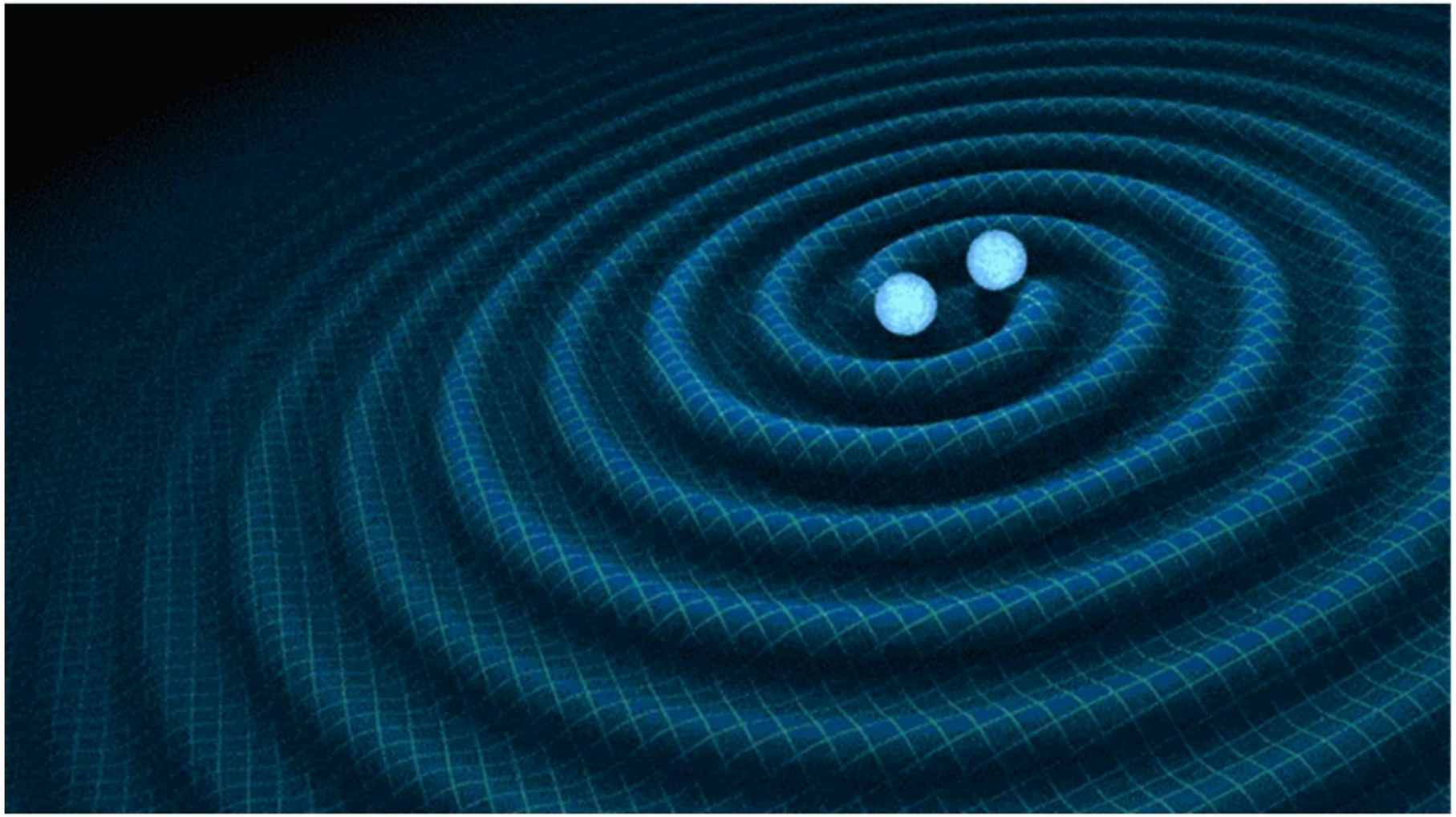


Searching For Gravitational Waves

Annoucnements

- You have a pset due this Friday at Midnight
- Pset is available on canvas
- Please send me/Divij your comments and concerns

Slides

- See this link for animations:

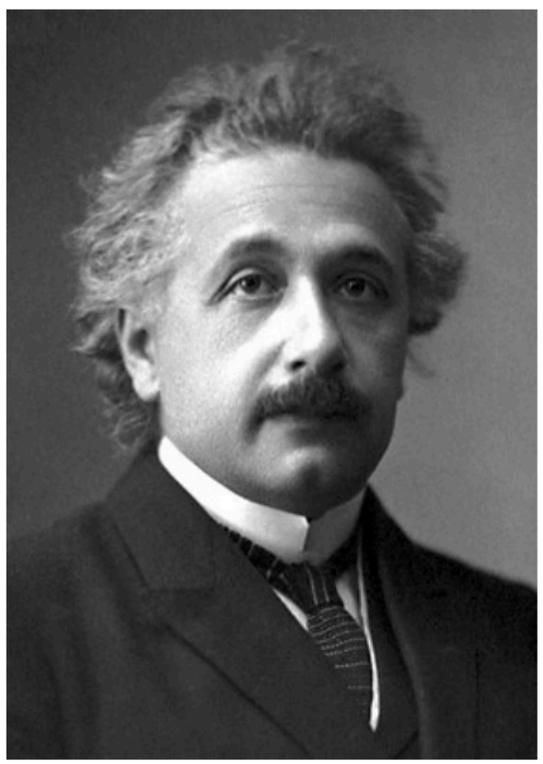
- https://www.dropbox.com/s/44ew35qlz89xono/PCH_Lecture2_LigoAnims_8S50.pptx?dl=0

Gravity

There is a limiting speed in Nature, the speed of light (1905)

geometry of spacetime

stress-energy tensor

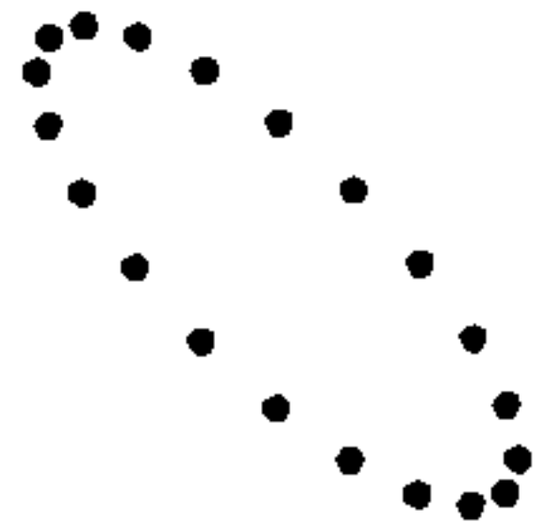


$$G_{\alpha\beta} = \frac{8\pi G}{c^4} T_{\alpha\beta}$$

Gravity: manifestation of spacetime curvature (1915)

A Gravitational Wave

$$\left(\nabla^2 - \frac{1}{c^2}\frac{\partial^2}{\partial t^2}\right) h = 0$$

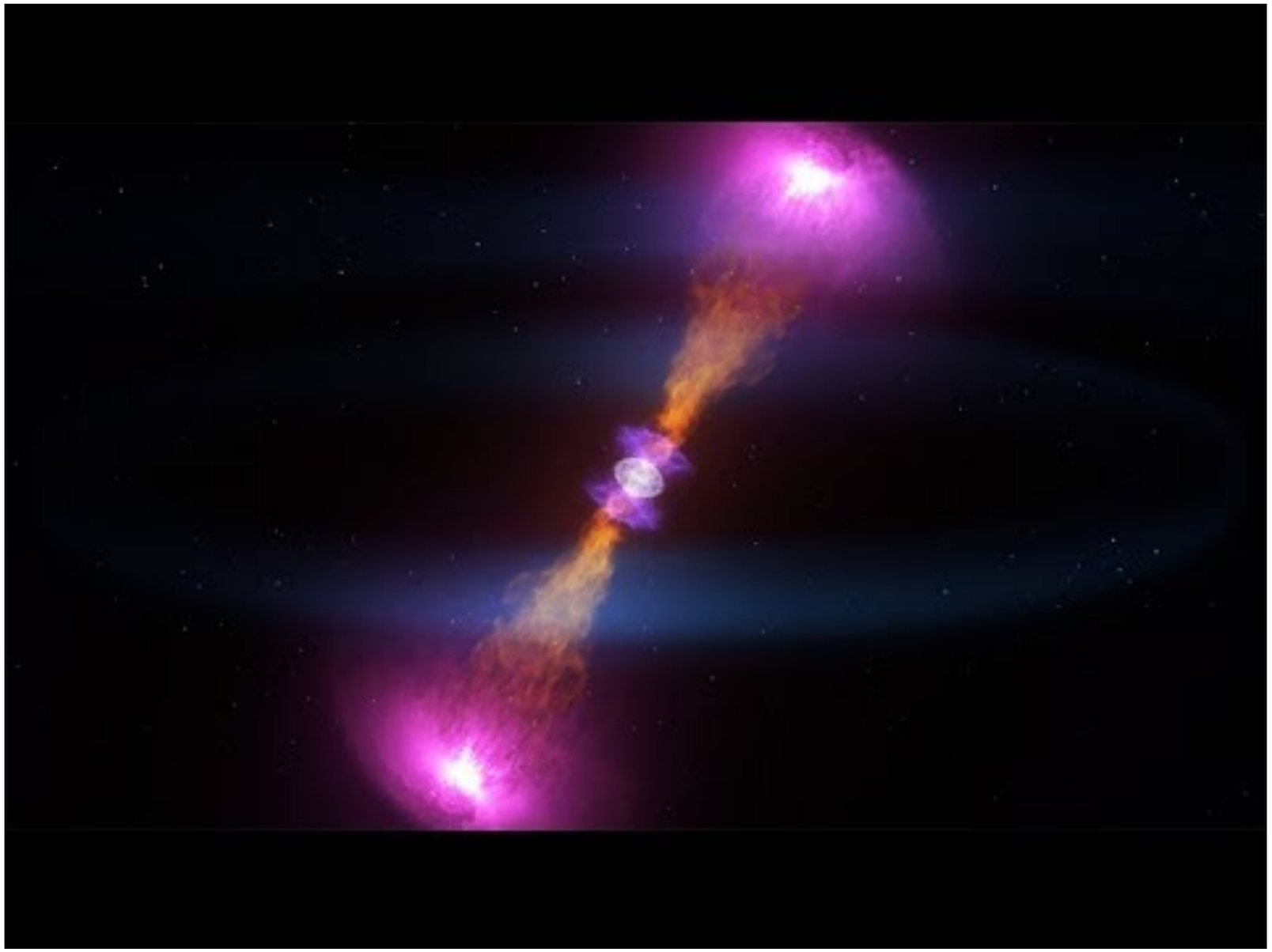


$$h_{\mu\nu} = \frac{2G}{c^4 r}\ddot{I}_{\mu\nu} \quad \Rightarrow \quad h \approx \frac{4\pi^2 G M R^2 f_{orb}^2}{c^4 r}$$

Gravitational Waves lead to space time distrotions

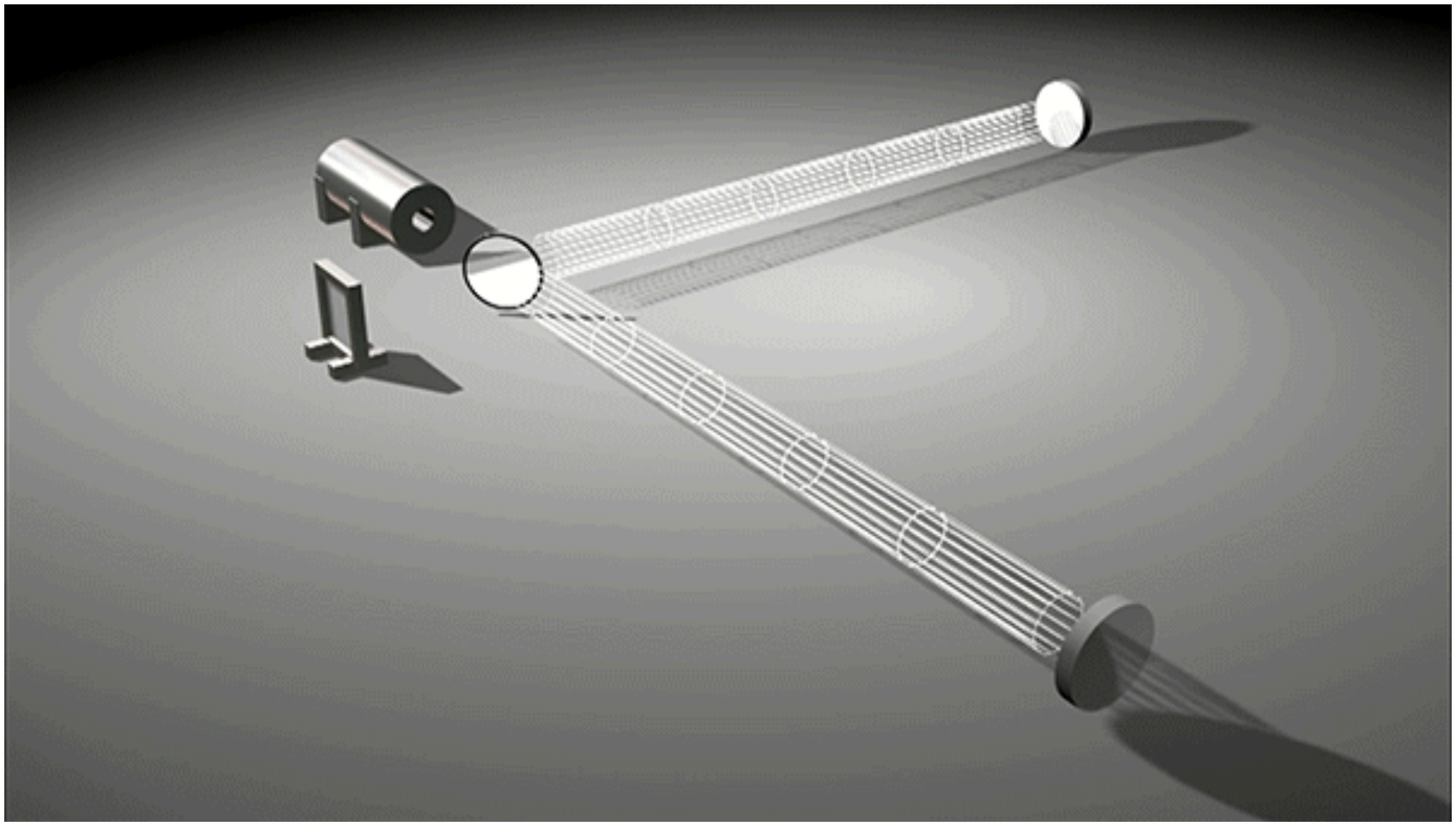
The distortions correspond ot a stretching and compression

Detecting GW Mergers



Astrophysical Events Can sometimes produce light
But can always produce Gravitational Waves

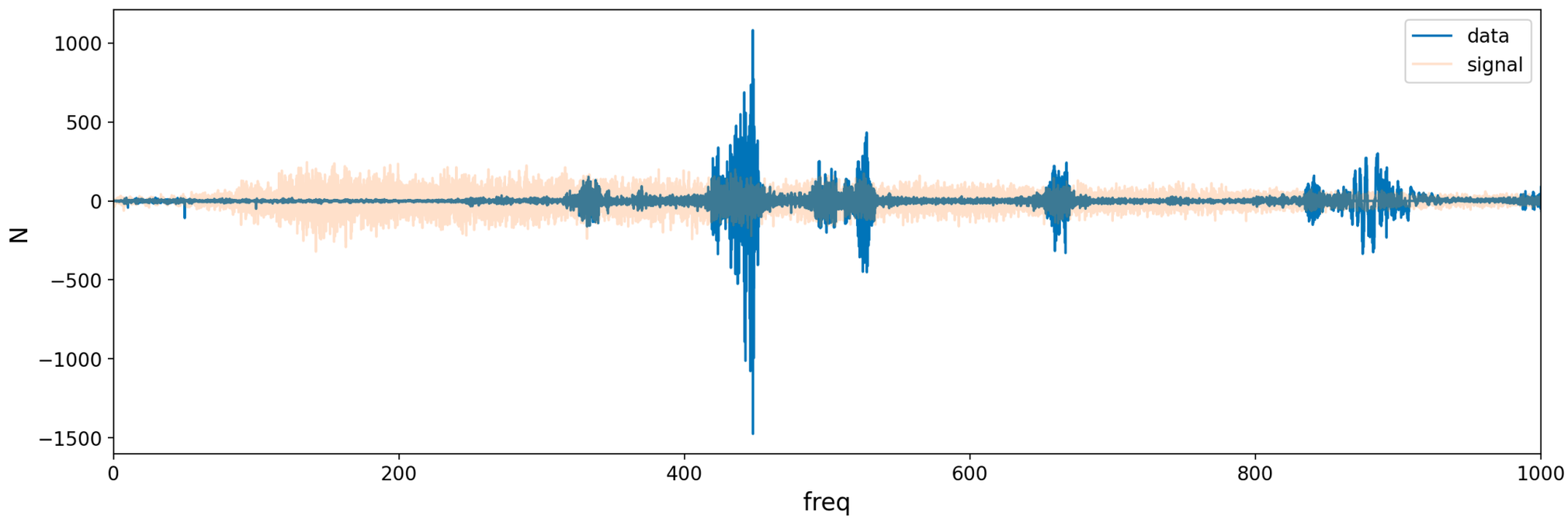
Detecting Black Holes



We can measure waves by measuring distorition in space

Distortions are on the order 10^{-19} m over a 4 km length

Typical LIGO Signal



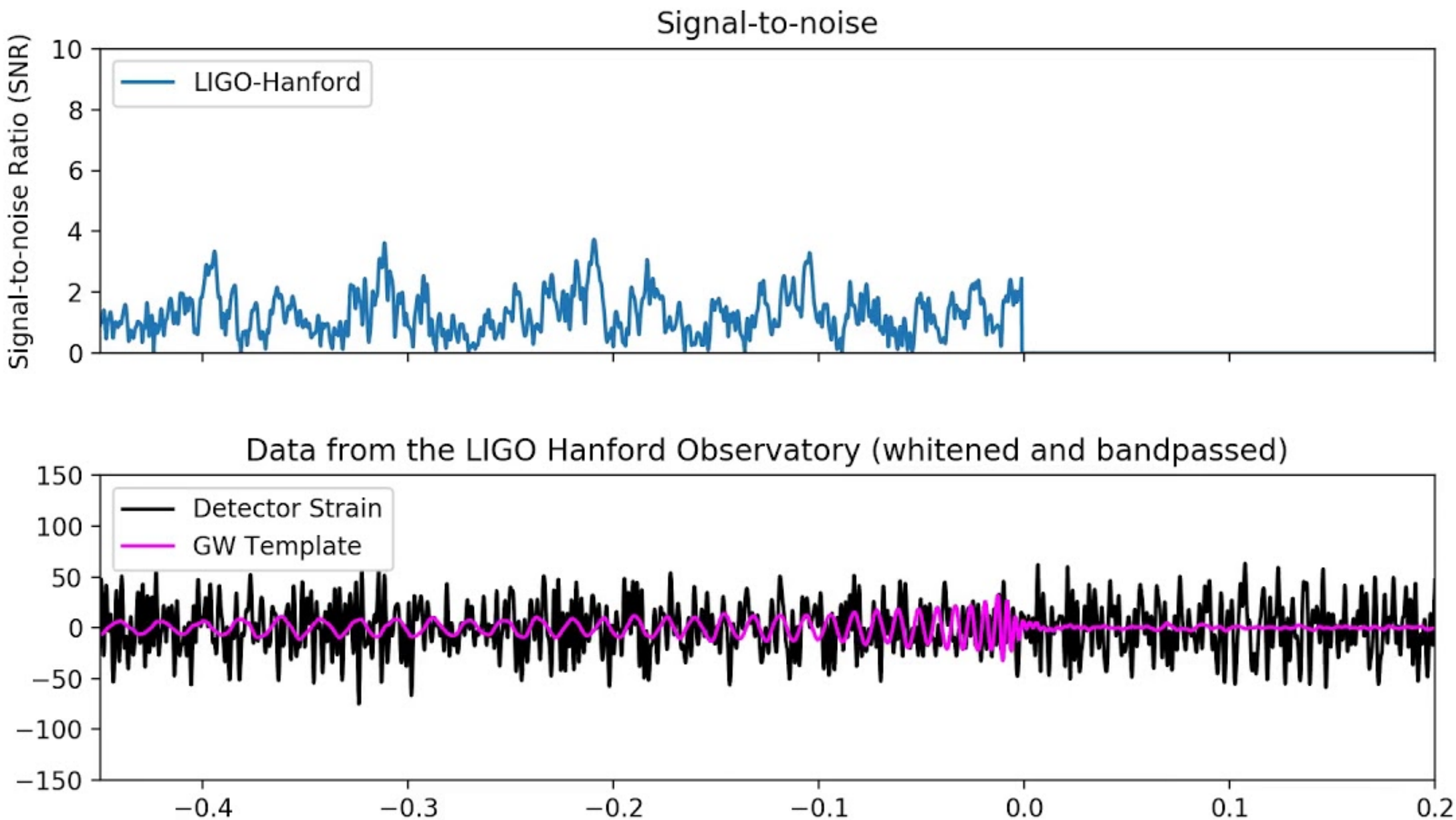
Challenge is to hear a hidden signal on top of a lot of noise

We often have a numerical/analytic form for the signal

We have no form and limited understanding of the noise

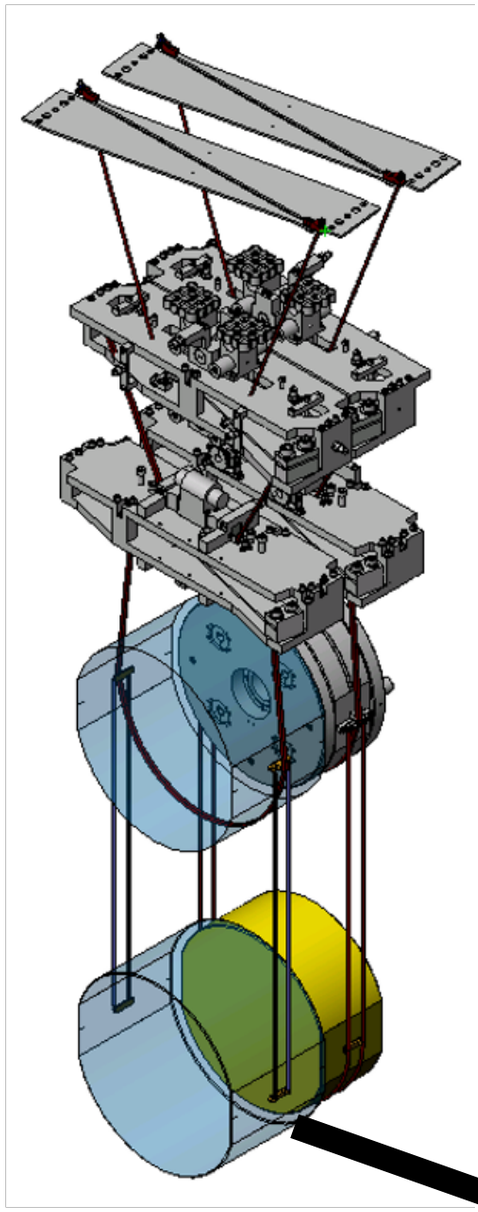
Ungraciously taken from Erik Katsavounidis

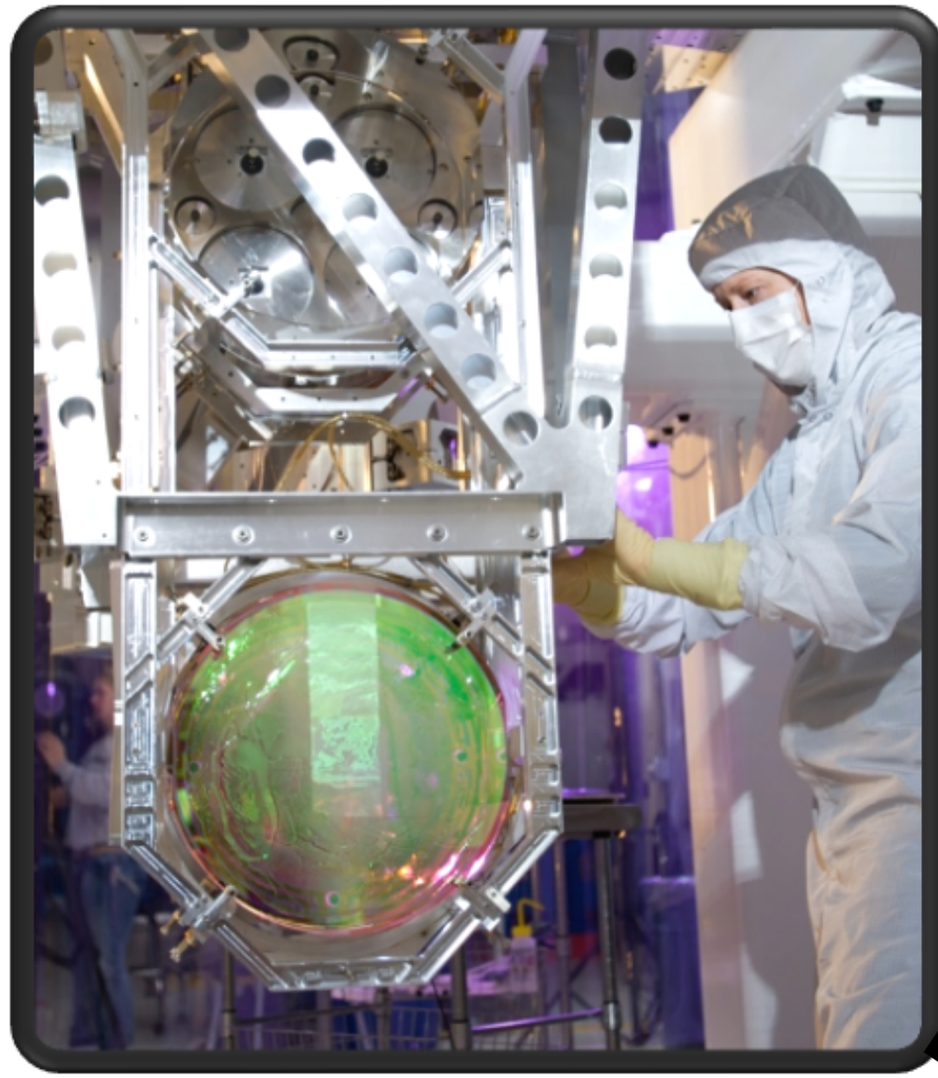
Typical LIGO Signal

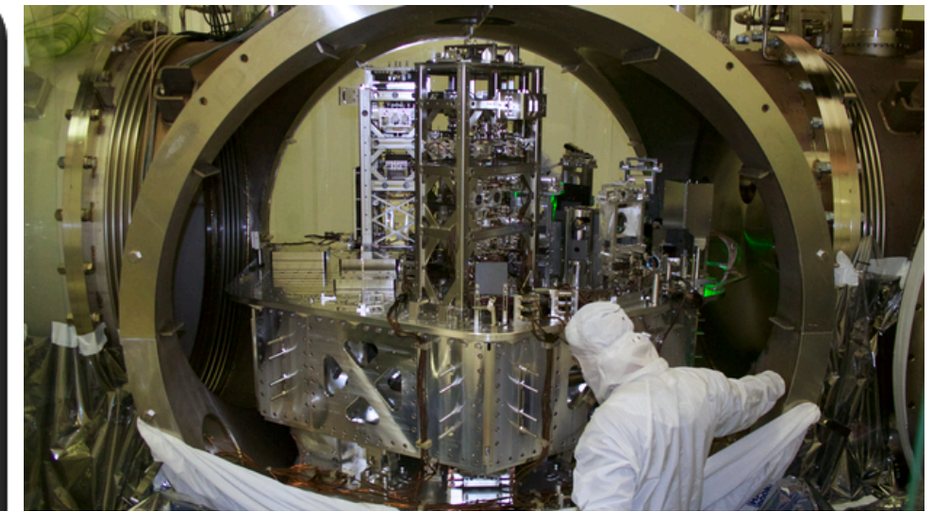


To ensure we aren't seeing a glitch we use at multiple detectors
2 LIGO detectors in US + Virgo detector in Europe + Kagra in Japan

Where does it come from?







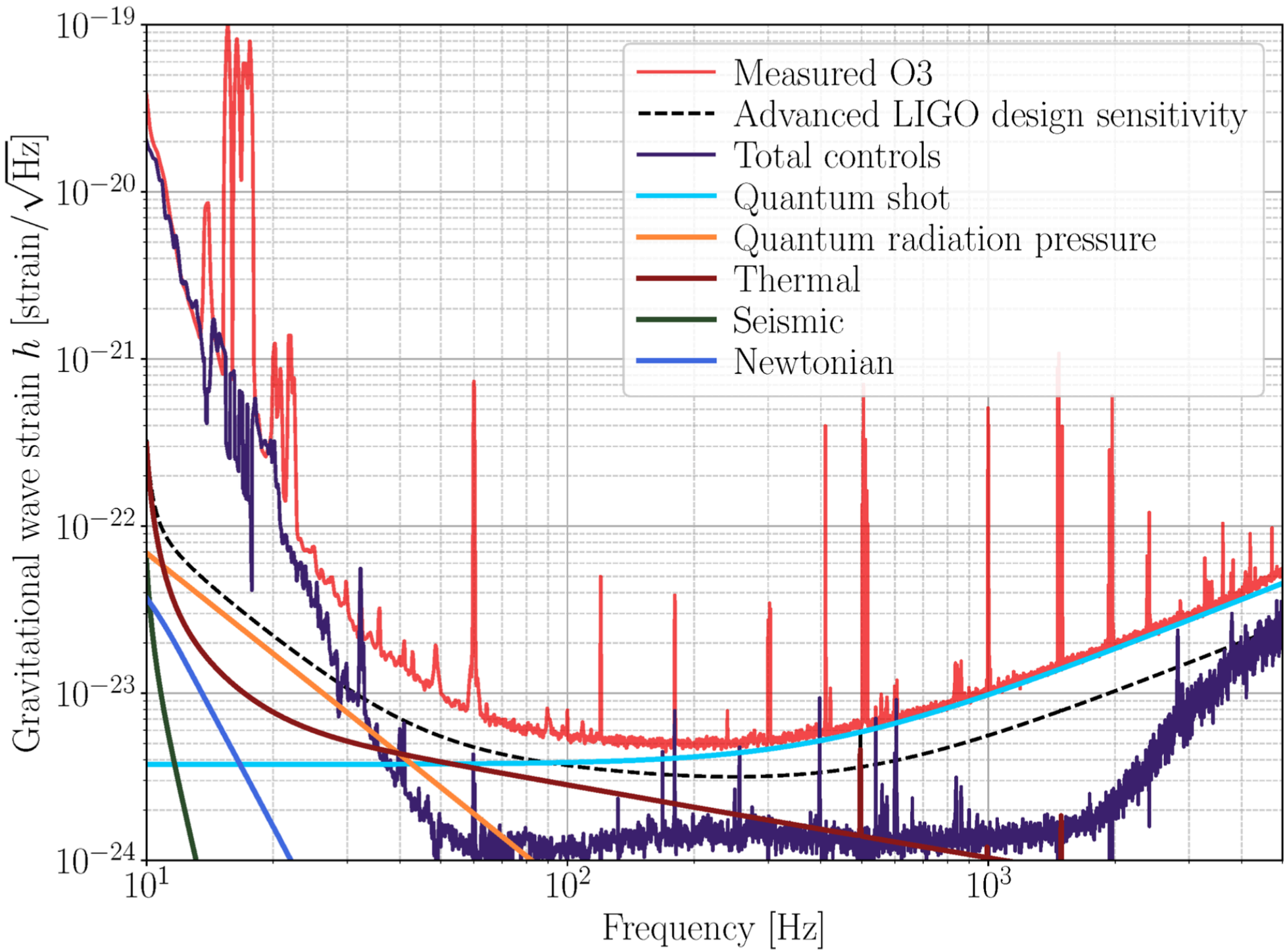
Advanced Optics & Controls

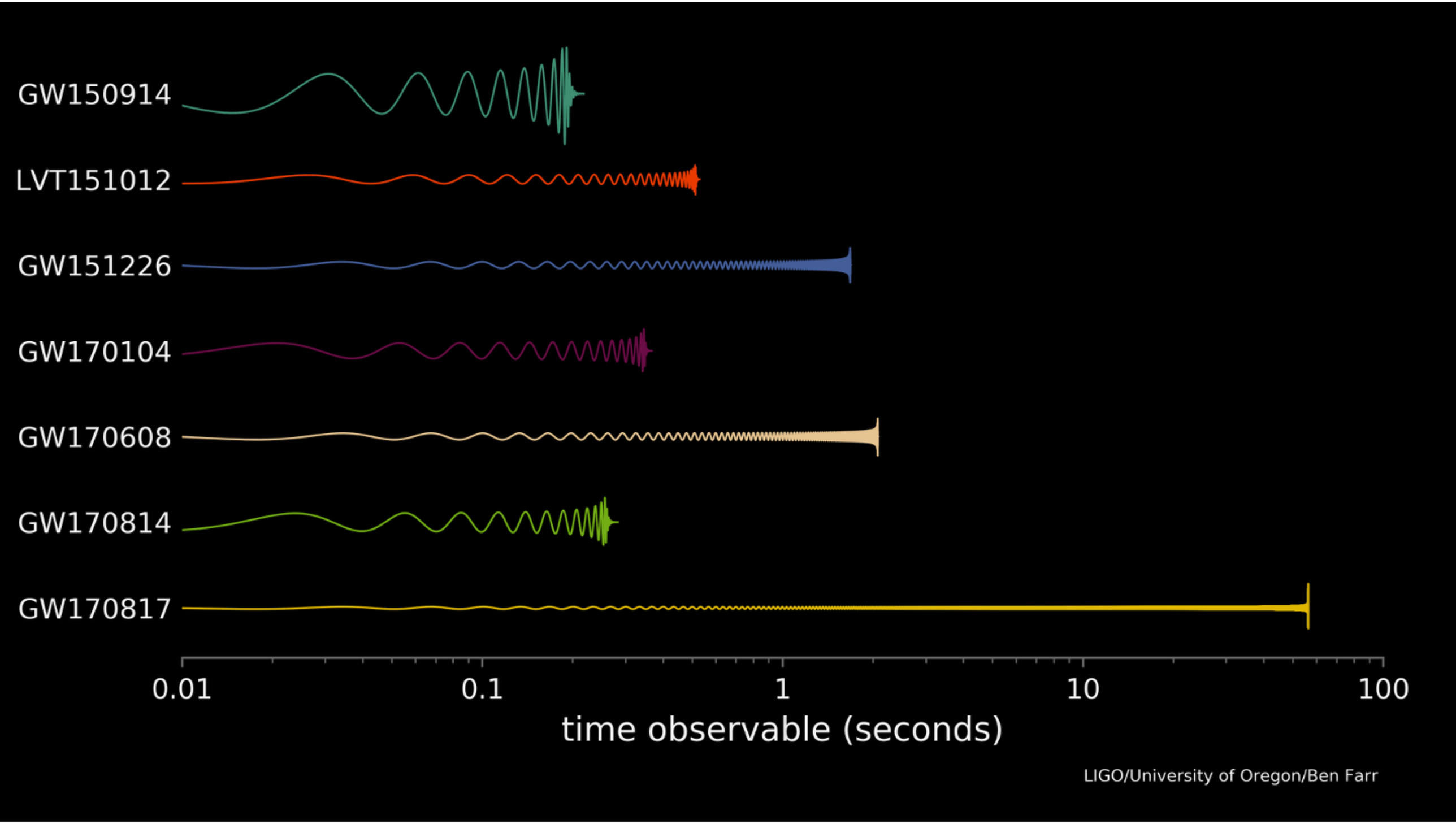
Heavy, cleaned mirrors

Multi staged suspensions

To control the noise, we monitor everything
LIGO has 100k monitor channels
100k channels + 1 signal channel

Challenge of Denoising





Masses distance and noise vary our ability to find them
However, mergers have a pretty clear form

How do we construct ?

$$\boxed{h(t)} = \boxed{s(t)} + \boxed{n(t)}$$

Signal Model: From
Numerical GR(templates)
Sometimes something else

Noise Model : from data
No simulation for this

Modeling Signals
Really Means
Modeling it All

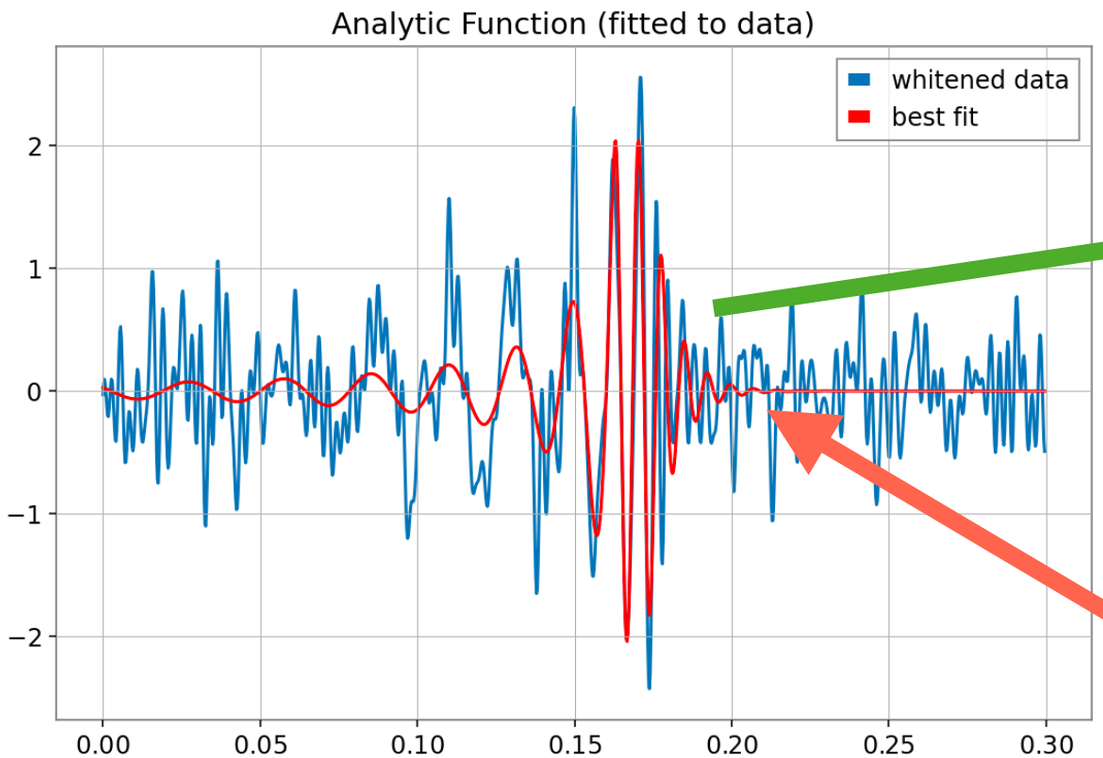
$$n(t) = \boxed{n_{nw}(t)} + \boxed{n_w(t)}$$

Non-reducible noise
Shot Noise/Thermal

Reducible Noise
Correlated w/witness

What do we need to do

We don’t know what the Frequency of the signal



Need to scan (up to) 15 parameters with a non-analytic template

Noise is hard to characterize our whitened(noise corrected) signal loses its analytic form

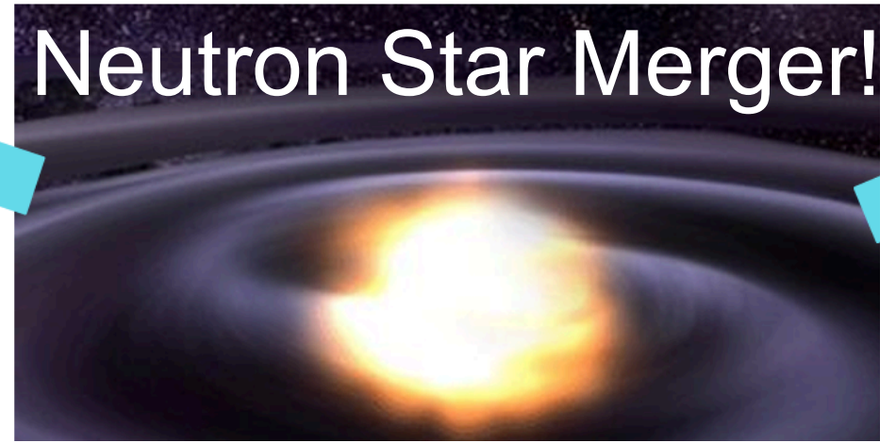
We don’t know the noise model

When we combine noise + signal it adds confusion

We need to do this as fast as possible (< 1s)

Multi-Messenger Astronomy

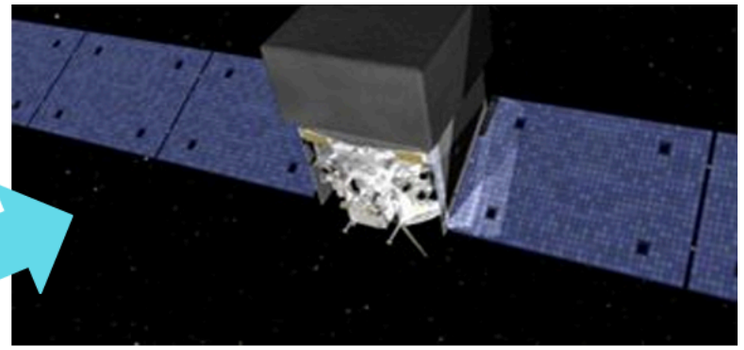
Gravitational waves



A gravitational wave will see a Neutron star before meger

Multi-Messenger Astronomy

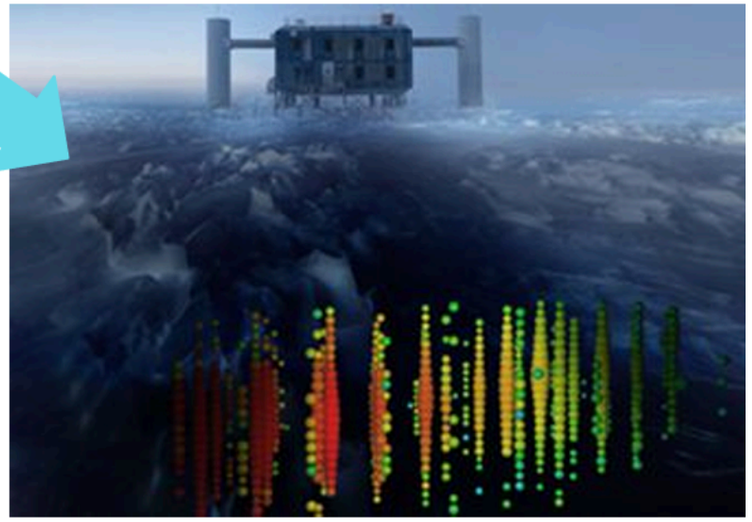
Gravitational waves



X-rays/Gamma-rays

Visible/infrared light

Radio waves

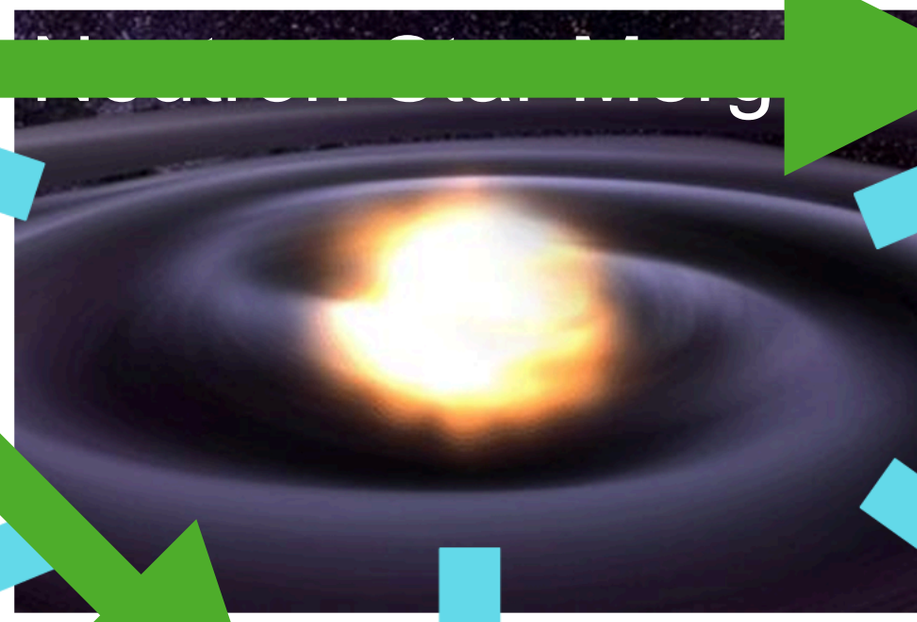


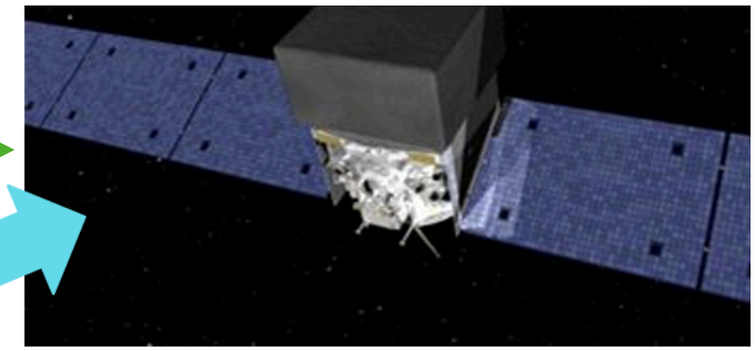
Neutrinos

Everybody Else will see it much further after

Multi-Messenger Astronomy

Gravitational waves





X-rays/Gamma-rays

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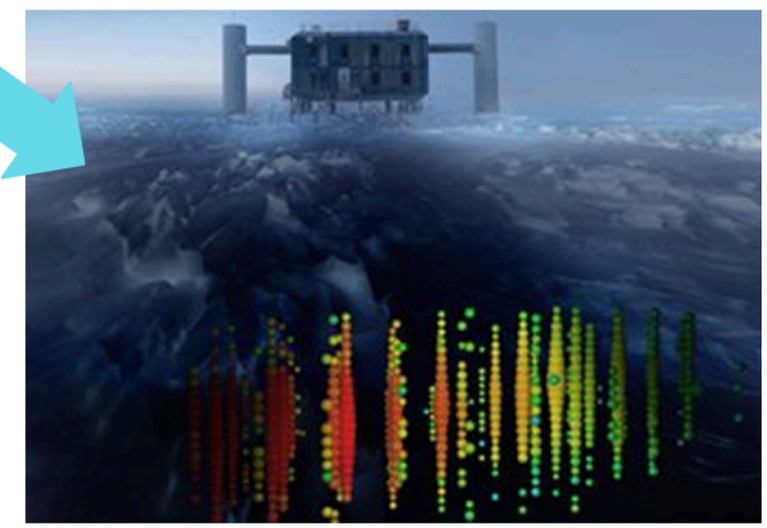


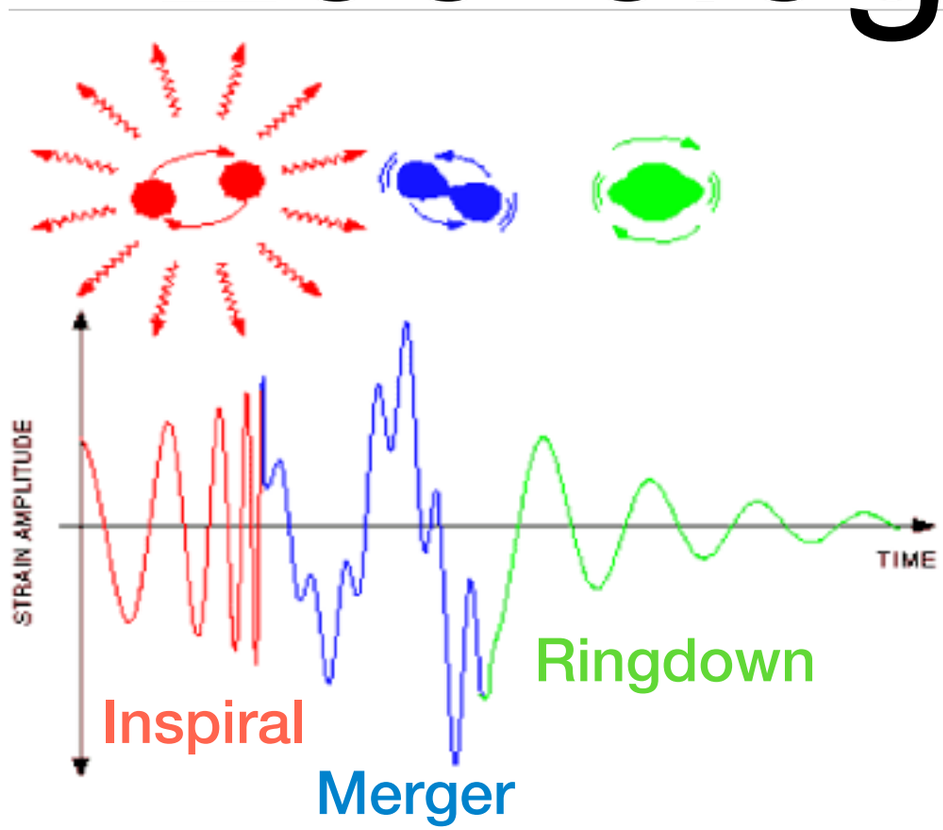
Neutrinos

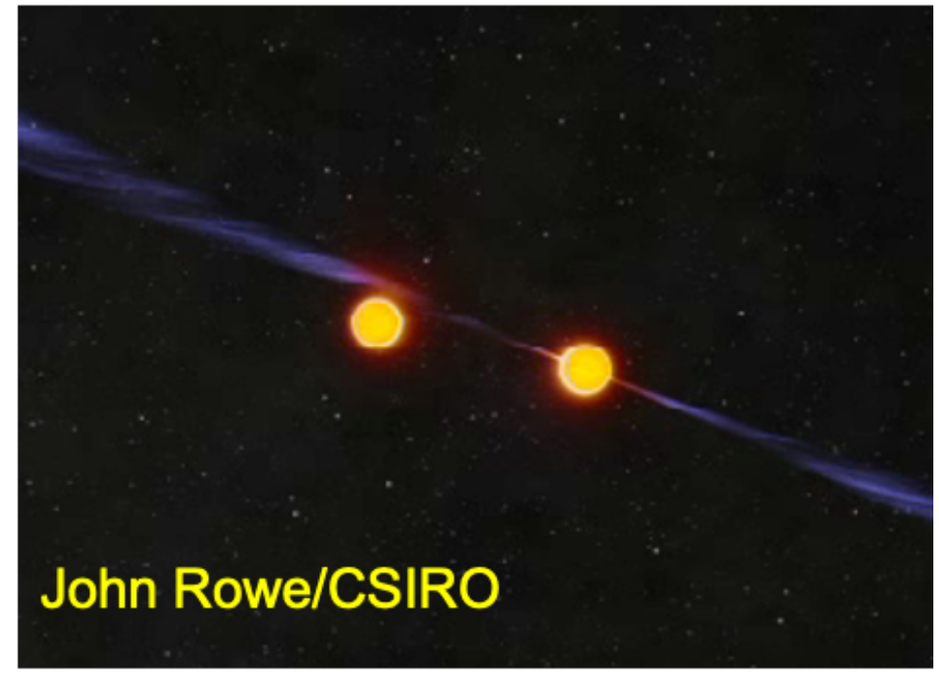
Performing fast identification of GWs critical to alerting world!

Zoo-ology of Events

Compact Binary Coalescence (CBC)

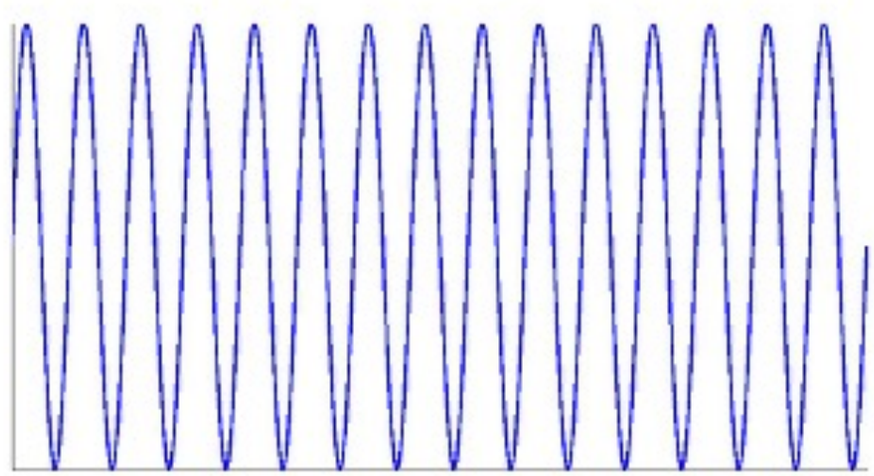
Two Objects
Black holes
Neutron Stars

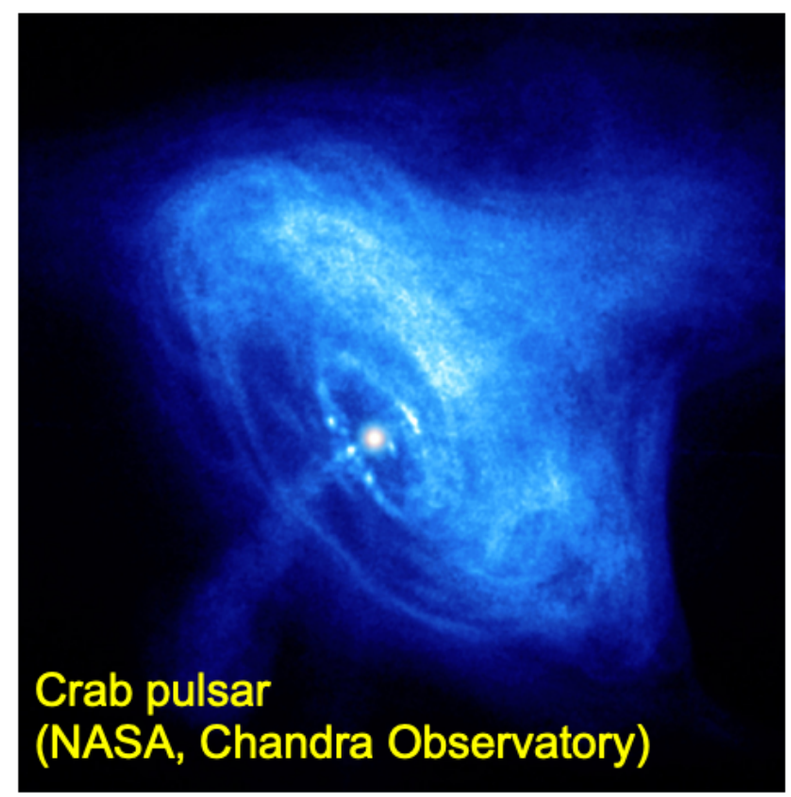




Periodic Waves

Continuous Wave
Isolated Neutron stars
Low mass binary

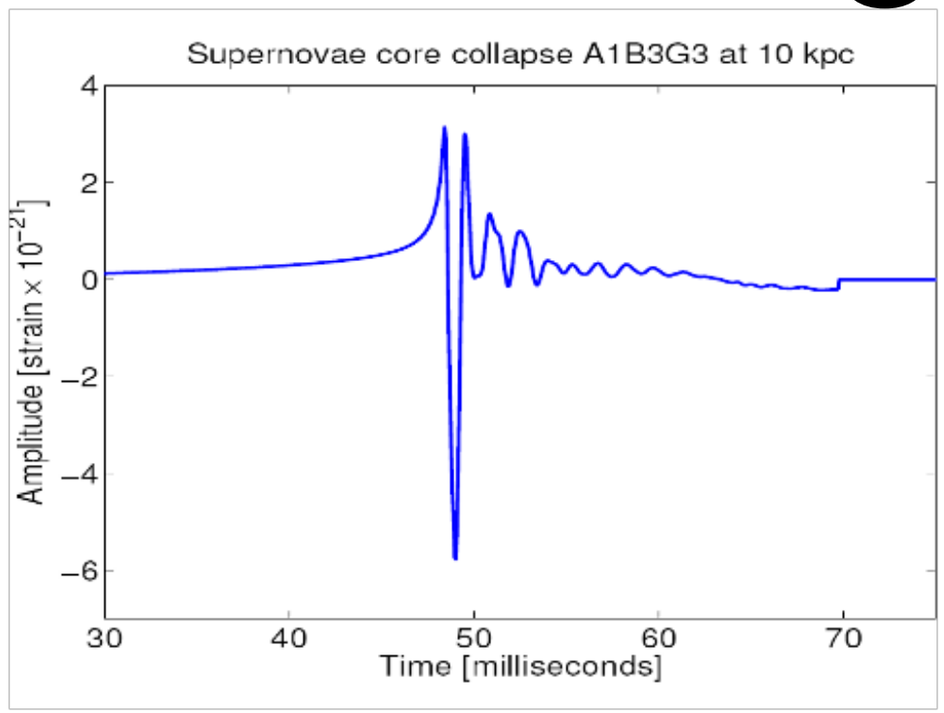


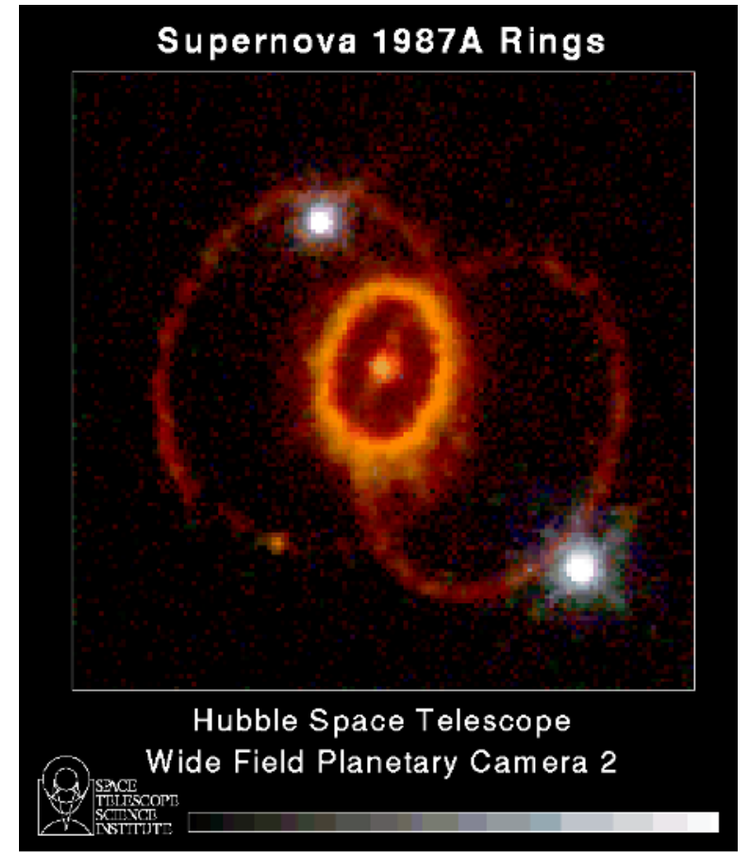


Zoo-ology of Events

Unmodelled Bursts

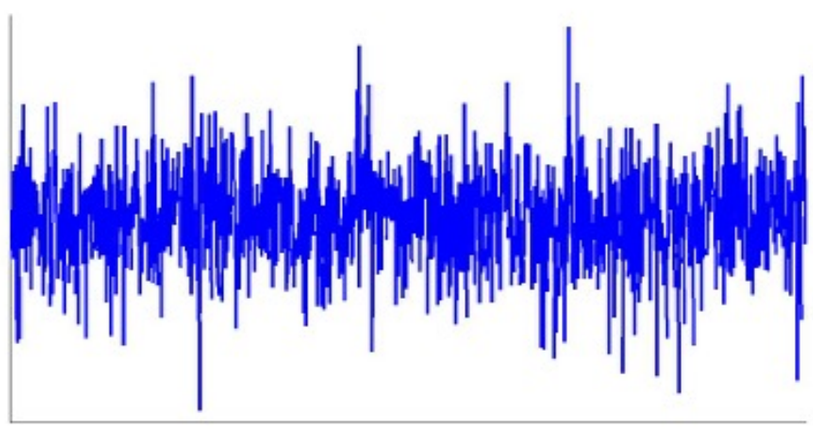
Anomaly Detection
Supernovae
Cosmic Strings
Eccetnric BBHs

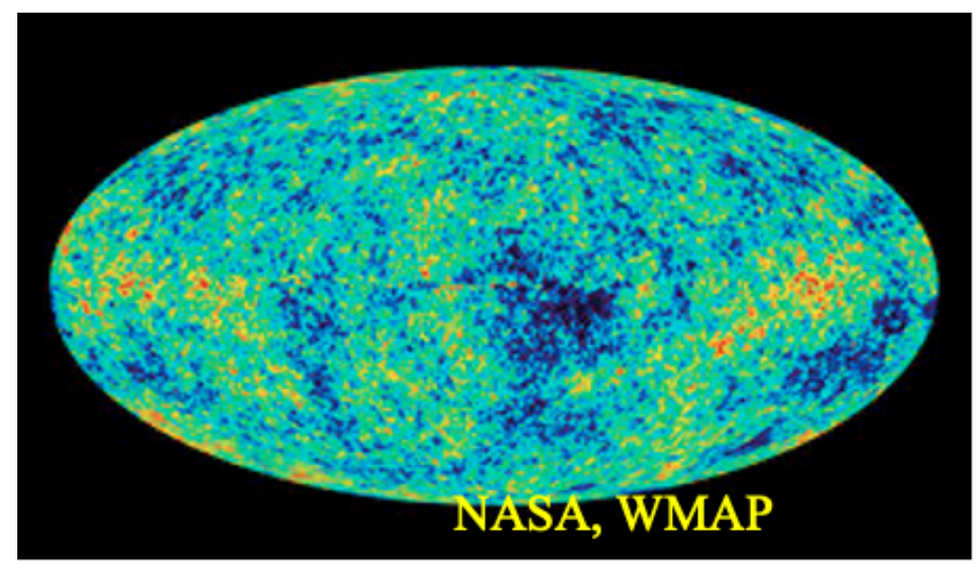




Stochastic
background

irregular, everpresent
Big bang
Early Universe



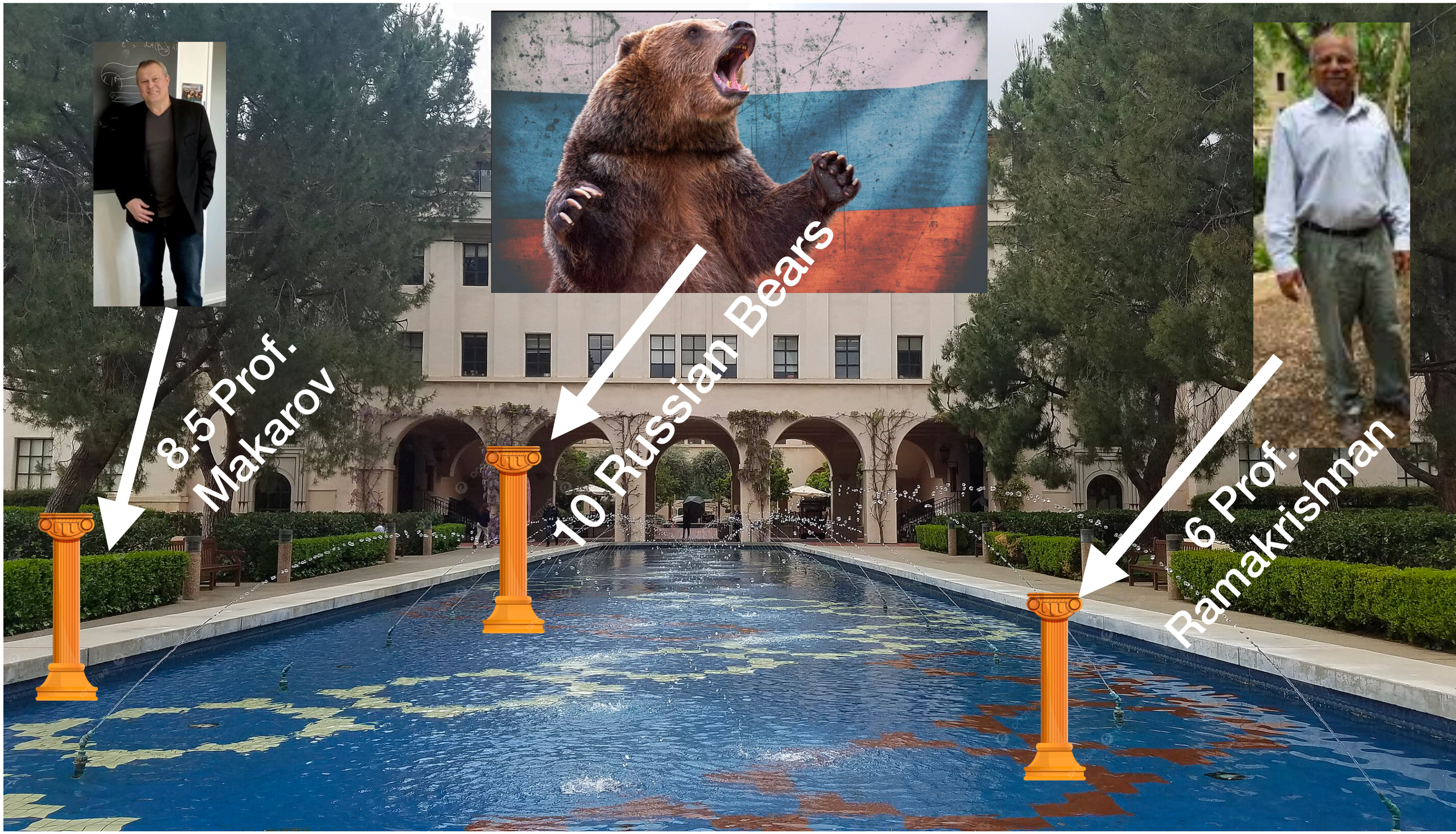


Caltech Ditch Day

Caltech Ditch Day

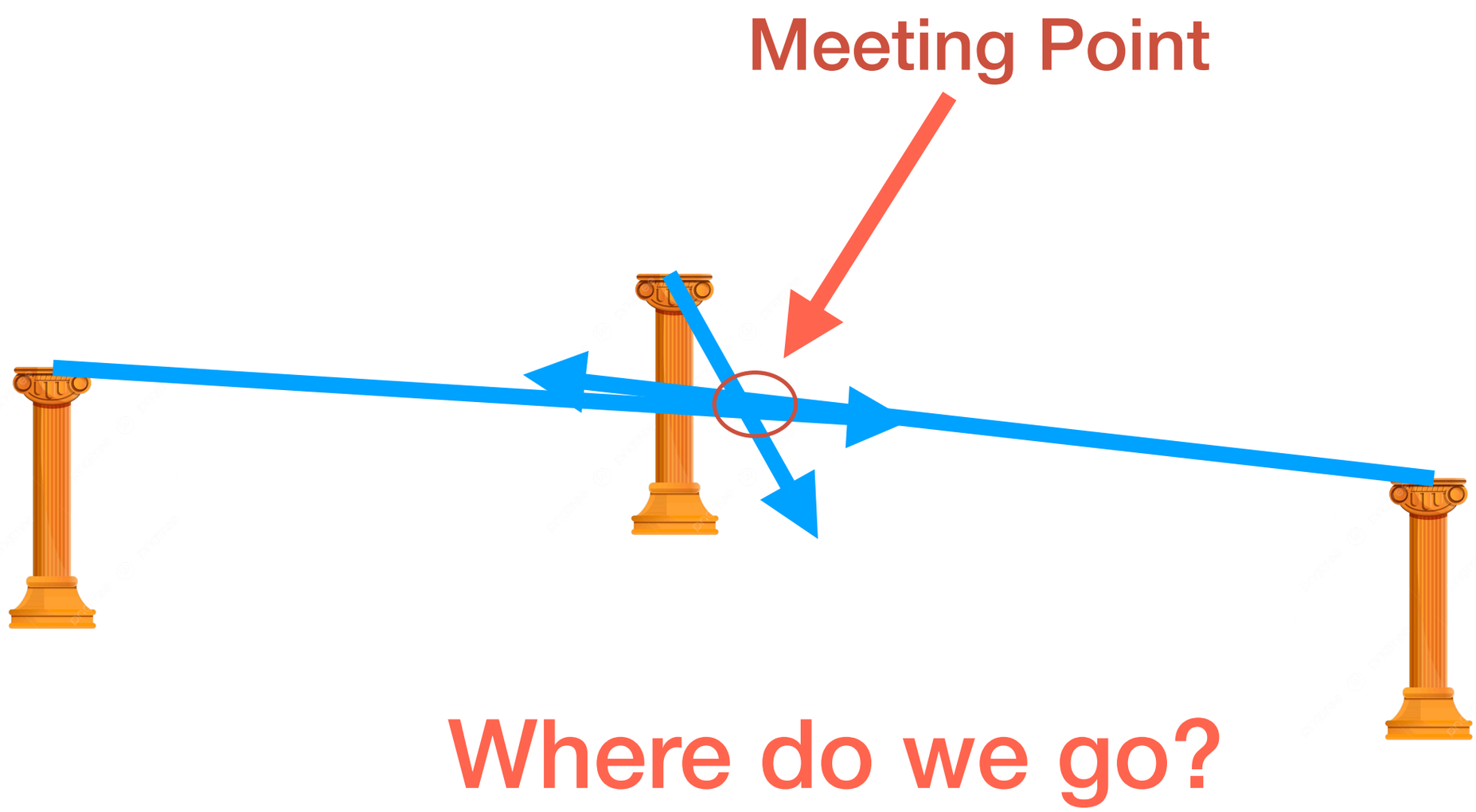
Caltech Ditch Day

Caltech Ditch Day



Caltech Ditch Day

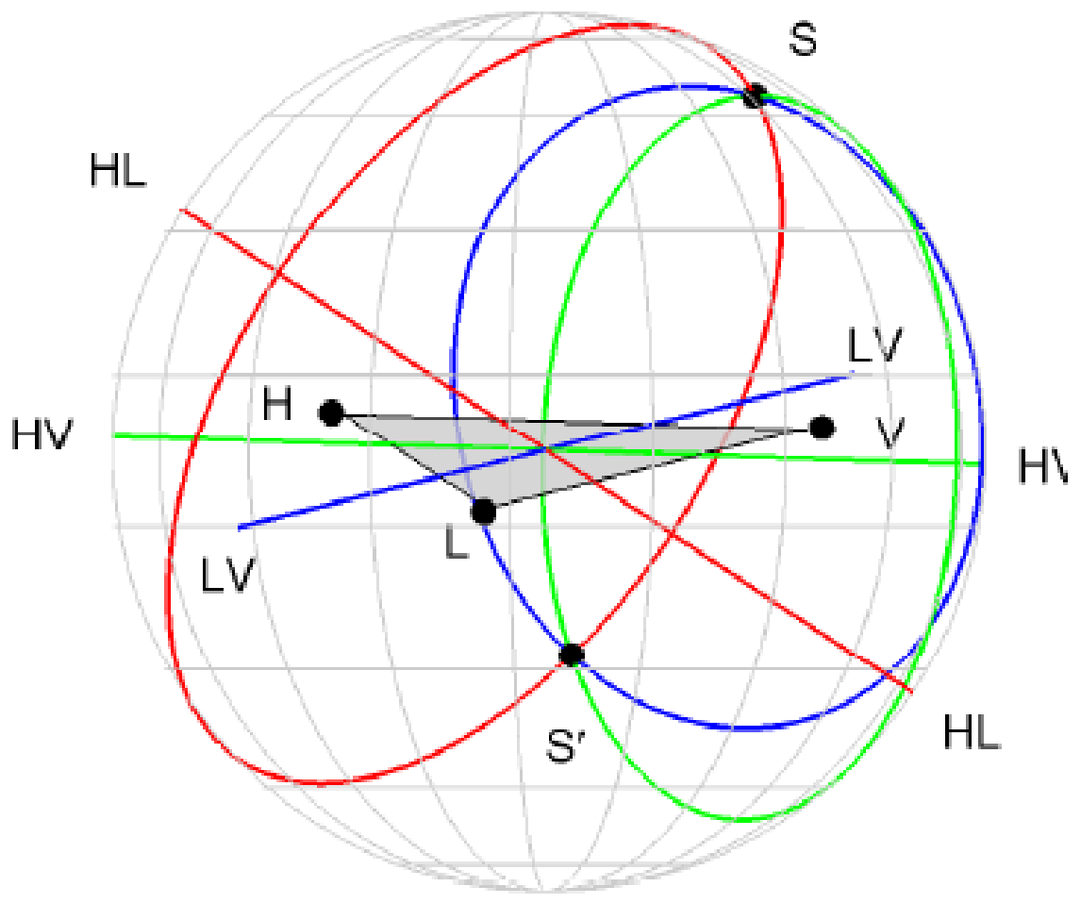
If we take the 3 distances
we want to connect them and find the central location
However, the distances were too long

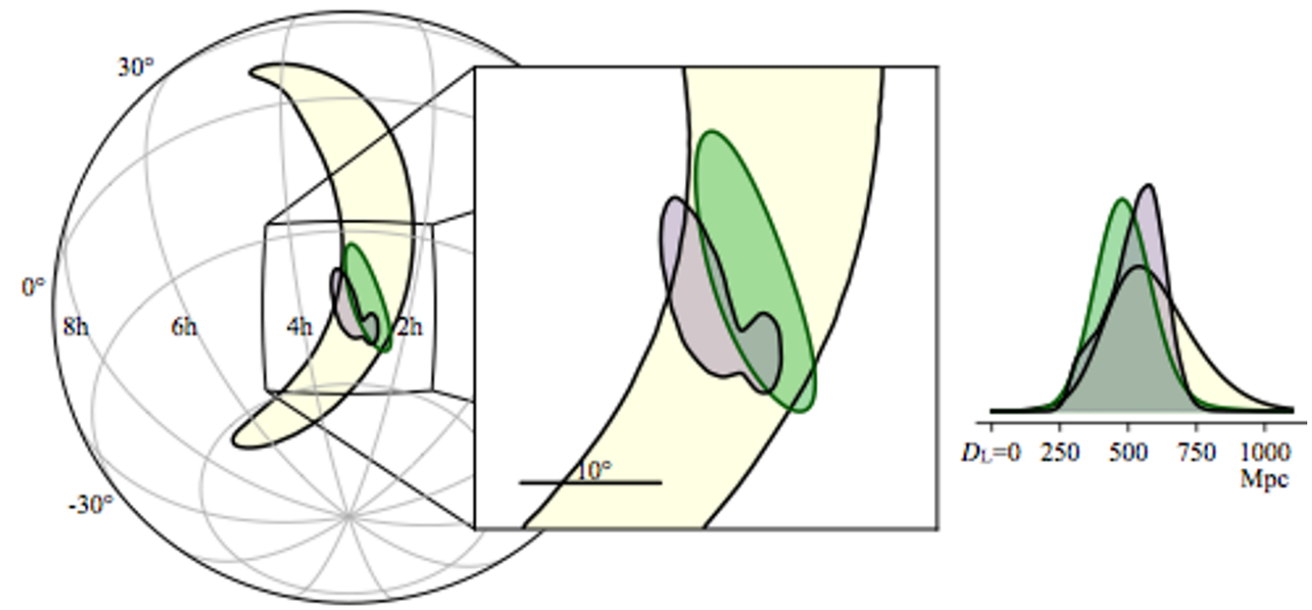


Caltech Ditch Day

The undergound tunnels

Triangulation for Sky Localization





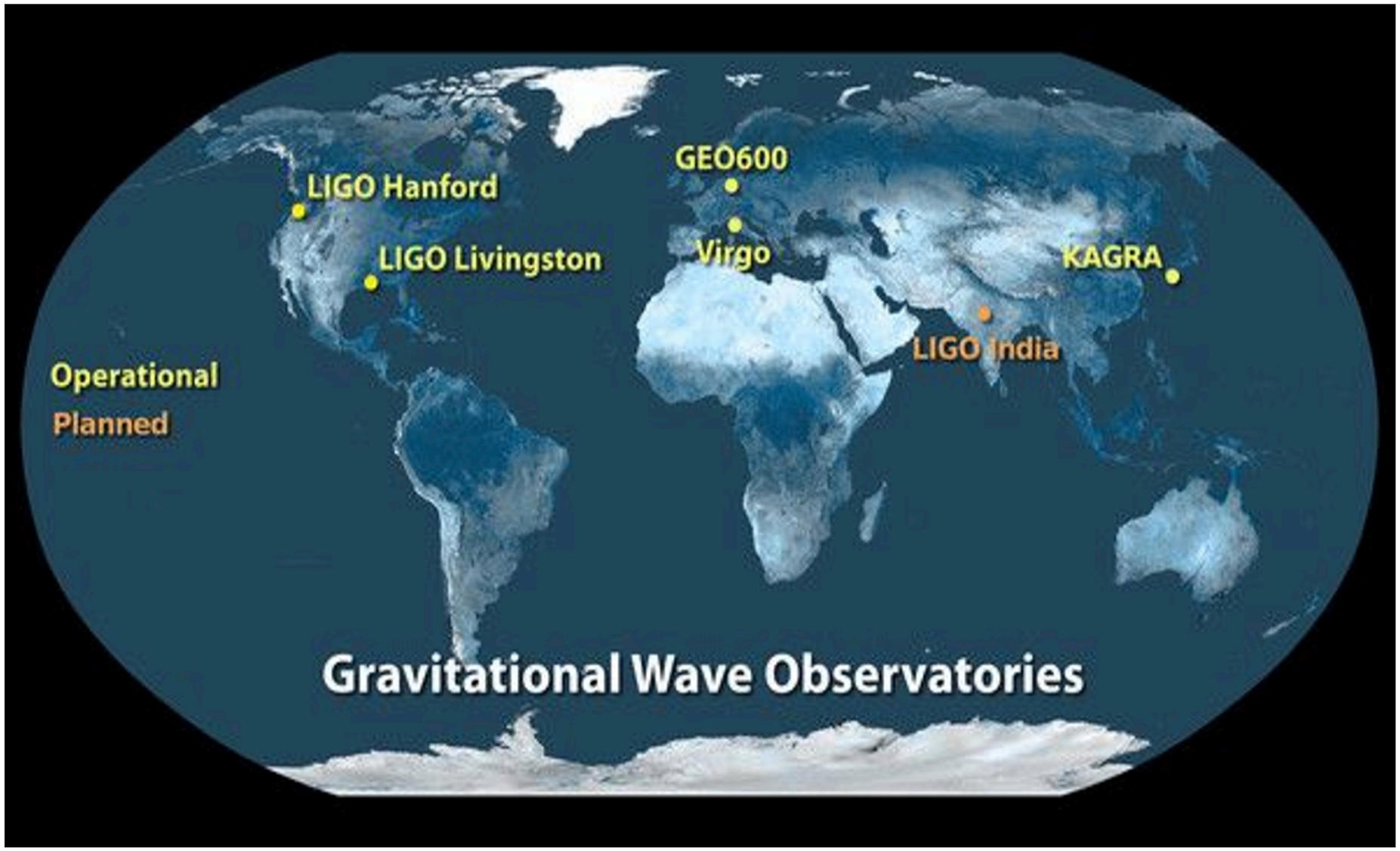
LIGO and Virgo Collaborations
Phys. Rev. Lett., 119:141101, 2017

2 Interferometers (LIGO)
3 Interferometers(HLV)
Final Slow PE

By align two or 3 interferometers we get a Δt, than we can point to sky

Gravitational Waves

International Gravitational
Wave Network to characterize
Gravitational Wave

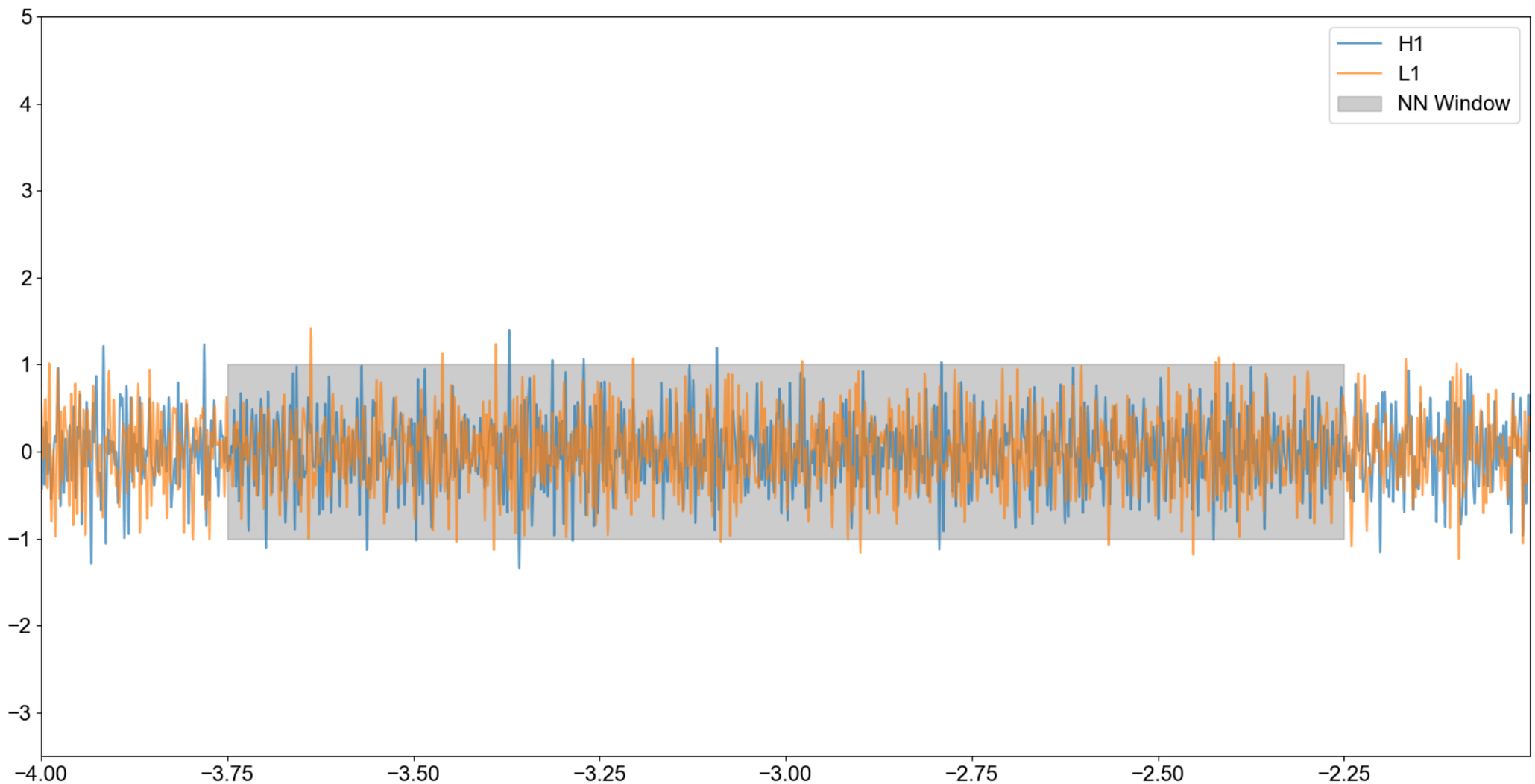


Slides

- See this link for animations:

- https://www.dropbox.com/s/44ew35qlz89xono/PCH_Lecture2_LigoAnims_8S50.pptx?dl=0

Time Series AI Architectures



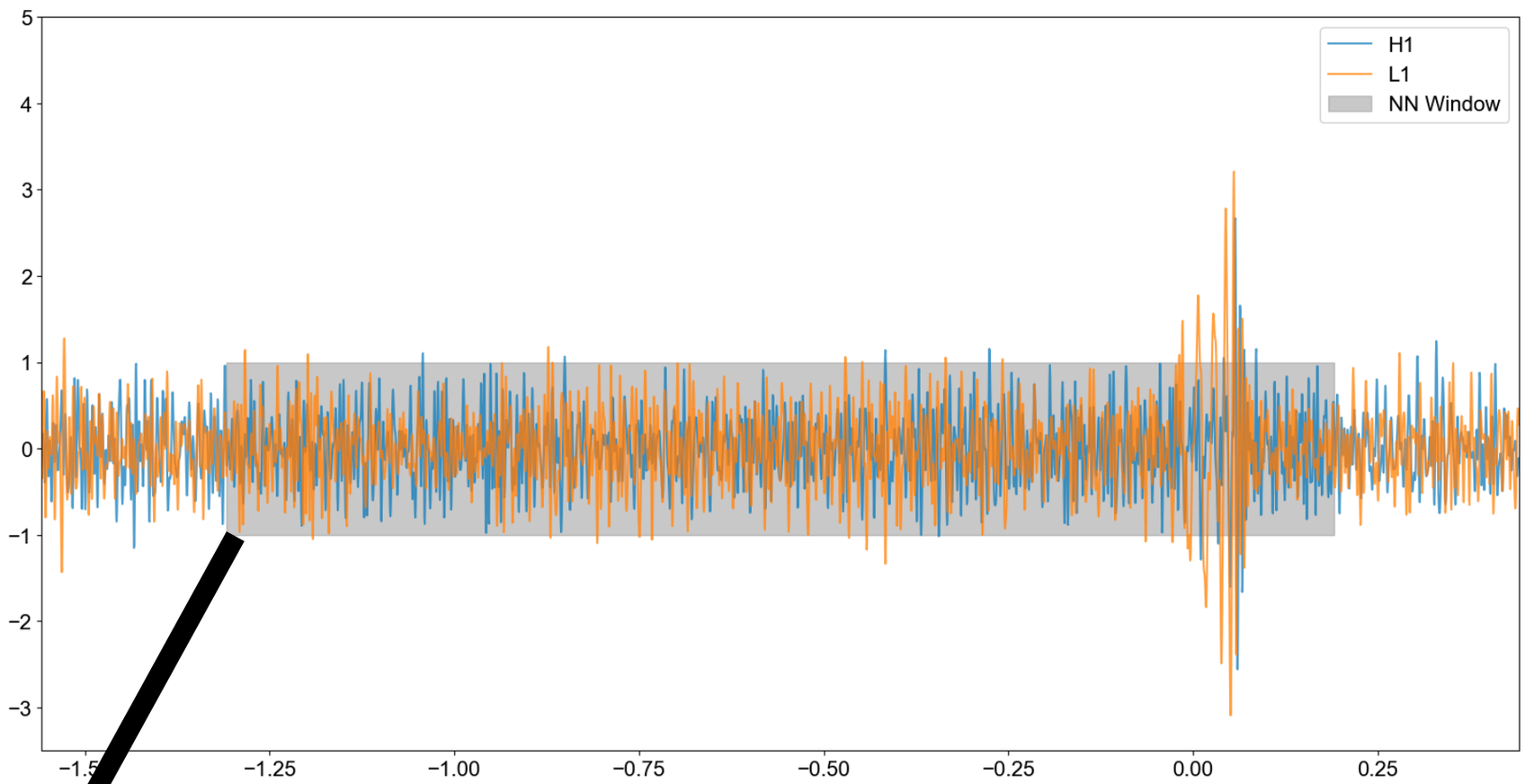
Data is time series from at least two detectors

We aim for a correlated signal

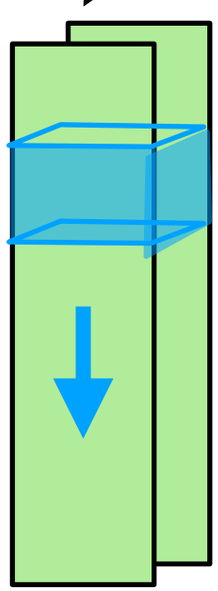
Sampling is taken@16384 Hz often reduce it down (1000s of inputs)

For LIGO we have 2 or 3 or 4 channels (LIGO/Virgo/Kagra)

Time Series AI Architectures



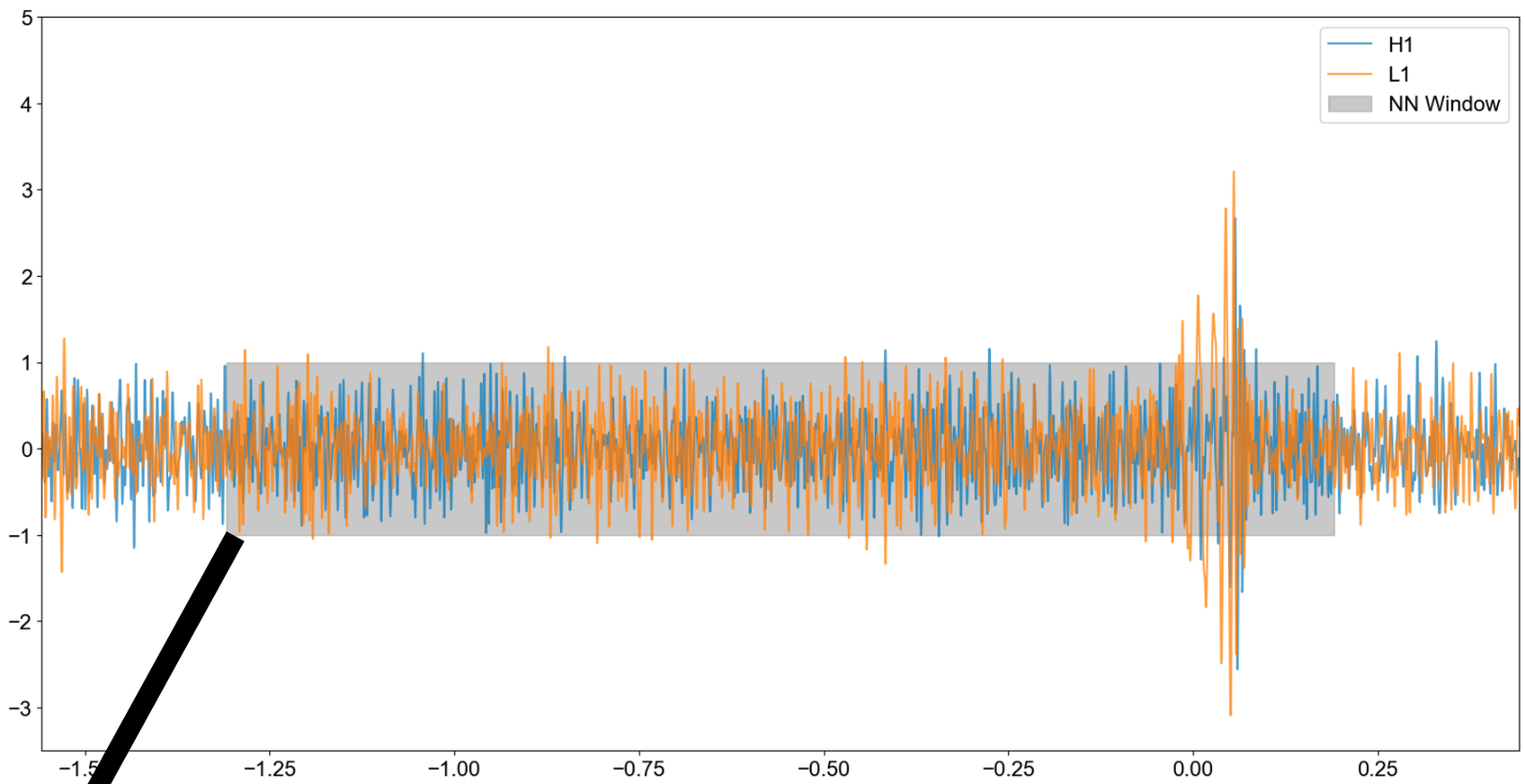
Time Series has flummoxed the AI world



Conv1d
Is a standard

Fourier Transform

Time Series AI Architectures



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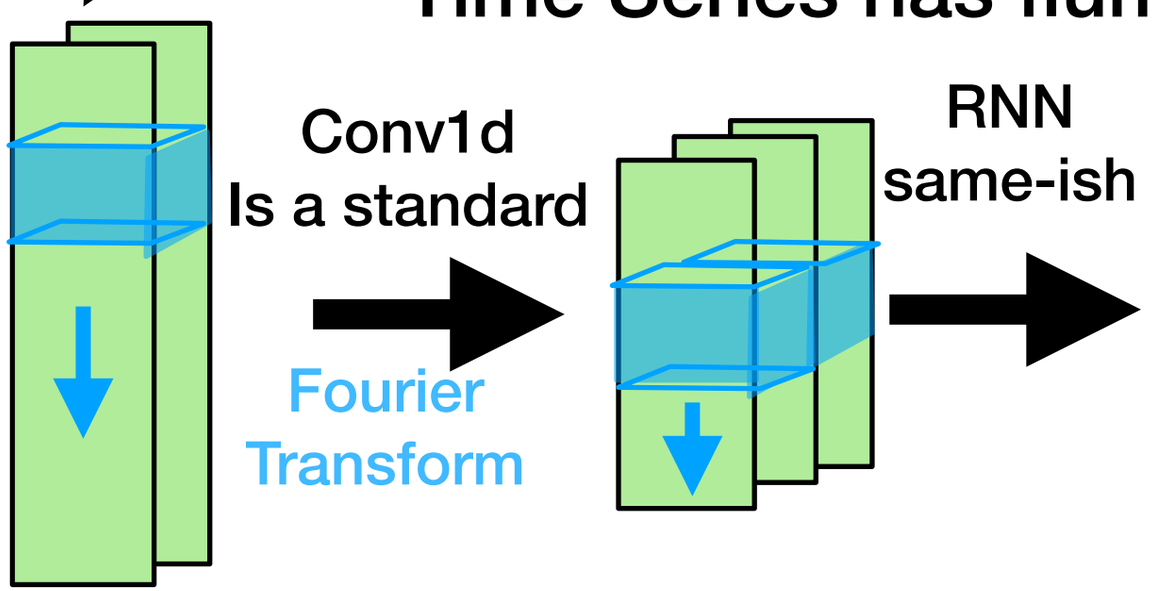
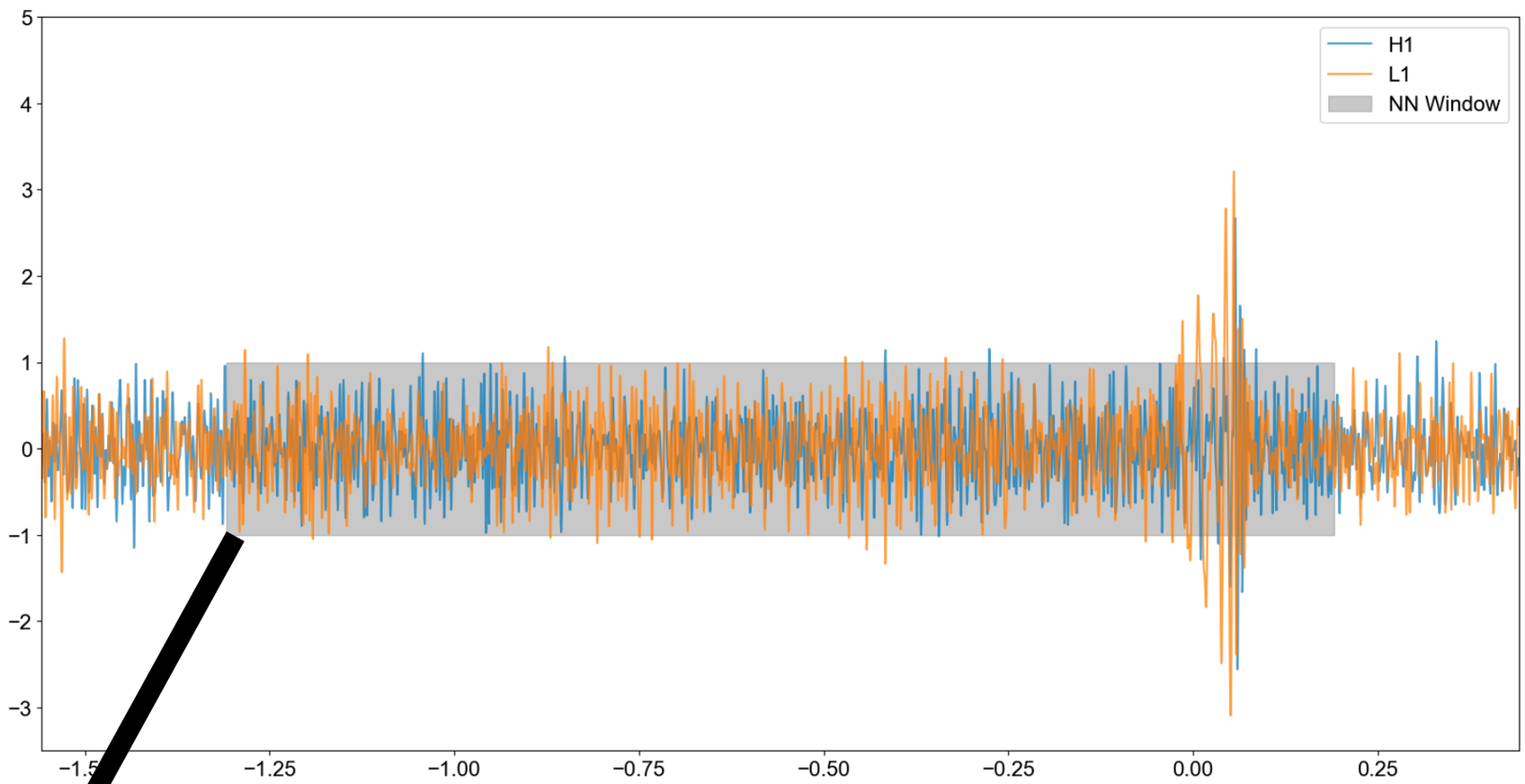


Time Series AI Architectures



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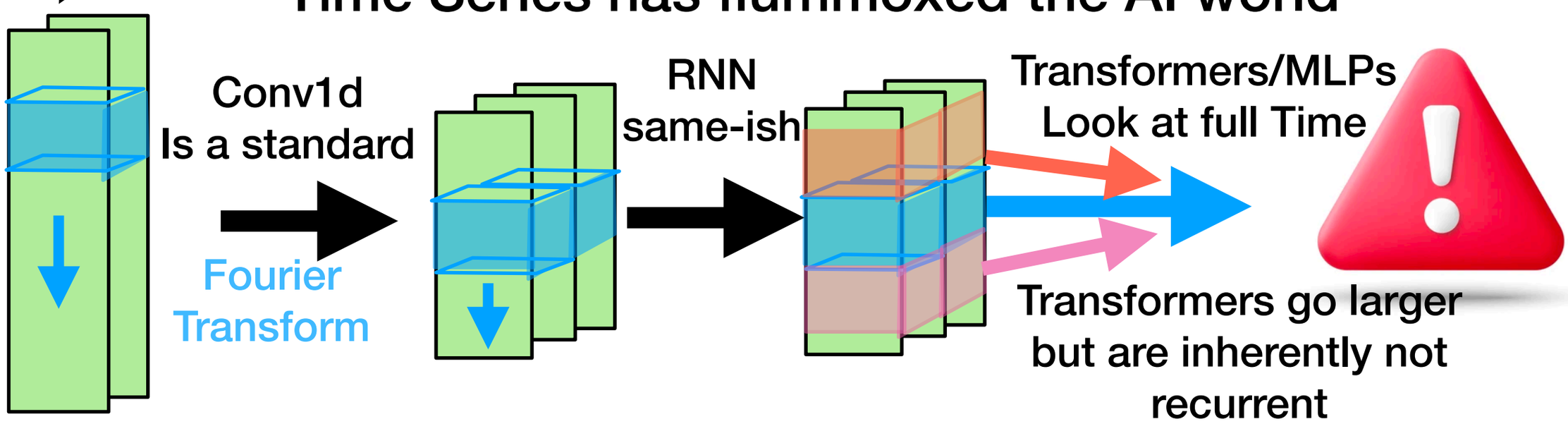
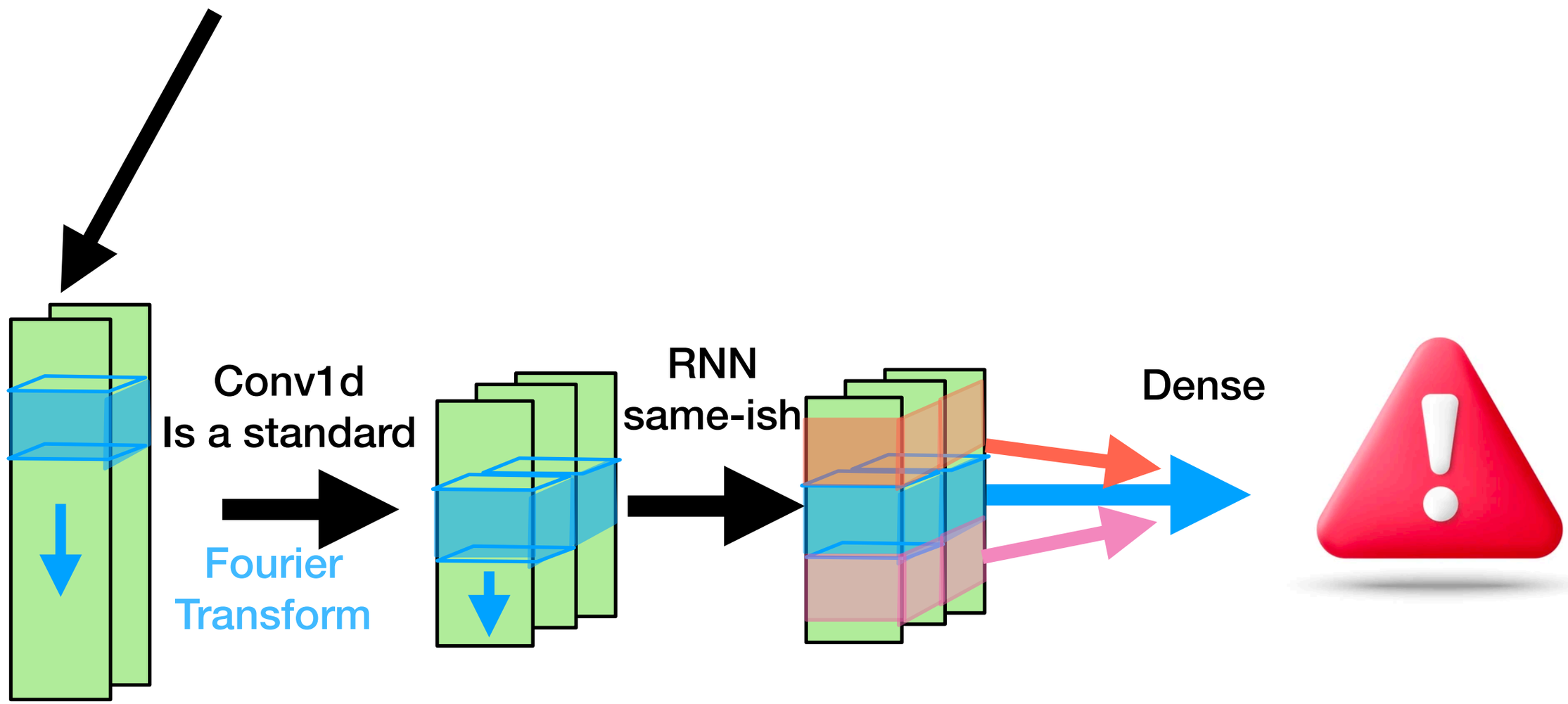


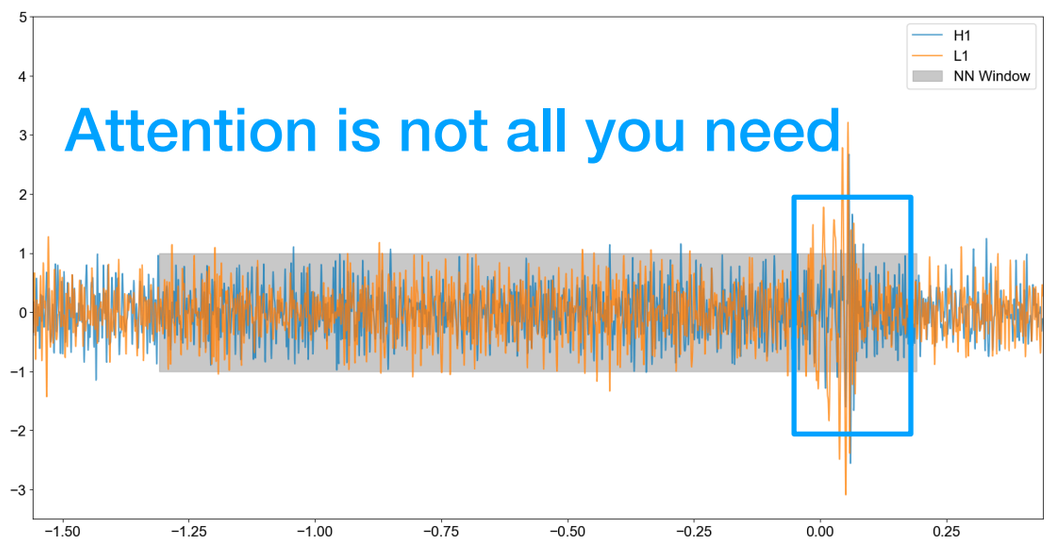
Time Series AI Architectures

This is our standard architecture
We will use variations of Conv1D + MLPs
for everything

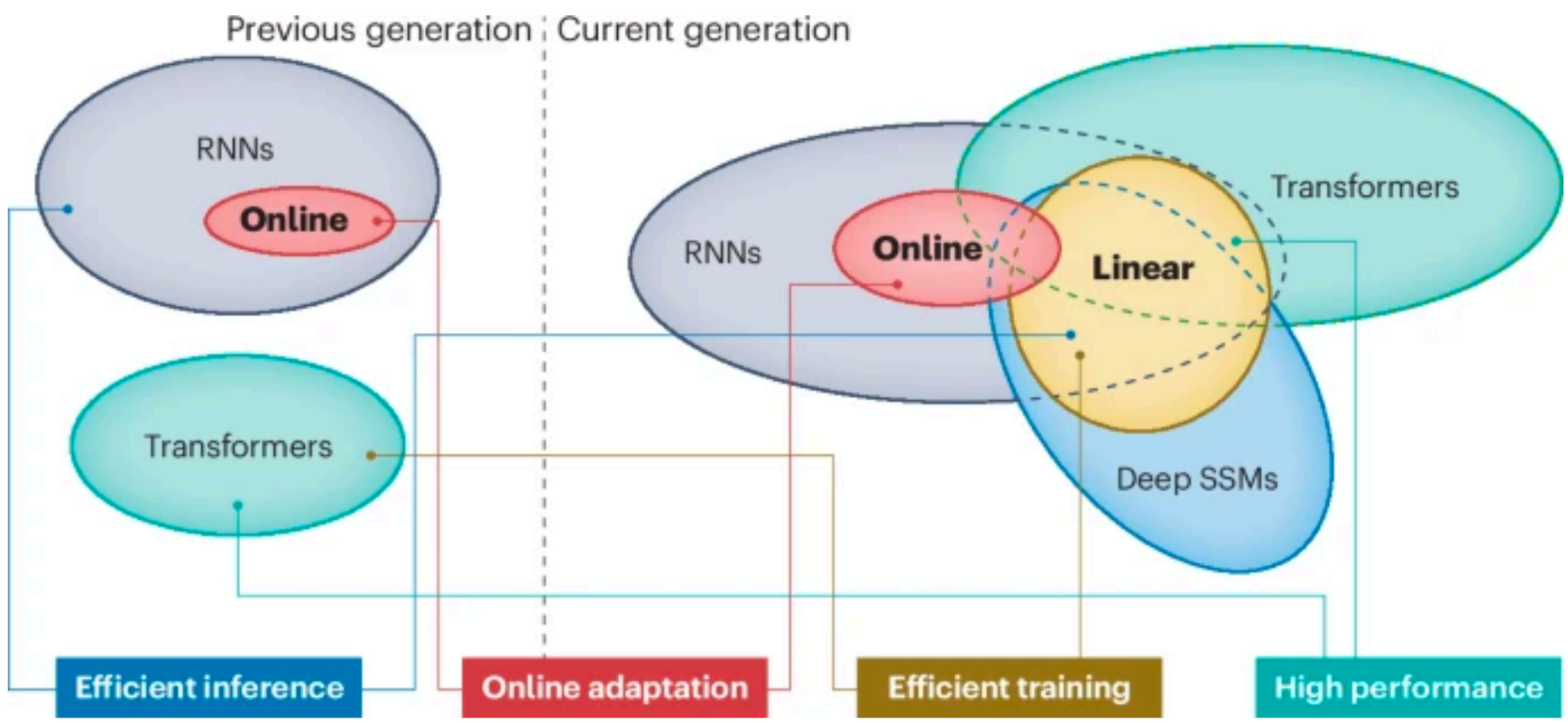
There is no clear “better” architecture for time series



Beyond Conv1D/RNNS/...



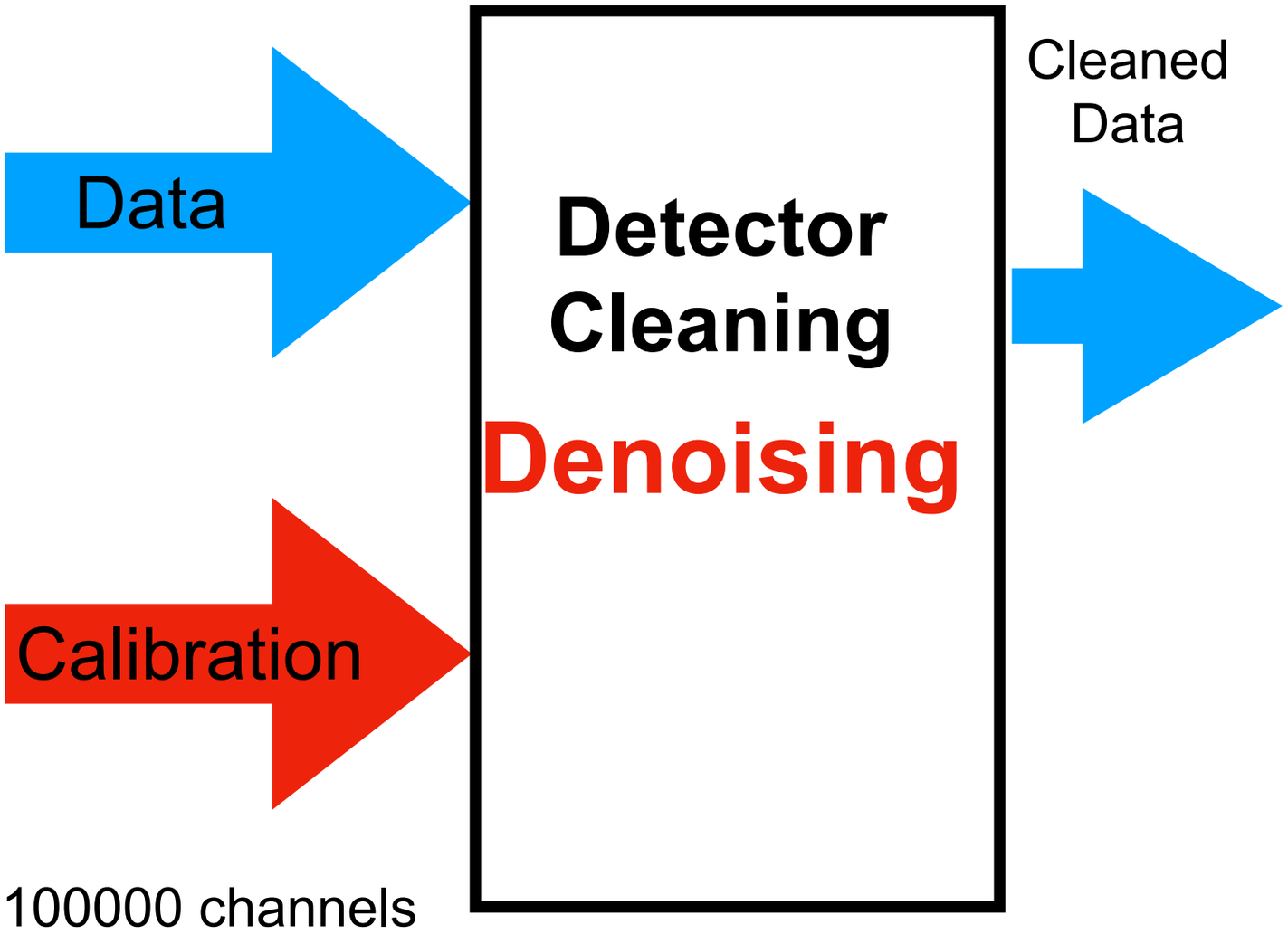
Recent literature: An emergence of combining recurrent strategies w/ Transformers into architectures that look at featurize over ranges of time series (e.g. State Space Models)



https://www.nature.com/articles/s42256-025-01034-6

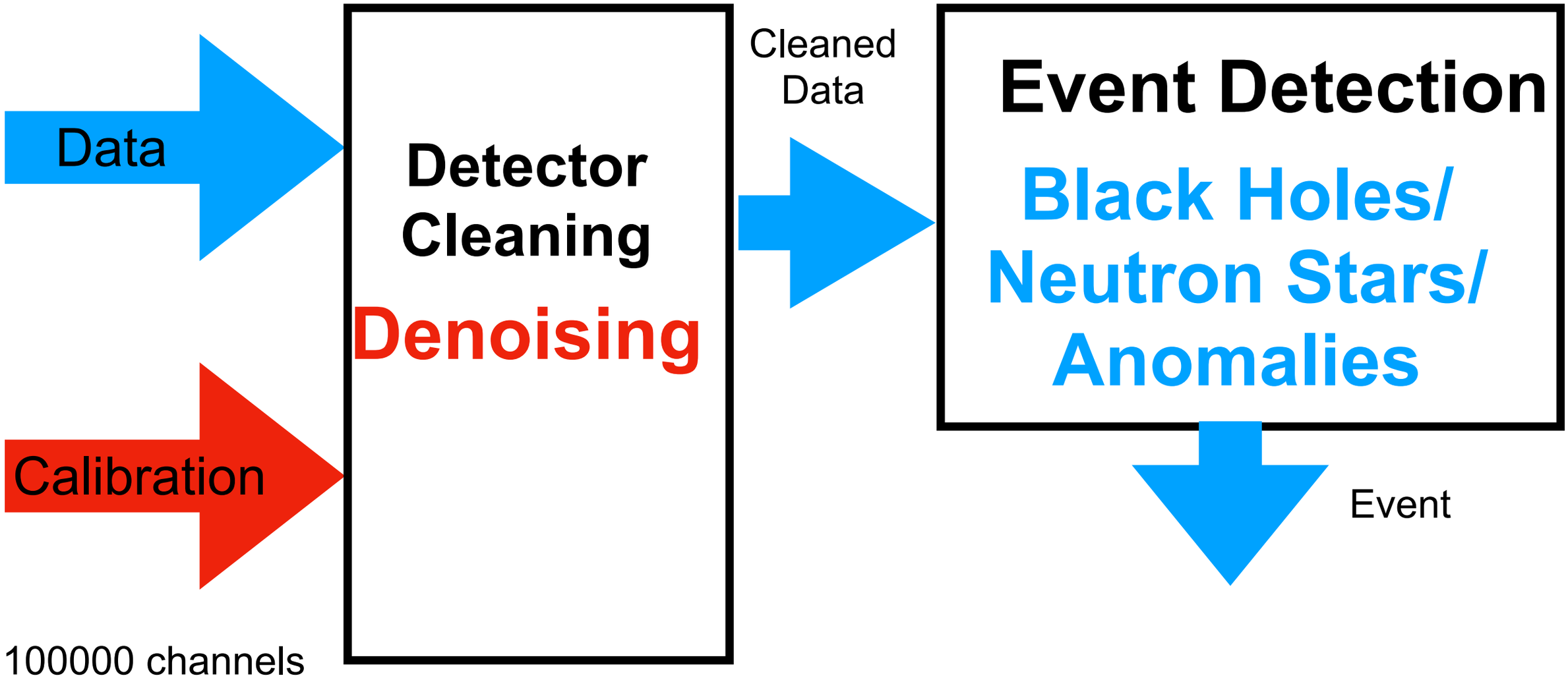
GW Data Workflow

GW Data Workflow



arXiv:2108.12430 (Nature)

GW Data Workflow



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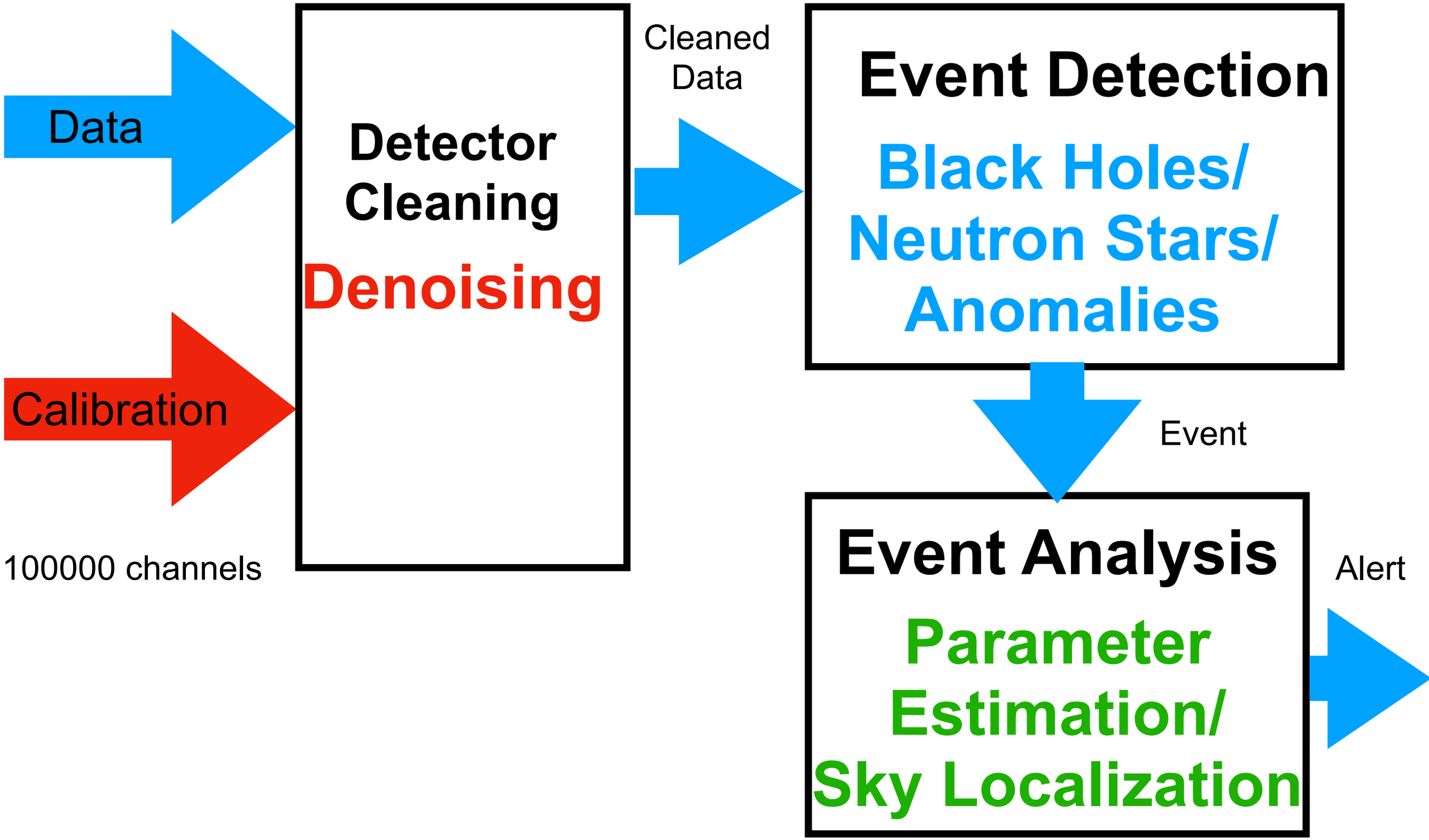
GW Data Workflow



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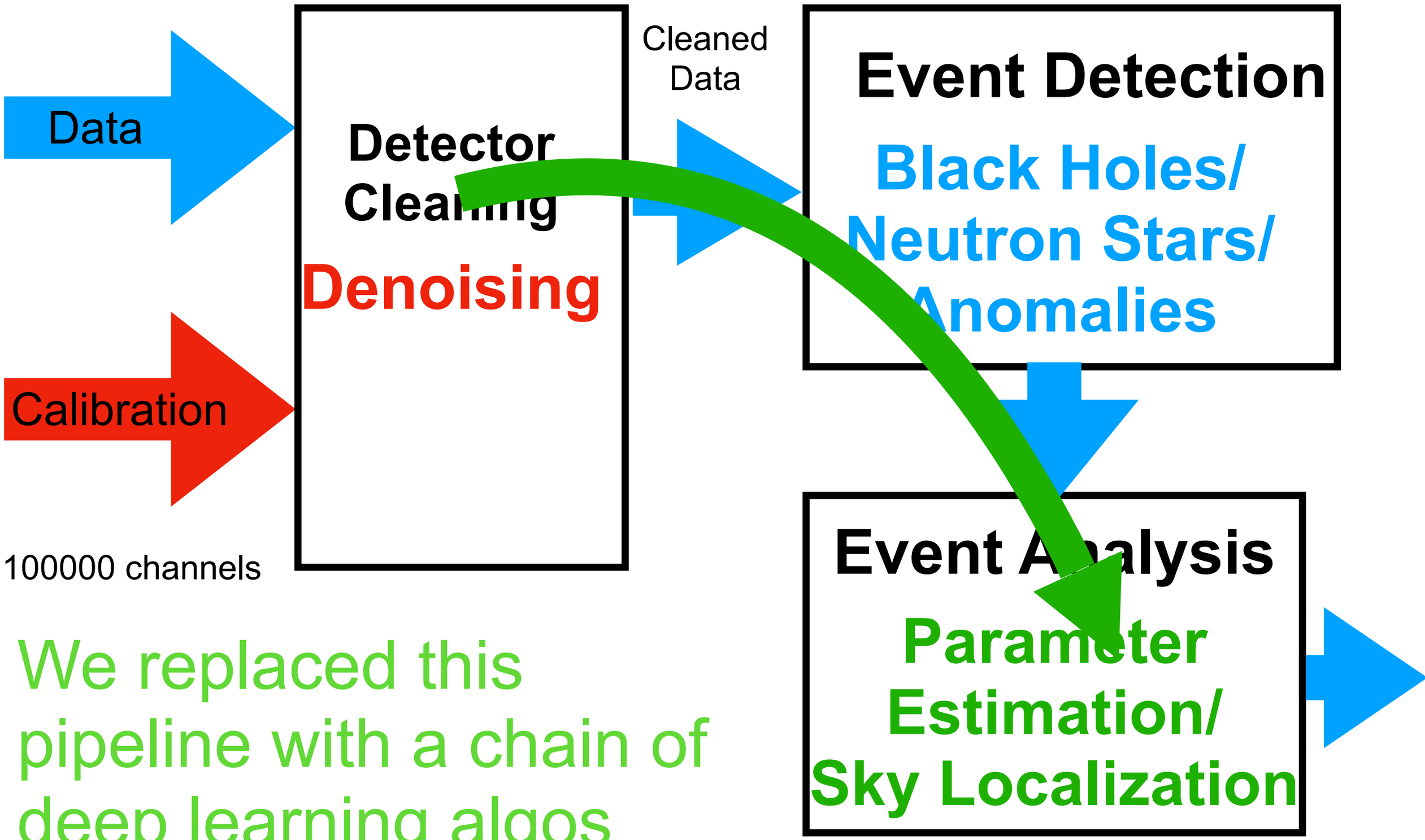
GW Data Workflow



We replaced this pipeline with a chain of deep learning algos

Current Workflow

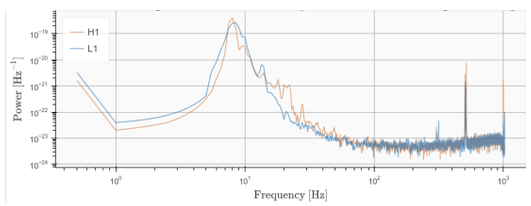
Data

8192 Hz/detector

Calibration

100000 channels
8192 Hz/channel

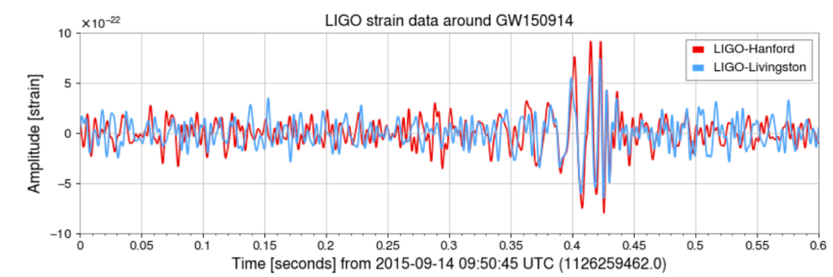
Detector Cleaning



Correlation On previous data

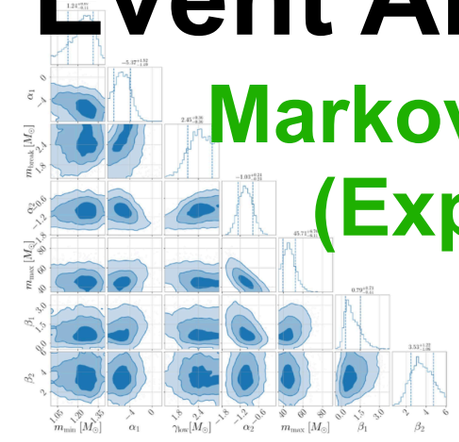
Cleaned Data

Event Detection



Fast Template Matching

Event Analysis



Markov chain MC (Expensive)

Current workflow
Uses (CPU) LIGO data grid
With rule based algorithms

Our Upgraded Workflow

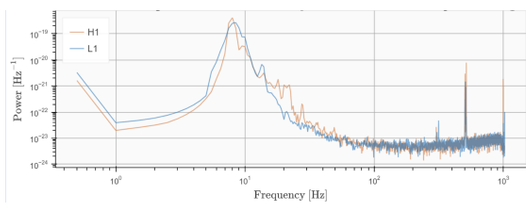
Data

8192 Hz/detector

Calibration

100000 channels
8192 Hz/channel

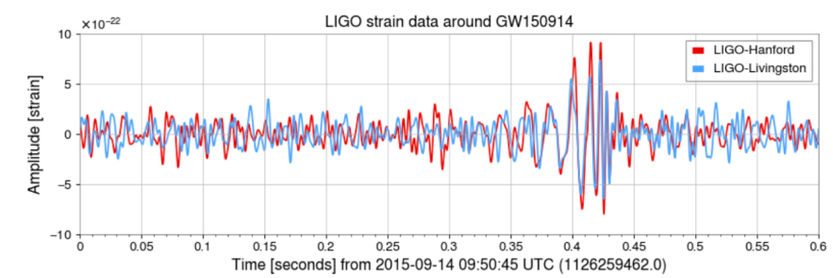
Detector Cleaning



DeepClean
NN based AE

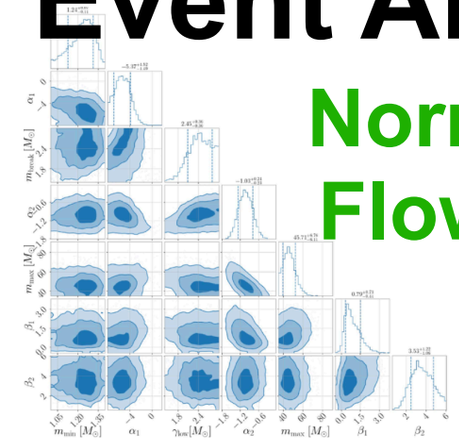
Cleaned Data

Event Detection



NN-based Algos
A-Frame/Neutron Star/GWAK

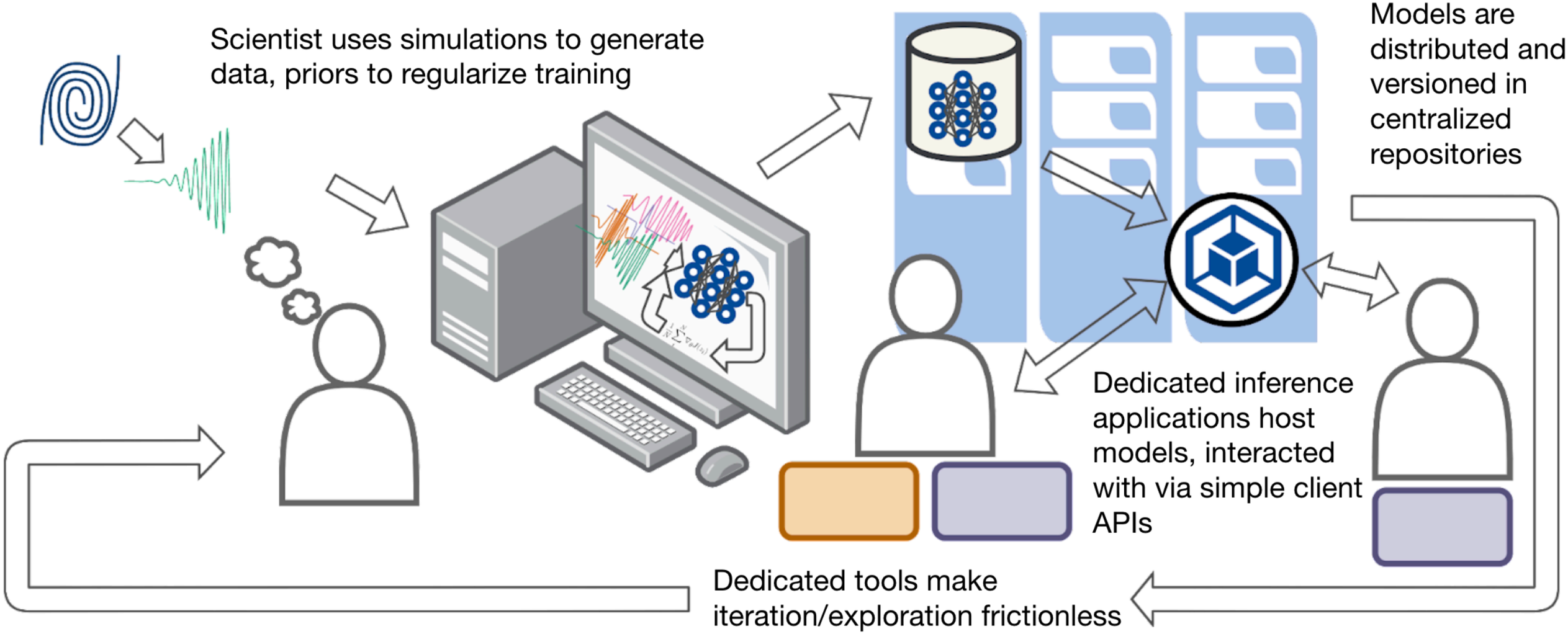
Event Analysis



Normalizing Flows (SBI)

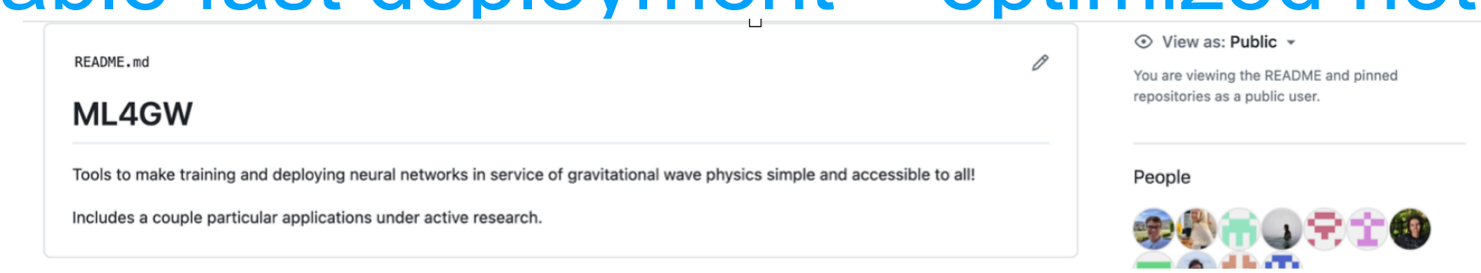
ML Based Workflow
Almost 100% GPU based
Only a handful of GPUs for real-time

MLOps Toolkit



ML4GW Toolkit

To enable fast deployment + optimized heterogeneity



ML Requirements

Training

- Load time-series data from disk and efficiently move it to GPU
- Leverage simulations to create robust datasets
- Implement signal processing operations on GPU

Inference

- Offline - produce predictions on O(months-years) of data
- Online - produce predictions on real-time data in O(ms)
- Stream time-series data into NN
- Heterogeneous backends/dtypes

Design Goals

Intuitive - maps on to familiar, physically meaningful concepts

Composable - hierarchical layers of abstraction support new use cases seamlessly

Integrated - ecosystem of tools following same standards and nomenclature

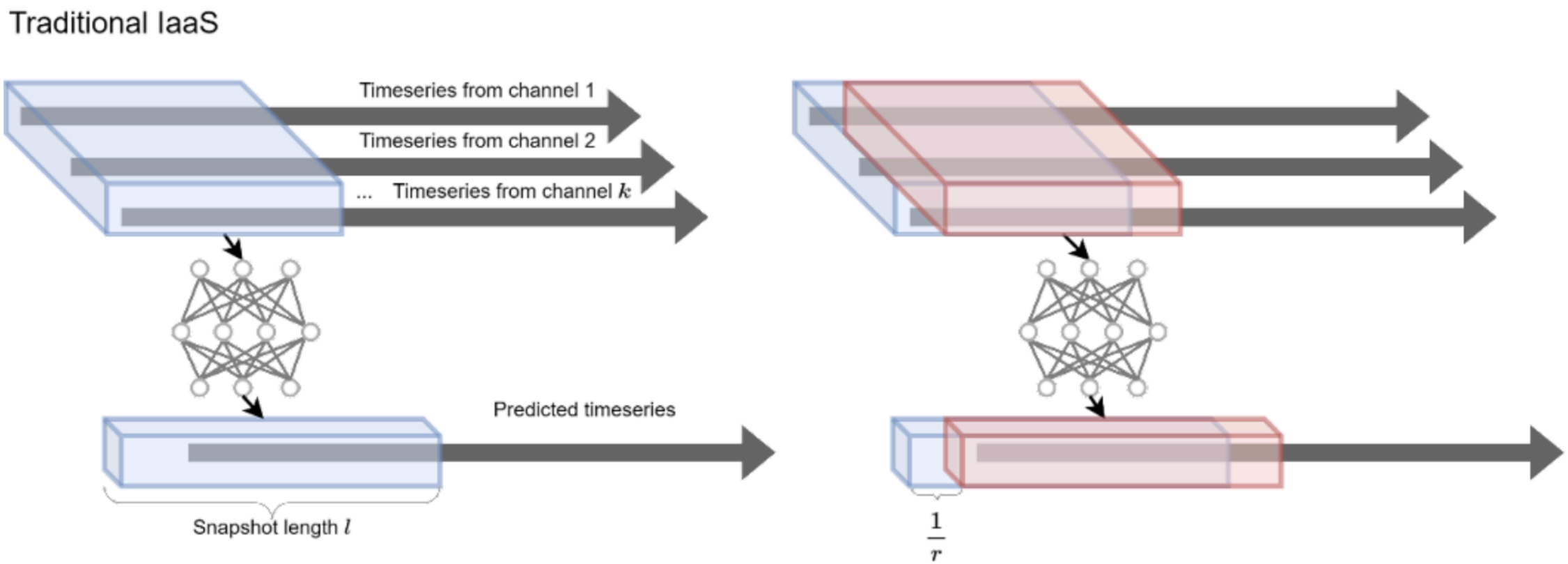
Efficient - make the most out of parallel computing resources

Example: Stateful Caching

Conventional Processing of Time series data

First ML Inference on data

Second ML Algorithm for data

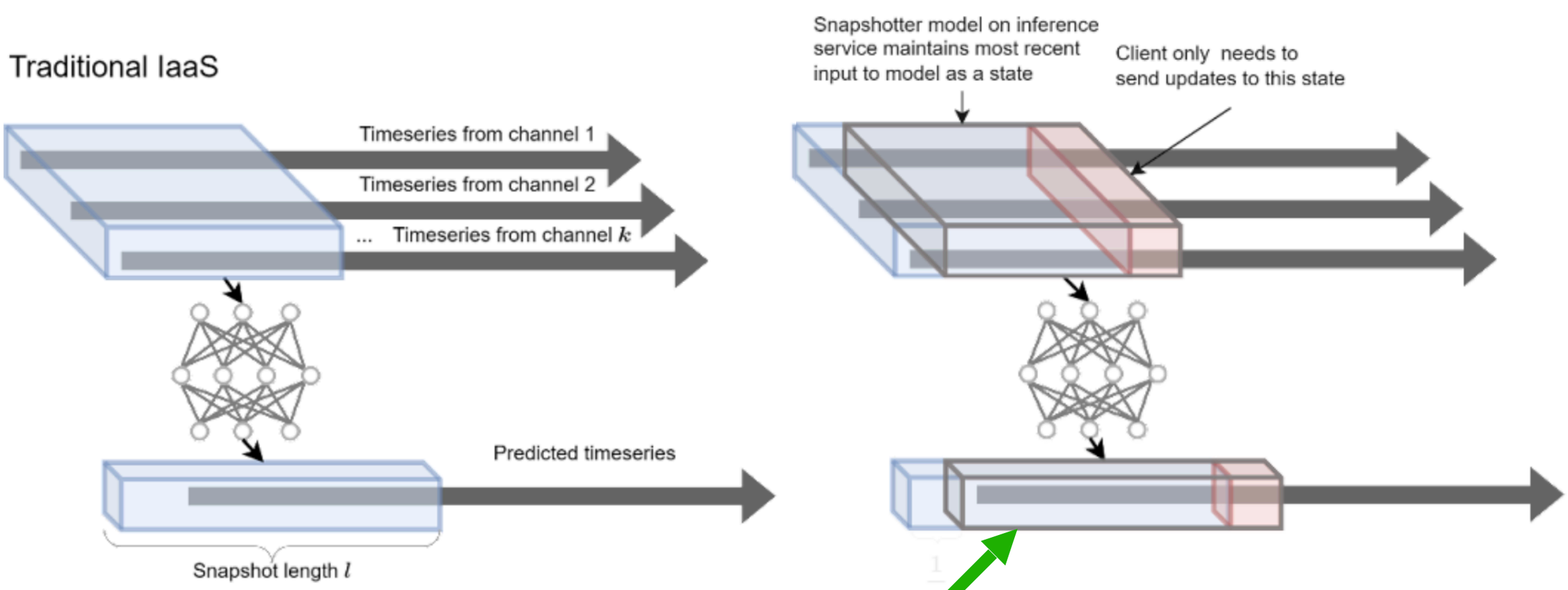


Example: Stateful Caching

Optimzied Processing of Time series data

First ML Inference on data

Second ML Algorithm for data

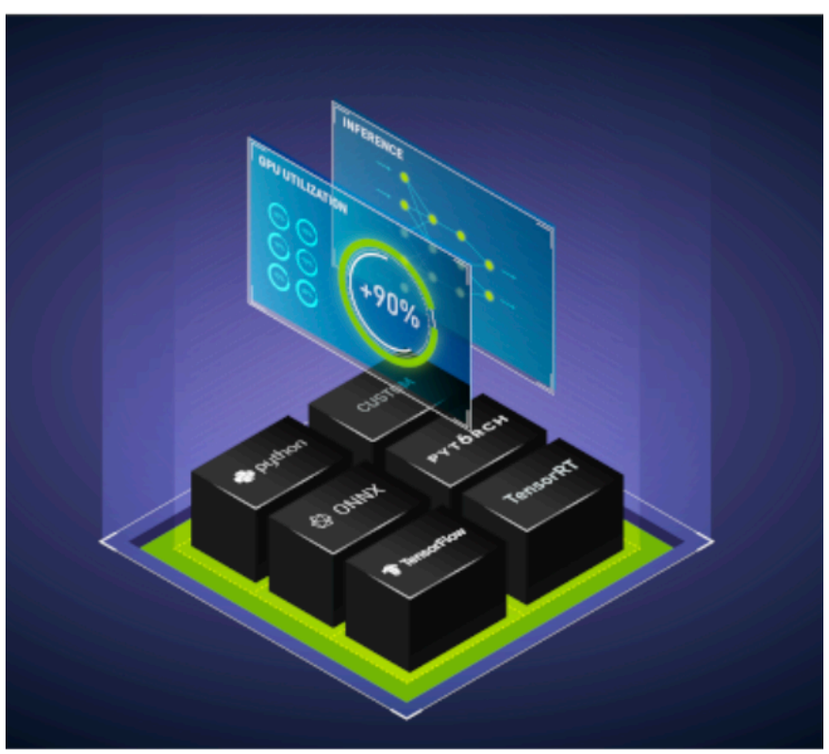


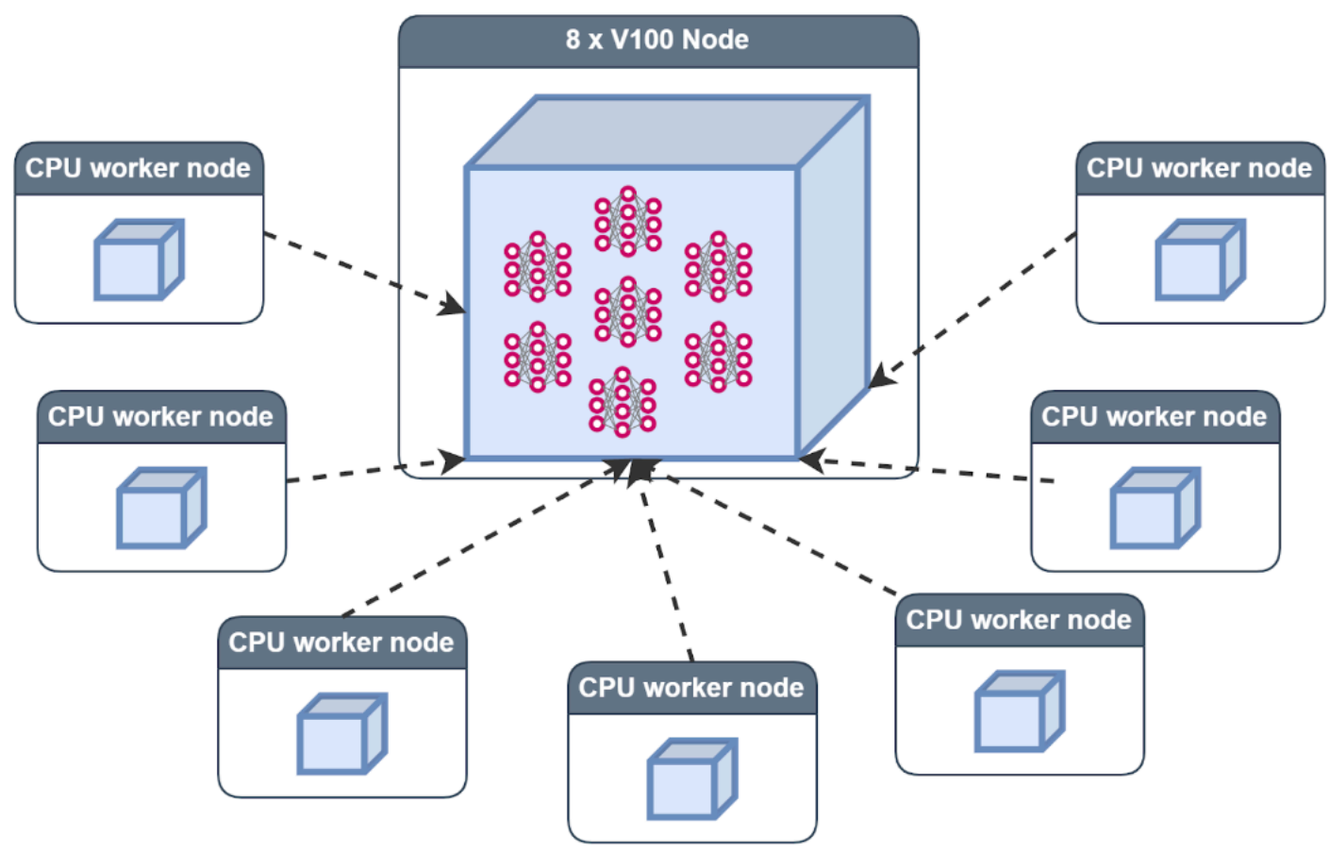
Cache on the GPU

Cacheing+optimizations speeds up ML by 10x over vanilla pytorch

SuperSONIC Resource Balancing

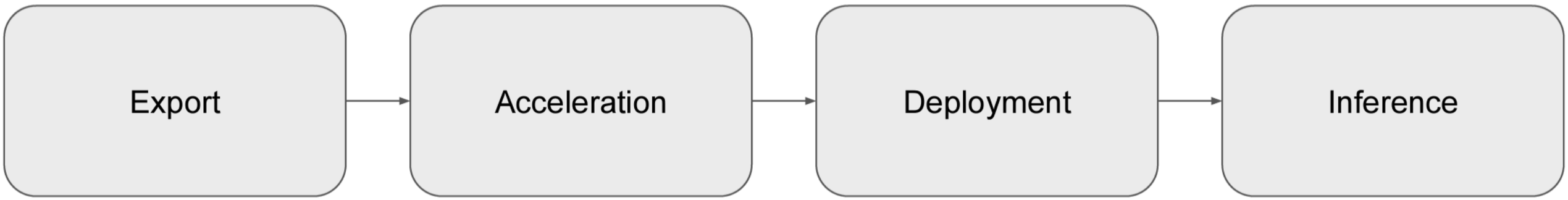
- To ensure optimized use of resources
  - We rely on Nvidia Triton inference as a service paradigm
  - Off the shelf standard tool for deployment
    - Servers built within Kubernetes can balance resourcs





Hermes: Inference -as-a service deployment

https://github.com/ML4GW/hermes



- Managing model repository
- Pythonic interfaces to protobuf configs
- Simple support for stateful streaming models
- Supports Torch and TensorFlow export

- Conversion of Torch models to ONNX
- ONNX → TensorRT conversion with FP16 support

- Python contexts for deploying a local inference service
- Throughput and latency metrics monitoring service

- Asynchronous inference request submission and response handling
- Input/output shape/dtype inference

Hermes is our python package for end to end inference-as-a service

Computing Ecosystem

RAY

APPTAINER

PyTorch Lightning

luigi

law

luigi analysis workflow

- Ray: Handle distribution of CPU brokers for data
- PyTorch Lighting: Optimized training and model development
- Apptainer: containerization to enable maximum flexibility
- Luigi: lightweight task execution, Kubernetes support contrib (Spotify)
- LAW: Wrapper for Luigi to enable Condor/Slurm support (HEP)
- Kubernetes for distribued server balance

Open source tools some from industry

ML in GW Processing

Online

Real-time analysis with goal of alerting electromagnetic astronomers (MMA) of significant events

Detect events → Localize on Sky → Send public alerts

Main consideration is ***latency***

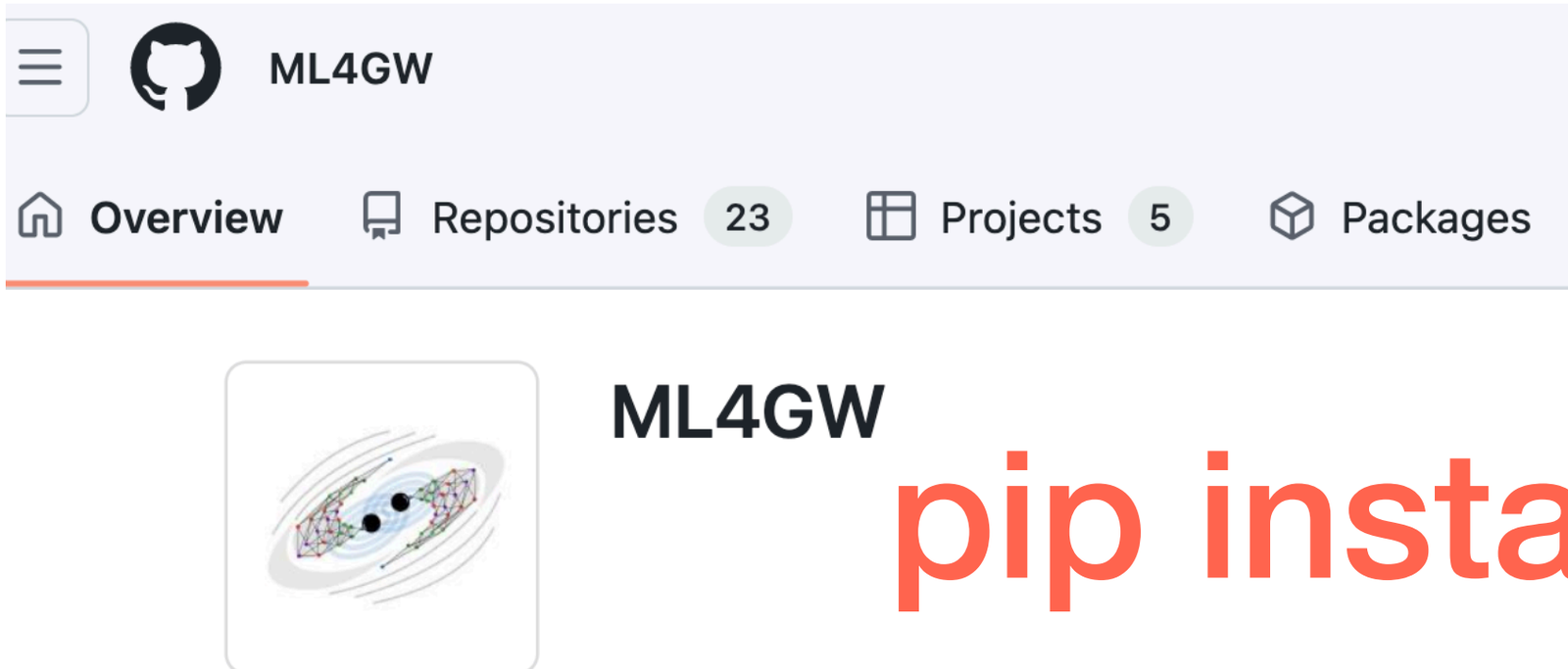
Offline

Large scale analysis of archival data for

- End to end searches
- Validating new methods, performing new research

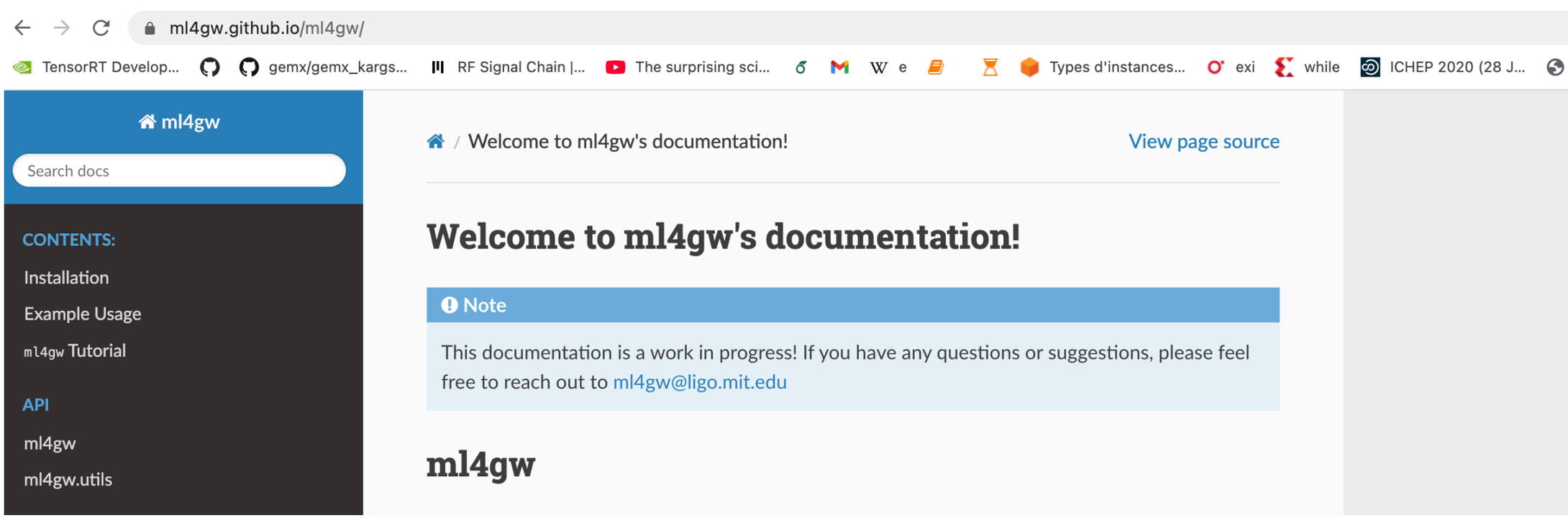
Main consideration is ***throughput***

Feel Free to Install

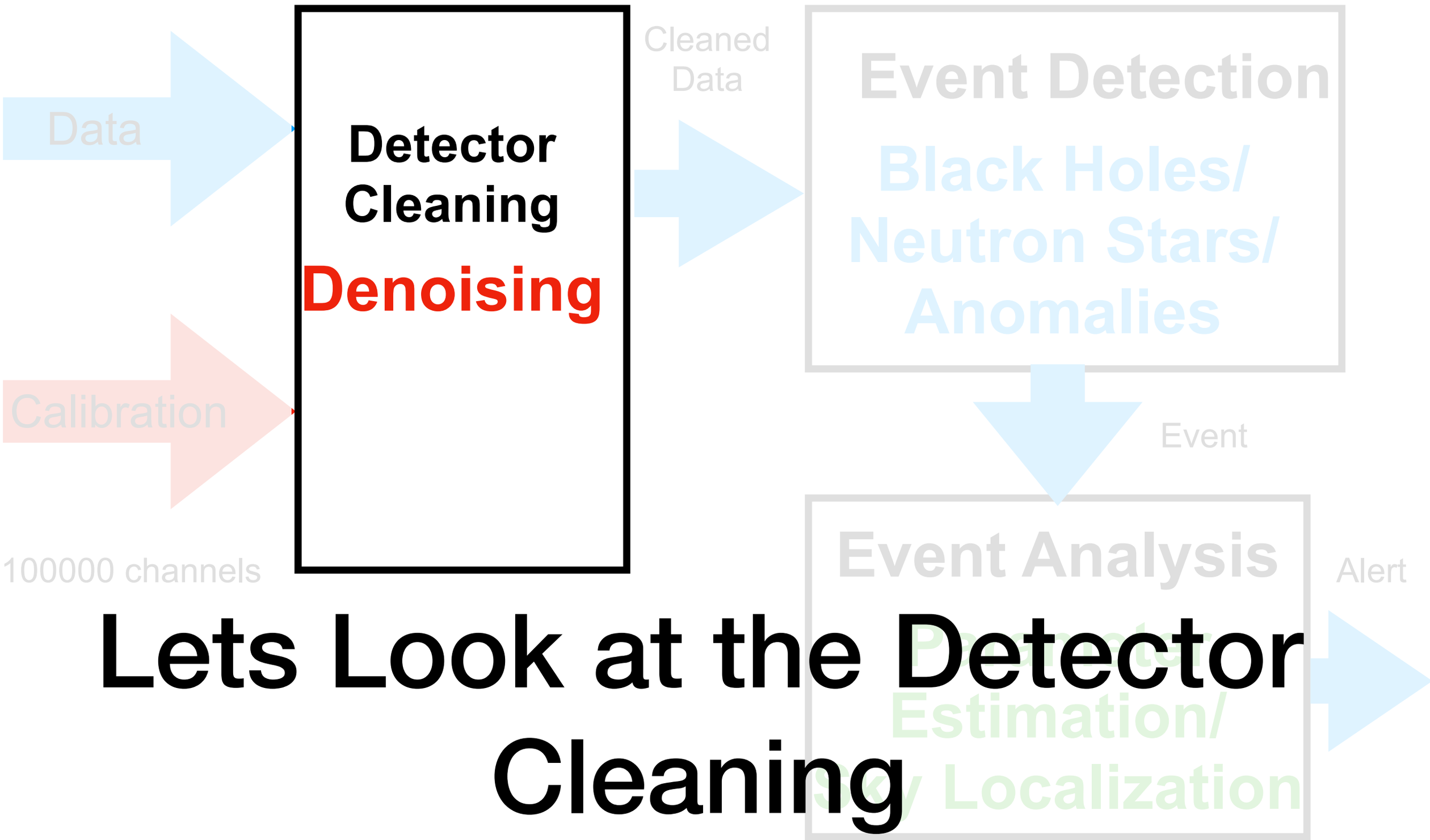


pip install ML4GW

https://github.com/ML4GW https://ml4gw.github.io/ml4gw/



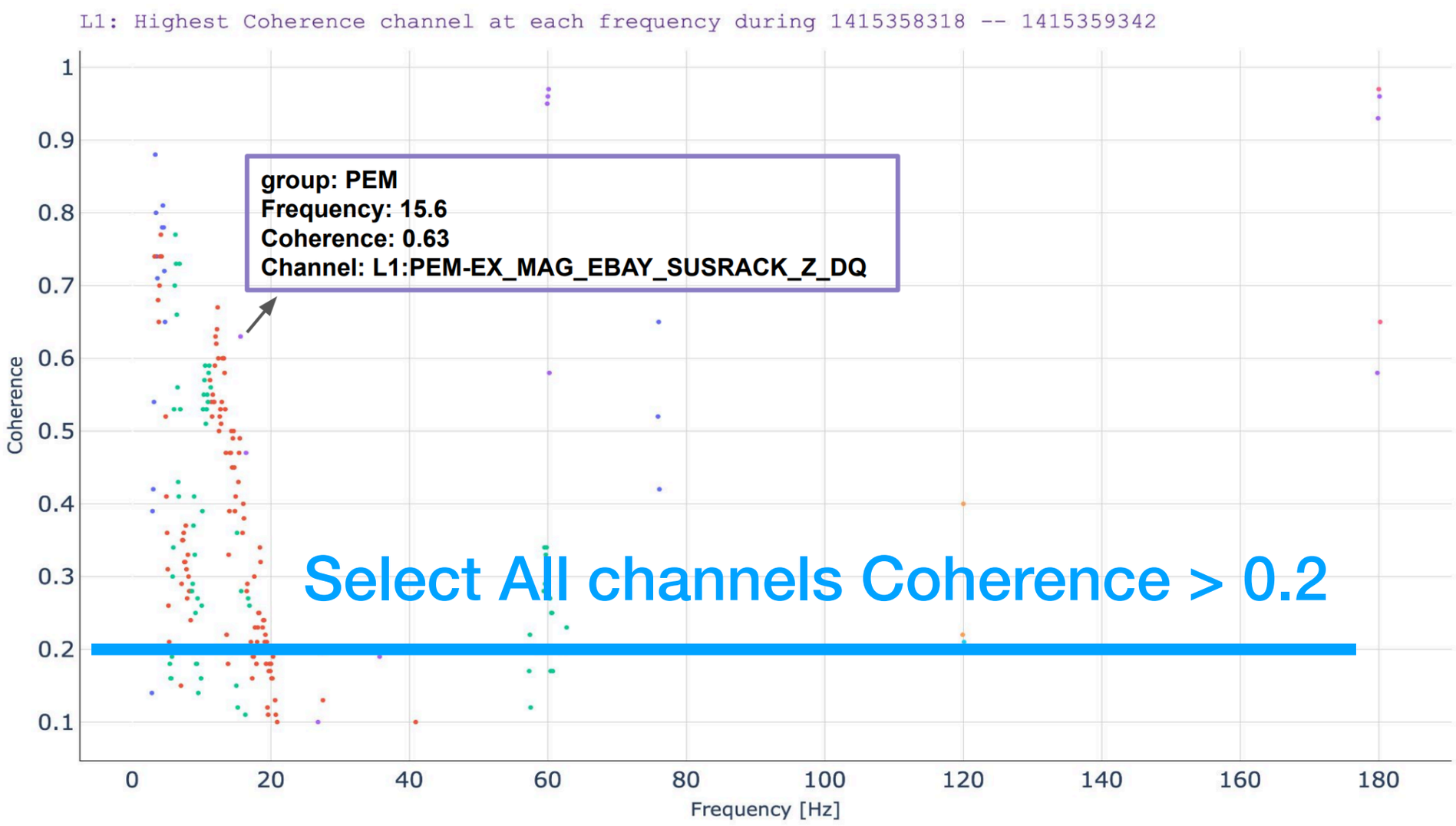
GW Data Workflow



Lets Look at the Detector Cleaning

https://arxiv.org/pdf/2501.04883

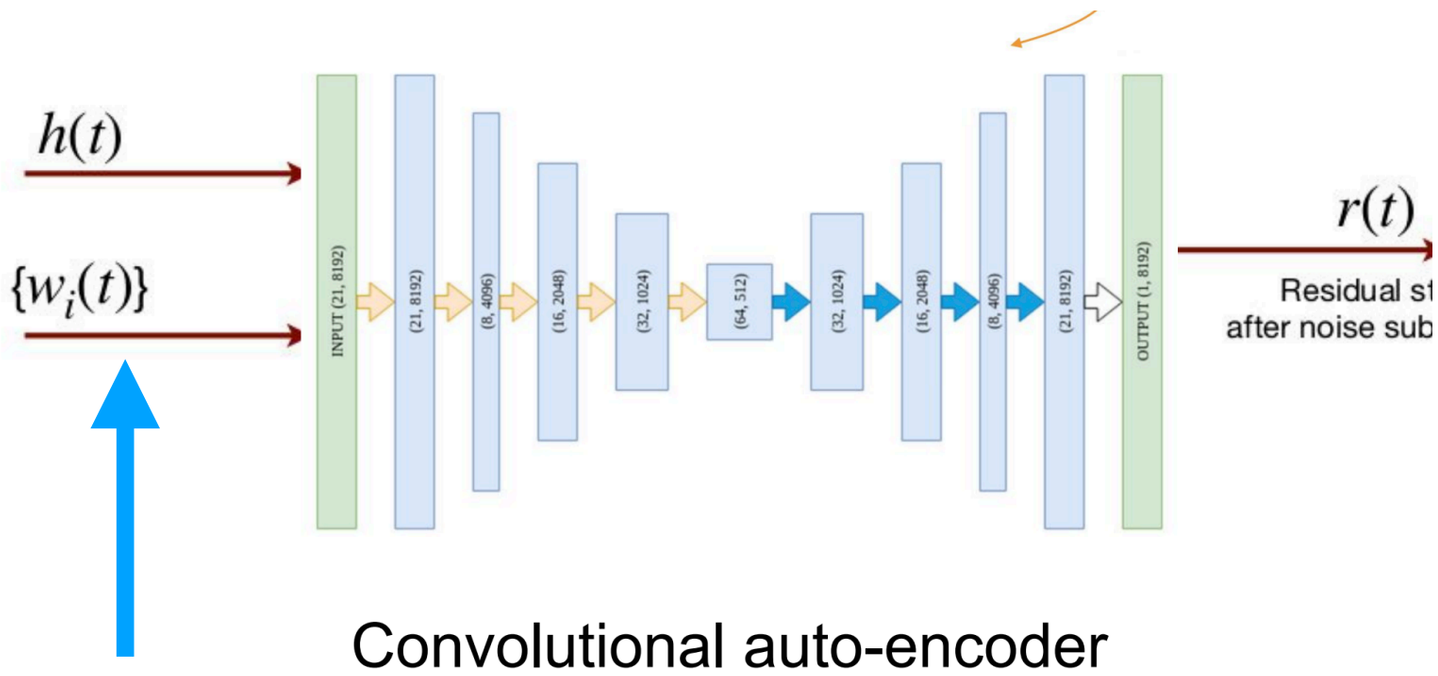
Deep Clean: Step1 Get Inputs

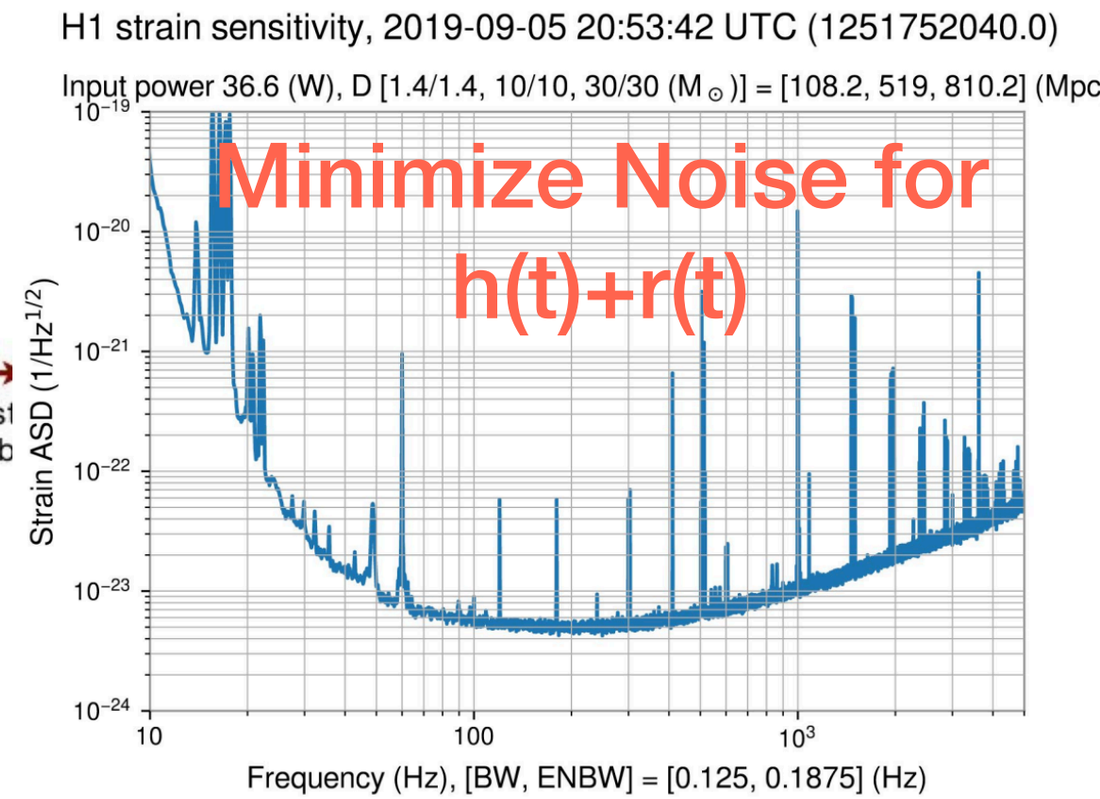


Scan 1000 auxiliary channels for correlations with strain
Take the(O(50)) channels with a non-zero linear correlation
Do this in bins of frequency from 10-200 Hz

https://arxiv.org/pdf/2501.04883

Deep Clean: Step2 Train



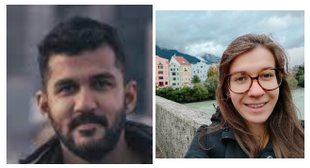


Witness channels

```
H1:ASC-CSOFT_P_OUT_DQ
H1:PEM-CS_MAG_LVEA_OUTPUTOPTICS_X_DQ
H1:ASC-CHARD_Y_OUT_DQ
H1:ASC-DHARD_Y_OUT_DQ
H1:ASC-DSOFT_P_OUT_DQ
H1:PEM-CS_MAG_EBAY_LSCRACK_X_DQ
H1:LSC-POP_A_RF45_I_ERR_DQ
```

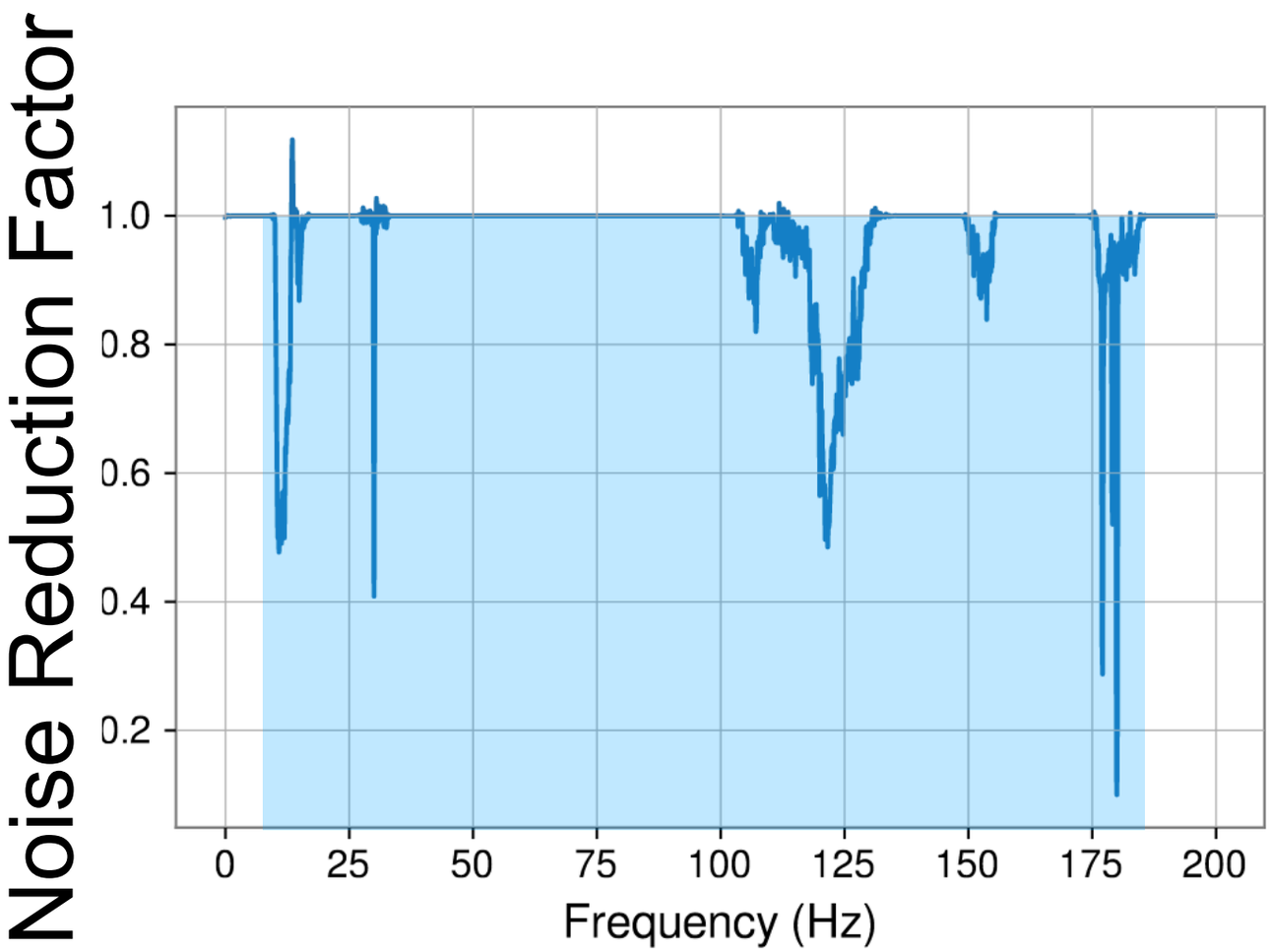
Train a network with these inputs and output residual:

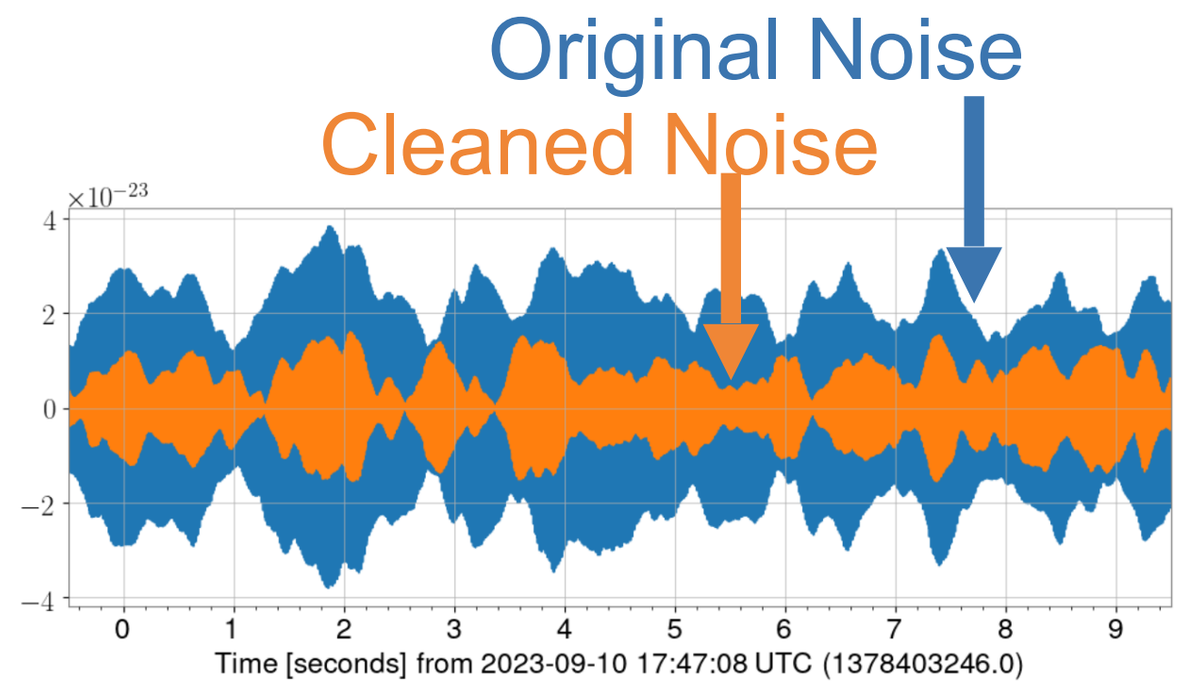
Our loss is to minimize correcte data (h(t)+r(t)) in Fourier Space



https://arxiv.org/pdf/2501.04883

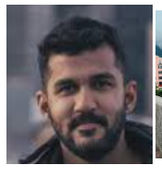
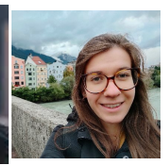
Deep Clean: Step3 Apply to data





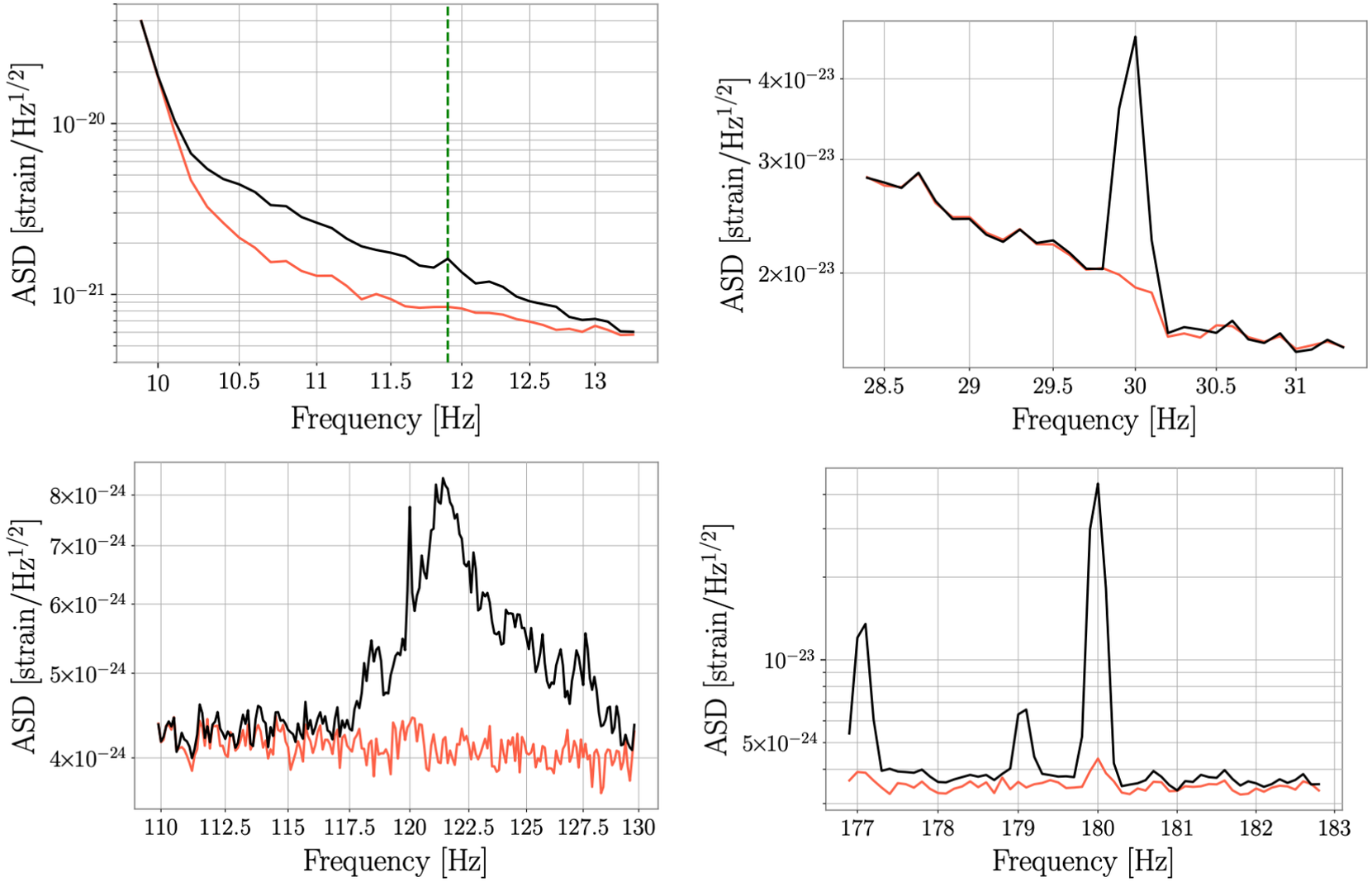
We actually train many networks in different frequency bins

Future Algos, will hopefully consolidate this work

https://arxiv.org/pdf/2501.04883

DeepClean: Does it work?

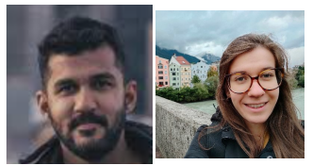


Removing many critical noise sources

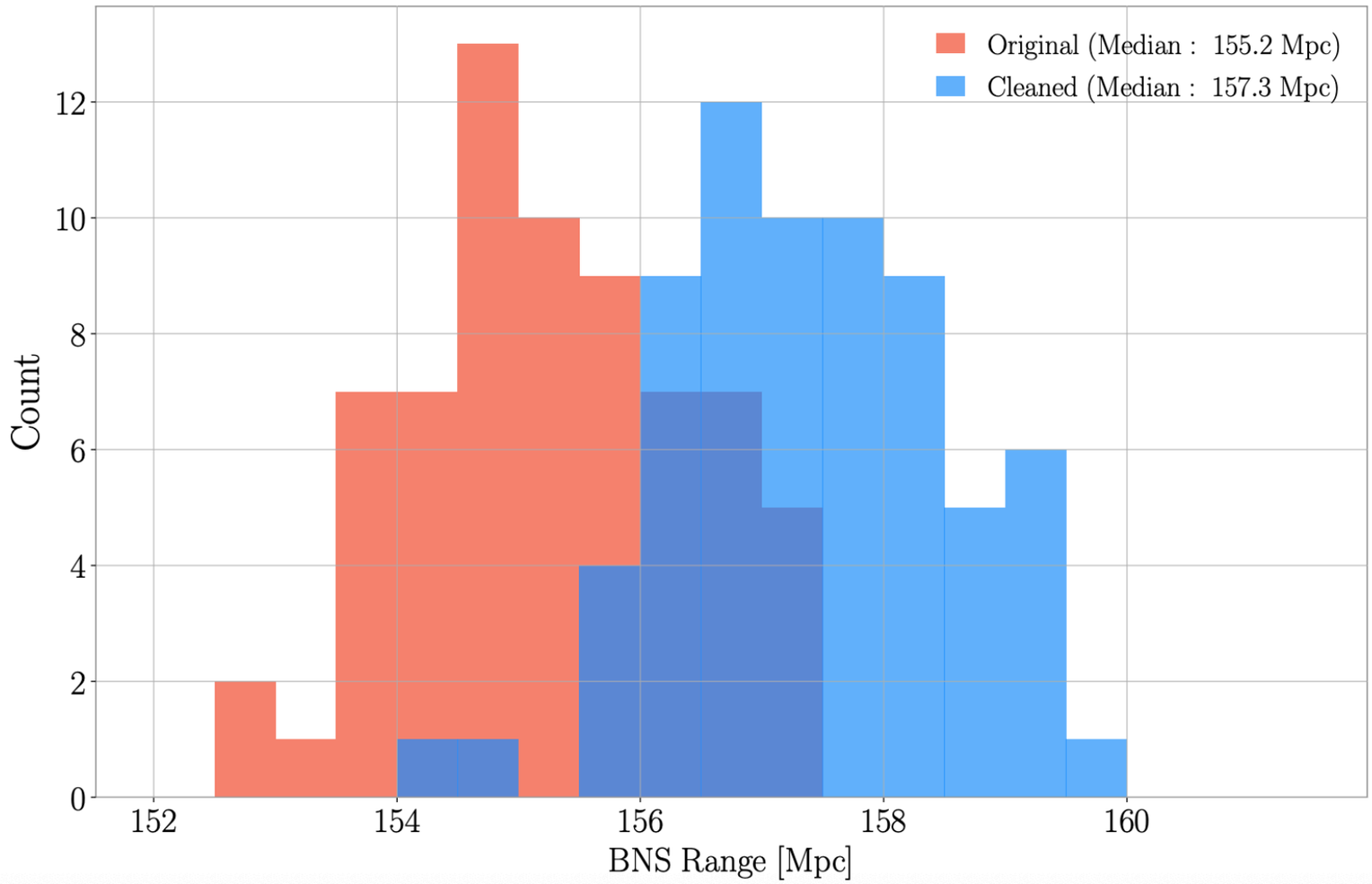
Sometimes know origin(ac/humidifer/seismic/…)

Sometimes we don’t

Just the beginning



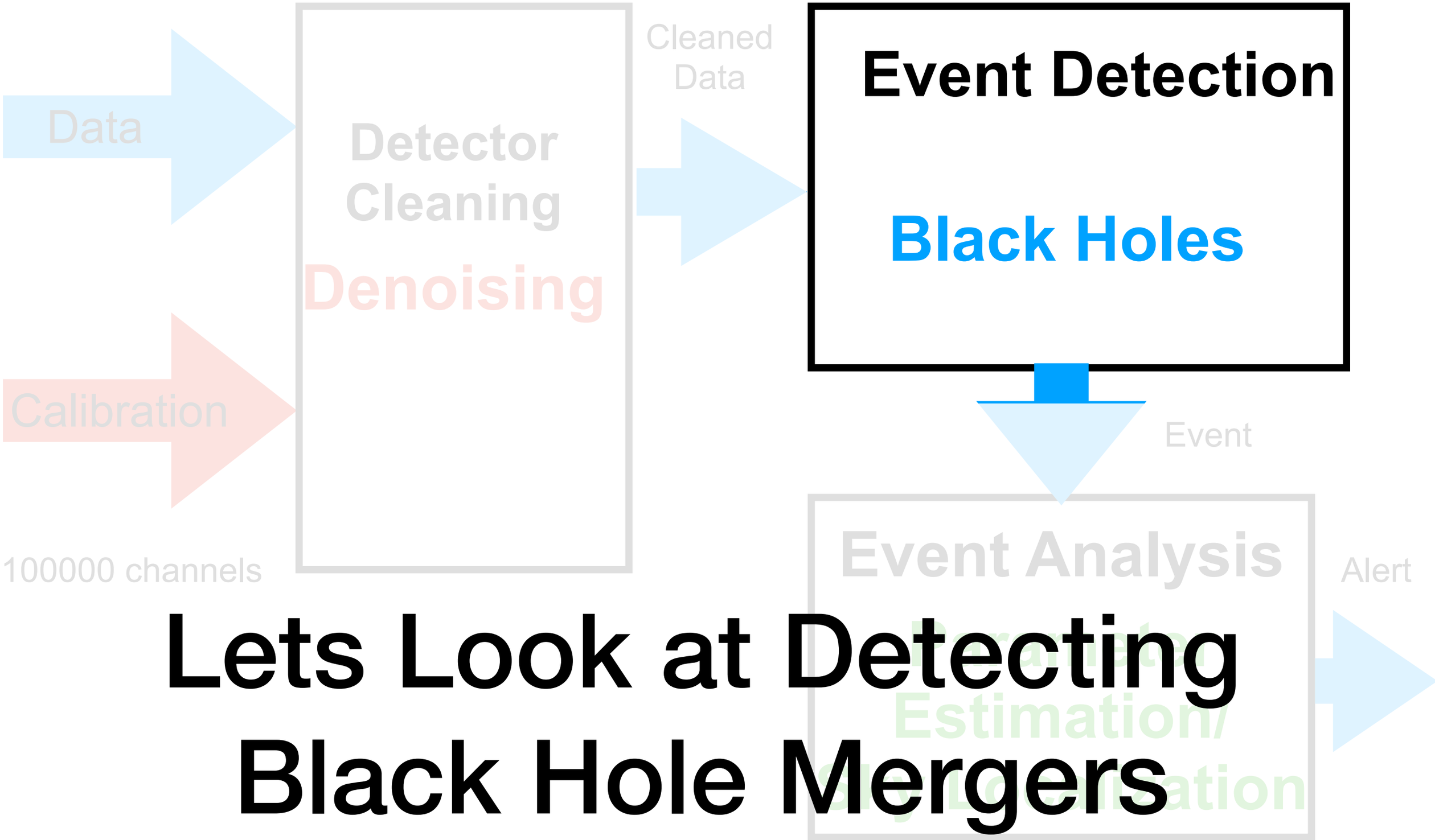
DeepClean: Does it work?



We can probe 5% more volume of universe

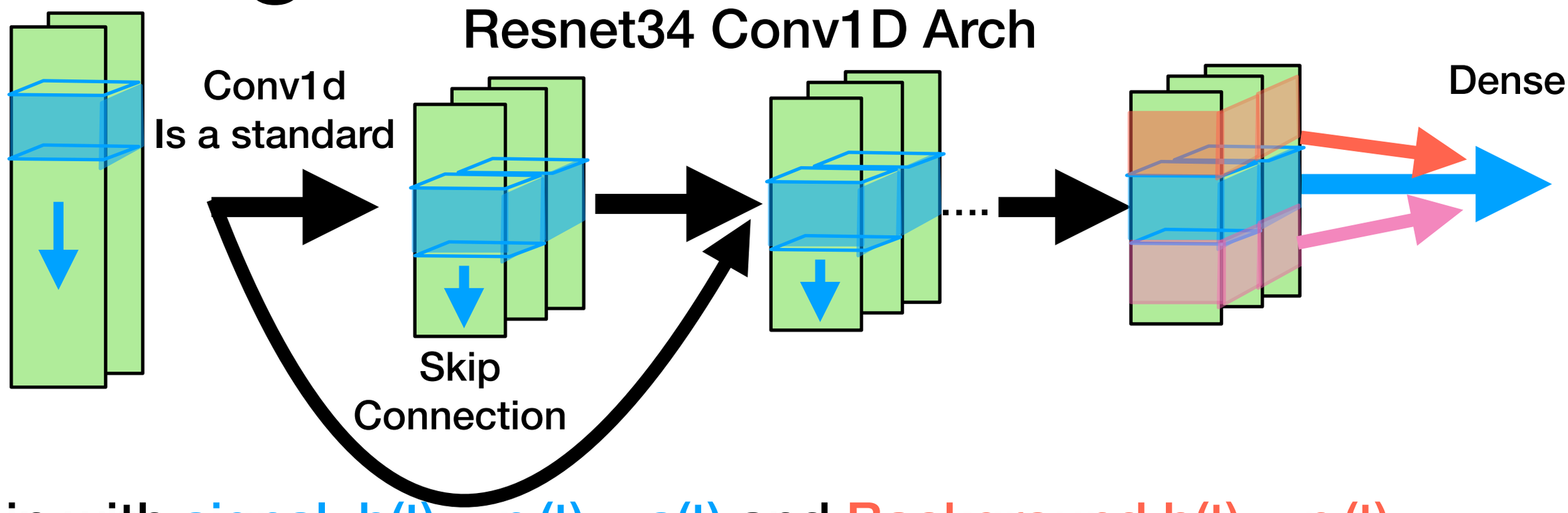
Just the beginning…many ideas to follow

GW Data Workflow



Lets Look at Detecting Black Hole Mergers

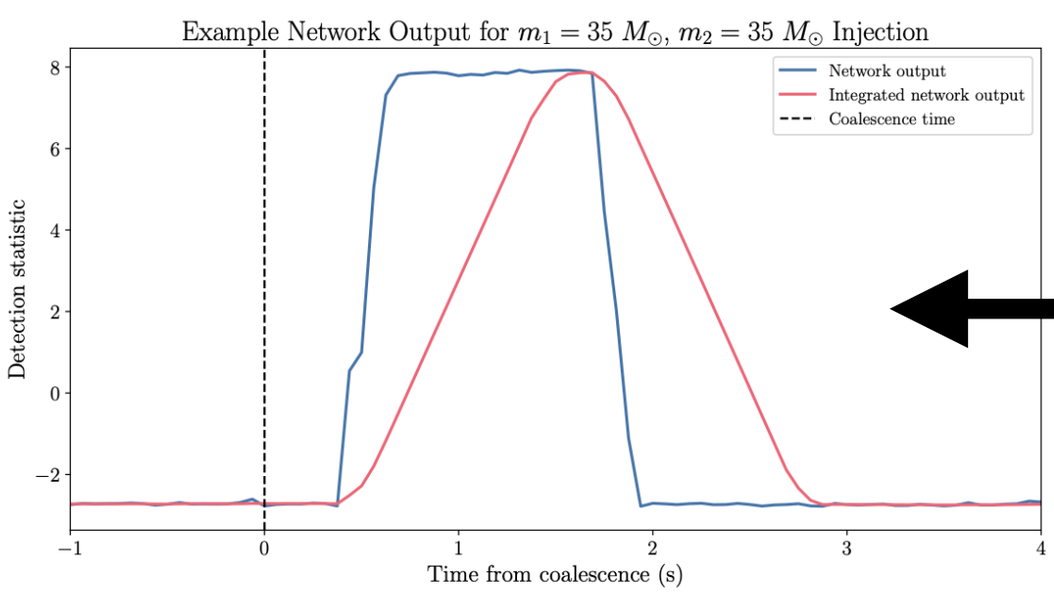
Finding Black Holes w/ AFrame



Train with signal: $h(t) = n_i(t) + s(t)$ and Background $h(t) = n_j(t)$

$n_i(t)$ is signal free data from recent running

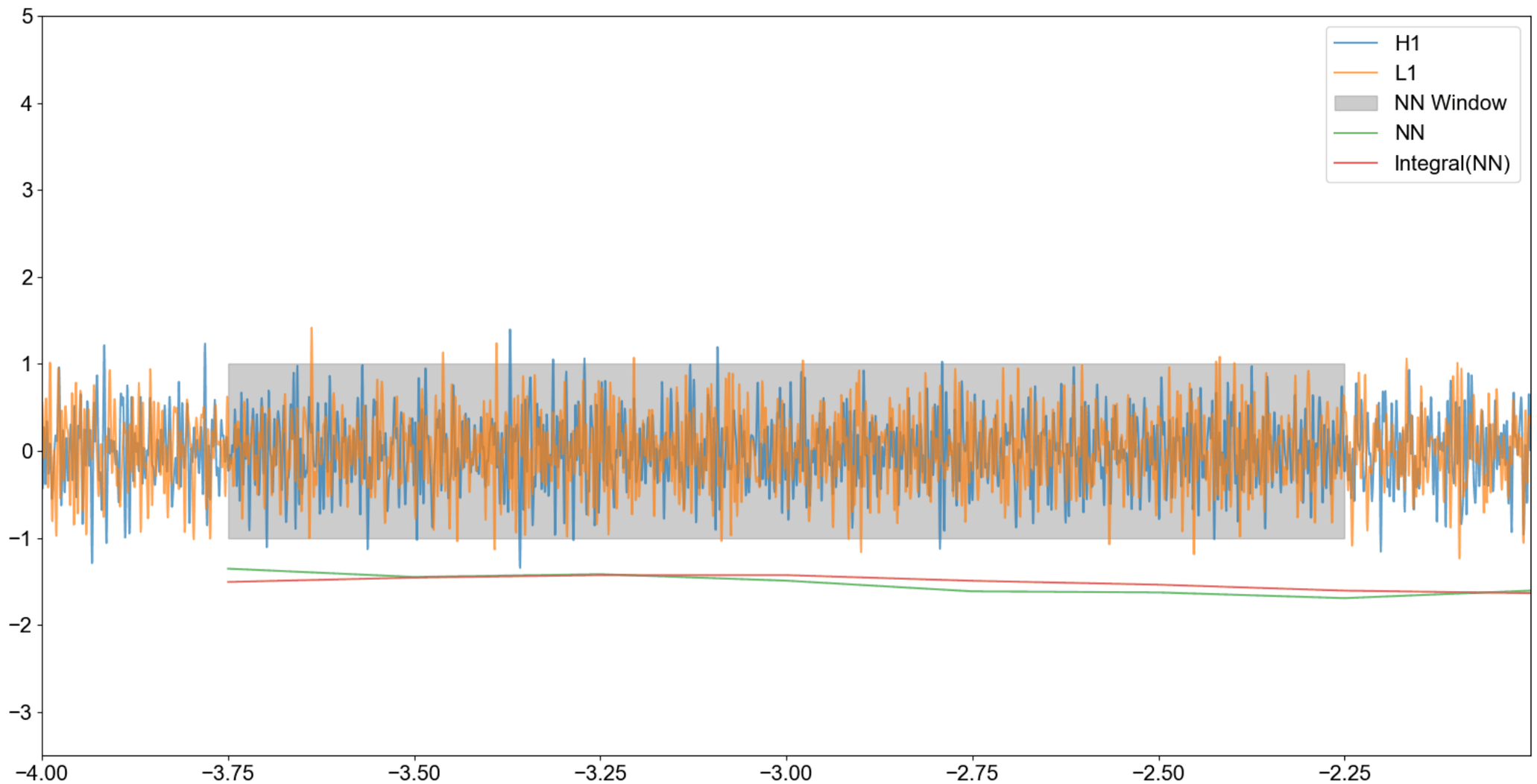
We make a point of training on actual data



Integrate the output over a time window

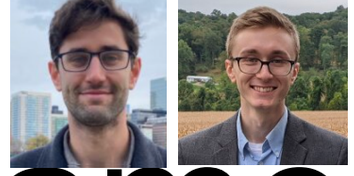
arXiv:2403.18661

A-Frame(Black Hole Mergers)

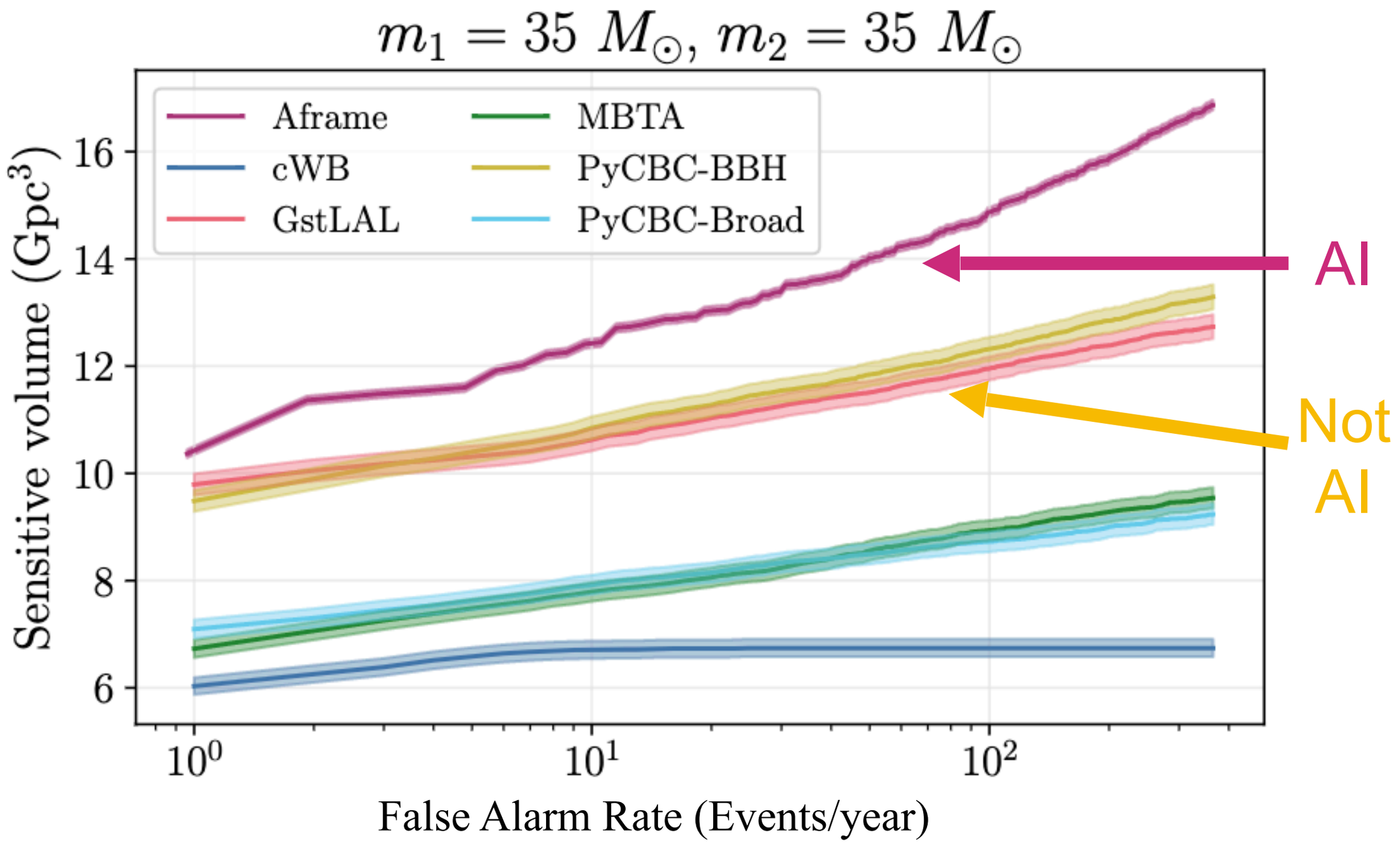


We select mergers when they are above a threshold

arXiv:2403.18661

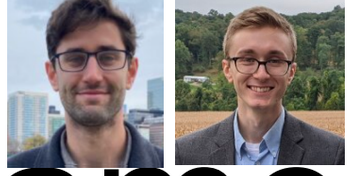


A-Frame(Black Hole Mergers)

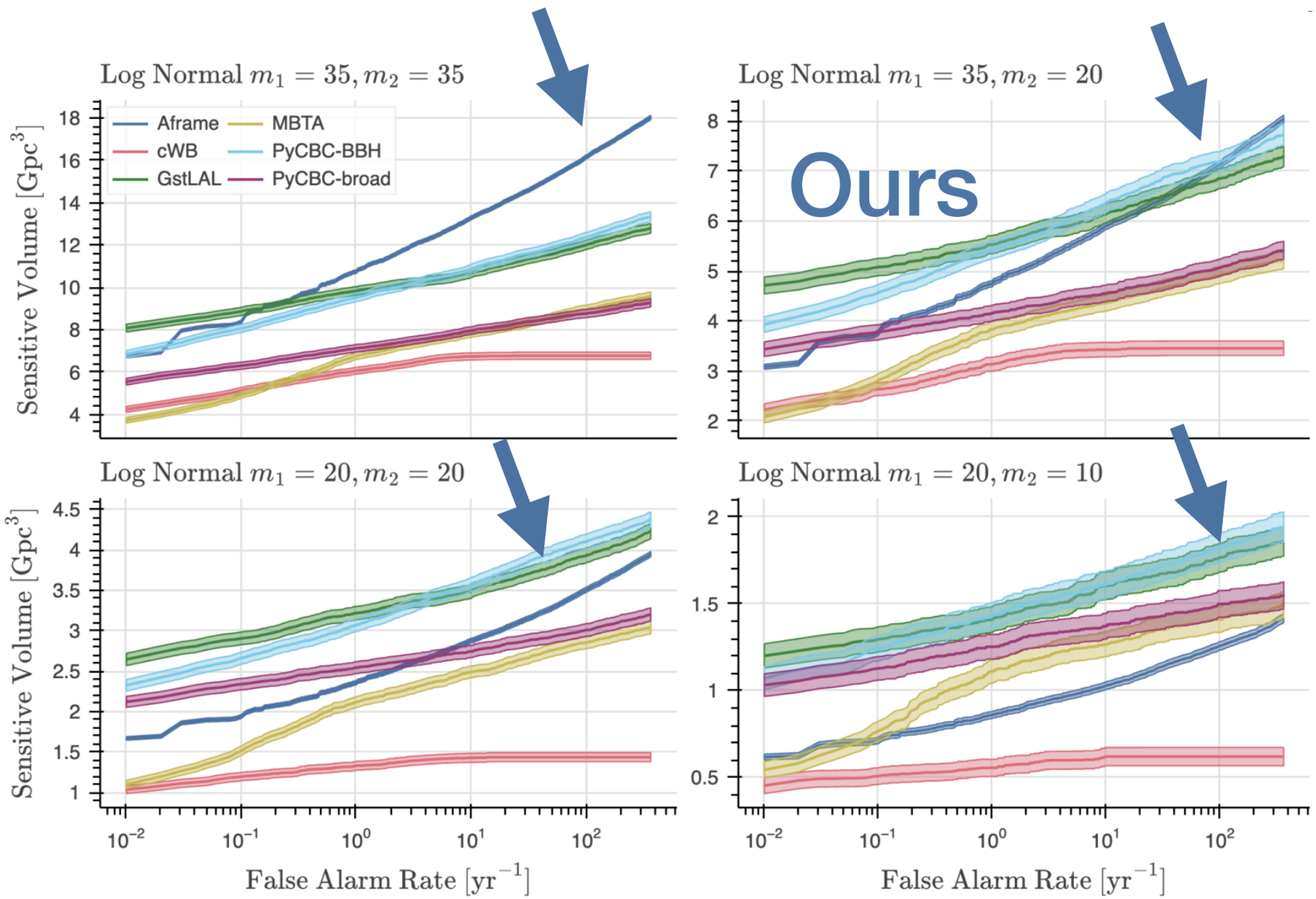


Probes 10% of the known universe for Heavy Mergers

arXiv:2403.18661



A-Frame(Black Hole Mergers)

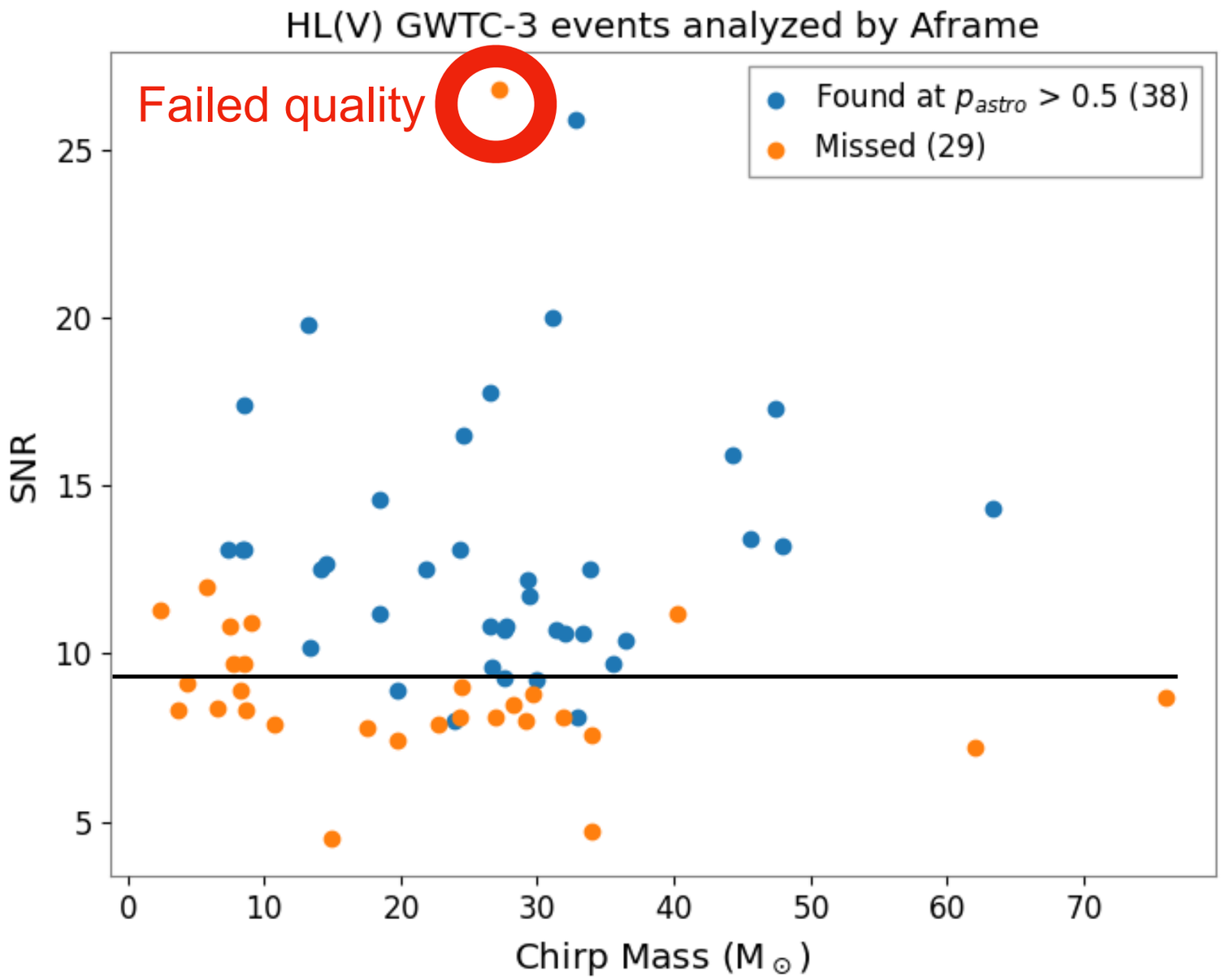


For low mass mergers we are of similar sensitivity to other pipelines

We have already made some improvements to the above

arXiv:2505.21261

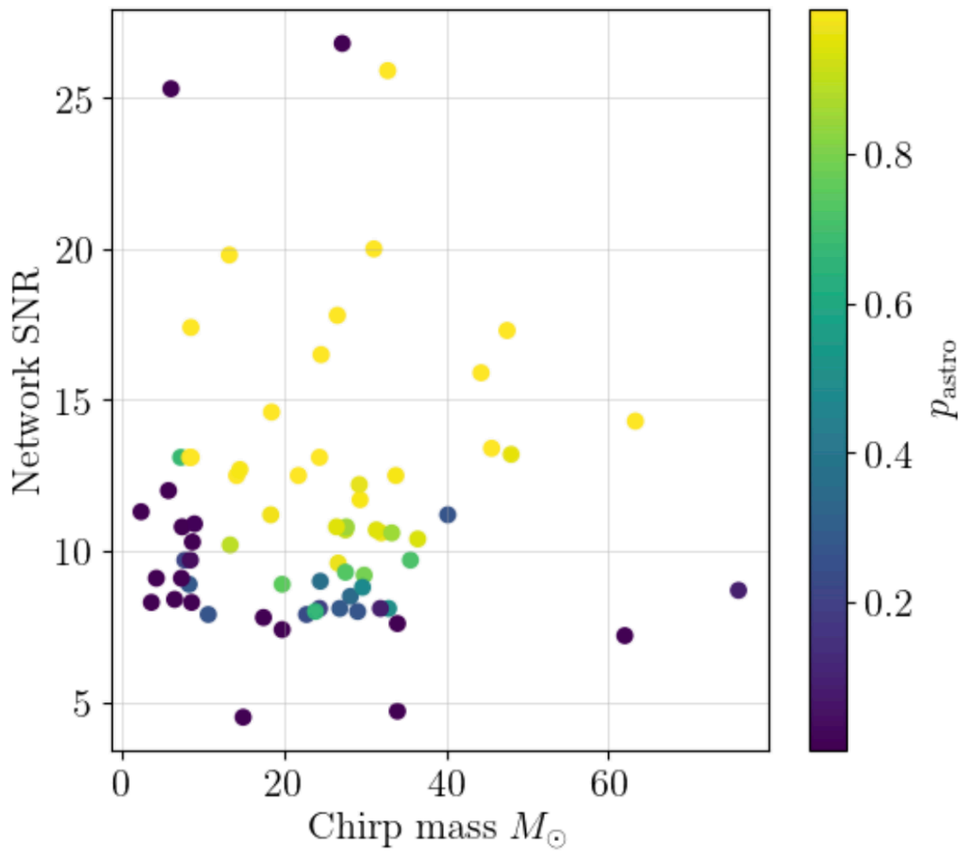
A-Frame(Black Hole Mergers)

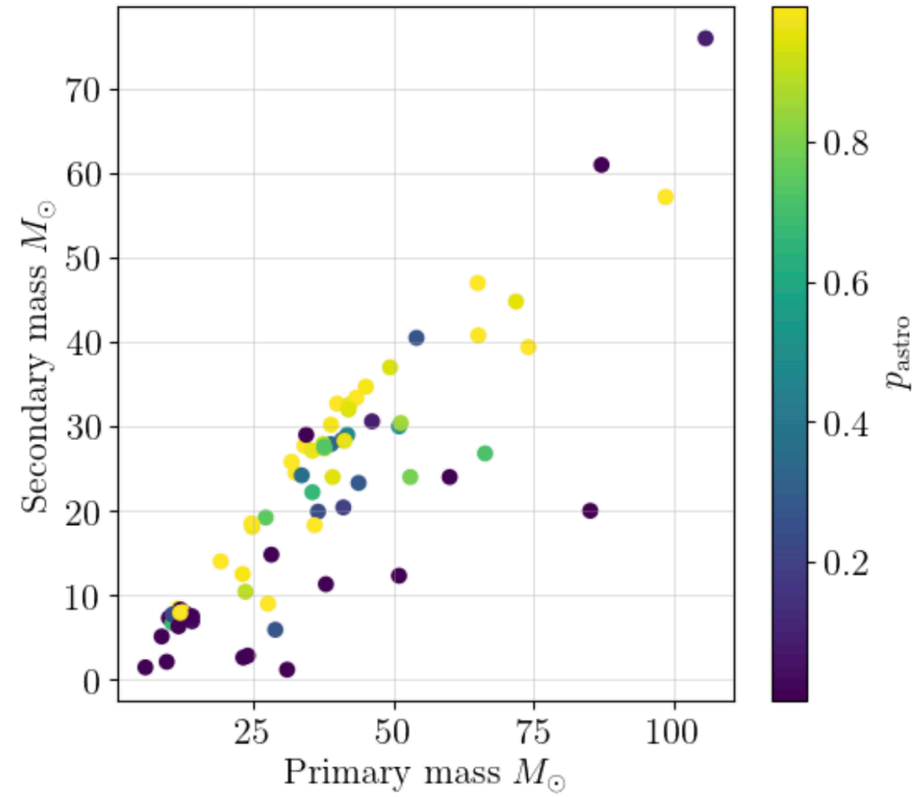


Found all high signal Black hole mergers in previous running

arXiv:2403.18661

A-Frame(Black Hole Mergers)

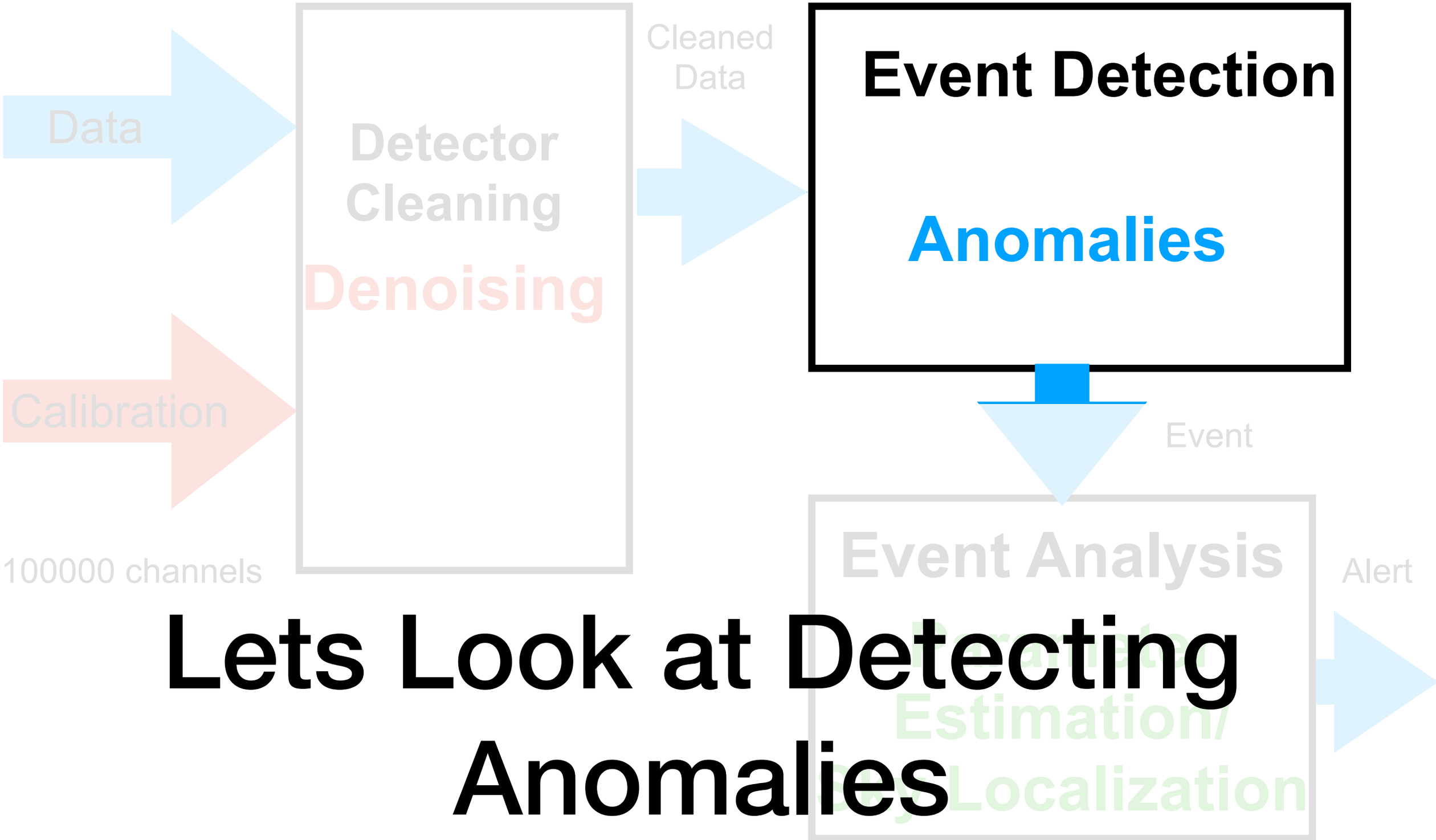




	Event	$\mathcal{M}_c^{\rm src}(M_\odot)$	$m_1^{\rm src}(M_\odot)$	$m_2^{\rm src}(M_\odot)$	D_L (Gpc)	$\chi_{\rm eff}$
1	GW200106_134123	$29.8^{+4.5}_{-3.7}$	$44.2^{+8.6}_{-7.3}$	$27.6^{+6.9}_{-6.4}$	$4.06^{+1.79}_{-1.35}$	$0.12^{+0.19}_{-0.18}$
2	GW190707_083226	$36.5^{+5.5}_{-4.3}$	$55.2^{+11.1}_{-9.3}$	$33.9^{+8.4}_{-8.8}$	$3.53^{+1.72}_{-1.25}$	$-0.02^{+0.15}_{-0.17}$
3	GW190818_232544	$41.0^{+6.5}_{-5.7}$	$82.7^{+12.8}_{-16.9}$	$28.8^{+13.8}_{-8.3}$	$4.09^{+1.56}_{-1.12}$	$0.49^{+0.12}_{-0.16}$

Also found 3 mergers that were not in LIGO catalog
Found by other searches (IAS/OGC searchess)

GW Data Workflow



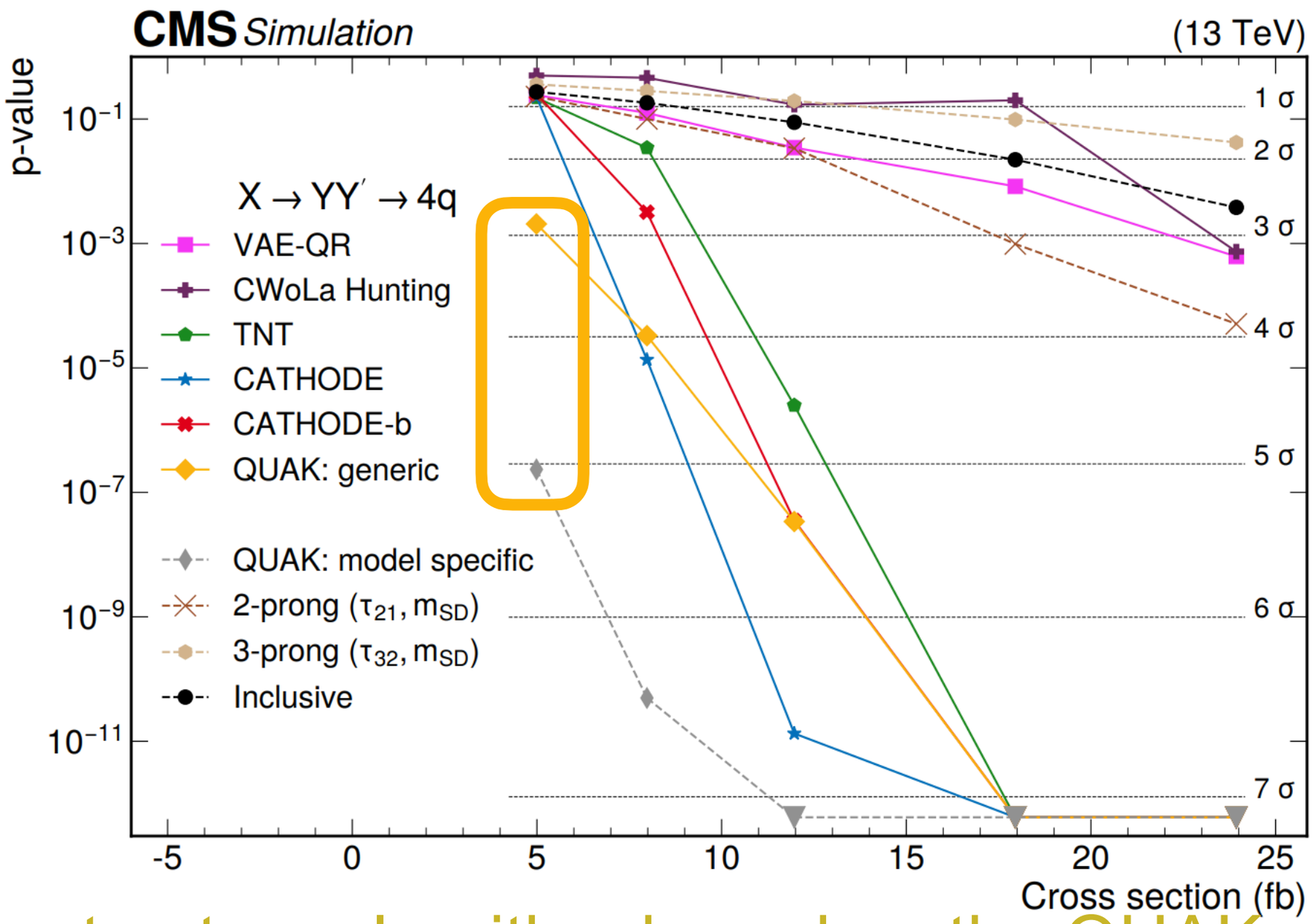
Lets Look at Detecting Anomalies

GWAK: Anomaly Detection

So far, we just did Binary Mergers
But what about the other phenomena that we can find
Unfortunately, hard, if not impossible, to model
AI-anomaly detection provides a way to search

GWAK Paradigm

GWAK stands for GW (QU)AK like guacamole

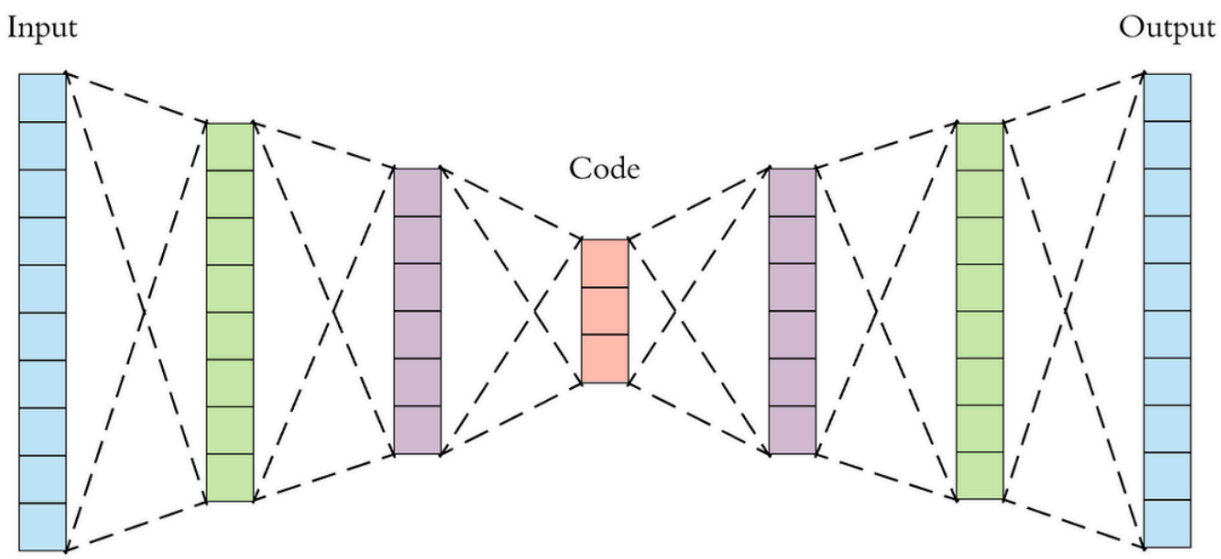


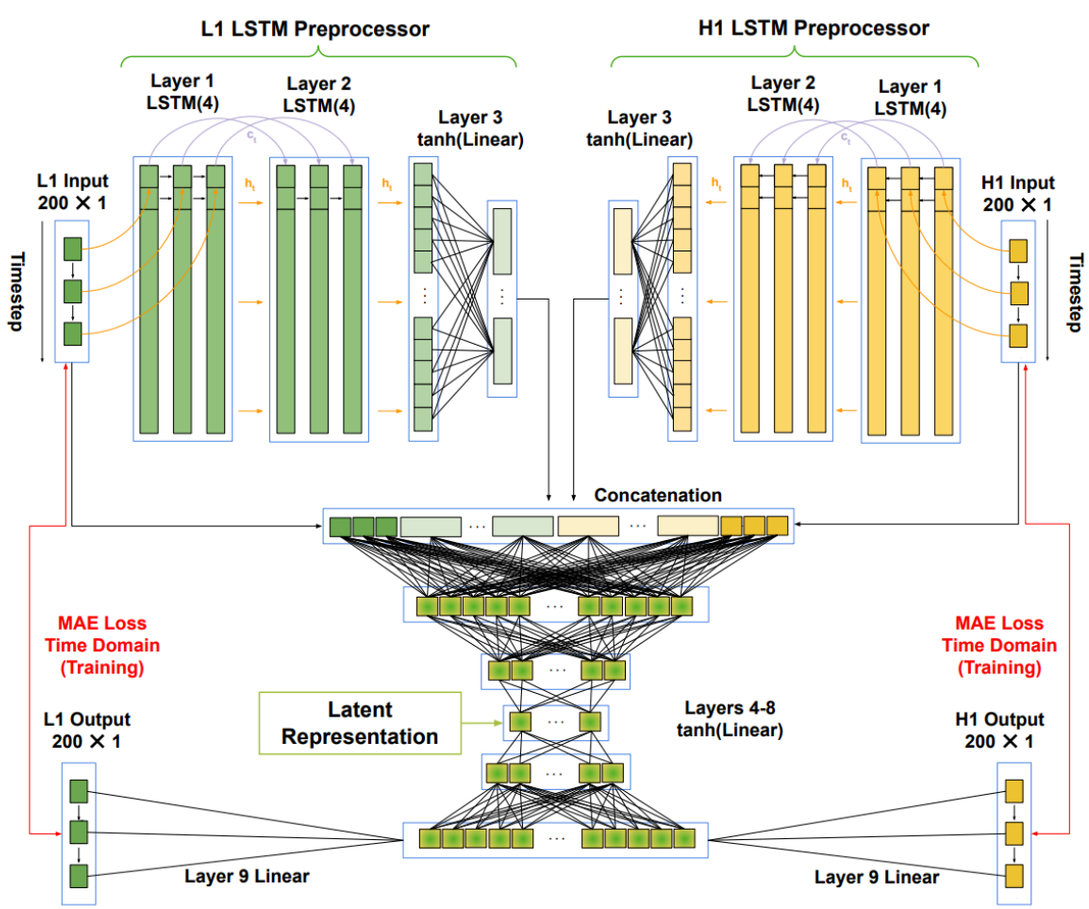
We construct an algorithm based on the QUAK method

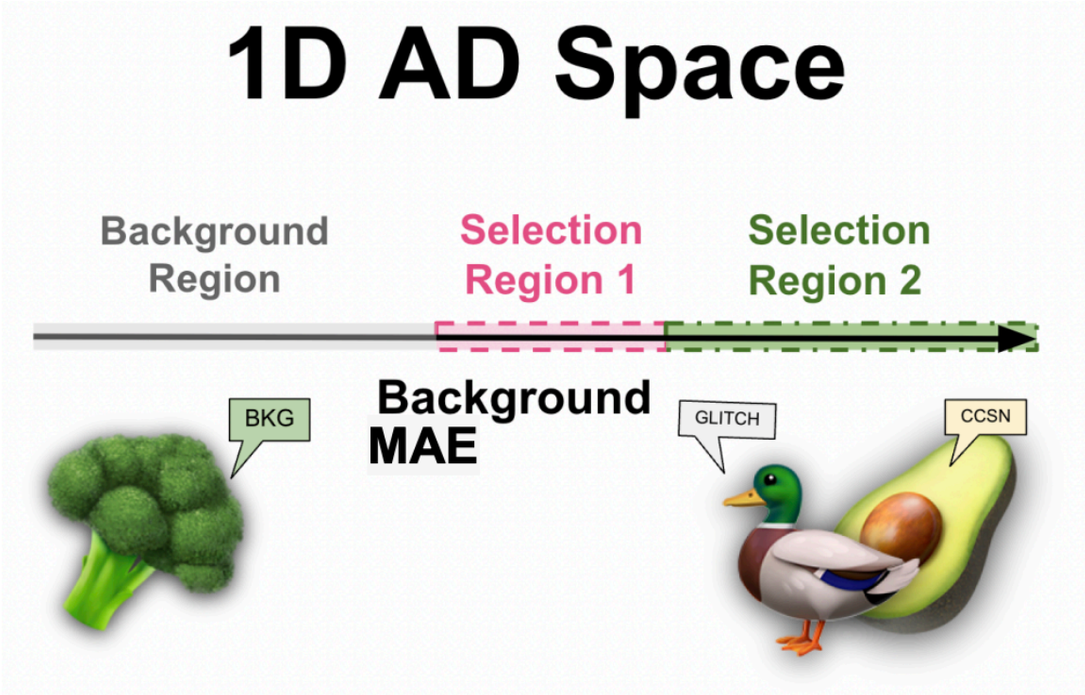
arxiv:2309.11537

GWAK Paradigm

LSTM Autoencoders



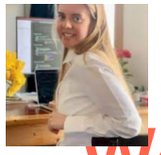




We start first by training an autoencoder on the background

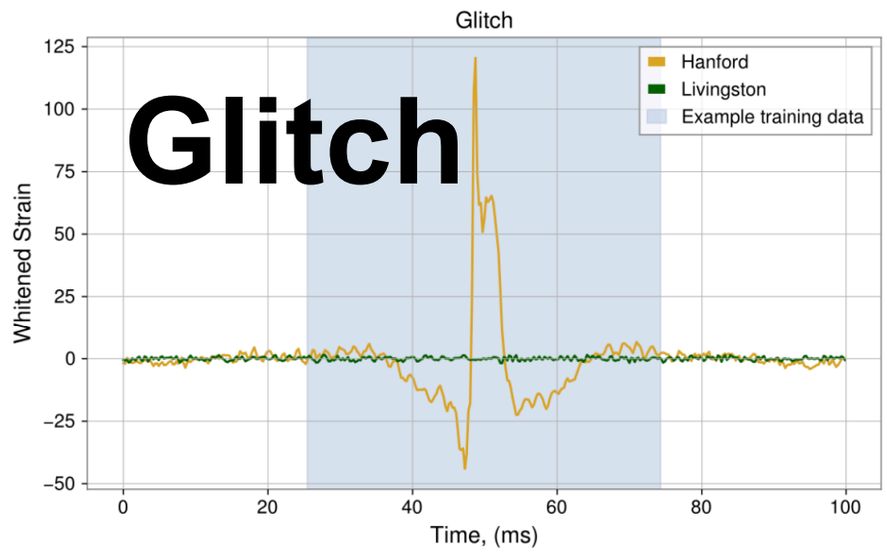
Just finds detector glitches not enough physics info for what signals look like

arxiv:2309.11537

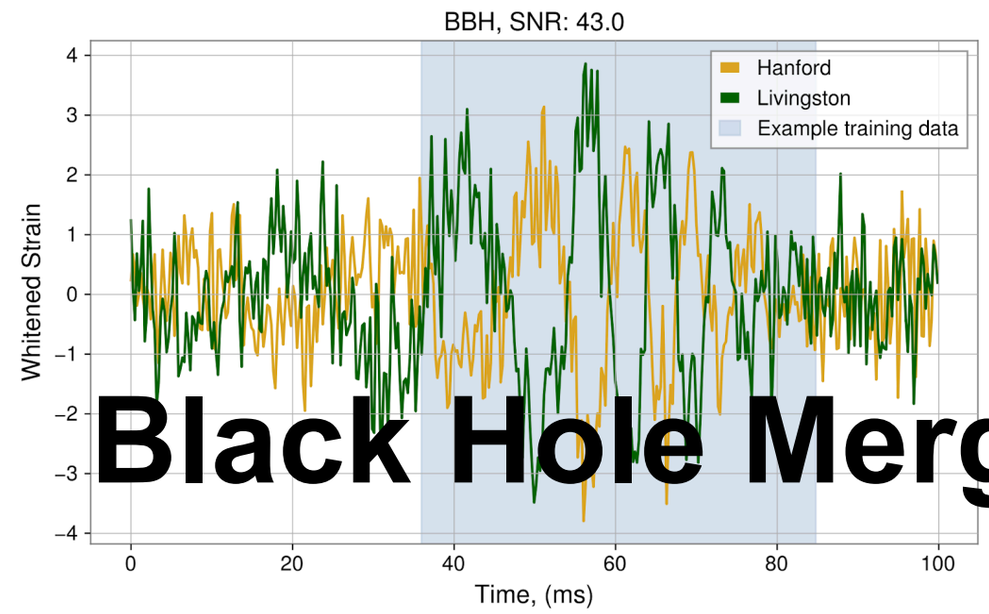


Lots of different signals

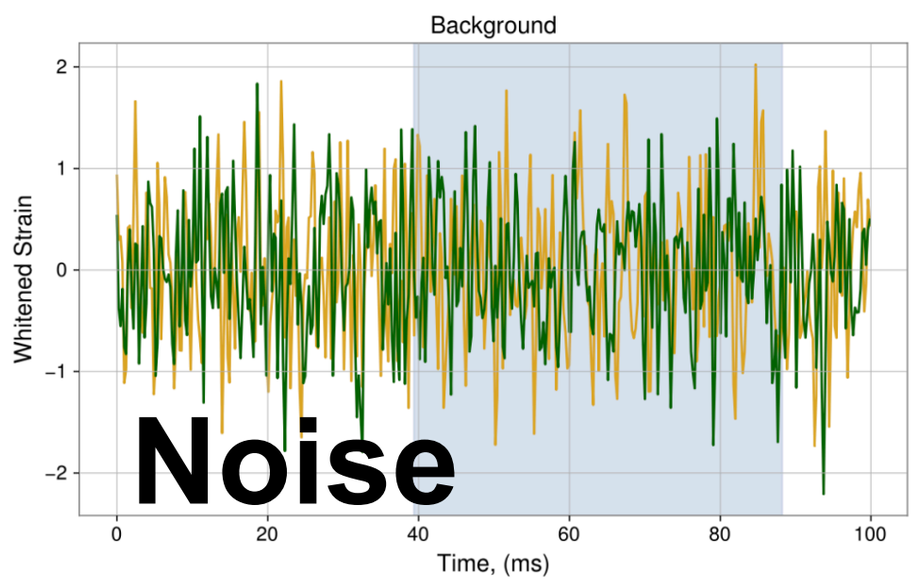
We can at least bound our signals by adding some Inductive Bias



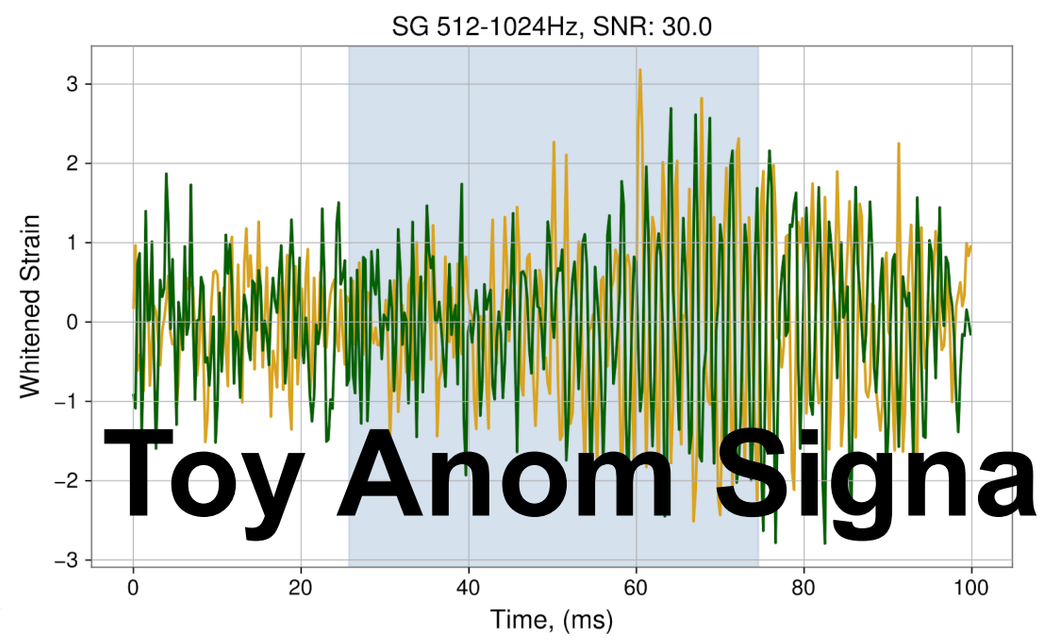
Glitch



Black Hole Merger



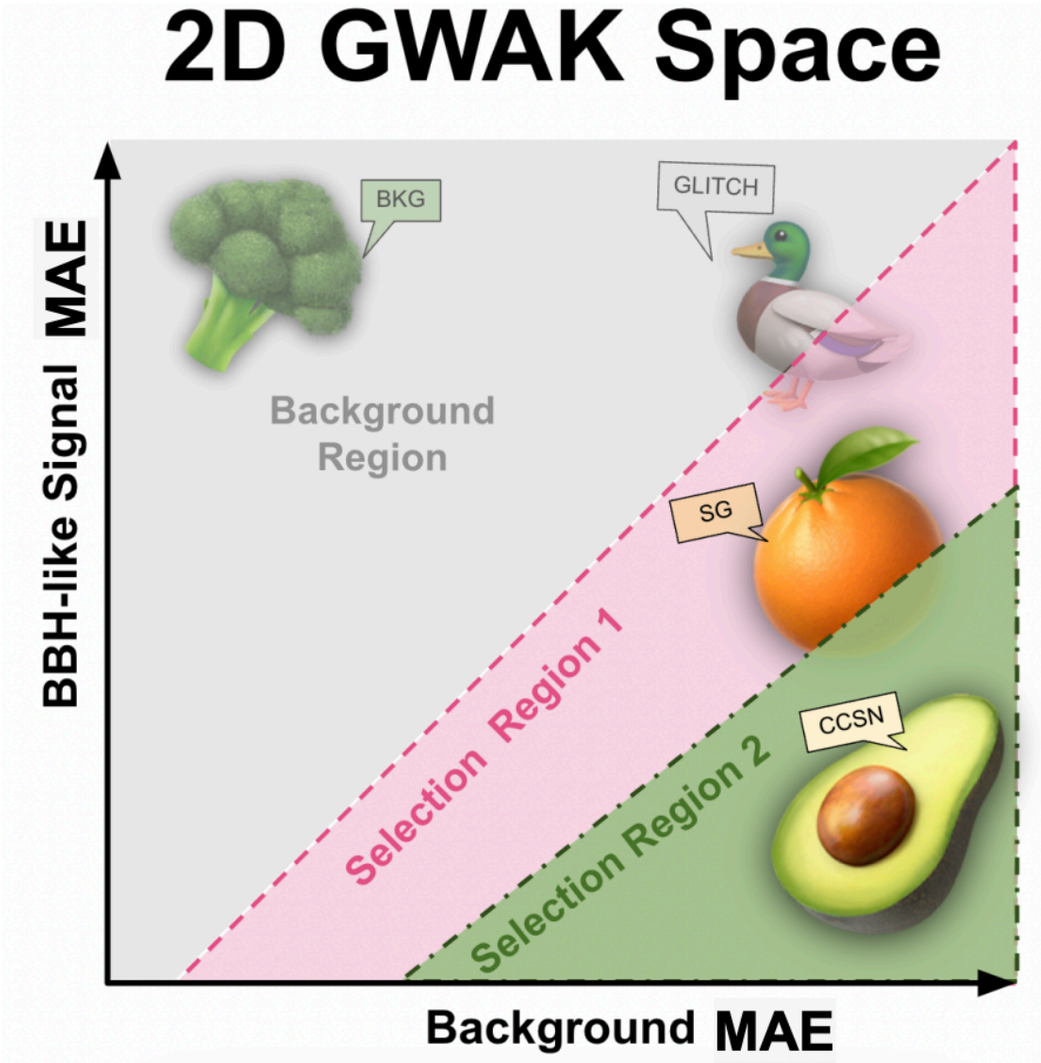
Noise

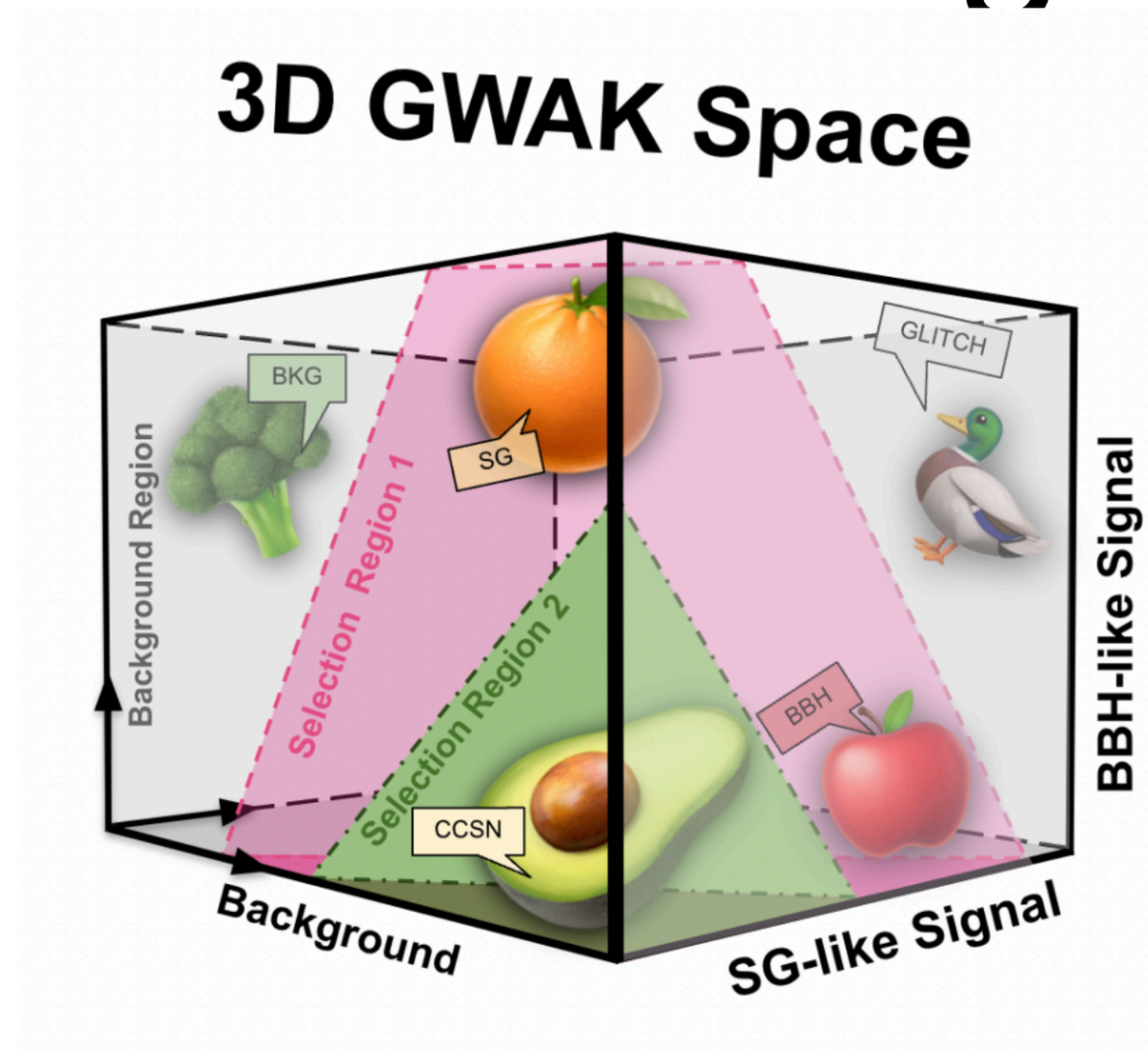


Toy Anom Signal

arxiv:2309.11537

GWAK Paradigm





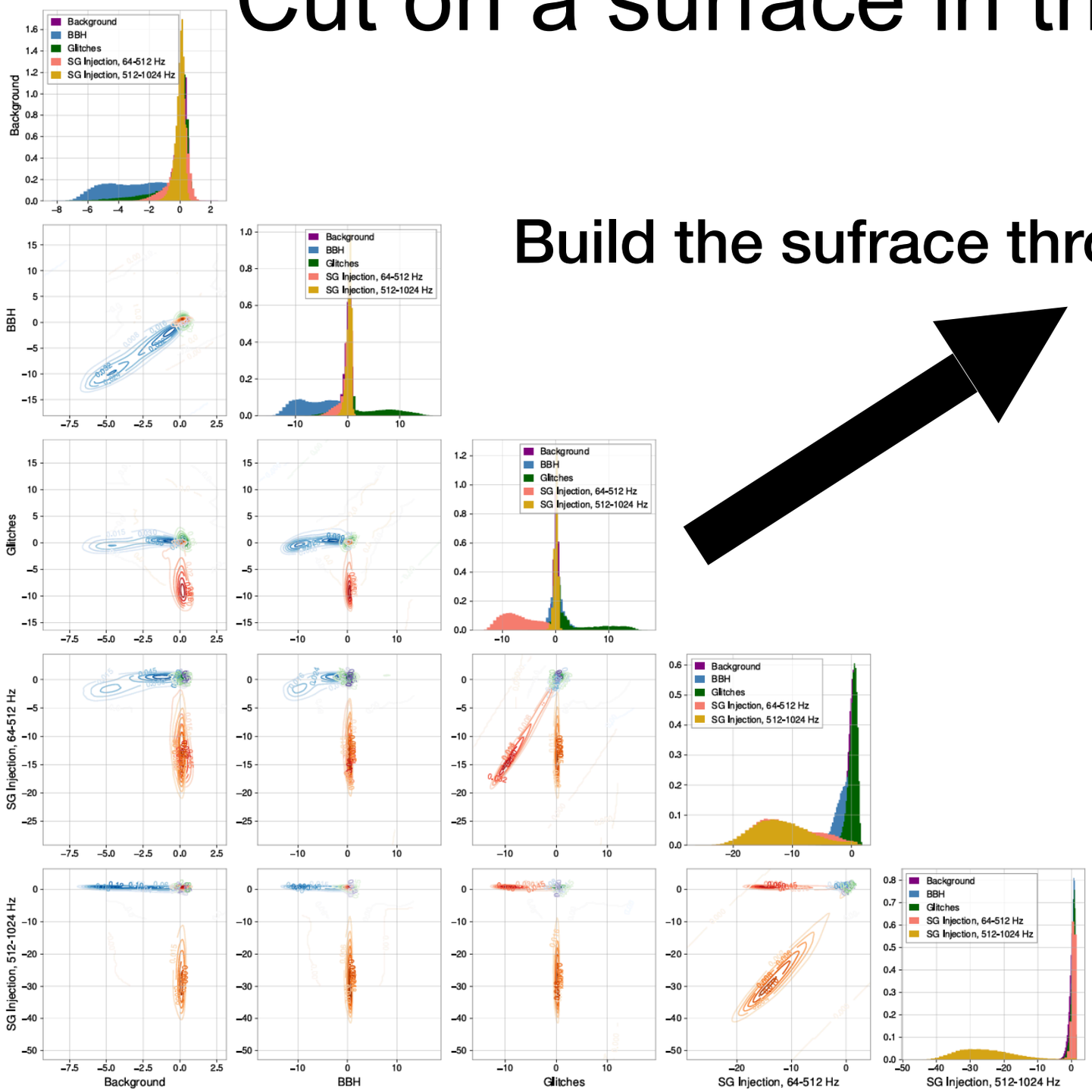
Add dimensions with autoencoders trained on hypothetical signals

Select on a hypersurface in this space to look for the anomalies

arxiv:2309.11537

GWAK Space

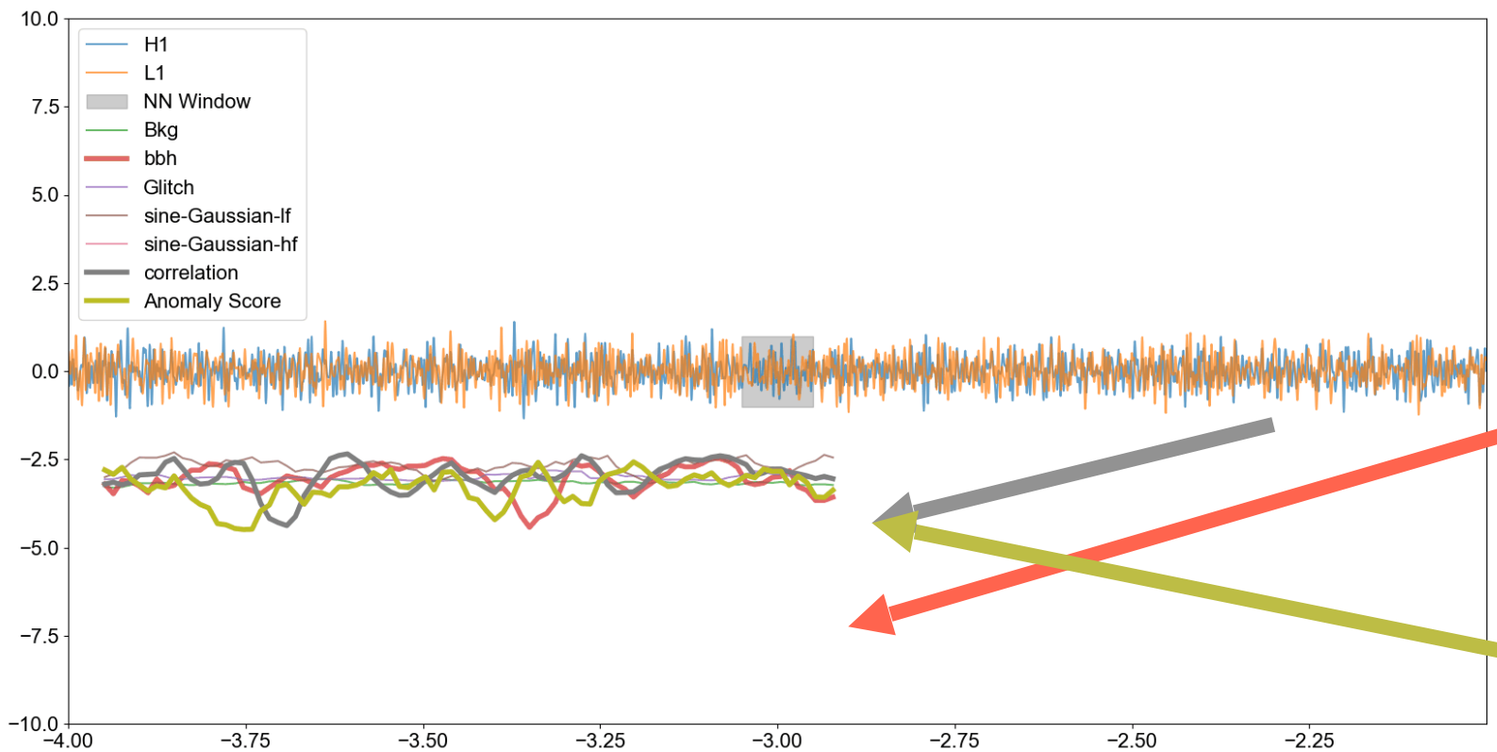
Cut on a surface in the 11D Space



Build the sufrace through an SVM on the space

arxiv:2309.11537

GWAK:Anomaly Detection



Key Insights

11D space

Correlation

BBH Prob

Others

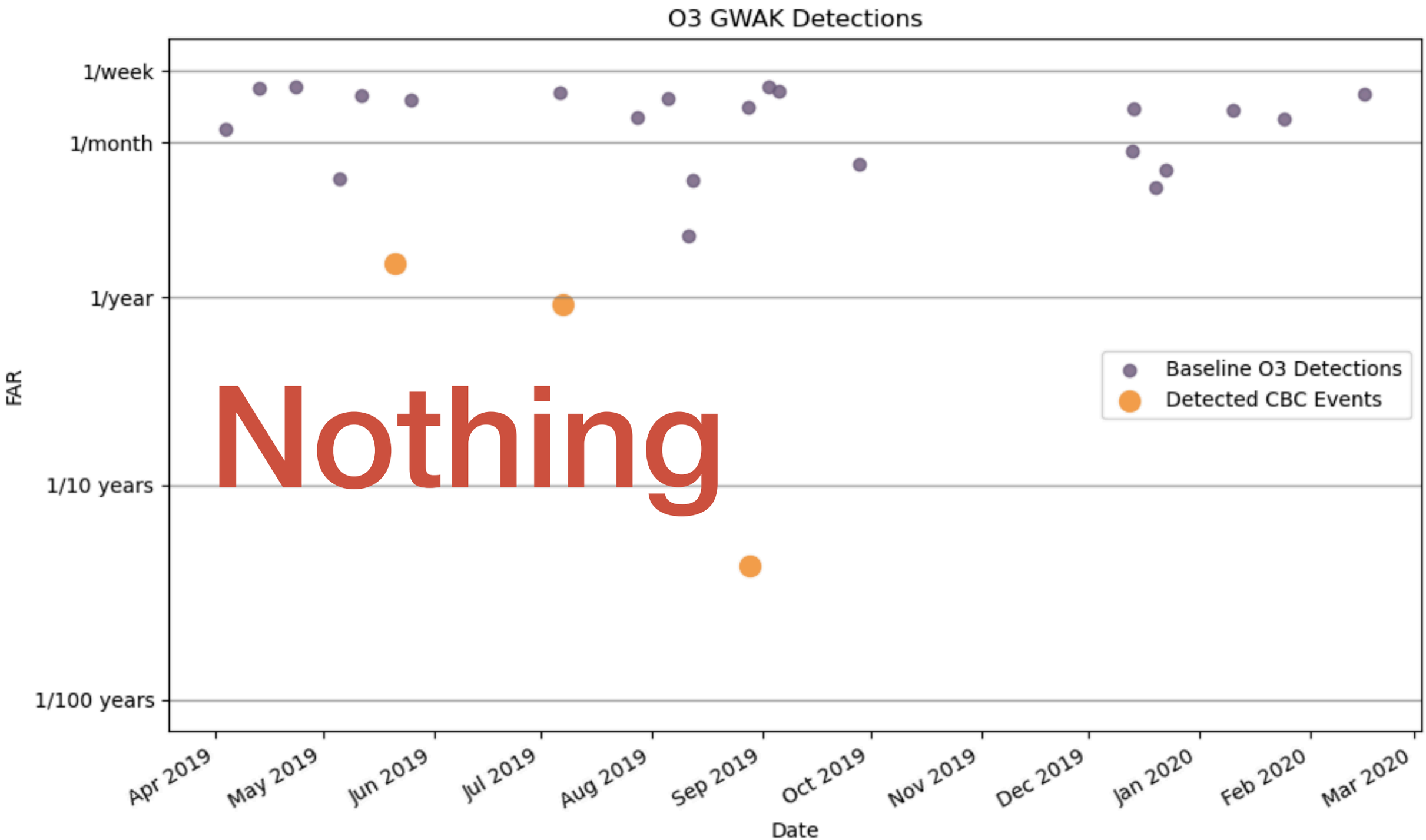
Total Score

Outputs a comprehensive series of scores in a 11D space

Our combined anomaly targets stuff that is not standard

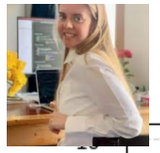
Arxiv:2412.19883

GWAK On Data

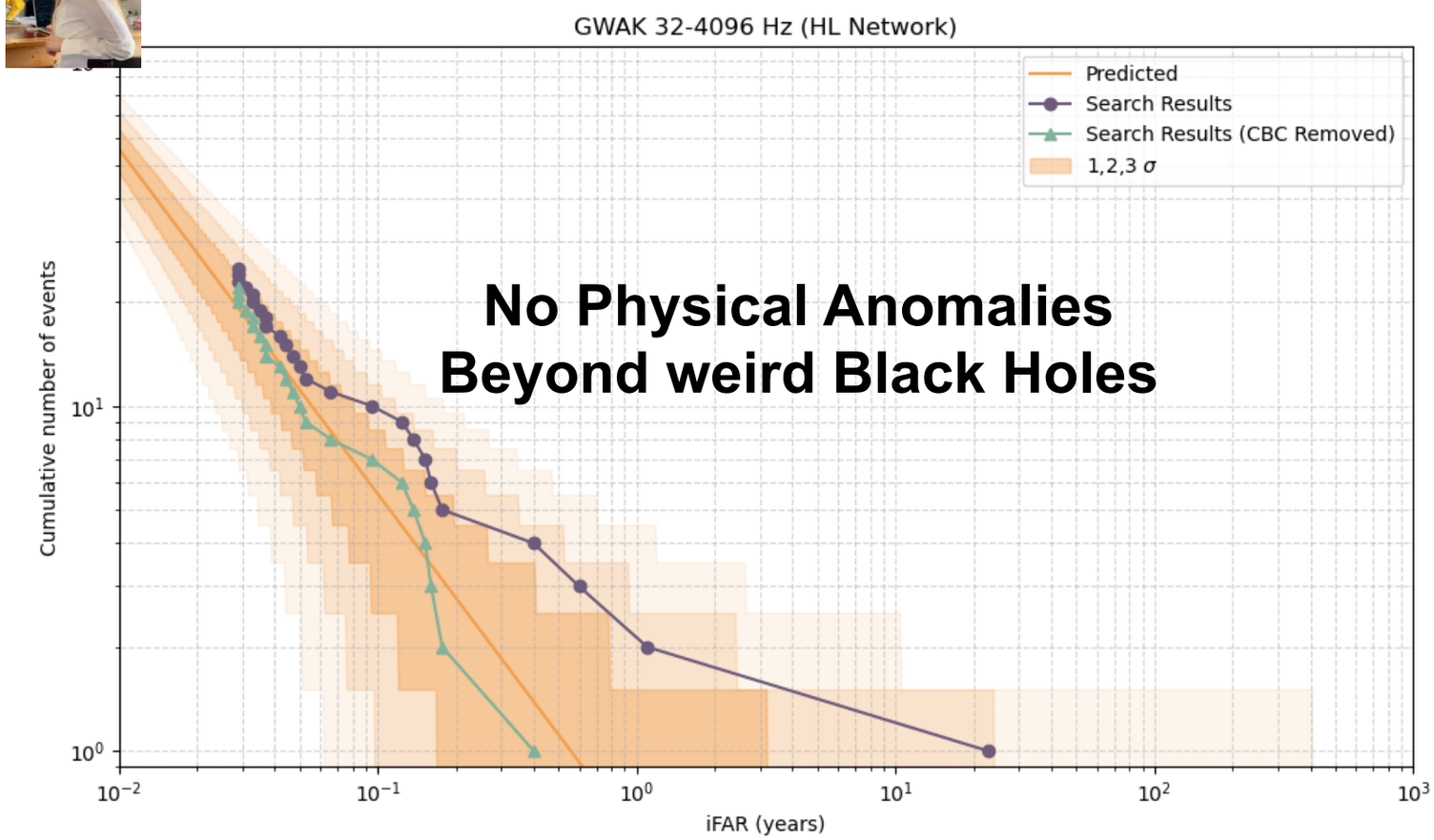


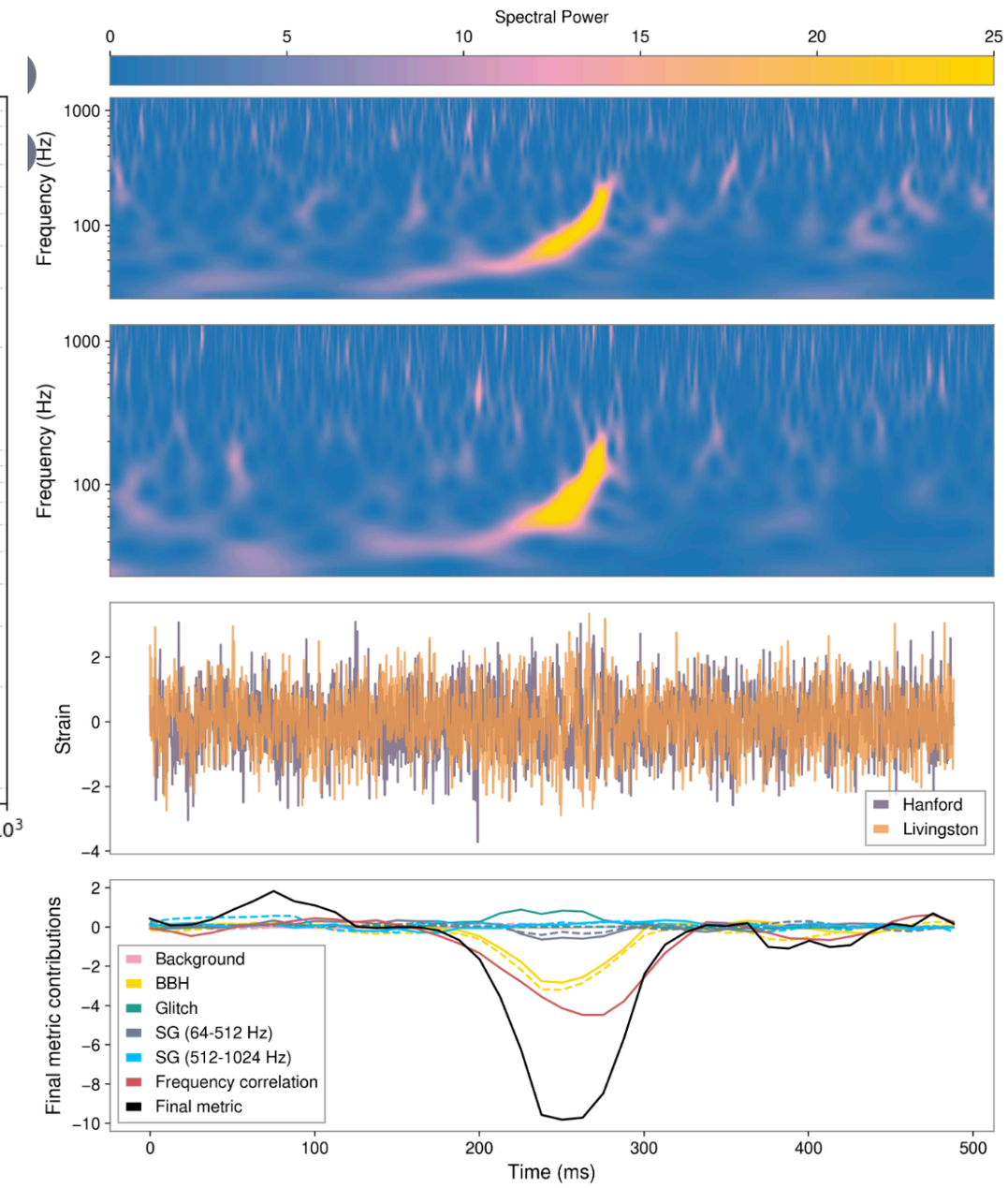
Nothing

Arxiv:2412.19883



GWAK On Data





No glaring true anomalies

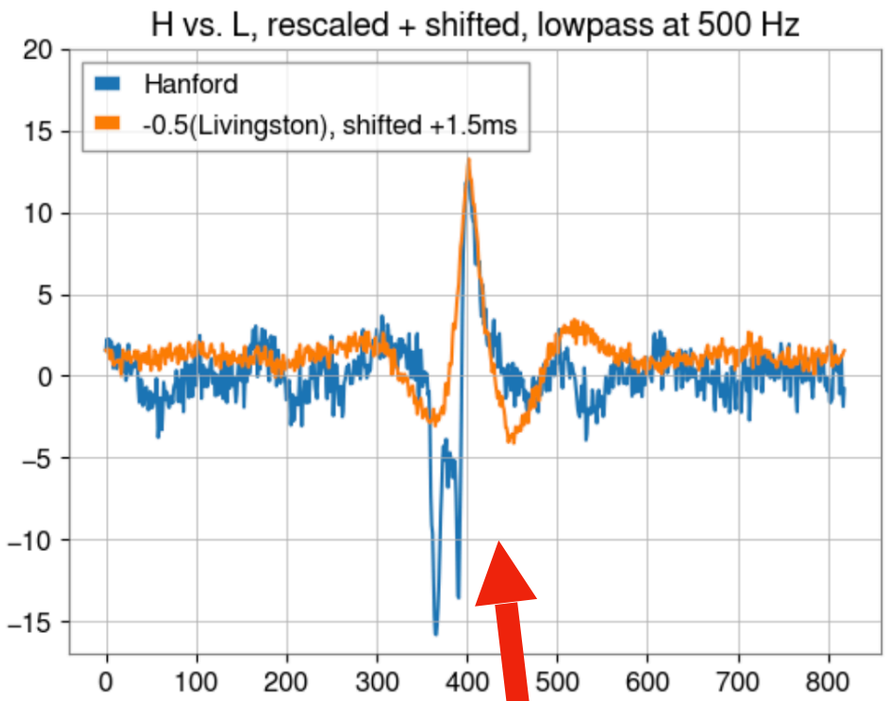
We found weird black hole mergers + weird glitches

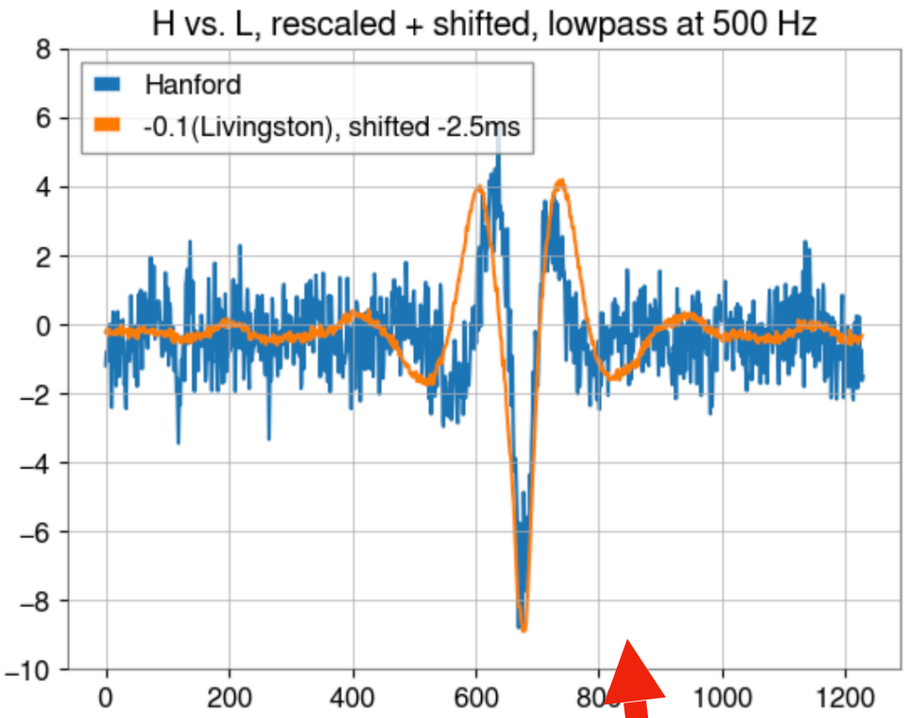
Most sensitive bounds on few models in O3 (Sine Gaussians)

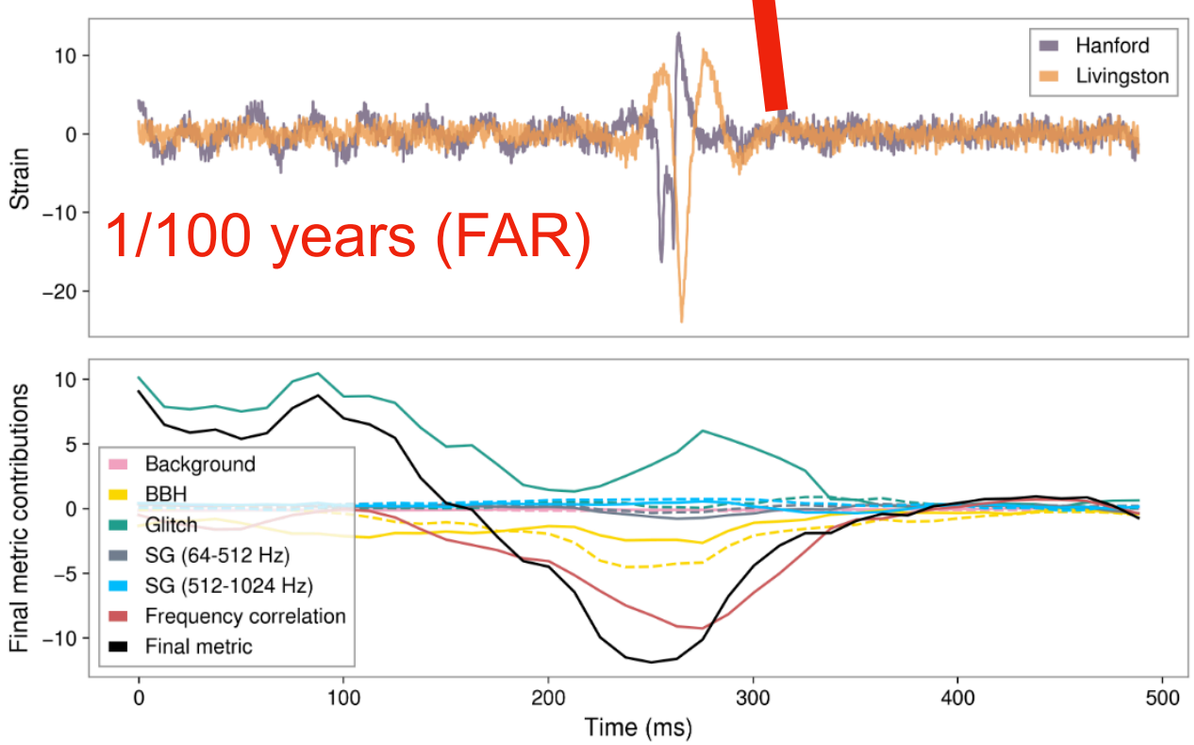
Arxiv:2412.19883

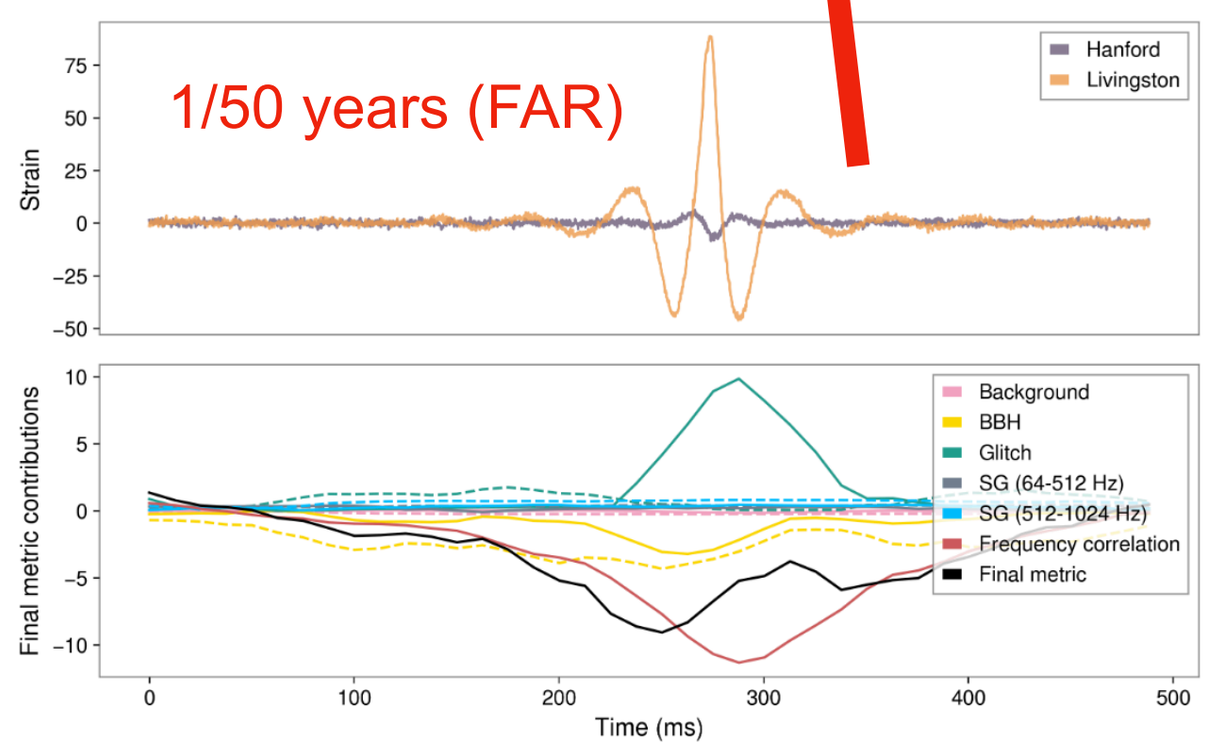
Crazy Anomalies

Occurred during noisy times of LIGO operation

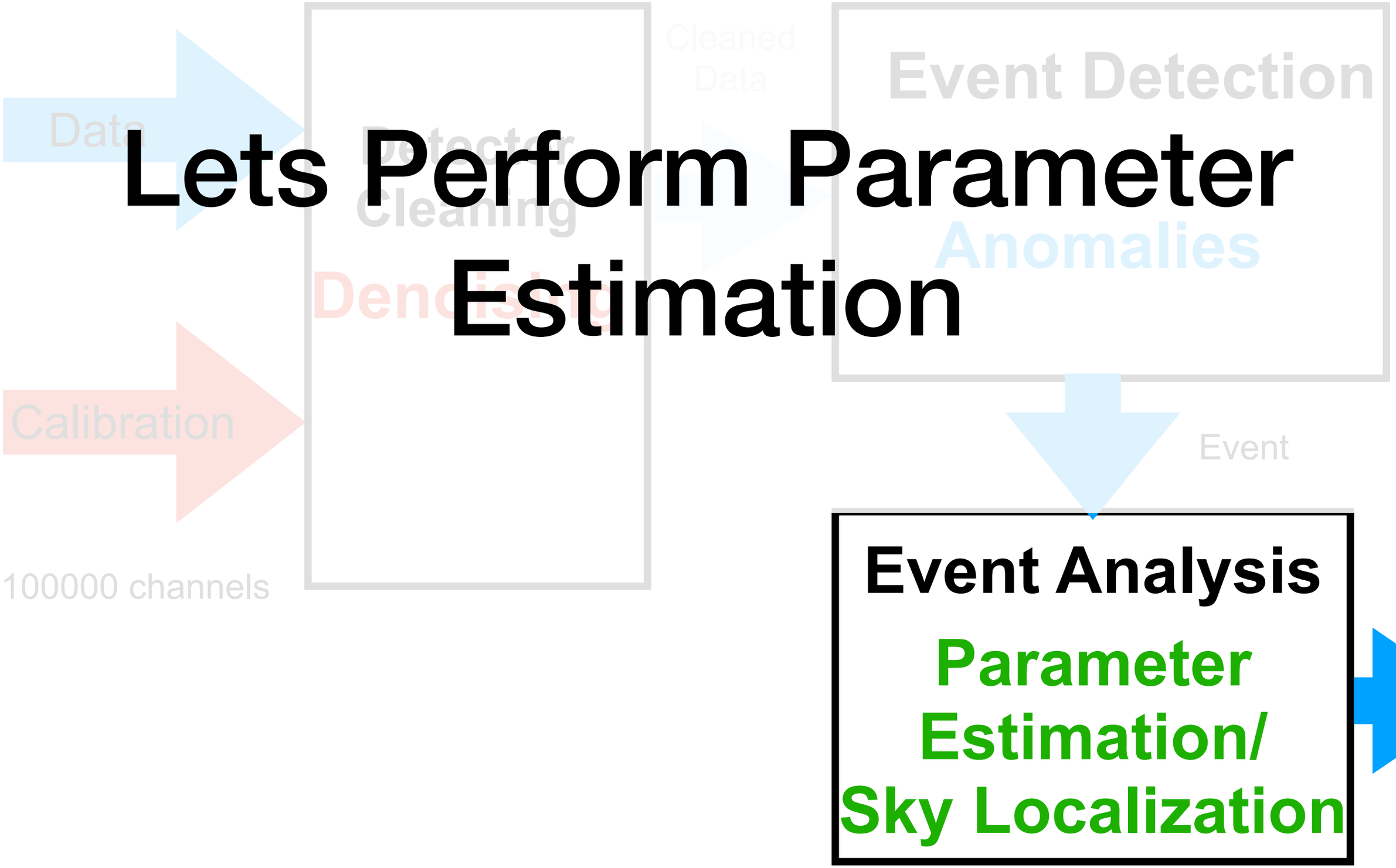








GW Data Workflow

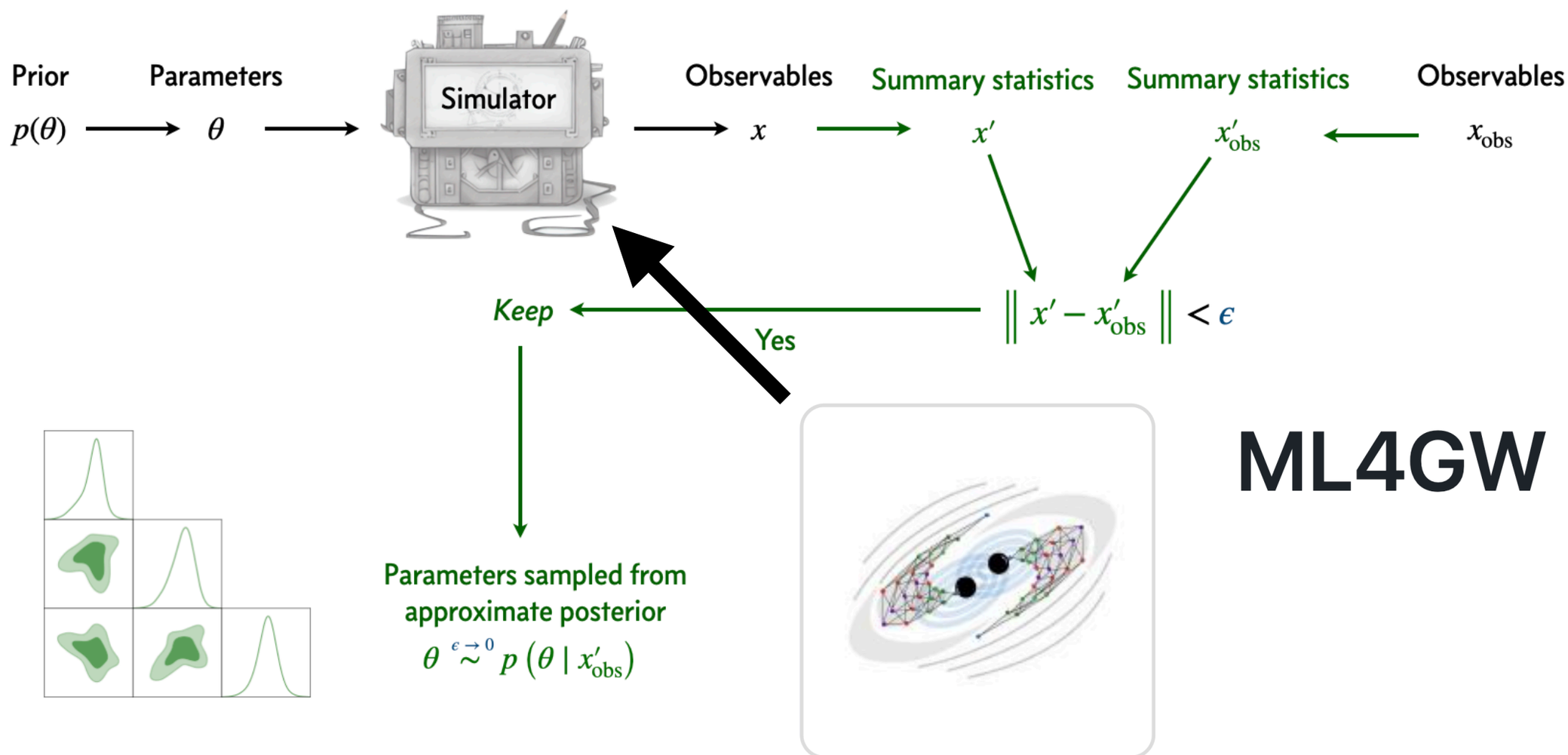


Lets Perform Parameter Estimation

Parameter Estimation

"Traditional" SBI: *Approximate Bayesian Computation*

[Rubin 1984]



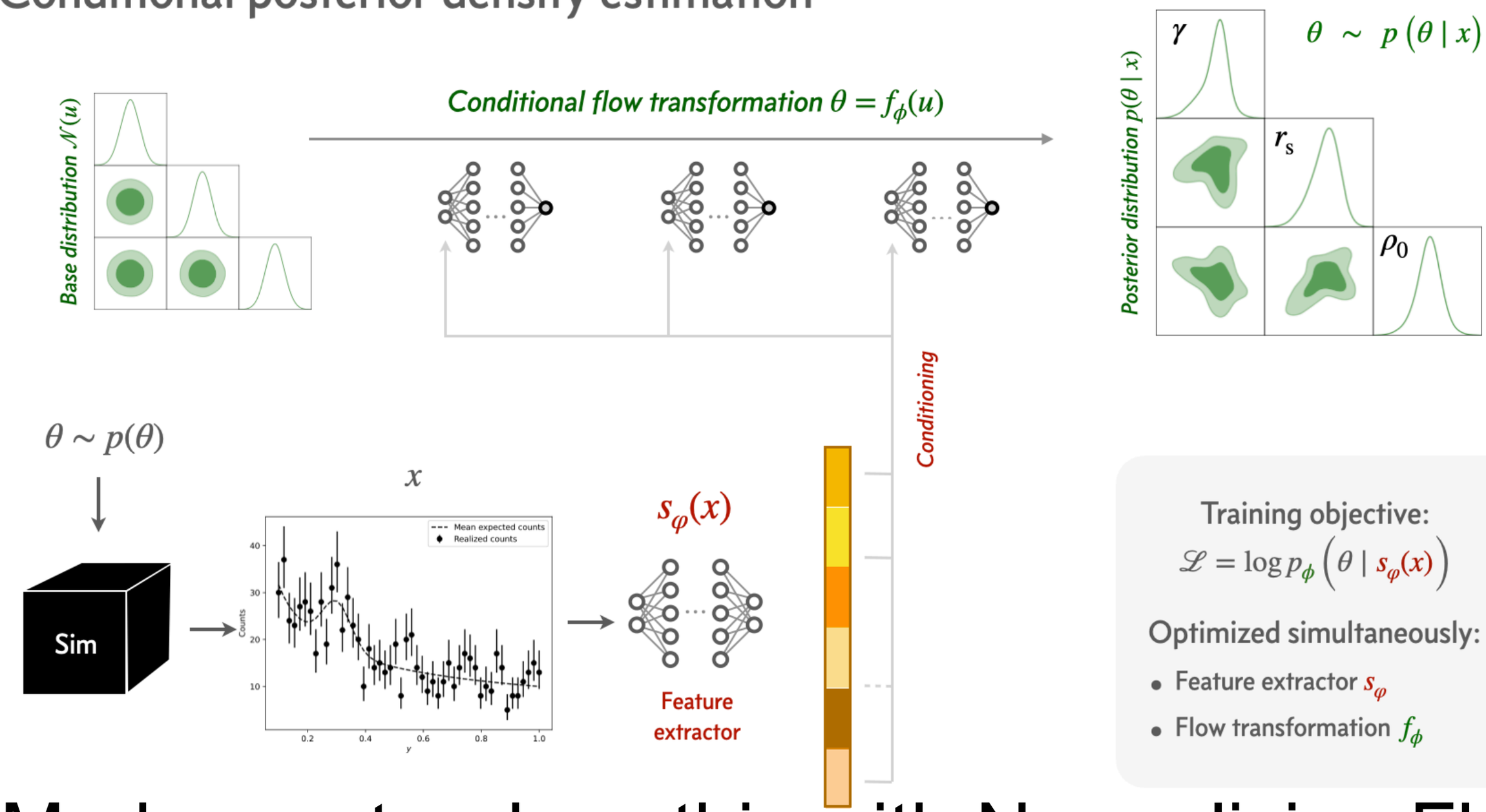
ML4GW

We follow the standard Astro approach of Simulation Based Inference w/MCMC sampling

arXiv:NeurIPS_ML4PS_2023_69

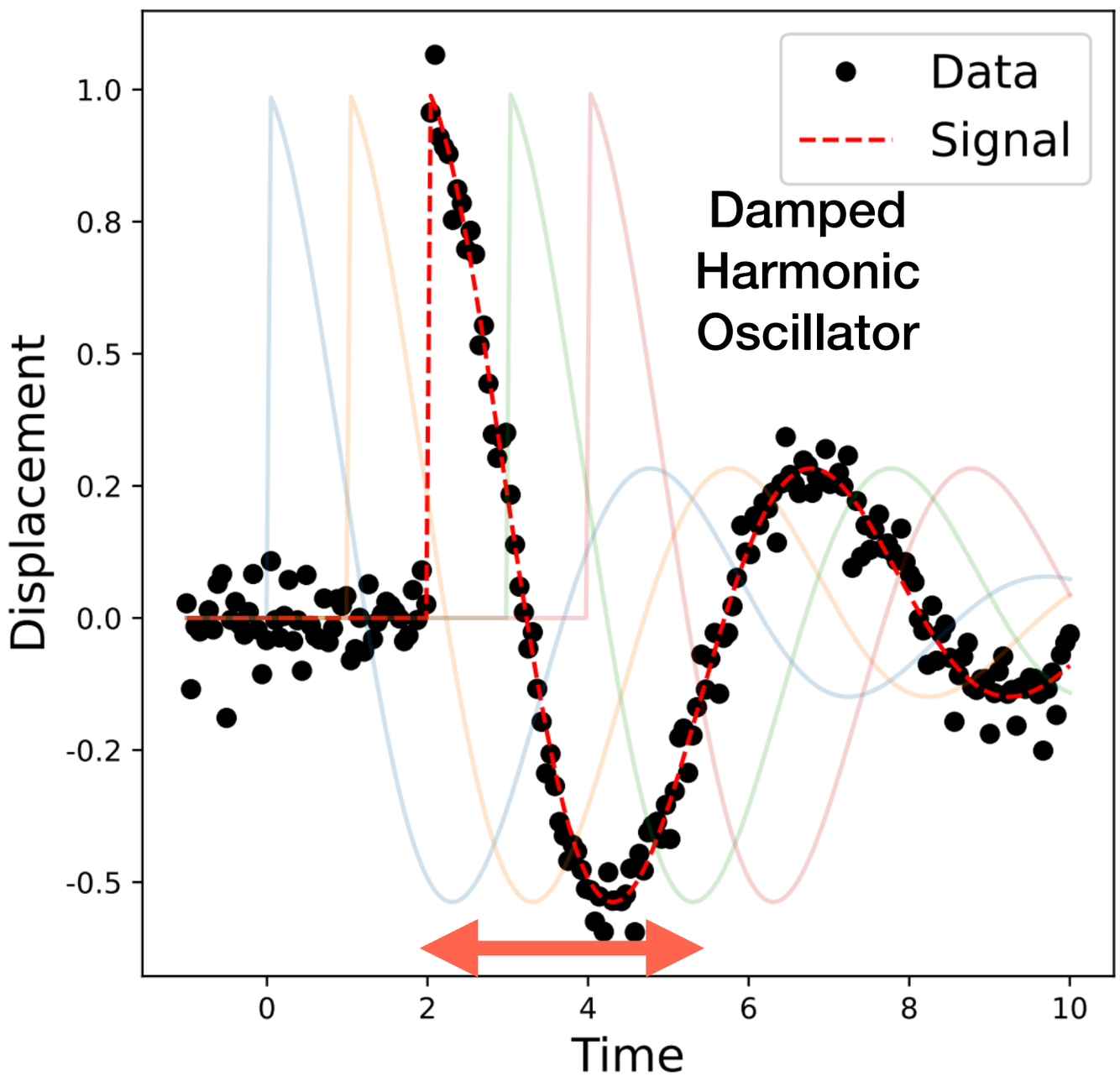
Parameter Estimation

Conditional posterior density estimation



Modern astro does this with Normalizing Flows

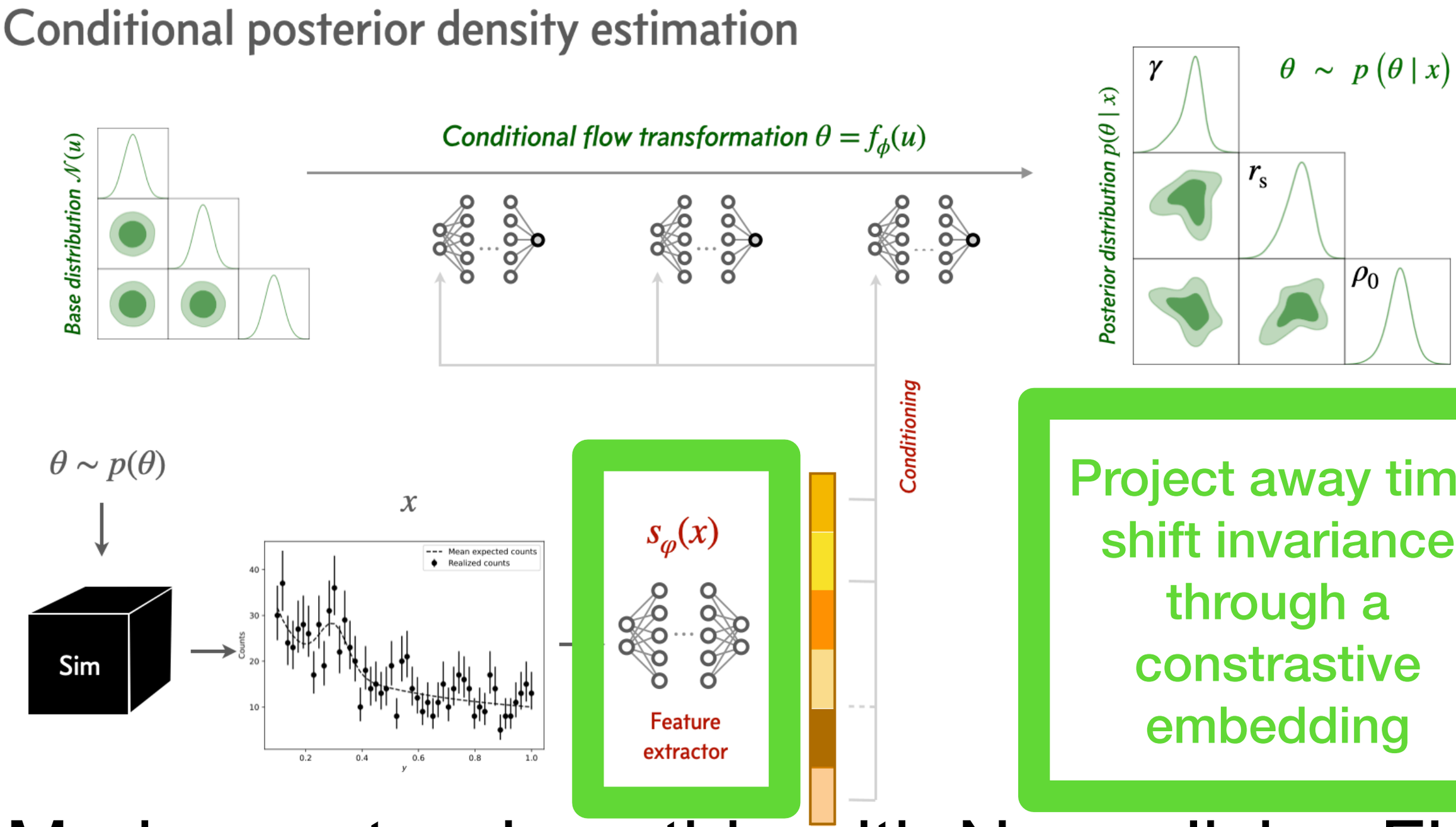
Parameter Estimation



Challenge is
to find the right
parameters

We don’t care about the arrive time, we want the other parameters

Parameter Estimation

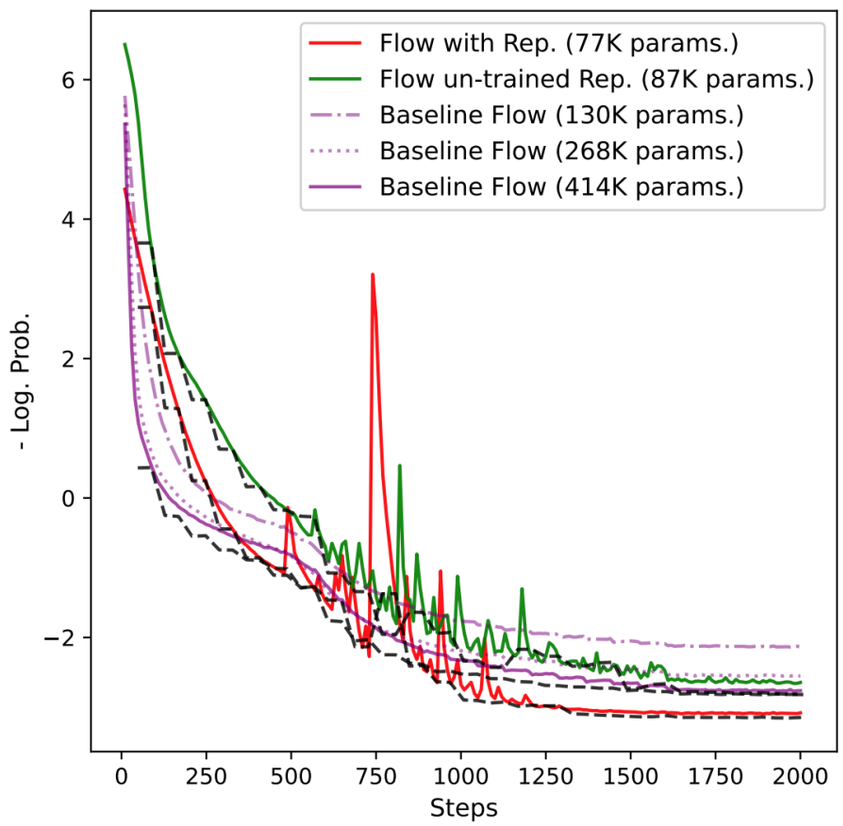


Project away time shift invariance through a constrastive embedding

Modern astro does this with Normalizing Flows

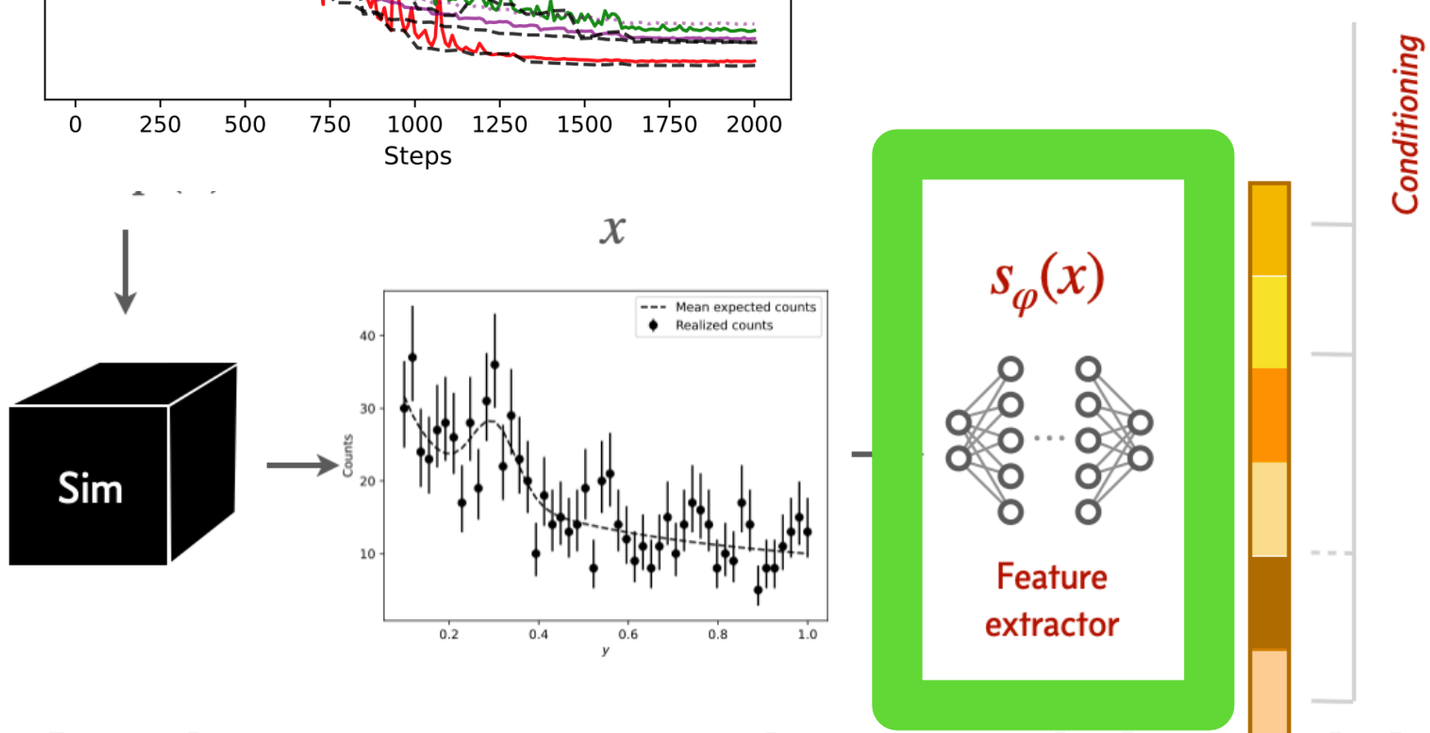
arXiv:NeurIPS_ML4PS_2023_69

Parameter Estimation



Projecting away dimensions yields better overall parameter estimation
VICReg with timeshift invariance

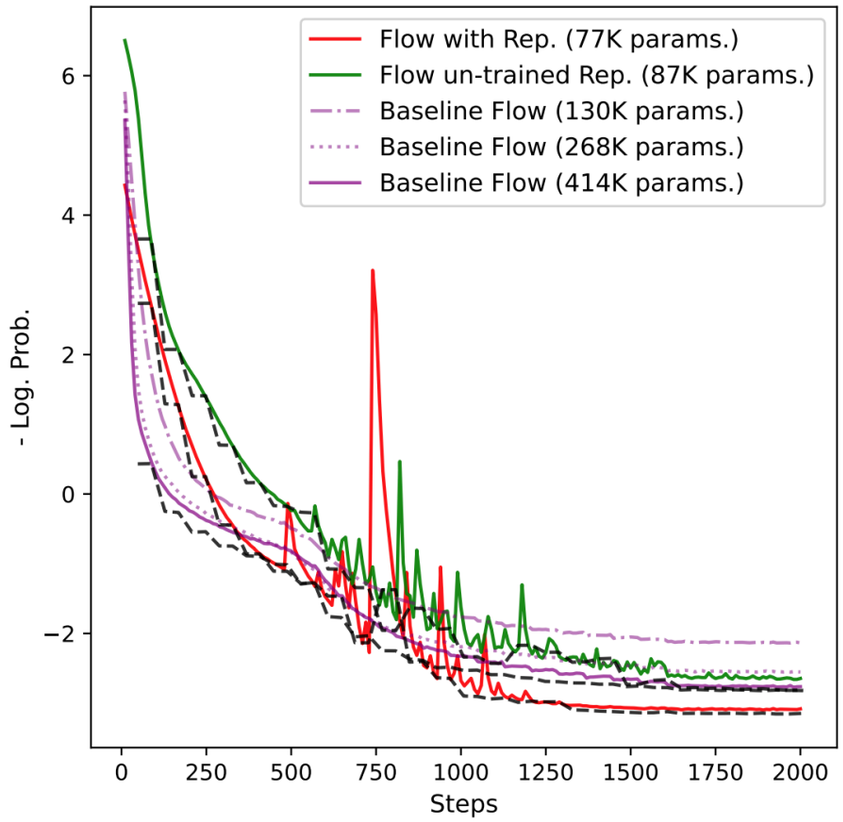
Reduces the size of the models



Project away time shift invariance through a constrastive embedding

Modern astro does this with Normalizing Flows

Parameter Estimation



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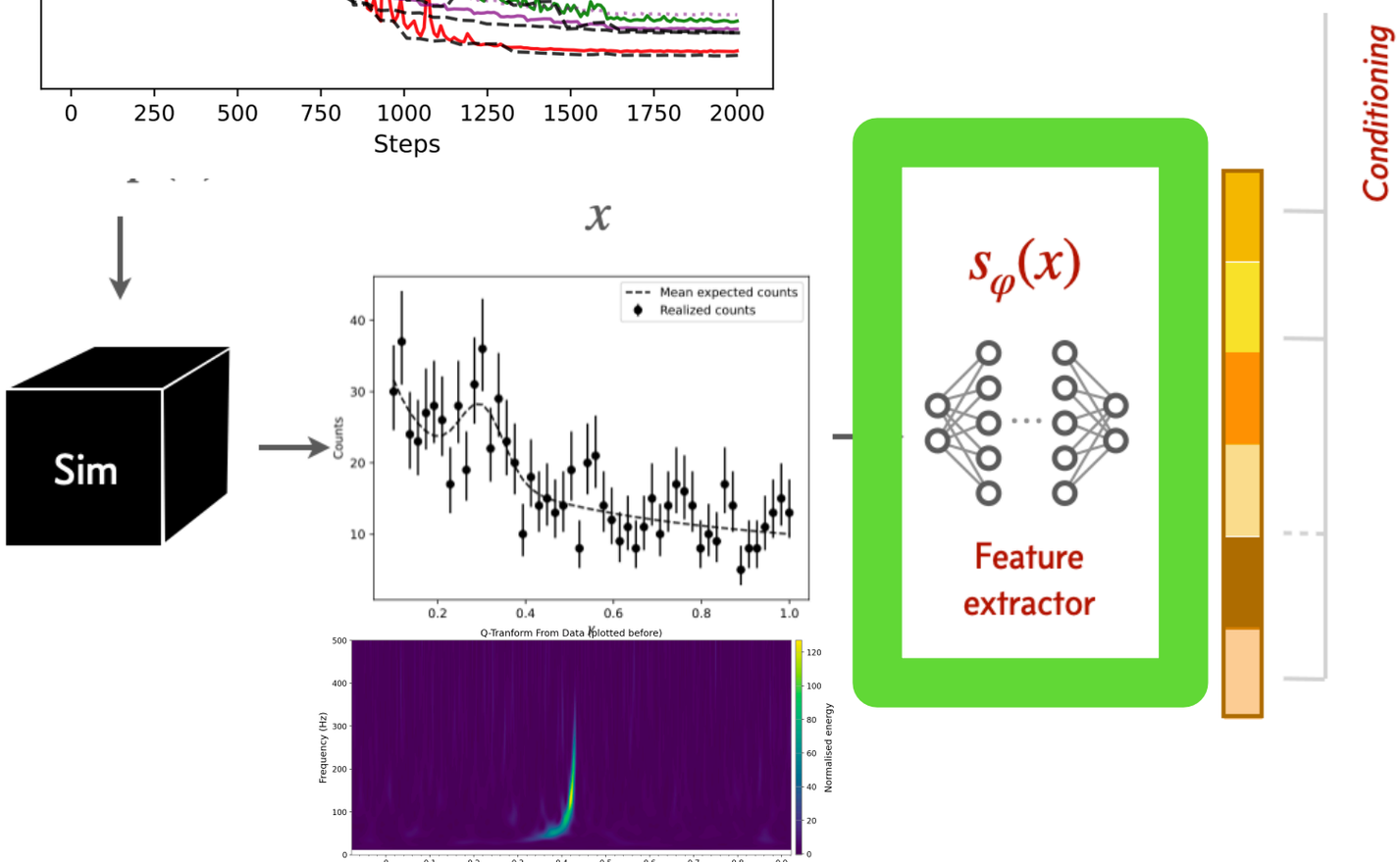
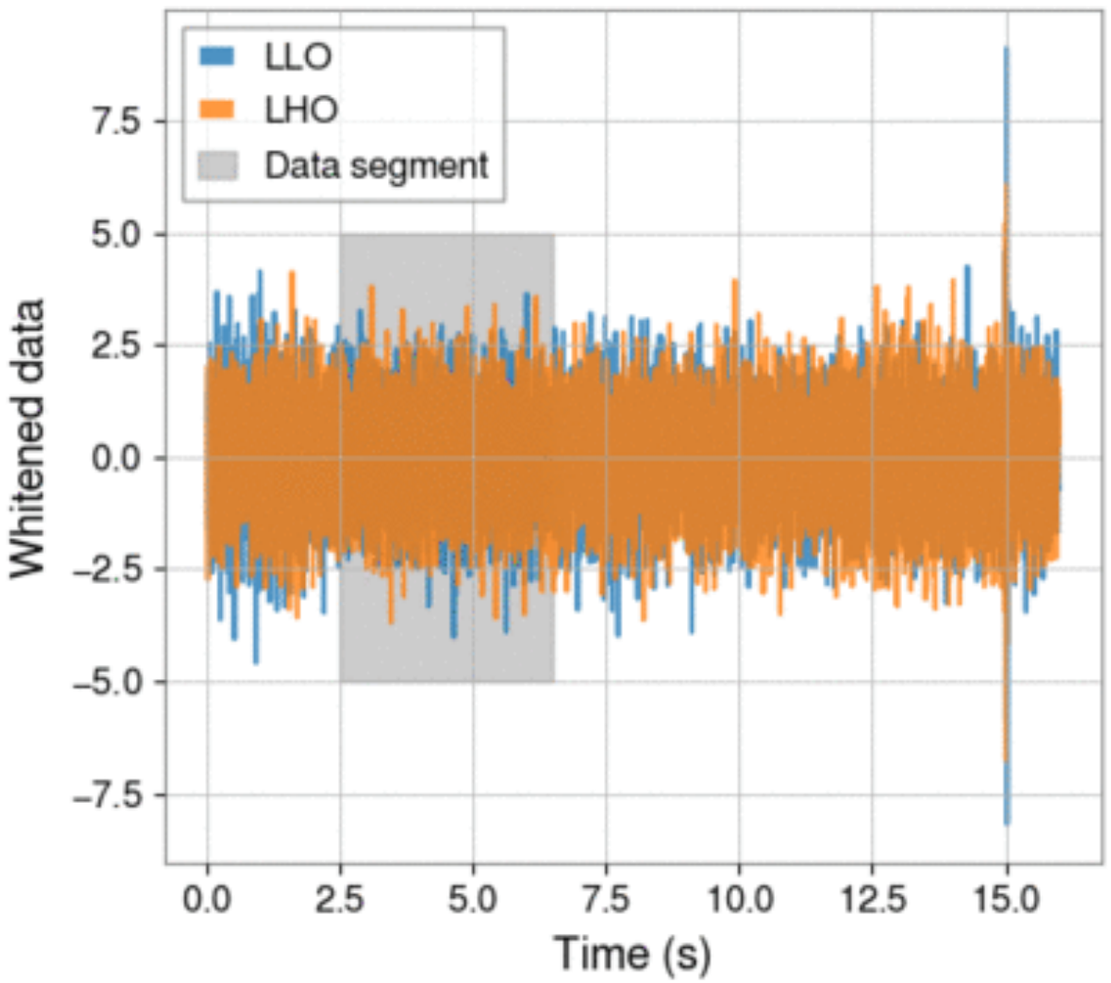
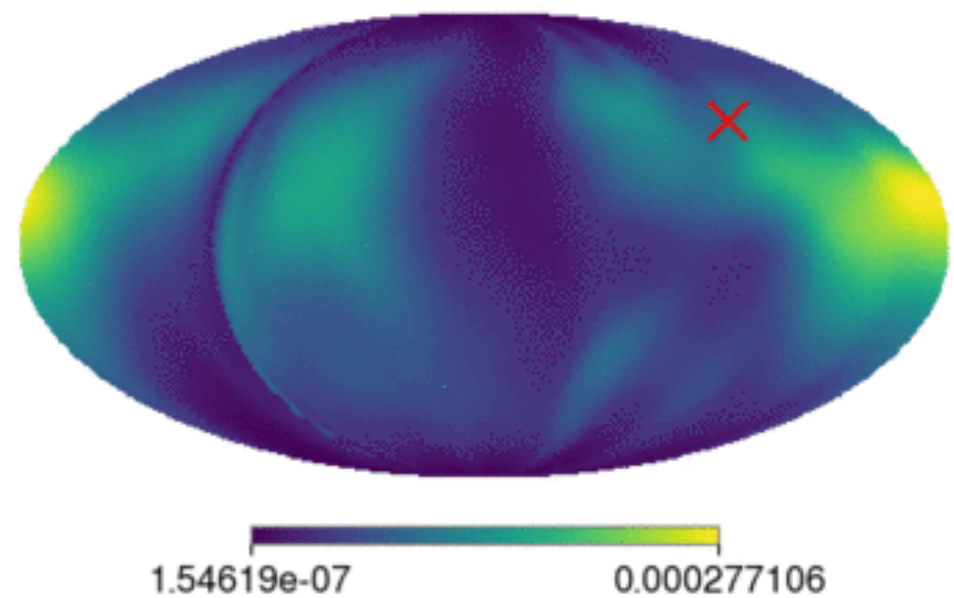


Combines both time and Fourier Transofrmed info to get good perf

arXiv:2407.19048

Parameter Estimation

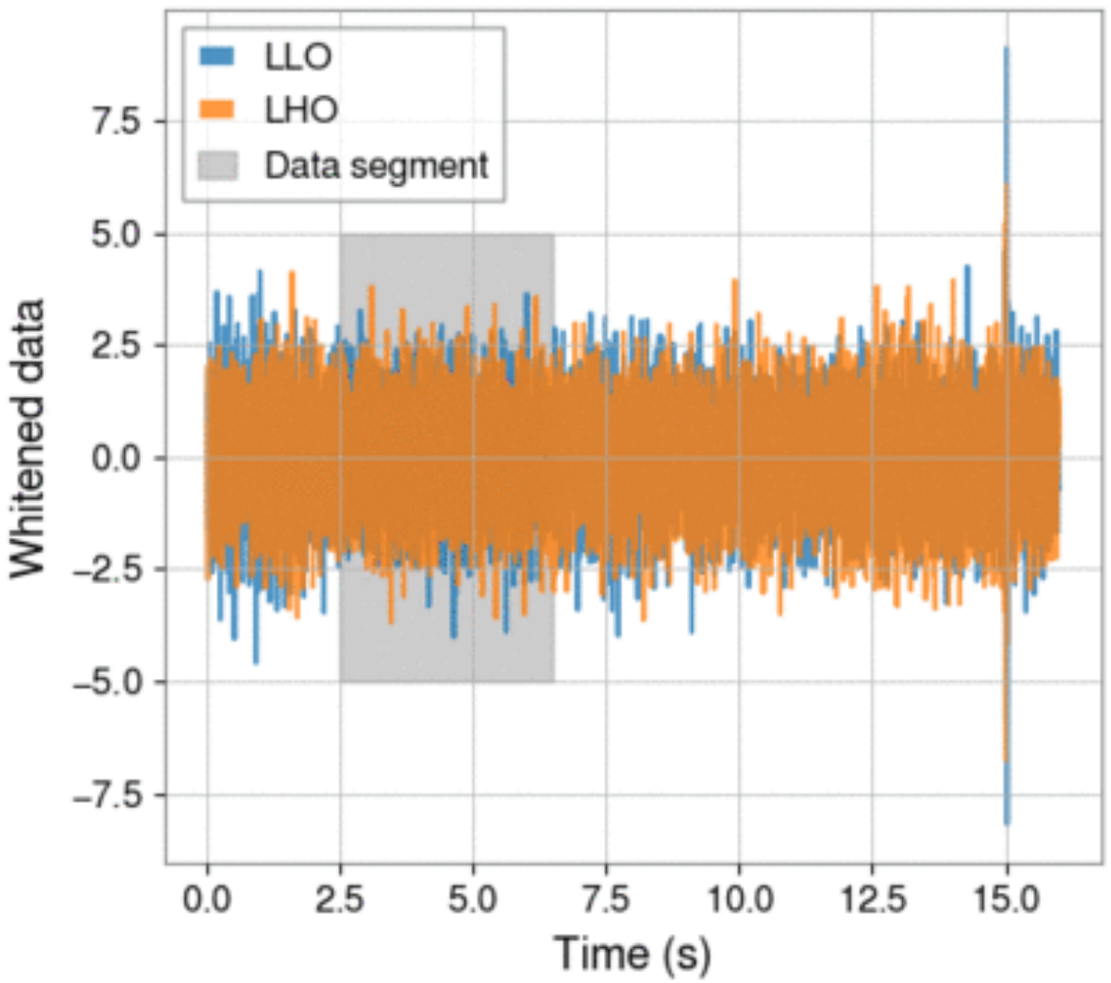


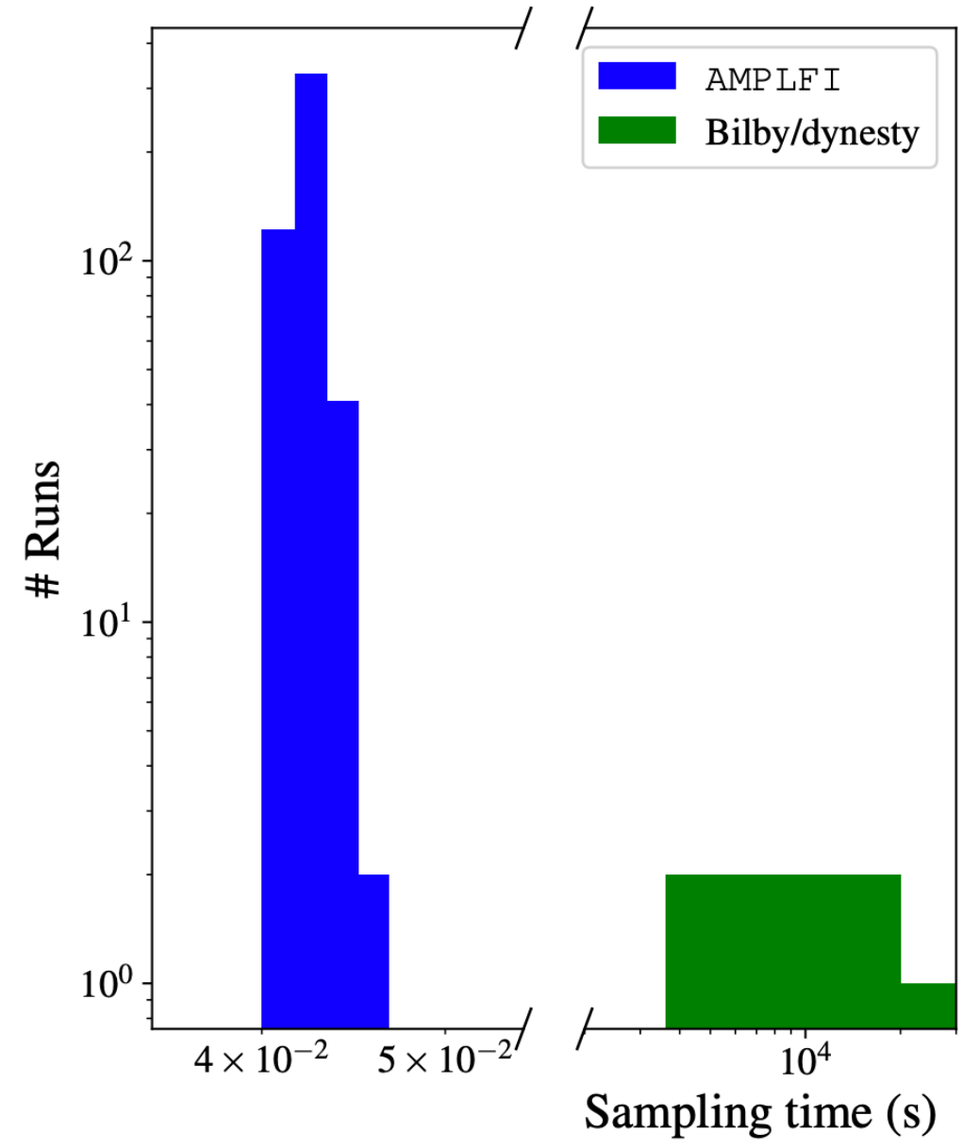


Neural Network Parameter estimation
100,000x times faster than conventional parameter estimation
Close full resolution on all parameters (aimed for speed)

arXiv:2407.19048

Parameter Estimation



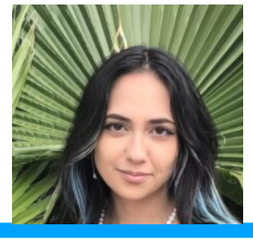


Neural Network Parameter estimation

>10,000x times faster than conventional parameter estimation

Further optimized larger model takes < 1s (current default)

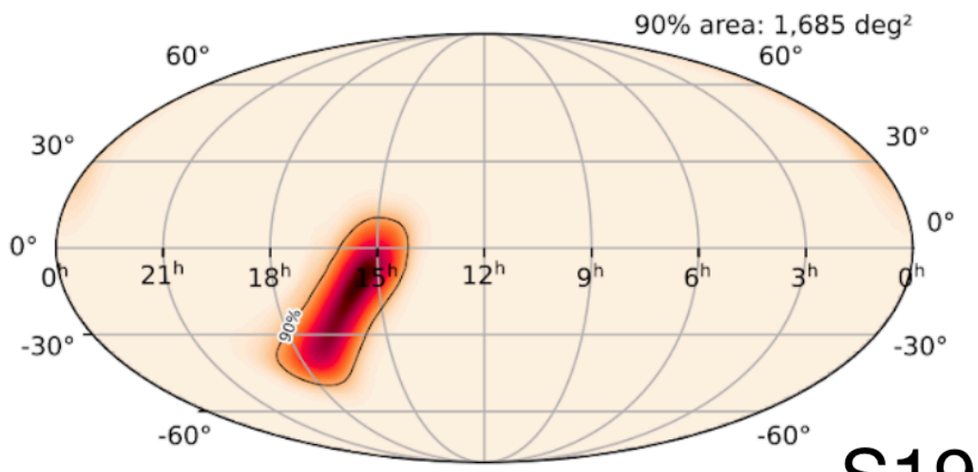
arXiv:2407.19048



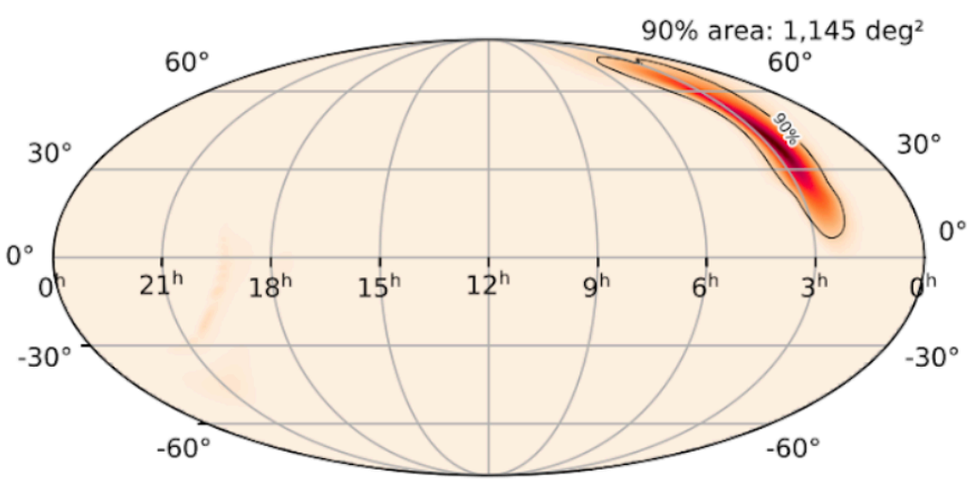
Parameter Estimation

AMPLFI

S190512at



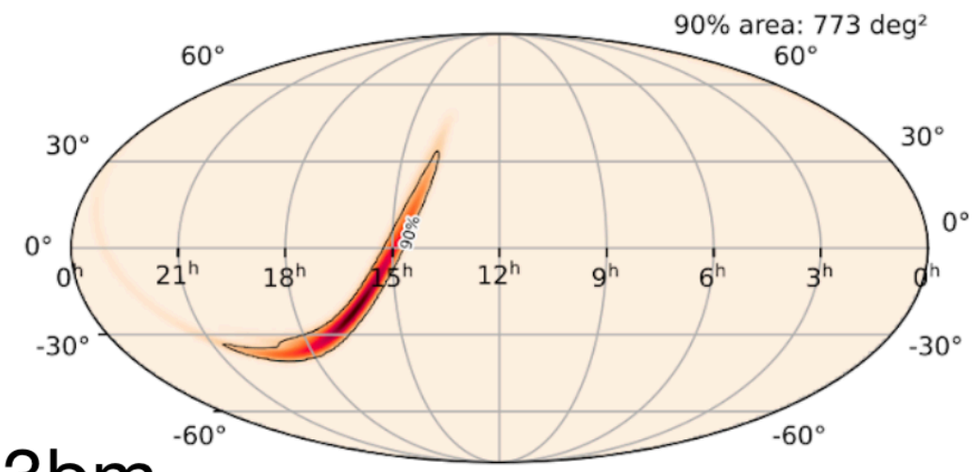
S190513bm

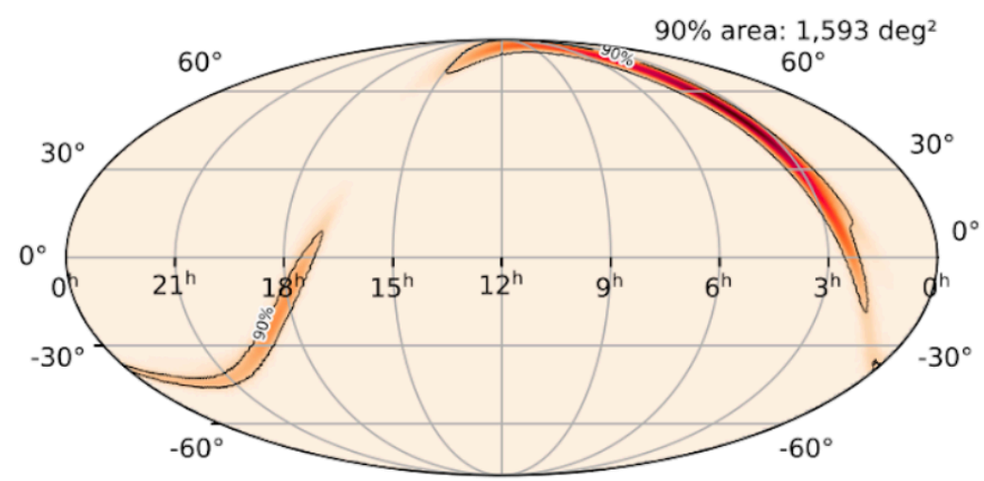


ML Based PE

FIXME

BAYESTAR



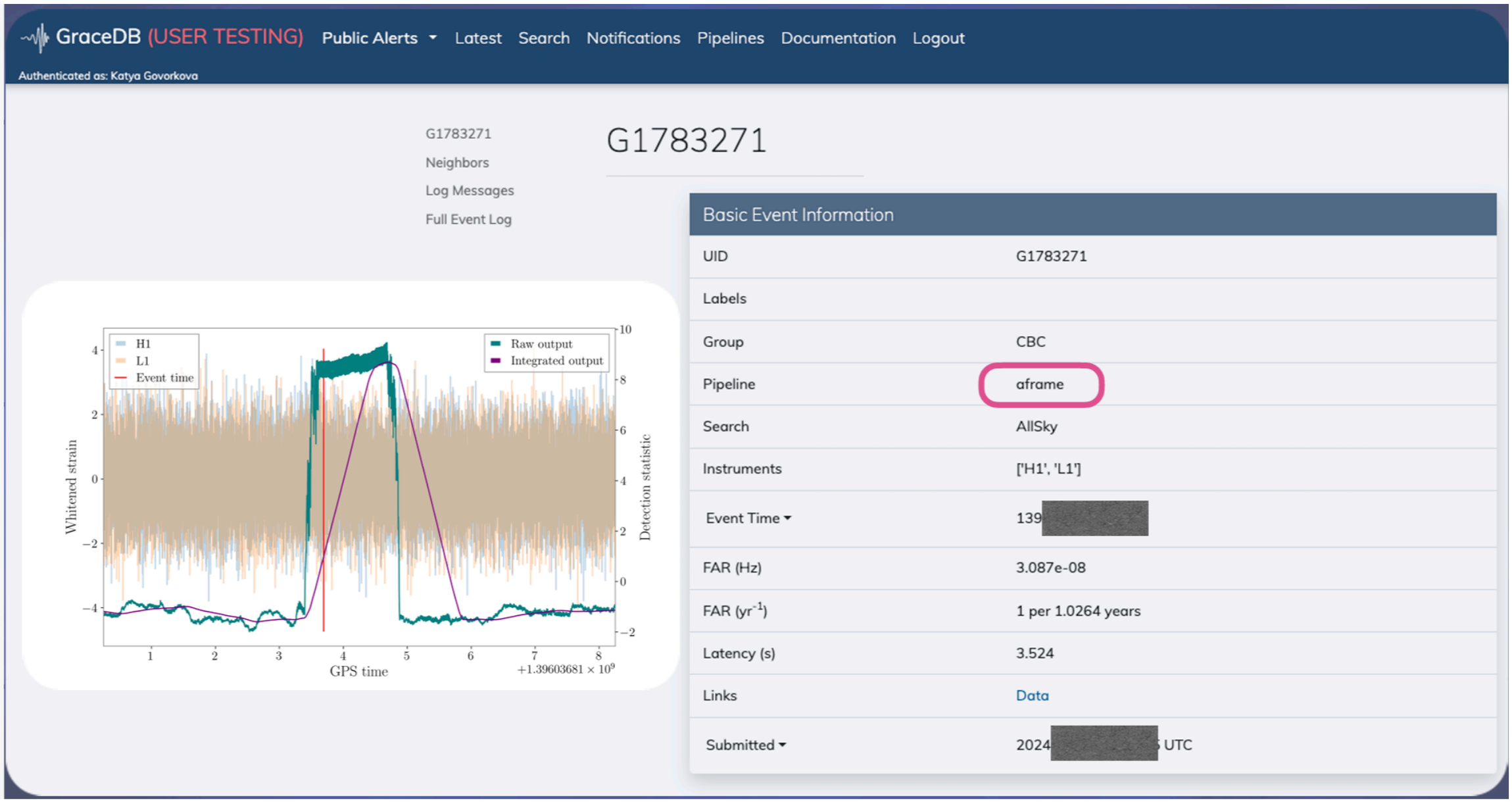


Rule-Based

100,000x Faster

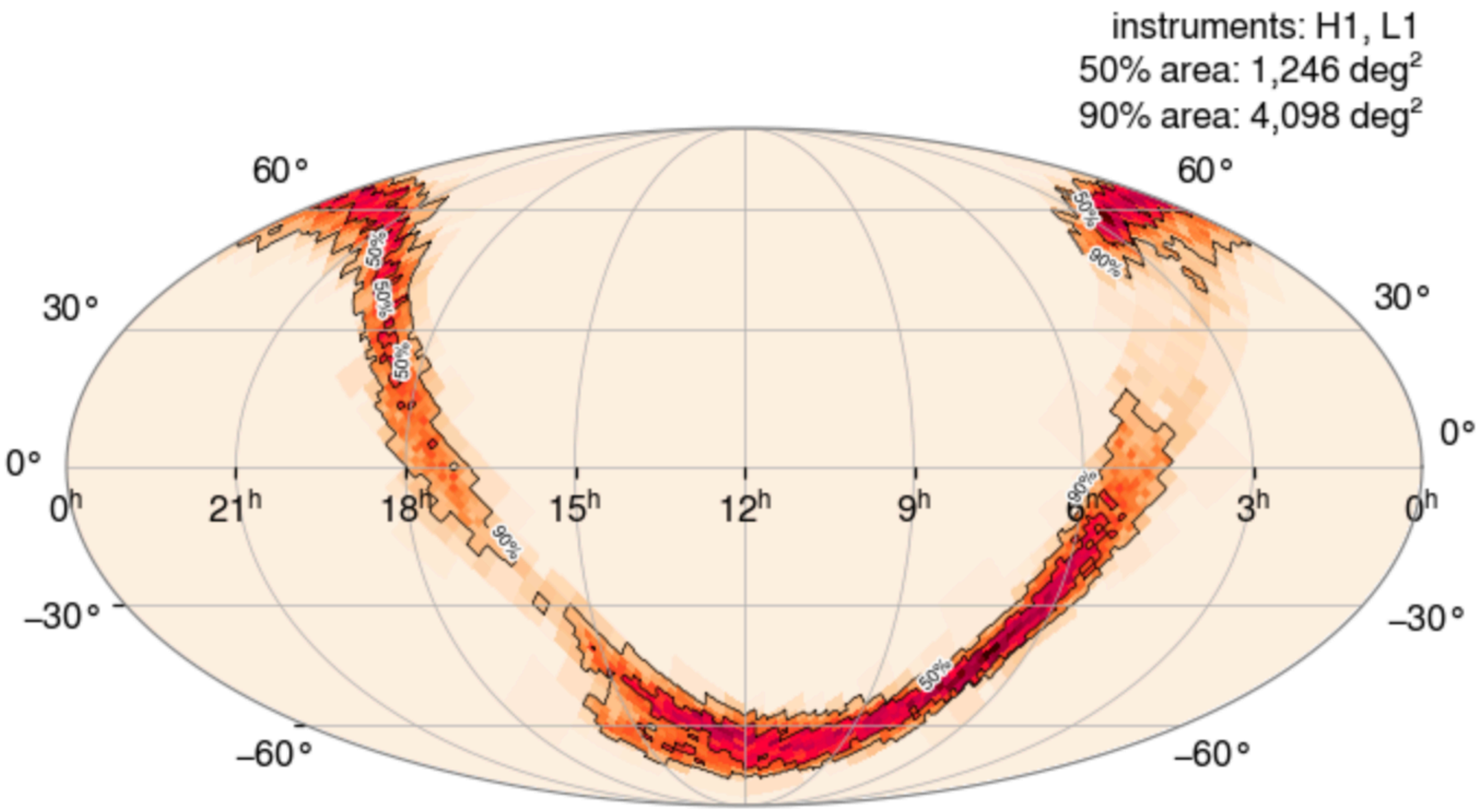
Our System is running Live!(Public Soon!)

Accelerated AI Algorithms for Data-Driven Discovery



Our system is now fully integrated into LVK operations

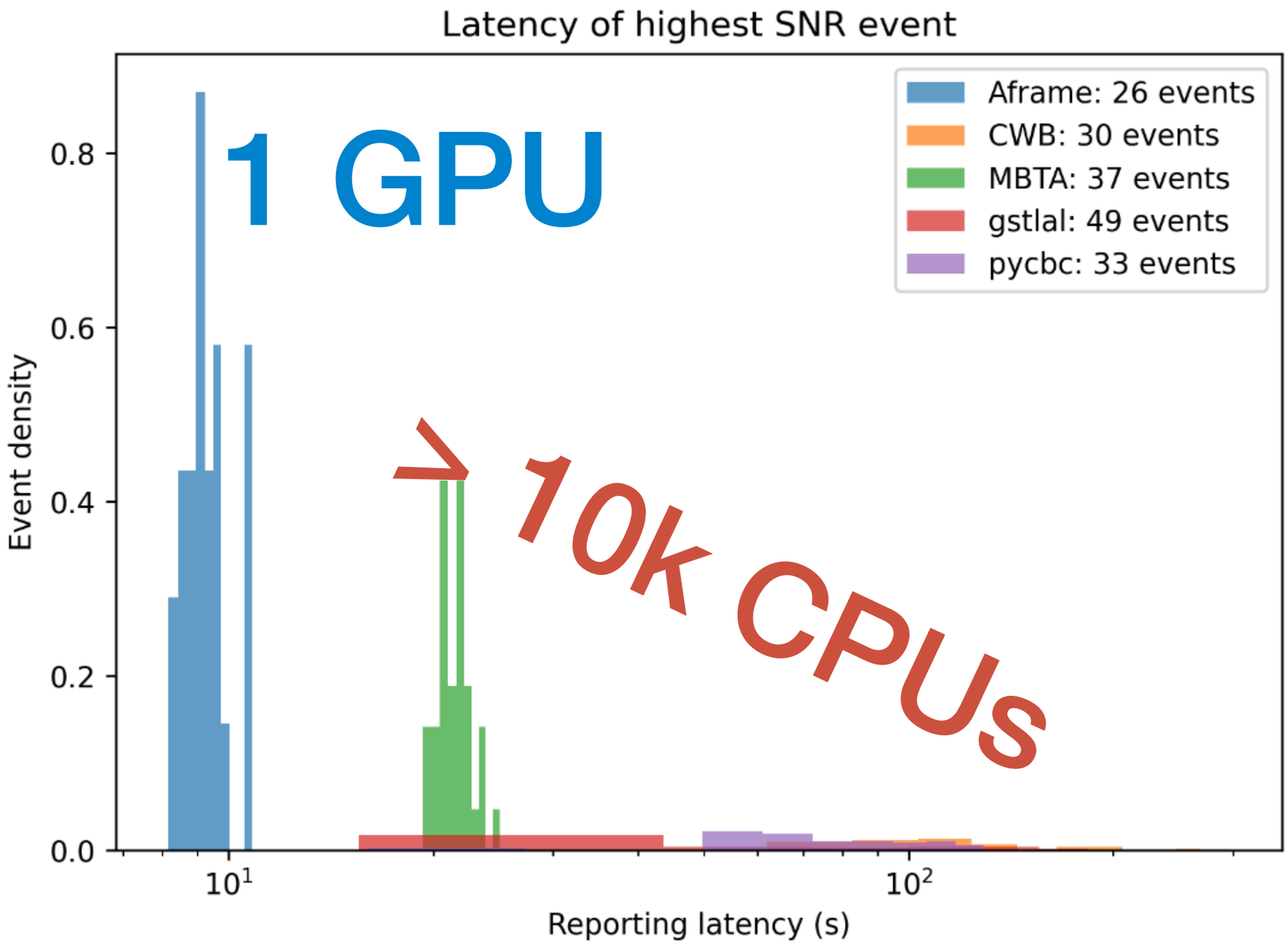
Impact Already



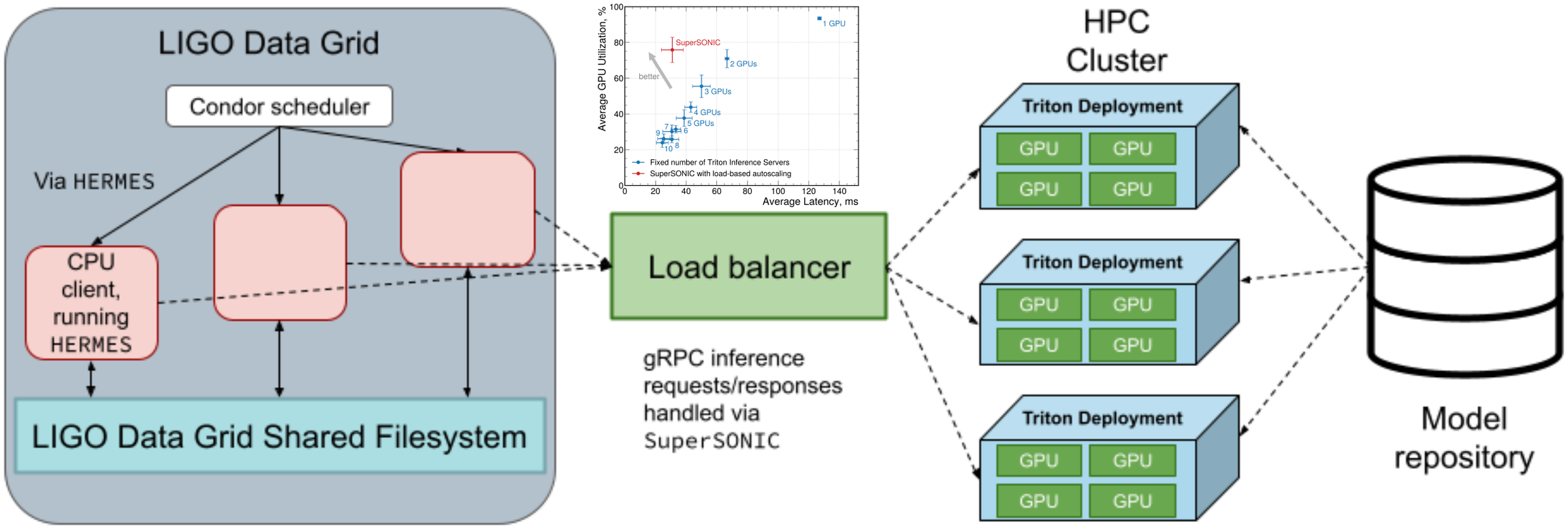
https://gcn.nasa.gov/circulars/41601

We are now running online officially

Impact Already



Our pipeline found all the large signal events
Our pipeline is 10-100x faster than others

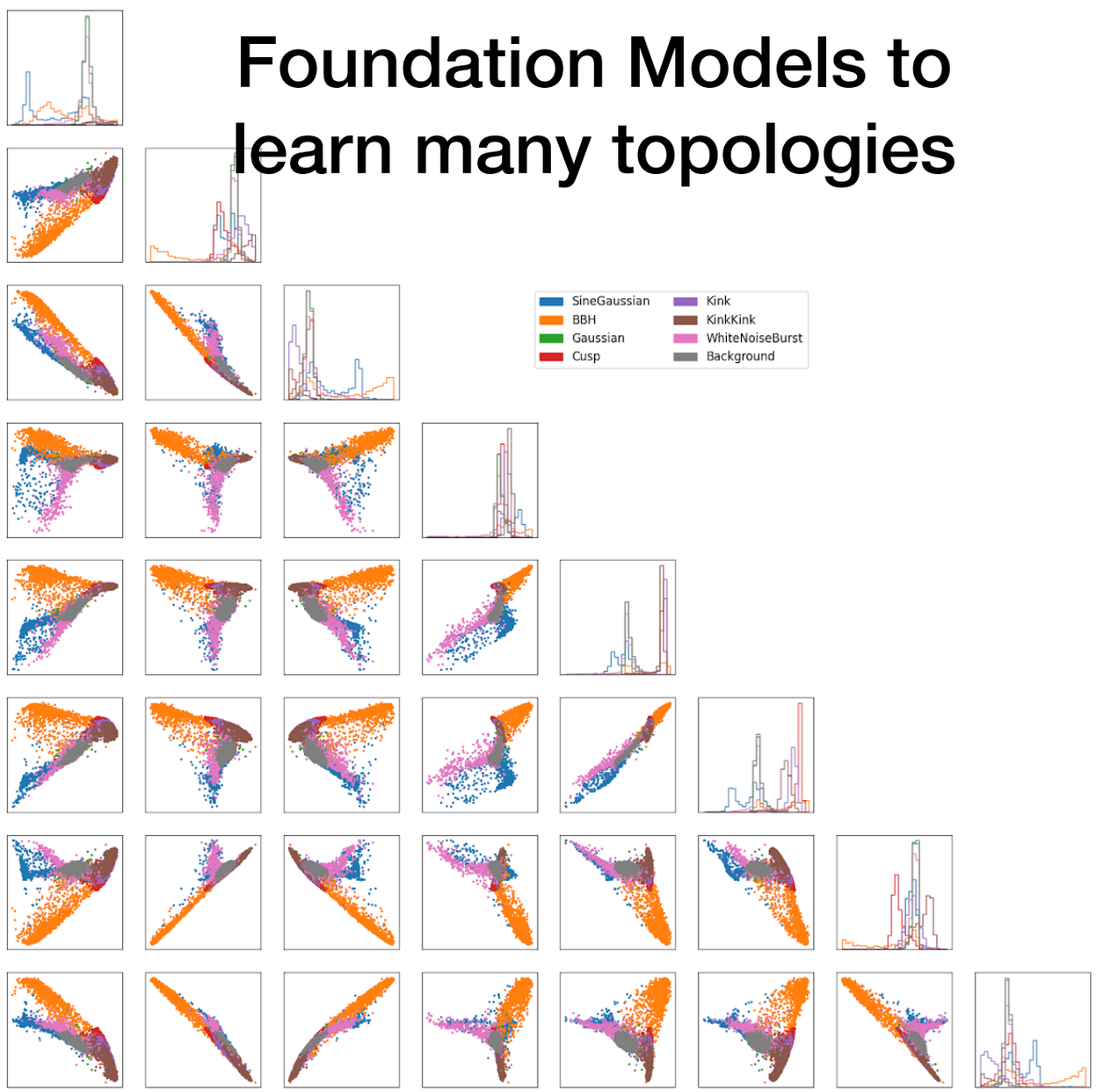

LIGO Data Grid
Condor scheduler
Via HERMES
CPU client, running HERMES
LIGO Data Grid Shared Filesystem
Average GPU Utilization, %
Average Latency, ms
1 GPU
SuperSONIC
2 GPUs
better
3 GPUs
4 GPUs
5 GPUs
Fixed number of Triton Inference Servers
SuperSONIC with load-based autoscaling
Load balancer
gRPC inference requests/responses handled via SuperSONIC
HPC Cluster
Triton Deployment
GPU
Model repository

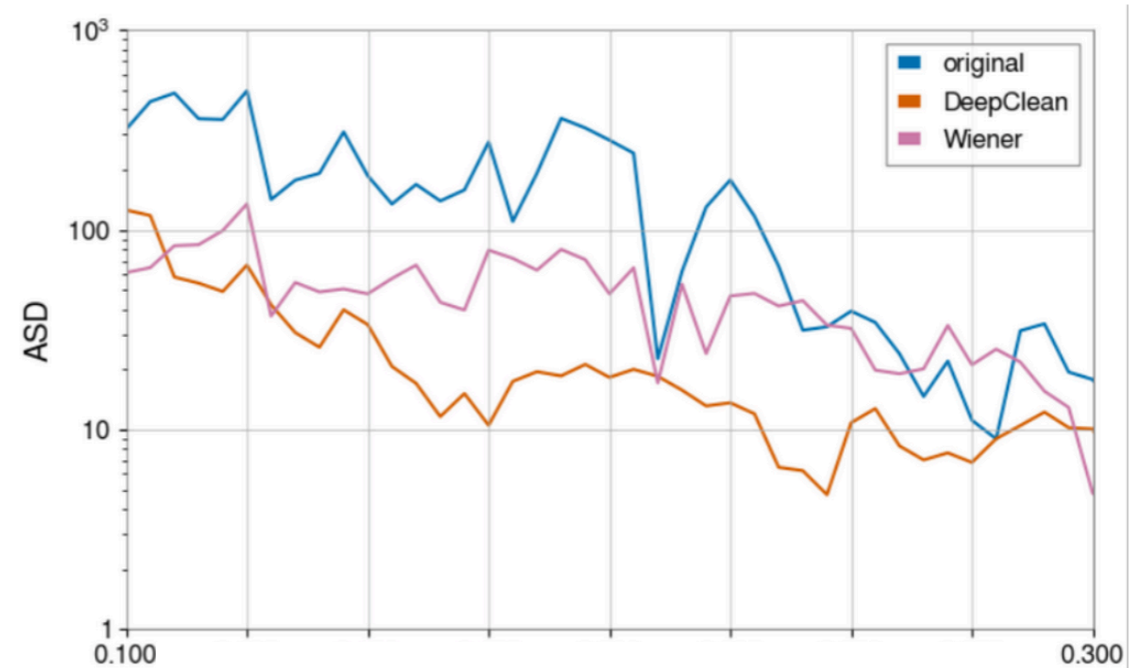
Alerting Everyone Fast

We will now be able to alert telescopes much faster

The Future

Foundation Models to learn many topologies





Automated Detector controlled denoising

This is just the beginning

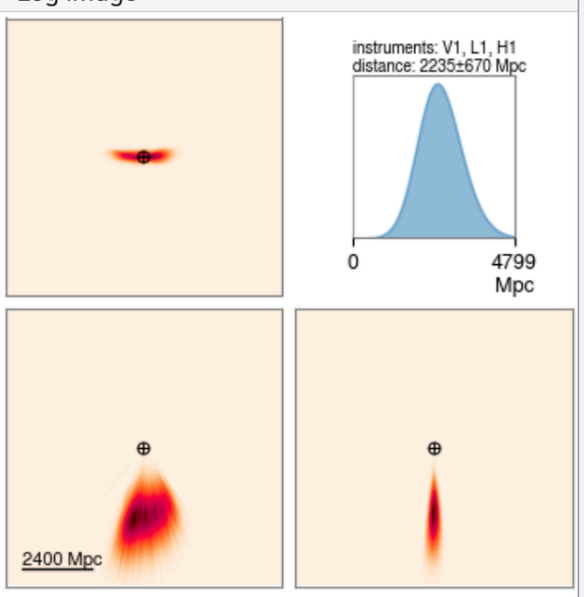
Our System is Live!

Accelerated AI Algorithms for Data-Driven Discovery

Per-Pipeline Event Information

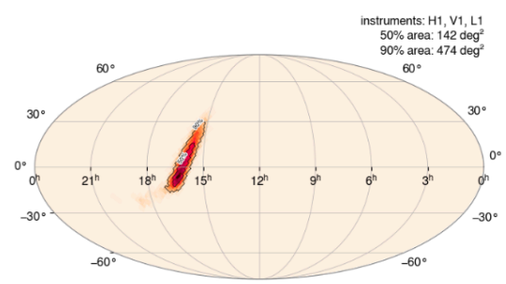
UID	Group	Pipeline	Search	gpstime	FAR (Hz)
G597361	CBC	pycbc	AllSky	1441016546.022	3.168e-10
G597350	CBC	aframe	AllSky	1441016545.998	3.154e-10
G597364	CBC	CWB	BBH	1441016546.020	6.083e-11
			AllSky	1441016545.995	1.164e-14
			AllSky	1441016546.002	1.596e-25

Log Image



Volume rendering of amplfi.multiorder.fits,0
— Submitted by read-cvmfs-emfollow robot on September 4, 2025 10:22:37 UTC

Log Image



Mollweide projection of amplfi.multiorder.fits,0
— Submitted by read-cvmfs-emfollow robot on September 4, 2025 10:22:36 UTC

We are publicly running since August 30th 2025
Delivering robust alerts

Our System is running Live!

GCN Circular 41606

Subject LIGO/Virgo/KAGRA S250830bp: Identification of a GW compact binary merger candidate
Event LIGO/Virgo/KAGRA S250830bp
Date 2025-08-30T10:55:06Z (a month ago)
From Pedro Jeronimo Santos da Silva <pedro.jeronimo@unesp.br>
Via Web form

The LIGO Scientific Collaboration, the Virgo Collaboration, and the KAGRA Collaboration report:

We identified the compact binary merger candidate S250830bp during real-time processing of data from LIGO Hanford Observatory (H1), LIGO Livingston Observatory (L1), and Virgo Observatory (V1) at 2025-08-30 10:24:18.852 UTC (GPS time: 1440584676.852). The candidate was found by the Aframe [1] cWB [2], cWB BBH [3], GstLAL [4], MBTA [5], MLy [6], PyCBC Live [7], and SPIIR [8] analysis pipelines.

S250830bp is an event of interest because its false alarm rate, as estimated by the online analysis, is 3.2e-10 Hz, or about one in 1e2 years. The event's properties can be found at this URL:

https://gracedb.ligo.org/superevents/S250830bp

The classification of the GW signal, in order of descending probability, is BBH (84%), NSBH (16%), Terrestrial (<1%), or BNS (<1%).

Two sky maps are available at this time and can be retrieved from the GraceDB event page:
* amplfi.multiorder.fits,0, an initial localization generated by AMPLFI [10] distributed via GCN and SCiMMA notices about 24 seconds after the candidate event time.
* bayestar.multiorder.fits,0, an initial localization generated by BAYESTAR [11], distributed via GCN and SCiMMA notices about 5 minutes after the candidate event time.

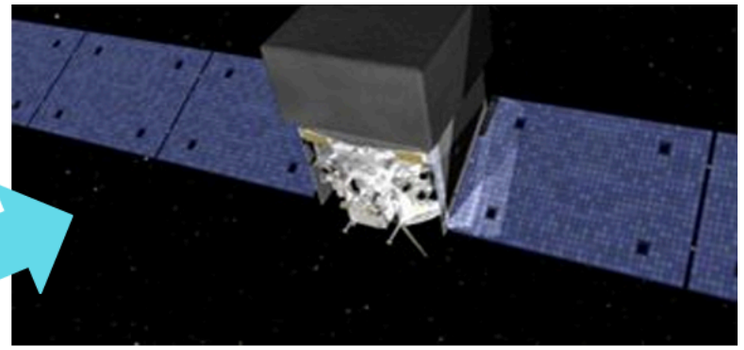
Even with a system not designed for speed we are 10x faster

https://gcn.nasa.gov/circulars/41606?query=S250830bp

Questions?

Multi-Messenger Astronomy

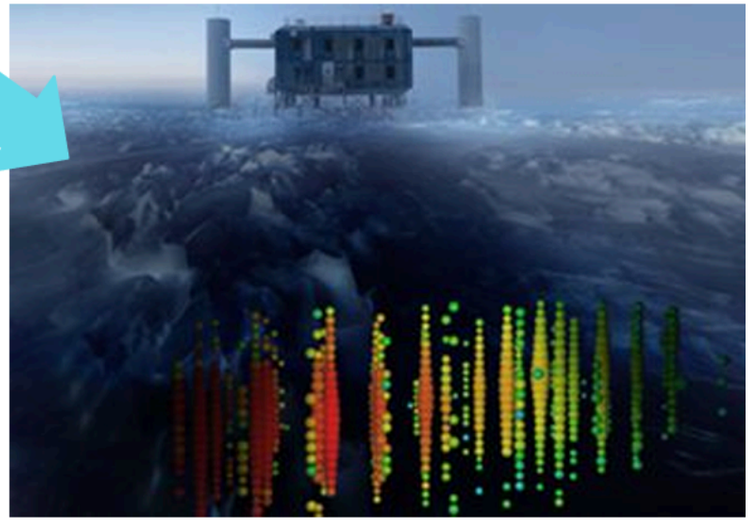
Gravitational waves



X-rays/Gamma-rays

Visible/infrared light

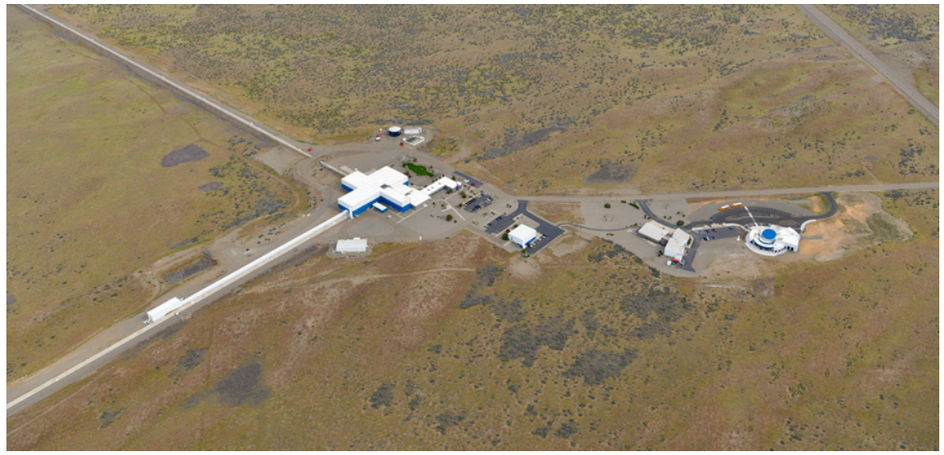
Radio waves

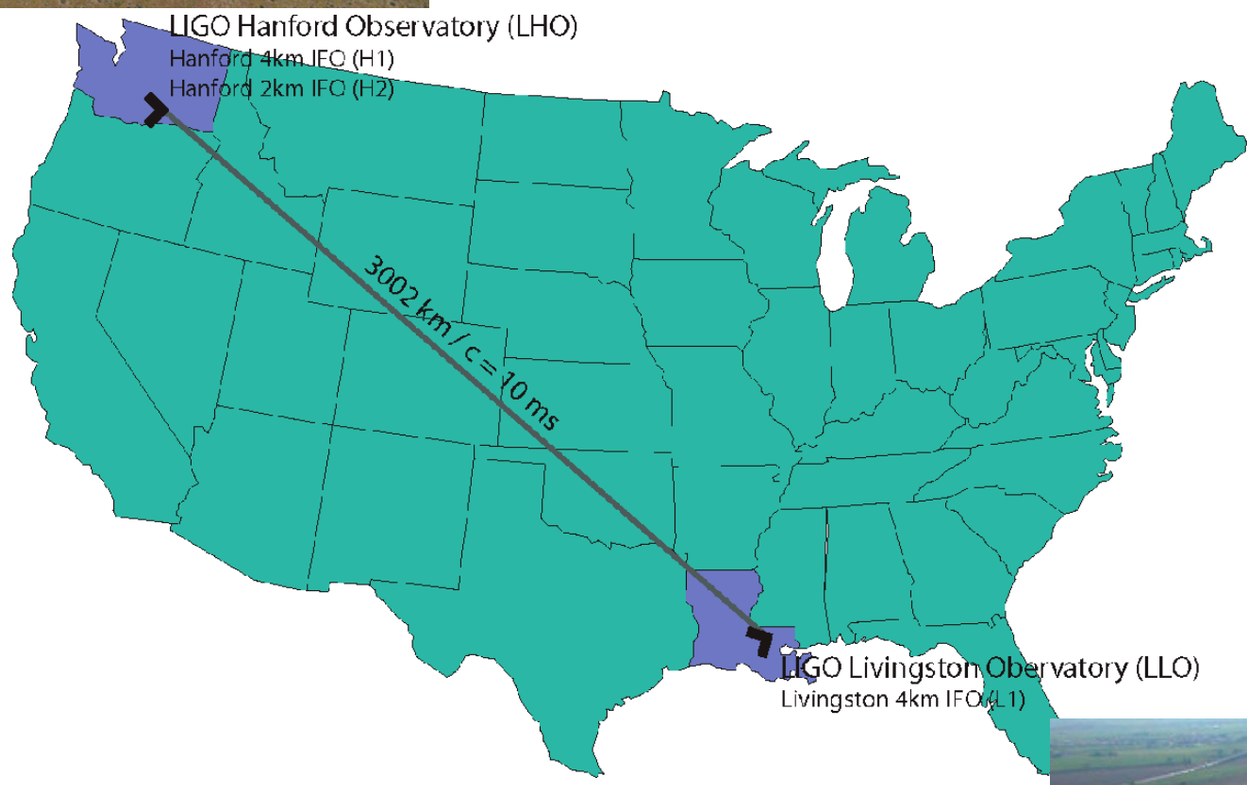


Neutrinos

Performing fast identification of GWs critical to alerting world!

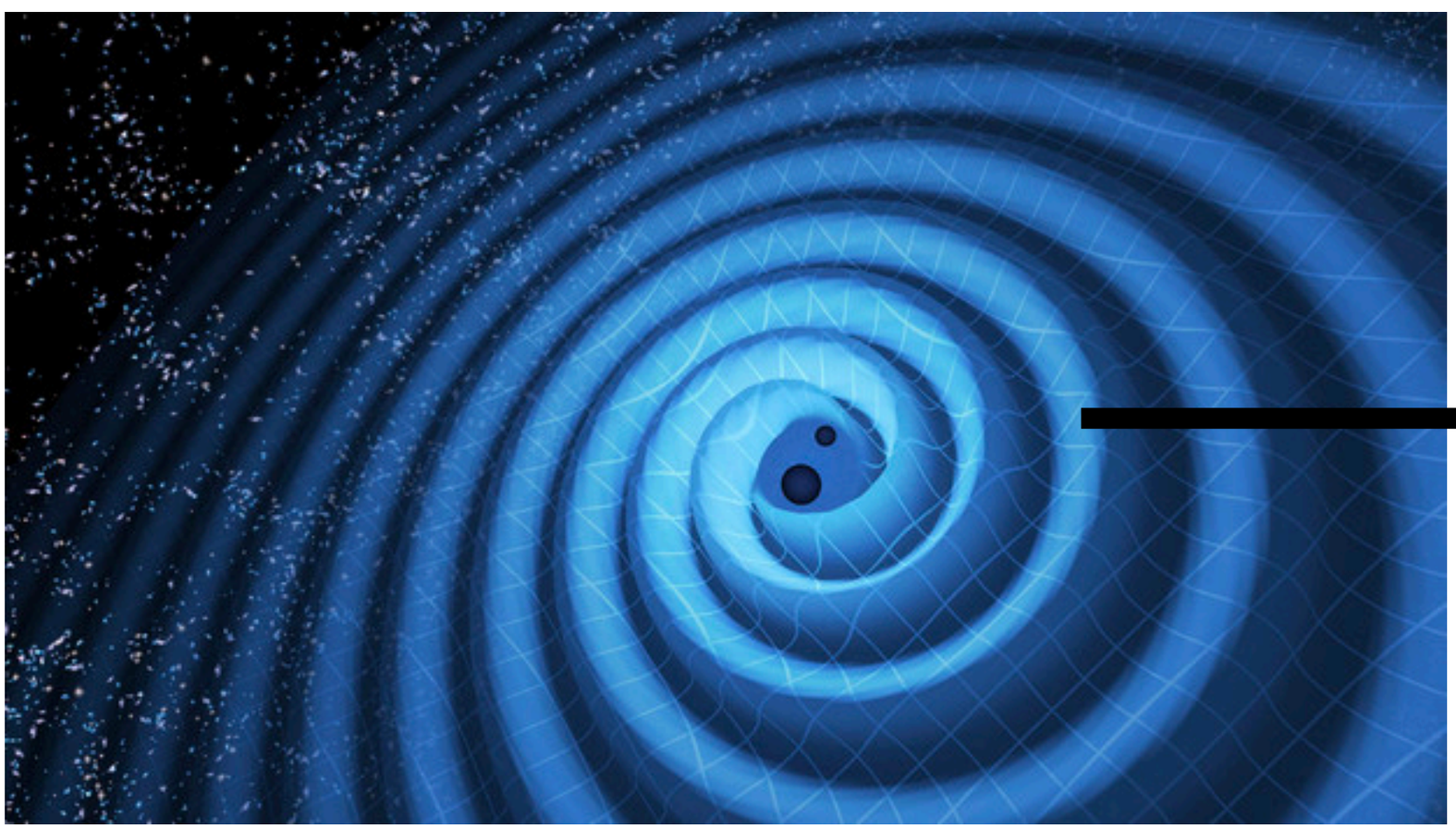
LIGO





Two detectors that are sensitive to GW

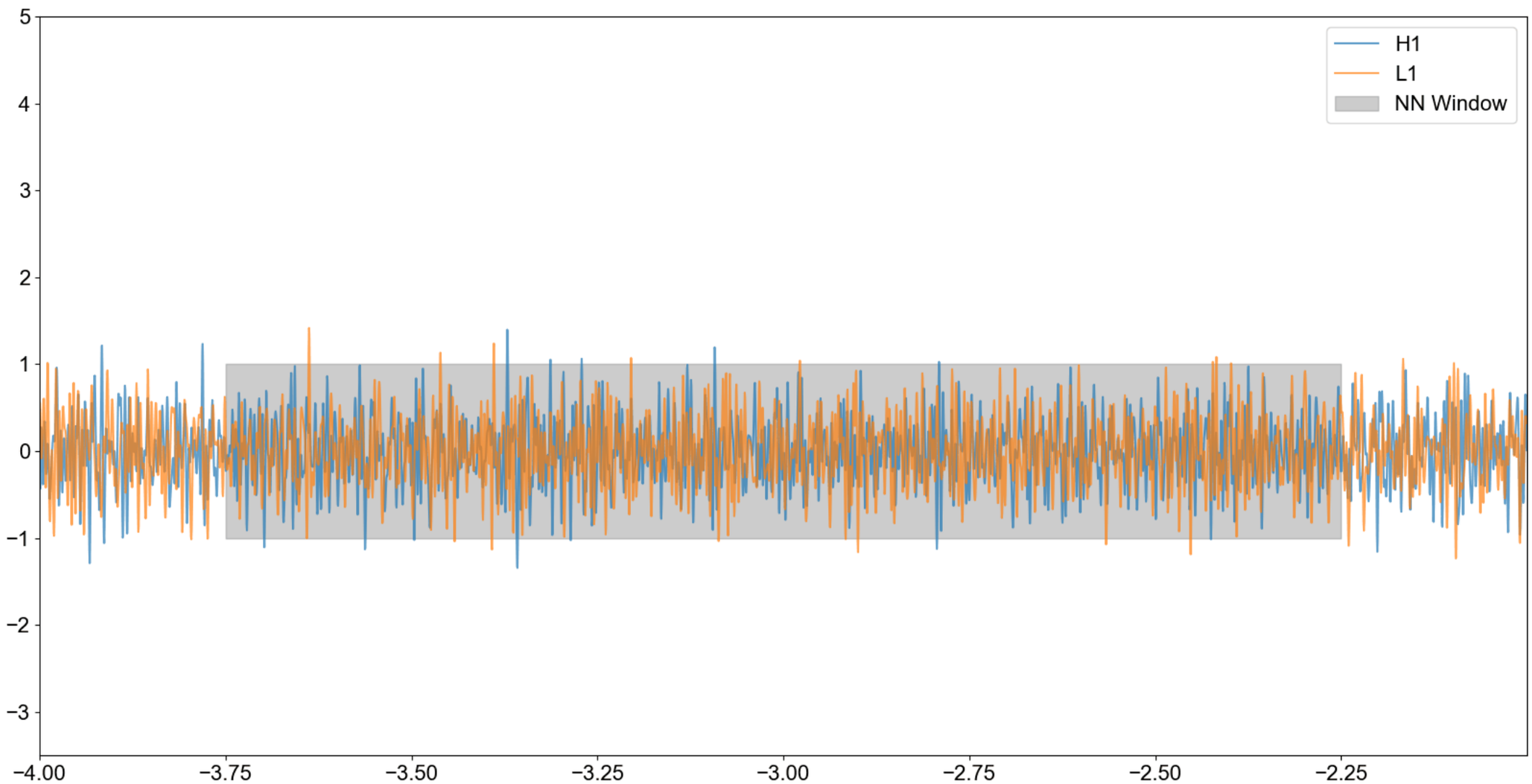
Graviational Waves



Many detectors
2 in US(LIGO)

Ripples

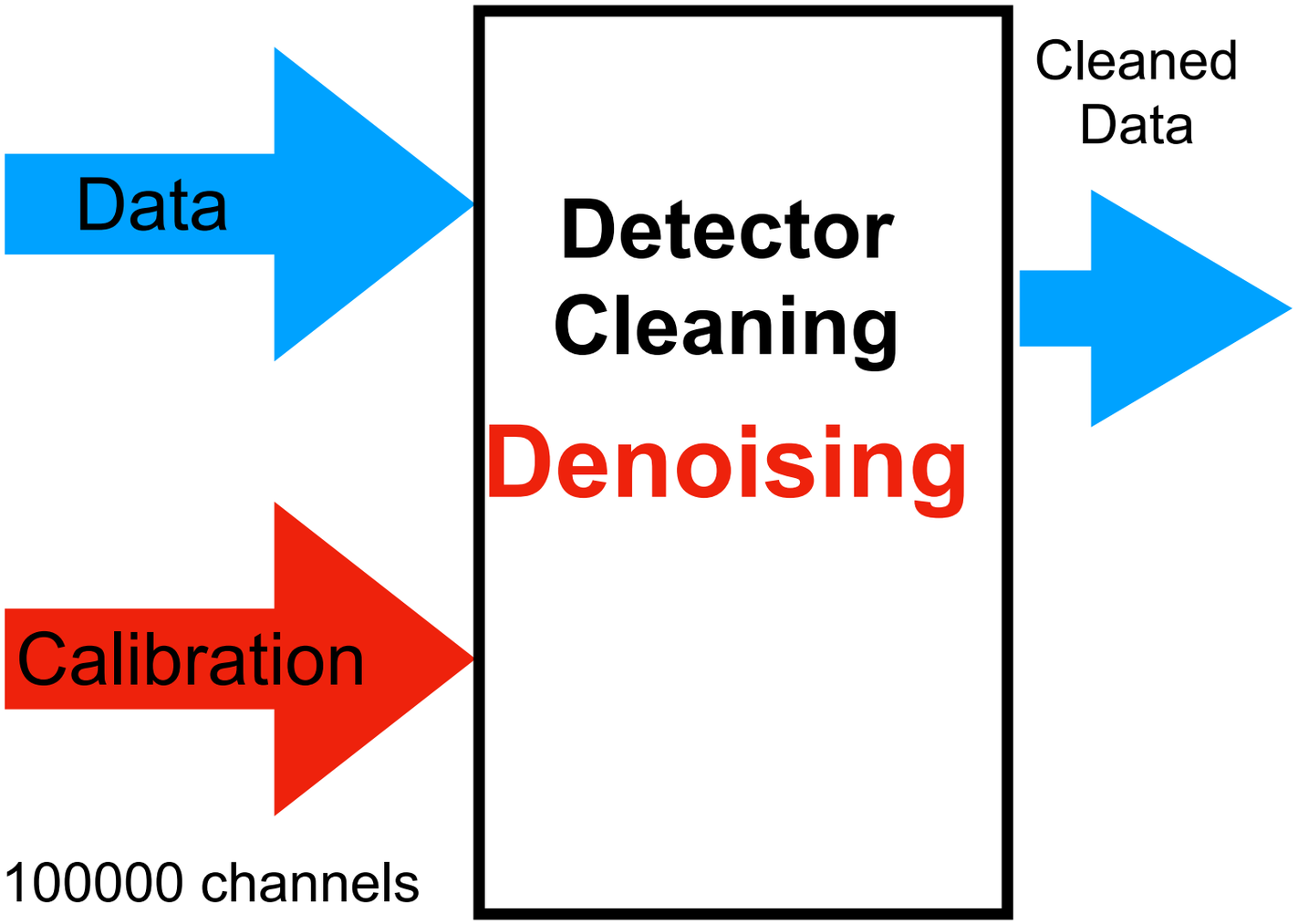
Gravitational Wave Data



Data is time series from at least two detectors
We aim for a correlated signal

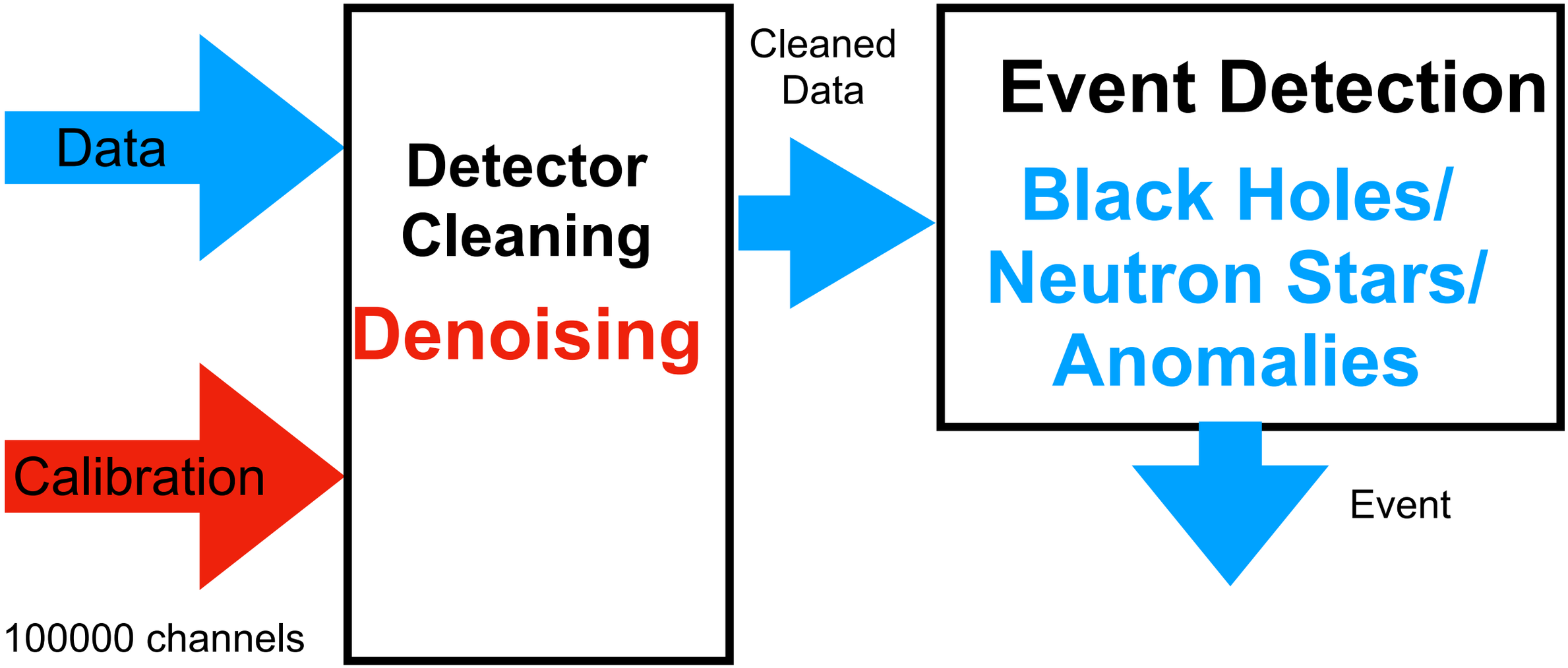
arXiv:2108.12430 (Nature)

GW Data Workflow



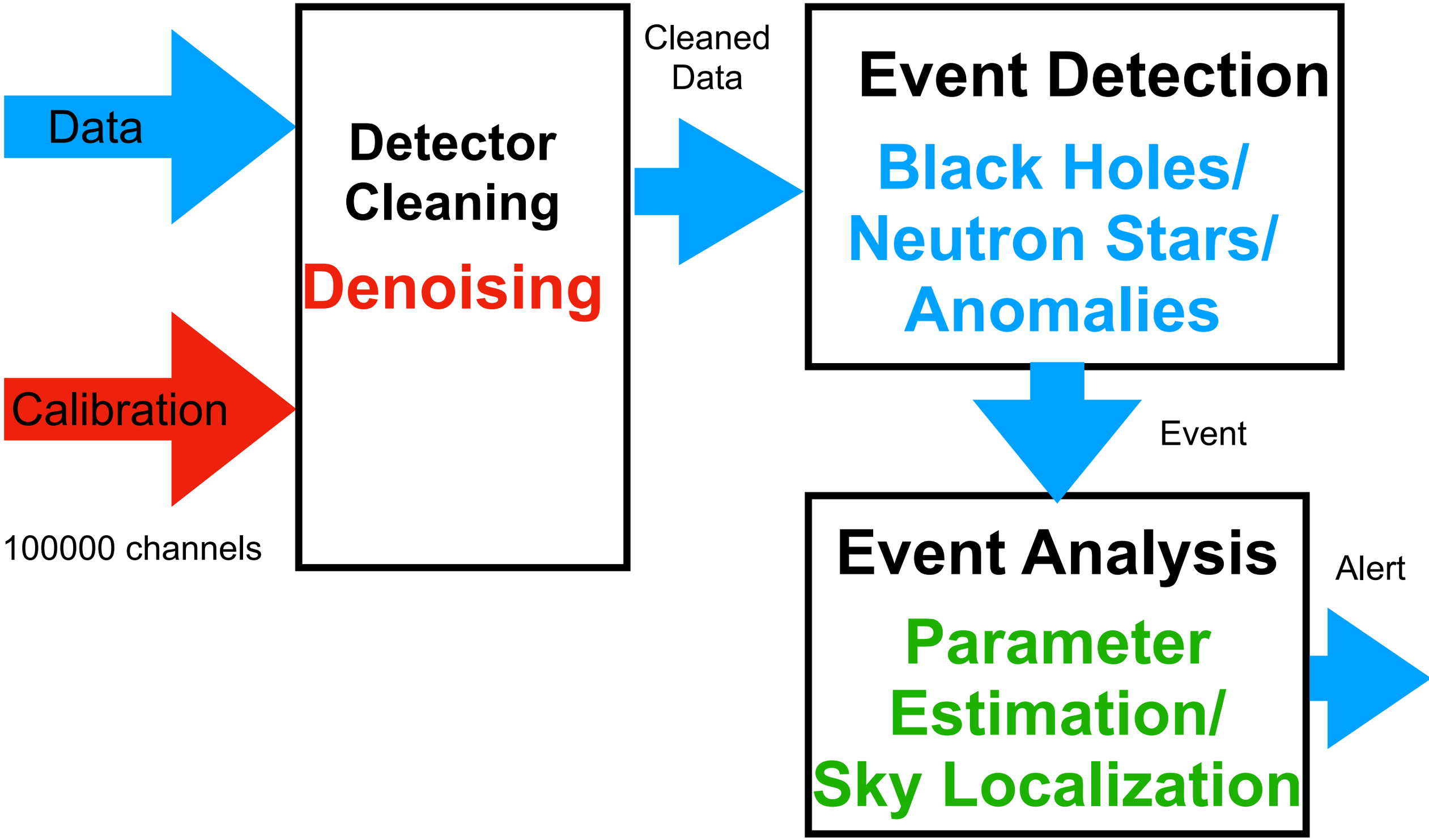
arXiv:2108.12430 (Nature)

GW Data Workflow



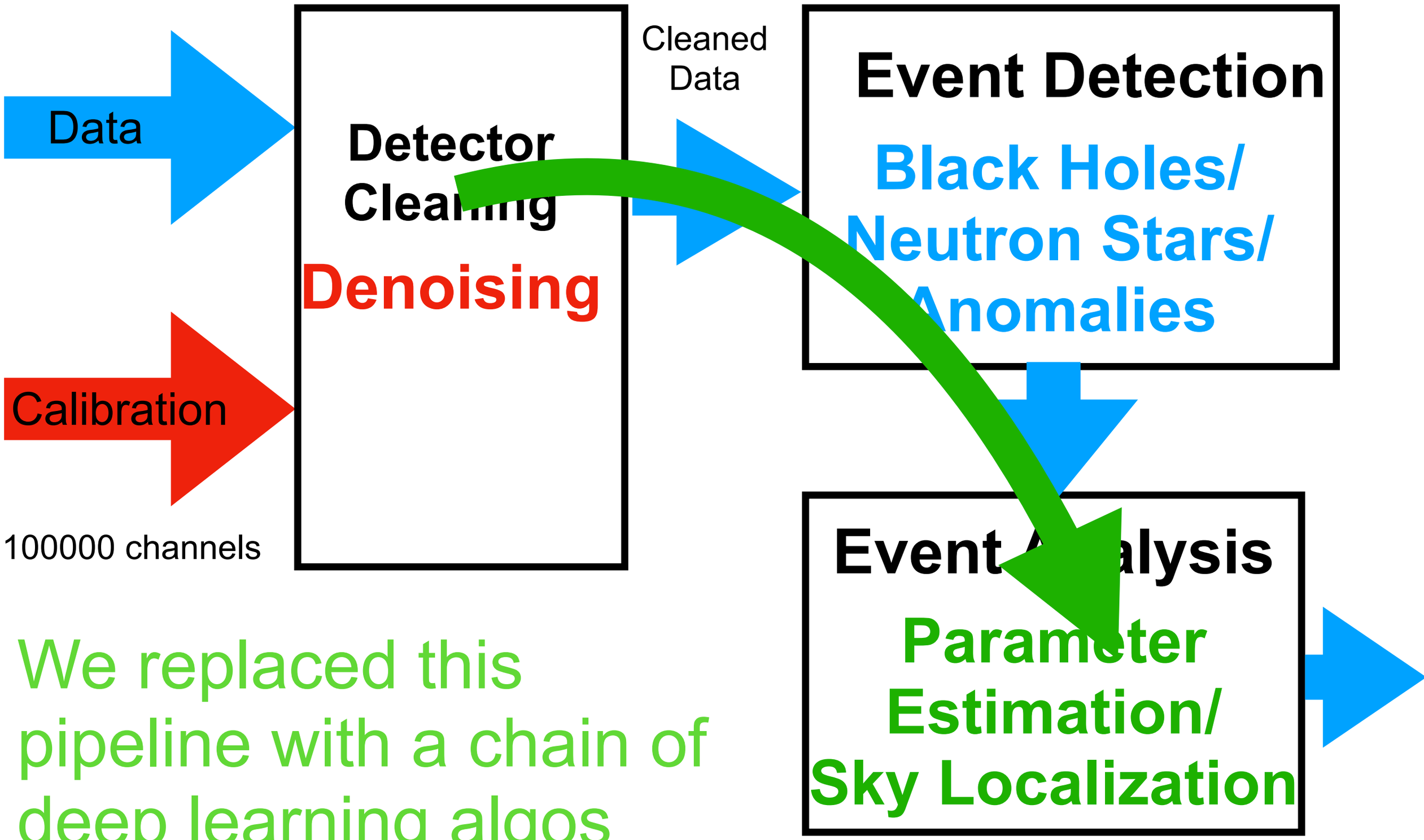
arXiv:2108.12430 (Nature)

GW Data Workflow

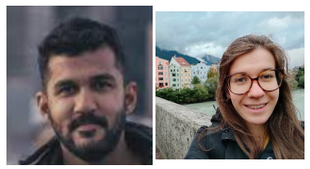


arXiv:2108.12430 (Nature)

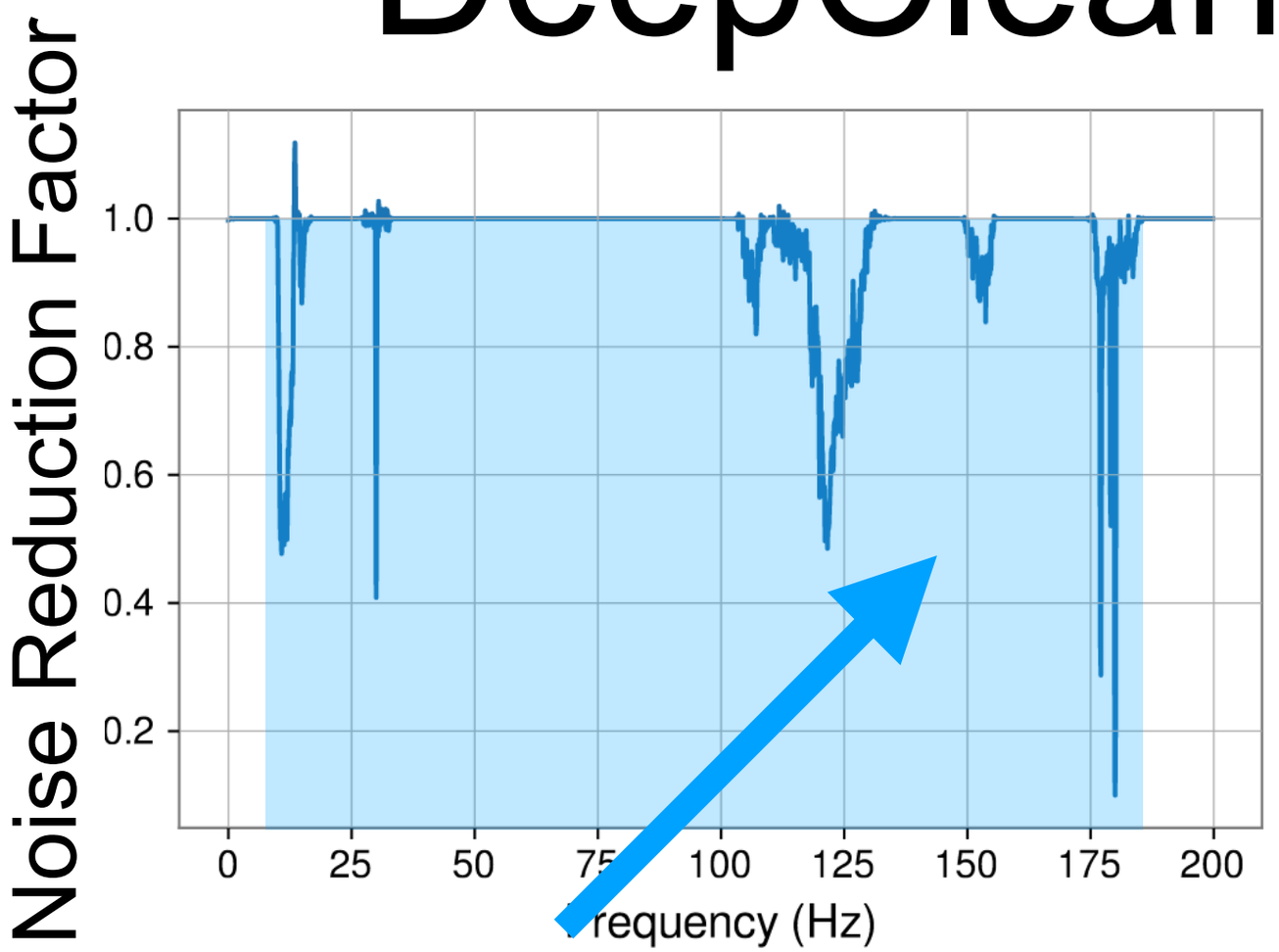
GW Data Workflow

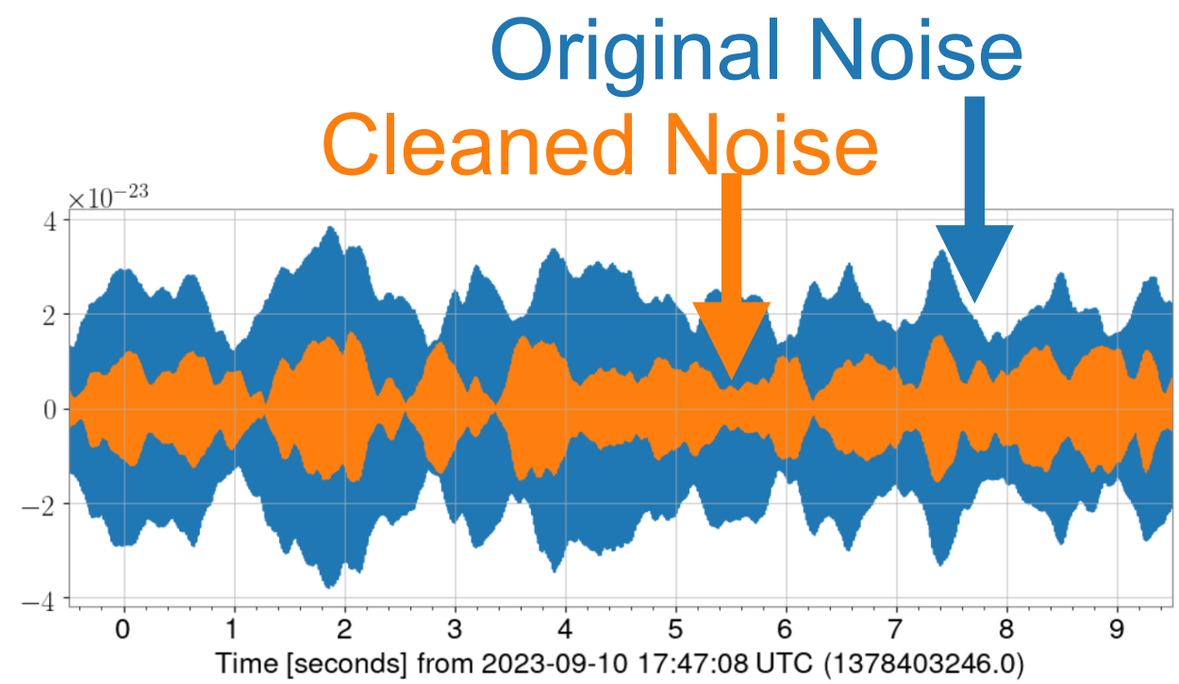


We replaced this pipeline with a chain of deep learning algos



DeepClean: Does it work?



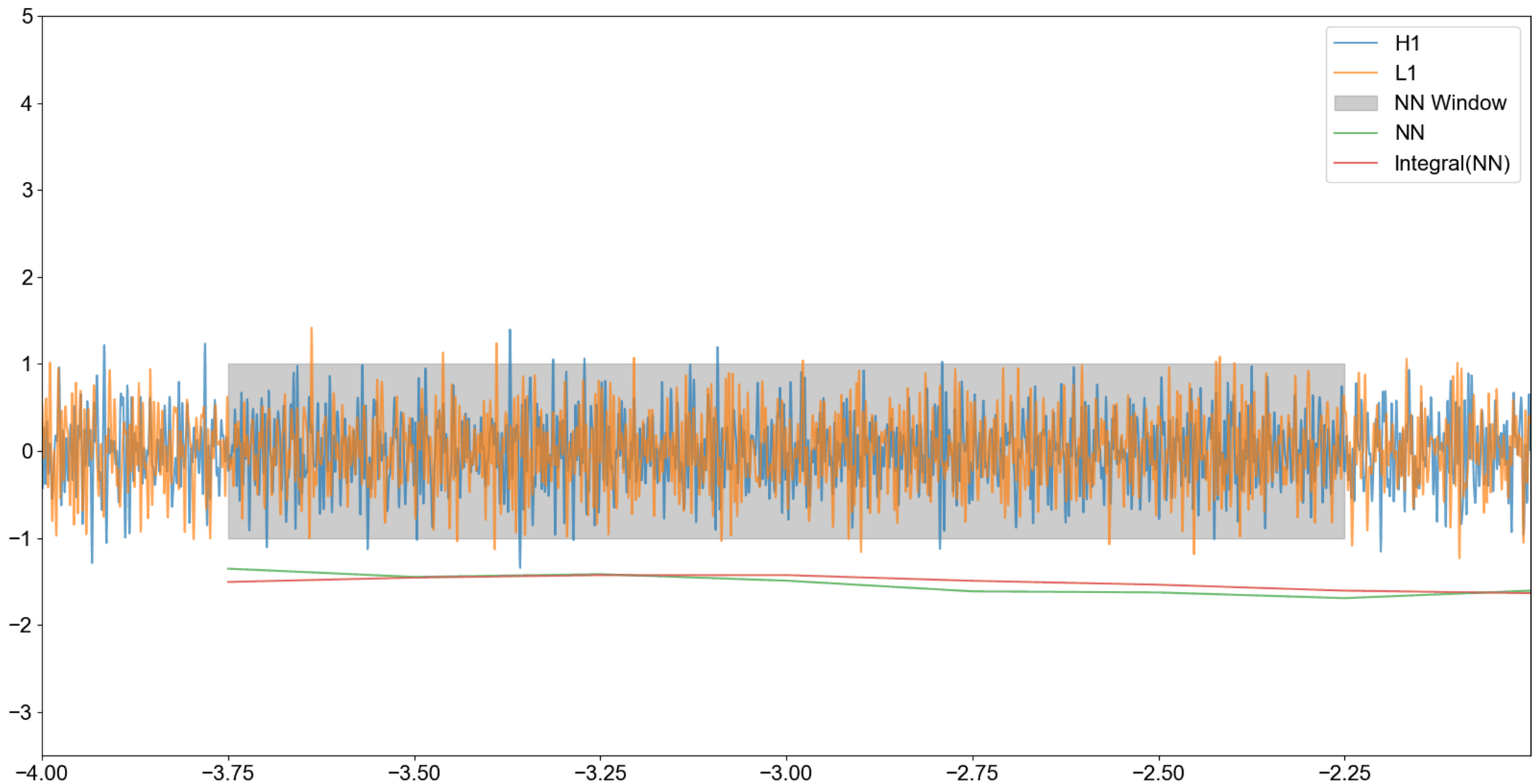


Probe an additional 5% more of the universe

Just the beginning

arXiv:2403.18661

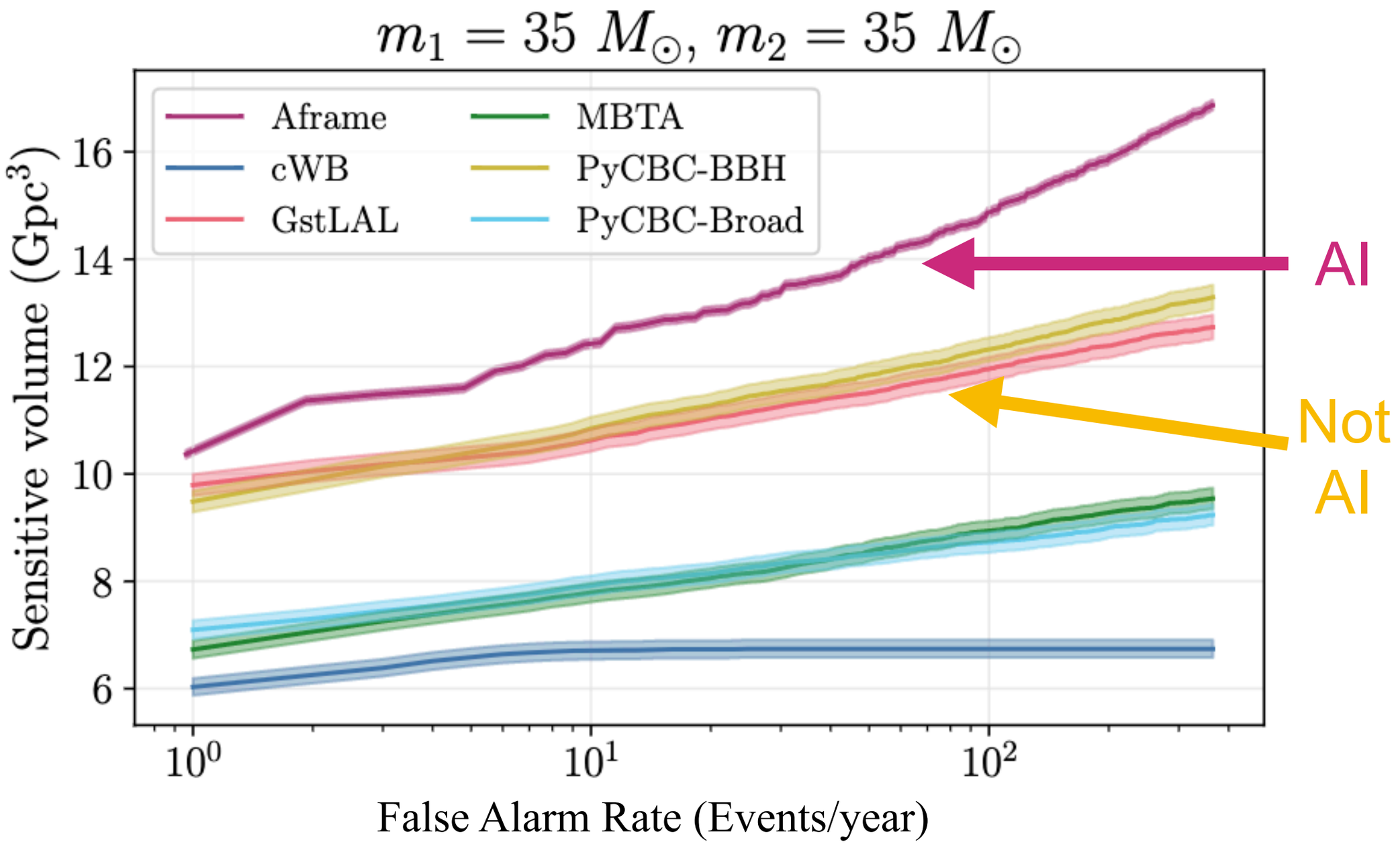
A-Frame(Black Hole Mergers)



Neural network targeting Black Hole Mergers

arXiv:2403.18661

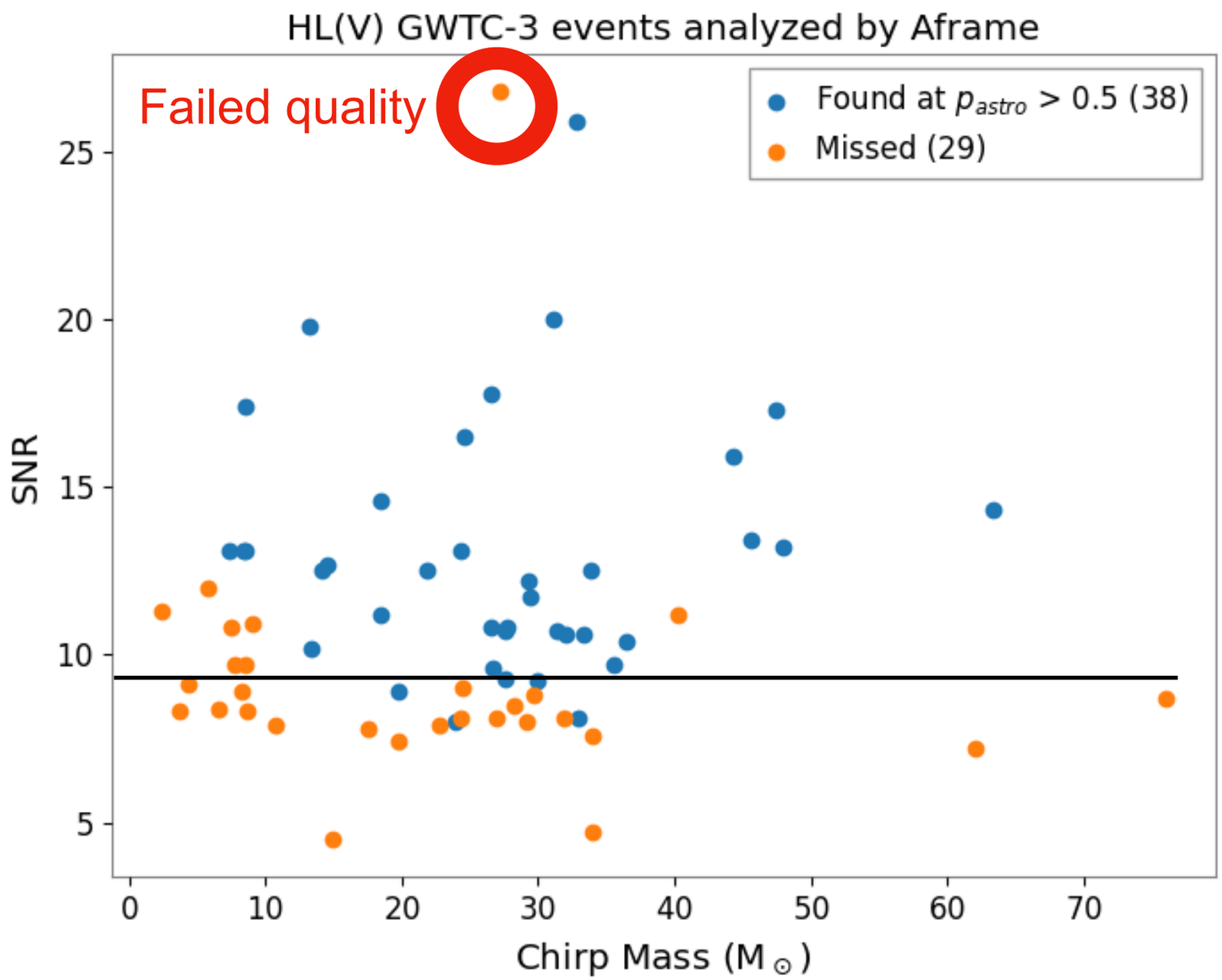
A-Frame(Black Hole Mergers)



Probes 10% of the known universe for Heavy Mergers

arXiv:2403.18661

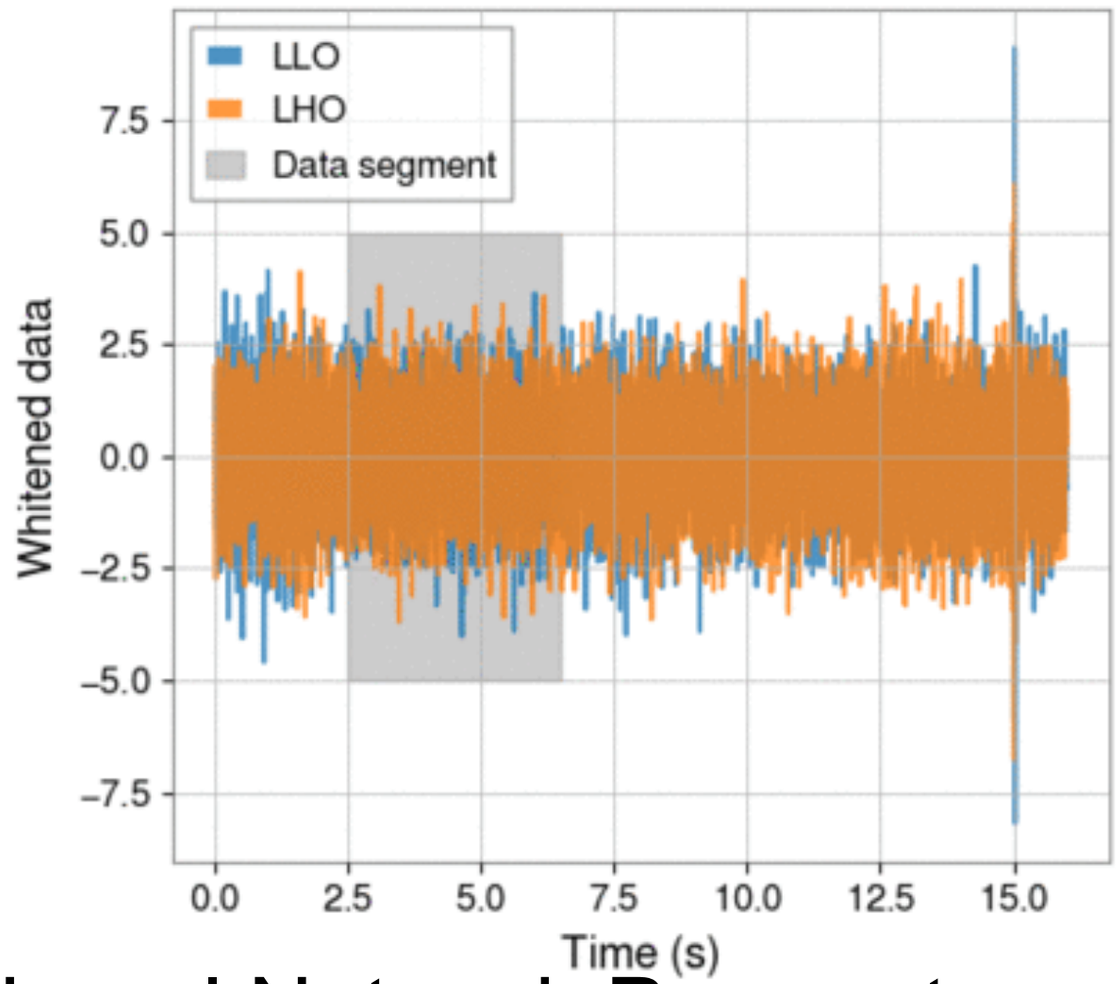
A-Frame(Black Hole Mergers)

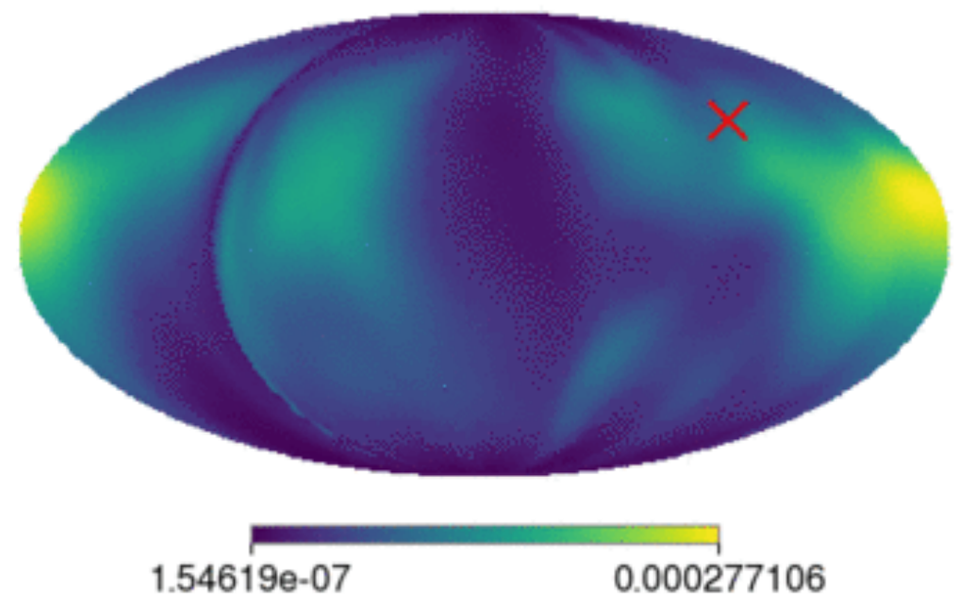


We found all the high signal Black hole mergers

arXiv:2407.19048

Parameter Estimation





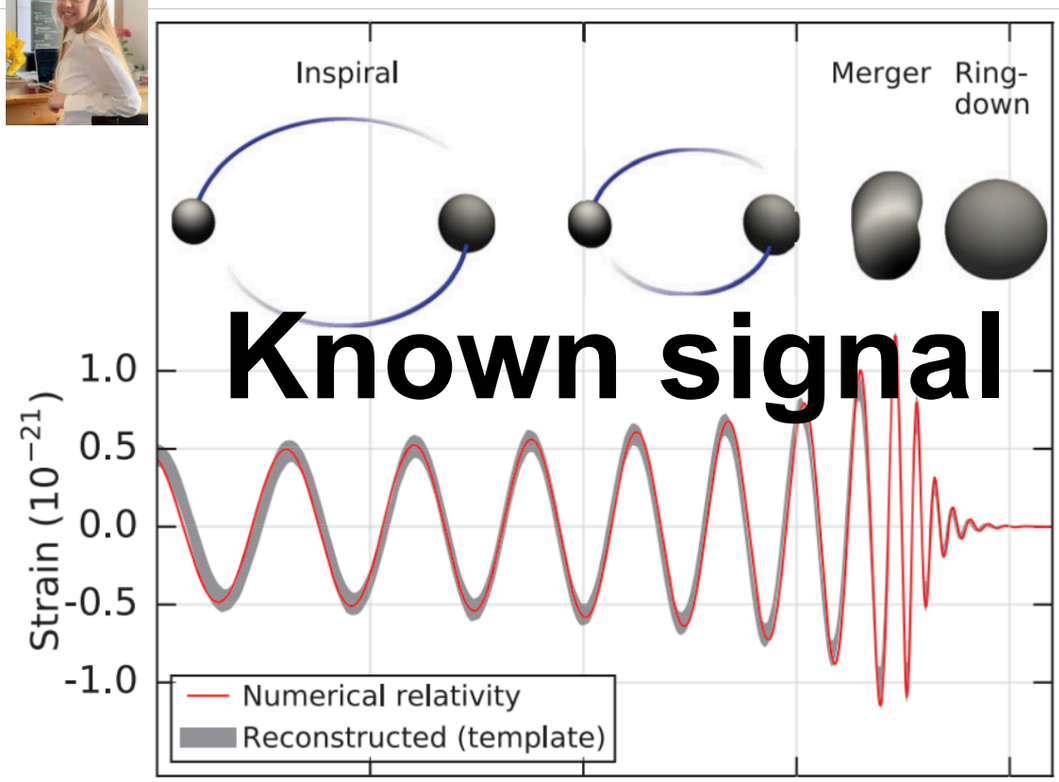
Neural Network Parameter estimation

100,000x times faster than conventional parameter estimation

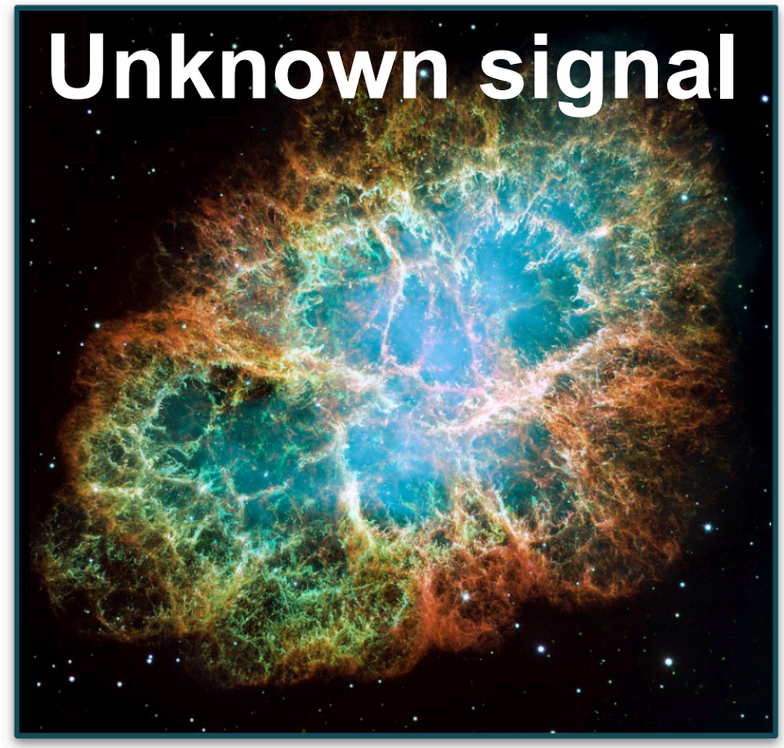
Not yet full resolution on all parameters (aimed for speed)

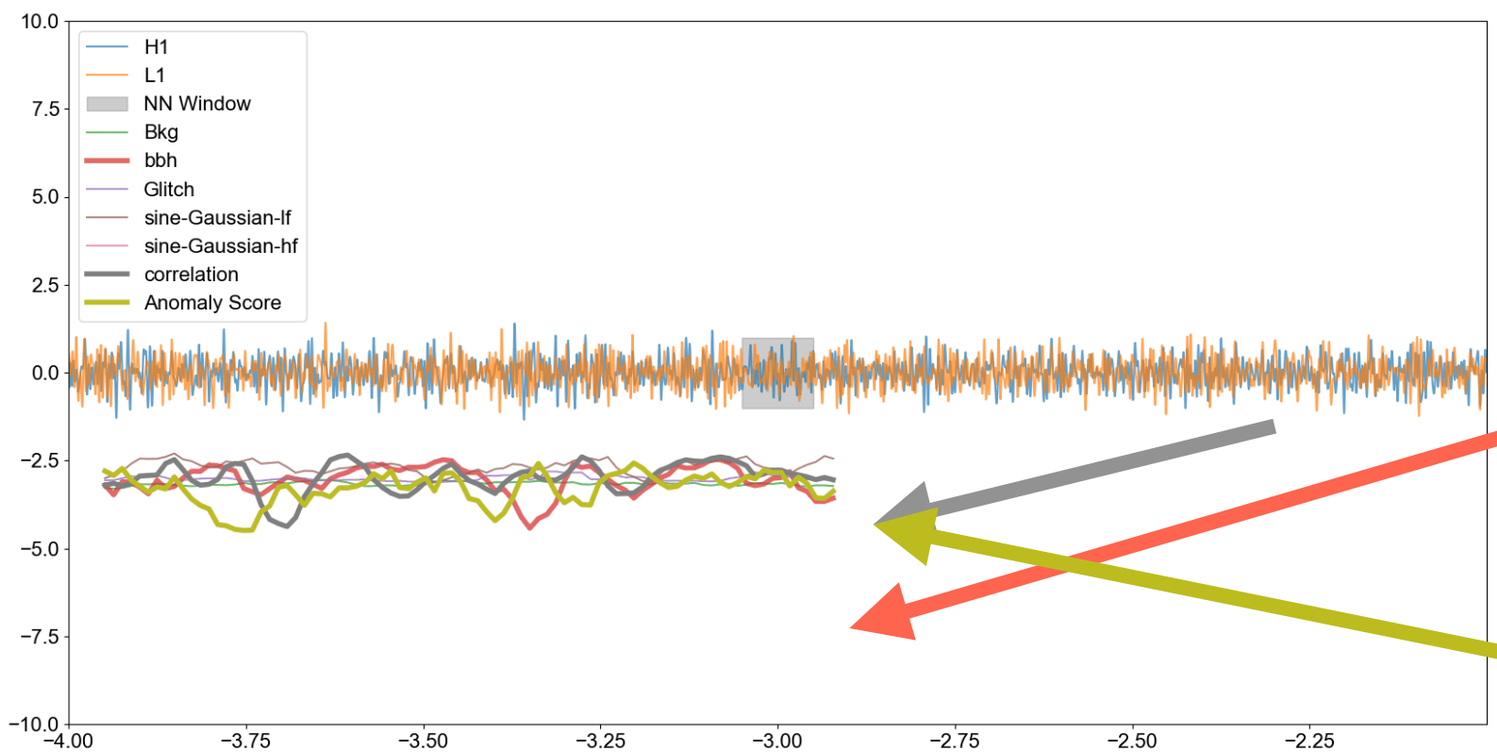
arxiv:2309.11537

GWAK:Anomaly Detection



Core-collapse supernova (CCSN)





Key Insights

11D space

Correlation

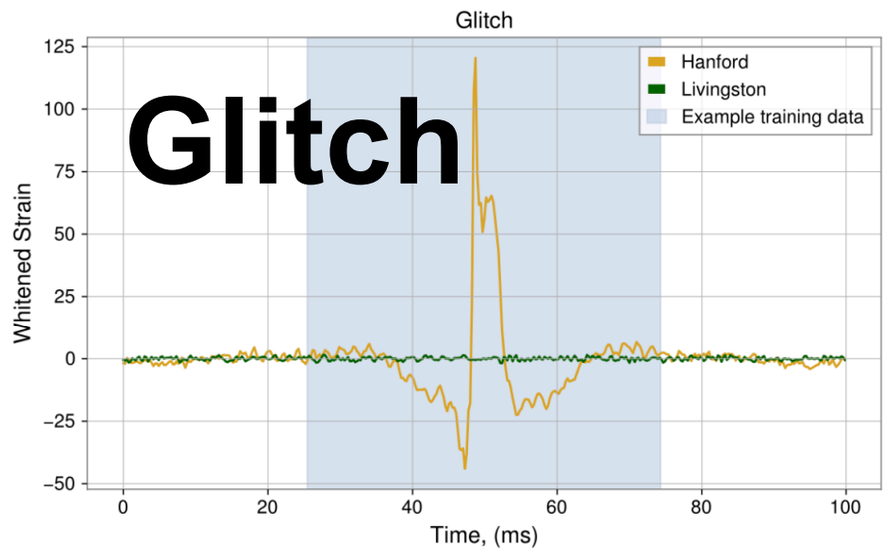
BBH Prob

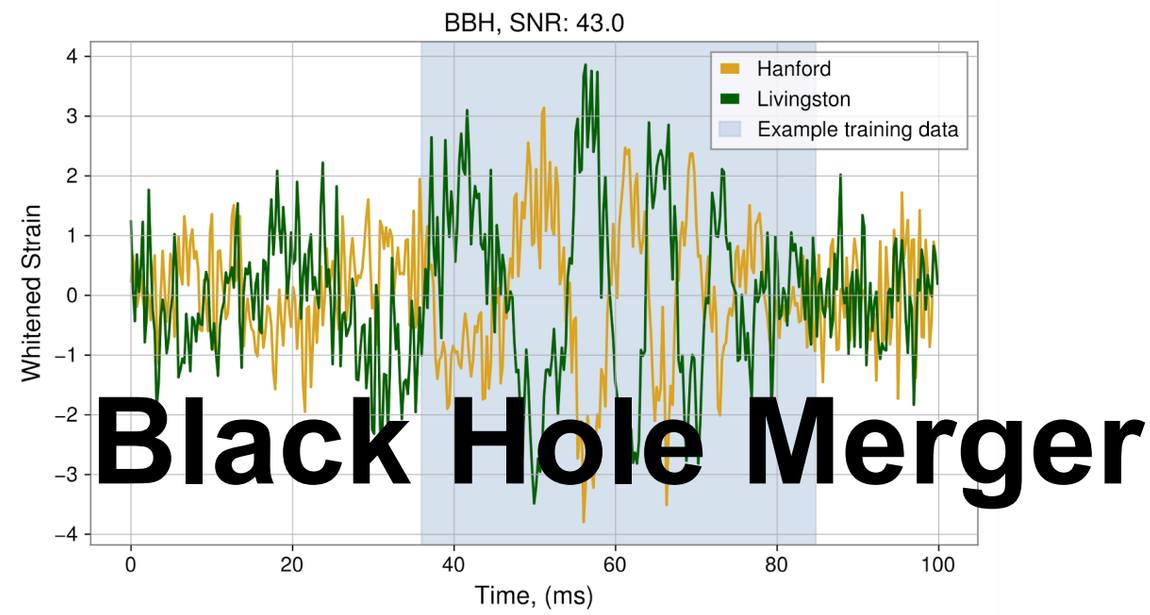
Others

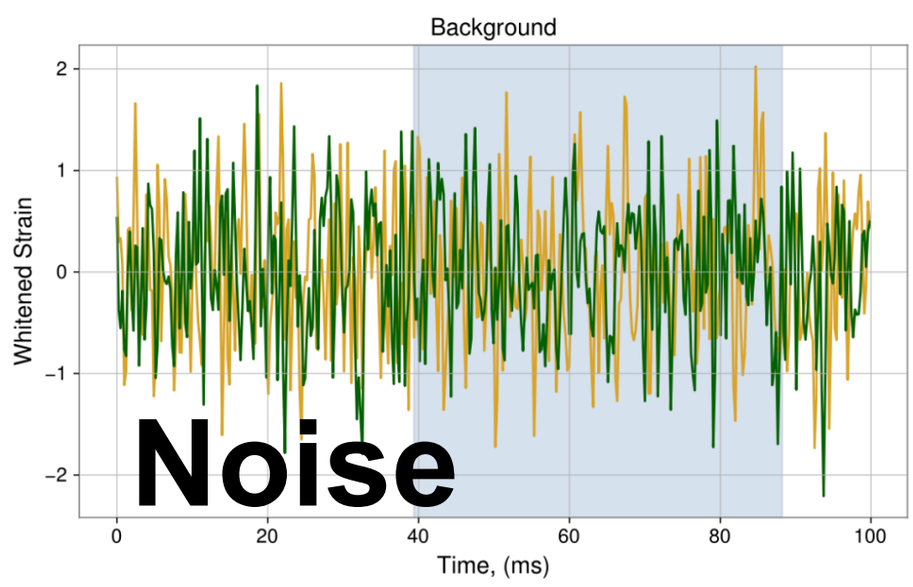
Total Score

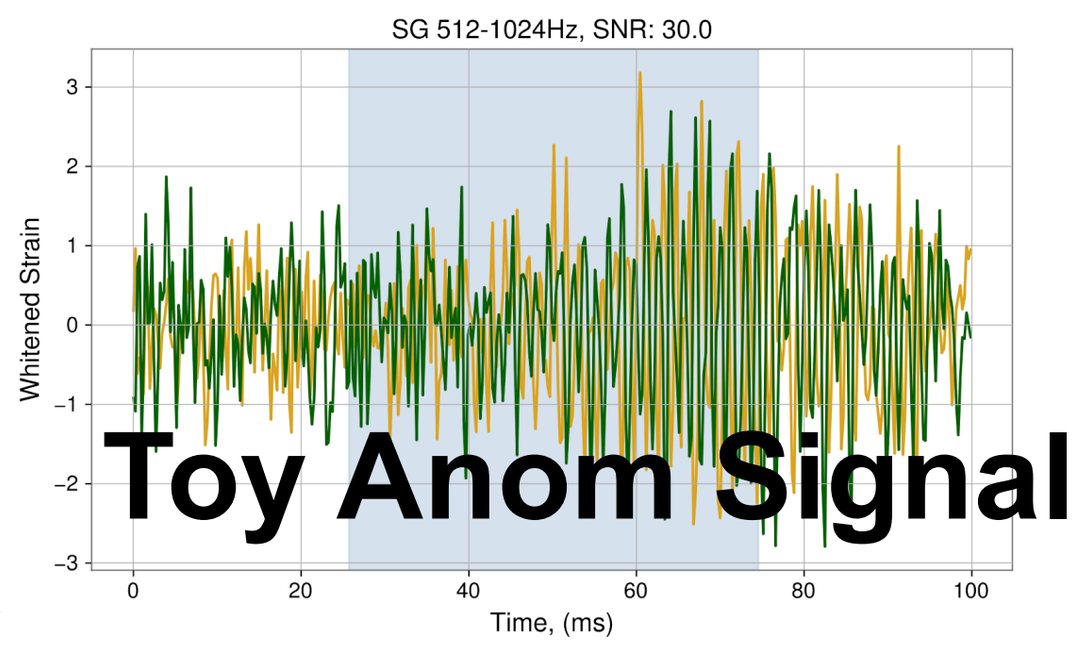
GWAK Space

- GWAK stands for GW (QU)AK like guacamole

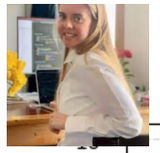




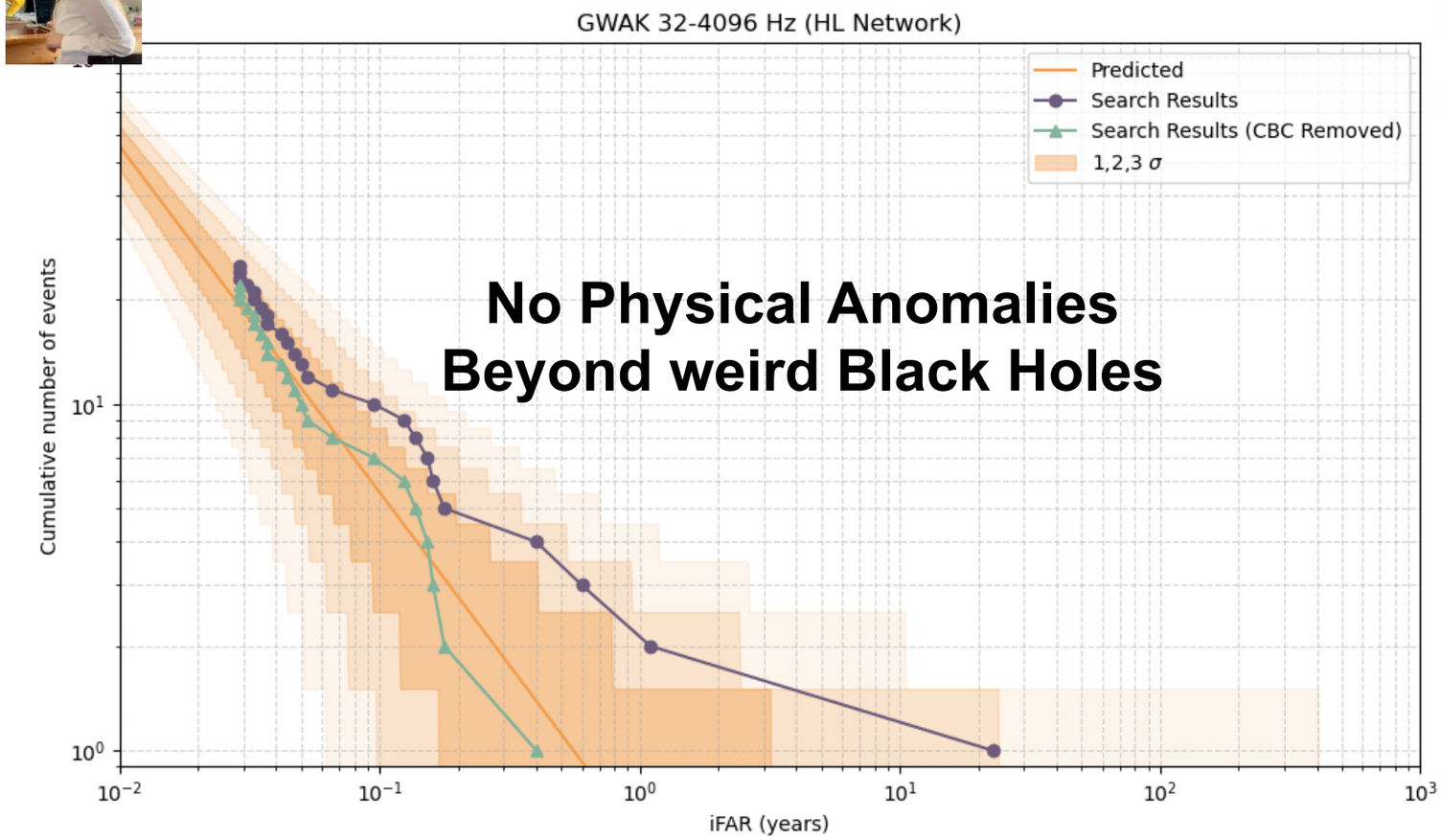


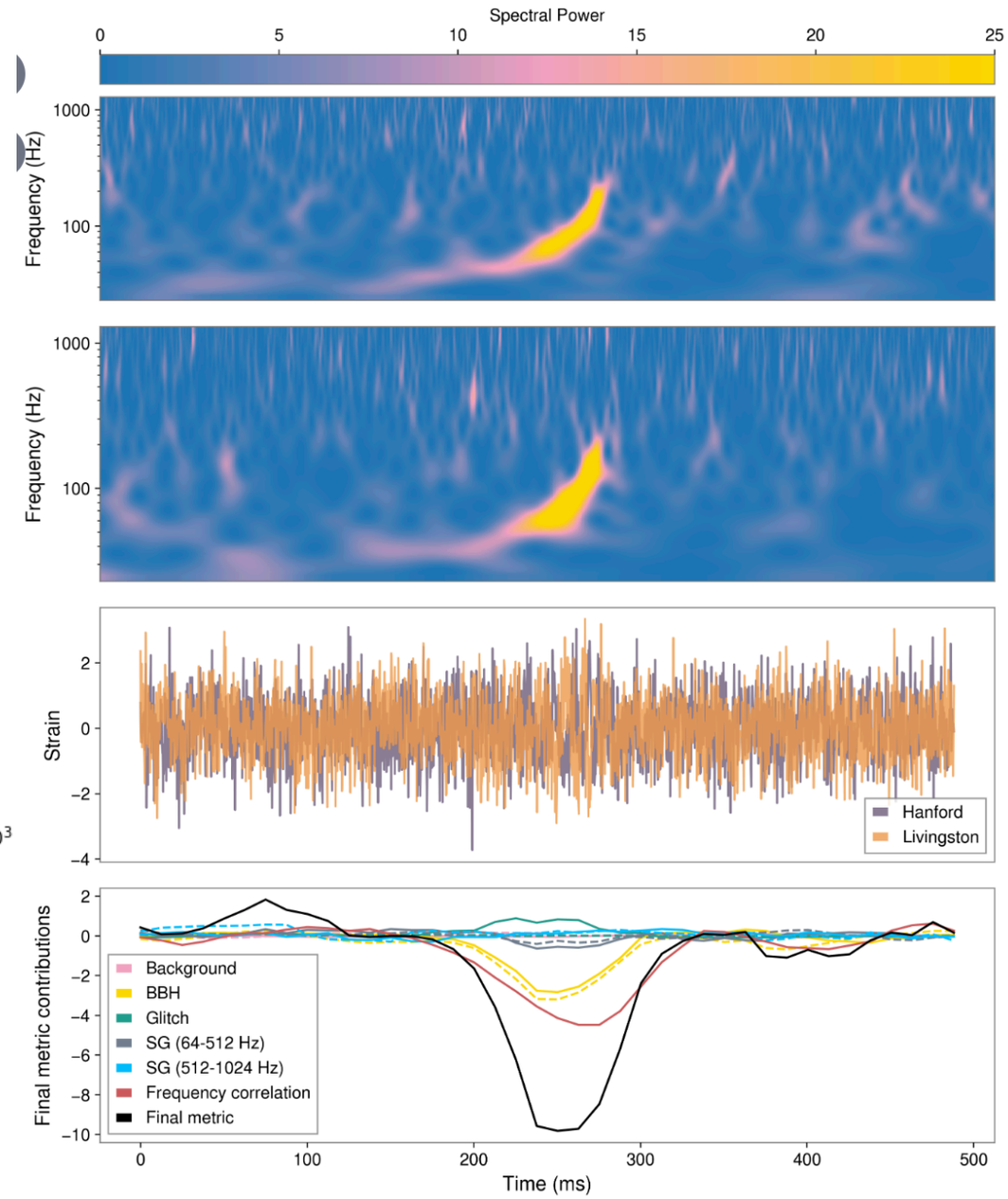


Arxiv:today



GWAK On Data



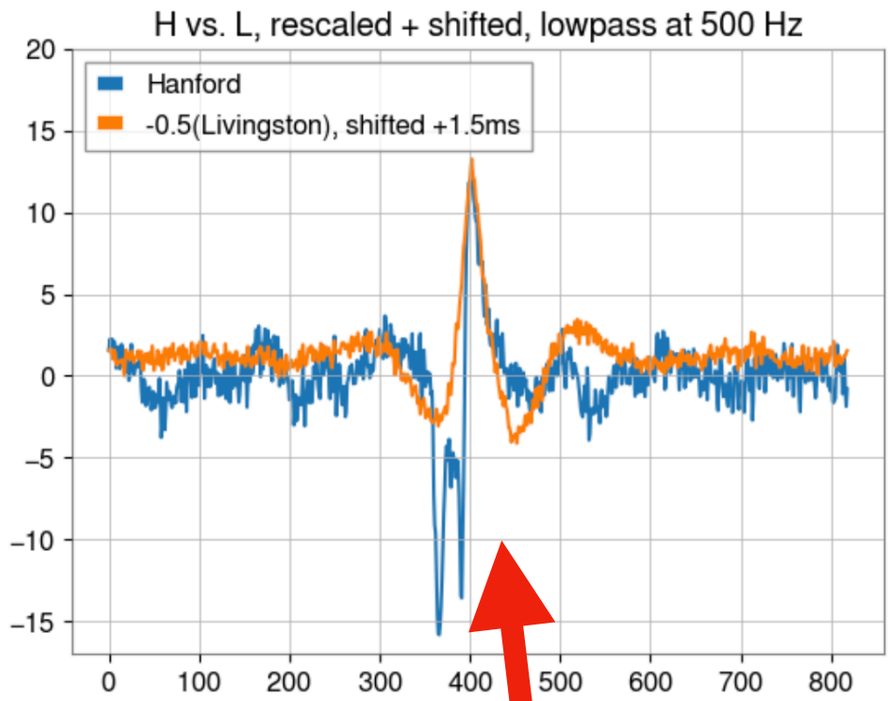


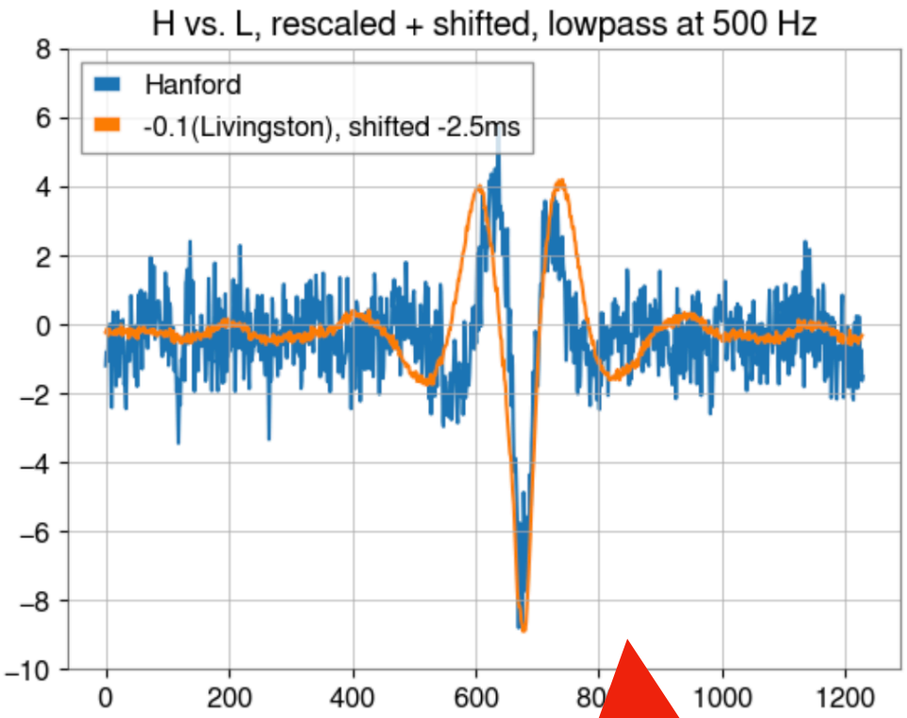
No glaring true anomalies

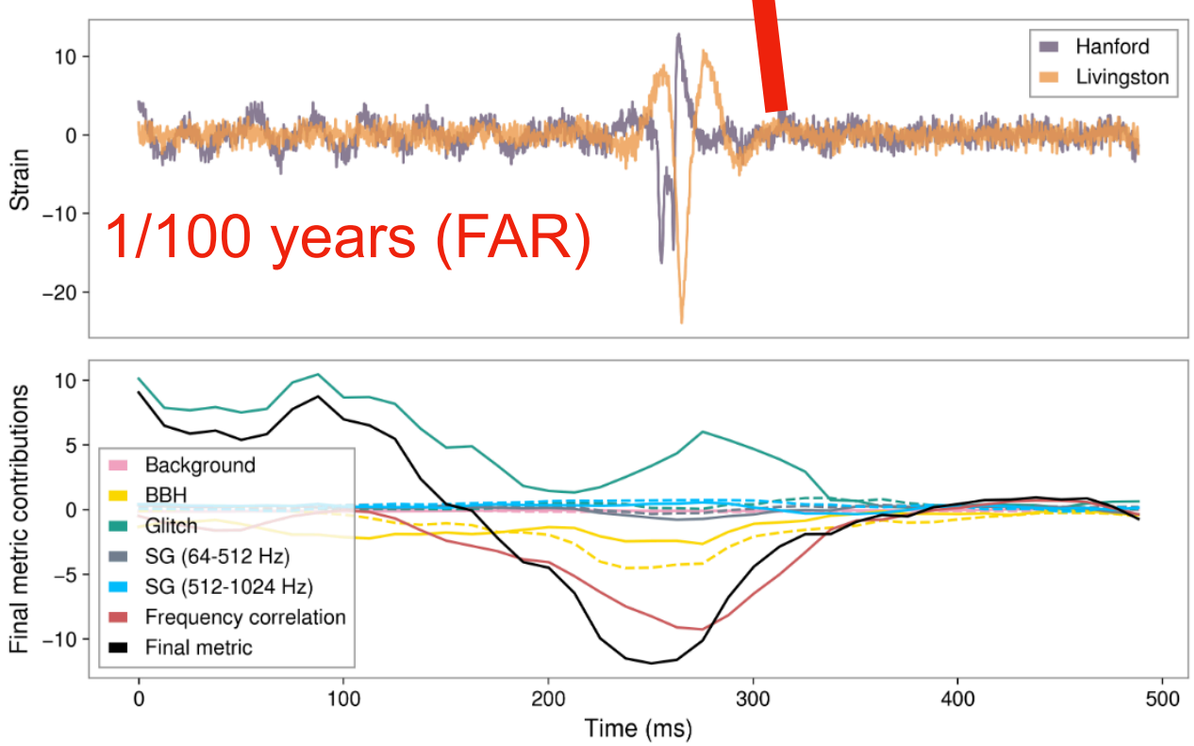
We found weird black hole mergers + weird glitches

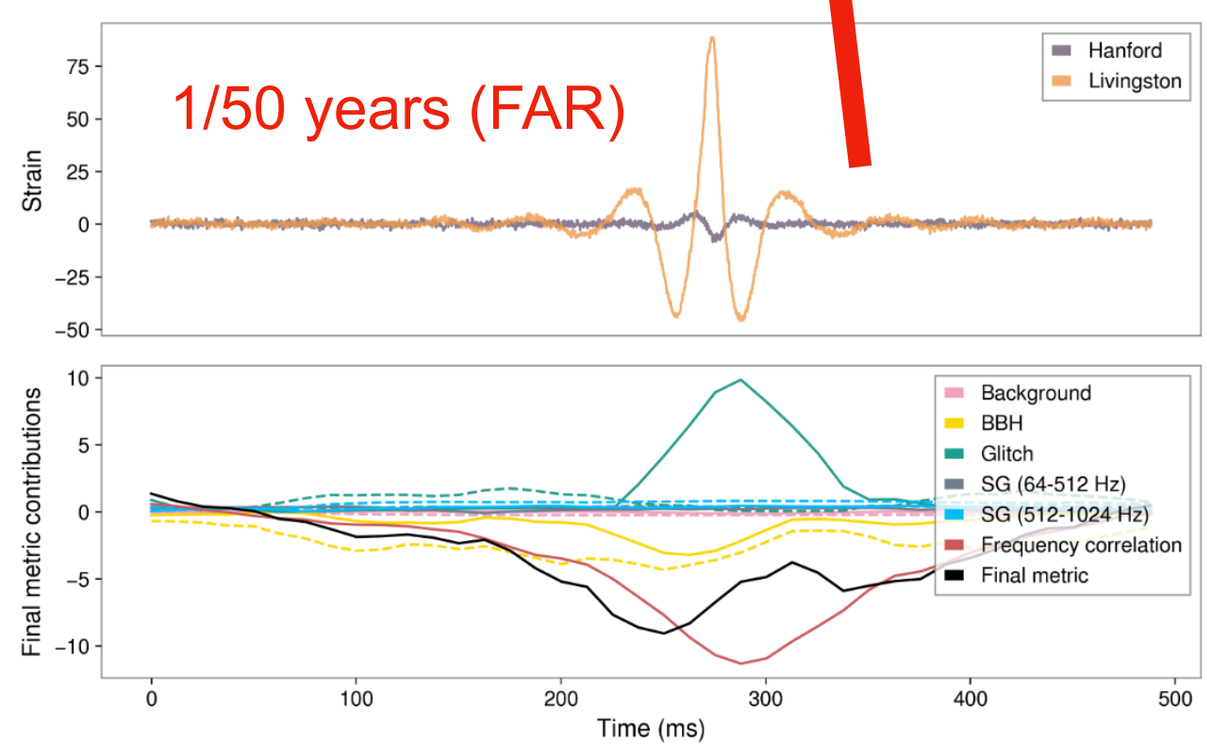
Crazy Anomalies

Occurred during noisy times of LIGO operation









Our System is running Live!

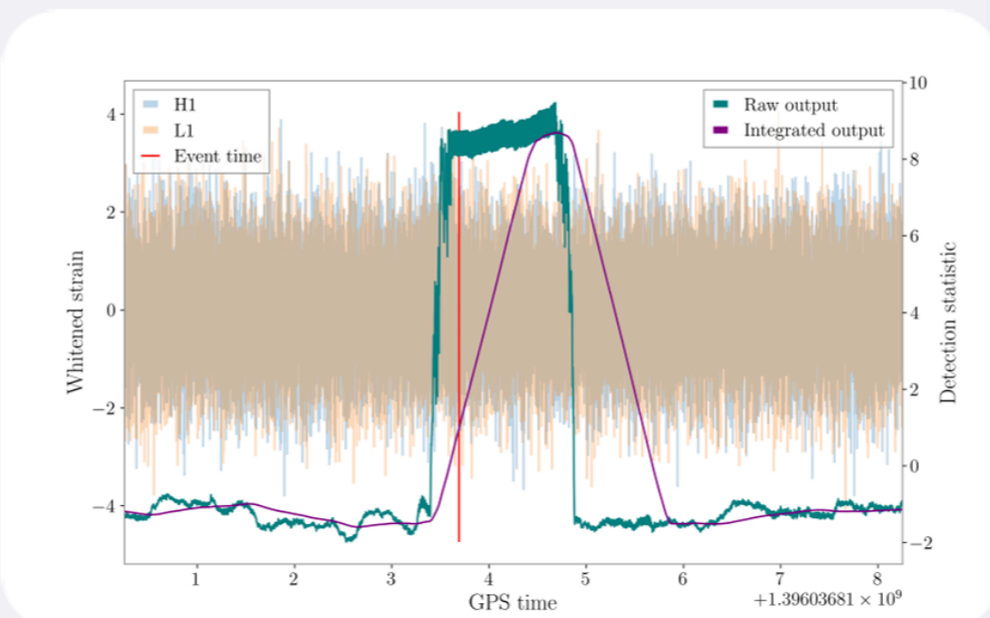
Accelerated AI Algorithms for Data-Driven Discovery

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

Authenticated as: Katya Govorkova

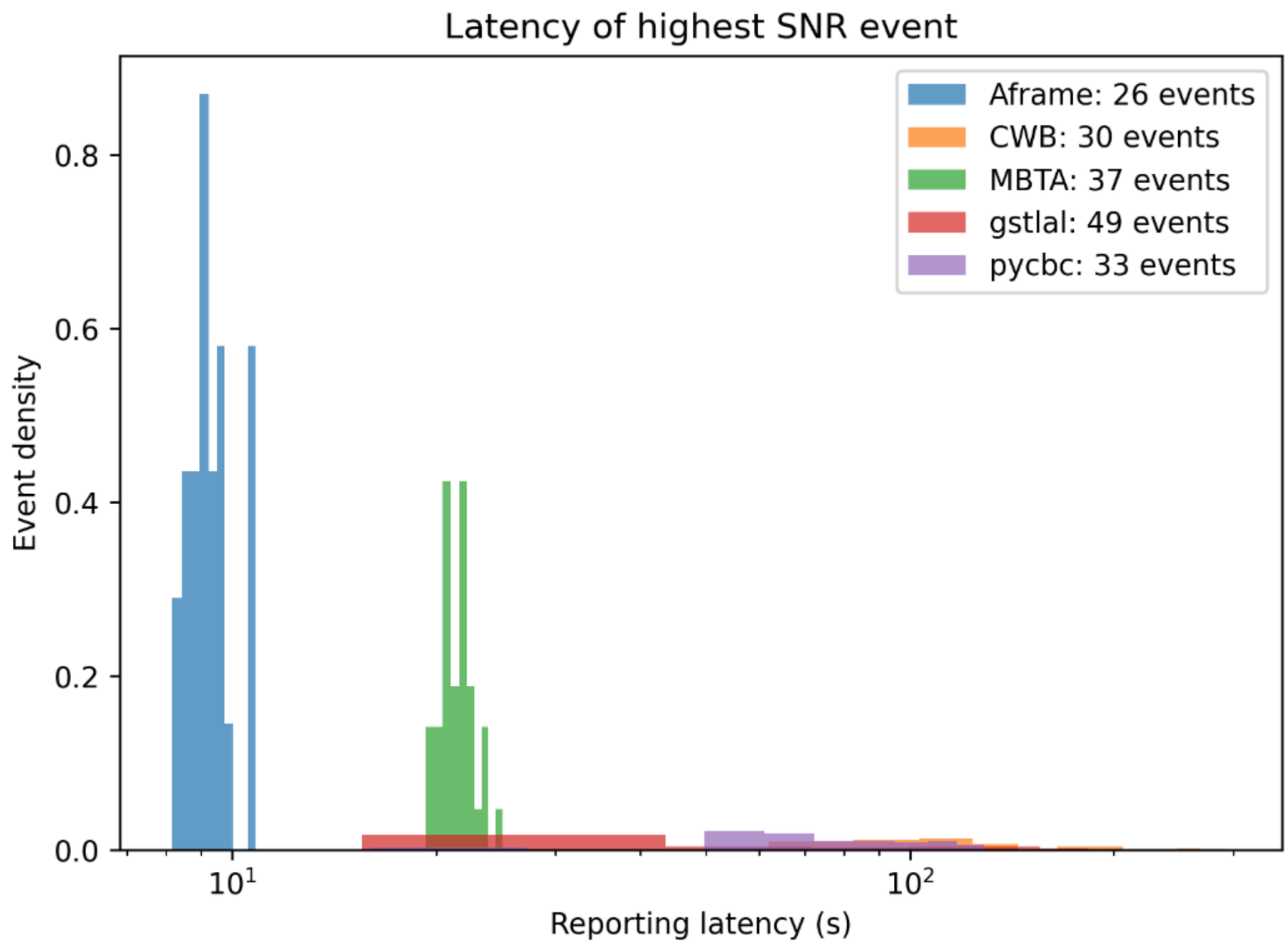
G1783271
Neighbors
Log Messages
Full Event Log

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

Impact Already



Our pipeline found all the large signal events
Our pipeline is 10-100x faster than others

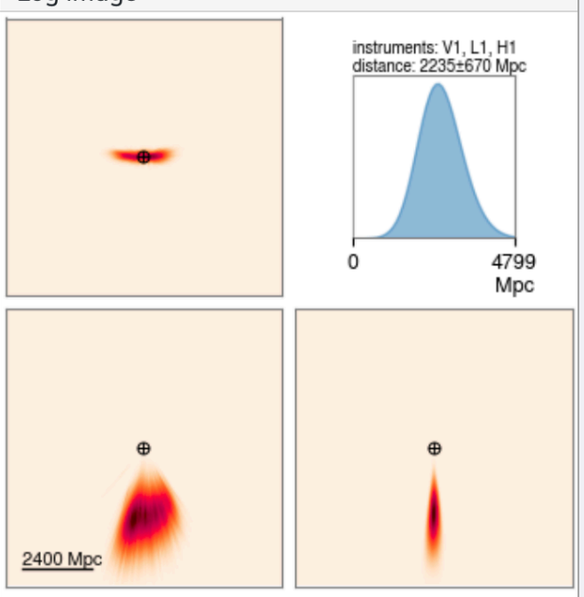
Our System is Live!

Accelerated AI Algorithms for Data-Driven Discovery

Per-Pipeline Event Information

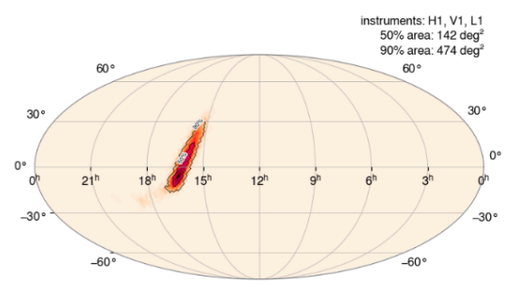
UID	Group	Pipeline	Search	gpstime	FAR (Hz)
G597361	CBC	pycbc	AllSky	1441016546.022	3.168e-10
G597350	CBC	aframe	AllSky	1441016545.998	3.154e-10
G597364	CBC	CWB	BBH	1441016546.020	6.083e-11
			AllSky	1441016545.995	1.164e-14
			AllSky	1441016546.002	1.596e-25

Log Image



Volume rendering of amplfi.multiorder.fits,0
— Submitted by read-cvmfs-emfollow robot on September 4, 2025 10:22:37 UTC

Log Image



Mollweide projection of amplfi.multiorder.fits,0
— Submitted by read-cvmfs-emfollow robot on September 4, 2025 10:22:36 UTC

We are publicly running since August 30th 2025
Delivering robust alerts

Our System is running Live!

GCN Circular 41606

Subject LIGO/Virgo/KAGRA S250830bp: Identification of a GW compact binary merger candidate
Event LIGO/Virgo/KAGRA S250830bp
Date 2025-08-30T10:55:06Z (a month ago)
From Pedro Jeronimo Santos da Silva <pedro.jeronimo@unesp.br>
Via Web form

The LIGO Scientific Collaboration, the Virgo Collaboration, and the KAGRA Collaboration report:

We identified the compact binary merger candidate S250830bp during real-time processing of data from LIGO Hanford Observatory (H1), LIGO Livingston Observatory (L1), and Virgo Observatory (V1) at 2025-08-30 10:24:18.852 UTC (GPS time: 1440584676.852). The candidate was found by the Aframe [1] cWB [2], cWB BBH [3], GstLAL [4], MBTA [5], MLy [6], PyCBC Live [7], and SPIIR [8] analysis pipelines.

S250830bp is an event of interest because its false alarm rate, as estimated by the online analysis, is 3.2e-10 Hz, or about one in 1e2 years. The event's properties can be found at this URL:

https://gracedb.ligo.org/superevents/S250830bp

The classification of the GW signal, in order of descending probability, is BBH (84%), NSBH (16%), Terrestrial (<1%), or BNS (<1%).

Two sky maps are available at this time and can be retrieved from the GraceDB event page:
* amplfi.multiorder.fits,0, an initial localization generated by AMPLFI [10] distributed via GCN and SCiMMA notices about 24 seconds after the candidate event time.
* bayestar.multiorder.fits,0, an initial localization generated by BAYESTAR [11], distributed via GCN and SCiMMA notices about 5 minutes after the candidate event time.

Even with a system not designed for speed we are 10x faster

https://gcn.nasa.gov/circulars/41606?query=S250830bp

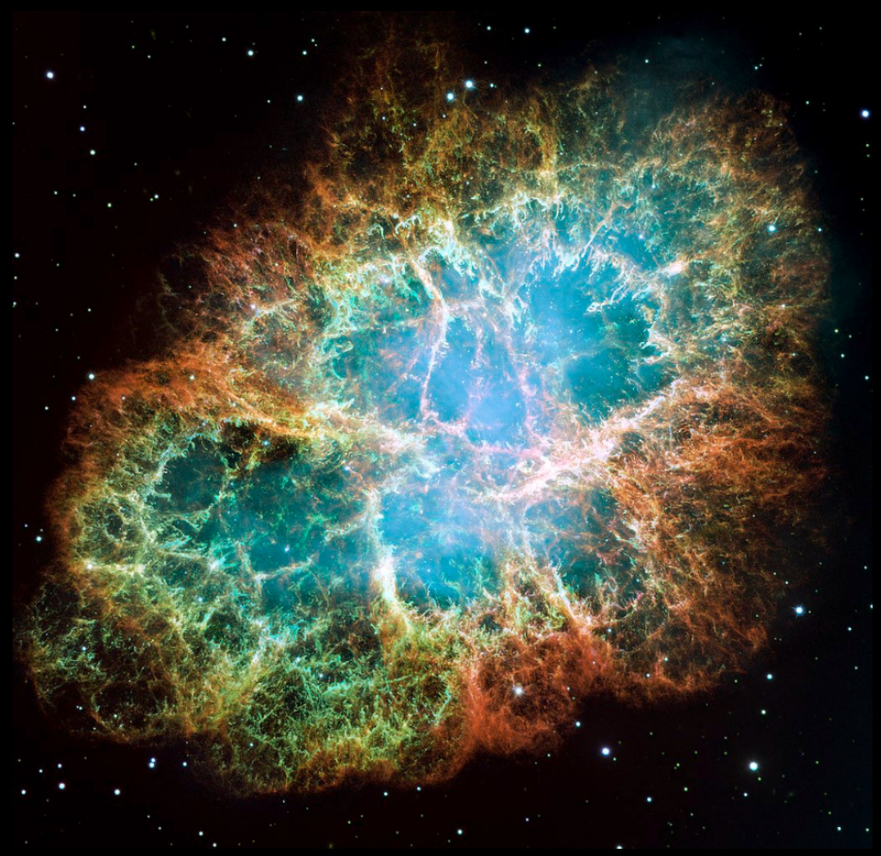
Questions?

Anomalous Gravitational Wave Sources

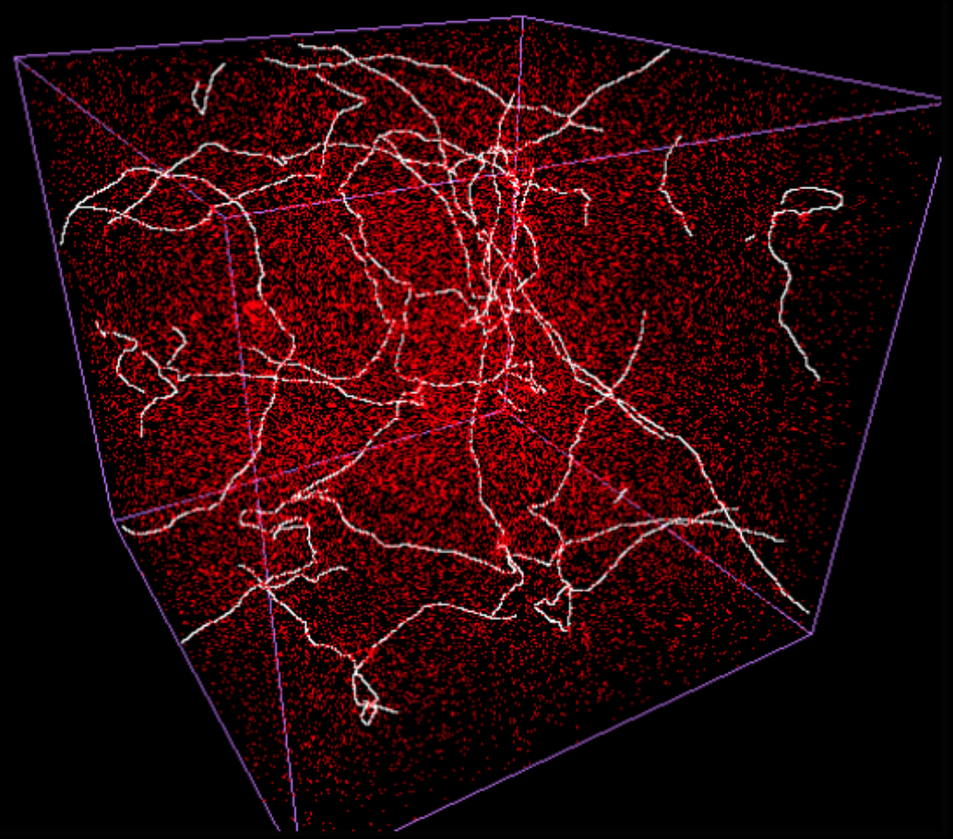
There are other possible signal sources that can not be modelled and therefore cannot be detected using the match filtering pipeline

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

Core-collapse supernova (CCSN)



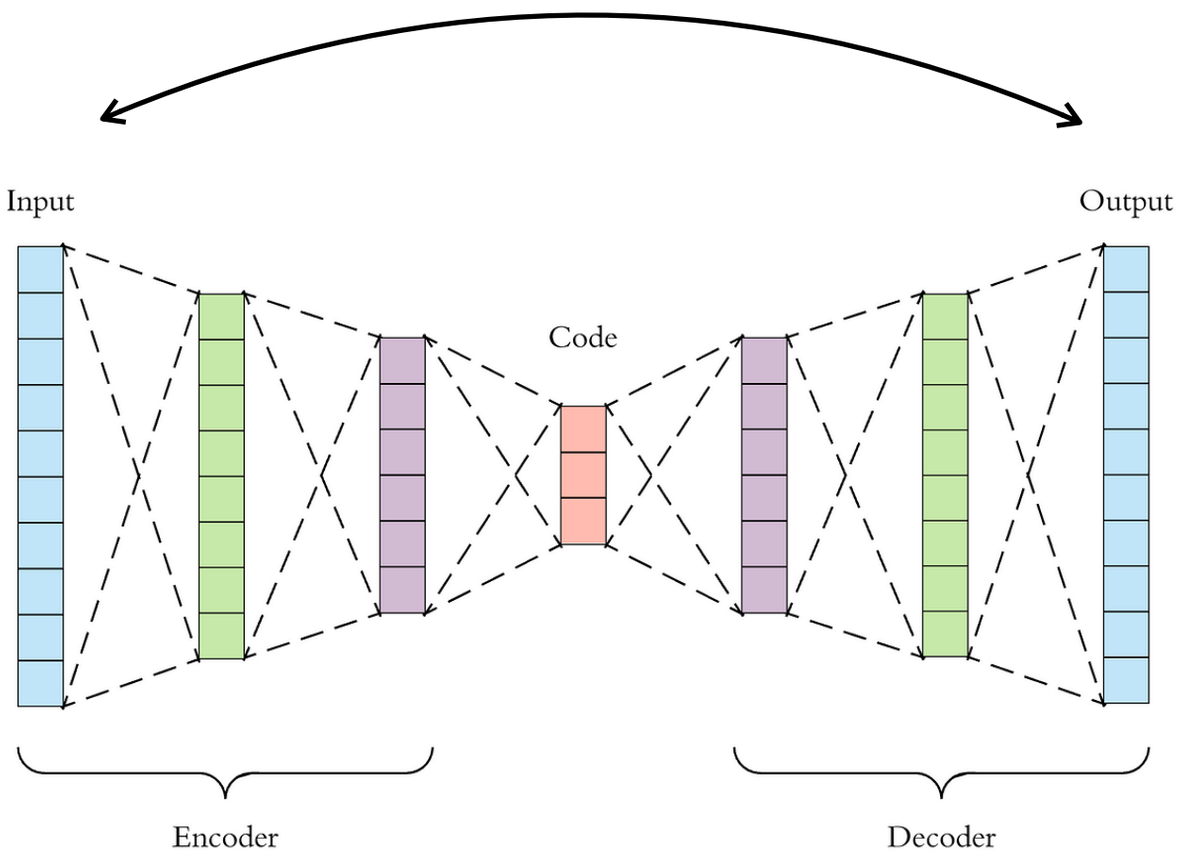
Cosmic strings



Vanilla Anomaly Detection

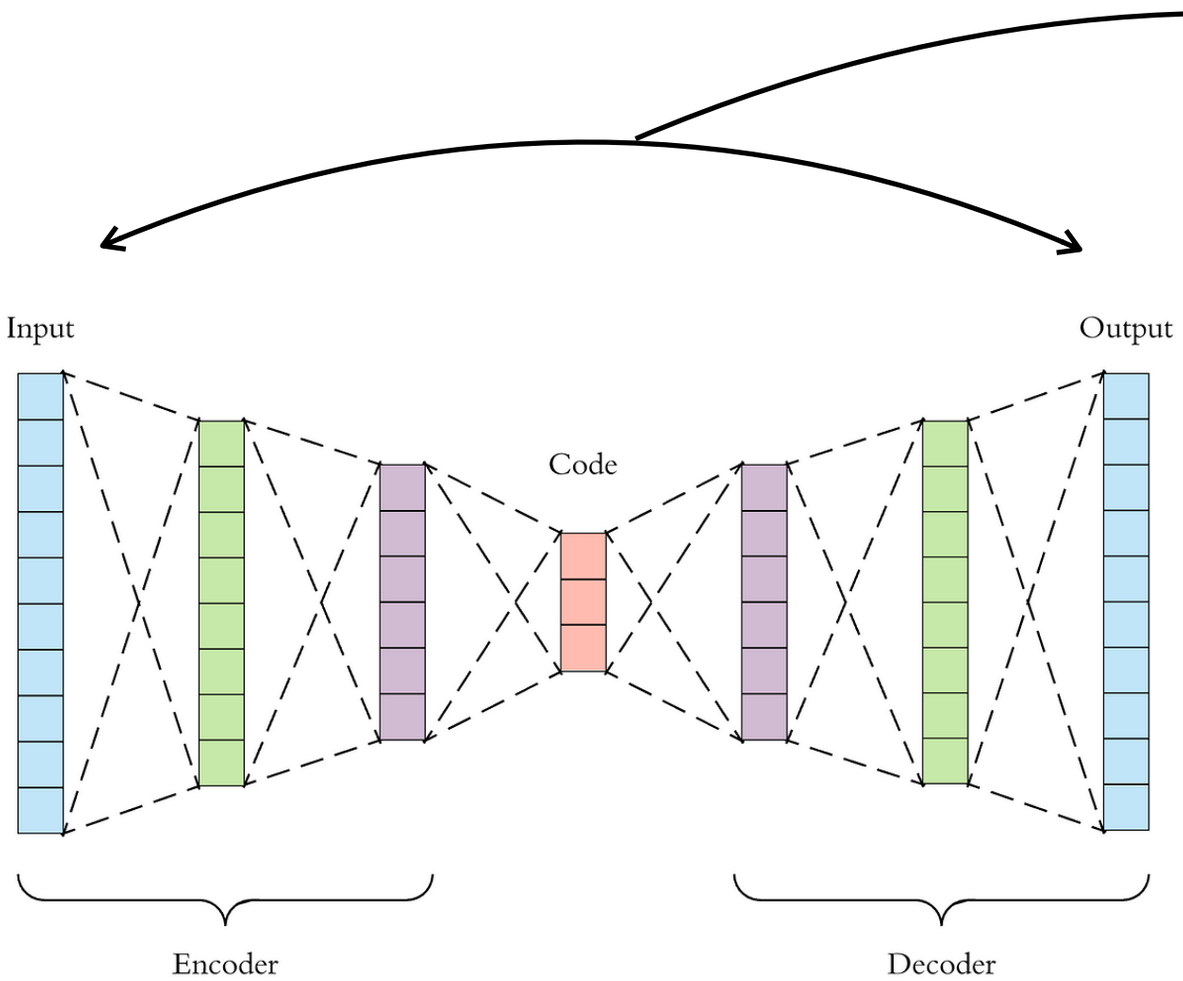
arxiv2309.11537

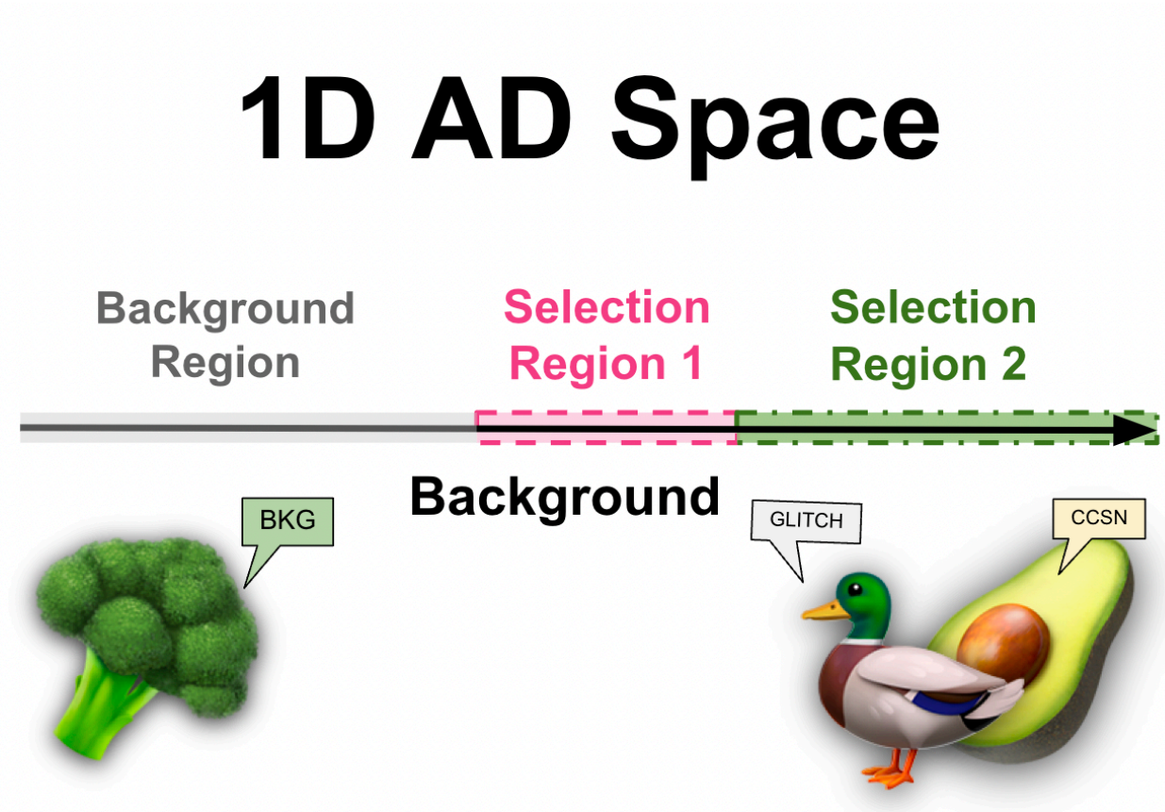
Use the distance between the input and output as a metric for anomaly detection



ARXIV2309.11537

USE THE DISTANCE BETWEEN THE INPUT AND OUTPUT AS A METRIC FOR ANOMALY DETECTION

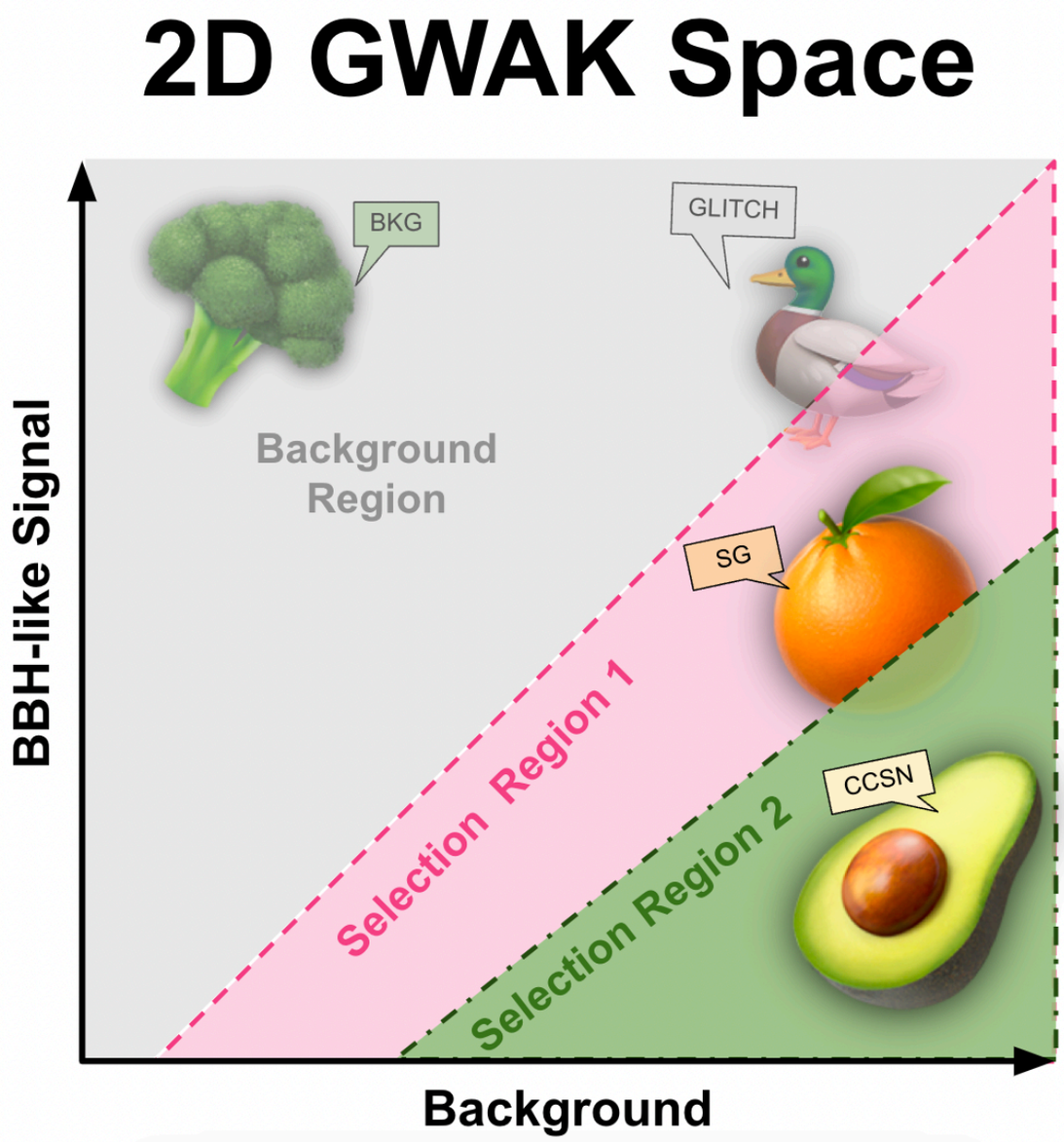




Adding axes to include more information

arxiv2309.11537

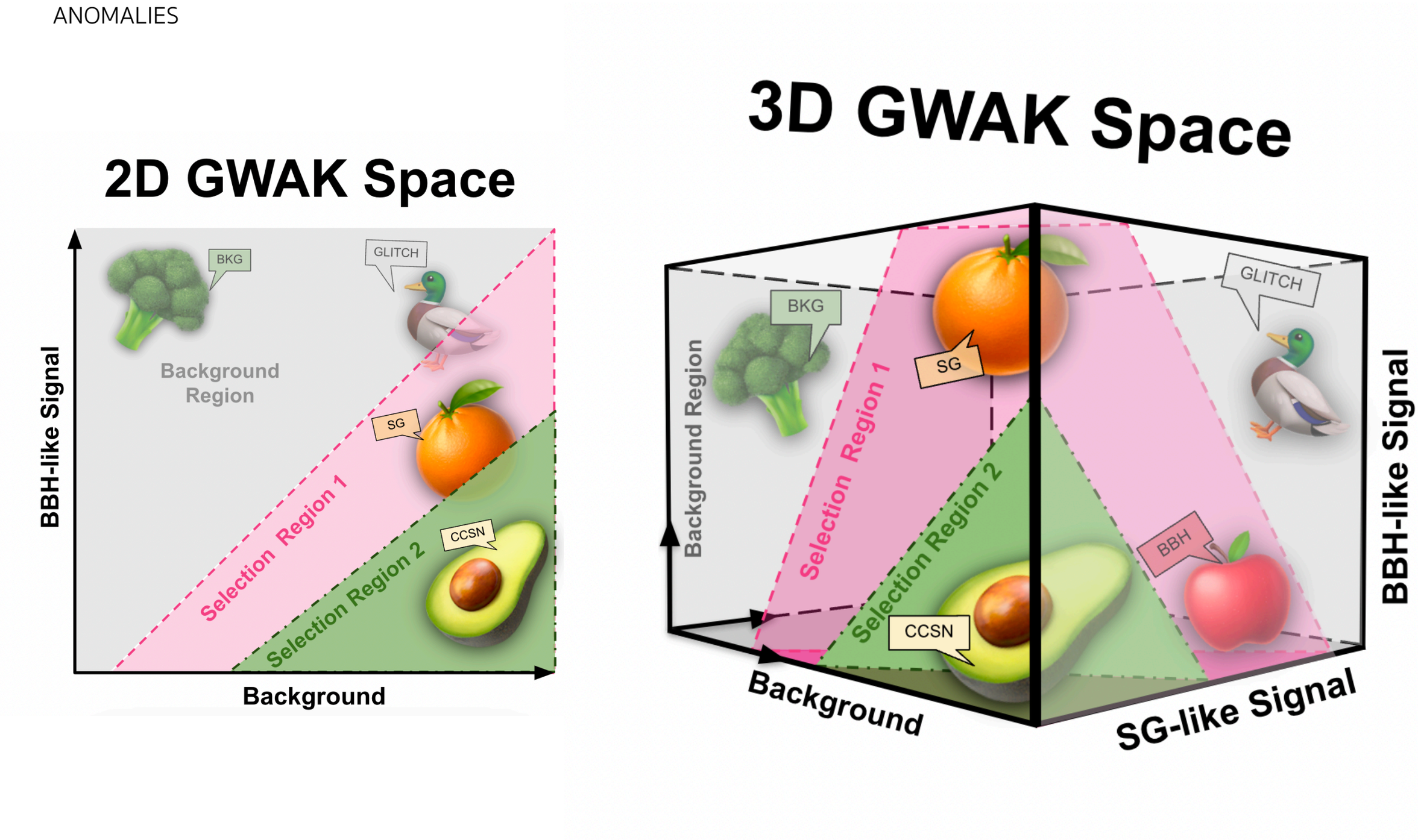
Including more axes, both signal and background, allows to more efficiently select a signal-like anomalies



Adding axes to include more information

arxiv2309.11537

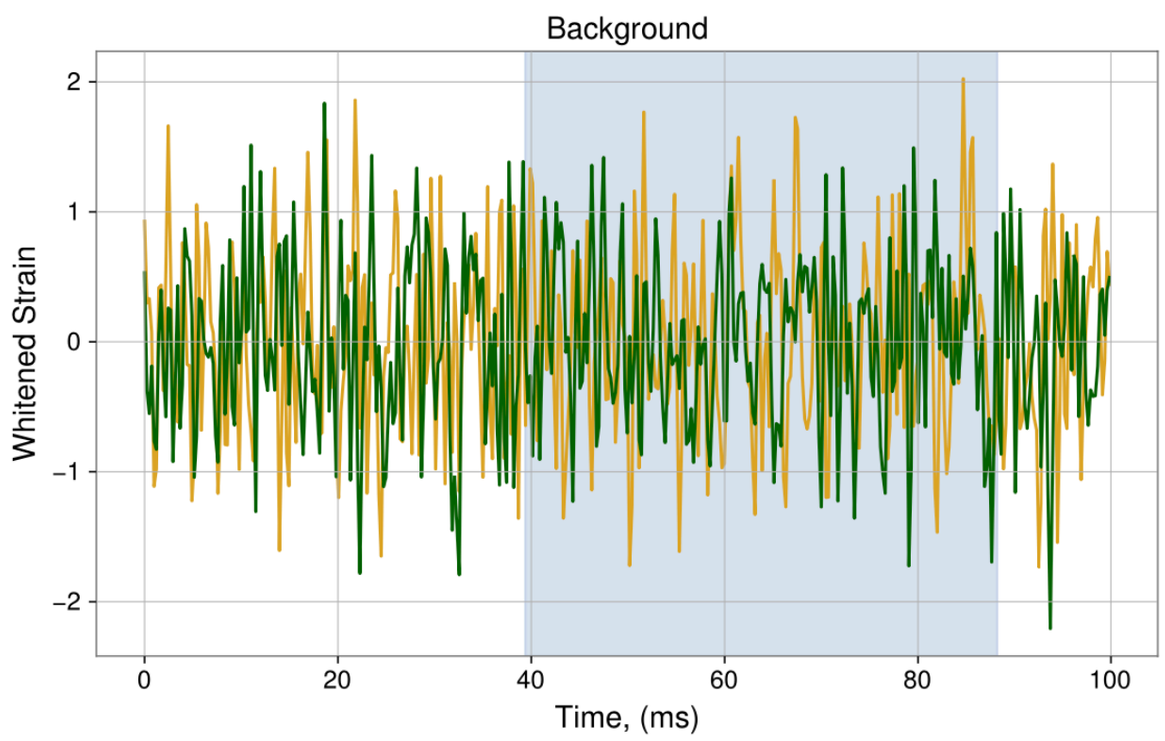
Including more axes, both signal and background, allows to more efficiently select a signal-like anomalies

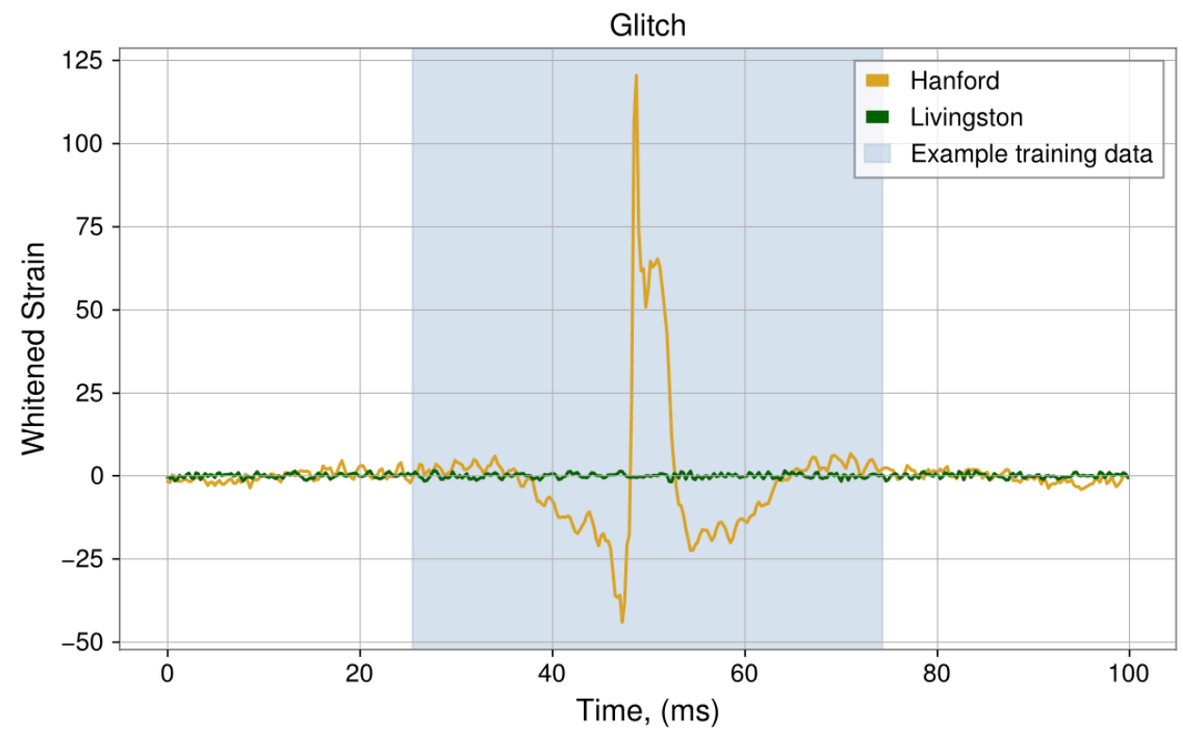


arxiv2309.11537

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



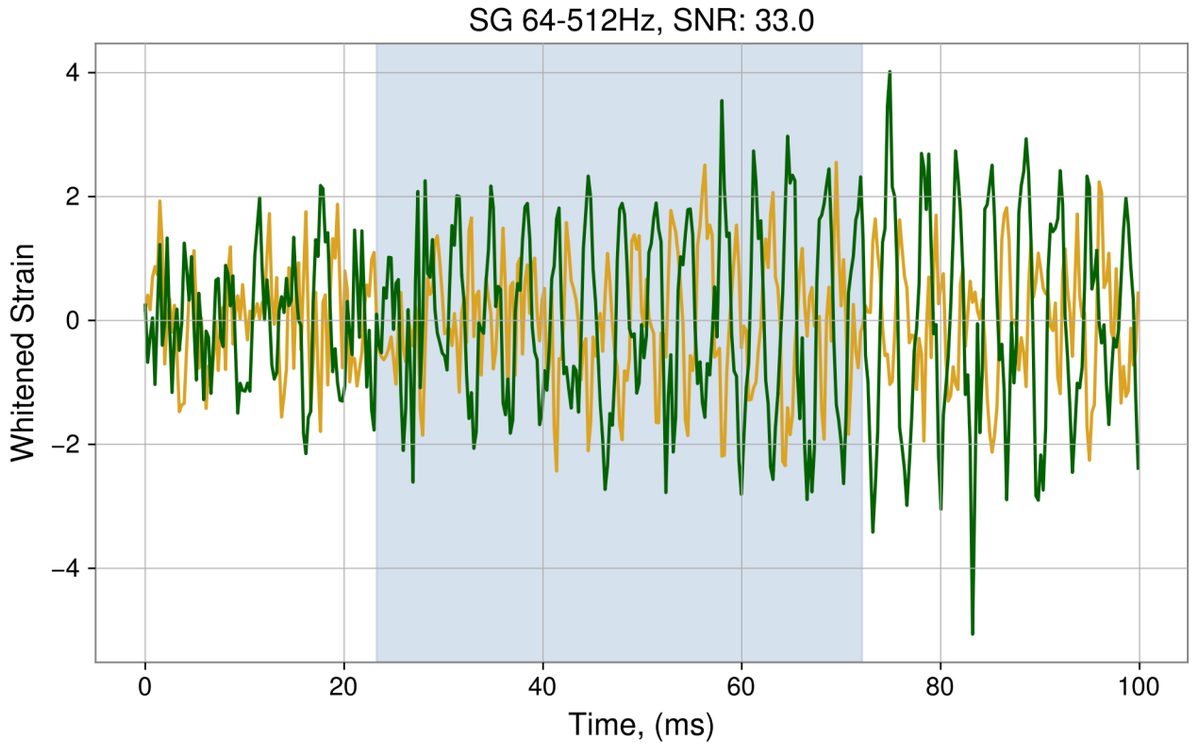


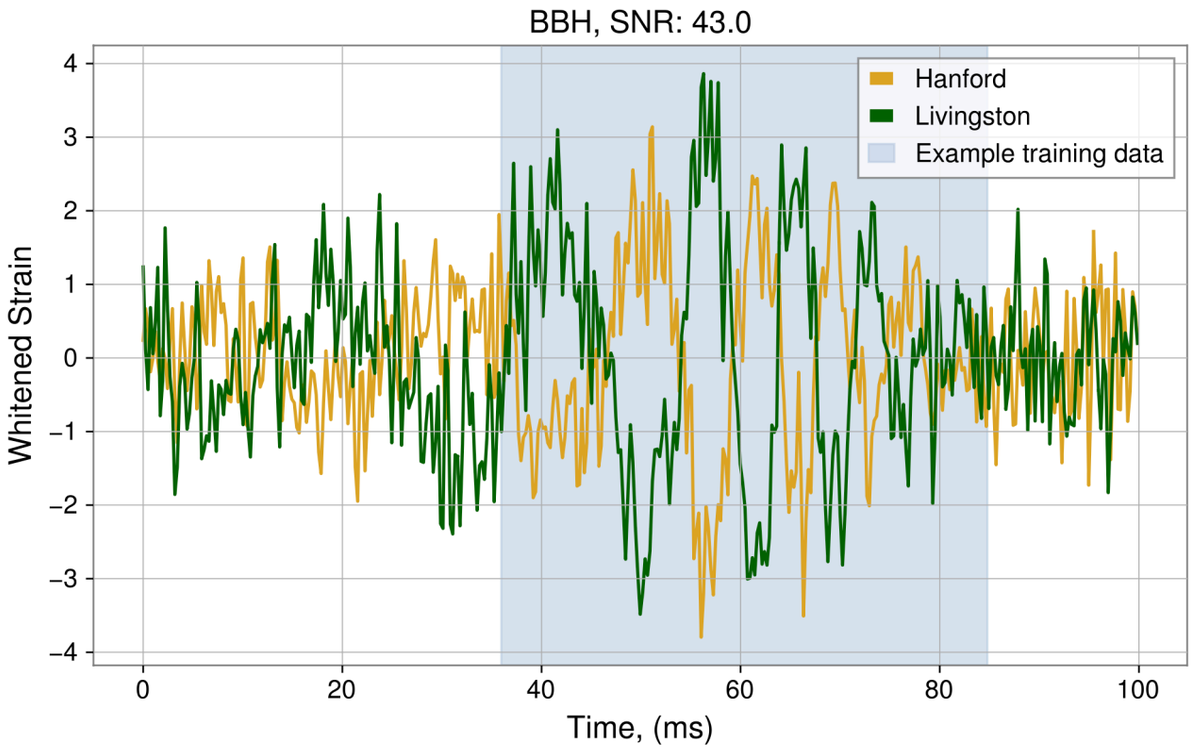
Signal datasets

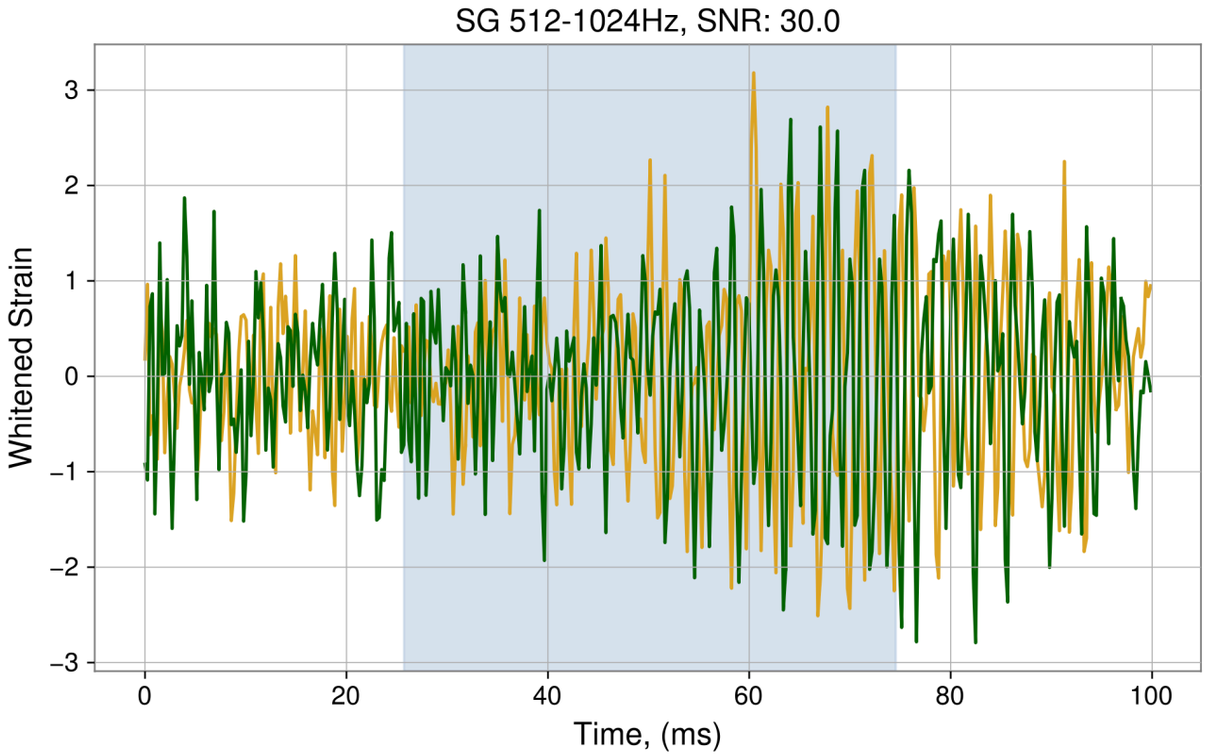
arxiv2309.11537

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

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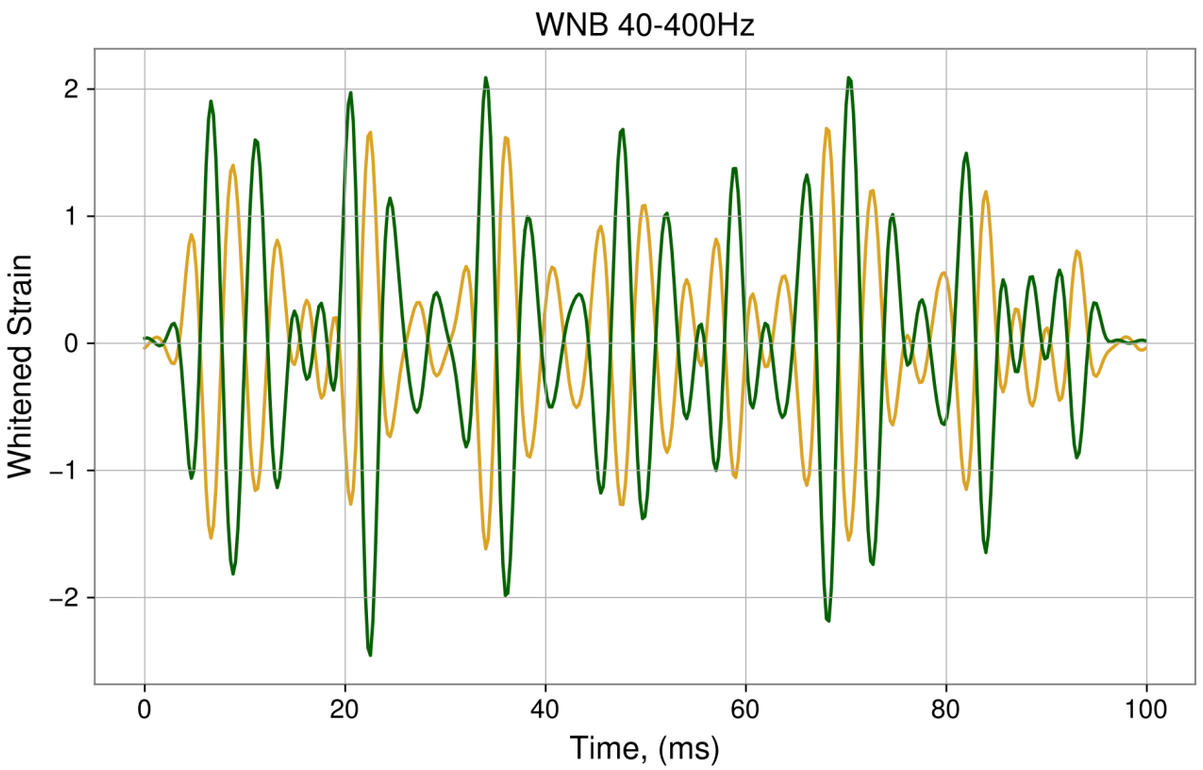
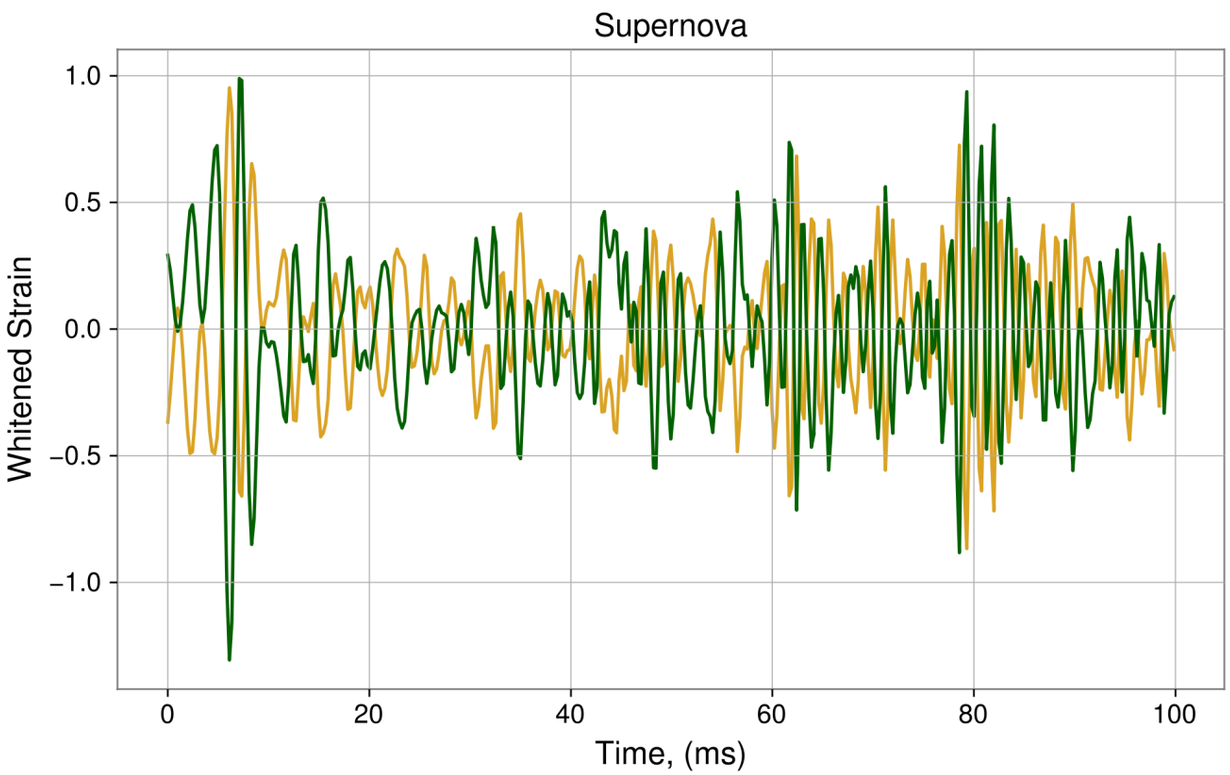
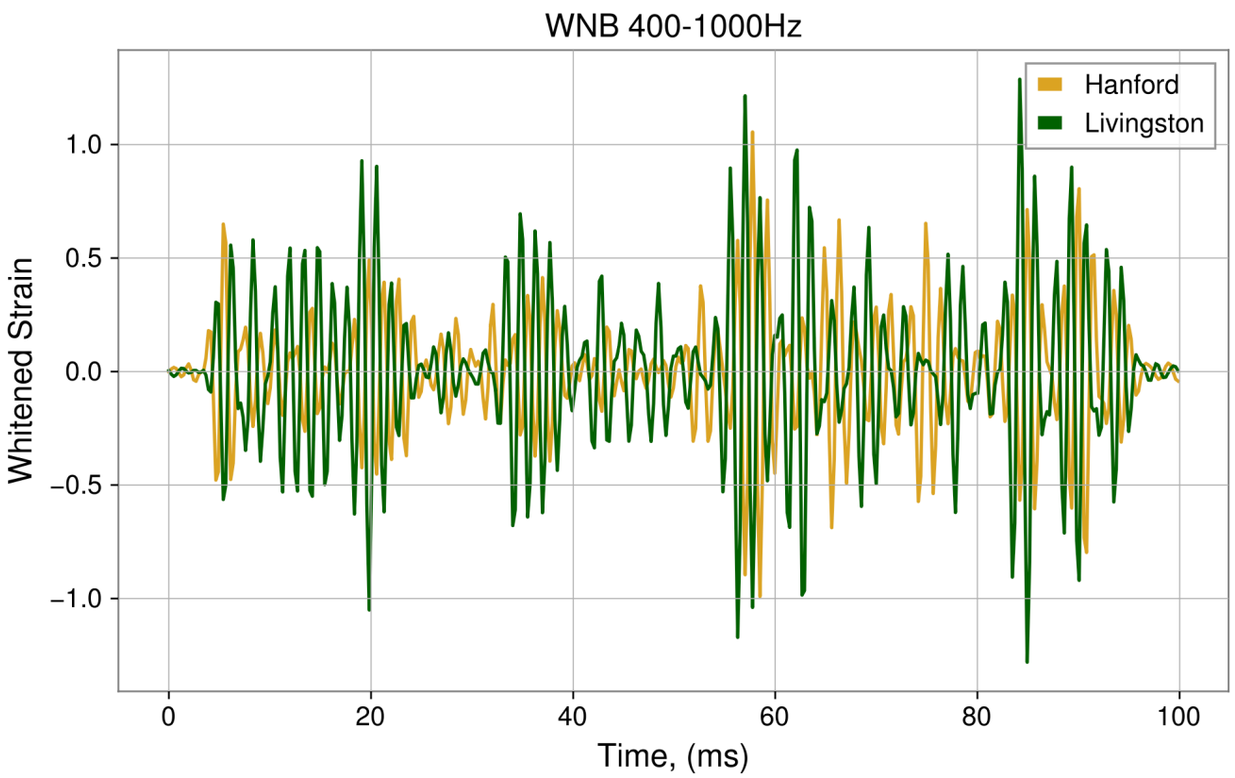
Example of signal-like classes: Supernova and white noise burst strains from Livingston and Hanford

Those anomalies are not used to create the GWAK







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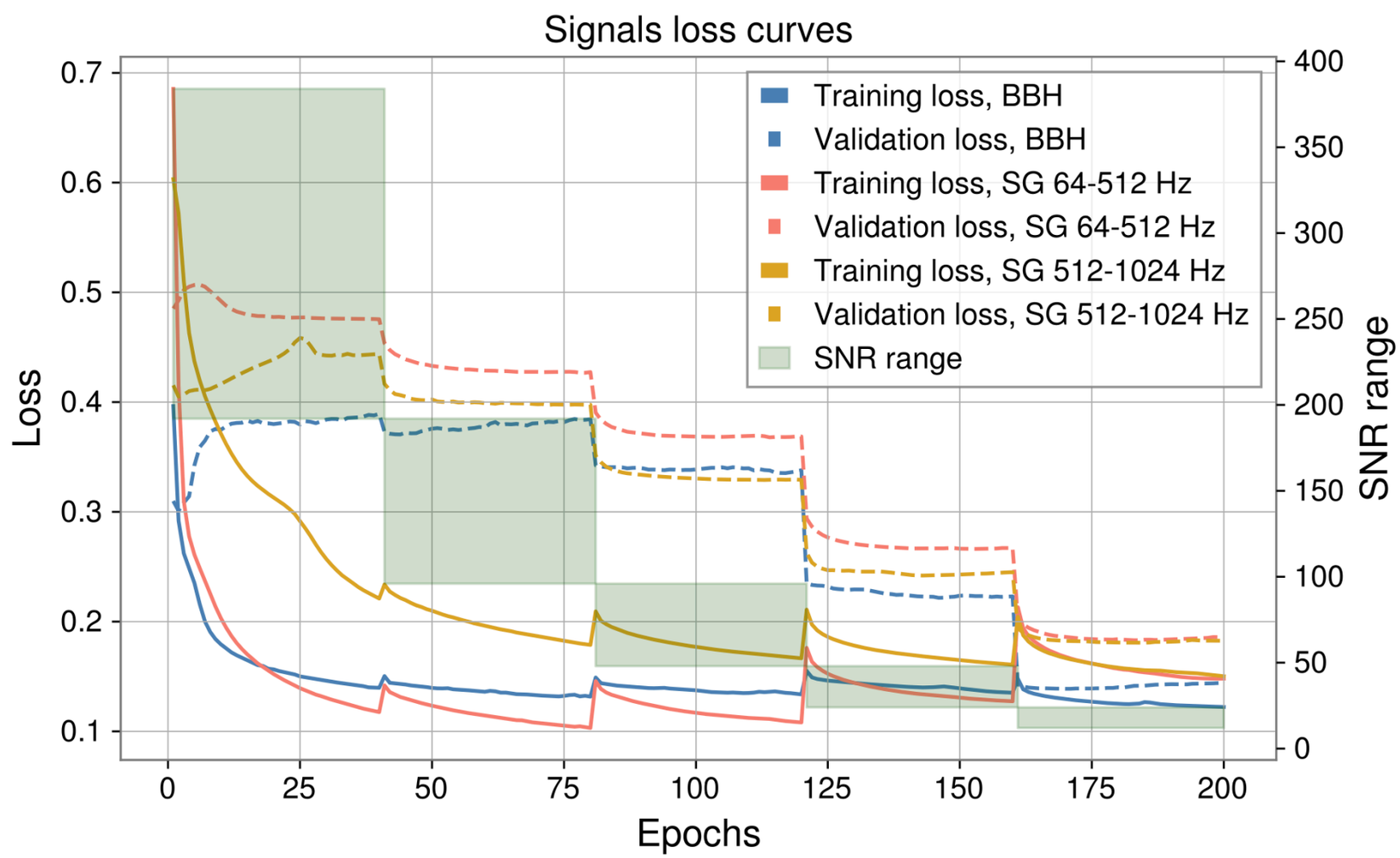
Autoencoder training and validation losses for signal classes, using curriculum learning to progressively reduce validation loss

The validation loss for each training SNR range is computed on the validation data from the last SNR step

In solid/dashed colours are the training/validation losses for BBH, SG 64-512 Hz and SG 512-1024 Hz

A light green shaded region depicts the SNR range for each step of training, spanning the range of injected SNR corresponding to each curriculum.



Autoencoder recreations

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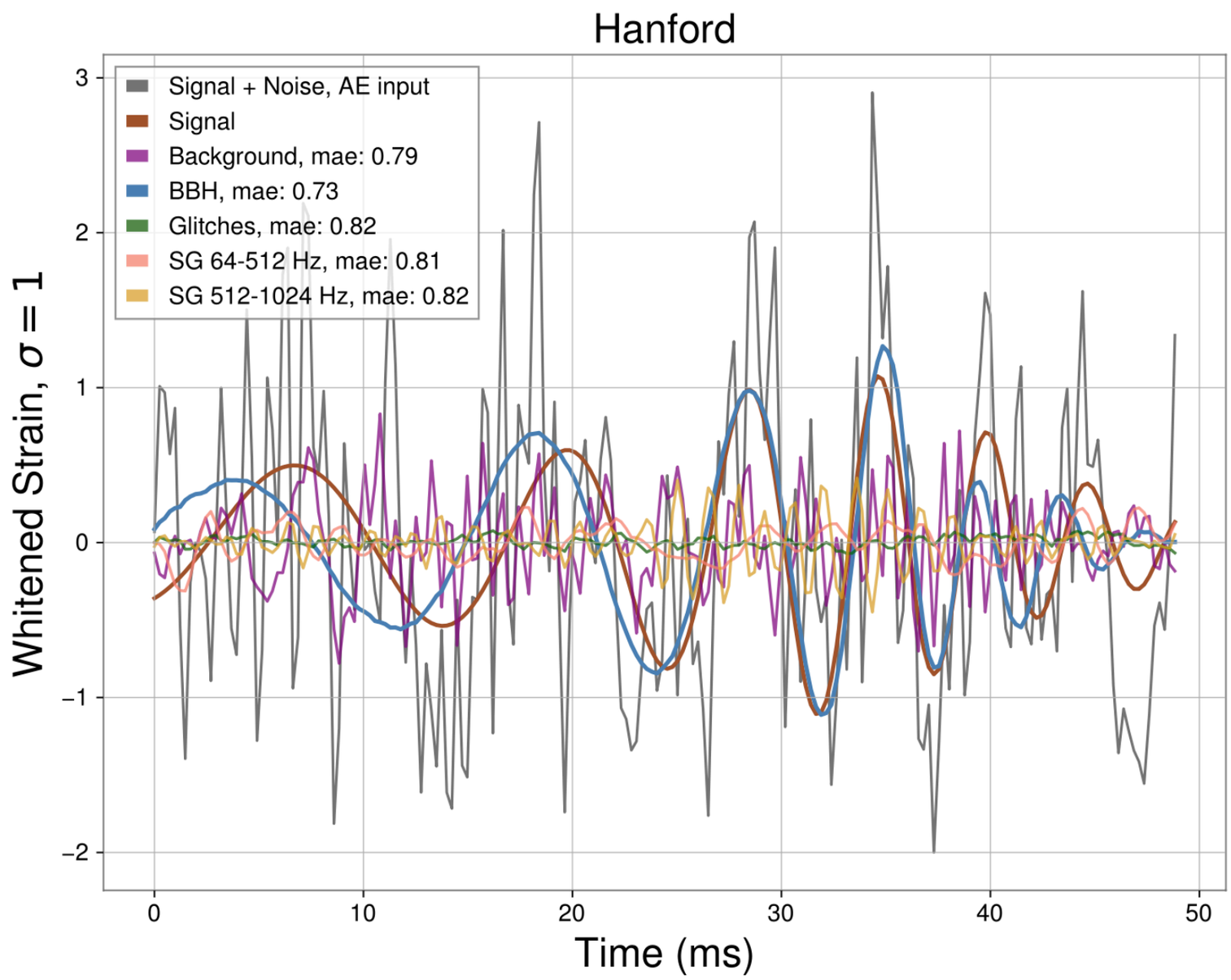
Example of recreation on injected BBH signal, with the noise-less template shown as well

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 Pipeline

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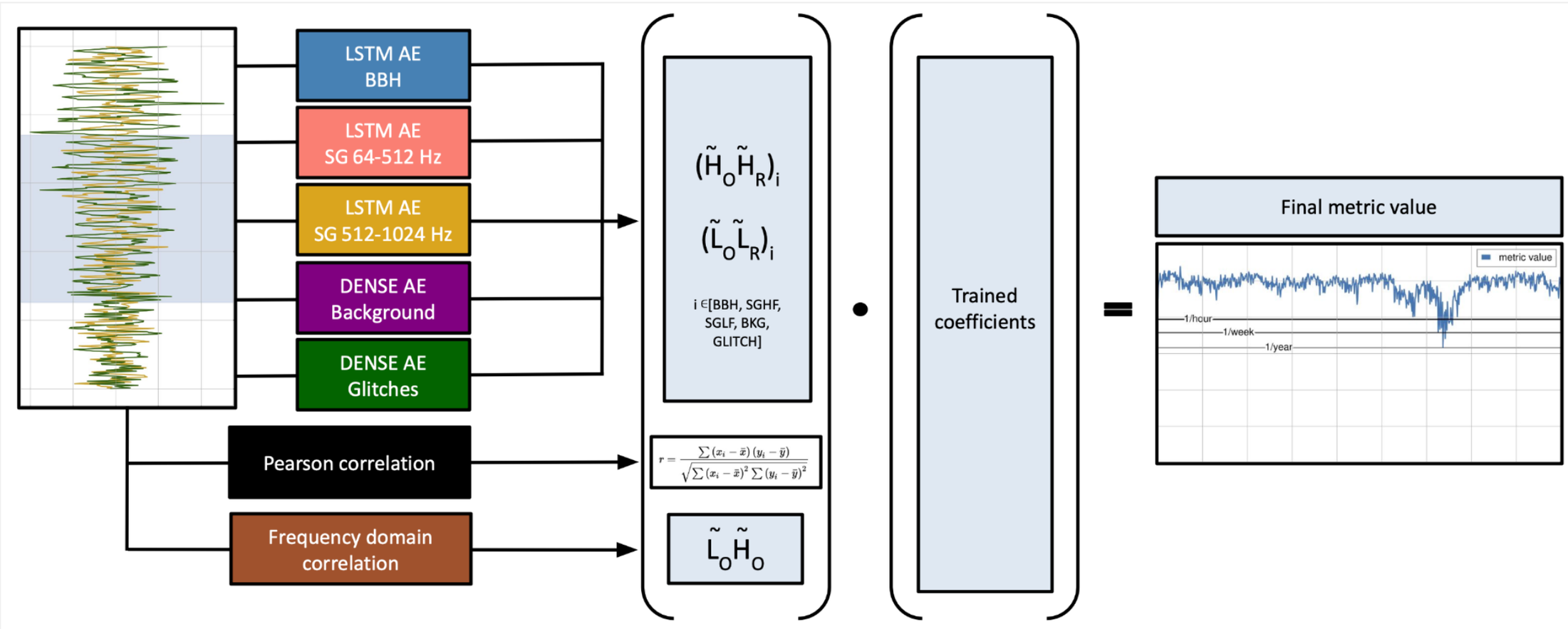
Example of metric calculation on a hypothetical event

1. The event is reconstructed with each of the 5 pre-trained autoencoders, 2 features per AE
2. Pearson and frequency domain correlation are computed on the given input
3. Each of the values is multiplied with a corresponding coefficient which arises from the pre-trained linear metric
4. The sum of all the features multiplied by their coefficients is referred to as the final metric and is used to make a decision on if the event is signal-like



The GWAK Detection

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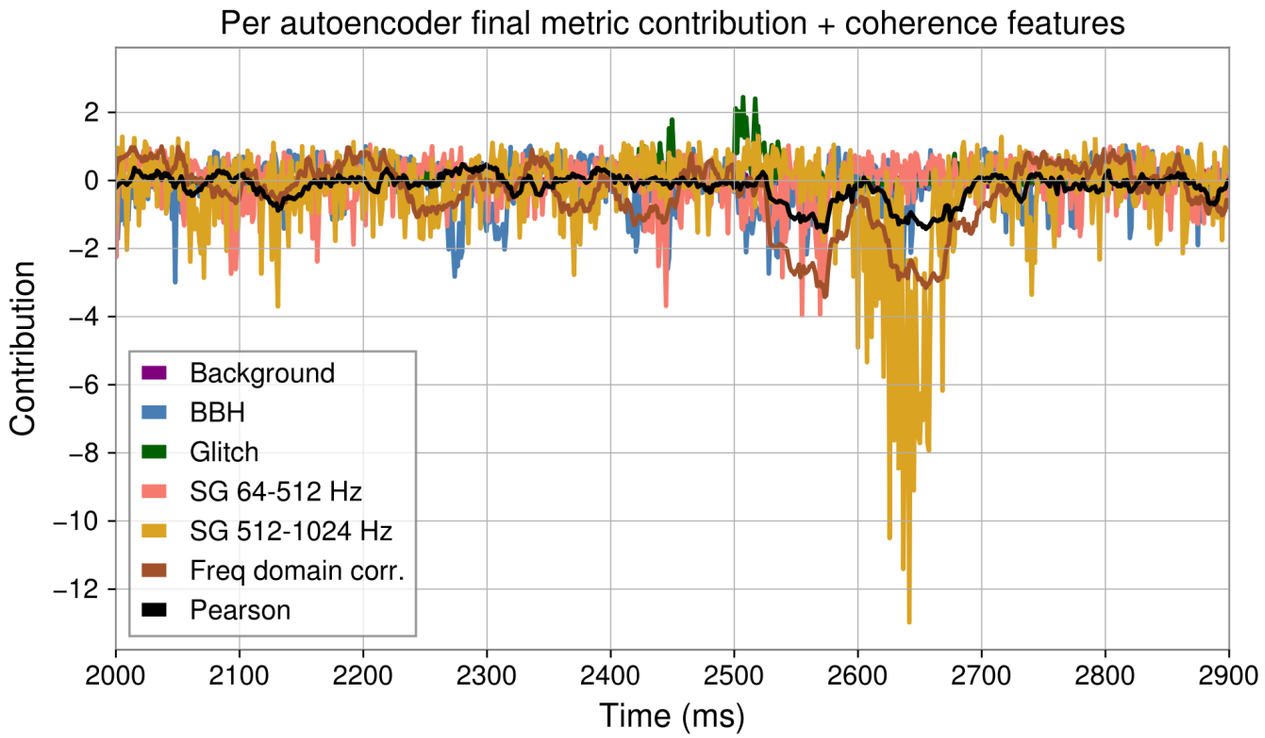
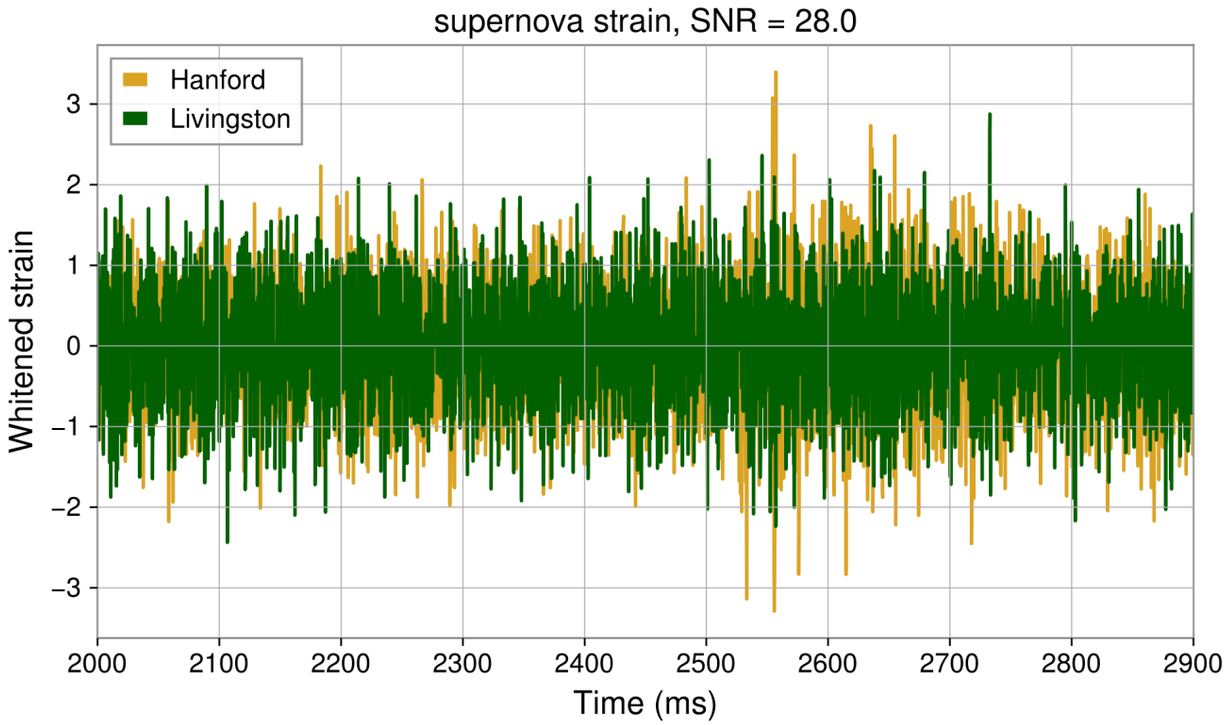
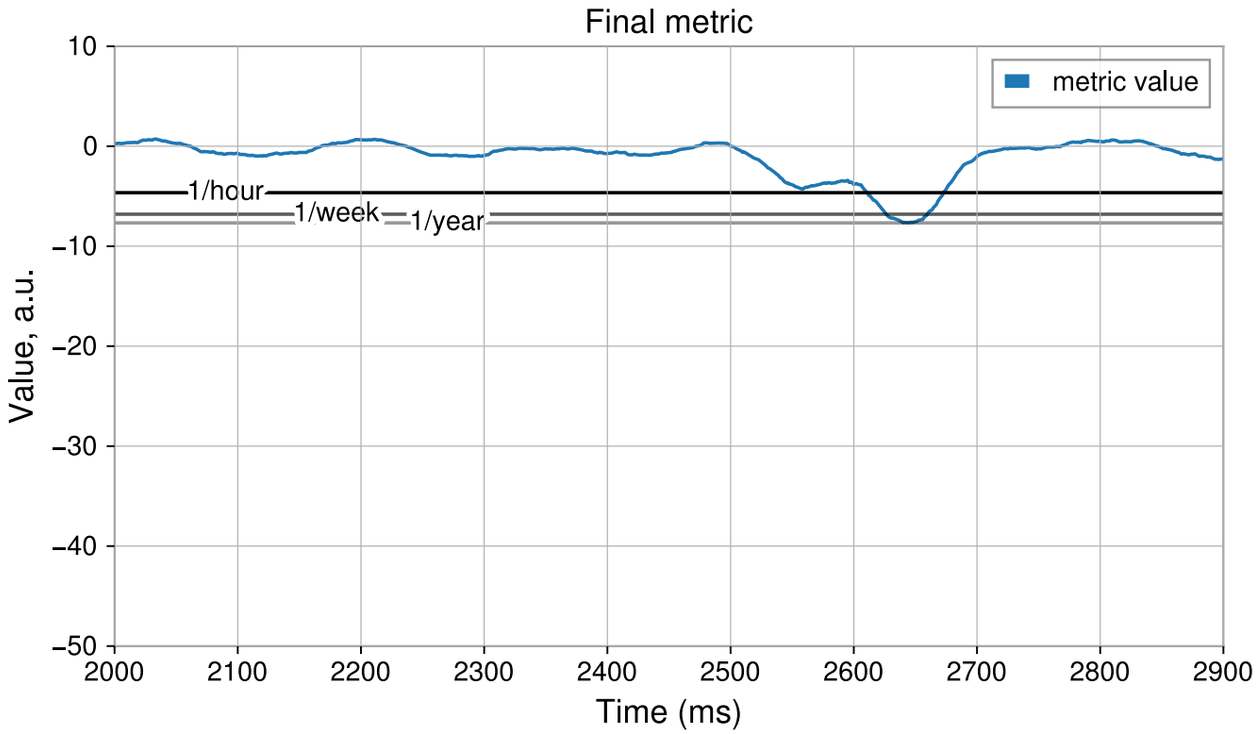
Strain, GWAK metric response and final metric response for Supernova simulated signal

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







The GWAK Efficiency

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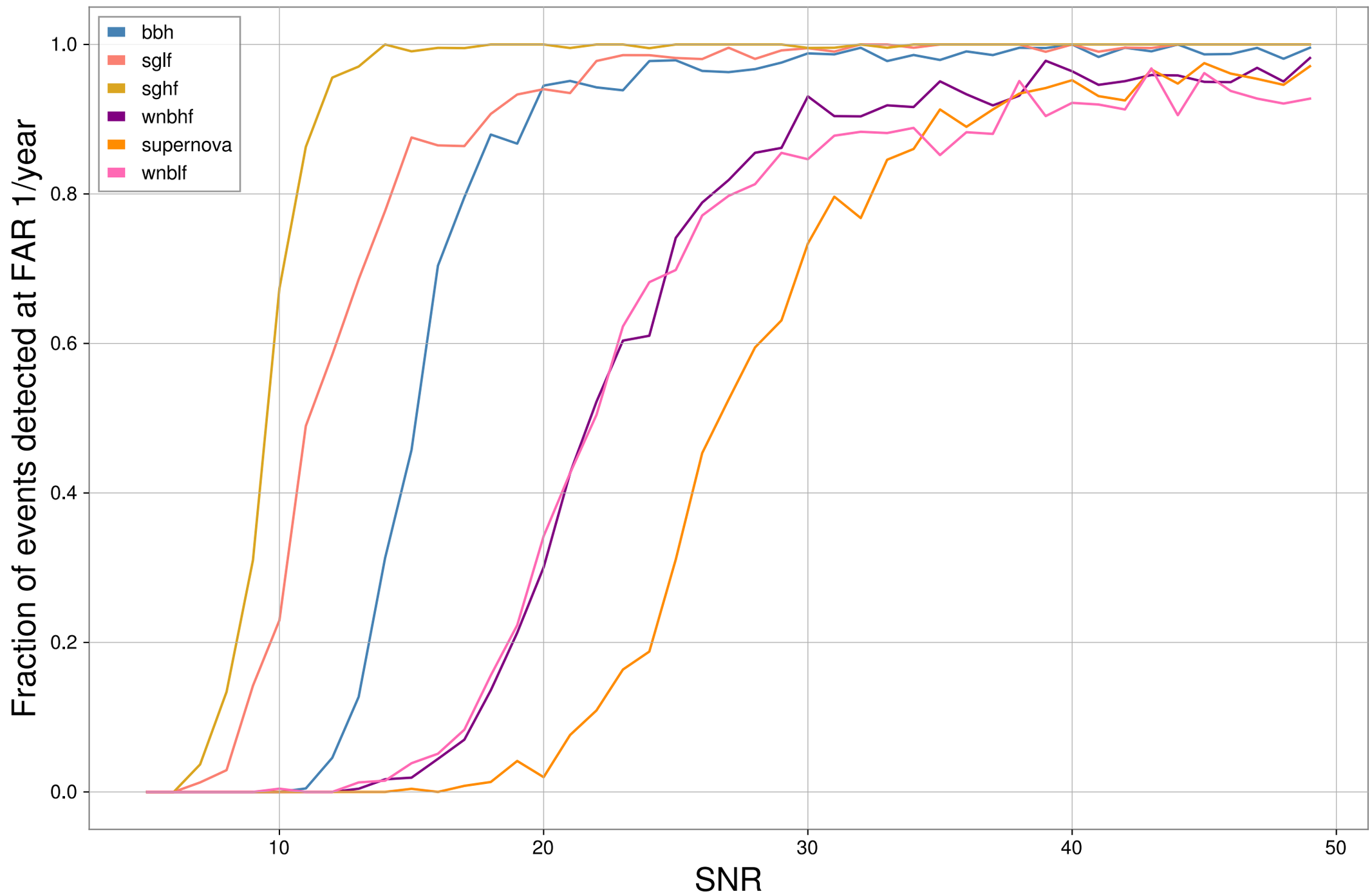
The final metric as a function of SNR for GWAK axes training signals, BBH, SG 64-512 Hz, SG 512-1024 Hz and for potential anomalies, WNB 40-400 Hz, WNB 400-1000 Hz, and Supernova



Conclusions

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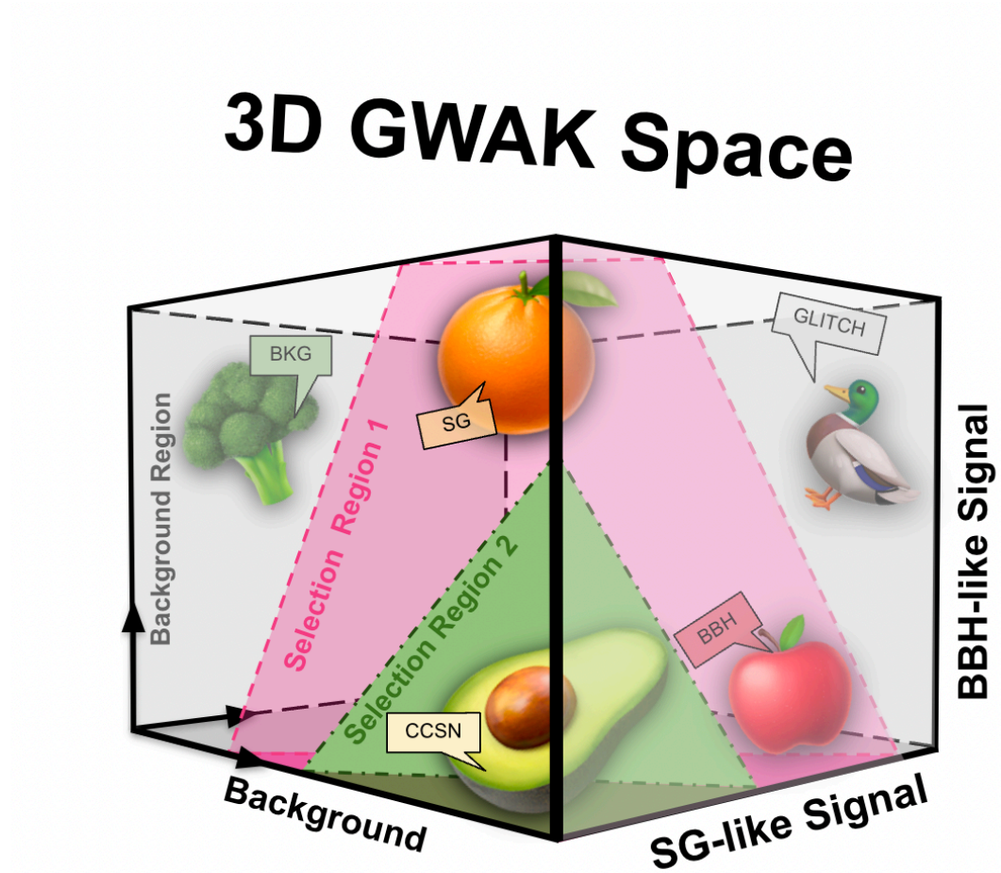
We present a new semi-supervised approach to gravitational-wave anomaly detection

Our method constructs a 12-dimensional embedded space (GWAK space) that is cut with a hyperplane

We find that the GWAK method provides good discrimination power over correlation metrics