

# Machine-Learning For Global Fit

**How can you teach a machine something you don't fully understand yourself?**

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Research Engineer

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# Motivation

- LISA will detect **many overlapping GW** signals from different type of source
- Classical Bayesian inference methods are **computationally expensive**
- Explore deep learning for efficient **source separation and sampling**

## The global fit

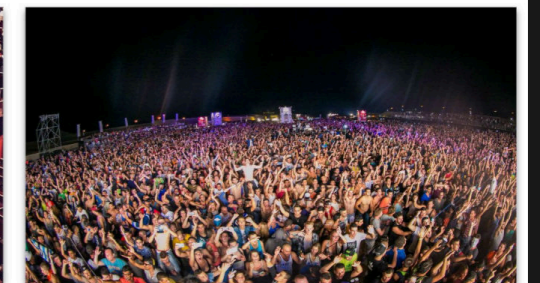
Scores from a penguin cacophony



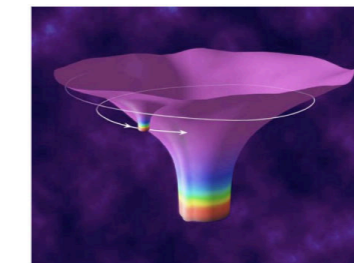
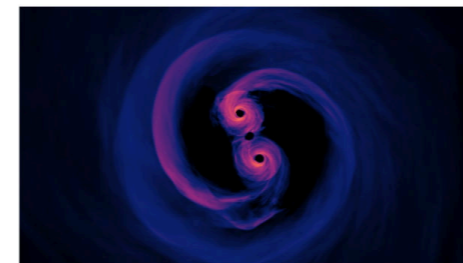
Hundreds



Tens to thousands



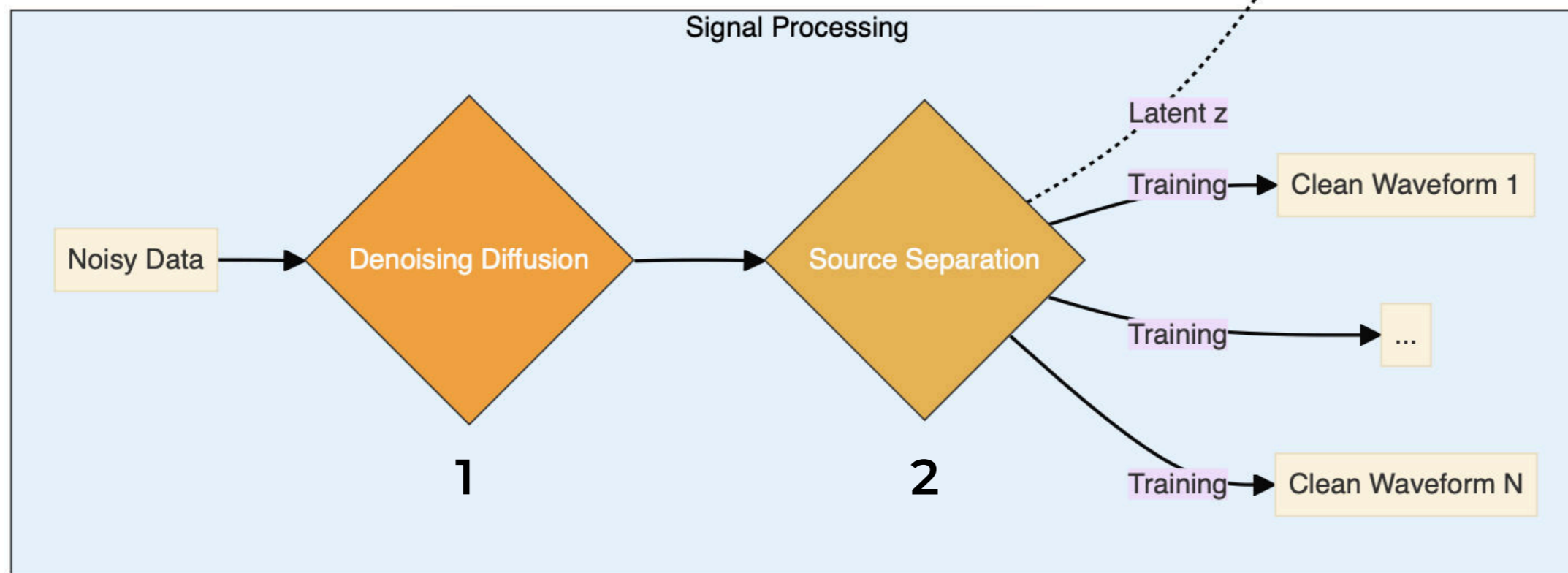
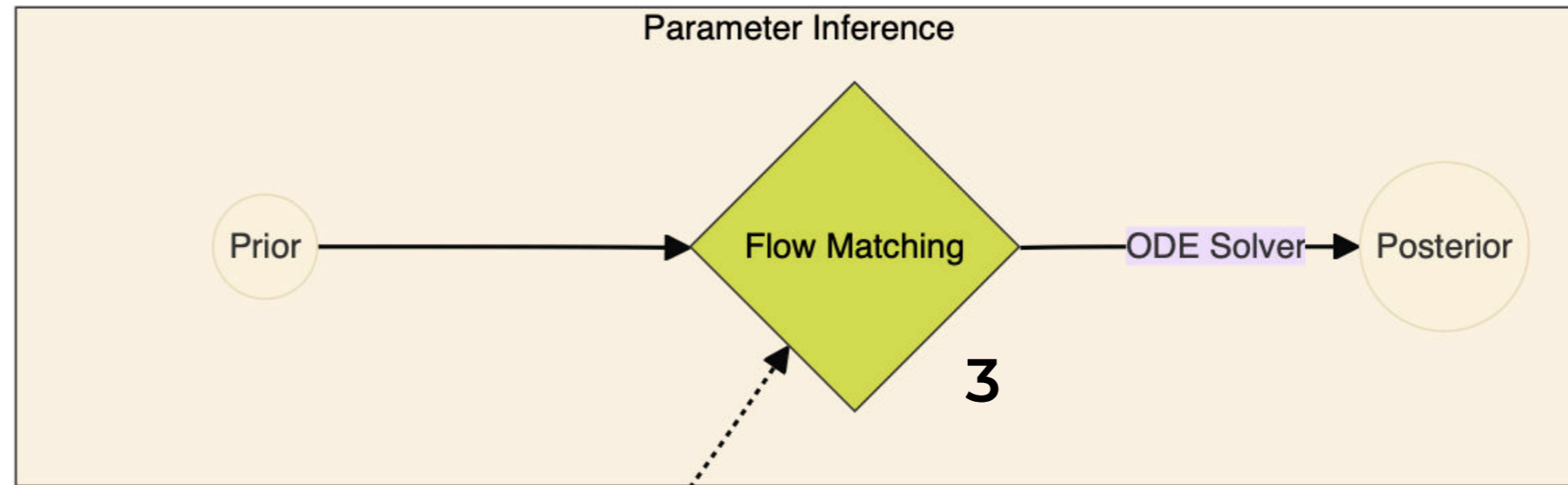
Millions



from R. Buscicchio's talk, Toulouse, 10/2024

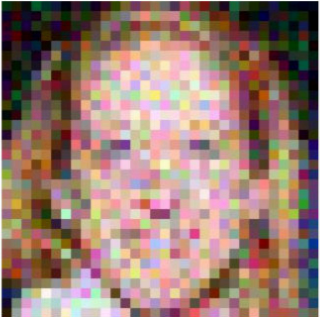




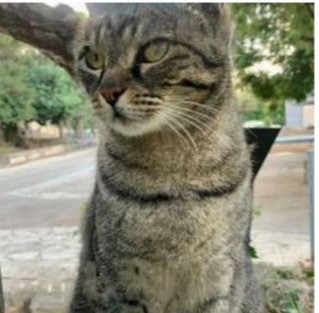
# Proposed Hybrid Architecture

1. Bayesian sampling (glitches & gaps mitigation)
2. Data reduction into global latent workspace
3. Amortized trans-dimensional inference



# Bayesian Deep Learning

## Denoising Diffusion Restoration Models

	Super-resolution	Inpainting	Deblurring
Observations (Inputs) $y$			
Outputs from our method $x_0$			

[NeurIPS 2022] Denoising Diffusion Restoration Models

## Applicable to other domains as well!

### Speech

#### A VERSATILE DIFFUSION-BASED GENERATIVE REFINER FOR SPEECH ENHANCEMENT

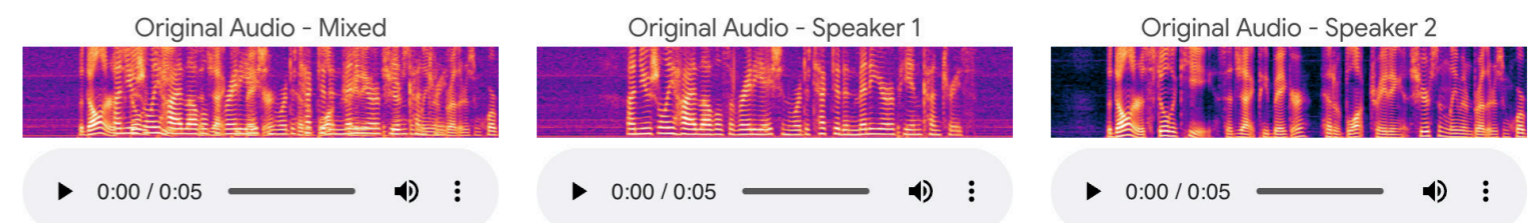
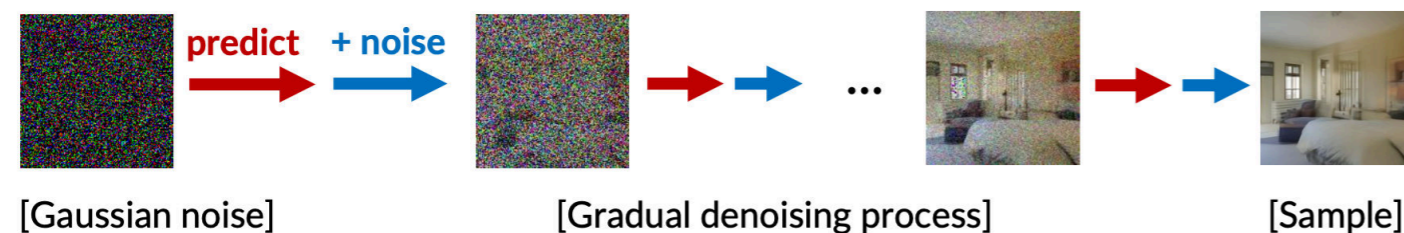
Ryosuke Sawata Naoki Murata Yuhta Takida Toshimitsu Uesaka  
Takashi Shibuya Shusuke Takahashi Yuki Mitsufuji

Sony Group Corporation, Tokyo, Japan

#### UNSUPERVISED VOCAL DEREVERBERATION WITH DIFFUSION-BASED GENERATIVE MODELS

Koichi Saito Naoki Murata Toshimitsu Uesaka Chieh-Hsin Lai  
Yuhta Takida Takao Fukui Yuki Mitsufuji

Sony Group Corporation, Tokyo, Japan



# Amortized Trans-dimensional Inference

<https://arxiv.org/pdf/2511.23228>

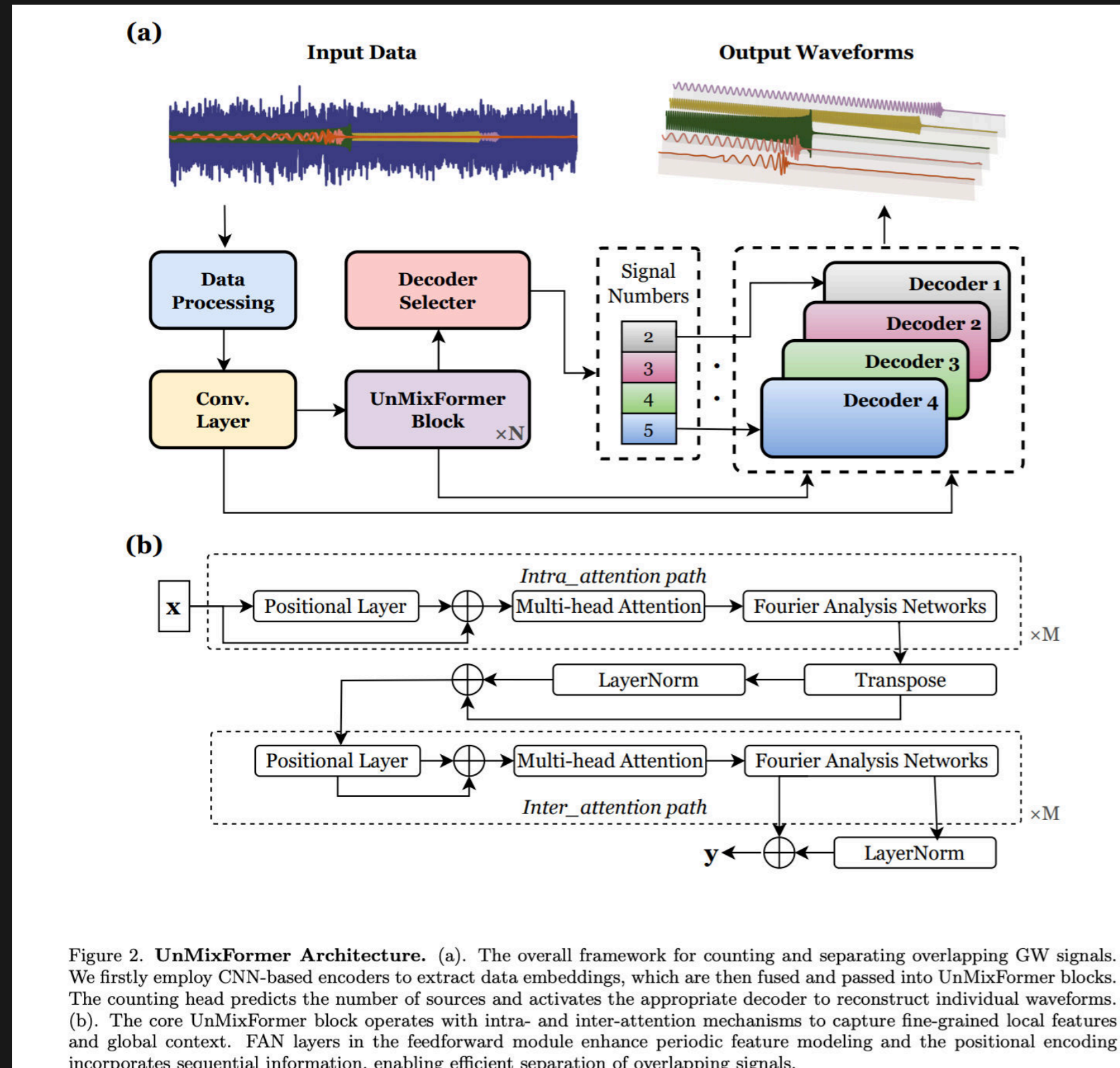


Figure 2. **UnMixFormer Architecture.** (a). The overall framework for counting and separating overlapping GW signals. We firstly employ CNN-based encoders to extract data embeddings, which are then fused and passed into UnMixFormer blocks. The counting head predicts the number of sources and activates the appropriate decoder to reconstruct individual waveforms. (b). The core UnMixFormer block operates with intra- and inter-attention mechanisms to capture fine-grained local features and global context. FAN layers in the feedforward module enhance periodic feature modeling and the positional encoding incorporates sequential information, enabling efficient separation of overlapping signals.

<https://arxiv.org/pdf/2412.18259>

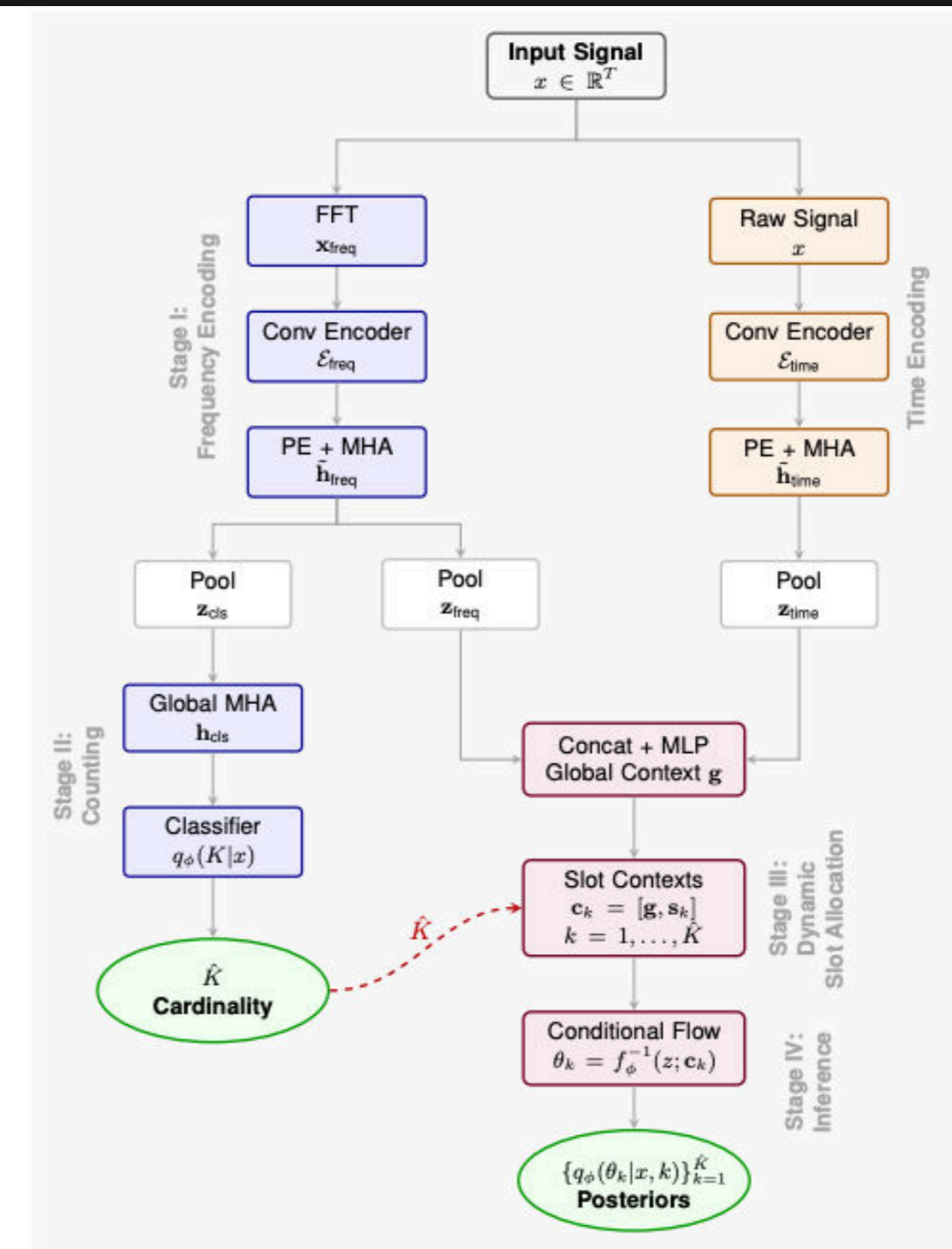


Figure 1: **SlotFlow Architecture.** The model processes input signals through four stages: (I) *Dual-stream encoding* (FFT/time) via convolutional encoders and multi-head attention; (II) *Cardinality estimation* via pooled global features; (III) *Slot context generation* fusing global and slot-specific embeddings; and (IV) *Conditional flow inference* producing per-component posteriors. The red control arrow denotes how the predicted  $\hat{K}$  dynamically sets the number of slot contexts.

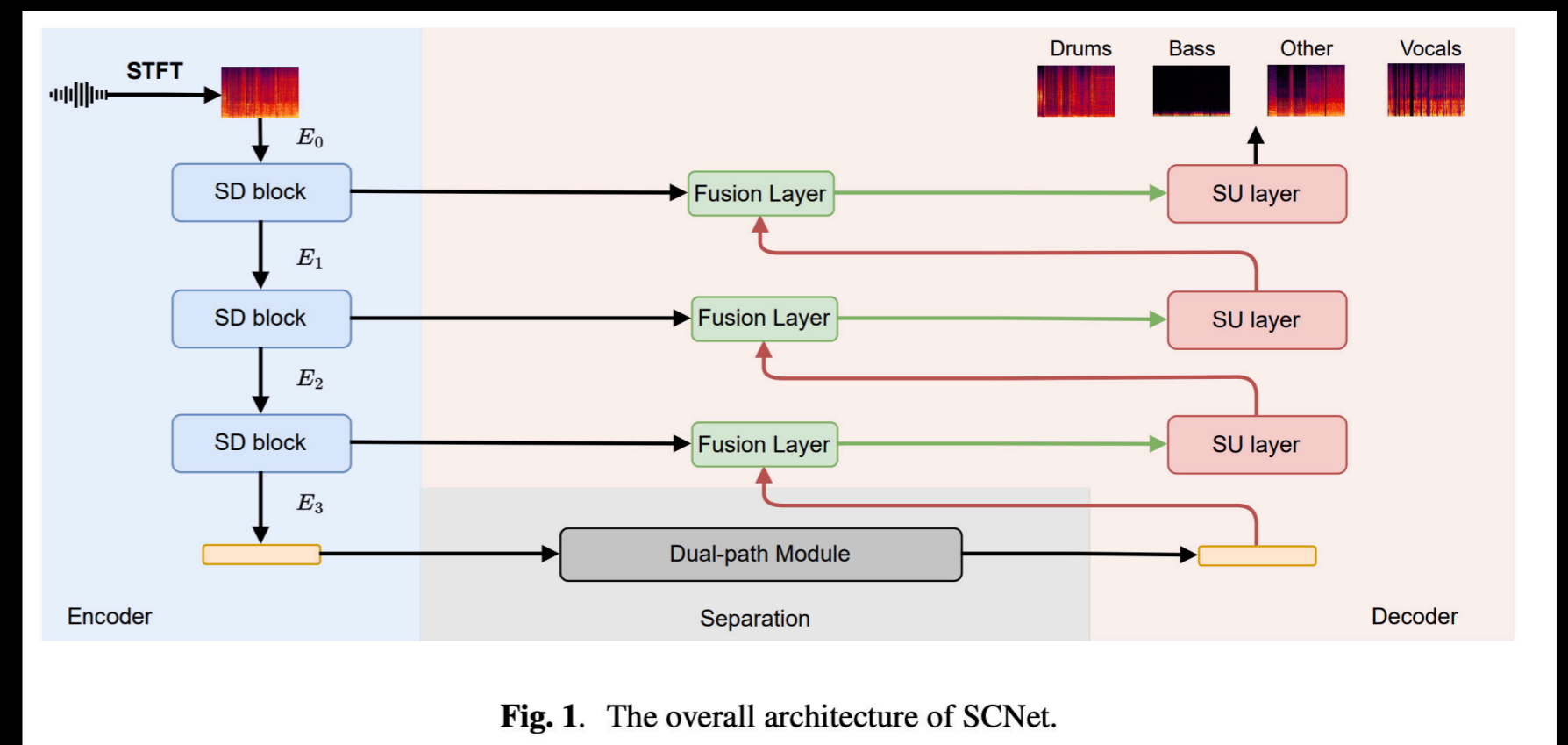


# GWINESS

GRAVITATIONAL WAVE INFERENCE  
NEURAL SOURCE SEPARATION



- **GWINNESS** project started in January 2025
- Blind source separation of overlapping GWs
- Inspired by **music/speech separation**
- **SCNet** deep learning architecture for music source separation in Time-Freq Domain



**Fig. 1.** The overall architecture of SCNet.



### Data Input

Drop HDF5 files here  
or  
[Browse Files](#)

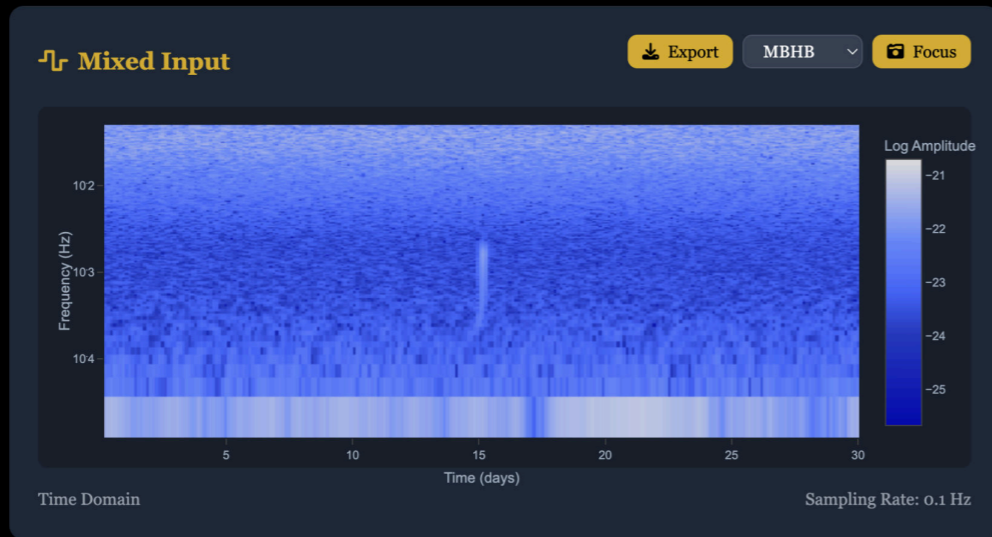
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### Visualization Controls

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[Fullscreen](#)



### Analysis Tools

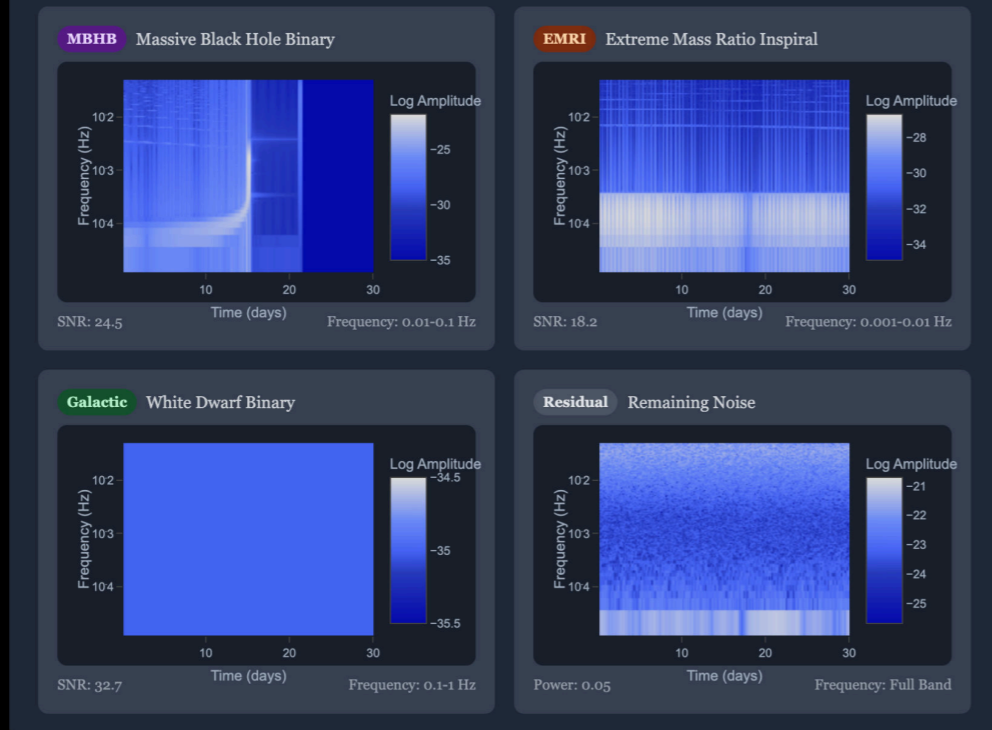
[Spectrogram](#) [Parameter](#) [Correlation](#)

### Source Information

- MBHB** GW150914-like 2.3 Gpc
- EMRI** Extreme Mass Ratio 4.1 Gpc
- Galactic** White Dwarf Binary 8 kpc

### Separated Outputs

[Hide](#) [All](#) [Show](#)



### Data Input

Drop HDF5 files here  
or  
[Browse Files](#)

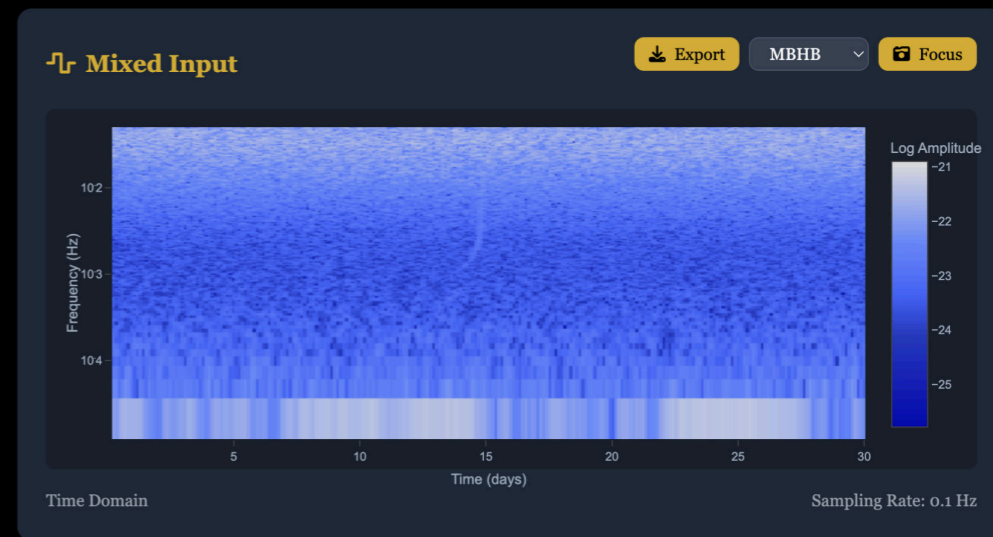
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### Visualization Controls

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[Fullscreen](#)



### Analysis Tools

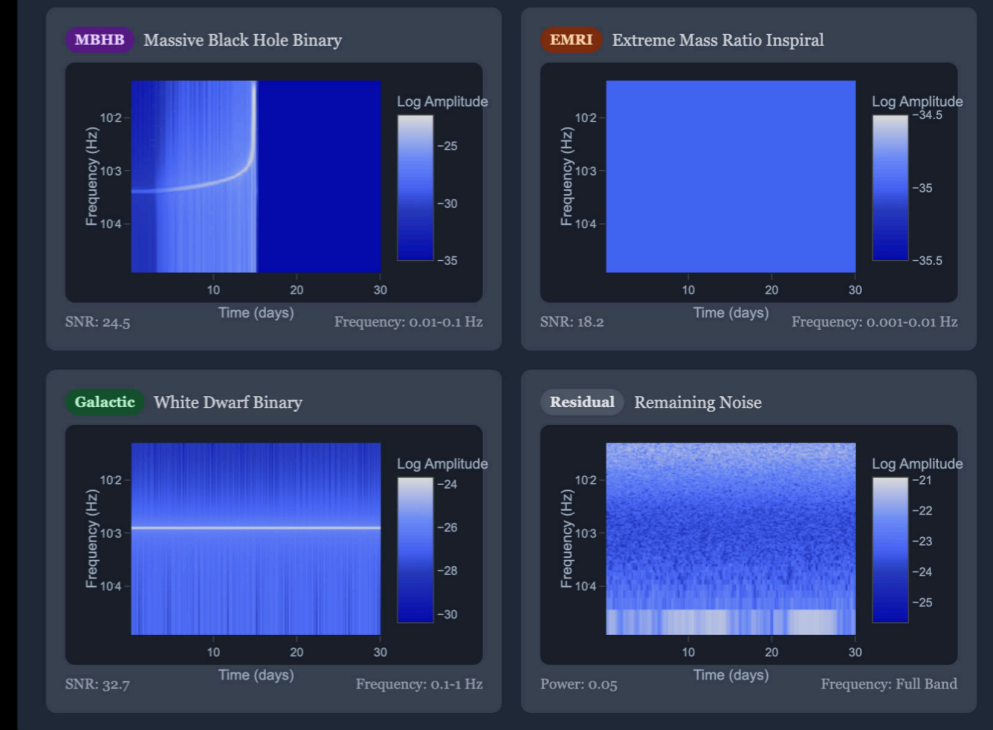
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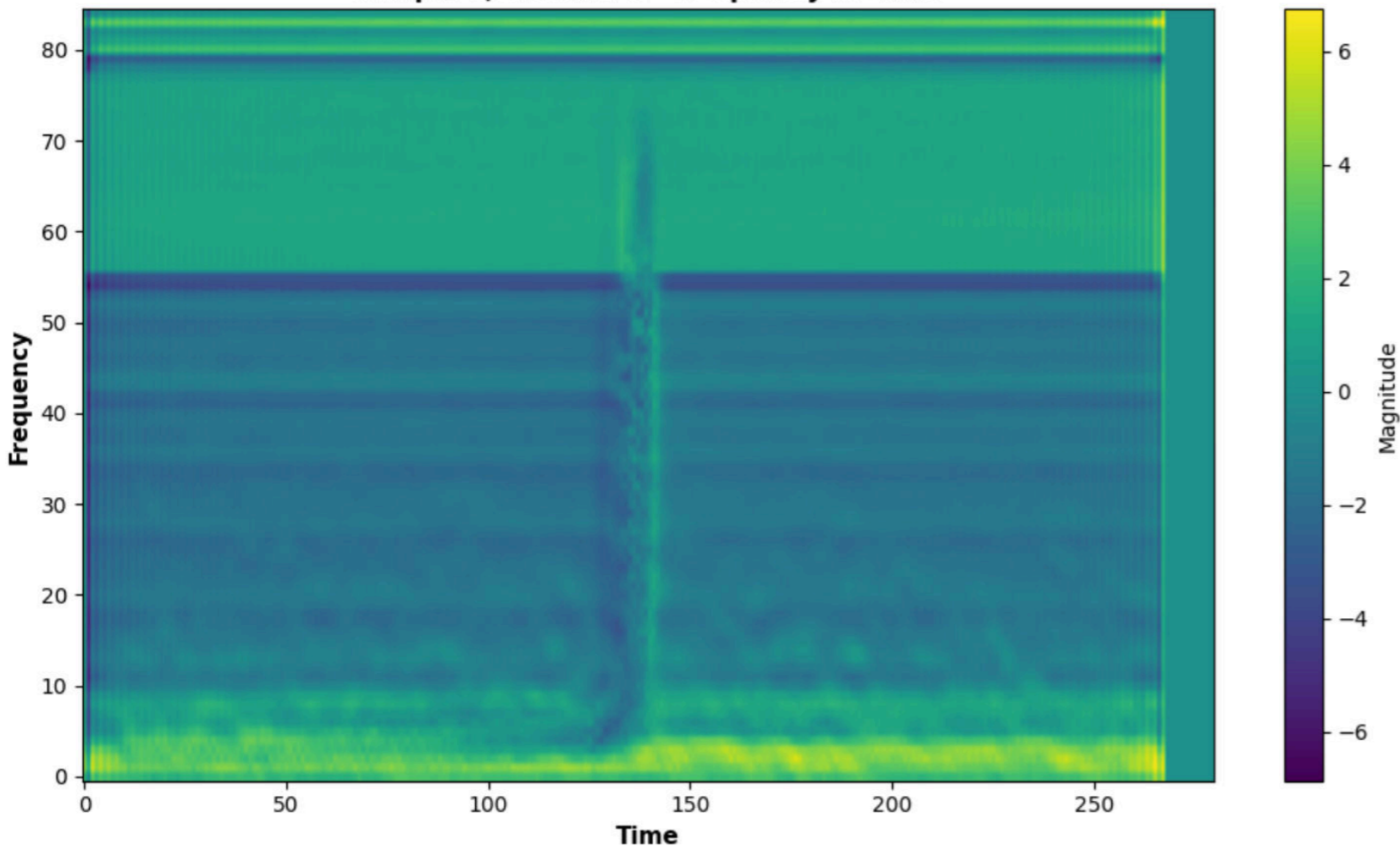
- MBHB** GW150914-like 2.3 Gpc
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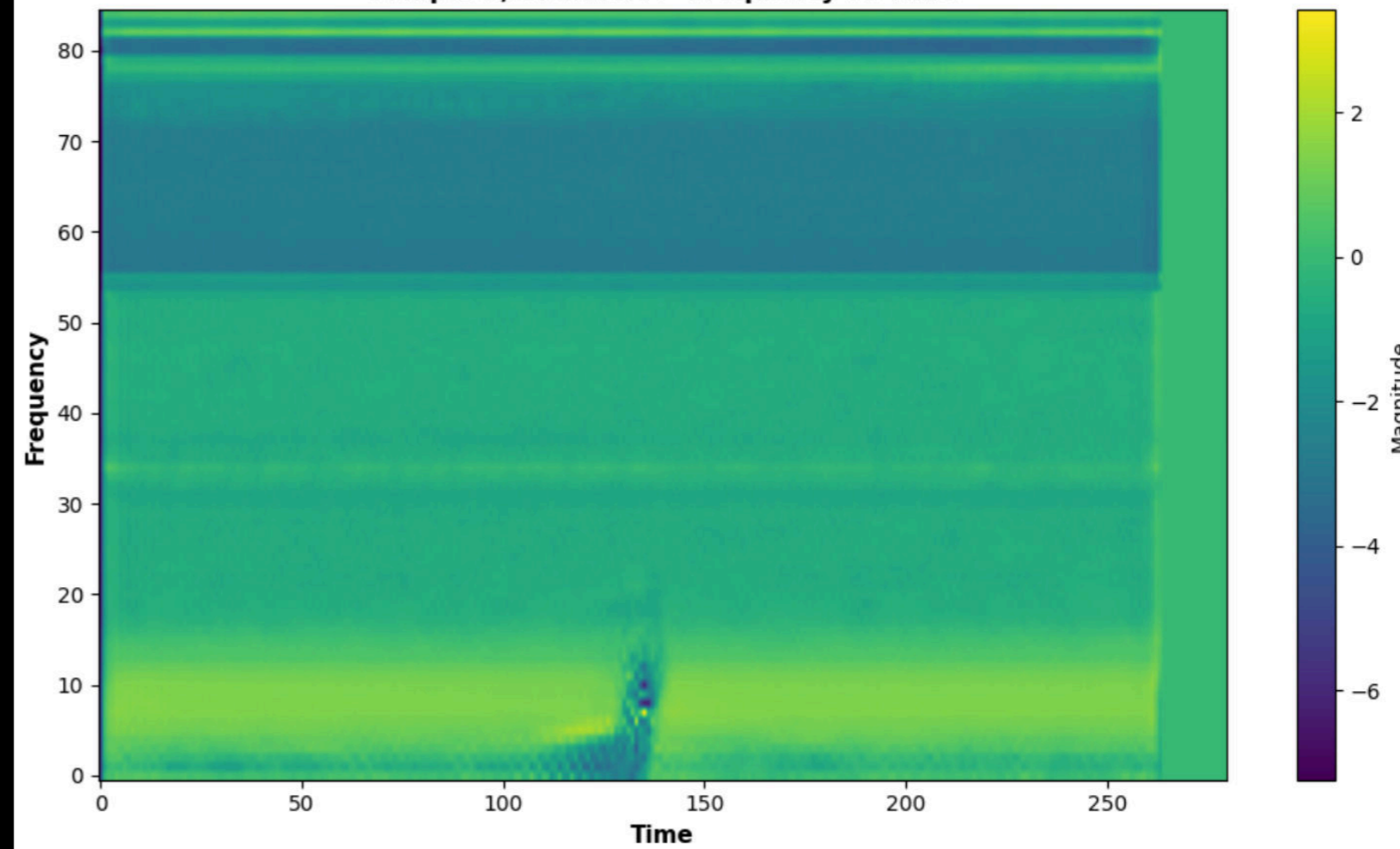
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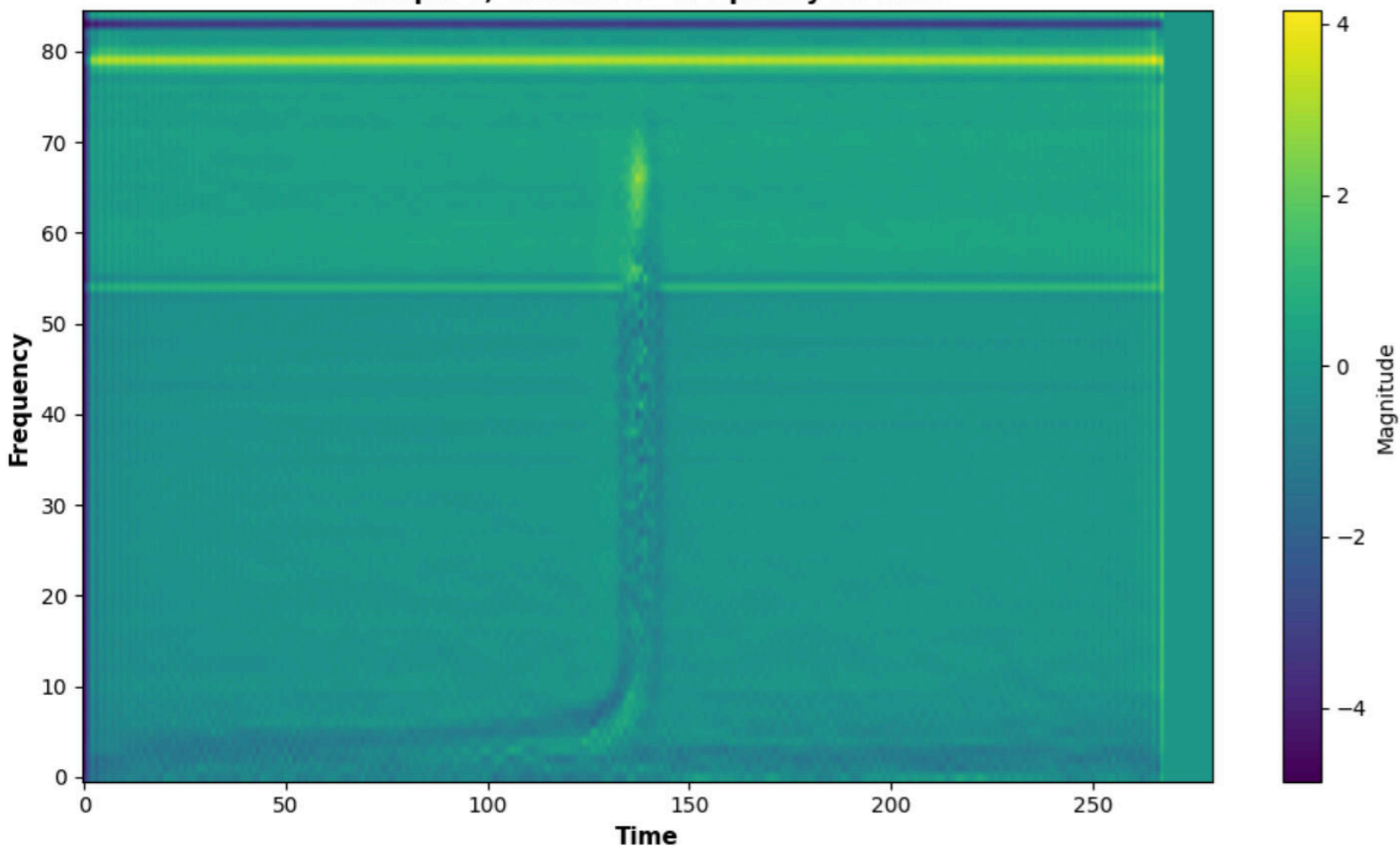
Sample 0, Channel 0 - Frequency vs Time



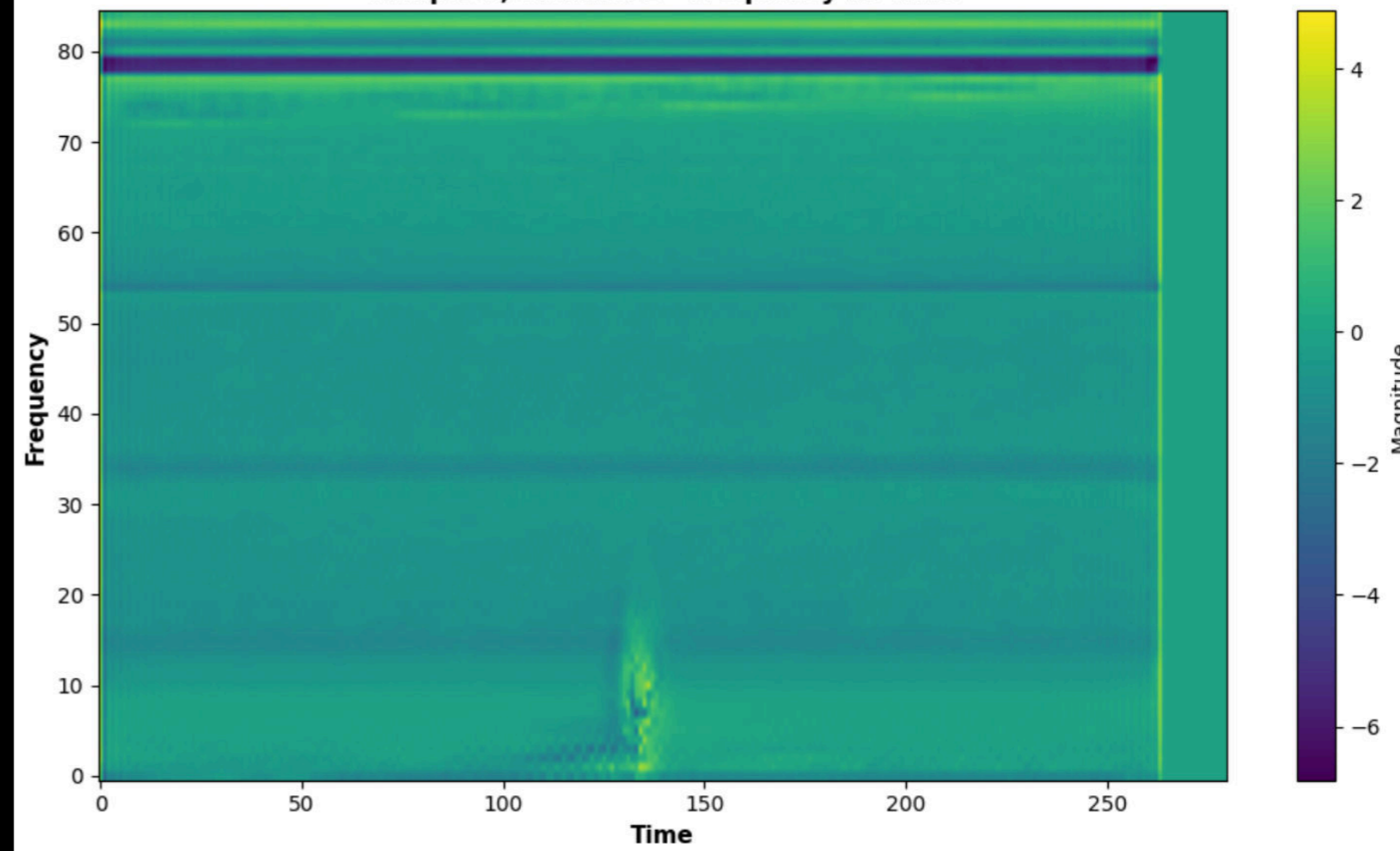
Sample 9, Channel 1 - Frequency vs Time



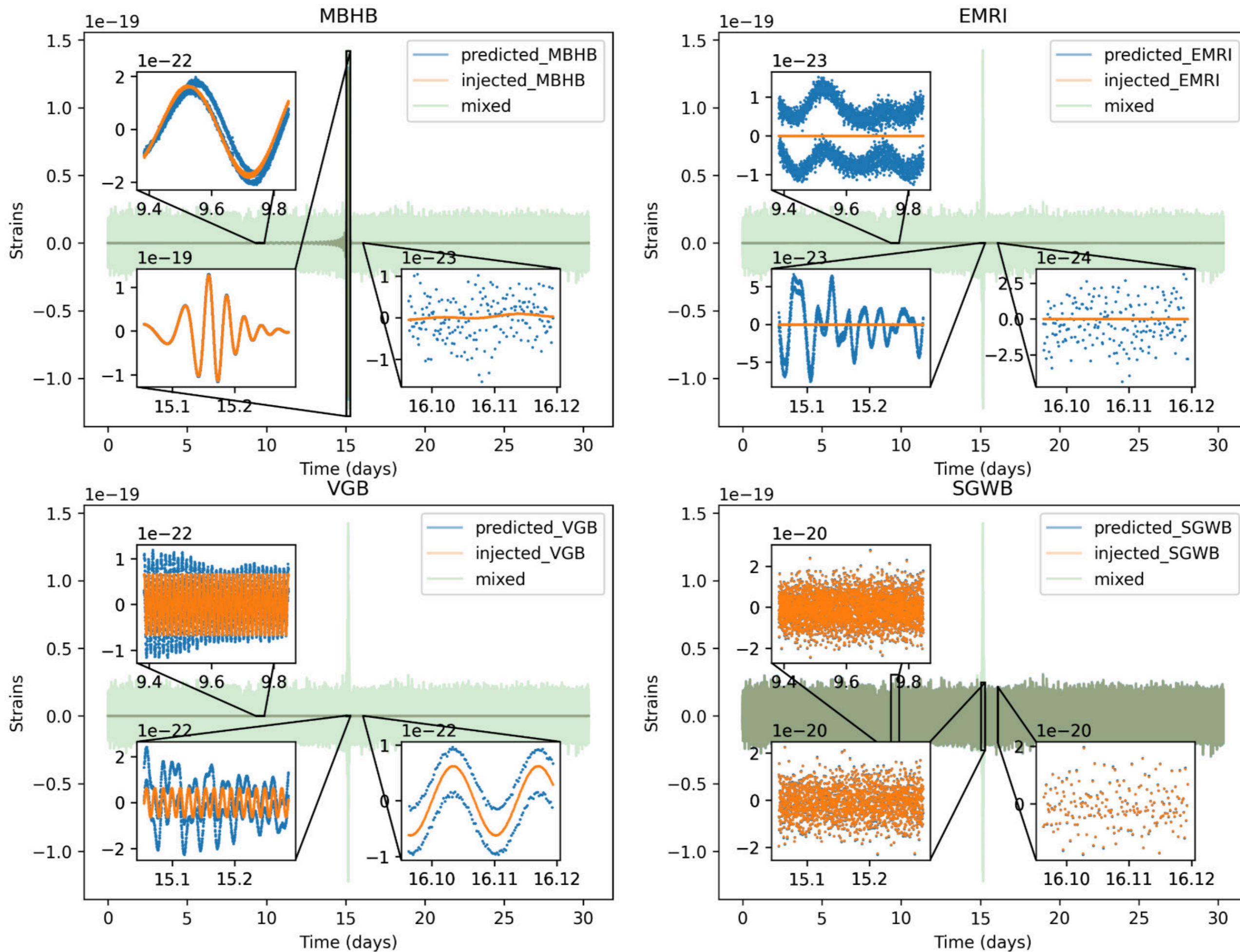
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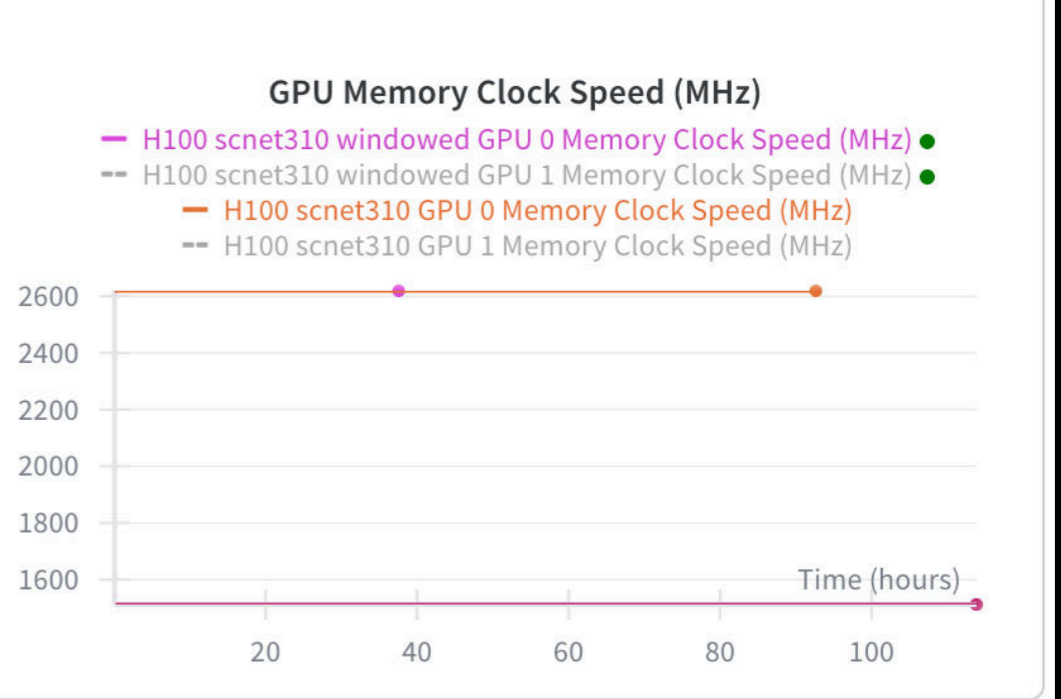
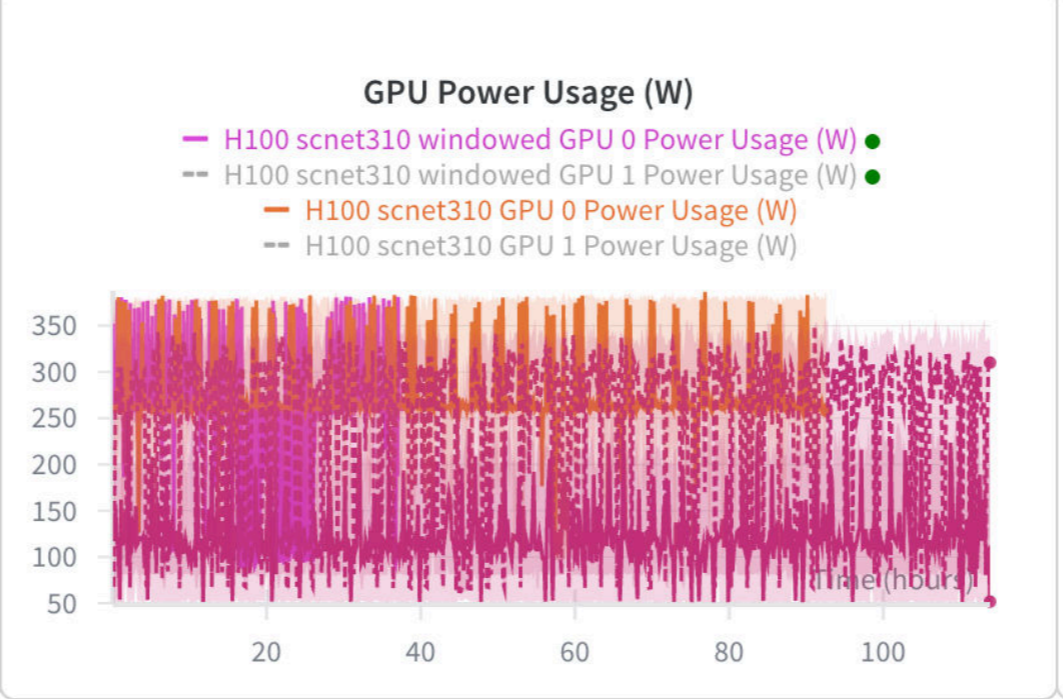
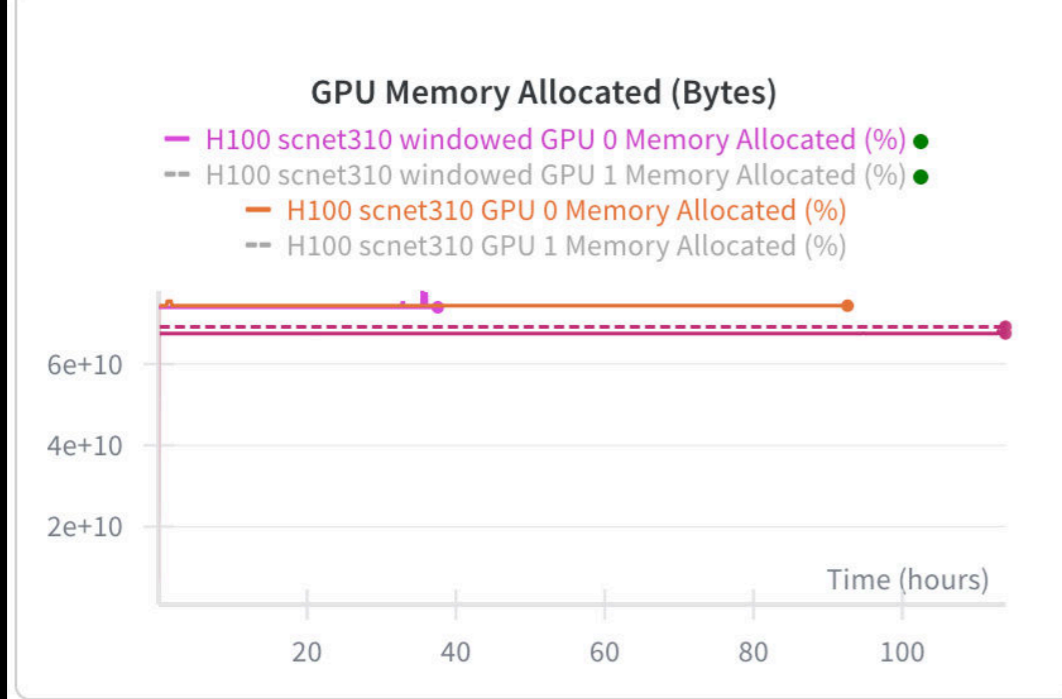
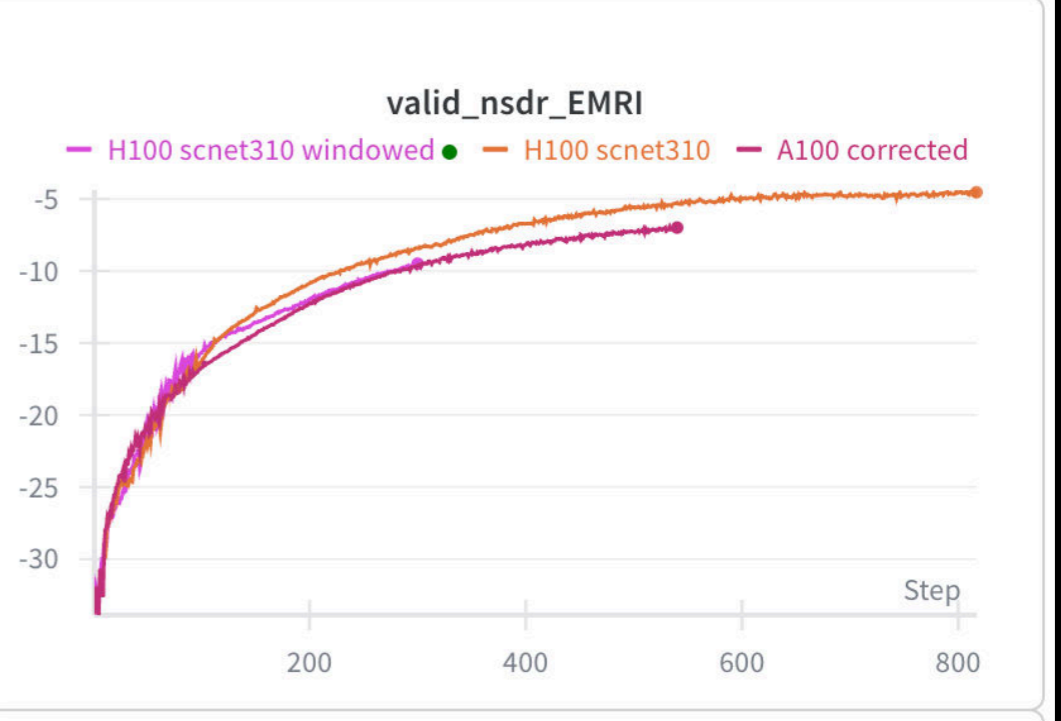
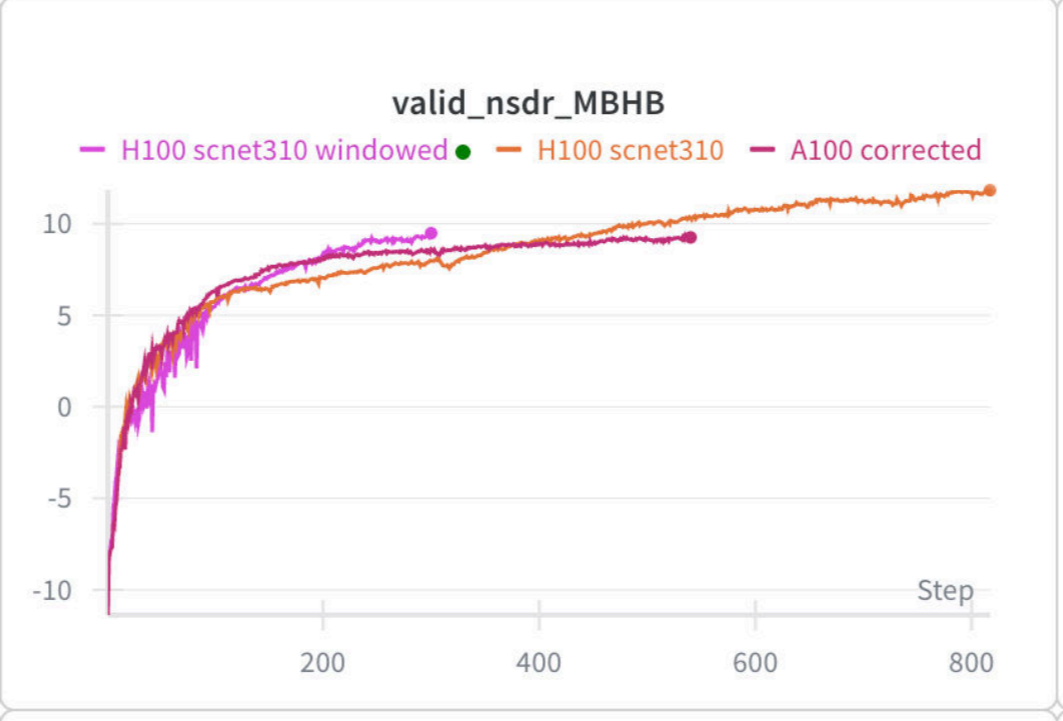
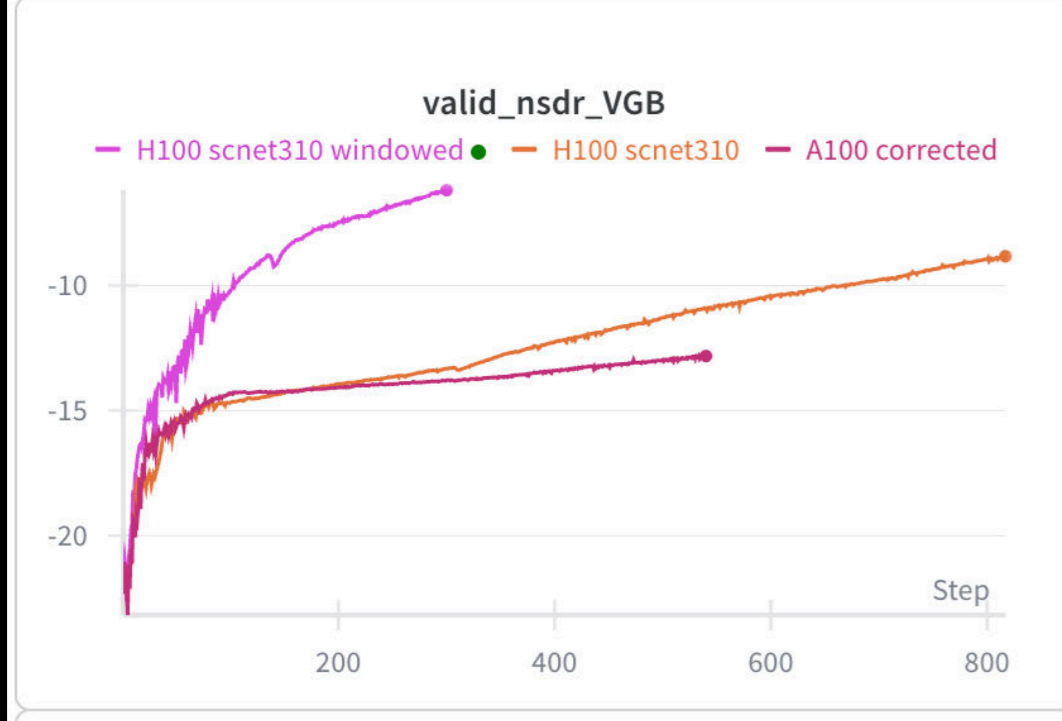
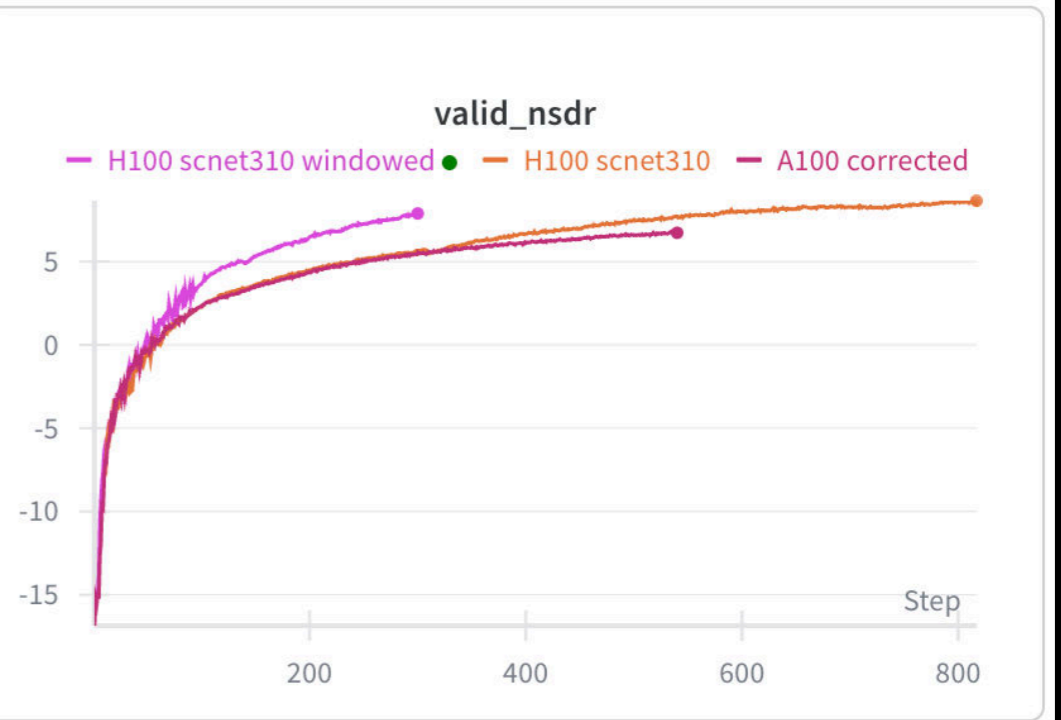
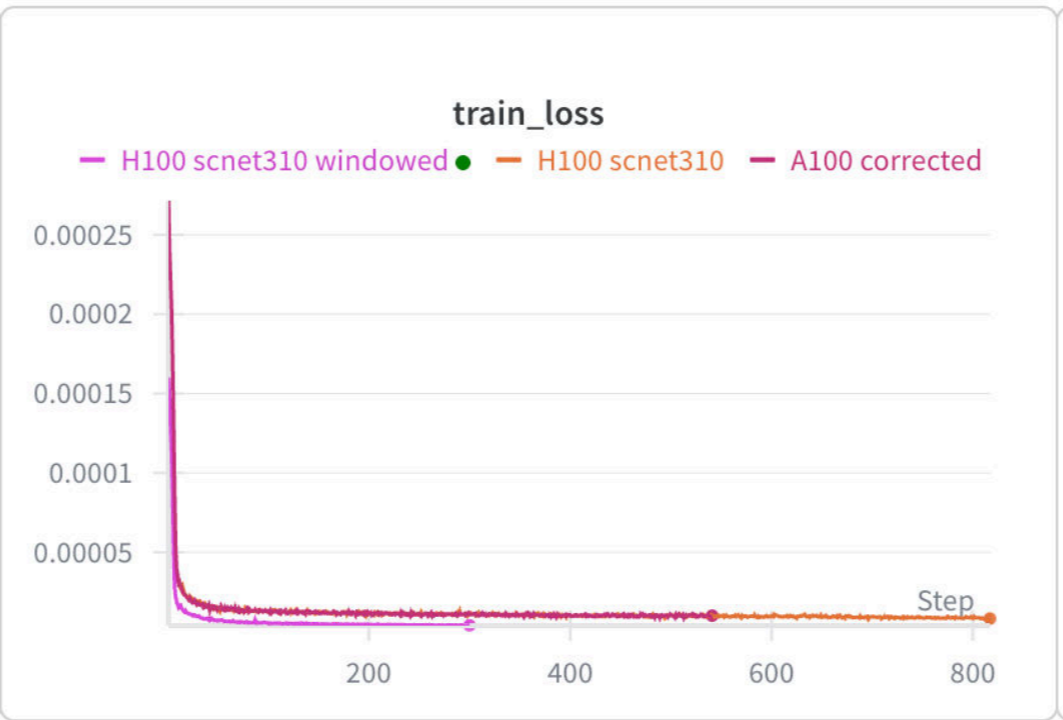
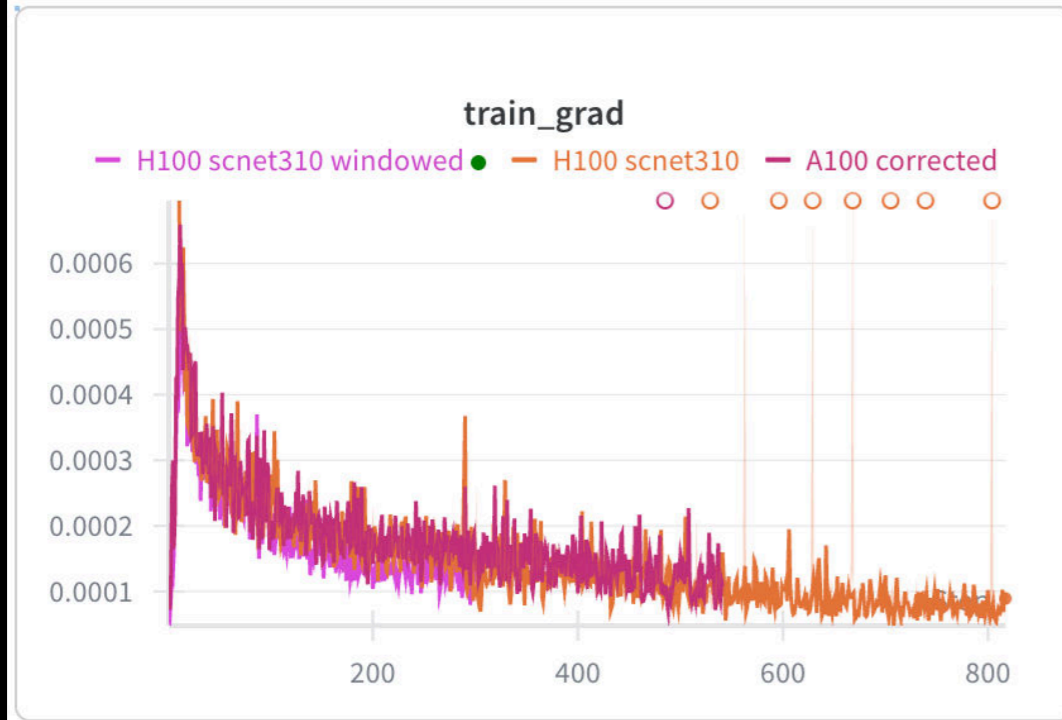


Sample 9, Channel 2 - Frequency vs Time

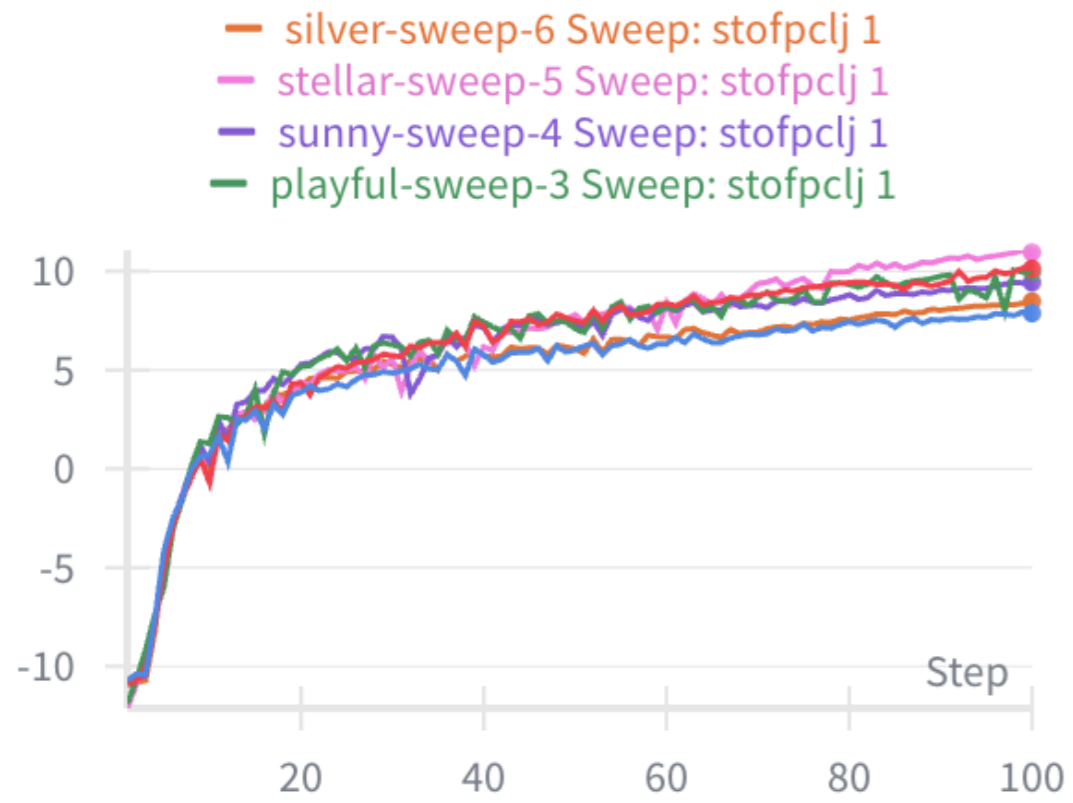


Neural source separation: inference vs. injection

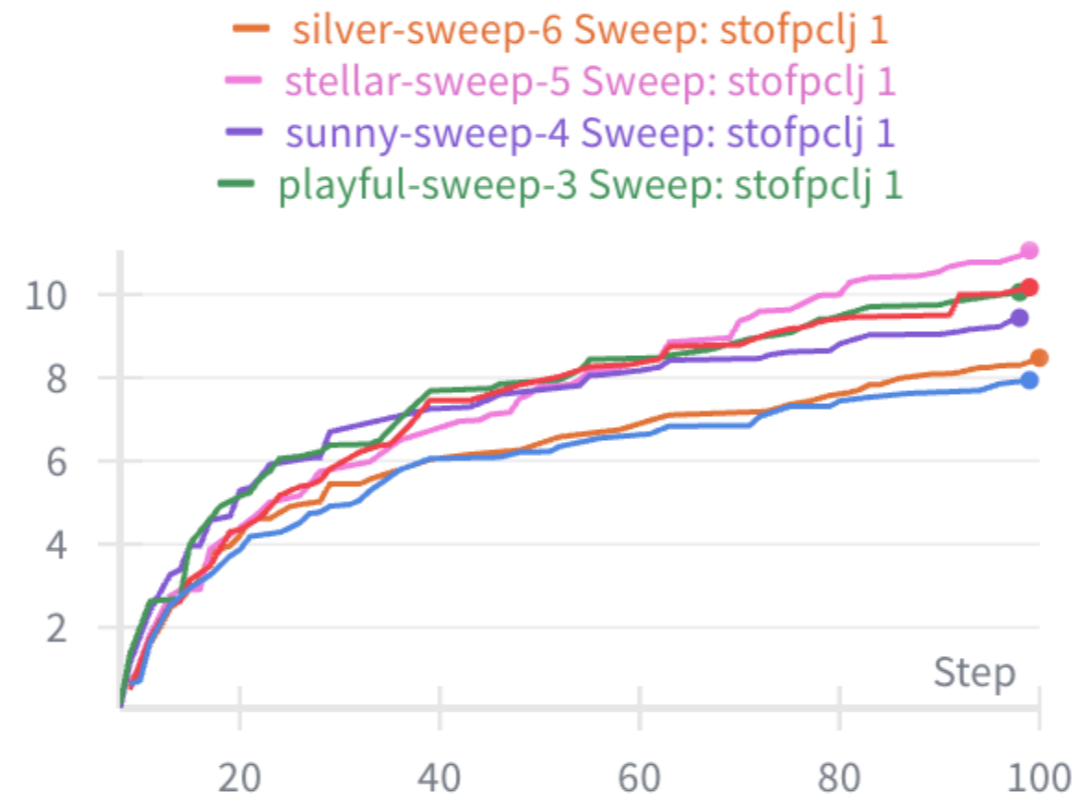




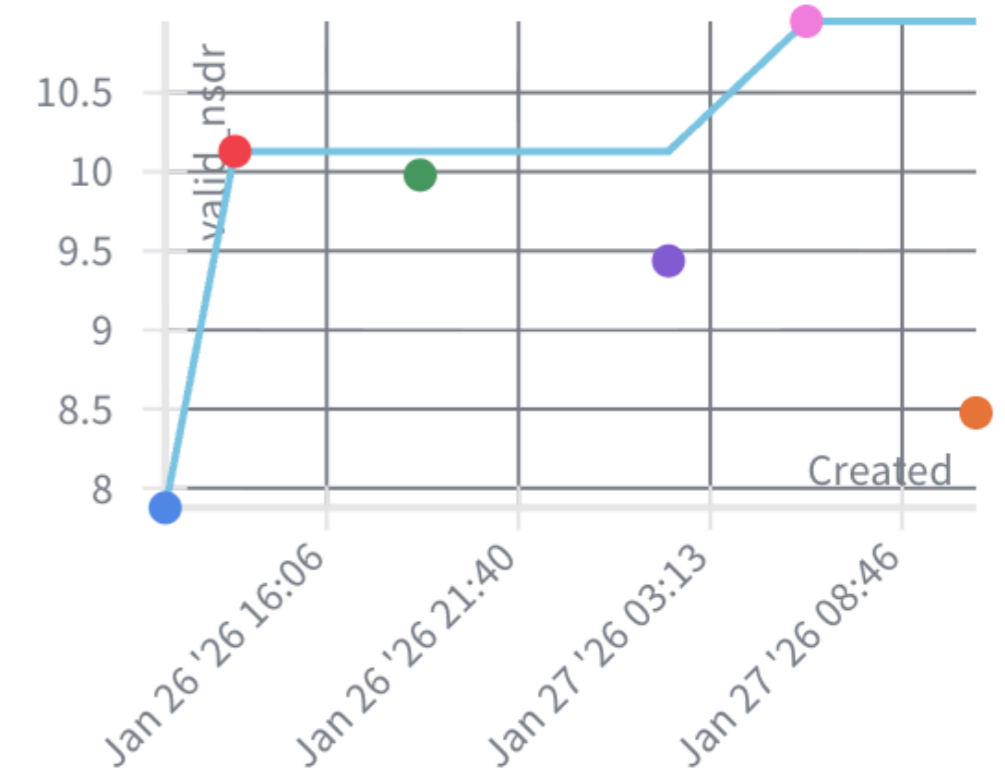
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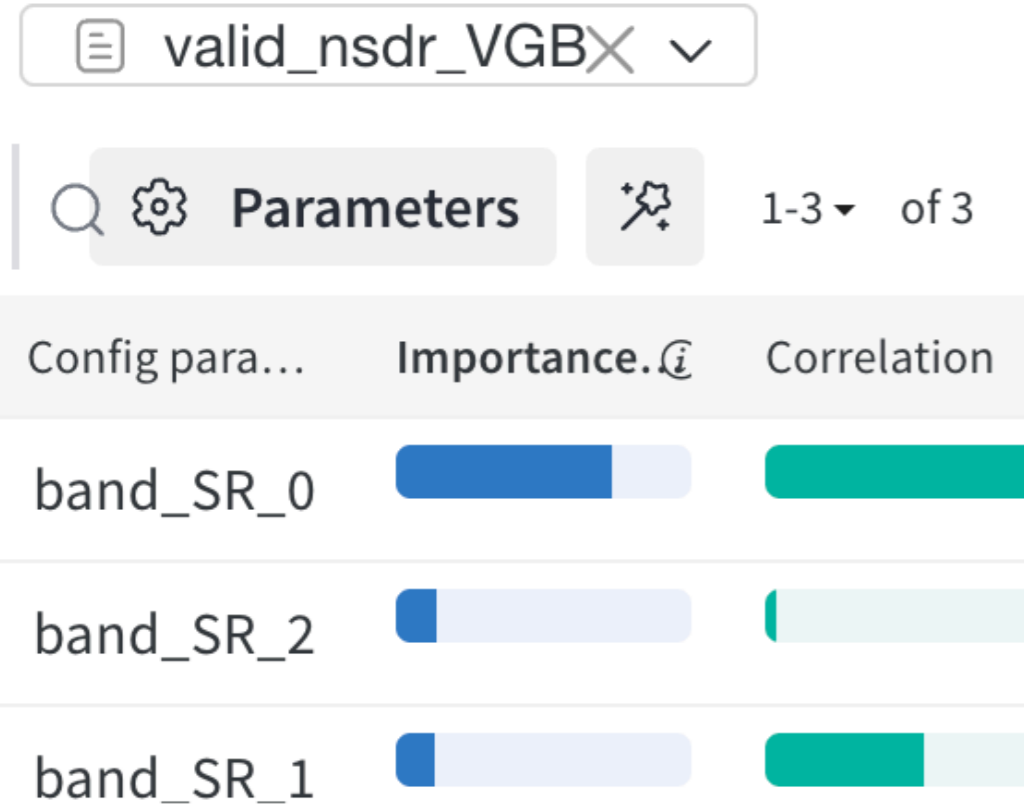
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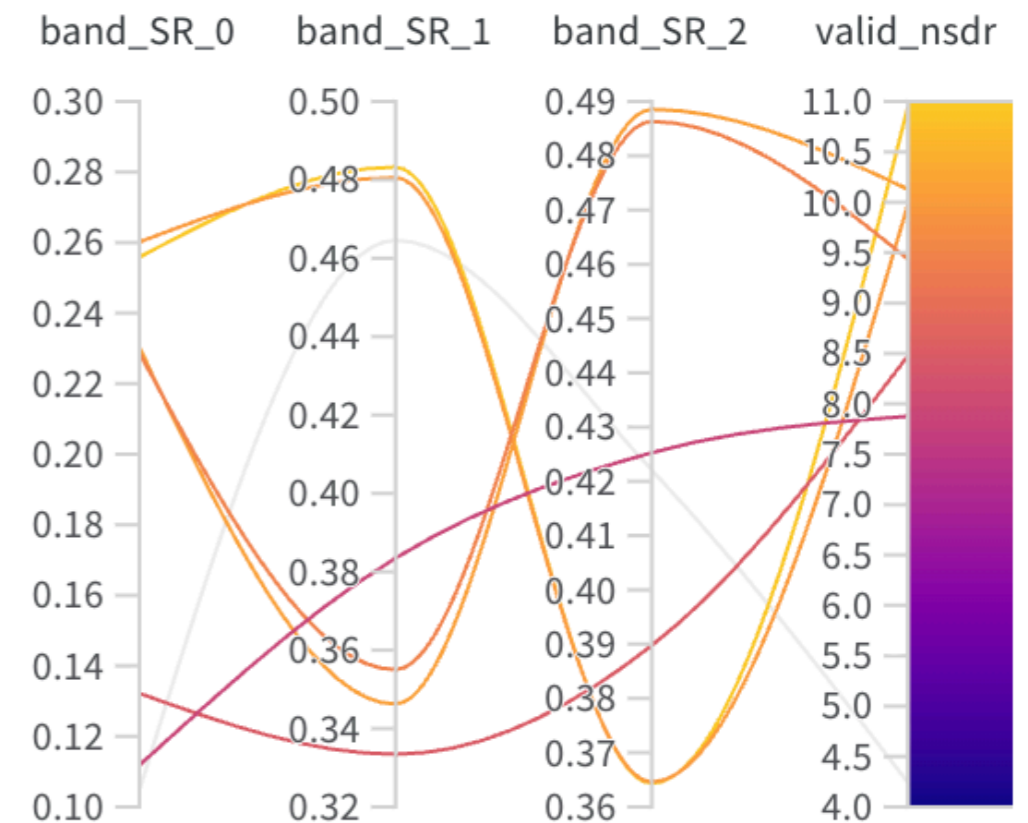
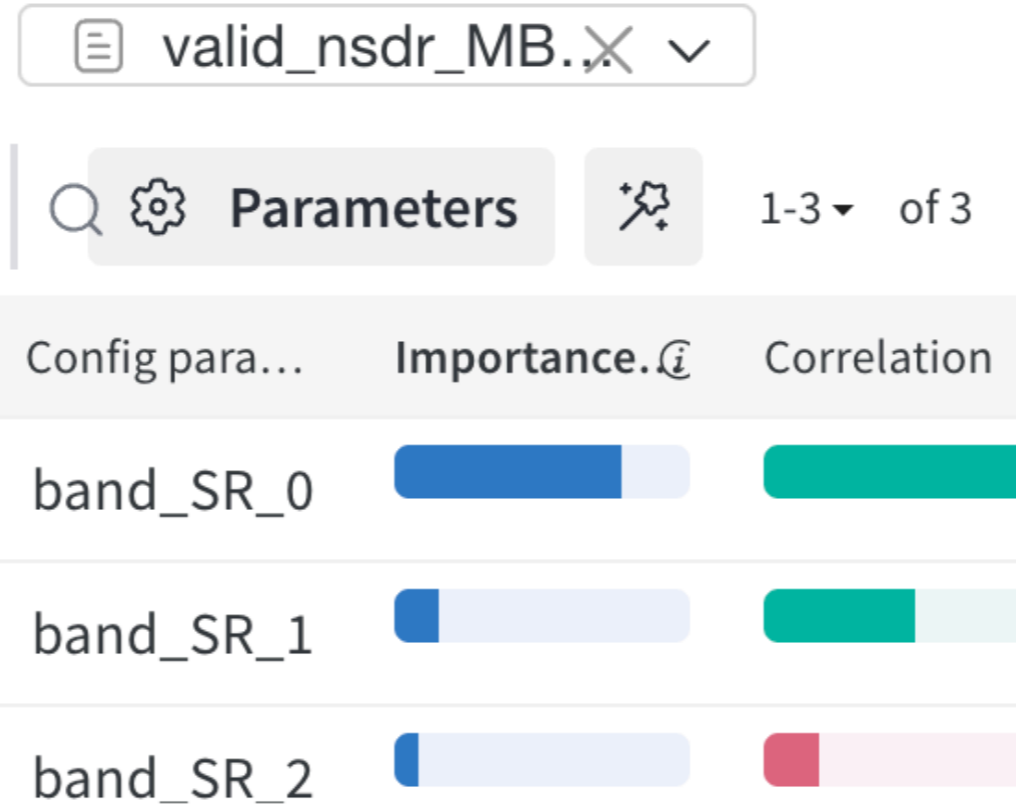
valid\_nsdr v. created



Parameter importance with respect to



Parameter importance with respect to



# Future directions

While the **benefits** are clear, there are also many **challenges** to consider:

- working on a proof of concept (Mojito Lite)
- looking for collaboration
- product assurance / acceptable AI

The **GWINESS** approach requires further investigation:

- dataset generation during training (many overlapping sources)
- hyperparameter tuning
- test with parameter estimation

**Data quality** and **computational resources** impact its effectiveness:

- implement fast waveform generator for L2A / L2D (CU-WAV?)
- develop training dataset pipeline for L2A / L2D (CU-SIM?)
- need a GPU-based cluster suited for large model training (SysTeam?)



# Thanks!

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