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Center for Dynamical Systems, Signal Processing and Data Analytics

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Performance Modeling for Correlation-based Neural Decoding of Auditory Attention to Speech

Simon Geirnaert
Joint work with Jonas Vanthornhout, Tom Francart, and Alexander Bertrand

website paper

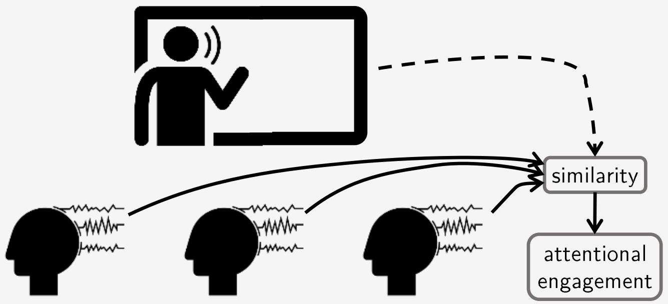
Our lab focuses on signal processing algorithms for neural (attention) decoding to natural stimuli (speech, video)

Prof. Alexander Bertrand

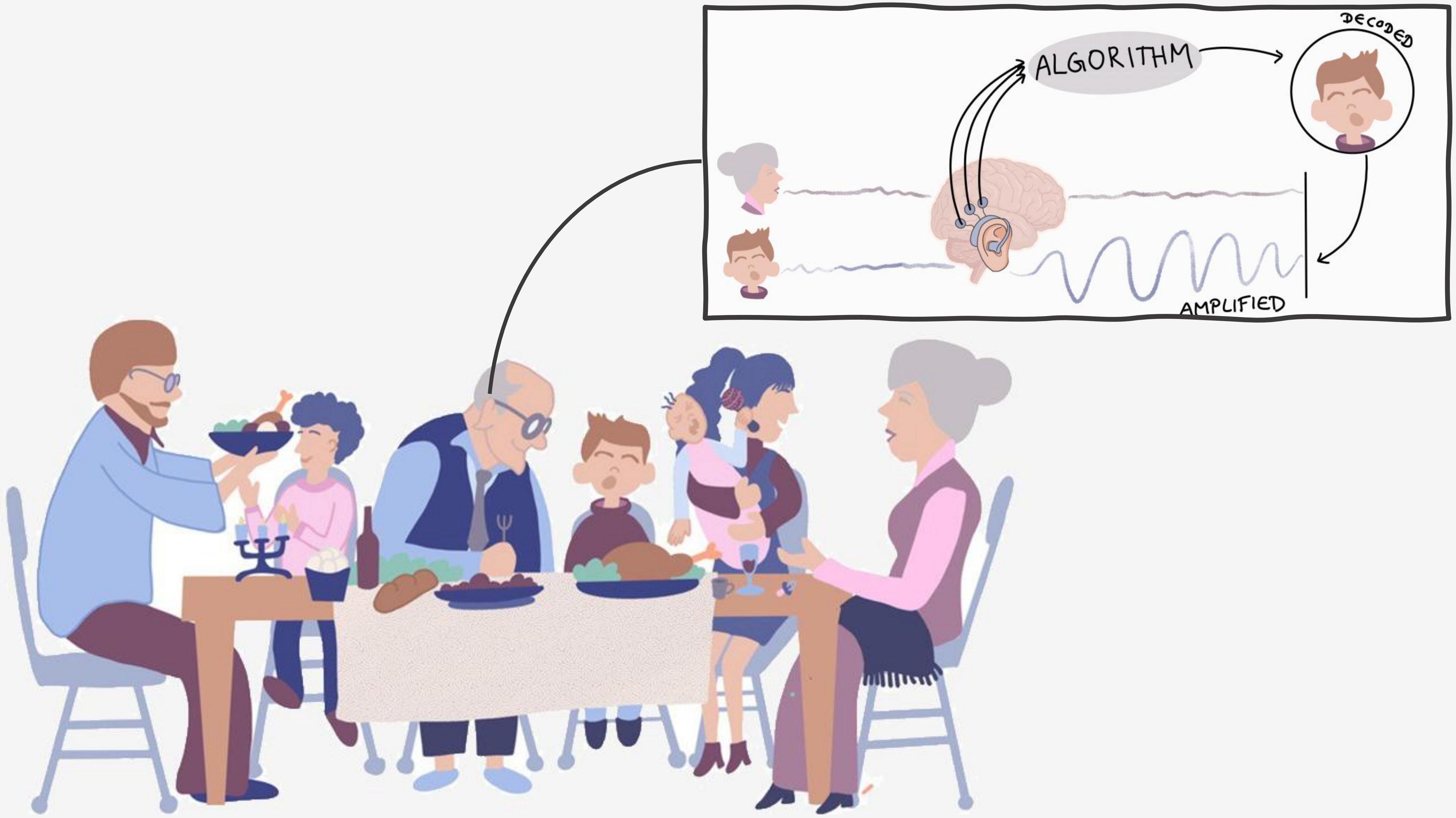
With applications in ‘natural’ brain-computer interface technology, e.g.:

neuro-steered **hearing devices**

educational neuroscience



Neuro-steered hearing devices for cocktail party scenarios



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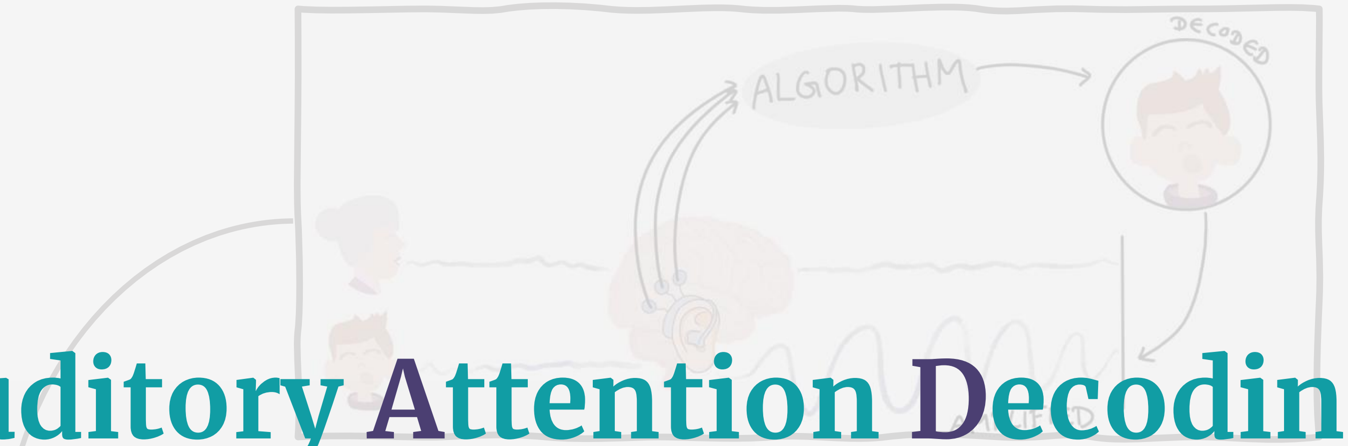
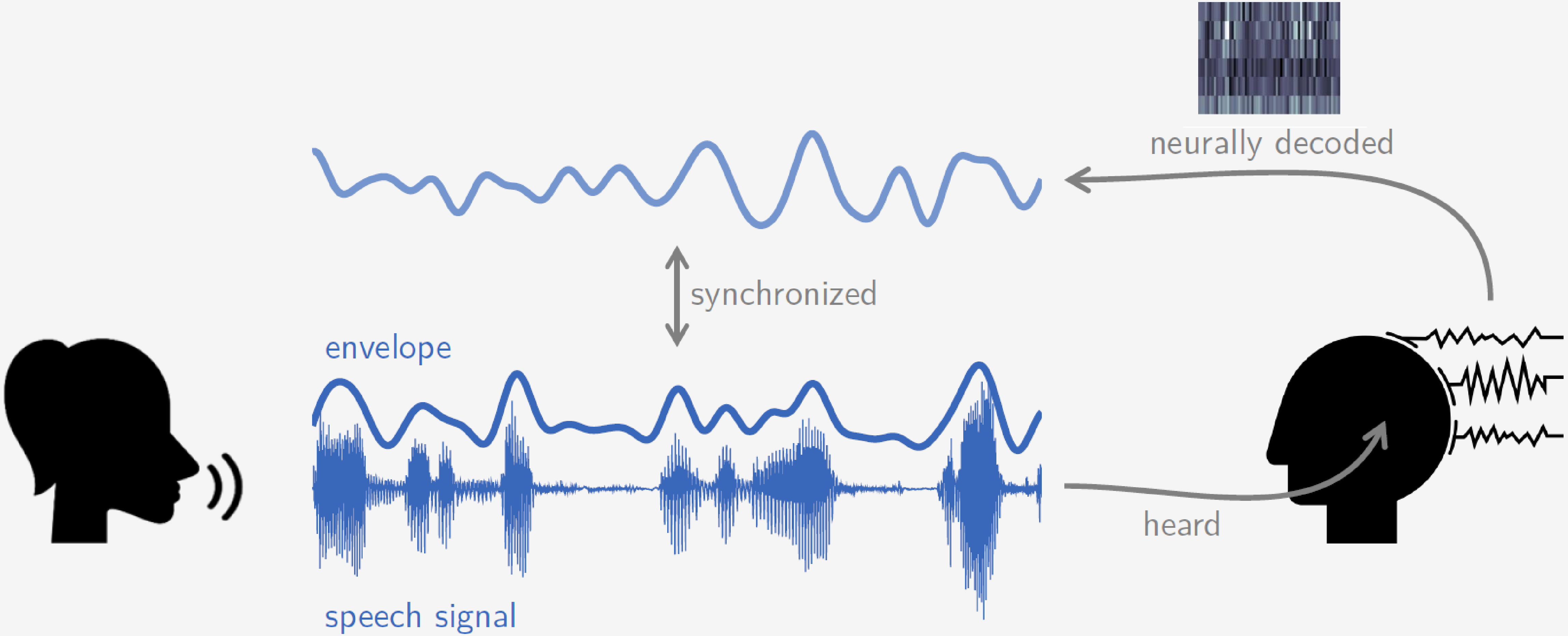


Selective Auditory Attention Decoding (AAD) problem

In AAD, the EEG-stimulus decoding-encoding paradigm is often used, based on neural tracking



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

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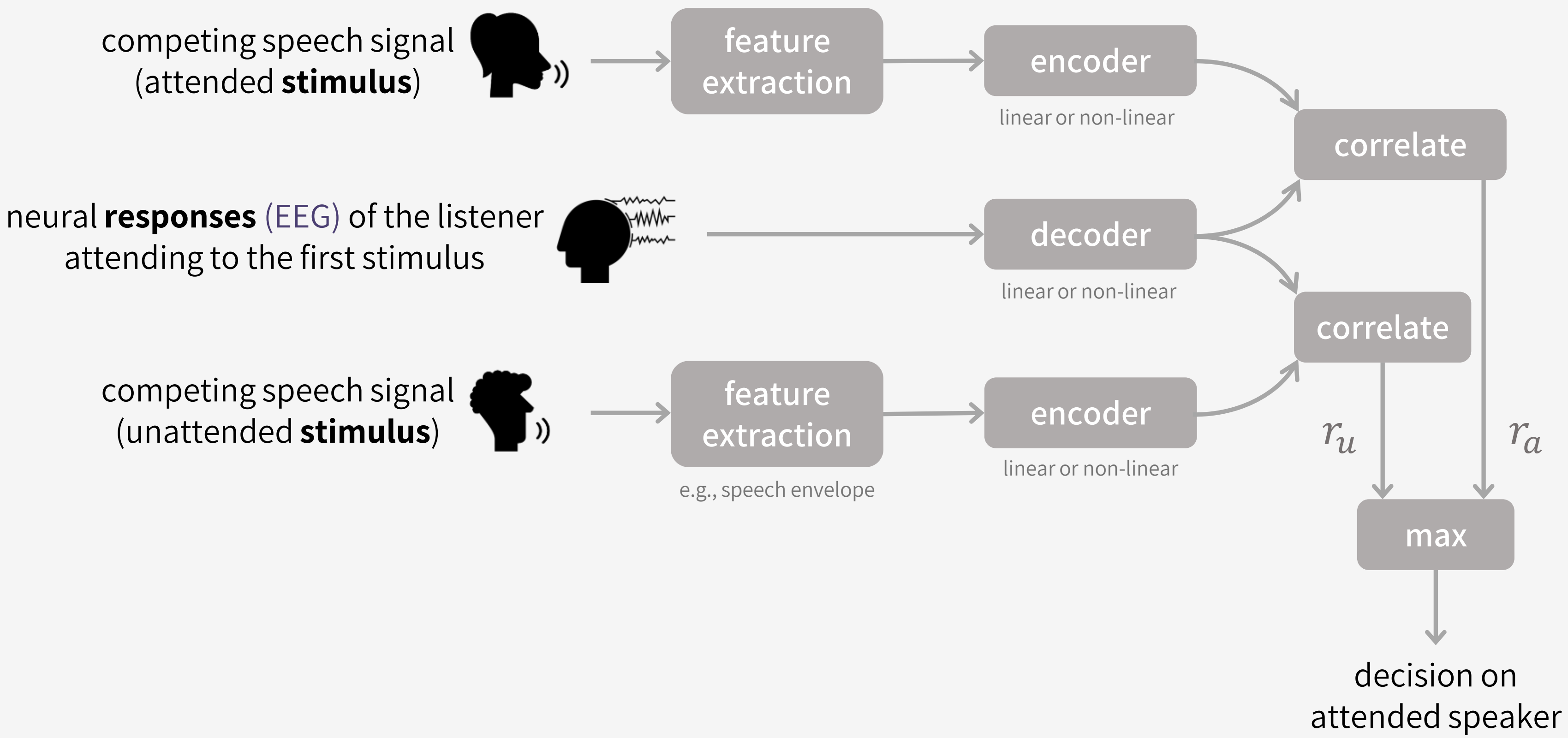

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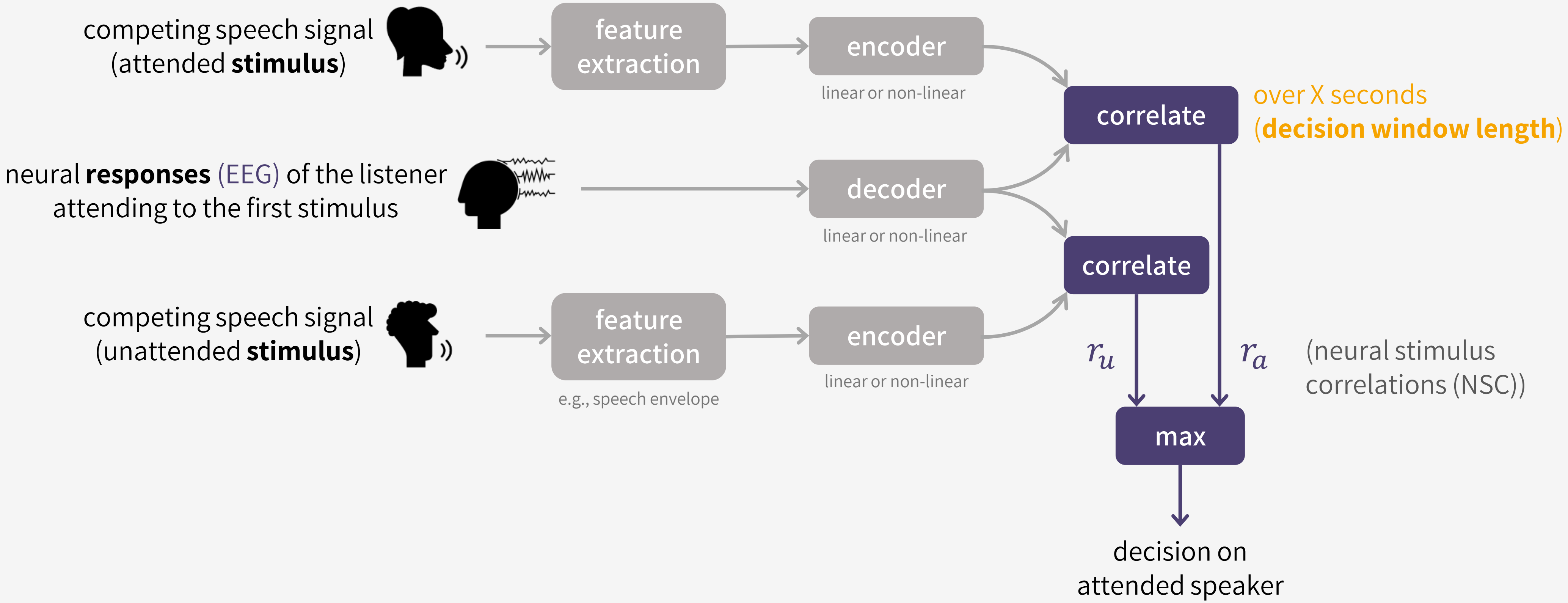
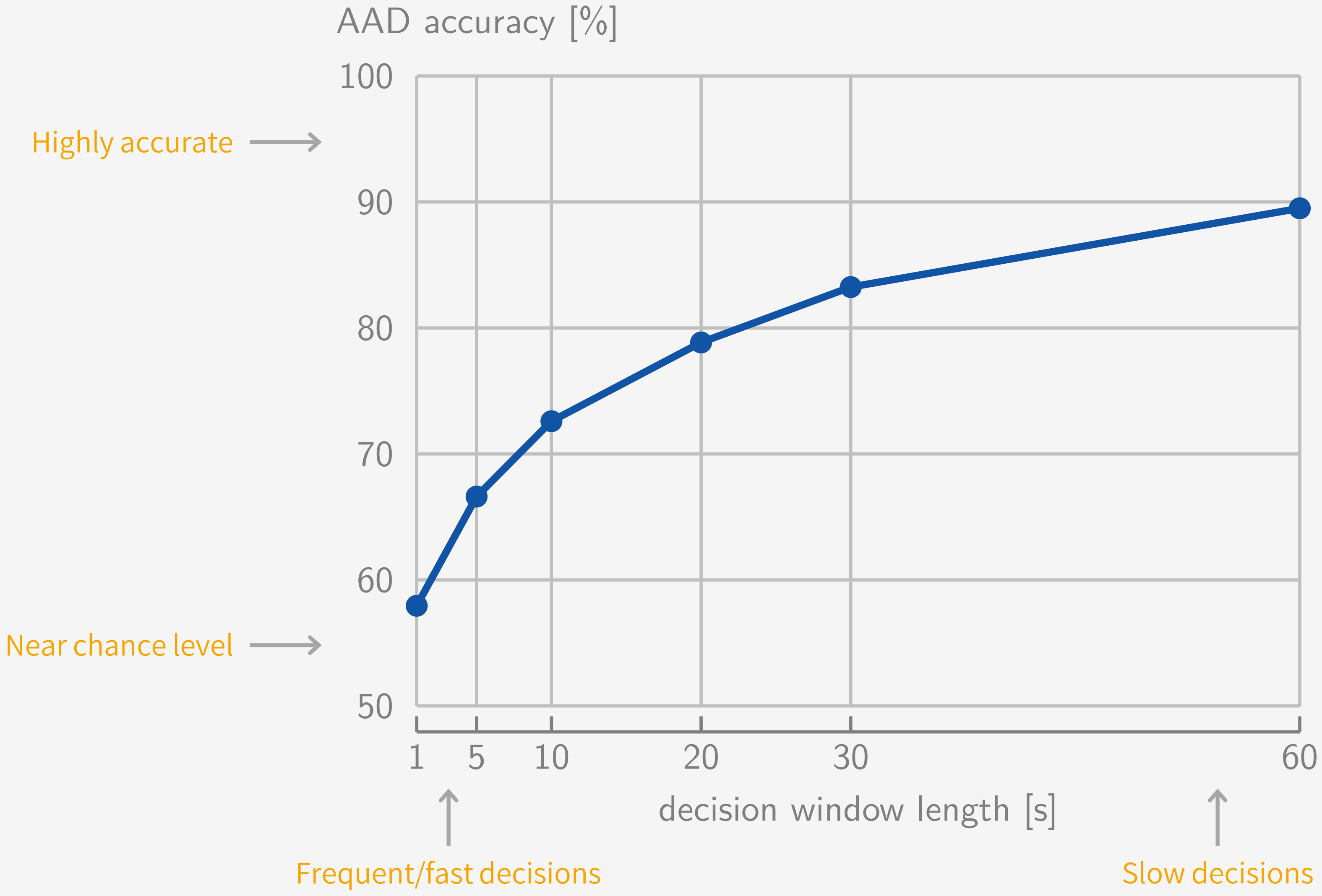
In AAD, the EEG-stimulus decoding-encoding paradigm is often used, i.e., 'correlation'-based paradigms



The performance curve allows quantifying the effect of the critical decision window length parameter



S. Geirnaert et al., "An Interpretable Performance Metric for Auditory Attention Decoding Algorithms in a Context of Neuro-Steered Gain Control", *IEEE TNSRE*, vol. 28, no. 1, pp. 307-317, 2020

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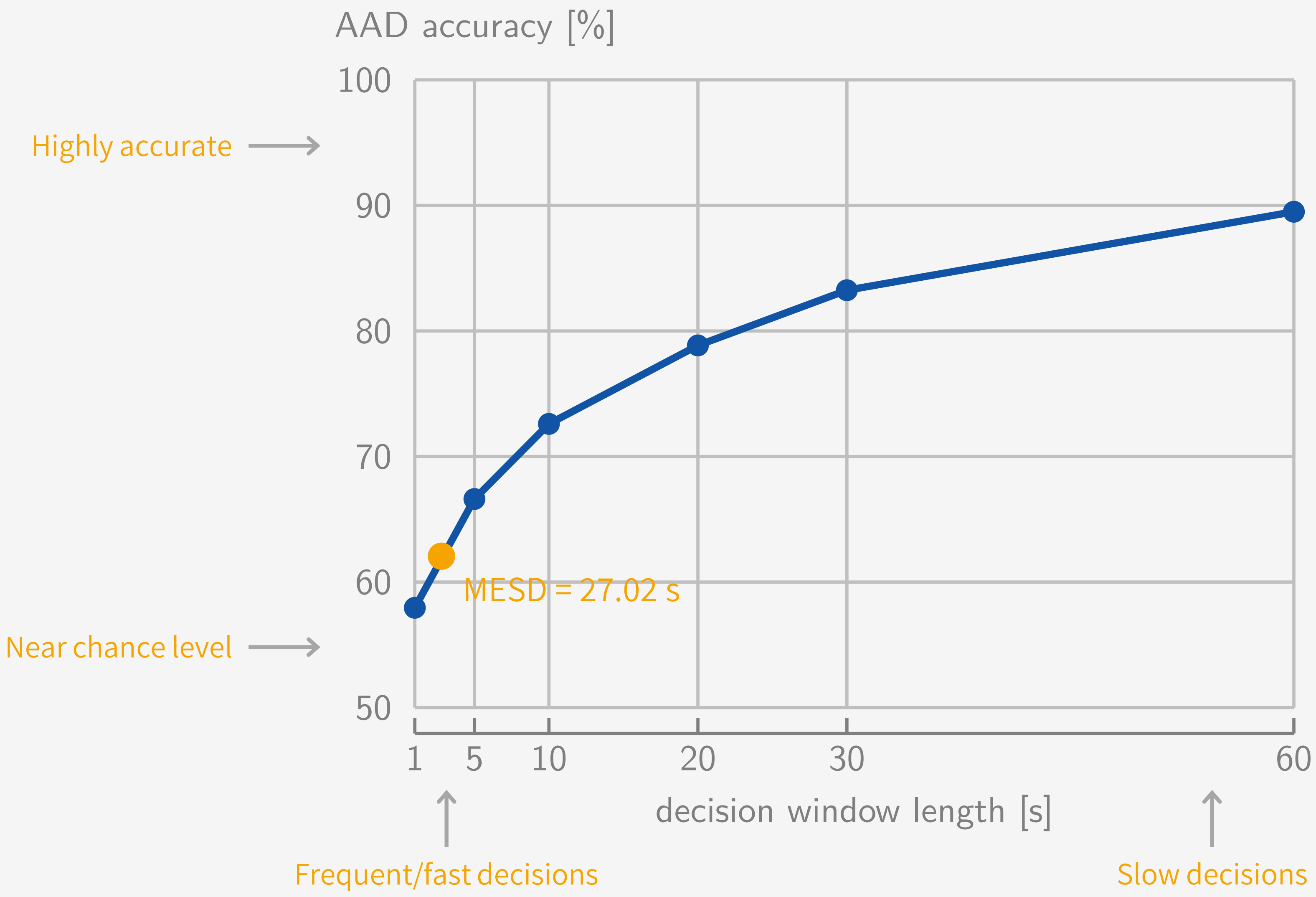

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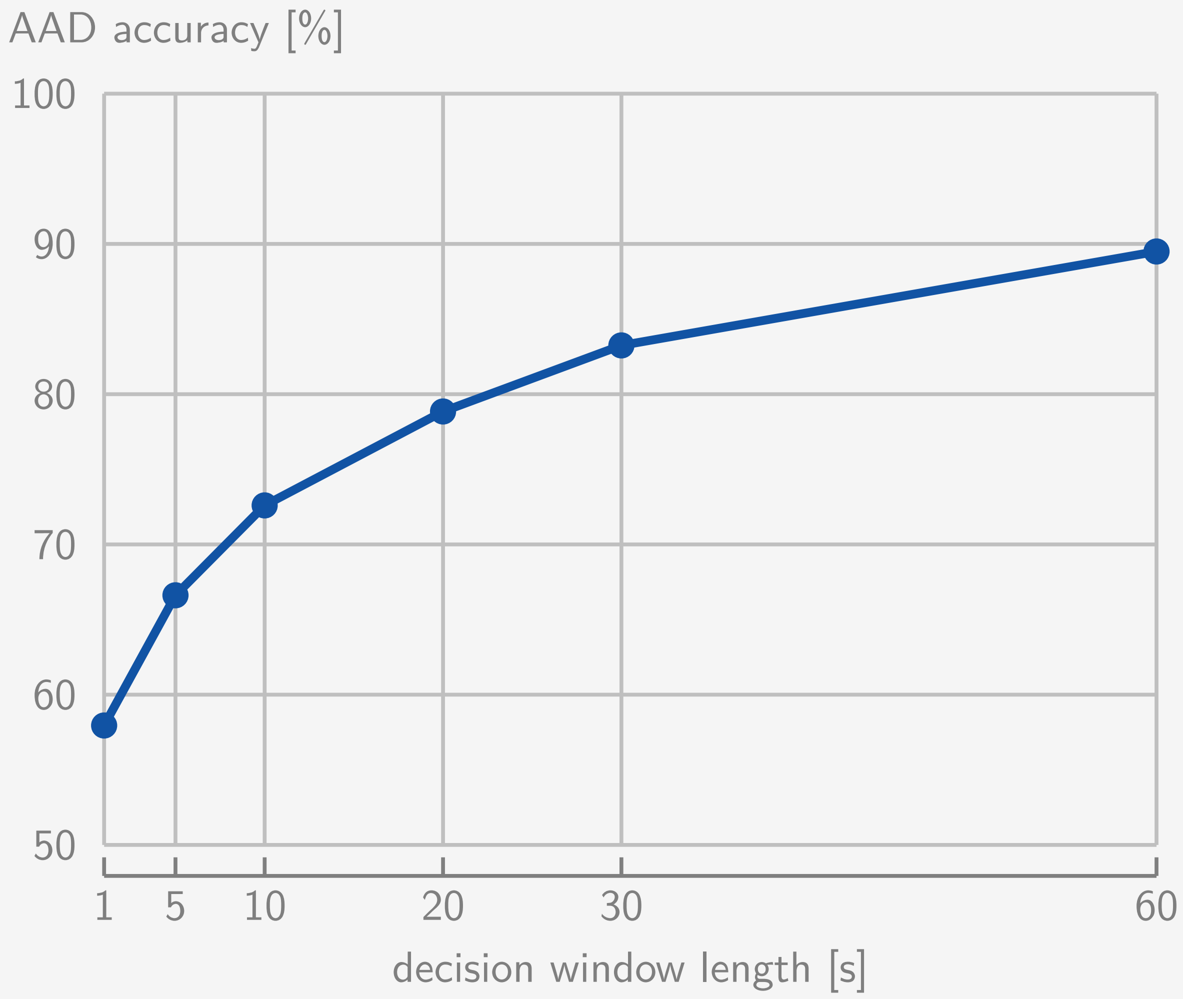
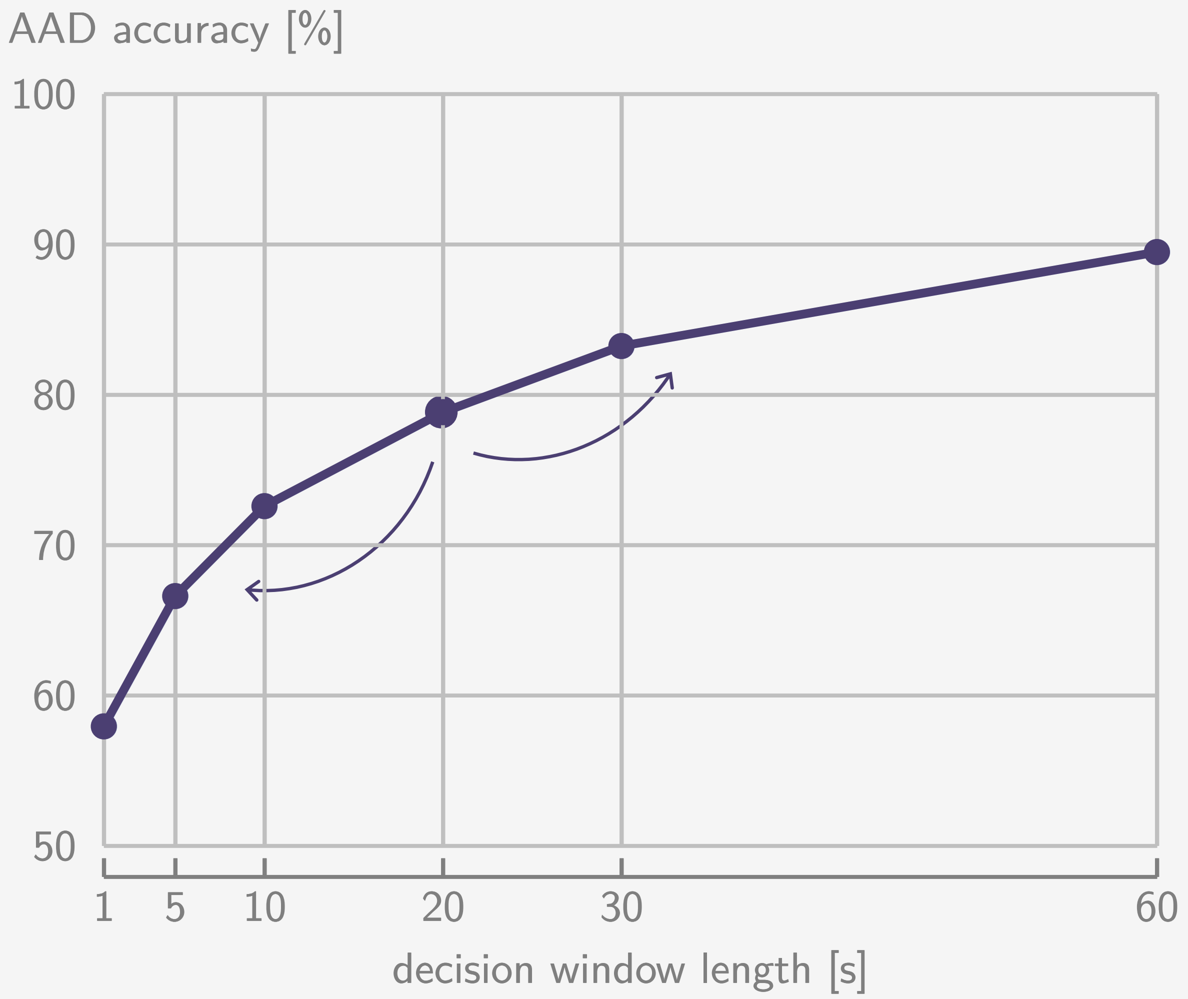


Objective

Model and predict the whole **performance curve** starting **from** the neural stimulus correlations (NSC) on **only *one* window length**



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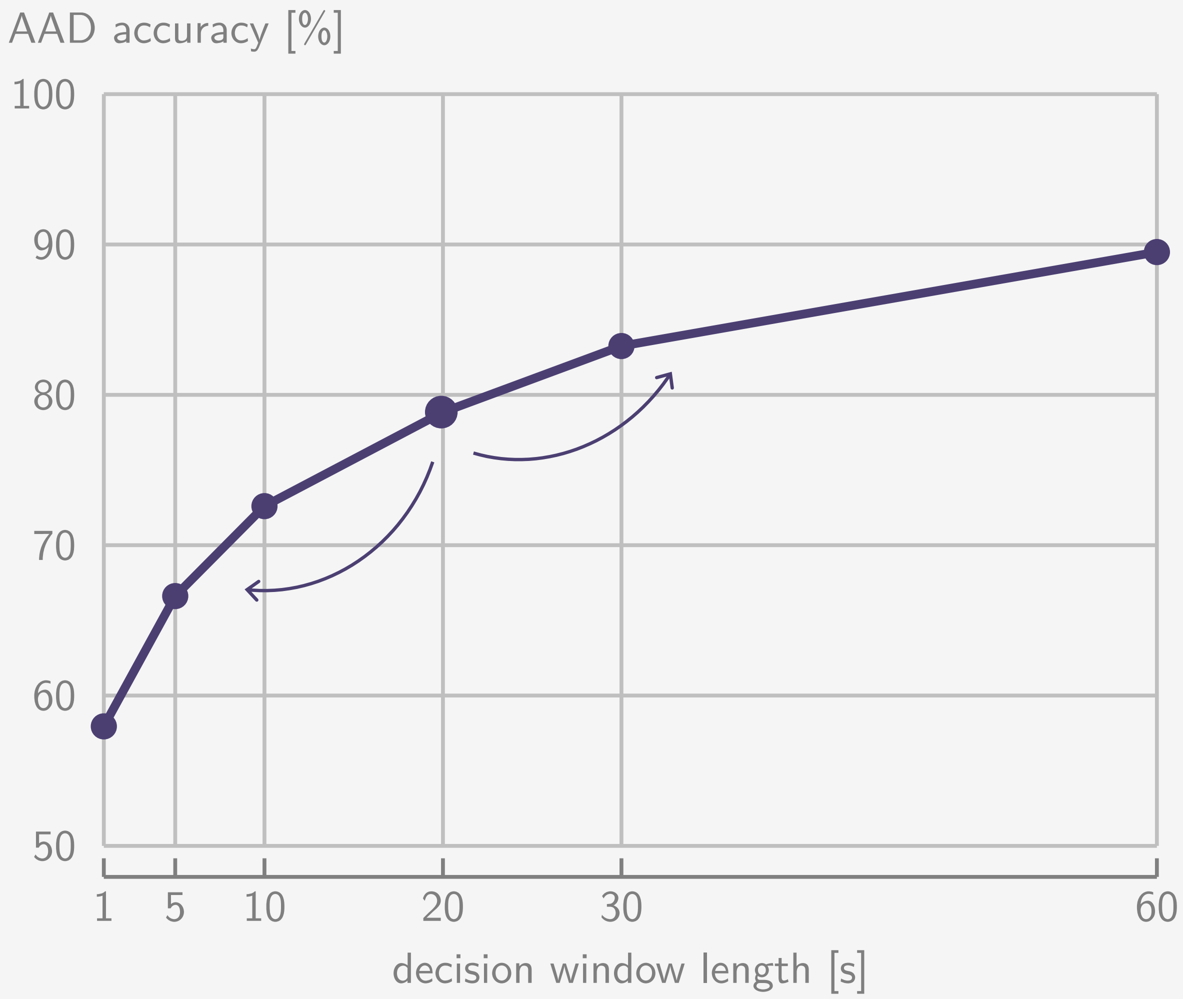


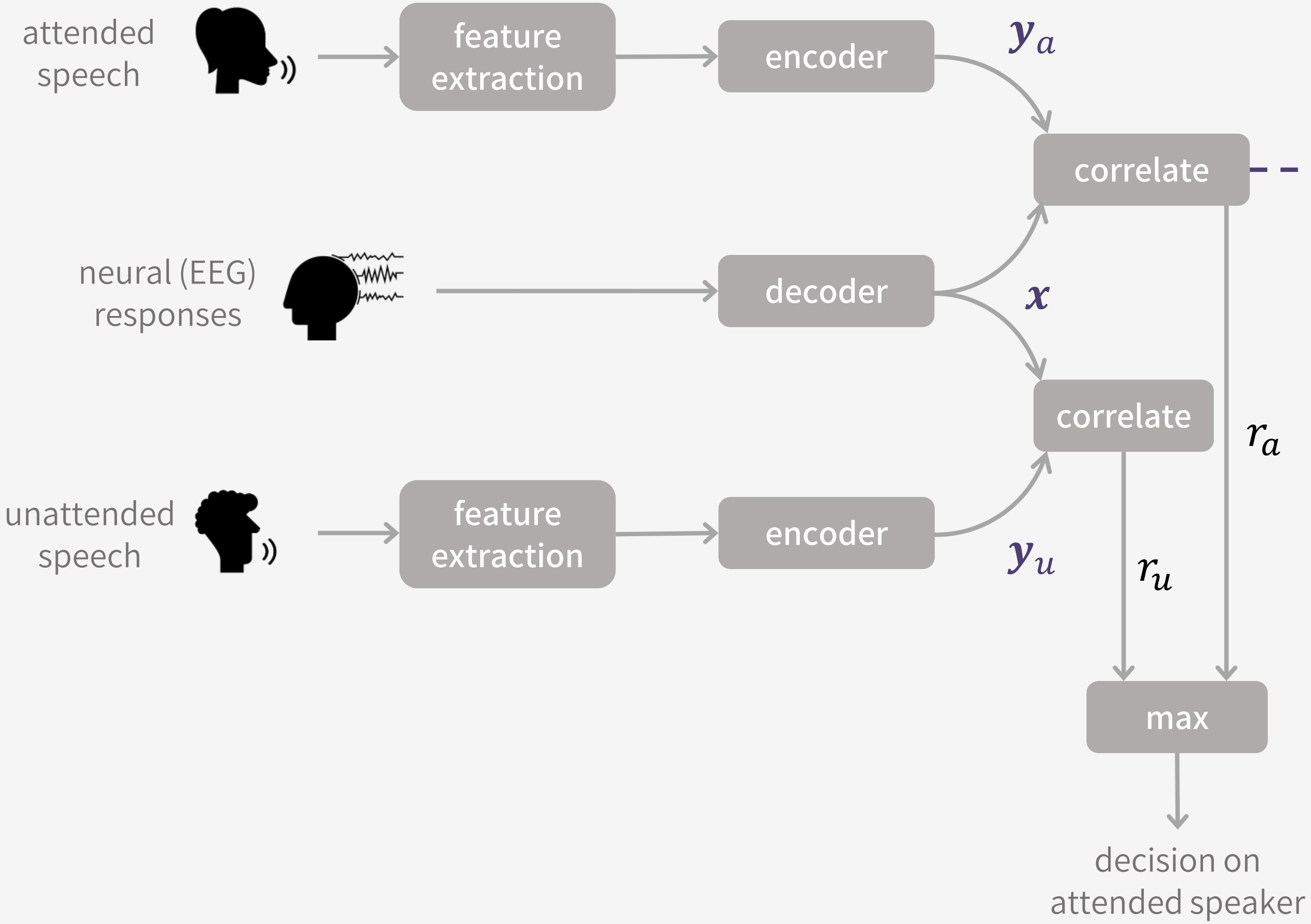
Objective

Model and predict the whole performance curve starting from the neural stimulus correlations (NSC) on only *one* window length

Applications

1. Continuous and efficient monitoring of the accuracy-decision window length trade-off
2. Theoretical model to translate accuracy targets into correlation targets and vice versa

Modeling correlations in the AAD decision system



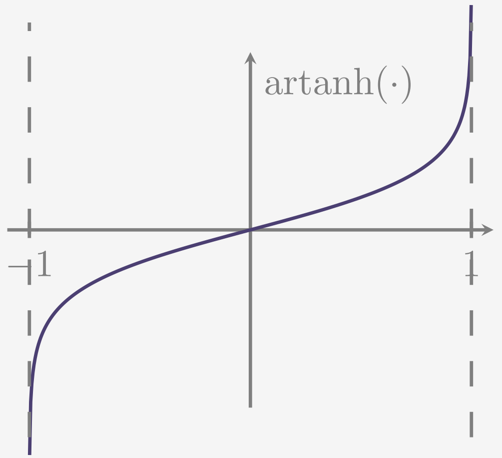
Pearson correlation

$$r_a = \frac{\sum_{n=1}^{N} x_n y_{a,n}}{\sqrt{\sum_{n=1}^{N} x_n^2}\sqrt{\sum_{n=1}^{N} y_{a,n}^2}}$$

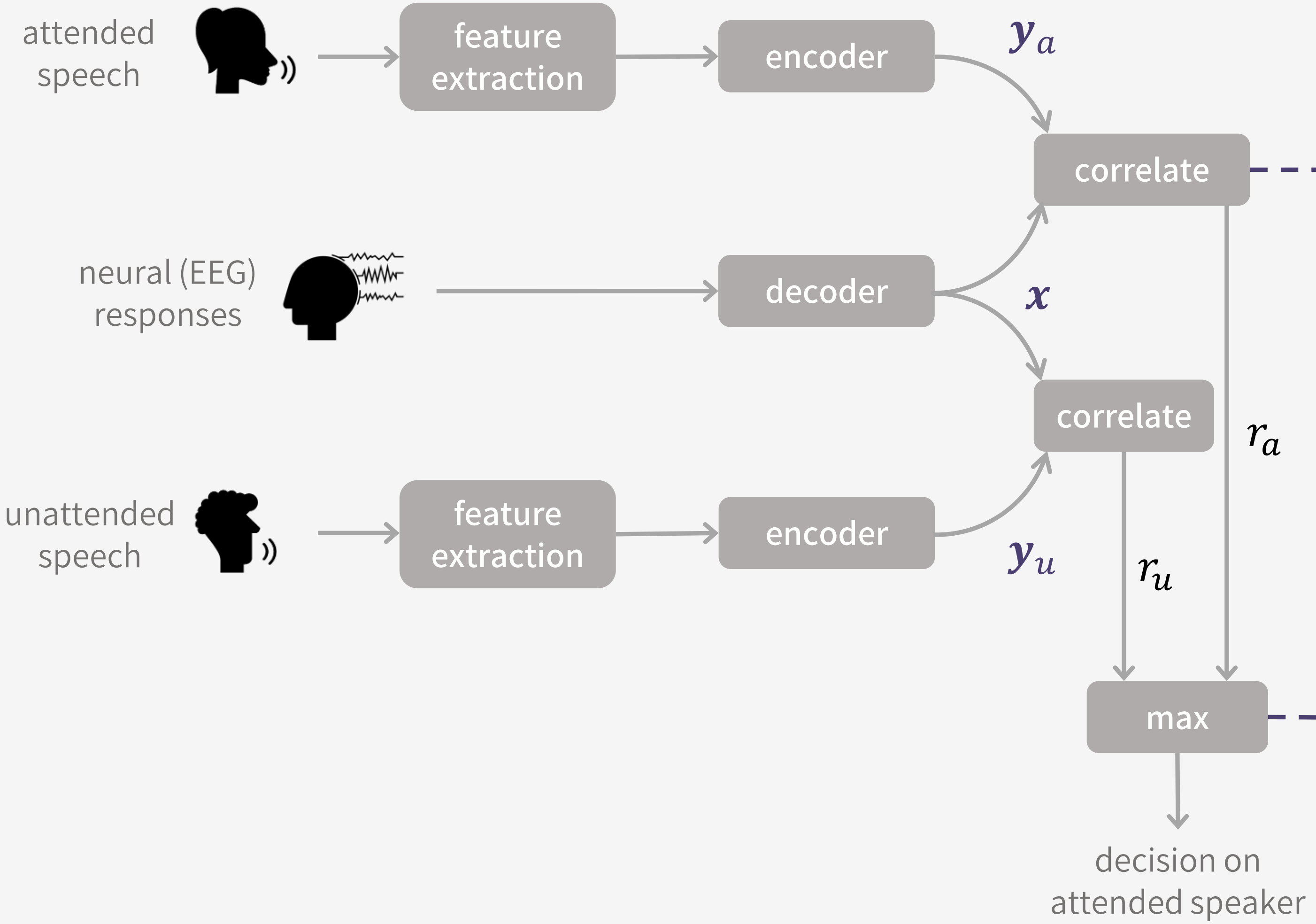
R. Fisher, "On the 'Probable Error' of a Coefficient of Correlation Deducted from a Small Sample," *Metron*, vol. 1, pp. 1-21, 1921

Fisher transformation

$$z_{a/u} = \operatorname{artanh}(r_{a/u}) \sim \mathcal{N}\left(\mu_{a/u}, \sigma_{a/u}^2\right)$$



Modeling decisions in the AAD decision system



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Fisher transformation

$$z_{a/u} = \operatorname{artanh}(r_{a/u}) \sim \mathcal{N}\left(\mu_{a/u}, \sigma_{a/u}^2\right)$$

artanh is monotonically increasing

AAD decision rule

$$\max(z_a, z_u) = \max(r_a, r_u)$$

AAD decision variable

$$z_a - z_u \sim \mathcal{N}\left(\mu_a - \mu_u, \sigma_a^2 + \sigma_u^2\right) \lessgtr 0$$

Quantifying AAD accuracy

AAD decision variable

$$z_a - z_u \sim \mathcal{N}\left(\mu_a - \mu_u, \sigma_a^2 + \sigma_u^2\right) \lessgtr 0$$

using the normal cumulative distribution function F(.)

$$\text{AAD accuracy} = 100\left(1 - F(0; \mu_a - \mu_u, \sigma_a^2 + \sigma_u^2)\right)$$

$$\sigma_a^2 + \sigma_u^2 \approx \frac{2}{N-1}$$

number of samples (N)

Hotelling series expansion

$$\mu_a - \mu_u \approx \operatorname{artanh}(\rho_a) - \operatorname{artanh}(\rho_u) + \frac{\rho_a - \rho_u}{2(N-1)}$$

$$\rho_a = \mathbb{E}\{r_a\} \qquad \rho_u = \mathbb{E}\{r_u\}$$

R. T. Fouladi and J. H. Steiger, "The Fisher transform of the Pearson Product Moment Correlation Coefficient and Its Square: Cumulants, Moments, and Applications, *Commun. Stat. Simul. Comput.*, vol. 37, no.5, pp. 928-944, 2008

Extrapolating AAD accuracy across decision window lengths

$$\text{AAD accuracy} = 100\left(1 - F(0; \mu_a - \mu_u, \sigma_a^2 + \sigma_u^2)\right)$$

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N: number of samples

Extrapolating AAD accuracy across decision window lengths

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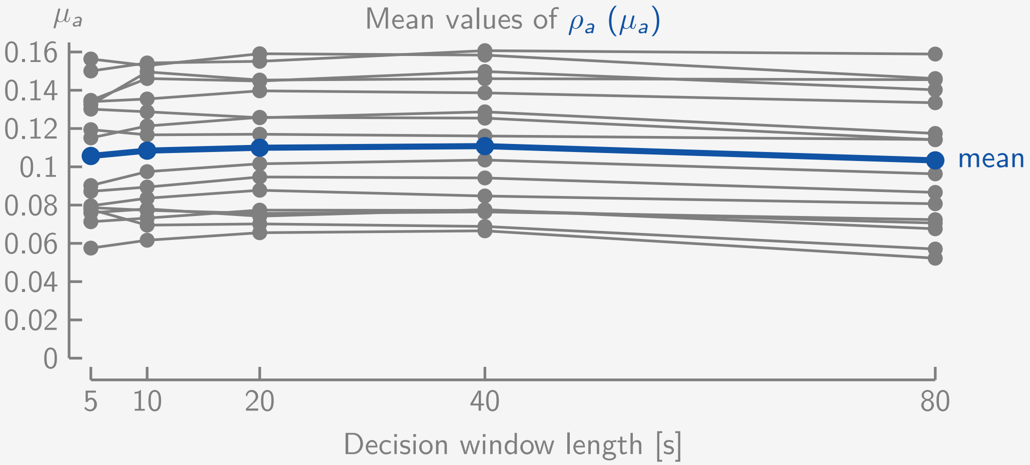
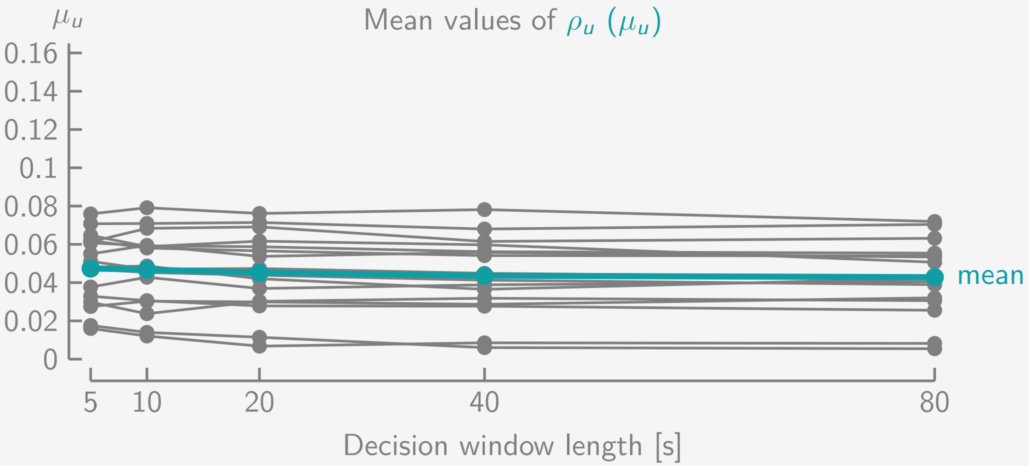
Hotelling series expansion

$$\mu_a - \mu_u \approx \operatorname{artanh}(\rho_a) - \operatorname{artanh}(\rho_u) + \frac{\rho_a - \rho_u}{2(N-1)}$$

$\operatorname{artanh}(\rho_a) = \mathbb{E}\{r_a\}$, $\quad \operatorname{artanh}(\rho_u) = \mathbb{E}\{r_u\}$

remain **constant**
across decision window lengths





M. A. Lopez-Gordo, S. Geirrnaert, and A. Bertrand, “Unsupervised Accuracy Estimation for Brain-Computer Interfaces based on Selective Auditory Attention Decoding,” *IEEE Trans. Biomed. Eng.*, vol. 72, no. 8, pp. 2388-2399, 2025

Extrapolating AAD accuracy across decision window lengths

Given **known/estimated parameters** on window length $w_1 = N_1 f_s$:

$$\text{AAD accuracy}(w_1) = 100\left(1 - F(0; \underbrace{\mu_a^{(1)} - \mu_u^{(1)}}, \underbrace{\sigma_a^{(1)^2} + \sigma_u^{(1)^2}})\right)$$

→ known $\left(\approx \frac{2}{N_1-1}\right)$

→ known $\left(\approx \text{artanh}(\rho_a) - \text{artanh}(\rho_u) + \frac{\rho_a - \rho_u}{2(N_1-1)}\right)$

AAD accuracy on **new window length** $w_2 = N_2 f_s$ can be approximated as:

$$\text{AAD accuracy}(w_2) = 100\left(1 - F(0; \underbrace{\mu_a^{(2)} - \mu_u^{(2)}}, \underbrace{\sigma_a^{(2)^2} + \sigma_u^{(2)^2}})\right)$$

→ $= \left(\sigma_a^{(1)^2} + \sigma_u^{(1)^2}\right) \frac{N_1-1}{N_2-1}$

→ $= \mu_a^{(1)} - \mu_u^{(1)} + \frac{(N_2-N_1)(\rho_a-\rho_u)}{2(N_2-1)(N_1-1)}$

Algorithm performance curve modeling

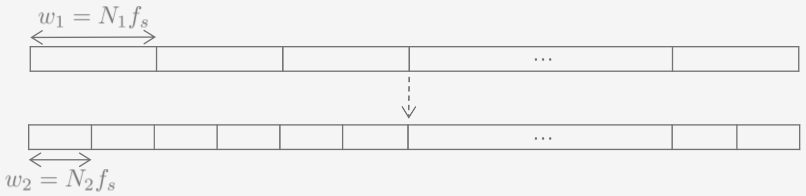
code

① Estimate parameters at w_1

1. $\rho_{a/u} = \underset{\text{over } m}{\text{mean}}(r_{a/u}^{(m)})$
2. $\mu_a^{(1)} - \mu_u^{(1)} = \underset{\text{over } m}{\text{mean}} \left(\text{artanh}\left(r_a^{(m)}\right) - \text{artanh}\left(r_u^{(m)}\right)\right)$
3. ${\sigma_a^{(1)}}^2 + {\sigma_u^{(1)}}^2 = \underset{\text{over } m}{\text{variance}} \left(\text{artanh}\left(r_a^{(m)}\right) - \text{artanh}\left(r_u^{(m)}\right)\right)$

② Extrapolate to $w_2 = N_2 f_s$

$$\begin{cases} \mu_a^{(2)} - \mu_u^{(2)} = \mu_a^{(1)} - \mu_u^{(1)} + \dfrac{(N_2-N_1)(\rho_a-\rho_u)}{2(N_2-1)(N_1-1)} \\ {\sigma_a^{(2)}}^2 + {\sigma_u^{(2)}}^2 = \left({\sigma_a^{(1)}}^2 + {\sigma_u^{(1)}}^2\right) \dfrac{N_1-1}{N_2-1} \end{cases}$$



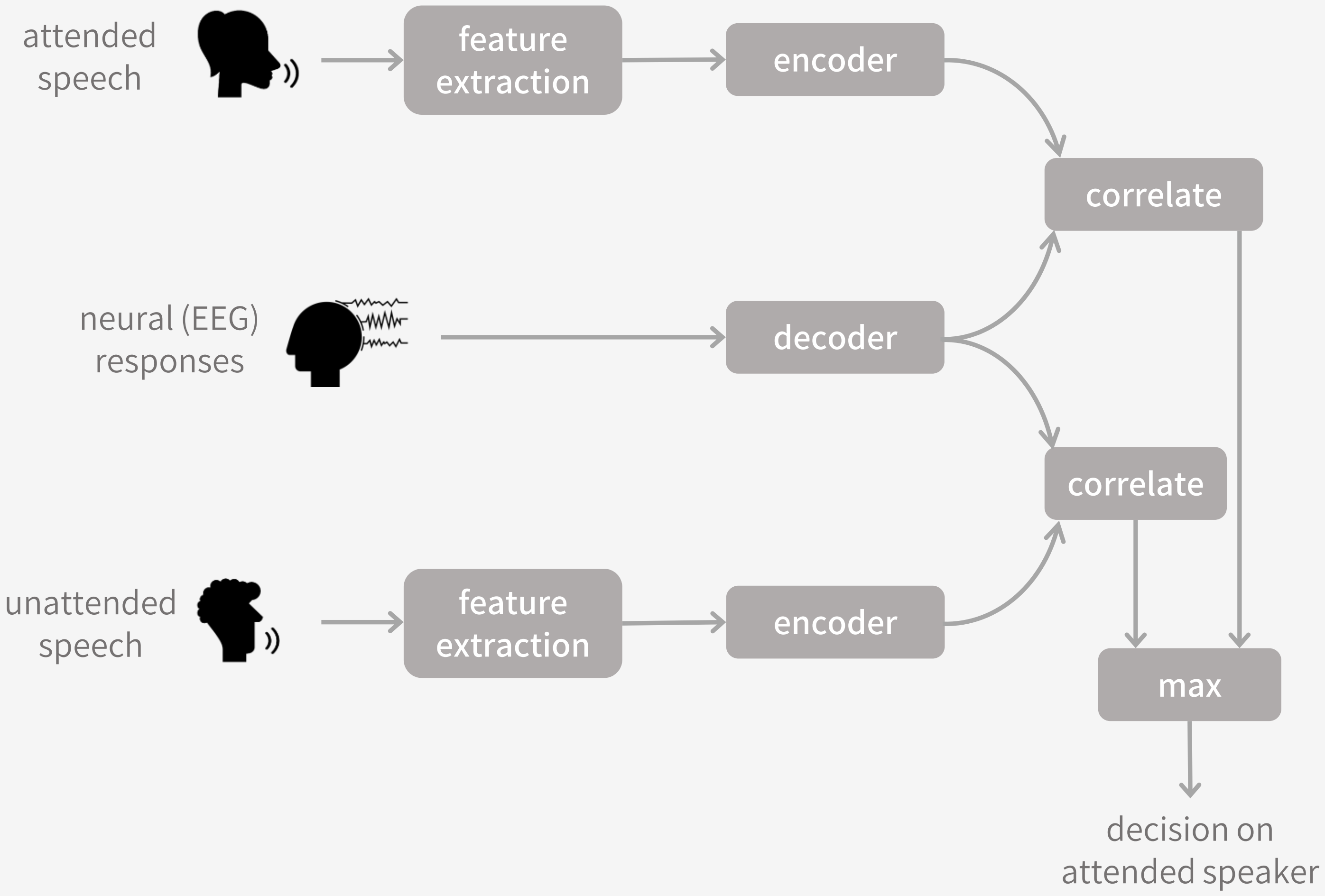
③ Compute AAD accuracy

$$\text{AAD accuracy}\,(w_2) = 100\left(1 - F(0; \mu_a^{(2)} - \mu_u^{(2)}, {\sigma_a^{(2)}}^2 + {\sigma_u^{(2)}}^2)\right)$$

F: CDF of normal distribution

Validation on two datasets and two correlation-based algorithms

Setting 1: linear decoding on Das-2016 dataset



Validation on two datasets and two correlation-based algorithms

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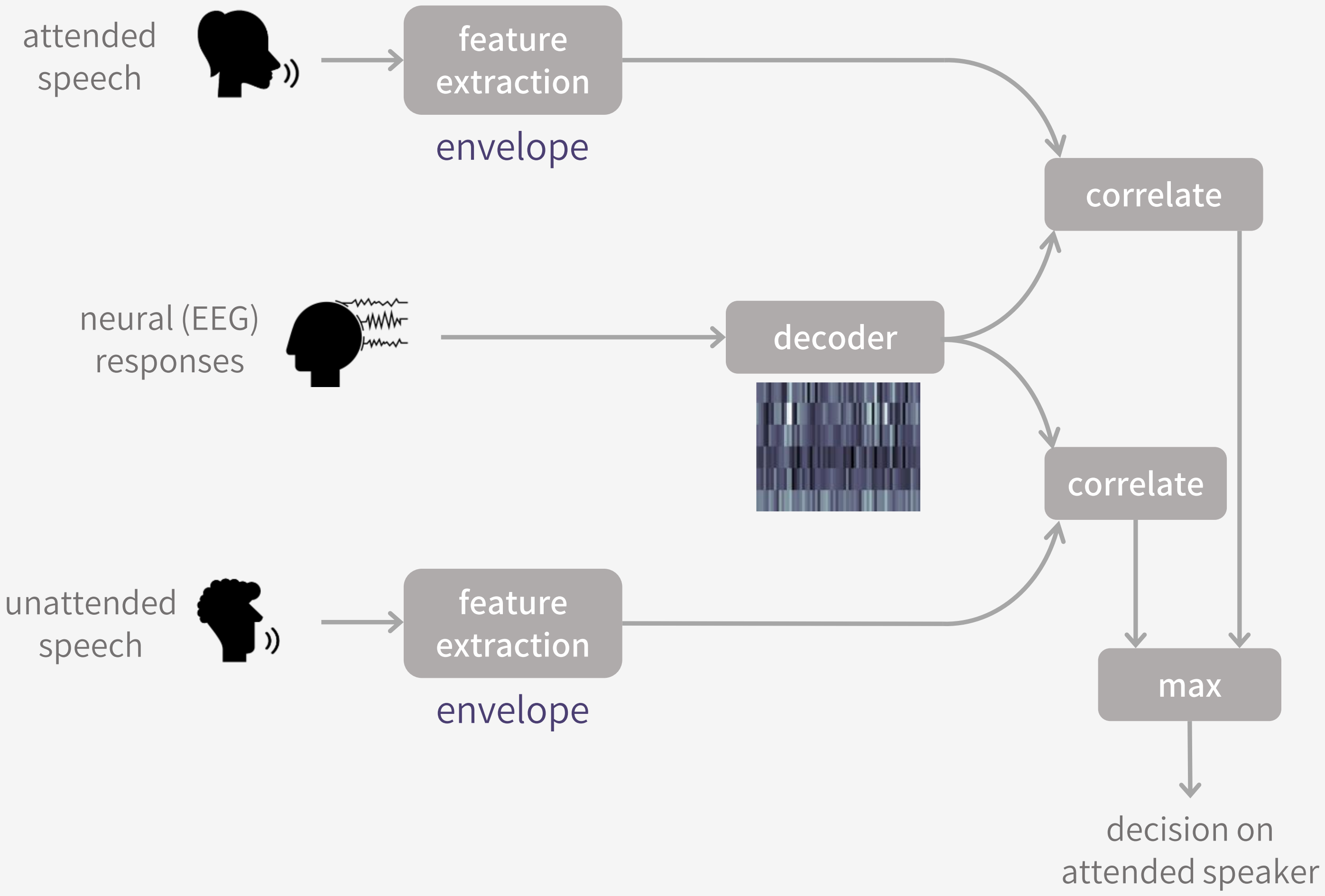


16 participants

72 min per participant

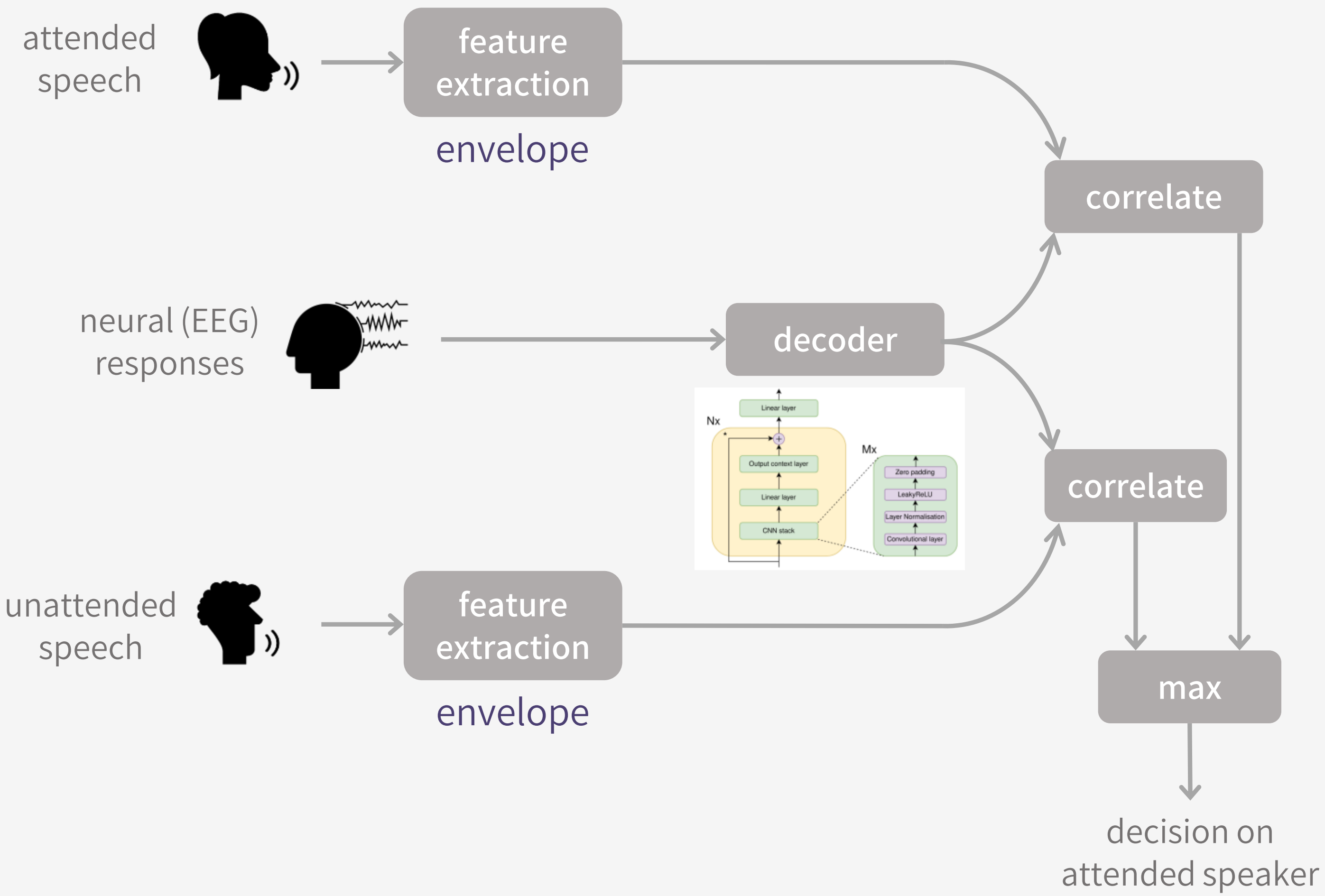
participant-specific decoding

5-fold cross-validation

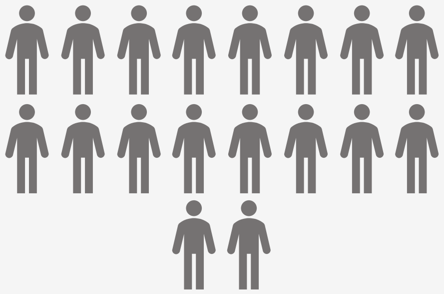
J. O'Sullivan et al, "Attentional Selection in a Cocktail Party Environment Can Be Decoded from Single-Trial EEG", *Cerebral Cortex*, vol. 25, no. 7, pp. 1697–1706, 2014

Validation on two datasets and two correlation-based algorithms

Setting 2: VLAAI deep neural network on Fuglsang-2018 dataset



18 participants



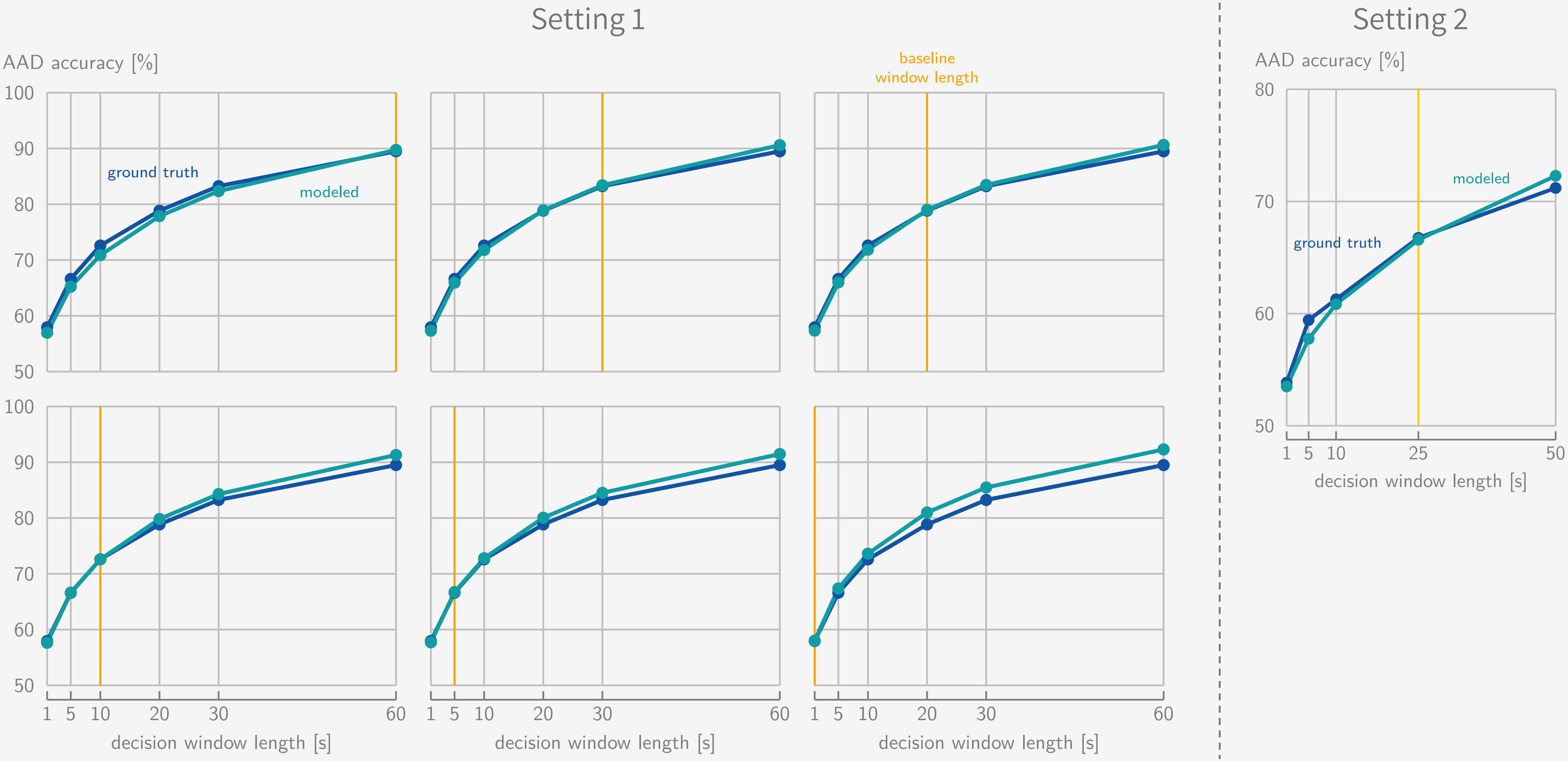
50 min per participant

participant-independent decoding

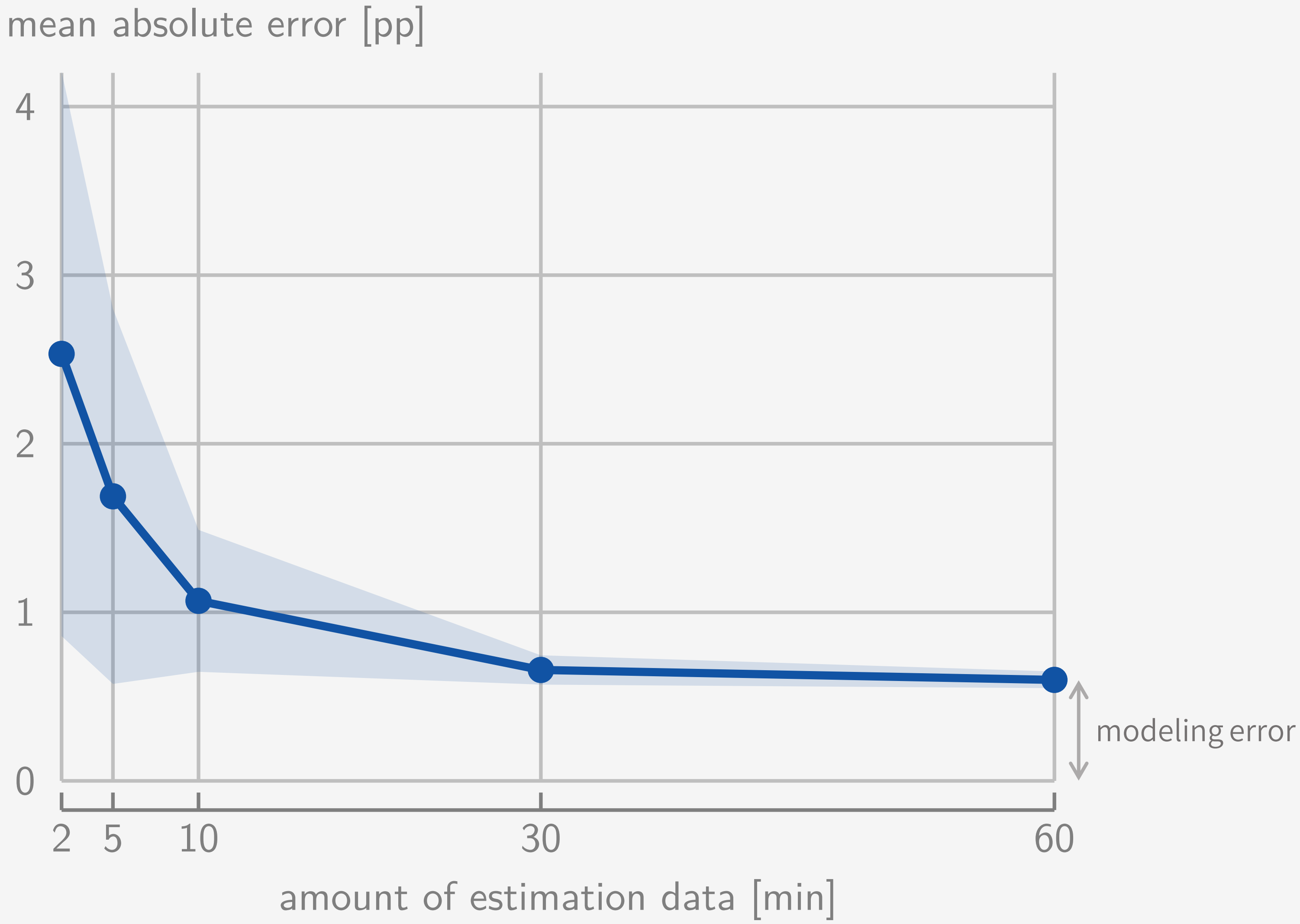
leave-one-participant-out cross-validation

B. Accou et al., “Decoding of the speech envelope from EEG using the VLAAI deep neural network,” *Sci. Rep.*, vol. 13, no. 812, 2023

The average performance can be closely approximated, especially with a baseline window length in the middle



The amount of estimation data controls a trade-off between adaptivity and estimation error



Individual performance curve estimation can be done accurately

Setting 1

Part.	Accuracy [%] per decision window length [s]												Abs. error		% in CI
	60		30		20		10		5		1				
	true	pred	true	pred	true	pred	true	pred	true	pred	true	pred	mean	std	
1	81.9	80.4	74.3	72.9	66.2	69.1	64.1	63.8	60.9	59.9	54.7	54.4	2.2	1.8	100.0
2	94.4	95.3	93.8	88.4	85.6	83.6	77.8	75.6	71.5	68.8	59.7	58.7	2.6	2.1	80.0
3	94.4	96.0	91.7	89.5	86.6	84.8	78.0	76.7	72.8	69.7	59.8	59.1	2.4	1.6	90.0
4	93.1	95.4	86.1	88.4	81.9	83.5	74.8	75.5	68.8	68.7	59.4	58.6	1.7	1.2	96.7
5	94.4	97.4	92.4	91.7	88.9	87.1	80.6	78.9	70.6	71.6	59.8	60.1	2.0	1.6	83.3
6	93.1	91.2	82.6	83.2	80.1	78.4	70.6	71.1	66.7	65.3	57.4	57.0	1.6	1.3	100.0
7	93.1	93.5	83.3	85.9	79.2	81.0	75.5	73.3	68.2	67.0	58.1	57.8	1.7	1.4	100.0
8	79.2	75.7	71.5	69.0	67.1	65.7	63.0	61.3	58.6	58.0	55.2	53.6	2.4	2.6	91.7
9	76.4	79.3	68.1	72.0	64.4	68.4	62.3	63.3	58.2	59.5	54.1	54.3	3.5	2.9	88.3
10	91.7	94.3	84.7	87.0	81.5	82.1	74.5	74.3	66.4	67.8	58.8	58.2	2.0	1.4	100.0
11	86.1	86.5	80.6	78.3	72.7	73.9	69.0	67.5	63.2	62.6	56.6	55.7	2.0	1.6	96.7
12	79.2	81.8	69.4	74.1	70.4	70.1	65.0	64.6	63.0	60.4	56.3	54.7	2.7	2.2	91.7
13	90.3	90.9	85.4	82.8	79.6	78.1	71.5	70.9	65.2	65.1	57.2	56.9	1.8	1.6	98.3
14	97.2	98.7	95.1	94.3	91.2	90.1	82.9	82.0	76.5	74.1	62.4	61.4	1.5	1.1	91.7
15	91.7	93.1	85.4	85.4	81.9	80.5	74.3	72.9	67.4	66.7	58.7	57.6	1.7	1.1	100.0
16	95.8	95.4	87.5	88.4	84.3	83.6	77.8	75.6	68.1	68.9	58.8	58.7	1.6	1.5	95.0
Mean	95.8	95.4	87.5	88.4	84.3	83.6	77.8	75.6	68.1	68.9	58.8	58.7	2.1	1.7	94.0

Setting 2

	Participant																		Mean
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	
mean abs err.	2.3	2.9	2.5	2.4	3.1	2.4	2.2	2.3	2.4	1.9	2.7	2.7	2.6	2.4	2.1	2.9	2.6	2.5	2.5
std abs err.	1.8	2.7	2.8	1.9	2.2	2.4	1.7	1.4	2.3	1.5	2.6	3.0	2.1	1.8	1.6	2.1	1.7	2.4	2.1
% in 95%-CI	88	94	92	98	86	92	94.	90	94	96	98	98	90	88	96	88	82	96	92.2

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