Neuro-steered music source separation with EEG-based auditory attention decoding and Contrastive-NMF

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MIPFrontiers

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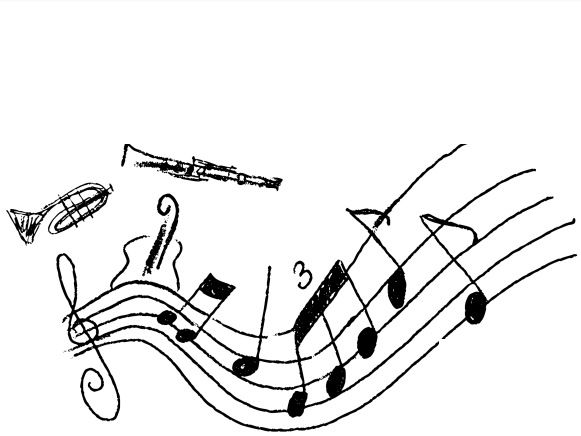
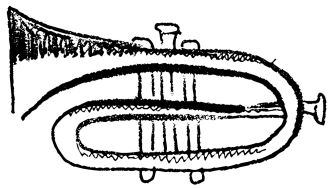
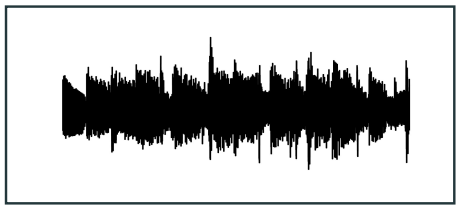
Background

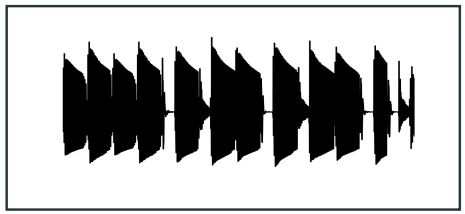
Blind Audio Source Separation







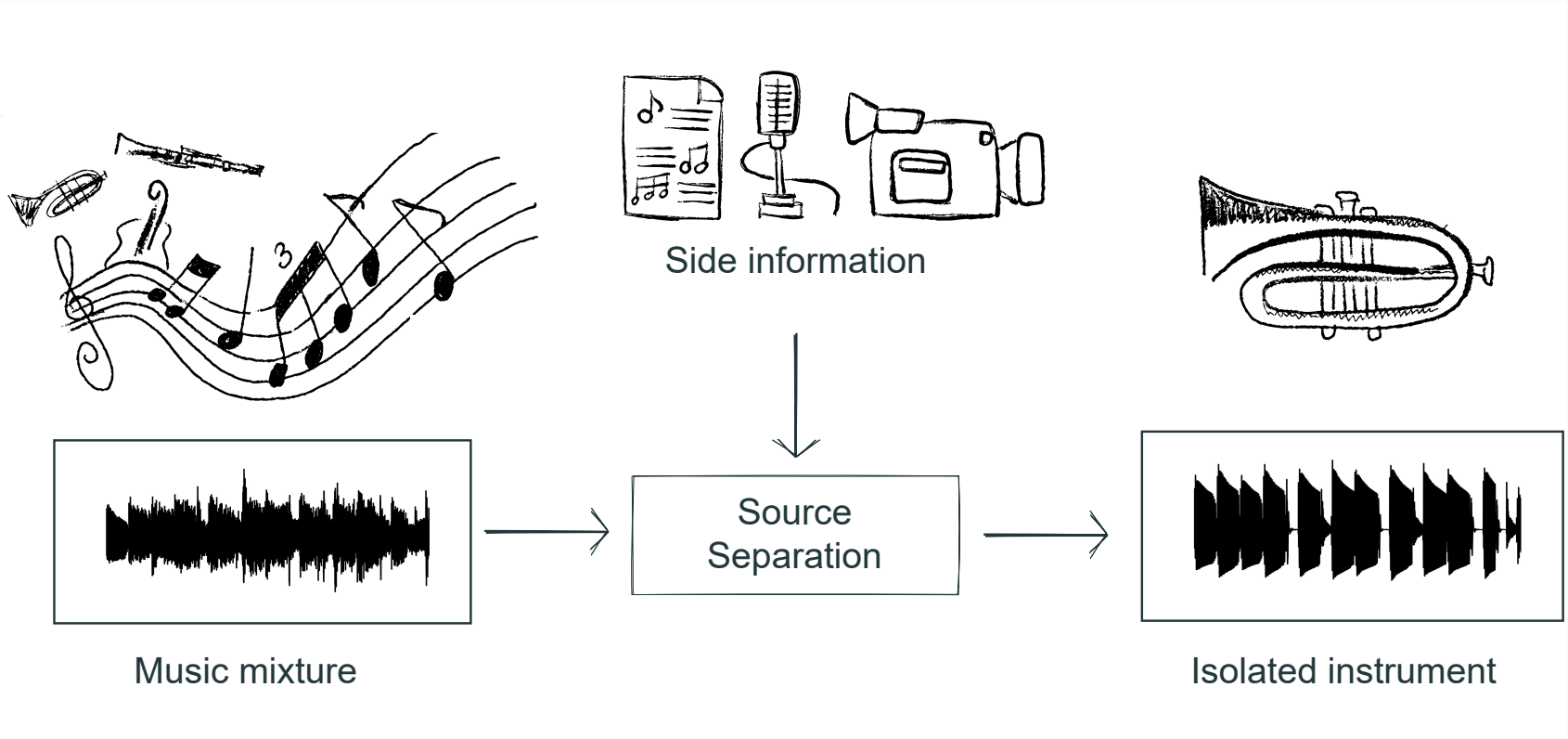
Source Separation



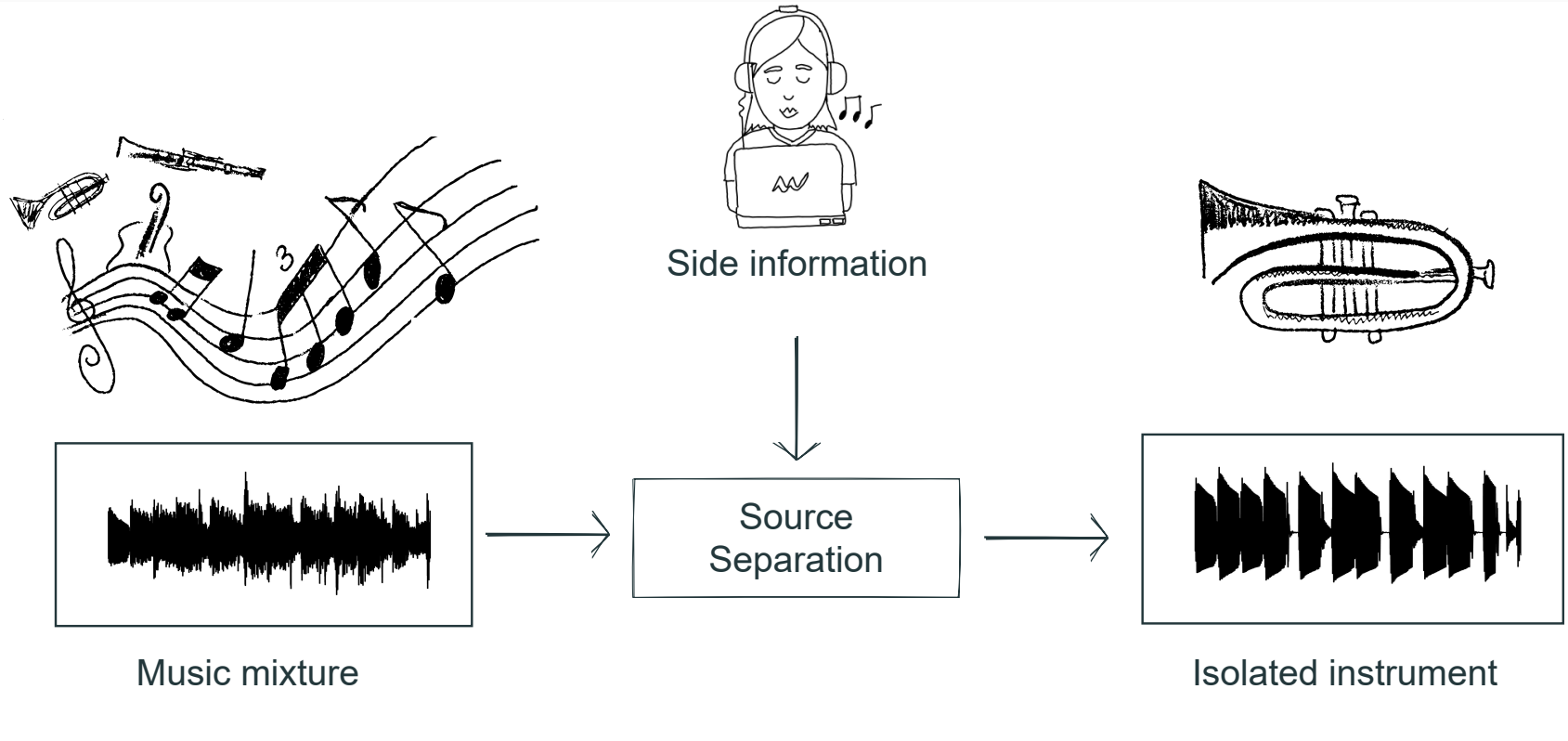
Music mixture

Isolated instrument

Informed Audio Source Separation



User-driven Audio Source Separation



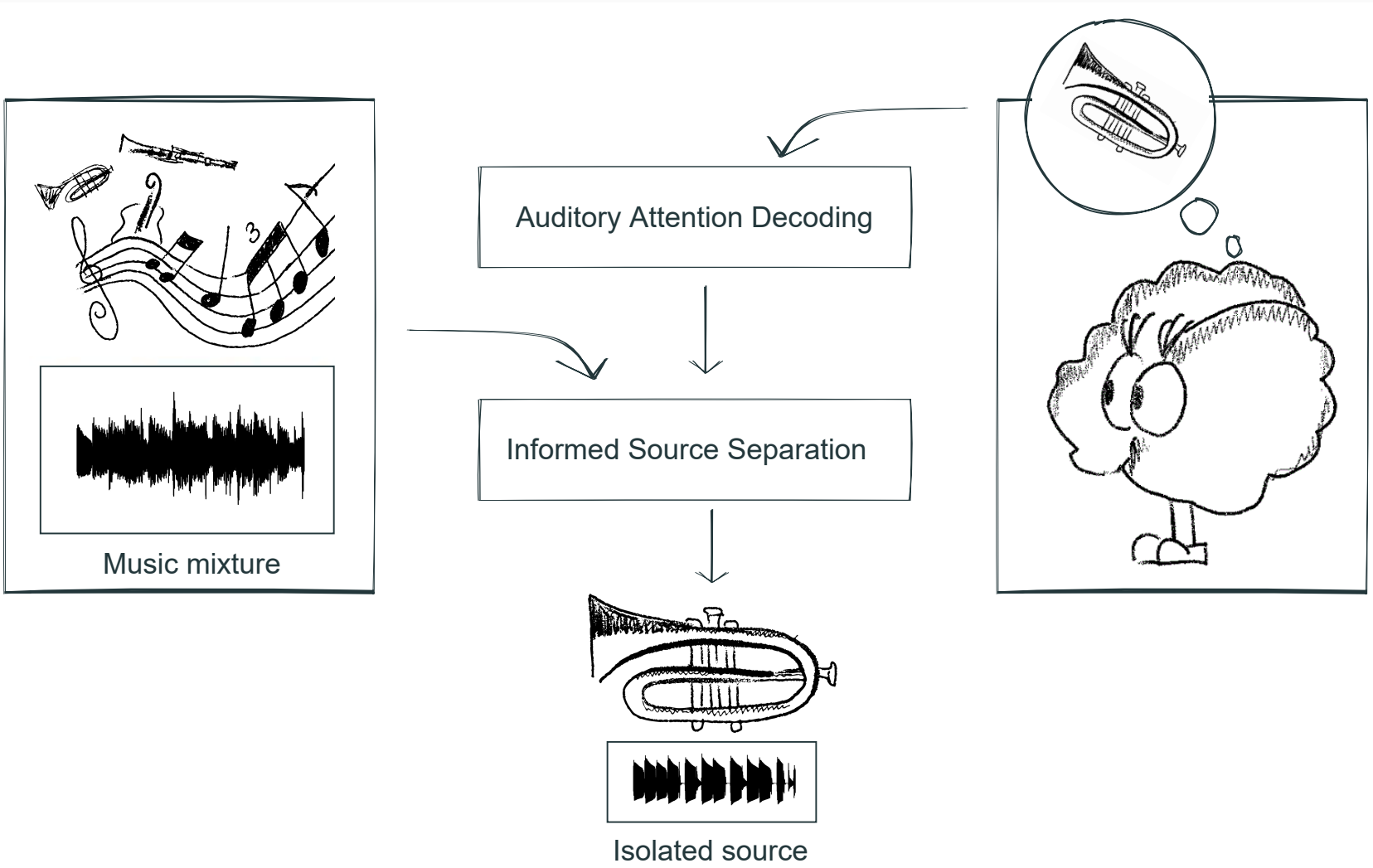
Auditory Attention

Auditory attention *is the cognitive mechanism that allows humans to focus on a sound source of interest in noisy environment.*

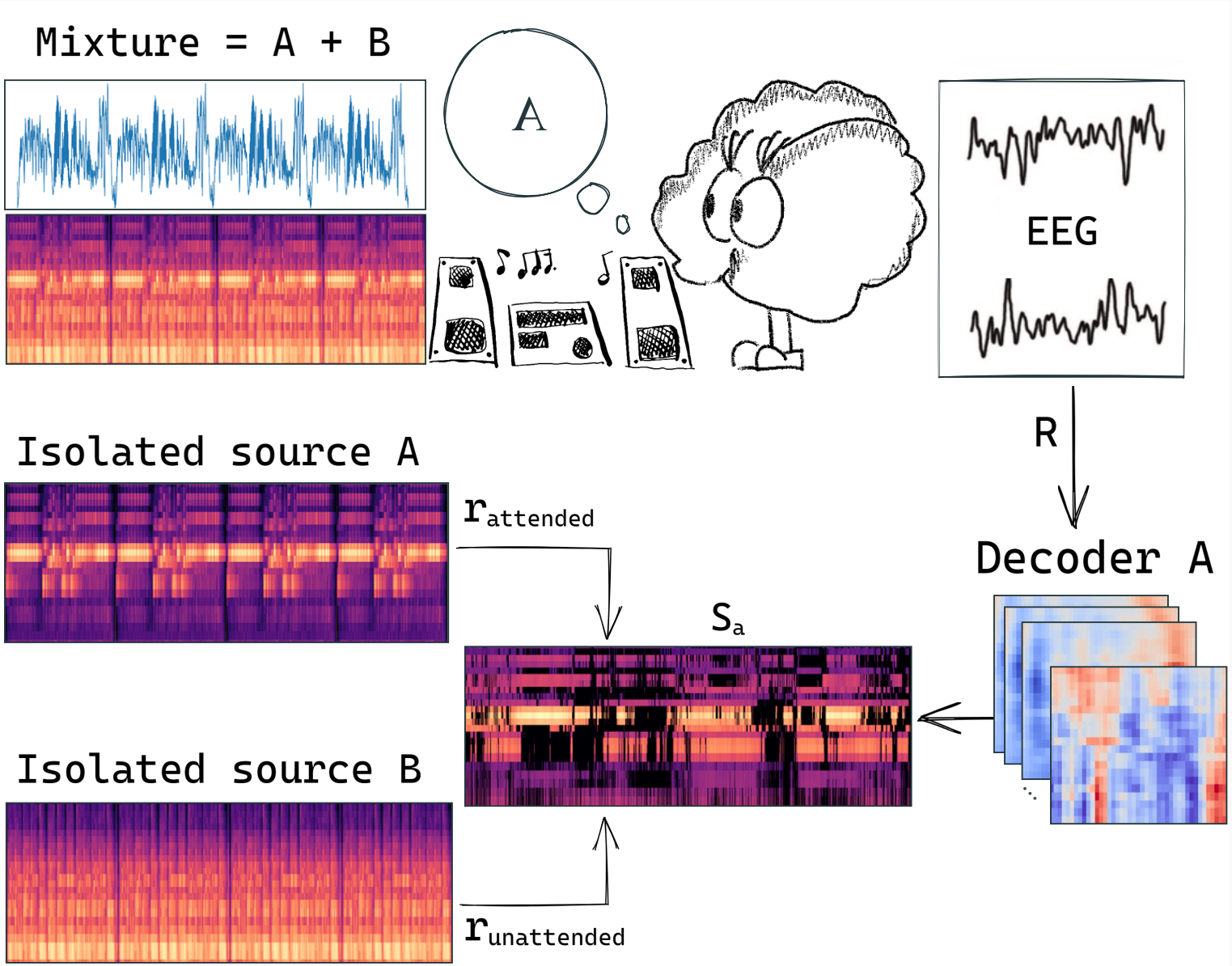
- can be tracked in the **neural activity** (EEG, ECoG, MEG);
- the attended source's neural encoding is **stronger** than the other ones;

[Mesgarani et al., 2009, Mesgarani and Chang, 2012, O'sullivan et al., 2014]

Neuro-steered Audio Source Separation



EEG-based Auditory Attention Decoding



Neuro-steered Speech Enhancement

Typically the separation and the decoding tasks are tackled **sequentially**:

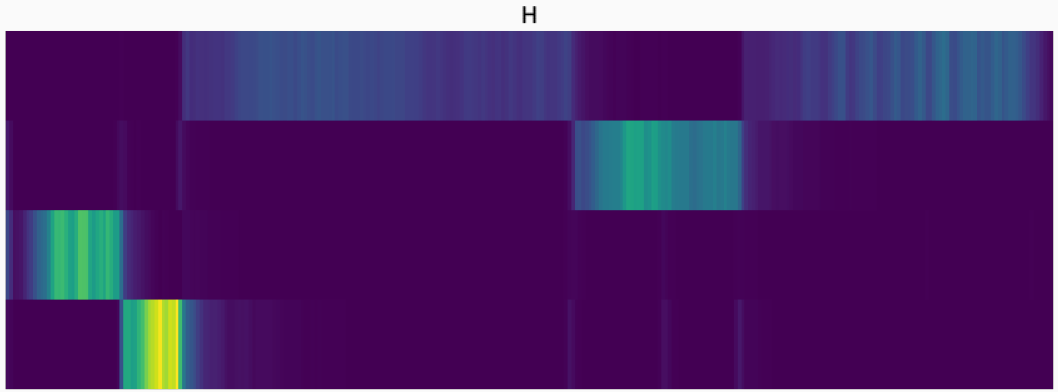
- a separation system provides the reference sources for the decoding;
- and the decoding system selects the source which needs to be enhanced.

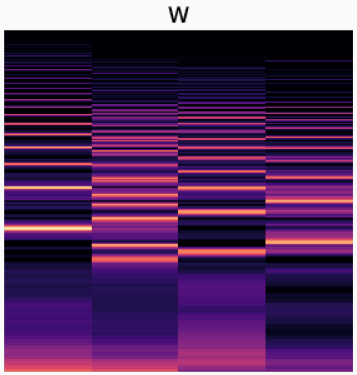
[Aroudi and Doclo, 2020, Van Eyndhoven et al., 2017, Das et al., 2020, O'Sullivan et al., 2017, Han et al., 2019, Ceolini et al., 2020]

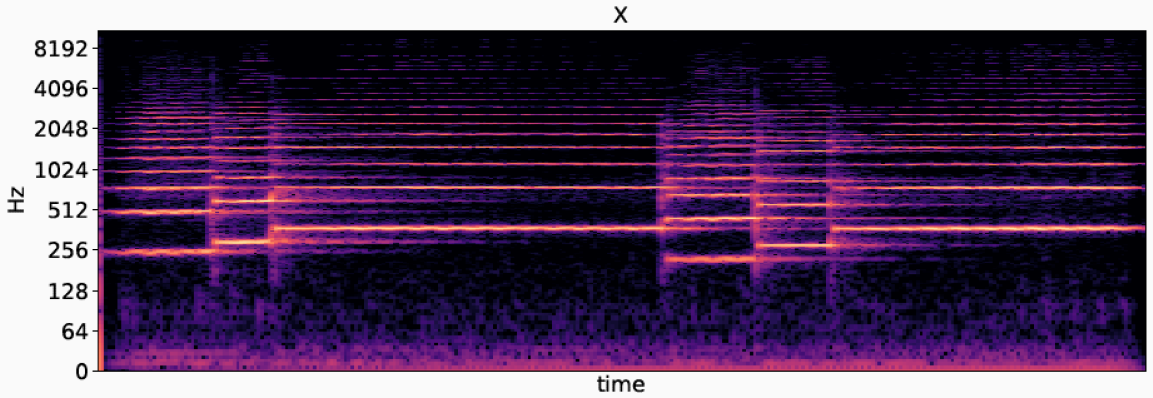
Framework

NMF for Audio Source Separation

$$\begin{cases} C(W,H) = \underbrace{D(X|WH)}_{\text{audio factorization}} + \underbrace{\mu\|H\|_1 + \beta\|W\|_1}_{\text{sparsity}} \\ W,H \geq 0. \end{cases}$$



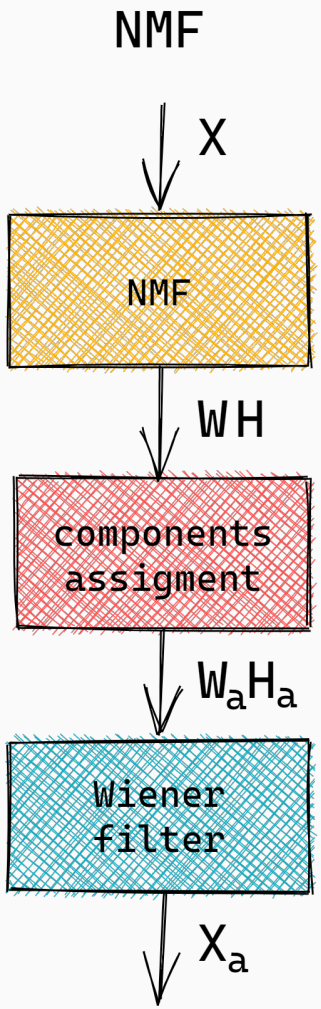




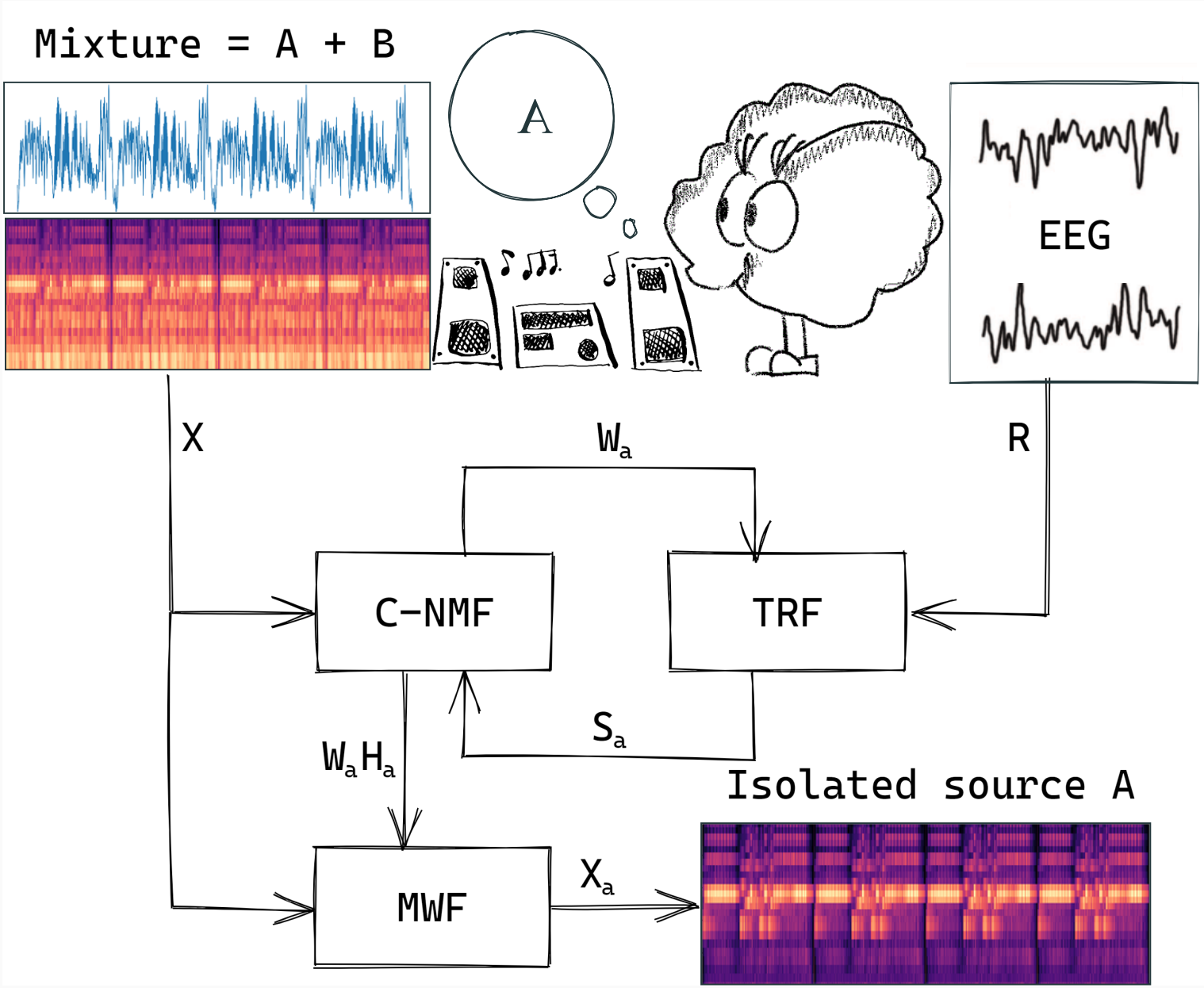
NMF for Audio Source Separation

$$\begin{cases} C(\mathrm{W},\mathrm{H}) = \underbrace{D(\mathrm{X}|\mathrm{WH})}_{\text{audio factorization}} + \underbrace{\mu\|\mathrm{H}\|_1 + \beta\|\mathrm{W}\|_1}_{\text{sparsity}} \\ \mathrm{W},\mathrm{H} \geq 0. \end{cases}$$

$$\mathrm{X}_a = \frac{\mathrm{W}_a\mathrm{H}_a}{\mathrm{WH}} \otimes \tilde{\mathrm{X}}.$$



Proposed model



Contrastive-NMF (C-NMF)

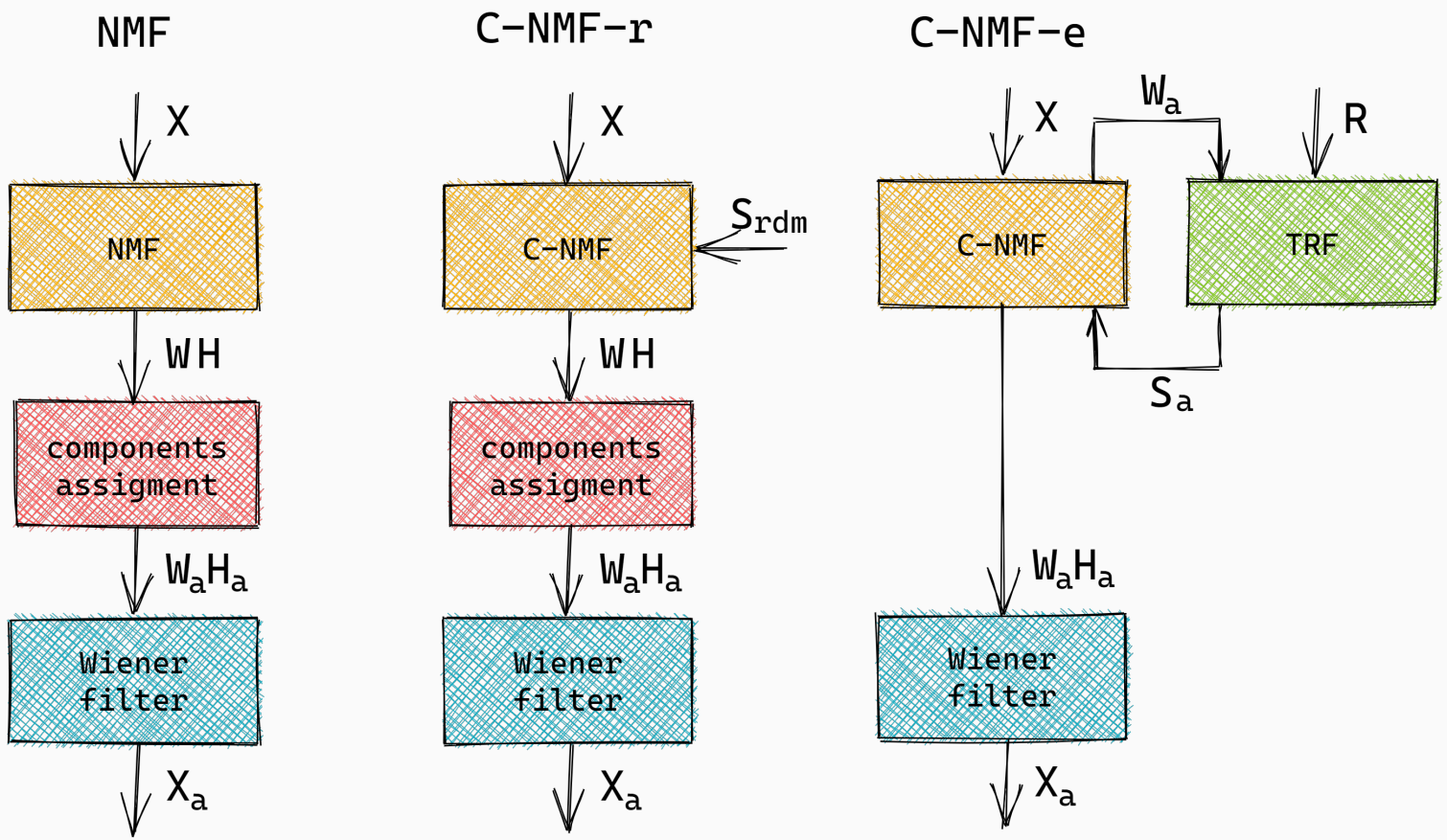
$$\begin{cases} C(\mathrm{W},\mathrm{H}) = \underbrace{D(\mathrm{X}|\mathrm{WH})}_{\text{audio factorization}} + \underbrace{\mu\|\mathrm{H}\|_1 + \beta\|\mathrm{W}\|_1}_{\text{sparsity}} - \underbrace{\delta(\|\mathrm{H}_a\mathrm{S}_a^T\|_F^2 - \|\mathrm{H}_u\mathrm{S}_a^T\|_F^2)}_{\text{contrast}} \\ \mathrm{W},\mathrm{H},\mathrm{S}_a \geq 0 \\ \|\mathbf{h}_{k:}\|_2 = 1, \|\mathbf{s}_{k:}\|_2 = 1. \end{cases}$$

The proposed cost aims at:

- **decomposing** the mixture spectrogram;
- **maximising** the similarity of S_a with H_a;
- **minimising** the similarity of S_a with H_u.

Experiments

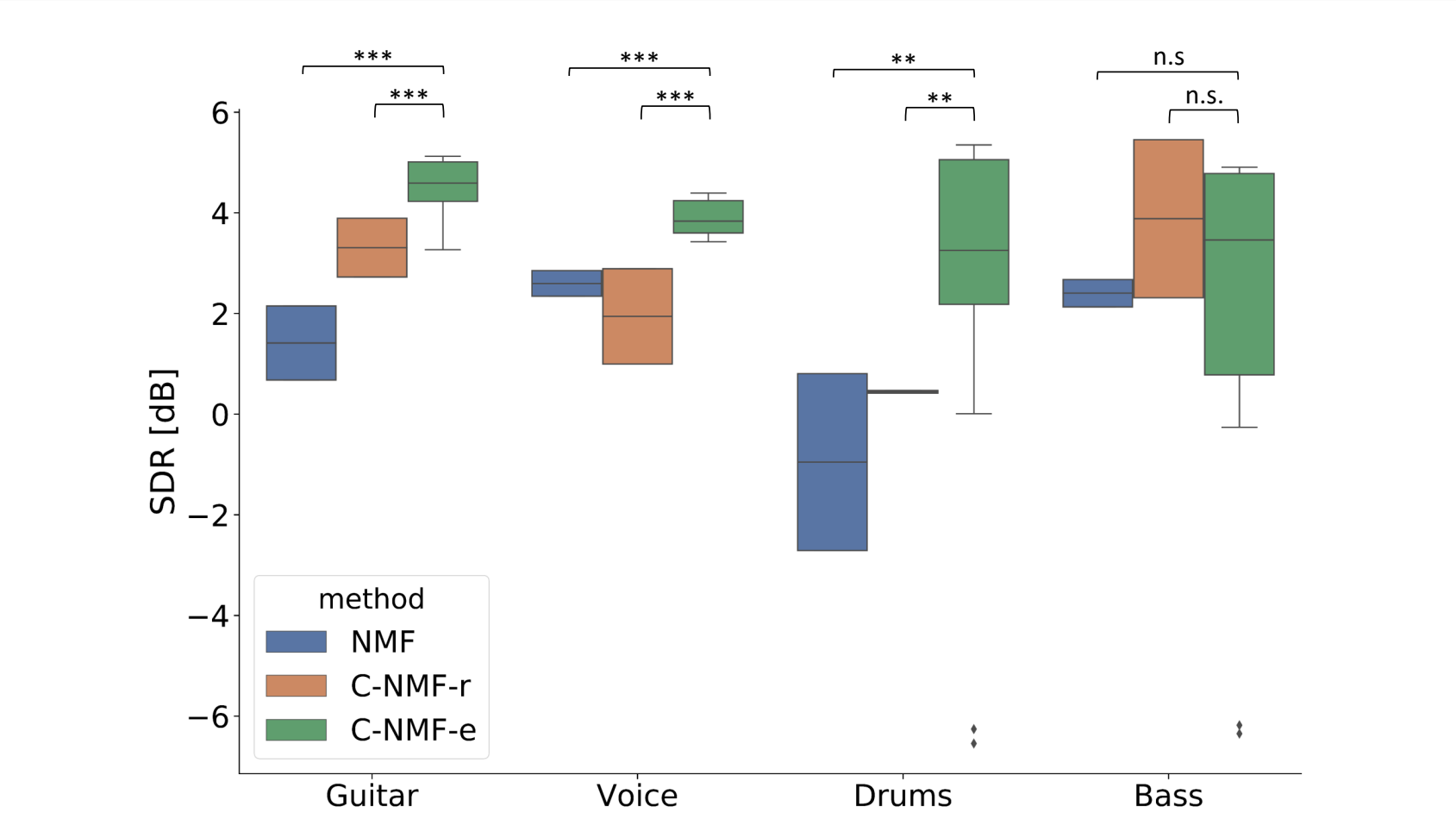
Experiments



Data: 20-channel EEG signals recorded from 8 subjects while they were attending to a particular instrument in polyphonic music [Cantisani et al., 2019].

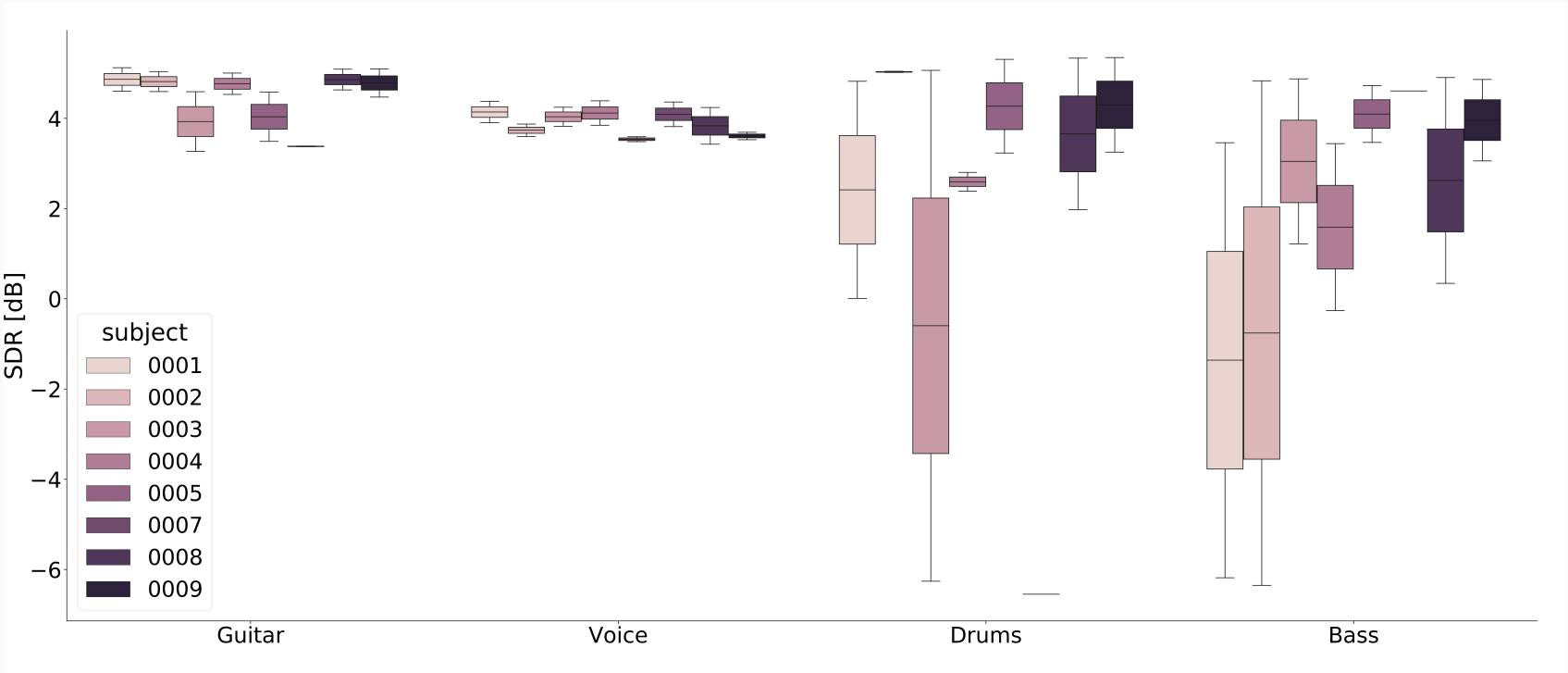
Evaluation: Signal-to-Distortion Ratio (SDR) expressed in dB.

Separation quality



C-NMF performs significantly better than both the baselines except for the bass

Inter-subject variability



- *high inter and intra-subject variability*
- *dependency on the level of attention and musical expertise*

Spatial rendering

SDR [dB]	mono	stereo
Guitar	4.6	**5.0**
Vocals	3.8	**4.3**
Drums	3.2	**5.0**
Bass	**4.0**	0.3

- *the stereo setting helps to localize the target instrument*
- *localizing the instruments helps the attention task*

Conclusions

We propose a new model for **neuro-steered music source separation**:

- **improves the separation**, especially in difficult cases;
- **automatically separates the attended source**;
- auditory attention decoding **without the reference sources**.

Resources

Thank you for the attention!

GitHub Code

Demo

Update rule

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