

Edinburgh Imaging

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Biennial SPM course 2017



Statistical inferences in fMRI

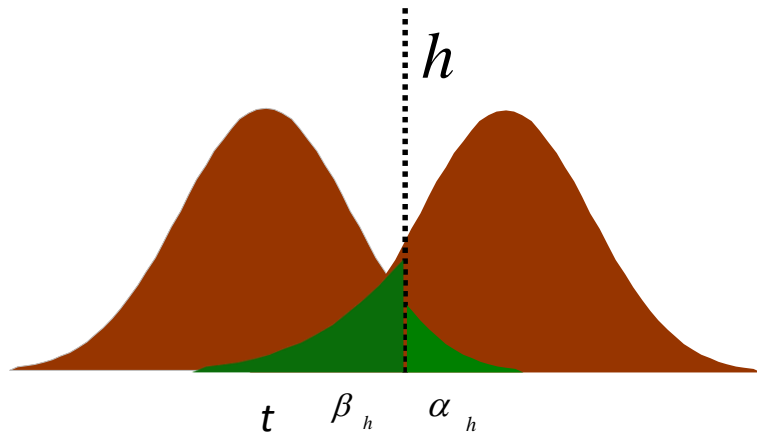
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Overview

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

Error at a single voxel



Decision:

H_0 , H_1 : zero/non-zero activation

Decision rule (threshold) h ,

determines related error rates α_h β_h

Convention: Penalize complexity

Choose h to give acceptable α_h under H_0

$$t = \frac{\text{contrast of estimated parameters}}{\sqrt{\text{variance estimate}}}$$

Types of error

		Reality	
		H_0	H_1
Decision	H_1	False positive (FP) α_h	True positive (TP)
	H_0	True negative (TN)	False negative (FN) β_h

specificity: $1 - \alpha_h$
= $TN / (TN + FP)$
= proportion of actual negatives which are correctly identified

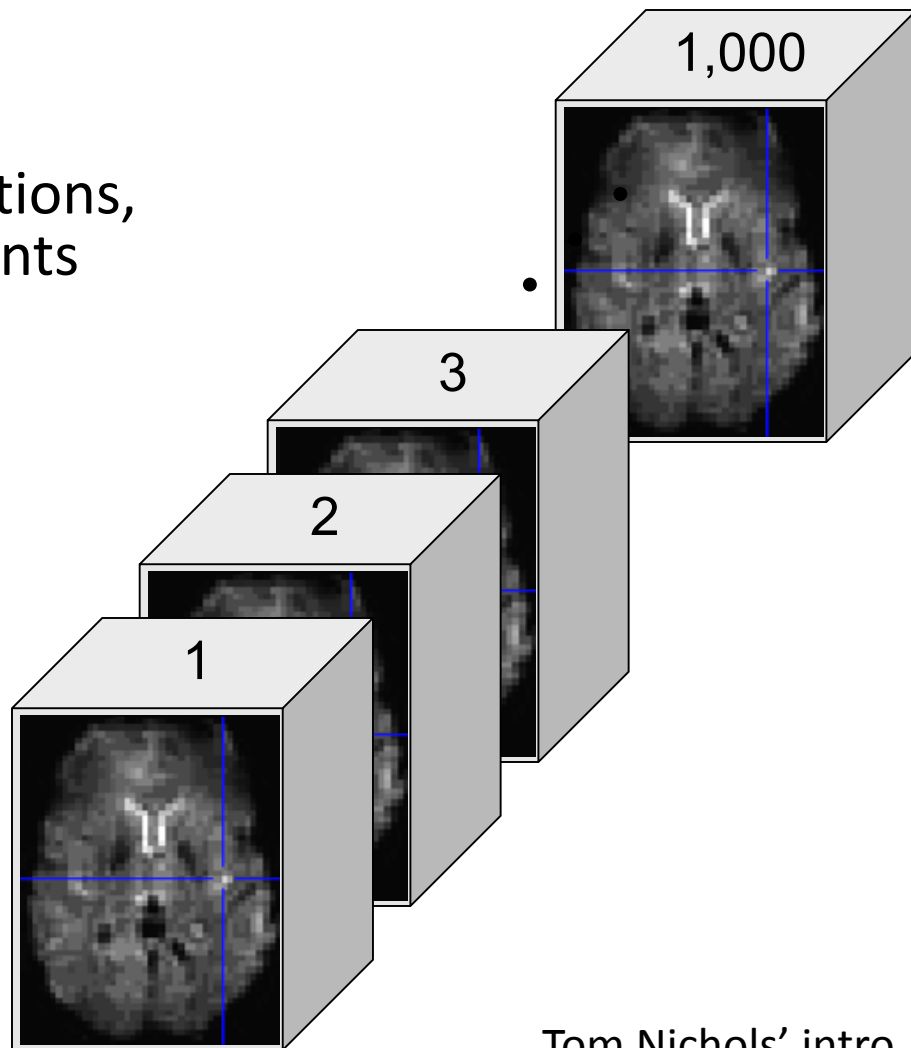
sensitivity (power): $1 - \beta_h$
= $TP / (TP + FN)$
= proportion of actual positives which are correctly identified

Multiple comparisons correction

Avoiding false positives

What Problem?

- 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!



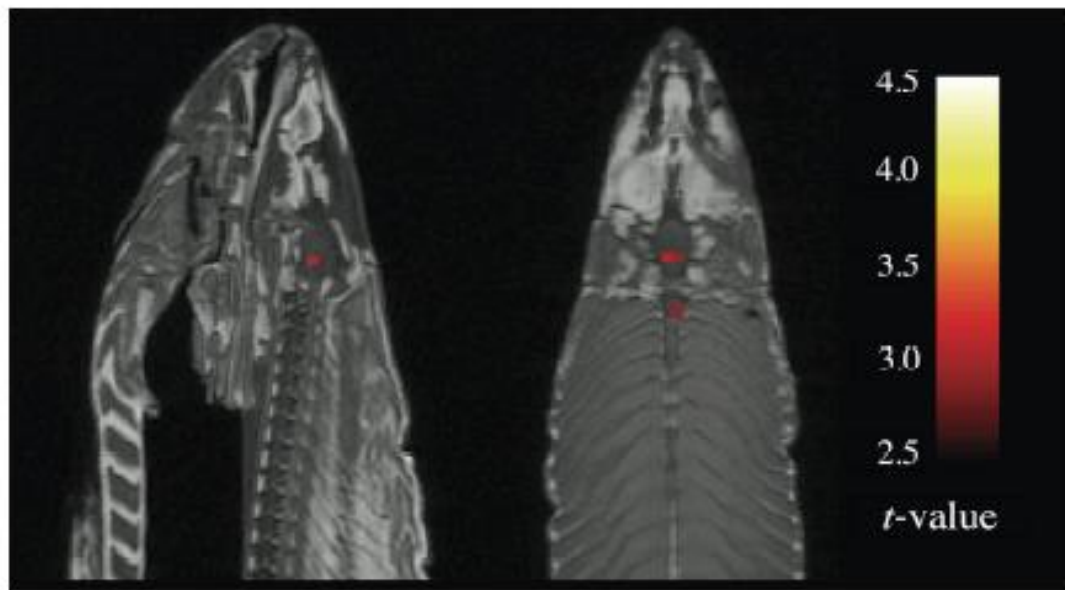
What Problem?

- 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.

What Problem?

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

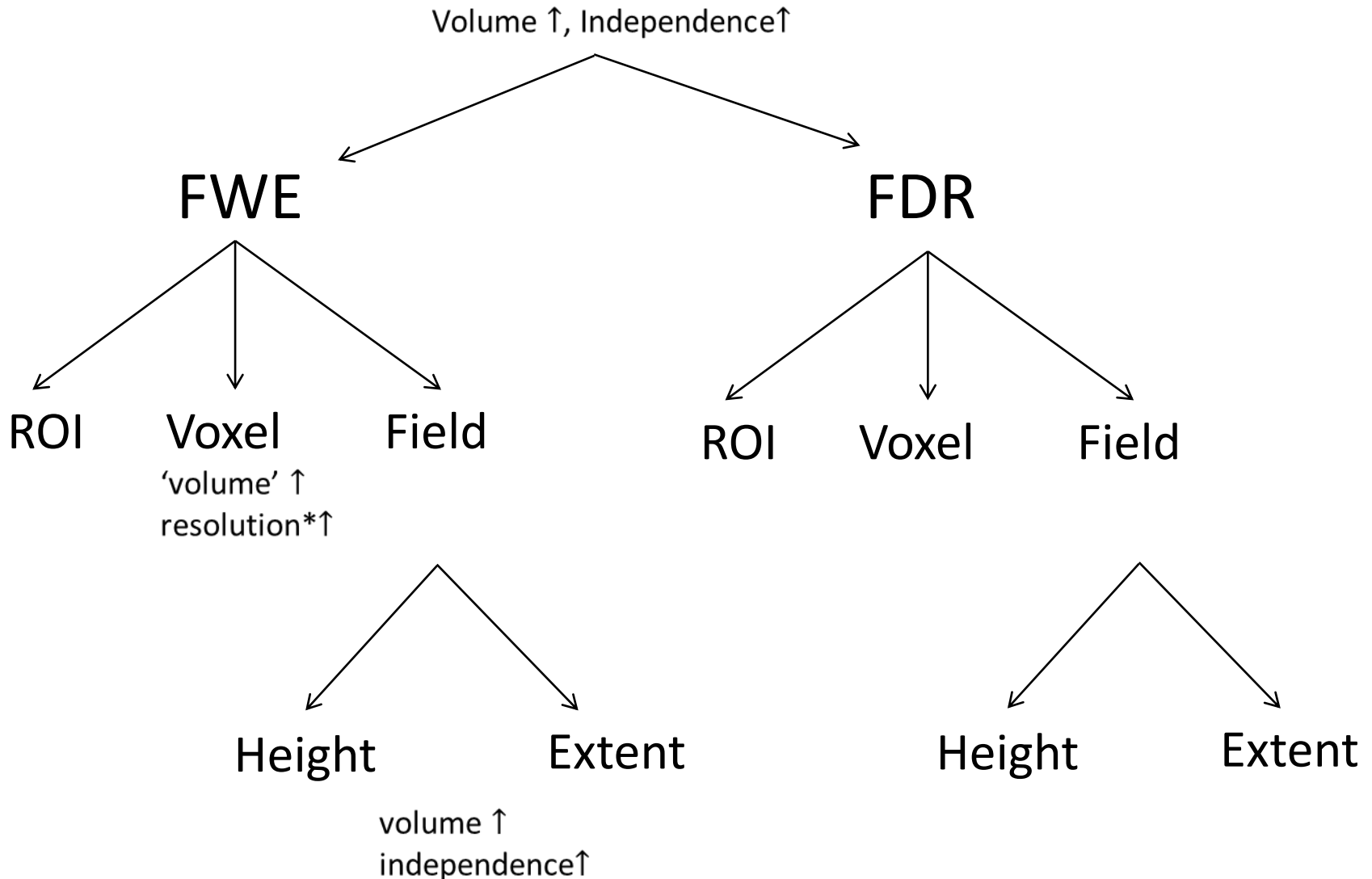
What Problem?



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 $t(131) > 3.15$, $p(\text{uncorrected}) < 0.001$, 3 voxel extent threshold.

- The cluster was 81mm^3 ! – 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

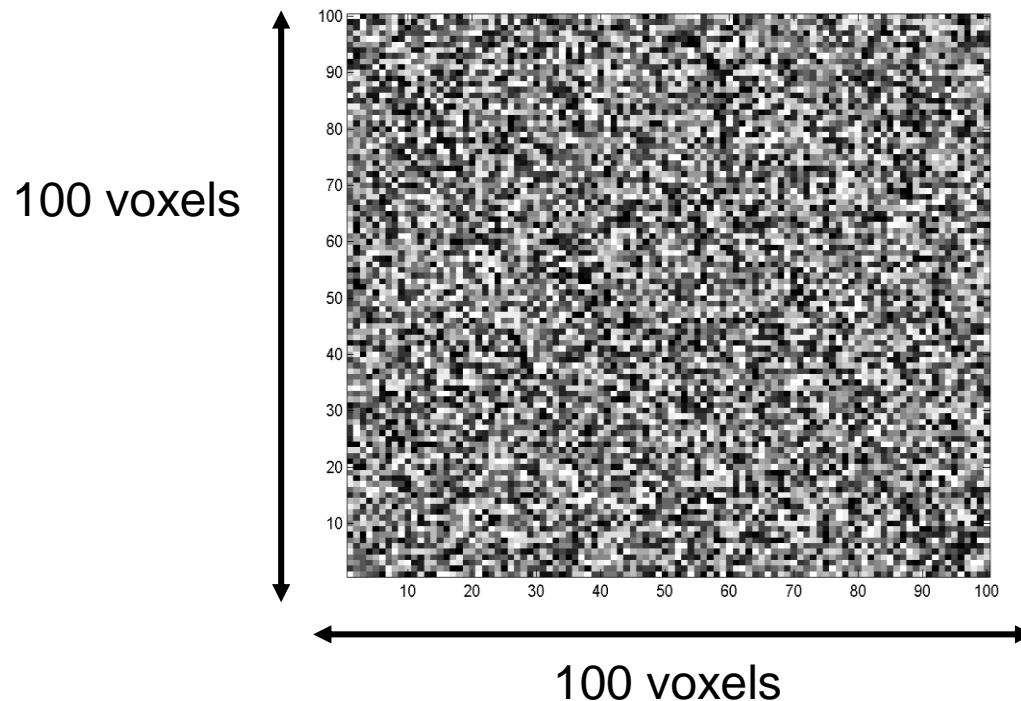
Bonferroni correction allows to keep the FWER at 5% by simply dividing alpha by the number of tests

$$P(T_i \geq u | H_0) \leq \frac{\alpha}{m} \quad \text{Find } u \text{ to keep the FWER} < \alpha/m$$

$$\begin{aligned} \text{FWER} &= P(\cup_{i \in V} \{T_i \geq u\} | H_0) \leq \alpha \\ &\leq \sum P(T_i \geq u | H_0) \quad \text{Boole's inequality} \\ &\leq \sum_i \frac{\alpha}{m} = \alpha \end{aligned}$$

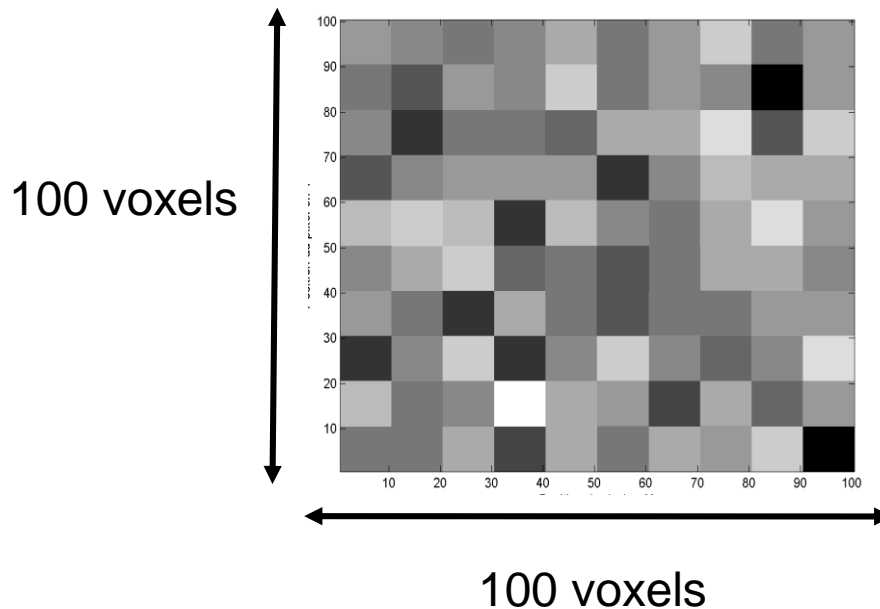
Bonferroni Correction

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



Bonferroni Correction

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

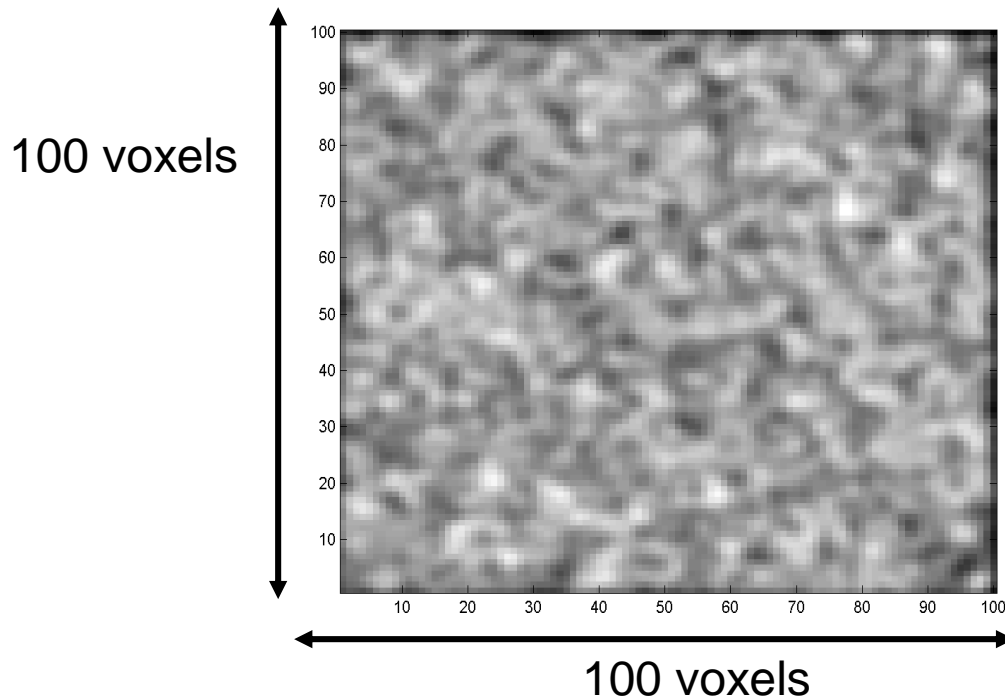


Solutions for MCP

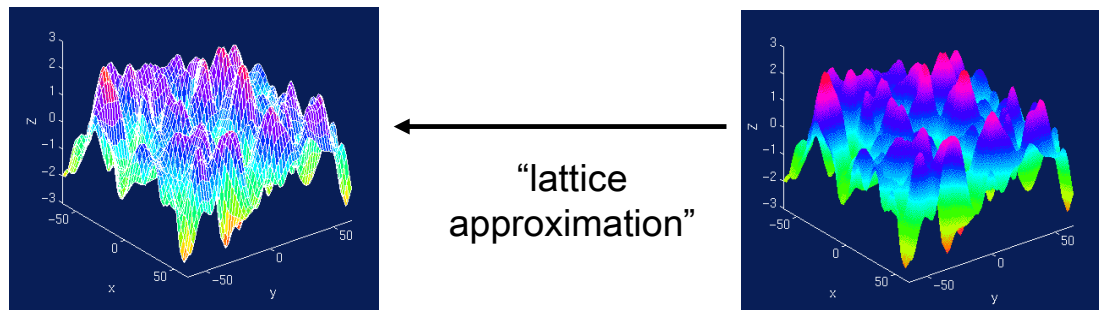
- An important feature of neuroimaging data is that we have a family of stat values that has topological features (Bonferroni for instance consider tests as independent)
- Why considering data as a smooth lattice? (Chumbley et al., 2009 NeuroImage 44)
 - fMRI/PET are projection methods of data points 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 ?



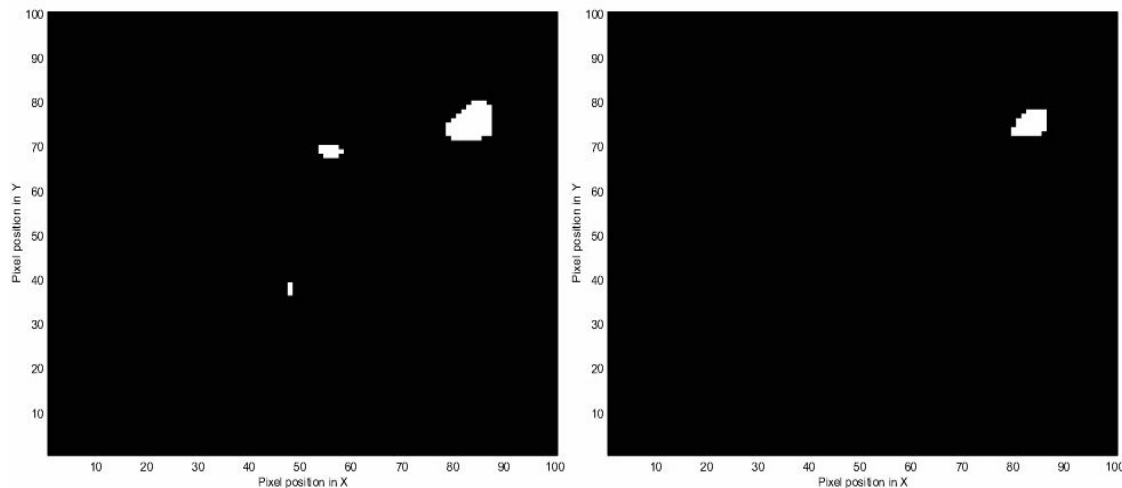
RFT



- 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) = $f(\text{nb voxels, FWHM})$
- 2 expected Euler characteristic = number of clusters above the threshold
- 3 Calculation of the threshold

Random Field Theory

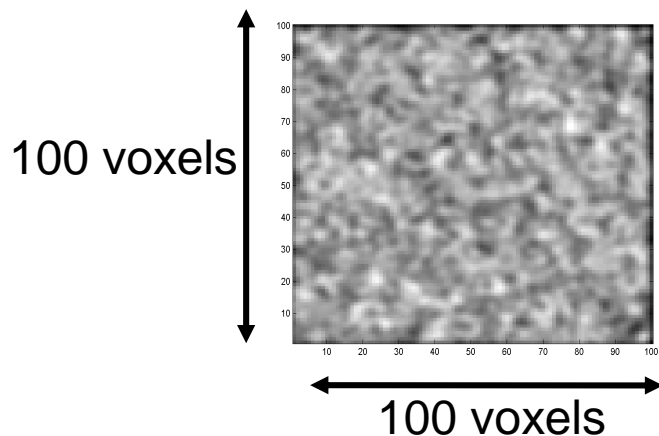
- The Euler characteristic can be seen as the number of blobs in an image after thresholding (p value that you select in SPM)
- At high threshold, $EC = 0$ or 1 per resel: $E[EC] \approx p^{FWE}$



$E[EC] = R \cdot (4 \log_e 2) \cdot (2\pi)^{-2/3} \cdot Z_t \cdot e^{-1/2 Z_t^2}$ 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



α	number of resels in the image	Bonferroni		RFT
		threshold	score Z	score Z
0.05	100	$\frac{0.05}{100}$	3.3	
				3.8

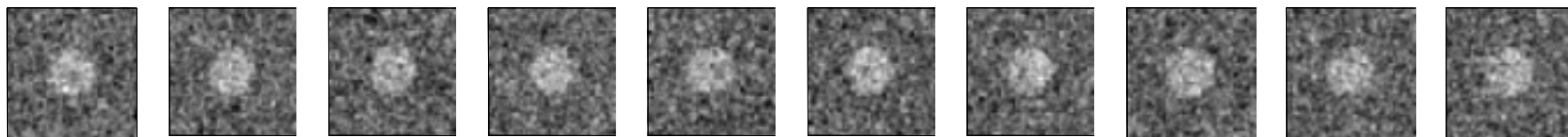
- If the resel size is much larger than the voxel size then $E[EC]$ only depends on the nb of resels otherwise it also depends on the volume, surface and diameter of the search area (i.e. shape and volume matter)

False Discovery Rate

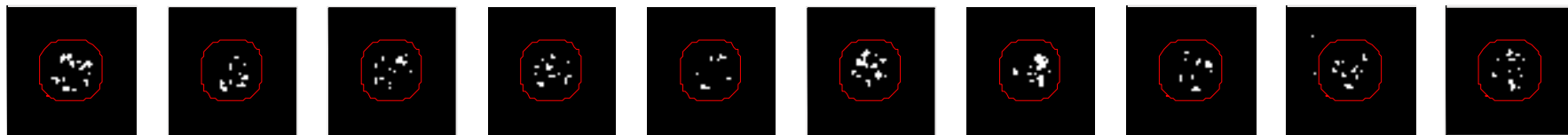
- Whereas family wise approach corrects for any false positive, the FDR approach aim at correcting among positive results only.
1. Run an analysis with $\alpha = x\%$
 2. Sort the resulting positive data
 3. Threshold to remove the false positives

False Discovery Rate

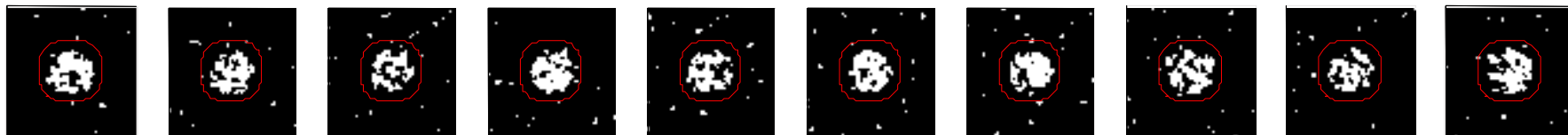
Signal+Noise



FEW correction



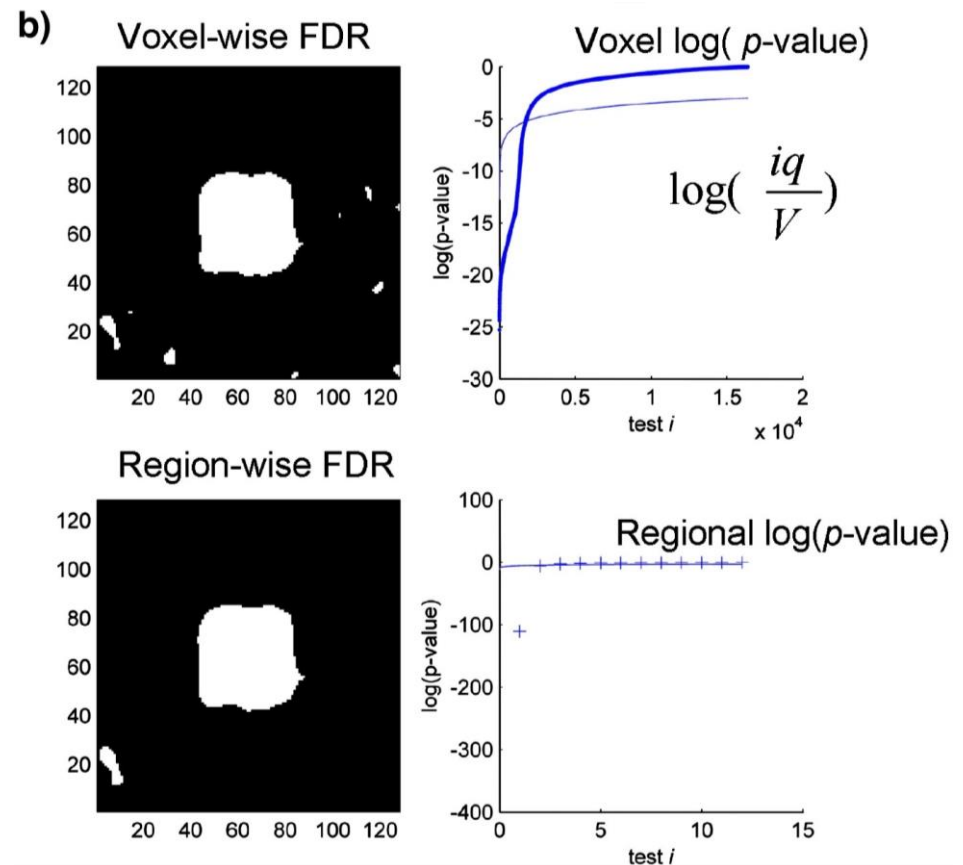
FDR correction



False Discovery Rate for clusters

Under H_0 the nb of voxels per cluster is known \rightarrow uncorrected p value for clusters \rightarrow apply FDR on the clusters (volume-wise correction)

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



Levels of inference

Voxel, cluster and set

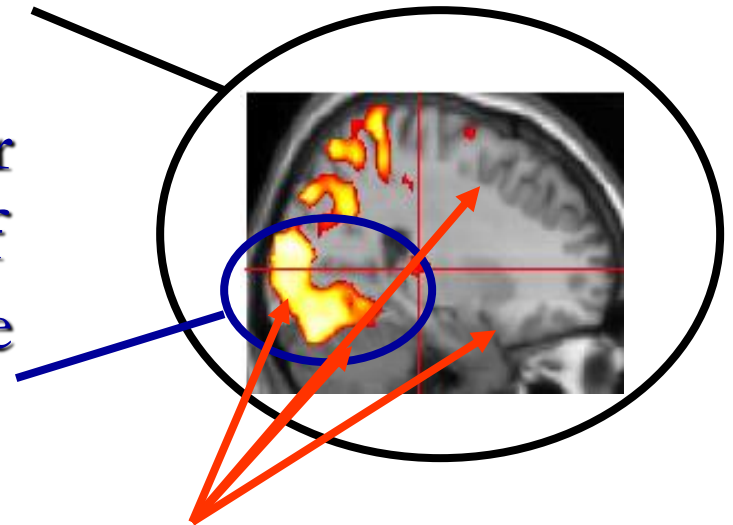
Levels of inference

- 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):
 $P_w(u, k, c)$

Levels of inference

- Set level: we can reject H_0 for an omnibus test, i.e. there are some significant clusters of activation in the brain.

- Cluster level: we can reject H_0 for an area of a size k , i.e. a cluster of 'activated' voxels is likely to be true for a given spatial extend.



- Voxel level: we can reject H_0 at each voxel, i.e. a voxel is 'activated' if exceeding a given threshold

Levels of inference

- 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

Levels of inference

Uncorrected (bad)

Statistics: *p-values adjusted for search volume*

set-level		cluster-level				peak-level					mm mm mm		
<i>p</i>	<i>c</i>	<i>p</i> _{FWE-corr}	<i>q</i> _{FDR-corr}	<i>k</i> _E	<i>p</i> _{uncorr}	<i>p</i> _{FWE-corr}	<i>q</i> _{FDR-corr}	<i>T</i>	(<i>Z</i> _≡)	<i>p</i> _{uncorr}			
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
						0.001	0.025	5.73	5.71	0.000	50	-8	56
		0.000	0.001	16	0.001	0.000	0.004	6.08	6.05	0.000	46	-44	4
		0.000	0.000	23	0.000	0.000	0.011	5.90	5.87	0.000	48	-34	0

table shows 3 local maxima more than 8.0mm apart

Height threshold: *T* = 4.96, *p* = 0.000 (0.050)
 Extent threshold: *k* = 0 voxels
 Expected voxels per cluster, <*k*> = 1.702
 Expected number of clusters, <*c*> = 0.05
 FWEp: 4.959, FDRp: 5.735, FWEc: 1, FDRc: 5

Degrees of freedom = [1.0, 1728.0]
 FWHM = 6.6 7.1 6.7 mm mm mm; 3.3 3.6 3.3 {voxels}
 Volume: 1155888 = 144486 voxels = 3383.6 resels
 Voxel size: 2.8 2.0 2.0 mm mm mm; (resel = 39.21 voxels)
 Page 1



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

Circularity issues in fMRI

Definition

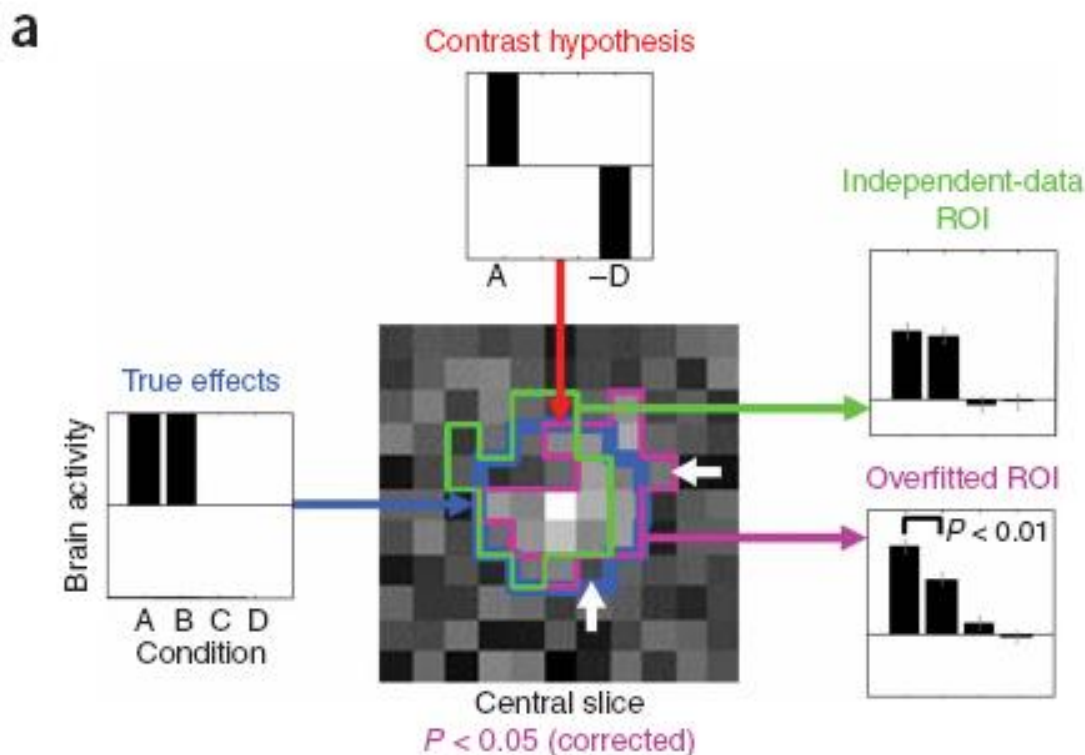
- Refers to the problem of selecting data for analysis
- How data (areas usually) are selected, analysed and sorted is key to avoid circularity
- Put forward by Vul et al. 2009, *Perspectives on Psychological Science*. 4
- Better explained in Kriegeskorte et al., 2009 *Nat. Neuroscience* 12

Circularity

- Double dipping problem: “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 group of subjects and measure RTs, then take 2 subgroups from the same subjects and re-do some analysis?? → increases the difference.
- 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 $C_{\text{selection}}^T (X^T X)^{-1} C_{\text{test}}$)
 3. Select using a subset of data, test with another one

Questions ?