Universität Zürich | MethLab Journal Club

The «Ocular Response Function»

for encoding and decoding oculomotor related neural activity

Gehmacher et al., 2024

What are Temporal Response Functions?

The Ocular Response Function

- Deconvolution Algorithm
- Encoding and Decoding Models
- Localization
- Extracting Encoding and Decoding Results

Validation Study: Passive Listening Task

- Methods
- Results
- Conclusion

What are Temporal Response Functions?

TRFs model the relationship between a **continuous input** and a **continuous output** (e.g., brain response) over time

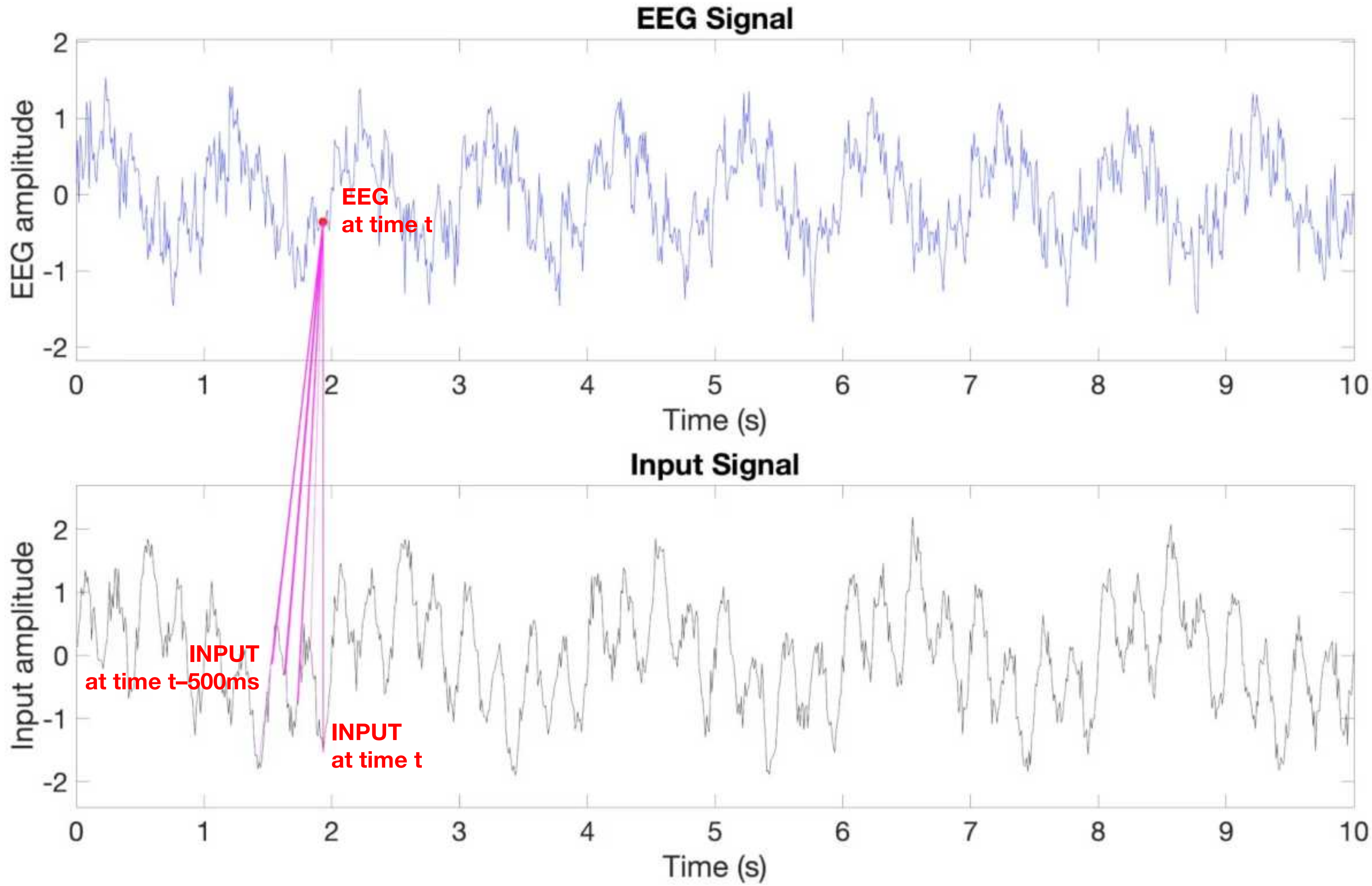
- TRFs map stimulus to M/EEG response in a **continuous-time** framework
  - Estimate the brain's response by finding a **best-fit model** between the input and EEG data
  - Reveal response timing = **when** specific neural responses occur
    - TRFs show how each moment of input contributes to the output at subsequent **time lags**

Mathematical Analogy

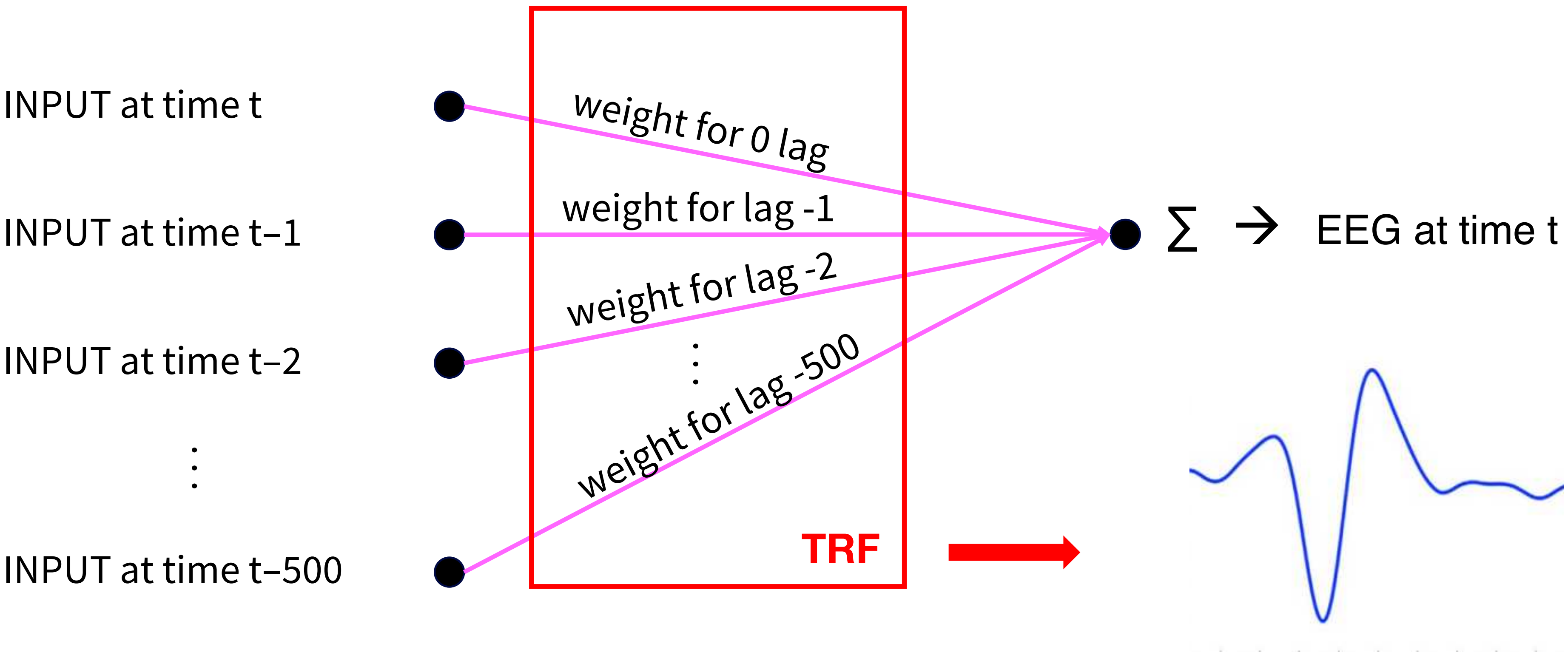
- **TRFs** act as a linear filter; predict EEG signal by **convolution** with **continuous input**
    - Output (e.g., EEG signal) is a weighted sum of values of the input

→ Advantage of TRFs in **naturalistic settings**, where discrete event segmentation is challenging (complex or natural stimuli; e.g., **continuous signals** such as speech or vision)

What are Temporal Response Functions?



What are Temporal Response Functions?



EEG = TRF x INPUT

What are Temporal Response Functions?

How do I get the weights? Using of **boosting** to estimate the filter kernel (=TRF)

Boosting is an iterative approach that starts with a zero filter kernel and gradually refines it:

- Predict Y from the current estimate of h
- Compute the residual (the difference between the predicted and actual Y)
- Adjust the TRF weights in the direction that best reduces the current residual
- Repeat until convergence or until a stopping criterion is met

→ Easy implementation in Eelbrain: Simply specify the time-lag window and the input/output data; the boosting routine returns the TRF weights that best map your input to the neural signal over time

Cross Validation

Training the λ (weights) **value** → Leave-one-out or k-fold Cross Validation

What are Temporal Response Functions?

The Ocular Response Function

- Deconvolution Algorithm
- Encoding and Decoding Models
- Localization
- Extracting Encoding and Decoding Results

Validation Study: Passive Listening Task

- Methods
- Results
- Conclusion

The Ocular Response Function

→ Ocular Response Function (ORF) = TRFs to link eye movements with neural activity

  – «Establishing an eye–response relationship for time-continuous input»

– Using a deconvolution algorithm

– Paradigm: Simultaneous MEG and ET during resting state (eyes open, fixation cross)

What are Temporal Response Functions?

The Ocular Response Function

Deconvolution Algorithm

Encoding and Decoding Models

Localization

Extracting Encoding and Decoding Results

Validation Study: Passive Listening Task

Methods

Results

Conclusion

Deconvolution Algorithm for ORF

TRFs typically use a **deconvolution** approach (here: **boosting**) to estimate how an input drives neural responses across time

– For ORFs, the input is ocular activity (eye-tracking signals), and the output is MEG data

Implementation

– **Boosting**: An iterative method that fits a filter kernel (the TRF) by gradually **minimising the prediction error**

– **Regularisation**: Controls **overfitting**, ensuring the TRF captures genuine temporal relationships rather than noise

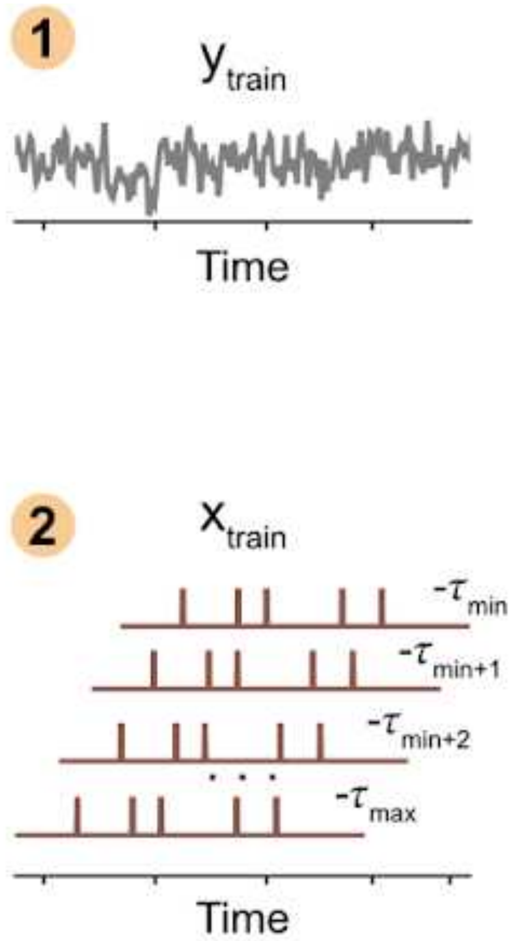
– **Time Lags**: The algorithm examines a **window of time lags** (here: -1s to + 1s) around each ocular event

Advantages of Deconvolution

– Separates overlapping events (e.g., multiple saccades in short succession)

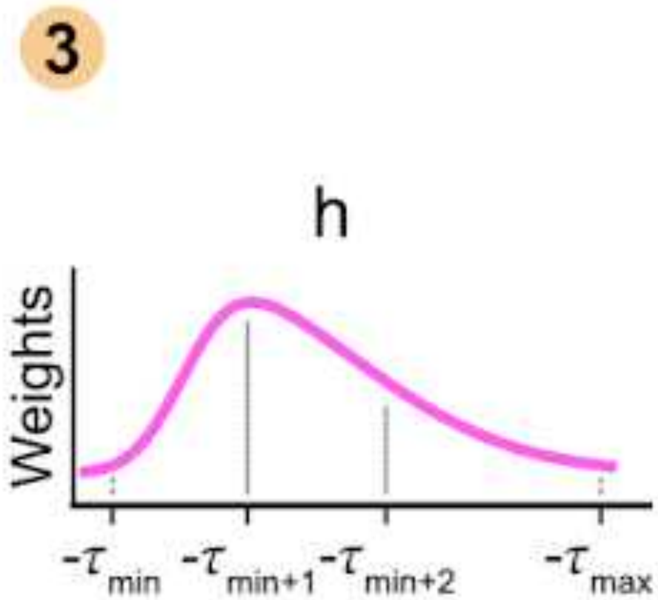
Deconvolution Algorithm for ORF

- Eye-(x)-response-(y)-relationships are estimated using deconvolution (Boosting), where **neural activity** (1; $\mathbf{y_{train}}$) is linked to an **ocular action** (2; $\mathbf{x_{train}}$, e.g. saccades) with time-shifted versions to capture the brain's delayed response.
- The TRF (filter kernel, h) represents how the brain processes the stimulus over time.
- This filter is then applied (using convolution) to new stimulus data (x test) to predict the neural response (y pred).
- Finally, the predicted response is compared to the actual neural activity (y test) to assess the model fit and evaluate how accurately the TRF captures the brain's response dynamics.



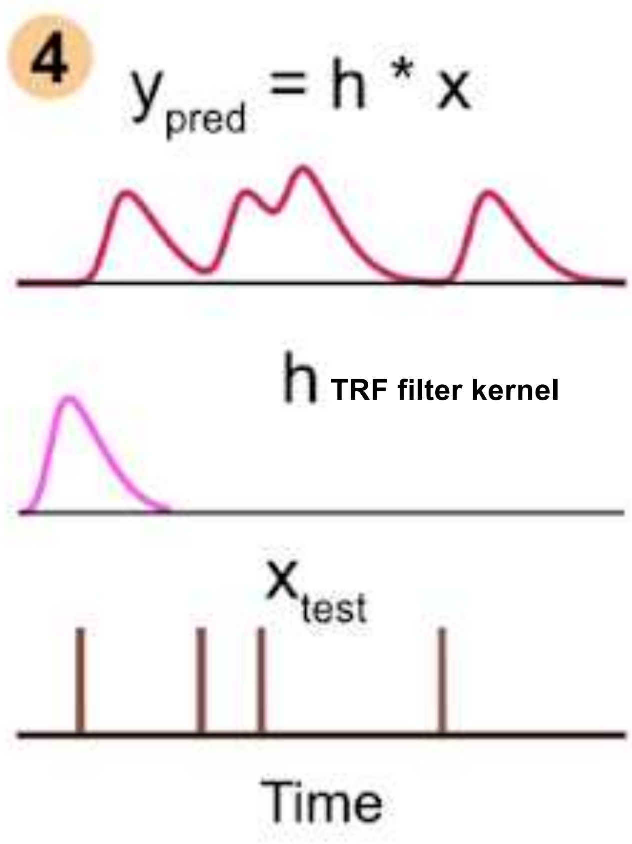
Deconvolution Algorithm for ORF

- Eye-(x)-response-(y)-relationships are estimated using deconvolution (Boosting), where **neural activity** (1; $\mathbf{y}_{\mathbf{train}}$) is linked to an **ocular action** (2; $\mathbf{x}_{\mathbf{train}}$, e.g. saccades) with time-shifted versions to capture the brain's delayed response.
- The **TRF** (3; **filter kernel, h**) represents how the brain processes the stimulus over time.
- This filter is then applied (using convolution) to new stimulus data (x test) to predict the neural response (y pred).
- Finally, the predicted response is compared to the actual neural activity (y test) to assess the model fit and evaluate how accurately the TRF captures the brain's response dynamics.



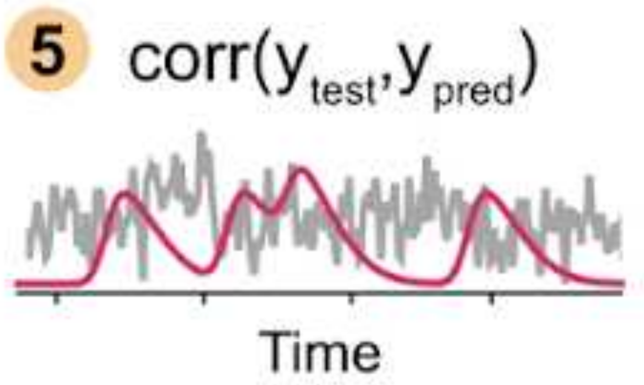
Deconvolution Algorithm for ORF

- Eye-(x)-response-(y)-relationships are estimated using deconvolution (Boosting), where **neural activity** (1; $\mathbf{y}_{\mathbf{train}}$) is linked to an **ocular action** (2; $\mathbf{x}_{\mathbf{train}}$, e.g. saccades) with time-shifted versions to capture the brain's delayed response.
- The **TRF** (**filter kernel, h**) represents how the brain processes the stimulus over time.
- This **filter is then applied** (using **convolution**) to new stimulus data ($\mathbf{x}_{\mathbf{test}}$) to predict the neural response ($\mathbf{y}_{\mathbf{pred}}$).
- Finally, the predicted response is compared to the actual neural activity (y test) to assess the model fit and evaluate how accurately the TRF captures the brain's response dynamics.



Deconvolution Algorithm for ORF

- Eye-(x)-response-(y)-relationships are estimated using deconvolution (Boosting), where **neural activity** (1; $\mathbf{y}_{\mathbf{train}}$) is linked to an **ocular action** (2; $\mathbf{x}_{\mathbf{train}}$, e.g. saccades) with time-shifted versions to capture the brain's delayed response.
- The **TRF** (**filter kernel, h**) represents how the brain processes the stimulus over time.
- This **filter is then applied** (using **convolution**) to new stimulus data ($\mathbf{x}_{\mathbf{test}}$) to predict the neural response ($\mathbf{y}_{\mathbf{pred}}$).
- Finally, the **predicted response is compared to the actual neural activity** ($\mathbf{y}_{\mathbf{test}}$) to **assess the model fit** and evaluate how accurately the TRF captures the brain's response dynamics.



What are Temporal Response Functions?

The Ocular Response Function

- Deconvolution Algorithm
- **Encoding and Decoding Models**
- Localization
- Extracting Encoding and Decoding Results

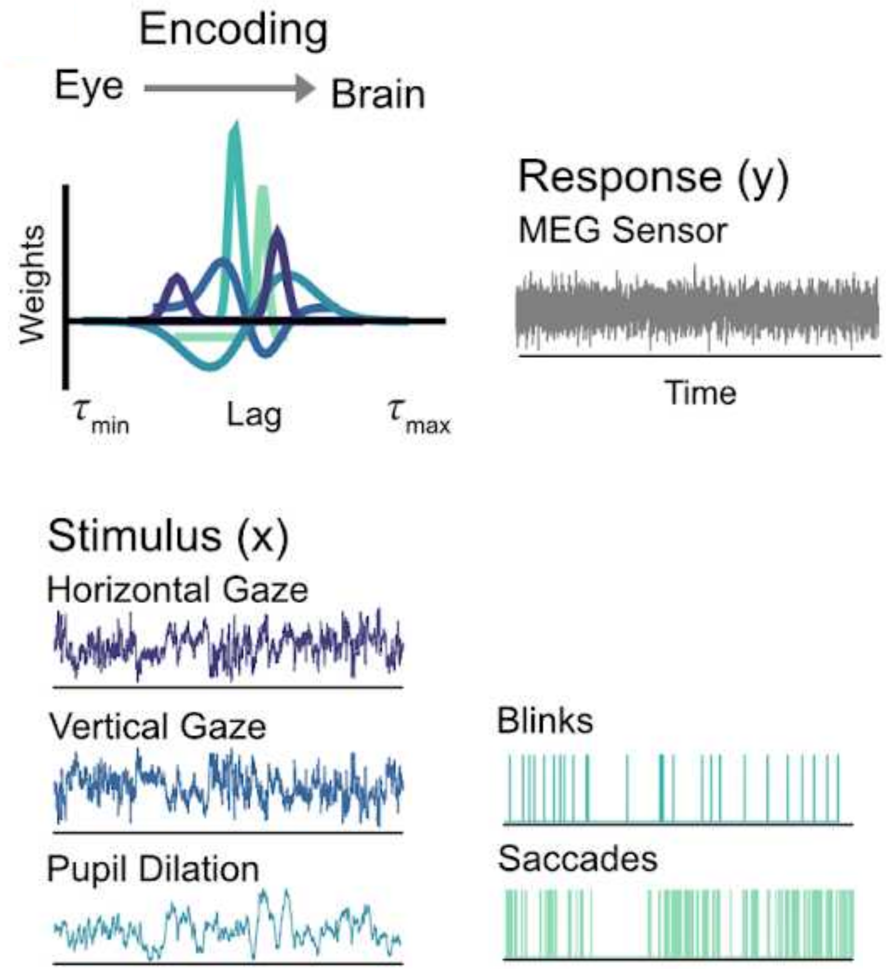
Validation Study: Passive Listening Task

- Methods
- Results
- Conclusion

Forward Encoding Model

Forward model: ORFs leverage the deconvolution algorithm approach by **predicting resting state brain activity from eye features** (gaze, pupil dilation, blinks, saccades)

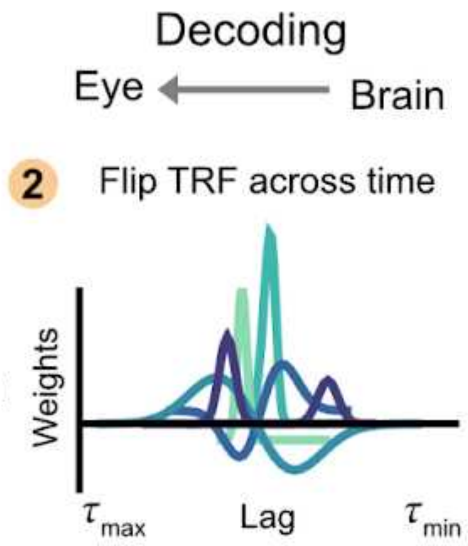
- One ORF is generated per eye feature per sensor
- Links the gaze metrics to the MEG data
  - ORFs specify **how each ocular feature drives the neural signal over time**

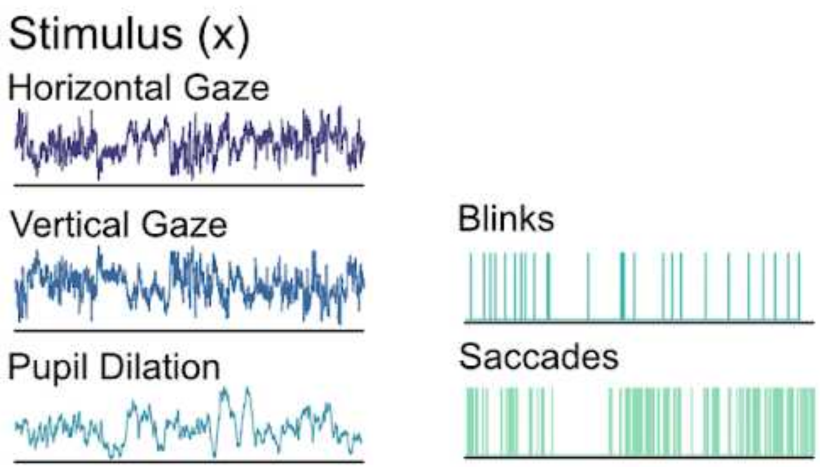


Backward Decoding Model

Backward model: **Predicts eye movements from brain data**

– **Flipping** the ORF along the temporal axis and convolve with brain signal to predict eye data





What are Temporal Response Functions?

The Ocular Response Function

- Deconvolution Algorithm
- Encoding and Decoding Models
- **Localization**
- Extracting Encoding and Decoding Results

Validation Study: Passive Listening Task

- Methods
- Results
- Conclusion

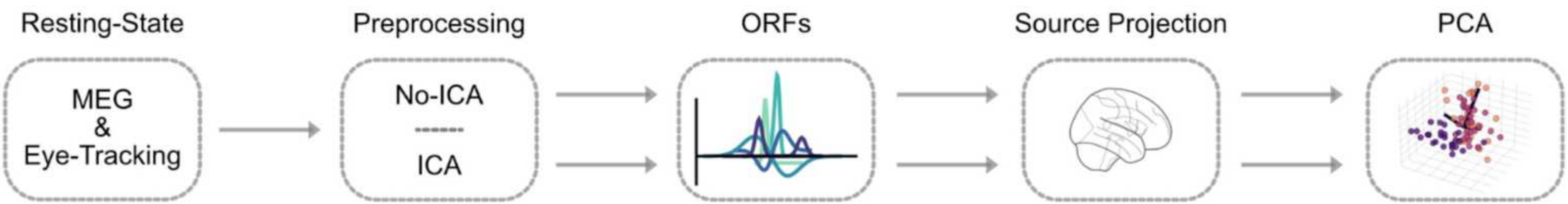
Localization

Source Projection

- ORFs initially derived at **sensor level** (MEG channels)
- Projected into **source space** to map ocular–neural relationships onto brain anatomy (cortical/subcortical regions)

Principal Component Analysis (PCA)

- Applied to **reduce dimensionality** of source-projected ORFs
- Focuses on the main spatial-temporal components that **explain the most variance**
- Helps identify **distinct networks or regions** that respond to eye movements



What are Temporal Response Functions?

The Ocular Response Function

- Deconvolution Algorithm
- Encoding and Decoding Models
- Localization
- **Extracting Encoding and Decoding Results**

Validation Study: Passive Listening Task

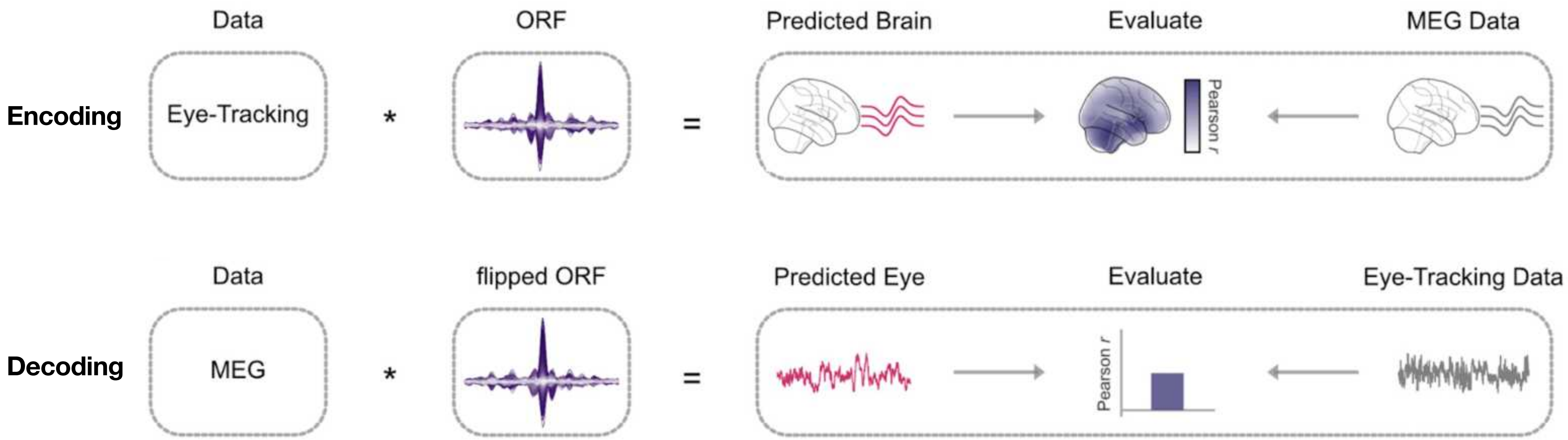
- Methods
- Results
- Conclusion

Extracting Encoding and Decoding Results

Convolution for Prediction

- Encoding: Convolve **eye signals** with **ORFs** → get predicted brain activity → correlate with actual brain signals
- Decoding: Convolve **brain signals** with **time-reversed ORFs** → get predicted eye activity → compare with actual eye signals

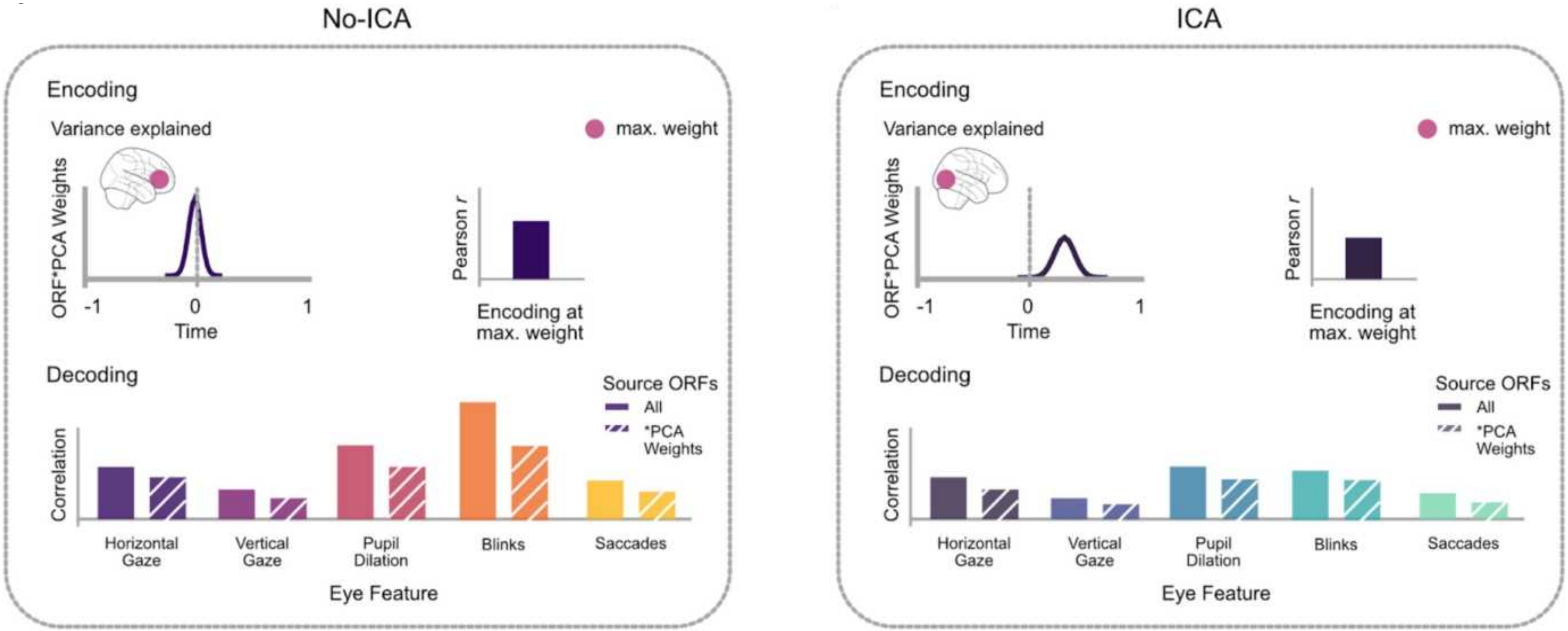
Evaluation with Pearson's *r* or Matthew's Correlation Coefficient (MCC) for model fit with actual data



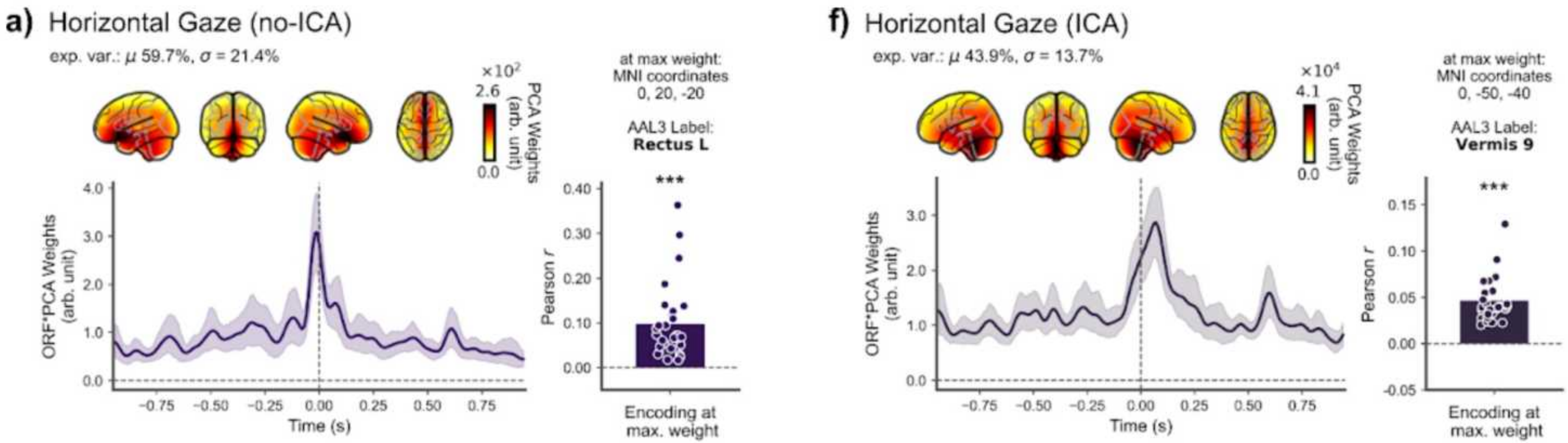
Extracting Encoding and Decoding Results

ORFs were weighted using PCA matrices to assess brain region contributions

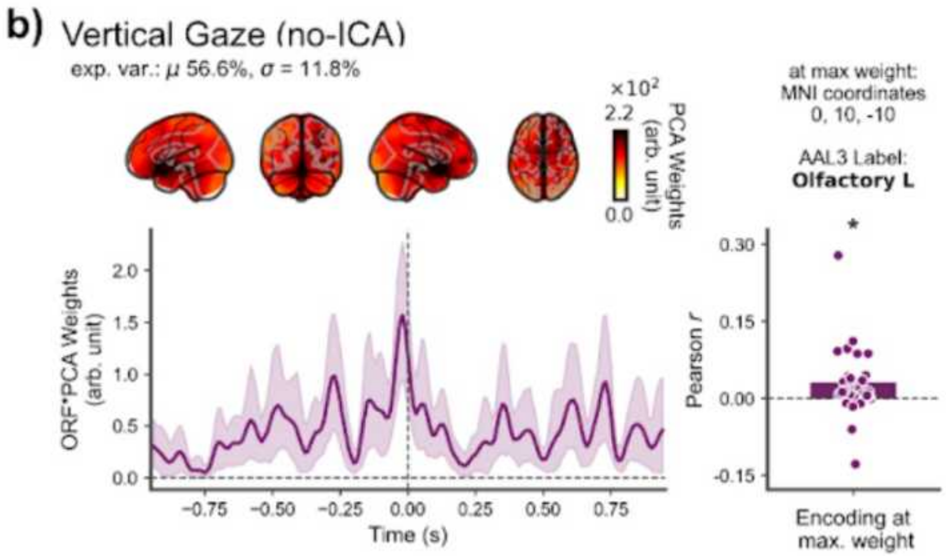
- No-ICA: First PC with strongest loading over fronto-central regions, near the eyeballs
- ICA: First PC(s) over cerebellar and subcortical structures

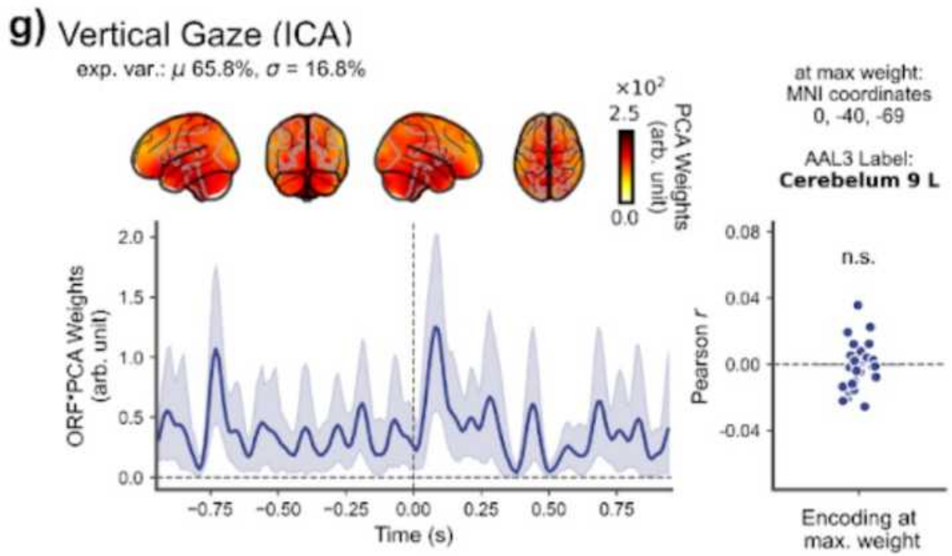


Encoding and PCA Results (PC1): Horizontal Gaze

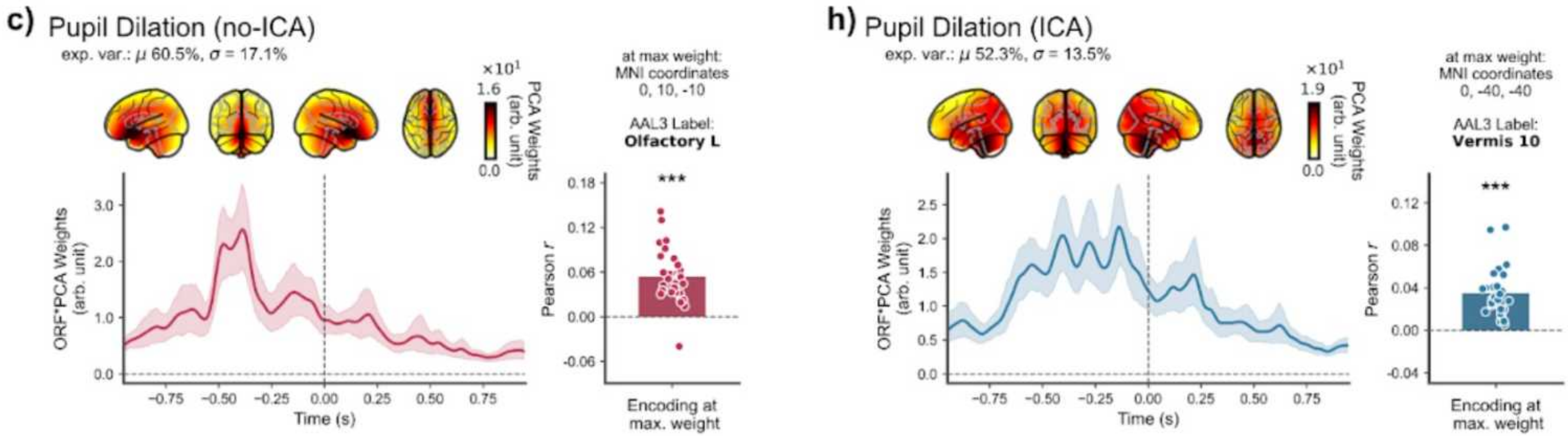


Encoding and PCA Results (PC1): Vertical Gaze

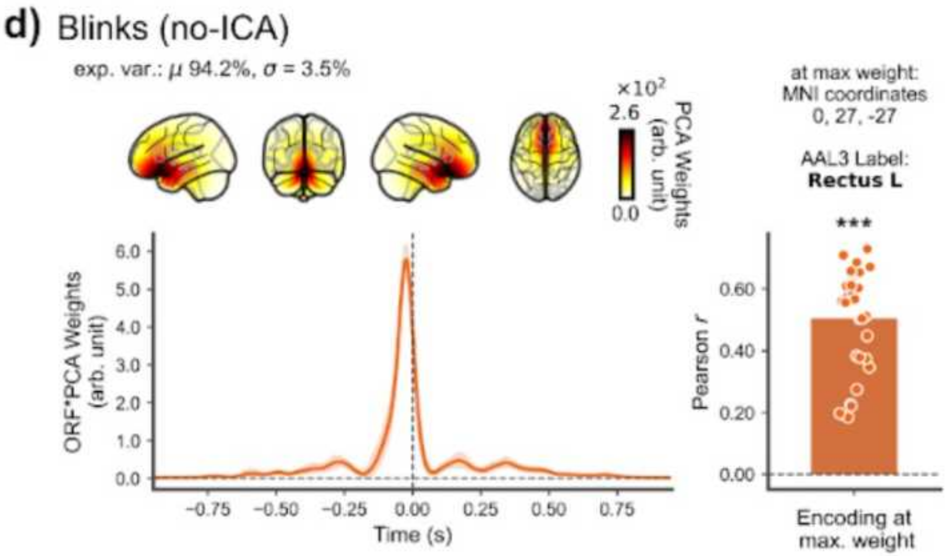


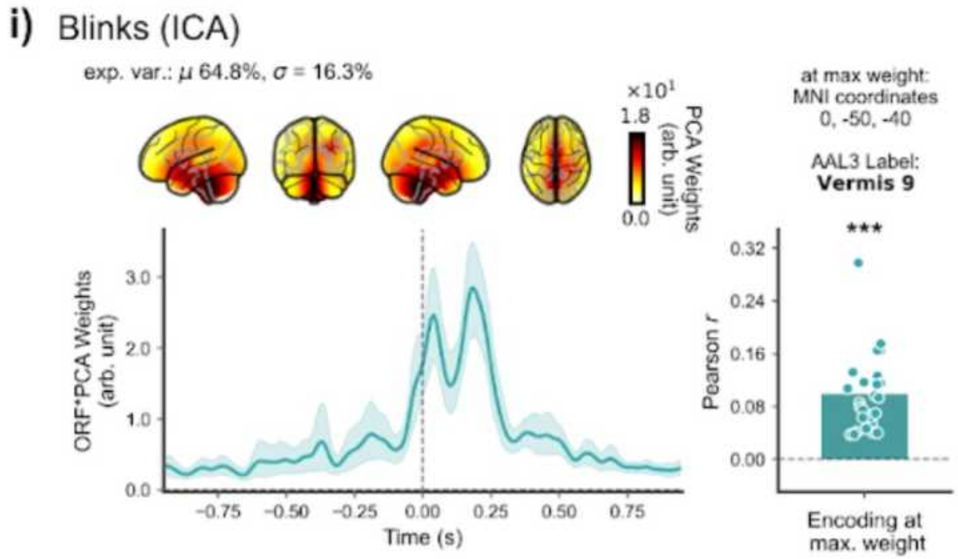


Encoding and PCA Results (PC1): Pupil Dilation

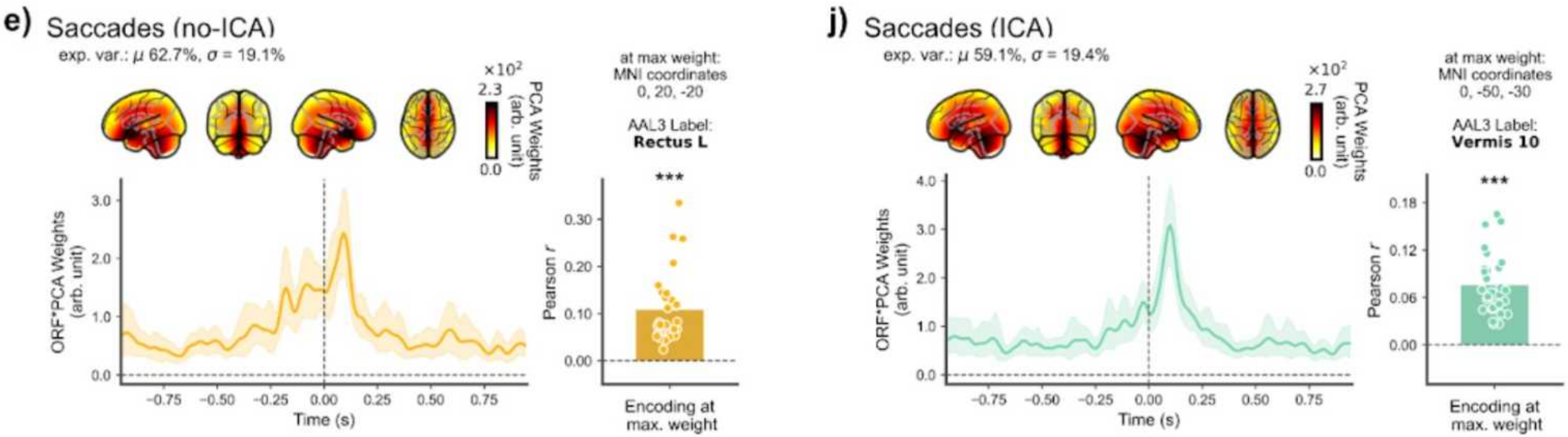


Encoding and PCA Results (PC1): Blinks



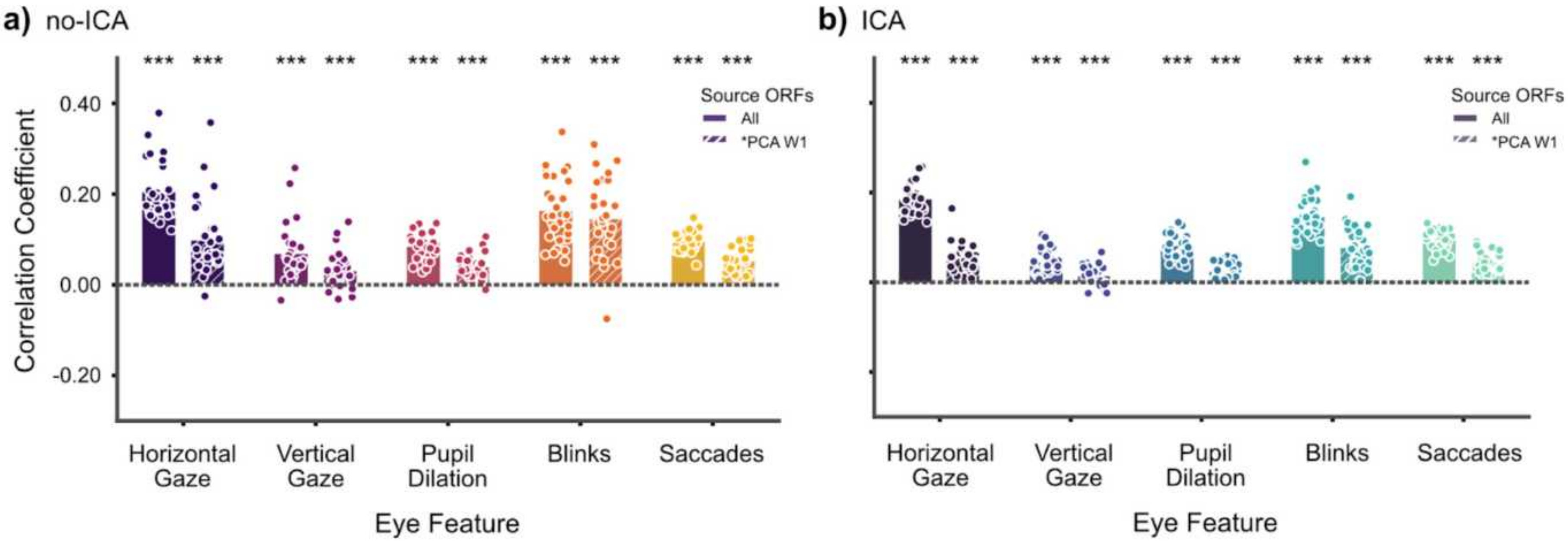


Encoding and PCA Results (PC1): Saccades



Decoding Results

«Overall, ocular behaviour was reliably decoded across all eye features and preprocessing strategies.»



What are Temporal Response Functions?

The Ocular Response Function

- Deconvolution Algorithm
- Encoding and Decoding Models
- Localization
- Extracting Encoding and Decoding Results

Validation Study: Passive Listening Task

- Methods
- Results
- Conclusion

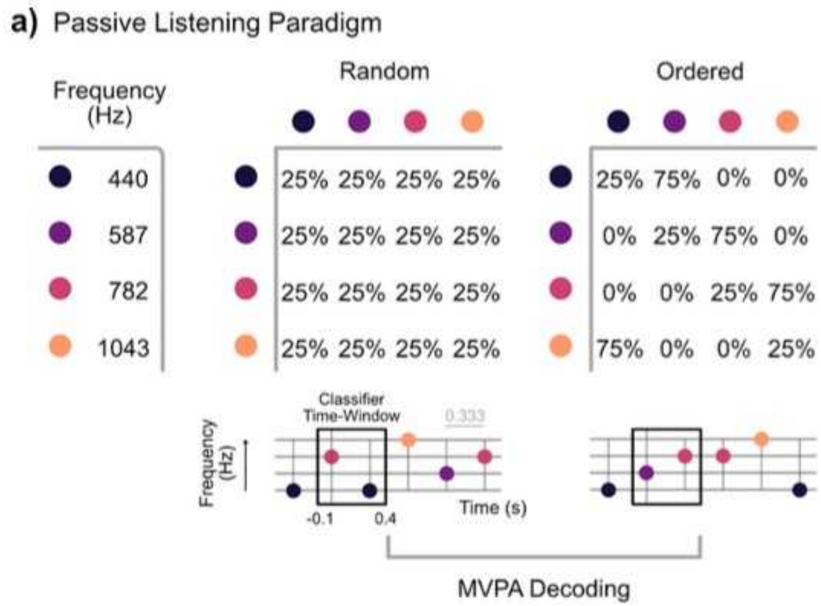
Methods

Passive listening task: Sequences of tones (3 Hz presentation rate) + **fixation cross** (Schubert et al. 2023)

- Regularity Manipulation: ‘Ordered’ vs. ‘Random’ tone transitions
  - Ordered Condition: More frequent ascending steps, fewer repetitions
  - Random Condition: All transitions equally likely

Simultaneous MEG and eye-tracking recording

- Analysis Window: -100 ms to +400 ms around each tone
- Preprocessing with and without ICA
- Multi-Variate Pattern Analysis (MVPA) to decode neural responses to ordered vs. random tone sequences



What are Temporal Response Functions?

The Ocular Response Function

Deconvolution Algorithm

Encoding and Decoding Models

Localization

Extracting Encoding and Decoding Results

Validation Study: Passive Listening Task

Methods

Results

Conclusion

Task-related Oculomotor vs. Neural Activity

MVPA: Significant decoding cluster 100–190 ms post-tone onset

→ sensitivity to regularity in auditory cortices (CBPT)

Saccade-Related Neural Activity

ORFs for saccades during resting vs. task → saccade-driven predicted activity also distinguished ordered vs. random → subtle but consistent differences in saccadic behaviour (or saccade-linked neural dynamics) across conditions

Spatial Overlaps and Differences

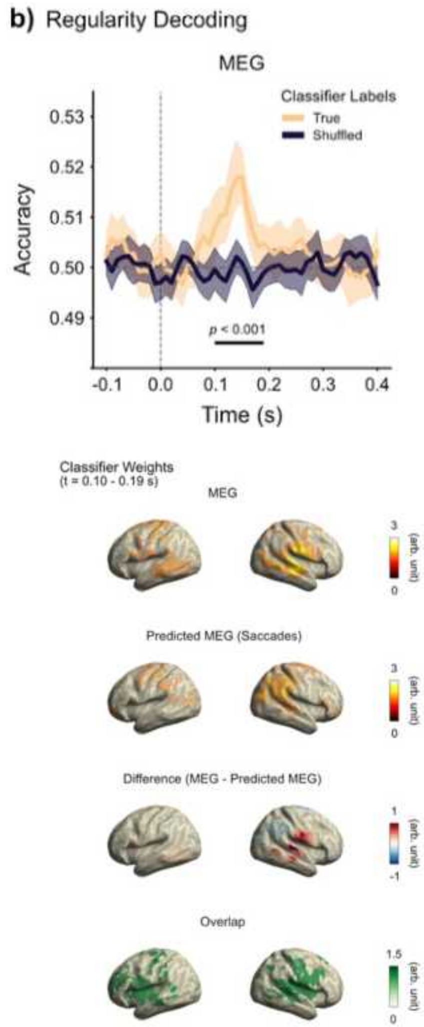
MEG Classifier Weights: Stronger in auditory areas (especially right hemisphere)

Predicted MEG from Saccades: Parietal and midbrain, but overlapped partly with temporal structures

→ Indicates saccades may modulate or coincide with auditory processing in these regions

Decoding Ocular Features / Generalizability of ORFs beyond Resting State

Even in auditory task: ocular features (horizontal gaze, blinks, etc.) could still be decoded from brain data using ORFs



What are Temporal Response Functions?

The Ocular Response Function

Deconvolution Algorithm

Encoding and Decoding Models

Localization

Extracting Encoding and Decoding Results

Validation Study: Passive Listening Task

Methods

Results

Conclusion

Conclusion (Paper / ORF)

Proof-of-principle of TRFs for oculomotor-neural link (ORFs)

– ORFs allow **prediction of neural activity from oculomotor action** and conversely

Validation Study

– ORFs derived from resting-state can be applied to **task conditions**
– Confirms that **oculomotor–neural relationships persist**
  – even when participants are engaged in auditory processing
  – even though eye movements are not typically expected to influence cognitive processing

Conclusion (Arne's PhD)

Use ORFs to find **oculomotor-neural link within alpha-band**

Not only relation of oculomotor activity and alpha power as averaged metrics over trials

→ Inclusion of **temporal lag**

showing **preparatory neural activity for eye movements** (decoding)

→ Use ORFs for analysis time window of alpha power

ORFs could be used very well!

But only for resting state data?

No! → Validated in auditory task

But only continuous data?

Or does this work with non-continuous tasks as well? We'll see!

→ Maybe ask them for their data and run alpha-band-filtered analysis