Exploring the Cognitive Space: A Framework for Cognitive Function Mapping

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Abstract

Obtaining an accurate topography of cognitive functions is a major endeavour in human brain imaging. Recent advancements have been driven by intensive within-subject scanning, known as deep phenotyping, to address inter-subject variability. However, work is still needed to quantify how specific cognitive functions contribute to brain activation. In this study, we integrate statistical summaries from the Individual Brain Charting project (IBC) with the Cognitive Atlas. Each fMRI contrast map was annotated with cognitive components derived from its associated concepts. We then applied dictionary learning to estimate the contribution, or weight, of each component to a given contrast map. The resulting weights were used as regressors in a General Linear Model (GLM) analysis that incorporated contrast maps from all IBC tasks. This approach provided a more sensitive cognitive mapping of brain functions at the individual level.

Introduction

Functional Magnetic Resonance Imaging (fMRI) has significantly advanced our knowledge of human cognition. However, understanding how different brain functions contribute to task execution remains challenging. We aimed to investigate brain function beyond predefined task structures.

We leveraged the Individual Brain Charting (IBC) project(Pinho et al., 2018, 2024), which provides extensive fMRI data from 12 participants that performed over 80 cognitive tasks. We used the Cognitive Atlas(Poldrack et al., 2011) (CA), an ontology of cognitive functions, to annotate over 300 IBC contrast maps with the cognitive processes they engage. This allowed us to construct a concept space that describes brain activation in terms of cognitive components.

Using dictionary learning, we assigned weights to the concept space matrix to estimate each cognitive function's contribution to neural activations. This generated individualized cognitive maps, providing detailed localization of cognitive functions across tasks.

Methods

Constructing a Cognitive Feature Space

Figure 1 illustrates our approach. Using IBC dataset annotations(Aggarwal, Ponce, & Thirion, 2024), we constructed a matrix representing the cognitive space. We selected $p = 406$ "main contrasts" and assigned cognitive components based on annotations, resulting in a binary contrast-by-component matrix, with entries marked as 1 where a component is present. To ensure full-rank, we removed linearly dependent components, resulting in a final matrix of size 406×146. We used data from 12 subjects. Data availability varied slightly per subject: 8 subjects had the full 406×146 matrix, while others had fewer contrast maps, with matrices as small as 250×107.

Weighting the Cognitive Feature Space

We reasoned that matrix components did not need to be strictly binary, as cognitive components likely contribute to activation in varying degrees. To model this, we adapted dictionary learning(Mairal, Bach, Ponce, & Sapiro, 2009), a method of signal decomposition that represents a signal (in this case, a contrast map) as a sparse linear combination of basis elements from a learned dictionary.

In our framework, the sparse code represents the cognitive feature space, while the basis dictionary captures possible voxel activations. Consequently, contrast maps can be described as a structured combination of cognitive components and their corresponding brain locations. To achieve this, we followed these steps: For each subject, we started with the initial binary matrix as the sparse code ($\mathbf{A}$) and the collection of contrast maps as the set of signals to decompose ($\mathbf{Y}$).

1. **Dictionary Estimation**: We computed the dictionary matrix ($\mathbf{D}$) using a linear regression of $\mathbf{Y}$ onto $\mathbf{A}$, normalizing rows to ℓ_2-norm of 1.
2. **Sparse Code Update**: Updated the sparse code $\mathbf{A}$ using $\mathbf{D}$ and `SparseCoder` from Scikit-Learn(Pedregosa et al., 2011), enforcing non-negativity constraints.
3. **Objective Function Evaluation**: Reconstruction error with ℓ_1-regularized loss was computed to monitor convergence.

Iterations of this process stopped when the objective function no longer decreased. At the end, each subject's sparse code was no longer binary but contained continuous coefficients that represented contrast-specific weights for cognitive components. Finally, we averaged the sparse code matrices across subjects to obtain a single cognitive feature space.

Cognitive Mapping

We then performed a General Linear Model (GLM) analysis using Nilearn's `SecondLevelModel`(Abraham et al., 2014). The model was fitted with all contrast maps, using the updated cognitive feature space as the design matrix, where each cognitive component was treated as a regressor. This produced statistical maps for each component, totaling 107 to 146 concept maps per subject.

Results and Discussion

We used a community-defined concept space from the CA to describe activation maps from multiple tasks in individual subjects. We achieved a detailed localization of cognitive functions across numerous protocols.

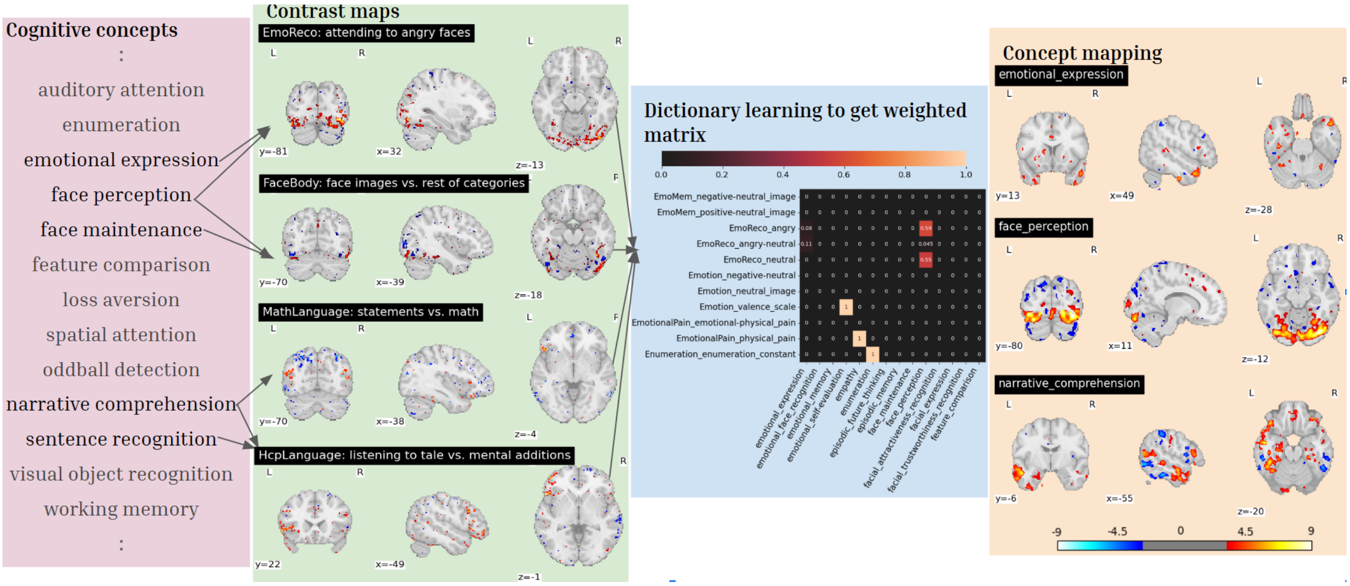

Figure 1: **Cognitive Mapping Process.** (Pink) Cognitive terms were collected to define the cognitive space. (Green) IBC contrast maps were annotated based on the occurrence of these terms. The maps display z-values from a standard GLM analysis. (Blue) Dictionary learning was used to estimate each component's contribution to the contrast maps. (Orange) These weights served as regressors in a GLM analysis across all IBC tasks, producing a statistical map for each component. The colorbar indicates the z-values of the GLM results.

Our approach assumes that tasks (e.g., face recognition) involve multiple cognitive components (perception, maintenance, etc) with varying degrees of contribution. Using dictionary learning, we assigned weights to these components, decomposing brain contrast maps accordingly. Figure 2 shows the variance explained using a binary vs. weighted matrix in the GLM, with the weighted matrix yielding a better fit.

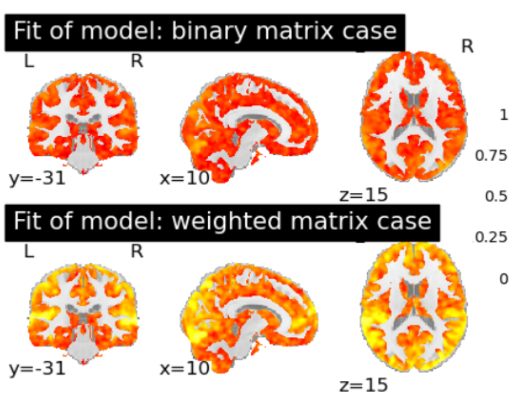

Figure 2: **GLM model fit.** R^2 maps for sub-06, using the original binary matrix (top) and the weighted sparse matrix averaged across all subjects except sub-05 and sub-06 (bottom).

Results aligned with existing literature. Well-established functions, such as movement localization and visual stimulus mapping, appear in expected regions of the motor and visual cortex. However, the richness of the IBC dataset allowed us to explore further. We were able to map finer domain-specific differentiations. For instance, we distinguished between auditory recognition and auditory word recognition. We also obtained separate maps for related cognitive processes, such as working memory and maintenance. Figure 3 illustrates the mapping of some cognitive concepts in two representative subjects.

Our method is limited by the inherent nature of annotations but provides a valuable tool to examine the influence of different terms on brain activations and establishes a foundation for deeper exploration of the cognitive space.

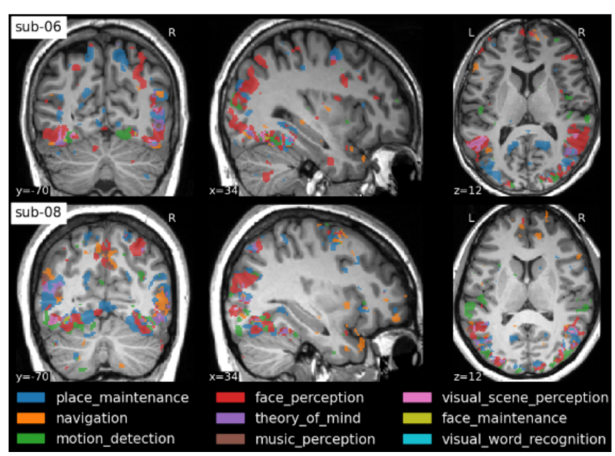

Figure 3: **Individual Mapping** Results for example subjects. Nine concept maps were selected and thresholded at $z > 3.1$.

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