Analyzing Human Brain Patterns

by using deep approaches

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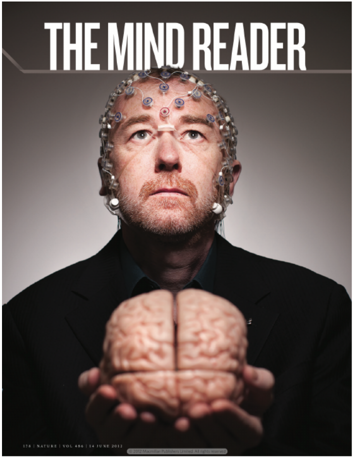
Outline

1. Analyzing Brain Patterns
2. Hyperalignment
3. Deep Hyperalignment
4. Deep Hyperalignment: Optimization
5. Experiments
6. Conclusion

The Mind Reader (in theory)



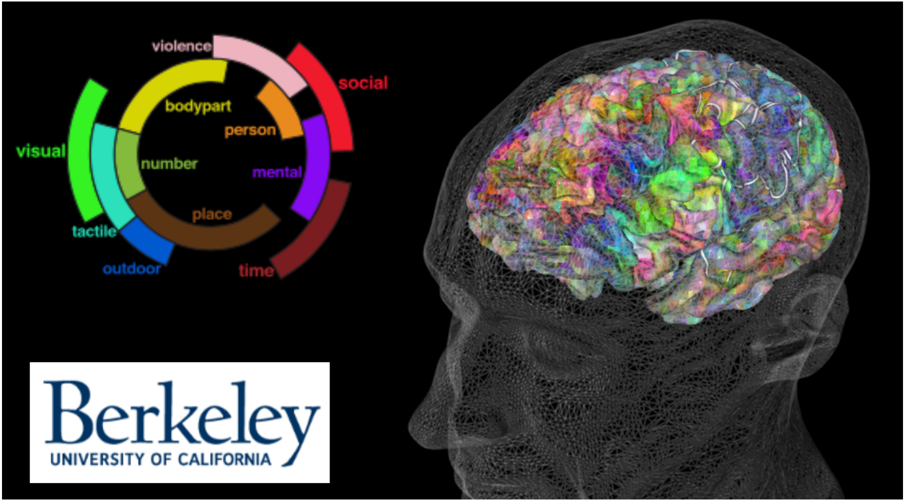
Smith, Nature, 2013

Optogenetics

Recovery Movies from Human Brain

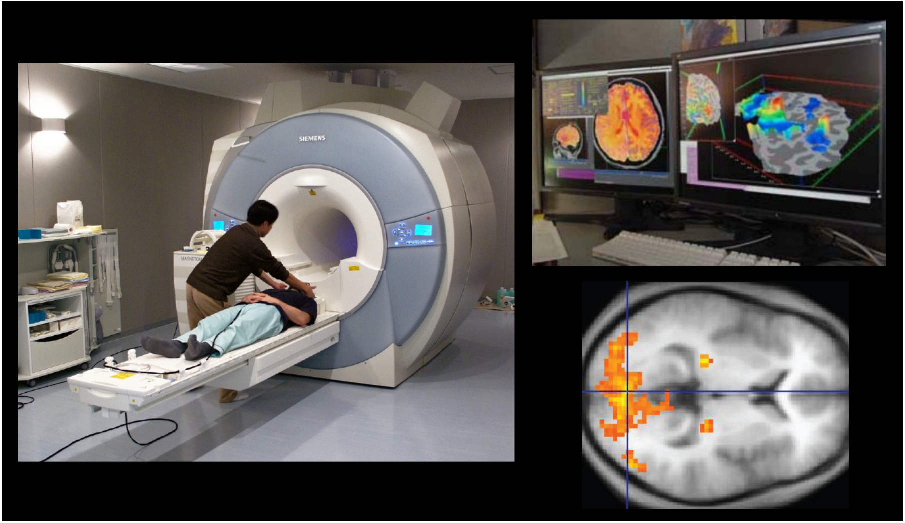
Nishimoto, Current Biology, 2011

Semantic Maps



Huth, Nature, 2016

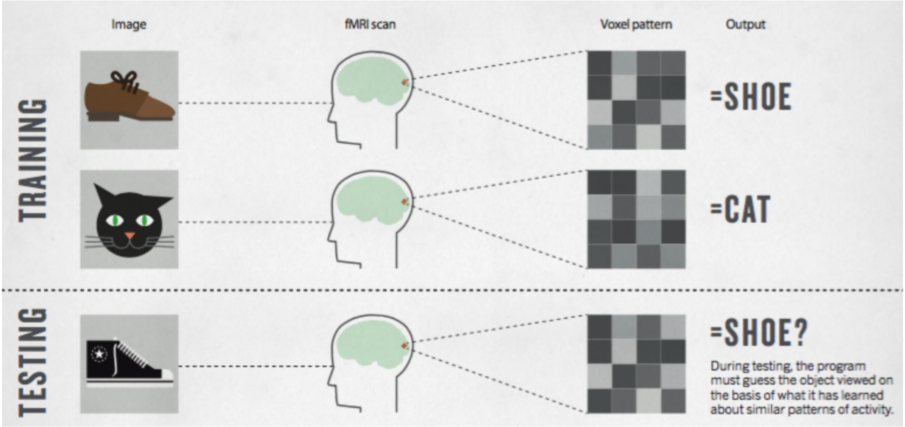
functional Imaging: functional MRI (fMRI)



fMRI vs. Other Modalities

- Prior to the discovery that **within-area patterns** of response in fMRI carried information that **afforded decoding of stimulus distinctions**.
- It was generally believed that the **spatial resolution of fMRI** allowed investigators to ask only which task or stimulus activated a region globally.
- Instead of asking what a regions function is, in terms of a single brain state associated with global activity, fMRI investigators can now ask **what information is represented in a region**, in terms of brain states associated with distinct patterns of activity, and how that information is encoded and organized.
- A wide range of **open source** fMRI datasets.

The Human Brain Decoding: Problem Definition



Smith, Nature, 2013

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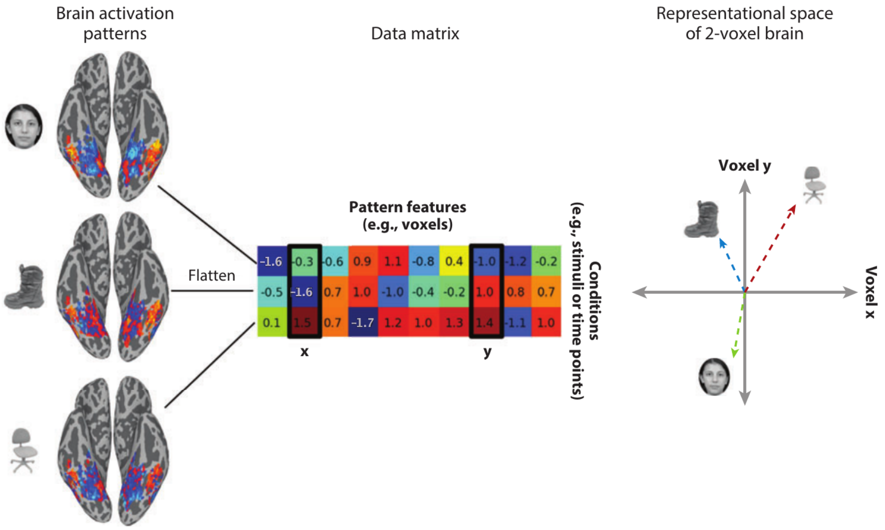
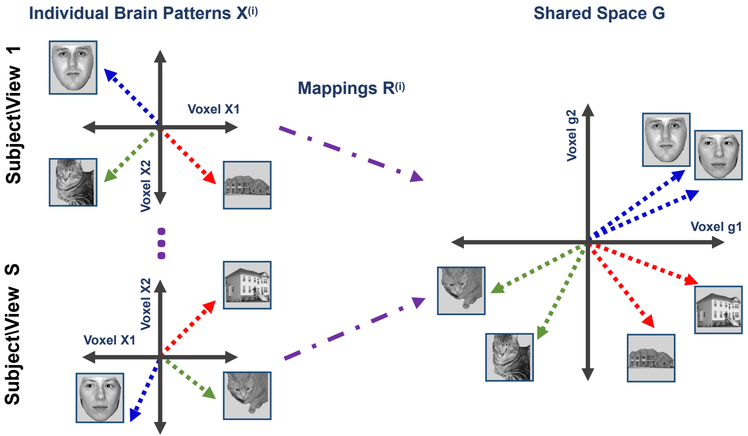
Representational Space: Example



Haxby, Annual Review Neuroscience, 2014

Hyperalignment



- The main assumption in Hyperalignment is that the neural actives in different brains are noisy ‘rotations’ of a common space **Haxby, Neuron, 2011**.
- It can be formulated as extracting shared space from multi-view (multi-subject) data.

Classical Hyperalignment

Classical Hyperalignment can be formulated by Generalized Canonical Correlation Analysis (CCA): **Haxby, Neuron, 2011**

$$\min_{\mathbf{R}^{(i)},\mathbf{G}} \sum_{i=1}^{S} \left\| \mathbf{X}^{(i)}\mathbf{R}^{(i)} - \mathbf{G} \right\|_F^2$$

$$\text{subject to } \left(\mathbf{X}^{(\ell)}\mathbf{R}^{(\ell)}\right)^\top \mathbf{X}^{(\ell)}\mathbf{R}^{(\ell)} = \mathbf{I}$$

where the common space can be denoted by:

$$\mathbf{G} \in \mathbb{R}^{T\times V} = \frac{1}{S}\sum_{j=1}^{S} \mathbf{X}^{(j)}\mathbf{R}^{(j)},$$

- $\mathbf{X}^{(\ell)} \in \mathbb{R}^{T\times V}$ denotes the neural activities, and $\mathbf{R}^{(\ell)} \in \mathbb{R}^{V\times V}$ is the mappings.

Regularized Hyperalignment

- RHA's Objective Function can be denoted as follows:

$$\min_{\mathbf{R}^{(i)},\mathbf{G}} \sum_{i=1}^{S} \left\| \mathbf{X}^{(i)}\mathbf{R}^{(i)} - \mathbf{G} \right\|_F^2$$

$$\text{subject to } \left(\mathbf{R}^{(\ell)}\right)^\top \left(\left(\mathbf{X}^{(\ell)}\right)^\top \mathbf{X}^{(\ell)} + \epsilon \mathbf{I}\right)\mathbf{R}^{(\ell)} = \mathbf{I}$$

- The common space: $\mathbf{G} = \frac{1}{S}\sum_{j=1}^{S} \mathbf{X}^{(j)}\mathbf{R}^{(j)}$
- Here, the regularization term ϵ can improve the stability of alignment by providing a better inverse of the covariance matrix for $\mathbf{X}^{(i)}$.

Xu, IEEE SSP, 2012

Kernelized Hyperalignment

- KHA's Objective Function can be denoted as follows:

$$\min_{\mathbf{R}^{(i)},\mathbf{G}} \sum_{i=1}^{S} \left\| \mathbf{\Phi}(\mathbf{X}^{(i)})\mathbf{R}^{(i)} - \mathbf{G} \right\|_F^2$$

$$\text{subject to } \left(\mathbf{\Phi}(\mathbf{X}^{(\ell)})\mathbf{R}^{(\ell)}\right)^\top \mathbf{\Phi}(\mathbf{X}^{(\ell)})\mathbf{R}^{(\ell)} = \mathbf{I}$$

- The common space: $\mathbf{G} = \frac{1}{S}\sum_{j=1}^{S} \mathbf{\Phi}(\mathbf{X}^{(j)})\mathbf{R}^{(j)}$
- Here, $\mathbf{\Phi}(.)$ is a standard kernel function that can handle nonlinear datasets.
- However, classical kernel functions are limited by a restricted fixed representational space.

Lorbert, NIPS, 2012

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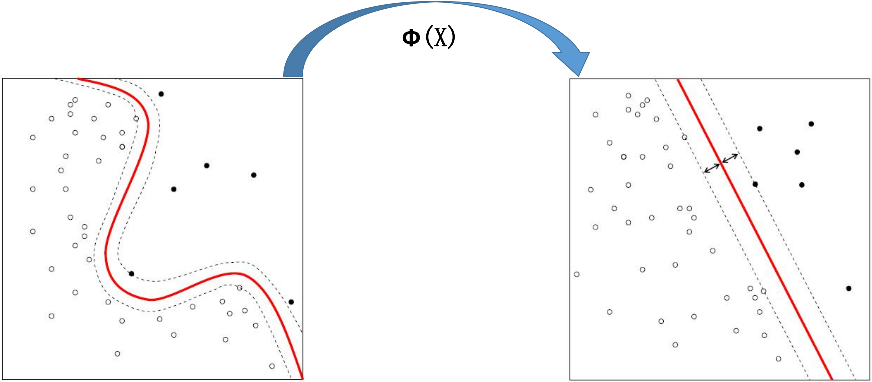
Challenges

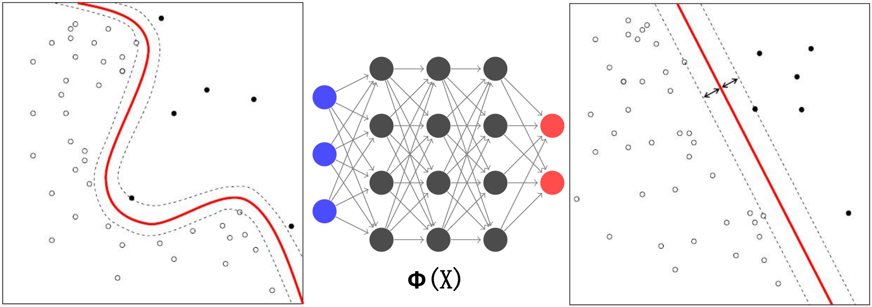
There are some long standing challenges for calculating accurate functional alignments:

- High Dimensionality
- Sparsity
- Nonlinear Features
- Large Number of Subjects

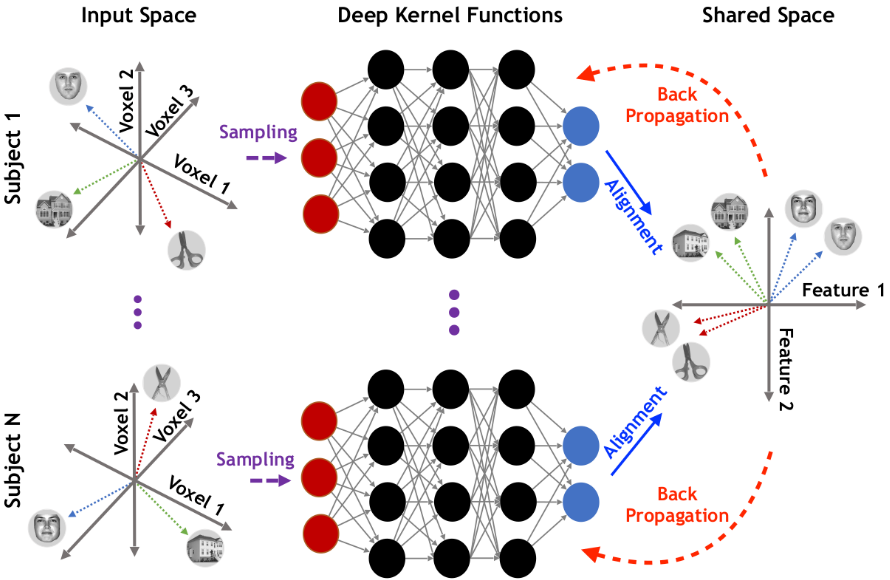
Kernel Function



Deep Kernel Function



Deep Hyperalignment (DHA)



Deep Hyperalignment: Objective Function

- DHA's Objective Function can be denoted as follows:

$$\min_{\mathbf{G},\mathbf{R}^{(i)},\theta^{(i)}} \sum_{i=1}^{S} \left\| \mathbf{G} - f_i\left(\mathbf{X}^{(i)};\theta^{(i)}\right)\mathbf{R}^{(i)} \right\|_F^2$$

$$\text{subject to } \left(\mathbf{R}^{(\ell)}\right)^\top \left(\left(f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)\right)^\top f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right) + \epsilon\mathbf{I} \right)\mathbf{R}^{(\ell)} = \mathbf{I}$$

- The common space: $\mathbf{G} = \frac{1}{S}\sum_{j=1}^{S} f_j\left(\mathbf{X}^{(j)};\theta^{(j)}\right)\mathbf{R}^{(j)}$
- Here, f_ℓ is the deep neural network such as:

$$f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right) = \text{mat}\left(\mathbf{h}_C^{(\ell)}, T, V_{new}\right),$$

$$\mathbf{h}_m^{(\ell)} = g\left(\mathbf{W}_m^{(\ell)}\mathbf{h}_{m-1}^{(\ell)} + \mathbf{b}_m^{(\ell)}\right)$$

where $\mathbf{h}_1^{(\ell)} = \text{vec}\left(\mathbf{X}^{(\ell)}\right)$ and $m = 2{:}C$.

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Deep Hyperalignment: Objective Function

- Firstly, we employ the rank-m SVD as follows:

$$f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right) \overset{SVD}{=} \mathbf{\Omega}^{(\ell)}\mathbf{\Sigma}^{(\ell)}\left(\mathbf{\Psi}^{(\ell)}\right)^\top, \qquad \ell = 1{:}S$$

- Then, projection matrix can be calculated as follows:

$$\mathbf{P}^{(\ell)} = f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)\left(\left(f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)\right)^\top f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right) + \epsilon\mathbf{I}\right)^{-1}\left(f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)\right)^\top$$
$$= \mathbf{\Omega}^{(\ell)}\left(\mathbf{\Sigma}^{(\ell)}\right)^\top\left(\mathbf{\Sigma}^{(\ell)}\left(\mathbf{\Sigma}^{(\ell)}\right)^\top + \epsilon\mathbf{I}\right)^{-1}\mathbf{\Sigma}^{(\ell)}\left(\mathbf{\Omega}^{(\ell)}\right)^\top = \mathbf{\Omega}^{(\ell)}\mathbf{D}^{(\ell)}\left(\mathbf{\Omega}^{(\ell)}\mathbf{D}^{(\ell)}\right)^\top$$

- Here, we have a diagonal product $\mathbf{D}^{(\ell)}\left(\mathbf{D}^{(\ell)}\right)^\top = \left(\mathbf{\Sigma}^{(\ell)}\right)^\top\left(\mathbf{\Sigma}^{(\ell)}\left(\mathbf{\Sigma}^{(\ell)}\right)^\top + \epsilon\mathbf{I}\right)^{-1}\mathbf{\Sigma}^{(\ell)}$. Thus, calculating the inverse of matrix is easy!

Yousefnezhad, NIPS, 2017

Deep Hyperalignment: Optimization (Step 1)

Theorem

By considering fixed mapping functions $\mathbf{R}^{(i)}$ and fixed network parameters $\theta^{(i)}$, DHA's Objective Function can be reformulated as follows:

$$\min_{\mathbf{G},\mathbf{R}^{(i)},\theta^{(i)}} \sum_{i=1}^{S} \left\| \mathbf{G} - f_i\left(\mathbf{X}^{(i)};\theta^{(i)}\right)\mathbf{R}^{(i)} \right\| \equiv \max_{\mathbf{G}}\left(tr(\mathbf{G}^\top \mathbf{A}\mathbf{G}) \right)$$

where the sum of projection matrices can be calculated as follows:

$$\mathbf{A} = \sum_{i=1}^{S} \mathbf{P}^{(i)} = \widetilde{\mathbf{A}}\widetilde{\mathbf{A}}^\top, \quad \text{where} \quad \widetilde{\mathbf{A}} \in \mathbb{R}^{T \times mS} = \left[\mathbf{\Omega}^{(1)}\mathbf{D}^{(1)} \dots \mathbf{\Omega}^{(S)}\mathbf{D}^{(S)}\right]$$

Theorem

By using **Incremental SVD**, *the shared space* $\mathbf{G}$ *can be calculated as follows, where* $\mathbf{\Lambda} = \left\{\lambda_1 \dots \lambda_T\right\}$ *is the eigenvalues of* $\mathbf{A}$*:*

$$\mathbf{A}\mathbf{G} = \mathbf{G}\mathbf{\Lambda} \implies \widetilde{\mathbf{A}} = \mathbf{G}\widetilde{\mathbf{\Sigma}}\widetilde{\mathbf{\Psi}}^\top$$

Deep Hyperalignment: Optimization (Step 2)

Theorem

By considering fixed share space $\mathbf{G}$ *and fixed network parameters* $\theta^{(i)}$*, DHA's mapping functions can be calculated as follows:*

$$\mathbf{R}^{(\ell)} = \left(\left(f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)\right)^\top f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right) + \epsilon\mathbf{I}\right)^{-1}\left(f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)\right)^\top \mathbf{G}$$

Deep Hyperalignment: Optimization (Step 3)

Theorem

By considering fixed share space $\mathbf{G}$ *and fixed mapping functions* $\mathbf{R}^{(i)}$*, we use back-propagation algorithm for seeking an optimized parameters for the deep network as follows:*

$$\frac{\partial \mathbf{Z}}{\partial f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)} = 2\mathbf{R}^{(\ell)}\mathbf{G}^\top - 2\mathbf{R}^{(\ell)}\left(\mathbf{R}^{(\ell)}\right)^\top\left(f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)\right)^\top$$

where $\mathbf{Z}$ *is the sum of the eigenvalues of* $\mathbf{A}$*:*

$$\mathbf{Z} = \sum_{\ell=1}^{T} \lambda_\ell$$

Deep Hyperalignment: Algorithm

Algorithm 1 Deep Hyperalignment (DHA)

Input: Data $\mathbf{X}^{(i)}$, $i = 1{:}S$, Regularized parameter ϵ, Number of layers C, Number of units $U^{(m)}$ for $m = 2{:}C$, HA template $\widehat{\mathbf{G}}$ for testing phase (default $\emptyset$), Learning rate η (default 10^{-4} [13]).
Output: DHA mappings $\mathbf{R}^{(\ell)}$ and parameters $\theta^{(\ell)}$, HA template $\mathbf{G}$ just from training phase
Method:

01. Initialize iteration counter: $m \leftarrow 1$ and $\theta^{(\ell)} \sim \mathcal{N}(0, 1)$ for $\ell = 1{:}S$.
02. Construct $f_\ell\left(\mathbf{X}^{(\ell)};\theta^{(\ell)}\right)$ based on (4) and (5) by using $\theta^{(\ell)}$, C, $U^{(m)}$ for $\ell = 1{:}S$.
03. **IF** ($\widehat{\mathbf{G}} = \emptyset$) **THEN** *% The first step of DHA: fixed $\theta^{(\ell)}$ and calculating $\mathbf{G}$ and $\mathbf{R}^{(\ell)}$ ↓*
04. Generate $\widetilde{\mathbf{A}}$ by using (8) and (10).
05. Calculate $\mathbf{G}$ by applying Incremental SVD [15] to $\widetilde{\mathbf{A}} = \mathbf{G}\widetilde{\mathbf{\Sigma}}\widetilde{\mathbf{\Psi}}^\top$.
06. **ELSE**
07. $\mathbf{G} = \widehat{\mathbf{G}}$.
08. **END IF**
09. Calculate mappings $\mathbf{R}^{(\ell)}$, $\ell = 1{:}S$ by using (12).
10. Estimate error of iteration $\gamma_m = \sum_{i=1}^{S} \sum_{j=i+1}^{S} \left\| f_i\left(\mathbf{X}^{(i)};\theta^{(i)}\right)\mathbf{R}^{(i)} - f_j\left(\mathbf{X}^{(j)};\theta^{(j)}\right)\mathbf{R}^{(j)} \right\|_F^2$.
11. **IF** $\left((m > 3) \text{ and } (\gamma_m \geq \gamma_{m-1} \geq \gamma_{m-2})\right)$ **THEN** *% This is the finishing condition.*
12. **Return** calculated $\mathbf{G}$, $\mathbf{R}^{(\ell)}$, $\theta^{(\ell)}(\ell = 1{:}S)$ related to $(m\text{-}2)\text{-}th$ iteration.
13. **END IF** *% The second step of DHA: fixed $\mathbf{G}$ and $\mathbf{R}^{(\ell)}$ and updating $\theta^{(\ell)}$ ↓*
14. $\nabla\theta^{(\ell)} \leftarrow \text{backprop}\left({}^{\partial \mathbf{Z}}/_{\partial f_\ell(\mathbf{X}^{(\ell)};\theta^{(\ell)})}, \theta^{(\ell)}\right)$ by using (13) for $\ell = 1{:}S$.
15. Update $\theta^{(\ell)} \leftarrow \theta^{(\ell)} - \eta\nabla\theta^{(\ell)}$ for $\ell = 1{:}S$ and then $m \leftarrow m + 1$
16. **SAVE** all DHA parameters related to this iteration and **GO TO** Line *02*.

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Datasets

Title	ID	S	K	T	V	X	Y	Z	Scanner	TR	TE
Mixed-gambles task	DS005	48	2	240	450	53	63	52	S 3T	2	30
Visual Object Recognition	DS105	71	8	121	1963	79	95	79	G 3T	2.5	30
Word and Object Processing	DS107	98	4	164	932	53	63	52	S 3T	2	28
Auditory and Visual Oddball	DS116	102	2	170	2532	53	63	40	P 3T	2	25
Multi-subject, multi-modal	DS117	171	2	210	524	64	61	33	S 3T	2	30
Forrest Gump	DS113	20	10	451	2400	160	160	36	S 7T	2.3	22
Raiders of the Lost Ark	N/A	10	7	924	980	78	78	54	S 3T	3	30

S is the number of subject; K denotes the number of stimulus categories; T is the number of scans in unites of TRs (Time of Repetition); V denotes the number of voxels in ROI; X, Y, Z are the size of 3D images; Scanners include S=Siemens, G = General Electric, and P = Philips in 3 Tesla or 7 Tesla; TR is Time of Repetition in millisecond; TE denotes Echo Time in second; Please see *openfmri.org* for more information.

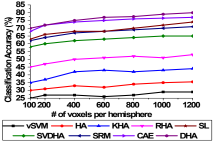
Simple Task Analysis: Accuracy of HA methods

↓Algorithms, Datasets→	DS005	DS105	DS107	DS116	DS117
ν-SVM	71.65±0.97	22.89±1.02	38.84±0.82	67.26±1.99	73.32±1.67
Hyperalignment (HA)	81.27±0.59	30.03±0.87	43.01±0.56	74.23±1.40	77.93±0.29
Regularized HA	83.06±0.36	32.62±0.52	46.82±0.37	78.71±0.76	84.22±0.44
Kernel HA	85.29±0.49	37.14±0.91	52.69±0.69	78.03±0.89	83.32±0.41
SVD-HA	90.82±1.23	40.21±0.83	59.54±0.99	81.56±0.54	95.62±0.83
Shared Response Model	91.26±0.34	48.77±0.94	64.11±0.37	83.31±0.73	95.01±0.64
SearchLight	90.21±0.61	49.86±0.4	64.07±0.98	82.32±0.28	94.96±0.24
Convolutional Autoencoder	94.25±0.76	54.52±0.80	72.16±0.43	**91.49±0.67**	95.92±0.67
Deep HA	**97.92±0.82**	**60.39±0.68**	**73.05±0.63**	90.28±0.71	**97.99±0.94**

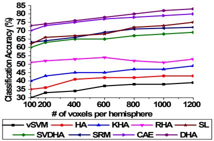
Simple Task Analysis: AUC of HA methods

↓Algorithms, Datasets→	DS005	DS105	DS107	DS116	DS117
ν-SVM [17]	68.37±1.01	21.76±0.91	36.84±1.45	62.49±1.34	70.17±0.59
Hyperalignment (HA)	70.32±0.92	28.91±1.03	40.21±0.33	70.67±0.97	76.14±0.49
Regularized HA	82.22±0.42	30.35±0.39	43.63±0.61	76.34±0.45	81.54±0.92
Kernel HA	80.91±0.21	36.23±0.57	50.41±0.92	75.28±0.94	80.92±0.28
SVD-HA	88.54±0.71	37.61±0.62	57.54±0.31	78.66±0.82	92.14±0.42
Shared Response Model	90.23±0.74	44.48±0.75	62.41±0.72	79.20±0.98	93.65±0.93
SearchLight	89.79±0.25	47.32±0.92	61.84±0.32	80.63±0.81	93.26±0.72
Convolutional Autoencoder	91.24±0.61	52.16±0.63	**72.33±0.79**	87.53±0.72	91.49±0.33
Deep HA	**96.91±0.82**	**59.57±0.32**	70.23±0.92	**89.93±0.24**	**96.13±0.32**

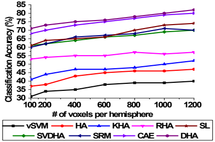
Complex Task Analysis



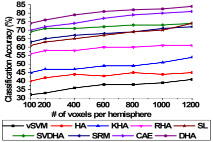
(a) Forrest Gump (TRs = 100)



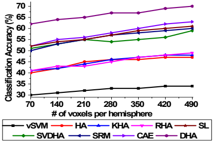
(b) Forrest Gump (TRs = 400)



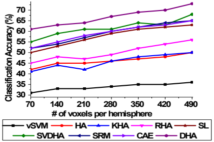
(c) Forrest Gump (TRs = 800)



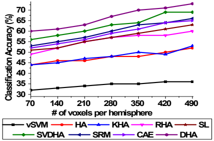
(d) Forrest Gump (TRs = 2000)



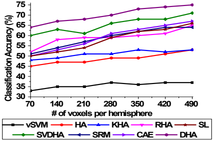
(e) Raiders (TRs = 100)



(f) Raiders (TRs = 400)

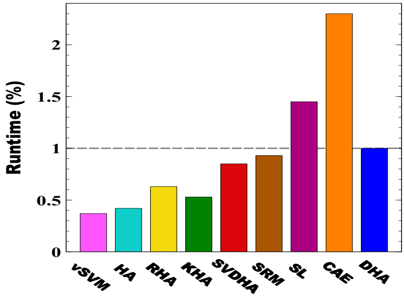


(g) Raiders (TRs = 800)

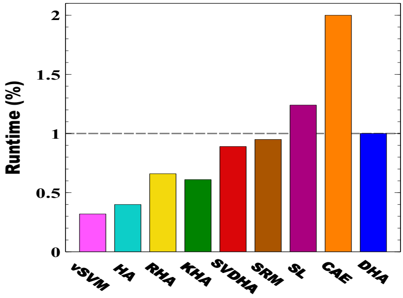


(h) Raiders (TRs = 2000)

Runtime Analysis

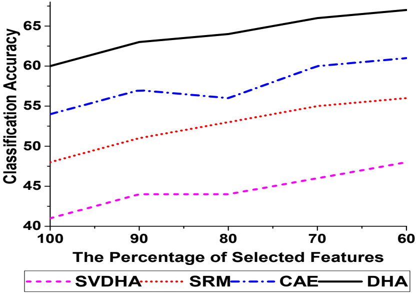


(A) DS105

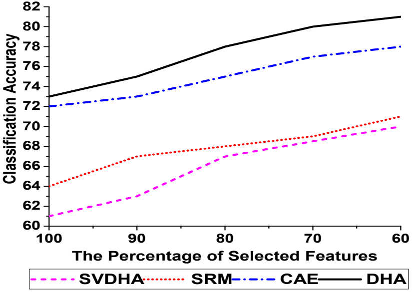


(B) DS107

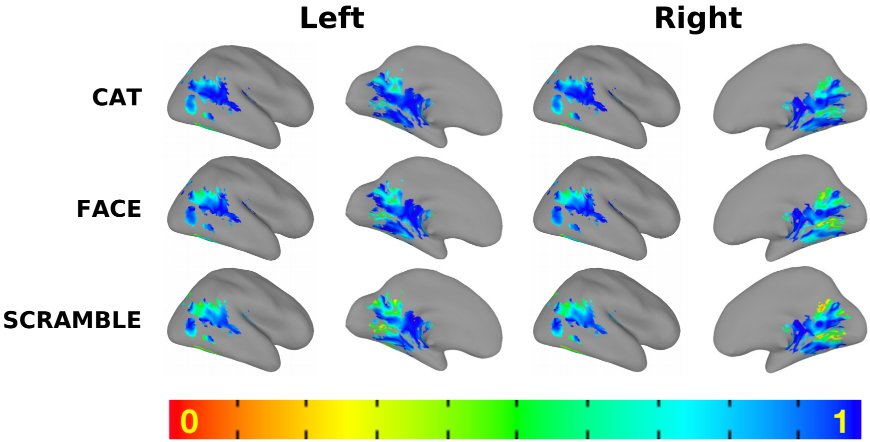
Alignment by selecting features



(A) DS105



(B) DS107


Left
Right
CAT
FACE
SCRAMBLE
0
1

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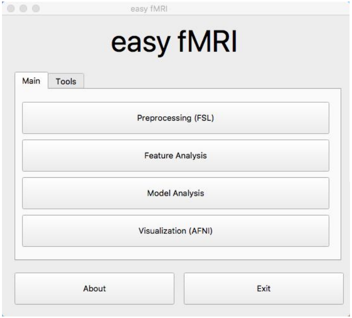
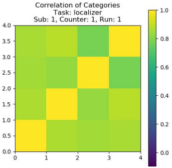
Conclusion

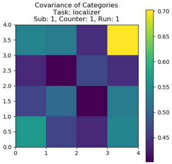
- Our knowledge from human brain is so **limited**.
- In order to understand the human brain, we need to develop new methods in Neuroscience, Psychology, **Mathematics, and Computer Science**.
- Not only can Artificial Intelligence use as a powerful tool for understanding the human brain but also this understanding can be employed reversely to develop AI tools, **e.g. Deep Learning**.

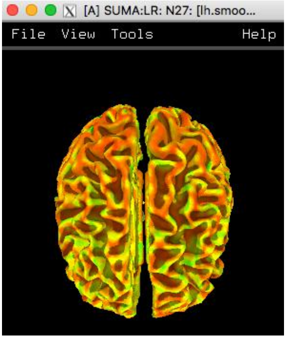
easy fMRI Project

Open Source + Free + Python + SK-Learn + MPI + Tensorflow



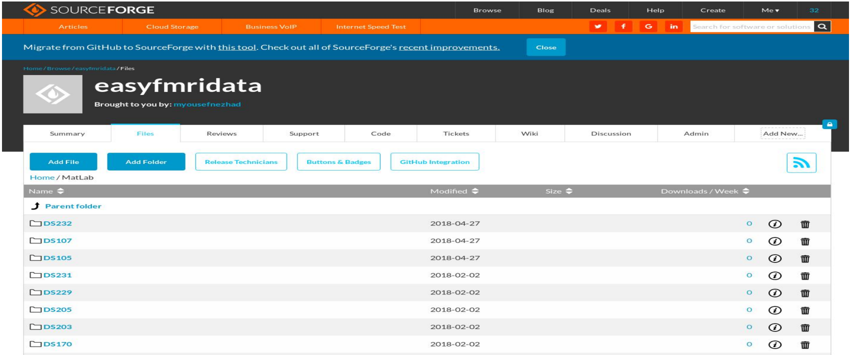






https://easyfmri.gitlab.io/
https://easyfmri.github.io/
https://easyfmri.sourceforge.io/

Matlab + 40 dataset + 200 cognitive tasks + 1000 subjects



https://easydata.gitlab.io/
https://easyfmridata.github.io/
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Thank You
Q & A

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