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ICA components reliability

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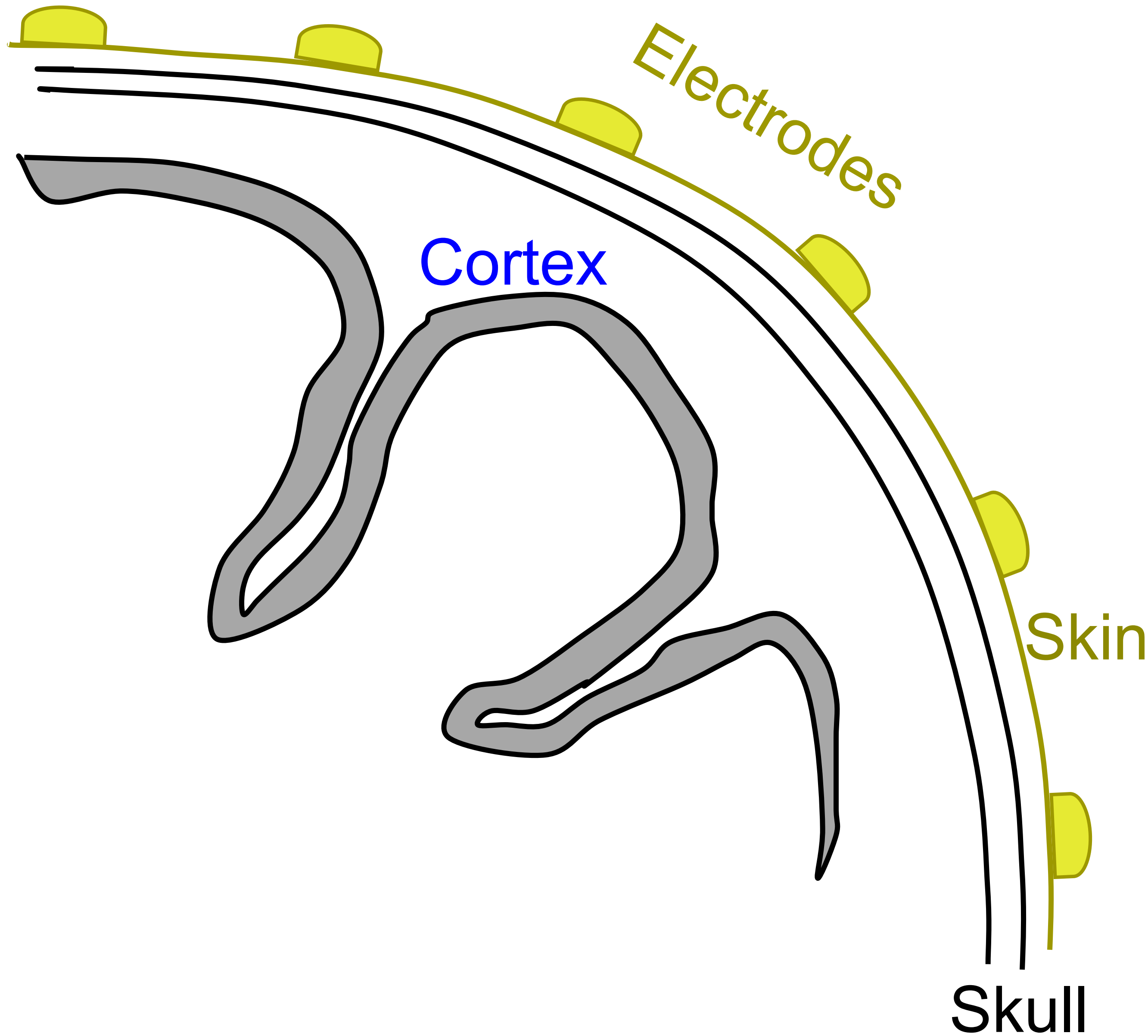
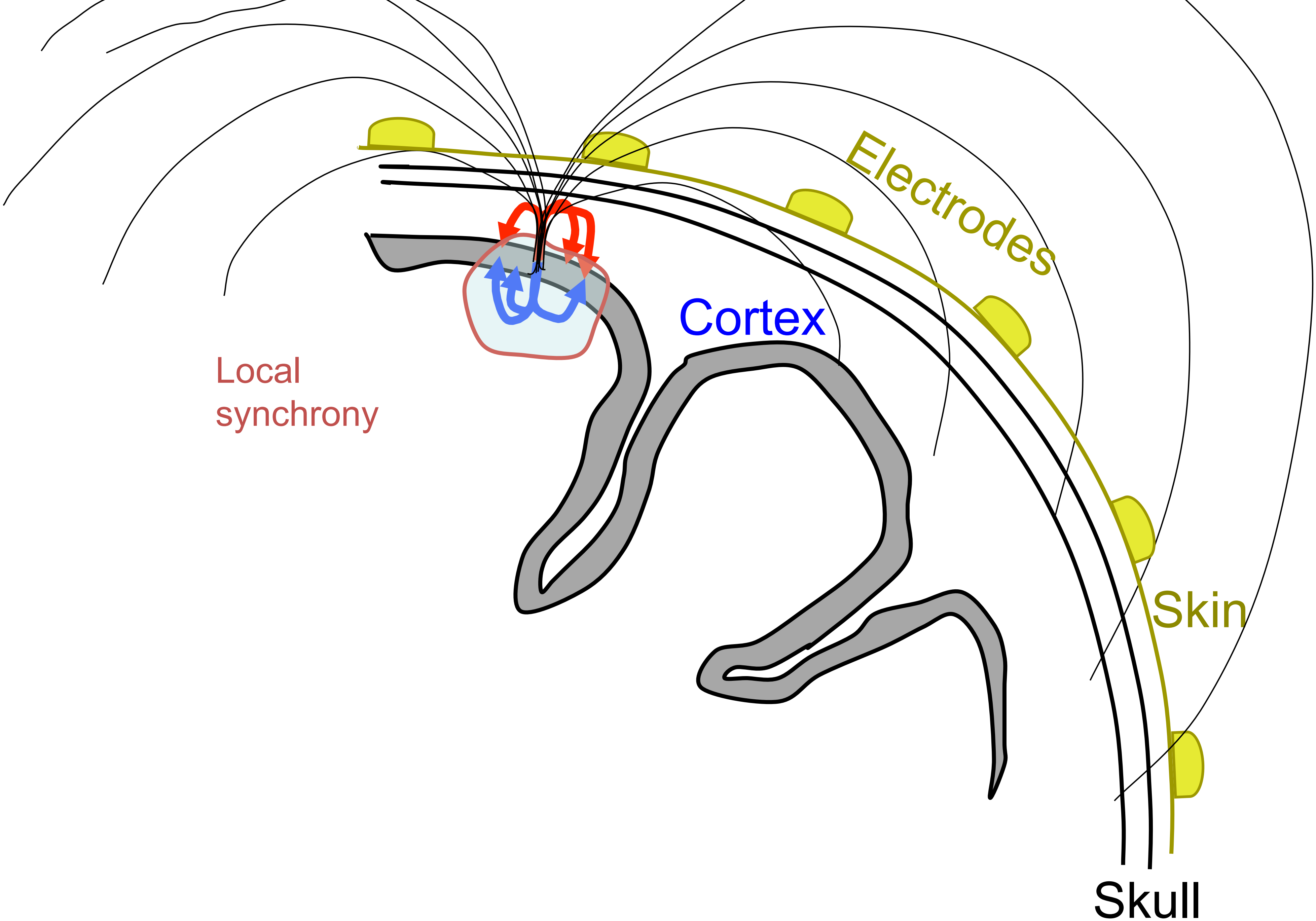
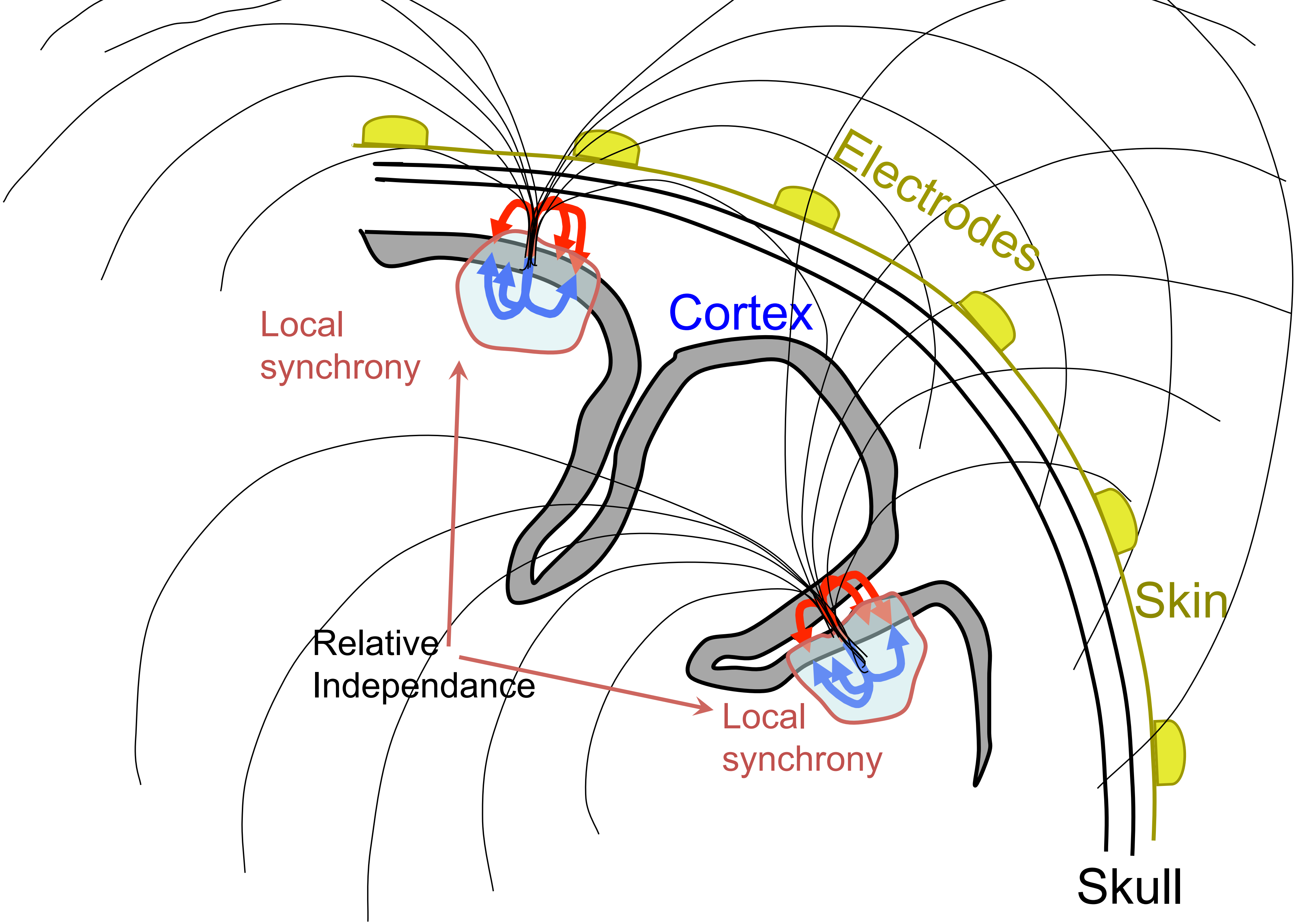
STCcl-PRC99-19 Hubble Space Telescope Key Team & NASA

Outline

- ICA basic theory
- ICA reliability within subjects
- ICA reliability across subjects


Electrodes
Cortex
Skin
Skull

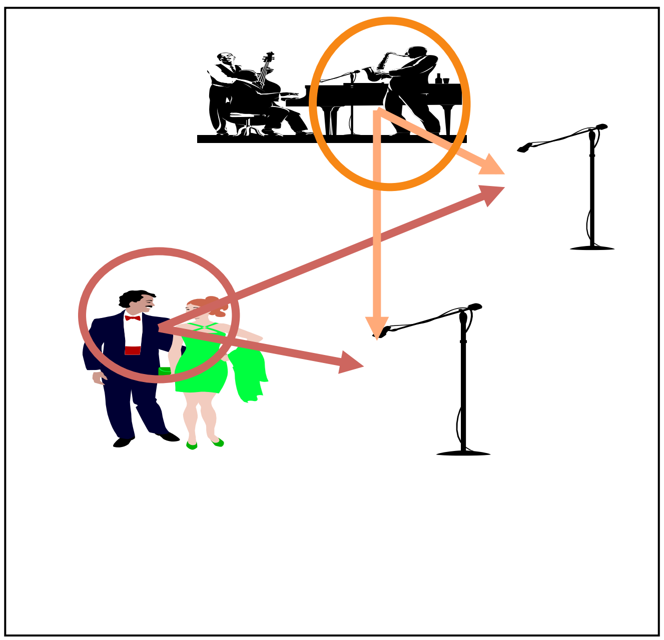

Electrodes
Cortex
Local
synchrony
Skin
Skull

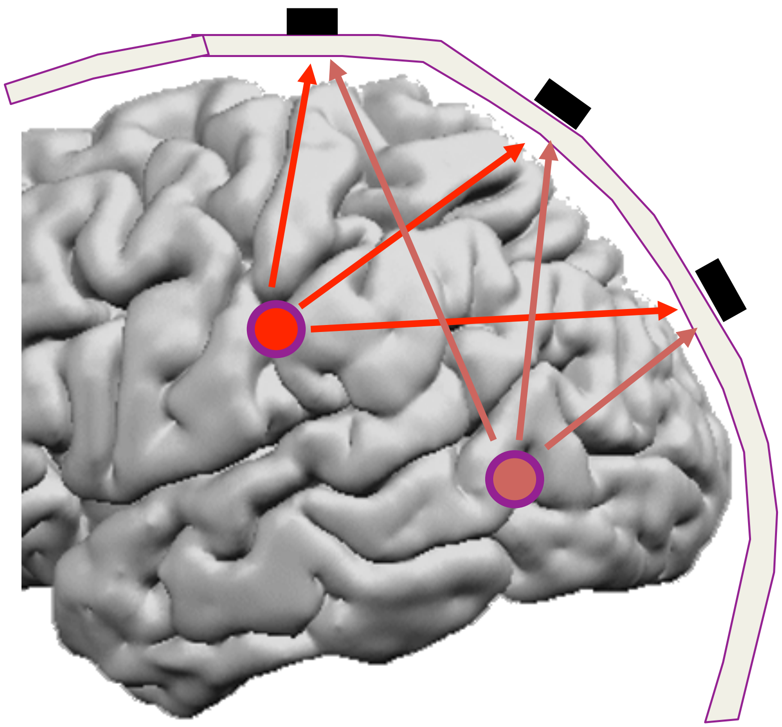

Electrodes
Cortex
Local
synchrony
Skin
Relative
Independance
Local
synchrony
Skull

Independent component analysis

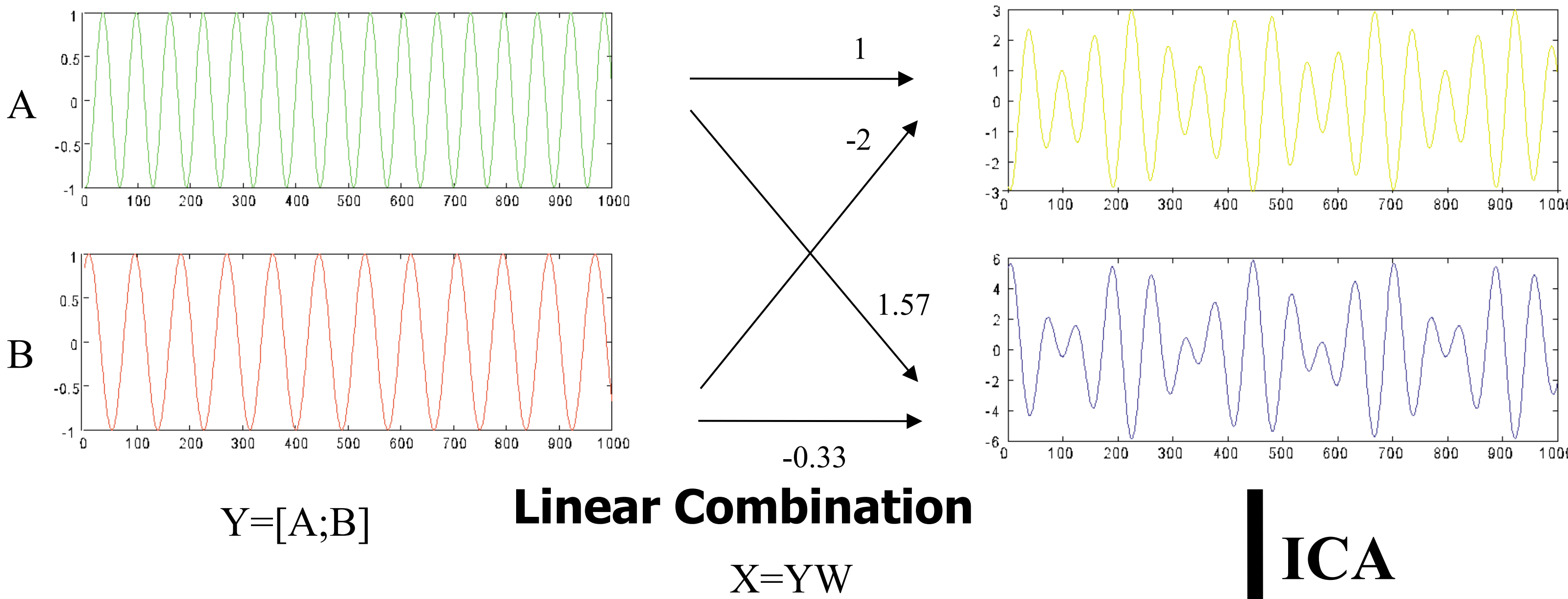
Mixture of Brain source activity

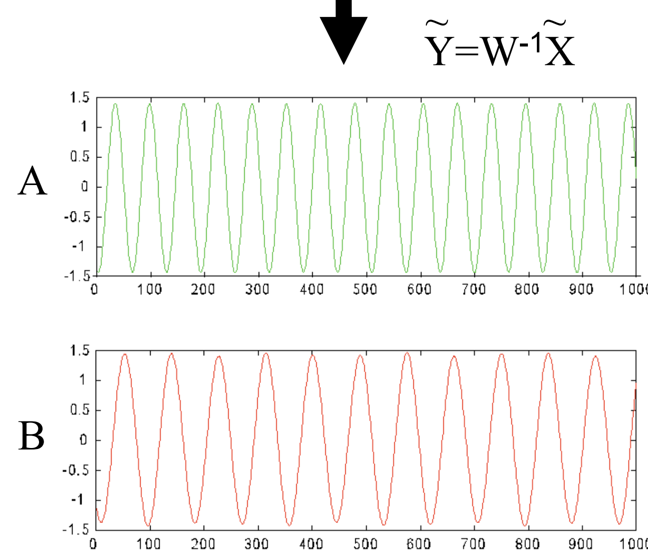
Cocktail Party





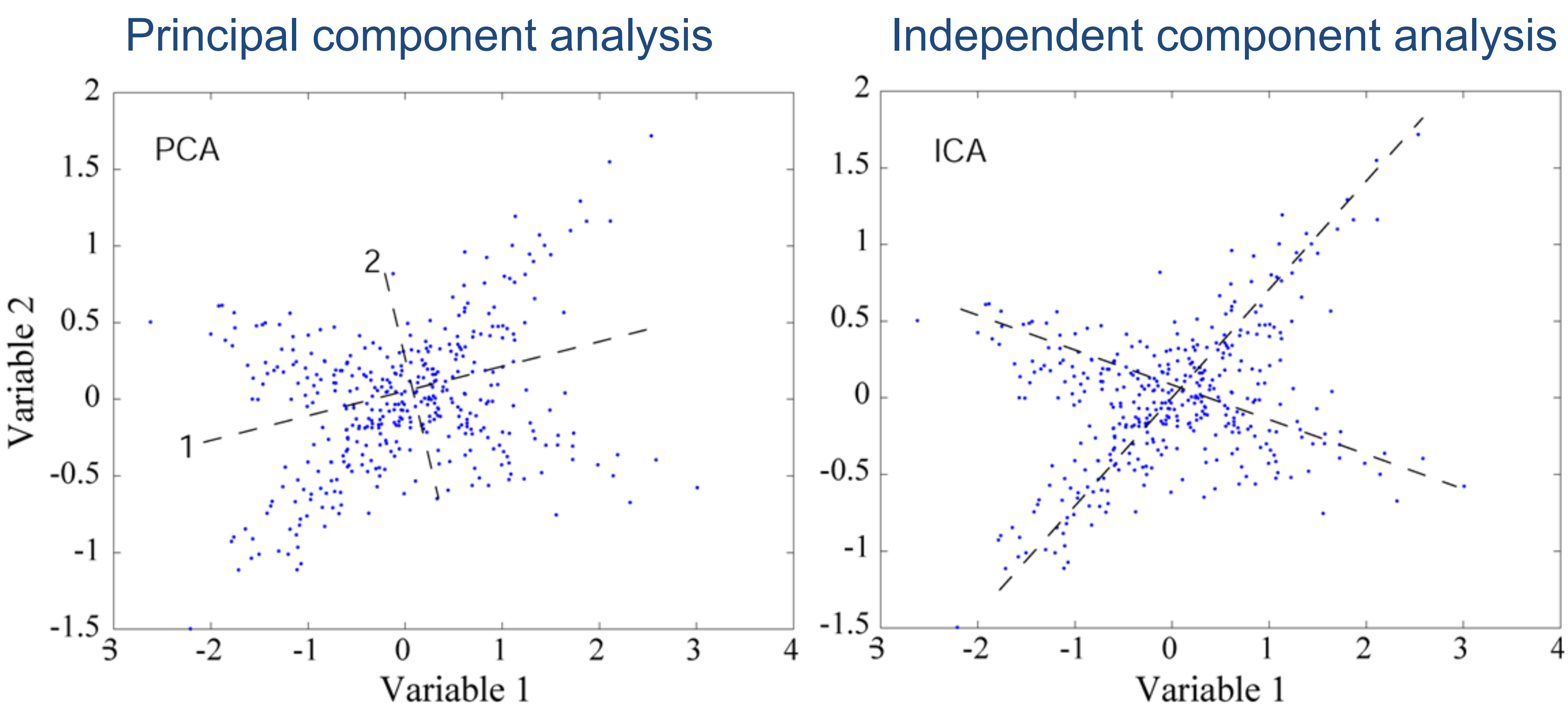
Infomax ICA


A
B
Y=[A;B]
1
-2
1.57
-0.33
Linear Combination
X=YW
ICA

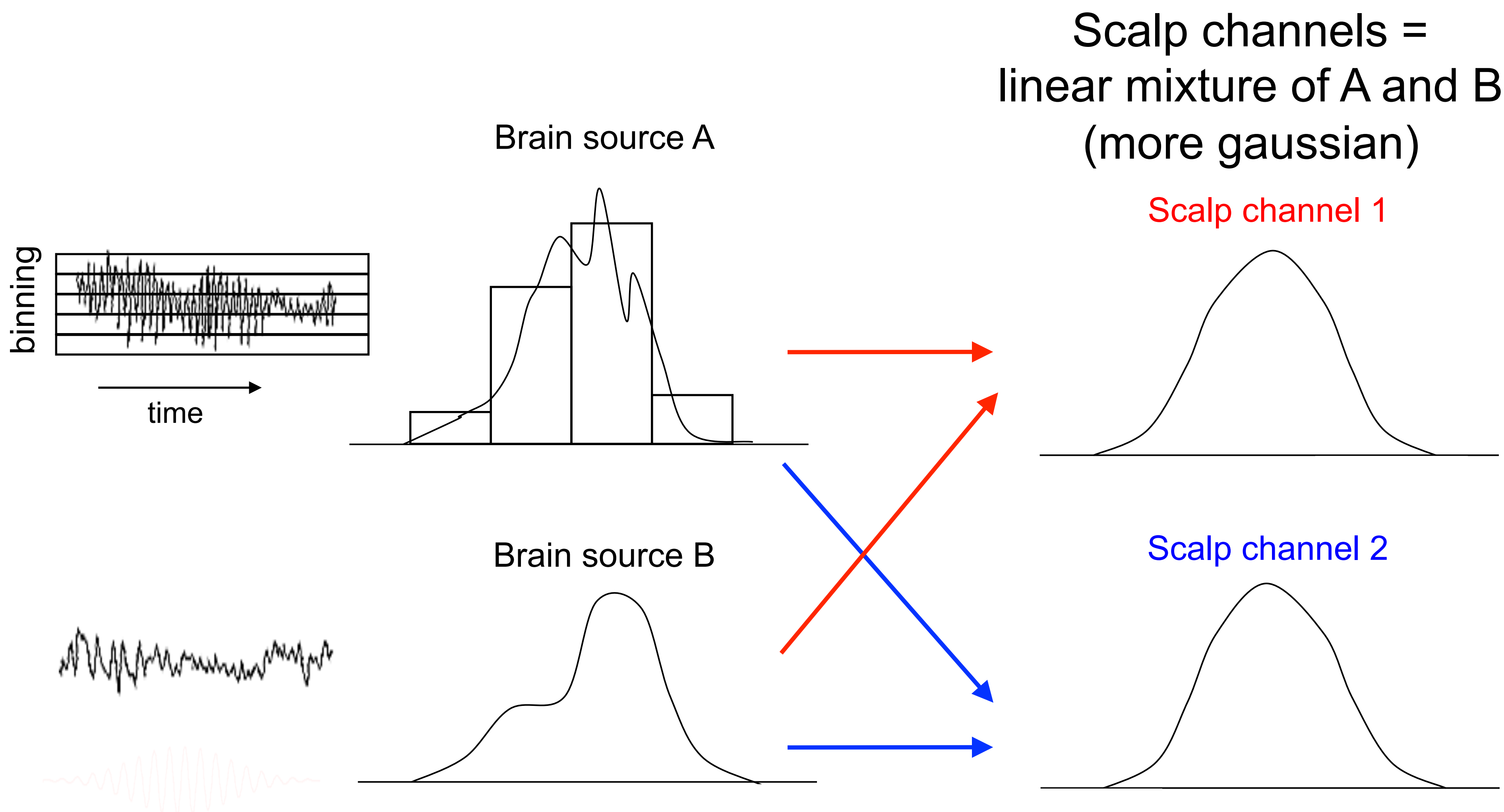

$\tilde{Y}=W^{-1}\tilde{X}$
A
B

ICA and PCA

While PCA simply decorrelates the outputs (using an orthogonal matrix W), ICA attempts to make the outputs statistically independent, while placing no constraints on the matrix W.

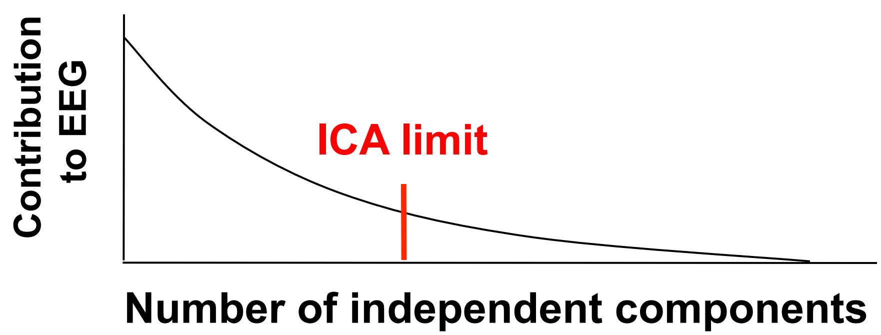


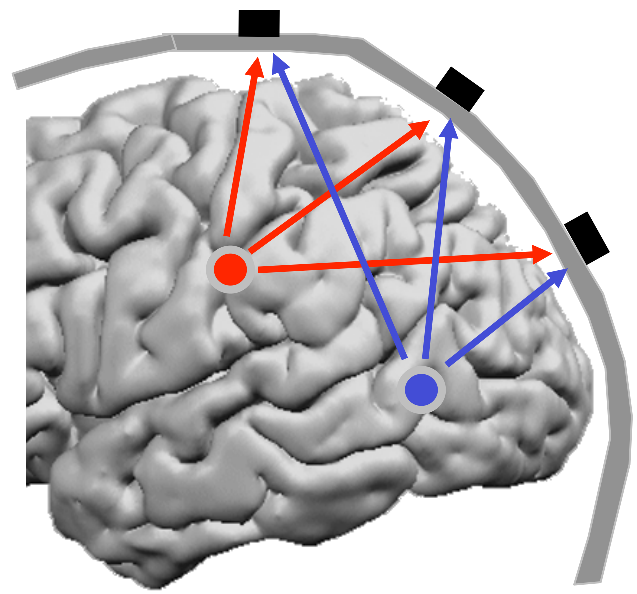
Central limit theorem



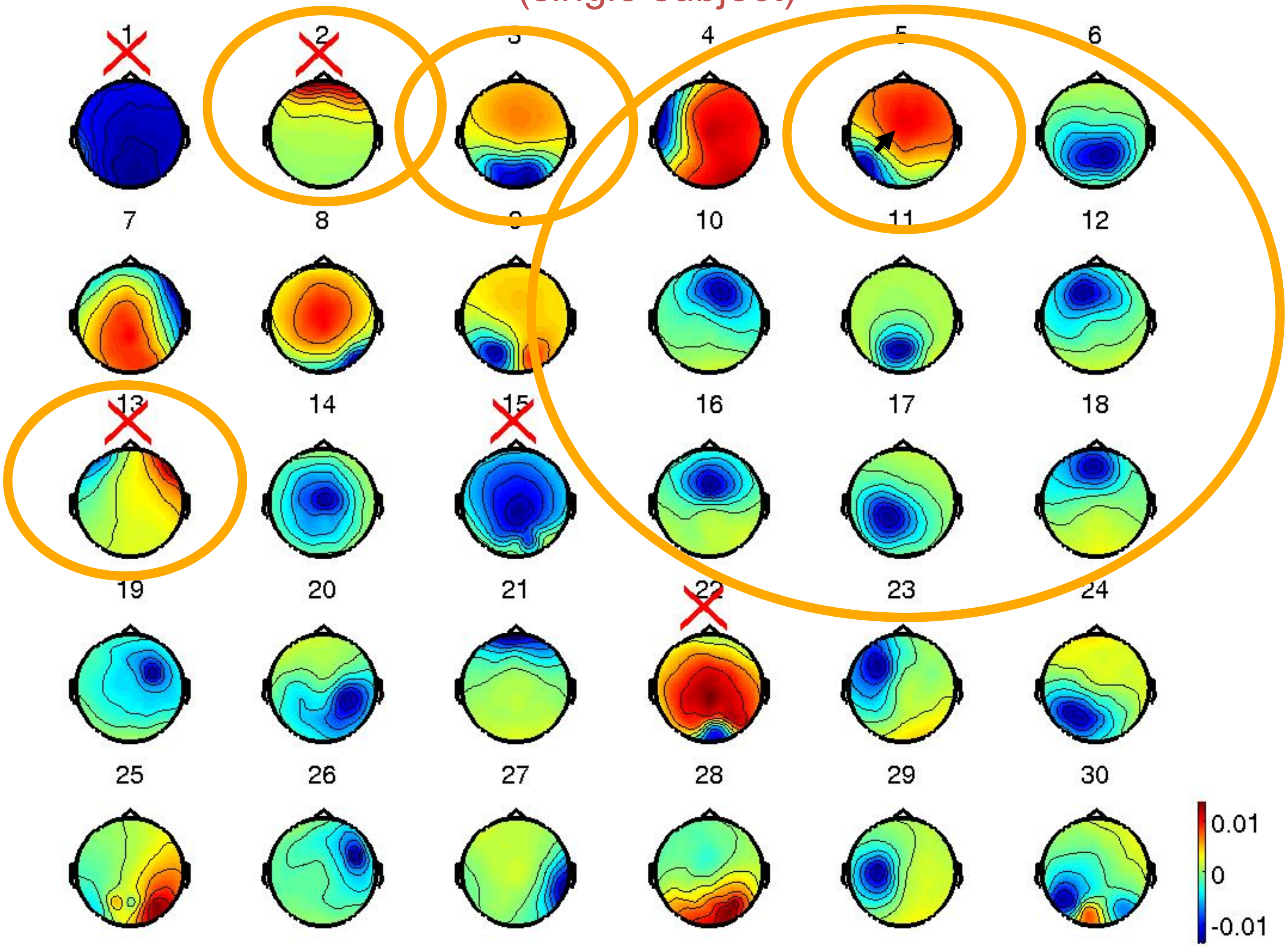
ICA/EEG Assumptions

- Mixing is linear at electrodes **OK**
- Propagation delays are negligible **OK**
- Component time courses are independent **~**
- Number of components less than the number of channels.

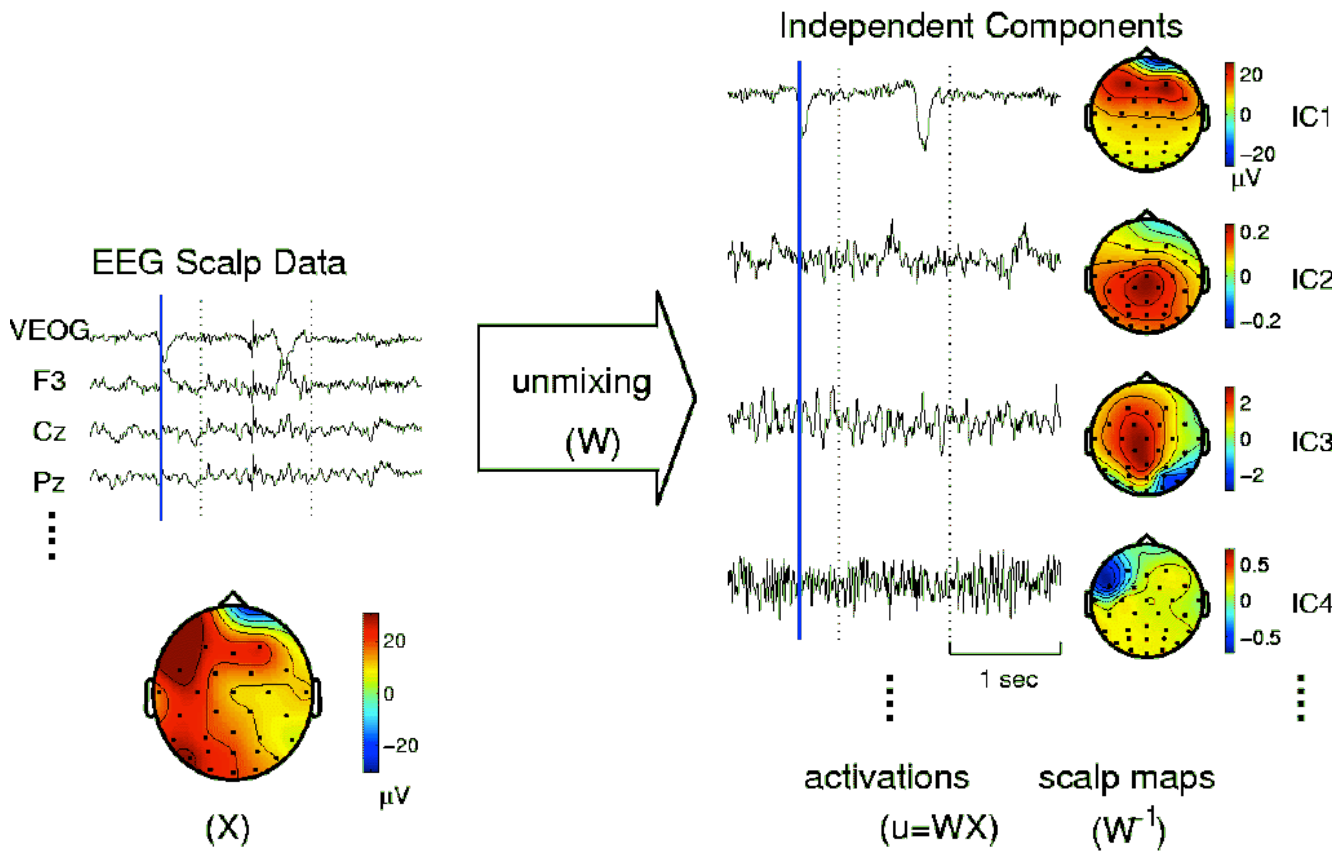




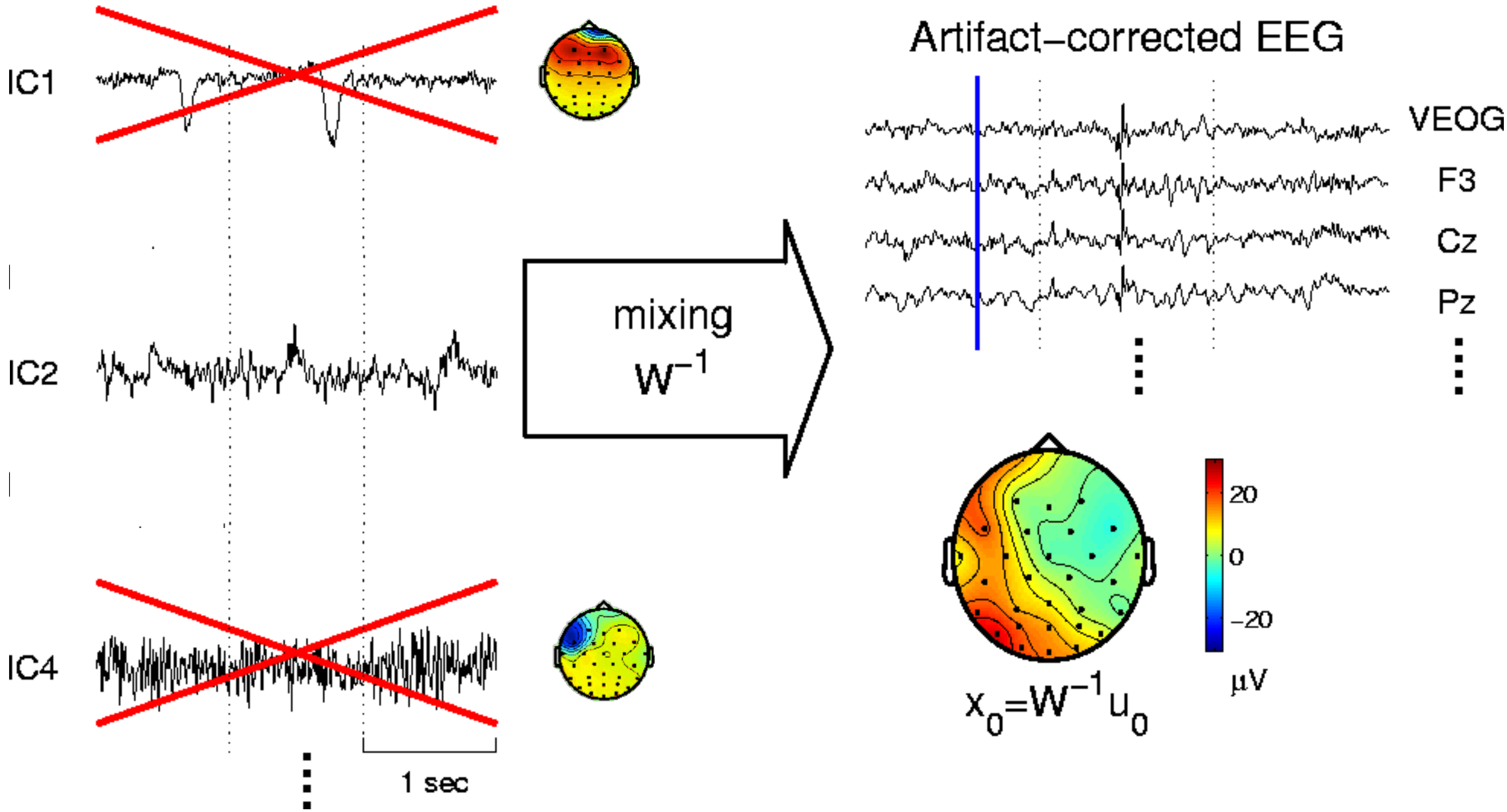
Largest 30 Independent Components
(single subject)



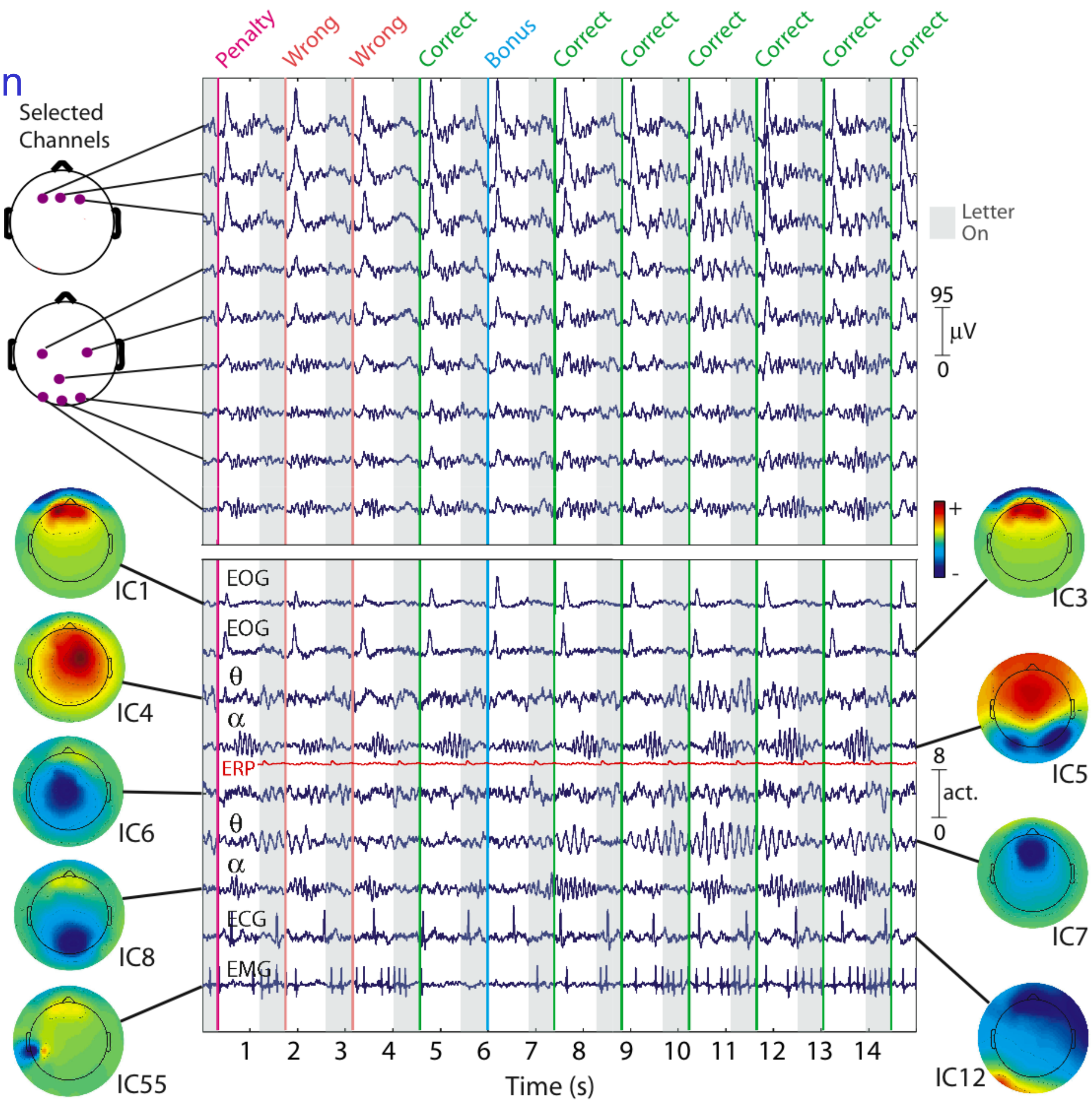
ICA Decomposition into Independent Components



Selective Projection onto Scalp Channels



Sample EEG Decomposition



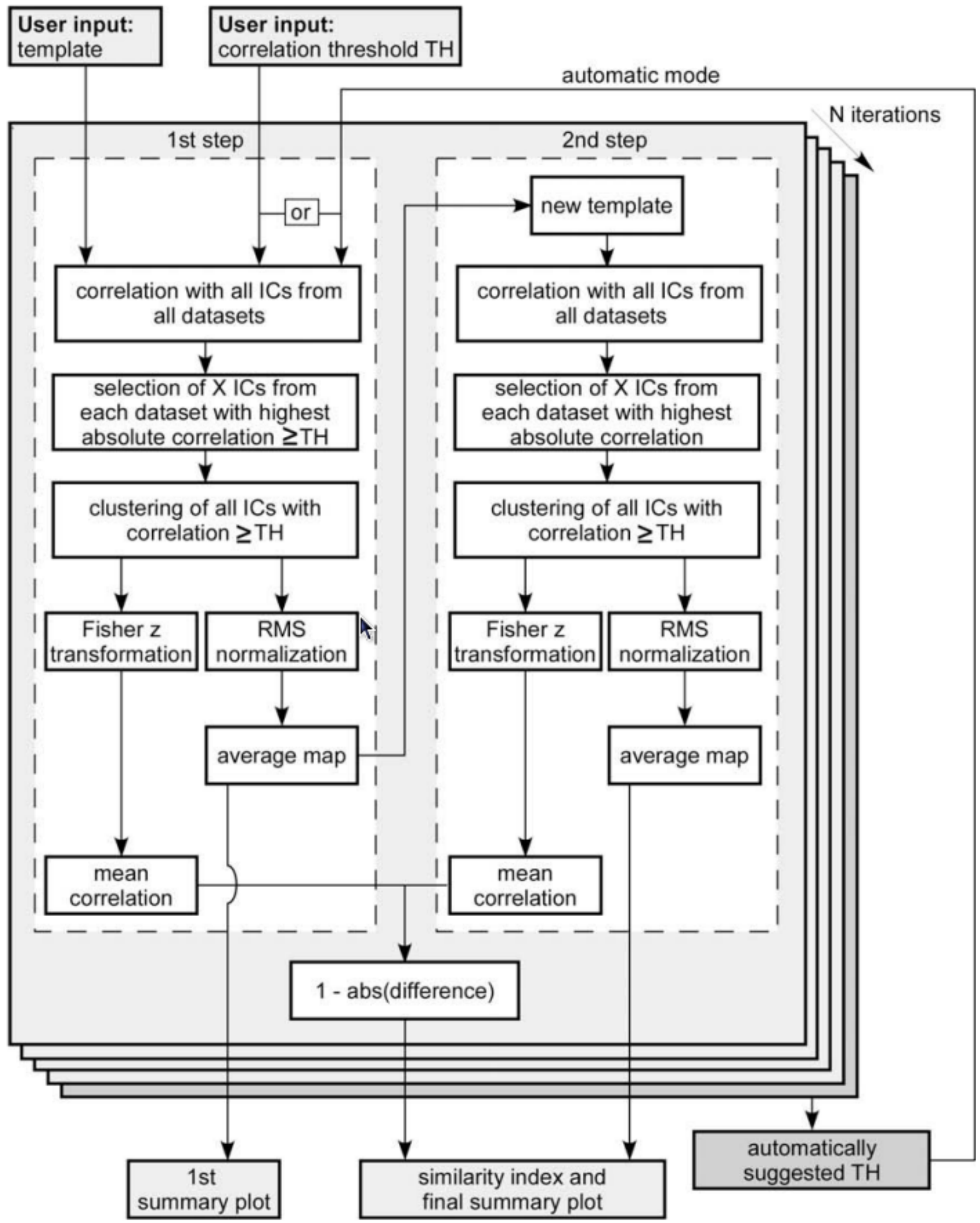
Credit: J. Onton

Outline

- ICA basic theory
- ICA reliability within subjects
- ICA reliability across subjects

ICA decomposition of multiple data sets from the same individuals

- Experimental protocol
  - Mind wandering experiment
  - 2 subjects
  - 11 x 30 min. sessions
  - 2 sessions per week
  - EEG from Biosemi 64 channels
  - Fs=1024 Hz

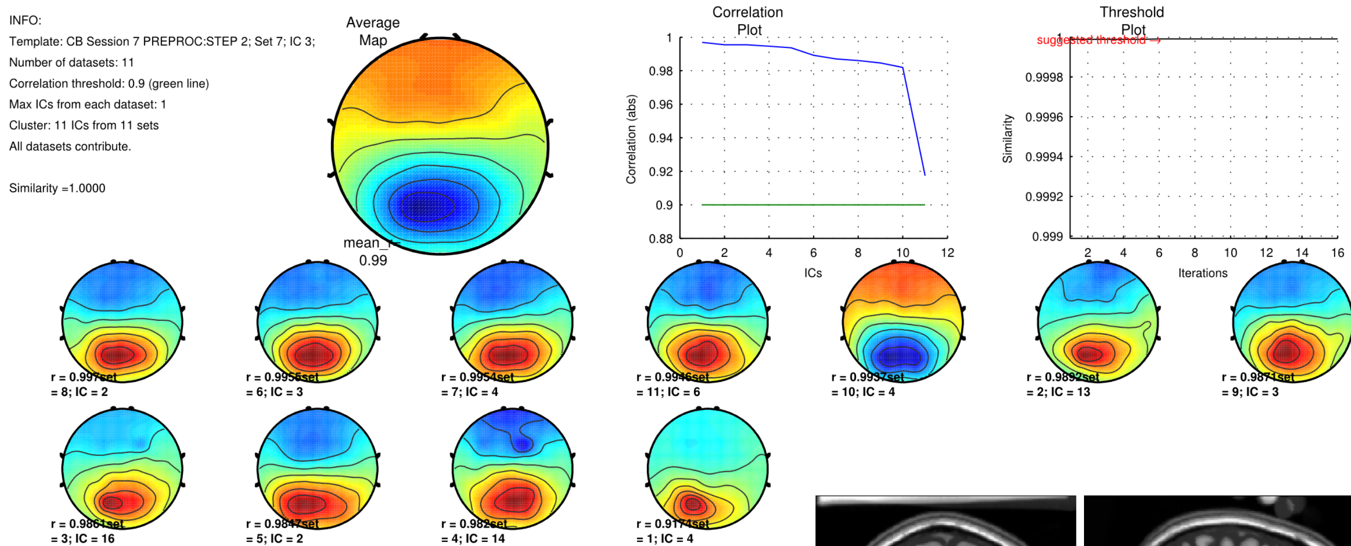


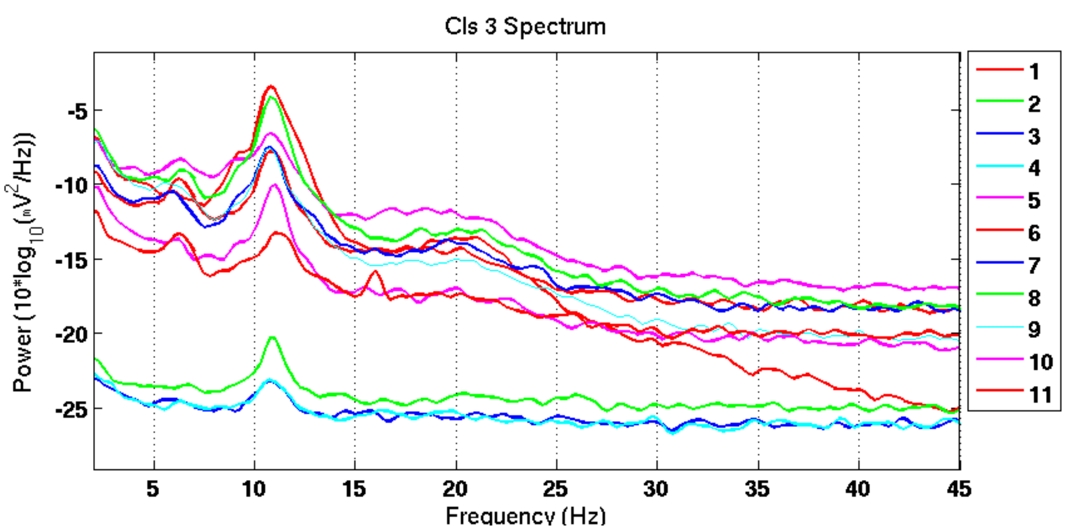
F. Campos Viola et al., “Semi-automatic identification of independent components representing EEG artifact,” Clinical Neurophysiology 120, no. 5 (2009): 868–877.

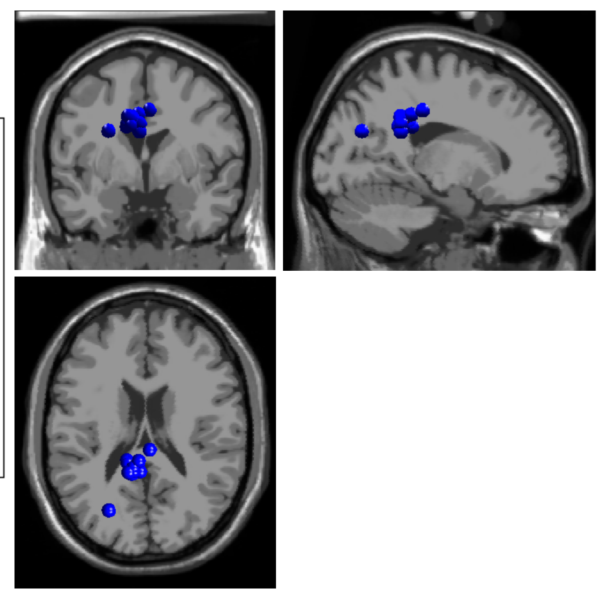
suggested as the automatic correlation threshold.

Results (Cluster 1)

100 % Sessions contribute

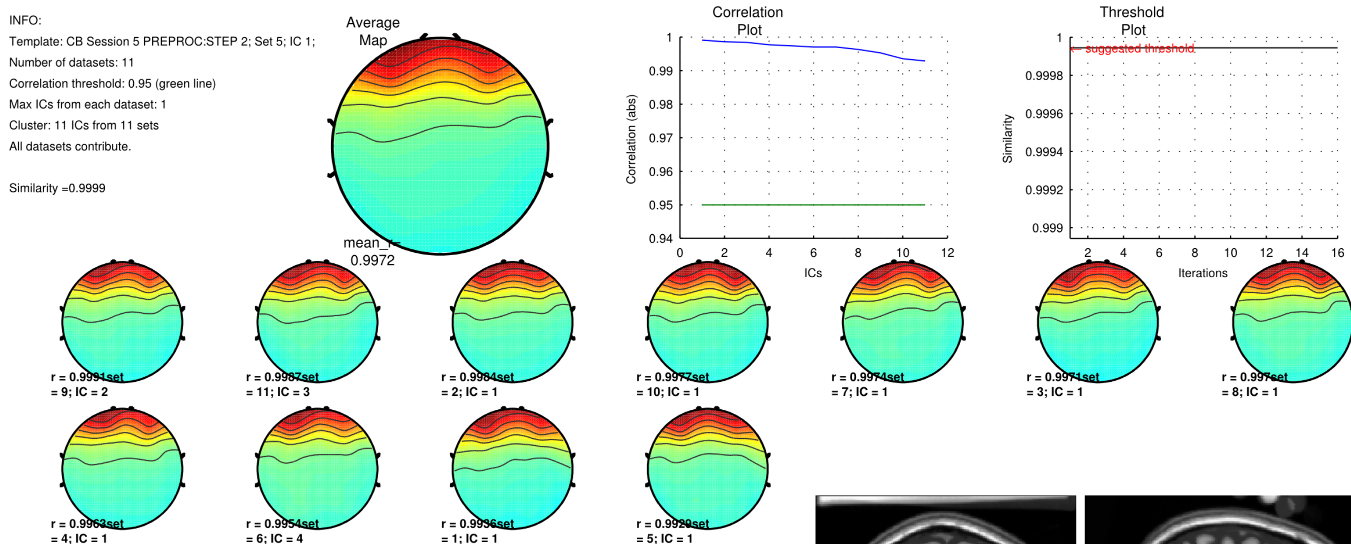


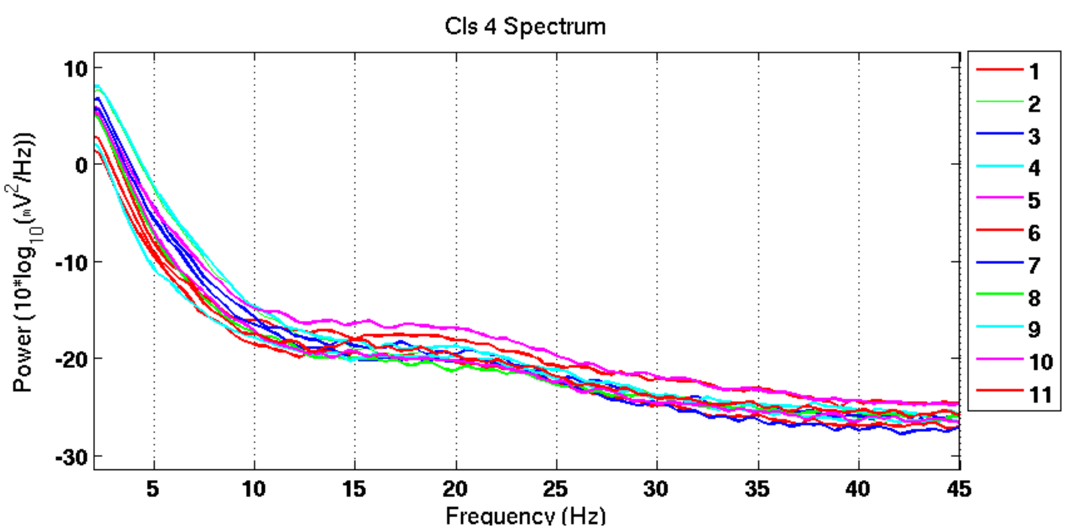


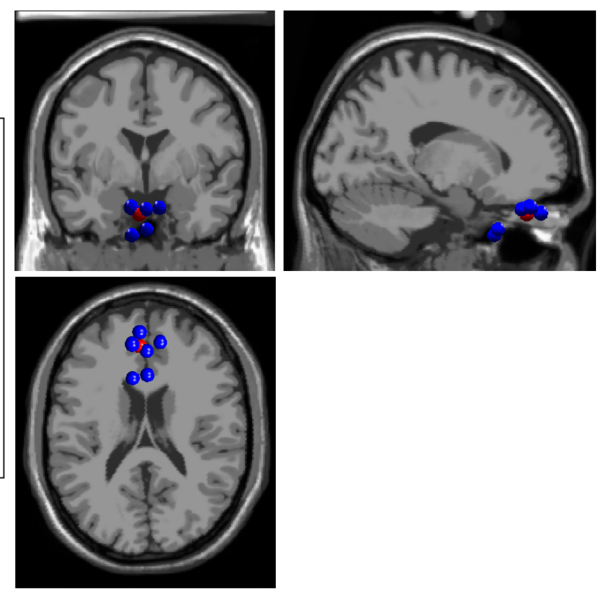


Results (Cluster 2)

100 % Sessions contribute

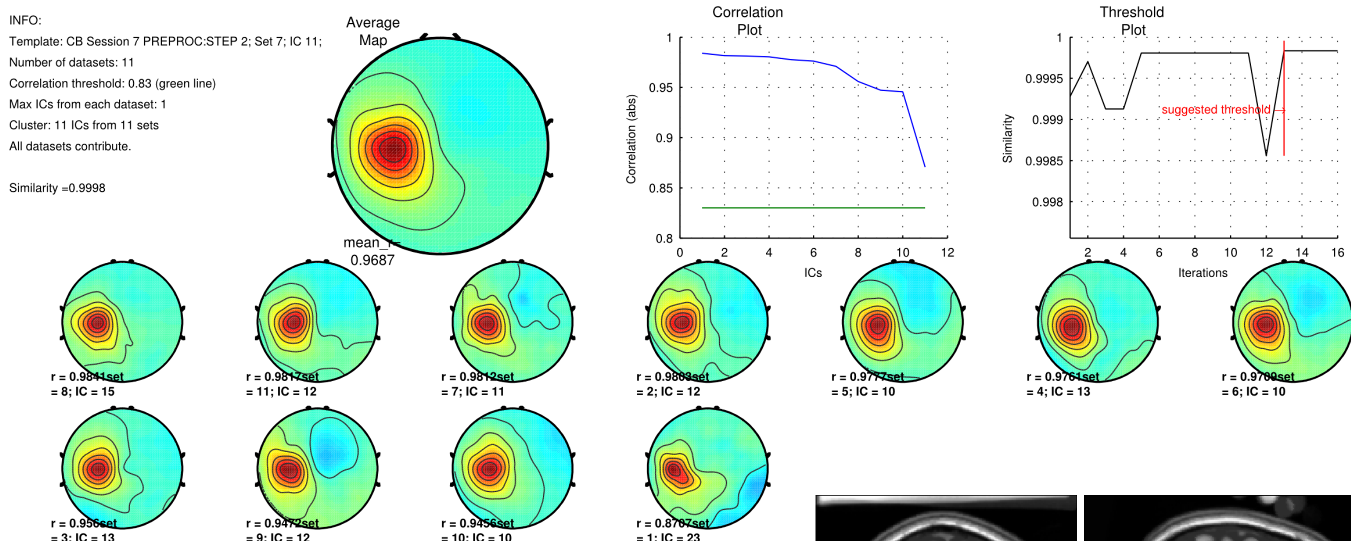


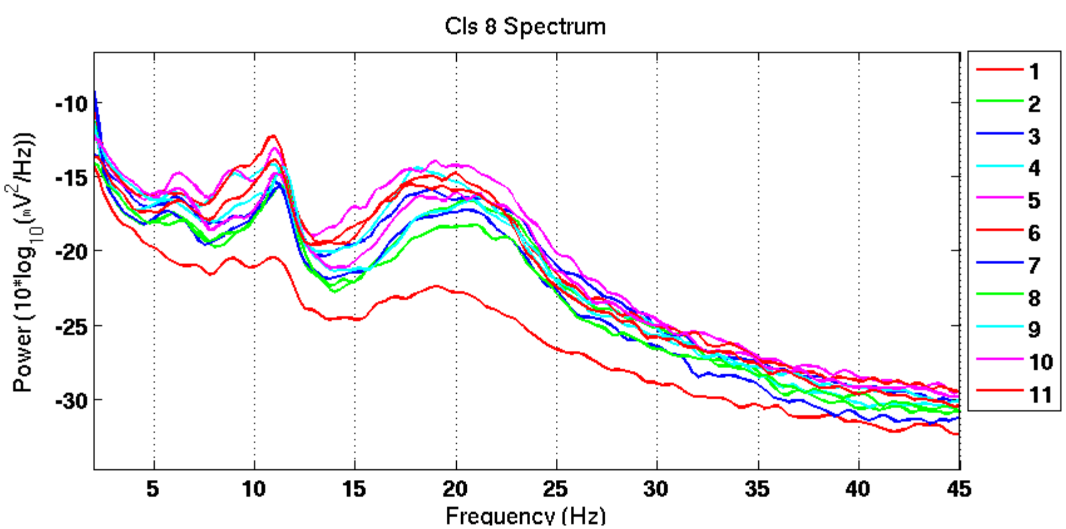


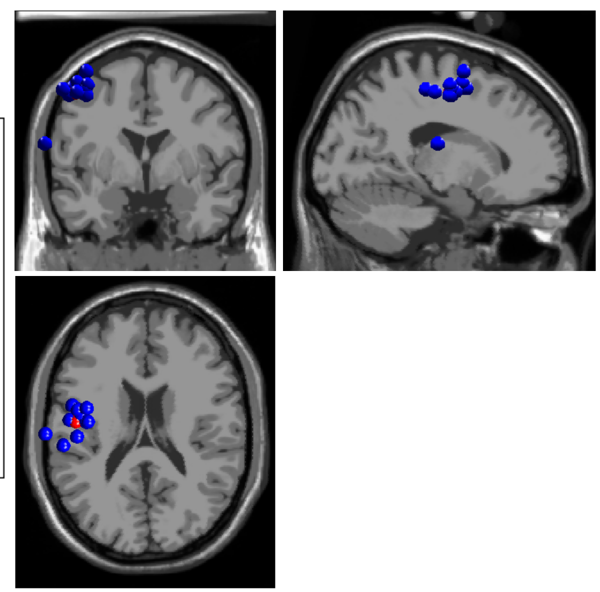


Results (Cluster 8)

100 % Sessions contribute

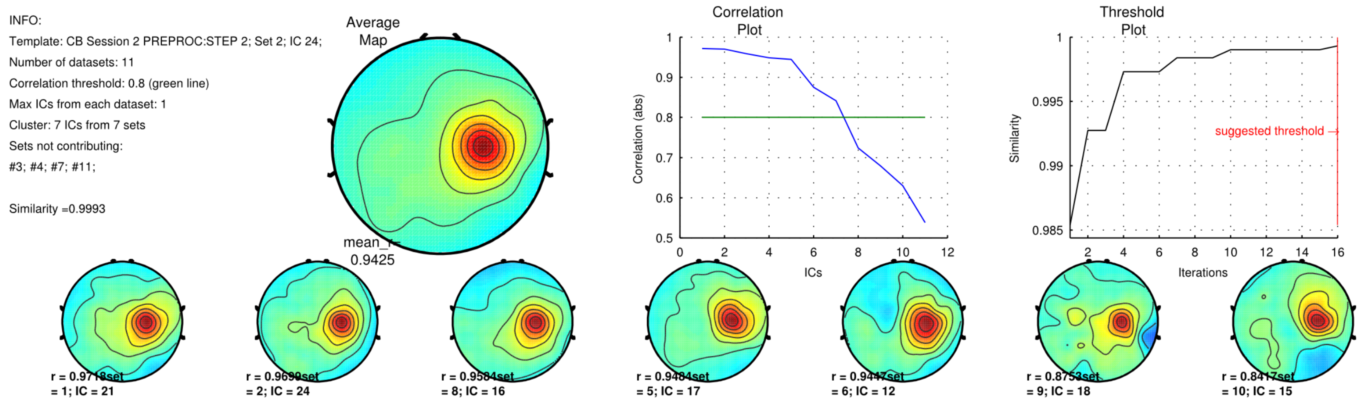


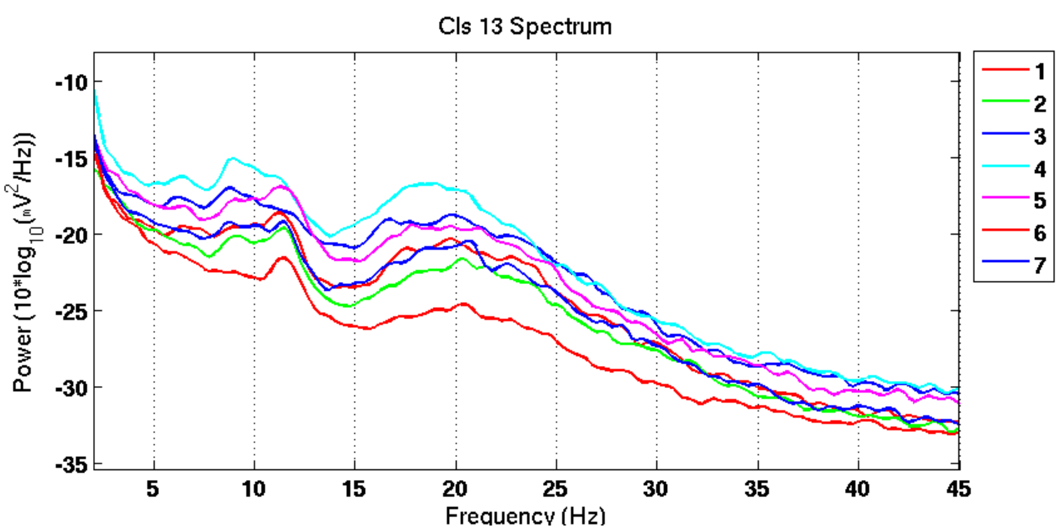


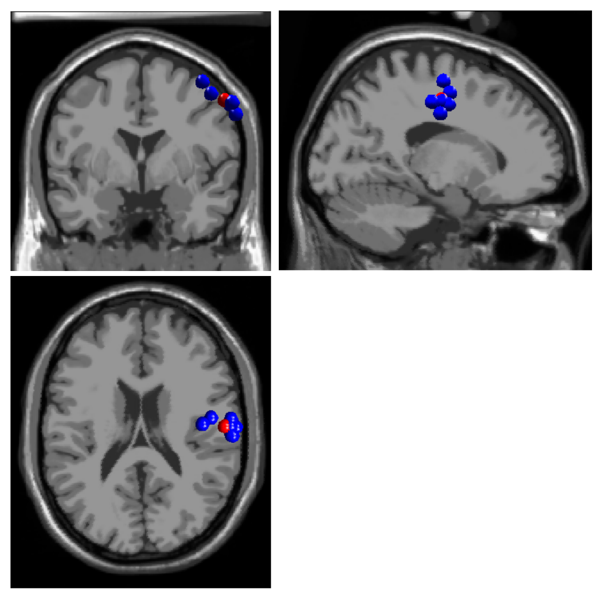


Results (Cluster 13)

63.64% Sessions contribute

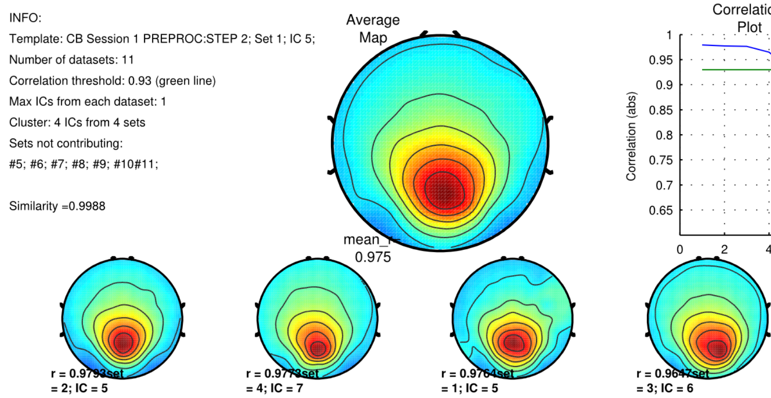


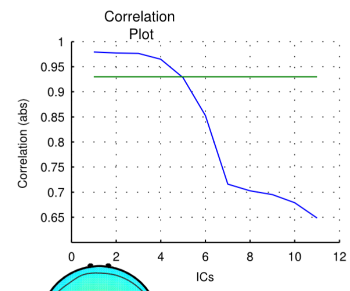


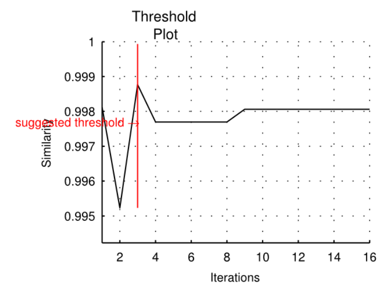


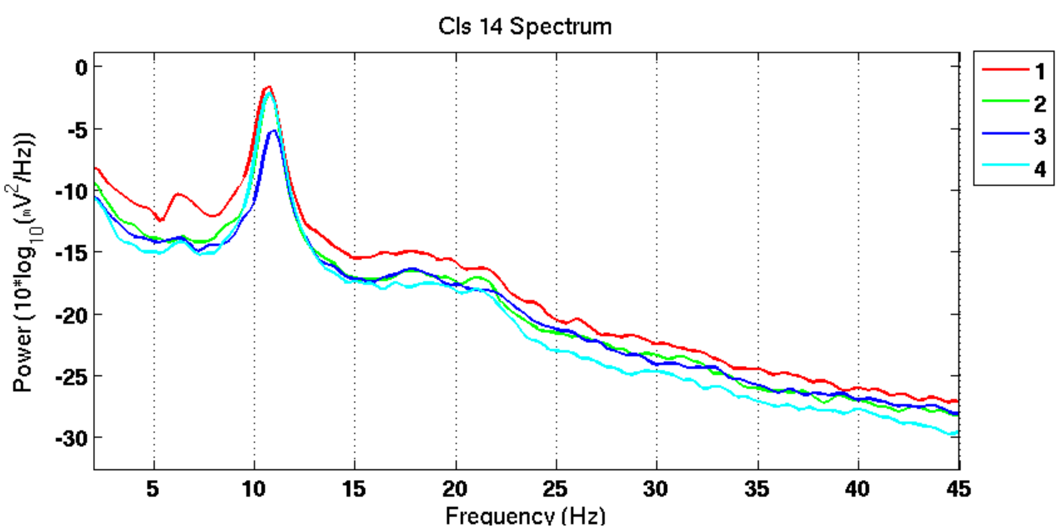
Results (Cluster 14)

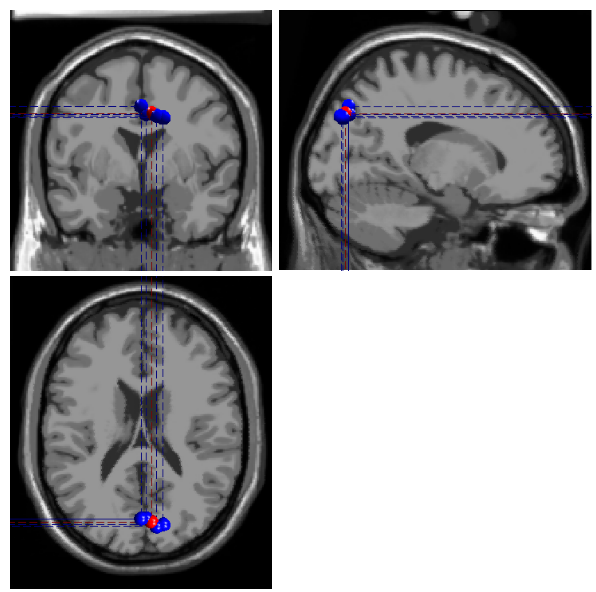
36.36% Sessions contribute











Inter iteration Cluster Consistency

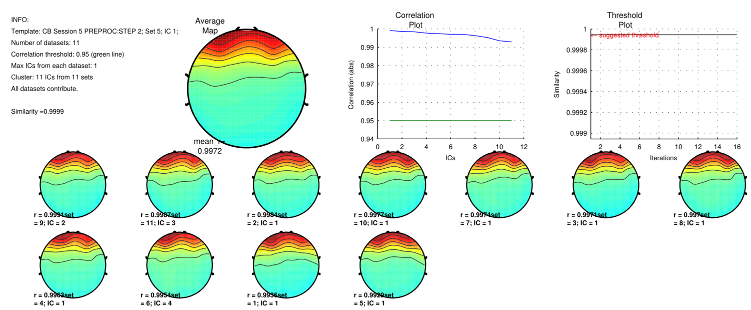
Iterations

Clusters

	1	2	3	4	5	6	7	8	9	10	Mean
3	100	100	100	100	100	100	100	100	100	100	**100**
4	100	100	100	100	100	100	90	100	100	100	**99**
5	90	40	10	90	90	60	100	10	60	90	**64**
6	60	0	100	60	100	90	60	60	90	60	**68**
7	90	100	90	90	60	90	90	100	90	90	**89**
8	80	80	60	80	40	80	80	80	80	100	**76**
9	60	90	50	60	80	60	0	10	60	50	**52**
10	40	90	10	40	0	50	50	0	50	60	**39**
11	60	20	0	0	10	60	10	90	60	60	**37**
12	100	50	50	100	50	100	100	50	100	50	**75**
13	50	10	20	50	90	50	50	10	50	20	**40**
14	20	10	10	20	20	30	20	20	30	30	**21**

ICA reliability within subjects

ICA components are stable within subjects



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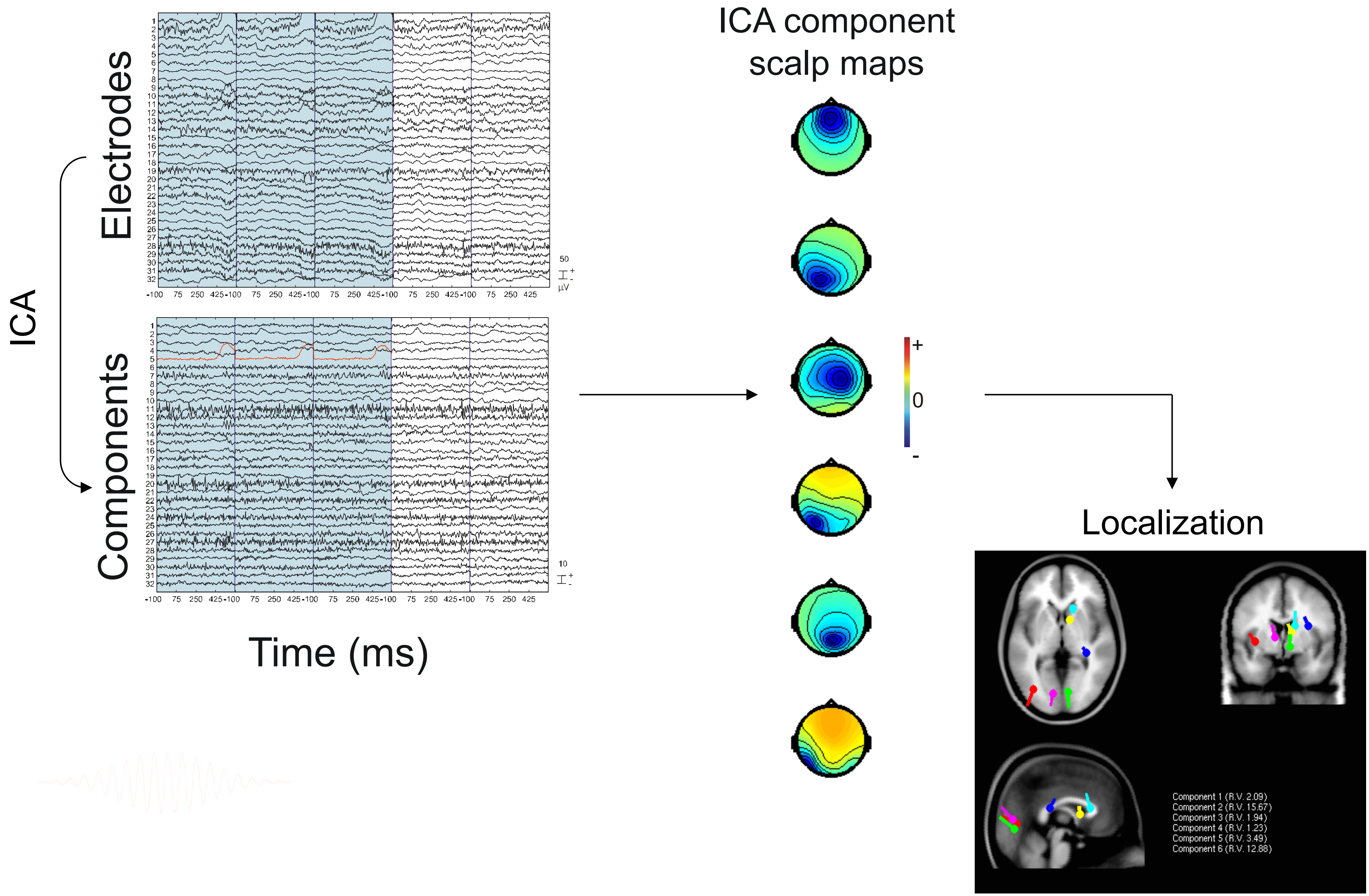
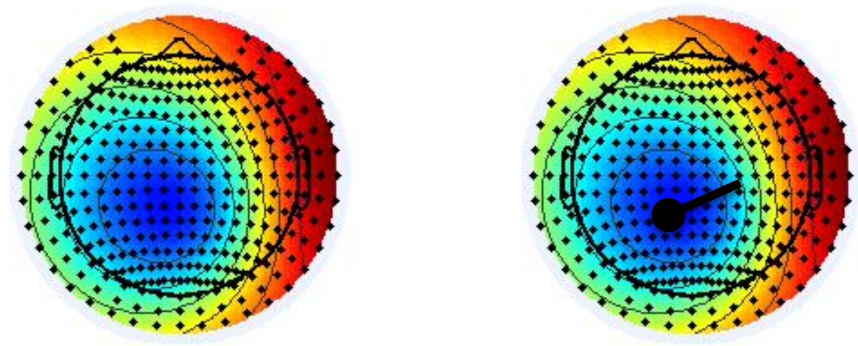
Localization



Computing residual variance (%)

Actual Dipole projection



$$r = \sum (x_i - \tilde{x}_i)^2 / \sum x_i^2$$

Validation of the ICA algorithm for EEG

Data

• 13 subjects performing a memory task
• 71 electrodes including EOGs
• more than 300,000 data points/subject

Decomposition

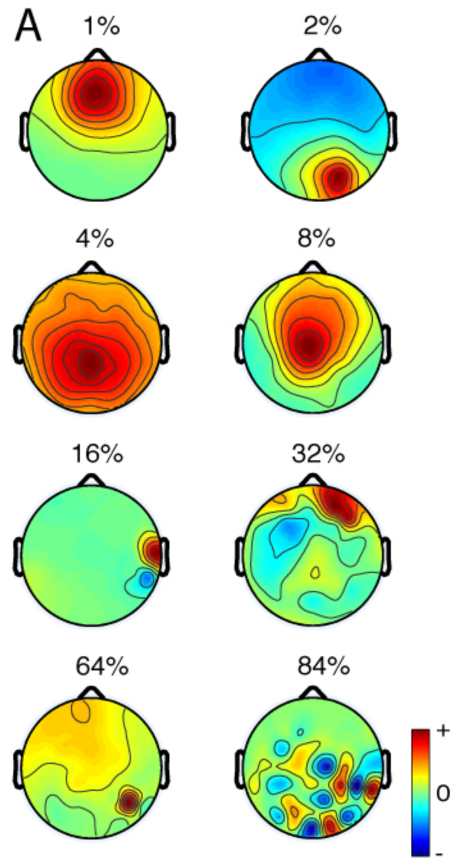
• 23 ICA algorithms plus PCA and Promax

Analysis

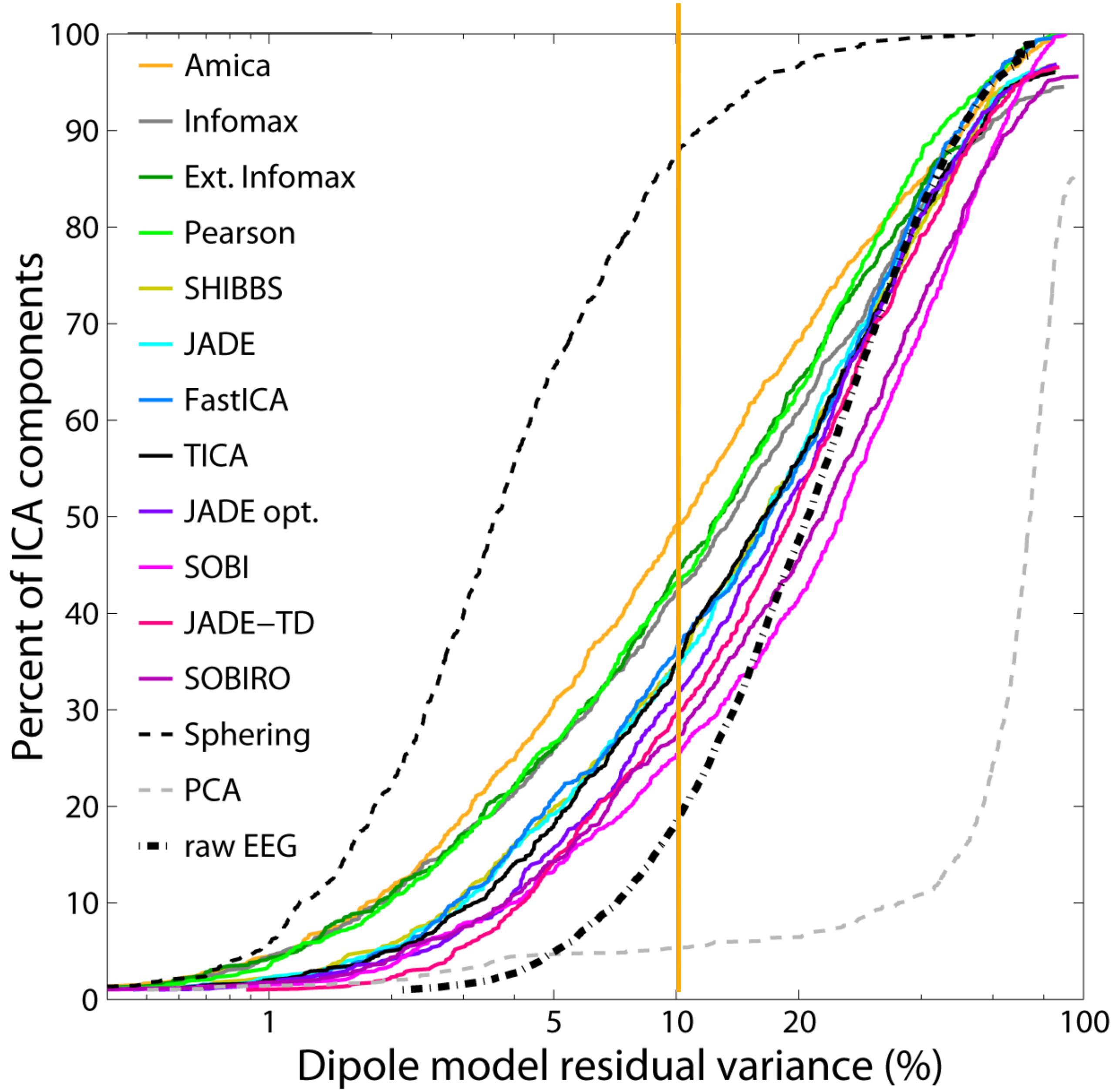
• Localization of all components with a single dipole
(4-shell spherical model)

Algorithm (Matlab func.)	D%	LL	Origin
Extended Infomax (runica)	29.9	178	EEGLAB 4.515
Pearson	29.1	169	ICAcentral (6)
Infomax (runica)	28.2	160	EEGLAB 4.515
ERICA	26.9	184	ICALAB 1.5.2
SONS	25.4	183	ICALAB 1.5.2
SHIBBS	23.7	169	ICAcentral (5)
FastICA*	23.5	169	ICAcentral (2)
JADE (jader)	23.4	169	EEGLAB 4.515
TICA	23.4	169	ICALAB 1.5.2
JADE optimized (jade_op)	21.4	169	ICALAB 1.5.2
JADE w/ time delay (jade_td)	20.2	169	ICALAB 1.5.2
eeA	19.0	305	ICAcentral (8)
Infomax (icaML) †	18.8	212	ICA DTU Tbox
FOBI	18.6	169	ICALAB 1.5.2
SOBIRO (acsobiro)	17.9	167	EEGLAB 4.515
EVD 24	17.7	169	ICALAB 1.5.2
EVD	17.0	169	ICALAB 1.5.2
SOBI	16.1	583	EEGLAB 4.515
icaMS†	10.6	169	ICA DTU Tbox
AMUSE	8.5	169	ICALAB 1.5.2
PCA	3.1	583	EEGLAB 4.515
Promax	33.7	467	EEGLAB 4.515
Whitening/Sphering	57.6	164	EEGLAB 4.515

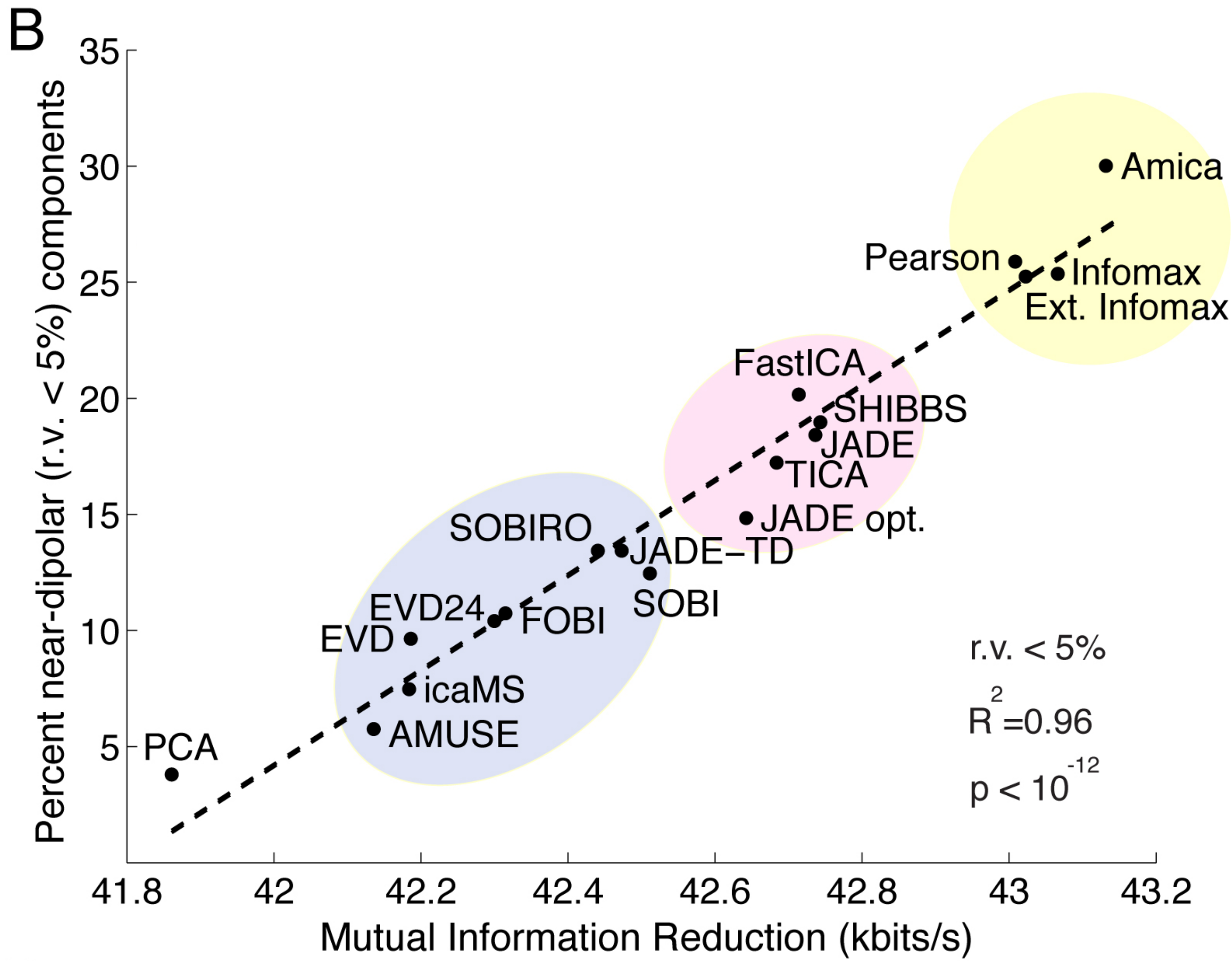
Component examples

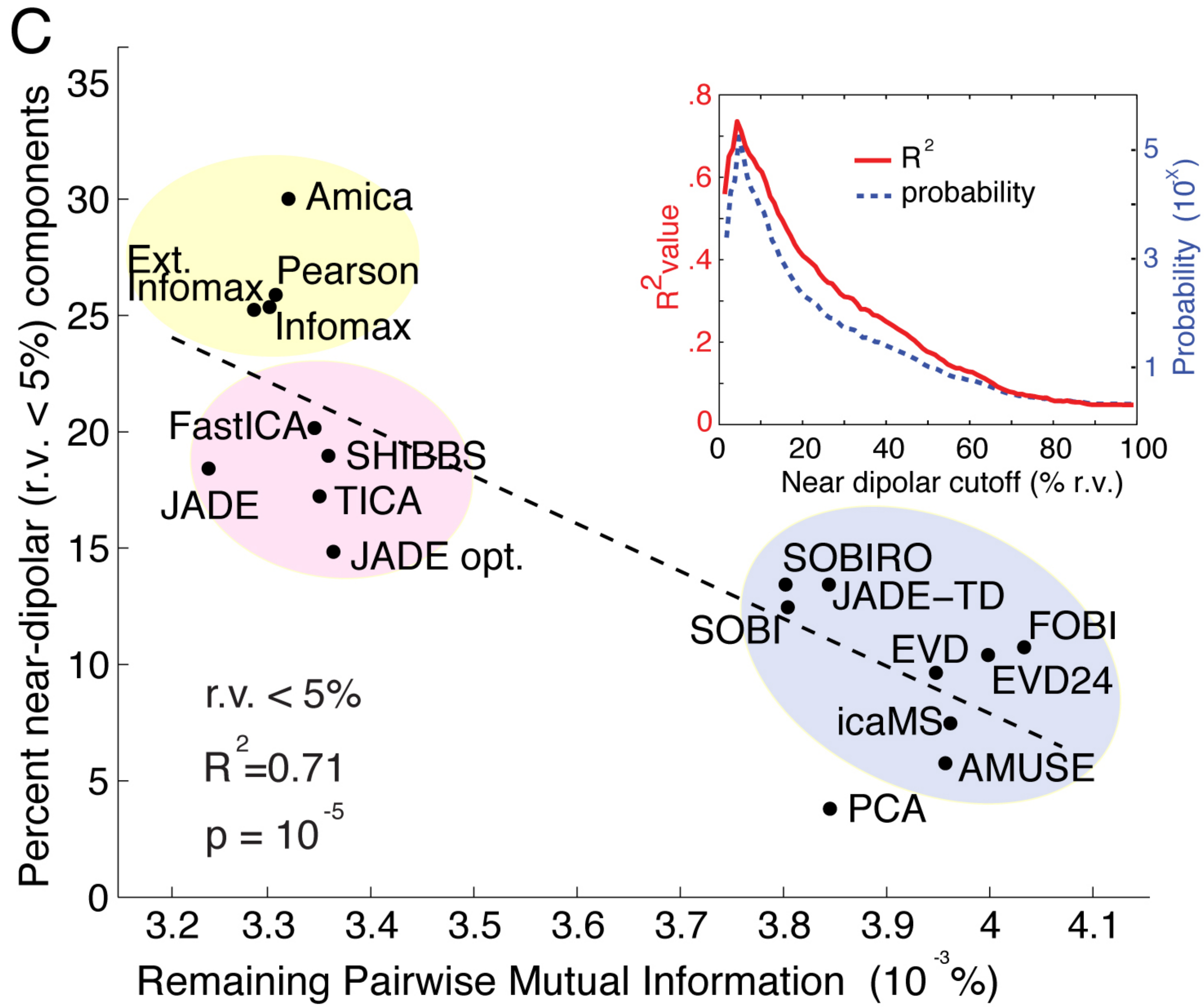


Nombre de composants inférieurs à chaque seuil de variance résiduelle



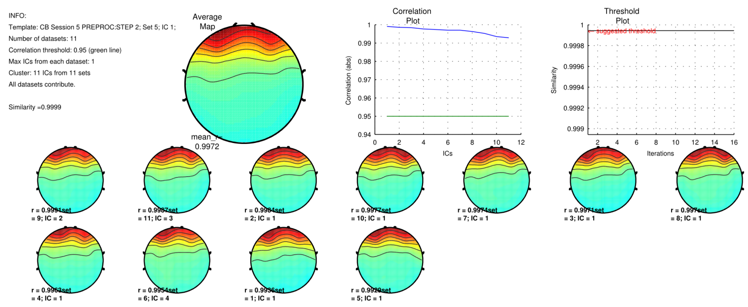
More independence -> more biological components



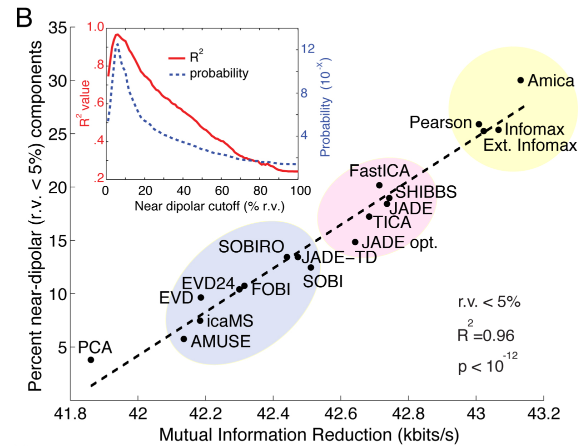

C
Percent near-dipolar (r.v. < 5%) components
Remaining Pairwise Mutual Information (10^-3 %)
Amica
Ext. Infomax
Pearson
Infomax
FastICA
SHIBBS
JADE
TICA
JADE opt.
SOBIRO
JADE−TD
SOBI
FOBI
EVD
EVD24
icaMS
AMUSE
PCA
r.v. < 5%
R^2=0.71
p = 10^-5
R^2
probability
R^2 value
Probability (10^x)
Near dipolar cutoff (% r.v.)

ICA reliability

• ICA components are stable within subjects



• Across subjects, the ICA algorithms that return the most biologically plausible solutions are also the one that return the most independent decompositions



Thanks to:

Jason Palmer

Romain Grandchamp

Claire Braboszcz

Scott Makeig