Building a Novel Pipeline for searching Anomalous Gravitational Wave Bursts

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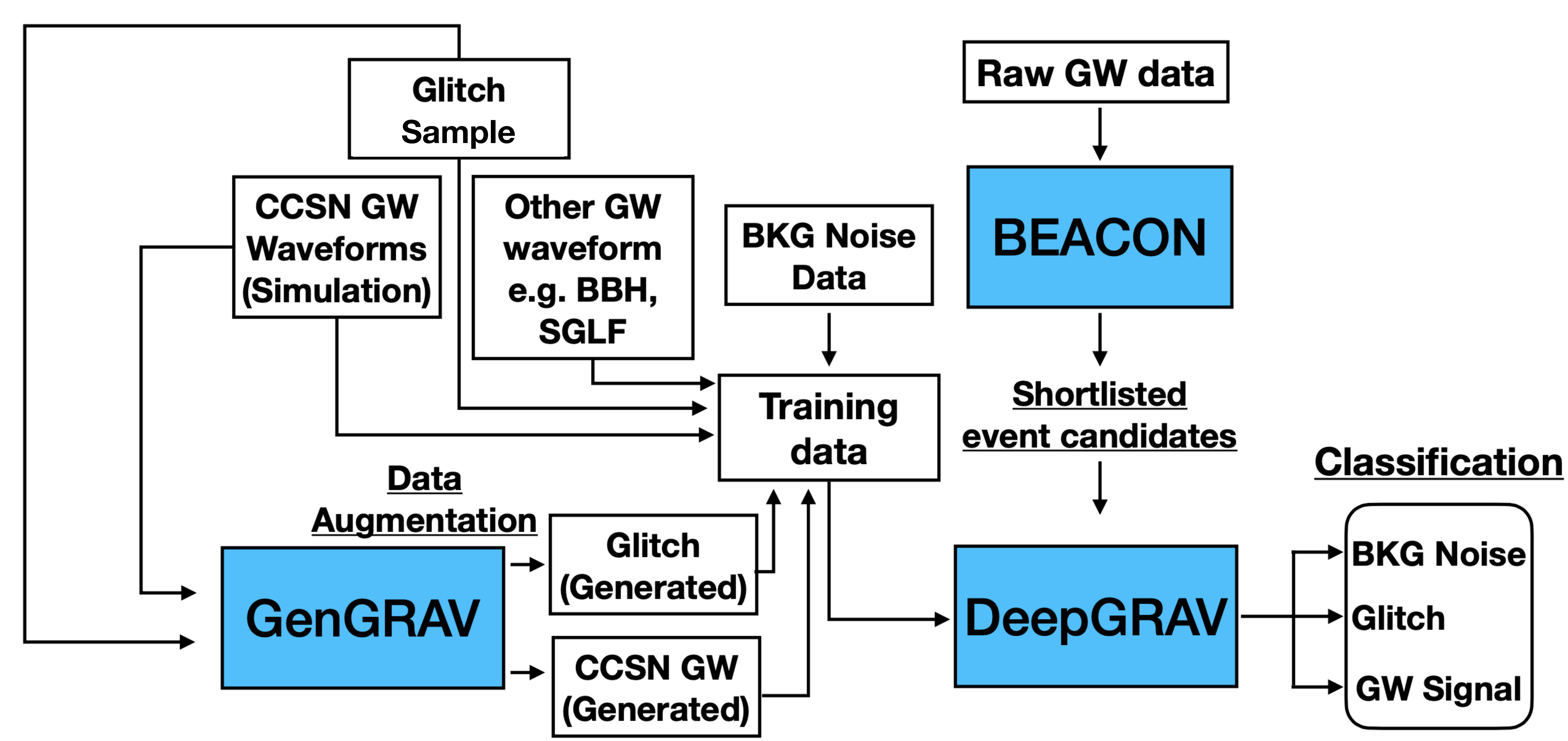
Wish List

- Develop a pipeline for detecting gravitational wave burst without knowing exactly the waveform
- Capable for low-latency detection
- Enhance the detectability for weak unmodeled signals (e.g. CCSNe)
- Classifying the signals
- Bulid-in glitch veto

Preliminary Design of our pipeline



3 Basic Components

- **BEACON** — Swift compilation of event candidate list
- **DeepGRAV** — Classifying event candidate list compiled by BEACON
- **GenGRAV** — Enhancing the performance of DeepGRAV

Similar to real time object detection

BEACON

Burst **E**vent **A**nomaly **C**lustering **&** **O**utlier **N**otification

- Design for swiftly spotting promising event candidates upon continuous data-streaming and passing the corresponding noise-subtracted time-segments for the next step.

It comprises 4 steps:

(a) Background subtraction with seqARIMA

(b) Anomaly clustering

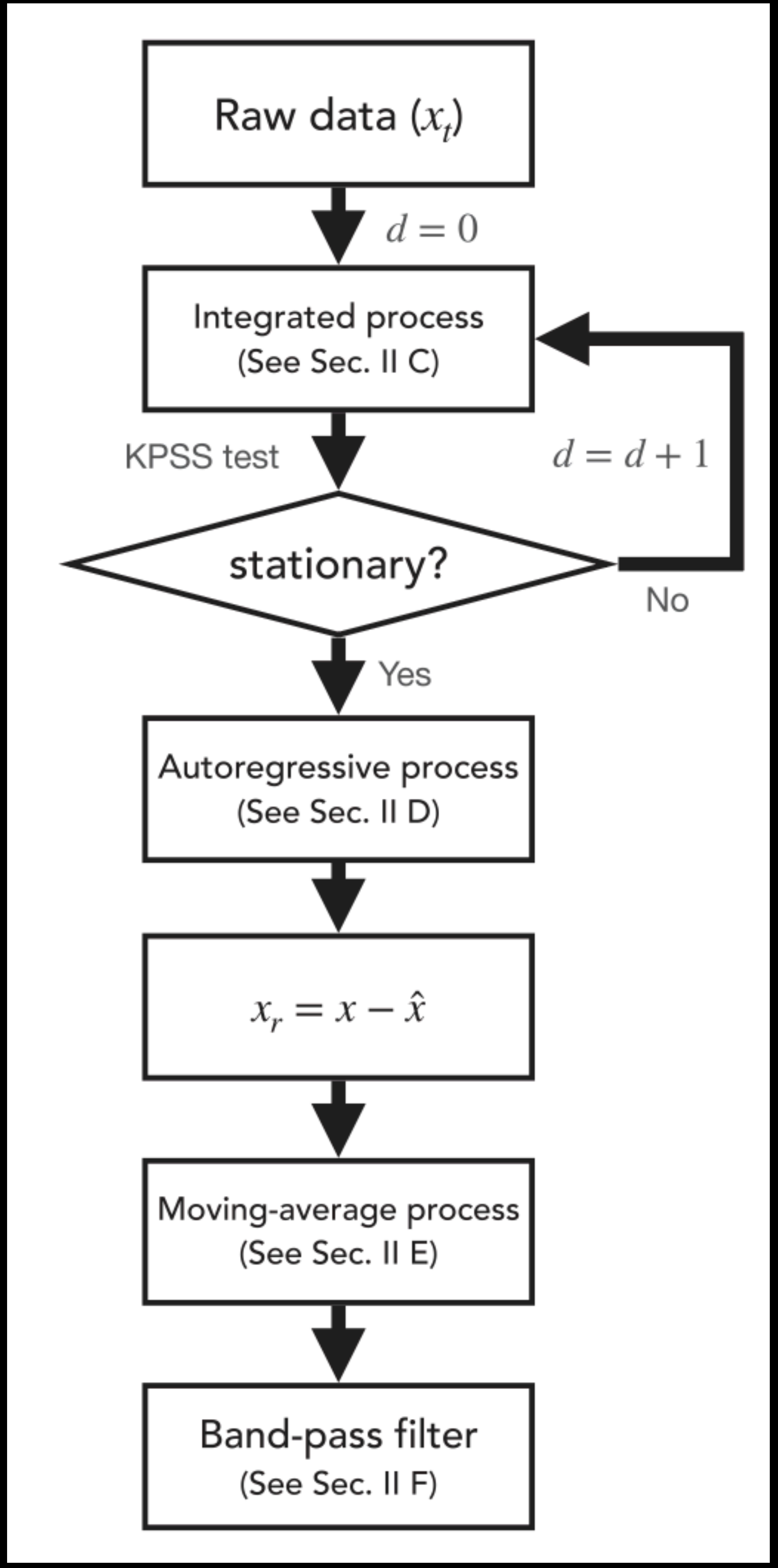
(c) Significance evaluation

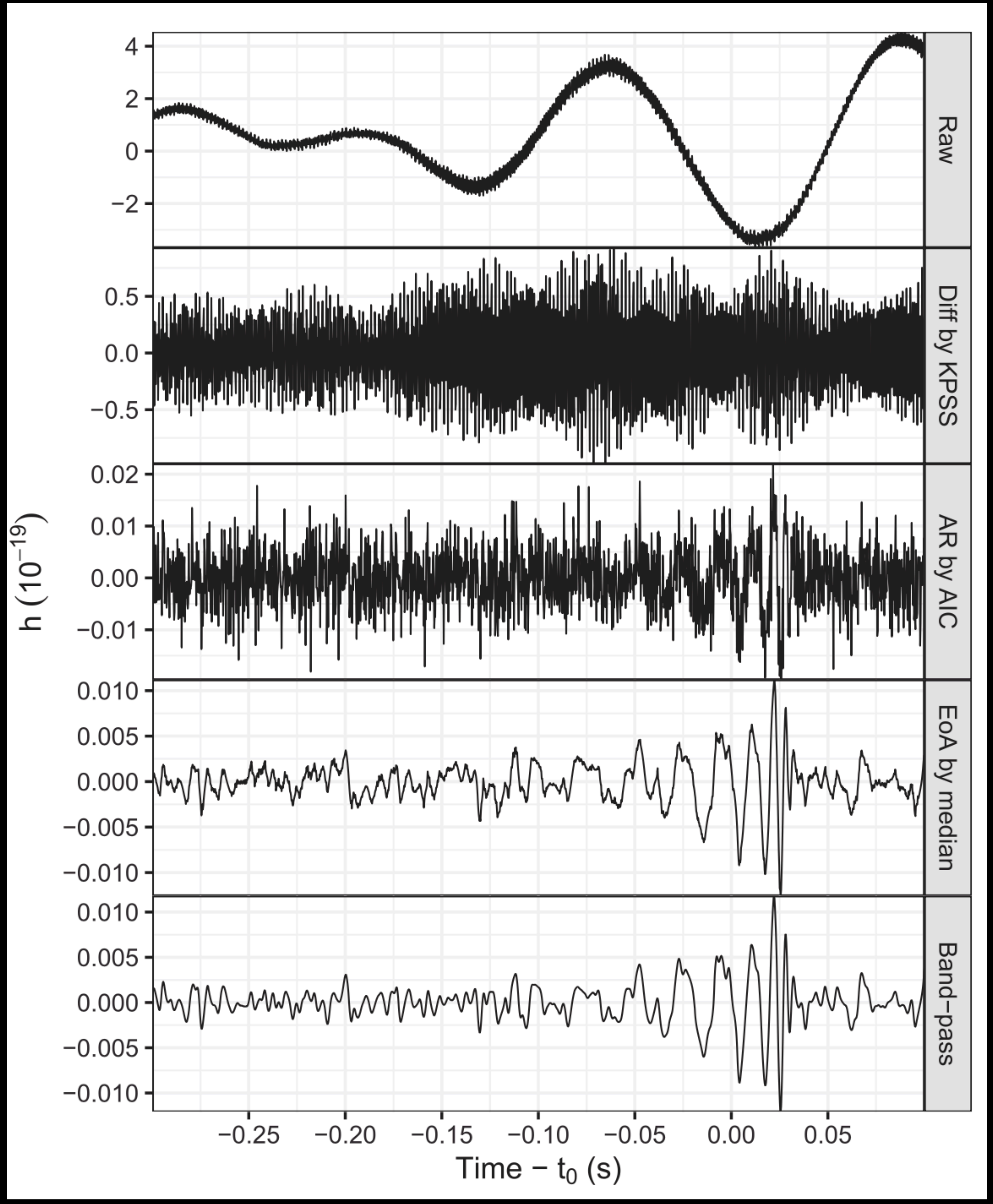
(d) Coincidence in detector network

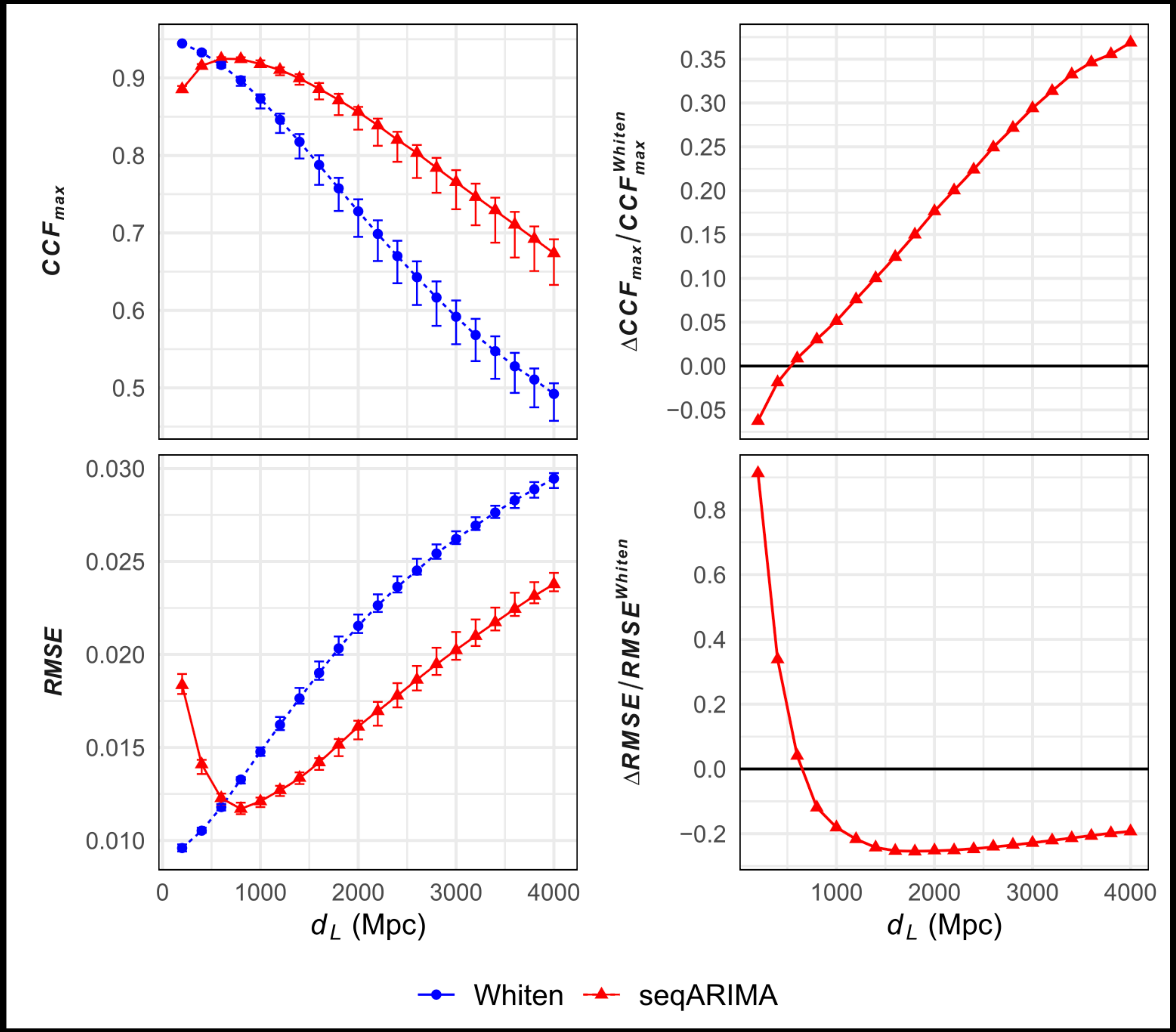
See Dr. Sangin Kim's talk for details

Denoising with sequential-ARIMA (seqARIMA)

De-noising technique based on autoregressive modeling

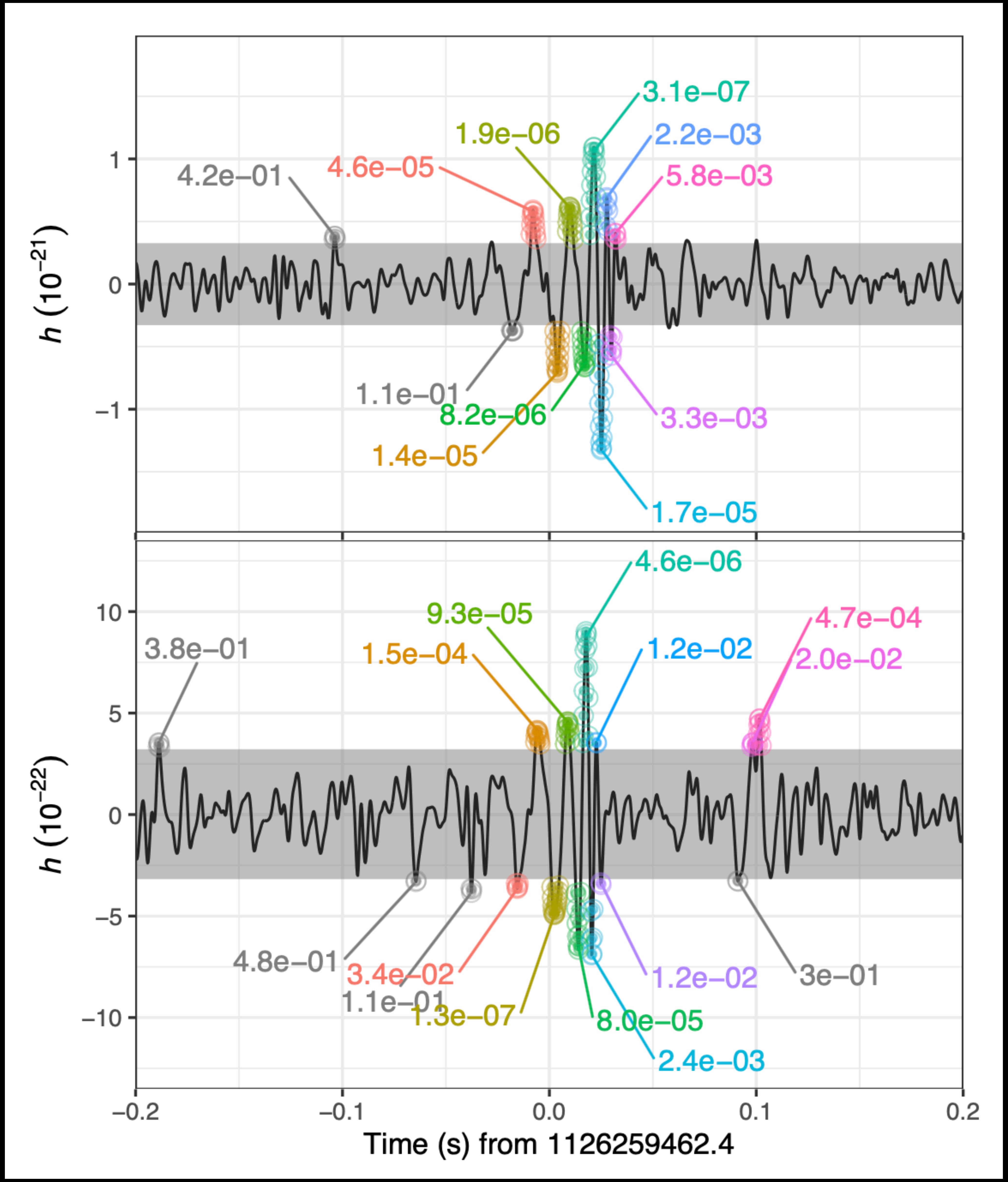


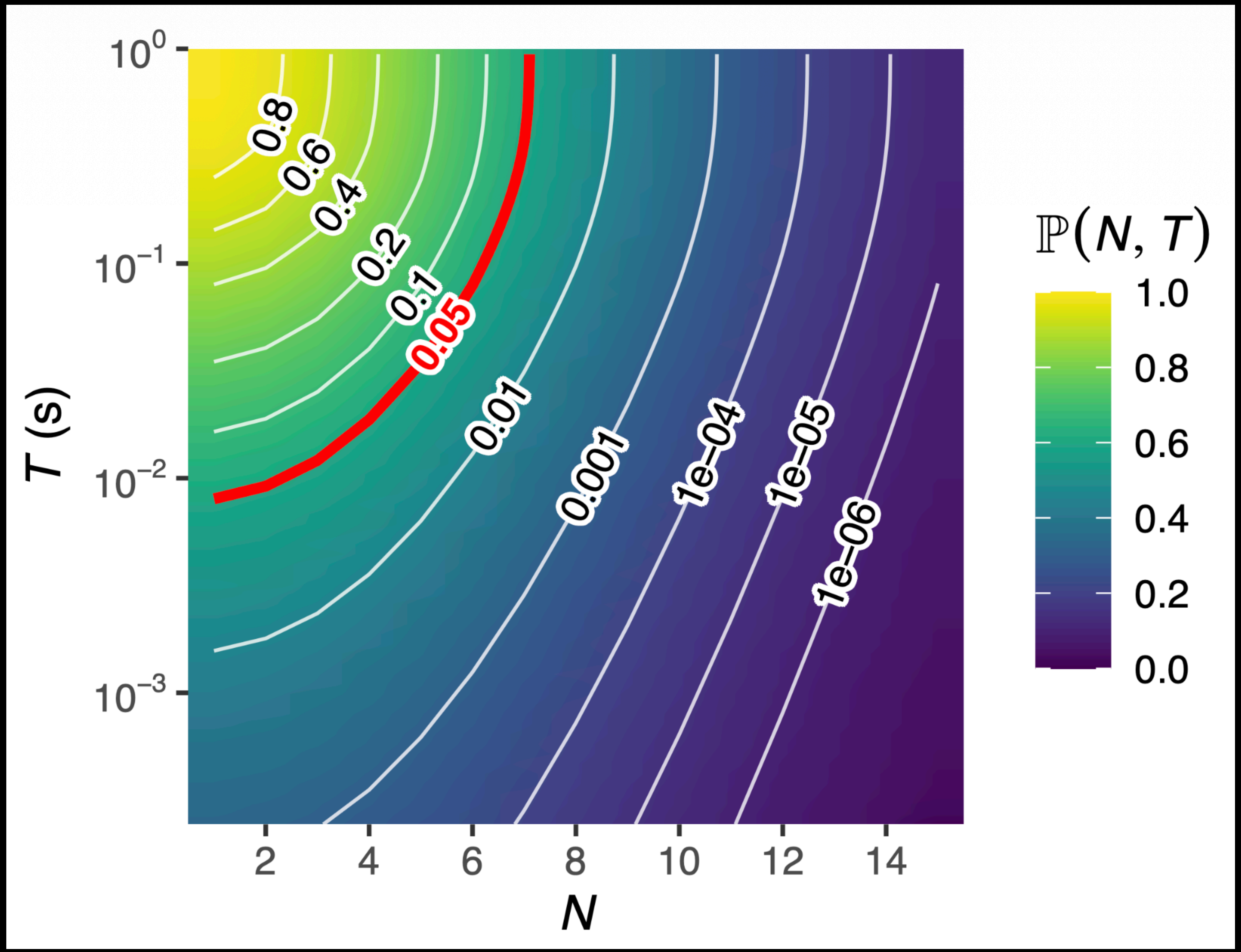




Kim et al. 2024

Anomaly Clustering + Significance Evaluation



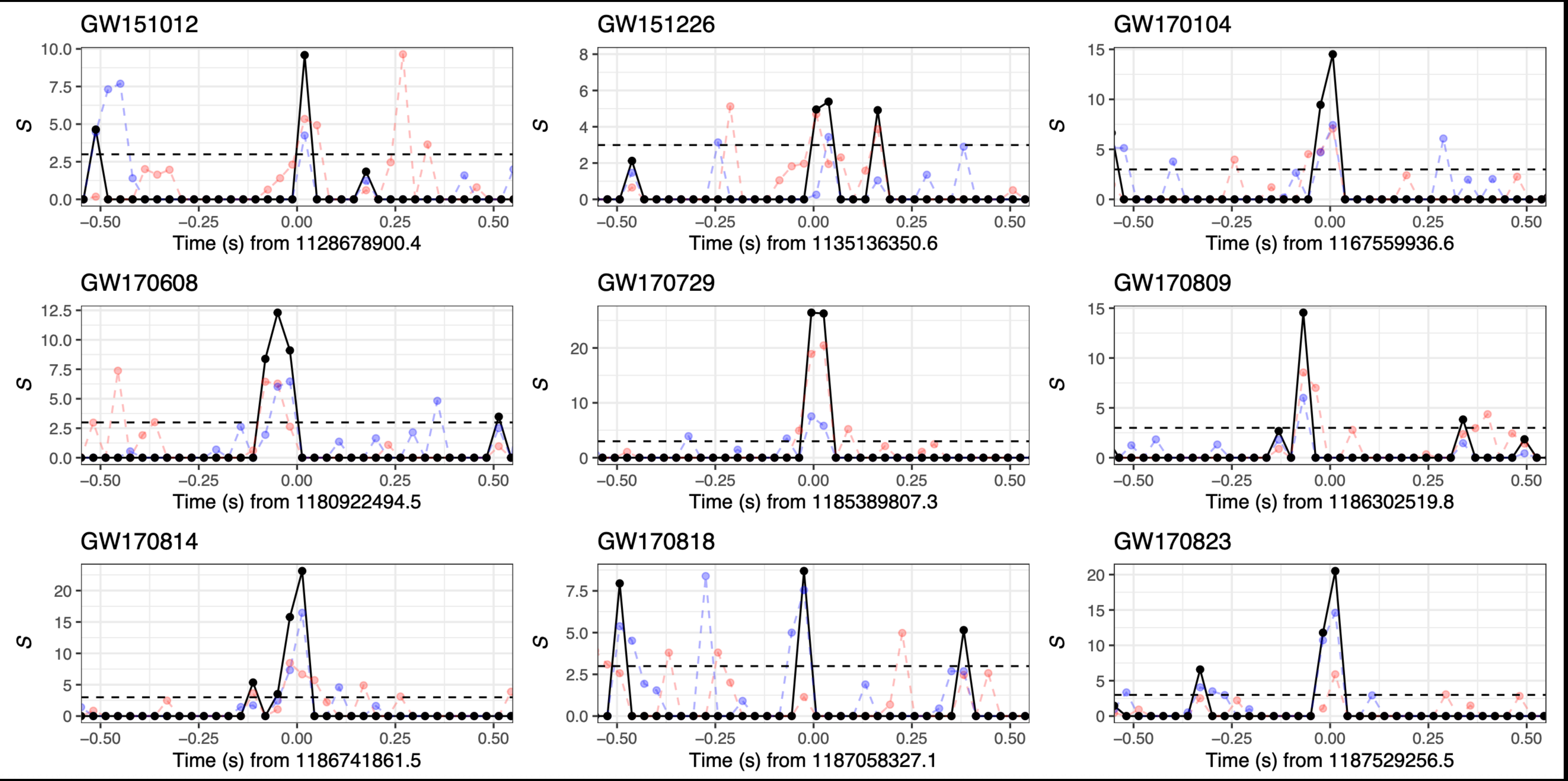


- Null probability model is dynamically updated at real time (i.e. adopted to local time-segment)

Kim et al. 2025 submitted

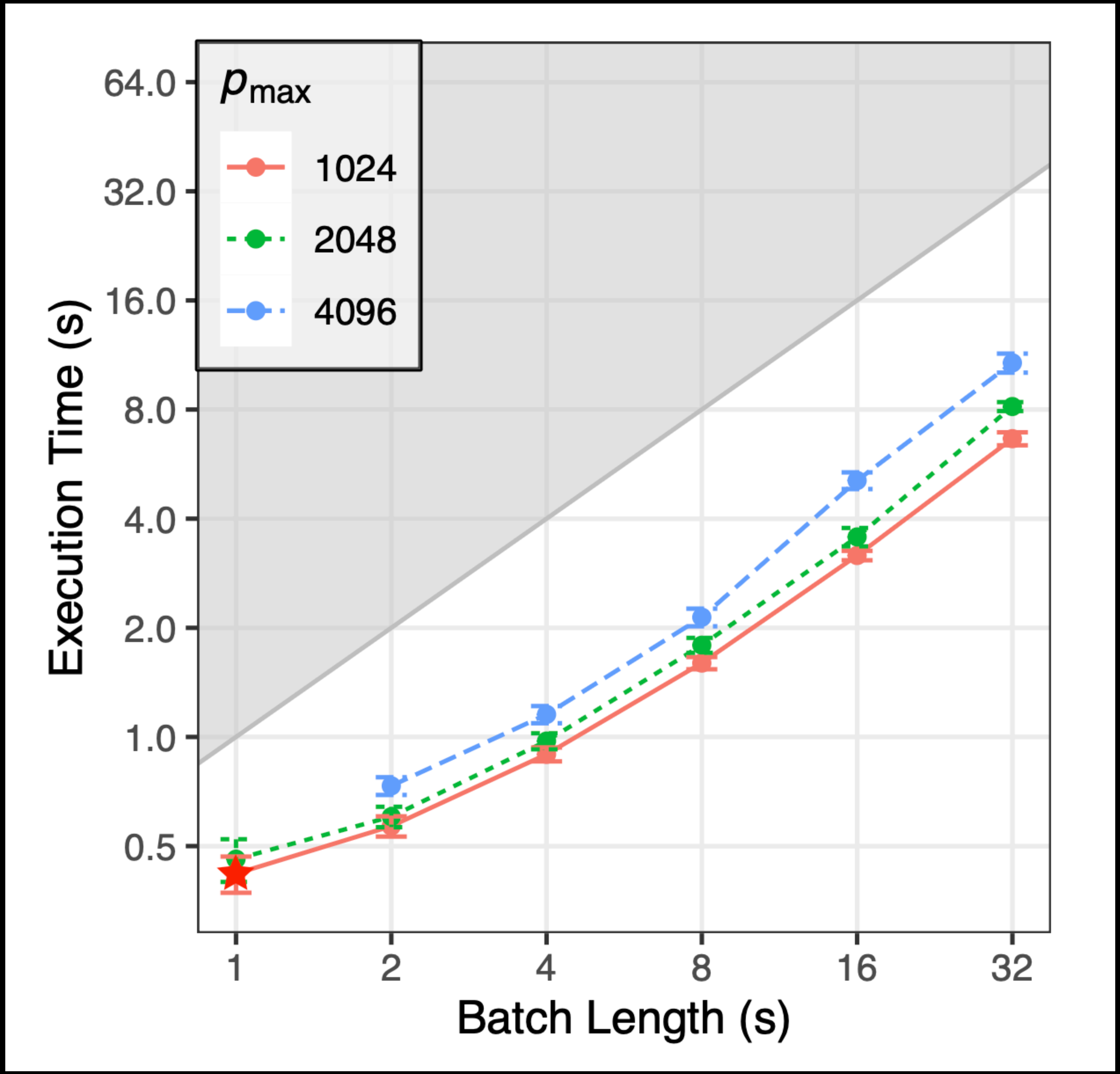
Coincidence Analysis

Suppressing false alarms from individual detector



Kim et al. 2025 submitted

Computational Efficiency



Kim et al. 2025 submitted

- For a low-latency search, we require the execution time to be shorter than the streaming batch length.
- At all settings, BEACON generally take < 50% of the batch length for execution.
- Leave sufficient room for other plug-in of the pipeline.

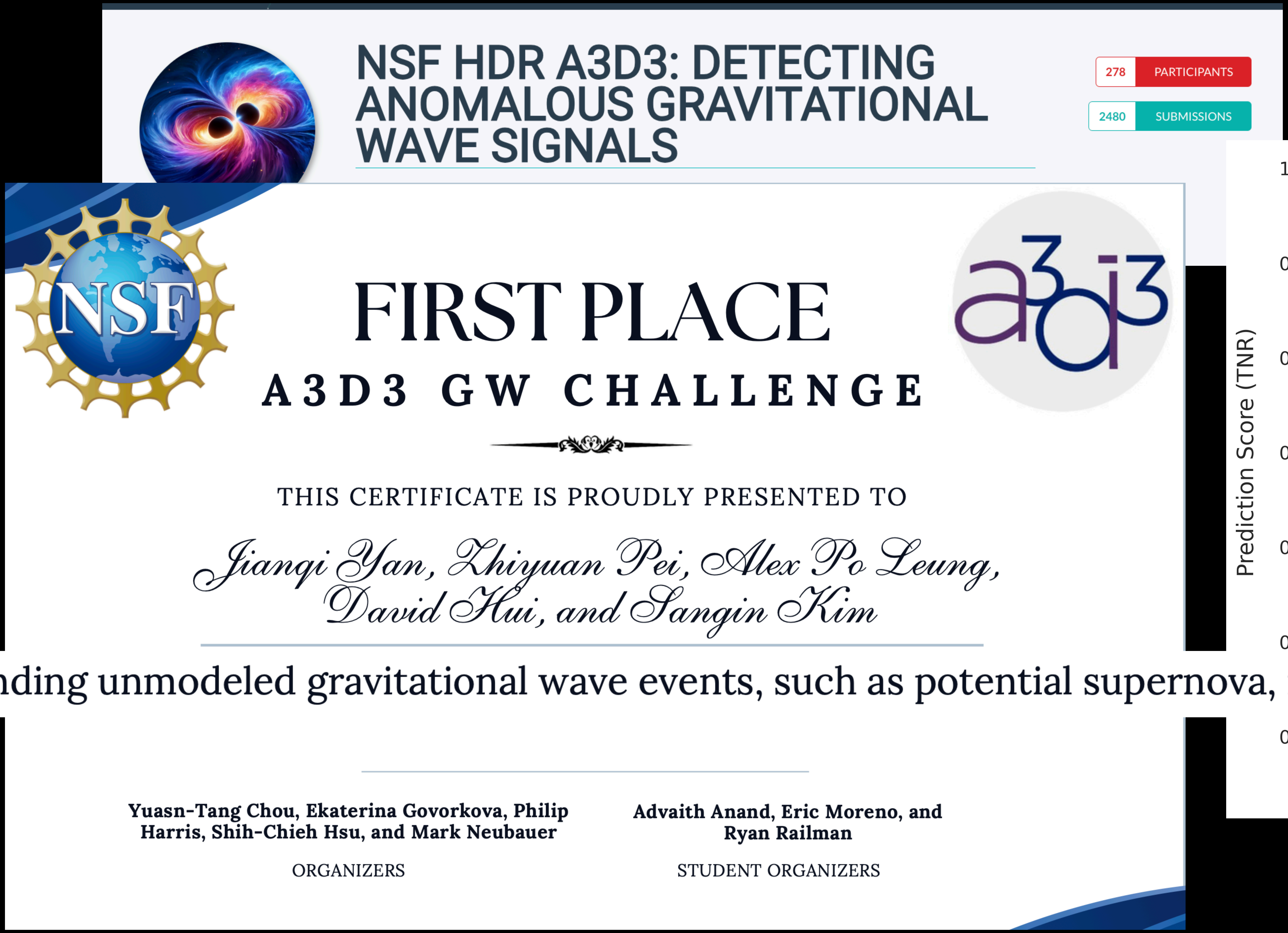
DeepGRAV

Anomalous GW detection through deep latent features

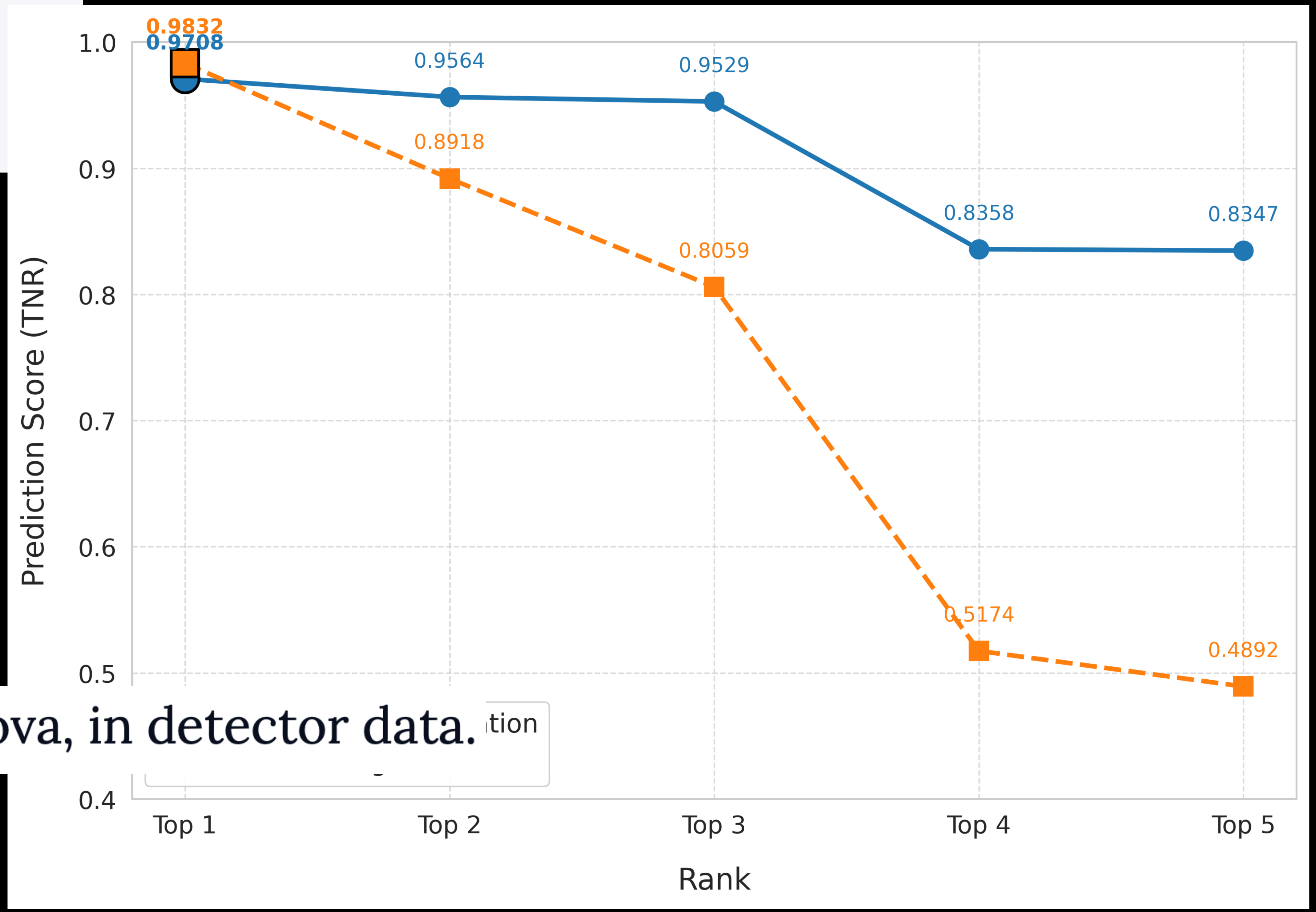
- BEACON gives a set of time segments that might contain interesting signals.
- There still can be a fraction of these candidates can be resulted from the unwanted non-Gaussian noise anomalies (i.e.glitches) that pass through the sieve of BEACON.
- We need a second sieve for distinguishing the subtle difference between noise and astrophysically-interesting signals.
- DeepGRAV provides this second sieve.

DeepGRAV

Anomalous GW detection through deep latent features



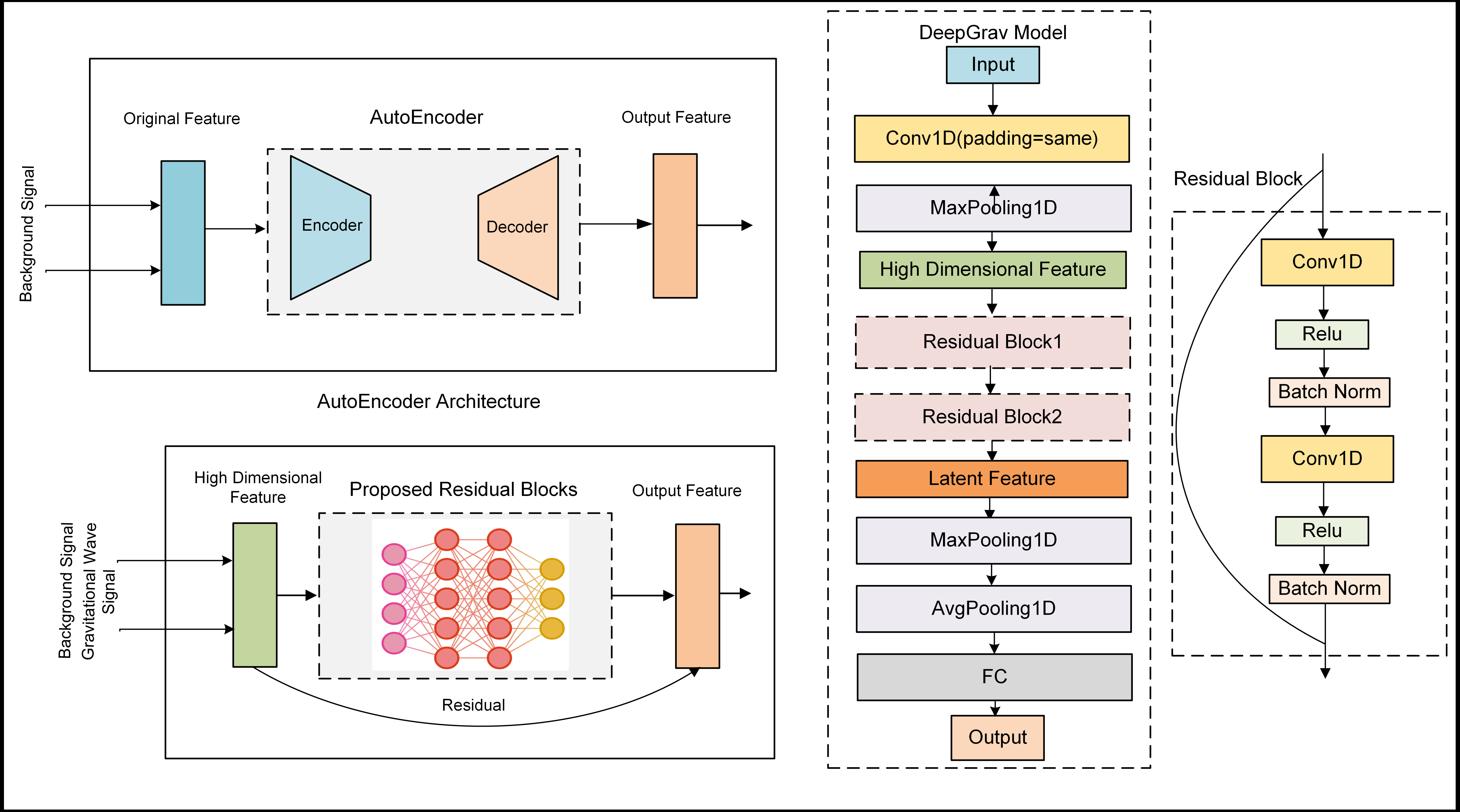
Finding unmodeled gravitational wave events, such as potential supernova, in detector data.



Yan et al. 2025

DeepGRAV

Architecture combines CNN + ResNet + latent variable model



Yan et al. 2025

DeepGRAV

Architecture combines CNN + ResNet + latent variable model

- **1-D CNN** — Instead of inputting the time segment, we first exact the high dimensional features for passing to the next module.

- **Residual block** — With the skip connection, the neural network models the residual which we speculate that may better capture the subtle differences between a weak signal and the background.

- **High dimensional latent feature** — Constructing the hyperplane for distinguishing signal/background

DeepGRAV

NSF HDR A3D3 Competition data (Final round)

Training set

- Background (BKG x100000)

Signal Class

- Binary Black hole (BBH x100000)
- Sine-Gaussian Low-Frequency (SGLF x100000)

Blind test set (released after competition)

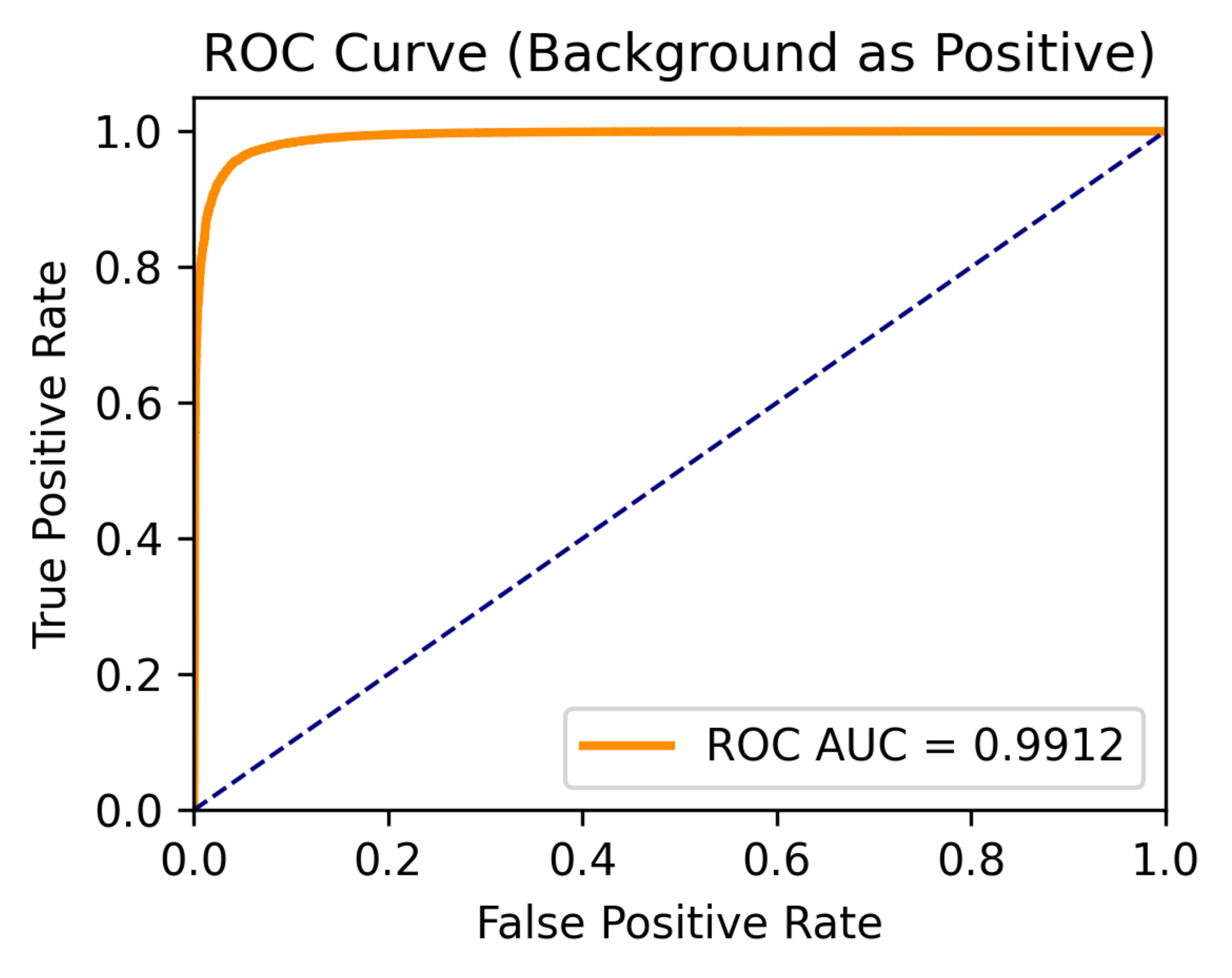
- BKG x50000

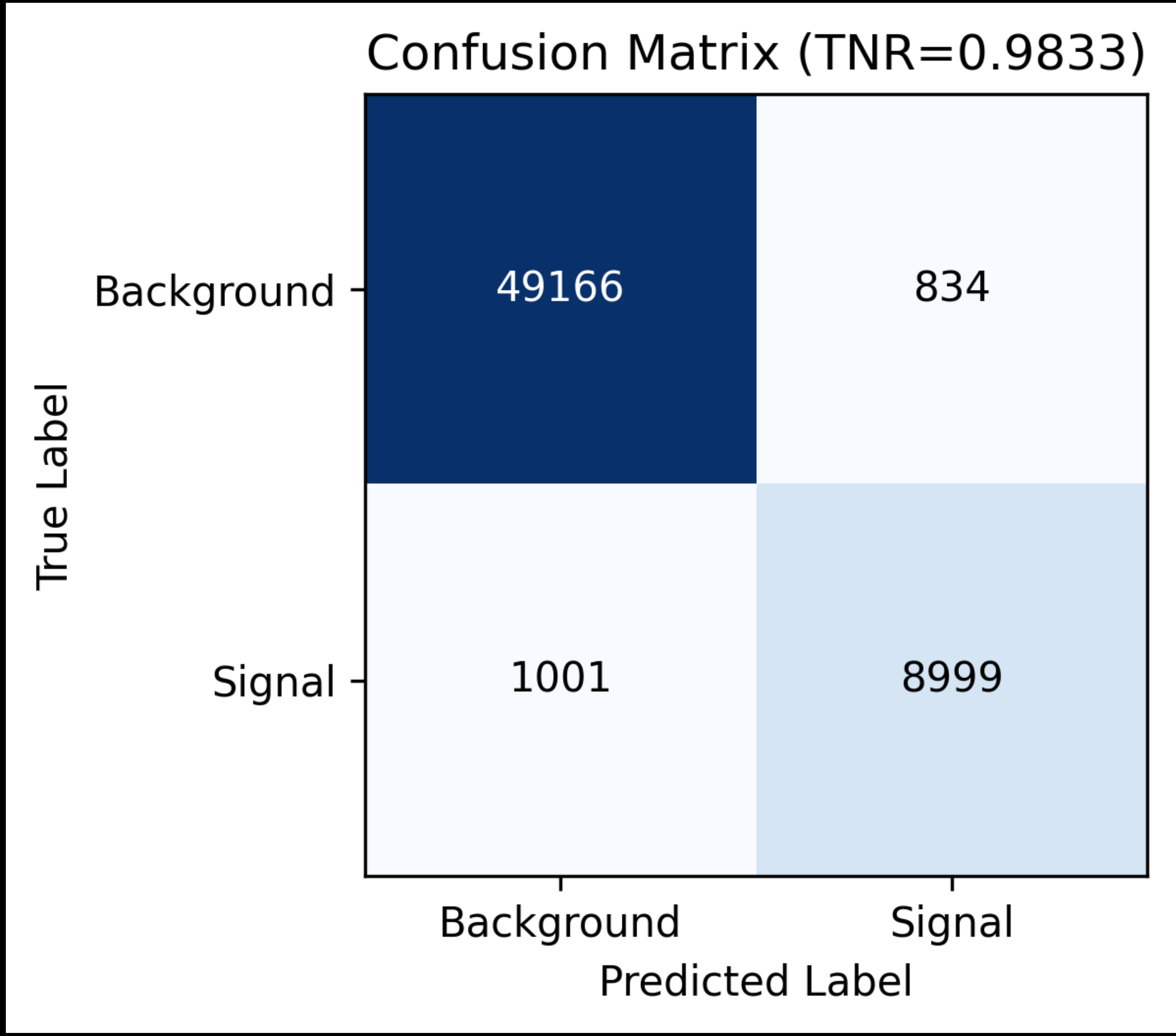
Signal Class

- **Supernova (CCSN x5000)**
- **White Noise Burst (WNB x 5000)**

DeepGRAV

NSF HDR A3D3 Competition data (Final round)





At least ~80% modeled CCSN GW bursts have been detected, even none of this type of signal was included in the training.

Yan et al. in prep

DeepGRAV

Data Augmentation

Algorithm 1: Data augmentation for background, BBH, SGLF Signals

Input: Number of augmented signals N, number of selected signals n, and selected signals from the training set $\mathbf{S}$.
Output: Augmented signals $\mathbf{S}'$.

Initialize the augmented signal set: $\mathbf{S}' \leftarrow \emptyset$;
for $i = 1$ **to** N **do**
Randomly select n signals from $\mathbf{S}$ to form the subset $\mathbf{S}_{\text{sub}}$;
Compute the average:

$$\mathbf{S}'_i \leftarrow \frac{1}{n} \sum_{j=1}^{n} (\mathbf{S}_{\text{sub}})_j$$

end

Can we do better than this?

- Enlarge the training sample by 3x (i.e. 300000 samples for each class)
- Data split: 70% training; 10% validation; 20% test set
- In the model-tuning stage, this simple method improves the accuracy from 98.8% to 99.5% on our test set.

Yan et al. 2025

GenGRAV

Data Augmentation with Generative AI

- Our aim is to construct a general-purpose GW waveform emulator which can be applied to any classes of signals or glitches.

- By combining GenGRAV and DeepGRAV, we are able to:

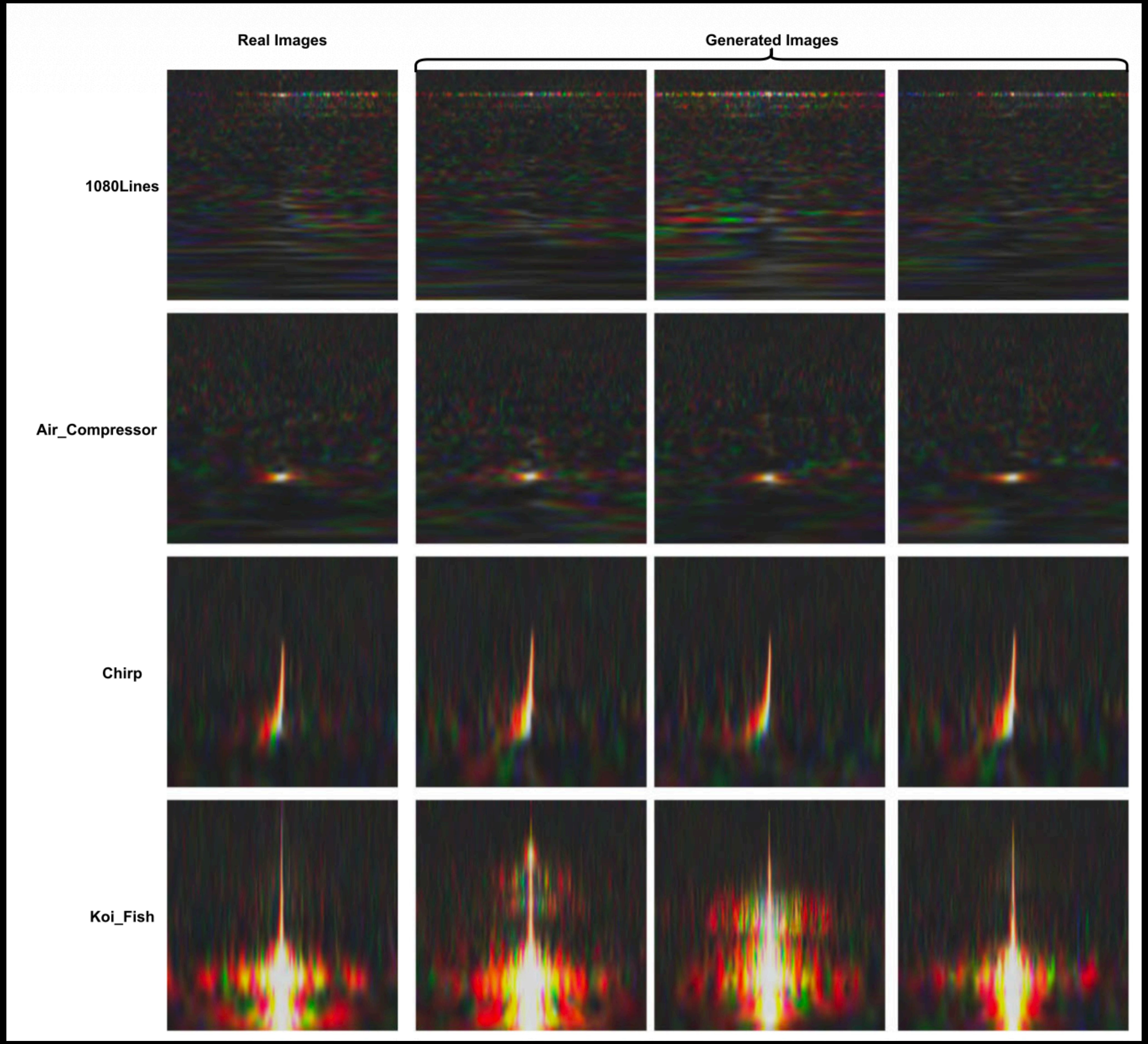
  1. Enhancing the detectability of GW from CCSNe

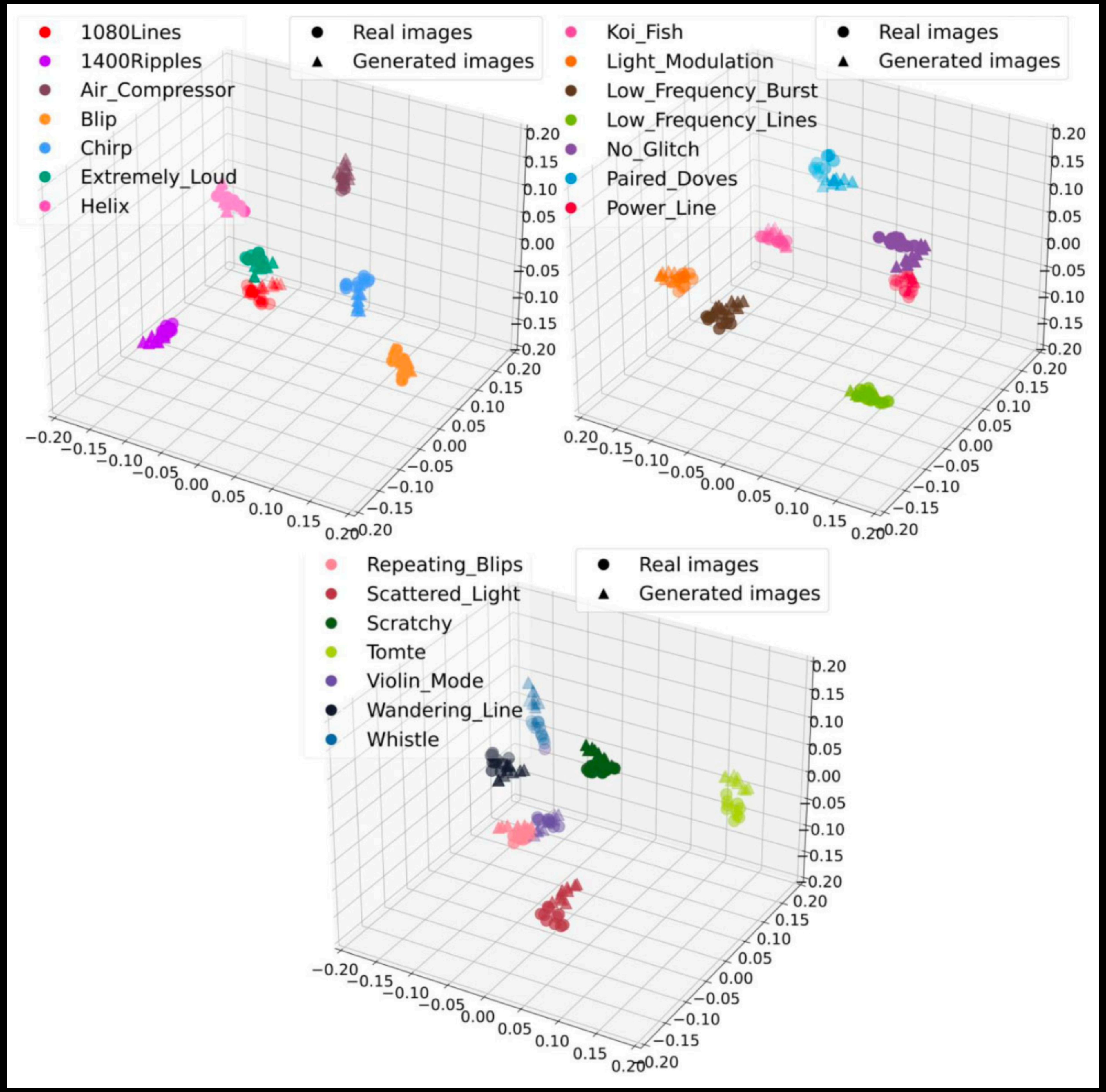
  2. Facilitating vetoing of glitches

- Infer underlying distribution of data, help characterize the nature and variation of the data (e.g. glitches).

Previous work on Glitch Classification with GAN

- We have employed GAN for data augmentation on *Gravity Spy* data.





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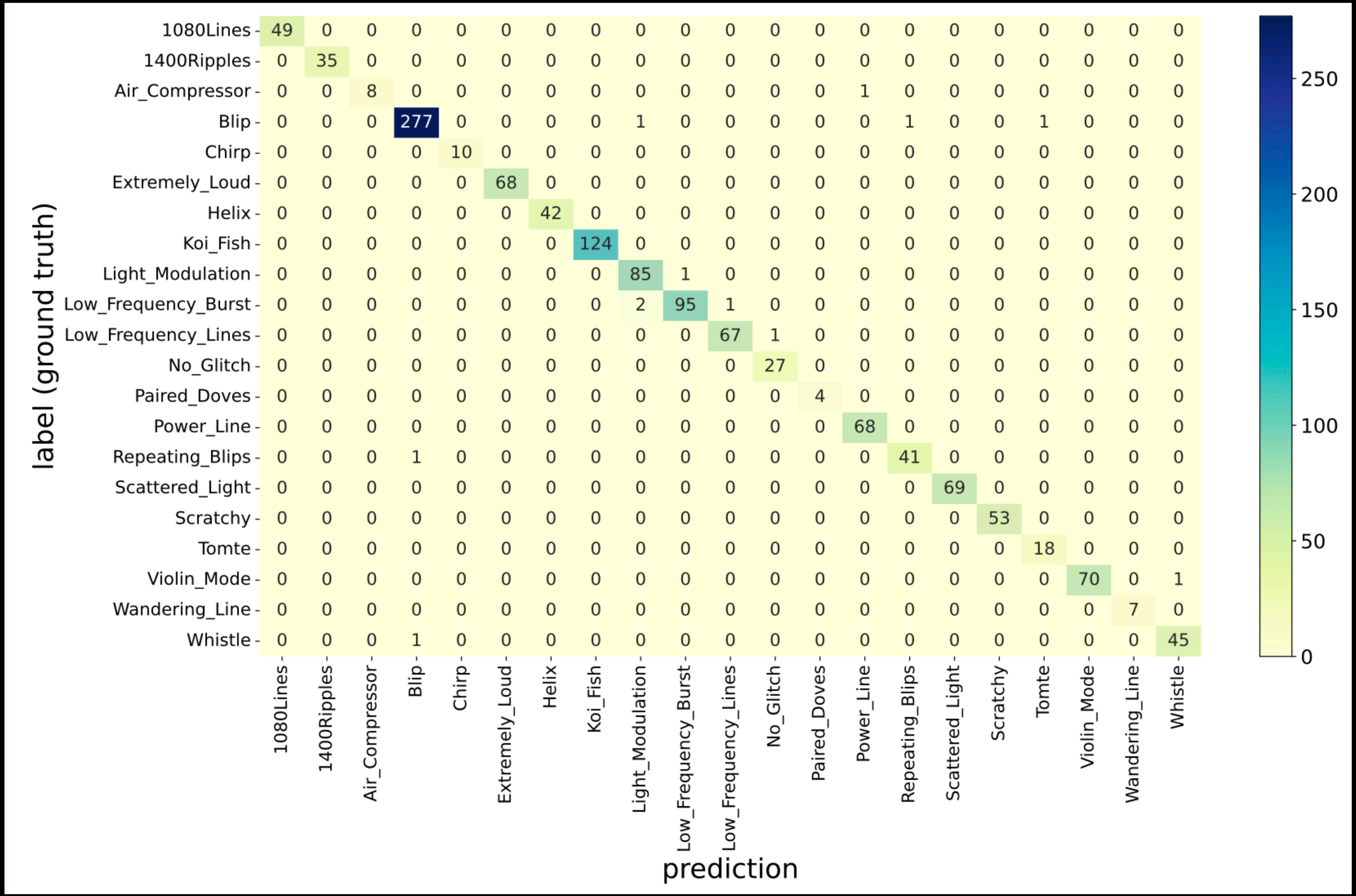
Previous work on Glitch Classification with GAN

- Improve glitch classification (higher accuracy, less flucutation)



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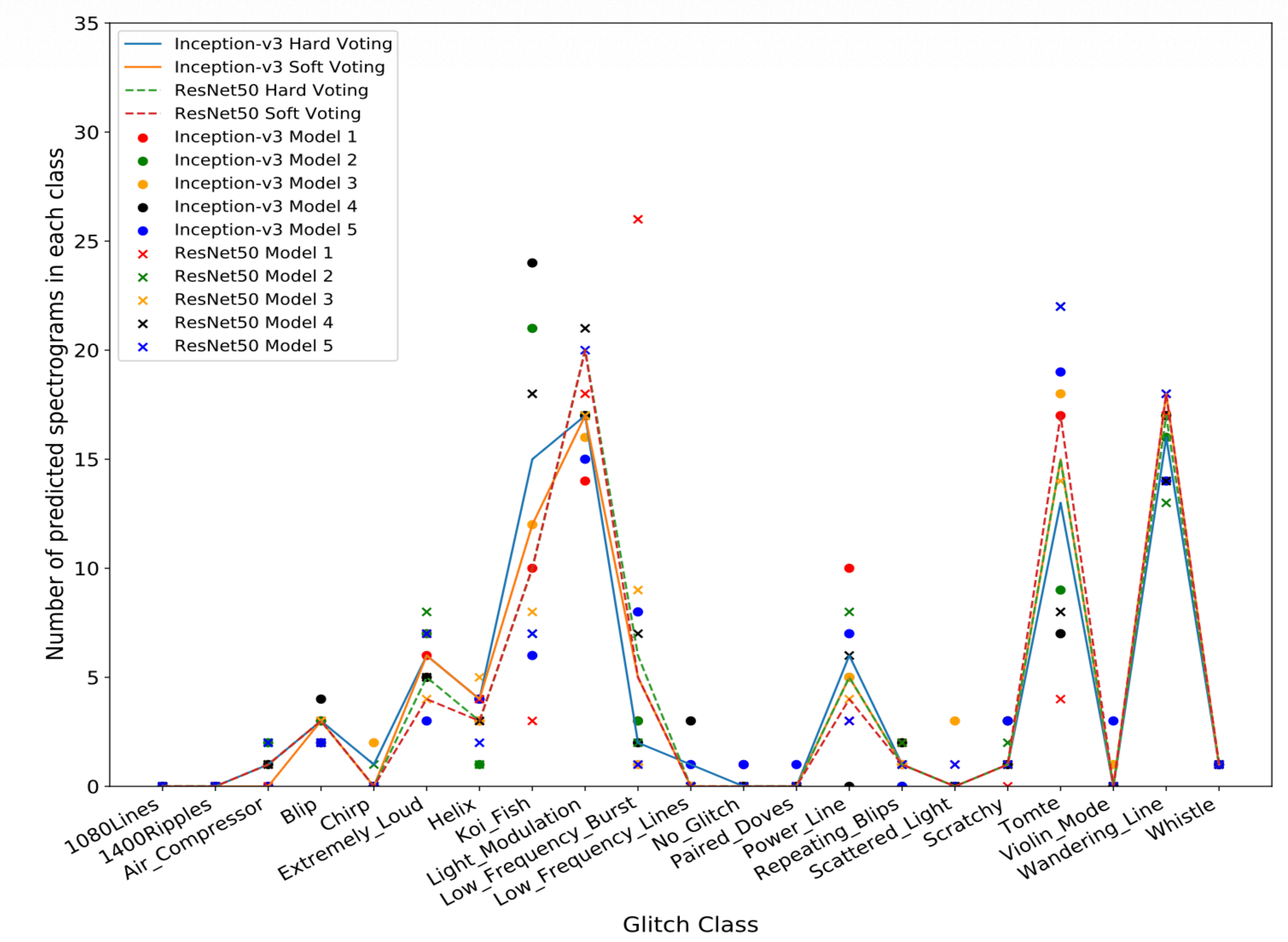
Previous work on Glitch Classification with GAN

- Attempt to classify "*None_of_the_above*" in Gravity Spy data



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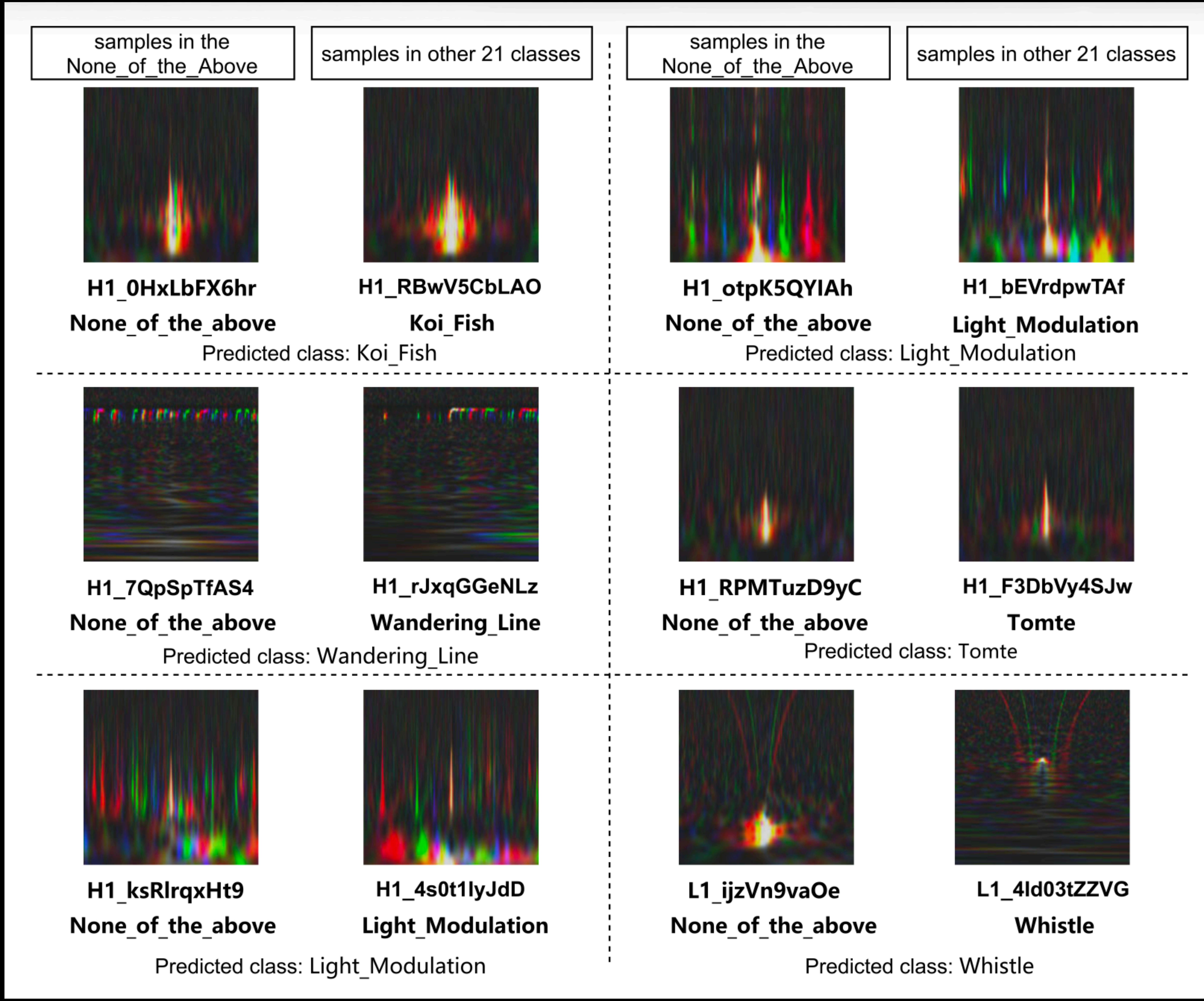

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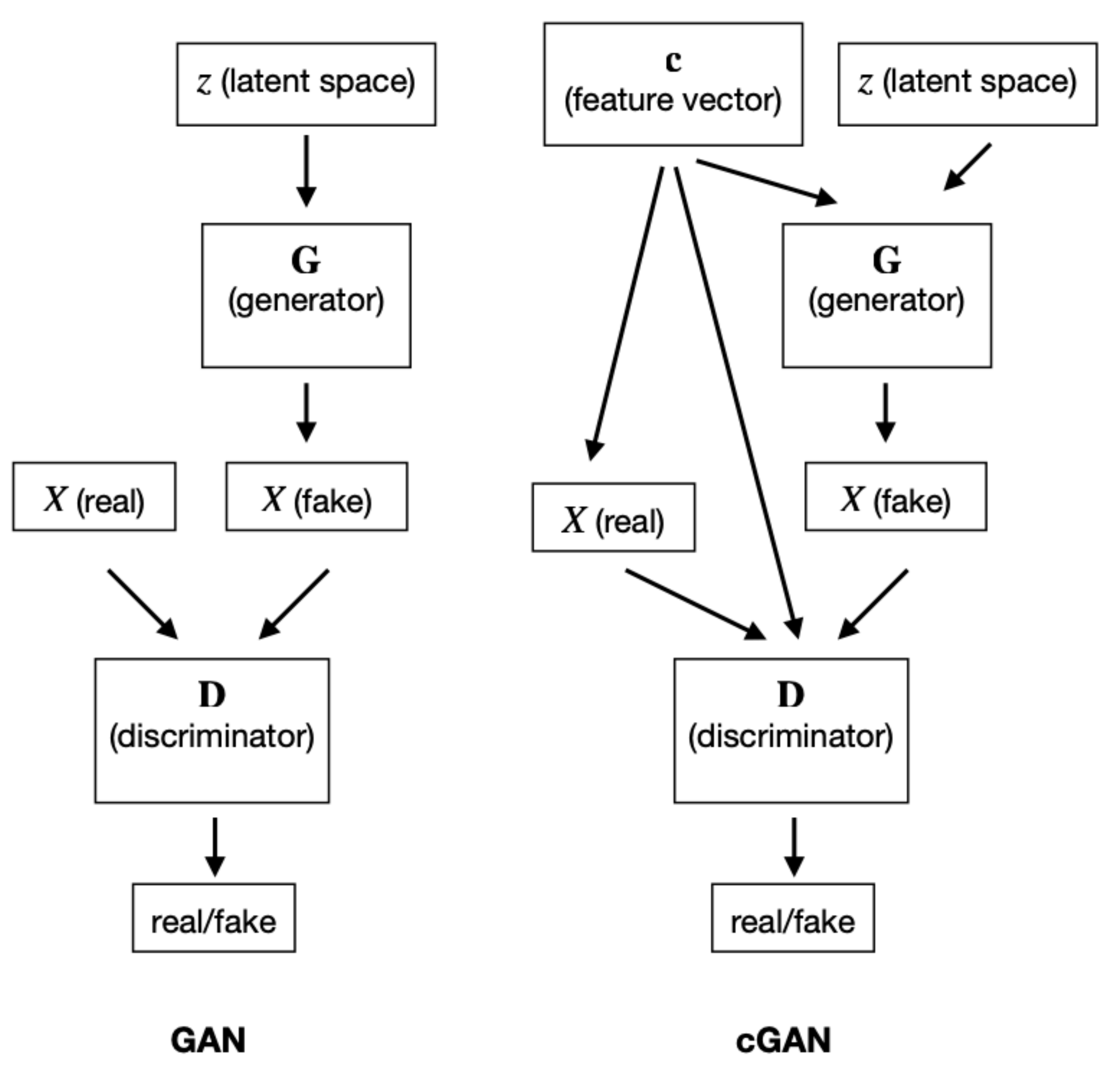
Conditional Generative Model

Expanding the training sample with better coverage in parameter space

e.g. Feature vector for magneto-rotational driven CCSNe

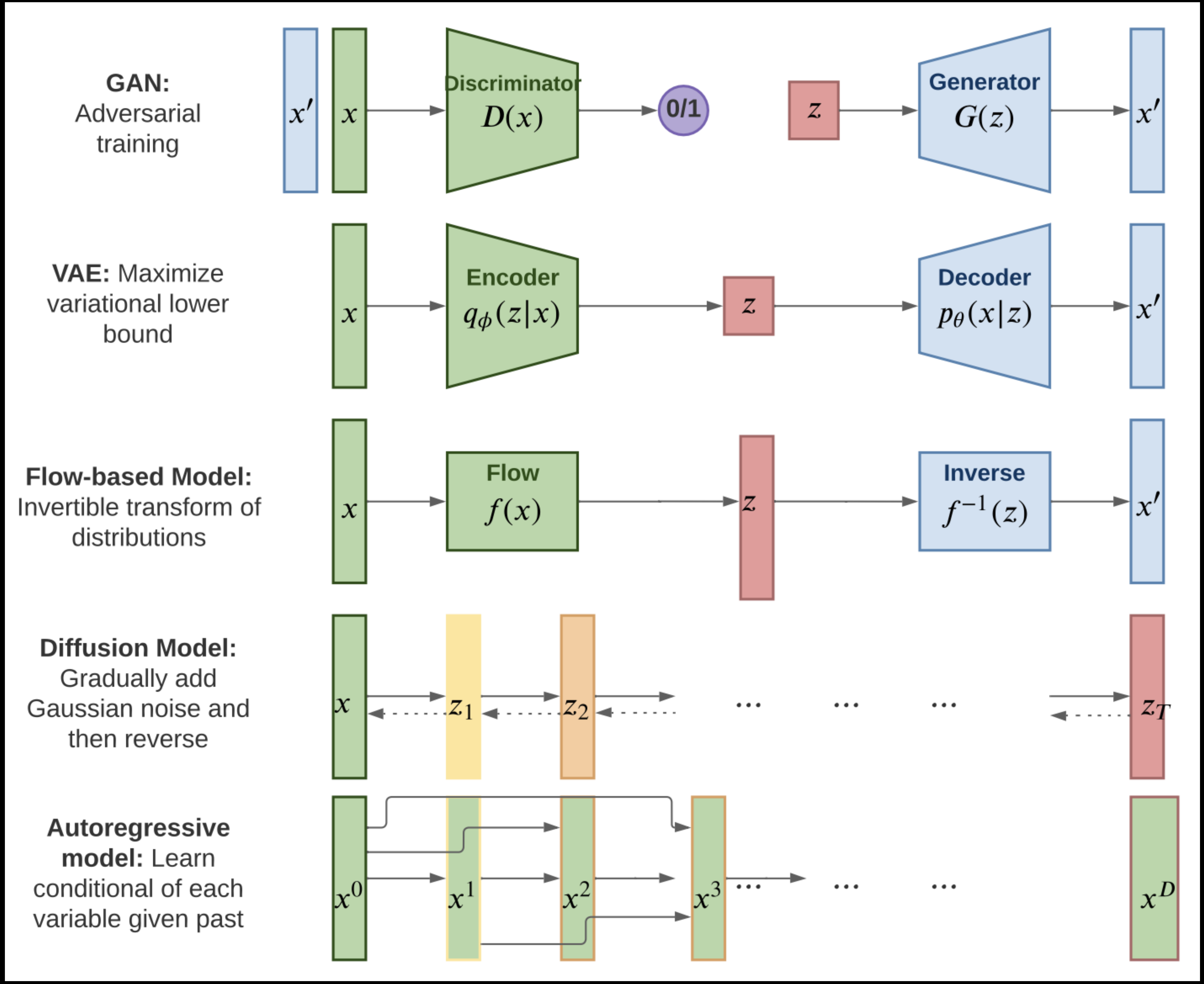
A(km) -- differential rotation parameter in Equation 5
D*bounce_amplitude_1(cm) -- The minimum of the first (negative) GW strain peak, multiplied by distance.
D*bounce_amplitude_2(cm) -- The maximum of the second (positive) GW strain peak, multiplied by distance.
EOS -- the equation of state used in the simulation
MbarICgrav(Msun) -- gravitational mass of the inner core, averaged over time after core bounce
Mgrav1_IC_b(Msun) -- gravitational mass of the inner core at bounce
Mrest_IC_b(Msun) -- rest mass of the inner core at bounce
SNR(aLIGOfrom10kpc) -- signal to noise ratio of the GW signal, assuming a distance of 10kpc and aLIGO sensitivity
T_c_b(MeV) -- central temperature at bounce
Ye_c_b -- central electron fraction at bounce
alpha_c_b -- central lapse at bounce
beta1_IC_b -- ratio of rotational kinetic to gravitational potential energy of the inner core at bounce
fpeak(Hz) -- frequency of the post-bounce GW oscillations
j_IC_b() -- angular momentum of the inner core at bounce
omega_0(rad|s) -- initial (pre-collapse) rotation rate used in Equation 5
omega_max(rad|s) -- maximum rotation rate achieved outside of 5km
rPNSequator_b(km) -- radius of the rho=10^11 g/ccm contour along the equator at bounce
rPNSpole_b(km) -- radius of the rho=10^11 g/ccm contour along the pole at bounce
r_omega_max(km) -- radius where omega_max occurs
rho_c_b(g|ccm) -- central density at bounce (not time averaged)
rhobar_c_postbounce(g|ccm) -- central density time averaged after bounce
s_c_b(kB|baryon) -- central entropy at bounce
t_postbounce_end(s) -- time of the end of the postbounce signal (t=0 is core bounce)
tbounce(s) -- time of core bounce (t=0 is the beginning of the simulation)

Richers et al. 2025



Conditional Generative Model

Various architecture will be explored (e.g. diffusion, autoregressive)



More updates will come!