# Task unrelated activity in fMRI

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neuromatch academy

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Team name: Finalprojectname.docx

# Scientific Questions & Background

How can we characterize task-unrelated activity in event-related fMRI data?

How similar or different is this task-unrelated activity to resting state connectivity?

- In modeling of BOLD response, hemodynamic functions often consider task-unrelated data as "noise" (Shan et al., 2014)
- Hypotheses: Ongoing "task-unrelated" activity may be reflective of traits usually studied during spontaneous activation of resting-state networks (Fair et al., 2007), or is reflective of vascular structure of the brain (aka noise)

# Data

HUMAN Connectome PROJECT

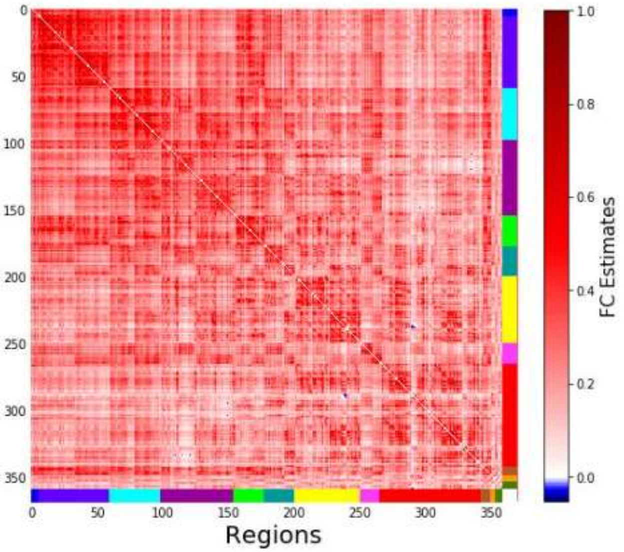
- Subset of the Human Connectome Project:
    - 339 subjects, aged 22-35
    - Parcellated cortical regions, 180/hemisphere (Glasser et al., 2016)
- Tasks:
    - 2 runs of each task, averaged
    - **Emotion** (Face Matching)
    - **Gambling** (Card Guessing)
    - **Motor** (Move fingers, toes or tongue)
    - **Language** (Story-Math)
    - **Social** (Theory of Mind)
    - **Relational Processing** (Feature Relations v Matching)
    - **Working Memory** (N-back)
- Resting state:
    - 4 different runs
    - ~15 min each

https://protocols.humanconnectome.org/HCP/3T/task-fMRI-protocol-details.html

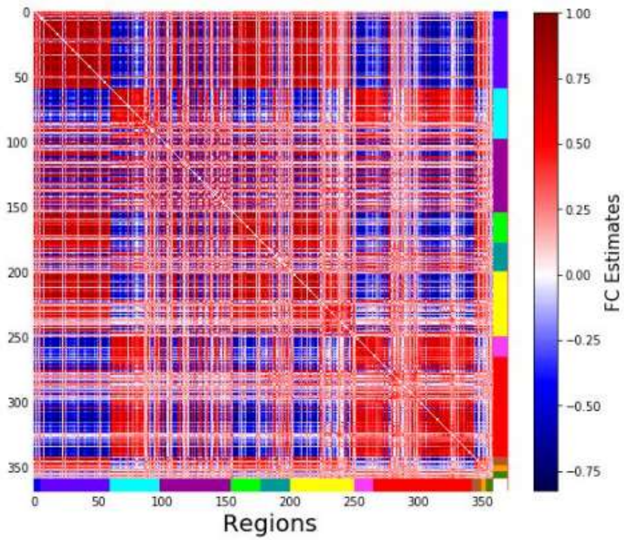
# Planned Analyses and Modeling

1. Model task-related activity using a univariate generalized linear model (GLM) with experimenter-controlled (block) conditions and other nuisance regressors related to signal drift
2. Take out ‘task-unrelated activity’ by extracting residuals from the block-design based GLM, and create connectivity matrices from these residuals
3. Model resting-state activity of time-series correlations between brain parcels
4. Compare connectivity matrices from task-unrelated fMRI and resting-state, further characterize changes in networks via dimensionality reduction

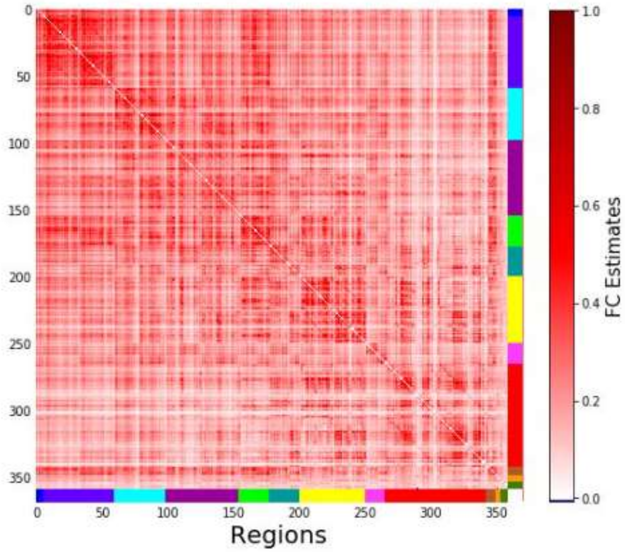
# Results: FC of rest, task-unrelated and task-related activity




FC at rest

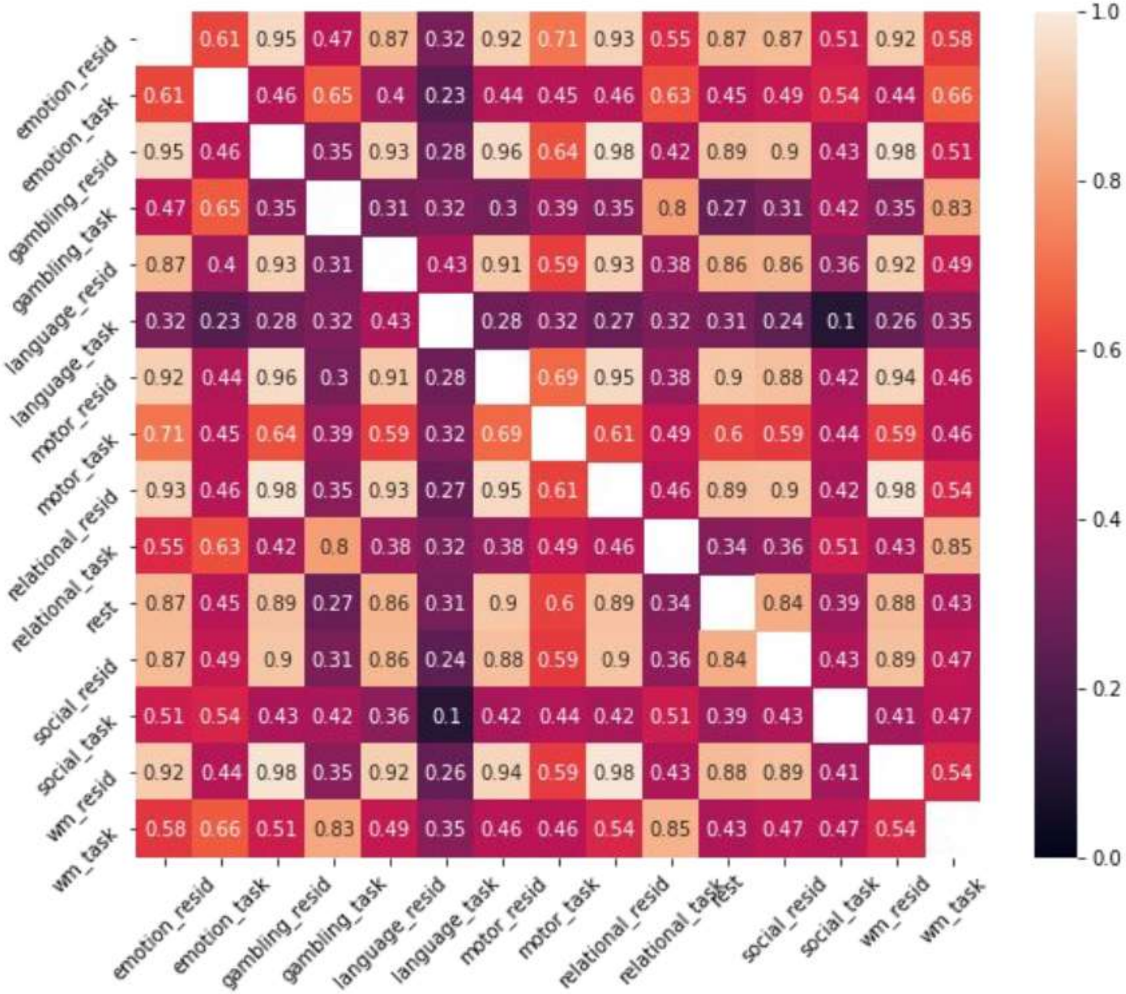



FC for gambling task activity

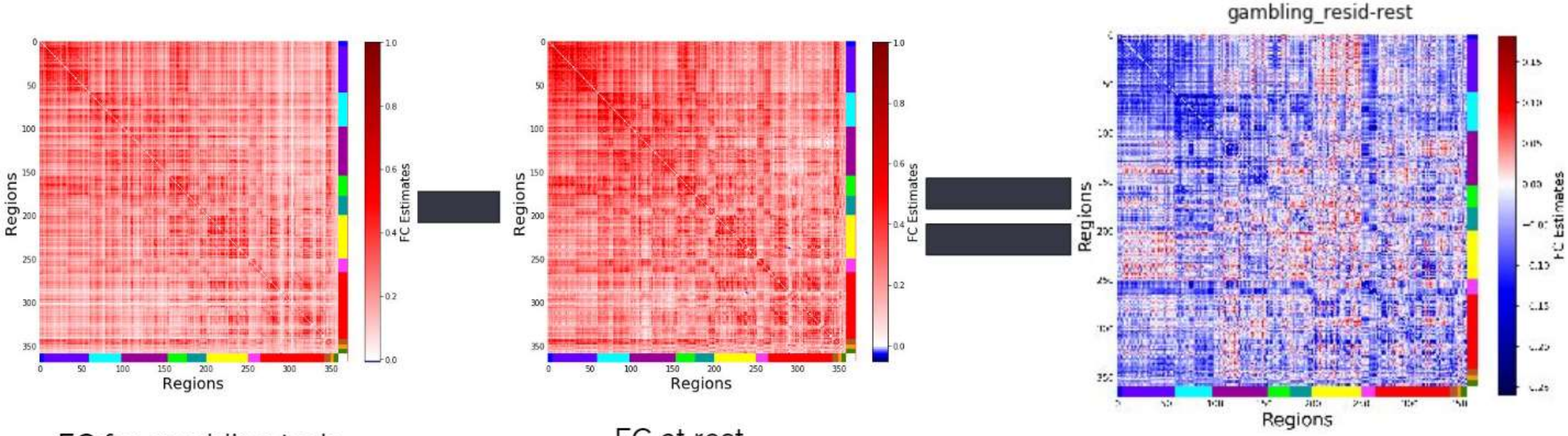



FC for gambling task residuals

# Results: Correlation matrices



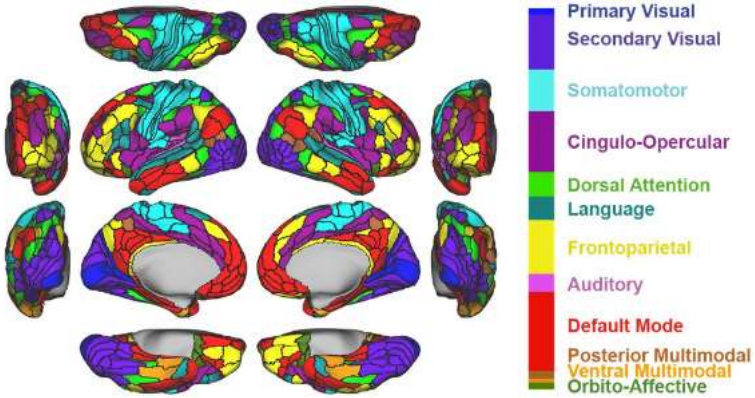
# Results: resting state subtraction

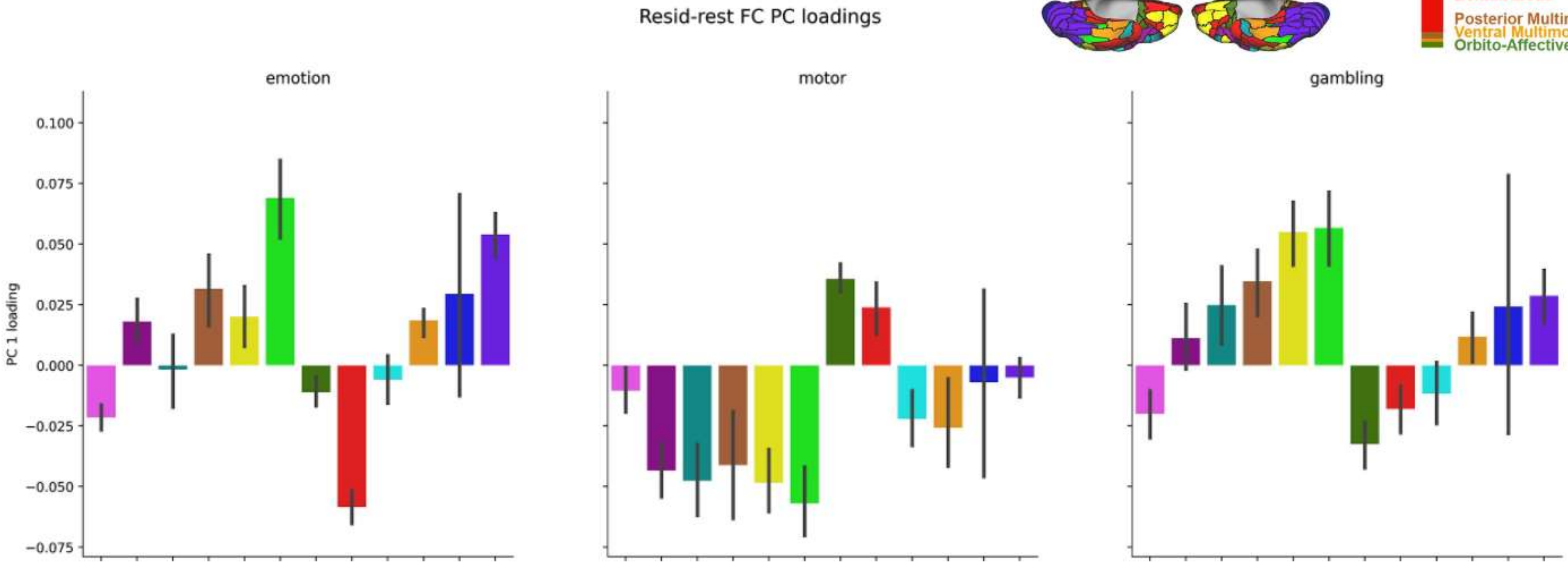



FC for gambling task residuals

FC at rest

# Results: PCA and eigenvectors



# References

Cole, M. W., Bassett, D. S., Power, J. D., Braver, T. S., & Petersen, S. E. (2014). Intrinsic and task-evoked network architectures of the human brain. *Neuron*, *83*, 238-251.

Fair, D. A., Schlaggar, B. L., Cohen, A. L., Miezin, F. M., Dosenbach, N. U., Wenger, K. K., Fox, M. D., Snyder, A. Z., Raichle, M. E., & Petersen, S. E. (2007). A method for using blocked and event-related fMRI data to study "resting state" functional connectivity. *Neuroimage*, *35*(1), 396-405.

Glasser, M. F., Coalson, T. S., Robinson, E. C., Hacker, C. D., Harwell, J., Yacoub, E., Ugurbil K., Andersson, J., Beckmann, C. F., Jenkinson, M., Smith, S. M., & Van Essen, D. C. (2016). A multi-modal parcellation of human cerebral cortex. *Nature*, *536*(7615), 171-178.

Shan, Z. Y., Wright, M. J., Thompson, P. M., McMahon, K. L., Blokland, G. G., De Zubicaray, G. I., Martin, N. G., Vinkhuyzen, A. A., & Reutens, D. C. (2014). Modeling of the hemodynamic responses in block design fMRI studies. *Journal of Cerebral Blood Flow & Metabolism*, *34*(2), 316-324.

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Zeynep Enkavi


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Jo Fritzinger


Dr. John Murray

# The Predictive Power of Task-Based Functional Connectivity



Ladan Shahshahani

Davide Momi



Corey Richier

Nora Bradford



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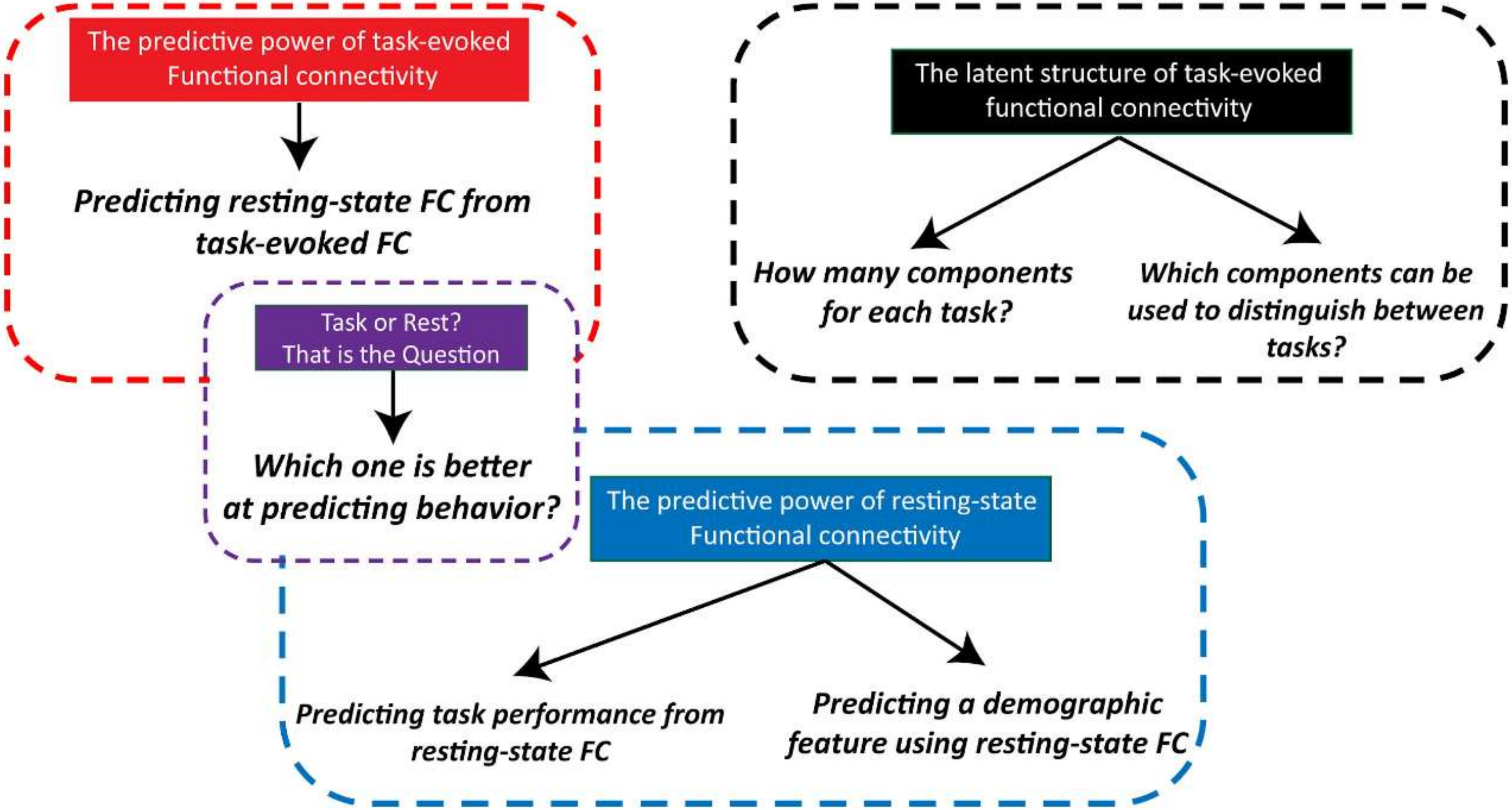
**TA:** Raul Rodriguez Cruces
**Mentor:** Nidhi Seethapathi

# Introduction



# Methods

## *Predicting resting-state FC from task-evoked FC*

Genralized Linear Model (Ridge Regression)

## *The latent structure of task-evoked functional connectivity*

1. PCA to task-specific FCs separately
   * What is the number of components we need to retain in order to explain 95% of variance in each task?
2. PCA to all tasks to retain 95% variance
   * stacking FC of all the tasks, what is the number of components needed to retain 95% of variance?

## *Task or Rest?*

1. Apply PCA to rest and task separately
2. Regressing performance on wm task onto rest PCs and task PCs separately using SVR
3. Compare R2 values

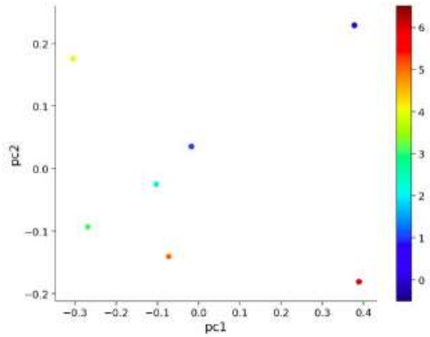
## *The predictive power of resting-state Functional connectivity*

1. Task Performance on a working memory task
   * Use Ridge regression with resting-state FC to predict task performance
   * Which nodes are more "important"?
2. Predicting gender from resting-state FC
   * Use CNN to predict gender (playing around with CNN)

# Results

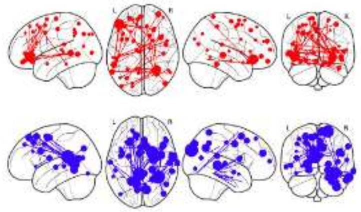
## PCA on task fMRI


***Result:*** *Motor task needs more components to explain 95% of the variance than other tasks*



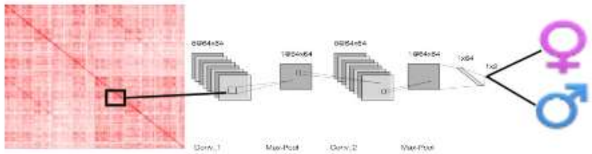

***Result:*** *Plotting component loadings for the second component vs the first component. Data points are coloured according to tasks. From the plot, two data points seem to be standing out: the data point representing task id 0 (motor task) and 6 (social task) are indistinguishable using pc1, but using pc2 the difference between the two tasks is HUGE! This is also the case for tasks 3 and 4*

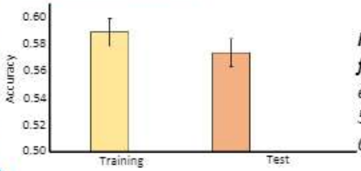
## Using rs-FC to predict wm performance



***Result:*** *Nodes belonging to the Fronto-Parietal and Default Mode Network were respectively positively and negatively related to wm performance*

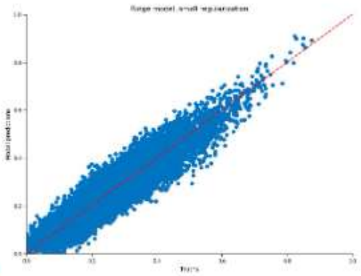
## CNN for predicting Gender



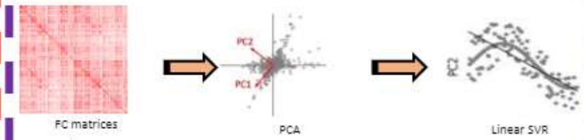


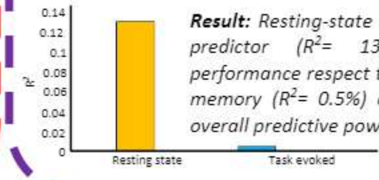

***Result: Average of accuracy for all 20 epochs.*** *Over 20 epochs the CNN moved from 50% of accuracy to peak of 62% on test set.*

## Ridge Regression for predicting resting state based on task evoked



## Of task and rest, which one is better at predicting behavior?




***Result:*** *Resting-state was found as a better predictor ($R^2$= 13%) of behavioural performance respect to task-evoked working memory ($R^2$= 0.5%) activity. However, the overall predictive power was not high.*

# Story of how it all adds up

By: Akshi, Kanishk and Yash
Team: BirdBrains, Pod: Authentic Jackdaws

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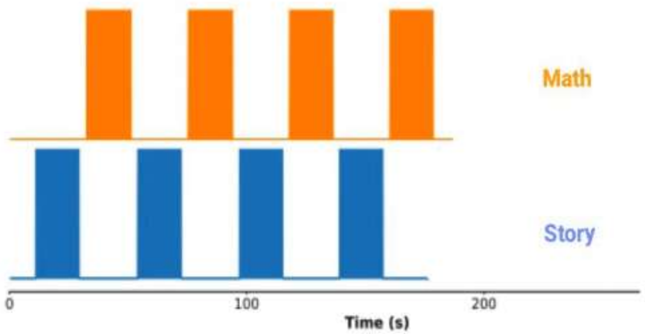
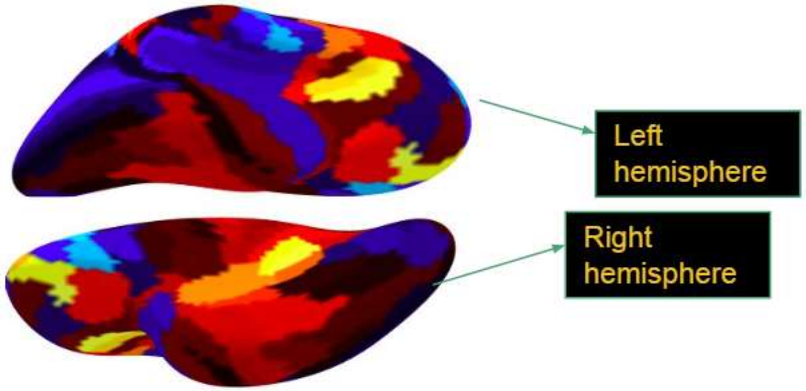
# The Question: Can signature brain activity of story comprehension and arithmetic calculation be used to classify the fMRI data into these two categories?

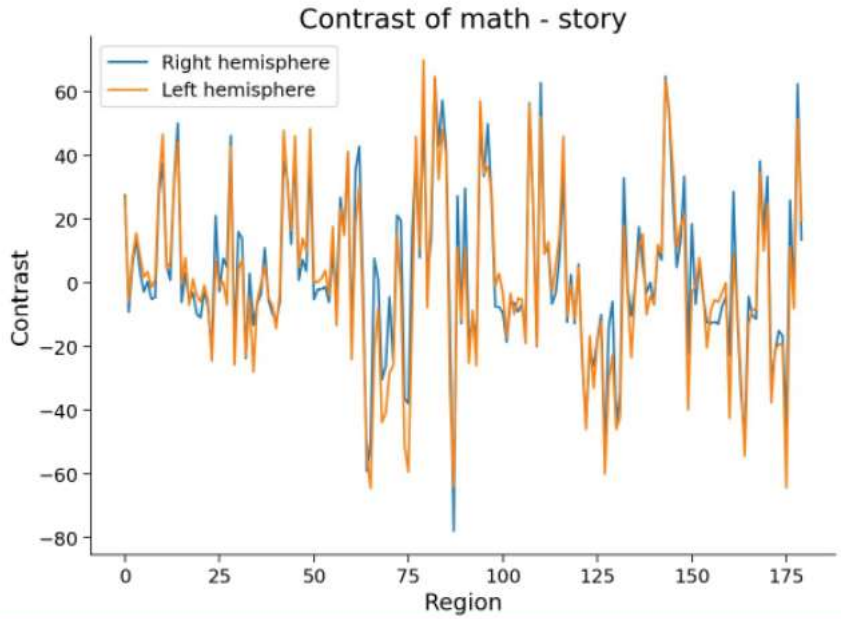



HCP Language Processing dataset

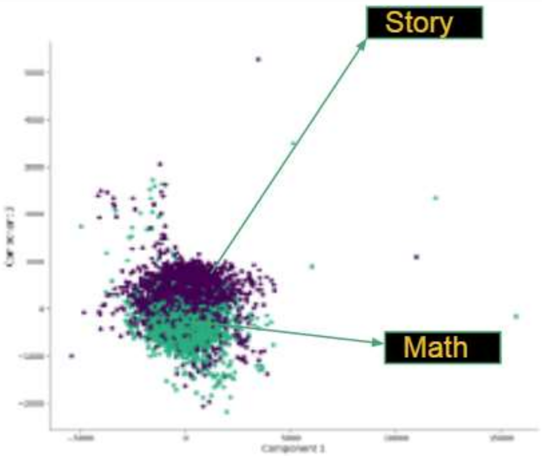



Inflated surfaces of left and right hemispheres

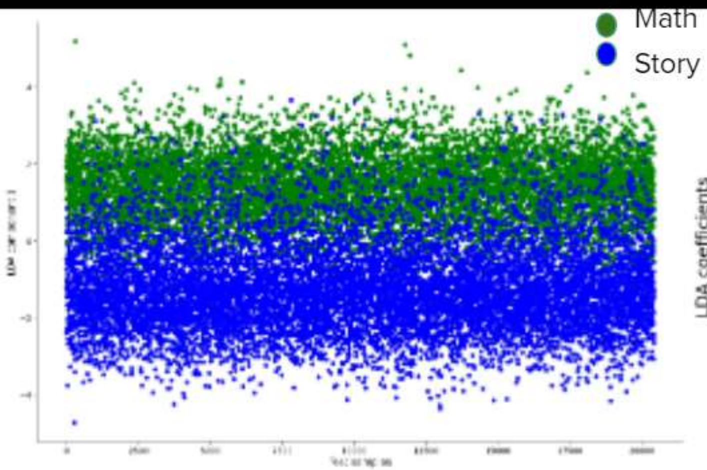
- Parcellation of brain: **360 parcels**
- Structure of data:
  - **Row: Parcel**
  - **Column: Timestamp**
- Number of participants: **339**



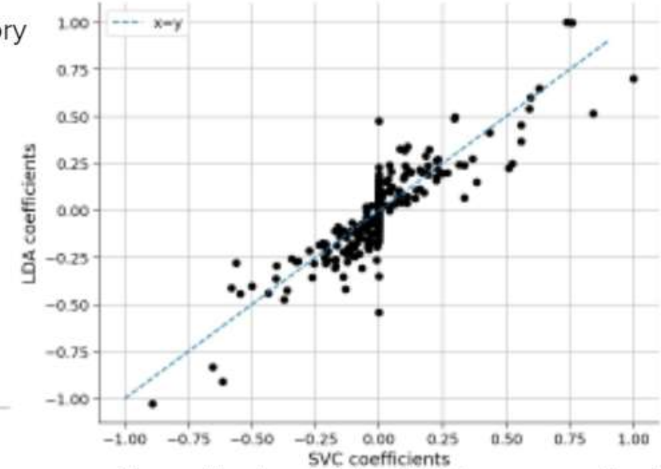
# PCA(Unsupervised)+SVC vs LDA (supervised + class preservation) vs SVC




Accuracy with 2 components: 0.80
Accuracy with **3** components: **0.84**

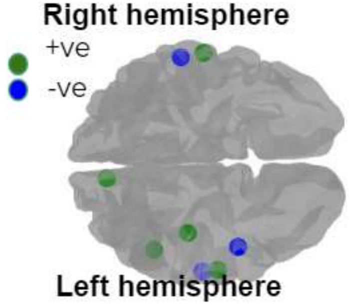



Accuracy: 0.8995838433292533 ≈ **0.9**




Normalised weights of LDA vs normalised weights of SVC

| | | |
|---|---|---|
| **Parcels found most important for classification:** | **1. L_SCEF:** Supplementary and Cingulate Eye Field | **2. L_PGi:** Area PGi |
| **3. R_PSL:** PeriSylvian Language Area | **4. L_PSL:** PeriSylvian Language Area | **5. L_A4:** Auditory for Complex |
| **6. L_AIP:** Anterior IntraParietal Area | **7. L_AIP:** Anterior IntraParietal Area | **8. R_PF:** Area PF |



# Conclusion + Future directions + Experiences

- We were able to classify with 90% accuracy if the fMRI data was recorded during the story task or the math task.

- Based on the weights of classifiers, we were then able to extract the parcels which had the highest contribution in the signature brain activity of a story/math task. Interpretation of these weights and the interplay between various regions can be a possible direction of future work.

- We were able to establish relation between our findings and existing research.

- We had a blast working on this project right from brainstorming about project ideas to weighing pros and cons of possible approaches to finding things through our analysis and being overjoyed when the existing literature confirmed them! We appreciate the freedom provided by NMA to come up with our own project proposals! This gave us the opportunity to dive into the neuroscience of language which is something that has fascinated us for a long time.

- A sincere thanks to our Mentor (Dr. Anne Urai) and our TAs (Alish Dipani and Anindita Bhattacharjee) for their invaluable guidance and suggestions.

# References

**[1]** Binder, J. R., Gross, W. L., Allendorfer, J. B., Bonilha, L., Chapin, J., Edwards, J. C., Grabowski, T. J., Langfitt, J. T., Loring, D. W., Lowe, M. J., Koenig, K., Morgan, P. S., Ojemann, J. G., Rorden, C., Szaflarski, J. P., Tivarus, M. E., & Weaver, K. E. (2011). Mapping anterior temporal lobe language areas with fMRI: A multicenter normative study. *NeuroImage*, *54*(2), 1465-1475. https://doi.org/10.1016/j.neuroimage.2010.09.048

**[2]** Wang, M., Li, C., Zhang, W., Wang, Y., Feng, Y., Liang, Y., Wei, J., Zhang, X., Li, X., & Chen, R. (2019). Support vector machine for analyzing contributions of brain regions during task-state fMRI. *Frontiers in Neuroinformatics*, *13*. https://doi.org/10.3389/fninf.2019.00010

**[3]** Barch, D. M., Burgess, G. C., Harms, M. P., Petersen, S. E., Schlaggar, B. L., Corbetta, M., Glasser, M. F., Curtiss, S., Dixit, S., Feldt, C., Nolan, D., Bryant, E., Hartley, T., Footer, O., Bjork, J. M., Poldrack, R., Smith, S., Johansen-Berg, H., Snyder, A. Z., … Van Essen, D. C. (2013). Function in the human connectome: Task-fMRI and individual differences in behavior. *NeuroImage*, *80*, 169-189. https://doi.org/10.1016/j.neuroimage.2013.05.033

**[4]** Yusoff, A. N., Ng, S. B., Teng, X. L., & Abd. Hamid, A. I. (2014). Investigating brain activation and neural efficacy during simple arithmetic addition task in quiet and in noise: An fMRI study. *Jurnal Sains Kesihatan Malaysia*, *12*(1), 23-33. https://doi.org/10.17576/jskm-1201-2014-04

**[5]** Haufe, S., Meinecke, F., Görgen, K., Dähne, S., Haynes, J., Blankertz, B., & Bießmann, F. (2014). On the interpretation of weight vectors of linear models in multivariate neuroimaging. *NeuroImage*, *87*, 96-110. https://doi.org/10.1016/j.neuroimage.2013.10.067

# Truthful Inchworm
# #404 Errors

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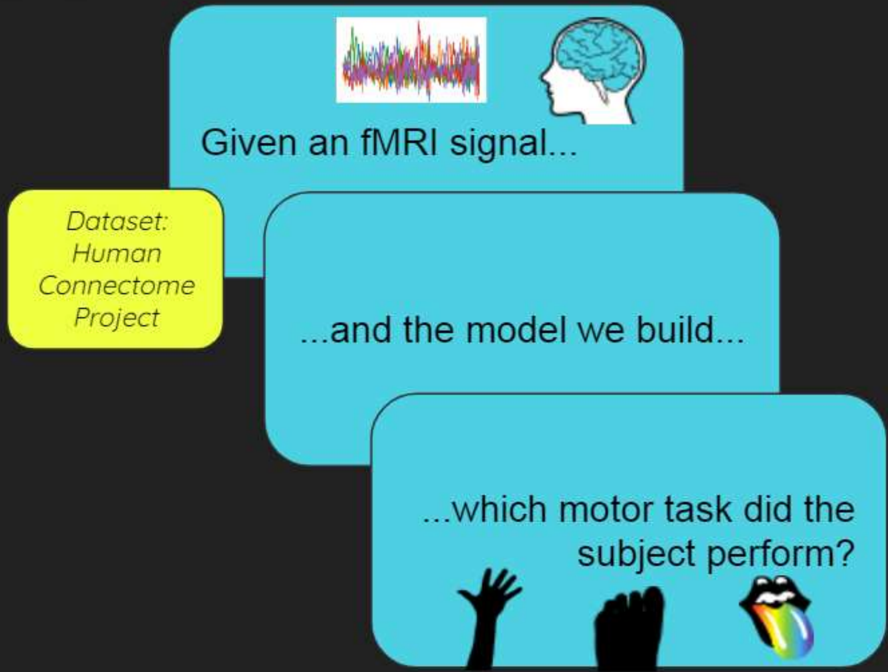
truthful

# Decoding Task Stimulus from fMRI BOLD time-series

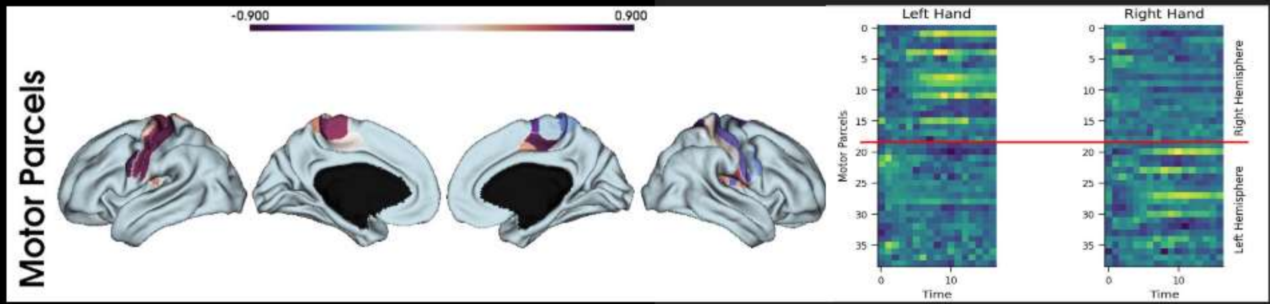



## A “what” model

## How does motor task stimulus decoding accuracy vary based on: Task-specific, Task-general, or whole brain activity?

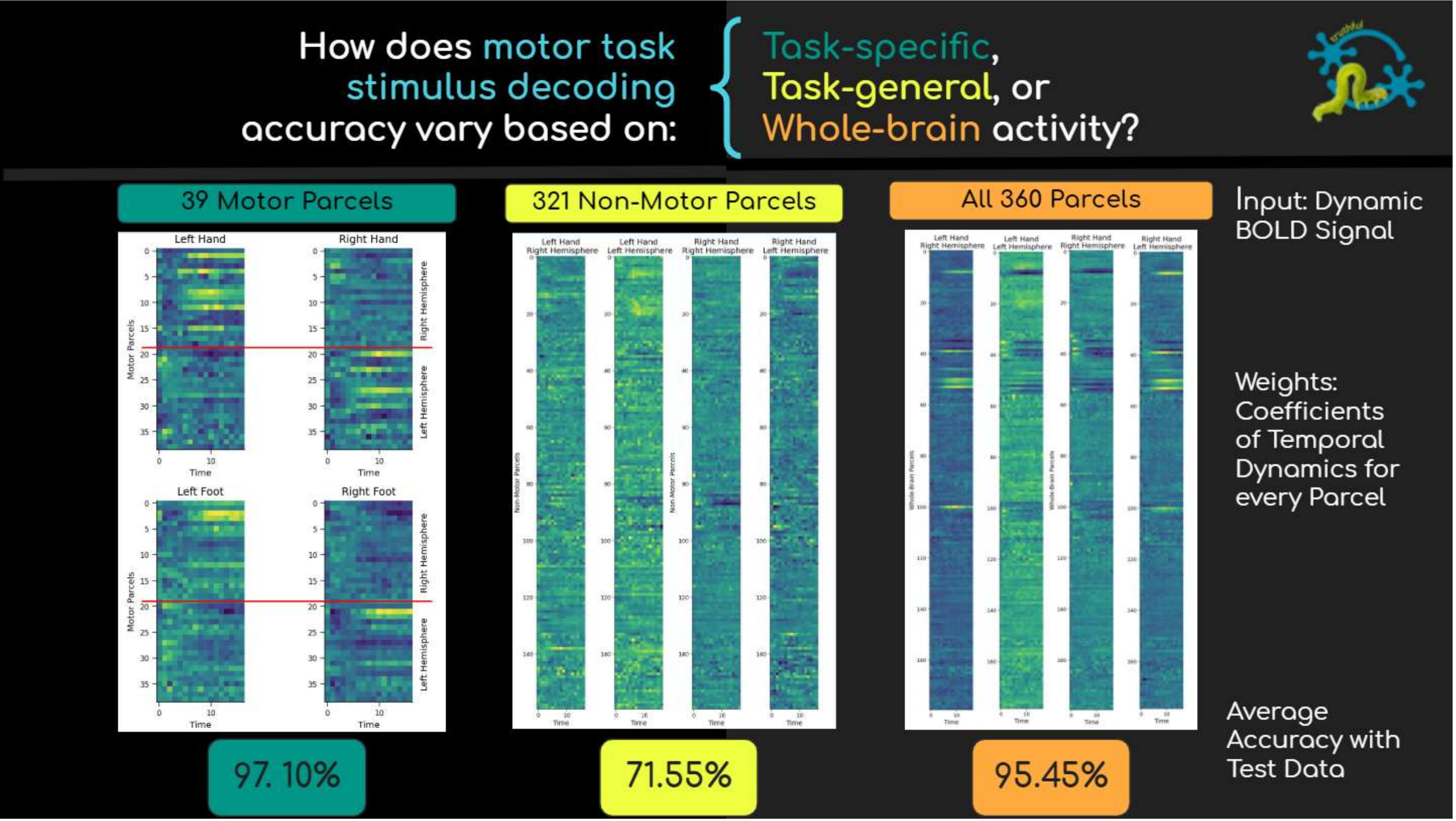
Input → Decoding

Dynamic BOLD signal (Glasser Parcels) → PCA → GLM - Logistic Regression → Stimulus




### The Debate: Modular vs Distributed processing

Our descriptive 'what' model aims to characterize the degree of distributed processing across brain regions during task-related brain activity



How does motor task stimulus decoding accuracy vary based on:
Task-specific, Task-general, or Whole-brain activity?
39 Motor Parcels
321 Non-Motor Parcels
All 360 Parcels
Input: Dynamic BOLD Signal
Left Hand
Right Hand
Left Foot
Right Foot
Motor Parcels
Right Hemisphere
Left Hemisphere
Time
Left Hand Right Hemisphere
Left Hand Left Hemisphere
Right Hand Right Hemisphere
Right Hand Left Hemisphere
Non-Motor Parcels
Whole-Brain Parcels
Weights: Coefficients of Temporal Dynamics for every Parcel
97. 10%
71.55%
95.45%
Average Accuracy with Test Data

# Functional Connectivity Associations with Face Perception during a Working Memory Task

Mohammed Abumuaileq, Gili Karni, Jovicarole Raya

## Introduction

The fusiform face area, FFA, is known as a region of the human brain that appears to play a key role in face perception (FP) [1]. Although the FFA shows the strongest increase in BOLD response to faces, it is not exclusive [2]. So, can we decode the type of stimuli based on neural activity? How does the brain discriminate faces from other visual stimuli? Specifically, what are the networks involved and how do these regions covary in visual working memory processes [3]?

## Methodology Overview

**Data** - We used the HCP dataset. The data include functional recordings from 360 cortical regions of N=339 participants undergo various cognitive tasks. We focused on the working memory task - a block design n-back task including stimuli of faces, bodies, places, and tools.

**Analysis** - We focused on two methods: logistic regression and correlation analysis. We used the logistic regression to decode stimuli from its corresponding neural activity and the correlations to further investigate the functional connectivity underlying this activity.

## Conclusions

Conclusion-

- We identified FP pathways and successfully discriminated between different stimuli

Future Directions -

- Explore the relationship between attention and FP
- Delve into hemisphere-specific contributions to FP

Learning Highlights

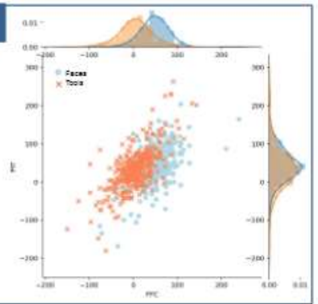
- Intra-disciplinary, cross-cultural collaboration
- Functional connectivity analysis & statistical analysis in python

## Acknowledgements

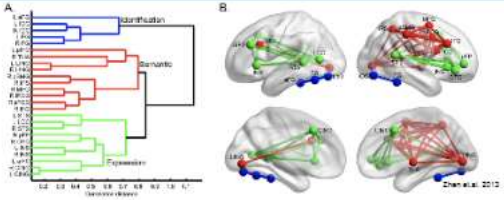
We would like to thank Neuromatch Academy for providing us with this open source education and connecting scientists around the world. We would also like to thank our mentor Pooya Pakarian for his guidance and our tutor Dana Glenn for all of her support.

## Can we discriminate the stimuli type using the functional activity?

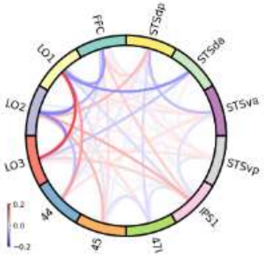
- We built a logistic regression model with an elastic-net regularizer. Using CV, we tuned the model's hyper-parameters. The testing set indicates a 100% discriminatory capacity between faces and tool (in the 2-back task). We were also suspicious. Importantly, the model performed approximately as well discriminating between any two categories.
- We investigated the difference between FFC and PIT activation. The plot demonstrates their discriminability.
- The top predictors (faces-tools) are the Fusiform face Cortex (FFC), the Posterior Inferior Temporal (PIT), and the dorsal anterior Superior Temporal Sulcus (STSda) - which are known to participate in face recognition, FP, and the interpretation of facial expressions, accordingly [7,5,4].
- The top 5 predictors discriminating between non face stimuli were all in the visual network whereas the predictors discriminating faces from non face stimuli included posterior ROIS, DAN ROIs, and DMN ROIs.




## What are the networks involved in the discrimination of faces from other stimuli?

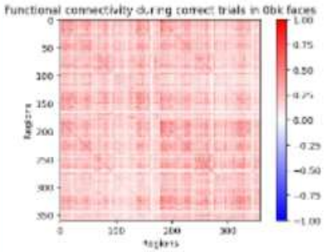


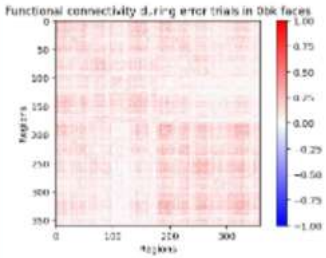

- The FFA is part of a few networks participating in facial processing, specifically there is evidence for FP in, among others, the inferior occipital gyrus (IOG), the STS, the intraparietal sulcus (IPS) [6,7]. See figure above.




- We calculated the partial correlations of (1) face stimuli and (2) tools stimuli activation to estimate the difference in functional connectivity. Using bootstrapping, we are able to present only significant results.
- Mostly, the lateral occipital sulcus showed stronger intra-connectivity to face stimuli (over tools stimuli). In addition its connectivity to the STS and FFA is stronger. Both are consistent with the literature [6].
- Unsupported by literature, some regions show a lower connectivity in faces compared to tools. Among them, LO1 and LO3, IPS connectivity to LOs and the FFS.

## How different is the activation pattern between correct and incorrect identification of faces?




- We used correlation to explore the differences between successful and unsuccessful instances during the face block of the 0-back task.
- The figures indicate that (A) the connectivity of the right hemisphere, regions 0-180, is weaker than the left hemisphere in both in the correct and in the incorrect instances and (B) the correct instances evoke all together a stronger correlation than the error ones.
- Current literature states that facial recognition favors of the right hemisphere while the left hemisphere had difficulty processing unfamiliar faces [8].
- The gap between the intra-hemisphere connectivity poses an interesting question about the respective roles of each hemisphere.

## Contact

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## References

1. Kanwisher, N., & Yovel, G. (2006). The fusiform face area: a cortical region specialized for the perception of faces. Philosophical Transactions of the Royal Society B: Biological Sciences, 361(1476), 2109-2128.
2. Tsao, D. Y., & Livingstone, M. S. (2008). Mechanisms of face perception. Annu. Rev. Neurosci., 31, 411-437.
3. Lamichhane, B., & Dhamala, M. (2015). Perceptual decision-making difficulty modulates feedforward effective connectivity to the dorsolateral prefrontal cortex. Frontiers in human neuroscience, 9, 498.
4. Direito B, Lima J, Simões M, et al. Targeting dynamic facial processing mechanisms in superior temporal sulcus using a novel fMRI neurofeedback target. Neuroscience. 2019;496:97-108. doi:10.1016/j.neuroscience.2019.02.024
5. Haxby indicates that a few studies have found face perception in the inferior temporal sulcus, with the majority of sites elsewhere in the brain: p.2, Haxby, et al. (2000) "The distributed human neural system for face perception" Trends in Cognitive Sciences 4 (6) June 2000. 11pp.
6. Zhen, Z., Fang, H., & Liu, J. (2013). The hierarchical brain network for face recognition. PloS one, 8(3), e59886.
7. Nagy, K., Greenlee, M. W., & Kovács, G. (2012). The lateral occipital cortex in the face perception network: an effective connectivity study. Frontiers in psychology, 3, 141.
8. Júnior, R. d. M., Marinho de Sousa, B., & Fukusima, S. (2014). Hemispheric specialization in face recognition: From spatial frequencies to holistic/analytic cognitive processing. Psychology & Neuroscience, 7(4), 503-511. http://dx.doi.org/10.3922/j.psns.2014.4.09

# DECODING SEVEN TASK STATES FROM FMRI ACTIVATION PATTERNS: A DEEP LEARNING APPROACH

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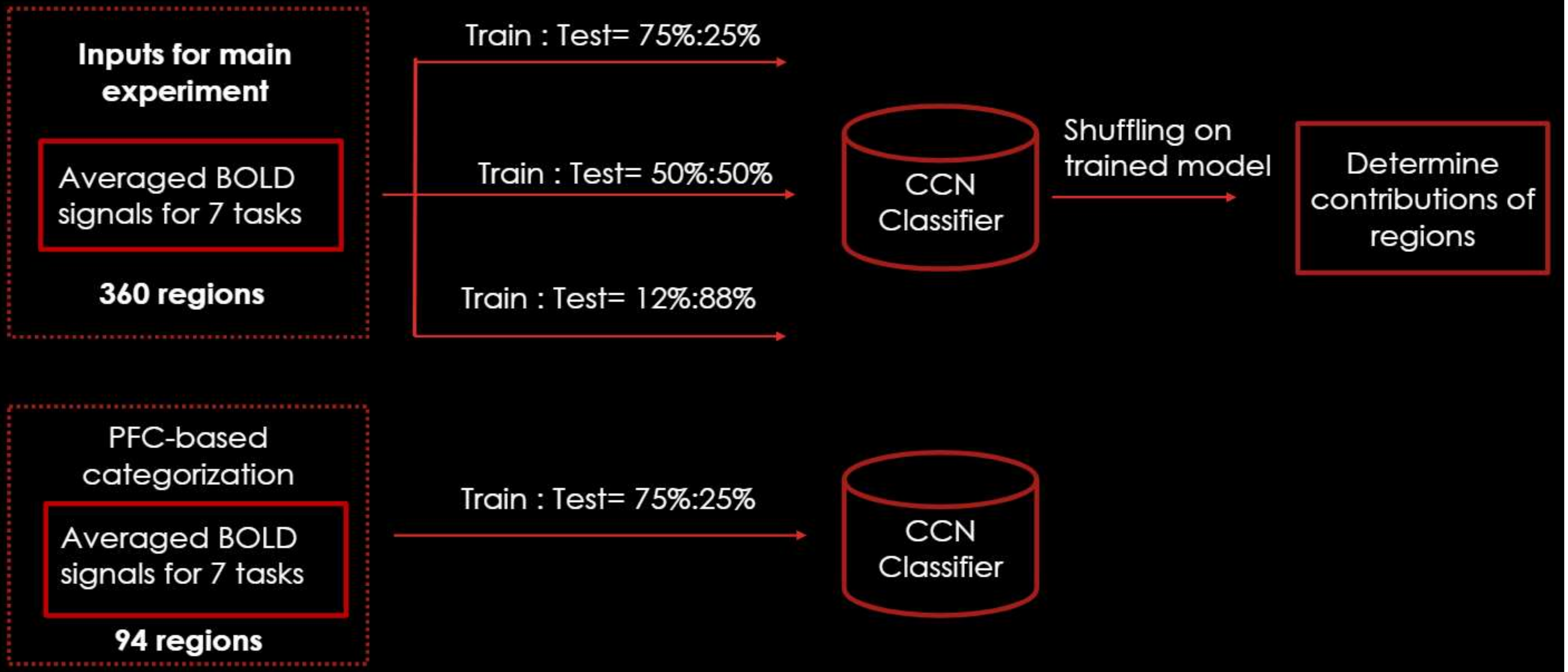
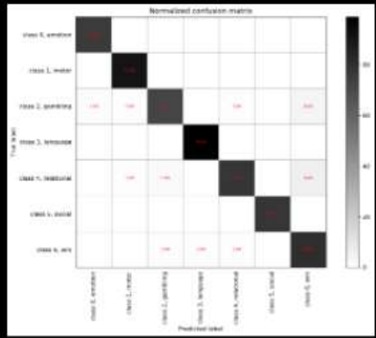
# AIM: USING CONVOLUTIONAL NEURAL NETWORKS (CNN) TO CLASSIFY 7 TASK STATES BASED ON TASK-BASED FMRI OF THE HUMAN BRAIN

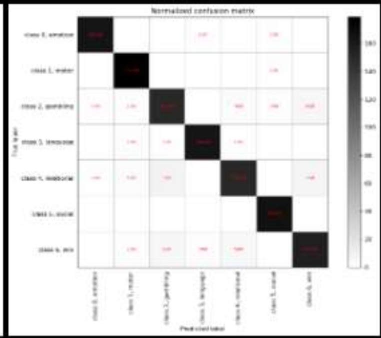


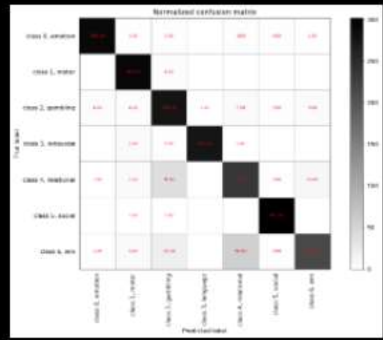
# RESULTS

- Classifying **7** task states from trial-averaged task-based fMRI activation patterns with the CNN algorithm attained an average accuracy of exceeding **90%** across tasks

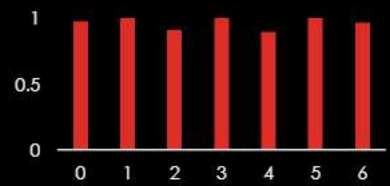
- ACC retains to above **90%** even after **decreasing** the training set to **40 subjects**





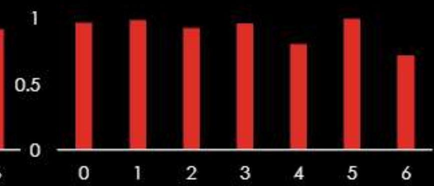


test_rate = 0.25 ACC




test_rate = 0.5 ACC


test_rate = 0.88 ACC



# RESULTS

- Shuffling the classification label of 1 in 22 sections
- Randomizing the classification label of the brain regions that belong to the shuffled section.

- ACC all above .72
- ACC varied within tasks
  - WM, relational <80%
  - Highest: social and motor
  - Emotion and math >90%
- Implication
  - Network-based classification