Non parametric representation for MBHB recovery from LISA data

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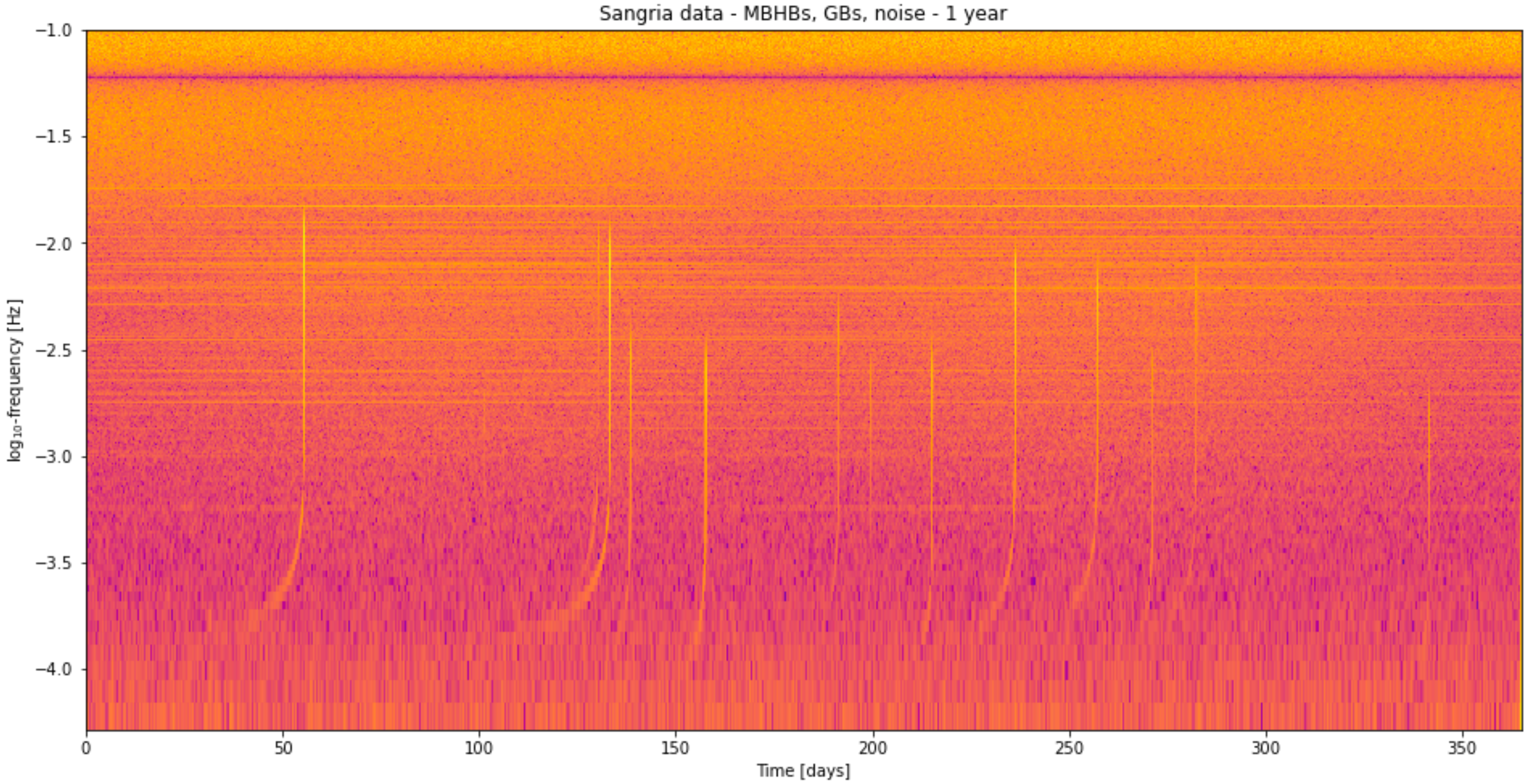
LISA non parametric analysis

Building fast and precise source representation models

- Detection and precise extraction
- Signal unmixing (Global Fit)
- Artefacts mitigation
- Quick processing (Low Latency alert)

→ Galactic Binaries
non parametric analysis[1,2]

→ Hybrid method to model
Massive Black-Hole Binaries



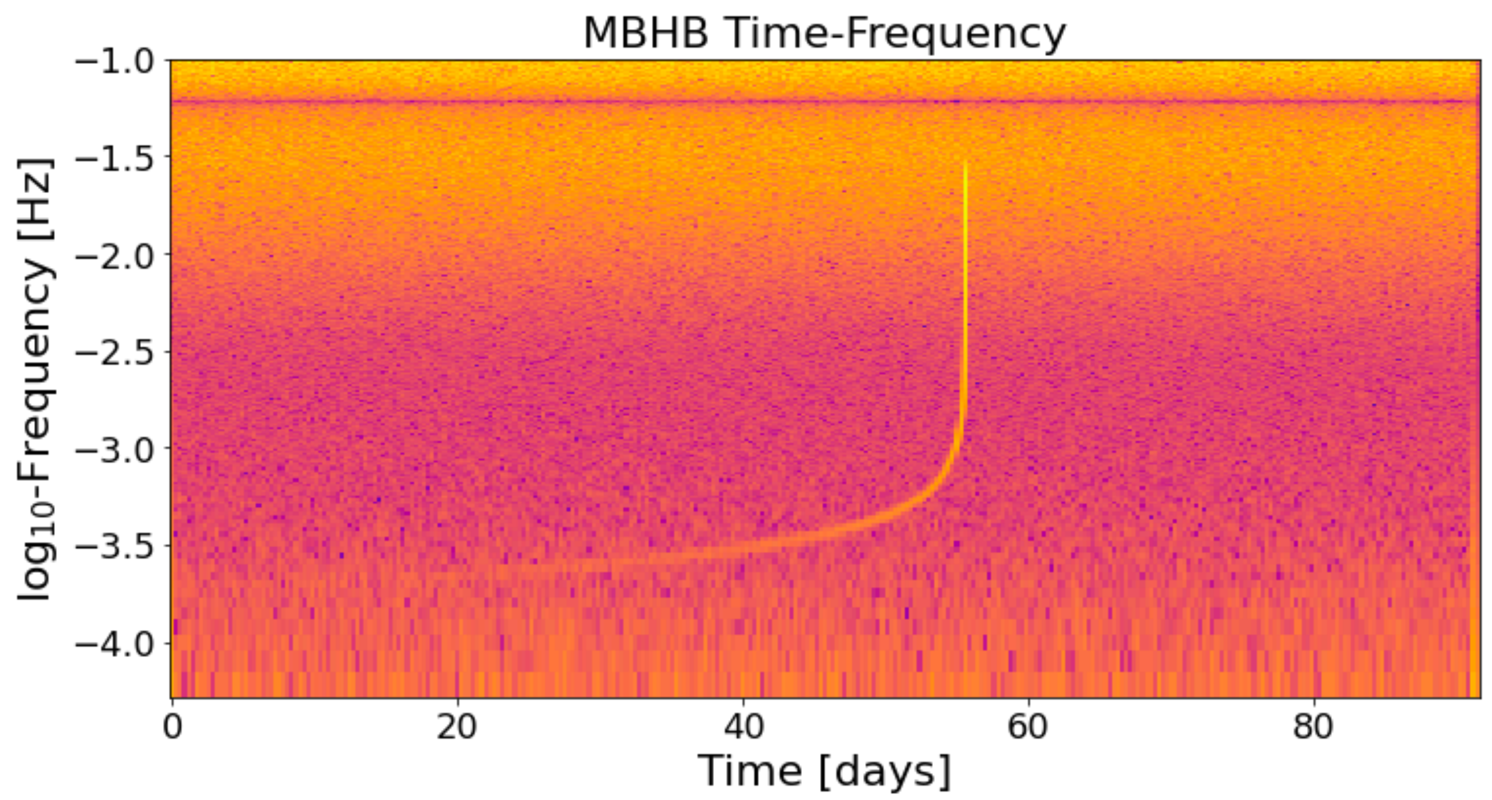
Sangria data challenge

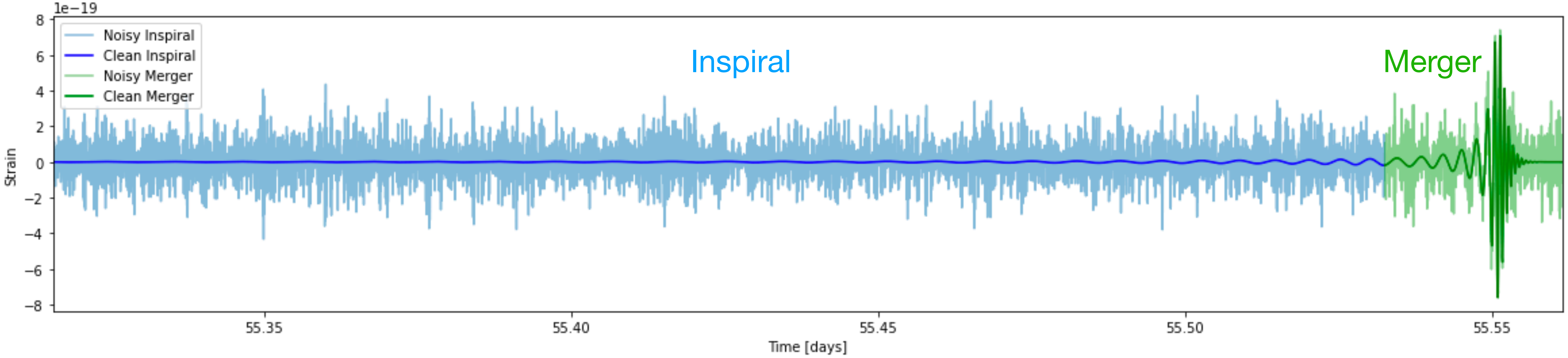
1 Blelly, A., Moutarde, H., & Bobin, J. (2020). Sparsity-based recovery of Galactic-binary gravitational waves. *Physical Review D*, *102*(10), 104053.
2 Blelly, A., Bobin, J., & Moutarde, H. (2022). Sparse data inpainting for the recovery of Galactic-binary gravitational wave signals from gapped data. *Monthly Notices of the Royal Astronomical Society*, *509*(4), 5902-5917.

MBHB signal

Successive stages of a chirp signal

- Inspiral - several days to weeks at low SNR
- Merger - several hours around peak SNR
- Ringdown - rapid decrease in power

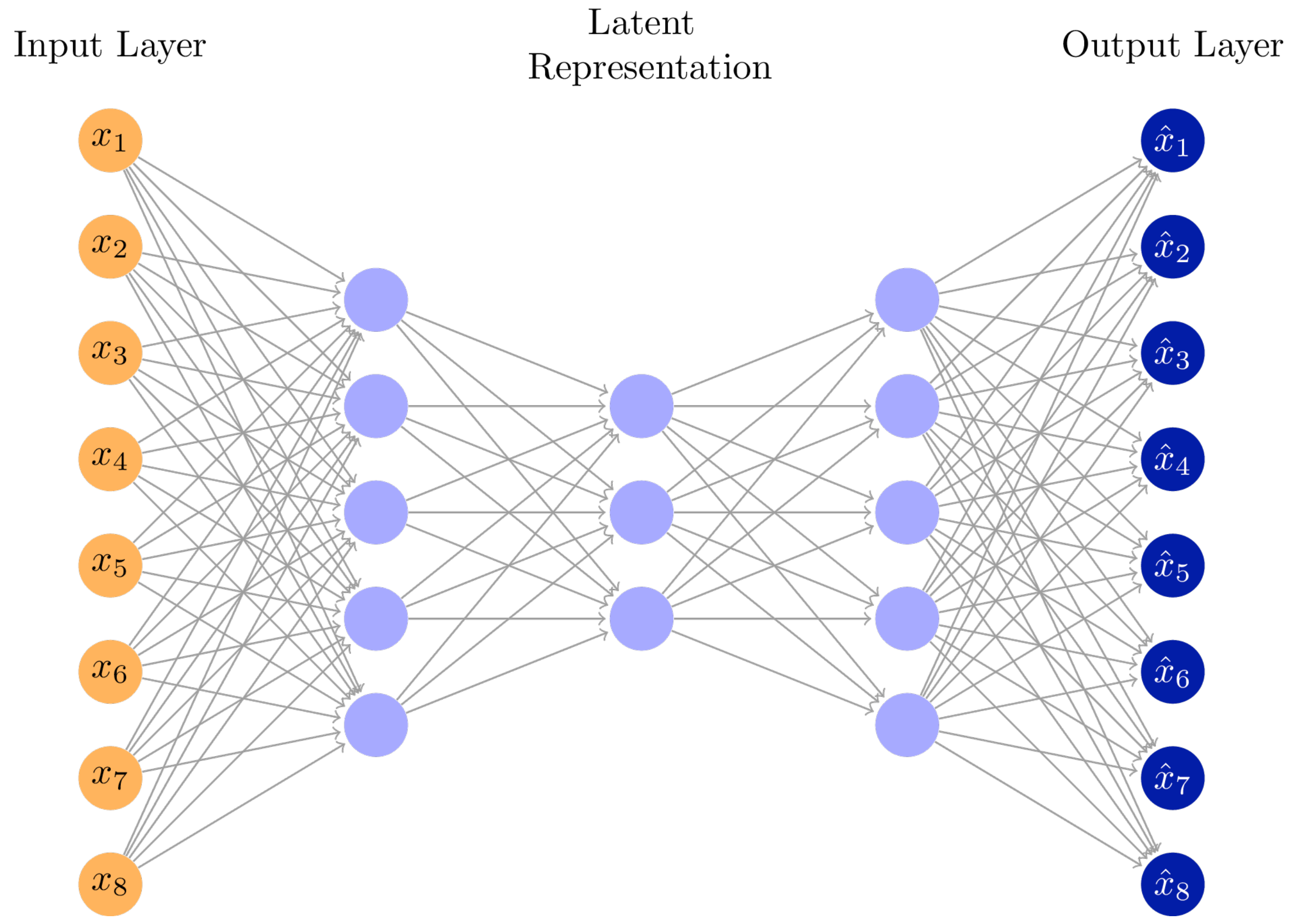




MBHB signal

Proposed MBHB hybrid model

Modular approach to capture inspiral and merger

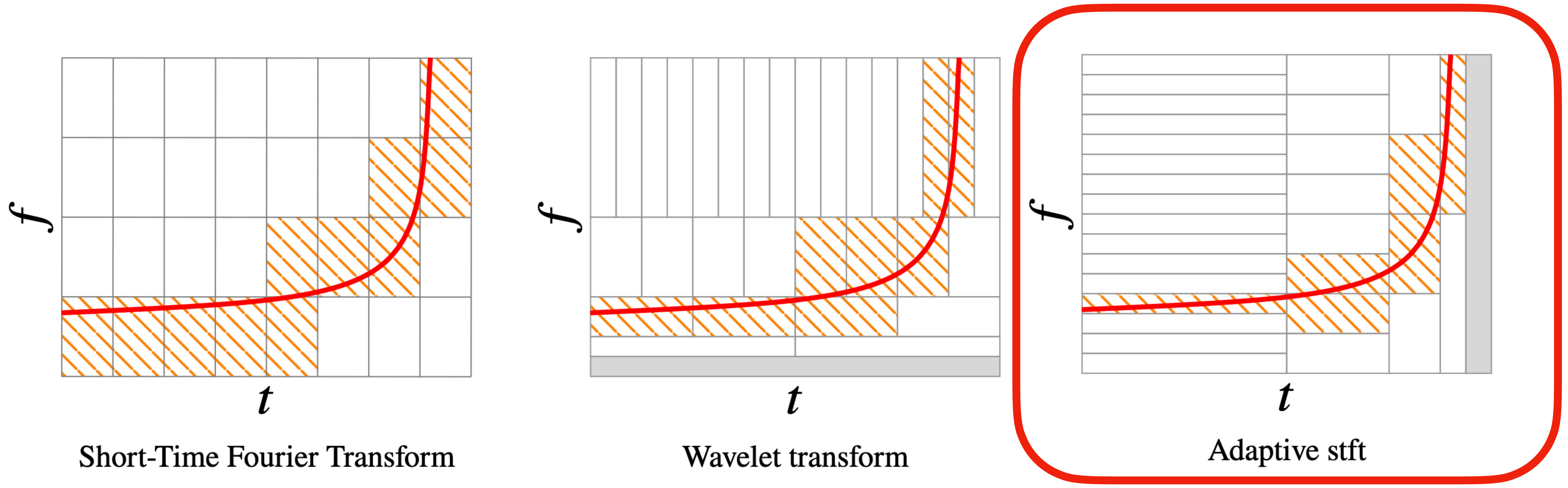


Merger : Learning based model

- Strong dynamics controlled by few parameters
- Relatively short signal (~ 1000 time samples)
- Dimension reduction approach

Inspiral : Sparsity based model

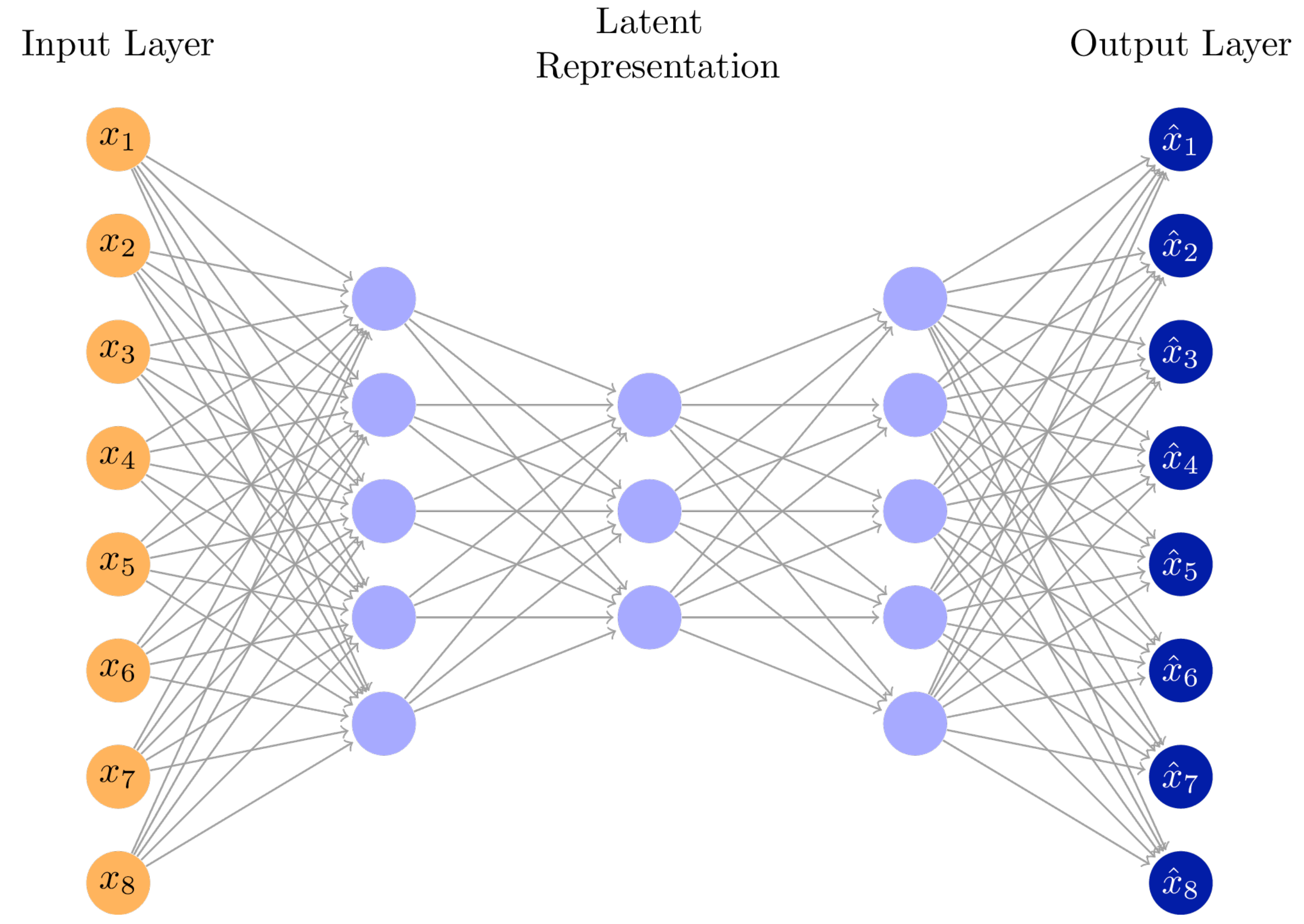
- Long signal (~ 100 000 time samples) with slow variations
- Adaptive Time-frequency sparse decomposition
- Constrained thresholding

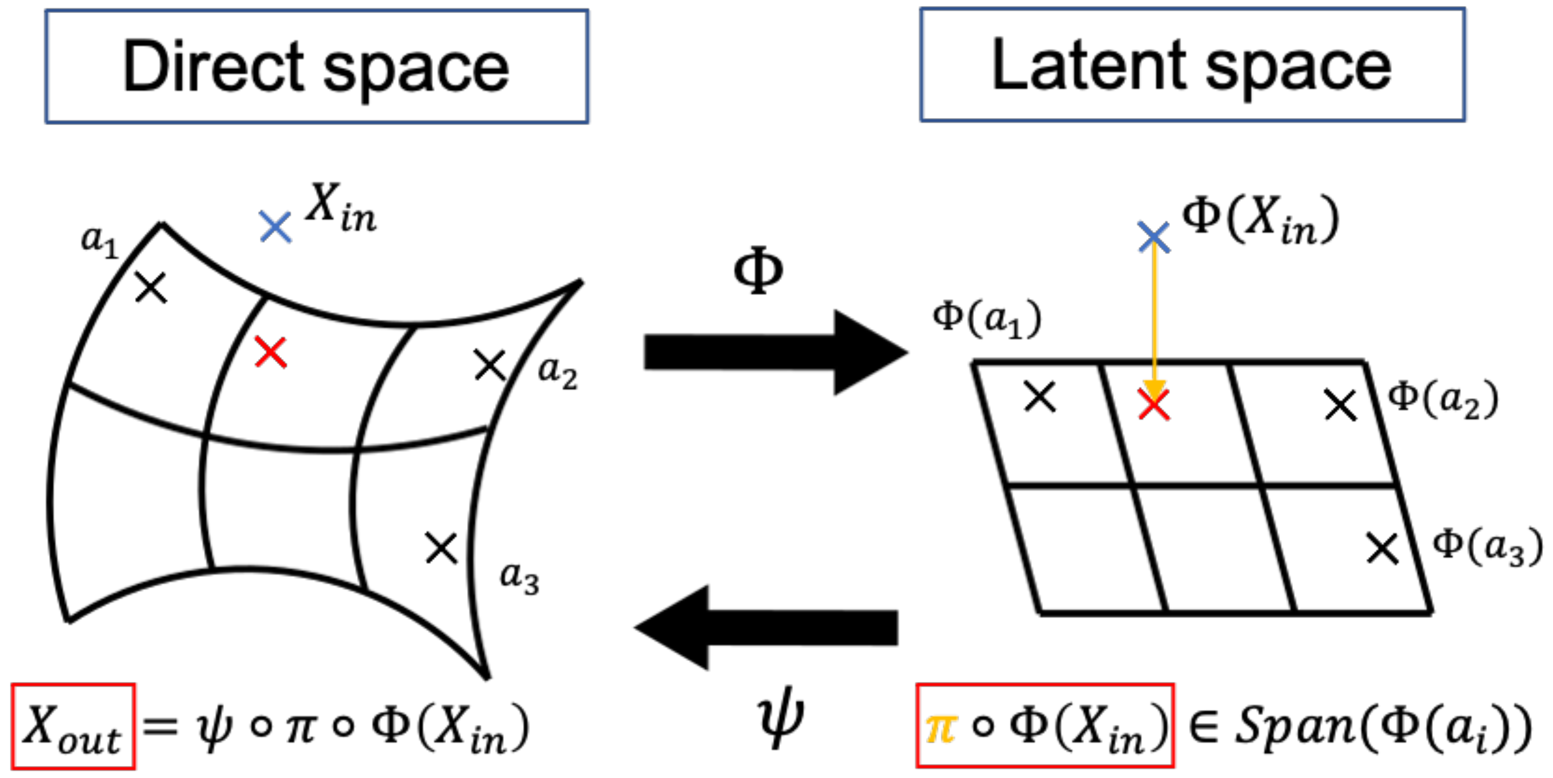


Merger model

Learning non-linear low dimension signal representations

- Auto encoder based approach
- Signal focused learned low-dimension representation
- Fast once trained
- Various applications (detection, extraction, fast parameters point estimate, …)

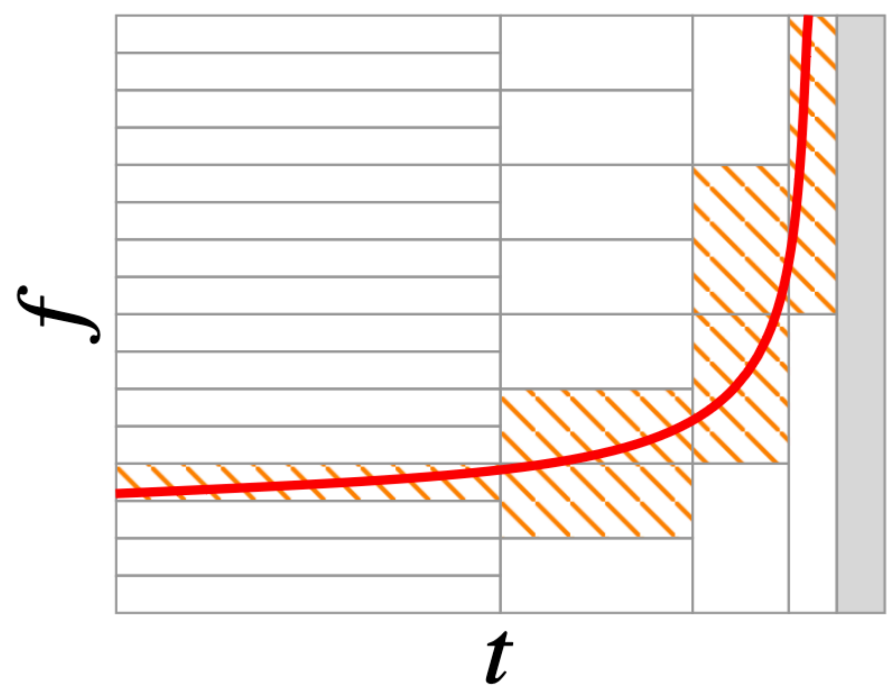




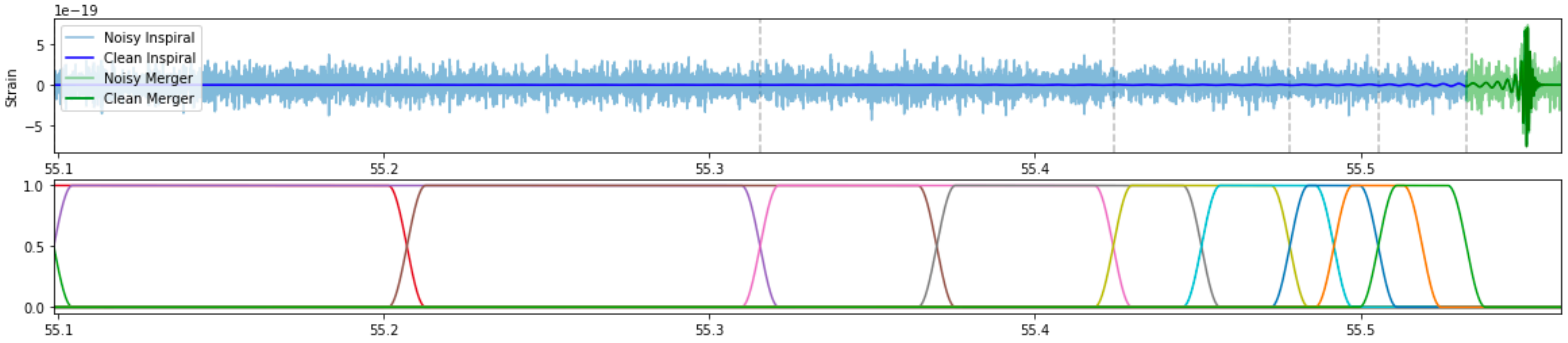
Inspiral model

Adaptive Short-Term Fourier Transform (ASTFT)

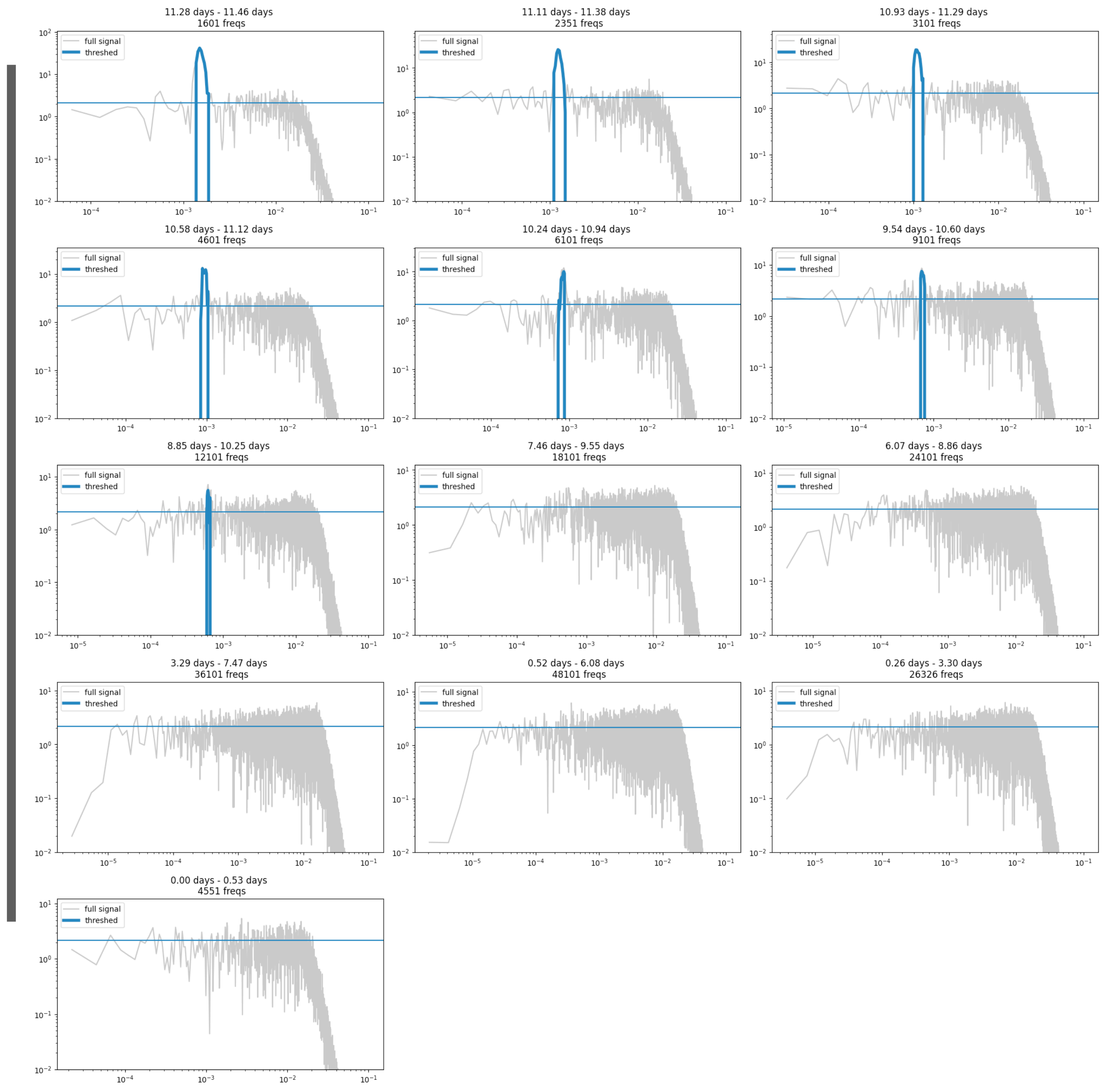
1. Time segmentation adapted to merger knowledge (coalescence time, chirp mass)
2. Non-stationary smooth windowing
3. Fourier transforms
4. Thresholding



Adaptive stft



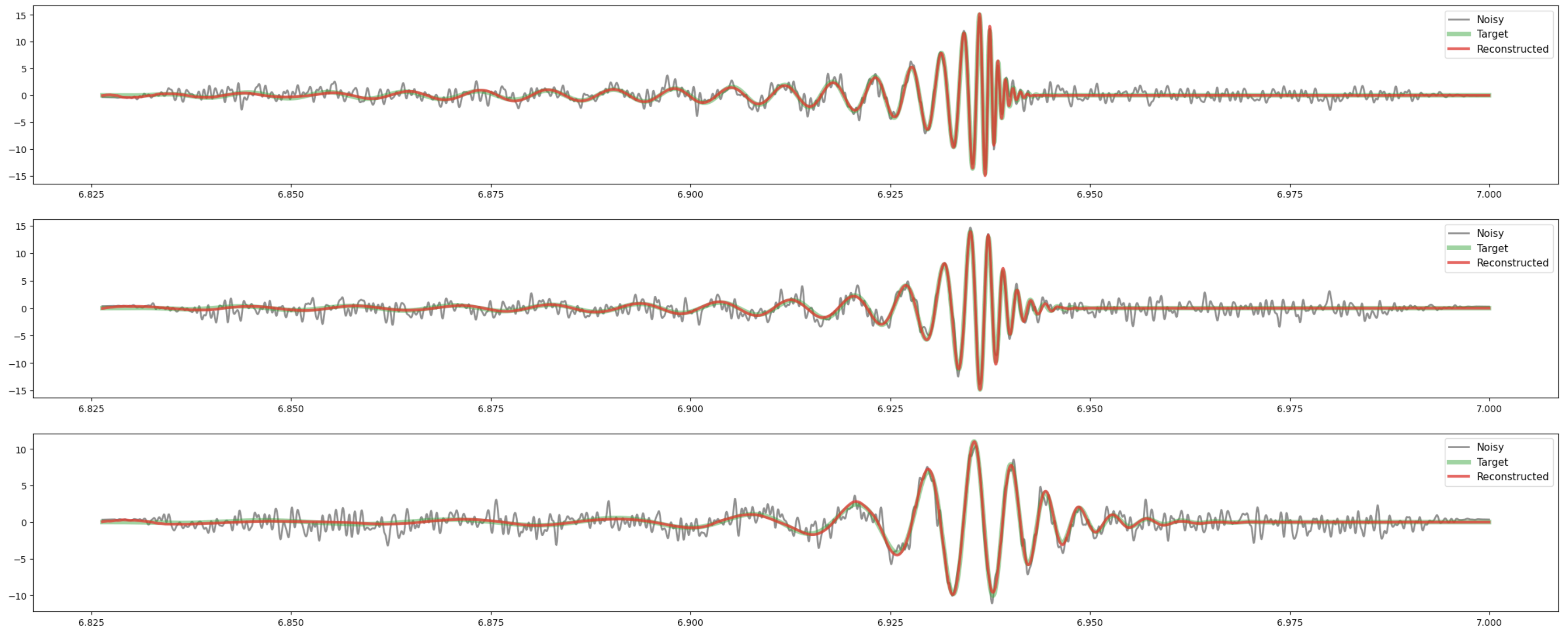
Dyadic overlapping time segmentation and smooth windowing



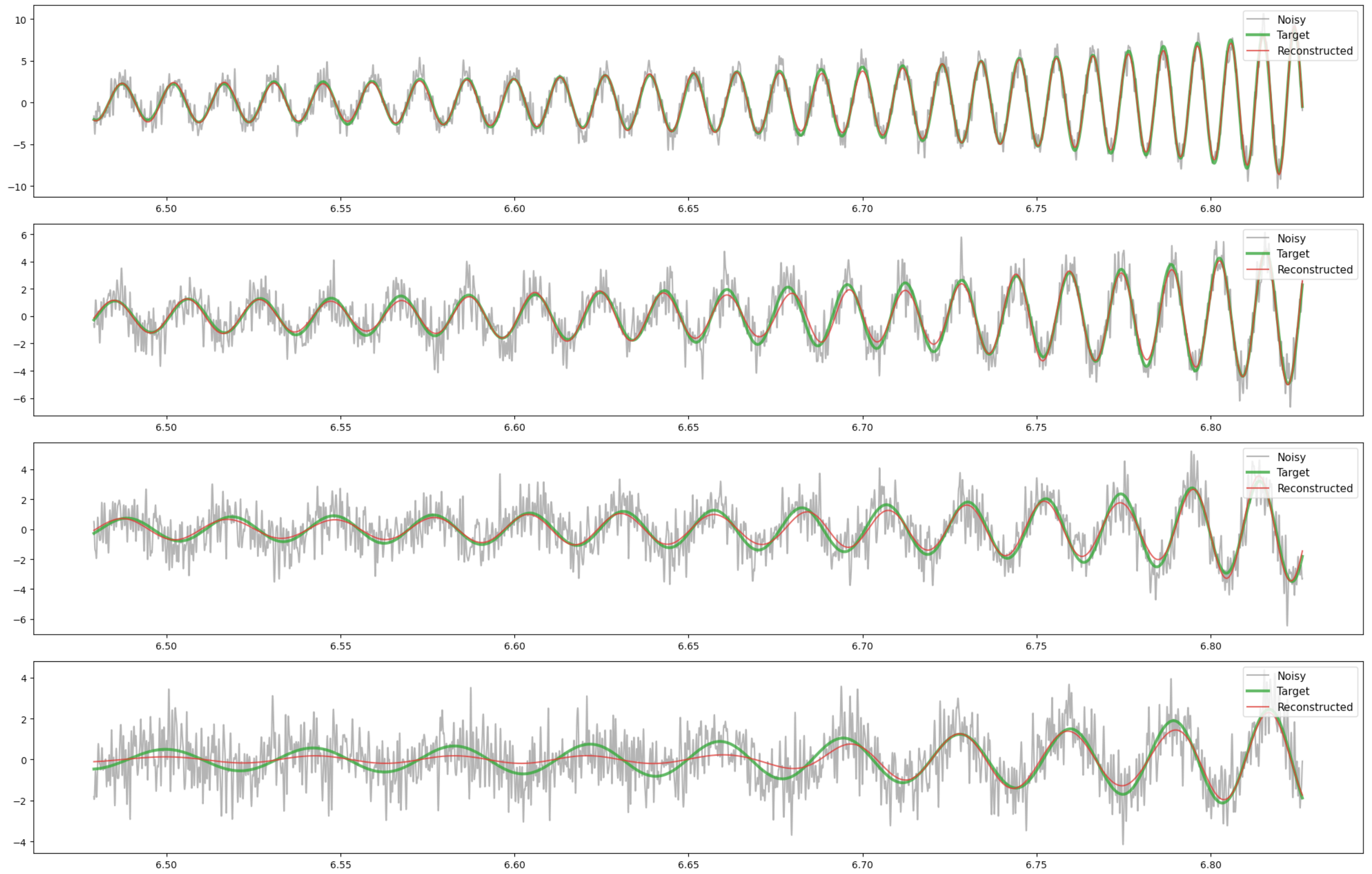
Results

Signal extraction

- Merger

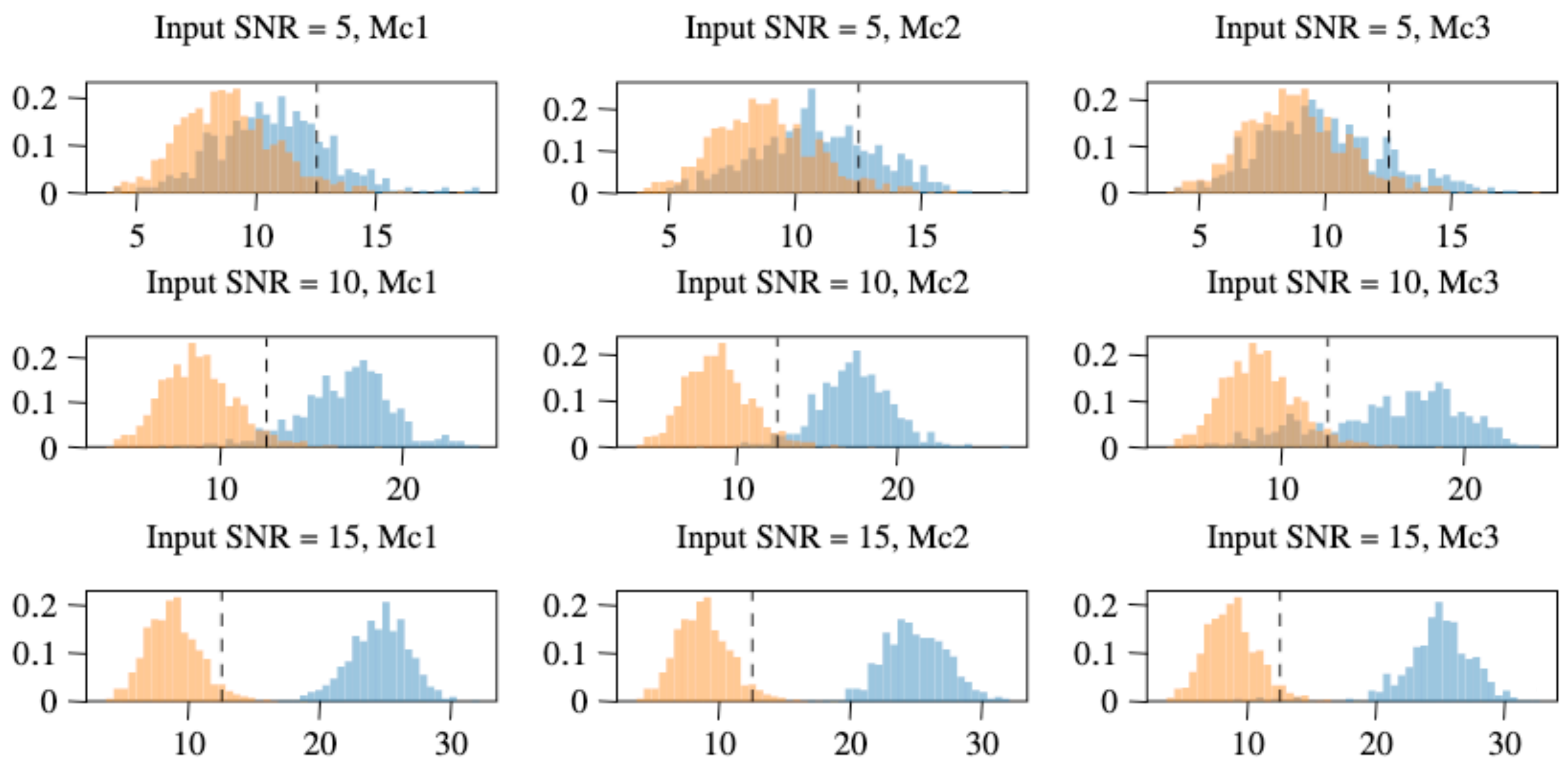


- Inspiral



Signal detection

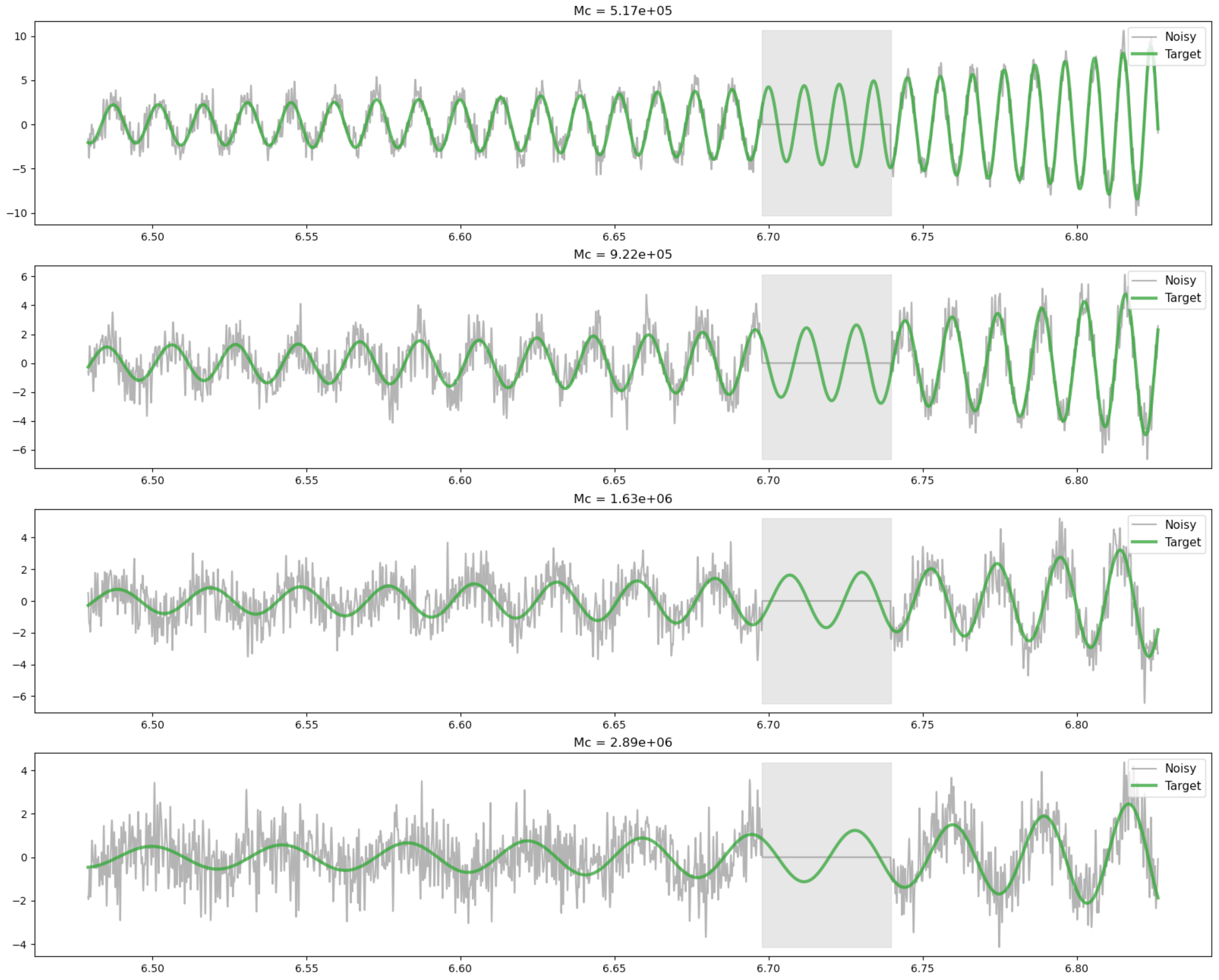
- Merger model
- Detector based on noise statistics
- Hypothesis testing with respect to noise only input



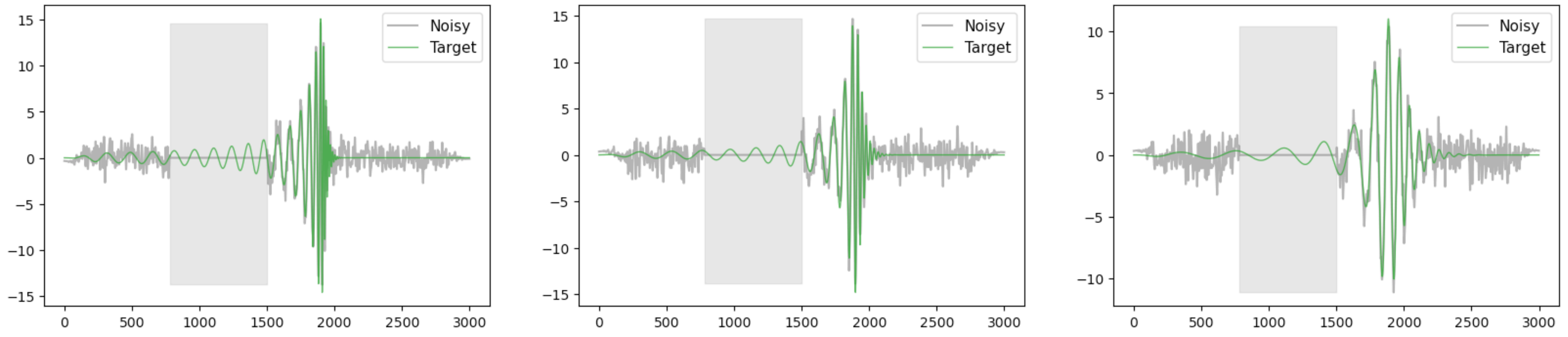
Gap artefacts in LISA data

Interruptions in data collection

- Planned or unplanned
- Can last from a few minutes to multiple hours
- In this analysis gaps last for one hour and less
- Gap impact depends on several factors
    - Gap position and length
    - MBHB parameters and SNR
    - MBHB model



1 hour gap during late inspiral



1 hour gap during merger

Gap mitigation - Inpainting methods

Inspiral

- Sparse inpainting techniques
- Exploiting decorrelation between sparse basis and gaps
- Iterative proximal methods such as Forward-Backward
- Common inverse problem[1,2]

$$\underset{\tilde{X}}{\text{minimize}}\ \frac{1}{2}\left\| M\Psi_S \tilde{X} - MY \right\|_2^2 + \gamma \left\| \tilde{X} \right\|_1$$

Merger

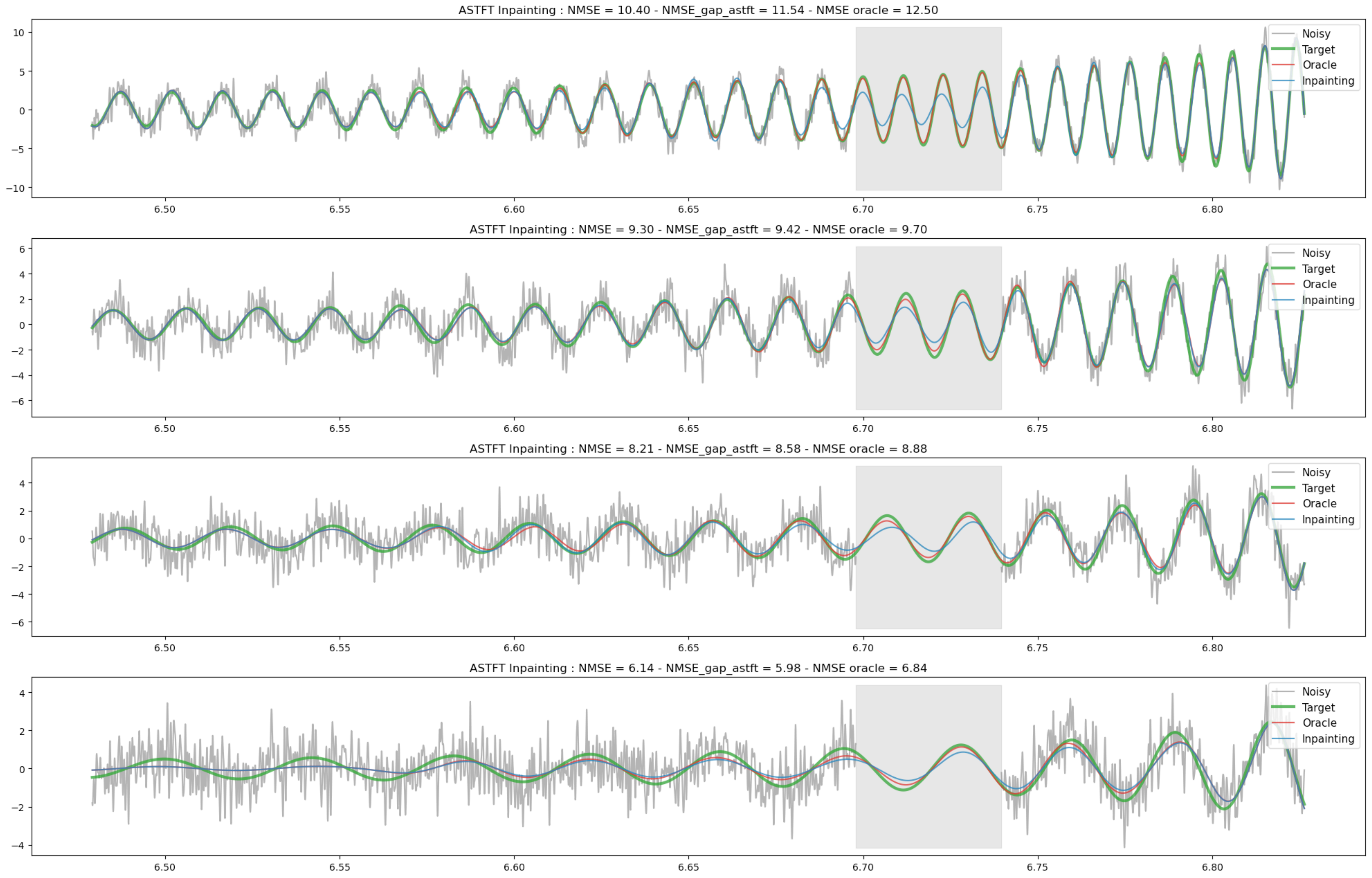
- Low dimension representation used as a generative model
- Exploiting signals correlations in and out of the gap
- Fitting on gapped data and generating full signal

$$\underset{\lambda}{\text{minimize}} \left\| M\Psi_{LD}\left(\sum_{i=1}^{n} \lambda_i \alpha_i\right) - MY \right\|_2^2$$

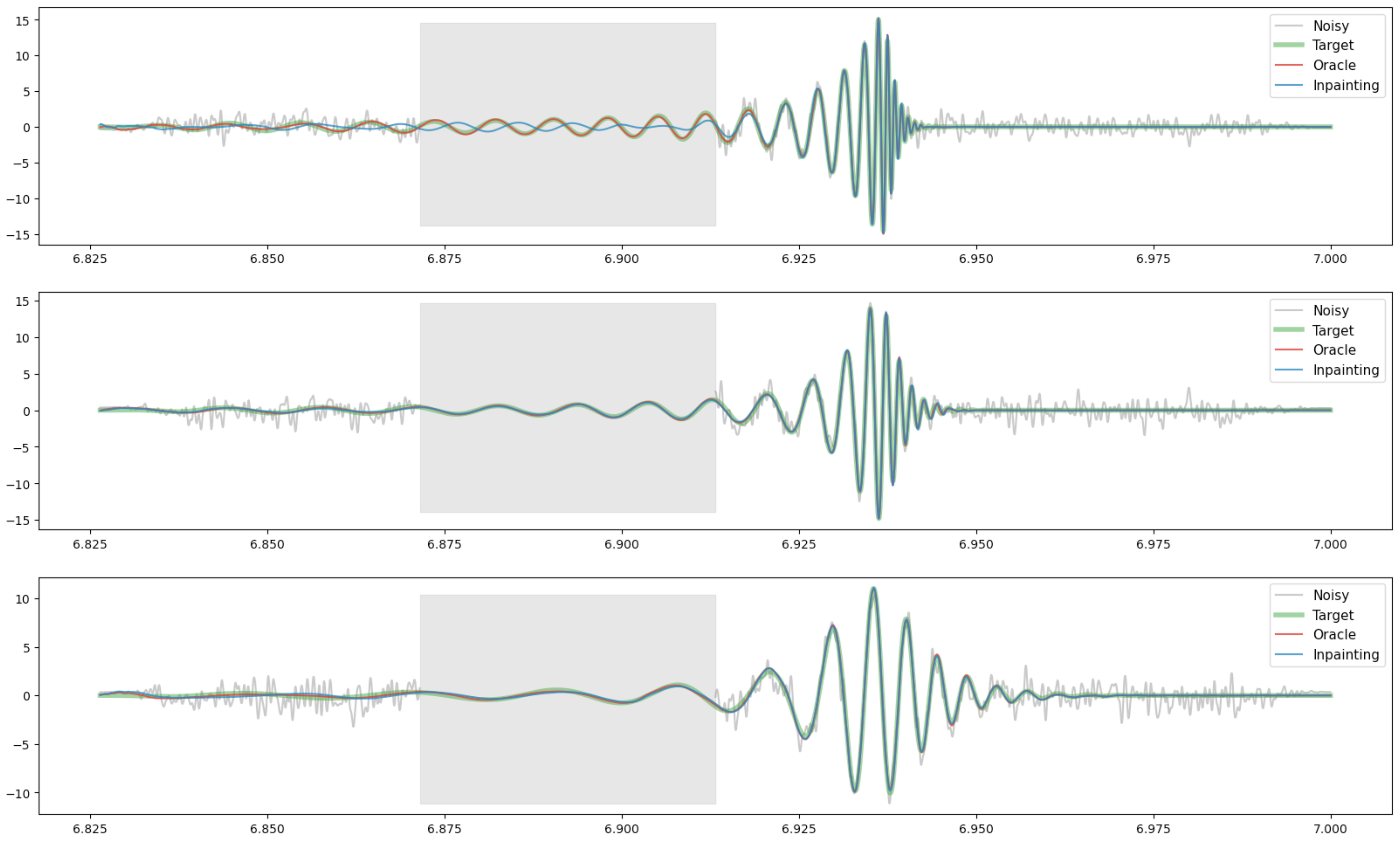
1 Bertalmio, M., Sapiro, G., Caselles, V., & Ballester, C. (2000, July). Image inpainting. In *Proceedings of the 27th annual conference on Computer graphics and interactive techniques* (pp. 417-424).
2 Fadili, M. J., Starck, J. L., & Murtagh, F. (2009). Inpainting and zooming using sparse representations. *The Computer Journal*, *52*(1), 64-79.

Gap mitigation - Inpainting results

Inspiral



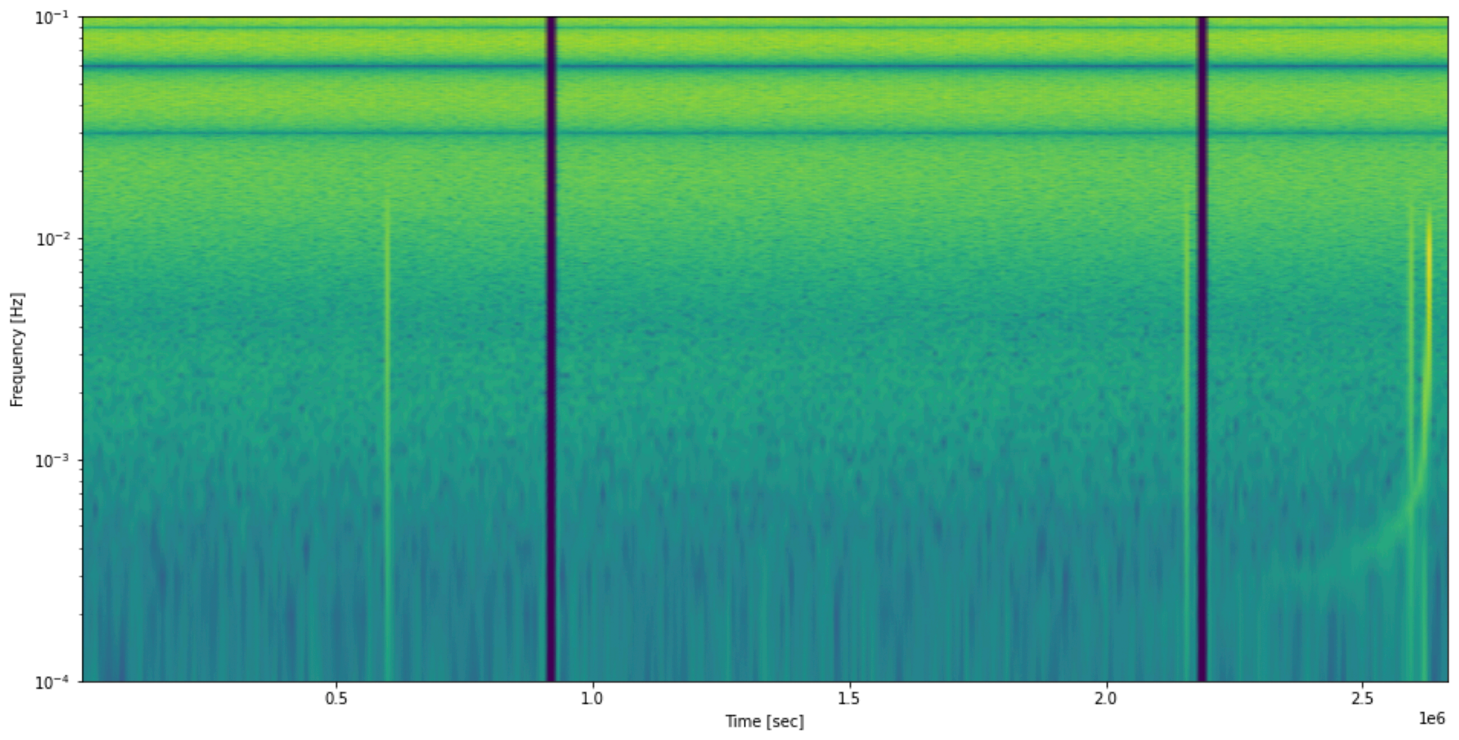
Merger



Conclusions and perspectives

- Hybrid model for MBHBs
  - Merger using dimension reduction
  - Inspiral using sparse representation
- Gap mitigation using inpainting approach

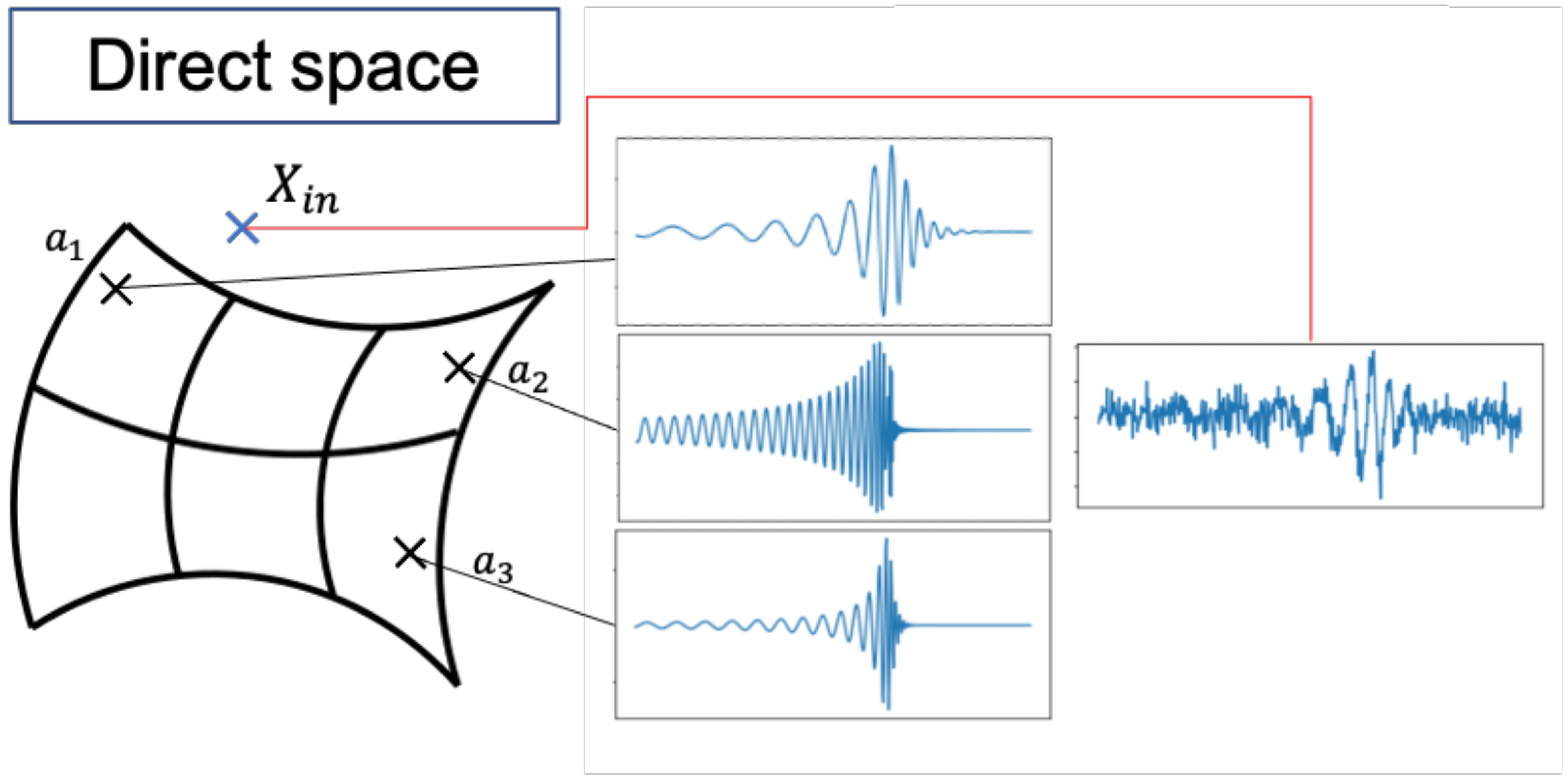
- Next step : full artefact mitigation with glitch removal
- Full artefact mitigation pipeline for MBHBs



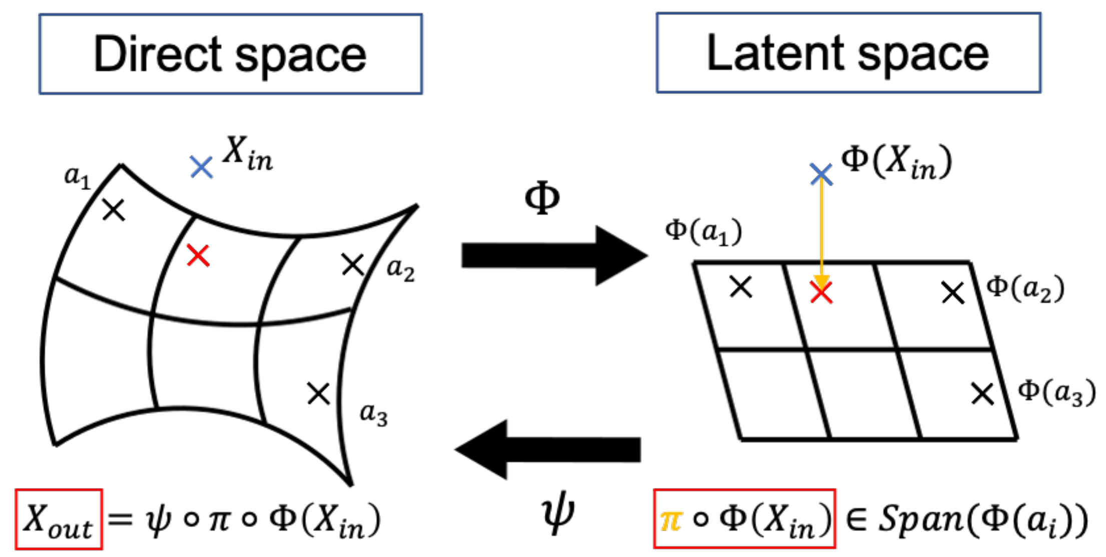
Spritz data challenge

Backup

IAE details



- Φ, Ψ 12 layers CNN, 10 anchor points
- Training the IAE : minimize$_{\Phi,\Psi}$ $\| X_{train} - \Psi \circ \pi \circ \Phi(X_{train}) \|_2^2 + \mu D\left(\phi(X_{train}), \mathscr{E}_{\Phi_\alpha}\right)^2$
- Barycentric weights : $\pi \circ \Phi(x) = \sum_{i=1}^{k+1} \lambda_i \Phi(\alpha_i) \quad s.t. \sum_{i=1}^{k+1} \lambda_i = 1$



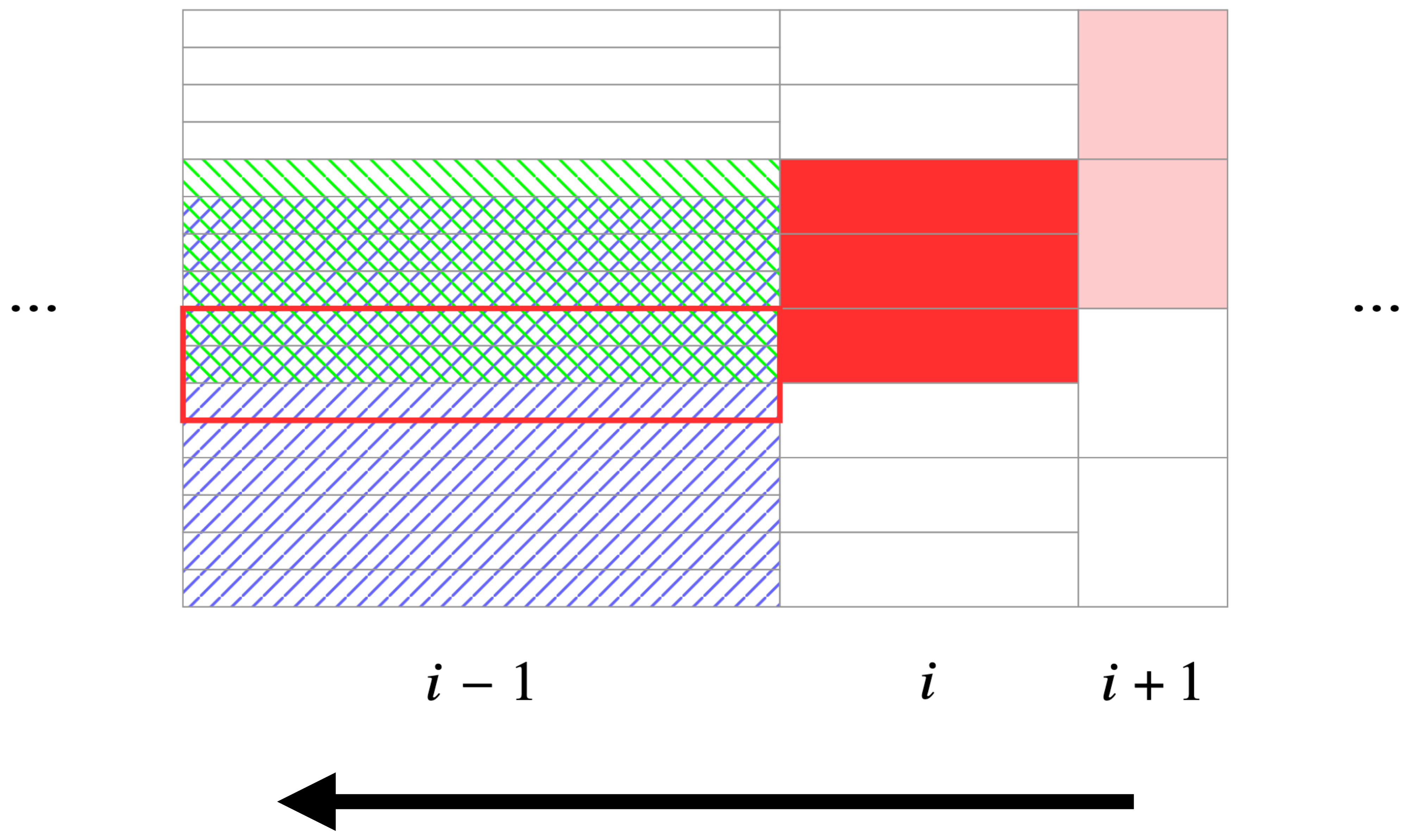
- How to determine weight ?
    - Fast Interpolation (FI) : orthogonal projection in latent space
    - Barycentric Span Projection (BSP) : minimize$_\lambda$ $\left\| X - \psi\left(\sum_{i=1}^{k+1} \lambda_i \phi(\alpha_i)\right) \right\|_2^2 \quad s.t. \sum_{i=1}^{k+1} \lambda_i = 1$

Thresholding details

Reweighted block l21 thresholding

- Reweighted : Debiasing the thresholding by adapting the threshold to signal power on active coefficients only
- Block thresholding : Summing coefficient power over blocks before applying threshold to account for local structure and mitigate false positives/negatives
- L21 : Sum power over the different channels then apply sparsity

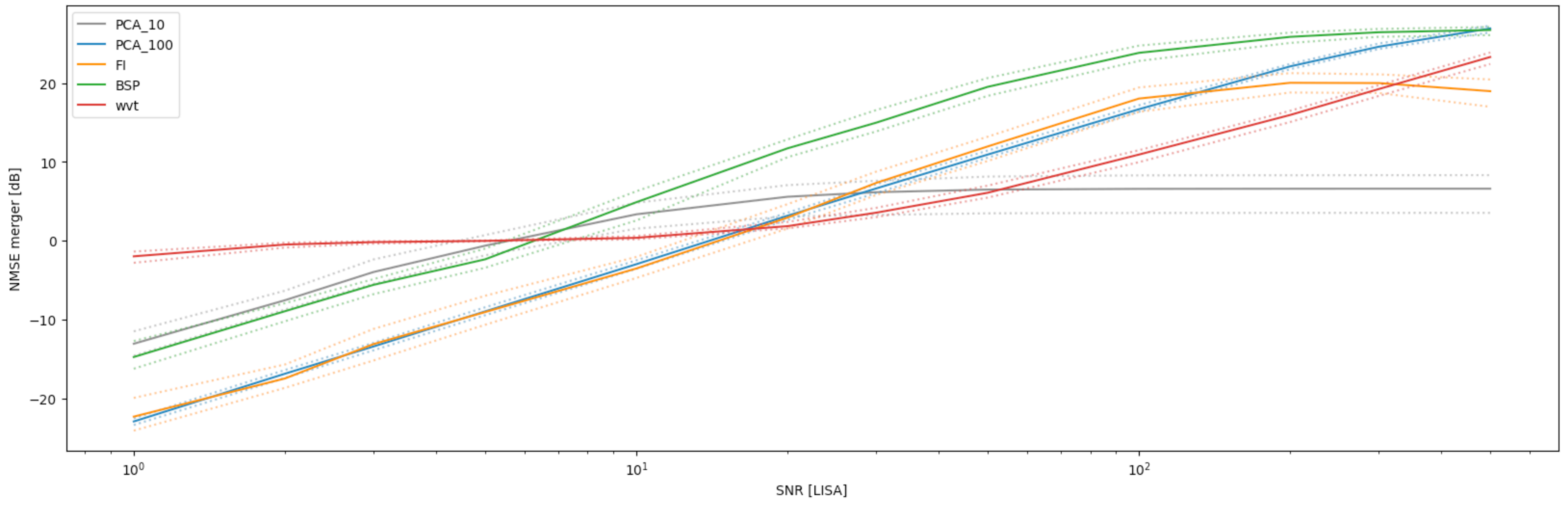
Constrained ASTFT thresholding

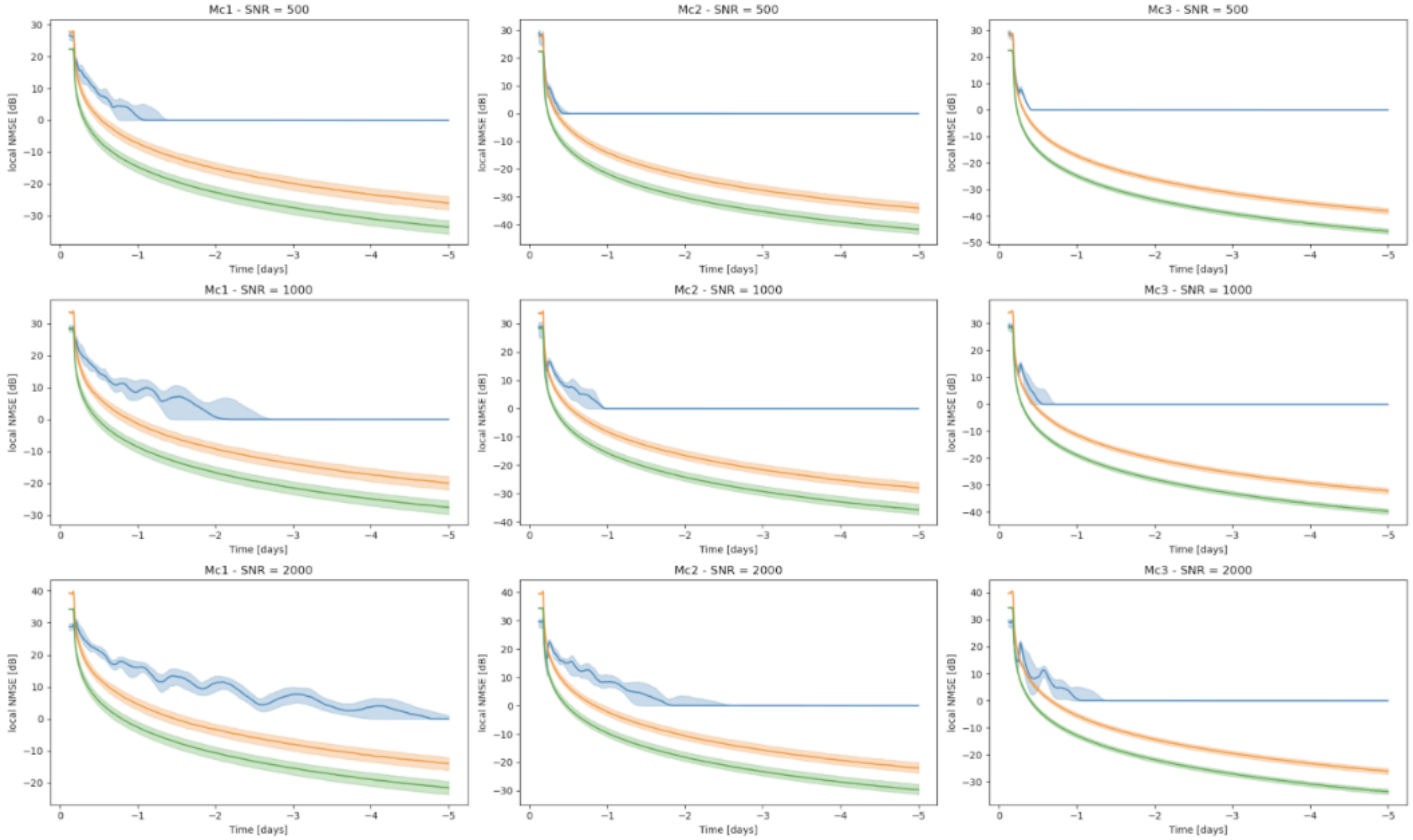


Quantitative results on extraction

NMSE curves

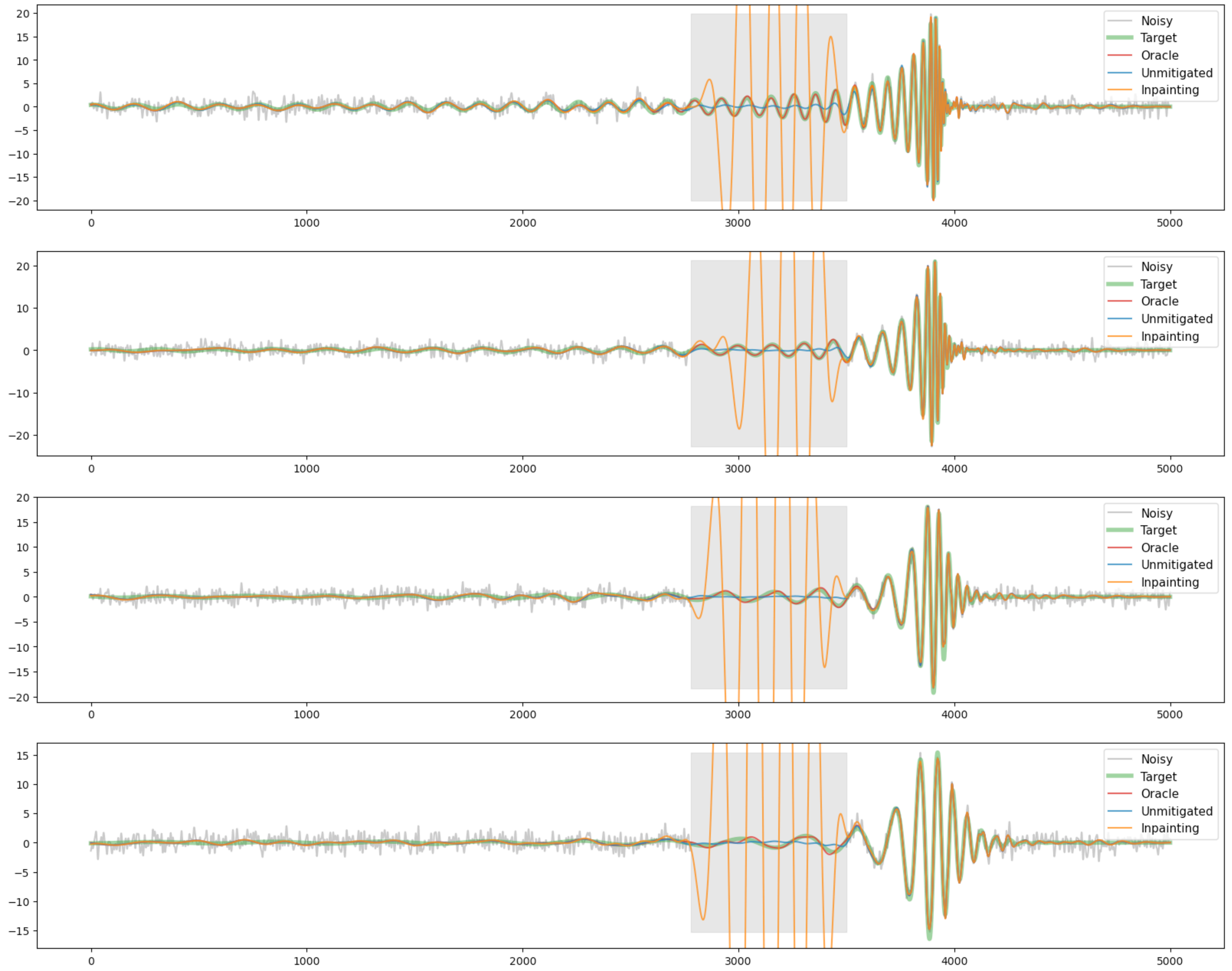
$$NMSE = -20\,log_{10}\left(\frac{||\hat{X} - X^*||_2}{||X^*||_2}\right)$$

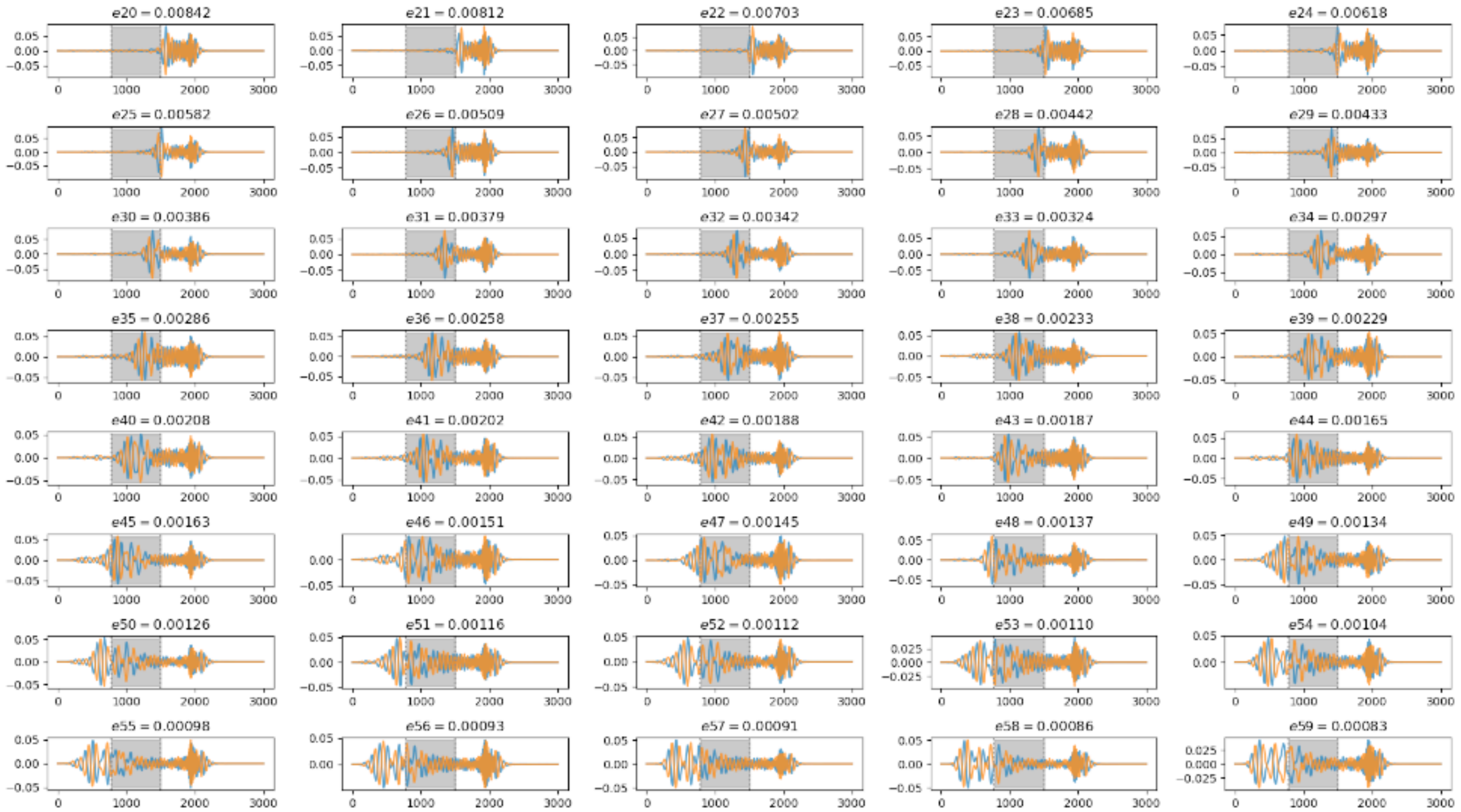




PCA inpainting
Linear low dimension inpainting

- Merger model
- Gap causes degeneracies in Principal Components
- Impossible to inpaint accurate signal
- Open question on number of principal components to select





Wavelet sparse inpainting

Same algorithm as ASTFT inpainting