Learning from M/EEG data with variable brain activation delays

by
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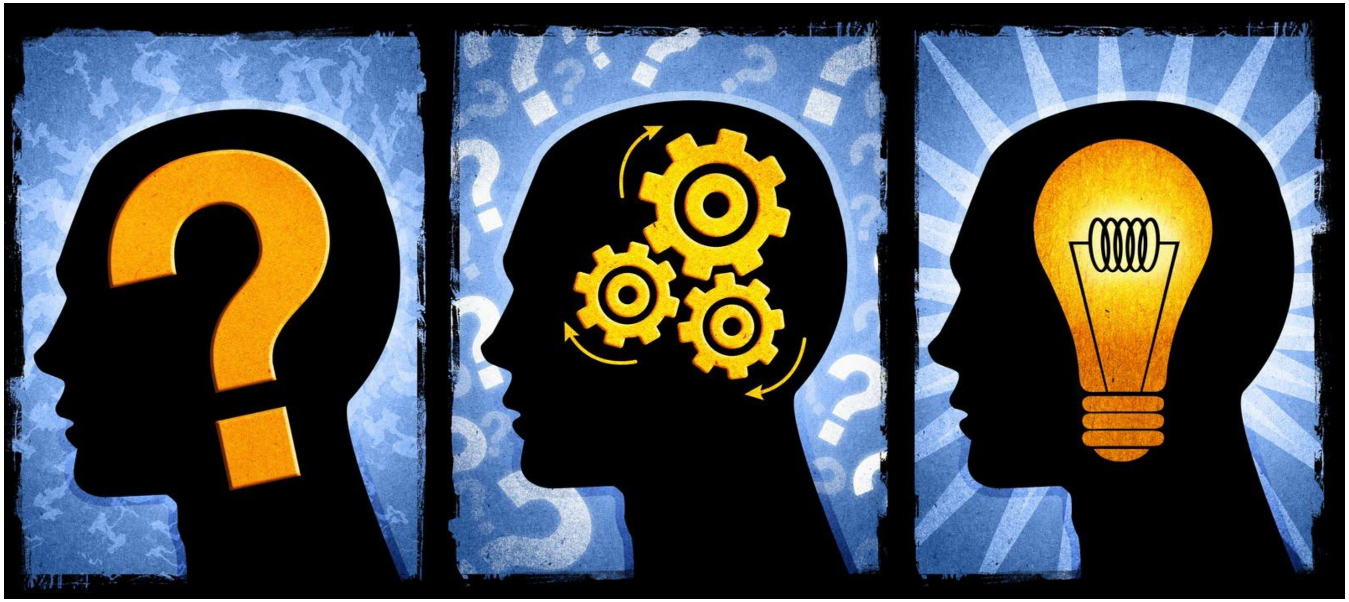
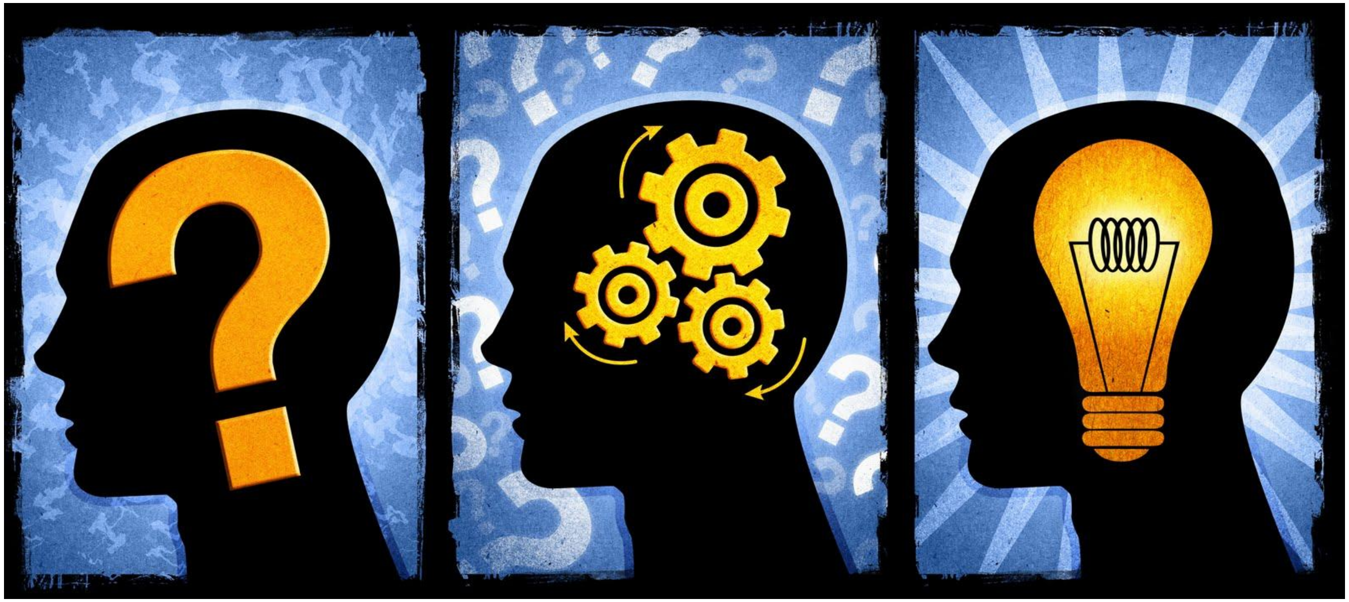
Observation

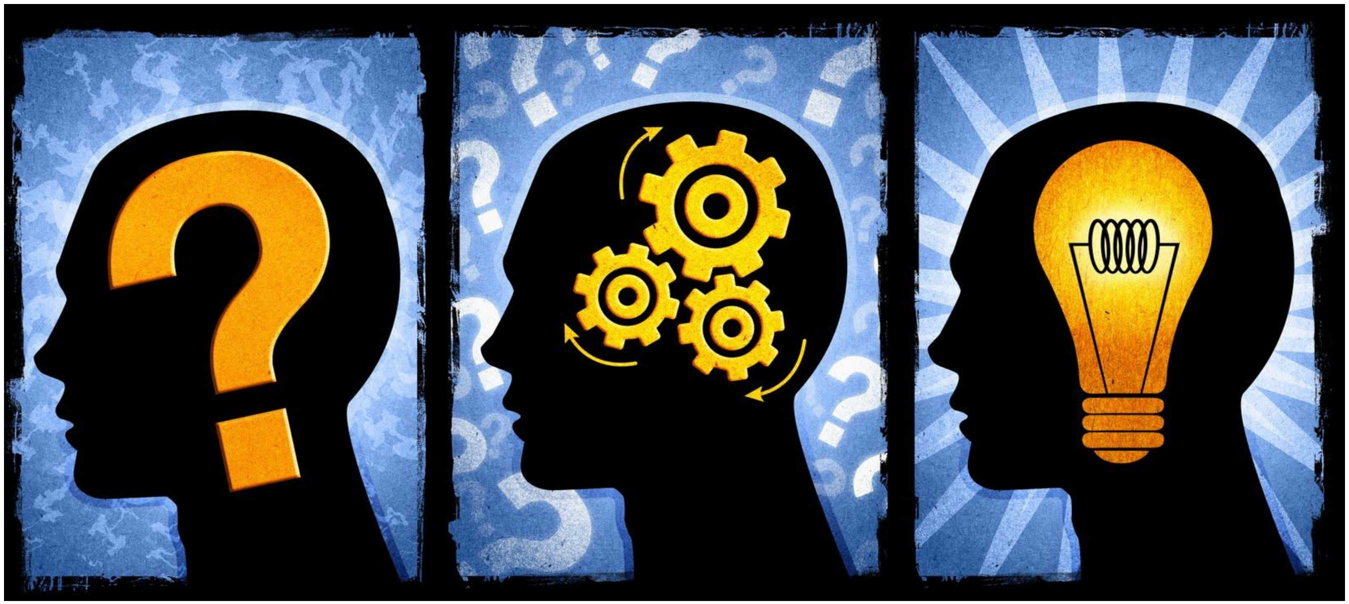


Observation



Takes **some** time

Implied assumption



The same brain process might take various time.

Outline

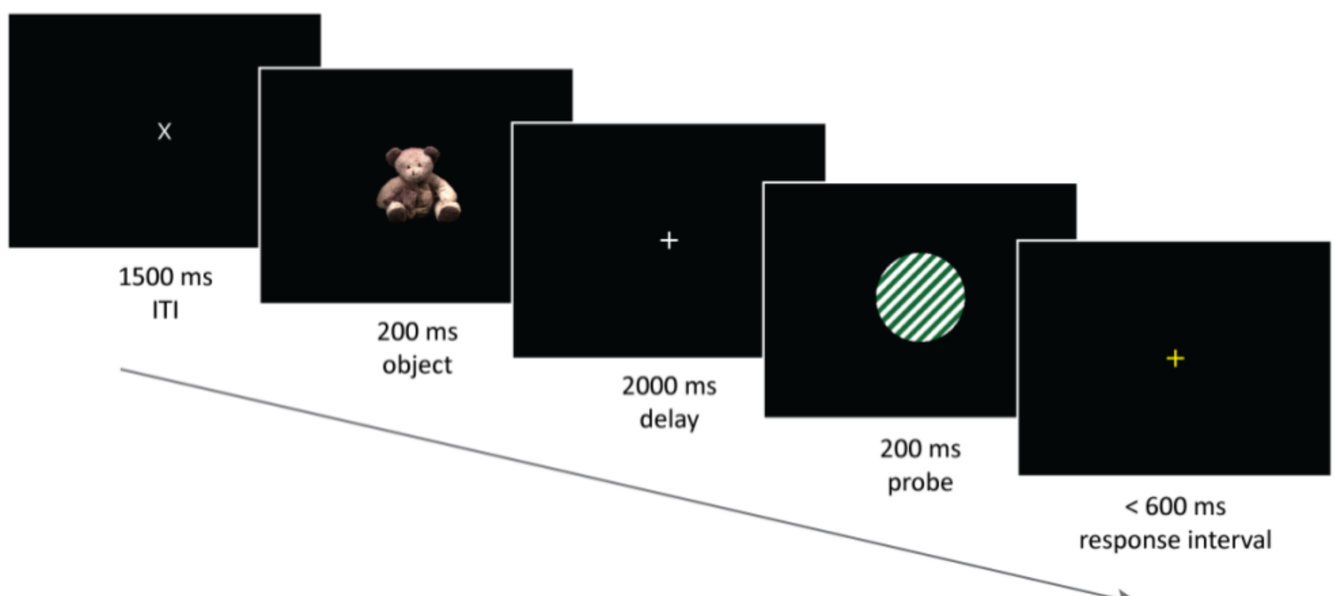
- Studies definition
- Methods
- Results

Studies definition

- electrical and magnetic impulses recorded from scalp (M/EEG)
- a single subject
- a single experiment with binary output repeated multiple times

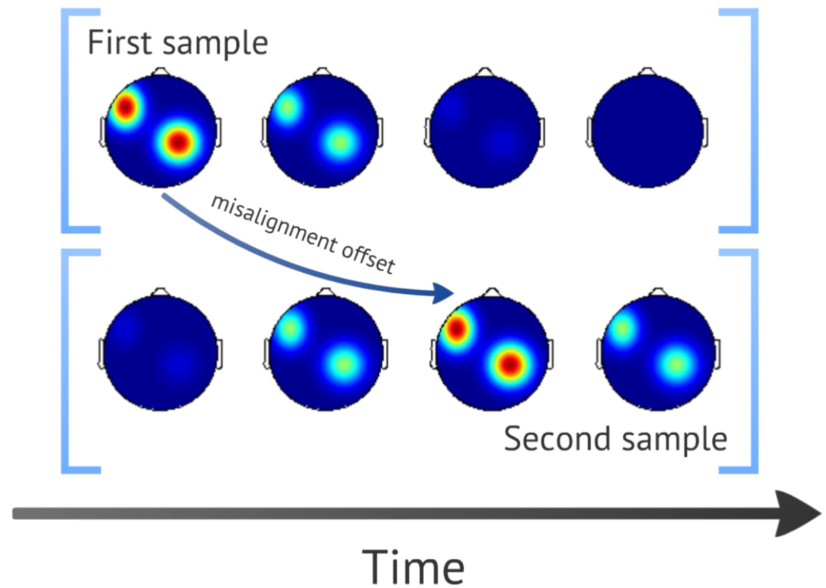
Studies on long term memory

- subject learnt multiple relations object to two possible colors (biomag 2012 LTM dataset)
- subject has to recall color based on object



Problem description

- delays in brain responses due to temporary subject condition
- delays are unknown



- Experiments
  a. How to improve prediction ?
  b. How to improve ERP visualization ?
  c. How to infer brain connectivity ?

Methods introduction - SVM

$$\min_{w,\xi} \frac{1}{2}\|w\|^2 + \sum_i \xi_i$$

$$y_i w^\top \phi(x_i) \quad - \quad \hat{y} w^\top \phi(x_i) \quad \geq 1 - \xi_i$$

$$\xi_i \geq 0,\ \hat{y} \neq y$$

Methods - Latent SVM

$$\min_{w,\xi} \frac{1}{2}\|w\|^2 + \sum_i \xi_i$$

$$\max_h y_i w^\top \phi(x_i, h) - \max_{\hat{h}} \hat{y} w^\top \phi(x_i, \hat{h}) \geq 1 - \xi_i$$

$$\xi_i \geq 0,\ \hat{y} \neq y,\ \hat{h} \in H$$

score for the predicted right (y,h) should be better than any other score.

Methods - Latent variable

$$x = (a_1, a_2, \ldots, a_n)^\top$$

$$\phi(x, h) = (a_{s+h}, a_{s+1+h}, \ldots, a_{l+h})^\top,$$

$$1 \leq s + h \leq l + h \leq n$$

Sliding window from s+h to l+h

Latent SVM - how to

$$\min_{w,\xi} \frac{1}{2}\|w\|^2 + \sum_i \xi_i$$

$$\max_h y_i w^\top \phi(x_i, h) - \max_{\hat{h}} \hat{y} w^\top \phi(x_i, \hat{h}) \geq 1 - \xi_i$$

$$\xi_i \geq 0,\ \hat{y} \neq y,\ \hat{h} \in H$$

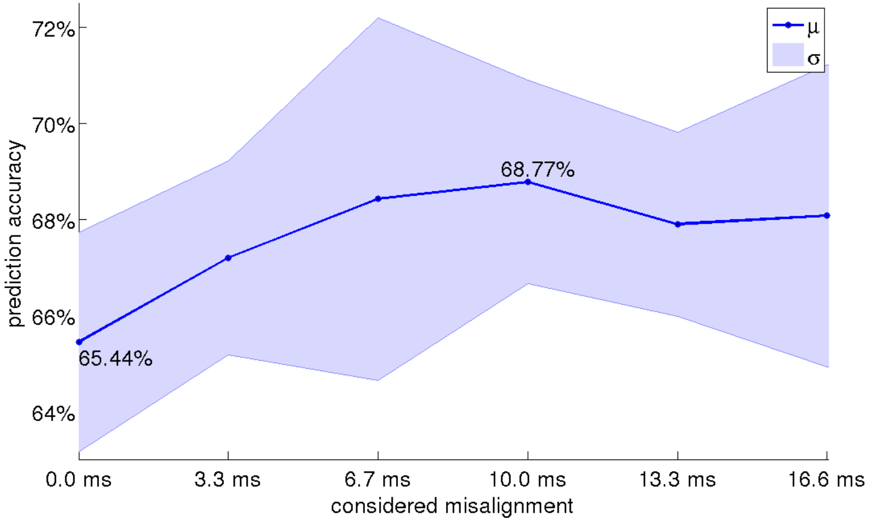
Algorithm alternates between:

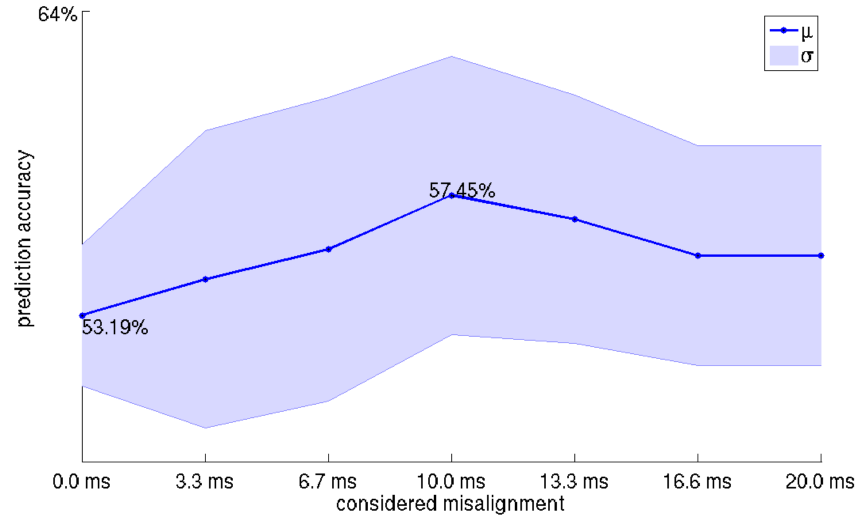
- Finding best h - assigns best offset
- Finding best w, psi - solves SVM

Gives good minimum, but joint optimization of delays is inherently non-convex

Results a) - prediction task

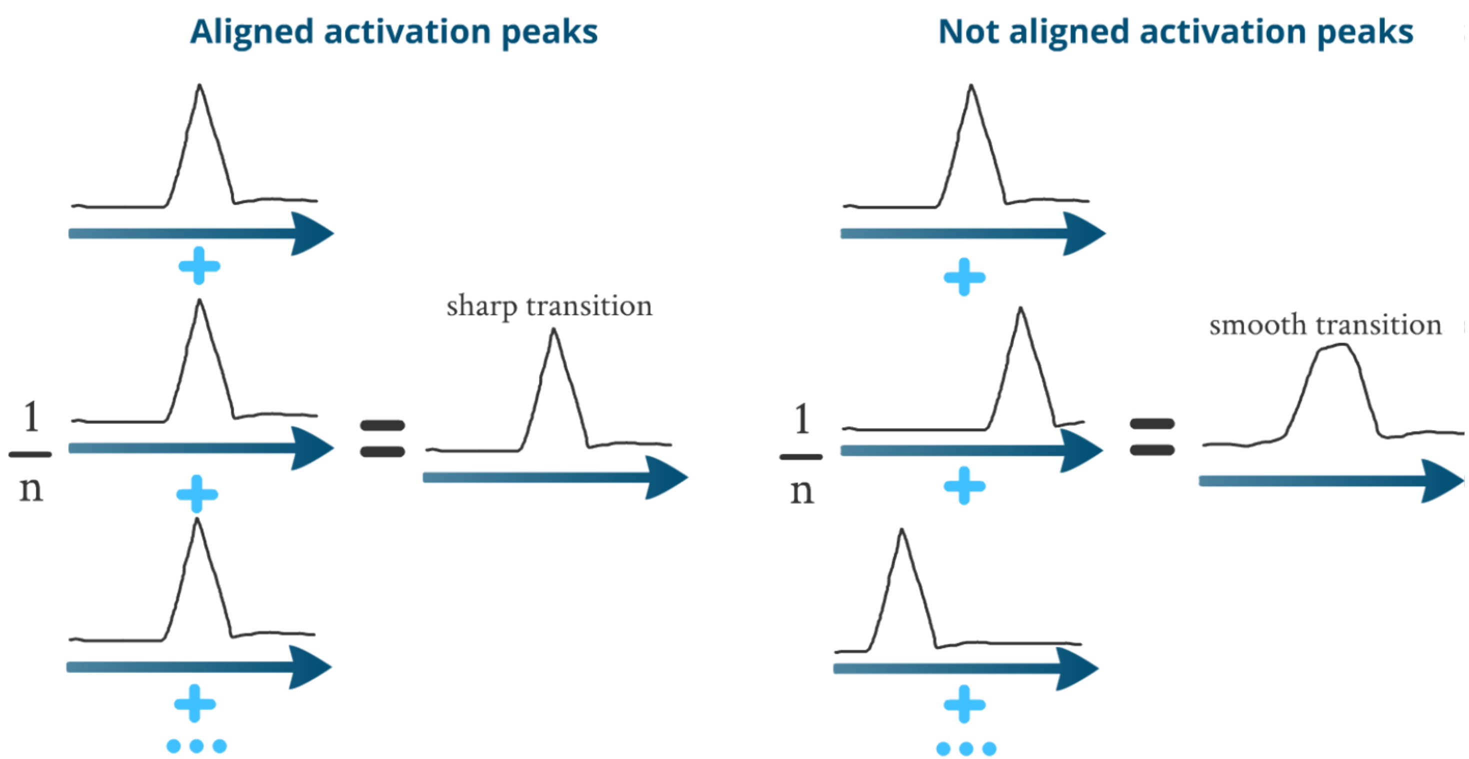
- best prediction for up to 10ms



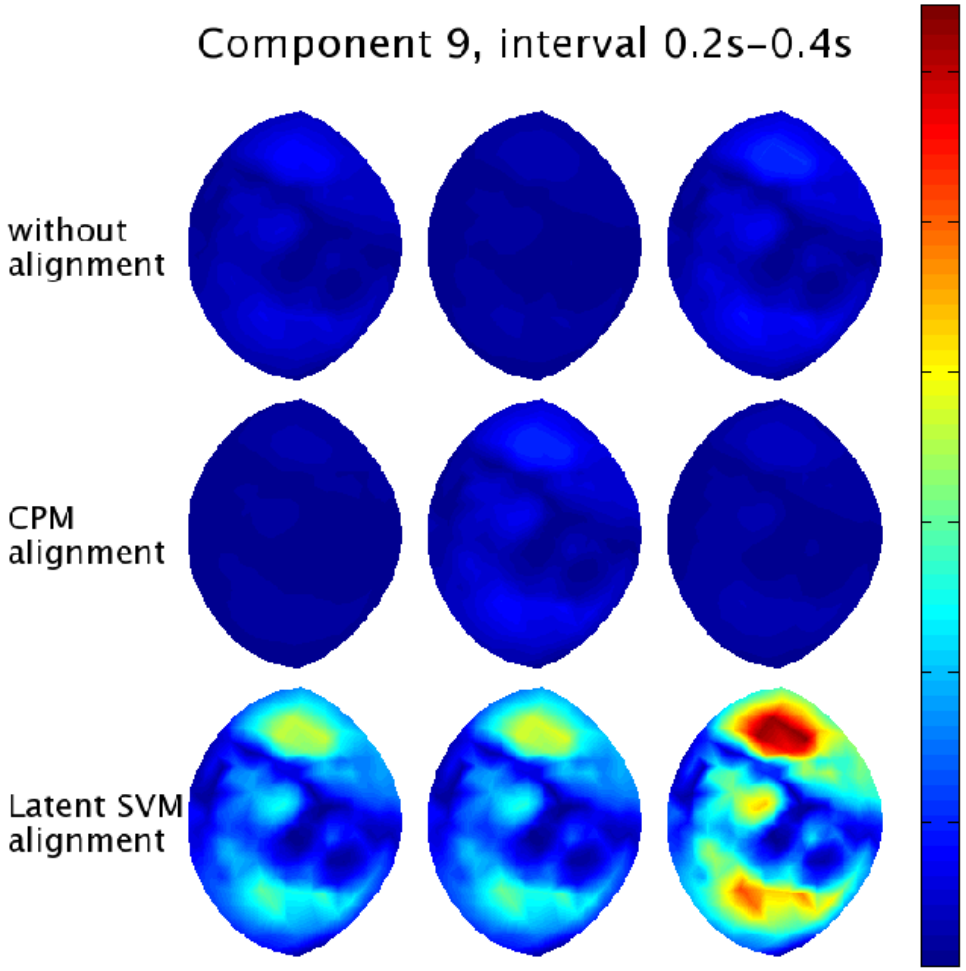


Results b) - component visualization

Averaging of not aligned data cause blurring

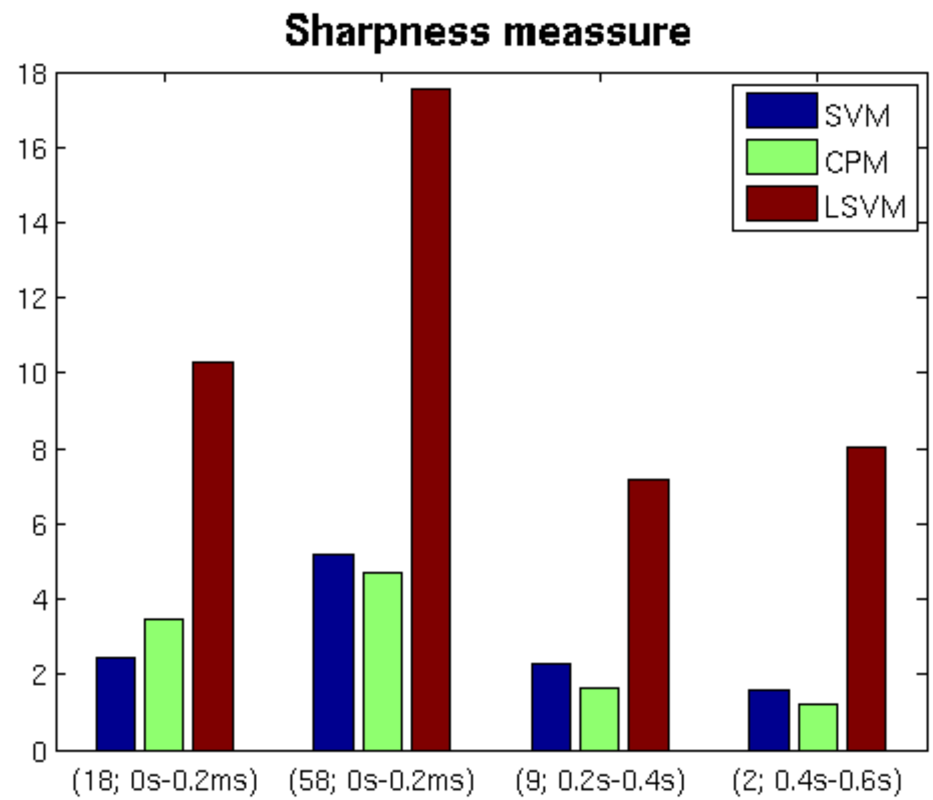


component visualization



Sharpness measure

- norm that explodes on edges



Results c) - functional connectivity

- based on common delays infer which sources communicate (*a.k.a.* signal propagation)
- considered for tuple(time intervals, component)
- sharpness as a proxy of correctness

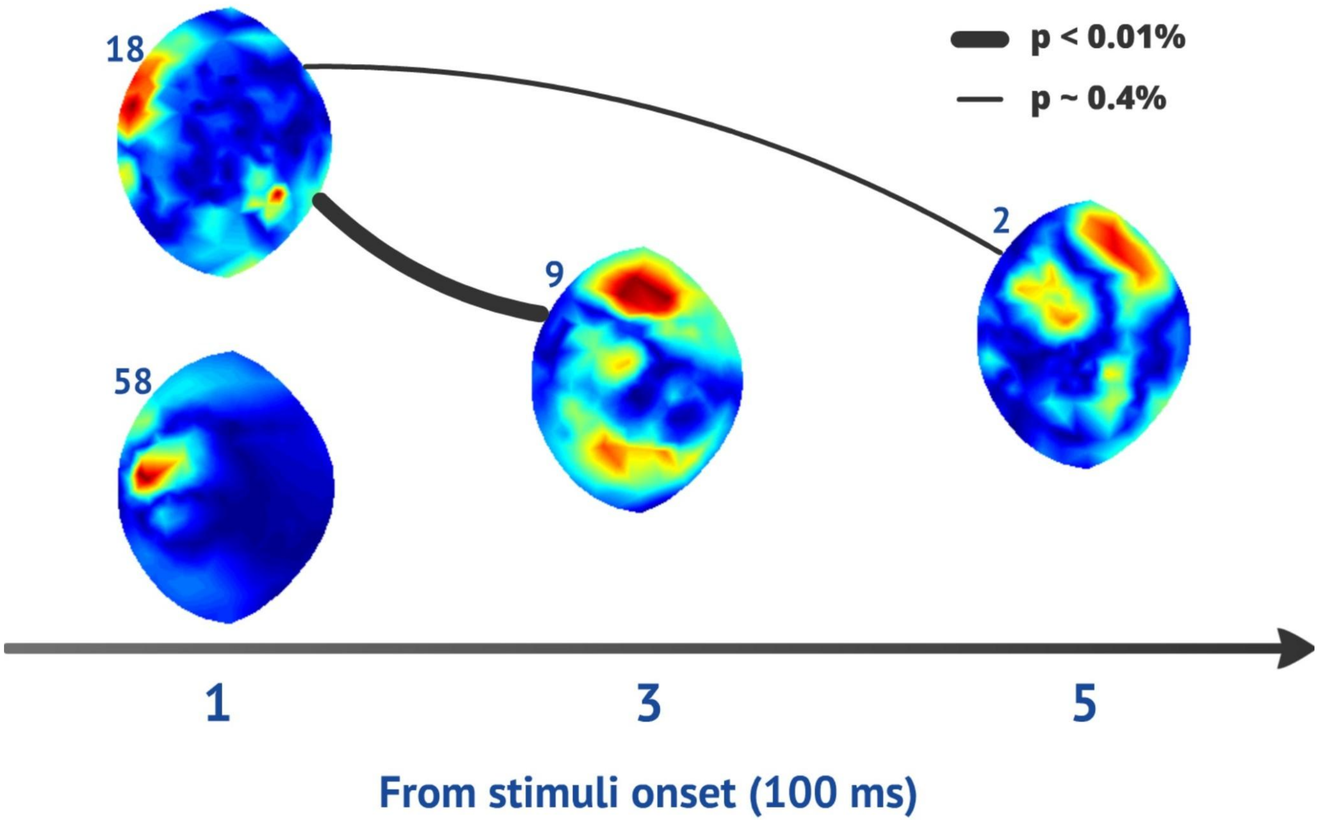
Functional connectivity

- common delay between two components locked

- join sharpness statistic achieved as a result of sharpness multiplication

- verified with permutational test

Functional connectivity



- visual cortex → deep subcortical source
- visual cortex → higher level cognitive processing

Future work

- analysis of interaction between many more sources
- sources localization
- further studies with multiple modalities

Summary

- Inferring activation offset improves prediction
- Averaged aligned recordings improve ERP visualization
- Delays allow to infer connectivity
- Latent SVM for other medical imaging problems ?

Download: https://github.com/wojzaremba/active-delays

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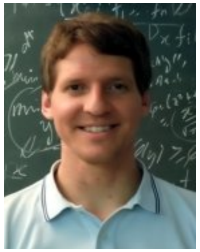

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