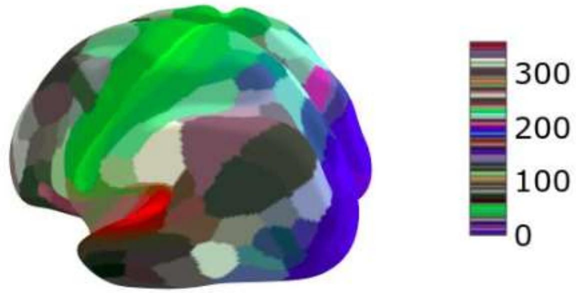
Hand movement vs resting state networks

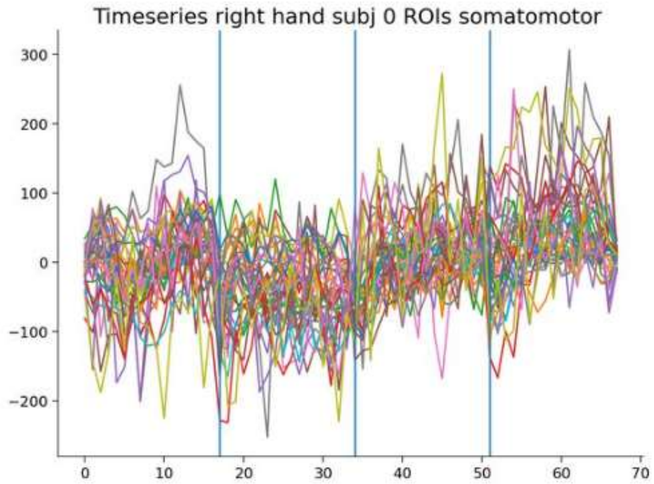
Is the connectivity of the brain regions during motor task additive to resting-state activity or are there more complex interactions between regions at stake?

HCP dataset

Are networks involved in resting state and hand movements additive?

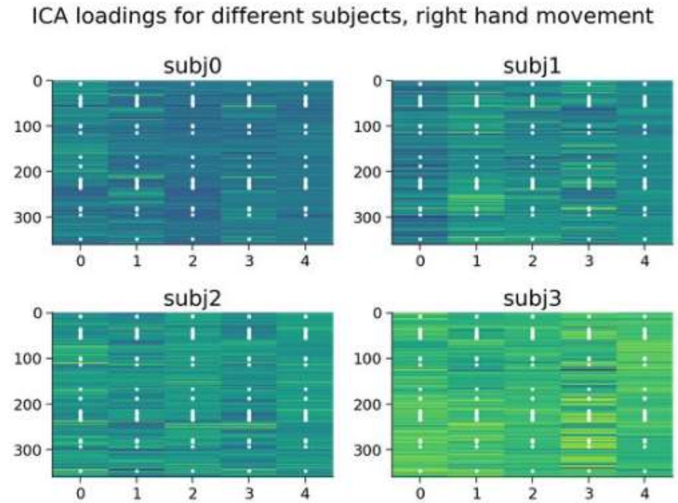
- Dataset: HCP fMRI data
  - 360 brain parcels
  - 339 subjects
  - several tasks: rest period and right hand movements
- How: PCA, (group) ICA
- Why: Identifying and comparing networks
- Who: Claire², Salma, Eva





Individual ICA vs Group ICA

- Individual ICA:
  - Intersubject variability
  - ICs not ordered : Comparing components across subjects?



- Group ICA:
  - Finding generalizable networks

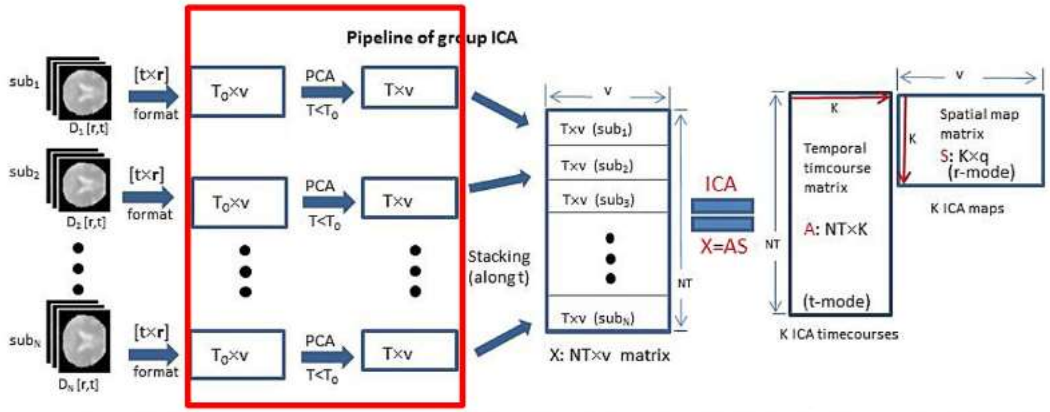


Fig. 3. Diagram for group ICA. Each subject dataset was arranged into a 2D time × space matrix. The 2D matrices were reduced in time dimension by PCA. All the subject matrices were stacked along the time dimension to make an augmented 2D matrix for ICA decomposition.

Chen, Z., Caprihan, A., Damaraju, E., Rachakonda, S., & Calhoun, V. (2018). Functional brain connectivity in resting-state fMRI using phase and magnitude data. Journal of Neuroscience Methods, 293, 299–309. https://doi.org/10.1016/j.jneumeth.2017.10.016

Dimensionality reduction with temporal PCA, time drift, denoising

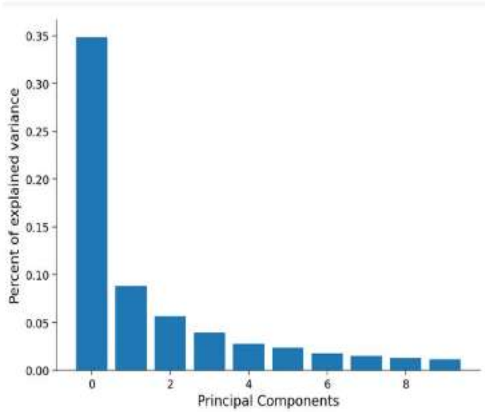
- PCA for reducing time series

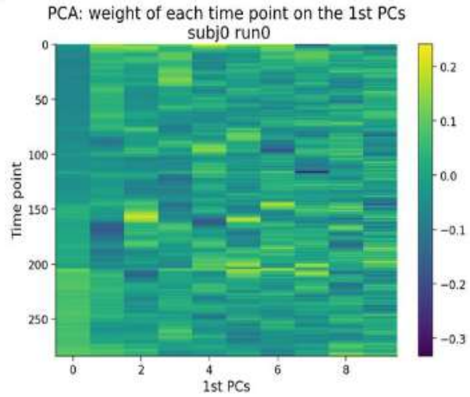
→ Drift in 1st PC

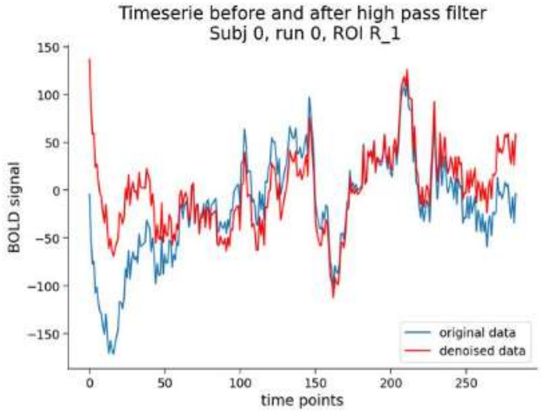
→ Preprocessing : high pass filter to remove low oscillations

- Group ICA on temporal PCs

→ High reconstruction error
Dimensionality reduction not needed

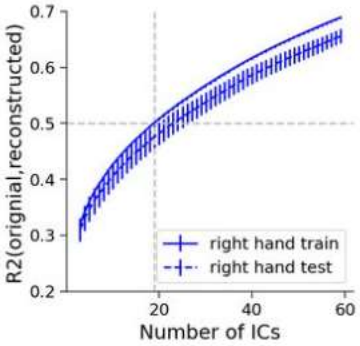


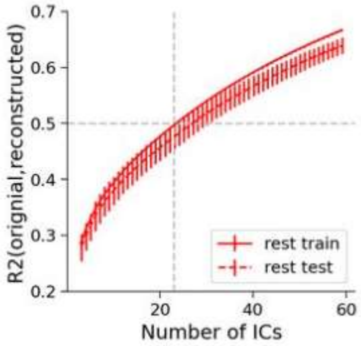




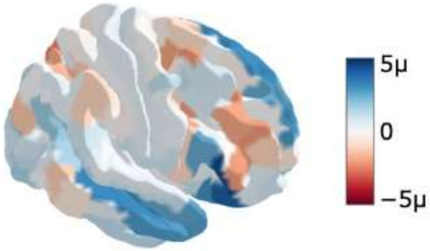
Dimensionality and number of ICs

- R2 original vs reconstructed: Cross validation



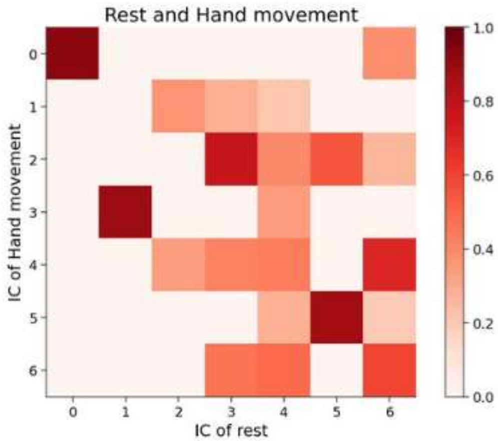


- Choose interpretable number of networks
  - 18 ICs, example component
  - 10 ICs, example component



Comparing networks

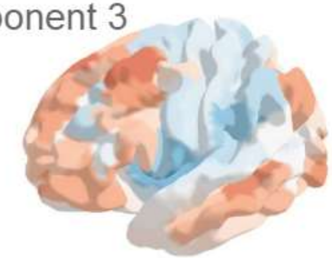
Correlations between ICs



Loadings representation

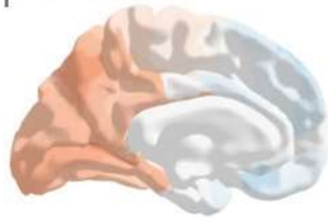
Rest component 0

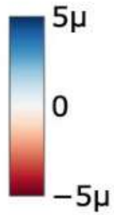
Rest component 3



Hand component 0

Hand component 4





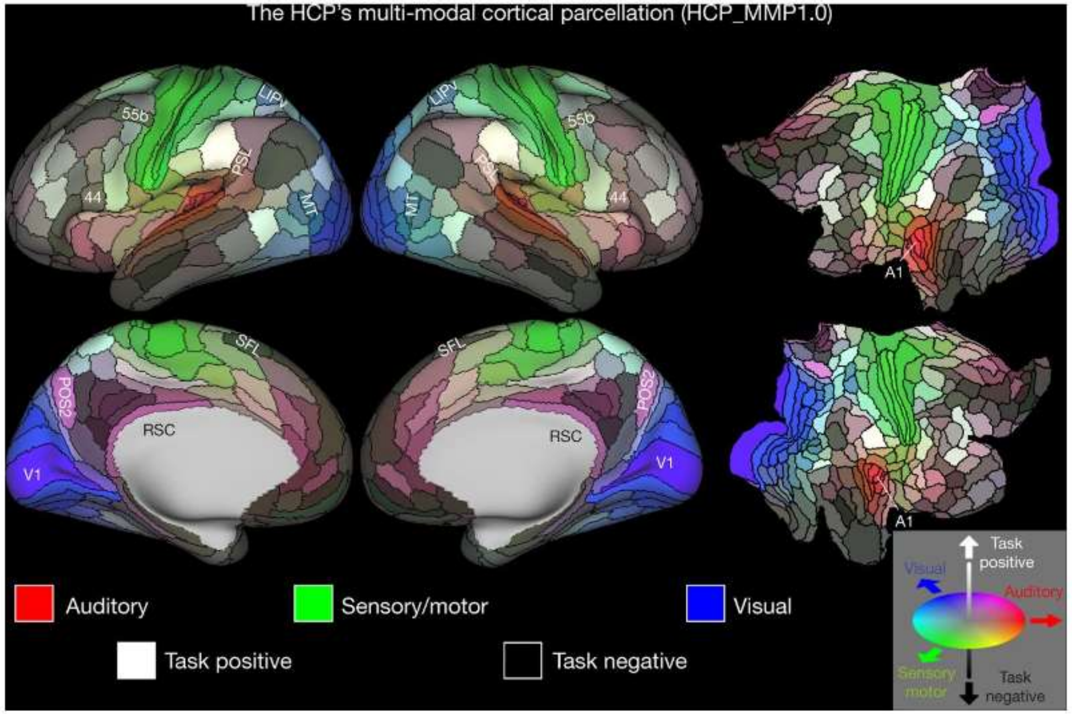
Functional Connectivity Gradient of human fMRI data

Project Summary: The Cooler Team
NeuroMatch Academy 2020

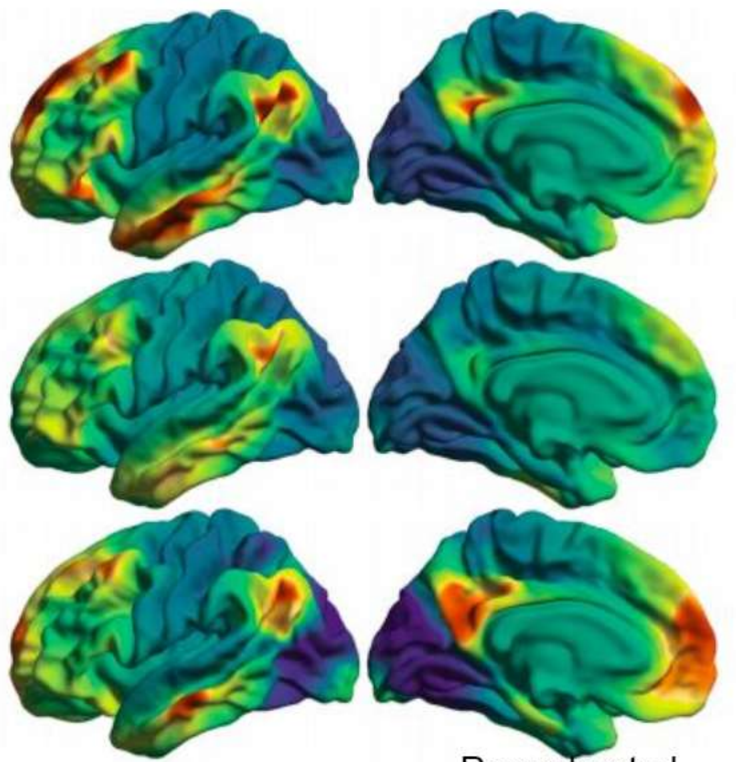
Aysha Motala, Jack Dolgin, Julio Alejandro Yanes, Linjing Jiang & Reza Koiler

Gradient analysis:

from discrete to continuous measure of neural organization

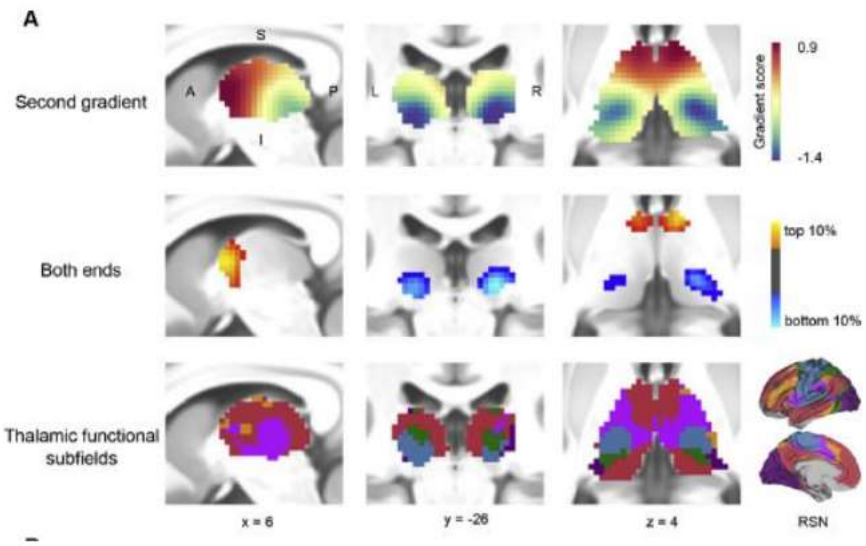


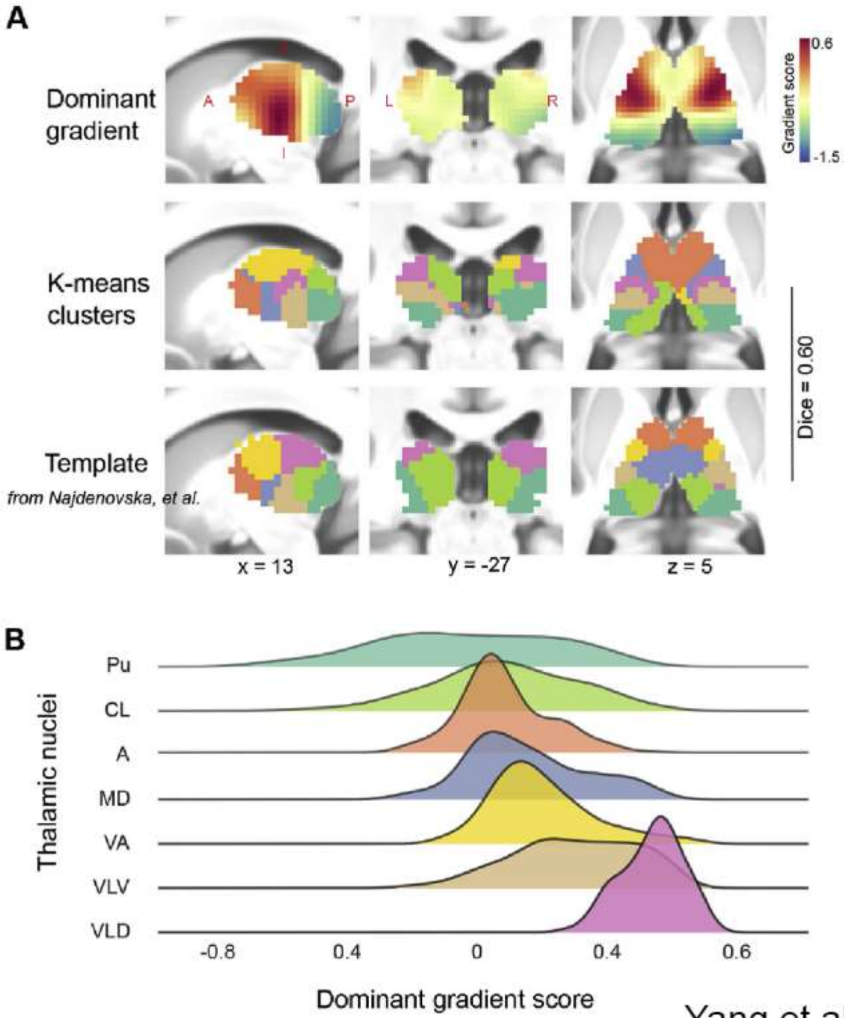
Glasser et al. 2016



Paquola et al. 2019

Connectivity gradient and topographical organization in thalamus





Yang et al. 2020

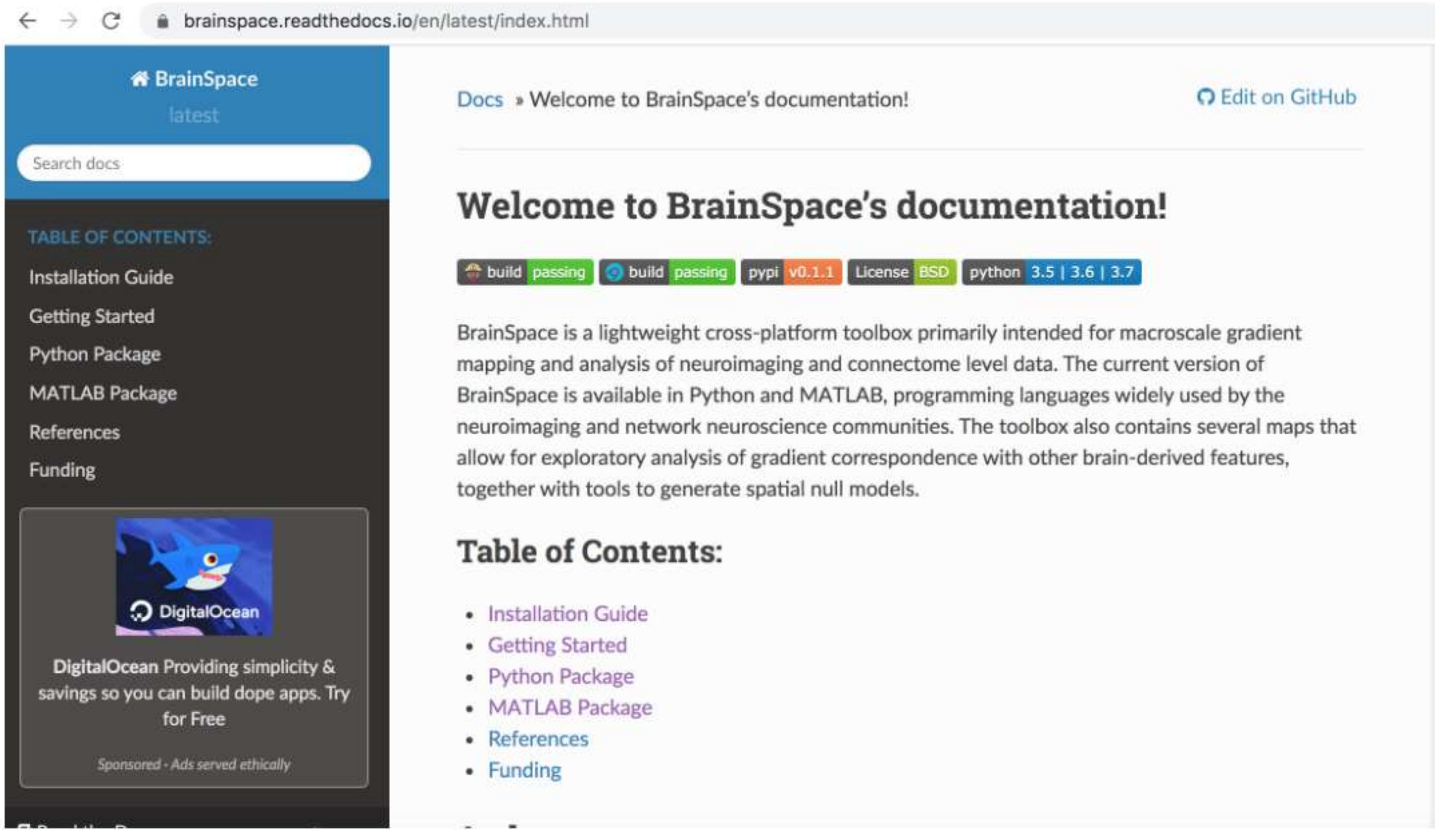
Project Plan

- Initial plan: Estimate continuous spatial representations (gradients) of the thalamus based on thalamocortical functional connectivity

- However…
- Current plan:
    - Examine and compare functional connectivity gradients of primary sensory cortices (primary visual, auditory and somatosensory cortex)

    - Compare gradient estimates across individual resting-state fMRI from Human Connectome Project (HCP) and Neurosynth meta-analytic data

Methods


brainspace.readthedocs.io/en/latest/index.html
BrainSpace
latest
Search docs
TABLE OF CONTENTS:
Installation Guide
Getting Started
Python Package
MATLAB Package
References
Funding
DigitalOcean
DigitalOcean Providing simplicity & savings so you can build dope apps. Try for Free
Sponsored · Ads served ethically
Docs » Welcome to BrainSpace's documentation!
Edit on GitHub
Welcome to BrainSpace's documentation!
build passing
build passing
pypi v0.1.1
License BSD
python 3.5 | 3.6 | 3.7
BrainSpace is a lightweight cross-platform toolbox primarily intended for macroscale gradient mapping and analysis of neuroimaging and connectome level data. The current version of BrainSpace is available in Python and MATLAB, programming languages widely used by the neuroimaging and network neuroscience communities. The toolbox also contains several maps that allow for exploratory analysis of gradient correspondence with other brain-derived features, together with tools to generate spatial null models.
Table of Contents:
Installation Guide
Getting Started
Python Package
MATLAB Package
References
Funding

Methods

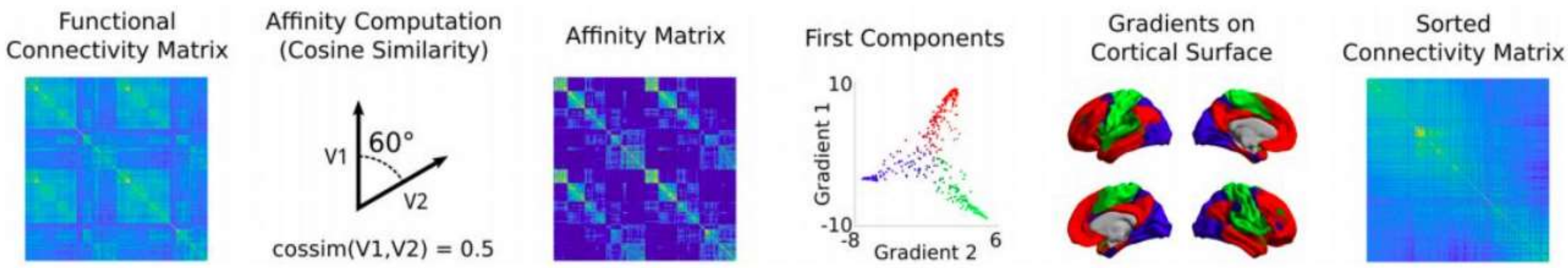
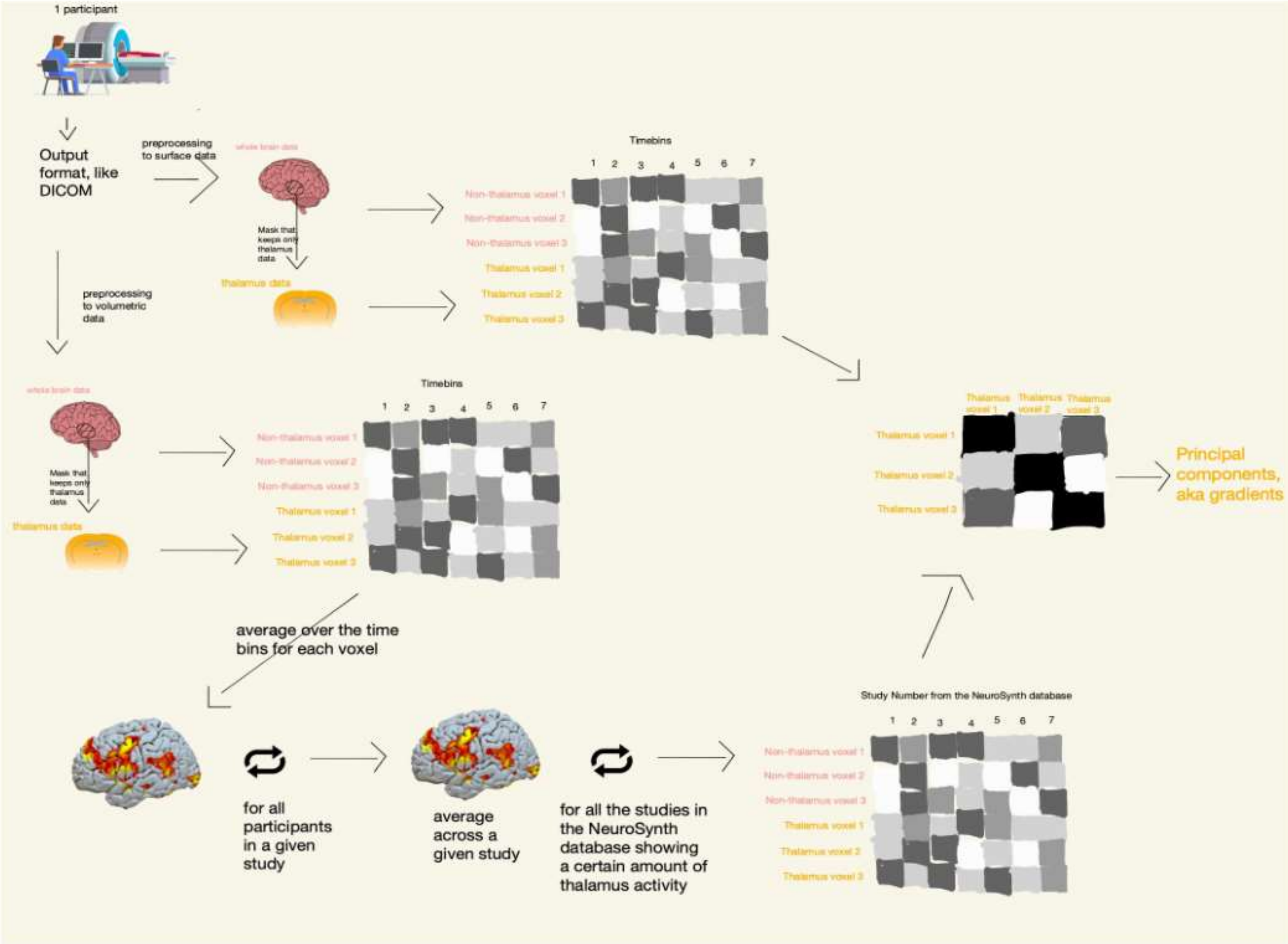


Fig. 1 A typical gradient identification workflow. Starting from an input matrix (here, functional connectivity), we use a kernel function to build the affinity matrix (here capturing the connectivity of each seed region). This matrix is decomposed, often via linear rotations or non-linear manifold learning techniques into a set of principal eigenvectors describing axes of largest variance. The scores of each seed onto the first two axes are shown in the scatter plot, with colors denoting position in this 2D space. These colors may be projected back to the cortical surface and the scores can be used to sort the input connectome.

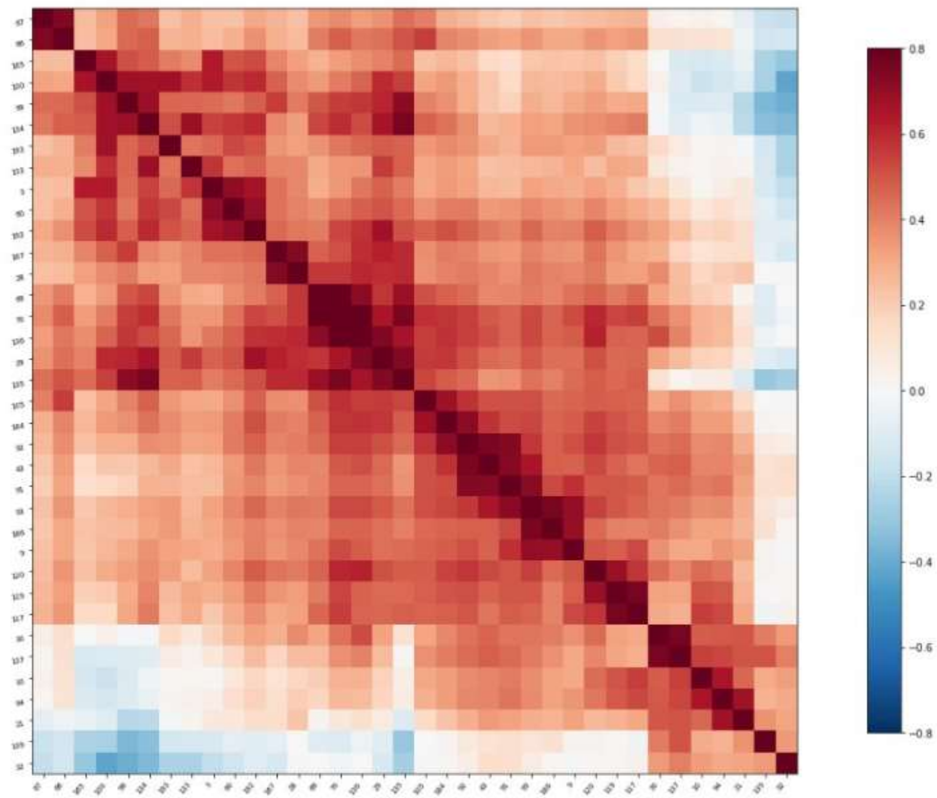
Vos de Wael et al. 2020

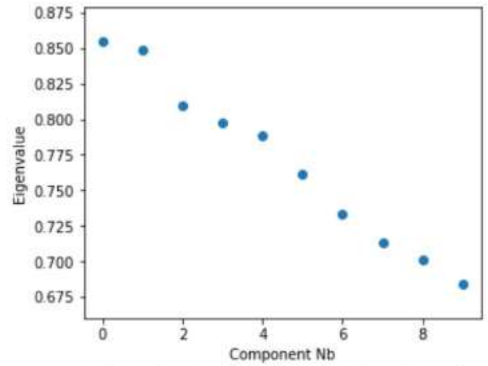

1 participant
Output format, like DICOM
preprocessing to surface data
whole brain data
Mask that keeps only thalamus data
thalamus data
Timebins
1 2 3 4 5 6 7
Non-thalamus voxel 1
Non-thalamus voxel 2
Non-thalamus voxel 3
Thalamus voxel 1
Thalamus voxel 2
Thalamus voxel 3
preprocessing to volumetric data
whole brain data
Mask that keeps only thalamus data
thalamus data
Timebins
1 2 3 4 5 6 7
Non-thalamus voxel 1
Non-thalamus voxel 2
Non-thalamus voxel 3
Thalamus voxel 1
Thalamus voxel 2
Thalamus voxel 3
Thalamus voxel 1
Thalamus voxel 2
Thalamus voxel 3
Thalamus voxel 1
Thalamus voxel 2
Thalamus voxel 3
Principal components, aka gradients
average over the time bins for each voxel
for all participants in a given study
average across a given study
for all the studies in the NeuroSynth database showing a certain amount of thalamus activity
Study Number from the NeuroSynth database
1 2 3 4 5 6 7
Non-thalamus voxel 1
Non-thalamus voxel 2
Non-thalamus voxel 3
Thalamus voxel 1
Thalamus voxel 2
Thalamus voxel 3

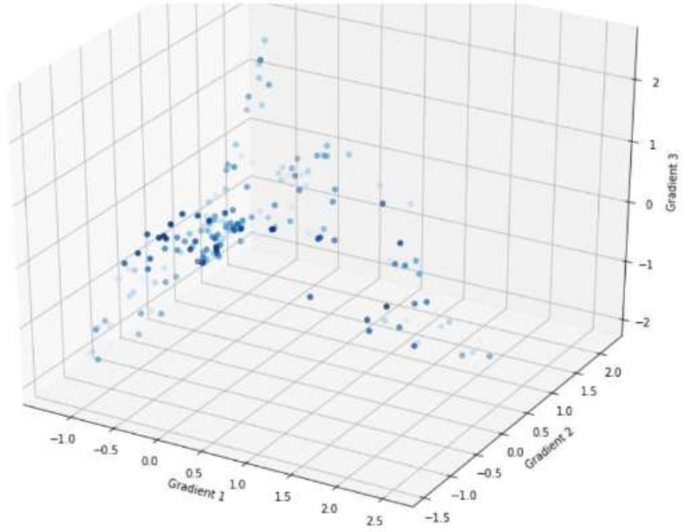
Methods

- Human Connectome Project (HCP) data
  - One resting-state fMRI session (phase encoding from left to right) from one subject (100206) of the HCP young adult, 1200 Subjects Database.
  - Volumetric (MNI) data minimally preprocessed by HCP (Glasser et al. 2014), and converted to surface space in Nilearn.
- Neurosynth (meta-analytic) data
  - Studies reporting (minimum) one coordinate of activation within bilateral postcentral gyrus (S1). In total, 4,918 studies (sample) out of 14,371 studies (total) were included in meta-analytic dataset.
  - Studies were (i) converted from coordinates to statistical maps, (ii) concatenated into 1 4D image, and (iii) converted from volumetric (MNI) space to surface space.
- Within region voxel-to-voxel correlations were then passed on to gradient analysis (diffusion embedding, 10 components).

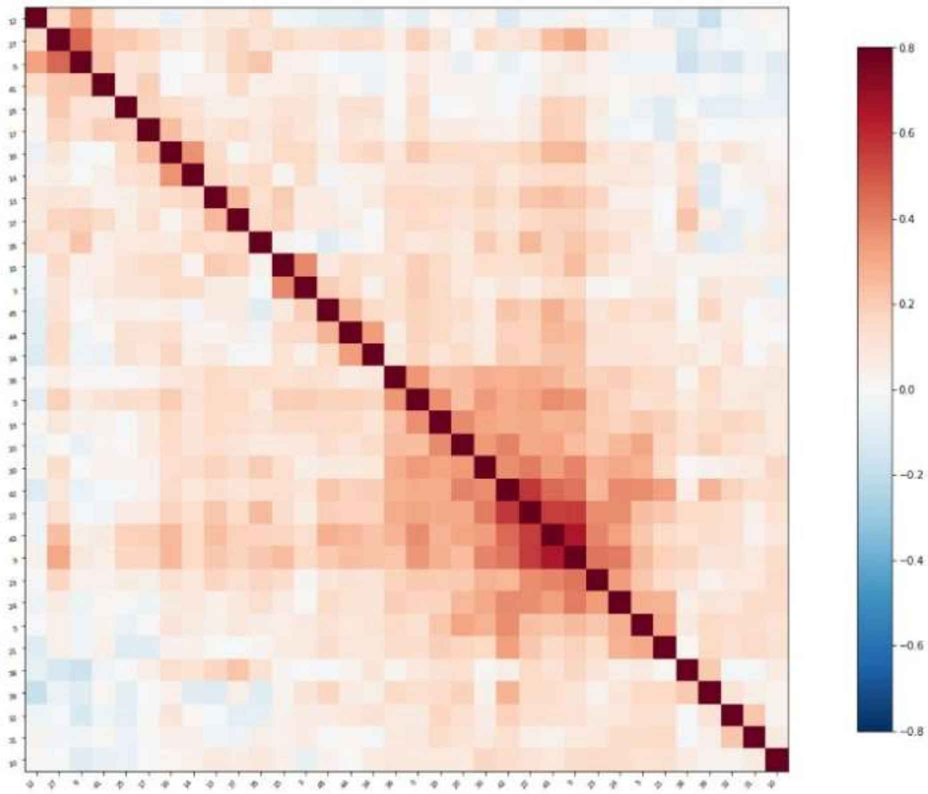
Results: HCP (Left primary visual cortex)

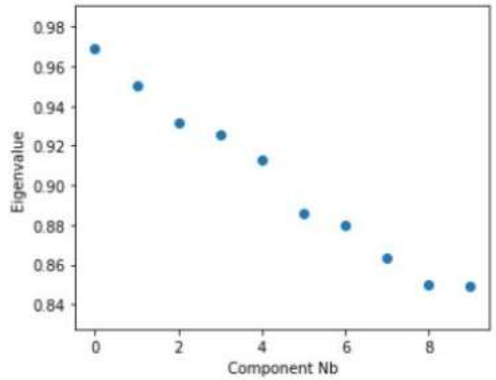


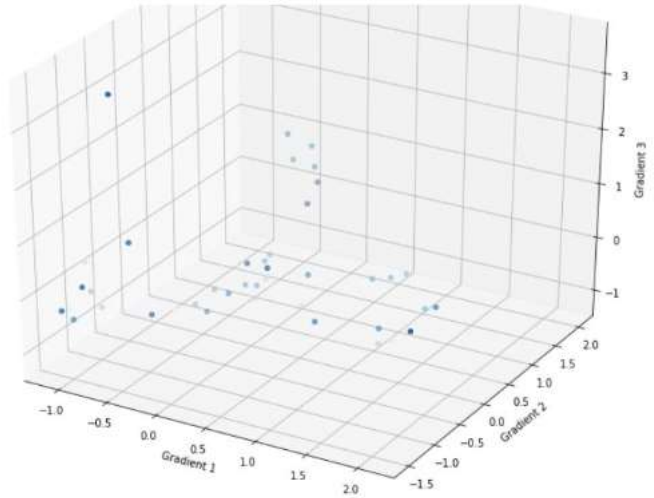




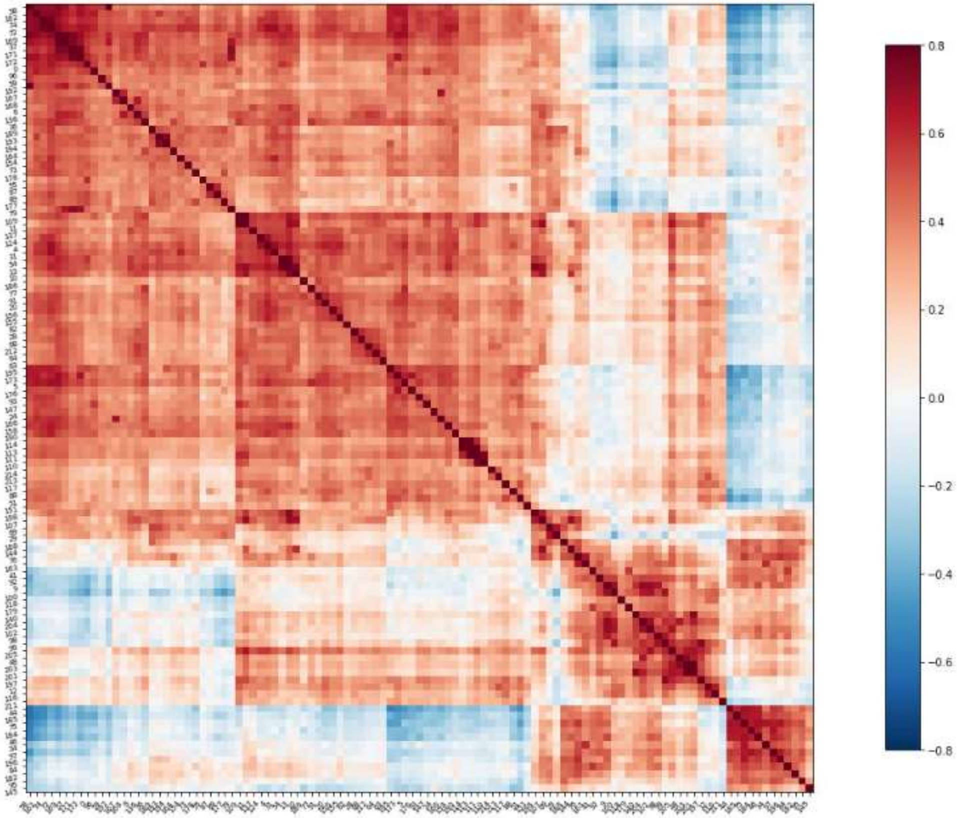
Results: HCP (Left primary auditory cortex)

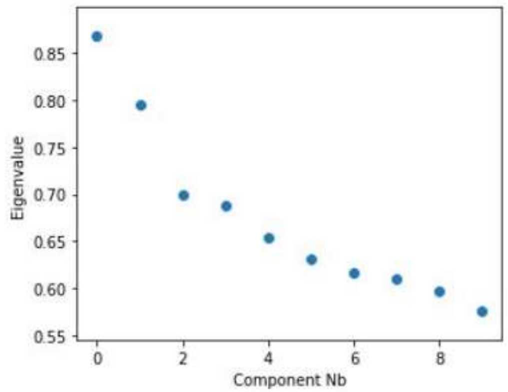


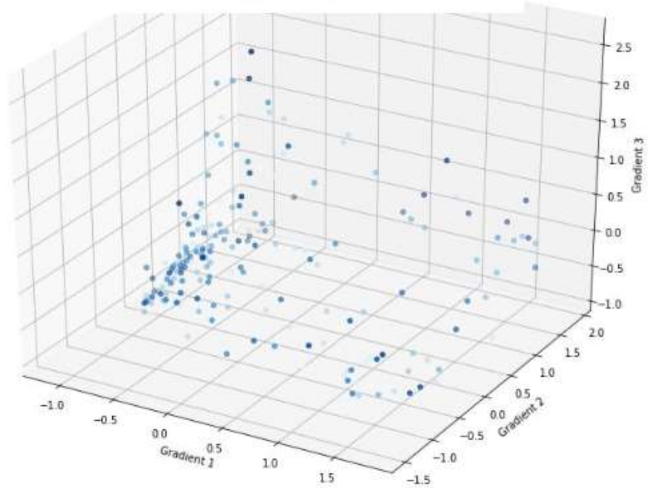




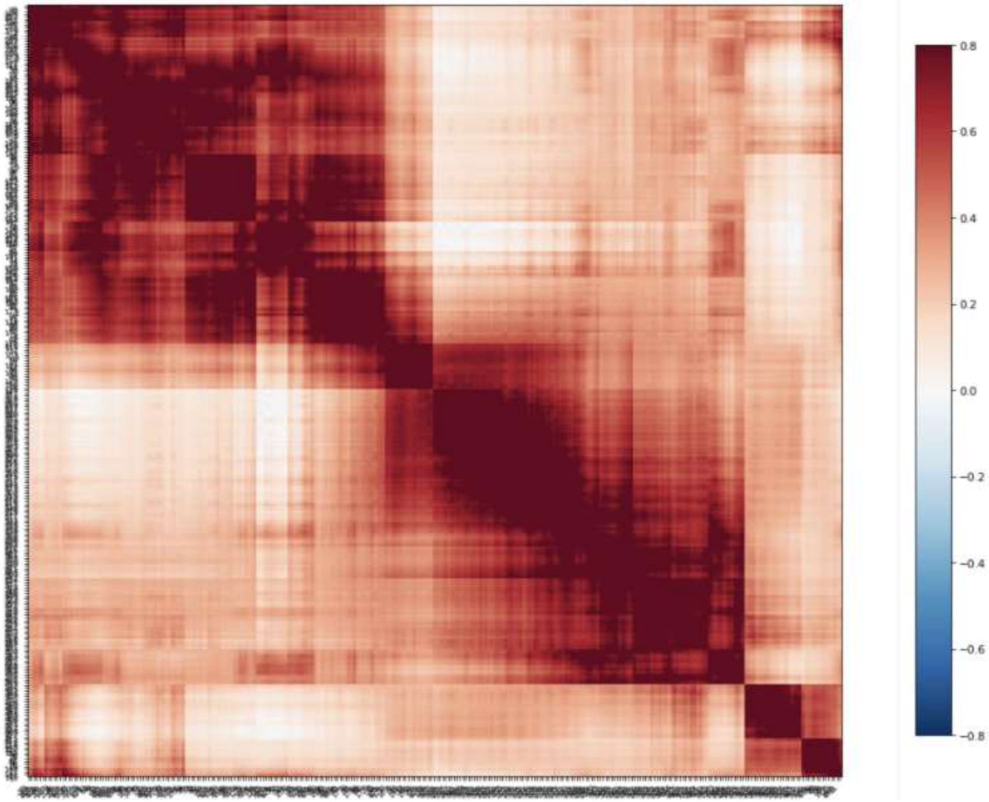
Results: HCP (Left primary somatosensory cortex)

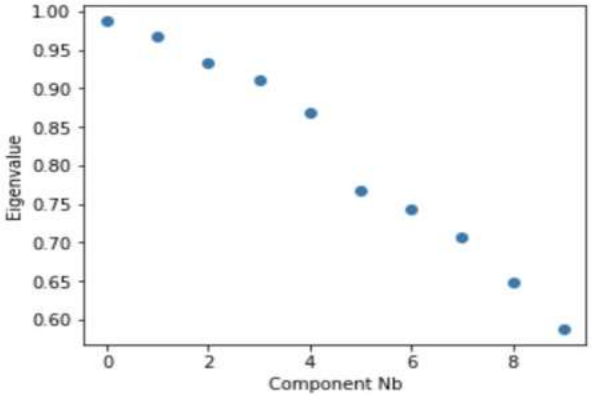


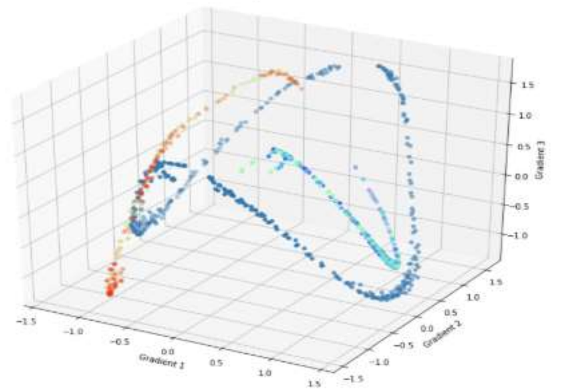




Results: Meta-analytic data (Left primary somatosensory cortex)







Summary

- Compare primary sensory cortices in HCP data
  - Primary visual cortex has 2 main gradients that capture over 80% variance of the data projected onto the gradients. Demonstrate lower correlations between vertices compared to auditory and somatosensory cortex
  - Primary auditory cortex has 5 main gradients that capture over 90% variance of the data projected onto the gradients. Fewer data points included in the analysis
  - Primary somatosensory cortex has 2 main gradients that capture over 80% variance of the data

- Compare individual fMRI session and meta-analytic data in primary somatosensory cortex
  - Meta-analytic data show more main gradients (5) that capture over 85% of the variance, as well as stronger correlations between vertices

Implications and future directions

- Individual differences in gradients

- Gradients in multi-modal imaging: structural (e.g., DTI) vs. functional

- Differences in gradients calculated from seed-to-brain connectivity and seed-to-seed self connectivity

- Interpretation of the gradients:
  - Relate gradients to anatomy and behaviors
  - Interpretation of meta-analytic gradients?

Roadblocks

- Importing data!!
- Surface vs Volume space technical issues
- Google Colabs and large data ?
- Plotting

Thanks for listening!

and a very special thanks to Brielle Stark and Shawn Rhoads for their mentorship and guidance! :)

Classifying Working Memory Performance

Neuromatch Academy 2020

Pod #006: Cunning Bears

Group: Classy Bears

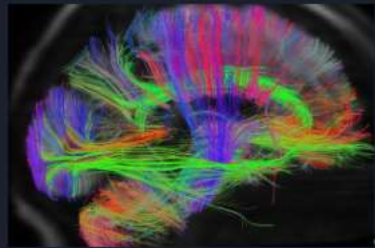
Alex Lascelles | Samyukta Jayakumar | Jiangang Shan | Yaxin Liu | Haroon Popal (TA) | Dr. Bradly Alicea (Faculty Mentor)

Research Questions and Approach

Our Questions:

1. Which brain areas are most important for a 2-back working memory task? (answered)
2. Can a participant's performance be predicted from these brain activations? (not yet answered)

Dataset:



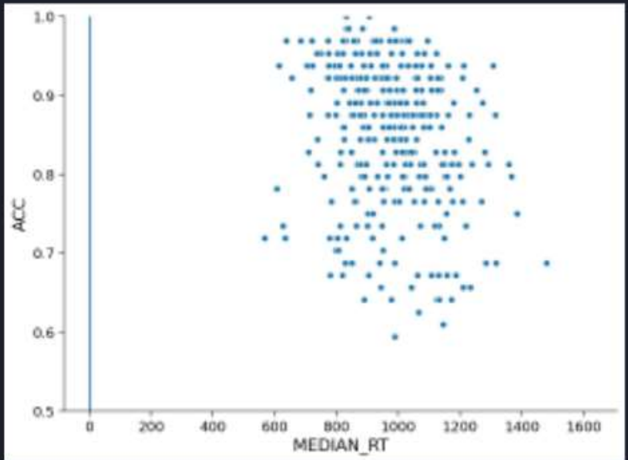
Human Connectome Project — fMRI data from 336 subjects doing the Working Memory task

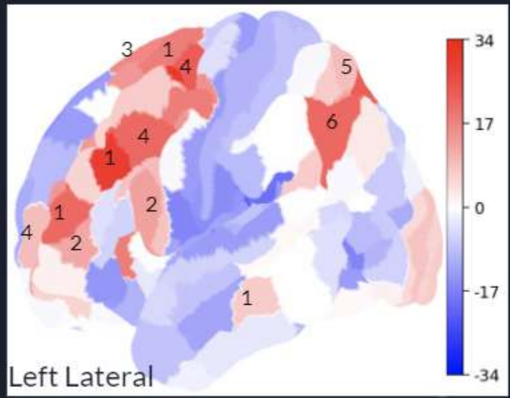
Approach:

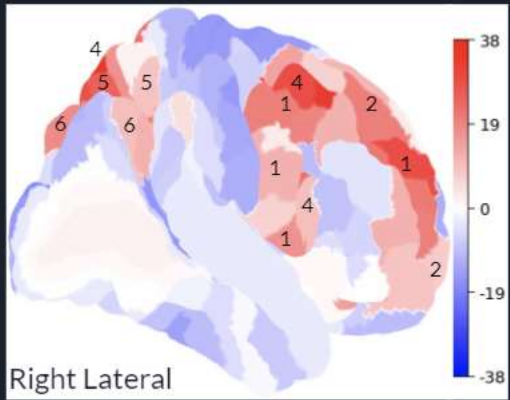
1. **Behavioural data** — plot accuracy and reaction times for 4 different 2-back WM tasks (faces, bodies, tools, places)
2. **PCA** — sanity check to explore differences between brain activity between 0-back and 2-back tasks
3. **GLM** —combining HRF, design matrix, and BOLD data to find average ROI activity across whole brain (360 parcels)
4. **Functional connectivity** — determine if there is a statistical relationship between measures of activity in our ROIs
5. **Visualization** — use NiBabel Freesurfer to plot results on the surface of a model brain for improved interpretability

Results: Behavioural Analysis and T-Contrast Visualization

Accuracy vs **median reaction time** for the working memory task shows the distribution of performance.







T-Contrast 0- vs 2-back

180 parcels per hemisphere (Glasser 2016)

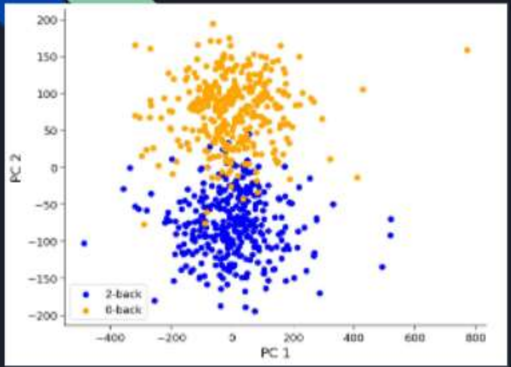
Color scale represents activity during 2-back vs 0-back WM tasks. Red = higher activation in the 2-back task compared to the 0-back task, indicating regions important for working memory. Blue represents activity during a task that is not related to working memory

Important regions/networks:

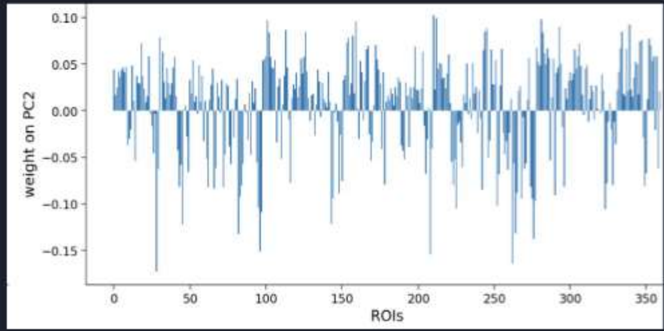
Right:
1=Cingulo-Opercular, 2=Default,
3=Dorsal-attentional, 4=Frontoparietal,
5=Language, 6=V2

Left:
1=Cingulo-Opercular, 2=Default,
3=Dorsal-attentional, 4=Frontoparietal,
5=Language, 6=Posterior-Mu

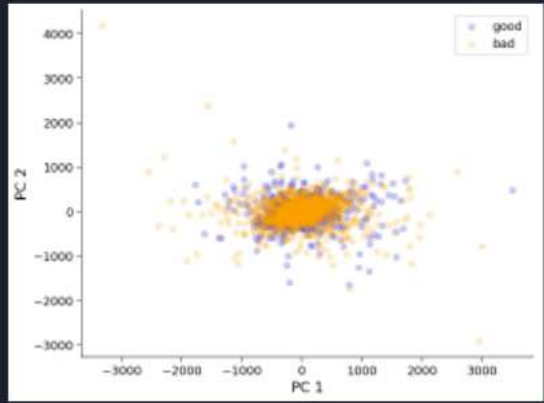
Results: Principal Component Analysis (PCA)



Classifying 2-back and 0-back tasks using PCA



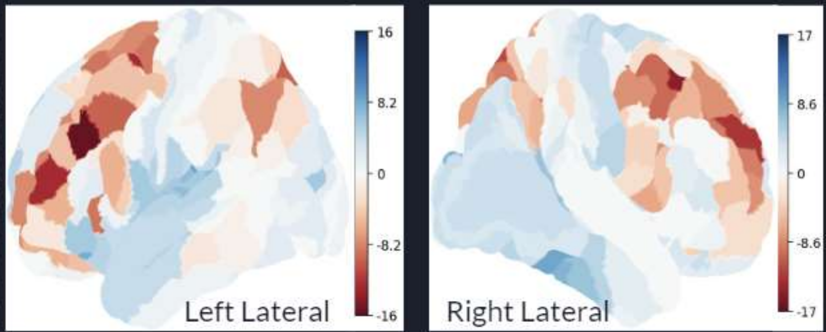
Weight of ROIs on PC2



Classifying good performance blocks (high accuracy) and bad performance blocks (low accuracy) using PCA

Regions that are more important according to PCA

PC2 to separate 0- vs 2-back

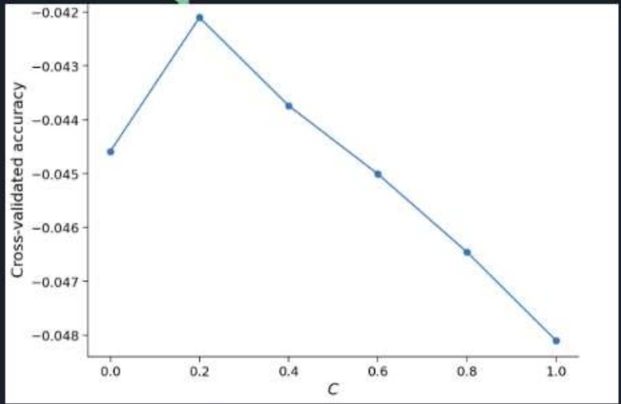


Principal component 2 (PC2) distinctly differentiates 0- and 2-back tasks, a sanity check that there is a working memory component present

PCA cannot capture the variance in neural response that determined whether the subject's performance on this block is good or bad.

Results: GLM Analyses

Best Alpha:
0.2 (-4.21% Accuracy)

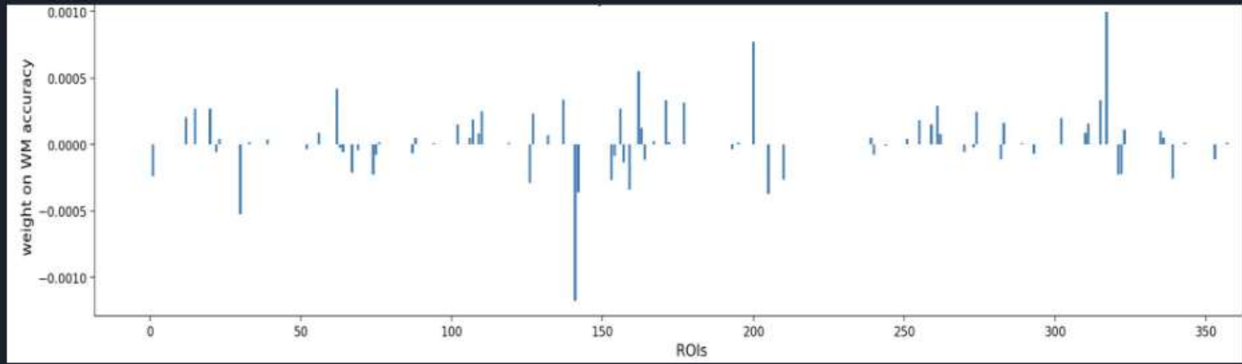


We performed GLM with L1 regularisation and used cross validation to pick the best alpha for L1.

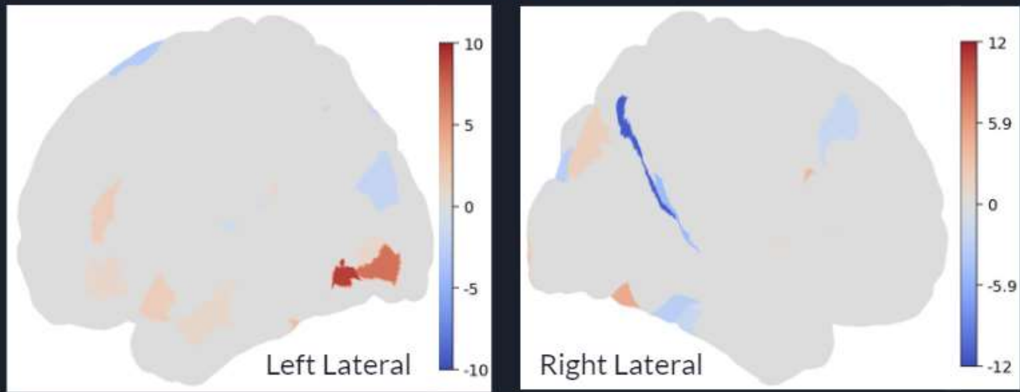
$$(1 / (2 * n\_samples)) * ||y - Xw||_2^2 + alpha * ||w||_1$$

Using the best alpha in our GLM equation, we found the weights, *w*. The weights with the biggest magnitude revealed the most important ROIs for good task performance, which we plotted on a 3D brain

Importance of ROIs



Plotting ROIs According to Weight (Importance)



Experience and Future Work

What went well

- PCA analyses
- Performing GLM
- Brain mapping
- Plotting
- Time management
- Peer programming

If we had more time

- Interpret functional connectivity analyses
- Interpret GLM Analysis
- MVPA Analysis
- Answering more of our questions

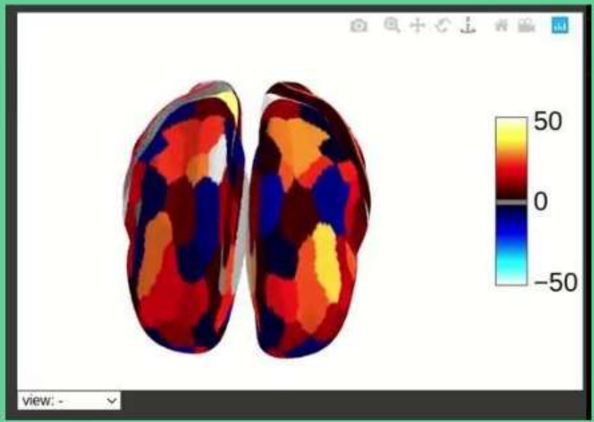
Future Ideas:

1. How can fMRI data be used to predict performance?
2. How does the subtask (faces, bodies, tools, places) alter fMRI activity and ROIs involved?
3. Can resting state be used to classify task performance?

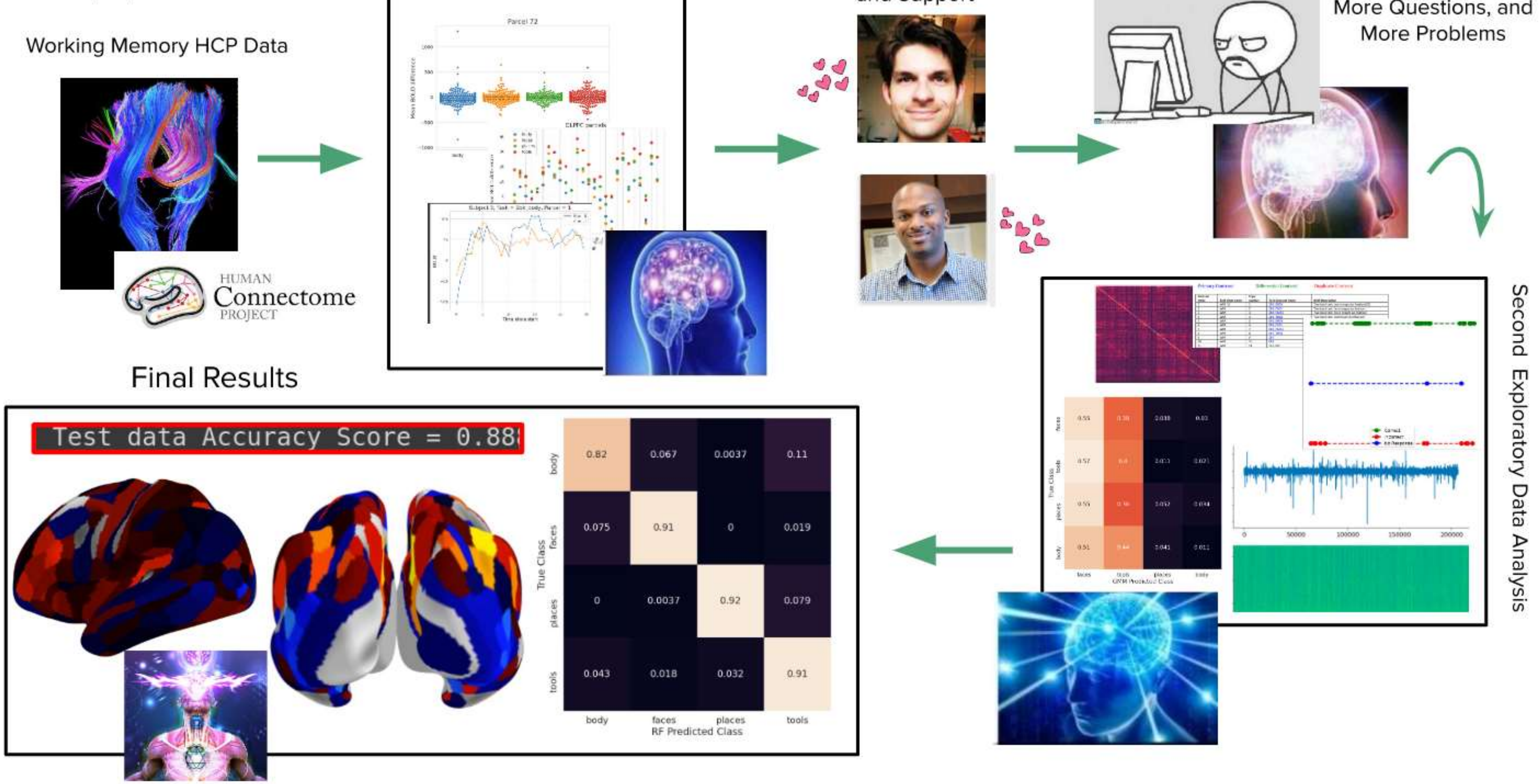
HCP Dataset on Working Memory

Ashley Feng, Mike Hellstern, Justin Le, Lleymi Martinez, Minnie Menezes, and Ana Souza

Initial Question: How does parcel activation in working memory differ when presented with different visual stimuli?



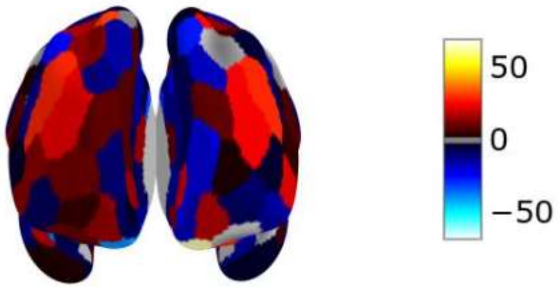
Approach


Approach
Working Memory HCP Data
HUMAN
Connectome
PROJECT
First Exploratory Data Analysis
Parcel 72
Much Appreciated Help
and Support
More Brainstorming,
More Questions, and
More Problems
Second Exploratory Data Analysis
Final Results
Test data Accuracy Score = 0.88
body
faces
places
tools
True Class
RF Predicted Class
0.82
0.067
0.0037
0.11
0.075
0.91
0
0.019
0
0.0037
0.92
0.079
0.043
0.018
0.032
0.91

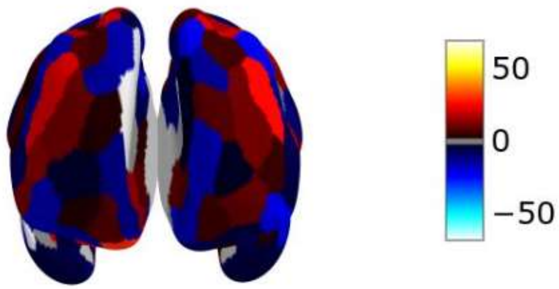
Data analysis:

- Is there evidence parcel activation differ across different image kinds?
    - Yes! The brains look different

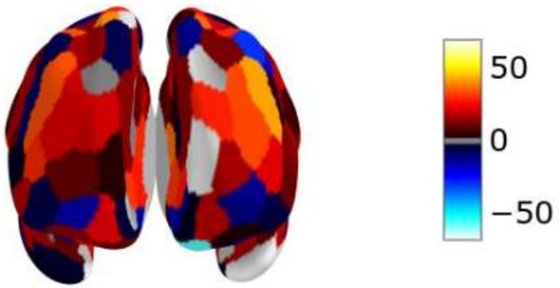
Faces



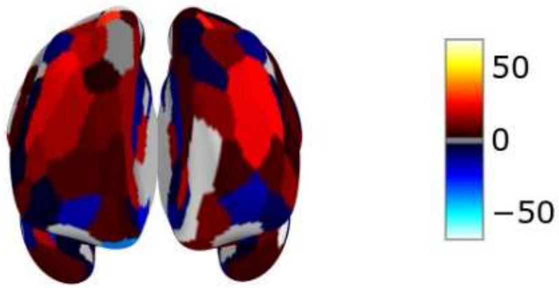
Body



Tools



Places



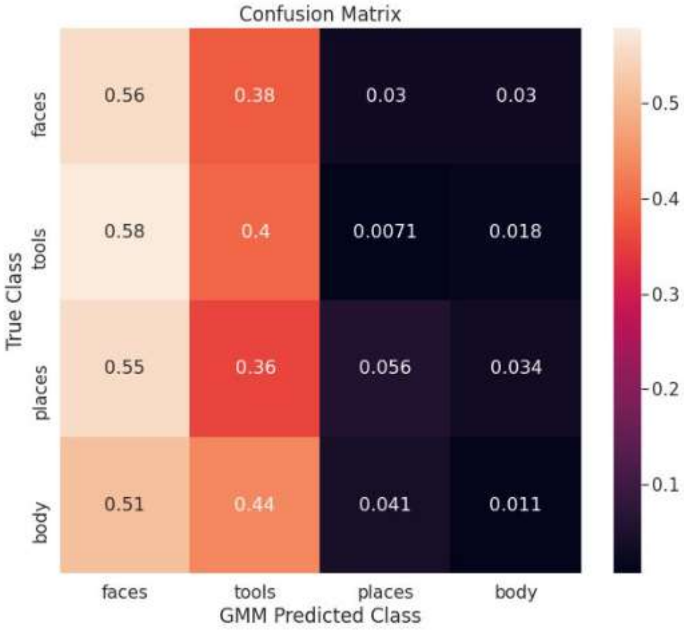
Revised question:

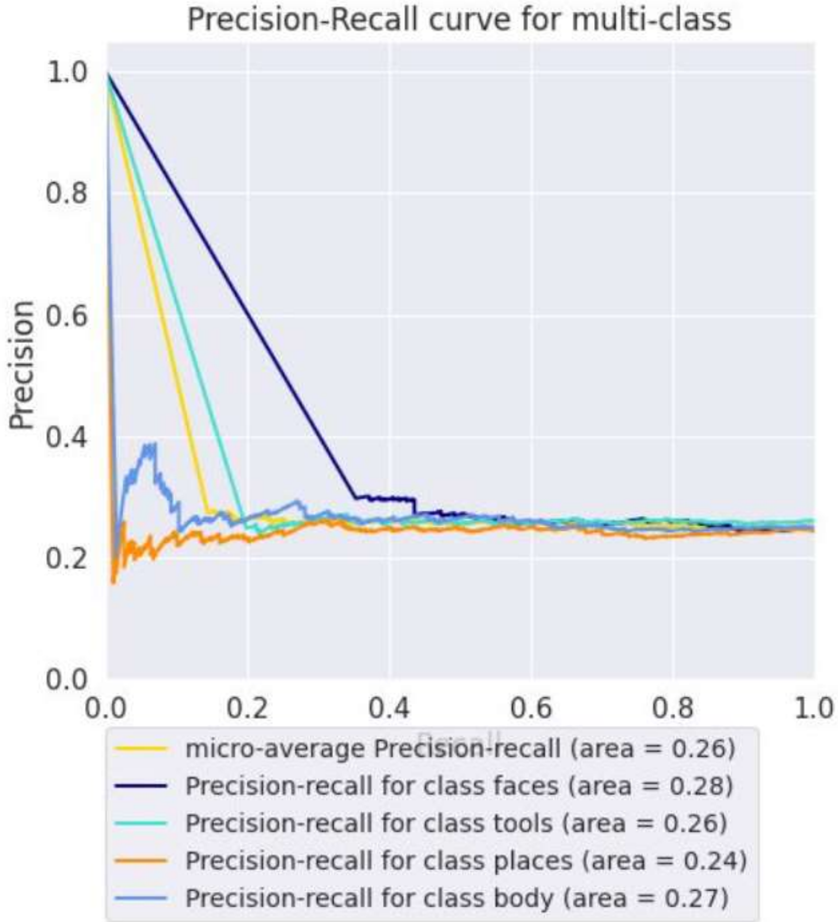
Given differences in parcel activation, can we predict image type?

- Discuss methods and direction with mentors
- Gaussian Mixture Model (GMM) for classification
  - Is the data well represented by a multiple Gaussian distributions?
  - Use linear sum assignment for class definitions
- Precision/Recall for accuracy

First attempt: GMM

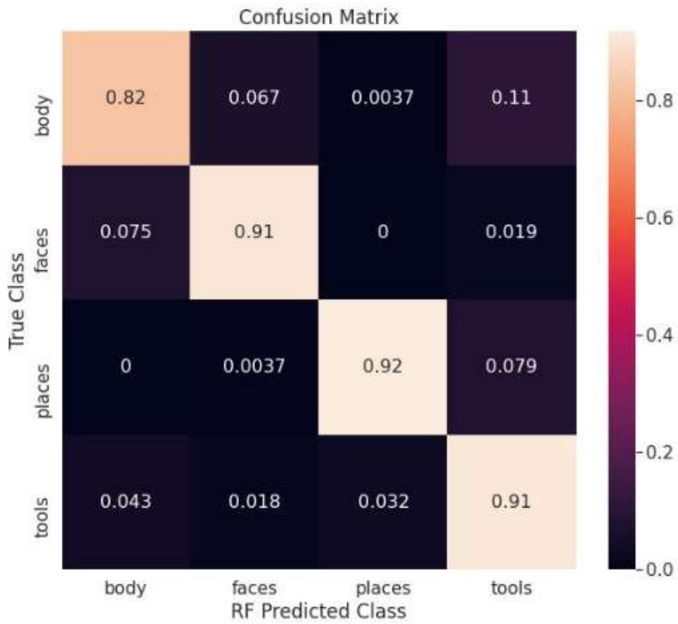
- Poor classification accuracy
  - Majority classified as two categories
  - **Classification accuracy**: 26%

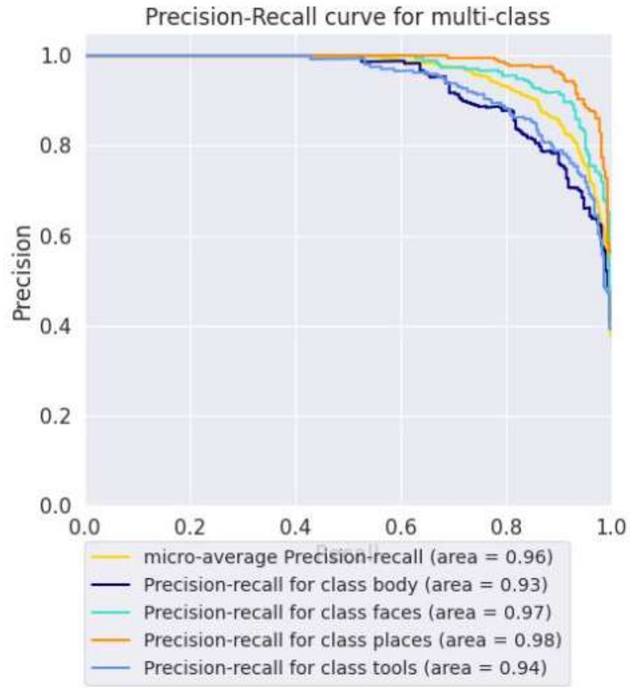




Second attempt: Random Forest (RF)

- Likely a non-linear separation between classes, used a non-linear classifier (RF)
    - **Classification accuracy:** 89%

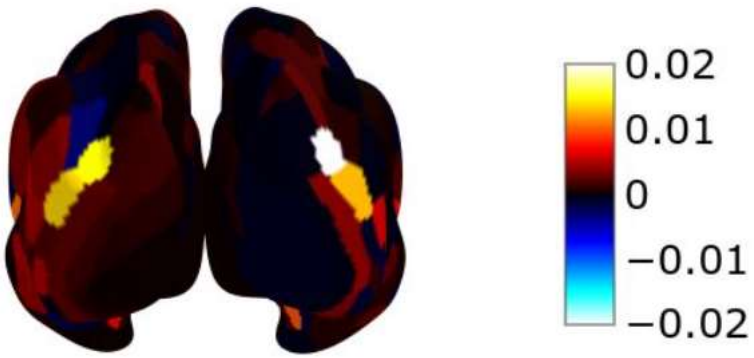




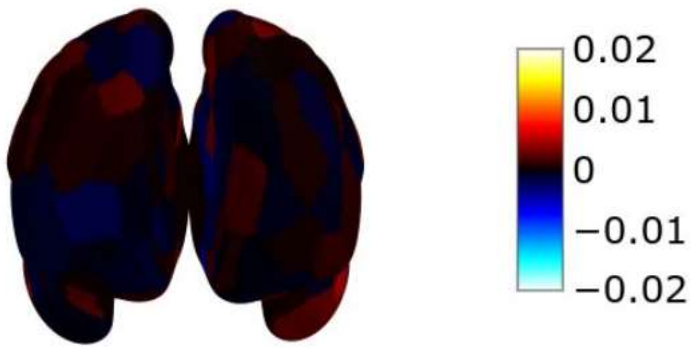
Feature importance

- Which parcels were the most important in the RF classification?
  - Occipital lobe (visual association area) has high contrast

Posterior view of brain



Anterior view of brain



What the Process Revealed / Experiences Gained

- Research questions get revised as you learn more about data
- Not all methods work out the way you expect
- Everything takes longer than you think it will!
- Not giving up on finding the solution eventually leads to the solution
- Playing to each other’s strengths from our different backgrounds helped us accomplish much more than we expected

References

- Breiman, Leo. "Random forests." *Machine learning* 45.1 (2001): 5-32.
- Reynolds, Douglas A. "Gaussian Mixture Models." *Encyclopedia of biometrics* 741 (2009).
- Glasser, M. F., Coalson, T. S., Robinson, E. C., Hacker, C. D., Harwell, J., Yacoub, E., ... & Smith, S. M. (2016). A multi-modal parcellation of human cerebral cortex. *Nature*, *536*(7615), 171-178.
- https://protocols.humanconnectome.org/HCP/3T/task-fMRI-protocol-details.html

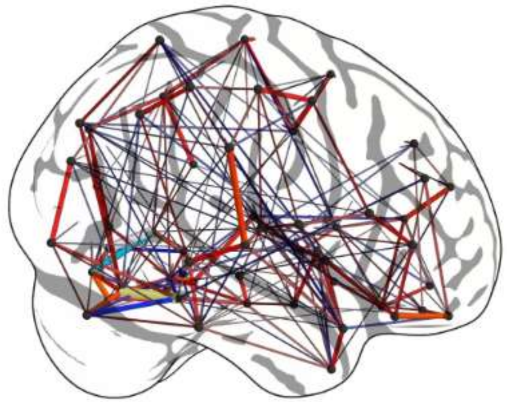
Does Resting-state network retained during task?

Team YAMAS
Pod 079 Valiant Whale

Introduction

Question: Does the resting-state network share the same basis set with the network during the task?

Dataset: HCP resting data and functional data (language task: ‘story’ and ‘math’)



Challenges we met !

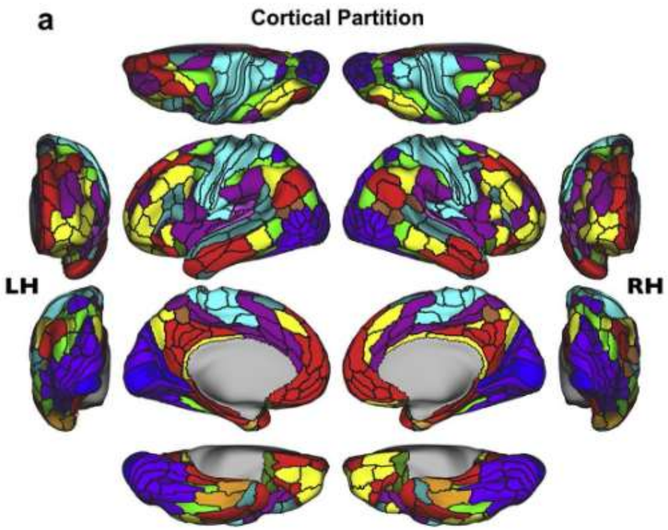
-Which network parcellation should we use ?

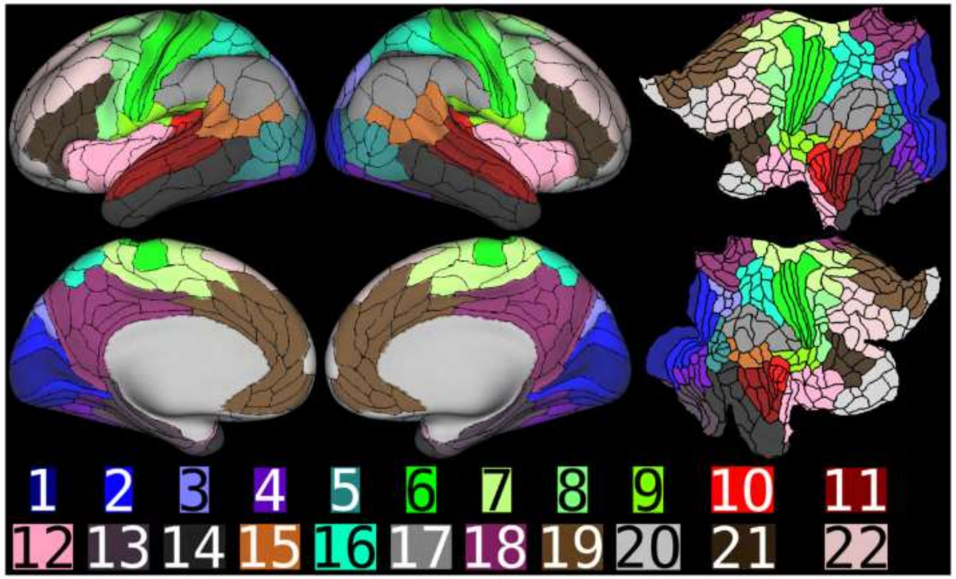
-How to get and save efficiently the Correlation matrix in each state?

-How to check if the resting-state network share the same basis set with the network during the task?which method?

-How to interpret the results ? Null model?

Which network parcellation should we use ?



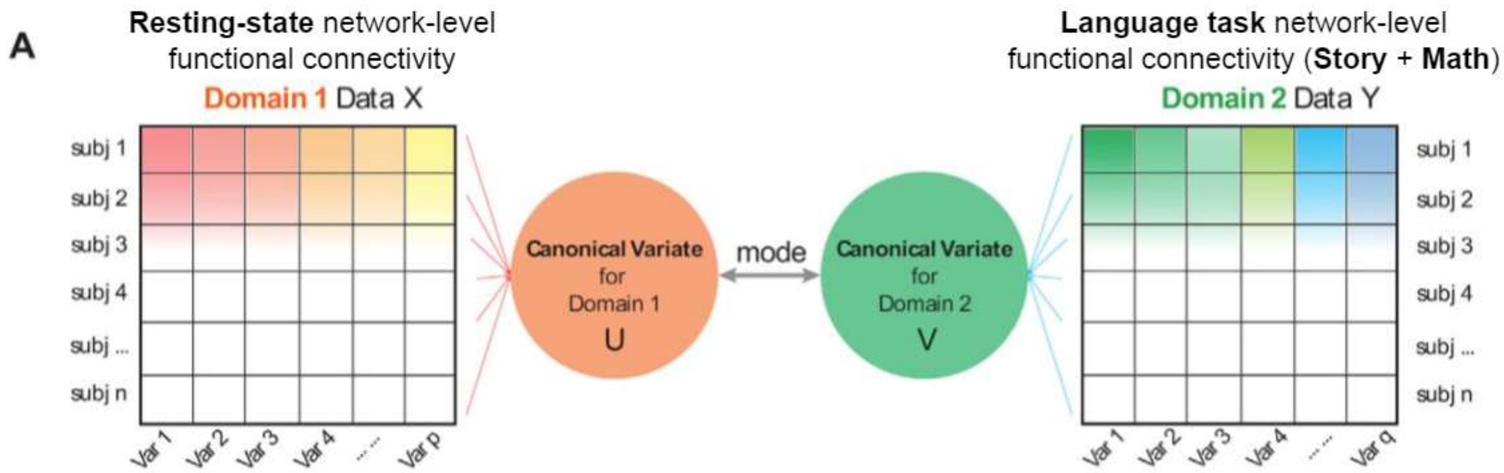


Ji et al., Neuroimage, 2018

Glasser et al., Nature, 2016

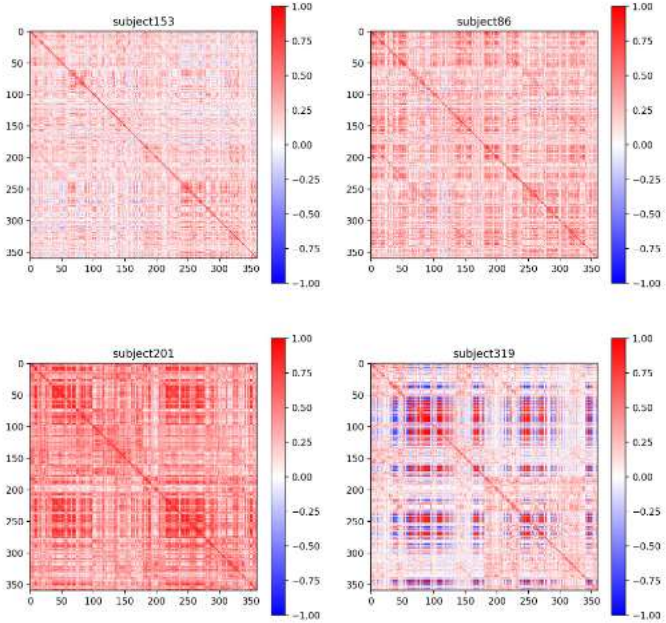
How to check if the resting-state network share the same basis set with the network during the task?which method?

canonical correlation analysis (CCA)



Hypothesis: % shared variance between two dataset will not be different from FC of randomly shuffled networks if the two dataset do not share the same basis set.

How to get and save efficiently the Correlation matrix in each state?



-Use predefined functions to extract **correlation coefficients**

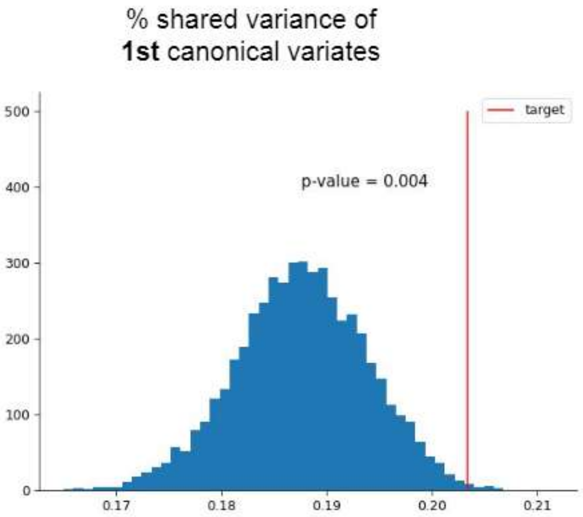
-Save the upper triangular matrix!*(Symmetry)*

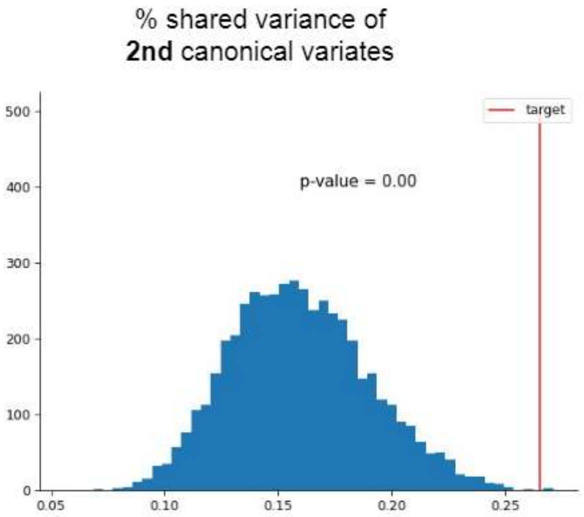
-Use **pickle** for serializing ! Pickle

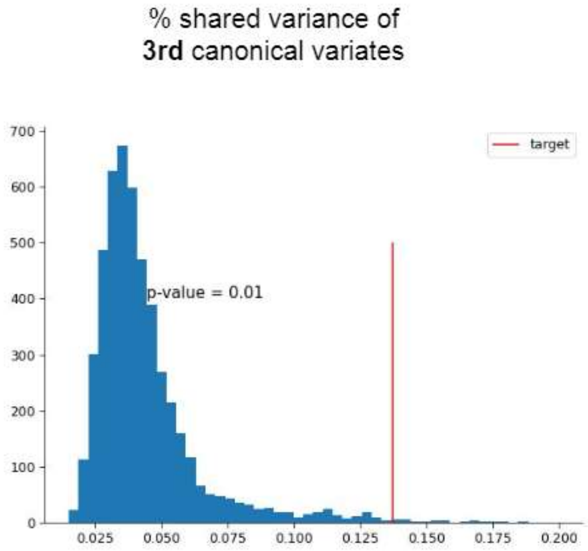
How to interpret the results ? Null model?

- *What to measure?* **shared variance of first three canonical variates**!
- *Null models ?* permutation Test: **5,000** randomly assigned networks
- *Which package?* Pyrcca (https://github.com/gallantlab/pyrcca)
- *Parameters?* regularization parameter: **1,000**

Results







Hypothesis: % shared variance between two dataset will not be different from FC of randomly shuffled networks if the two dataset do not share the same basis set.

Answer: % shared variance between two dataset do differ from the null distribution! The two dataset at least share a meaningful variance with regards to the same network definition.

Discussion

-Is our hypothesis correct for **other tasks**?

-Can we generate other Null models? Maybe **Spin test**

-Do our results correspond to **previous** works?

Who?

YAMAS team

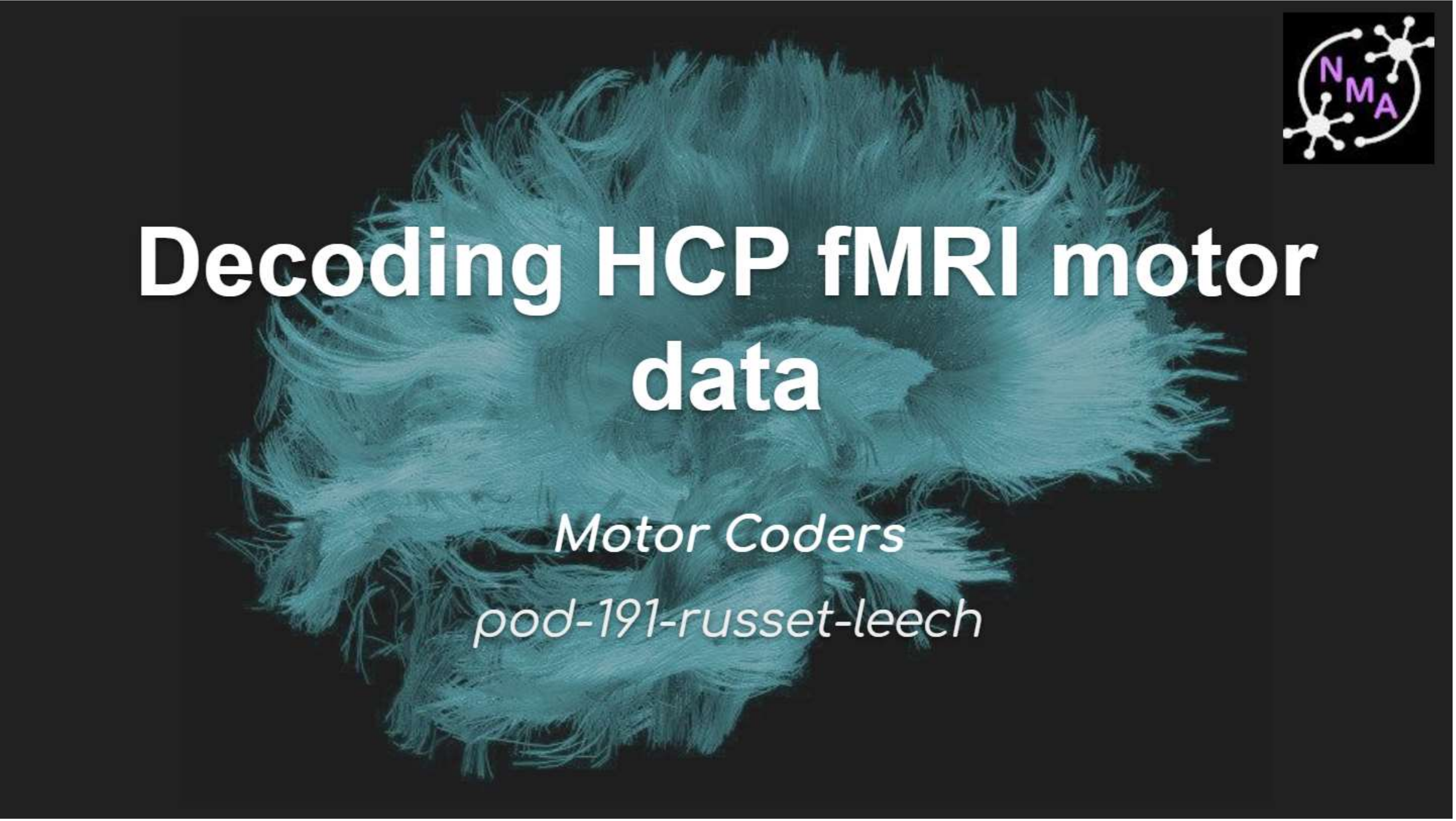
Minho
Shin

Yasaman
Asgari

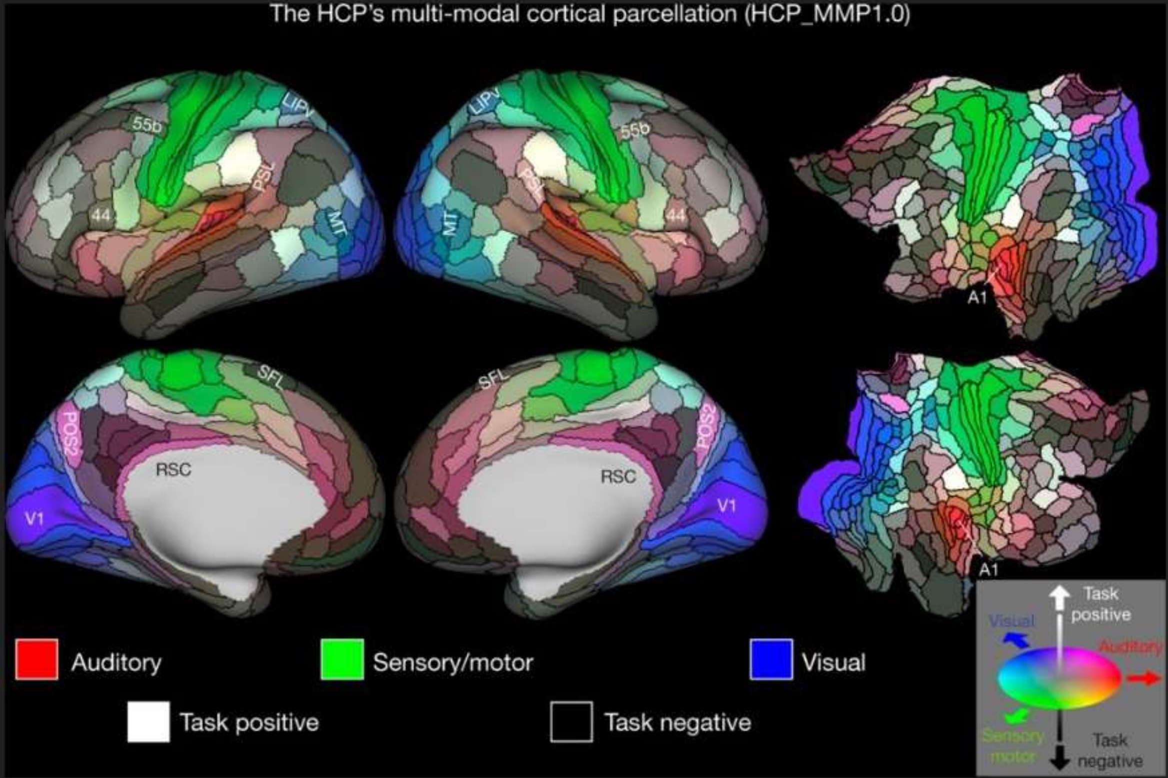
Mohammed
Sarbas

Aswin
V

… and our greatest mentor **James M. Shine**…!!


Decoding HCP fMRI motor data
Motor Coders
pod-191-russet-leech
NMA

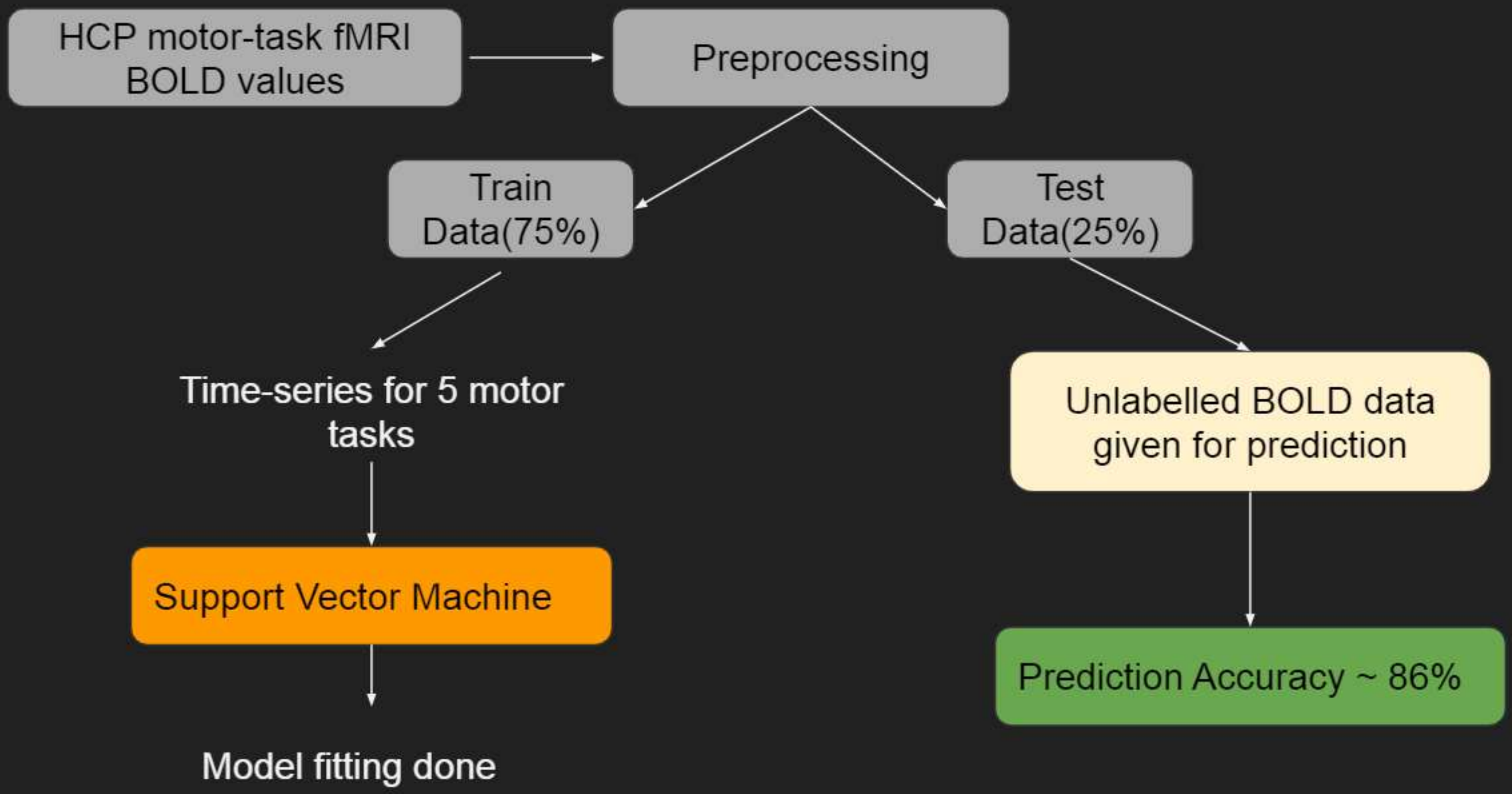
Decoding HCP fMRI motor data



by Motor Coders

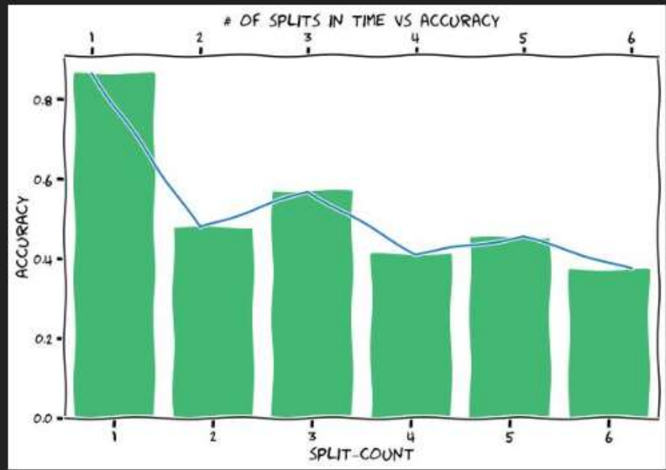
pod-191-russet-leech

Task Prediction Pipeline:



Which part of the task-fMRI data is most important for classification?

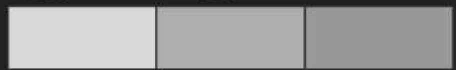
- Making sure the middle (~6 secs) of the time series is continuous aids accuracy of the classifier
- When split in odd parts, the middle's continuity is preserved
- Splitting in even vs odd parts of equal size



2 splits
0s 6s 12s

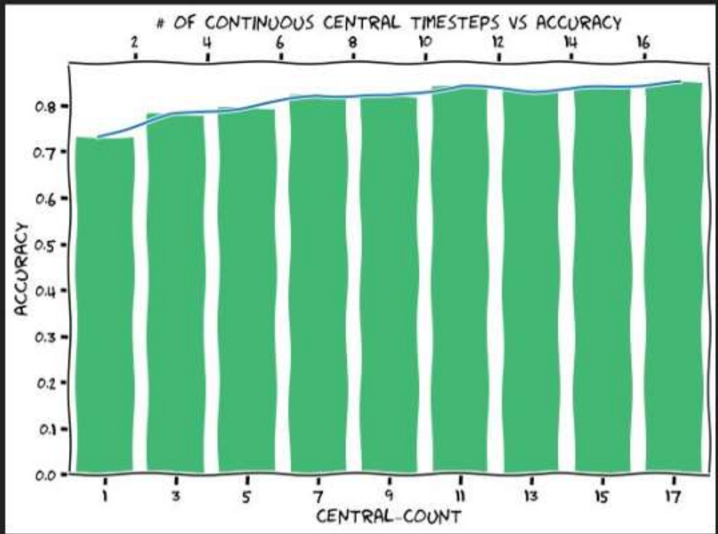
middle is split → low accuracy

3 splits
0s 6s 12s



middle is continuous→ better accuracy

What span of the middle segment is optimal?



- The longer the better!
- Most of the information is being captured by the central timestep

Challenges & Experience:

- Finding a suitable tool for our specific question demanded considerable deliberation

- Why we chose an SVM:
  - High number of features; 38 motor-related HCP parcels
  - Insufficient data to train a deep neural net

- What's next:
  - Could we reconstruct the data based on the most important principal components after a dimensionality reduction, and combine that with the most important time steps and decode the associated parcels?

Applying all these fresh concepts and newly learnt techniques was an exciting journey, and we learned a lot!

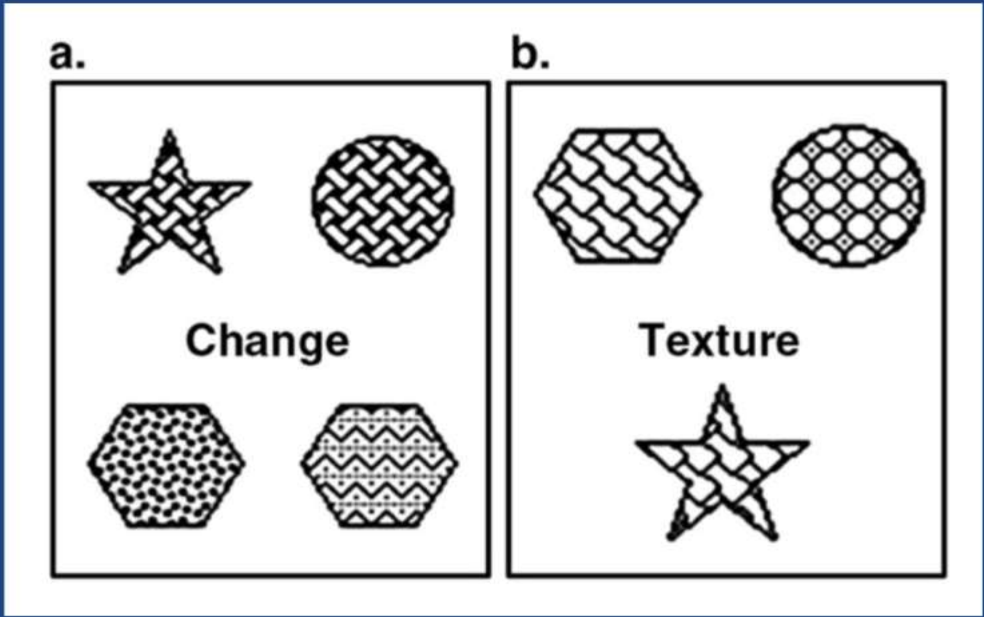
Thank You!

Thanks to NMA, our mentor Dr. Pfuhl, TAha Morshedzadeh, and our dear pod "pod-191-russet-leech" !

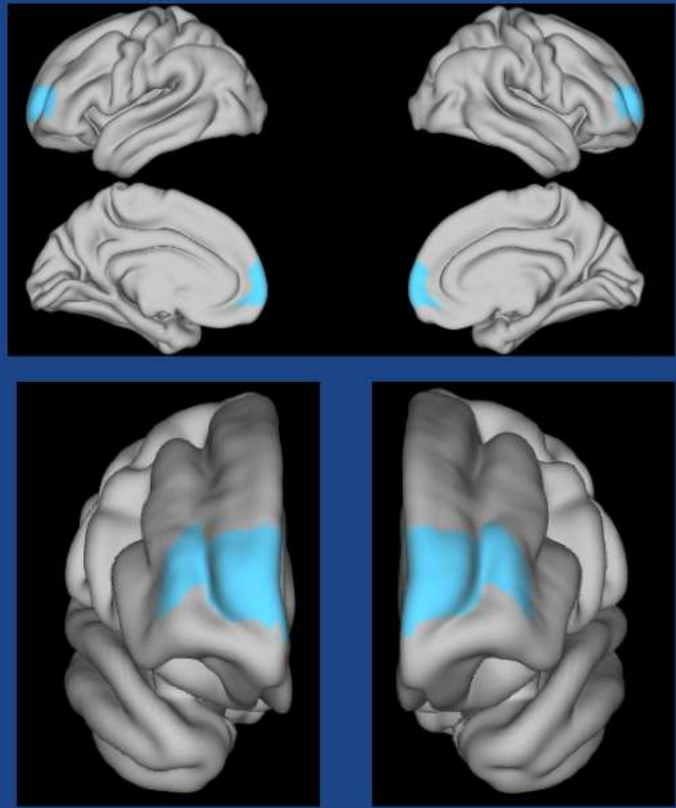
Can Functional Connectivity Predict Relational Reasoning?

Huden Nese, Merve Oral, Salih Geduk, Funda Yılmaz
Supervised by Ida Momennejad

Relational Reasoning



BA10



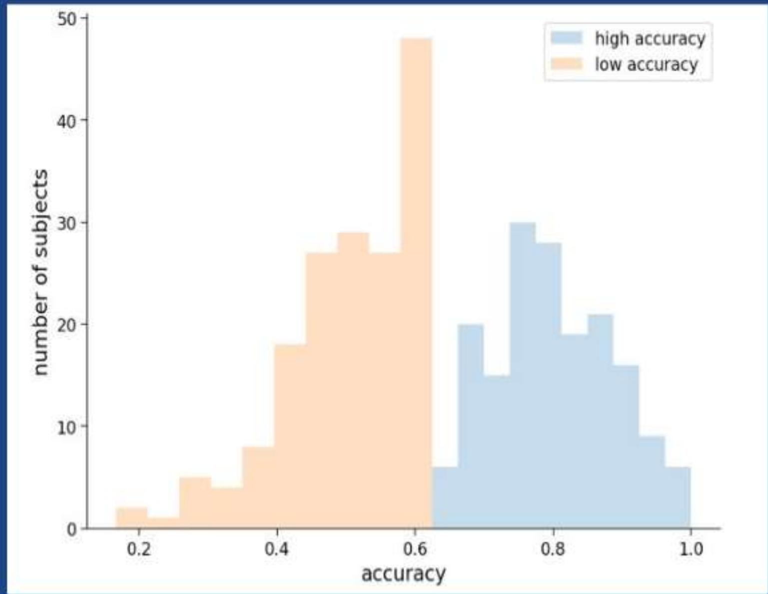
Can Functional Connectivity Predict Relational Reasoning?

HCP dataset (339 subjects)

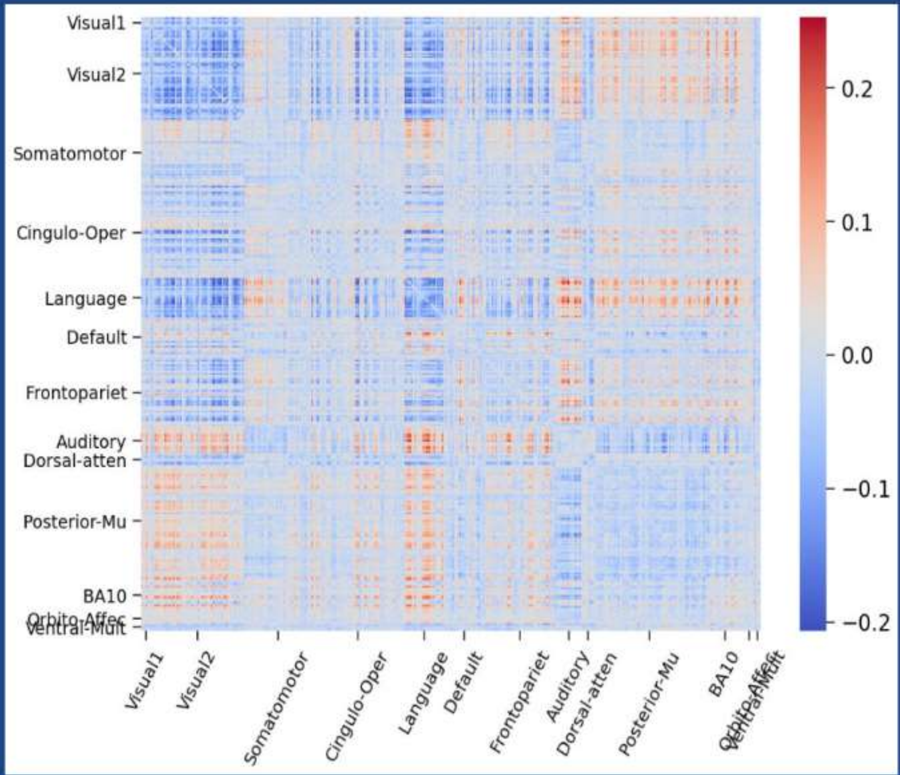
BA10 functional connectivity

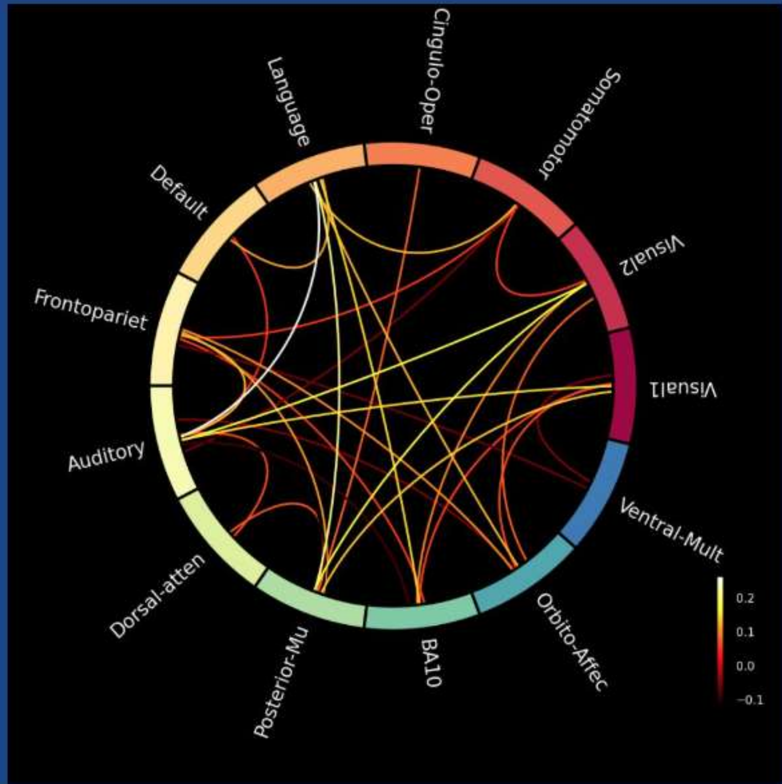
performance on relational reasoning?

relational ***reasoning*** vs. ***match*** task



ALL-TO ALL FUNCTIONAL CONNECTIVITY
Relational reasoning- Match (n=339)

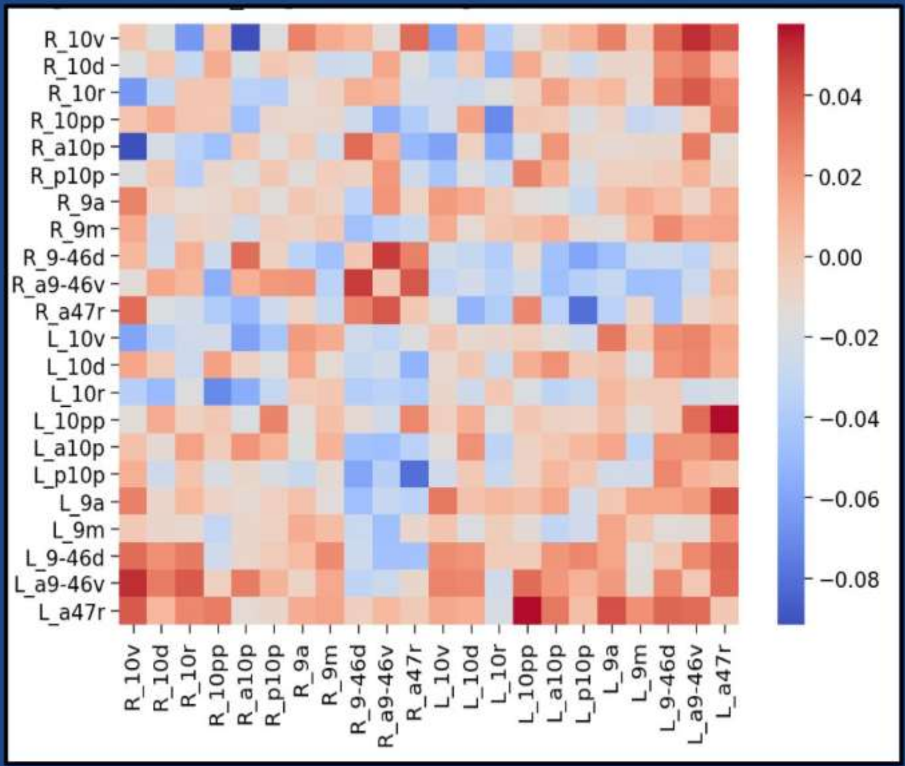


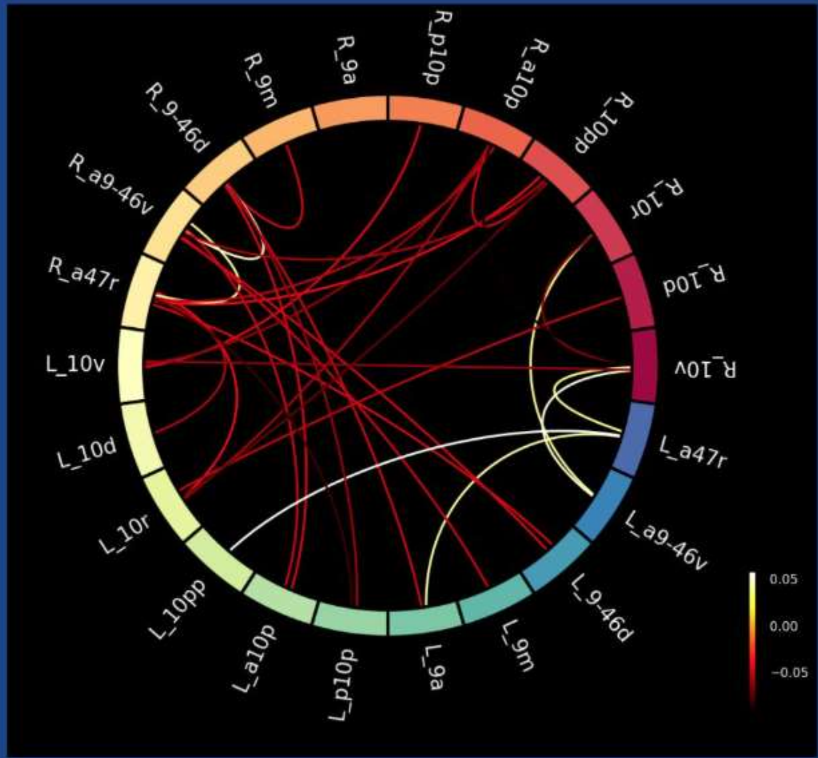


FUNCTIONAL CONNECTIVITY WITHIN BA10

Relational High (n=170) - Low (n=169)

higher lateral connectivity, lower medial-lateral connectivity





Predicting Relational Reasoning from Connectivity

- Train linear SVM (C=1) on connectivity matrix to classify the subjects ("good" vs "not good")
- Test on held out data (40-fold cross validation)
    - mean prediction accuracy

	FC for all regions	FC within BA10
Accuracy	0.583	0.531

Can mentalizing shapes lead to Empathy in humans?

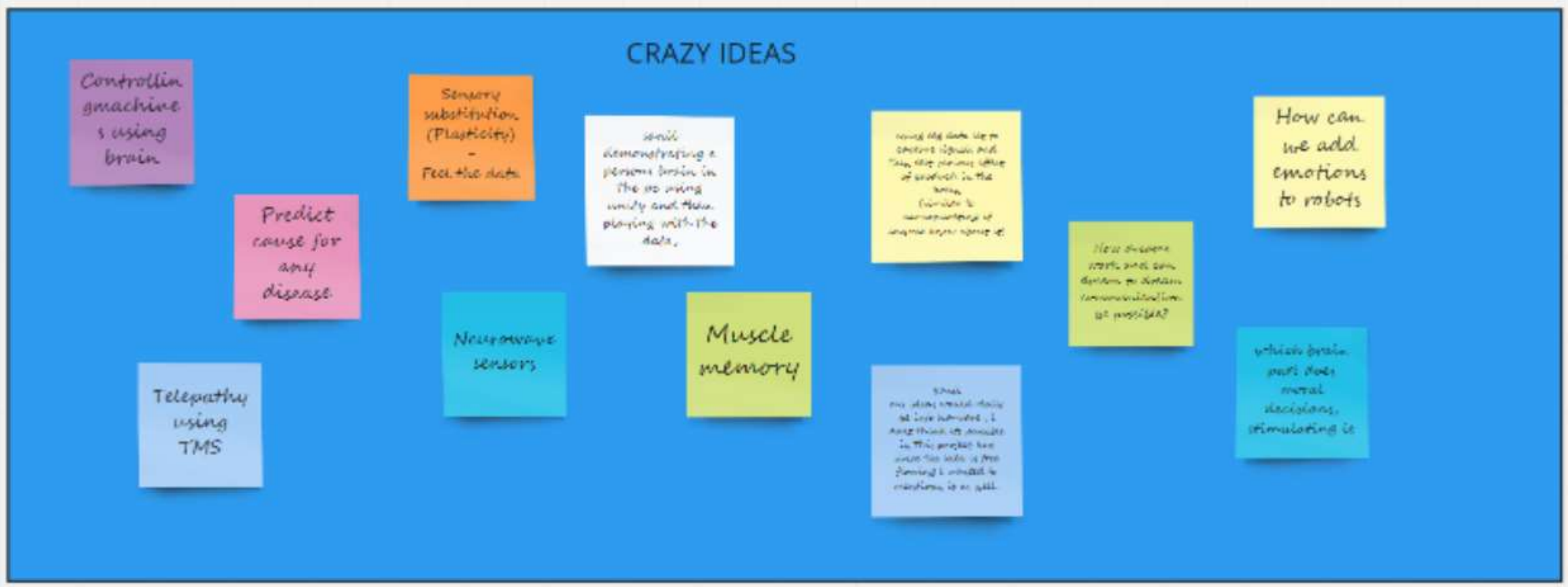
Varad Srivastava
Minaxi Goel
Suraj Joshi
Sanil Shrestha

Mentored by:
Dr. Laura Mikula
Dr. Marlene Cohen

Teaching Assistant:
Mehul Rastogi

neuromatch

Baby Steps : Crazy Ideas

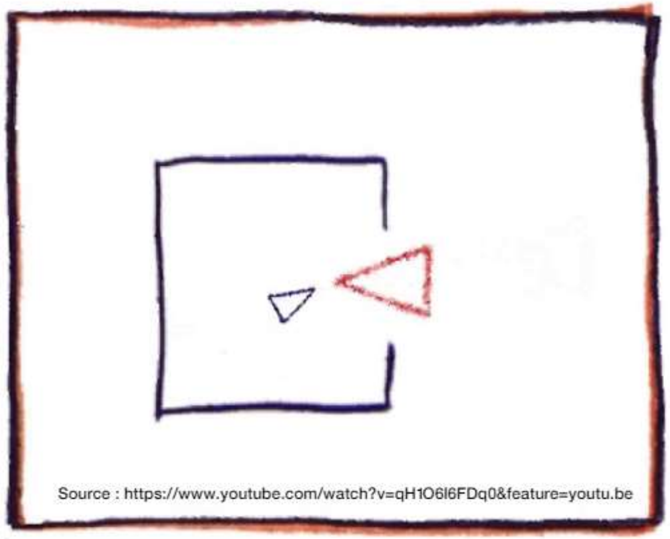


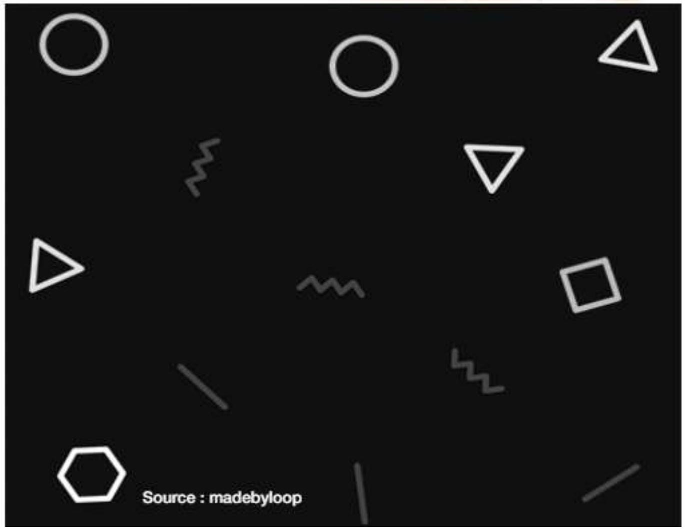
What did we study?

- Do people empathize with socially interacting shapes?
- Which networks in the brain are associated with empathy?
- Is there any kind of correlation among the regions involved in social cognition which leads to empathy?
- Is absence of a task or experimental stimuli (resting state), a good control for such tasks?

Drowning in dataset! – A Journey

- First time with fMRI, a week went in understanding the dataset!
- Human Connectome Project Dataset
  - Social Cognition
    - Classes of videos : Mental Interaction (M), Random Movement (R)
    - Responses Categories : Mental Interaction, Random Movement, Not Sure
    - Design of Events: Two Runs
      - 1st Run (2 M and 3 R Videos)
      - 2nd Run (3 M and 2 R Videos)
      - Videos of 23 s, 15 s fixation time
    - Random Stats : 339 participants, 360 parcels





How did we study?
(~70 hours of work, all nighters, and coffee!)

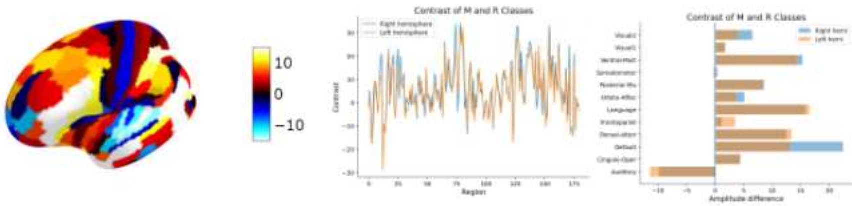


Fig. 1 : Subtraction Analysis Based on Video Classes

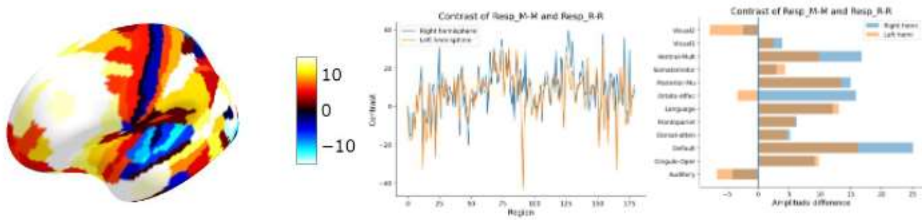


Fig. 2 : Subtraction Analysis Between Resp_M-M and Resp_R-R

Participant's Response \ True Class of Video	Mental Interaction	Random Movement
Mental Interaction	Resp_M-M	Resp_M-R
Random Movement	Resp_R-M	Resp_R-R

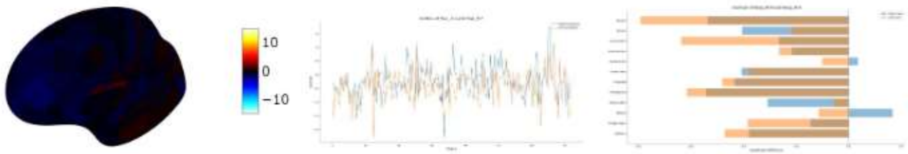


Fig. 3 : Subtraction Analysis Between Resp_M-M and Resp_R-M

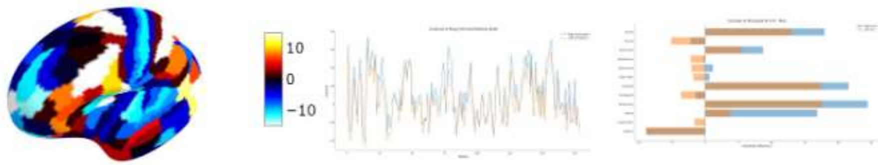
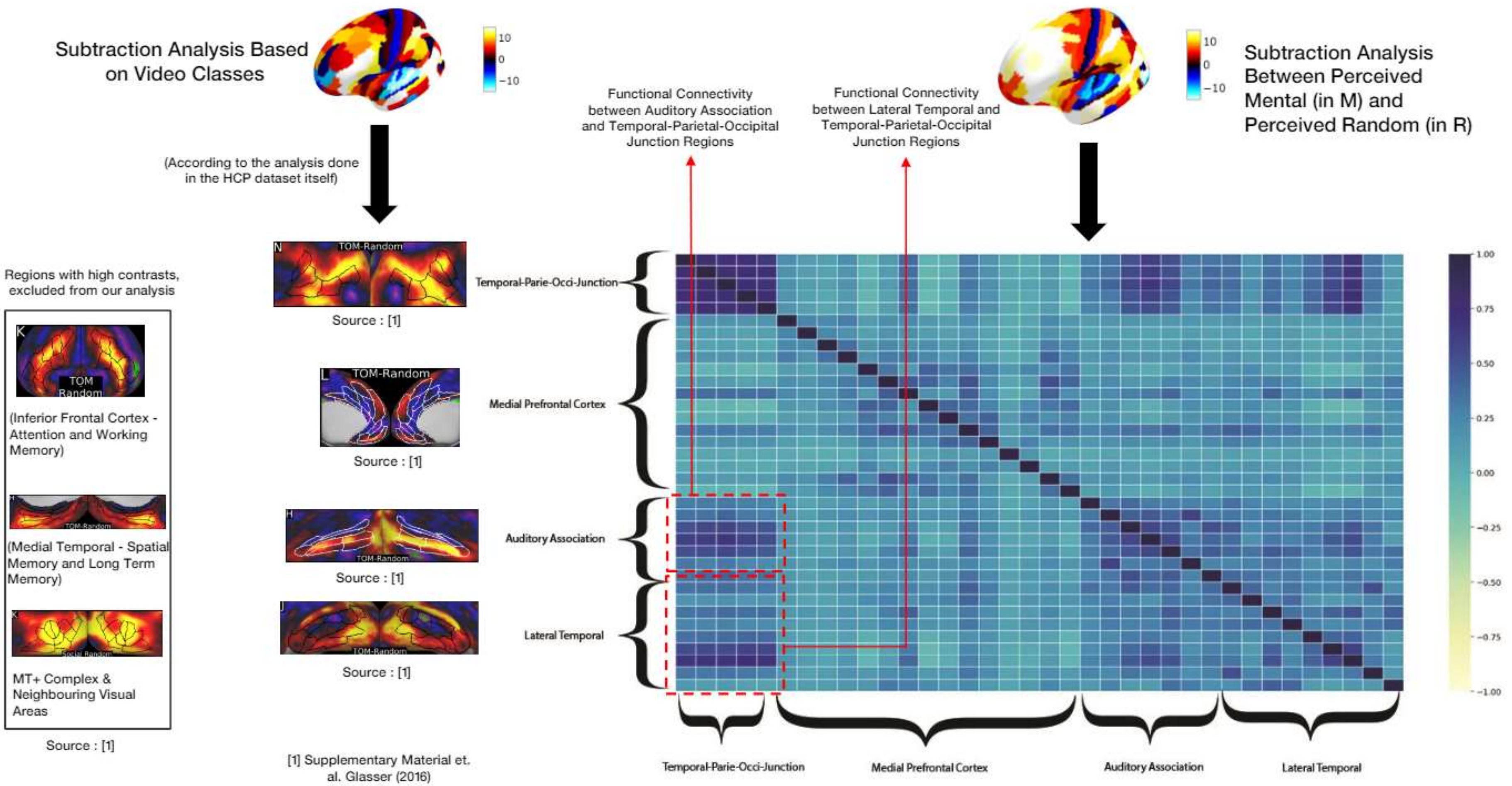


Fig. 4 : Subtraction Analysis taking Resting State as Control and Resp_M-M

Functional Connectivity Analysis



Back to the Future :

- Autistic people have been found to be less capable of empathy. Hence, we plan to include datasets involving clinical population in our further analysis, which can then help us predict autism and other disorders.

- Mentalizing, empathy and mirroring of emotional response are closely related. We'd also try to further investigate if we can comment on the presence of mirror neurons. (Now you get our team name! Ironical?!)

Who are we? (No, not night owls)

Varad Srivastava
M.S. Computer Science
@BHU, India

Minaxi Goel
M.S. (R) Computer Science
@IIIT Hyderabad, India

Suraj Joshi
Final year ECE Under-grad
Nepal

Sanil Shrestha
A.I. Research Intern
@NAAMII, Nepal

An Investigation of Social Accuracy in a Theory of Mind Task

By: Lindsey Tepfer, Mathew Schafer, Darshana Jayakumari
Pod-159-Green-Wombats / Clumsy Gerbils

neuromatch academy

What Question:

What underlies the differences in our ability to perceive social information from the world around us?

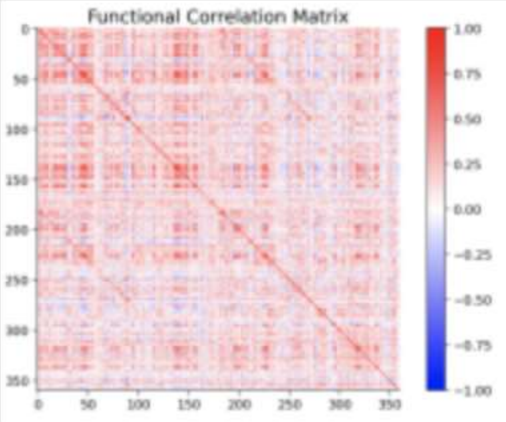
We investigated this question using the HCP dataset "Social Cognition" task, where participants are presented with short video clips featuring moving shapes and are instructed to choose from a set of three options: "mental", "random" and "unsure."

Individual participants vary in their responses to the stimuli: some are better than others at identifying which stimuli are indeed "mental" or "random", which brought us to our next question: what neural patterns might be underlying these behaviors?

To address this, we used a logistic regression to determine whether we could classify "high performers" from "low performers" using the behavioral data provided by the HCP.

neuromatch academy

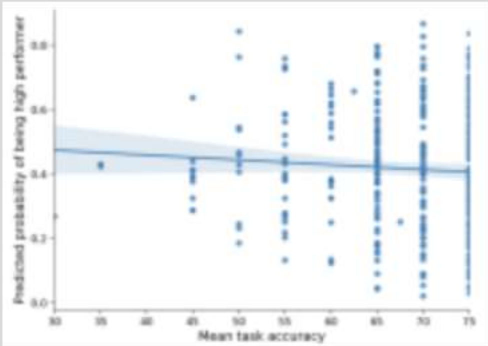
Analysis:

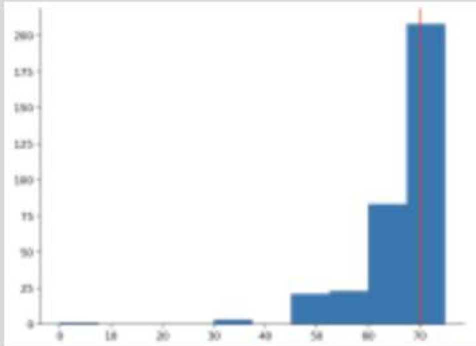


Lasso logisitic regression

High/low performer?

```
mean accuracy=0.6223 (std=0.01)
chance accuracy=0.5782
```





Experience:

- Brainstorming experience
- Asking the right question
- Doing preliminary analysis
- Getting stuck
- Further analysis
- Learning computational techniques and putting them into practice
- Thanks to everyone
  - Neuromatch, Lead TA, Superpod
  - TA(Saeed Salehinajafabadi)
  - Mentor(Edward Kim)
  - Our fellow pod (Clever gold fish)
  - Everyone

neuromatch academy