



## Statistical inferences in fMRI

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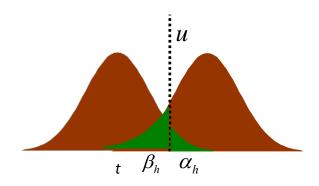
#### Overview

- Multiple comparisons correction procedures (RFT, FDR, TFCE)
- Levels of inferences (set, cluster, voxel)
- Circularity issues

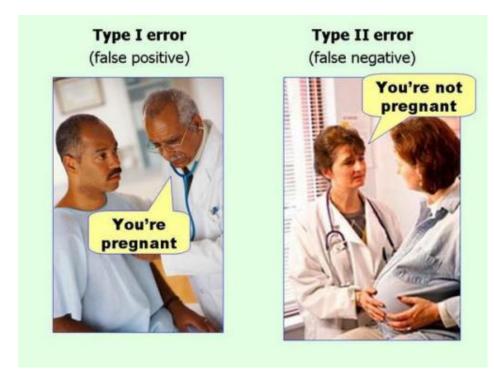
## Pearson-Newman hypothesis testing

• H0: no effect

• H1: there is an effect



Decision rule (threshold) *u*, determines related error rates



https://chemicalstatistician.wordpress.com

## **Types of error**

Decision

Reality

 $H_0$  $H_1$ False positive (FP) True positive (TP)  $H_1$ True negative (TN) False negative (FN)  $H_0$ 

specificity: 1-  $\alpha_h$  sensitivity (power): 1-  $\beta_h$  = TN / (TN + FP) = proportion of actual negatives which are correctly identified sensitivity (power): 1-  $\beta_h$  = TP / (TP + FN) = proportion of actual positives which are correctly identified

# Multiple comparisons correction

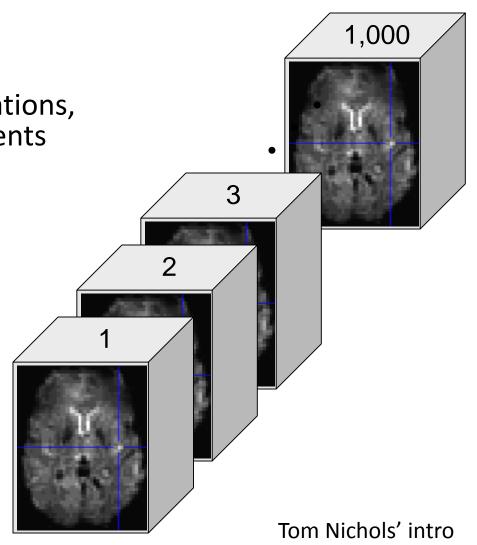
Avoiding false positives

4-Dimensional Data

 1,000 multivariate observations, each with > 100,000 elements

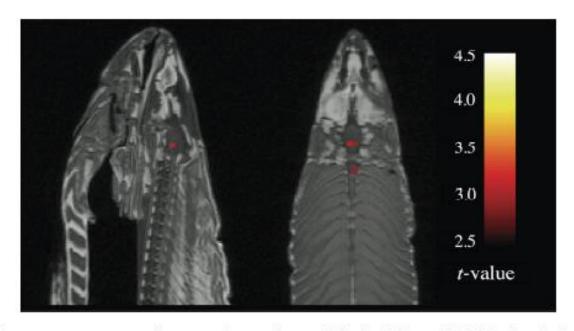
• 100,000 time series, each with 1,000 observations

- Massively Univariate Approach
  - 100,000 hypothesis tests
- Massive MCP!



- Typical brain ~ 130000 voxels
- @ p = .05, it is expected = 6500 false positives!
- @ a more conservative value like p = .001 we still expect 130 false positives.
- Using extend threshold k without correction is not enough as it, by chance, can cluster as well.

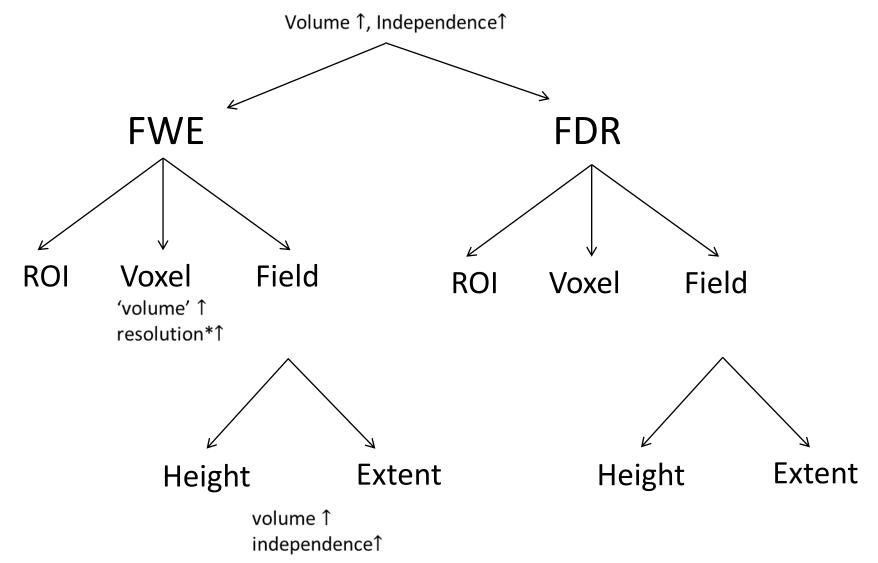
- Bennet et al., 2009
- <u>Task</u>: take a decision about emotions on pictures
- Design: blocks of 12 sec activation/rest
- Analysis: standard data processing with SPM
- Subject: a dead salmon!



A t-contrast was used to test for regions with significant BOLD signal change during the photo condition compared to rest. The parameters for this comparison were t(131) > 3.15, p(uncorrected) < 0.001, 3 voxel extent threshold.

• The cluster was 81mm<sup>3</sup>! – after multiple comparison corrections all false activations were removed.

## Detect an effect of *unknown* extent & location



#### **Bonferroni Correction**

FWER is the prob. that any stats > u, is a FP FWER is therefore also the prob. that the max stats > u is a FP

Bonferroni correction allows to keep the FWER at 5% by simply dividing alpha by the number of tests

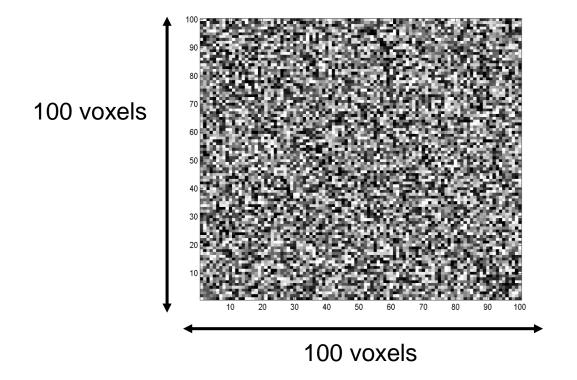
$$P(T_i \ge u | H0) \le \frac{\alpha}{m}$$
 Find  $u$  to keep the FWER  $< \alpha/m$ 

FWER  $= P(\bigcup_{i \in V} \{T_i \ge u\} | H_0) \le \alpha$ 
 $\le \sum P(T_i \ge u | H0)$  Boole's inequality

 $\le \sum_i \frac{\alpha}{m} = \alpha$ 

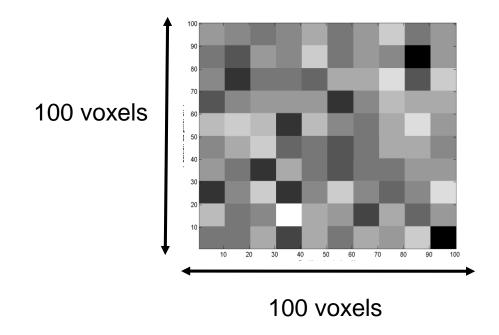
## **Bonferroni Correction**

- 10000 Z-scores ; alpha = 5%
- alpha corrected = .000005; z-score = 4.42



#### **Bonferroni Correction**

- 10000 Z-scores ; alpha = 5%
- 2D homogeneous smoothing 100 independent observations
- alpha corrected = .0005; z-score = 3.29

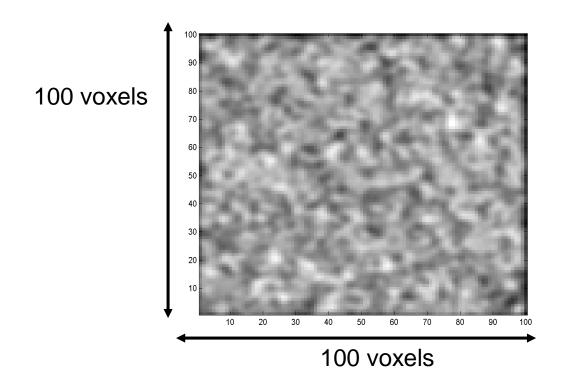


#### Solutions for MCP

- An important feature of neuroimaging data is that we have a family of stat values that has topological features (Bonferroni for instance consider tests as independent)
- Why considering data as a smooth lattice? (Chumbley et al., 2009 Neurolmage 44)
- ➤ fMRI/PET are projection methods of data points onto the whole space — MEEG forms continuous functions in time and are smooth by the scalp (space)
- Neural activity propagate locally through intrinsic/lateral connections and is distributed via extrinsic connections / Hemodynamic correlates are initiated by diffusing signals (e.g. NO)

## Random Field Theory

- 10000 Z-scores ; alpha = 5%
- Gaussian kernel smoothing –
- How many independent observations?



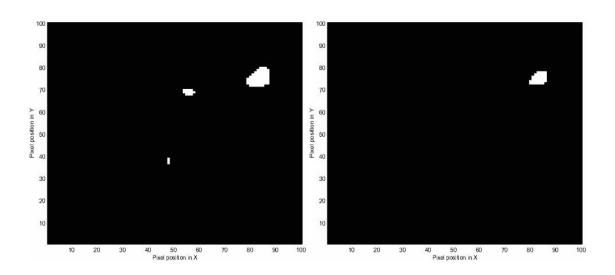
## **RFT**



- RFT relies on theoretical results for smooth statistical maps (hence the need for smoothing), allowing to find a threshold in a set of data where it's not easy to find the number of independent variables. Uses the expected Euler characteristic (EC density)
- 1 Estimation of the smoothness = number of resel (resolution element) = f(nb voxels, FWHM)
- 2 expected Euler characteristic = number of clusters above the threshold
- 3 Calculation of the threshold

## Random Field Theory

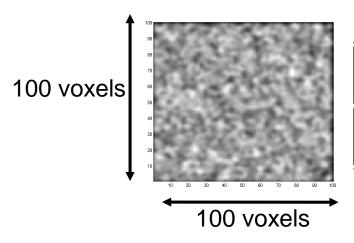
- The Euler characteristic can be seen as the number of blobs in an image after thresholding (p value that you select in SPM)
- At high threshold, EC = 0 or 1 per resel: E[EC]  $\approx p^{FWE}$



E[EC] = R · (4 log<sub>e</sub> 2) ·  $(2\pi)^{-2/3}$  · Z<sub>t</sub> · e<sup>-1/2 Z<sup>2</sup>t</sup> for a 2D image, more complicated in 3D

## Random Field Theory

• For 100 resels, the equation gives E[EC] = 0.049 for a threshold Z of 3.8, i.e. the probability of getting one or more blobs where Z is greater than 3.8 is 0.049



$\alpha$	number of resels	Bonfe	RFT		
	in the image	threshold	score Z	score Z	
0.05	100	0.05 100	3.3		
	100	_		3.8	

If the resel size is much larger than the voxel size then E[EC] only depends on the nb of resels otherwise it also depends on the volume, surface and diameter of the search area (i.e. shape and volume matter)

## False Discovery Rate

 Whereas family wise approach corrects for any false positive, the FDR approach aim at correcting among positive results only.

- 1. Run an analysis with alpha = x%
- 2. Sort the resulting positive data
- 3. Threshold to remove the false positives

## False Discovery Rate

#### Signal+Noise





















FEW correction





















FDR correction

















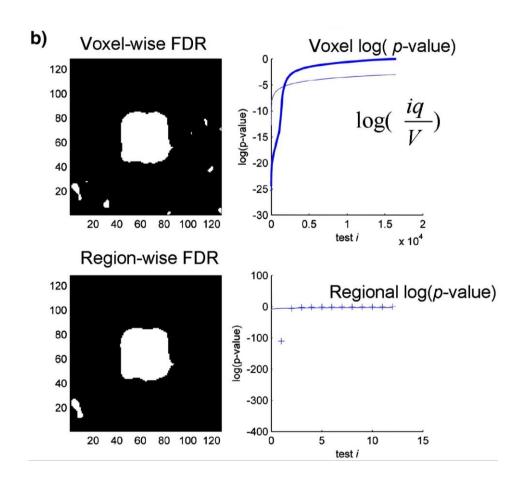




## False Discovery Rate for clusters

Under H0 the nb of voxels per cluster is known → uncorrected p value for clusters → apply FDR on the clusters (volume-wise correction)

Assumes that the volume of each cluster is independent of the number of clusters

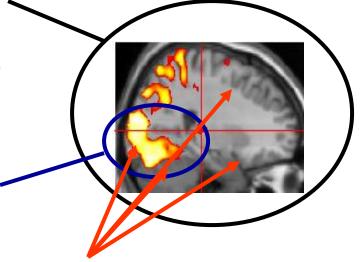


Voxel, cluster and set

- 3 levels of inference can be considered:
- Voxel level (prob associated at each voxel)
- Cluster level (prob associated to a set of voxels)
- Set level (prob associated to a set of clusters)
- The 3 levels are nested and based on a single probability of obtaining c or more clusters (set level) with k or more voxels (cluster level) above a threshold u (voxel level): P<sub>w</sub>(u,k,c)

 Set level: we can reject H0 for an omnibus test, i.e. there are some significant clusters of activation in the brain.

Cluster level: we can reject H0 for an area of a size k, i.e. a cluster of 'activated' voxels is likely to be true for a given spatial extend.



■ <u>Voxel level</u>: we can reject H0 at each voxel, i.e. a voxel is 'activated' if exceeding a given threshold

- Each level of inference is valid, but the inferences are different e.g. a set might be enough to check that subjects activated regions selected a priori for a connectivity analysis clusters might be good enough if hypotheses are about the use of different brain areas between groups
- Both voxel and cluster levels need to address the multiple comparison problem. If the activated region is predicted in advance, the use of corrected p values is unnecessary and inappropriately conservative — a correction for the number of predicted regions (Bonferroni) is enough

Uncorrected (bad)

set-level cluster-level			peak-level									
р	С	p <sub>FWE-corr</sub>	q <sub>FDR-corr</sub>	<sup>k</sup> E	Puncorr	p <sub>FWE-corr</sub>	q <sub>FDR-corr</sub>	T	(Z <sub>=</sub> )	p <sub>uncorr</sub>	mm mm mn	1
0.000	22	0.000	0.000	2519	0.000	0.000	0.000	19.07	Inf	0.000	-36 -18	-10
						0.000	0.000	13.63	Inf	0.000	-36 -54	-12
						0.000	0.000	12.28	Inf	0.000	-46 -50	-2
		0.000	0.000	2340	0.000	0.000	0.000	18.16	Inf	0.000	38 -44	-26
						0.000	0.000	17.50	Inf	0.000	40 -16	-20
						0.000	0.000	13.48	Inf	0.000	14 -56	-26
		0.000	0.000	285	0.000	0.000	0.000	12.54	Inf	0.000	-16 -40	50
		0.000	0.000	276	0.000	0.000	0.000	10.91	Inf	0.000	44 -50	44
						0.000	0.000	7.93	Inf	0.000	38 -38	44
						0.000	0.000	6.76	6.71	0.000	48 -58	56
		0.000	0.000	218	0.000	0.000	0.000	10.67	Inf	0.000	-22 10	66
						0.000	0.000	7.84	7.76	0.000	-34 22	54
						0.004	0.097	5.47	5.45	0.000	-28 18	62
		0.000	0.000	76	0.000	0.000	0.000	10.18	Inf	0.000	12 10	76
		0.000	0.000	248	0.000	0.000	0.000	9.23	Inf	0.000	38 -52	14
						0.000	0.000	7.65	7.58	0.000	34 -54	22
						0.000	0.000	7.52	7.46	0.000	38 -60	6
		0.000	0.000	172	0.000	0.000	0.000	8.03	Inf	0.000	-20 -56	28
						0.000	0.000	7.99	Inf	0.000	-22 -58	20
		0.000	0.000	66	0.000	0.000	0.000	7.27	7.21	0.000	-8 -58	44
						0.000	0.000	6.55	6.51	0.000	-14 -62	38
		0.000	0.000	76	0.000	0.000	0.000	7.01	6.96	0.000	-36 -20	58
		0.000	0.000	40	0.000	0.000	0.000	6.70	6.66	0.000	44 2	58
						0.000	0.000	6.46	6.42	0.000	54 2	50
		0.000	0.000	92	0.000	0.000	0.000	6.63	6.58	0.000	60 -30	48
		0.000	0.000	68	0.000	0.000	0.000	6.54	6.50	0.000	46 -18	60
		0.000	0.001	16	0.001	0.001	0.025	5.73	5.71	0.000	50 -8	56
		0.000	0.001	16 23	0.001	0.000	0.004	6.08 5.90	6.05	0.000	46 -44 48 -34	4
		0.000	0.000	23 tabi	e shows 3 local	0.000 maxima more tha	n 8.0mm apan	5.90	5.87	0.000	48 -34	0
		4.96, p = 0.000 (0	.050)		K T		freedom = [1.0					_
	shold: k = (						.6 7.1 6.7 mm n					
		duster, <k> = 1.1</k>					55888 = 14448					
xpected n	umber of o	:lusters, <c> = 0.0</c>	5			Voxel size:	2.9 2 0 2.0 mm	ı mm mm; (re	el = 39.21 vo:	xels)		

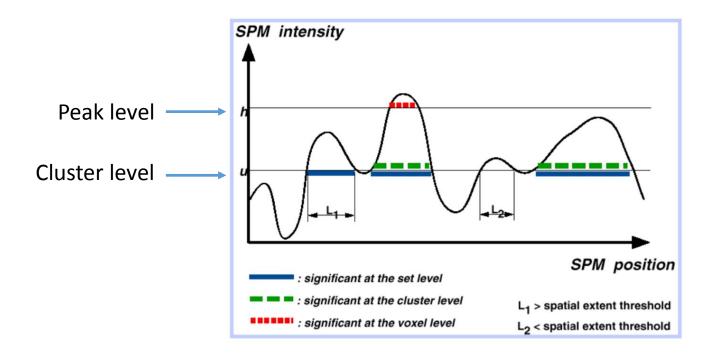
#### **RFT (Gaussian Random Fields)**

- -> Prob of size
- -> Prob of cluster peak (max voxel)

Using p=.001 this creates an excursion set with topology that satisfies RFT → FDR clusters size and height

## Threshold Free Cluster Enhancement

• TFCE: Integrate the cluster mass at multiple thresholds = no need to create an excursion set. A TFCE score is thus obtain per voxel but the value is a weighted function of the statistics by it's belonging to a cluster.



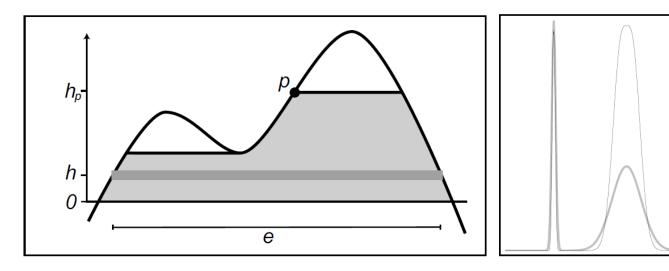


Figure 1: Illustration of the TFCE approach. Left: The TFCE score at voxel p is given by the sum of the scores of all incremental supporting sections (one such is shown as the dark grey band) within the area of "support" of p (light grey). The score for each section is a simple function of its height h and extent e. Right: Example input image and TFCE-enhanced output. The input contains a focal, high signal, a much more spatially extended, lower, signal and a pair of overlapping signals of intermediate extent and height. The TFCE output has the same maximal values for all three cases, and preserves the distinct local maxima in the third case.

original signal TFCE enhancement

# Circularity issues in fMRI

## **Definition**

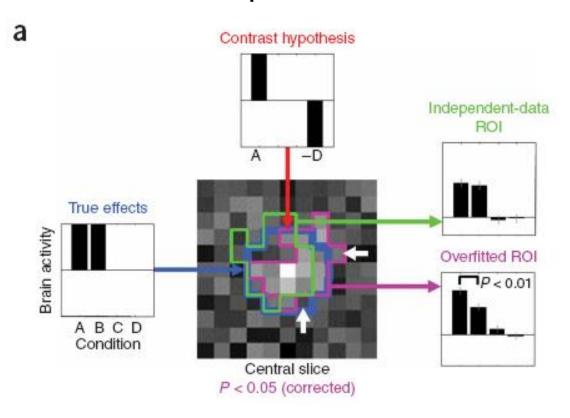
- Refers to the problem of selecting data for analysis
- How data (areas usually) are selected, analysed and sorted is key to avoid circularity
- Put forward by Vul et al. 2009, Perspectives on Psychological Science. 4
- Better explained in Kriegeskorte et al., 2009 Nat.
   Neuroscience 12

## Circularity

- Double dipping pblm: "data are first analyzed to select a subset and then the subset is reanalyzed to obtain the results. In this context, assumptions and hypotheses determine the selection criterion and selection can, in turn, distort the results."
- Take a gp of subjects and measures RTs, then take 2 subgroups from the same subjects and re-do some analysis?? → increases the diff.
- Take fMRI data and get activated areas, extract ROI and re-do some analyses??

## Circularity

 Selection and tests must be independent – non independence create spurious effects



## Circularity

- Independence of the selection and tests
- 1. Anatomic ROI, analysis of fMRI
- 2. SPM, minimal requirement is orthogonality of the contrasts (e.g. find regions using A+B>0 C=[1 1] and test A vs B C=[1 -1]) but if  $N_A$  and  $N_B$  are different there is still a bias when testing A-B (across subjects independence is ensured by  $C_{\text{selection}}^{T}(X^{T}X)^{-1}C_{\text{test}}$ )
- Select using a subset of data, test with another one

## **Questions?**