Individual brain parcellations for cognitive mapping obtained from a hierarchical Bayesian framework

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Abstract

In recent years, individual brain parcellations have become increasingly popular in human brain imaging as they provide better precision for functional localization than population-based atlases. Yet, often, there is only very little individual data available to define individual regions. Here, we exploit a *Hierarchical Bayesian Parcellation* (HBP) scheme to derive subject-specific parcellations extracted from a limited amount of individual task data and evaluate its performance using the *Distance-Controlled Boundary Coefficient*. We compare the HBP performance with Dual Regression and Dictionary Learning, two data-driven methods commonly used on resting-state and task-based data. In particular, we demonstrate that the Bayesian integration of individual data with a group prior—inferred from a large deep-behavioral phenotyping resource—provides substantial advantages in defining individual regions.

Keywords: Functional Brain Parcellation; Bayesian Hierarchical Modeling; Dictionary Learning; Dual Regression

Introduction

The functional organization of the human brain shows substantial inter-individual variability, posing significant challenges for the analysis of brain imaging data. Recent developments have demonstrated the benefits of individual- over population-level parcellations (Glasser et al., 2016; Gordon et al., 2017; Braga & Buckner, 2017; Kong et al., 2019). Data-driven parcellation schemes, leveraging task-based *functional Magnetic Resonance Imaging* (fMRI) data, have also been used for the extraction of individual brain parcellations (Pinho et al., 2021; Thirion, Thual, & Pinho, 2021; Thirion, Aggarwal, Ponce, Pinho, & Thual, 2024). Yet, to obtain reliable individual parcellations, a large amount of individual data is necessary. The burdensome requirement to collect independent data as a functional localizer before the main experiment explains why this approach has not been widely adopted.

To enable consistent individual parcellations from restricted data, we adopt herein a *Hierarchical Bayesian Parcellation* (HBP) scheme that optimally combines information from a group prior (probabilistic atlas) and individual data (Fig. 1 – top). The group prior can be learned with the same framework, integrating various task- and resting-state datasets (Zhi et al., 2023; Nettekoven et al., 2024). The balance between the group prior and the individual data is determined by the inter-individual variability (encoded in the group prior) and the concentration parameter for the data (estimated from their reliability, Fig. 1 – bottom). The posterior distribution of $\mathbf{U}^s$ represents the probabilistic individual parcellation. We compare the HBP model to two purely data-driven individual parcellation techniques—*Dual Regression* (Nickerson, Smith, Öngür, & Beckmann, 2017) and *online Dictionary Learning* (Mairal, Bach, Ponce, & Sapiro, 2009)—often employed in resting-state and task-based fMRI data, respectively. We evaluate

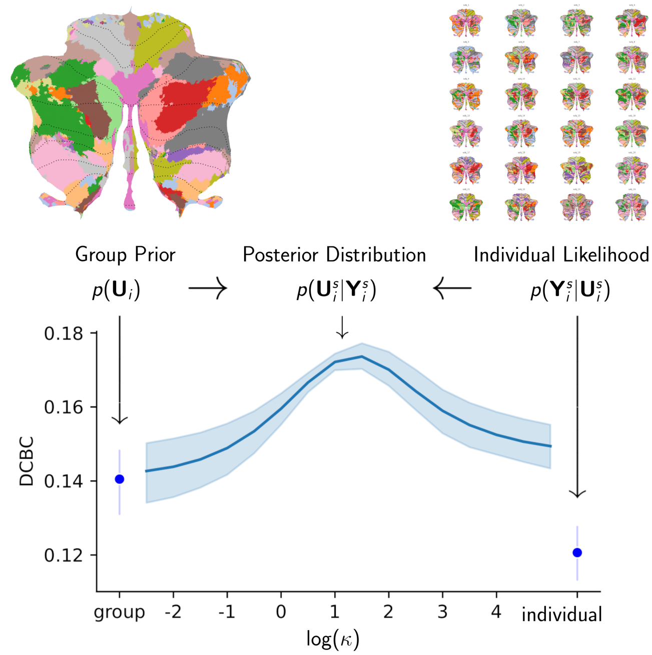

Figure 1: **Hierarchical Bayesian parcellation scheme.** A probabilistic group atlas ($p(\mathbf{U})$) is integrated with the individual data likelihood ($p(\mathbf{Y}_i|\mathbf{U}_i^s)$) to obtain an individual parcellation ($p(\mathbf{U}_i^s|\mathbf{Y}_i^s)$) of the human cerebellum *(top)*. The balance between group parcellation and individual data is determined by the concentration parameter κ *(bottom)*.

the performance of the three methods when learning from 20 minutes of individual task-based data.

Methods

Based on the principles of functional specialization, we stipulate that behavioral tasks are formed of elementary cognitive components associated with some sparse neural substrates. For a set of individual brain maps $\mathbf{Y}^s \in \mathbb{R}^{c \times p}$ where c is the number of task conditions and p the number of voxels, a common k-dimensional representation ($k < c$) of the tasks, i.e. $\mathbf{V} \in \mathbb{R}^{c \times k}$, and their individual spatial encoding $\mathbf{U}^s \in \mathbb{R}^{k \times p}$ define our prediction output as follows:

$$\hat{\mathbf{Y}}^s = \mathbf{V}\mathbf{U}^s \,, \;\; \text{where } \mathbf{U}^s \geq 0, \, \forall s \in [N] \tag{1}$$

We compare three models that minimize the difference between the original data $\mathbf{Y}^s$ and the reconstructed data $\hat{\mathbf{Y}}^s$ from (1).Yet, loss function and optimization algorithm vary depending on the model (Table 1).

	HBP	**Dual Regression**	**Dictionary Learning**
Estimation of $\mathbf{U}^s \vert \mathbf{V}$	E-step: $p(\mathbf{U}^s \vert \mathbf{V}, \mathbf{Y}^s) \propto p(\mathbf{U})p(\mathbf{Y}^s \vert \mathbf{V})$	NNLS: $\min_{\mathbf{U}^s} \Vert \mathbf{Y}^s - \mathbf{V}^s(\mathbf{U}^s) \Vert_2^2$	Sparse Coding: $\min_{\mathbf{U}^s} \Vert \mathbf{Y}^s - \mathbf{V}(\mathbf{U}^s) \Vert_{\text{Fro}}^2 + \alpha \Vert \mathbf{U}^s \Vert_1$
Update of $\mathbf{V} \vert \mathbf{U}^s$	M-step ($\mathbf{V} + \kappa$)	OLS: $\min_{\mathbf{V}^s} \Vert \mathbf{Y}^s - \mathbf{V}^s \mathbf{U}_g \Vert_2^2$	OLS: $\min_{\mathbf{V}^s} \Vert \mathbf{Y}^s - \mathbf{V}\mathbf{U}^s \Vert_{\text{Fro}}^2$
Combined estimation of $\mathbf{U}^s$ and $\mathbf{V}$	CD until convergence (EM-algorithm)	One step each	CD until convergence

Table 1: **HBP, Dual Regression and Dictionary Learning.** The probabilistic approach of HBP contrasts with the multiple-regression problem of Dual Regression and the non-negative matrix factorization of Dictionary Learning. We compare different optimization steps for $\mathbf{V}$ and $\mathbf{U}^s$ estimation that minimize the loss function. EM = Expectation Maximization; NNLS = Non-Negative Least Squares; OLS = Ordinary Least Squares; CD = Coordinate Descent.

Training and evaluation of the models were performed on data from the human cerebellum using the *Multi-Domain Task Battery* (MDTB) dataset (King, Hernandez-Castillo, Poldrack, Ivry, & Diedrichsen, 2019): a task-fMRI dataset covering a variety of cognitive domains and composed of two sessions per participant (N=24). Models were trained on 20 minutes of data from session 1 and evaluated on session 2, in a 8-fold cross-validation scheme. Evaluation was always performed on the entire session 2 (16 runs) using the *Distance-Controlled Boundary Coefficient* (DCBC) (Zhi, King, Hernandez-Castillo, & Diedrichsen, 2022), an unbiased metric which evaluates the goodness of clustering accounting for the spatial smoothness of fMRI data.

Results

For the HBP framework, both group and individual parcellations lead to a good prediction of functional boundaries in the test data. Importantly, however, the Bayesian integration of group with individual parcellation outperforms each one by itself (Zhi et al., 2023; Nettekoven et al., 2024). The integrated estimate also outperforms Dual Regression (DR) and Online Dictionary Learning (DL), highlighting the critical benefit of combining evidence from individual data with a group prior.

Among the data-driven models, DR shows the lowest DCBC values, with DL outperforming it. While DR estimates a subject-wise functional profile $\mathbf{V}^s$, DL uses a group $\mathbf{V}$. The subject-specific estimation of DR may lead to overfitting—especially when few data is available for training. However, both models—relying on the individual data only—show lower DCBC than the HBP parcellation. One possible disadvantage of these two models with respect to HBP pertains to the fact that they estimate $\mathbf{V}$ without using a spatial group prior.

To test this hypothesis, we plugged in the $\mathbf{V}$, obtained from HBP, to either model in order to estimate $\mathbf{U}^s$ (see Table 1, row 1). For both DR and DL, performance improved substantially, confirming the benefit of the HBP estimation of $\mathbf{V}$ using a group prior.

However, even when using the same $\mathbf{V}$, the two models performed worse than the HBP Individual. This result shows the additional benefit of HBP arising from the probabilistic data likelihood model (*von Mises-Fisher Mixture* model).

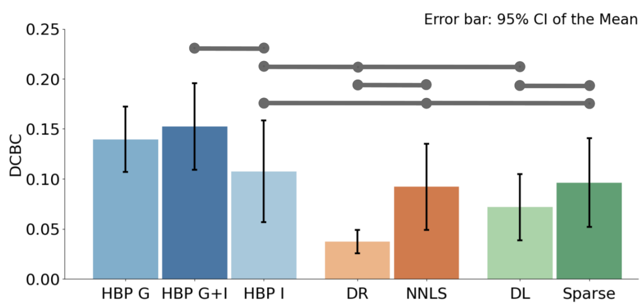

Figure 2: **DCBC evaluation of all prediction models across splits and subjects.** HBP model (G = Group; G + I = integrated; I = Individual), Dual Regression (DR), and Online Dictionary Learning (DL). NNLS and Sparse (*aka* Sparse Coding) refer to the estimation of $\mathbf{U}^s$ using directly the $\mathbf{V}$-estimate from HBP. Gray lines represent a significance level of $p \leq 1e-4$ for paired *t*-tests. Every paired *t*-test compares the DCBC evaluation between two models. Each line refers to all possible pairs of nodes forming it, wherein each node corresponds to the model below it.

Conclusion

Traditionally, individual parcellations require an extensive amount of data (Marek et al., 2018; Thirion et al., 2024). Our HBP model provides individual functional parcellations for new subjects using only 20 minutes of individual fMRI data. It outperforms both a standard group map or individualized data-driven models.

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