The 8th International Conference on Brain Inspired Cognitive Systems (BICS 2016)

Decoding visual stimuli in human brain by using Anatomical Pattern Analysis on fMRI images

Muhammad Yousefnezhad, Daoqiang Zhang

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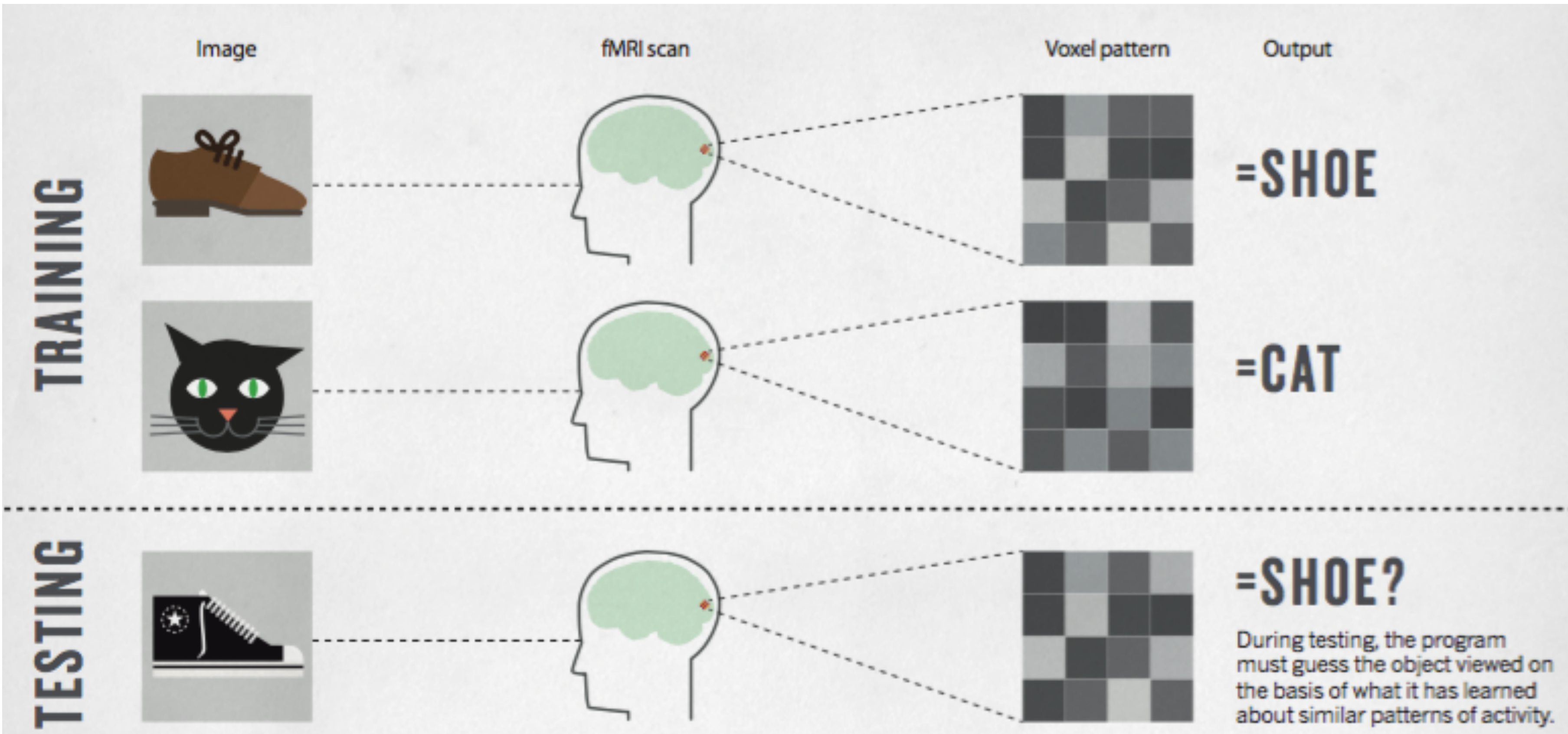
Motivation



[Smith, Nature, 2013]

Outline

1 Preliminaries

2 The Proposed Method

2.1 Feature Extraction

2.2 Classification Algorithm

3 Experiments

4 Conclusion

Modalities of Measurement

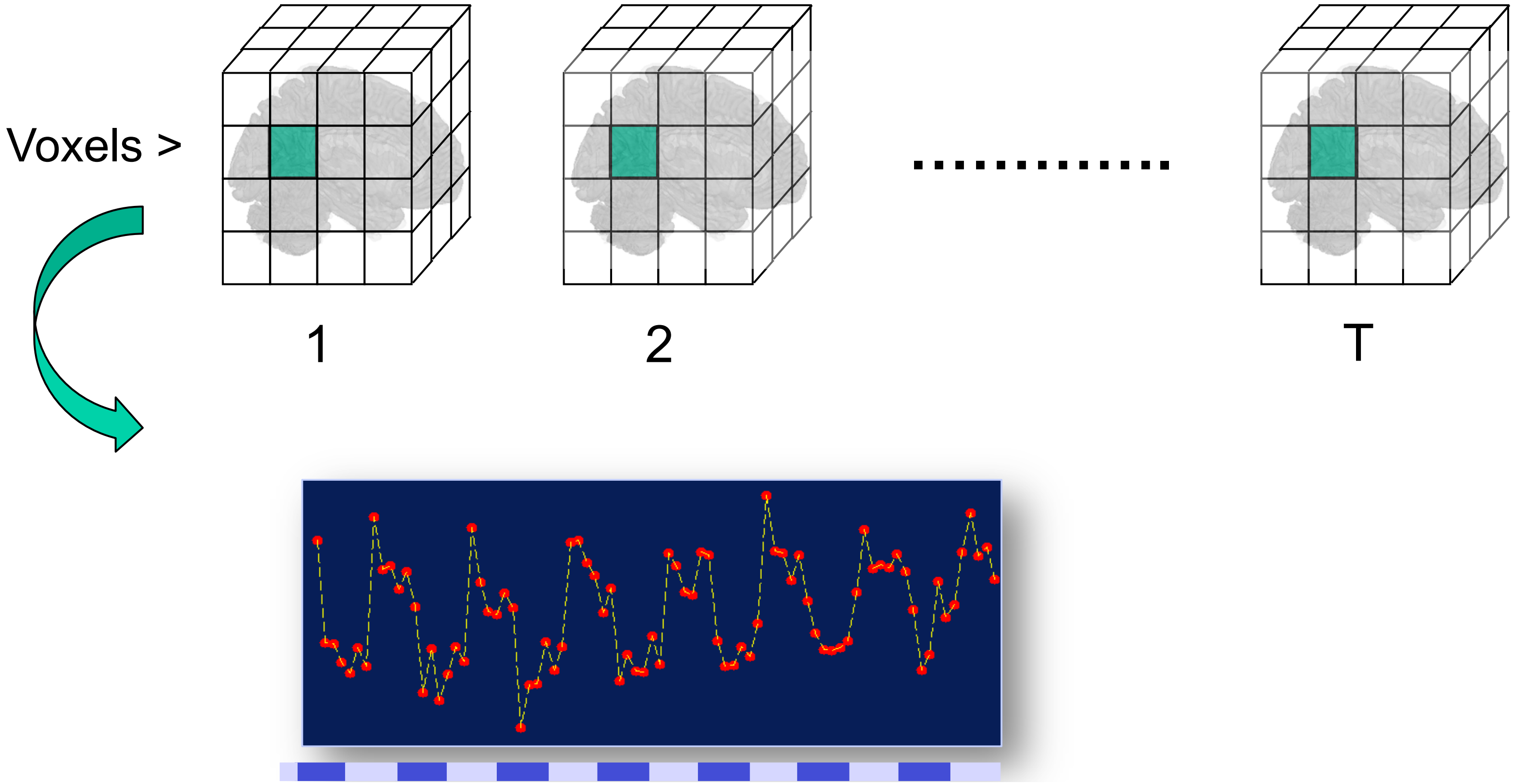
- Modalities of measure:
  - ✓ Single-unit recording
  - ✓ Electrocorticography (ECoG)
  - ✓ electroencephalography (EEG)
  - ✓ Magnetoencephalographic (MEG)
  - ✓ functional Magnetic Resonance Imaging (fMRI)

- The spatial resolution of fMRI allowed investigators to ask what information is represented in a region instead of asking what a region's function is?

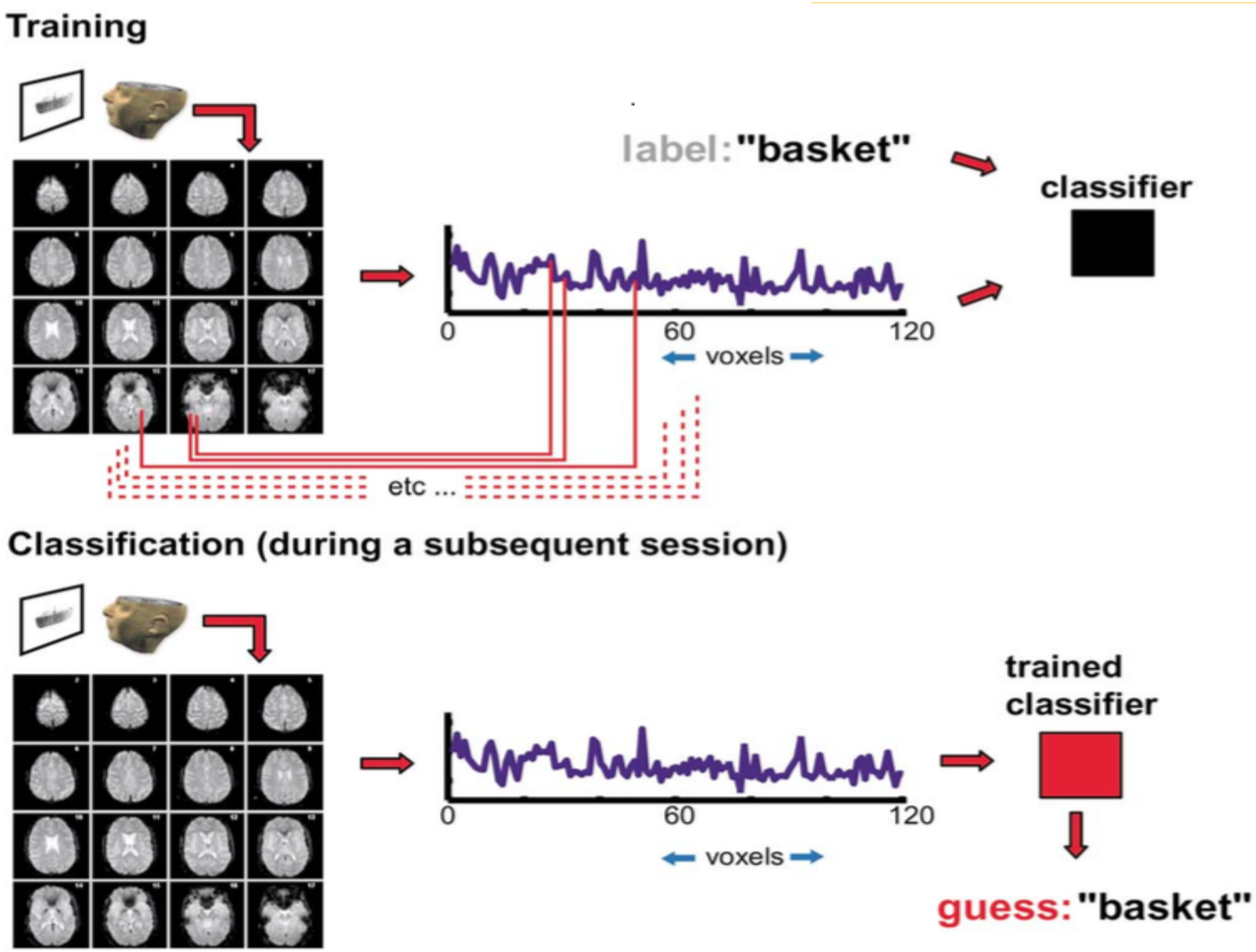
- Our method contributions are:
  - ✓ Automatically detecting the Region of Interests (ROIs)
  - ✓ A new feature representation for removing noise and sparsity
  - ✓ A customized classification algorithm for brain decoding problems

fMRI Data

- Tracking the intensity over time gives us a time series.



Multivariate Pattern Classification (MVP)



[Cox et al. 2003]

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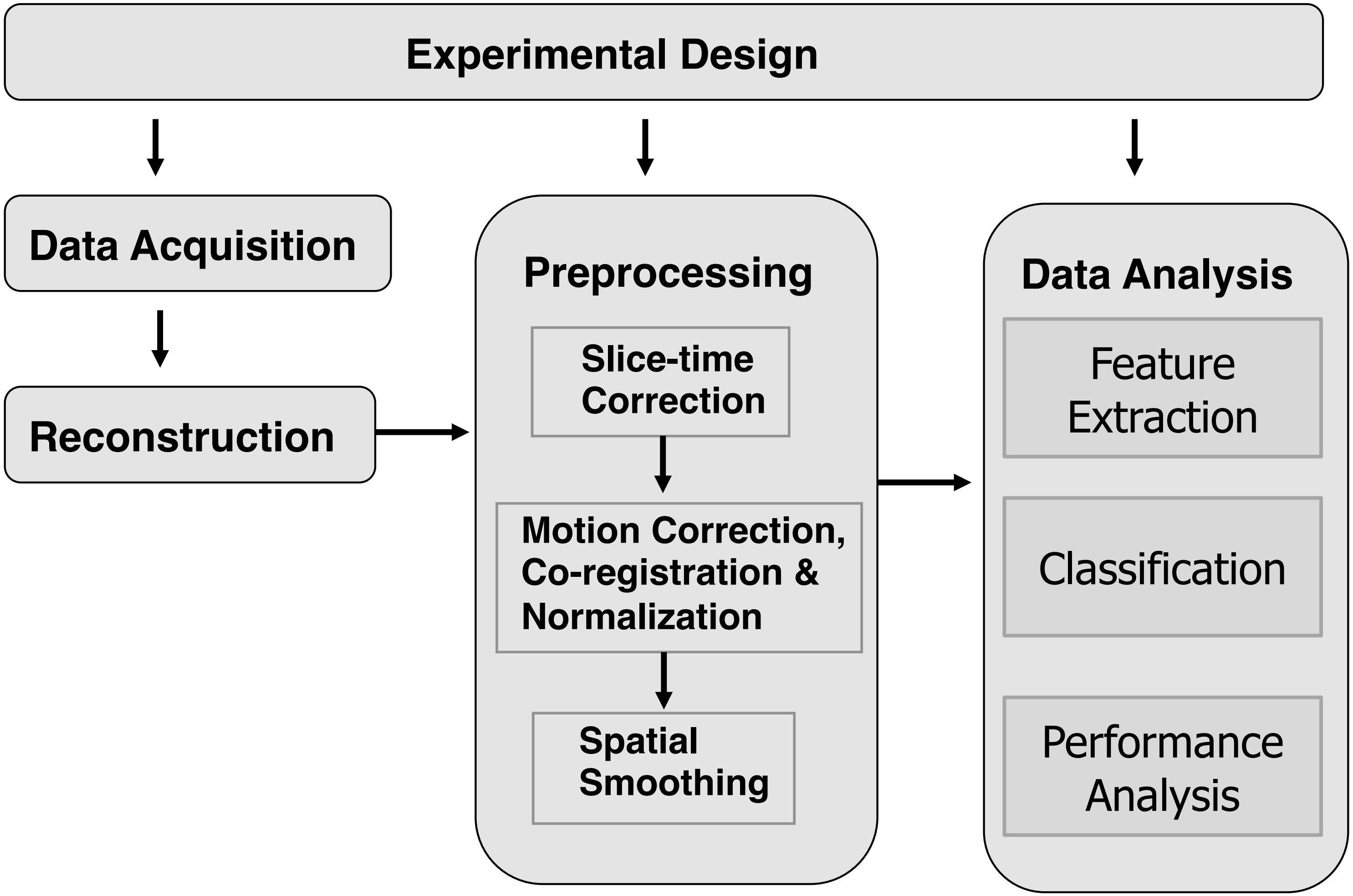
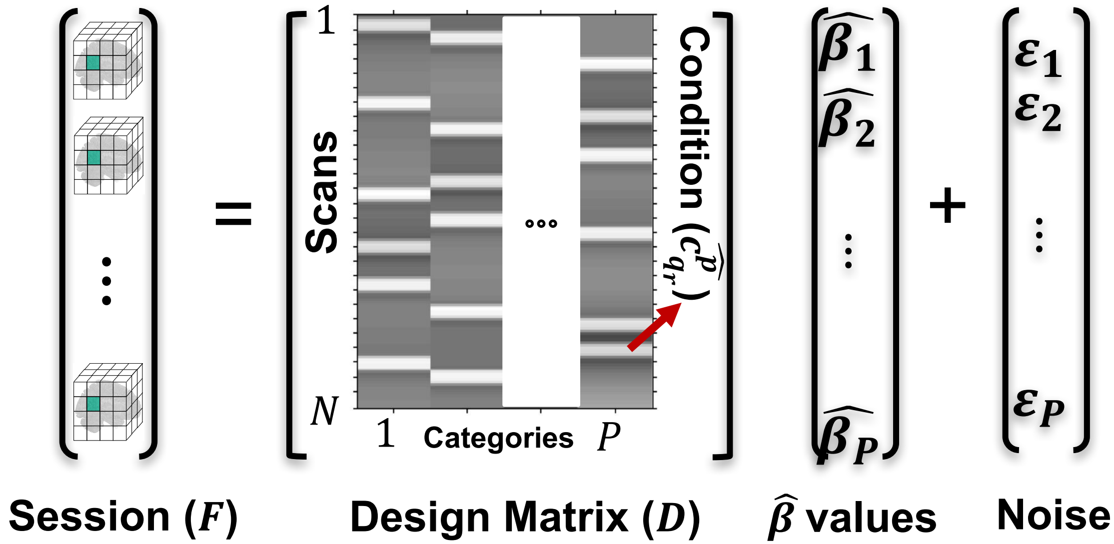
Outline

General framework of study



Outline

General Linear Model for Each Session



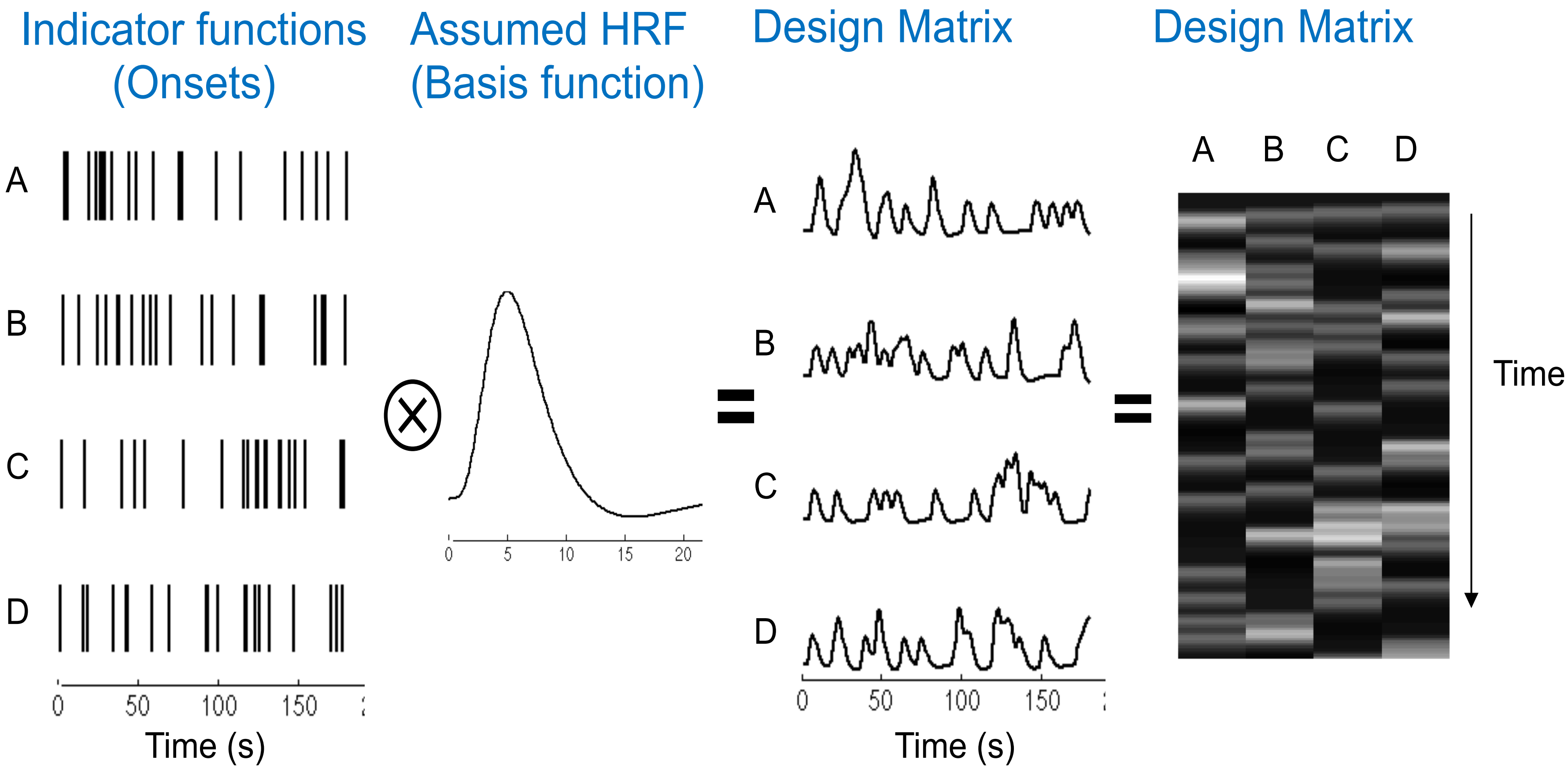
$$F = D\hat{\beta} + \varepsilon$$

- This paper uses Generalized Least Squares (GLS) approach for estimating optimized solution:

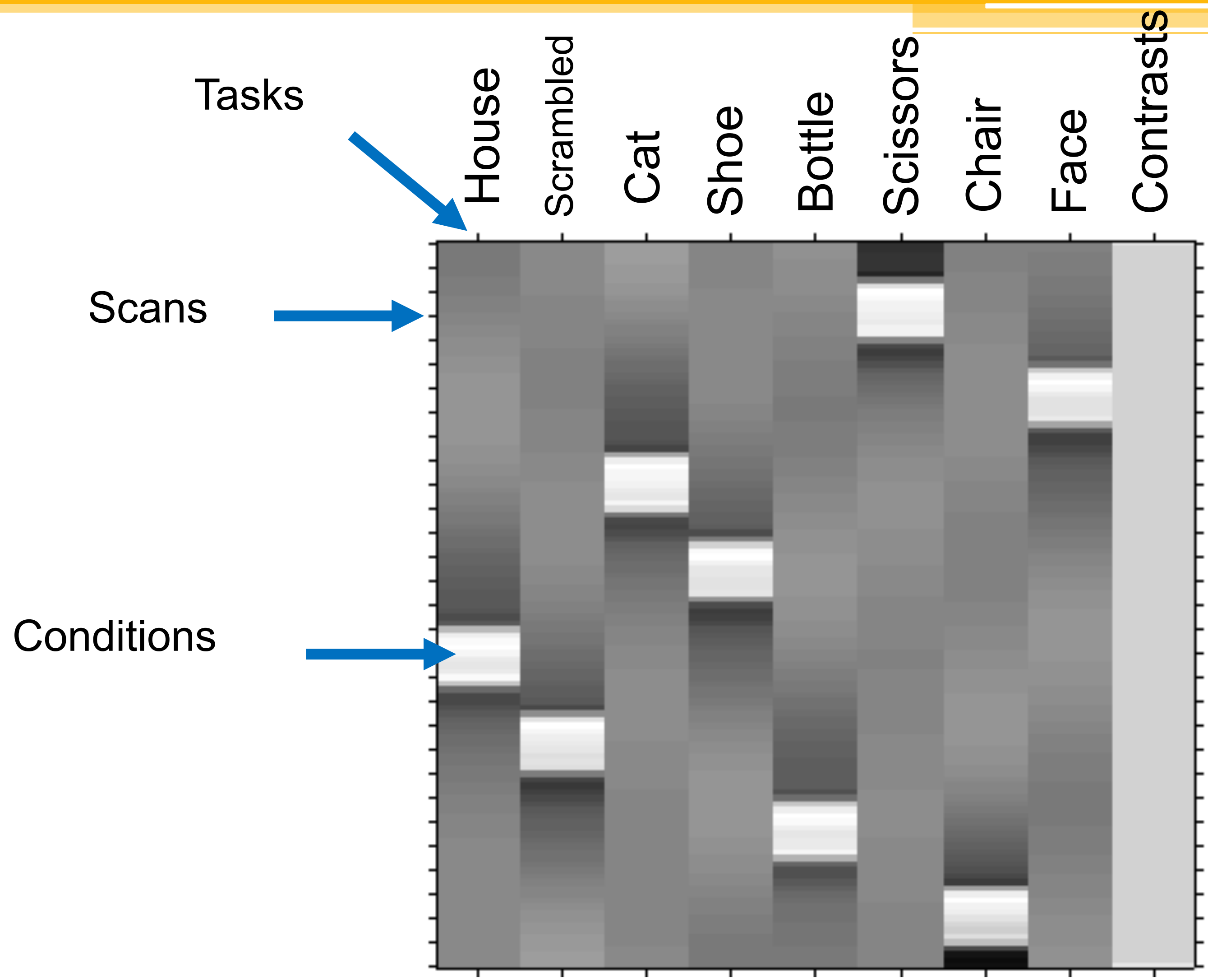
$$\hat{\beta} = (D^\intercal V^{-1} D)^{-1} D^\intercal V^{-1} F$$

$$Var(\varepsilon) = V\sigma^2 \neq \mathbb{I}\sigma^2$$

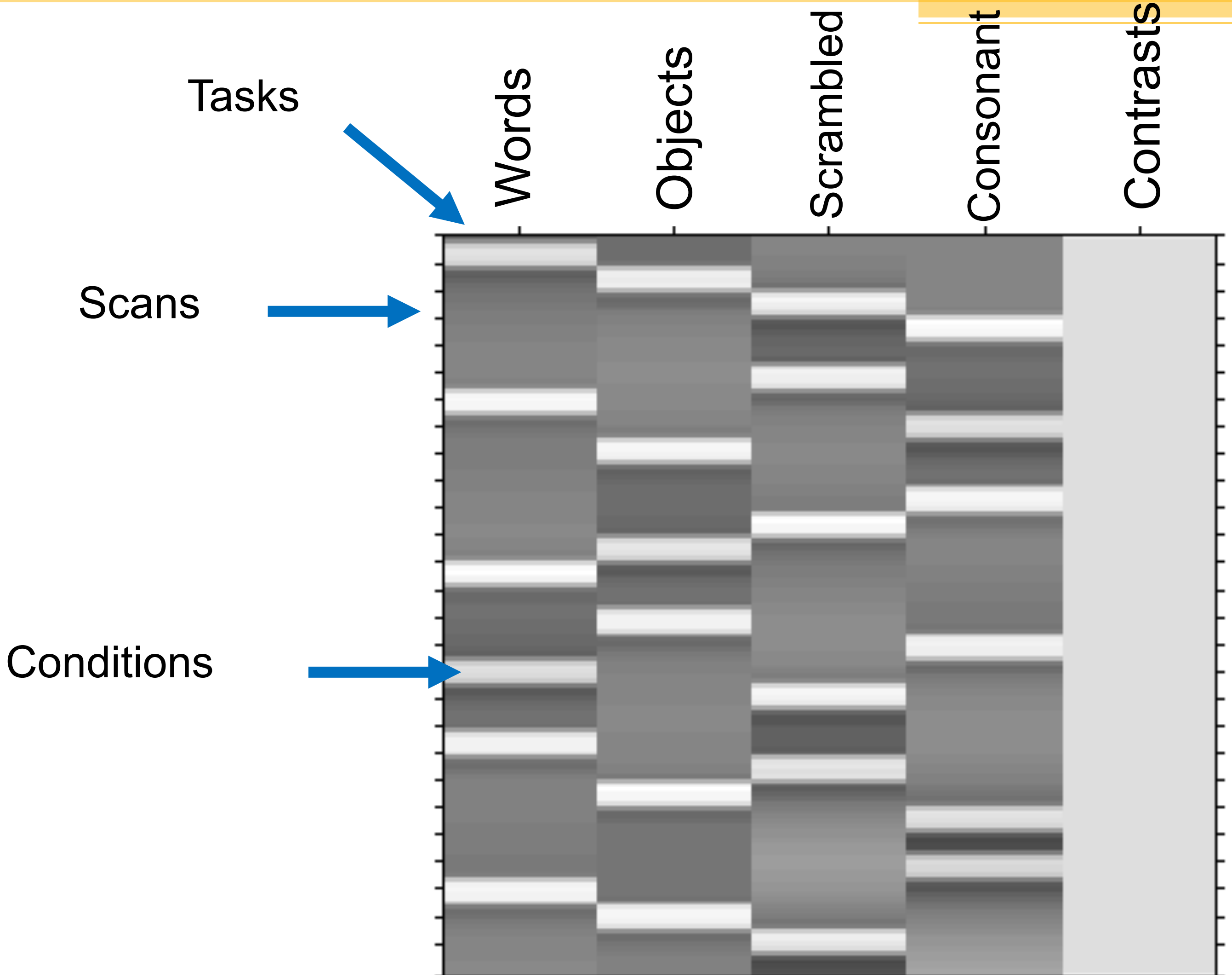
The first level analysis



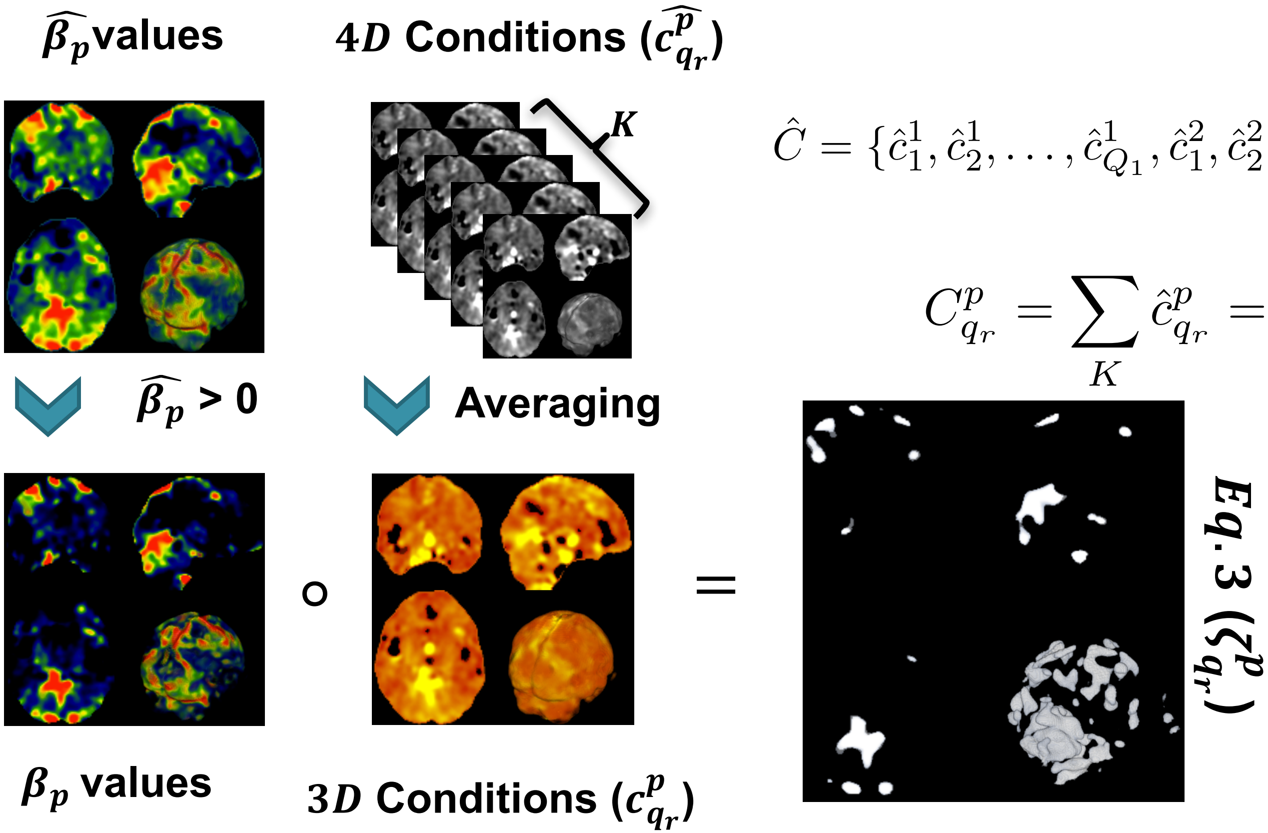
Example of Design Matrix



Example of Design Matrix (cont.)



Feature Extraction

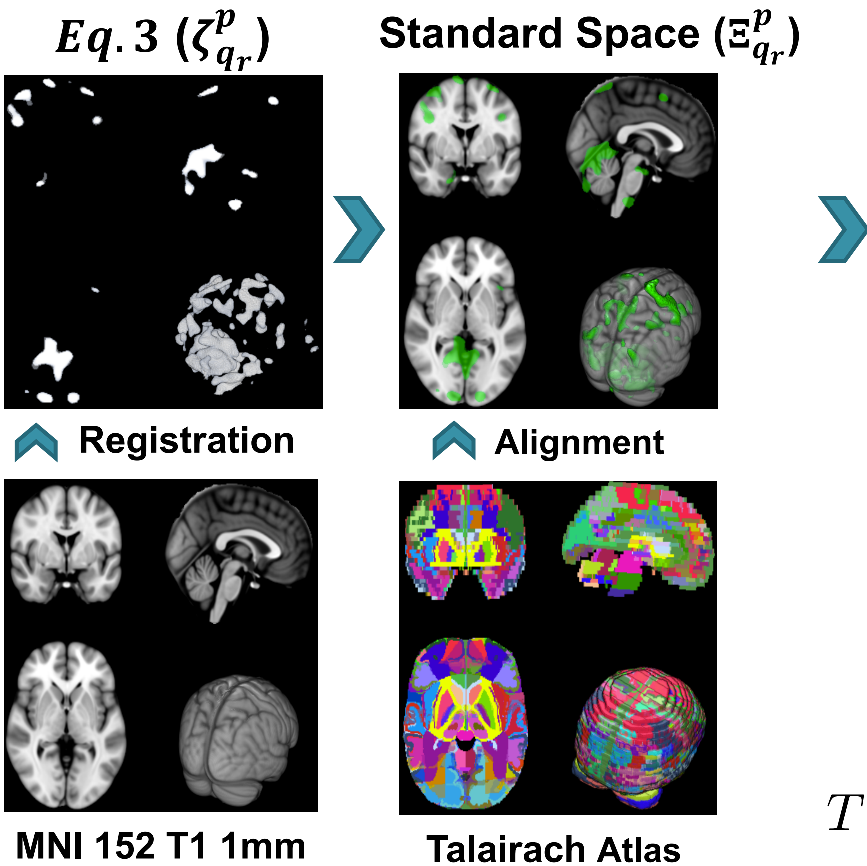


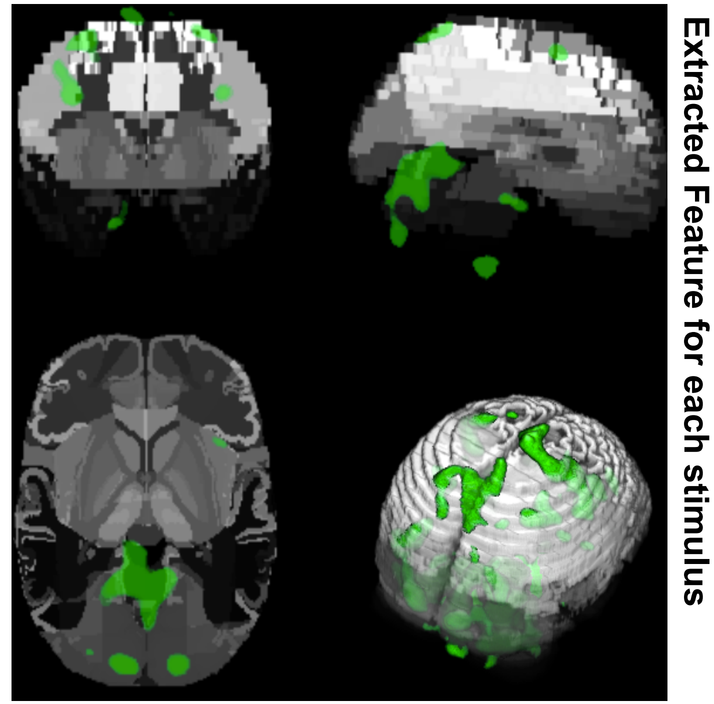
$$\hat{C} = \{\hat{c}^1_1, \hat{c}^1_2, \dots, \hat{c}^1_{Q_1}, \hat{c}^2_1, \hat{c}^2_2, \dots, \hat{c}^2_{Q_2}, \dots, \hat{c}^p_1, \hat{c}^P_2, \dots, \hat{c}^P_{Q_R}\}$$

$$C^p_{q_r} = \sum_K \hat{c}^p_{q_r} = \sum_{k=1}^{K^p_{q_r}} \hat{c}^p_{q_r}[k, :, :, :]$$

$$\zeta^p_{q_r} = \beta_p \circ C^p_{q_r} = \{\forall [x, y, z] \in C^p_{q_r} \implies (\zeta^p_{q_r})_{[x,y,z]} = (\beta_p)_{[x,y,z]} \times (C^p_{q_r})_{[x,y,z]}\} \quad (3)$$

Feature Extraction (cont.)





$$T^* = argmin_{T \in S_T}(NMI(Ref, \Xi^p_{q_r})) \quad (4)$$

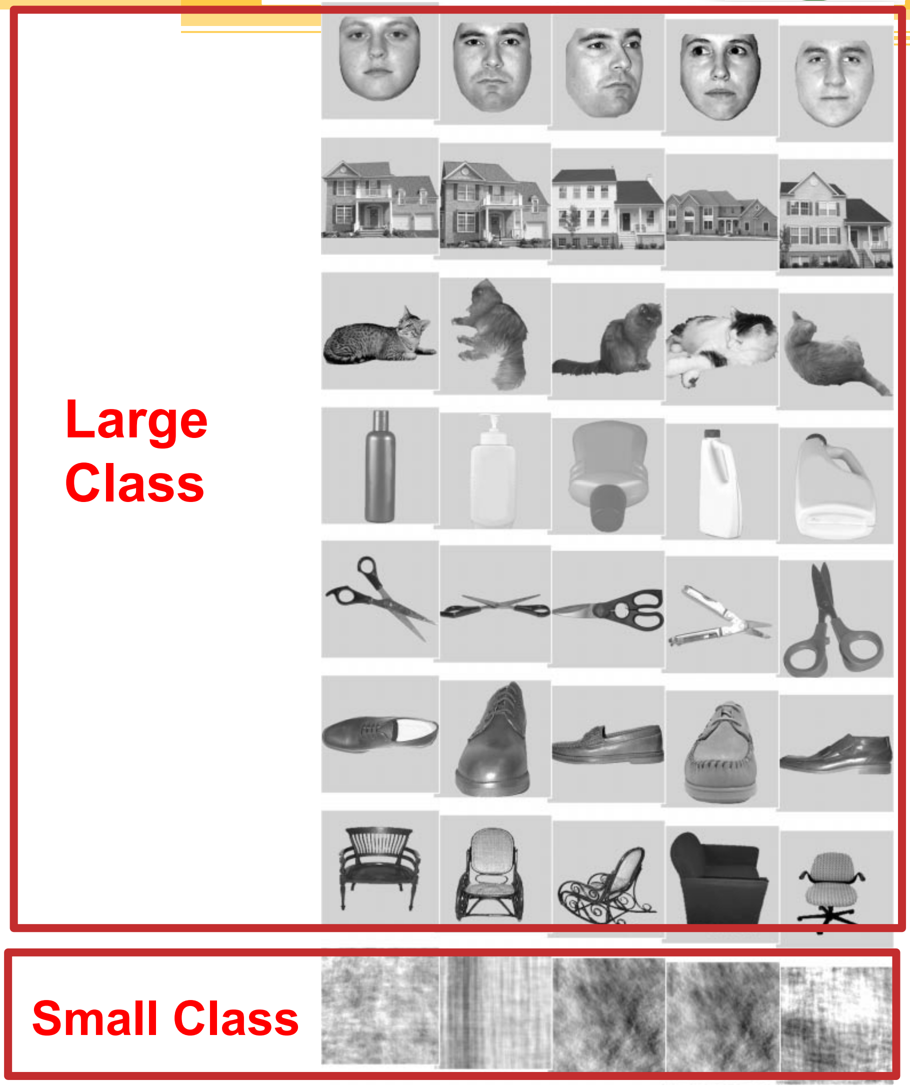
$$\forall a_v = [x_v, y_v, z_v] \in A_l \implies \Gamma^p_{q_r}(l) = \frac{1}{\mid A_l \mid} \sum_{v=1}^{|A_l|} (\Xi^p_{q_r})[a_v] = \frac{1}{\mid A_l \mid} \sum_{v=1}^{|A_l|} (\Xi^p_{q_r})[x_v, y_v, z_v] \quad (5)$$

Outline

One Vs. All (OVA) strategy

- Most of previous studies used One vs. All (OVA) strategy for training binary classification.

- While (non-)linear SVM is mostly used for creating classification method, the OVA strategy generate an imbalance sampling.



Ensemble Approach

- Each iteration contains all samples of small class, randomized selected samples from large class, and the samples that made errors in the pervious iteration.
- The number of randomized selected samples from large class is equal to the number of samples in the small class.
- Randomize sampling is without replacement.

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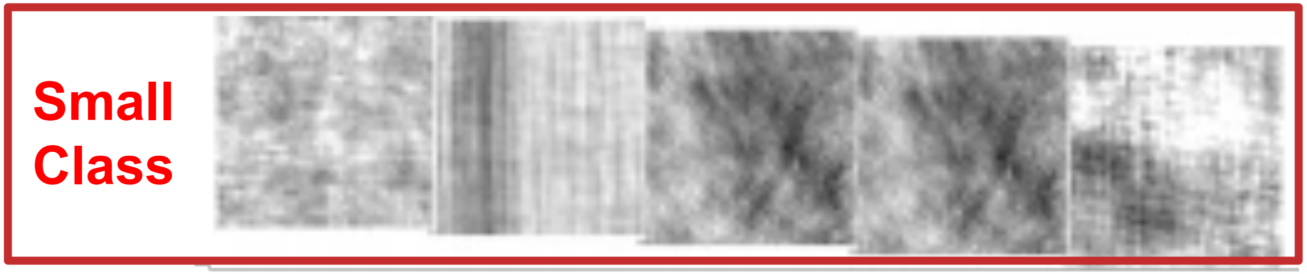

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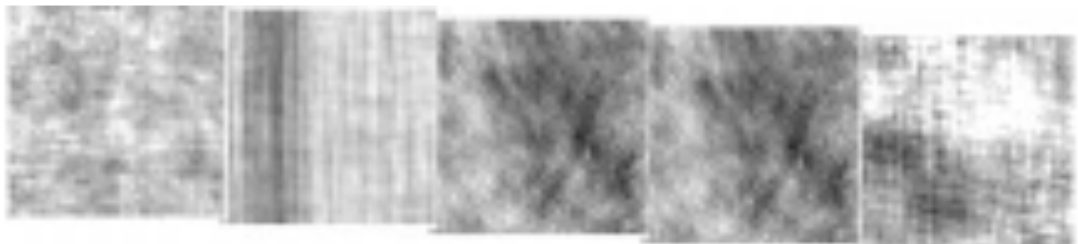

Selected Large Class

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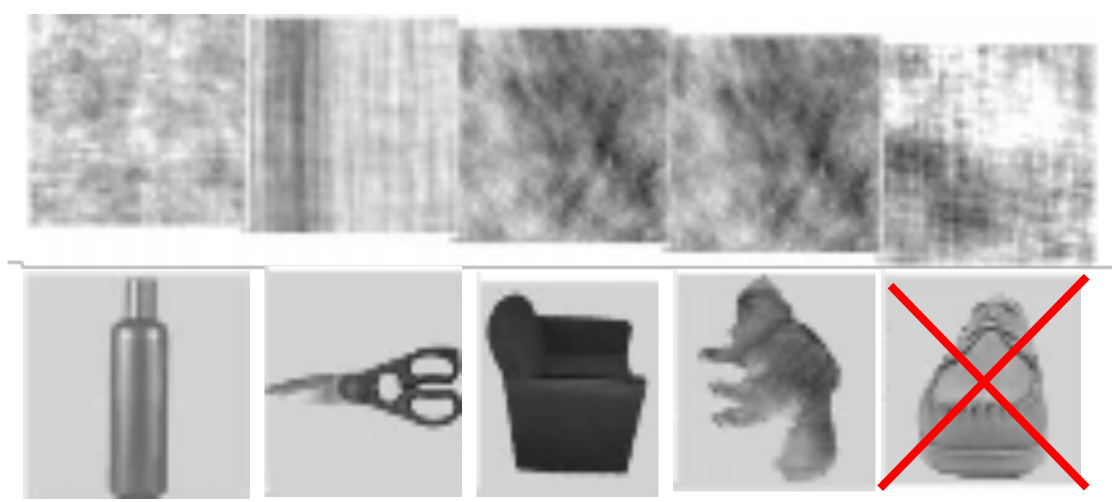

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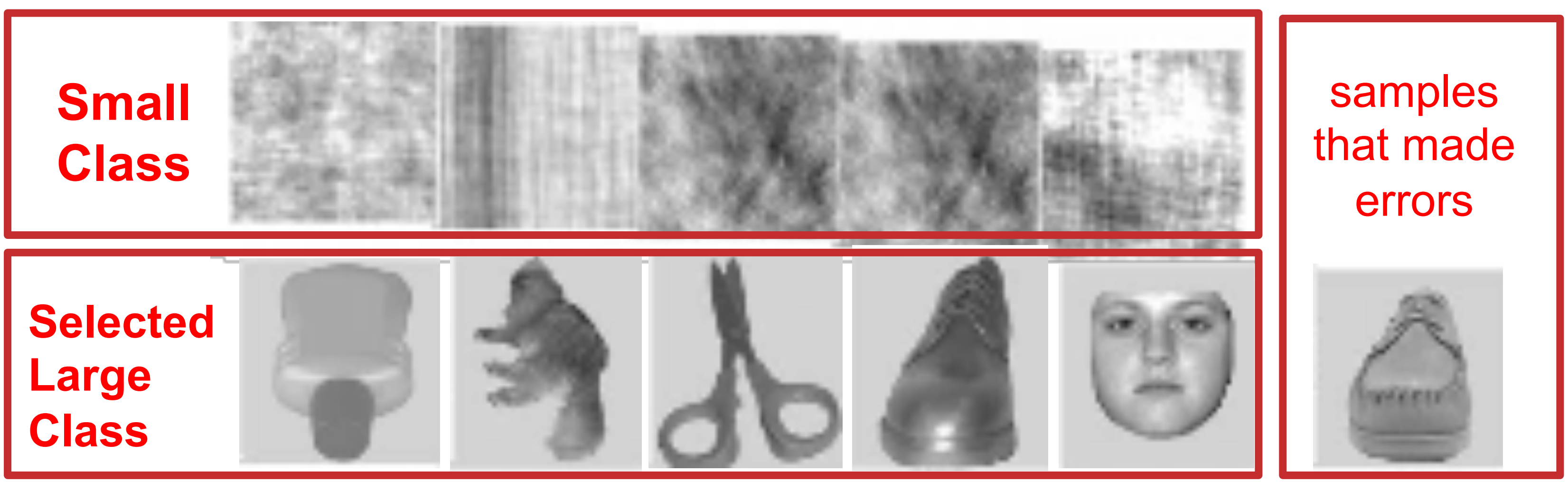
Iteration #2



A modified version of AdaBoost algorithm

Algorithm 1 The proposed binary classification algorithm

Input: Data set G_{tr} : is train set, I_{tr} : denotes real class labels of the train sets,
Output: Classifier E,
Method:

1. Partition $G_{tr} = \{G_{tr}^S, G_{tr}^L\}$, where G_{tr}^S, G_{tr}^L are Small and Large classes.
2. Calculate $J = Int(\mid G_{tr}^S \mid / \mid G_{tr}^L \mid)$ based on number of elements in classes.
3. Randomly sample the $G_{tr}^L = \{G_{tr}^L(1), \ldots, G_{tr}^L(J)\}$.
4. By considering $\bar{G}_1 = \bar{I}_1 = \emptyset$, generating $j = 1, \ldots, J+1$ classifiers:
5. Construct $G_j = \{G_{tr}^S, G_{tr}^L(j), \bar{G}_j\}$ and $I_j = \{I_{tr}^S, I_{tr}^L(j), \bar{I}_j\}$
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7. Train $\theta_j = Classifier(G_j, I_j, W_j)$.
8. Construct $\bar{G}_{j+1}$, $\bar{I}_{j+1}$ as the set of instances cannot truly trained in θ_j.
9. **If** $(j \leq J+1)$: go to line 5; **Else:** return $\Theta_p = \{\theta_1, \ldots, \theta_{J+1}\}$ as final classifier.

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Multi-class Approach

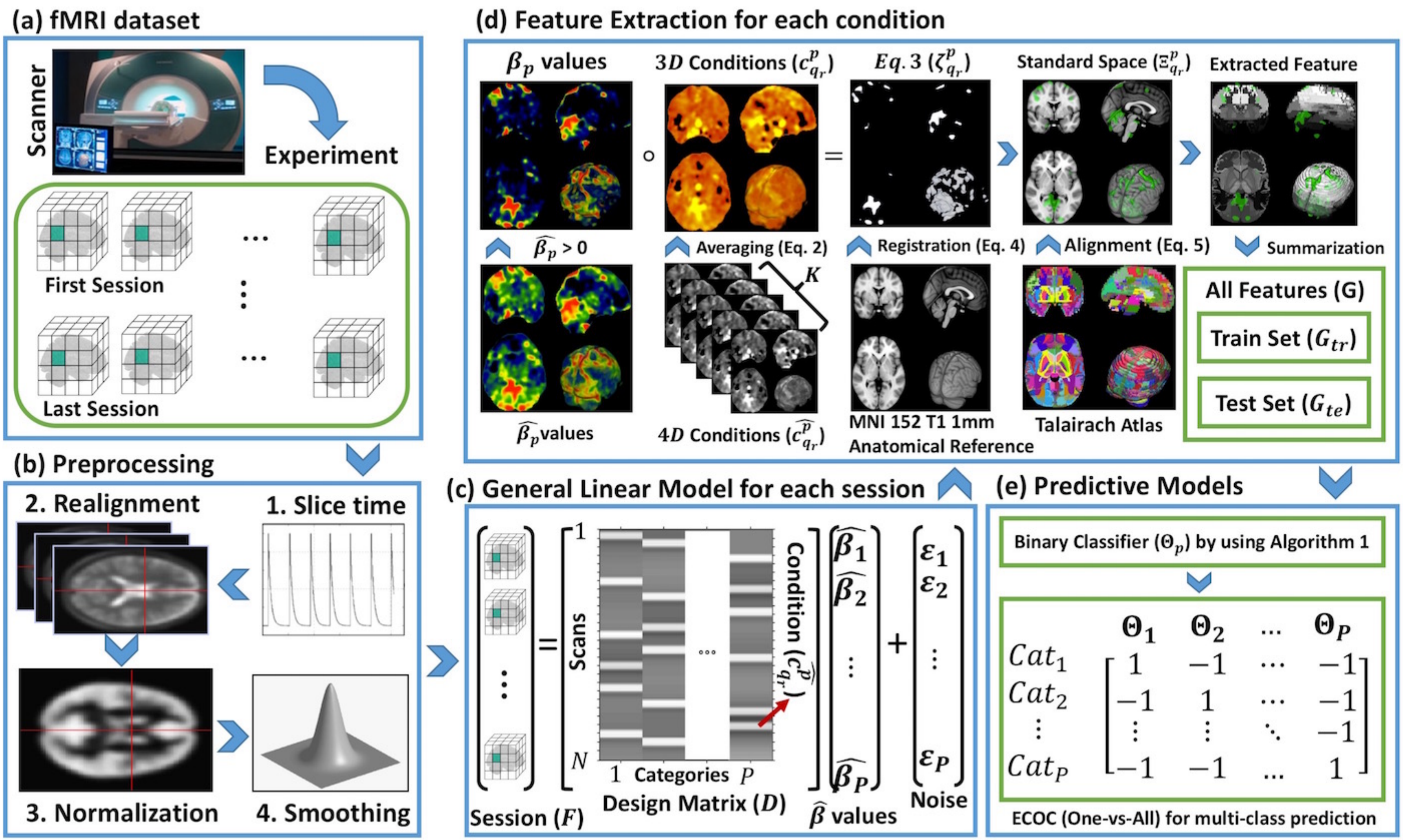
- This paper utilizes Error-Correcting Output Codes (ECOC) method for applying multi-class classification.

- Our method uses a one-versus-all encoding strategy for training the ECOC method, where an independent category of the visual stimuli is compared with the rest of categories.

- Indeed, the number of classifiers in this strategy is exactly equal to the number of categories.

- This method also assigns the brain response to the category with closest hamming distance in decoding stage.

Summery



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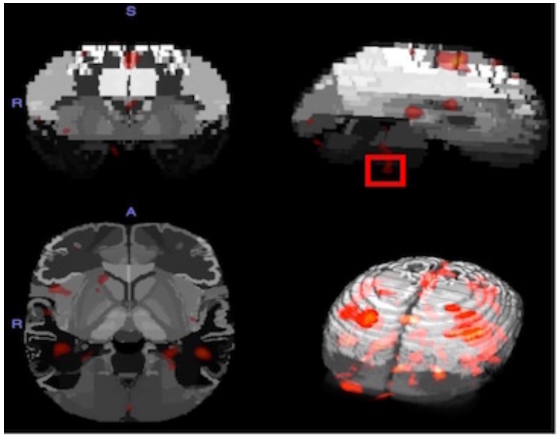
Data Sets

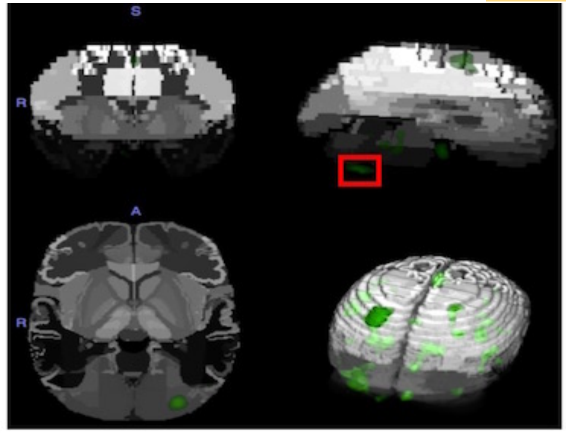
- This paper employs two datasets, shared by openfmri.org, for running empirical studies.

Title	ID	# of Subjects	# of Samples	# of Stimuli
Visual Object Recognition	DS105	6	568	8
Word and Object Processing	DS107	49	1568	4

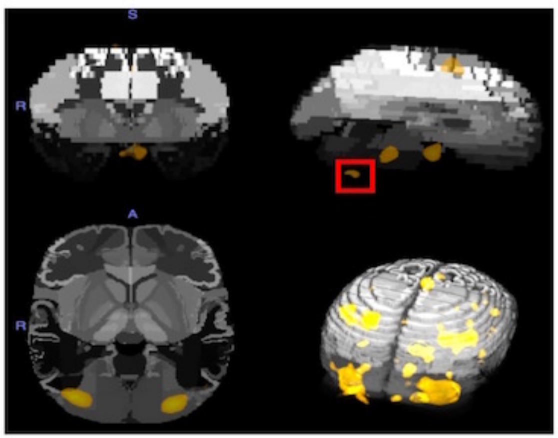
The Error of Registration



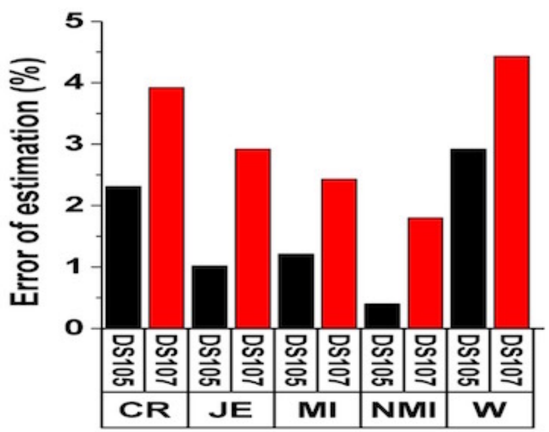
(a) Word



(b) Object



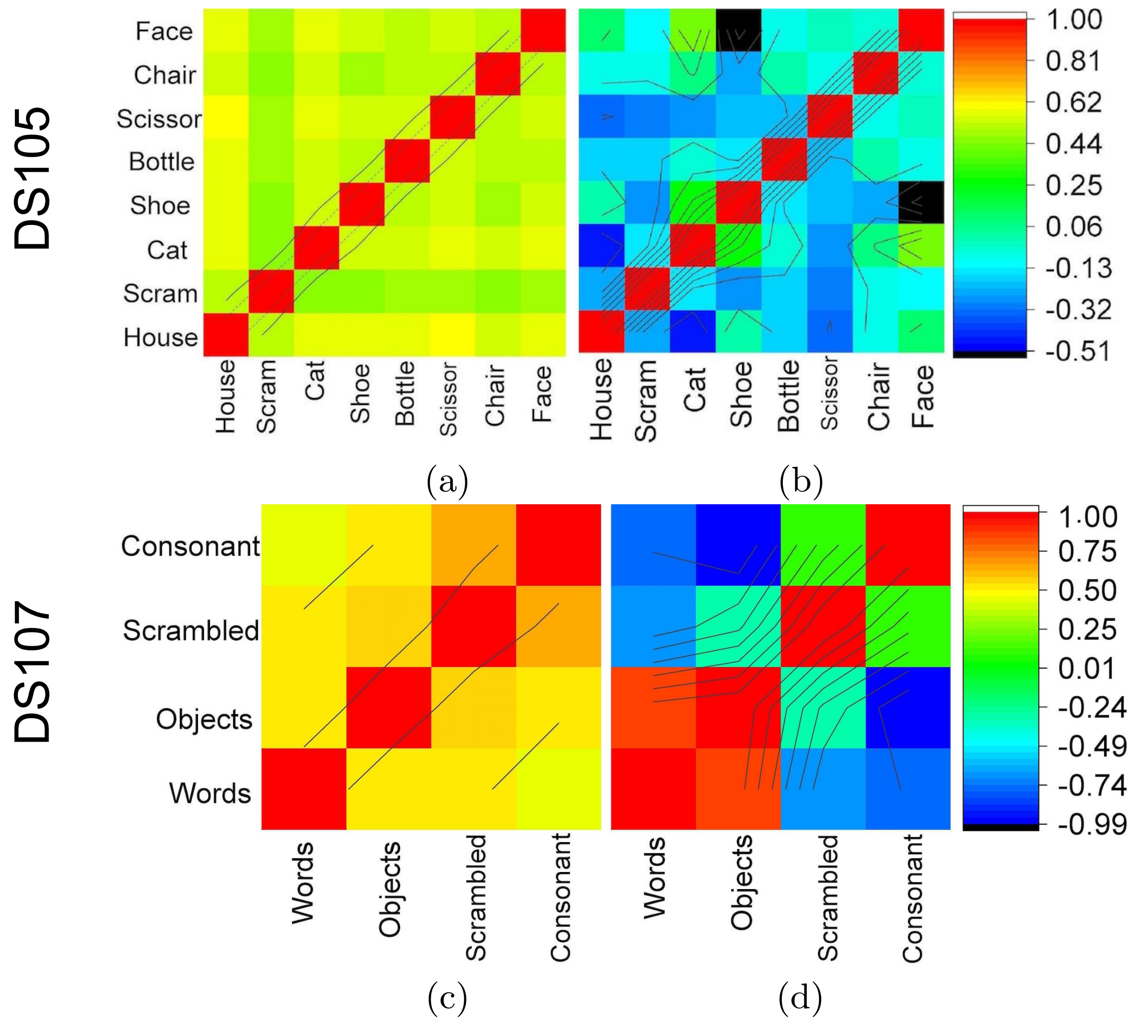
(c) Scramble



(d) Registration

- Woods function (W)
- Correlation Ratio (CR)
- Joint Entropy (JE)
- Mutual Information (MI)
- Normalized MI (NMI)

Correlation Analysis



Binary Classification (OVA)

Table 1: Accuracy of binary predictors

Data Sets	Cox & Savoy	McMenamin et al.	Mohr el al.	Osher et al.	Binary-APA
DS105-Objects	71.65±0.97	83.06±0.36	85.29±0.49	90.82±1.23	**98.37±0.16**
DS107-Words	69.89±1.02	89.62±0.52	81.14±0.91	94.21±0.83	**97.67±0.12**
DS107-Consonants	67.84±0.82	87.82±0.37	79.69±0.69	95.54±0.99	**98.73±0.06**
DS107-Objects	65.32±1.67	84.22±0.44	75.32±0.41	**95.62±0.83**	95.06±0.11
DS107-Scramble	67.96±0.87	86.19±0.26	78.45±0.62	93.1±0.78	**96.71±0.18**

Table 2: Area Under the ROC Curve (AUC) of binary predictors

Data Sets	Cox & Savoy	McMenamin et al.	Mohr el al.	Osher et al.	Binary-APA
DS105-Objects	68.37±1.01	82.22±0.42	80.91±0.21	88.54±0.71	**96.25±0.92**
DS107-Words	67.76±0.91	86.35±0.39	78.23±0.57	93.61±0.62	**97.02±0.2**
DS107-Consonants	63.84±1.45	85.63±0.61	77.41±0.92	94.54±0.31	**96.92±0.14**
DS107-Objects	63.17±0.59	81.54±0.92	73.92±0.28	94.23±0.94	**95.17±0.03**
DS107-Scramble	66.73±0.92	85.79±0.42	76.14±0.47	92.23±0.38	**96.08±0.1**

Multi-class Classification

Table 3: Accuracy of multi-class predictors

Data Sets	Cox & Savoy	McMenamin et al.	Mohr el al.	Osher et al.	Multi-APA
DS105 (P=8)	18.03±4.07	38.34±3.21	29.14±2.25	50.61±4.83	**57.93±2.1**
DS107 (P=4)	38.01±2.56	71.55±2.79	64.71±3.14	89.69±2.32	**94.21±2.41**
ALL (P=4)	32.93±2.29	68.35±3.07	63.16±4	80.36±3.04	**95.67±1.25**

Outline

Conclusion

- This paper proposes Anatomical Pattern Analysis (APA) framework for decoding visual stimuli in the human brain.
  - ✓ A new feature extraction method.
  - ✓ A customized classification algorithm.

- In future, we plan to apply the proposed method to different brain tasks such as low-level visual stimuli, emotion and etc.

- M. Yousefnezhad, D. Zhang, Local Discriminant Hyperalignment for multi-subject fMRI data alignment. 34th AAAI Conference on Artificial Intelligence (AAAI-17), San Francisco, California, USA, February/4-9, 2017.

Thanks for your attention!

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