Computational Sensorimotor Systems Lab

The progression of neural representations of speech in the brain, from acoustics to semantics

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http://www.isr.umd.edu/Labs/CSSL/simonlab

UMD Math Bio Seminar, 2 May 2023

Acknowledgements

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Jonas Vanthornhout
Richard Williams
Peng Zan

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NIDCD
NIH NIA
NSF
DARPA
University of Maryland 1856

Outline

- Measuring Brain Responses with Magnetism
- Linear Shift-Invariant Kernels
- Motivation: neural response as convolution with stimulus
- Examples: neural response as convolution with stimulus
- Example: objective measure of intelligibility

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Magnetoencephalography (MEG)

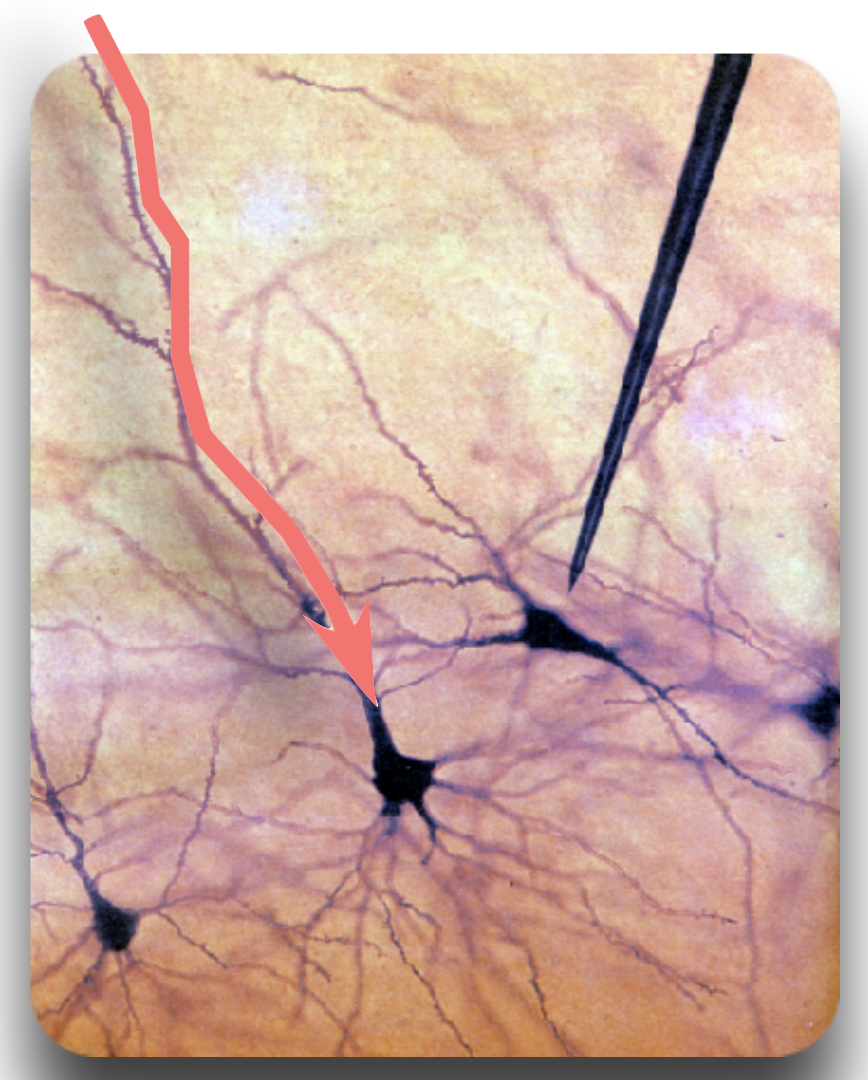
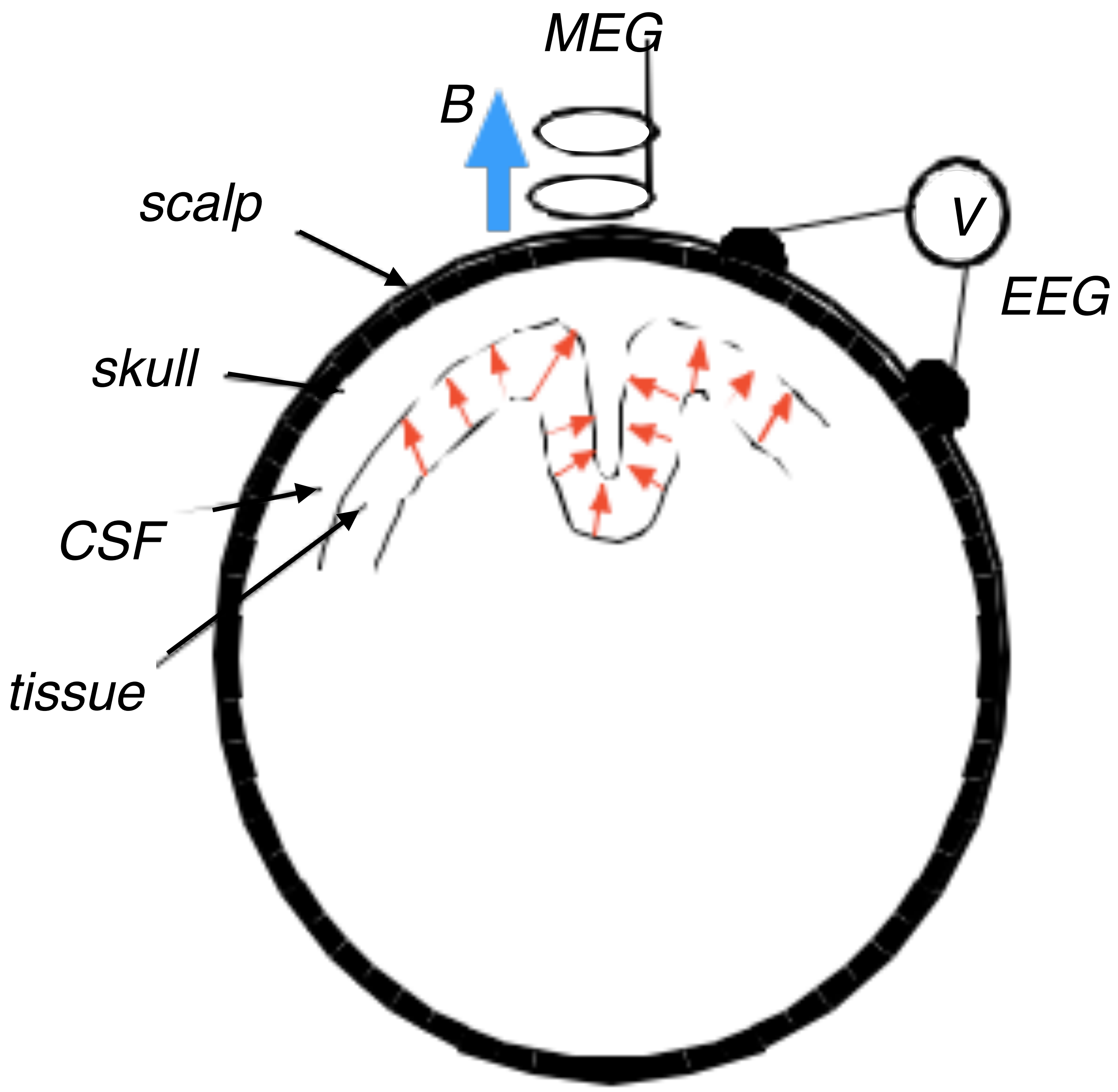
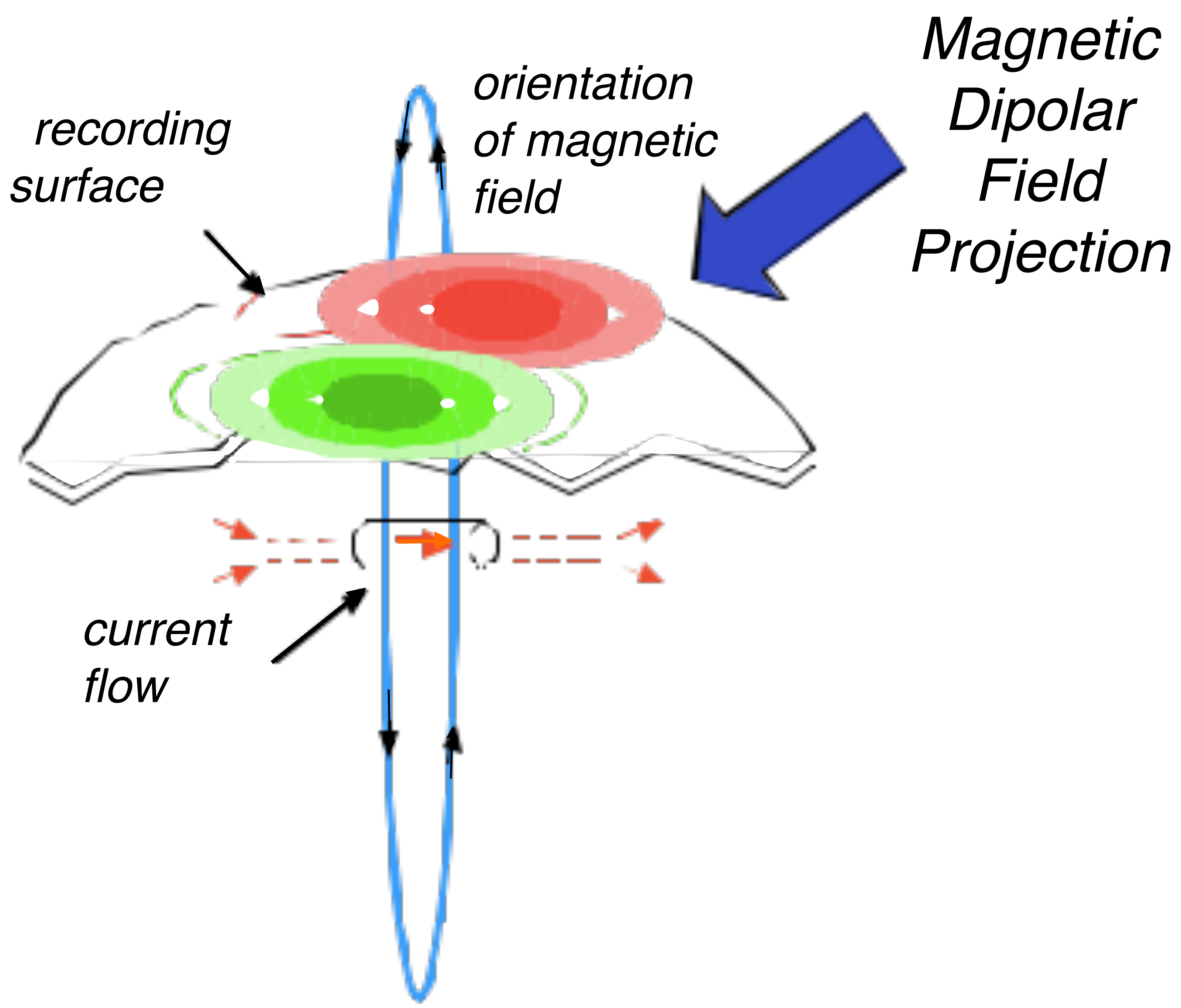


Photo by Fritz Goro





- Direct electrophysiological measurement
  - not hemodynamic
  - real-time
- No unique solution for distributed source

- Measures spatially synchronized cortical activity
- Fine temporal resolution (~ 1 ms)
- Moderate spatial resolution (~ 1 cm)

Magnetoencephalography (MEG)

- Non-invasive, passive, silent neural recordings from cortex
- Simultaneous whole-head recording (~200 sensors)
- Sensitivity
  - high: ~100 fT (10^{-13} Tesla)
  - low: ~10^4 – ~10^6 neurons
- Temporal resolution: ~1 ms
- Spatial resolution
  - coarse: ~1 cm
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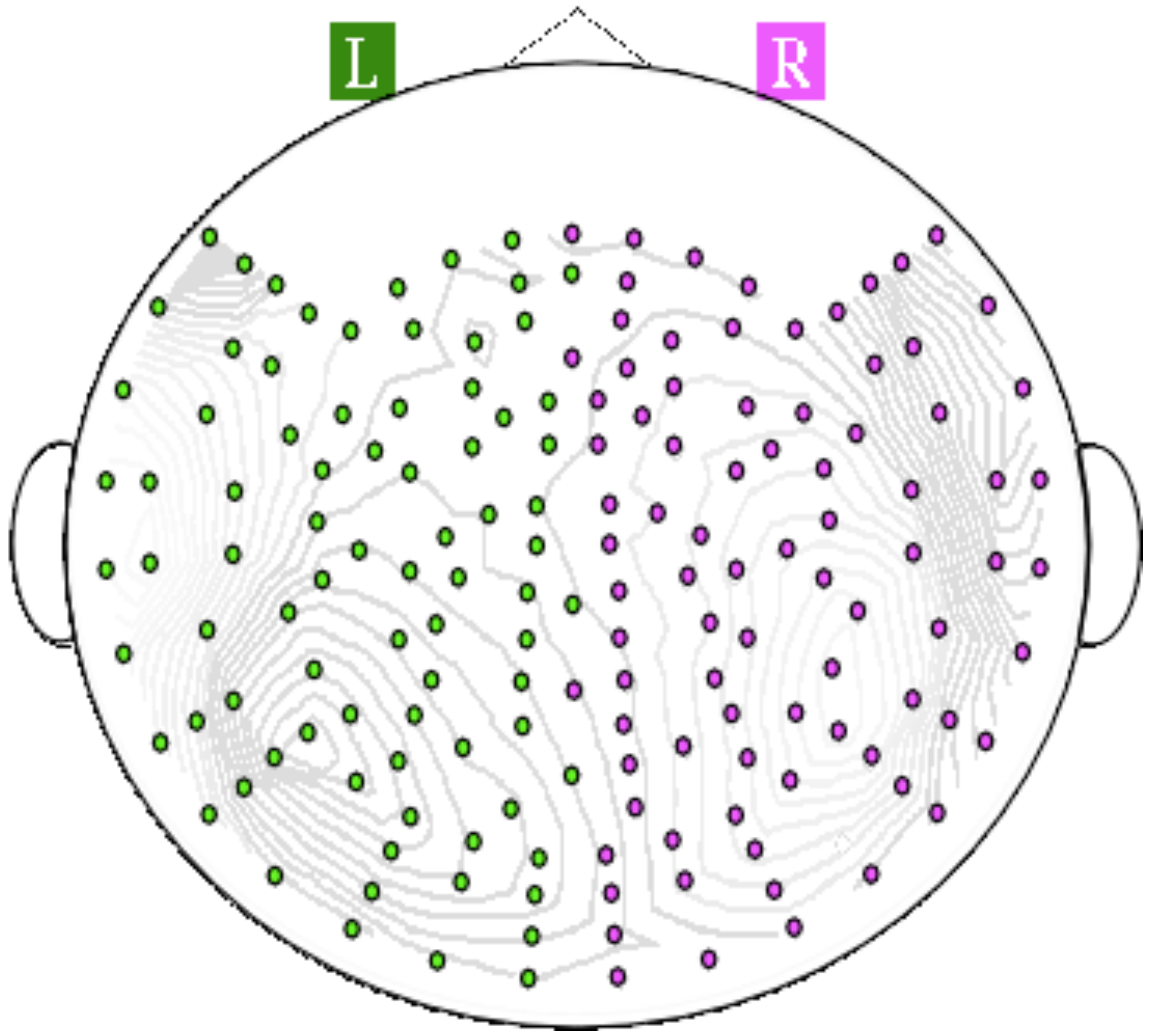

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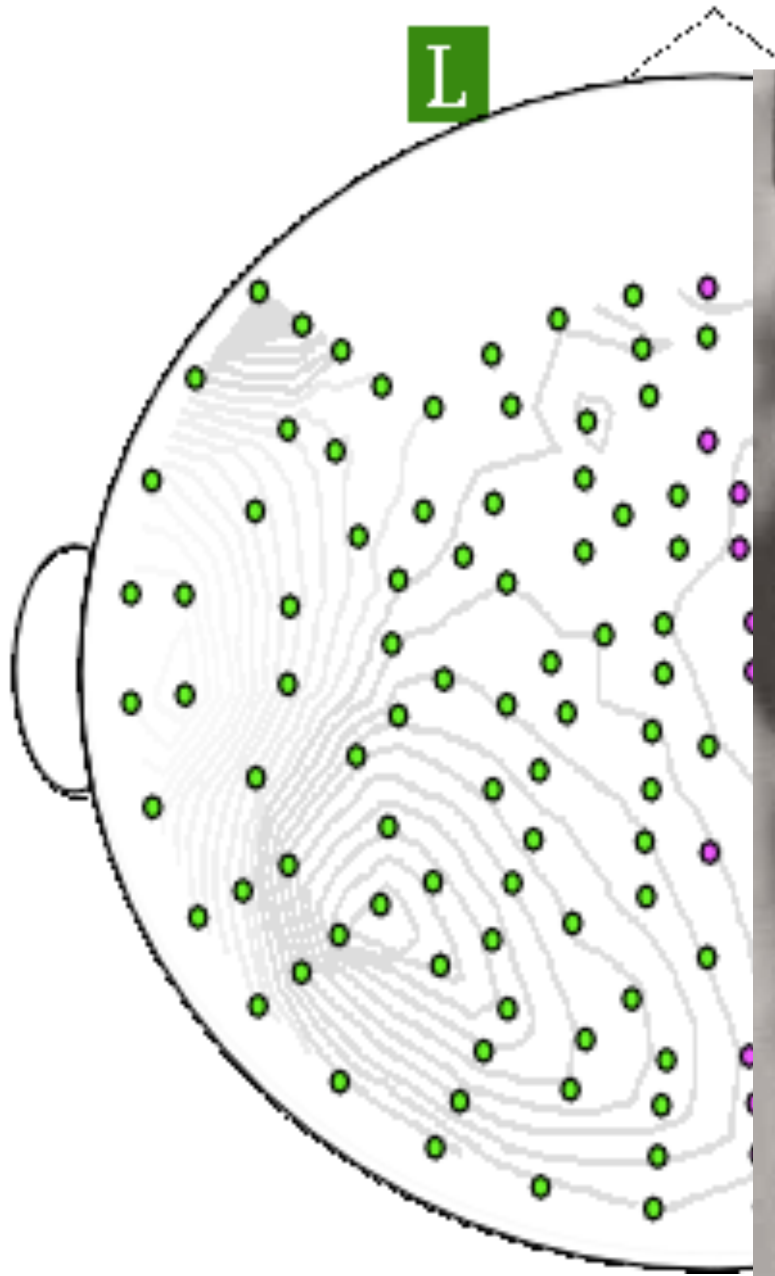

http://www.darkroastedblend.com/2007/05/mystery-devices-issue-2.html

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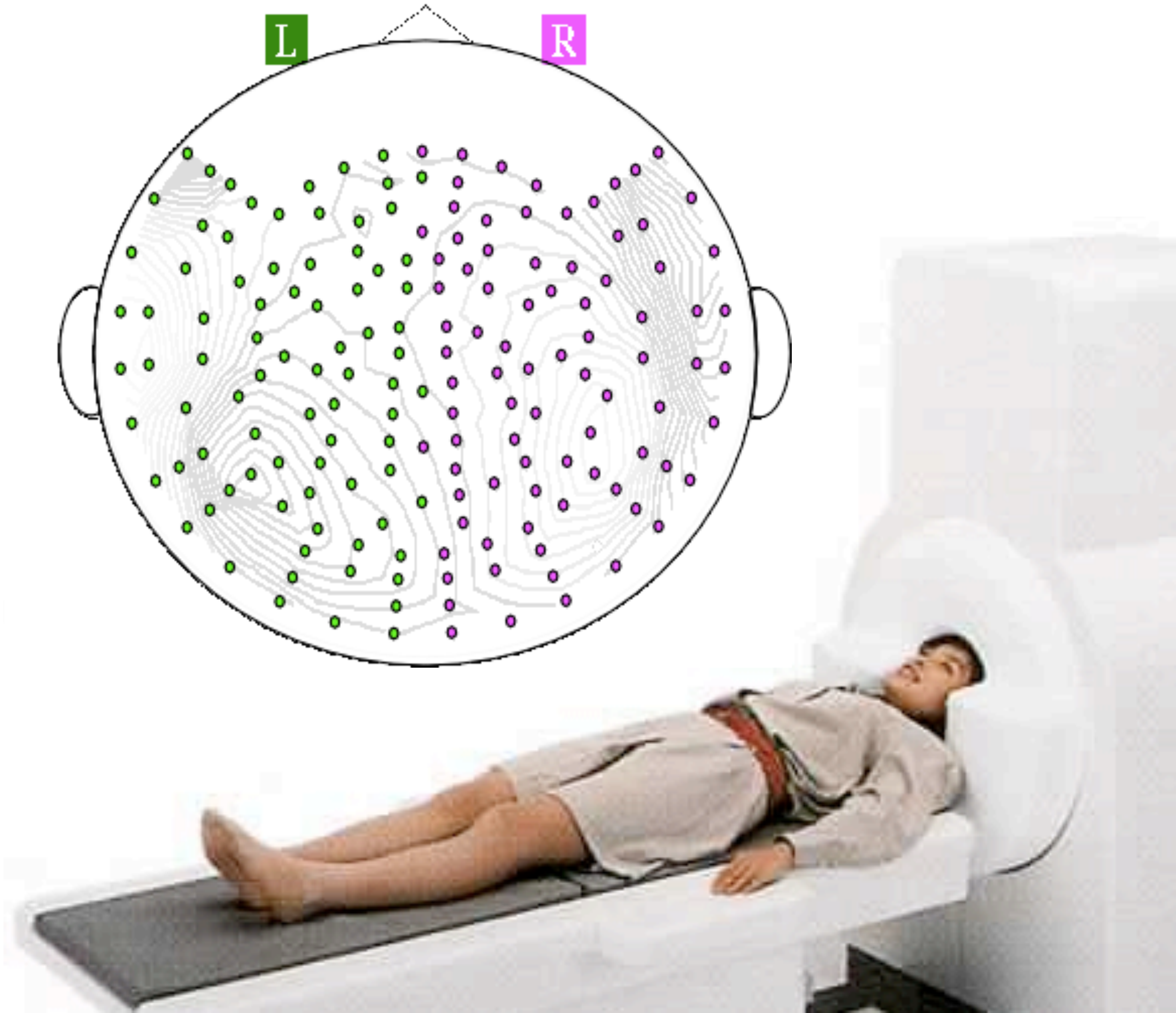
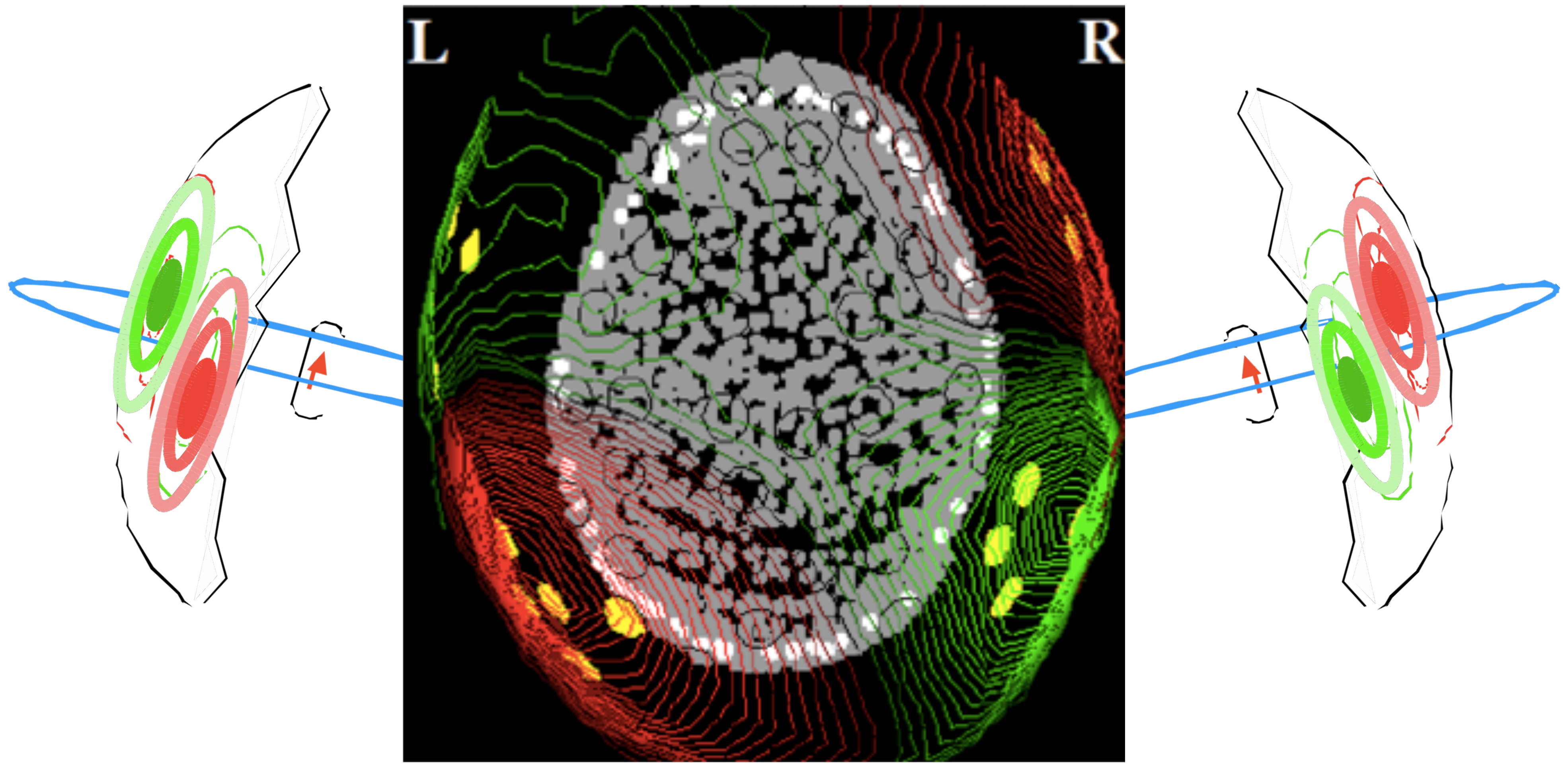


Neural Source Problem



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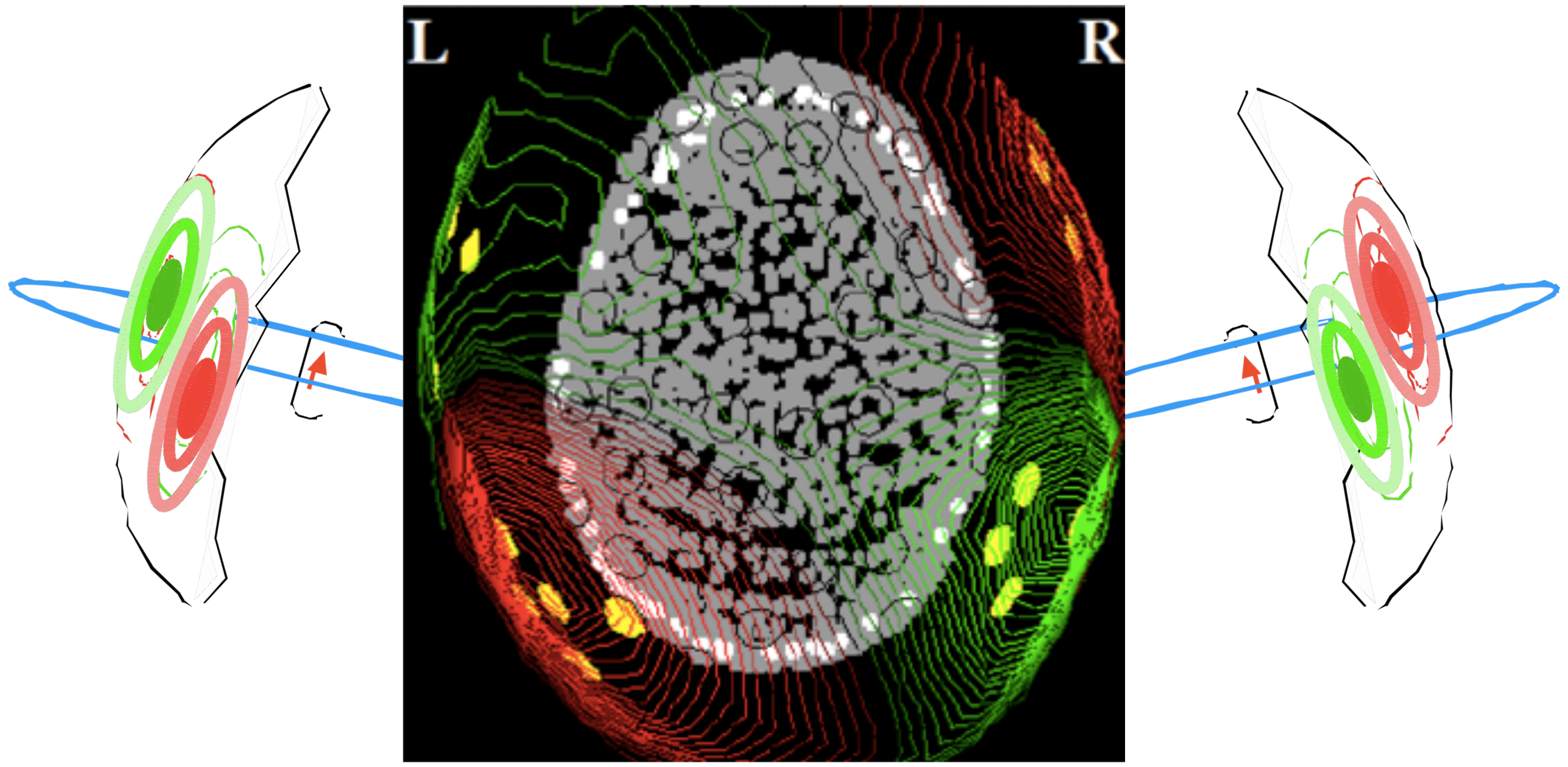

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N magnetic field sensor measurements

N x *M* "Lead Field" Matrix

M brain dipole current sources UNKNOWN

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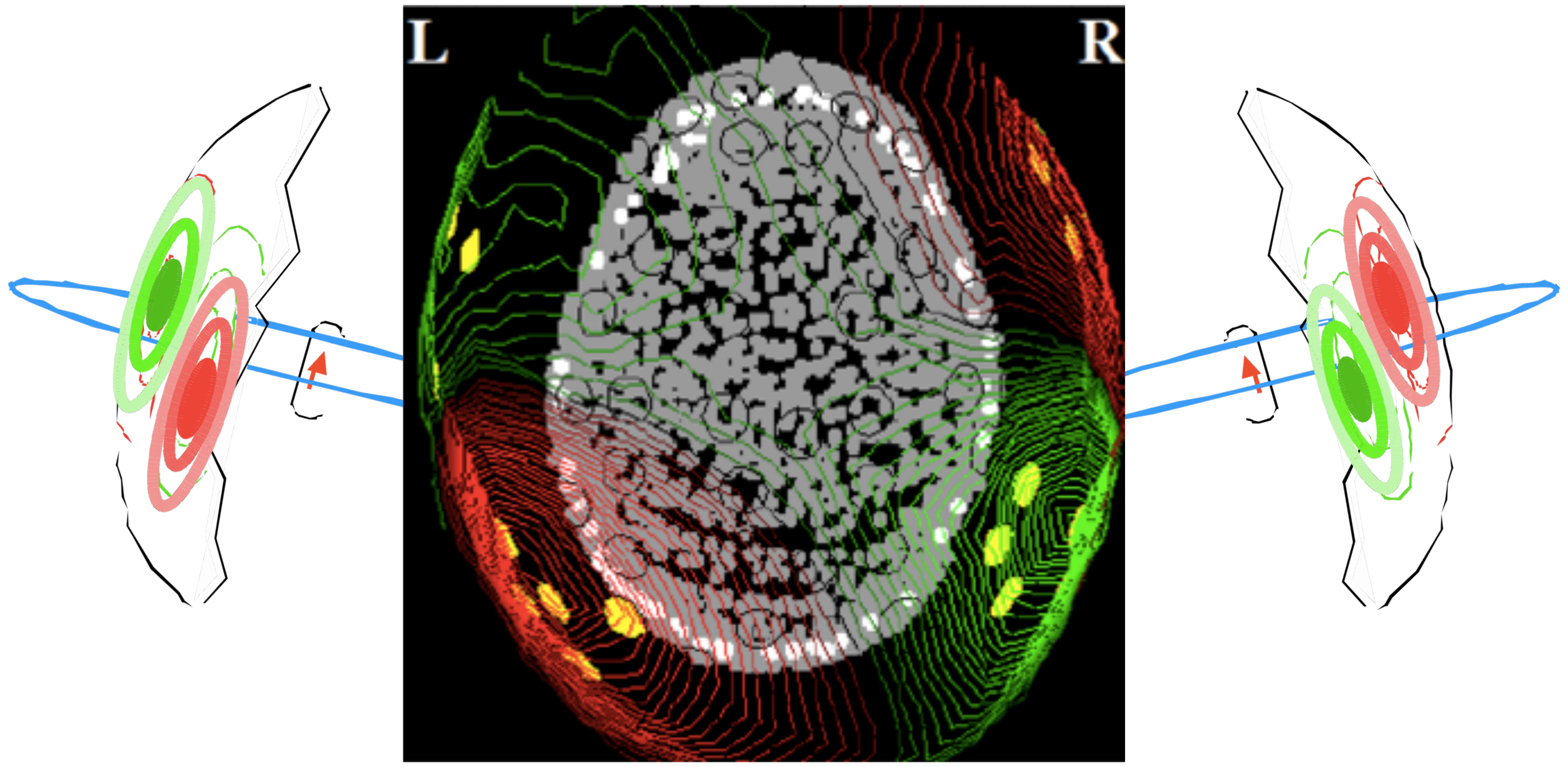

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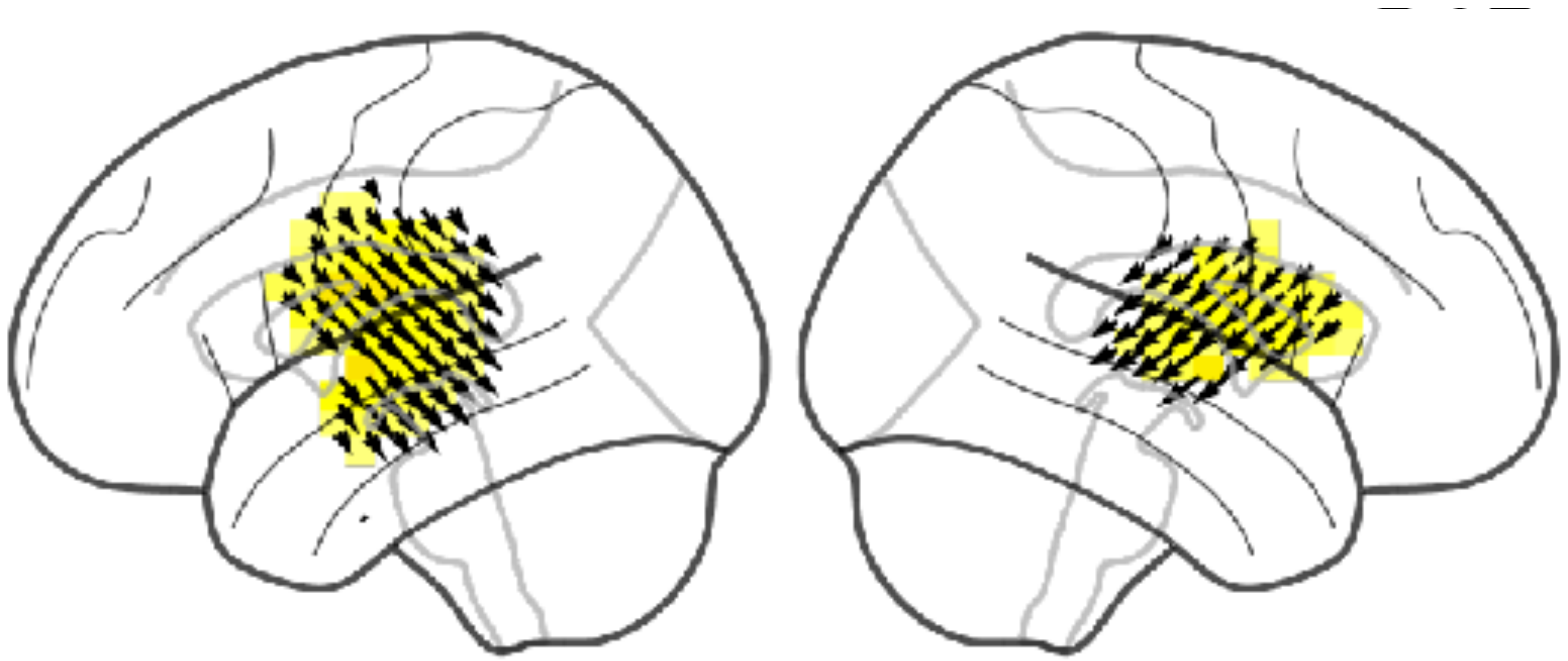

Das et al., NeuroImage (2020)

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Linear Shift Invariant Kernel

convolution/shifts in time

$$y(t) = \int h(t - t')x(t')dt'$$

output kernel input

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no shifting of frequencies $$Y(f) = H(f)\ X(f)$$

Linear Systems Theory

$$r(t) = \int h(t - t')s(t')dt'$$

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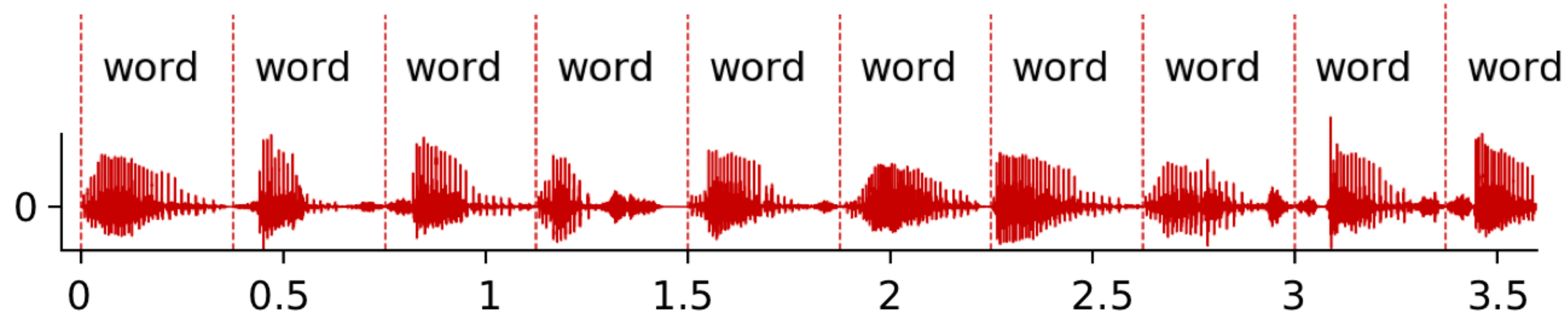
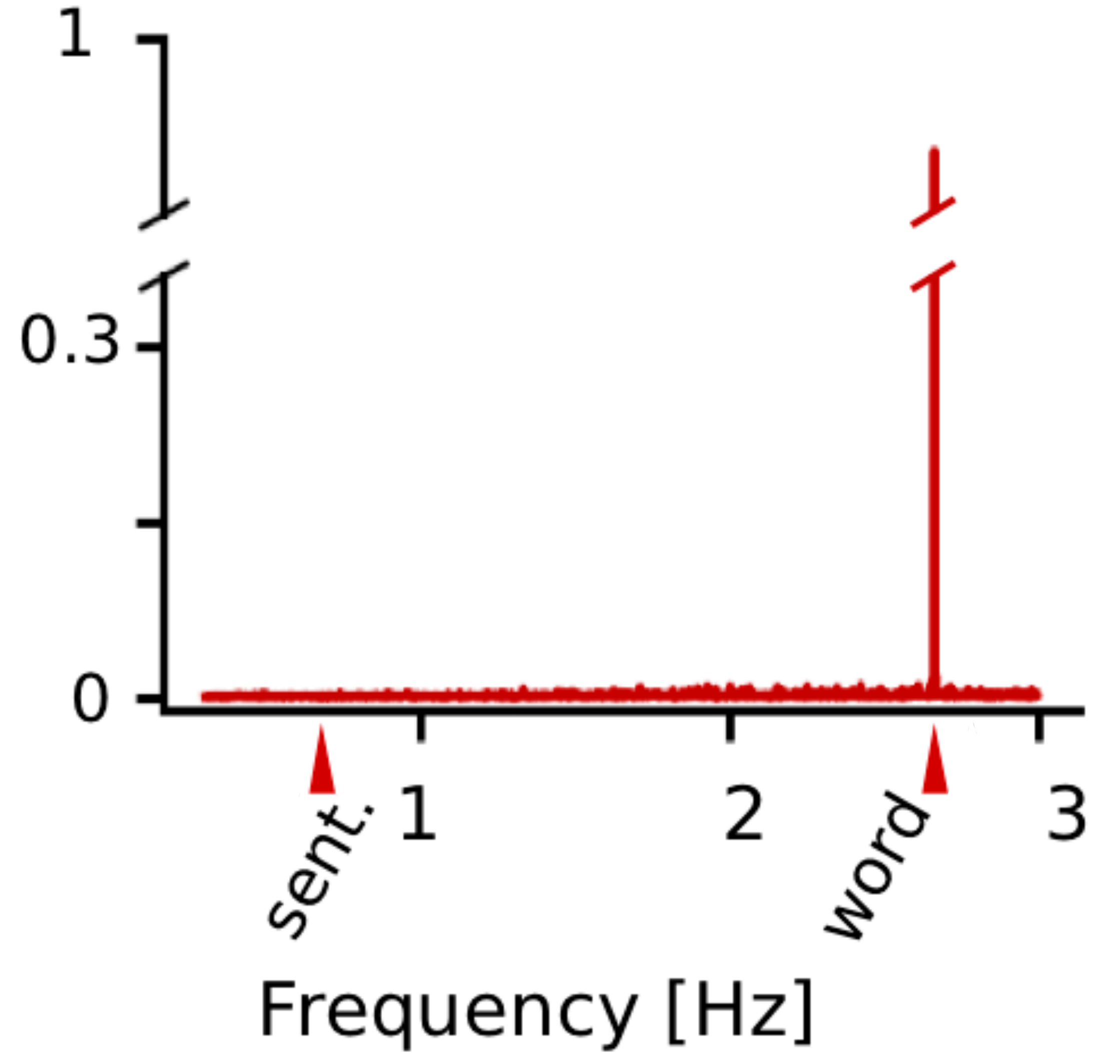
Isochronous Speech

Acoustics



Acoustical
Spectrum
(envelope)



Ding et al. (2016) Nat Neurosci
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Isochronous Speech

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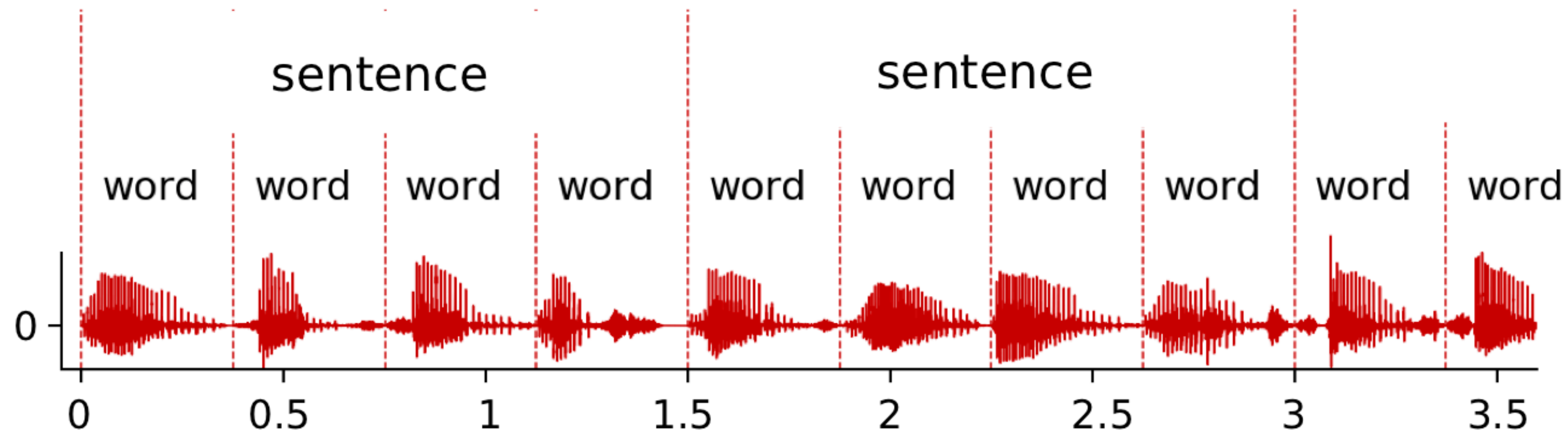

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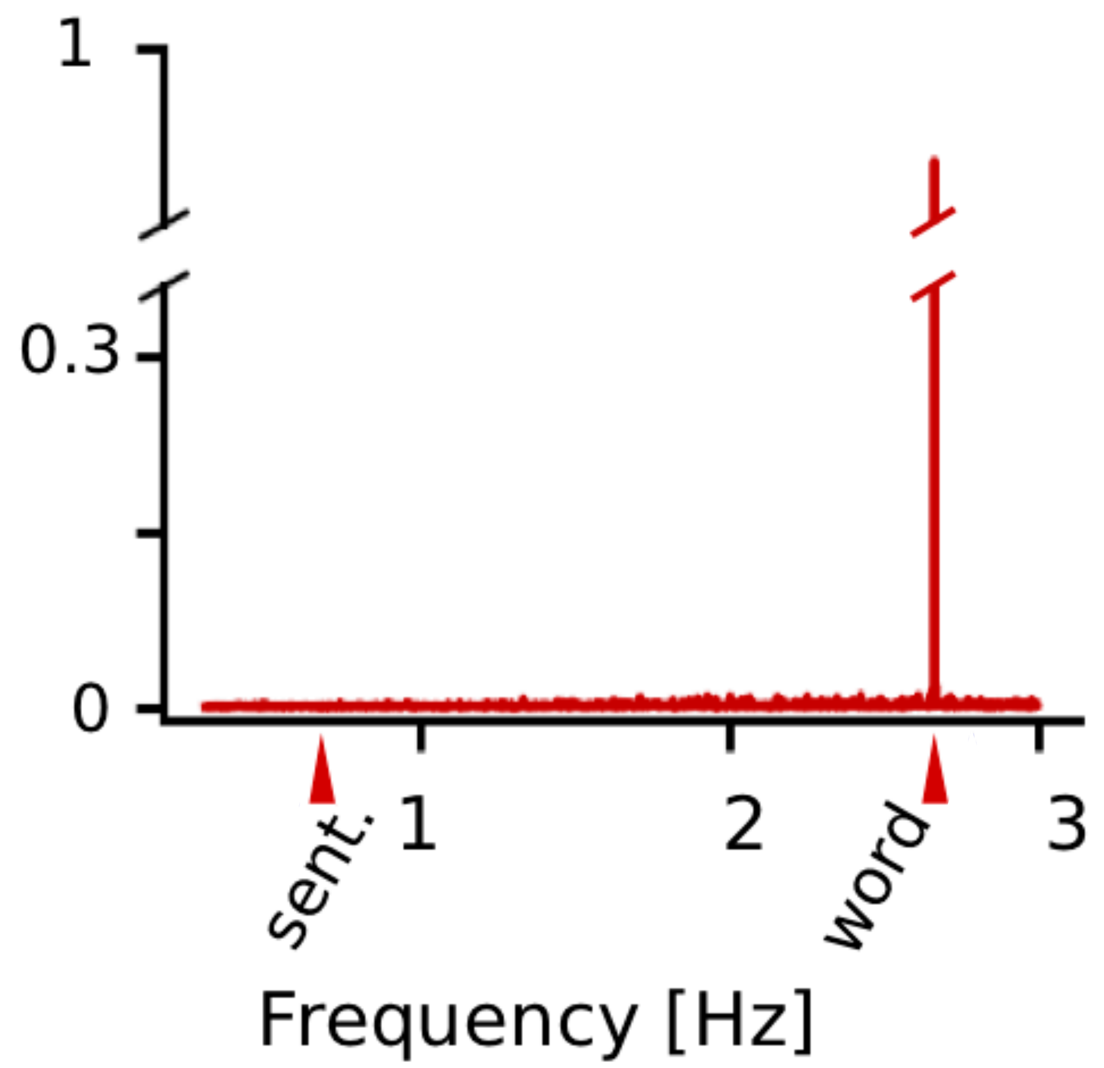

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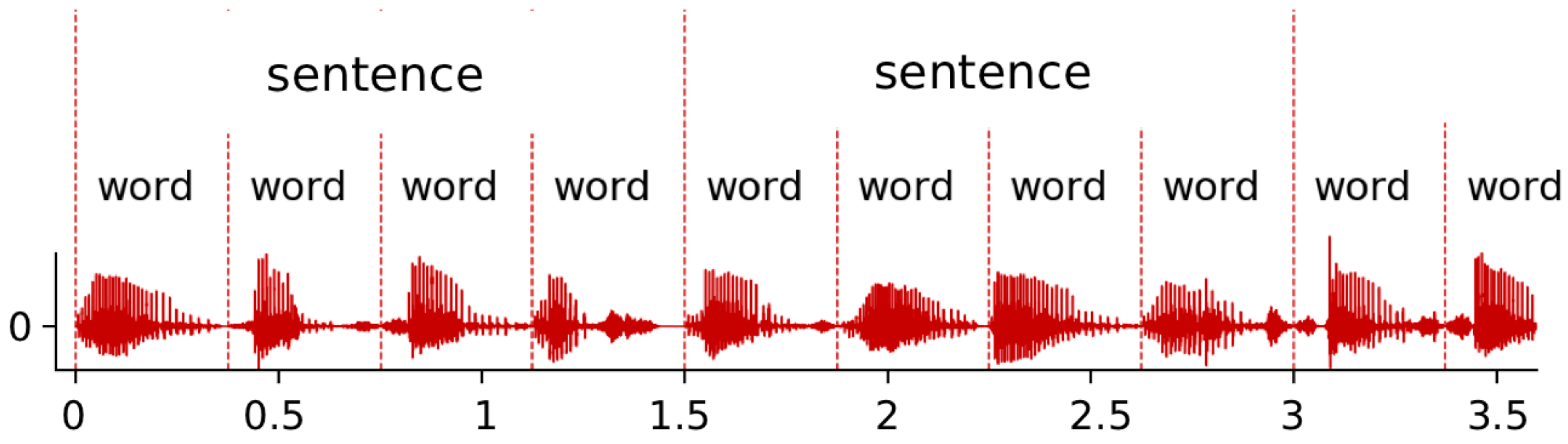

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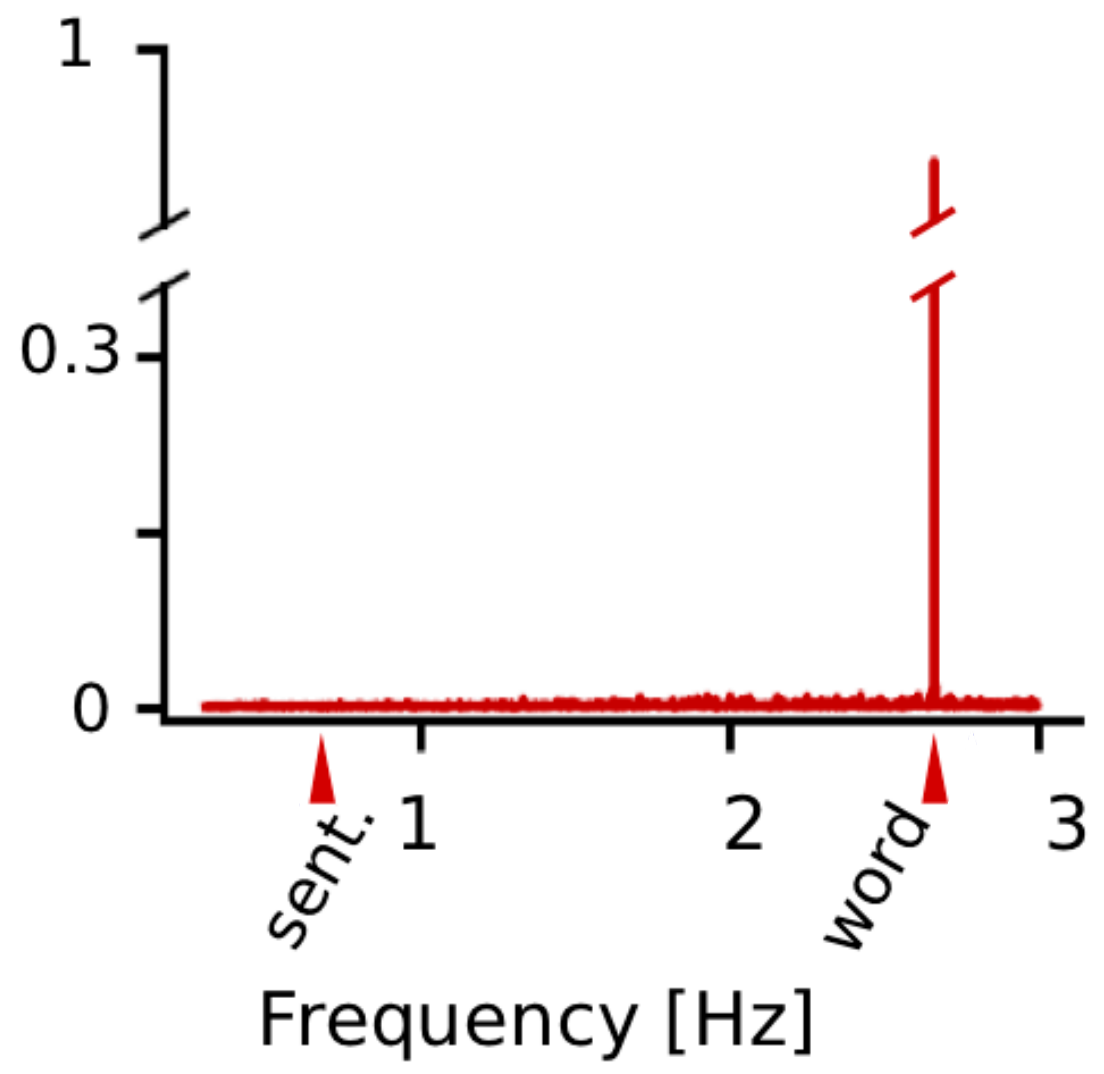

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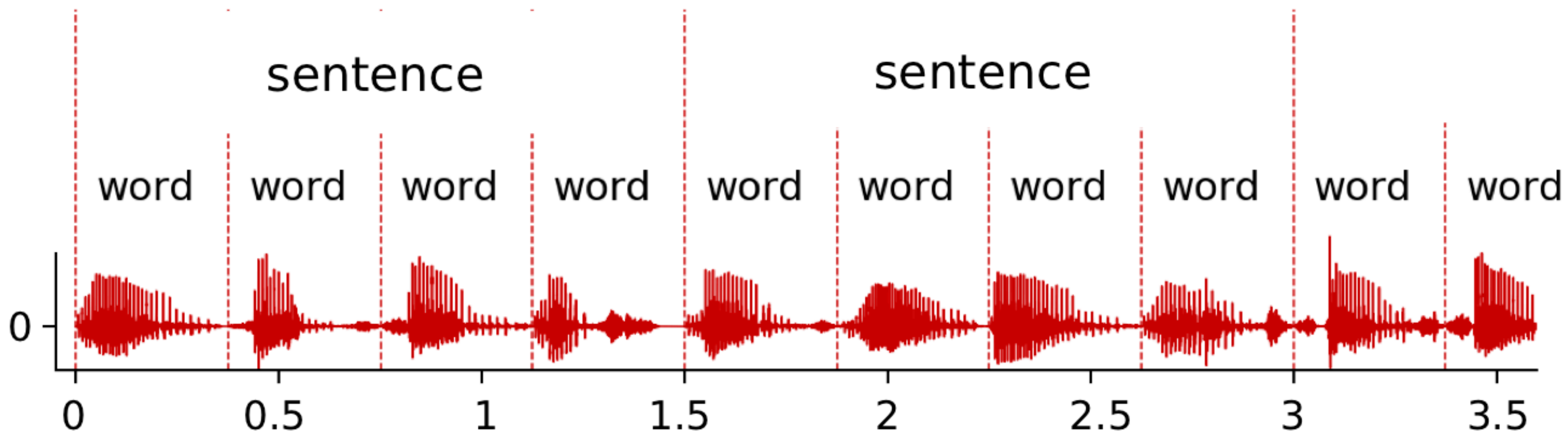

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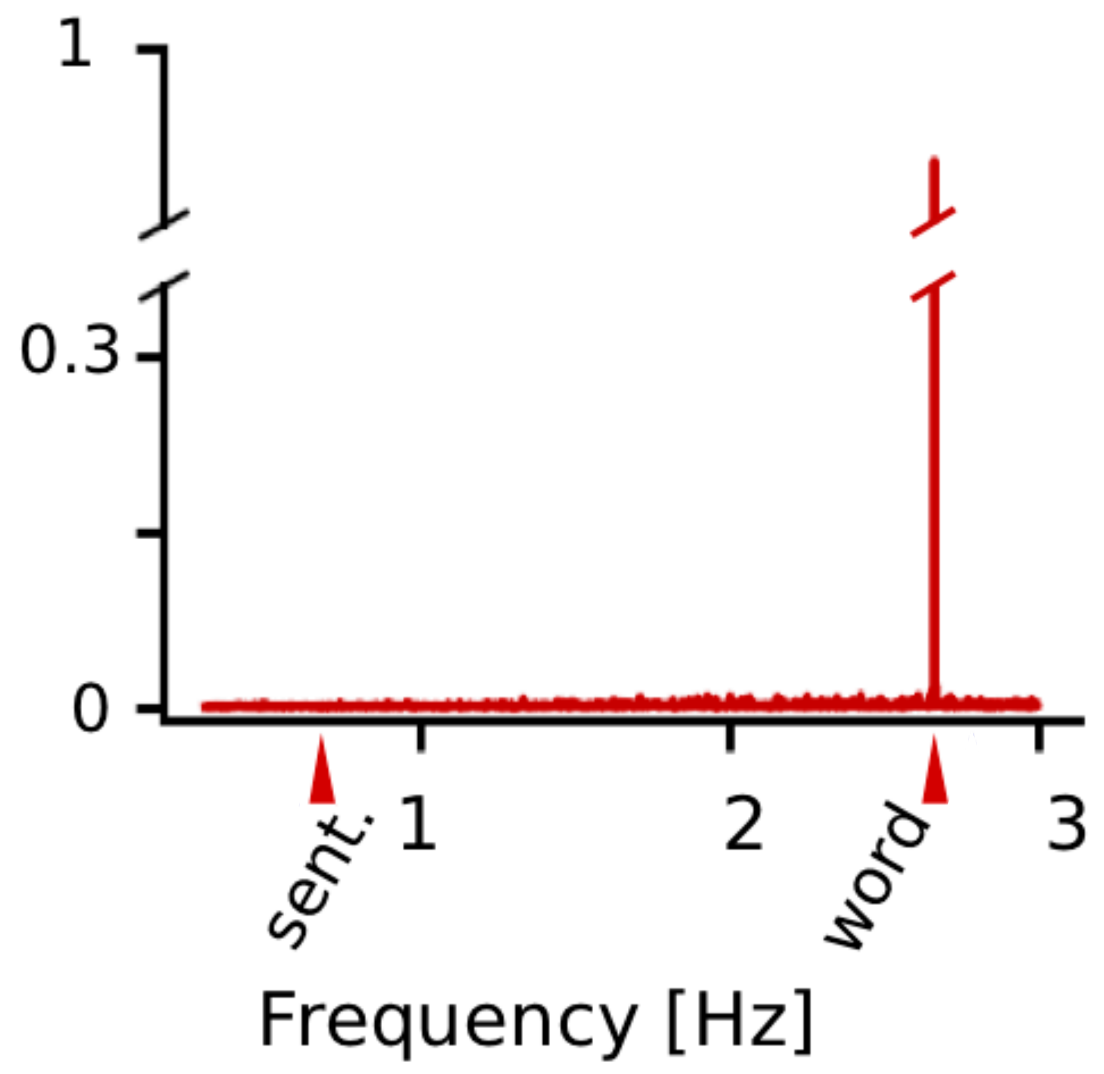

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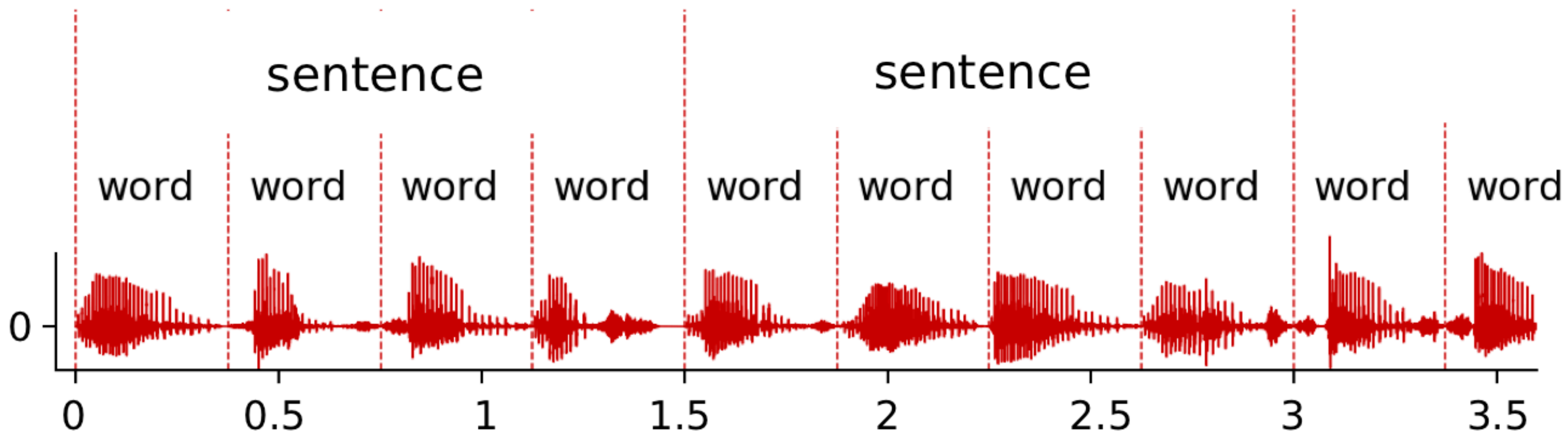

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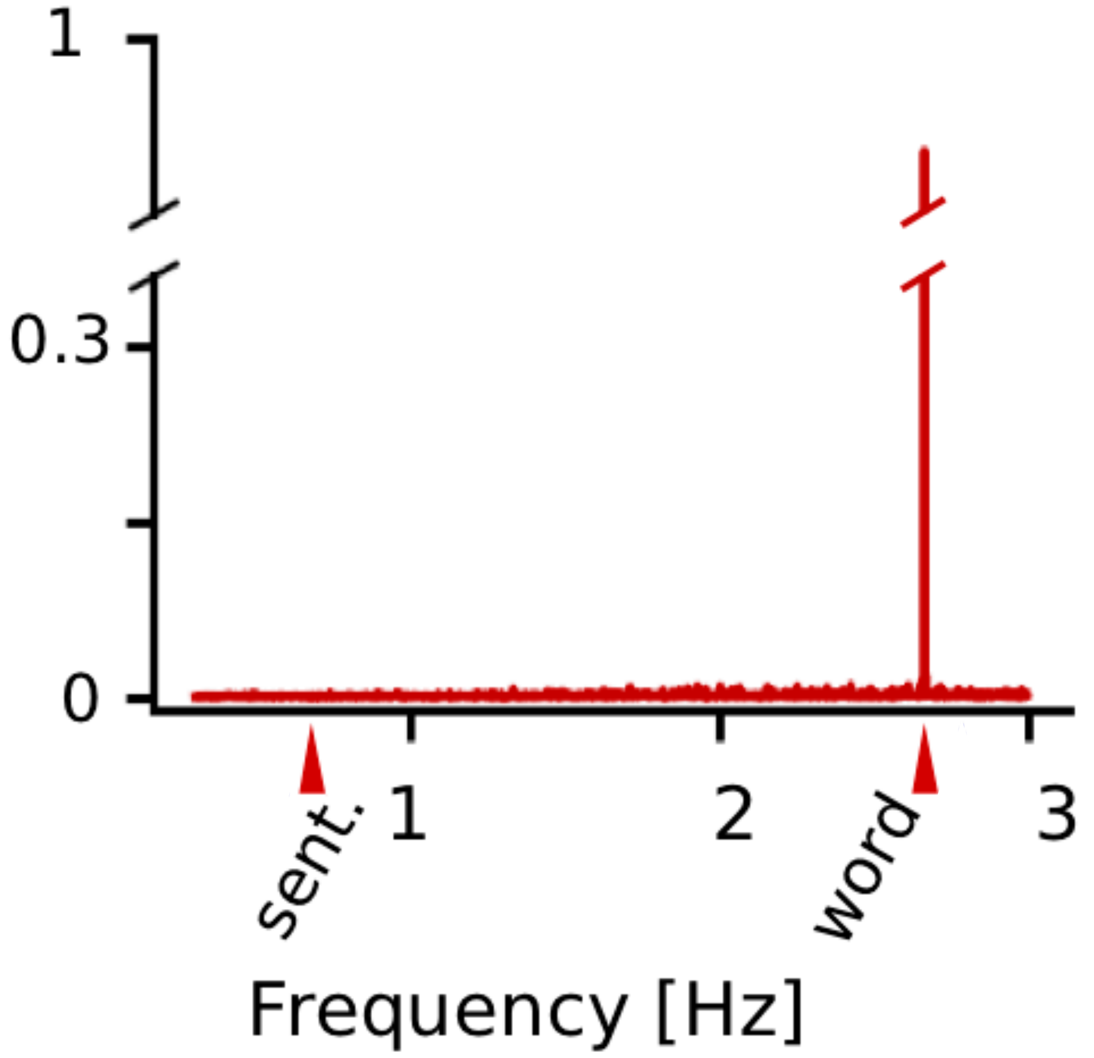
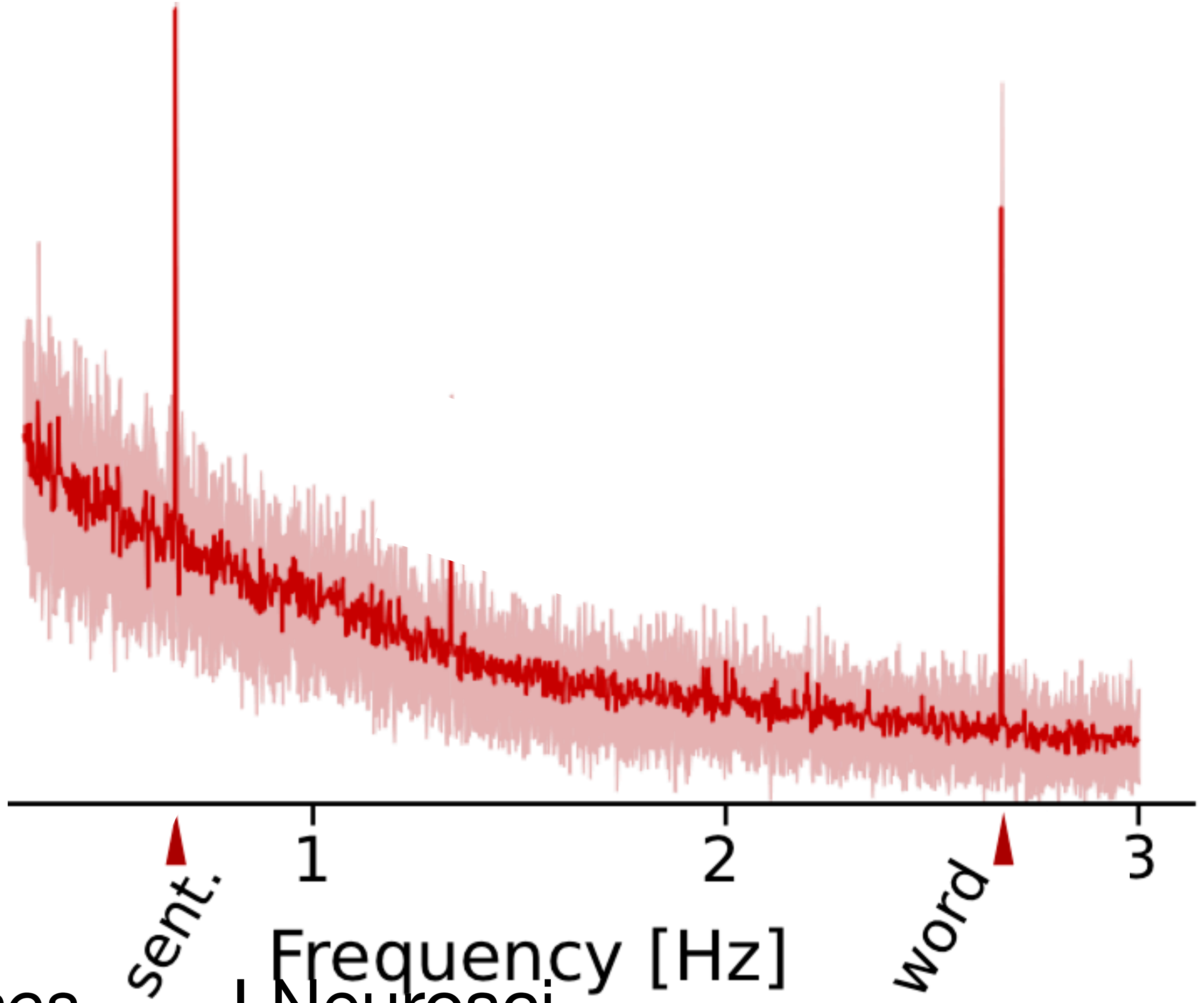


Perception?



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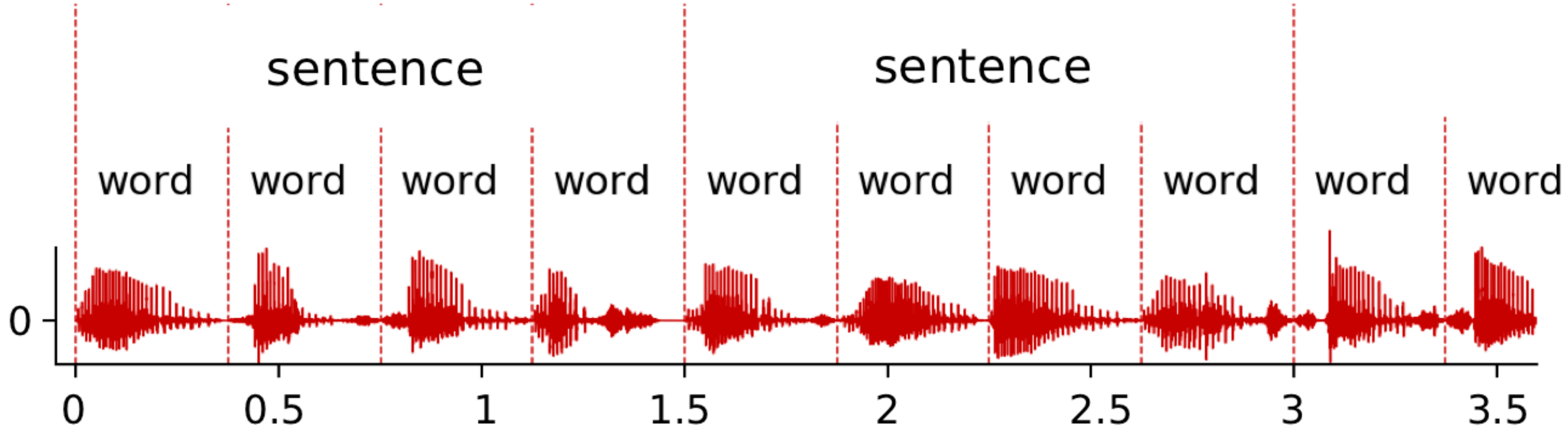

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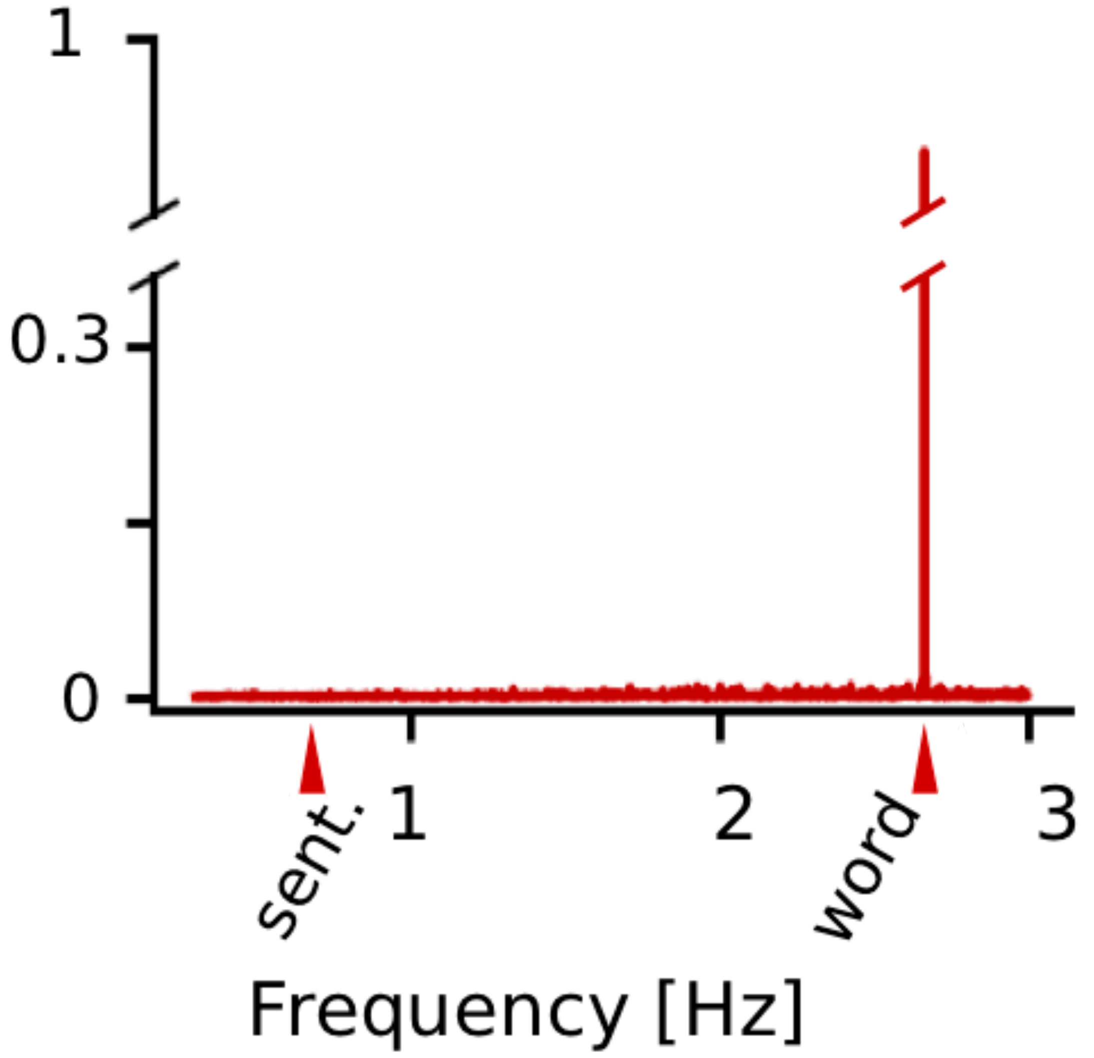

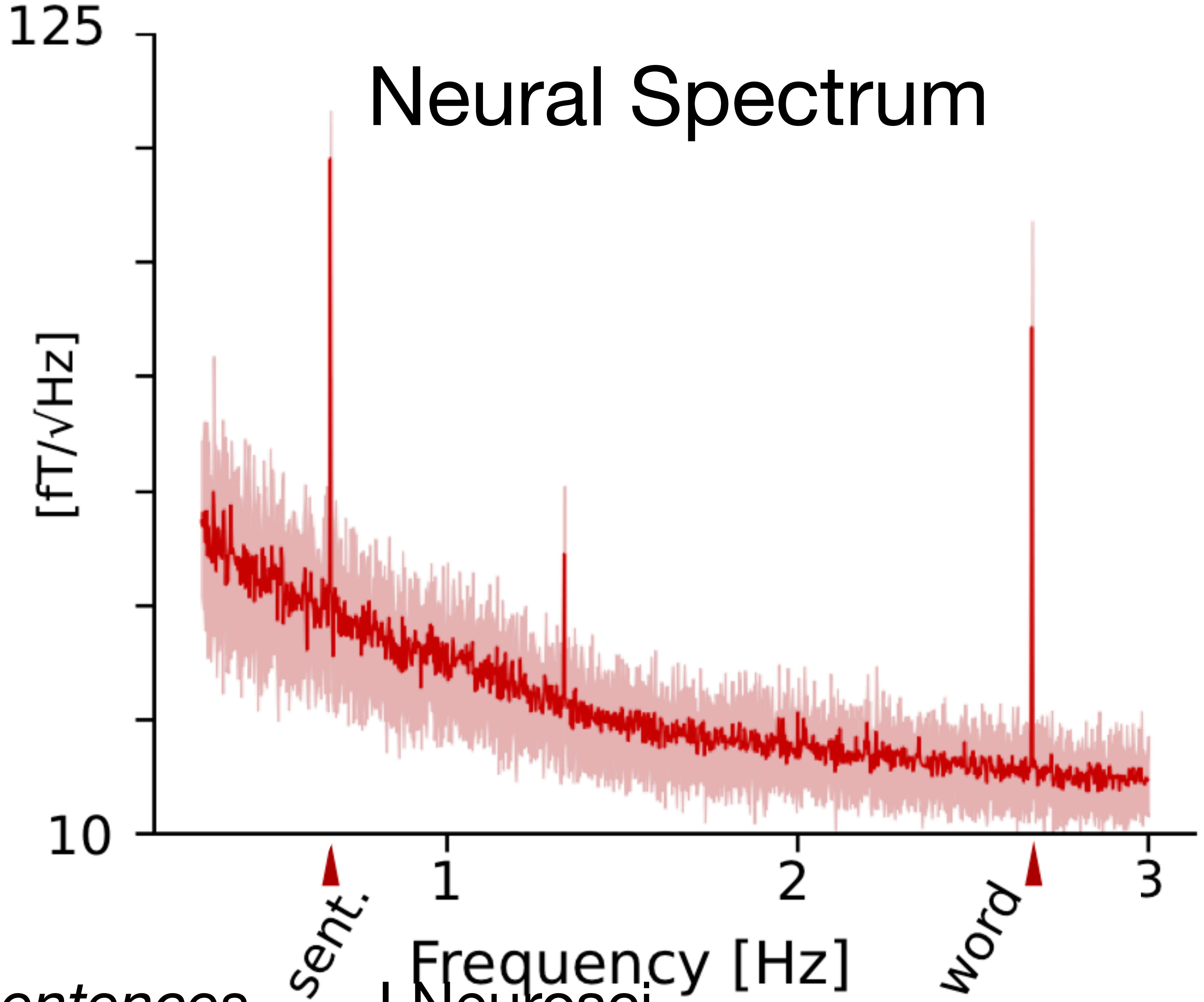

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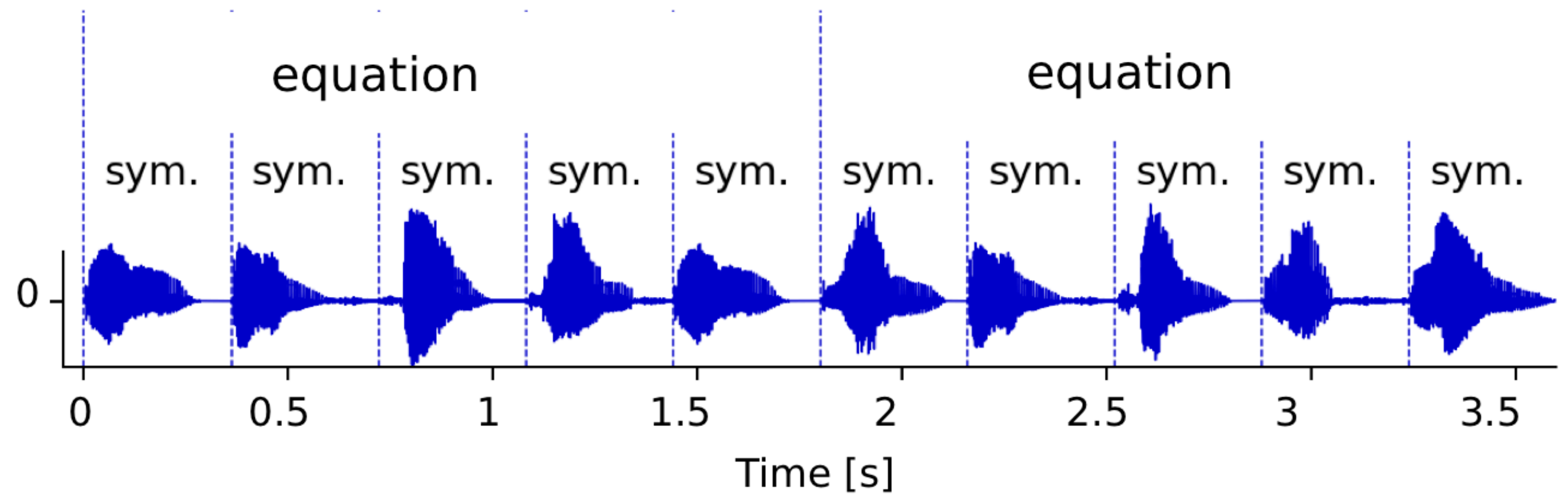
Isochronous Arithmetic



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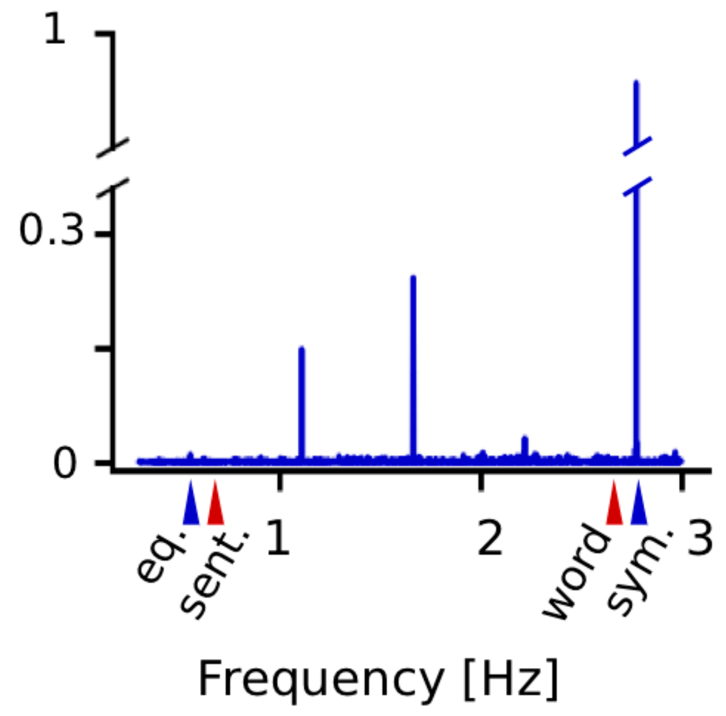

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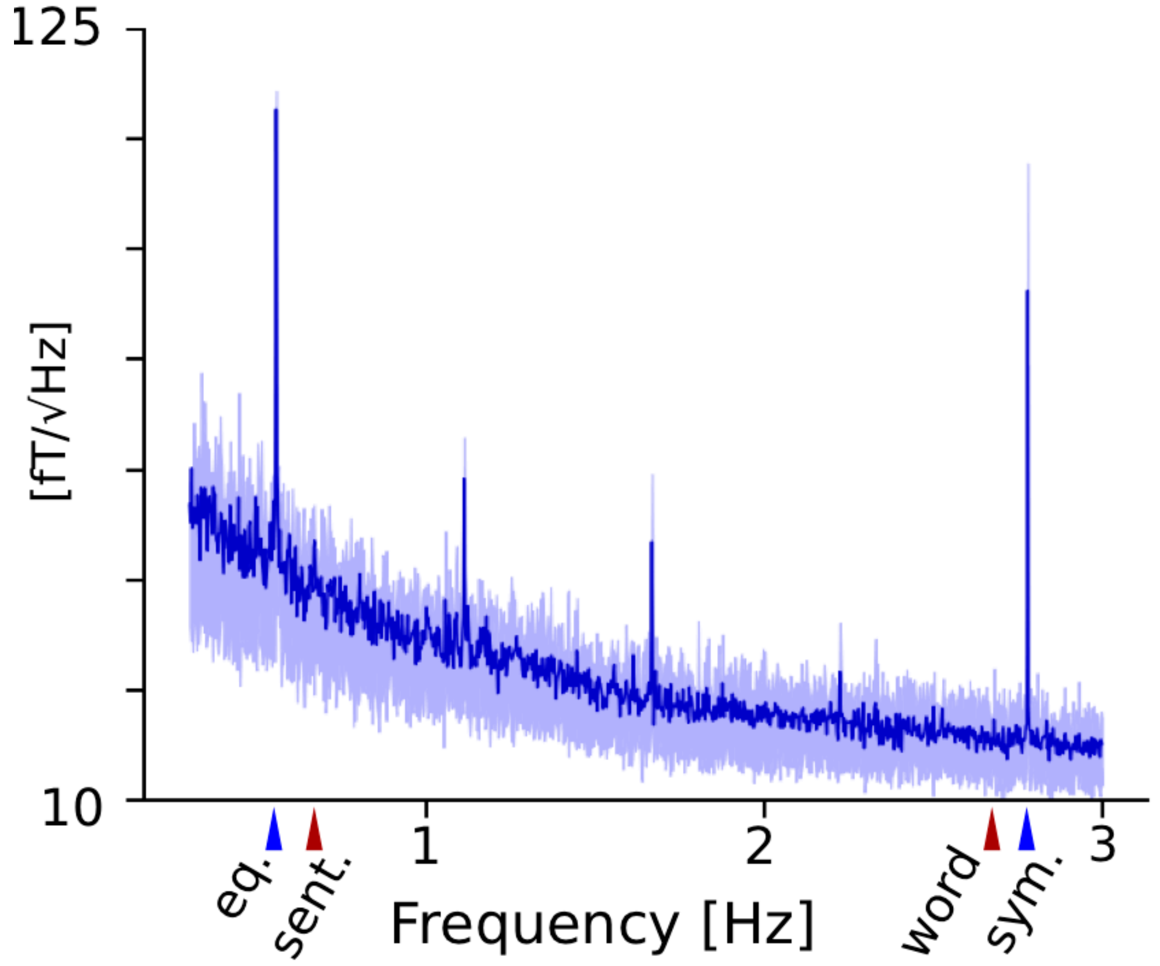

Neural Spectrum

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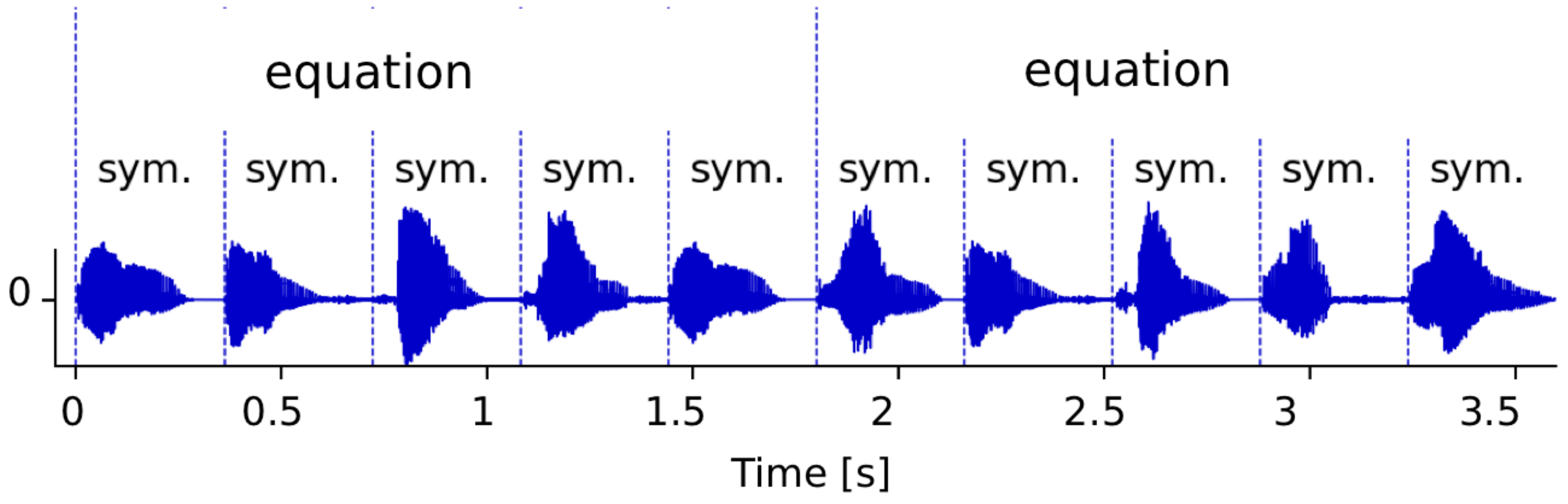

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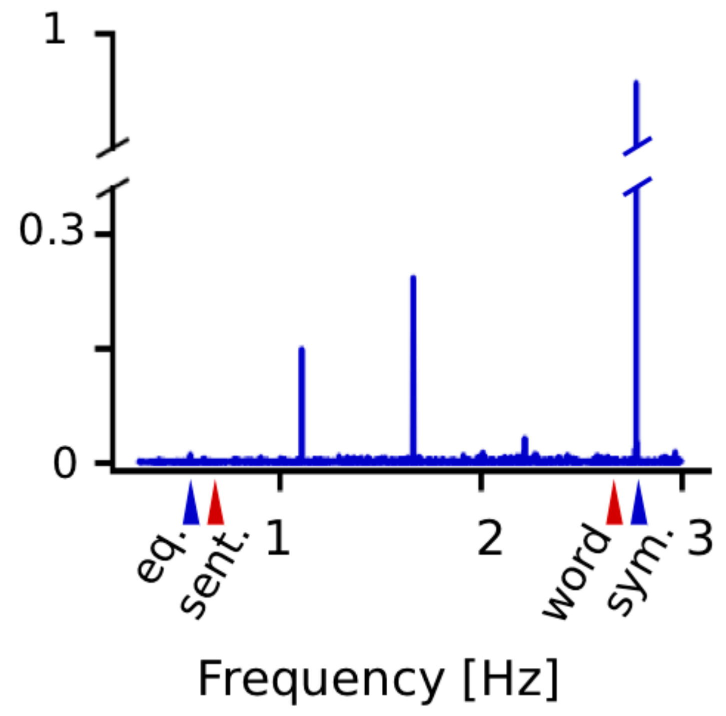

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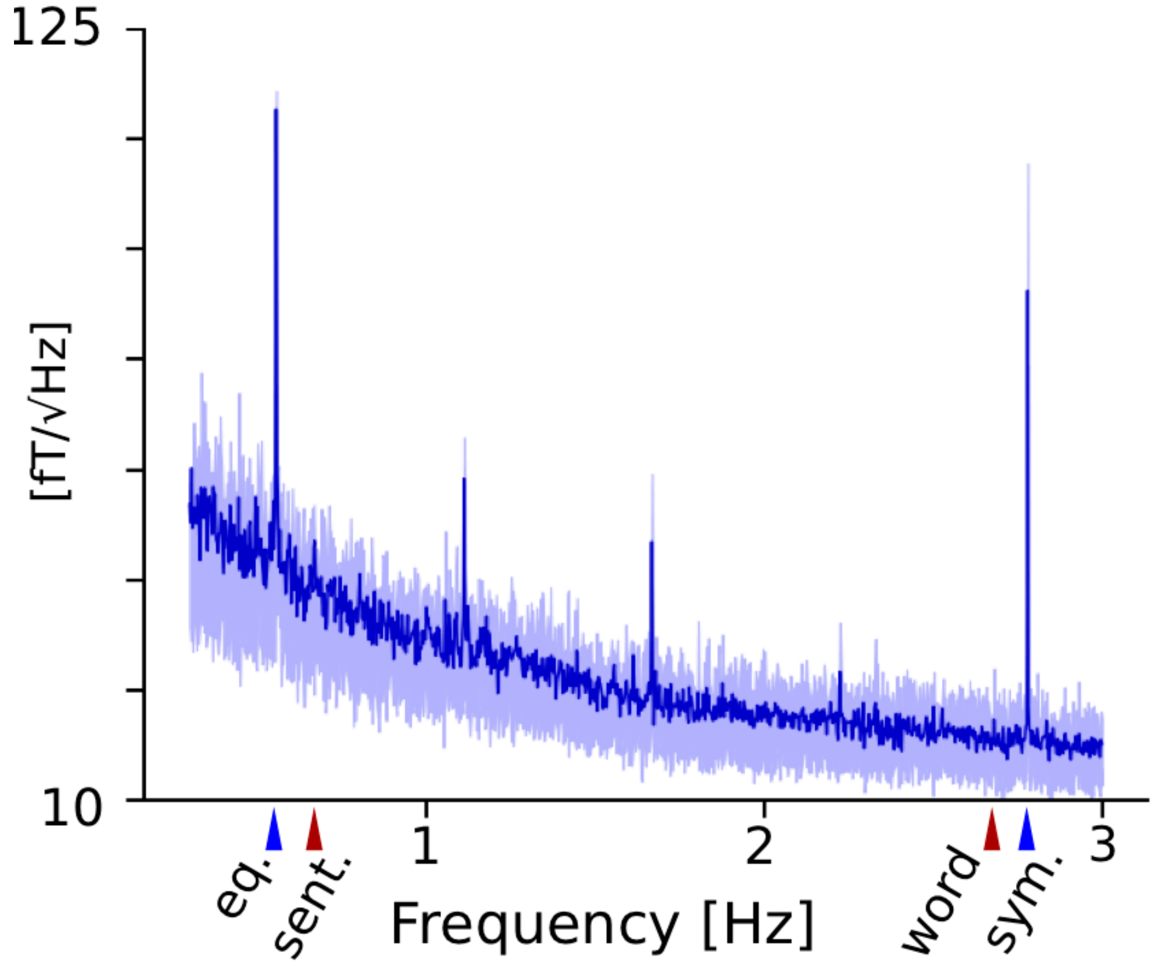

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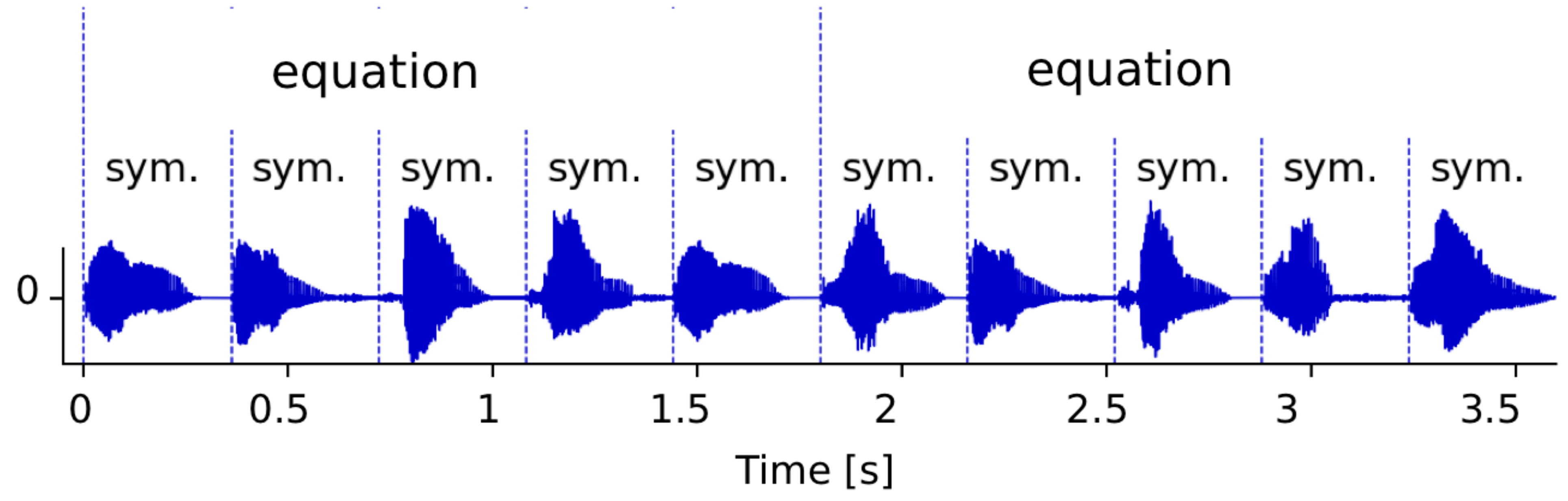

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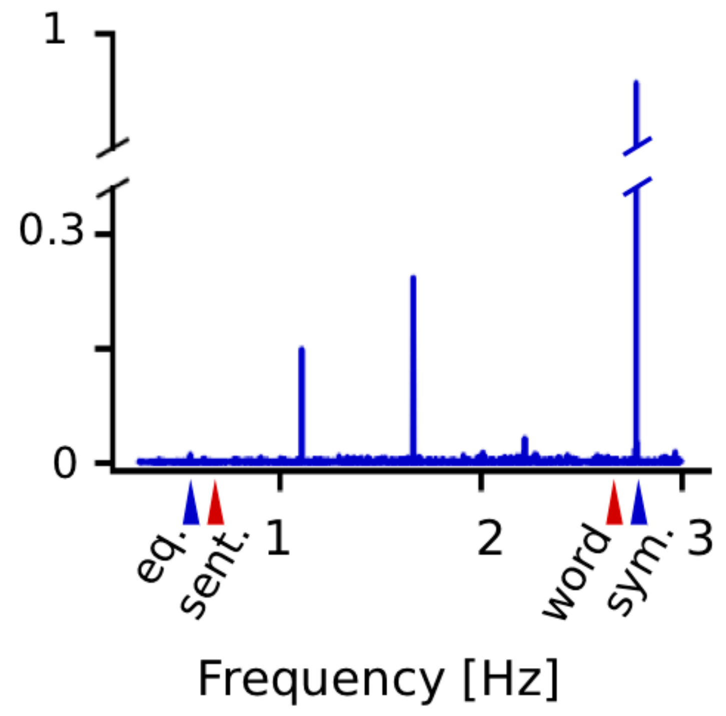

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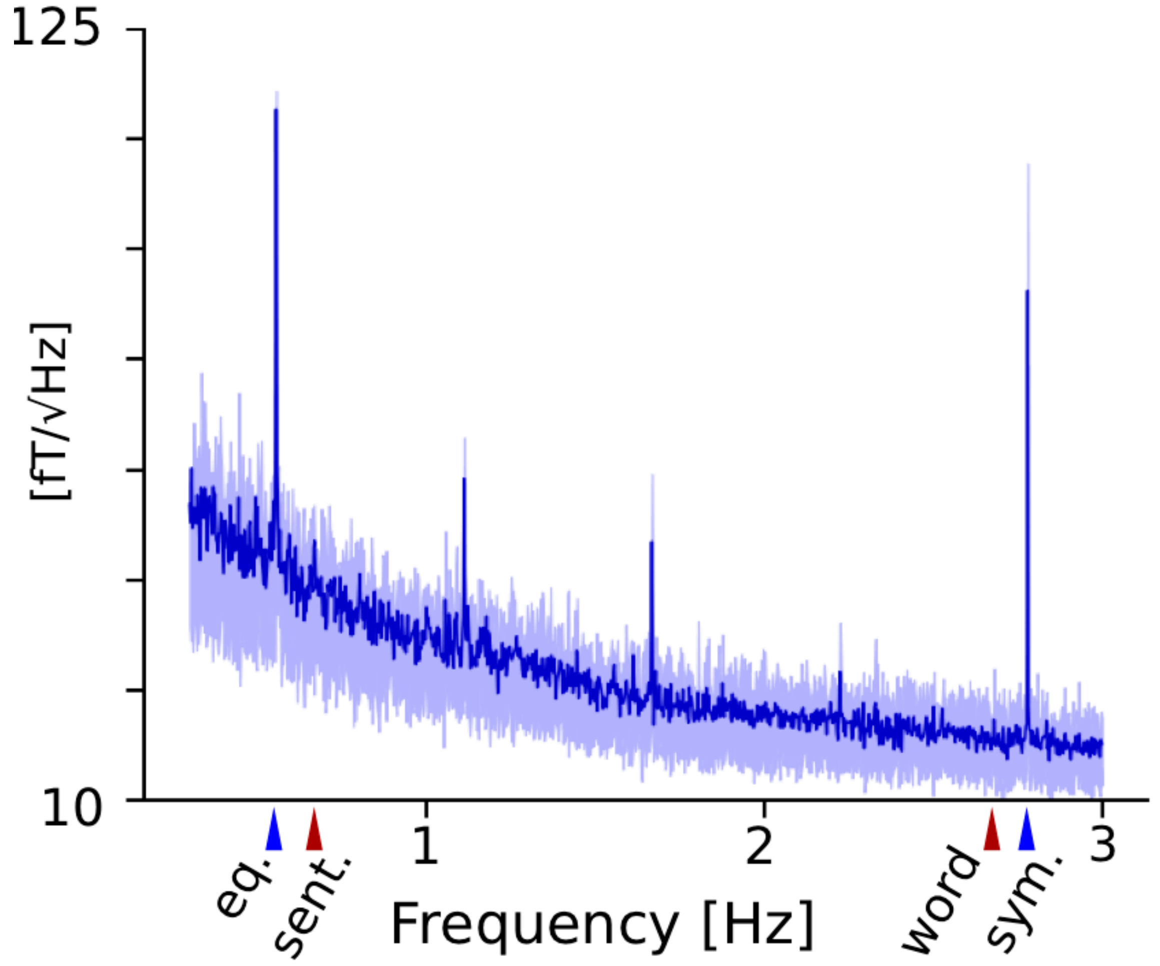

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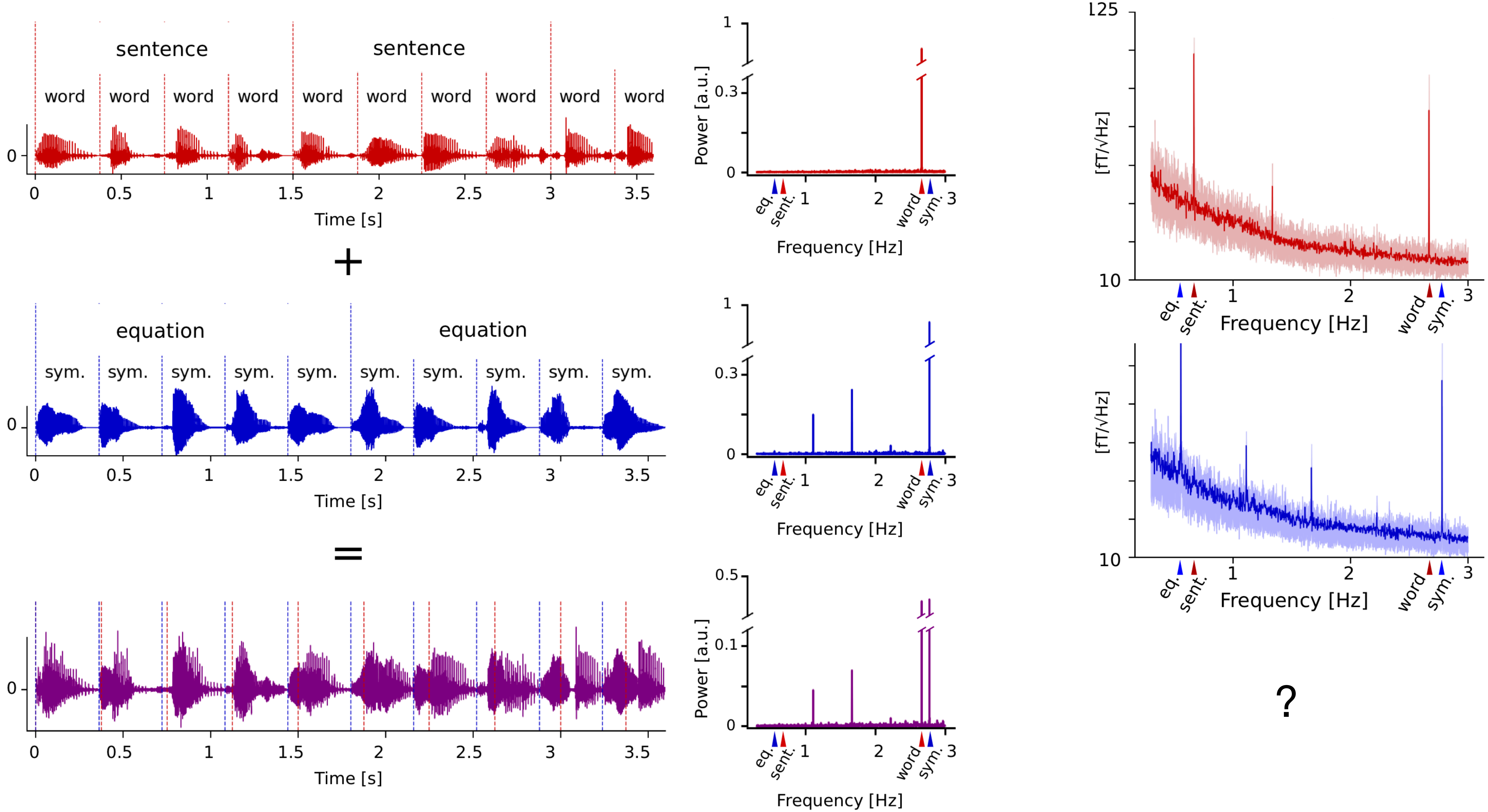
Isochronous Cocktail Party



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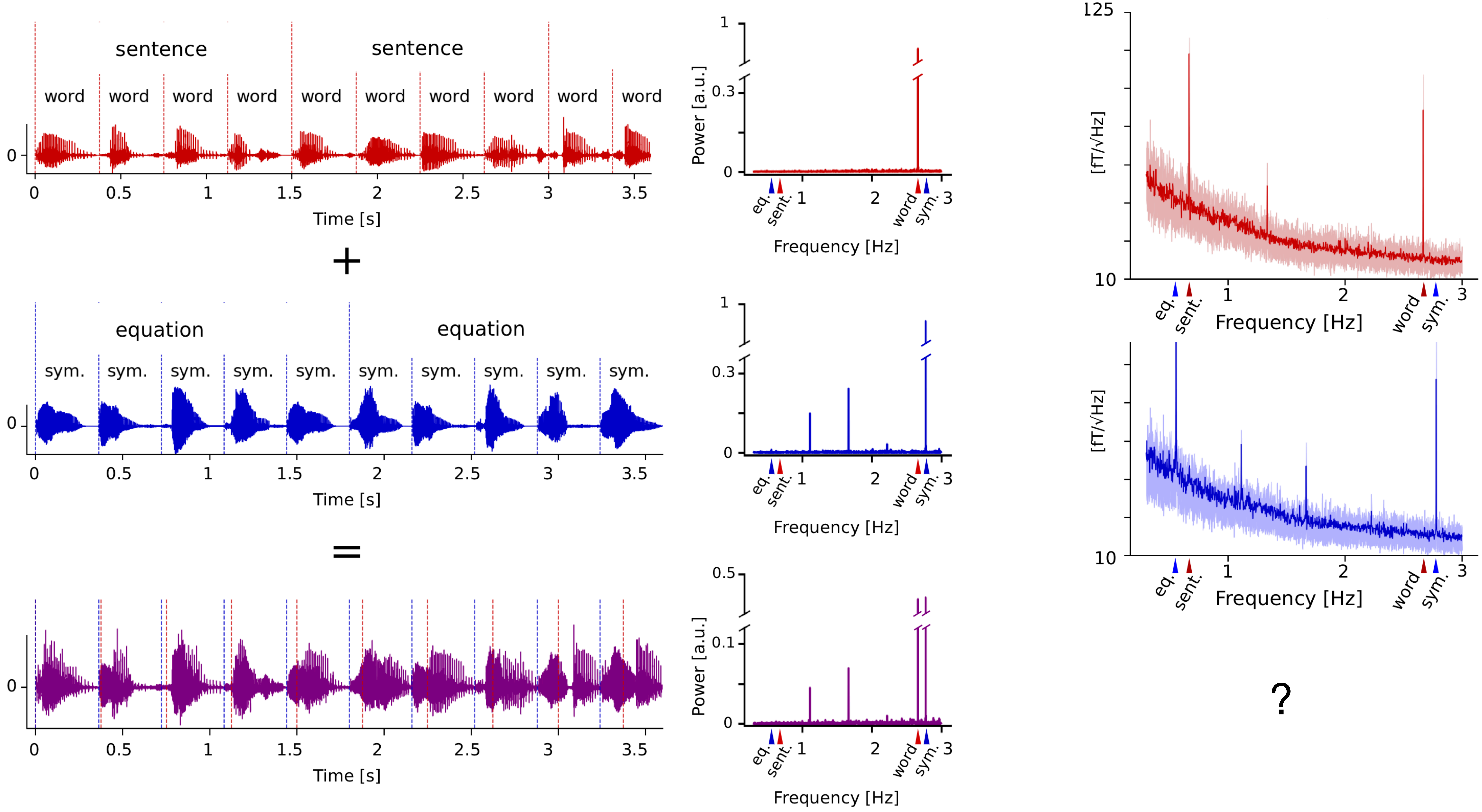

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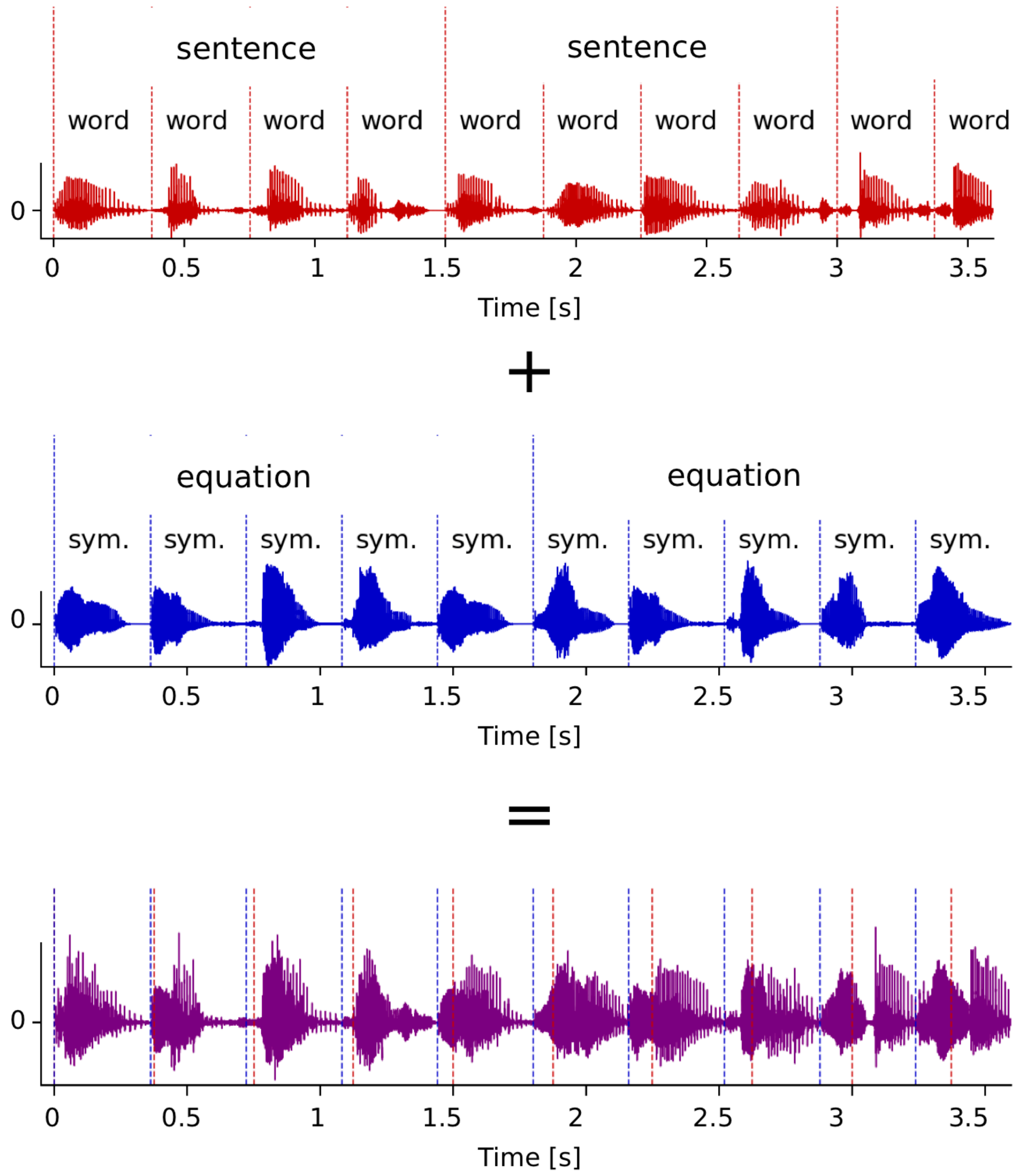

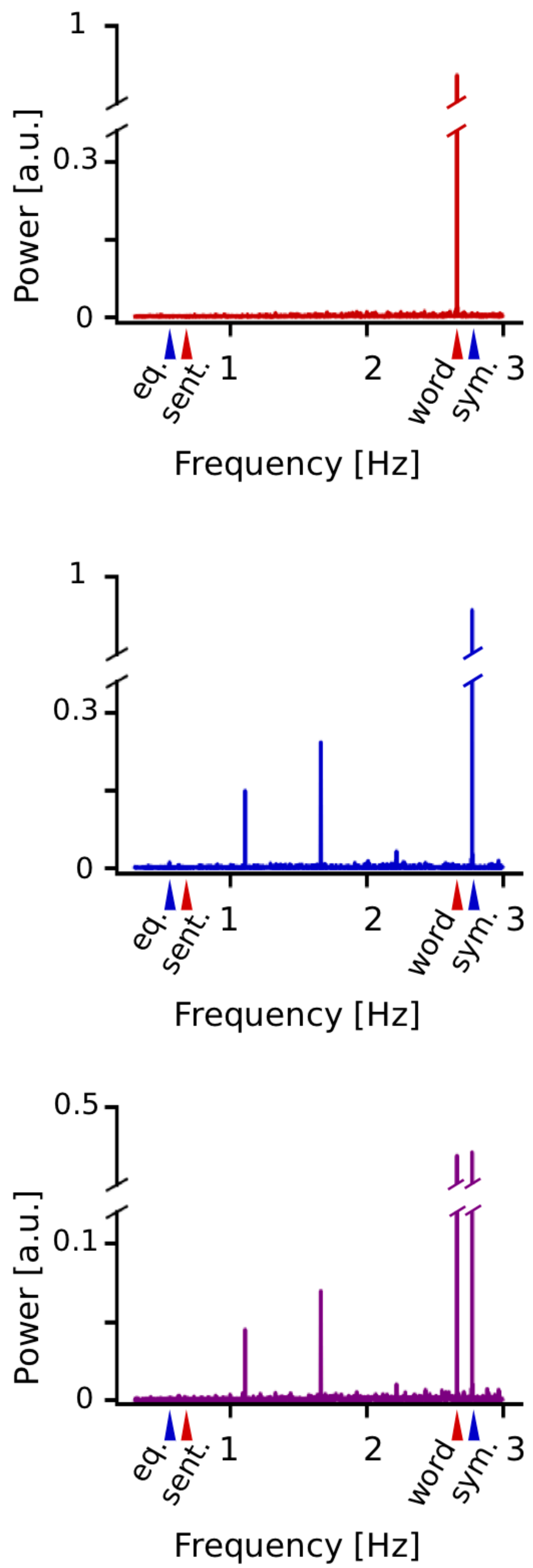

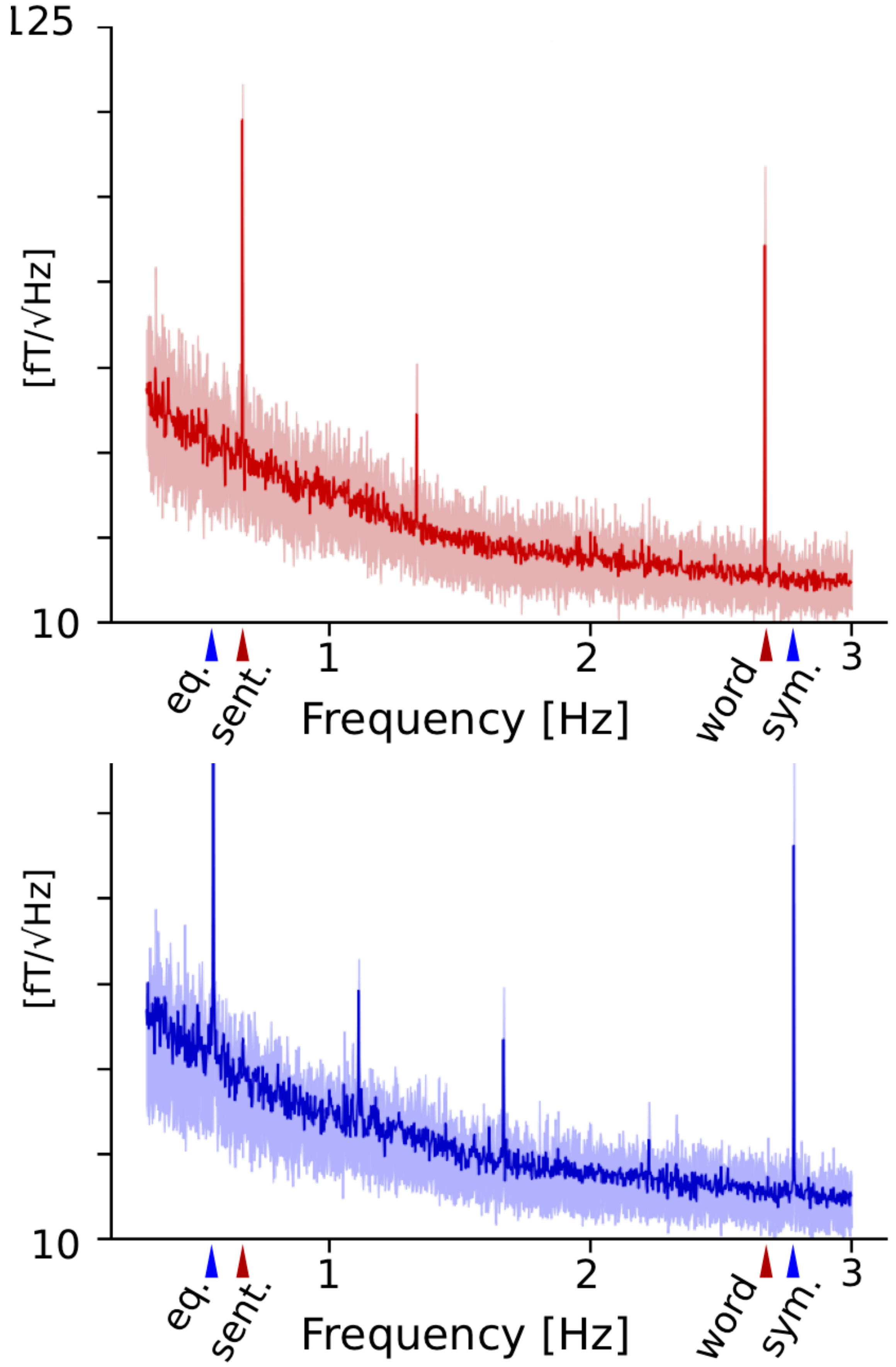

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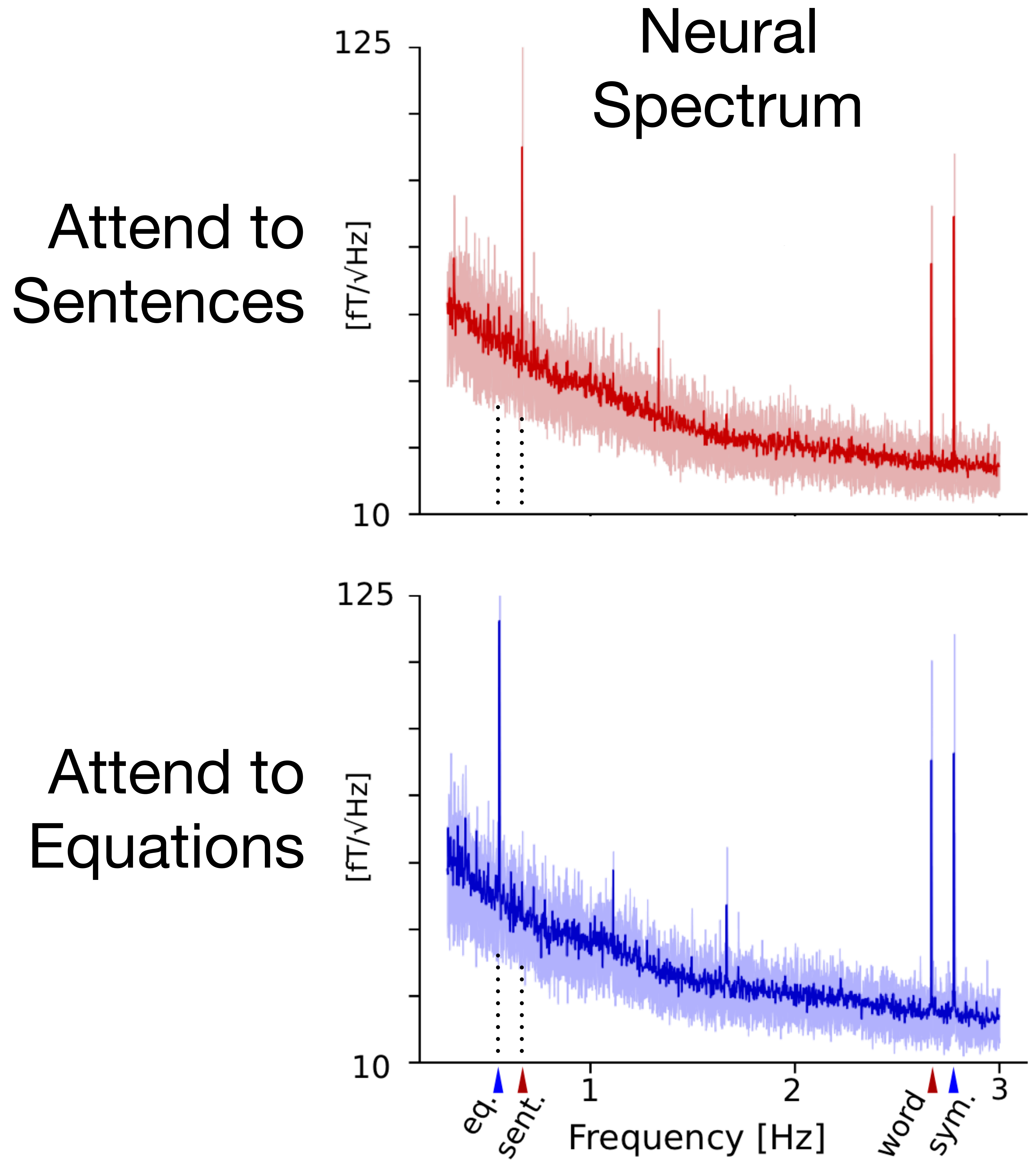

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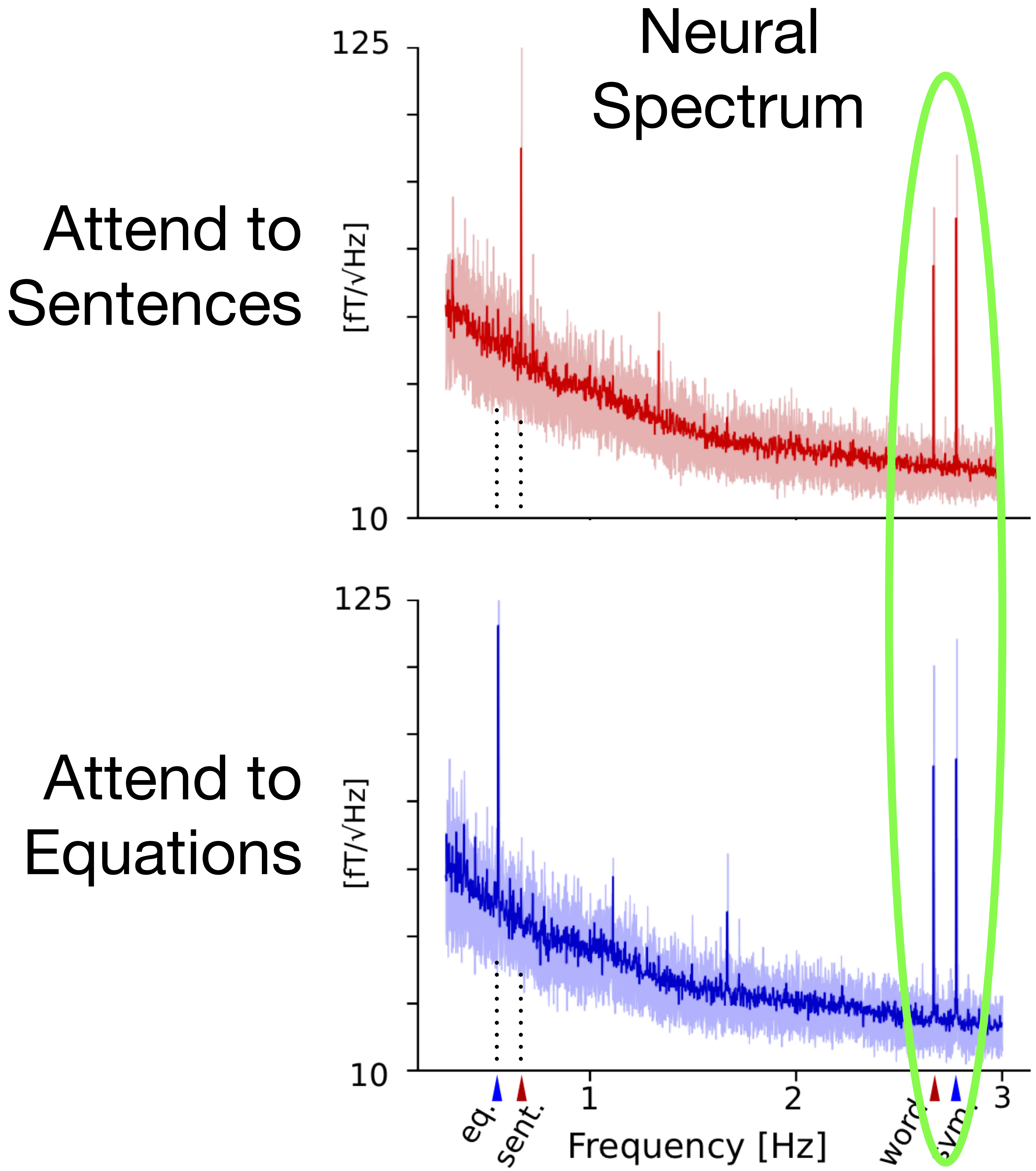

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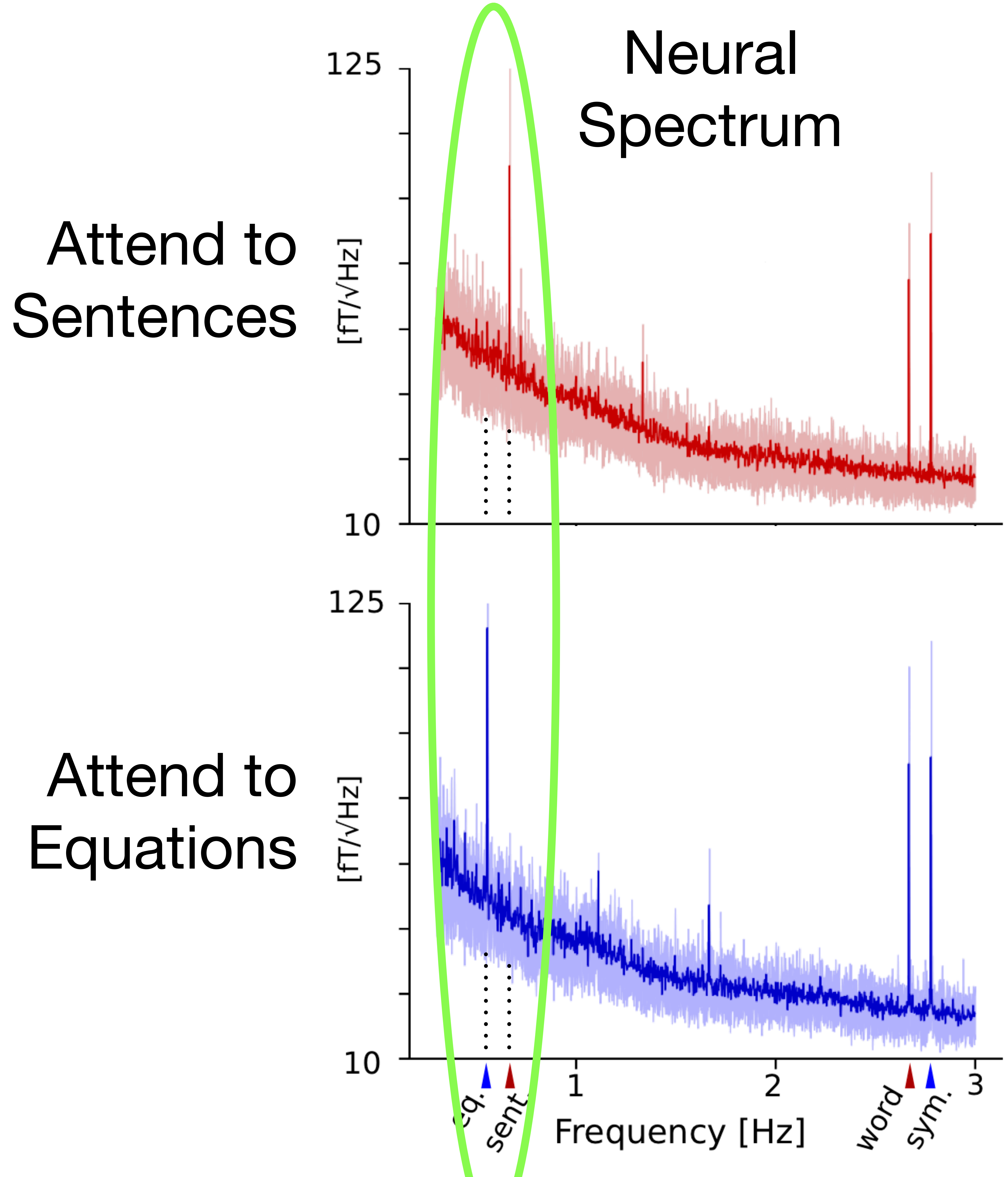

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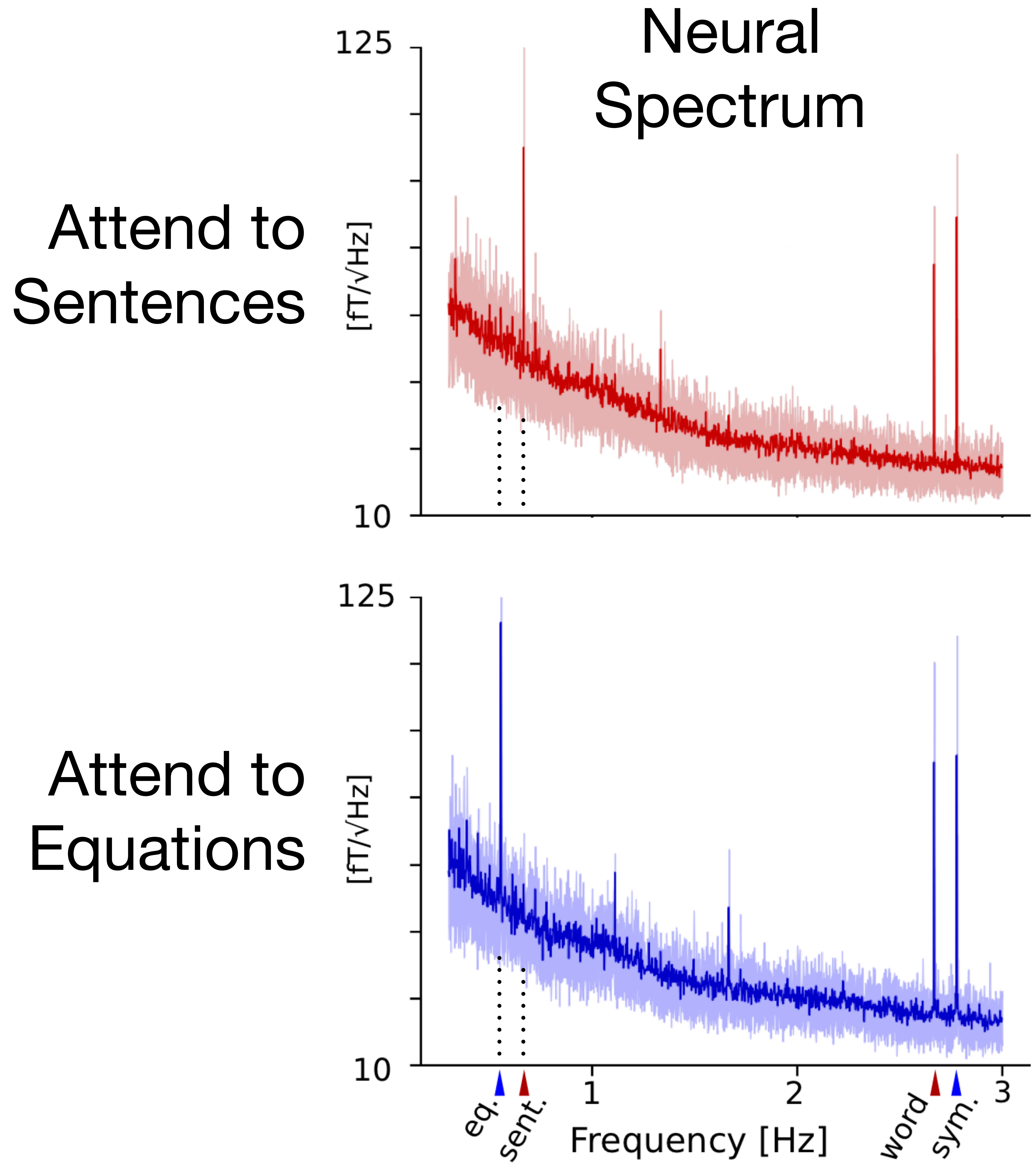

Linear Systems Theory

$$R(f) = H(f)\ S(f)$$

no shifting of frequencies

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convolution = smearing in time

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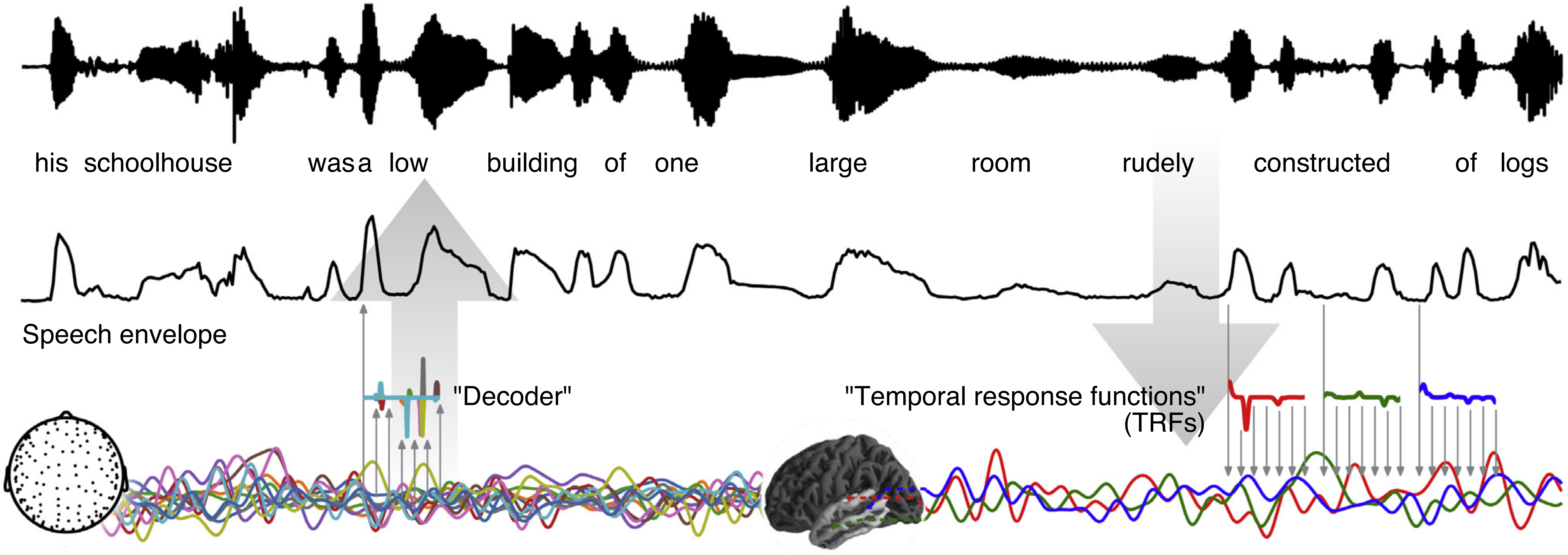
- Measure *time-locked* responses to temporal pattern of speech features (in humans)
- Any speech feature of interest: acoustic envelope, lexical, pitch, semantic, etc.
- Infer spatio-temporal neural origins of neural responses



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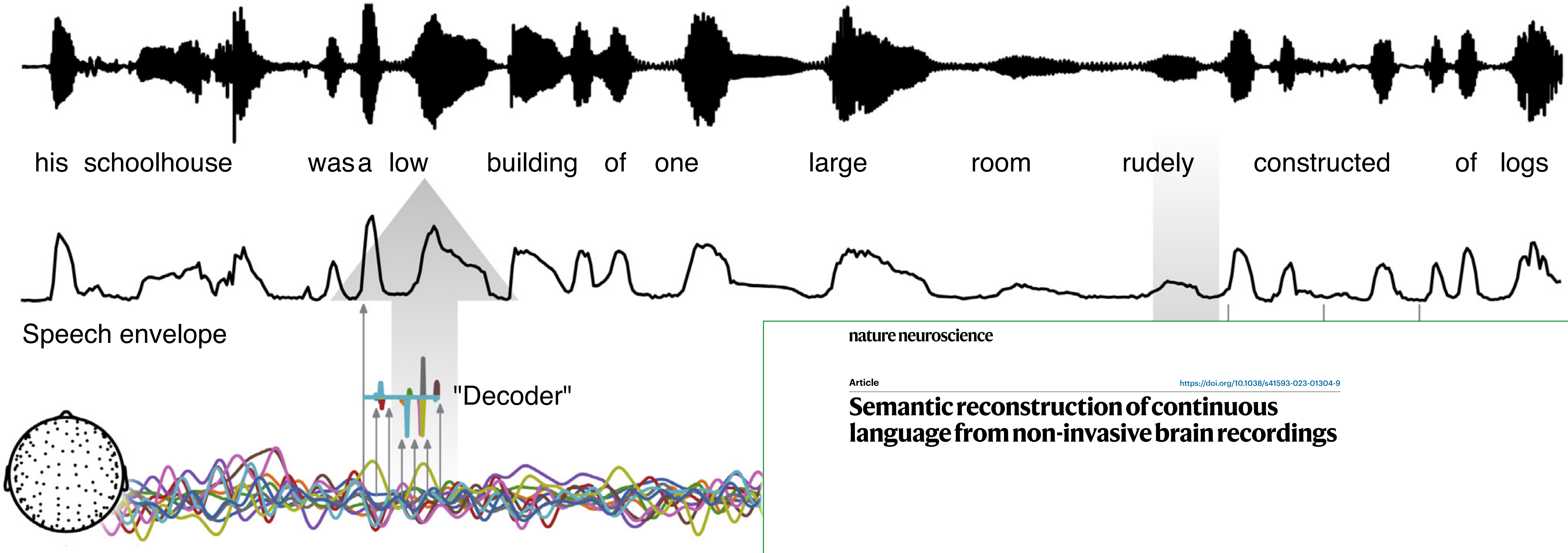

nature neuroscience

Article https://doi.org/10.1038/s41593-023-01304-9

Semantic reconstruction of continuous language from non-invasive brain recordings

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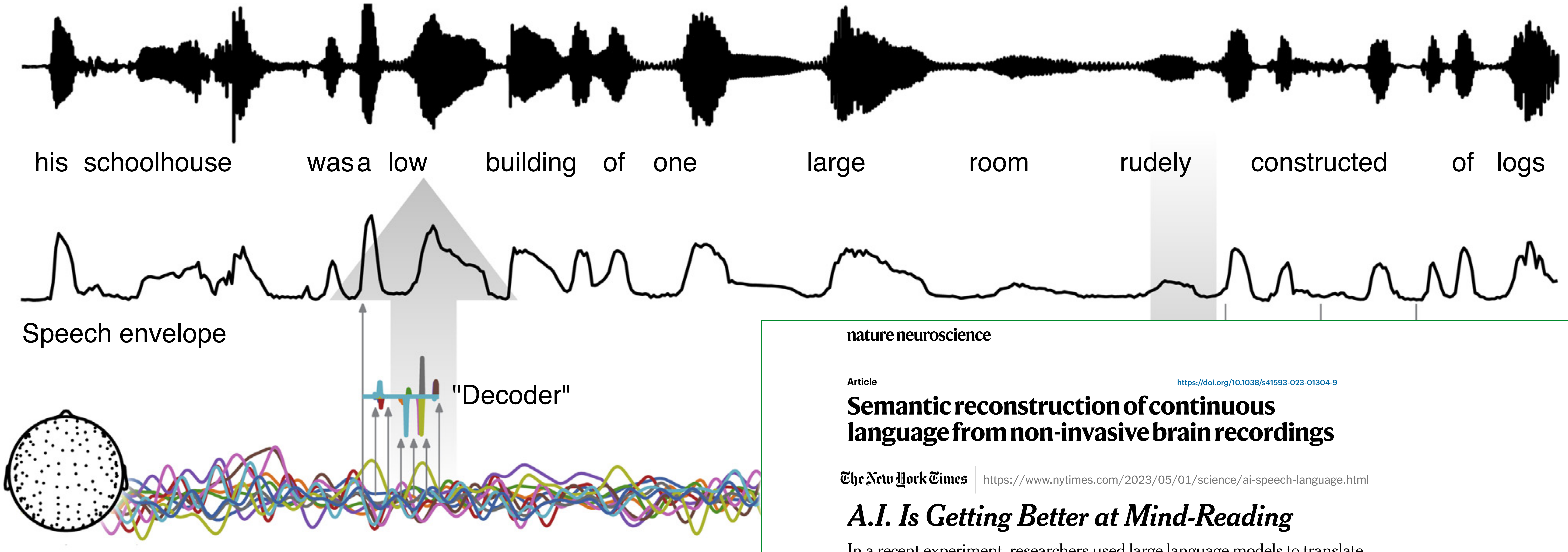

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Semantic reconstruction of continuous language from non-invasive brain recordings

The New York Times https://www.nytimes.com/2023/05/01/science/ai-speech-language.html

A.I. Is Getting Better at Mind-Reading

In a recent experiment, researchers used large language models to translate brain activity into words.

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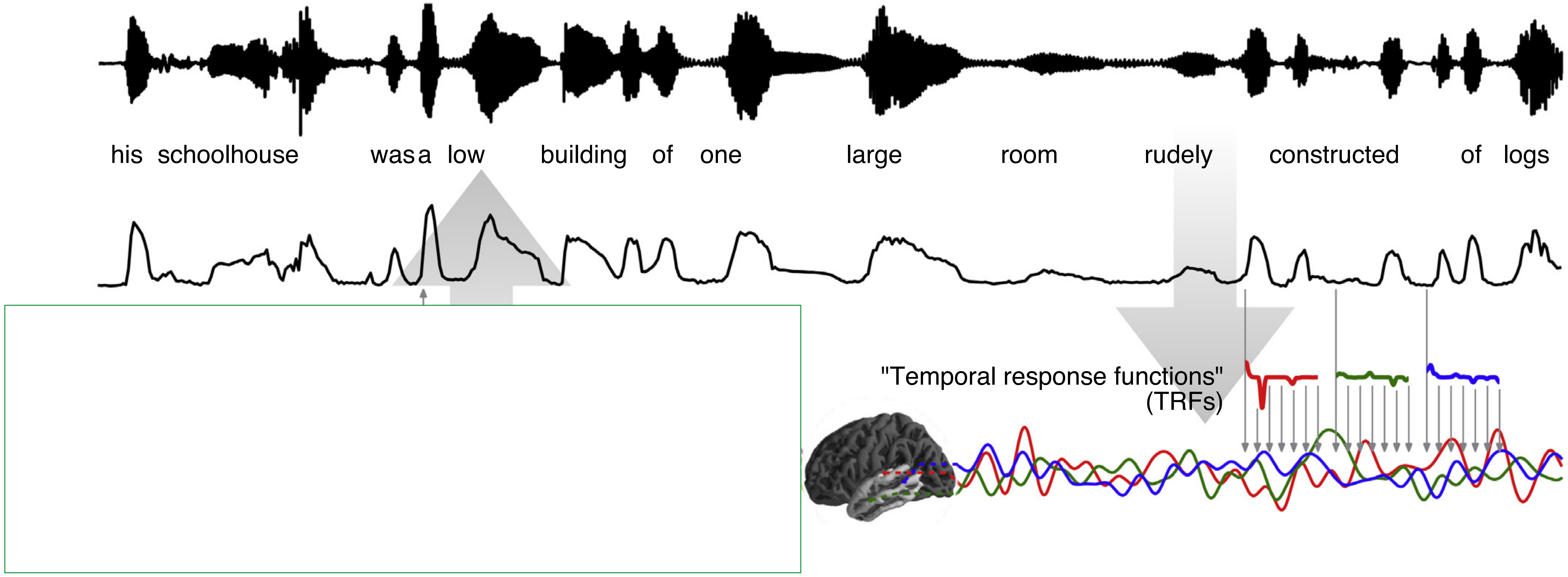

Temporal Response Functions

Temporal
Response
Function
(TRF)

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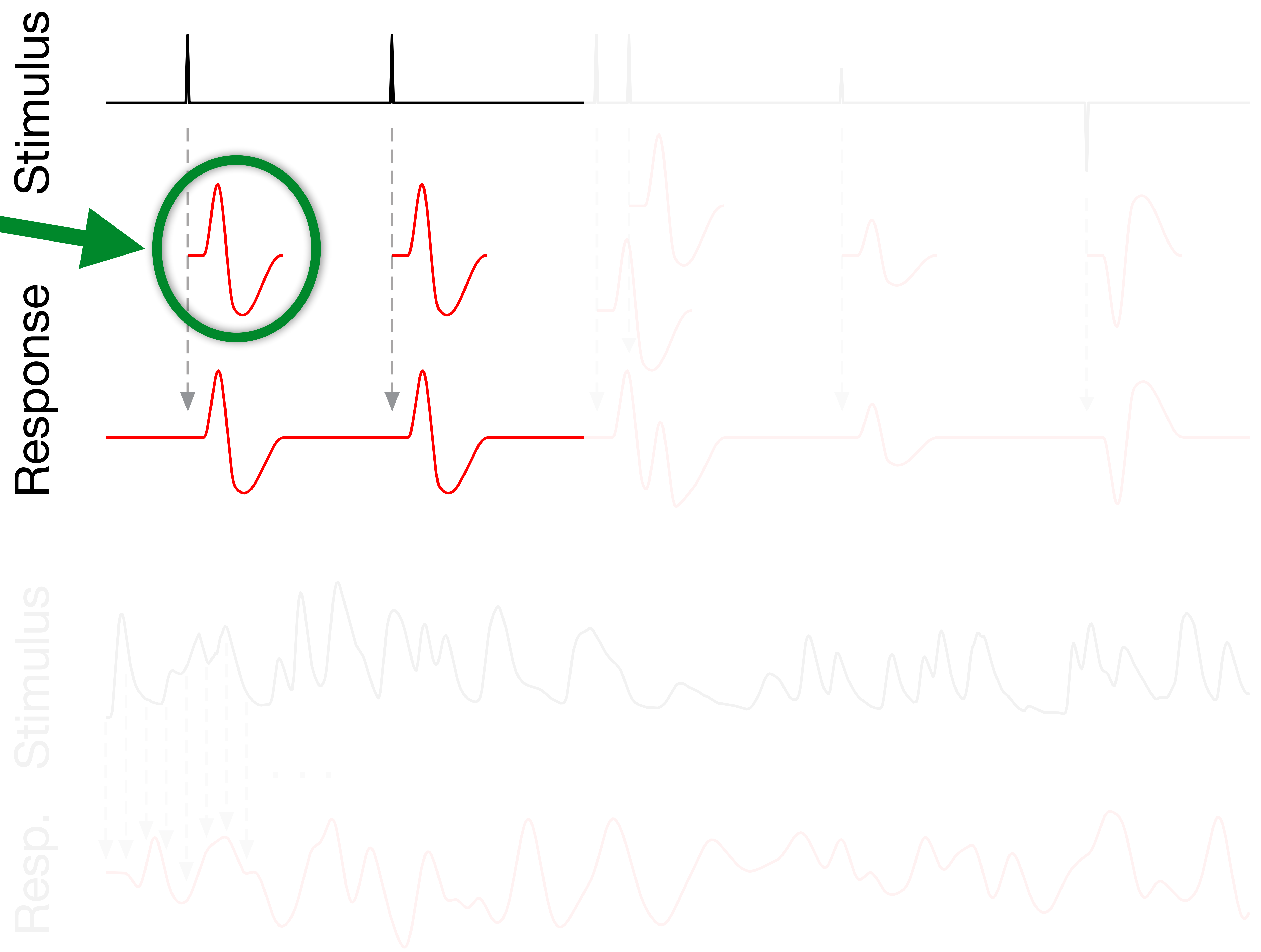

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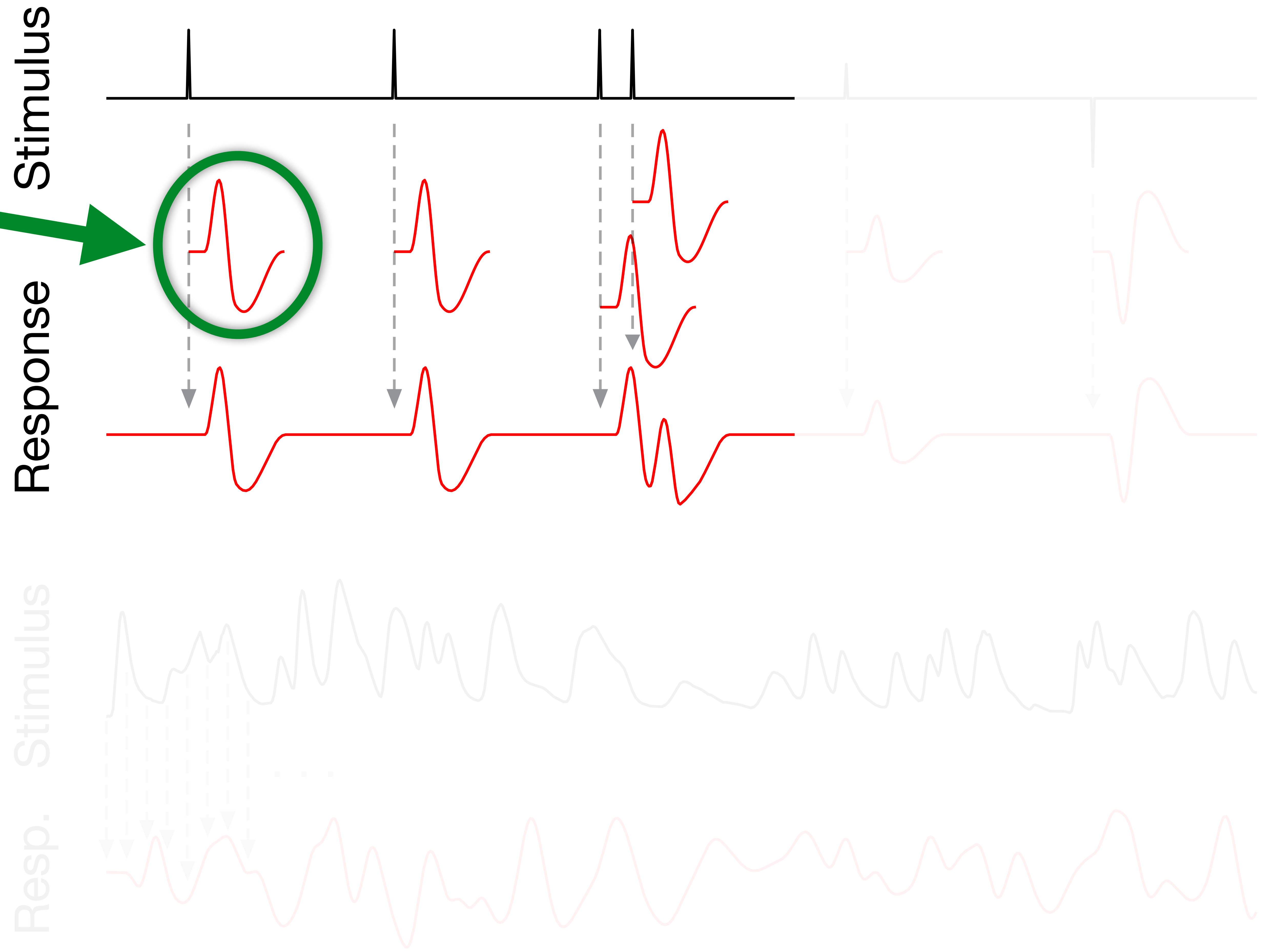

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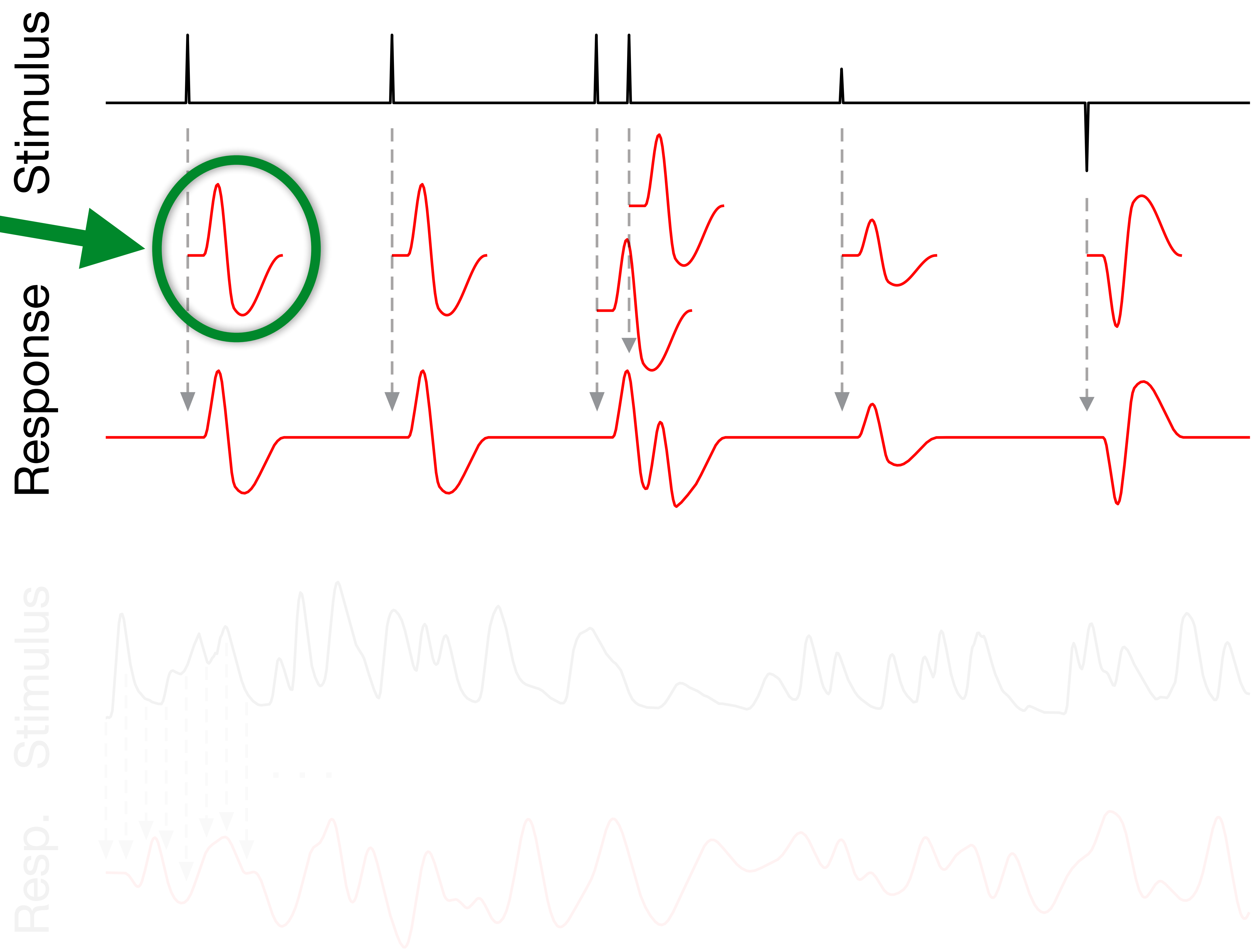

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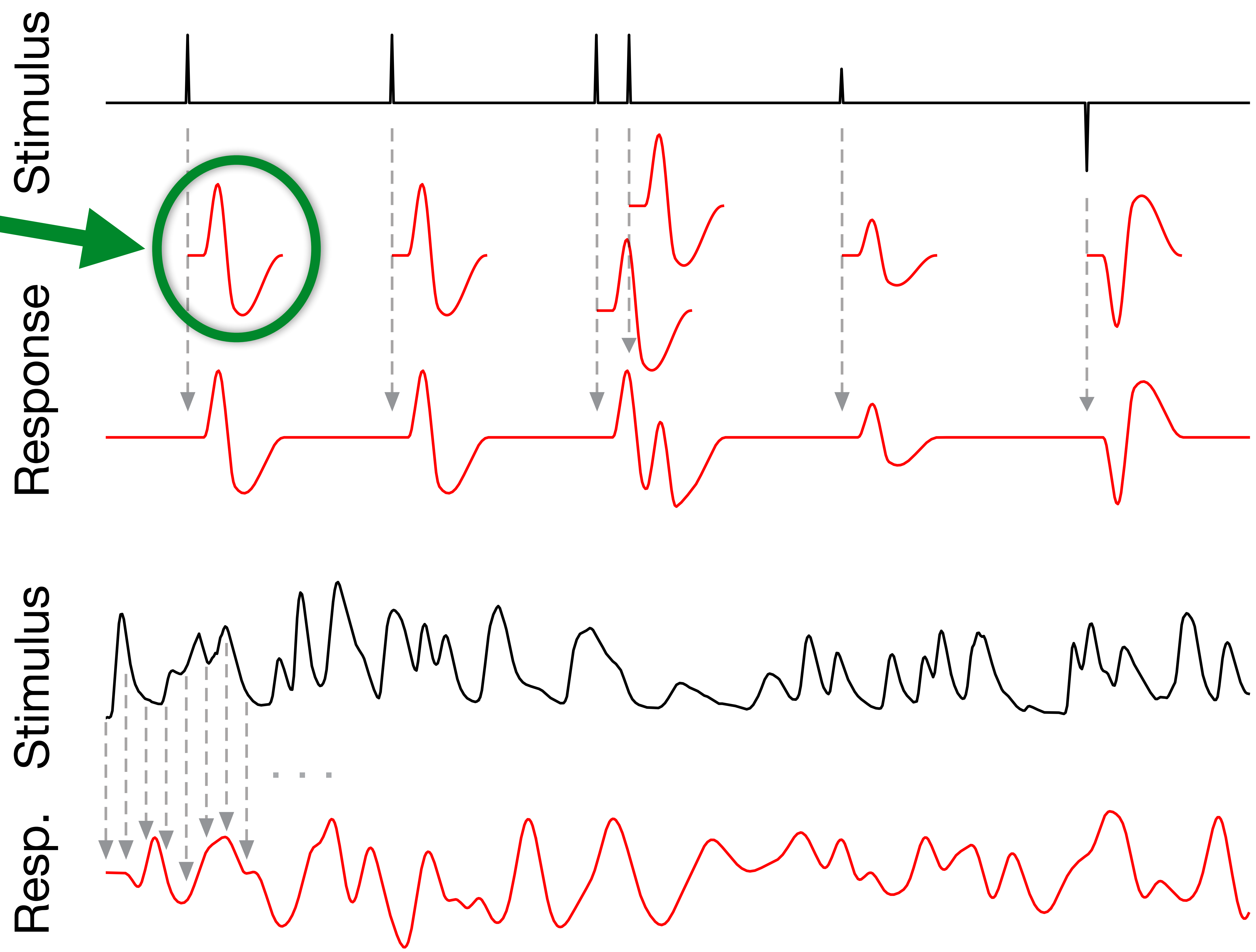

TRF Model Estimation & Fit

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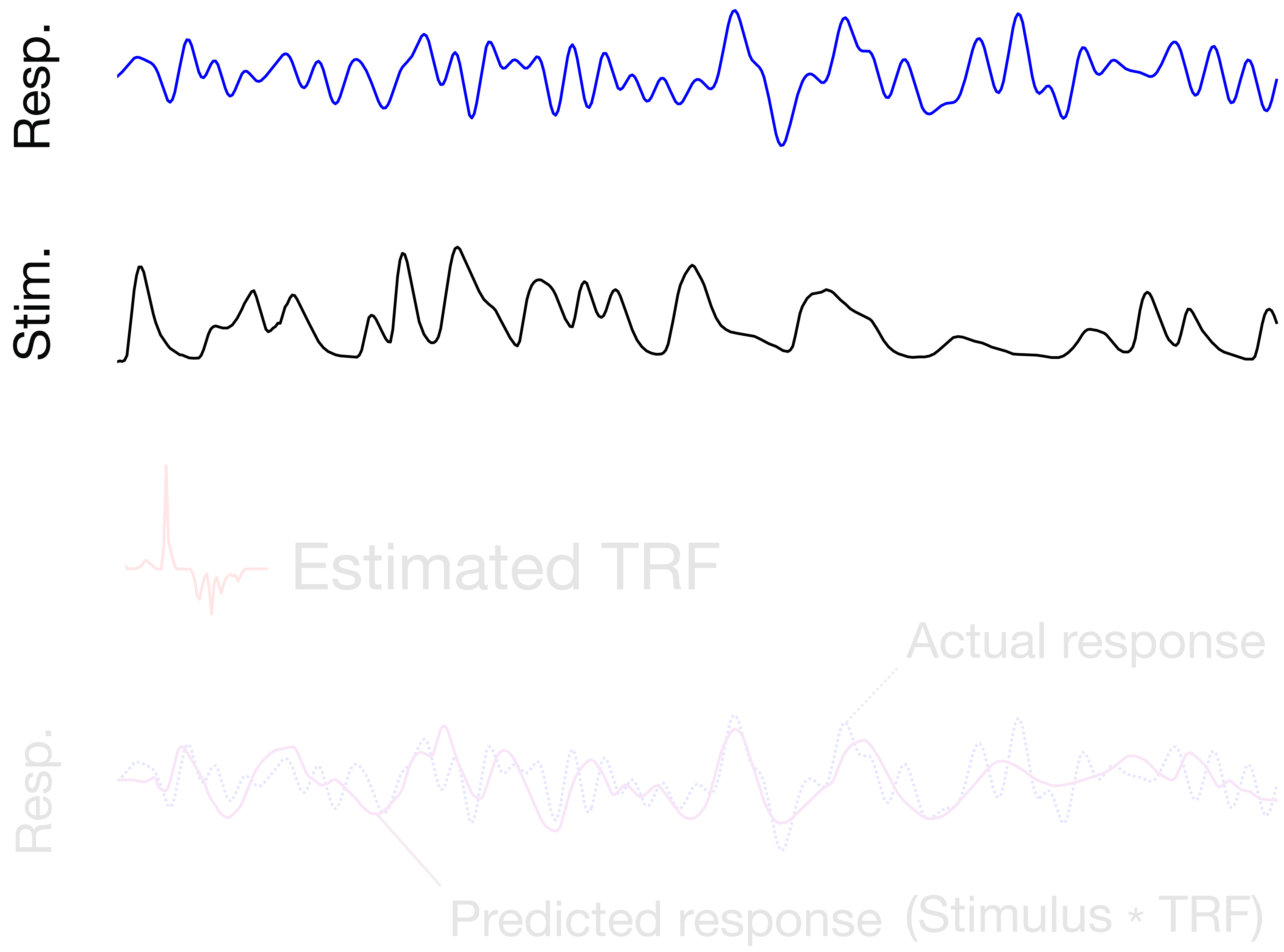
Stimulus and response are known; find the best TRF to produce the response from the stimulus:



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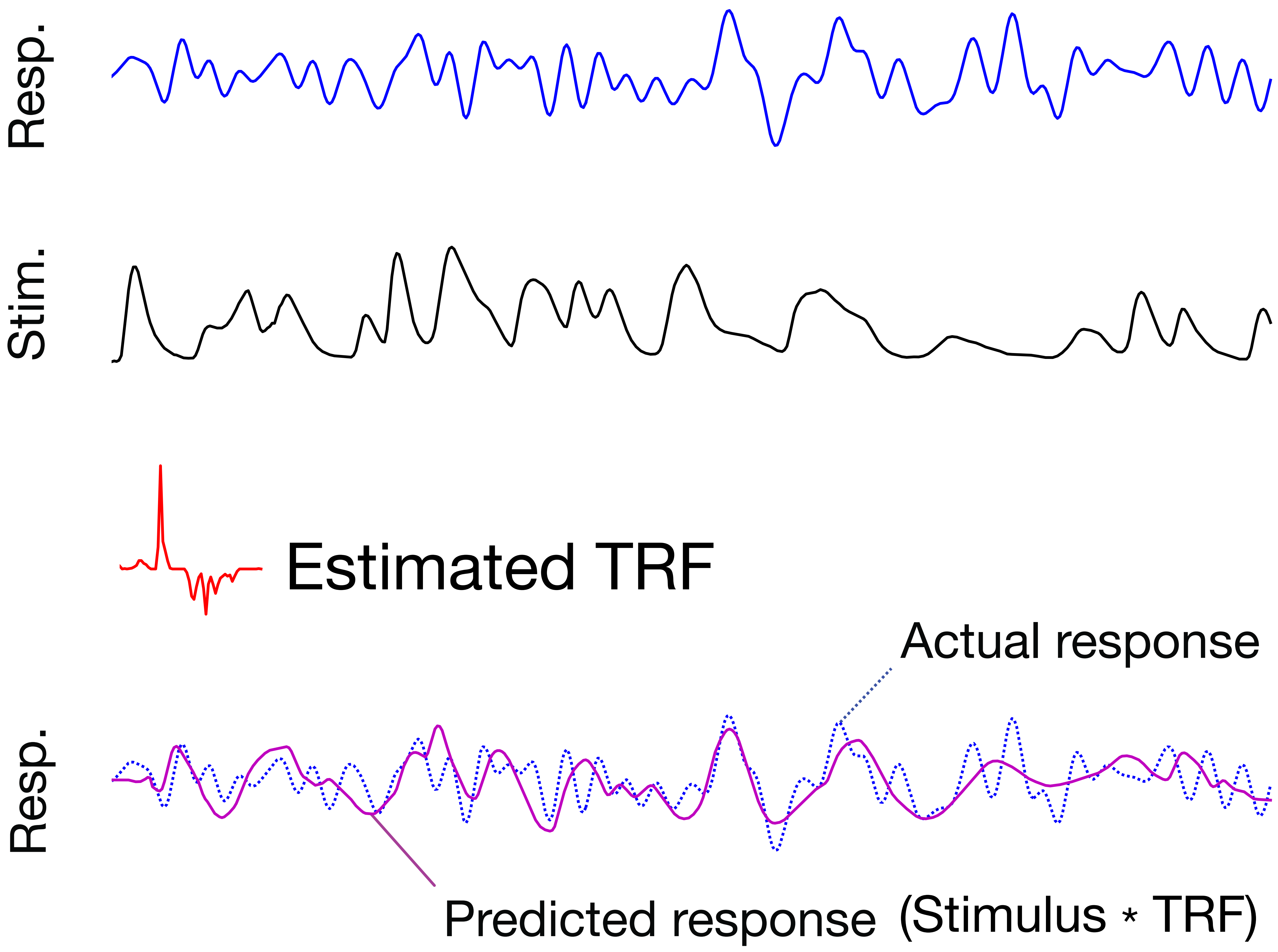

Lalor & Foxe (2010) *Neural Responses to Uninterrupted Natural Speech …* Eur J Neurosci
Ding & Simon (2012) *Neural Coding of Continuous Speech in Auditory Cortex …* , J Neurophys

Neural Representations: Encoding

- predicting future neural responses from current stimulus features,
  - wide variety of stimulus features
  - via Temporal Response Function (TRF)
- typically harder than reconstruction, since stimulus dimension ≪ response dimension
- Why bother looking at encoding? It *often* tells us more about the brain
  - TRF analogous to evoked response
  - peak amplitude ≈ processing measure
  - peak latency ≈ source location
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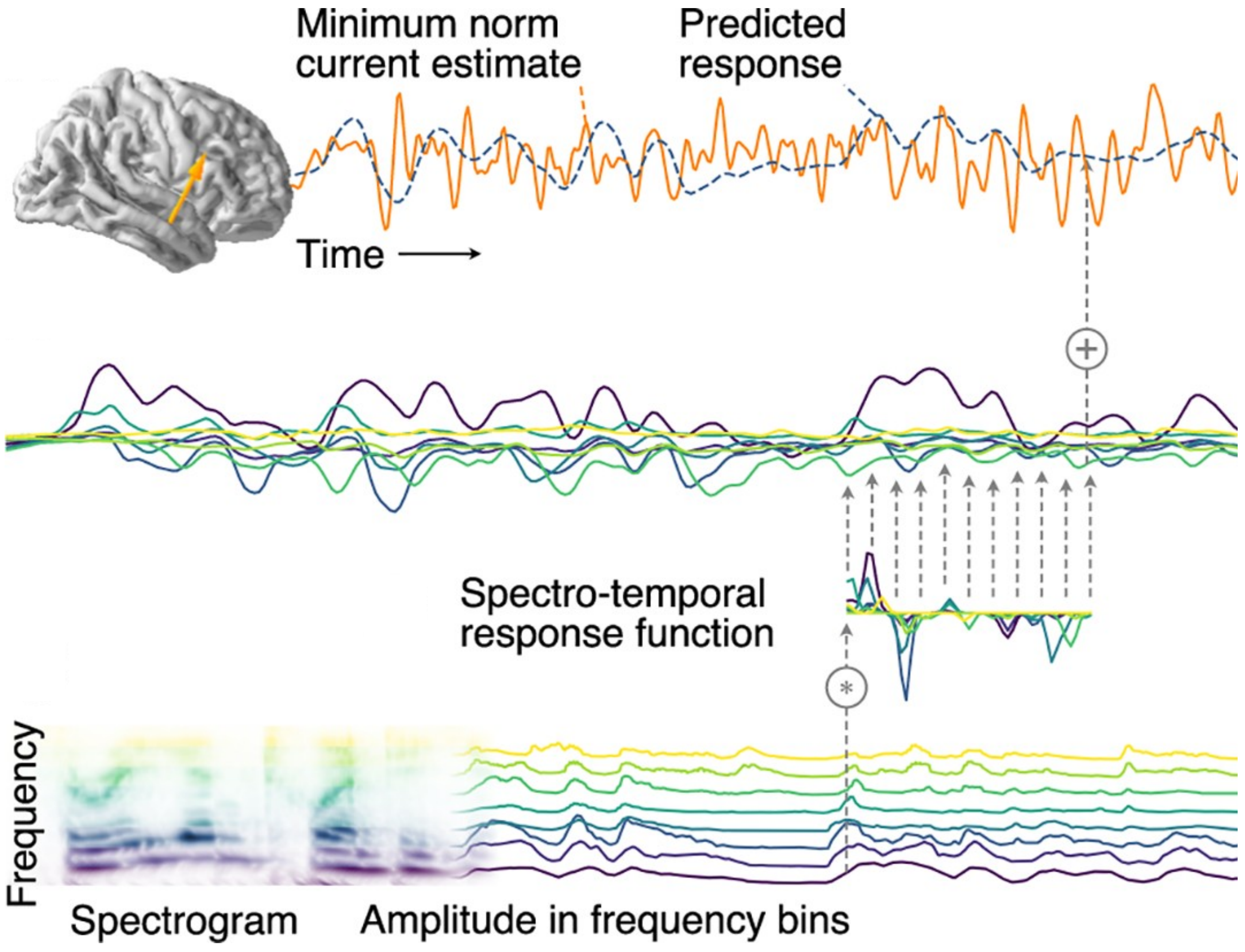

Example: MEG Prediction of Voxel Responses

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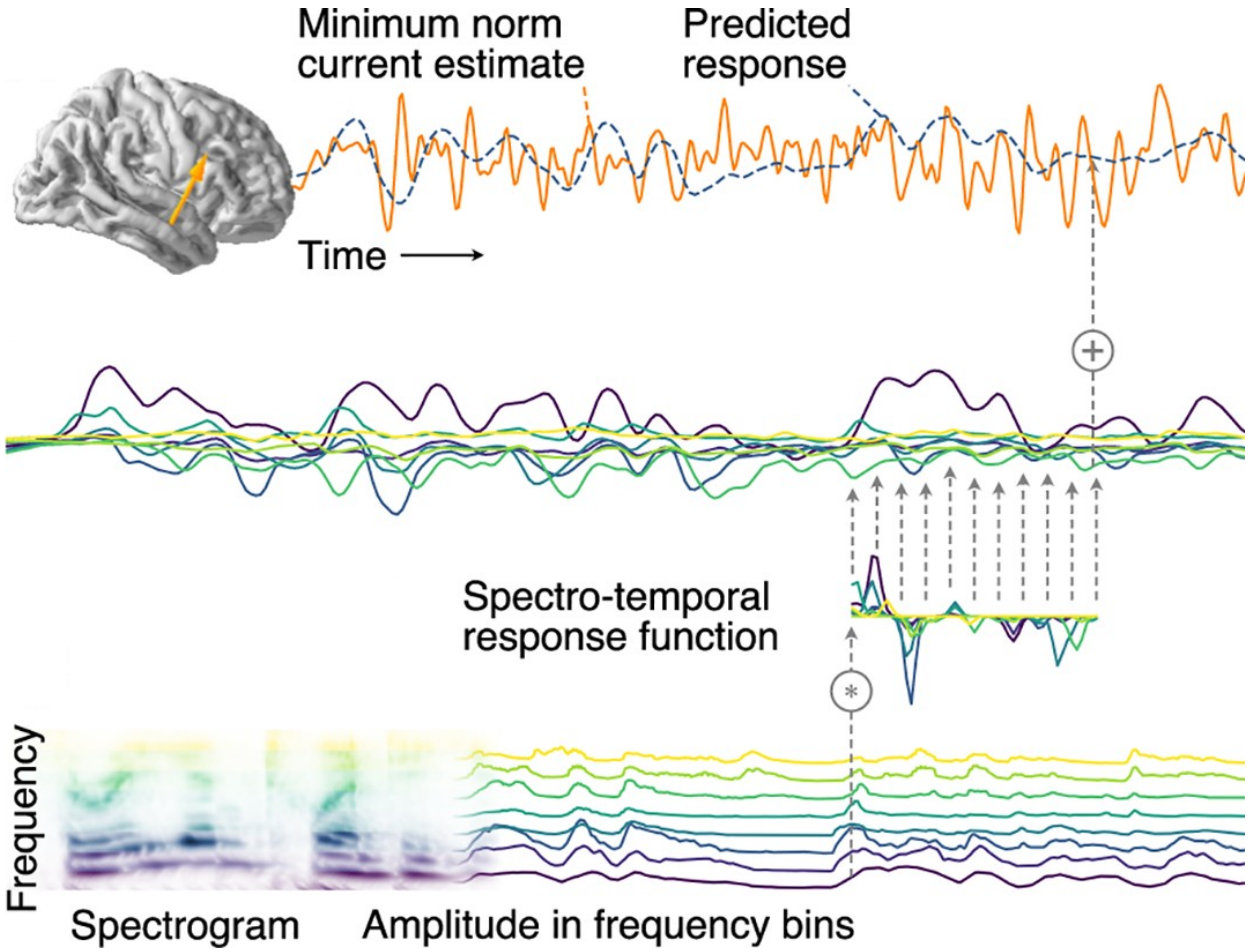

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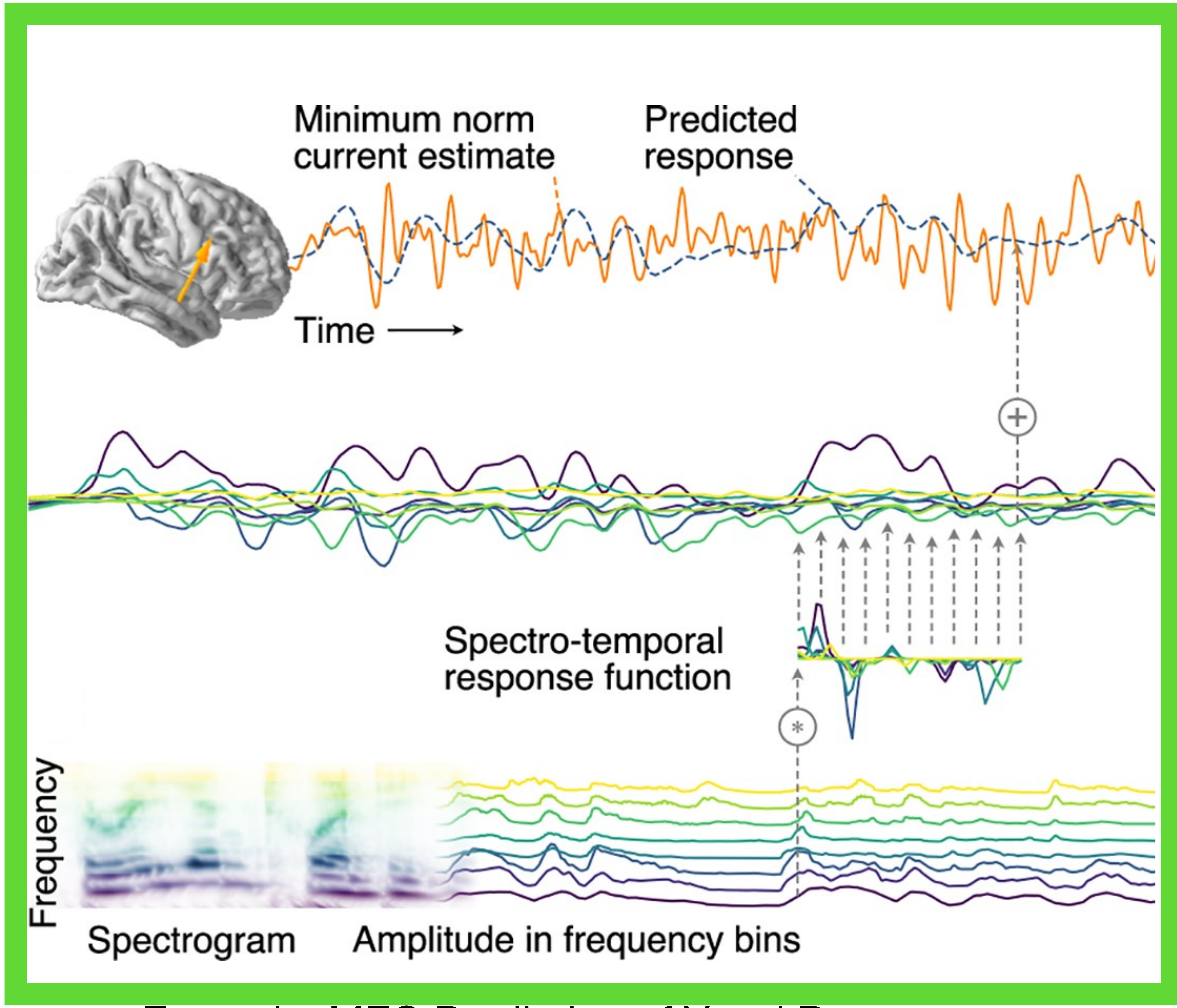

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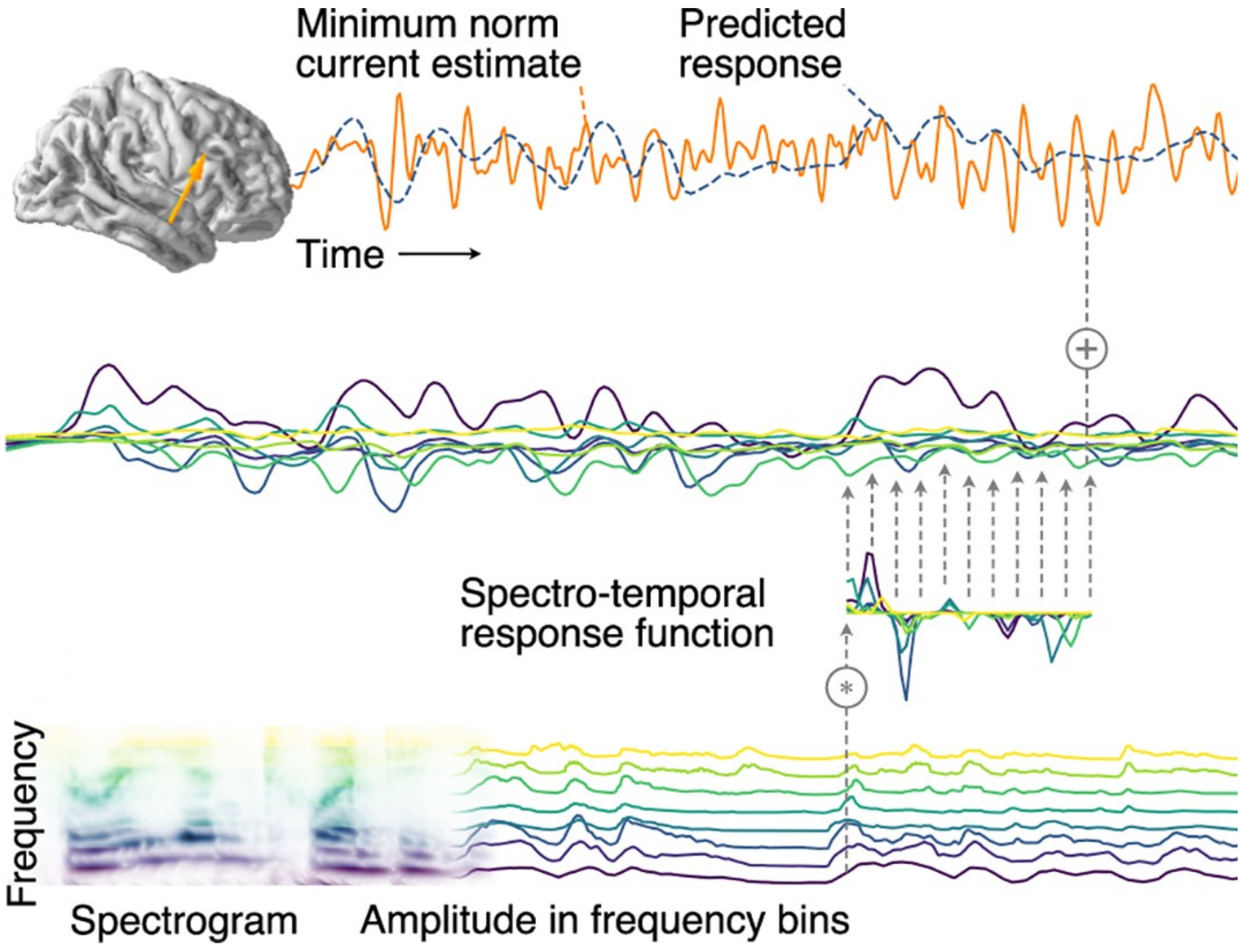


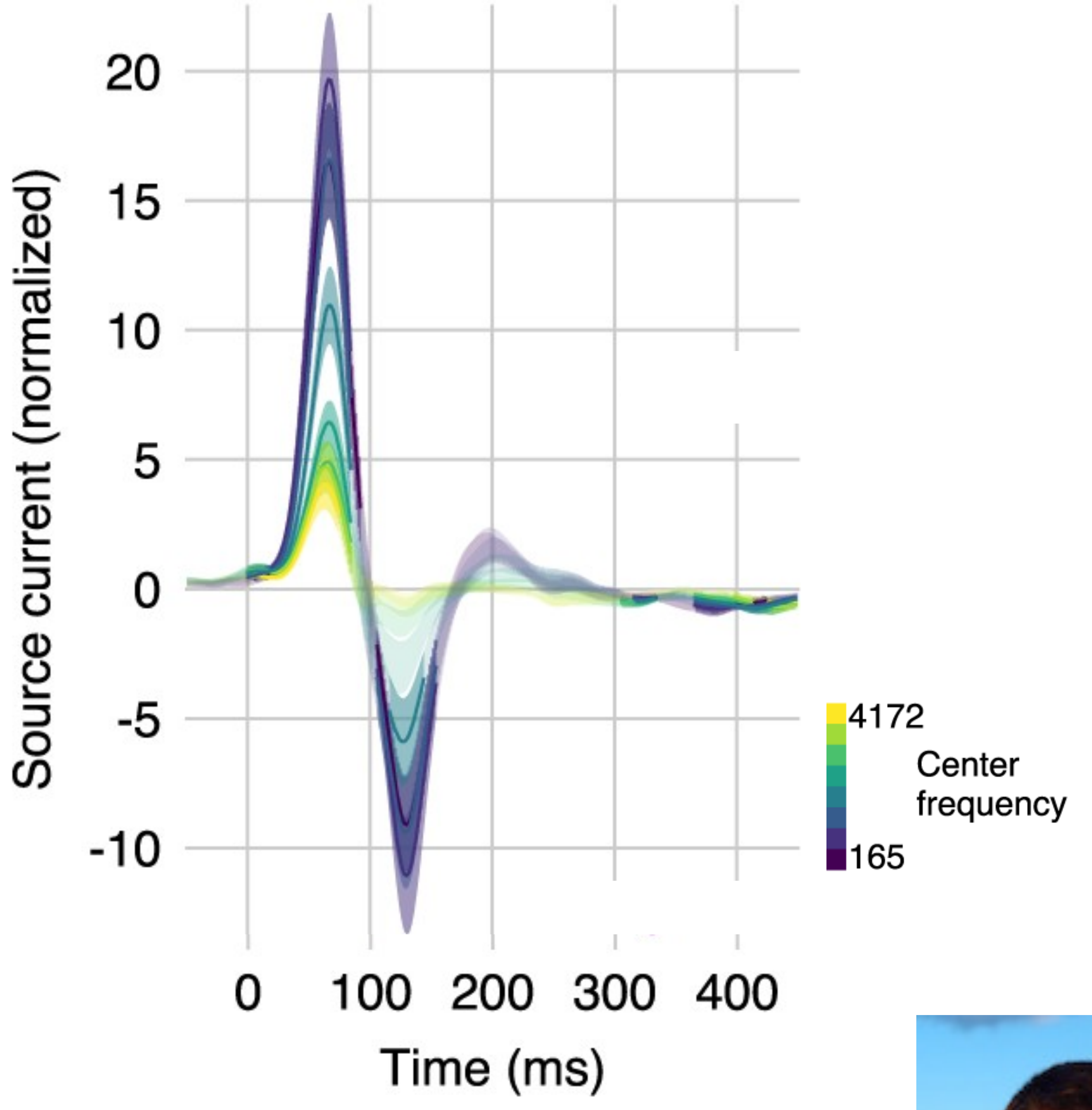
Example: MEG Prediction of Voxel Responses

Example: Representation of Speech Envelope

- TRF interpretable a la evoked response
  - Has M50 (~"P1") & M100 (~"N1") peaks, but from instantaneous speech envelope
  - early peak localizes to primary auditory areas (HG)
  - later peak localizes to associative areas (PT)
  - caveat: actually from envelope *onset*

- This is from a single talker, clean speech
  - simple but limiting
  - what about noise? other speakers? attention?
  - can the speech representation be cleaned?

Temporal Response Functions

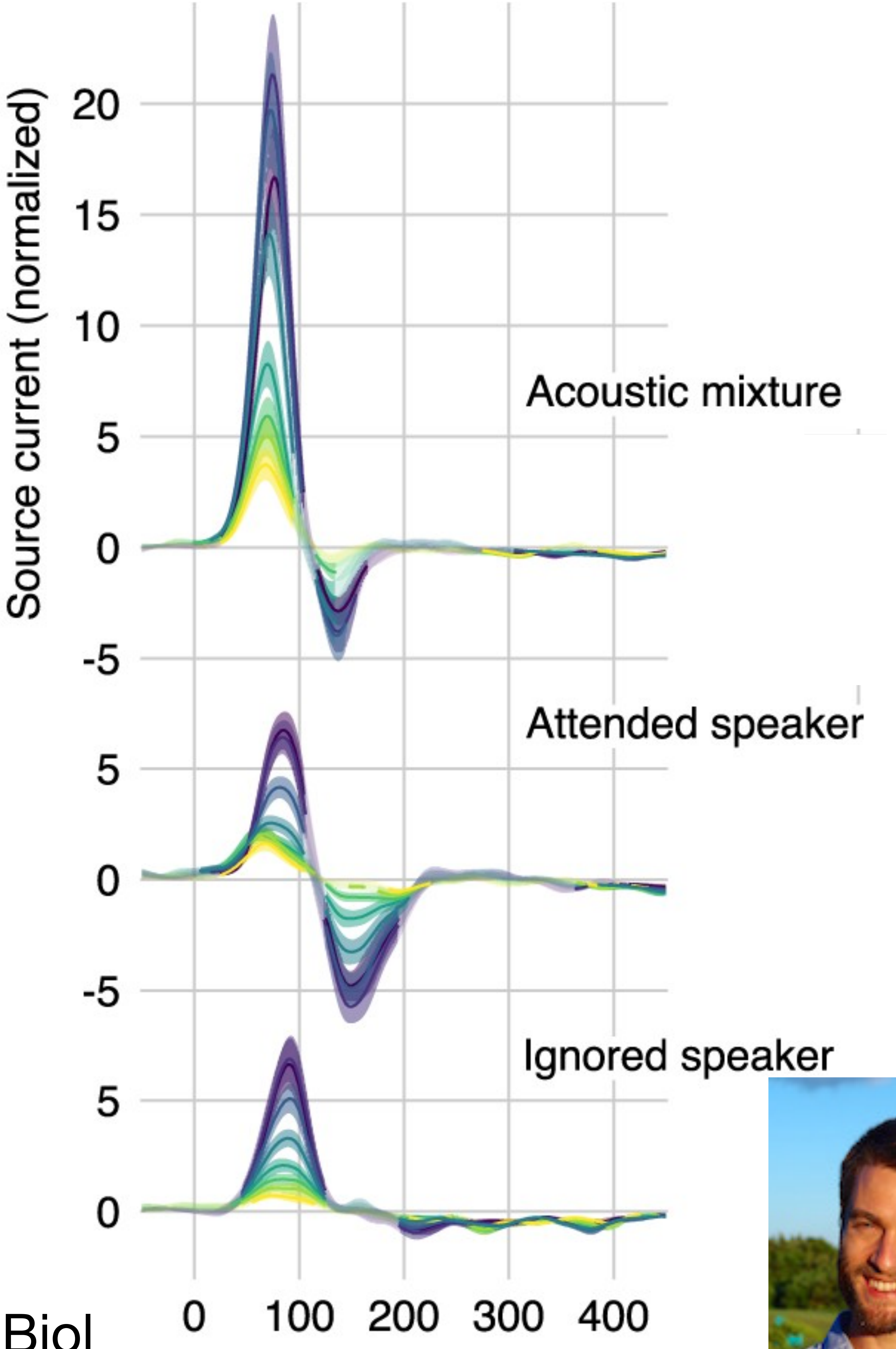


Brodbeck et al. (2020) *Neural Speech Restoration at the Cocktail Party …*, PLoS Biol

Neural Representations: Selective Attention

Two competing speakers, selectively attend to one

- more illuminating since more complex auditory scene
- need more care re: "stimulus" responsible for responses
  - acoustic mixture entering ears
  - foreground speech
  - background speech
- estimate all TRFs simultaneously
  - compete to explain variance



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Simultaneous Temporal Response Functions

- TRFs predict neural response to speech
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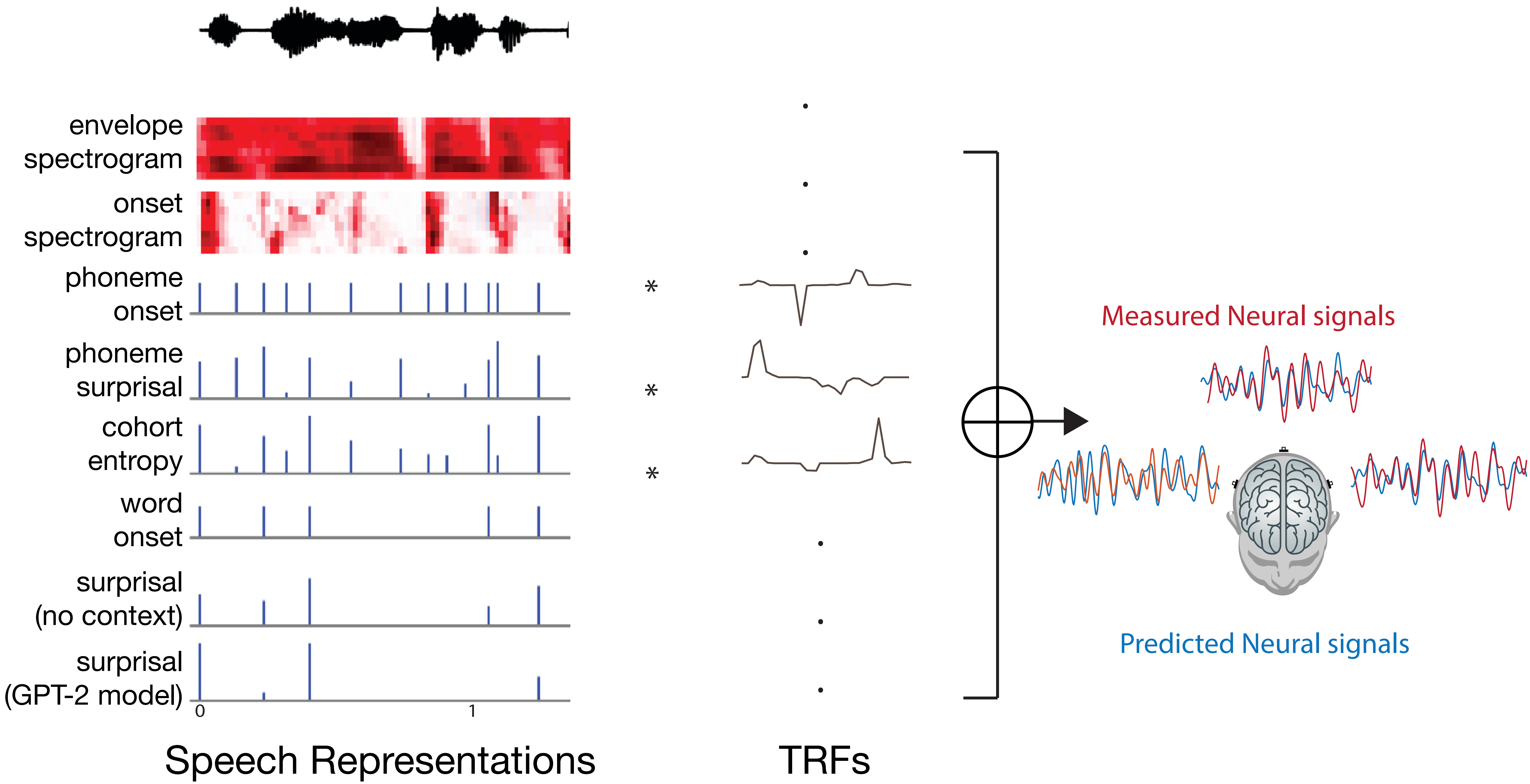
- Multiple TRFs estimated simultaneously
  - compete to explain variance (advantage over evoked response)



Crosse et al. (2016) *The Multivariate Temporal Response Function (mTRF) Toolbox* … , Front Hum Neurosci
Brodbeck et al. (2021) *Eelbrain: A Python Toolkit for Time-Continuous Analysis* … , bioRxiv

Simultaneous Temporal Response Functions

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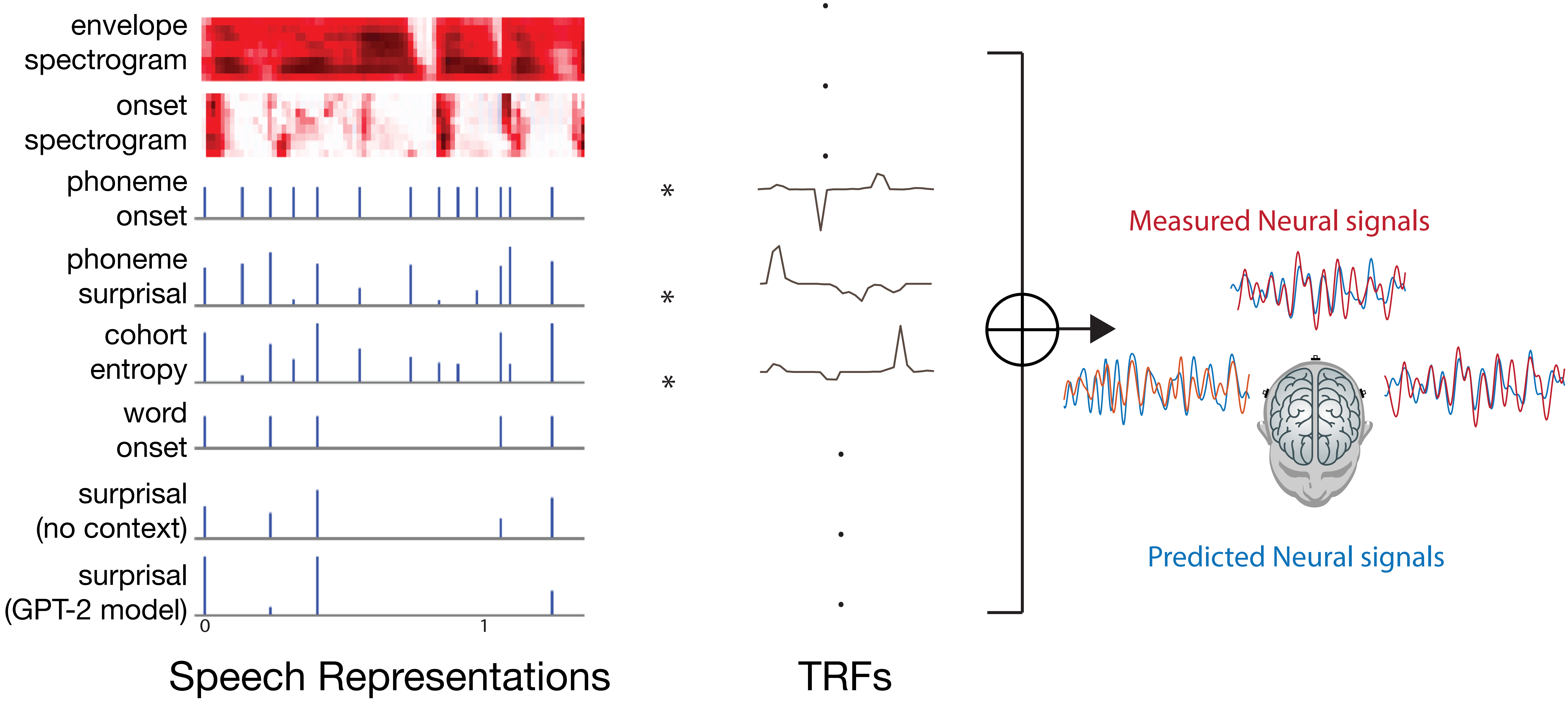

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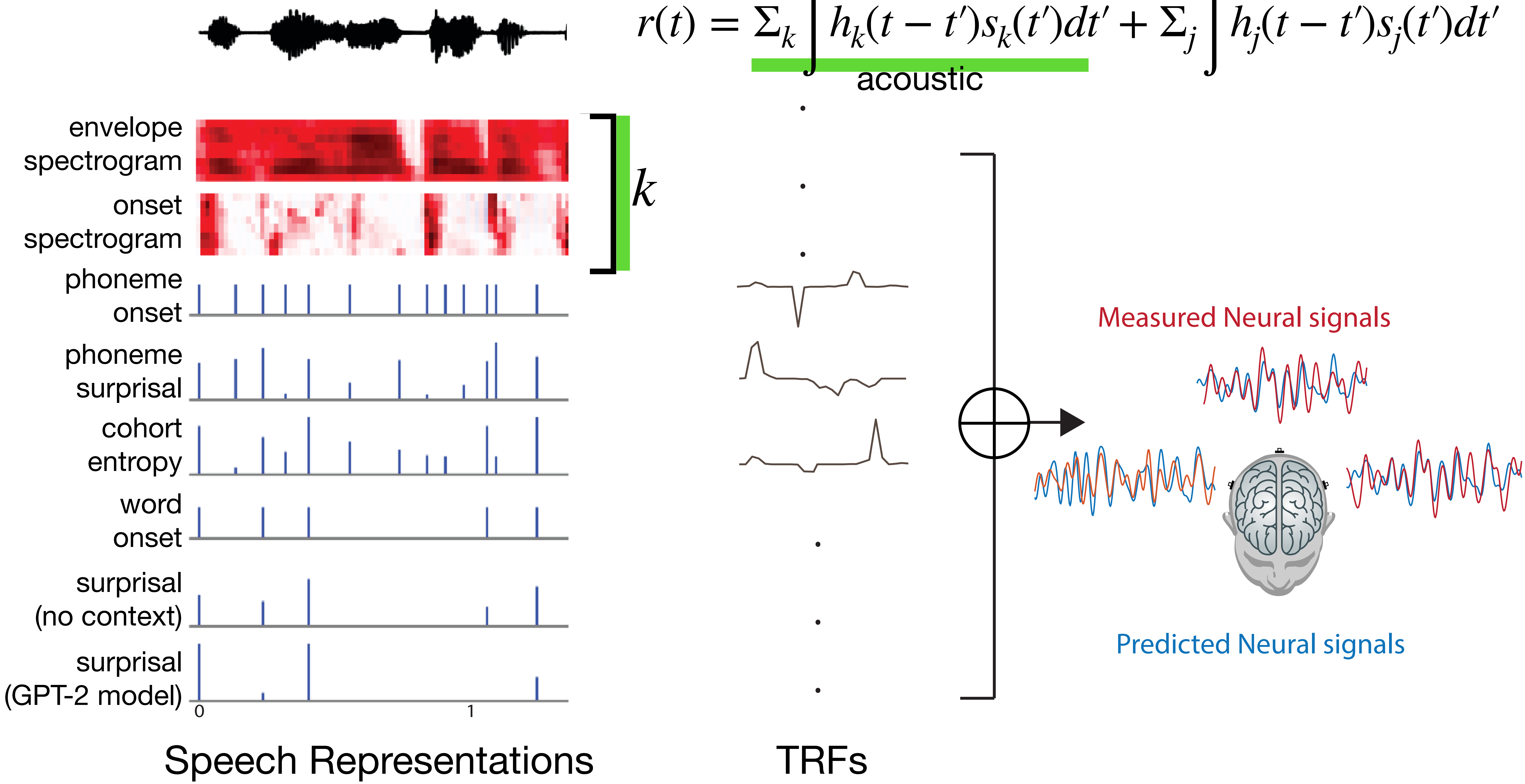

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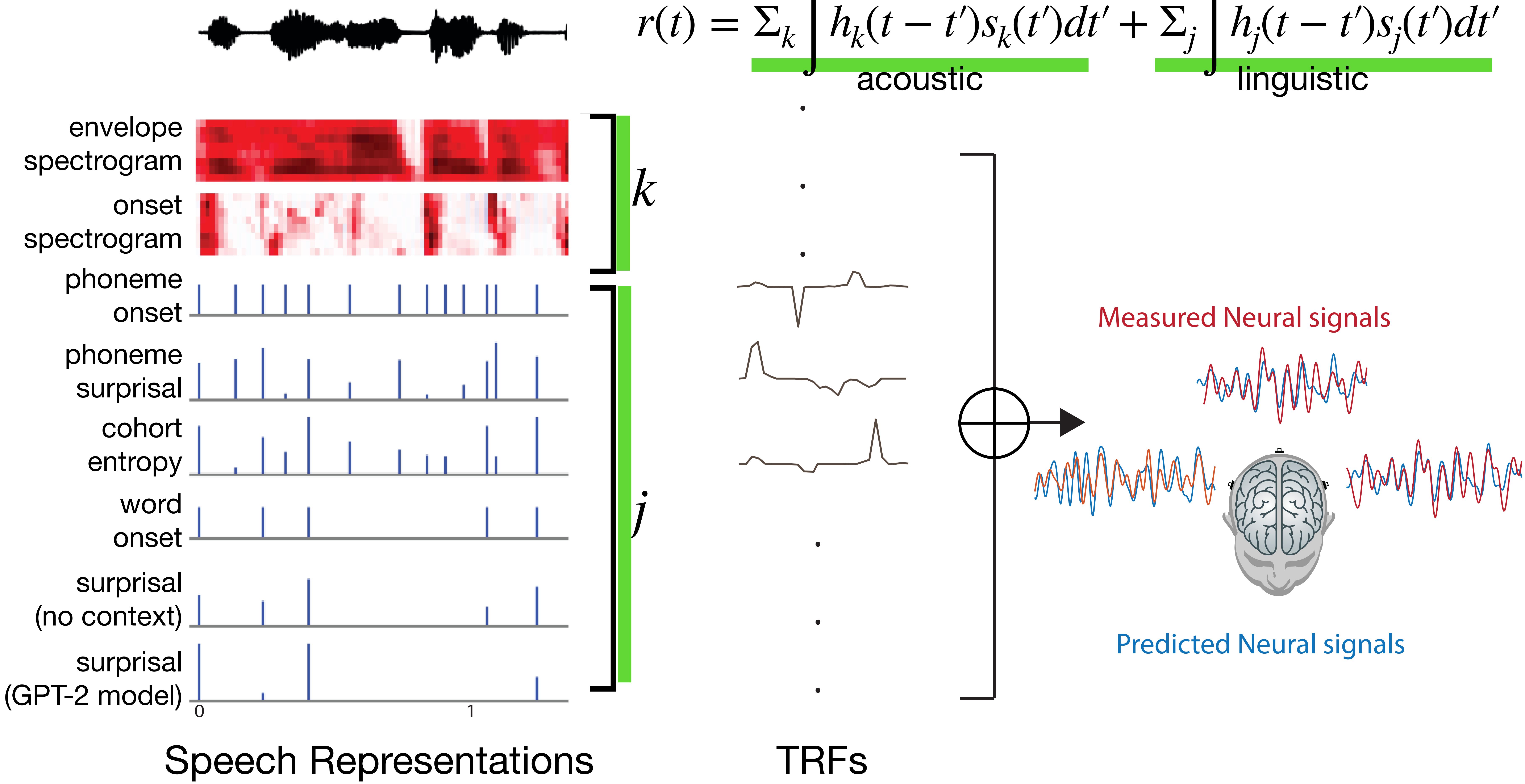

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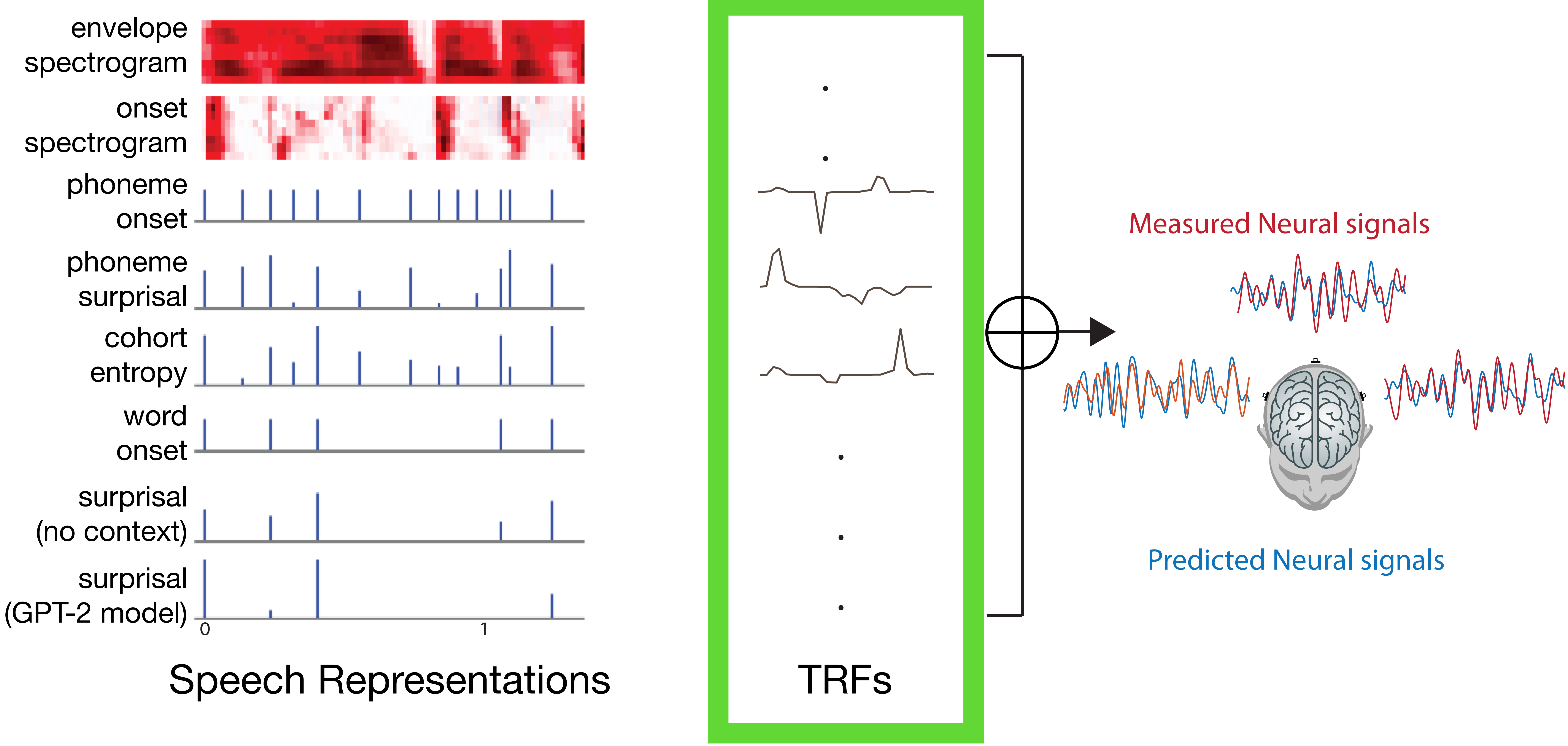

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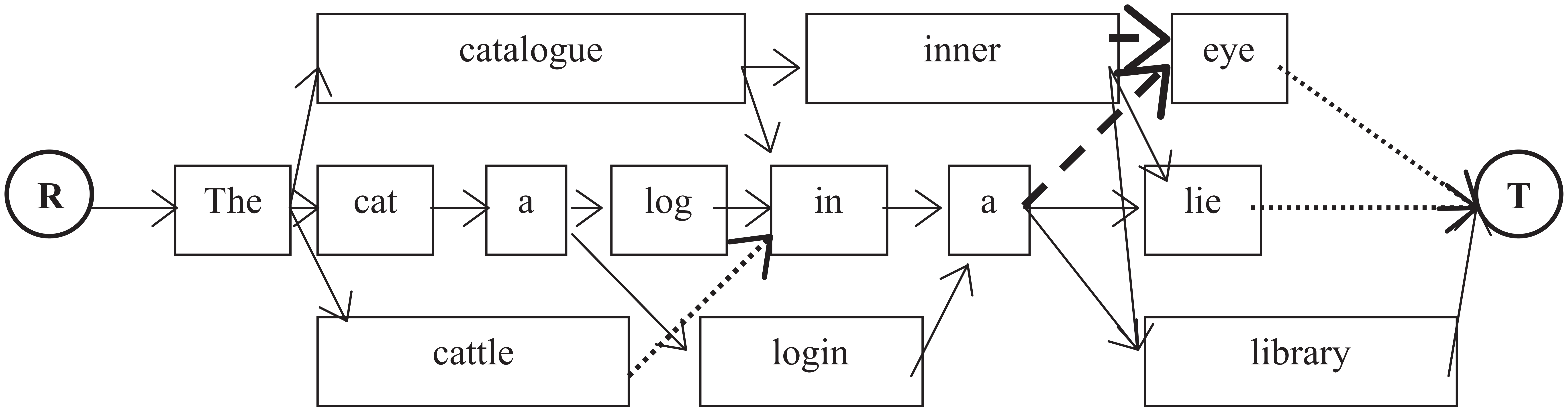
Word Onsets

Do we…

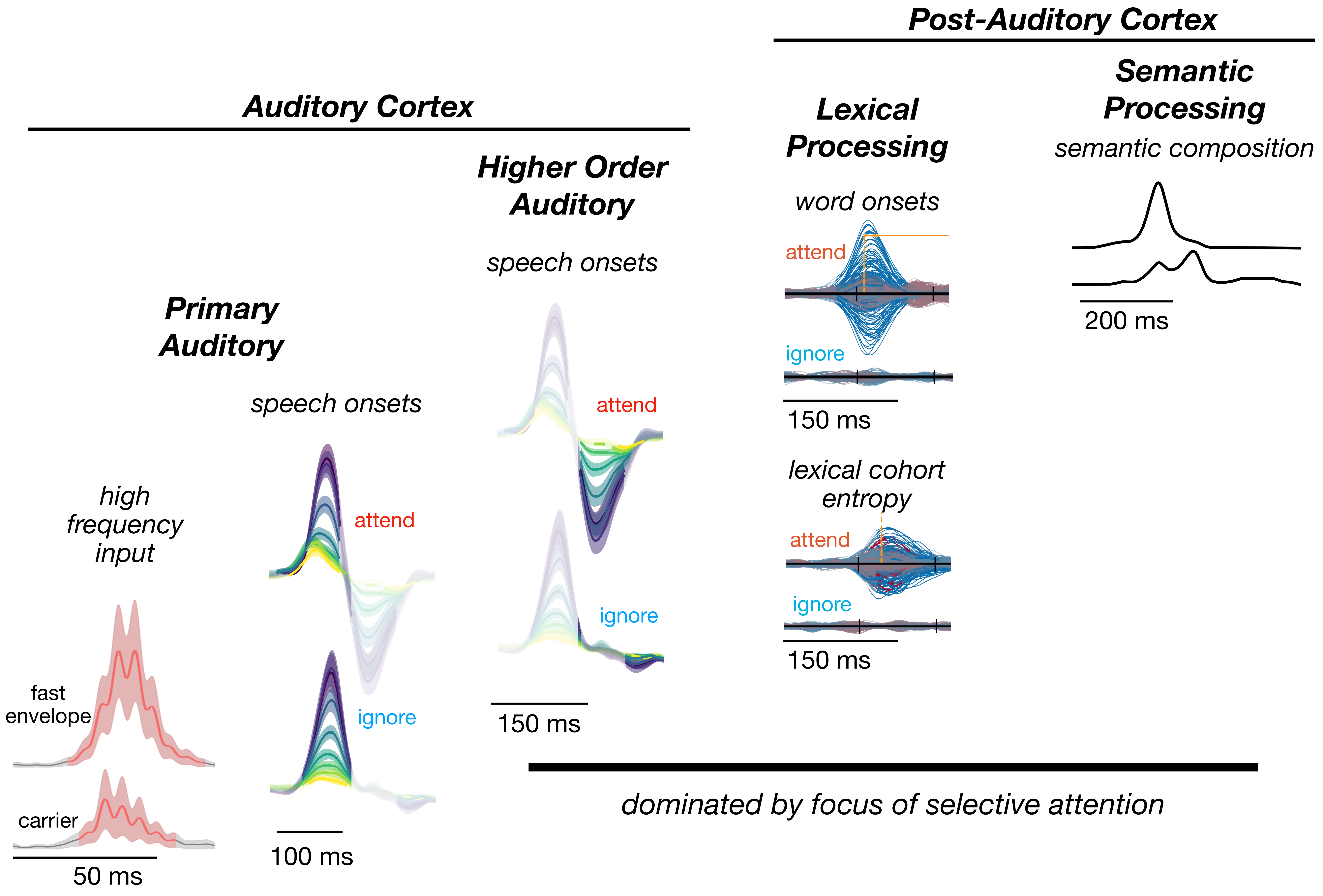
- Anticipate word boundaries based on context?
- Infer them later based on consistency?



"The catalogue in a library"

(Norris & McQueen, 2008)

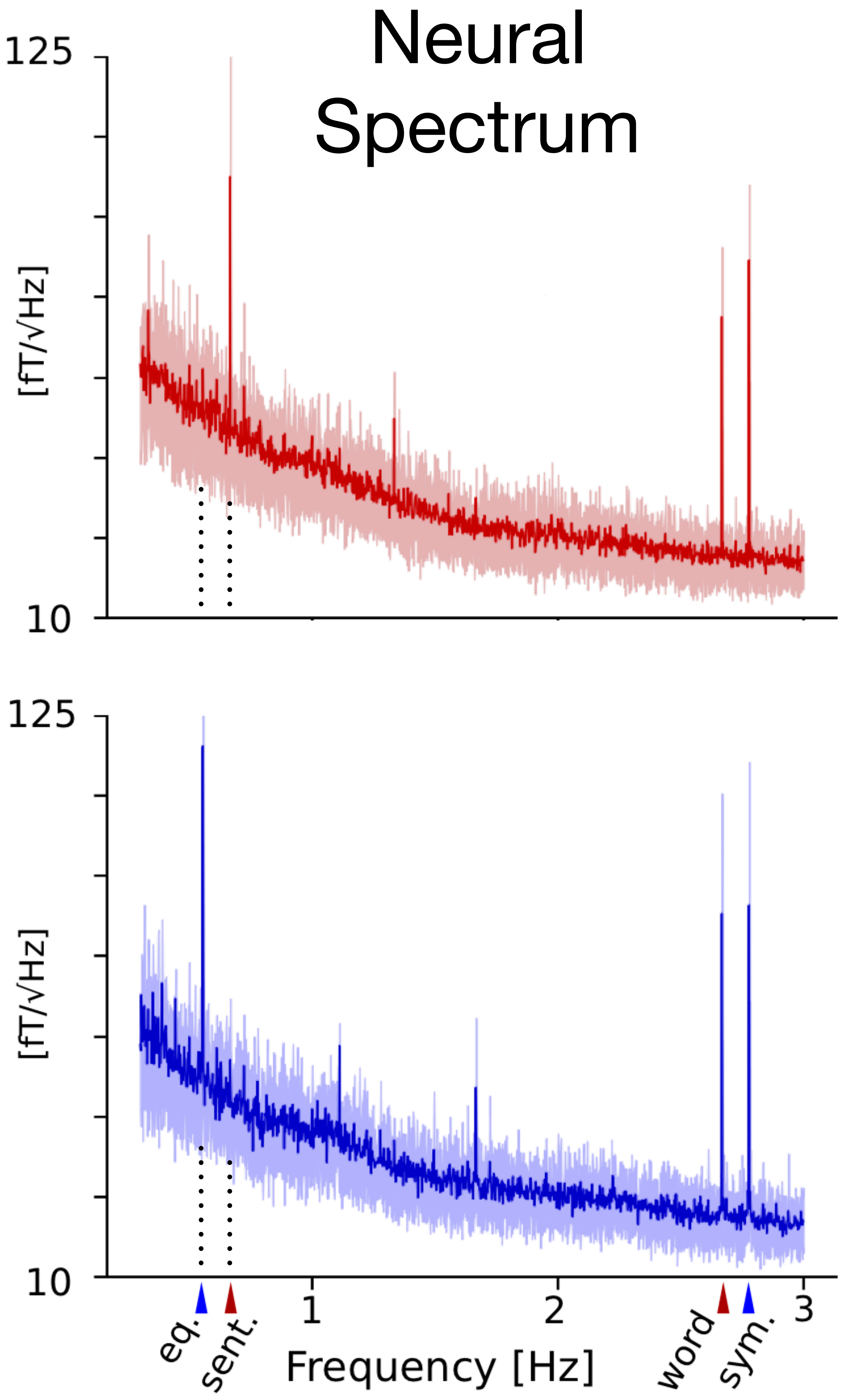
Cortical Representations Across Cortex



Isochronous Cocktail Party

Attend to Sentences

Attend to Equations



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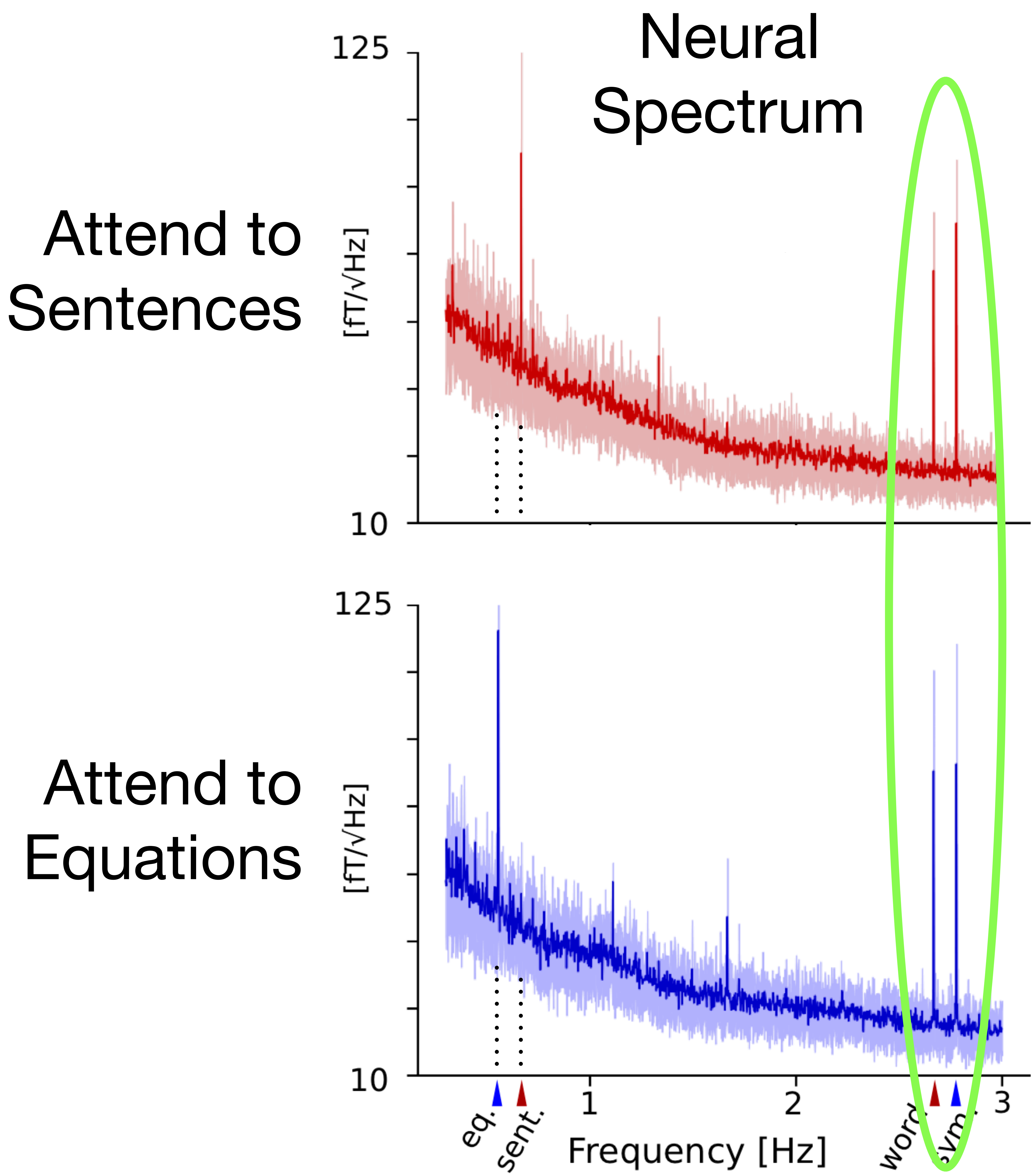

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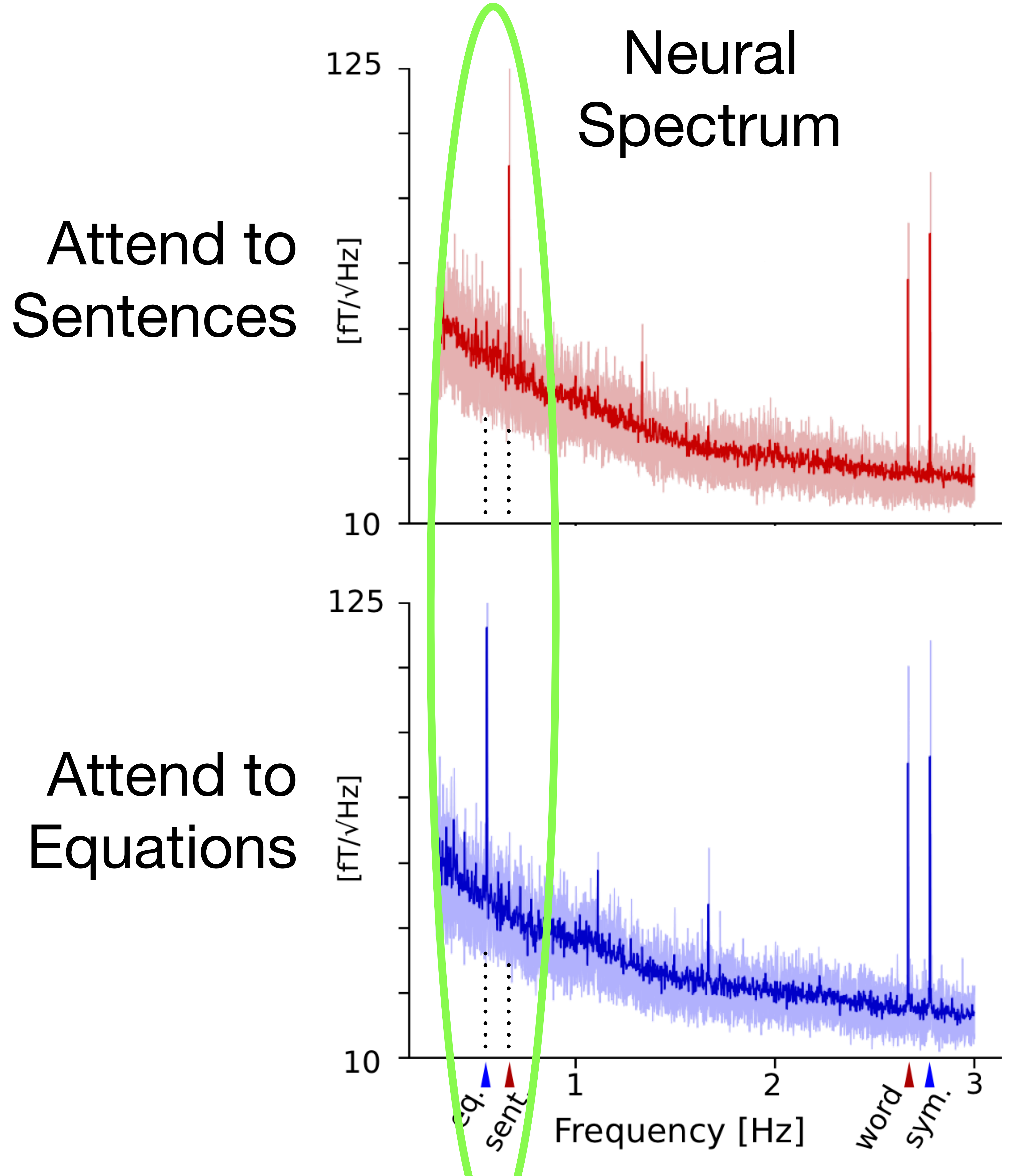

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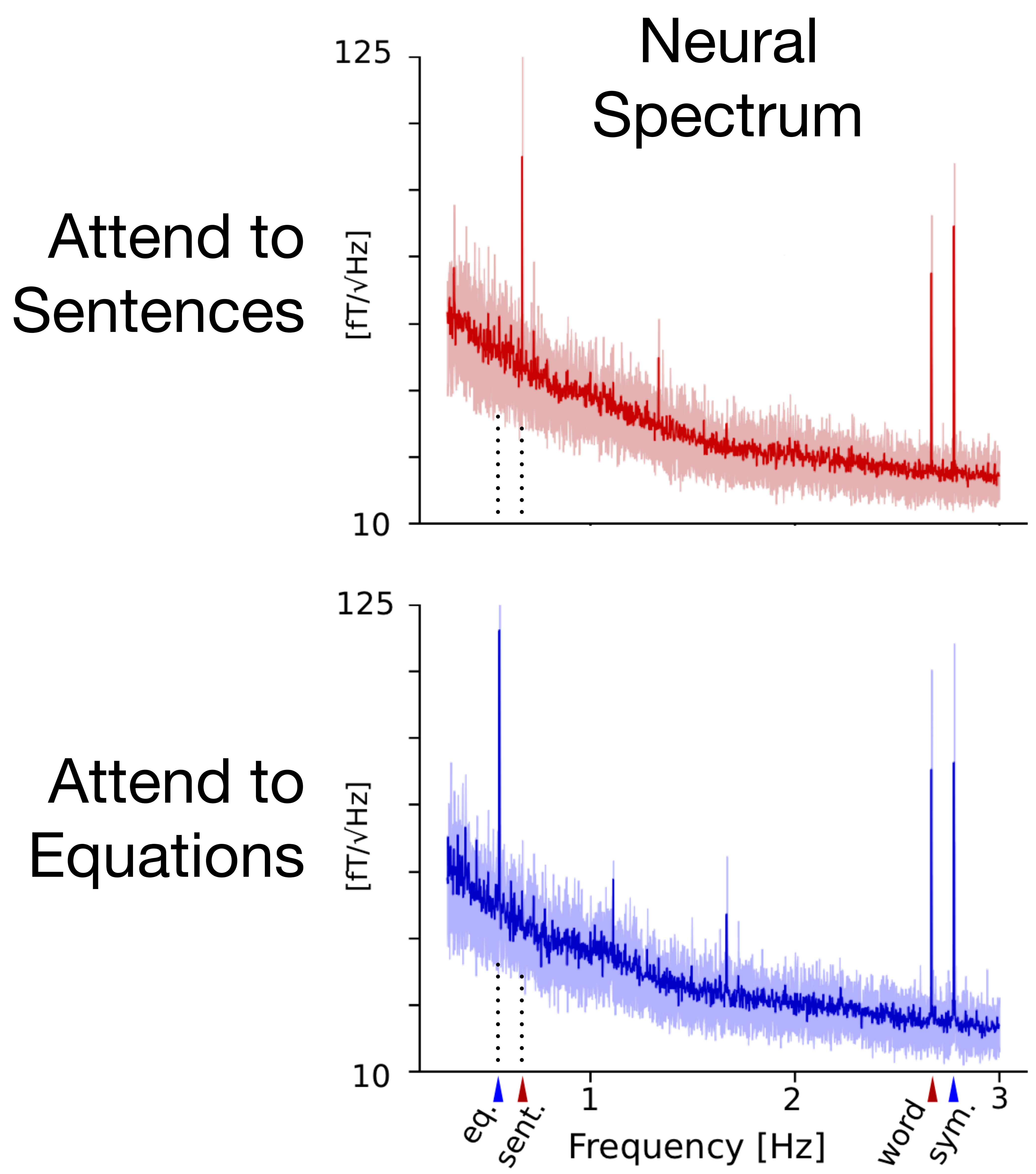
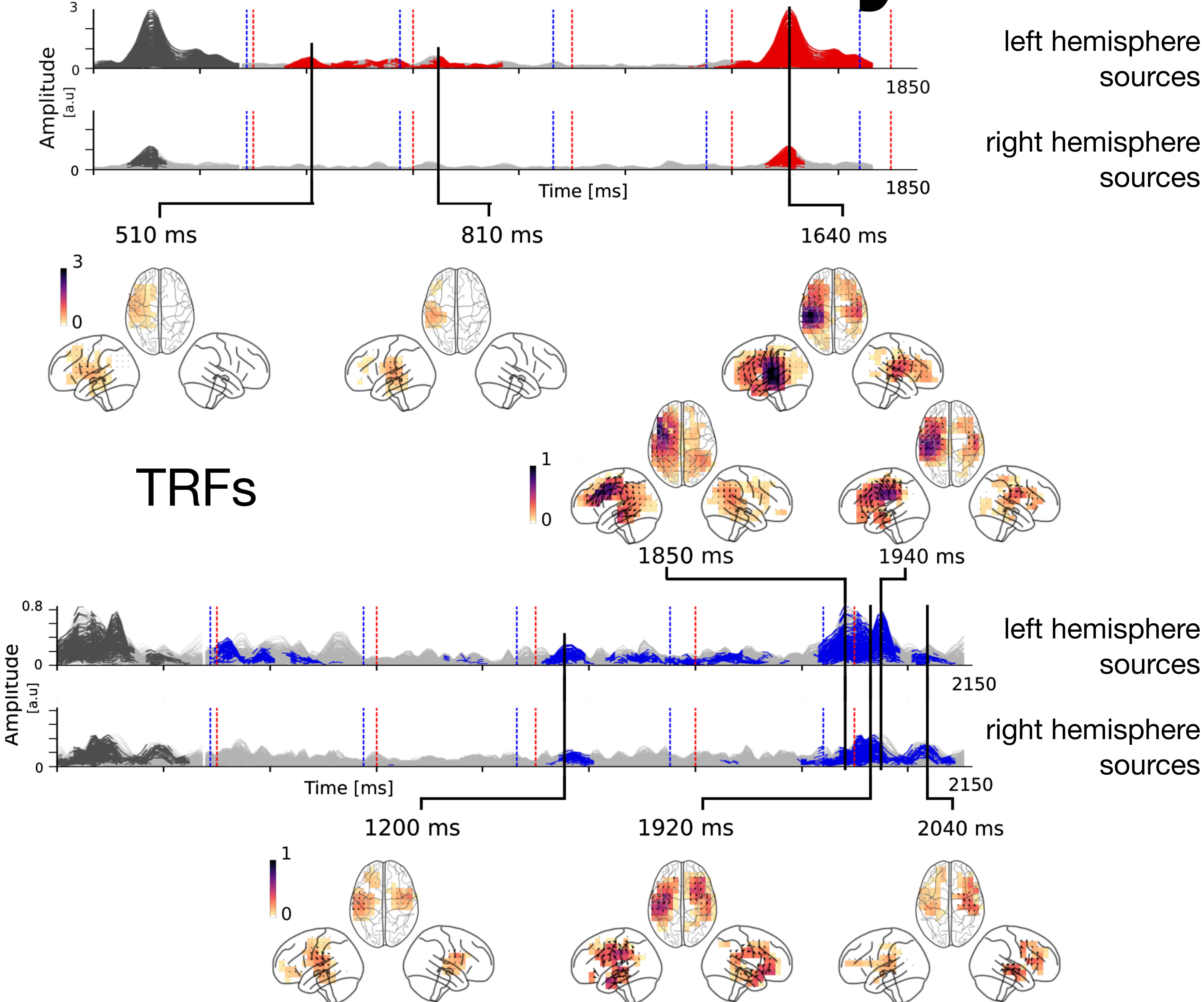




Outline

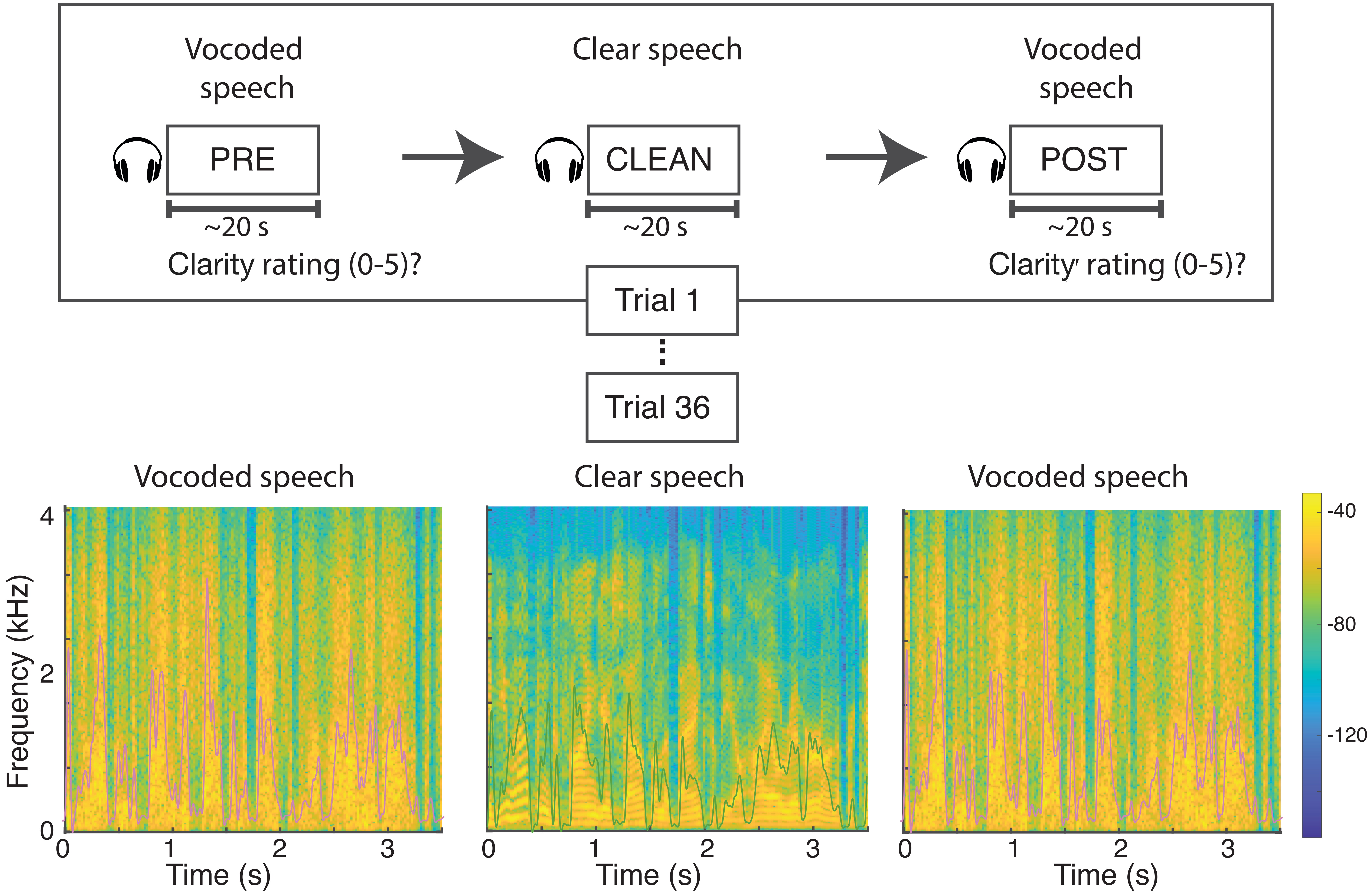
- Measuring Brain Responses with Magnetism
- Linear Shift-Invariant Kernels
- Motivation: neural response as convolution with stimulus
- Examples: neural response as convolution with stimulus
- Example: objective measure of intelligibility

Neural Markers of Speech Intelligibility

- Neural correlate of understanding/intelligibility?
  - very high clinical potential
  - most intelligibility manipulations alter acoustics, *but not all*
  - can use “priming” to alter intelligibility
  - corresponding neural response?
  - good candidates: linguistic predictors, e.g., *word onsets*

Intelligibility Experimental Design

- Manipulate intelligibility but keep acoustics unchanged
  - Speech acoustics: three-band noise-vocoded speech
  - Intelligibility manipulated via priming
- Hypothesized intelligibility measure(s)
  - word boundaries



Karunathilake et al. *in preparation*

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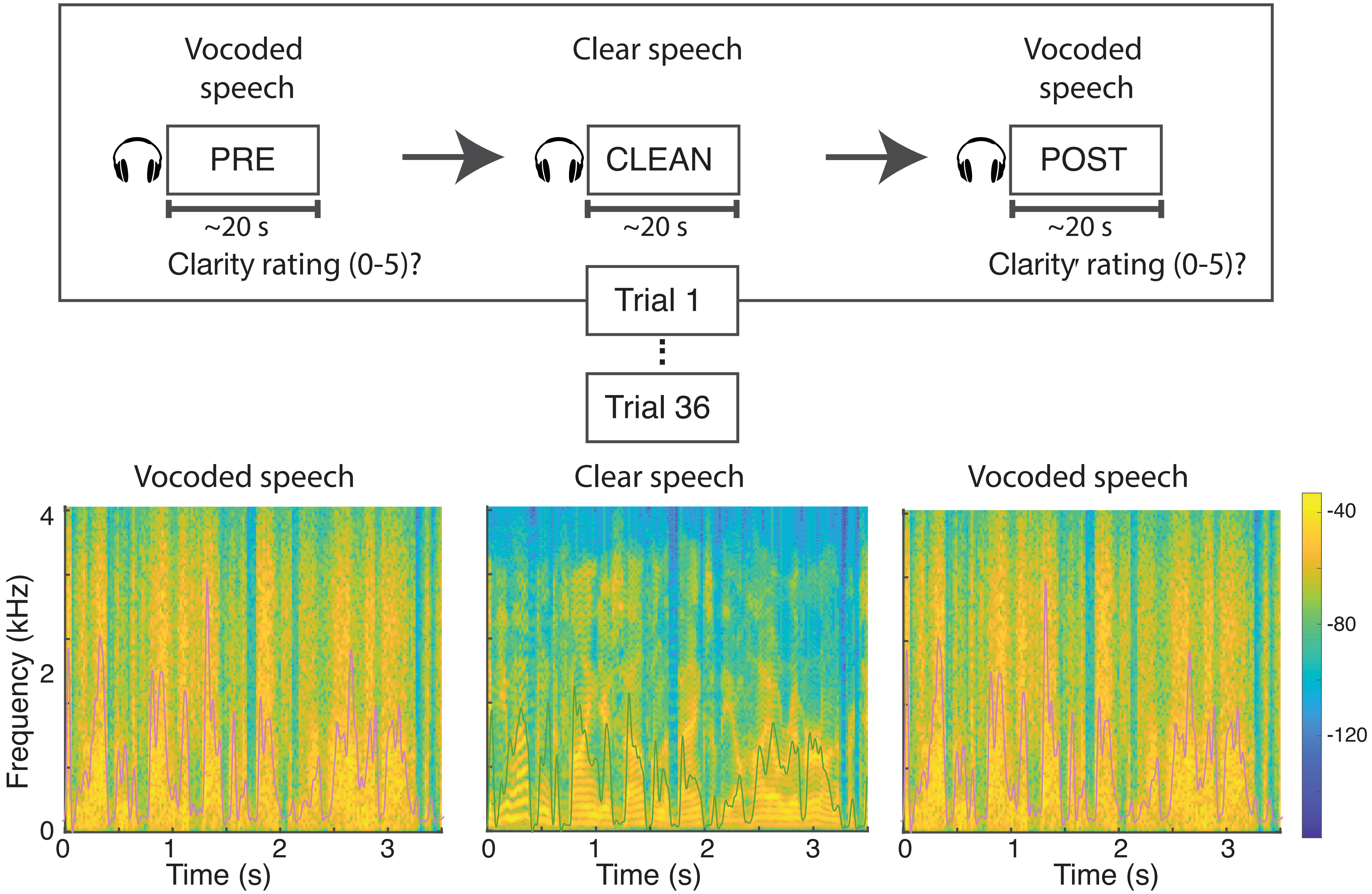

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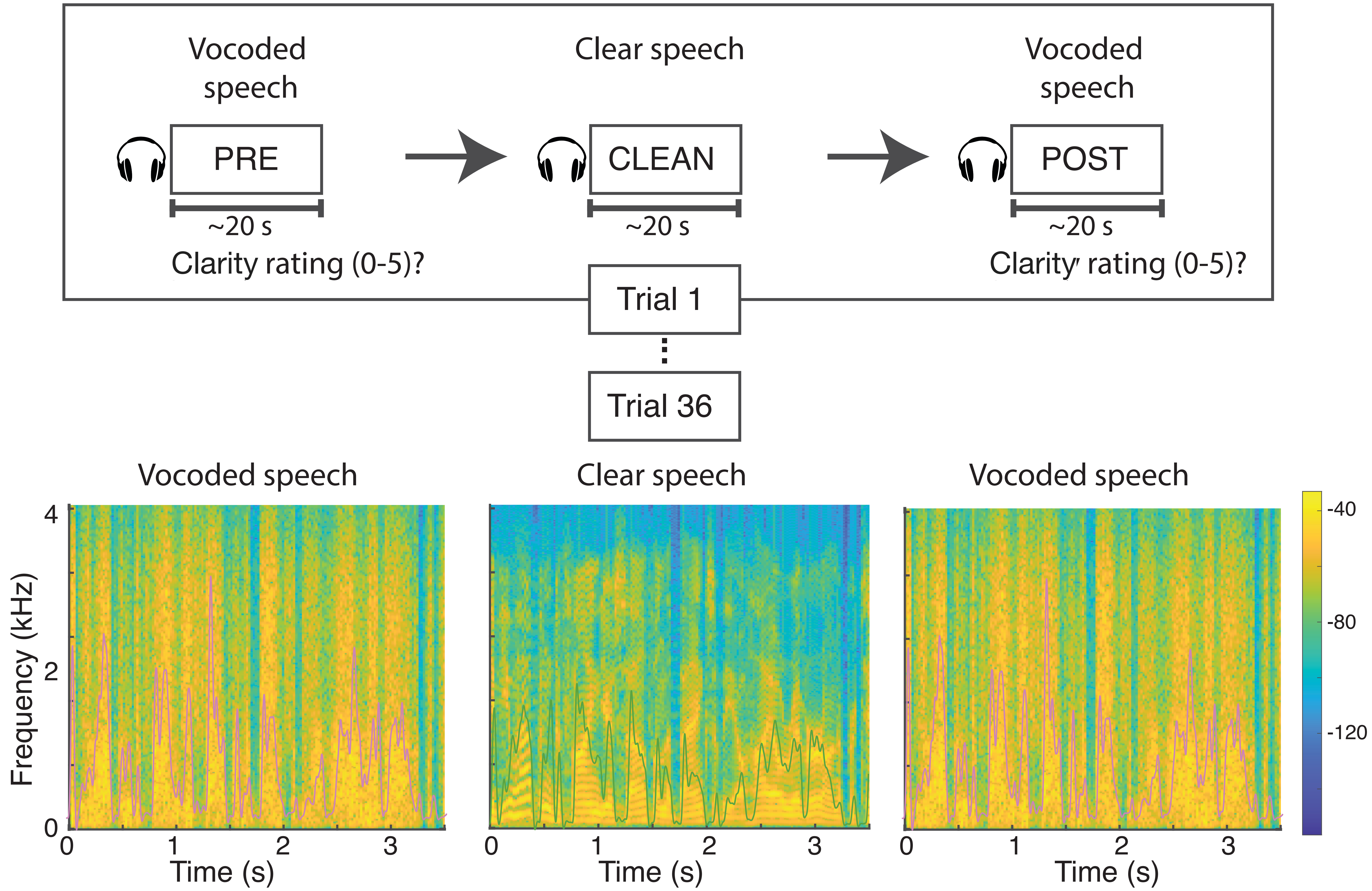

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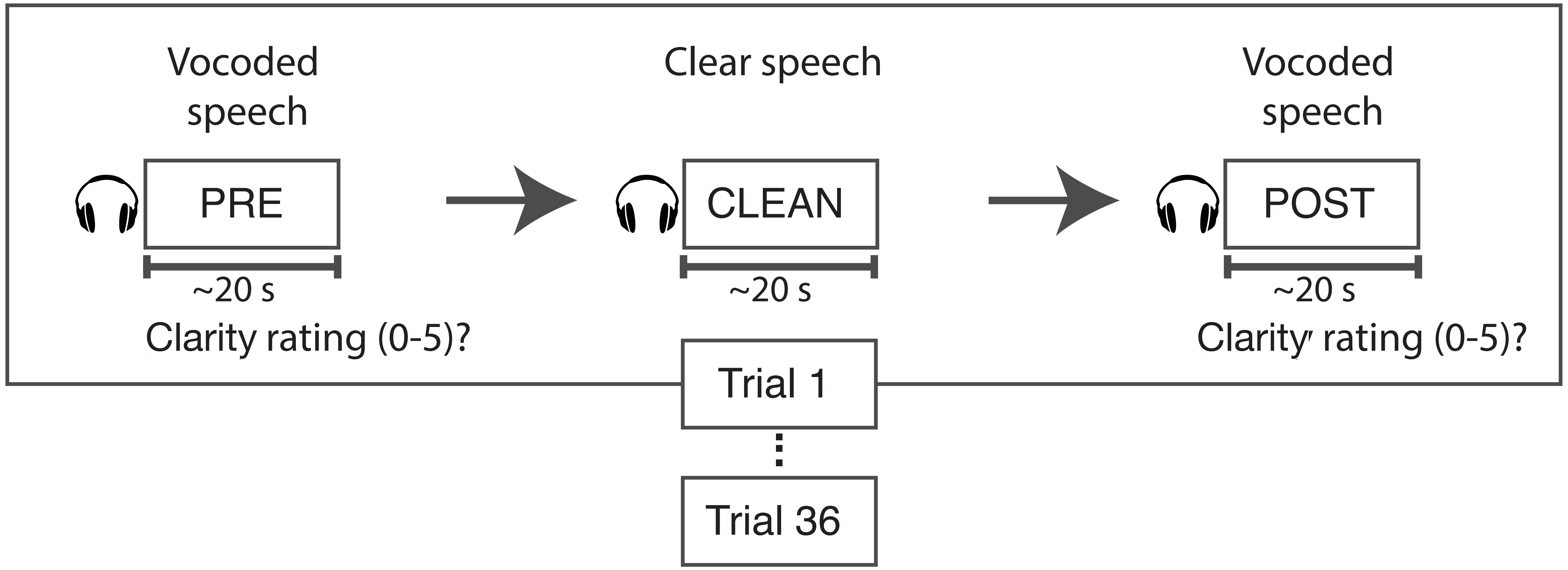

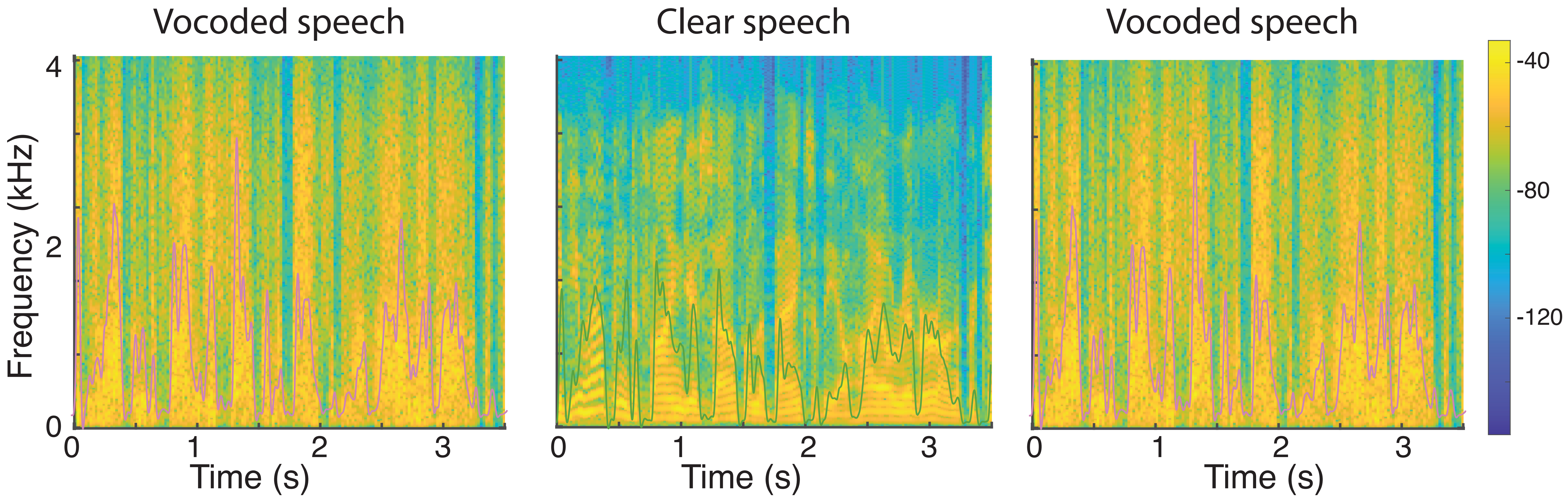

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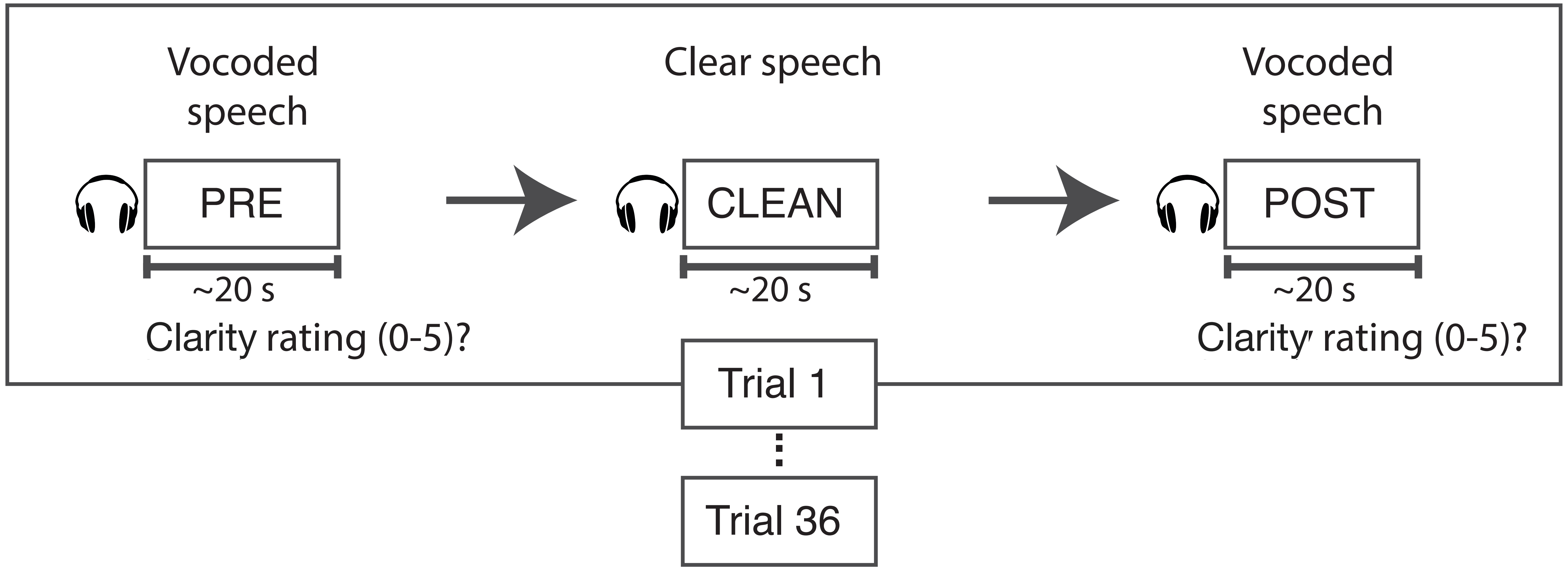

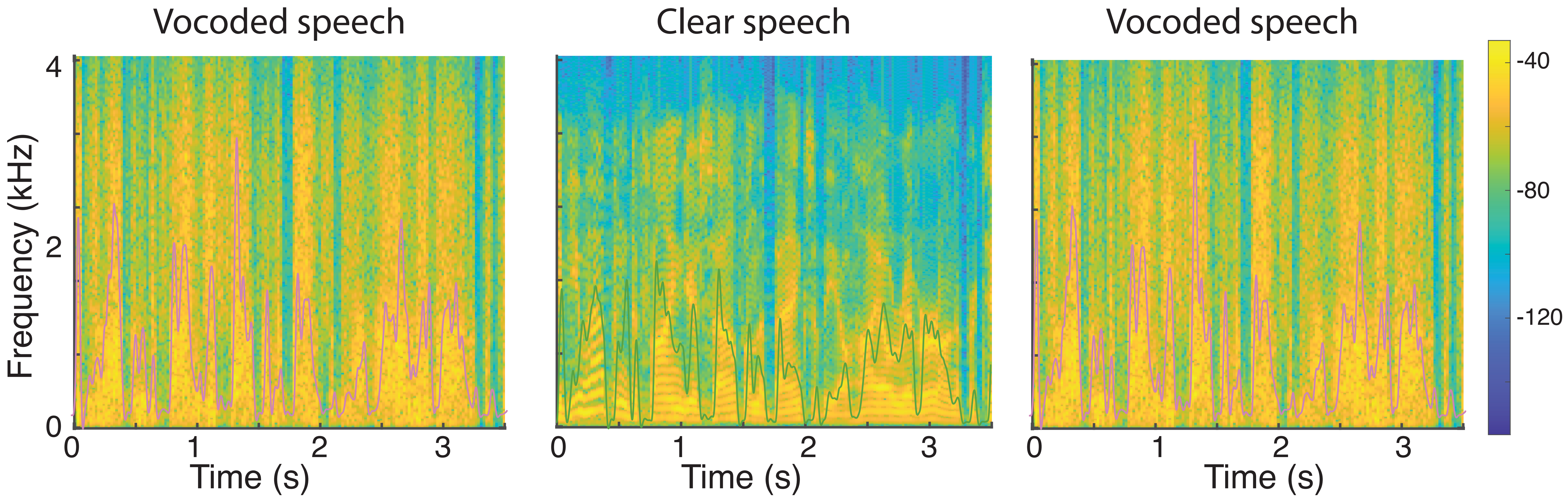

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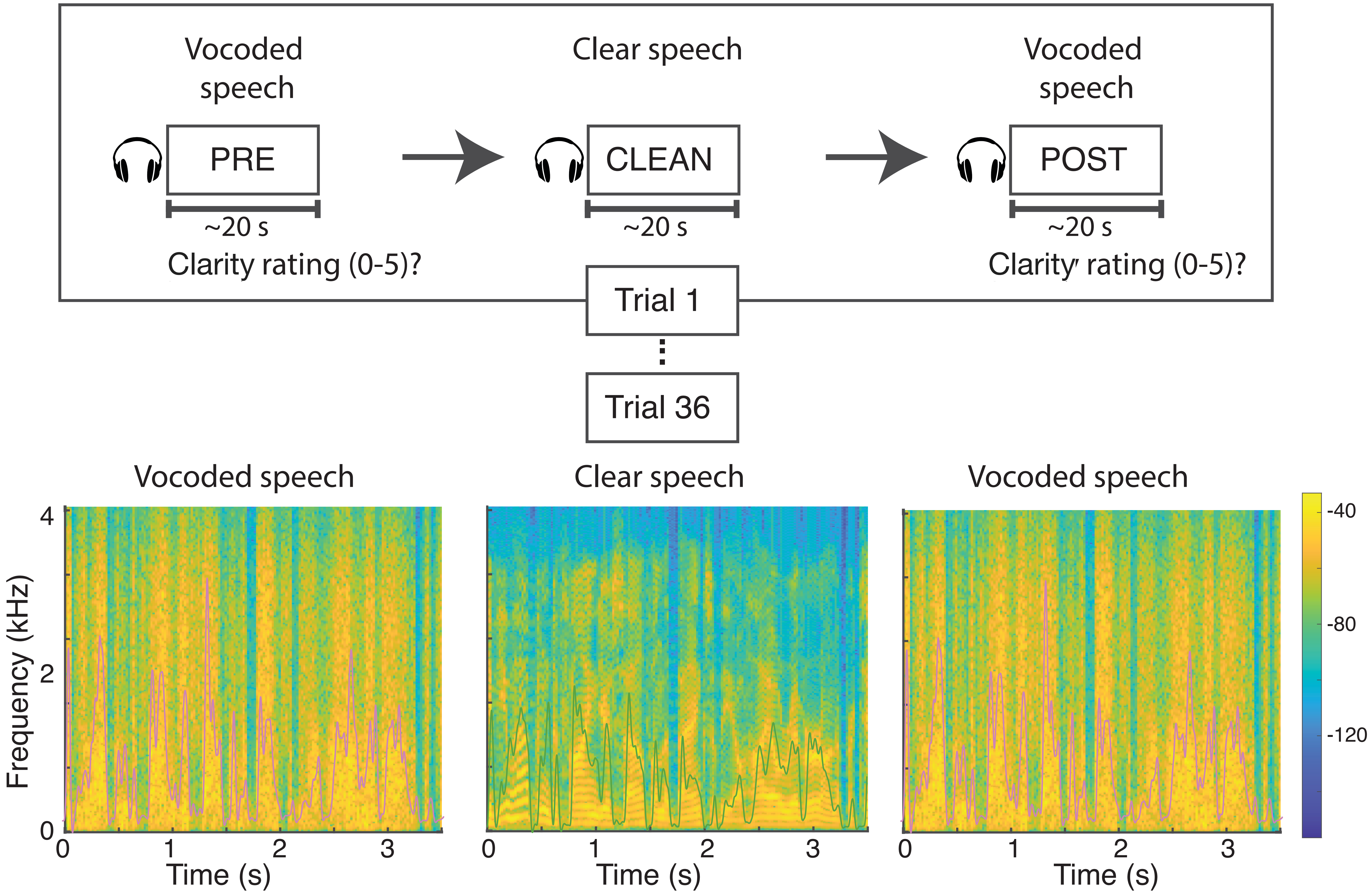

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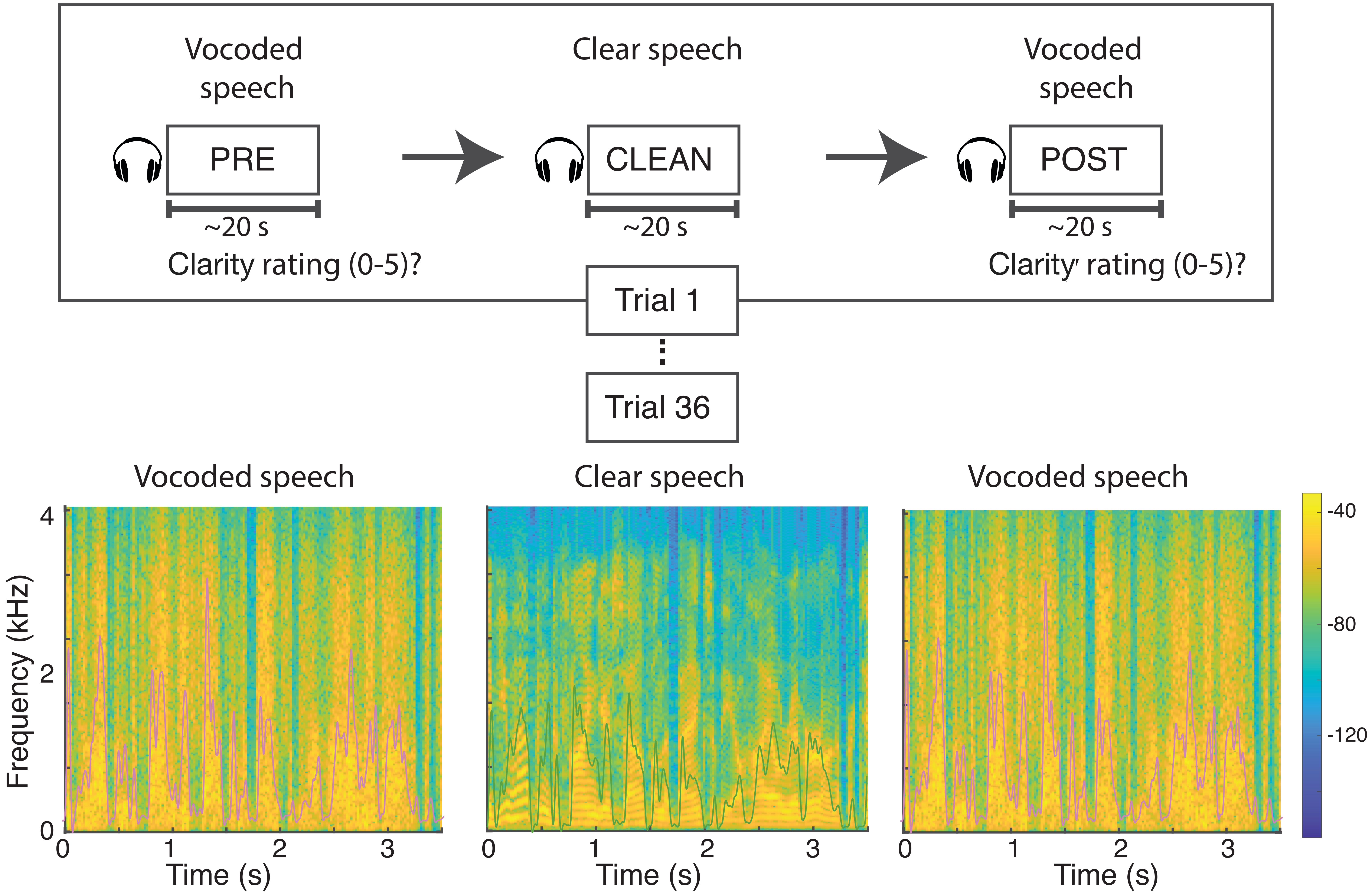

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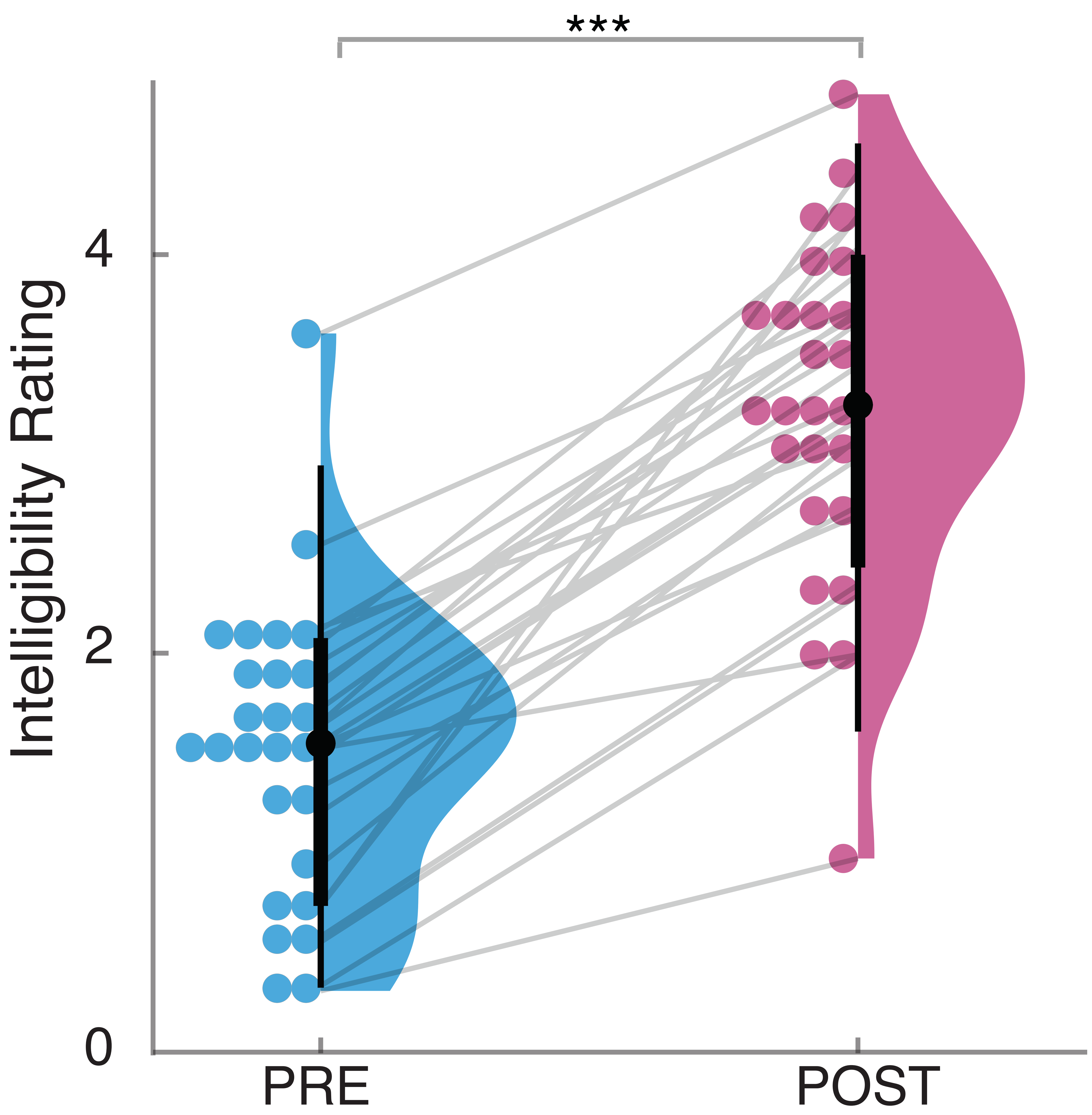
Behavioral Results: Clarity

Clarity rating **increases** from PRE condition to POST condition

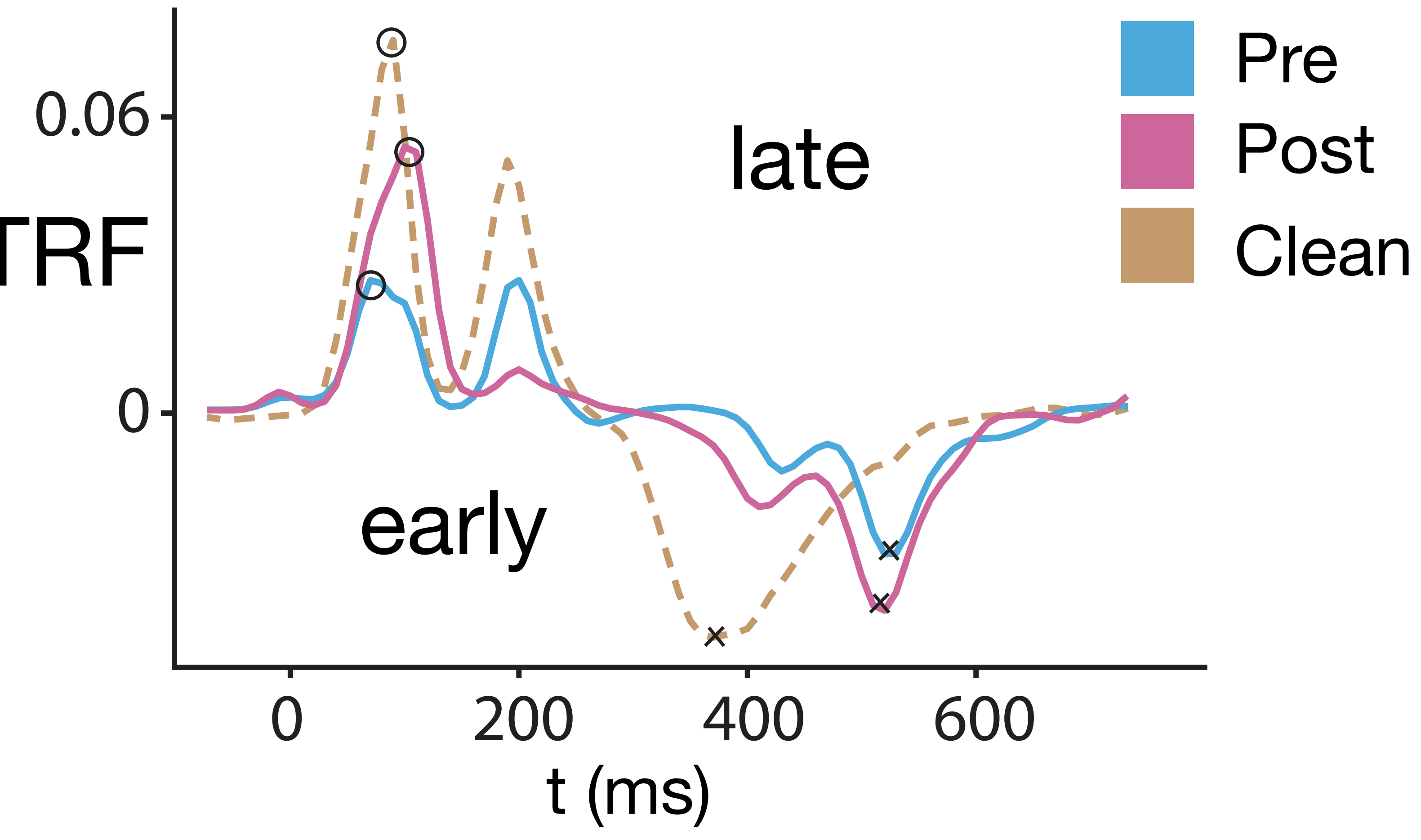


Intelligibility Neural Results

- **Word onset** TRF shows both early (+) and late (-) processing stages

Word onset TRF

single subject



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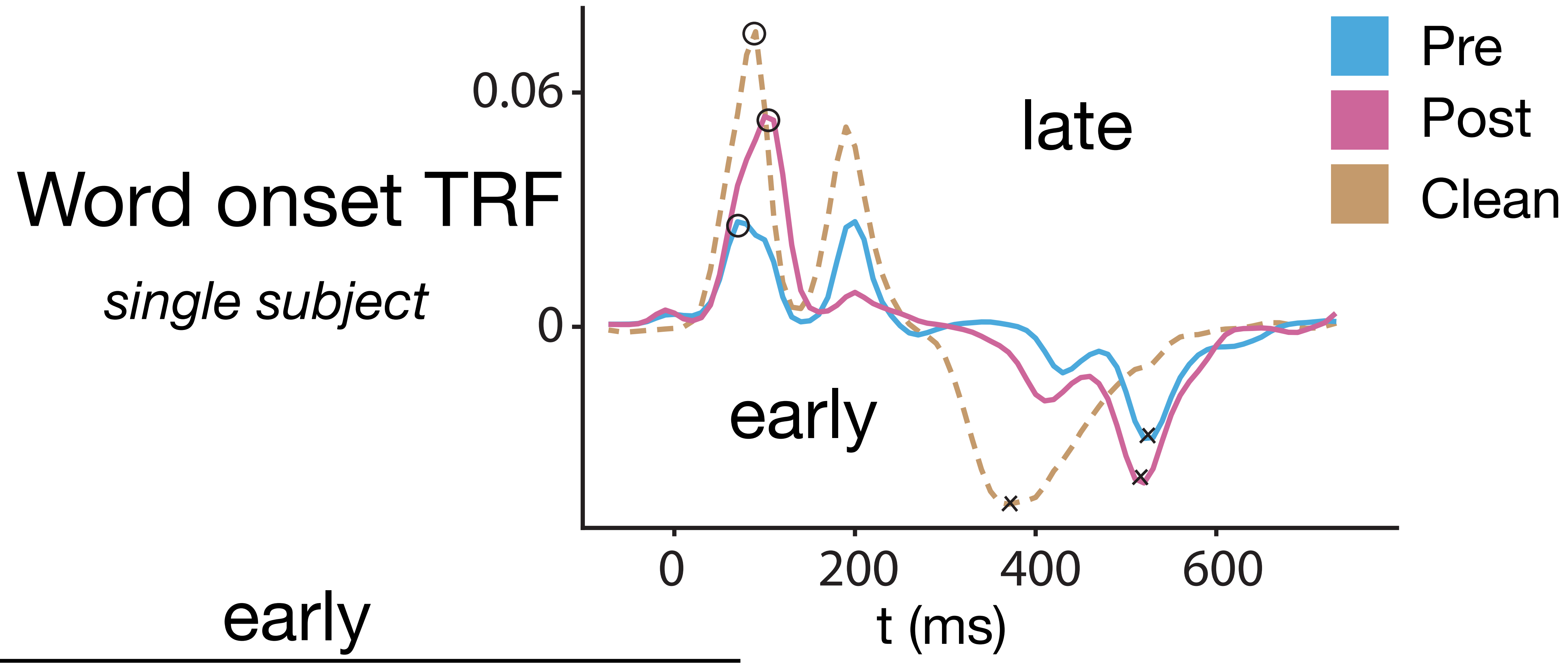

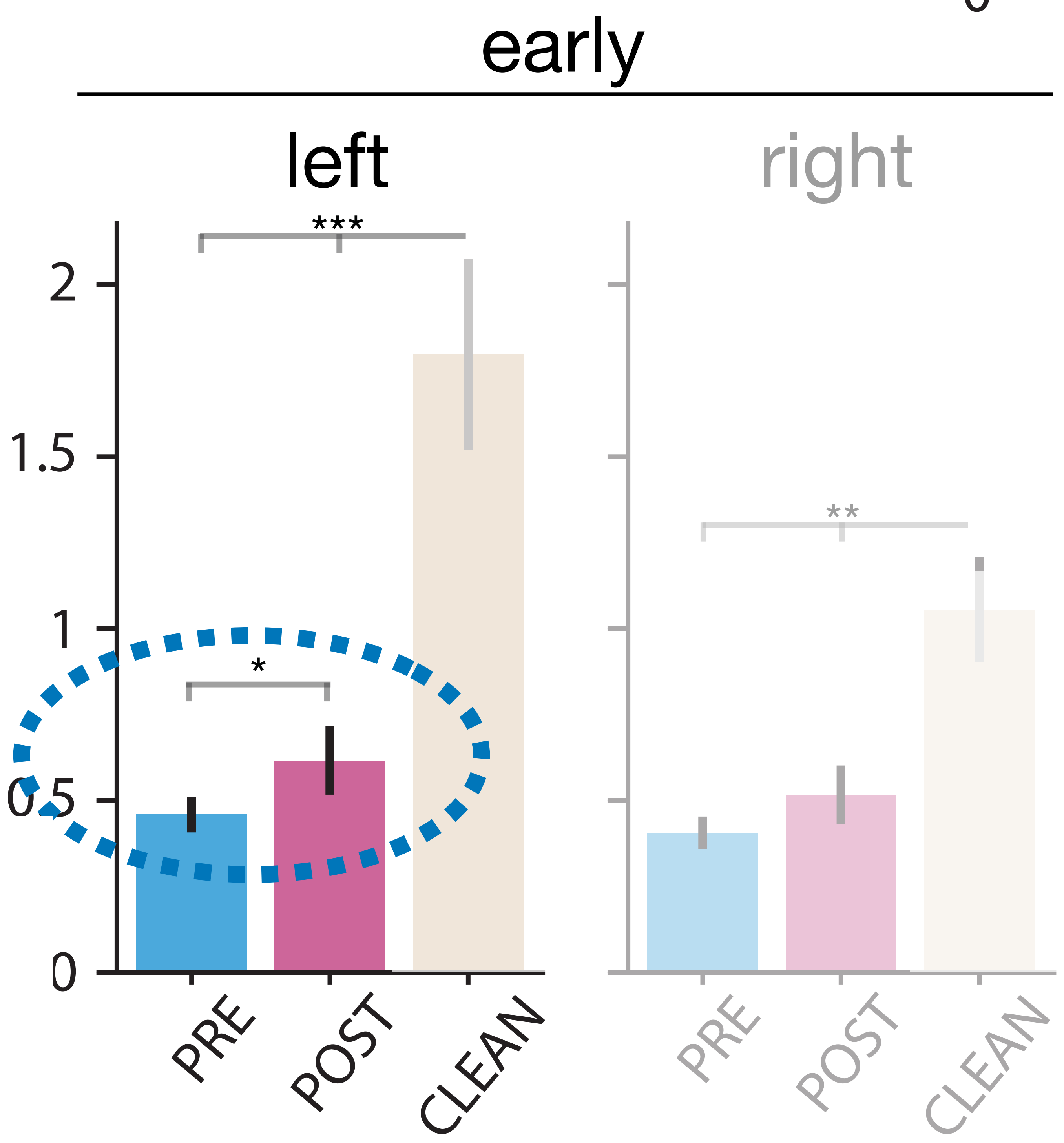

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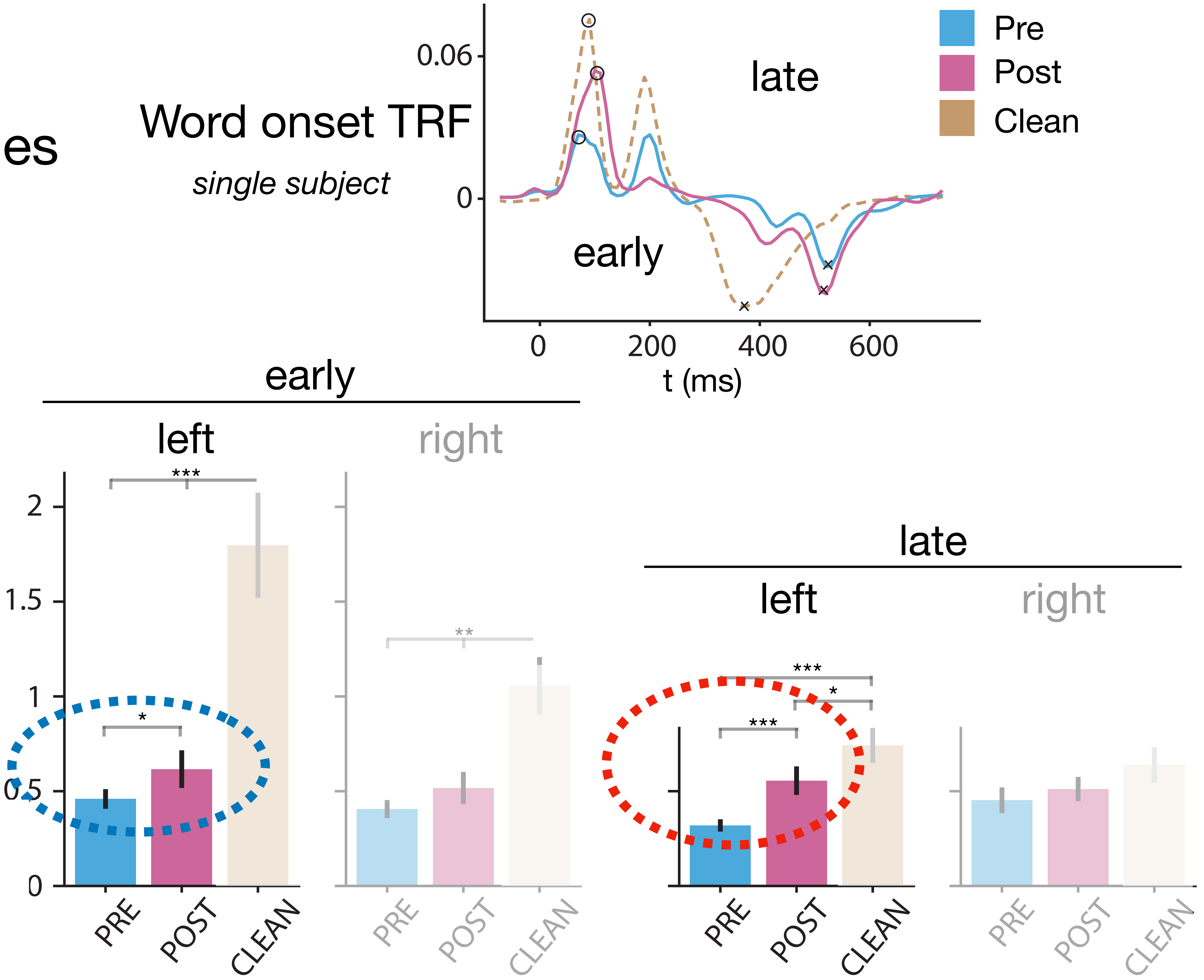

Intelligibility Neural Results

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- Response increases Pre→Post
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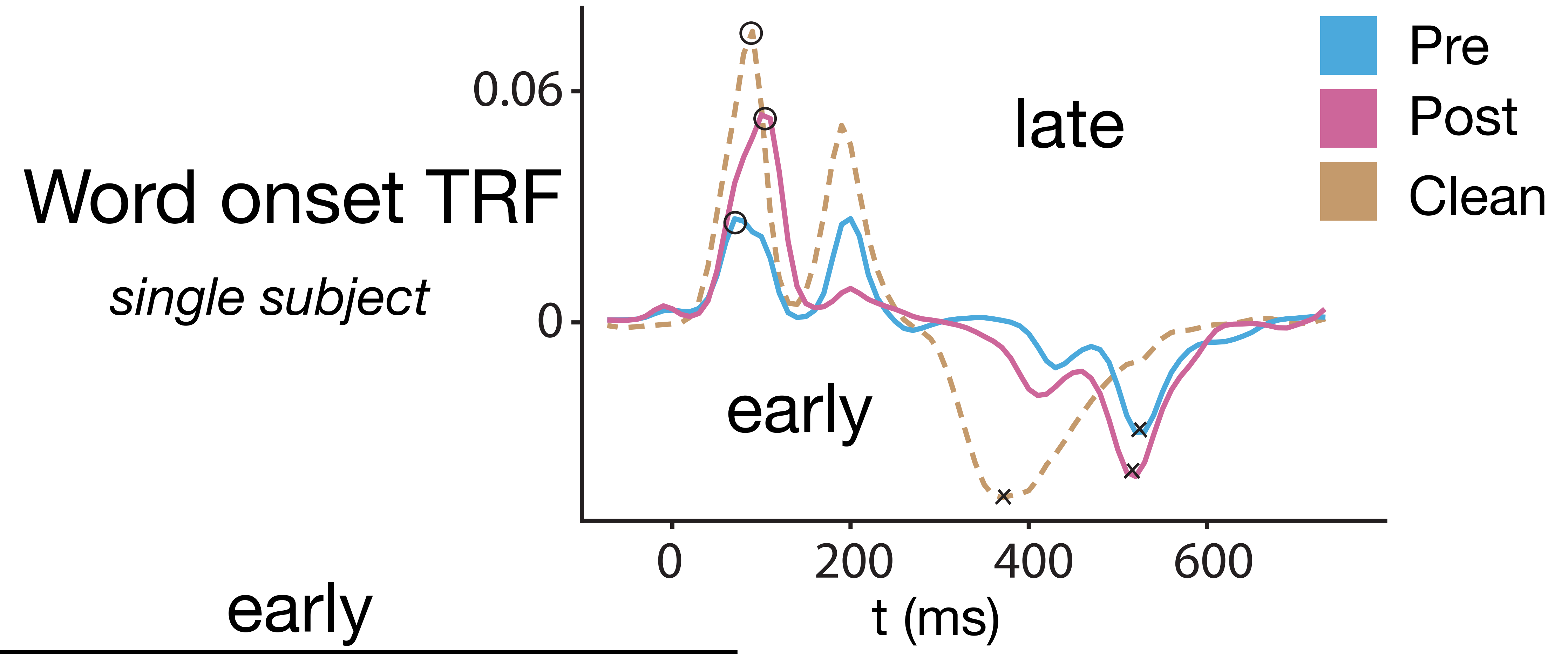
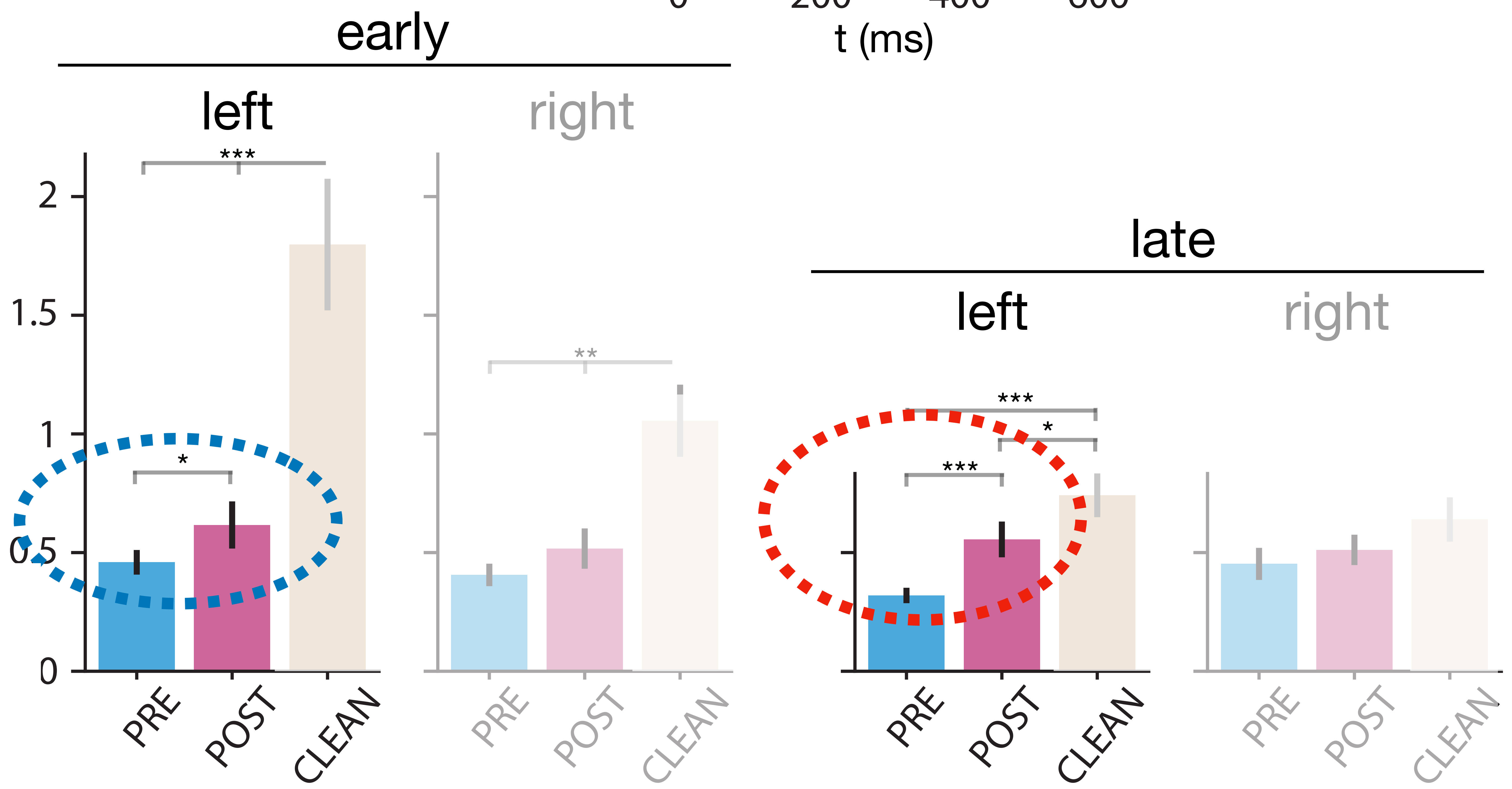
- Response to Word Onset: *Objective measure of intelligibility*
  - Acoustic responses: no change





Summary

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$$\mathbf{B} = \mathbf{LJ}$$

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thank you

These slides
available at:
ter.ps/simonpubs

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http://www.isr.umd.edu/Labs/CSSL/simonlab