Independent Component Analysis (ICA) of EEG, Concepts and Methods
Part 1 – Concepts

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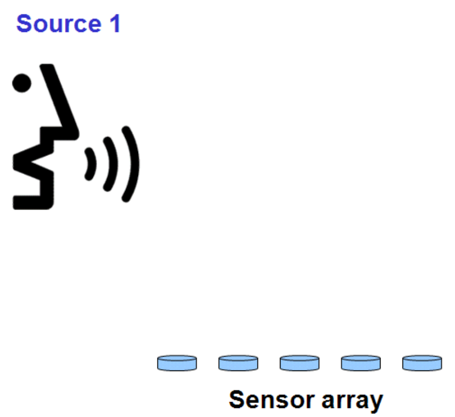
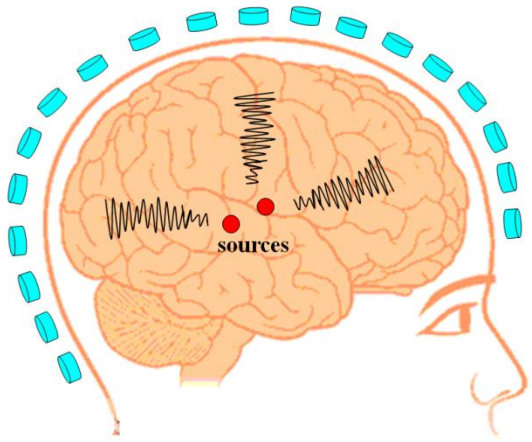
Outline

- EEG and the cocktail party problem
- Linear superposition of EEG sources
- Typical EEG sources
- Back-projection of separated sources
- Dependency and subspaces
  - ICA separates dependent subspaces from other activity
  - Back-projection of subspaces
  - Dynamic components
- Non-stationarity

Cocktail Party Problem

- EEG analysis as separation of ***multiple simultaneously active*** brain sources, similar to microphones recording and multiple simultaneous speakers, e.g. at a cocktail party

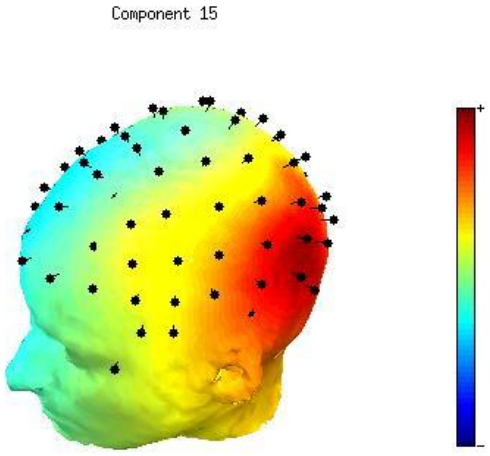




- ICA originally proposed for separation of multiple independent audio signals (early '90s)
- Scott Makeig proposed ICA for EEG source separation (1996), in collaboration with Tony Bell and Terry Sejnowski at Salk

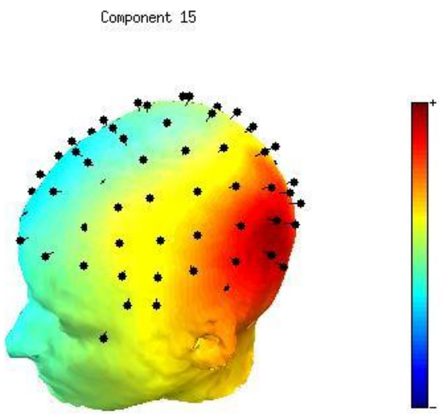
EEG Sources

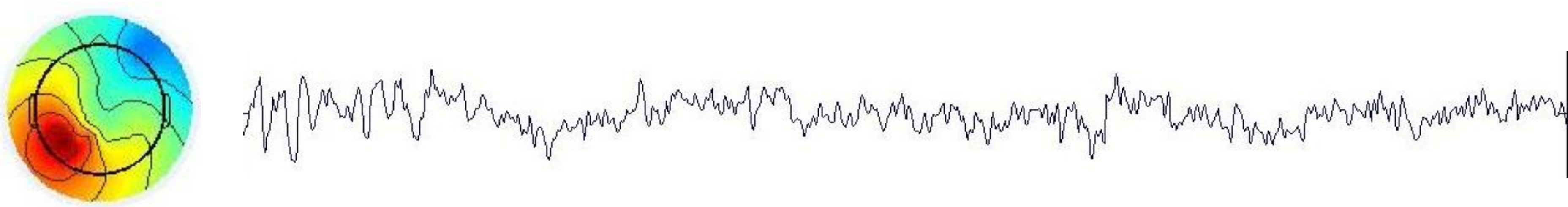
- A source is essentially defined by the pattern of electrical potential that it projects onto the electrodes (by volume conduction)



EEG Sources

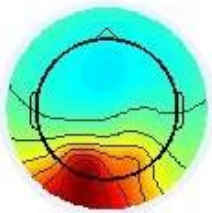
- Stationary source activity (local and stable) fluctuates, or oscillates, around zero, causing alternation of positive and negative potentials at the scalp

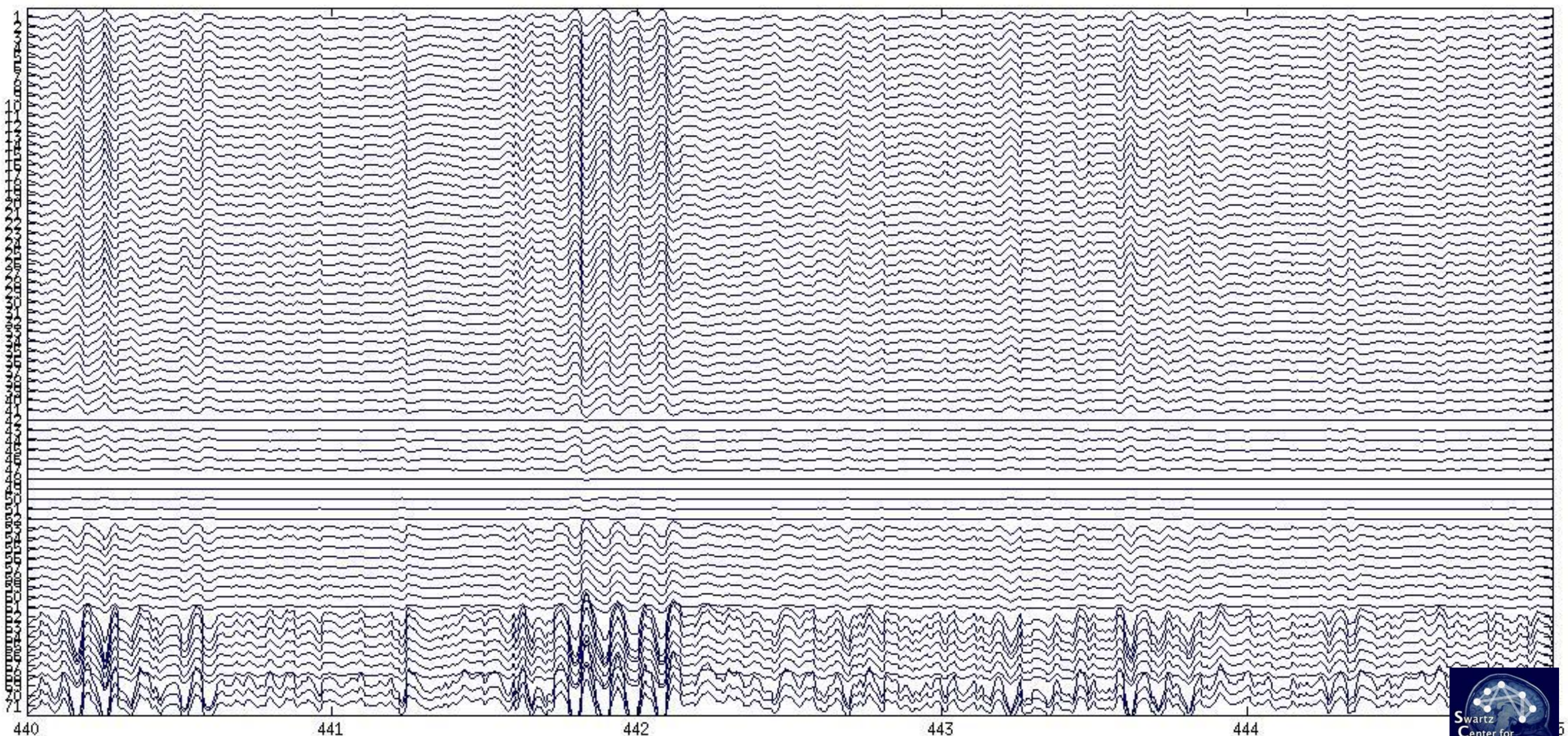




EEG of one source

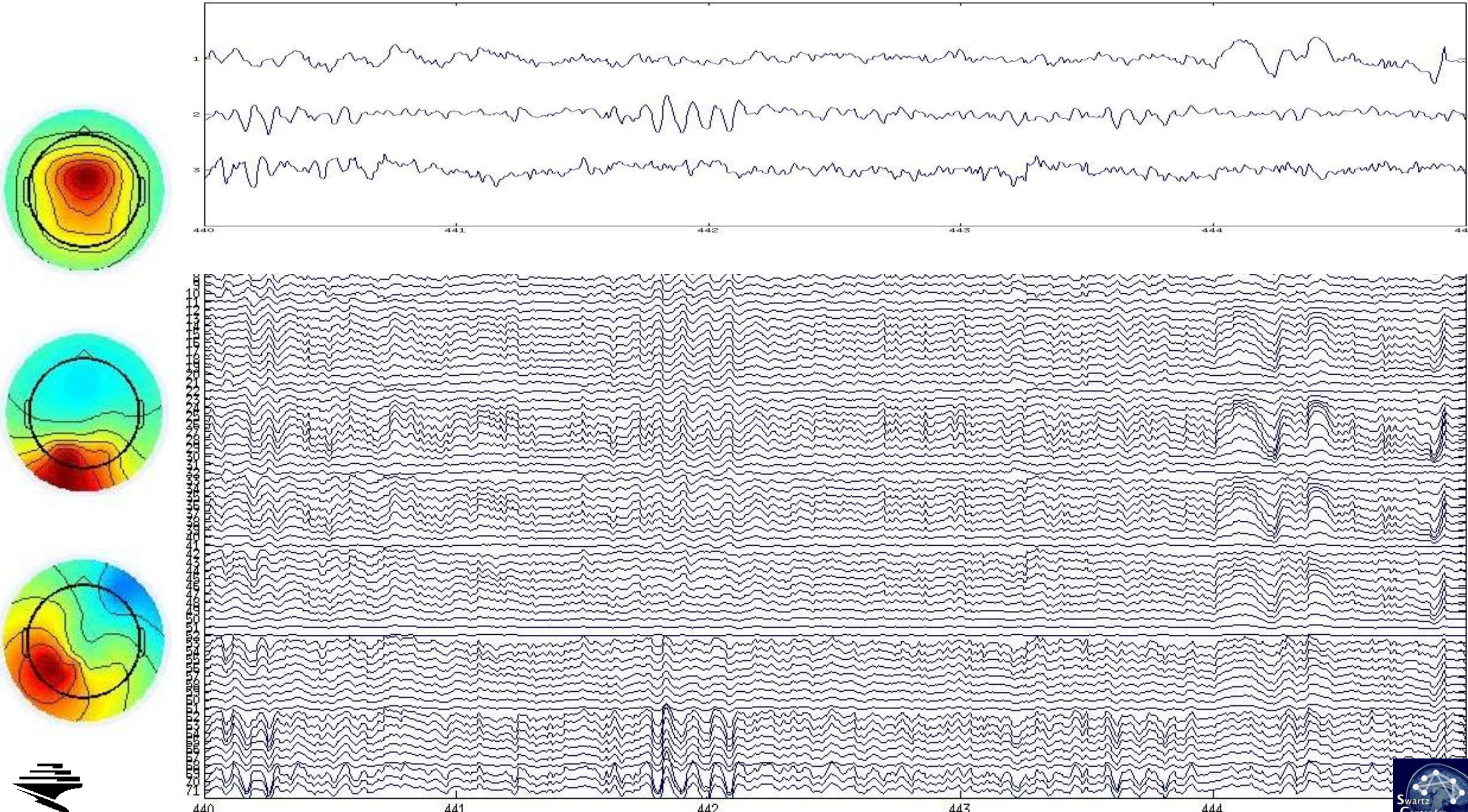
- EEG electrodes record the source activity weighted by different values depending on electrode location relative to the source





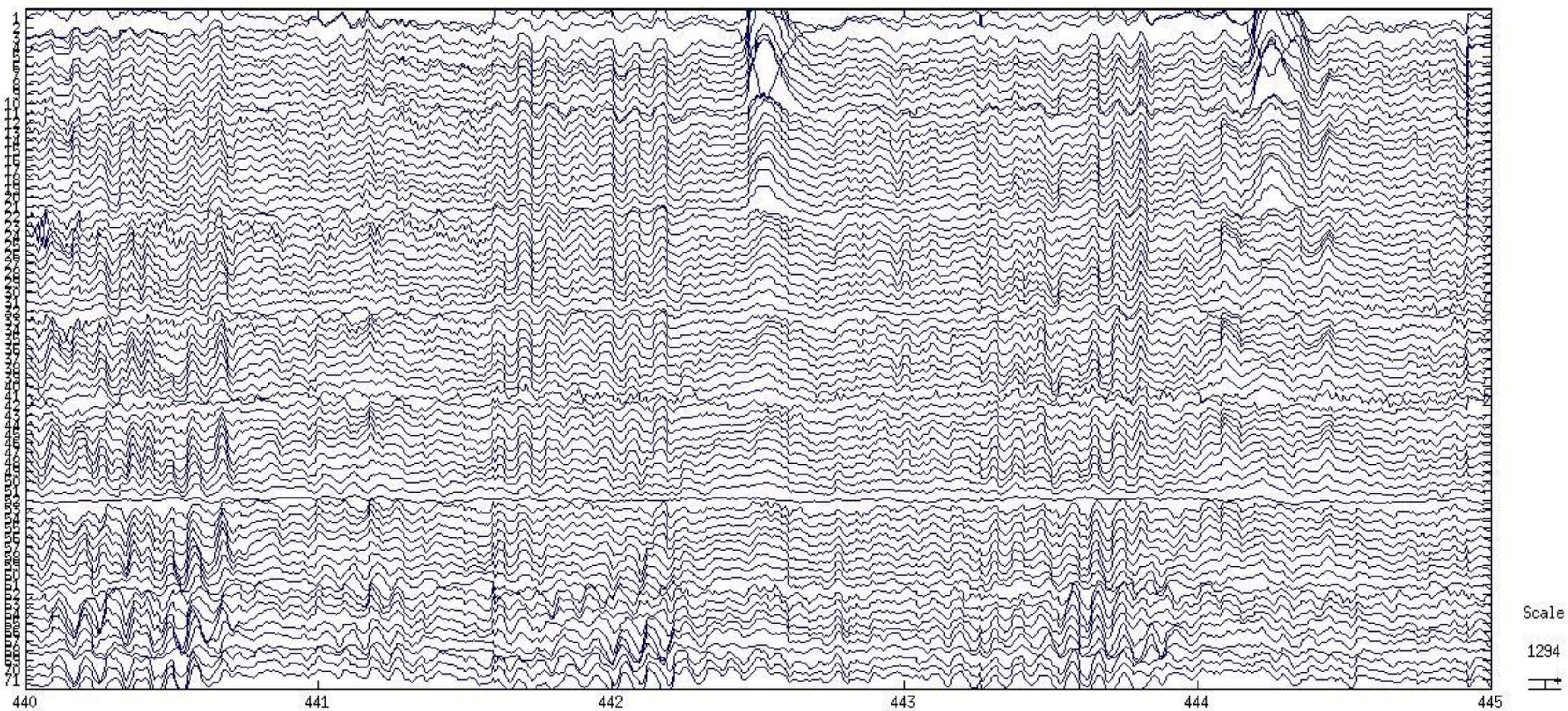
EEG of three sources

- EEG records multiple sources that are simultaneously active



EEG Data

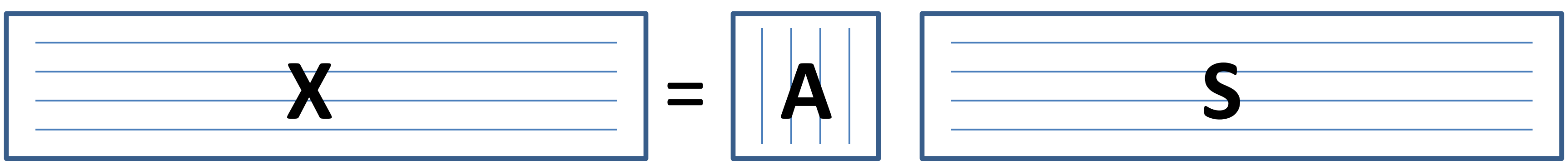
- Raw EEG records large number of simultaneously active sources
- From physics, we know that EEG at one instant is simply the sum of all source activity at that instant



Linear Superposition

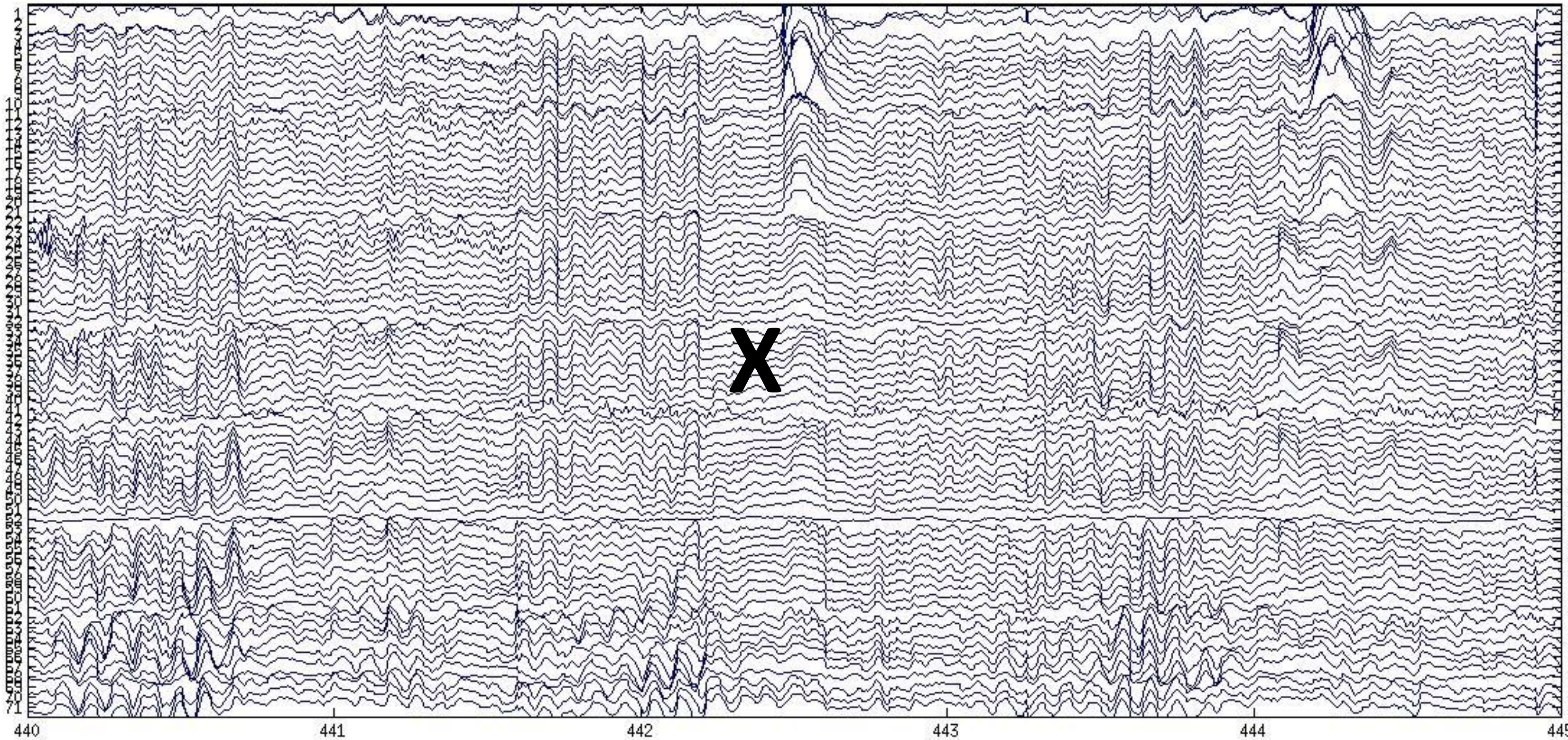
- Let the EEG data be represented by the vector of time varying electrode potentials $\mathbf{x}(t)$, and let the source activities be $s_i(t)$, $i = 1, \ldots, n$
- Let the scalp maps (patterns of potential) be represented by vectors $\mathbf{a}_i$, $i = 1, \ldots, n$
- The EEG data is the sum:

$$\mathbf{x}(t) \;=\; s_1(t)\,\mathbf{a}_1 \;+\; s_2(t)\,\mathbf{a}_2 \;+ \ldots +\; s_n(t)\,\mathbf{a}_n$$



Decomposition of EEG

- Given the EEG data, **X**, we would like to decompose it into source scalp maps multiplied by source activity, **X** = **AS**, with **A** and **S** unknown



= AS

Scale
1294

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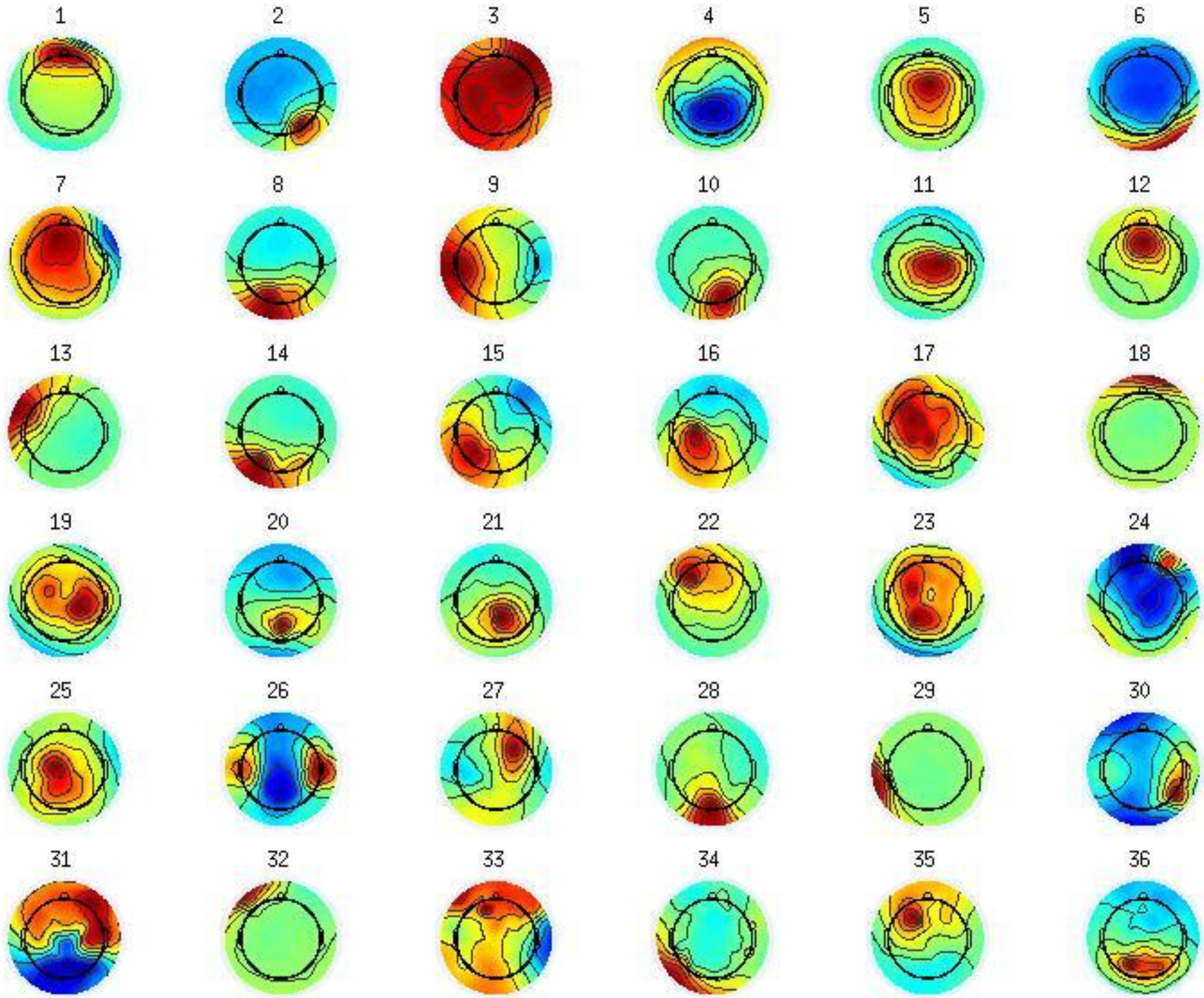
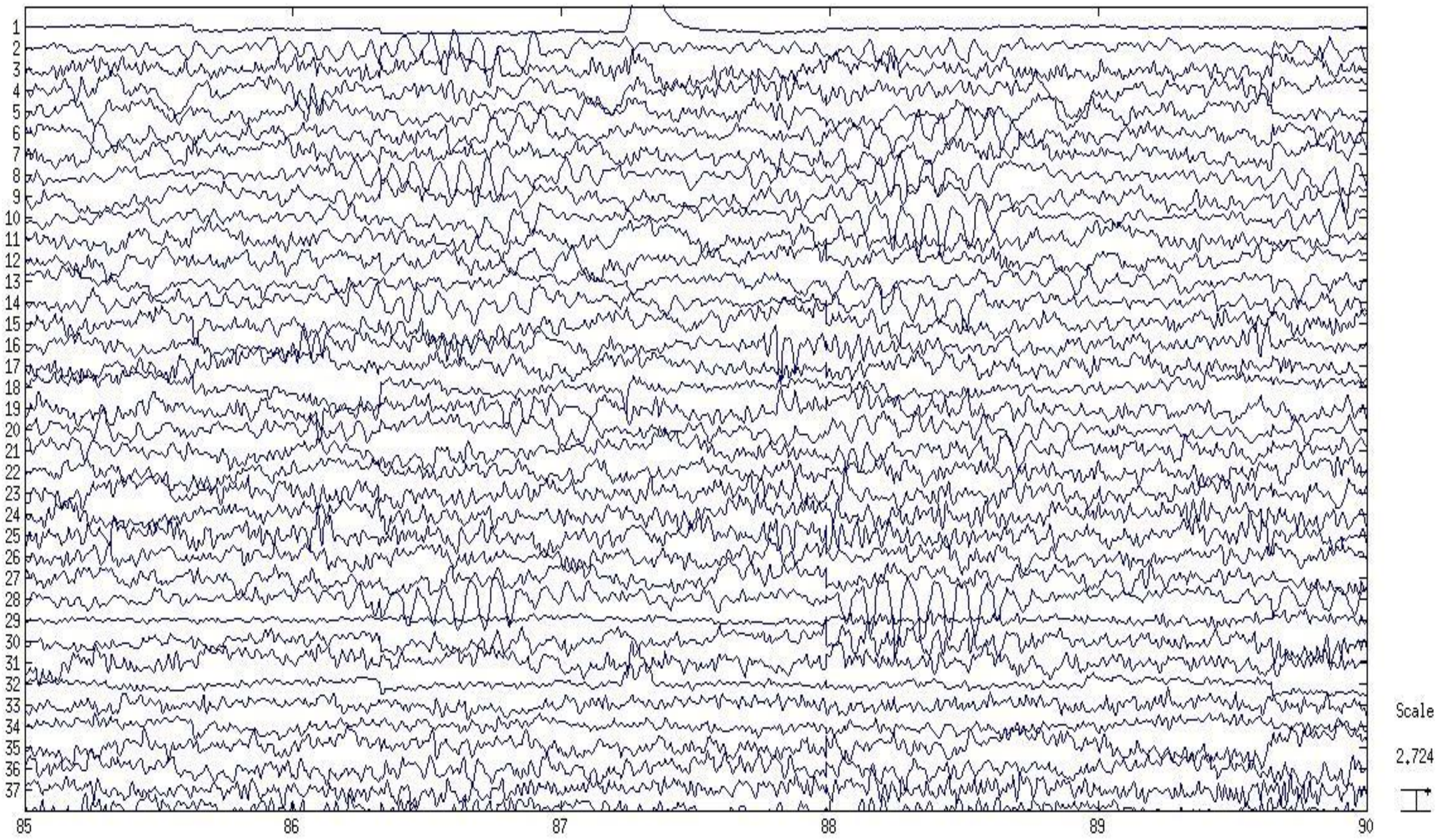
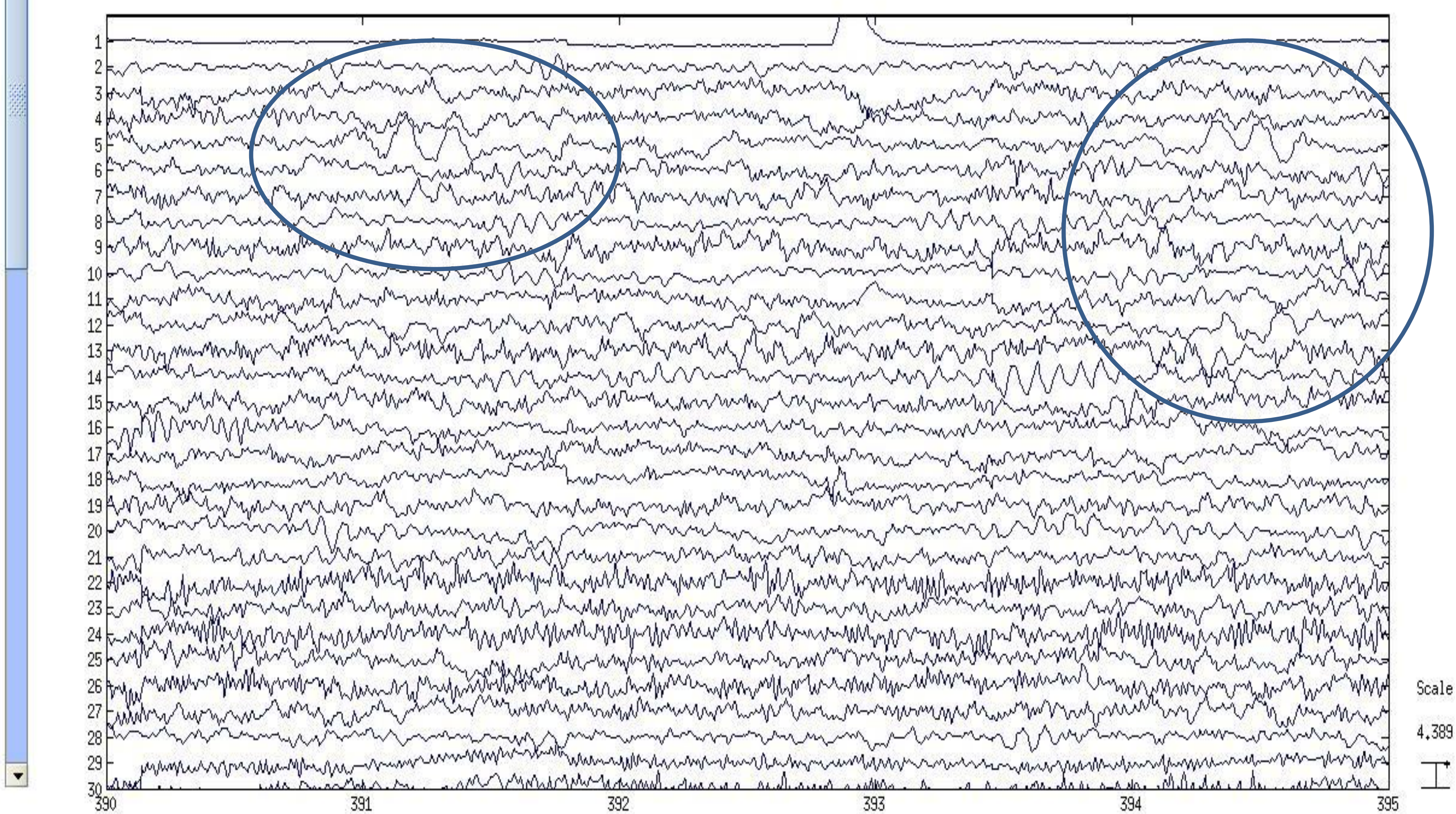
Typical ICA scalp maps



Typical ICA sources – alpha

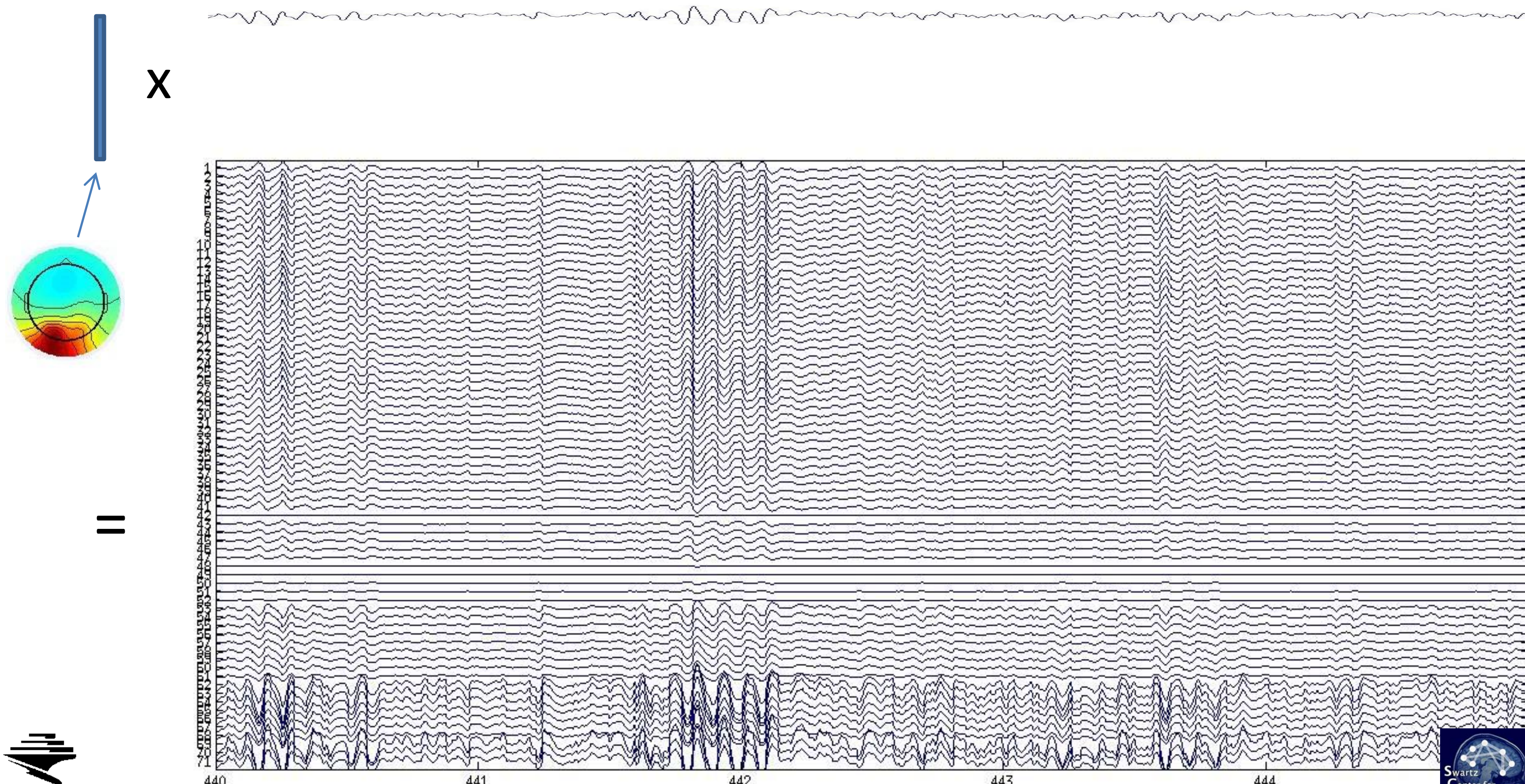


Typical ICA sources – theta



Back-projection

- Separated sources can be "back-projected" to the scalp to examine contribution of individual sources at electrodes



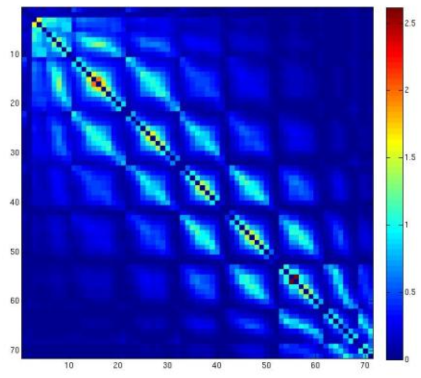
Pairwise mutual information

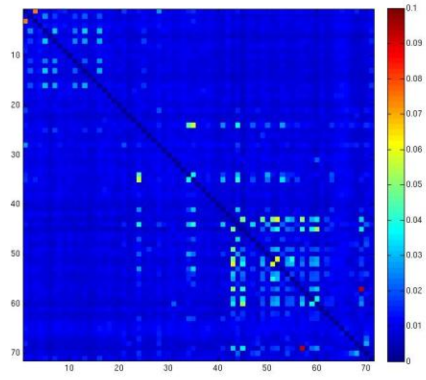
- Pairwise mutual information (PMI):

$$[\mathrm{M}]_{ij} = \mathrm{I}(x_i; x_j) = h(x_i) + h(x_j) - h(x_i, x_j)$$

PMI is a measure of dependence between sources

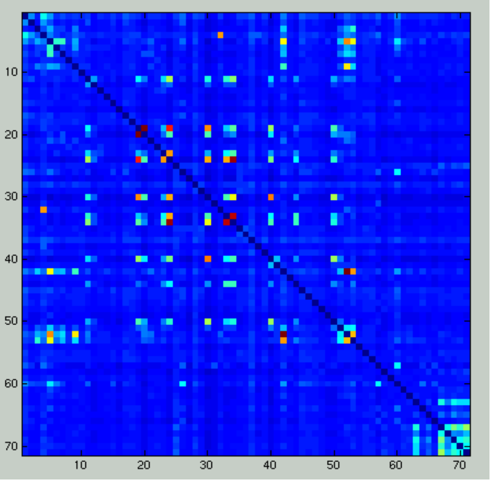
- Comparison of PMI for original data and ICA

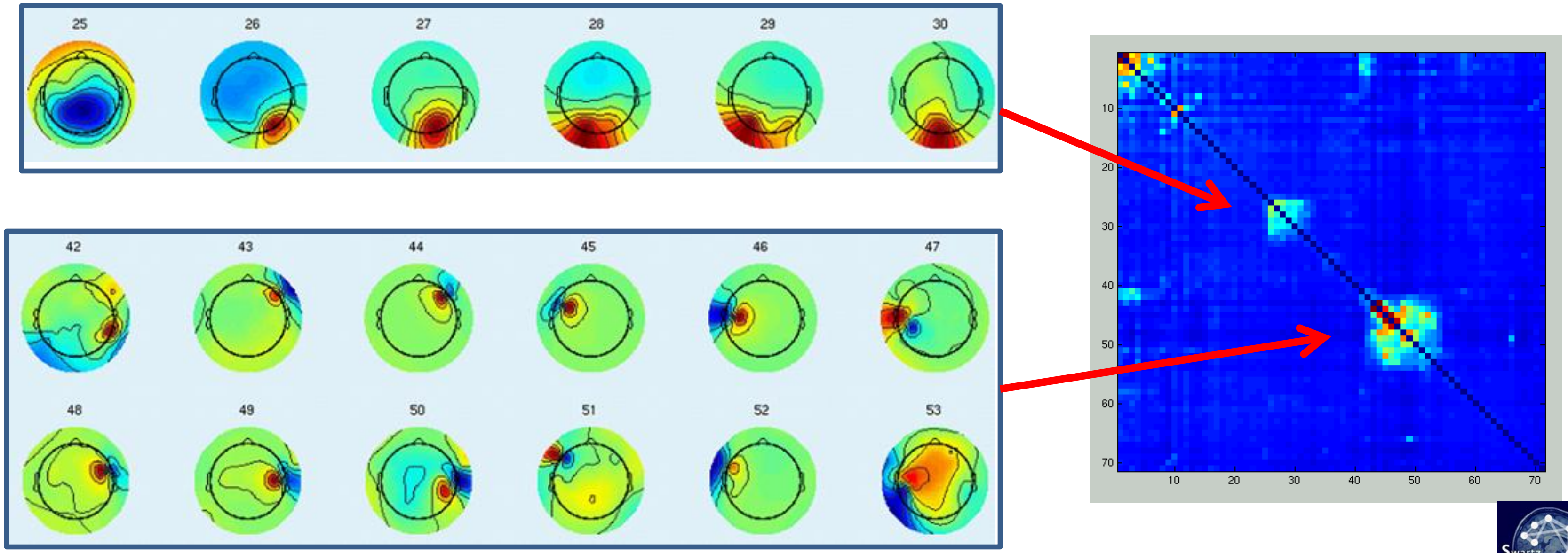




Dependent subspaces

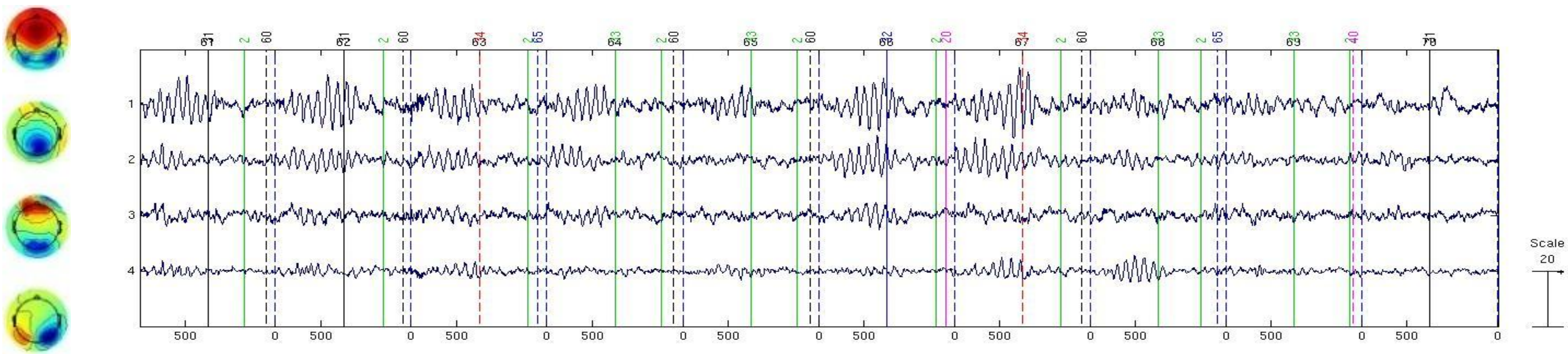
- Residual dependence structure can be seen using Pairwise Mutual Information (PMI) plot
- Block diagonalizing this matrix (heuristically), we see blocks corresponding to dependent subspaces of components





Alpha dependence

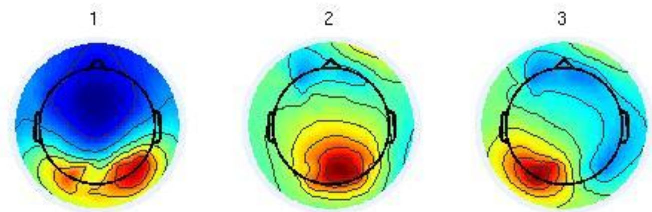
- Below four alpha components are shown



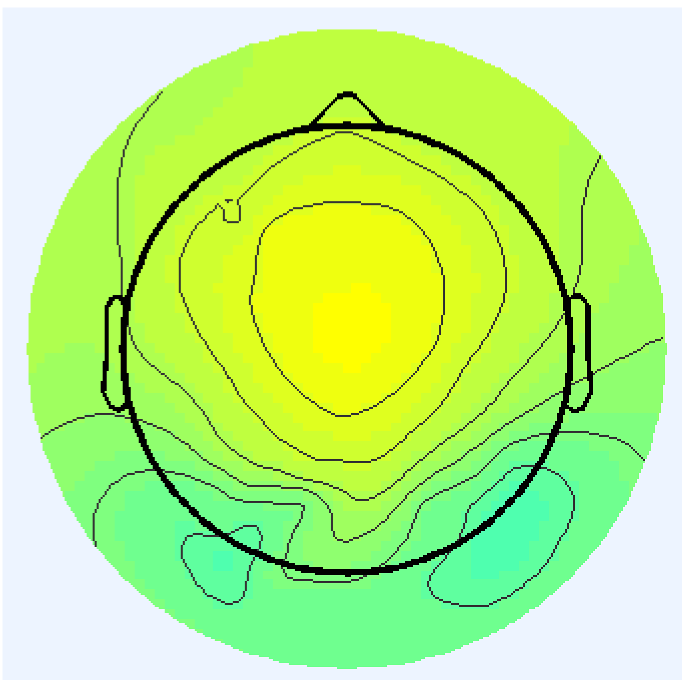
- This alpha activity exhibits dependence and coherence
- There is actually an alpha “subspace”
- Is alpha a “distributed dynamic” phenomenon?

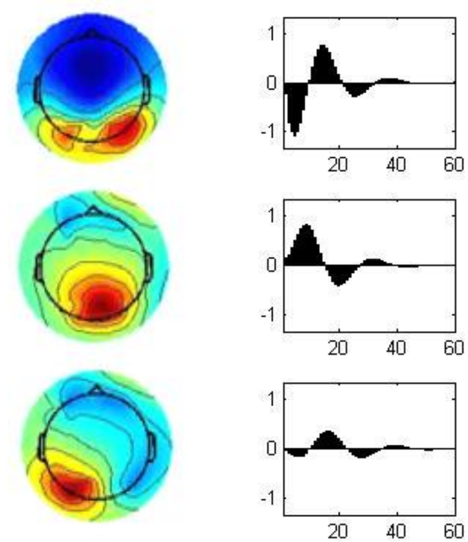
Alpha Dynamic Component

- Alpha component maps:



- Subspace can be extracted along with dynamics and played as a movie:





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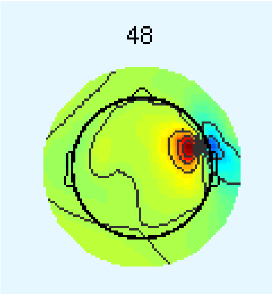
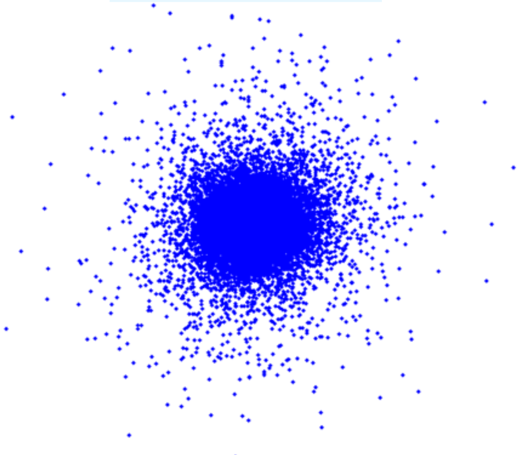
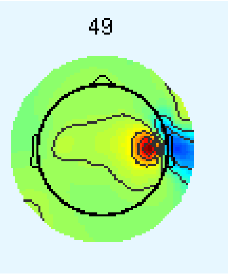
Muscle dependence

- Muscle components tend to be active at the same time

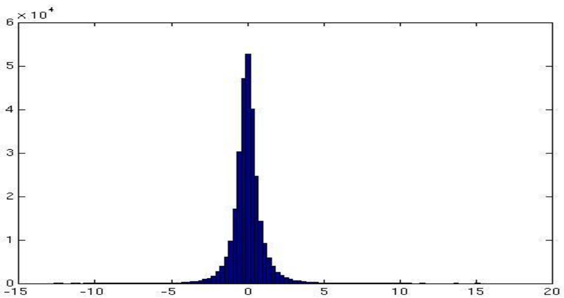


- Activity is uncorrelated, but nevertheless dependent



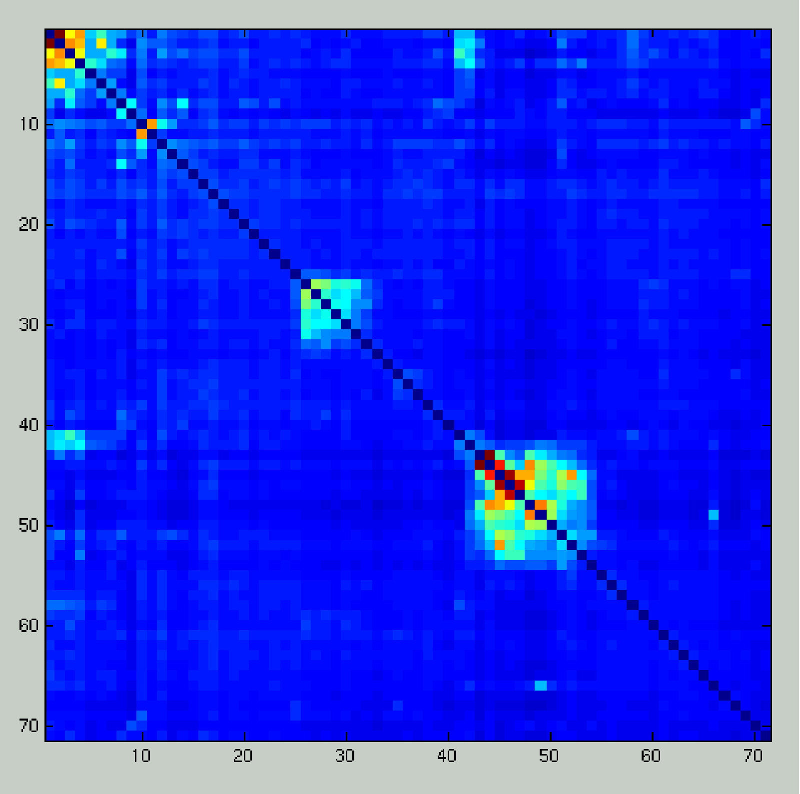


- Activity is non-Gaussian, marginal histograms are "sparse"



Variance Dependence and ICA

- We can show that minimizing the total mutual information will separate variance dependent sources



- PMI can be used to analyze dependence structure after ICA has been performed

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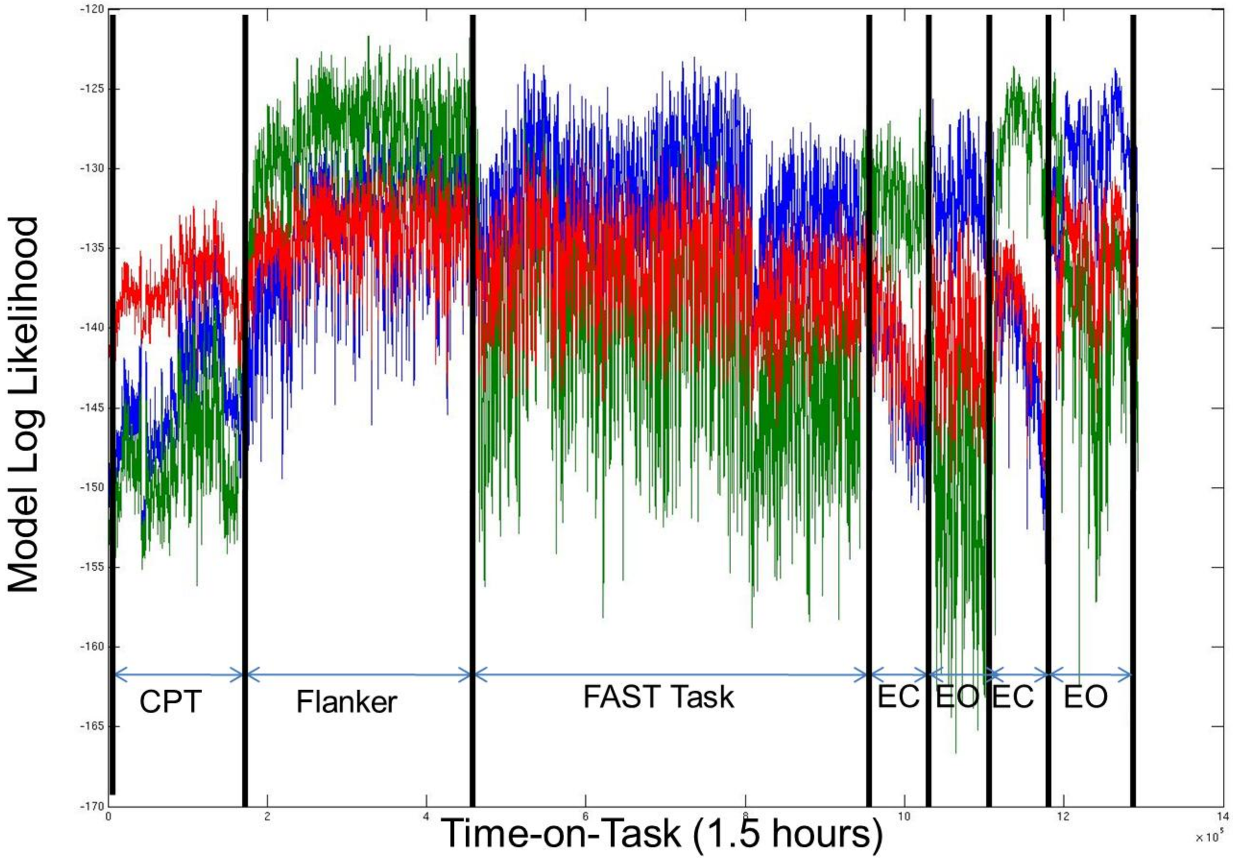
Non-stationarity

- Typical EEG recordings are non-stationary—souces and distributions differ over course of recording.
- We use a mixture model approach to learn multiple ICA models



Conclusion

- Problem of separating EEG sources is similar to the “cocktail party problem” of separating simultaneous audio sources
- Individual sources, e.g. contributing to ERPs, can be separated an back-projected to examine activity at the scalp electrodes, or map can be “localized” to determine source location in brain
- Sources may exhibit residual dependency, but ICA usually separates a “subspace” from other sources
- Data may be non-stationary, but a mixture of ICA models can be used to represent different time periods with different ICA models
- Part 2 after lunch …

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