M/EEG Decoding and Brain-Computer Interfacing

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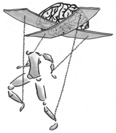
Max Planck Institute for Intelligent Systems
Department Empirical Inference
Tübingen, Germany

June 8, 2014

MAX-PLANCK-GESELLSCHAFT



Brain-Computer Interfacing in ALS

Outline

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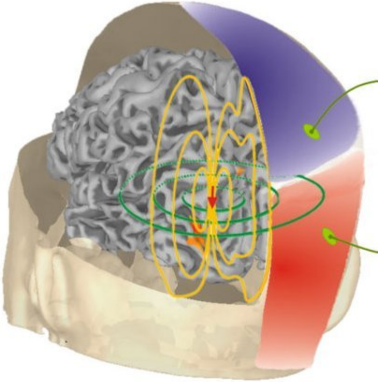
1. M/EEG Decoding Models

2. Brain-Computer Interfacing

The brain's electromagnetic field (EMF)



http://www.canada-meg-consortium.org/

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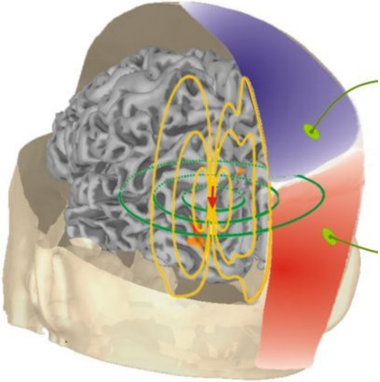

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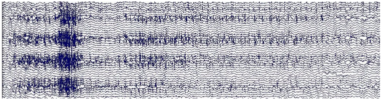

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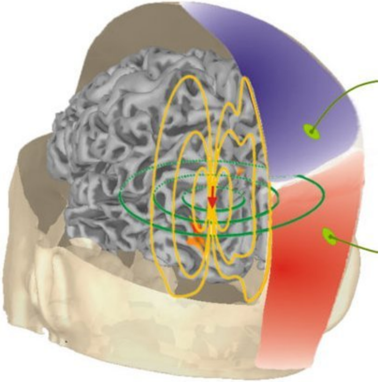

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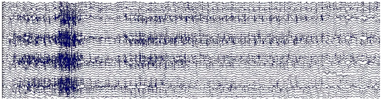

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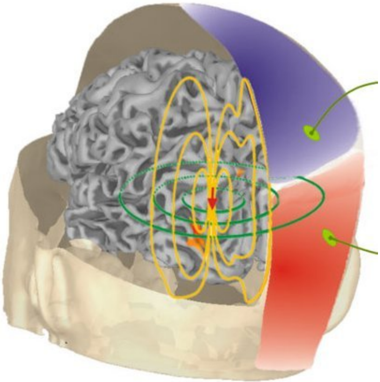

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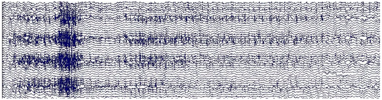

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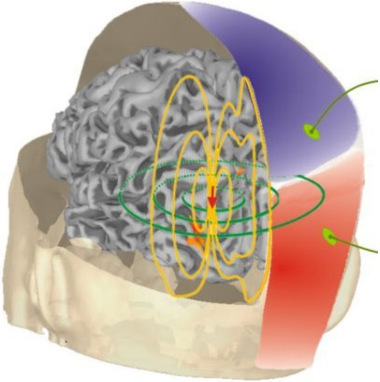

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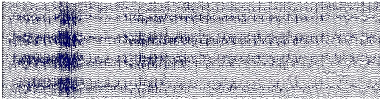

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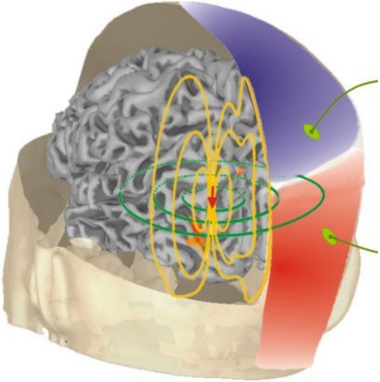

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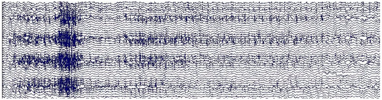

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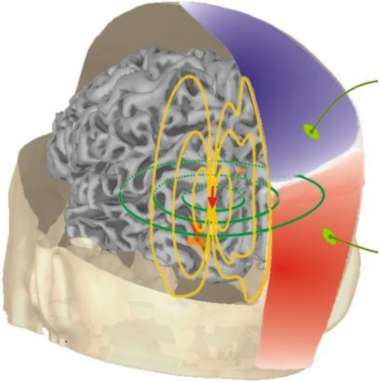

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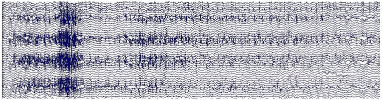

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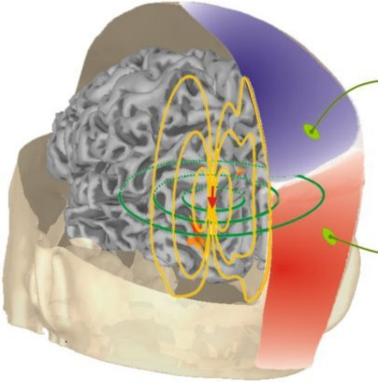

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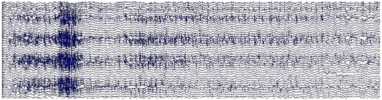

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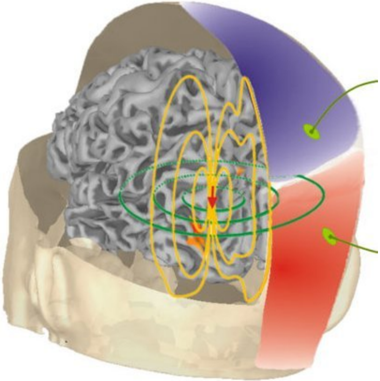

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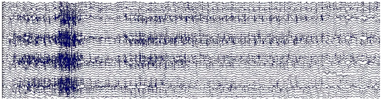

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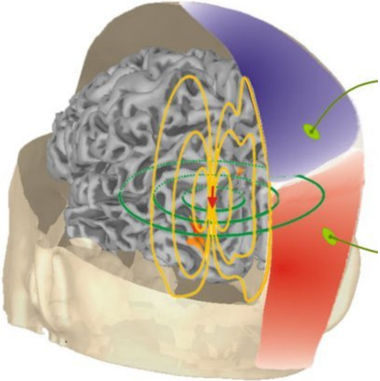

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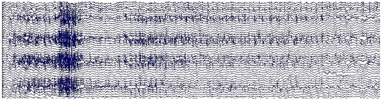

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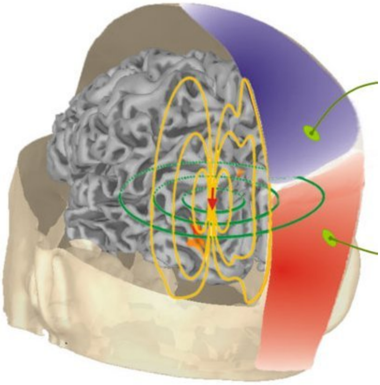

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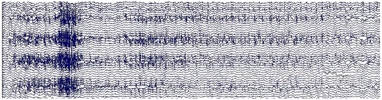

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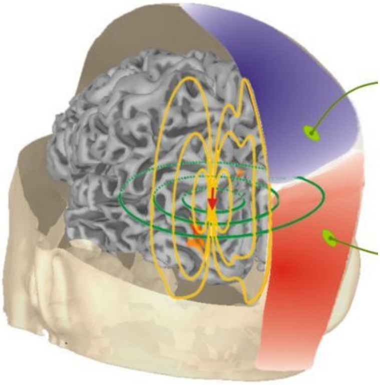

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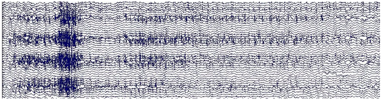

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- Typically i.i.d. sampling is assumed

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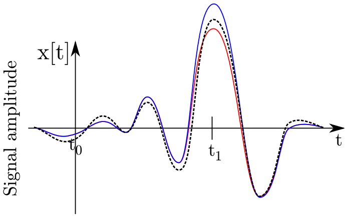

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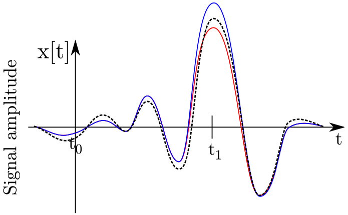

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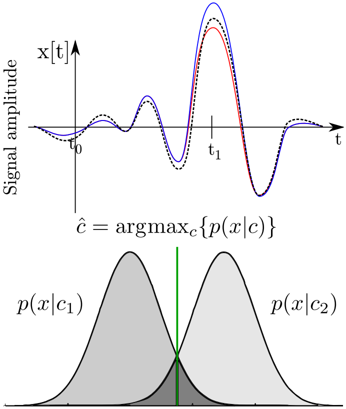

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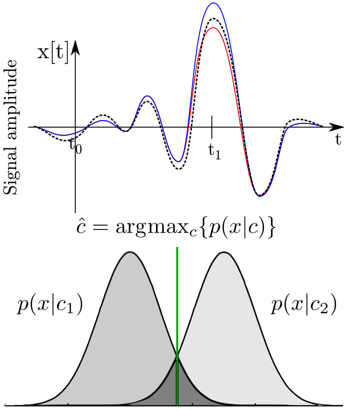

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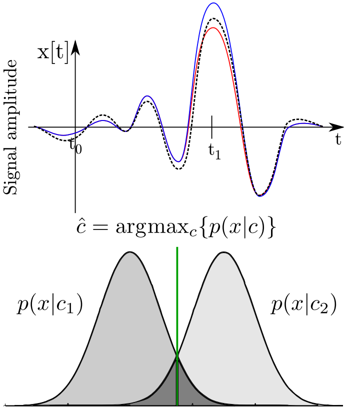

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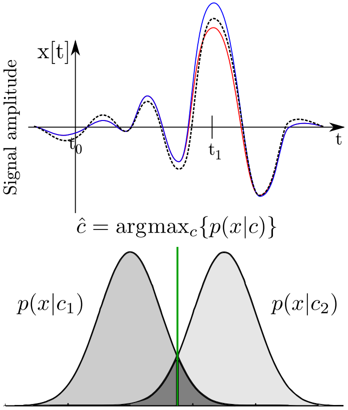

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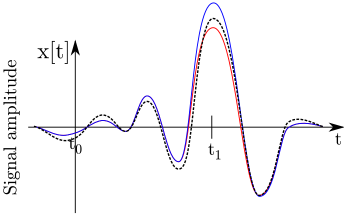

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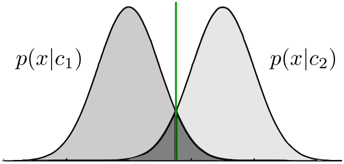

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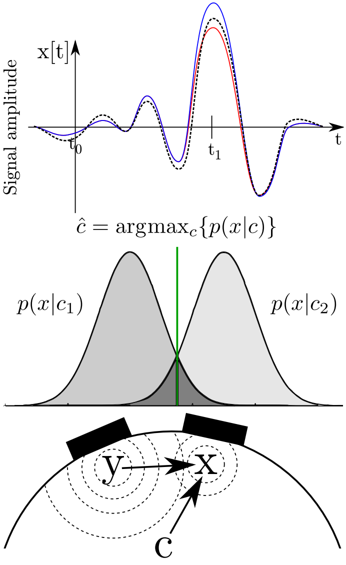

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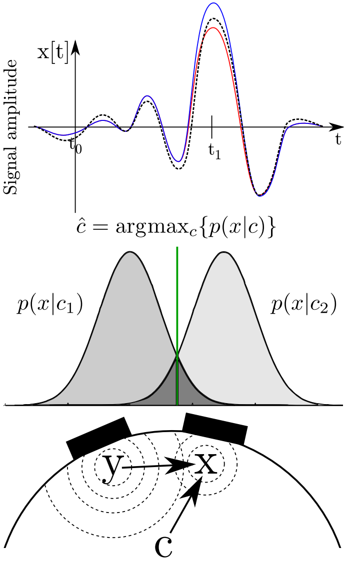

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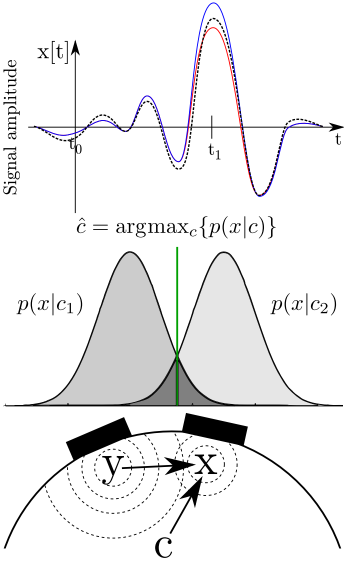
- Disadvantage $f : \mathbb{R}^{N \times T} \mapsto \{-1, +1\}$ needs to be learned from $\mathcal{D}$.



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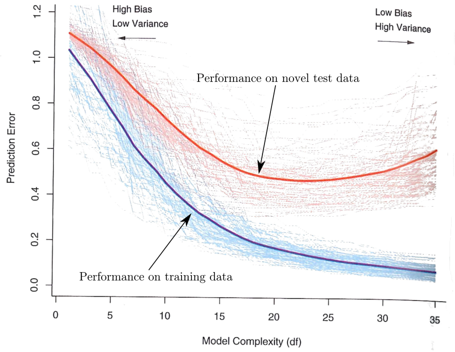

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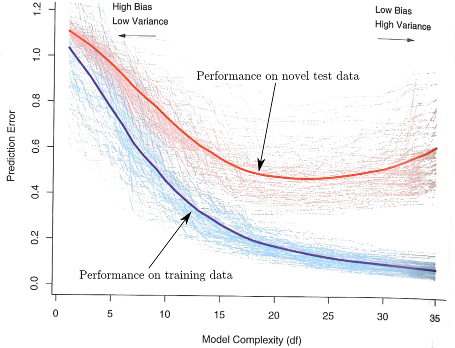

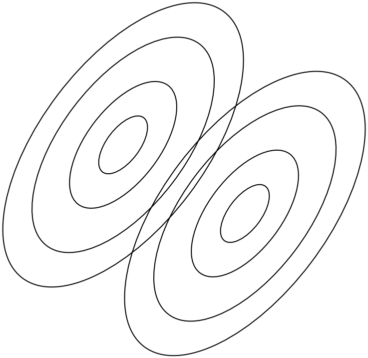

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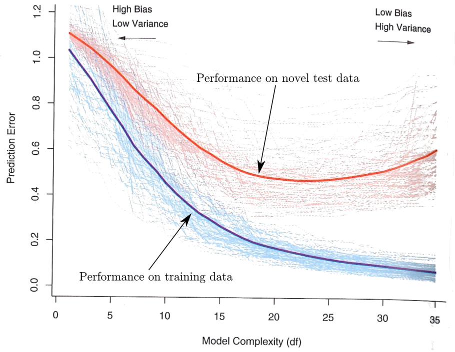

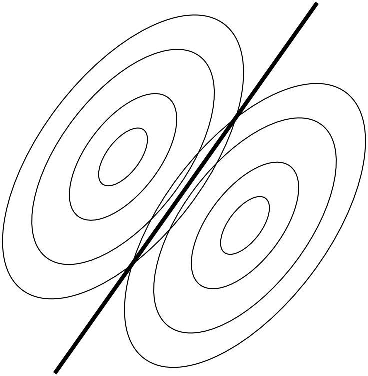

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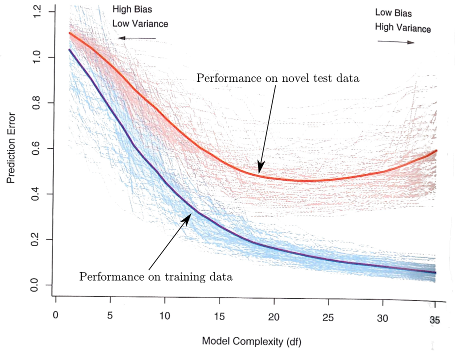

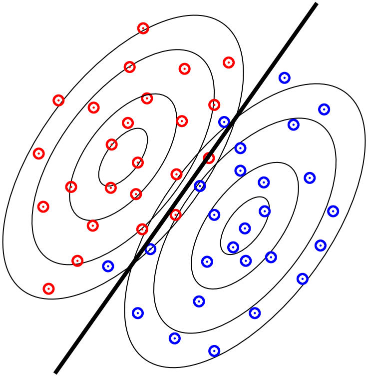

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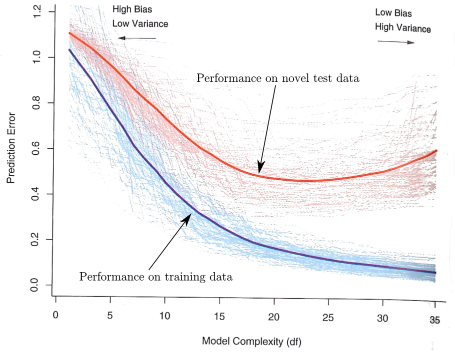

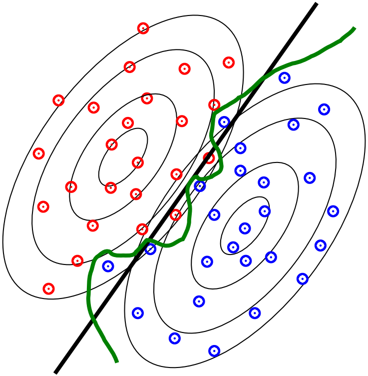

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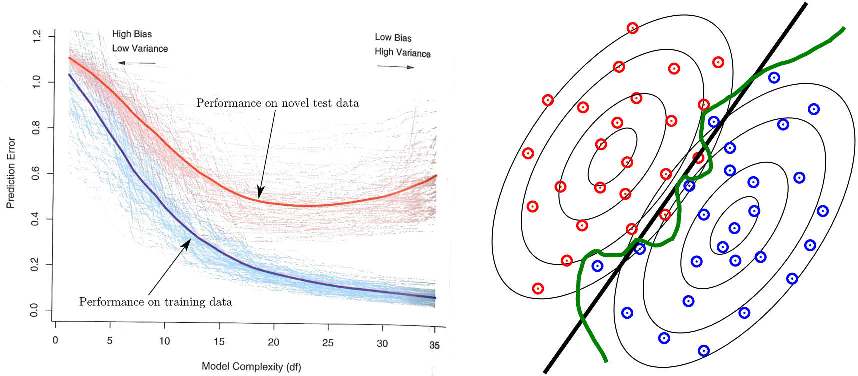

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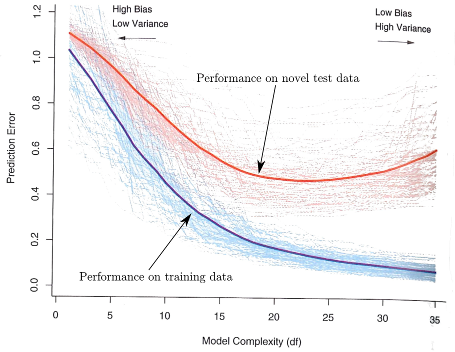

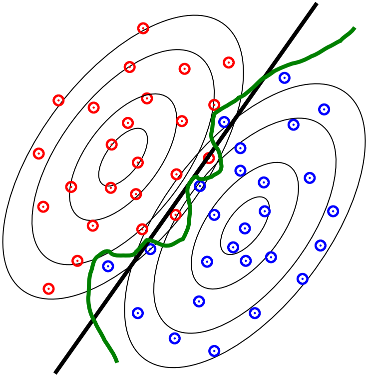

How do we determine which model generalizes best?Cross-validation!

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Learning decoding models II

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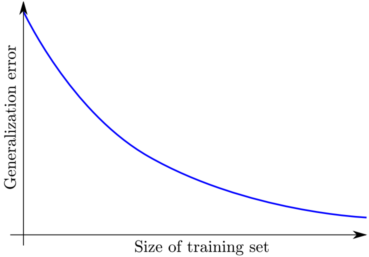

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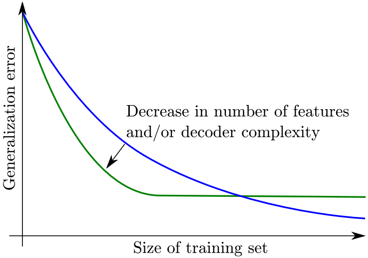

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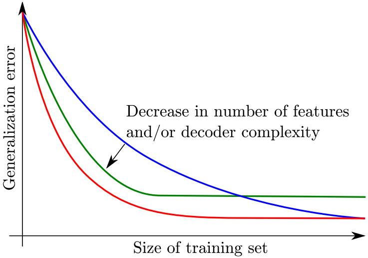

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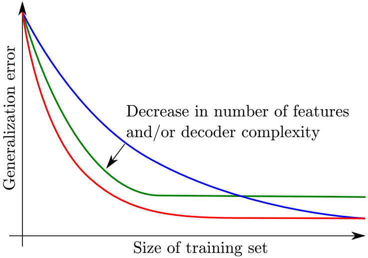

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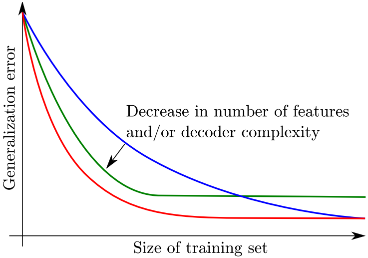

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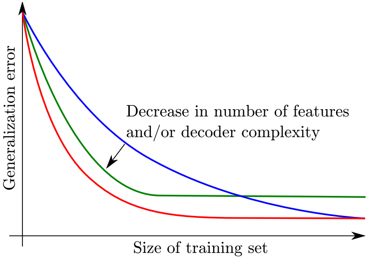

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Reducing the number of M/EEG channels (N)

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$$\mathbf{x}[t] = \quad L\mathbf{s}[t]$$

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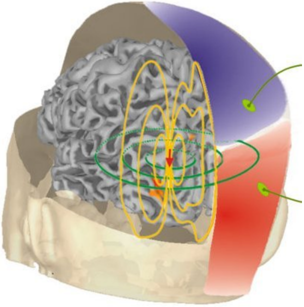

http://www.canada-meg-consortium.org/

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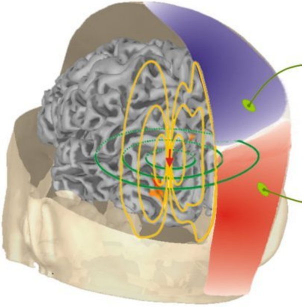

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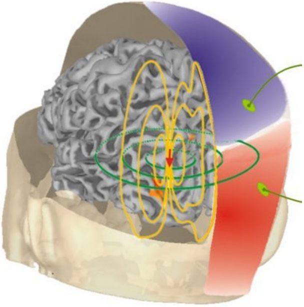

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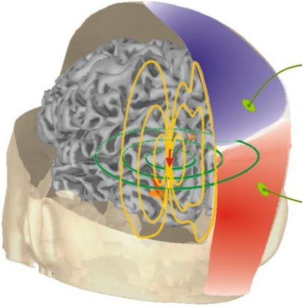

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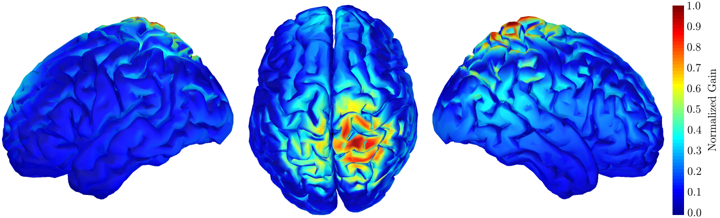

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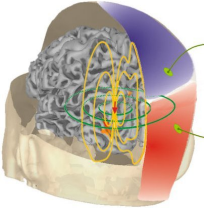

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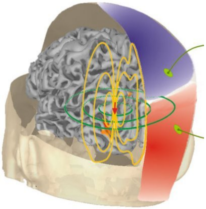

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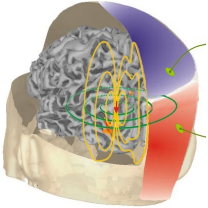

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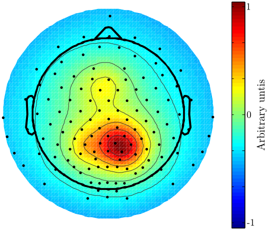

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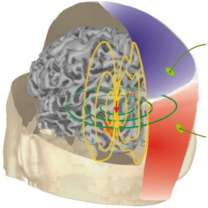

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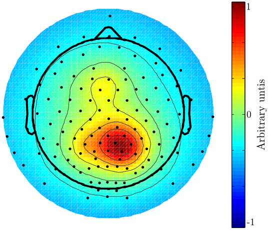

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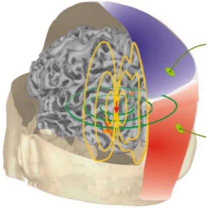

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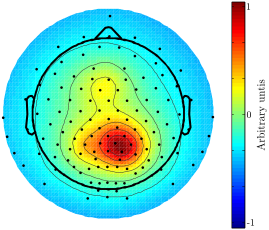

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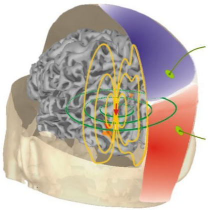

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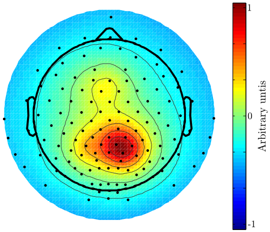

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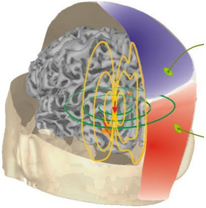

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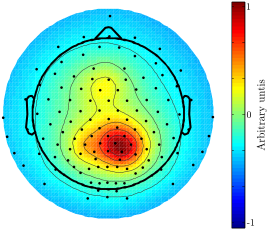

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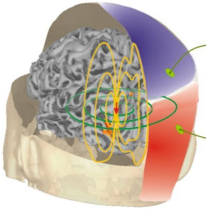

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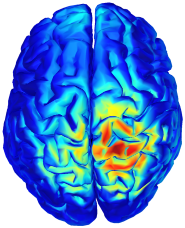

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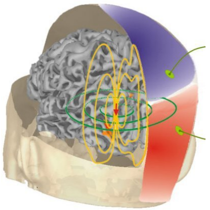

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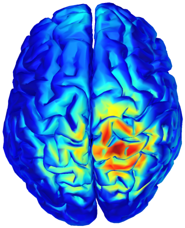

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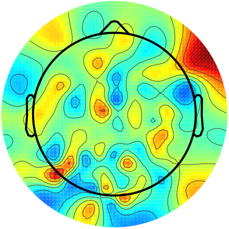

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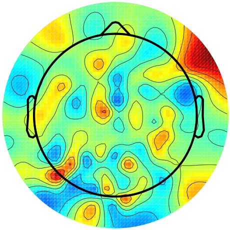

- Covariance matrices $\Sigma_{c=+1}$ & $\Sigma_{c=-1}$
- Optimization problem:
  $\mathbf{w} = \text{argmax}_{\mathbf{w}} \left\{ \frac{\mathbf{w}^{\mathsf{T}} \Sigma_{c=+1} \mathbf{w}}{\mathbf{w}^{\mathsf{T}} \Sigma_{c=-1} \mathbf{w}} \right\}$
- Solution: Largest λ for which $\Sigma_{c=+1}^{-1} \Sigma_{c=-1} \mathbf{w} = \lambda \mathbf{w}$
- Matlab: [V,D] = eig($\Sigma_{c=+1}$,$\Sigma_{c=-1}$)
- Columns of V are spatial filters
- Rows of V are spatial patterns

(Ramoser et al. Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE TBME*, 2000)

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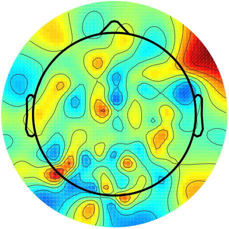

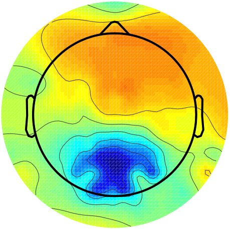

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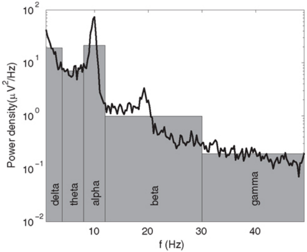

(van Albada & Robinson, *Frontiers in Human Neuroscience*, 2013)

Reducing the number of time points (T)

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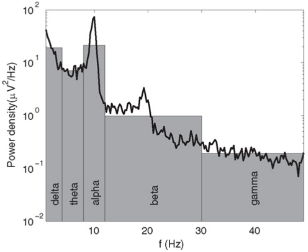

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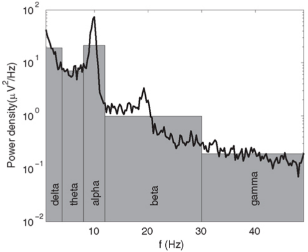

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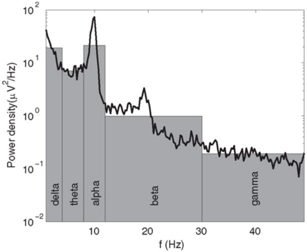

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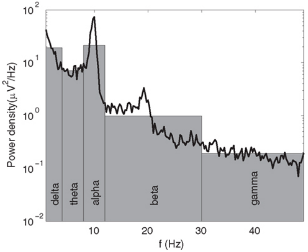

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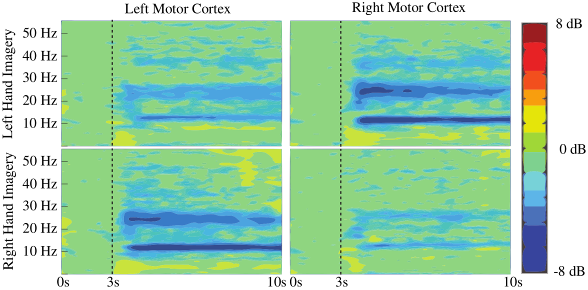

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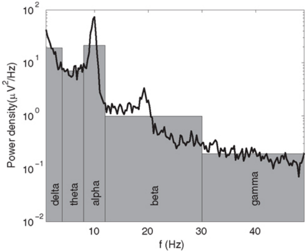
- For log-bandpower features, linear decoders appear sufficient.



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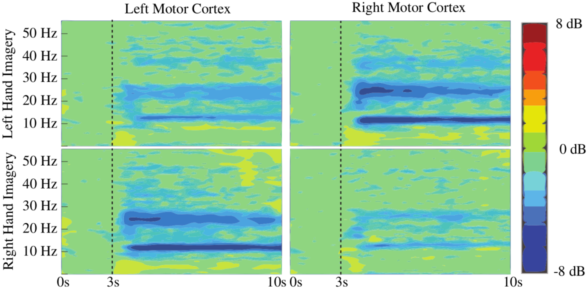
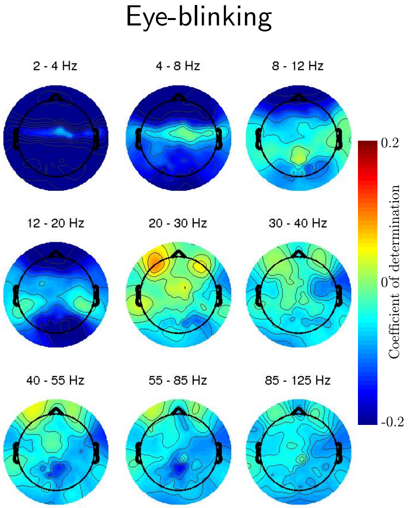
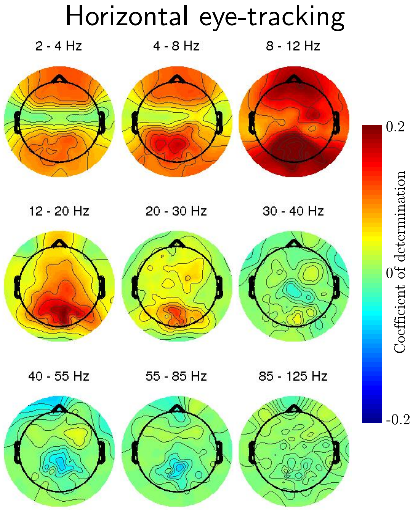
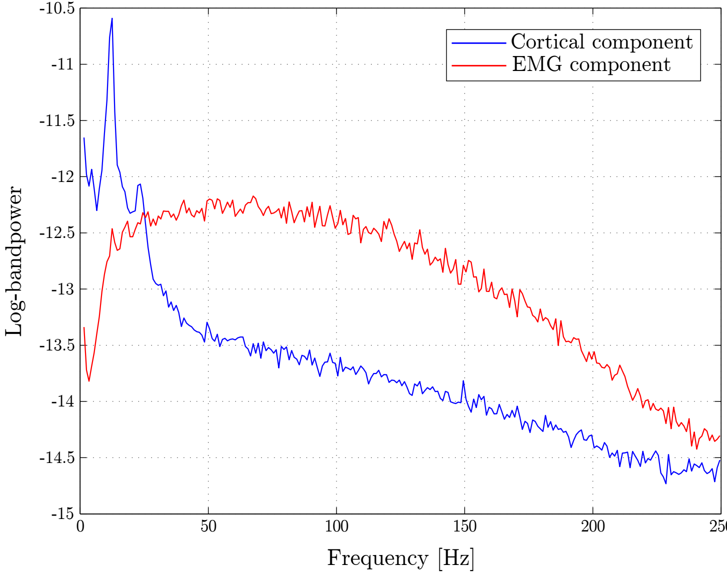


Confounding by EOG-artifacts



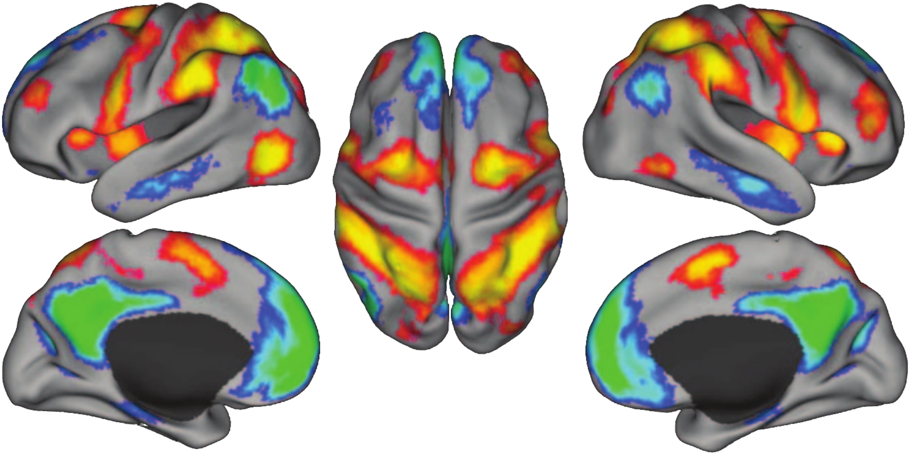


Confounding by EMG-artifacts



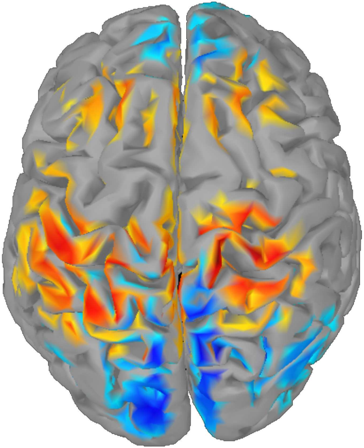
Outline

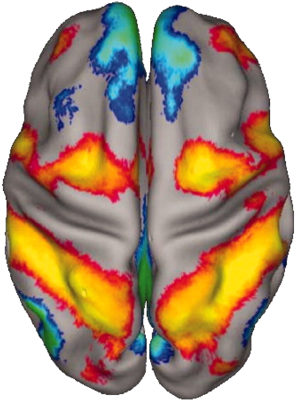
Large-scale brain networks



(Adapted from Fox et al., 2005)

Can large-scale cortical networks be observed in the EEG?





(Fox et al., PNAS, 2005)

(Grosse-Wentrup & Schölkopf, High Gamma-Power Predicts Performance in SMR BCIs, *Journal of Neural Engineering*, 2012)

Patient GH: Neurofeedback of parietal δ-power

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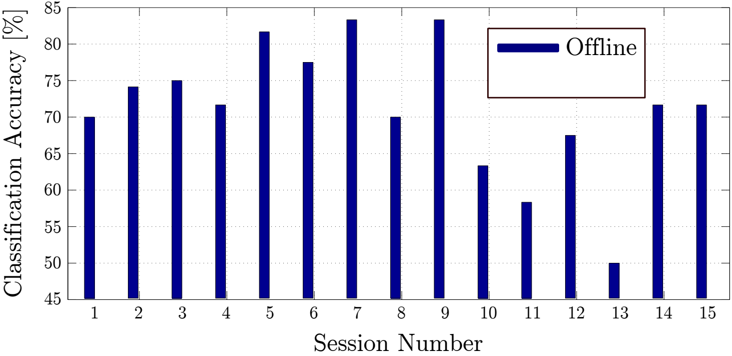

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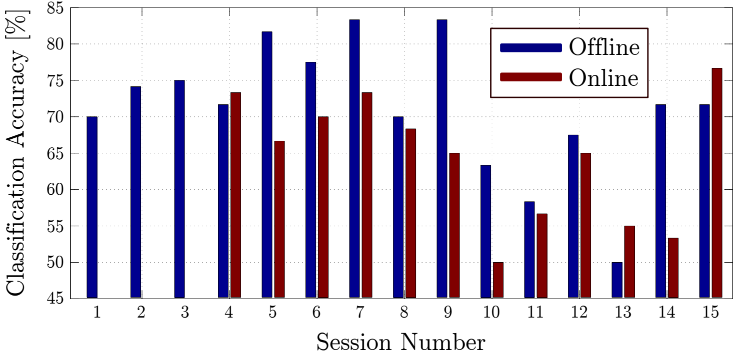

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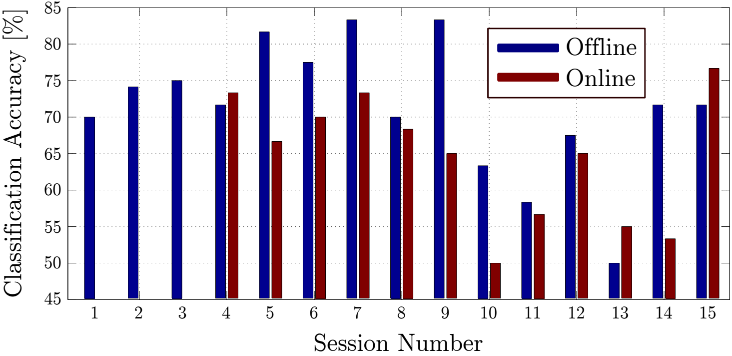
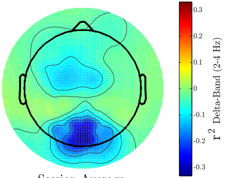


Mean offline/online decoding accuracy: 71.3%/64.4%

Patient GH: fMRI-study



Session Average

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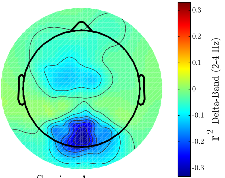

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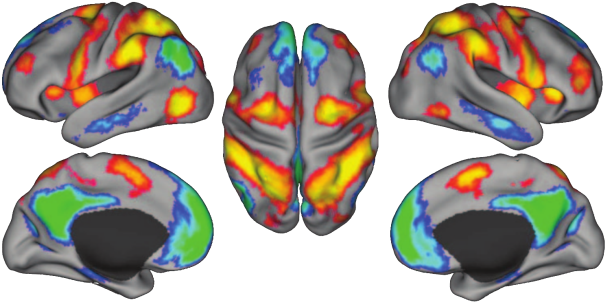

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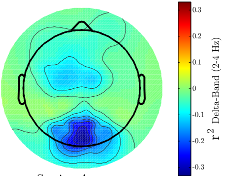

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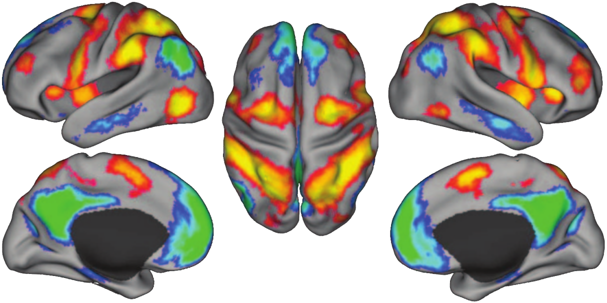

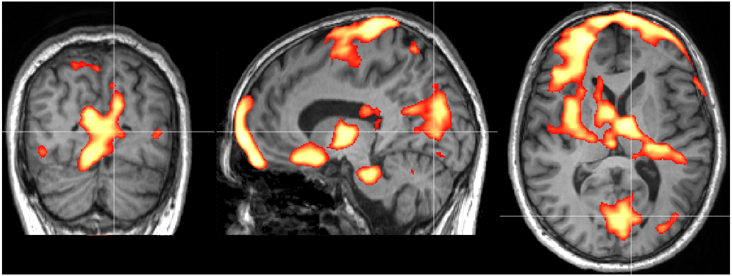

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- Natalie Widmann
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- Thomas Ethofer

http://brain-computer-interfaces.net