

# Spatiotemporal Searchlight Representational Similarity Analysis (ssRSA) of MEG

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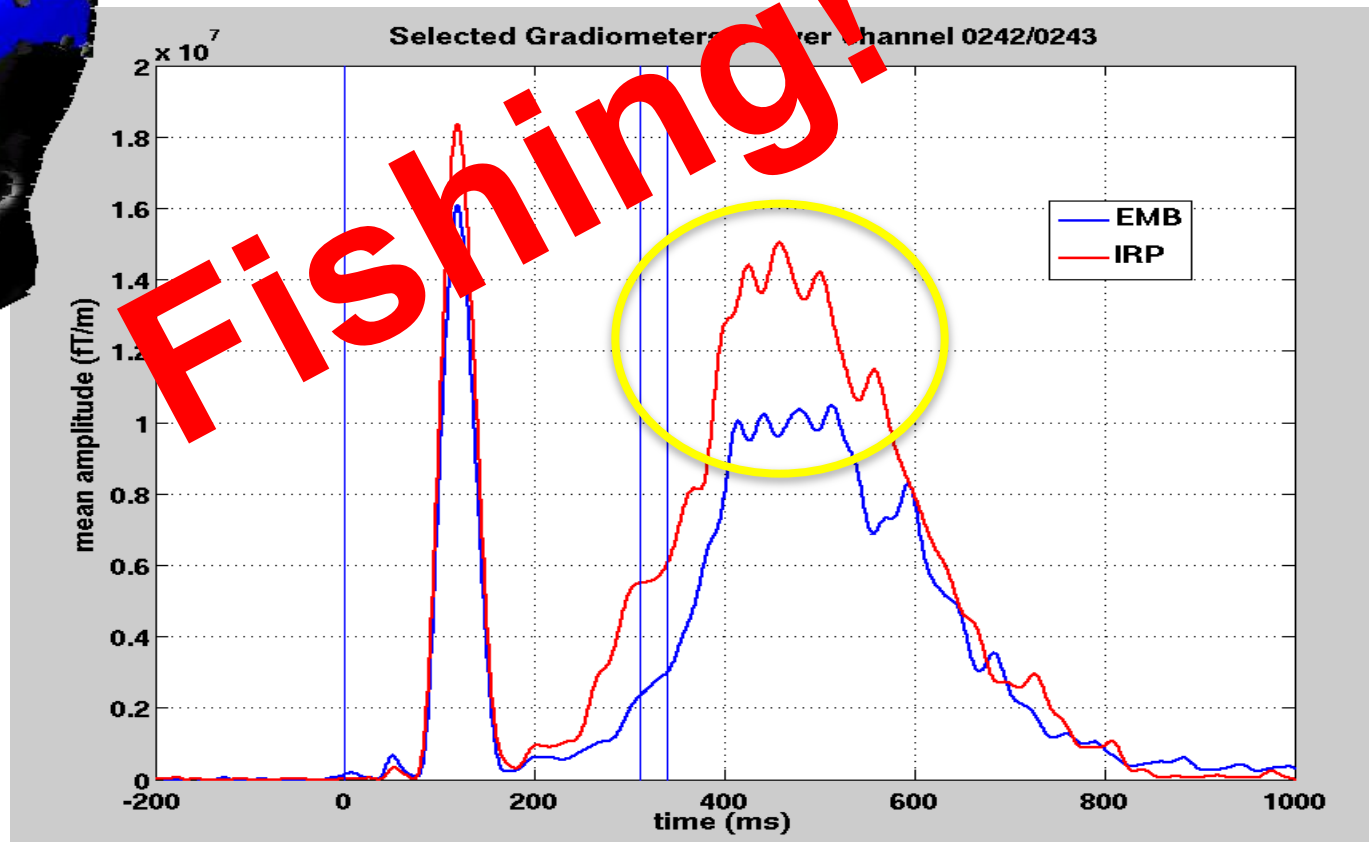
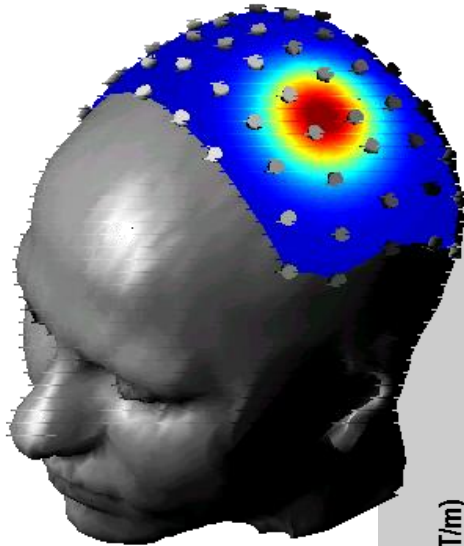
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# Overview

- Our aim is to understand dynamic large scale processing systems in the human brain operating on millisecond timescales.
  - Whole brain
  - Population code – representations
  - Dynamic changes – computation (operations applied to representations in order to ...)
  - Interactions – connectivity (implementations)
  - Statistic
- Problems with current MEG analysis approaches
- Spatiotemporal searchlight representational similarity analysis (ssRSA, Su et al., 2012)
  - With an example of combined MEG/EEG source analysis

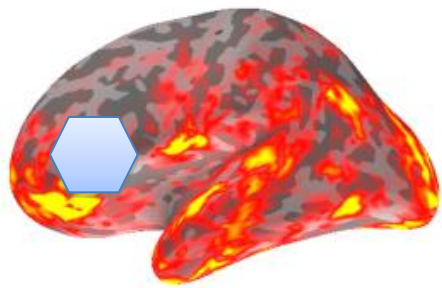
# Univariate Analysis of MEG



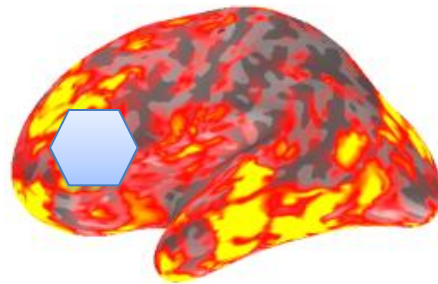
# Spatiotemporal Searchlight RSA

- Multivariate Pattern Analysis (MVPA), e.g. SVM and RSA, has been successfully applied to fMRI, but less so to MEG (additional temporal dimension)
- Conventional univariate analysis loses the rich spatiotemporal information by averaging across space (and time)
- Representational Similarity Analysis (RSA) with spatiotemporal searchlight
  - enables whole brain analysis, and
  - avoids pre-selections of time window
- Nonparametric (permutation) and spatiotemporal-clustering analysis are used for statistical testing of source data, controlling the family wise error rate

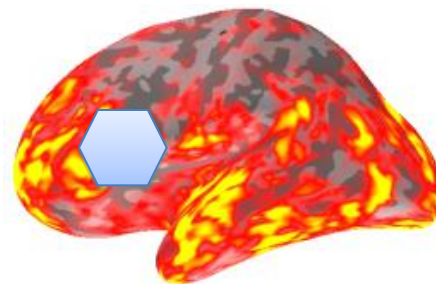
# Spatiotemporal Searchlight



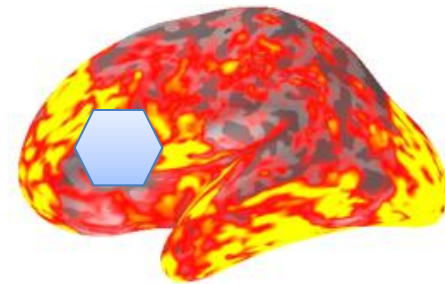
$t = T \text{ ms}$



$t = T + 1 \text{ ms}$

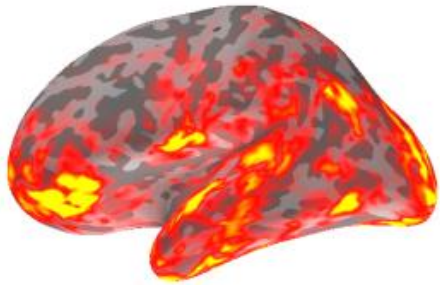
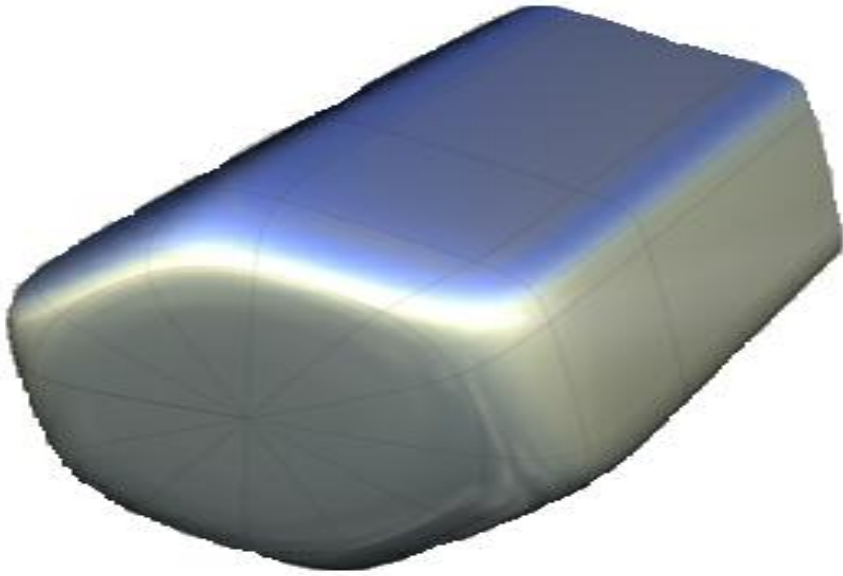


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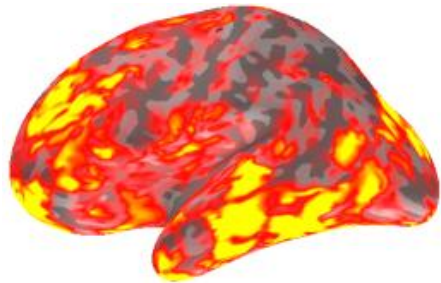


$t = T + N \text{ ms}$

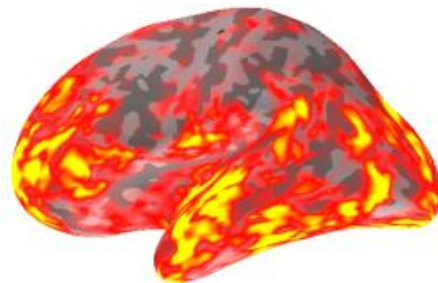
# Spatiotemporal Searchlight



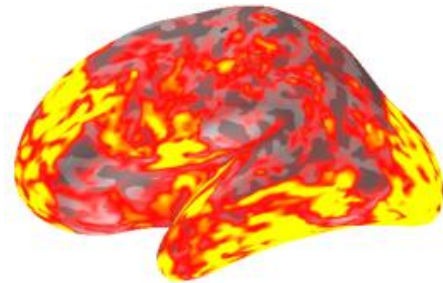
$t = T \text{ ms}$



$t = T + 1\text{ms}$



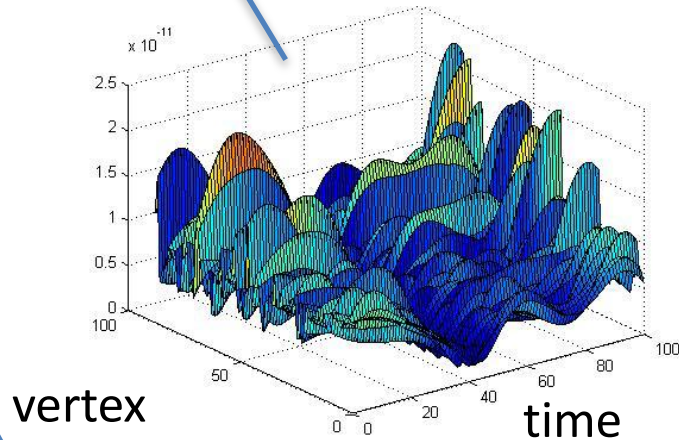
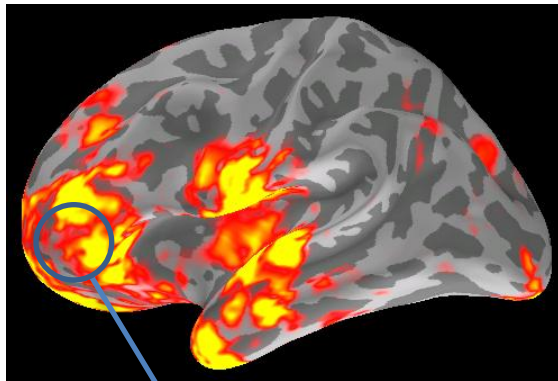
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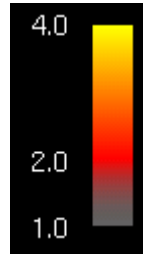
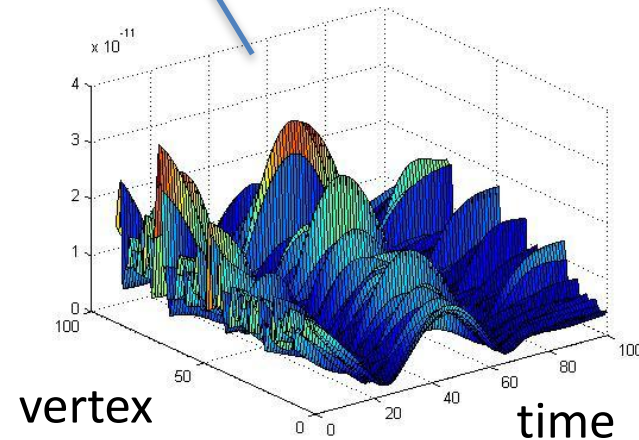
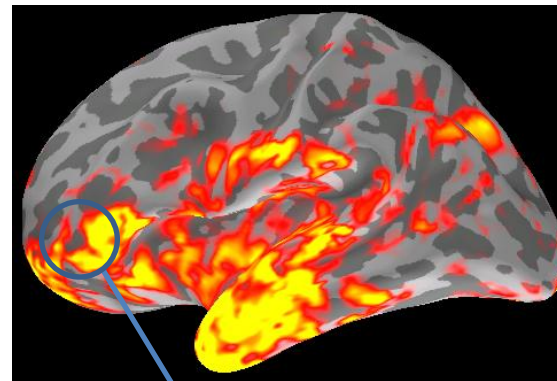
$t = T + 20\text{ms}$

# Spatiotemporal Distribution of MEG Source Data Carries Information

Condition A



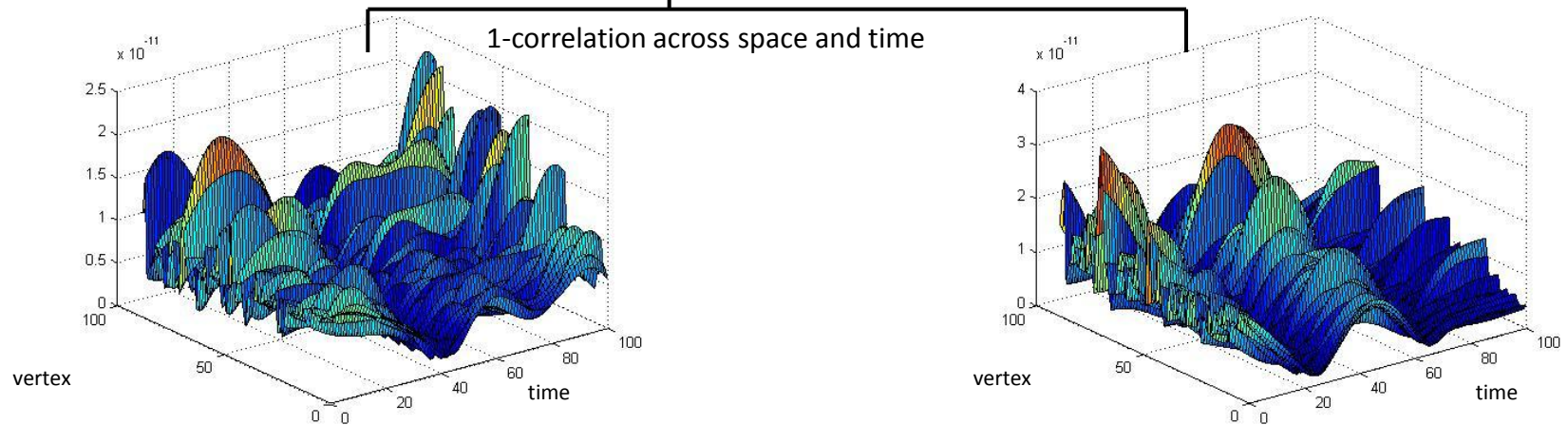
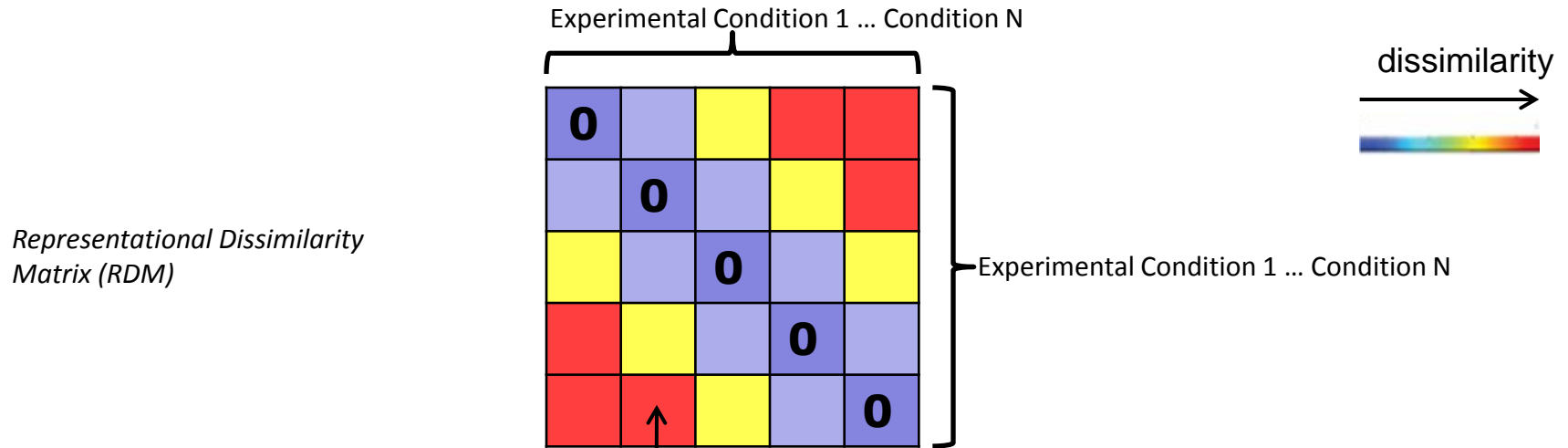
Condition B



$A_m \times 10^{-11}$



# Brain-data (Spatiotemporal) Representational Dissimilarity Matrix (RDM)

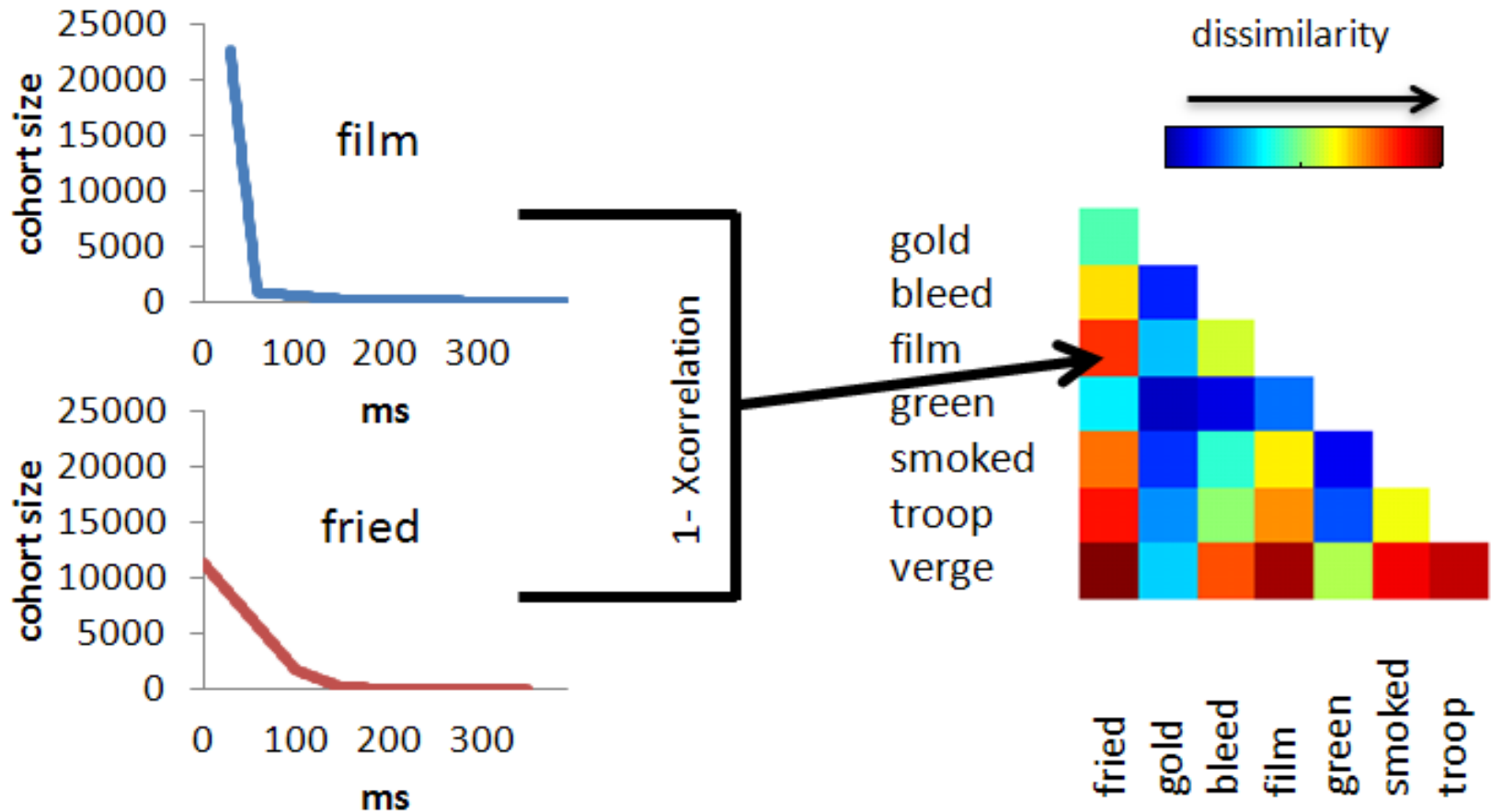


Experimental Condition 1 ... Condition N

(ssRSA, Su et al., 2012)



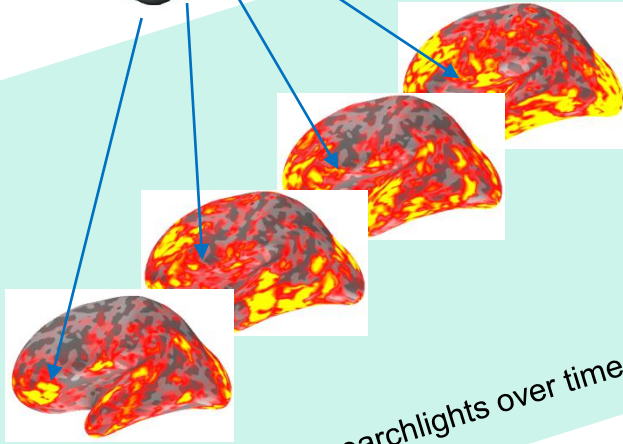
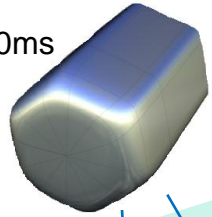
# Model RDM e.g. Change in Cohort Size



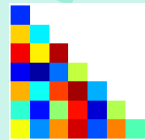
\* Other psychological processes can be modelled similarly

# Explore in space (searchlight) and time (sliding time window)

20mm x 20ms

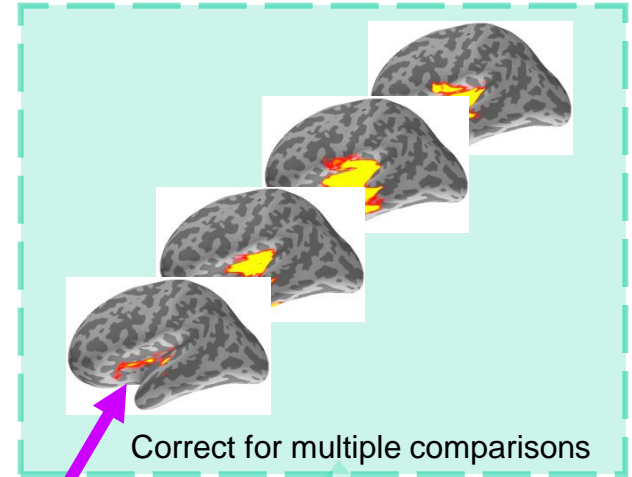
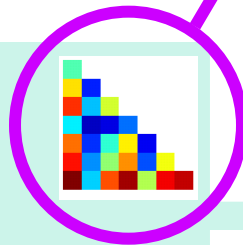


Simultaneous searchlights over time points



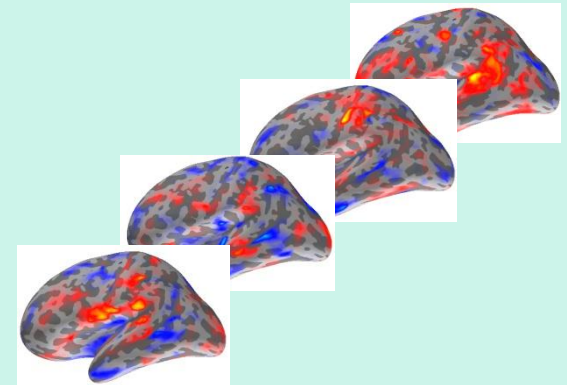
One RDM for each vertex and time point

Compare brain-data RDM with model RDM



Correct for multiple comparisons

thresholding



Spearman r-map over time

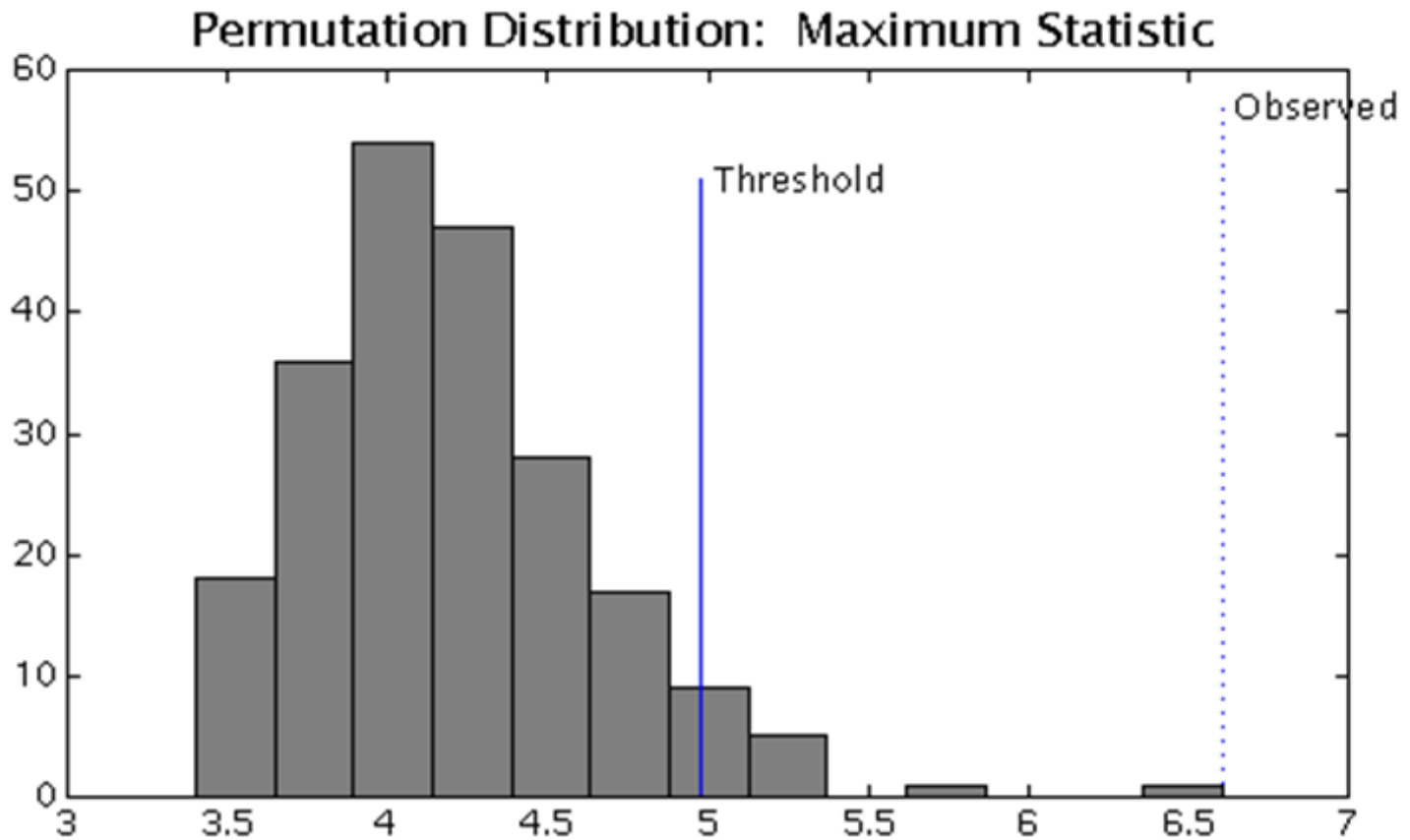
# Violations of Normality Assumptions

- Large group study, i.e. 81 subjects (Thirion et al., 2007), found substantial departures from normality (22% of voxels in fMRI)
- Normality assumptions are not always true for multivariate approaches, such as classification accuracy measures
- So, some have suggested permutation-based tests with cluster-level statistics (Haysaka and Nichols, 2003; Bullmore et al., 1996 and Brammer et al., 1997)
- Incidentally, the t statistic itself was intended ( by Gosset in the original paper in 1908) as a parametric approximation to a permutation test for large samples!!

# Nonparametric Test based on Cluster-level Randomization

1. Calculate statistical maps for each subject
2. At each vertex, compute summary stats (e.g. t-value) over subjects
3. Threshold the map and form spatiotemporal clusters by continuity (observed clusters)
4. Compute the maximum cluster-level statistics among all clusters, and save it
5. Simulate the null distribution by flipping the sign of the entire statistical map (thus preserving the spatiotemporal autocorrelation) for a random subset of subjects and repeat steps (2-5) many times
6. P values are computed by calculating where the observed cluster-level statistics locate in the null distribution

# Permutation Distribution

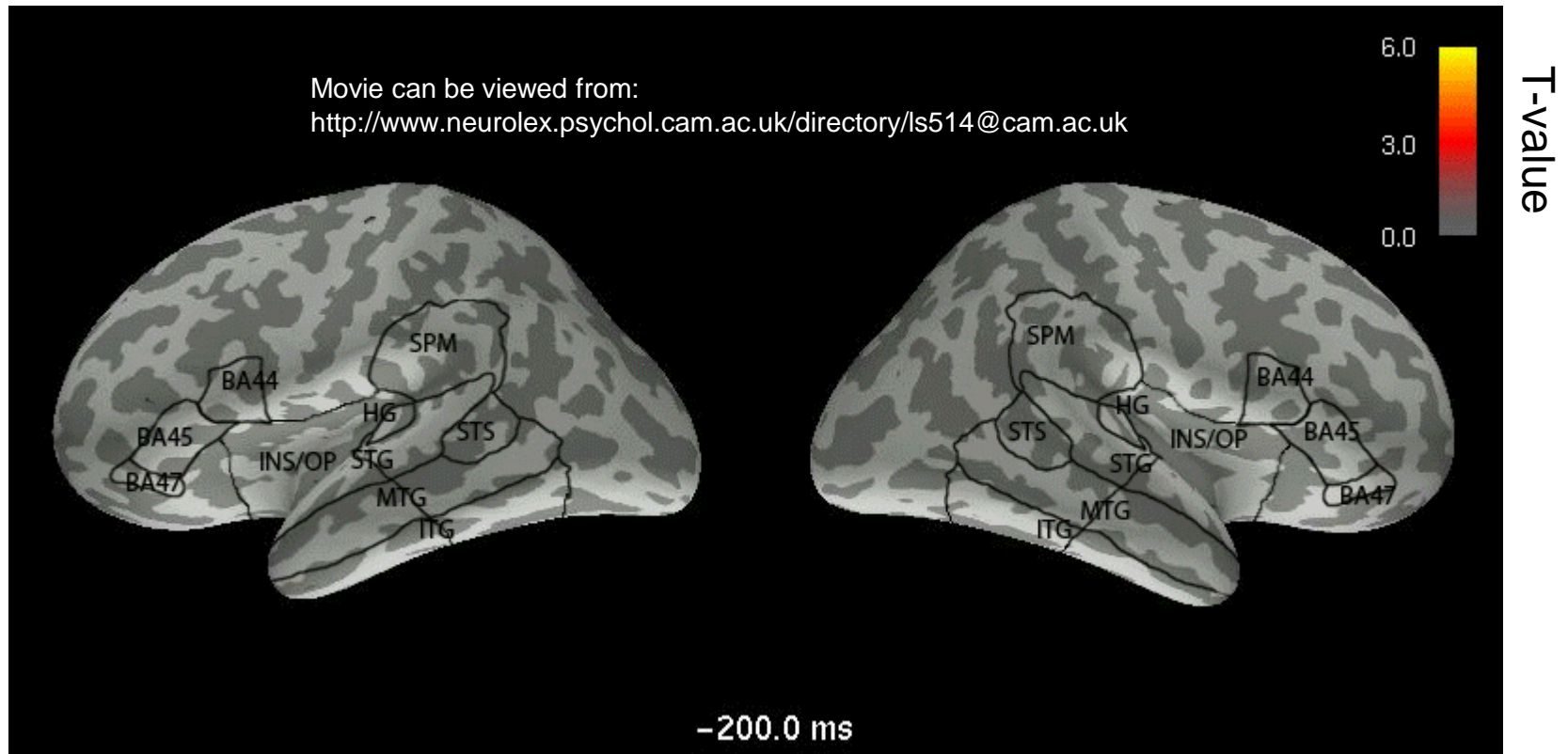


# An Example: Word Comprehension

- Experimental Details
  - 17 healthy, right-handed, native English speakers listened passively to English words (e.g. *fried, film, dream*) and occasionally performed a 1-back memory task
- MEG/EEG (EMEG) Acquisition
  - 306-channel Vectorview MEG, 70-channel EEG and three-compartment boundary-element forward model using structural MRI (3T)
- Multimodal Source Reconstruction
  - Source estimation using minimum-norm estimation (MNE)
  - Distributed-source solution combining both MEG and EEG scalp information with constraints from MRI structural images
- Alignment to the onset of the last phoneme
  - Epochs (-200 to +200ms) were located relative to alignment point

# Whole Brain Searchlight Results

random effect,  $p < 0.001$ , whole brain corrected at cluster level



Model RDM is based on the similarity of Cohort size  
Time 0 – onset of the last phoneme



# Conclusions

- Spatiotemporal searchlight RSA is the key to capturing fine-grained dynamic neural computations in the brain, and can do so on a large scale – encompassing the whole brain.
- We described nonparametric procedures that address the spatiotemporal multiple-comparisons problem.
- The ability to directly analyze pattern information in both space and time from neural activity in the brain enables us to generate and validate computational models and cognitive theories in a natural and informative way.
- RSA is able to closely relate dynamic patterns at the neuronal level, measured electrophysiologically, with patterns derived from higher-level cognitive theories.