Classification of Brain Conditions: Identification of Significant Regions and Analysis of Temporal Dynamics

Valeriya Kirova [1] **Fyodor Ratnikov** [1]

[1] *HSE University, Moscow, Russia*. Correspondence to: V. Kirova lera.orlanovna@gmail.com.

1. Abstract

We use ML and statistical methods to analyze fMRI data from the Human Connectome Project. The main goal is to identify key brain regions involved in these tasks. Feature importance analysis reveals unique activation patterns for each state. Additionally, we show that the temporal structure of the data plays a key role in forming functional connections between brain regions.

2. Description of the Experimental Data

We use fMRI data from 581 participants who performed 7 tasks designed to activate different brain regions. Each task includes 2 states of brain activity, resulting $k = 14$ brain states and 8134 fMRI data units.

Table 1: Two brain states for each cognitive task

Cognitive Task	**State 1**	**State 2**
Working Memory	0-back	2-back
Gambling	win	loss
Motor Task	left hand or foot	right hand or foot
Language Processing	story	math
Social Cognition	random motion	mental interaction
Relational Processing	relation	similarity
Emotion Processing	neutral	fear

Structure of fMRI Data Unit:

- Each observation is represented as an activity matrix $\mathbf{X}_{n \times m}$, where n is the number of brain regions and m is the length of the time series. The elements $x_{ij} \in \mathbf{X}$ represents the activity of the i-th brain region at time point j, where $x_{ij} \in [-1, 1]$.
- The time series vector $\mathbf{x}_i = [x_{i1}, ..., x_{im}]$ describes its activity over the entire time interval.

Data Preprocessing: In each activity matrix $\mathbf{X}$, the time series $\mathbf{x}_i$ is averaged for each brain region ($i = \overline{1, n}$). Thus, each data unit is represented as a vector of mean brain region activities.

3. Research Methodology

We considered linear models (SVM, LDA, SGD, perceptron and others) due to their interpretability, efficiency on medium-sized data, noise resistance, computational simplicity, scalability, and theoretical foundation. All models achieved an accuracy of $0.84\breve{}0.92$, confirming the relevance of classical algorithms for MRI data analysis. We selected logistic regression using the "One-vs-All" approach. The classification report is provided in Table.

Table 2: Classification Report with One-vs-All

Class name	**Precision**	**Recall**	**F1-Score**	**Support**
Neutral	0.88	0.88	0.88	120
Fear	0.87	0.89	0.88	124
Loss	0.78	0.69	0.73	108
Win	0.85	0.81	0.83	117
Math	0.97	0.97	0.97	120
Story	0.96	0.97	0.97	104
Random motion	0.97	0.97	0.97	125
Mental interaction	0.95	0.98	0.97	99
0-back	0.83	0.86	0.84	127
2-back	0.78	0.89	0.83	98
Left hand or foot	0.92	0.95	0.93	129
Right hand or foot	0.99	0.97	0.98	116
Similarity	0.79	0.77	0.78	124
Relation	0.88	0.85	0.87	116
Accuracy		0.89 (1627)		
Macro Avg	0.89	0.89	0.89	1627
Weighted Avg	0.89	0.89	0.89	1627

4. Identification of the Most Significant Features

Features were ranked by the absolute values of their weights and iteratively removed, starting with the least significant. At each step, the model was retrained, and accuracy (TPR at FPR = 0.05) was evaluated. The Fig.1 shows that feature selection can be performed without significant accuracy loss up to a certain threshold. If removing a feature reduced accuracy by more than 5%, it was restored, and the process terminated. The remaining features formed the set $\mathcal{M}$ of significant features.

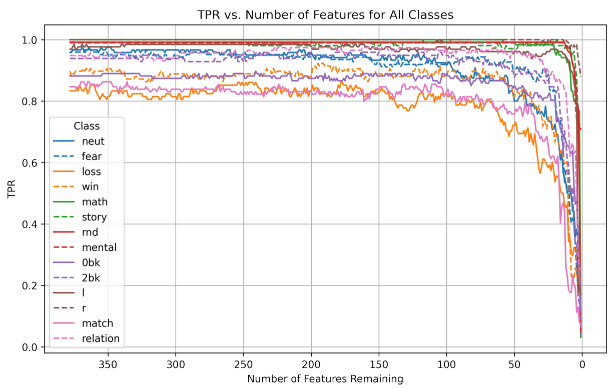

Fig. 1: Accuracy plot depending on the number of features

The graphs in Fig. 2 show that: Different brain states require varying numbers of significant brain regions for classification. For brain states with high classification accuracy, the $|\mathcal{M}|$ is small, indicating key brain regions that form these brain states

Analysis of similarity between significant features of different classes.

For all classes, we performed pairwise compar-

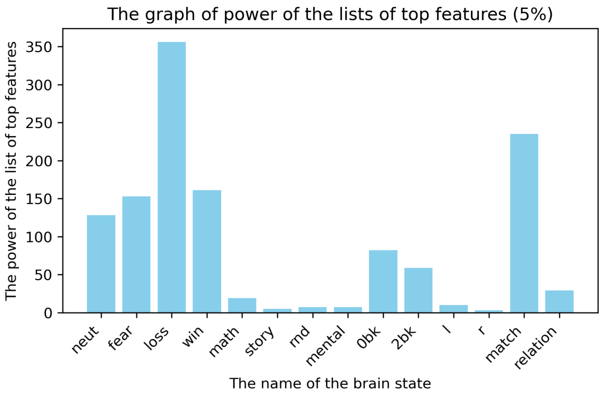

Fig. 2: The cardinality of the top feature sets

isons of the obtained sets $\mathcal{M}_i$ and $\mathcal{M}_j$ $(i,j = \overline{1,k})$ and constructed a Jaccard coefficients $J(\mathcal{M}_i, \mathcal{M}_j) \in [0,1]$ (where 1 indicates identical sets, and 0 indicates no common elements) matrix (Fig. 3). We observed that high-accuracy classes have sets $\mathcal{M}$ with near-zero overlap.

Analysis of Temporal Dynamics. We disrupt the temporal structure of brain region activity to determine its importance for identifying functional connections between them. For each class $c = 1, ..., k$, we perform the following steps.

We extract the time series $\{\mathbf{x}_1, \ldots, \mathbf{x}_{n_c}\}$ of significant features from $\mathcal{M}_c$ in the activity matrix $\mathbf{X}$, and shuffle them:

$$\mathbf{x}_i^{\text{shuffled}} = [x_{\pi(1)}, \ldots, x_{\pi(m)}],$$

where $\pi : \{1, 2, \ldots, m\} \to \{1, 2, \ldots, m\}$ is a random permutation of the time point indices.

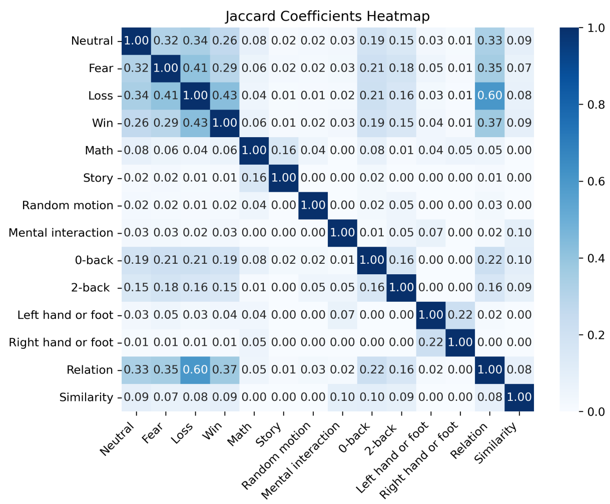

Fig. 3: The Jaccard coefficient matrix

Analysis of the significance of the time structure. We construct

$$P_1(corr(\mathbf{x}_i, \mathbf{x}_j)), P_2(corr(\mathbf{x}_i^{\text{shuffled}}, \mathbf{x}_j^{\text{shuffled}}))$$

the distributions of the Pearson correlation coefficients between original and shuffled time series of significant features $i, j \in \mathcal{M}_c$ for all activity matrices of current class.

Do the two distributions P_1 and P_2 originate from the same population? For each pair (i,j) we perform the KS-test to compare the distributions. Result: for almost all pairs of features in each class, the p-values $< \alpha = 0.03$. Thus, the distributions of correlation coefficients between the original time series significantly differ from the distributions between the shuffled time series.

5. Conclusions

Currently, advanced methods for working with fMRI data, which are often available in limited quantities, are being actively developed. We demonstrated the effectiveness of classical machine learning methods in classifying fMRI data, emphasizing the importance of starting with simple methods when analyzing complex datasets like fMRI. Our analysis revealed unique sets of significant brain regions for each brain state, with minimal overlap between classes, highlighting their functional specificity. Furthermore, correlation analysis and the Kolmogorov-Smirnov (KS) test confirmed the crucial role of temporal data structure in forming functional connections, as disrupting this structure significantly alters correlation patterns. Additionally, states with low classification accuracy were characterized by a large number of significant features, indicating complex and distributed activation of brain regions. This complexity underscores the need for further research to better understand the underlying mechanisms of these states.

References

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