Exploring Brain Meta Activation Patterns Using Neuroimaging Data

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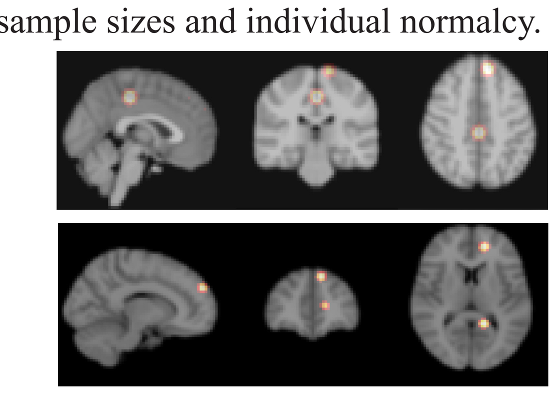
Introduction

- Neuroimaging data can help us understand and visualize brain activity patterns, which are the spatial distribution of neuronal activation (BOLD signal) driven by an experimental task (Van Den Heuvel & Pol, 2010).
- There is no current agreed upon cognitive ontology for studying the relationship between psychological processes and brain activation patterns. Research suggests that our current cognitive ontologies based off of psychological theory may not be accurate for studying neuronal processes. Some researchers have called for a brain-based cognitive ontology that is constructed from neuronal activation patterns (Laird et al., 2015).
- We can cluster similar activation patterns together to visualize which structures activate simultaneously in response to a particular task or stimulus, allowing us to describe a new ontology. We aim to bring consistency to cognitive neuroscience vocabulary and understanding of meta activation patterns.

Data

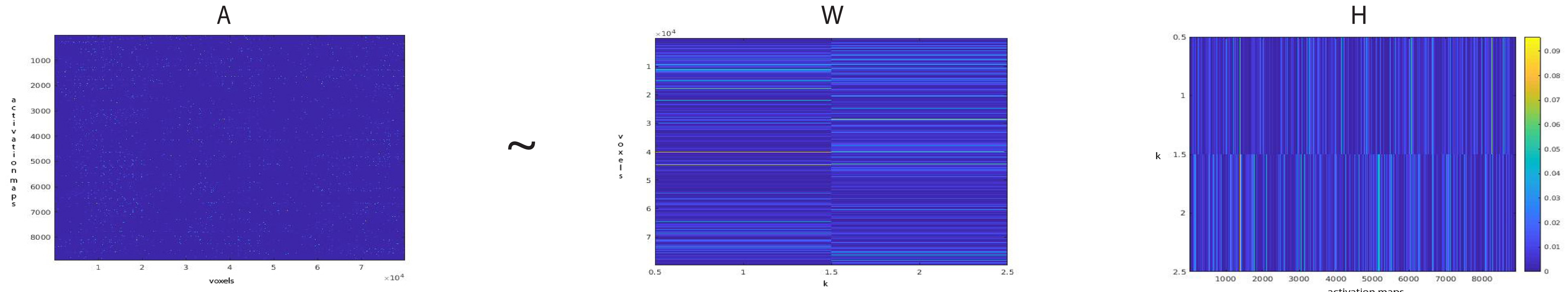
- BrainMap is a database of published neuroimaging experiments with 3D brain coordinates of where activation occurred for that experiment. These coordinates enable us to represent the brain activation with a Gaussian kernel (Laird, Lancaster, & Fox, 2005).
- BrainMap has upward of 15,000 experiments from which we selected 8,919 to work with based upon sufficient sample sizes and individual normalcy.

Instruction	ExtVariable	Context	Modality	Contrast	PC	BD
Encode,Recall	None	Normal Mapp	PET	Instruction	Encoding,Tone Monitor/Discrimination	Cognition.Memory.Explicit
Encode,Recall	None	Normal Mapp	PET	Instruction	Paired Associate Recall,Tone Monitor/Discrimination	Cognition.Memory.Explicit
Discriminate,Encode	None	Normal Mapp	PET	Stimulus Type	Encoding,Tone Monitor/Discrimination	Cognition.Attention
Discriminate,Encode	None	Normal Mapp	PET	Stimulus Type	Divided Auditory Attention,Encoding,Tone Monitor/Discrimin	Cognition.Attention
Discriminate	Accuracy,Reaction Time	Normal Mapp	fMRI	Stimulus Type	Visuospatial Attention	Cognition.Attention
Discriminate	Accuracy,Reaction Time	Normal Mapp	fMRI	Stimulus Type	Visuospatial Attention	Cognition.Attention
Passive/Rest,Recall	None	Normal Mapp	PET	Stimulus Mod	Recitation/Repetition (Overt)	Emotion.Other
Recall	None	Normal Mapp	PET	Group	Recitation/Repetition (Overt)	Emotion.Other
Recall	None	Normal Mapp	PET	Stimulus Type	Recitation/Repetition (Overt)	Emotion.Happiness
Attend	None	Normal Mapp	PET	Stimulus Type	Passive Viewing	Perception.Vision.Shape
Attend	Accuracy,Reaction Time	Normal Mapp	PET	Stimulus Type	Encoding	Cognition.Memory.Explicit
Discriminate	Accuracy,Reaction Time	Normal Mapp	PET	Stimulus Type	Semantic Monitor/Discrimination	Cognition.Language.Semantics,Cognition.Me
Attend,Discriminate	Accuracy,Reaction Time	Normal Mapp	PET	Stimulus Type	Semantic Monitor/Discrimination	Cognition.Language.Semantics
Detect	None	Normal Mapp	fMRI	Stimulus Type	Passive Listening	Cognition.Language.Speech
Detect,Discriminate	None	Normal Mapp	fMRI	Stimulus Type	Semantic Monitor/Discrimination	Cognition.Language.Semantics,Cognition.Lan

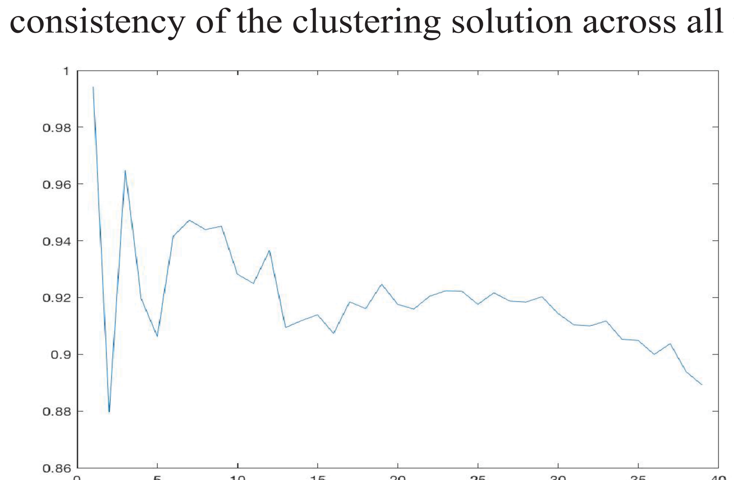


Methods

- We utilized nonnegative matrix factorization, a nondeterministic dimension reduction technique that decomposes one matrix into two: the W matrix (voxels by # of dimensions) that represents meta activation patterns, and the H matrix (# of dimensions by activation maps) that represents the expression of each meta activation pattern in each activation map (Devarajan, 2008).
  - ran for k = 2-40 fifty times each



- To determine which number of clusters to choose we performed a consensus clustering algorithm on the H matrix (Brunet et al., 2004).
  - cophenetic correlation: represents the consistency of the clustering solution across all runs for that solution



- To yield a psychological interpretation we performed a behavioral decoding procedure that computed the probability of a certain category (working memory, passive listening, etc.) being in a cluster:

$$\frac{\#\text{appearances in cluster N} \,/\, (\#\text{appearances in all clusters})}{\text{probability of cluster N}}$$

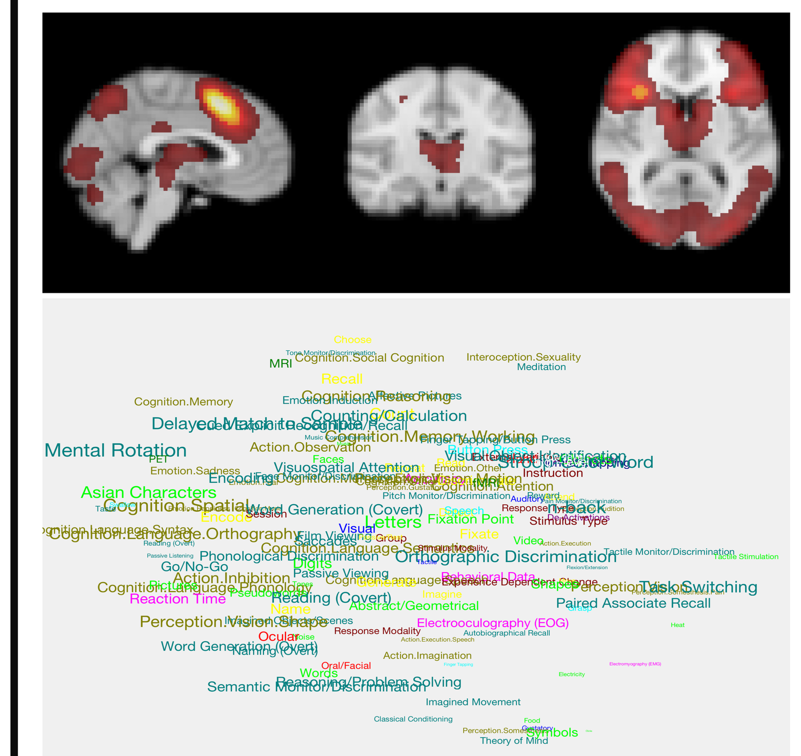
  - where N is a behavioral category

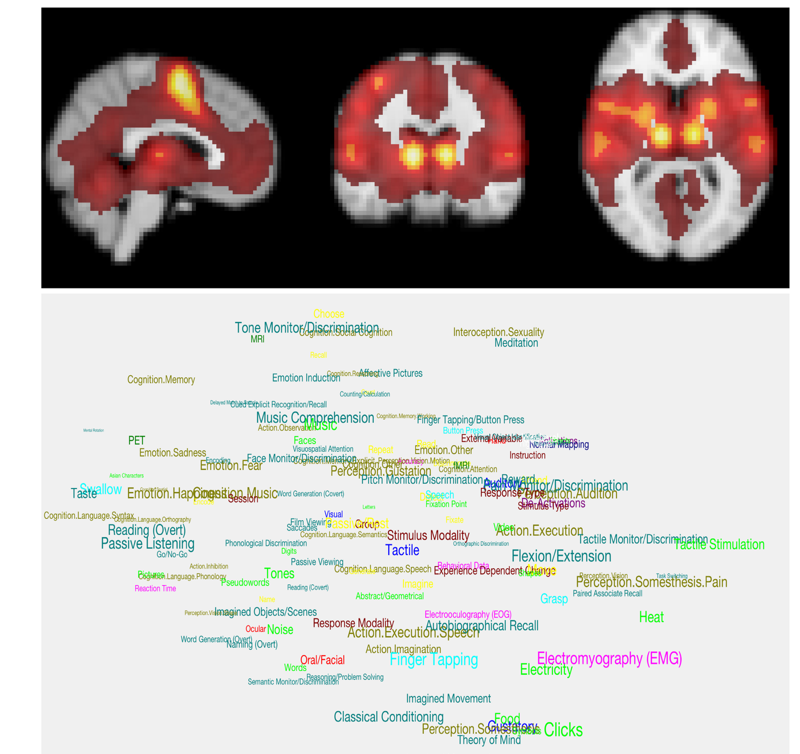
- WordCloud: color is based on which domain (stimulus type, behavioral domain, etc.) the word falls under, the size is based on the equation above, and the position is based on the probability that two words appear together

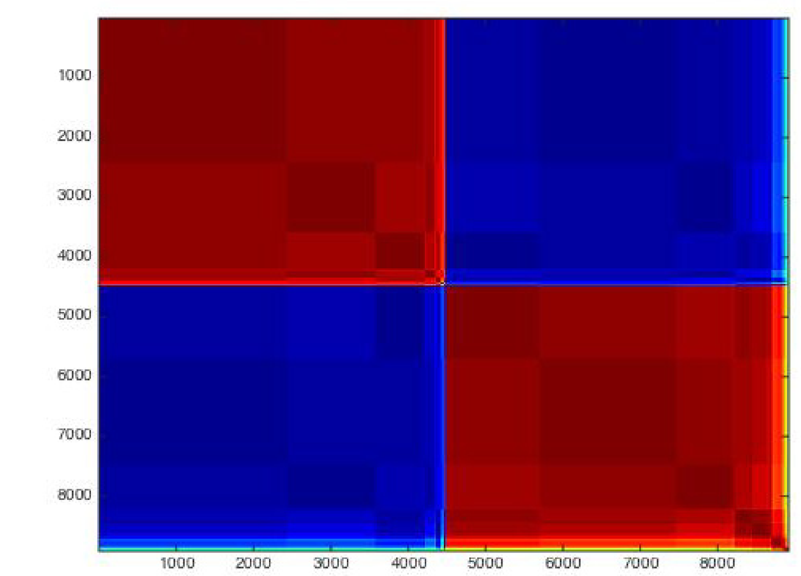
Conclusions

- The 2, 4, 8 and 13 cluster solutions group the BrainMap data most efficiently. There are clear cut meta activation patterns that come out of these solutions, such as salience processing and spatial reasoning. The 2 cluster solution is the most stable solution while the 8 cluster solution is also quite stable but is more descriptive as it has a greater possibility for specificity.
- With this database of meta activation patterns we can work towards a holistic cognitive ontology that allows for better communication throughout the field.
- Future work will involve using different clustering algorithms to compare and contrast with these results. Using multiple different algorithms will allow us to find the best solutions.

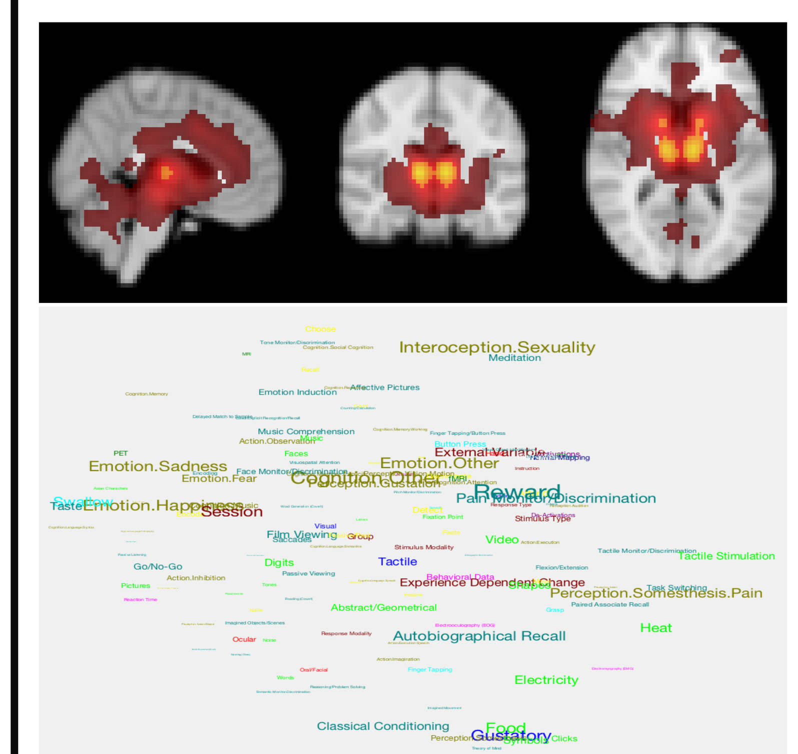
2 Cluster Solution

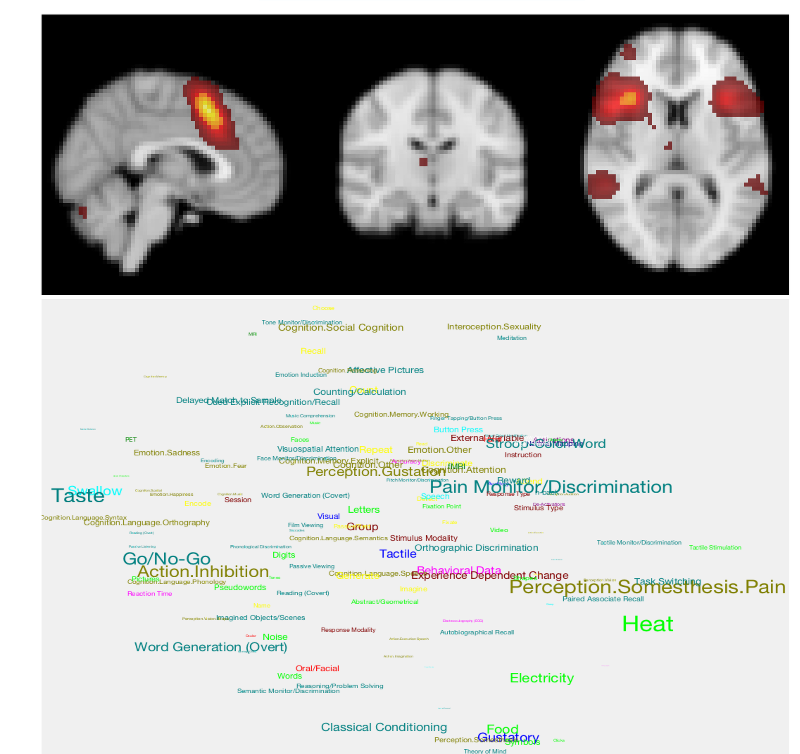

Visual and Semantic Processing

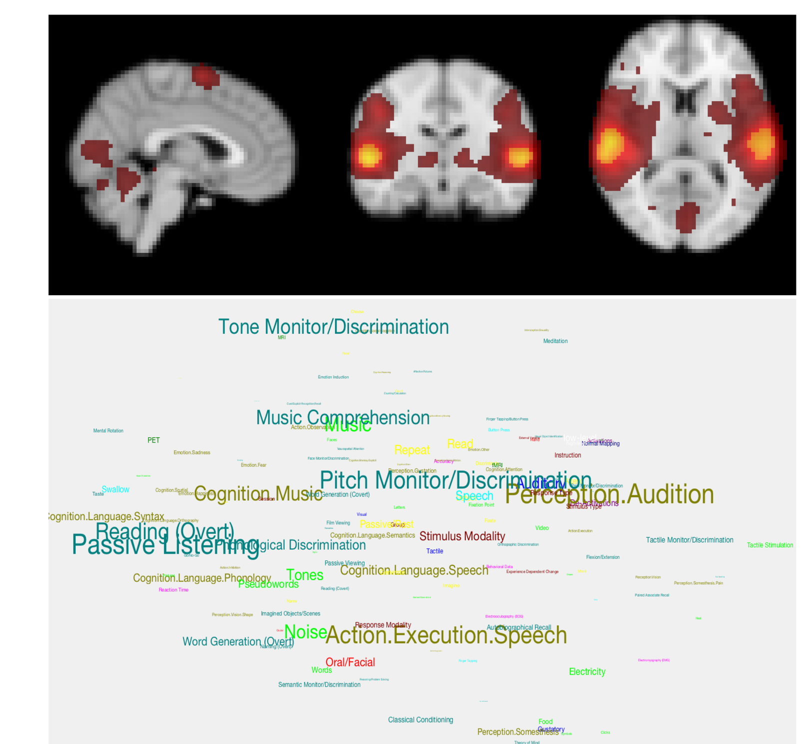

Movement and Auditory Processing

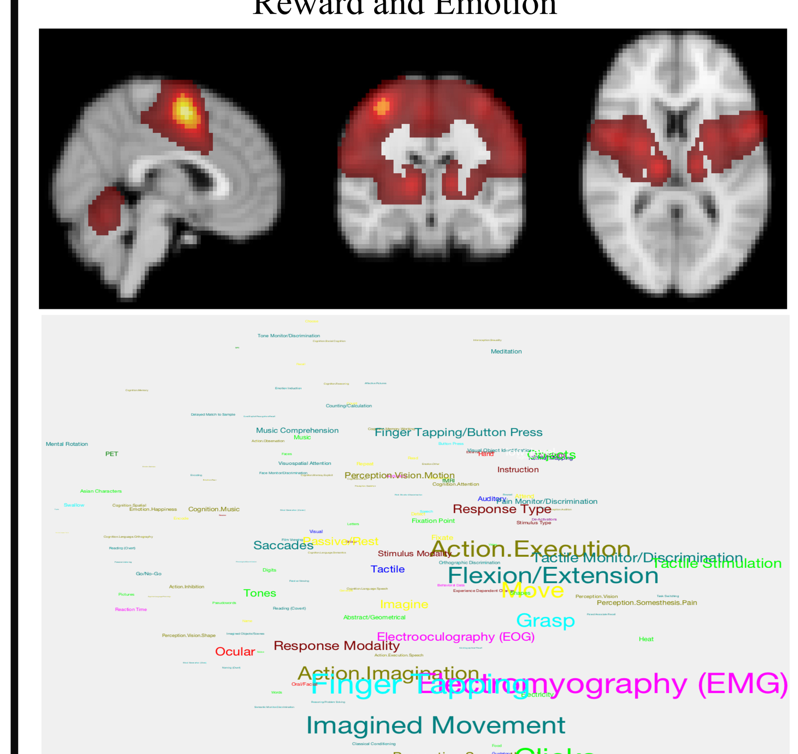


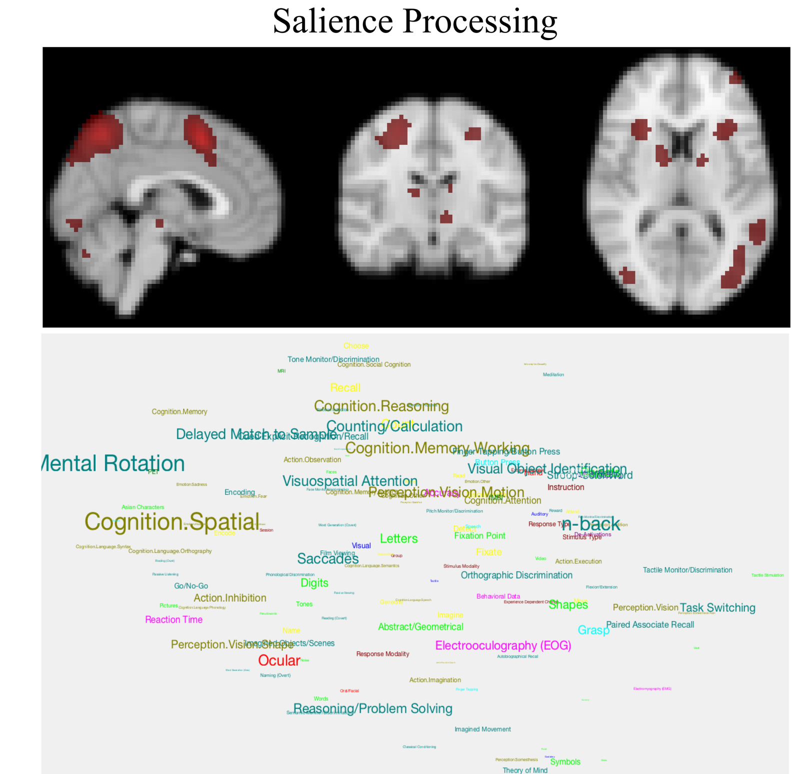
8 Cluster Solution

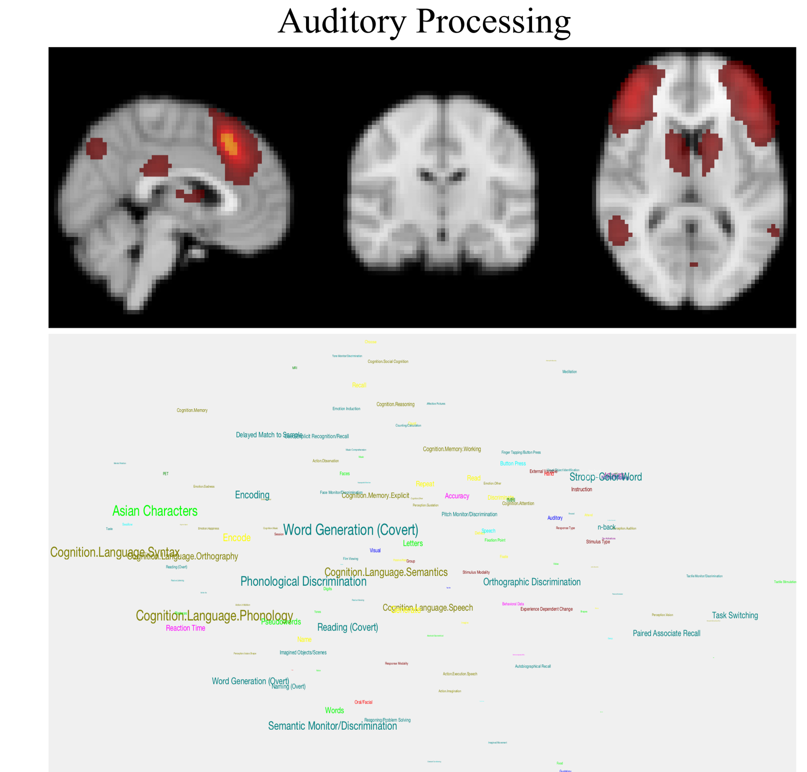

Reward and Emotion

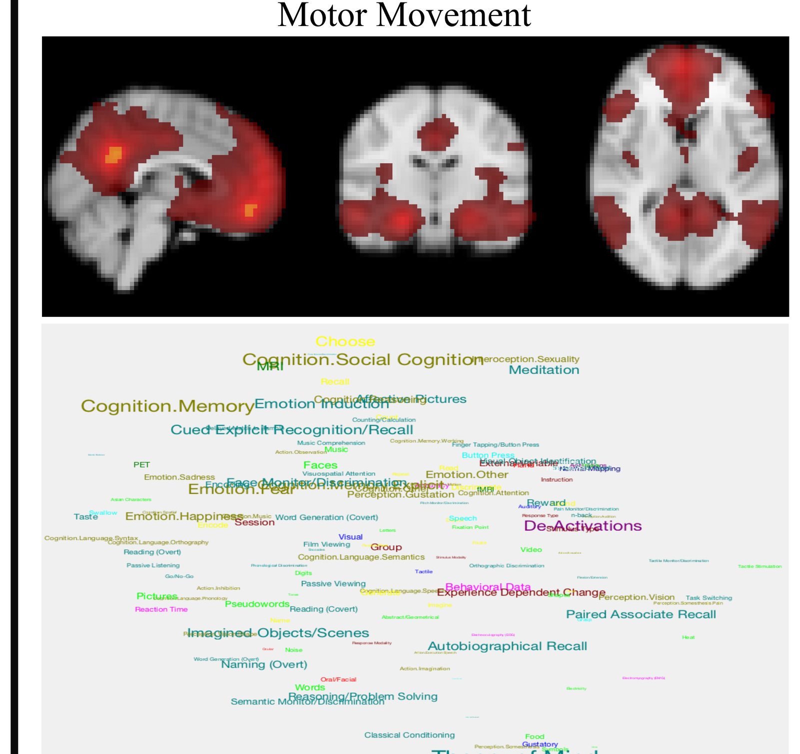

Salience Processing

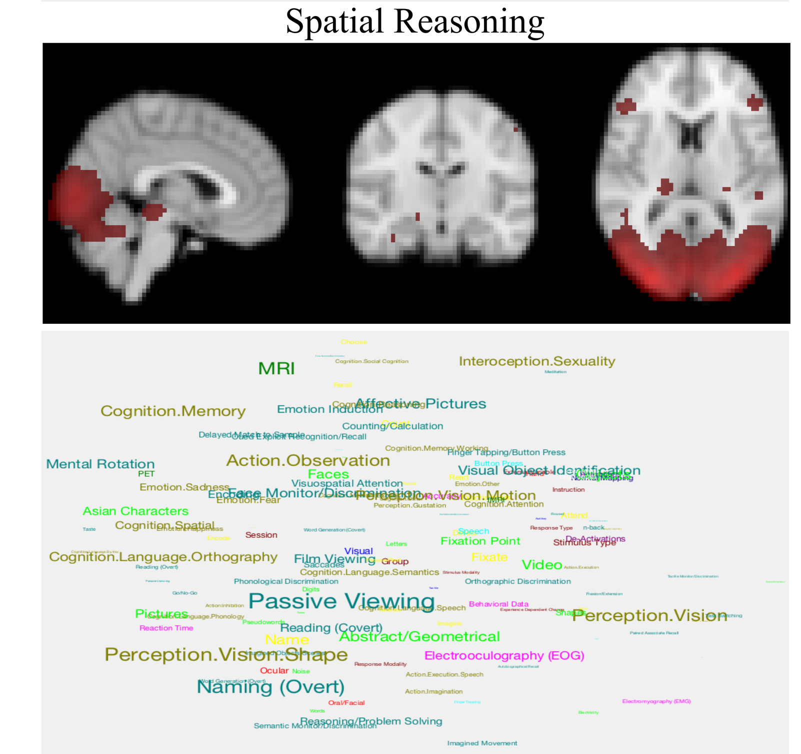

Auditory Processing

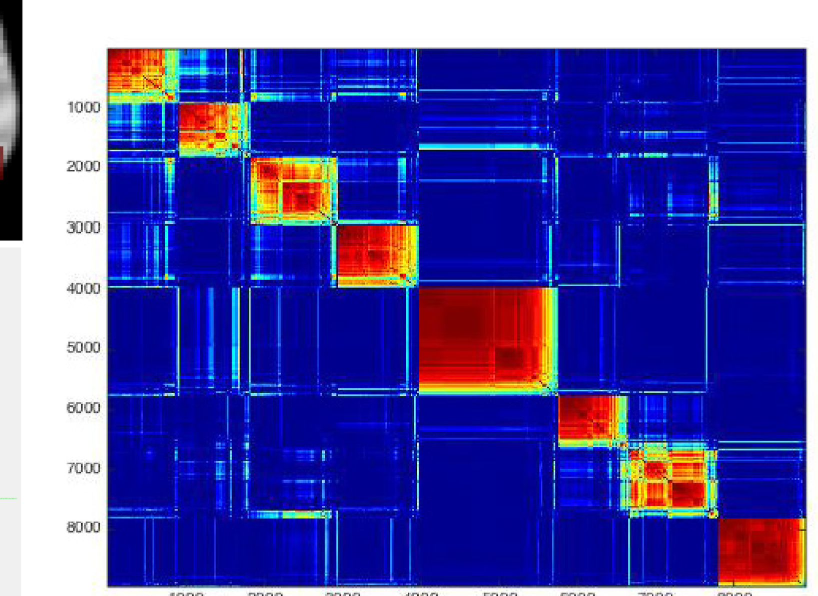

Motor Movement


Spatial Reasoning


Semantic Processing


Default


Visual Processing



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