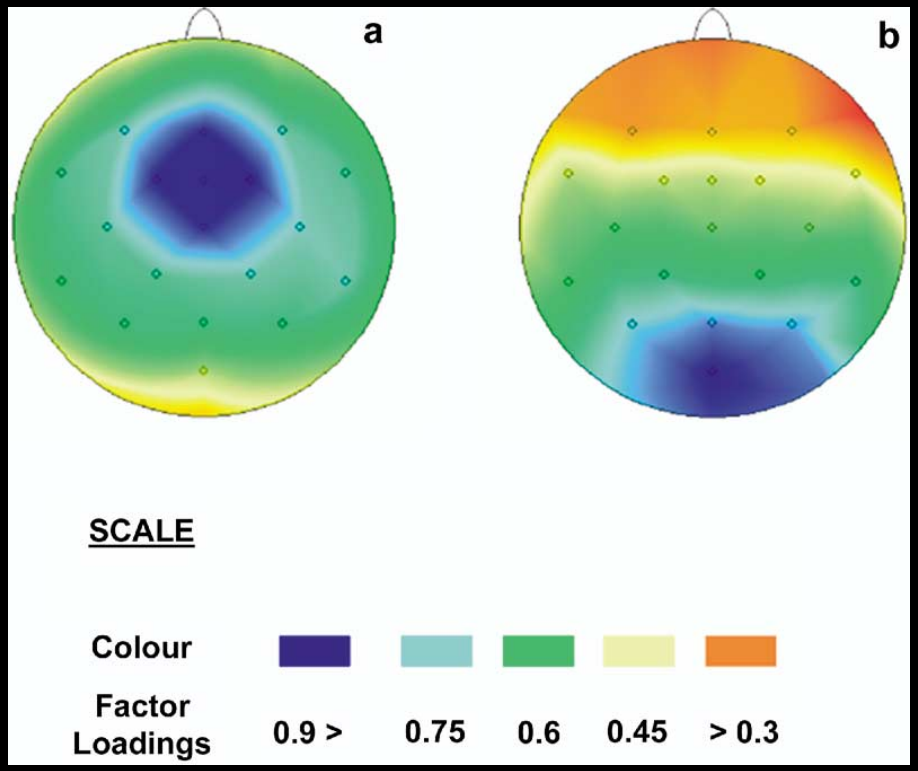
PCA and ICA

The Bottom Line

The data we are working with is very complex and we are making some very broad and simple assumptions to estimate properties of the data and/or correct/adjust/remove bits of the data.

What do they do?

Both PCA and ICA reduce data into a series of smaller components.

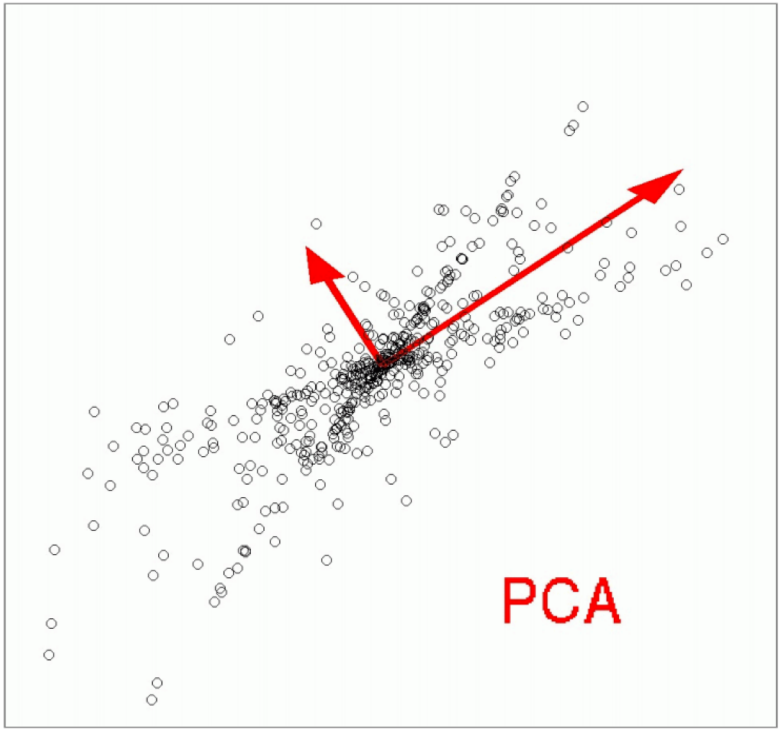


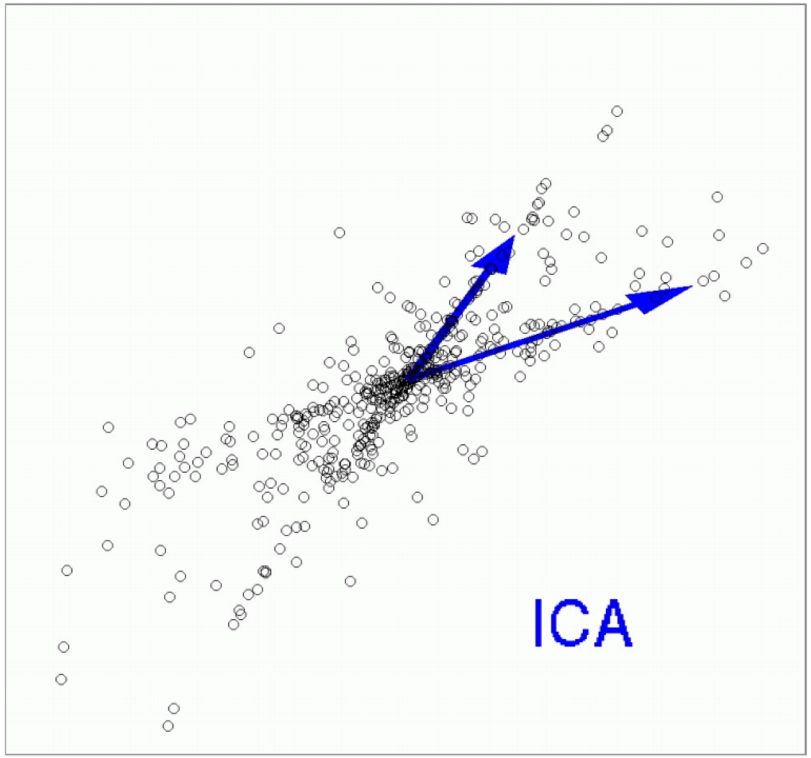
PCA

Utilizes the first and second moments of the measured data, hence relying heavily on Gaussian features.

ICA

Exploits inherently non-Gaussian features of the data and employs higher moments.


PCA


ICA

PCA and EEG

PCA is typically used in EEG research to identify spatial, temporal, and/or spatial-temporal components in the data.

At the end of the day…

DIMENSION REDUCTION

As opposed to having a bunch of channels/time points you have a "spatial component" or a "temporal component"

Dimension Reduction Before PCA

Channels x Time x Conditions x Participants

4 Dimensions

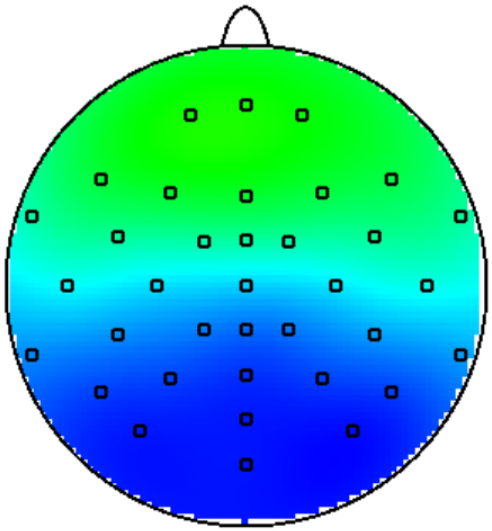
Dimension Reduction After Spatial PCA

Time x Conditions x Participants

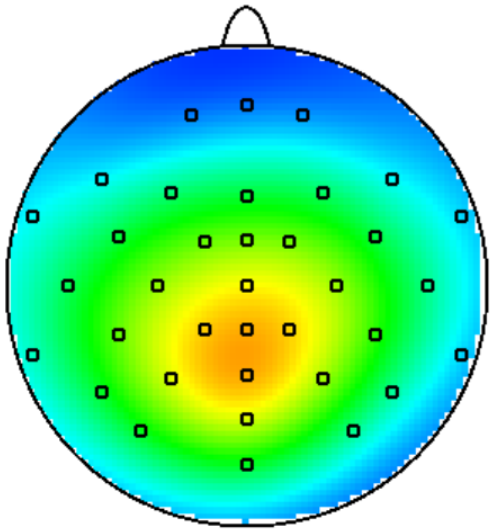
3 Dimensions

for each Spatial Factor

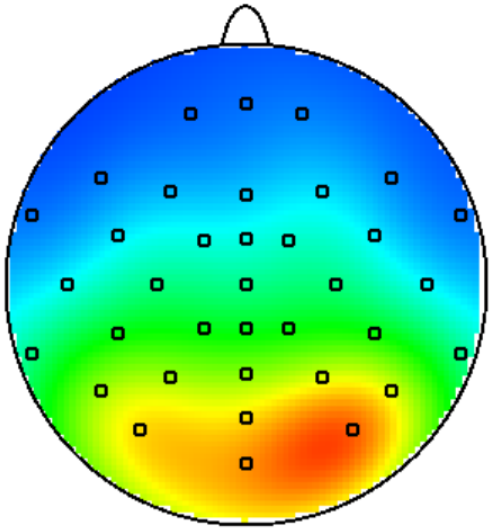
Spatial Factors



P1



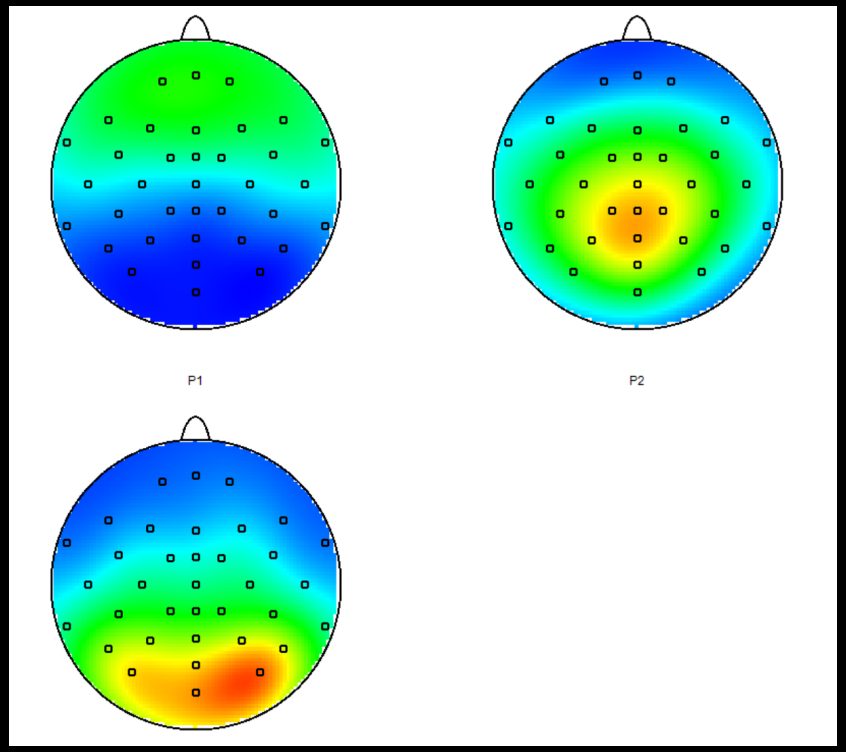
P2



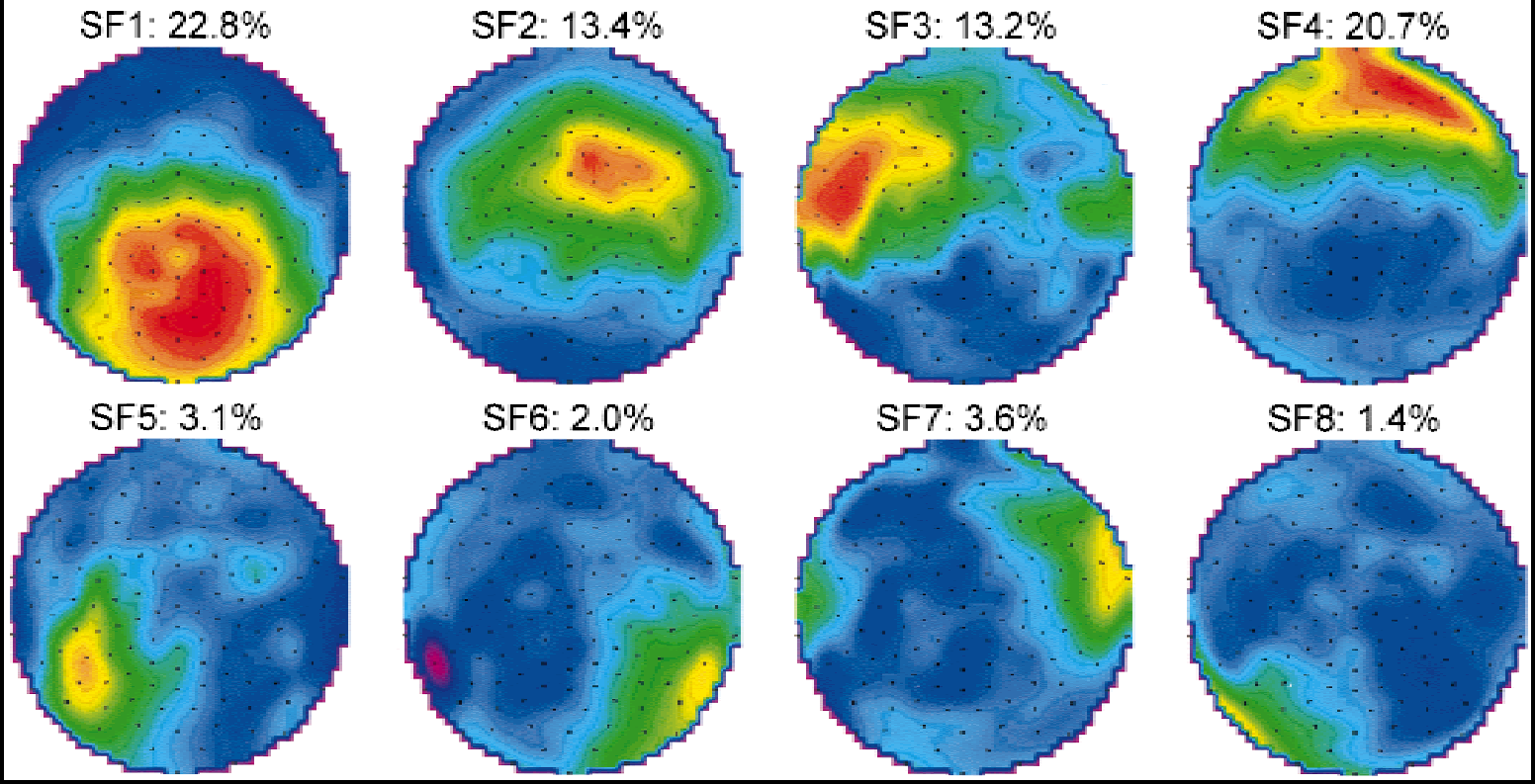
Spatial Factors:
Each factor will have loadings or weights that when plotted topographically show the spatial components.

What is a Spatial Component?

Component	Fpz	Fz	FCz	Cz	Cpz	Pz	POz	Oz
1	0.1	0.4	0.9	0.8	0.4	0.3	0.2	0.1
2	0.1	0.1	0.1	0.1	0.4	0.7	0.5	0.2
3	0.9	0.5	0.2	0.1	0.1	0.1	0.1	0.1



Spatial Factor Loadings (Virtual Electrodes)



But how is the data reduced?

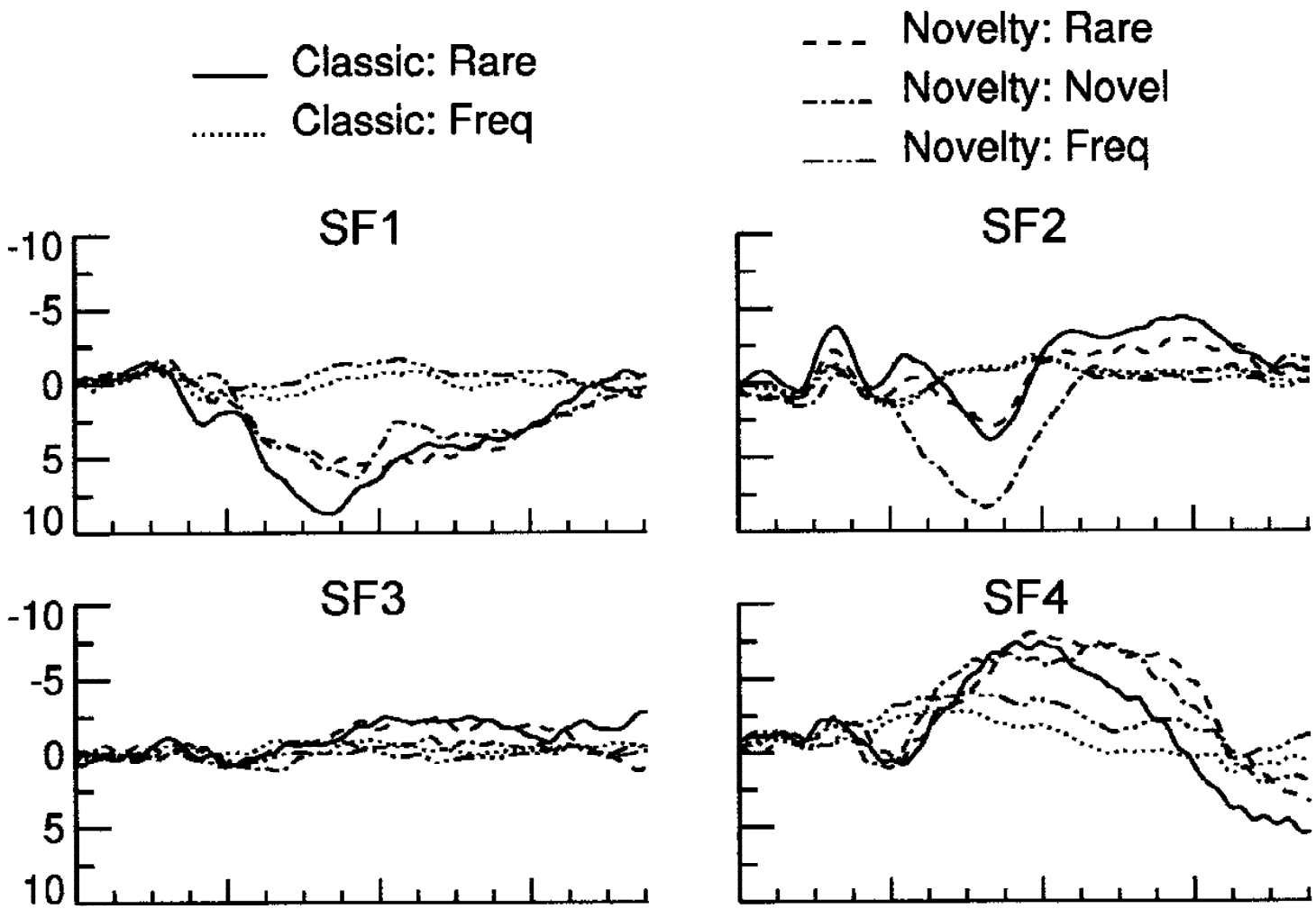
The component weighting matrix (loadings) are multiplied with the data to create component scores.

Think of it this way, each point in time for each condition for each subject would be weighted by that component relative to the original data value present.

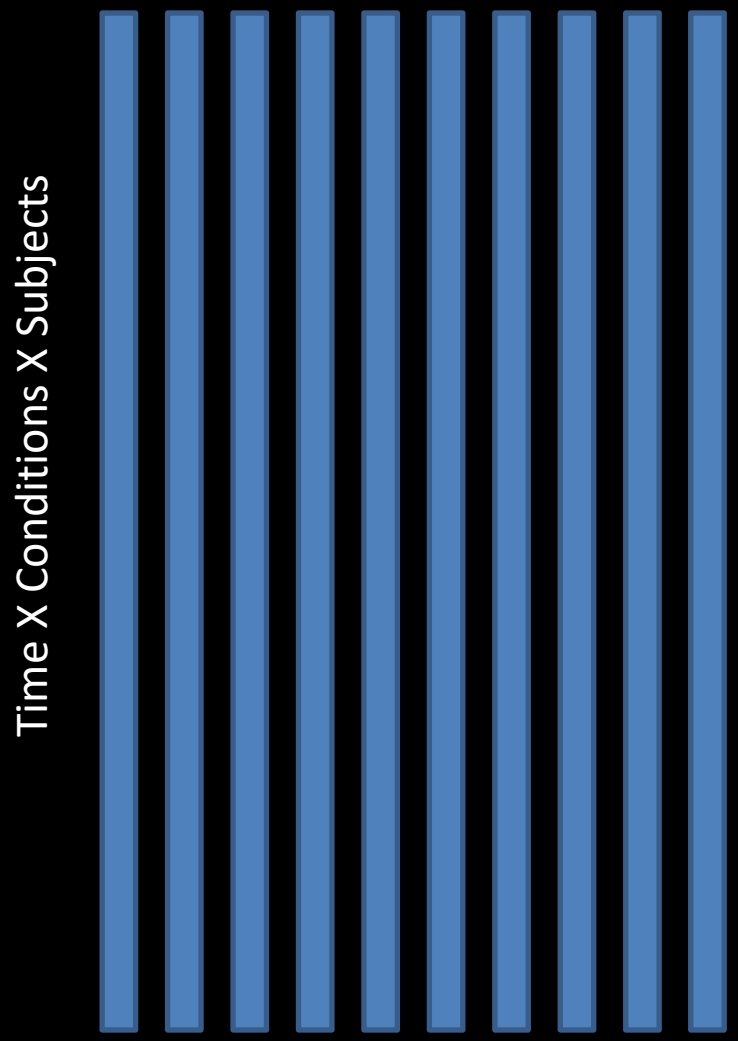
Virtual ERPs

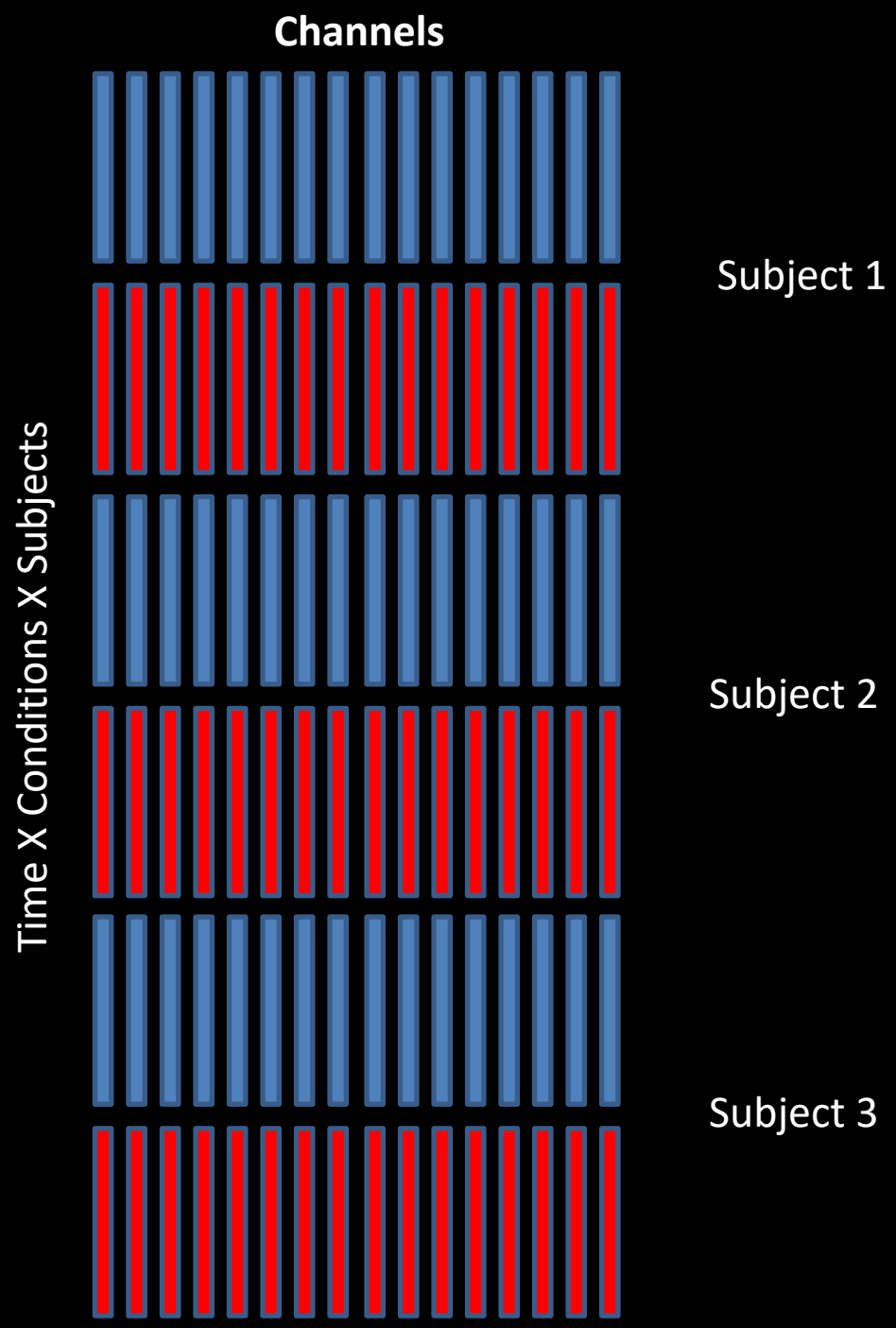
Once this is done, you can reshape the scores back into the original data format, but with the dimensionality greatly reduced.

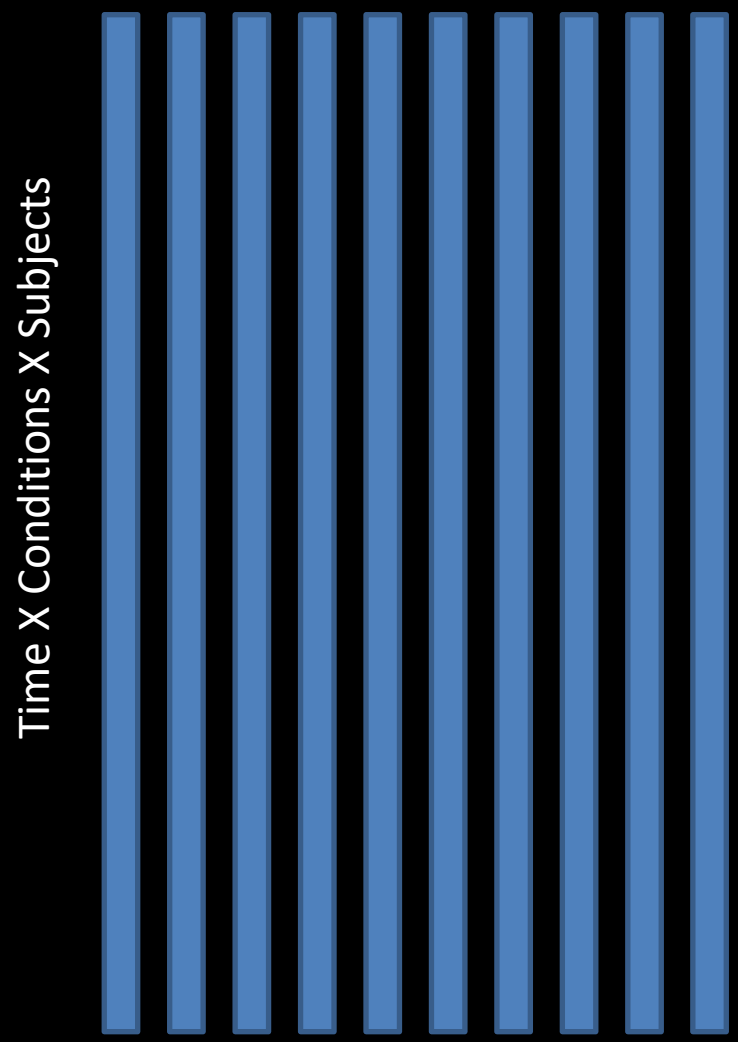
Virtual ERPs: "Attend" Tasks (SF1-8)

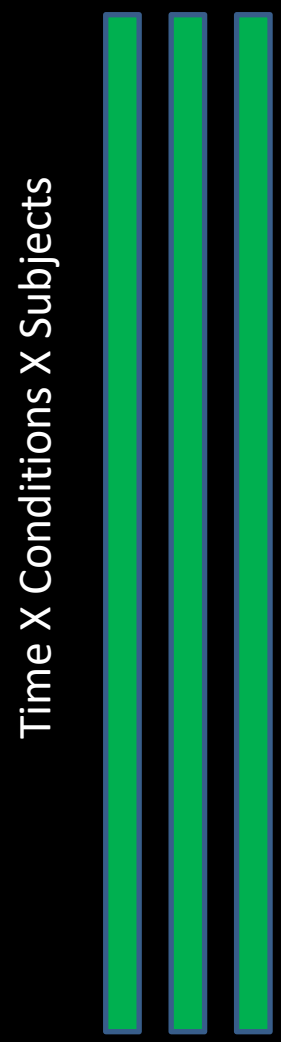


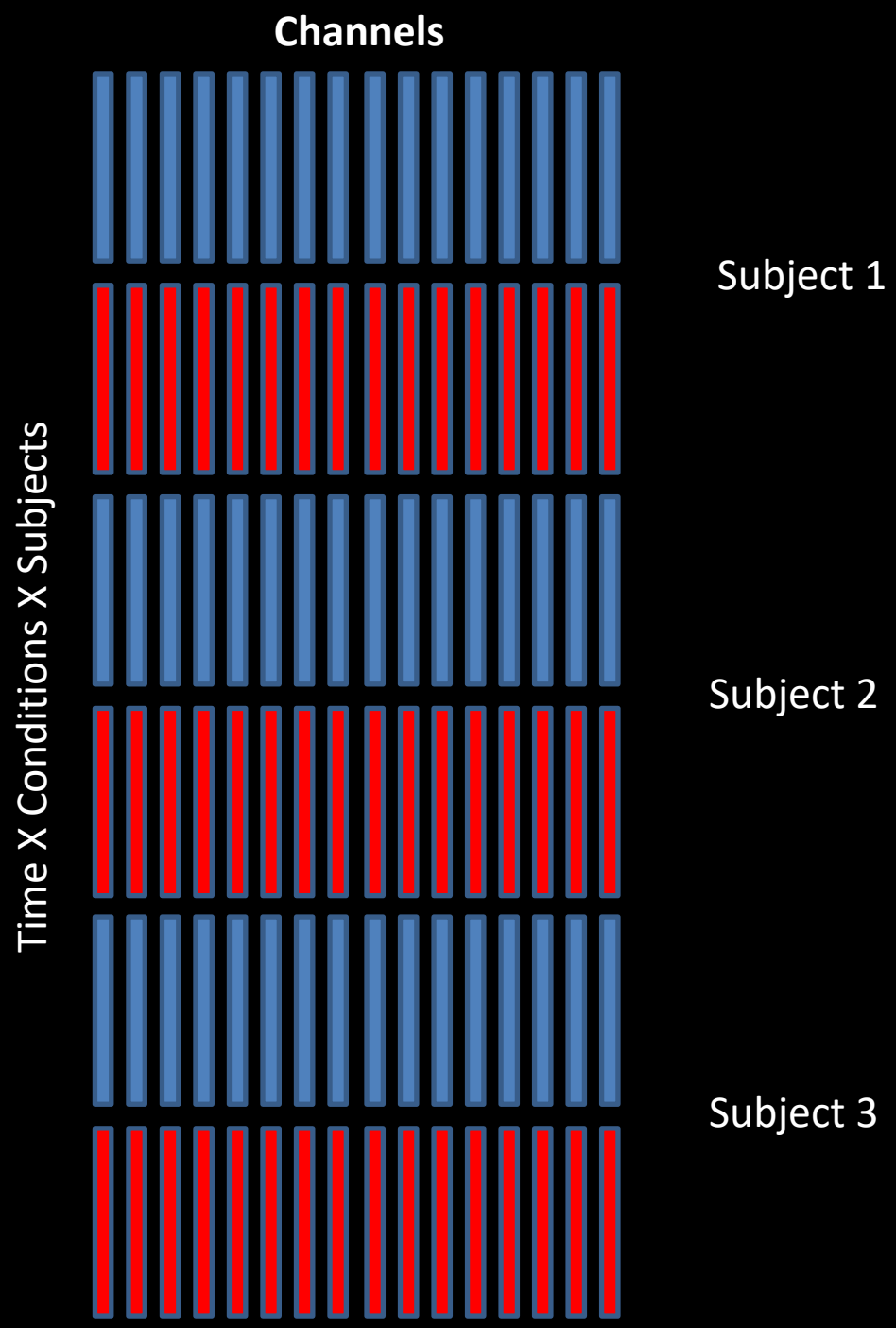
Channels



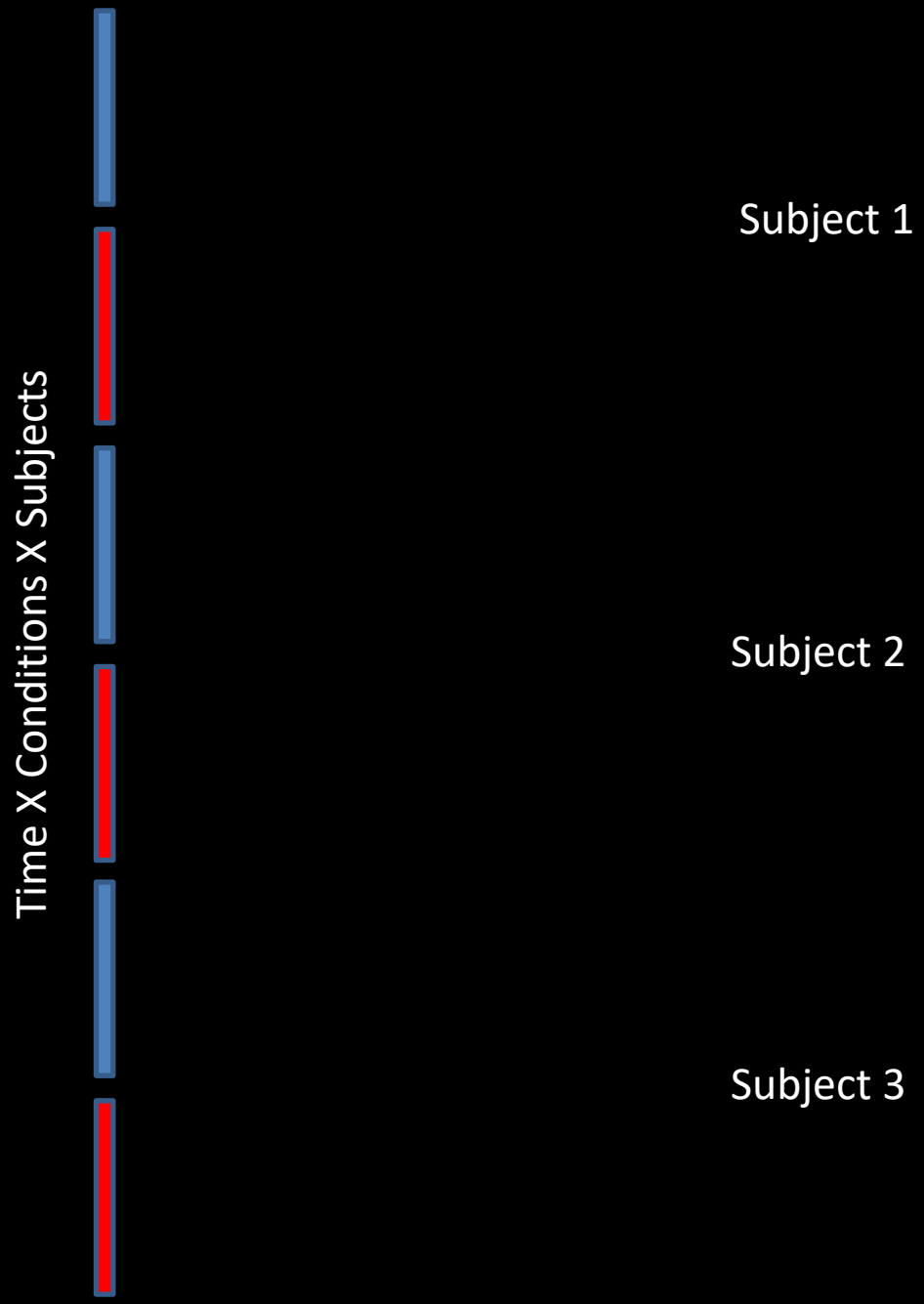

Channels
Time X Conditions X Subjects
Subject 1
Subject 2
Subject 3


Channels
Time X Conditions X Subjects


Components
Time X Conditions X Subjects


Channels
Time X Conditions X Subjects
Subject 1
Subject 2
Subject 3

Component 1 Scores



Virtual ERPs

Temporal PCA

The same logic as Spatial PCA but with Time Points as the DV.

Dimension Reduction Before PCA

Channels x Time x Conditions x Participants

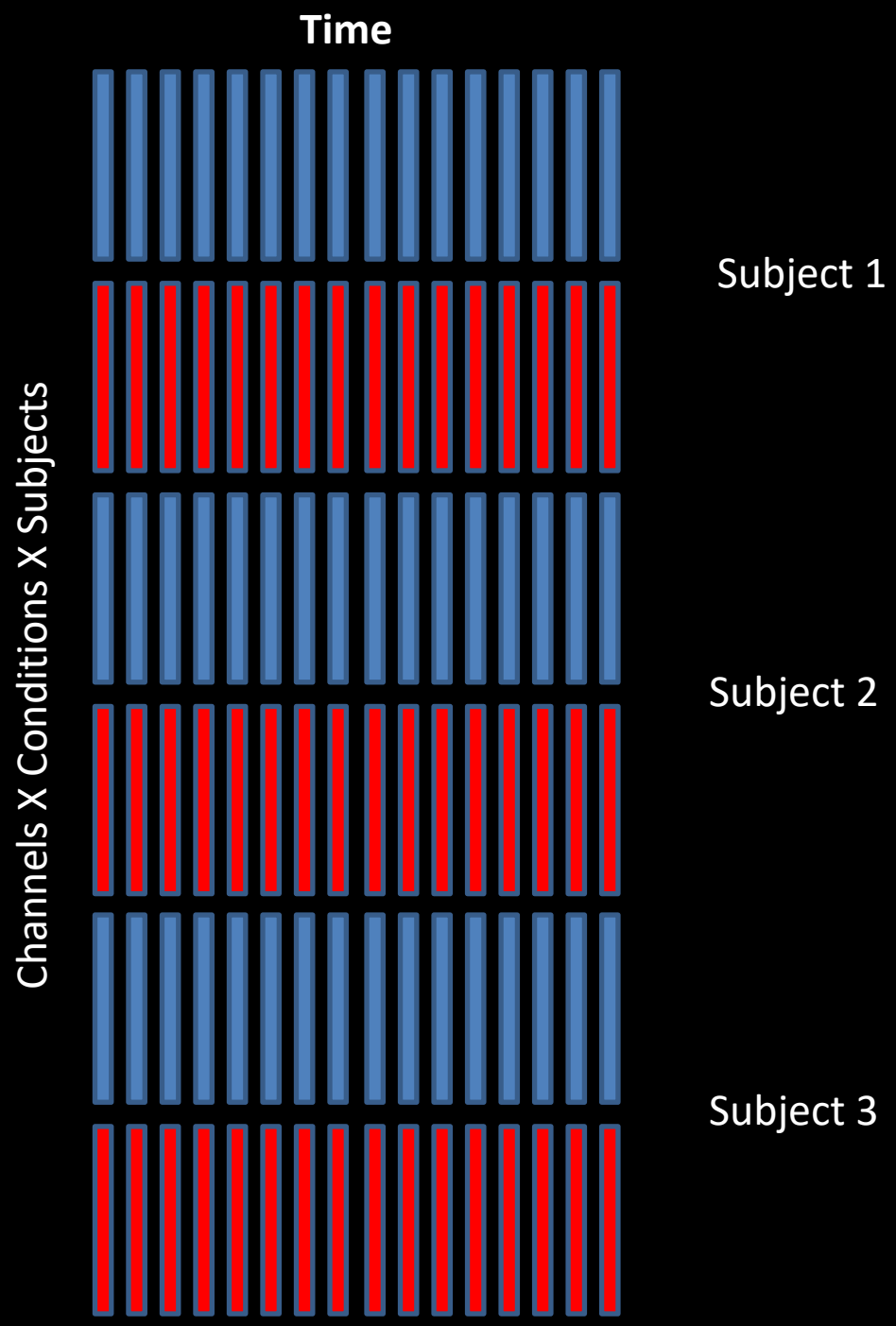
4 Dimensions

Dimension Reduction After Temporal PCA

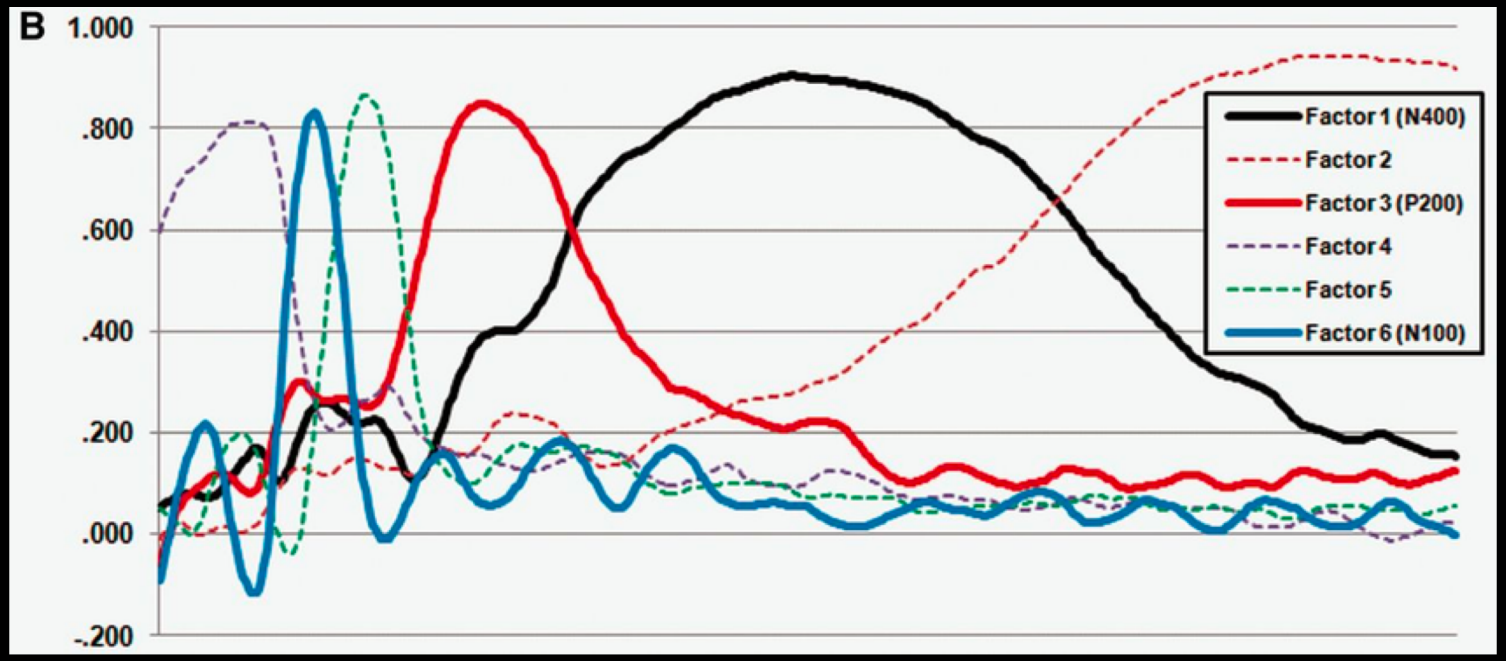
Channels x Conditions x Participants

3 Dimensions

for each Temporal Factor


Time
Channels X Conditions X Subjects
Subject 1
Subject 2
Subject 3

Temporal Factor Loadings



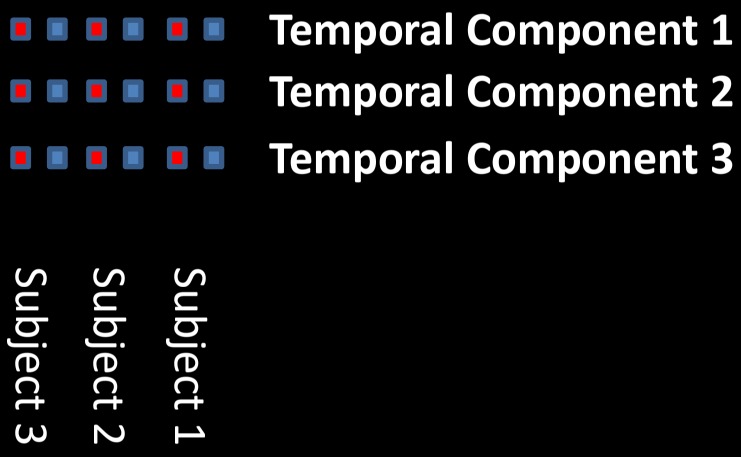
Spatial – Temporal
or
Temporal – Spatial PCA

The logic is simple – you run a PCA on either the spatial or temporal dimension first and then you run a second PCA on the virtual data from one of the factors from the first PCA to reduced the dimensionality further.

Virtual ERPs

The second PCA would collapse the time dimension to a series of factors.
For each factor you would have a score. For example, a factor might be maximal between 200 to 300 ms.
As such, when you reshape the data one last time, you would have a single score for each participant for each condition. The score reflects the value of a single spatial and temporal compoment.

Conditions X Subjects



Conditions X Subjects

Temporal Component 1

Conditions

Subjects

Spatiotemporal analysis of the late ERP responses to deviant stimuli

KEVIN M. SPENCER[a], JOSEPH DIEN[b], AND EMANUEL DONCHIN[c]

[a]Department of Psychiatry, Harvard Medical School/Brockton VAMC, USA
[b]Department of Psychology, Tulane University, New Orleans, USA
[c]Department of Psychology and Beckman Institute, University of Illinois at Urbana-Champaign, USA

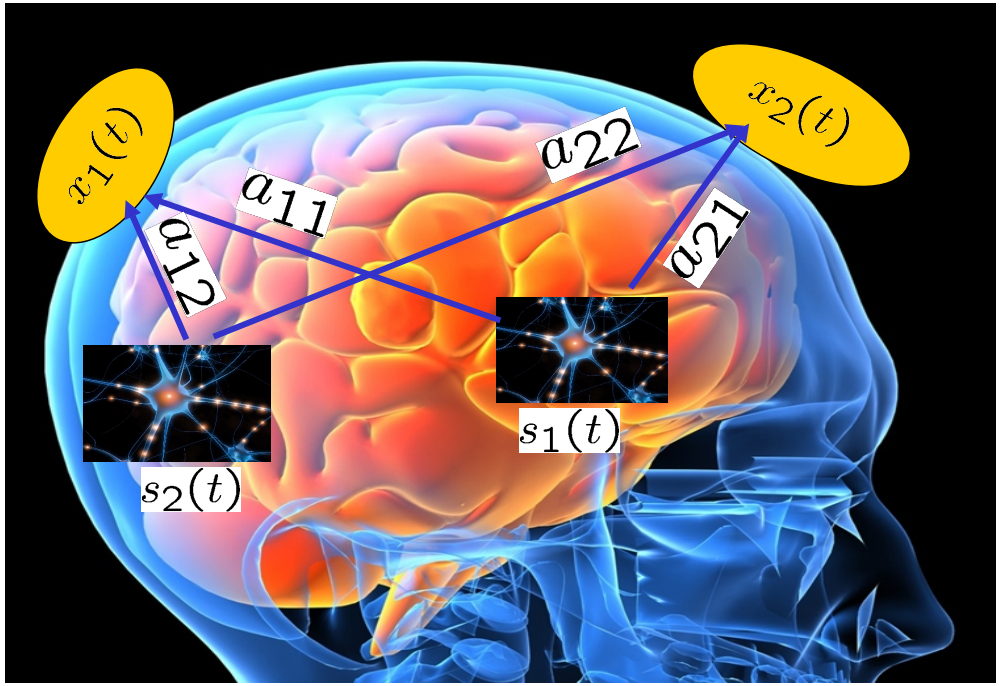
ICA

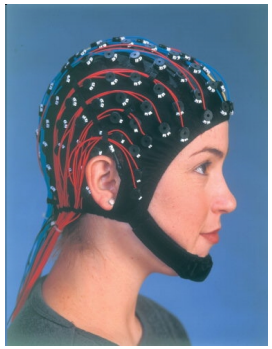
ICA has been primarily used in EEG research to correct ocular artifacts but can be used to isolate spatial components as well.

Independent Component Analysis

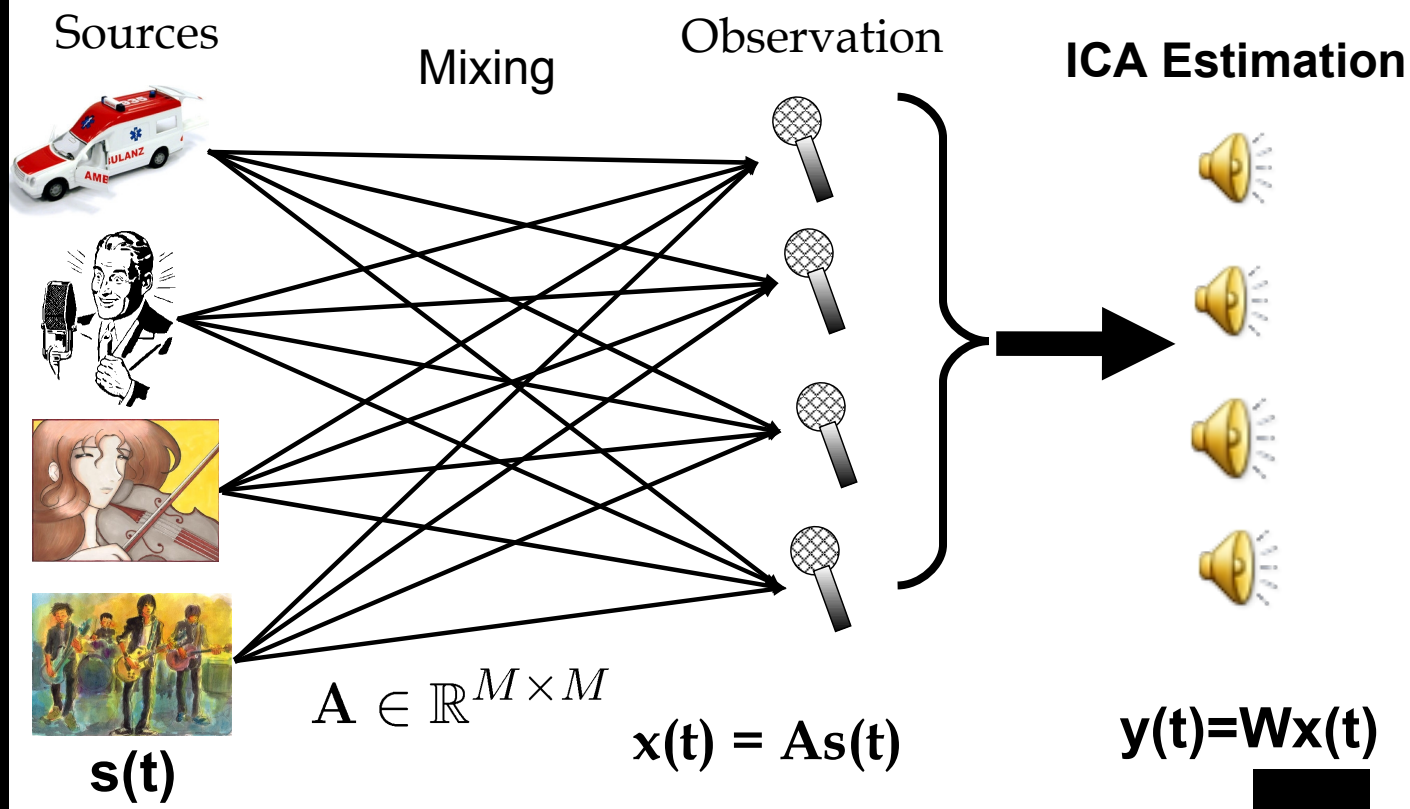
$$
\begin{aligned}
x_1(t) &= a_{11}s_1(t) + a_{12}s_2(t) \\
x_2(t) &= a_{21}s_1(t) + a_{22}s_2(t)
\end{aligned}
$$

Goal: Estimate $\{s_i(t)\}$,
(and also $\{a_{ij}\}$)

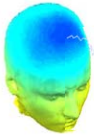




The Cocktail Party Problem
SOLVING WITH ICA



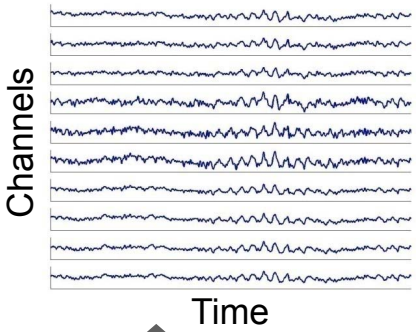
Independent Component Analysis



x = scalp EEG

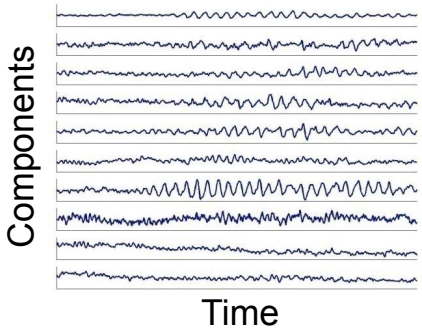
W = unmixing matrix

u = sources



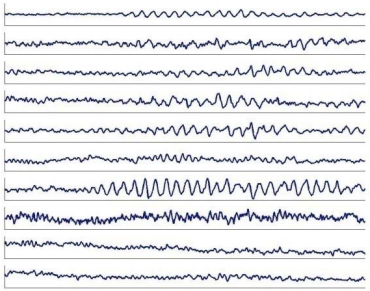
$W*x = u$

ICA



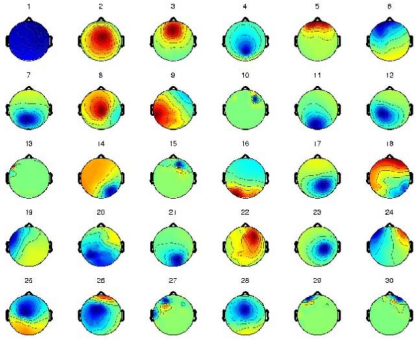
$x = W^{-1}*u$

u = sources

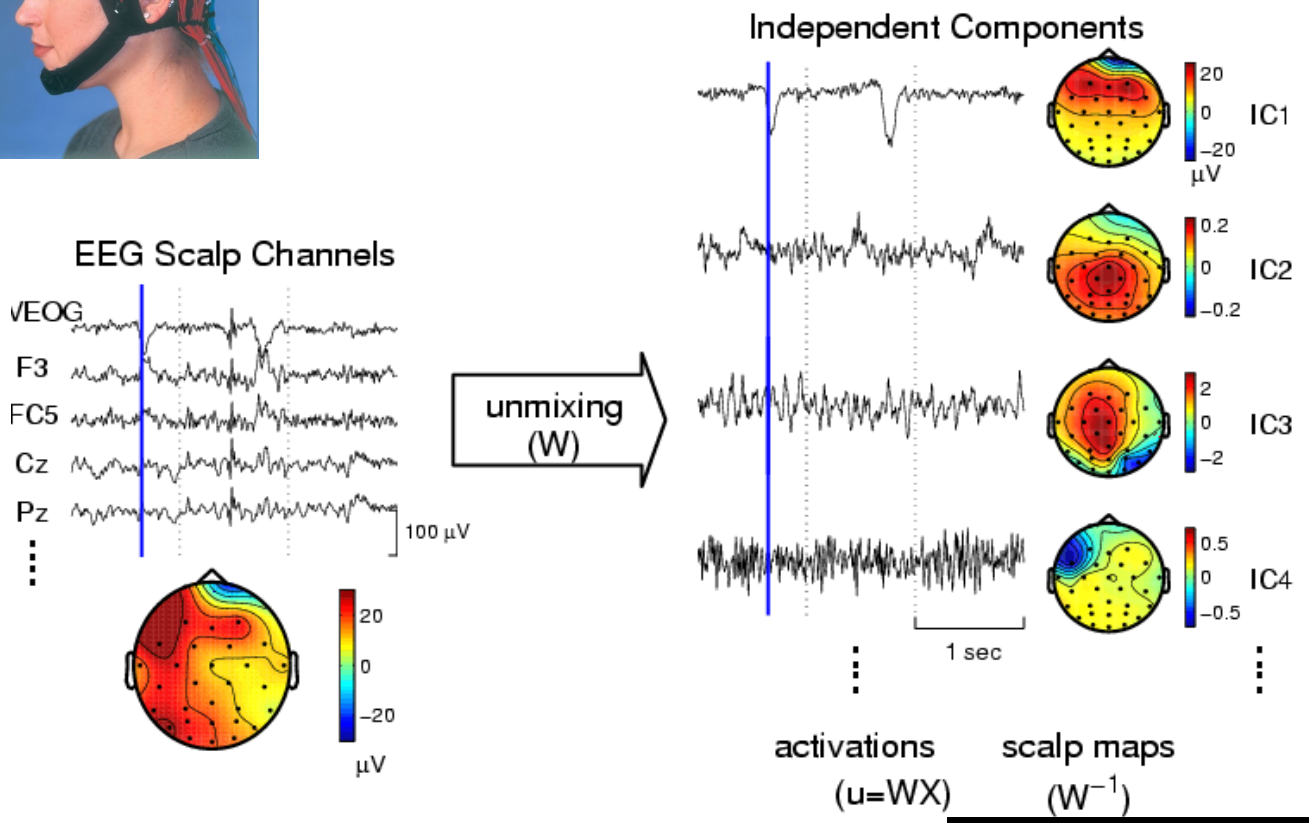


*

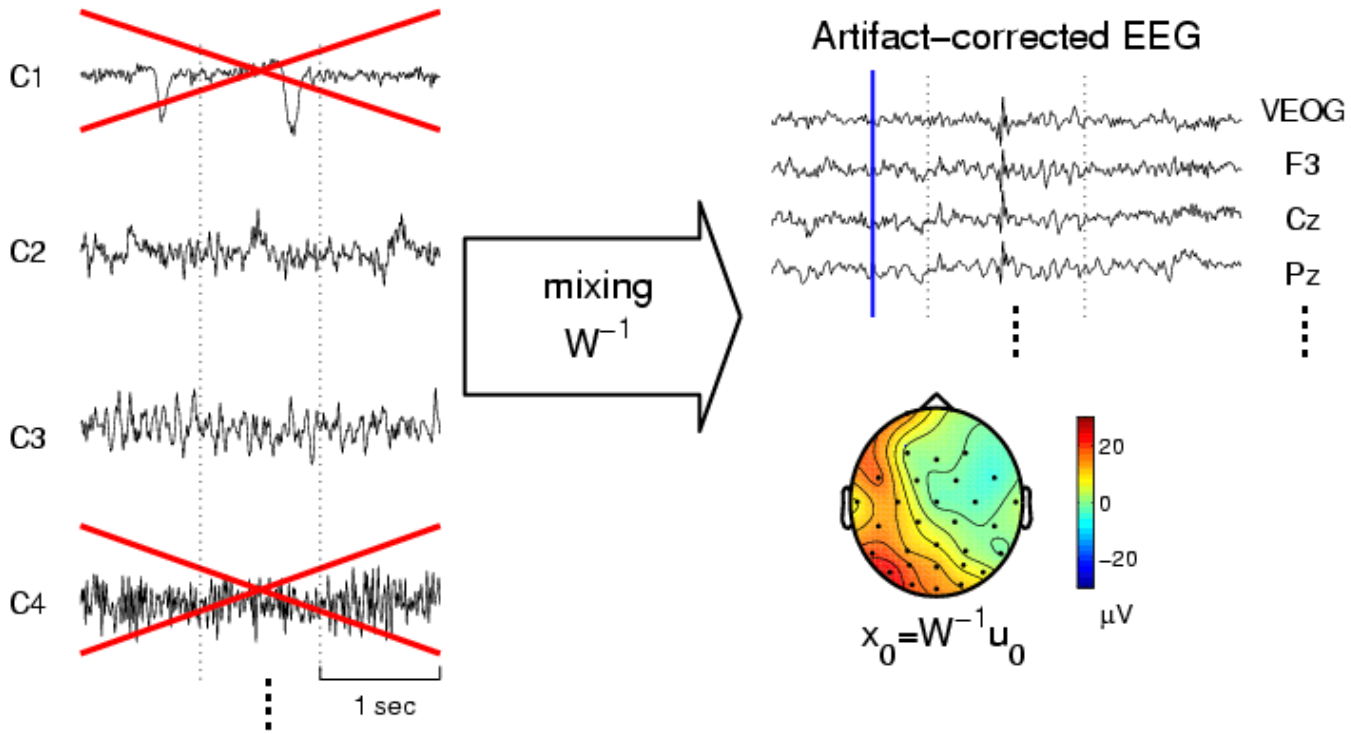
W^{-1} (scalp projections)



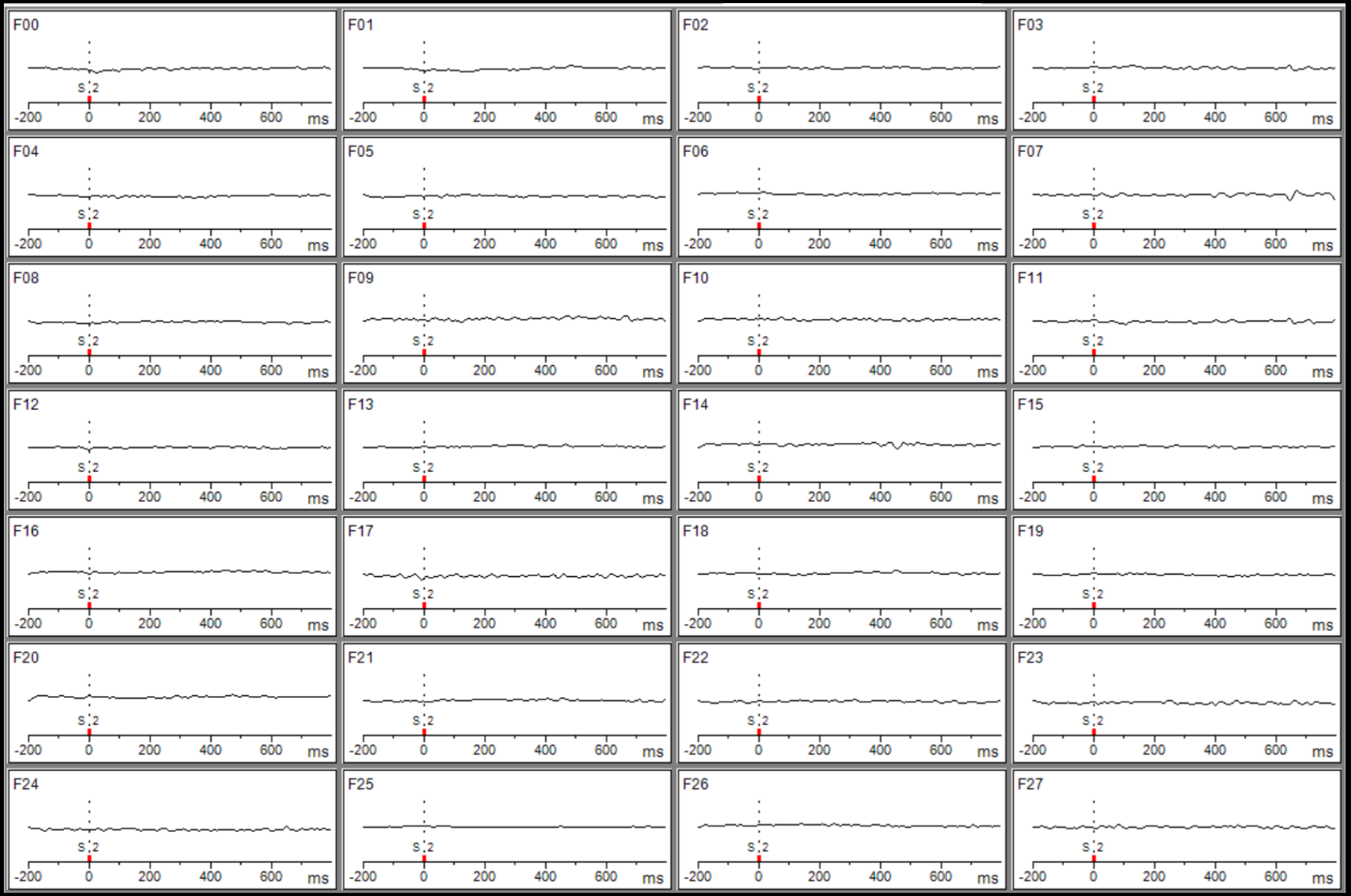
ICA decomposition

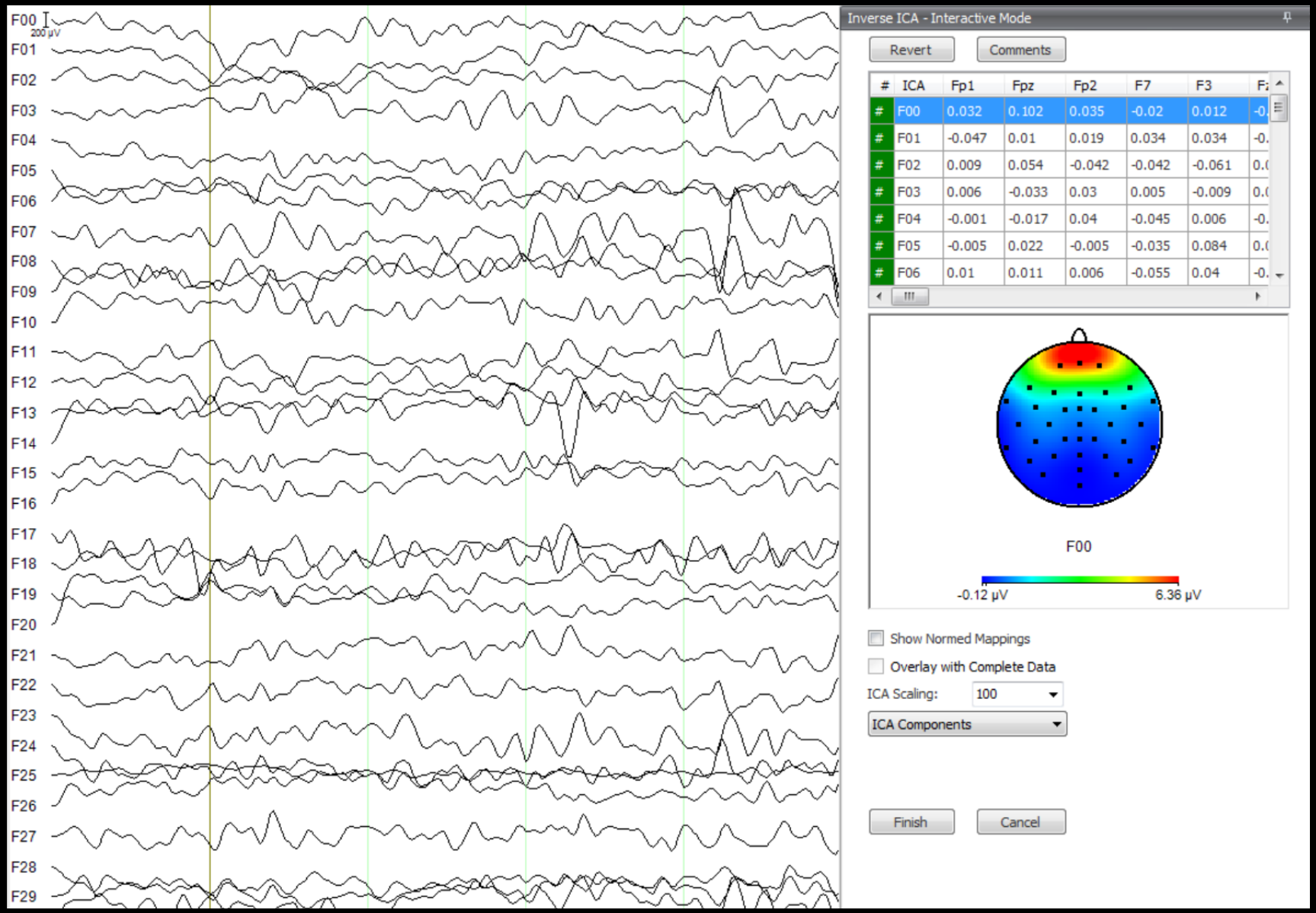


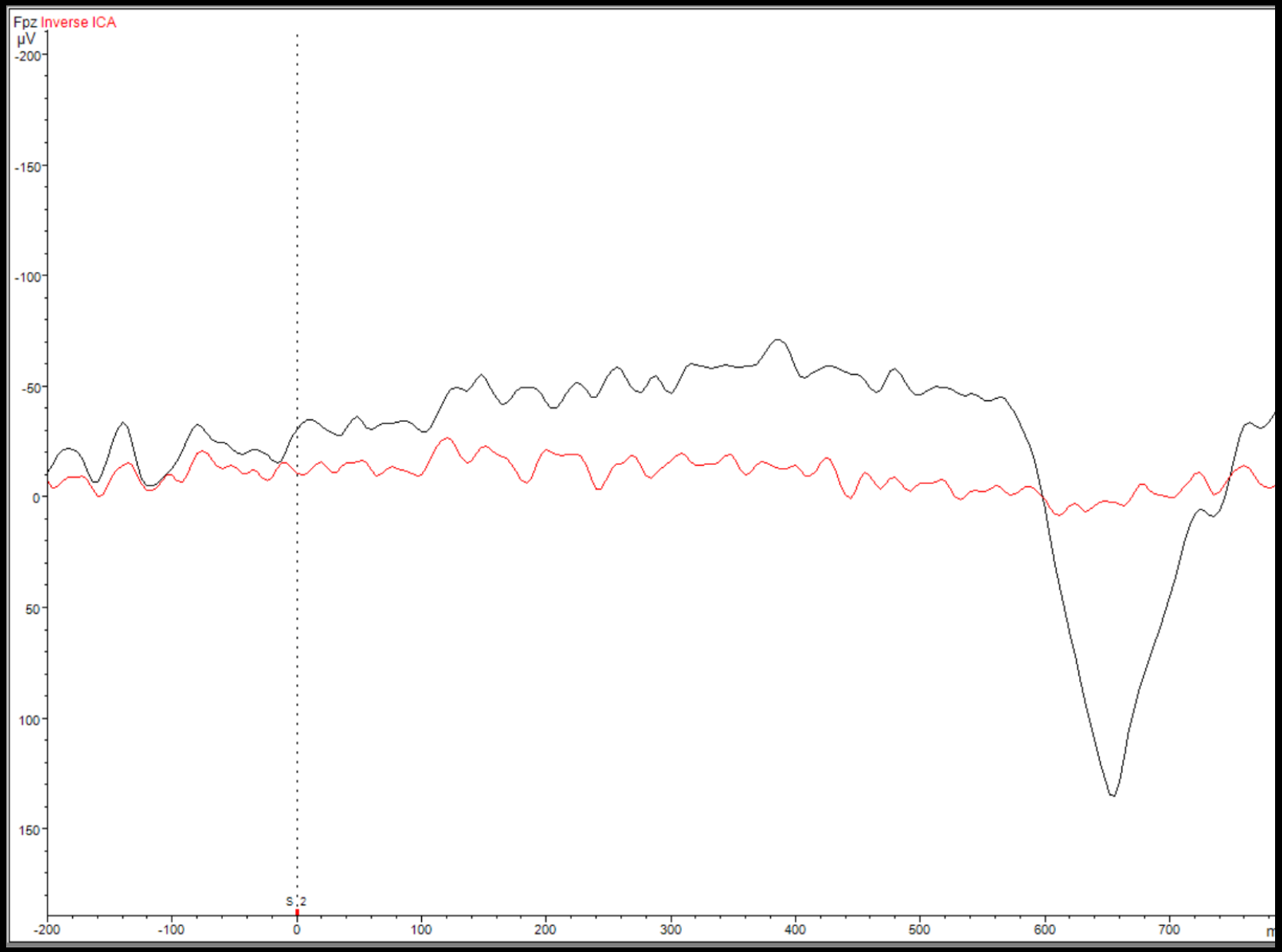
Summed Projection of Selected Components



In Analyzer


F00
F01
F02
F03
F04
F05
F06
F07
F08
F09
F10
F11
F12
F13
F14
F15
F16
F17
F18
F19
F20
F21
F22
F23
F24
F25
F26
F27
s 2
-200 0 200 400 600 ms


F00
200 µV
F01
F02
F03
F04
F05
F06
F07
F08
F09
F10
F11
F12
F13
F14
F15
F16
F17
F18
F19
F20
F21
F22
F23
F24
F25
F26
F27
F28
F29
Inverse ICA - Interactive Mode
Revert
Comments
ICA Fp1 Fpz Fp2 F7 F3
F00 0.032 0.102 0.035 -0.02 0.012
F01 -0.047 0.01 0.019 0.034 0.034
F02 0.009 0.054 -0.042 -0.042 -0.061
F03 0.006 -0.033 0.03 0.005 -0.009
F04 -0.001 -0.017 0.04 -0.045 0.006
F05 -0.005 0.022 -0.005 -0.035 0.084
F06 0.01 0.011 0.006 -0.055 0.04
F00
-0.12 µV
6.36 µV
Show Normed Mappings
Overlay with Complete Data
ICA Scaling:
100
ICA Components
Finish
Cancel


Fpz Inverse ICA
µV
-200
-150
-100
-50
0
50
100
150
S 2
-200
-100
0
100
200
300
400
500
600
700

ICA and EEG

More recently it has been proposed to do the reverse, only keep components with a topography that is of interest.

gonogo0002/Raw Data/Topographic Interpolation/Filters/New Reference/Segmentation/DC Detrend/ICA/Inverse ICA - Analyzer 2.0

File Display Transformations Add Ins Export Macros Solutions History Template Help

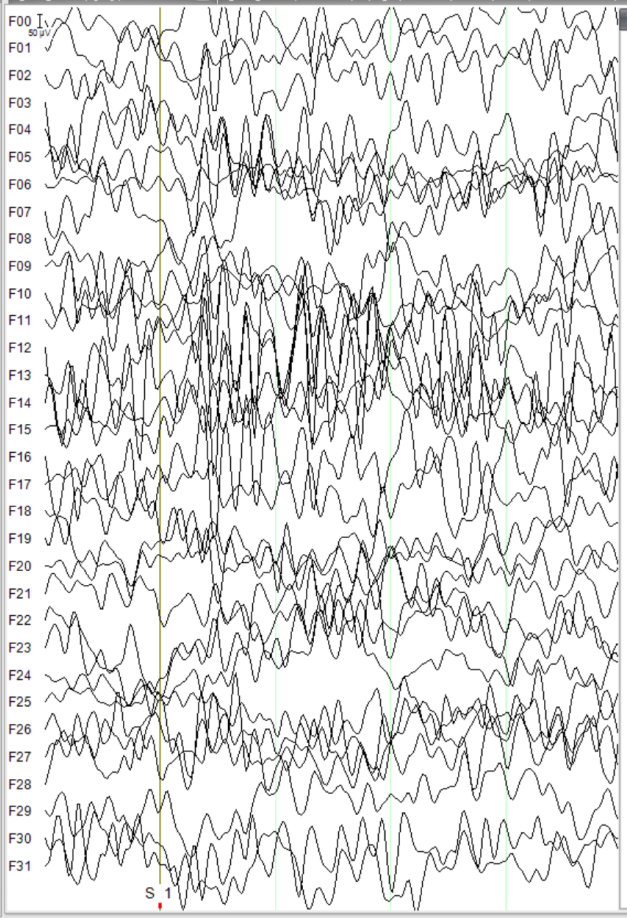
Windows

Primary

- Raw Data
  - Topographic Interpolation
    - Filters
      - New Reference
        - Segmentation
          - DC Detrend
            - OcularCorrection
              - Artifact Rejection
                - BaselineCorrection
                - Segmentation S1
                - INF
                - Generic Data Export
                - Segmentation S2
                - FRE
                - Generic Data Export
            - ICA
              - Inverse ICA
- gonogo0002
  - Raw Data
    - Topographic Interpolation
      - Filters
        - New Reference
          - Segmentation
            - DC Detrend
              - OcularCorrection
                - Artifact Rejection
                - BaselineCorrection
                - Segmentation S1
                - INF
                - Generic Data Export
                - Segmentation S2
                - FRE
                - Generic Data Export
              - ICA
                - Inverse ICA
- gonogo0003
- gonogo0004
- gonogo0005
- gonogo0006
- gonogo0007
- gonogo0008
- gonogo0009
- gonogo0010
- gonogo0011

Primary Secondary History

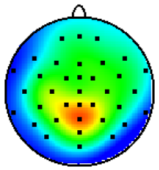
gonogo0002/ [...] /DC Detrend | gonogo0002/Raw Data/Topographic Interpolation/Filters/New Reference/Segmentation/DC Detrend/ICA | gonogo0002/Raw Data/Topographic Interpolation/Filters/Ne



Inverse ICA - Interactive Mode

Revert Comments

#	ICA	Fp1	Fpz	Fp2	F7	F3	Fz	F4	F8
#	F00	-0.013	-0.005	-0.014	0.043	-0.028	-0.016	0.047	-0.004
#	F01	0.023	0.007	0.154	0.02	-0.049	-0.014	-0.047	-0.029
#	F02	0.023	0.004	-0.052	-0.023	-0.001	0.004	-0.001	0.001
#	F03	0.006	-0.004	-0.016	0.017	0.075	0.01	-0.097	0.041
#	F04	0	0.007	0	-0.009	0.052	0.018	-0.01	-0.013
#	F05	-0.002	0.013	-0.028	0.014	-0.059	-0.002	0.091	-0.125
#	F06	0.014	-0.146	0.078	0.008	0.051	-0.006	0.029	0.03



Show Normed Mappings

Overlay with Complete Data

ICA Scaling: 100

ICA Components

Finish Cancel

Navigation Bar

Standard Montage | Seg: 1/300 | Chan: F12 | Value: 265.17 µV | Pos: 0.796 s | Oddball

6:50 PM
12/12/2013

Continuous or Segmented Data

PCA is ran on segmented data.

Continuous or Segmented Data

ICA will work on continuous or segmented data.

If you want to remove ocular artifacts continuous data is fine but you will have to train the ICA on a subset of the data – which you may want to clean with the Raw Data Inspector.

If you use full data then looking for components of interest will be very difficult.

Continuous or Segmented Data

ICA will work on continuous or segmented data.

If you want to use ICA on segmented data you can train it on the whole data set but blinks may not be the first component if there are not very many.

ICA Demonstration