

# Neural Surprise in Human Somatosensation

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NEUROCOMPUTATION  
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UNIT

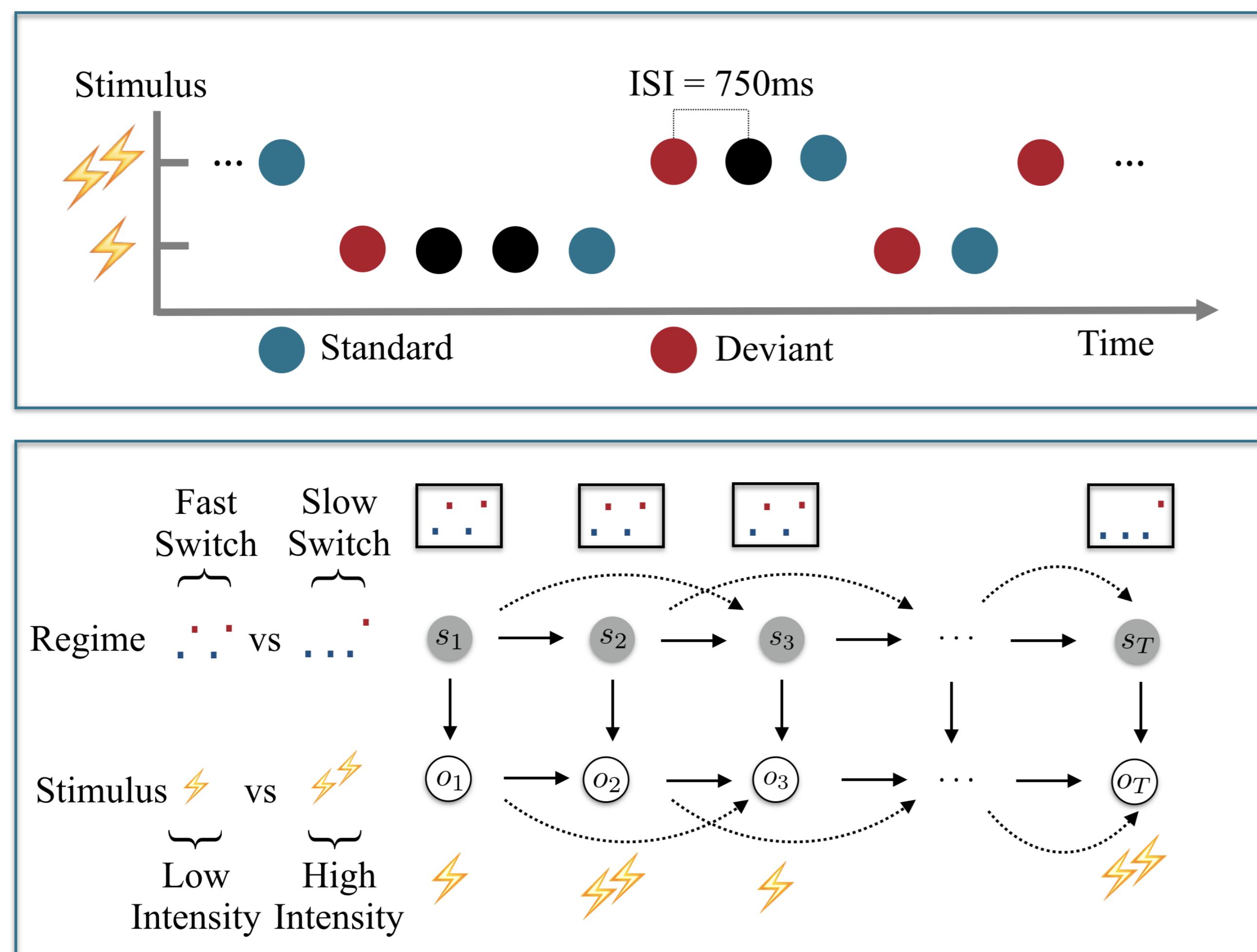
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## MOTIVATION

- The Bayesian brain hypothesis posits that the brain employs probability distributions over sensory input and Bayesian inference to continuously update its beliefs about (hidden states) of the world.
- The updating of these belief distributions may be probed by studying proxies of neural surprise signals recorded with EEG (Ostwald *et al.*, 2012).
- There are many ways to realize both a sequential Bayesian model and surprise quantification. In order to learn about the distinguishing features we compare a selection of Bayesian models with different surprise functions. Furthermore, this study investigates how the brain tracks hidden states in the environment.

## EXPERIMENTAL DESIGN

- 23 participants were administered median nerve stimulation in consecutive trains of alternating stimulus intensities using a roving paradigm. To ensure subjects kept their attention on the stimulation, they were instructed to count the occurrences of catch trials which consisted of a short burst of three stimuli.
- 64-channel EEG data were recorded at 2048Hz.



- Trials are sampled from a graphical model, which allows for 1st and 2nd order Markov dependencies on the regime as well as stimulus level.

## ERP ANALYSIS

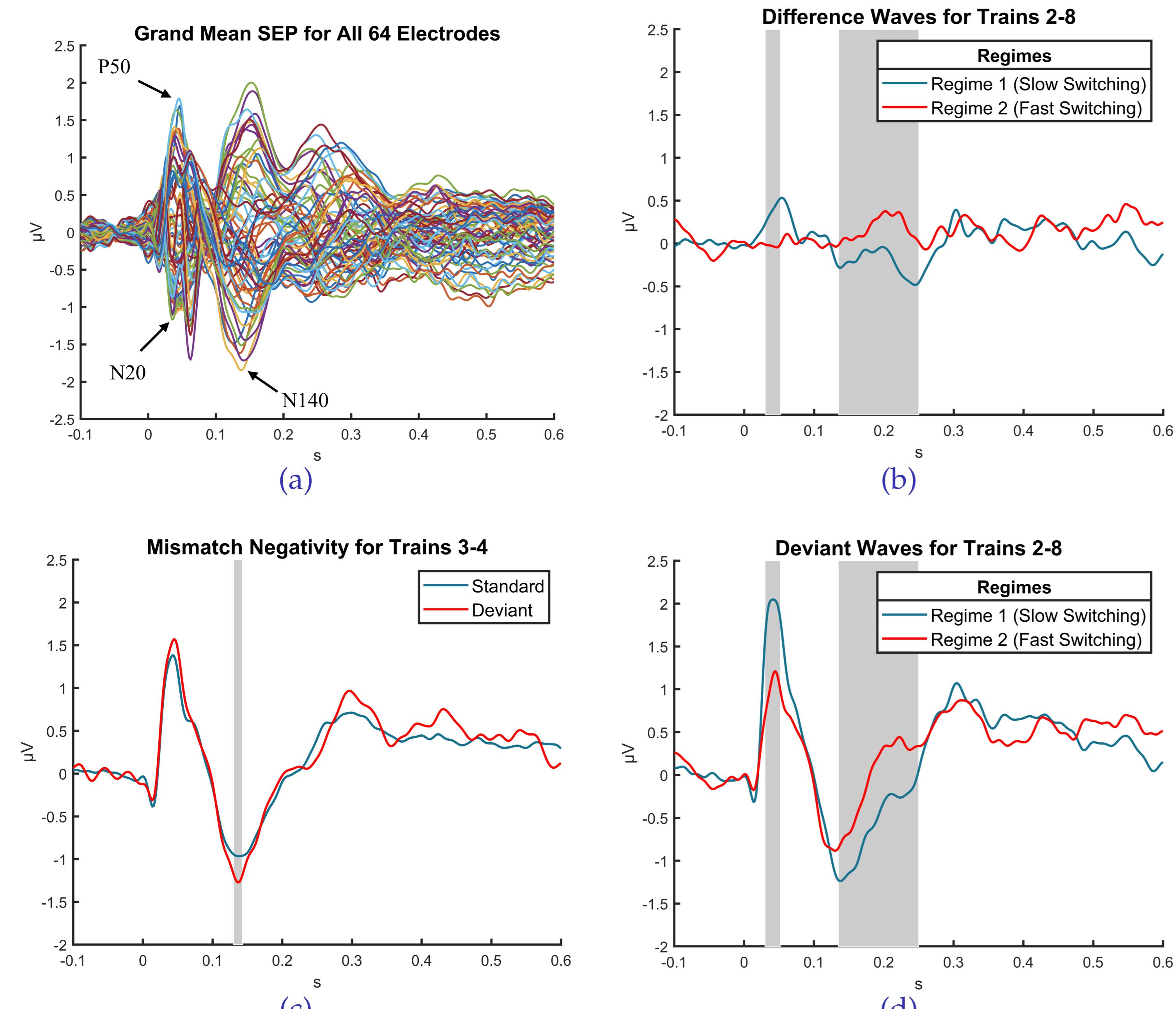
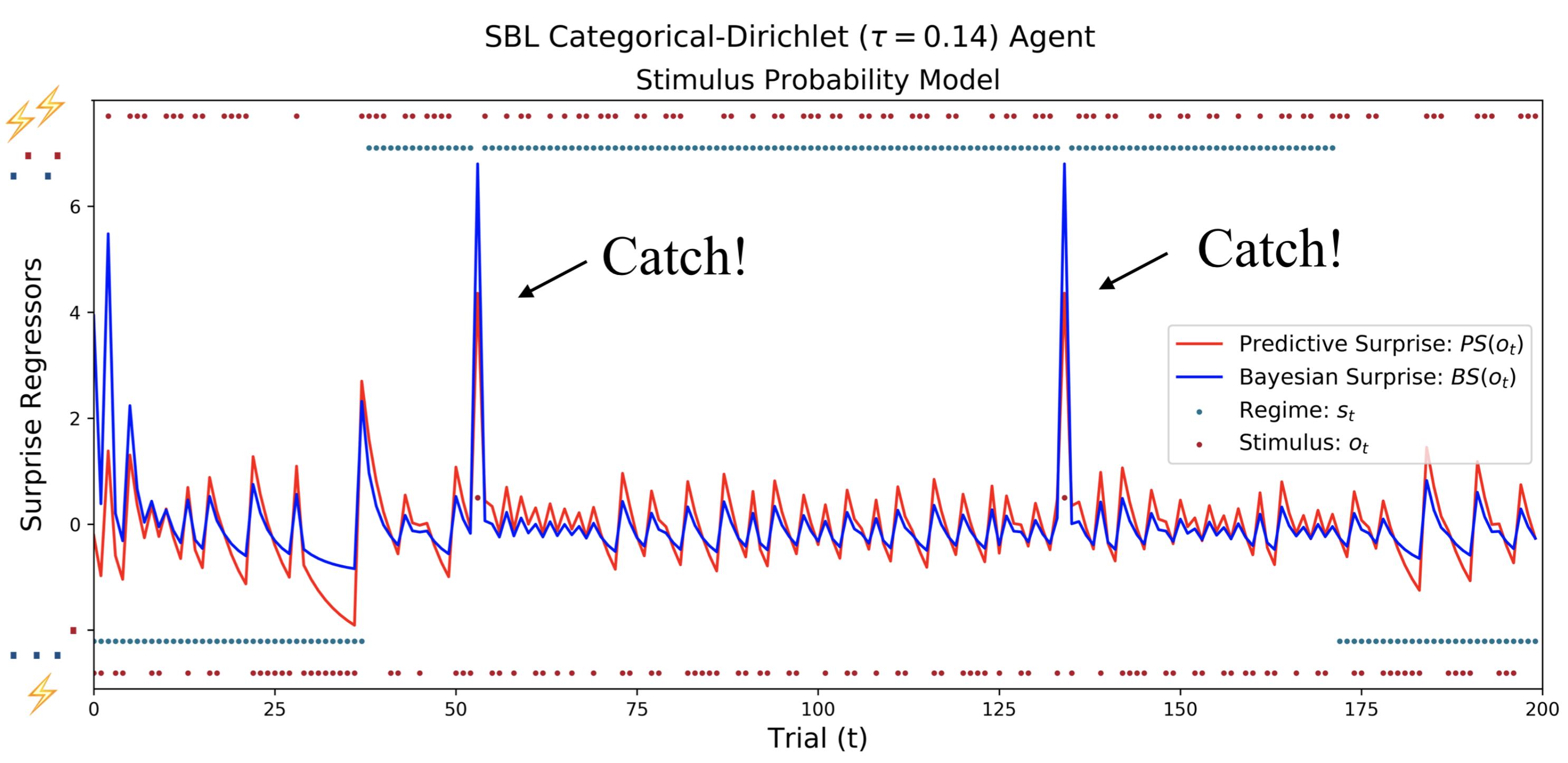


Figure 1: Event-Related Potentials (n=21)

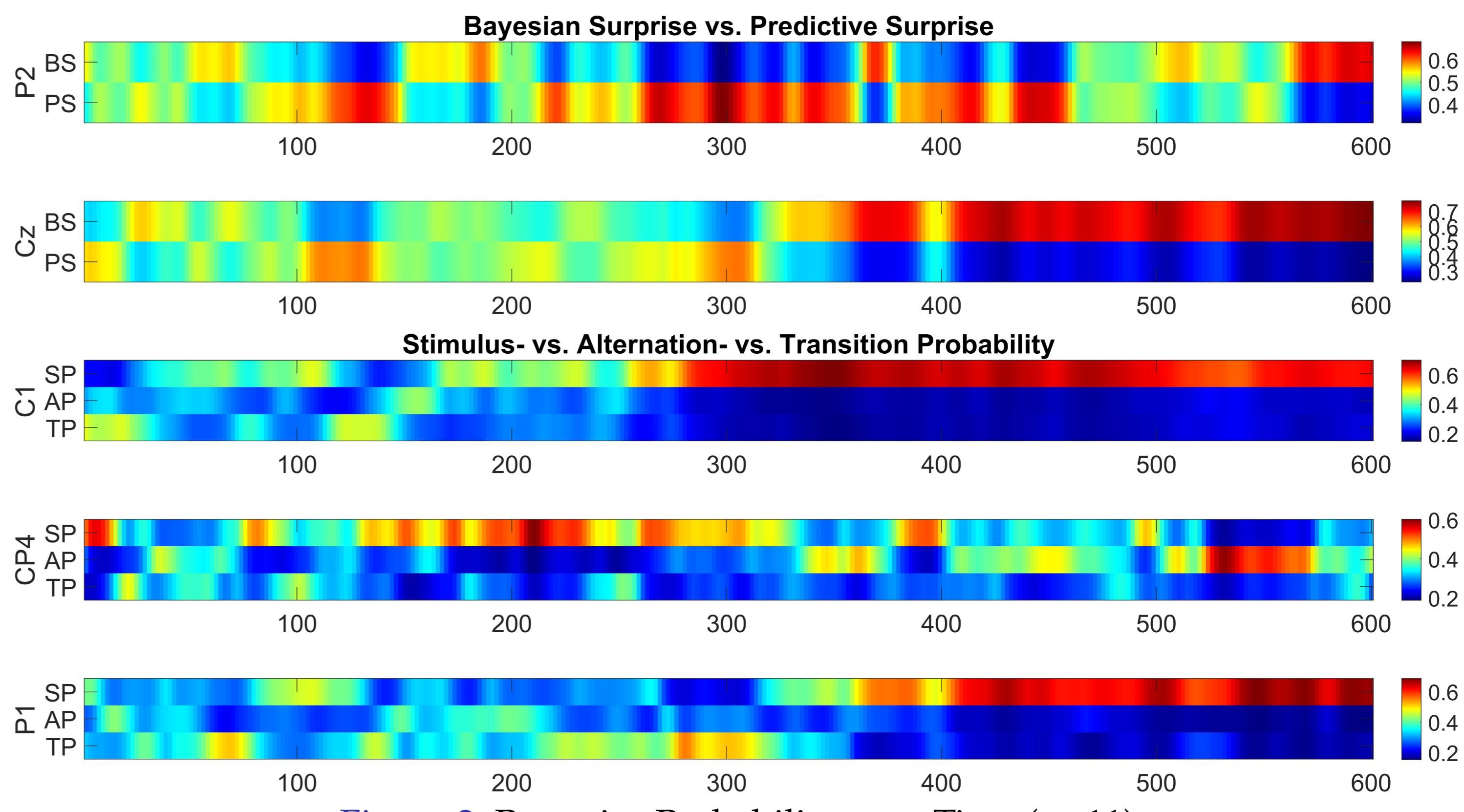
- A significant somatosensory mismatch negativity effect was observed when comparing standard and deviant ERPs (fig. 1c;  $p=0.02$  for 130-143ms).
- The P50 was found to be significantly weaker in Regime 2 compared to Regime 1 (fig. 1b, 1d;  $p=0.00004$  for 30-52ms).
- The same comparison reveals a greater mismatch negativity in Regime 1 than for Regime 2 (fig. 1b, 1d;  $p=0.01$  for 135-250ms).

## MODELLING NEURAL SURPRISE

	Hidden State	Observations
SP	$s \in \mathcal{S}_M$	$y_t = o_t \in [1, 2, \dots, M]$
AP	$s \in \mathcal{S}_2$	$y_t = \begin{cases} 1, & \text{if } o_t \neq o_{t-1} \\ 0, & \text{else.} \end{cases}$
TP	$s^i \in \mathcal{S}_M$	$y_t = o_t \in [1, 2, \dots, M] \quad \forall i = 1, \dots, M$
Categorical-Dirichlet Model		
	$\{\alpha_0^j\}_{j=1}^M \sim Dir(\alpha)$	
	$s \sim Cat(s)$	
	$y_1, y_2, \dots, y_T$	
Closed-Form Posterior		
	$p(s_t   y_1, \dots, y_t) = Dir(\alpha^t)$	
	$\alpha_j^t = \alpha_j^0 + \sum_{i=1}^t e^{-\tau(t-i)} \mathbf{1}\{y_i = j\}$	
Neural Surprise Regressors		
Predictive Surprise:	$PS(o_t) = -\ln p(y_t   s_t)$	
Bayesian Surprise:	$BS(o_t) = KL(p(s_{t-1}   y_{1:t-1})    p(s_t   y_{1:t}))$	



## BAYESIAN MODEL SELECTION



- Following an interpolation of the EEG-data into 2D space, we compute log-model evidence maps based on Bayesian GLMs. Posterior probabilities were then computed using variational Bayes methods allowing for a random effects approach to model selection (Stephan *et al.*, 2009; Harris *et al.*, 2018).
- PS outperforms BS for early effects (N140 and P300) over somatosensory cortex, while BS posterior probability exceeds for the later, central components (P600).
- The simpler SP model has an advantage over AP and TP models, especially late in the trial at central electrodes.

## OUTLOOK

- Given the promising ERP results, hidden state learning will be further investigated by extending the model selection with a Hidden Markov model.
- For a more thorough comparison of the combinations of Bayesian models and surprise functions, confidence-corrected surprise will be implemented.

## REFERENCES

- Harris, Clare D, Rowe, Elise G, Randeniya, Roshini, & Garrido, Marta I. 2018. Bayesian Model Selection Maps for group studies using M/EEG data. *Frontiers in neuroscience*.
- Ostwald, Dirk, Spitzer, Bernhard, Guggemos, Matthias, Schmidt, Timo T, Kiebel, Stefan J, & Blankenburg, Felix. 2012. Evidence for neural encoding of Bayesian surprise in human somatosensation. *NeuroImage*, 177-188.
- Stephan, Klaas Enno, Penny, Will D, Daunizeau, Jean, Moran, Rosalyn J, & Friston, Karl J. 2009. Bayesian model selection for group studies. *NeuroImage*, 1004-1017.



GitHub Repository