Title

Predicting an Individual's Cerebellar Activity from Functional Connectivity Fingerprints

Running Title: Connectome Fingerprinting of the Cerebellum

Authors

Vaibhav Tripathi, David C. Somers
Psychological and Brain Sciences, Boston University, 64 Cummington Mall, Boston, MA 02215

Corresponding author: vaibhavt@bu.edu

Abstract

The cerebellum is gaining scientific attention as a key neural substrate of cognitive function; however, individual differences in the cerebellar organization have not yet been well studied. Individual differences in functional brain organization can be closely tied to individual differences in brain connectivity. 'Connectome Fingerprinting' is a modeling approach that predicts an individual's brain activity from their connectome. Here, we extend 'Connectome Fingerprinting' (CF) to the cerebellum. We examined functional MRI data from 160 subjects (98 females) of the Human Connectome Project young adult dataset. For each of seven cognitive task paradigms, we constructed CF models from task activation maps and resting-state cortico-cerebellar functional connectomes, using a set of training subjects. For each model, we then predicted task activation in novel individual subjects, using their resting-state functional connectomes. In each cognitive paradigm, the CF models predicted individual subject cerebellar activity patterns with significantly greater precision than did predictions from the group average task activation. Examination of the CF models revealed that the cortico-cerebellar connections that carried the most information were those made with the non-motor portions of the cerebral cortex. These results demonstrate that the fine-scale functional connectivity between the cerebral cortex and cerebellum carries important information about individual differences in cerebellar functional organization. Additionally, CF modeling may be useful in the examination of patients with cerebellar dysfunction, since model predictions require only resting-state fMRI data which is more easily obtained than task fMRI.

Highlights

- Cortico-cerebellar functional connectivity predicts cerebellar task activation
- A single connectome measurement can predict across a multi-domain task battery
- Predictions are unique to the individual
- Findings indicate highly specific cerebellar contributions to cognition

Introduction

Although traditionally viewed primarily as a motor structure, the cerebellum supports a broad range of non-motor cognitive functions, including working memory, attention, language and higher cognition (Stoodley & Schmahmann, 2009; Schmahmann, 2019; Brissenden et al., 2021). This view is supported both by studies of patients with cerebellar damage and by neuroimaging studies of healthy subjects (Schmahmann et al., 2007; Stoodley et al., 2012). Brain networks supporting specific forms of cognition comprise not only cerebral cortical regions but also cerebellar regions and there's growing evidence for fine-scale cerebro-cerebellar connectivity (Buckner et al., 2011; Liu et al., 2022). The fact that cerebro-cerebellar anatomical connectivity is not monosynaptic complicates the analysis of these networks. Descending connections pass via the pons and ascending connections pass via the thalamus (Steriade & Llinas, 1988). Resting-state functional MRI has proven an effective way to reveal multisynaptic brain networks generally (Gordon et al., 2017) and cerebro-cerebellar networks more specifically (Guell et al., 2018).

Most neuroimaging investigations of cerebellar function have been focused on group-level analyses. In contrast, individual subject-level analysis offers a number of potential advantages, including the ability to observe fine-scale structures that would be blurred by group analyses and the ability to develop precision medicine diagnostics for individual patients (Braga & Buckner, 2017; Somers et al., 2021; Xue et al., 2021). Here we extend individual subject research methods that have been applied to the cerebral cortex to the cerebellum.

Passingham and colleagues proposed that each cortical area has a unique pattern of cortico-cortical connections – a *'connectional fingerprint'* – that could be used to functionally localize cortical areas in individuals (Mars et al., 2018). Multiple studies have utilized functional and structural connectivity measures to model an individual region's connectivity fingerprints and use them to make functional network predictions (Tavor et al., 2016; Cole et al., 2016; Murty et al., 2020; King et al., 2023; Bernstein-Eliav & Tavor, 2022). Connectome Fingerprinting (CF) is a computational neuroimaging technique that combines non-invasive connectome measurements to predict fine-scale functional brain organization in individual subjects (Osher et al., 2016; Saygin et al., 2012; Tobyne et al., 2018). CF modeling approaches based on connectomes derived from structural or resting-state functional MRI have been successfully applied throughout the cerebral cortex; however, the cerebellum has received little attention to date. King et. al. (2023) utilized an activity flow method (Cole et al., 2016) to model cerebellar connectivity and relationship with cortical task activations. Connectome Fingerprinting predicts voxel-wise activations to a particular task from the resting state functional connectivity from voxels in a search space to regions in a parcellation

scheme. Utilizing high-quality resting state data, we can predict with sufficient accuracy the activations in out-of-sample subjects (Tavor et al., 2016) even with low n datasets (Osher et al., 2019; Tobyne et al., 2018).

We utilized task and resting-state fMRI data from the Human Connectome Project (HCP) young adult dataset (n=160). The HCP examined seven cognitive paradigms that probed a diverse set of brain networks: Working memory, Gambling, Motor, Language, Social, Relational, and Emotion. Each task compared an experimental condition with a control condition as well as a fixation baseline condition. The Working Memory and Motor tasks also included sub-conditions, with different categories of visual images in the working memory task and different body parts in the motor task. Group-level task activation in these paradigms is reported by Barch et al. (2013). We developed CF models for the seven cognitive tasks and compared our performance with group average activation as the baseline. We then compared the specificity of an individual's connectome in its functional activation prediction compared to other subjects and group-averaged connectomes. We also analyzed the degree to which cerebellar-cortical connectivity varies across the cerebellum. We further examined the relationship between model coefficients and cortical activations to highlight the close link between cerebellar-cortical function and connectivity.

Methods

Dataset

We used 160 subjects (98 females) from the Human Connectome Project Young Adult (HCP-YA) dataset (Van Essen et al., 2012) who had acquisitions on both 3T and 7T scanners. The HCP Young Adult initiative collected high-quality structural, resting state and task data on a population of young adults (ages 22-35 years).
The study was approved by the Washington University Institutional Review Board and all subjects gave informed consent for the study. The dataset is available to all on HCP's data management platform, ConnectomeDB (https://db.humanconnectome.org).
A custom Siemens CONNECTOM Skyra MRI Scanner was used. All subjects participated in two days of scanning which included a high-resolution structural T1 weighted MRI, T2 weighted MRI. During resting-state scans (32 channel head coil, voxel resolution = 2 mm isotropic, in-plane FOV = 208 × 180 mm, 72 slices, multi-band factor 8, TR = 720 ms, TE = 33.1 ms, 1200 TRs) subjects were asked to visually fixate on a cross and do nothing, in particular. Resting-state scans consisted of four runs of

fifteen minutes each collected in two separate sessions. The task runs had the same acquisition protocol but differed in the number of frames (TRs). Half of the task and resting-state runs were acquired using left-to-right phase encoding and another half on the right-to-left phase encoding.

The subjects participated in seven task experiments in the scanner that examined different aspects of cognition: Working memory, Gambling, Motor, Language, Social, Relational, Emotion. We describe the tasks briefly here, details can be found in the initial HCP task fMRI paper (Barch et al., 2013). The working memory task involved a '2-back' working memory condition in which subjects were asked to report when the current stimulus matched a stimulus presented two trials prior, and a '0-back' control condition in which subjects were asked to report when a presented stimulus matched a target that was presented at the start of the block. Stimuli were presented in blocks and across blocks four different categories of images were employed: places, faces, body parts and tools. There were 8 task blocks per run, half of the blocks were 2-back, and the other half were 0-back. Task blocks were 25 s long with 10 trials per block. There were also 4 fixation blocks per run of 15 s each. Total 405 TRs were collected per run. We explored the 2-back vs 0-back, 2-back body, 2-back face, 2-back place, and 2-back tool contrasts.

The Gambling task compared reward processing to loss processing using a shared task paradigm; the key manipulation was to covertly change the odds of rewards/losses across blocks of trials. On each trial, a mystery card was presented on the screen and the subject had to guess if the number on the card would be higher or lower than five. Reward blocks had mostly reward trials (6 out of 8, and others could be loss and/or neutral trials) whereas Punish blocks had mostly loss trials (6 out of 8, and others could be neutral and/or reward trials). Each run had two blocks of reward and punish 28 s each and four fixation blocks of 15 s each and a total of 253 TRs. We explored the Punish-Fix and Reward-Fix conditions.

The Motor task involved visual cues where subjects were asked to tap either their left or right fingers, squeeze either their left or right toes or move the tongue. The blocks were 12 s long and each run consisted of two blocks for each movement (Left Hand, Right Hand, Left Foot, Right Foot, and Tongue) and three fixation blocks of 15 s each. Total of 284 TRs per run were collected. We analyzed the vs average (AVG) contrasts for all the five conditions (LH, LH, RF, RH, T) where the average included all other than selected condition. The Language task consisted of four 'story' task and four 'math' task blocks per run. The 'story' condition blocks consisted of stories from Aesop's fables and subjects were asked to respond via button press to a 2-alternative forced-choice (2-AFC) question about the topic of the story. The 'math' condition blocks consisted of

auditory presentations of math calculations like “eight plus five equals” followed by two possible answers; subjects reported the correct answer via button press. The duration of the blocks were fixed at 30 s, some subjects performed the math computations faster, so they were given additional trials to match the duration of the story blocks. Each run was 316 TRs long and we studied the Math vs Story contrast for the language task.

The Social Cognition Task or ‘Theory of Mind’ task incorporated video clips of 20 s long of simple shapes (e.g., squares, circles and triangles) that moved across a background. In the ‘Theory of Mind’ condition, the coordinated movement of the shapes suggested a social interaction between them, while in the control condition the shapes moved about independently of one another. Each run had five video blocks, a total of ten across the two runs (five for each of the two conditions). The subjects were asked to report whether they observed a social interaction, no interaction or were not sure about the interaction. Each run had 5 fixation blocks of 15 s each and a total of 274 TRs and we examined the Random vs Fix and Theory of Mind vs Fix conditions.

The Relational Task asked subjects to infer a relationship between two objects and to examine that relationship between another pair of objects. Stimuli consisted of shapes that had a certain texture. In the relational task condition, subjects had to compare two shapes on the top of the screen with each other to determine whether they differed in shape or texture and then report whether the two shapes on the bottom also differed along the same dimension or not. In the matching control condition, subjects were presented with two shapes on the top, one on the bottom and a cue (shape or texture) and were asked to report whether the bottom shape was similar to either of the top shapes in the cued dimension. Each run had three relational and three match blocks that lasted 18 s and three fixation blocks of 16 s length, with a total of 232 TRs and we analyzed the Match vs fix and Relational vs fix contrasts.

The Emotion task asked subjects to examine facial expressions of emotions. Stimuli consisted of faces (experimental) and shapes (control) conditions during which subjects were presented with two faces/shapes on the top and one face/shape on the bottom and they were ask to match the bottom face/shape with the top ones and report via button press which top face/shape was similar to the bottom one. The faces had either angry or fearful expressions. Each run consisted of three faces and three shapes blocks (all 18 s long) and had a total of 176 TRs and we looked over the Faces vs fix and Shapes vs fix contrasts.

Preprocessing

We used the minimally preprocessed data as available on the HCP database portal. The preprocessing pipeline (Glasser et al., 2013) included corrections for artifact, gradient non-linearity correction, motion and EPI distortion followed by temporal denoising and bandpass filtering (0.001 - 0.008 Hz). The structural and functional images were registered from the native space to MNI space. Freesurfer pipeline (Dale et al., 1999; Fischl et al., 1999) was used to convert it to the 168k fsaverage space which was converted to the 32k CIFTI “grayordinates” space which included the two cerebral hemispheres as surfaces and the subcortical regions as volumes registered in the MNI 2mm space. The data was spatially smoothed with a 2 mm FWHM. We demeaned the resting state data across time within each voxel/vertex and regressed out the mean global signal and concatenated the four runs resulting in 60 minutes (total 4800 TRs) of resting-state data per subject.

GLM Analysis

General Linear Model analysis of the task data was performed using modified scripts (https://github.com/Washington-University/HCPpipelines/tree/master/TaskfMRIAnalysis) as made available by the HCP consortium (Barch et al., 2013; Glasser et al., 2016). The already analyzed files were downloaded from the analysis section from the HCP database (db.humanconnectome.org). The modified scripts run the FSL-based GLM analysis (Jenkinson et al., 2012) on each voxel/vertex in the 91k grayordinates space. Block-based analysis was performed using a double gamma HRF as implemented in FSL. The contrasts used for various tasks are Working Memory (2BK_BODY vs. fix, 2BK_FACE vs. fix, 2BK_PLACE vs. fix, 2BK_TOOL vs. fix, 2BK vs. 0BK), Gambling (PUNISH vs. fix, REWARD vs. fix), Motor (LH vs AVG, RH vs. AVG, LF vs. AVG, RF vs. AVG, T vs. AVG), Language (MATH vs. STORY), Social (Theory of Mind/TOM vs. fix, RANDOM vs. fix), Relational (REL vs. fix, MATCH vs. fix), Emotion (FACES vs. fix, SHAPES vs. fix).

Connectivity Fingerprinting

We used the connectivity fingerprinting (CF) approach using resting-state functional connectivity data as described in (Tobyne et al., 2018), illustrated in Figure 1. First, we divided our 160 subjects into test and training datasets consisting of 80 subjects in each group. Prior work demonstrates that as few as 20 training subjects can be sufficient for strong model performance, as the number of fMRI task time points in the training set is generally more important than the number of subjects (Tik et al., 2023). For a selected contrast, we computed the cerebellar search space as the region with the absolute value of the group average activations greater than 1.5 t-statistic value. Based on the criteria for the selection of search space, few contrasts (Gambling: PUNISH vs REWARD; Language: MATH, STORY; Social: TOM vs RANDOM; Relational MATCH

vs REL; Emotion: FACES vs SHAPES) did not have task-relevant voxels and were not included further in the analysis. For all voxels in the selected search space, we created a resting-state functional connectivity matrix of dimensions voxels x ROIs where the ROIs were defined in the cortex using the Schaefer 400 atlas (Schaefer et al., 2017). The resting-state time series data were averaged in the ROIs and then the functional connectivity matrix was computed. We appended the connectivity matrices across the training dataset, and we created a composite predictor matrix. The target matrix was composed of the task activations across the search space appended across the subjects in the training dataset. Using a k-fold (10 folds) ridge regression method as implemented in Scikit Learn (Pedregosa et al., 2011), we trained a model separately for each contrast. The k-folds were used to optimize the hyperparameter in the ridge regression. Using the trained model, we applied our model to the test dataset and computed the prediction accuracy as the Pearson correlation between the actual and the predicted activations. We plotted the predicted activations back on the search space for visualization. To compare the performance of the CF model, we used group average (GroupAvg) as the control model where group averaged t statistic values in the search space for the selected task contrast were taken as the prediction for all subjects and compared with the actual activations. We compared the prediction accuracies using the CF and the GroupAvg model using paired t-test as defined in the statsmodels python package (Seabold & Perktold, 2010). Visualizations in the SUIT space (Diedrichsen & Zotow, 2015) were done using the SUITpy python toolbox (https://github.com/diedrichsenlab/SUITPy/releases/latest). To determine if the individual's functional connectivity was better suited for within-subject prediction, we used the subject's own functional connectivity (self) and other subjects' connectivity (others) to predict and compare with the subject's activation. We also used the group average functional connectivity to make individual predictions.

We also analyzed the variance of task activity explained by individual subjects' activations and group activations by taking the square of the Pearson correlation between group averaged activations and our subjects' individualized task activations. We also computed the across-subjects variance in the cerebellar-cortical connectivity using the approach by Marek and colleagues (Marek et al., 2018) where we computed the Fisher-z transformation across all cerebellar-cortical connectivity followed by computing the variance across subjects, averaging it across parcels and then taking a square root to get standard deviation values.

The coefficients from the trained model for each contrast were correlated with task activations averaged across the ROIs and subjects to analyze what predictors contributed more to the predictions. The analysis codes were written in Python and

used Numpy (Harris et al., 2020), Scipy (Virtanen et al., 2020) and Nipy (https://github.com/nipy/nipy) toolboxes.

Results

Prediction accuracy for CF models across various tasks

We analyzed the ability to use resting-state functional connectivity to predict task activations in the human cerebellum using the HCP dataset. We used the Connectome Fingerprinting approach as demonstrated in Figure 1. We evaluated the quality of predictions by examining the correlation between the actual pattern and the predicted pattern of t-statistics across the cerebellar search space. We also examined the correlation between each subject's actual pattern of activation and the group-averaged pattern of activation for the selected task contrast. This analysis was performed for all subjects of the test set and performance was compared between the CF and group-average predictions.

The Working Memory task visually presented sequences of images and asked subjects to report when a stimulus matched the stimulus shown two stimuli before (2-back task). This was contrasted with a 0-back condition in which subjects were asked to report when a stimulus match a target stimulus presented prior to the block of trials. The 2-back condition created greater working memory demands (e.g., encoding, manipulation) than did the 0-back condition. The CF model predicted individual subject activations in the cerebellum in the 2-back vs. 0-back (2BK_0BK, Figure 2) contrast significantly better than did the group average approach (CF Mean accuracy=0.30, SD=0.17; GroupAvg M=0.08, SD=0.05; paired t test - $t(79) = 12.00$, $p<0.0001$, Cohen's d=1.78). The 2-back trials were presented in blocks in which the stimuli were restricted to one of four categories of images: bodies, faces, places, or tools. These sub-conditions were each contrasted with the fixation condition, yielding four additional contrasts of interest: 2BK_BODY, 2BK_FACE, 2BK_PLACE, and 2BK_TOOL. For each of these contrasts the CF models outperformed the group average predictions: 2BK_BODY (CF M=0.30, SD=0.13; GroupAvg M=0.15, SD=0.06; $t(79) = 10.44$, $p<0.0001$, Cohen's d=1.52); 2BK_FACE (CF M=0.30, SD=0.13; GroupAvg M=0.10, SD=0.06; $t(79) = 12.90$, $p<0.0001$, Cohen's d=1.52); 2BK_PLACE (CF M=0.32, SD=0.12; GroupAvg M=0.11, SD=0.06; $t(79) = 15.48$, $p<0.0001$, Cohen's d=2.26), 2BK_TOOL (CF M=0.31, SD=0.13; GroupAvg M=0.14, SD=0.05; $t(79) = 12.01$, $p<0.0001$, Cohen's d=1.73).

The Gambling task involved reward based processing and the CF model made significant predictions (Figure 3) for the PUNISH (CF (M=0.34, SD=0.15), GroupAvg

(M=0.18, SD=0.07); t(79) = 9.49, p<0.0001, Cohen's d=1.41) and REWARD (CF(M=0.36,SD=0.12), GroupAvg(M=0.08,SD=0.06); t(79) = 18.55, p<0.0001, Cohen's d=2.75) conditions.

In the Motor task, subjects had to tap their left hand, left foot, right hand, right foot and tongue during different task blocks. The overall prediction accuracy for the CF models (Figure 4) was lower for the motor contrasts but significant for Left Hand - Average (CF(M=0.16, SD=0.15) GroupAvg (M=0.07, SD=0.11); t(79) = 5.07, p<0.001, Cohen's d=0.68), RIght Hand - Average (CF(M=0.22, SD=0.17), GroupAvg(M=0.08,SD=0.09); t(79) = 7.41, p<0.0001, Cohen's d=1.08), Right Foot - Average (CF(M=0.15, SD=0.15), GroupAvg(M=0.05, SD=0.12); t(79) = 4.77, p<0.001, Cohen's d=0.69) but not significant for Left Foot - Average (CF (M=0.09, SD=0.12), GroupAvg(M=0.07, SD=0.14); t(79) = 1.37, p=0.175, Cohen's d=0.18) and Tongue - Average (CF(M=0.39,SD=0.15) GroupAvg(M=0.41,SD=0.13); t(79) = -1.66, p=0.100, Cohen's d=-0.12). In the motor task, the average is computed across all conditions except the contrasted condition, for example, in the Left Hand - Average contrast, the average is computed over the right hand, left and right foot and tongue.

In the language task, subjects had to either perform mental calculations in the math condition or comprehend a story and answer true or false questions related to the story. In the MATH-STORY contrast, the prediction accuracy (Figure 5) was high for the CF models as well as Group average models (CF(M=0.68, SD=0.14), GroupAvg(M=0.68, SD=0.08) but there was no statistical difference between the two models (t(79) = 0.21, p=0.836, Cohen's d=0.03)

The social task involved looking at the interactions between different shapes moving and making a sense of whether the interaction was random or involved the theory of mind (TOM) condition. The prediction accuracy for CF model (Figure 6) was significantly higher as compared to Group Average model for both random (CF(M=0.34, SD=0.12), GroupAvg(M=0.11, SD=0.09); t(79) = 15.56, p<0.0001, Cohen's d=2.13) and TOM (CF(M=0.36, SD=0.12), GroupAvg(M=0.13, SD=0.08); t(79) = 15.69, p<0.0001, Cohen's d=2.21) conditions. In the relational task, subjects had to compare shapes or textures of objects presented on the screen to whether they related along a dimension or one object match the others along the cued dimension. The CF model (Figure 7) performed significantly better in both Match control (CF(M=0.37, SD=0.11), GroupAvg(M=0.14, SD=0.07); t(79) = 17.82, p<0.0001, Cohen's d=2.49) and Relational (CF(M=0.40, SD=0.13), GroupAvg(M=0.19, SD=0.06); t(79) = 15.08, p<0.0001, Cohen's d=2.10) conditions.

The emotion task involved looking at faces with affect and non-affective shapes to elicit and observe the neural responses to emotions. Though the number of task-relevant voxels were less in the cerebellum for the emotion task, CF model (Figure 8) performed significantly better than the Group average model for both the Faces (CF(M=0.35, SD=0.16), GroupAvg(M=0.03, SD=0.14); $t(79) = 14.20$, $p<0.0001$, Cohen's d=2.19) and Shapes conditions (CF(M=0.35, SD=0.34), GroupAvg(M=0.16, SD=0.34); $t(79) = 3.48$, $p<0.001$, Cohen's d=0.54). The Faces-Shapes contrast did not have task-relevant voxels so was not included in the prediction analysis.

We analyzed the effect of the number of training subjects required for optimal model building and found that beyond thirty subjects, our model performance plateaus (Figure S1). We also replicated these findings for all contrasts, examining an additional 78 testing subjects (see Supplementary Material). We did not observe any significant differences ($F(1,1097) = 2.8$, $p = 0.08$) in model performance between the two test subject pools (Figures S2, S3) for any of the contrasts.

Individual variability in connectivity drives predictions

How does the subjects' connectivity affect the predictions made through the CF model? We tested the prediction accuracy of the model using different subjects' resting-state functional connectivity (Figure 9, Figure S4) and compared if it was better than predictions made using subjects' own functional connectivity which is represented along with the diagonal axis in Fig. 9. Using the subject's own functional connectivity, the predictions across contrasts were higher (Table 1, Column 2) when compared to using other subjects' connectivity (Table 1, Column 3). We found that for all such pairwise combinations possible for 80 subjects (6320), in more than 98% of combinations the subject's connectivity made better predictions for the different contrasts in the working memory task (2BK_BODY- 98.03 %, 2BK_FACE 98.76 %, 2BK_PLACE 99.14 %, 2BK_TOOL 0.98.37). The 2BK-0BK contrast had a reduced value of 93.24 %. The contrasts in the motor tasks had reduced performance within-subject connectivity vs across (LF-AVG 69.09%, LH-AVG 77.08 %, RF-AVG 76.37 %, RH-AVG 87.92 %, T-AVG 89.81 %). The two conditions in the Gambling task also had a very high degree of within-subject connectivity performance (PUNISH - 97.92 %, REWARD - 98.98 %). We saw similar results with the Social task (RANDOM - 98.65 %, TOM 99.38 %) and the Relational task (MATCH 99.25 %, REL 98.97 %). The Emotion task shapes contrast did around 93.11 %, and Language MATH-STORY 92.86 %. The two-sided Kolmogorov-Smirnov statistic for all contrasts except MOTOR LF-AVG came out greater than 0.35, with all $p < 10^{-10}$.

There is a large amount of variability in the cerebellar-cortical connectivity across subjects as other studies have also suggested (Marek et al., 2018). We computed the Fisher-z transform of the correlation between connectivity between the cerebellum and the cortical parcels from the Schaefer 400 atlas. And then computed the variance across subjects followed by averaging across parcels resulting in a variance map. We plotted the across-subjects variance in Figure S9 and found that the cerebellar-cerebral connectivity varied most across the posterior parts of the cerebellum as earlier studies (Marek et al., 2018) have also shown. We found that for most task-relevant search spaces, the connectivity across subjects was weakly correlated (Table 1, Column 4).

We can use subject-averaged functional connectivity to make predictions for a subject's task activation and we found that for most contrast the mean prediction accuracy across the 80 test subjects was pretty low (Table 1, Column 5). The math-story contrast in the language task had strong prediction using subject-averaged functional connectivity but that was still weaker than individual subjects' predictions ($t(79)=-9.7389$, $p<0.0001$) but for the tongue-avg contrast in the motor task had stronger predictions using group average functional connectivity than individual connectivity ($t(79)=6.4604$, $p<0.0001$) suggesting that there is less variability in the tongue regions' cerebellar-cerebral connectivity which is comparable to the CF and GroupAvg predictions discussed in the earlier section.

Table 1: Analysing the averaged model prediction using one's own connectivity, other subjects' connectivity and group-averaged connectivity. And looking at cross-subject correlations which are computed using the correlation between the cerebellar cortical connectivity across subjects.

Task_Contrast	**Averaged prediction using self-connectivity (r)**	**Averaged prediction using others' connectivity (r)**	**Cross-Subject Correlations (r)**	**Averaged prediction using group averaged connectivity (r)**
WM_2BK_BODY	0.3	0.02	M=0.15, SD=0.06	M=0.07, SD=0.09
WM_2BK_FACE	0.3	0.02	M=0.15, SD=0.06	M=0.06, SD=0.08
WM_2BK_PLACE	0.32	0.02	M=0.15, SD=0.06	M=0.07, SD=0.08
WM_2BK_TOOL	0.31	0.03	M=0.14, SD=0.06	M=0.08, SD=0.08

WM_2BK-0BK	0.3	0.01	M=0.18, SD=0.07	M=0.03, SD=0.11
GAMBLING_PUNISH	0.34	0.03	M=0.15, SD=0.07	M=0.09, SD=0.09
GAMBLING_REWARD	0.36	0.02	M=0.15, SD=0.07	M=0.06, SD=0.09
MOTOR_LF-AVG	0.09	0.01	M=0.02, SD=0.05	M=0.07, SD=0.11
MOTOR_LH-AVG	0.16	0.02	M=0.05, SD=0.06	M=0.10, SD=0.13
MOTOR_RF-AVG	0.15	0.02	M=0.03, SD=0.05	M=0.07, SD=0.13
MOTOR_RH-AVG	0.22	0	M=0.05, SD=0.06	M=0.02, SD=0.17
MOTOR_T-AVG	0.39	0.22	M=0.08, SD=0.05	M=0.50, SD=0.12
LANGUAGE_MATH-STORY	0.68	0.43	M=0.18, SD=0.07	M=0.60, SD=0.12
SOCIAL_RANDOM	0.34	0.03	M=0.14, SD=0.06	M=0.09, SD=0.07
SOCIAL_TOM	0.36	0.04	M=0.15, SD=0.06	M=0.14, SD=0.08
RELATIONAL_MATCH	0.37	0.03	M=0.14, SD=0.06	M=0.11, SD=0.09
RELATIONAL_REL	0.4	0.04	M=0.15, SD=0.06	M=0.14, SD=0.10
EMOTION_FACES	0.35	0	M=0.15, SD=0.11	M=0.00, SD=0.18
EMOTION_SHAPES	0.35	0.02	M=0.15, SD=0.20	M=0.08, SD=0.31

We analyzed the variance of cerebellar activity patterns across various tasks and task contrasts to determine how much could be explained by the group-averaged map as compared to the individual map. We found that group average maps can explain about 2-10% of the variance (Table 2) and the rest is explained by the individual maps suggesting a large amount of individual variability. The tongue and the math-story contrast from the language task had the most amount of variance explainable by the group map.

Table 2: Variance of individualized cerebellar task activations explained by group average map.

Task_Contrast	Group Average Map Variance (%age)
WM_2BK_BODY	M=0.02, SD=0.01
WM_2BK_FACE	M=0.02, SD=0.02
WM_2BK_PLACE	M=0.02, SD=0.02
WM_2BK_TOOL	M=0.02, SD=0.02
WM_2BK-0BK	M=0.02, SD=0.02
GAMBLING_PUNISH	M=0.02, SD=0.02
GAMBLING_REWARD	M=0.02, SD=0.02
MOTOR_LF-AVG	M=0.06, SD=0.06
MOTOR_LH-AVG	M=0.05, SD=0.04
MOTOR_RF-AVG	M=0.05, SD=0.05
MOTOR_RH-AVG	M=0.04, SD=0.03
MOTOR_T-AVG	M=0.28, SD=0.12
LANGUAGE_MATH-STORY	M=0.39, SD=0.13
SOCIAL_RANDOM	M=0.04, SD=0.03
SOCIAL_TOM	M=0.06, SD=0.04
RELATIONAL_MATCH	M=0.04, SD=0.03
RELATIONAL_REL	M=0.05, SD=0.03
EMOTION_FACES	M=0.03, SD=0.05
EMOTION_SHAPES	M=0.14, SD=0.18

Relationship between model coefficients and cortical task activations

Earlier studies (Osher et al., 2019) have shown that the model coefficients are similar to group averaged task activations. We saw similar behaviour but with coefficients for predictions in the cerebellum and group averaged task activations in the cortex which were not part of the model dataset. For the contrasts in the Working Memory task, we saw a significant correlation (WM_2BK_BODY: $r(398) = 0.62$, $p<0.0001$; WM_2BK_FACE: $r(398) = 0.66$, $p<0.0001$; WM_2BK_PLACE: $r(398) = 0.68$, $p<0.0001$; WM_2BK_TOOL: $r(398) = 0.65$, $p<0.0001$; WM_2BK-0BK: $r(398) = 0.70$, $p<0.0001$)

between the task activations and ridge regression model coefficients as can be seen in Figure 10 and Figure S5. We saw similar correlations (Figure S7, S8) for Social (RANDOM: $r(398) = 0.46$, $p<0.0001$; TOM: $r(398) = 0.38$, $p<0.001$), Relational (MATCH $r(398) = 0.44$, $p<0.0001$), Language (MATH-STORY: $r(398) = 0.47$, $p<0.0001$) and Gambling tasks (PUNISH: $r(398) = 0.54$, $p<0.0001$; REWARD: $r(398) = 0.33$, $p<0.001$). The activations in the motor regions and coefficients were proportional (Figure S6) but the correlations between coefficients and averaged task activations across the whole brain did not come out to be significant. We did not see correlations between the task activations and coefficients for Emotion tasks.

Discussion

There has been an impetus for predictive modeling of the brain activations during cognitive and somatomotor tasks using resting-state functional connectivity (Cole et al., 2016; Tavor et al., 2016; Tobyne et al., 2018; Osher et al., 2019; Bernstein-Eliav & Tavor, 2022). We extended the connectivity fingerprinting based approach for the cerebellum and found that models created using resting-state connectivity with the cerebral cortex perform much better than only group average based predictions across tasks related to various cognitive modalities like working memory, emotion, theory of mind, gambling, relational and motor task. Our work extends the current literature on the association between connectivity between brain regions and the function of brain regions to the cerebellum which for a long time was thought only to respond to motor movements. Recent studies have found cerebellar involvement in attention (Brissenden et al., 2016), working memory (Brissenden et al., 2018, 2021), emotion and other higher cognitive functions (Schmahmann, 1996, 2010, 2019; Stoodley et al., 2012)

We found out that our Connectome Fingerprinting approach predicts task activations significantly better than the group averaged activations in all seven tasks of the HCP dataset. As we limited our search space to task-relevant voxels, some of the contrasts like Language-Math, Language-Story, Gambling_Punish-Reward, Emotion_Faces-Shapes, Social_TOM-Random, Relational_Match-Rel did not have sufficient activation in the cerebellum to be included in the analysis. It could be due to a lack of differences in the activation of these conditions in the cerebellum or across the brain. Our model also did not outperform statistically for the group average model Motor_Tongue-Average, Language_Math-Story and Emotion_Shapes-fix.

Earlier studies have shown the link between the coefficients of CF models trained on cortical search spaces and cortical task activations (Osher et al., 2019). Here, we see that the coefficients of our models based on search spaces defined in the cerebellum were similar to task activations in the cortical regions suggesting a close link between connectivity and function in the cerebellum. Interestingly, we did not see a similar trend for the emotion tasks which could be due to the small number of voxels that were task-relevant in the cerebellum and hence selected in the search space suggesting that the emotion representations in the cerebellum are not strong. The coefficients for motor areas in the cortex were proportional to the cortical motor area activation but not across all the cortical regions. We also saw the specificity of the individual subjects' functional connectivity in predicting their own activations which other papers have mentioned earlier (Osher et al., 2019; Tavor et al., 2016; Tobyne et al., 2018) suggesting that the cerebellar-cortical connectivity is also individual specific.

Studies have used other approaches to associate connectivity and function. The activity flow model proposed by Cole and colleagues (Cole et al., 2016) models the activity within a region as the accumulation of activity across other regions weighted by their connectivity. King et. al. (2023) utilized this approach to model the cerebellar activity using cortical connectivity in the Multi Domain Task Battery (MDTB) dataset (King et al., 2019). There are differences between the approaches, whereas we identified associations between a region's connectivity and function for a selected task contrast, King and colleagues integrated information across multiple tasks from the cortex and weighted it by different connectivity weights to predict activations in the cortex. We did not explicitly use the cortical activation data in the modeling but our model coefficients incidentally exhibit proportionality to cortical activity. Both studies highlight the organizational structure of the cerebellum in complementary ways. CF modeling has the advantage that cross-subject generalization is built into the model and we don't require a separate dataset for model validation.

Activity flow methods have demonstrated the disruption of connectivity and activation with various cognitive disorders (Hearne et al., 2021; Tik et al., 2021). Models trained to associate connectivity and function can allow for the prediction of individual-specific functional activations for populations like subjects with ADHD, Alzheimer's, Dementia or other disorders who can not perform different cognitive tasks in the scanner. It can also allow us to predict task-specific regions in clinical populations with brain tumors which can aid in better presurgical planning (Parker Jones et al., 2017; Tie et al., 2014; Yao et al., 2021).

There are a few limitations of the work namely the task design in the HCP protocol. HCP dataset is of very high quality in terms of the acquisition using the latest MR

sequences and multi-modal registration approaches like the Multi-Surface Matching (MSM) (Robinson et al., 2014). But the tasks may not be the best to elicit responses for a particular cognitive modality. The data was also limited by the number of runs per modality. Studies have shown that the more amount of data per subject improves the reliability and the robustness of the results (Braga & Buckner, 2017; Gilmore et al., 2021; Gordon et al., 2017; Somers et al., 2021; Xue et al., 2021). The field has been termed deep imaging (Gratton & Braga, 2021). We had a large amount of resting-state data per subject but fewer runs of task data per subject which could have resulted in weaker models overall. Our current approach was limited to regularized regression models which perform better than ordinary least squares models (Tobyne et al., 2018) but there might be better performing non-linear models which would require further exploration in future studies.

Our current paper focused on the tasks in the HCP dataset. We could extend our approach to different datasets which have more focused runs per subject in a specific cognitive modality. We can also perform cross-scanner predictions by training on deep imaging subjects and testing them on studies with large cohorts. The combination of models trained on different tasks for the same cognitive modality requires more in-depth research.

Acknowledgements

We'd like to acknowledge NSF Grant BCS-1829394 for their gracious support of the project.

Code/Data Availability

Human Connectome Project dataset is available on db.humanconnectome.org
Codes are available on request to the authors.

Figures

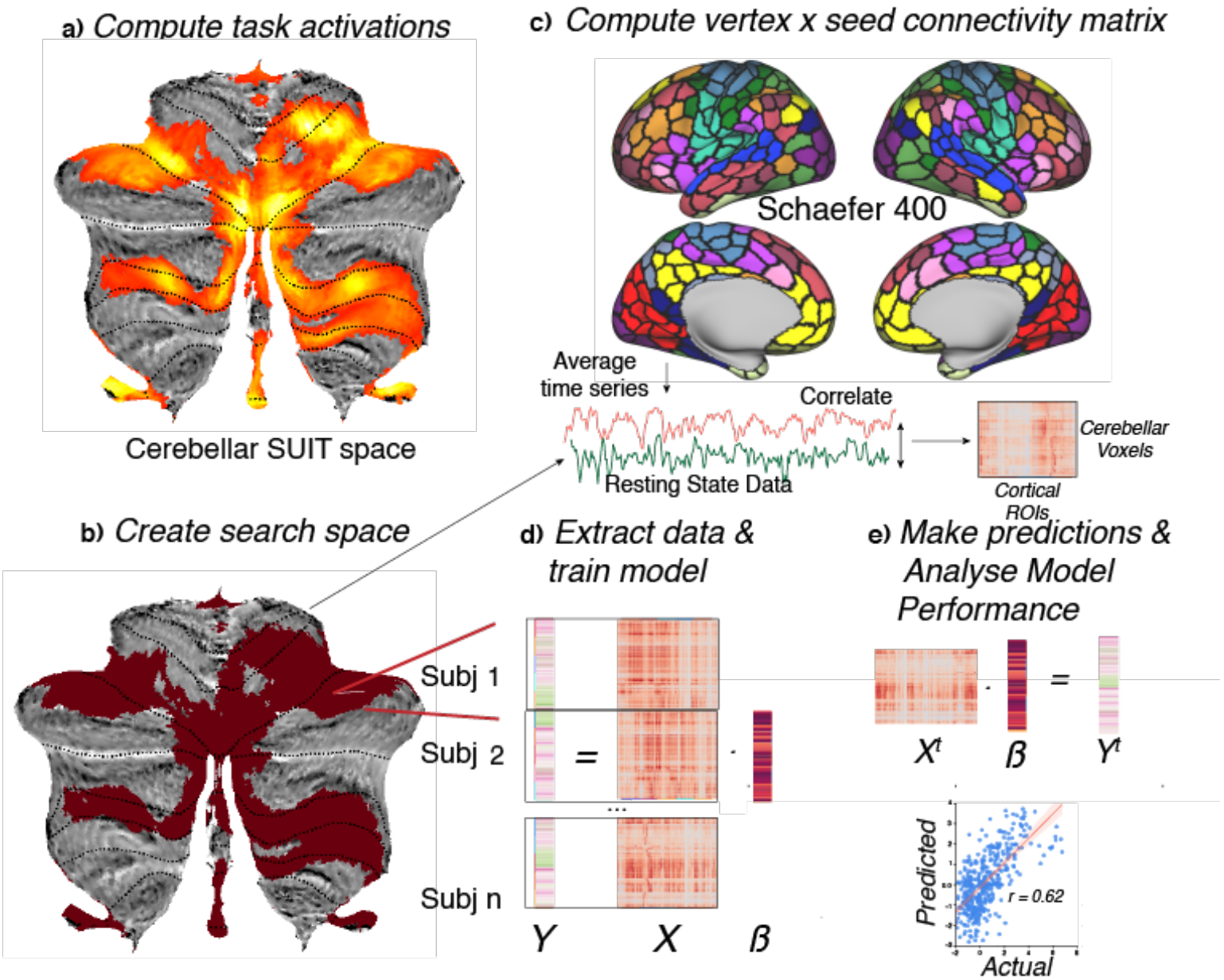

Figure 1: Connectome Fingerprinting Method: We compute the task activations in the cerebellum for a given task and estimate the search space with task-relevant voxels. Then, we create a functional connectivity matrix from the voxels in the search space to cortical parcels defined by a parcellation scheme (here, Schaefer 400 atlas). The connectivity matrices are appended across subjects in the training dataset to create the predictor matrix X. The task activations in the cerebellar search space are appended across training dataset subjects to create the target matrix Y. We then train a ridge regression model with a k-fold cross-validation scheme. The trained model is used to predict activations in the test dataset and the

performance is analyzed across the task. The process is repeated for relevant contrasts across the seven tasks of the Human Connectome Project dataset.

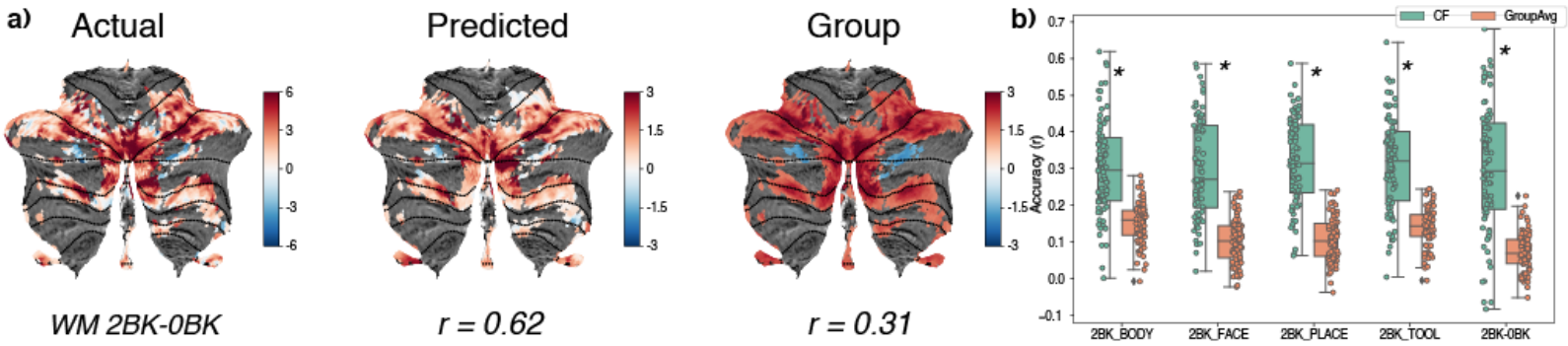

Figure 2: Working memory task predictions. a) Predictions using the CF model (middle panel) and control Group Average model (right panel) for the working memory 2 back vs 0 back contrast. The left panel depicts the actual task activations visualized on the SUIT surface space. b) Prediction accuracy computed as the Pearson correlation coefficient between the predicted and actual activations for the test dataset in the search space for the five contrasts in the working memory task: 2 back Body, 2 back faces, 2 back places, 2 back tools and 2 back vs 0 back. Asterisk depicts statistically significant differences between the prediction accuracies of the two model types.

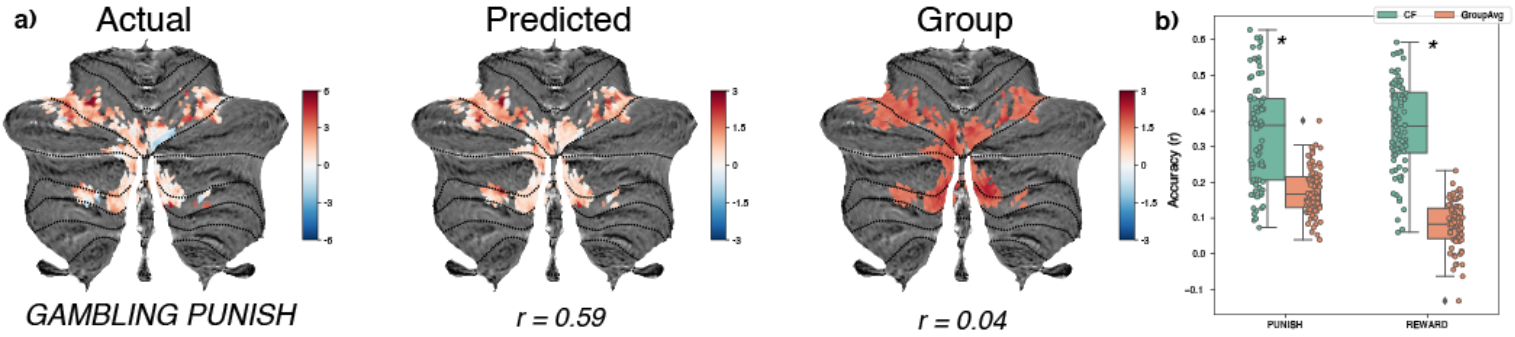

Figure 3: Gambling task predictions. a) Predictions using the CF model (middle panel) and control Group Average model (right panel) for the gambling task punish condition. The left panel depicts the actual task activations. b) Prediction accuracies for the two conditions in the gambling task: Punish (mostly loss trials) and Reward (mostly gain trials). Asterisk depicts statistically significant differences between the prediction accuracies of the two model types.

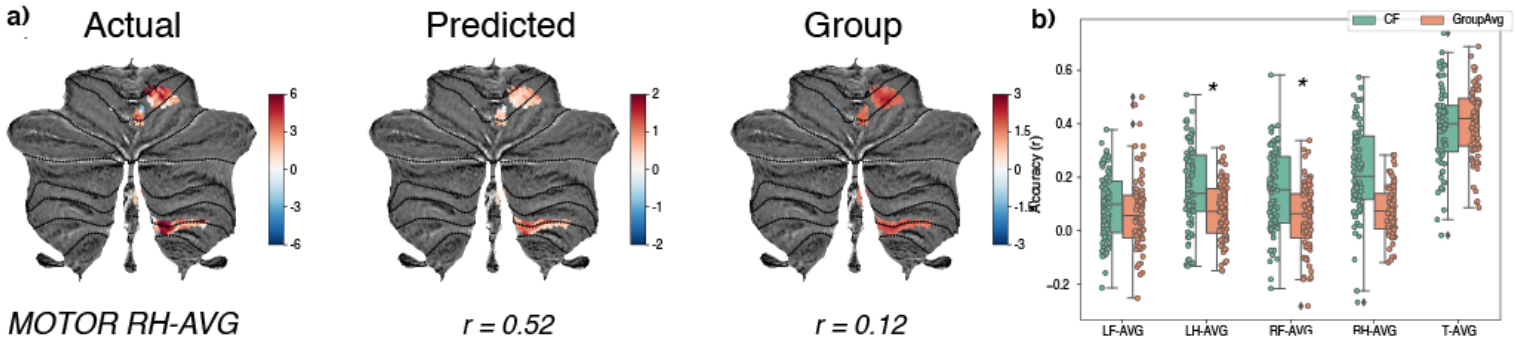

Figure 4: Motor task predictions. a) Predictions using the CF model (middle panel) and control Group Average model (right panel) for the motor task right hand vs average contrast. The left panel depicts the actual task activations. b) In this task subject tapped left and right hand and toes and tongue during a block-based paradigm. Average here refers to average across all except the contrasted one. Prediction accuracies for the five contrasts in the motor task: Left Foot vs Average (LF-AVG), Left Hand vs Average (LH-AVG), Right Foot vs Average (RF-AVG), Right Hand vs Average (RH-AVG) and Tongue vs Average (T-AVG). Asterisk depicts statistically significant differences between the prediction accuracies of the two model types.

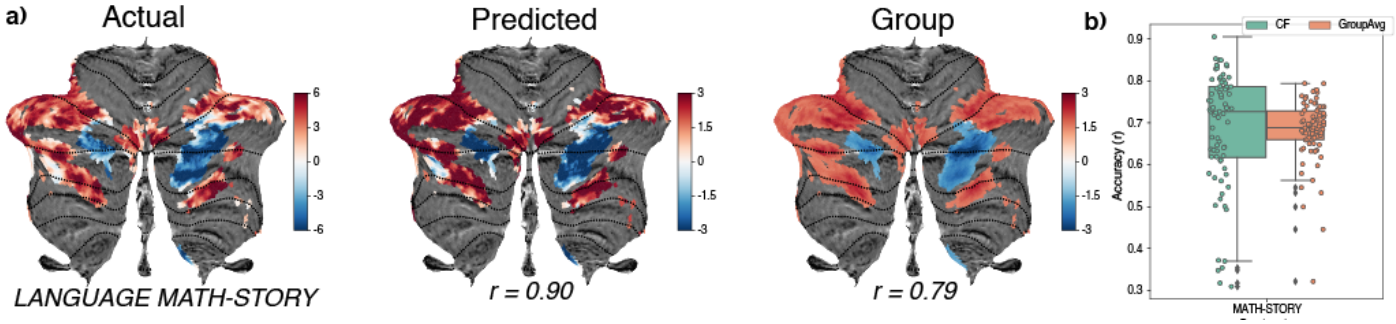

Figure 5: Language task predictions. a) Predictions using the CF model (middle panel) and control Group Average model (right panel) for the language task math vs story contrast. The left panel depicts the actual task activations visualized on the SUIT surface space. b) Prediction accuracy across all subjects using the CF and Group Average control model in the math vs story contrast for the language task where subjects either solve a simple math audio question presented or understand the premise of a short story from Aesop's fables. Asterisk depicts statistically significant differences between the prediction accuracies of the two model types.

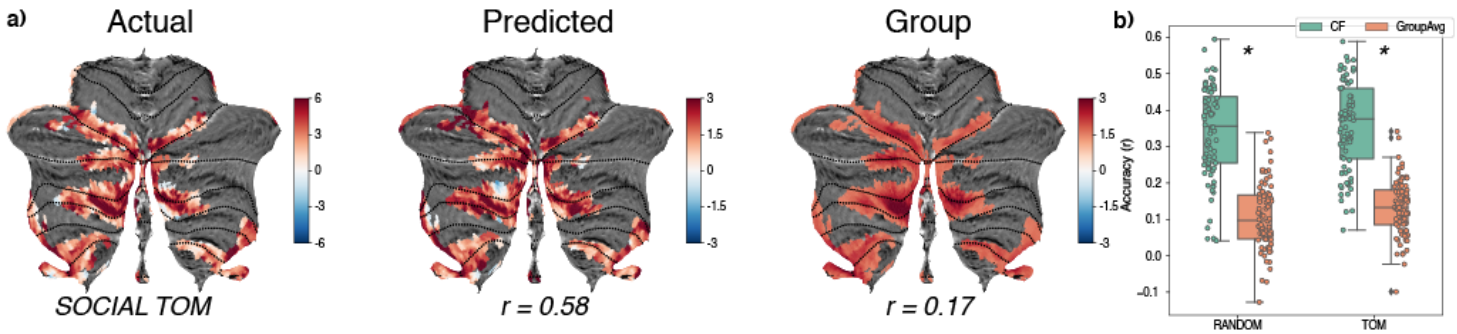

Figure 6: Social task predictions. a) Predictions using the CF model (middle panel) and control Group Average model (right panel) for the social task theory of mind (TOM) condition. The left panel depicts the actual task activations visualized on the SUIT surface space. b) Prediction accuracies across the two model types for all subjects in the random condition where objects on the screen moved randomly or the Theory of Mind (TOM) condition where the objects appeared to have social interaction. Asterisk depicts statistically significant differences between the prediction accuracies of the two model types.

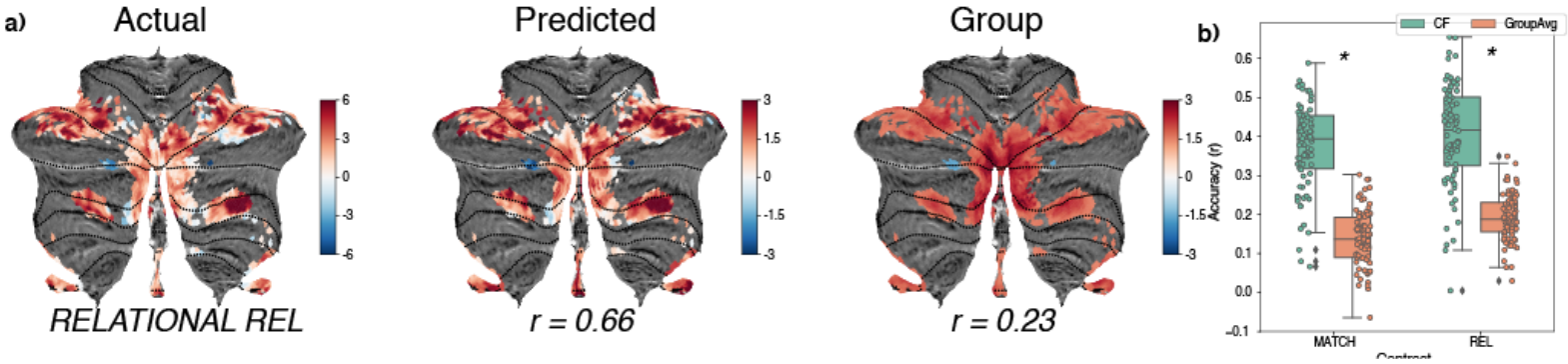

Figure 7: Relational task predictions. a) Predictions using the CF model (middle panel) and control Group Average model (right panel) for the relational task where subjects had to match or compare objects that differed along the dimension of shape or texture. The left panel depicts the actual task activations visualized on the SUIT surface space. b) Prediction accuracies across all subjects in the test dataset compared across the two model types for the match and relational conditions. Asterisk depicts statistically significant differences between the prediction accuracies of the two model types.

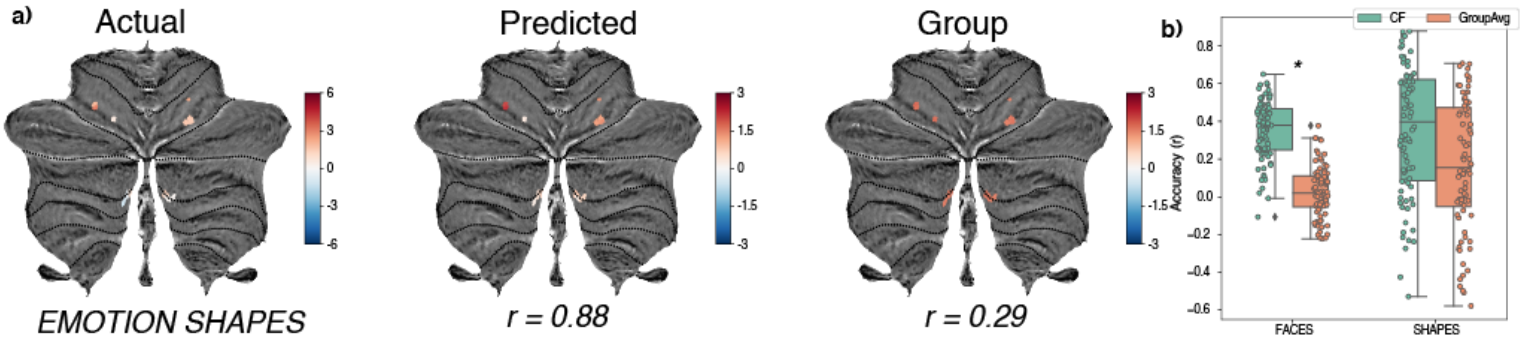

Figure 8: Emotion task Predictions. a) Predictions using the CF model (middle panel) and control Group Average model (right panel) for the emotion task where subjects had to compare either affective faces or shapes. The left panel depicts the actual task activations visualized on the SUIT surface space. b) A very small area of the cerebellum had task-relevant voxels for the emotion task conditions. Prediction accuracies across the test subjects for the two conditions: faces and shapes across the two model types: CF and Group Average. Asterisk depicts statistically significant differences between the prediction accuracies of the two model types.

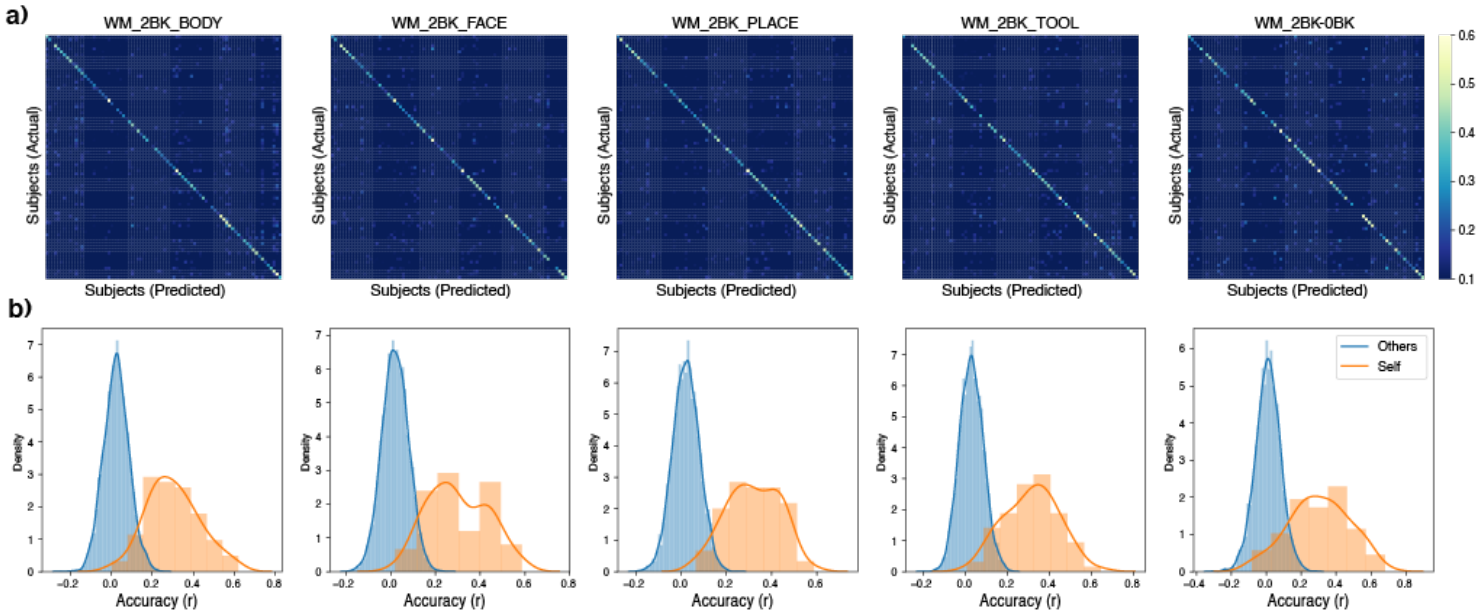

Figure 9: Cross connectivity predictions: a) Predicting a subject's task activation using their own functional connectivity (self) or other subjects' functional connectivity (others) for the working memory task contrasts. We see a diagonal heavy matrix which suggests that there are individual differences in cerebellar-cortical connectivity which is better at predicting the subject's own task activations as compared to other subjects. b) The distribution of the accuracies made using other subjects' connectivity (blue) compared to self connectivity (orange).

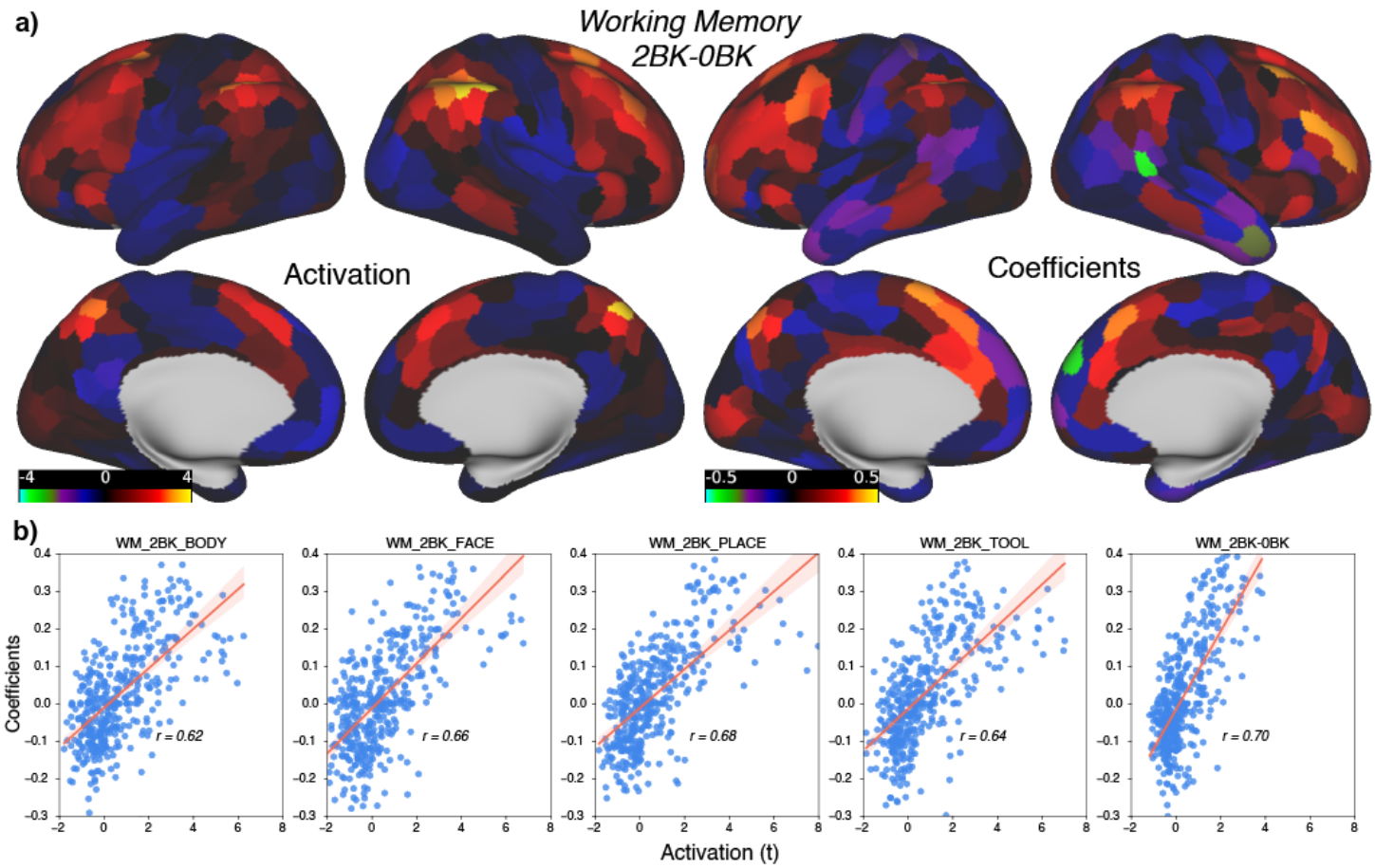

Figure 10: Coefficients and task activations: a) Looking at the distribution of the model coefficients across the cortex for the working memory task (2 back vs 0 back contrast). Group averaged task activations on the left panel and the model coefficients on the right panel. The coefficients have a similar distribution to cortical task activations which were not a part of the training or test model suggesting a link between cerebellar-cortical connectivity and cortical functional areas. b) Scatter plot of model coefficients vs activations (GLM t statistic) for the five contrasts from the working memory task: 2 back body, 2 back faces, 2 back places, 2 back tools and 2 back vs 0 back. A strong association between the model coefficients and the cortical task activations corroborate the link between functional connectivity and function.

References

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., & Essen, D. C. V. (2013). Function in the Human Connectome: Task-fMRI and Individual Differences in Behavior. *NeuroImage*, *80*, 169. https://doi.org/10.1016/j.neuroimage.2013.05.033

Bernstein-Eliav, M., & Tavor, I. (2022). The Prediction of Brain Activity from Connectivity: Advances and Applications. *The Neuroscientist: A Review Journal Bringing Neurobiology, Neurology and Psychiatry*, 10738584221130974. https://doi.org/10.1177/10738584221130974

Braga, R. M., & Buckner, R. L. (2017). Parallel Interdigitated Distributed Networks within the Individual Estimated by Intrinsic Functional Connectivity. *Neuron*, *95*(2), 457-471.e5. https://doi.org/10.1016/j.neuron.2017.06.038

Brissenden, J. A., Levin, E. J., Osher, D. E., Halko, M. A., & Somers, D. C. (2016). Functional evidence for a cerebellar node of the dorsal attention network. *Journal of Neuroscience*, *36*(22), 6083–6096. https://doi.org/10.1523/JNEUROSCI.0344-16.2016

Brissenden, J. A., Tobyne, S. M., Halko, M. A., & Somers, D. C. (2021). Stimulus-Specific Visual Working Memory Representations in Human Cerebellar Lobule VIIb/VIIIa. *Journal of Neuroscience*, *41*(5), 1033–1045. https://doi.org/10.1523/JNEUROSCI.1253-20.2020

Brissenden, J. A., Tobyne, S. M., Osher, D. E., Levin, E. J., Halko, M. A., & Somers, D. C. (2018). Topographic Cortico-cerebellar Networks Revealed by Visual Attention and Working Memory. *Current Biology*, *28*(21), 3364-3372.e5. https://doi.org/10.1016/j.cub.2018.08.059

Buckner, R. L., Krienen, F. M., Castellanos, A., Diaz, J. C., & Yeo, B. T. T. (2011). *The organization of the human cerebellum estimated by intrinsic functional connectivity Somatomotor Topography in the Cerebellum*. *106*(5), 2322–2345.

https://doi.org/10.1152/jn.00339.2011

Cole, M. W., Ito, T., Bassett, D. S., & Schultz, D. H. (2016). Activity flow over resting-state networks shapes cognitive task activations. *Nature Neuroscience*, *19*(12), Article 12. https://doi.org/10.1038/nn.4406

Dale, A. M., Fischl, B., & Sereno, M. I. (1999). Cortical Surface-Based Analysis: I. Segmentation and Surface Reconstruction. *NeuroImage*, *9*(2), 179–194. https://doi.org/10.1006/nimg.1998.0395

Diedrichsen, J., & Zotow, E. (2015). Surface-Based Display of Volume-Averaged Cerebellar Imaging Data. *PLOS ONE*, *10*(7), e0133402. https://doi.org/10.1371/journal.pone.0133402

Fischl, B., Sereno, M. I., & Dale, A. M. (1999). Cortical surface-based analysis. II: Inflation, flattening, and a surface-based coordinate system. *NeuroImage*, *9*(2), 195–207. https://doi.org/10.1006/nimg.1998.0396

Gilmore, A. W., Nelson, S. M., & McDermott, K. B. (2021). Precision functional mapping of human memory systems. *Current Opinion in Behavioral Sciences*, *40*, 52–57. https://doi.org/10.1016/j.cobeha.2020.12.013

Glasser, M. F., Smith, S. M., Marcus, D. S., Andersson, J. L. R., Auerbach, E. J., Behrens, T. E. J., Coalson, T. S., Harms, M. P., Jenkinson, M., Moeller, S., Robinson, E. C., Sotiropoulos, S. N., Xu, J., Yacoub, E., Ugurbil, K., & Essen, D. C. V. (2016). *The Human Connectome Project ' s neuroimaging approach*. *v*(9), 1175–1187. https://doi.org/10.1038/nn.4361

Glasser, M. F., Sotiropoulos, S. N., Wilson, J. A., Coalson, T. S., Fischl, B., Andersson, J. L., Xu, J., Jbabdi, S., Webster, M., Polimeni, J. R., Van Essen, D. C., & Jenkinson, M. (2013). The minimal preprocessing pipelines for the Human Connectome Project. *NeuroImage*, *80*, 105–124. https://doi.org/10.1016/j.neuroimage.2013.04.127

Gordon, E. M., Laumann, T. O., Gilmore, A. W., Newbold, D. J., Greene, D. J., Berg, J. J.,

Ortega, M., Hoyt-Drazen, C., Gratton, C., Sun, H., Hampton, J. M., Coalson, R. S., Nguyen, A. L., McDermott, K. B., Shimony, J. S., Snyder, A. Z., Schlaggar, B. L., Petersen, S. E., Nelson, S. M., & Dosenbach, N. U. F. (2017). Precision Functional Mapping of Individual Human Brains. *Neuron*, *95*(4), 791-807.e7. https://doi.org/10.1016/j.neuron.2017.07.011

Gratton, C., & Braga, R. M. (2021). Editorial overview: Deep imaging of the individual brain: past, practice, and promise. *Current Opinion in Behavioral Sciences*, *40*, iii–vi. https://doi.org/10.1016/j.cobeha.2021.06.011

Guell, X., Schmahmann, J. D., Gabrieli, J. D. E., & Ghosh, S. S. (2018). Functional gradients of the cerebellum. *ELife*, *7*, 1–22. https://doi.org/10.7554/eLife.36652

Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., del Río, J. F., Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Hearne, L. J., Mill, R. D., Keane, B. P., Repovš, G., Anticevic, A., & Cole, M. W. (2021). Activity flow underlying abnormalities in brain activations and cognition in schizophrenia. *Science Advances*, *7*(29), eabf2513. https://doi.org/10.1126/sciadv.abf2513

Jenkinson, M., Beckmann, C. F., Behrens, T. E. J., Woolrich, M. W., & Smith, S. M. (2012). FSL. *NeuroImage*, *62*(2), 782–790. https://doi.org/10.1016/j.neuroimage.2011.09.015

King, M., Hernandez-Castillo, C. R., Poldrack, R. A., Ivry, R. B., & Diedrichsen, J. (2019). Functional boundaries in the human cerebellum revealed by a multi-domain task battery. *Nature Neuroscience*, *22*(8), 1371–1378. https://doi.org/10.1038/s41593-019-0436-x

King, M., Shahshahani, L., Ivry, R. B., & Diedrichsen, J. (2023). A task-general connectivity model reveals variation in convergence of cortical inputs to functional regions of the cerebellum. *ELife*, *12*, e81511. https://doi.org/10.7554/eLife.81511

Liu, X., d'Oleire Uquillas, F., Viaene, A. N., Zhen, Z., & Gomez, J. (2022). A multifaceted gradient in human cerebellum of structural and functional development. *Nature Neuroscience*, *25*(9), Article 9. https://doi.org/10.1038/s41593-022-01136-z

Marek, S., Siegel, J. S., Gordon, E. M., Raut, R. V., Gratton, C., Newbold, D. J., Ortega, M., Laumann, T. O., Adeyemo, B., Miller, D. B., Zheng, A., Lopez, K. C., Berg, J. J., Coalson, R. S., Nguyen, A. L., Dierker, D., Van, A. N., Hoyt, C. R., McDermott, K. B., … Dosenbach, N. U. F. (2018). Spatial and Temporal Organization of the Individual Human Cerebellum. *Neuron*, *100*(4), 977-993.e7. https://doi.org/10.1016/j.neuron.2018.10.010

Mars, R. B., Passingham, R. E., & Jbabdi, S. (2018). Connectivity Fingerprints: From Areal Descriptions to Abstract Spaces. *Trends in Cognitive Sciences*, *22*(11), 1026–1037. https://doi.org/10.1016/j.tics.2018.08.009

Murty, N. A. R., Teng, S., Beeler, D., Mynick, A., Oliva, A., & Kanwisher, N. (2020). Visual experience is not necessary for the development of face-selectivity in the lateral fusiform gyrus. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(37), 23011–23020. https://doi.org/10.1073/pnas.2004607117

Osher, D. E., Brissenden, J. A., & Somers, D. C. (2019). Predicting an individual's Dorsal Attention Network activity from functional connectivity fingerprints. *Journal of Neurophysiology*, 232–240. https://doi.org/10.1152/jn.00174.2019

Osher, D. E., Saxe, R. R., Koldewyn, K., Gabrieli, J. D. E., Kanwisher, N., & Saygin, Z. M. (2016). Structural Connectivity Fingerprints Predict Cortical Selectivity for Multiple Visual Categories across Cortex. *Cerebral Cortex*, *26*(4), 1668–1683. https://doi.org/10.1093/cercor/bhu303

Parker Jones, O., Voets, N. L., Adcock, J. E., Stacey, R., & Jbabdi, S. (2017). Resting connectivity predicts task activation in pre-surgical populations. *NeuroImage: Clinical*, *13*, 378–385. https://doi.org/10.1016/j.nicl.2016.12.028

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M.,

Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., & Cournapeau, D. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*.

Robinson, E. C., Jbabdi, S., Glasser, M. F., Andersson, J., Burgess, G. C., Harms, M. P., Smith, S. M., Van Essen, D. C., & Jenkinson, M. (2014). MSM: A new flexible framework for Multimodal Surface Matching. *NeuroImage*, *100*, 414–426. https://doi.org/10.1016/j.neuroimage.2014.05.069

Saygin, Z. M., Osher, D. E., Koldewyn, K., Reynolds, G., Gabrieli, J. D. E., & Saxe, R. R. (2012). Anatomical connectivity patterns predict face selectivity in the fusiform gyrus. *Nature Neuroscience*, *15*(2), 321–327. https://doi.org/10.1038/nn.3001

Schaefer, A., Kong, R., Gordon, E. M., Laumann, T. O., Zuo, X.-N., Holmes, A. J., Eickhoff, S. B., & Yeo, B. T. T. (2017). Local-Global Parcellation of the Human Cerebral Cortex from Intrinsic Functional Connectivity MRI. *Cerebral Cortex*, *July 2017*, 1–20. https://doi.org/10.1093/cercor/bhx179

Schmahmann, J. D. (1996). From movement to thought: Anatomic substrates of the cerebellar contribution to cognitive processing. *Human Brain Mapping*, *4*(3), 174–198. https://doi.org/10.1002/(SICI)1097-0193(1996)4:3<174::AID-HBM3>3.0.CO;2-0

Schmahmann, J. D. (2010). The role of the cerebellum in cognition and emotion: Personal reflections since 1982 on the dysmetria of thought hypothesis, and its historical evolution from theory to therapy. *Neuropsychology Review*, *20*(3), 236–260. https://doi.org/10.1007/s11065-010-9142-x

Schmahmann, J. D. (2019). The cerebellum and cognition. *Neuroscience Letters*, *688*, 62–75. https://doi.org/10.1016/j.neulet.2018.07.005

Schmahmann, J. D., Weilburg, J. B., & Sherman, J. C. (2007). The neuropsychiatry of the cerebellum—Insights from the clinic. *The Cerebellum*, *6*(3), 254–267. https://doi.org/10.1080/14734220701490995

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and Statistical Modeling with Python. *Proceedings of the 9th Python in Science Conference*, *Scipy*, 92–96. https://doi.org/10.25080/majora-92bf1922-011

Somers, D. C., Michalka, S. W., Tobyne, S. M., & Noyce, A. L. (2021). Individual subject approaches to mapping sensory-biased and multiple-demand regions in human frontal cortex. *Current Opinion in Behavioral Sciences*, *40*, 169–177. https://doi.org/10.1016/j.cobeha.2021.05.002

Steriade, M., & Llinas, R. R. (1988). The Functional States of the Thalamus and the Associated Neuronal Interplay. *Physiological Reviews*, *68*(3).

Stoodley, C. J., & Schmahmann, J. D. (2009). Functional topography in the human cerebellum: A meta-analysis of neuroimaging studies. *NeuroImage*, *44*(2), 489–501. https://doi.org/10.1016/j.neuroimage.2008.08.039

Stoodley, C. J., Valera, E. M., & Schmahmann, J. D. (2012). Functional topography of the cerebellum for motor and cognitive tasks: An fMRI study. *NeuroImage*, *59*(2), 1560–1570. https://doi.org/10.1016/j.neuroimage.2011.08.065

Tavor, I., Jones, O. P., Mars, R. B., Smith, S. M., Behrens, T. E., & Jbabdi, S. (2016). Task-free MRI Predicts Individual Differences in Brain Activity During Task Performance. *Science*, *352*(6282), 1–33.

Tie, Y., Rigolo, L., Norton, I., Huang, R. Y., Wu, W., Orringer, D. A., Mukundan, S., & Golby, A. J. (2014). Defining language networks from resting-state fMRI for surgical planning—A feasibility study. *Human Brain Mapping*, *35*(3), 1018–1030. https://doi.org/10.1002/hbm.22231

Tik, N., Livny, A., Gal, S., Gigi, K., Tsarfaty, G., Weiser, M., & Tavor, I. (2021). Predicting individual variability in task-evoked brain activity in schizophrenia. *Human Brain Mapping*, *42*(12), 3983–3992. https://doi.org/10.1002/hbm.25534

Tik, N., Gal, S., Madar, A., Ben-David, T., Bernstein-Eliav, M., & Tavor, I. (2023). Generalizing prediction of task-evoked brain activity across datasets and populations. *NeuroImage*, *276*, 120213. https://doi.org/10.1016/j.neuroimage.2023.120213

Tobyne, S. M., Somers, D. C., Brissenden, J. A., Michalka, S. W., Noyce, A. L., & Osher, D. E. (2018). Prediction of individualized task activation in sensory modality-selective frontal cortex with 'connectome fingerprinting.' *NeuroImage*. https://doi.org/10.1016/j.neuroimage.2018.08.007

Van Essen, D. C., Ugurbil, K., Auerbach, E., Barch, D., Behrens, T. E. J., Bucholz, R., Chang, A., Chen, L., Corbetta, M., Curtiss, S. W., Della Penna, S., Feinberg, D., Glasser, M. F., Harel, N., Heath, A. C., Larson-Prior, L., Marcus, D., Michalareas, G., Moeller, S., … Yacoub, E. (2012). The Human Connectome Project: A data acquisition perspective. *NeuroImage*, *62*(4), 2222–2231. https://doi.org/10.1016/j.neuroimage.2012.02.018

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., … Vázquez-Baeza, Y. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in Python. *Nature Methods*, *17*(3), 261–272. https://doi.org/10.1038/s41592-019-0686-2

Xue, A., Kong, R., Yang, Q., Eldaief, M. C., Angeli, P. A., DiNicola, L. M., Braga, R. M., Buckner, R. L., & Yeo, B. T. T. (2021). The detailed organization of the human cerebellum estimated by intrinsic functional connectivity within the individual. *Journal of Neurophysiology*, *125*(2), 358–384. https://doi.org/10.1152/jn.00561.2020

Yao, S., Rigolo, L., Yang, F., Vangel, M., Haijun Wang, Haijun Wang, Wang, H., Golby, A. J., Liebenthal, E., & Tie, Y. (2021). Movie-watching fMRI for presurgical language mapping in patients with brain tumour. *Journal of Neurology, Neurosurgery, and Psychiatry*. https://doi.org/10.1136/jnnp-2020-325738

Supplementary Methods

In order to validate our findings on additional subjects from the Human Connectome Project - Young Adult dataset, we included an additional sample of 78 subjects (39 males). We used our prediction models, across all seven tasks and various contrasts, trained on the original training dataset and applied it across the additional testing dataset.

Supplementary Figures

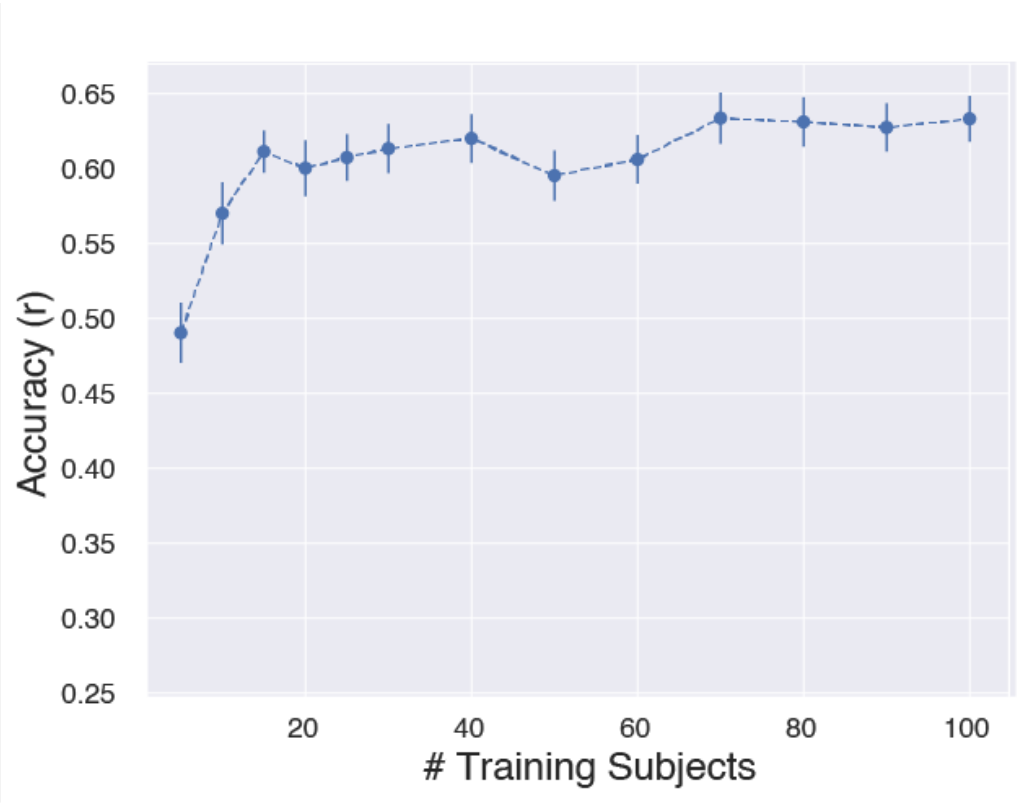

Figure S1: The relationship between prediction accuracy and the number of subjects in the training dataset for using Ridge regression with 50-50 split in test and training data (RidgeSplit). We see a plateau beyond thirty subjects.

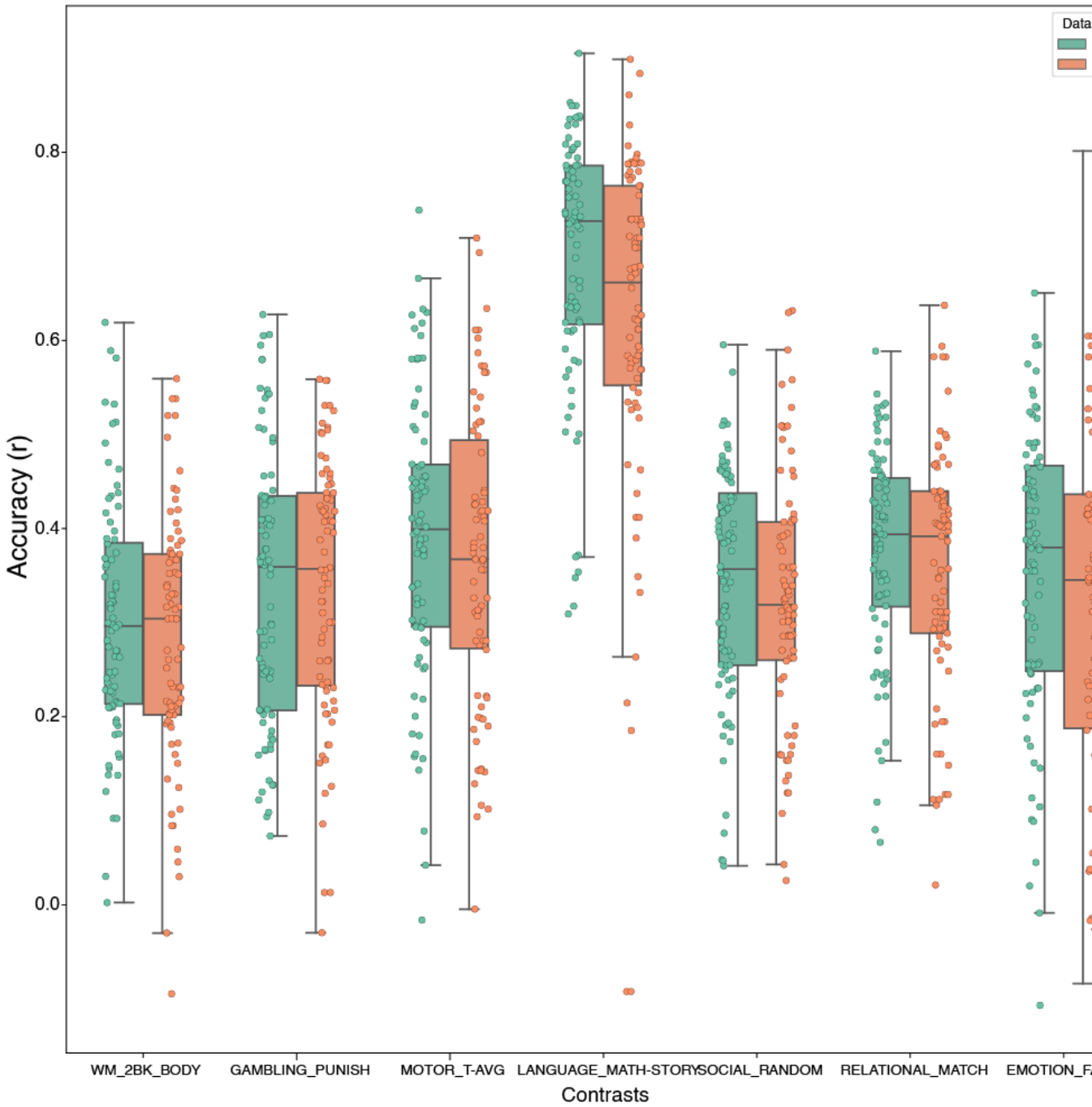

Figure S2: Model performance across additional testing dataset: We analysed the performance of our prediction models on an additional set (Set 2) of 78 subjects from the HCP data and found no significant differences in model predictions across various tasks and contrasts in the two testing datasets.

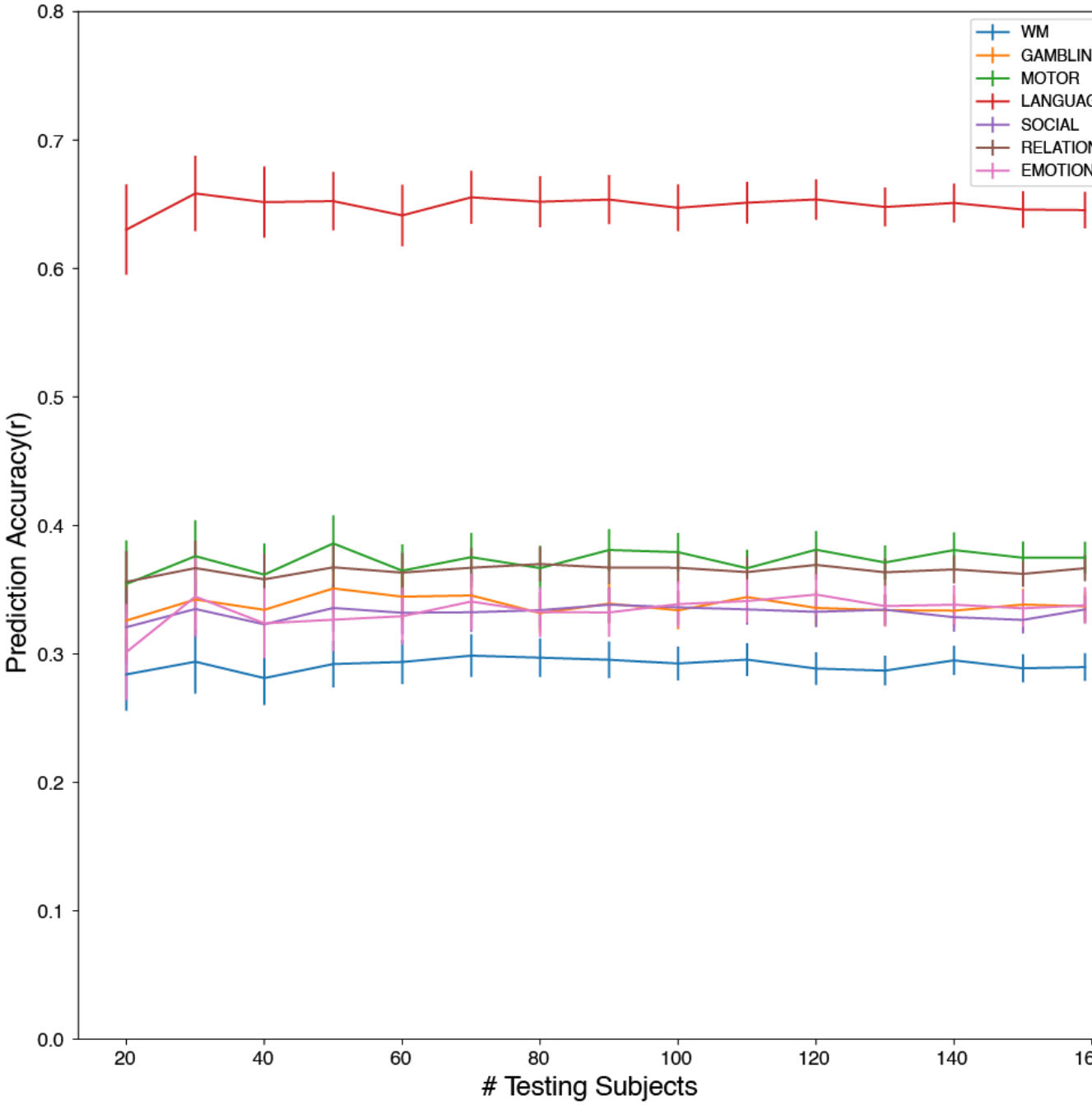

Figure S3: Effect of the number of subjects in the testing dataset on the prediction accuracy: Here, we systematically varied the number of testing subjects from 20 to 158 (with ten random permutations for each number of subjects). The model performance was not dependent on the number of test subjects for the various tasks and contrasts in the HCP dataset.

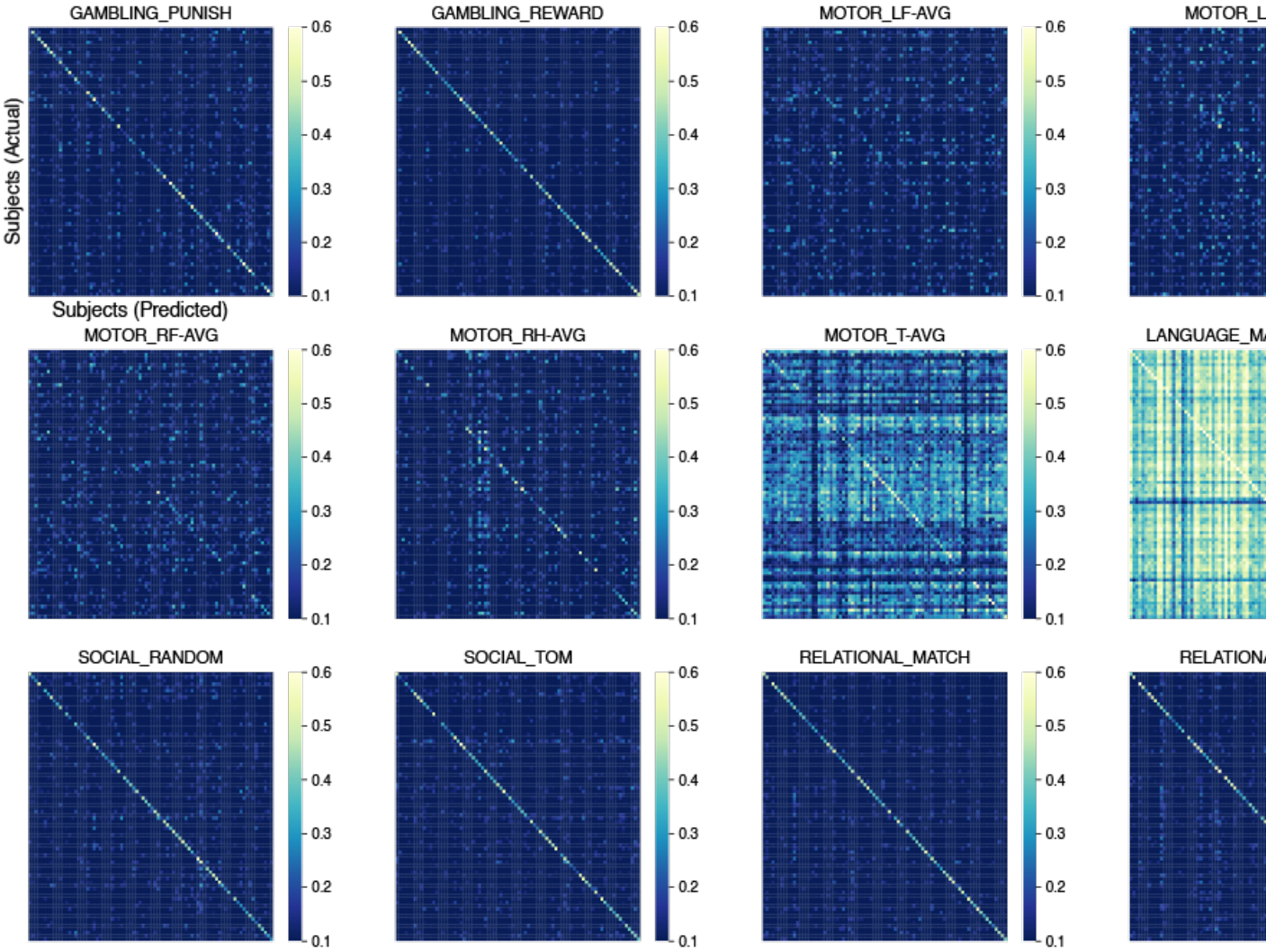

Figure S4:Cross connectivity predictions for the contrasts across the other cognitive tasks. We see that a subject's own functional connectivity better predicts its task activation as compared to other subjects in gambling, social, relational and language tasks but not so much in the contrasts in the motor task suggesting that cerebellar-cortical connectivity for motor regions is not strongly individual specific.

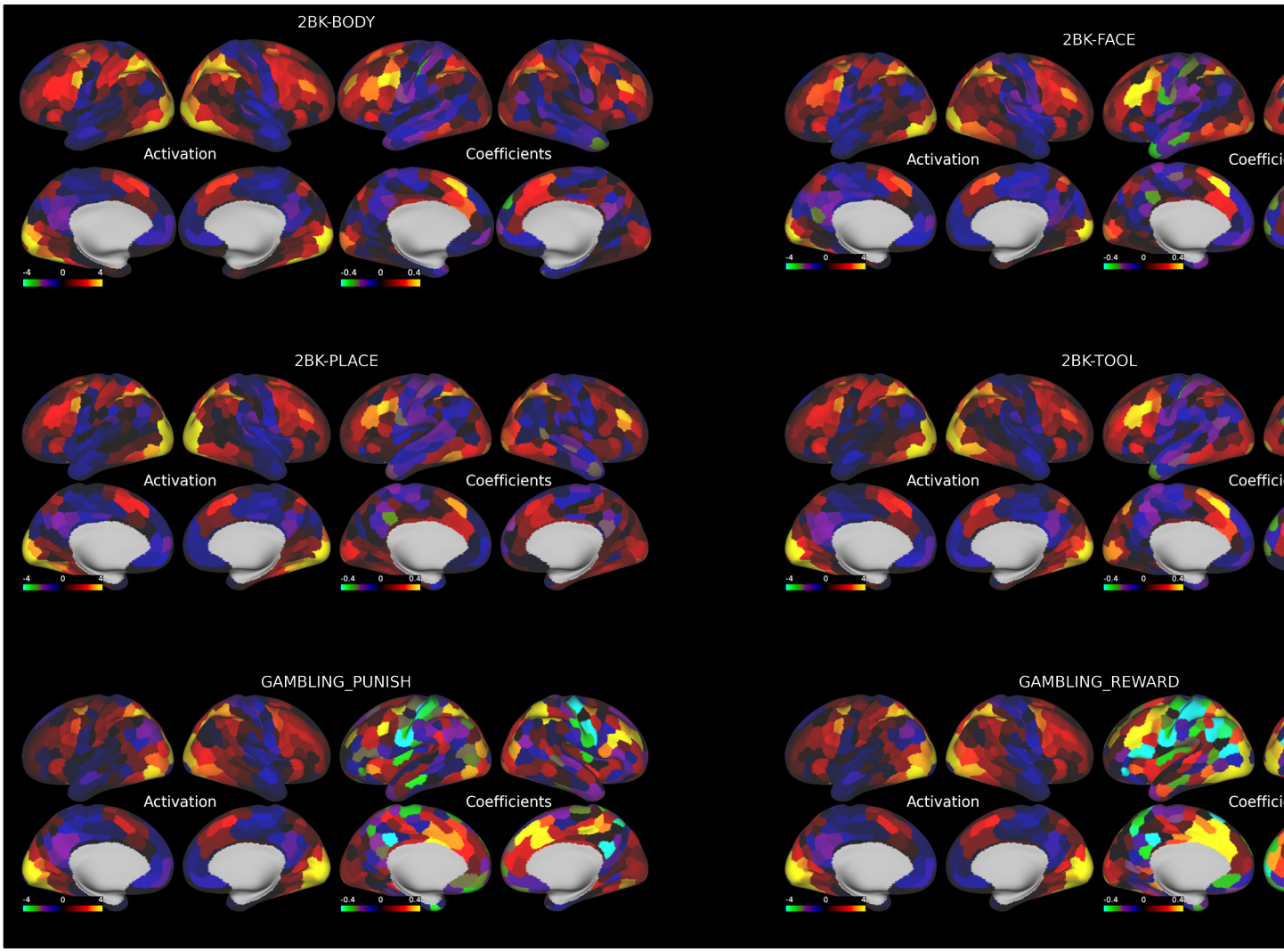

Figure S5:Coefficients and task activations: Plotting out the surface maps for the coefficients and task activations for the working memory and gambling tasks.

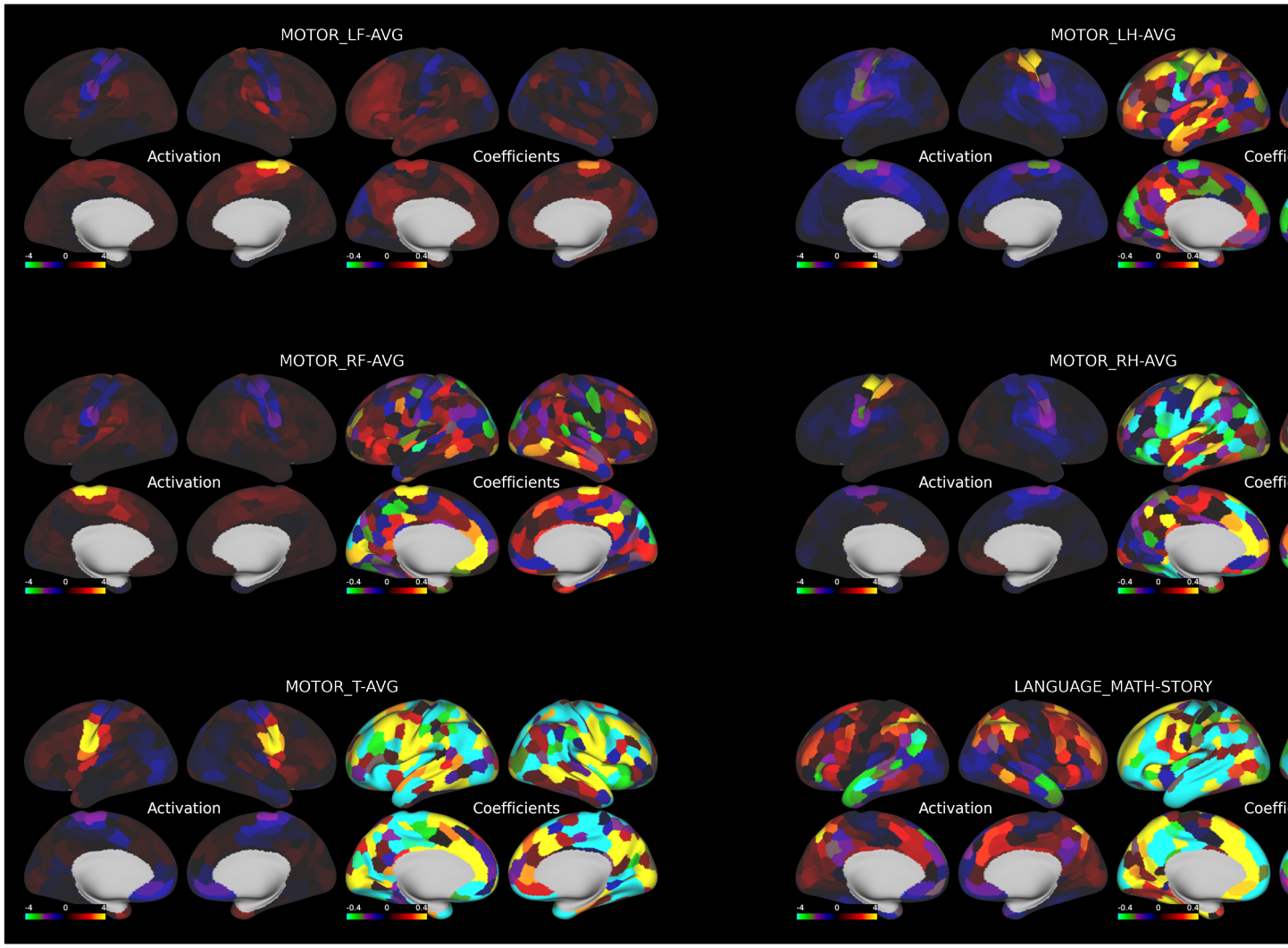

Figure S6:Coefficients and task activations: Plotting out the surface maps for the coefficients and task activations for the motor and language tasks.

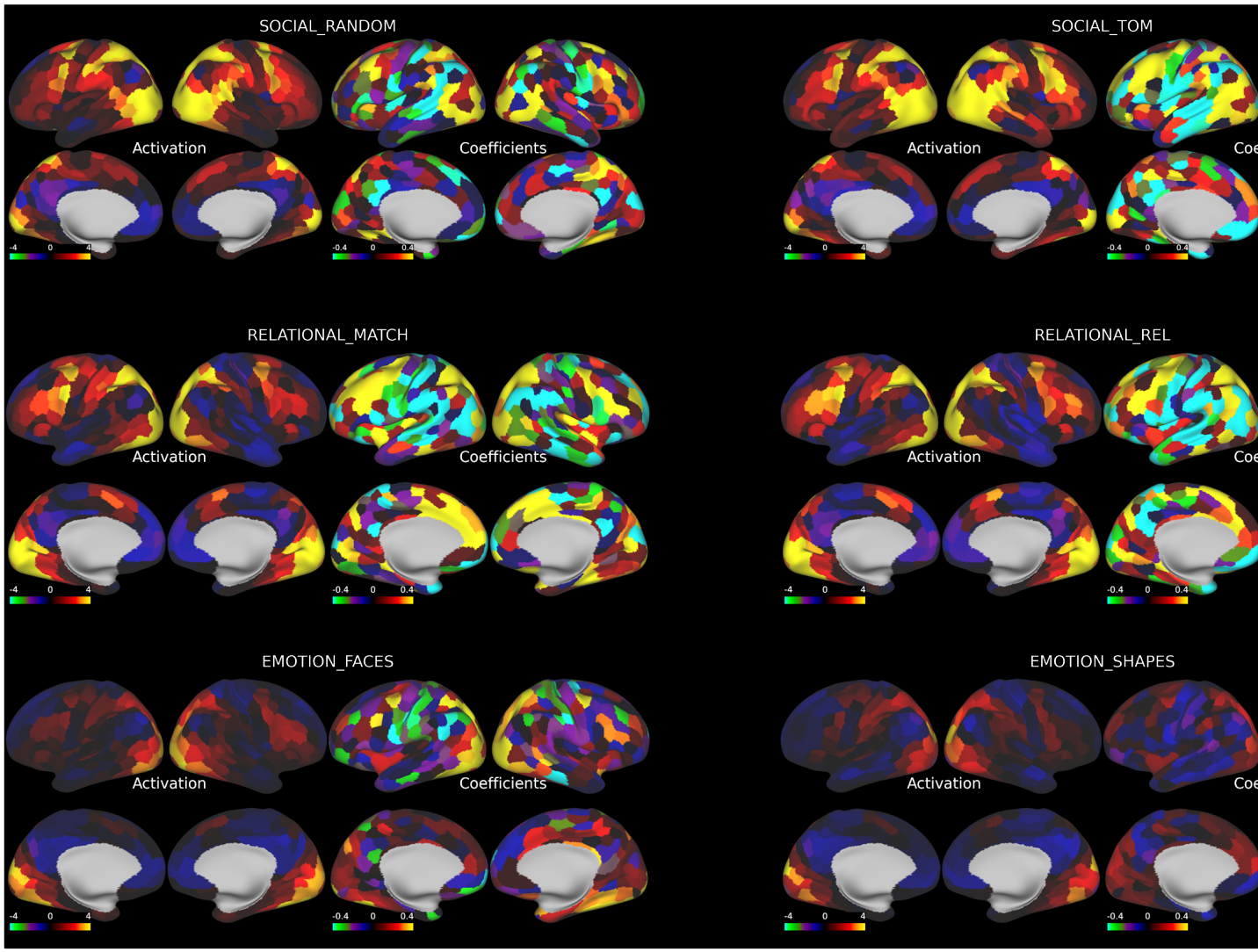

Figure S7:Coefficients and task activations: Plotting out the surface maps for the coefficients and task activations for the social, relational and emotion tasks.

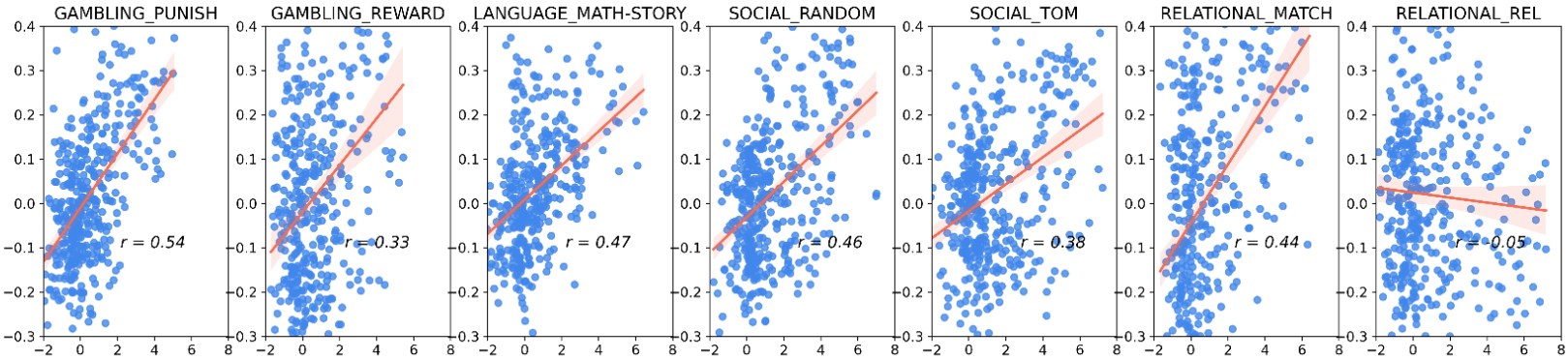

Figure Coefficients and task activations: Scatter plots between the model coefficients and task activations for the remaining tasks. Contrasts and tasks with no relationship are not shown here.

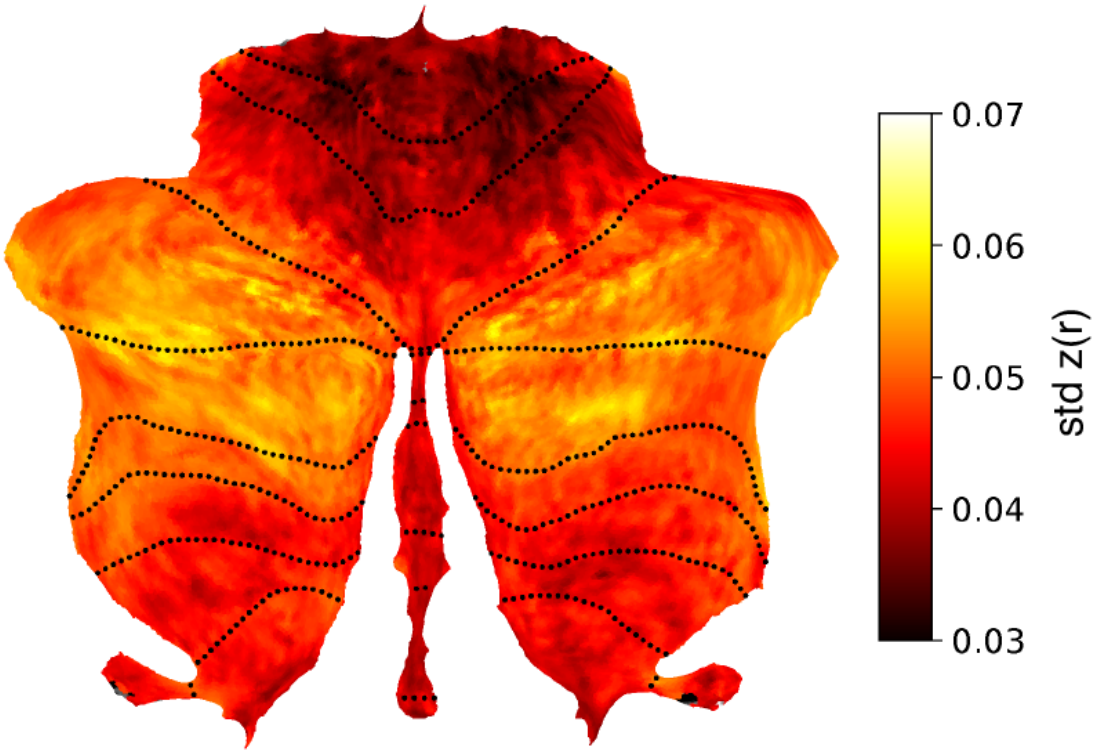

Figure S9: Variance in Cerebellar-cortical connectivity across subjects.