Combining fMRI, DTI and Behavioral Information : A Novel Modeling Approach

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1 Introduction

This write-up presents the approach discussed towards simulating a working model towards generating fMRI, DTI and behavioral information. The code and clear instructions are available at http://www.github.com/srini21/fmri-sim

2 Modeling methodology

The integral part of the approach is that the fMRI and the DTI share the same basic structure but the strength of the connections i.e the weight modified by the behavioral data varies. The basic steps discussed are explained as follows:

2.1 Graph Topology

The first step involves determining the graph topology. The discussions involved using either ring topology or star topology to represent the brain structure. It was finalized to align as close as possible to the simulations done by Smith et al [1] is shown in the figure 1. $\mathcal{G}_{s,t} \in \mathbb{R}^{n*n}$ represents the adjacency matrix of the above mentioned graph where n represents the number of nodes in the brain.

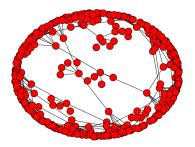


Figure 1: Representation of the graph structure with star topology. Number of nodes = 300, number of sub-nodes = 5

2.2 Age

As an outcome of our meeting dated July 22, we decided that the age of the subjects ranged from 7 to 22. Hence, $\forall individual$, we generate $\{A_p\}_{p=1}^n = \{a_1, a_2, ...a_n\}$ where n is the number of age samples for every individual.

2.3 Behavioral Information

 $b_i \in \Re^d$ represents the behavioral information at age i where d represents the number of behavioral features collected from every individual. $\exists b_0 \forall$ individuals drawn from $\mathcal{N}(0,1)$. This b_0 is used to generate a time series of behavioral information $\forall ages$ for that person using the formula

$$b_{a+1} = \mathcal{F}_p b_a + noise$$

where $\mathcal{F} \in \Re^{d*d}$ is also drawn from $\mathcal{N}(0,1) \forall person$.

In order to preserve the effects of age, the behavior vector used for computa-

tion will be $\mathcal{X} \in \Re^{d+2} = \begin{bmatrix} b_i \\ i \\ 1 \end{bmatrix}$ where $b_i \in \Re^d$ represents the computed behavior vector for age i.

2.4 fMRI Weights and DTI weights

 \mathcal{W}^d and $\mathcal{W}^f \in \Re^{n*n*(d+2)}$ represent the weights associated with the DTI and the fMRI data respectively where n represents the number of nodes in the graph and d represents the behavioral features. The weight matrices are generated so that they preserve block sparsity i.e $\mathcal{W}^f_{s,t}, \mathcal{W}^d_{s,t} = 0$ if $\mathcal{G}_{s,t} = 0$

2.5 $\theta_{s,t}$ for fMRI and DTI

The formula for generating θ^f and θ^d are shown below :

$$\begin{aligned} \forall_{s,t} \quad & \theta_{s,t}^f(b,a) = (\mathcal{W}_{s,t}^f) * \mathcal{X} \\ \forall_{s,t} \quad & \theta_{s,t}^d(b,a) = (\mathcal{W}_{s,t}^d) * \mathcal{X} \end{aligned}$$

where
$$\mathcal{X} = \begin{bmatrix} b_i \\ i \\ 1 \end{bmatrix} \in \Re^{d+2}$$
 and $\theta \in \Re^{n*n}$

2.6 Sampling \mathcal{Y}

We finally sample \mathcal{Y} where $\mathcal{Y}^f, \mathcal{Y}^d \in \mathbb{R}^d$ as follows:

$$\mathcal{Y}^f \sim \mathcal{P}(\mathcal{Y}; \theta^f)$$

 $\mathcal{Y}^d \sim \mathcal{P}(\mathcal{Y}; \theta^d)$

3 Further Steps

Next steps involve discussing the fitting procedure and other alternatives during our meeting on 7/30.

3.1 Prediction

The main goal as discussed in the meeting on 7/22 is to predict mental health symptoms using imaging and behavioral data. Russ suggested that it would be ideal the predictive model are directly interpretable in terms of changes in the brain networks. Pradeep suggested a muti-view predictive model.

Two potential approaches as suggested by Sanmi were:

Approach 1: Direct predictive model using all the information sources. This has the advantage of being relatively straightforward. Interpretability will likely be achieved using sparsity constraints on the predictive weights.

Approach 2: A two-step model. The first step extracts the (fMRI, DTI) graphs from the brain data, and the second step is a predictive model from the network to the phenotypes of interest. It turns out that the brain image data is missing for the majority of the subjects. An advantage of this approach is that it can address this missing data issue.

References

[1] Stephen M. Smith, Karla L. Miller, Gholamreza Salimi-Khorshidi, Matthew Webster, Christian F. Beckmann, Thomas E. Nichols, Joseph D. Ramsey, Mark W. Woolrich, Network modelling methods for FMRI, NeuroImage, Volume 54, Issue 2, 15 January 2011, Pages 875-891, ISSN 1053-8119, http://dx.doi.org/10.1016/j.neuroimage.2010.08.063