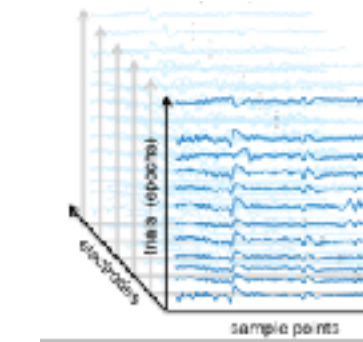
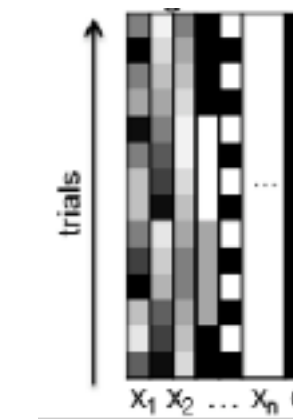
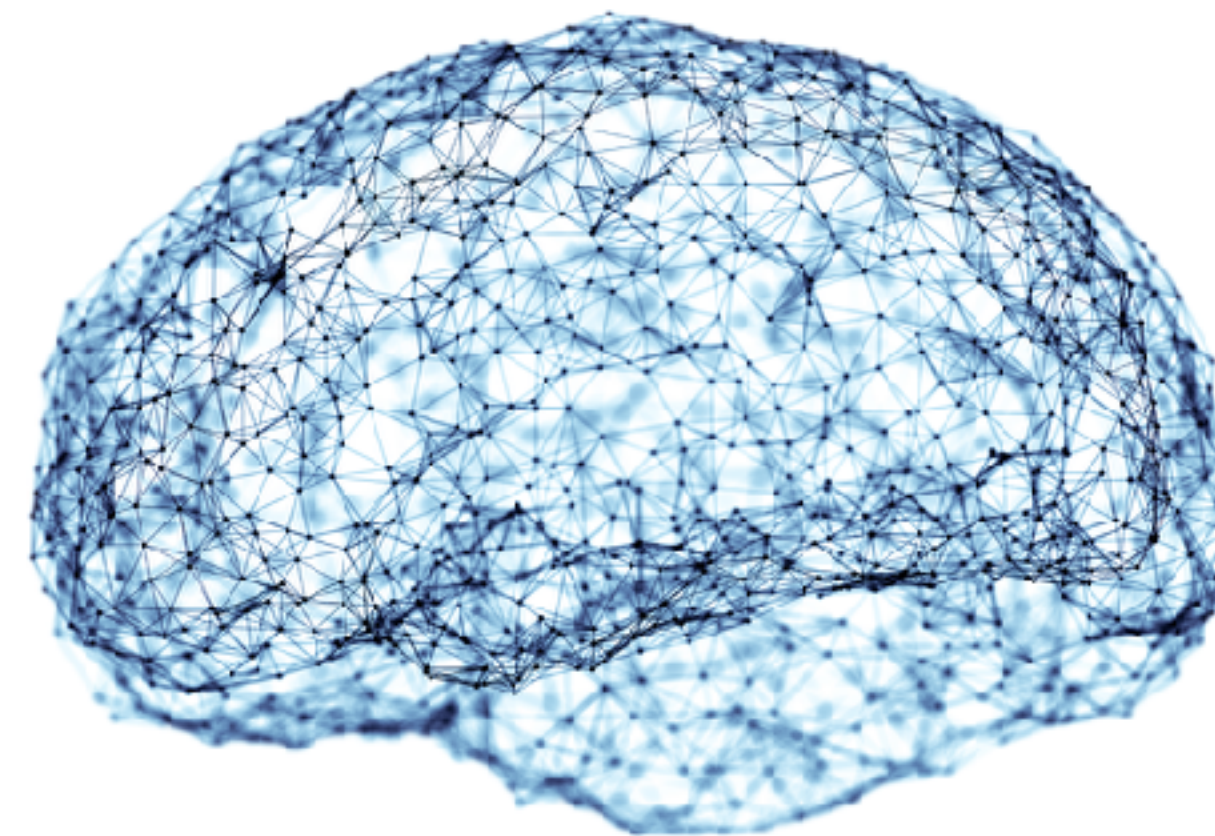
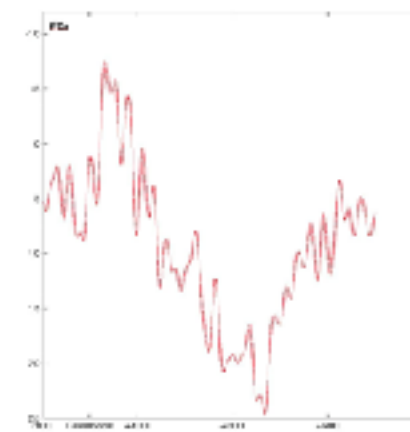


Advanced EEG single-trial analysis techniques

Adrian G Fischer & Jan R Wessel



**7th International Symposium on
Motivational and Cognitive Control**

**16th - 18th September 2019
Berlin**



Organisation I

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- The bad: most of the scripts are not yet a fully validated toolbox and have **no GUI**
- The good: this means that the code is much more easy to understand (if you want to dig into it and maybe change it for your own applications) and also: you are welcome to participate / provide ideas how to make the collection of scripts better!

- Coffee break 1: 10:25 - 10:40
- Lunch: 12:30 - 13:30
- Coffee break 2: 14:45 - 15:00

- Download all required data here:
 - www.adrianfischer.de/teaching.html
 - ➔ password for data: *st_workshop*
 - ➔ data itself: <http://kumo.ovgu.de/~afischer/workshop/data.zip>
 - ➔ COMPASS data: <http://kumo.ovgu.de/~afischer/workshop/COMPASS.zip>

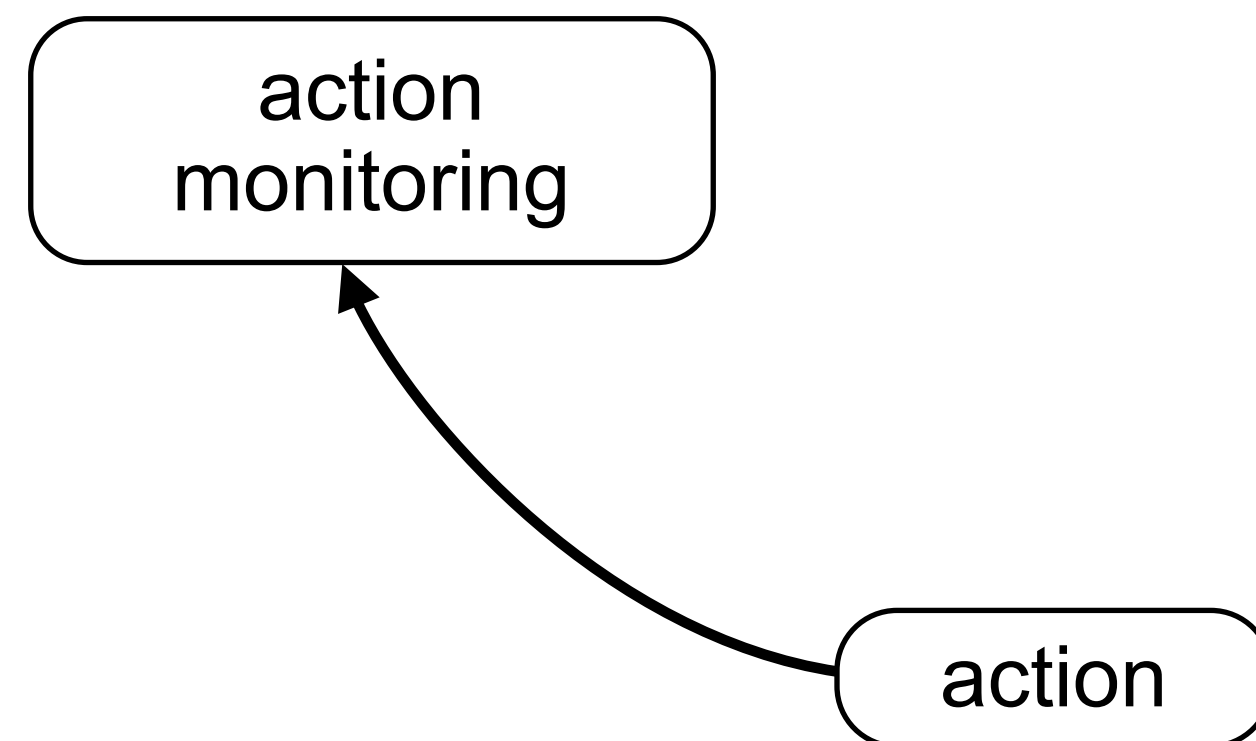
- **Session 1 - Why single-trial EEG analyses?**
- Session 2 - Pre-processing, introduction to ICA
 - Example session I: Setting-up your data and running a single-trial regression analysis with the *STA-TB*
- Session 3 - ICA as a tool to increase SNR in EEG data
 - Example session II: COMPASS to select ICs
 - Example session III: EEG regression with independent component activity
- Session 4 - Within-subject to across-subject analyses
 - Example session IV: Combine data across participants
- Session 5 - Time-frequency decomposition and single-trial analyses
 - Example session V: Run a TF decomposition and GLM analysis
- End and Discussion

Action Monitoring and Behavioral Adaptation

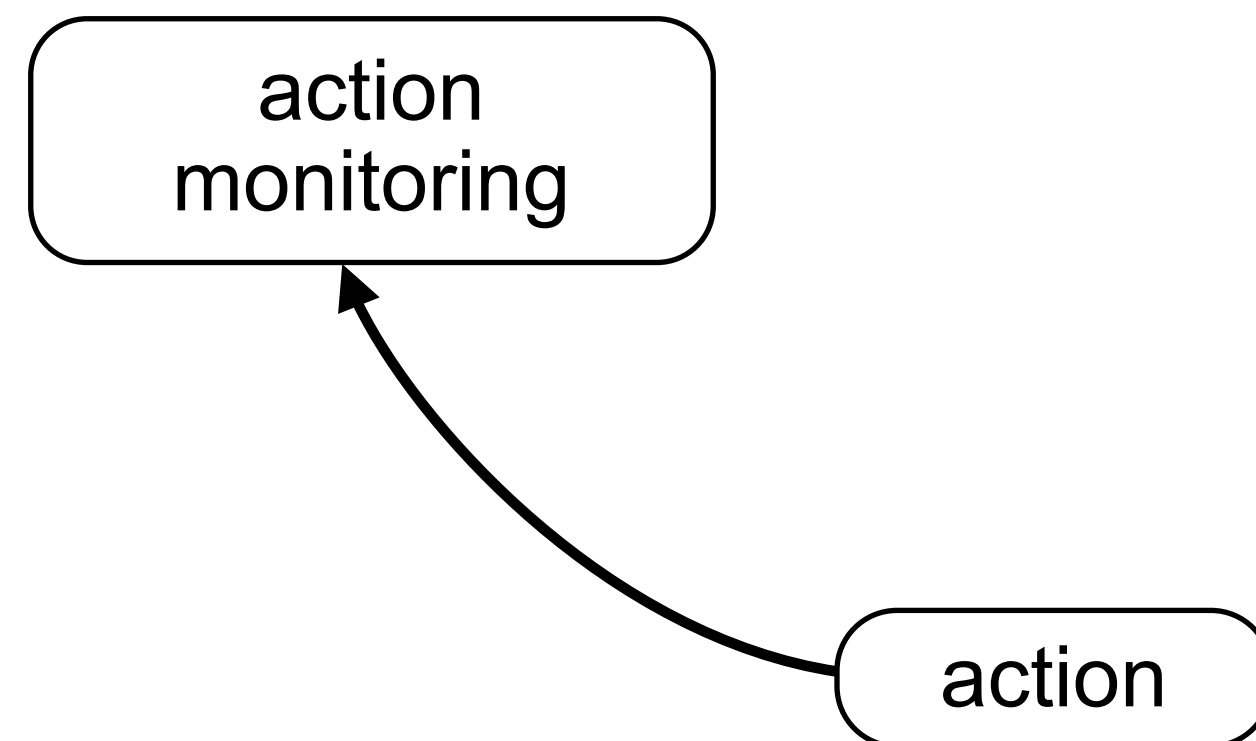
Action Monitoring and Behavioral Adaptation

action

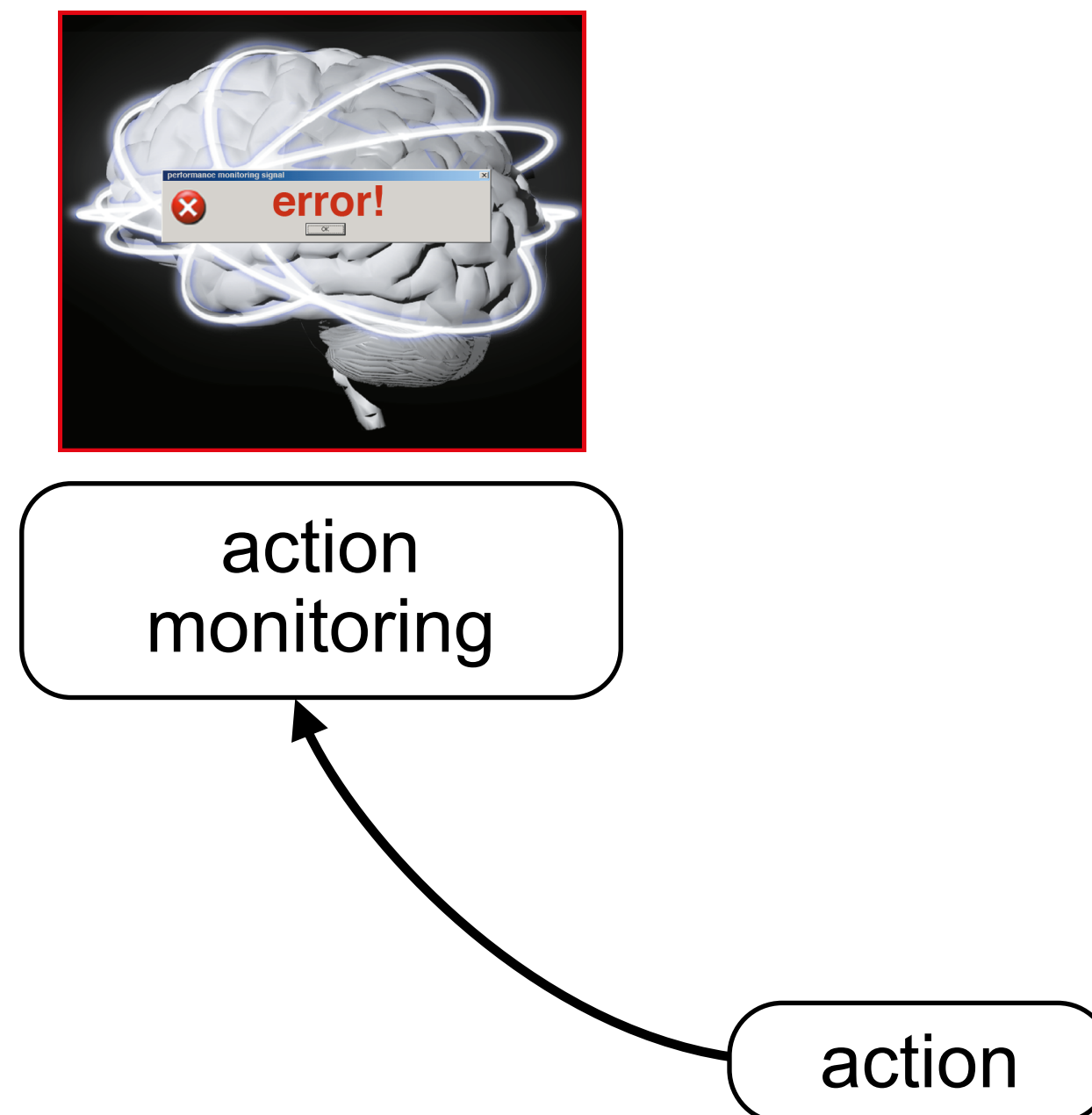
Action Monitoring and Behavioral Adaptation



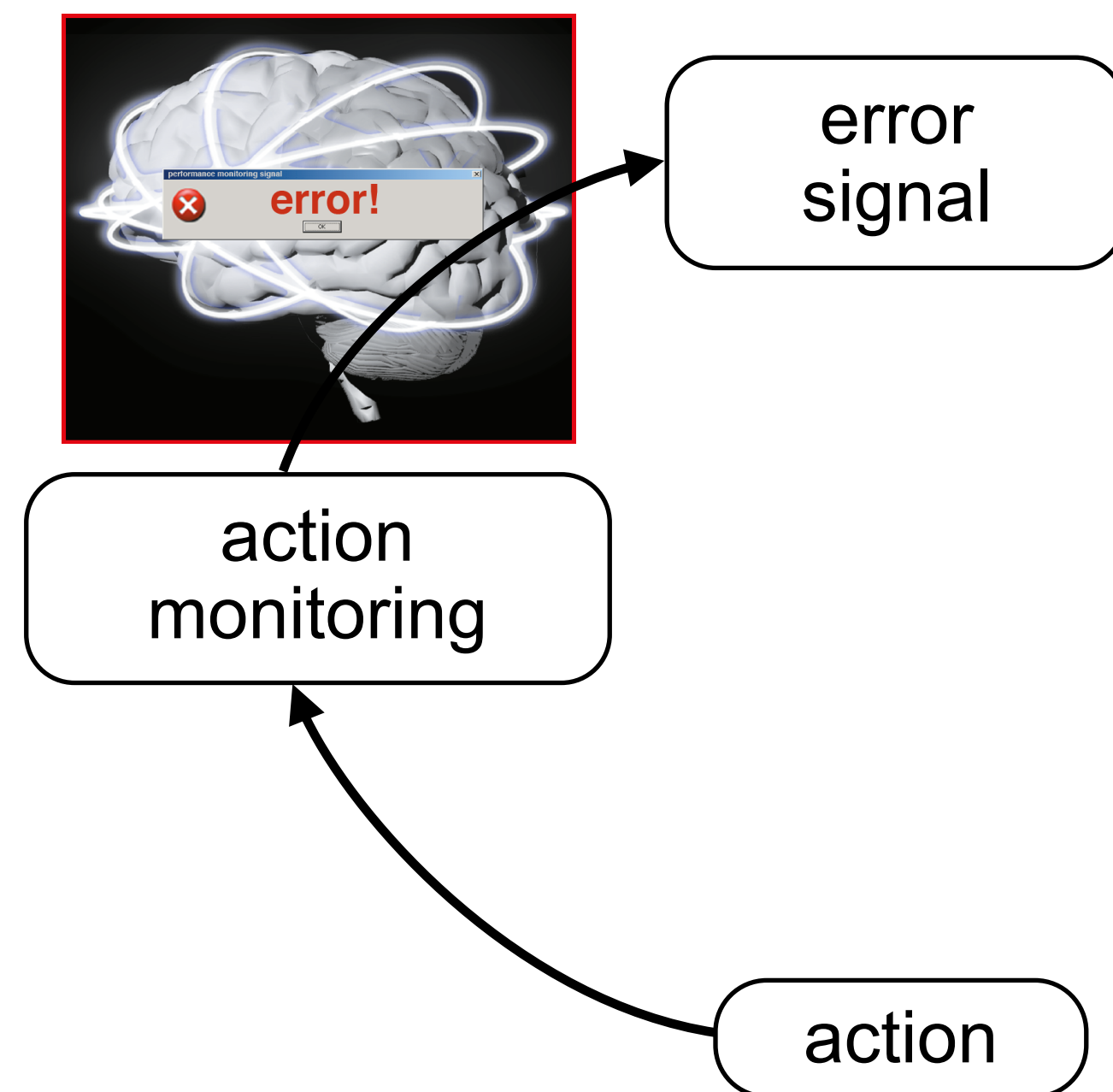
Action Monitoring and Behavioral Adaptation



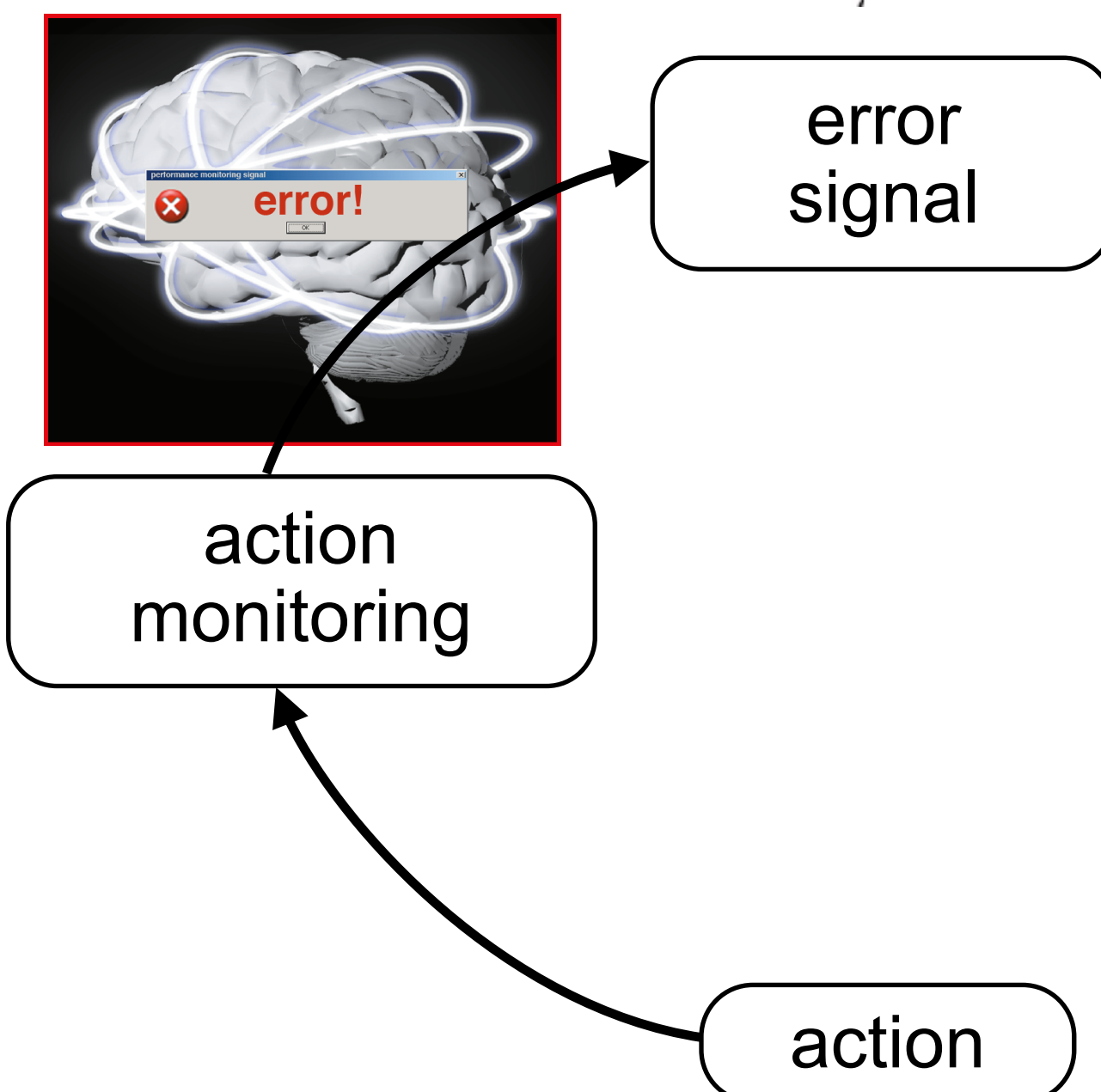
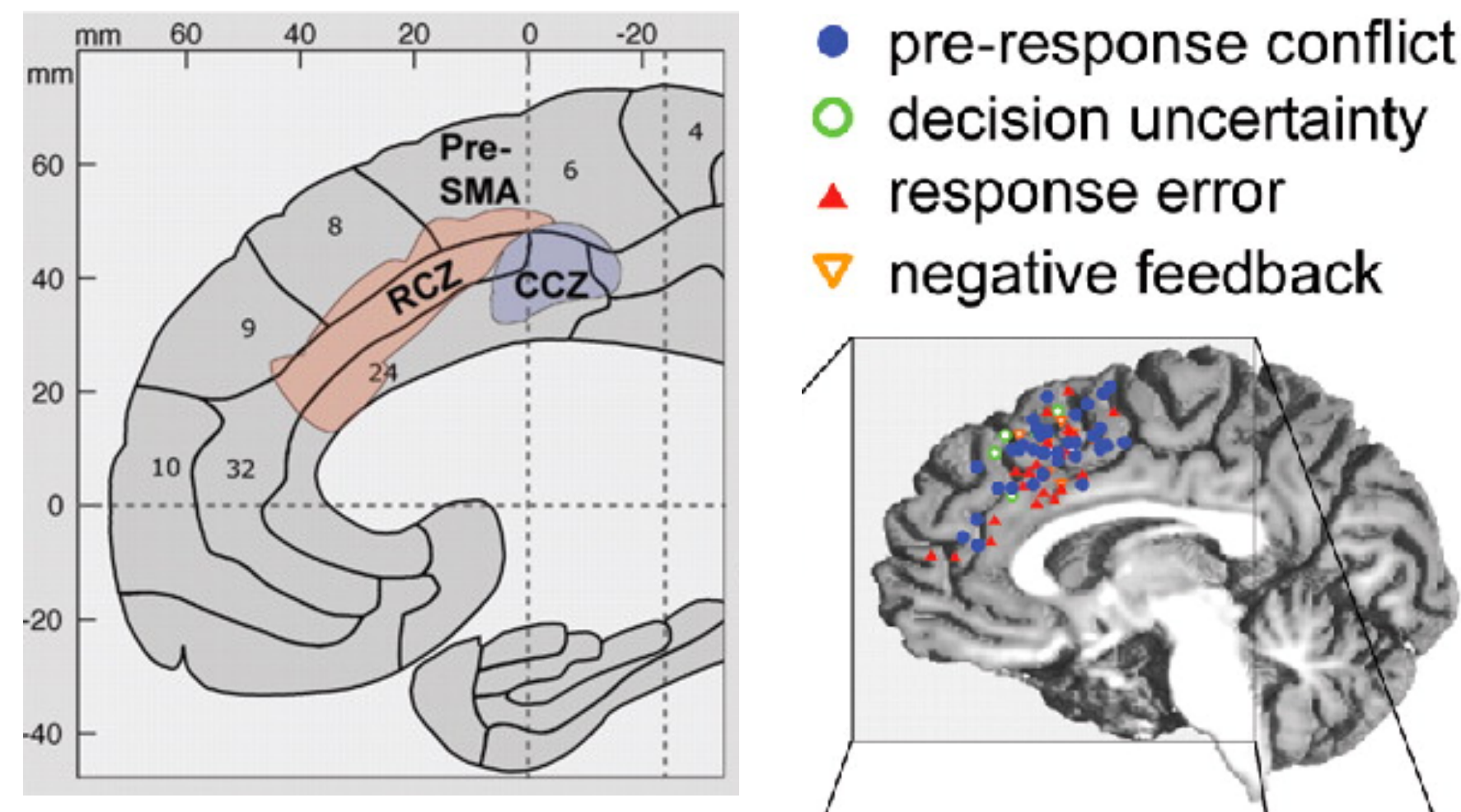
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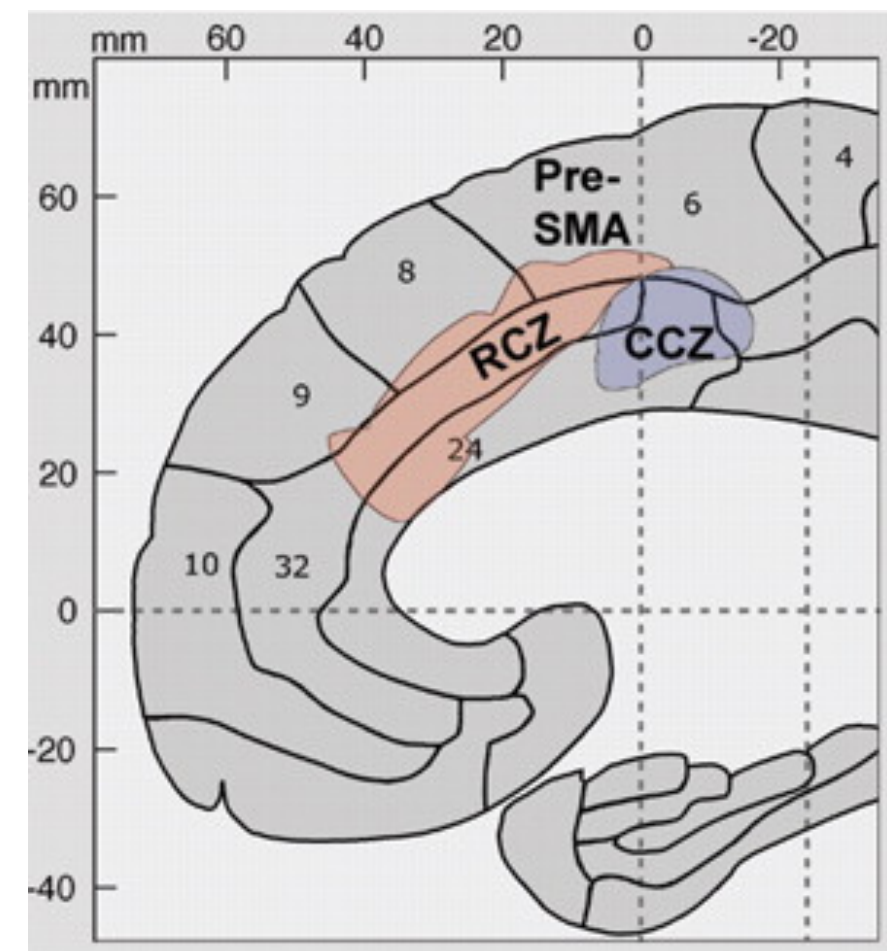
Action Monitoring and Behavioral Adaptation



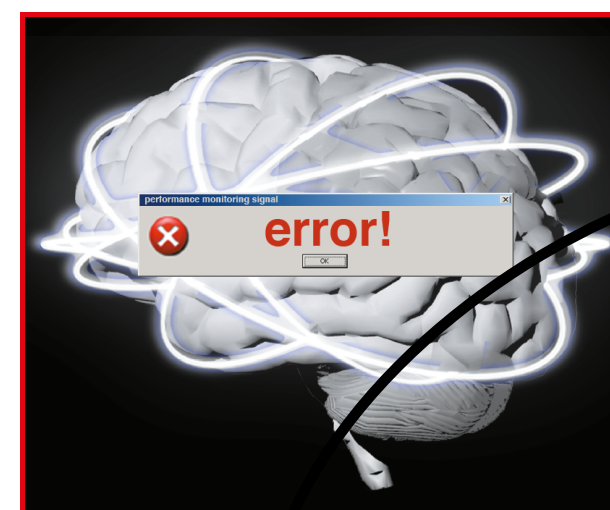
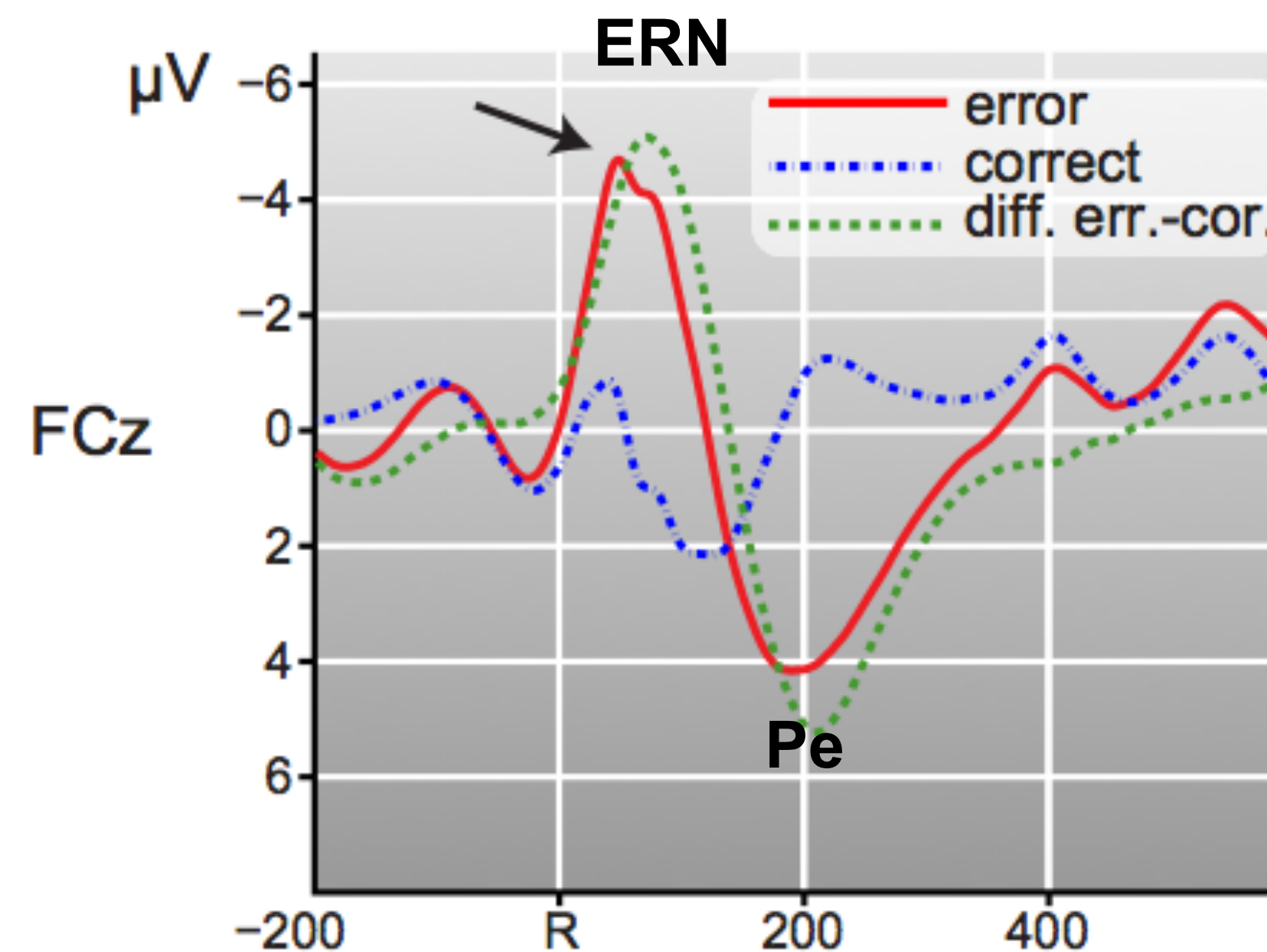
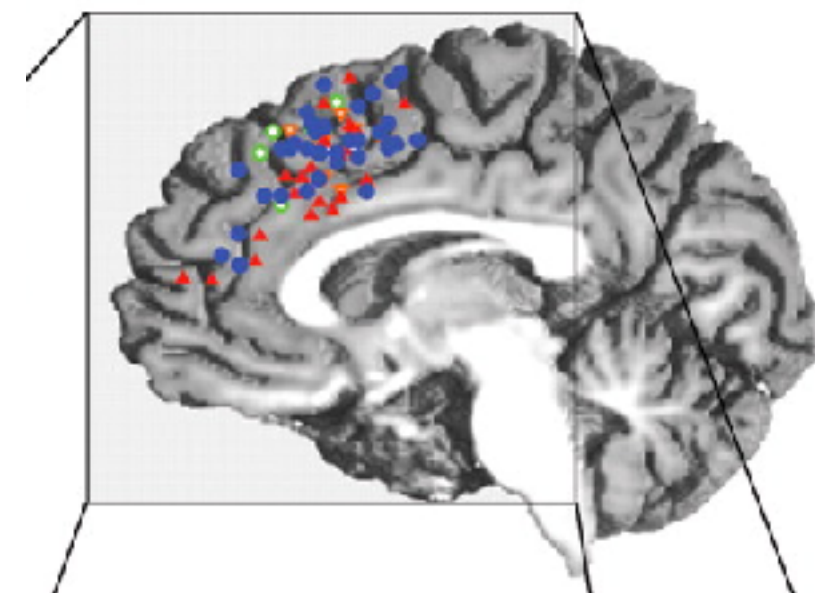
Action Monitoring and Behavioral Adaptation



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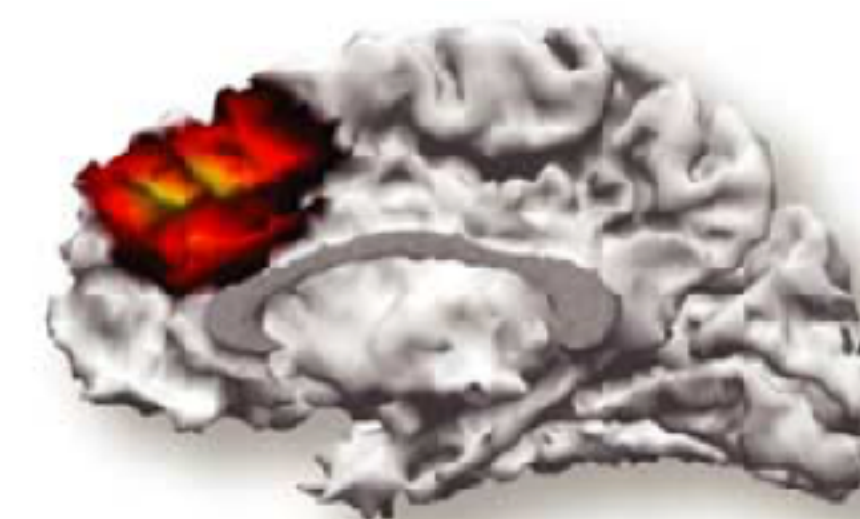
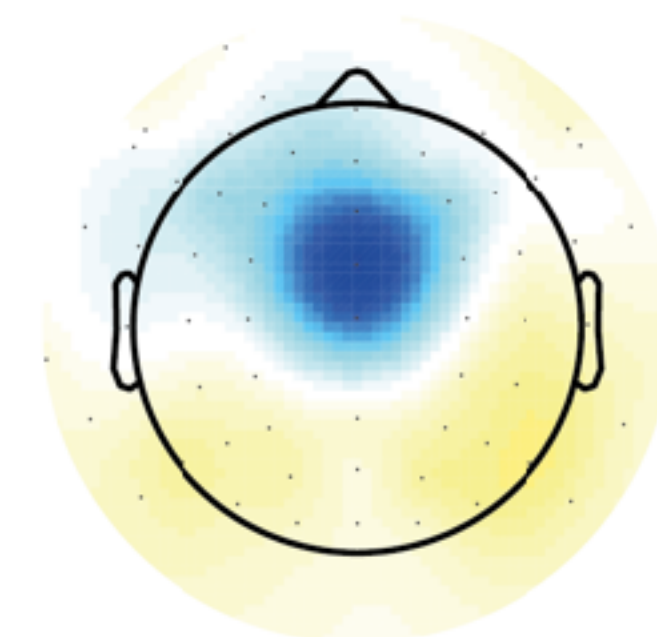
- pre-response conflict
- decision uncertainty
- ▲ response error
- ▼ negative feedback



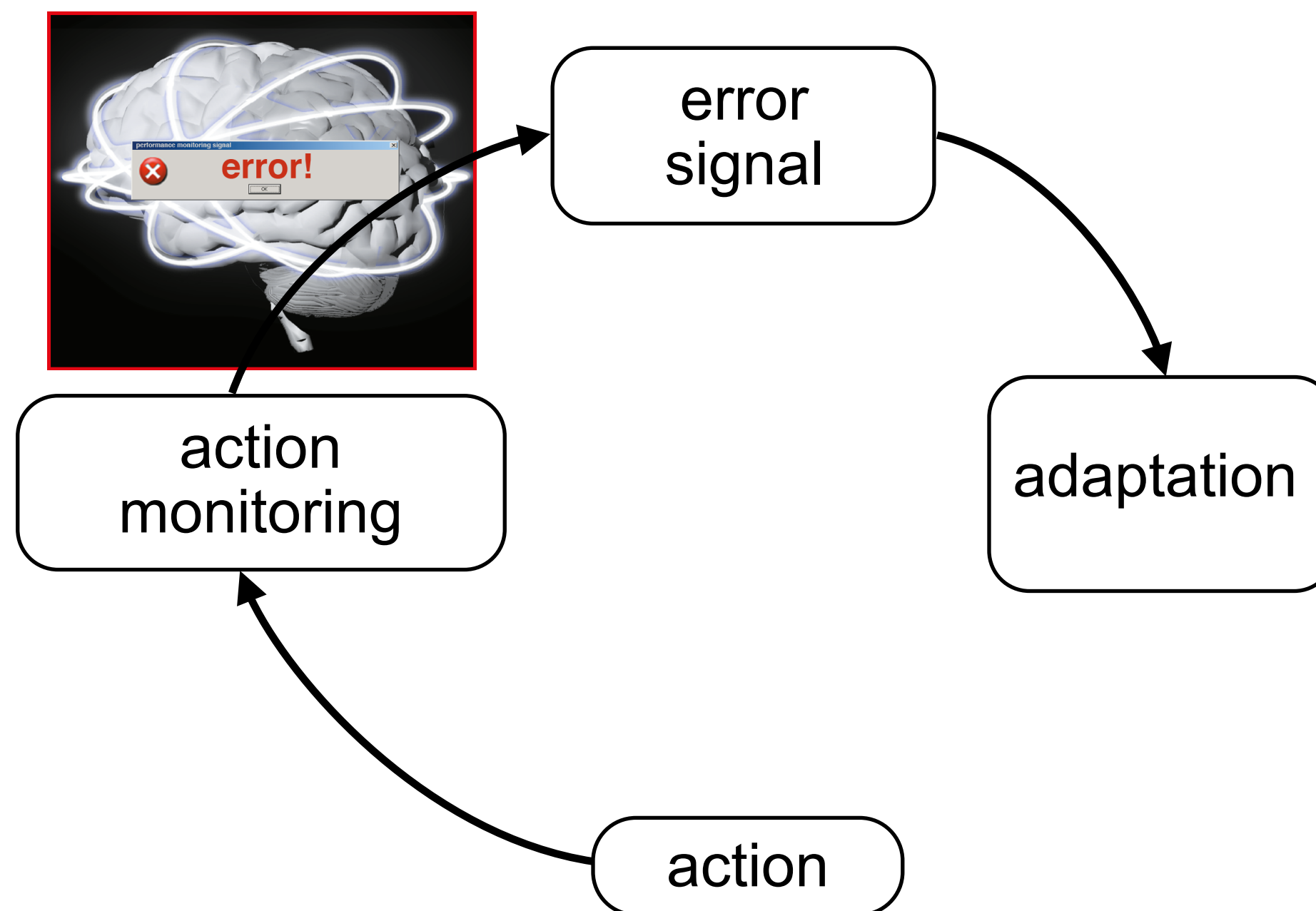
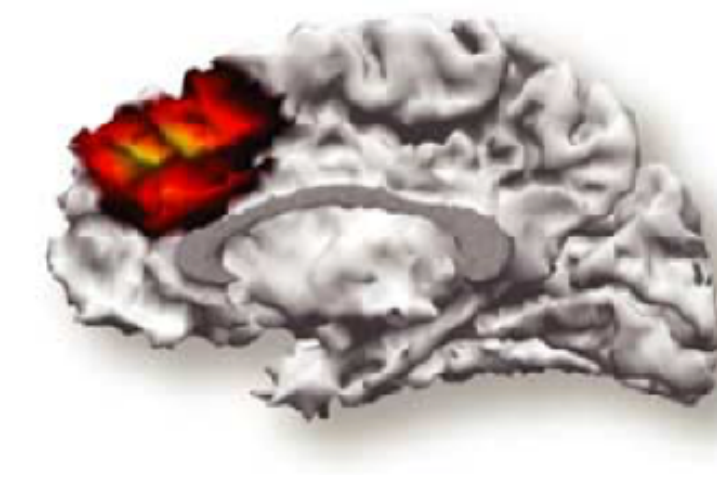
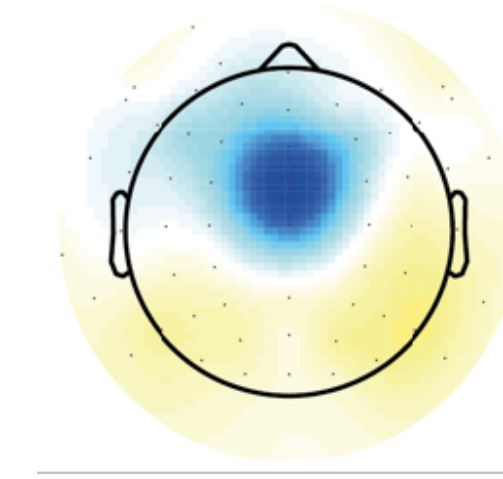
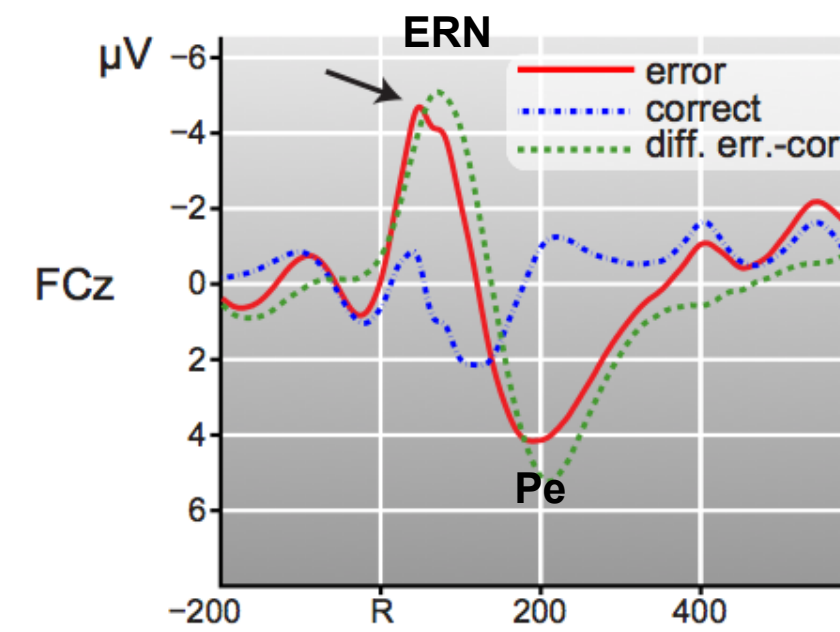
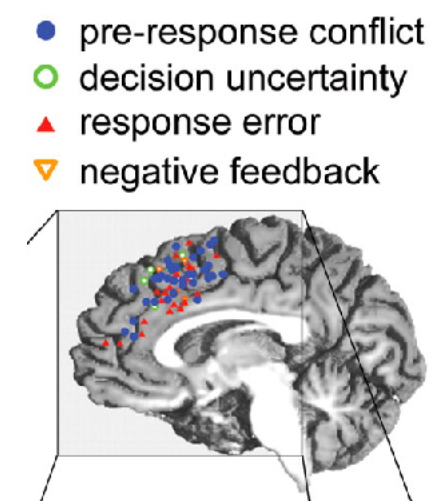
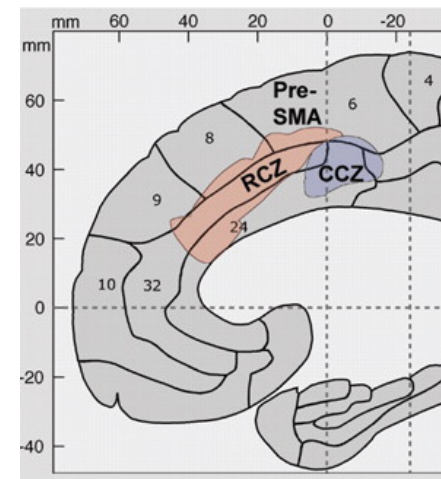
error
signal

action
monitoring

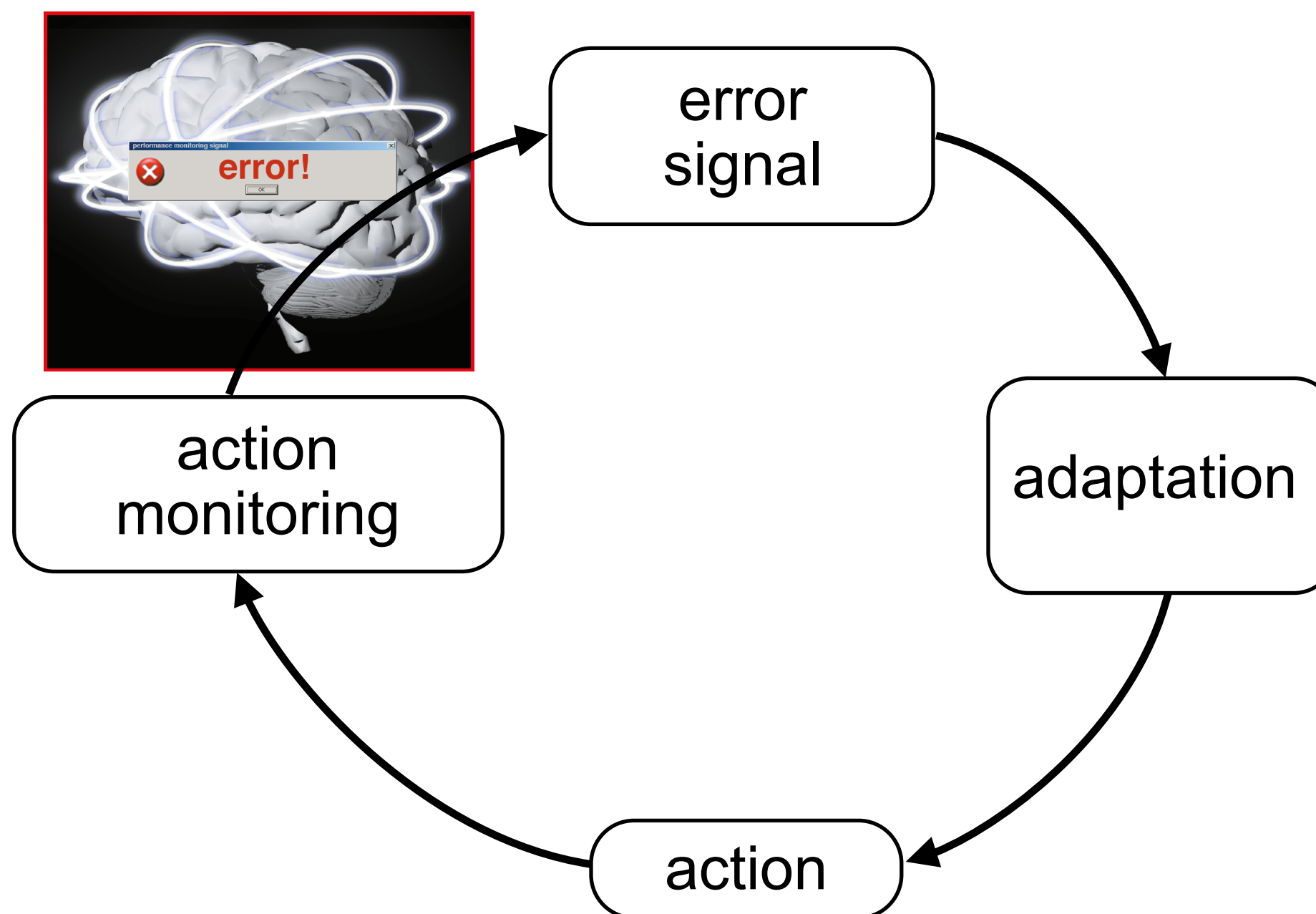
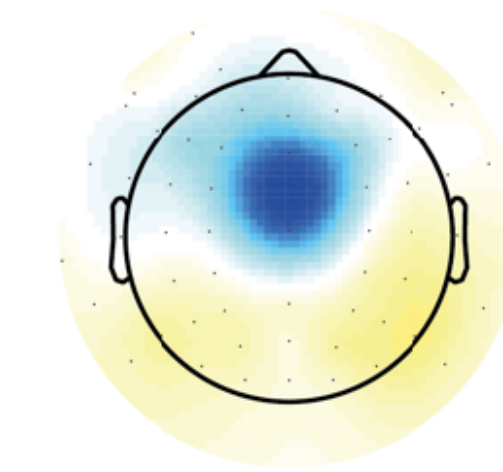
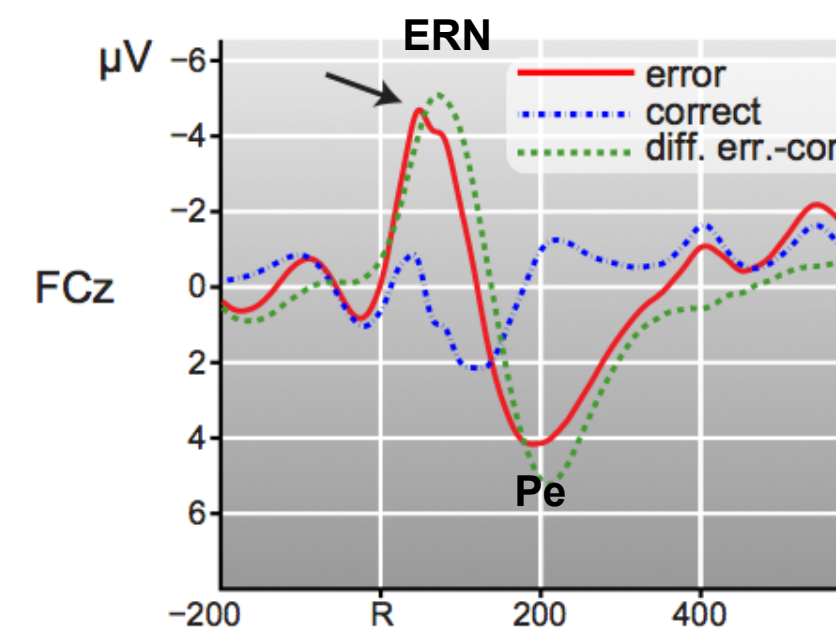
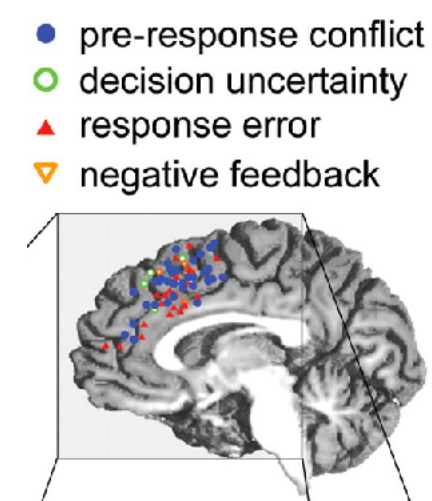
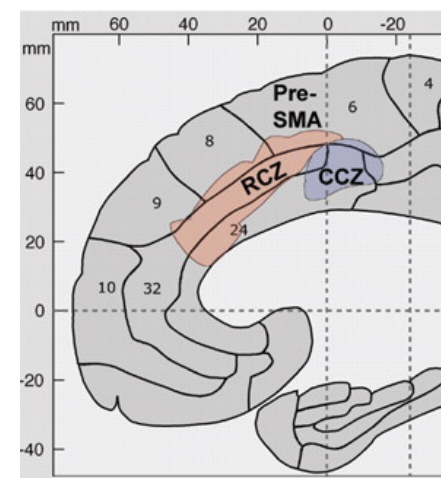
action



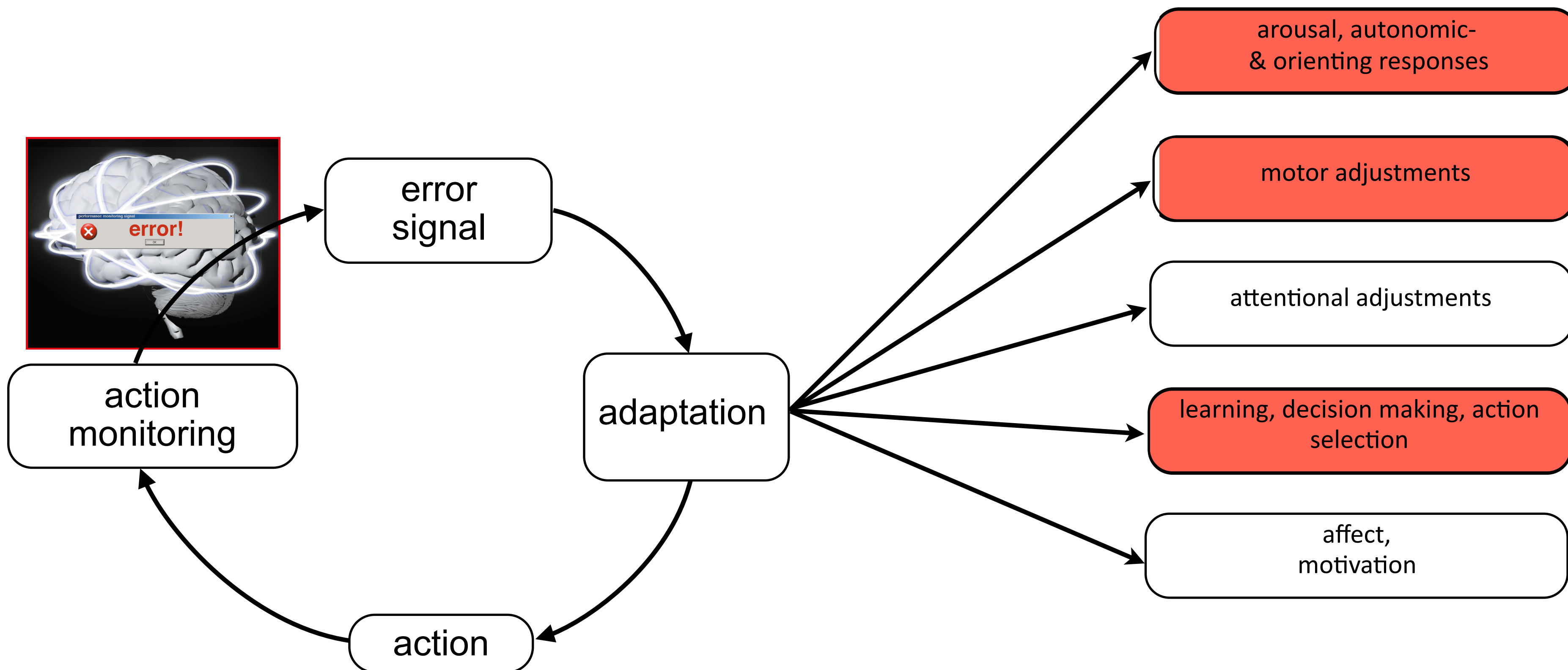
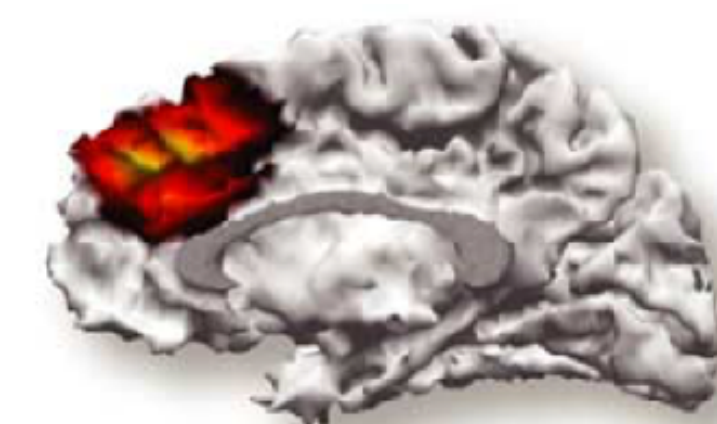
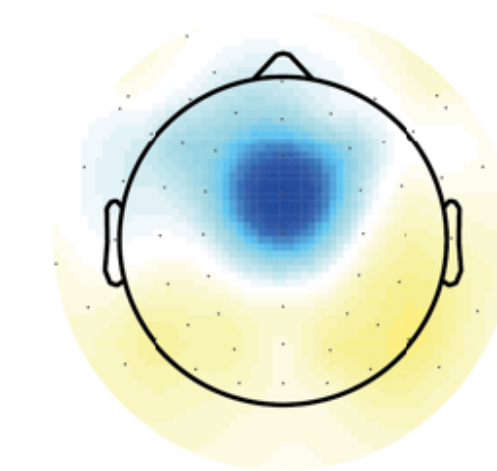
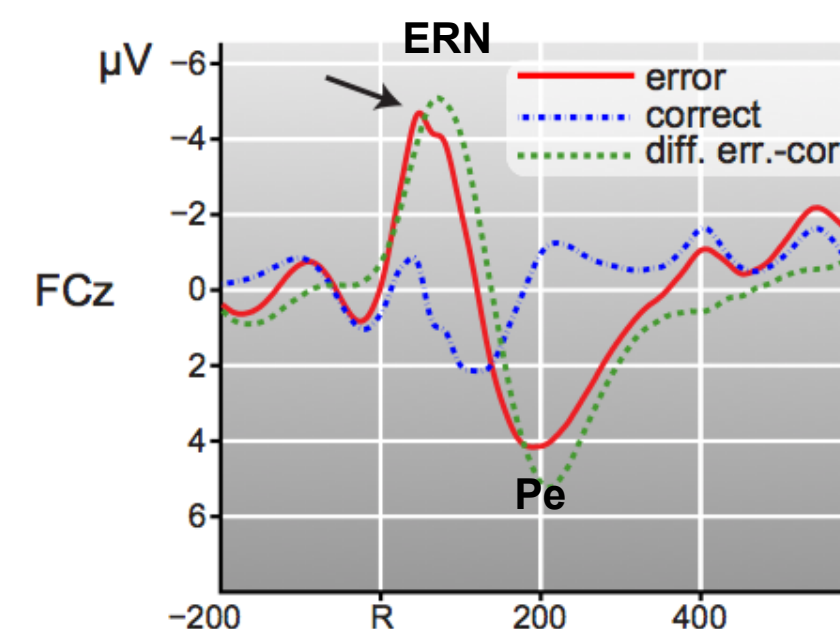
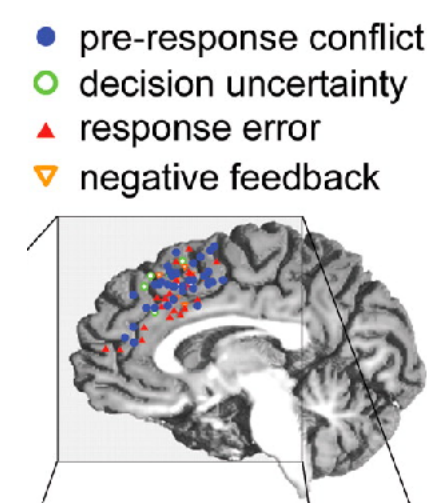
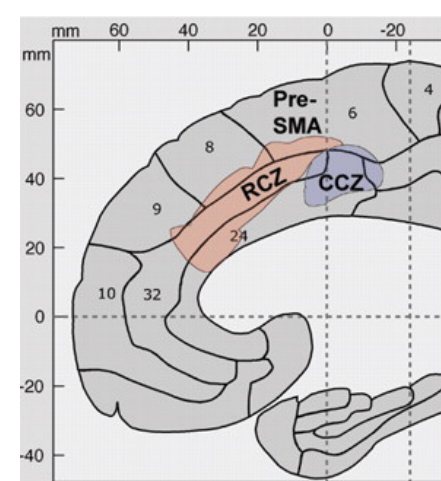
Action Monitoring and Behavioral Adaptation

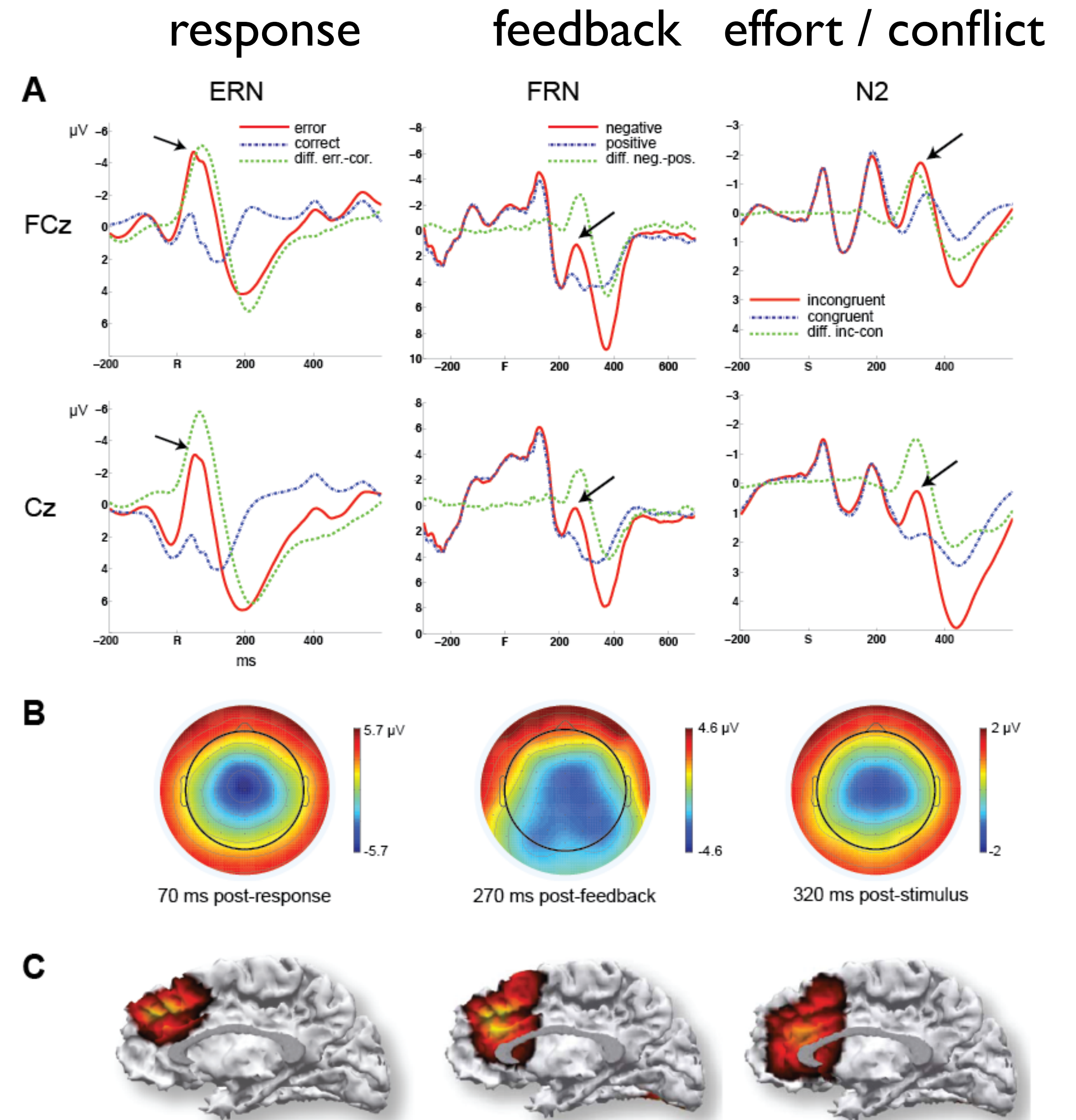


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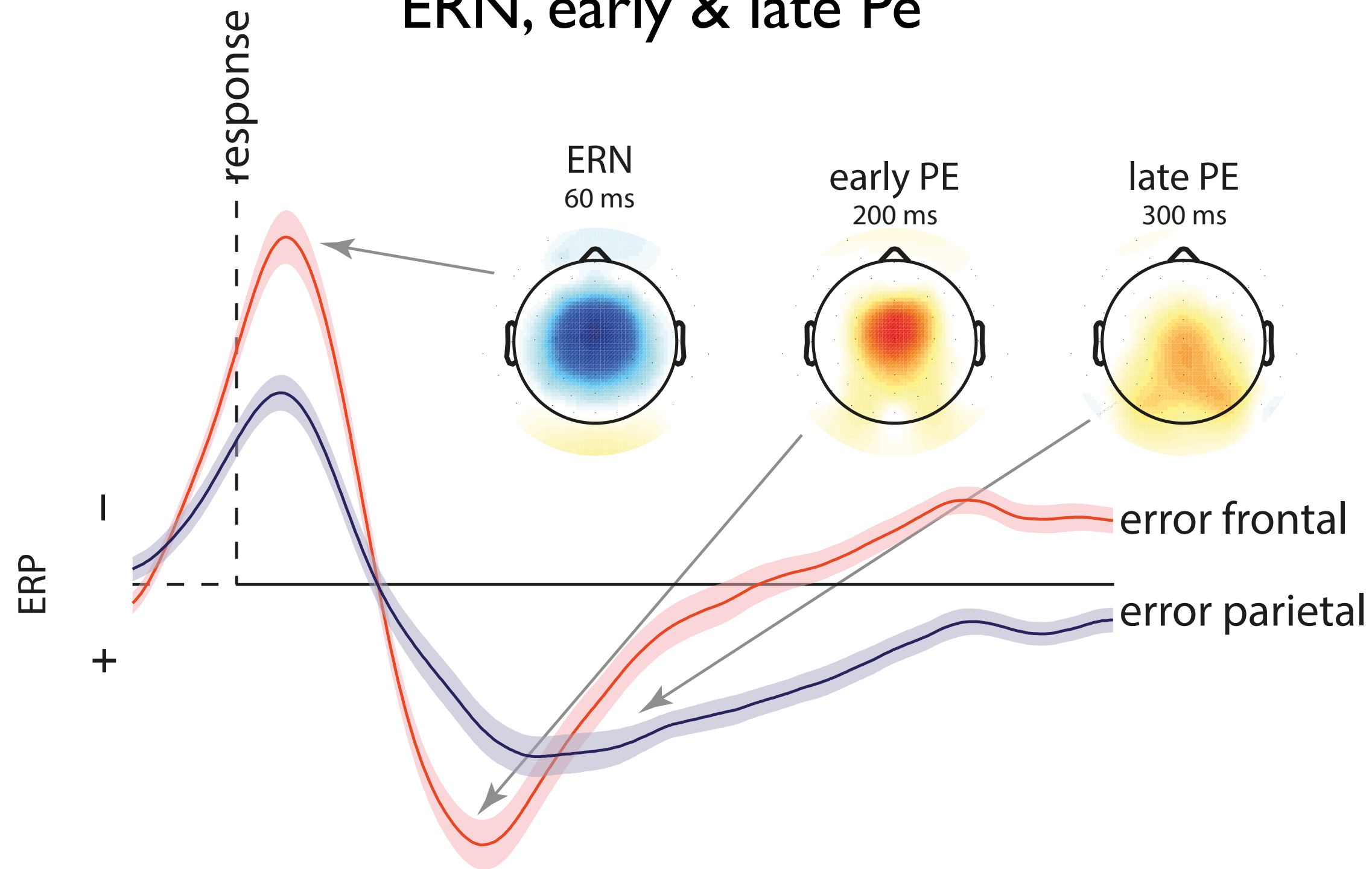


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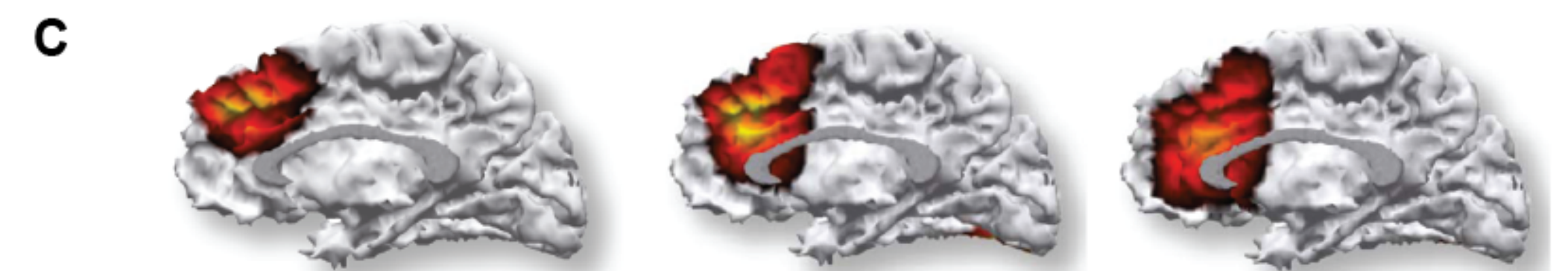
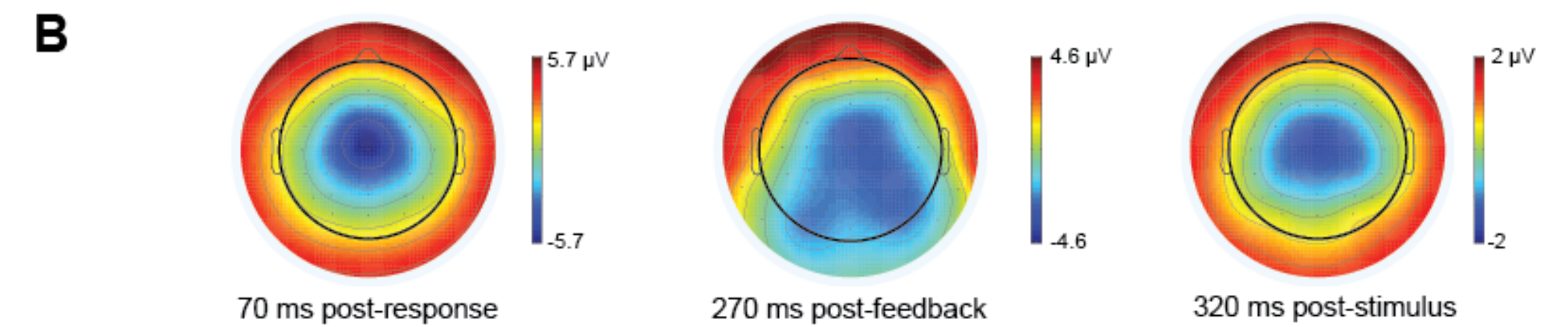
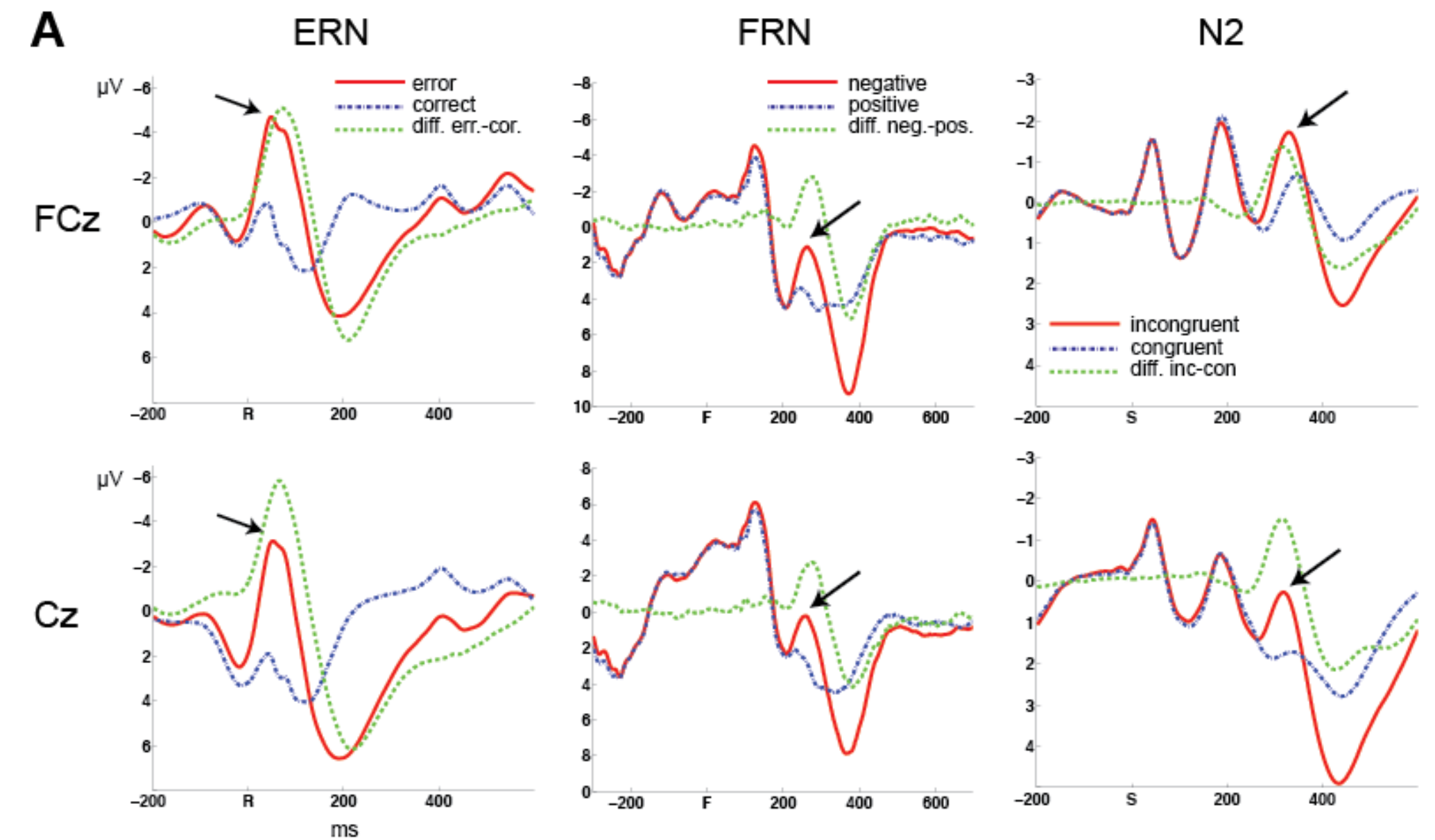




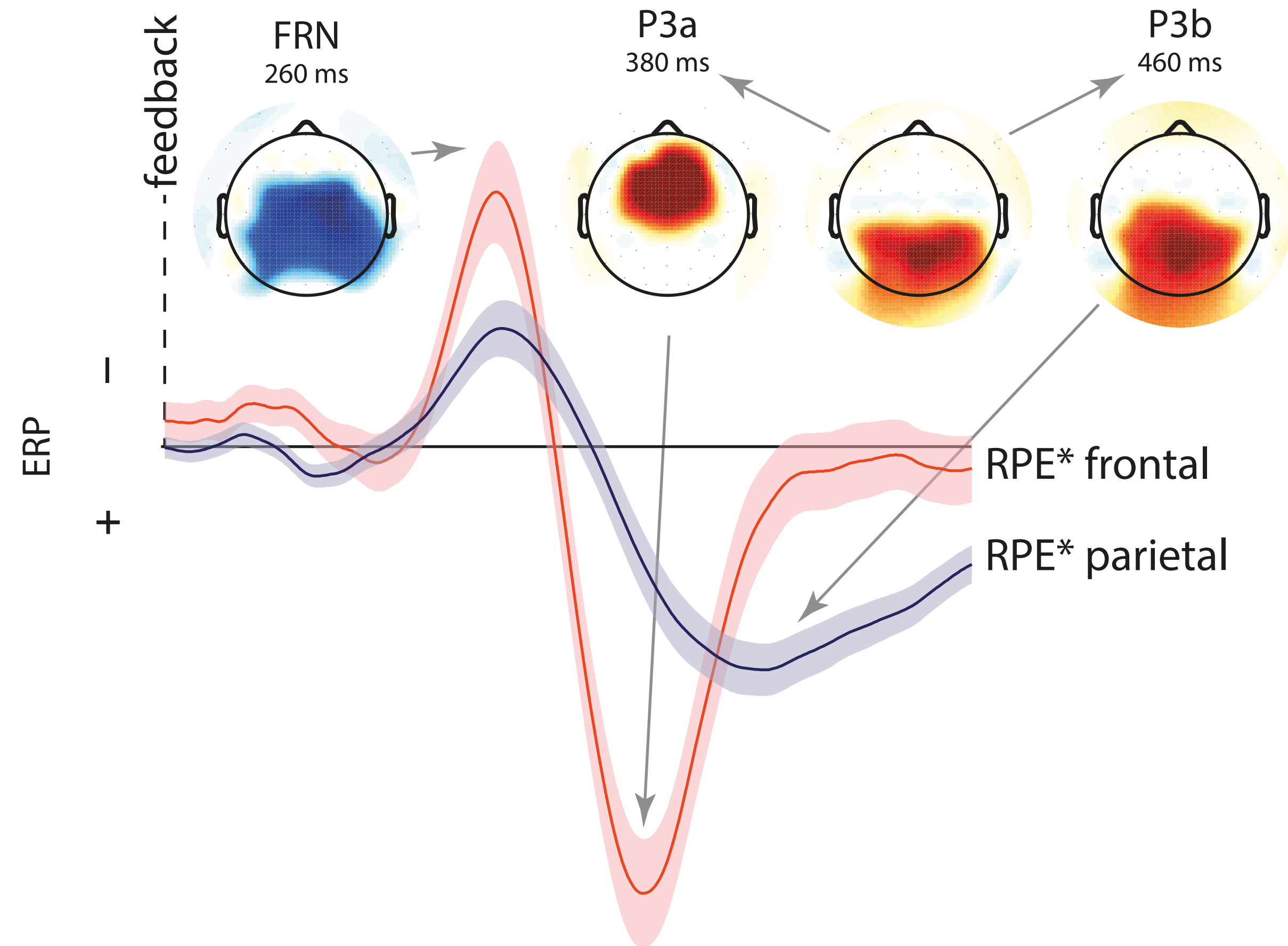
ERN, early & late Pe



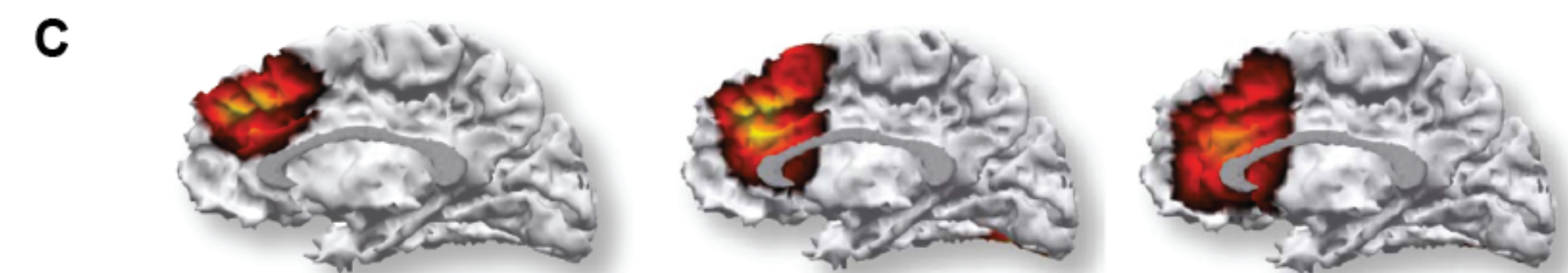
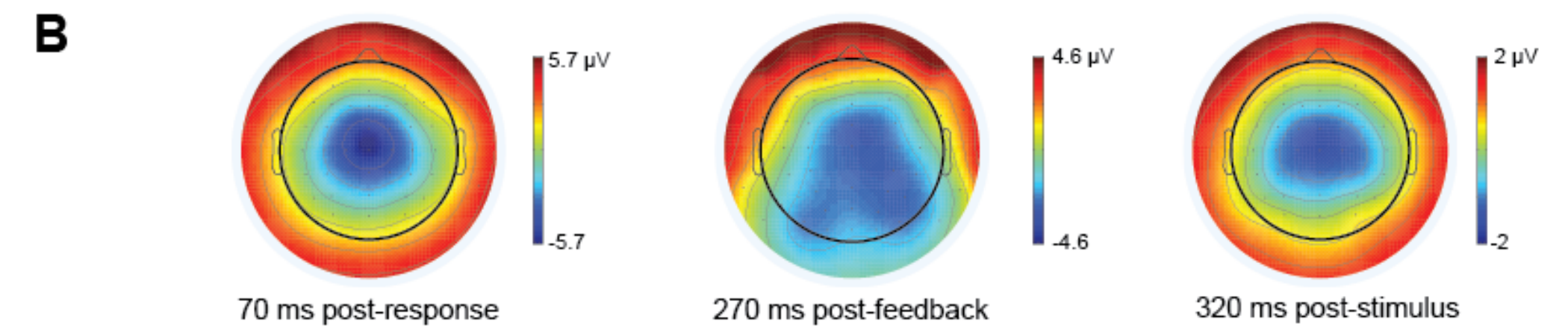
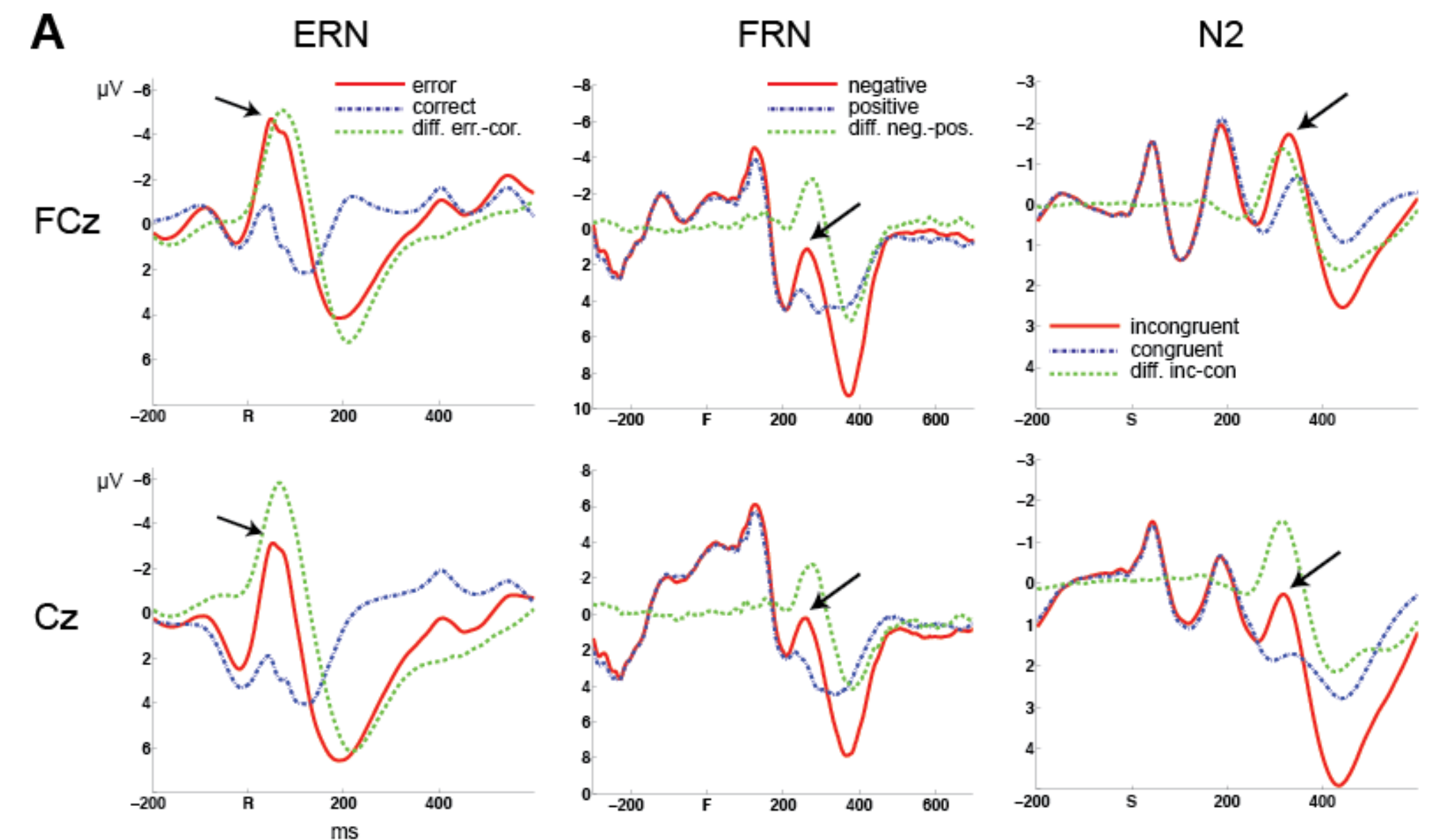
response feedback effort / conflict



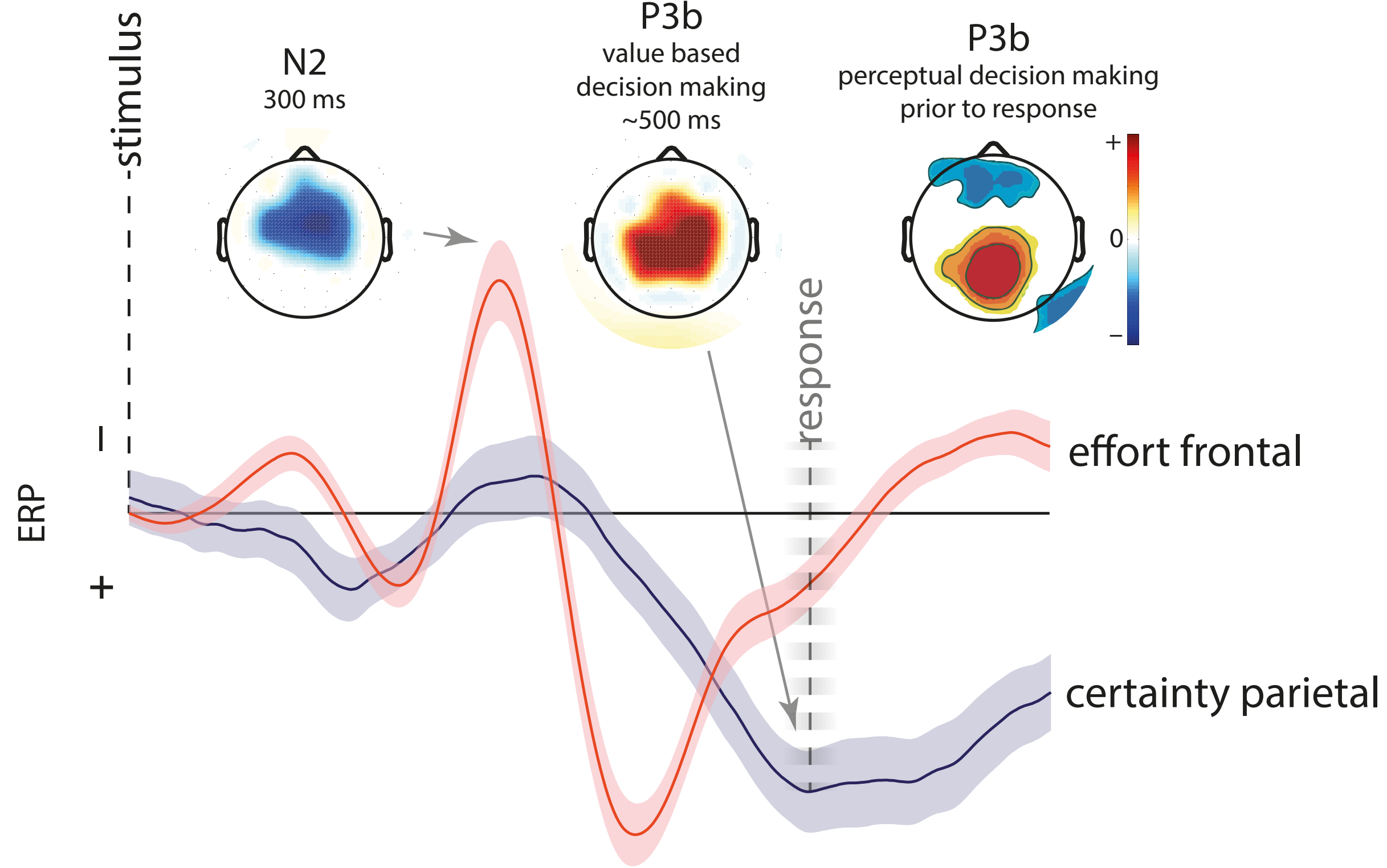
FRN, P3a & P3b



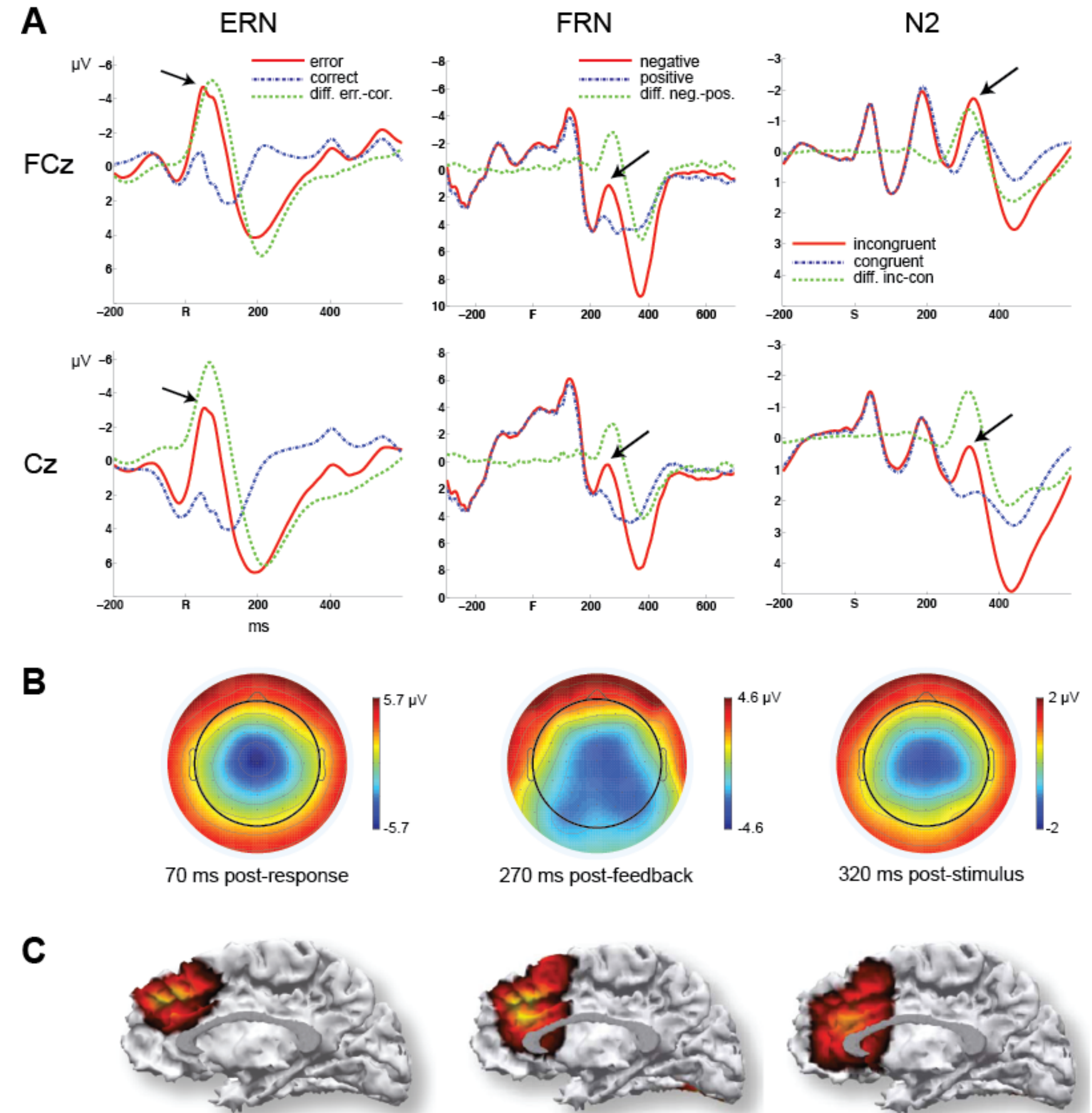
response feedback effort / conflict



N2, P3a & P3b



response feedback effort / conflict

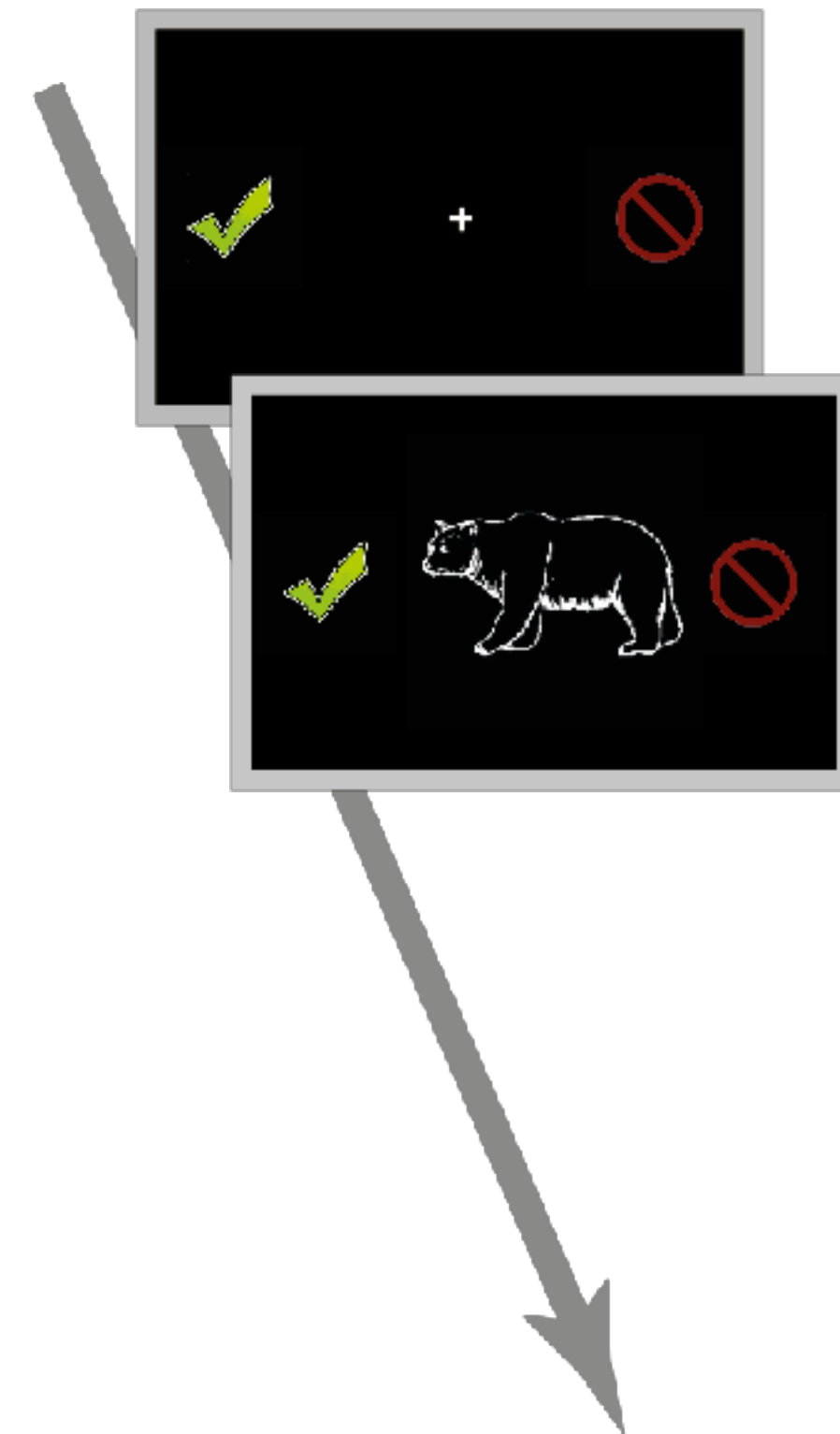


Why single-trial EEG analyses?

- Many reasons!
 - ▶ Most stringent test of brain-behavior interactions (Cavanagh & Shackman, *J Physiol Paris*, 2014; Lim et al., *PNAS*, 2009)
 - ▶ Can increase statistical power (by controlling for confounds on a within-participant level, or multivariate approaches like MVPA)
 - ▶ Allows to model neural activity, rather than simple correlations / categorical differences
 - ▶ Unifies approaches between different research modalities (GLMs in fMRI and MEG) and with behavioral analyses (same GLM can be used for EEG and behavior)
 - ➡ additionally, EEG activity can be added into a behavioral single-trial regression as an additional predictor
- ... and an example

Task

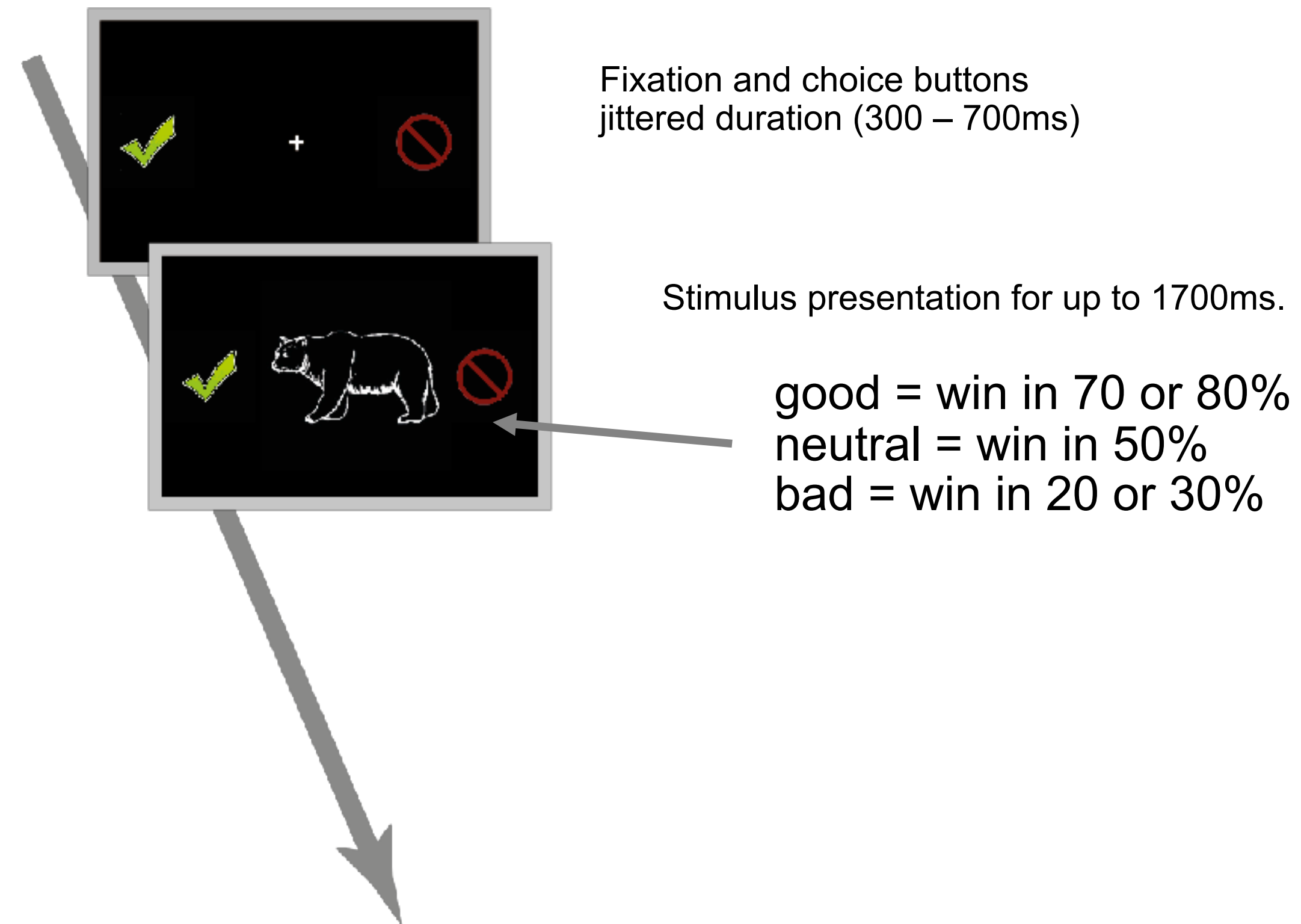
Task



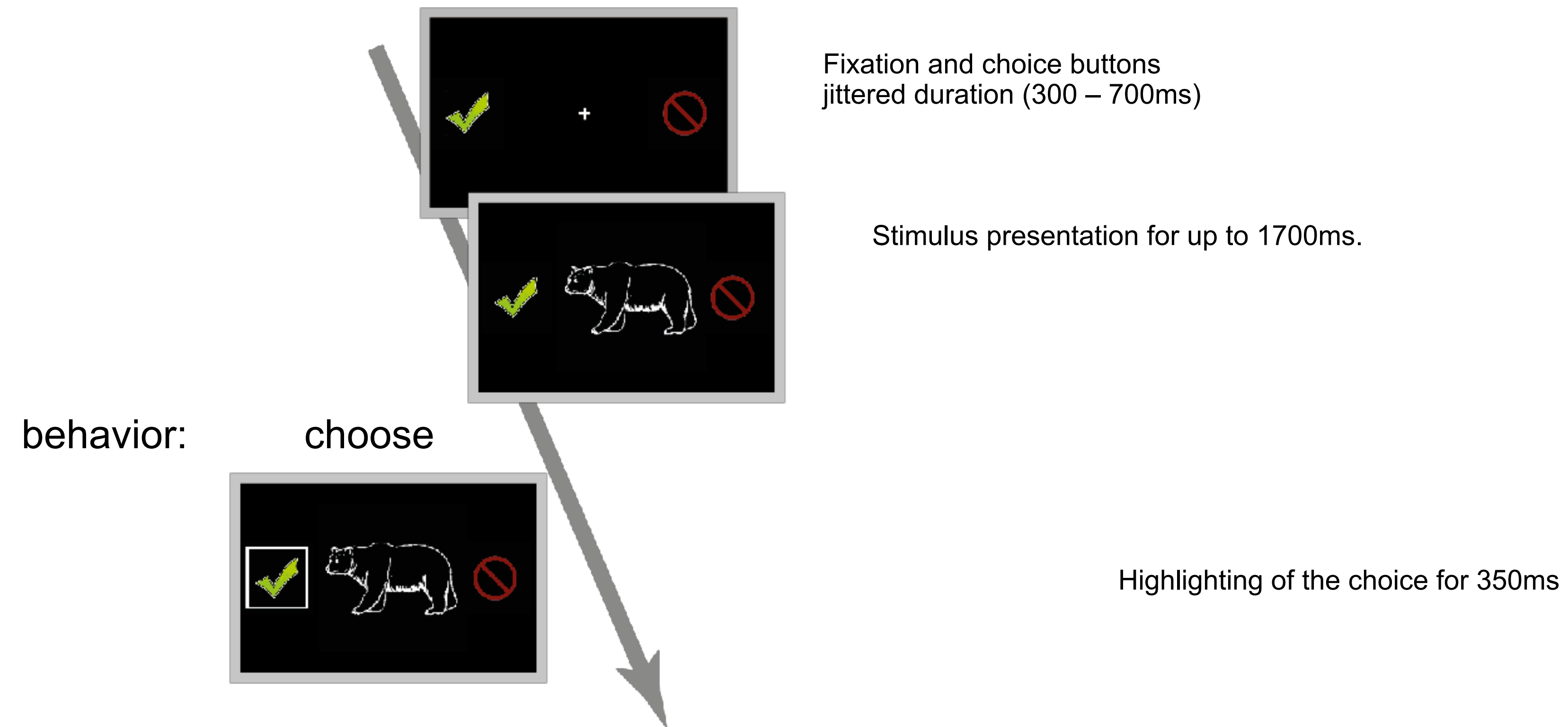
Fixation and choice buttons
jittered duration (300 – 700ms)

Stimulus presentation for up to 1700ms.

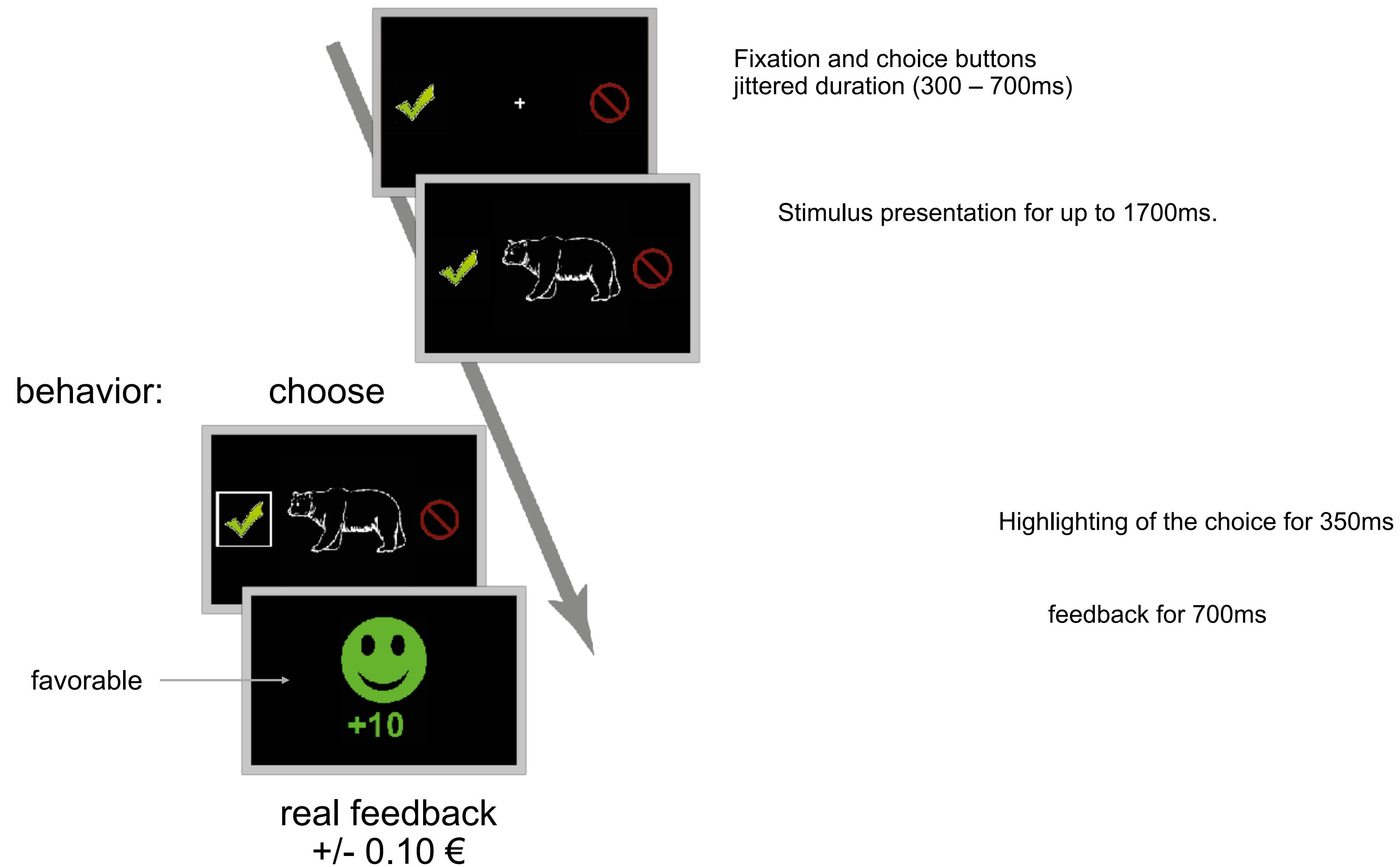
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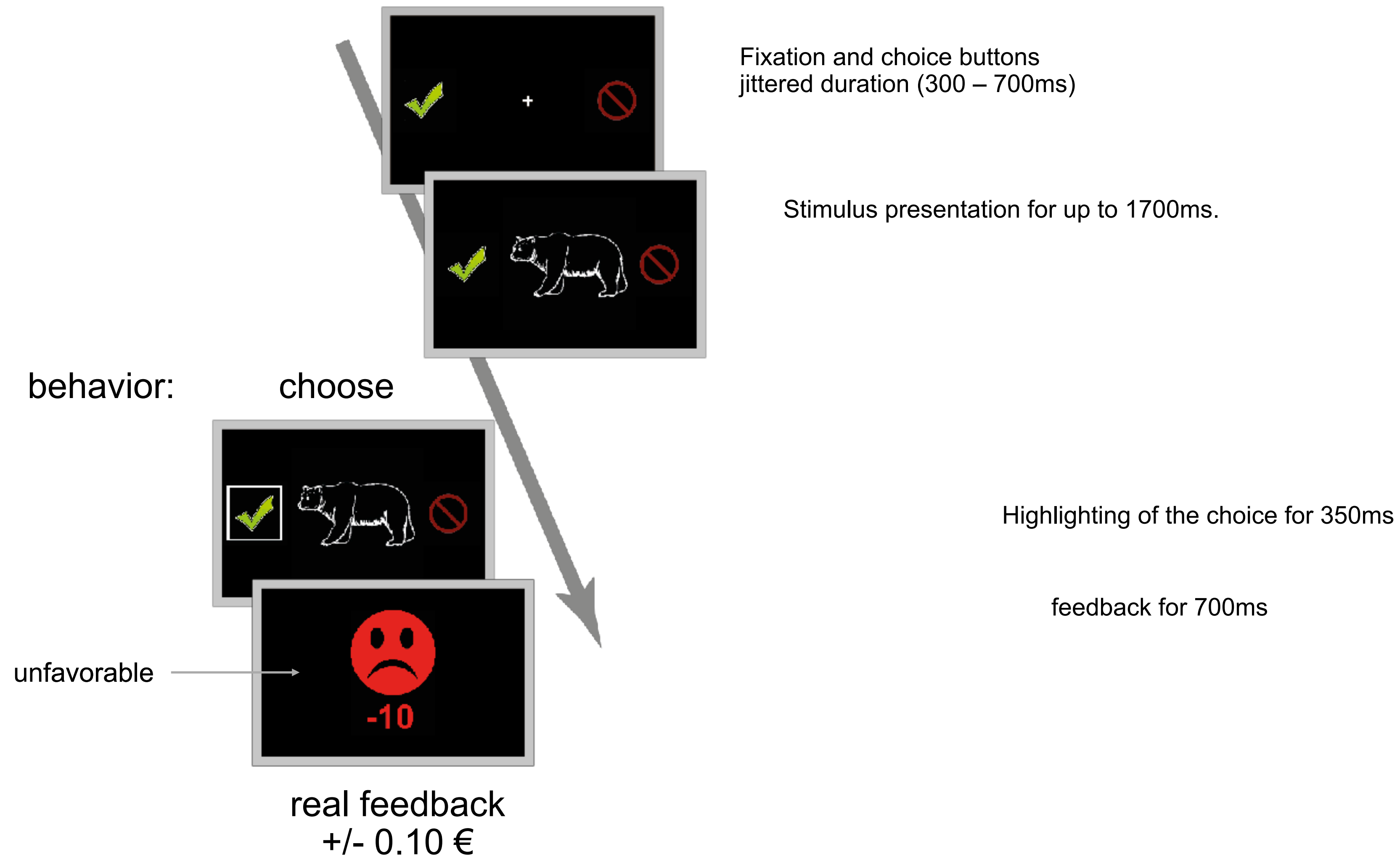
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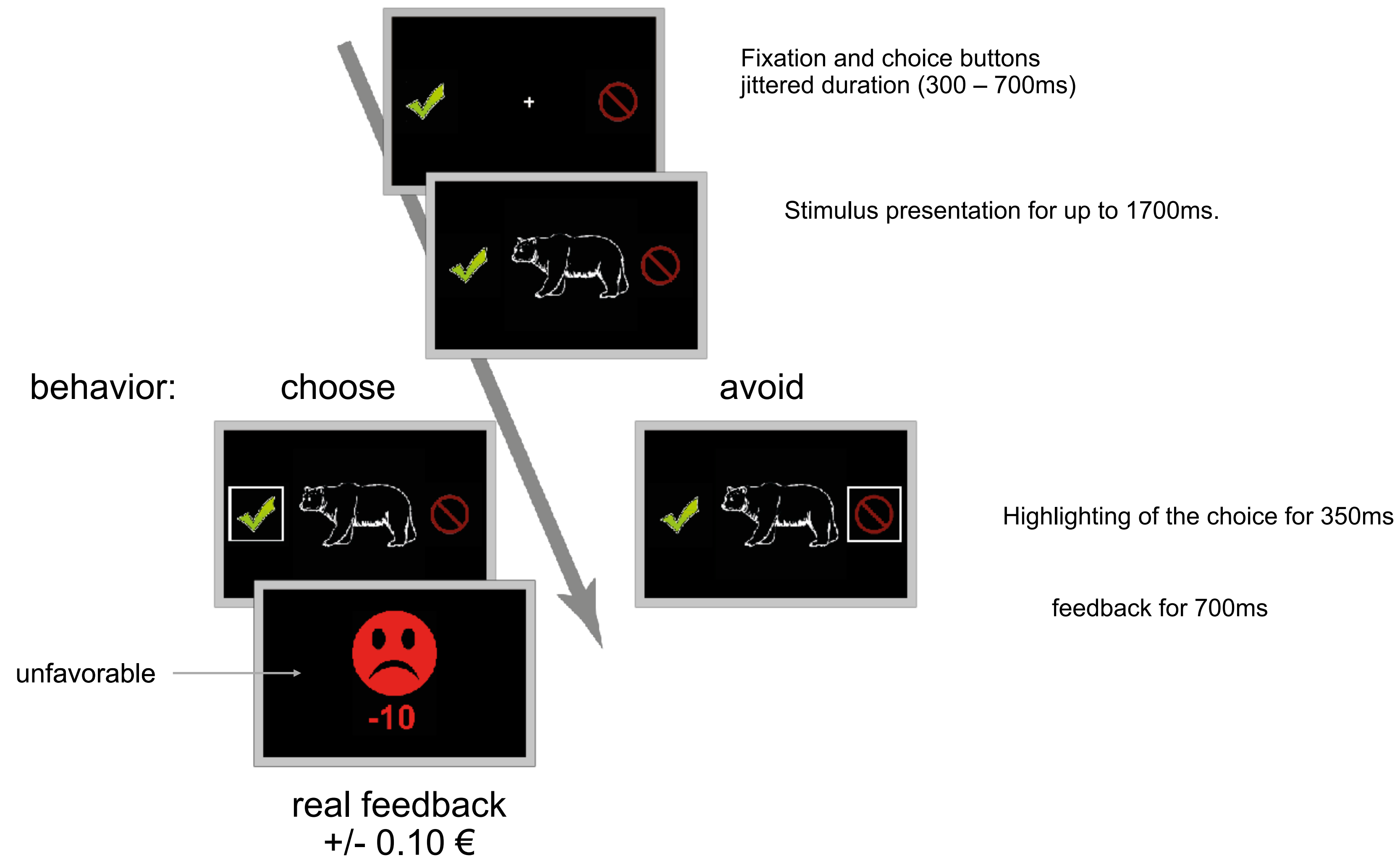
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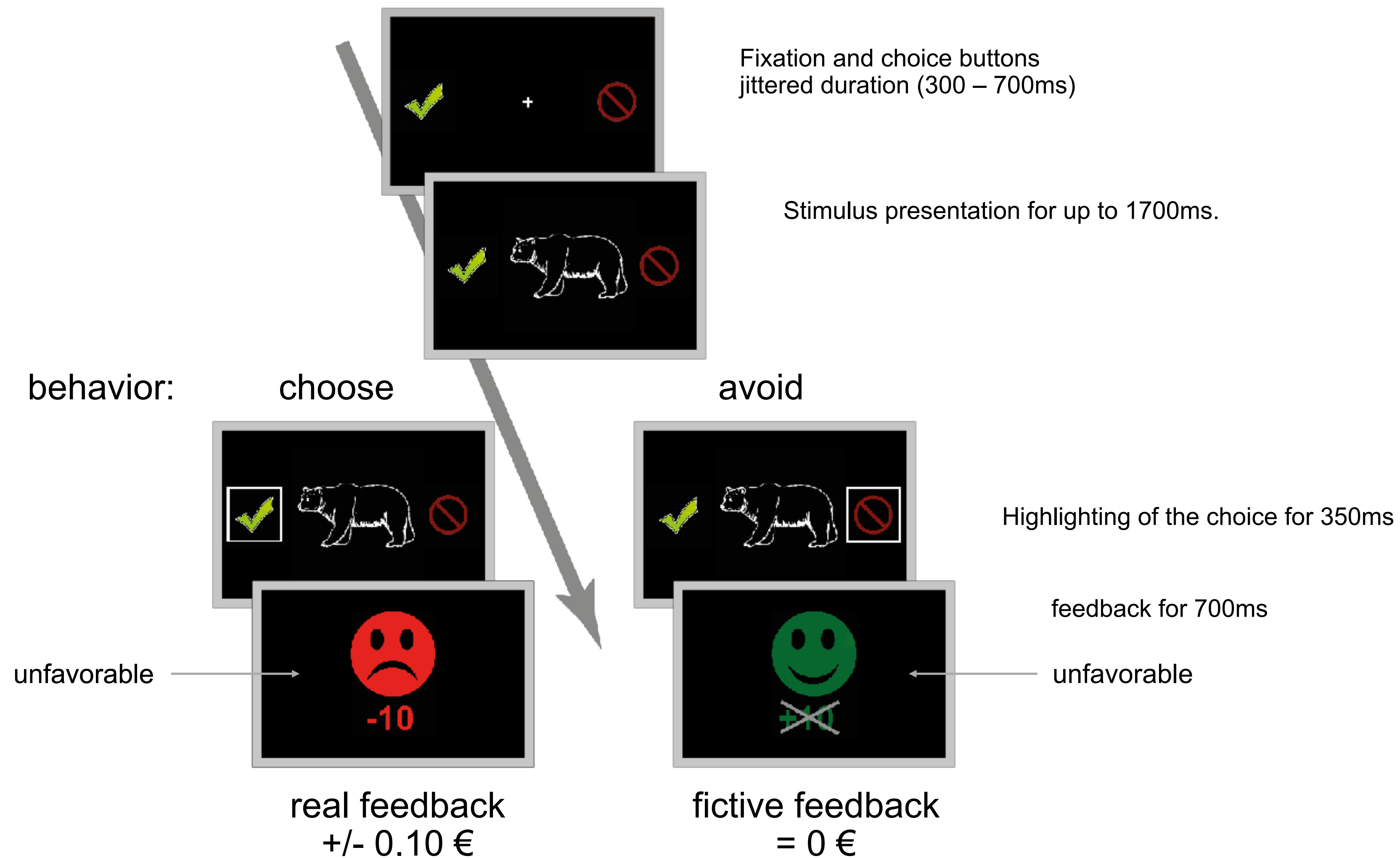
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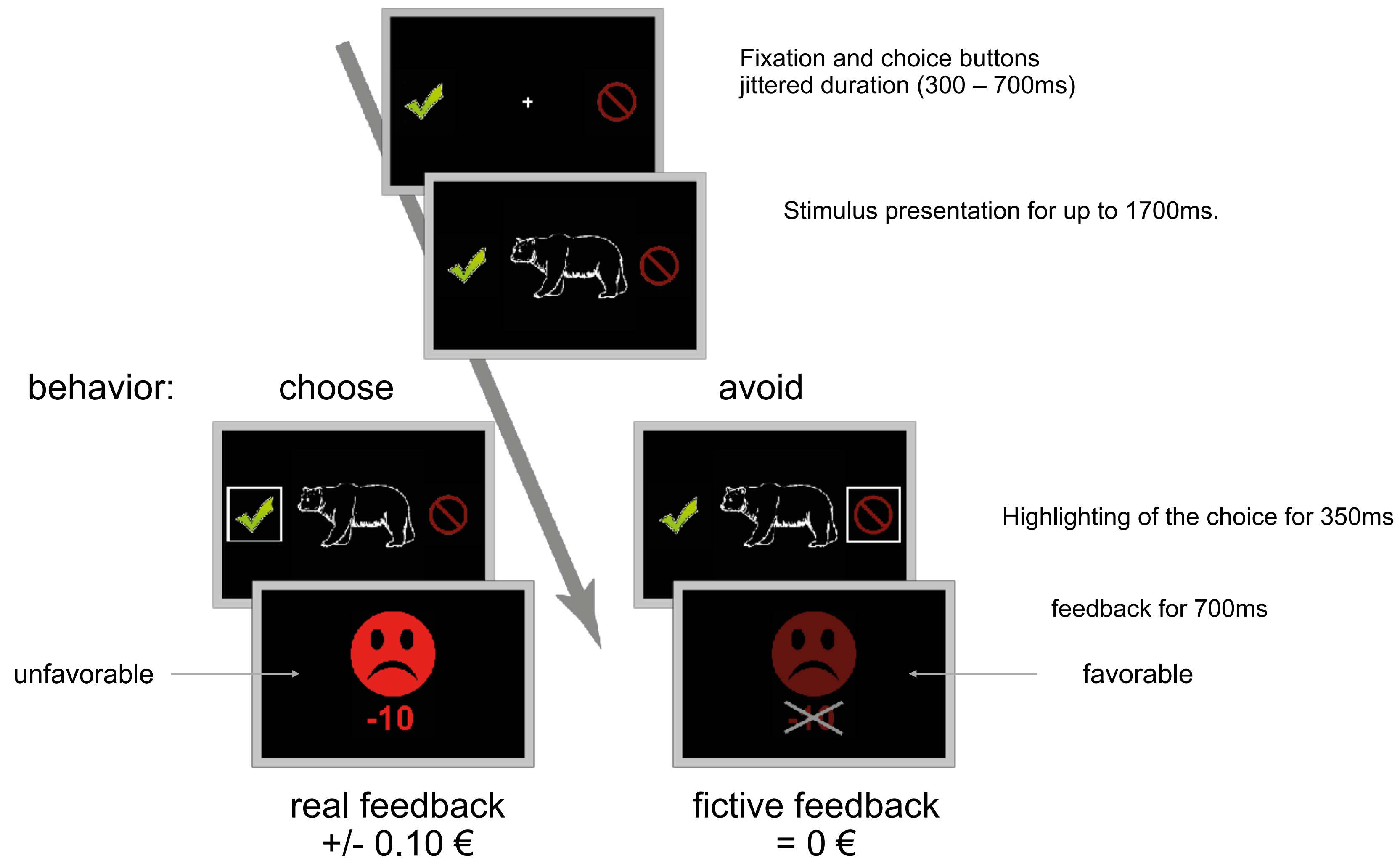
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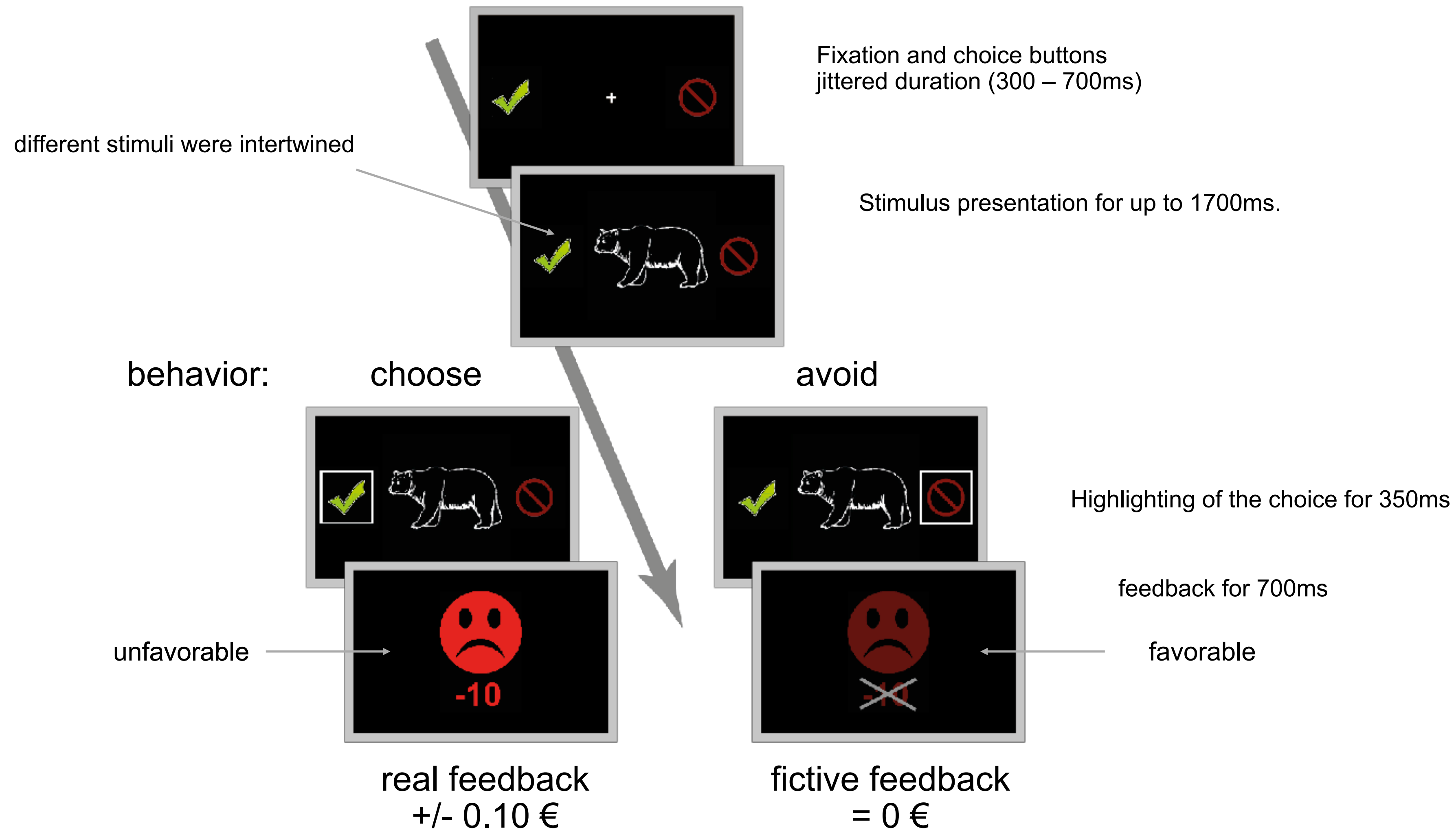
Task



Task



Task



Computational Model

Learning rate: Amount of value updating that decreases over time

$$\alpha_{c,t} = \frac{\alpha_{c,1}}{2^{\left(\frac{t-1}{Hl_c}\right)}} \text{ and } \alpha_{a,t} = \frac{\alpha_{a,1}}{2^{\left(\frac{t-1}{Hl_a}\right)}}$$

Prediction error: Signed deviation from expected outcome

$$\delta_t = R_t - Q_t$$



	real	fictive
positive δ	favorable	unfavorable
negative δ	unfavorable	favorable

Expected value of the stimulus:

$$Q_{t+1} = \begin{cases} Q_t + \alpha_{c,t}\delta_t & \text{if chosen} \\ Q_t + \alpha_{a,t}\delta_t & \text{if avoided} \end{cases}$$

Likelihood:

$$P_{c,t} = \frac{1}{1 + \exp(-Q_t\beta)} \text{ and } P_{a,t} = 1 - P_{c,t}$$

Computational Model

Single-trial model predictions: 

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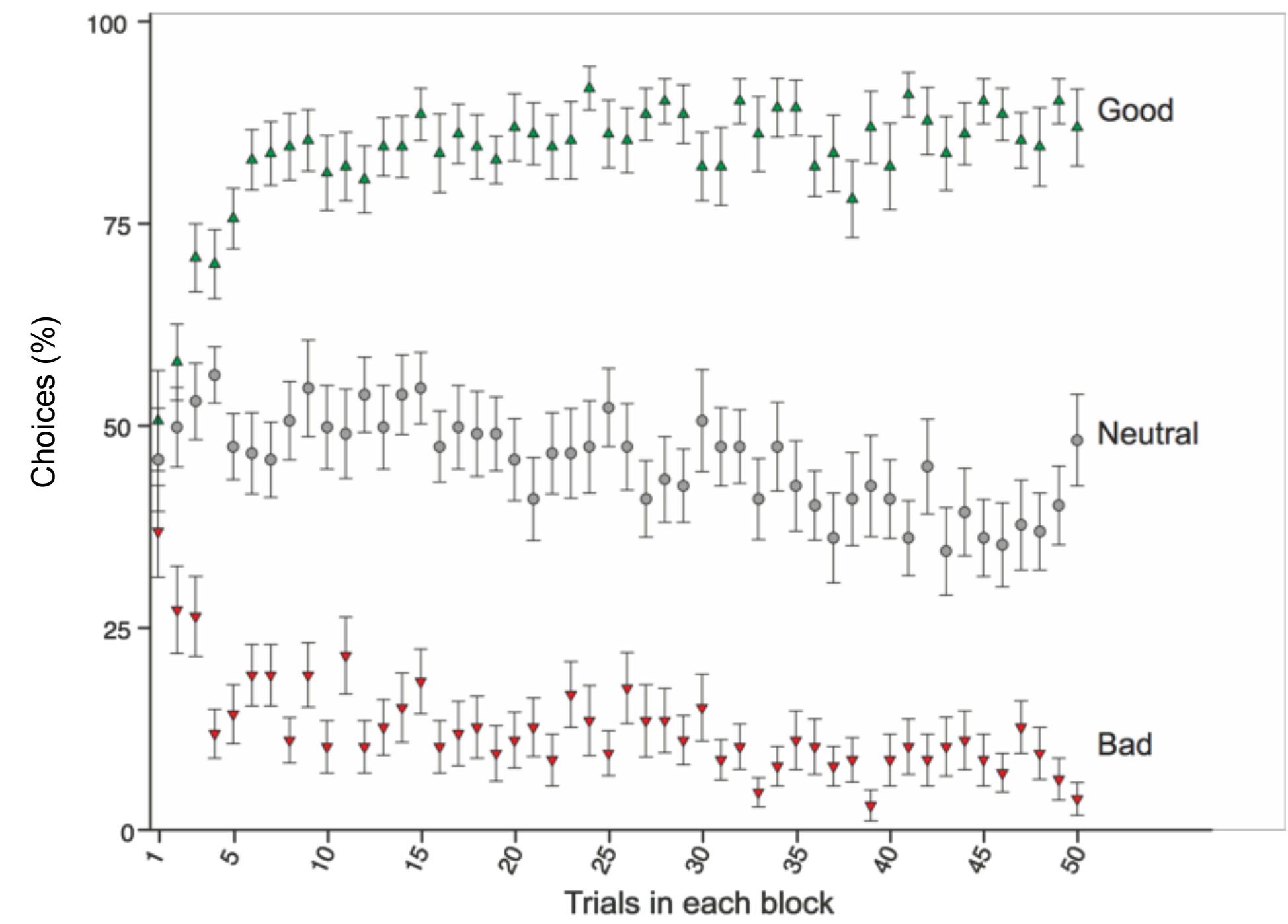
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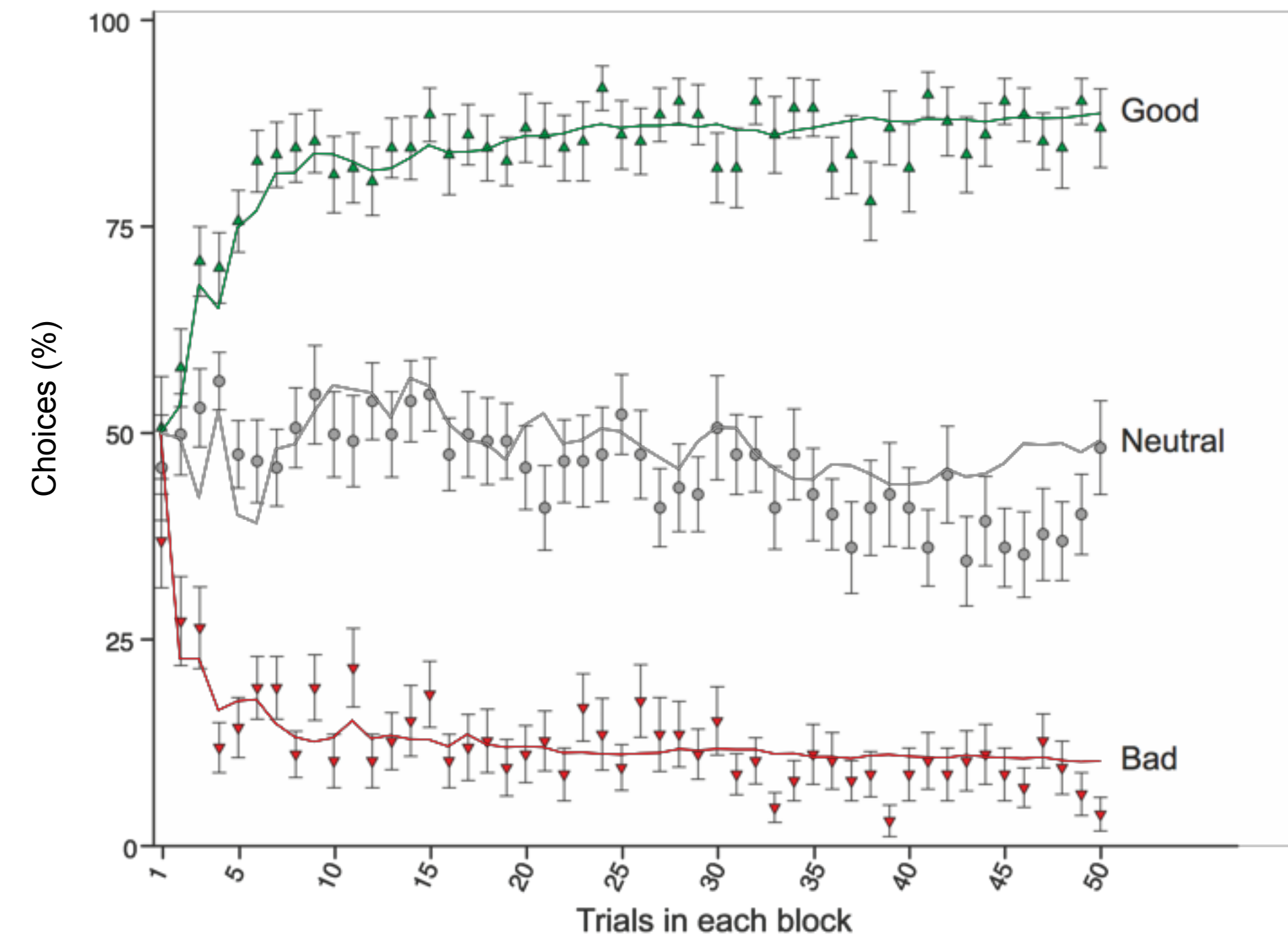
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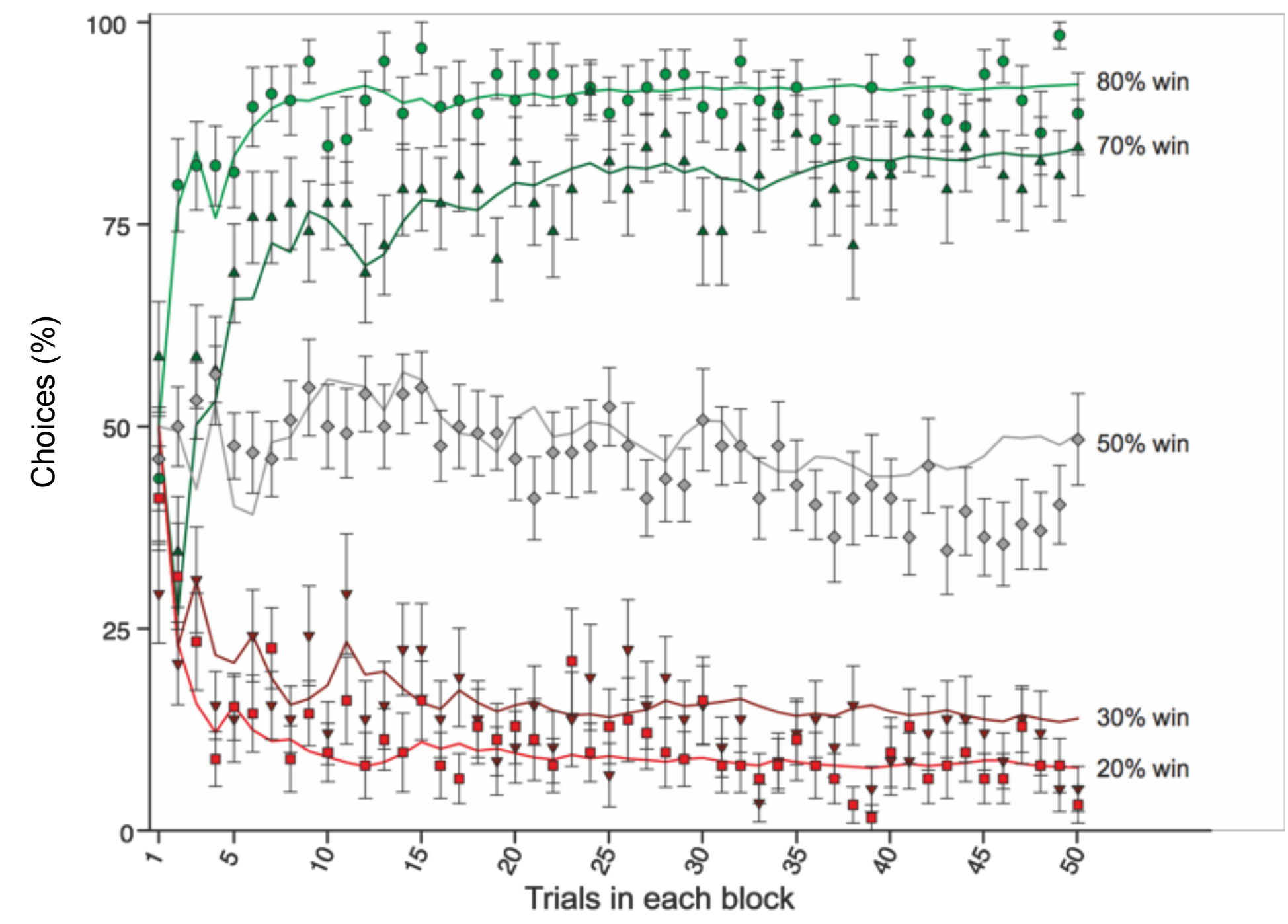
Computational Model

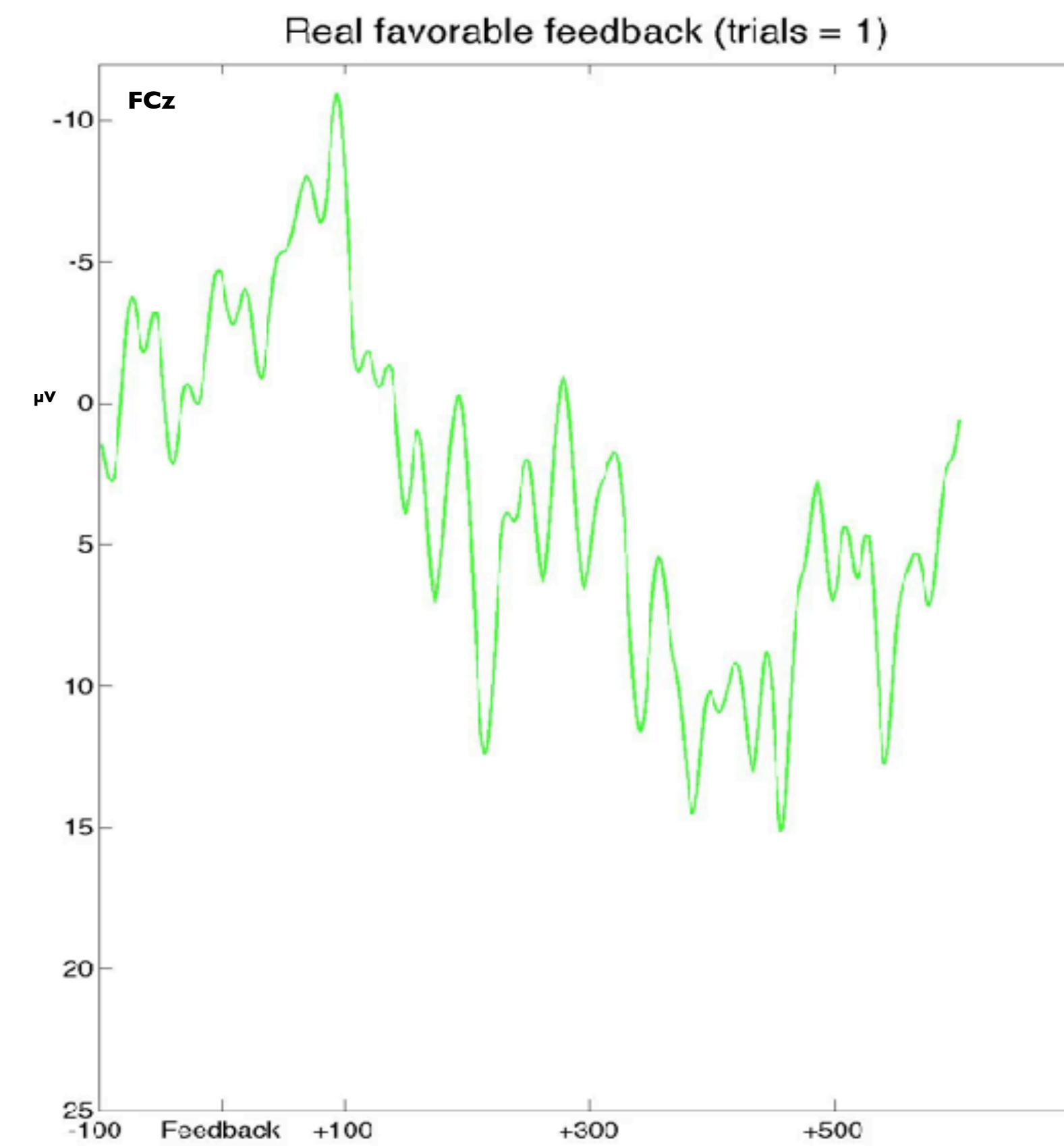
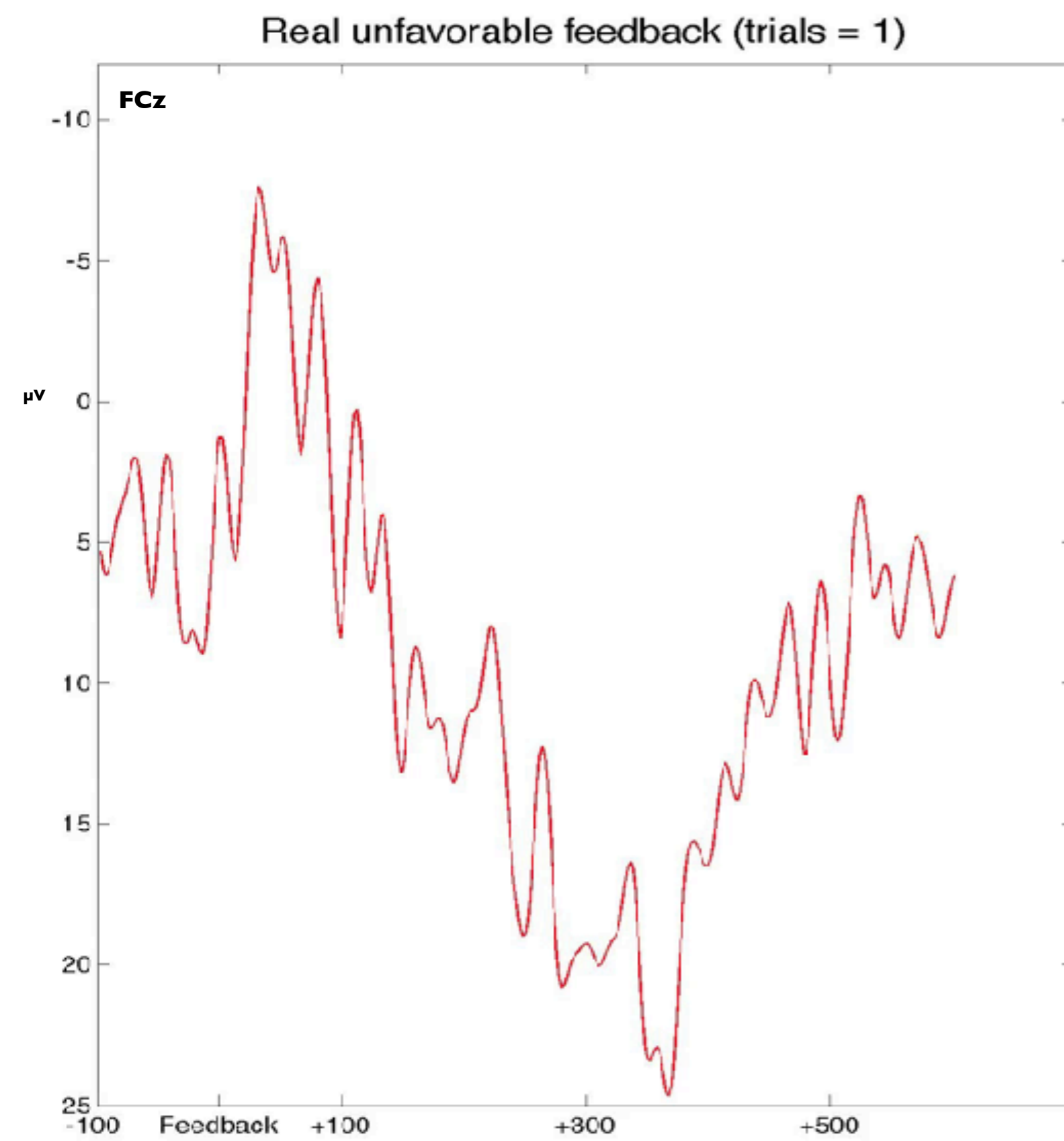


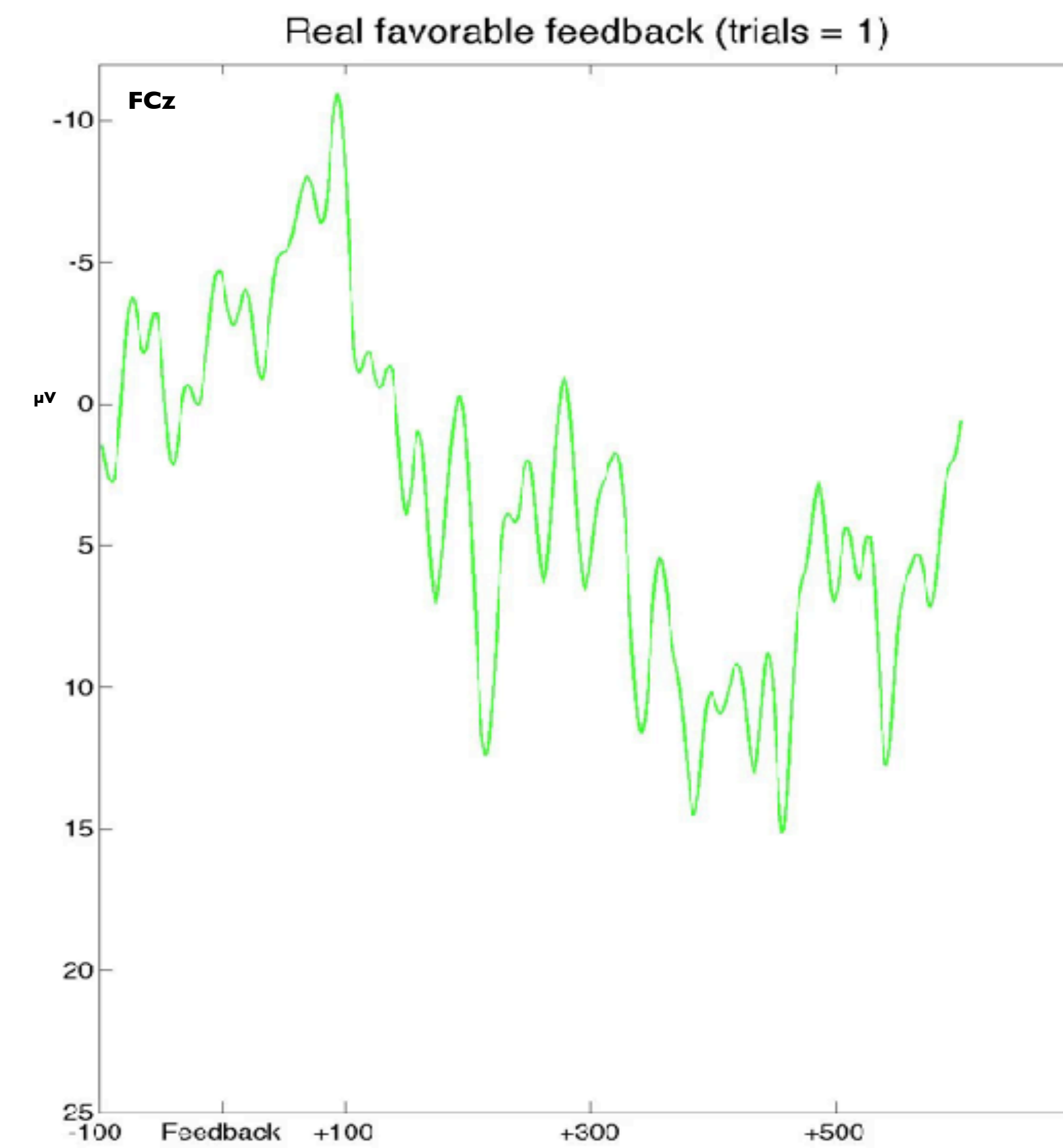
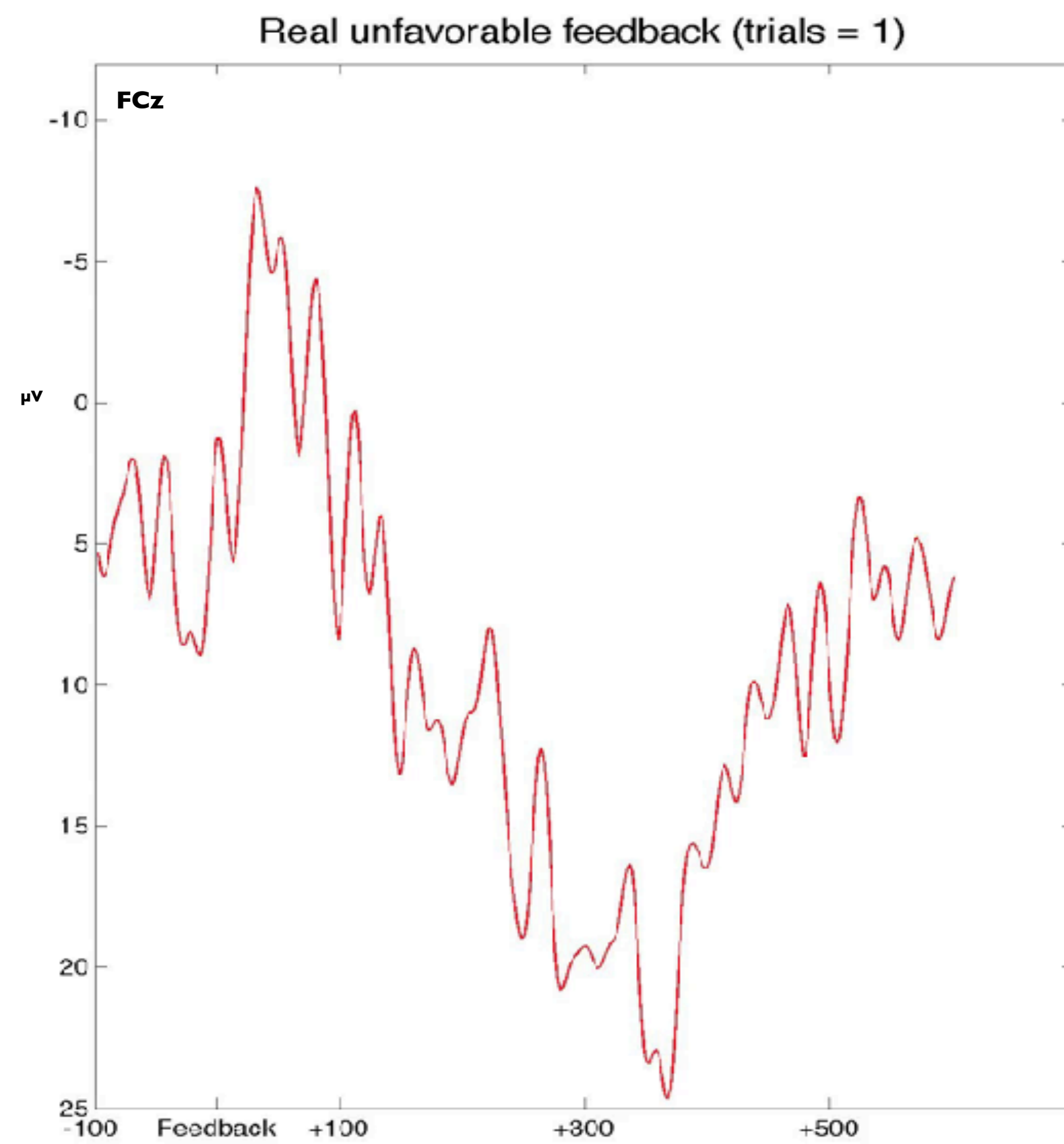
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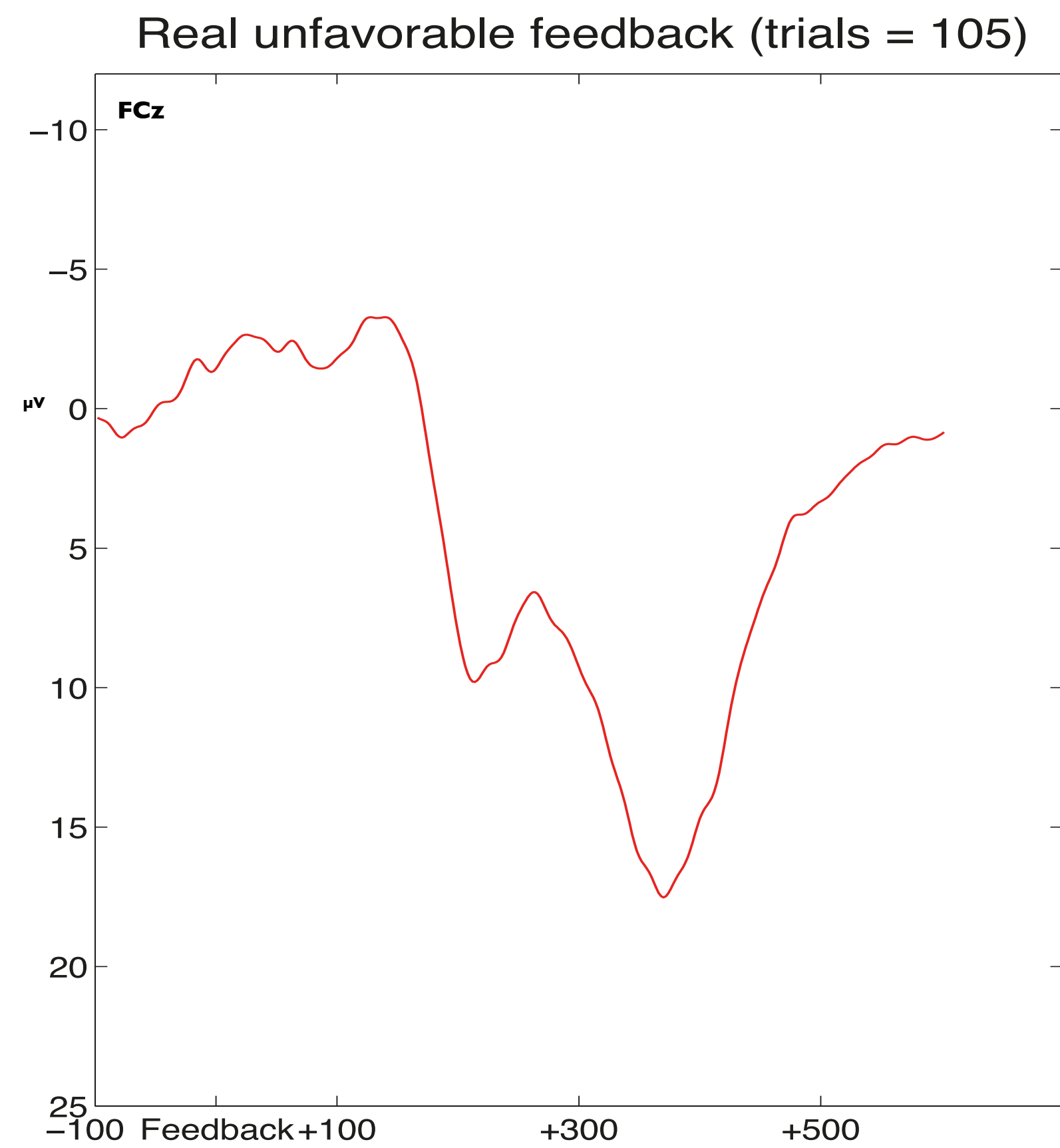


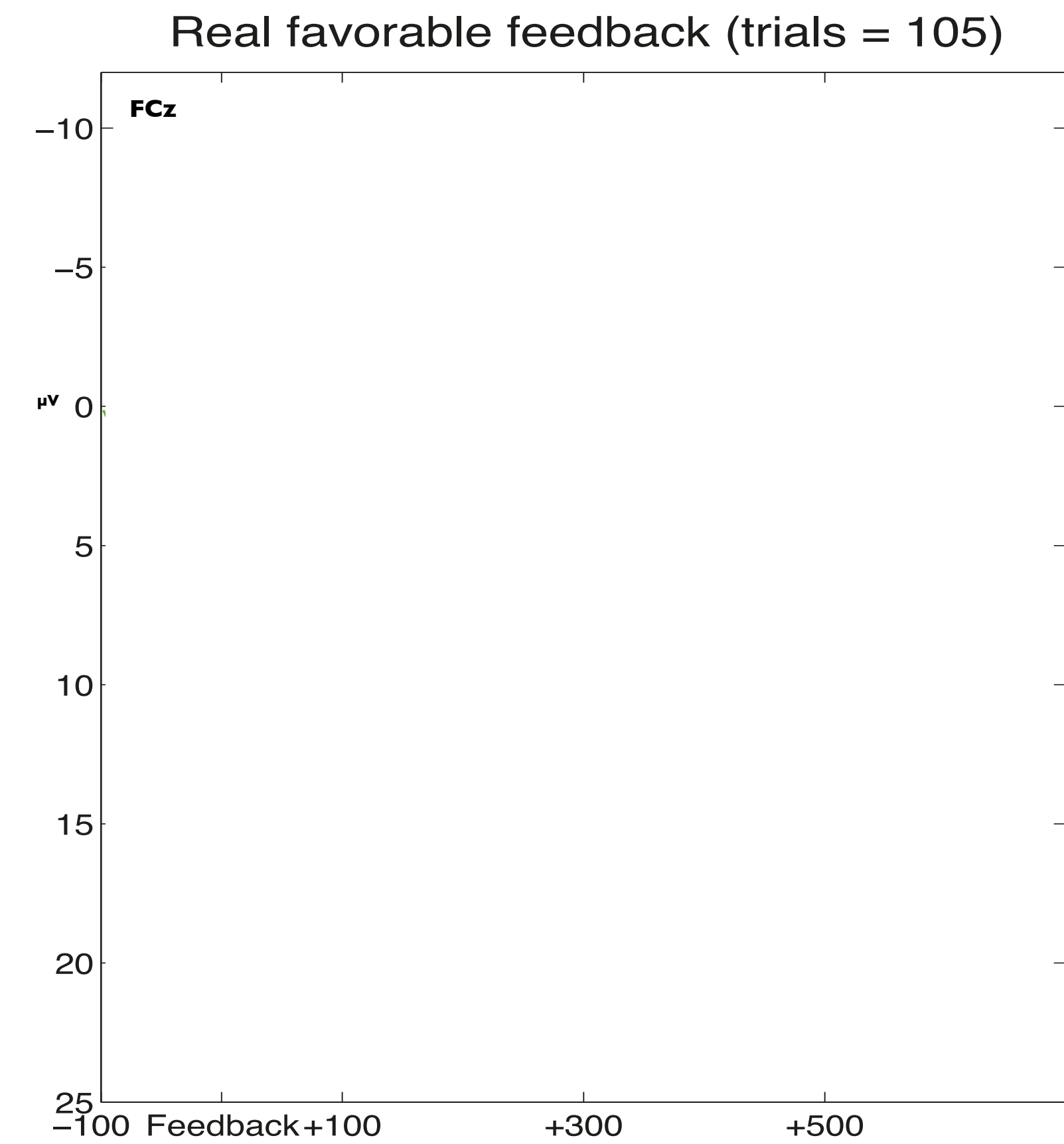
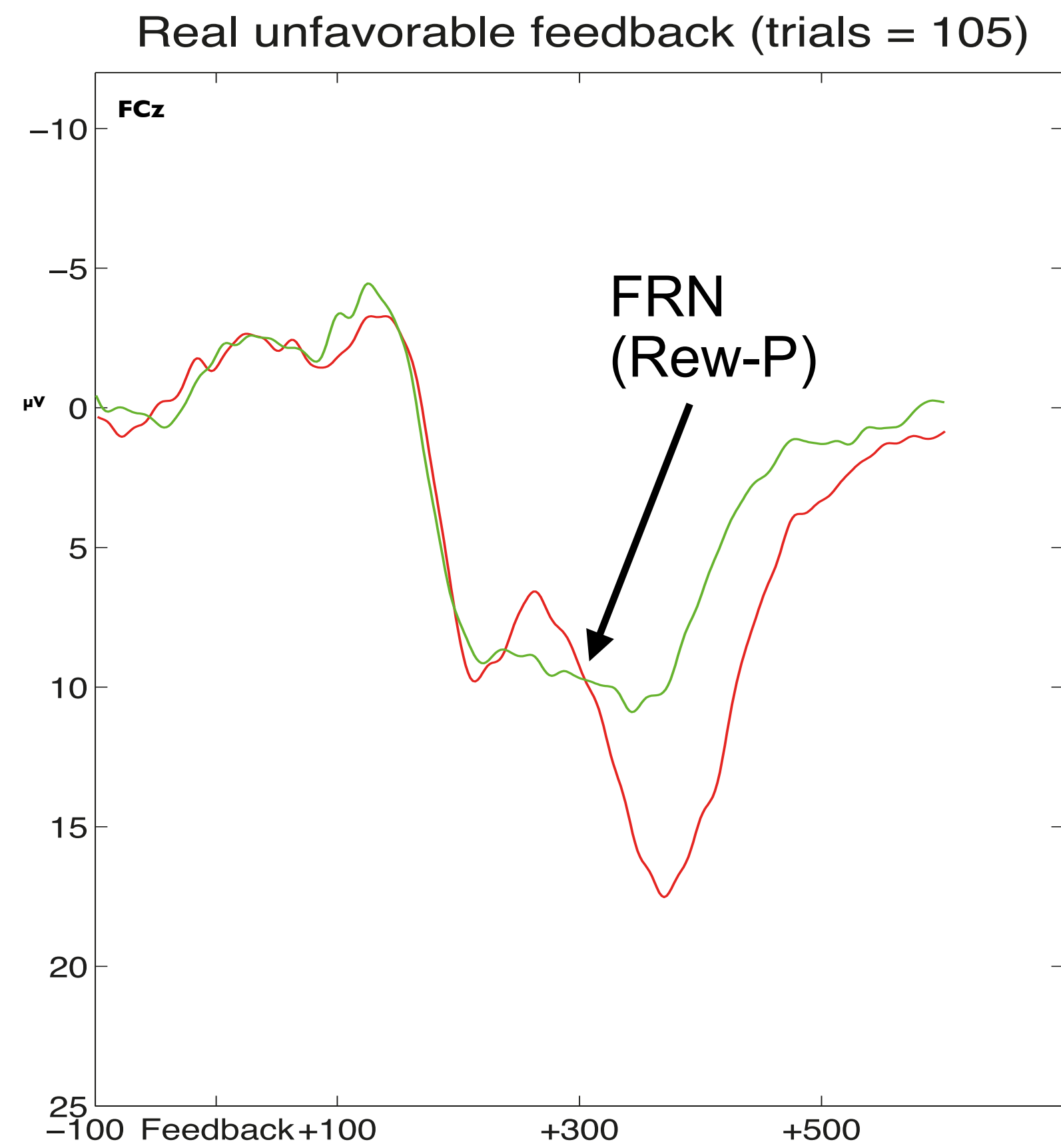
Computational Model









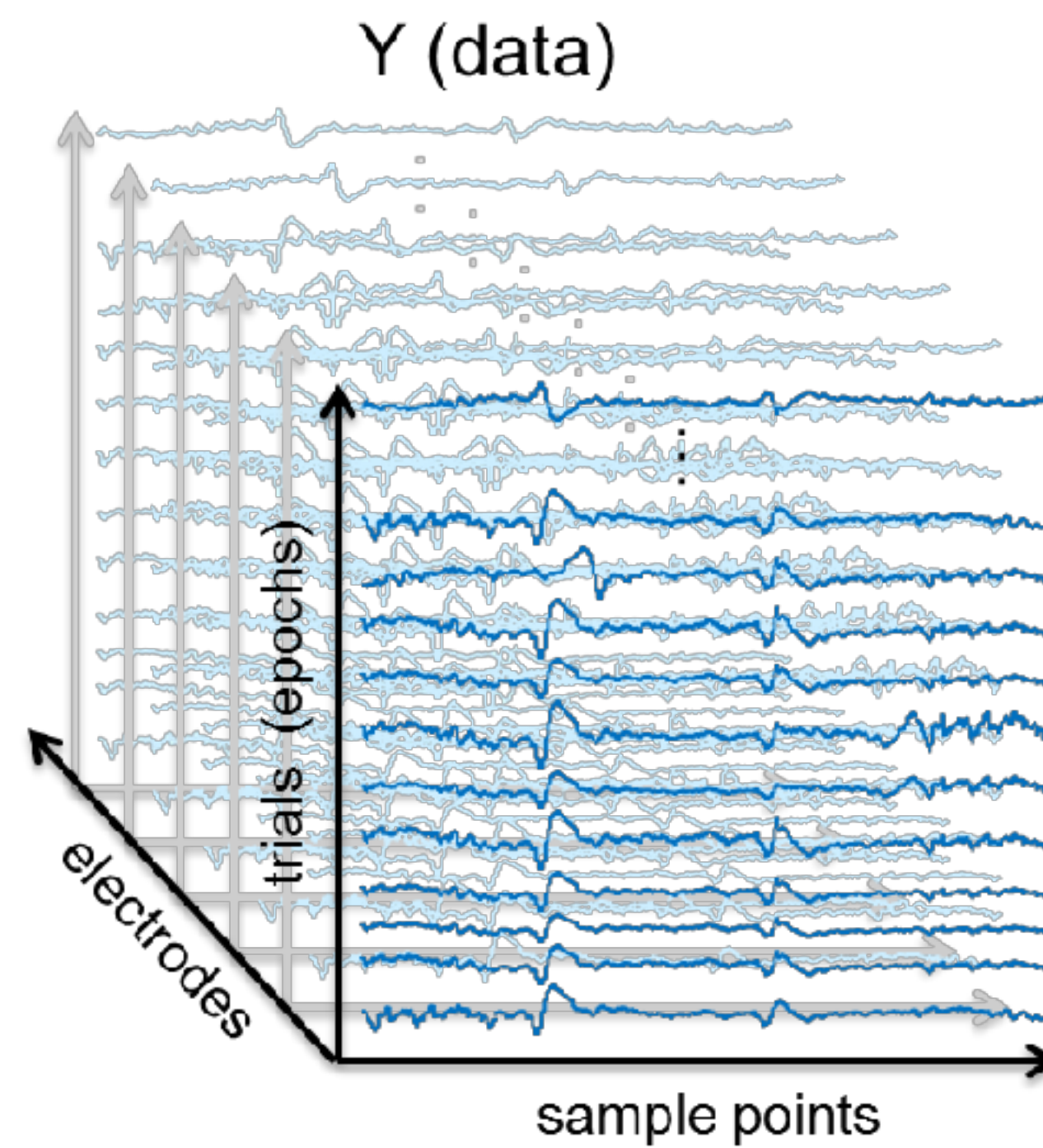


1st level

$$Y = \beta X + \varepsilon$$

1st level

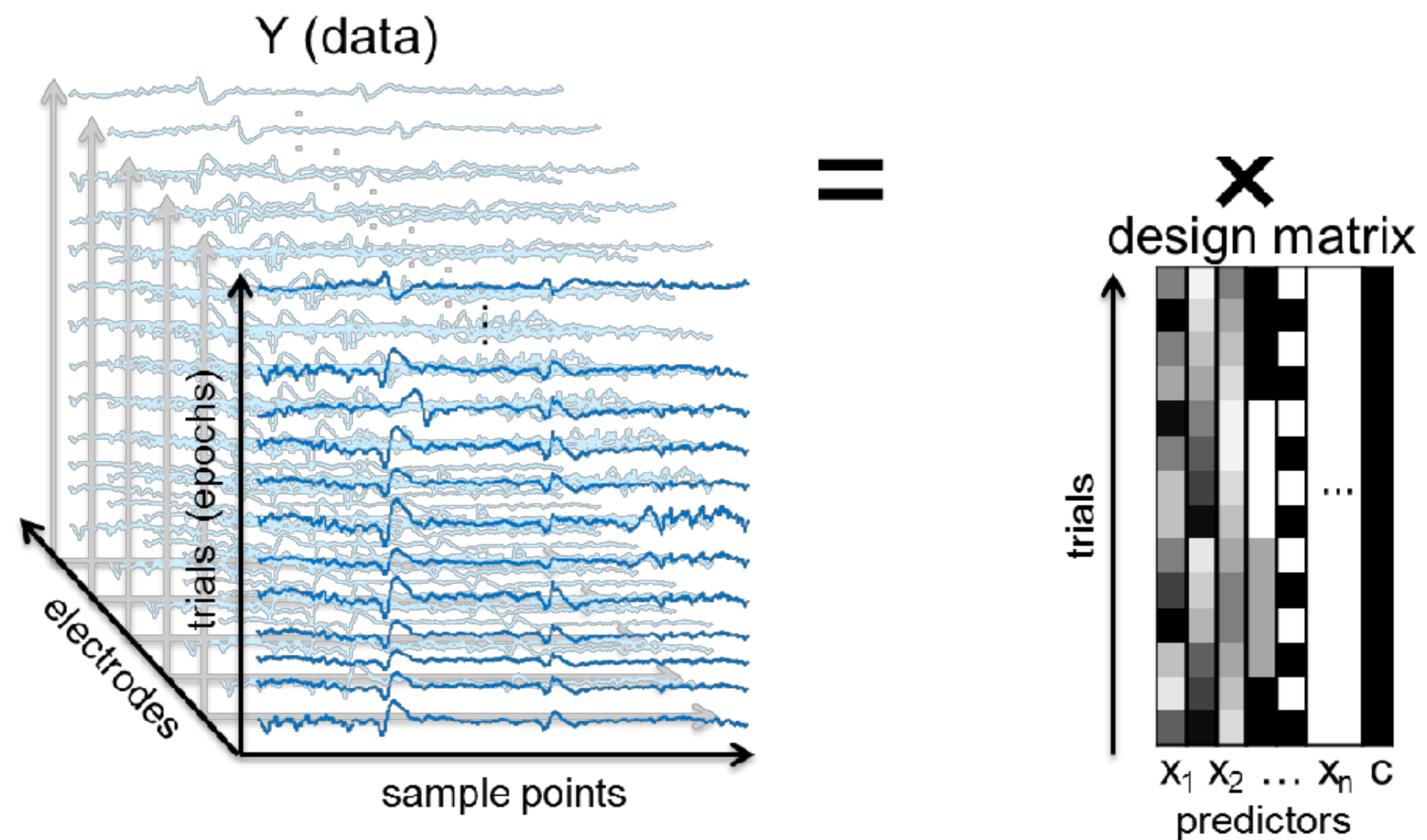
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GLM for EEG

1st level

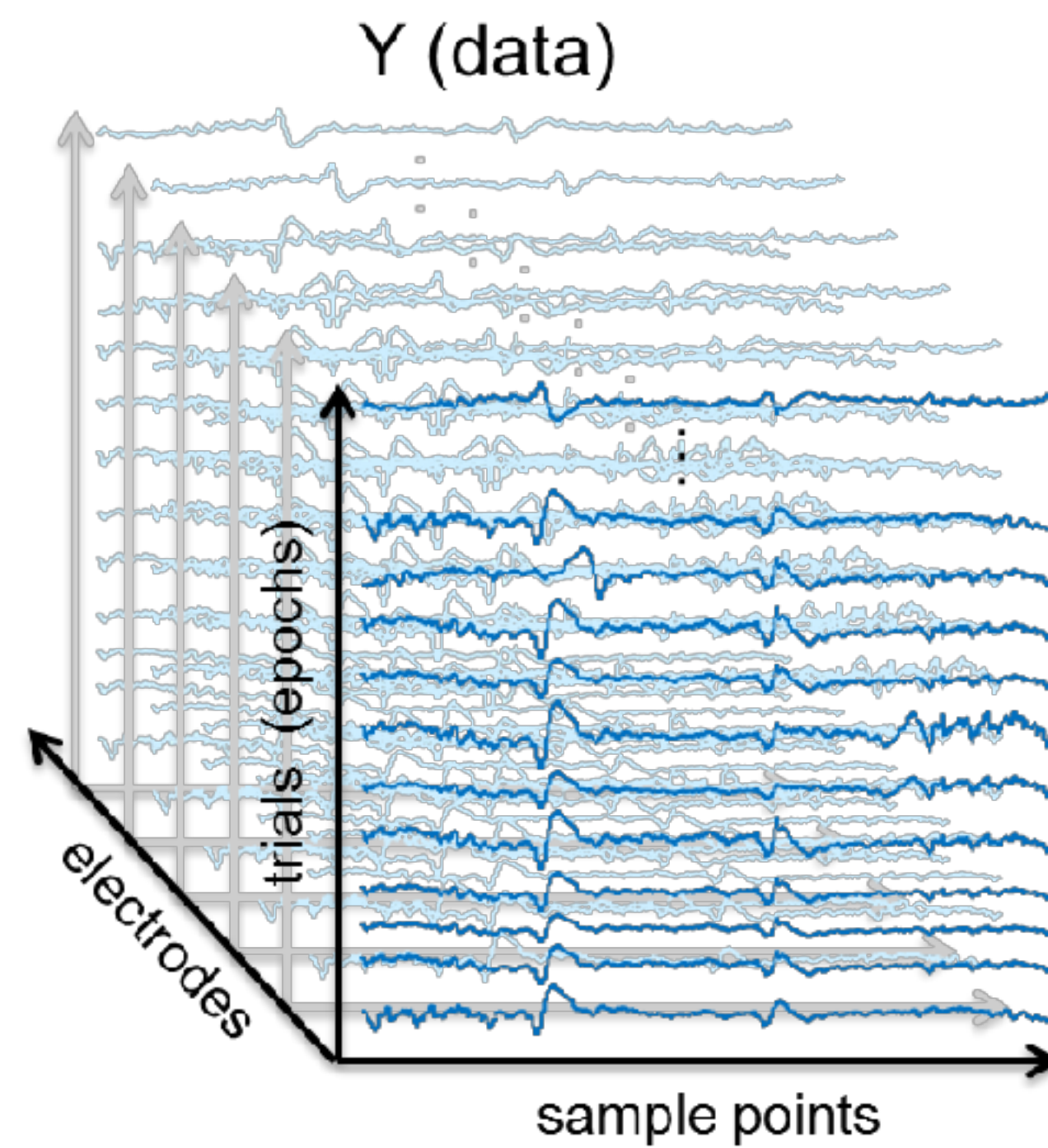
$$Y = \beta X + \varepsilon$$



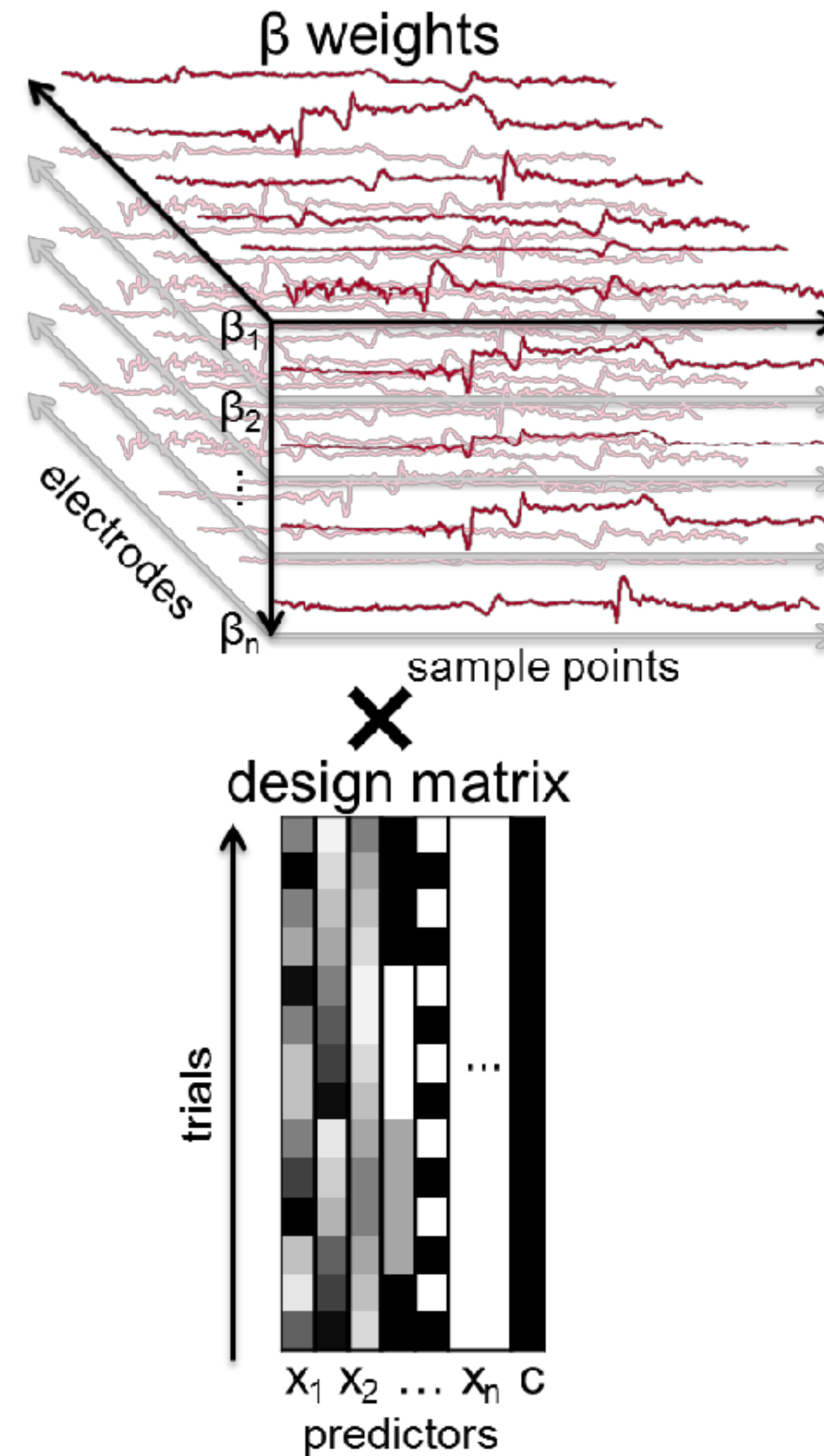
GLM for EEG

1st level

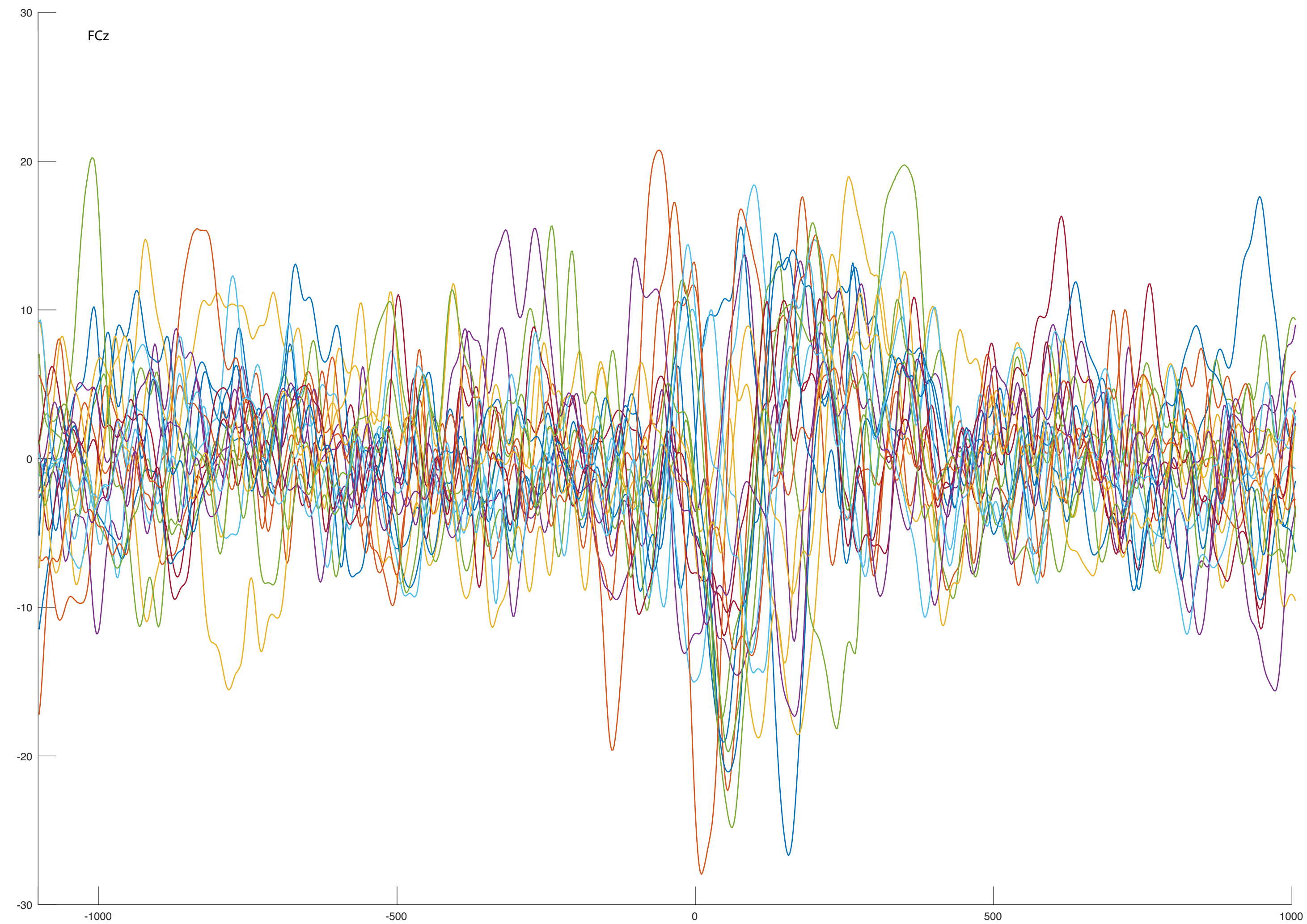
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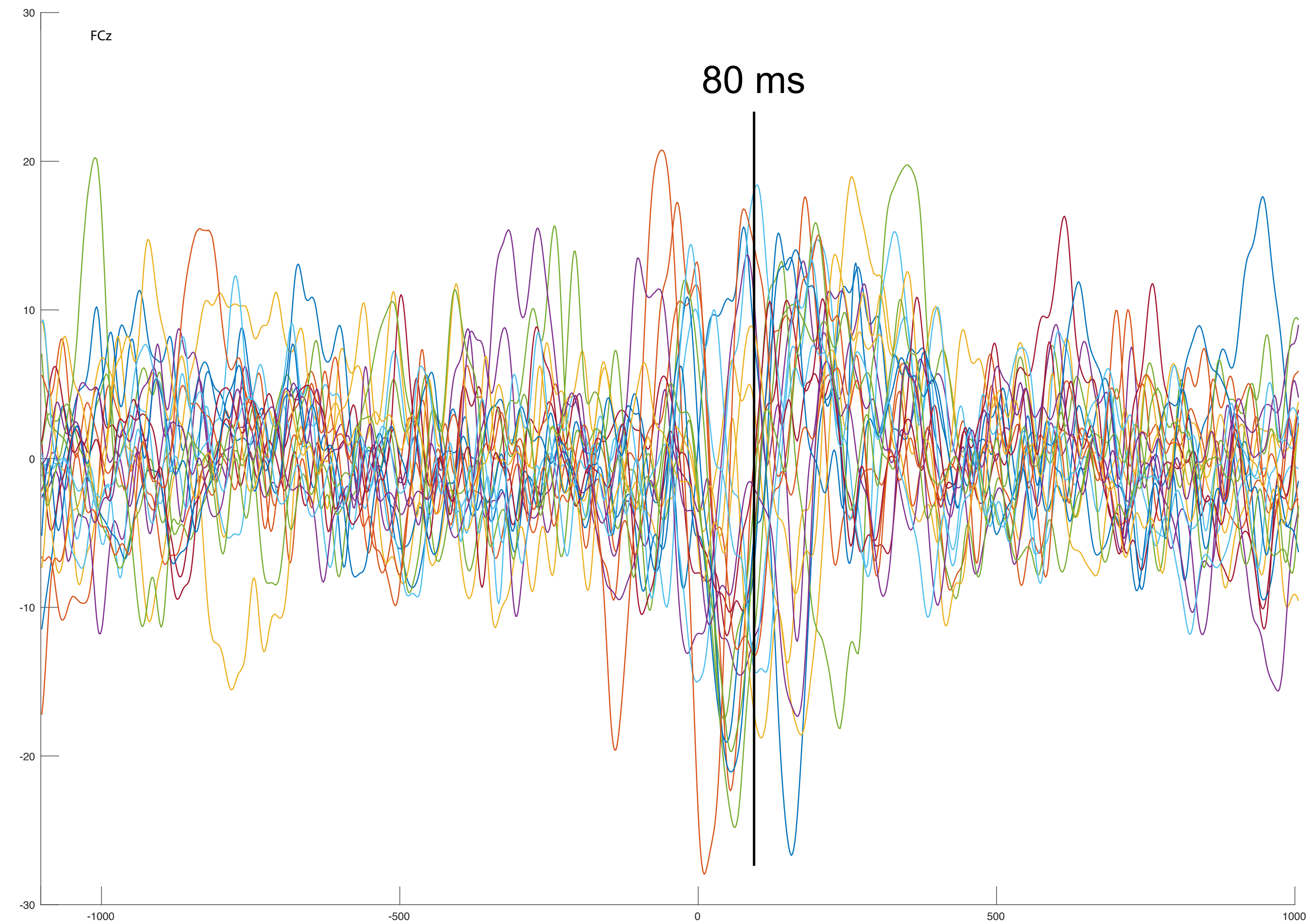
=



GLM for EEG

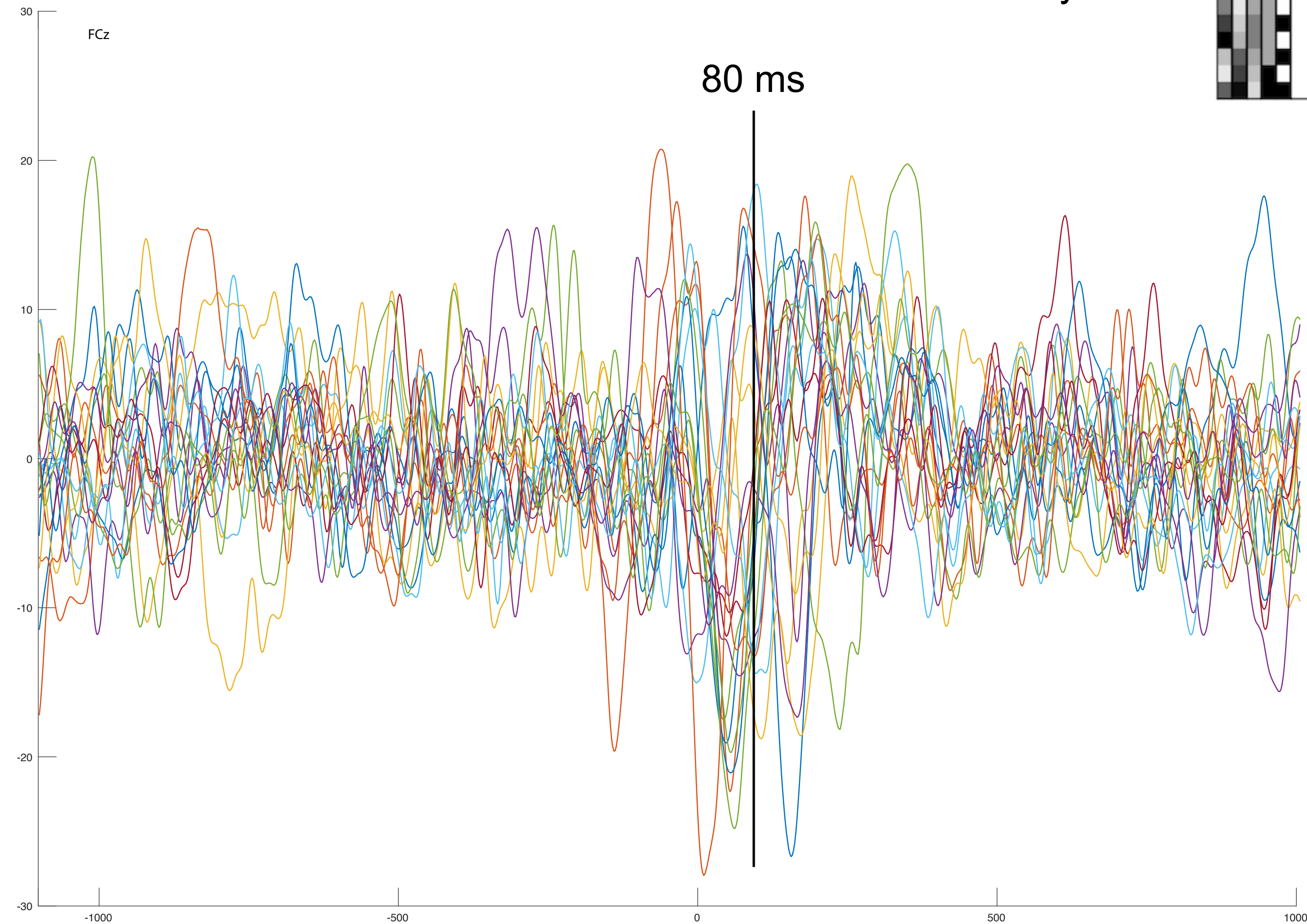
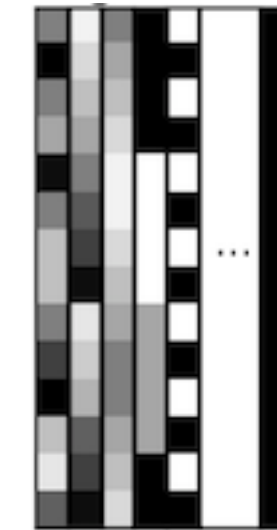


GLM for EEG

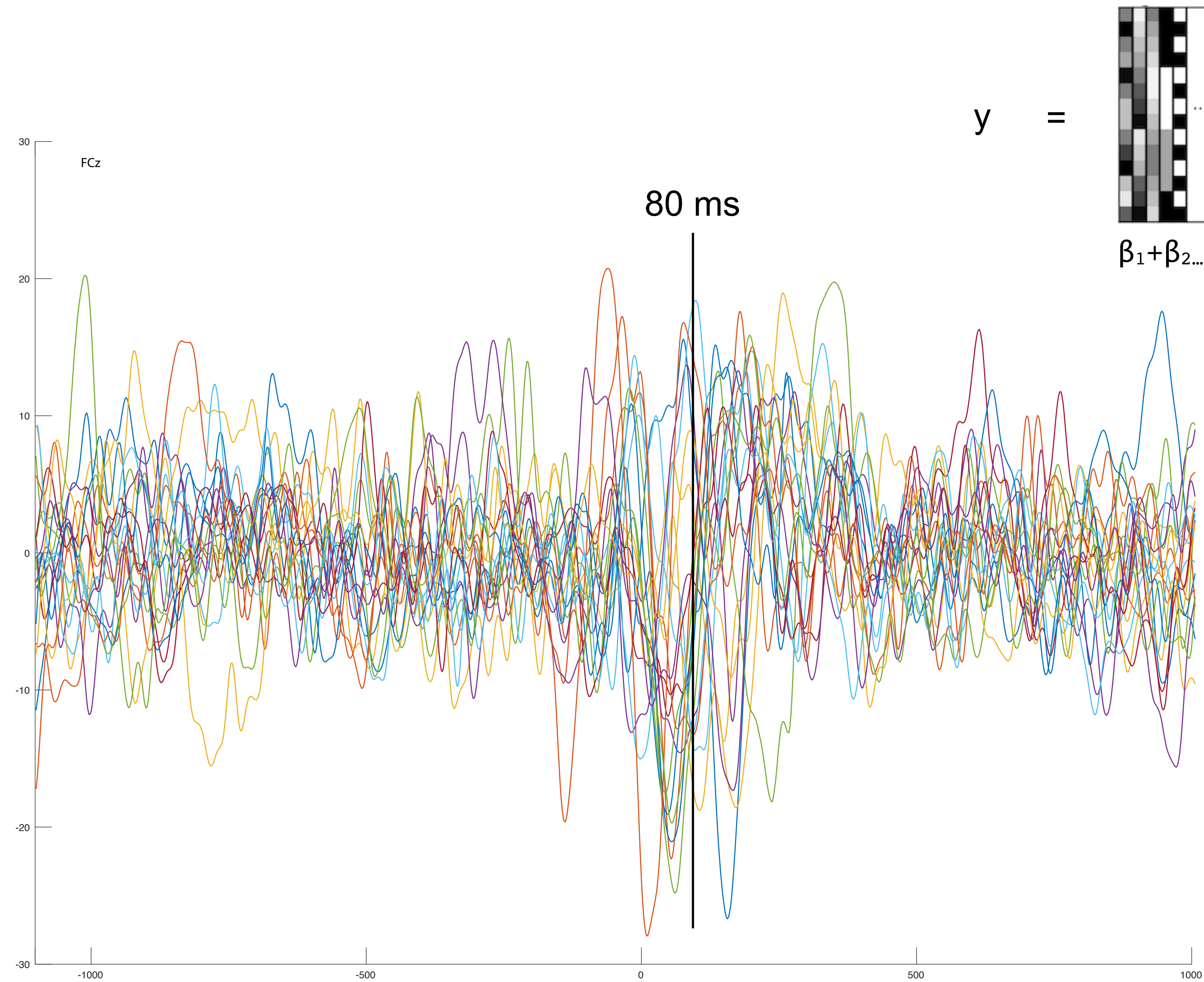


GLM for EEG

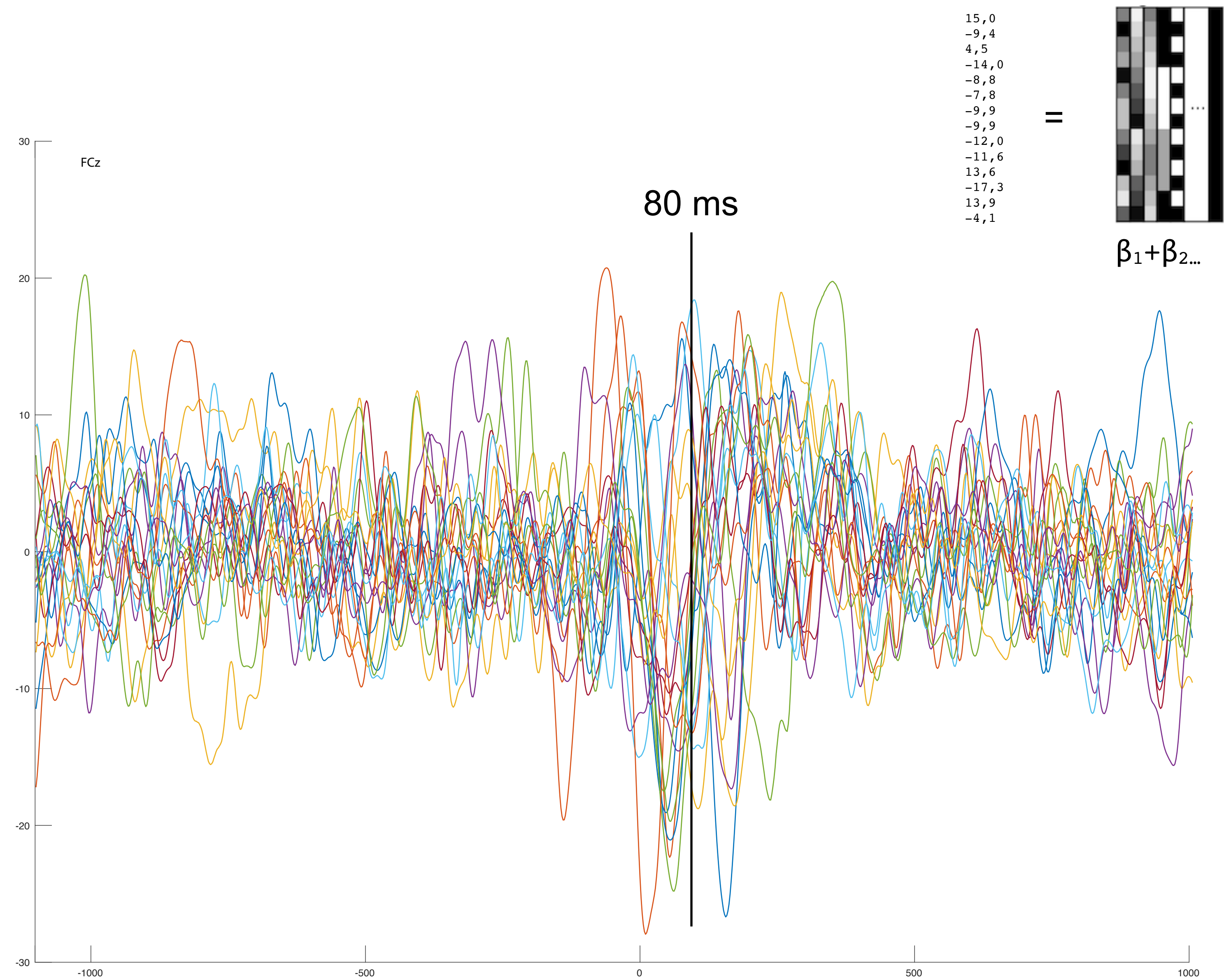
$y =$



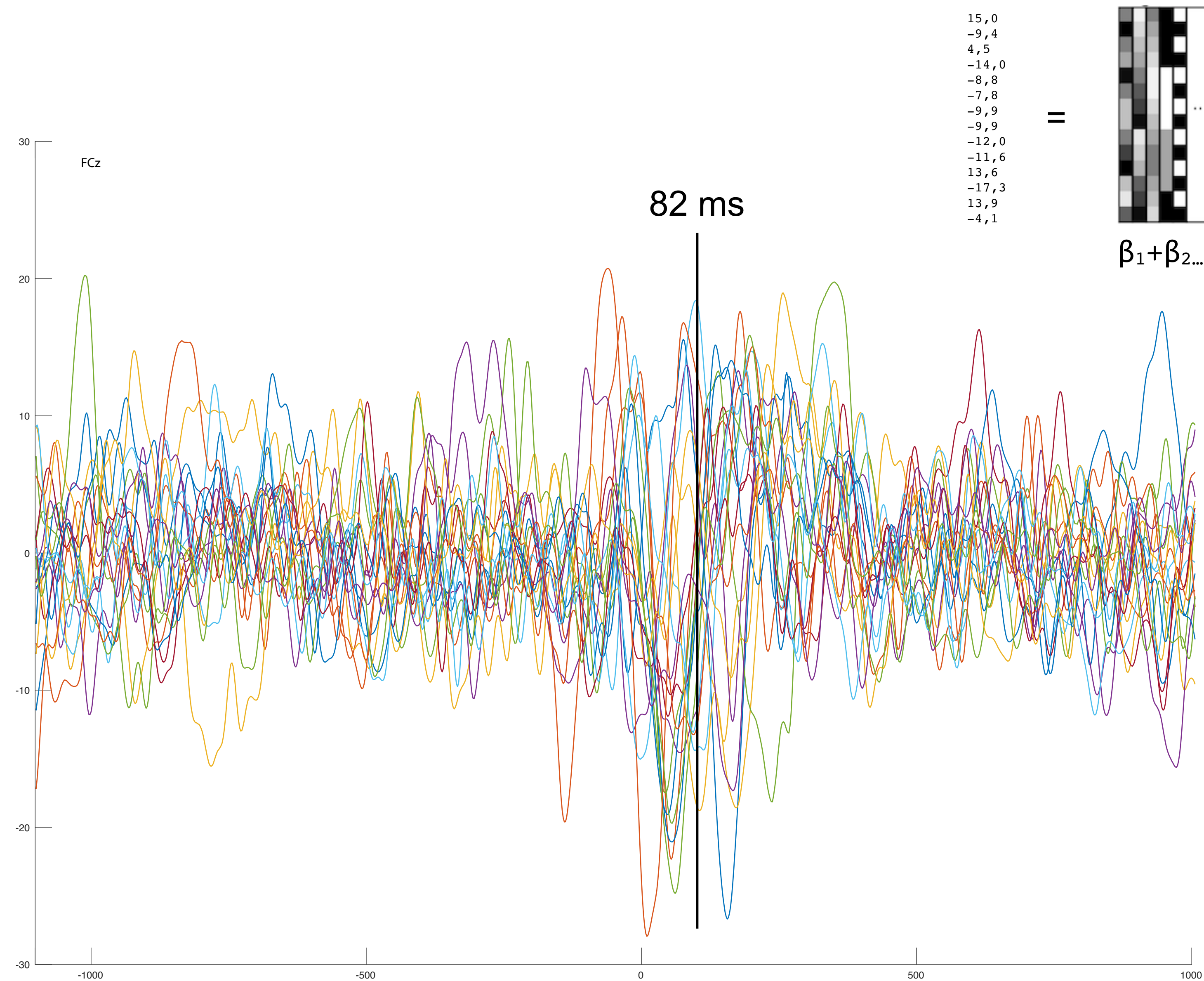
GLM for EEG



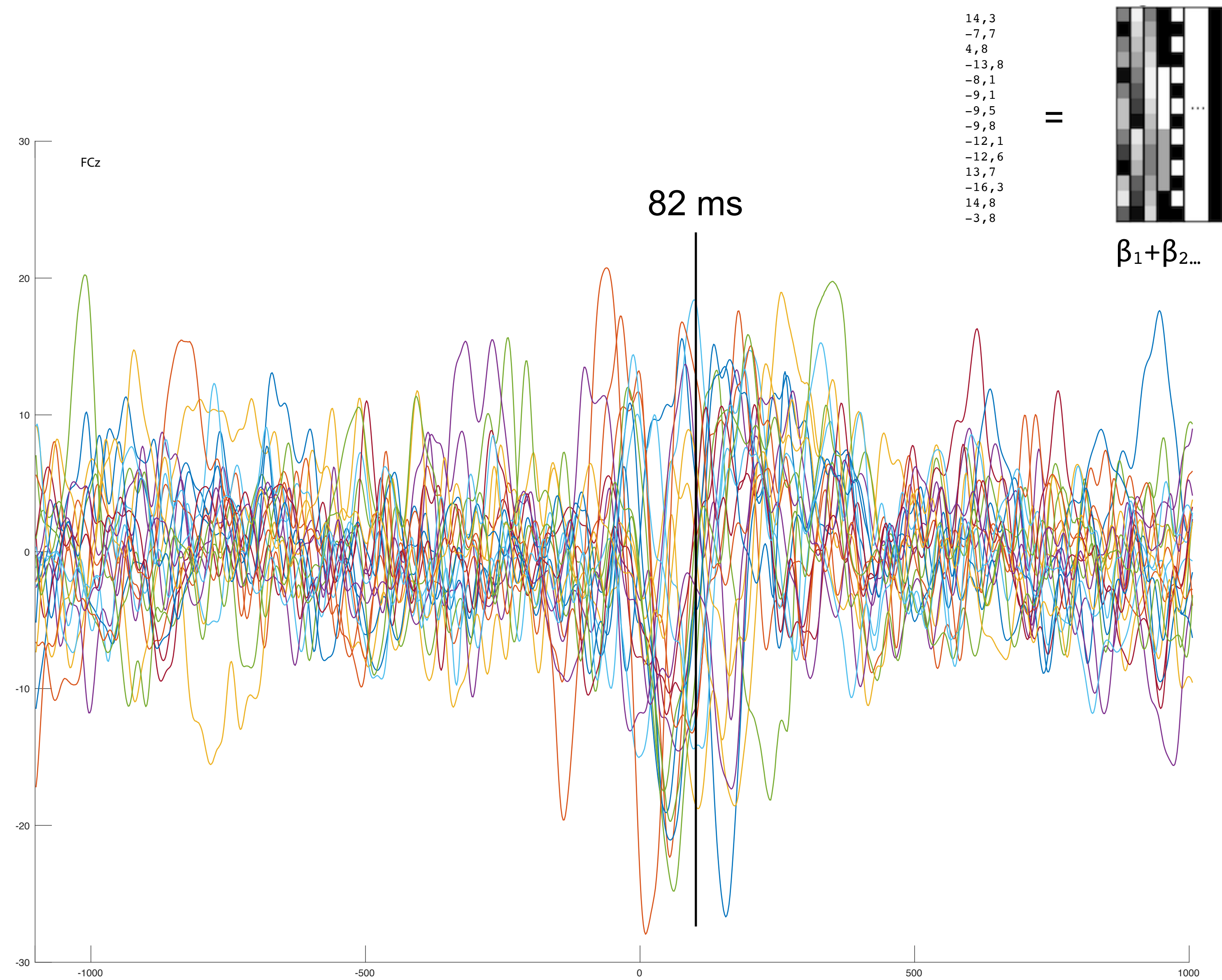
GLM for EEG



GLM for EEG



GLM for EEG



GLM for EEG



- Difference to fMRI: no convolution necessary (we want to preserve the temporal resolution)

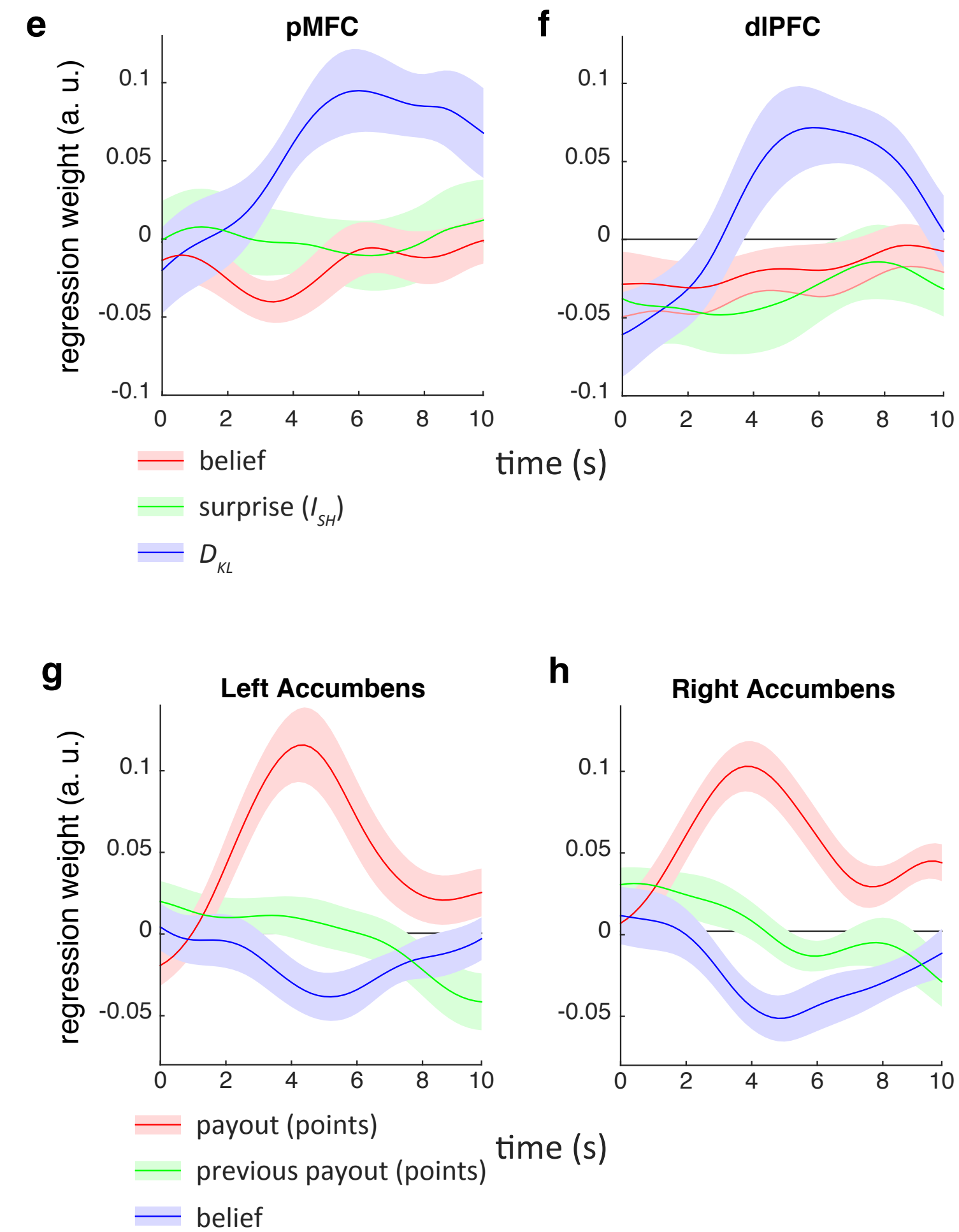
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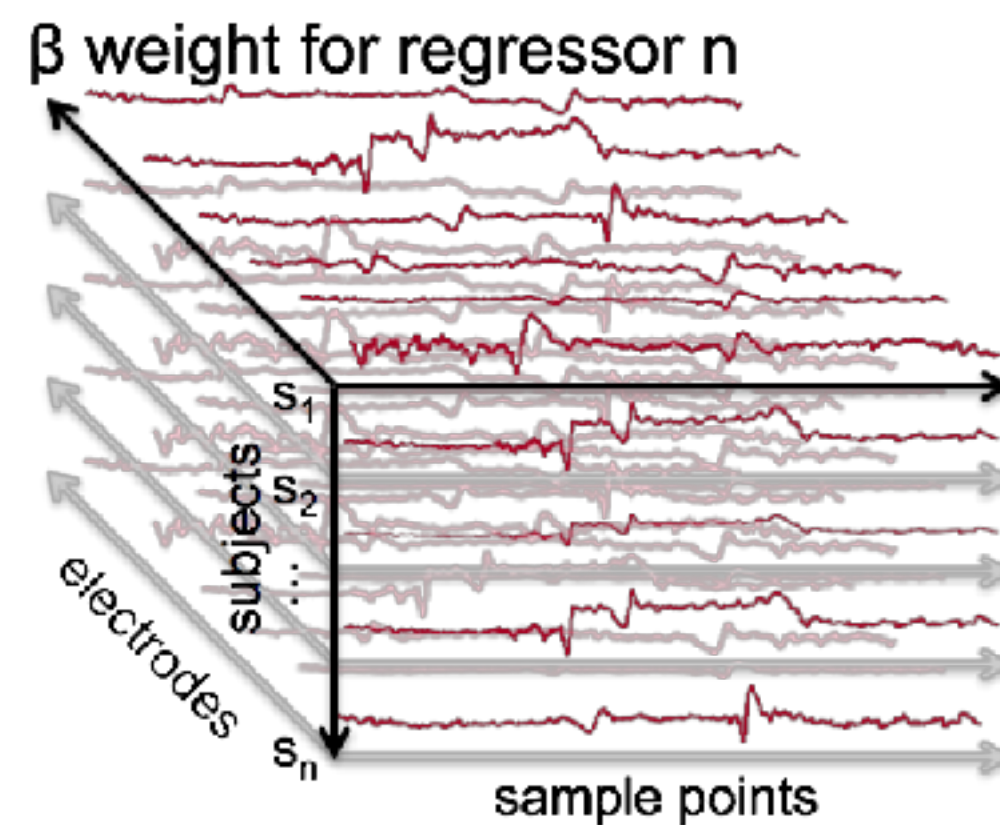
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 - ▶ but there are ways to reduce dimensionality (ICA (Jan later) and MVPA)

- Time-resolved analyses are not restricted to EEG



2nd level:

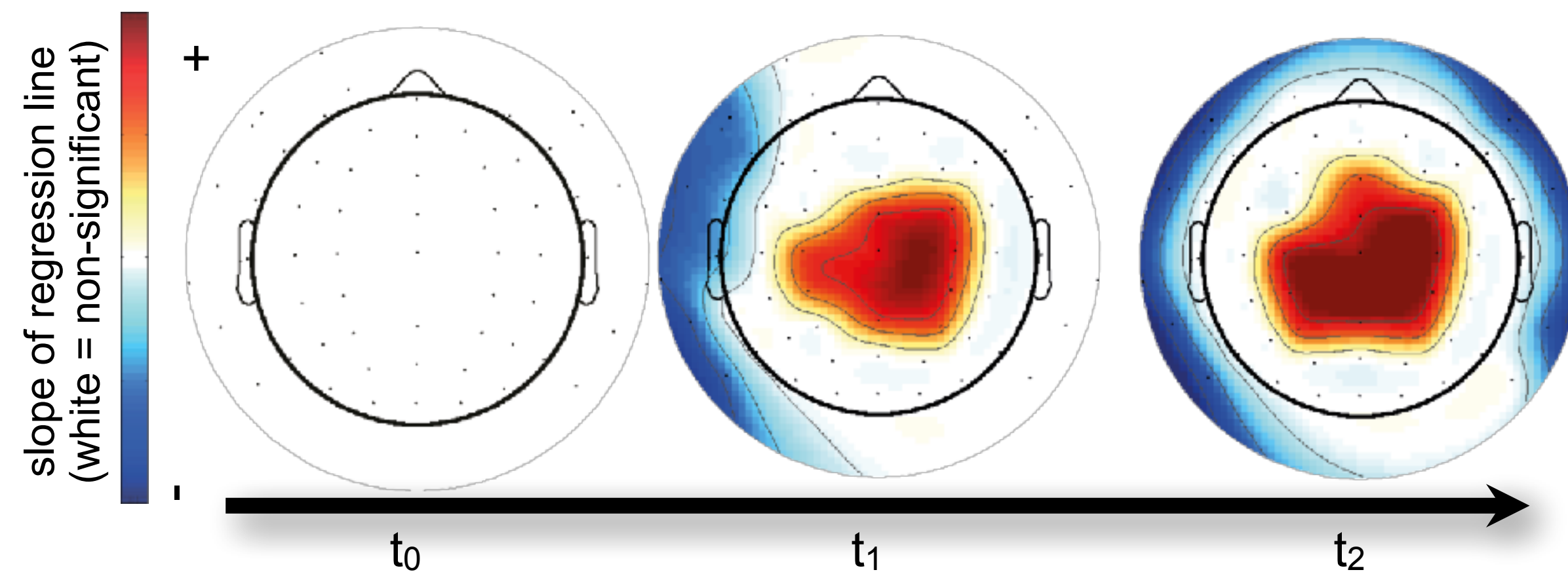
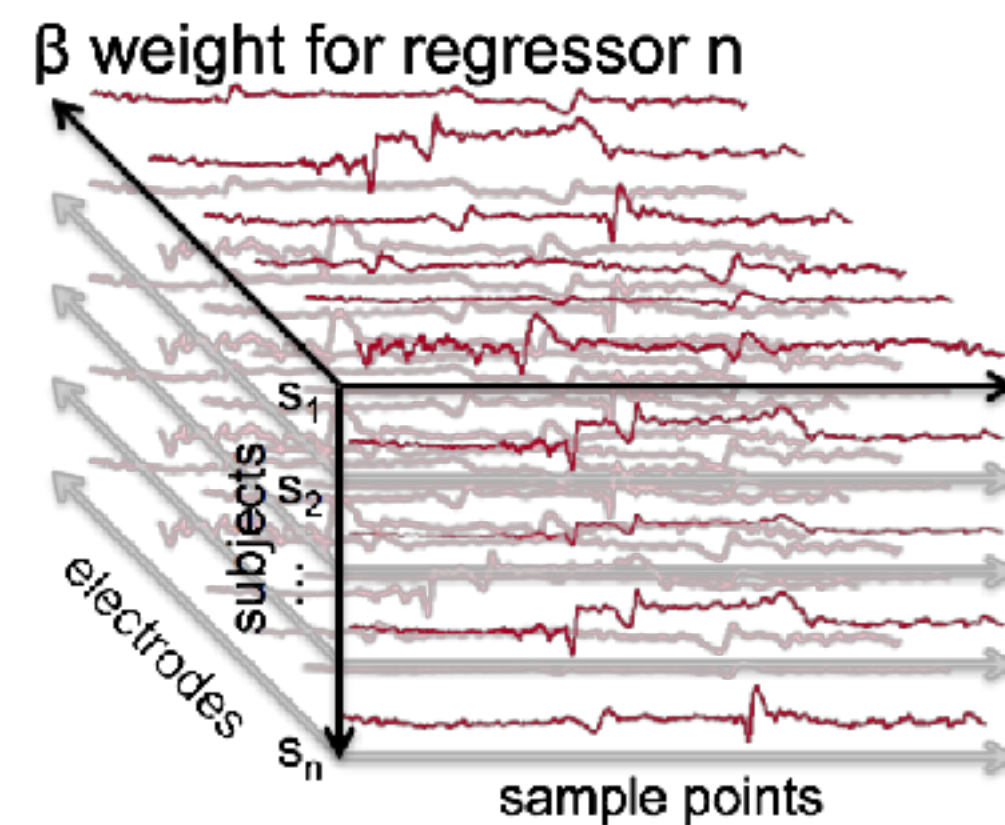
- b - or t -value time-courses for every predictor and subject
- t -tests and correction for multiple comparisons using (e.g.) false discovery rate (FDR) (Benjamini & Yekutieli, *Ann Stat*, 2001)
- averaged over subjects revealing time-courses and scalp topographies
- 2nd level model can also include across participants factors (group, age, sex —> *afternoon session*)



GLM for EEG

2nd level:

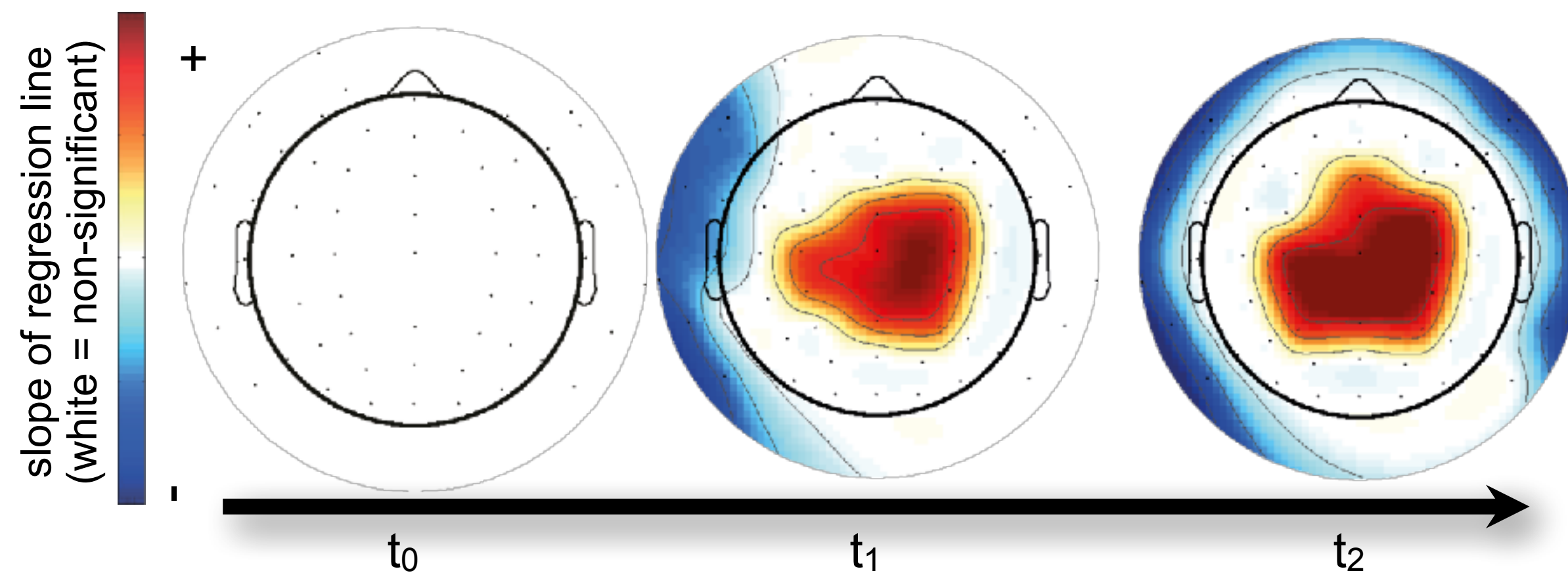
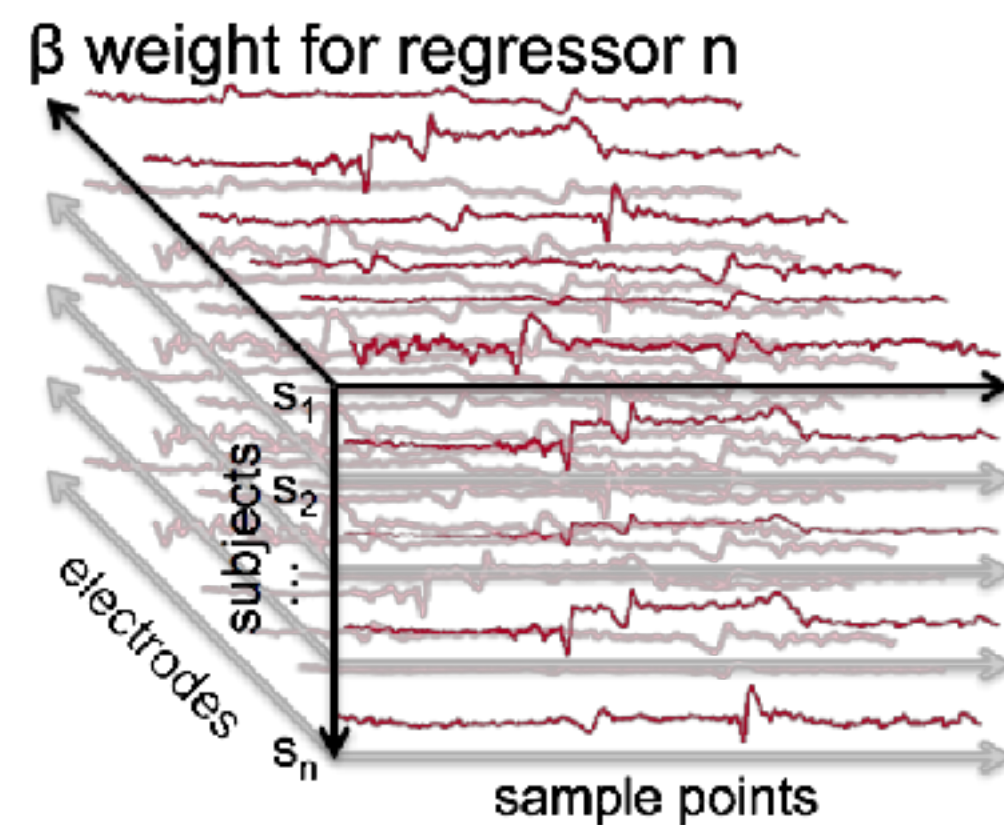
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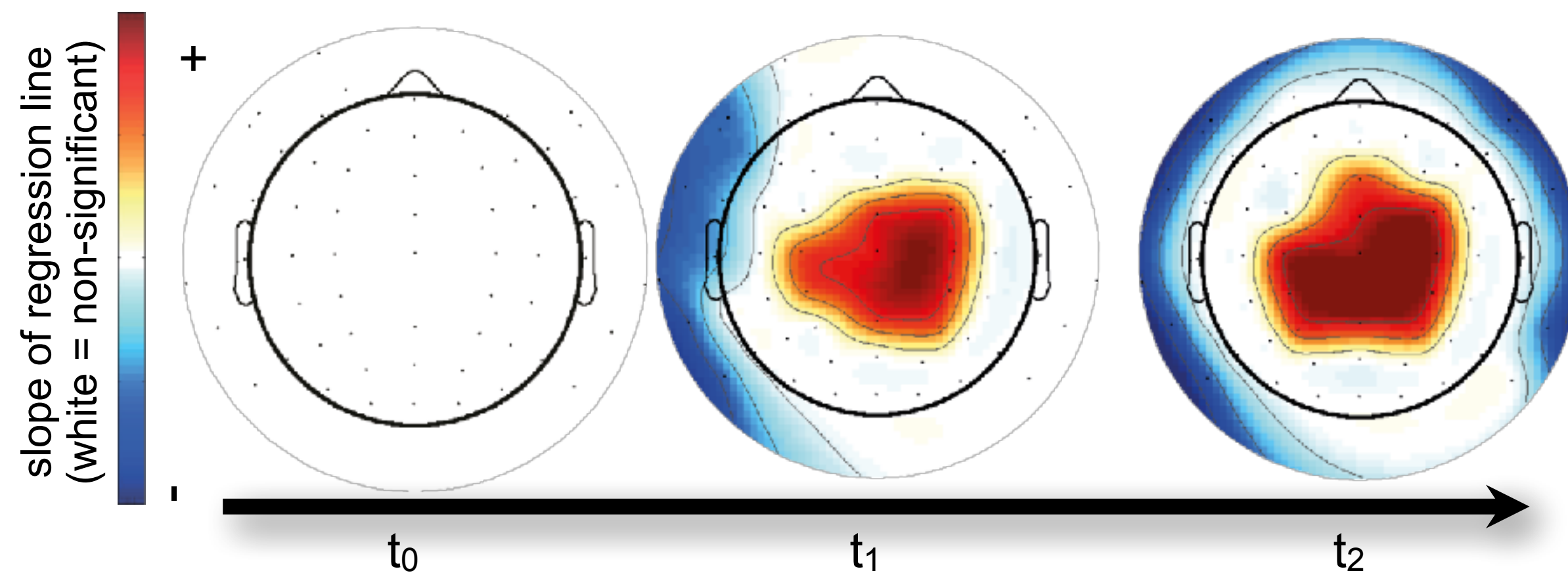
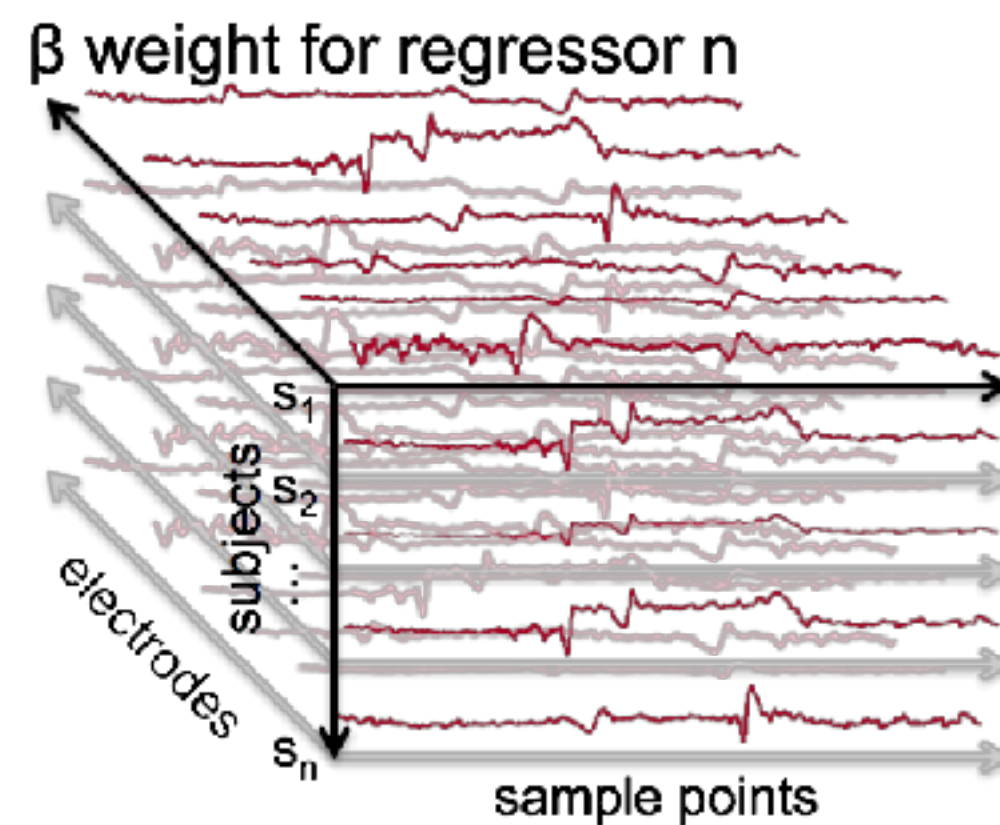
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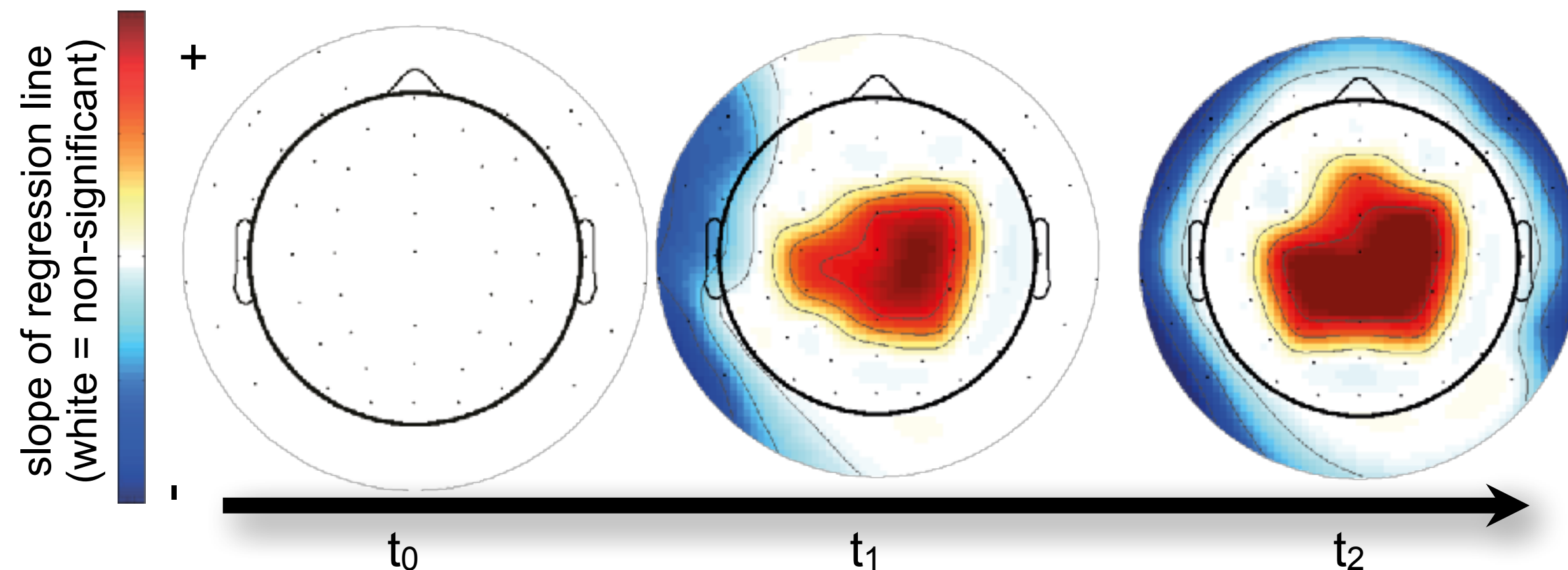
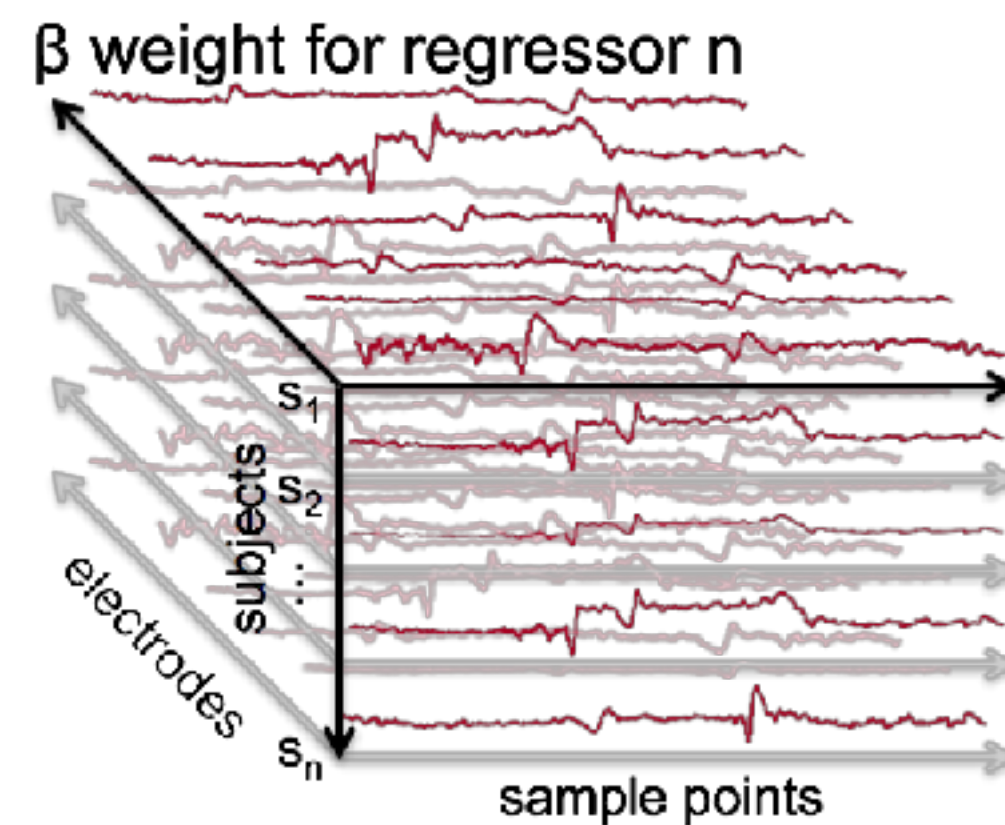


feedback-locked analysis:

GLM for EEG

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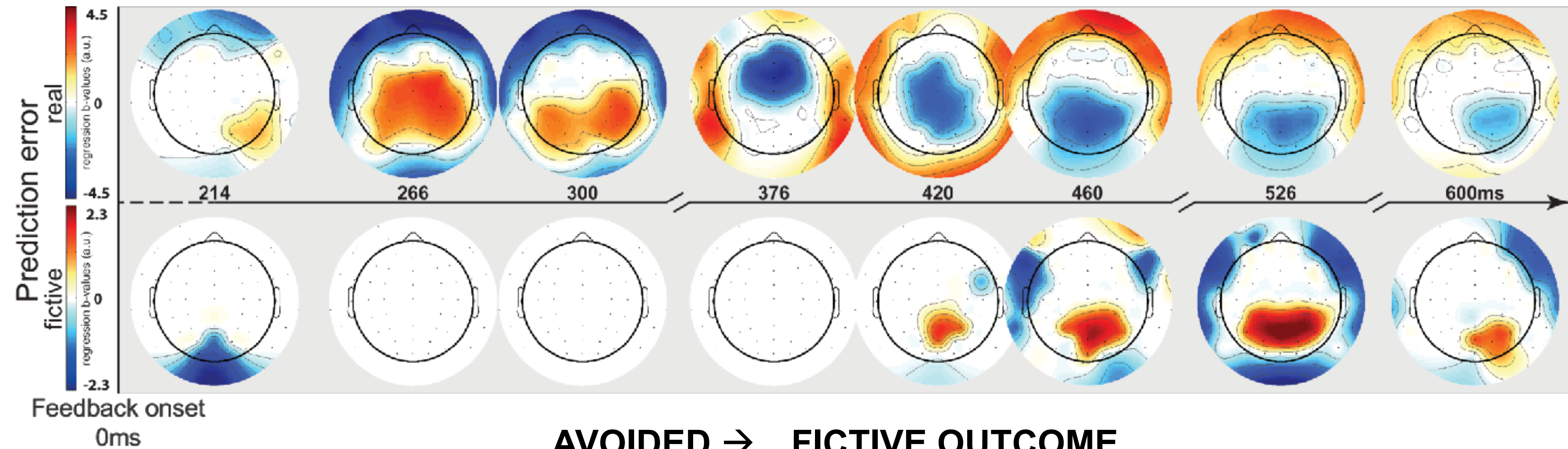


feedback-locked analysis:

predictors: δ_t , α_t , switch/stay on next trial with same stimulus using 2 separate models for real and fictive outcomes

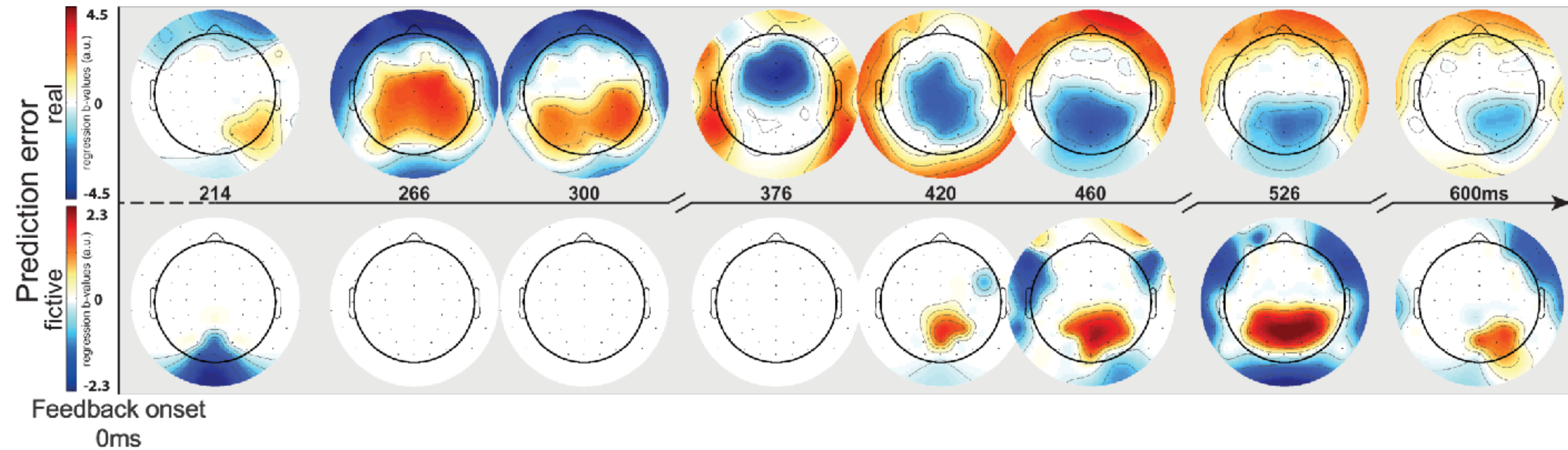
Feedback-Locked Analysis: Prediction-Error (δ)

CHOSEN → REAL OUTCOME

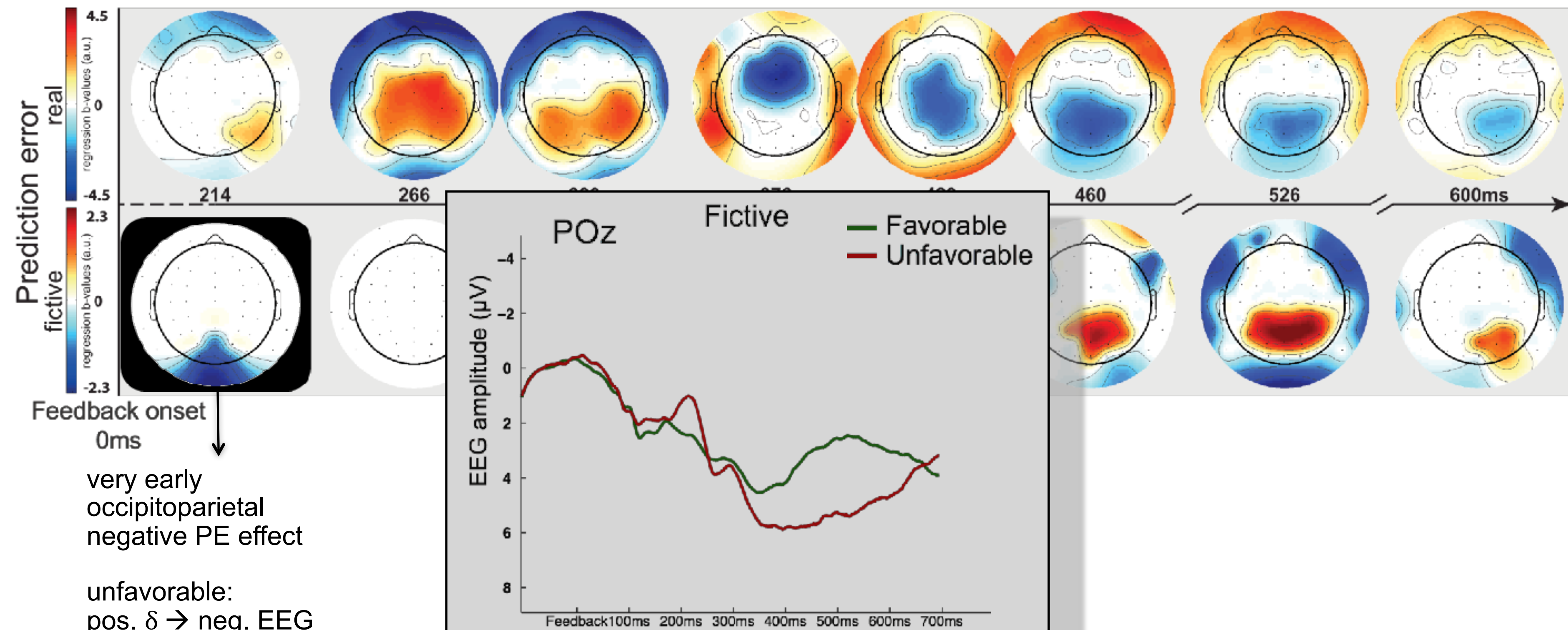


AVOIDED → FICTIVE OUTCOME

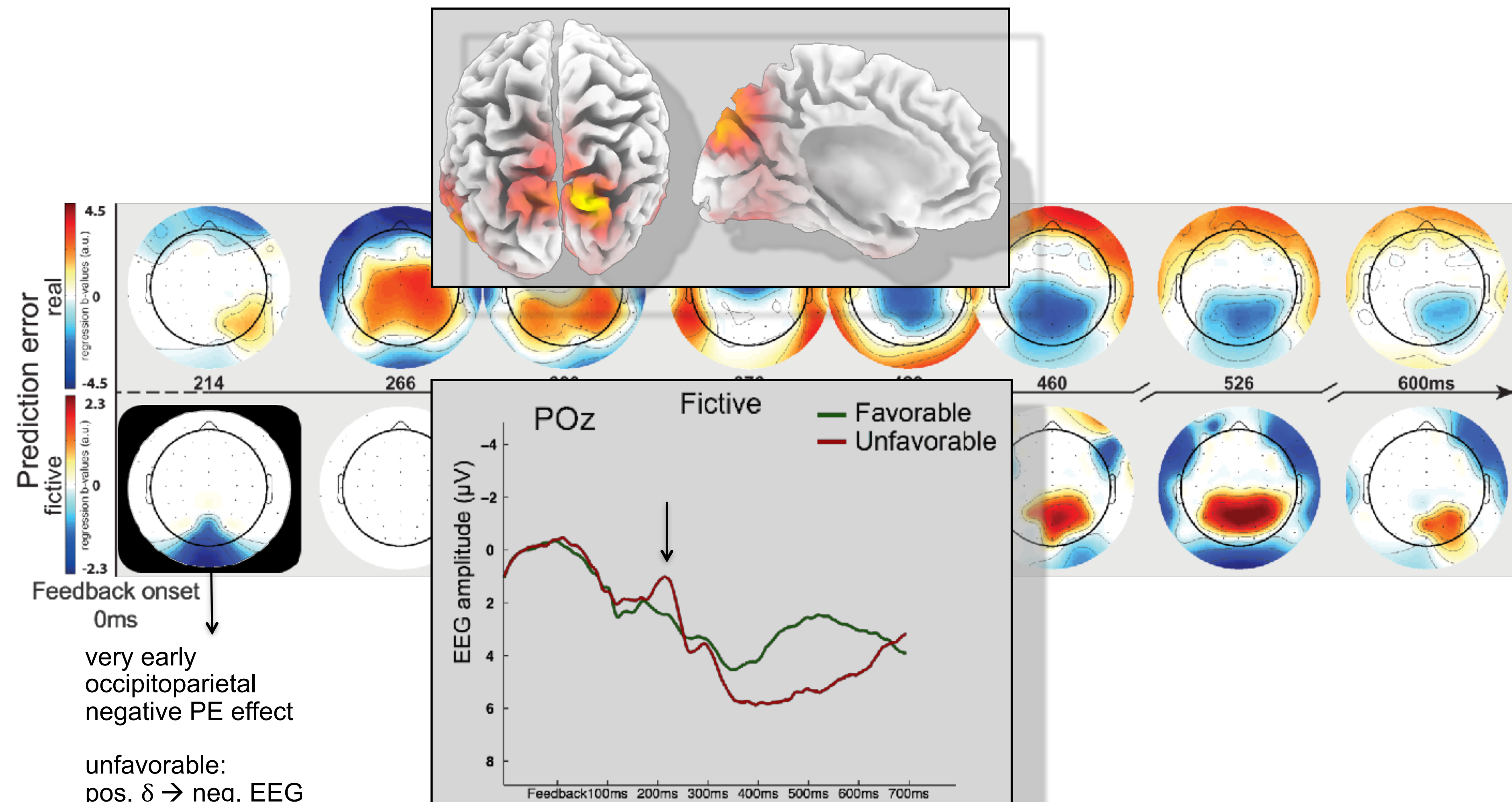
Feedback-Locked Analysis: Prediction-Error (δ)



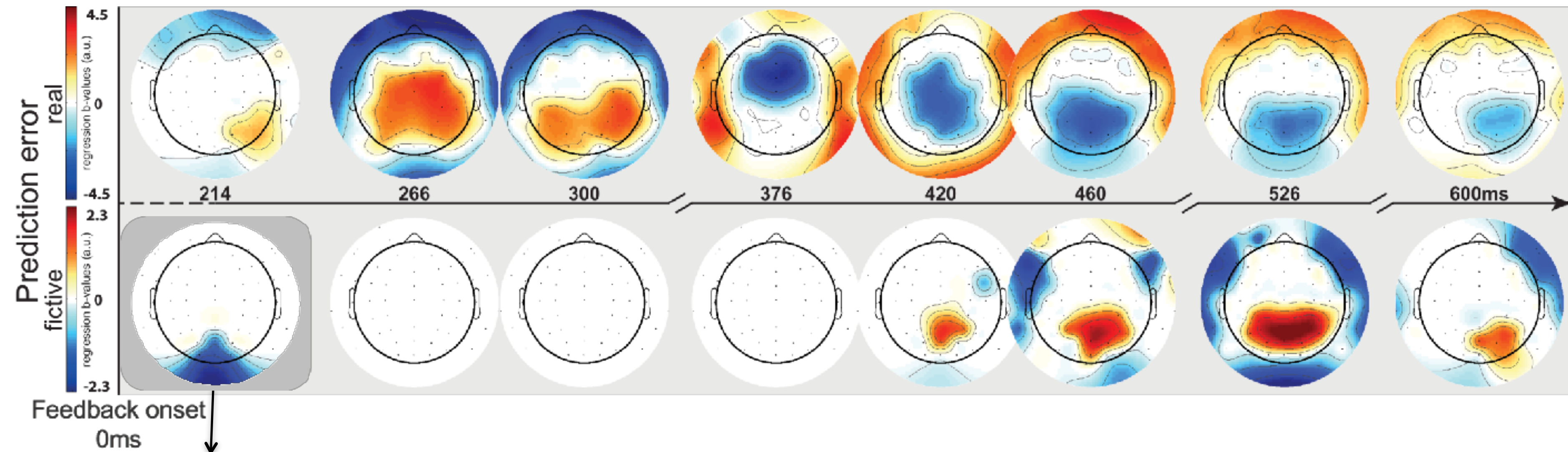
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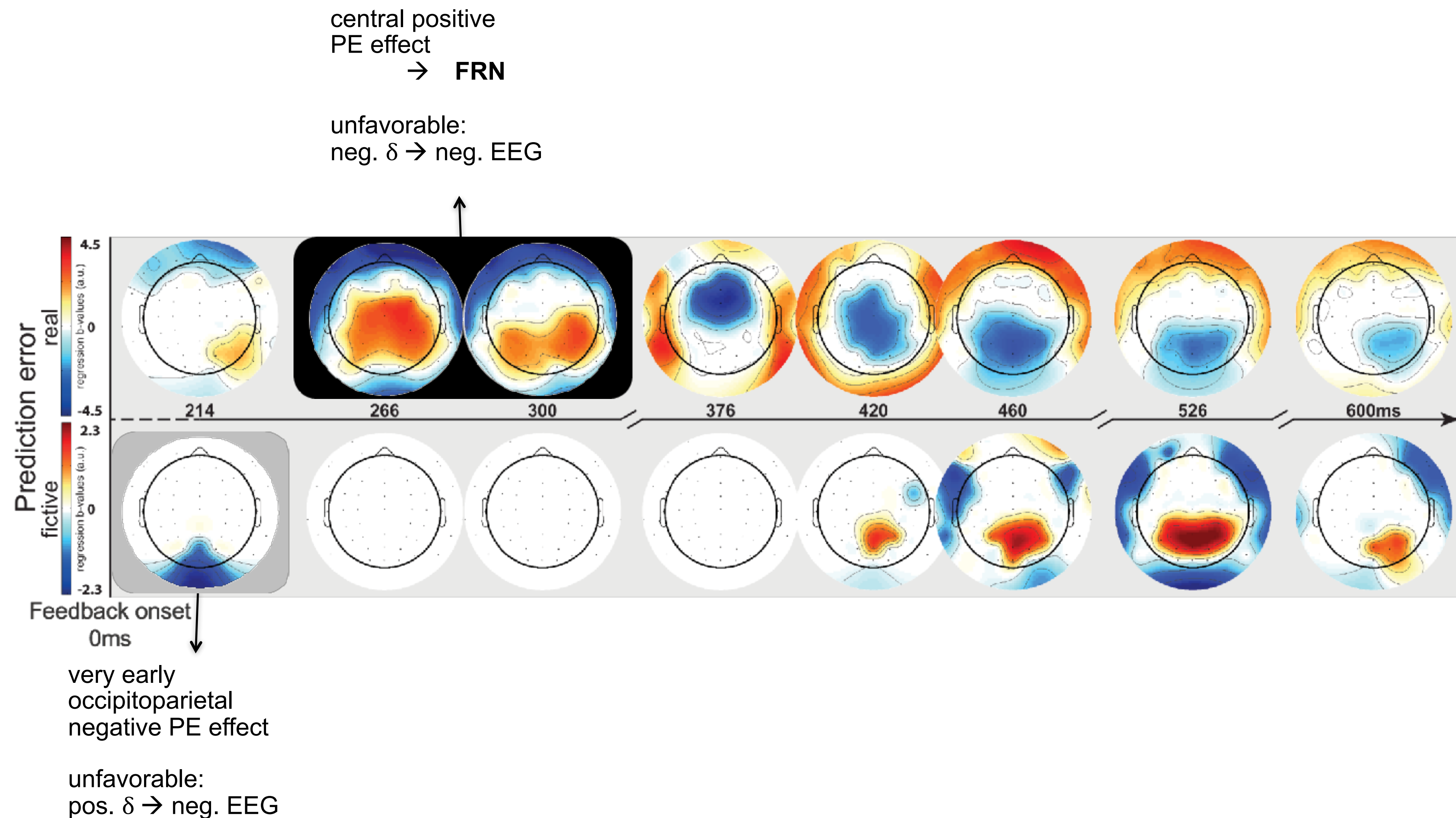
Feedback-Locked Analysis: Prediction-Error (δ)



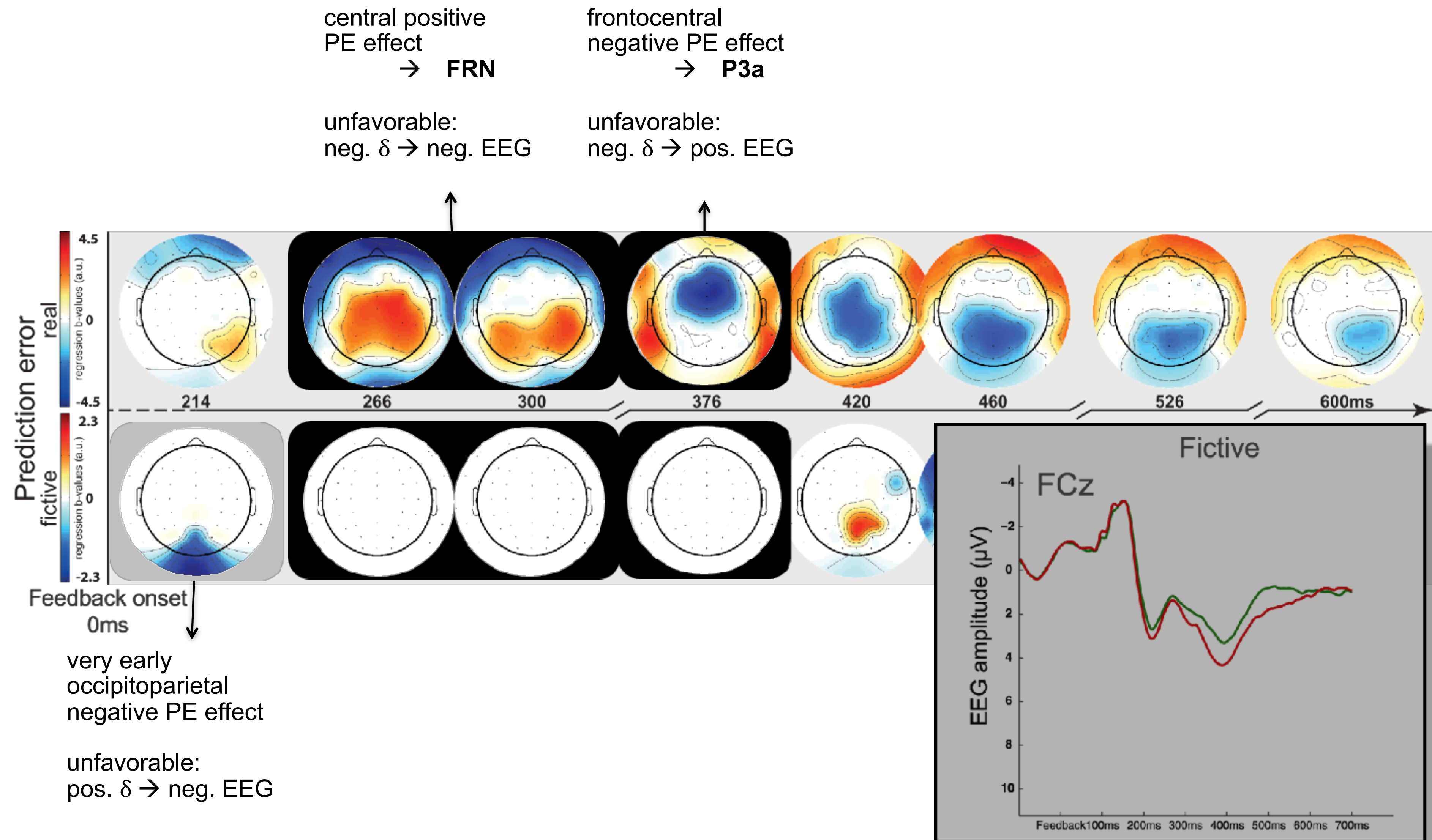
very early
occipitoparietal
negative PE effect

unfavorable:
pos. $\delta \rightarrow$ neg. EEG

Feedback-Locked Analysis: Prediction-Error (δ)

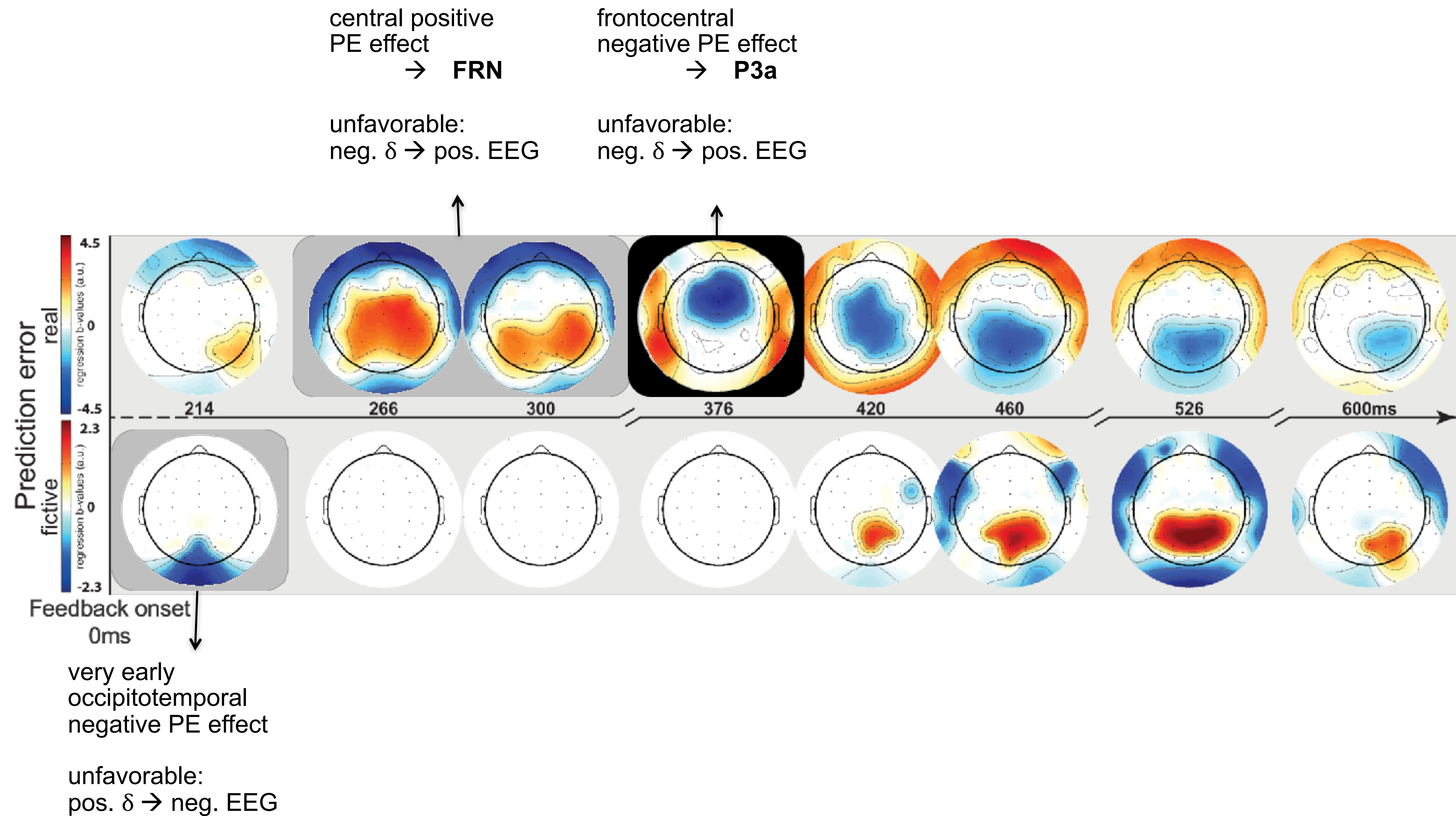


Feedback-Locked Analysis: Prediction-Error (δ)

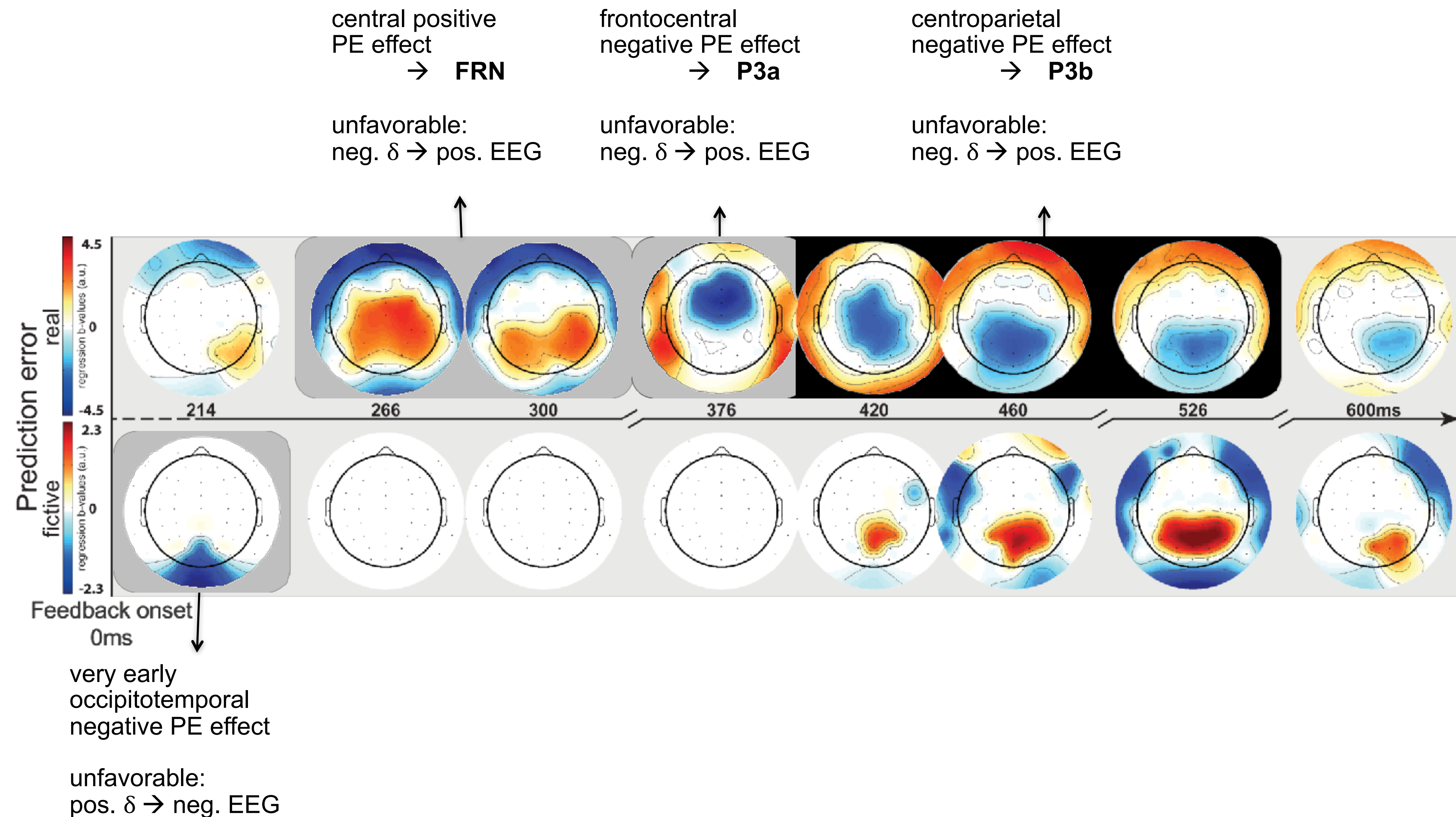


Ullsperger, *Neuron*, 2013

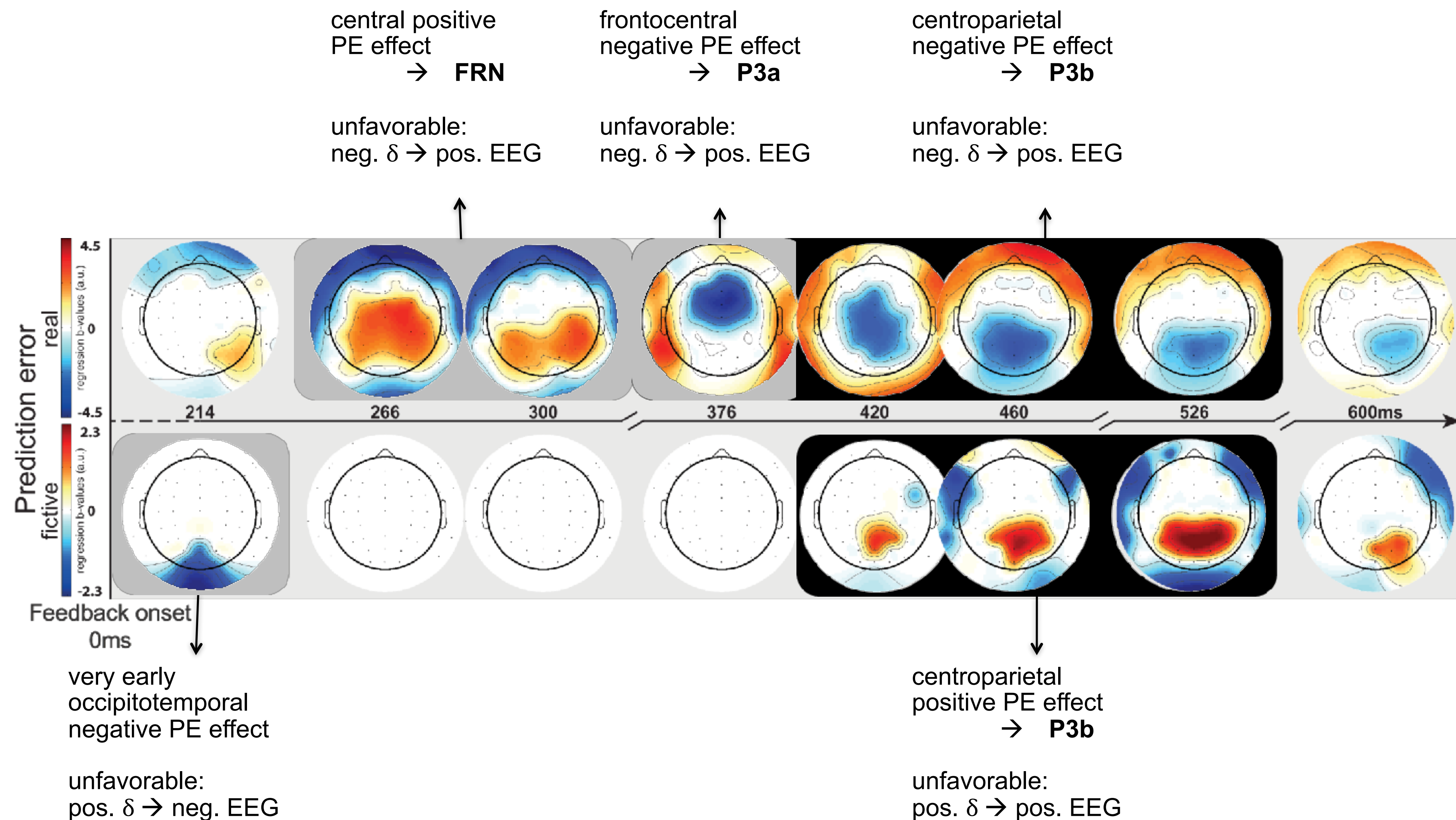
Feedback-Locked Analysis: Prediction-Error (δ)



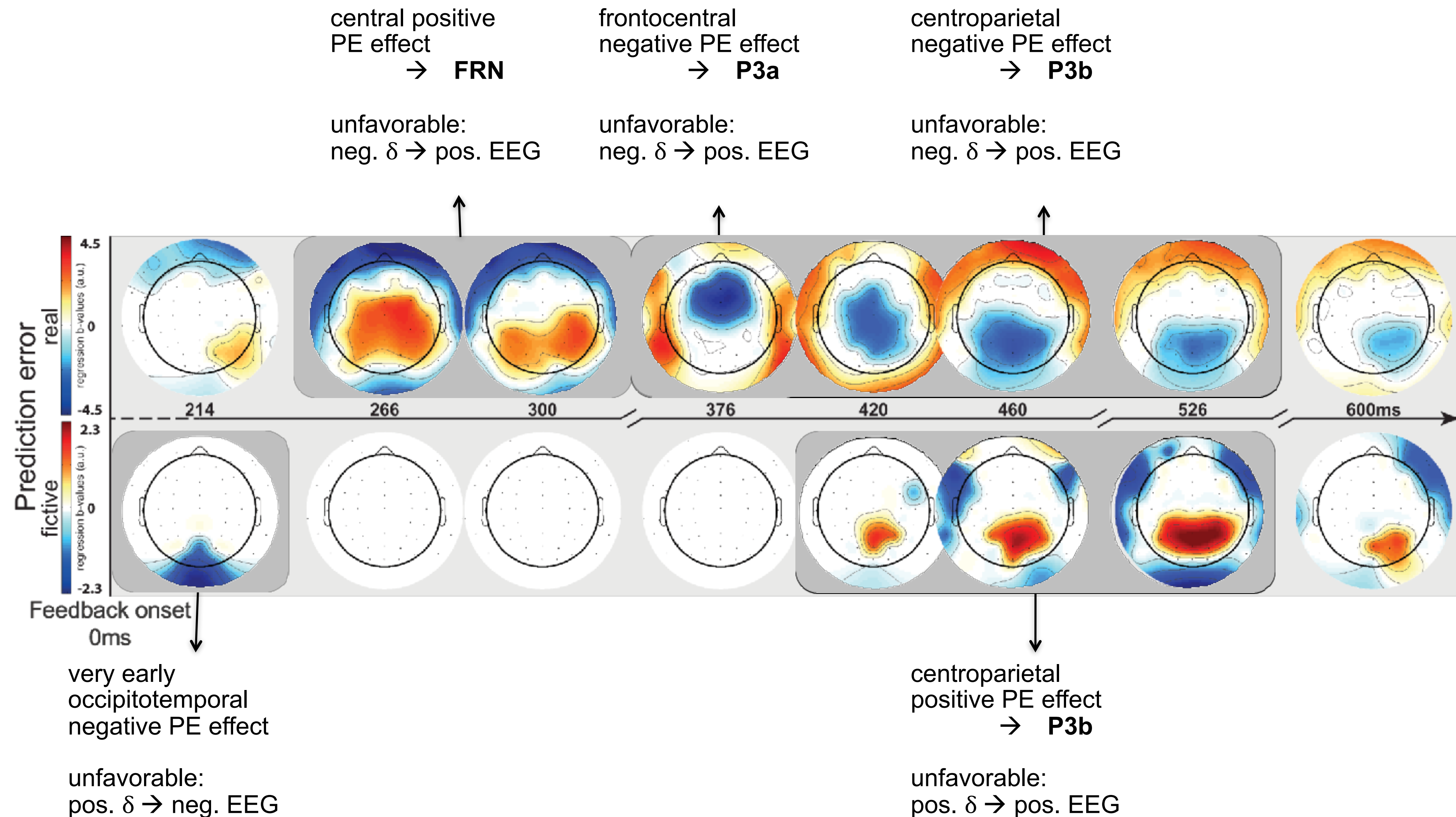
Feedback-Locked Analysis: Prediction-Error (δ)



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When is it a Prediction-Error?

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- An RPE signal has to reflect (Caplin & Dean, *Curr. Opin. Neurobiol.*, 2008)

$$\delta_t(\chi_t) = R_t(\chi_t) - Q_t(\chi_t)$$

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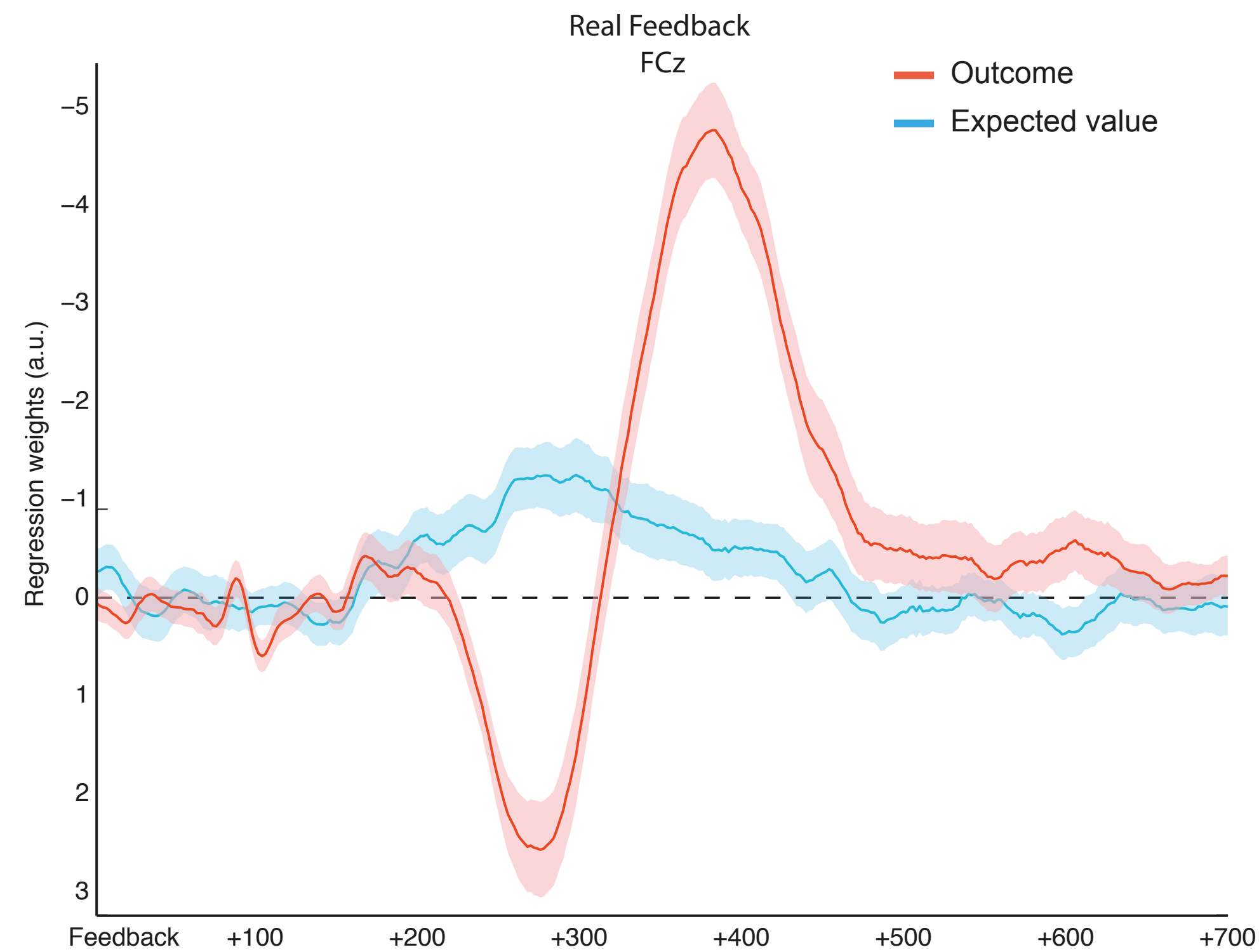
$$\delta_t(\chi_t) = R_t(\chi_t) - Q_t(\chi_t)$$

↑
outcome & expectancy
increase *decrease*

- include reward (0 | 1) and expectancy (Q_t)

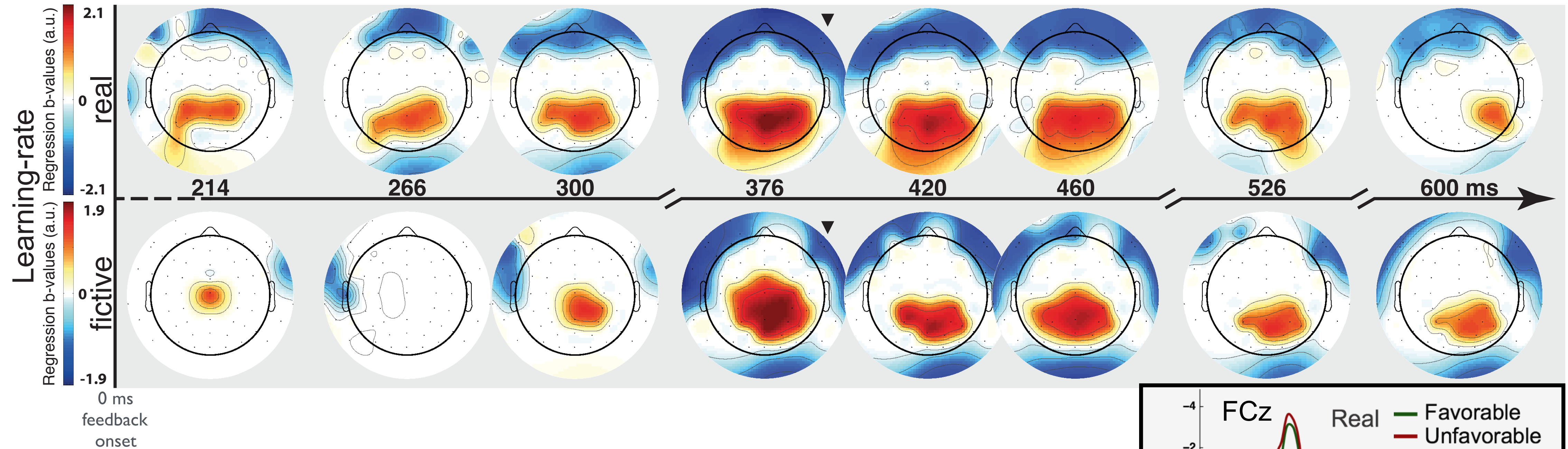
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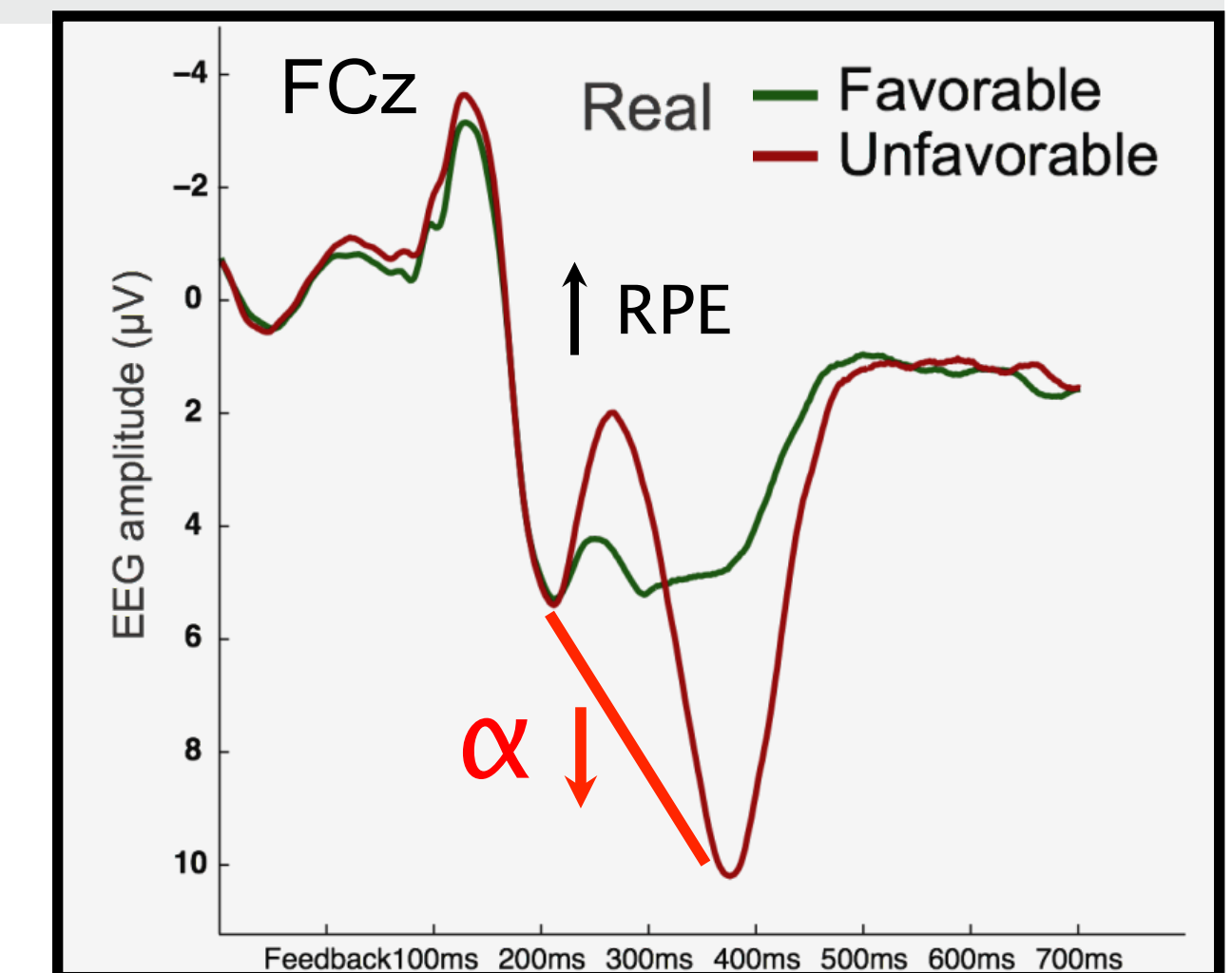


➡ *the FRN satisfies necessary and sufficient criteria of a prediction-error signal*

Decaying Learning-Rate

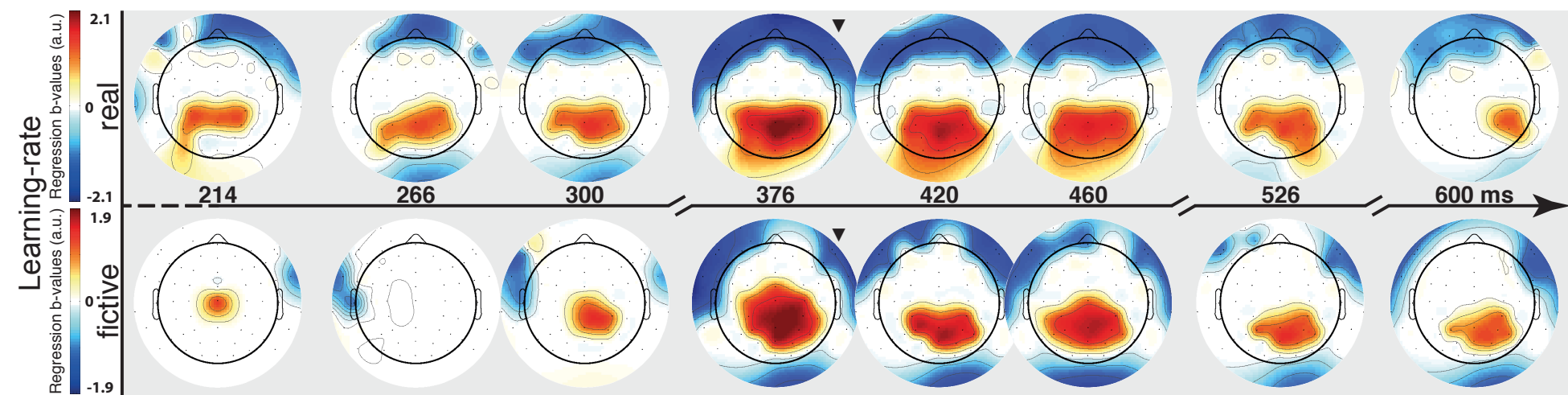


- sustained centro-parietal positive shift
- maximal between FRN and P3a
- higher learning-rate \rightarrow more positive EEG

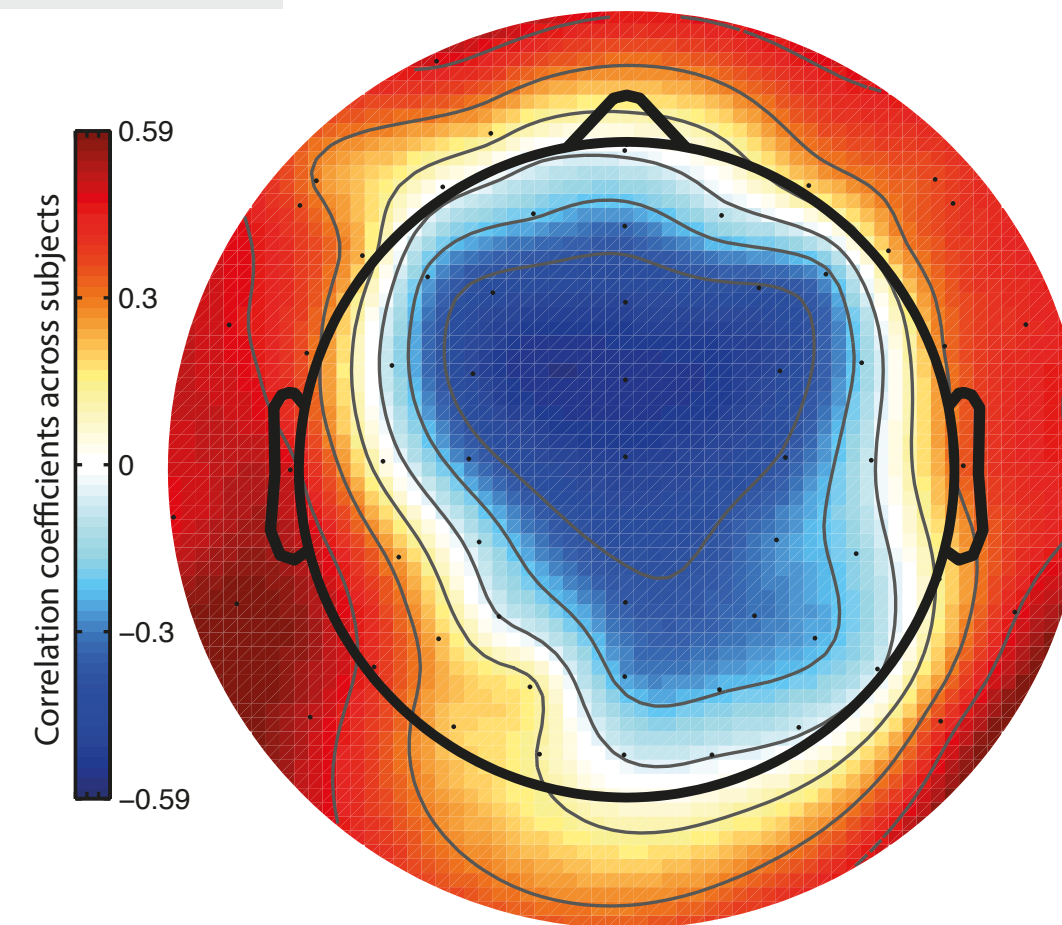


Fischer, Ullsperger, *Neuron*, 2013

Decaying Learning-Rate

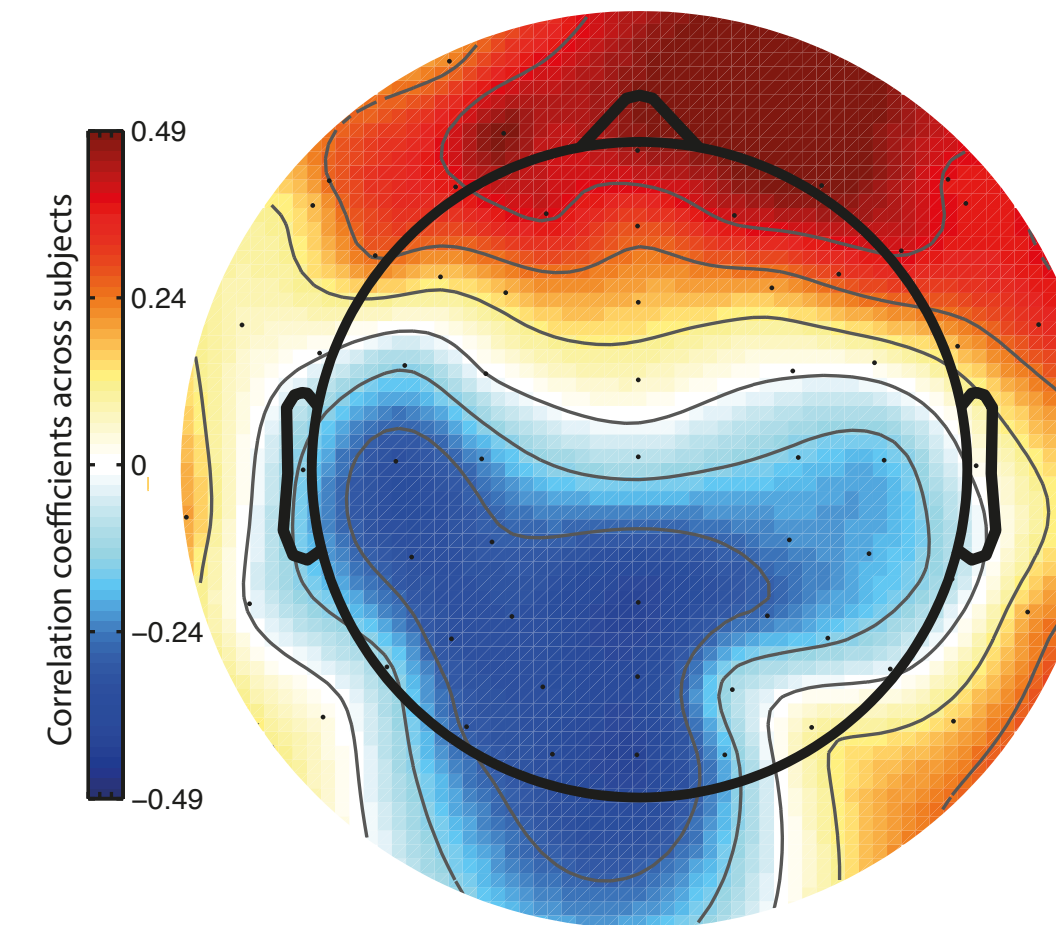


Fictive learning rate at 376 ms



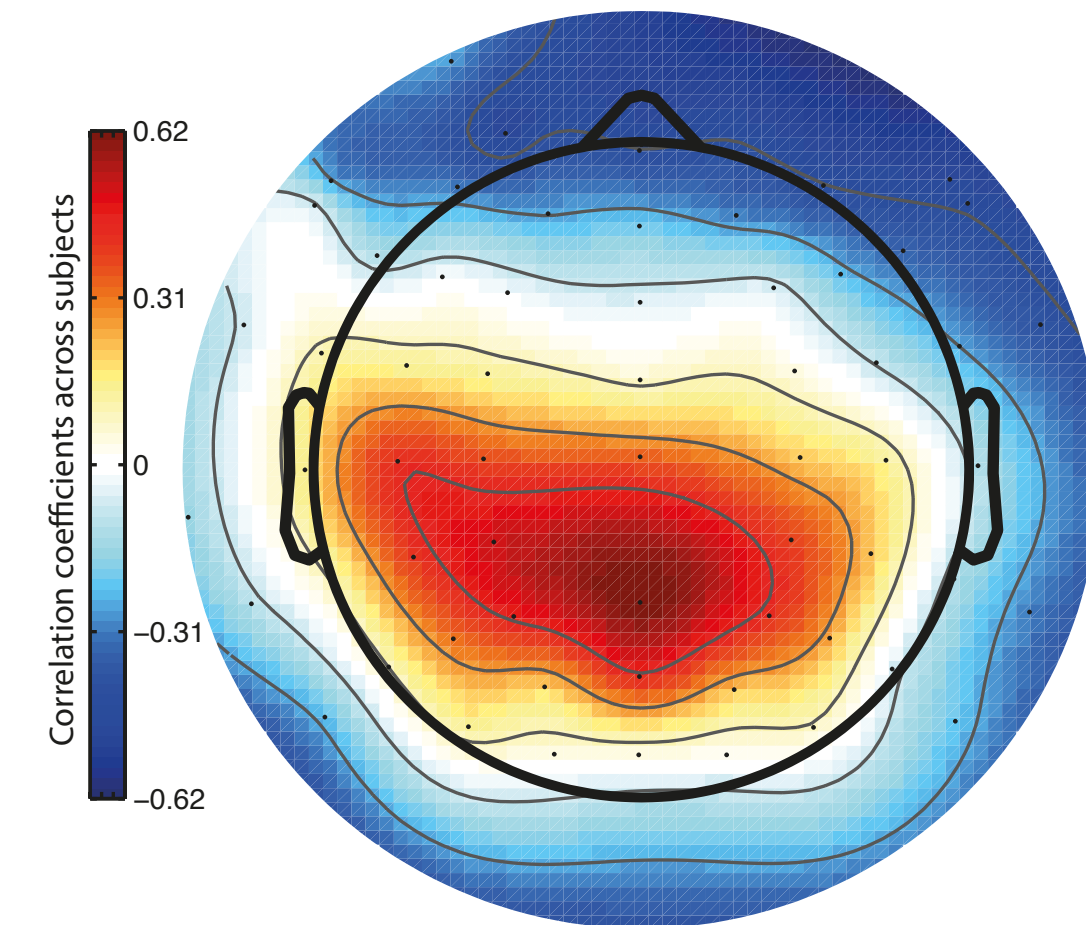
$r = -0.52, p = 0.0023$

Real learning rate at 370 ms



$r = -0.43, p = 0.014$

Real PE at 460 ms



$r = 0.68, p = 0.00002$

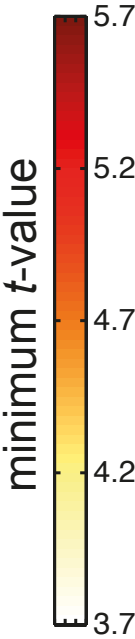
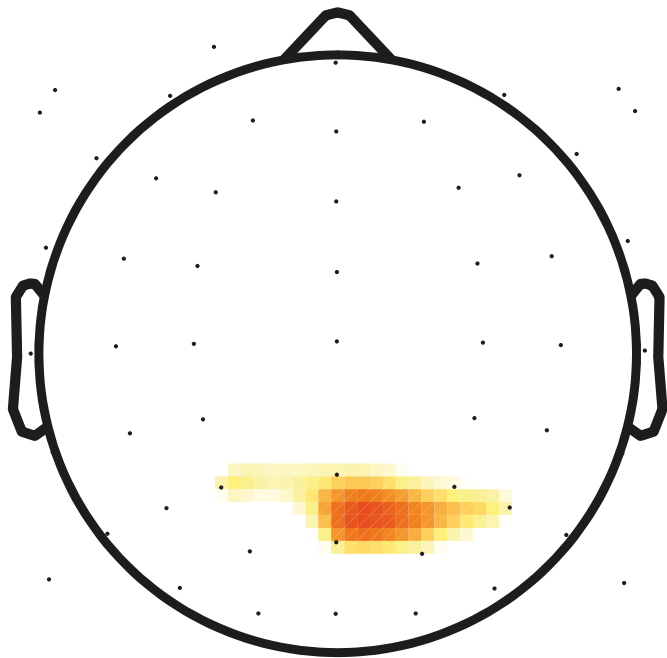
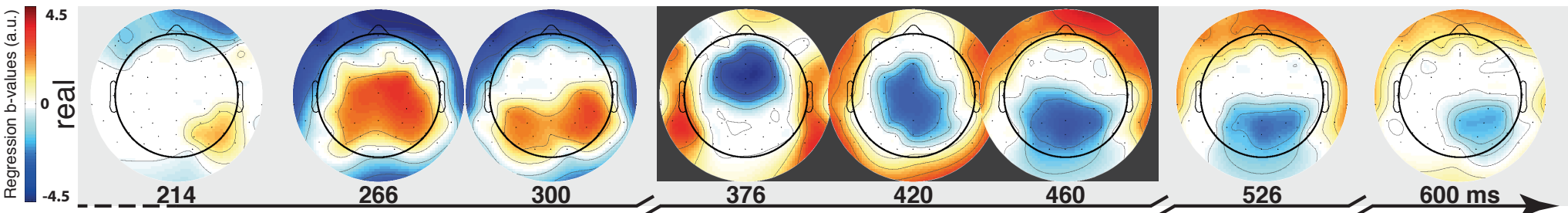
- the better learning-rates in real and fictive conditions were reflected in the EEG signal, the fewer mistakes participants made in the task

P3b: A Common Final Pathway

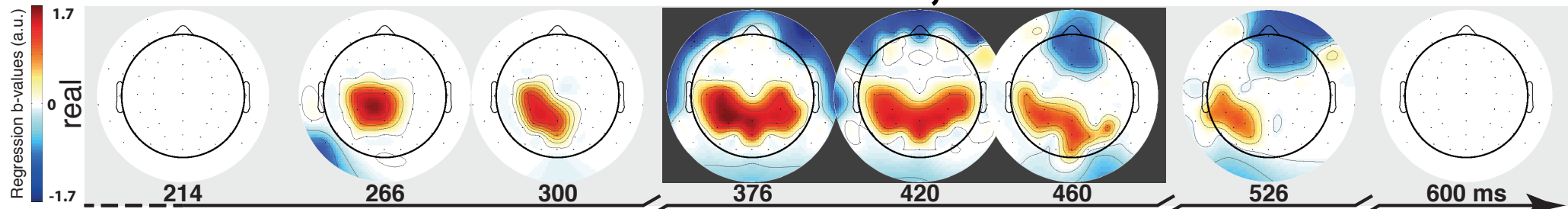
6-way conjunction

Feedback P3b conjunction

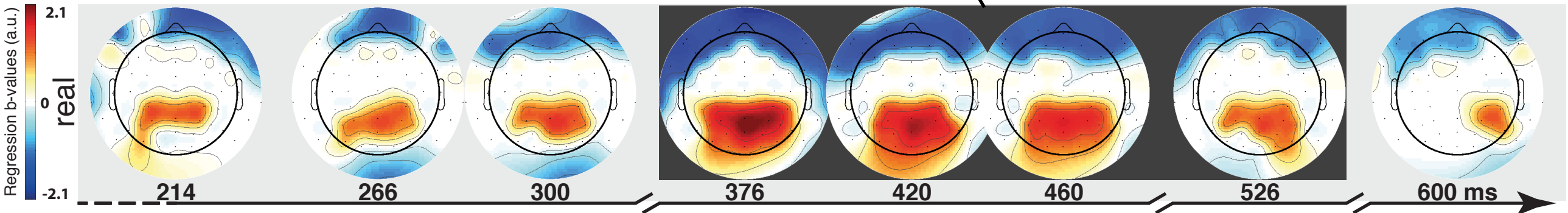
unfavorable outcome (RPE effect)



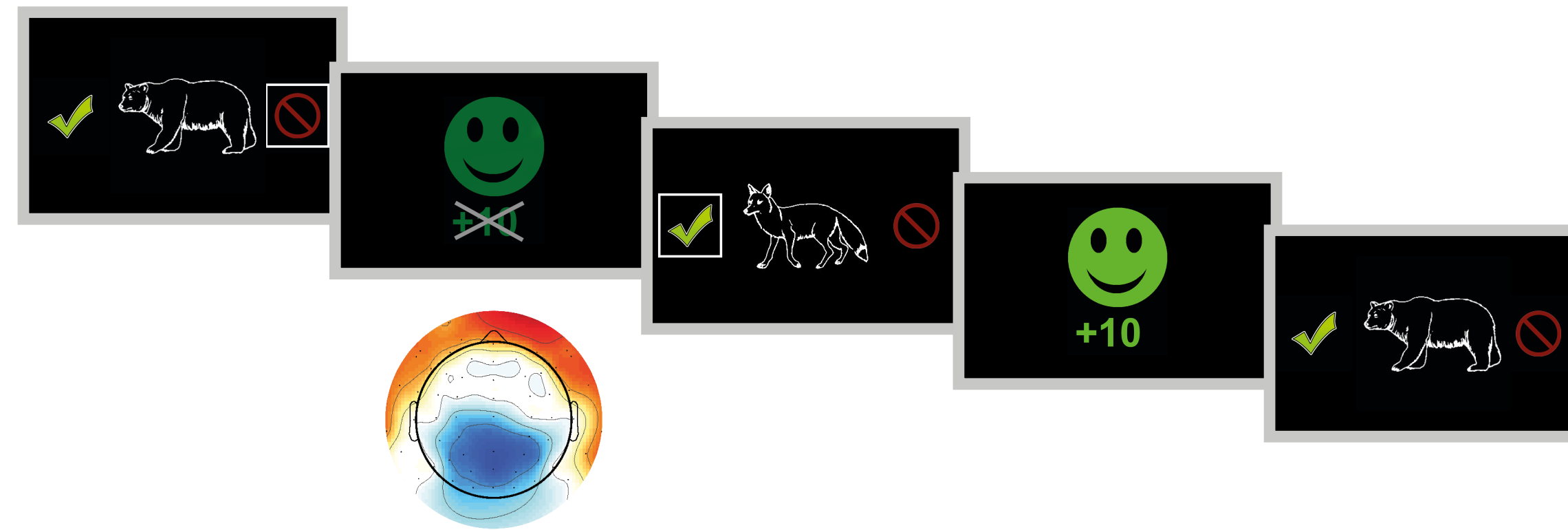
uncaptured / spontaneous switches



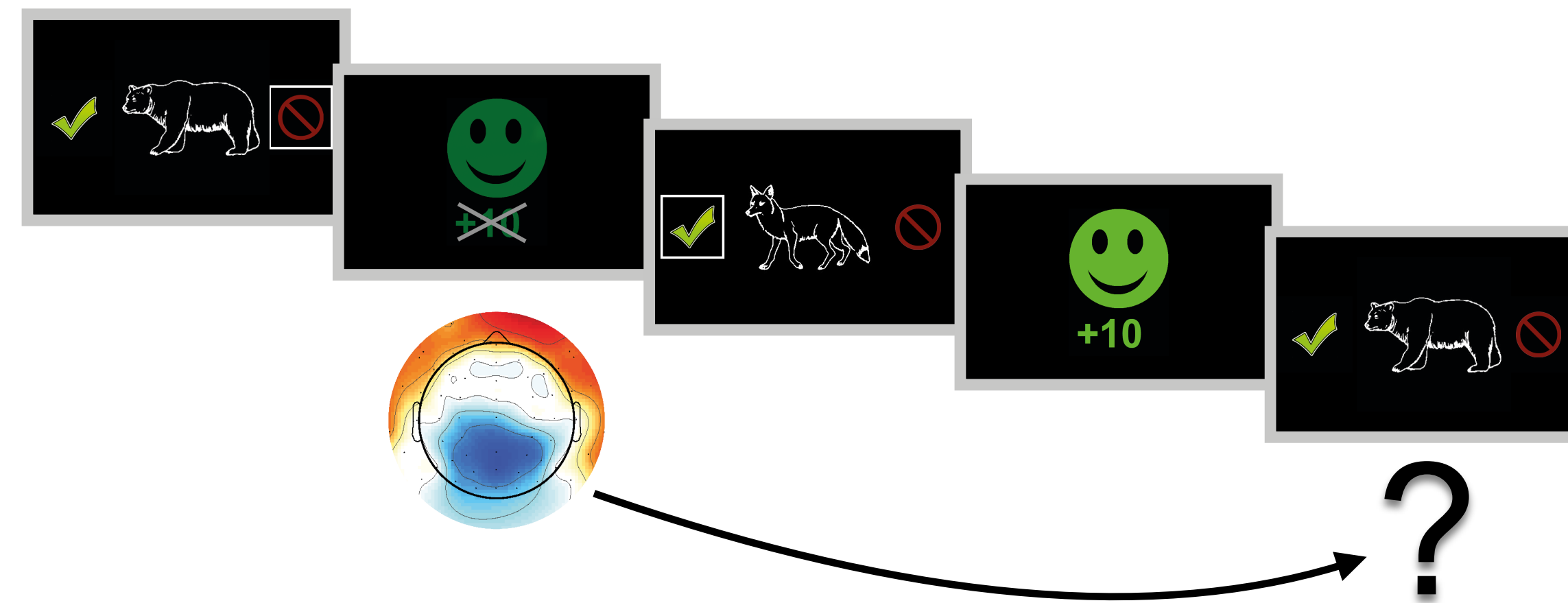
learning-rate (α effect)



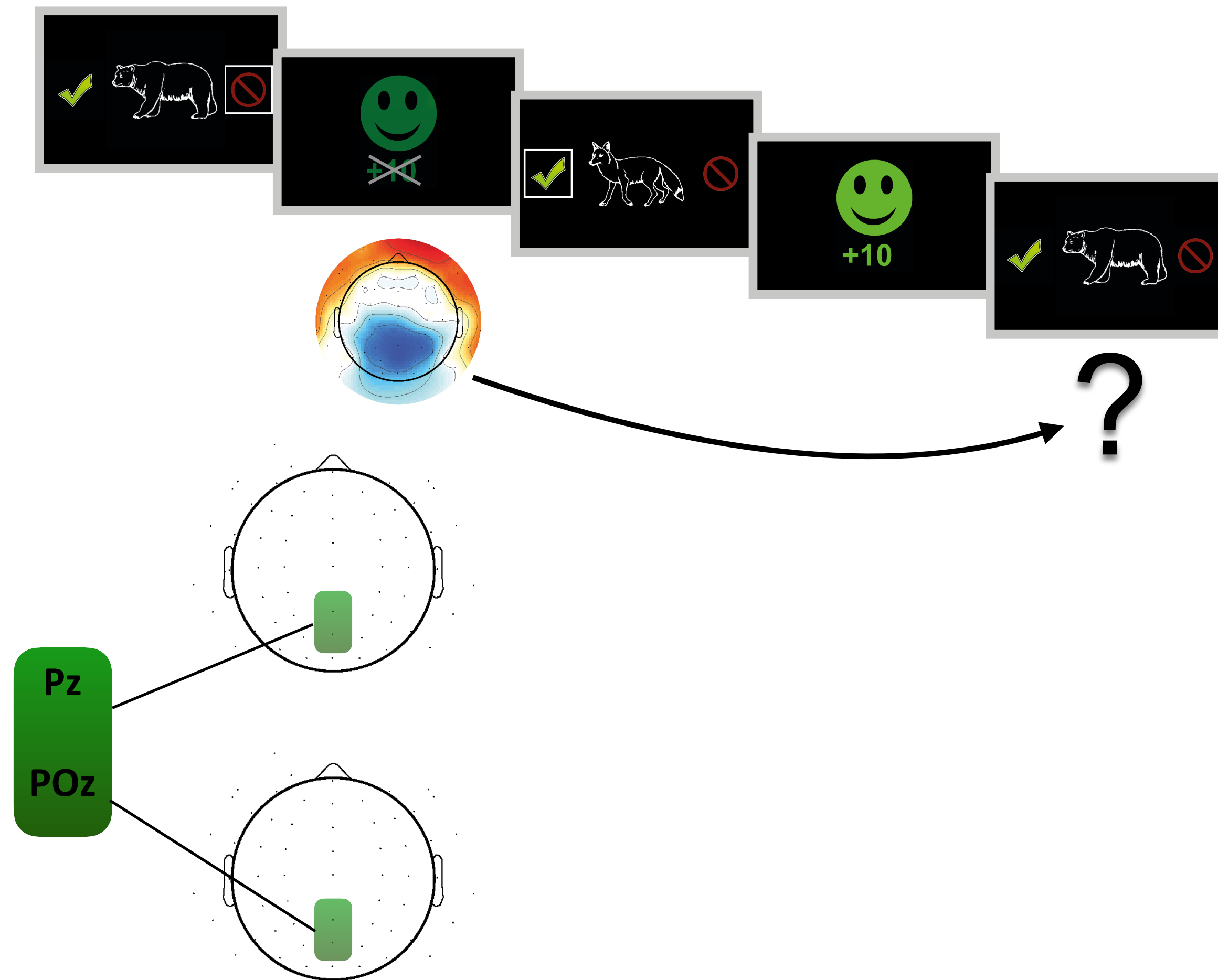
P3b: Predicts Future Decisions



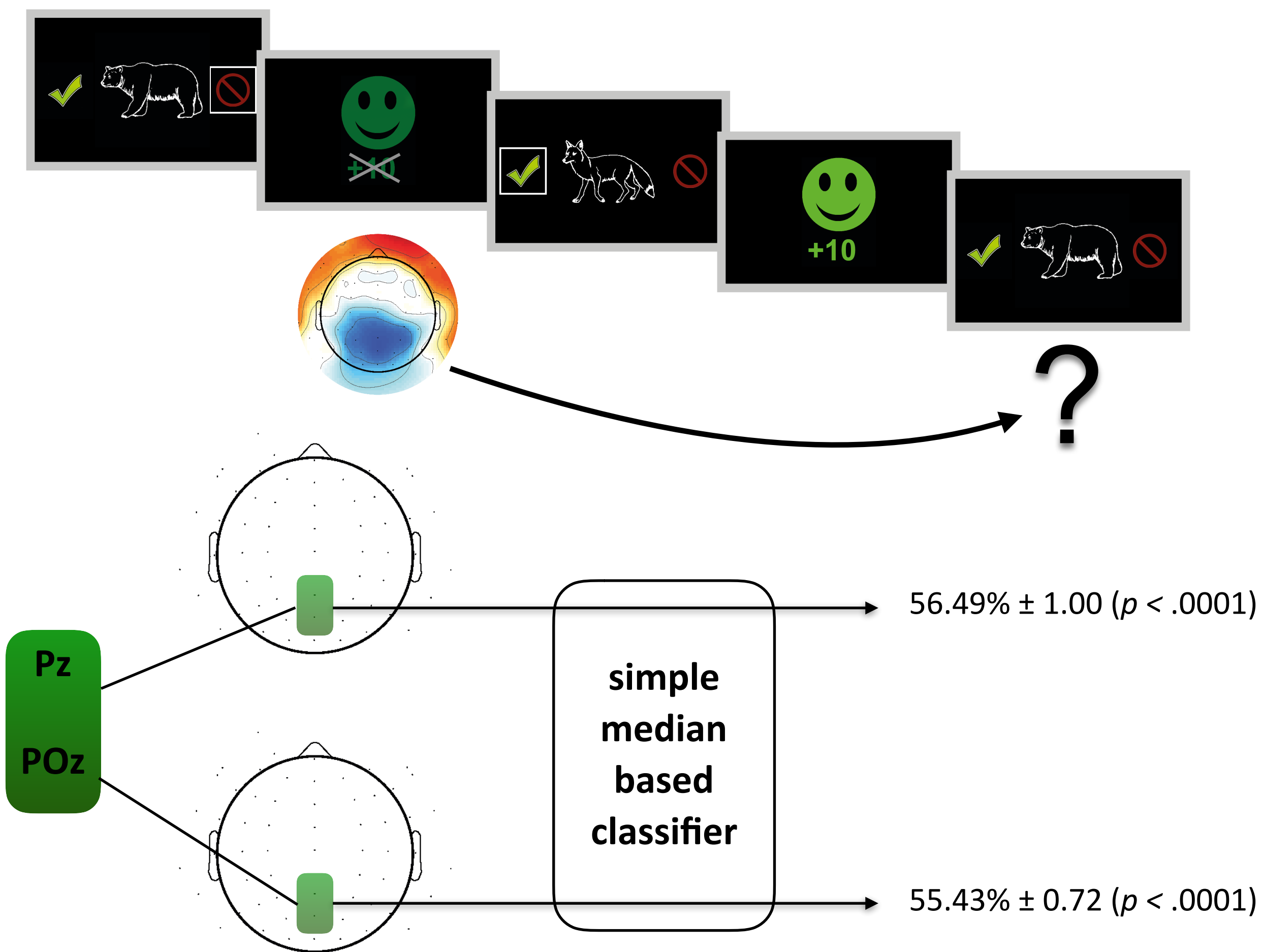
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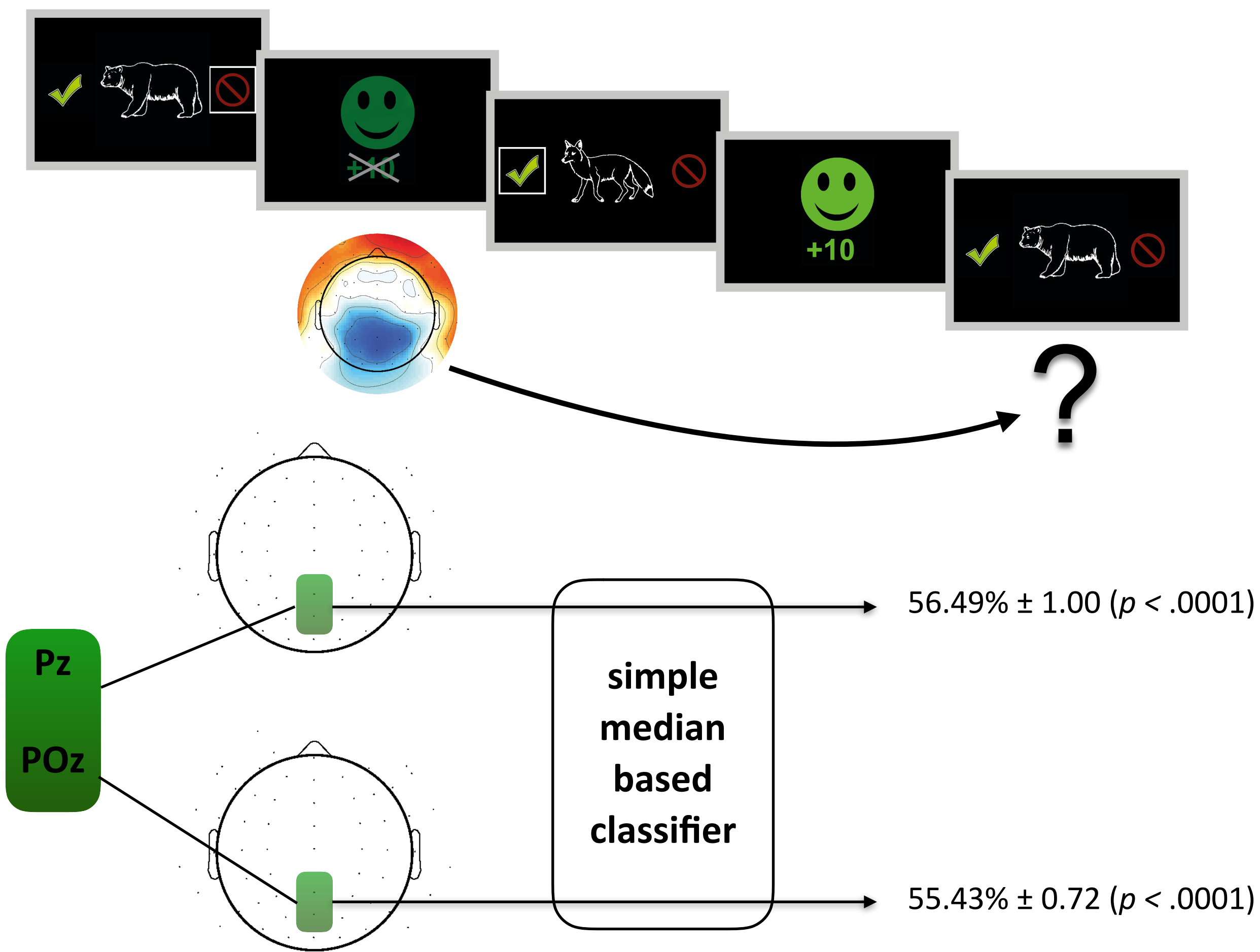
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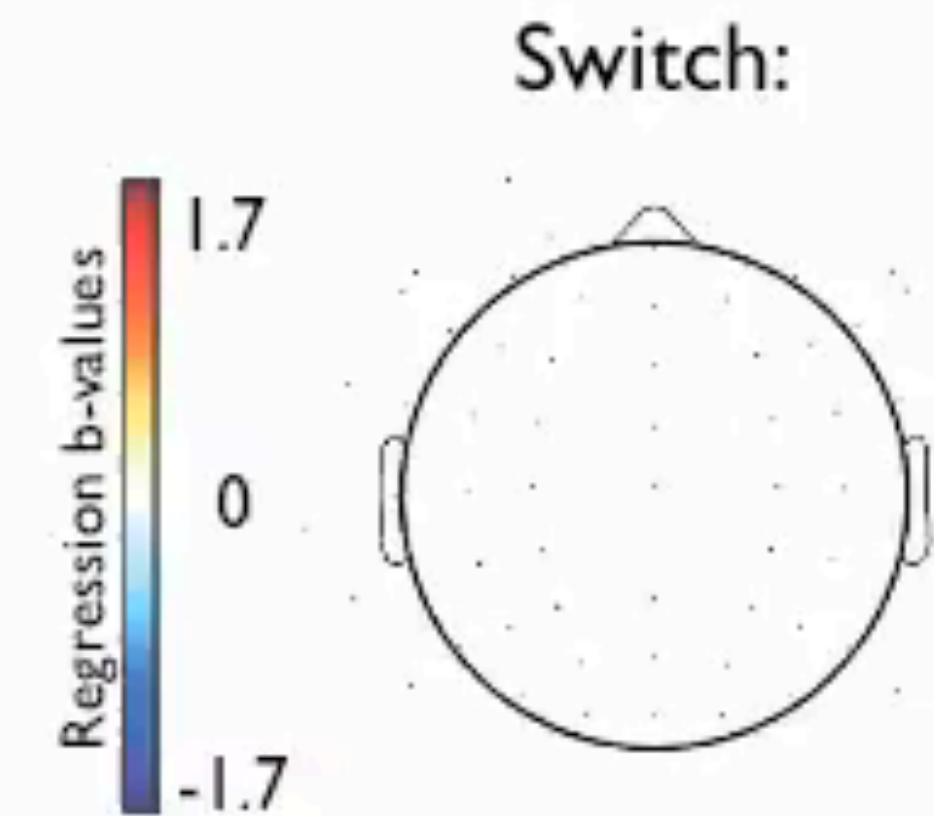
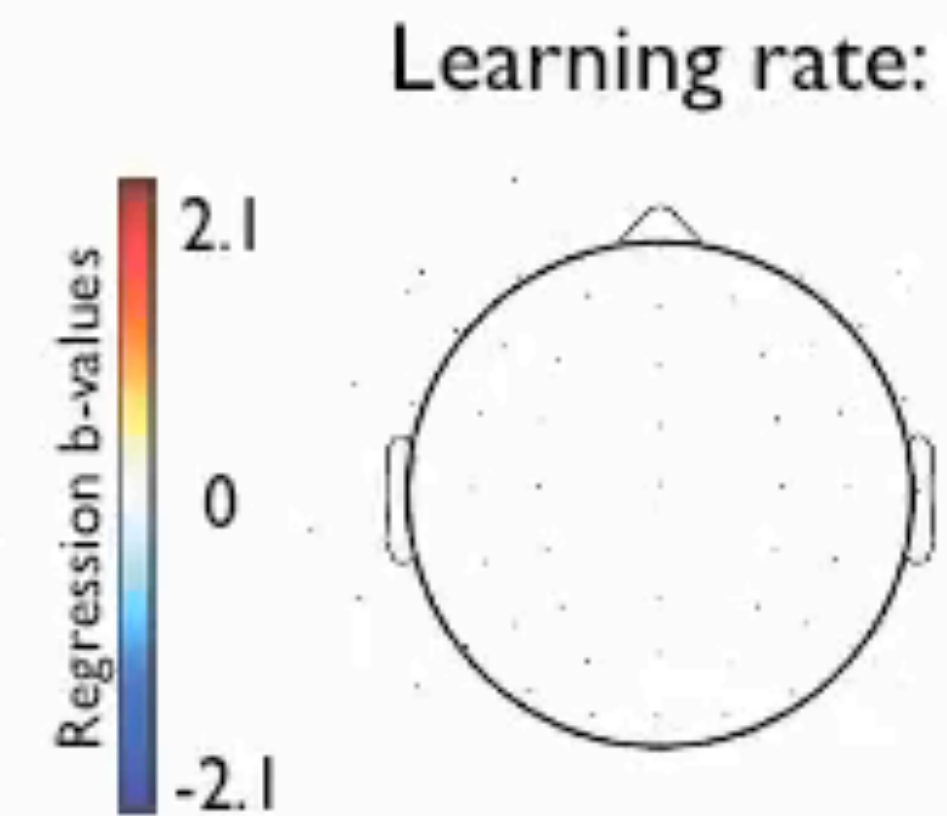
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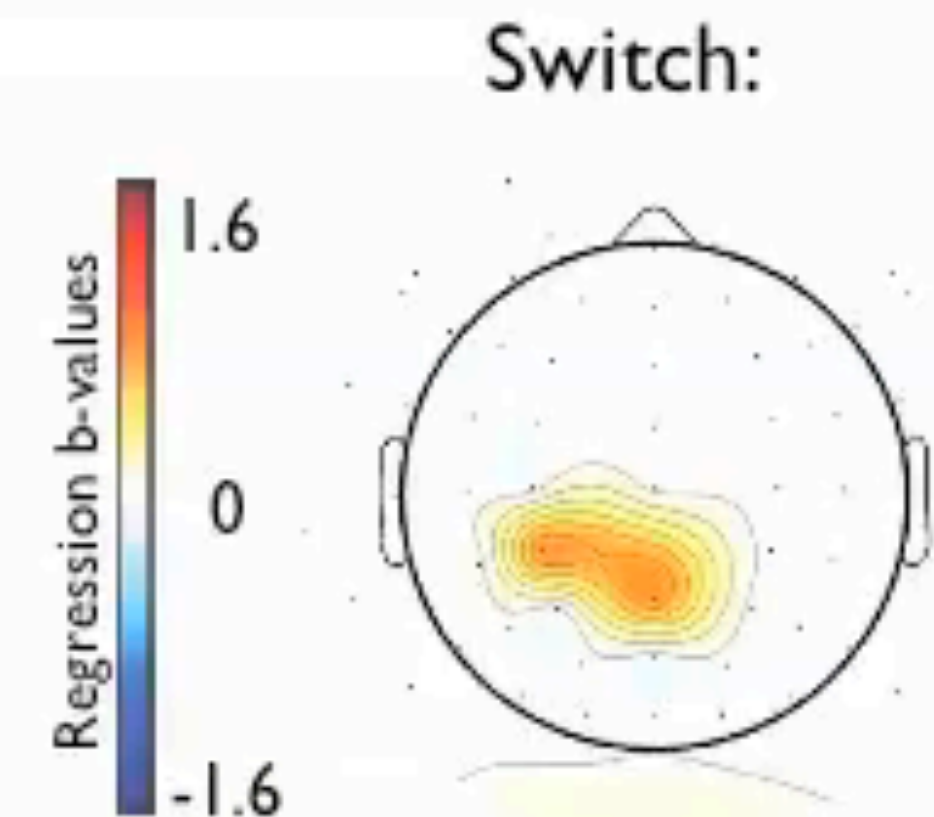
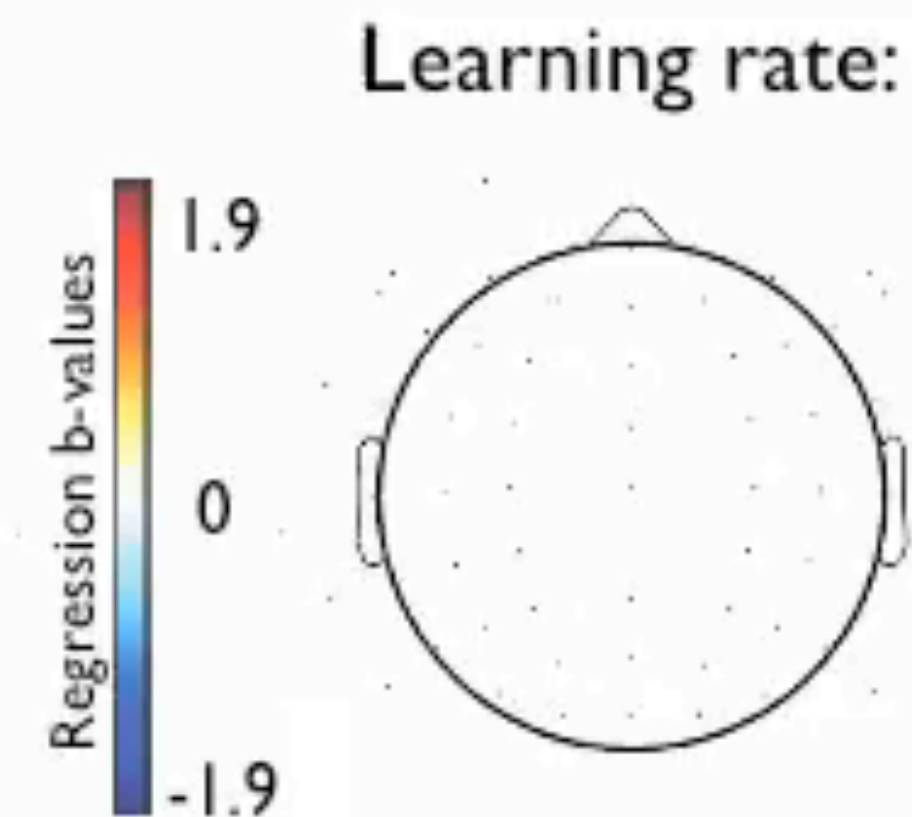
P3 reflects decision-making in the form a staying with a response, or switching away from it.

All at the same time

Real feedback



Fictive feedback



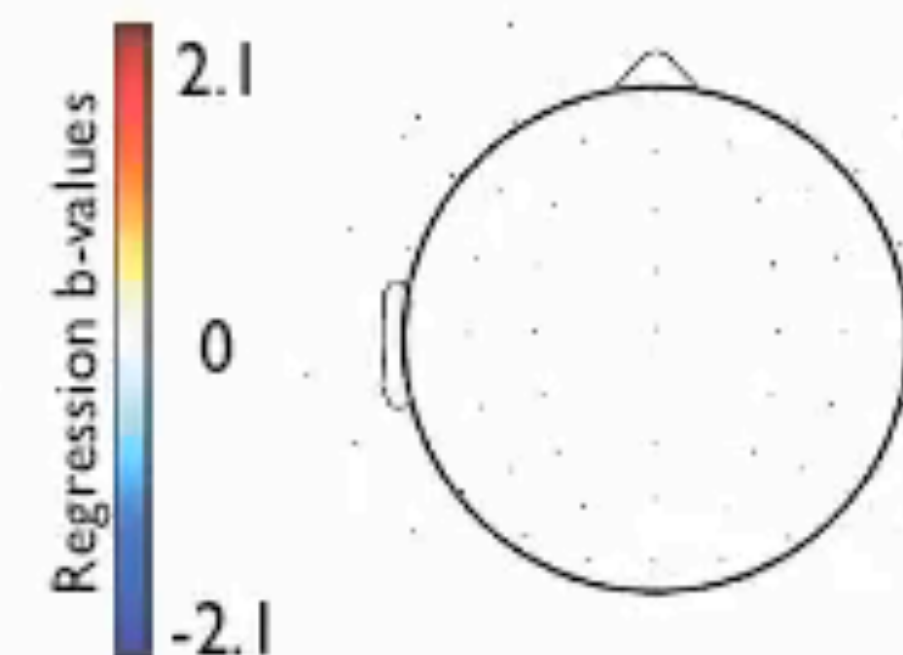
0ms

All at the same time

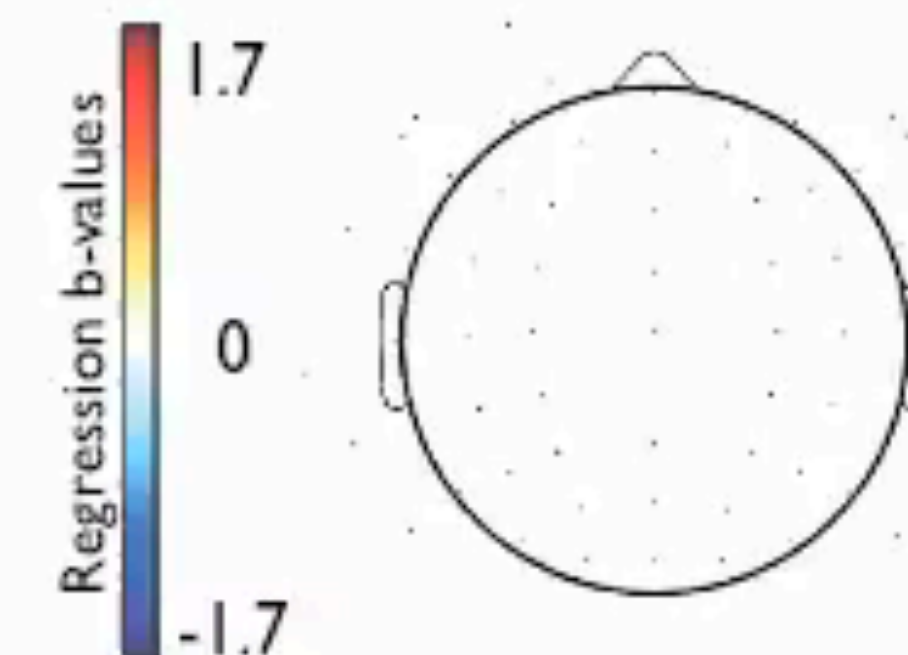
Real feedback



Learning rate:



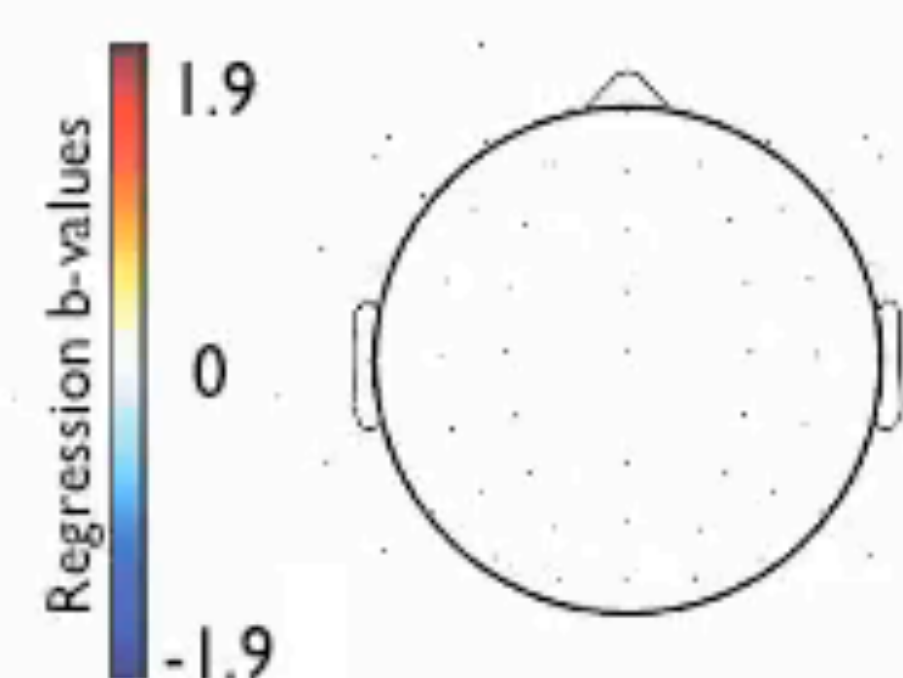
Switch:



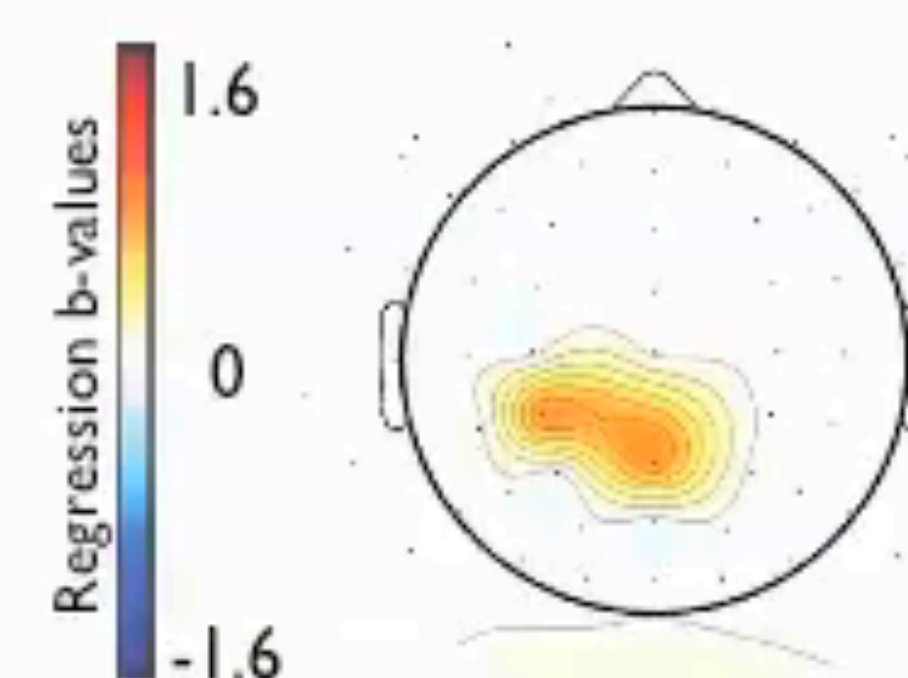
Fictive feedback



Learning rate:

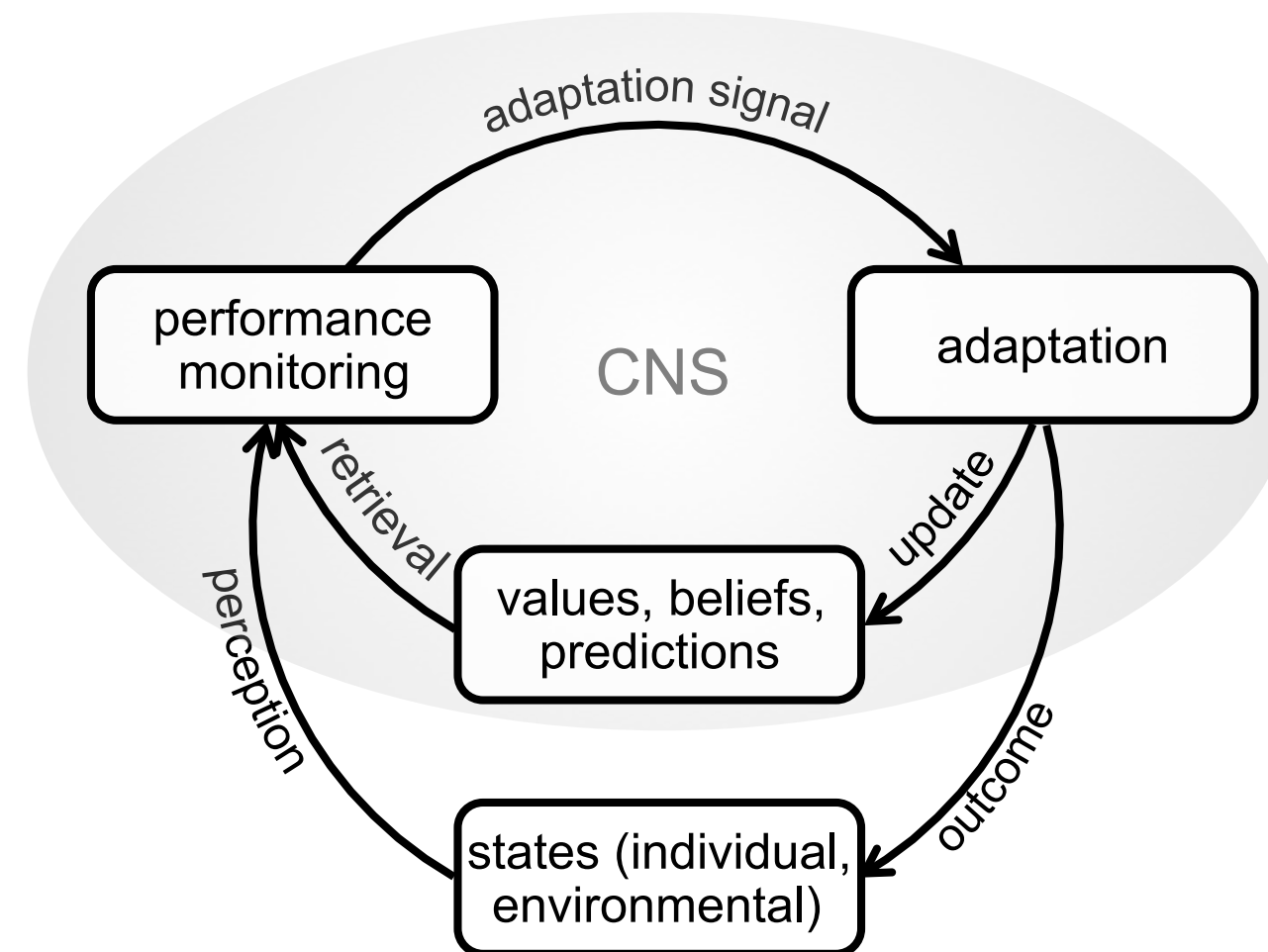


Switch:

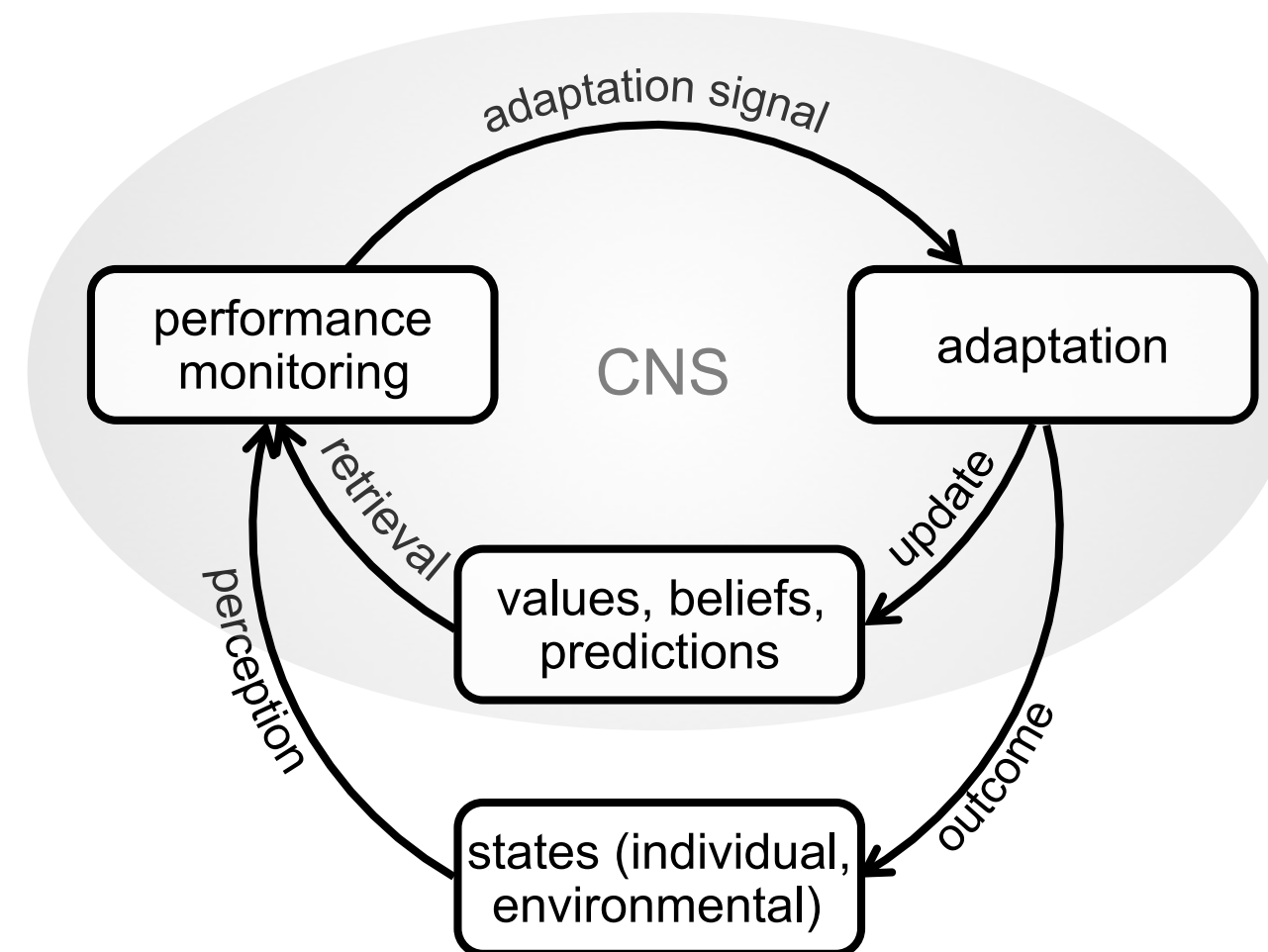


0ms

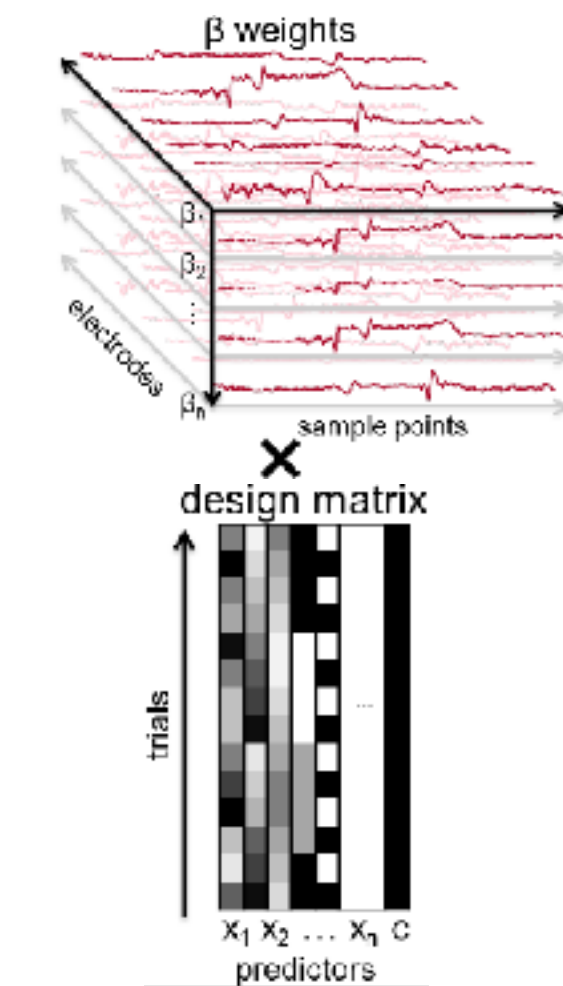
Summary



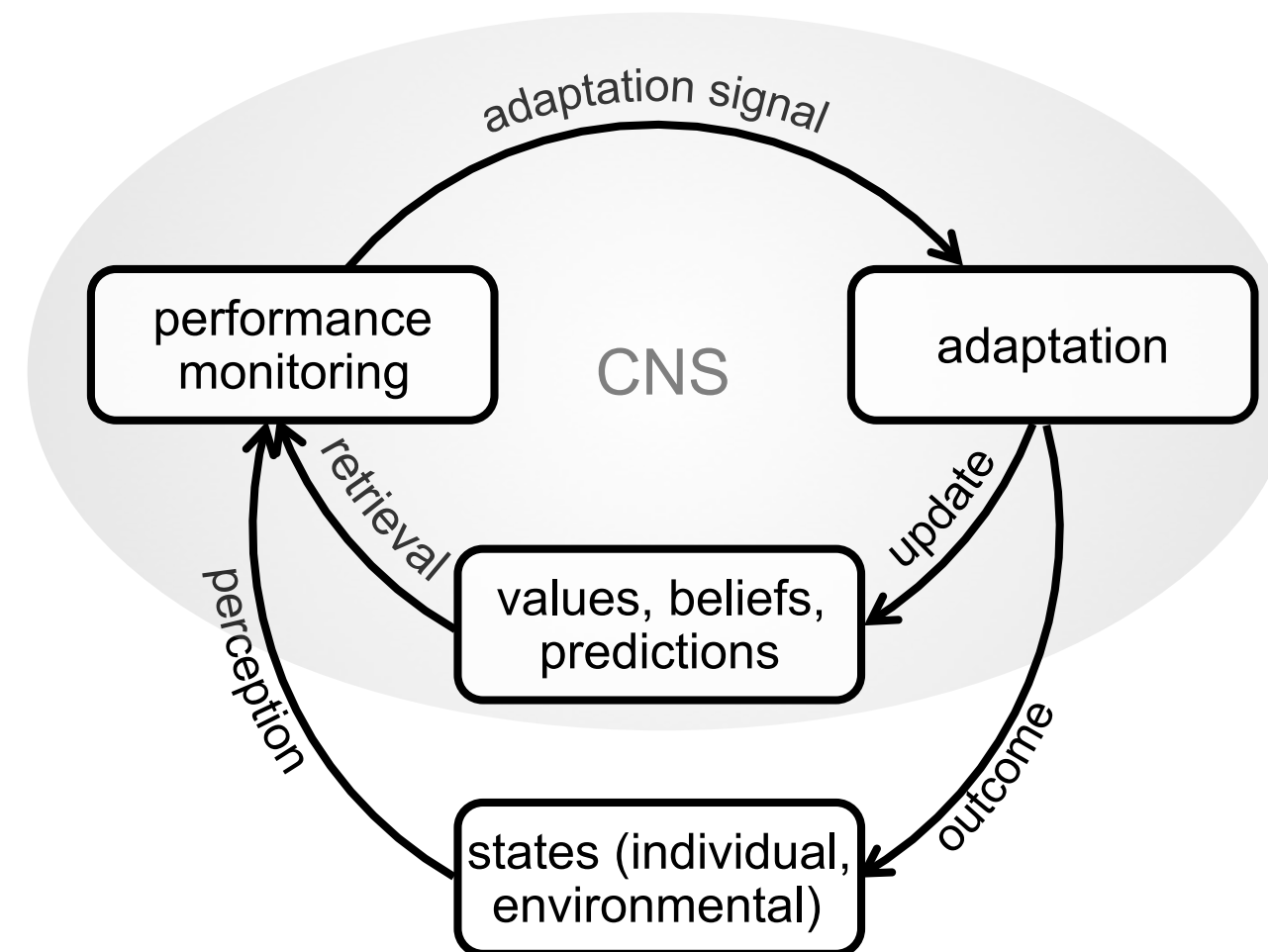
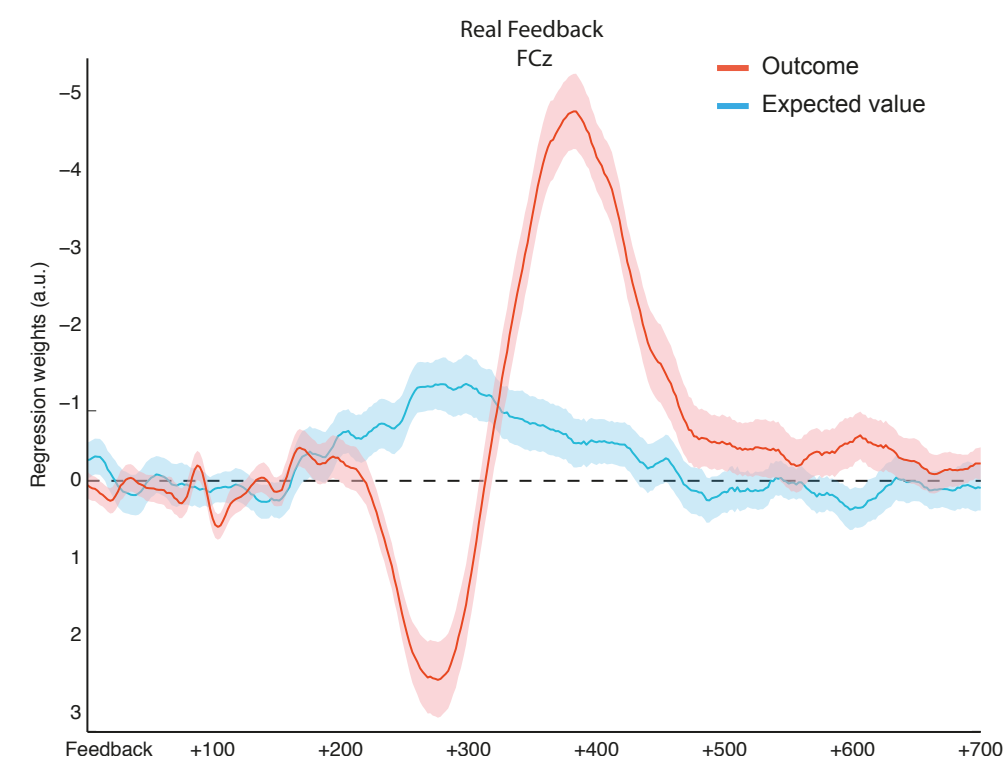
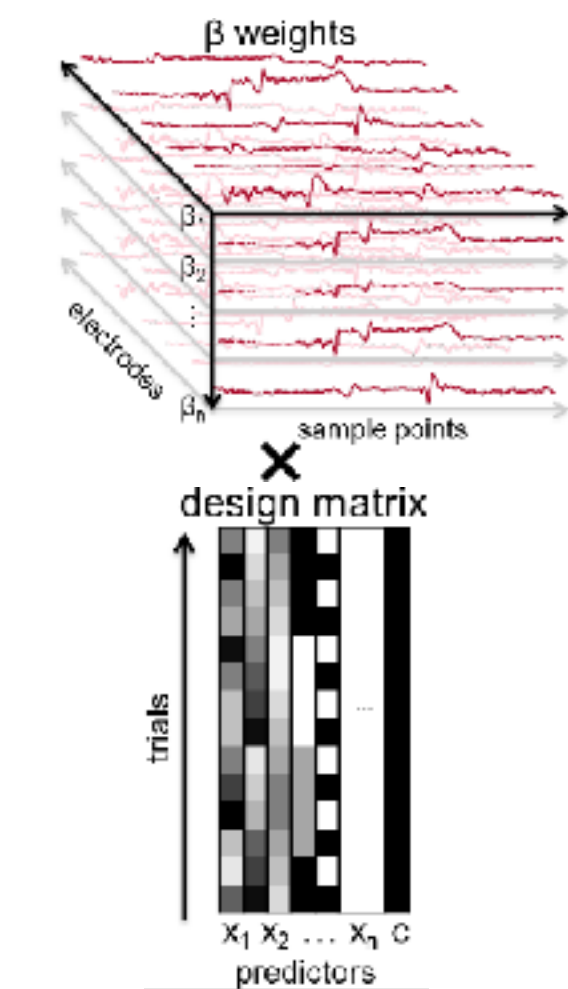
Summary



- Single-trial regression offers possibilities to conveniently combine electrophysiology and model-based analyses

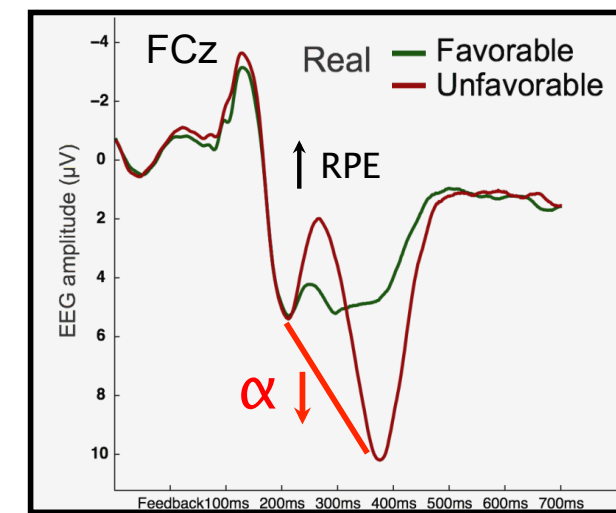


Summary

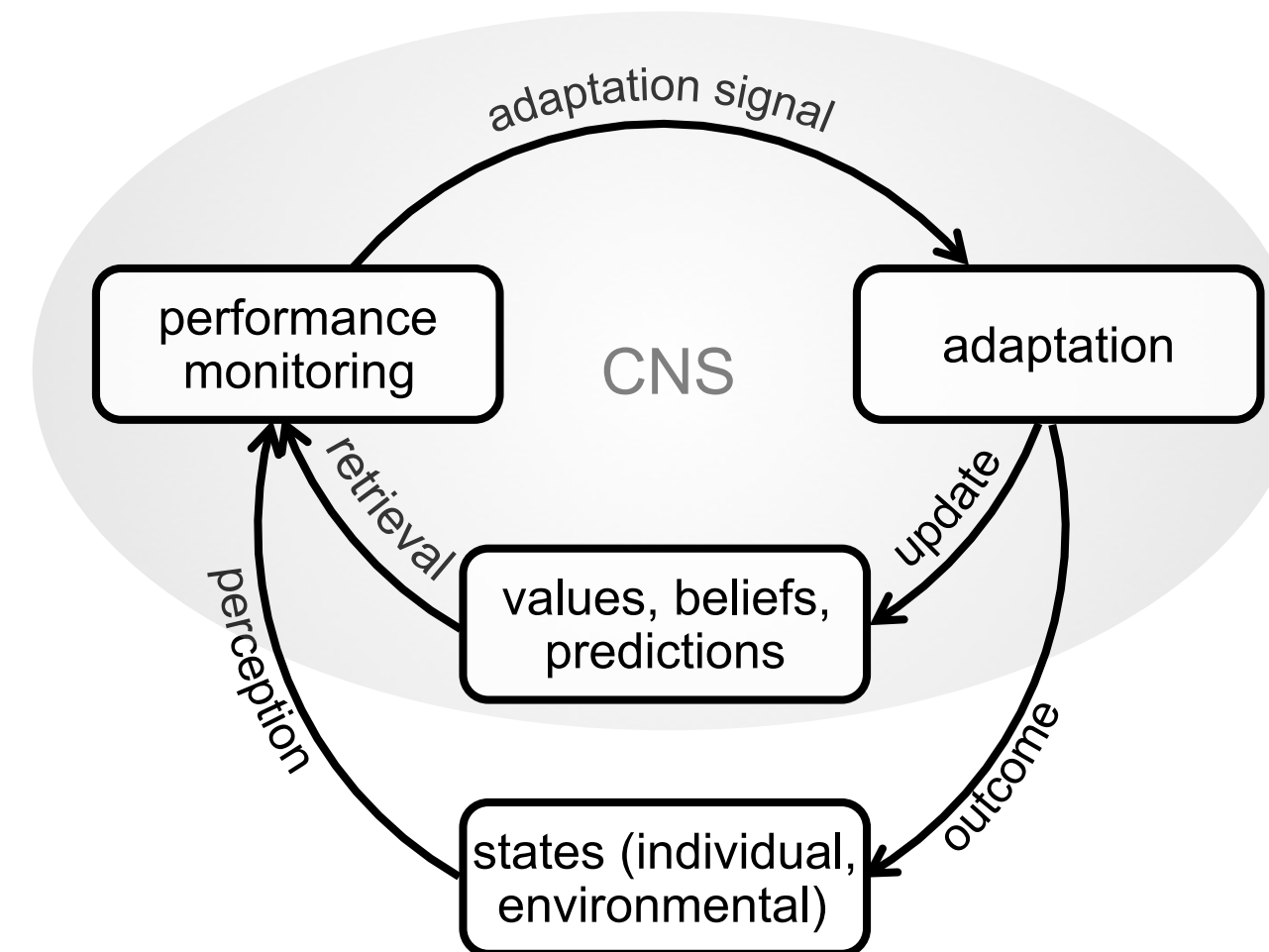
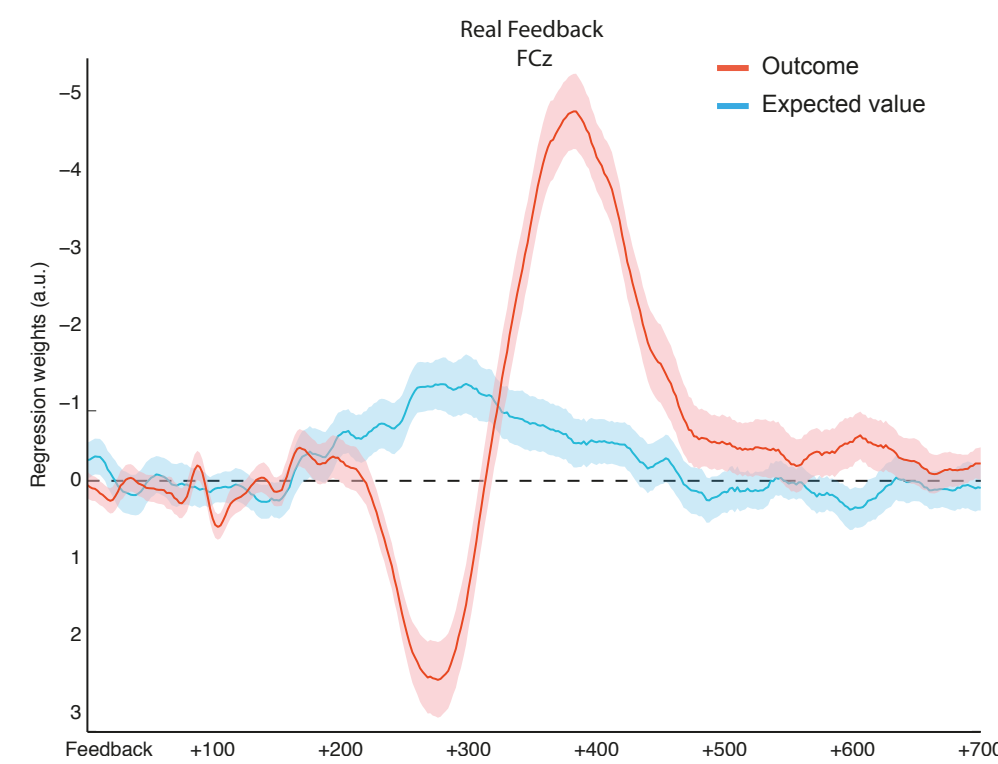


- Single-trial regression offers possibilities to conveniently combine electrophysiology and model-based analyses
- FRN fulfills necessary and sufficient criteria of prediction-error signal

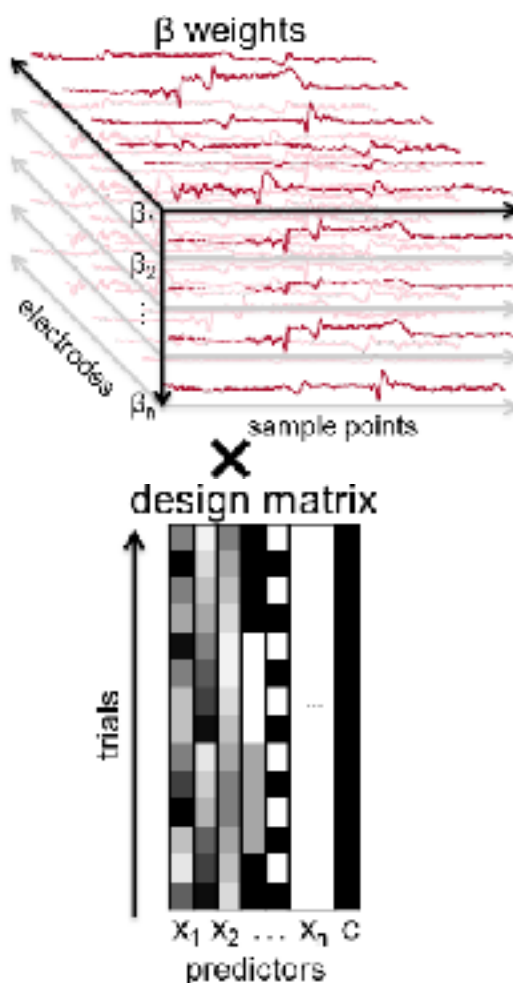
Summary



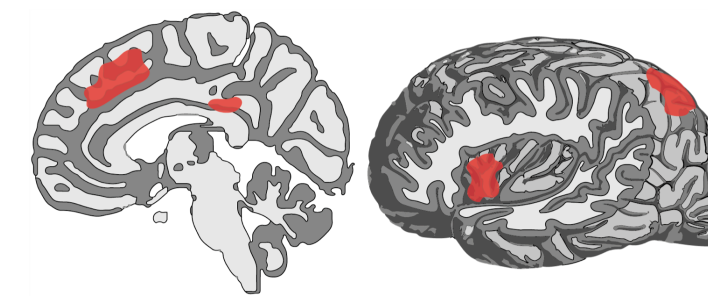
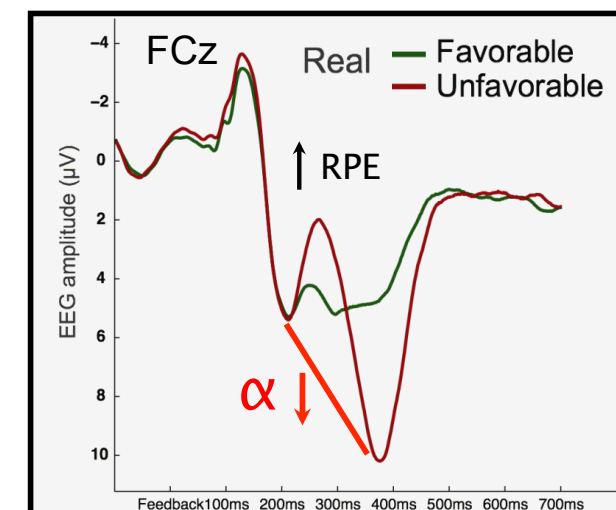
weighting



- Single-trial regression offers possibilities to conveniently combine electrophysiology and model-based analyses
- FRN fulfills necessary and sufficient criteria of prediction-error signal
- Exponentially declining and adaptive learning-rates modulate the baseline of FRN and P3a

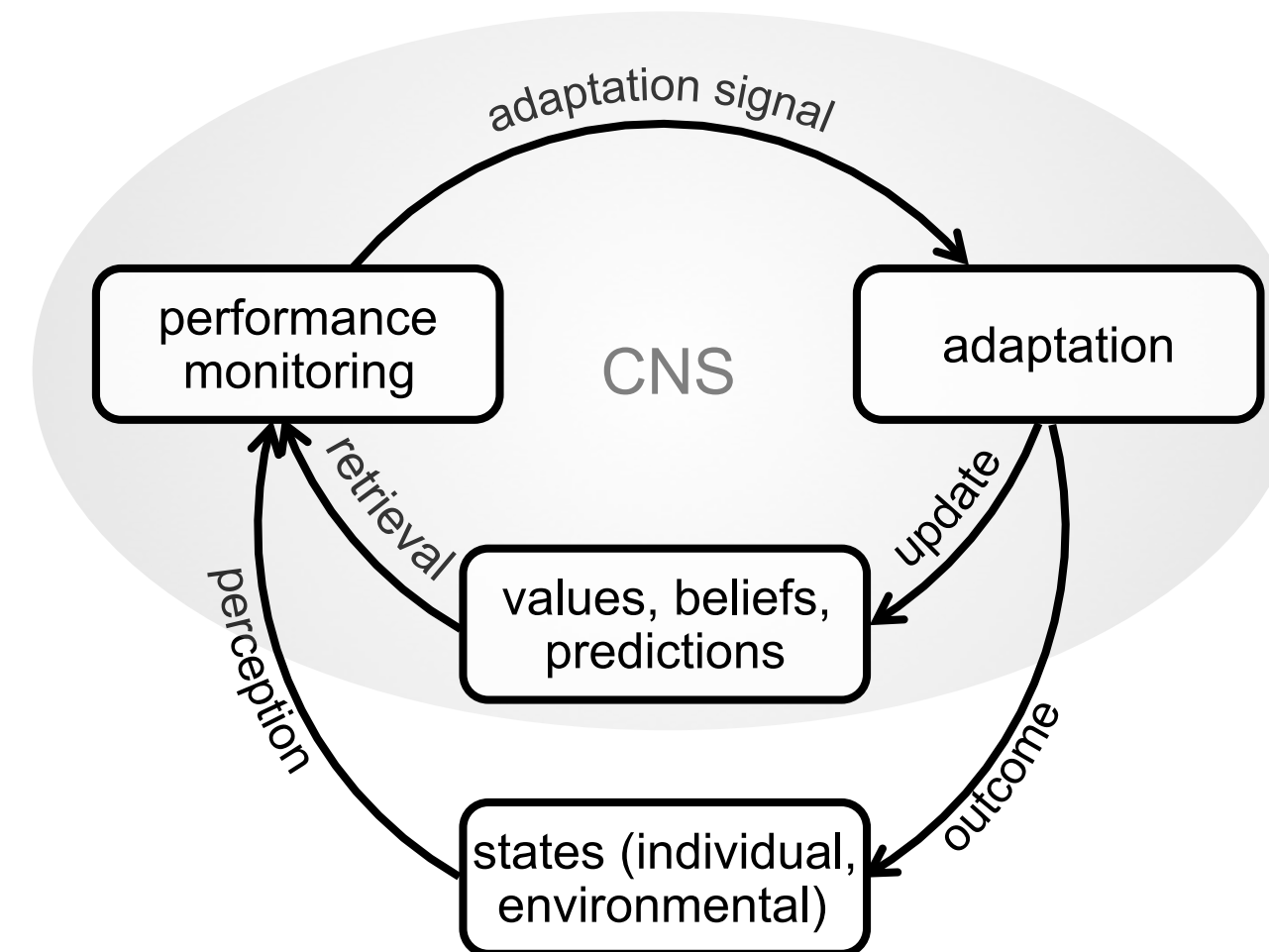
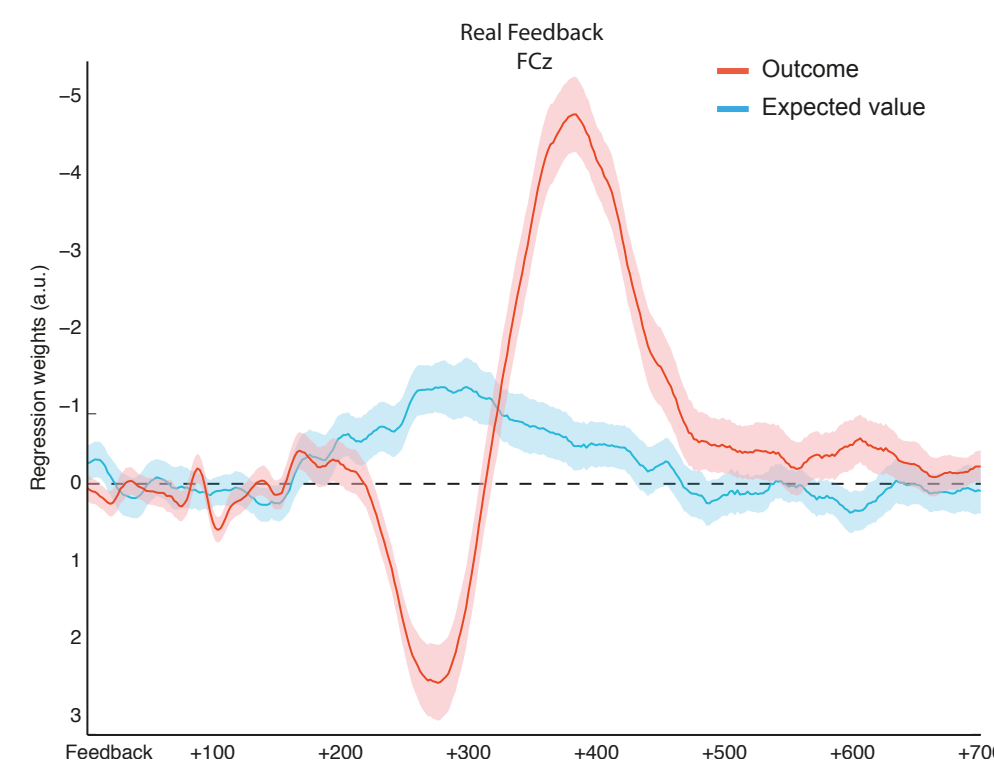


Summary

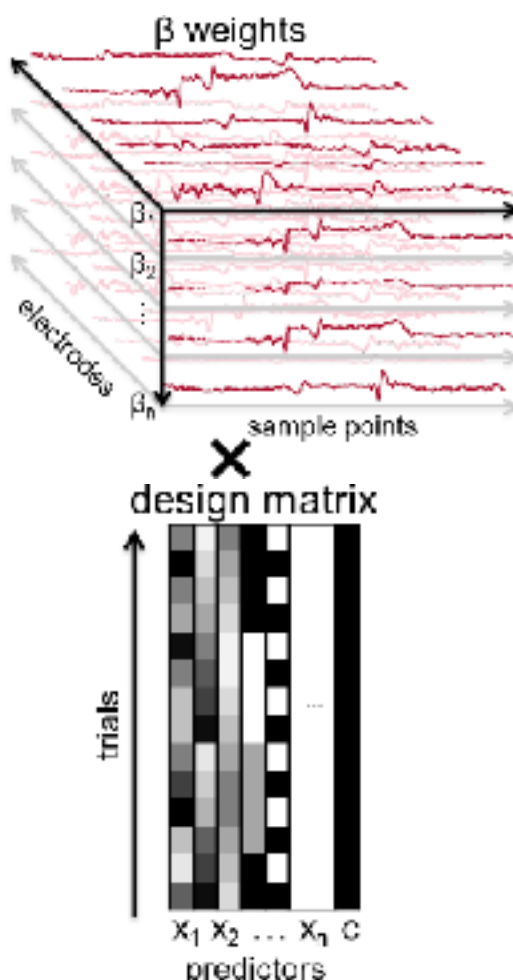


necessity
magnitude
type → of adaptation

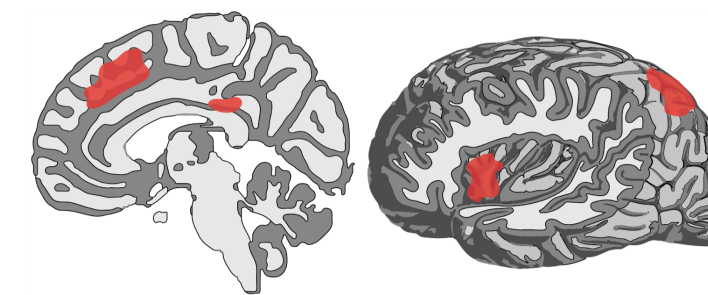
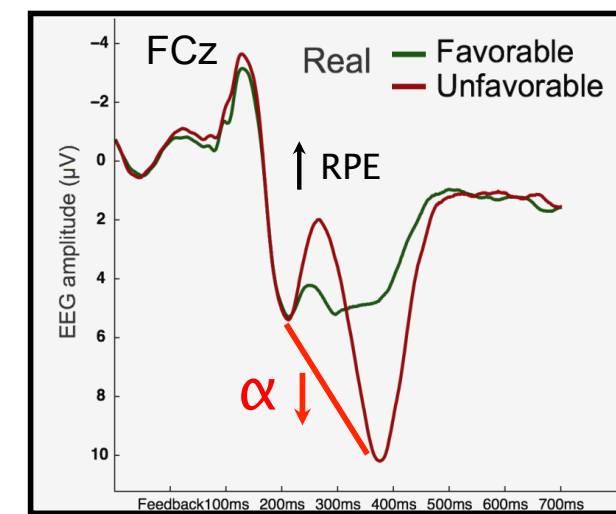
weighting



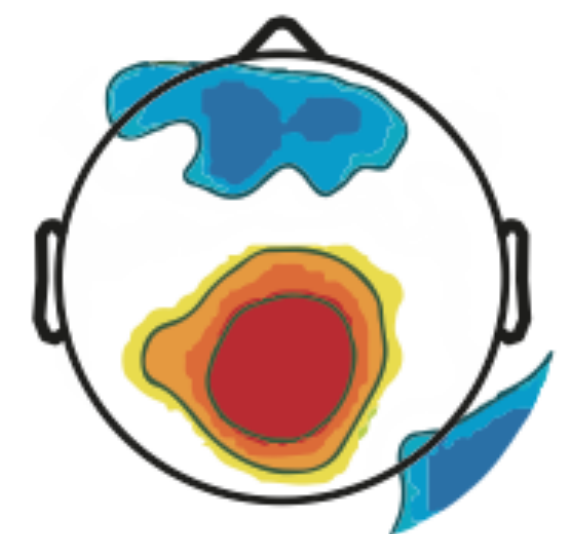
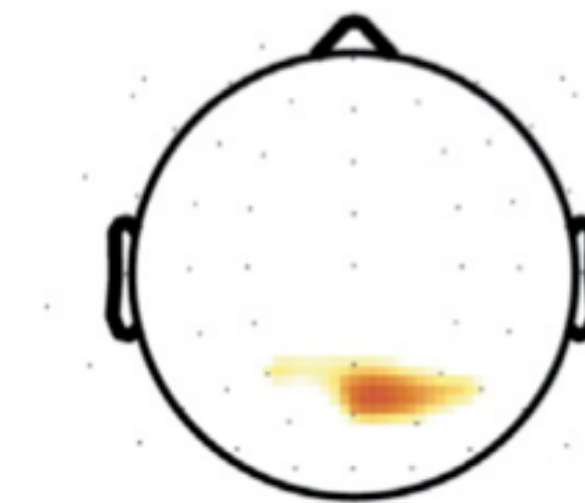
- Single-trial regression offers possibilities to conveniently combine electrophysiology and model-based analyses
- FRN fulfills necessary and sufficient criteria of prediction-error signal
- Exponentially declining and adaptive learning-rates modulate the baseline of FRN and P3a



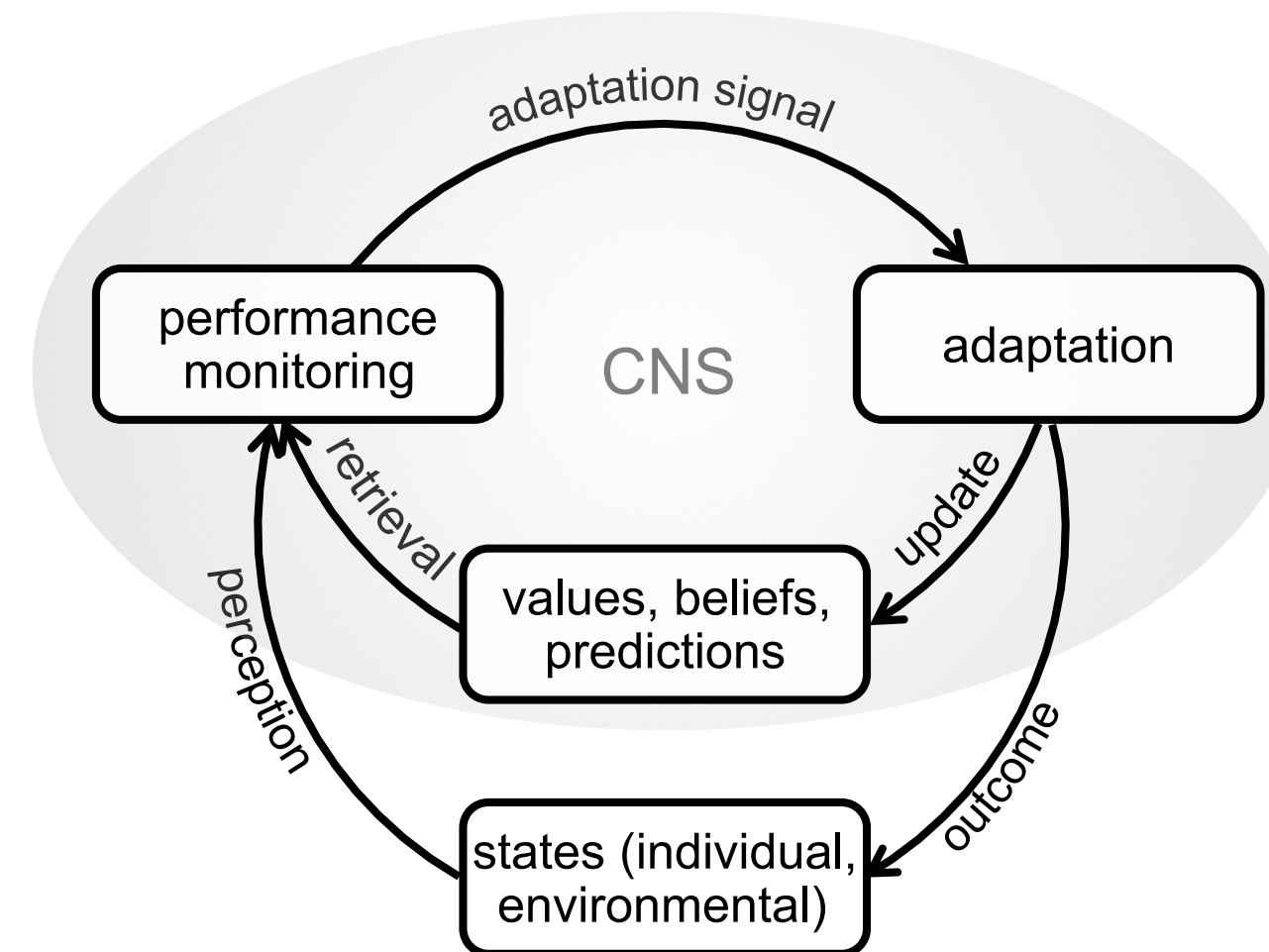
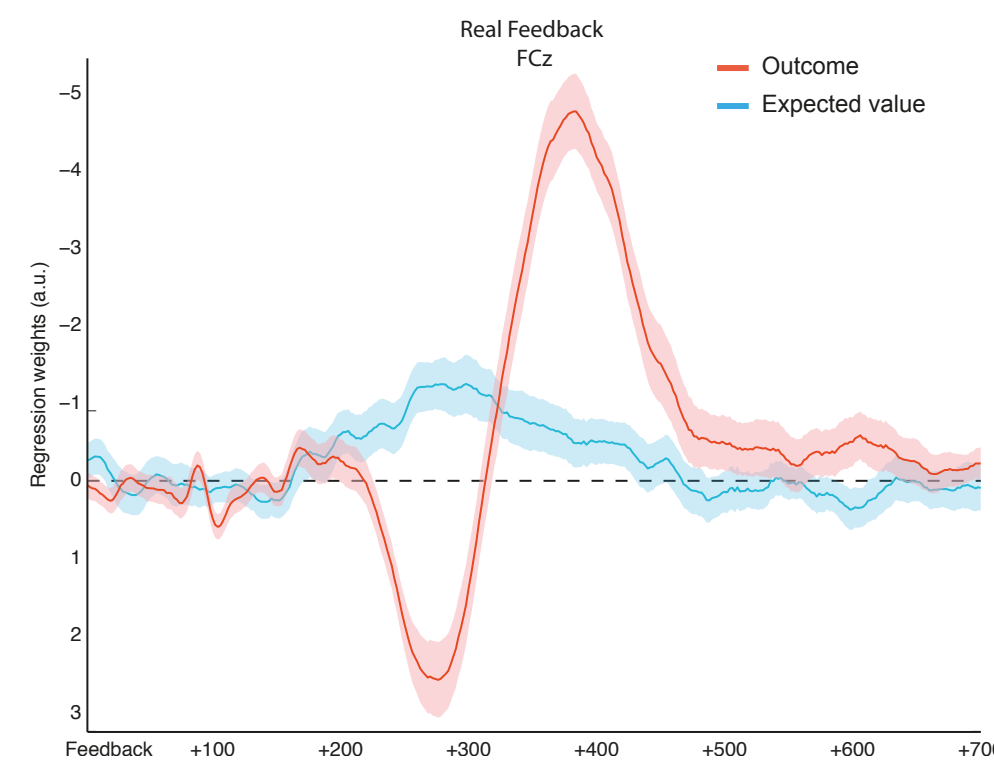
Summary



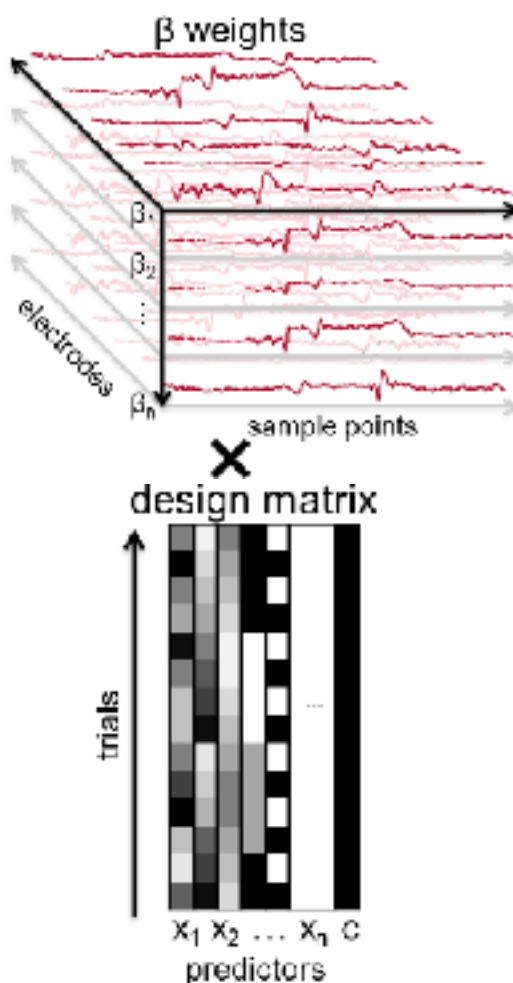
necessity
magnitude
type → of adaptation



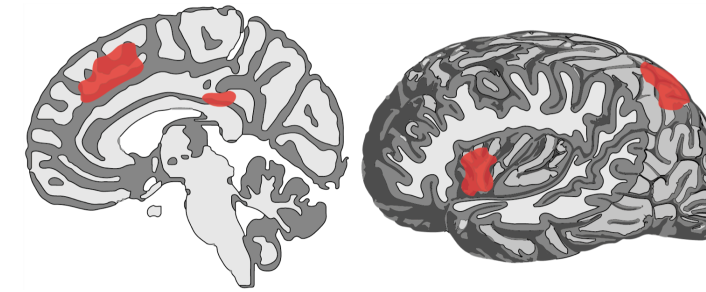
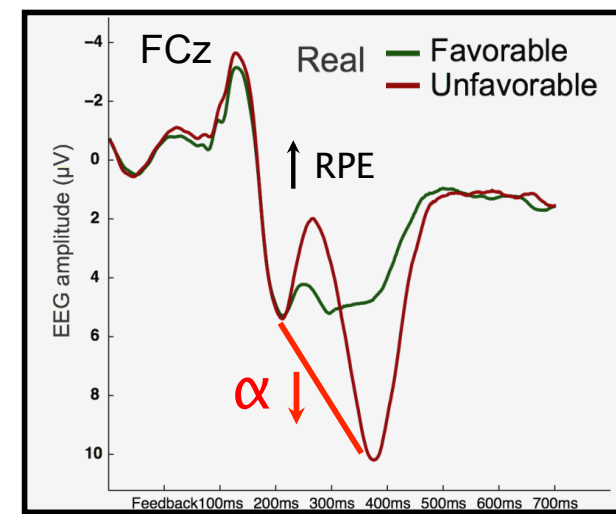
weighting



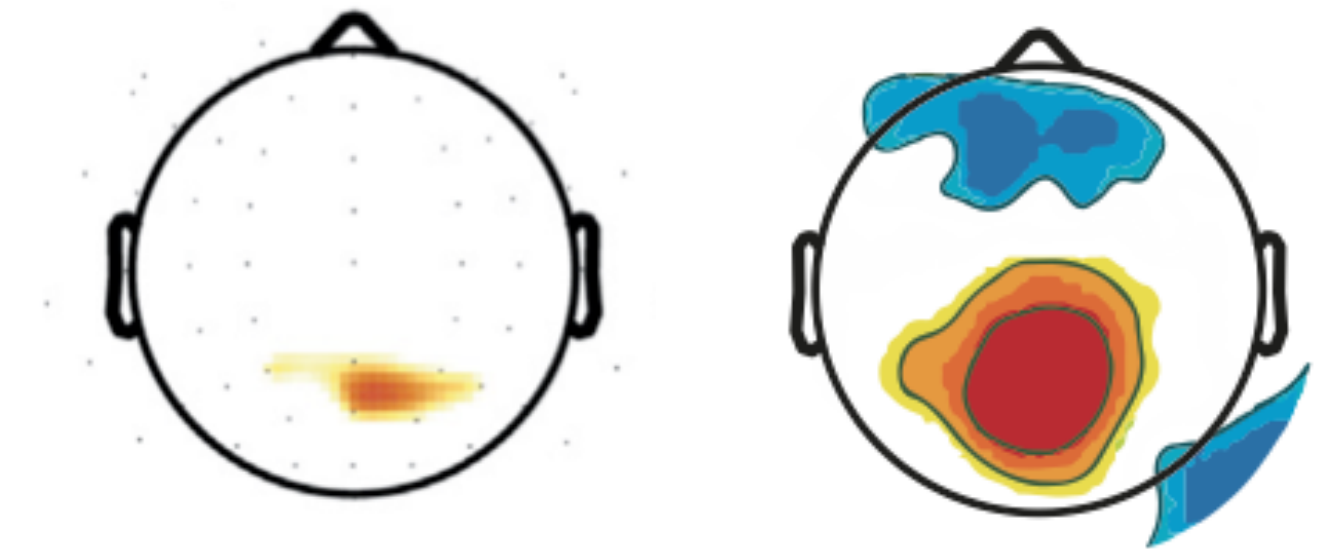
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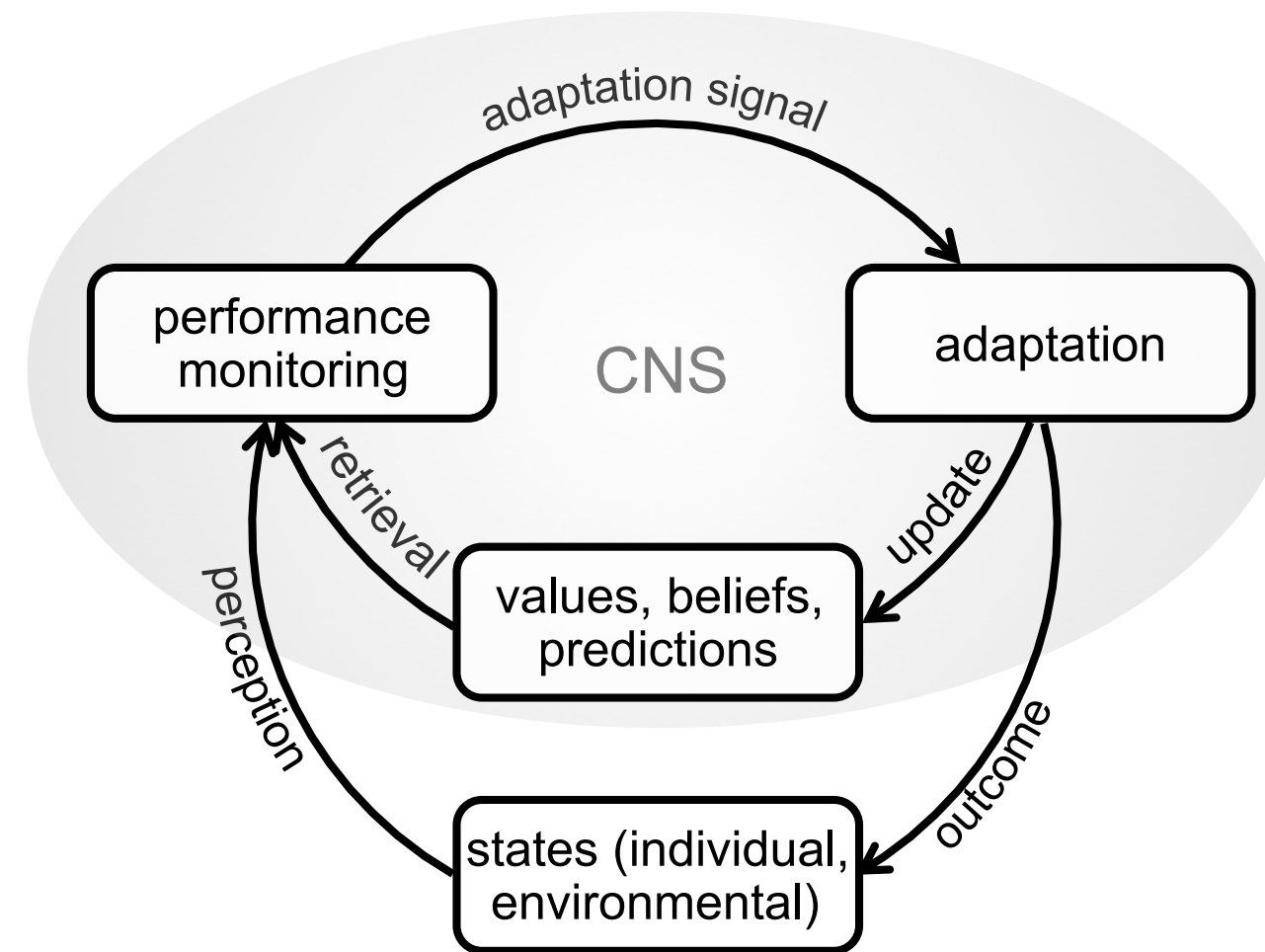
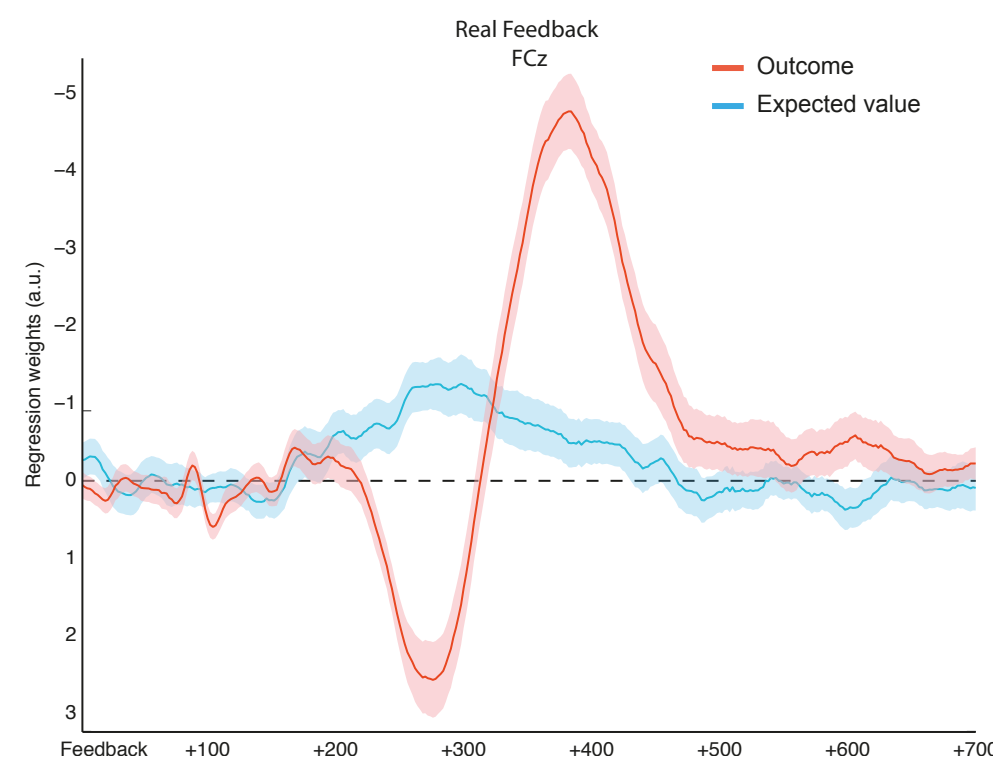
Summary



necessity
magnitude
type → of adaptation

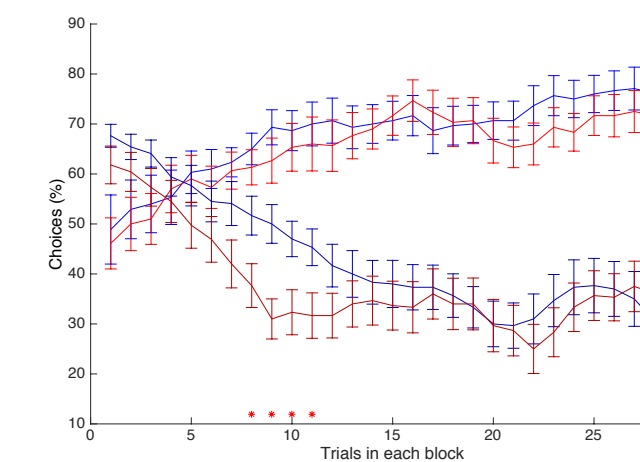


weighting

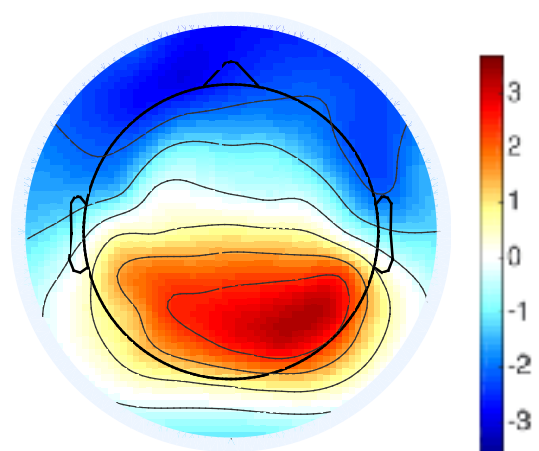


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- ▶ the modulation of this signal by avoided favorable outcomes is reduced in OCD patients who also learn to avoid negative stimuli faster compared to healthy controls



Group Effect



- Session 1 - Why single-trial EEG analyses?
- **Session 2 - Pre-processing, introduction to ICA**
 - Example session I: Setting-up your data and running a single-trial regression analysis with the *STA-TB*
- Session 3 - ICA as a tool to increase SNR in EEG data
 - Example session II: COMPASS to select ICs
 - Example session III: EEG regression with independent component activity
- Session 4 - Within-subject to across-subject analyses
 - Example session IV: Combine data across participants
- Session 5 - Time-frequency decomposition and single-trial analyses
 - Example session V: Run a TF decomposition and GLM analysis
- Session 6 - MvPA for EEG
 - Example session VI: Time-resolved classification of EEG data
- End and Discussion