# Enhancing Functional Connectivity with Dictionary Learning for Brain Fingerprints

Pratik Jain

New Jersey Institute of Technology

# Contents


- Introduction to Resting state fMRI
- Research objectives
- Functional Connectivity and Resting state Networks
- Enhancing the Network Specific Individual Characteristics
- Conclusions
- Future scope

# Human Brain

Image Source: Wikipedia

NJIT

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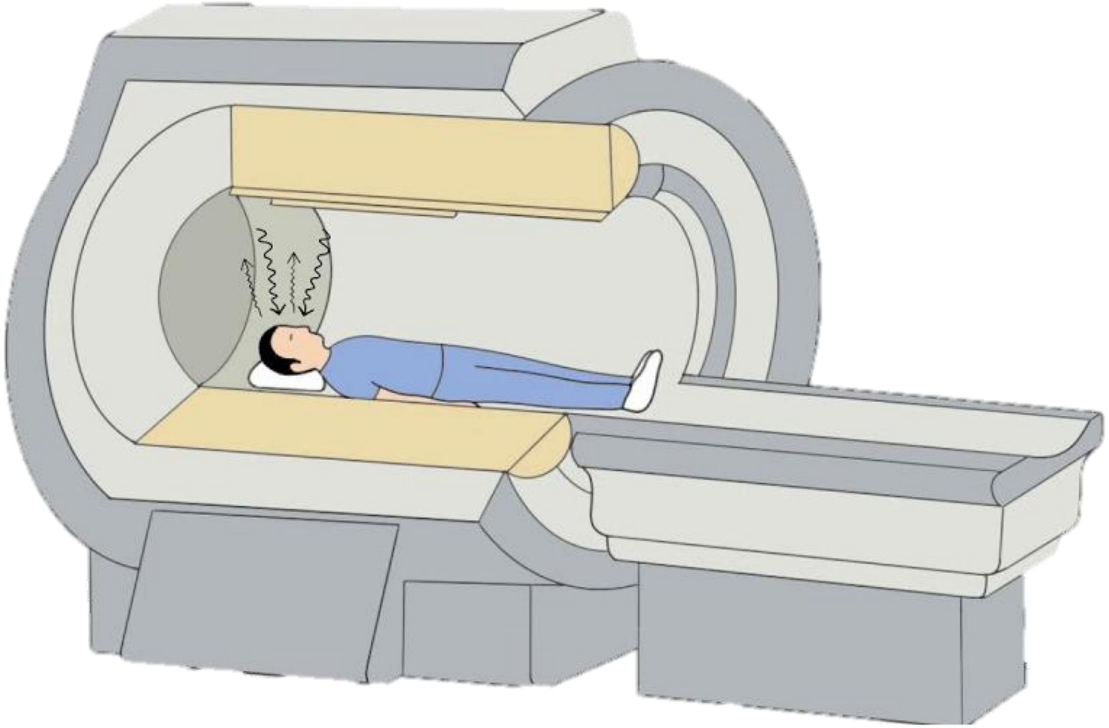

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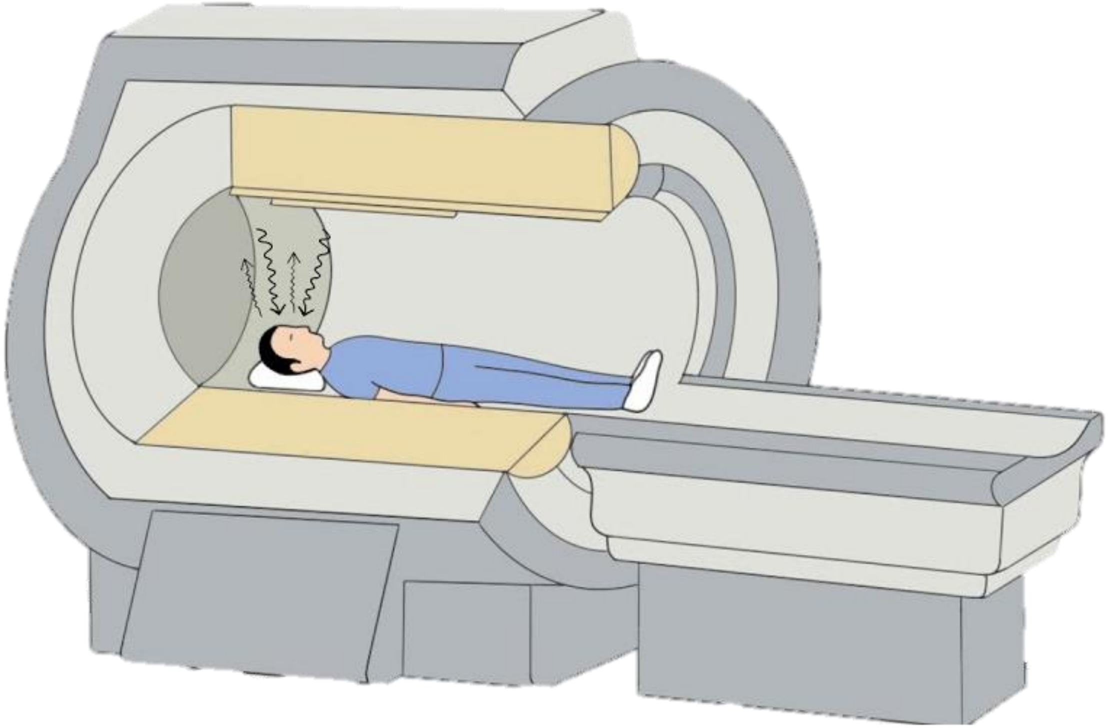

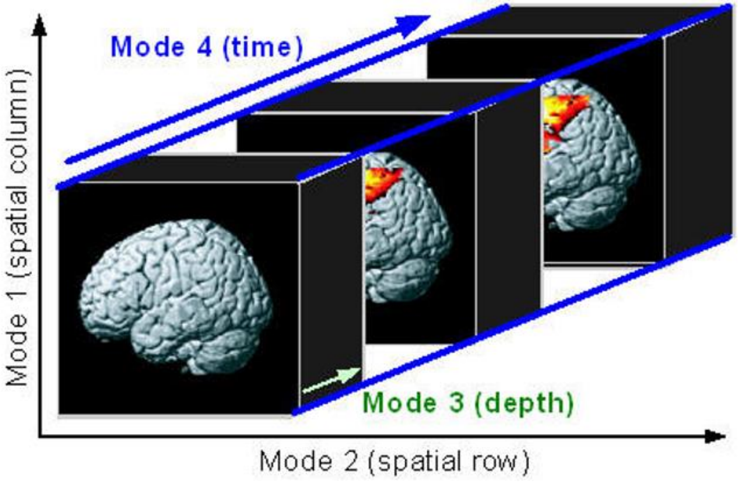

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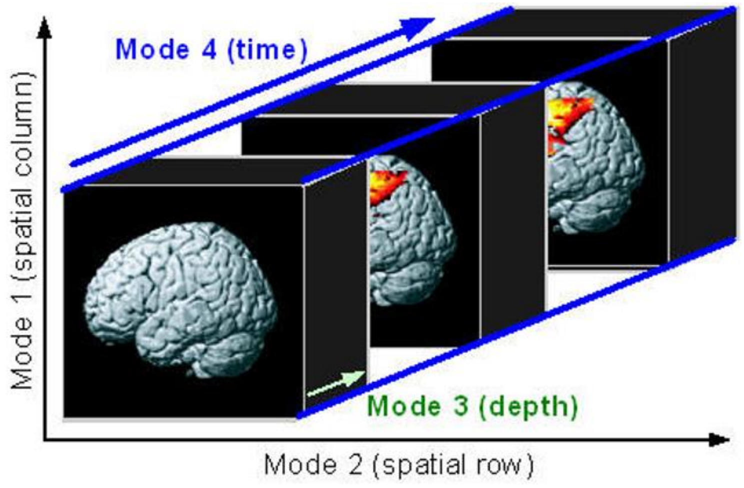

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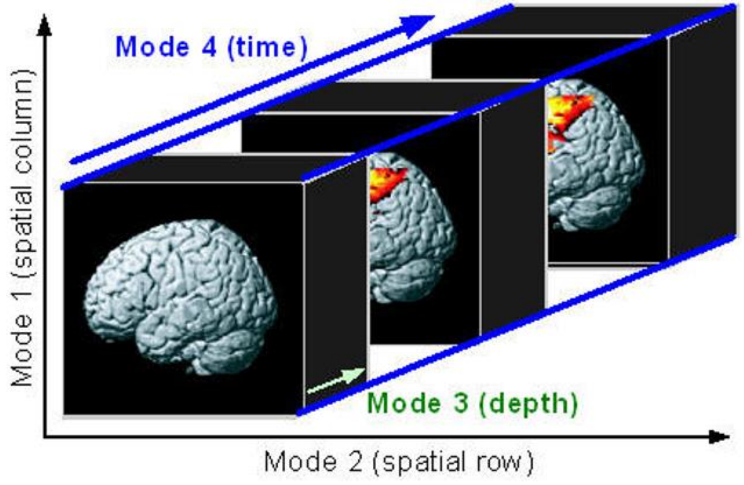


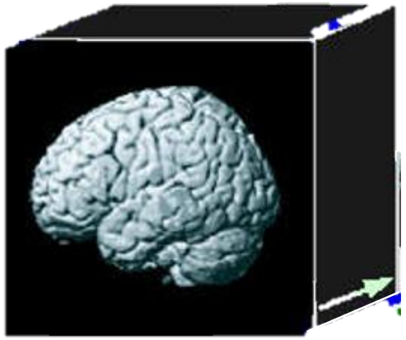

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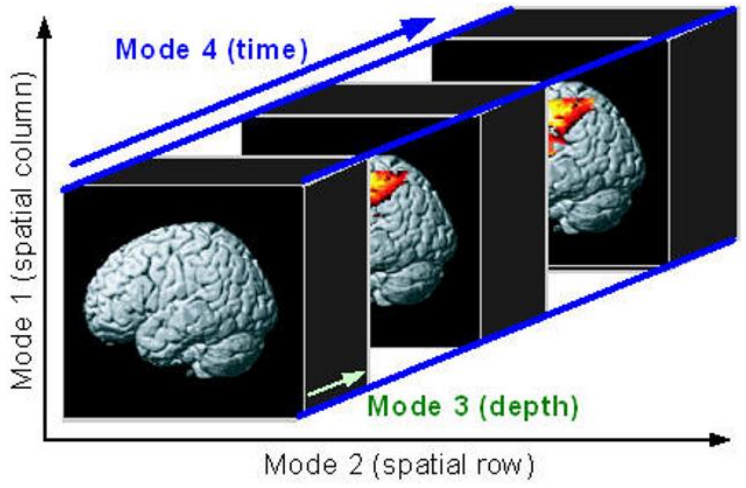


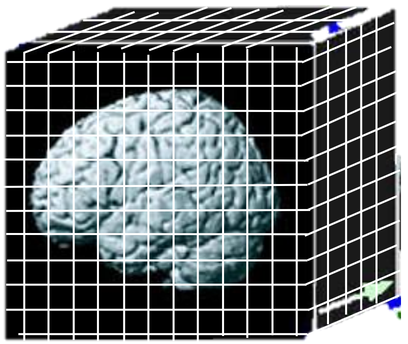

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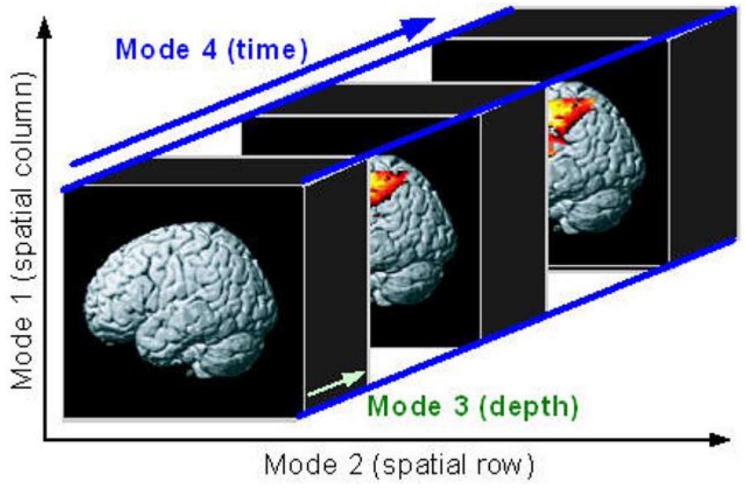


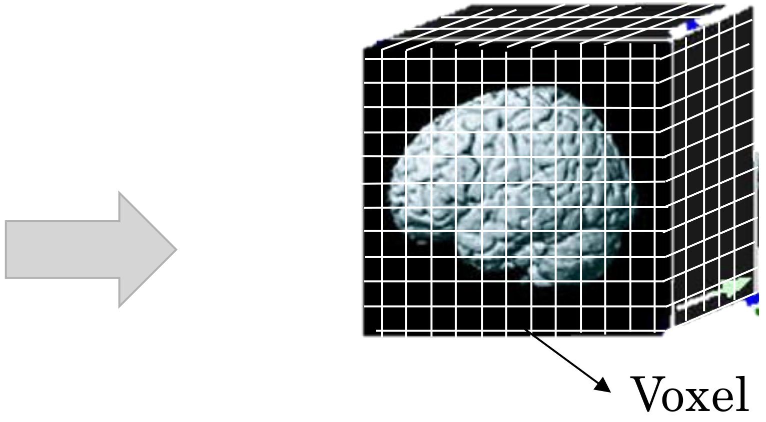

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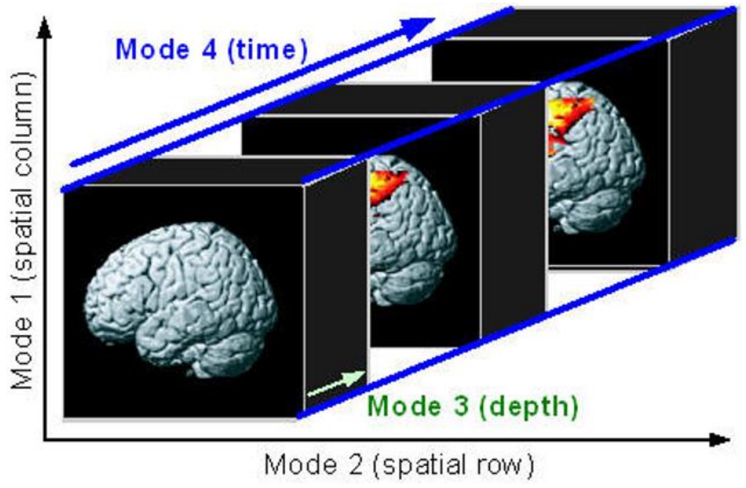
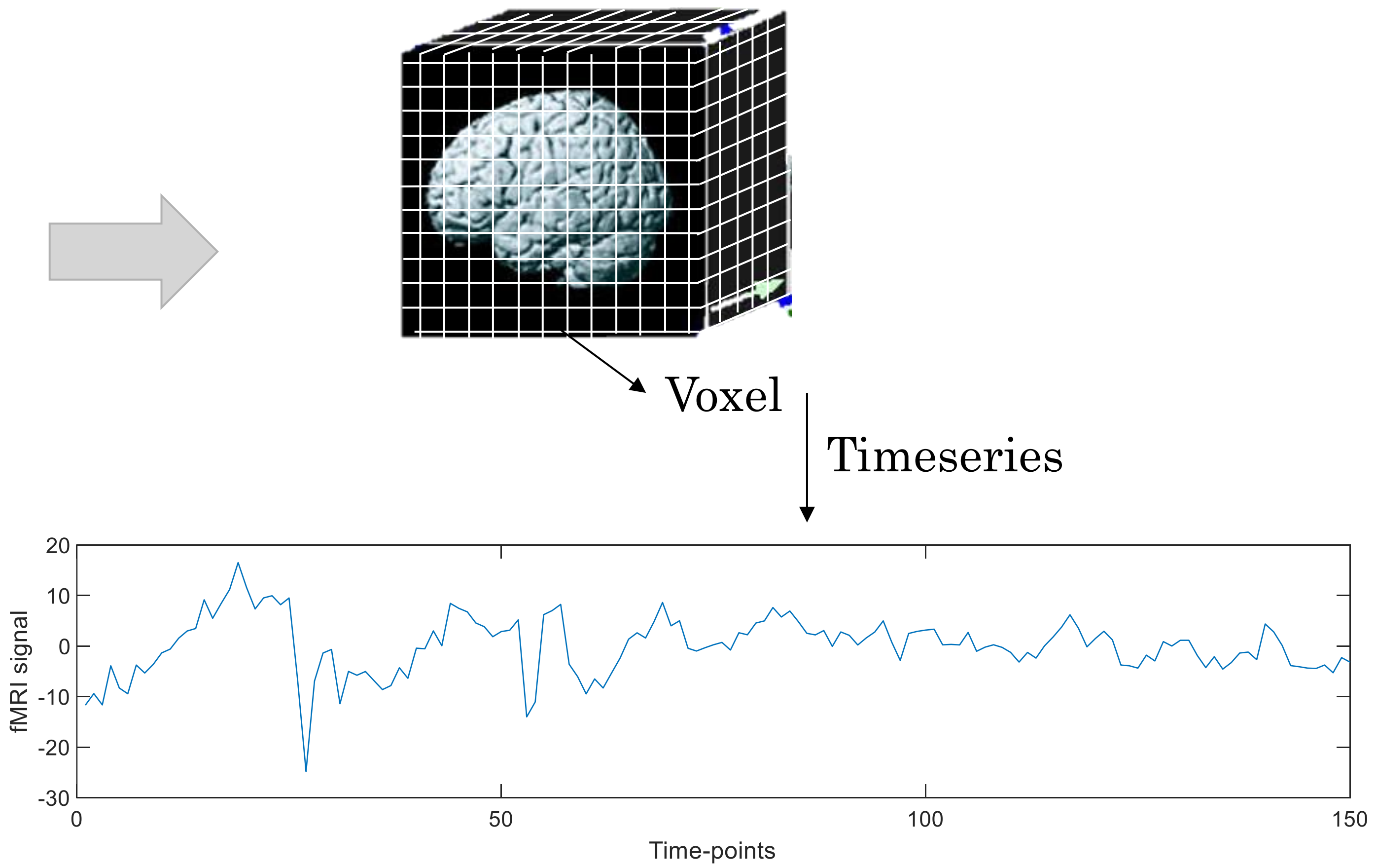
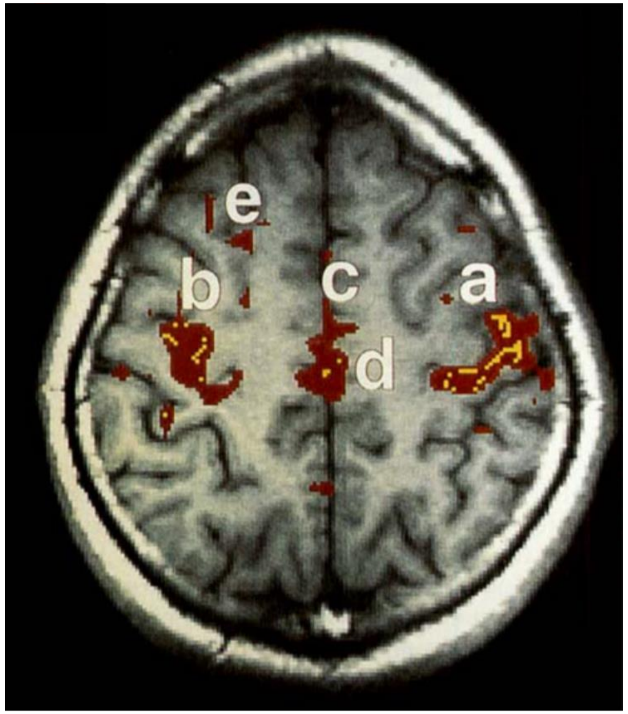


# Functional Connectivity (FC)




Red → Correlations > 0.35
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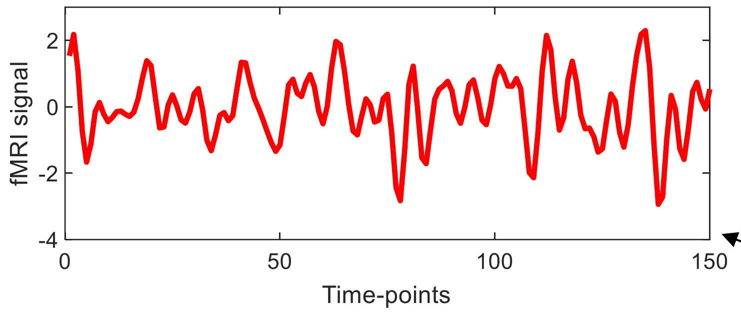


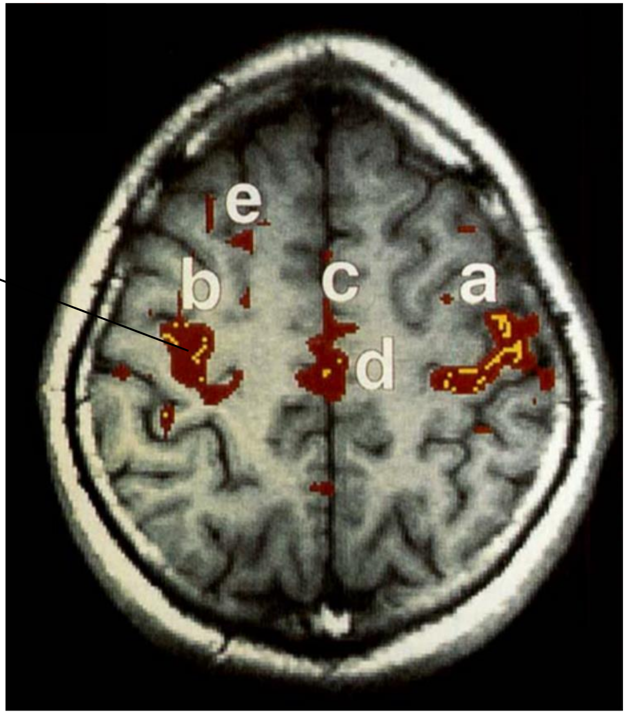


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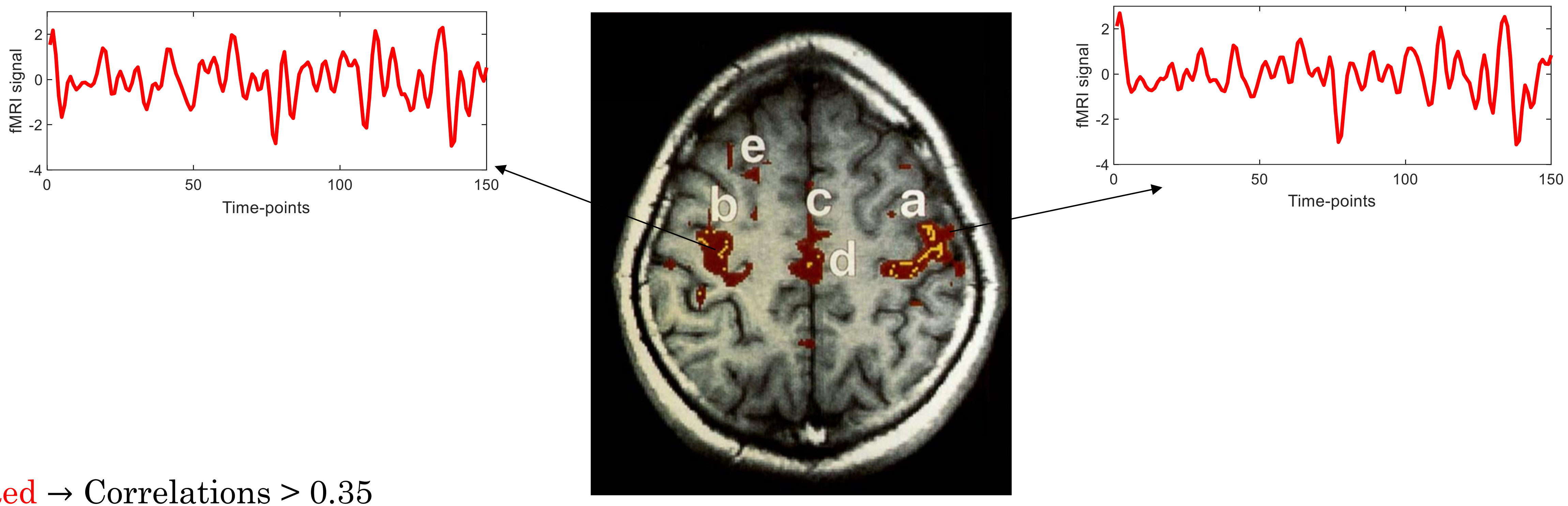


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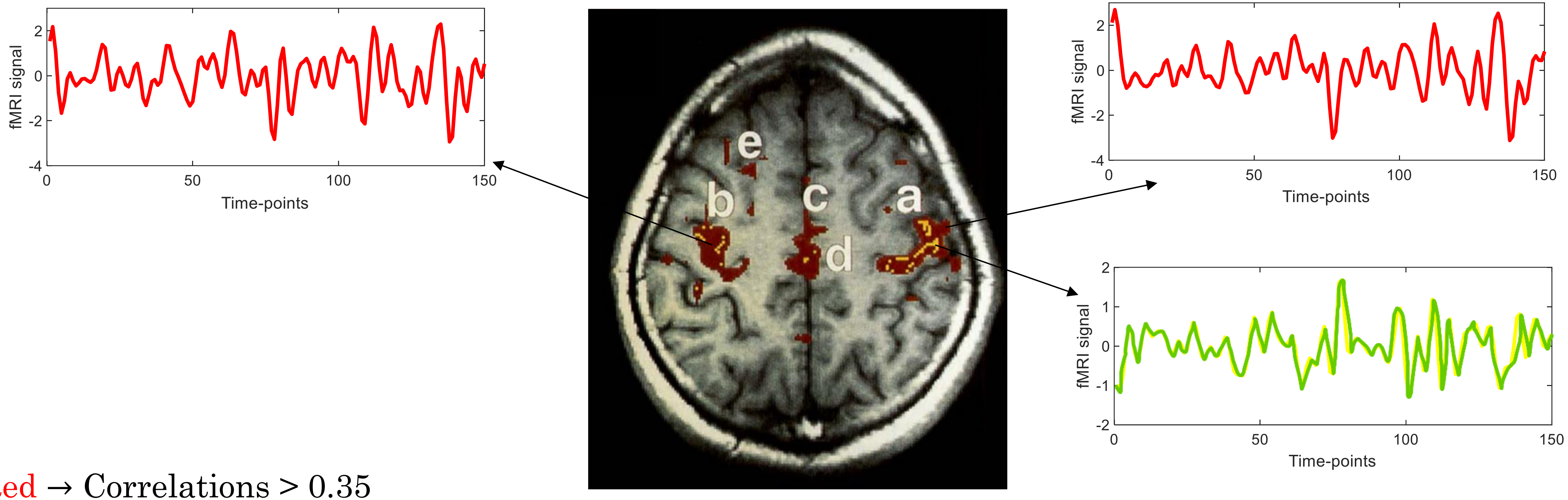


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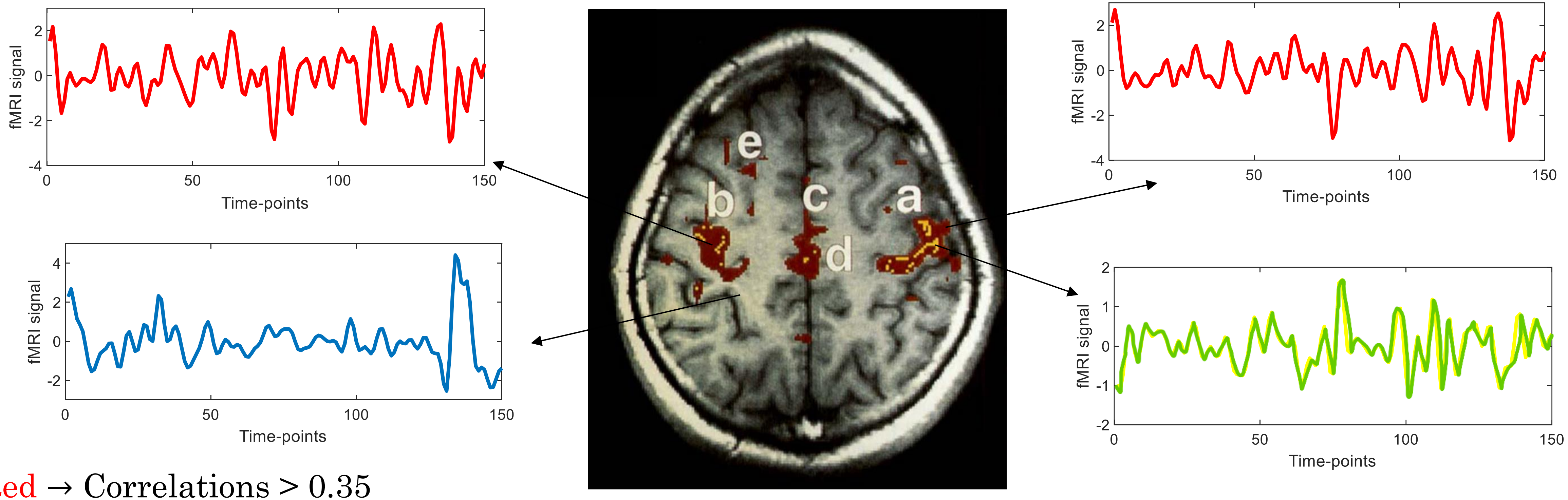


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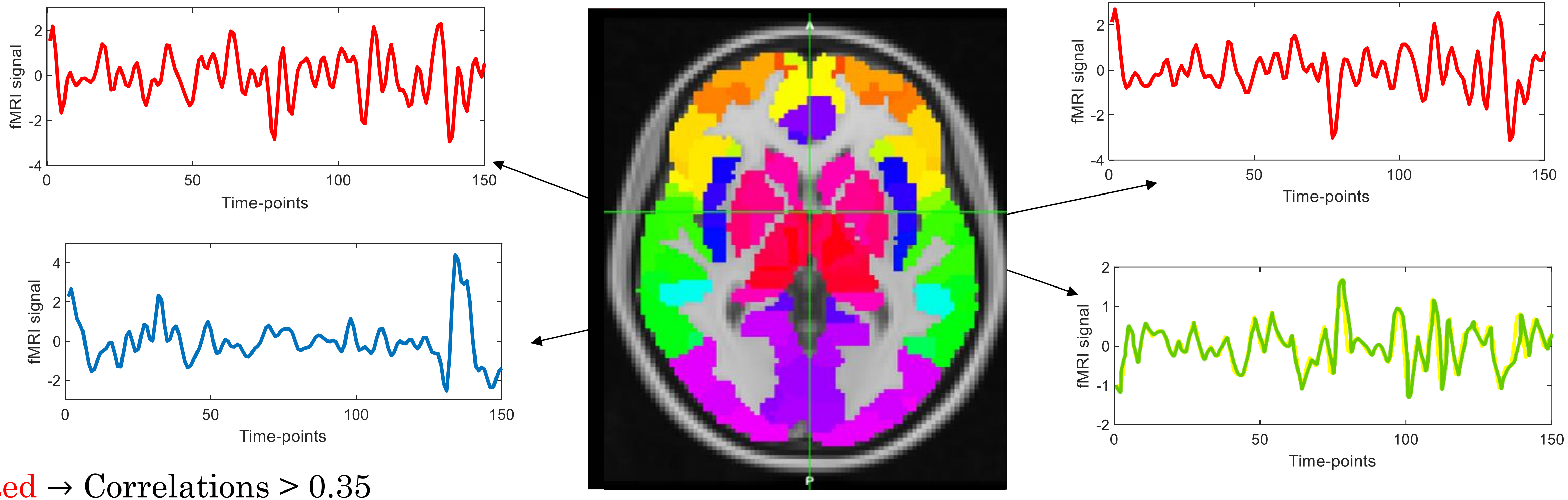


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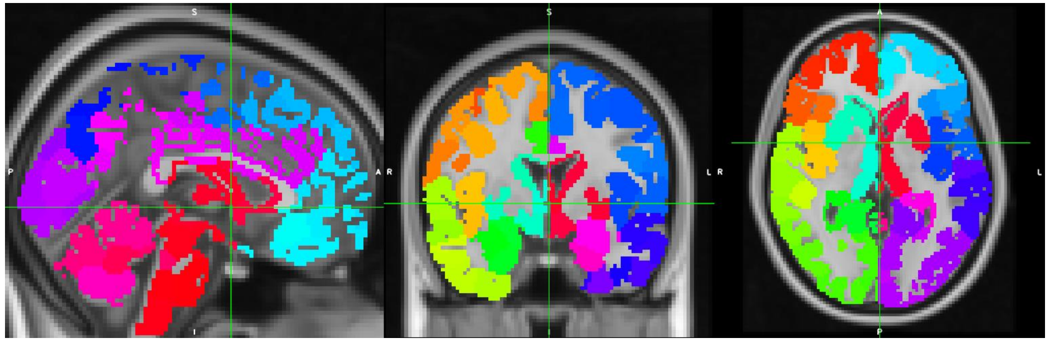
Brain Atlas



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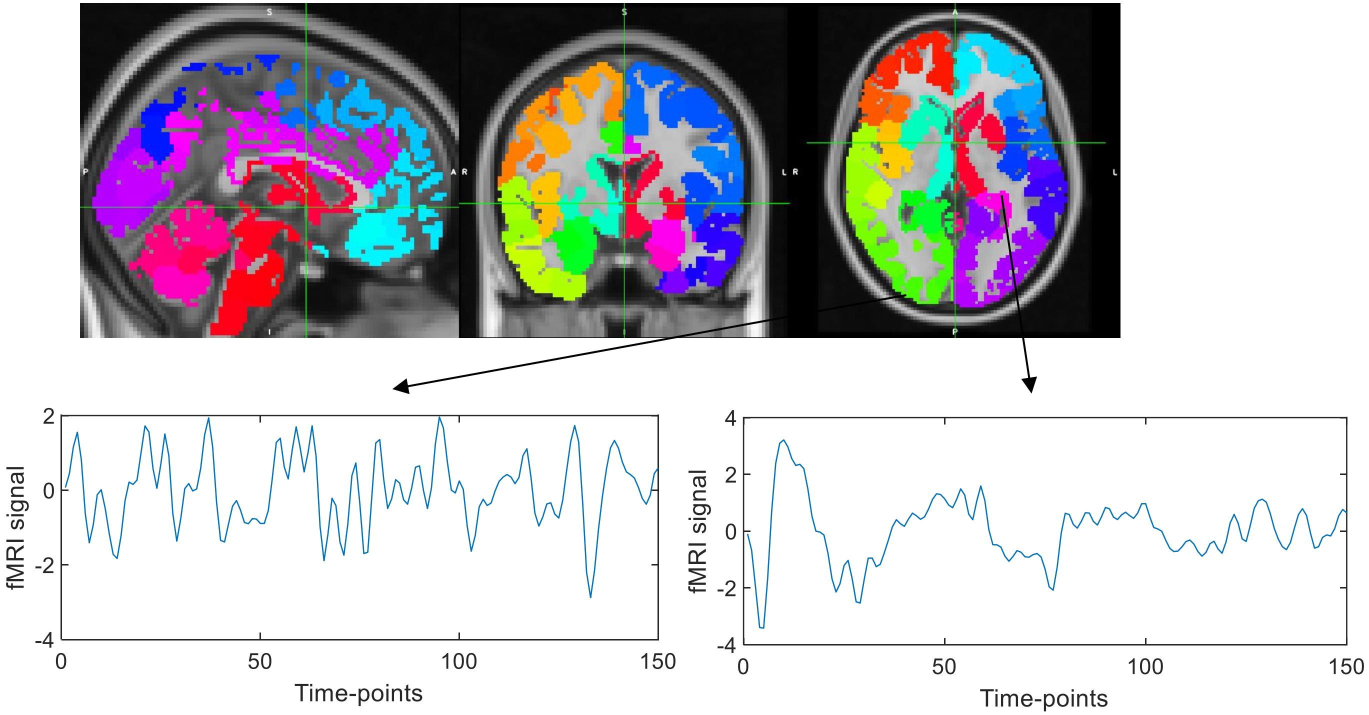


Averaged Time-series for a region

# FC matrix

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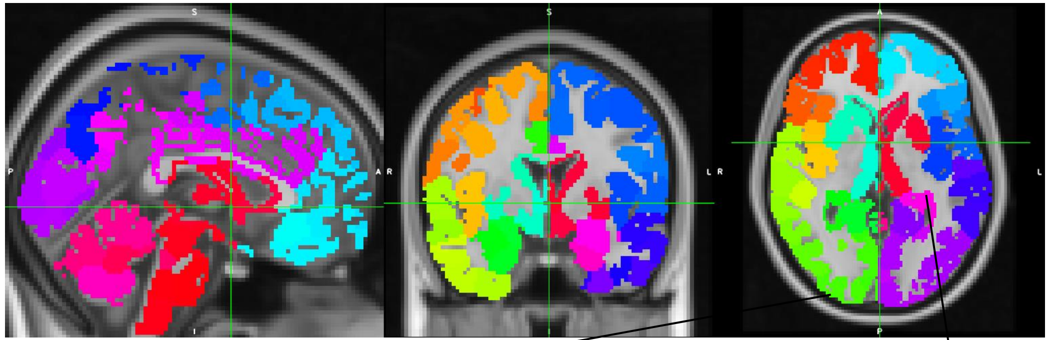

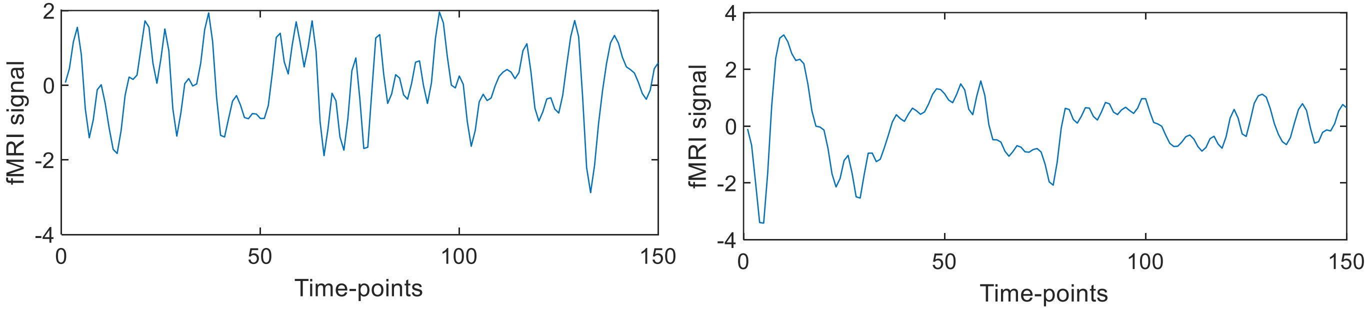


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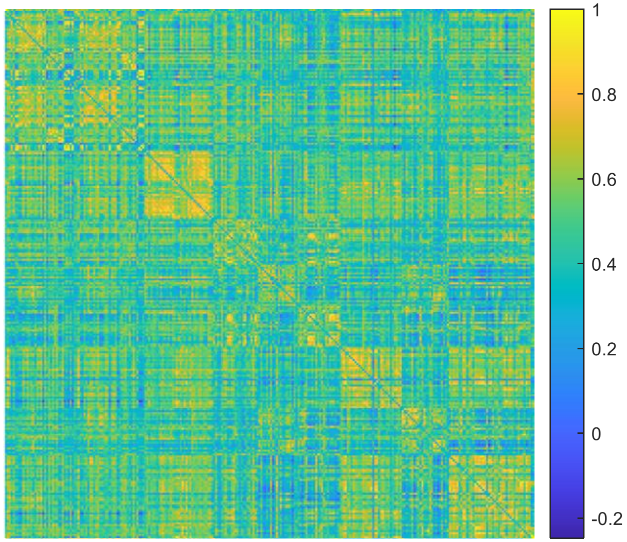
n

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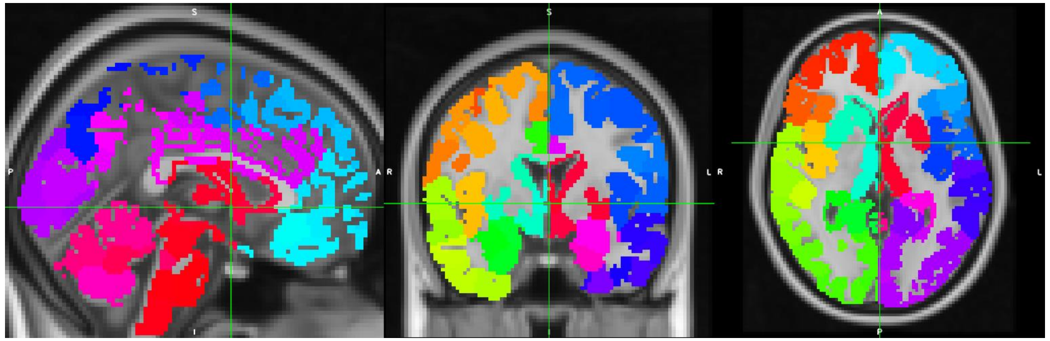

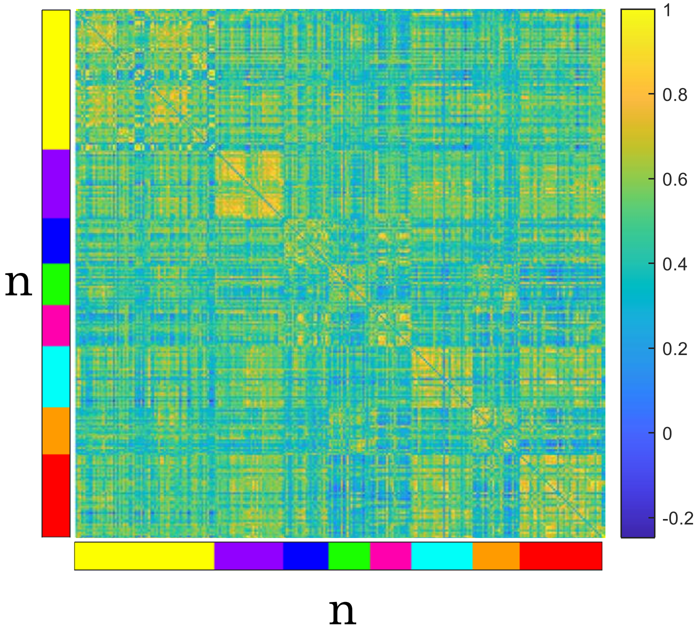


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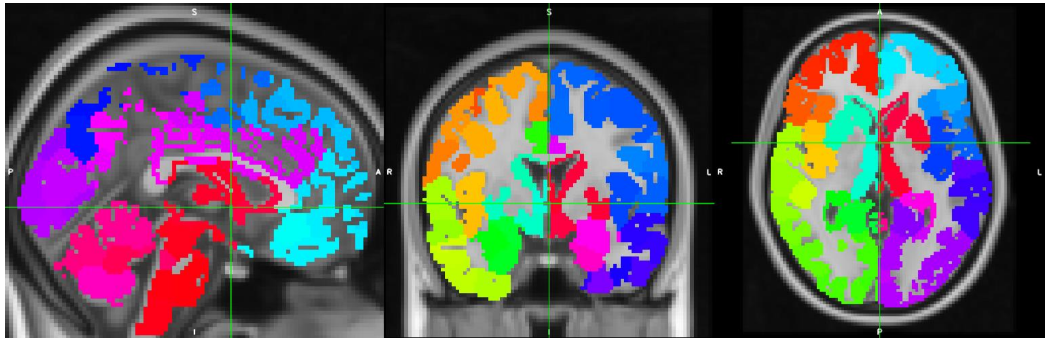

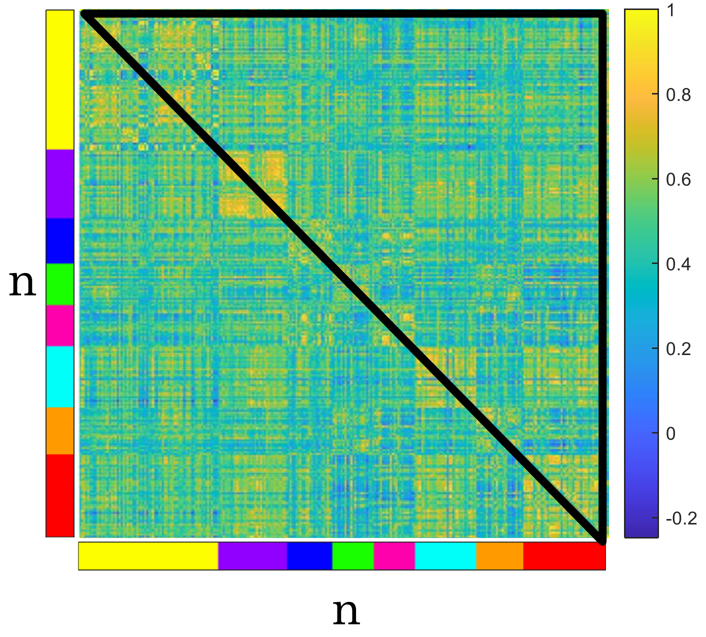


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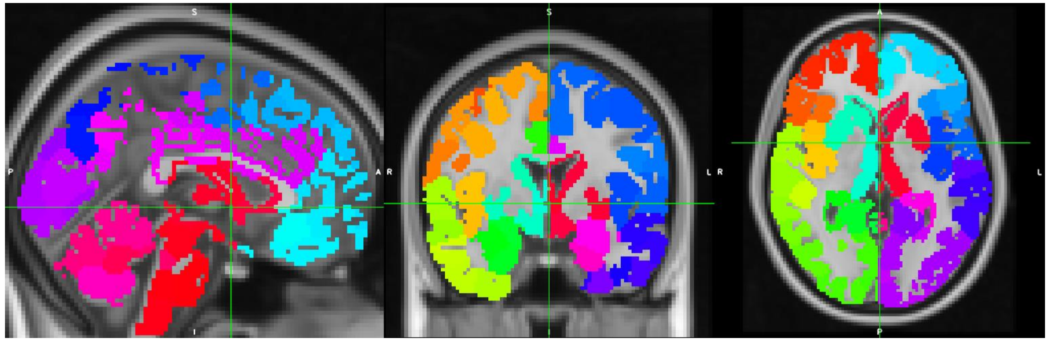

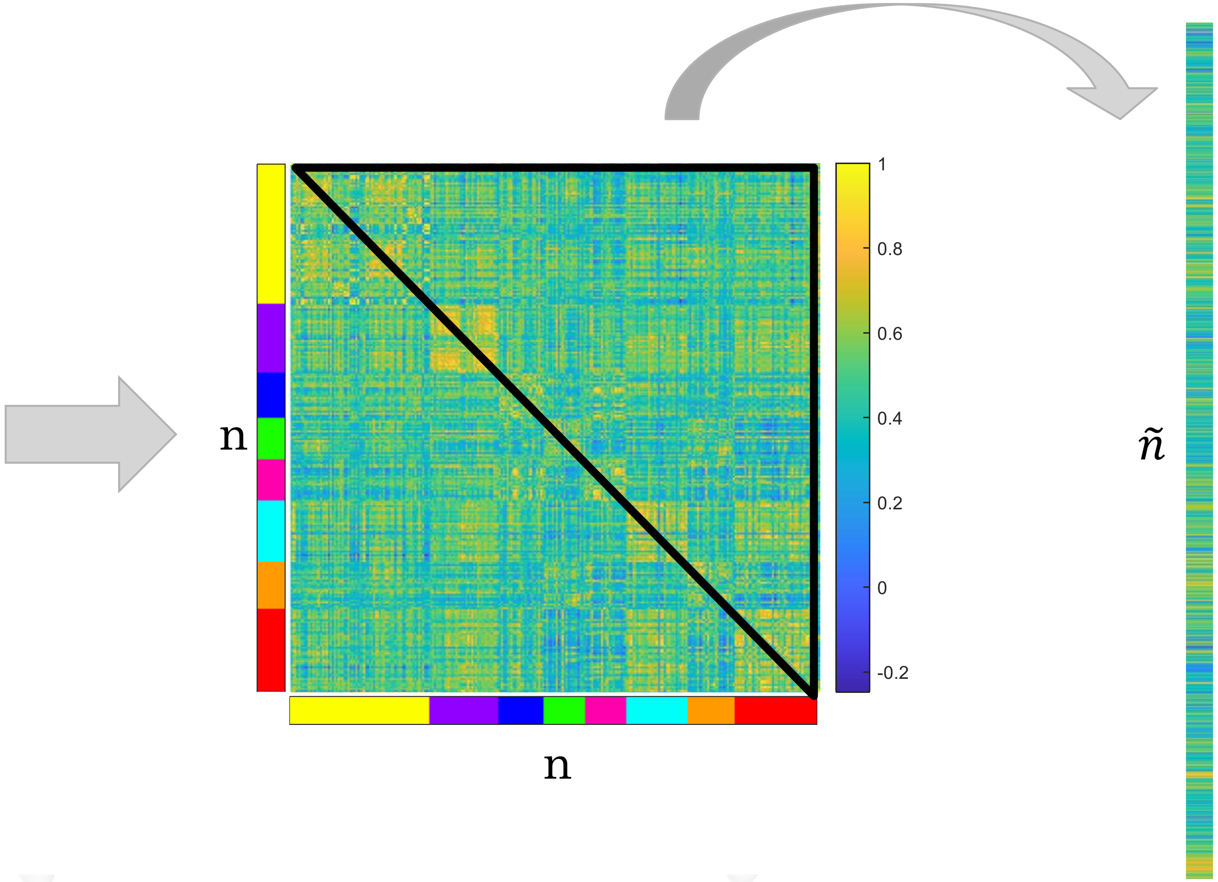


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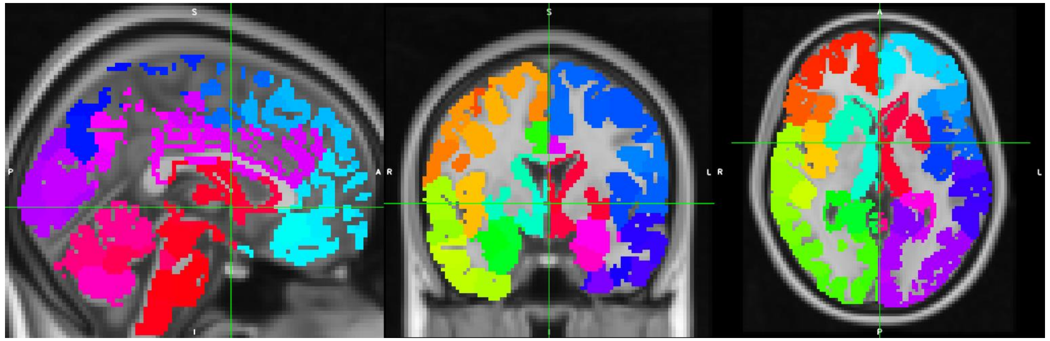

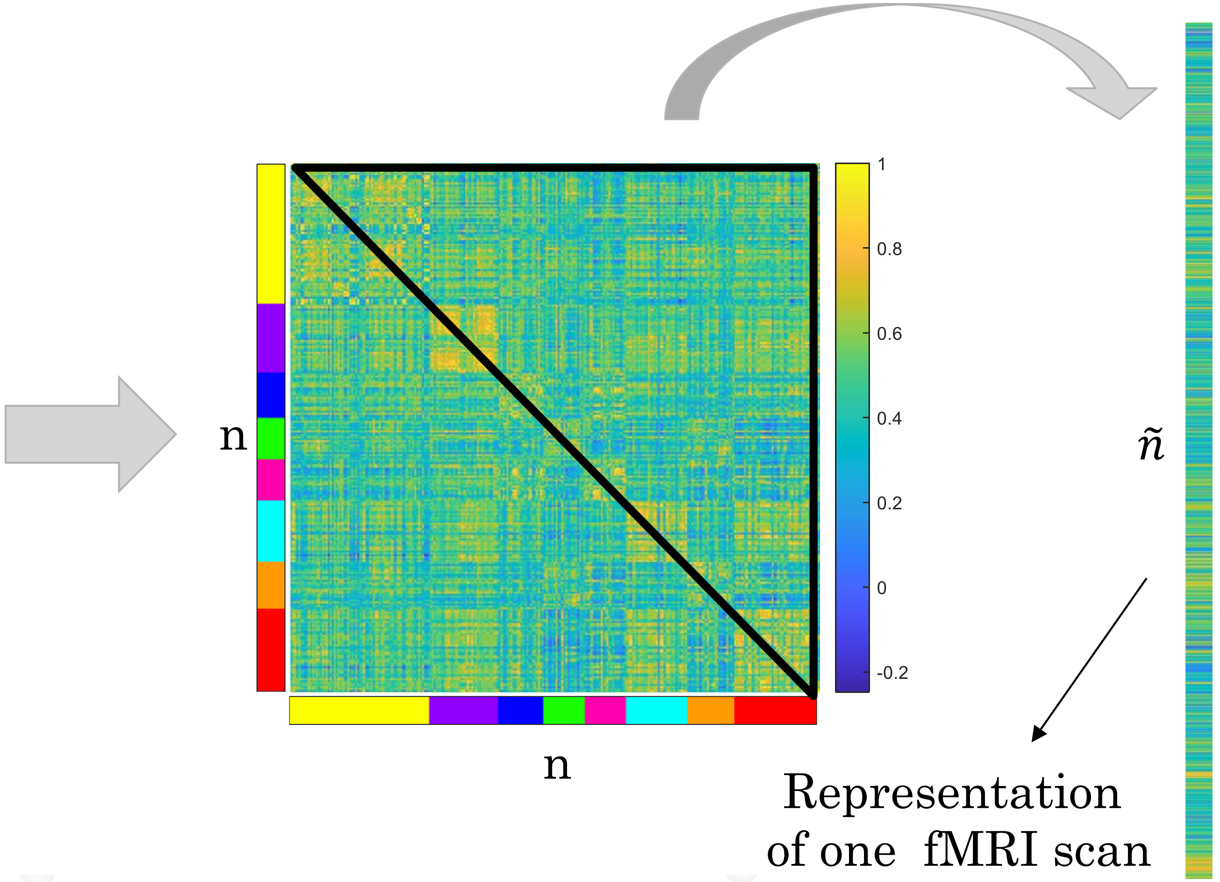


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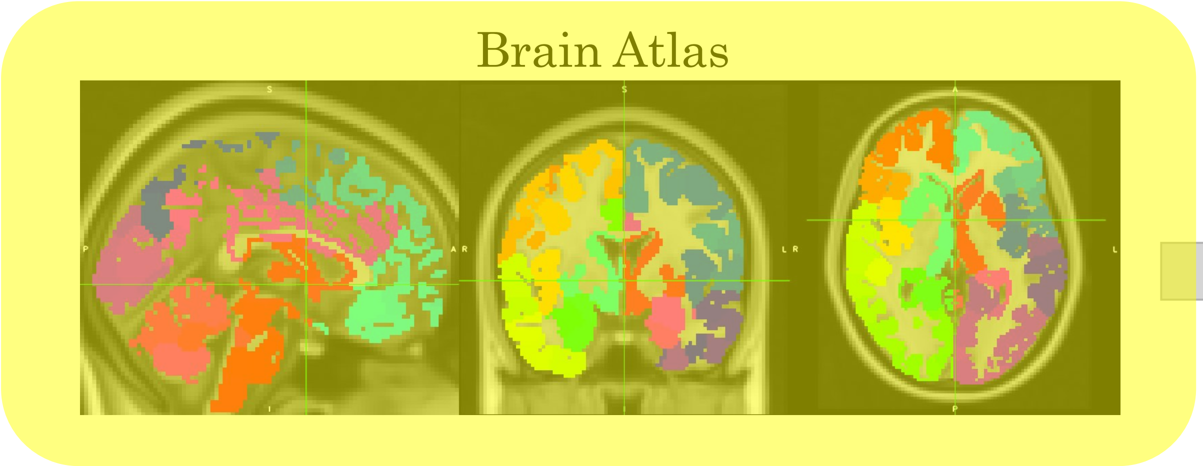


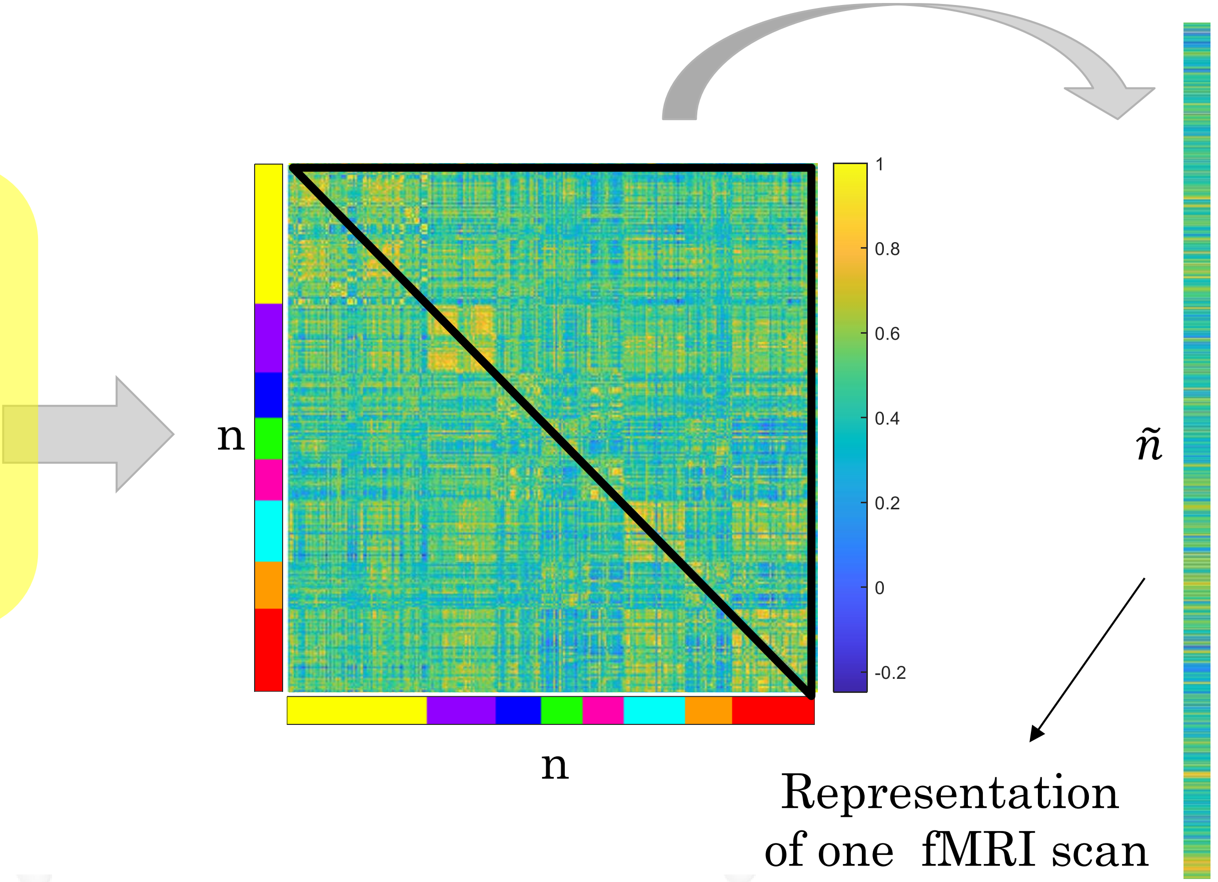


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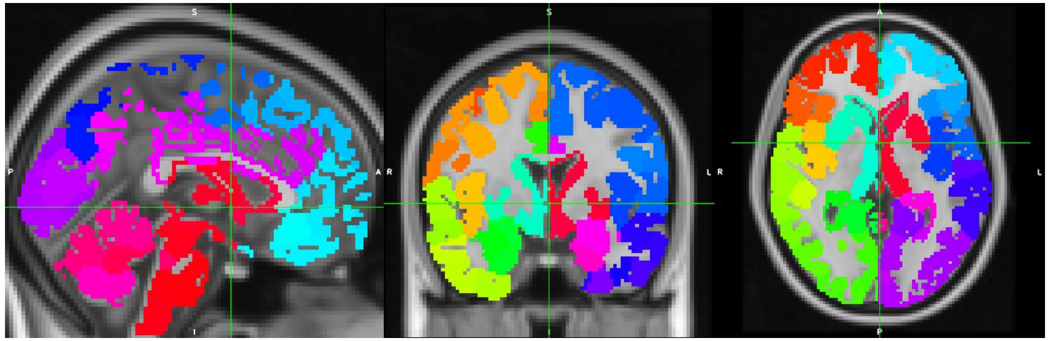

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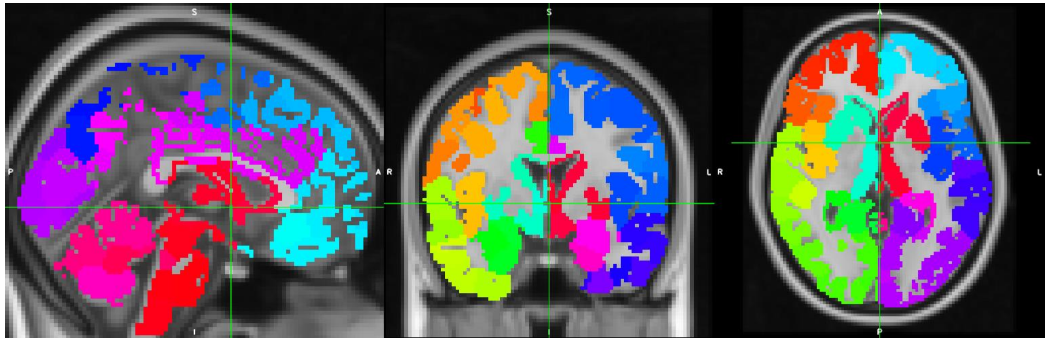

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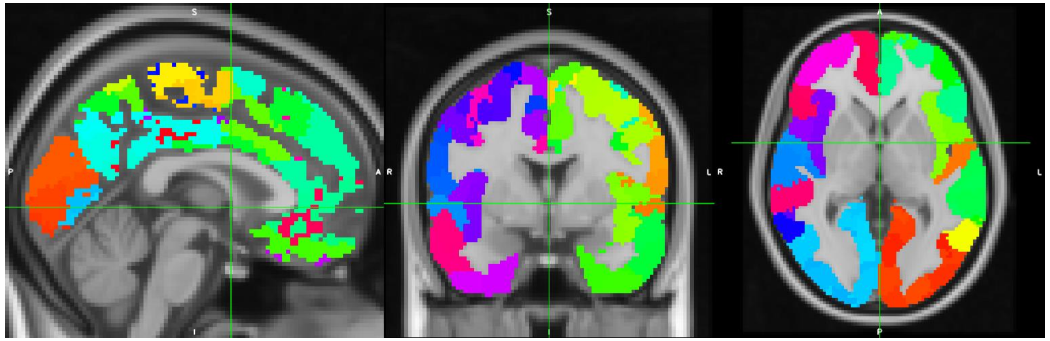

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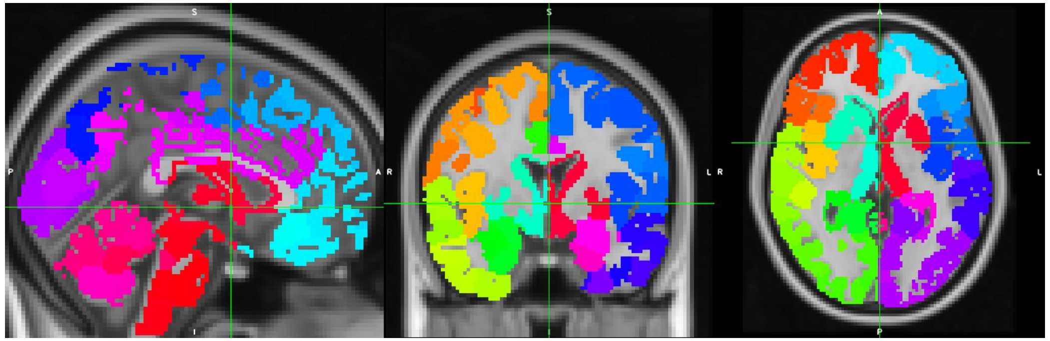

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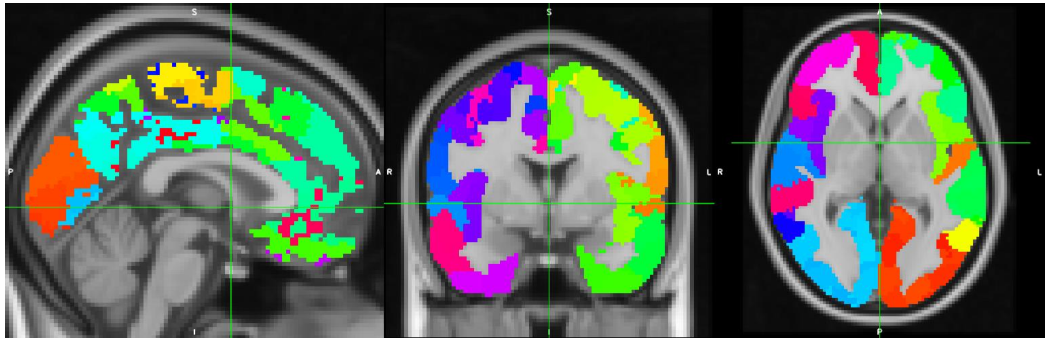
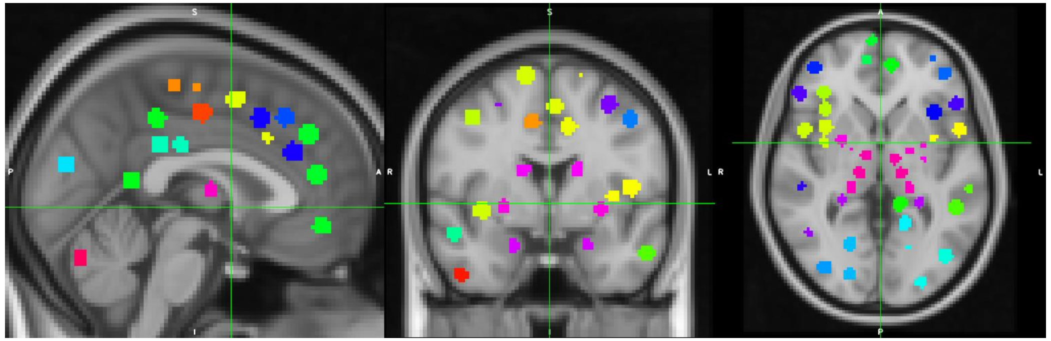


Spherical ROIs



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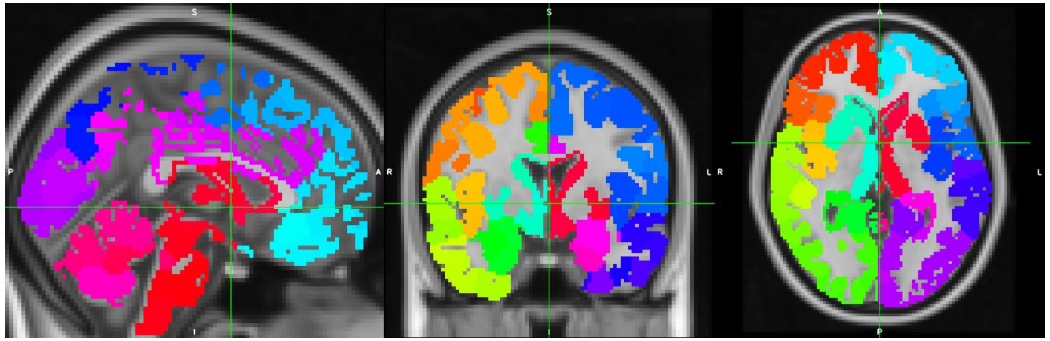

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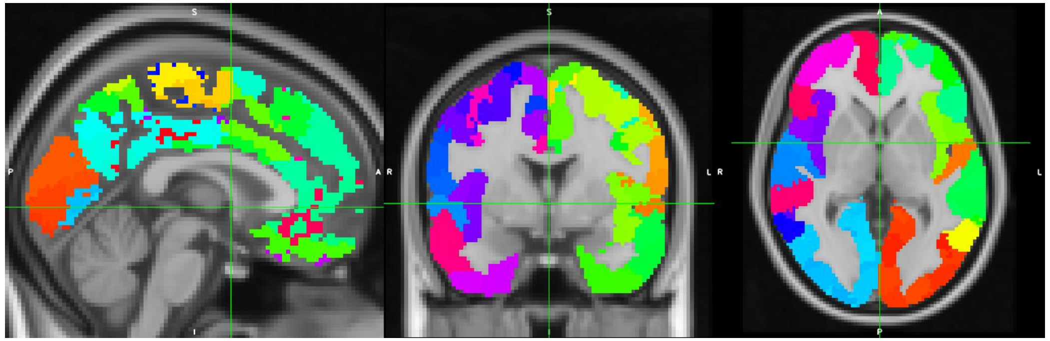

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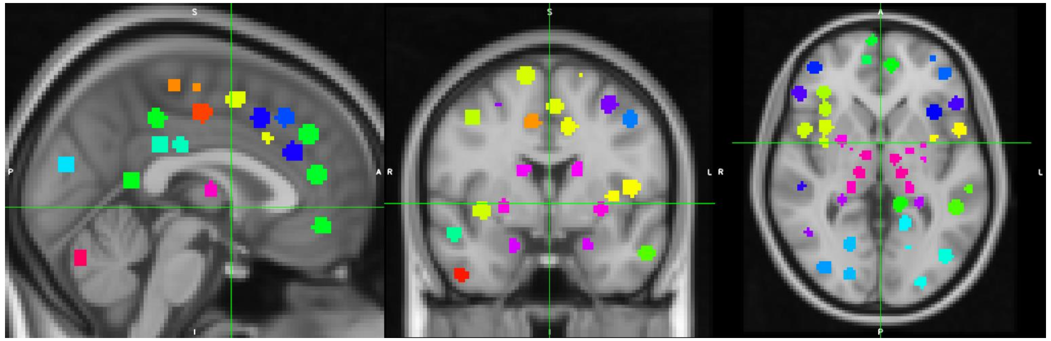

Which to use ?

# Brief details of Atlases Used

| Atlases | ROIs | Average Voxel per ROI | Spherical ROIs | Contains Subcortical Nodes |
|---|---|---|---|---|
| AAL | 116 | 1160 | No | Yes |
| Dosenbach | 164 | 123 | Yes | No limbic nodes |
| Brainnetome | 246 | 477 | No | No Cerebellum nodes |
| Power | 264 | 8 | Yes | Yes |
| Shen | 268 | 601 | No | Yes |
| Seitzman | 300 | 58 | Yes | Yes |
| Gordon | 333 | 205 | No | No |
| Schaefer | 100, 200, 300, 400, 500 | 1320, 660, 440, 330, 264 | No | No |

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- Look at the effect of changing the Brain atlas.
- Look at the Brin fingerprints in different resting state networks.

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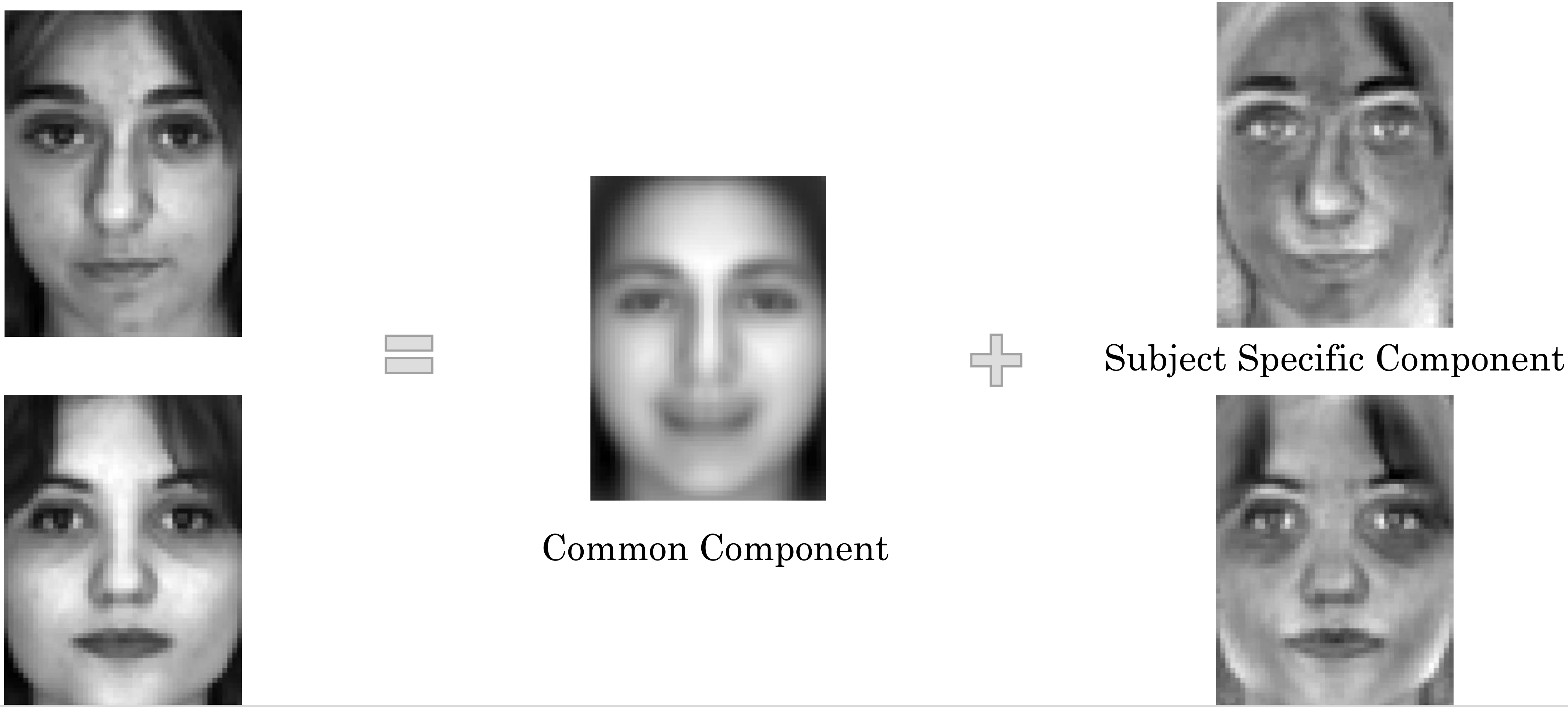


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Can we do this with FC ?

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# Dataset

Midnight scan Club

- 10 Subjects
- 10 Scans per Subject

HNU dataset

- 30 Subjects
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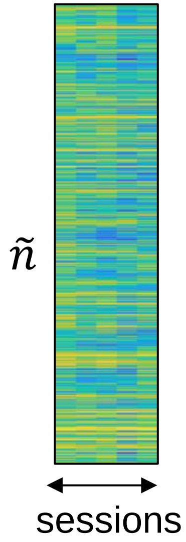
Total

- 40 Subjects
- 10 Scans per Subject

Data matrix

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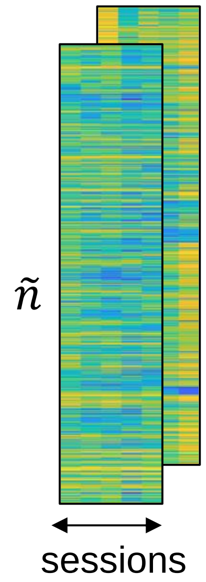


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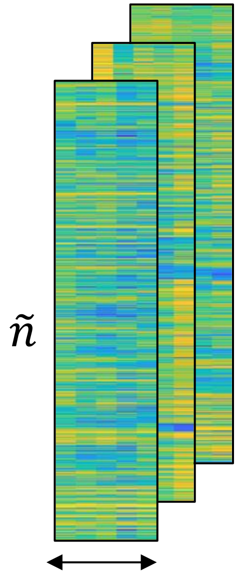


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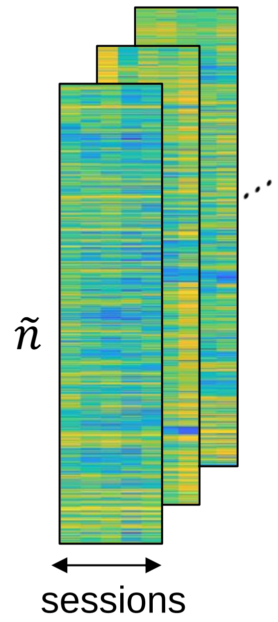


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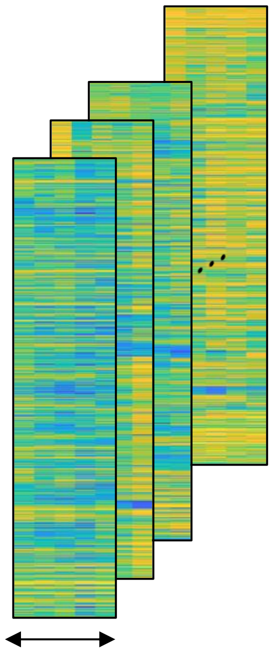

sessions

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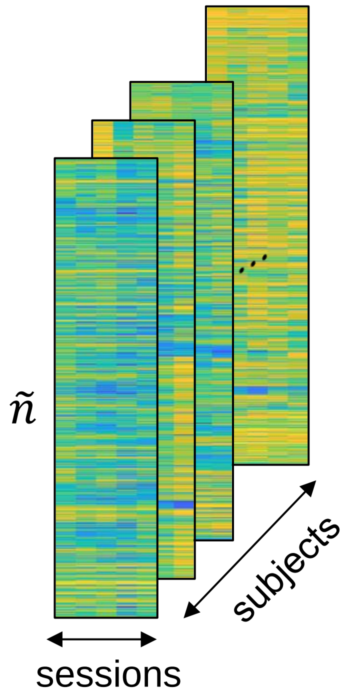
Data matrix




Midnight Scan Club dataset link
HNU dataset link

# Dataset

Midnight scan Club

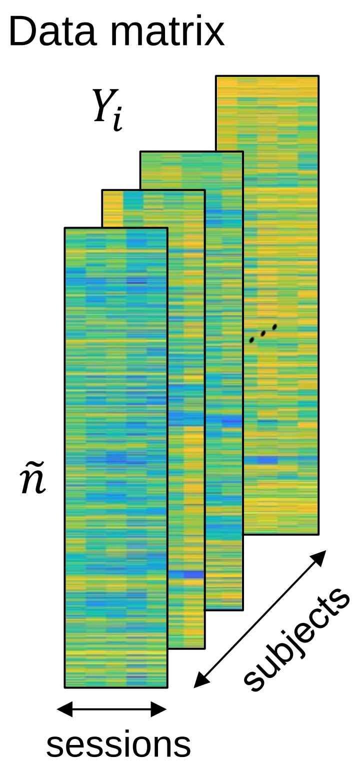
- 10 Subjects
- 10 Scans per Subject

HNU dataset

- 30 Subjects
- 10 Scans per Subject

Total

- 40 Subjects
- 10 Scans per Subject




Midnight Scan Club dataset link
HNU dataset link

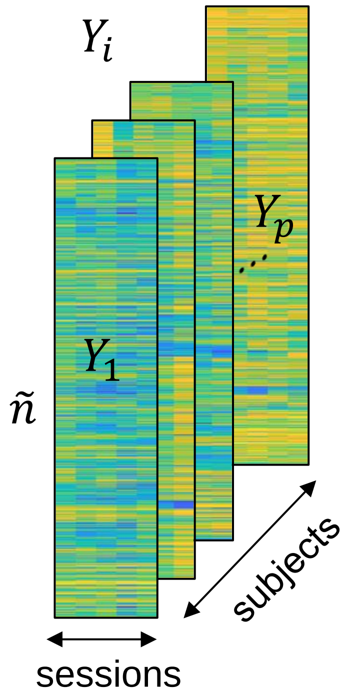
# Dataset

Midnight scan Club
- 10 Subjects
- 10 Scans per Subject

HNU dataset
- 30 Subjects
- 10 Scans per Subject

Total
- 40 Subjects
- 10 Scans per Subject

Data matrix

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# Common Orthogonal Basis Extraction (COBE)

- $\boldsymbol{Y}_i = \boldsymbol{D}\boldsymbol{X}_i + \boldsymbol{D}_i\breve{\boldsymbol{X}}_i$

G. Zhou et al. "Group Component Analysis for Multiblock Data: Common and Individual Feature Extraction". *In*: *IEEE Trans Neural Network Learn System* (2016)

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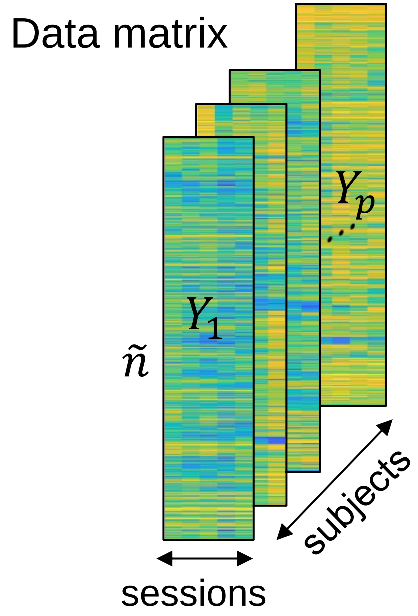


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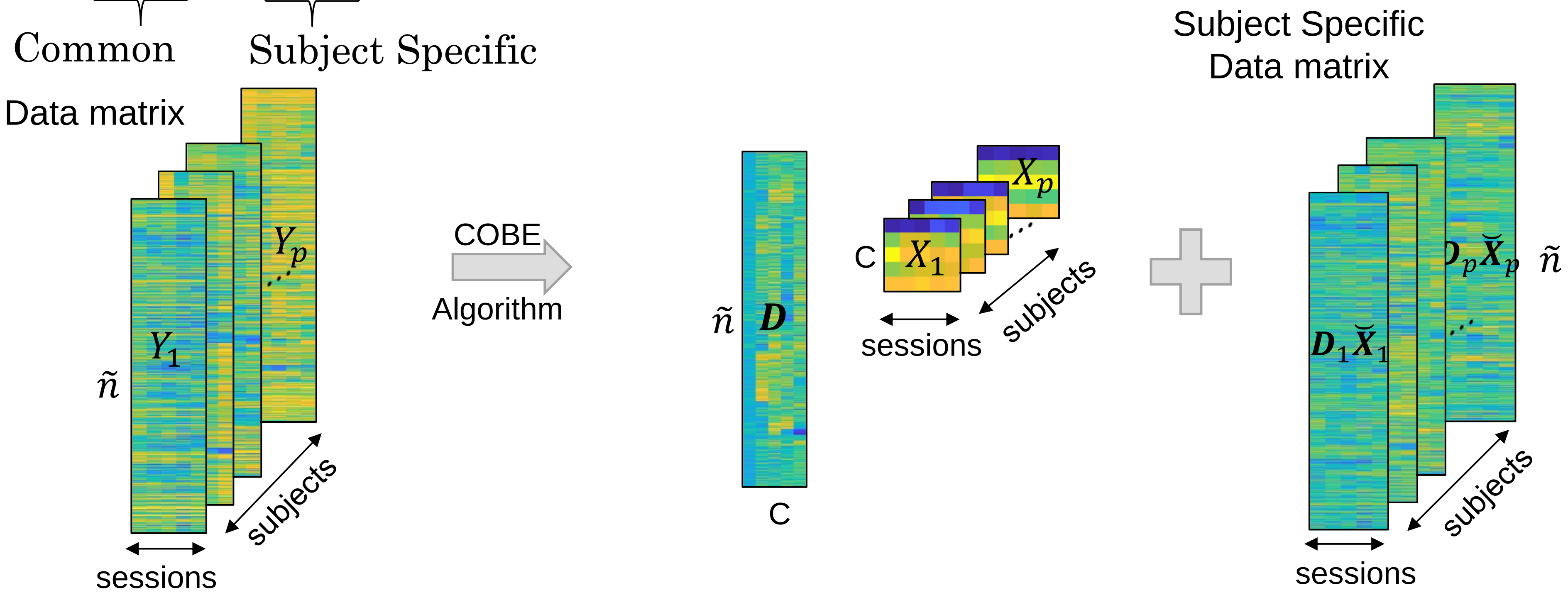


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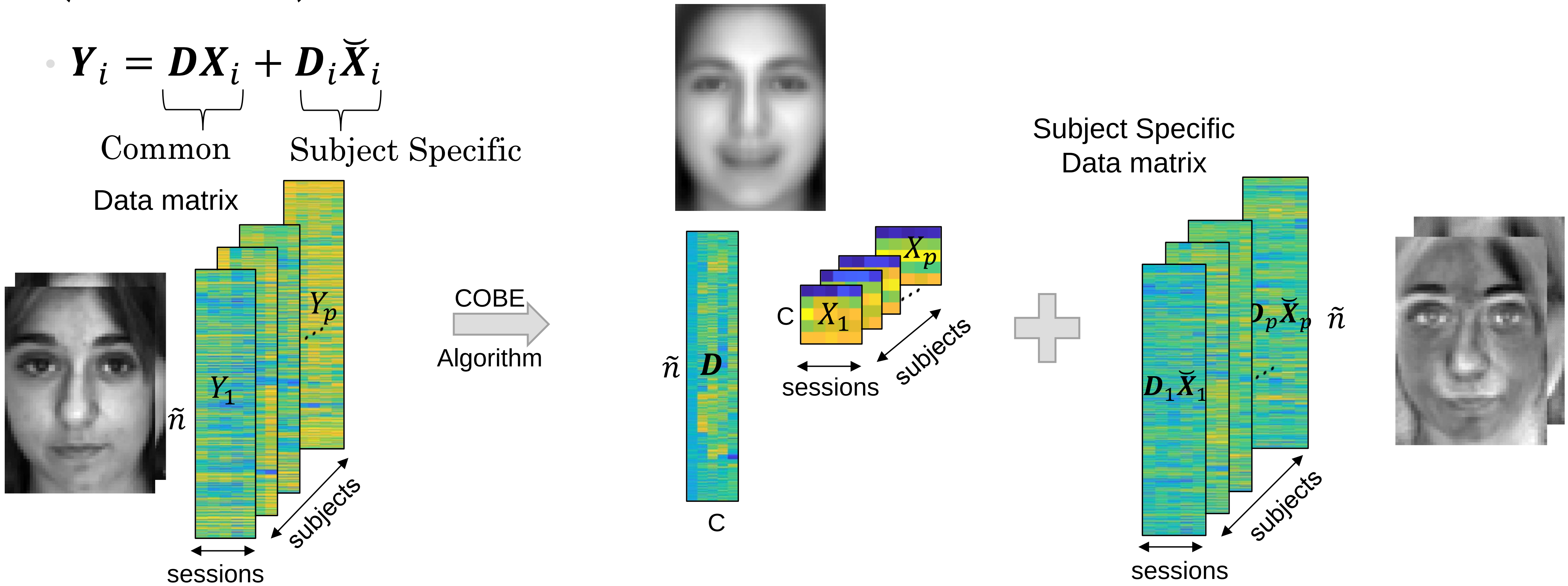



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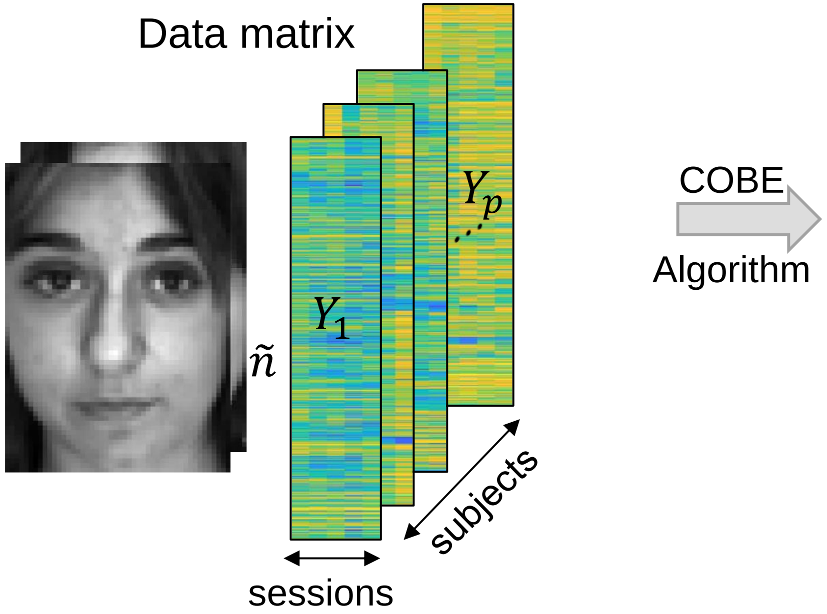


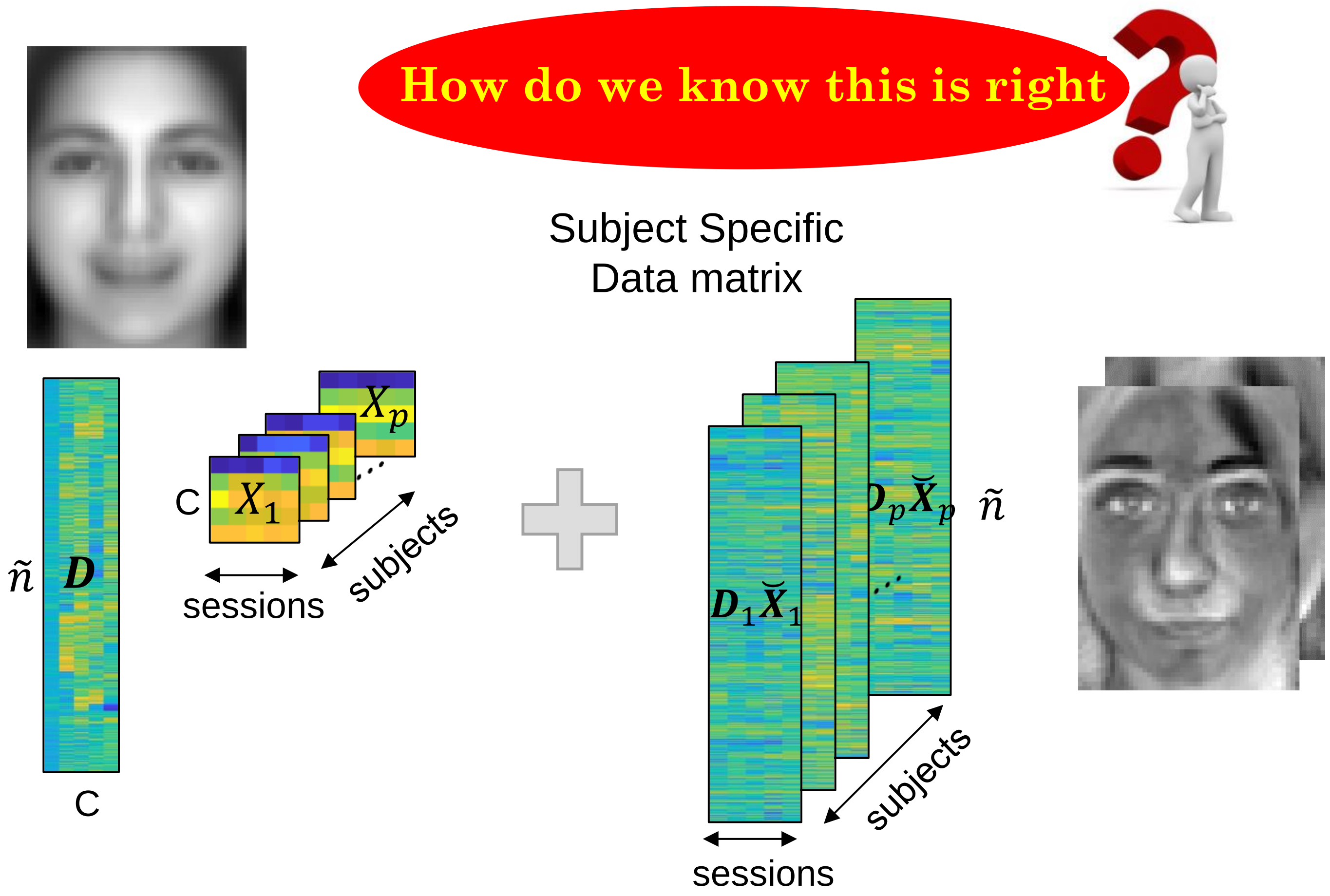


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Subject 1
Scan 1

Subject 1
Scan 2

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Scan 1

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Scan 2

Analogy
face images

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Subject 1
Scan 1

← Similar →

Subject 1
Scan 2

Analogy
face images

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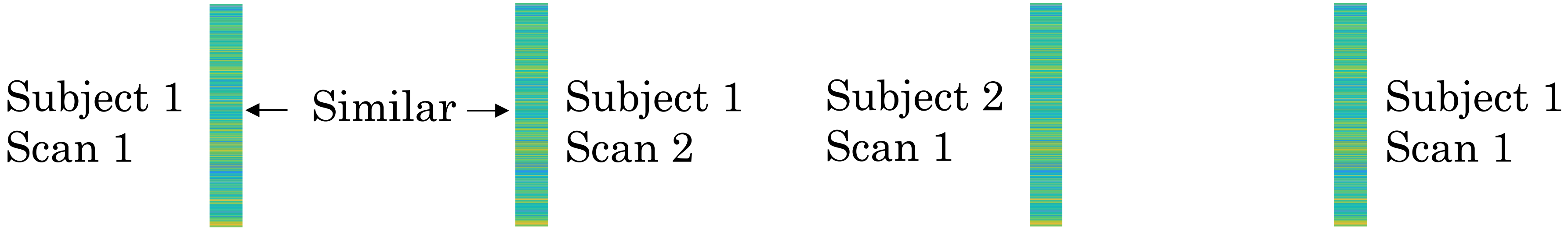


Analogy face images

# How do we quantify brain uniqueness?-

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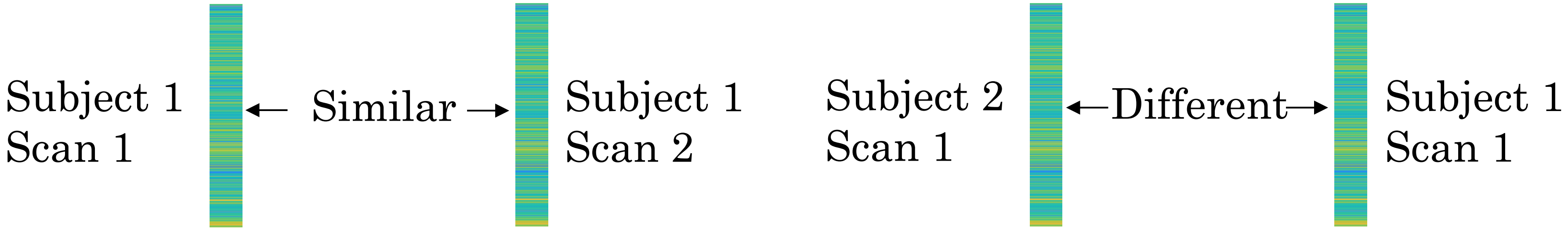


Analogy face images

# How do we quantify brain uniqueness?-

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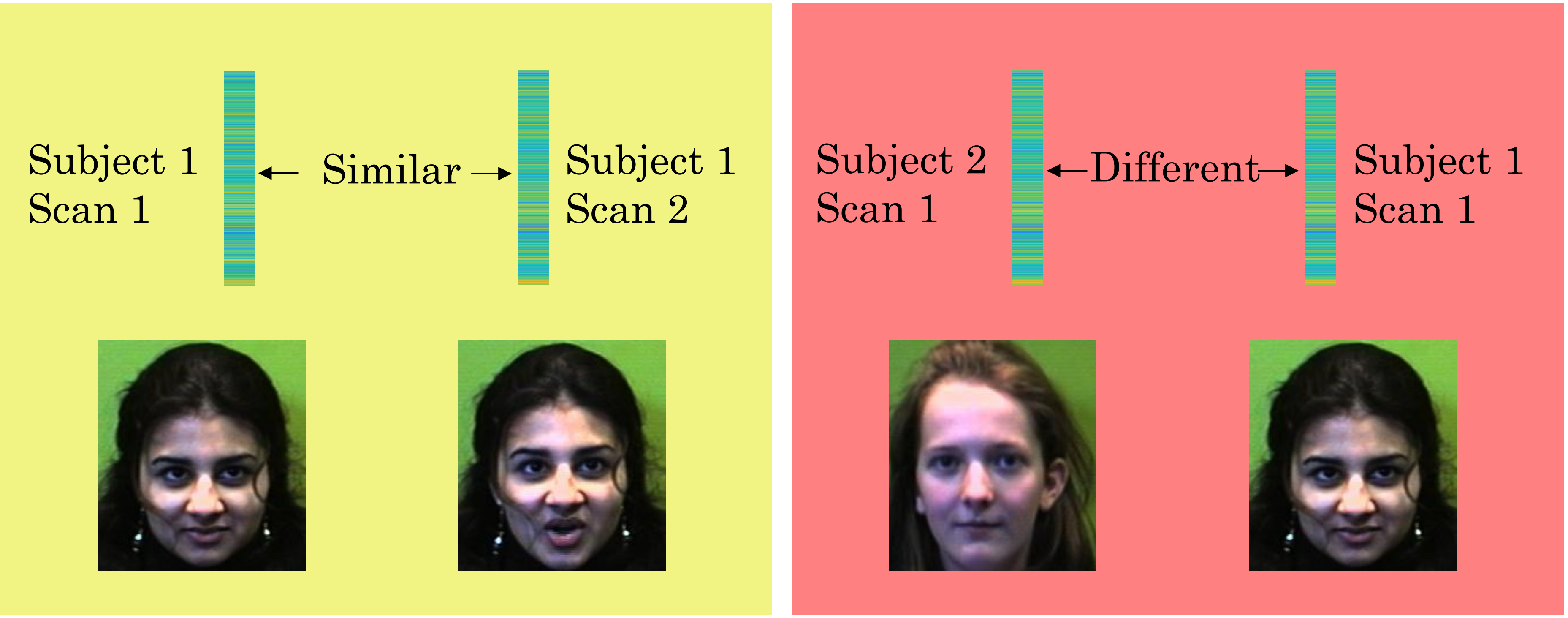
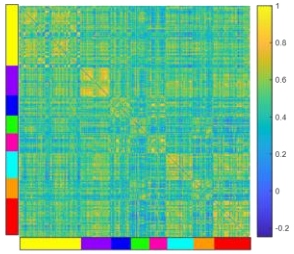
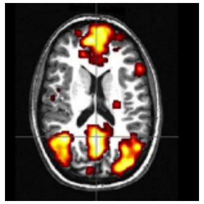


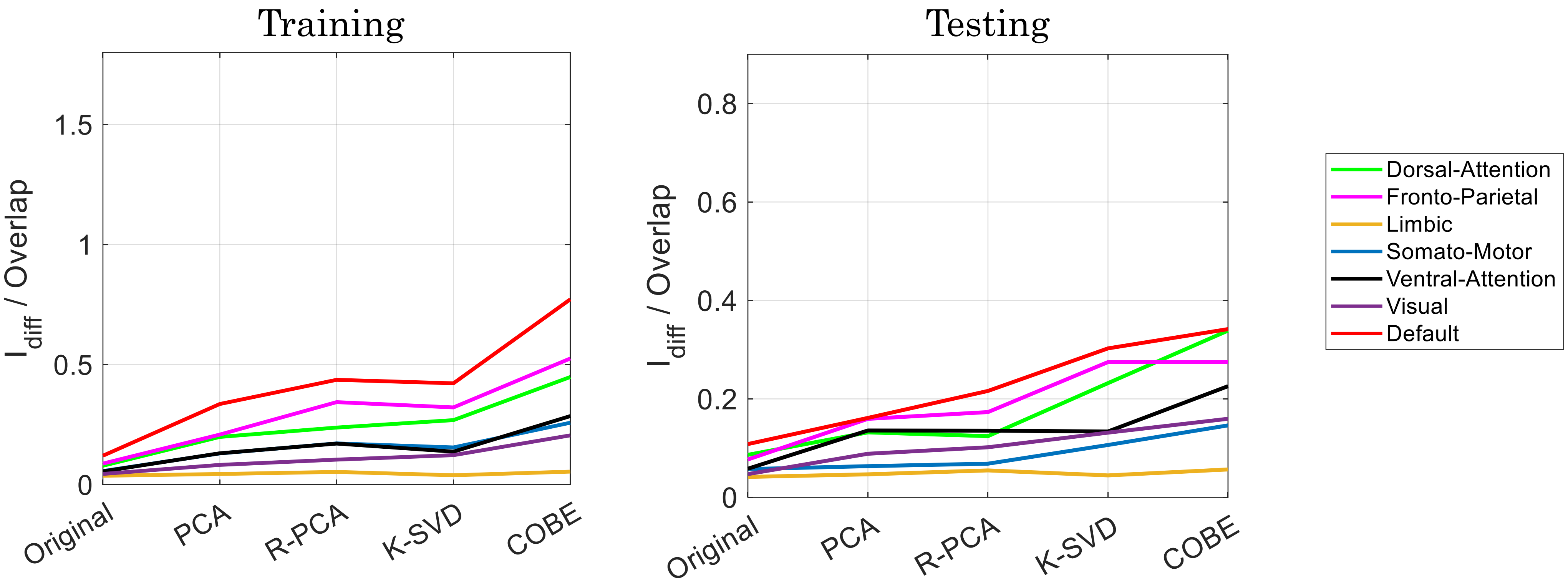

Analogy
face images

# Results



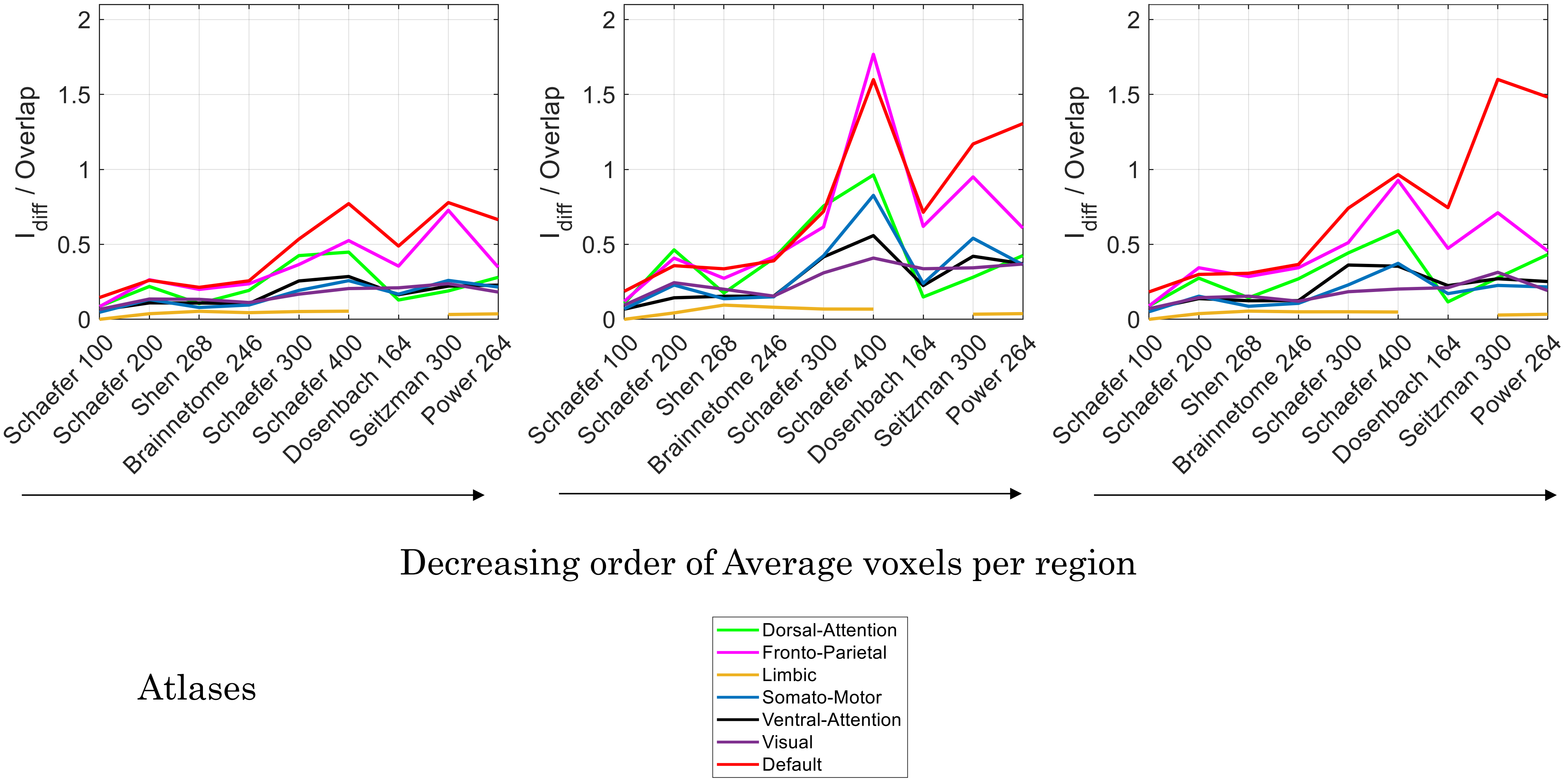


Default mode network




$\frac{I_{diff}}{Overlap}$ → Higher the value, more the scans within same subject are similar and different between different subjects.

# Variation with atlas




Decreasing order of Average voxels per region

Atlases

# Conclusion

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# Conclusion

- COBE dictionary learning algorithm is better than PCA, RPCA and K-SVD in extracting the subject-specific FC (brain fingerprints)
- Default Mode and Fronto-Parietal Network have better features than other resting state networks.
- High resolution atlas with low average number of voxels per ROI are desirable.

# References


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- Bharat Biswal et al. Functional connectivity in the motor cortex of resting human brain using echo-planar MRI. @In: Magnetic Resonance in Medicine (1995)
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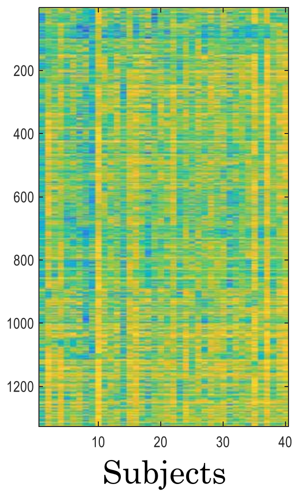
- G. Zhou et al. “Group Component Analysis for Multiblock Data: Common and Individual Feature Extraction”. @In: IEEE Trans Neural Network Learn System (2016)
- **Jain P, Chakraborty A, Hafiz R, Sao AK, Biswal B. Enhancing the network specific individual characteristics in rs-fMRI functional connectivity by dictionary learning. @ In:Human Brain Mapping (2023)**

# Thank You

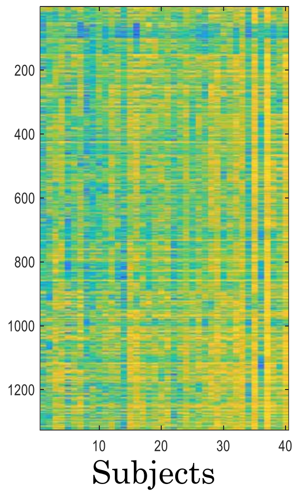
Questions?

# Metrics - $I_{diff}$ (Existing)

$Y^i$




$Y^j$



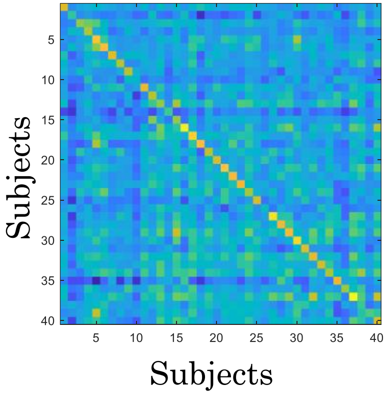

$\tilde{n}$

$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

Correlation

$C_{i,j} = corr\left(Y^i, Y^j\right)$




Mean of diagonal elements $\rightarrow$ $I_{self}^{i,j}$

Mean of non diagonal elements $\rightarrow$ $I_{others}^{i,j}$

$$I_{diff}^{i,j} = \left(I_{self}^{i,j} - I_{others}^{i,j}\right) * 100$$

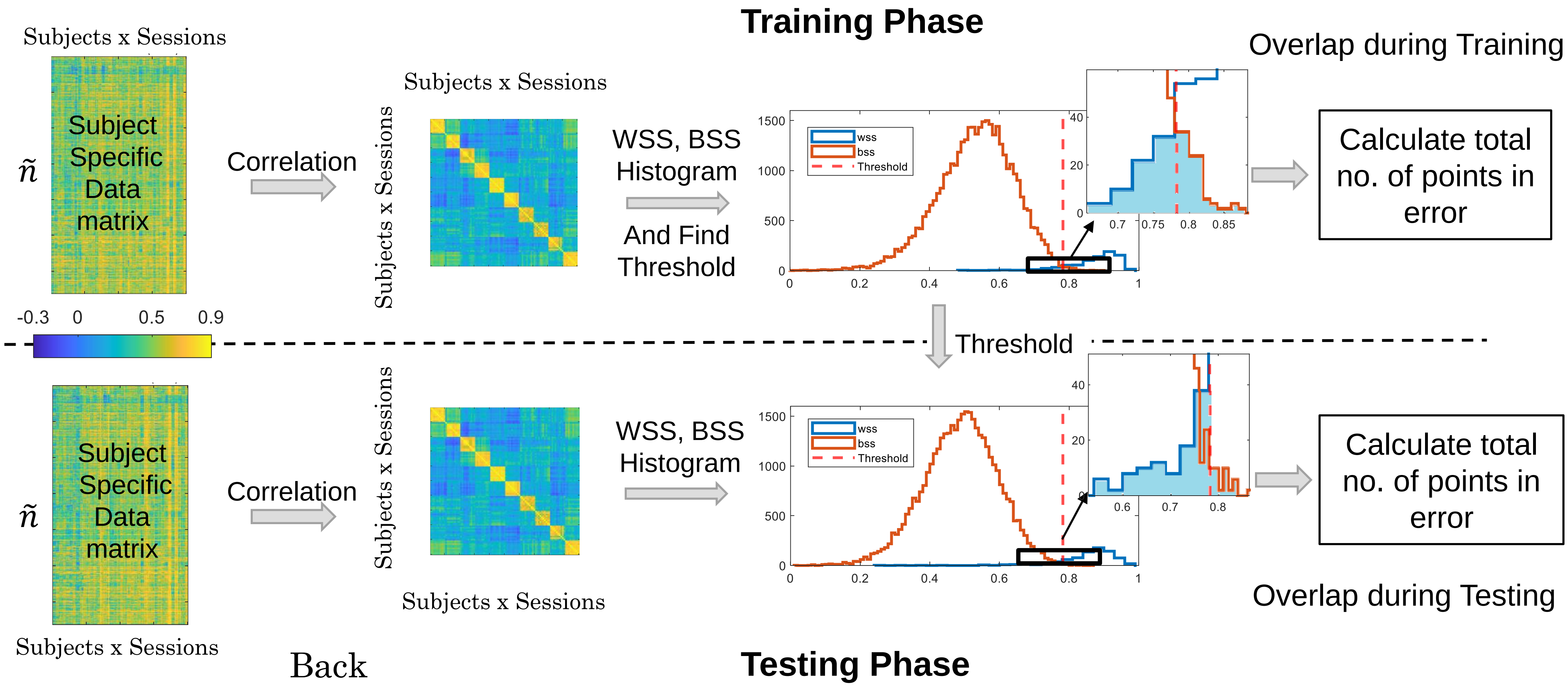
$s = Number\ of\ sessions$ $\qquad \tilde{s} = \frac{s \times (s-1)}{2}$

$$I_{diff} = \frac{1}{\tilde{s}} \sum_{i,j} I_{diff}^{i,j} \qquad i = 1,2, \ldots s \qquad j = i+1, i+2, \ldots, s$$

Back

E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (*May* 2018)

# Metric - Overlap (Proposed)




Back

# COBE

- COBEC
- $\boldsymbol{Y_n}^T = \boldsymbol{X_n}^T \boldsymbol{D}^T + \breve{\boldsymbol{X}}_{\boldsymbol{n}}{}^T \boldsymbol{D_n}^T$
- $\boldsymbol{X_n}^T \boldsymbol{D}^T = \boldsymbol{Y_n}^T - \breve{\boldsymbol{X}}_{\boldsymbol{n}}{}^T \boldsymbol{D_n}^T$
- $\boldsymbol{X_n}^T = \left(\boldsymbol{Y_n}^T - \breve{\boldsymbol{X}}_{\boldsymbol{n}}{}^T \boldsymbol{D_n}^T\right) \boldsymbol{D}(\boldsymbol{D}^T \boldsymbol{D})^{-1}$ using least squares
- $\boldsymbol{X_n}^T = \boldsymbol{Y_n}^T \boldsymbol{D} - \breve{\boldsymbol{X}}_{\boldsymbol{n}}{}^T \boldsymbol{D_n}^T \boldsymbol{D}$ $\boldsymbol{D}^T \boldsymbol{D} = \mathbf{I}$
- $\boldsymbol{X_n}^T = \boldsymbol{Y_n}^T \boldsymbol{D}$ $\boldsymbol{D_i}^T \boldsymbol{D} = \mathbf{I}$

Back

# COBE

- $\boldsymbol{Y_n = DX_n + D_n\breve{X}_n}$
- COBEC
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- $\boldsymbol{{X_n}^T = {Y_n}^T D - {\breve{X}_n}^T {D_n}^T D}$ $\boldsymbol{D^T D = \mathrm{I}}$
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Back

# COBE

- $\boldsymbol{Y_n} = \boldsymbol{D}\boldsymbol{X_n} + \boldsymbol{D_n}\breve{\boldsymbol{X}}_{\boldsymbol{n}}$
- $\boldsymbol{D}$ is found using the COBEC algorithm, $\boldsymbol{X_n}$ is then found as follows

Back

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- ${\boldsymbol{Y}_{\boldsymbol{n}}}^{T} = {\boldsymbol{X}_{\boldsymbol{n}}}^{T}\boldsymbol{D}^{T} + {\breve{\boldsymbol{X}}_{\boldsymbol{n}}}^{T}{\boldsymbol{D}_{\boldsymbol{n}}}^{T}$

Back

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Back

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Back

# COBEC algorithm

**Algorithm 2** COBE$C$ Algorithm

**Input:** $C$ and $\mathbf{Y}_n$, $n \in \mathcal{N}$.

1: Let $\mathbf{Y}_n = \mathbf{Q}_n \mathbf{H}_n$ such that $\mathbf{Q}_n^T \mathbf{Q}_n = \mathbf{I}_{R_n}$ for all $n$.
2: Initialize $\mathbf{Z}_n$ randomly.
3: **while** not converged **do**
4: $\quad \mathbf{P} = \sum_{n \in \mathcal{N}} \mathbf{Q}_n \mathbf{Z}_n$.
5: $\quad \mathbf{D} = \mathbf{E}\mathbf{V}^T$, where $[\mathbf{E}, \Lambda, \mathbf{V}] = \mathrm{tSVD}(\mathbf{P}, C)$.
6: $\quad \mathbf{Z}_n \leftarrow \mathbf{Q}_n^T \mathbf{D}$
7: **end while**
8: **return**

Back

# Training-Testing Pipeline (Proposed)

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**Training Phase**

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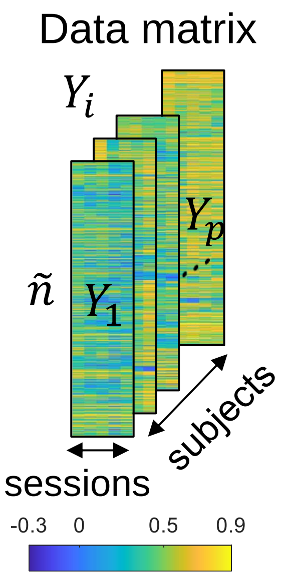
**Training Phase**



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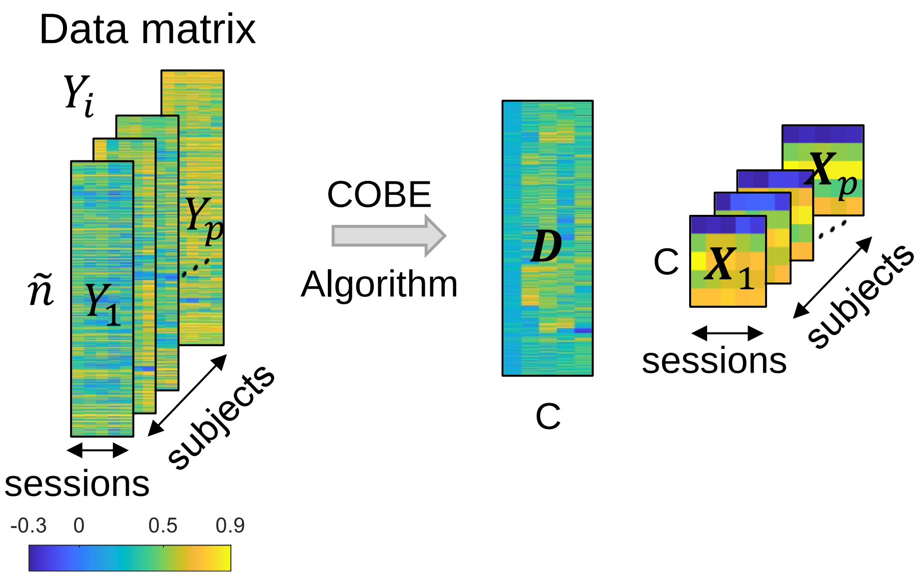
**Training Phase**



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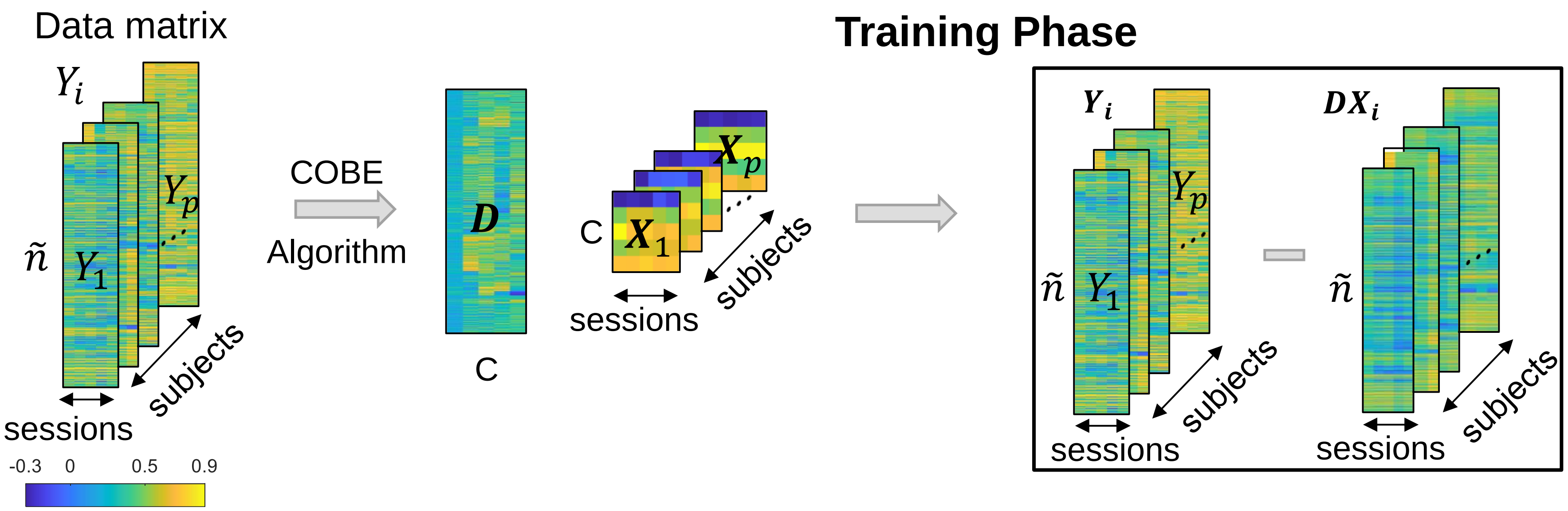

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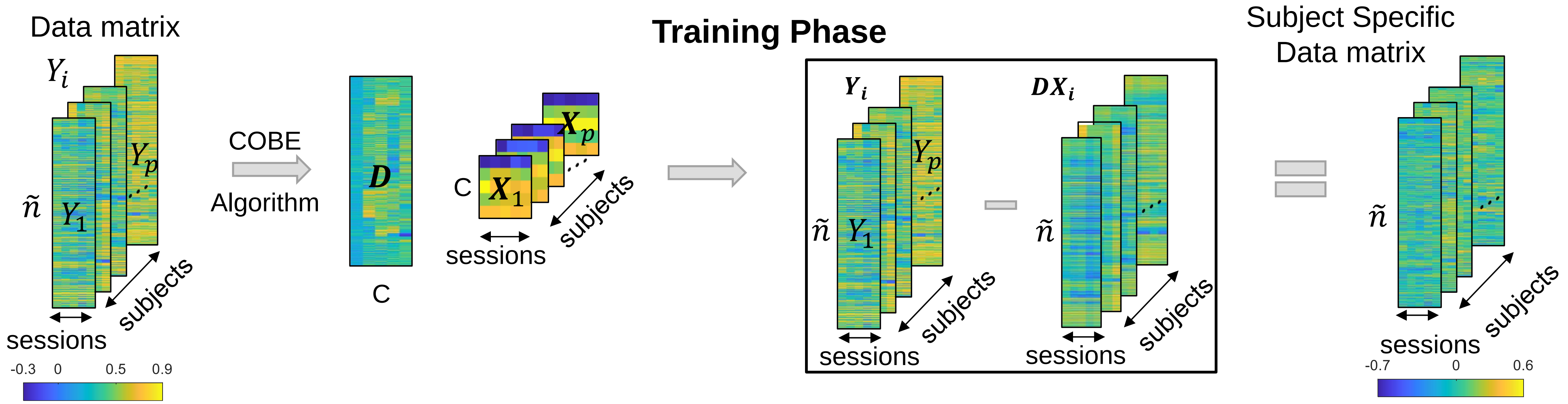

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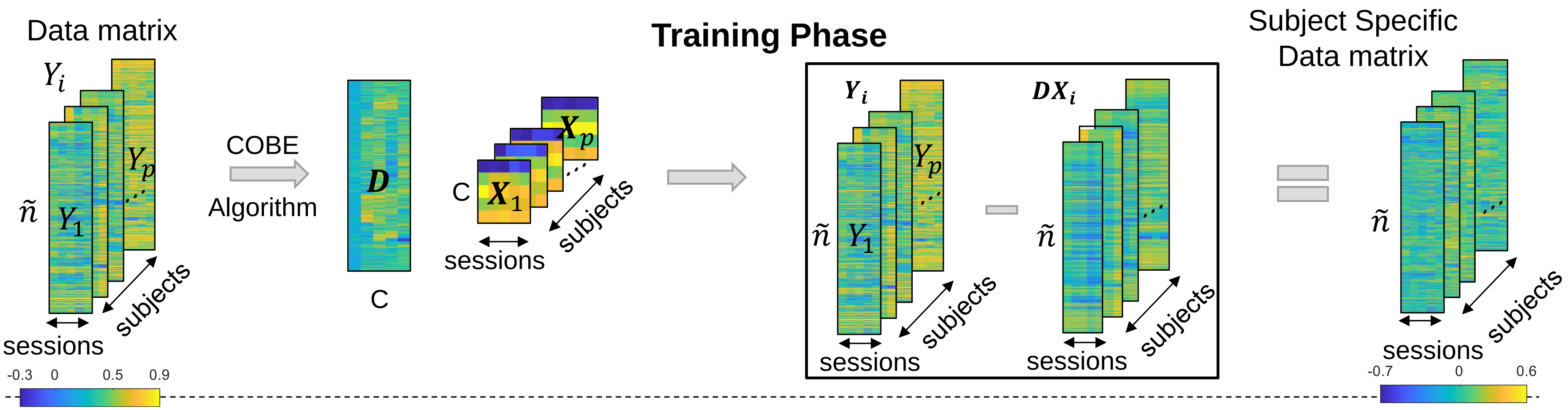


**Testing Phase**

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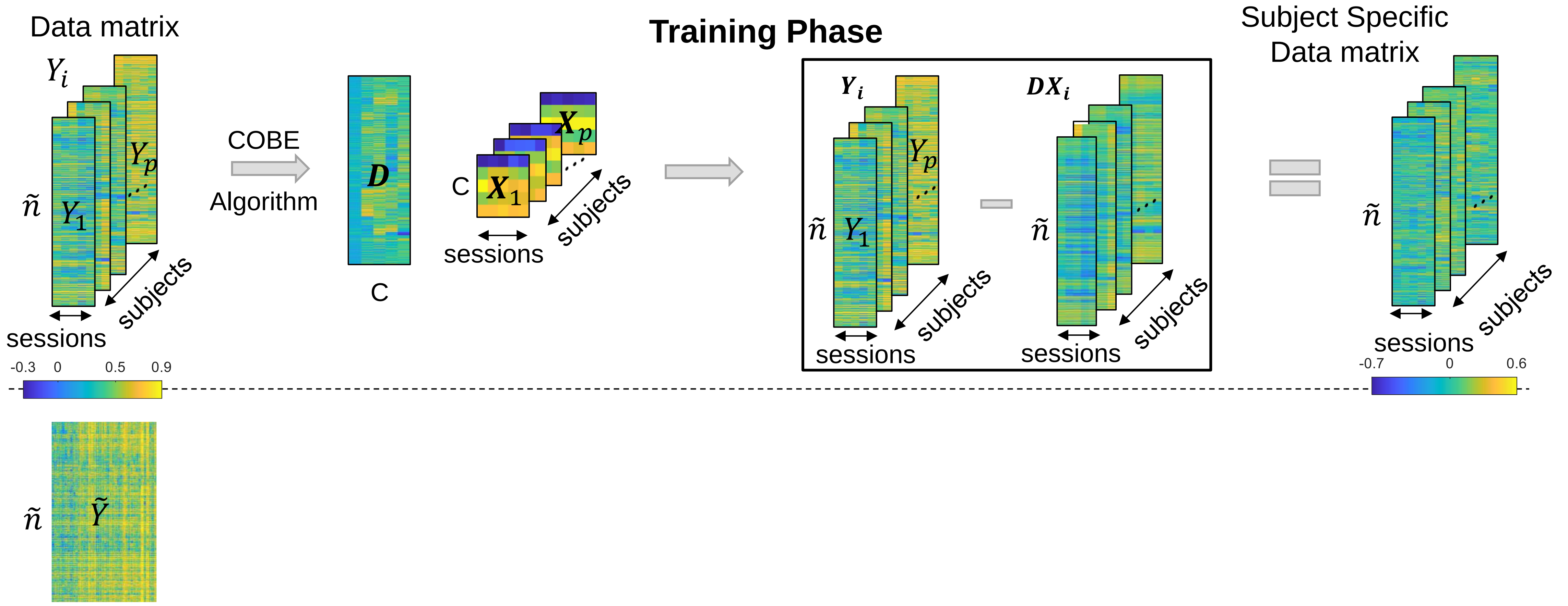


Subjects x Sessions

**Testing Phase**

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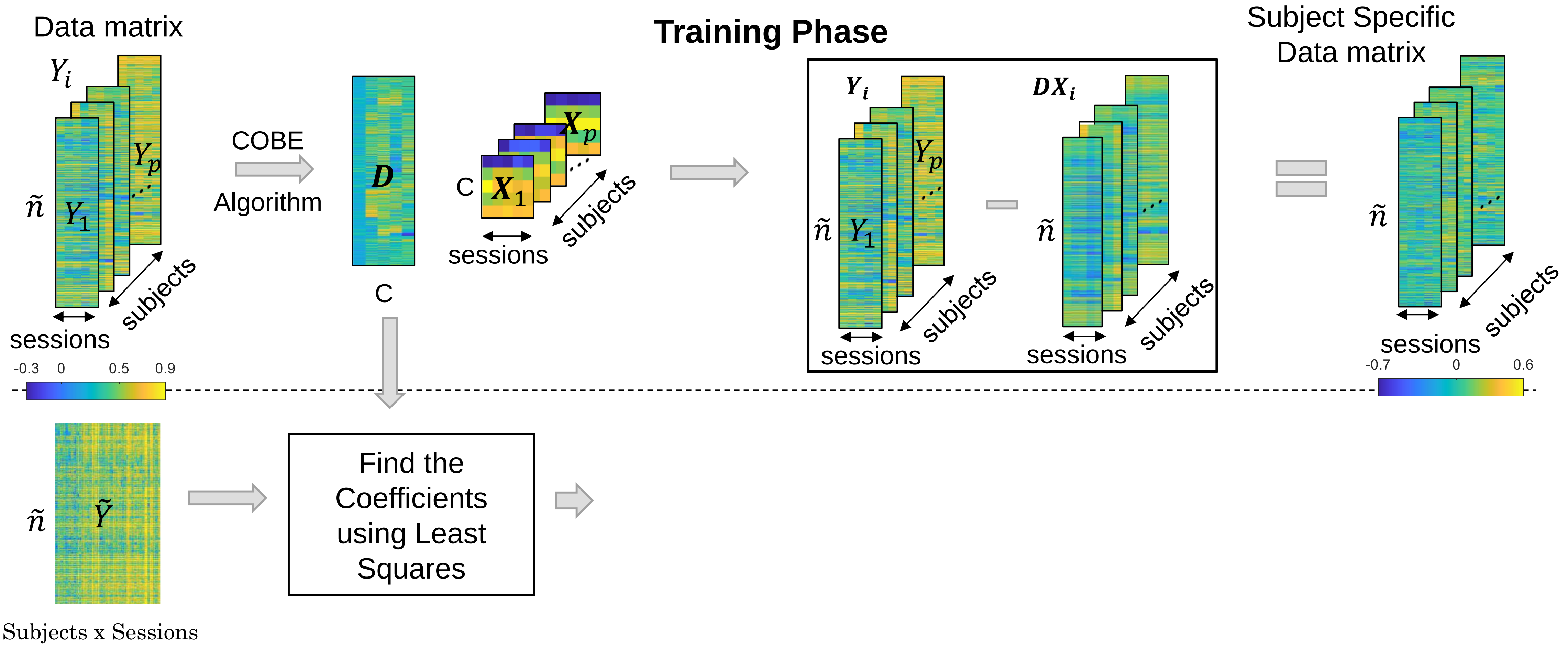
**Training Phase**

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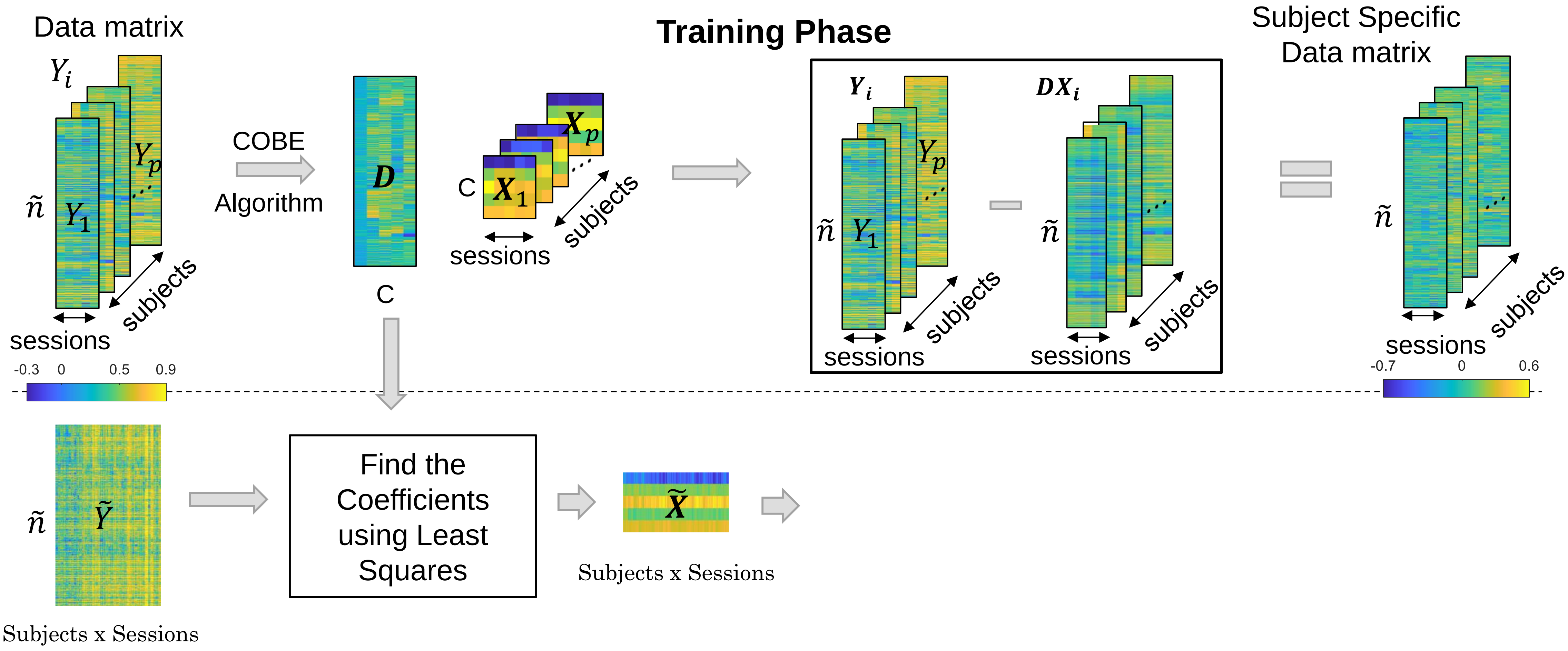


**Testing Phase**

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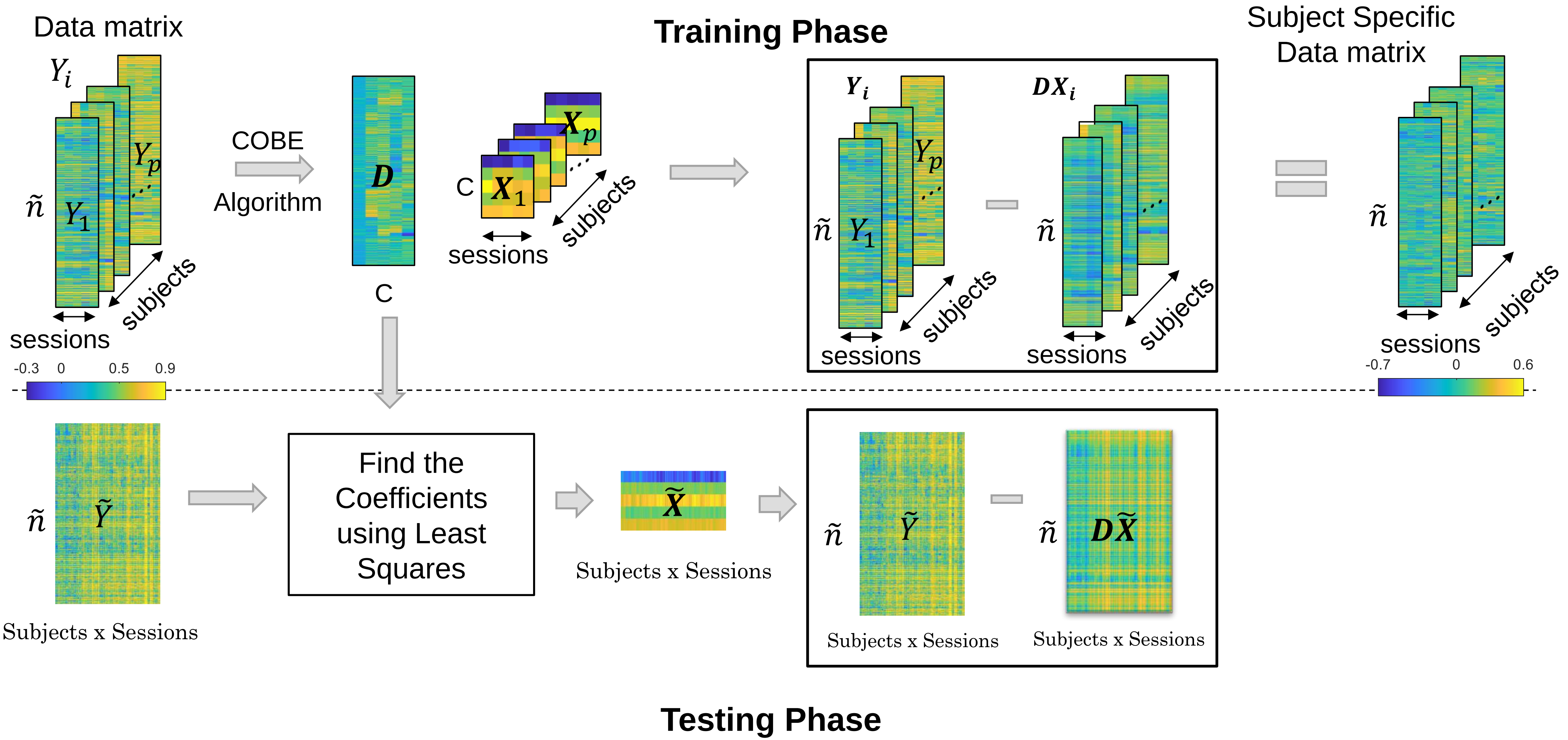

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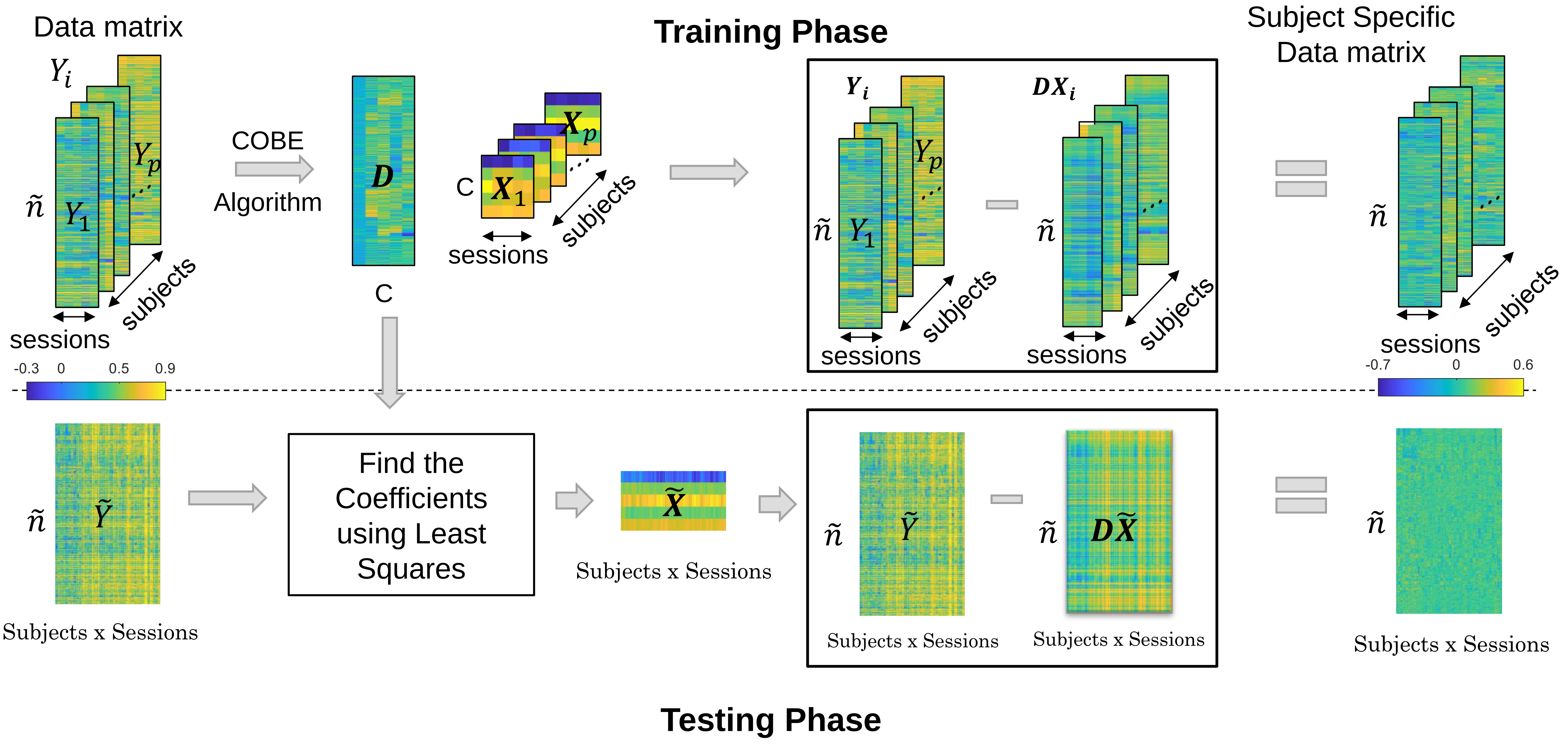
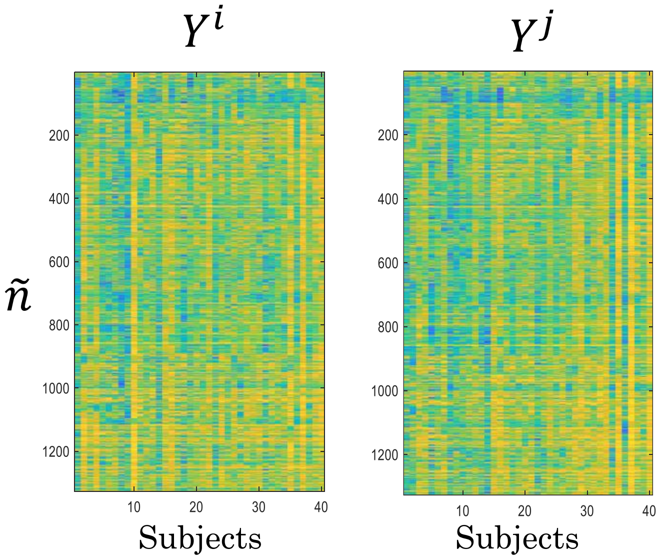


# Metrics - $I_{diff}$ (Existing)




$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

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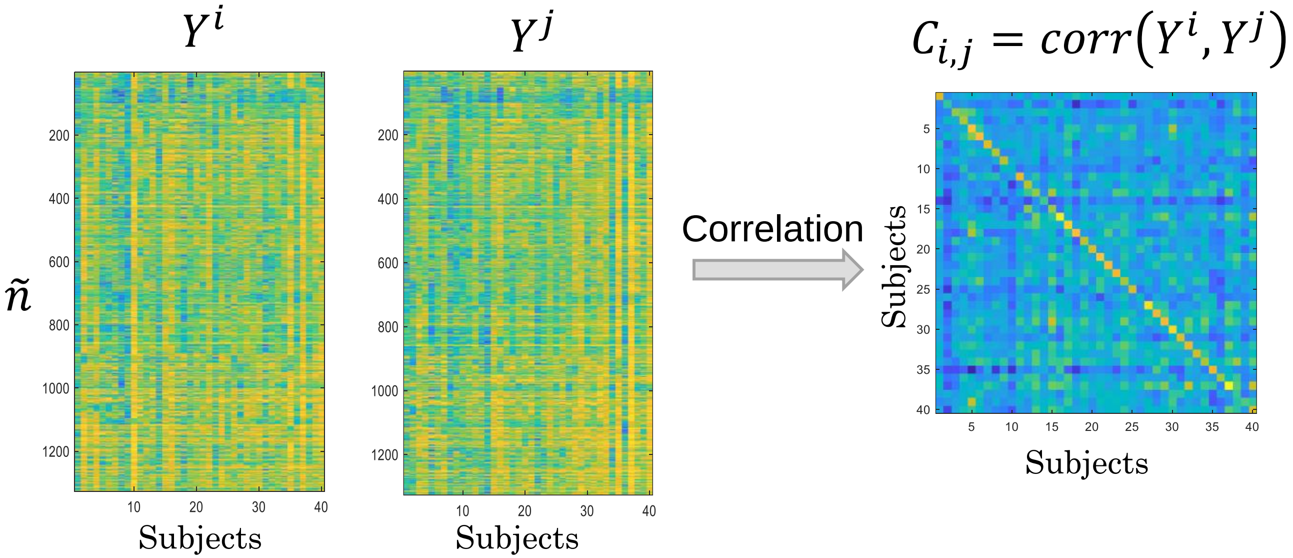


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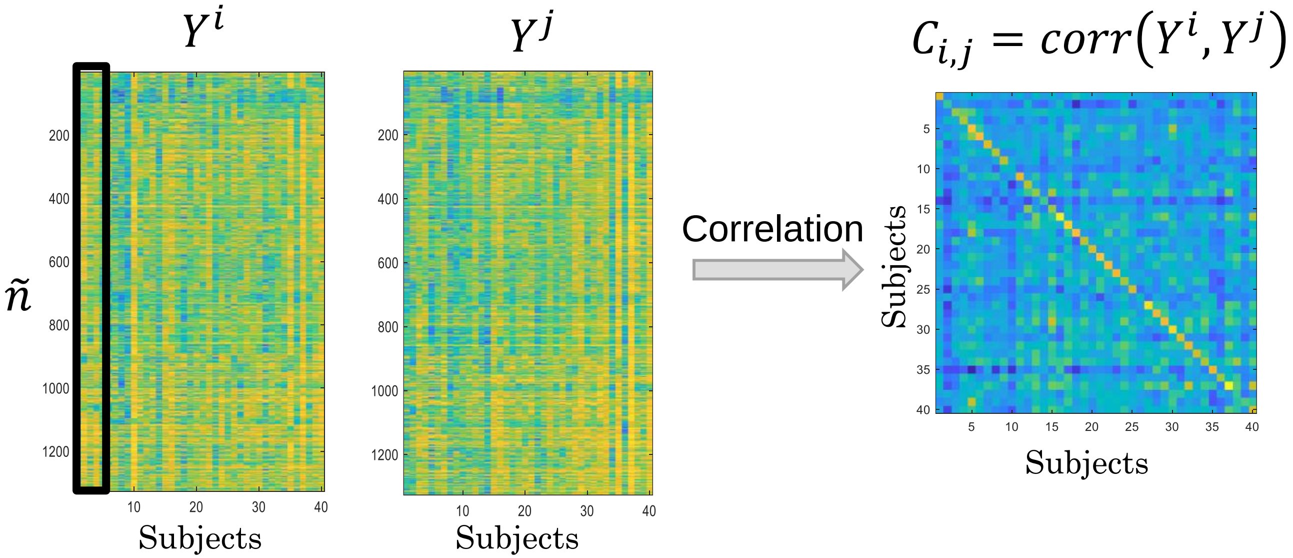


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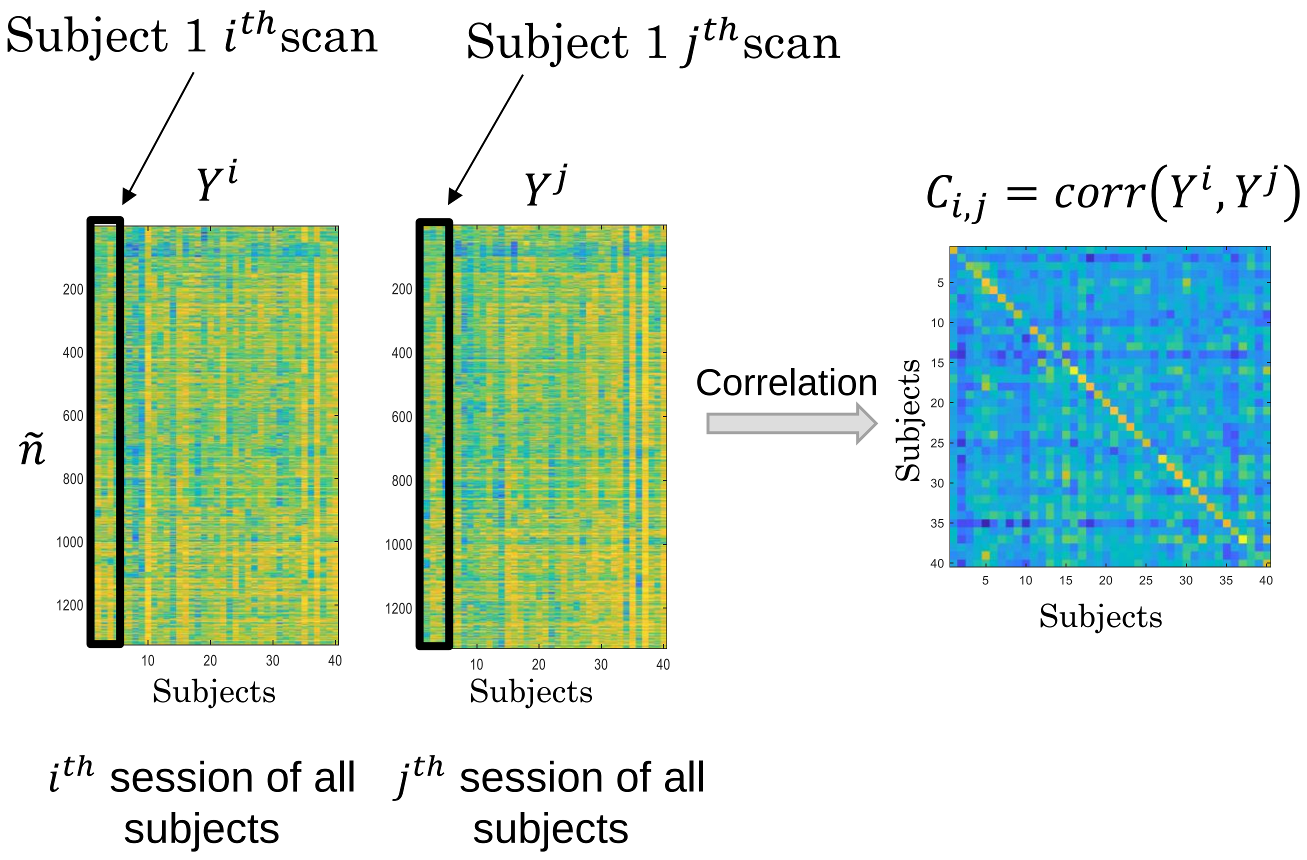


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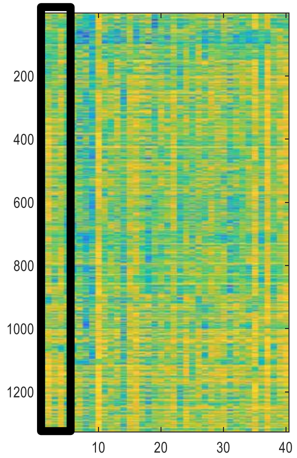
Subject 1 $i^{th}$scan

Subject 2 $j^{th}$scan

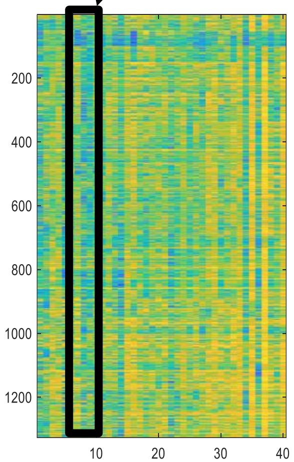
$Y^i$




$\tilde{n}$

Subjects

$Y^j$



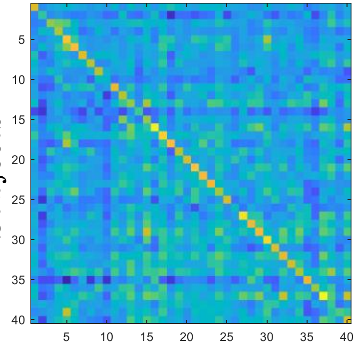

Subjects

$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

Correlation

$C_{i,j} = corr(Y^i, Y^j)$




Subjects

Subjects

E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metrics - $I_{diff}$ (Existing)

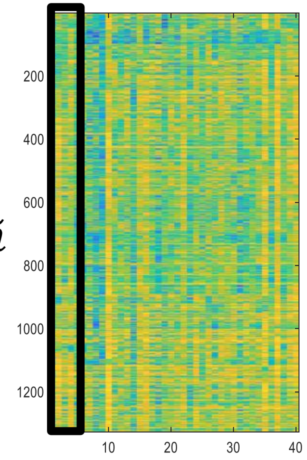
Subject 1 $i^{th}$scan

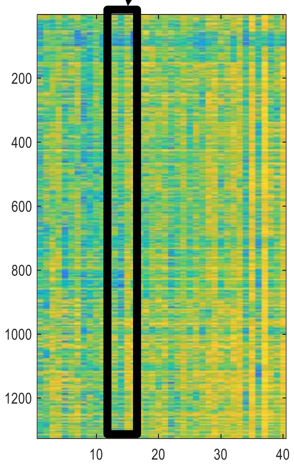
Subject 3 $j^{th}$scan

$Y^i$

$Y^j$

$\tilde{n}$



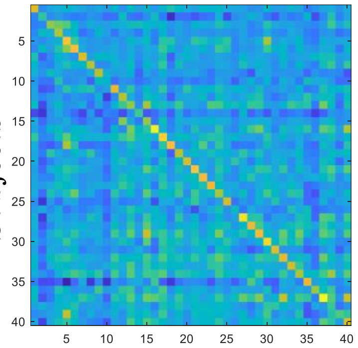




Subjects

Subjects

Correlation

$C_{i,j} = corr(Y^i, Y^j)$




Subjects

Subjects

$i^{th}$ session of all subjects

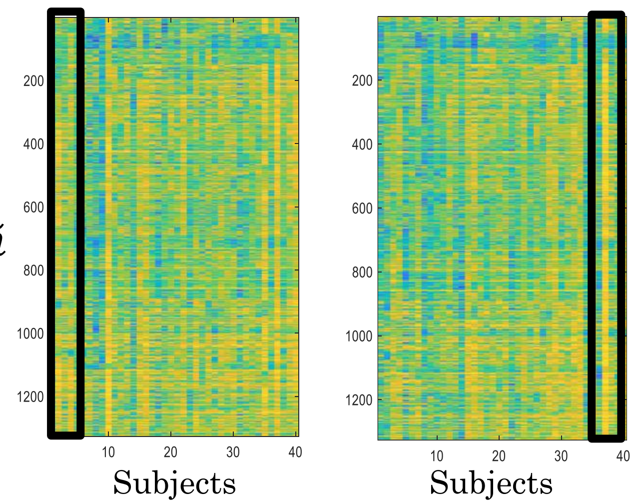
$j^{th}$ session of all subjects

E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metrics - $I_{diff}$ (Existing)

Subject 1 $i^{th}$scan

$Y^i$ $\quad$ $Y^j$

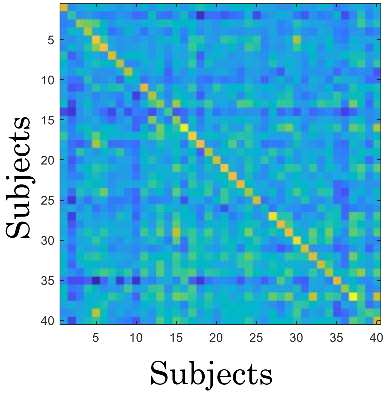



$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

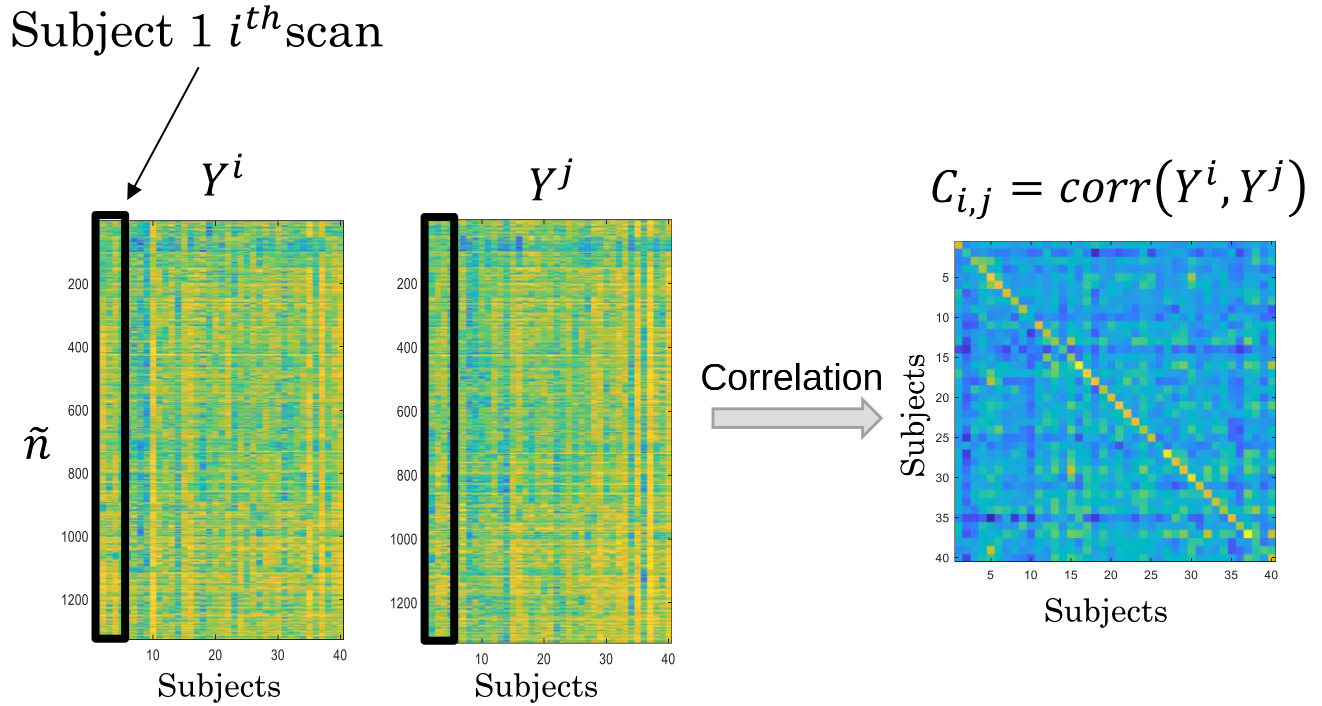
Correlation

$$C_{i,j} = corr\left(Y^i, Y^j\right)$$




E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metrics - $I_{diff}$ (Existing)

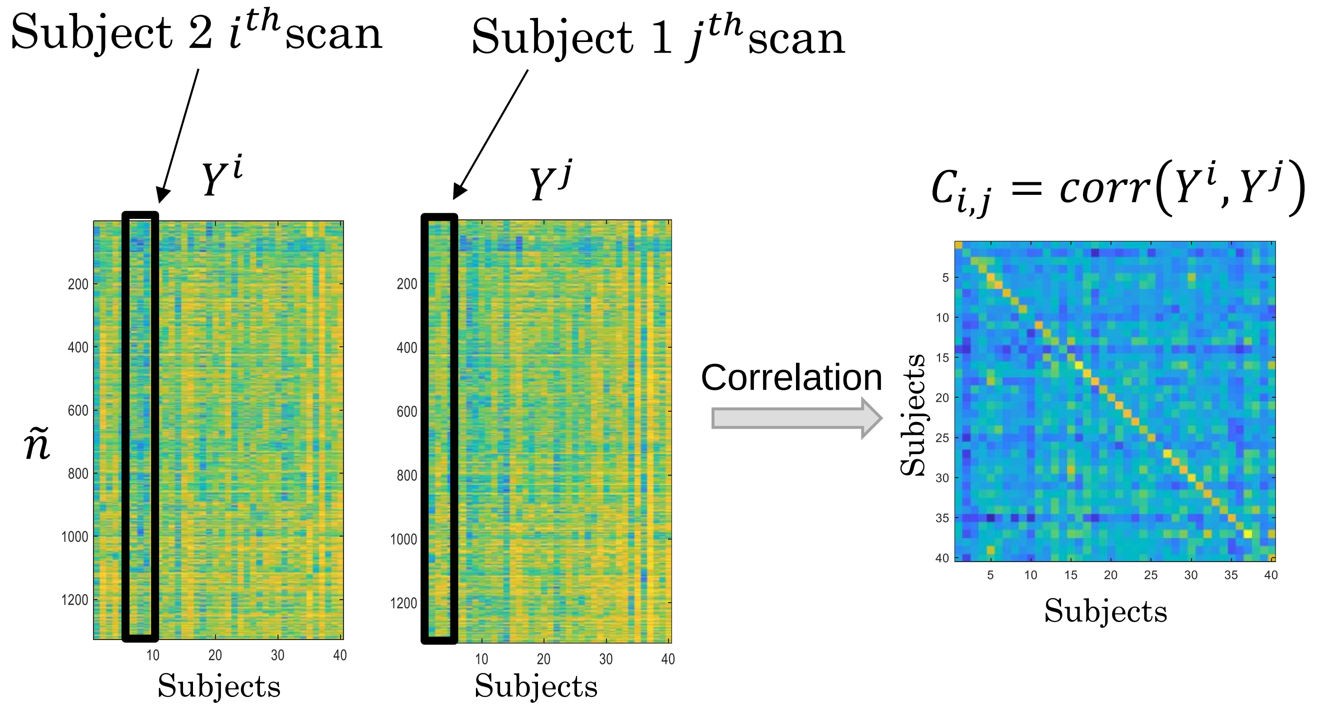



$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metrics - $I_{diff}$ (Existing)

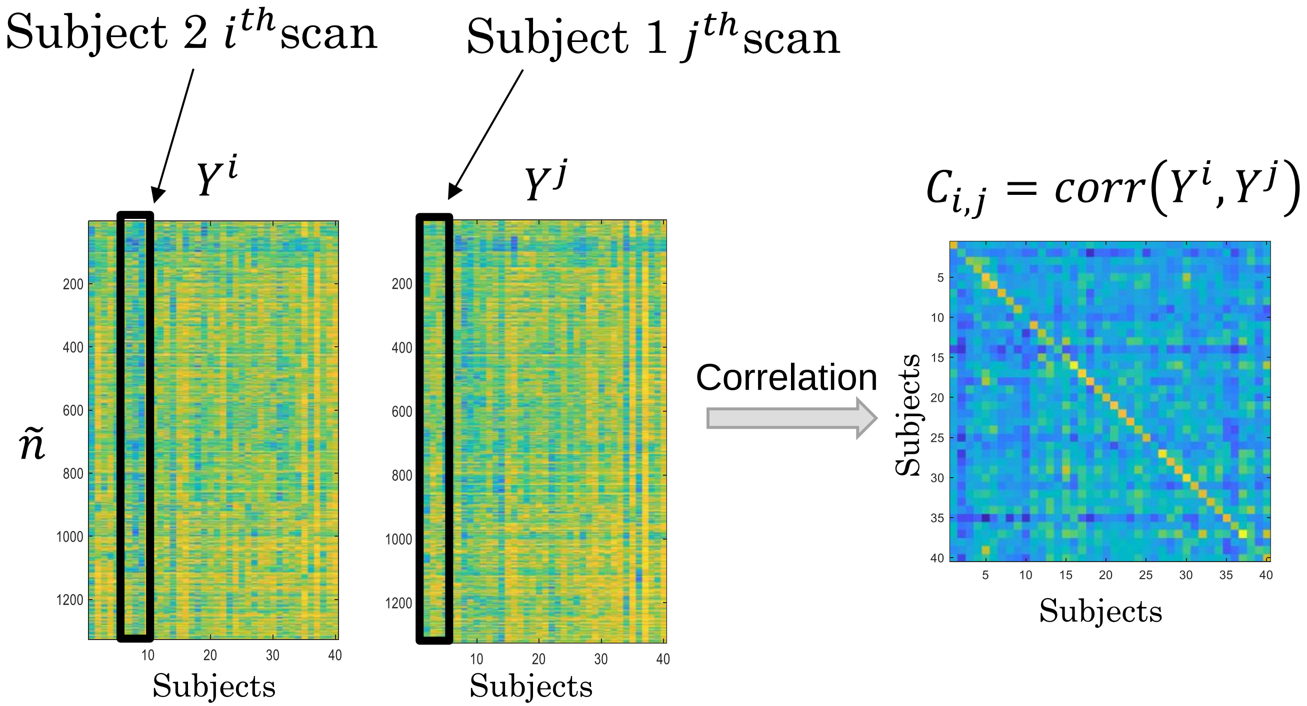



$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metrics - $I_{diff}$ (Existing)

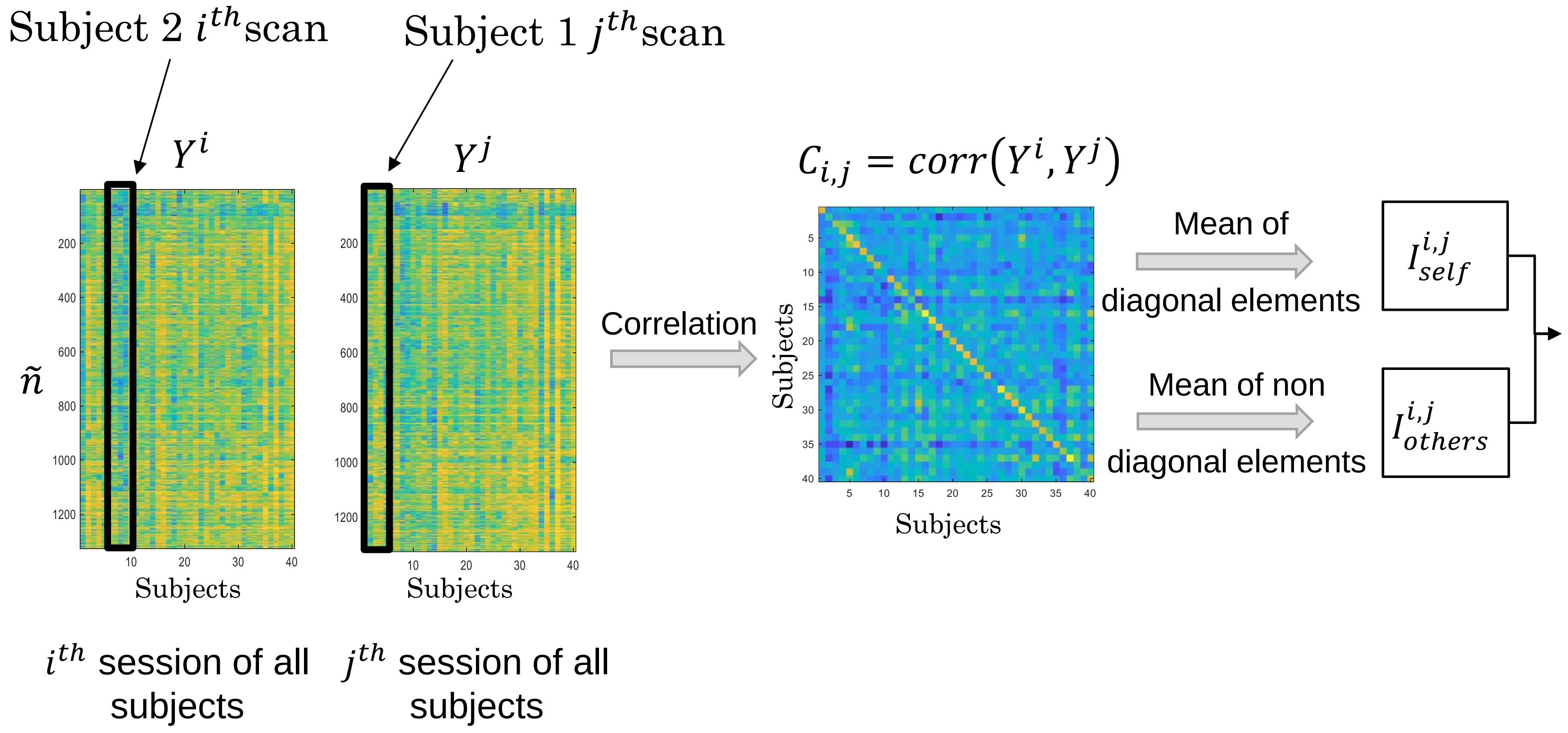



$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

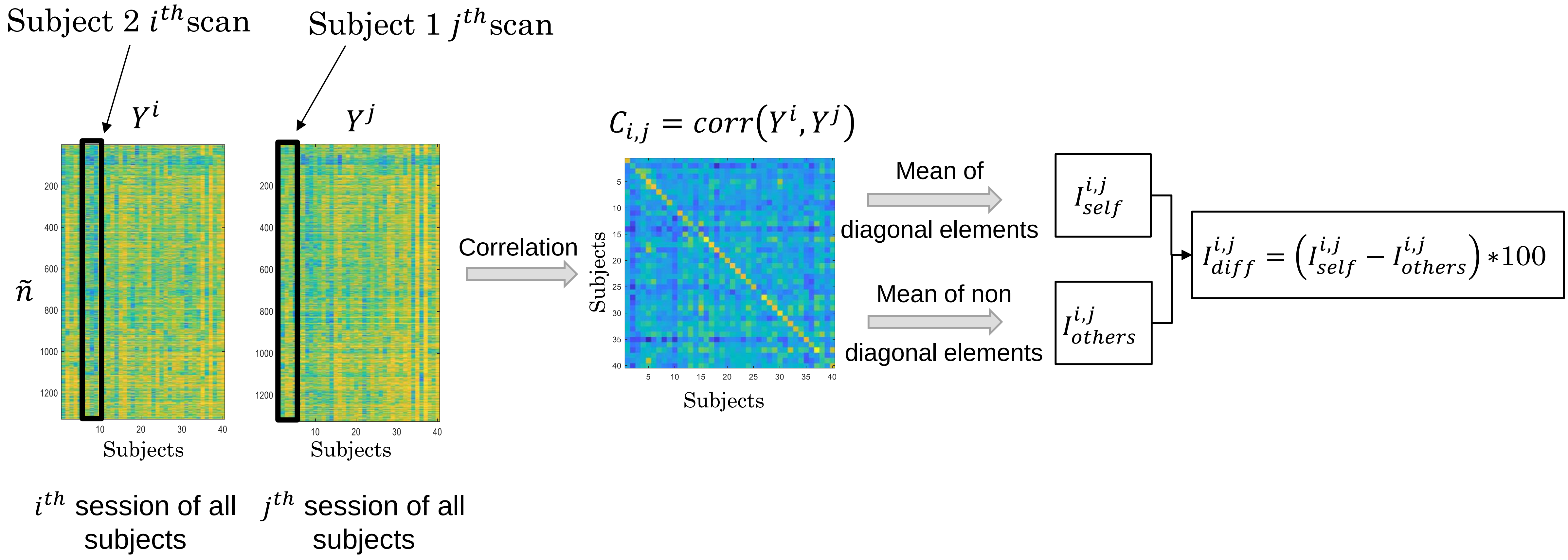
E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metrics - $I_{diff}$ (Existing)




E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metrics - $I_{diff}$ (Existing)




E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

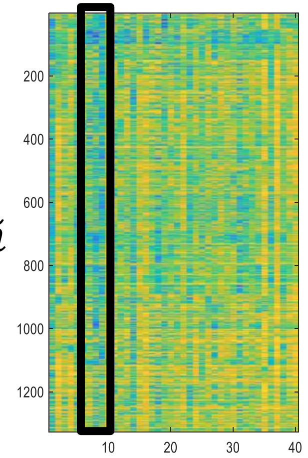
# Metrics - $I_{diff}$ (Existing)

Subject 2 $i^{th}$scan

Subject 1 $j^{th}$scan

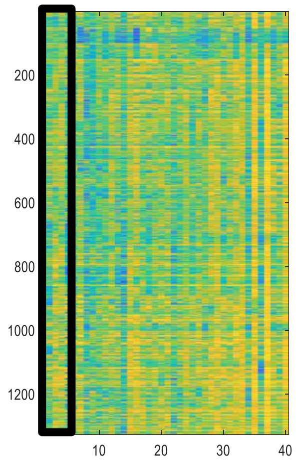
$Y^i$

$\tilde{n}$




Subjects

$Y^j$



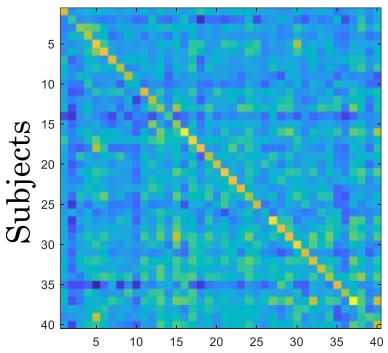

Subjects

$i^{th}$ session of all subjects

$j^{th}$ session of all subjects

Correlation

$C_{i,j} = corr\left(Y^i, Y^j\right)$




Subjects

Mean of diagonal elements

$I_{self}^{i,j}$

Mean of non diagonal elements

$I_{others}^{i,j}$

$$I_{diff}^{i,j} = \left(I_{self}^{i,j} - I_{others}^{i,j}\right) * 100$$

$$\tilde{s} = \frac{s \times (s-1)}{2}$$

$s = Number\ of\ sessions$

$$I_{diff} = \frac{1}{\tilde{s}} \sum_{i,j} I_{diff}^{i,j} \qquad i = 1,2, \dots s$$

$$j = i+1, i+2, \dots, s$$

E. Amico and J. Goñi. "The quest for identifiability in human functional connectomes". In: *Sci Rep* 8.1 (2018)

# Metric - Overlap (Proposed)

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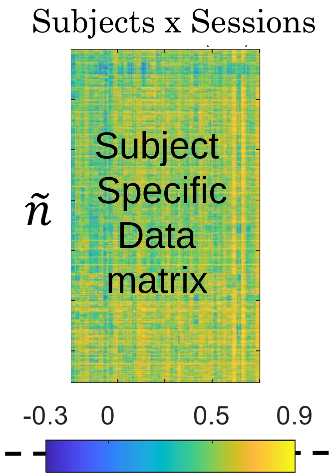
**Training Phase**

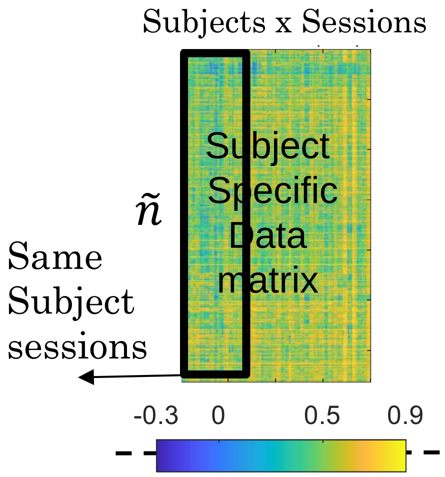
# Metric - Overlap (Proposed)

**Training Phase**



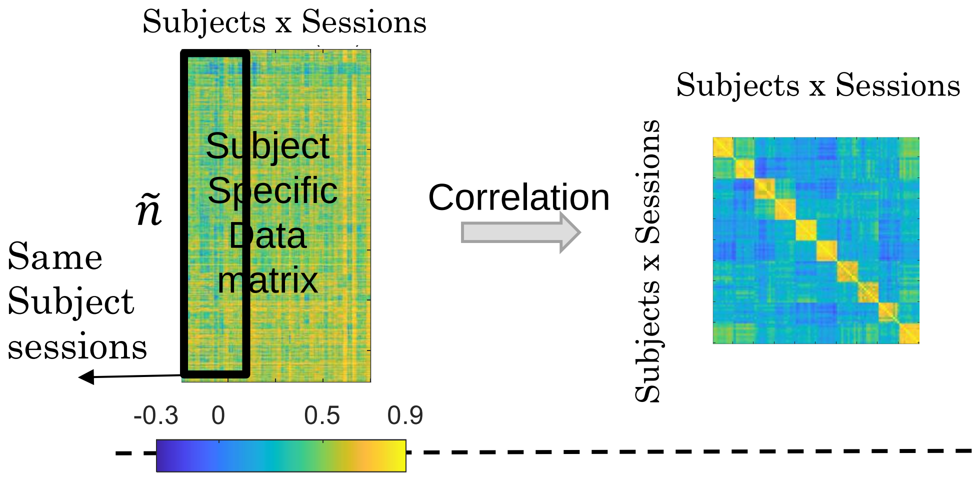
# Metric - Overlap (Proposed)

**Training Phase**

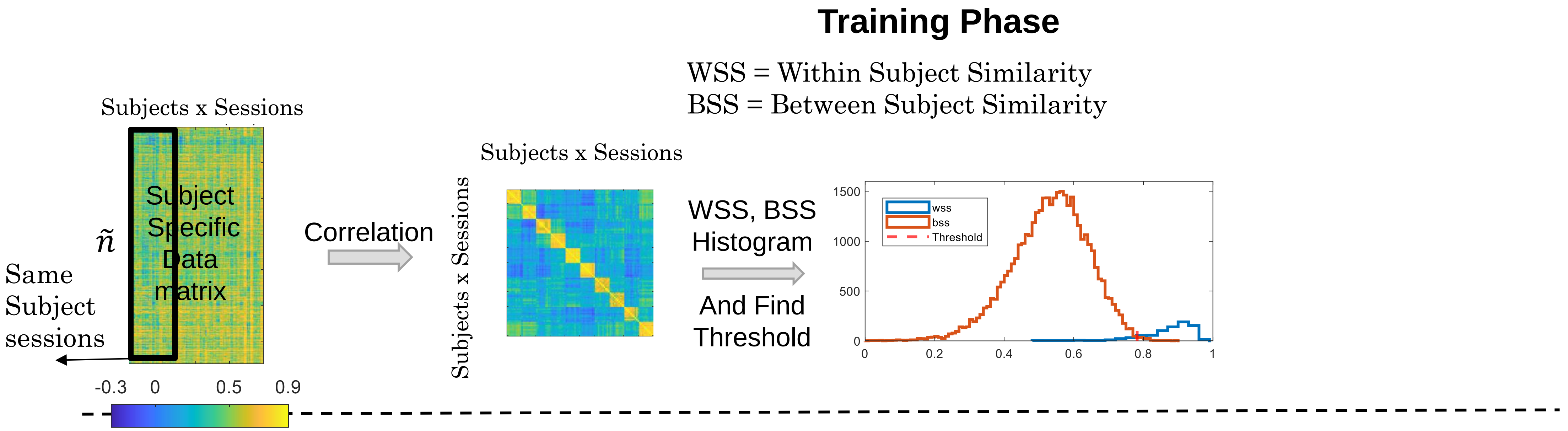


# Metric - Overlap (Proposed)

**Training Phase**



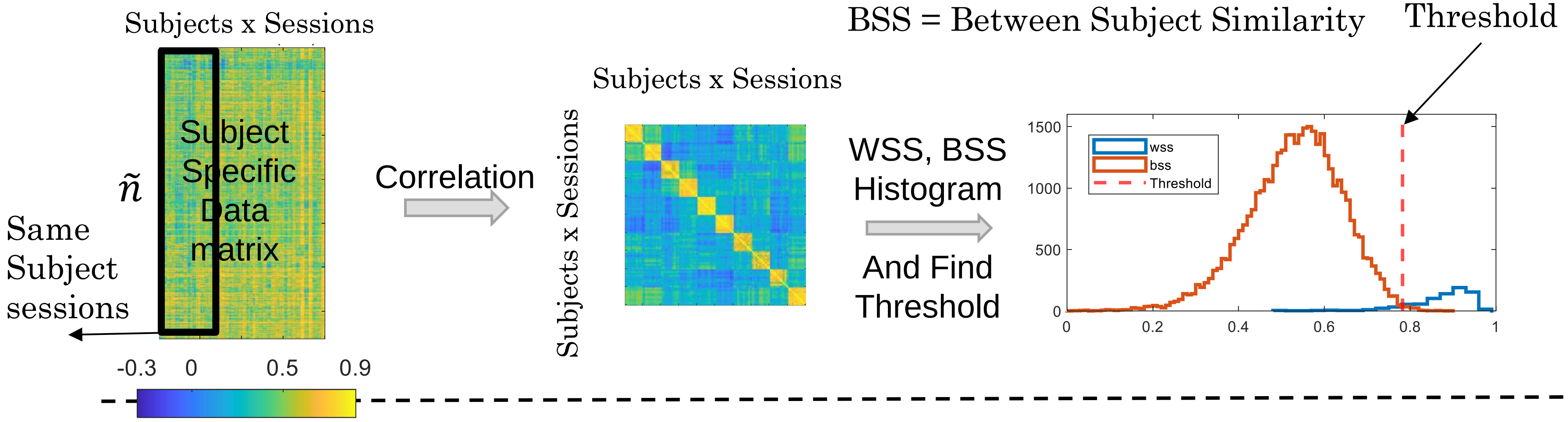
# Metric - Overlap (Proposed)



# Metric - Overlap (Proposed)

## Training Phase

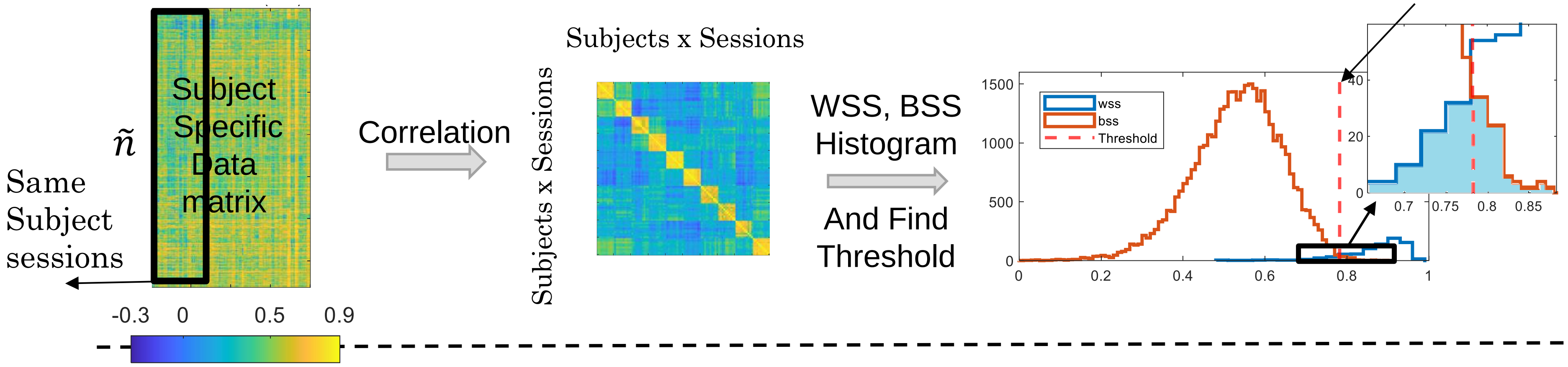
WSS = Within Subject Similarity
BSS = Between Subject Similarity



# Metric - Overlap (Proposed)

**Training Phase**

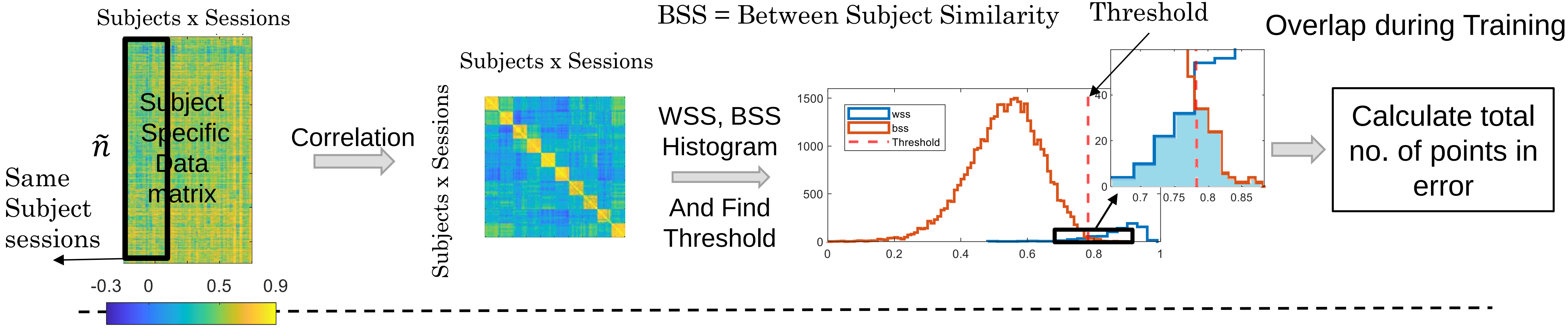
WSS = Within Subject Similarity
BSS = Between Subject Similarity



# Metric - Overlap (Proposed)

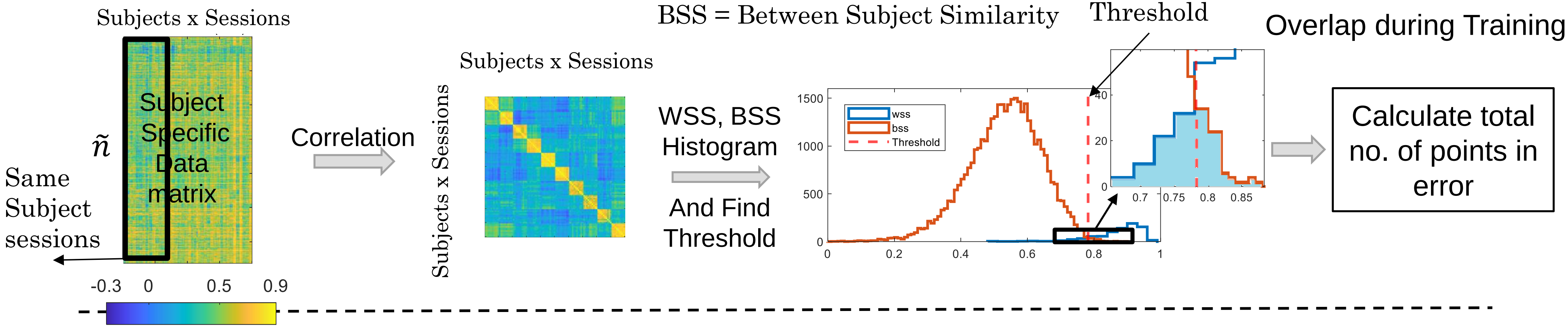
**Training Phase**

WSS = Within Subject Similarity
BSS = Between Subject Similarity



# Metric - Overlap (Proposed)

**Training Phase**

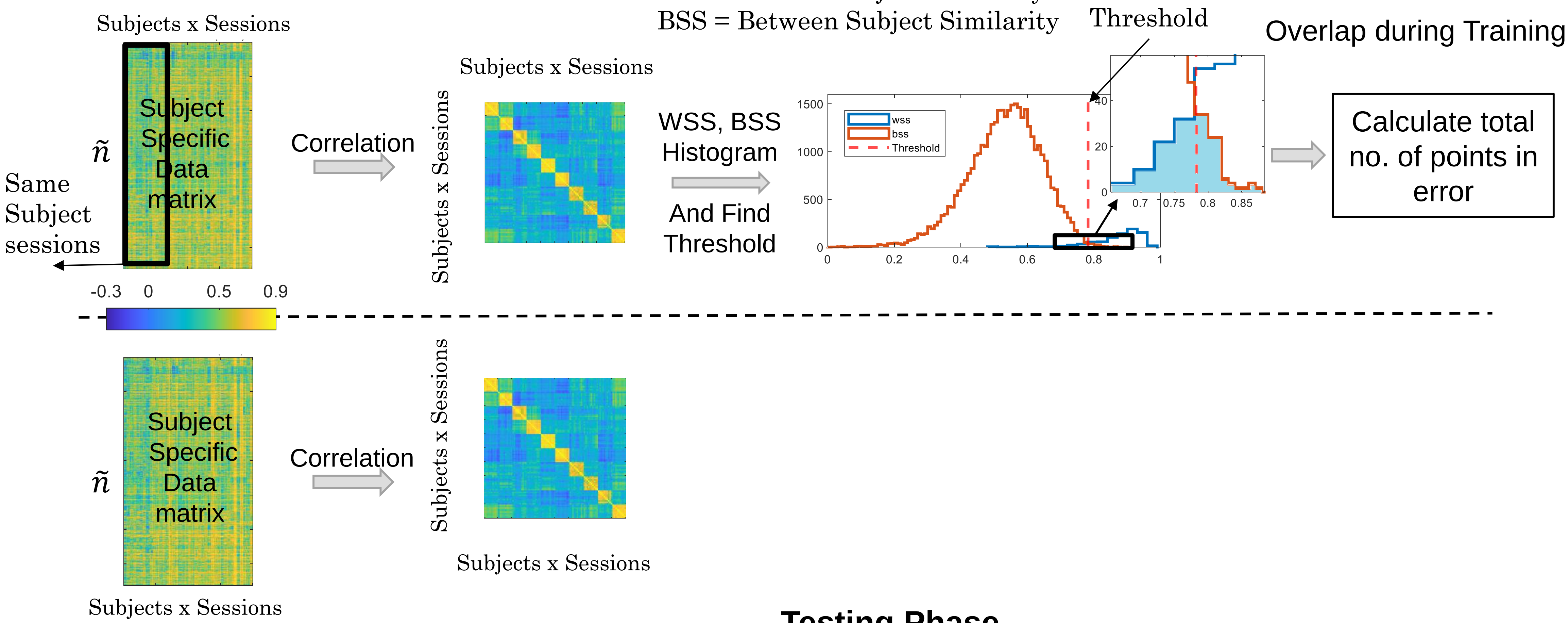



**Testing Phase**

# Metric - Overlap (Proposed)

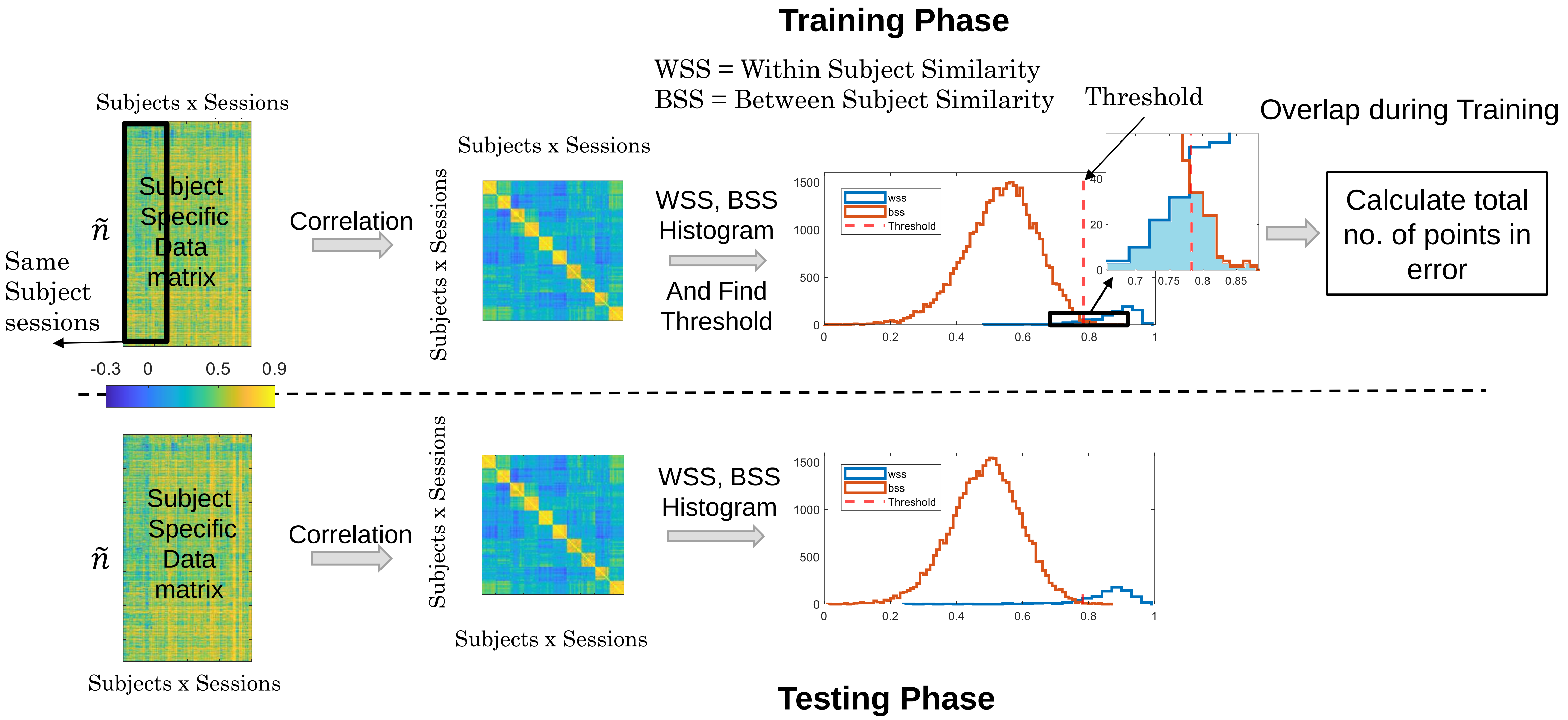
**Training Phase**

WSS = Within Subject Similarity
BSS = Between Subject Similarity

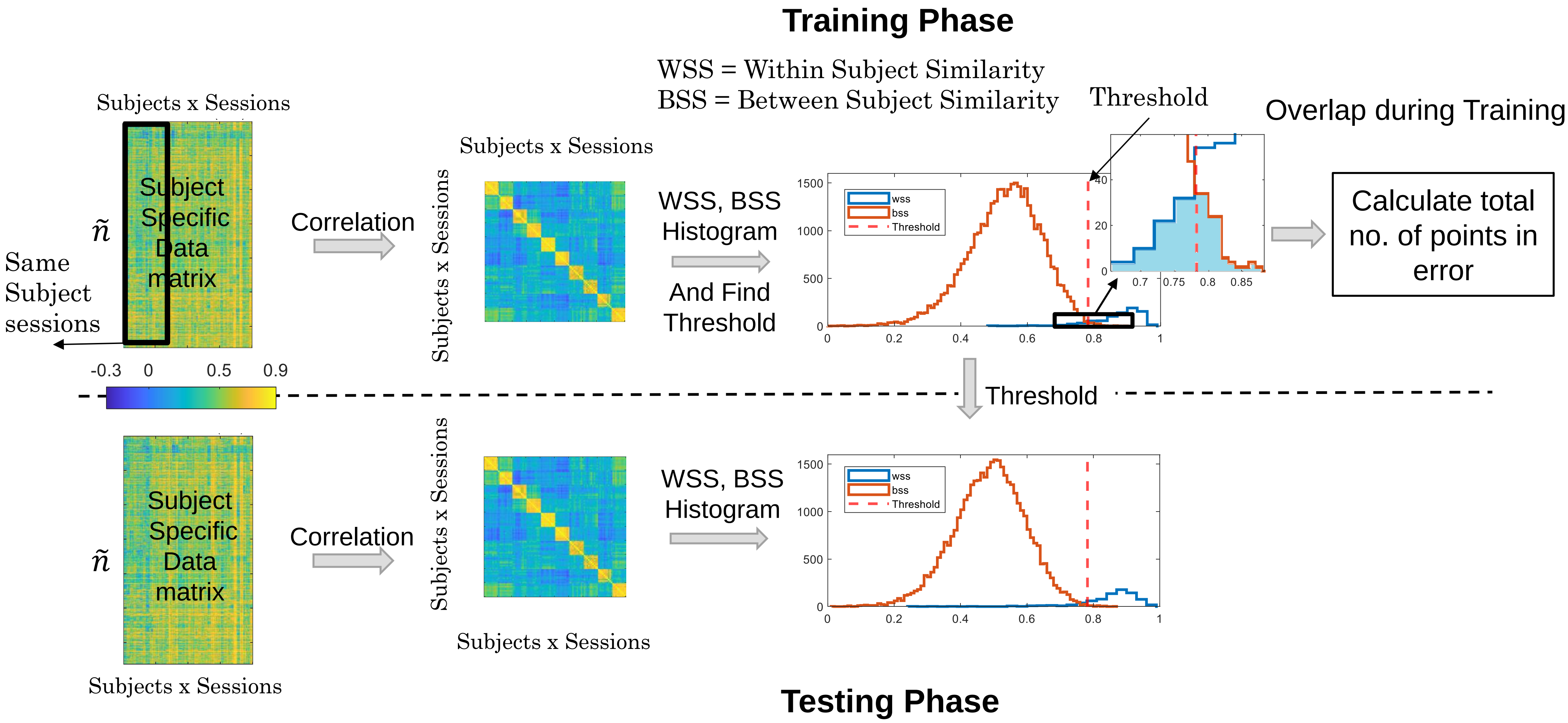



**Testing Phase**

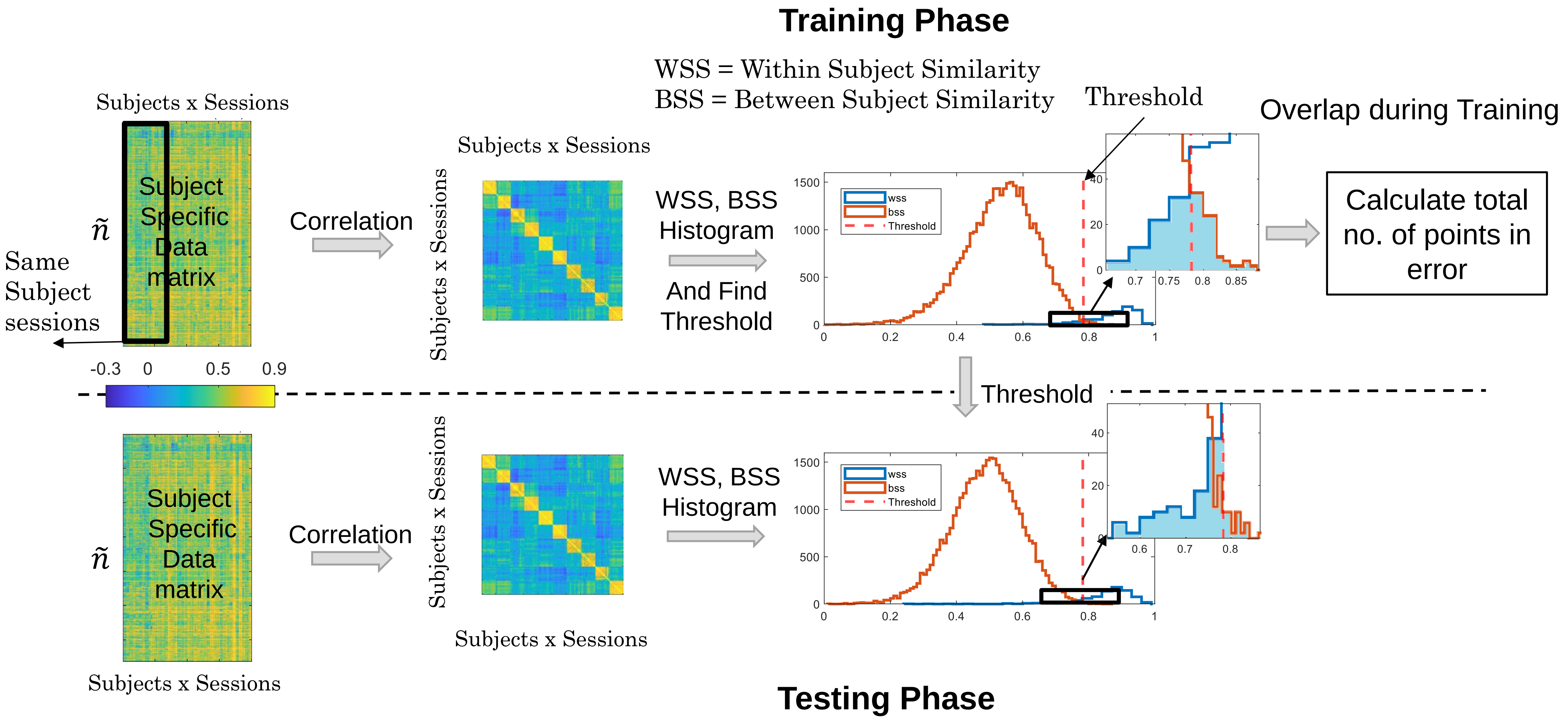
# Metric - Overlap (Proposed)



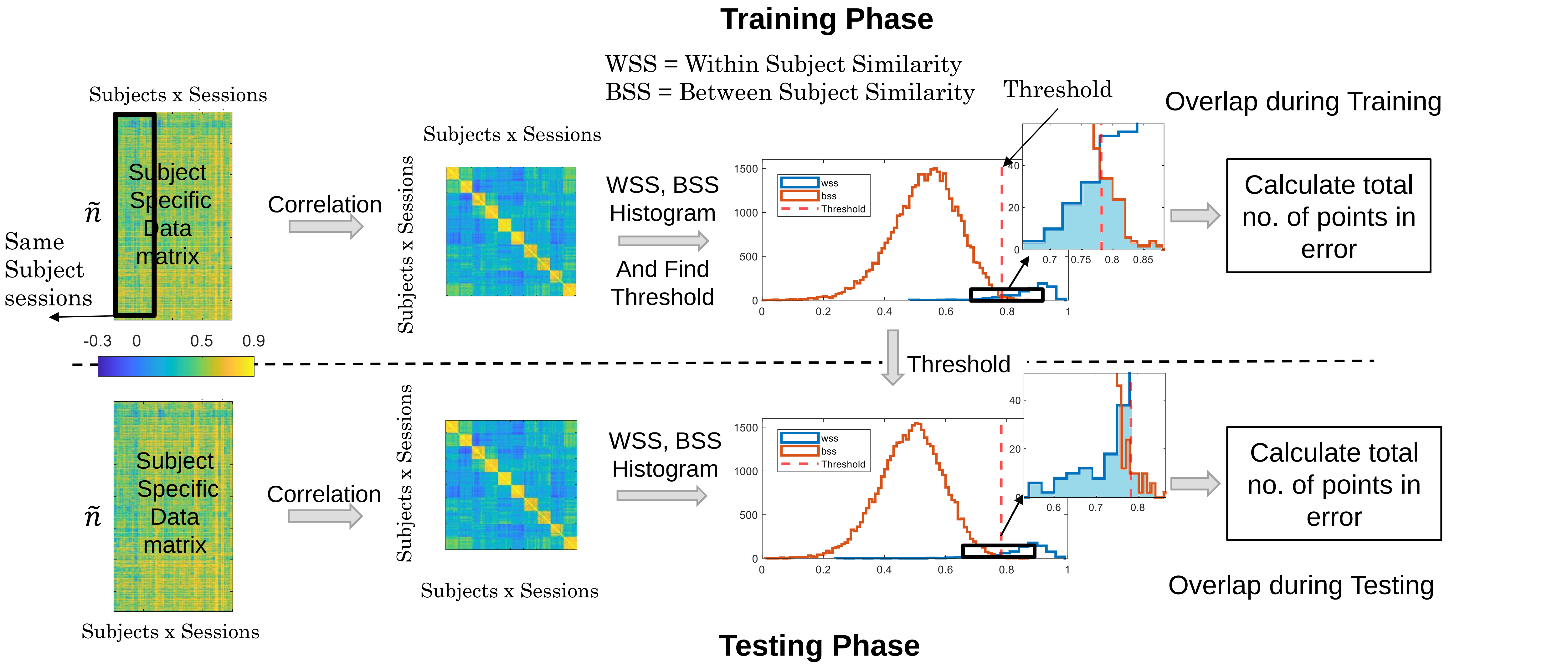
# Metric - Overlap (Proposed)



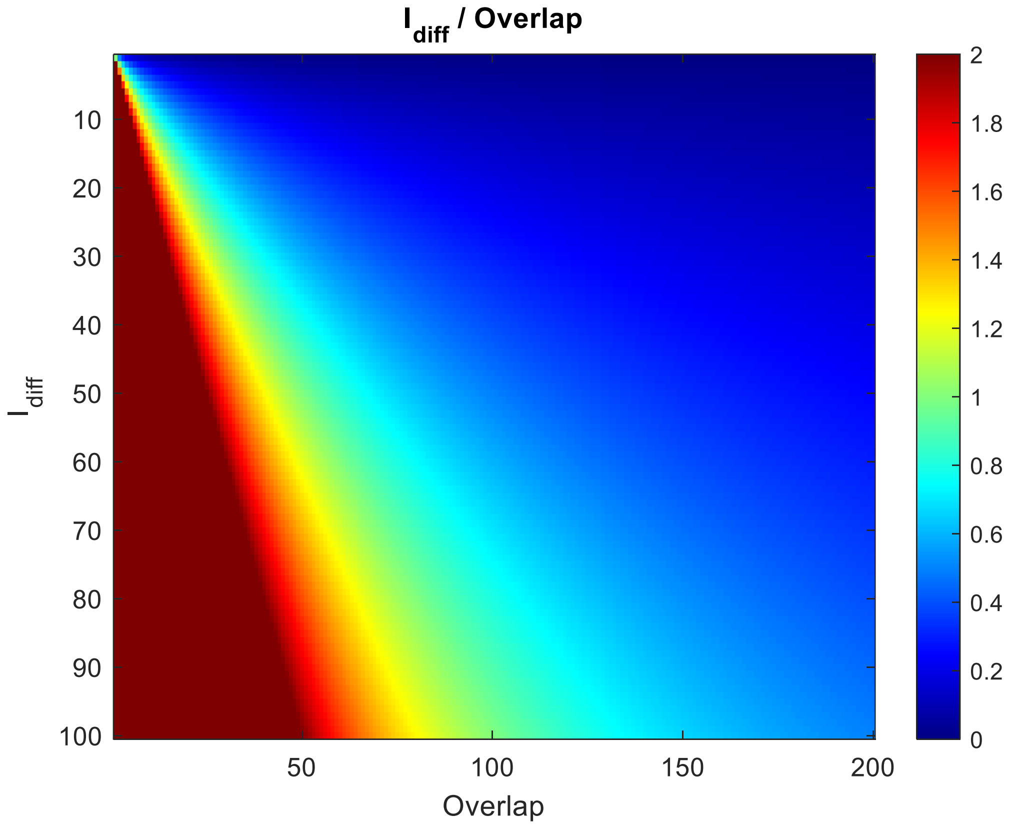
# Metric - Overlap (Proposed)



# Metric - Overlap (Proposed)

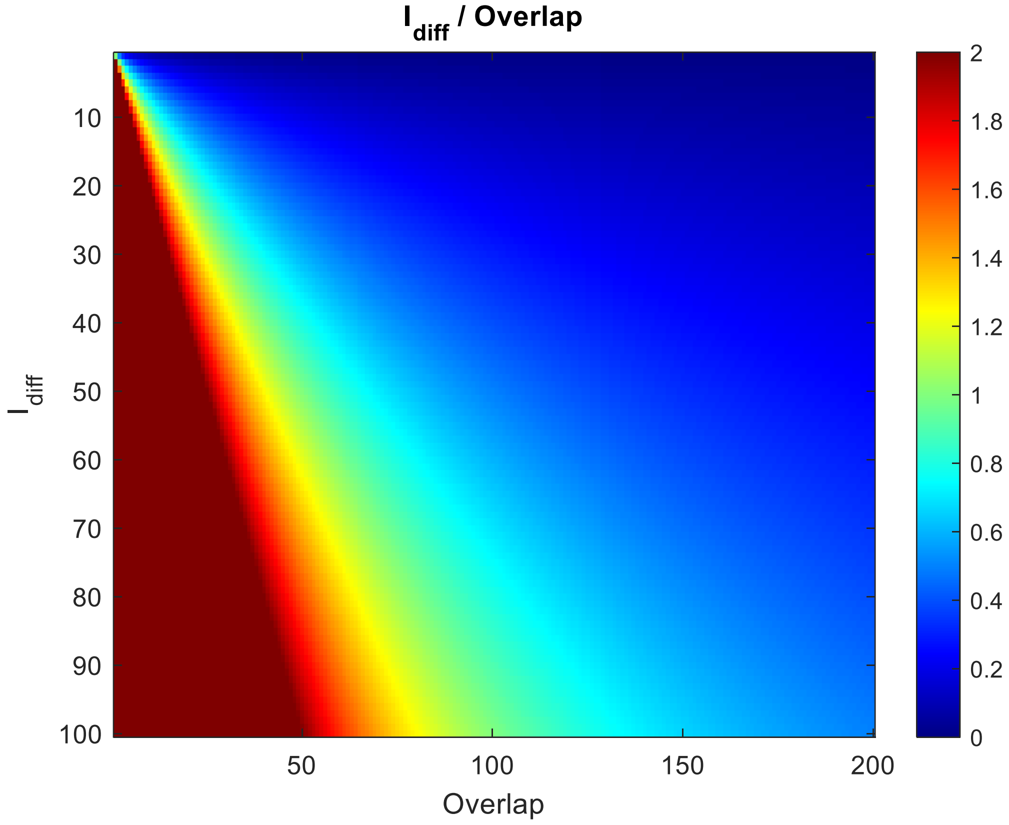


# Ratio of $I_{diff}$ to Overlap



# Ratio of $I_{diff}$ to Overlap

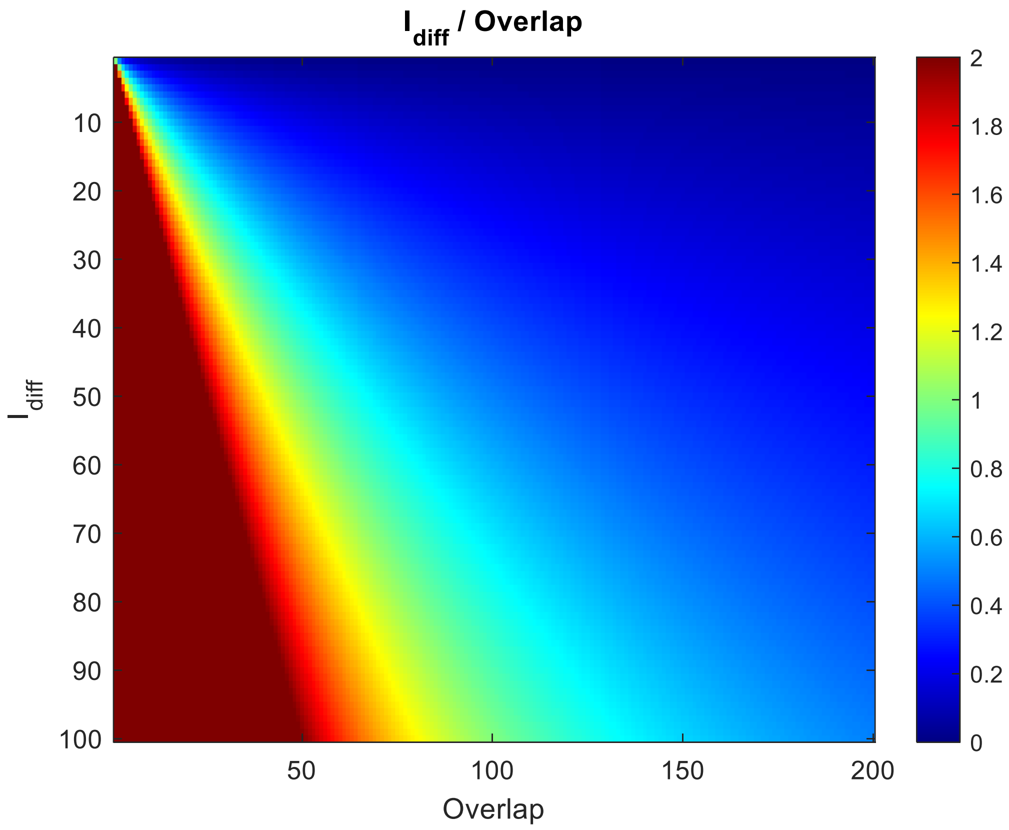
- $I_{diff}$ says the means of the within-subject, and the between-subject correlations should be far apart for better repeatability.



# Ratio of $I_{diff}$ to Overlap

- $I_{diff}$ says the means of the within-subject, and the between-subject correlations should be far apart for better repeatability.

- *Overlap* says there should be one threshold that can differentiate the within and between subjects with minimum error.

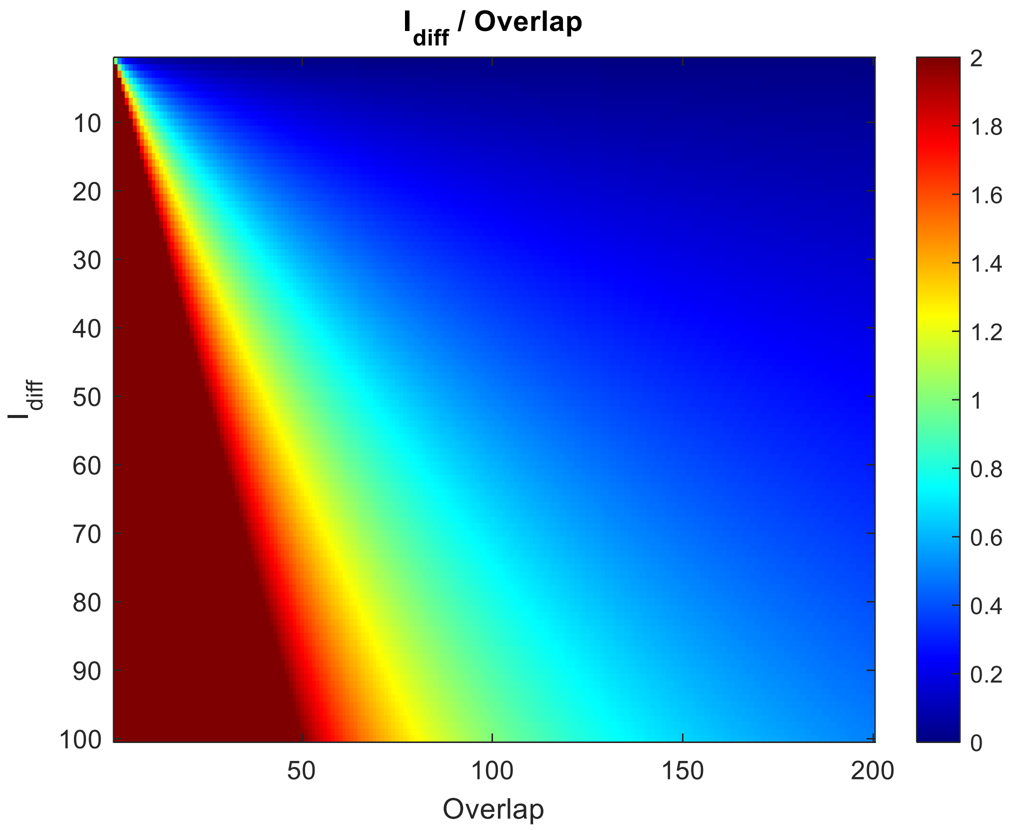


# Ratio of $I_{diff}$ to Overlap

- $I_{diff}$ says the means of the within-subject, and the between-subject correlations should be far apart for better repeatability.

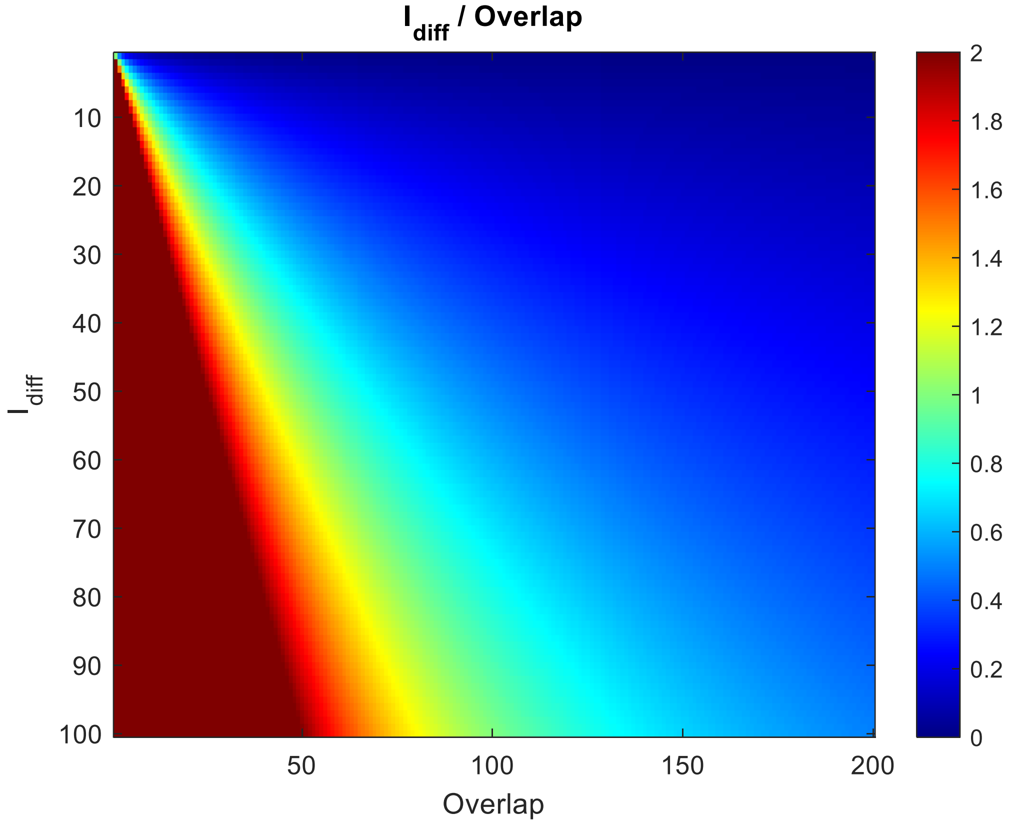
- *Overlap* says there should be one threshold that can differentiate the within and between subjects with minimum error.

- To account for both we combine them in one metric



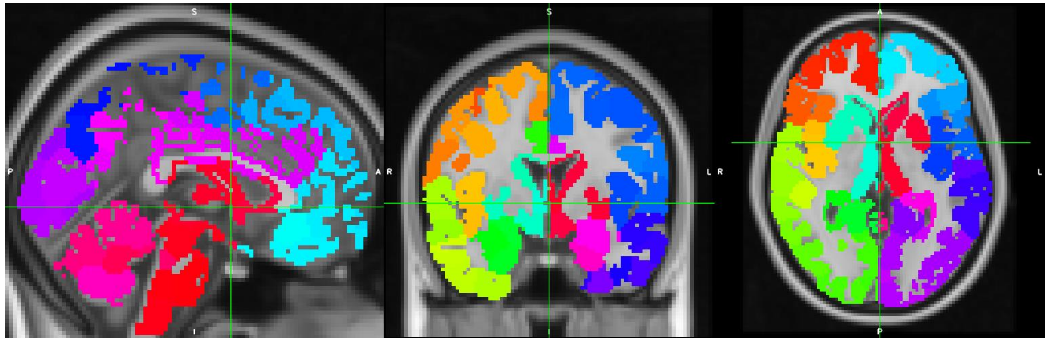
# Ratio of $I_{diff}$ to Overlap

- $I_{diff}$ says the means of the within-subject, and the between-subject correlations should be far apart for better repeatability.
- *Overlap* says there should be one threshold that can differentiate the within and between subjects with minimum error.
- To account for both we combine them in one metric
- Maximize $\frac{I_{diff}}{Overlap}$

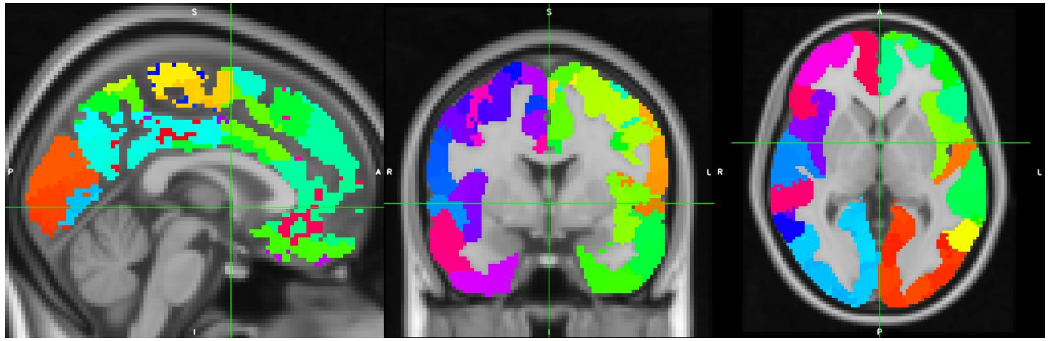


# Types of Brain Atlas

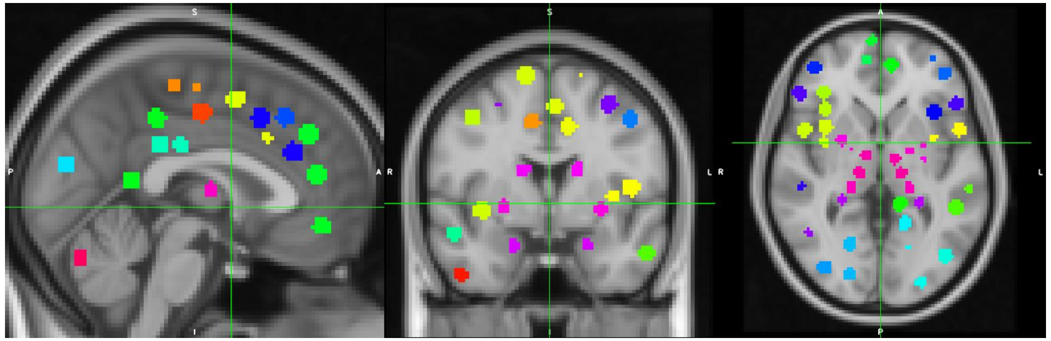
Whole Brain



Cortical Brain

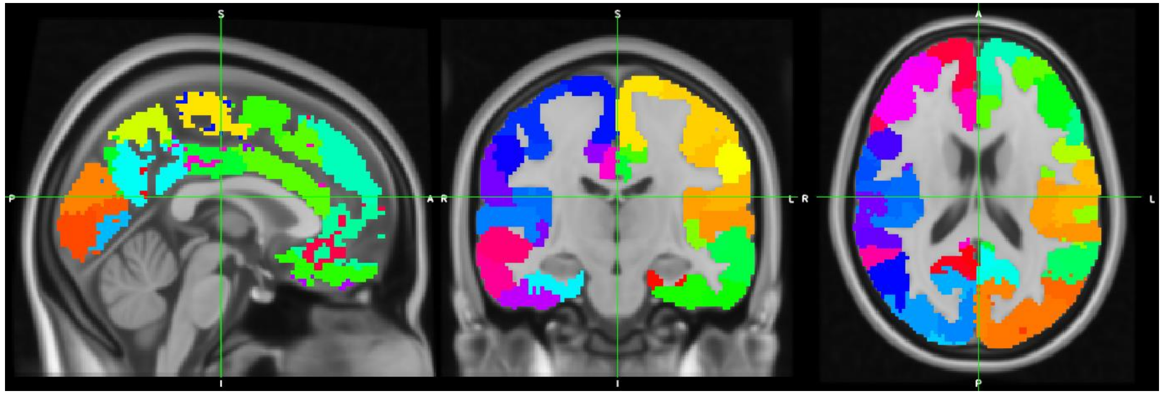


Spherical ROIs

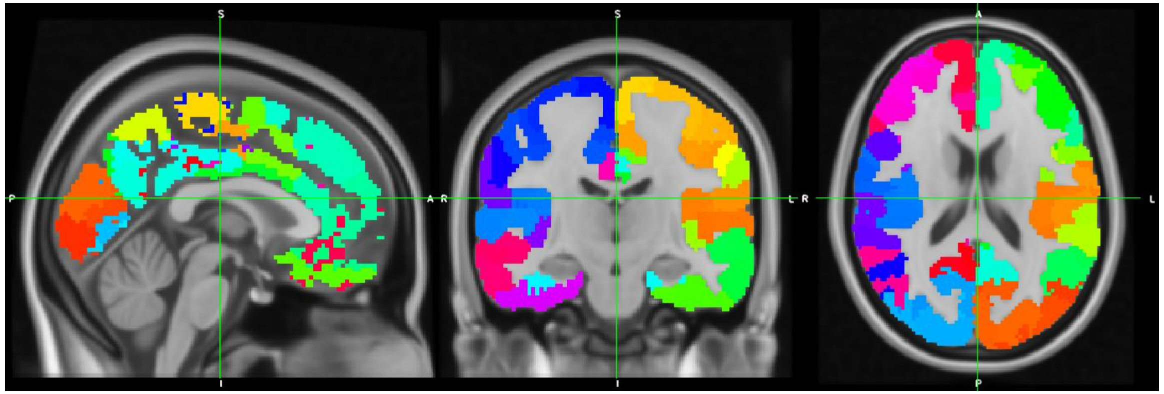


Atlases Back

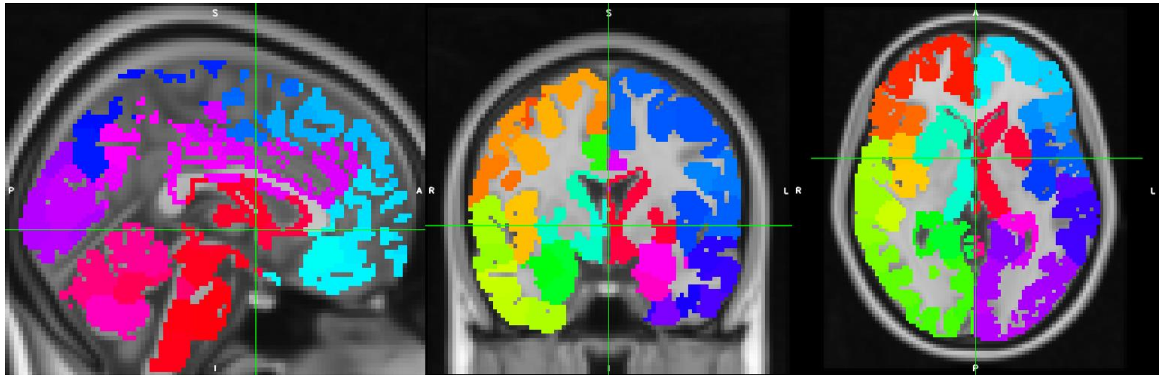
## Schaefer 100



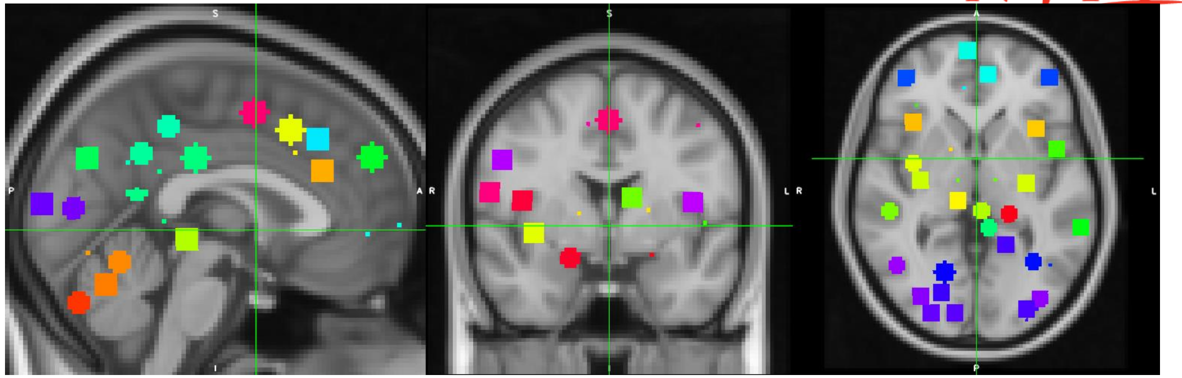
## Schaefer 200



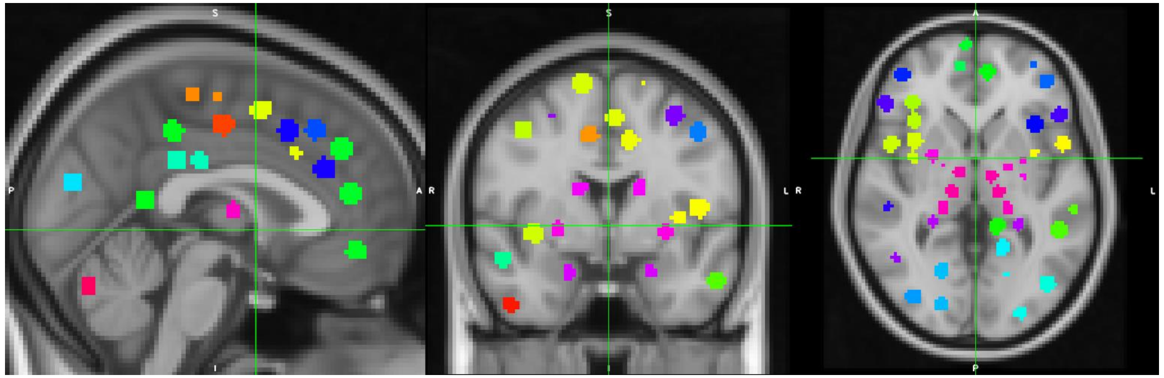
## Shen 268



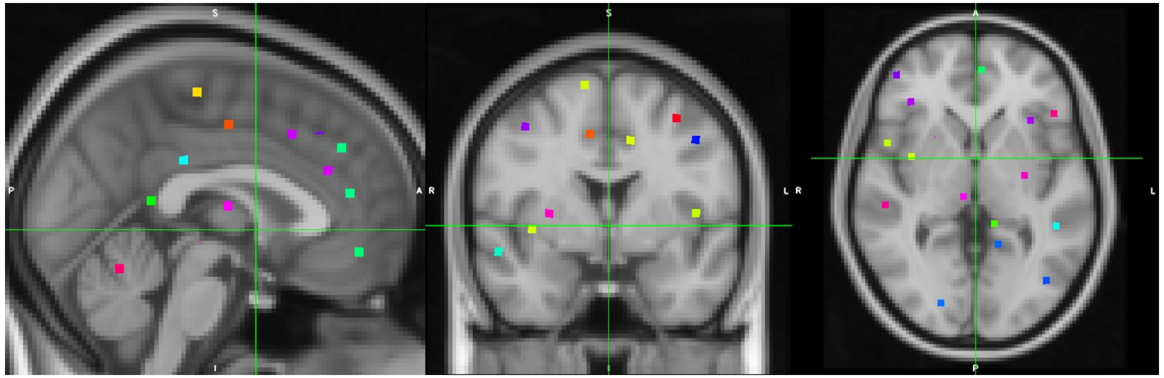
## Dosenbach 164



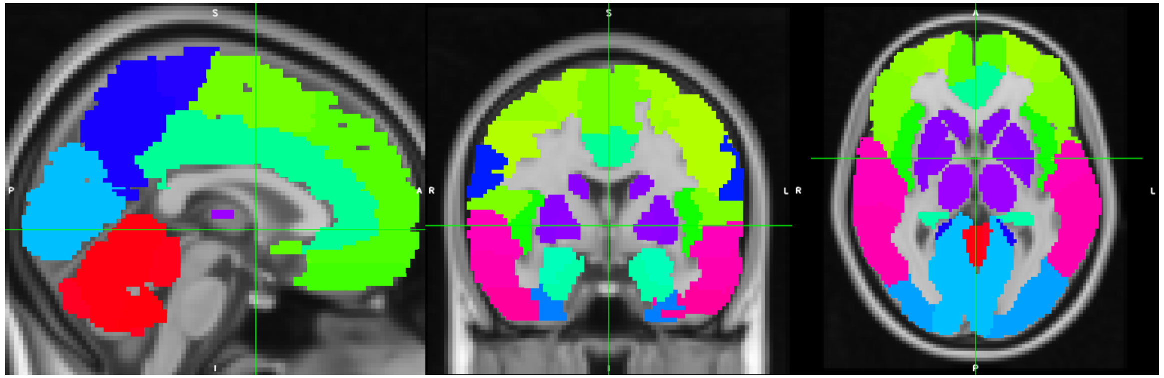
## Seitzman 300



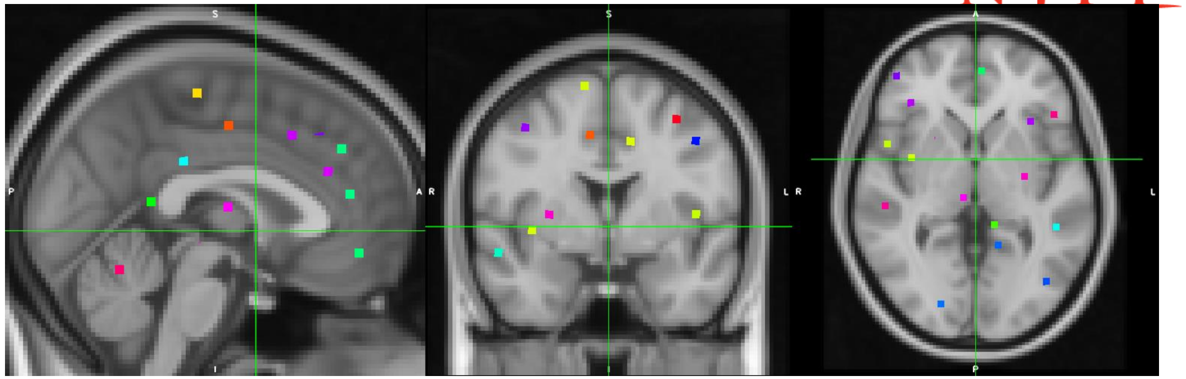
## Power 264



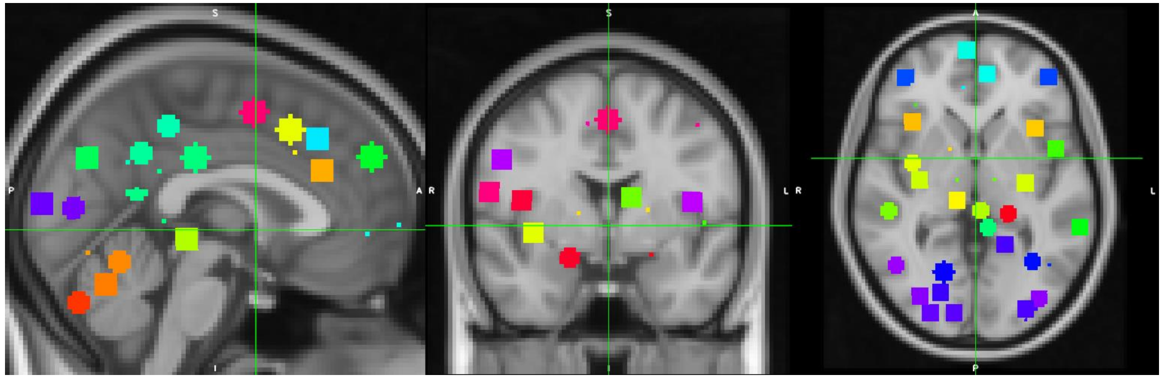
AAL 116



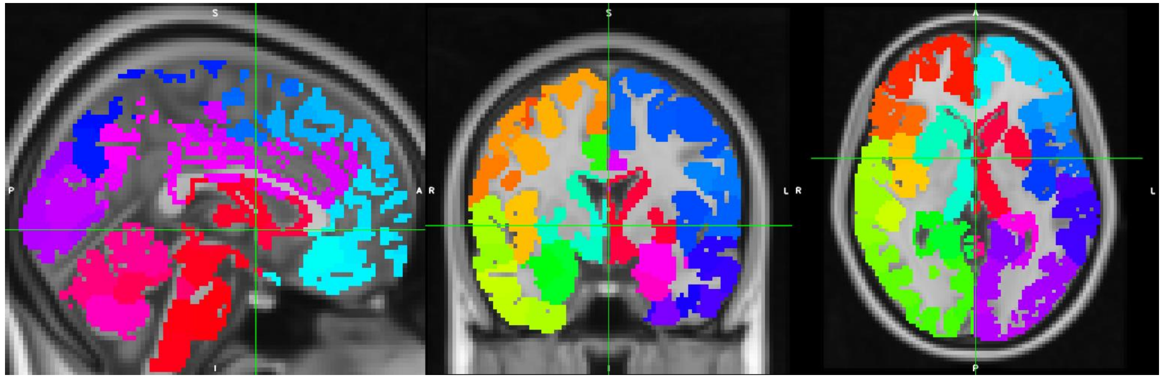
Power 264



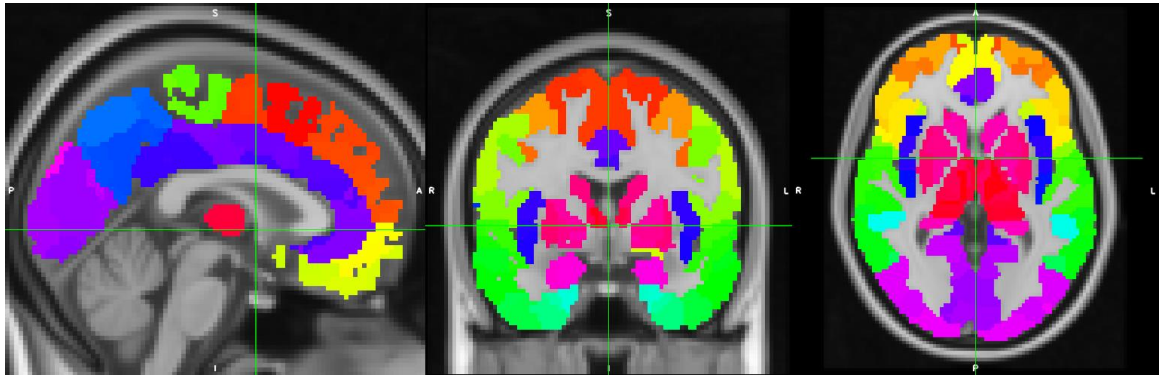
Dosenbach 164



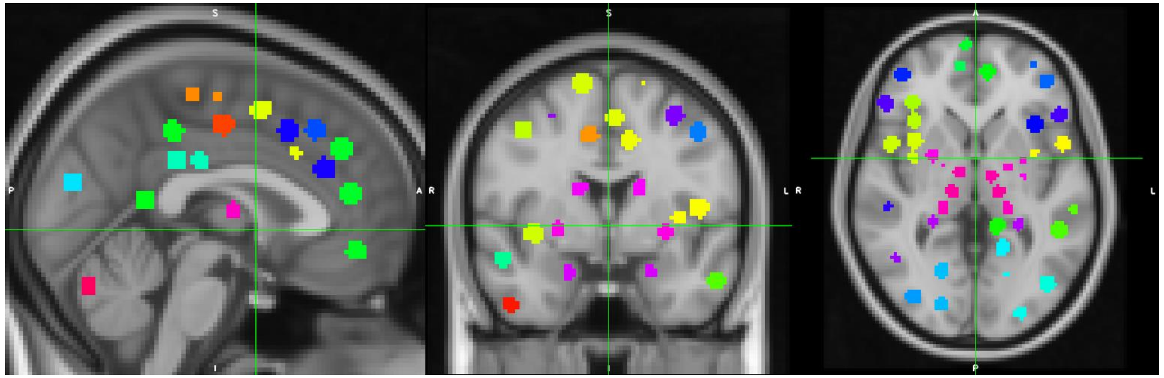
Shen 268



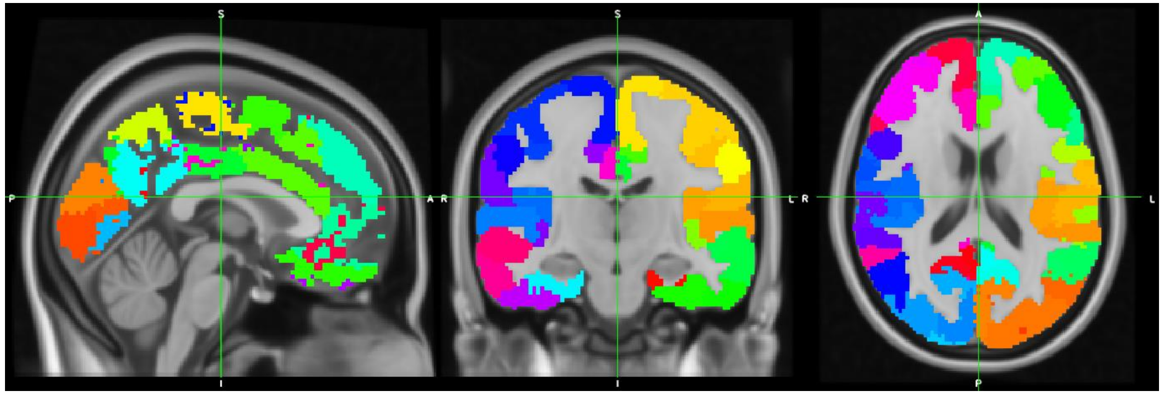
Brainnetome 246



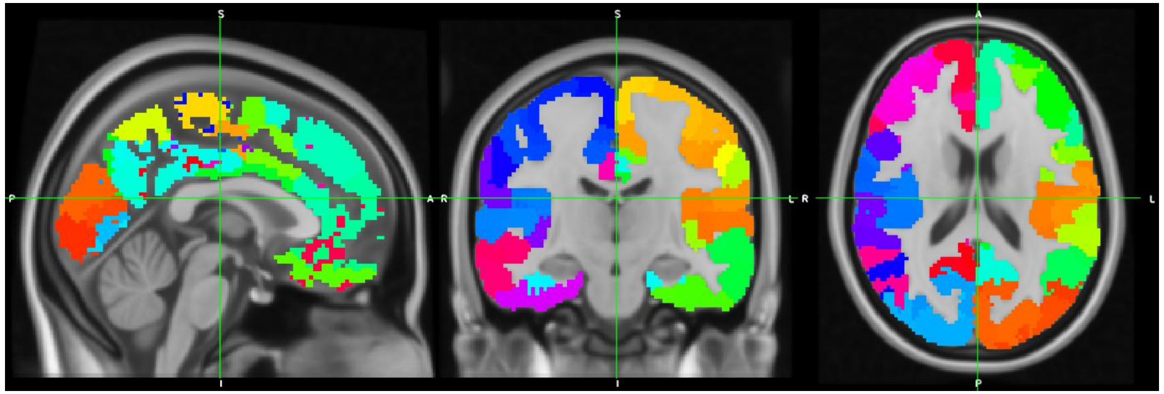
Seitzman 300



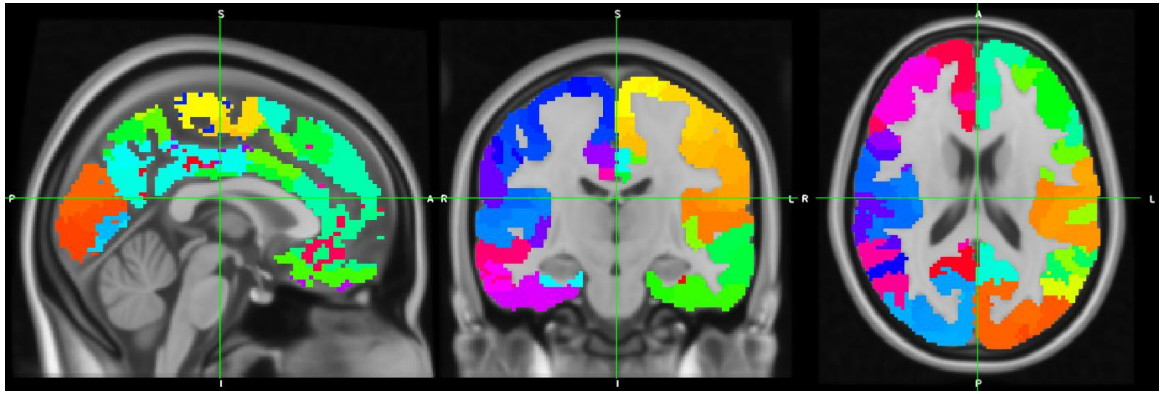
Schaefer 100



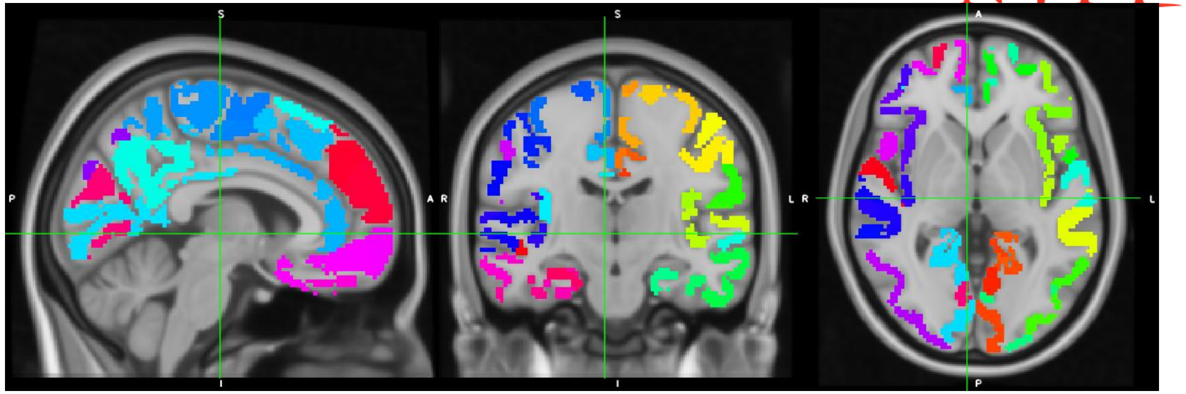
Schaefer 200



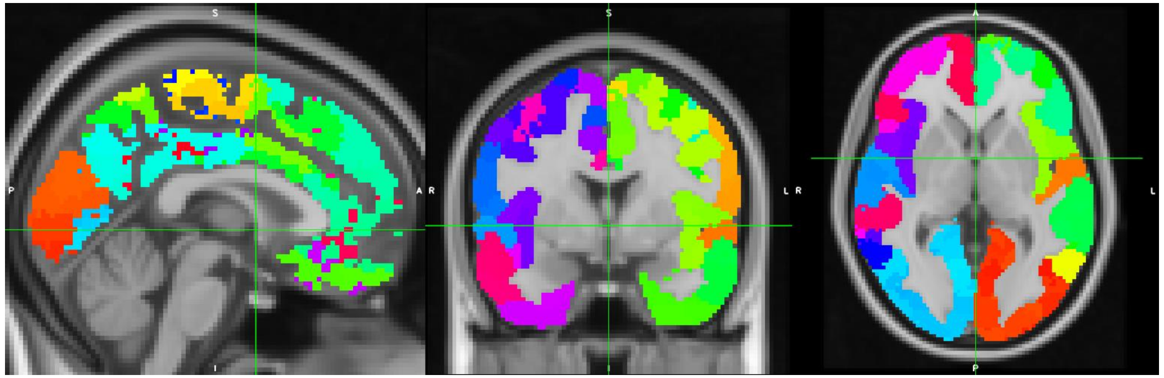
Schaefer 300



Gordon 333



Schaefer 400



Schaefer 500