf{x}, \theta)$$



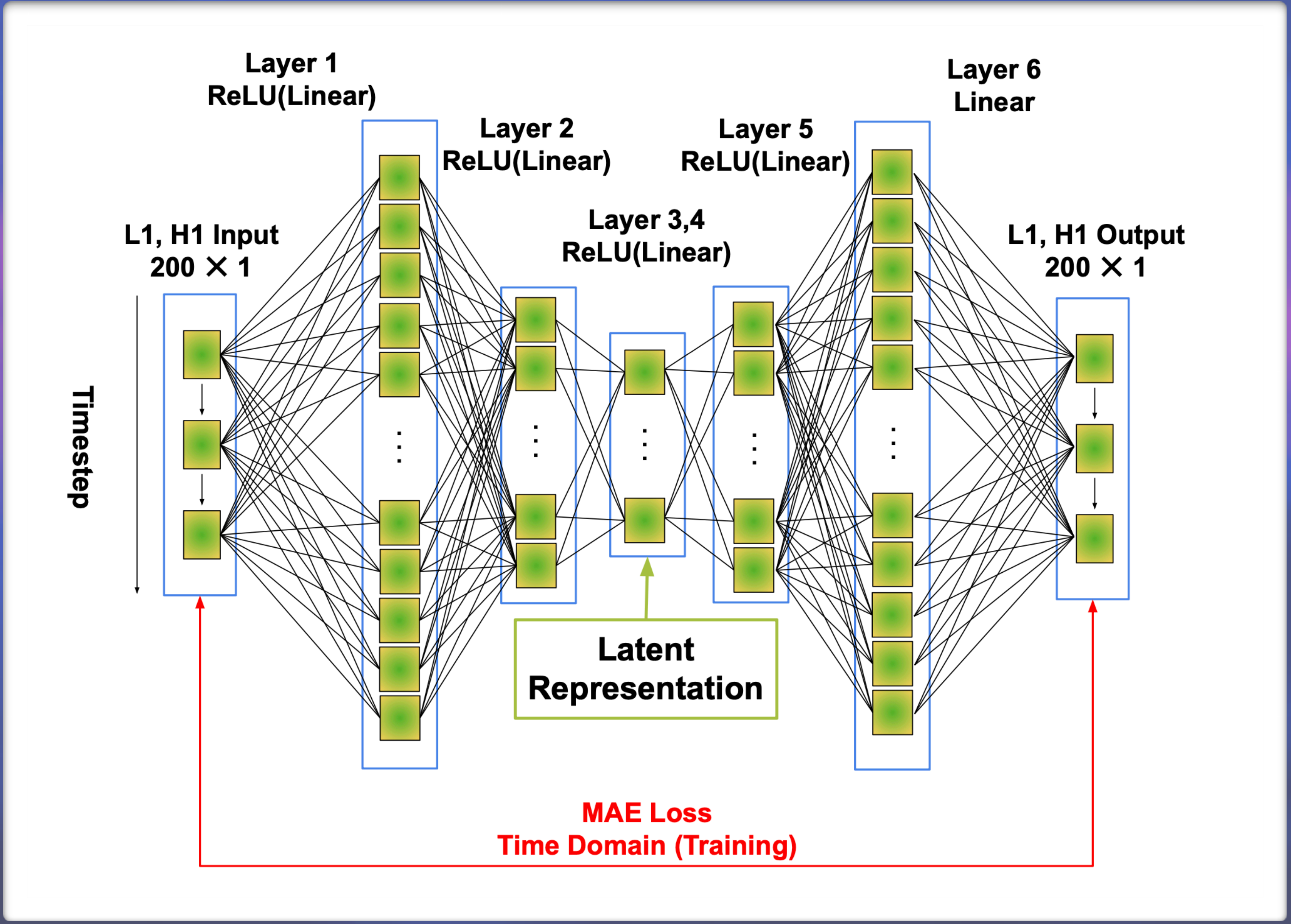
ARXIV2309.11537

We choose LSTM architecture to properly handle sequential data with temporal dependencies



ARXIV2309.11537

WE CHOOSE DENSE ARCHITECTURE FOR BACKGROUNDS TO PROPERLY HANDLE SEQUENTIAL DATA WITHOUT TEMPORAL DEPENDENCIES



"Signal" dataset priors

arXiv2309.11537

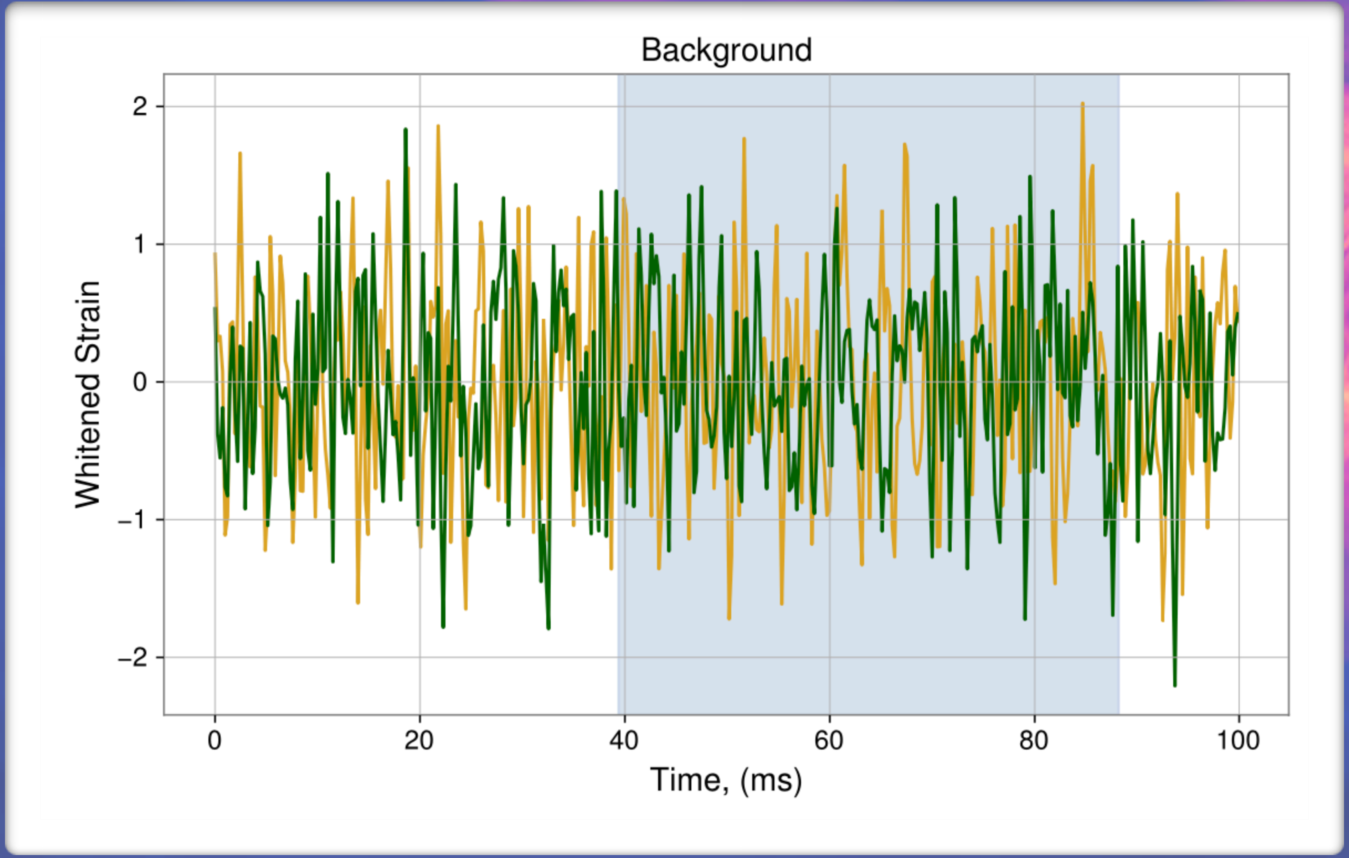
Sampling parameters and priors for BBH (top) and sine-Gaussian (bottom) injections.

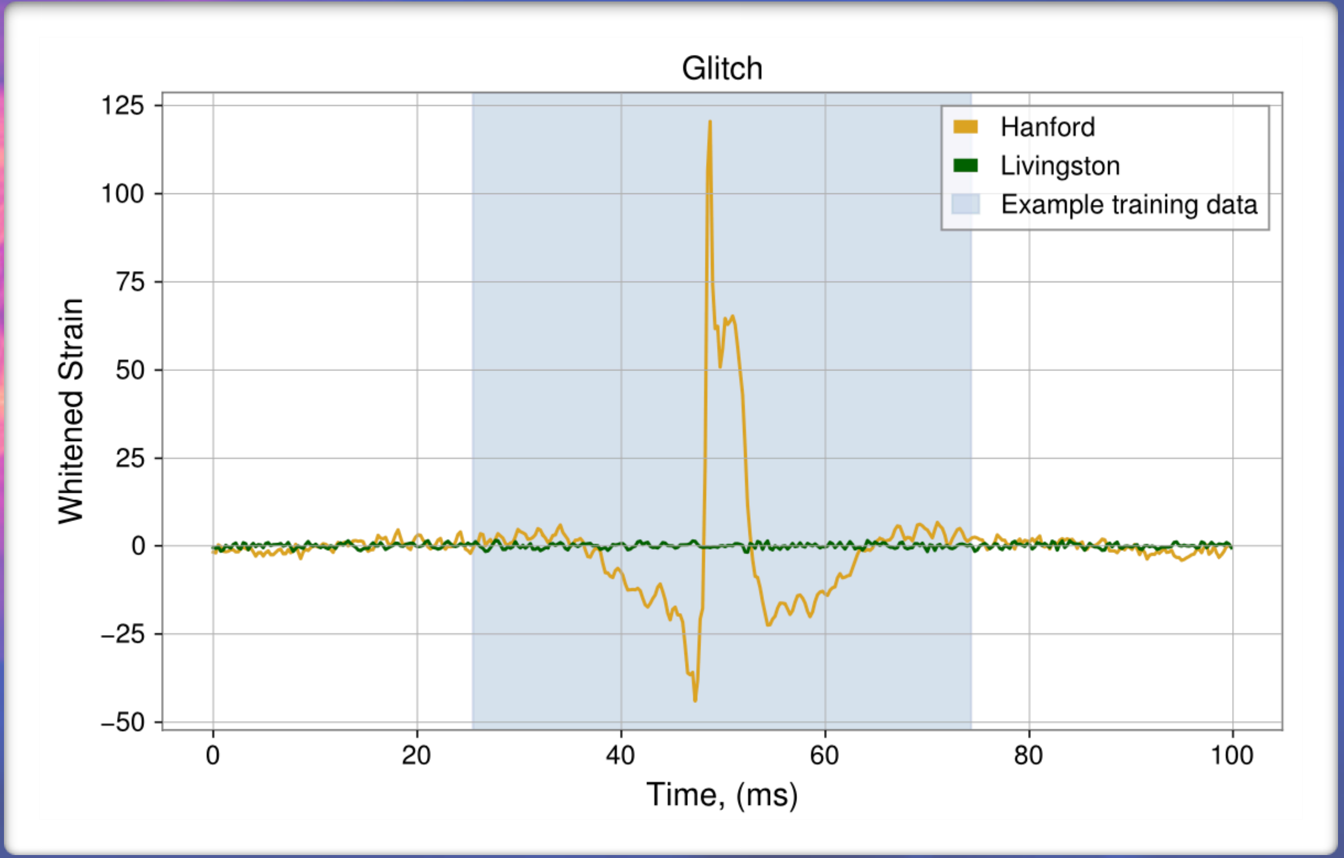
	Parameter	Prior	Limits	Units
BBH	m_1	-	$(5, 100)$	$M_\odot$
	m_2	-	$(5, 100)$	$M_\odot$
	Mass ratio q	Uniform	$(0.125, 1)$	-
	Chirp mass M_c	Uniform	$(25, 100)$	$M_\odot$
	Tilts $\theta_{1,2}$	Sine	$(0, \pi)$	rad.
	Phase ϕ	Uniform	$(0, 2\pi)$	rad.
	Right Ascension	Uniform	$(0, 2\pi)$	rad.
	Declination δ	Cosine	$(-\pi/2, \pi/2)$	rad.
sine-Gaussian	Q	Uniform	$(25, 75)$	-
	Frequency	Uniform	$(64, 512)$ and $(512, 1024)$	Hz
	Phase ϕ	Uniform	$(0, 2\pi)$	rad.
	Eccentricity	Uniform	$(0, 0.01)$	-
	Declination δ	Cosine	$(-\pi/2, \pi/2)$	rad.
	Right Ascension	Uniform	$(0, 2\pi)$	rad.
	Ψ	Uniform	$(0, 2\pi)$	rad.

ARXIV2309.11537

EXAMPLE OF GWAK CLASSES: GLITCH AND BACKGROUND STRAINS

THE LIGHT BLUE SHADING HIGHLIGHTS AN EXAMPLE REGION THAT IS PASSED AS INPUT TO THE AUTOENCODERS FOR TRAINING



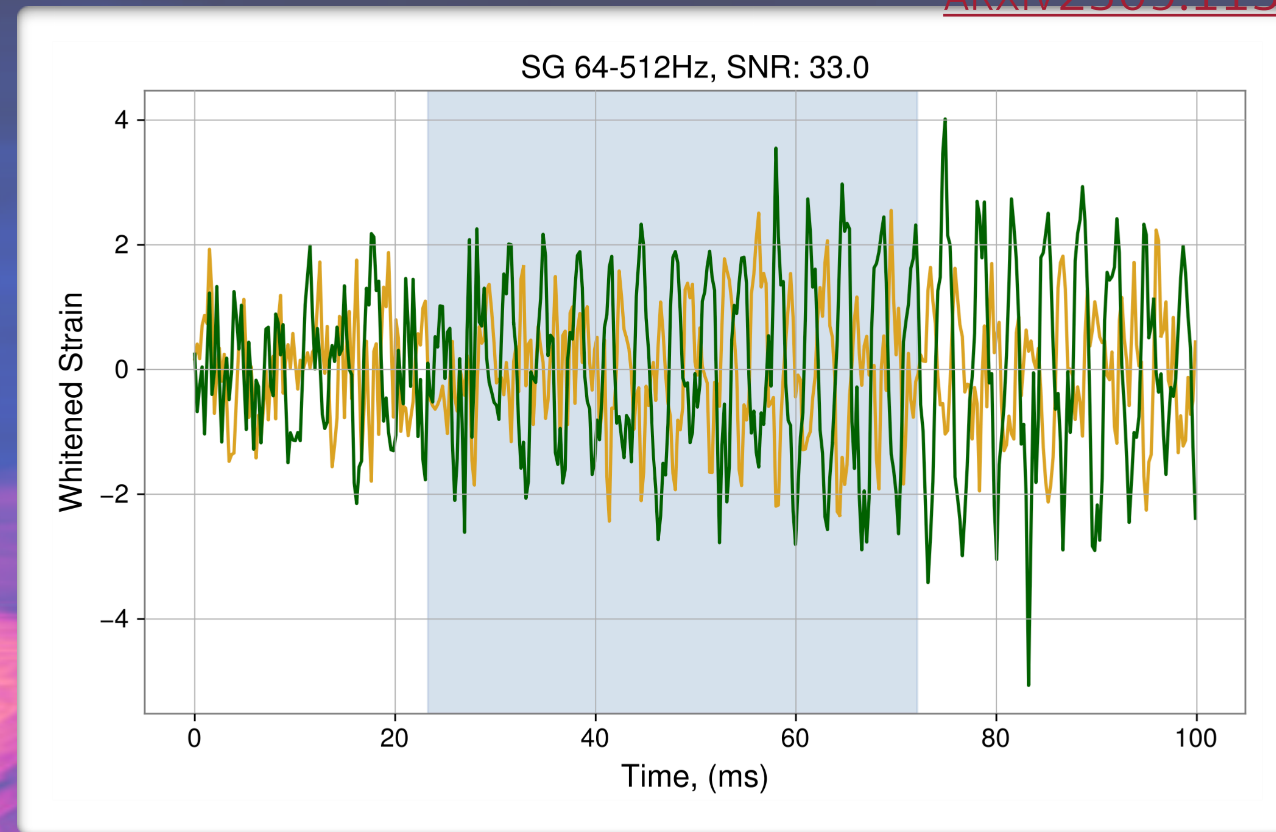


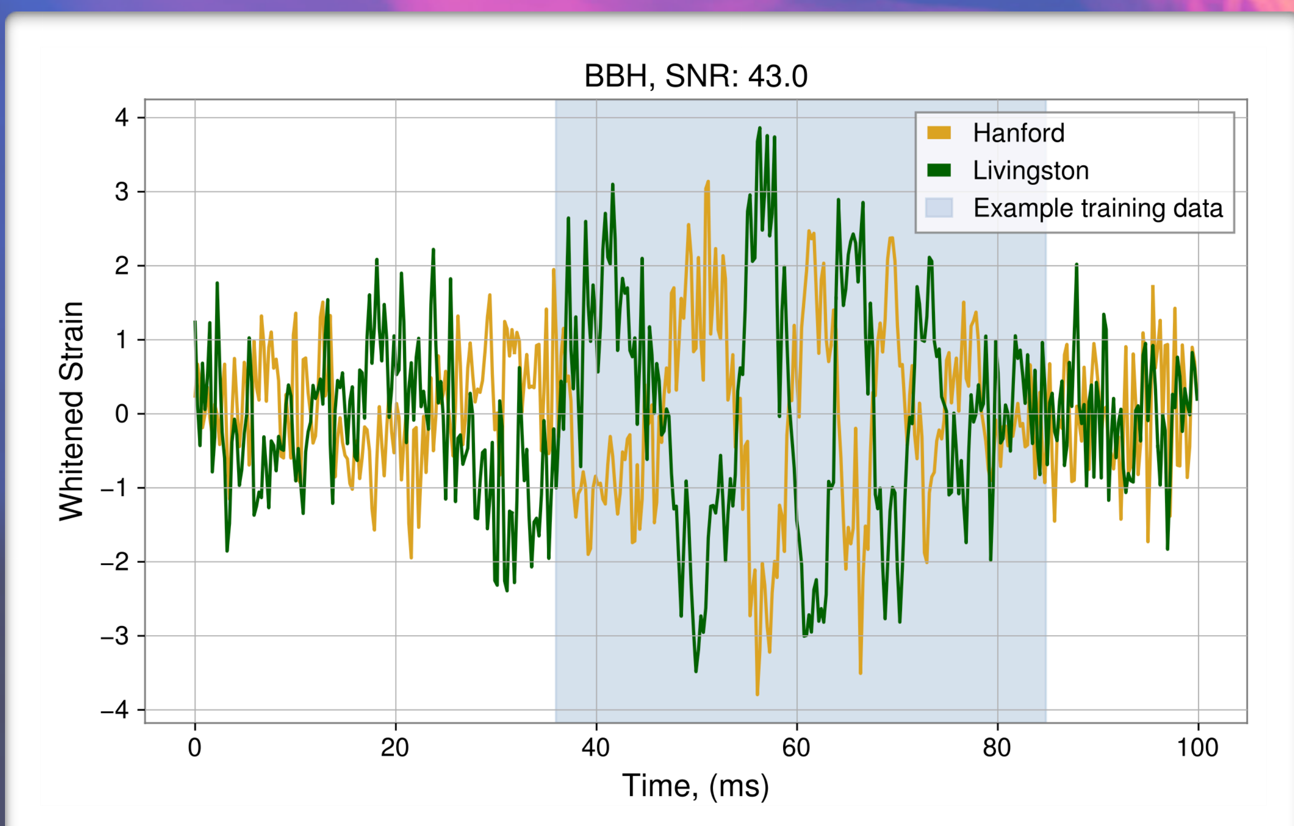
SIGNAL DATASETS

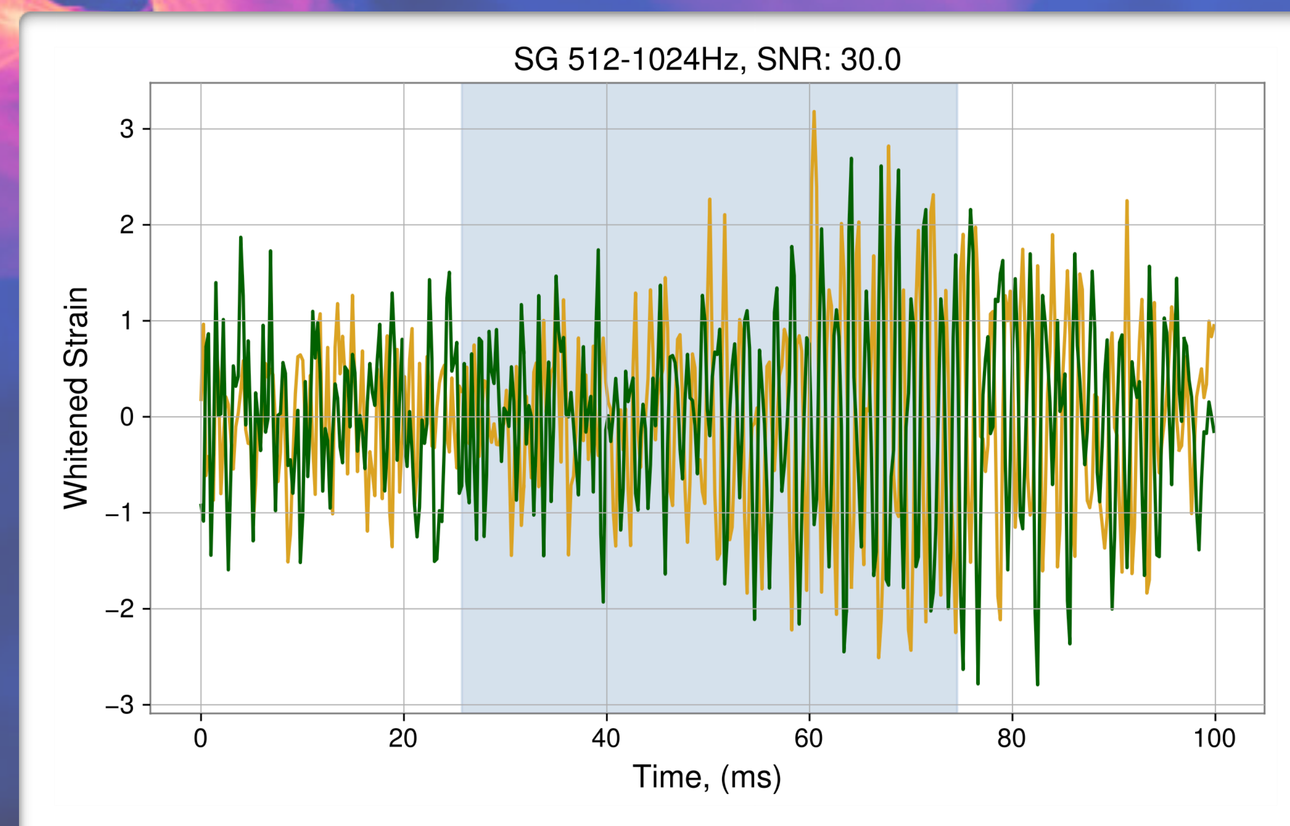
ARXIV2309.11537

EXAMPLE OF SIGNAL-LIKE CLASSES: BBH AND SINE-GAUSSIAN STRAINS FROM LIVINGSTON AND HANFORD

THE LIGHT BLUE SHADING HIGHLIGHTS AN EXAMPLE REGION THAT IS PASSED AS INPUT TO THE AUTOENCODERS FOR TRAINING





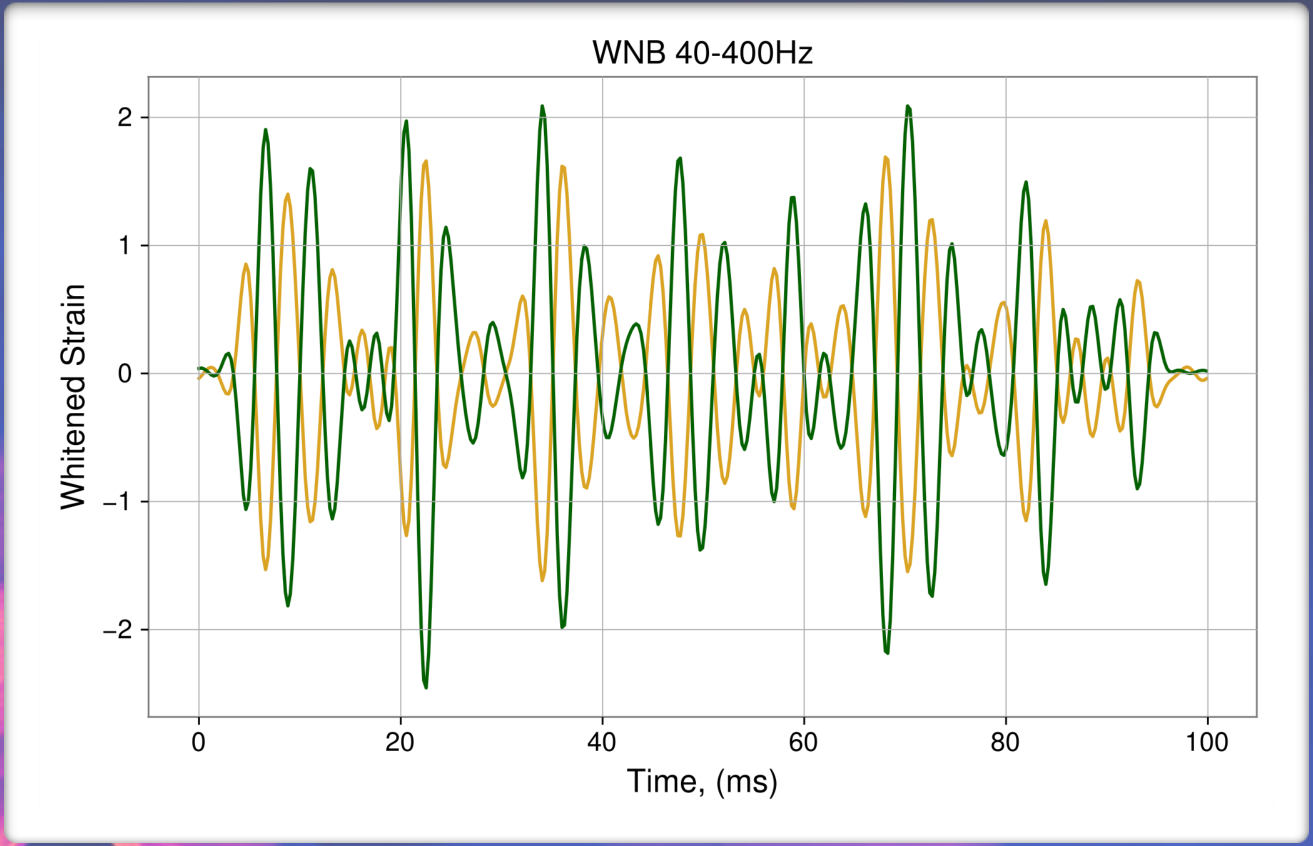


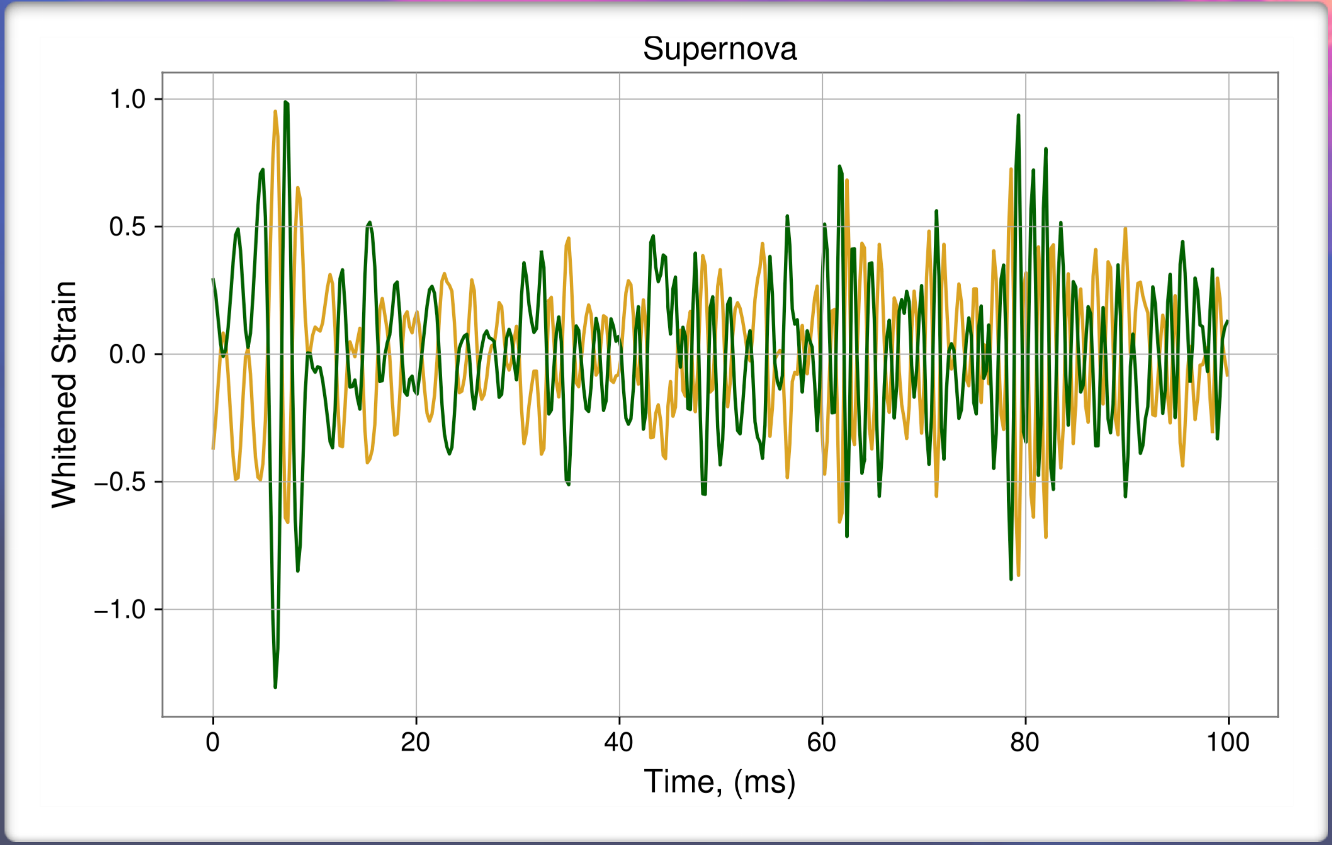
Anomaly datasets

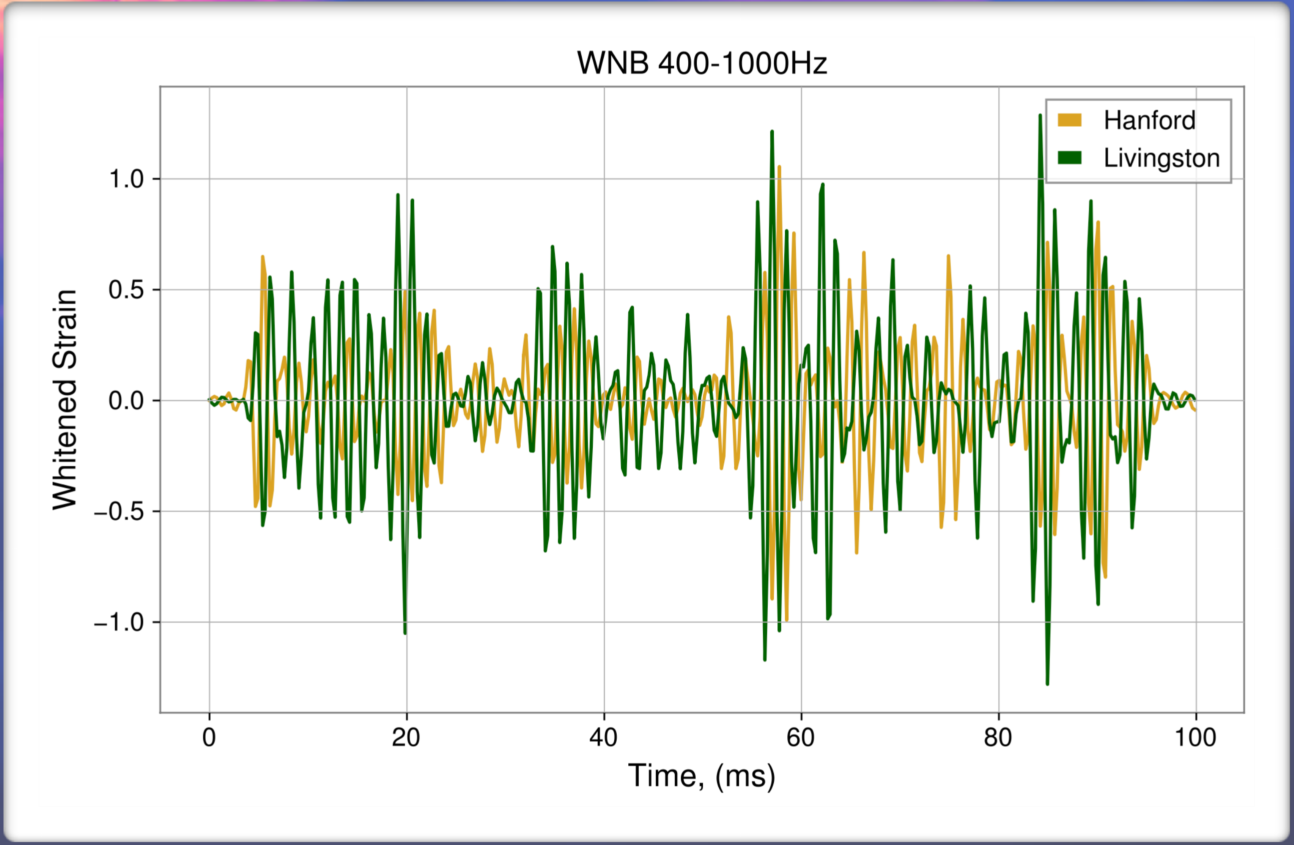
ARXIV2309.11537

Example of signal-like classes: Supernova and white noise burst strains from Livingston and Hanford

Those anomalies are not used to create the GWAK



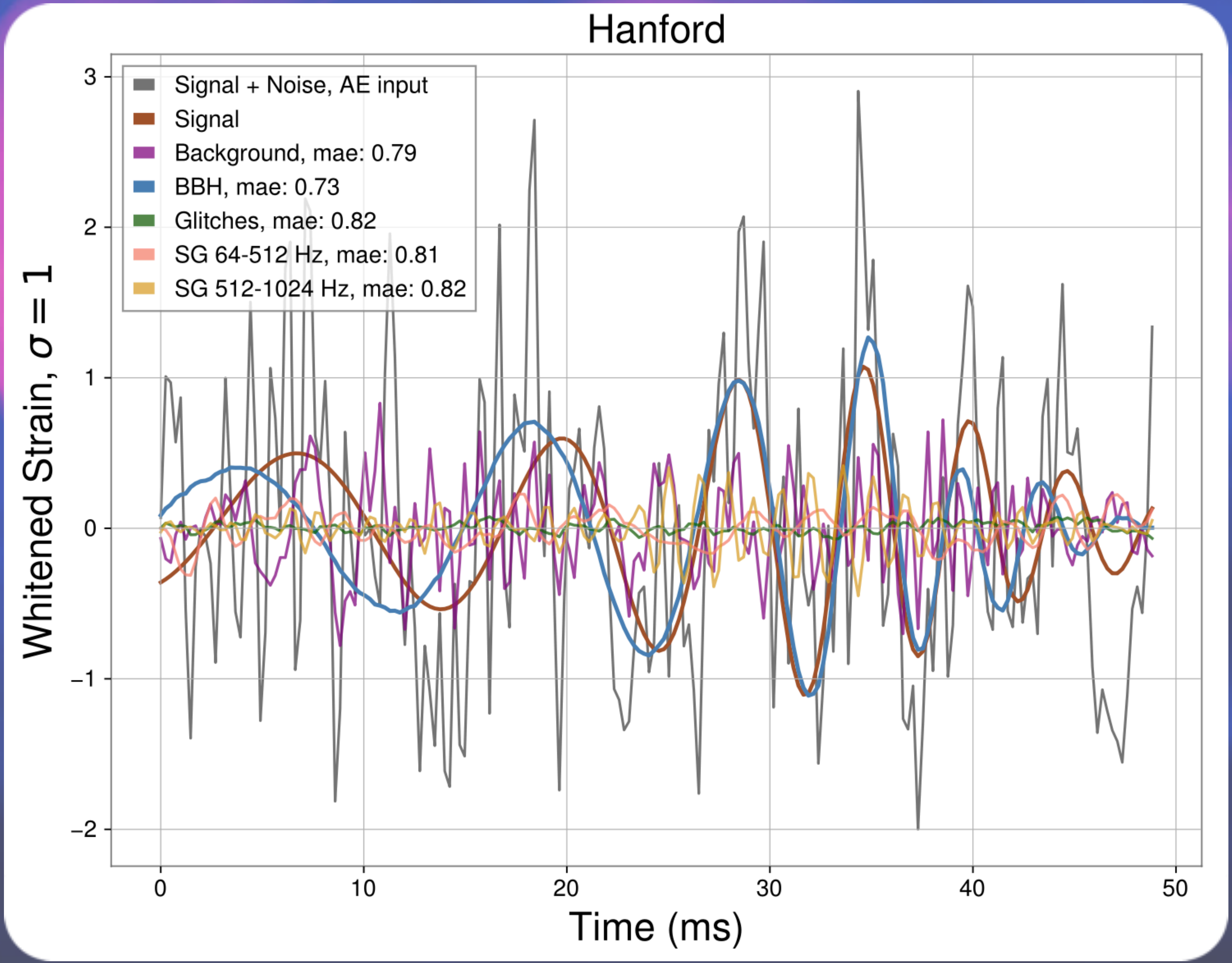




Autoencoder recreations

arxiv2309.11537

- Example of recreation on injected BBH signal, with the noise-less template shown as well
- The recreation of the BBH autoencoder follows closely the original signal injection
- While background, glitches, SG 64-512 Hz and SG 512-1024 Hz fail to reconstruct the injected BBH signal



The GWAK Efficiency

ARXIV2309.11537

The final metric as a function of SNR for GWAK axes training signals, BBH, SG 64-512 Hz, SG 512-1024 Hz and for potential anomalies, WNB 40-400 Hz, WNB 400-1000 Hz, and Supernova