# **Robust statistics**

Arnaud Delorme (with feedback/slides from C. Pernet & G. Roussellet)

#### **Robust statistics**

**Parametric & non-parametric statistics:** use mean and standard deviation (t-test, ANOVA, ...)

**Bootstrap and permutation methods:** shuffle/bootstrap data and recompute measure of interest. Use the tail of the distribution to asses significance.

**Correction for multiple comparisons:** computing statistics on time(/frequency) series requires correction for the number of comparisons performed.

# 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

# References

RANDOMIZATION, BOOTSTRAP AND MONTE CARLO METHODS IN BIOLOGY

Second Edition

Bryan F. J. Manly

**Texts in Statistical Science** 

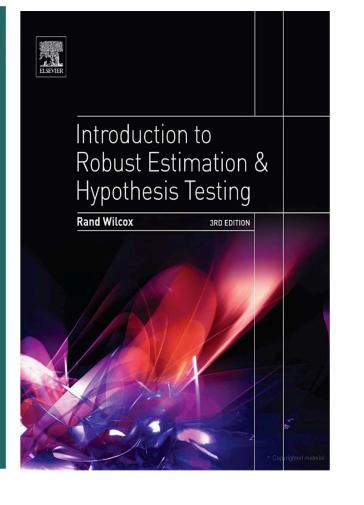
CHAPMAN & HALL/CRC

Monographs on Statistics and Applied Probability 57

An Introduction to the Bootstrap

Bradley Efron Robert J. Tibshirani

CHAPMAN & HALLICRC



# **Parametric statistics**

#### Assume gaussian distribution of data

**T-test:** Compare paired/ unpaired Samples for continuous data. In EEGLAB, used for grand-average ERPs.

t dist. Paired df=5  $t = \frac{Mean\_difference}{Standard\_deviation} \sqrt{N-1}$ 0.2 2.5% of 2.5% of Unpaired area area  $t = \sqrt{N} \frac{Mean_A - Mean_B}{\sqrt{(SD_A)^2 - (SD_B)^2}}$ 0 -10 0 10 0.8 F dist.  $df_n = 5$  $df_d = 10$ Variance<sub>interGroup</sub>  $N_{Group} - 1$ 0.4 F = -Variance<sub>WithinGroup</sub> 5% of area 0 5 0 10

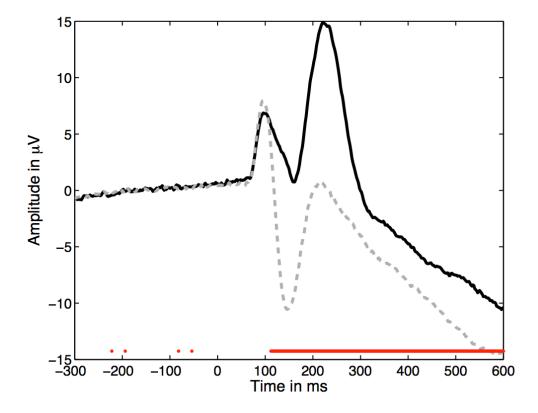
0.4

**ANOVA:** compare several groups (can test interaction between two factors for the repeated measure ANOVA)

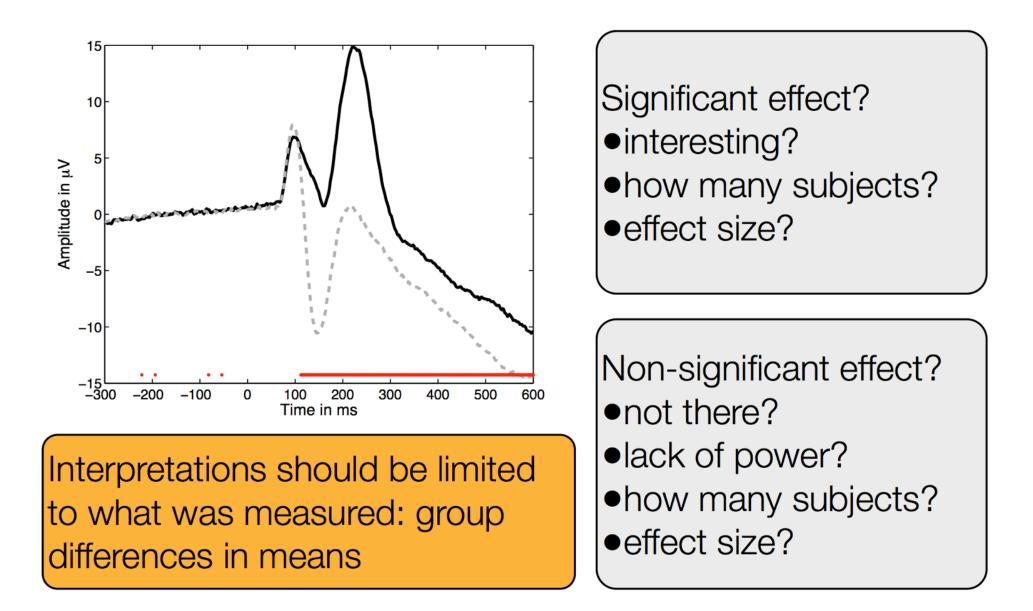
	Dataset		
Goal	Binomial or Discrete	Continuous measurement (from a normal distribution)	Continuous measurement, Rank, or Score (from non- normal distribution)
Example of data sample	List of patients recovering or not after a treatment	Readings of heart pressure from several patients	Ranking of several treatment efficiency by one expert
Describe one data sample	Proportions	Mean, SD	Median
Compare one data sample to a hypothetical distribution	$\chi^2$ or binomial test	One-sample t test	Sign test or Wilcoxon test
Compare two paired samples	Sign test	Paired t test	Sign test or Wilcoxon test
Compare two unpaired samples	$\chi^2$ square Fisher's exact test	Unpaired t test	Mann-Whitney test
Compare three or more unmatched samples	$\chi^2$ test	One-way ANOVA	Kruskal-Wallis test
Compare three or more matched samples	Cochrane Q test	Repeated-measures ANOVA	Friedman test
Quantify association between two paired samples	Contingency coefficients	Pearson correlation	Spearman correlation
	Matlab Statistics toolbox; Parra & Sajda plugin	EEGLAB FIELDTRIP LIMO EEG	Matlab Statistics toolbox

Delorme, A. (2006) Statistical methods. *Encyclopedia of Medical Device and Instrumentation*, vol 6, pp 240-264. Wiley interscience.

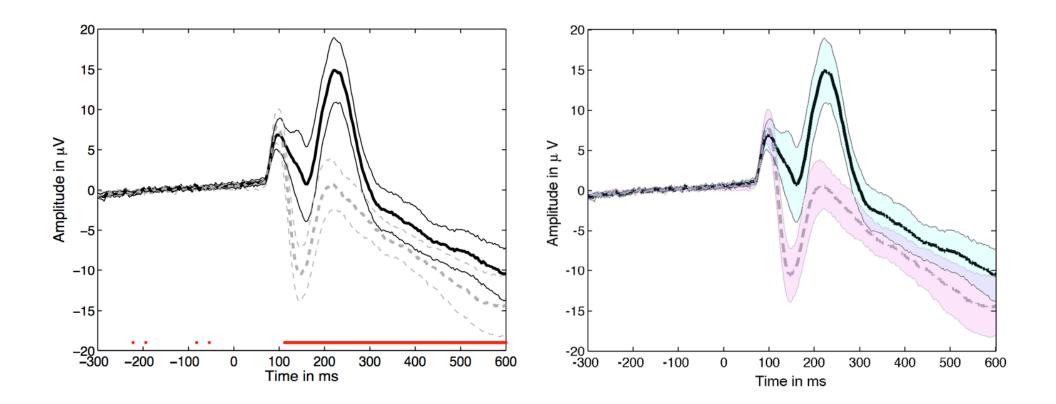
#### Why the standard figure is not good enough



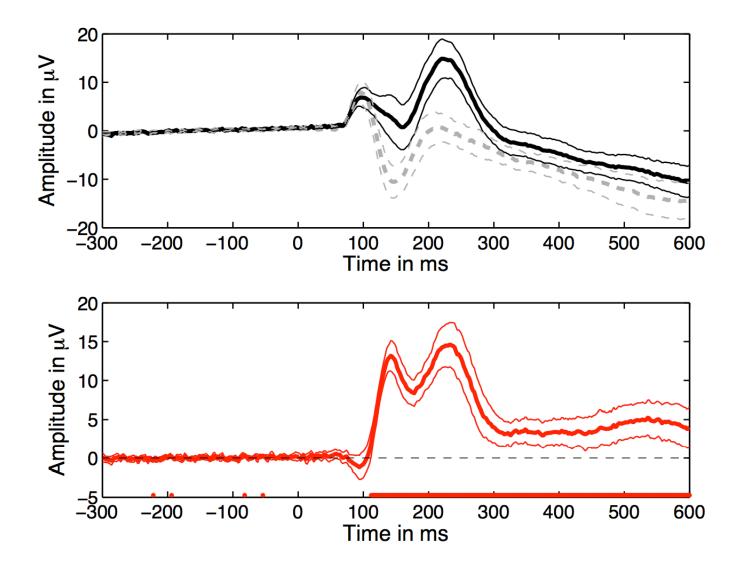
#### Why the standard figure is not good enough



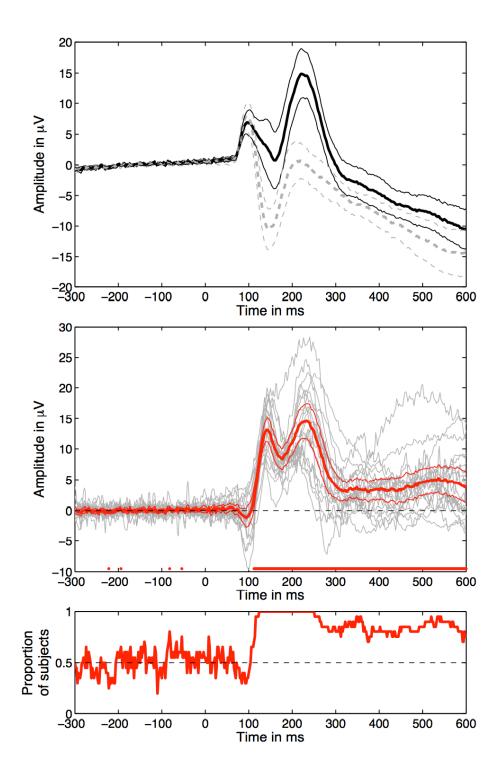
## Add confidence intervals



## Add plot of the difference



# How many subjects show an effect?



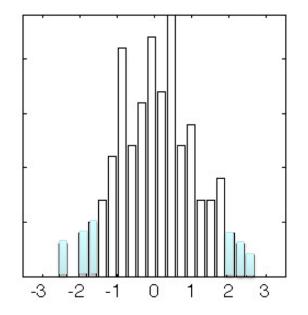
# Robust measures of central tendency (location)

Non-robust estimator

– Mean: mERP = mean(EEG.data,..)

- Robust estimators of central tendency
  - Median: mdERP = median(EEG.data,...)
  - Trimmed mean tmERP = trimmean(EEG.data,...)

# **Trimmed means**



- 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, *J. Vis.* + Desjardins 2013

# **Non-parametric statistics**

Paired t-test → Wilcoxon Unpaired t-test → Mann-Whitney One way ANOVA → Kruskal Wallis

Values

Ranks

#### **BOTH ASSUME NORMAL DISTRIBUTIONS**

# Problems

- Not resistant against outliers
- For ANOVA and t-test non-normality is an issue when distributions differ or when variances are not equal.
- Slight departure from normality can have serious consequences

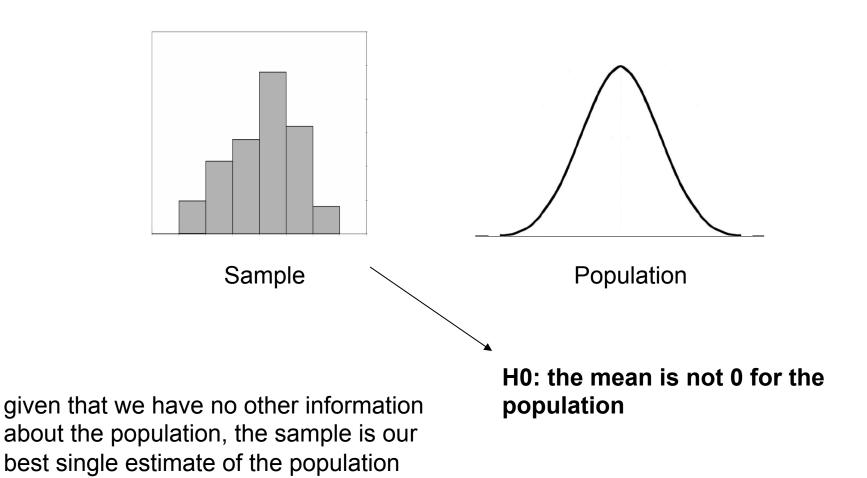
# Solutions

- 1. Randomization approach
- 2. Bootstrap approach

# Bootstrap: central idea

- "The bootstrap is a computer-based method for assigning measures of accuracy to statistical estimates." Efron & Tibshirani, 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, 1993

# Sample and population

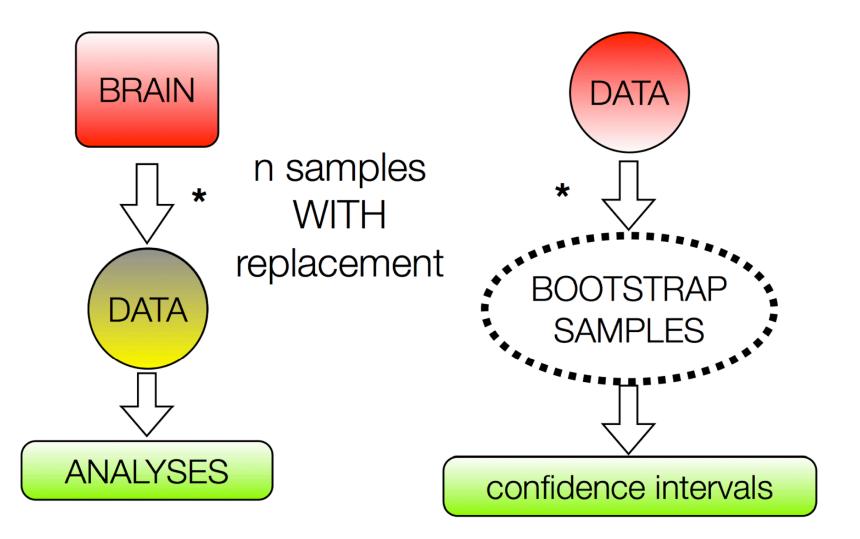


## Percentile bootstrap: general recipe

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

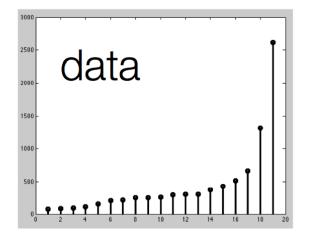
with B large enough the B estimates provide a good approximation of the distribution of the estimate of the sample

# Bootstrap philosophy



#### Percentile bootstrap estimate of confidence intervals

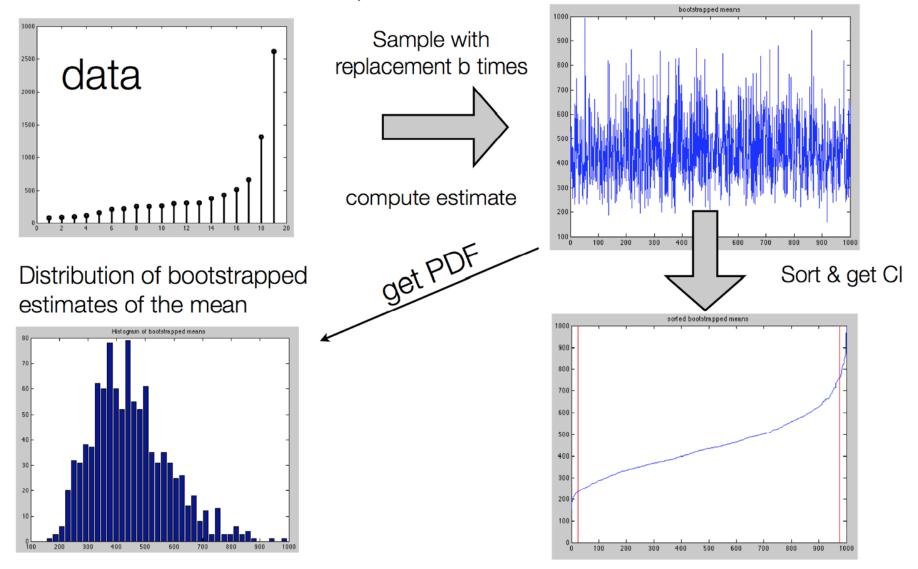
% self-awarness data, Wilcox, 200

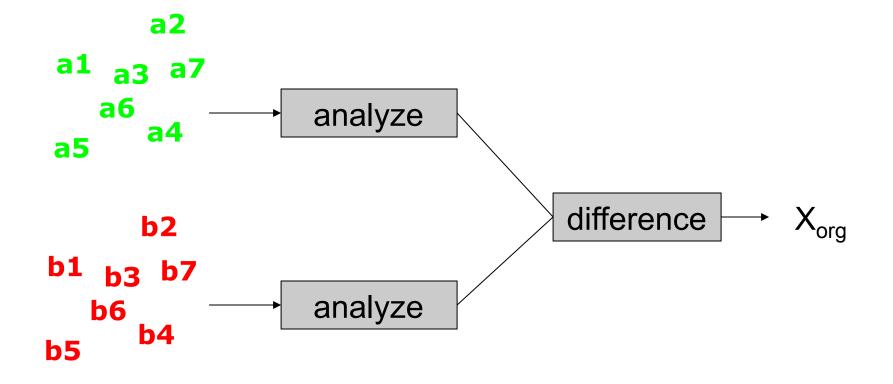


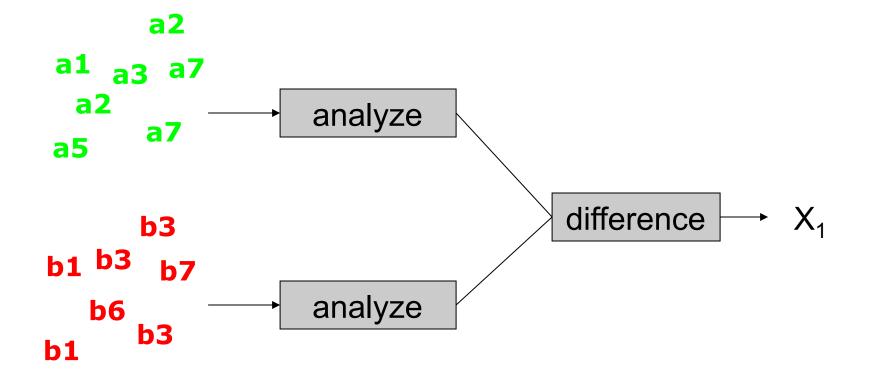
#### Percentile bootstrap estimate of confidence intervals

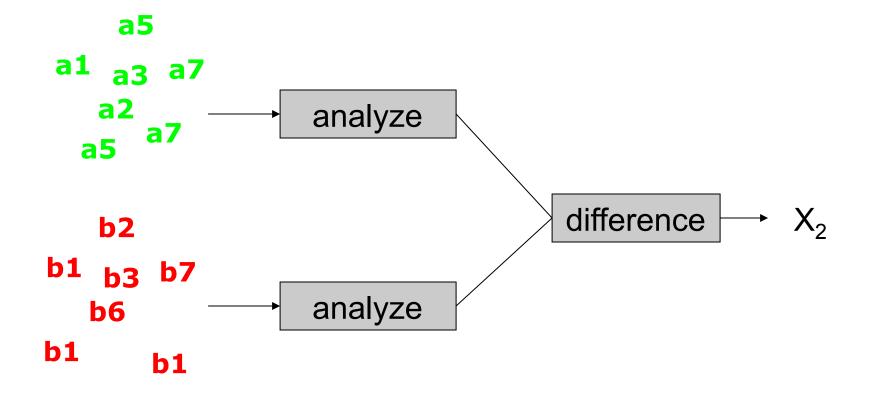
% self-awarness data, Wilcox, 2005, p58

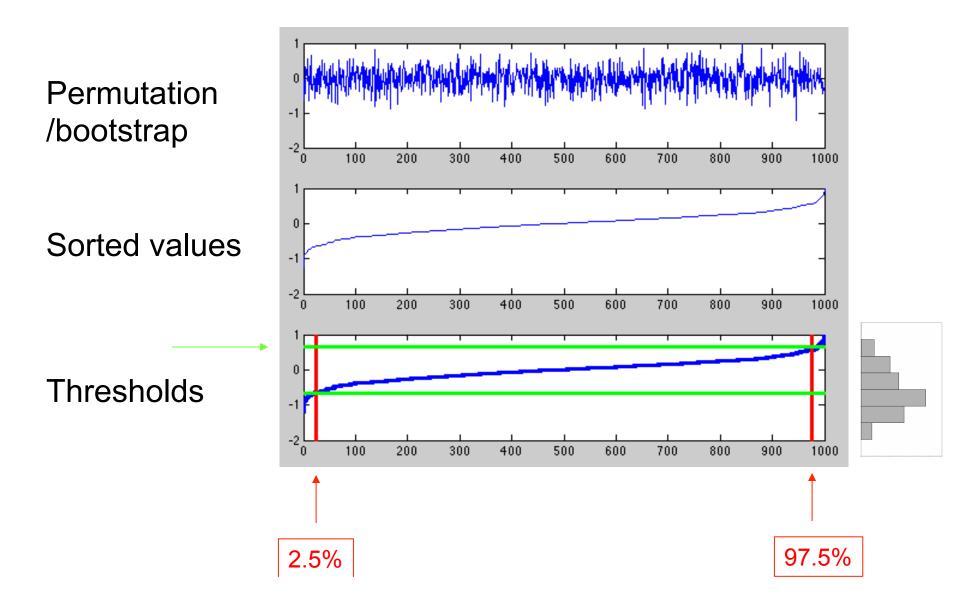
#### Bootstrapped estimates



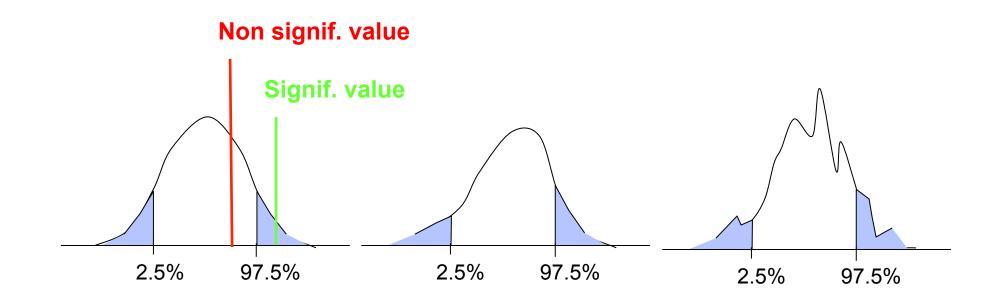




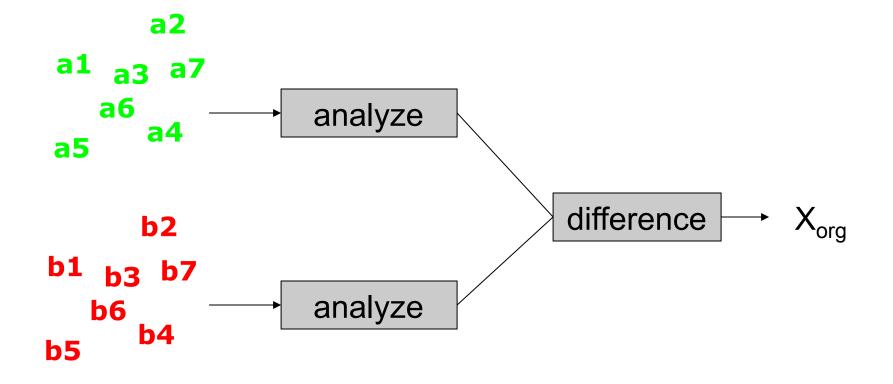


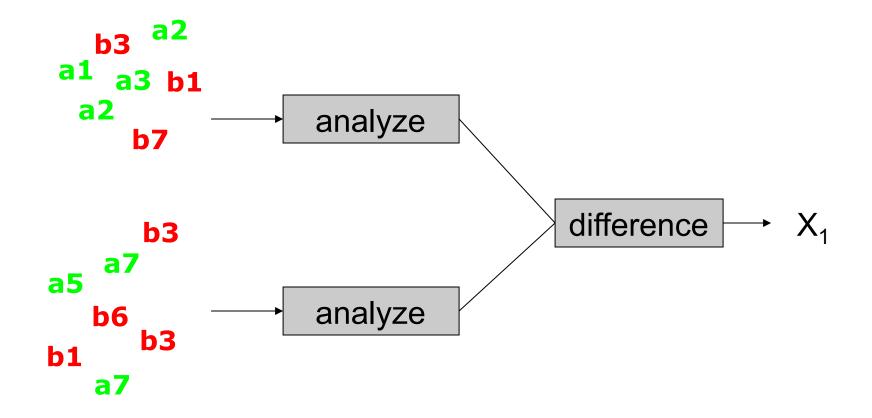


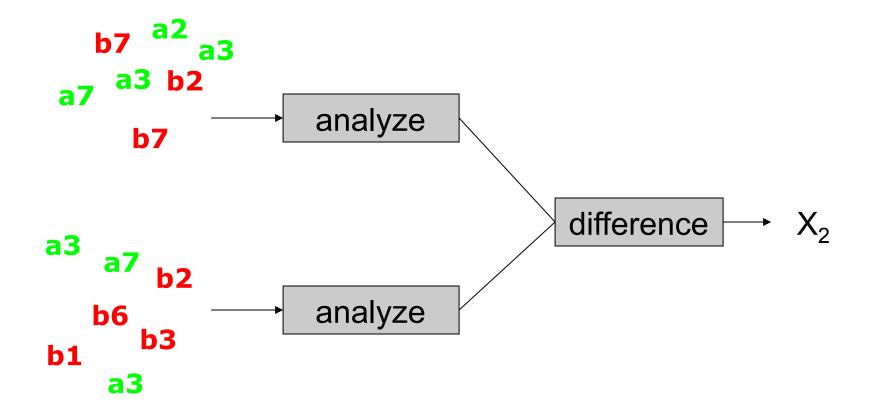
#### Distribution can take any shape

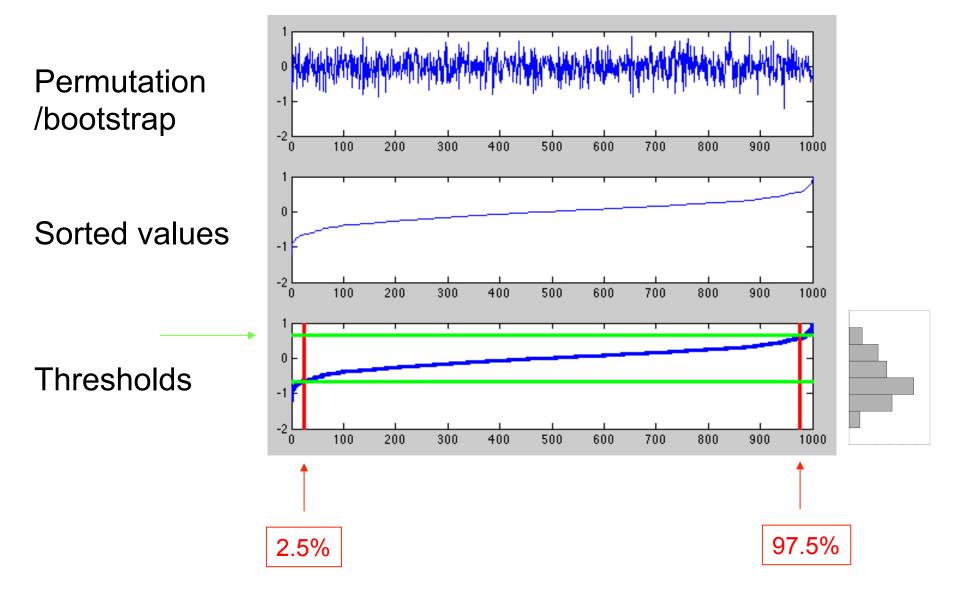


Once you have the 95% confidence interval for the difference: significance only involve assessing if 0 is included in the tails.

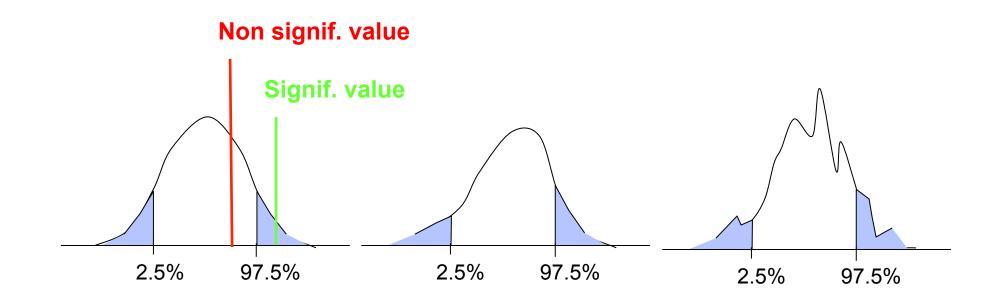








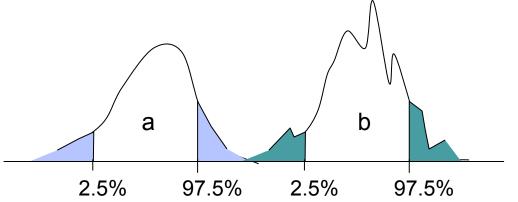
#### Distribution can take any shape



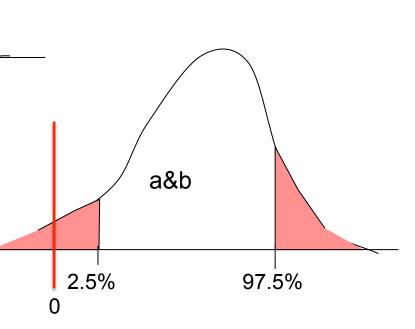
Once you have the 95% confidence interval for the difference: significance only involve assessing if 0 is included in the tails.

# Difference between the two bootstrap approches

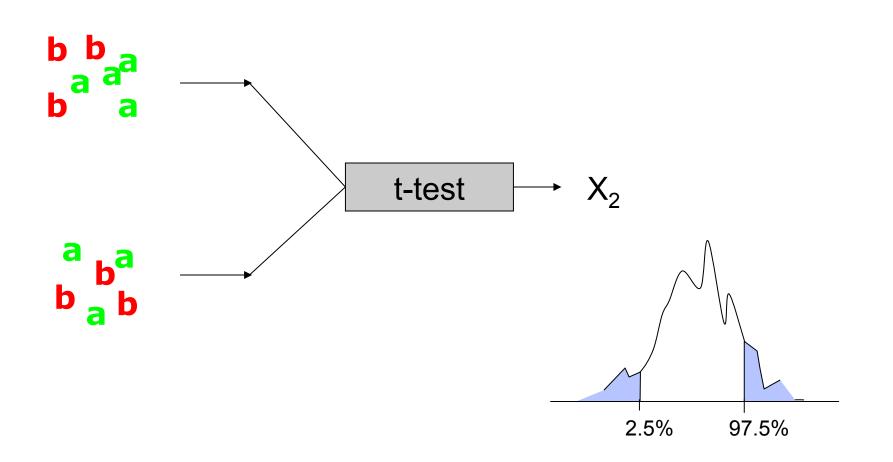
 Bootstrap 1 is testing against H1: the two samples originate from the different distributions.



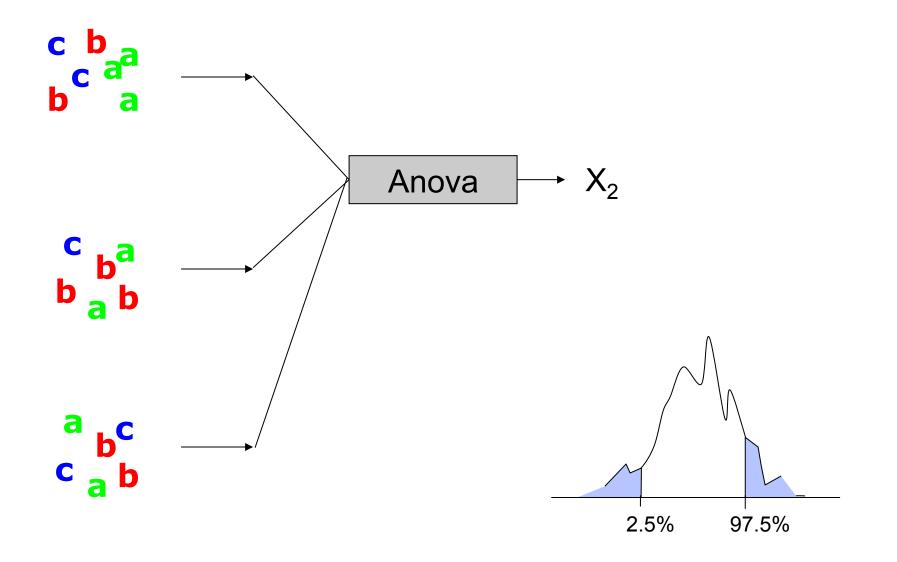
 Bootstrap 2 is testing against H0: the two samples originate from the same distribution.



# Measure for the bootstrap

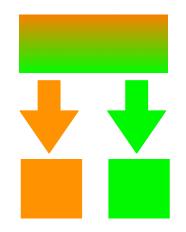


# Measure for the bootstrap



# Bootstrap versus permutation

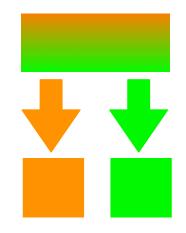
#### **Permutation**



each element only get picked once

Draws are dependent of each others

#### Bootstrap



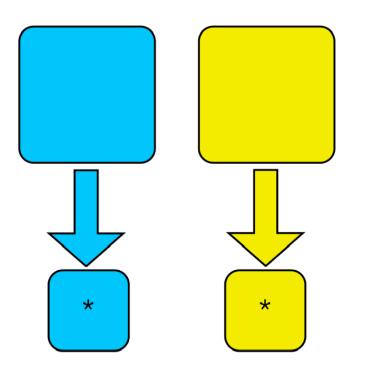
each element can get picked several times Draws are independent of each others

#### **Use bootstrap!**

# Resampling strategies: follow the data acquisition process

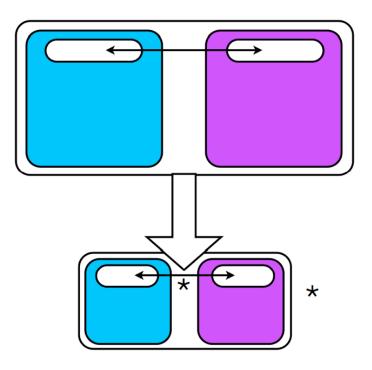
#### Independent sets:

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



#### **Dependent sets:**

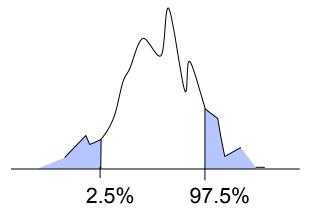
- 2 conditions in group analyses
- Correlations
- Linear regression



	·	
Husband	Wifes	
22	25	
32	25	
50	51	
25	25	
33	38	
27	30	
45	60	
47	54	
30	31	
44	54	
23	23	
39	34 25	
24		
22	23	
16	19	
73	71	
27	26	
36	31	
24	26	
60	62	
26	29	
23	31	
28	29	
36	35	

#### Are the two groups

different: that's an unpaired test (comparing the mean or median of husband and the mean or median of wife)



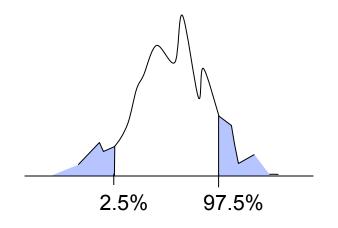
Diff= -1.88

Husband	Wifes	
22	25	
32	25	
50	51	
25	25	
33	38	
27	30	
45	60	
47	54	
30	31	
44	54	
23	23	
39	34 25 23 19	
24		
22		
16		
73	71	
27	26	
36	31	
24	26	
60	62	
26	29	
23	31	
28	29	
36	35	

Are the two groups different: that's an unpaired test (comparing the mean or median of husband and the mean or median of wife)

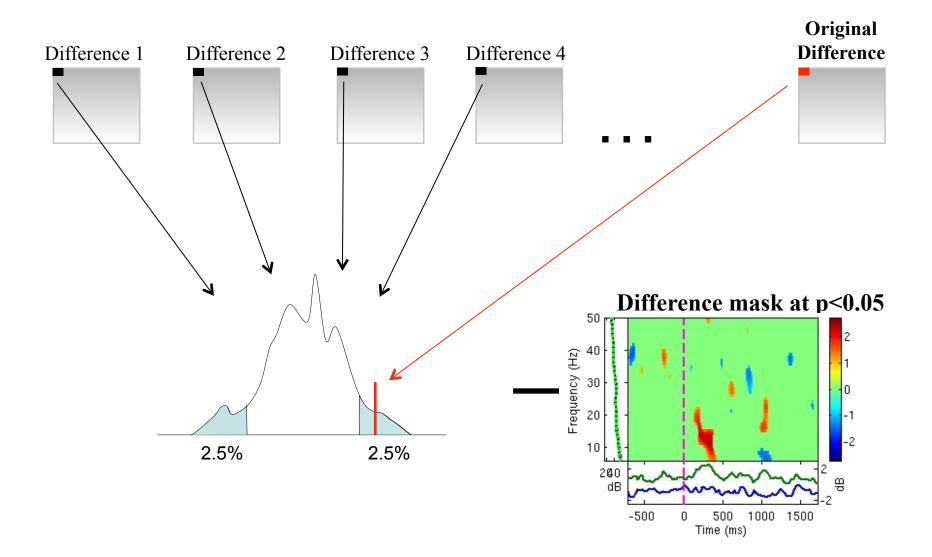
#### Are husbands older than wifes:

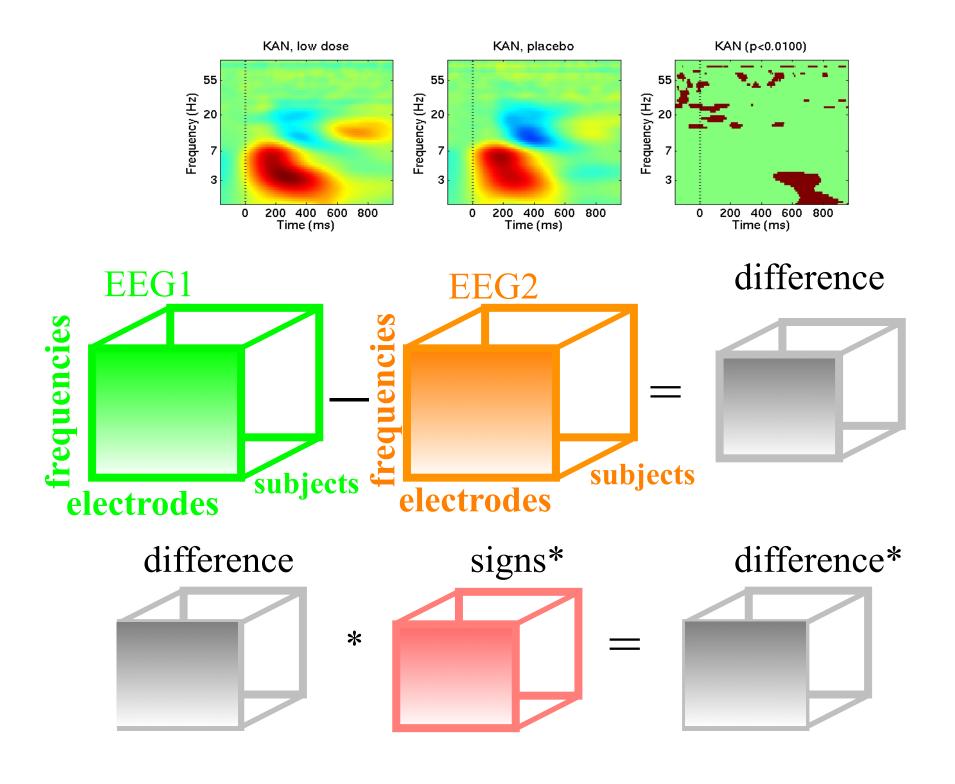
that's a paired test. Compute difference between the two and change sign to bootstrap.



Median

#### Assessing significance





## Correcting for multiple comparisons

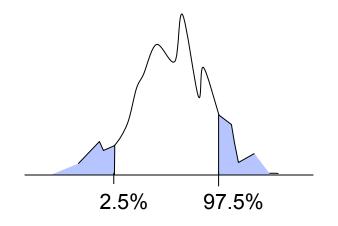
• Bonferoni correction: divide by the number of comparisons (Bonferroni CE. Sulle medie multiple di potenze. Bollettino dell'Unione Matematica Italiana, 5 third series, 1950; 267-70.)

- Holms correction: sort all p values. Test the first one against  $\alpha/N$ , the second one against  $\alpha/(N-1)$
- Max method
- False detection rate
- Clusters

## Max procedure

• for each permutation or bootstrap loop, simply take the MAX of the absolute value of your estimator (e.g. mean difference) across electrodes and/or time frames and/or temporal frequencies.

• compare absolute original difference to this distribution



#### **Procedure:**

Sort all p values (column C1)C3

- Create column C2 by computing  $j^*\alpha/N$ 

- 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* 

O1		
Index "j"	Actual	
1	0.001	
2	0.002	
3	0.01	
4	0.03	
5	0.04	
6	0.045	
7	0.05	
8	0.1	
9	0.2	
10	0.6	

C1

#### **Procedure:**

Sort all p values (column C1)C3

- Create column C2 by computing  $j^*\alpha/N$ 

- 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 Index "j" j\*0.05/10 Actual 0.001 0.005 1 2 0.002 0.01 3 0.01 0.015 0.03 0.02 4 5 0.04 0.025 0.045 0.03 6 0.035 7 0.05 8 0.1 0.04 0.045 9 0.2 10 0.6 0.05

#### **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	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	

Bonferoni

#### **Procedure:**

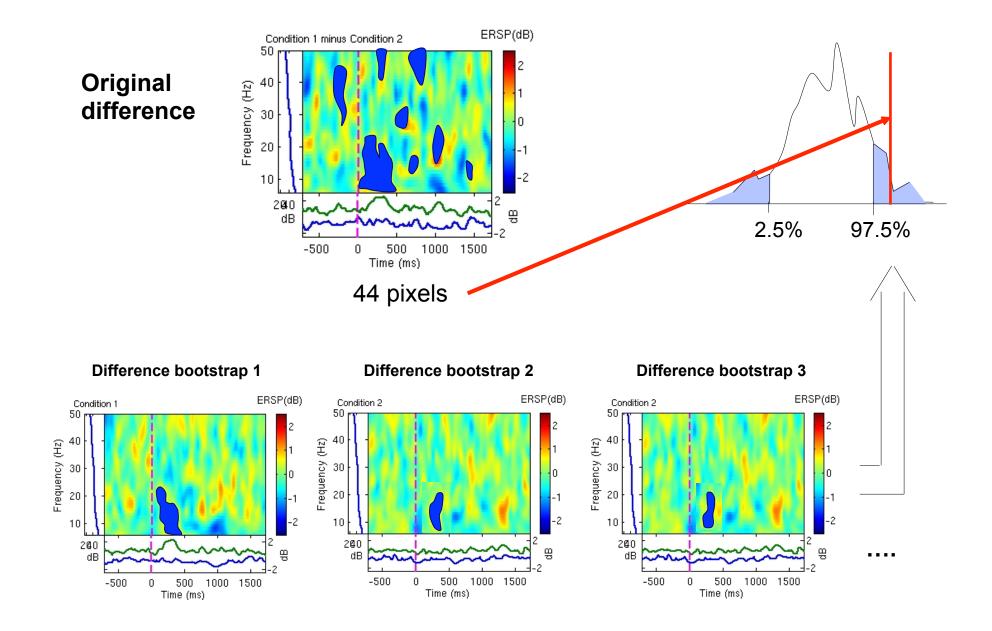
Sort all p values (column C1)C3

- Create column C2 by computing  $j^*\alpha/N$
- 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*

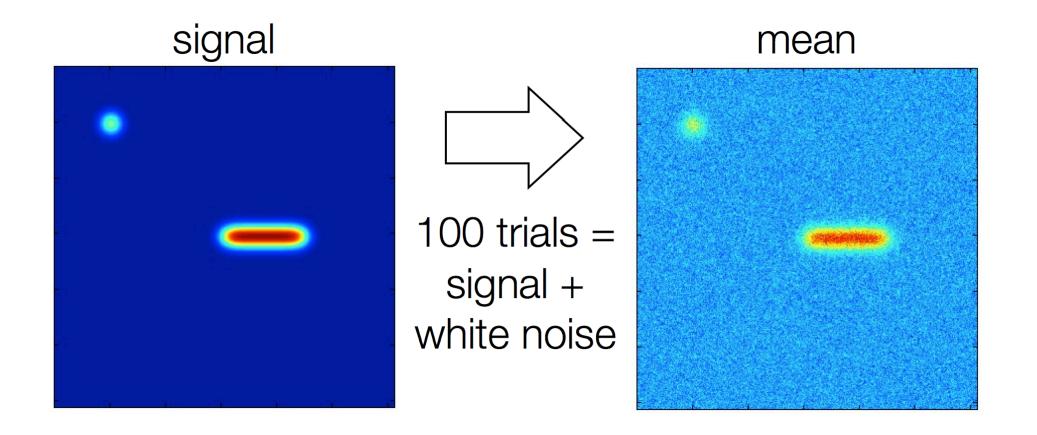
				1
		C1	C2	СЗ
Holms	Index "j"	Actual	j*0.05/10	C2-C1
	Ĩ	0.001	0.005	-0.004
FDR 🚽	2	0.002	0.01	-0.008
/N	3	0.01	0.015	-0.005
4	4	0.03	0.02	0.01
	5	0.04	0.025	0.015
	6	0.045	0.03	0.015
3	7	0.05	0.035	0.015
	8	0.1	0.04	0.06
	9	0.2	0.045	0.155
	10	0.6	0.05	0.55
alue				

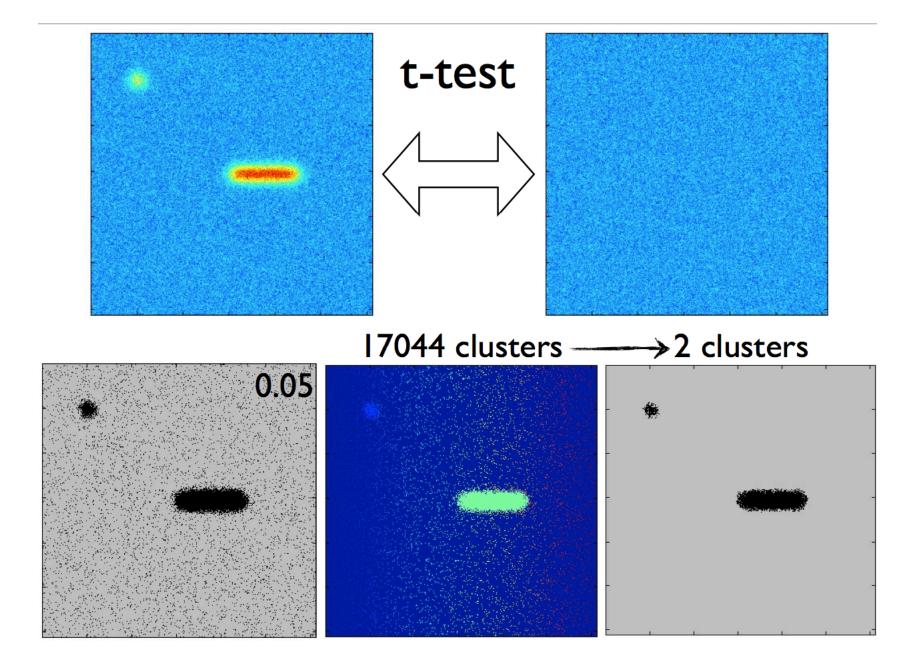
Uncorrected

### Cluster correction for multiple comparisons

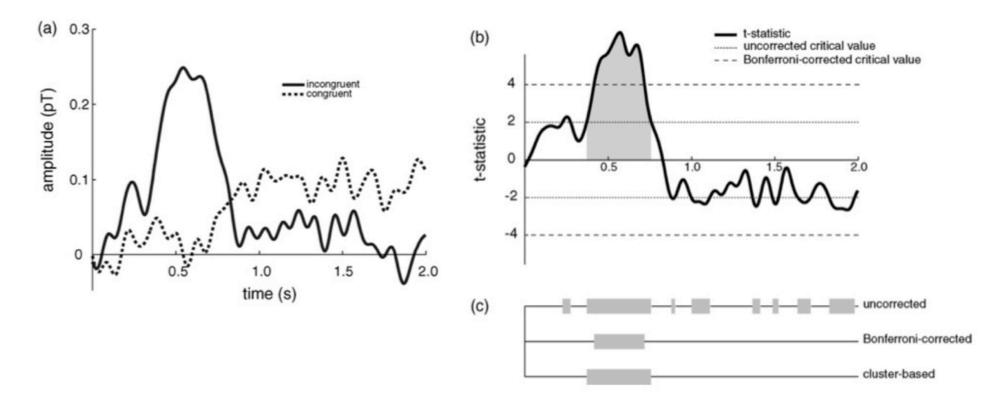


# Control for multiple comparisons cluster method





# Control for multiple comparisons cluster method



Maris & Oostenveld, J. Neurosci. Methods 2007

### References

Delorme, A. 2006. Statistical methods. *Encyclopedia of Medical Device and Instrumentation*, vol 6, pp 240-264. Wiley interscience.

Genovese et al. 2002. Thresholding of statistical maps in functional neuroimaging using the false discovery rate. *NeuroImage*, 15: 870-878

Nichols & Hayasaka, 2003. Controlling the familywise error rate in functional neuroimaging: a comparative review. *Statistical Methods in Medical Research*, 12:419-446

Maris, 2004. Randomization tests for ERP topographies and whole spatiotemporal data matrices. *Psychophysiology*, 41: 142-151

Maris et al. 2007. Nonparametric statistical testing of coherence differences. *Journal of Neuroscience Methods*, 163: 161-175

Groppe, D.M., Urbach, T.P., & Kutas, M. (2011) *Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review*. Psychophysiology, 48(12) pp. 1711-1725.

Thanks to G. Rousselet

## statcond function in EEGLAB

a = { rand(1,10) rand(1,10)+0.5 }; % pseudo 'paired' data vectors

[*t* df pvals] = **statcond**(a , 'mode', 'perm'); % perform paired t-test pvals = 5.2807e-04 % standard t-test probability value

% Note: for different rand() outputs, results will differ. [t df pvals surog] = statcond(a, 'mode', 'perm', 'naccu', 2000); pvals = 0.0065 % nonparametric t-test using 2000 permuted data sets

a = { rand(2,11) rand(2,10) rand(2,12)+0.5 };
[F df pvals] = statcond(a , 'mode', 'perm'); % perform an unpaired ANOVA

pvals =
 0.00025 % p-values for difference between columns
 0.00002 % for each data row

## statcond function in EEGLAB

a = { rand(3,4,10) rand(3,4,10) rand(3,4,10); ... rand(3,4,10) rand(3,4,10) rand(3,4,10)+0.5 };

% pseudo (2,3)-condition data array, each entry containing % ten (3,4) data matrices [F df pvals] = statcond(a , 'mode', 'perm'); % paired 2-way ANOVA

% Output: pvals{1} % a (3,4) matrix of p-values; effects across columns pvals{2} % a (3,4) matrix of p-values; effects across rows pvals{3} % a (3,4) matrix of p-values; interaction effects across rows and columns

## Exercice

- Experiment with the statcond function
  - Create 2 random vectors of values
  - Add "signal" to one of the variable
  - Use statcond EEGLAB function and compare permutation and parametric results
  - Repeat 100 times and plot the histogram of pvalues