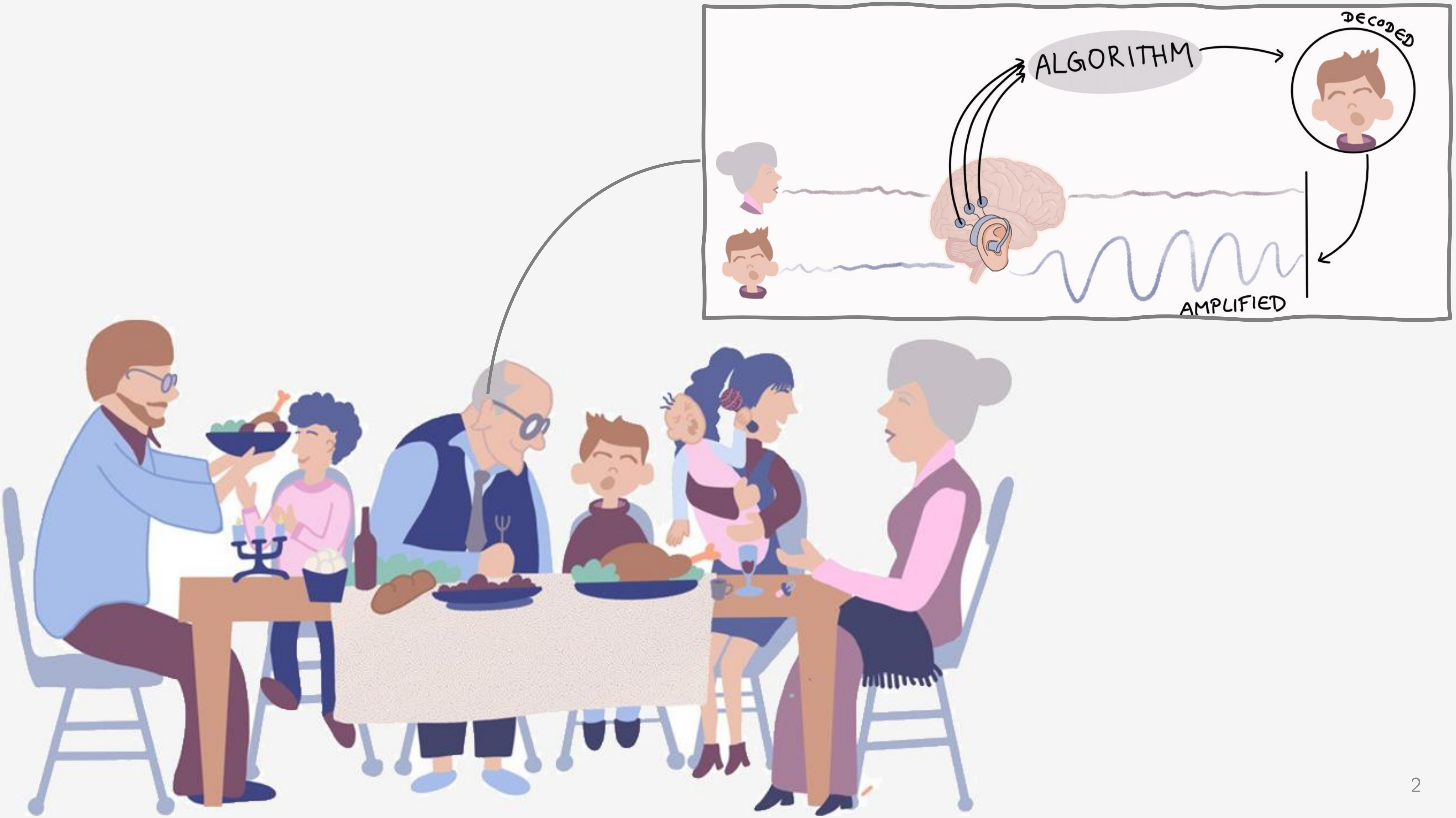
AAD signal processing Into The Wild

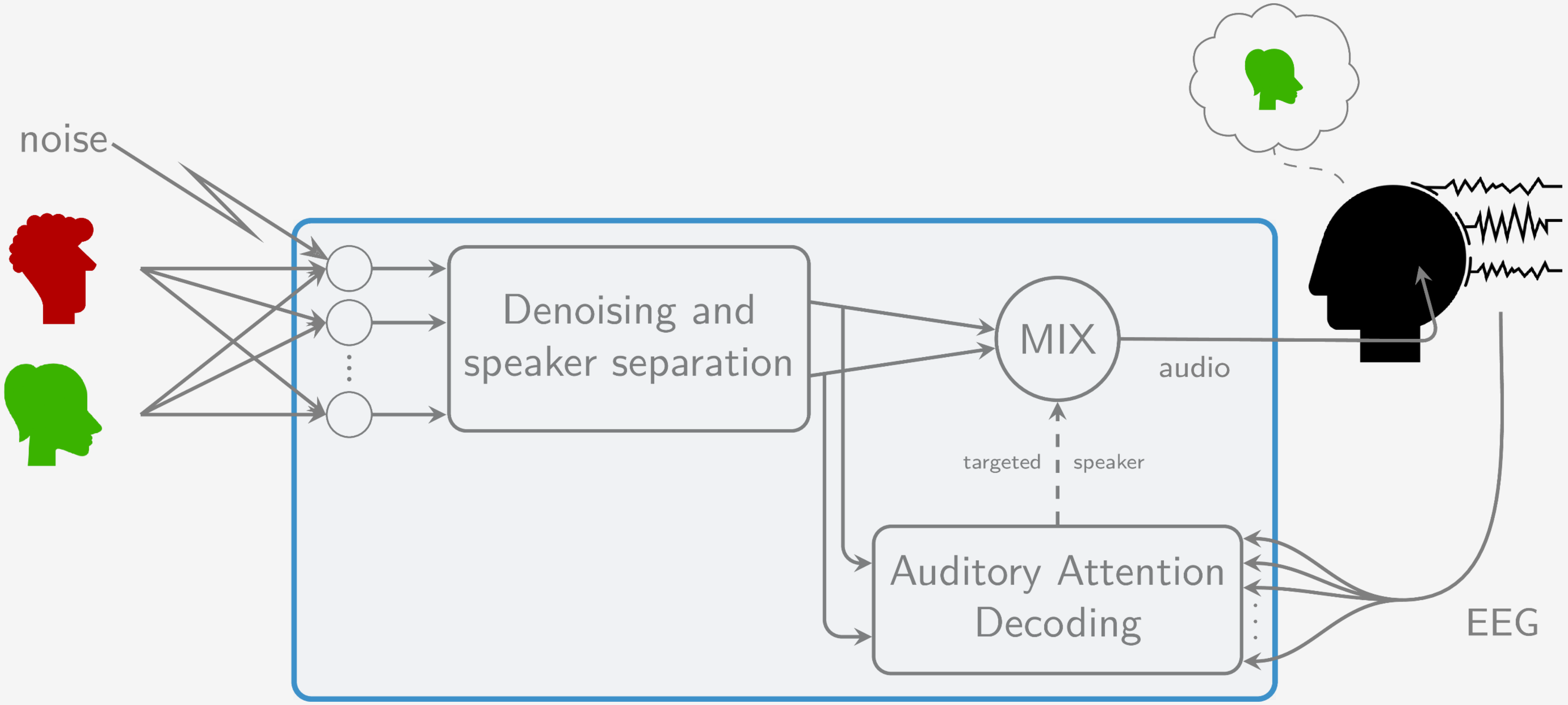
Simon Geirnaert

STADIUS Center for Dynamical Systems, Signal Processing and Data Analytics

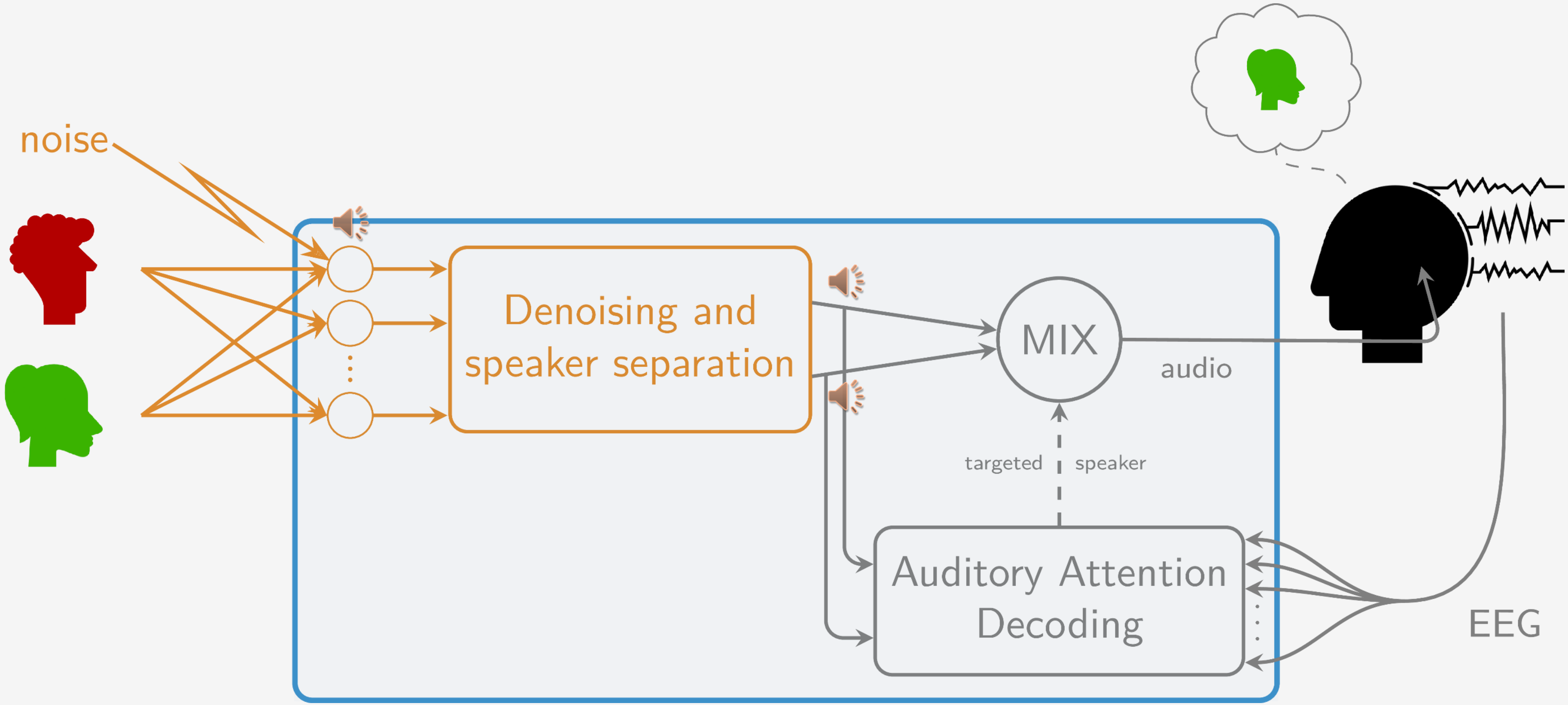
KU LEUVEN

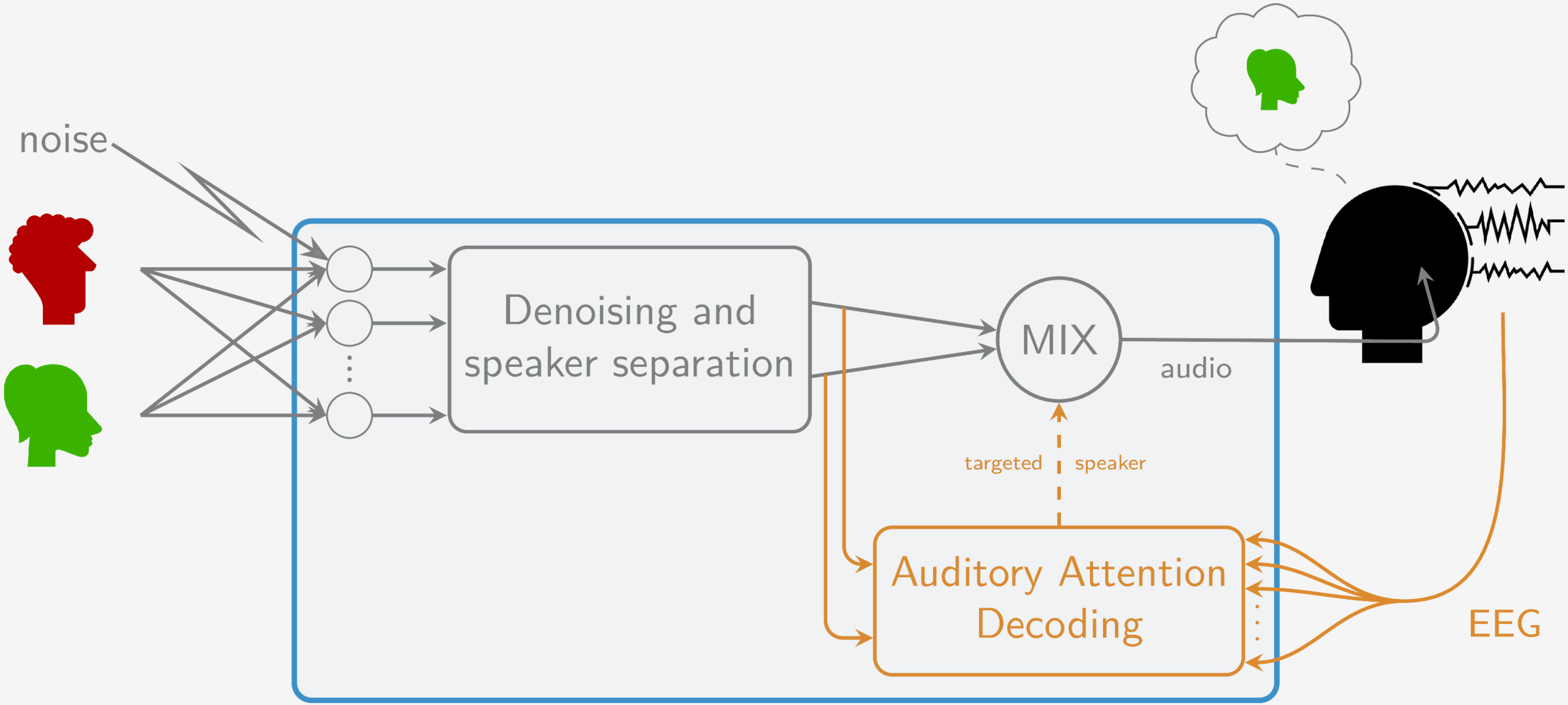
KU LEUVEN expORL


ALGORITHM
DECODED
AMPLIFIED



Smart neuro-steered hearing device


noise
Denoising and speaker separation
MIX
audio
targeted speaker
Auditory Attention Decoding
EEG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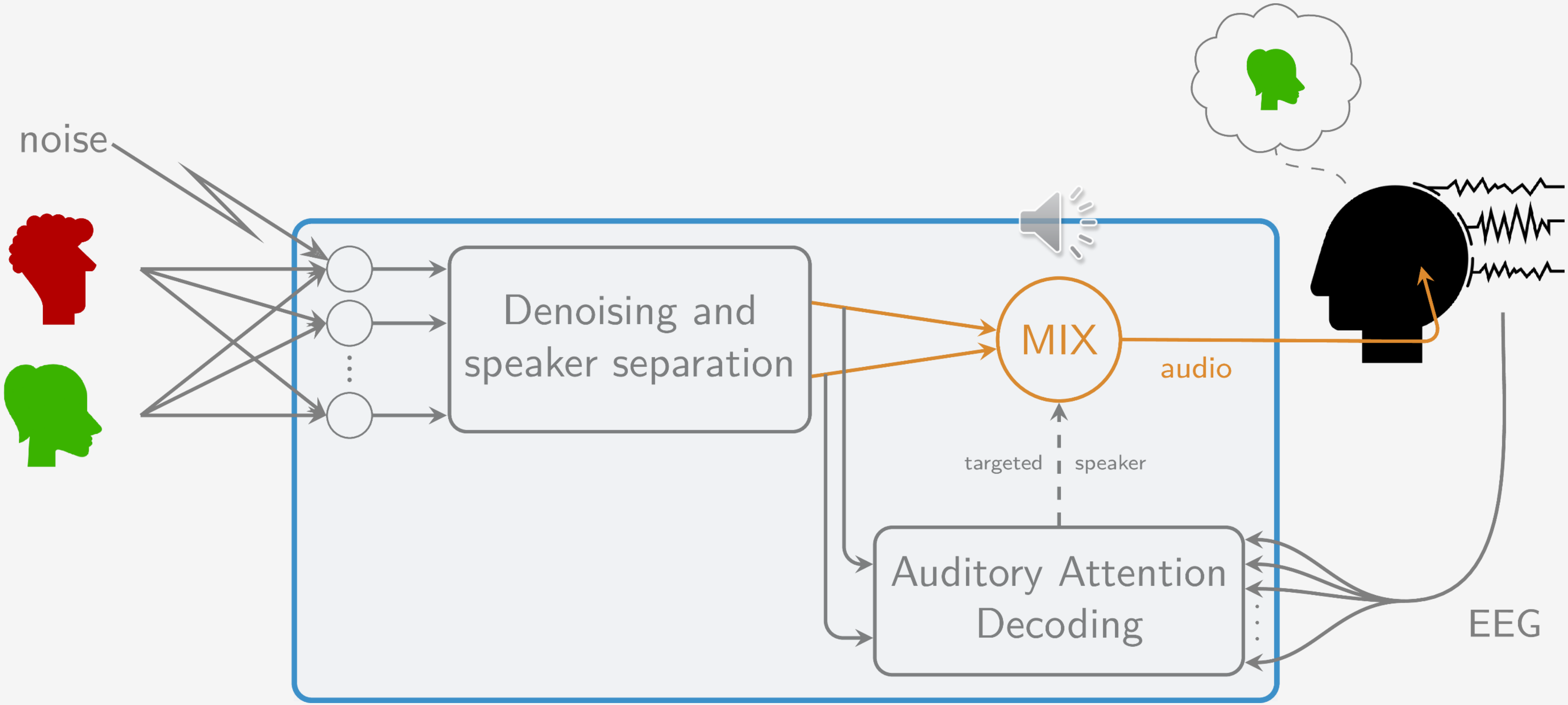
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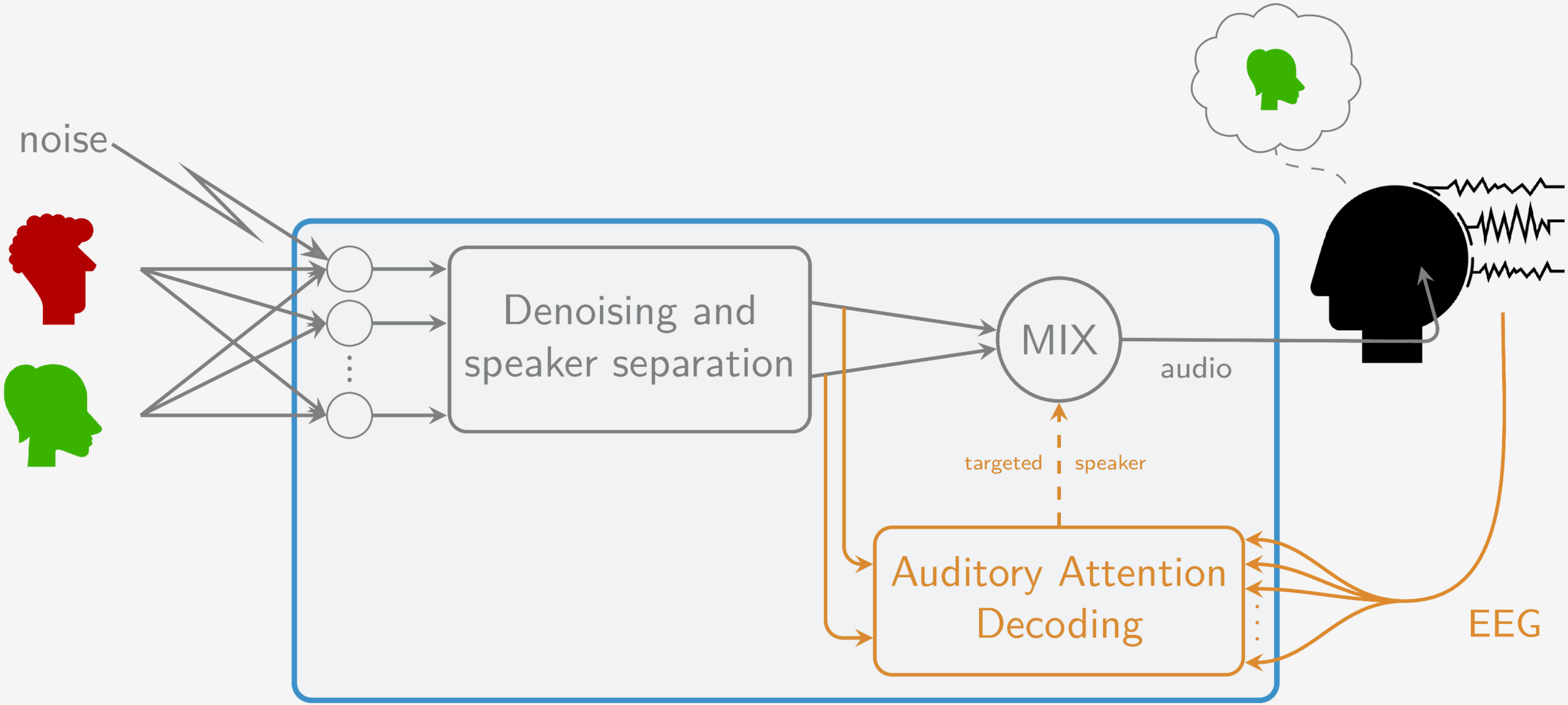
EEG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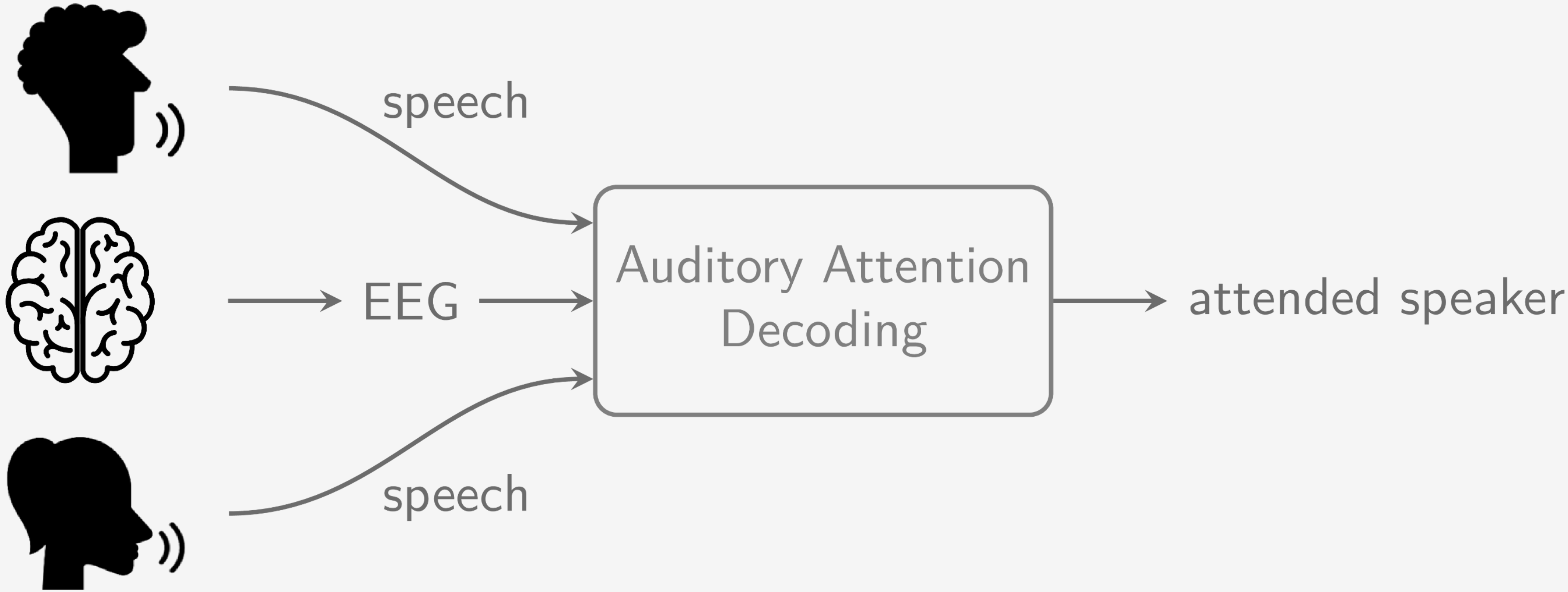
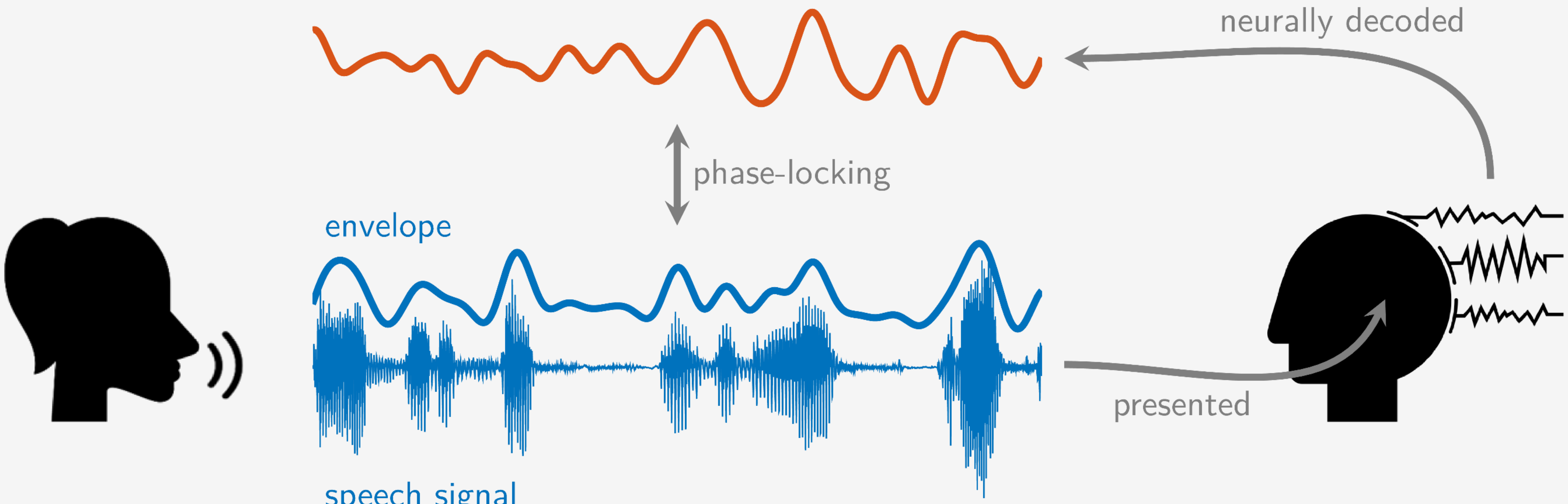
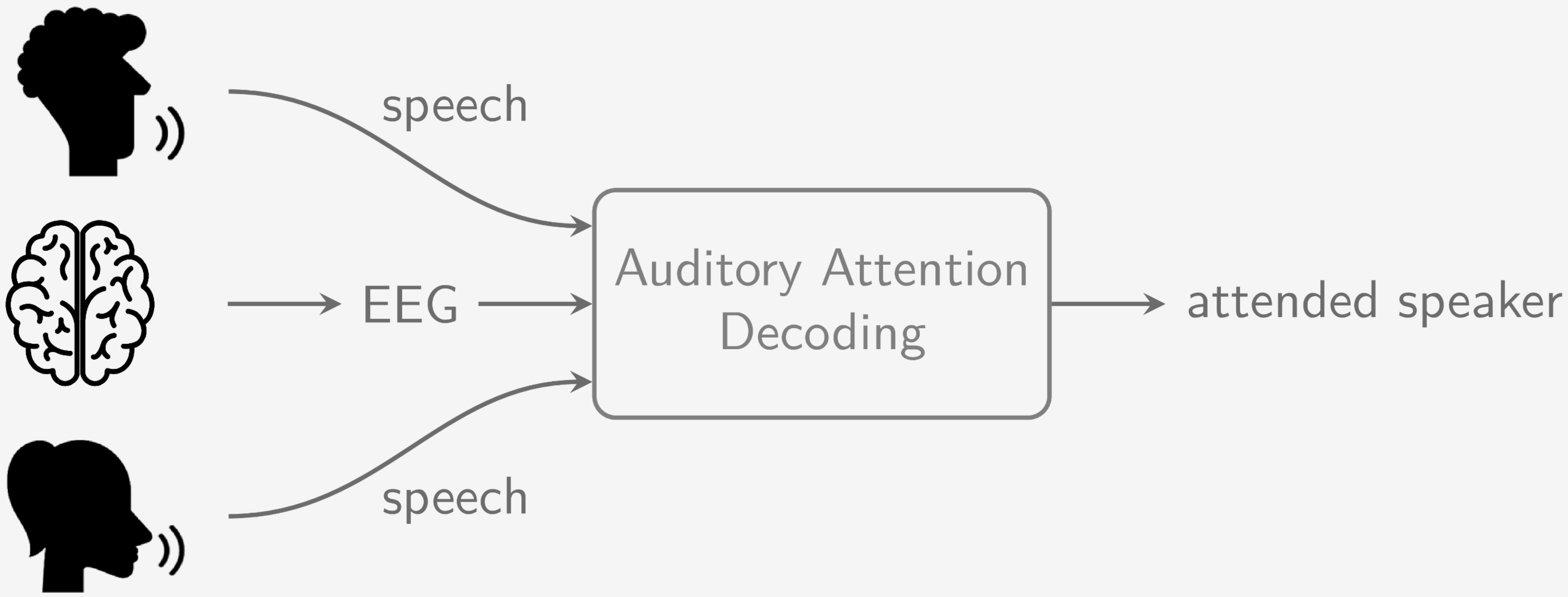
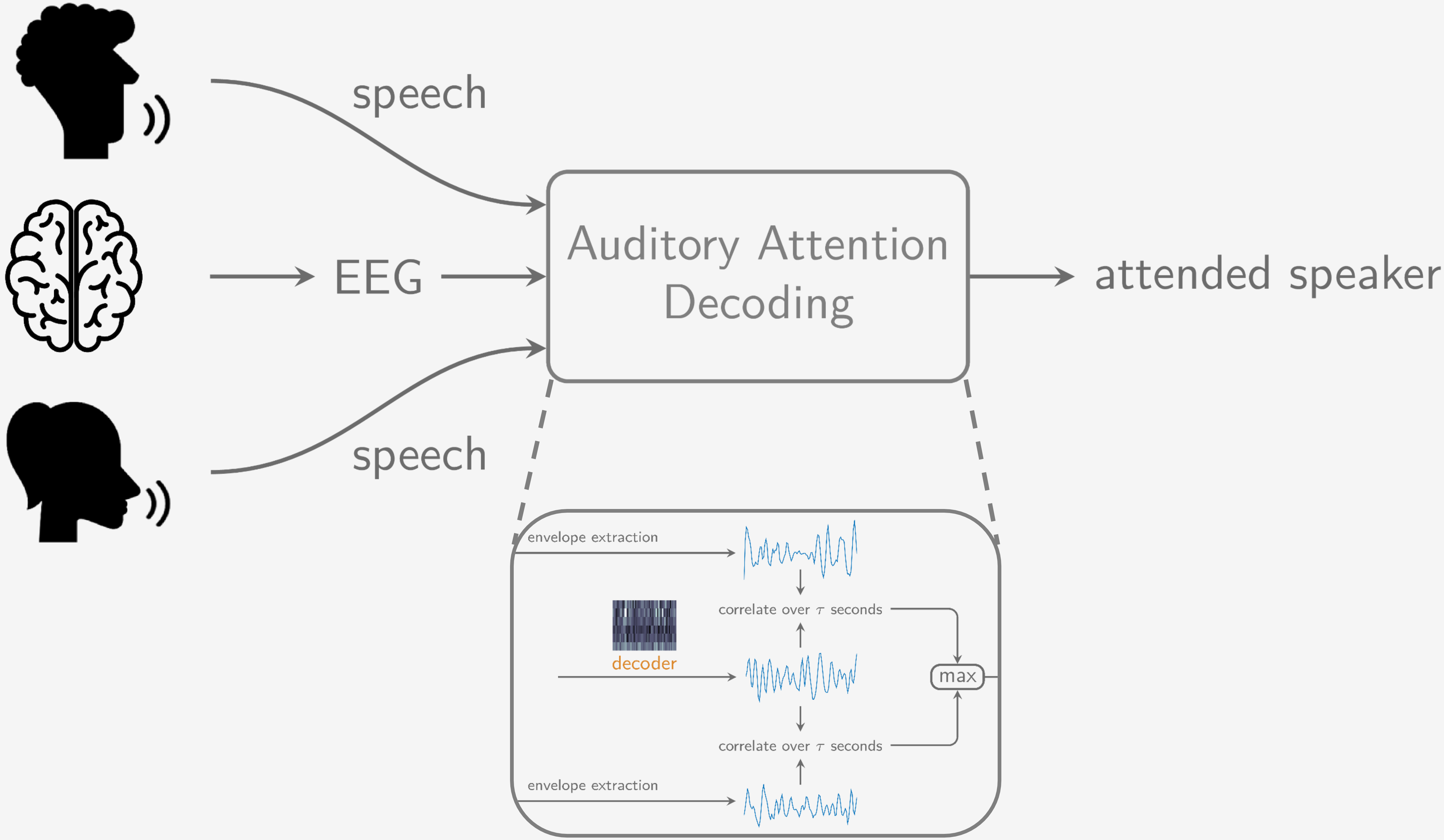
Auditory Attention Decoding
EEG


speech
EEG
Auditory Attention Decoding
attended speaker
speech

Neural tracking of speech

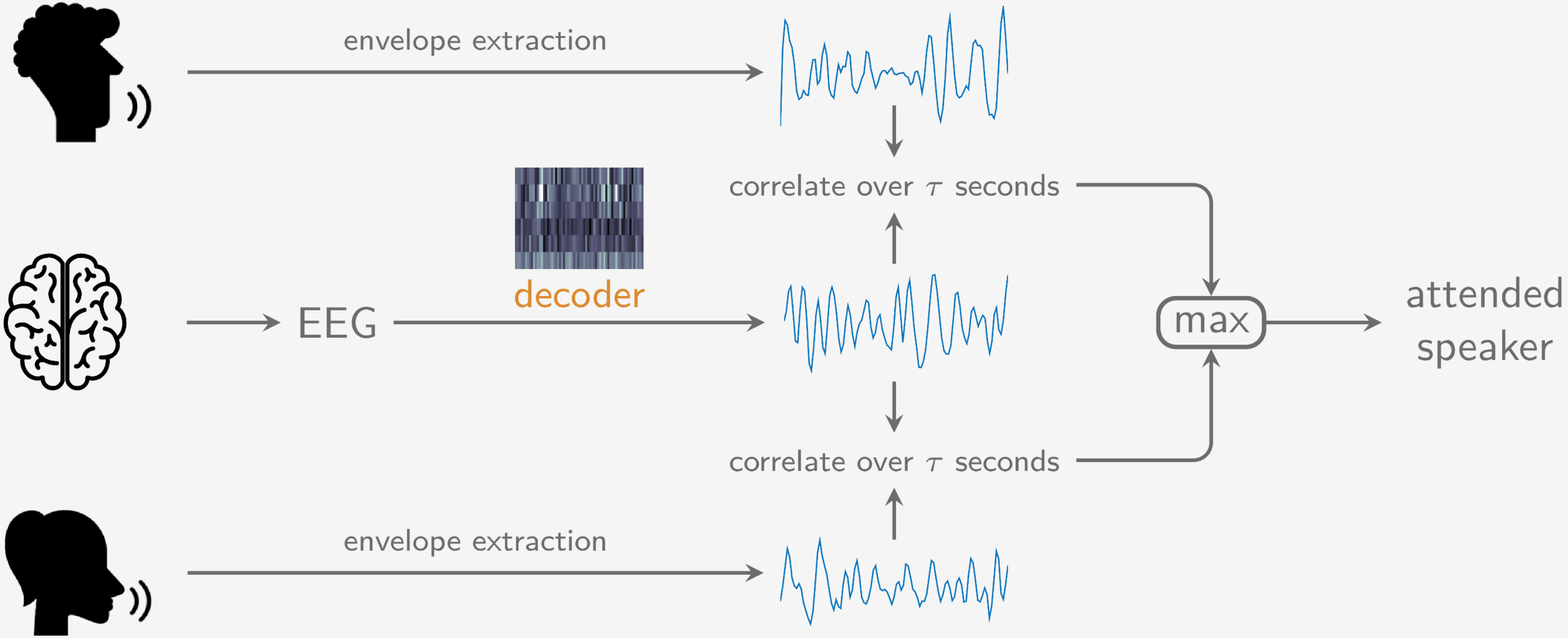



speech
EEG
Auditory Attention Decoding
attended speaker
speech



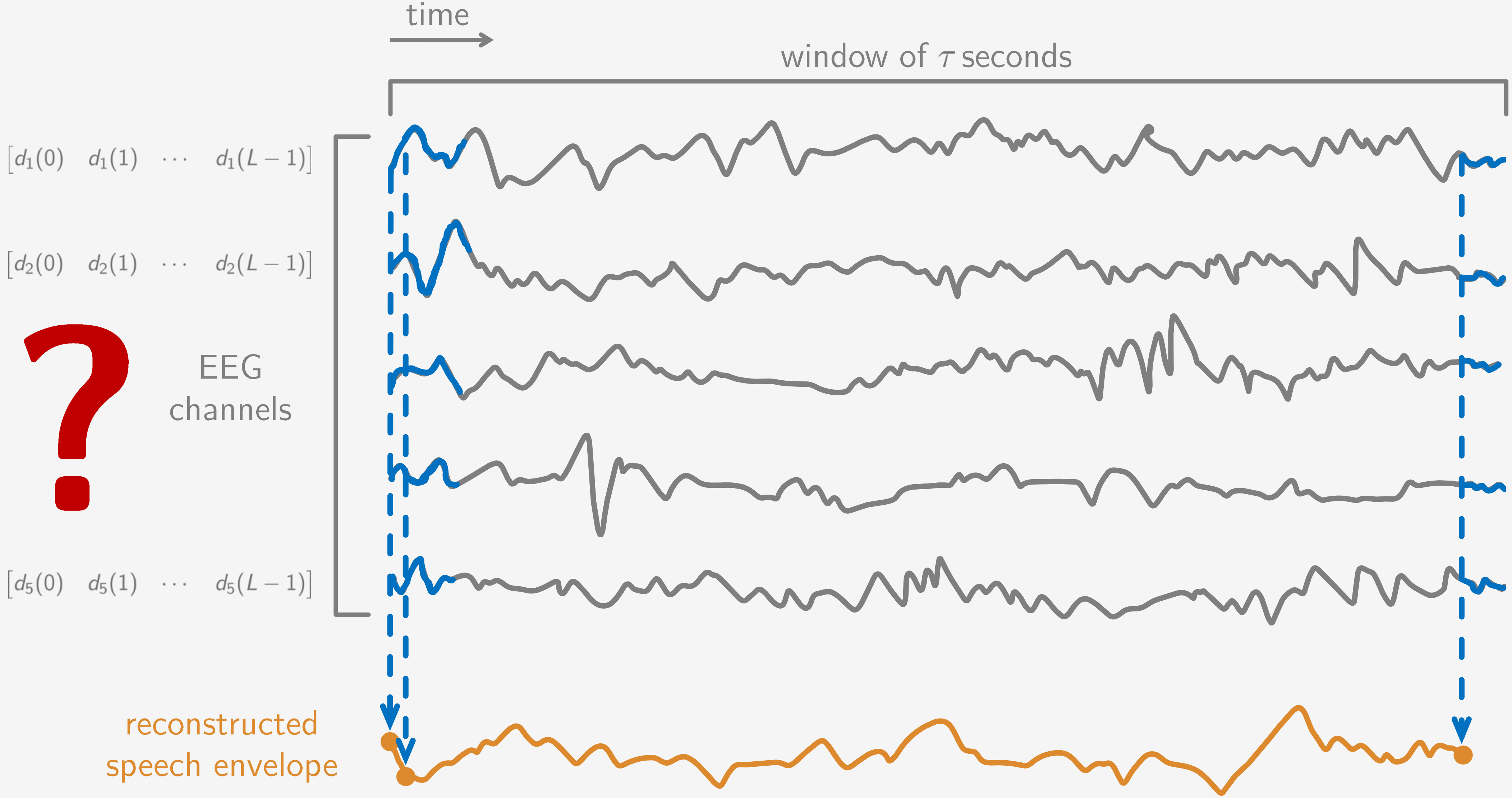
speech
EEG
speech
Auditory Attention Decoding
attended speaker
envelope extraction
correlate over τ seconds
decoder
max
correlate over τ seconds
envelope extraction

Stimulus reconstruction

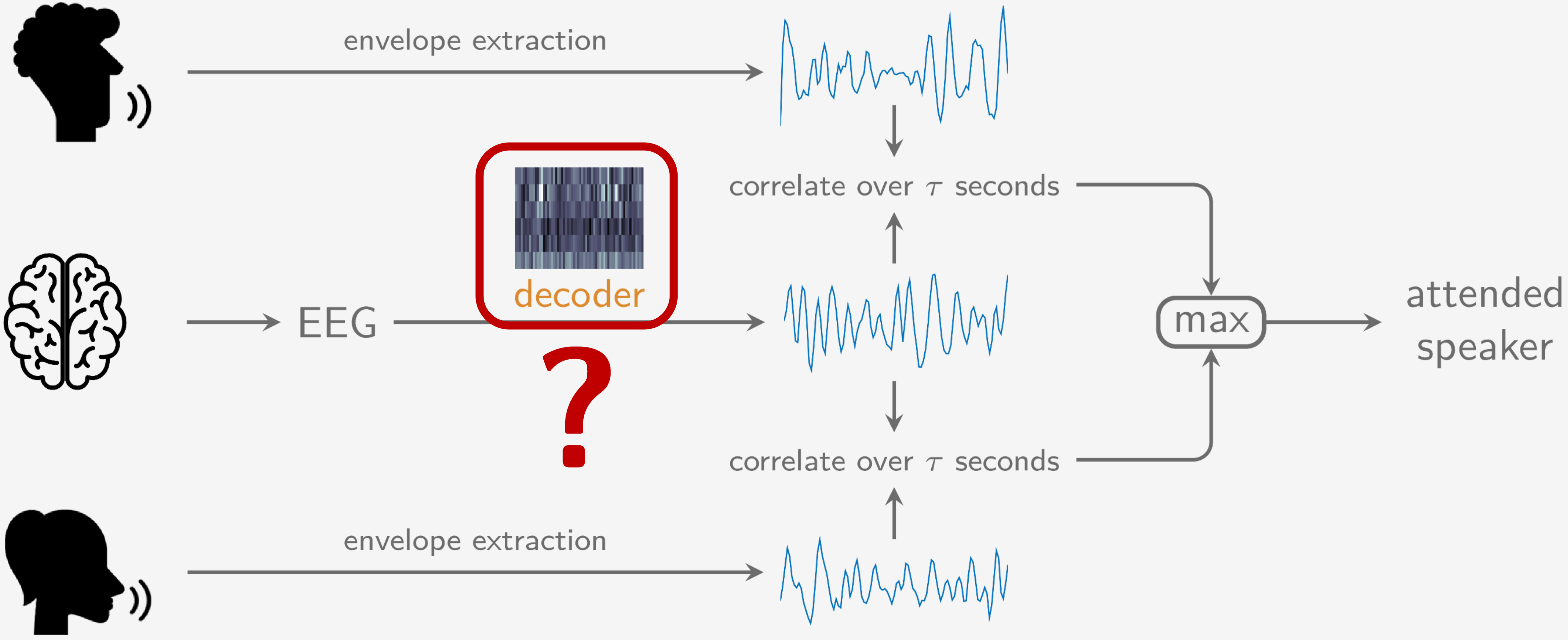


J. O'Sullivan et al, "Attentional Selection in a Cocktail Party Environment Can Be Decoded from Single-Trial EEG", *Cerebral Cortex*, vol. 25, no. 7, pp. 1697–1706, 2014

Linear spatio-temporal decoder

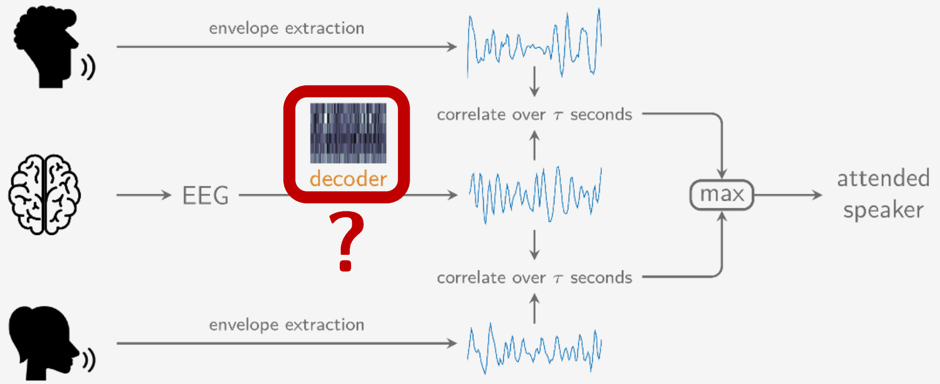


Stimulus reconstruction – backward decoding



J. O'Sullivan et al, "Attentional Selection in a Cocktail Party Environment Can Be Decoded from Single-Trial EEG", *Cerebral Cortex*, vol. 25, no. 7, pp. 1697–1706, 2014

Least-squares decoding



Target

$$\hat{\mathbf{d}} = \underset{\mathbf{d}}{\operatorname{argmin}} \; ||\mathbf{s}_\mathrm{a} - \mathbf{X}\mathbf{d}||_2^2$$

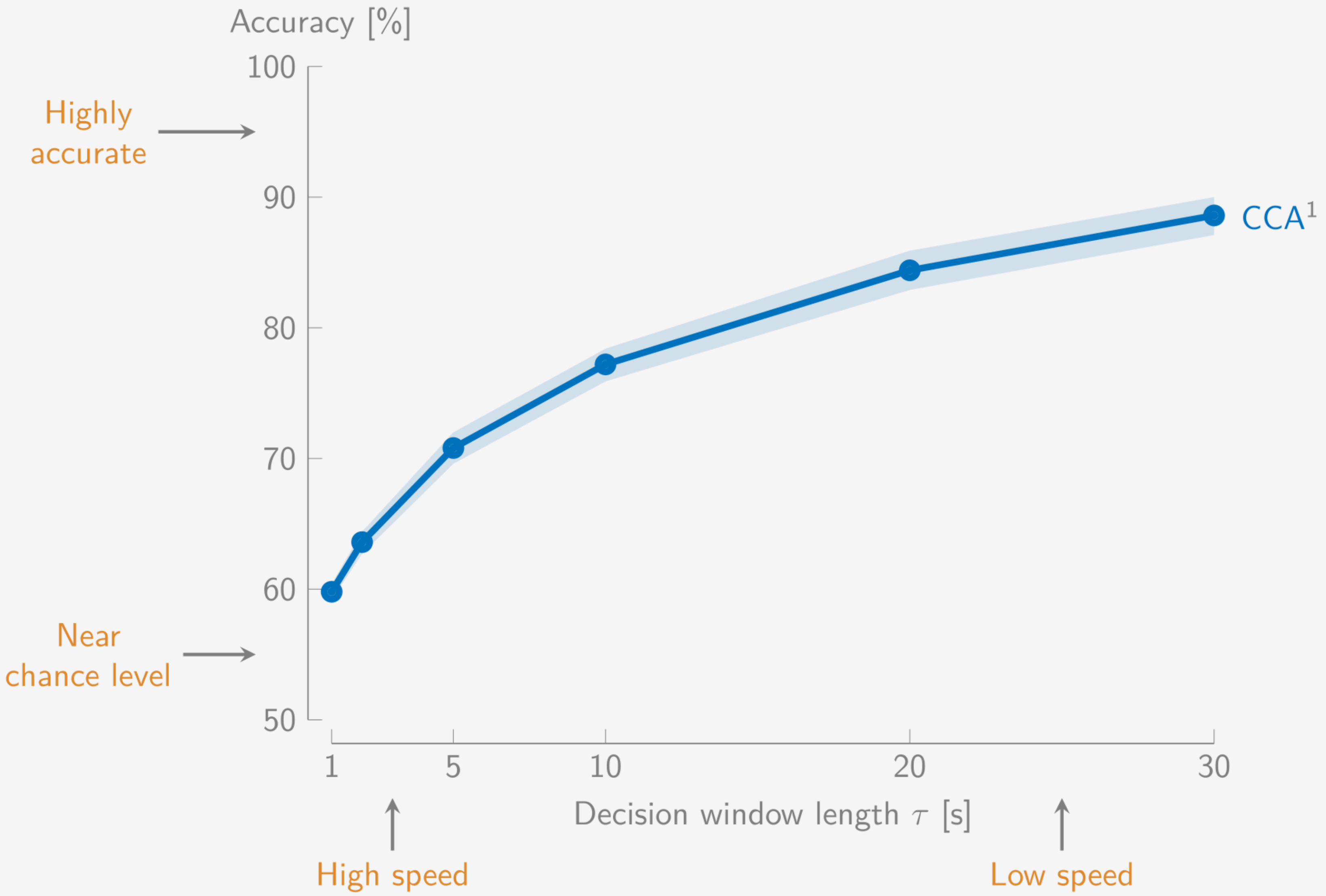
Solution

$$\hat{\mathbf{d}} = \mathbf{R}_{xx}^{-1}\mathbf{r}_{xs_a}$$

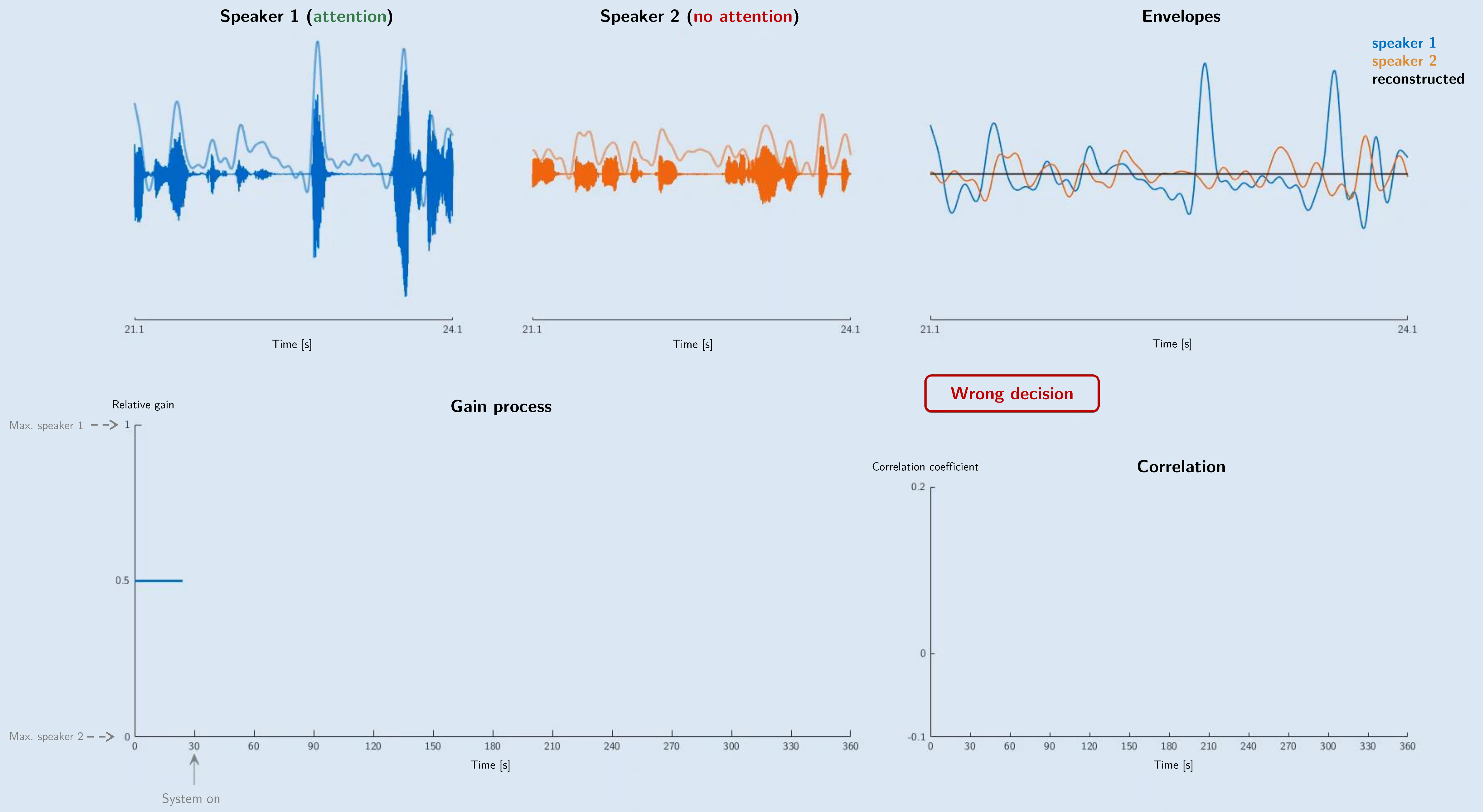
with $\mathbf{R}_{xx} = \mathbf{X}^\mathrm{T}\mathbf{X}$ and $\mathbf{r}_{xs_a} = \mathbf{X}^\mathrm{T}\mathbf{s}_a$

time
window of τ s
window of τ s
window of τ s
EEG channels
speech envelopes

Accuracy-speed tradeoff for stimulus reconstruction



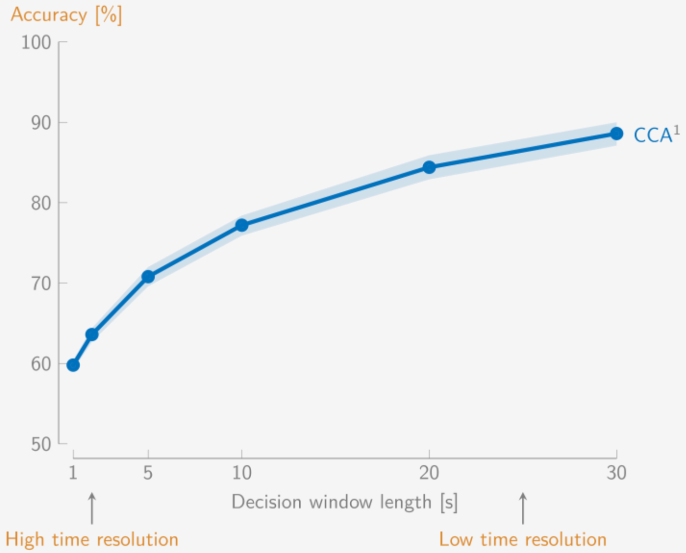
[1]A. de Cheveigné, D.D.E. Wong, G. M. Di Liberto, J. Hjortkjaer, M. Slaney, and E. C. Lalor, "Decoding the auditory brain with canonical component analysis," *NeuroImage*, vol. 172, pp. 206-216, 2018

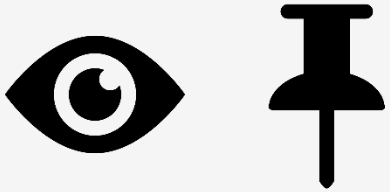


Speaker 1 (attention)
21.1
24.1
Time [s]
Speaker 2 (no attention)
21.1
24.1
Time [s]
Envelopes
speaker 1
speaker 2
reconstructed
21.1
24.1
Time [s]
Wrong decision
Relative gain
Gain process
Max. speaker 1
1
0.5
Max. speaker 2
0
0
30
60
90
120
150
180
210
240
270
300
330
360
Time [s]
System on
Correlation coefficient
Correlation
0.2
0
-0.1
0
30
60
90
120
150
180
210
240
270
300
330
360
Time [s]

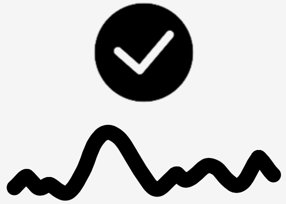
Focus on two signal processing challenges in AAD

1. Low signal-to-noise ratio leads to accuracy-speed tradeoff





2. Existing AAD algorithms need to be pre-trained offline in a supervised manner, and are fixed during operation



3. Existing AAD algorithms rely on the availability of clean speech signal envelopes

4. Existing AAD algorithms often assume bulky, non-wearable EEG setups

Focus on two signal processing challenges in AAD

1. Low signal-to-noise ratio leads to accuracy-speed tradeoff

2. Existing AAD algorithms need to be pre-trained offline in a supervised manner, and are fixed during operation

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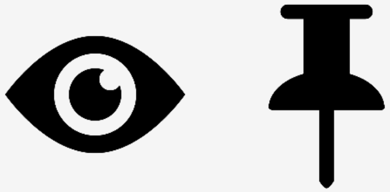
Focus on two signal processing challenges in AAD



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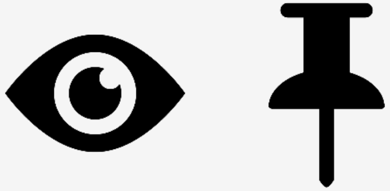
Focus on two signal processing challenges in AAD



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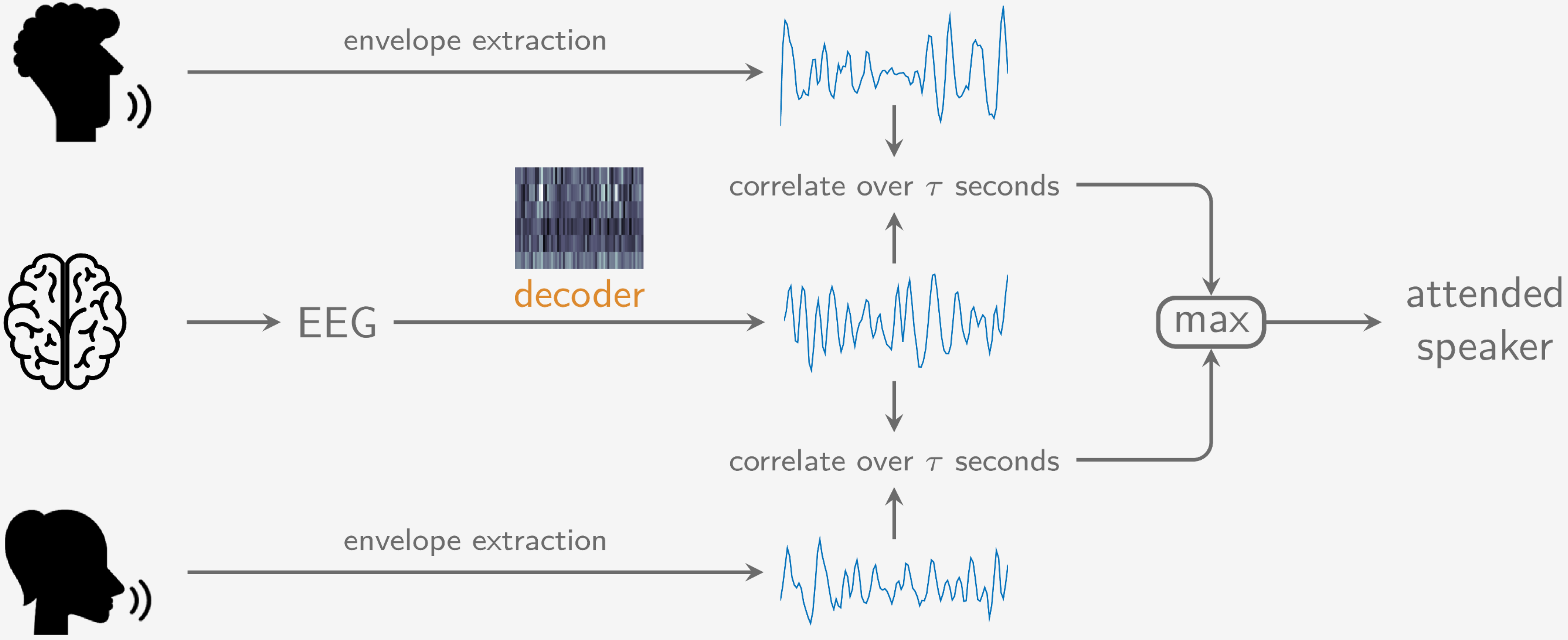
Supervised training of the stimulus decoder



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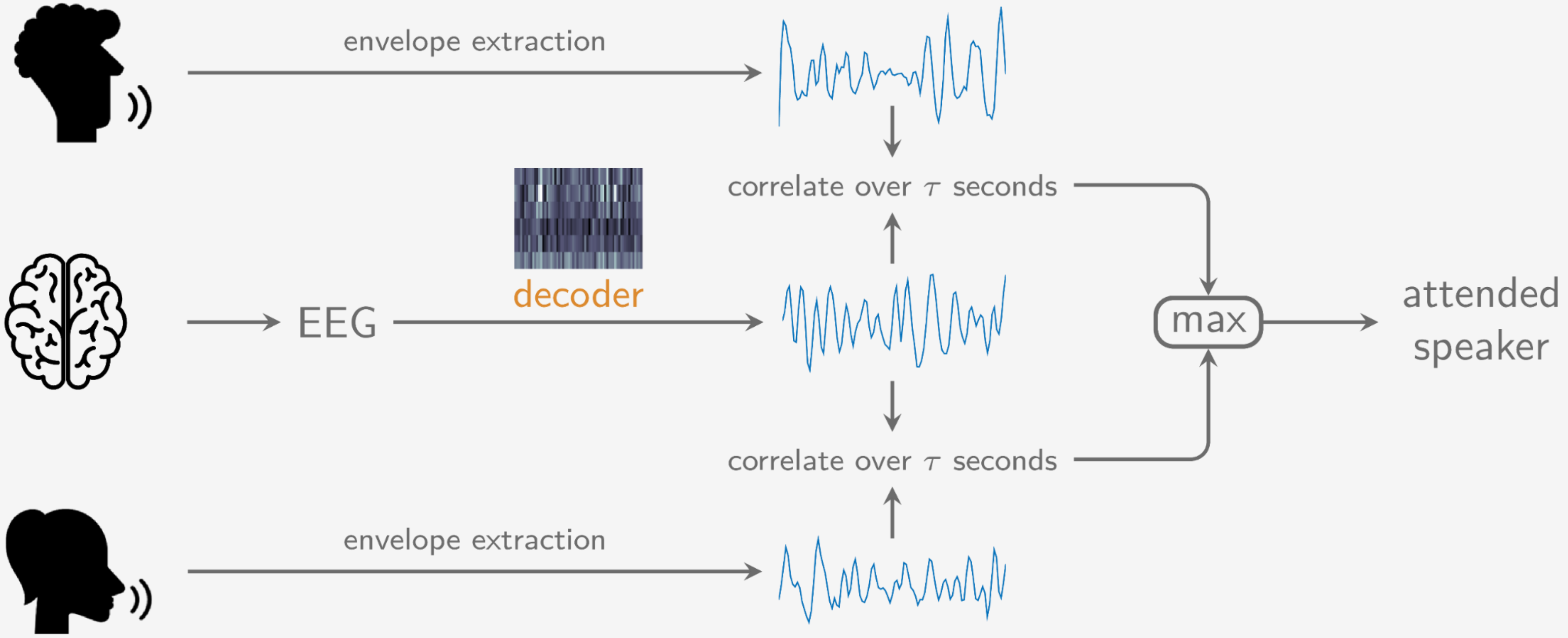

Least-squares decoder

$$\hat{\mathbf{d}} = \mathbf{R}_{xx}^{-1}\mathbf{r}_{xs_a}$$

with $\mathbf{R}_{xx} = \mathbf{X}^{\mathrm{T}}\mathbf{X}$ and $\mathbf{r}_{xs_a} = \mathbf{X}^{\mathrm{T}}\mathbf{s}_a$

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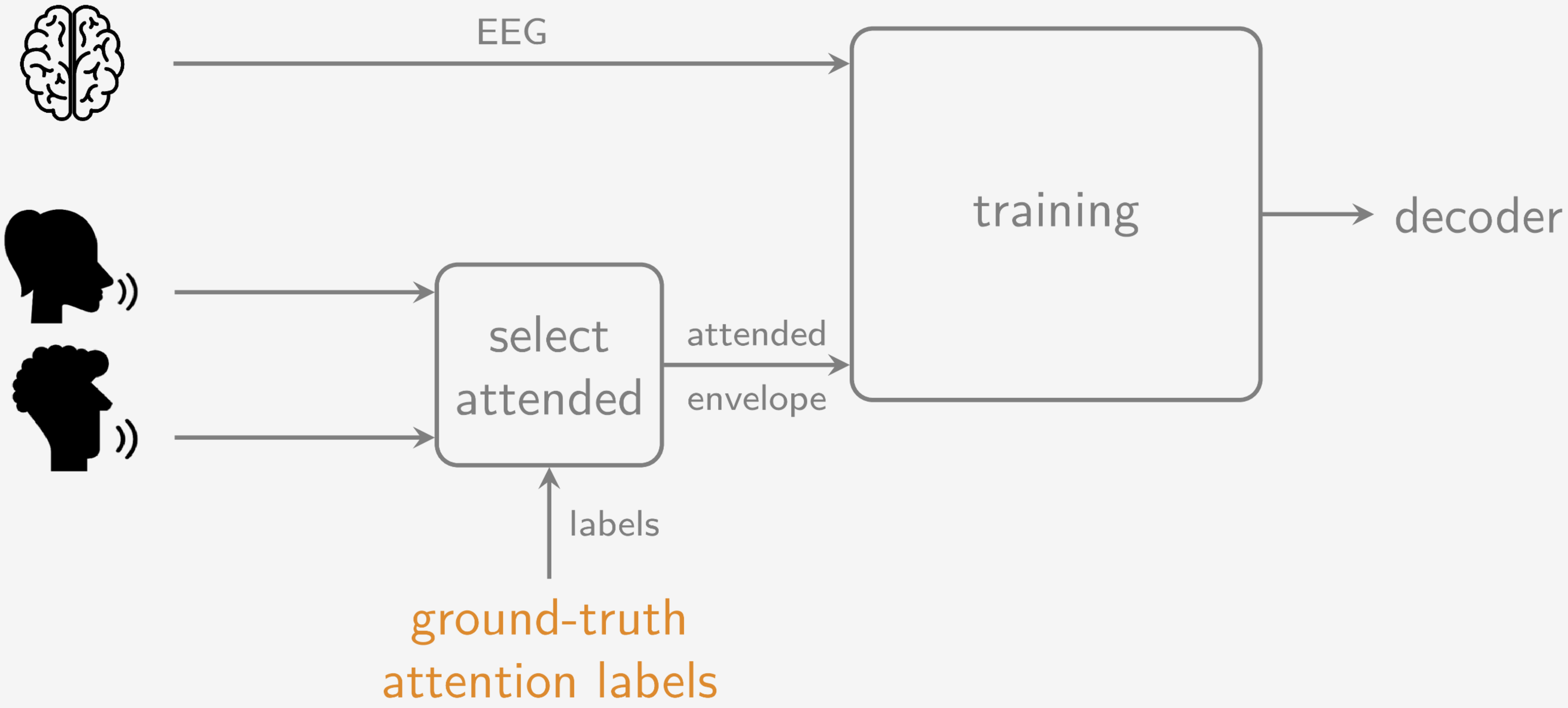
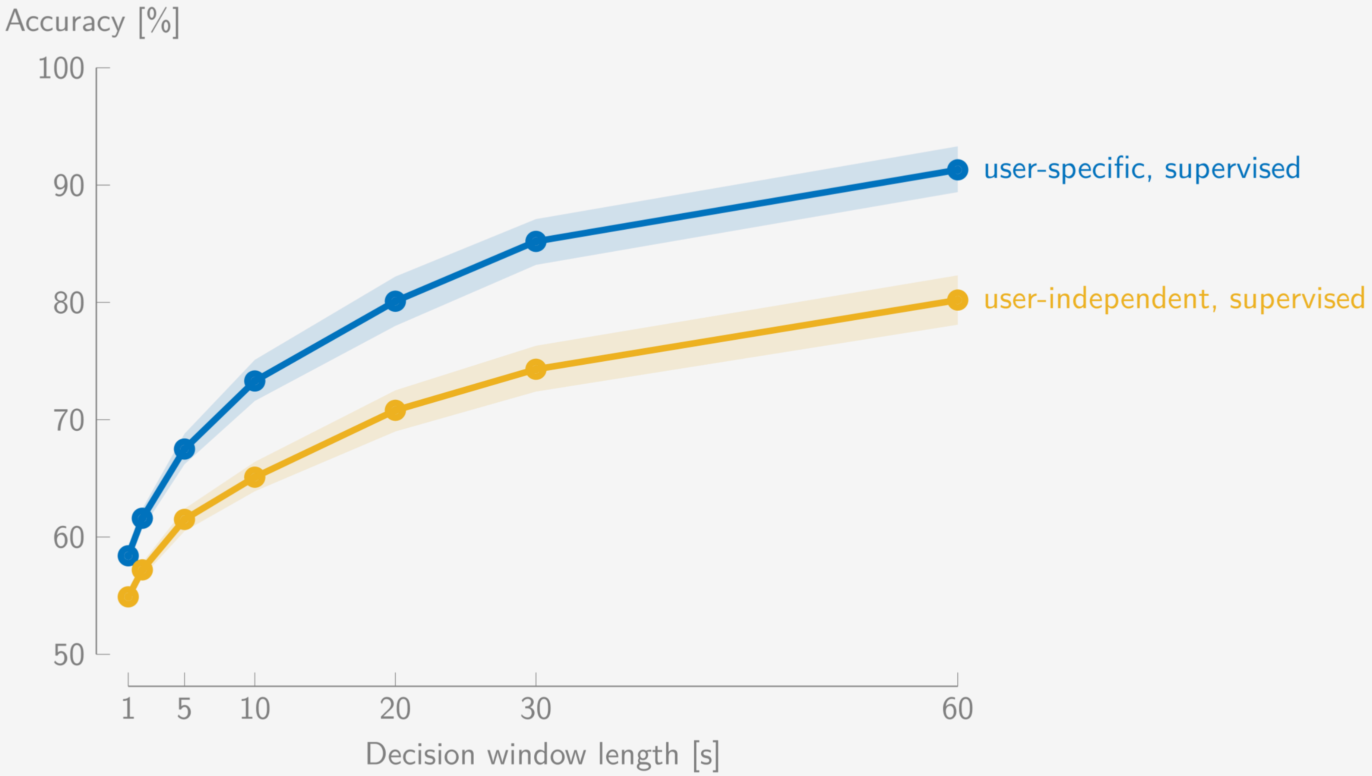


Supervised training of the stimulus decoder

User-specific	User-independent
Higher performance	**Lower** performance
Per-user training phase required	**Plug-and-play**



Supervised training of the stimulus decoder

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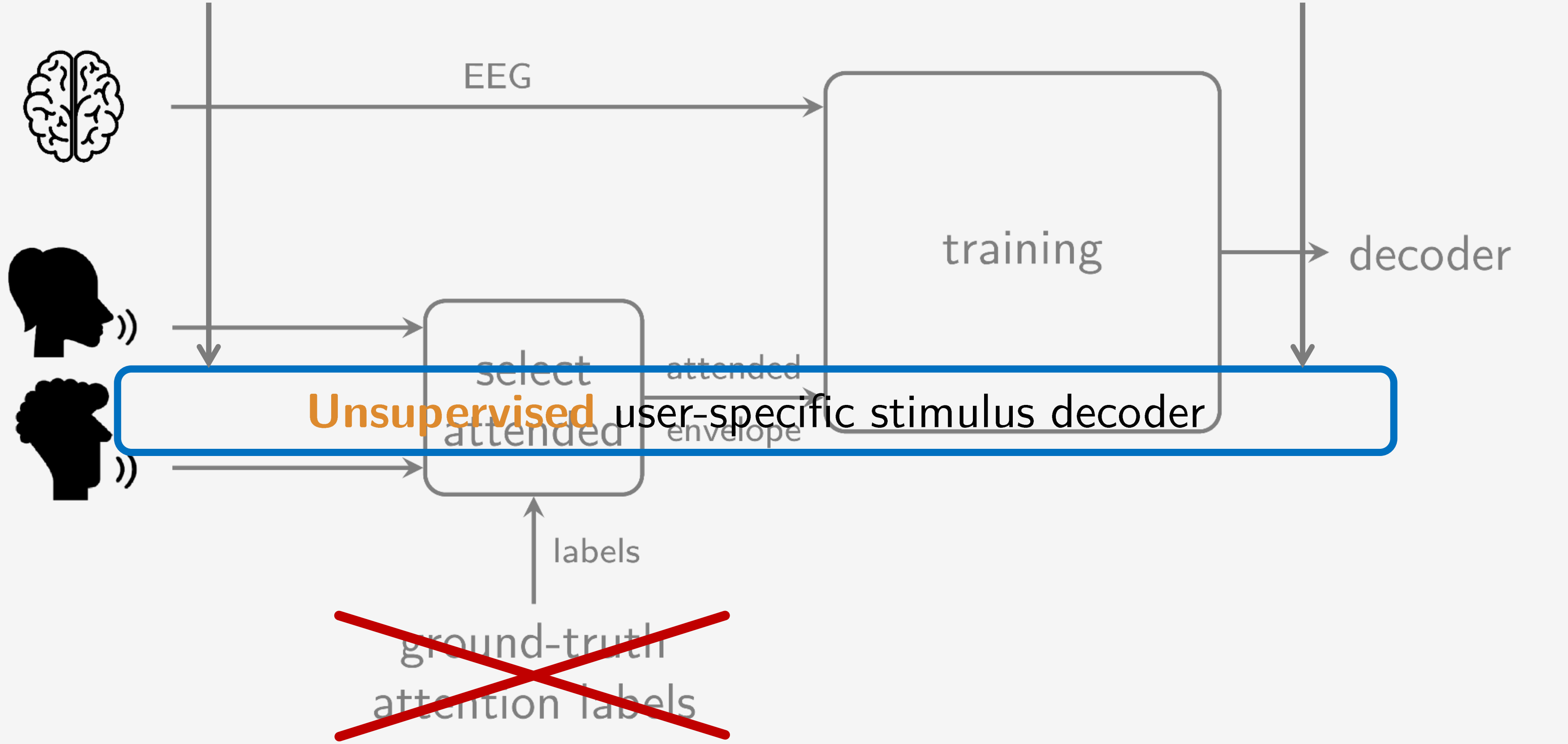
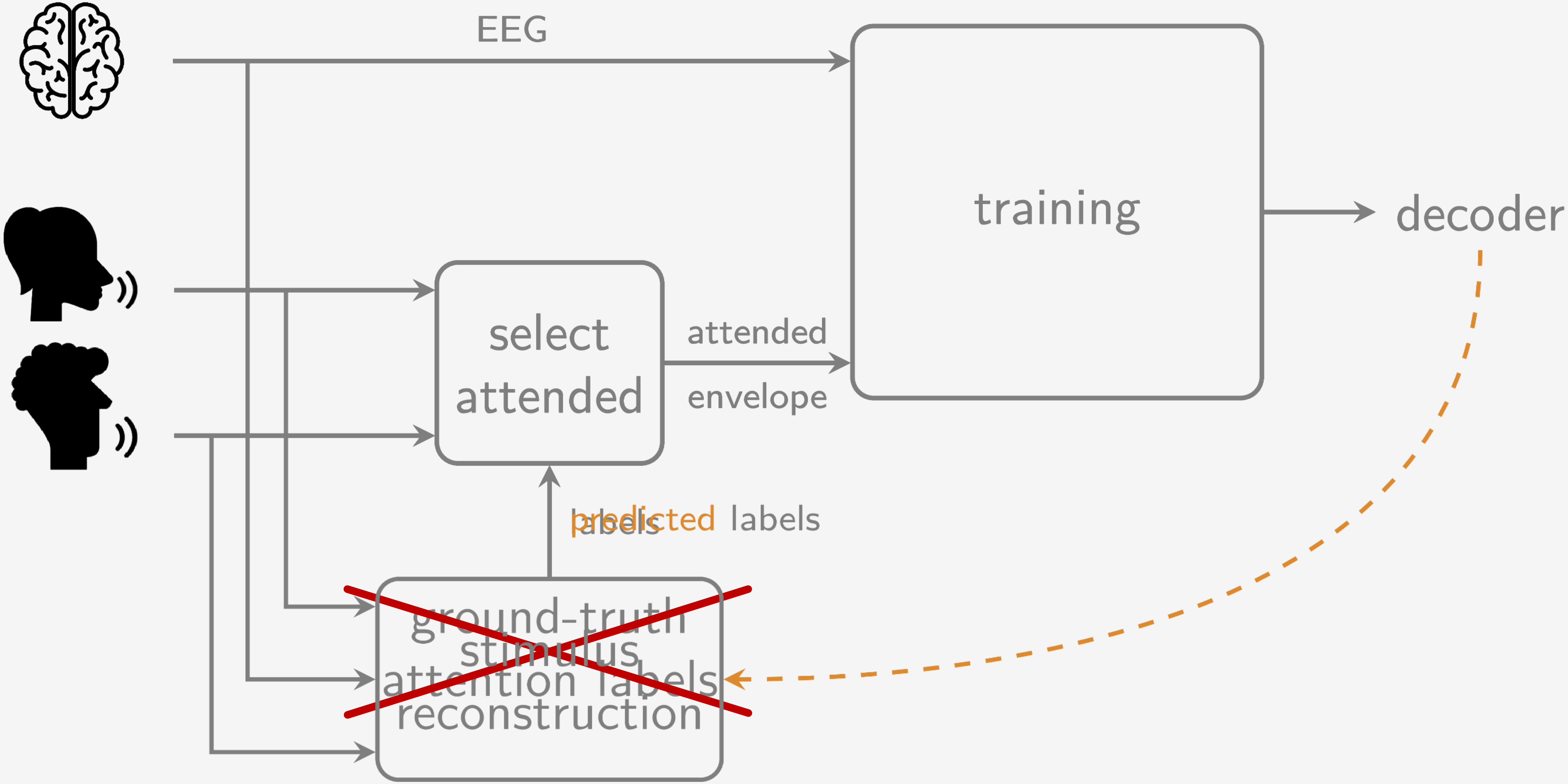
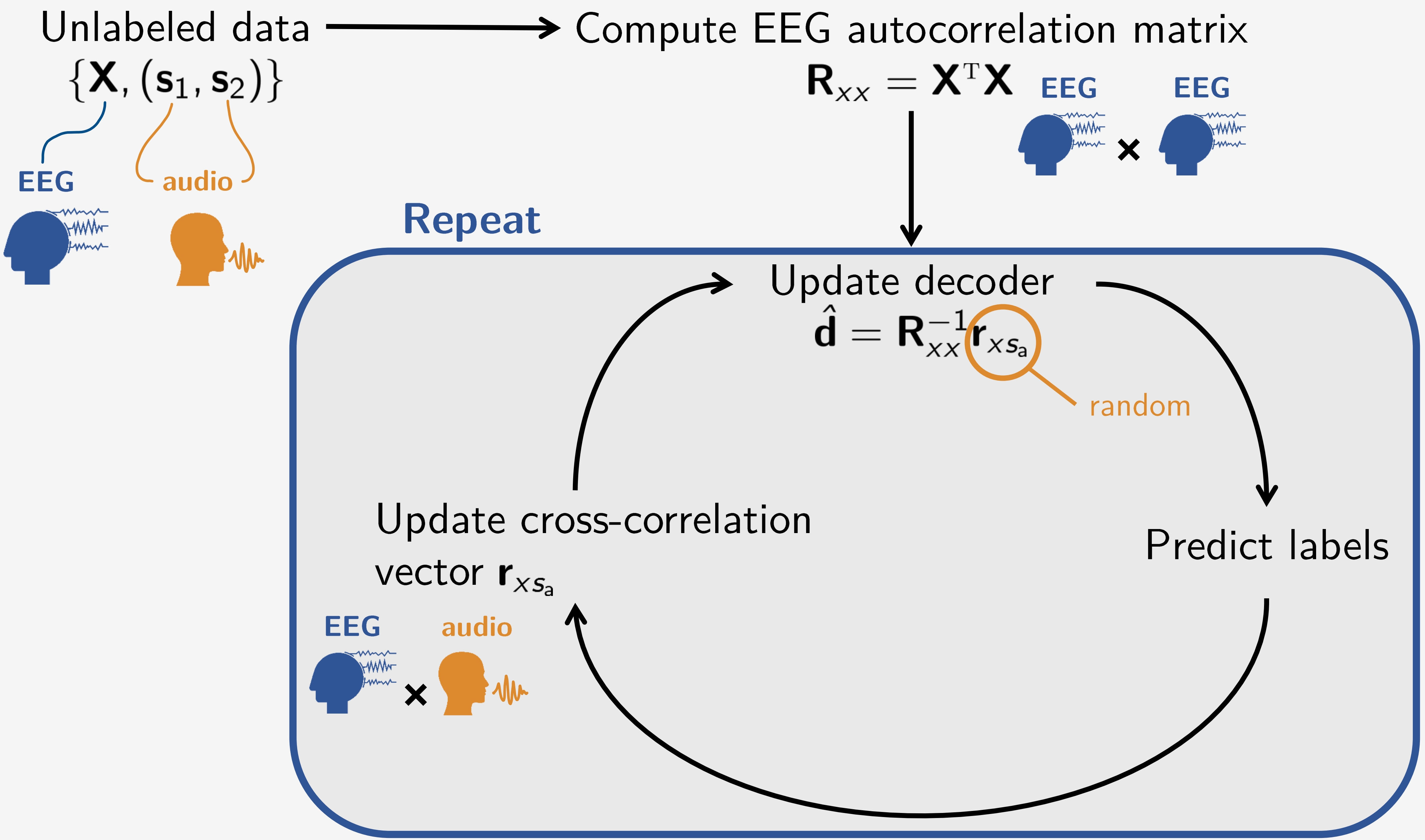
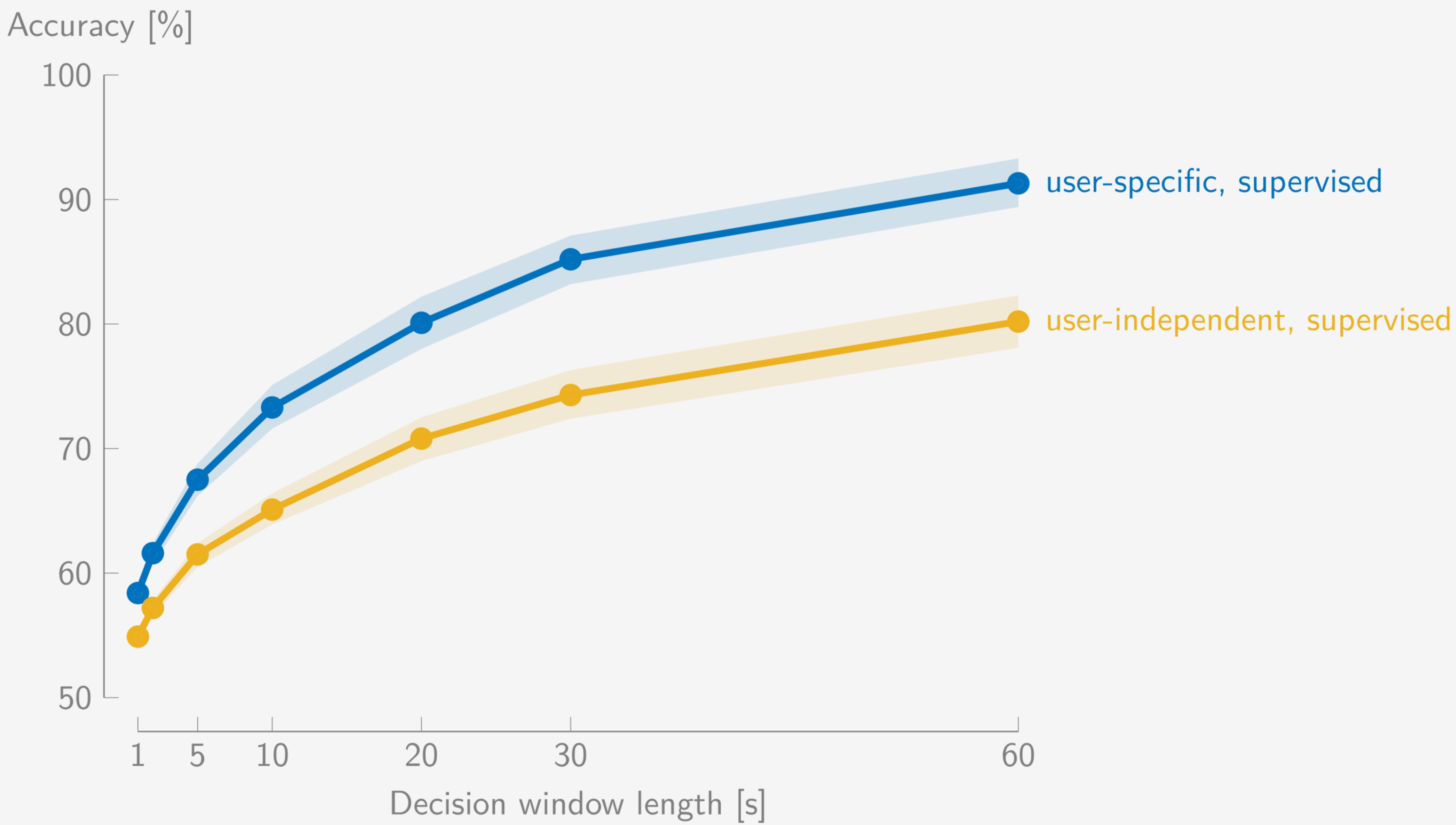


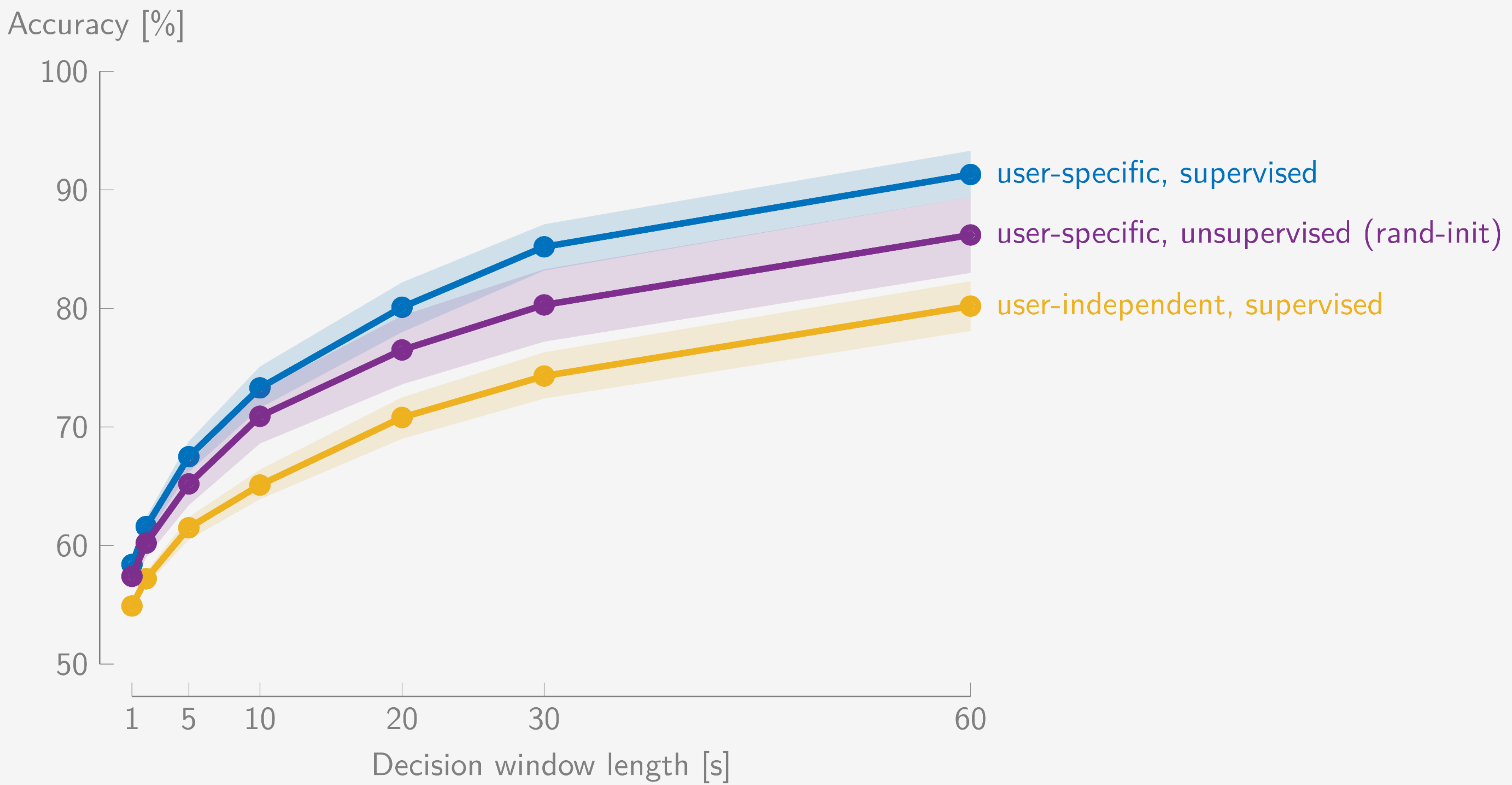
Unsupervised user-specific stimulus decoder

Unsupervised training of the stimulus decoder

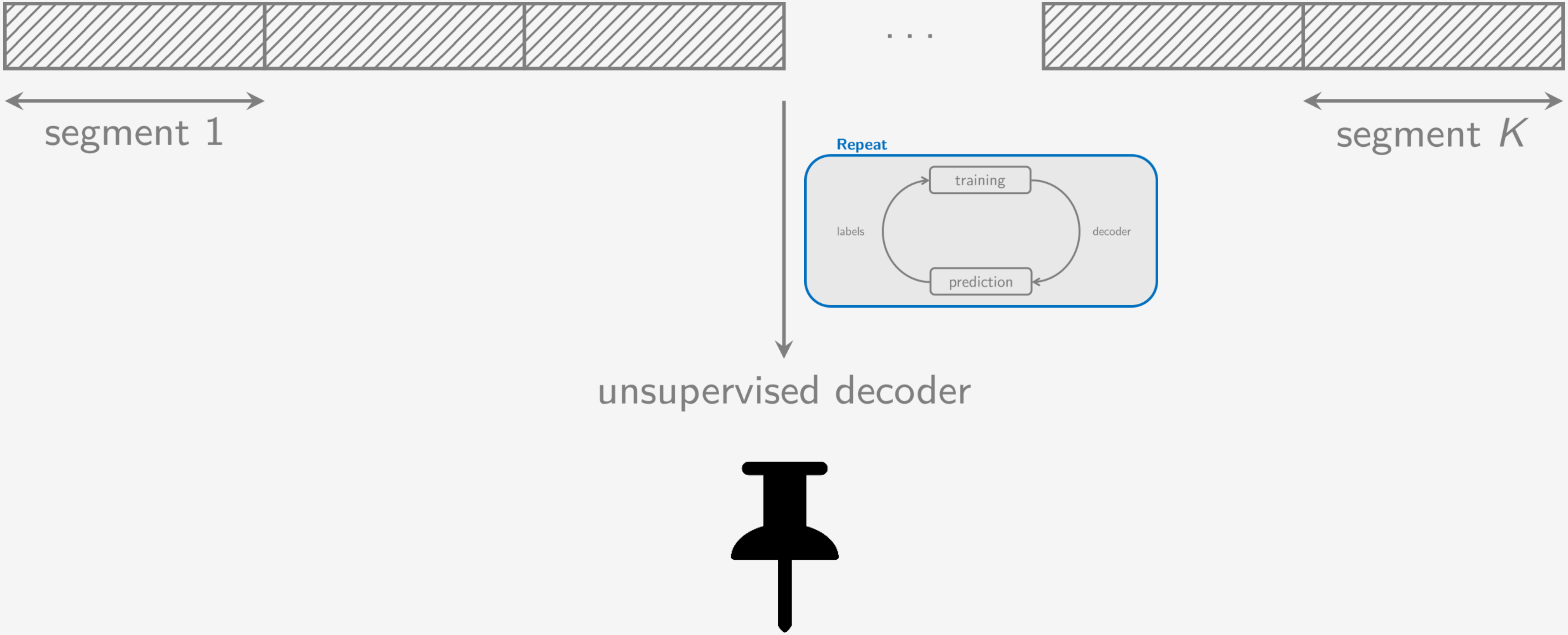



Unlabeled data
$\{\mathbf{X}, (\mathbf{s}_1, \mathbf{s}_2)\}$
EEG
audio
Compute EEG autocorrelation matrix
$\mathbf{R}_{xx} = \mathbf{X}^{\mathrm{T}}\mathbf{X}$
EEG
EEG
Repeat
Update decoder
$\hat{\mathbf{d}} = \mathbf{R}_{xx}^{-1}\mathbf{r}_{xs_\mathrm{a}}$
random
Predict labels
Update cross-correlation
vector $\mathbf{r}_{xs_\mathrm{a}}$
EEG
audio

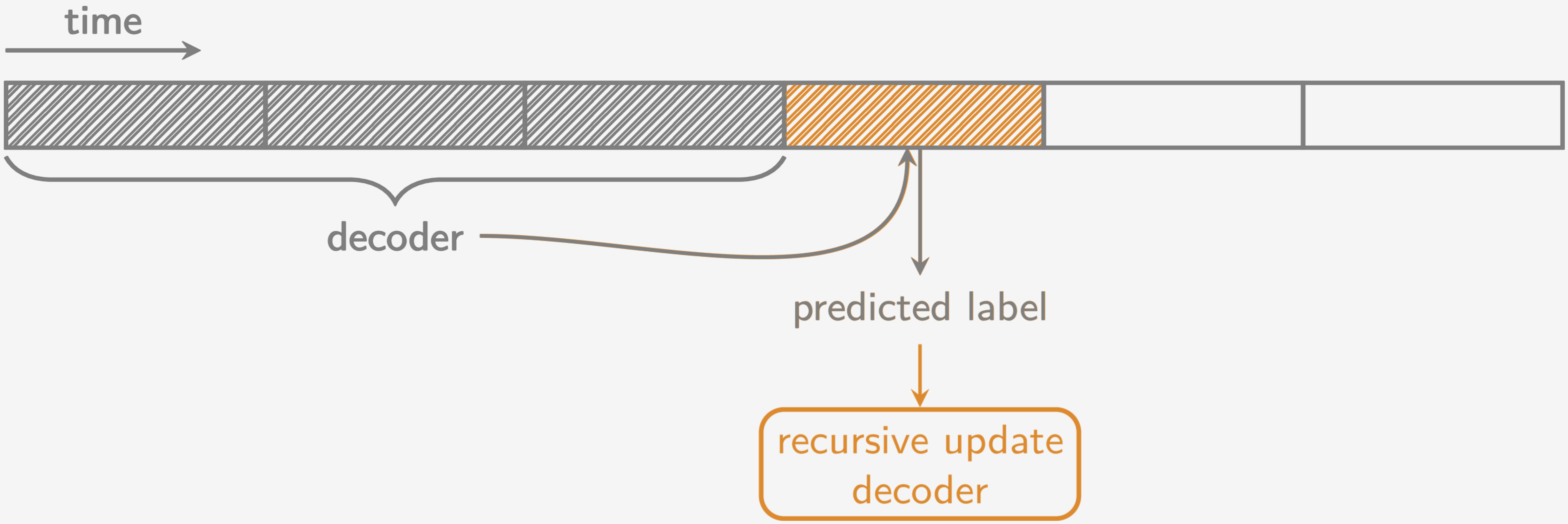

Accuracy [%]
100
90
80
70
60
50
1
5
10
20
30
60
Decision window length [s]
user-specific, supervised
user-independent, supervised

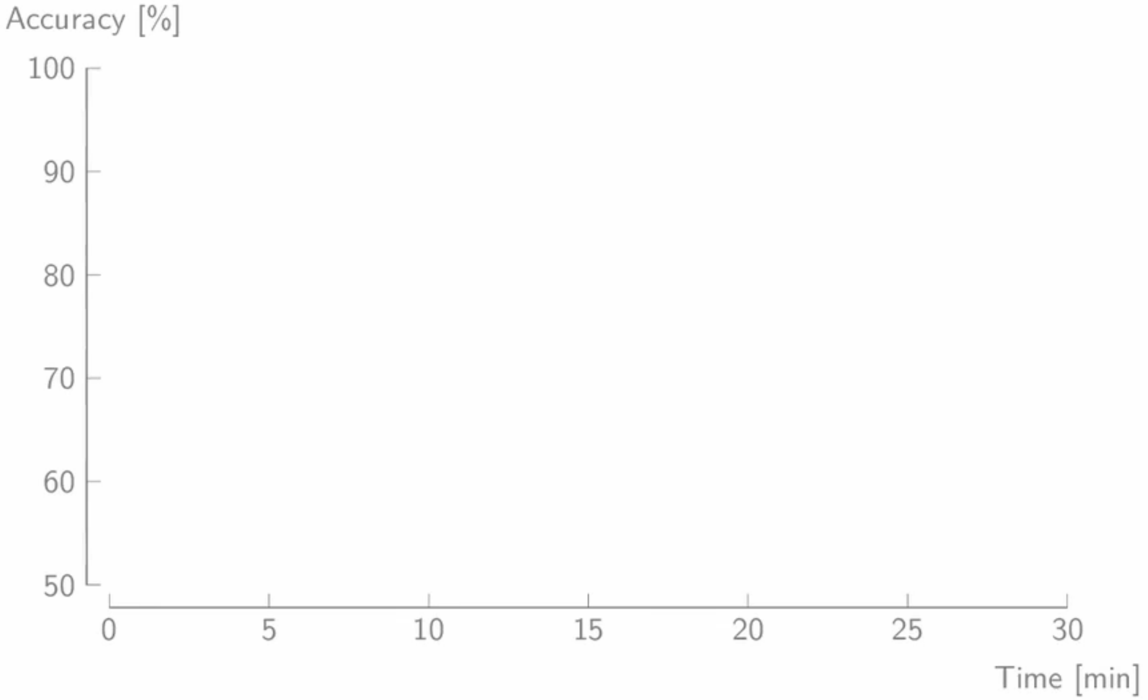

Accuracy [%]
100
90
80
70
60
50
1
5
10
20
30
60
Decision window length [s]
user-specific, supervised
user-specific, unsupervised (rand-init)
user-independent, supervised

Unsupervised stimulus decoder is still fixed

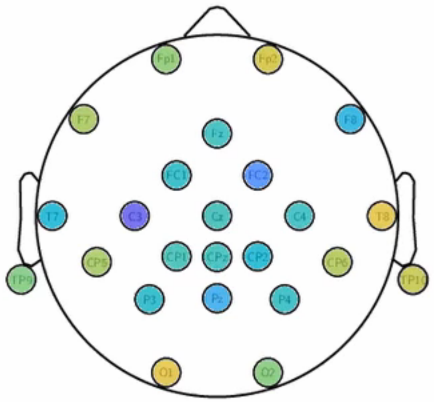


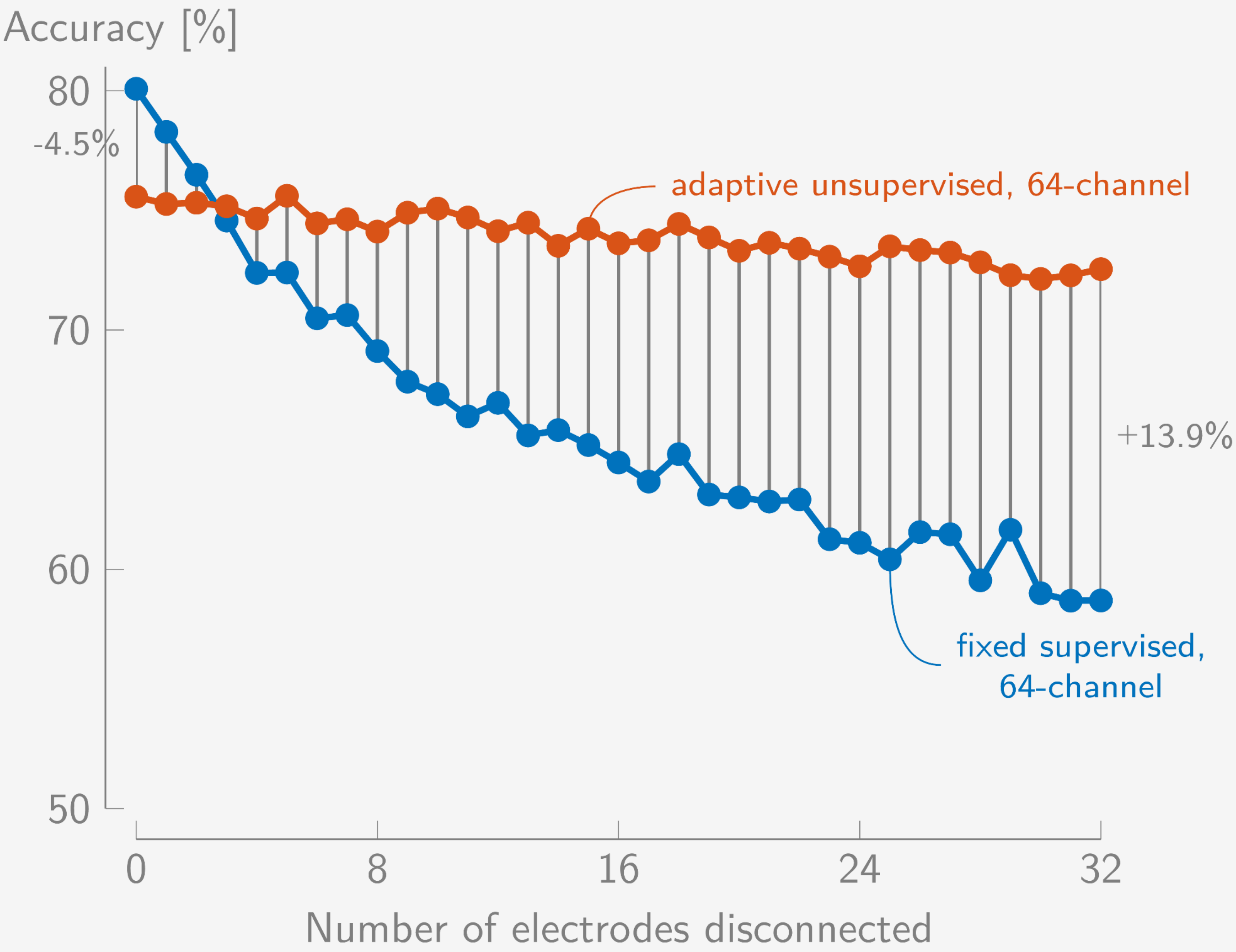
Time-adaptive unsupervised stimulus reconstruction decoding



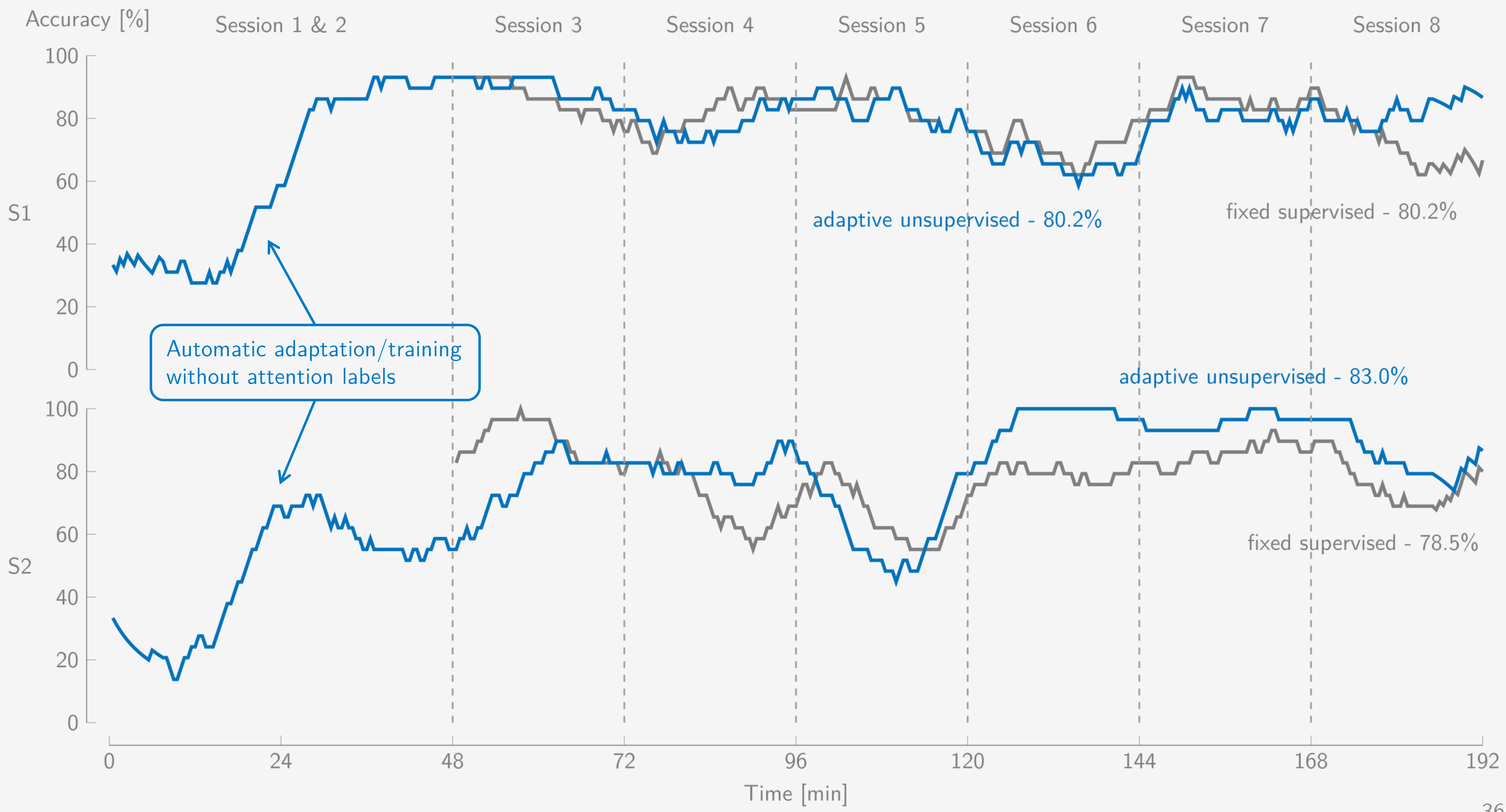


Fixed supervised decoder



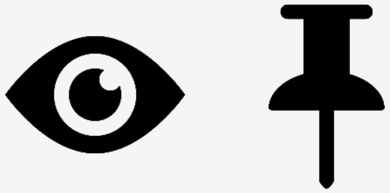


Accuracy [%]
80
70
60
50
-4.5%
adaptive unsupervised, 64-channel
+13.9%
fixed supervised,
64-channel
0
8
16
24
32
Number of electrodes disconnected



Accuracy [%]
Session 1 & 2
Session 3
Session 4
Session 5
Session 6
Session 7
Session 8
S1
S2
adaptive unsupervised - 80.2%
fixed supervised - 80.2%
Automatic adaptation/training without attention labels
adaptive unsupervised - 83.0%
fixed supervised - 78.5%
100
80
60
40
20
0
0
24
48
72
96
120
144
168
192
Time [min]

Focus on two signal processing challenges in AAD



Existing AAD algorithms need to be pre-trained offline in a supervised manner, and are fixed during operation

Existing AAD algorithms often assume bulky, non-wearable EEG setups

Focus on two signal processing challenges in AAD

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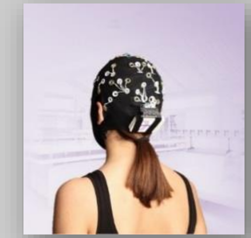
Existing AAD algorithms often assume bulky, non-wearable EEG setups

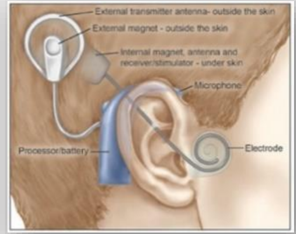
EEG in real life?

Wireless EEG headset

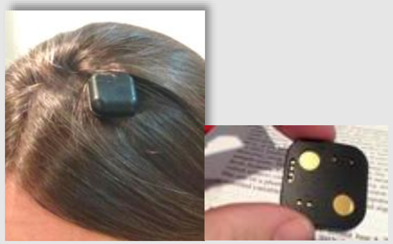

Cognionics


mBrainTrain

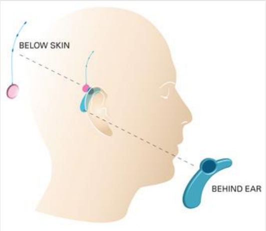
Miniaturized EEG



Record from CI
electrode

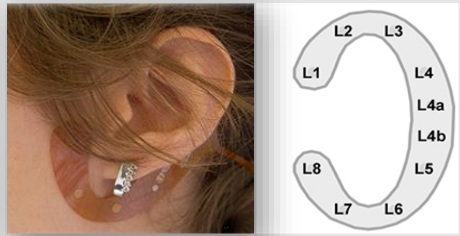

Pasted EEG module
Lehmkuhle et al. (2015)

Seize-IT device



Subcutaneously
Juhl et al. (2010)


In-ear EEG
Kidmose et al. (2013)



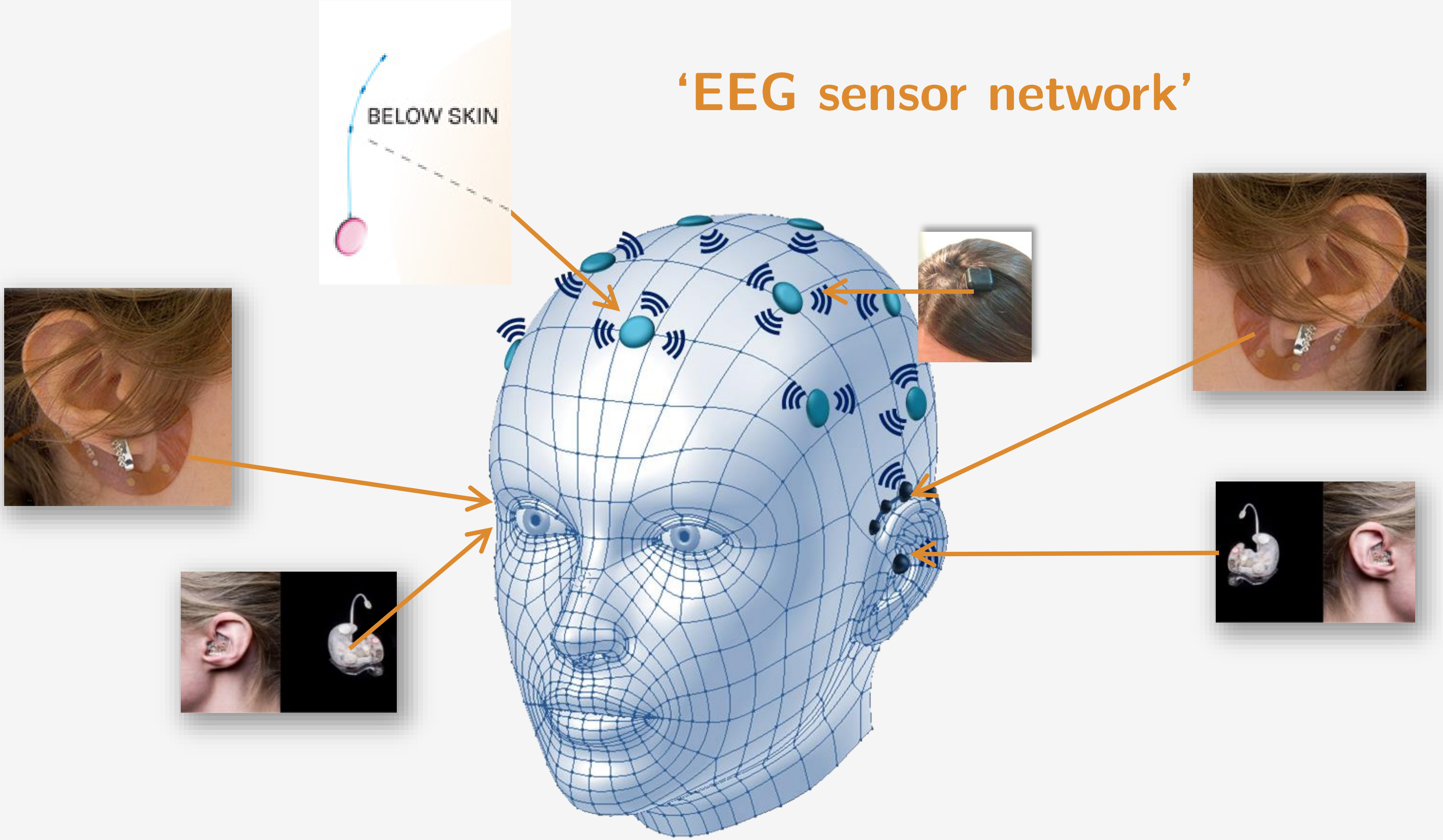
Around-the-ear EEG (‘cEEGrid’)
Mirkovic et al. (2016)


Printable e-skin
Rogers et al. (2011)

performance

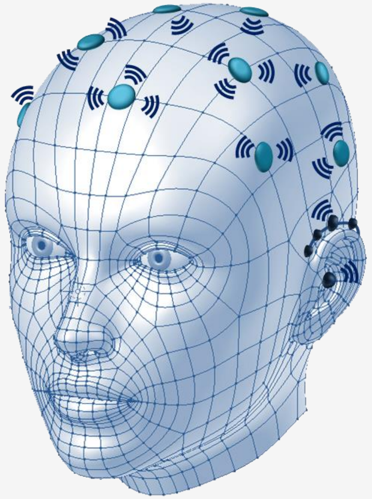
comfort, concealability

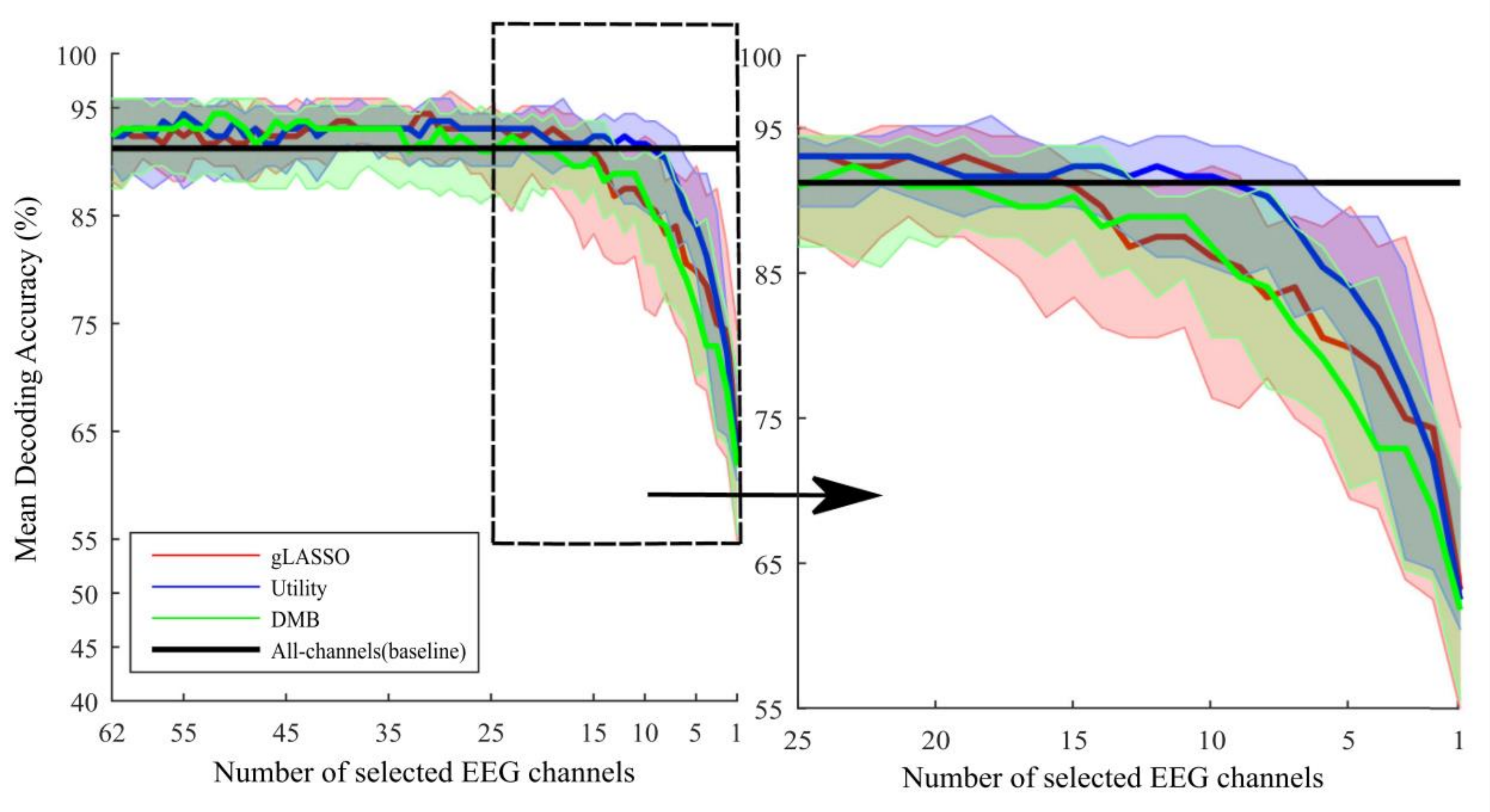
Combine multiple miniature EEG nodes at various positions



Top-down: EEG channel selection

Free placement: 64 channels → ~8 channels without performance decrease

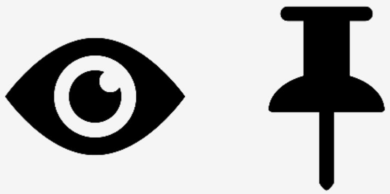




A. Mundanad Narayanan, and A. Bertrand, "Analysis of Miniaturization Effects and Channel Selection Strategies for EEG Sensor Networks with Application to Auditory Attention Detection," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 1, pp. 234-244, 2020

Focus on two signal processing challenges in AAD

Problem



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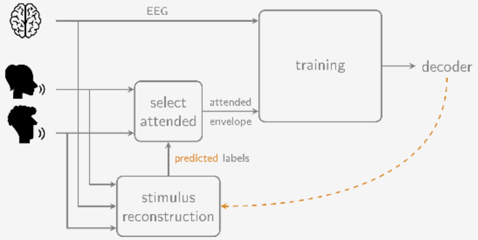
Solution



A **time-adaptive unsupervised** stimulus reconstruction algorithm

Towards **integrated in-ear** and **around-the-ear** EEG