

Statistical analysis of M/EEG Sensor- and Source-Level Data

Jason Taylor

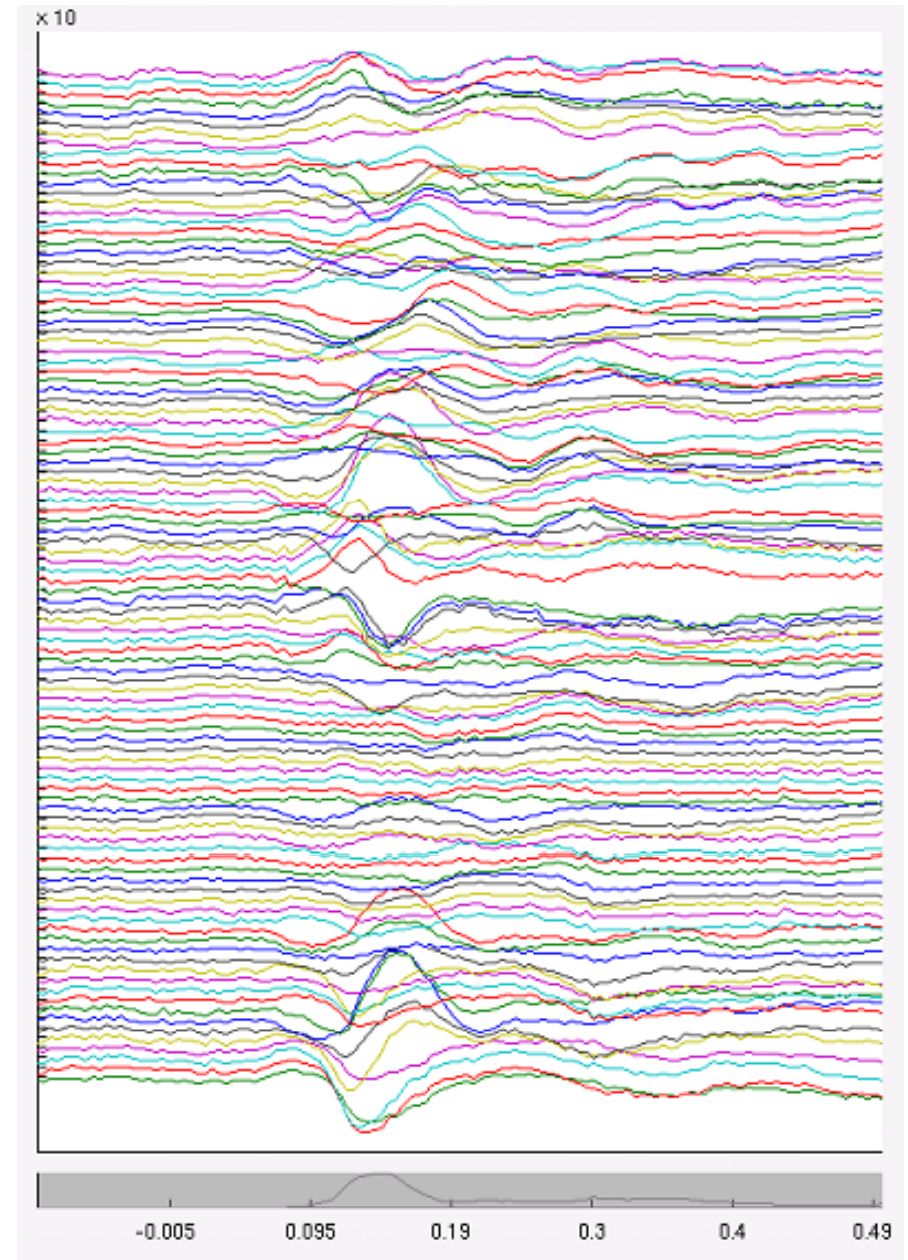
MRC Cognition and Brain Sciences Unit (CBU)

Cambridge Centre for Ageing and Neuroscience (CamCAN)

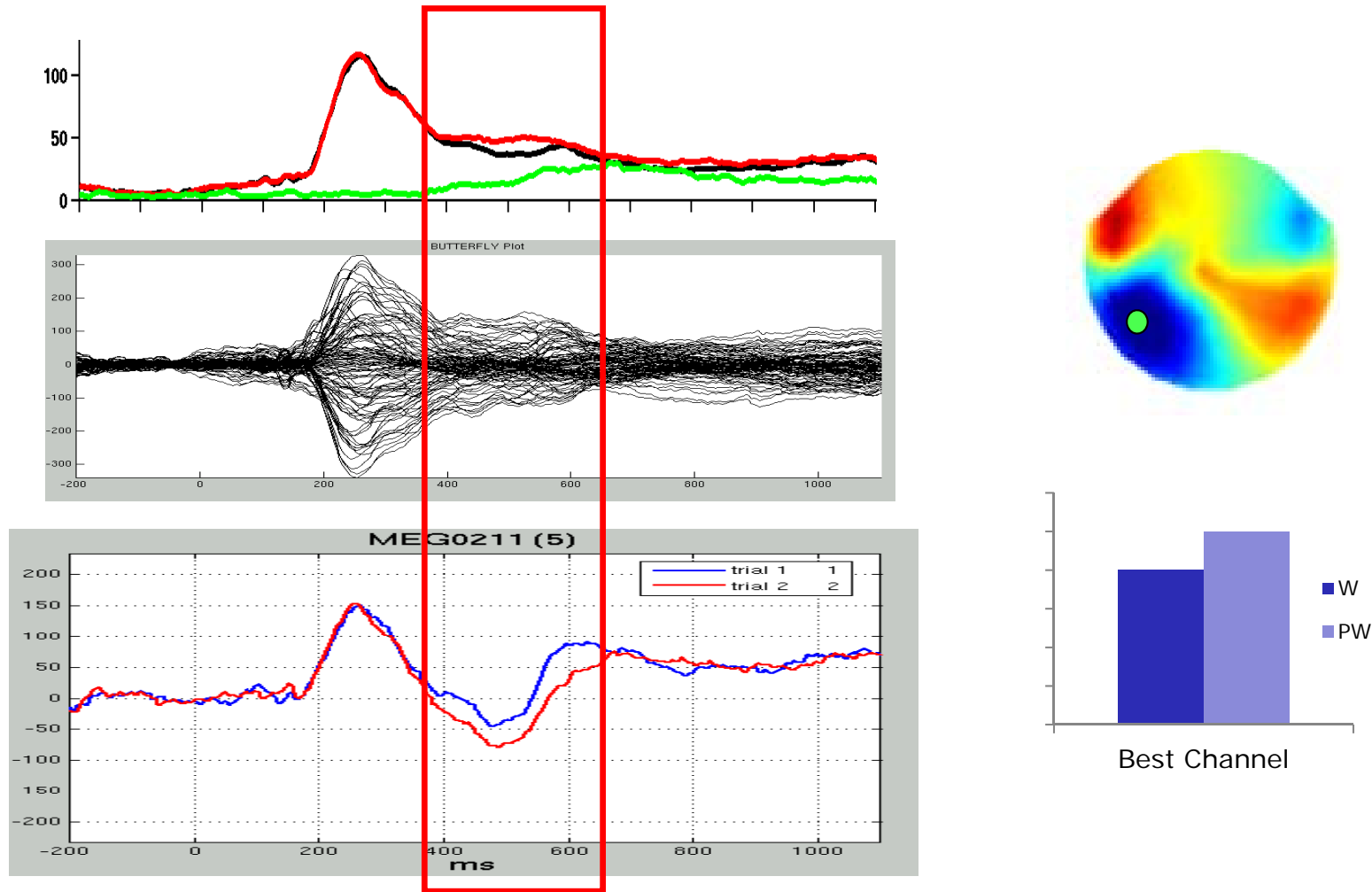
Cambridge, UK

9 Jan 2013 | MEG UK Workshop, Cambridge | jason.taylor@mrc-cbu.cam.ac.uk

When/Where is the effect reliable?



When/Where is the effect reliable?



Common approach:

- (1) View data, identify time-window containing effect, peak sensor(s)
- (2) Extract and average data for conditions and subjects
- (3) Compute statistics

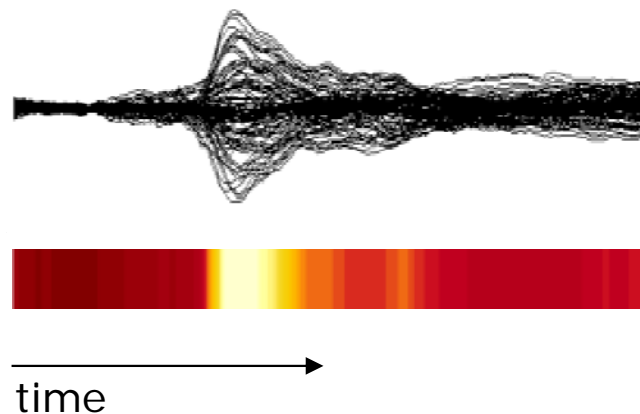
- * Circular if (1) performed on effect of interest
- * OK if orthogonal effect or from literature

The Multiple Comparison Problem

The Multiple Comparison Problem

- The more comparisons we conduct, the more Type I errors (false positives) we will make when the Null Hypothesis is true.
 - * Must consider *Familywise* (vs. *per-comparison*) Error Rate
- Comparisons are often made *implicitly*, e.g., by viewing (“eye-balling”) data before selecting a time-window or set of channels for statistical analysis.

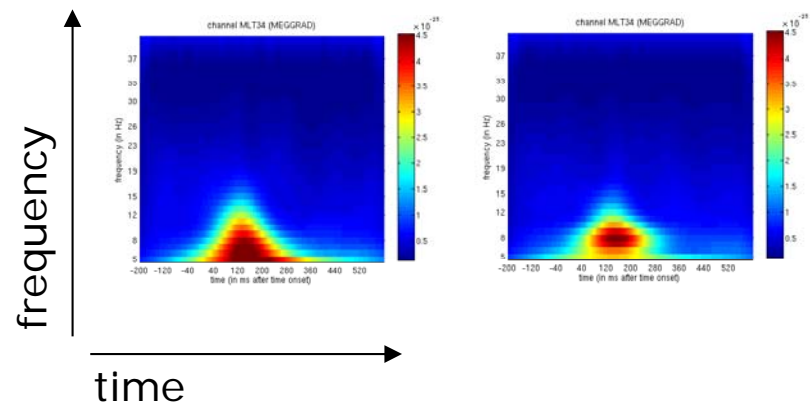
-> **When** is there
an effect in **time**
e.g., GFP (1D)?



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-> **When/at what frequency**
is there an effect
an effect in **time/frequency**
(2D)?

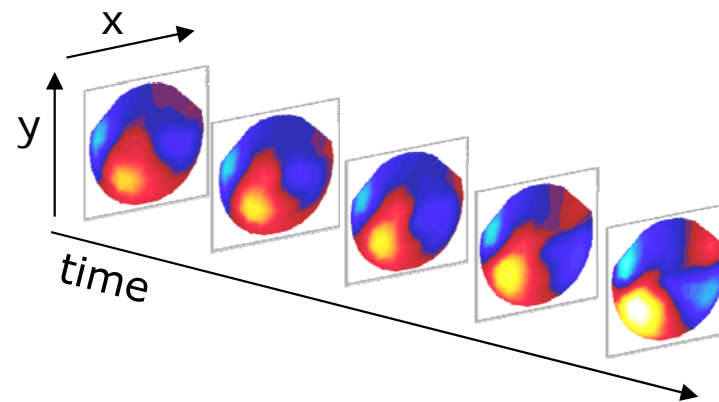


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-> **When/where**

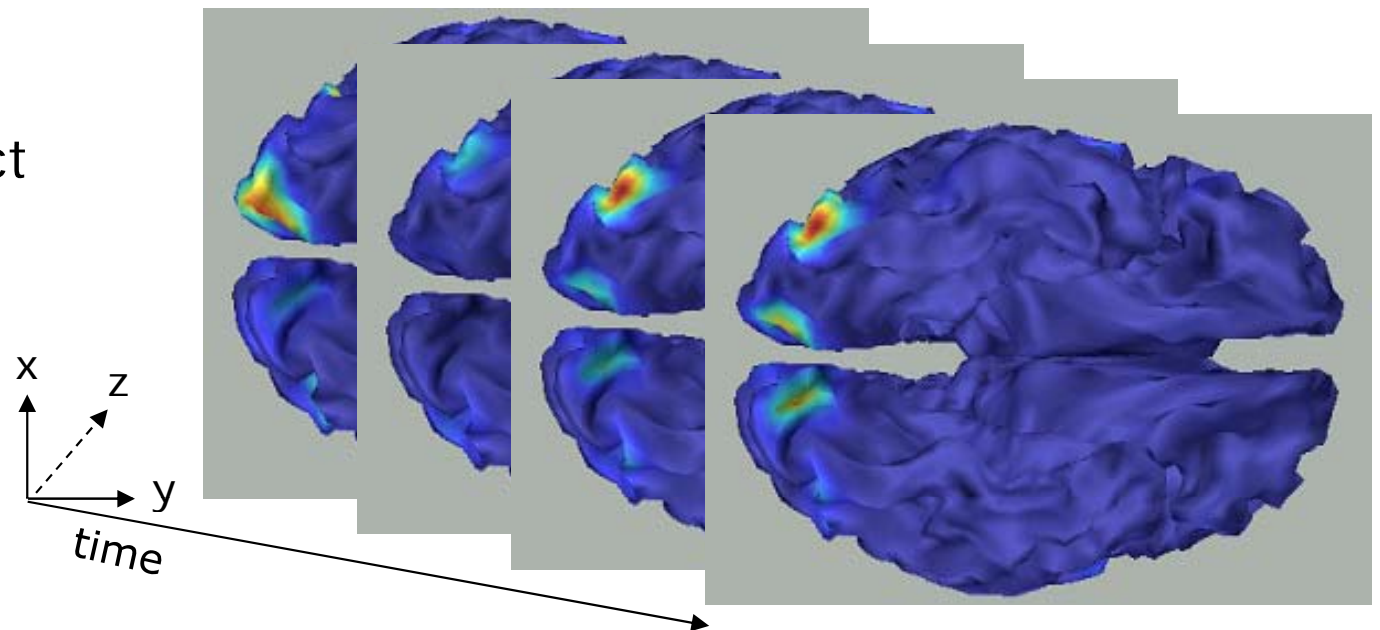
is there an effect
in **sensor-topography**
space/time (3D)?



The Multiple Comparison Problem

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-> **When/where**
is there an effect
in **source**
space/time
(4-ish-D)?



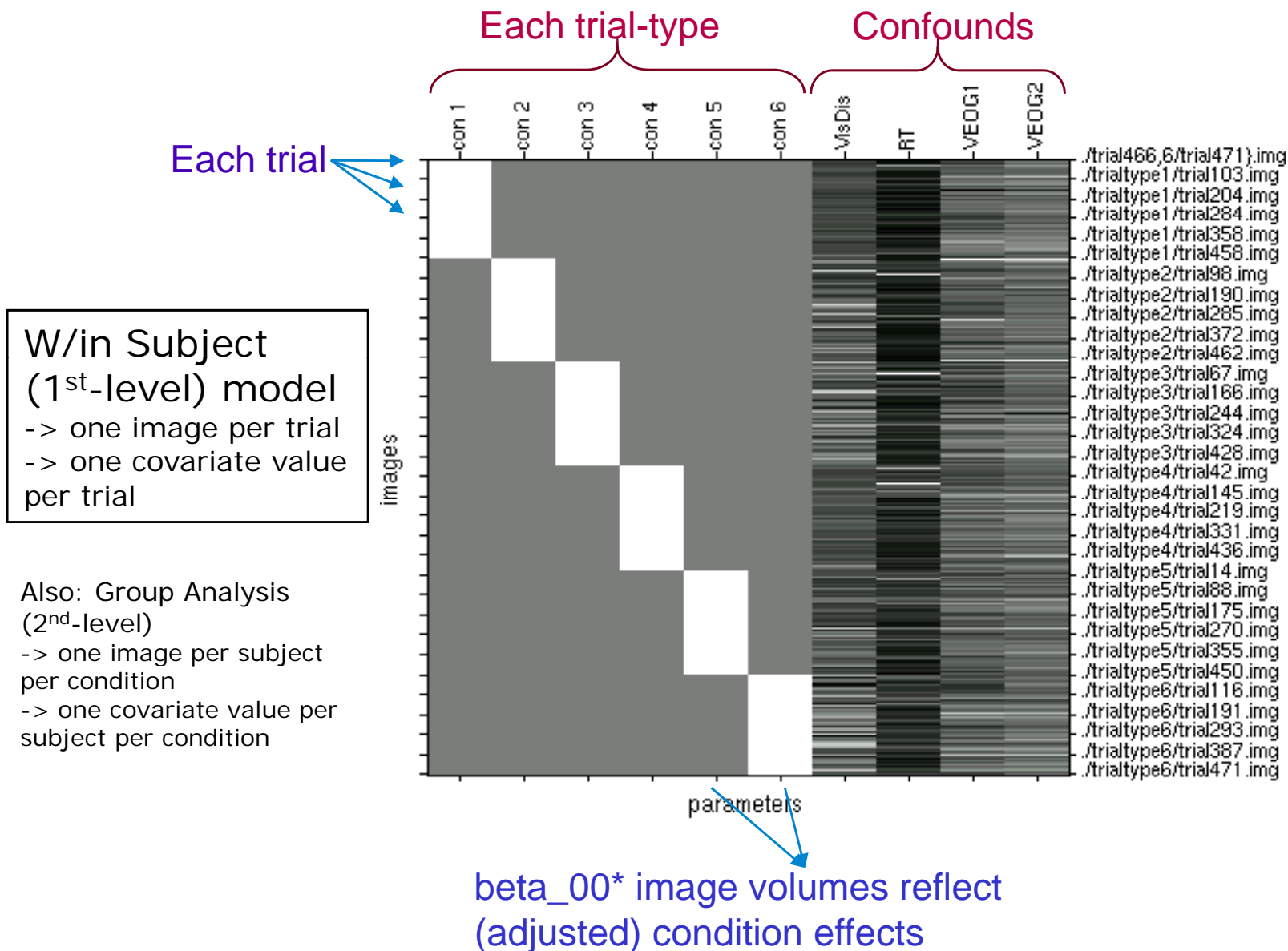
Statistical Parametric Mapping (SPM)

- A mass-univariate statistical approach to inference regarding effects in space/time/frequency (using replications across trials or subjects).
- Data are converted into images, submitted to general linear model (GLM)
- Uses much of the same machinery employed in statistical analysis of fMRI data.

Random Field Theory (RFT) is a method for correcting for multiple statistical comparisons with N-dimensional spaces (for parametric statistics, e.g., Z-, T-, F- statistics).

- * Correction depends on size of search volume
- * Takes smoothness of images into account

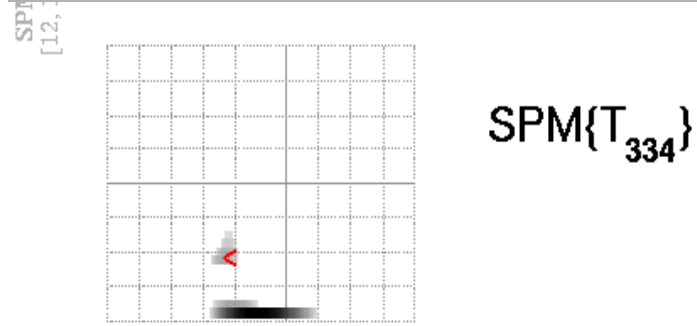
GLM: Condition Effects **after** removing variance due to **confounds**



Sensor-space analyses

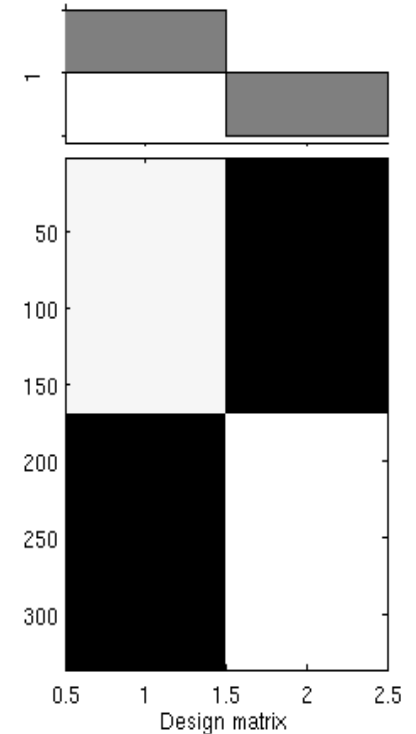
Where is an effect in **time-frequency space**?

1 subject (1st-level analysis)
 1 MEG channel
 Morlet wavelet projection
 1 t-x-f image per trial

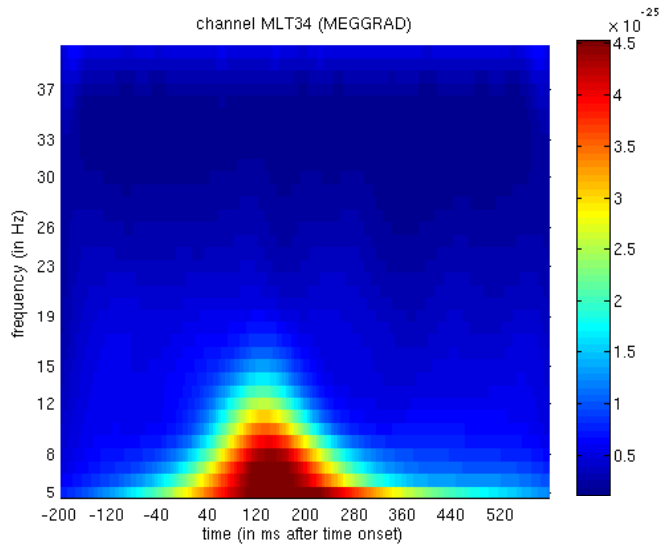


SPMresults: ./multimodal/MEG/TFstatsPow
 Height threshold T = 3.736016 {p<0.05 (FWE)}
 Extent threshold k = 0 voxels

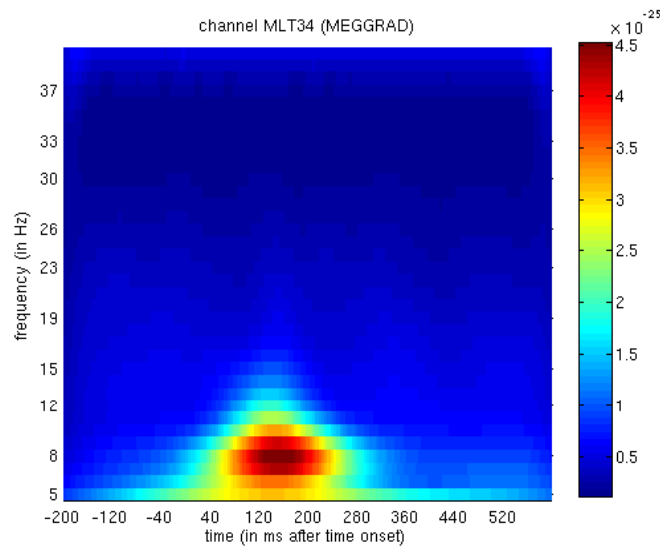
Faces > Scrambled



Faces



Scrambled



Statistics: *p-values adjusted for search volume*

set-level		cluster-level				peak-level					Hz ms
<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}	
0.001	2	0.000	0.006	79	0.003	0.000	0.002	5.40	5.28	0.000	5 185
		0.005	0.092	32	0.092	0.013	0.262	4.12	4.06	0.000	12 100

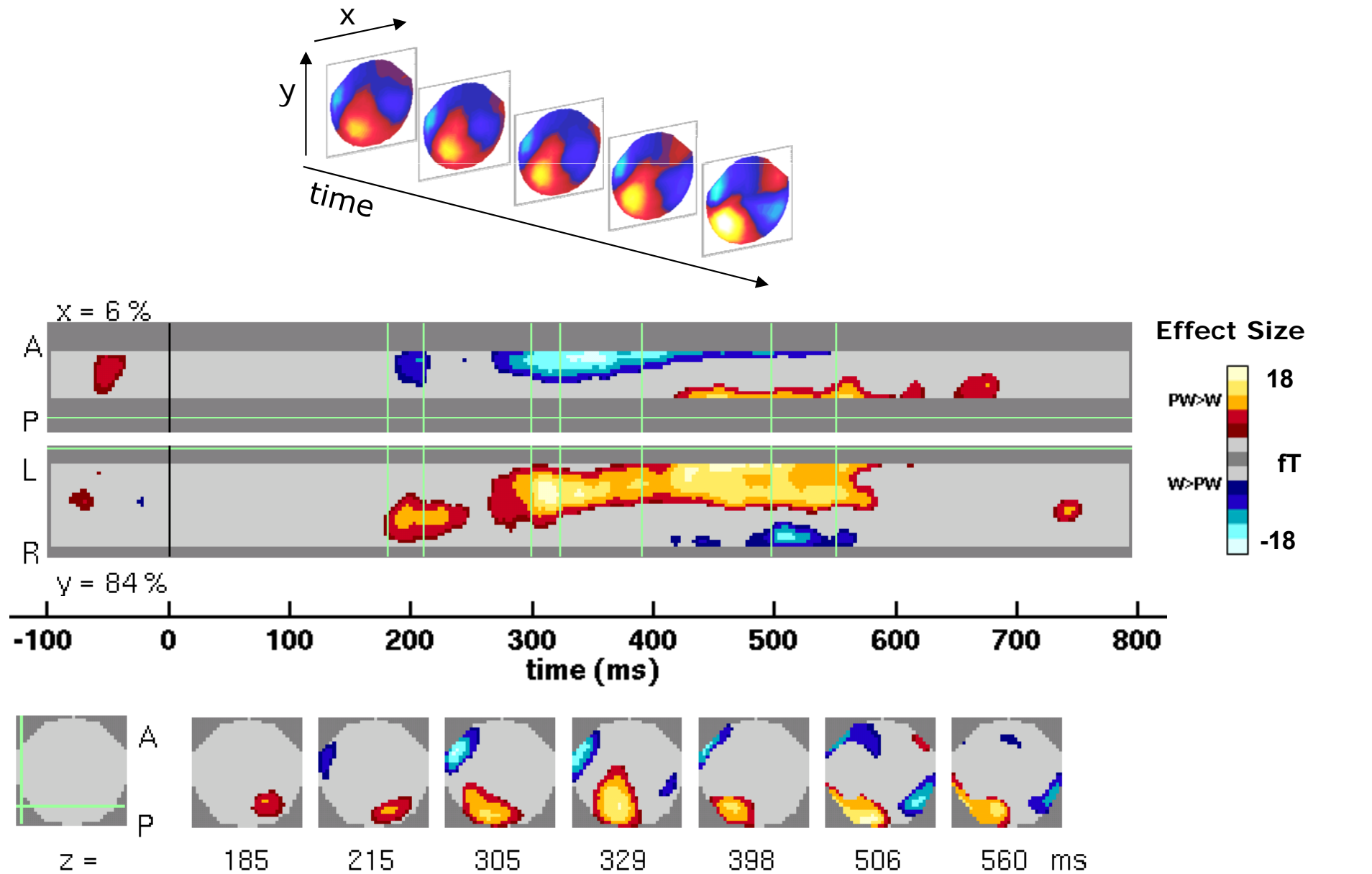
table shows 3 local maxima more than 8.0mm apart

Height threshold: T = 3.74, p = 0.000 (0.050)
 Extent threshold: k = 0 voxels, p = 1.000 (0.050)
 Expected voxels per cluster, <k> = 13.420
 Expected number of clusters, <c> = 0.05
 FWEp: 3.736, FDRp: 5.396, FWEc: 32, FDRc: 79

Degrees of freedom = [1.0, 334.0]
 FWHM = 7.5 58.5 Hz ms ; 7.5 11.7 (voxels)
 Volume: 28980 = 5796 voxels = 63.7 resels
 Voxel size: 1.0 5.0 Hz ms ; (resel = 87.91 voxels)

Where is an effect in **sensor-time space**?

Analysis over subjects (2nd Level): Words vs. Pseudowords



Source-space analyses

Where is an effect in **source space** (3D)?

STEPS:

Estimate evoked/induced energy (RMS) at each dipole for a certain time-frequency window of interest.

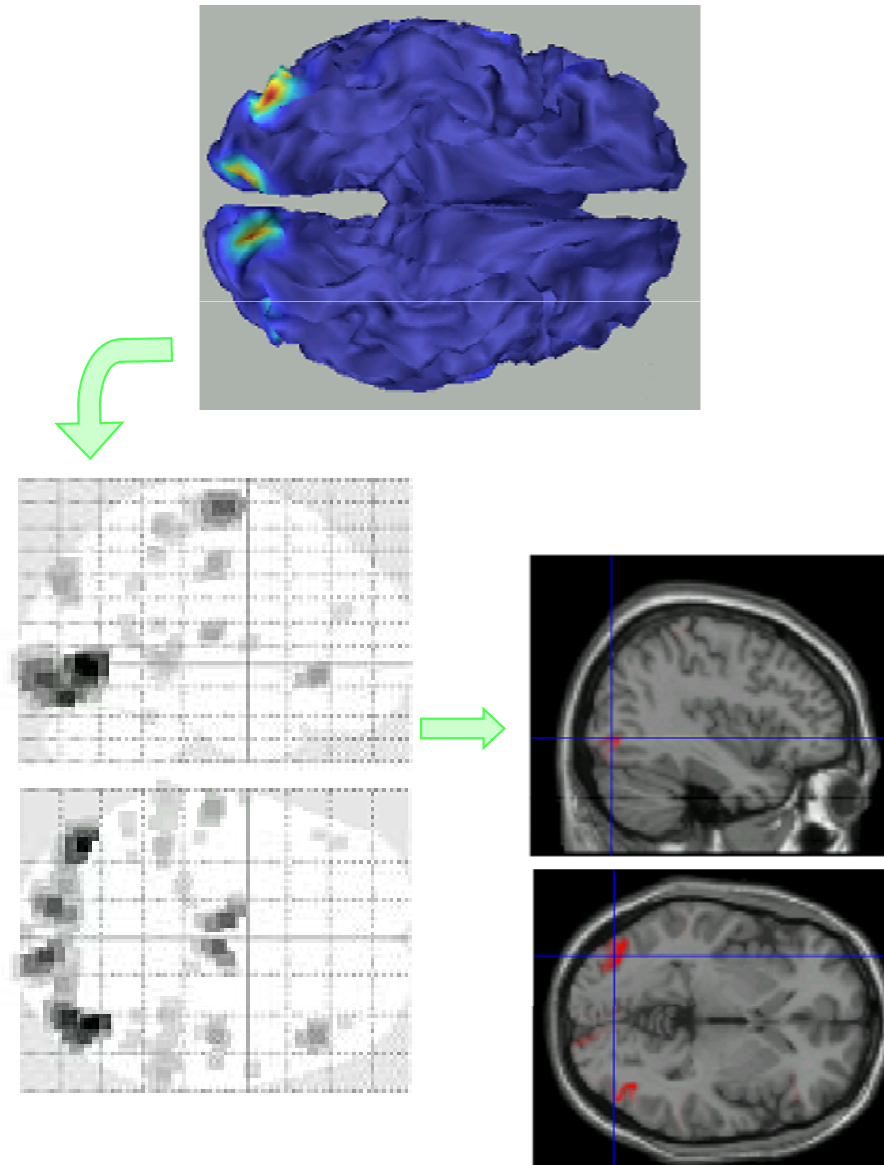
- e.g., 100-220ms, 8-18 Hz
- For each condition (Faces, Scrambled)
- For each sensor type OR fused modalities

Write data to 3D image

- in MNI space
- smooth along 2D surface

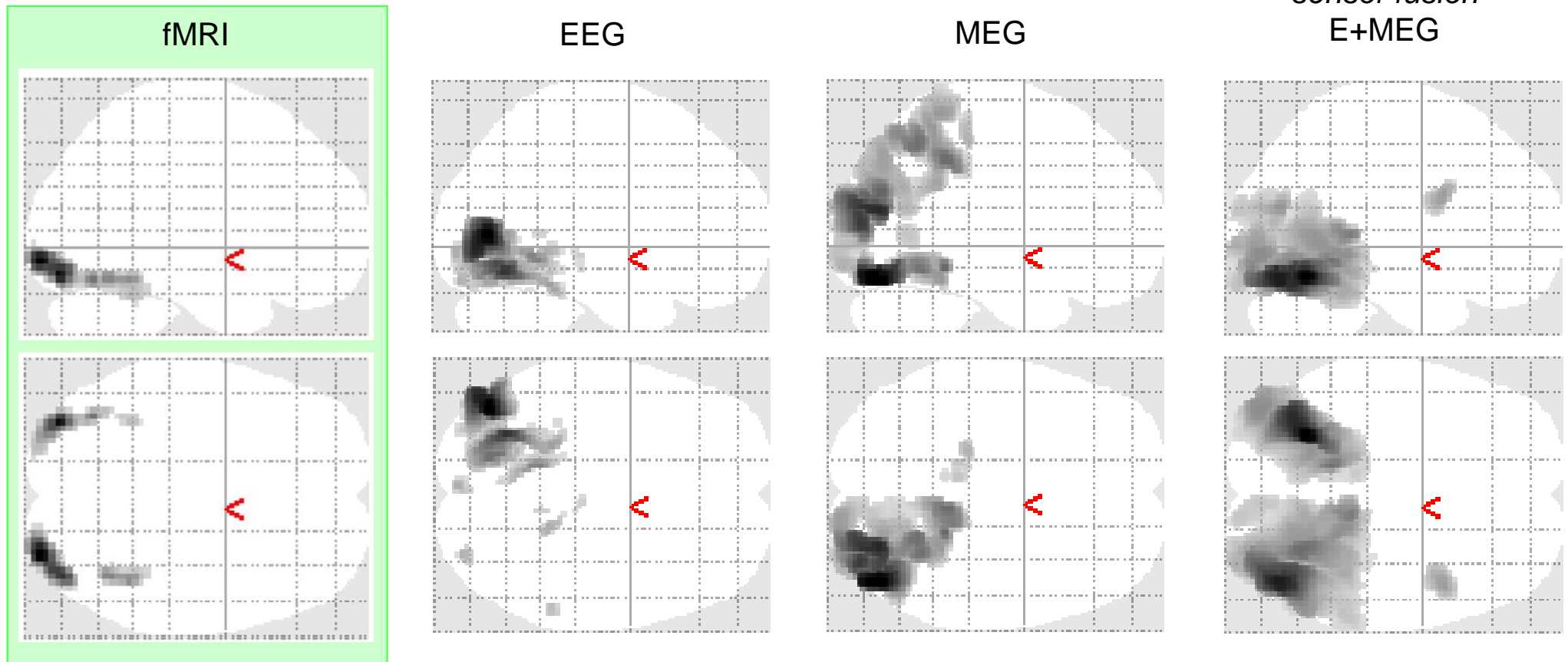
Smooth by 3D Gaussian

Submit to GLM



Where is an effect in **source space** (3D)?

RESULTS: Faces > Scrambled

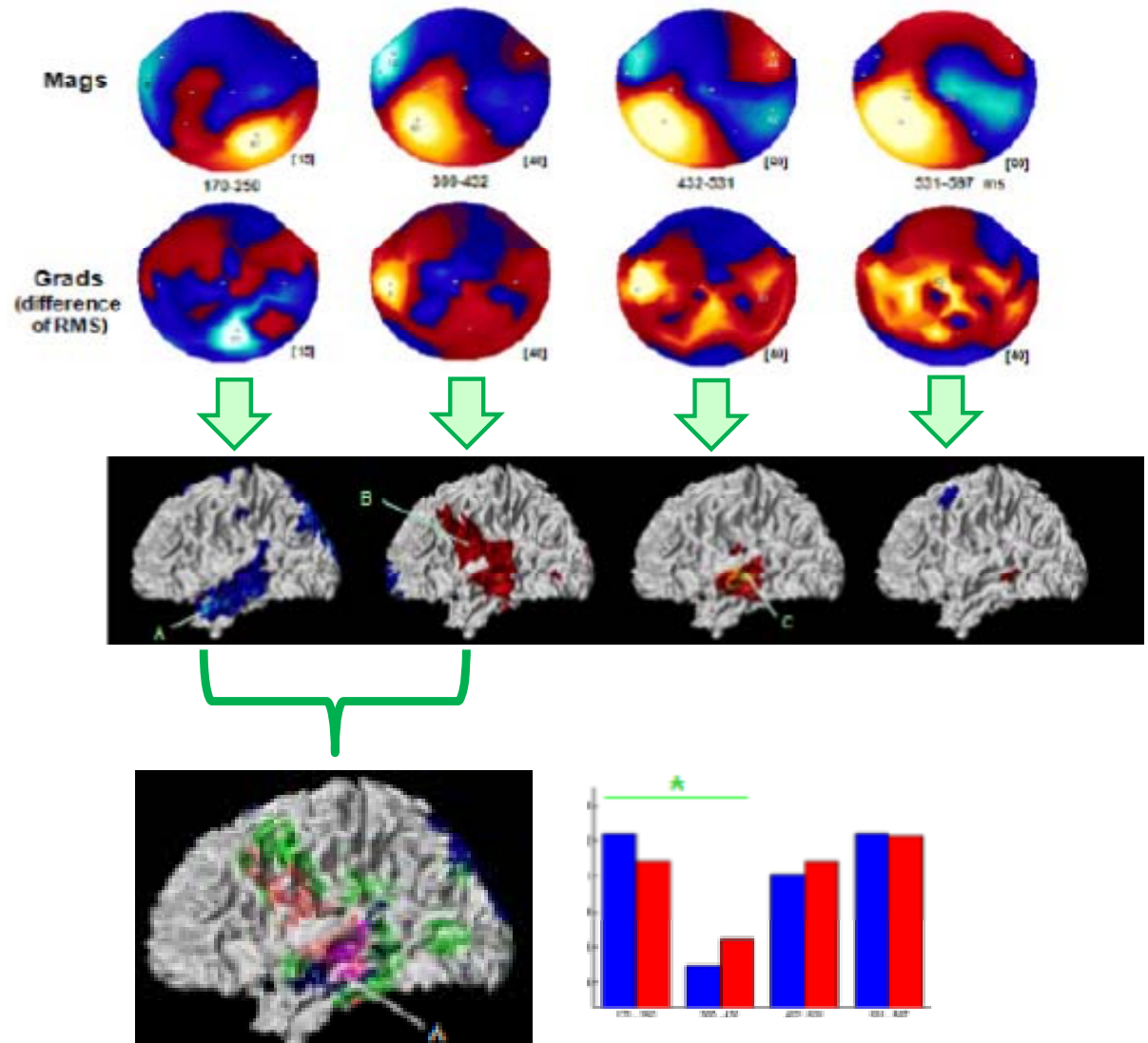


Where and When do effects **emerge/disappear** in source space (4-ish-D: time factorised)?

Condition x Time-window Interactions

Factorising time allows you to *infer* (rather than simply *describe*) when effects emerge or disappear.

- * estimate source energy in each sub-time-window
- * submit to GLM with conditions & time-windows as factors
- * Cond effects per t-win
- * Cond x t-win interaction



Alternative Approaches

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Non-Parametric Approach (SnPM)

Robust to non-Gaussian distributions

Less conservative than RFT when $dfs < 20$

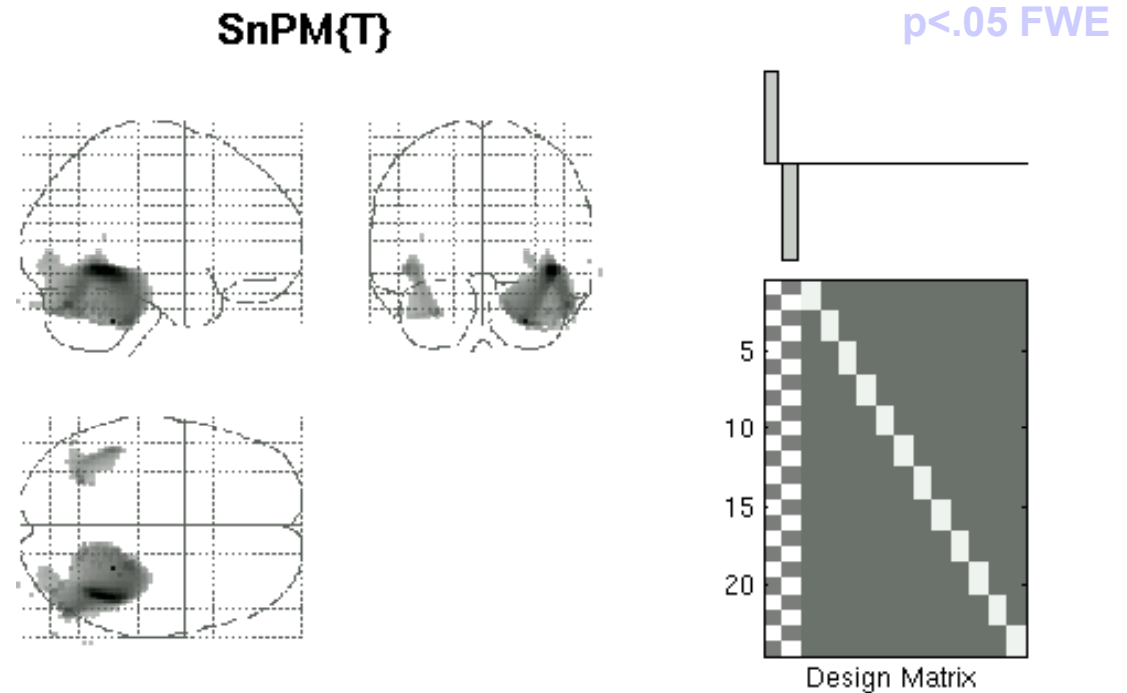
Caveats:

No idea of effect size (e.g., for power, future expts)

Exchangeability difficult for more complex designs

(Taylor & Henson, Biomag 2010)

SnPM Toolbox by Holmes & Nichols:
<http://go.warwick.ac.uk/tenichols/software/snpm/>



P values & statistics: `./MEG_Group/SourceSPMs/Inv2/mags/SnPM`

cluster-level	voxel-level				x,y,z mm			
	k	$P_{FWE-corr}$	$P_{FDR-corr}$	T				P_{uncorr}
4779		0.0002	0.0034	12.03	0.0002	42	-52	-6
		0.0002	0.0034	11.94	0.0002	44	-44	-8
		0.0002	0.0034	11.34	0.0002	26	-42	-38
619		0.0032	0.0034	8.27	0.0002	-26	-62	-32
		0.0032	0.0034	8.27	0.0002	-44	-44	-6
		0.0068	0.0034	7.55	0.0002	-40	-54	-6
1	0.0139	0.0034	6.89	0.0002	50	-80	-30	
1	0.0168	0.0034	6.63	0.0002	38	-34	-44	
1	0.0212	0.0051	6.44	0.0005	58	-64	-32	

Alternative Approaches

Posterior Probability Maps (PPMs)

Bayesian Inference

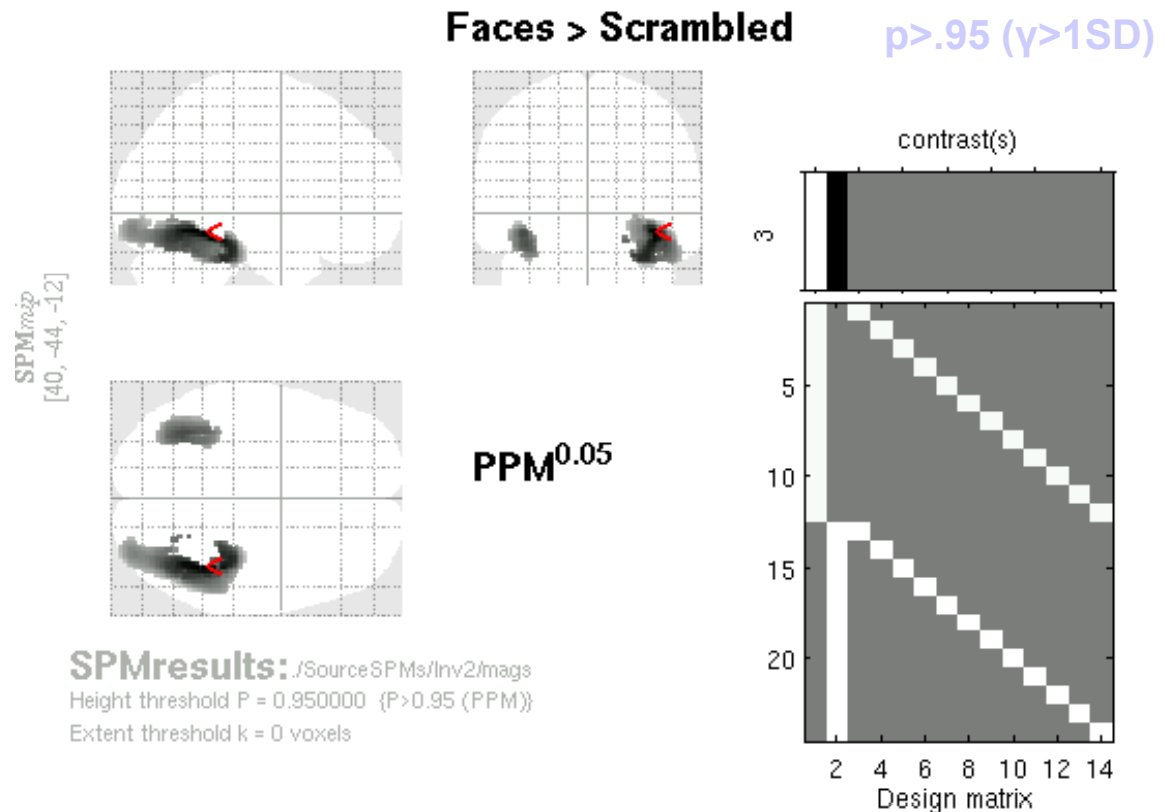
No need for RFT (**no MCP**)

Threshold on posterior probability of an effect greater than some size

Can show **effect size** after thresholding

Caveats:

Assume Gaussian distribution (e.g., of mean over voxels)



Statistics: *Posterior Probabilities*

set-level	cluster-level	peak-level	mm mm mm
<i>c</i>	<i>k_E</i>	<i>P</i> (<i>Z_E</i>)	
6	1239	0.18 -0.92	40 -44 -12
		0.17 -0.95	38 -56 -10
	395	0.17 -0.96	40 -34 -16
		0.14 -1.08	-38 -56 -12
	1	0.13 -1.13	-38 -46 -14
		0.12 -1.16	-34 -46 -22
	2	0.12 -1.15	22 -54 -16
		0.12 -1.15	24 -62 -16
	4	0.12 -1.20	22 -60 -14
		0.11 -1.23	30 -62 -4

-- The end --



- Thanks for listening
- Acknowledgements:
 - Rik Henson (MRC CBU)
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 - Vladimir, Karl, and the FIL Methods Group
- More info:
 - <http://imaging.mrc-cbu.cam.ac.uk/meg> (wiki)



jason.taylor@mrc-cbu.cam.ac.uk