Lecture 10: Neuroscience Aspects and Outlook

Introduction to Modern Brain-Computer Interface Design

Christian A. Kothe
SCCN, UCSD

Outline

1. Prerequisites
2. Source Signal Feature Extraction
3. Location-Based Prior Knowledge
4. Recent Example: Attention Shifting
5. Outlook
6. Further Reading

10.1 Prerequisites

Prerequisites

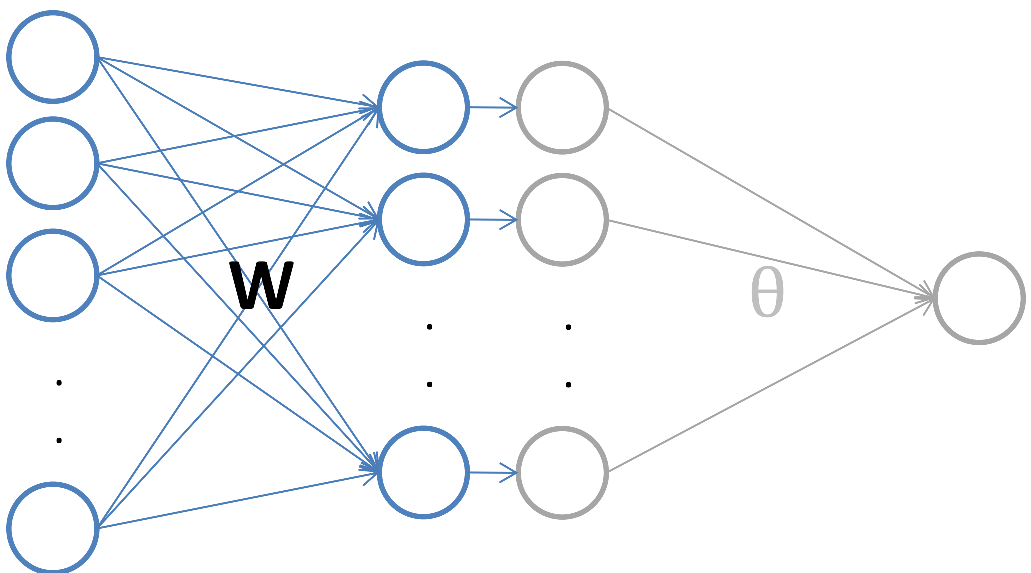
- Neuroscientifically interpretable BCI models rely on *being able to spatially locate the parameters* and the importance/weight assigned to them by models
- Can be accomplished in multiple ways:
  - Calculate 3d gain field for spatial filters
  - Represent models in terms of localizable signal components
  - Represent models in a very large space of cortical basis vectors (one per patch)

Prerequisites

- Currently in practice the easiest is to utilize spatially localizable components
- Can be done via Independent Component Analysis and Dipole fitting (our choice at SCCN)

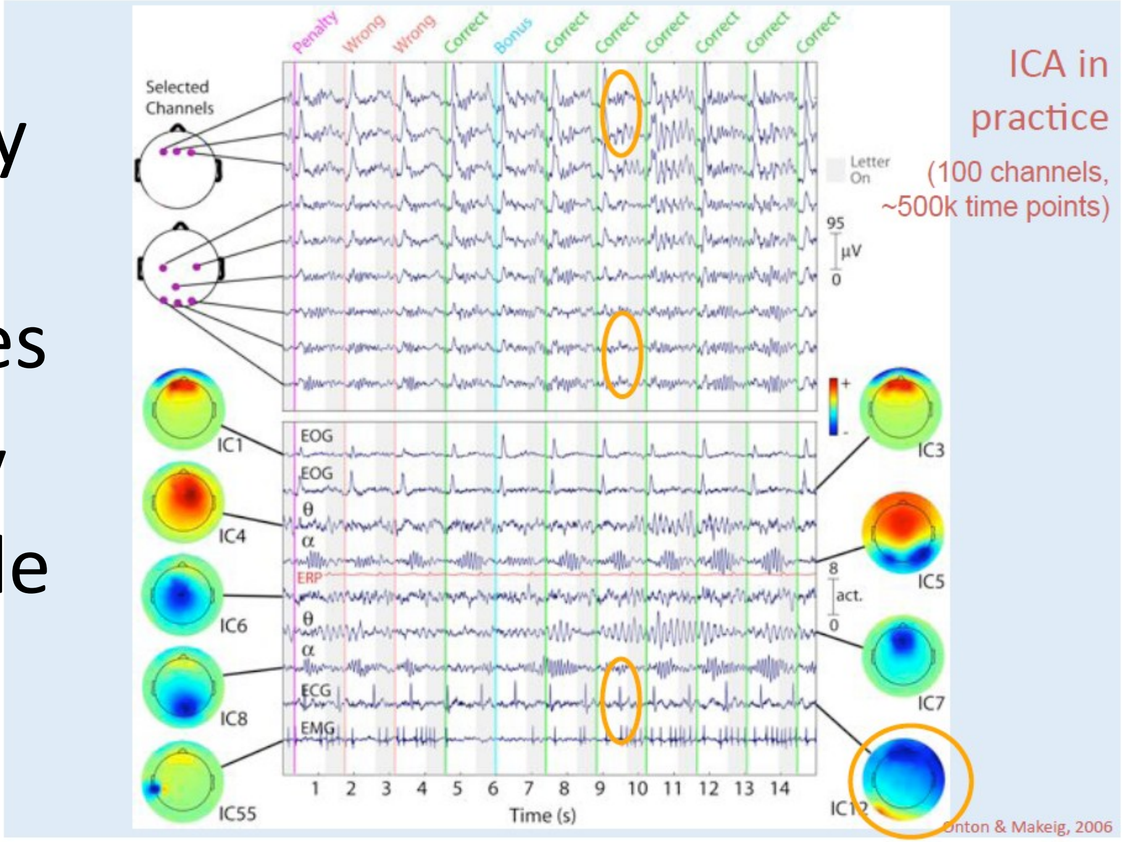
Independent Component Analysis

- ICA is a method to learn spatial filters for statistically independent brain sources in an unsupervised manner (i.e. no need for labels)
- Basic idea is to learn a square filter matrix W such that the filtered signal components are statistically maximally independent



Independent Component Analysis

- There are dozens of ways to implement it – currently best for EEG are extended Infomax and AMICA
- Surprisingly, many ICs have dipolar scalp topographies
- Can be practically localized via dipole fitting



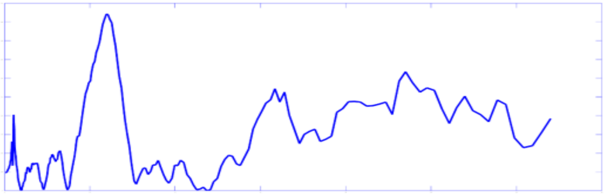
10.2 Source Signal Feature Extraction

Source Signal Feature Extraction

- Source components need no further spatial filtering, so features can be extracted directly from them, including:
  - spectral measures
  - non-linear temporal measures
  - higher-order (inter-component) features
- Since ICs are statistically independent, only a sparse set of components is relevant for any given (BCI or other) question – allows for sparsity assumptions

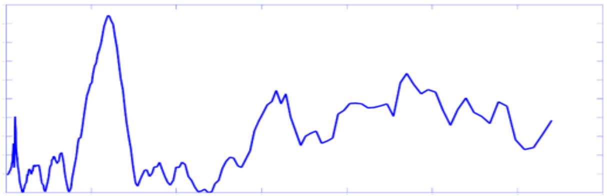
Component Spectral Features

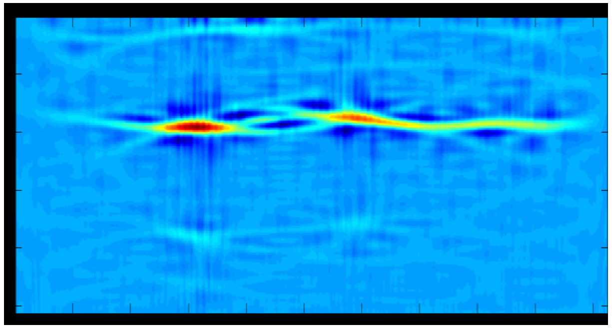
- Fourier spectrum
  - Windowed DFT/FFT
  - Welch spectral estimation
  - Multi-taper spectral estimation



Component Spectral Features

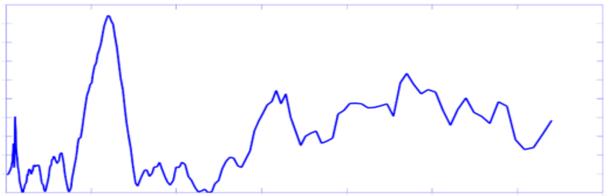
- Fourier spectrum
  - Windowed DFT/FFT
  - Welch spectral estimation
  - Multi-taper spectral estimation
- Time/Frequency representations
  - Short-Time Fourier Transform (STFT)
  - Continuous Wavelet Transform (CWT)
  - Discrete wavelet transform (DWT)
  - Time-frequency distributions

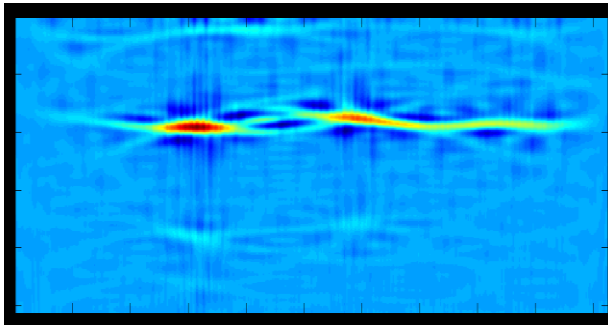


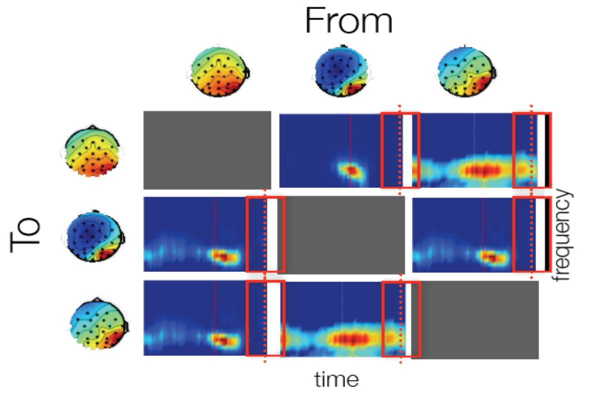


Component Spectral Features

- Fourier spectrum
  - Windowed DFT/FFT
  - Welch spectral estimation
  - Multi-taper spectral estimation
- Time/Frequency representations
  - Short-Time Fourier Transform (STFT)
  - Continuous Wavelet Transform (CWT)
  - Discrete wavelet transform (DWT)
  - Time-frequency distributions
- Between-Component Features
  - Coherence
  - Phase-Locking Value
  - Effective Connectivity

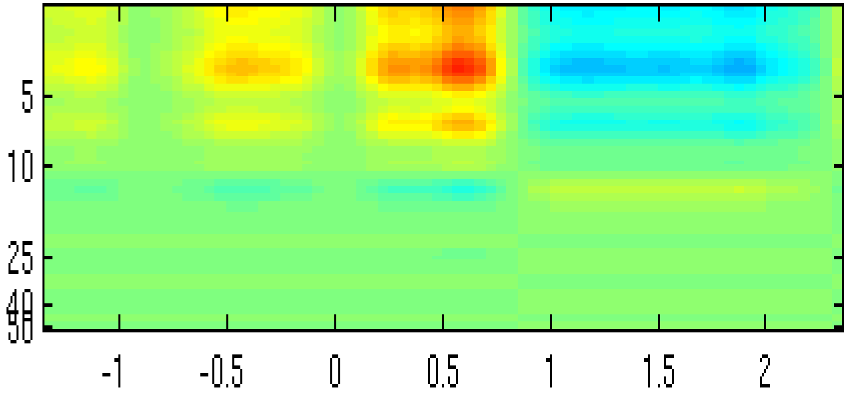




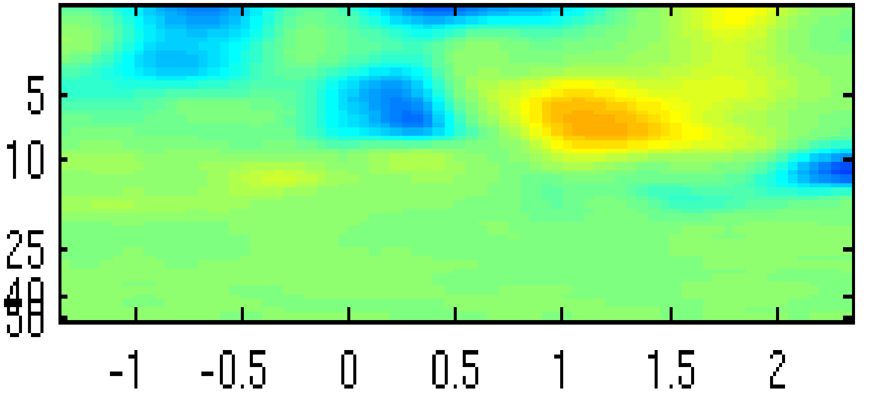


Integrating Structural Prior Knowledge

- Amounts to side assumptions about the data
- For example:
  - Spatial smoothness (correlation)
  - Sparsity, group sparsity
  - Shared latent structure between parameters



Low-Rank Assumption



Smoothness Assumption

Integrating Structural Prior Knowledge

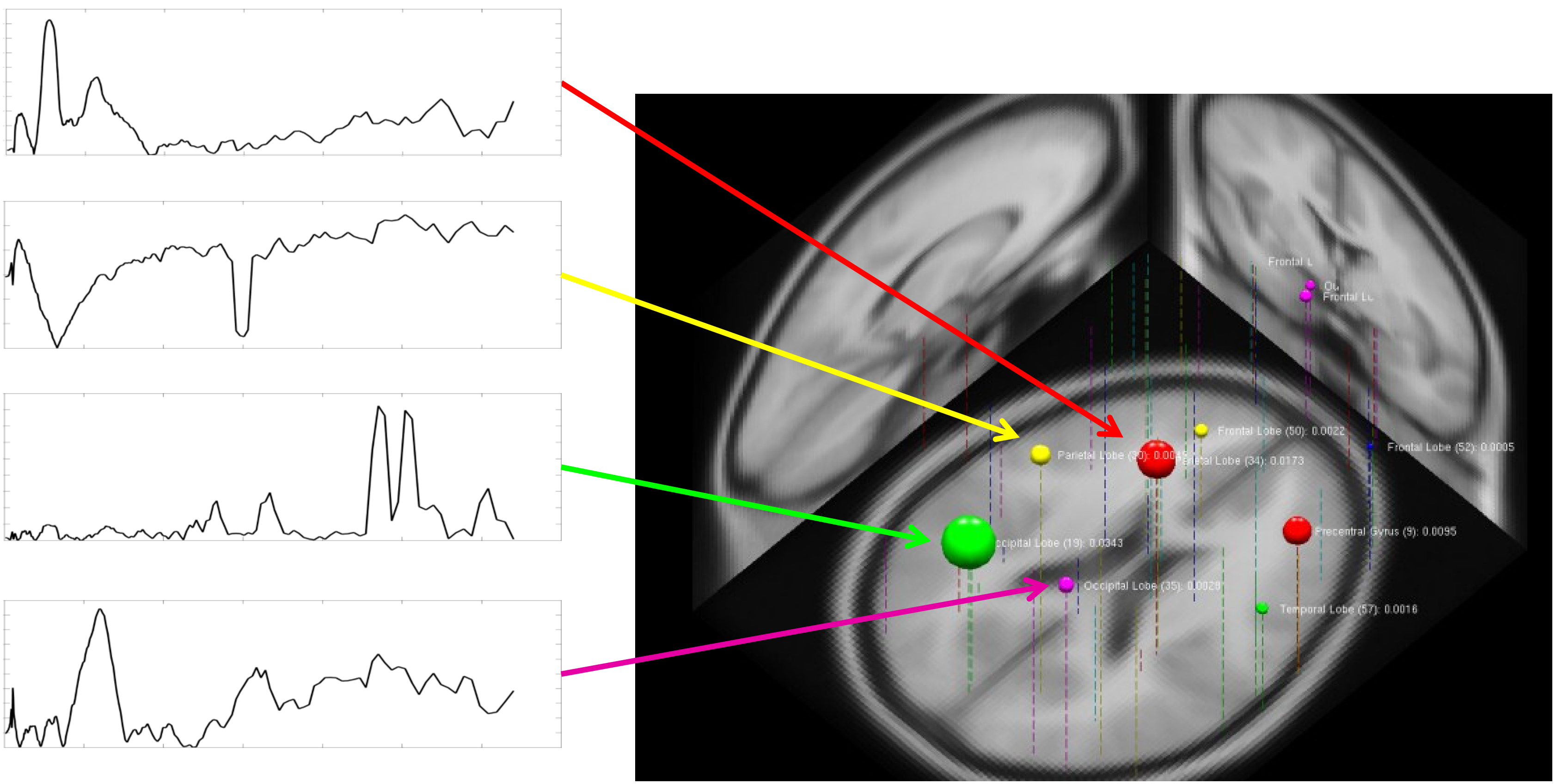
- Amounts to side assumptions about the data
- For example:
  - Spatial smoothness (correlation)
  - Sparsity, group sparsity
  - Shared latent structure between parameters
  - Kernels for non-linear features
  - “Dictionaries” of known (learned) features
  - Per-*trial* parameters (e.g. outlyingness, time shift)

Swartz Center for Computational Neuroscience

10.3 Location-based Prior Knowledge

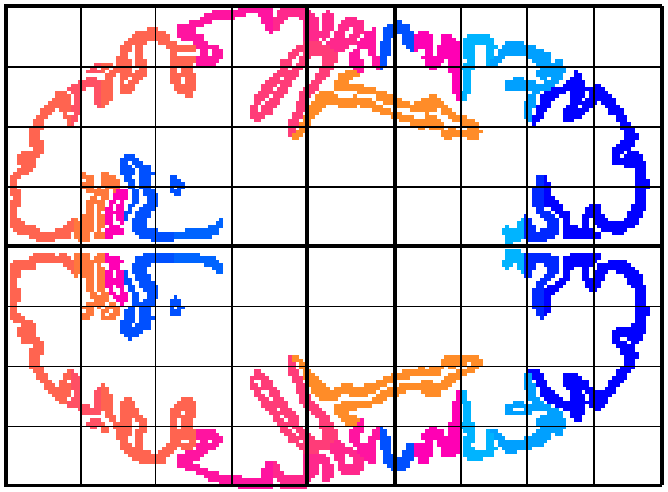
Source-Space Modeling

- If IC sources are localized using, e.g., dipole fitting or NFT, parameters ($\boldsymbol{\theta}$) have a location



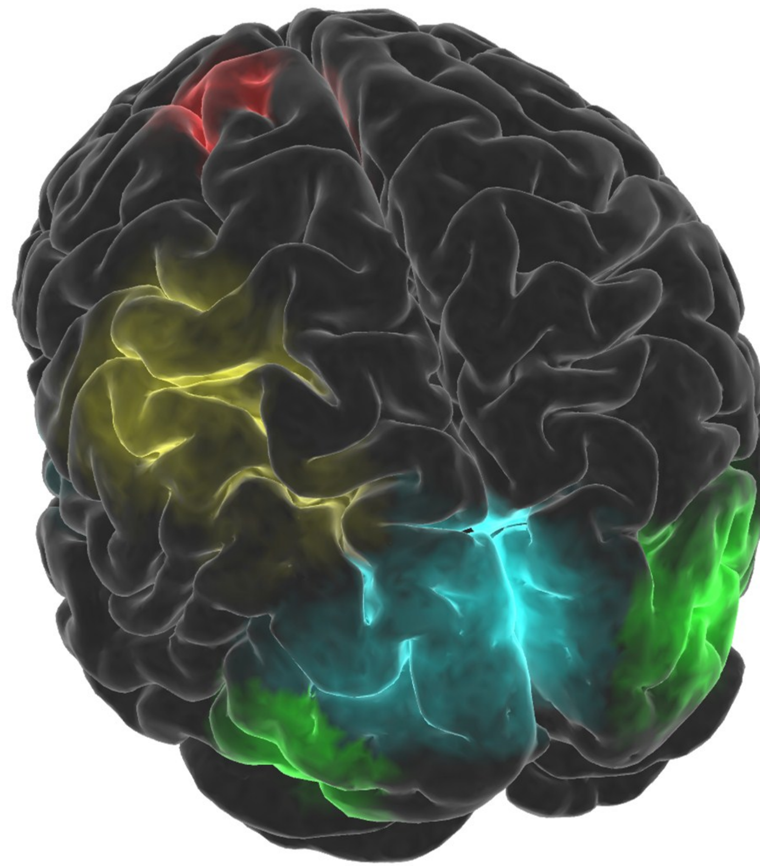
Integrating Quantitative Prior Knowledge

- If weights have an associated location (refer to a localized signal components), *anatomical prior knowledge* can be used
- For example, reweight the regularizing penalty based on probability of source being located inside a particular brain area
- Brain atlases: Talairach, LONI



Integrating Empirical Prior Knowledge

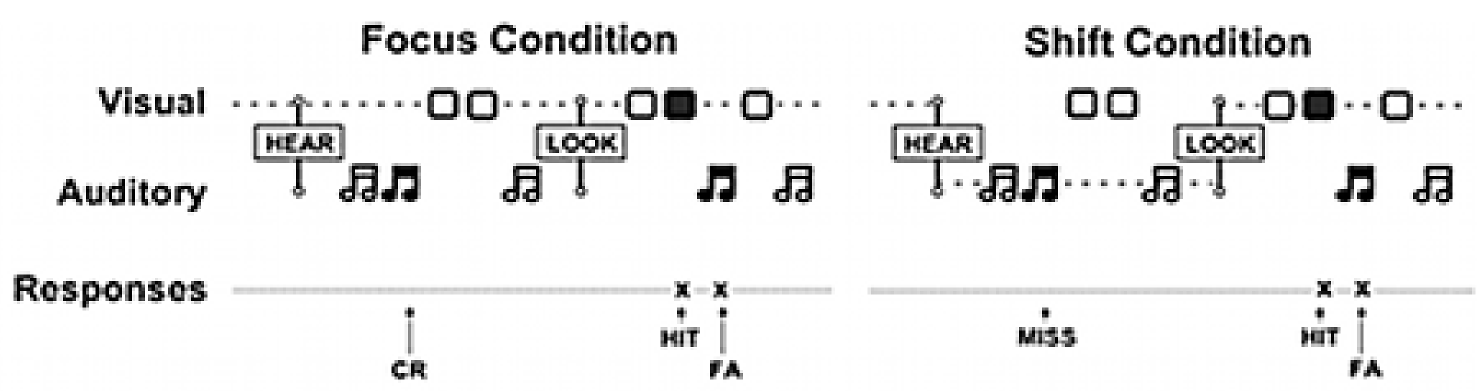
- Information gathered from other subjects can be factored into a given model (e.g., add an extra penalty or Bayesian pr
- Having spatially localized parameters enables *location-dependent priors* and *spatial coregistration* o alignment of multi-subject data



10.4 Recent Example: Attention Shifting

Experimental Task

- 38 subjects (2 age groups, ignored here)
- 32 channels EEG
- Stimulus stream: Targets (20%) & Non-Targets (80%), randomly interleaved order (100-400ms onset-to-onset SOA)
- Some delivered visually (bright and dark rectangles), others delivered acoustically (beeps and boops)
- Sporadically (6600ms onset-to-onset): **Instructions to switch to another sensory modality** (“LOOK” / “HEAR”), bimodal delivery
- Other blocks at beginning/end of experiment, ignored here
- Ca. 260 switch trials total per subject



Analysis Goal

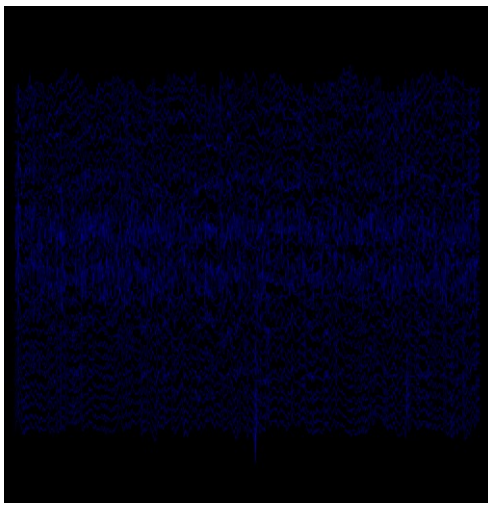
- Build a classifier that can determine the directionality of a subject’s attention switch (auditory to visual or visual to auditory)
- Parameterize the model in a way that is interpretable from a neuroscience perspective
- Evaluate its performance (mis-classification rate)

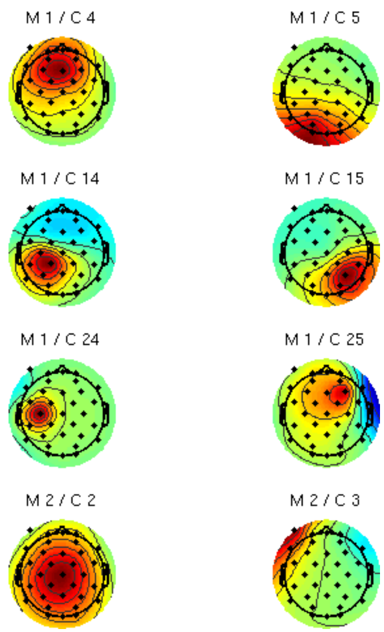
1. Signal Decomposition

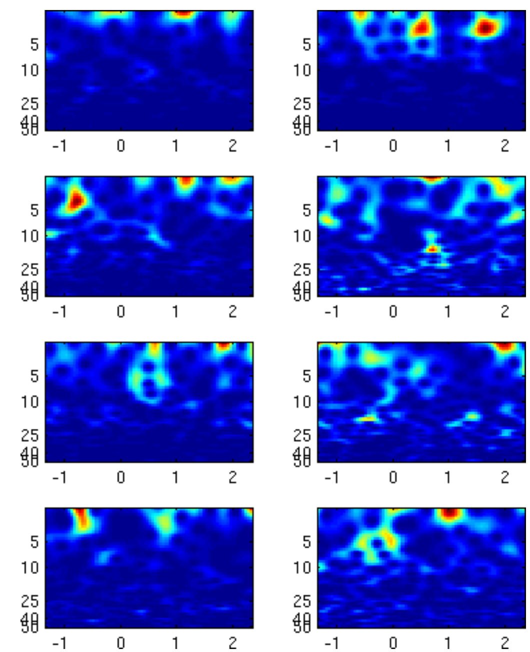
Raw EEG segments / trials

Linear spatial decomposition (multi-model AMICA)

Continuous wavelet time/frequency decomposition (complex Morlet)

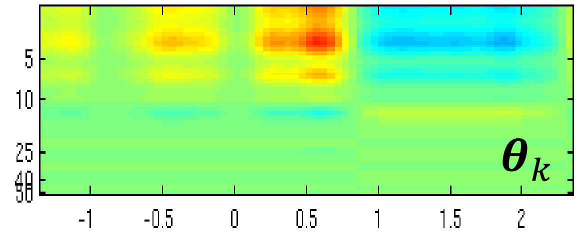






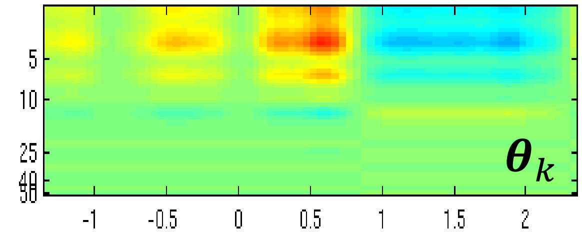
2. Predictive Model

- Severely underdetermined without additional side assumptions
- Assumptions here: sparse in components, low-rank in time/frequency
- Also an anatomical prior



2. Predictive Model

- Severely underdetermined without additional side assumptions
- Assumptions here: sparse in components, low-rank in time/frequency
- Also an anatomical prior
- Can be solved as a single large *convex* optimization problem:

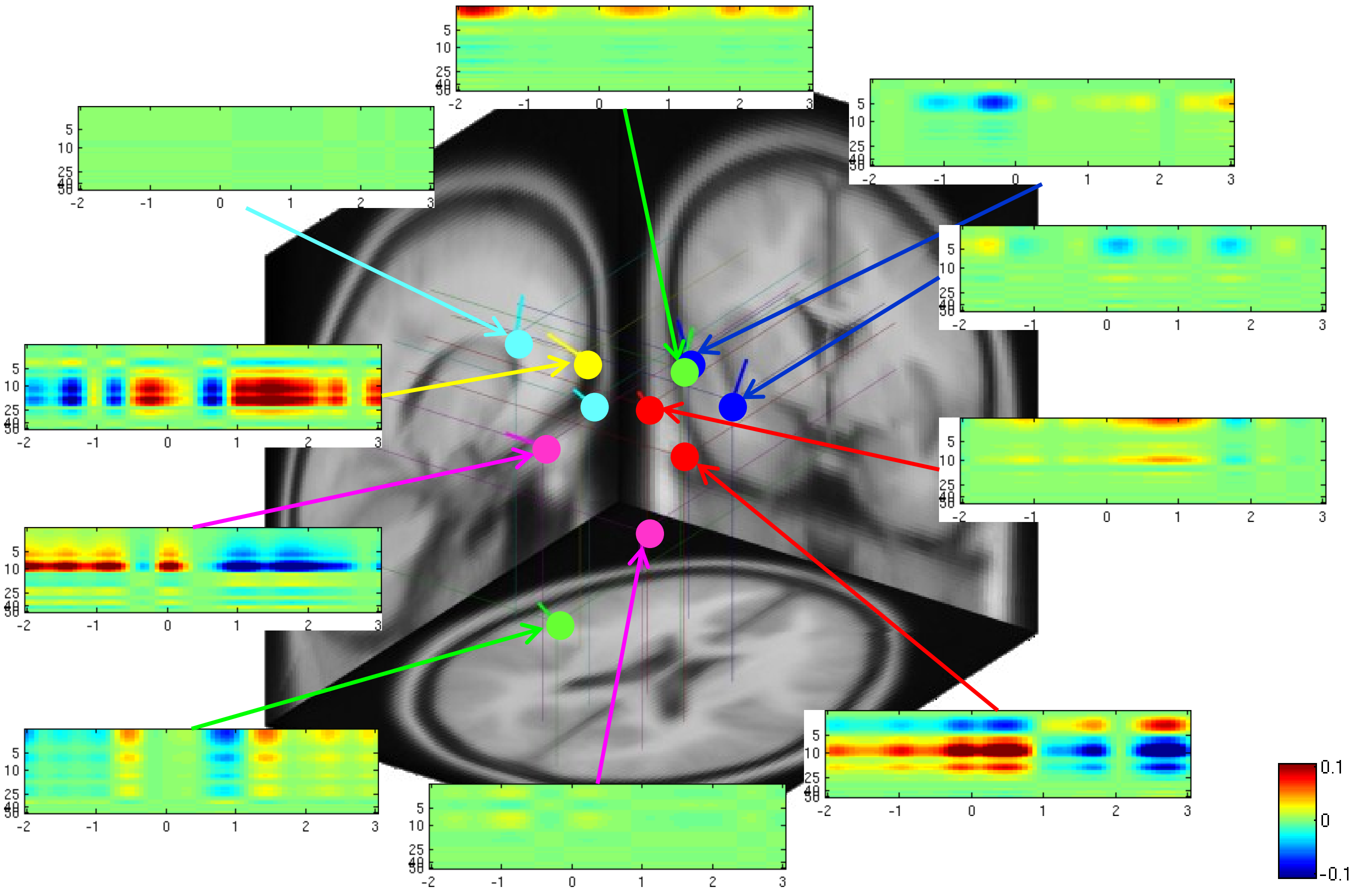


$$\min_{\boldsymbol{\Theta}} \log\left(1 + e^{-\boldsymbol{y}(\boldsymbol{\Theta X}+b)}\right) + \lambda \sum_{c=1}^{C} \sum_{k=1}^{rank(\boldsymbol{\theta}_c)} \sigma_k(\boldsymbol{\theta}_c)$$

Results: Classification Accuracy

- Analysis approach
  - 10-fold chronological cross-validation, 5 trials margin between training set and test set
  - Nested cross-validation on training set to optimize the regularization parameter (λ)
  - ICA and other data statistics only computed on the training set, recomputed for every fold
- Test-set prediction attained: mean **86.4%** correct across all subjects (chance level 50%), $p<0.001$

Results: Full Model Structure



Caveats

- Takes several hours to compute (currently)
- Independent Components are learned without label knowledge – not guaranteed that relevant processes are captured
- Spatial decomposition can be derailed by strong artifacts in the data (get artifact components rather than brain components)

Swartz Center for Computational Neuroscience

10.5 Outlook

Open Research Areas

- What are the fundamental accuracy limits imposed by our current EEG sensors?
- How far are we from these limits with our current approaches?
- Need a model that is mathematically optimal (under widely agreeable assumptions) to answer this question empirically

Open Research Areas

- Hierarchical models that include data from multiple people and sessions
- Inclusion of neuroscientific knowledge (from the book and from quantitative sources, e.g., data bases)
- Inclusion of auxiliary data (e.g., MoCap, etc.)
- Designing methods that are entirely principled and optimal
- Designing methods that directly target real-world applications (e.g., robustness)

What We Did Not Cover

- Fully Bayesian approaches (graphical models, variational inference, Bayesian model selection) and connections to optimization
- Existing multi-subject BCI approaches (e.g., Altun 2010, Fazli 2011)
- Beamforming techniques (e.g., Wentrup 2009)
- Connectivity-based approaches (e.g., Daly 2012)
- Non-standard signal features (e.g., Brodu 2012)

Some Concluding Remarks

- Simple and fast methods (e.g., LDA) often work remarkably well (much easier to write a paper if it takes 5 seconds to compute instead of 5 hours)
- But: approaches that take 5 hours today were largely intractable 10 years ago – so new territory to explore
- The importance of assumptions cannot be overstated (as opposed to getting sidetracked with ad hoc algorithms and questions)
- Provably optimal and well-defined methods allow us to directly test our assumptions (with fewer random or unexplained effects)
- It is too easy to evaluate things in not entirely proper ways – ultimately hampers progress, always do it right!

Swartz Center for Computational Neuroscience

10.6 Further Reading

BCI Papers Worth Reading

- B. Blankertz, S. Lemm, M. Treder, S. Haufe, and K.-R. Mueller, "Single-trial analysis and classification of ERP components - A tutorial", NeuroImage, vol. 56, no. 2, pp. 814–825, May 2011.
- F. Lotte and C. Guan, “Regularizing common spatial patterns to improve BCI designs: unified theory and new algorithms,” IEEE Transactions on Biomedical Engineering, vol. 58, no. 2, pp. 355-362, Feb. 2011.
- R. Tomioka and K.-R. Mueller, A regularized discriminative framework for EEG analysis with application to brain-computer interface", NeuroImage, vol. 49, no. 1, pp. 415–432, 2010.
- B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Mueller, and G. Curio, "The non-invasive Berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects", NeuroImage, vol. 37, no. 2, pp. 539–550, Aug. 2007.
- M. Grosse-Wentrup, C. Liefhold, K. Gramann, and M. Buss, "Beamforming in noninvasive brain-computer interfaces", IEEE Trans. Biomed. Eng., vol. 56, no. 4, pp. 1209–1219, Apr. 2009.

BCI Surveys

- A. Bashashati, M. Fatourechi, R. K. Ward, and G. E. Birch, "A survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals", J. Neural Eng., vol. 4, no. 2, pp. R32–R57, Jun. 2007.
- F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces", J. Neural Eng., vol. 4, no. 2, pp. R1–R13, Jun. 2007.
- S. Makeig, C. Kothe, T. Mullen, N. Bigdely-Shamlo, Z. Zhang, K. Kreutz-Delgado, "Evolving Signal Processing for Brain–Computer Interfaces", Proc. IEEE, vol. 100, pp. 1567-1584, 2012.

Interesting Technical Papers

- D.P. Wipf and S. Nagarajan, “A Unified Bayesian Framework for MEG/EEG Source Imaging,” NeuroImage, vol. 44, no. 3, February 2009.
- S. Haufe, R. Tomioka, and G. Nolte, “Modeling sparse connectivity between underlying brain sources for EEG/MEG,” Biomedical Engineering, no. c, pp. 1-10, 2010.
- S. Boyd, N. Parikh, E. Chu, and J. Eckstein, “Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers,” Information Systems Journal, vol. 3, no. 1, pp. 1-122, 2010.
- P. Zhao and B. Yu, “On Model Selection Consistency of Lasso,” Journal of Machine Learning Research, vol. 7 pp. 2541-2563, 2006.

Technical Papers, ct'd

- J. Ngiam, A. Khosla, M. Kim, J. Nam, H. Lee, and A. Ng, "Multimodal Deep Learning," in Proceedings of the 28th International Conference on Machine Learning, 2011.
- K. N. Kay, T. Naselaris, R. J. Prenger, and J. L. Gallant, "Identifying natural images from human brain activity," Nature, vol. 452, no. 7185, pp. 352-355, Mar. 2008.
- O. Jensen et al., "Using brain-computer interfaces and brain-state dependent stimulation as tools in cognitive neuroscience," Frontiers in Psychology, vol. 2, p. 100, 2011.
- D.-H. Kim1, N. Lu, R. Ma,. Y.-S. Kim, R.-H. Kim, S. Wang, J. Wu, S. M. Won, H. Tao, A. Islam, K. J. Yu, T.-I. Kim, R. Chowdhury, M. Ying, L. Xu, M. Li, H.-J. Cung, H. Keum, M. McCormick, P. Liu, Y.-W. Zhang, F. G. Omenetto, Y Huang, T. Coleman, J. A. Rogers, "Epidermal electronics," Science vol. 333, no. 6044, 838-843, 2011.

Researchers to Watch

- Klaus-Robert Mueller et al. (TU Berlin) – one of the leading BCI groups
  http://www.bbci.de/publications.html
- Marcel van Gerven et al. (Donders) – BCI and Neuroscience with a Bayesian approach
  https://sites.google.com/a/distrep.org/distrep/publications
- Ryota Tomioka (U Tokyo) – known for some technical achievements
  http://www.ibis.t.u-tokyo.ac.jp/RyotaTomioka
- Karl Friston et al. (UC London) – working on relevant underpinnings for neuroimaging (outside BCI)
  http://www.fil.ion.ucl.ac.uk/Research/publications.html
- Leading Statisticians and Machine Learners: Michael I. Jordan, Andrew Ng, Lawrence Carin, Zoubin Ghahramani, Francis Bach, Geoffrey Hinton, Ruslan Salakhutdinov, Yeh Whye Teh, David Blei, …

Swartz
Center for
Computational
Neuroscience

L10 Questions?