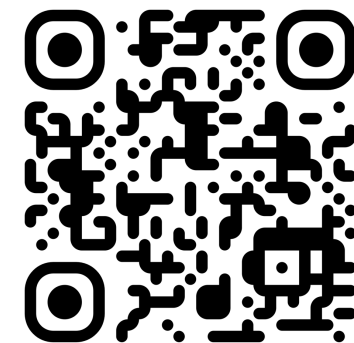# Inner Speech Decoding from EEG and MEG

Richard Csaky, Mats W.J. van Es, Oiwi Parker Jones, Mark Woolrich
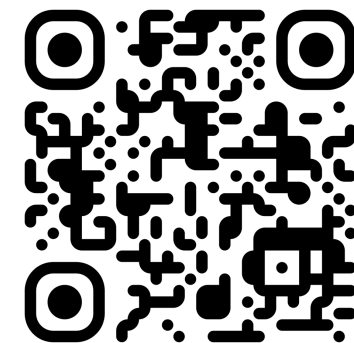
University of Oxford

Background

- Limited research on inner speech with non-invasive methods [1]

- Limited analysis of differences between repetitive and self-generated inner speech

- Such research can lead to word-level communication with BCIs [2]
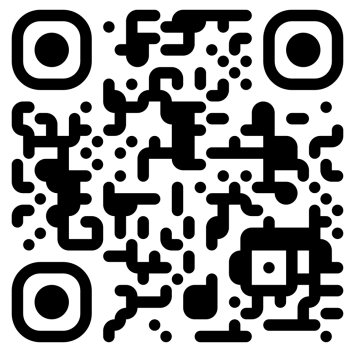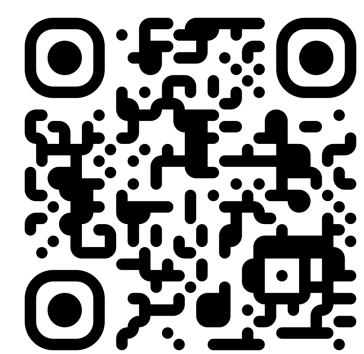
Metzger et al., 2022

Research questions

1. What inner speech decoding performance can be achieved in EEG and MEG with a large number of per-participant trials?

2. Can we transfer decoders across sessions and tasks?

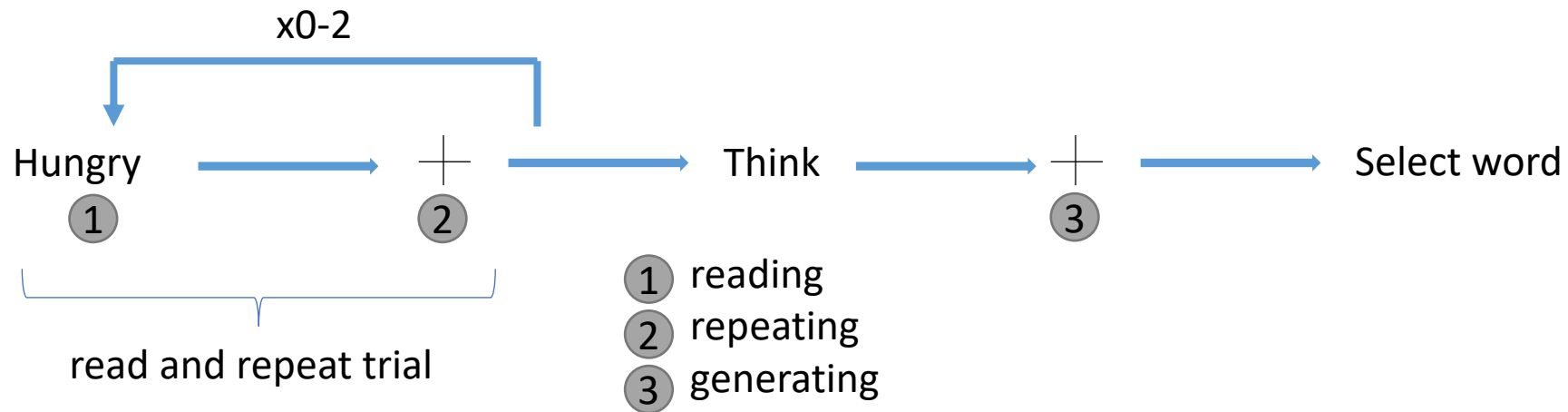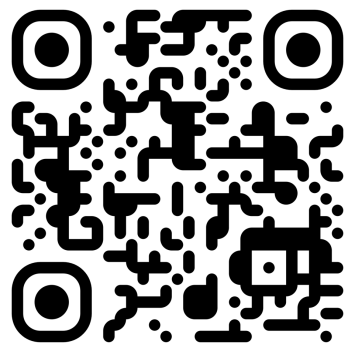3. What are the differences between repetitive and self-generated inner speech?

Data Collection

Experiment

- 5 words:
  - hungry, tired, thirsty, toilet, pain

x0-2

Hungry ⟶ + ⟶ Think ⟶ + ⟶ Select word

① ② ③

read and repeat trial

① reading
② repeating
③ generating
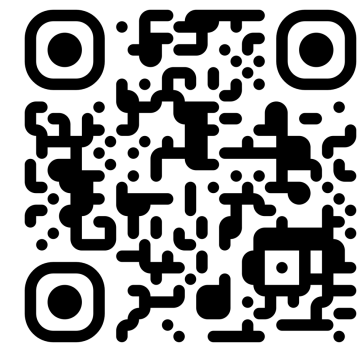
3 task versions

4 consecutive 1-second trials

Silent reading task only

Version 1	EEG	MEG
P1 sessions	6	6
P2 sessions	2	2
P3 sessions	2	2

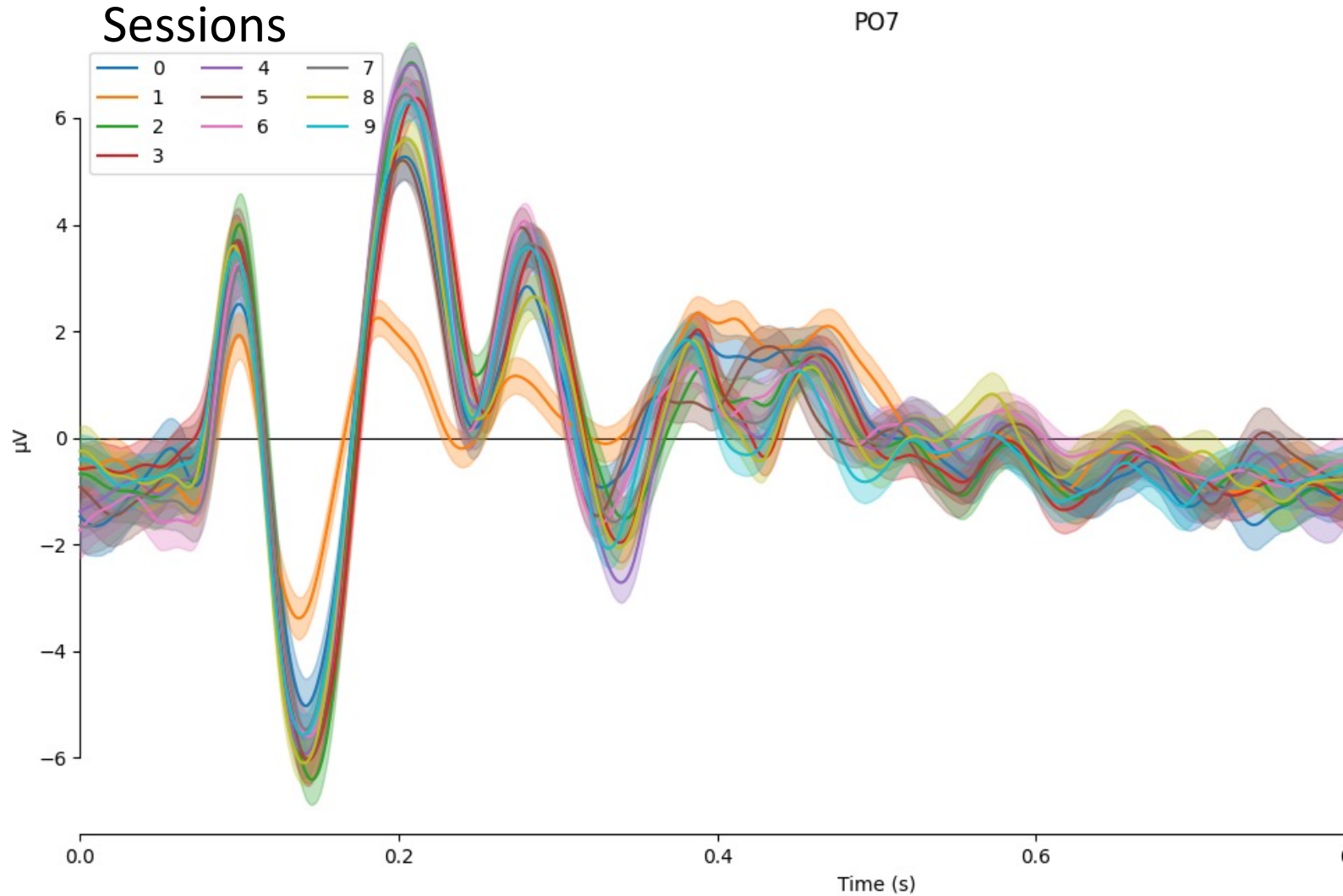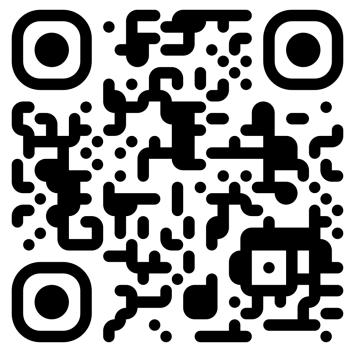| Version 2	EEG	MEG
P1 sessions	1	1
P2 sessions	1	1
P3 sessions	10	1

Version 3	EEG	MEG
P1 sessions	1	1
P2 sessions	1	1
P3 sessions	1	1

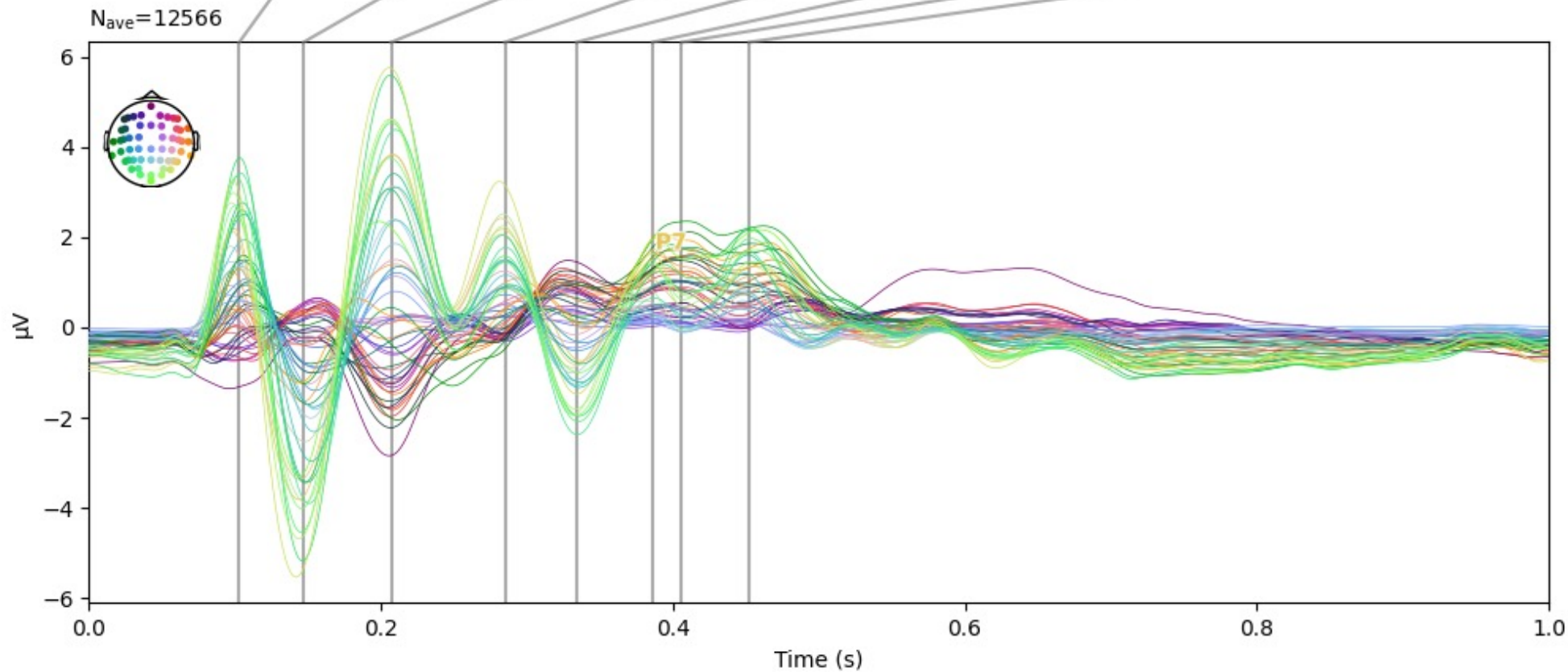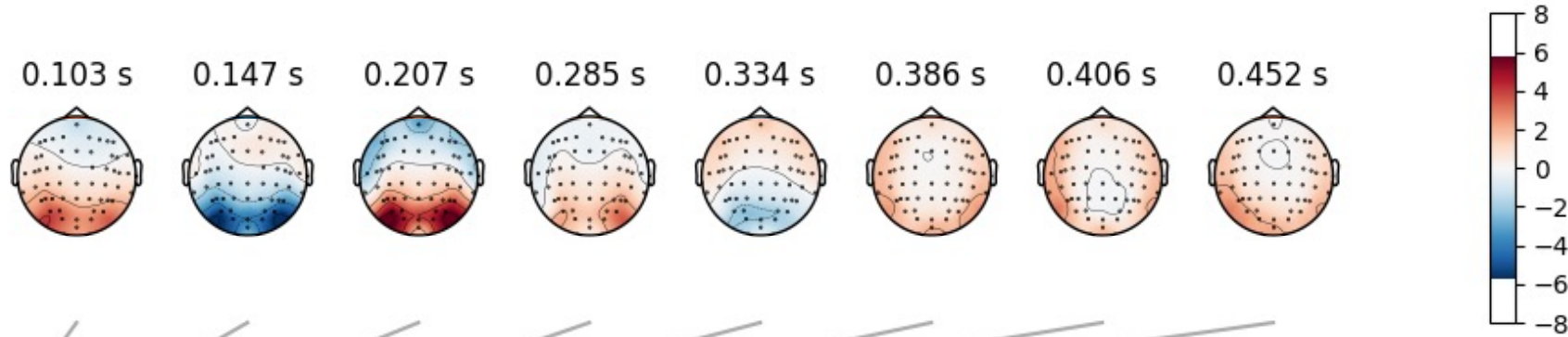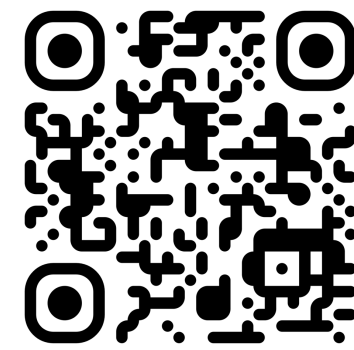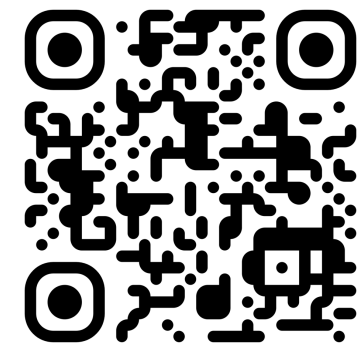| Total trials	EEG	MEG
Inner speech	20K	10K
Silent reading	9K	7.5K

EEG inner speech data analysis
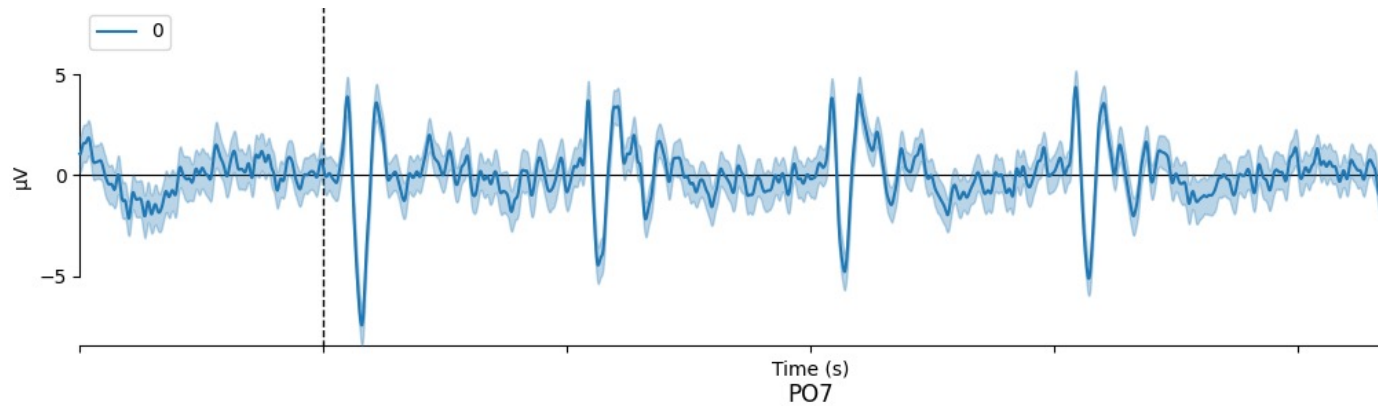
Evoked response across sessions
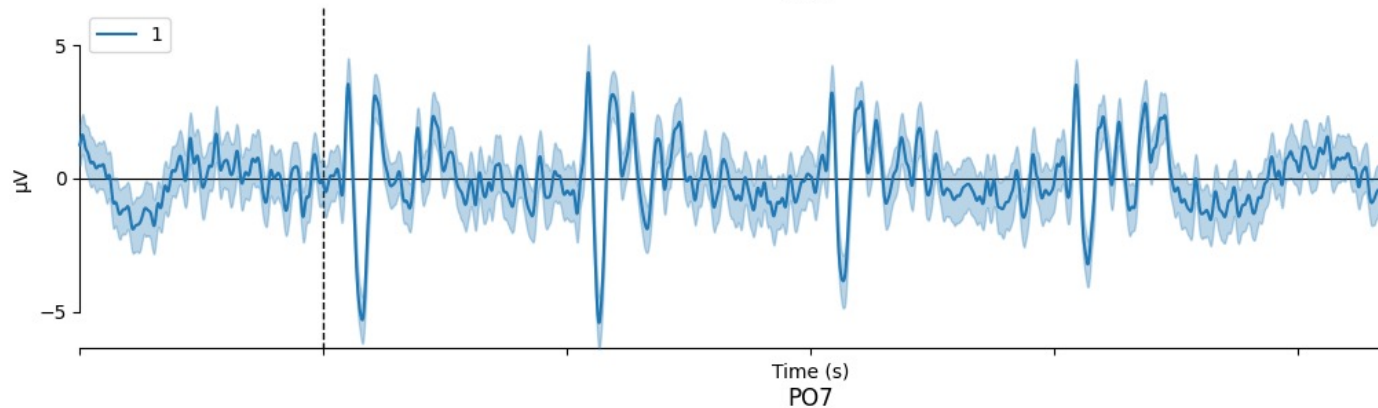
Evoked response across channels
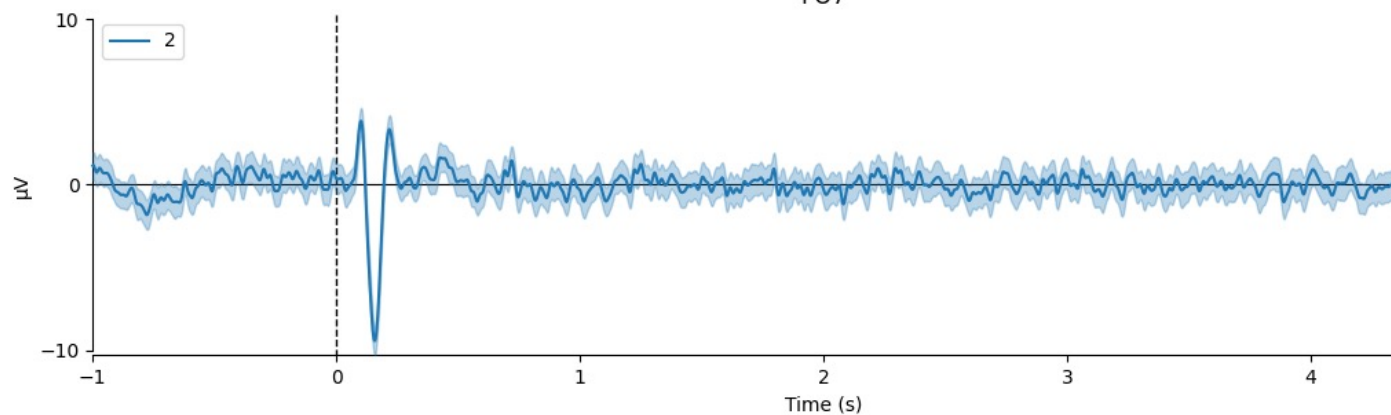
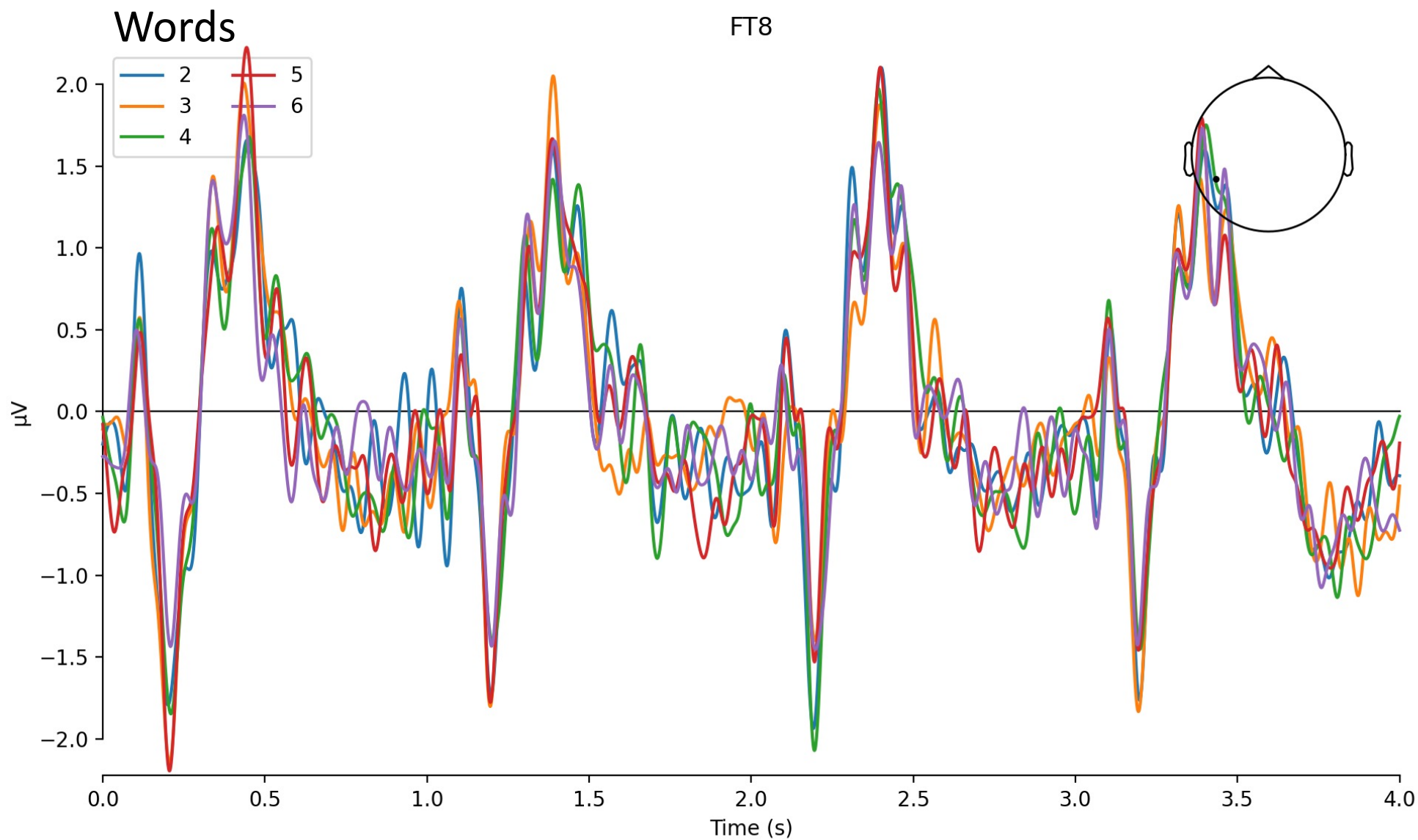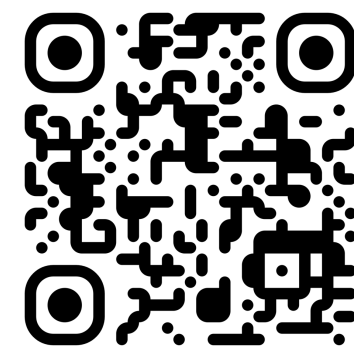# Separating visual and language activity
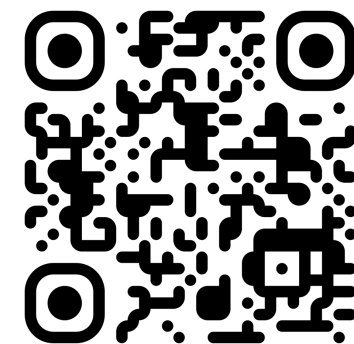
cross cues only
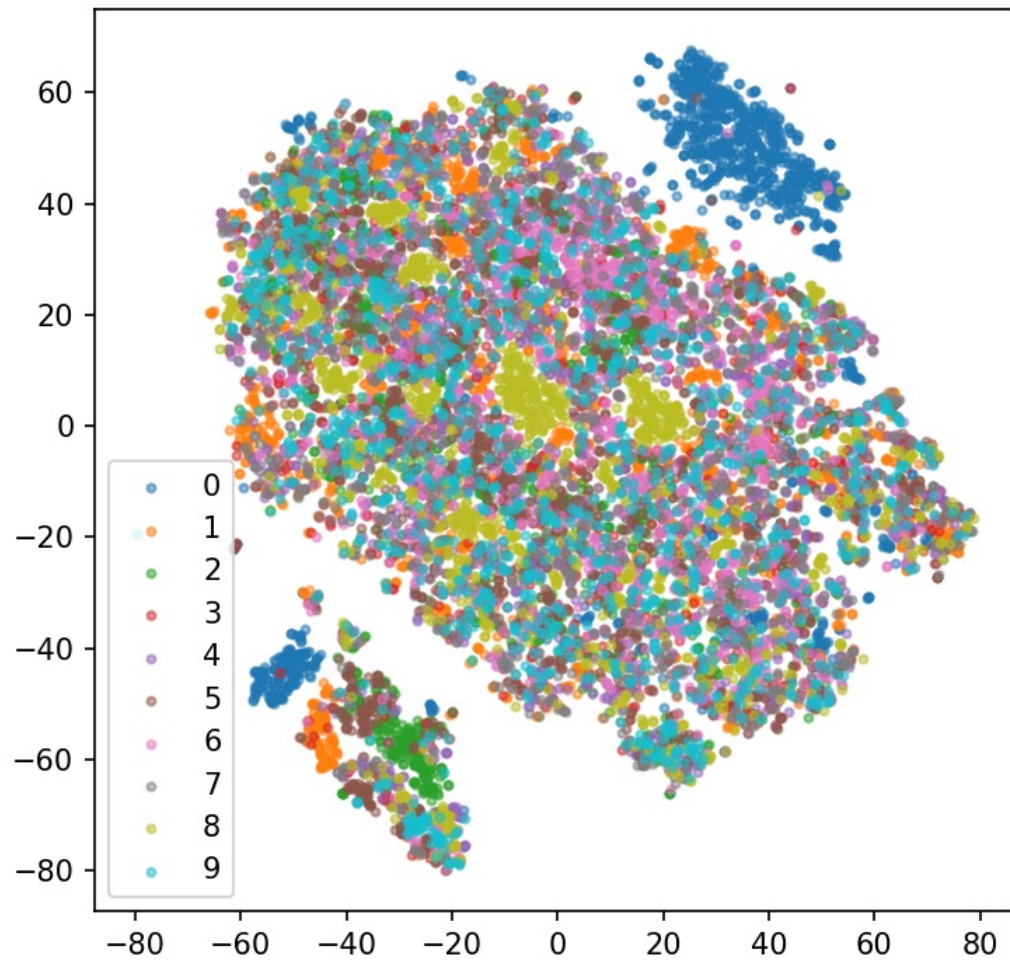
cross cues with
inner speech

1 cross cue and
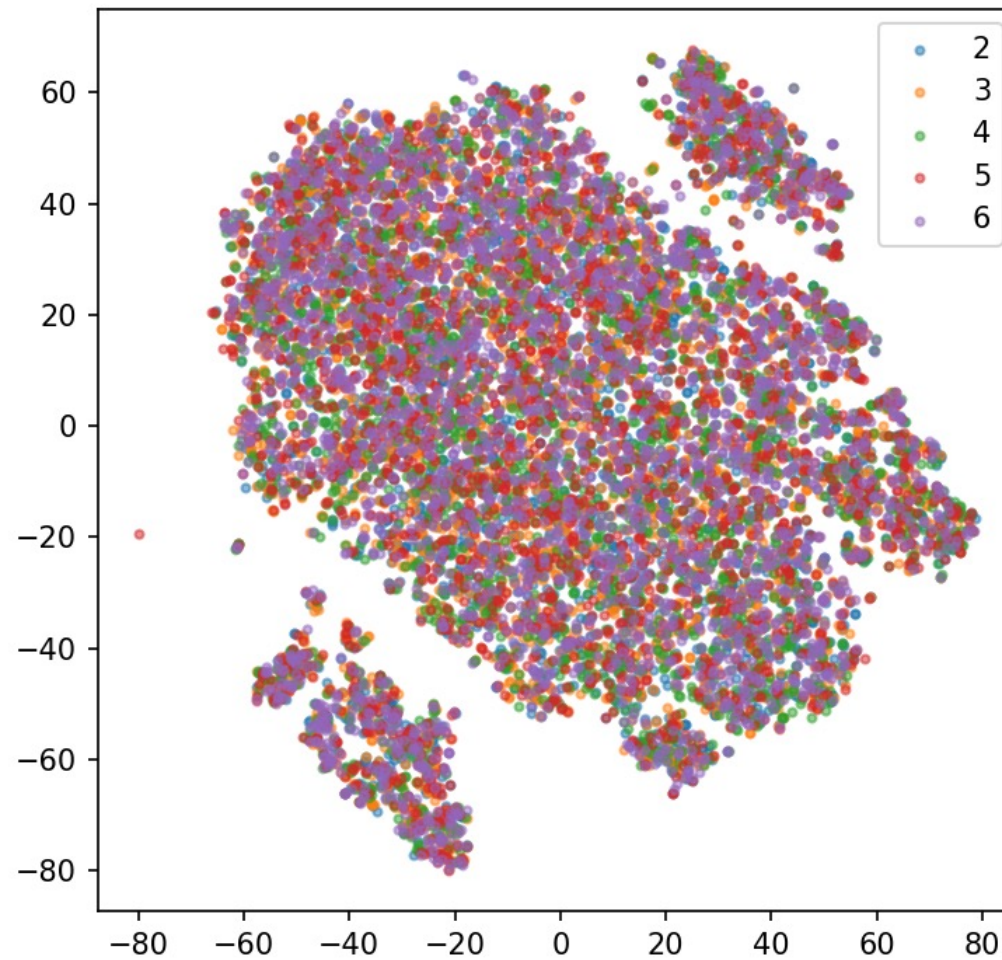4x inner speech

Per-word evoked response
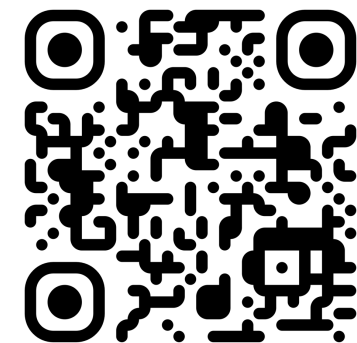
t-SNE projection of inner speech trial covariances
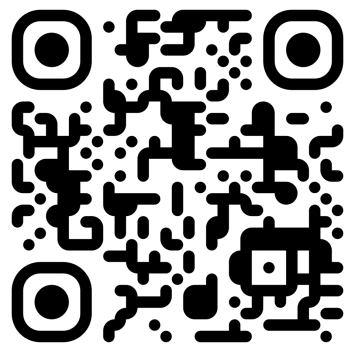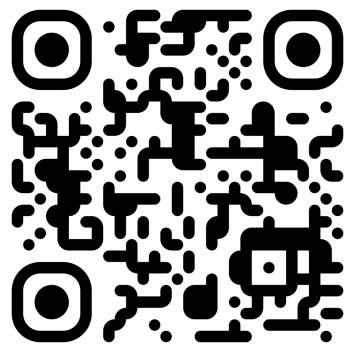
Session labeling

Word labeling

Decoding results

Preprocessing

1. Bandpass filter between 1-40Hz

2. Bad segment and channel removal

3. ICA with 64 components for MEG only

# MEG inner speech decoding at chance level

- Models
  - Fully-connected NN
  - CNN
  - LDA
  - Logistic Regression
- Features
  - Channel selection
  - Using the covariance matrix of the trial
  - Concatenating the 4 consecutive trials or averaging them
- Per-session decoding or using trials from all sessions
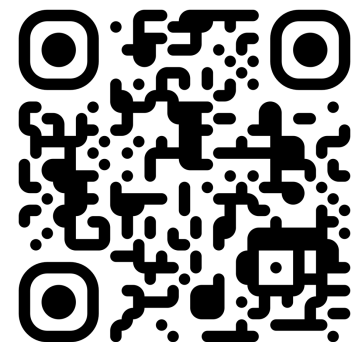
Inner speech above chance in 3/10 EEG sessions

- Method 1: 25% accuracy
  - covariance matrix features + LDA

- Method 2: 33% accuracy
  - single LDA model trained on all 3 sessions
  - concatenating the 4 consecutive trials
  - subtracting session-level evoked response and covariance from epochs

- Additional methods tried
  - Trial-level normalization; temporal alignment of trials; denoising with PCA, Xdawn clas-sifier with riemannian features; baseline correction; laplace denoising
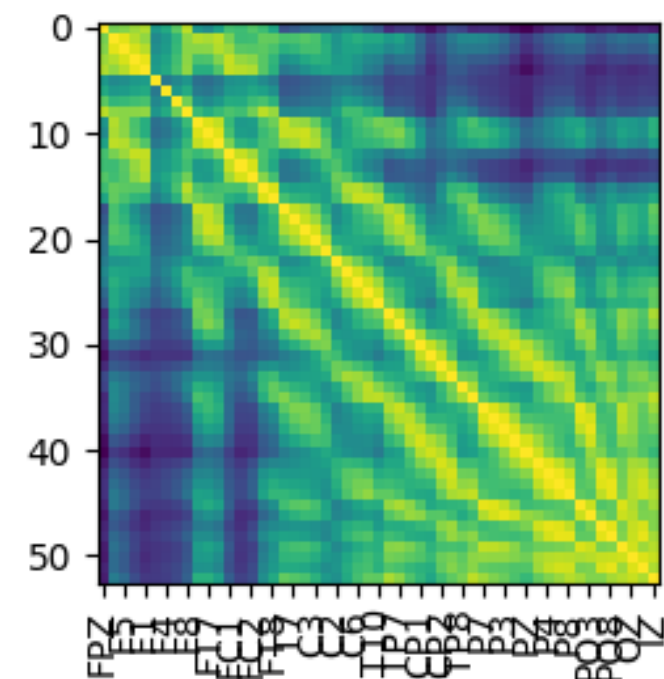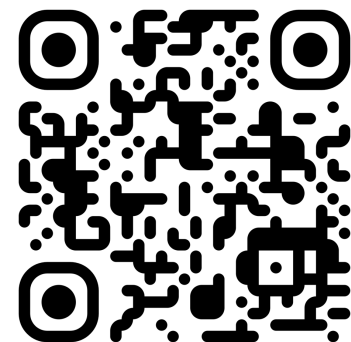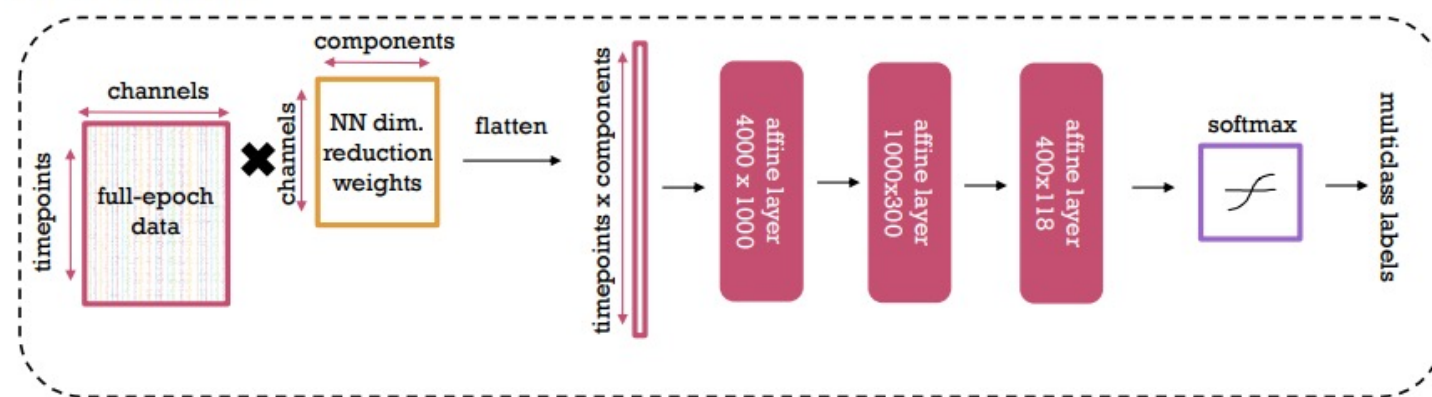
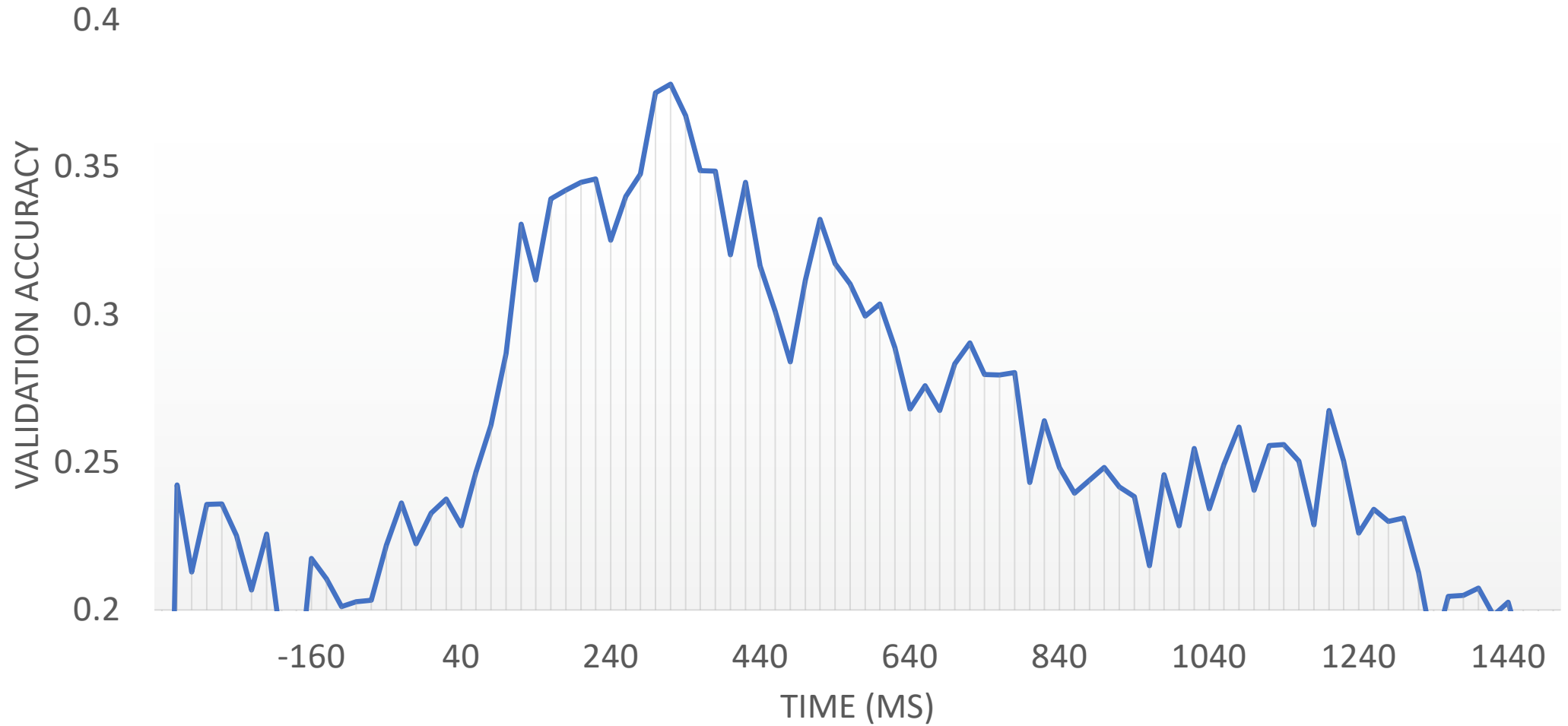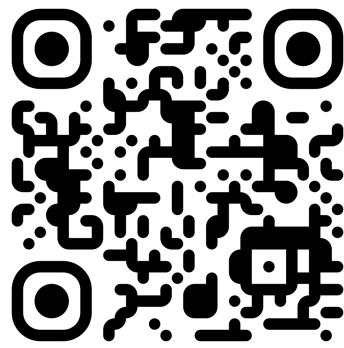# Silent reading decoding above chance in MEG and EEG

- Per-participant 2-layer linear neural network
- 1-second epoch flattened to a feature vector

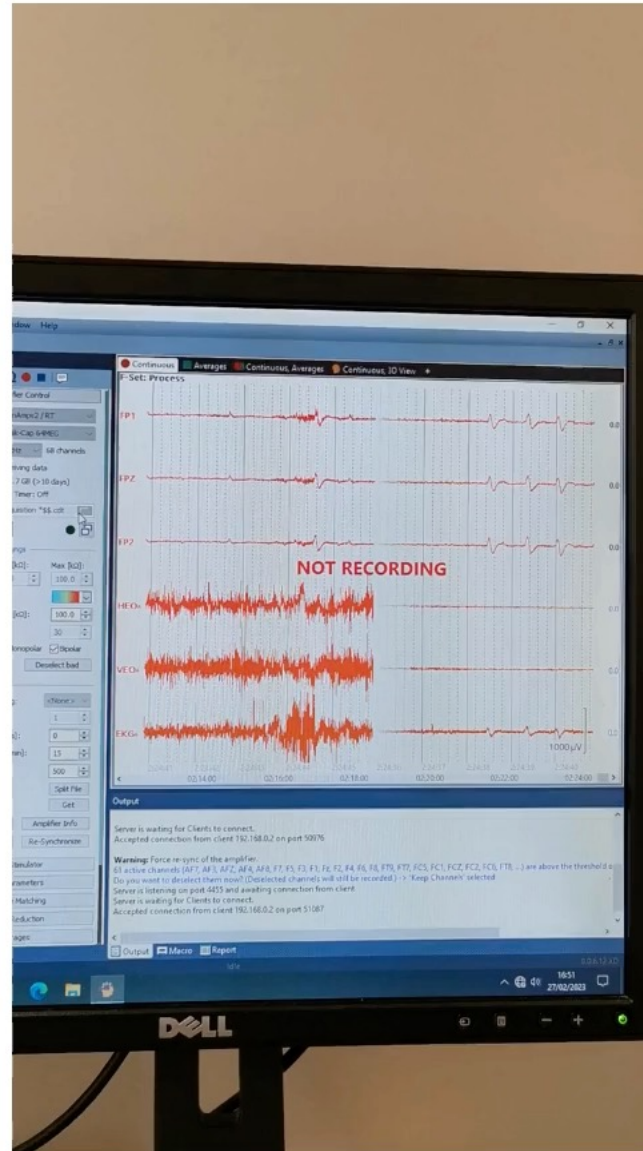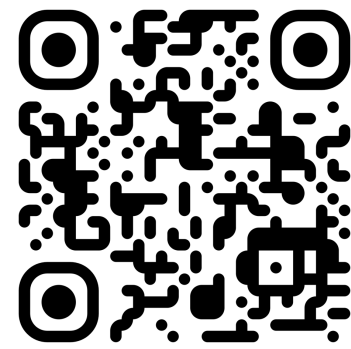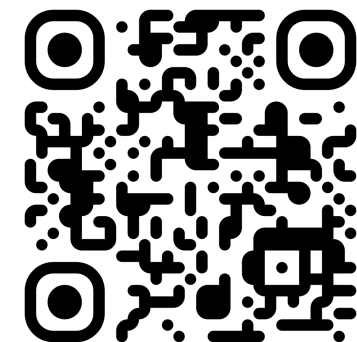|	MEG version 1	MEG version 3	EEG version 3
Validation accuracy	39.33%	35%	30%

Silent reading sliding-window LDA

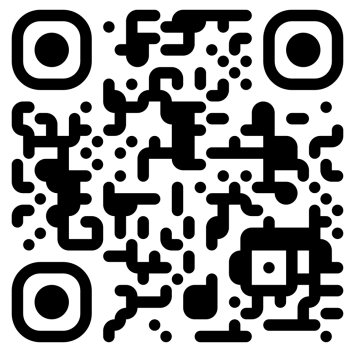# Closed-loop EMG silent speech prototype

Thank you!

References

[1] Panachakel, J.T. and Ramakrishnan, A.G., Decoding covert speech from EEG-a comprehensive review. *Frontiers in Neuroscience*, 2021

[2] Metzger, S.L., Liu, J.R., Moses, D.A., Dougherty, M.E., Seaton, M.P., Littlejohn, K.T., Chartier, J., Anumanchipalli, G.K., Tu-Chan, A., Ganguly, K. and Chang, E.F. Generalizable spelling using a speech neuroprosthesis in an individual with severe limb and vocal paralysis. *Nature Communications*, 13(1), pp.1-15, 2022
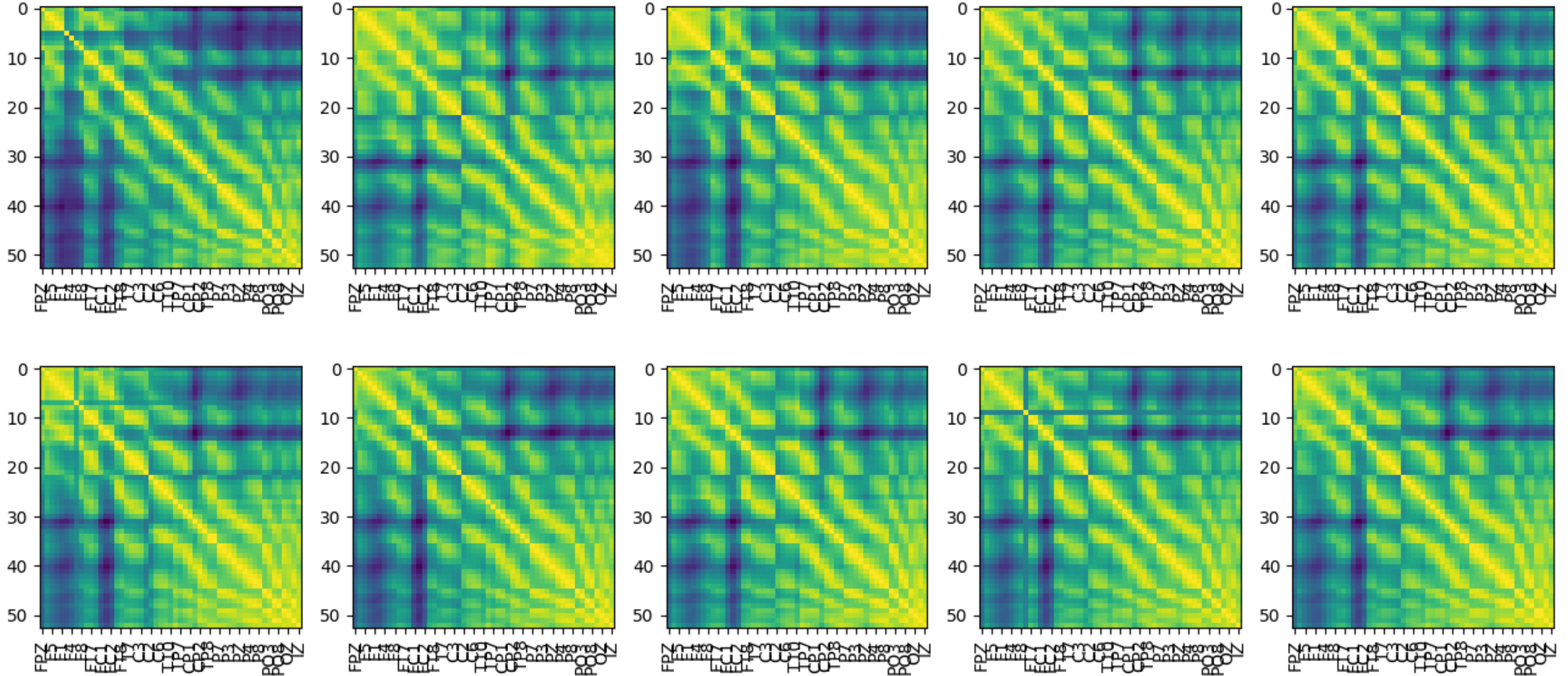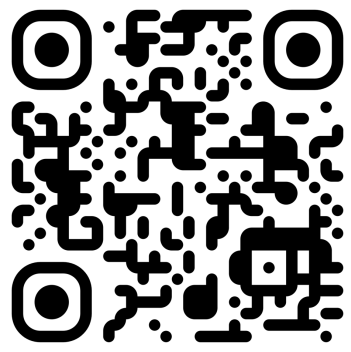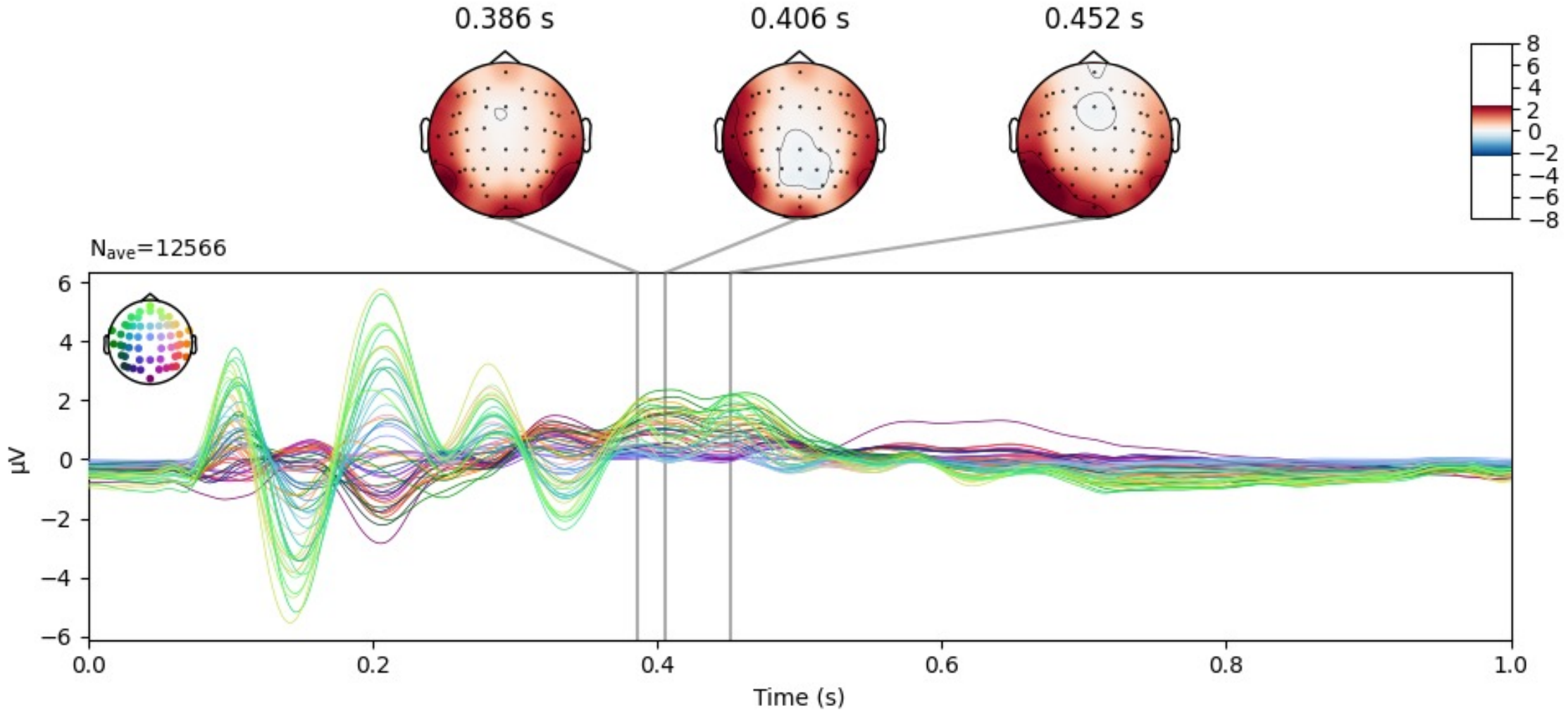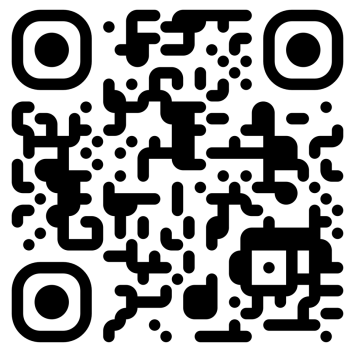
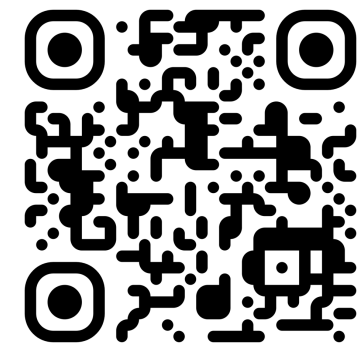# Per-word evoked response
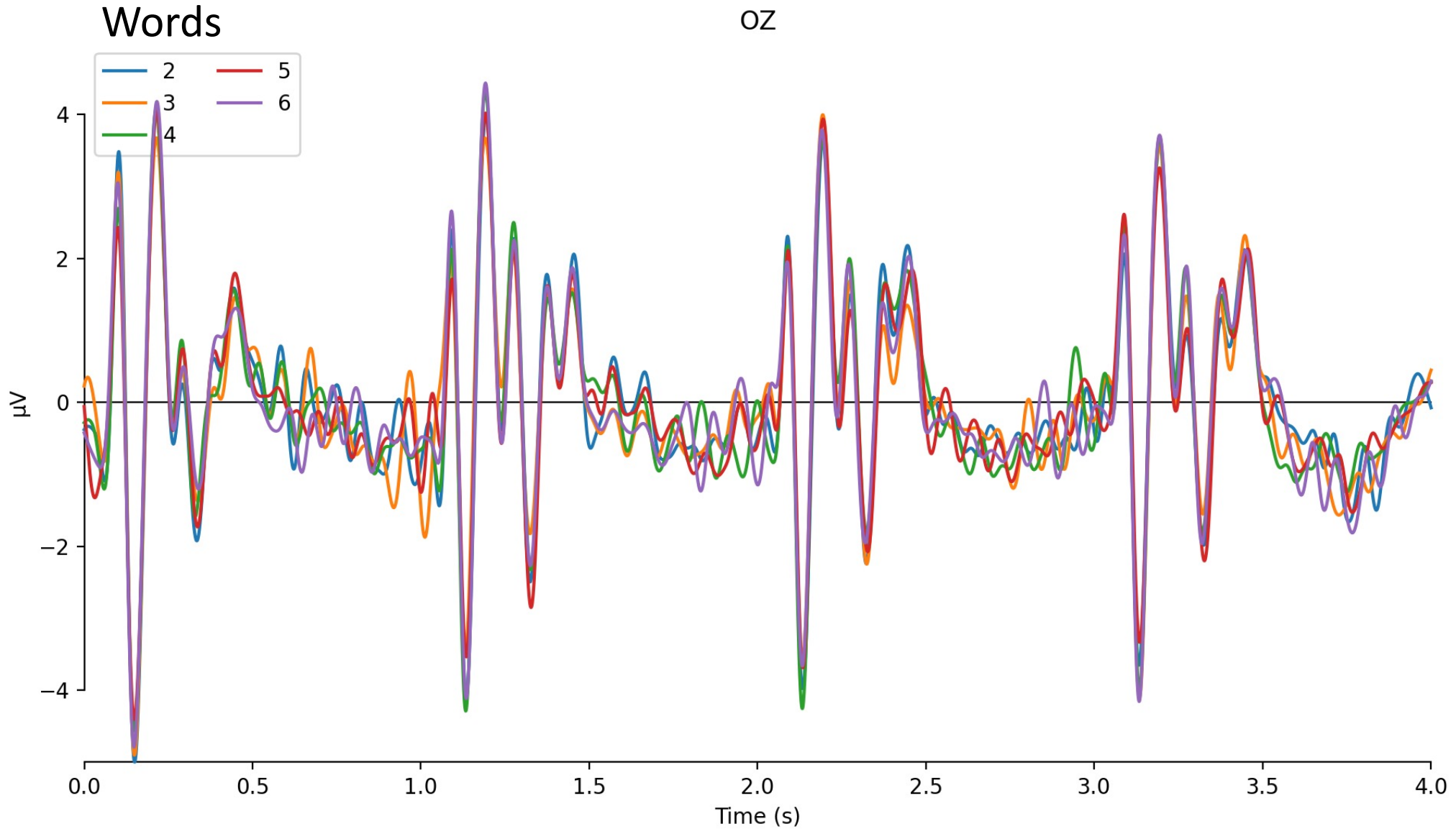
Evoked responses across sessions
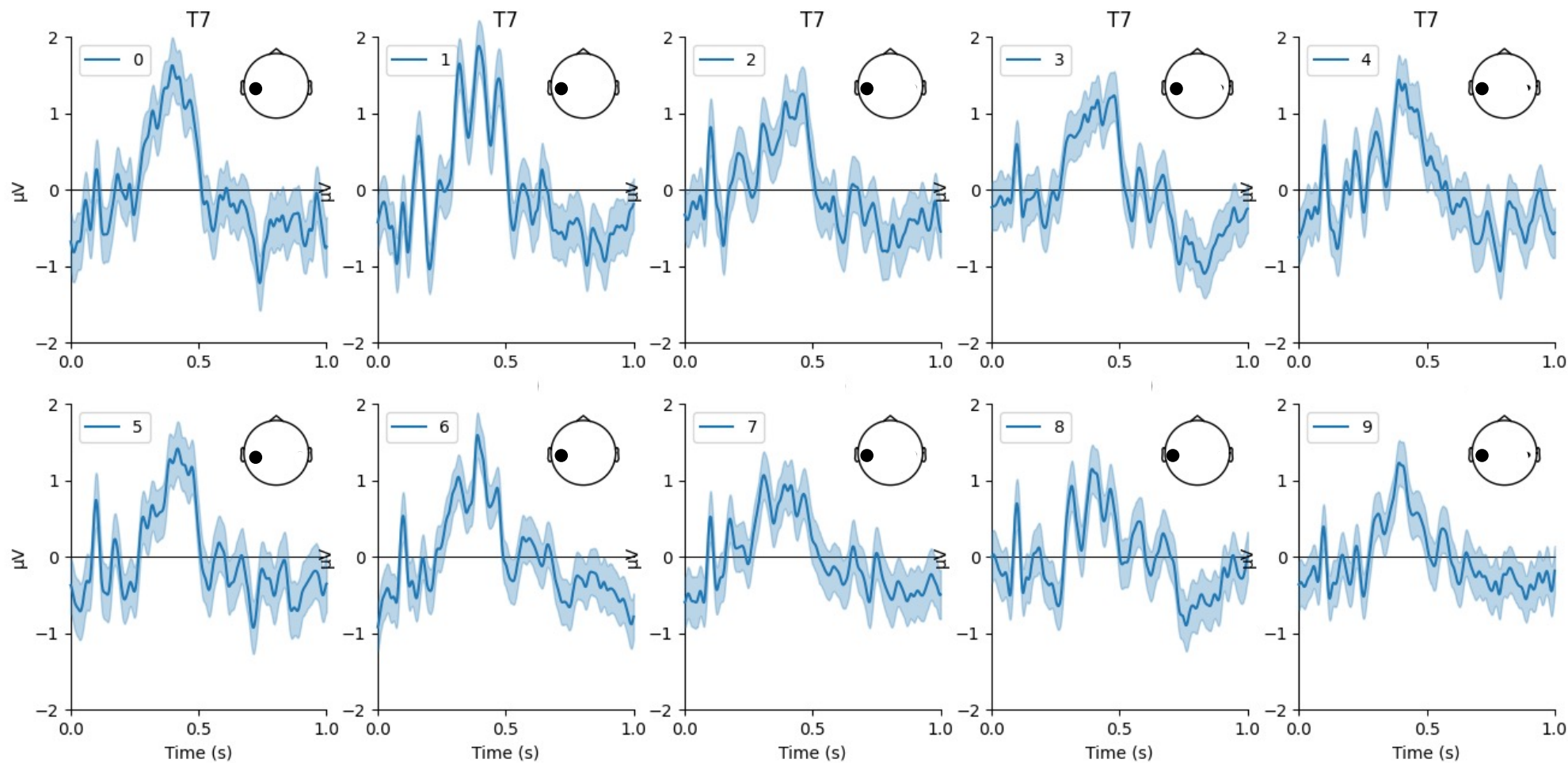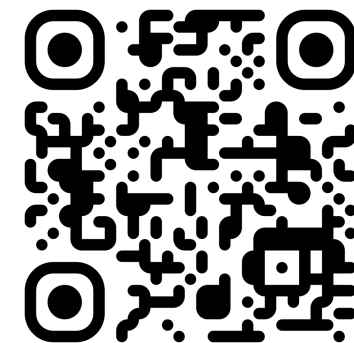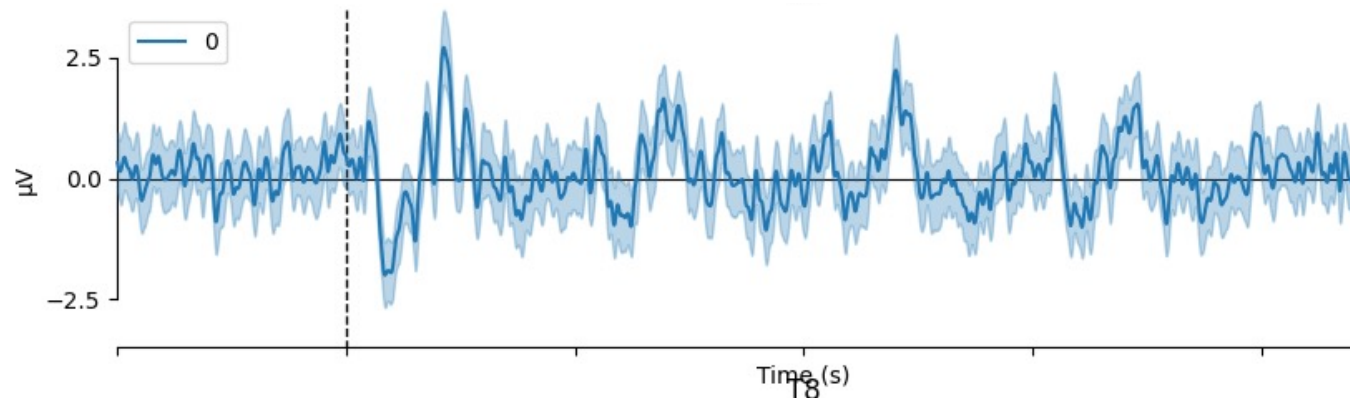
Session-level mean covariances
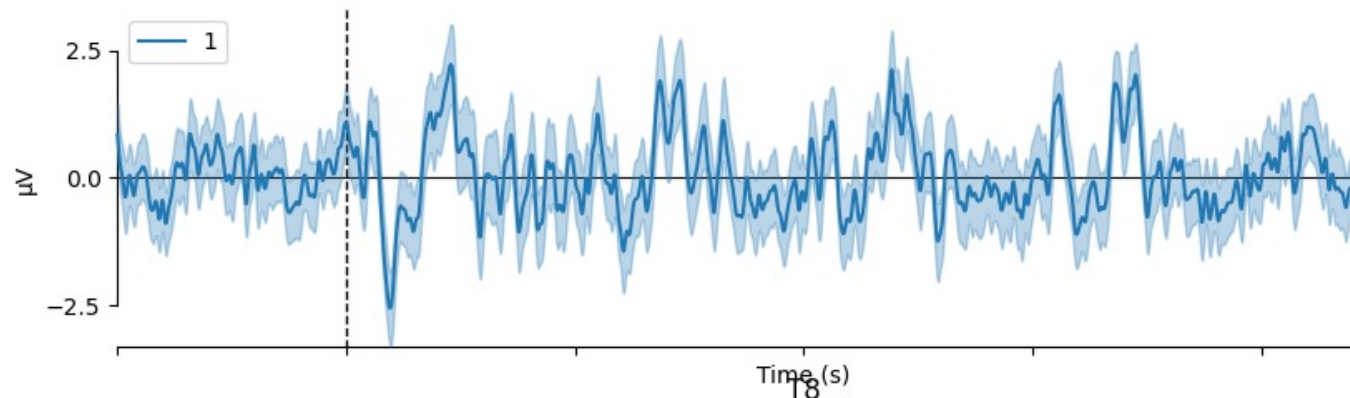
Temporal evoked activity
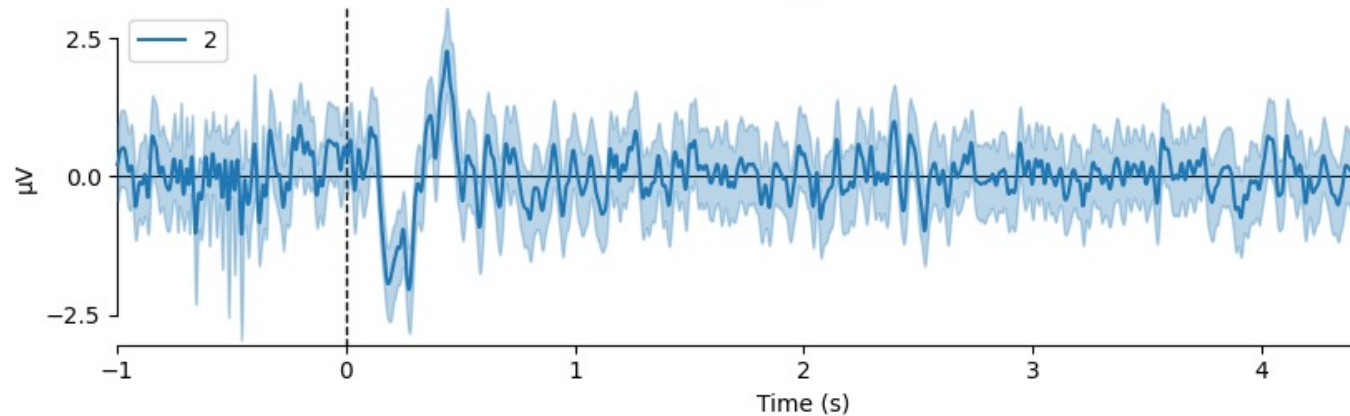
Separating visual and language activity

cross cues only

cross cues with
inner speech

1 cross cue and
4x inner speech

Evoked response