Shared Space Transfer Learning for analyzing multi-site fMRI data

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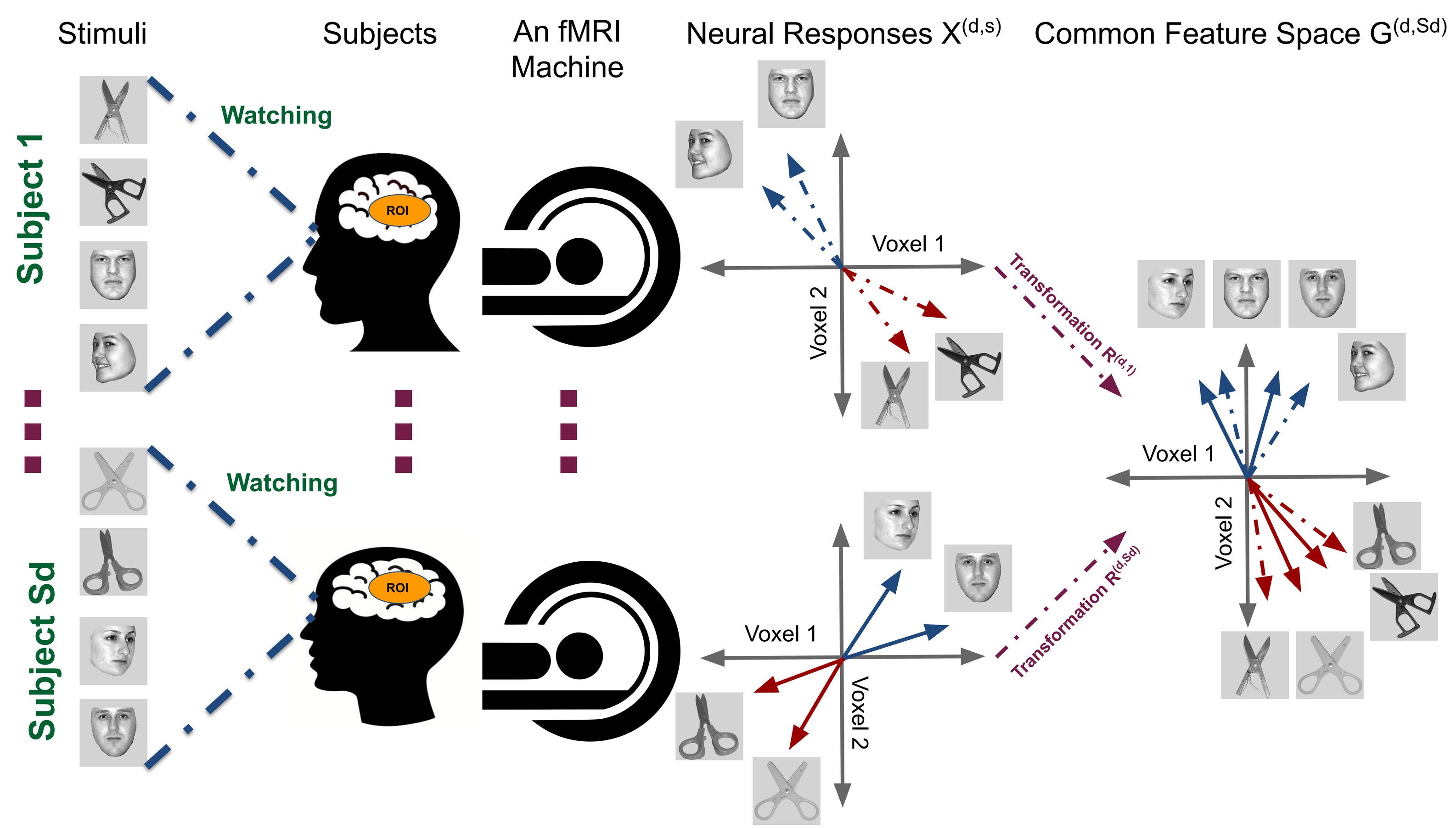
easy fMRI

Motivation

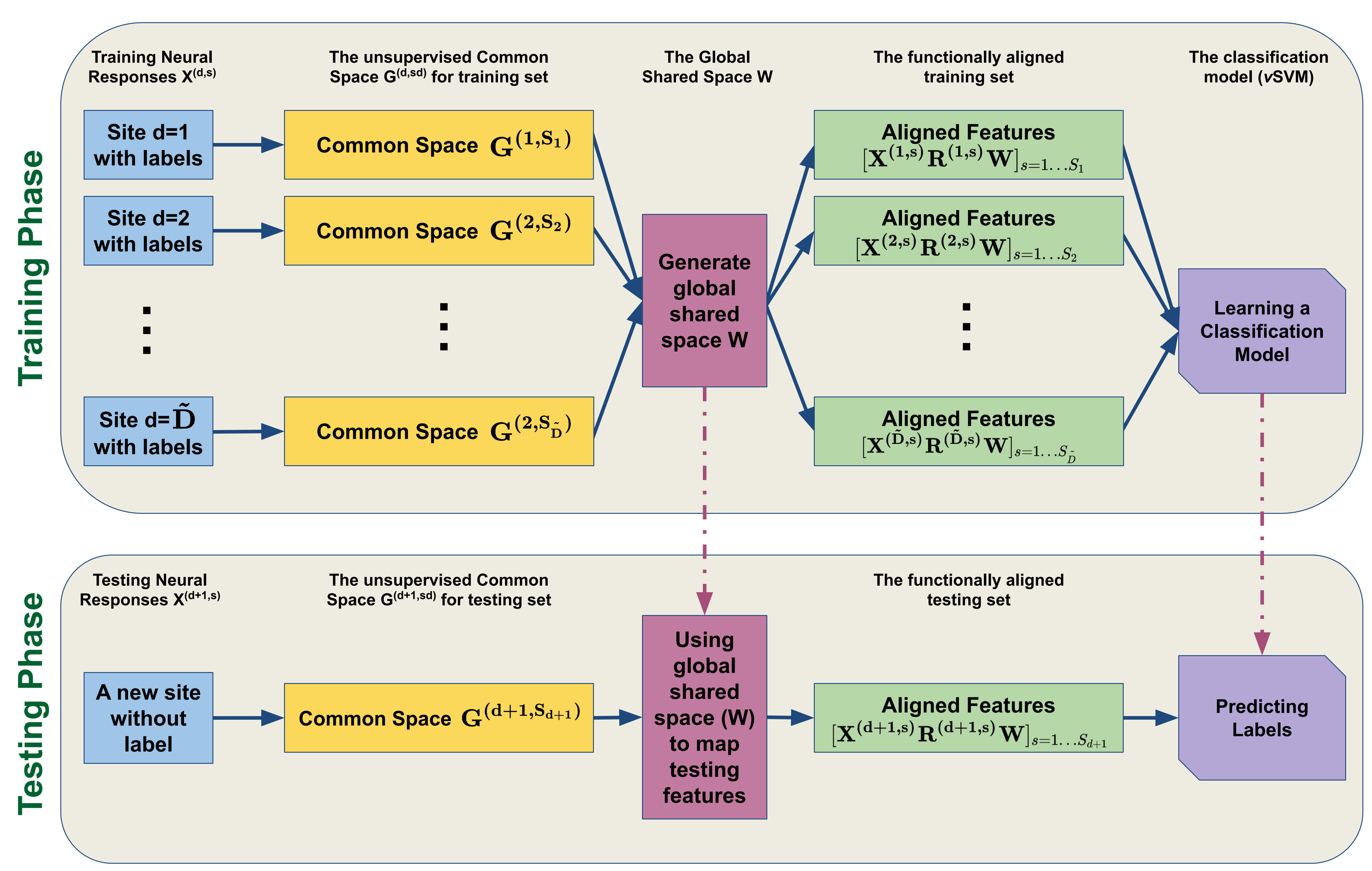
➤ **Functional alignment in a single-site fMRI dataset**



➤ Task-based functional magnetic resonance imaging (fMRI):
- a prevalent tool in neuroscience to analyze how human brains work.

➤ Challenging issues in most fMRI studies:
- **High-dimensionality** and noisy
- **Expensive** to collect with **small sample sizes**
- **Batch effects:** a set of external elements that may affect the performance of analysis

Shared Space Transfer Learning (SSTL)



➤ The proposed **Shared Space Transfer Learning (SSTL):**
- A novel **Transfer Learning (TL)** approach for **multi-site fMRI analysis**
- It can **functionally align homogeneous** multi-site fMRI datasets
- It **IS NOT LIMITED** to *overlapped datasets* (*i.e.,* share some subjects)
- It can improve the **prediction performance** in every site.

➤ SSTL learns a **TL model** by using a hierarchical **two-step** procedure:
- STEP 1: Extracting a set of **site-specific common features** for each site.
- STEP 2: Transferring **the common features** to a **site-independent, global, shared space.**

➤ SSTL uses a **single-iteration optimization approach**

SSTL: Objective Functions

➤ **STEP 1: Generating the common space for *each site:***

$$\mathcal{J}_C^{(d)}\left(\left[\mathbf{X}^{(d,s)}\right]_{s=1\dots S_d}\right) = \underset{\mathbf{R}^{(d,s)},\mathbf{G}^{(d,S_d)}}{\arg\min} \sum_{s=1}^{S_d}\left\|\mathbf{G}^{(d,S_d)} - \mathbf{X}^{(d,s)}\mathbf{R}^{(d,s)}\right\|_F^2,$$
$$\text{subject to} \quad \left(\mathbf{G}^{(d,S_d)}\right)^\top \mathbf{G}^{(d,S_d)} = \mathbf{I}_k.$$

- $X^{(d,s)}$ denotes the **neural responses** for *s-th* subject in *d-th* site
- $R^{(d,s)}$ denotes the **mapping matrices** for *s-th* subject in *d-th* site
- $G^{(d,sd)}$ denotes **the common space** for *d-th* site

➤ **STEP 2: Generating the global shared space**

$$\mathcal{J}_G\left(\mathbf{G}\right) = \underset{\mathbf{W}}{\arg\min}\left\|\mathbf{G} - \mathbf{G}\mathbf{W}\mathbf{W}^\top\right\|_F^2,$$
$$\text{subject to} \quad \mathbf{W}^\top\mathbf{W} = \mathbf{I}_k.$$

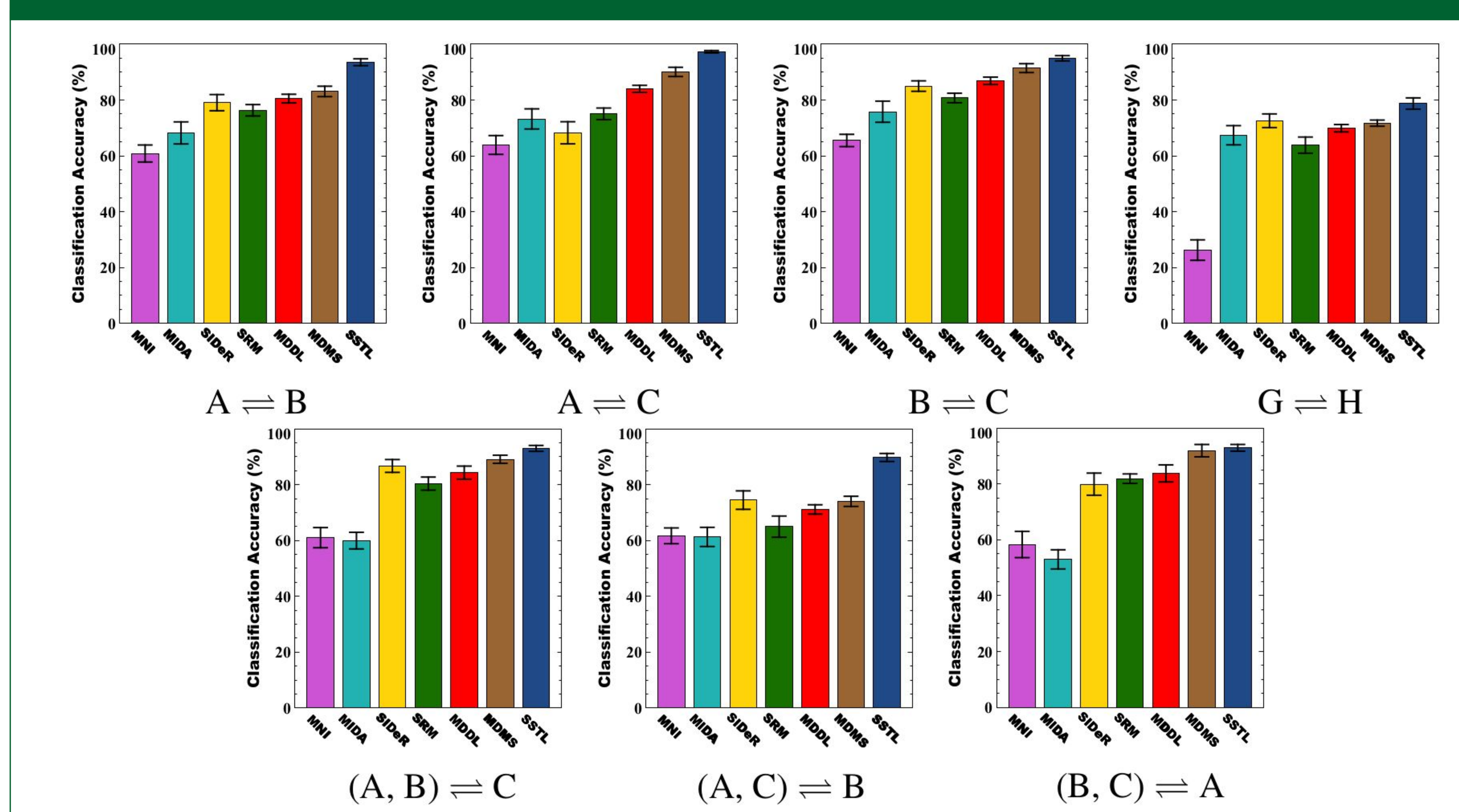
- G denotes the concatenated version of **all common spaces in the training set**
- W is the **global shared space**

Datasets

ID	Title (Open NEURO ID)	Type	S_d	#1	T_d	#2	#3
A	Stop signal with spoken pseudo word naming (DS007)	Decision	20	4	149	B, C	B, C, D
B	Stop signal with spoken letter naming (DS007)	Decision	20	4	112	A, C	A, C, D
C	Stop signal with manual response (DS007)	Decision	20	4	211	A, B	A, B, D
D	Conditional stop signal (DS008)	Decision	13	4	317		A, B, C
E	Simon task (DS101)	Simon	21	2	302		F
F	Flanker task (DS102)	Flanker	26	2	292		E
G	Integration of sweet taste – study 1 (DS229)	Flavour	15	6	580	H	H
H	Integration of sweet taste – study 3 (DS231)	Flavour	9	6	650	G	G

S_d is the number of subject; #1 is the number of stimulus categories; T_d is the number of time points per subjects; #2 lists the other datasets that overlap with this dataset; #3 lists the other datasets whose neural responses can be transferred to this dataset.

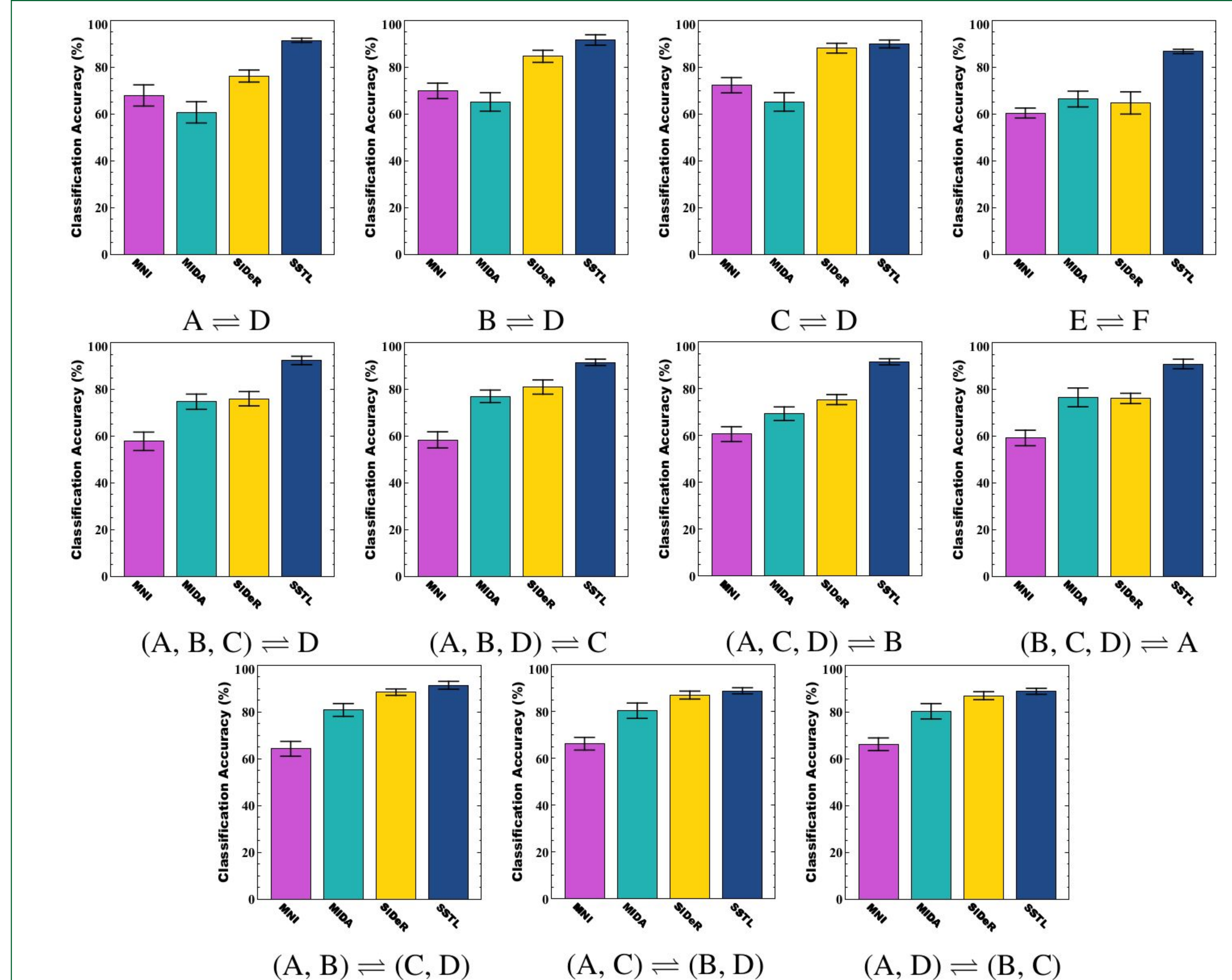
Multi-site classification analysis for pairs of datasets that overlap



➤ Multi-site classification analysis for datasets that overlap (*i.e.,* share some subjects). Error bars illustrate ±1 standard deviation.

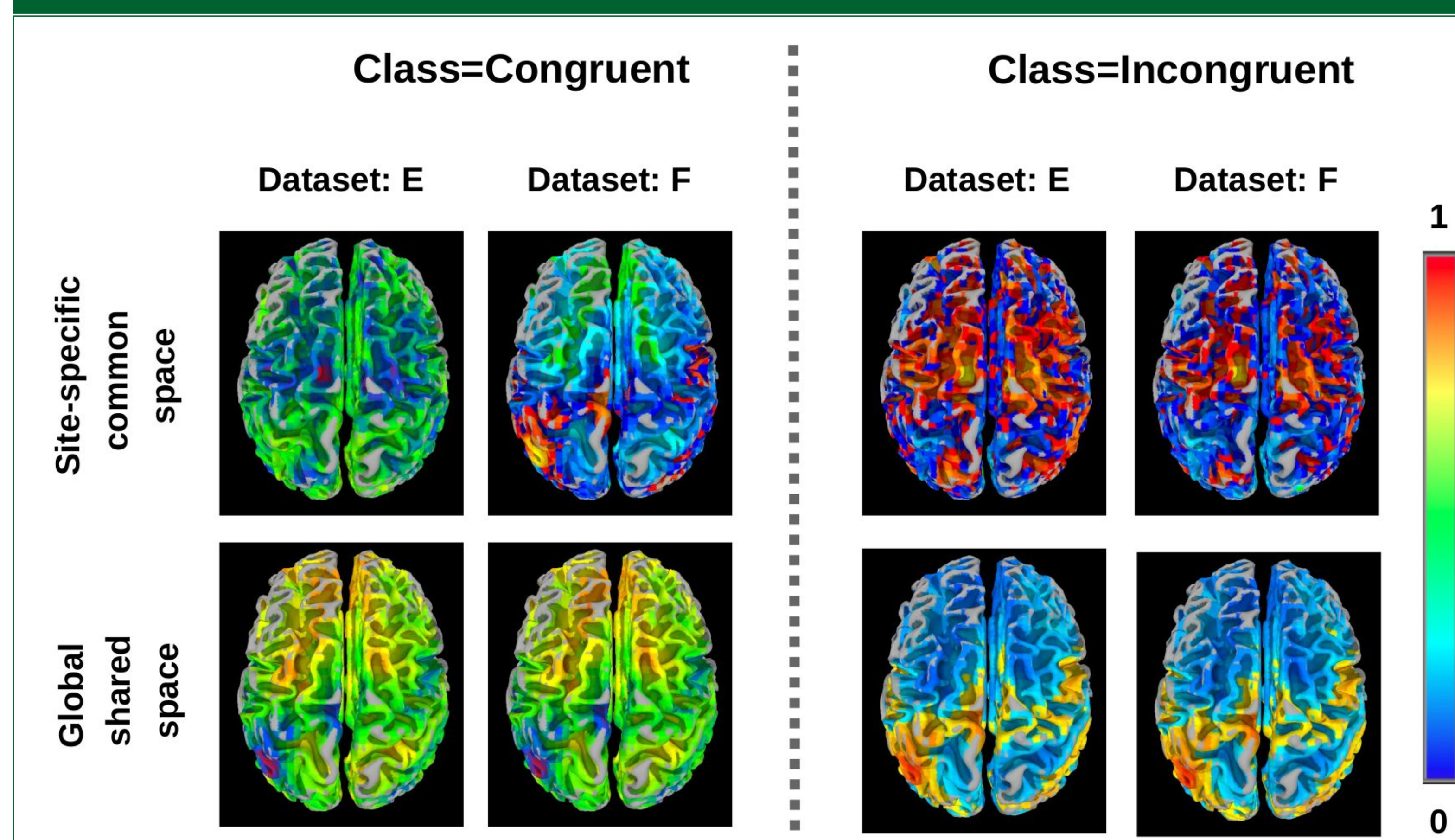
➤ We compare SSTL with *6 different* existing methods:
- Raw neural responses in **MNI** space without using TL methods
- Shared response model (**SRM**)
- Maximum independence domain adaptation (**MIDA**)
- Side Information Dependence Regularization (**SIDeR**)
- Multi-dataset dictionary learning (**MDDL**)
- Multi-dataset multi-subject (**MDMS**)

Multi-site classification analysis for sets of datasets that do not overlap



➤ Multi-site classification analysis for datasets that have no overlap (i.e., do not share any subjects). Error bars illustrate ±1 standard deviation.

Visualizing transferred neural responses



Conclusion

In this paper, we propose the *Shared Space Transfer Learning (SSTL)* as a novel transfer learning (TL) technique that can be used for homogeneous multi-site fMRI analysis. Our comprehensive experiments confirmed that SSTL achieves superior performance to other state-of-the-art TL analysis methods. We anticipate that SSTL's multi-view technique for transfer learning will have strong practical applications in neuroscience — such as functional alignment of multi-site fMRI data, perhaps of movie stimuli.