A SEMI-SUPERVISED METHOD FOR MULTI-SUBJECT FMRI FUNCTIONAL ALIGNMENT

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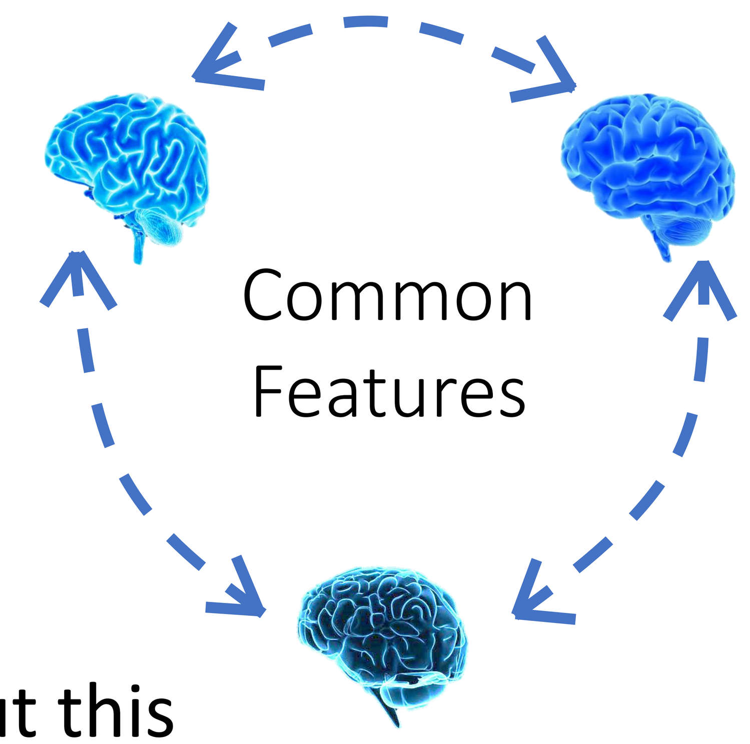
Multi-subject fMRI Functional Alignment

fMRI acquisition is constrained:
- Limited number of samples per subject.
- Reduced statistical power (more features than samples).

Use multi-subject data to increase statistical power.

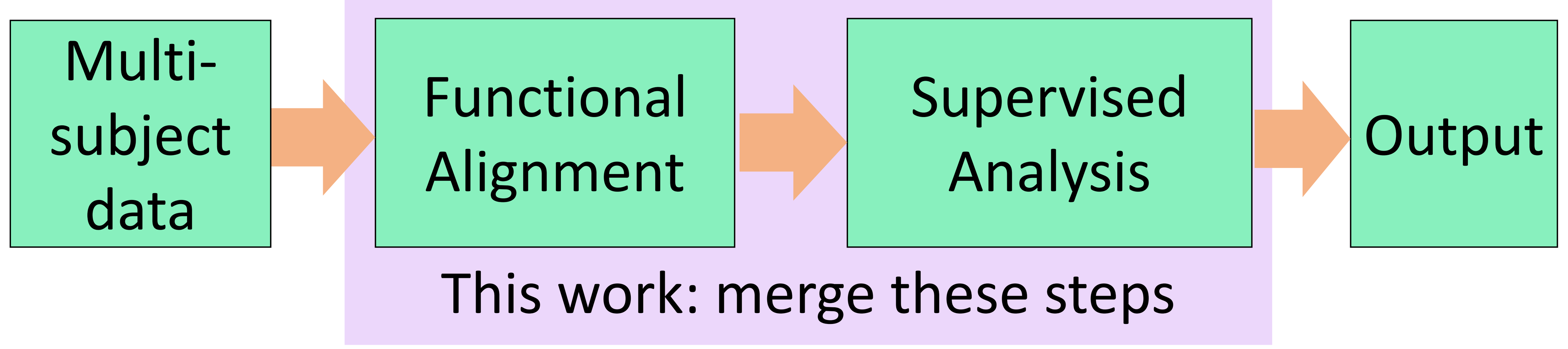
Need to align between subjects:
- Subjects have distinct anatomical and functional structures.
- Anatomical alignment does not ensure functional brain topographies alignment.



Use functional alignment methods, but this requires a task with "same thoughts" across subjects.

Multi-subject Experiment Workflow

Typically, experiments consist of a supervised analysis that uses functionally aligned data as input. We merge the alignment and analysis steps to address these challenges:
- Functional alignment requires many samples.
- Alignment does not capture the supervised information.
- It is costly to label data.



Semi-Supervised Method

$$\min_{\psi,\theta} (1-\alpha)\,\mathcal{L}_{Align}(\psi) + \alpha\mathcal{L}_{Sup}(\theta;\psi) + R(\theta),$$

Alignment — Supervised analysis — Regularization

$\alpha \in [0,1]$

Alignment: Shared Response Model (SRM)[1]

Map each subject *v*-dimensional *t*-measurements to a shared *k*-dimensional subspace (*k* << *v*).

$$\mathcal{L}_{SRM}\left(\{\mathbf{W}_i\}_i, \mathbf{S}; \{\mathbf{X}_i\}_i\right) = \frac{1}{2t}\sum_i \|\mathbf{X}_i - \mathbf{W}_i\mathbf{S}\|_F^2$$

$\mathbf{X}_i$: Subject *i* data $\quad$ $\mathbf{S}$: Shared response

$\mathbf{W}_i$: Subject *i* orthogonal mapping, i.e., $\mathbf{W}_i^T\mathbf{W}_i = \mathbf{I}_k$

Supervised Analysis: Multinomial Logistic Regression (MLR)

Multi-class classification of C classes on the shared response of *q*-labeled measurements of each subject.

$$\mathcal{L}_{MLR}\left(\mathbf{\Theta}, \mathbf{b}; \{\mathbf{Z}_i, \mathbf{y}_i, \mathbf{W}_i\}_i\right) = \frac{1}{\gamma}\sum_i \mathcal{L}_i$$

$$\mathcal{L}_i = -\frac{1}{2q}\sum_j \log\left(\mathrm{softmax}_{(\mathbf{y}_i)_j}\left(\mathbf{\Theta}^T\left(\mathbf{W}_i^T(\mathbf{Z}_i)_j\right) + \mathbf{b}\right)\right)$$

$\mathbf{Z}_i, \mathbf{y}_i$: Subject *i* supervised data and labels

$\mathbf{\Theta}, \mathbf{b}$: Classifier parameters $\quad$ $\gamma > 0$

Block Coordinate-Descent Approach

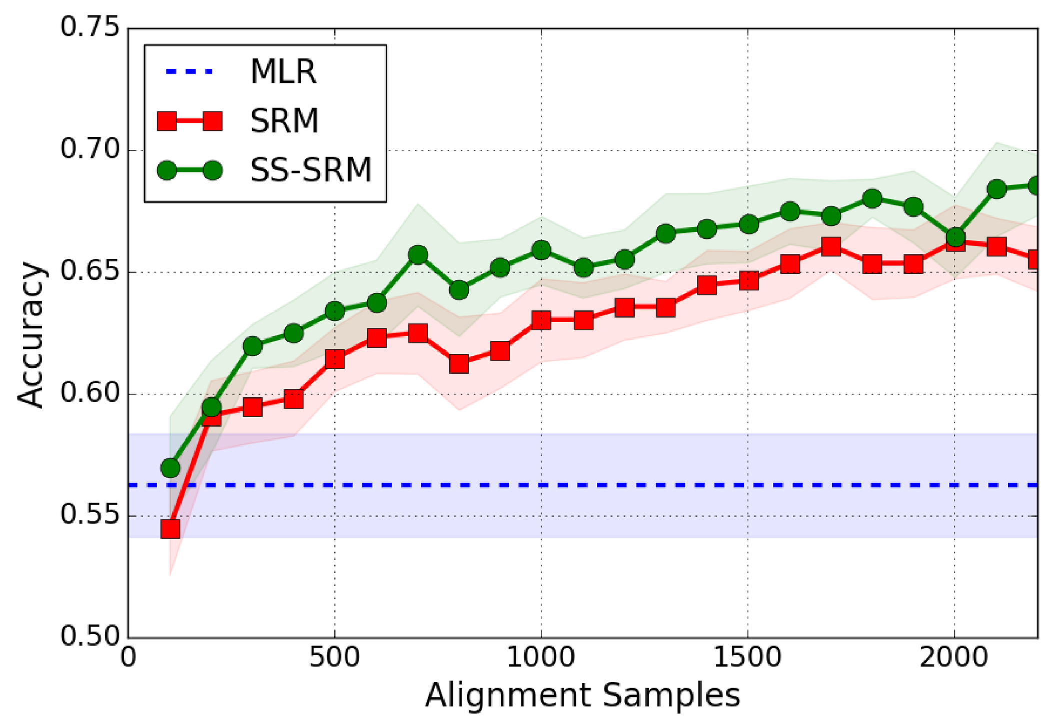
for iteration = 1,2,3,…
1. Update shared response: $\mathbf{S} = \frac{1}{N}\sum_i \mathbf{W}_i^T\mathbf{X}_i$
2. Update subject mappings (CG on Stiefel manifold):
   $\mathbf{W}_i \leftarrow \mathbf{W}_i + \delta\left[\nabla_{\mathbf{W}_i}\mathcal{L}_{SRM}(\mathbf{W}_i, \mathbf{S}) + \nabla_{\mathbf{W}_i}\mathcal{L}_{MLR}(\mathbf{\Theta}, \mathbf{b}; \mathbf{W}_i)\right]$
3. Update MLR parameters (common MLR algorithms)

Experimental Results

MLR: MLR without functional alignment.
SRM: SRM with independent MLR.
SS-SRM: Our work.

Dataset	Experiment	Subj / t / q / C	MLR	SRM	SS-SRM
raider	Image category	10/2203/ 56 / 7	56.25%	65.53%	**68.57%**
sherlock	Scene recall	17/1976/24-44/47	4.28%	5.31%	**6.12%**

Average accuracy (`raider`, k=50)



Potential reduction of input data: Same accuracy with half the alignment samples

Find our code at: **http://brainiak.org**

References

[1] P.-H. Chen, et. al., "A reduced-dimension fMRI shared response model," in NIPS 28th, 2015.