University of Glasgow | Institute of Neuroscience & Psychology

Centre for Cognitive Neuroimaging (CCNi)

Introduction to robust estimation of ERP data

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https://garstats.wordpress.com

@robustgar

Take-home messages

- ***Look at your data***

- ***Show your data***

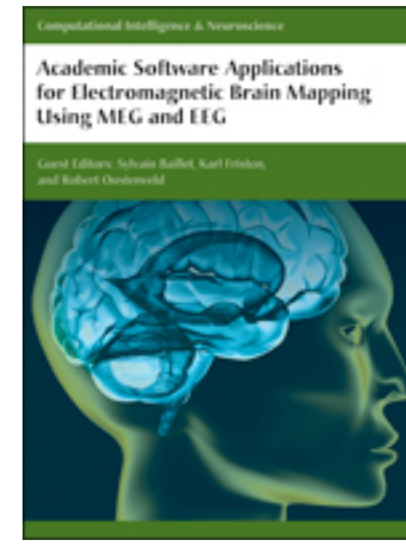
- ***A perfect & universal statistical recipe does not exist***

- ***Keep exploring: there are many great options, most of them available in free softwares and toolboxes***

Computational Intelligence and Neuroscience

Academic Software Applications for Electromagnetic Brain Mapping Using MEG and EEG

Guest Editors: Sylvain Baillet, Karl Friston, and Robert Oostenveld

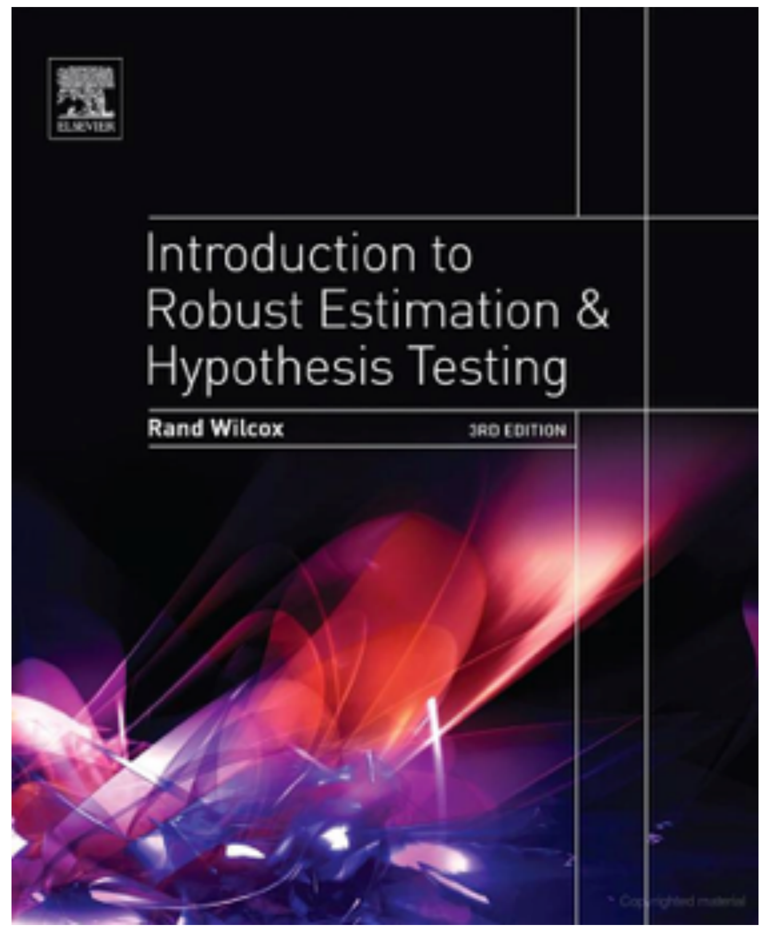


http://sccn.ucsd.edu/wiki/EEGLAB_Extensions

List of data processing extensions

Plug-in name	Version	Short plug-in description	Link	Contact	Comments
rERP	0.4	Estimate overlapping ERPs using multiple regression	Download	M. Burns	User comments
LIMO	1.5	LInear MOdelling of EEG data	Download	C. Pernet	User comments
corrmap	2.02	Cluster ICA components using correlation of scalp maps	Download	S. Debener	User comments
bioelectromag	1.01	Uses Bioelectromagnetism toolbox for ERP peak detection	Download	D. Weber	User comments
VisEd	1.05	Add/Edit dataset events	Download	J. Desjardins	User comments
loreta	1.10	Export and import data to and from LORETA software	Download	A. Delorme	User comments
iirfilt	1.02	Non linear filtering using IIR filter	Download	M. Pozdin	User comments
std_envtopo	2.34	Plot STUDY ICA cluster contribution to ERP	Download	M. Miyakoshi	User comments
std_backproj	0.21	Back-project cluster ICs to channels (beta)	Download	M. Miyakoshi	User comments
dipoleDensity	0.11	Plot STUDY ICA cluster dipole density (beta)	Download	M. Miyakoshi	User comments
std_ErpCalc	0.10	Test and visualize simple effects on ERP (beta)	Download	M. Miyakoshi	User comments
pvaftopo	0.10	Plot topography of percent variance accounted for (beta)	Download	M. Miyakoshi	User comments
trimOutlier	0.15	Trim outlier channels and datapoints interactively (beta)	Download	M. Miyakoshi	User comments
clean_rawdata	0.21	Cleans continuous data using Artifact Subspace Reconstruction	Download	Miyakoshi and Kothe	User comments
Mutual_Info_Clustering	1.00	Group single dataset ICA components by Mutual Information	Download	N. Bigdely	User comments
mass_univ	130502	Mass Univariate ERP Toolbox	Download	D. Groppe	User comments
REGICA	1.00	ICA regression based EOG removal	Download	M. Klados	User comments
MARA	1.1	Multiple Artifact Rejection Algorithm	Download	I. Winkler	User comments
firfilt	1.6.1	Routines for designing linear filters	Download	A. Widmann	User comments
PACT	0.14	Computes phase-amplitude coupling for continuous data	Download	M. Miyakoshi	User comments
fMRIb	2.00	Remove fMRI artifacts from EEG	Download	J. Dien & R. Niazy	User comments
SIFT	1.33	Analysis and visualization of multivariate connectivity	Download	T. Mullen	User comments
AAR	131130	ICA-based Automatic Artifact Removal	Download	G. Gomez-Herrero	User comments
Adjust	131130	Automatic Detector - Joint Use of Spatial and Temporal features	Download	Adjust Support	User comments
Cleanline	1.00	Removes sinusoidal artifacts (line noise)	Download	T. Mullen	User comments
Fieldtrip-lite	Daily	Adds source localization and statistics tools to EEGLAB	Download	R. Oostenveld	User comments
EYE-EEG	0.41	Open source MATLAB tool for simultaneous eye tracking & EEG	Download	O. Dimigen	User comments
BERGEN	131130	Remove fMRI artifacts from EEG	Download	M. Moosmann	User comments
CIAC	1.00	Cochlear Implant Artifact Correction	Download	S. Debener	User comments
LR	1.2	Linear Discrimination	Download	P. Sajda	User comments
GEVD	1.00	Generalized Eigenvalue Decomposition (GEVD)	Download	P. Sajda	User comments
CSP	1.1	Common Spatial Patterns	Download	P. Sajda	User comments
Eyesubtract	1.0	Eye Movement Artifact Removal	Download	P. Sajda	User comments
Peakfit	1.0	Single trial EEG peak fitting	Download	P. Sajda	User comments

Robust statistics: the one book you really need



Wilcox, R. R. (2012)

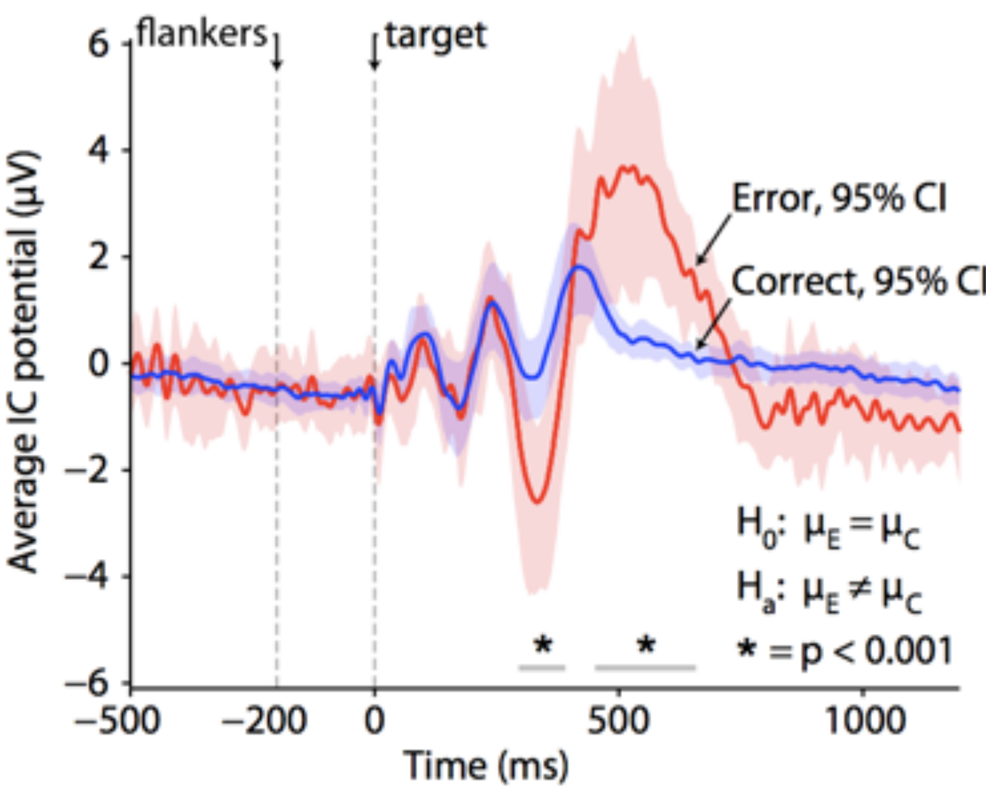
Introduction to robust estimation and hypothesis testing (3rd ed.)

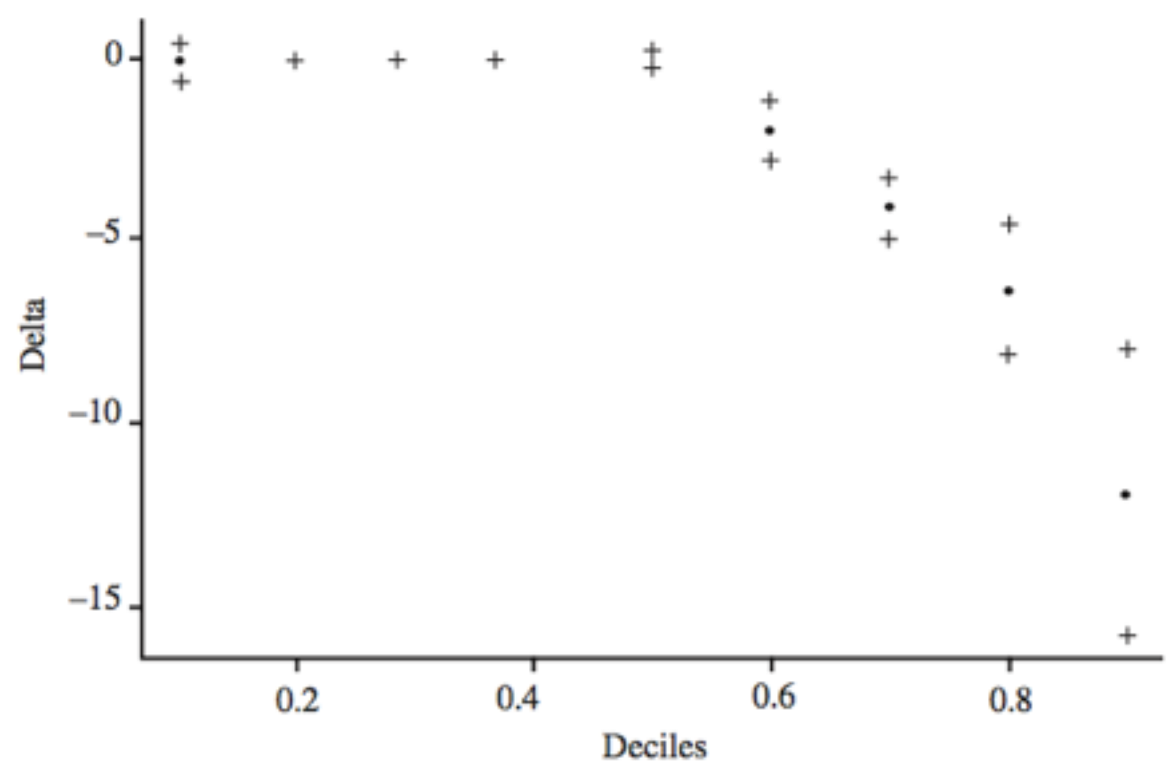
Academic Press

References: making more informative figures

Allen, E.A., Erhardt, E.B. & Calhoun, V.D. (2012) Data visualization in the neurosciences: overcoming the curse of dimensionality. Neuron, 74, 603-608.

Wilcox, R.R. (2006) Graphical methods for assessing effect size: Some alternatives to Cohen's d. Journal of Experimental Education, 74, 353-367.





ERP references

Rousselet GA and Pernet CR (2011)
Quantifying the time course of visual object processing using ERPs: it's time to up the game
Frontiers in Psychology 2:97. doi: 10.3389/fpsyg.2011.00107

Rousselet GA, Pernet CR, Caldara R and Schyns PG (2011)
Visual object categorization in the brain: what can we really learn from ERP peaks?
Frontiers in Human Neuroscience 5:156. doi: 10.3389/fnhum.2011.00156

menu

[1] Standard ERP figure

[2] Better figures

[3] Better stats: robust estimation & hypothesis testing

[4] Single-subject analyses

[5] Yet better figures

[6] Control for multiple comparisons

[7] ANOVA example

[8] ANCOVA & linear contrasts example

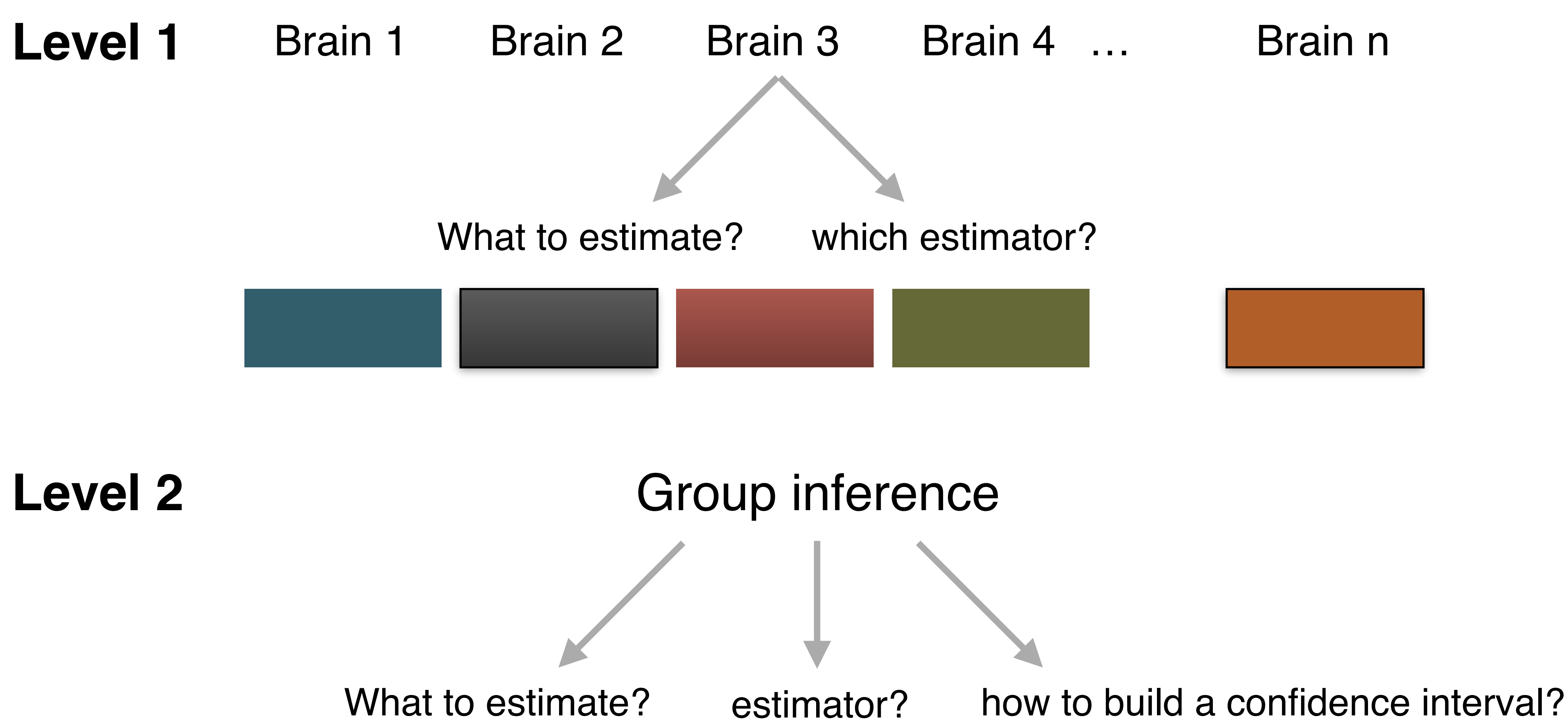
dataset

- 1 electrode only:
  - **erps.mat**: 20 subjects, 2 conditions, 500 Hz, -300:600 ms - single-trials
  - **erpm.mat**: averages with size (451x20x2)
  - **S1_1elec_epoch_ancova.set**: 2 subjects, ANCOVA - 500 Hz, single-trials

- All electrodes:
  - **S1_allelec_epoch.set**: 2 subjects, 250 Hz, -300:400 ms, single-trials

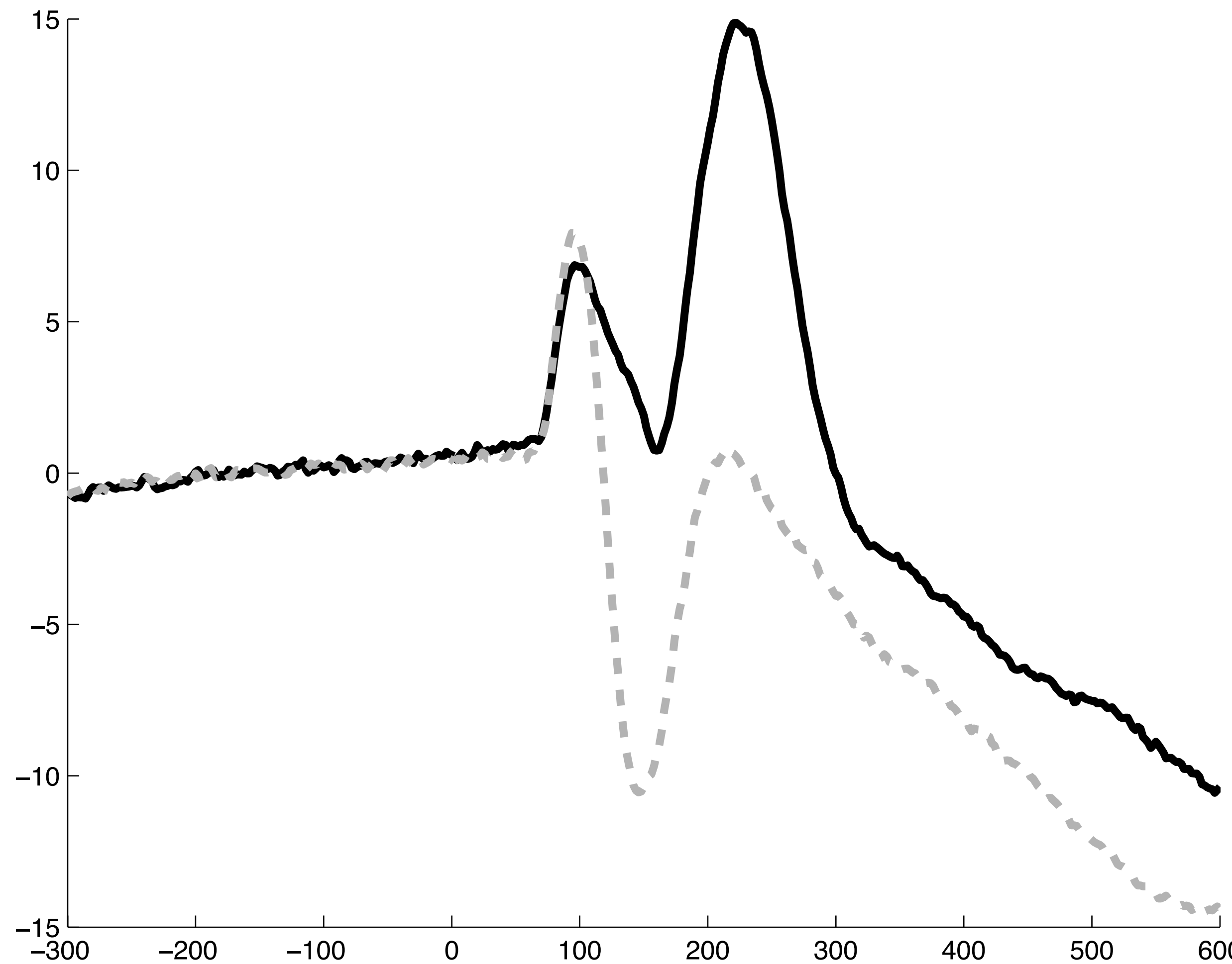
folders to add to your path:
eeglab + limo_eeg
shift_function

Levels of inferences

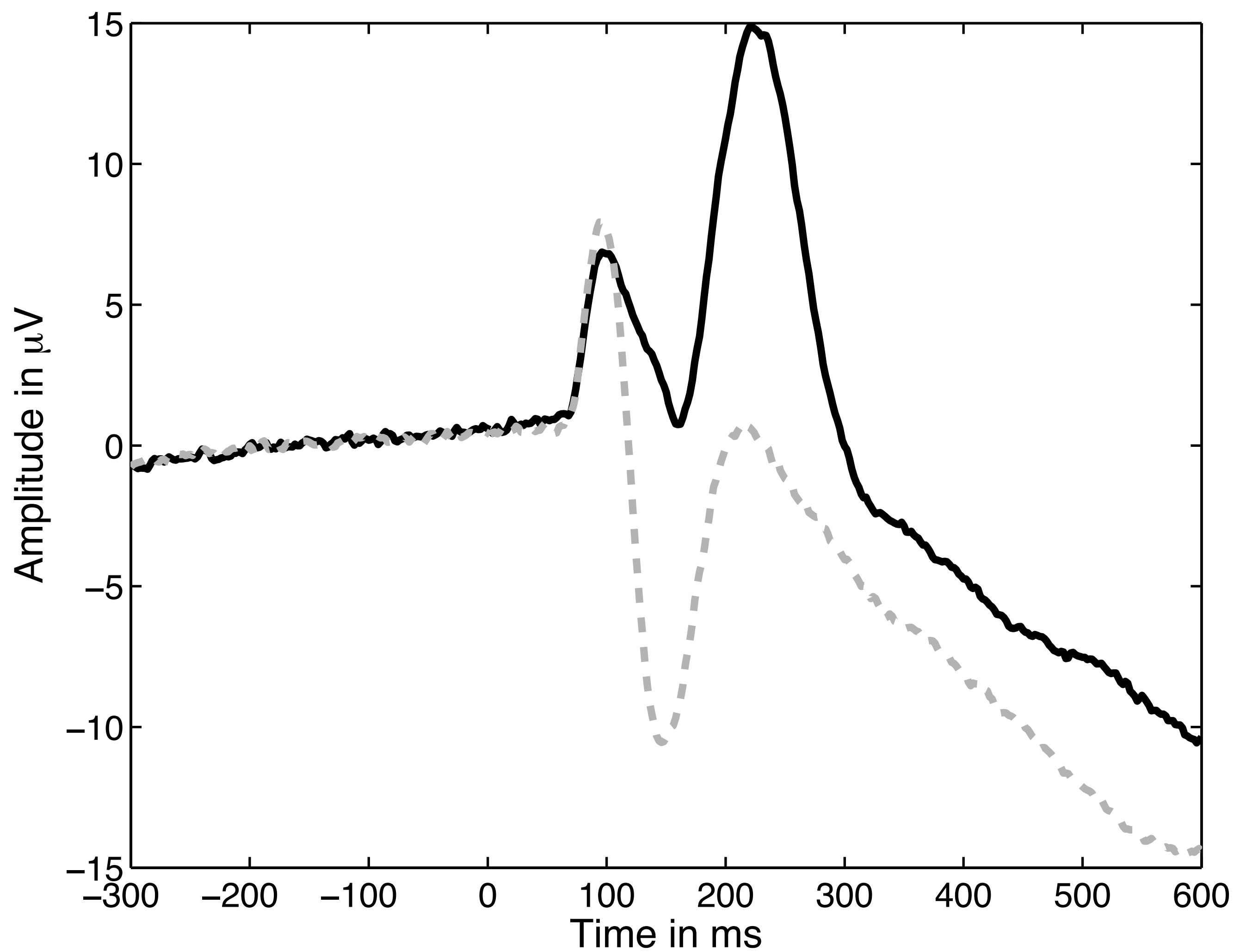


let’s get started: open Matlab...

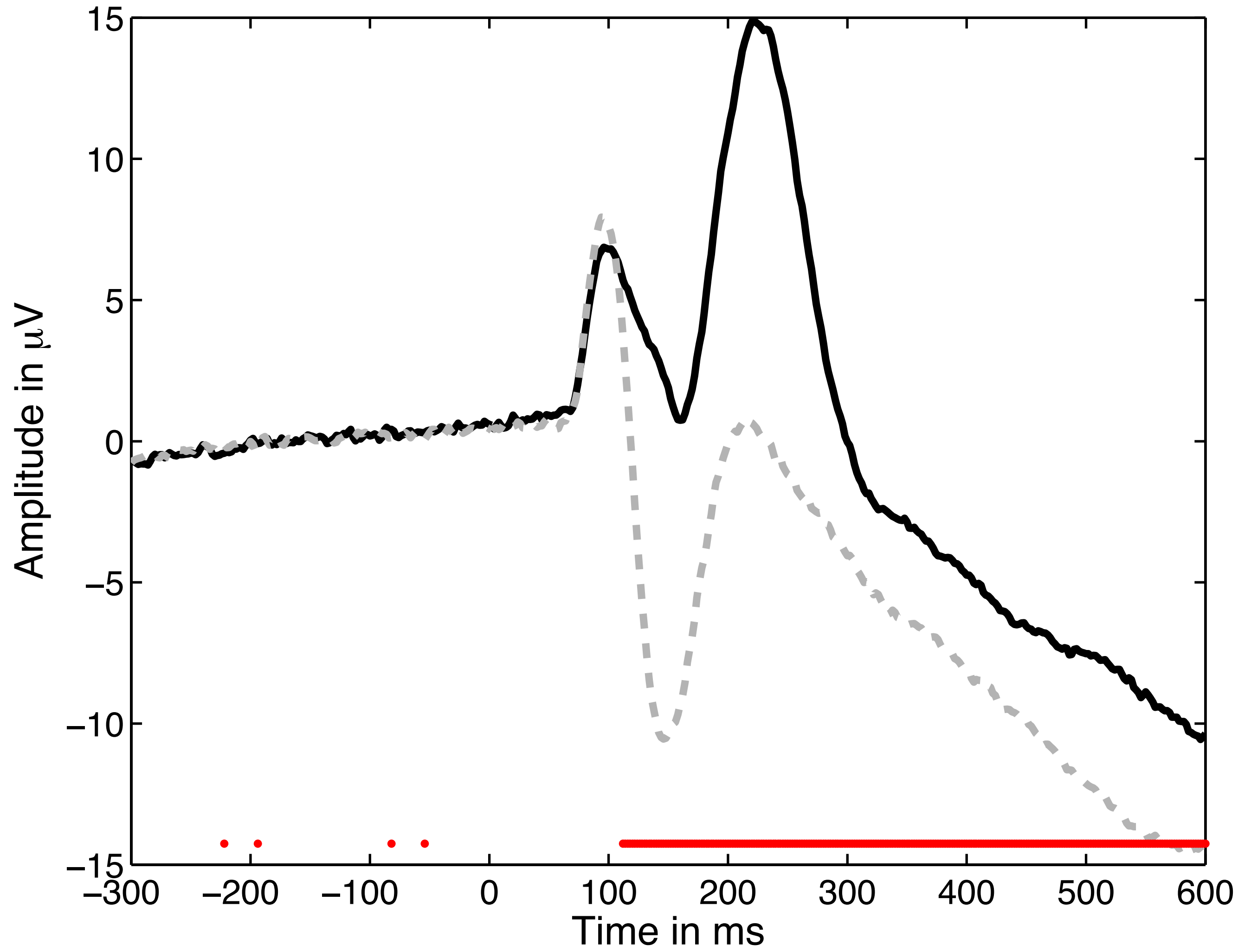
The standard ERP figure (1)



The standard ERP figure (2)

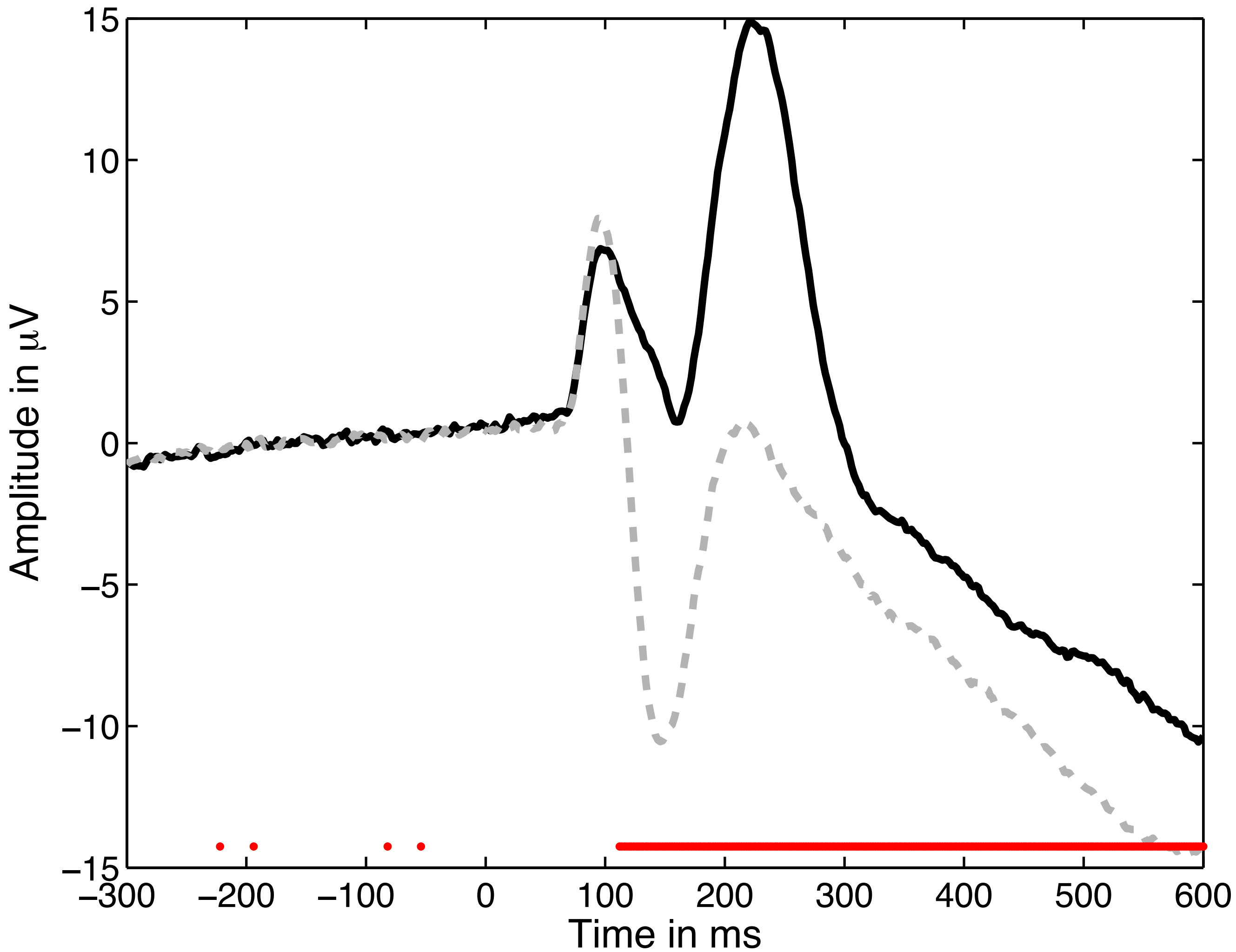


The standard ERP figure (3)



erp_workshop_1_standard_figure.m

Why the standard figure is not good enough



Interpretations should be limited to what was measured: group differences in means

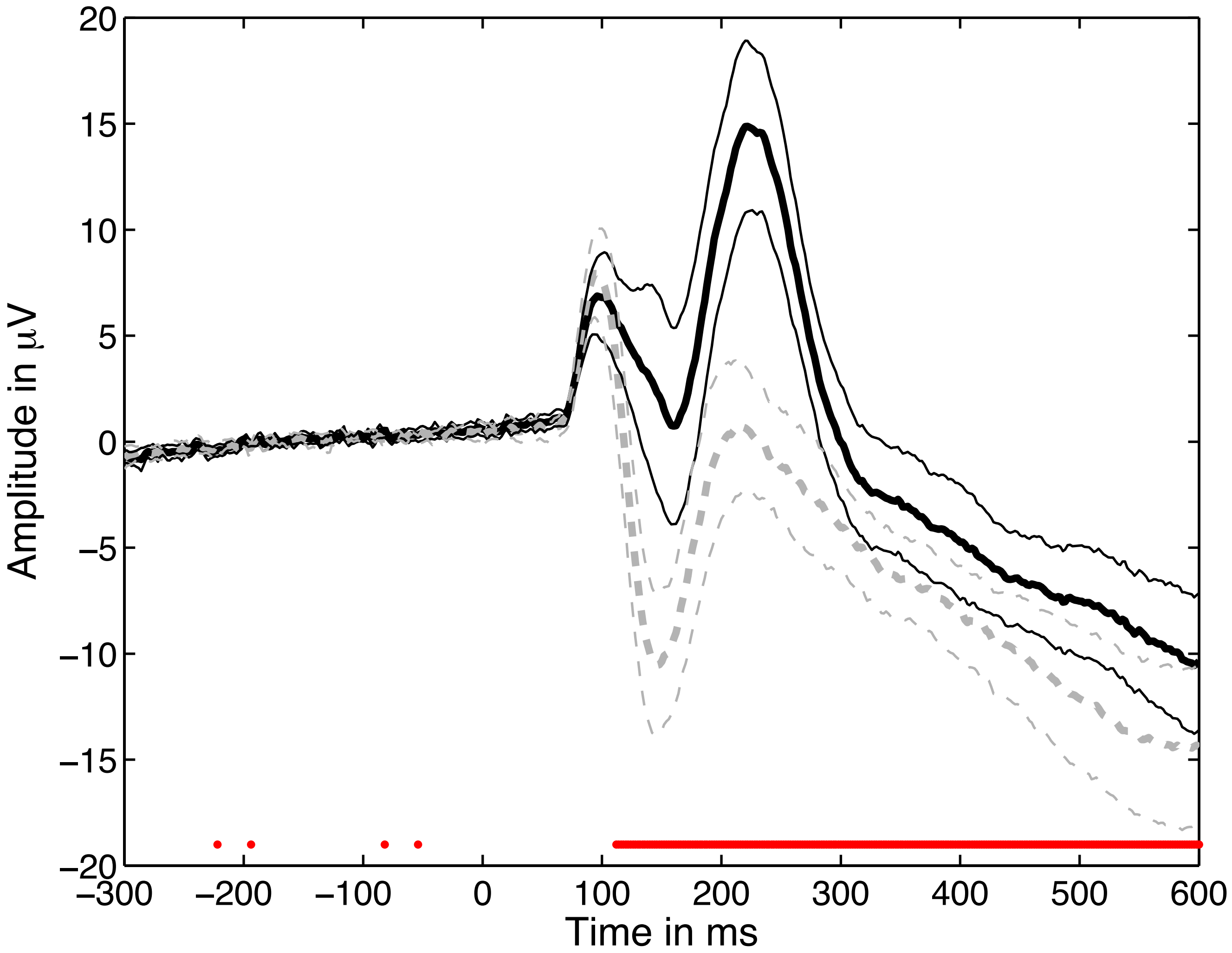
Significant effect?
- interesting?
- how many subjects?
- effect size?

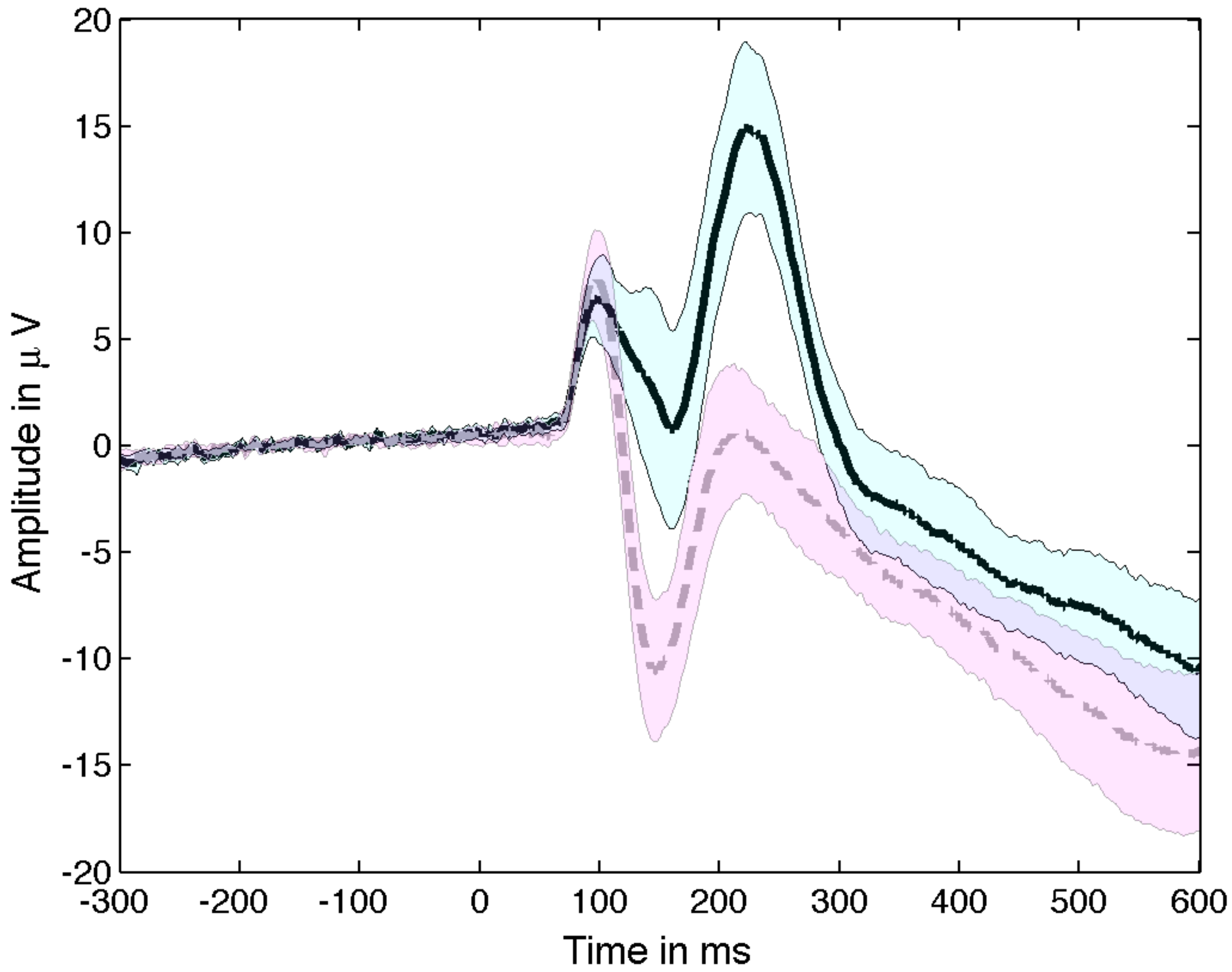
Non-significant effect?
- not there?
- lack of power?
- how many subjects?
- effect size?

Confidence intervals

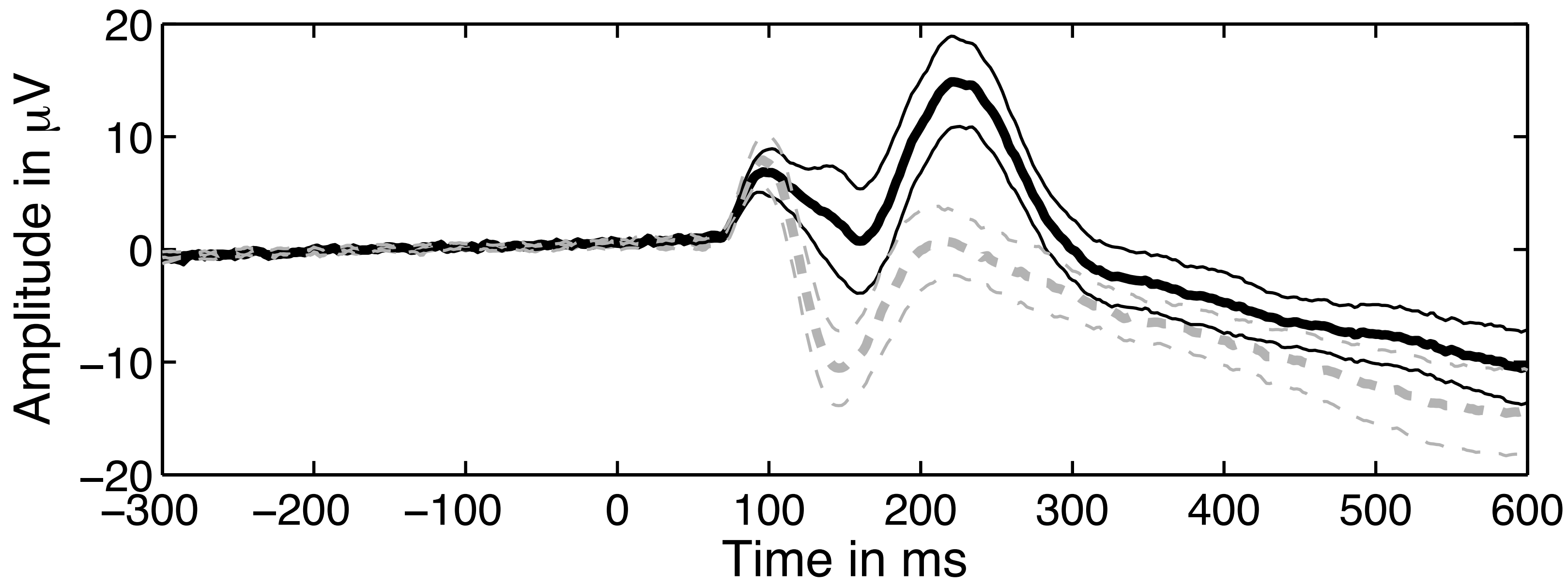
- ***limo_ttest***
- ***limo_trimci / limo_yuend_ttest / limo_yuen_ttest***
- ***limo_pbci***
- ***limo_boottttest1***
- ***limo_yuen_ttest_boot***
- *limo_central_tendency_and_ci*
- *limo_robust_ci*

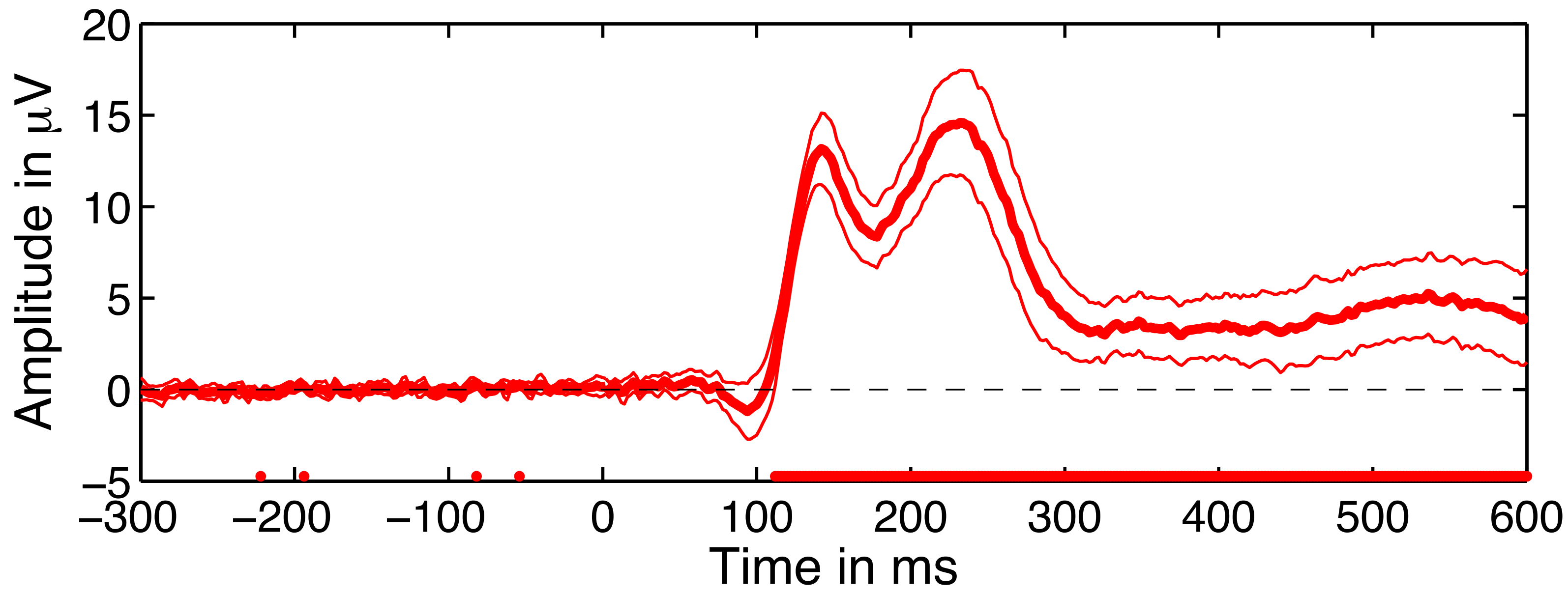
Add confidence intervals

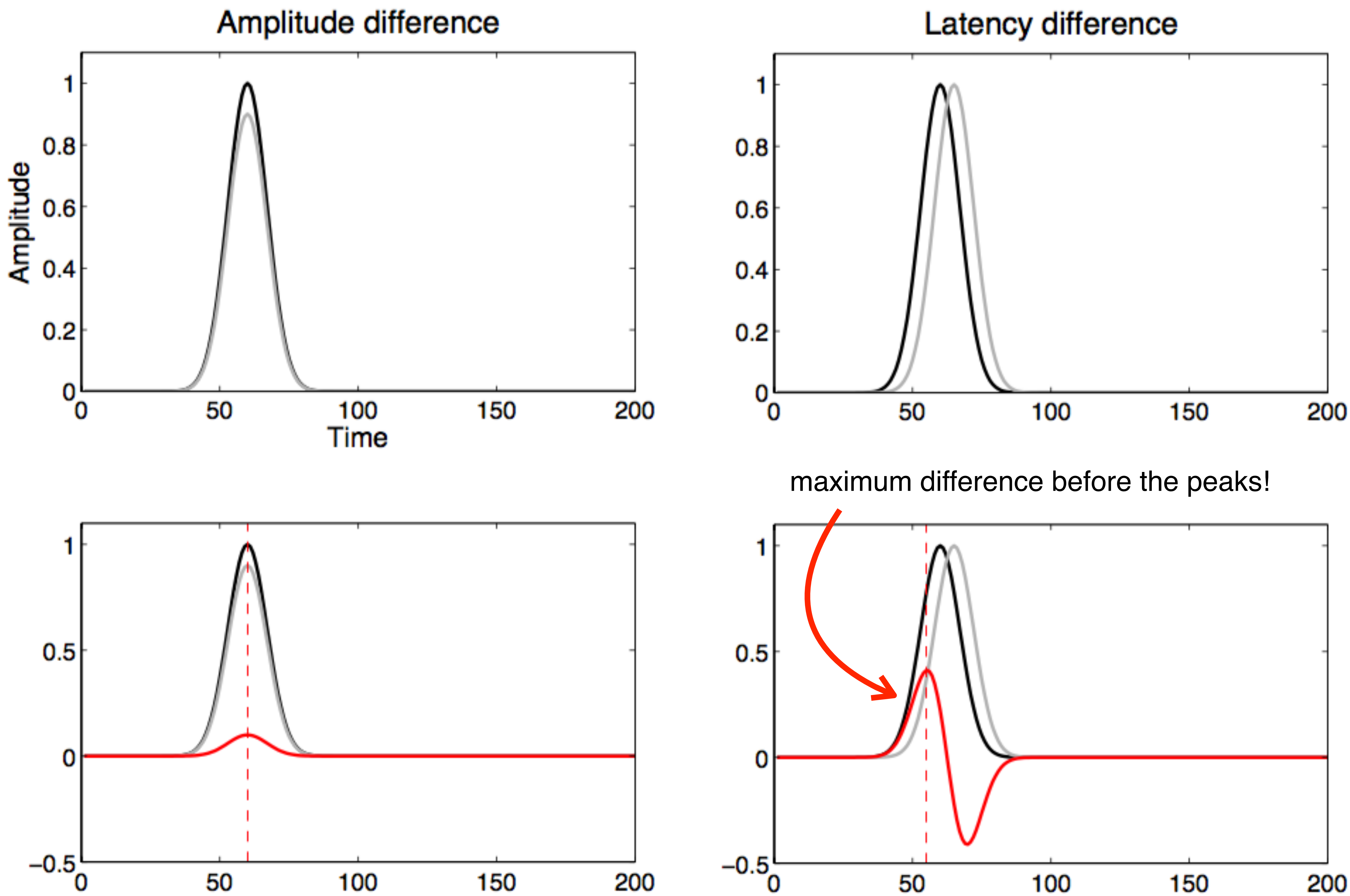




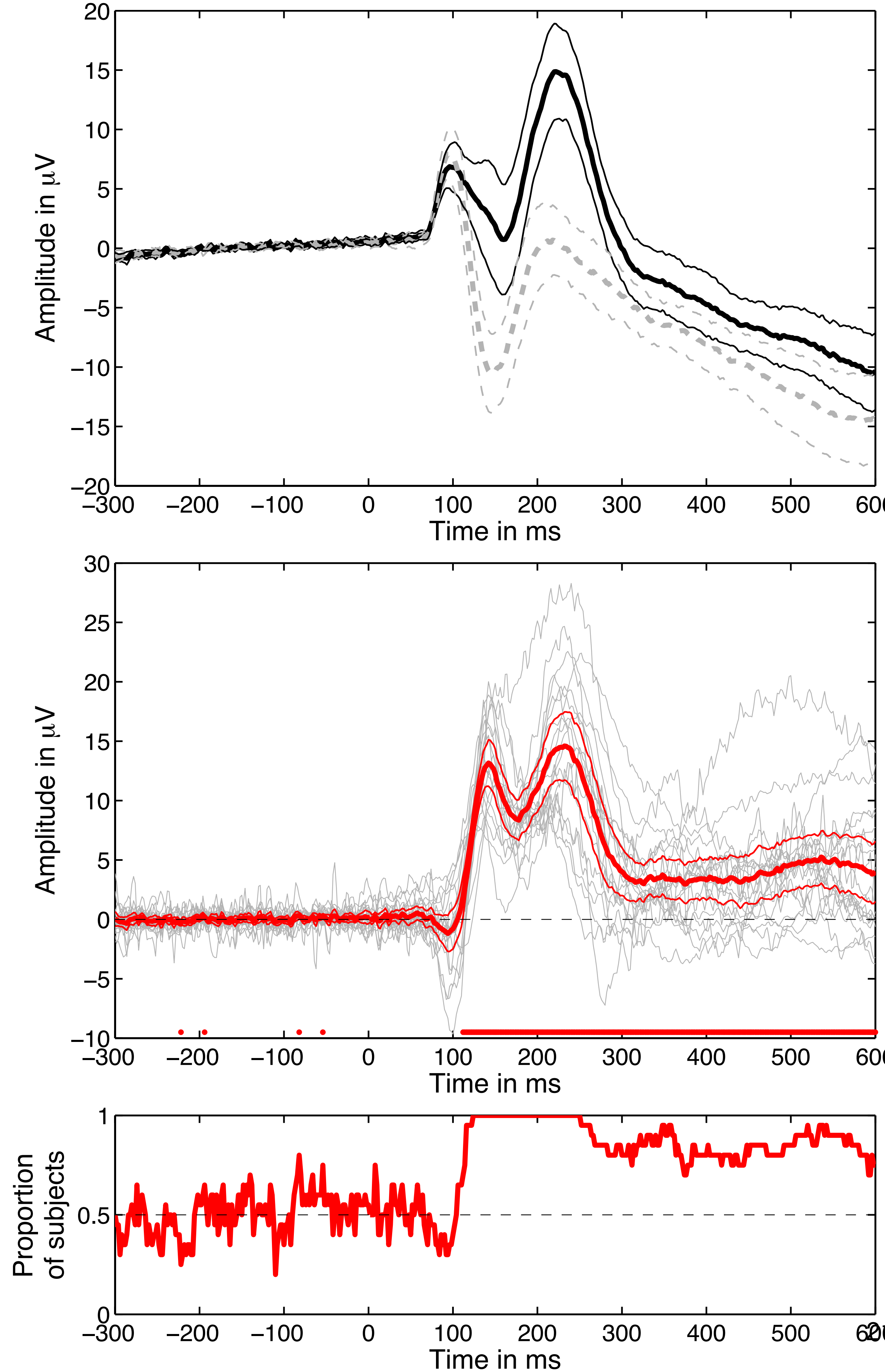
Add plot of the difference





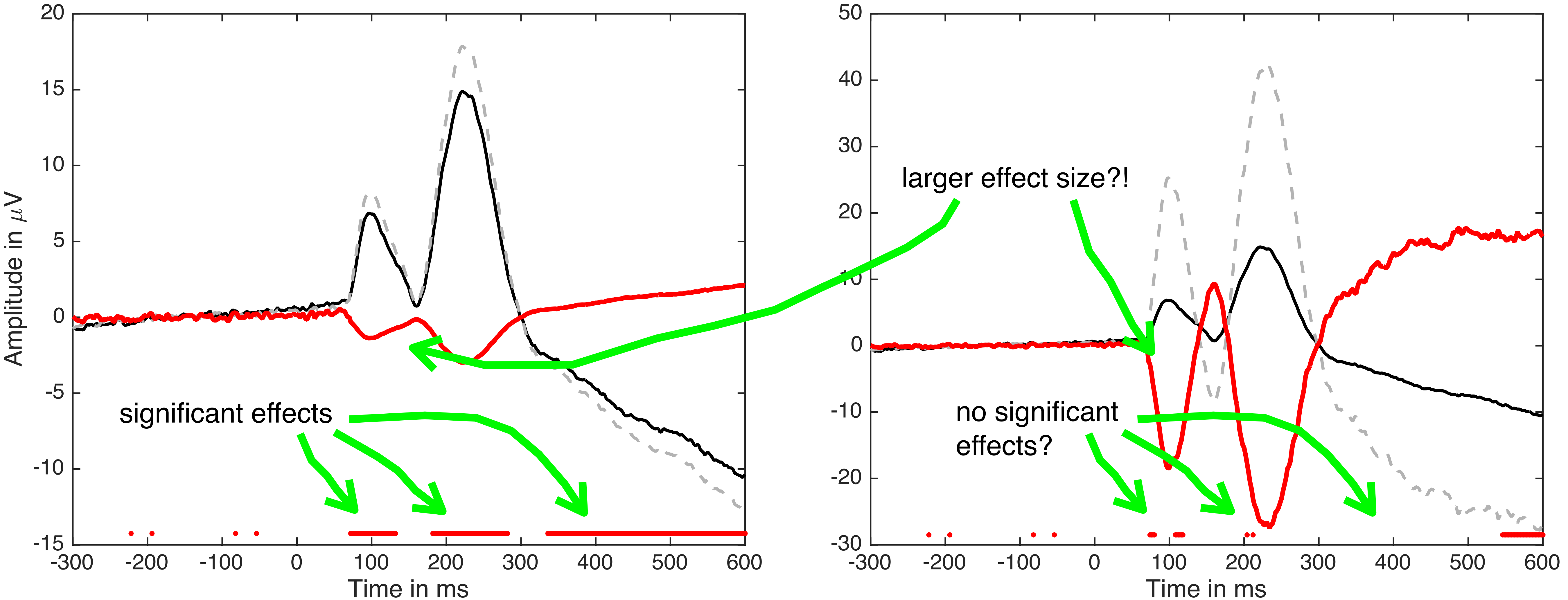

Amplitude difference
Latency difference
Amplitude
Time
maximum difference before the peaks!

How many subjects show an effect?

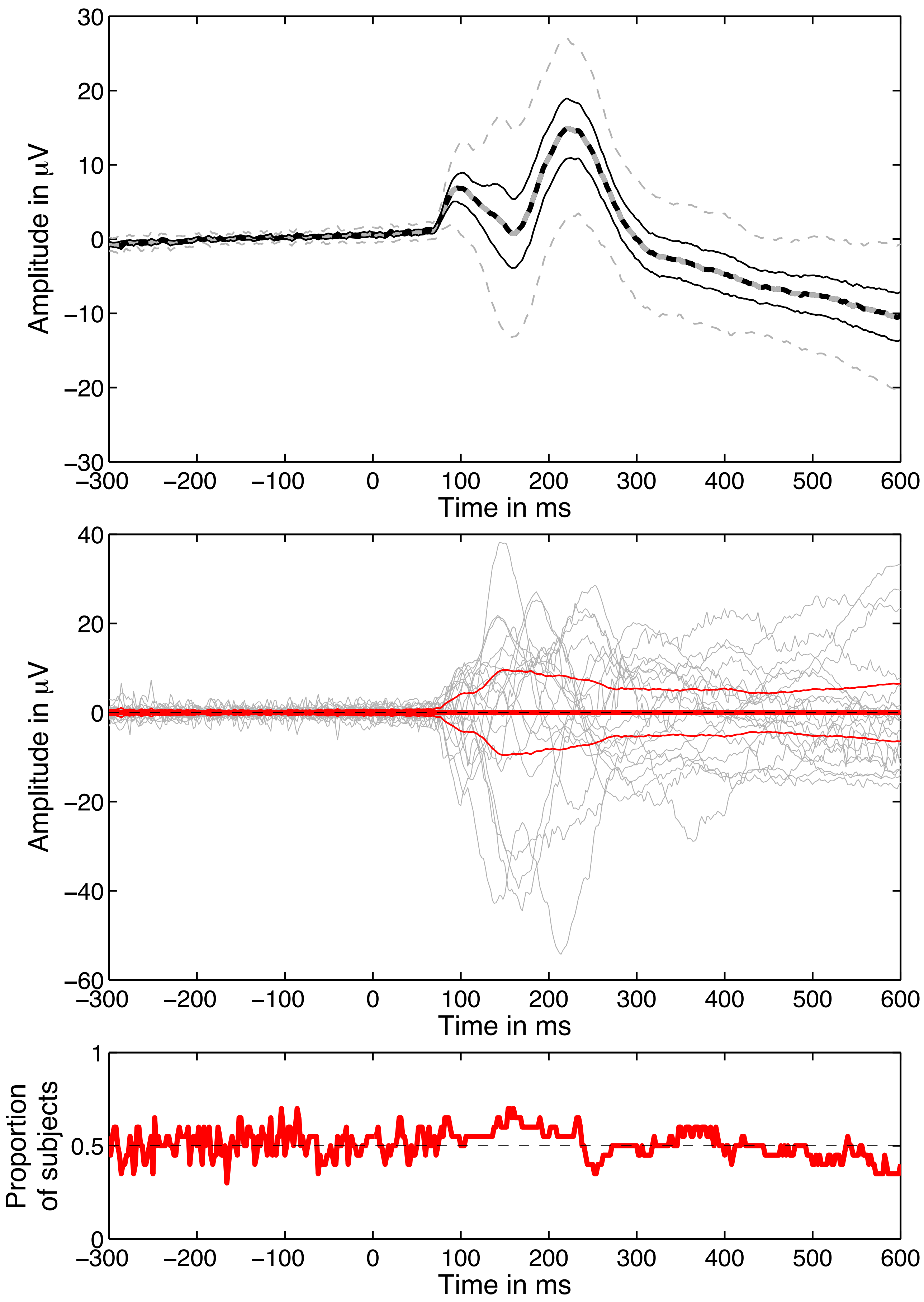


erp_workshop_2_better_figure.m

No effect? Case study 1



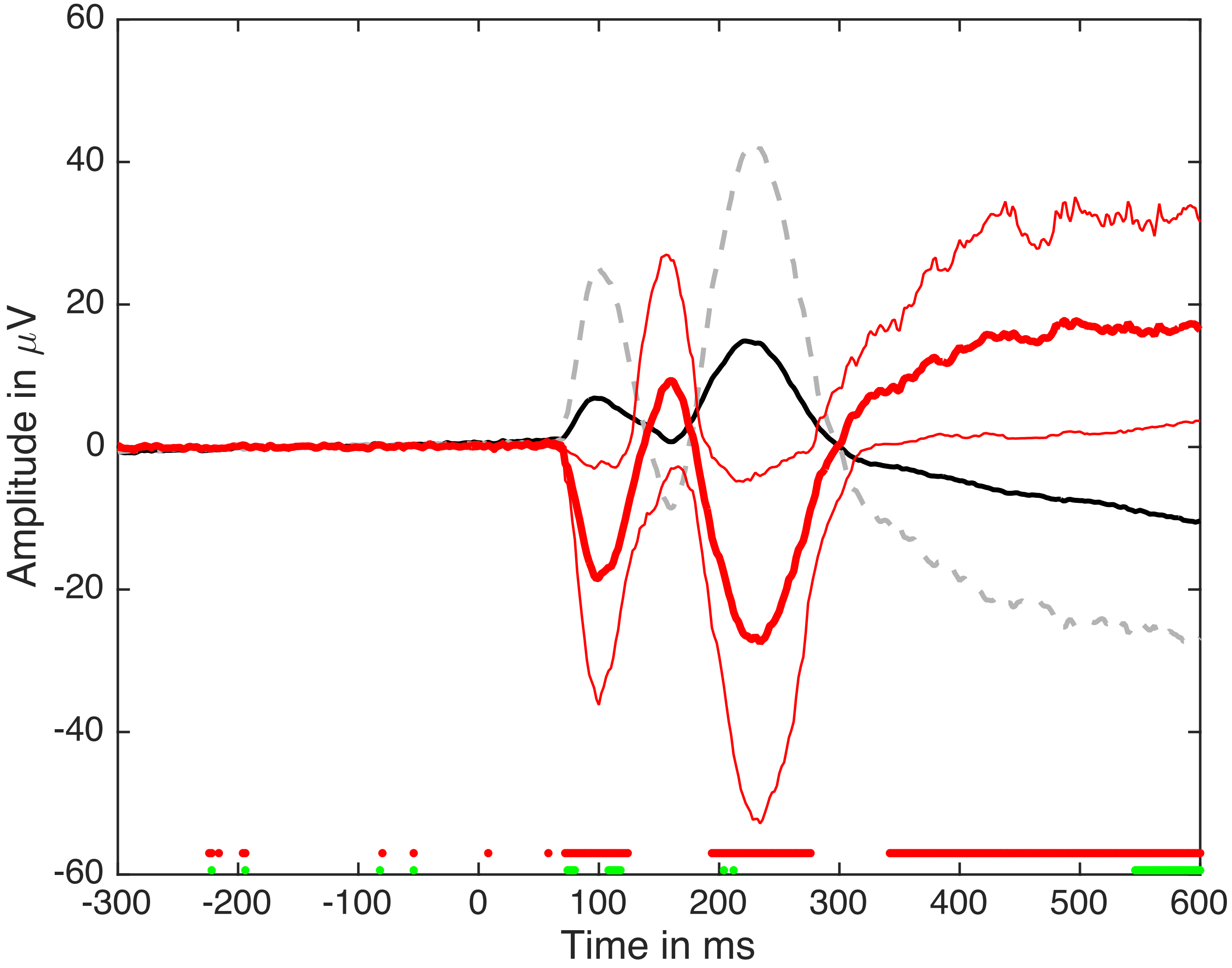
No effect? Case study 2



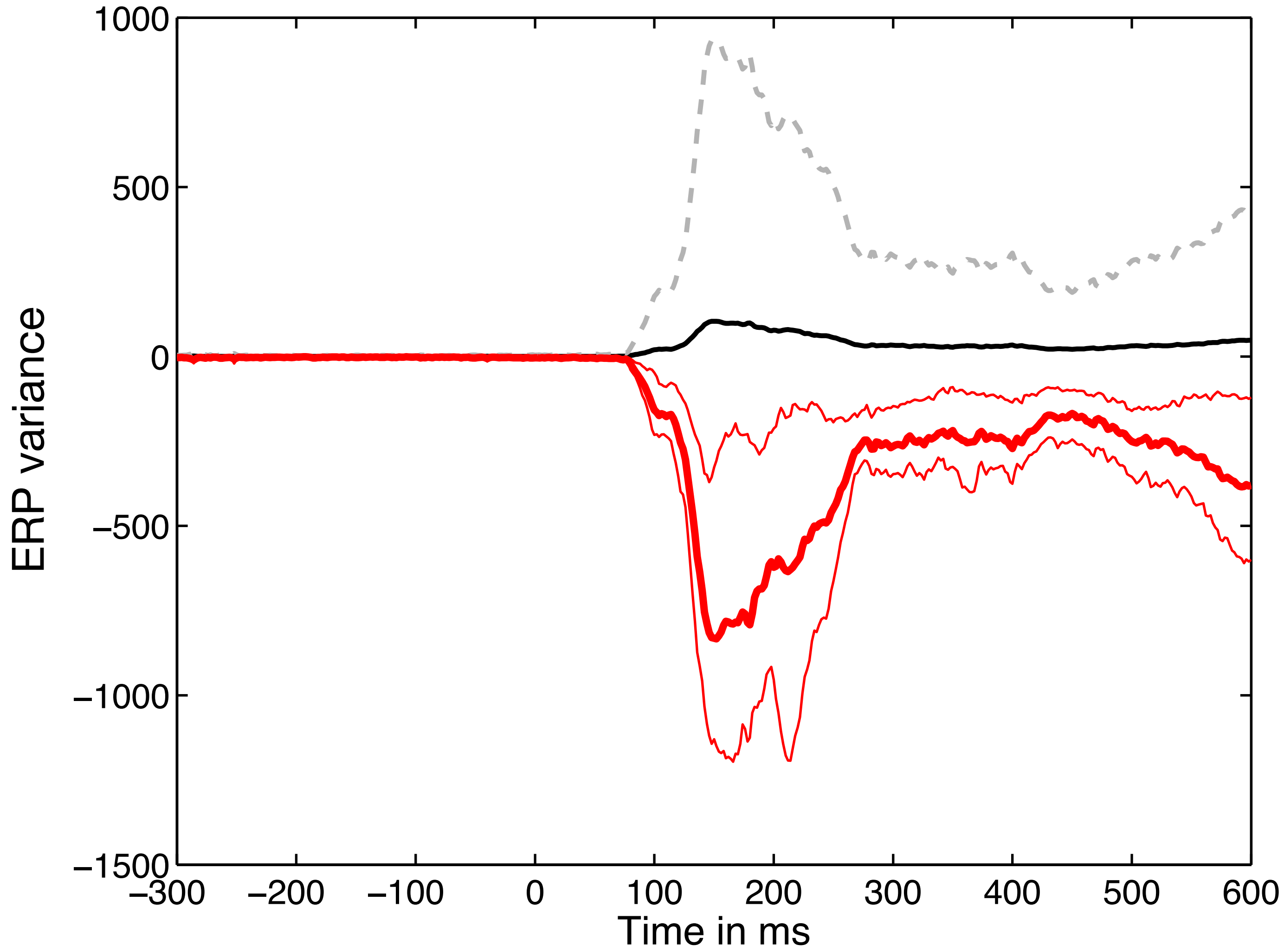
erp_workshop_3_case_studies.m

Solving case studies: percentile bootstrap

case 1: effect of outliers



case 2: difference in spread

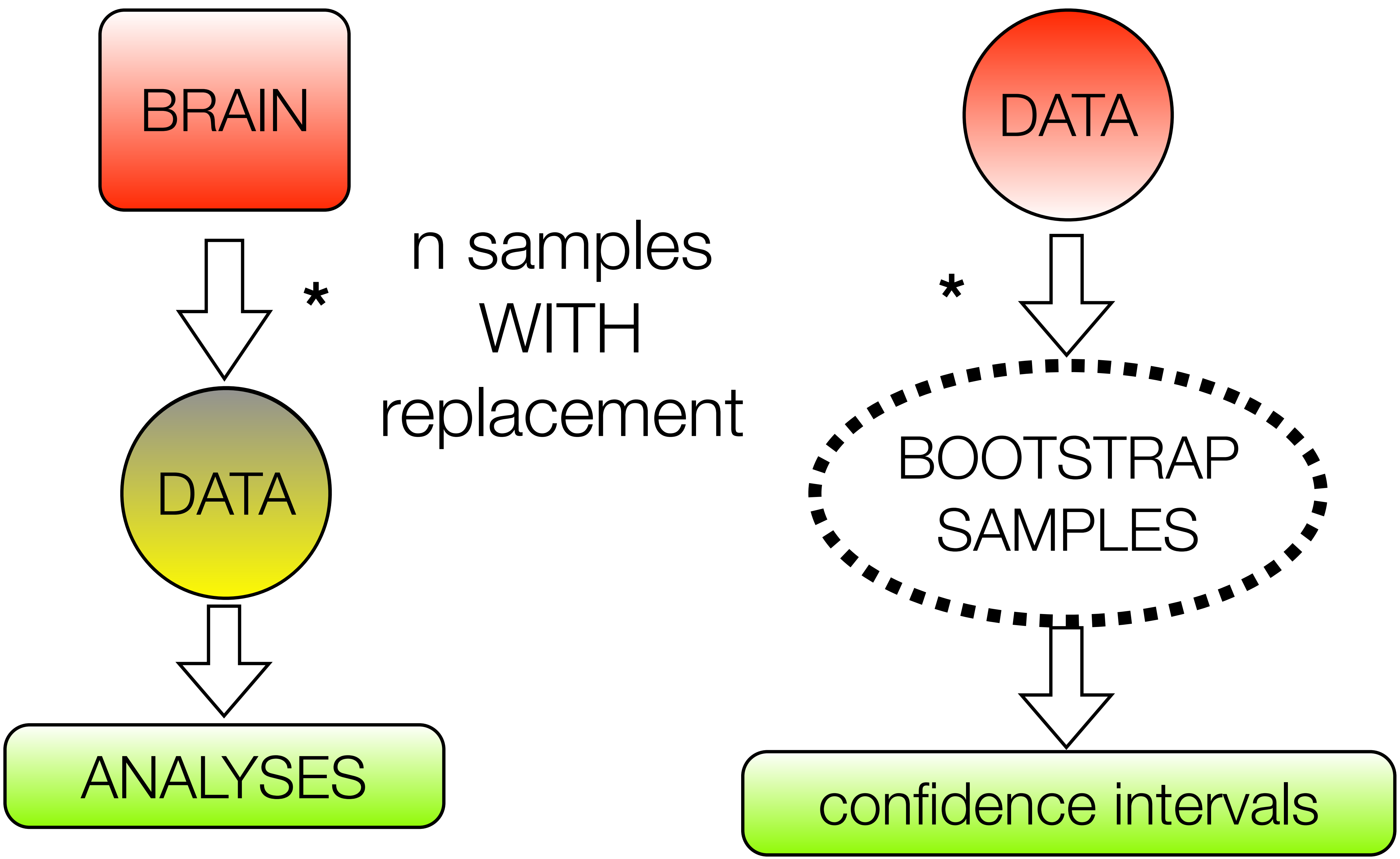


Bootstrap: central idea

- “The bootstrap is a computer-based method for assigning measures of accuracy to statistical estimates.” Efron & Tibshirani, An introduction to the bootstrap, 1993

- “The central idea is that it may sometimes be better to draw conclusions about the characteristics of a population strictly from the sample at hand, rather than by making perhaps unrealistic assumptions about the population.”
  Mooney & Duval, Bootstrapping, 1993

Bootstrap: philosophy



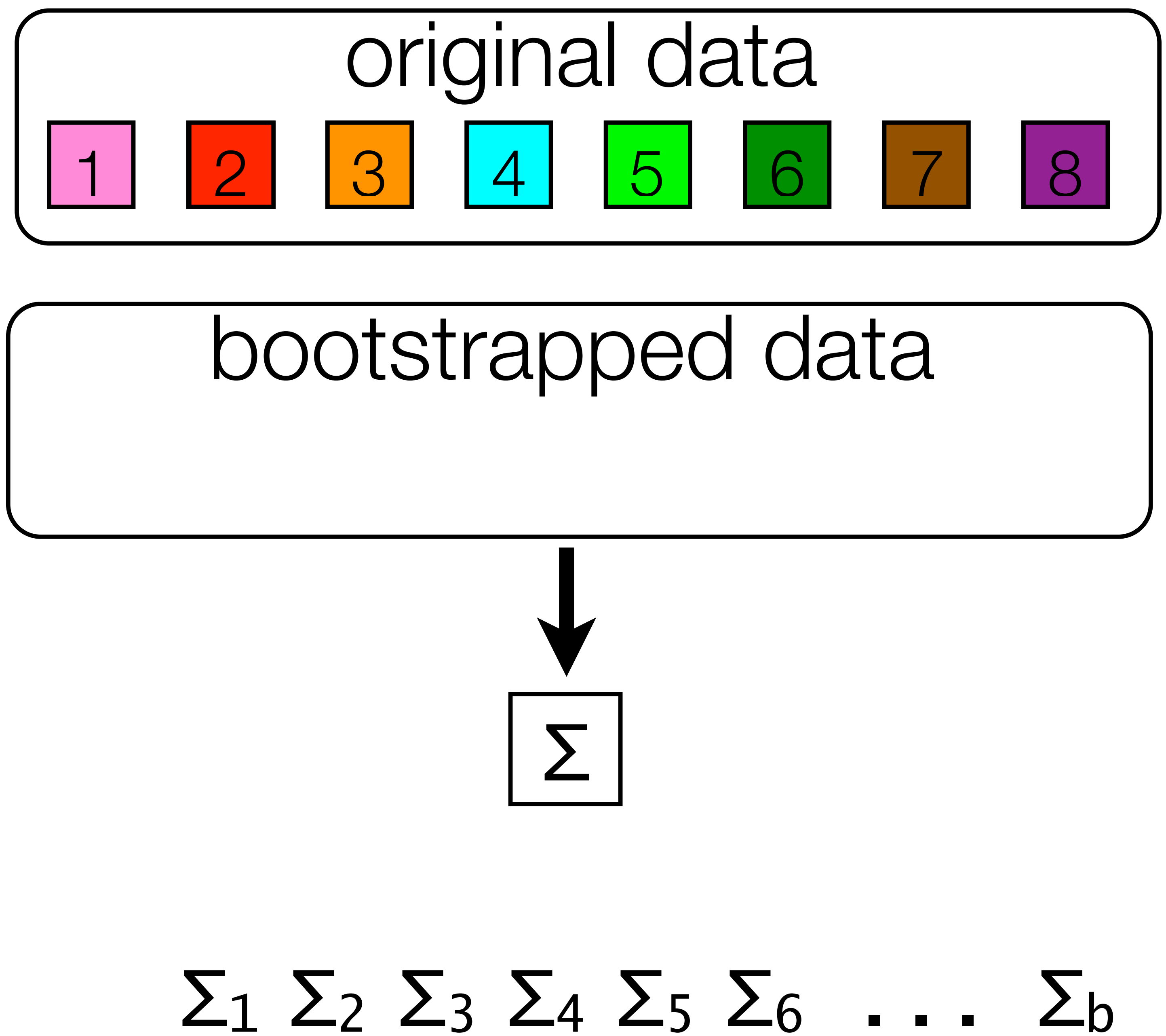
Percentile bootstrap: general recipe

- sample = X1, ..., Xn
- resample n observations with replacement
- compute estimate
- repeat B times

- with B large enough the B estimates provide a good approximation of the distribution of the estimate of the sample

The percentile bootstrap method allows the bootstrap estimate of the sampling distribution to conform to any shape the data suggest, taking into account the variance and the skewness of the sample.

Percentile bootstrap: general recipe



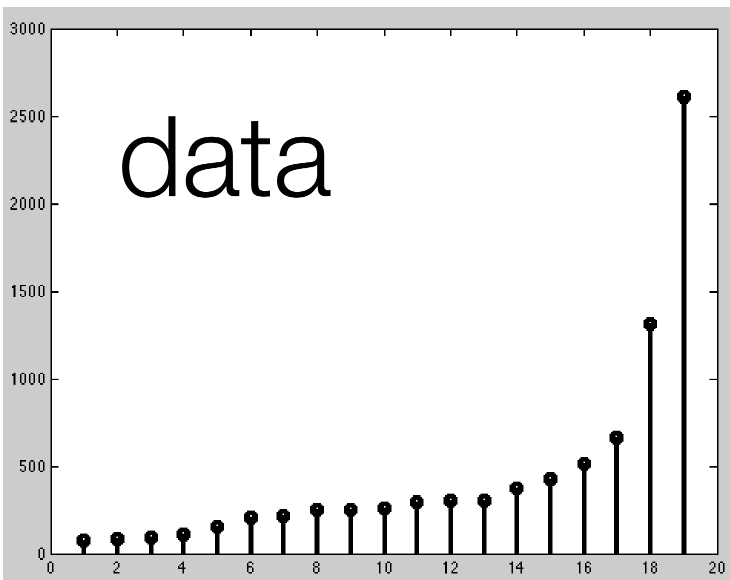
(1) sample WITH replacement n observations

(2) compute estimate
e.g. sum, trimmed mean

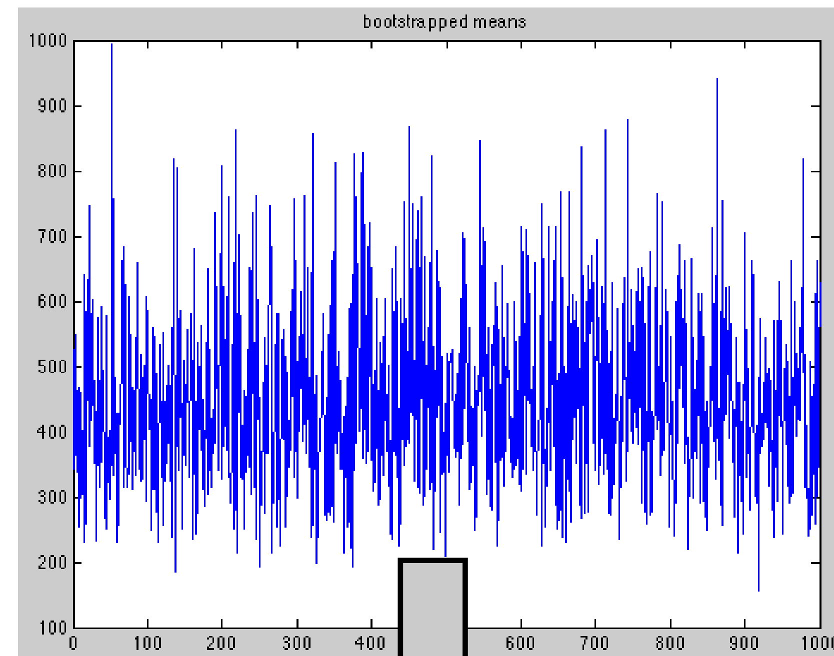
(3) repeat (1) & (2) b times
(4) sort the b estimates*
(5) get 1-alpha confidence interval

Percentile bootstrap estimate of mean

% self-awarness data, Wilcox, 2005, p58



Bootstrapped estimates



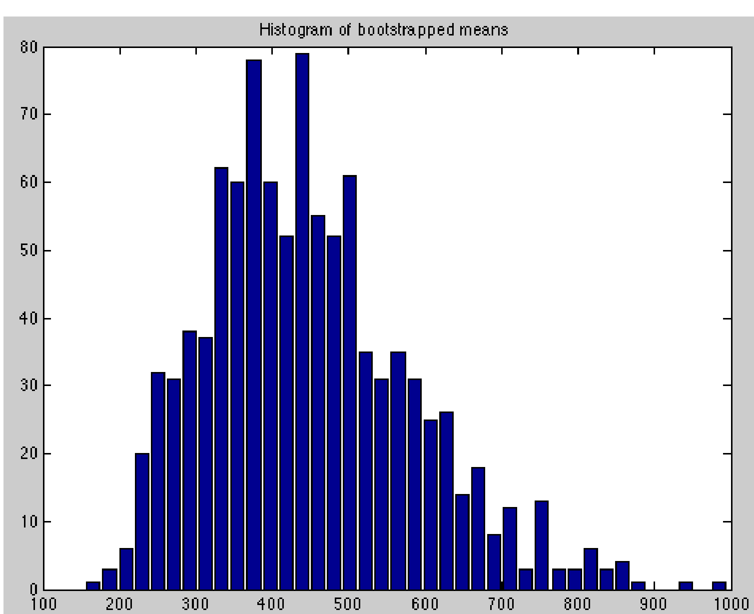
Sample with replacement b times

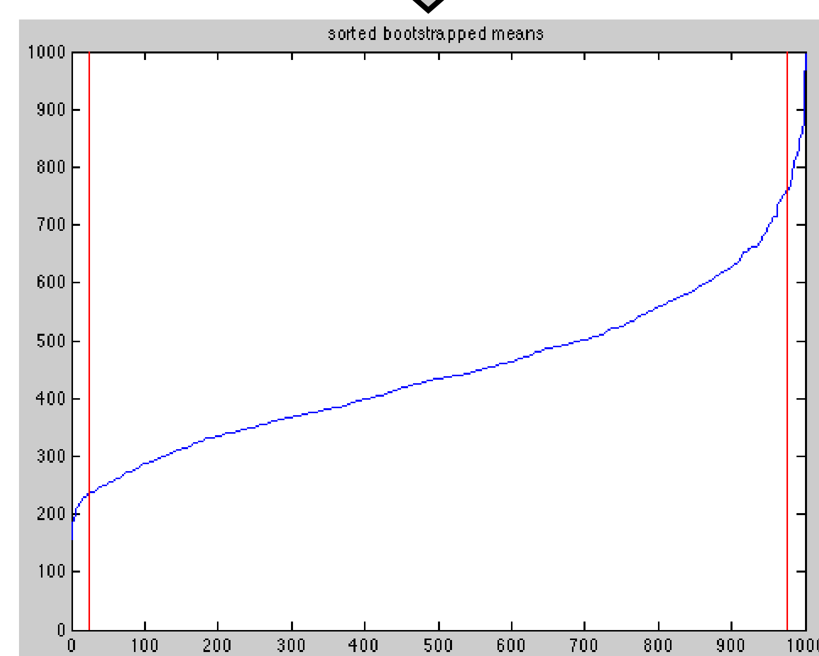
compute estimate

get PDF

Sort & get CI

Distribution of bootstrapped estimates of the mean

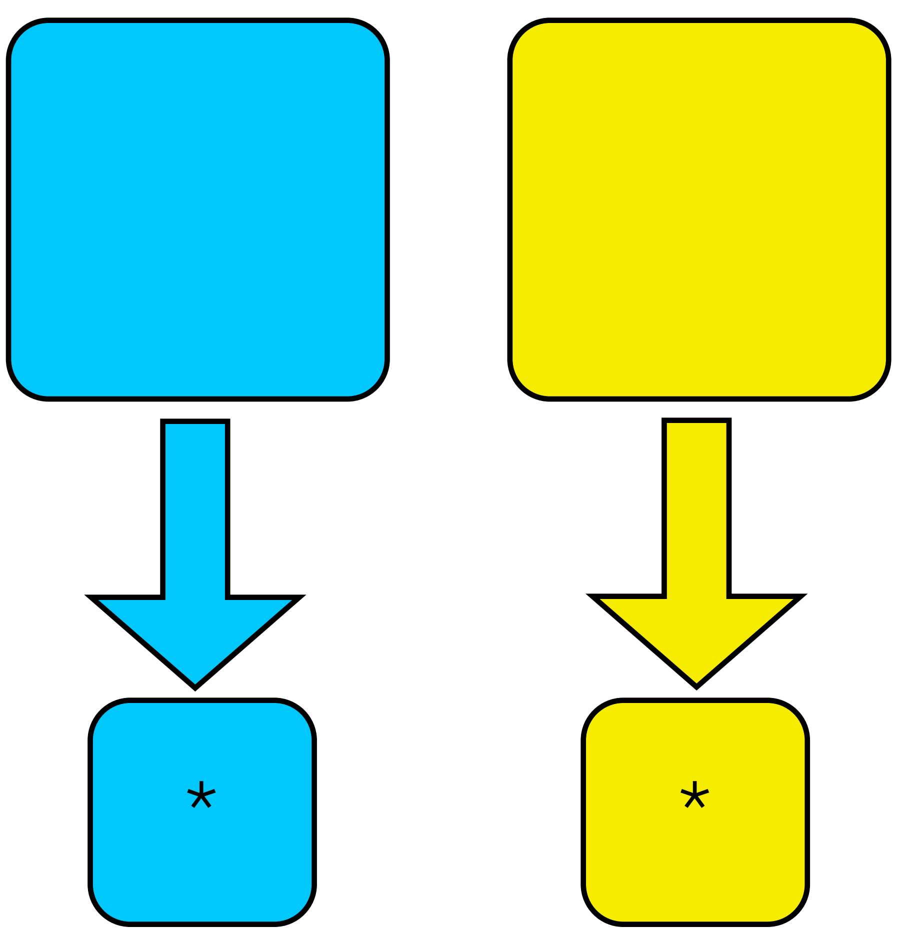




resampling strategies:
follow the data acquisition process

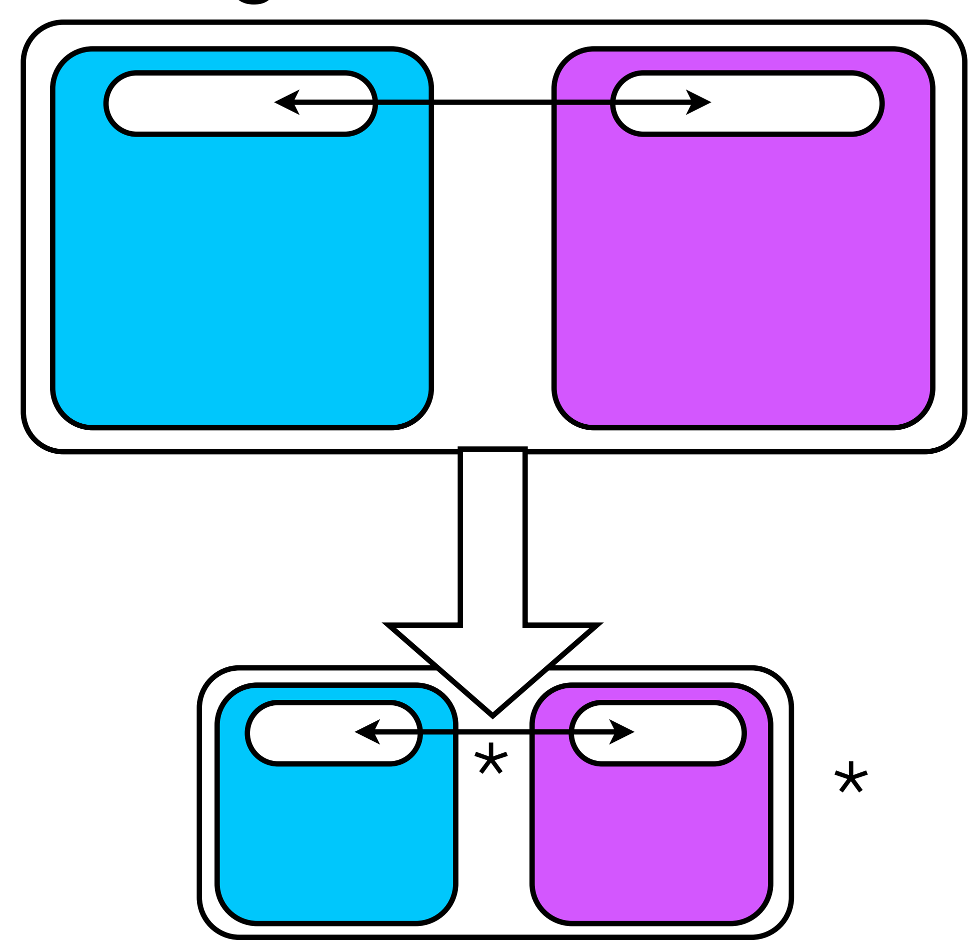
independent sets:

- 2 conditions in single-subject analyses
- 2 groups of subjects, e.g. patients vs. controls



dependent sets:

- 2 conditions in repeated-measure group analyses
- correlations
- linear regression



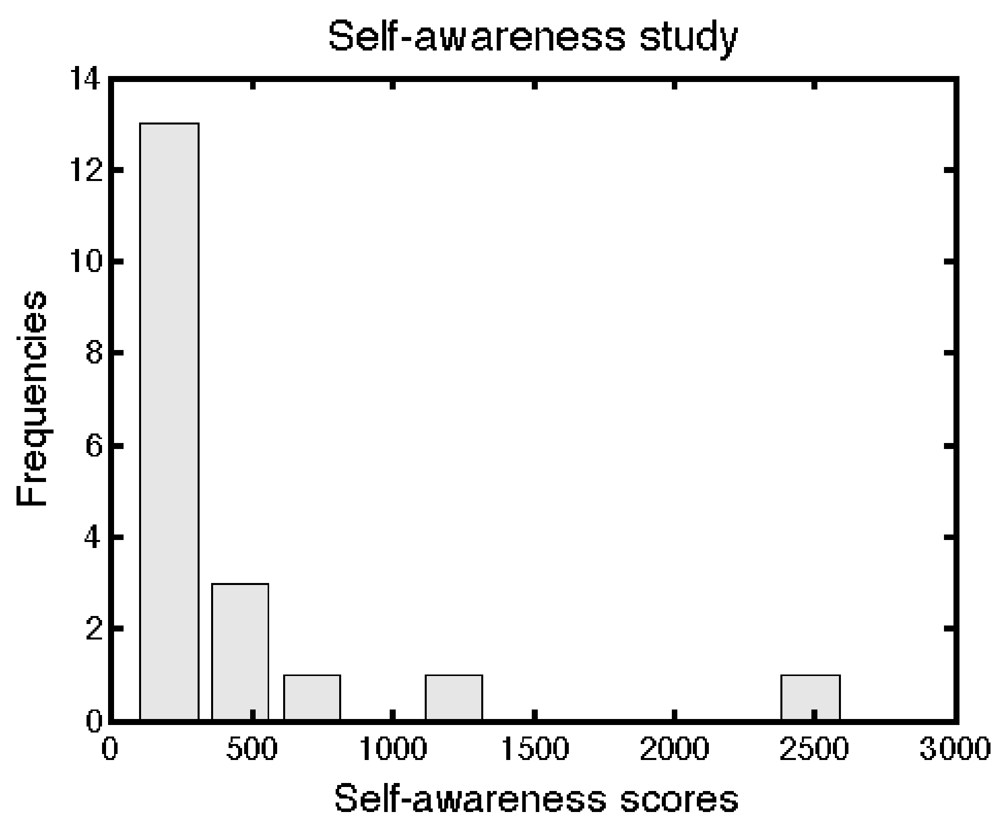
erp_workshop_4_percentile_bootstrap.m

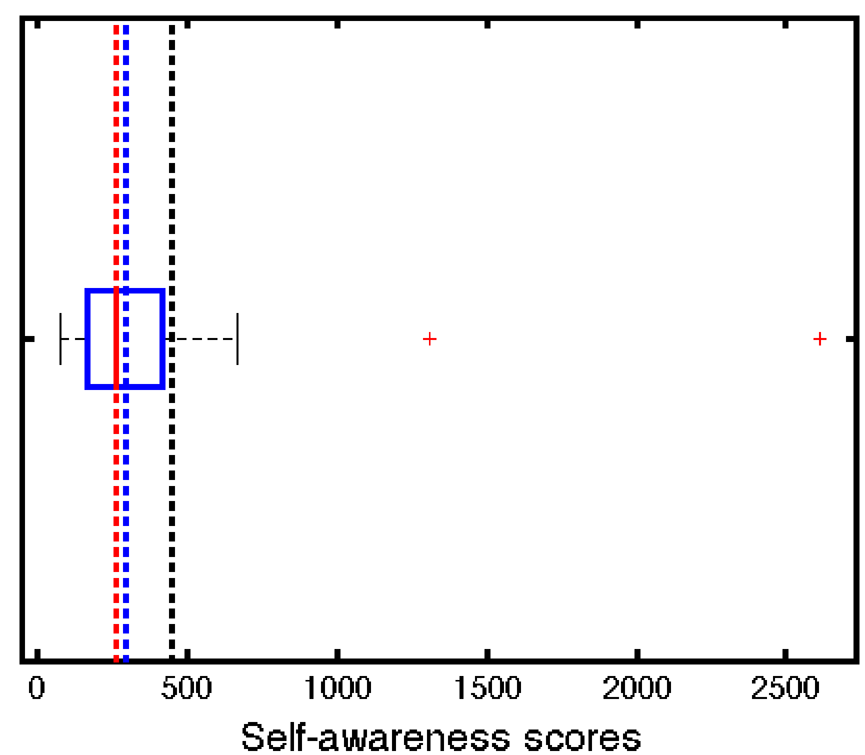
robust measures of central tendency

- mean $\sum(X_i - c)^2$ $\sum(X_i - c) = 0$ $c = \overline{X}$
- median $\sum|X_i - c|$
- trimmed mean
- Winsorized mean
- M estimators
- ...

Why do we need robust estimators?

$$t = \frac{\bar{X}_n - \mu}{s/\sqrt{n}}$$





The mean and the variance are very sensitive to small departures from normality, so that tests relying on them (t-tests & ANOVAs) can perform poorly.

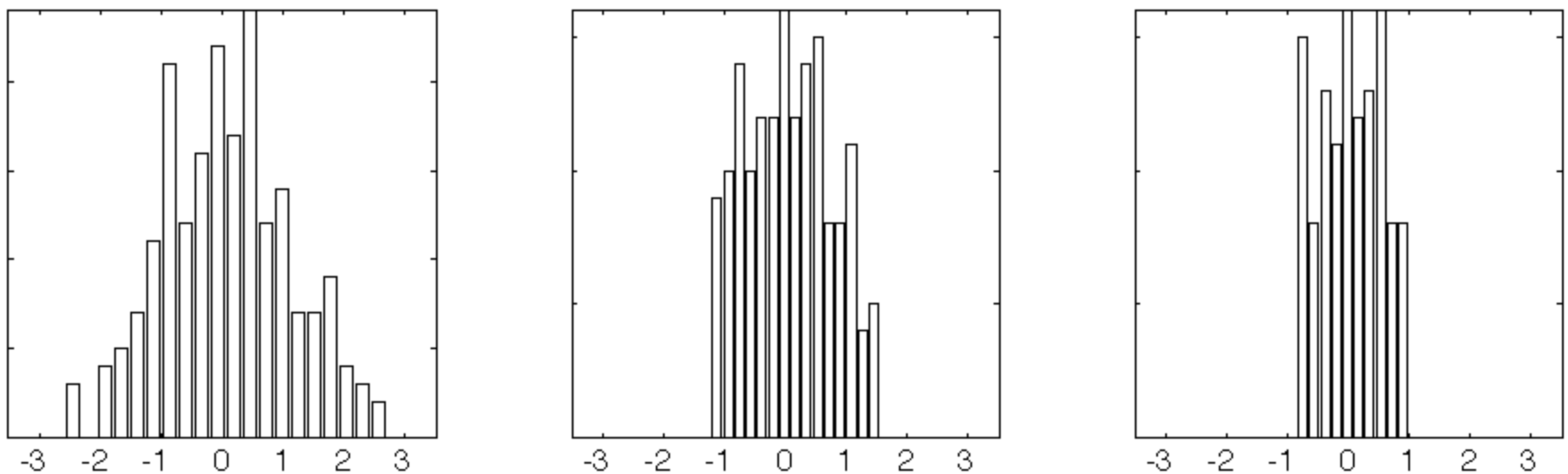
Wilcox, R. R., & Keselman, H. J. (2003). Modern robust data analysis methods: measures of central tendency. Psychol Methods, 8(3), 254-274.

Trimmed means

original distribution

10% trimmed distribution

20% trimmed distribution



- 20% trimmed means provide high power under normality and high power in the presence of outliers

Rand Wilcox, 2012, Introduction to Robust Estimation and Hypothesis Testing, Elsevier

ERP application: Rousselet, Husk, Bennett & Sekuler, 2008, *Journal of Vision*.

Robust estimators of central tendency

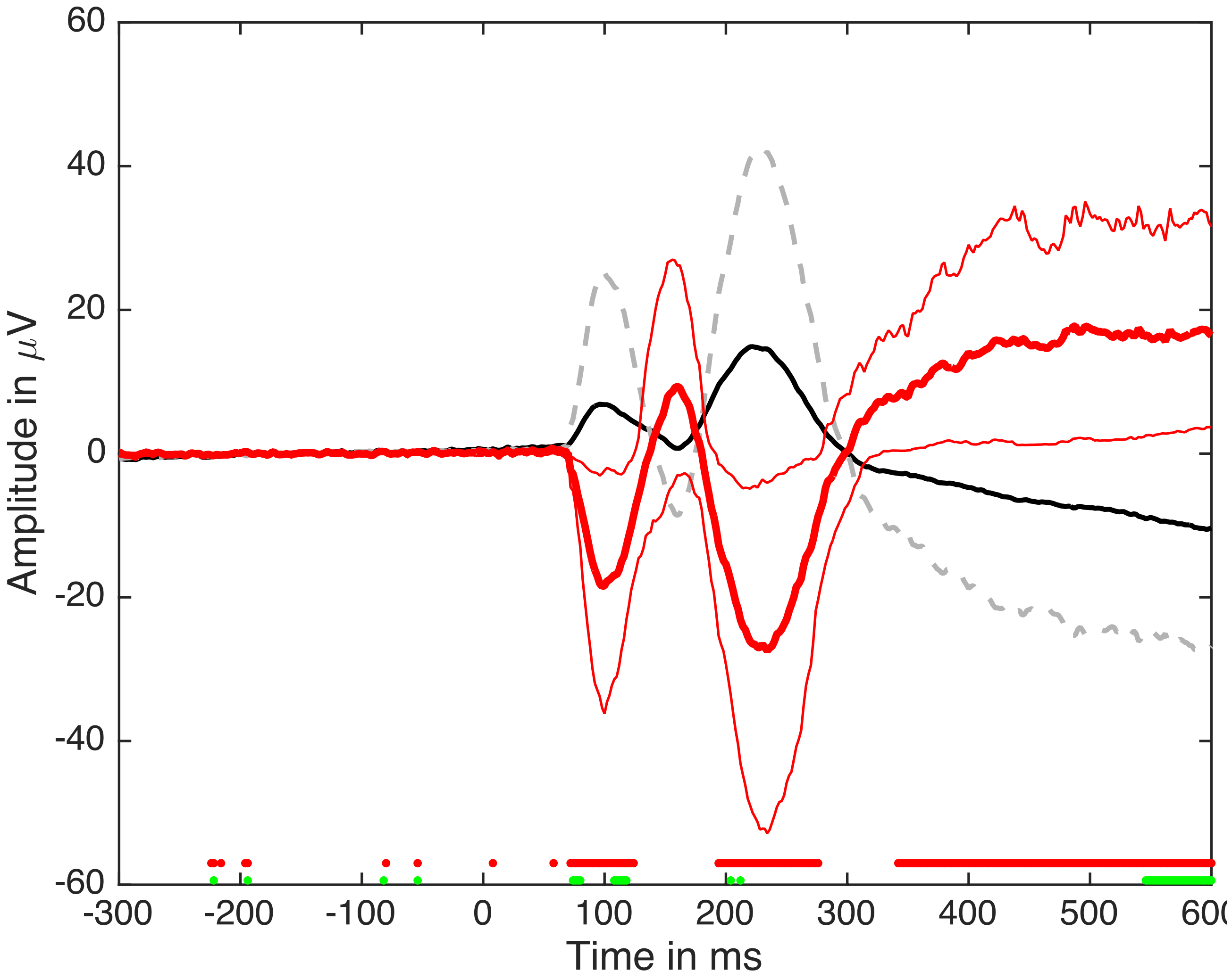
- tmERP = trimmean(EEG.data,...)
- mdERP = median(EEG.data,...)
- in LIMO EEG:
    - mdERP = limo_median(EEG.data,...)
    - tmERP = limo_trimmed_mean(EEG.data,...)
    - hdERP = limo_harrell_davis(EEG.data,...)

Robust estimators of dispersion

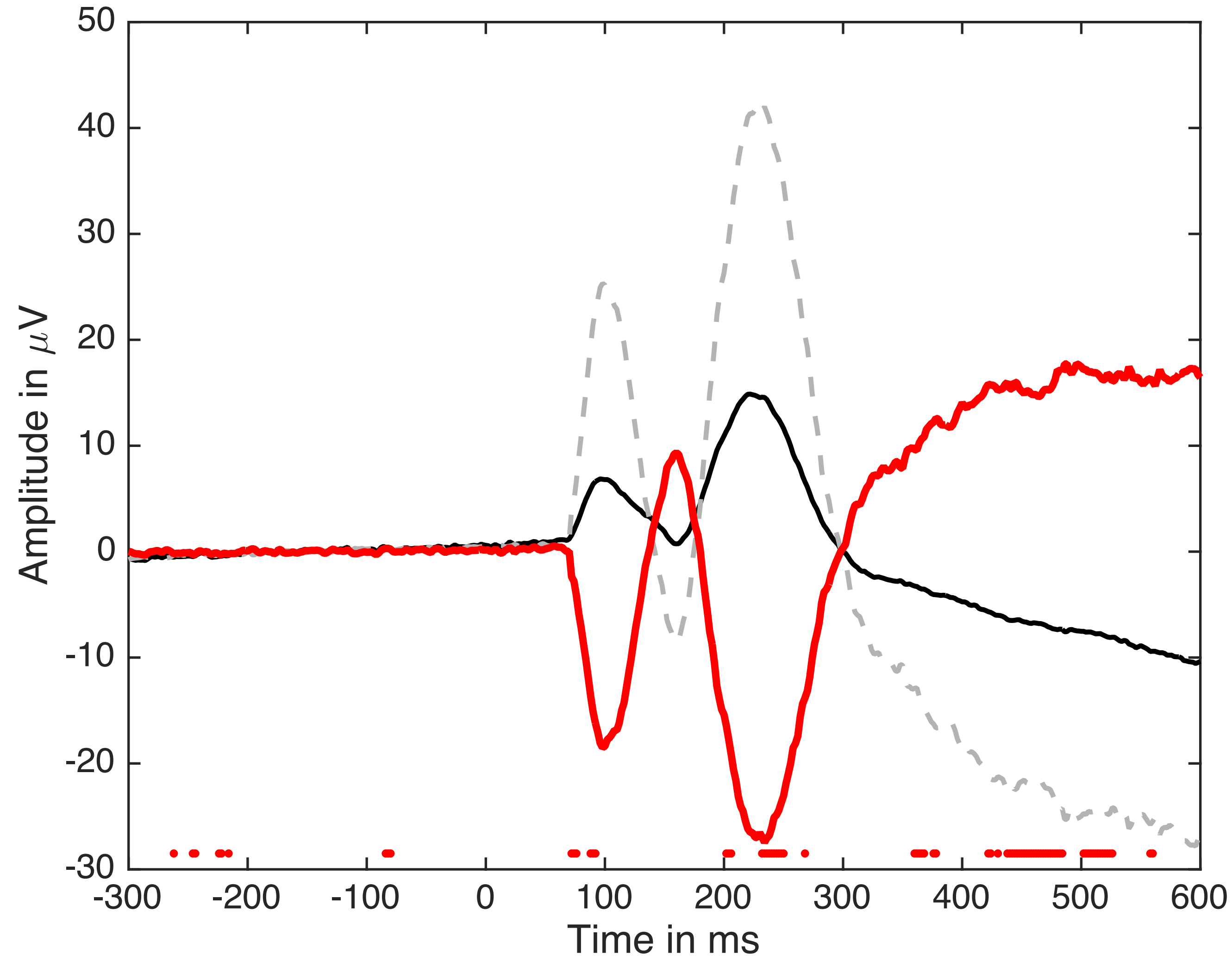
- madERP = mad(EEG.data,...)
- in LIMO EEG:
  - wERP = limo_winvar(EEG.data,...)
  - sehdERP = limo_bootse(EEG.data,...)

Solving case study 1: robust estimators

t-test vs. percentile bootstrap

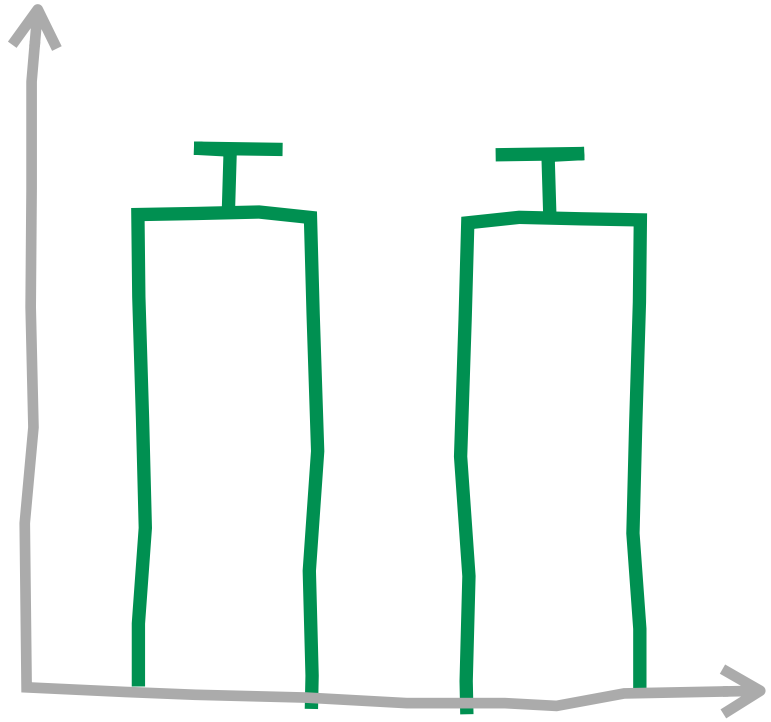


t-test on 20% trimmed means



erp_workshop_5_robust_estimators.m

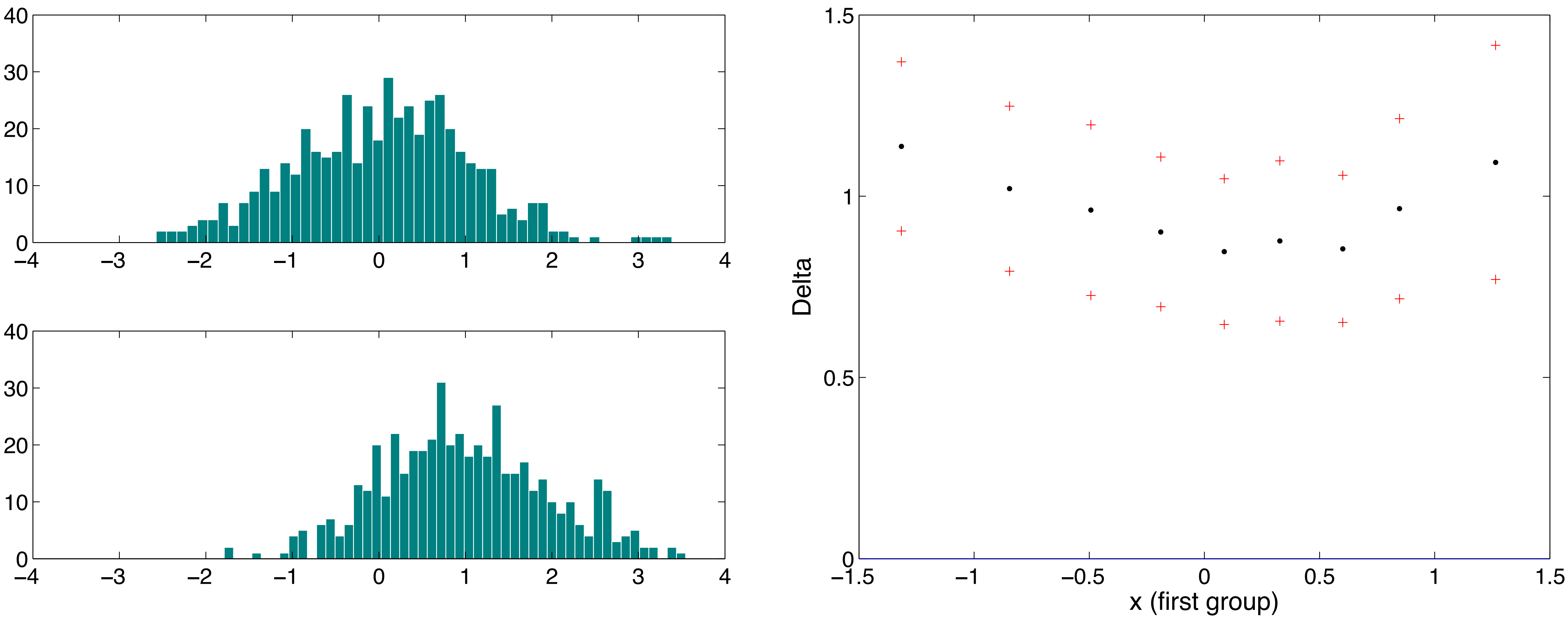
No effect? At all?



p > 0.05, therefore,
there is no evidence the two conditions differ

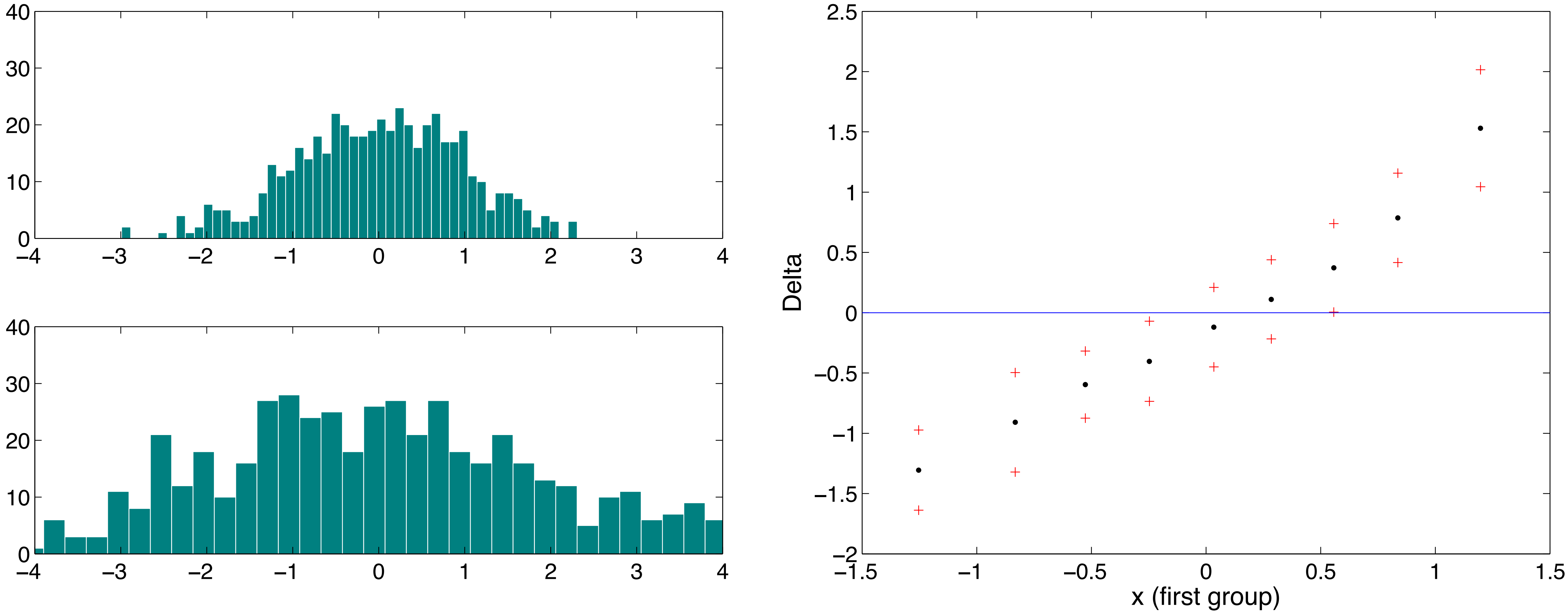

Don't let variability, outliers &
skewness hide: ban bar graphs
?
?
?

Compare entire distributions using the **shift function**



https://garstats.wordpress.com/2016/07/12/shift-function/

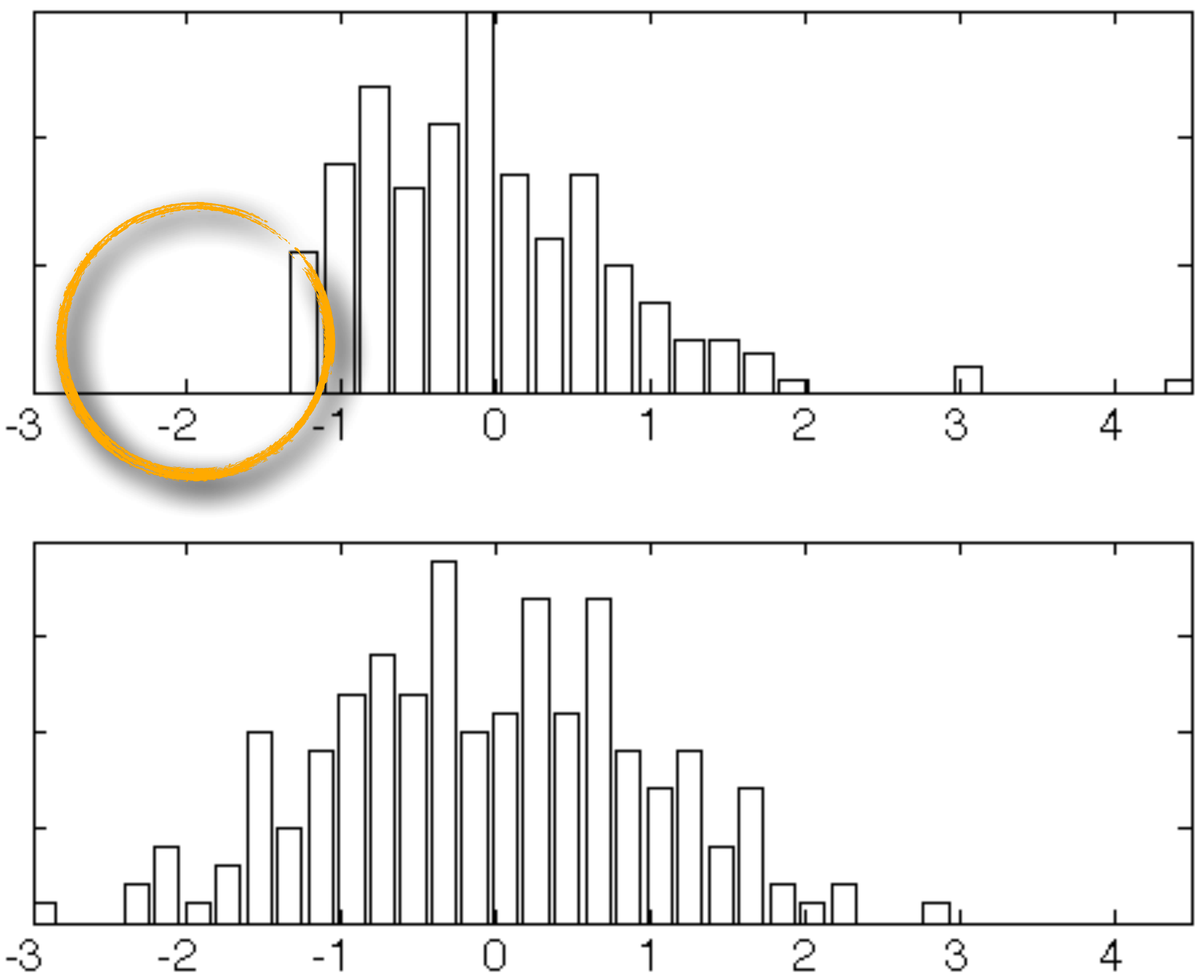
Compare entire distributions using the **shift function**

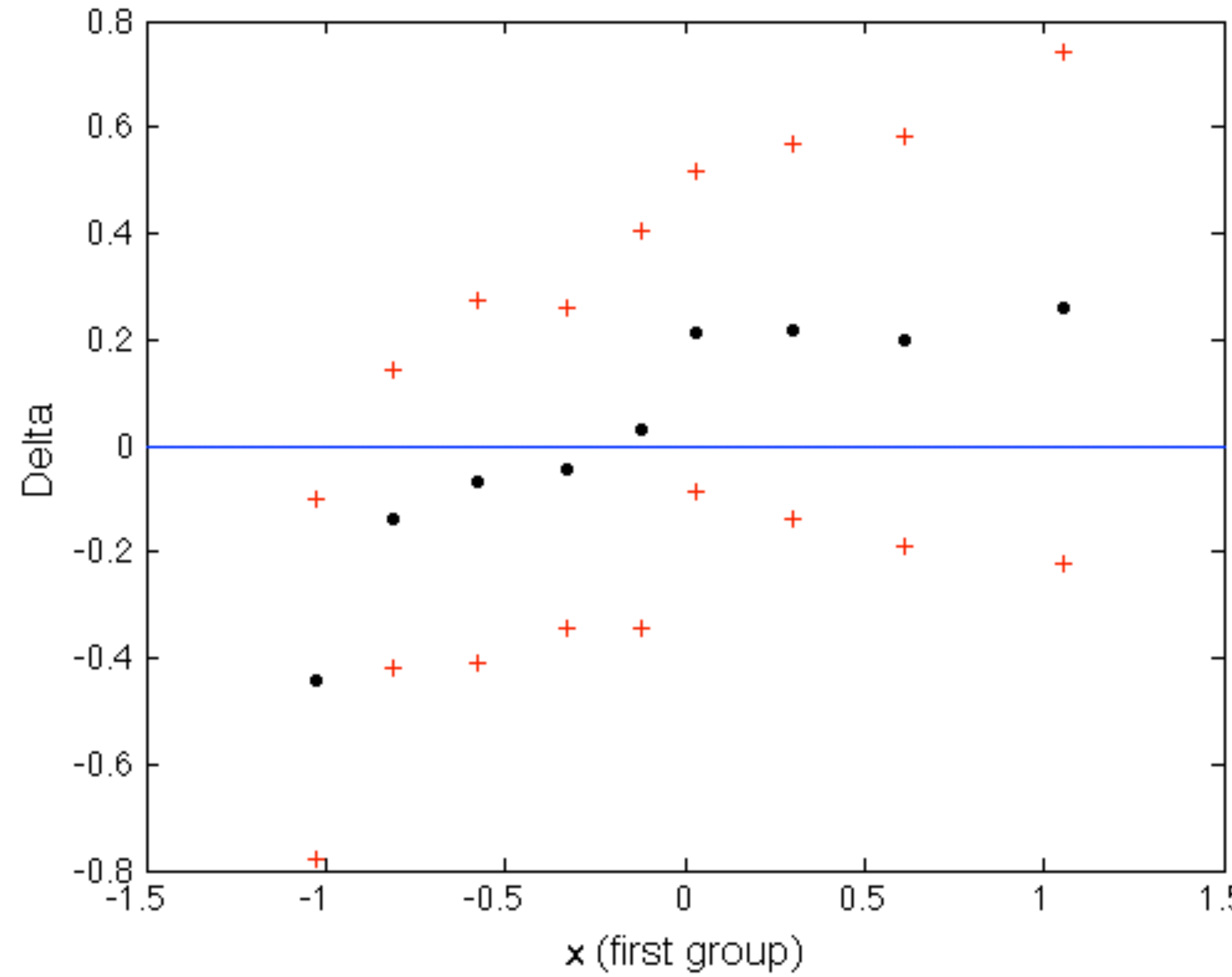


Compare entire distributions: the **shift function**

95% simultaneous confidence intervals
for the difference between deciles

mean=0, std=1



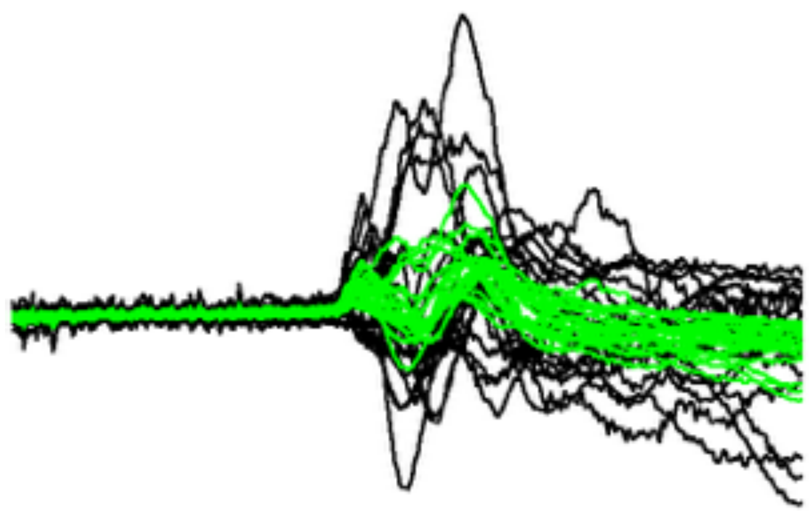


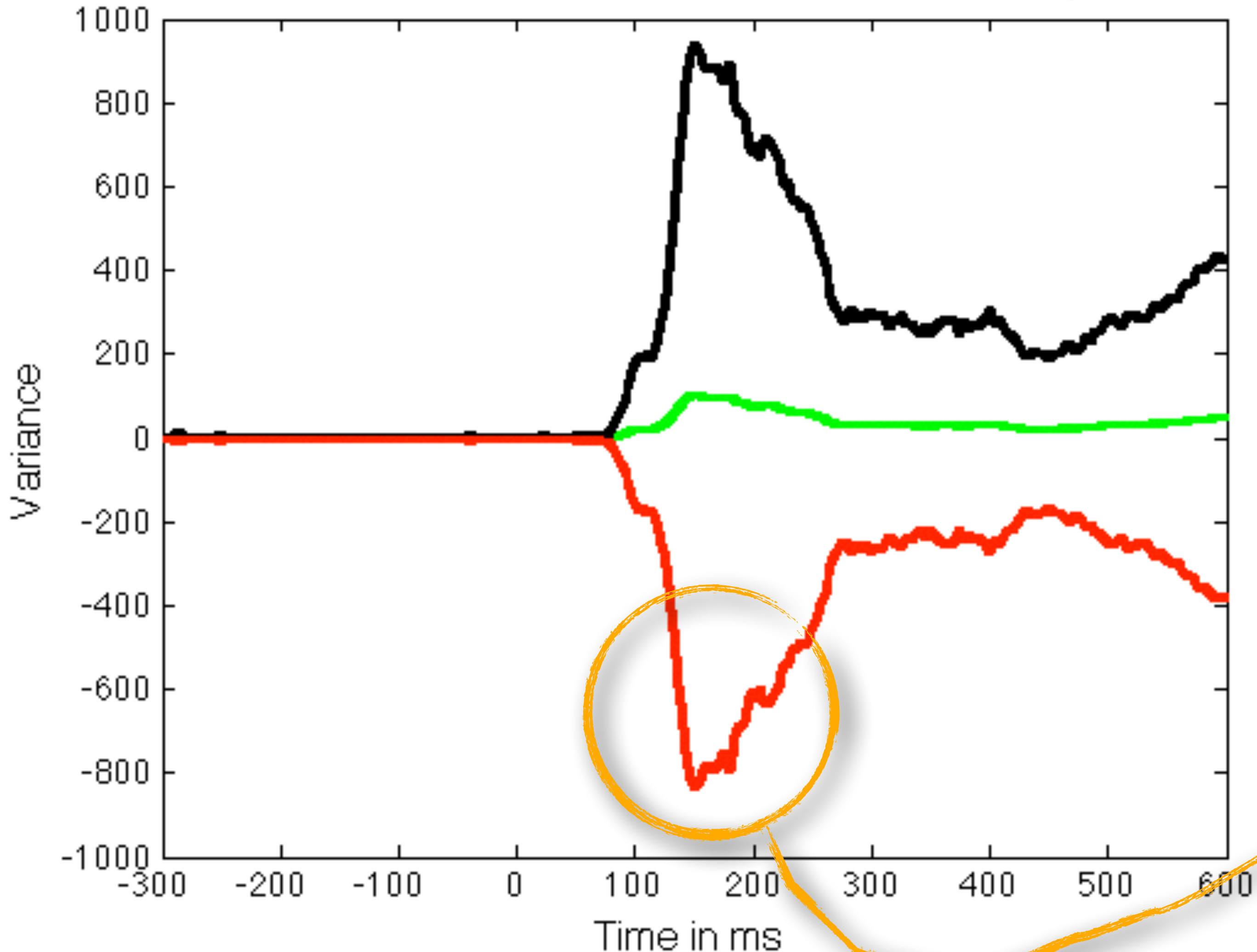
Doksum, K. (1974). Empirical Probability Plots and Statistical Inference for Nonlinear Models in the two-Sample Case. *Annals of Statistics*, *2*(2), 267–277.

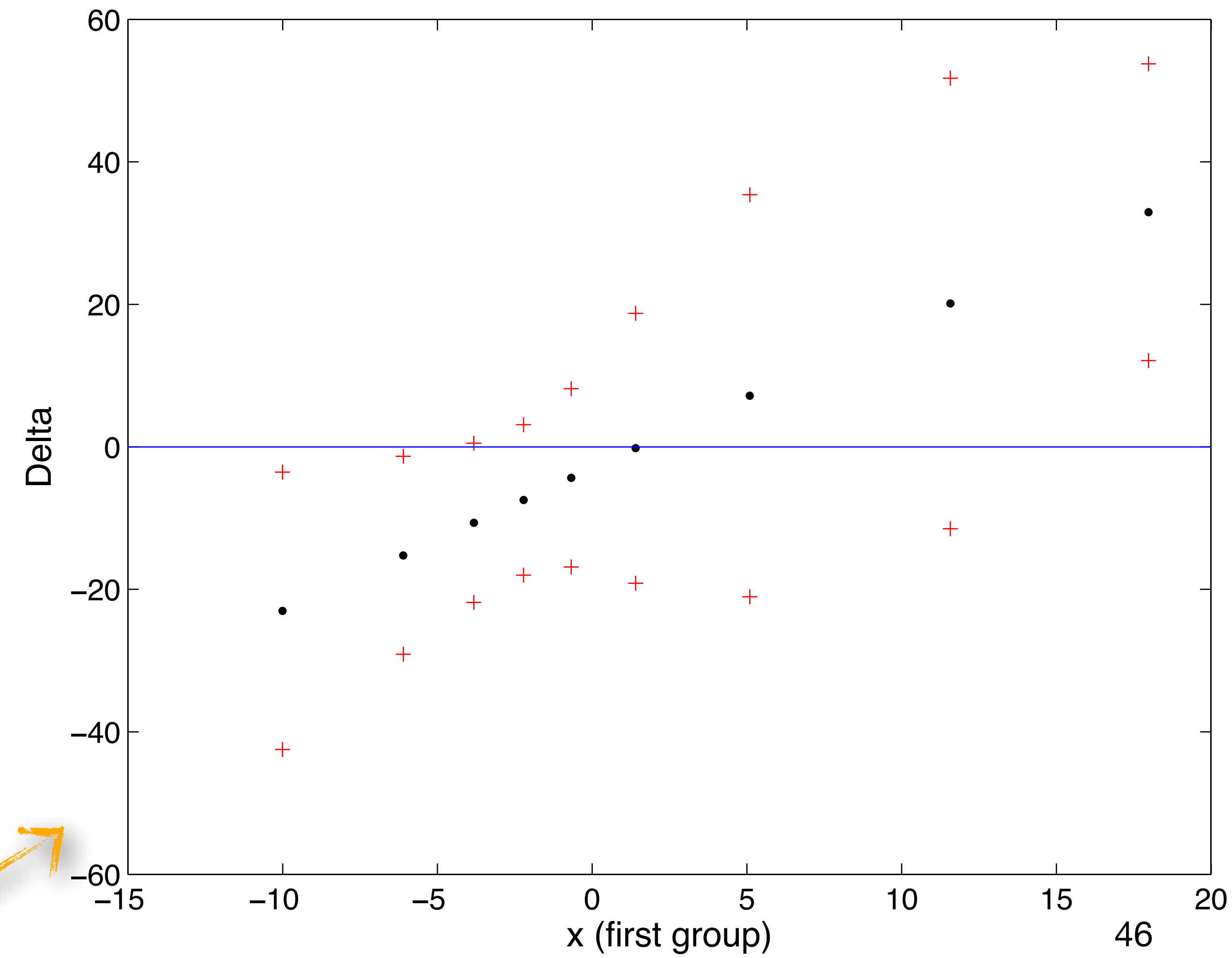
Harrell-Davis estimates of the quantiles

Application to ERP data:
Rousselet GA, Gaspar CM, Wieczorek KP and Pernet CR (2011)
Modelling single-trial ERP reveals modulation of bottom-up face visual processing by top-down task constraints (in some subjects)
Frontiers in Psychology 2:137. doi: 10.3389/fpsyg.2011.00137

Solving case study 2: shift function



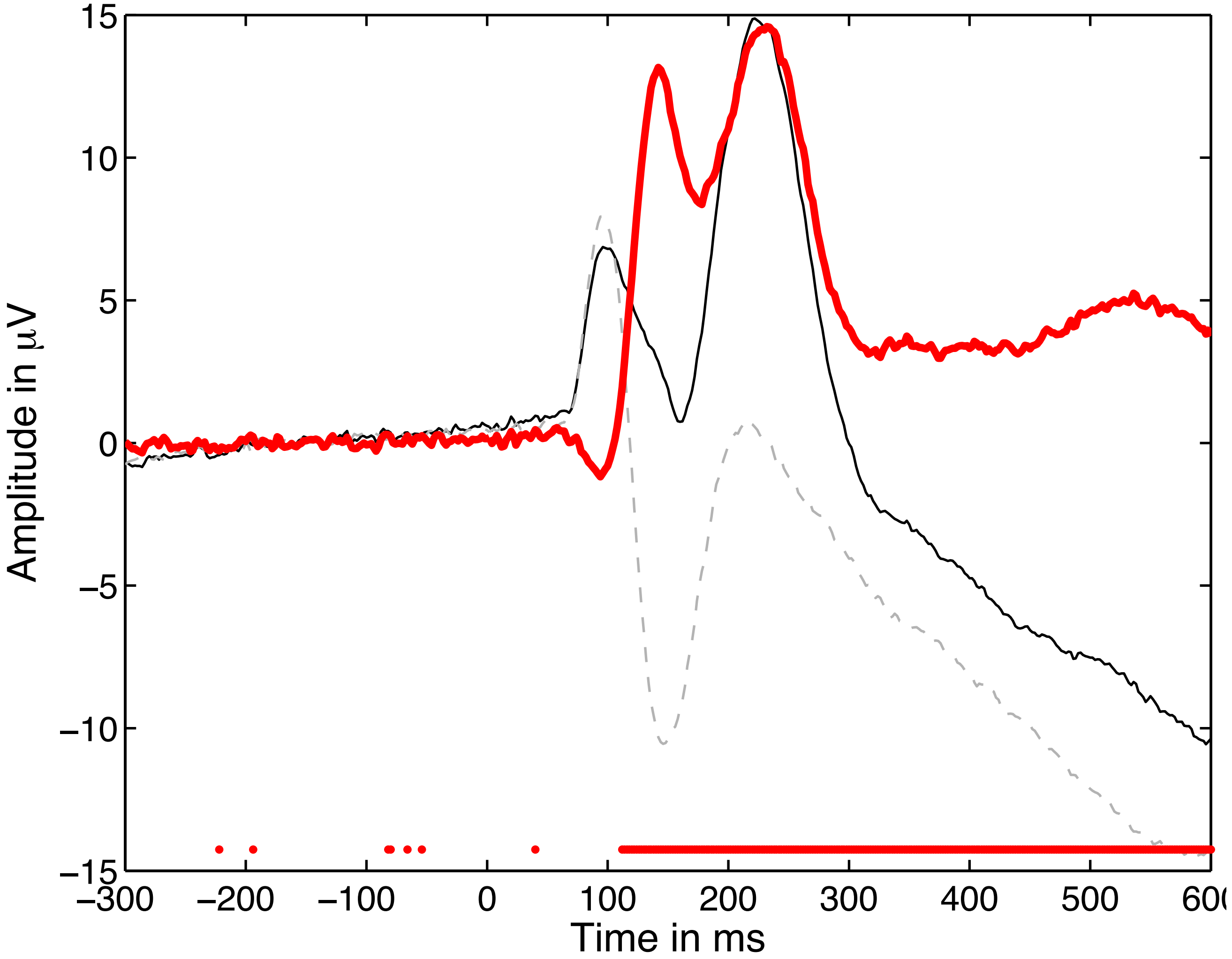




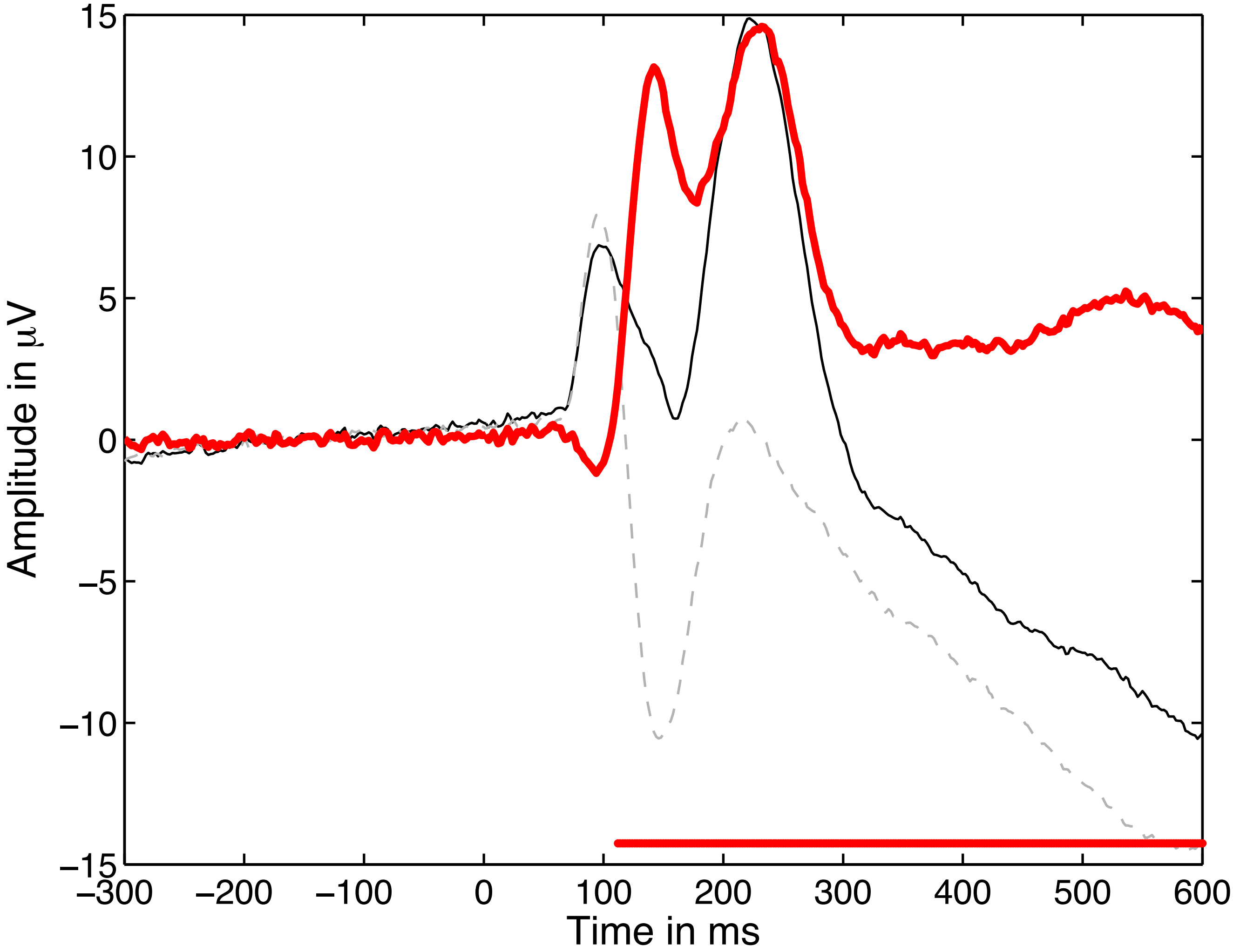
erp_workshop_6_shift_function.m

Control for multiple comparisons: bootstrap-t technique & spatial-temporal clustering

univariate thresholds

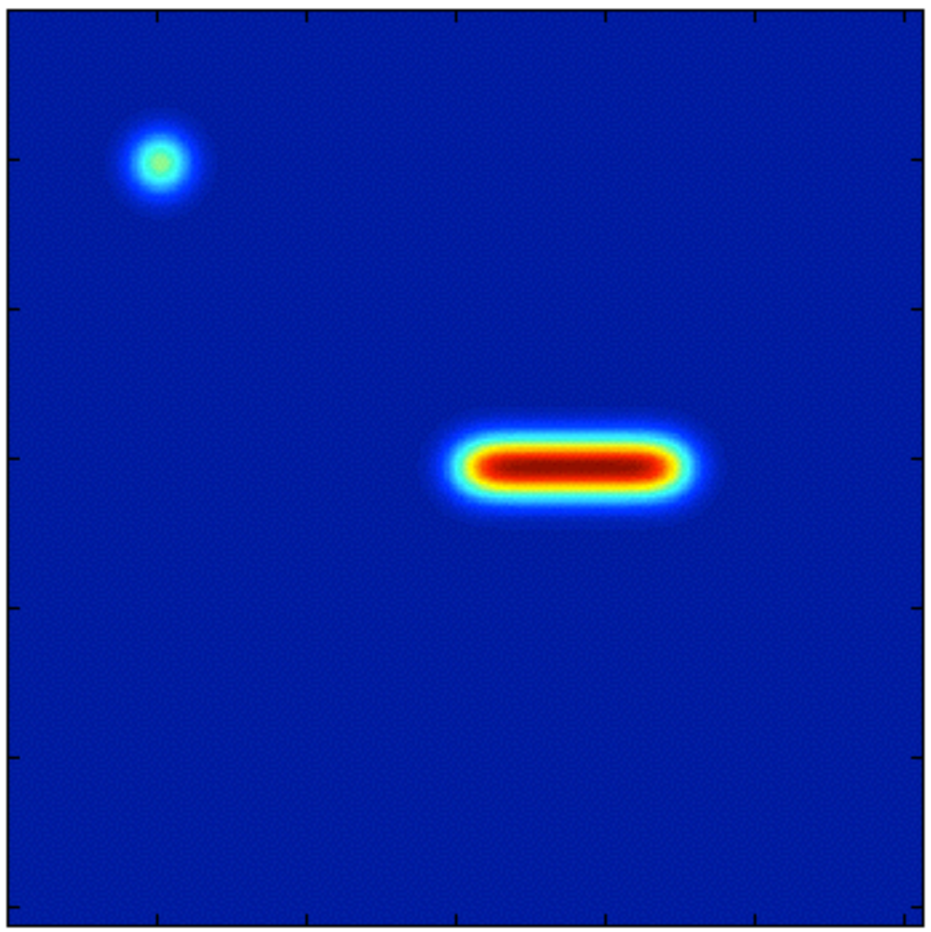


after correction



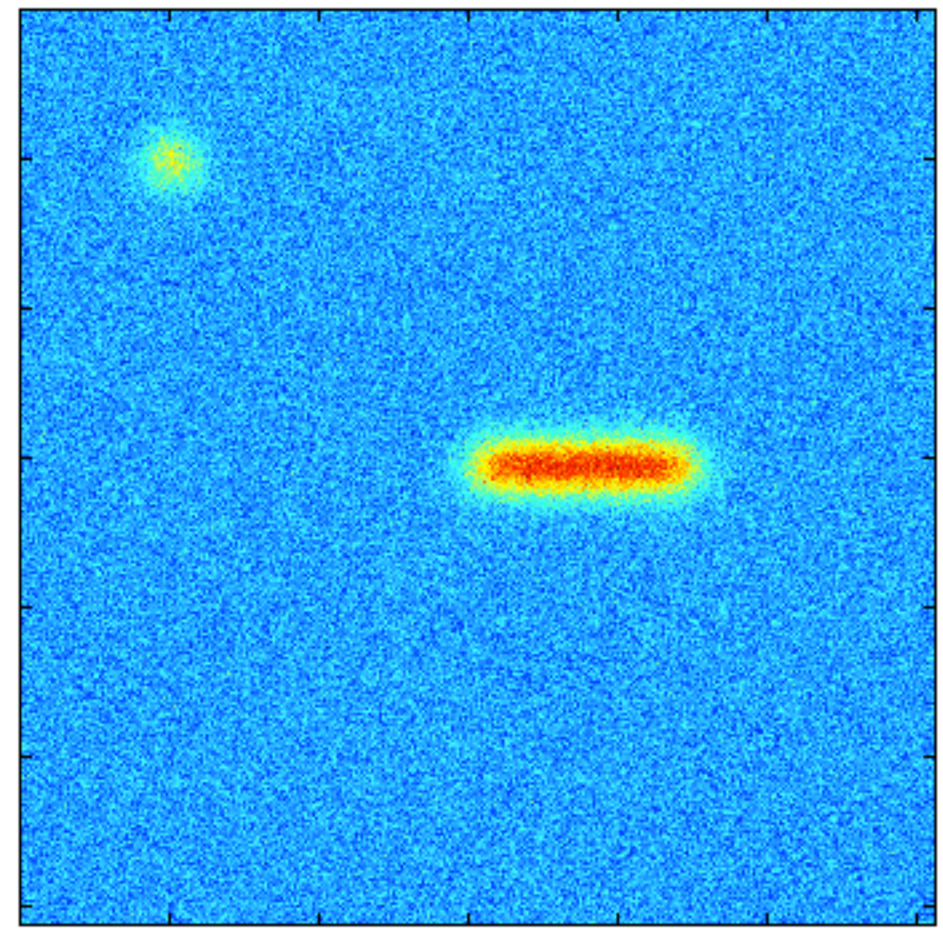
Control for multiple comparisons

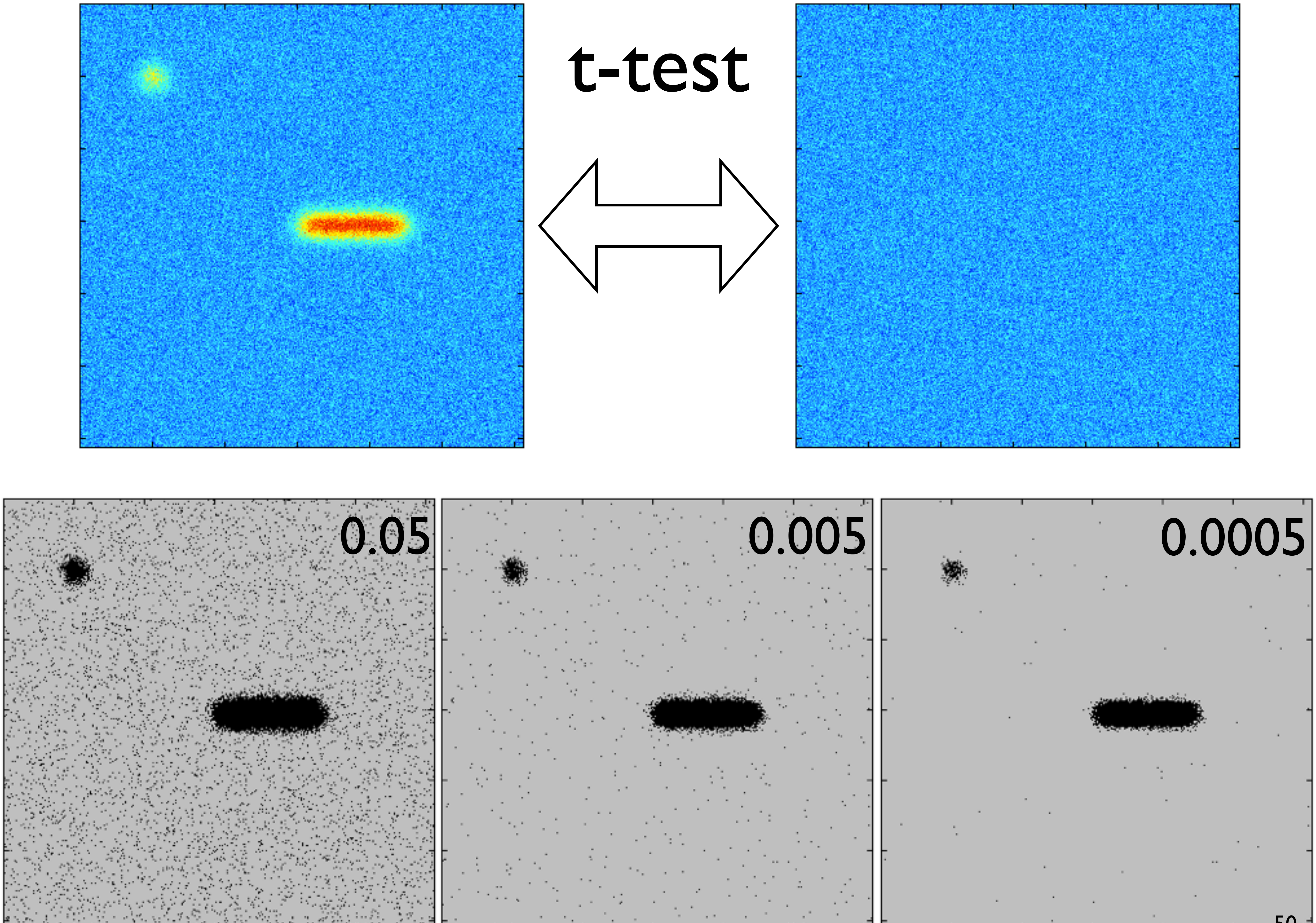
signal



100 trials =
signal +
white noise

mean




t-test
0.05
0.005
0.0005

max procedure

- in each bootstrap loop, take the MAX of the absolute value of your estimator (e.g. mean difference) across all pairwise comparisons.
- then: maxCI = diffsort(:,U);
- with U = round(b.*(1-alpha));
- compare absolute original difference to this distribution

False Discovery Rate procedure

Procedure:

- Sort all p values (column C1)

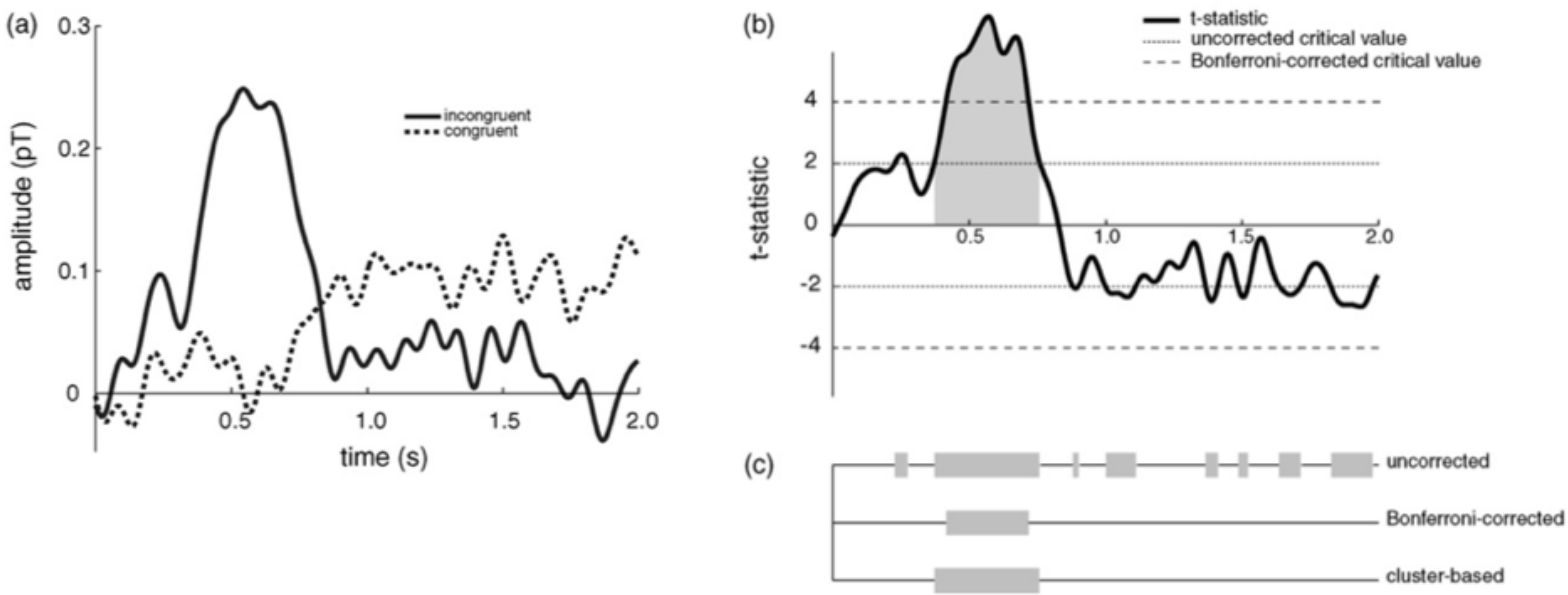
C3

- Create column C2 by computing *j*α/N*
- Subtract column C1 from C2 to build column C3
- Find the highest negative index in C3 and find the corresponding p-value in C1 *(p_fdr)*
- Reject all null hypothesis whose p-value are less than or equal to *p_fdr*

	C1	C2	C3
Index "j"	Actual	j*0.05/10	C2-C1
1	0.001	0.005	-0.004
2	0.002	0.01	-0.008
3	$\boxed{0.01}$	0.015	-0.005
4	0.03	0.02	0.01
5	0.04	0.025	0.015
6	0.045	0.03	0.015
7	0.05	0.035	0.015
8	0.1	0.04	0.06
9	0.2	0.045	0.155
10	0.6	0.05	0.55

http://www-personal.umich.edu/~nichols/FDR/

Control for multiple comparisons

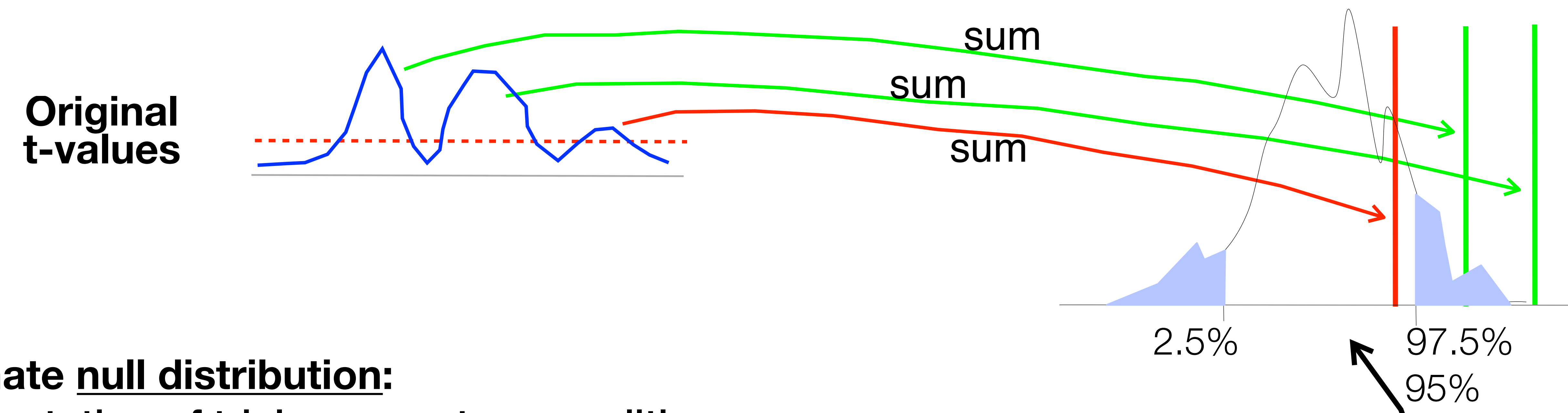


Maris & Oostenveld, J. Neurosci. Methods 2007

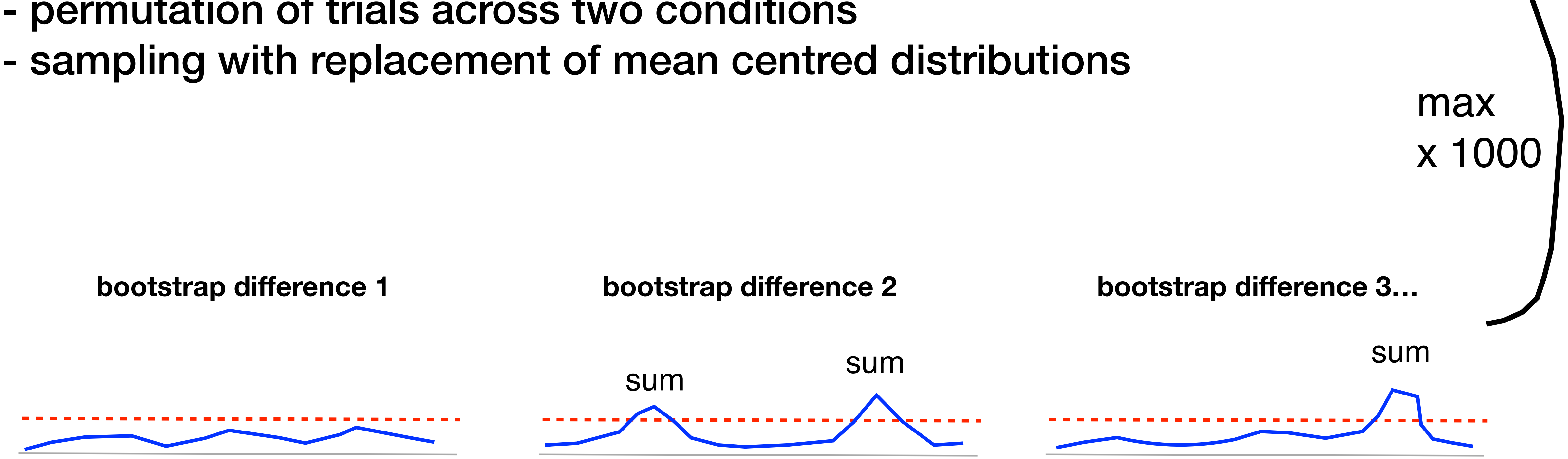
Matlab toolboxes: Fieldtrip + LIMO_EEG

Pernet, Latinus, Nichols & Rousselet (2015) Cluster-based computational methods for mass univariate analyses of event-related brain potentials/fields: A simulation study. Journal of neuroscience methods, 250, 85-93.

Cluster correction for multiple comparisons



estimate <u>null distribution</u>:
- permutation of trials across two conditions
- sampling with replacement of mean centred distributions



bootstrap-t method (percentile-t technique)

(1) t-test

original data

1 2 3 4 5 6 7 8

-> t value

(2) center data

mean centered data

1 2 3 4 5 6 7 8

- mean([S1…S8])

(3) sample WITH replacement n centered observations

bootstrapped centered data

(4) t-test

t* value

(5) repeat (3) & (4) b times

$t^*_1 \; t^*_2 \; t^*_3 \; t^*_4 \; t^*_5 \; ... \; t^*_b$

(6) sort the b estimates*

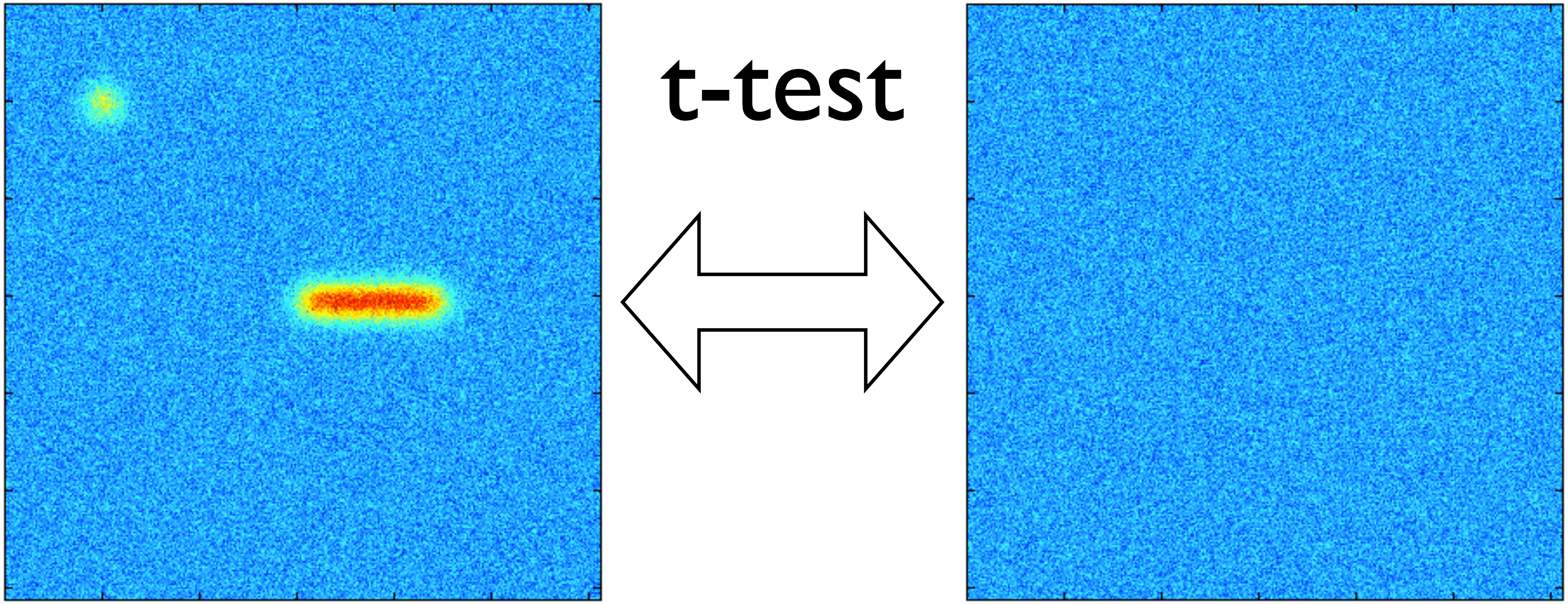
(7) get 1-alpha confidence interval

$$\left(\bar{X} - T^*_{(u)}\frac{s}{\sqrt{n}}, \bar{X} - T^*_{(l)}\frac{s}{\sqrt{n}}\right)$$

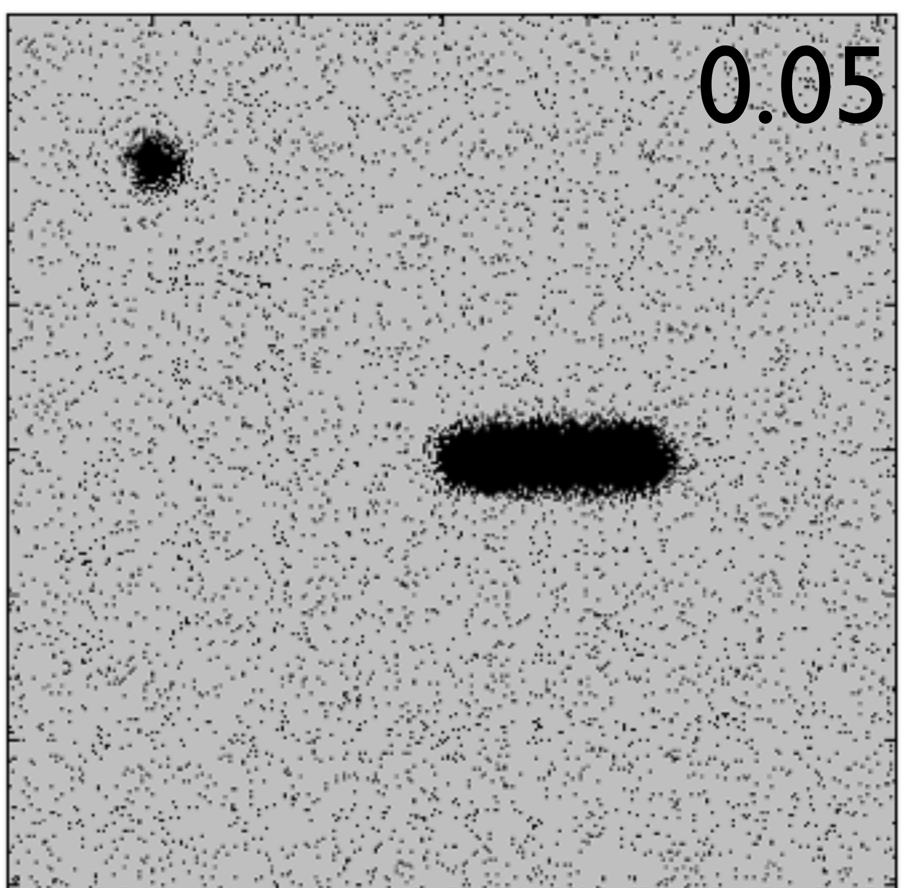
(8) compare t to t* threshold

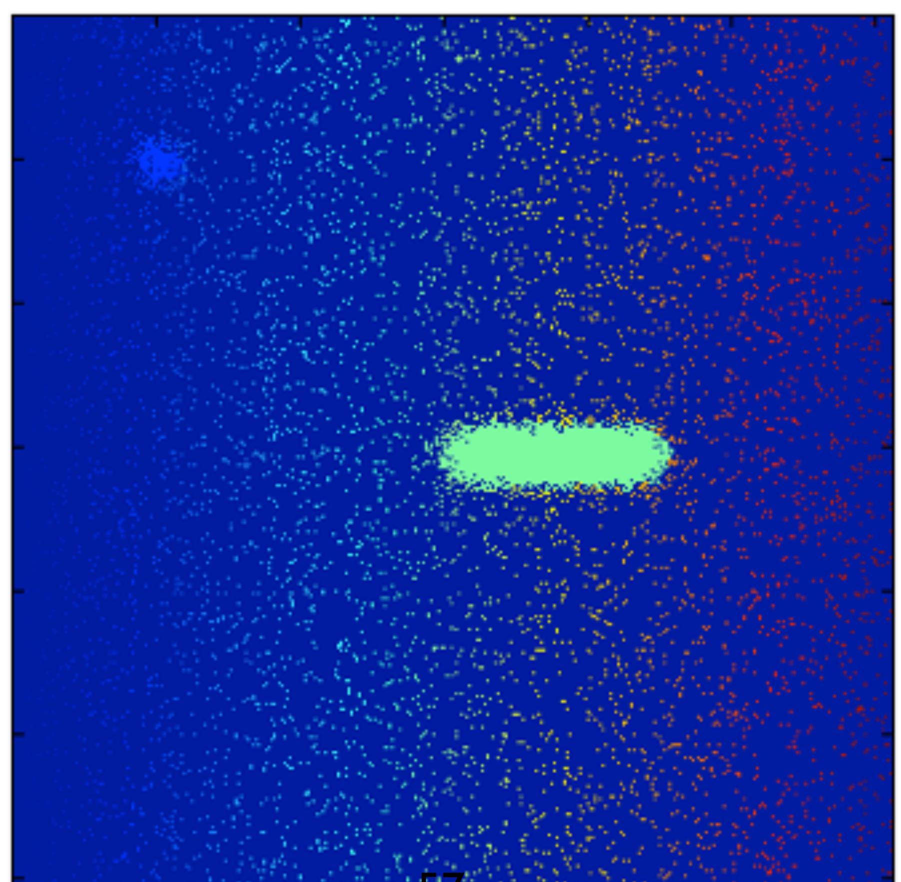
Which bootstrap method to use?

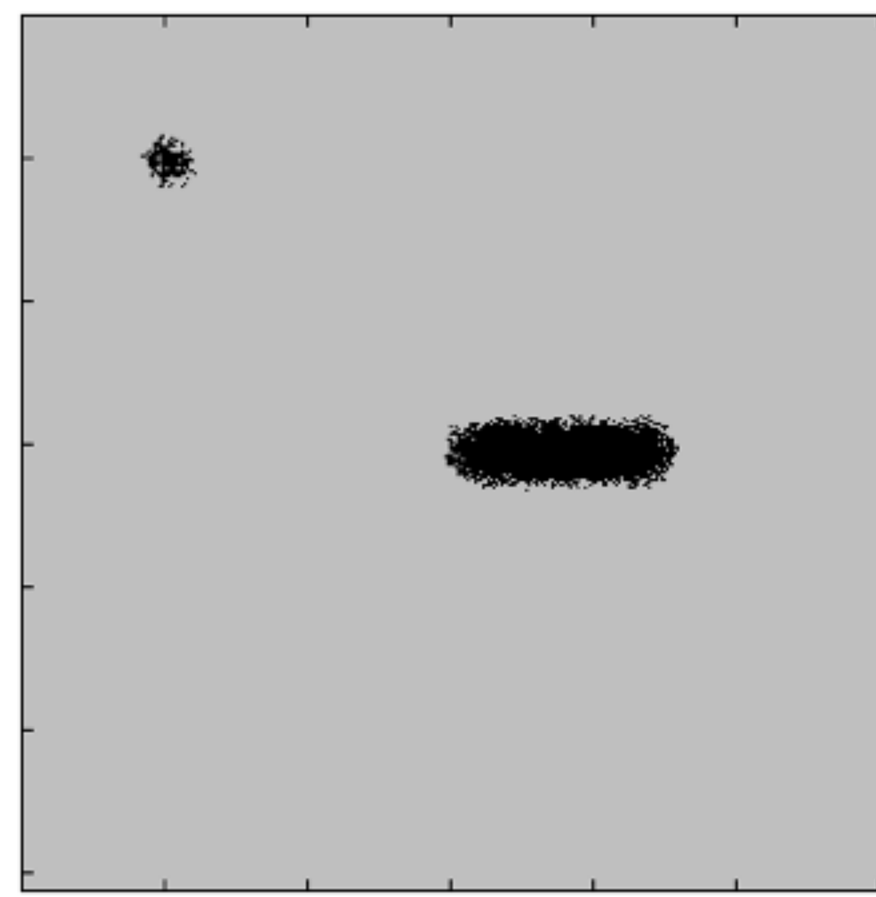
- How do we build good confidence intervals?
  - choose estimator
  - choose technique
- Rand Wilcox recommends:
  - trimming $\geq 20\%$: percentile technique
  - trimming $< 20\%$: percentile-t technique
  - M-estimators: percentile technique



17044 clusters → 2 clusters

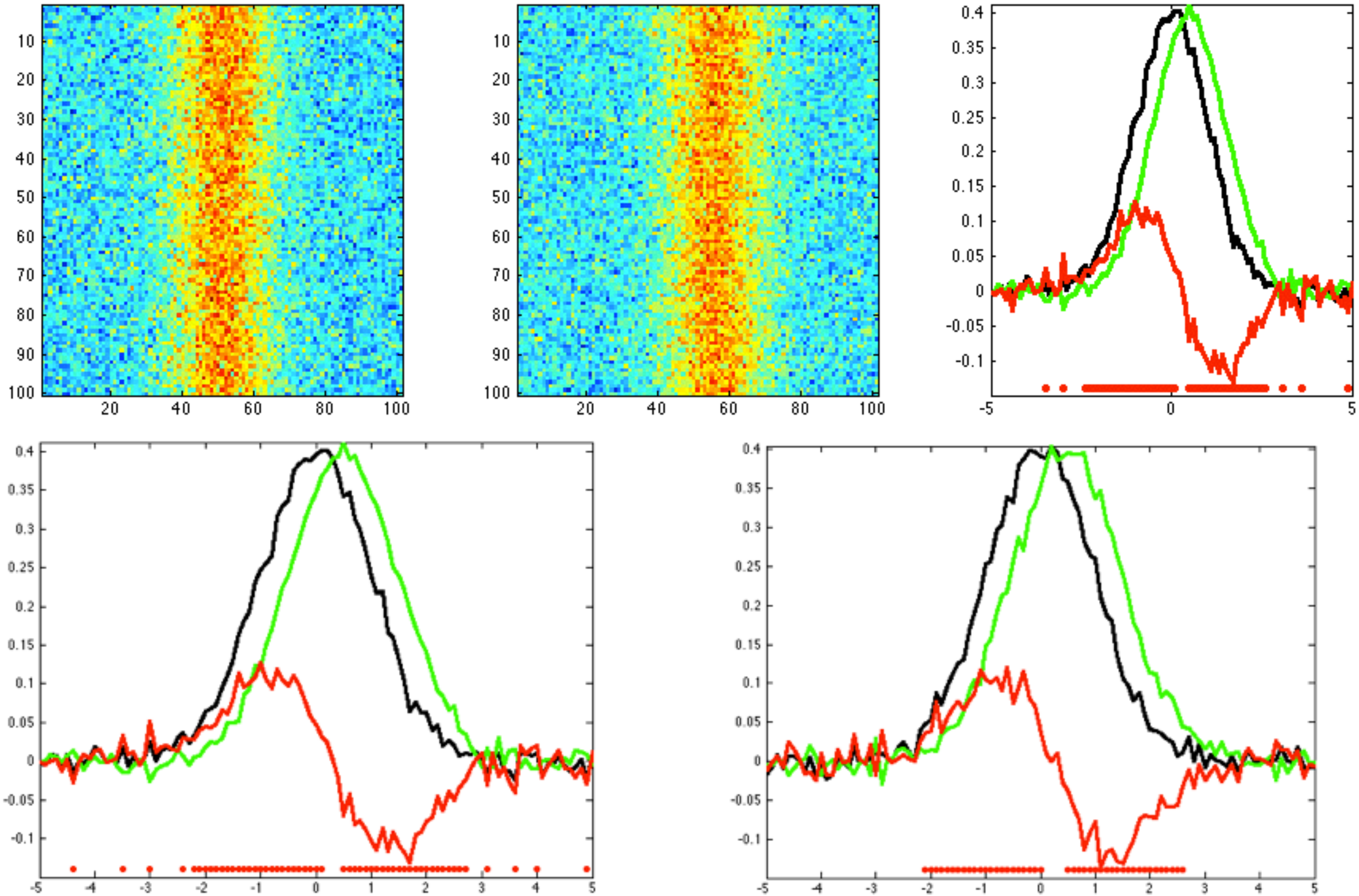






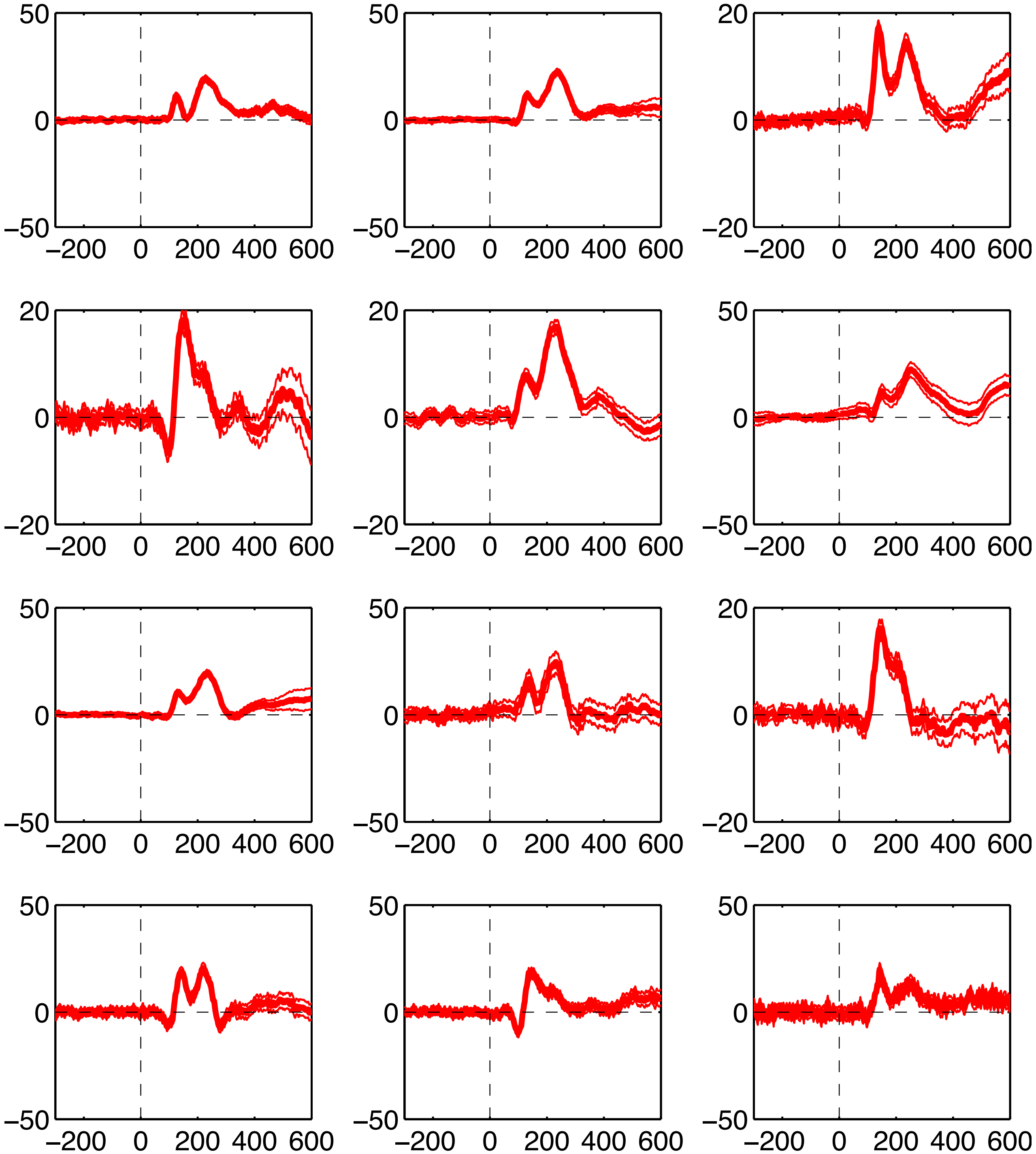
1D cluster test

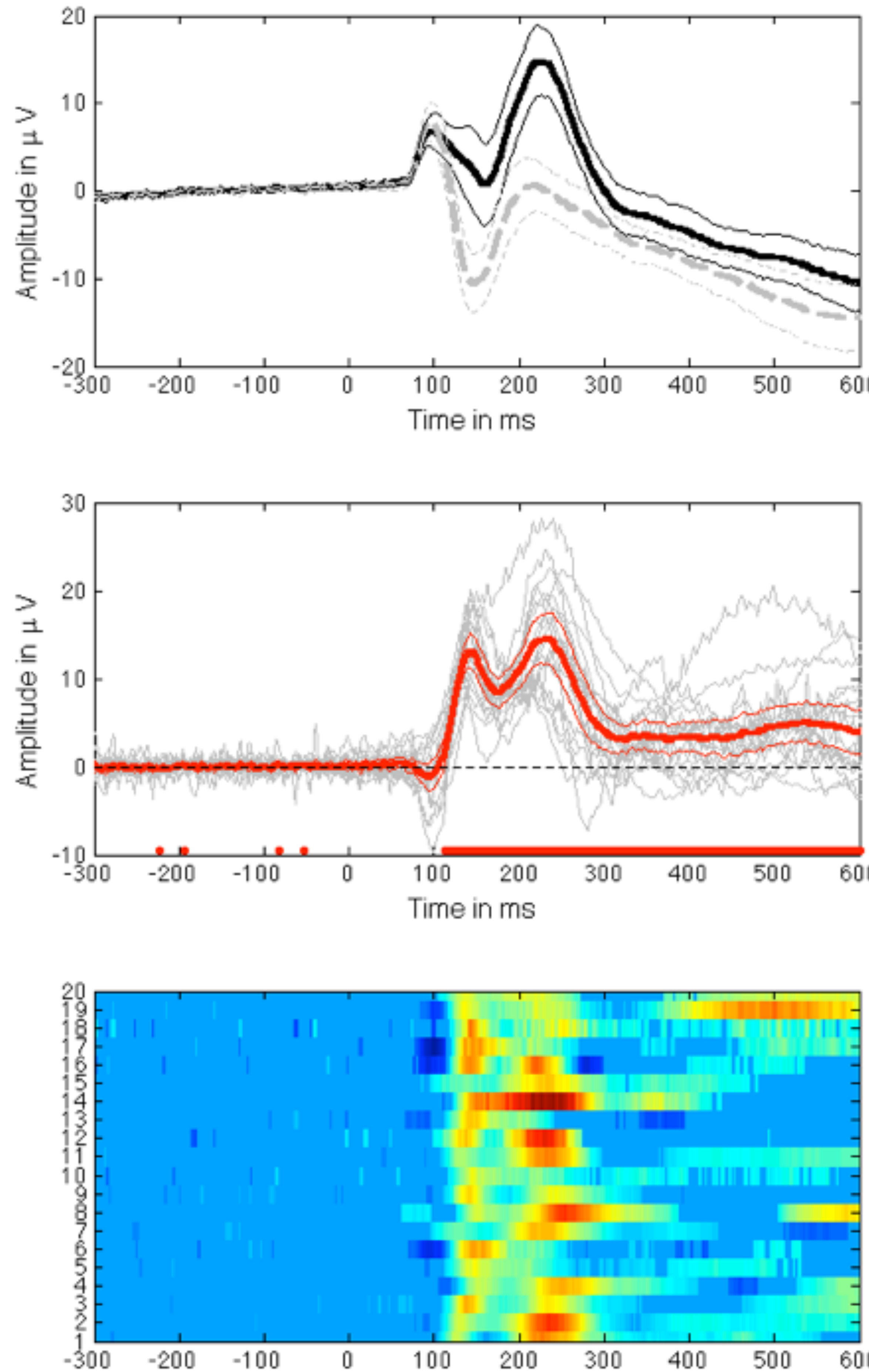
cmc_example.m



erp_workshop_7_cmc_group.m

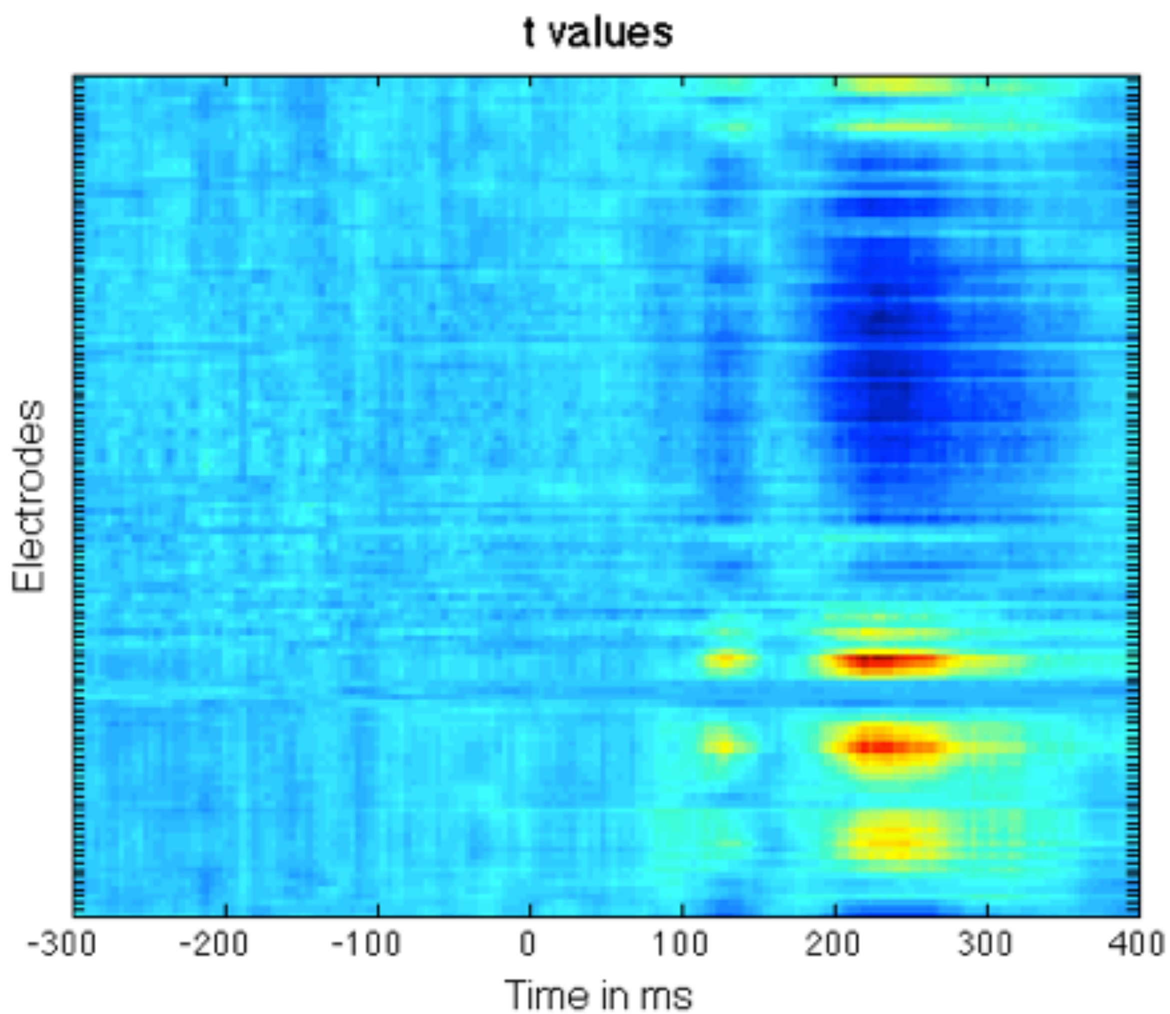
Single-subject analyses

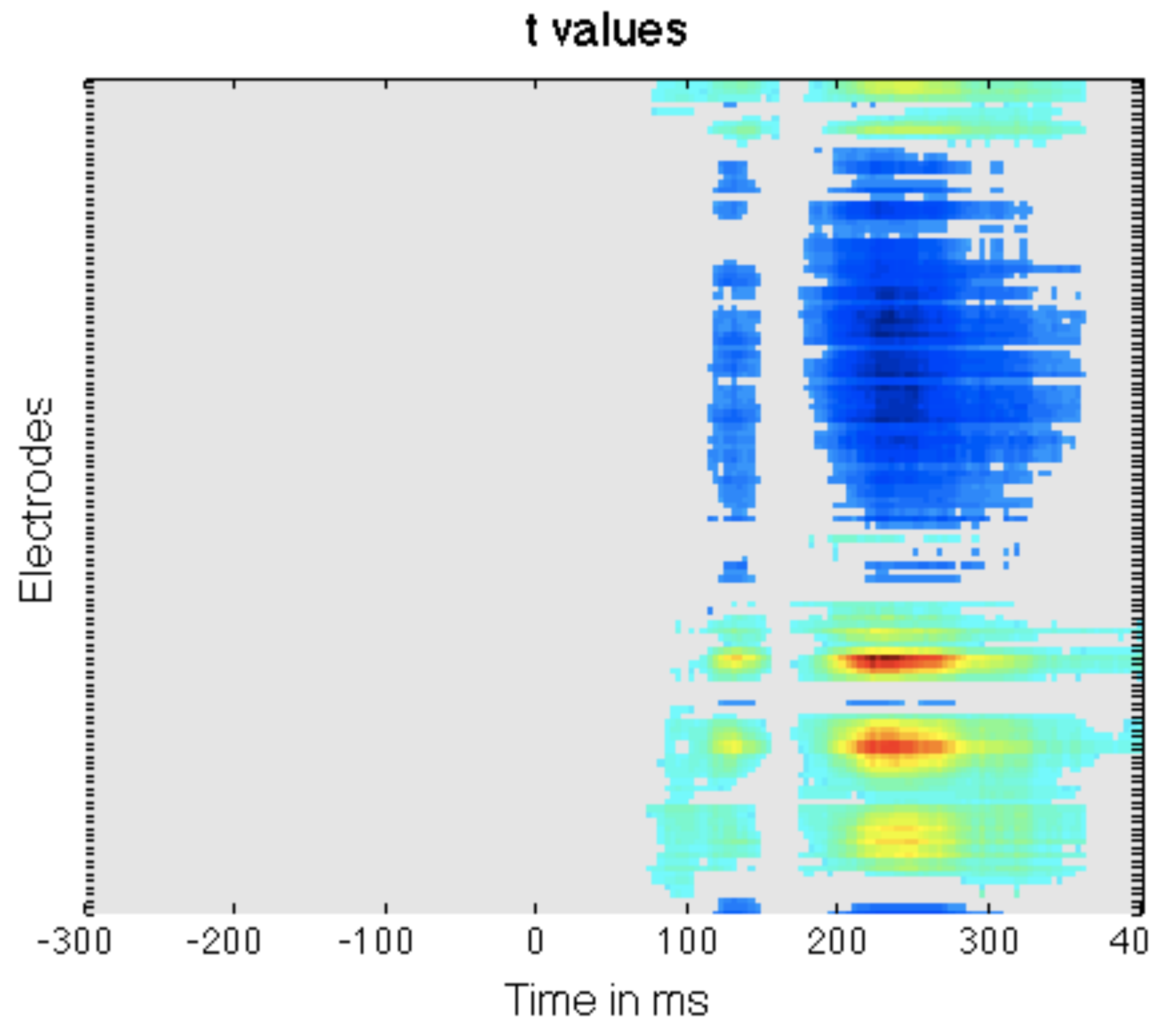


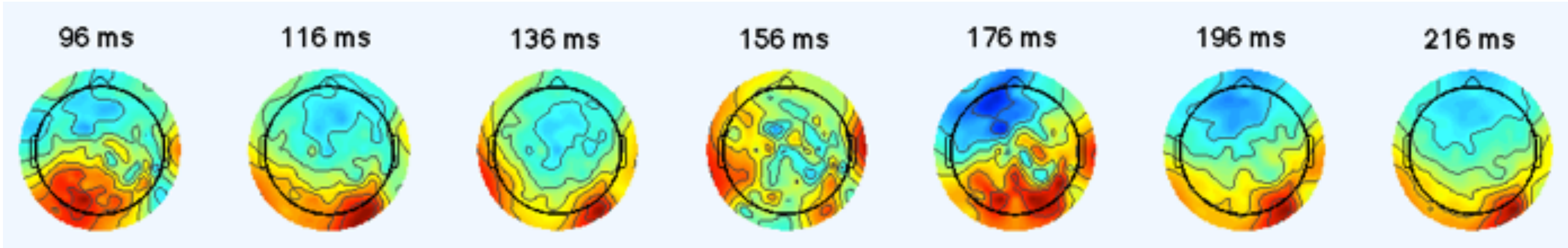


erp_workshop_8_single.m

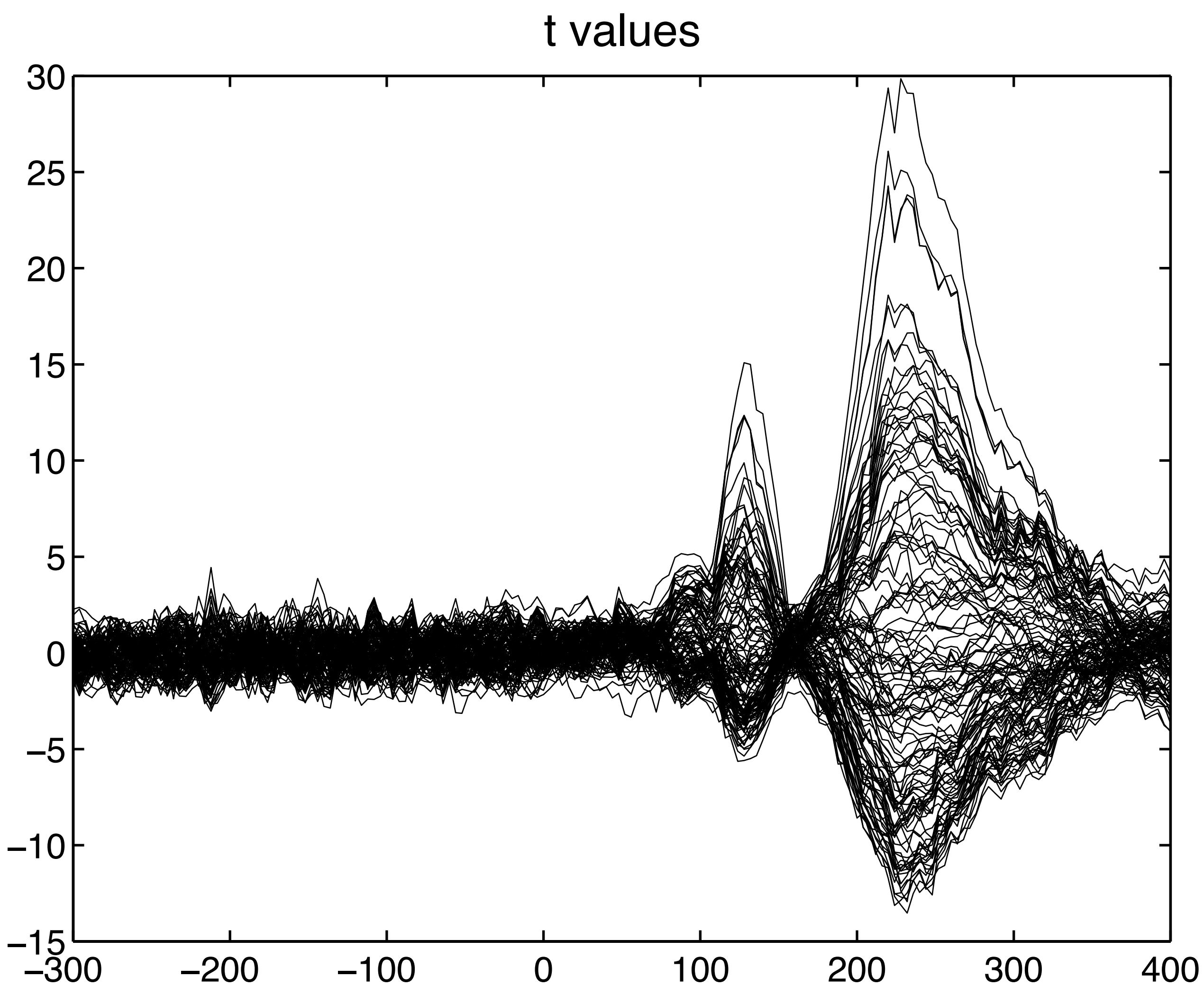
Single-subject analyses: all electrodes

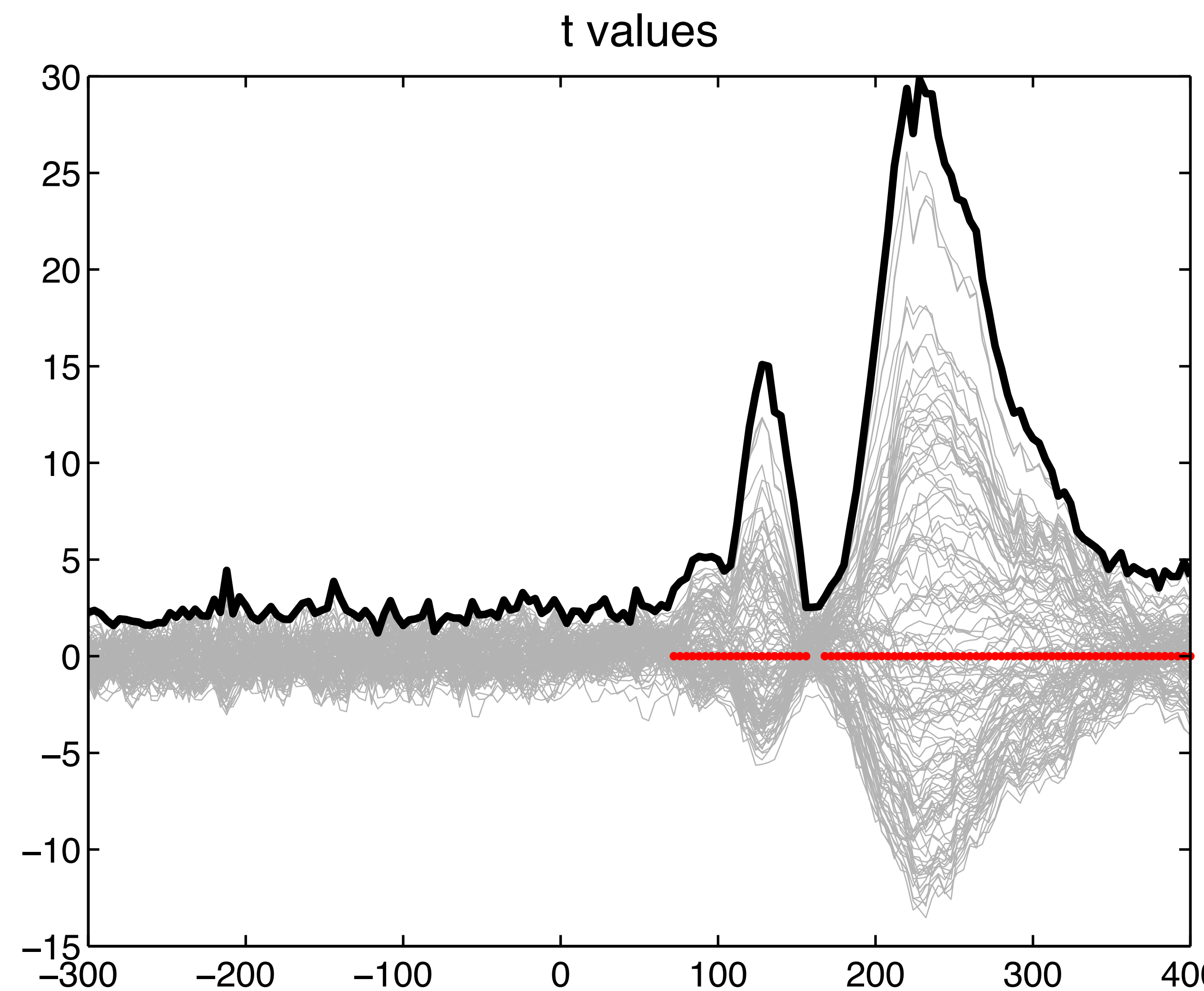






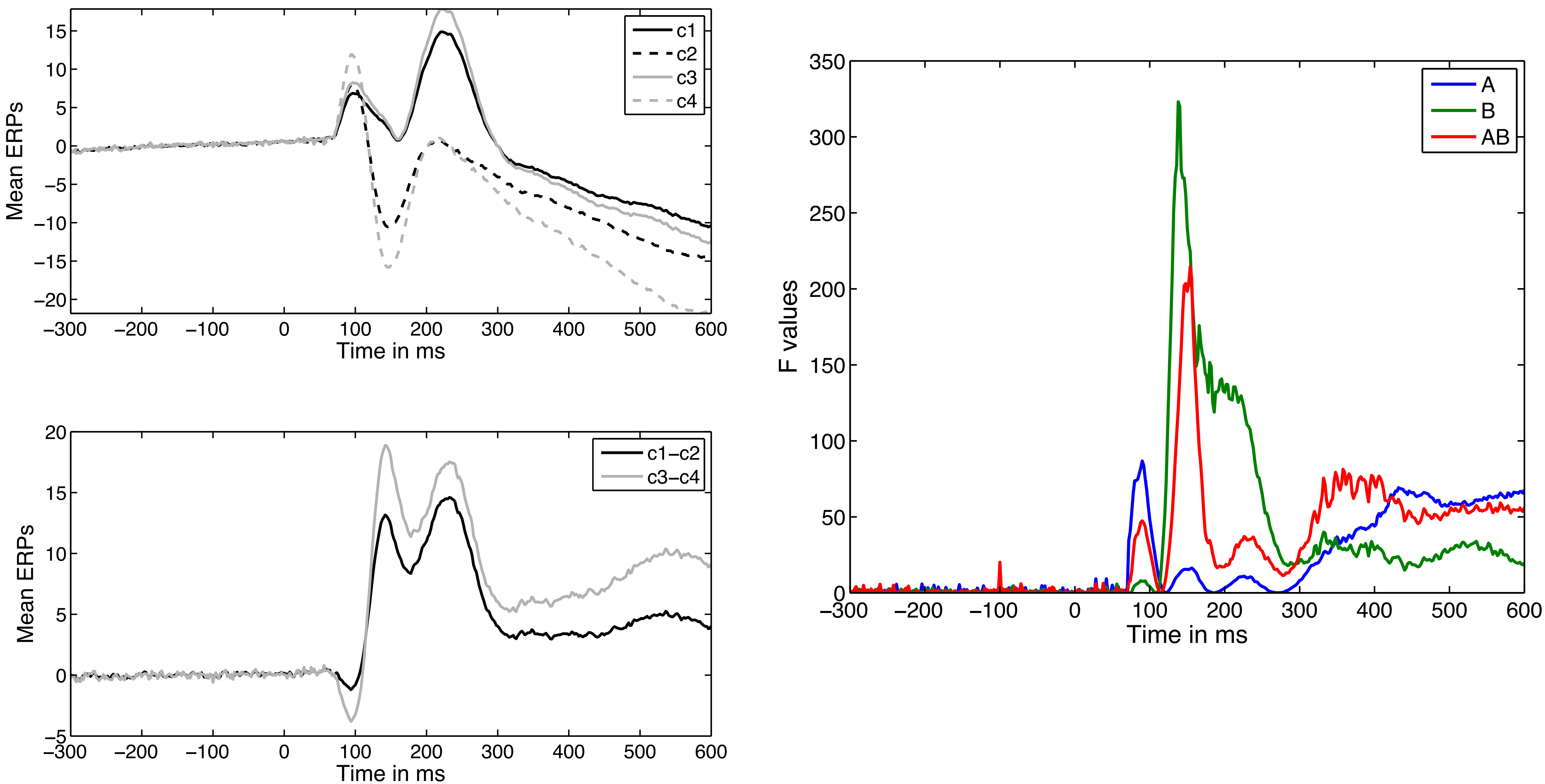
Single-subject analyses: all electrodes



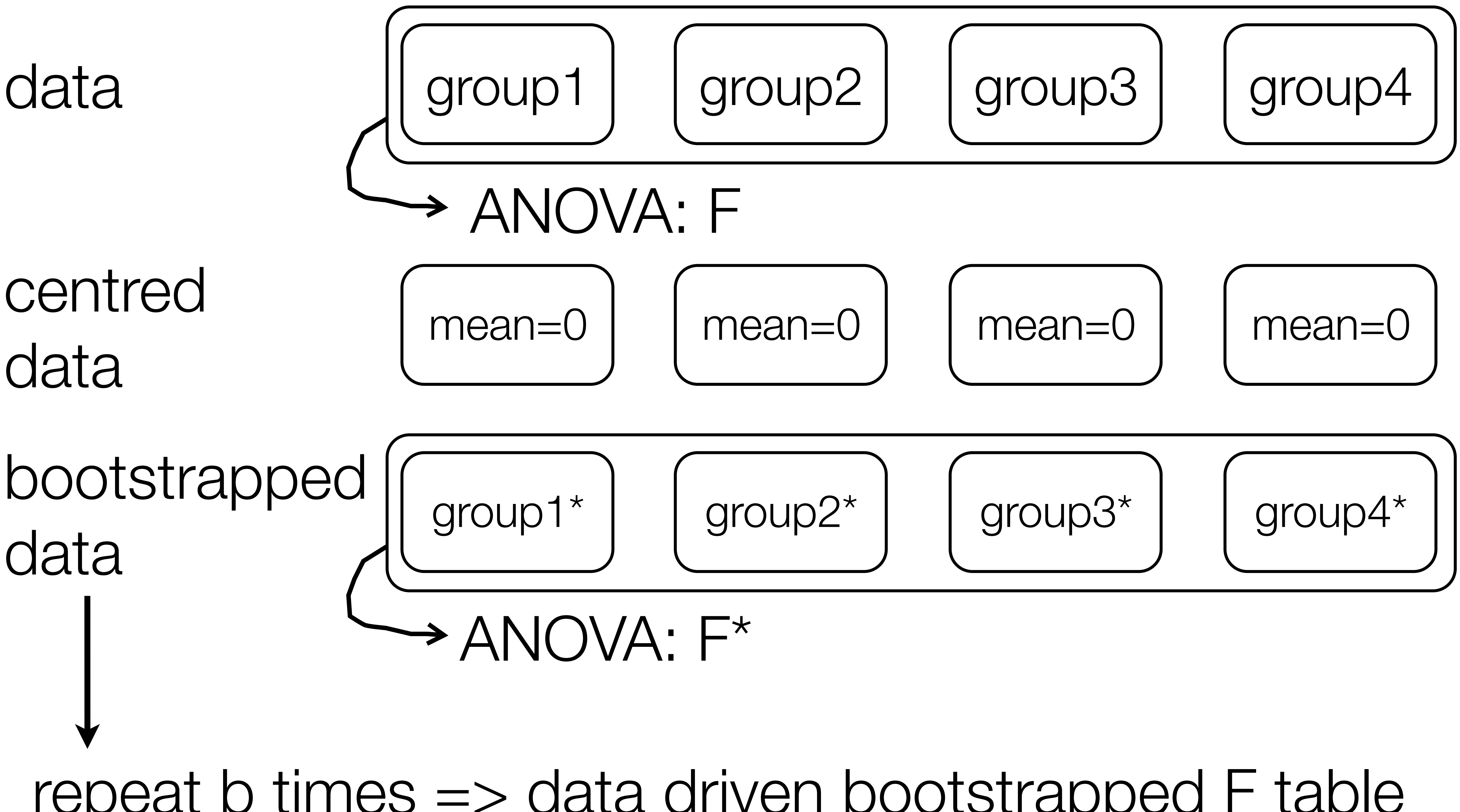


erp_workshop_9_cmc_single.m

Group analyses: ANOVA

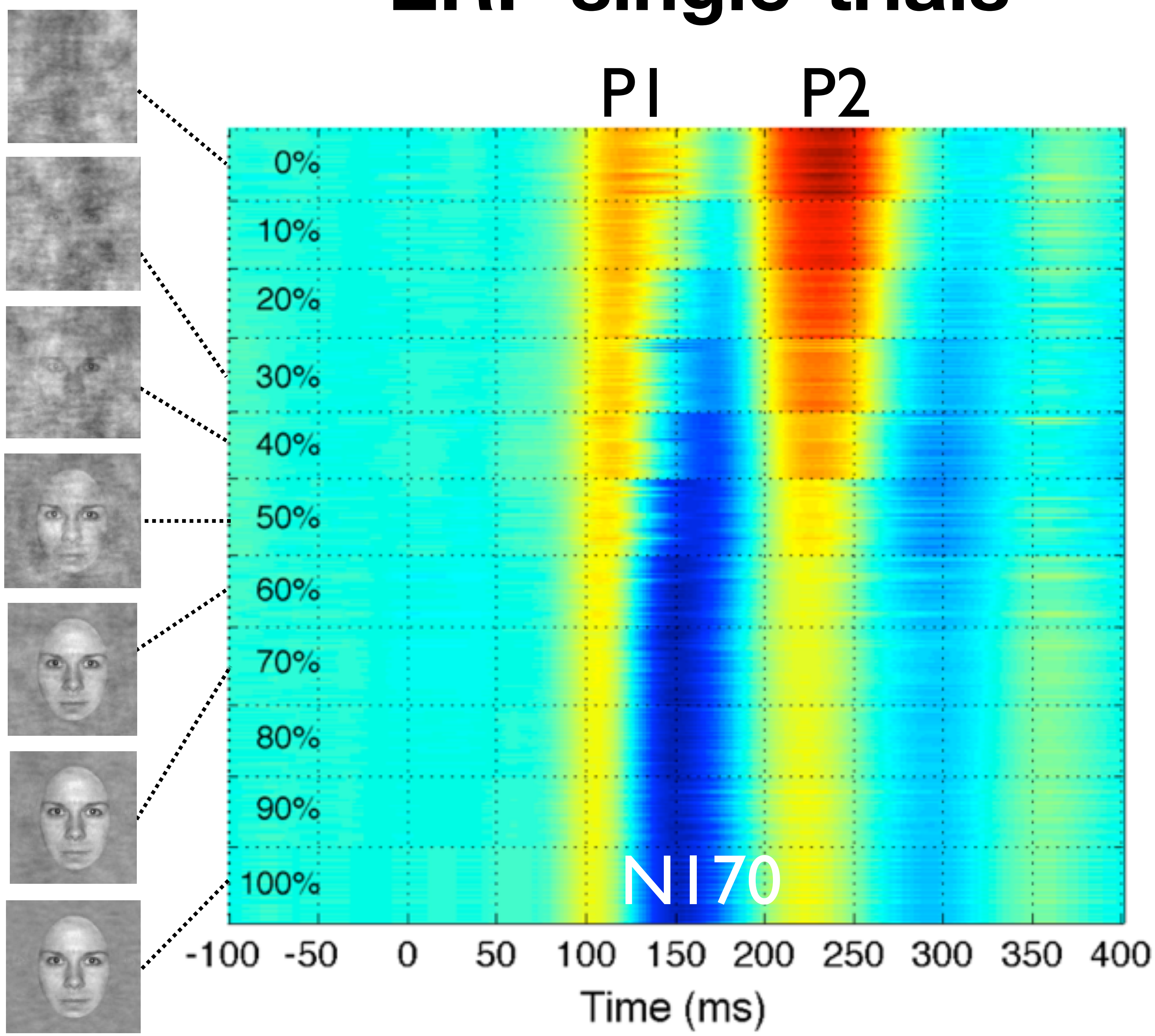


bootstrap-F technique



erp_workshop_10_anova.m

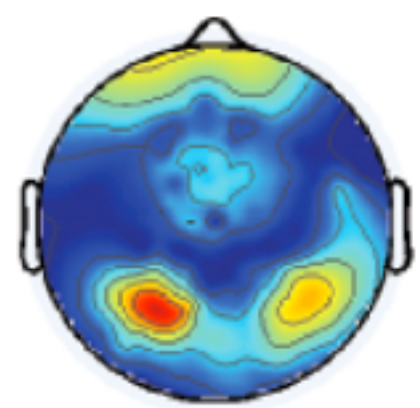
ERP single-trials



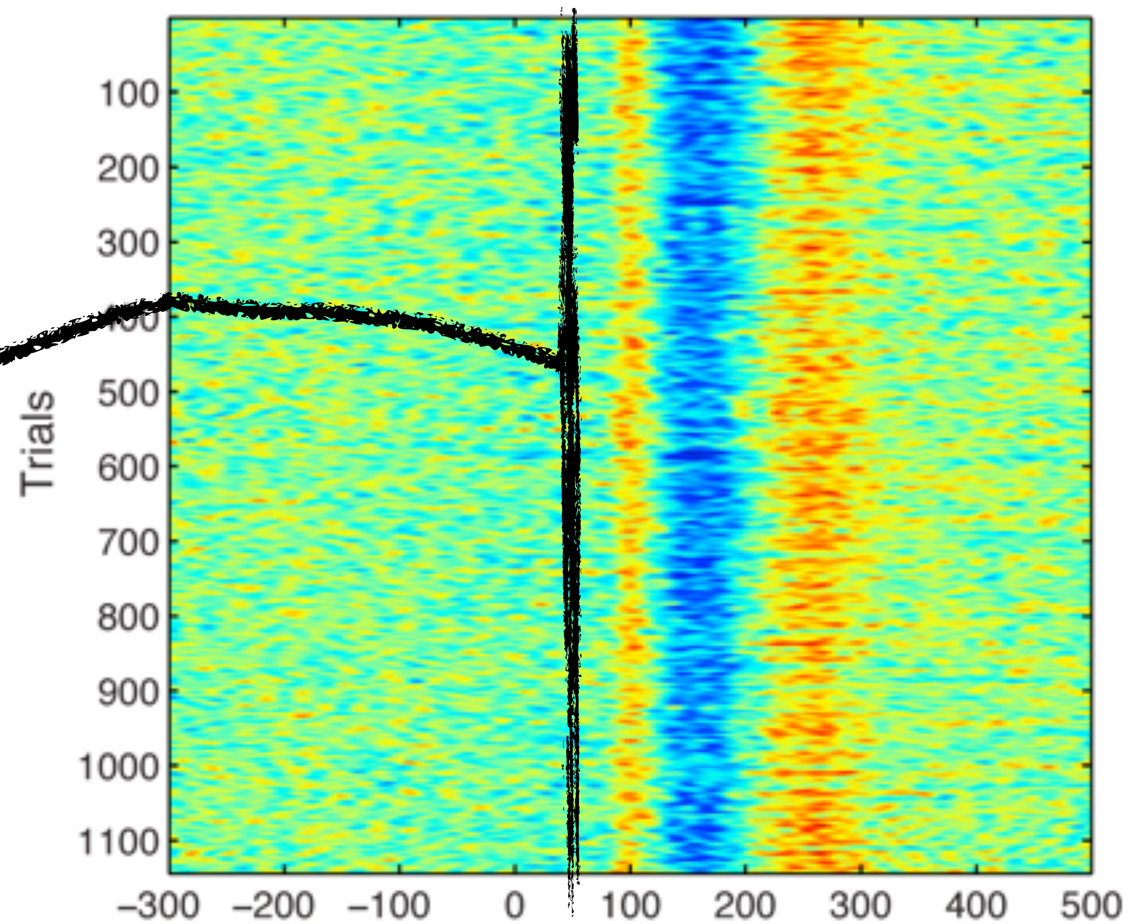
Phase noise sensitivity:

single subject

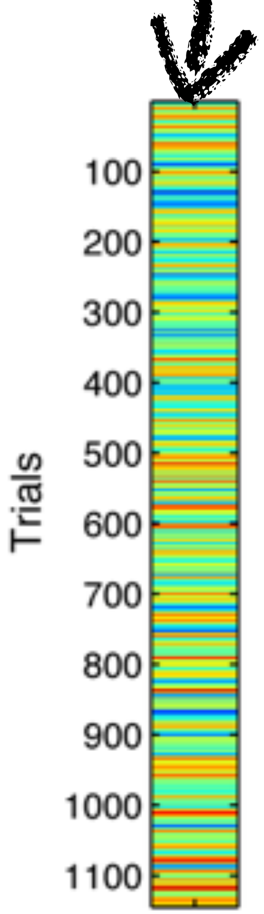
posterior electrode



Rousselet, Pernet, Bennett & Sekuler, *BMC Neuroscience*, 2008

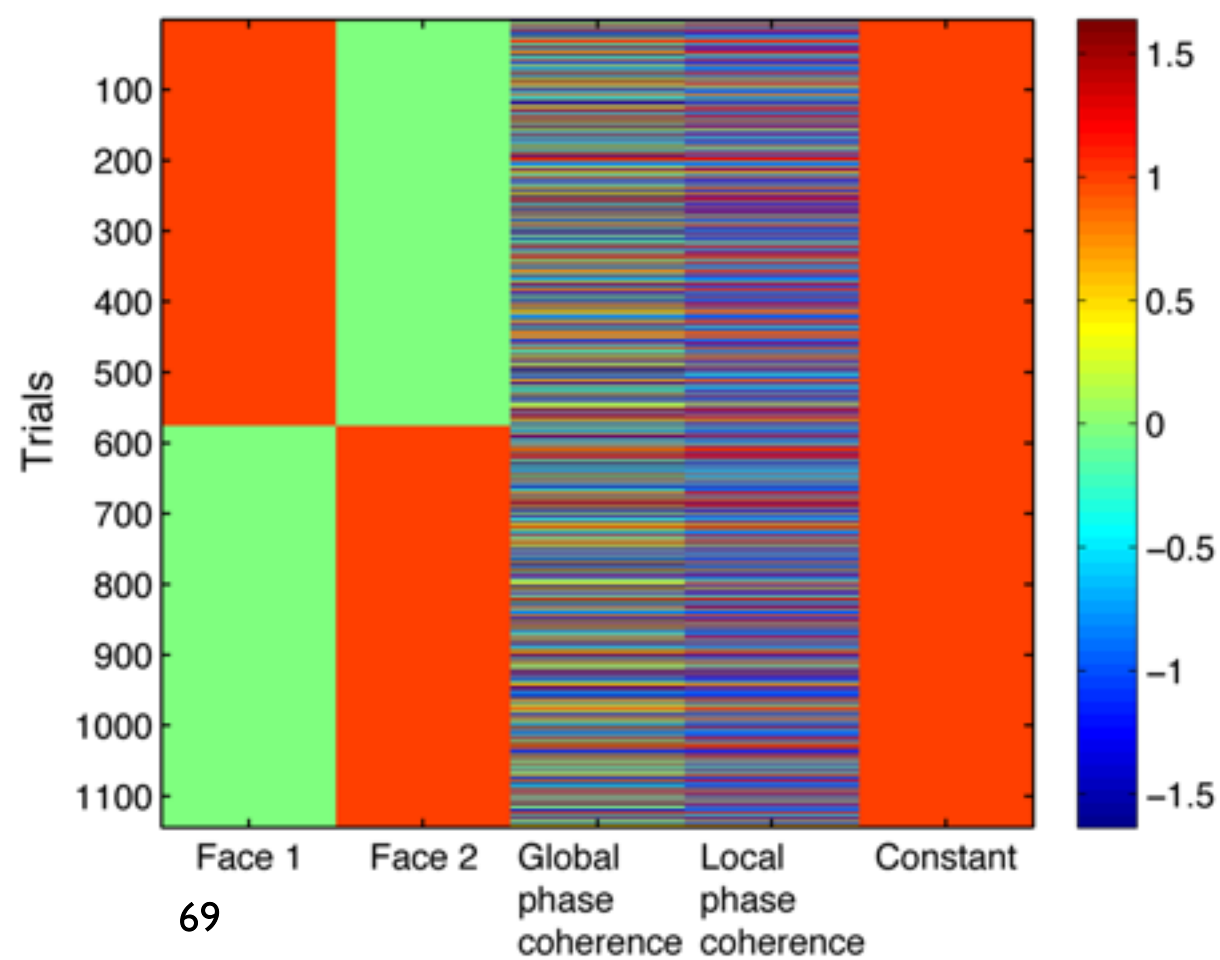


Design matrix

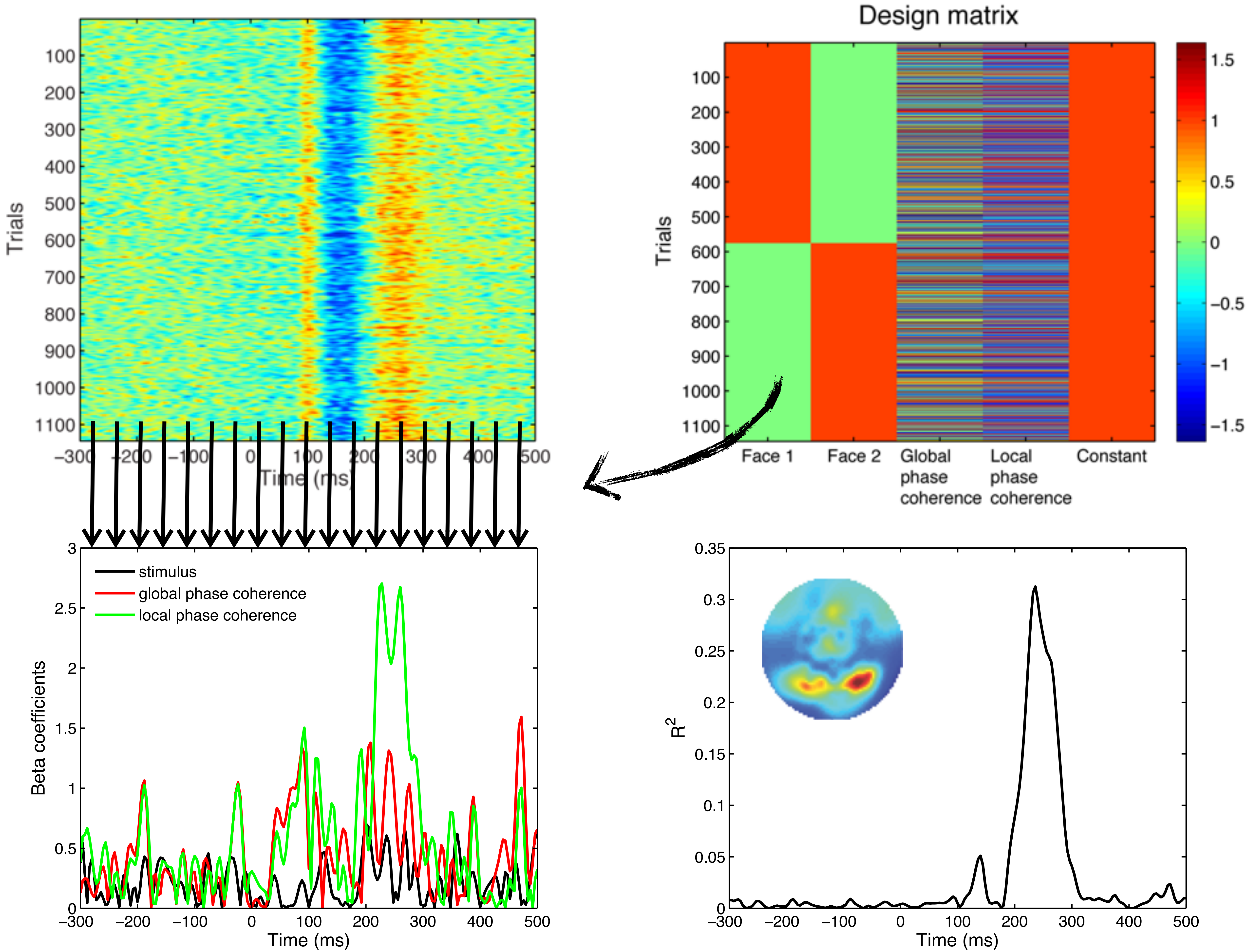


Beta coefficients

$$= [\, B_1 + B_2 + B_3 + B_4 + B_0 \,] \times$$

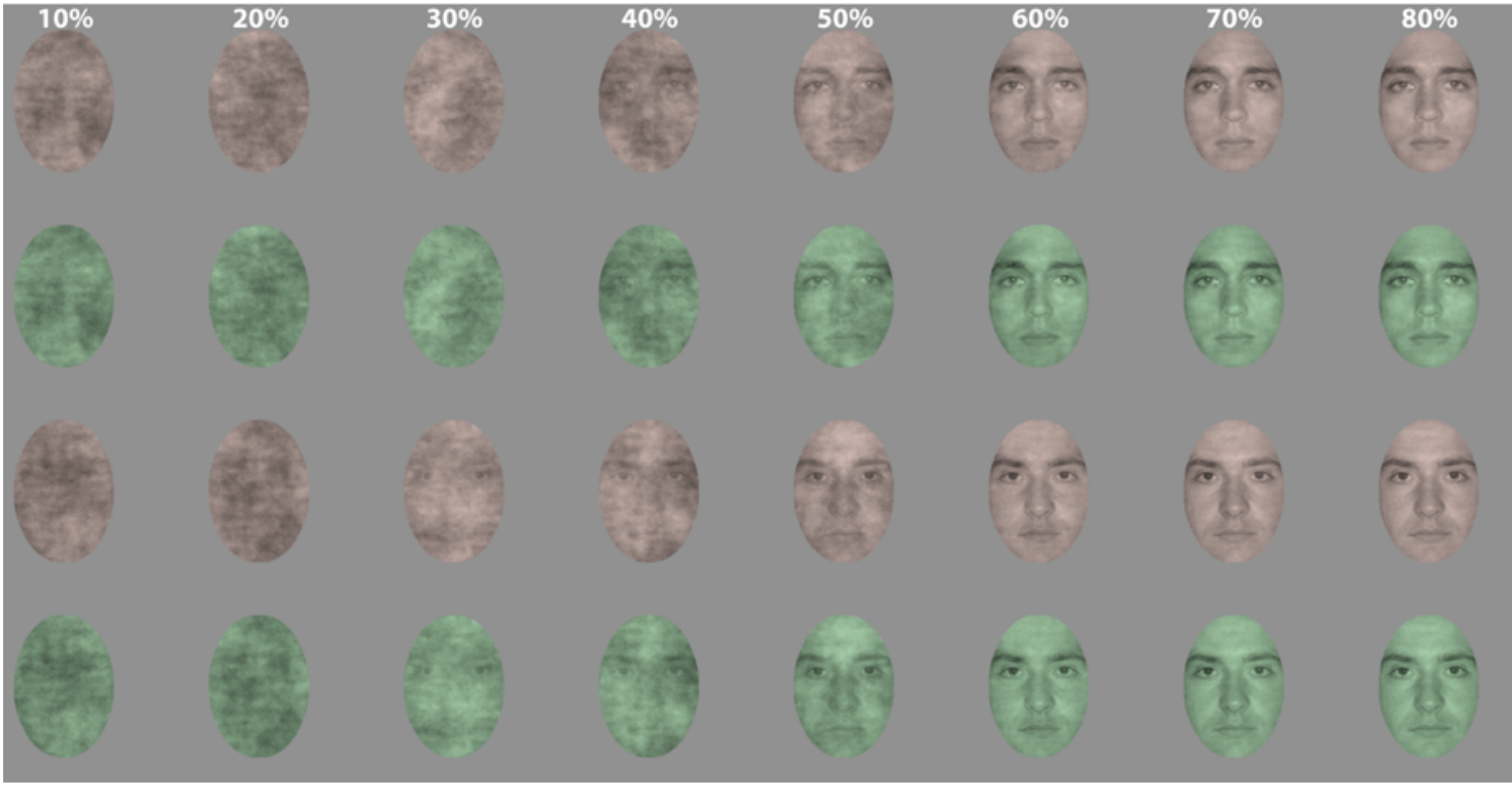


+ error



Trials
Time (ms)
Design matrix
Face 1
Face 2
Global phase coherence
Local phase coherence
Constant
stimulus
global phase coherence
local phase coherence
Beta coefficients
R^2

task effects on noise sensitivity?

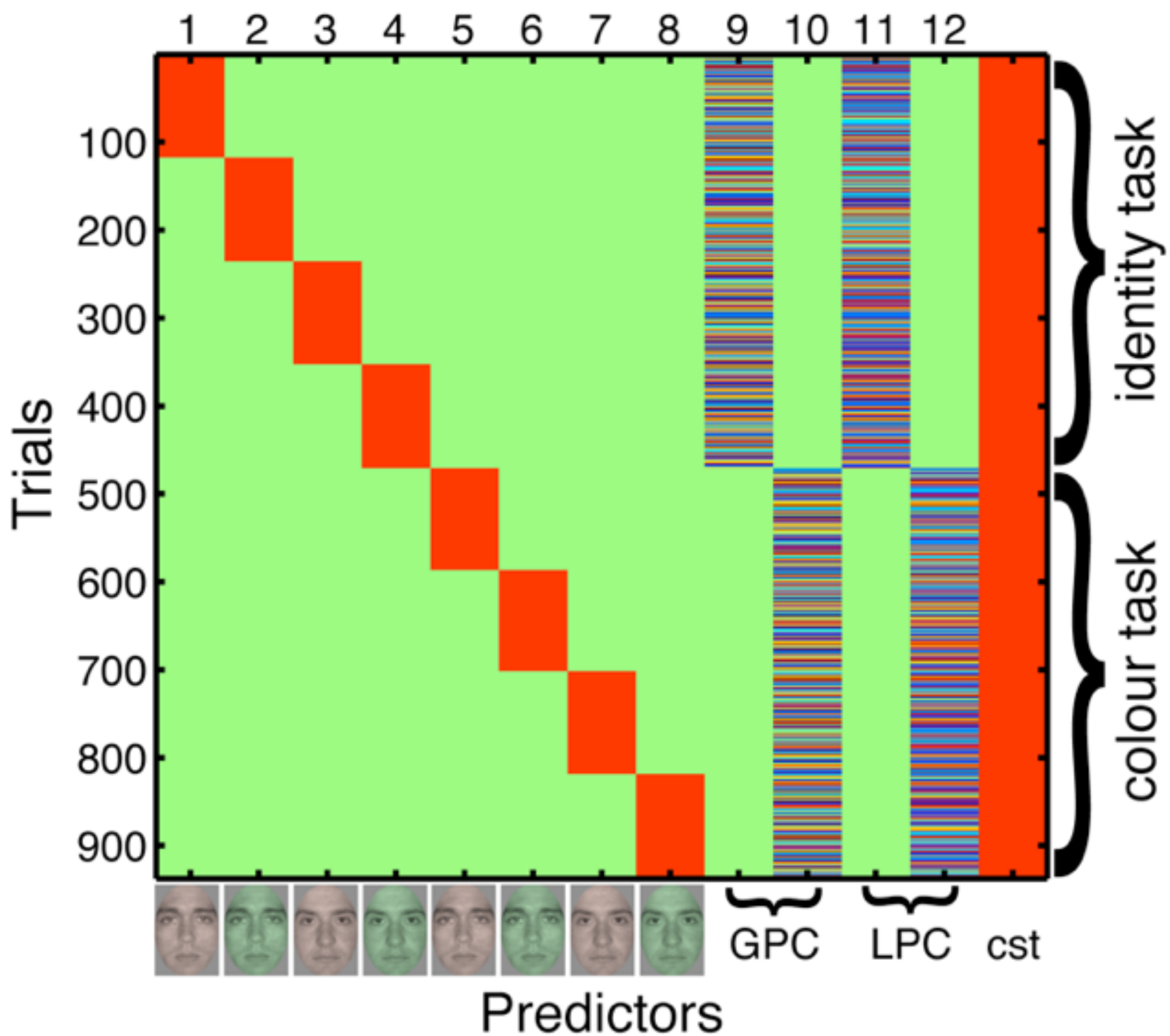


2 tasks - block design, 13 young subjects

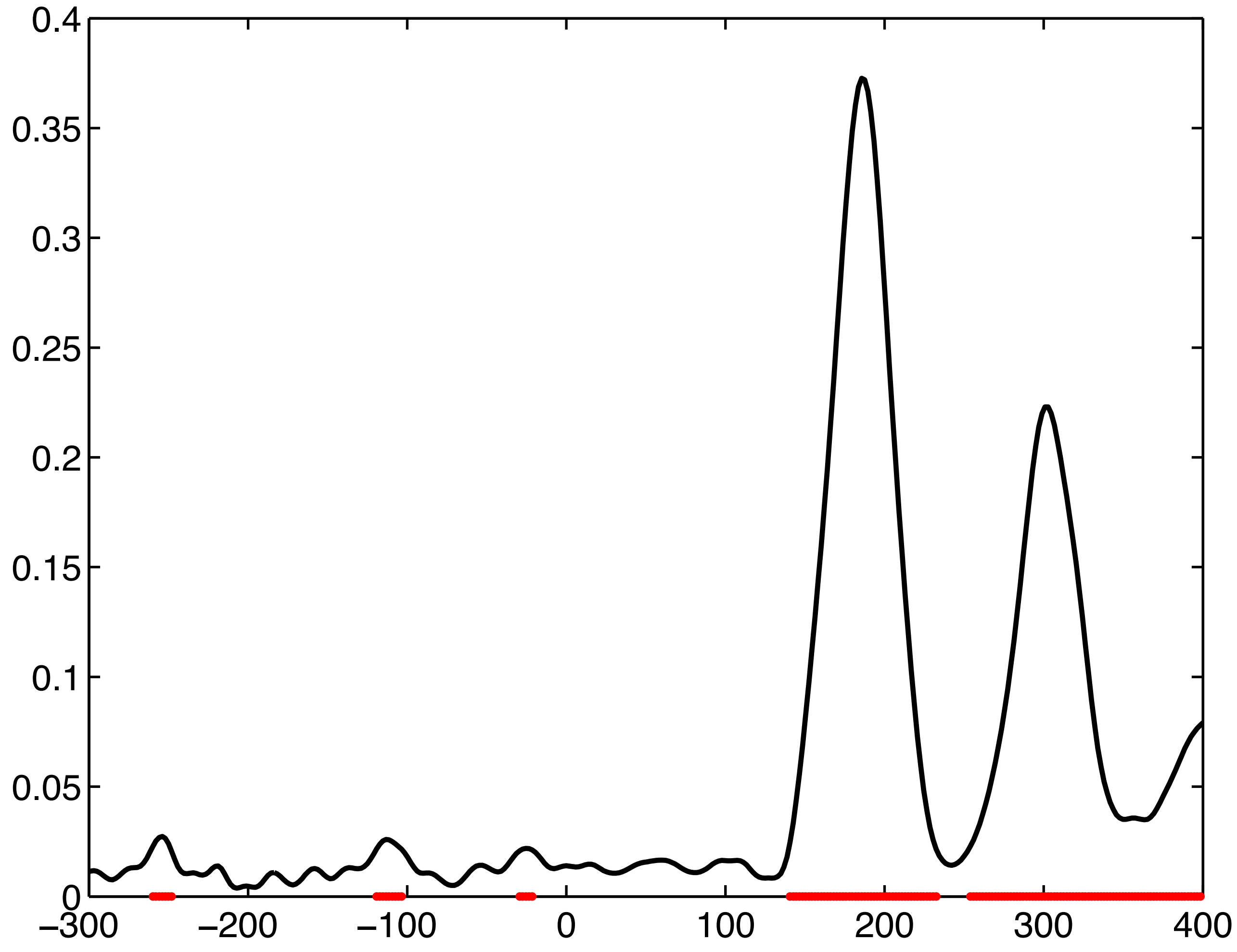
Rousselet, Gaspar, Wieczorek & Pernet (2011). *Frontiers in Psychology* 2(137)

how many subjects?
shift function

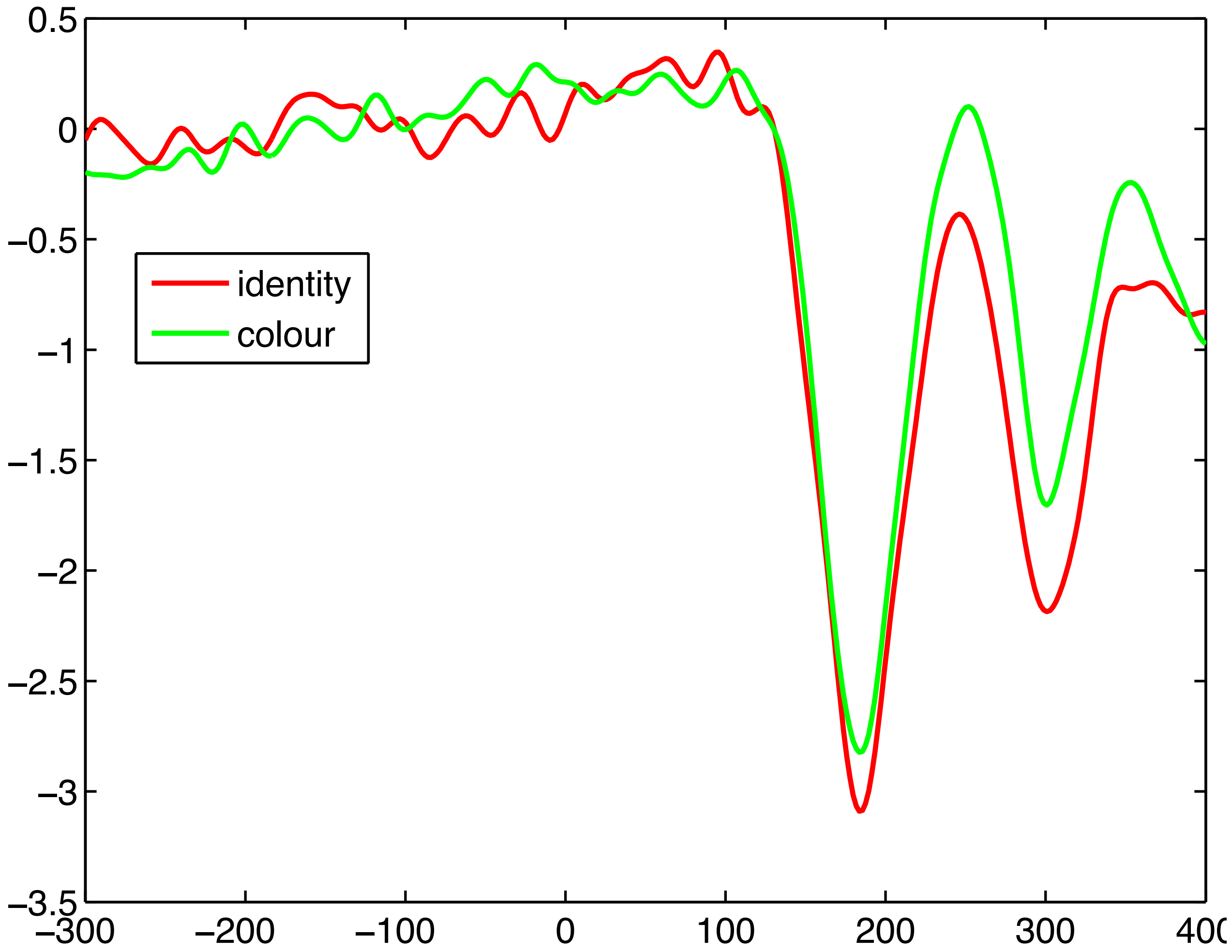
design matrix

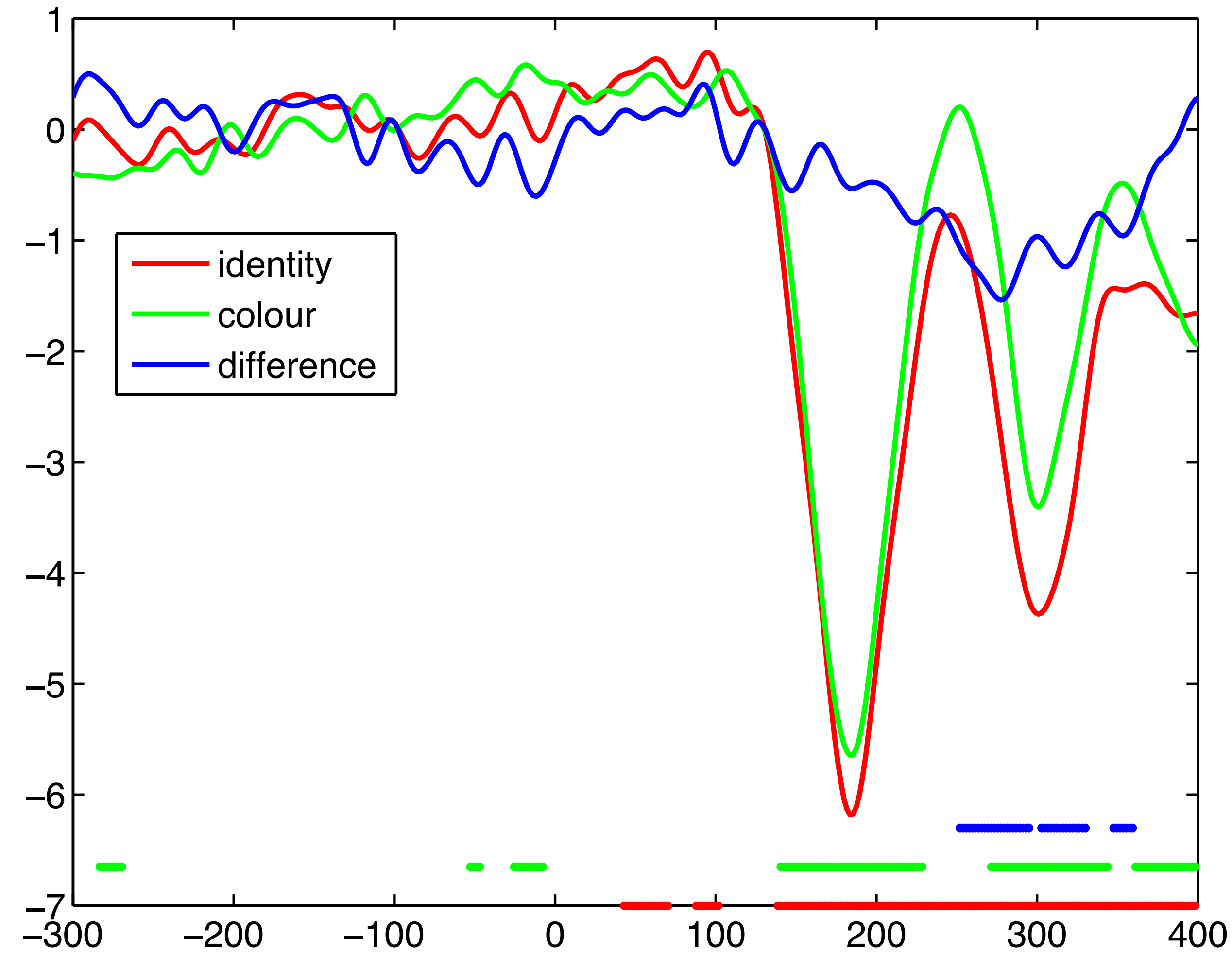


Global model R^2



Beta coefficients & linear contrasts





erp_workshop_11_ancova.m

Questions?

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