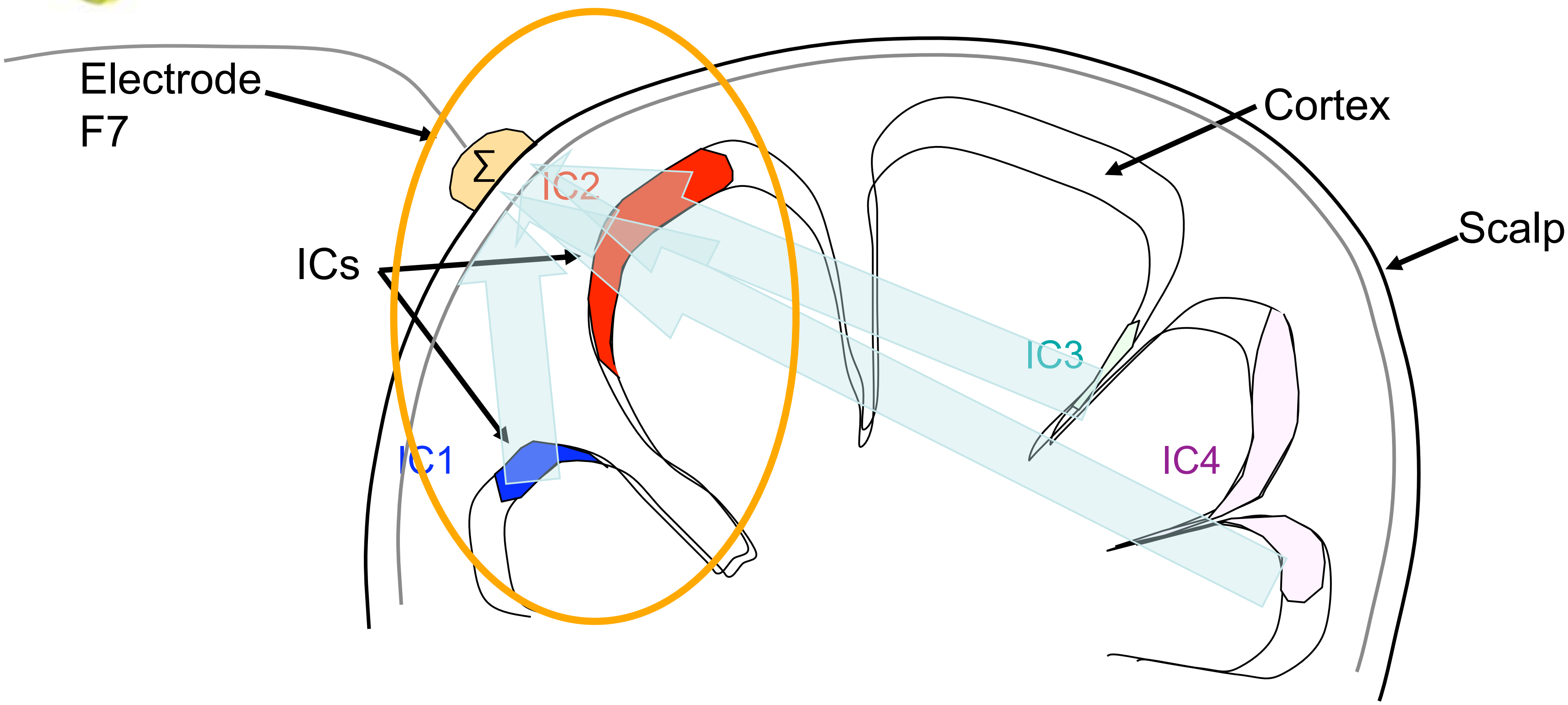
Why cluster components?

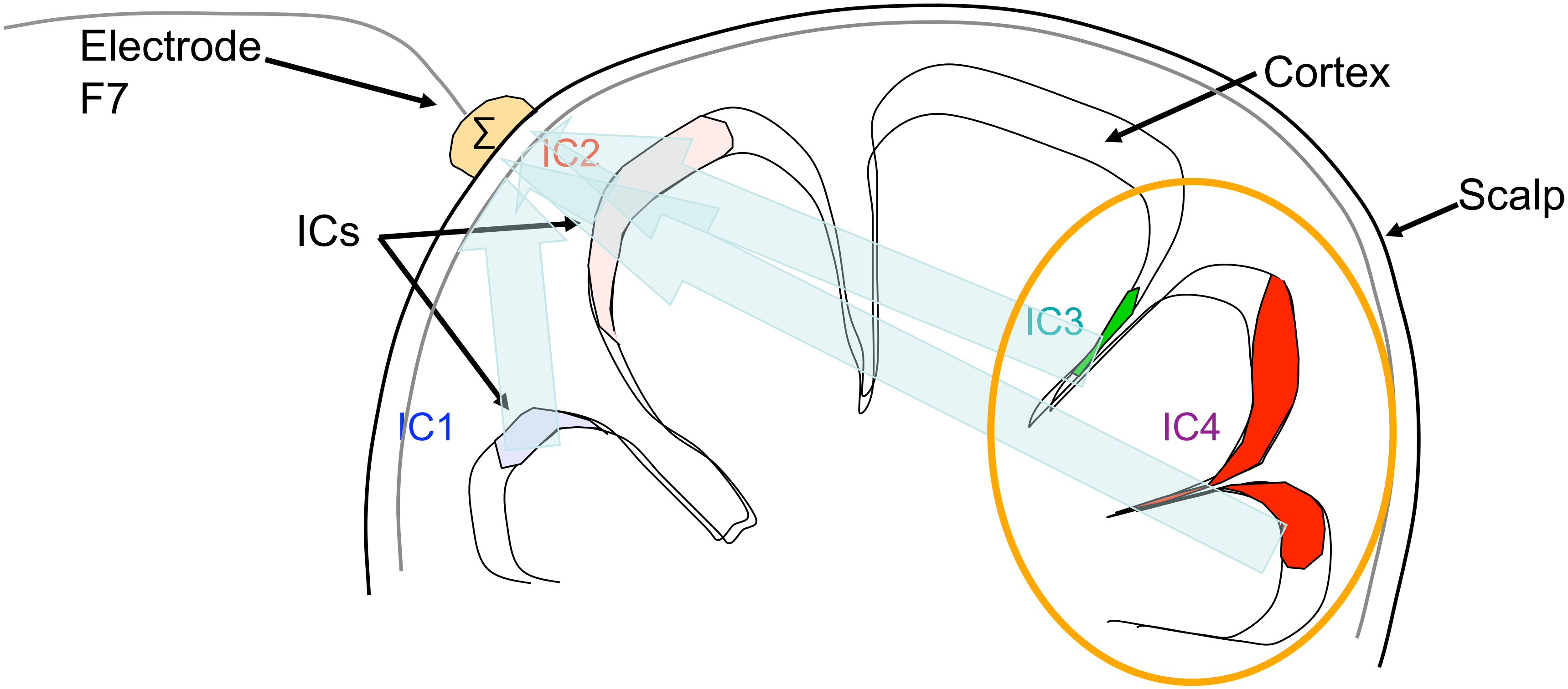
- ICA transforms the data from a channel basis (activity recorded at each channel)
  - to a component basis (activity computed at each independent spatially-filtered cortical or non-cortical component process).
- Normally, EEG researchers assume that electrode, say F7 == F7 == F7 ... in each subject – and then ‘cluster‘ their data by channel ...
- But this is only *roughly* correct!

Example: First Subject



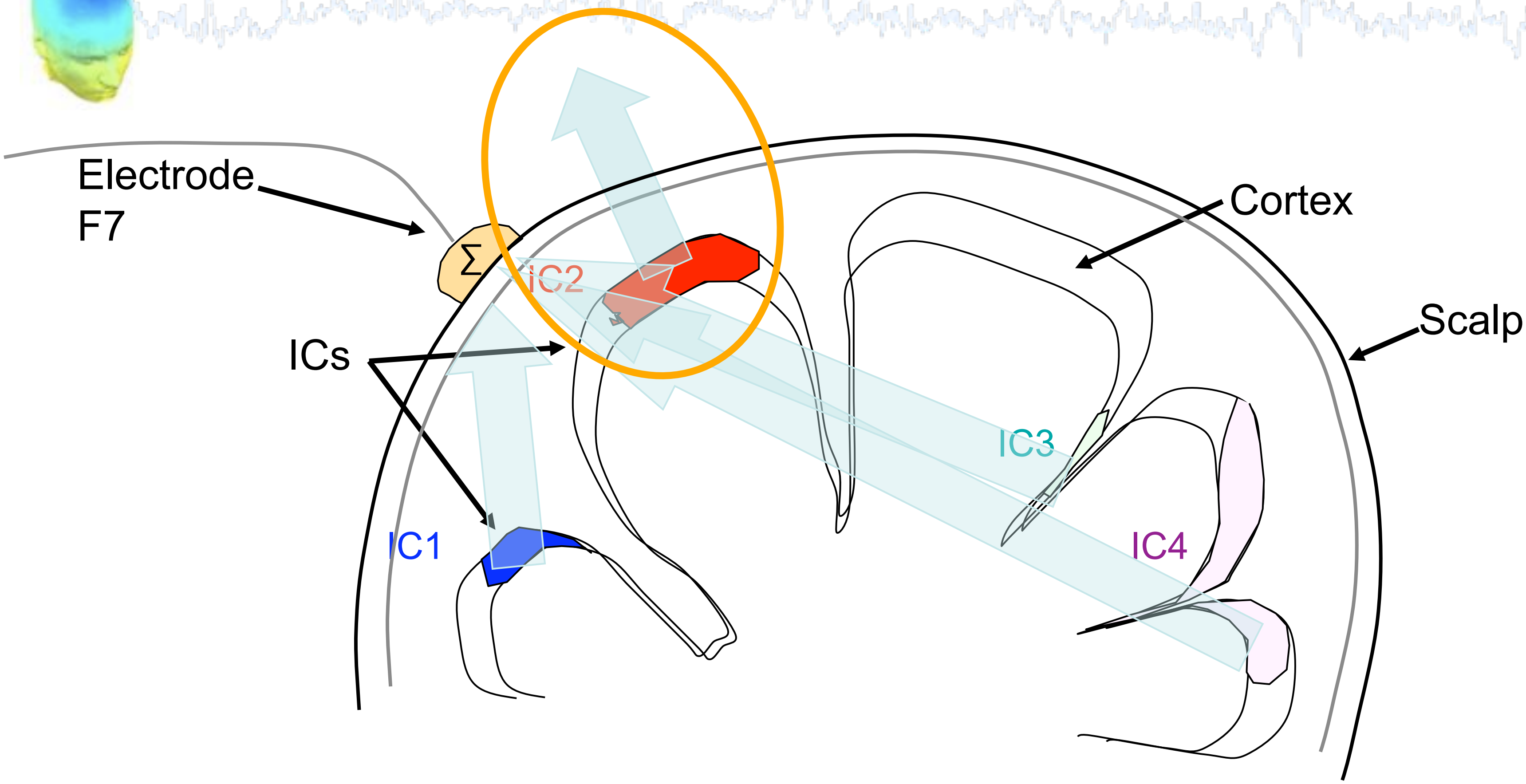
S. Makeig, 2005

Second Subject



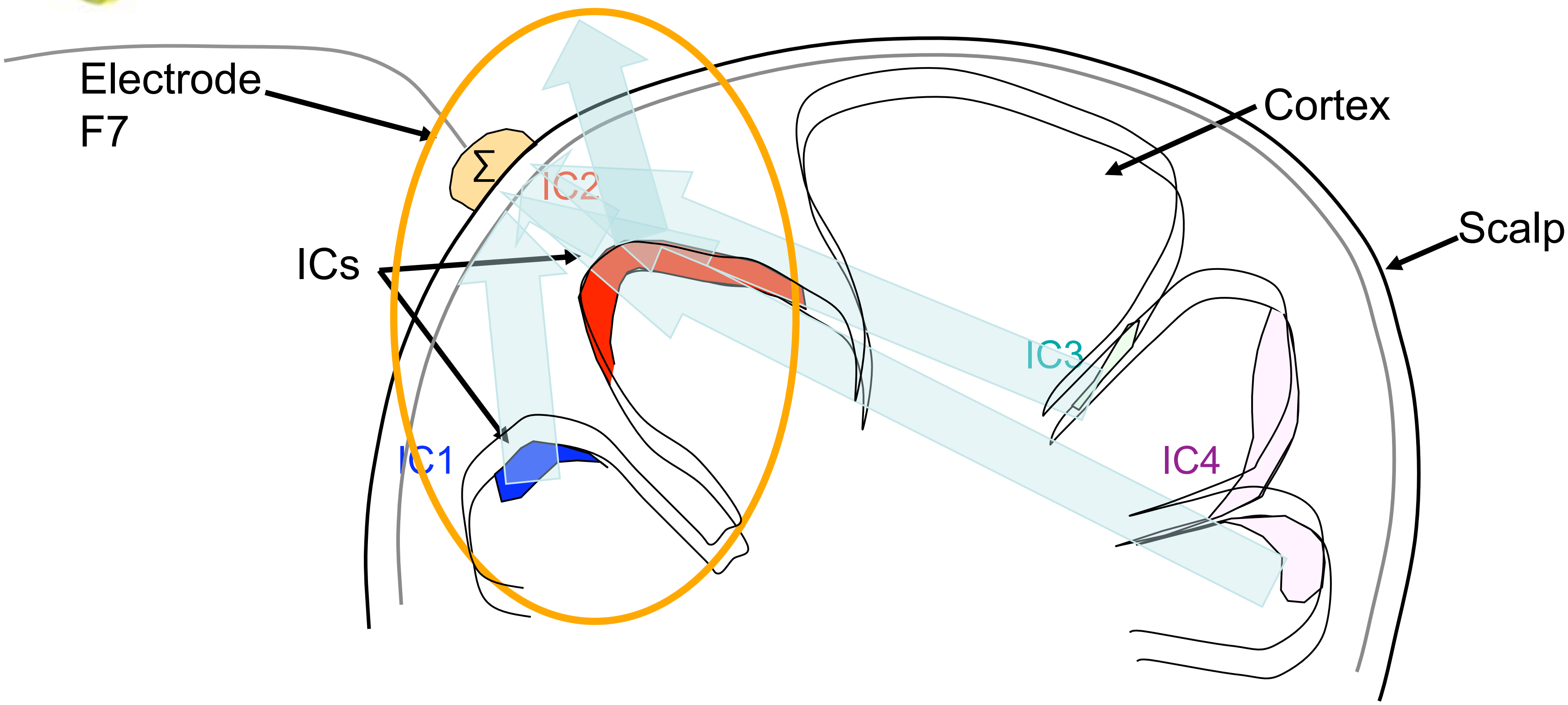
S. Makeig, 2005

Third Subject



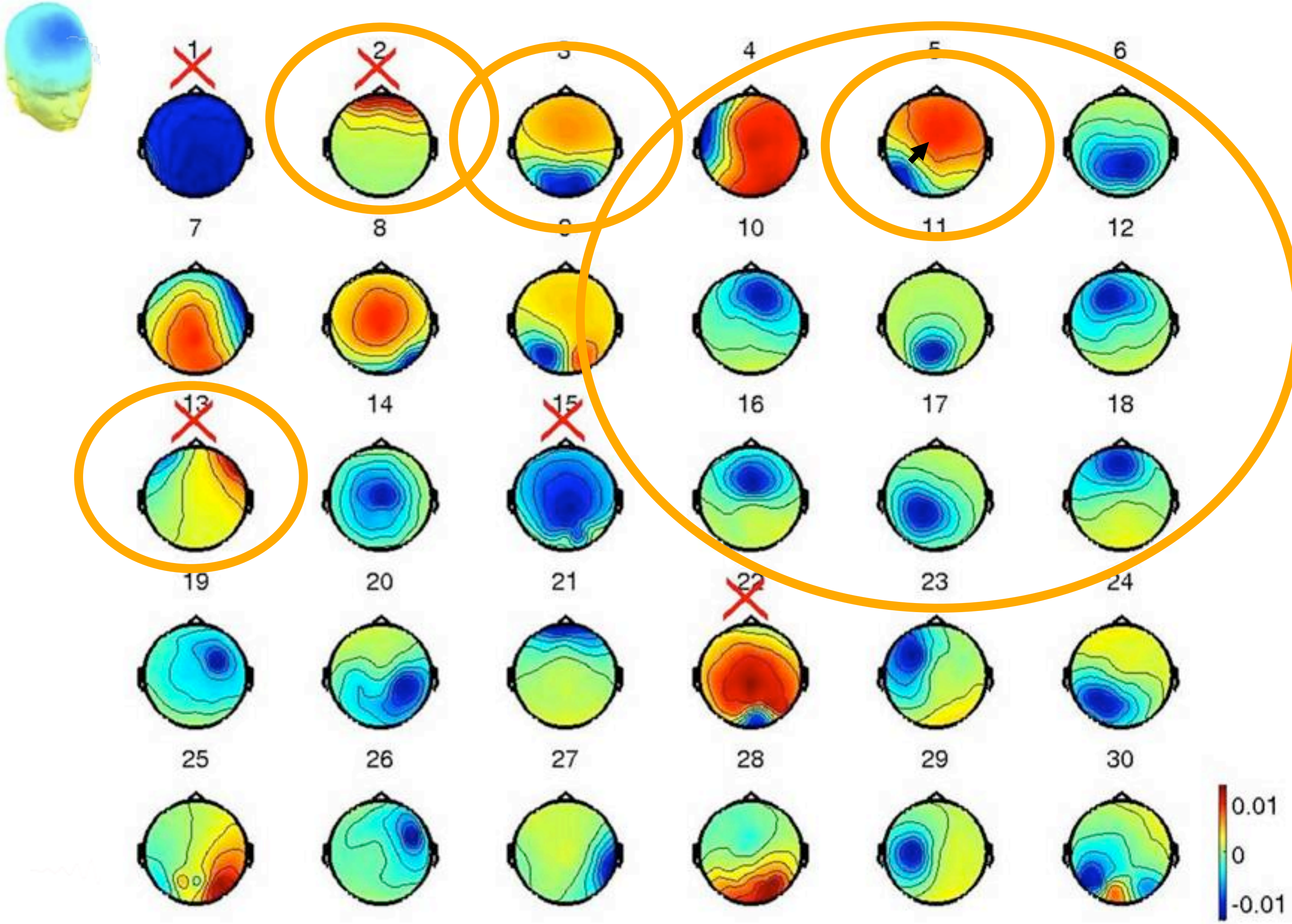
S. Makeig, 2005

Fourth Subject



S. Makeig, 2005

Largest 30 independent components (single subject)



So how to cluster components?

The same problems hold for clustering independent components

Across Ss, components don't even have "the same" scalp maps!

→ Are "the same" components found across subjects?

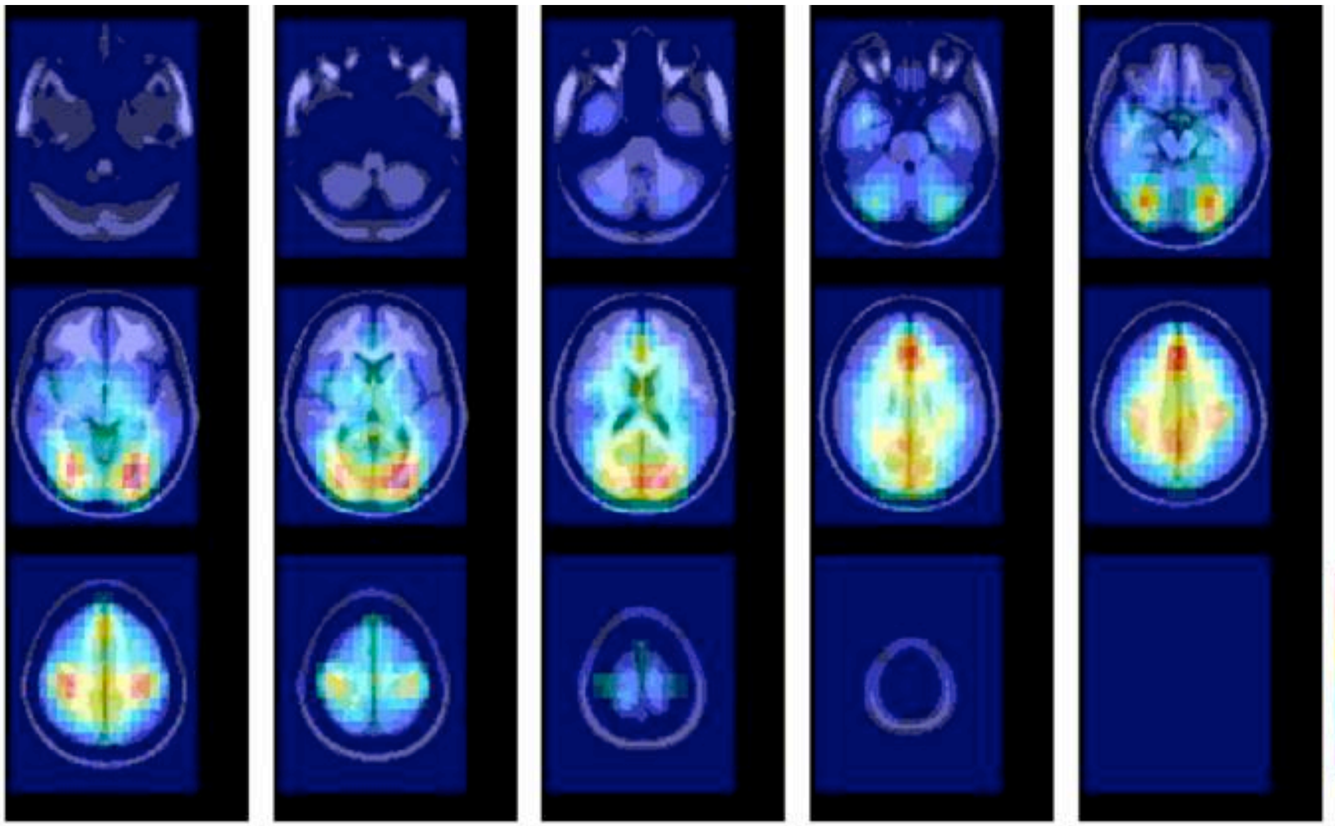
- What should define "the same" (i.e., "component equivalence")?
    - Similar scalp maps?
    - Similar cortical or 3-D equivalent dipole locations?
    - Similar activity power spectra?
    - Similar ERPs?
    - Similar ERSPs?
    - Similar ITCs?
    - OR …, Similar *combinations* of the above? …

Does the spatial distribution of independent components depend on the task the subject performs?

i.e.

Do “the same” components (and clusters) appear for every task?

Equivalent dipole density



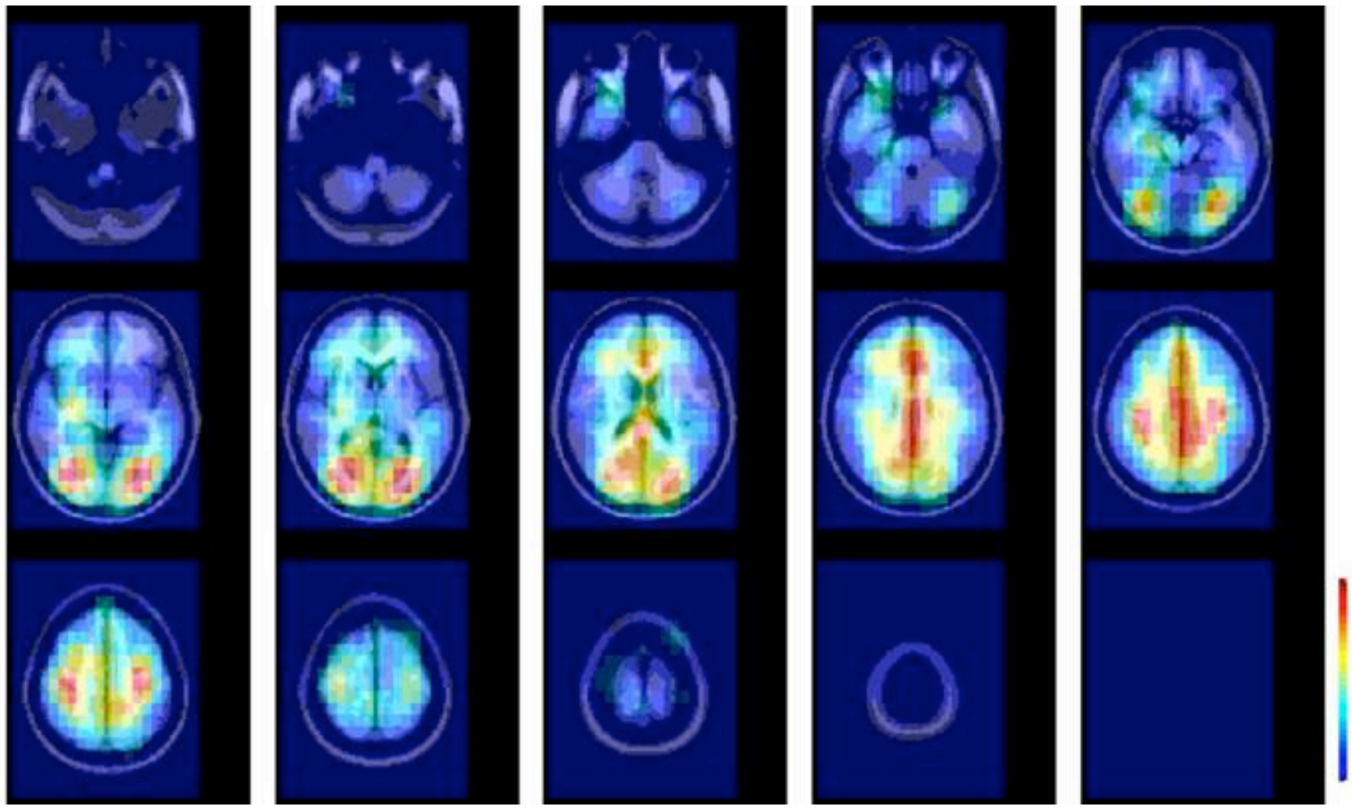
Sternberg letter memory task

>> dipoledensity()

Onton et al., 2005

Onton et al., '05

Equivalent dipole density



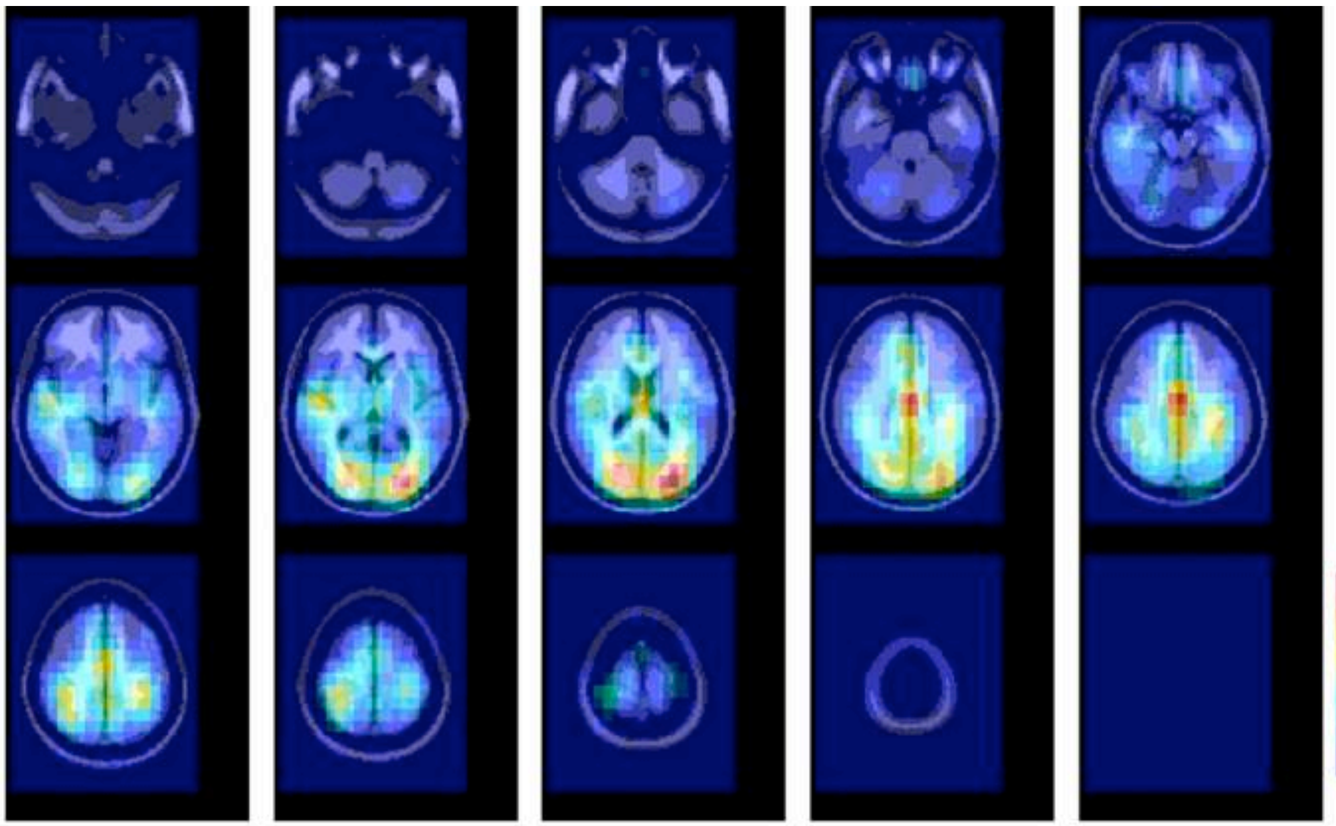
Letter twoback with feedback

>> dipoledensity()

Onton et al., 2005

Onton et al., ‘05

Equivalent dipole density



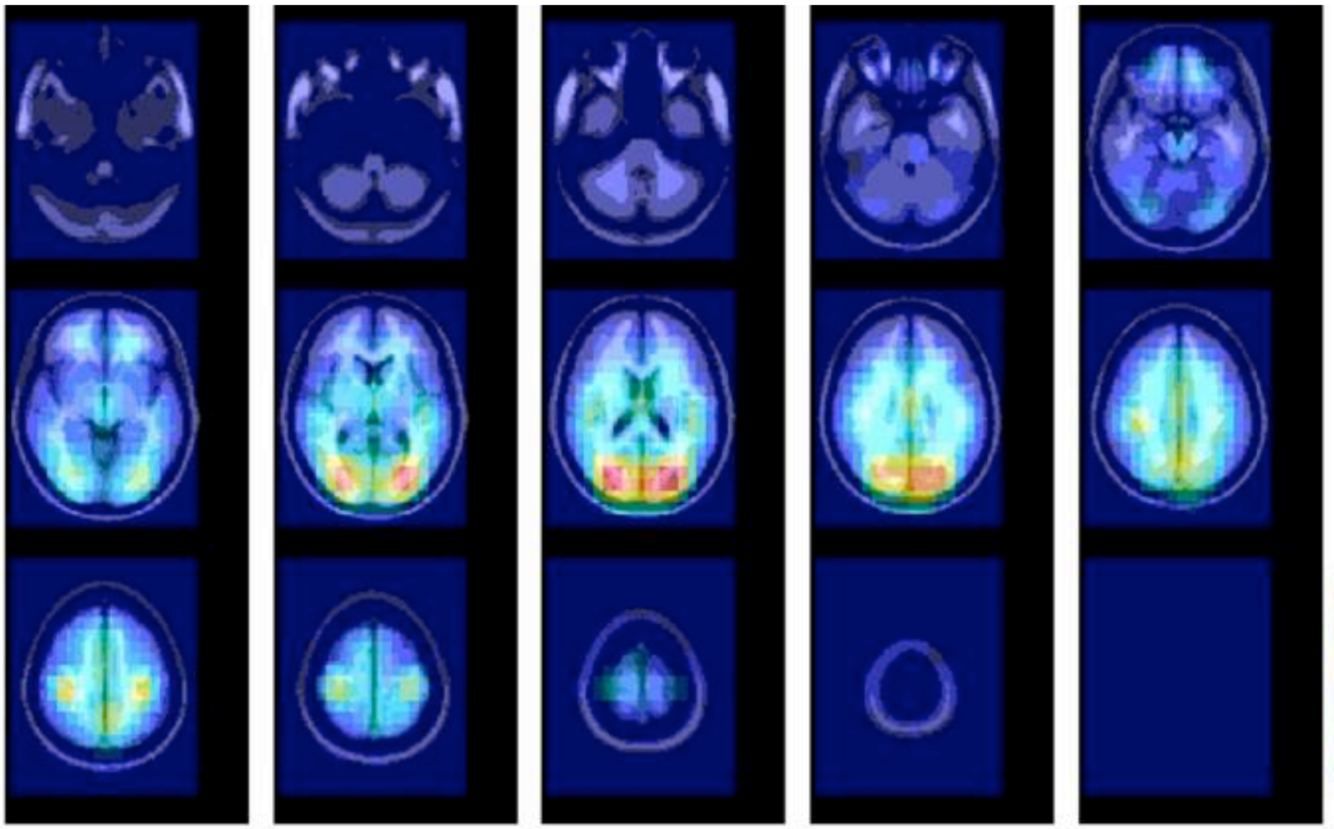
Auditory oddball plus novel sounds

>> dipoledensity()

Onton et al., 2005

Onton et al., '05

Equivalent dipole density



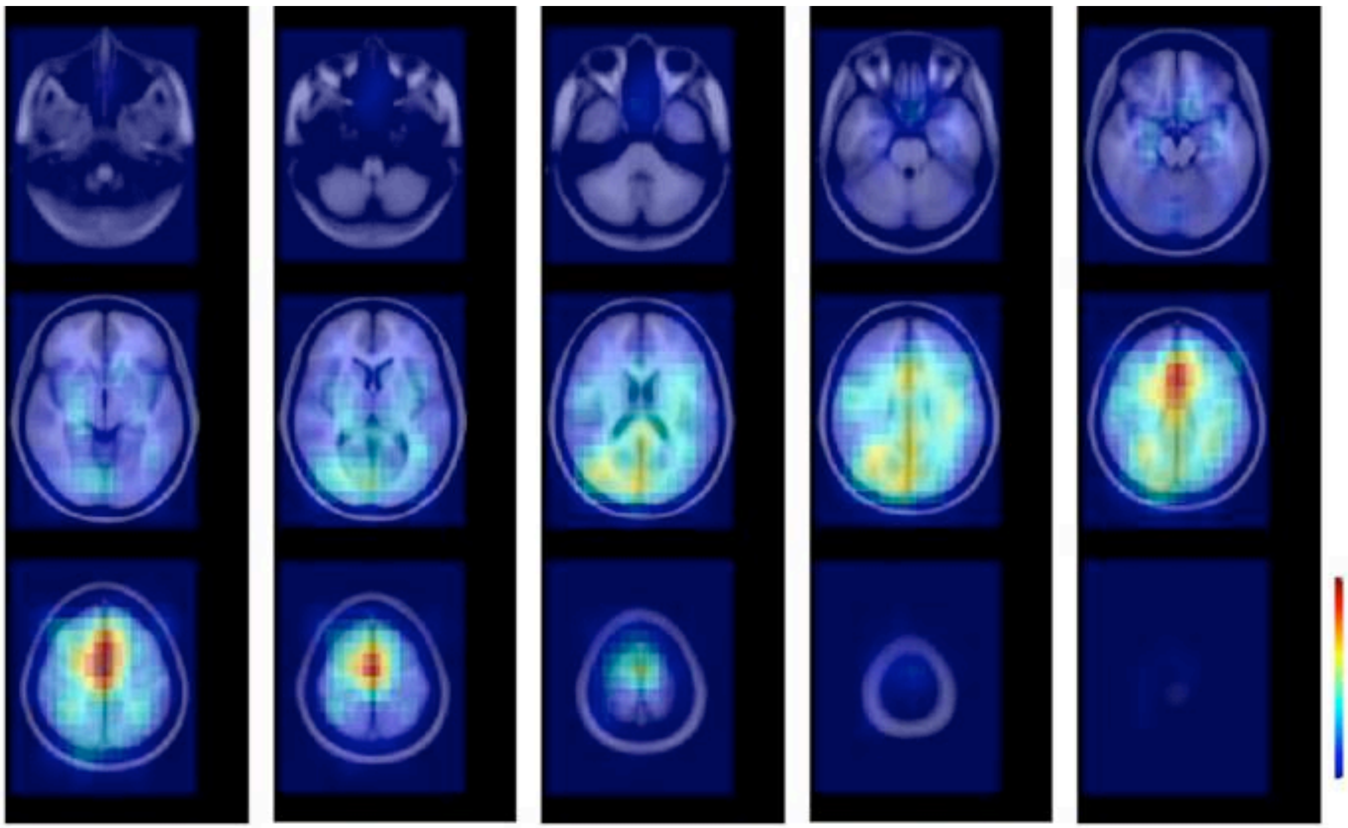
Emotion imagery task

>> dipoledensity()

Onton et al., 2005

Onton et al., '05

Equivalent dipole density Exp I

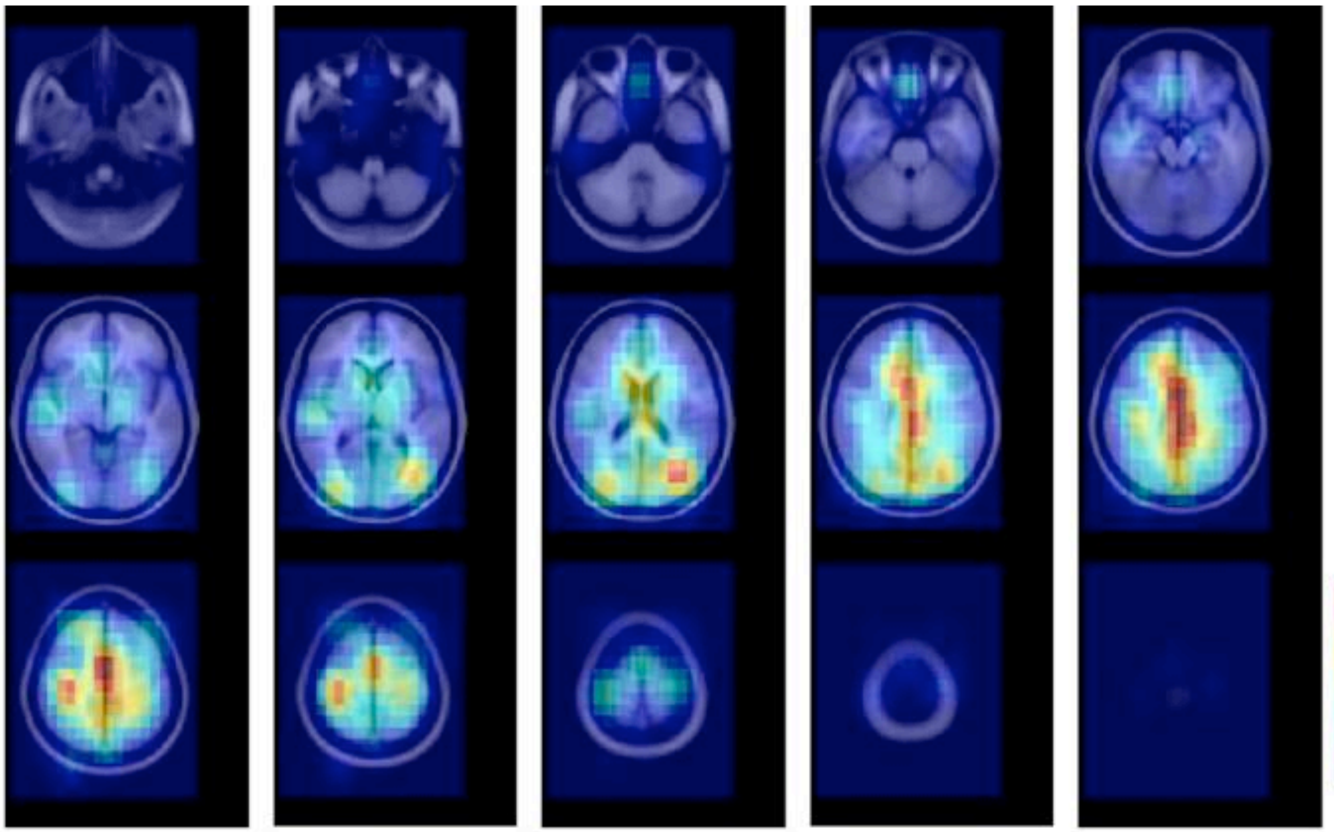


Word memory (old/new) task

>> dipoledensity()

Onton et al., '05

Equivalent dipole density Exp II



Visually cued button press task

>> dipoledensity()

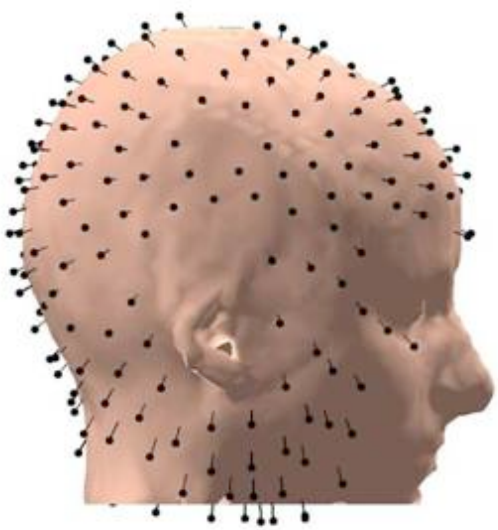
Onton et al., 2005

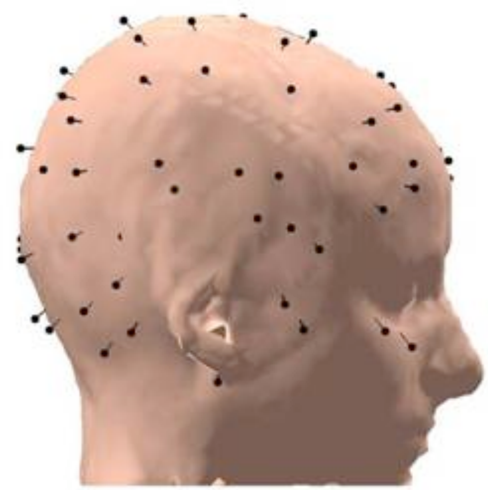
Onton et al., '05

… Some caveats

In this preliminary study …

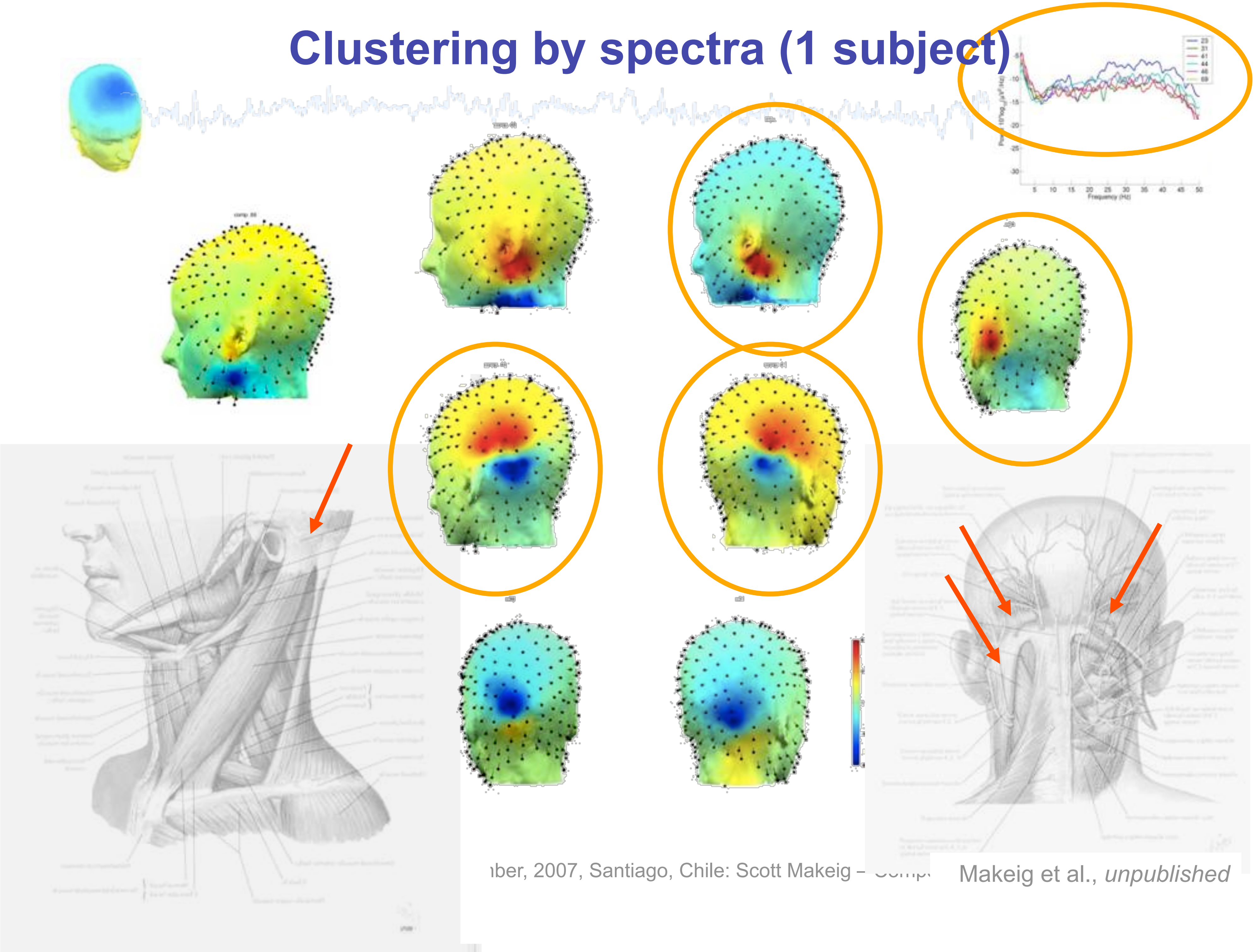
- The electrode locations were not individualized.
- MR images were not available → co-registration crude.
- Single versus dual-dipole model selection was subjective.
- Different electrode montages → possible location effects





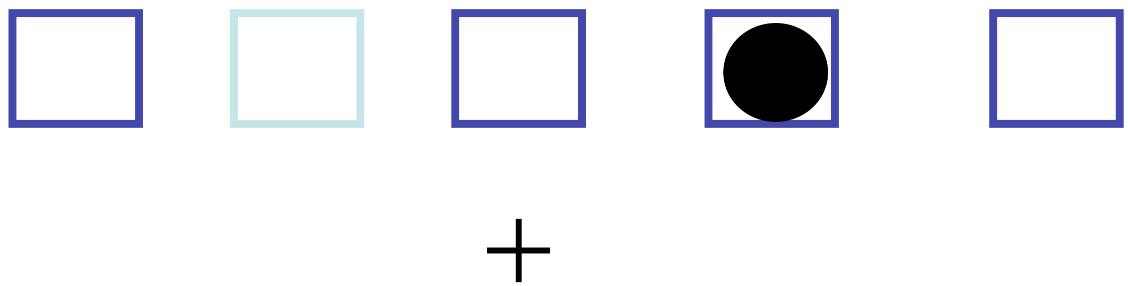
Onton, 2005

Clustering by spectra (1 subject)

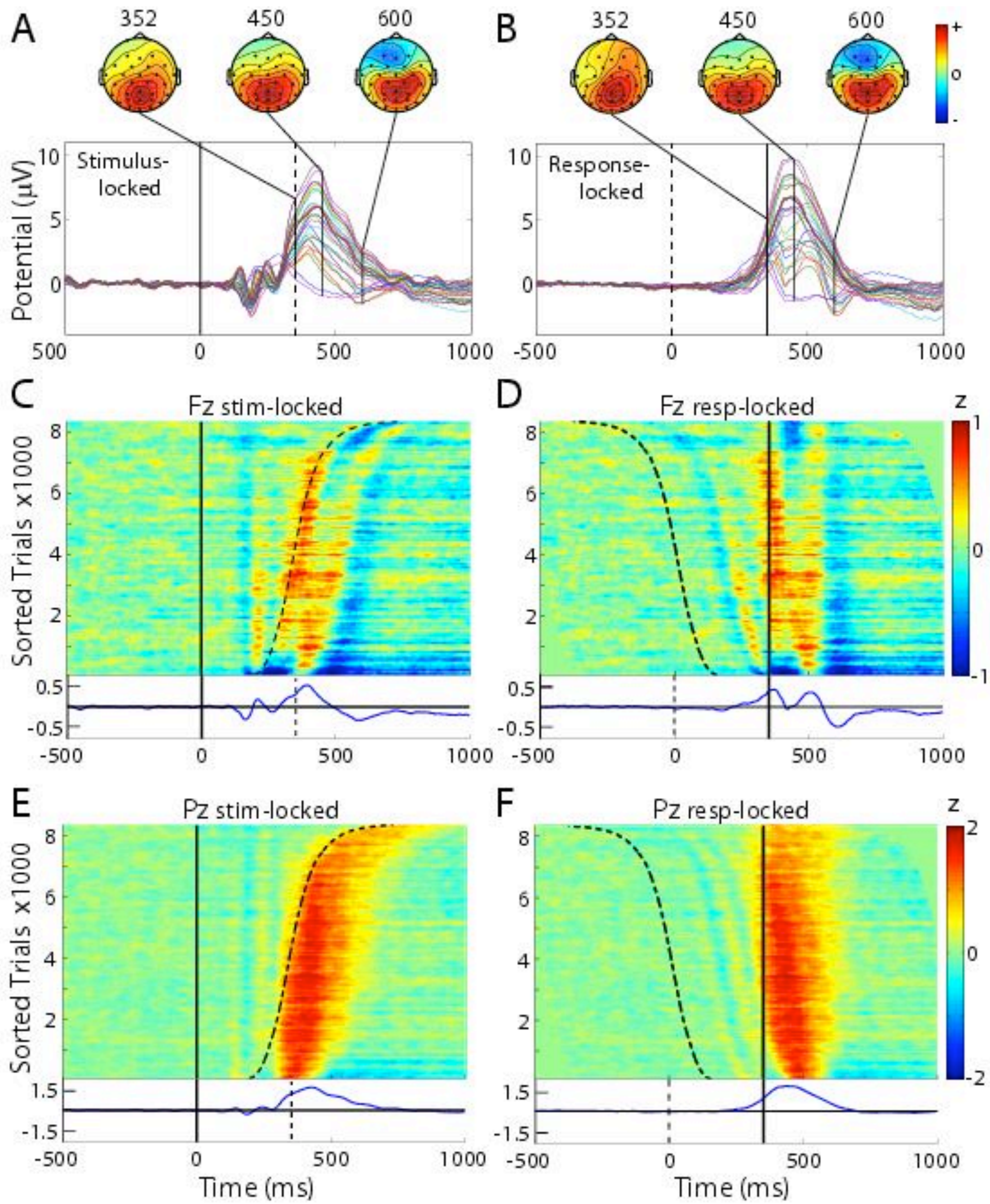


Makeig et al., *unpublished*

Visual Selective Attention Task



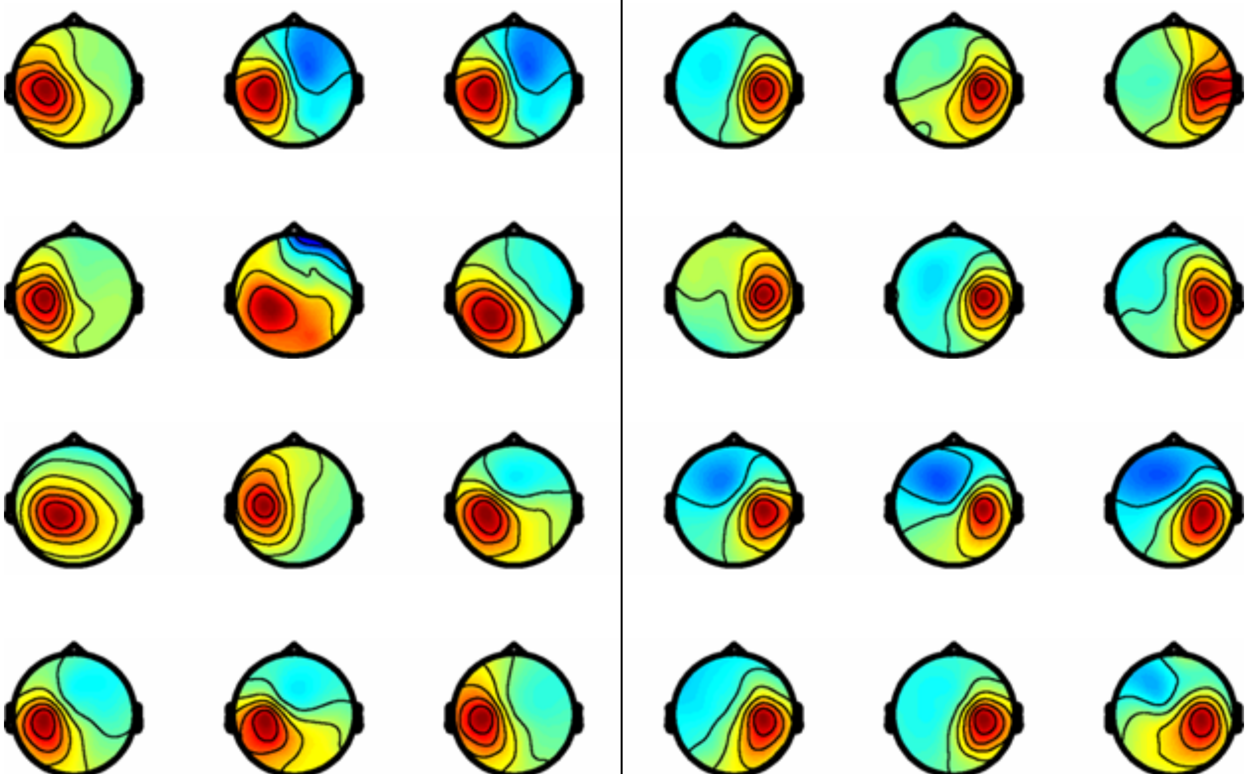
15 subjects



A
B
352
450
600
Stimulus-locked
Response-locked
Potential (μV)
Fz stim-locked
Fz resp-locked
Pz stim-locked
Pz resp-locked
Sorted Trials x1000
Time (ms)
C
D
E
F
z

Clustering ICA components by eye

Left mu | **Right mu**

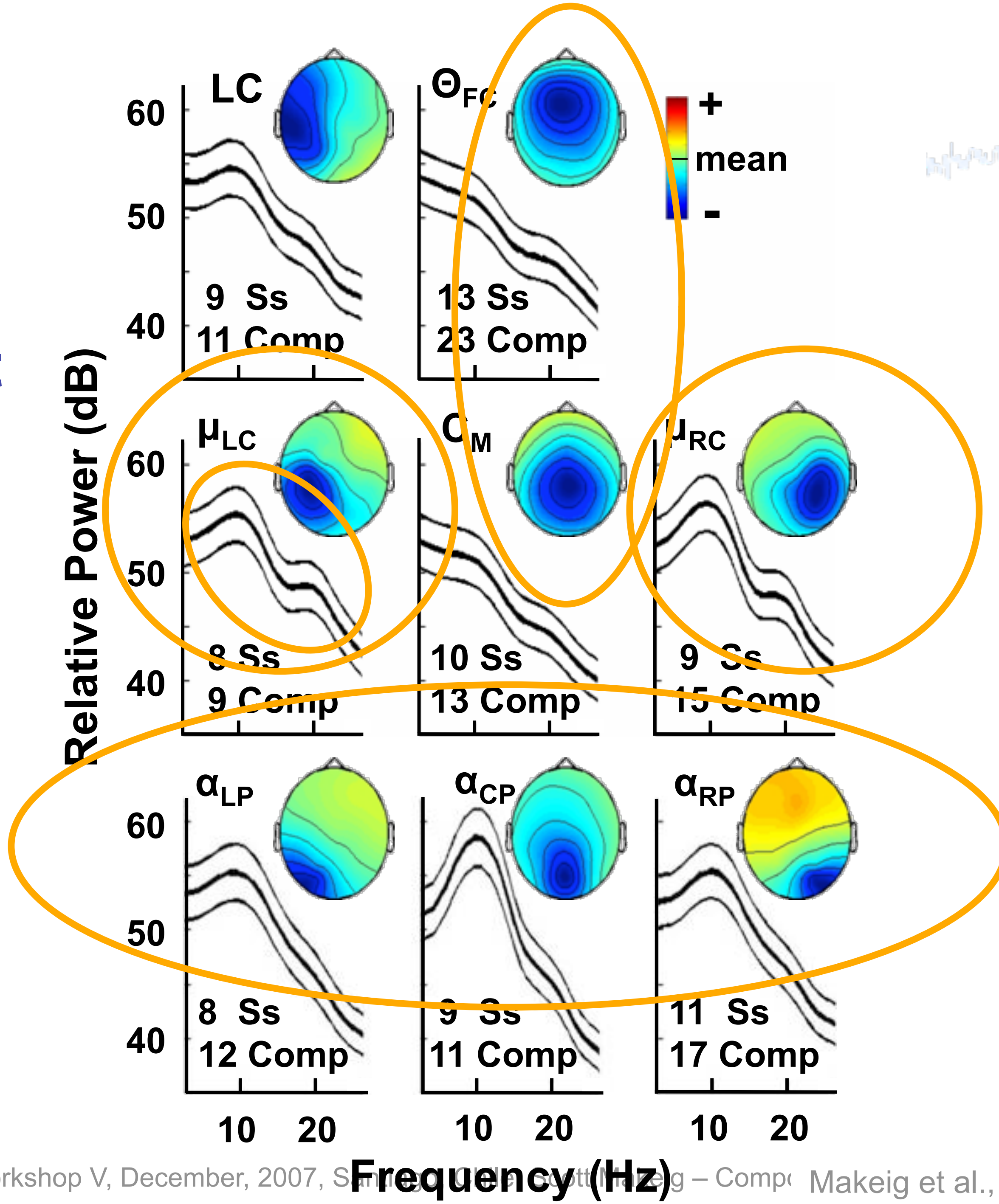


Makeig et al., *submitted*

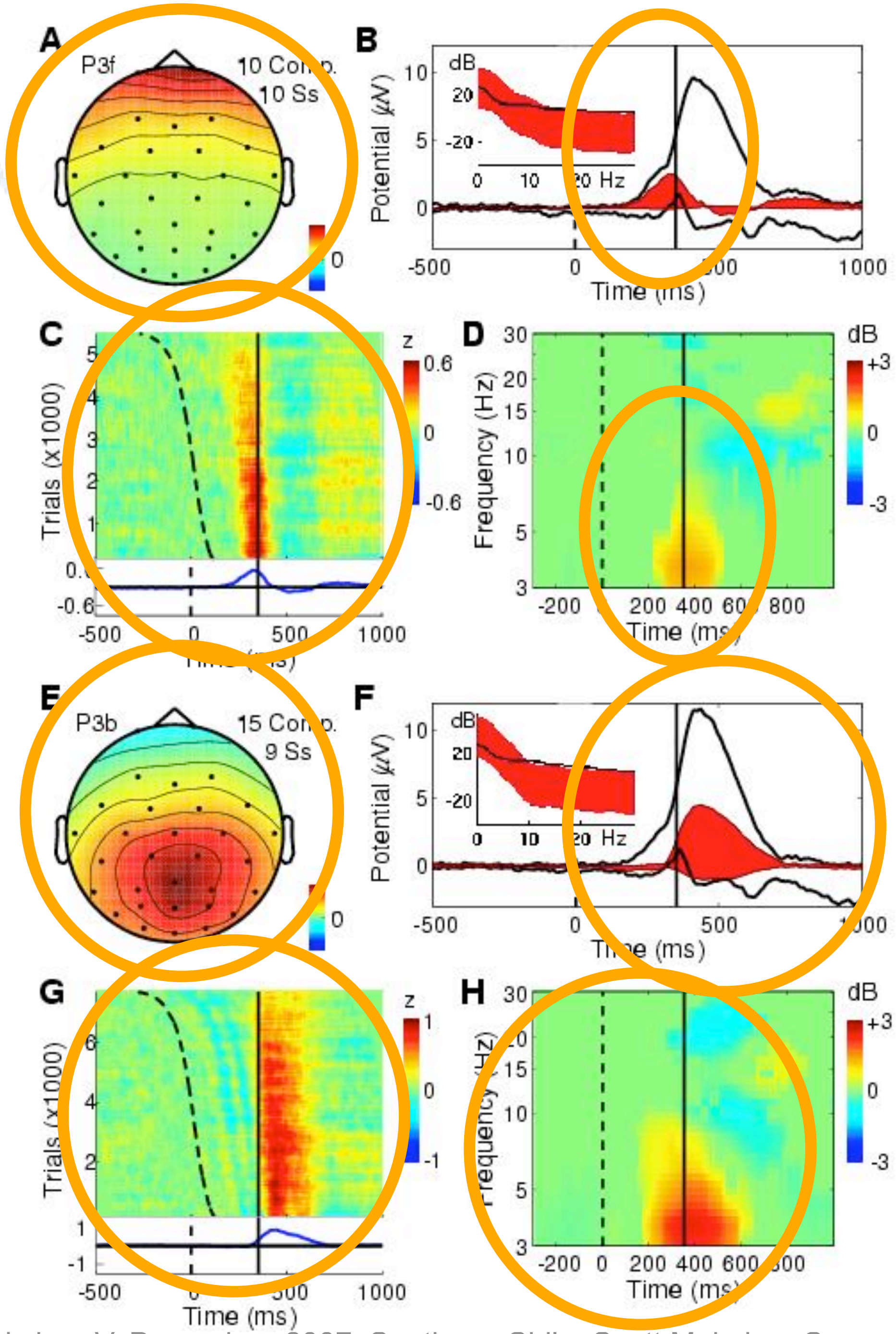
Semi-automated clustering

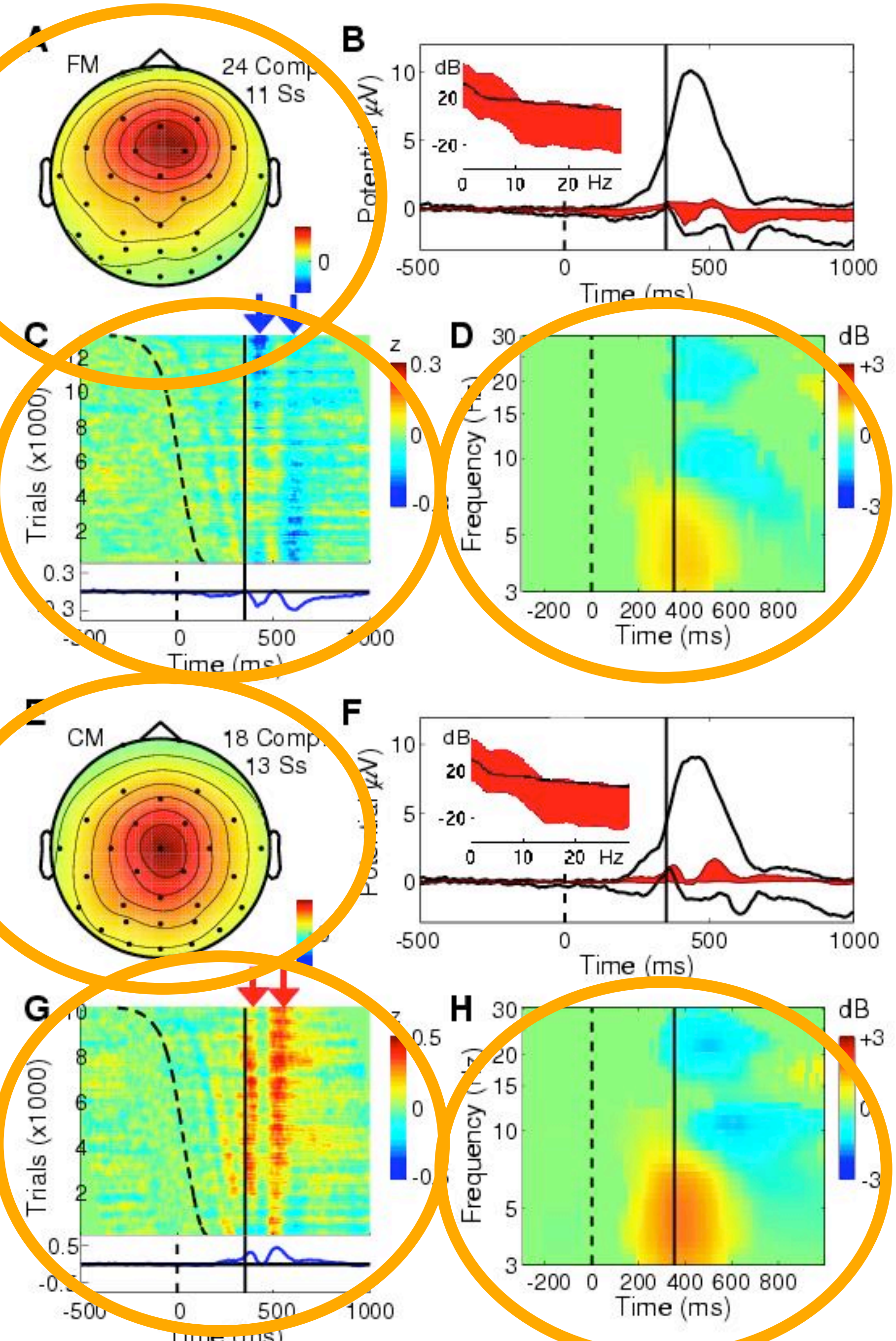
- Clustered components from 15 Ss using a ‘component distance metric’ incorporating differences between their (weighted) scalp maps, dipole locations, spectra, ERP, ERSP, and ITC patterns.
- Hand-adjusted clusters to remove outliers.
- Determined time/frequency regions of significant ERSP and ITC for each component using permutation-based statistics.
- Used binomial statistics to highlight time/frequency regions significantly active within clusters.

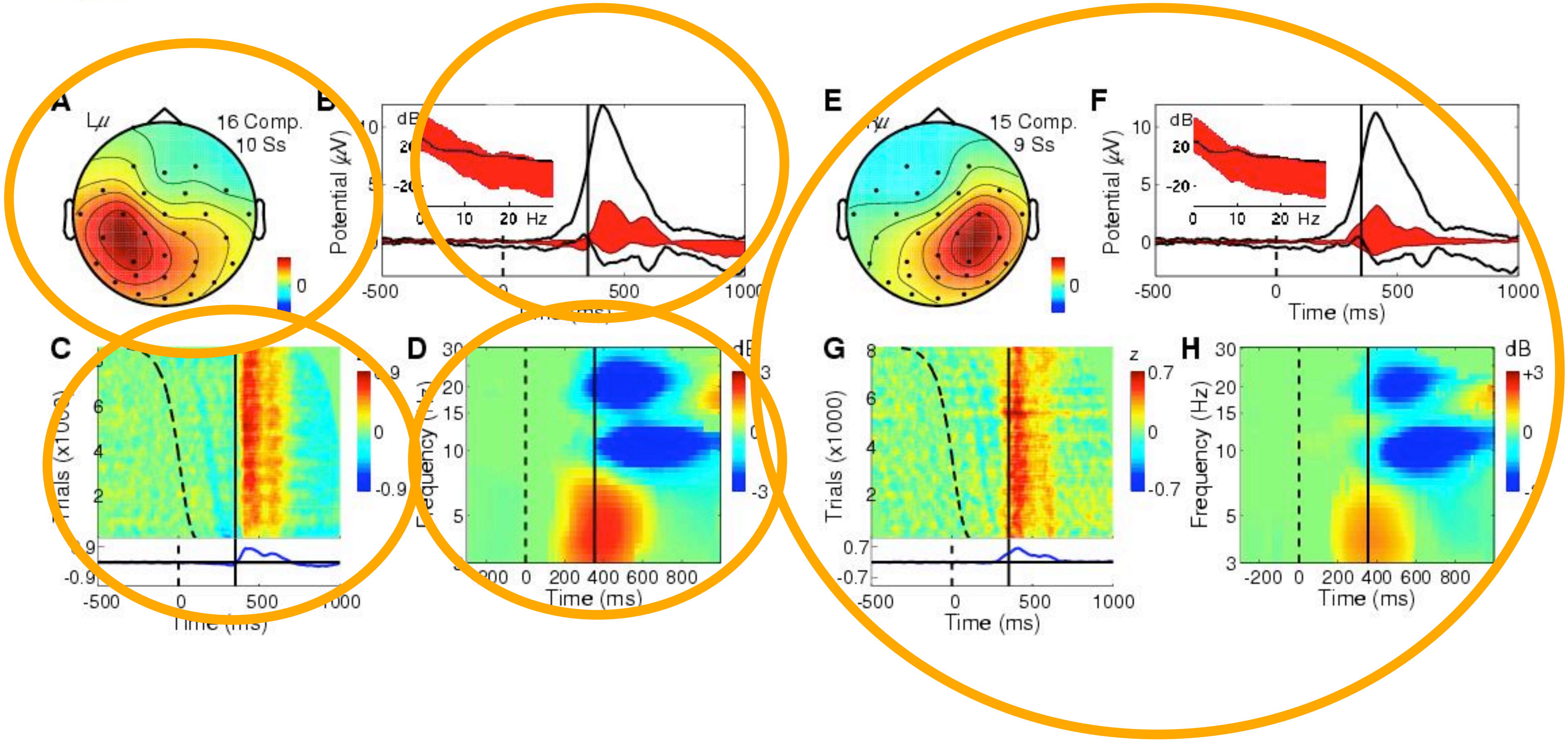
N1 Component Clusters

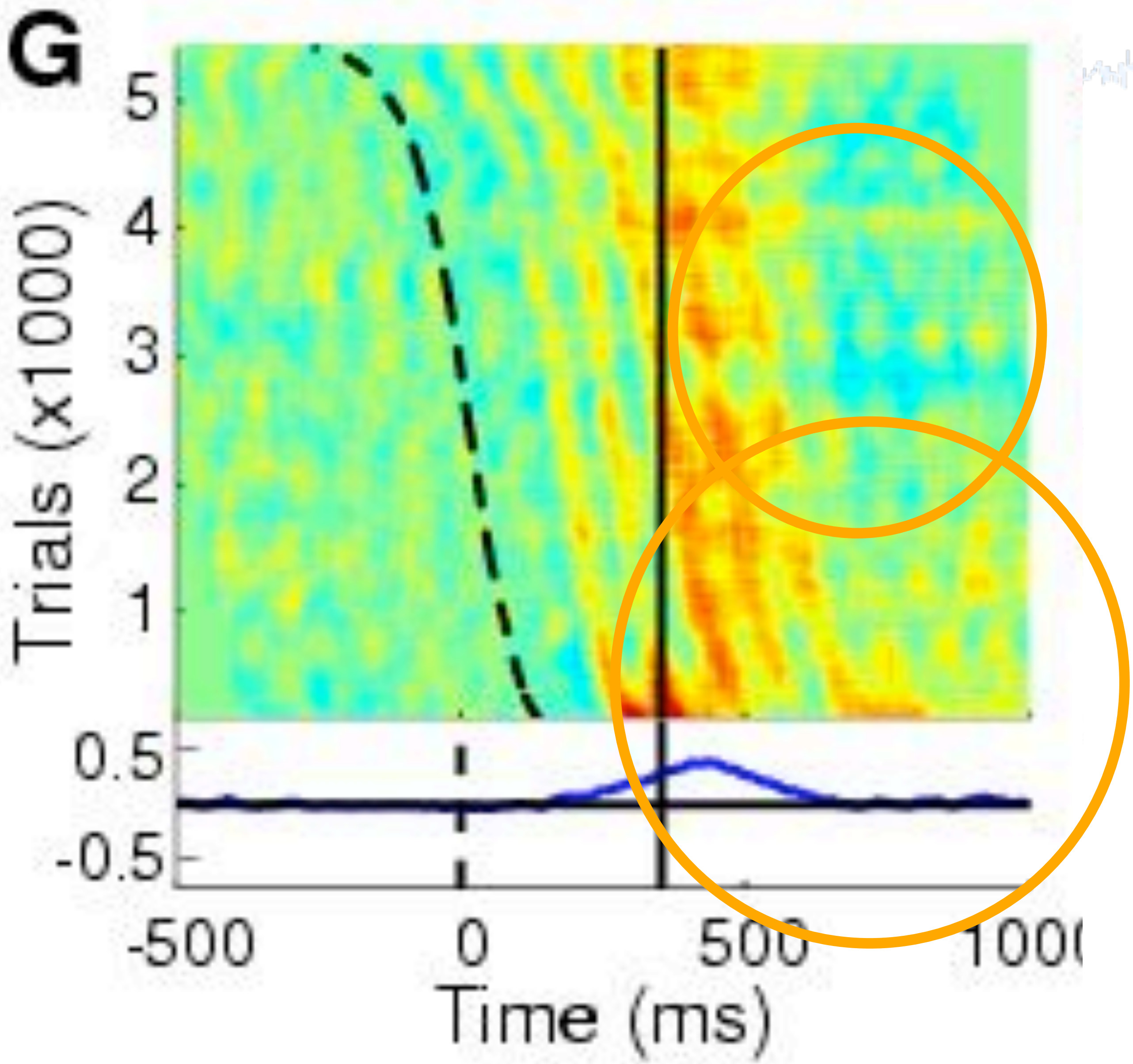


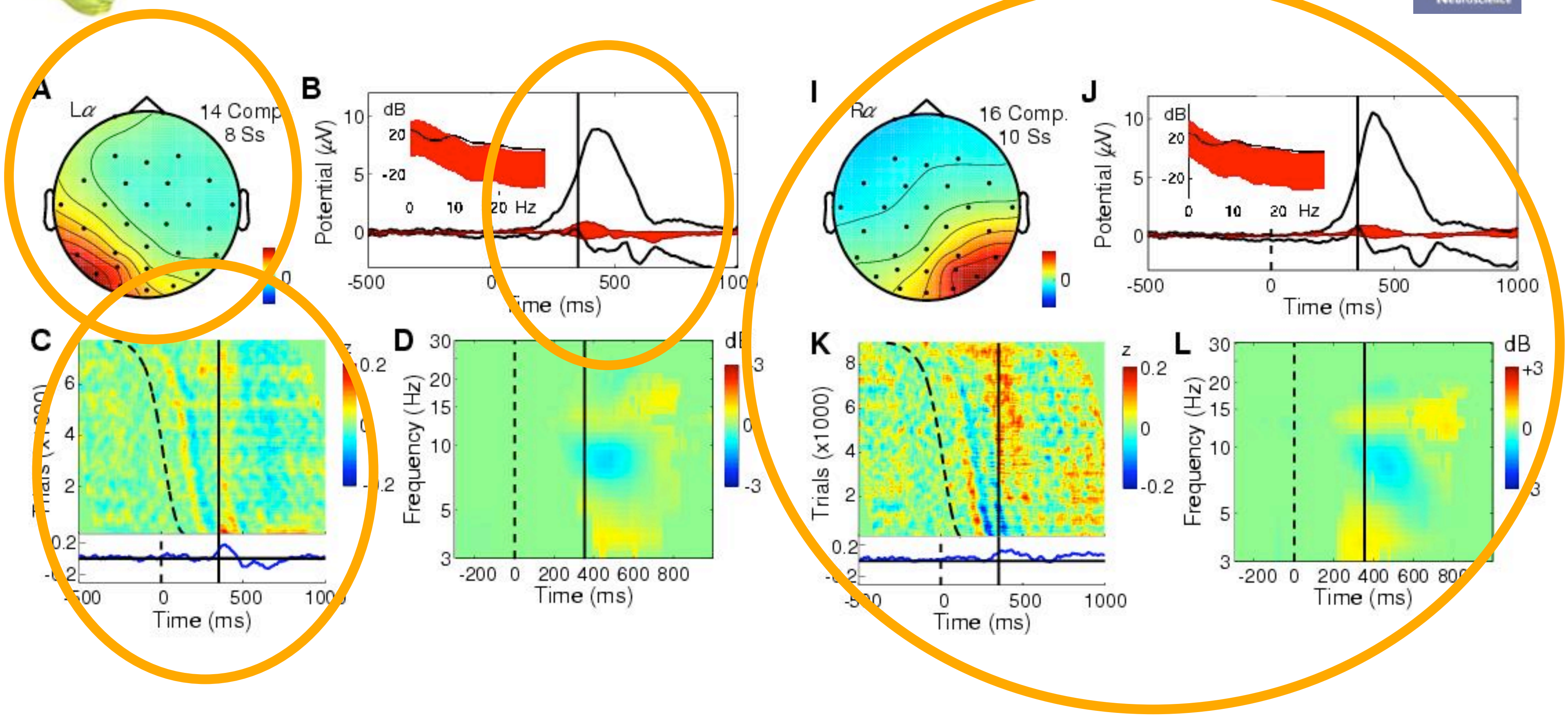
Makeig et al., *Science* 2002


A
P3f
10 Comp.
10 Ss
B
Potential (µV)
Time (ms)
dB
Hz
C
Trials (x1000)
z
D
Frequency (Hz)
Time (ms)
dB
E
P3b
15 Comp.
9 Ss
F
Potential (µV)
Time (ms)
G
Trials (x1000)
Time (ms)
H
Time (ms)

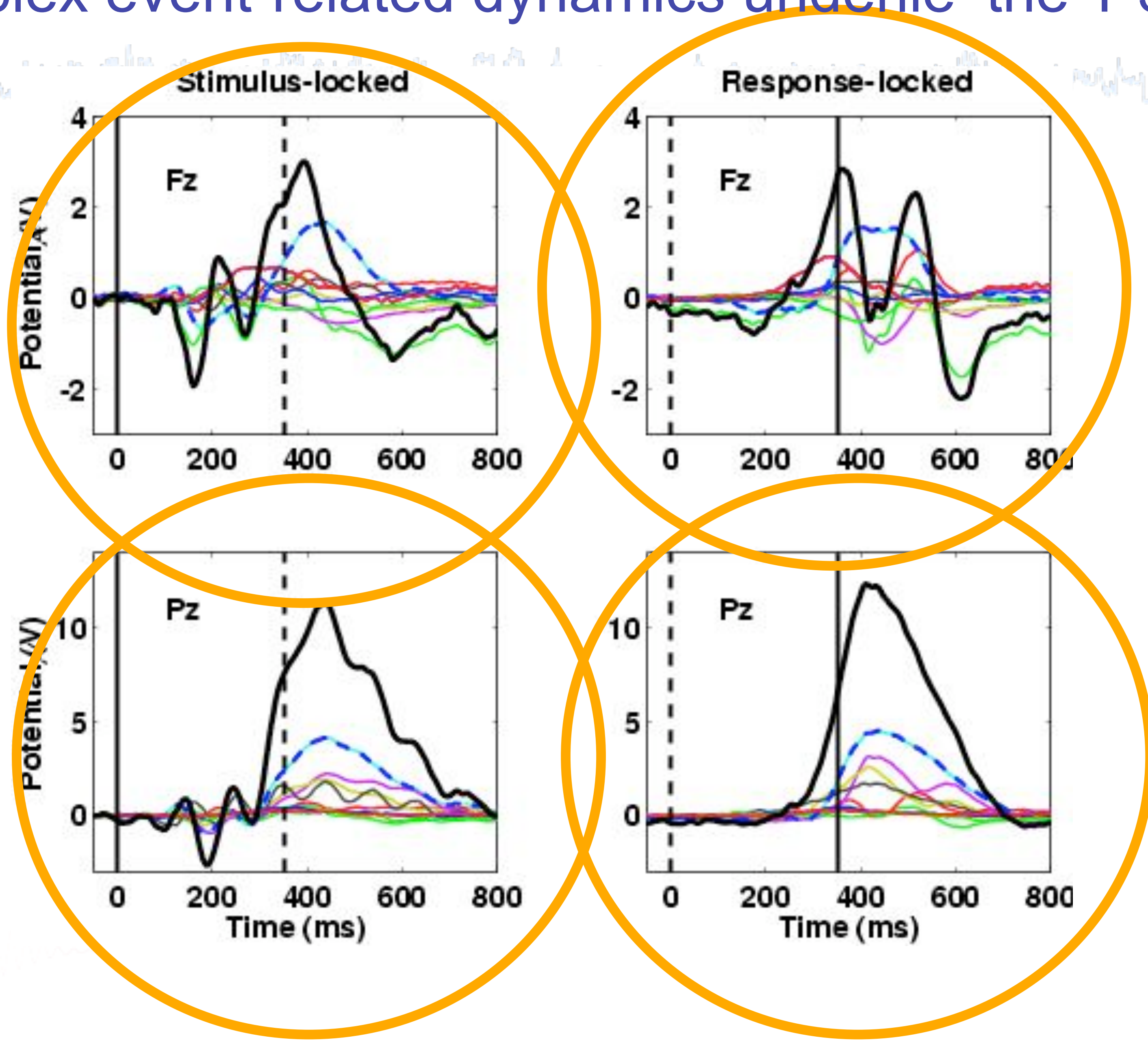

A
FM
24 Comp
11 Ss
B
dB
20
-20
0
10
20 Hz
10
5
0
-500
0
500
1000
Time (ms)
C
z
0.3
0
Trials (x1000)
Time (ms)
D
30
20
15
10
5
3
Frequency
dB
+3
0
-3
-200
0
200
400
600
800
Time (ms)
E
CM
18 Comp
13 Ss
F
dB
20
-20
0
10
20 Hz
10
5
0
-500
0
500
1000
Time (ms)
G
z
0.5
0
Trials (x1000)
-500
0
500
1000
H
30
20
15
10
5
3
Frequency
dB
+3
0
-3
-200
0
200
400
600
800
Time (ms)


A
16 Comp.
10 Ss
B
Potential (μV)
dB
10 20 Hz
-500
0
500
1000
C
D
Frequency
Time (ms)
E
15 Comp.
9 Ss
F
Potential (μV)
Time (ms)
G
Trials (x1000)
Time (ms)
H
Frequency (Hz)
dB
Time (ms)

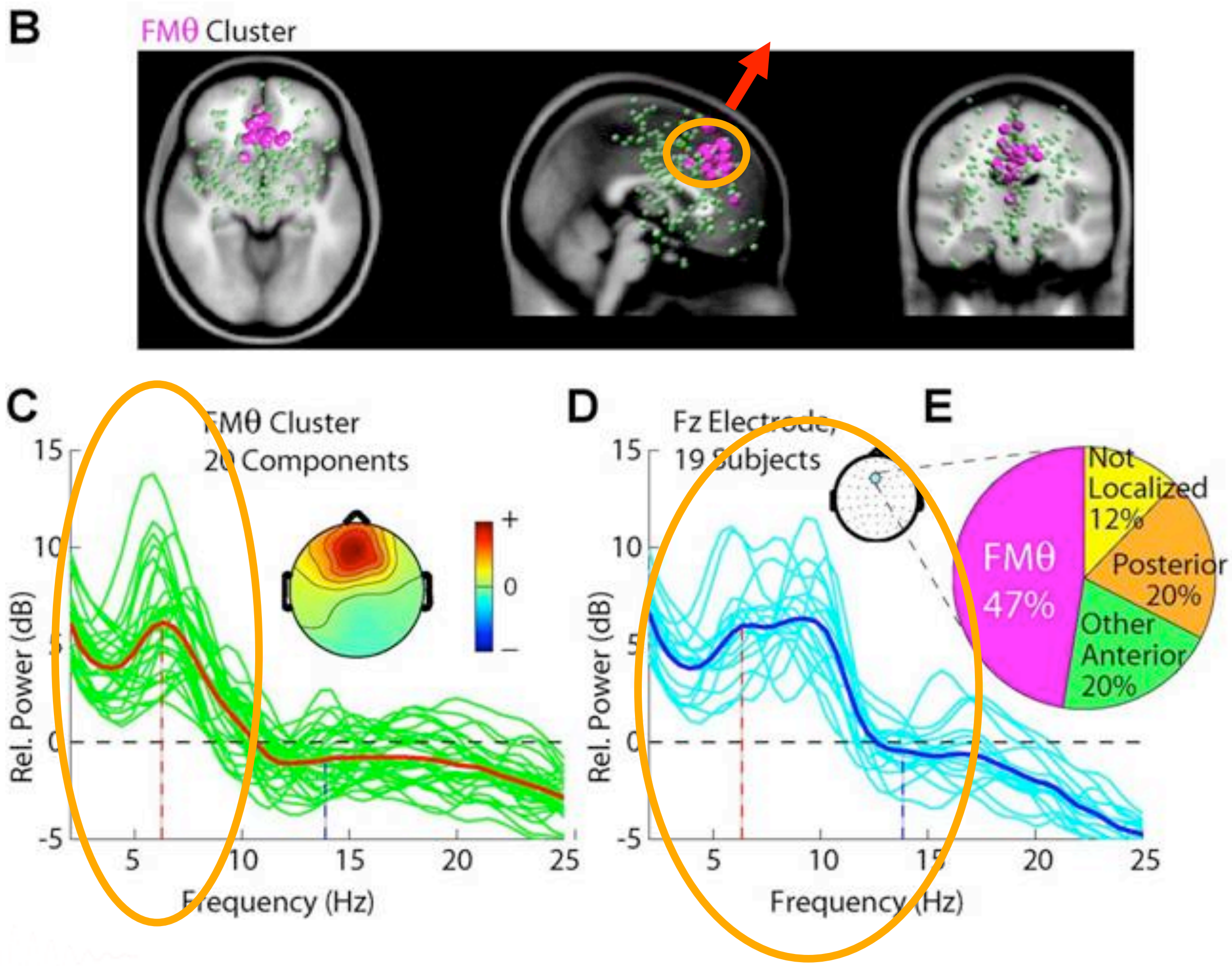

G
Trials (x1000)
5
4
3
2
1
0.5
-0.5
-500
0
500
Time (ms)


A
Lα
14 Comp.
8 Ss
B
Potential (μV)
dB
20
-20
0 10 20 Hz
-500 0 500 1000
Time (ms)
C
Time (ms)
D
Frequency (Hz)
Time (ms)
I
Rα
16 Comp.
10 Ss
J
Potential (μV)
dB
20
-20
0 10 20 Hz
-500 0 500 1000
Time (ms)
K
Trials (x1000)
z
0.2
0
-0.2
Time (ms)
L
Frequency (Hz)
dB
+3
-200 0 200 400 600 800
Time (ms)

Complex event-related dynamics underlie ‘the’ P300



A FMΘ cluster during working memory



Onton et al., *NeuroImage* 2005

Are obtained component clusters “real“?

- **Naïve realism**   (a.k.a. “expertise”)
  - “Yes! … because I know one when I see one!”
    - “If it appears where Mu components appear,

      and acts like Mu components act,

      then it IS a Mu component!”
- **Convergent evidence**   (a.k.a., “doublechecking”)
  - Two possible approaches:
    - Cluster on PLACE → Check ACTIVITY consistency (re task)
    - Cluster on ACTIVITY → Check PLACE consistency
- **Absolute truth:**
    - More ideal forward and inverse models
    - Invasive multiscale recordings + modeling

Should all subjects be included in each cluster?

Not all subjects contribute components to each cluster.

Why not?

- Different numbers of artifact components (~INR)
- Subject differences!?
- Is my subject group a Gaussian cloud??
  - → subject space

EEGLAB clustering procedure

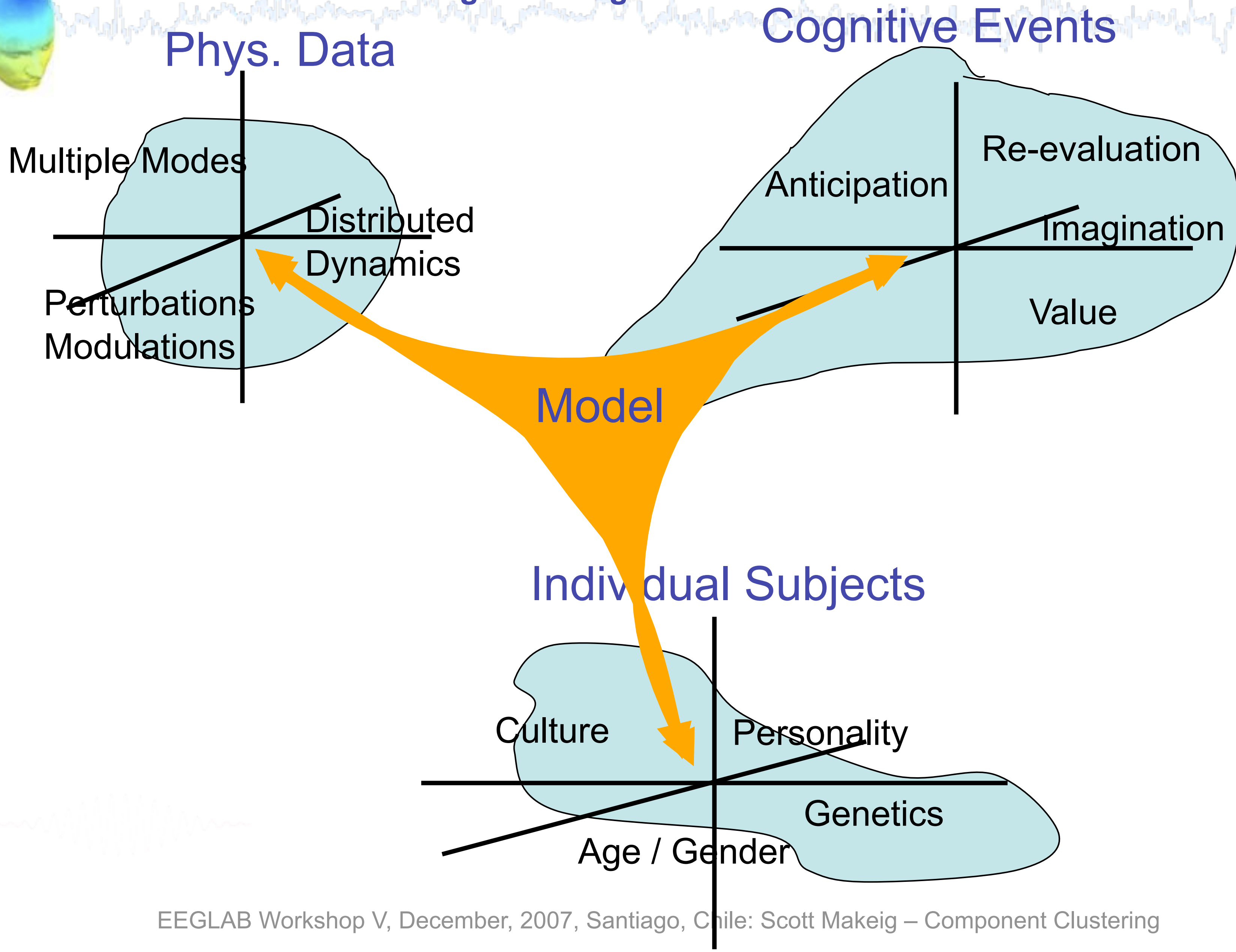
1. Identify a set of datasets as an EEGLAB **study** or '**studyset**'.
2. Specify the subject **group**, **subject** code, **condition** and **session** of each dataset in the study.
3. Identify **components to cluster** in each study dataset.
4. Decide on **component measures** to use in clustering the study and/or to evaluate the obtained component clusters.
5. Compute the component measures for each study dataset.
6. **Cluster the components** on these component measures.
7. Review the obtained **clusters** (e.g., their scalp maps, dipoles, and activity measures).
8. **Edit the clusters** (manually remove/shift components, make sub-clusters, merge clusters, re-cluster).
9. Perform **signal processing** within or between selected clusters.

EEGLAB Clustering strategy

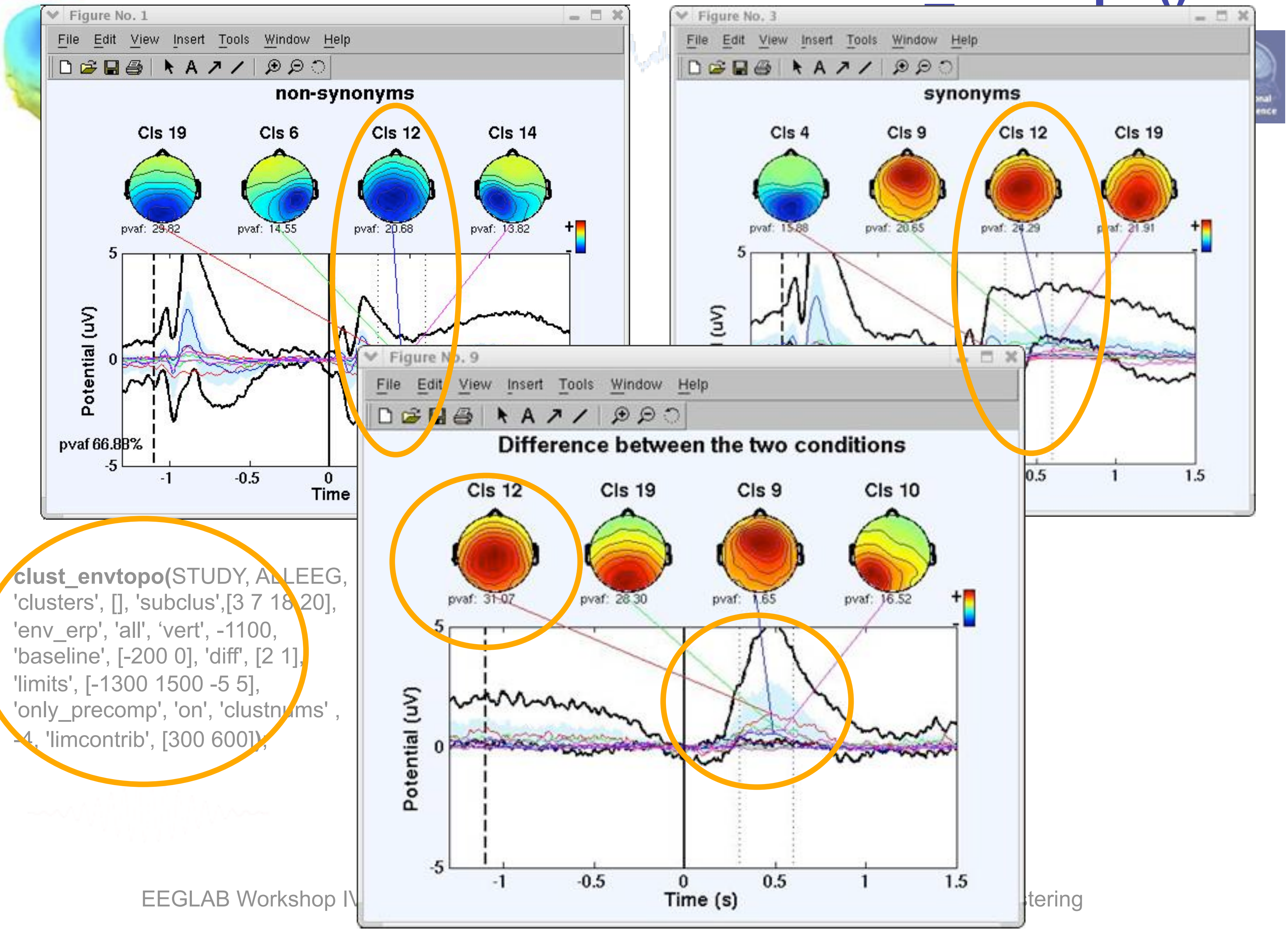
1. Cluster on **multiple measures** (dipole locations, scalp maps, spectra, ERPs, ITCs, ERSPs) in **one or more conditions**.
2. **Reduce the dimension** of each measure to a principal component subspace.
3. Compose a PCA-reduced **position vector** for each component.
4. **Cluster** the composed component vectors using k-means or other.
5. Use the computed component measures (not PCA-reduced) to **visualize the activities and spatial properties** of the clustered components.
6. Compute and visualize the **cluster-mean measures**.
7. Use the **clustered study set data** as input into **std_** functions.

Beyond Clustering

The goal of cognitive neuroscience



Cluster ERP contributions - clust_envtopo()




```
clust_envtopo(STUDY, ALLEEG,
'clusters', [], 'subclus',[3 7 18 20],
'env_erp', 'all', 'vert', -1100,
'baseline', [-200 0], 'diff', [2 1],
'limits', [-1300 1500 -5 5],
'only_precomp', 'on', 'clustnums' ,
-4, 'limcontrib', [300 600]);
```

Component clustering research issues

Issues:

- Alternative clustering methods (new method soon)
- Clustering goodness-of-fit
- Cluster plotting details
- Add new pre-clustering measures
- Study subject differences!?

Plan:

- New EEGLAB 'STUDY.DESIGN' definition:
  - Vector of conditions → uncoupled experimental STUDY.DESIGN structures
  - More flexible and complete STUDY.DESIGN statistics