

Aligning representations across individual models

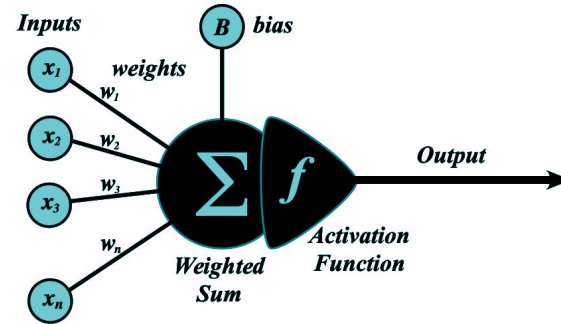
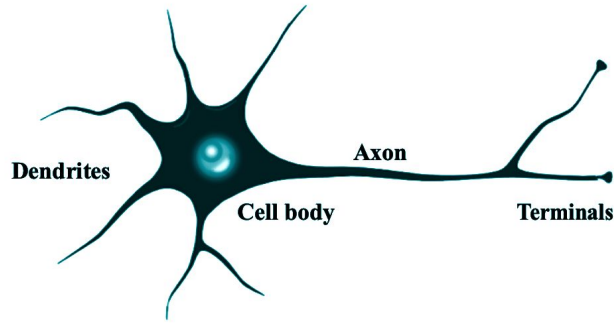
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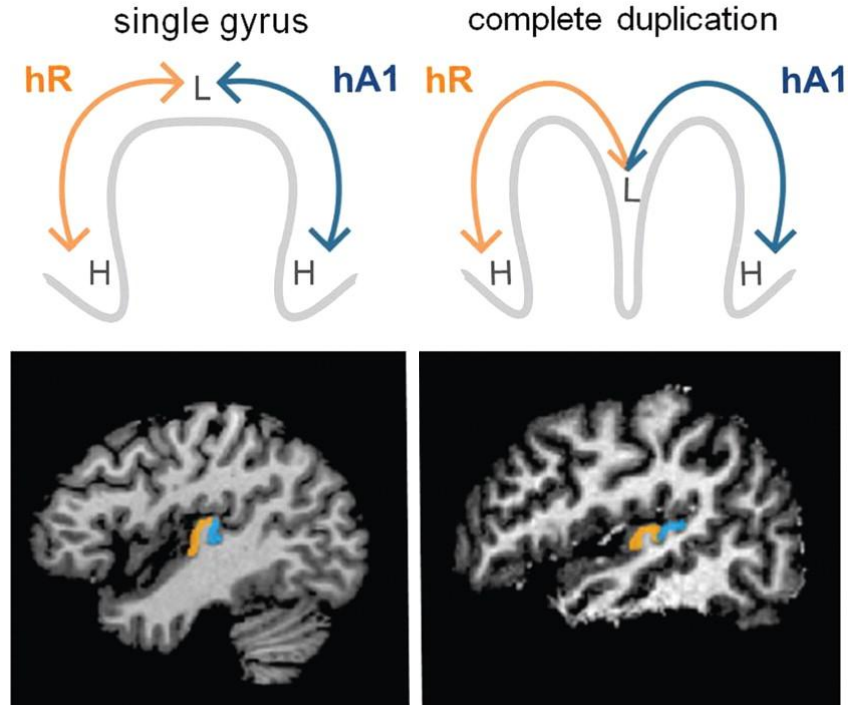


In NeuroAI, we are rarely comparing apples to apples.



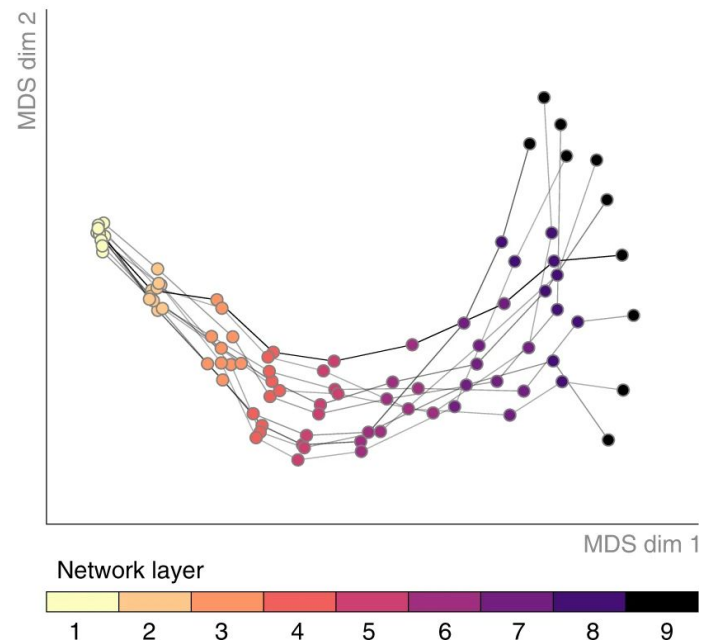
Challenges to inter-individual comparisons in biology

- Normalizing to a standardized anatomical space does not fully address inter-subject variability ([Rademacher et al., 1993](#); [Thirion et al., 2006](#))



Challenges to comparing trained artificial network instances

- Convolutional ([Mehrer et al., 2020](#)) and recurrent ([Maheswaranathan et al., 2019](#)) networks both show individual differences in learned representations
 - These differences persist with the same architecture and training set



Outline

- Measuring dissimilarity with metrics
- Using alignment to leverage similarity



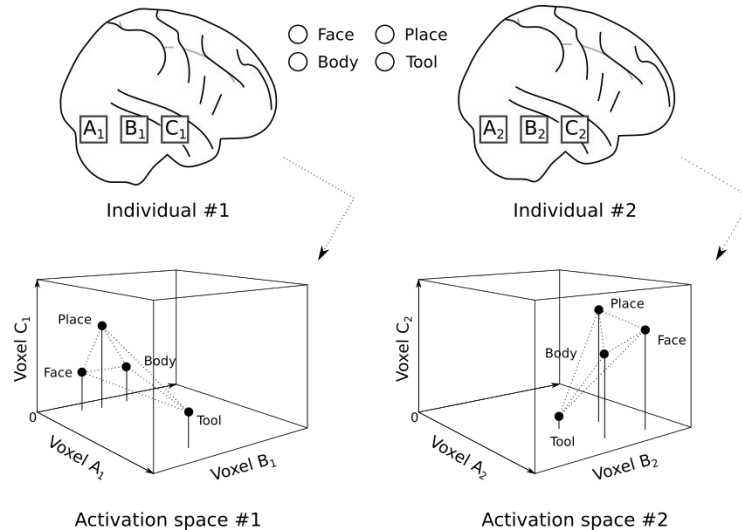
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Measuring dissimilarity with metrics

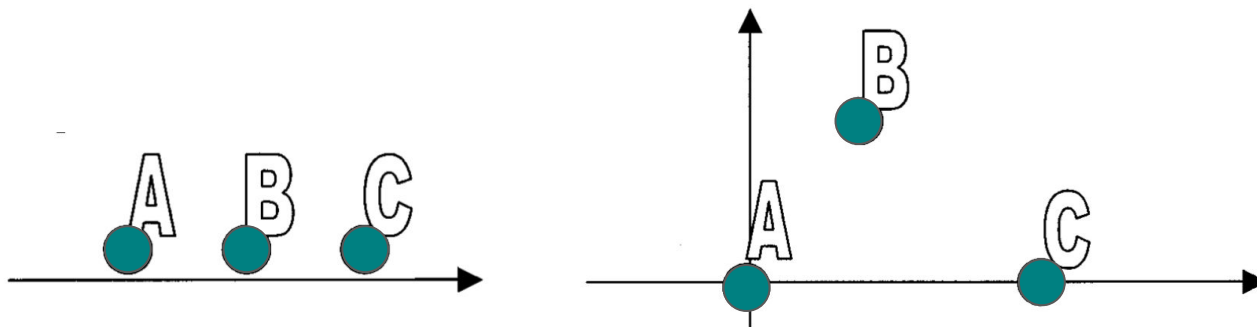
- To quantify differences between systems, individuals, or conditions, we can use metrics that measure their dissimilarity



Adapted from [Churchland \(1998\). J.Philo.](#)

Representational Similarity Analysis

- Representational Similarity Analysis (RSA; [Kriegeskorte et al., 2008](#)) is a popular approach to compare observed representational geometries



[Laasko and Cottrell \(2000\)](#)

Representational Similarity Analysis

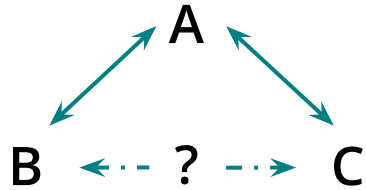
- Representational Similarity Analysis (RSA; [Kriegeskorte et al., 2008](#)) is a popular approach to compare observed representational geometries
- While RSA was originally proposed using correlation distance, this is not a true metric ([Williams et al., 2021](#)), complicating downstream analyses ([Thirion et al., 2015](#))

The measure of a metric

1. Equivalence if $A \rightarrow B = \emptyset ; A = B$

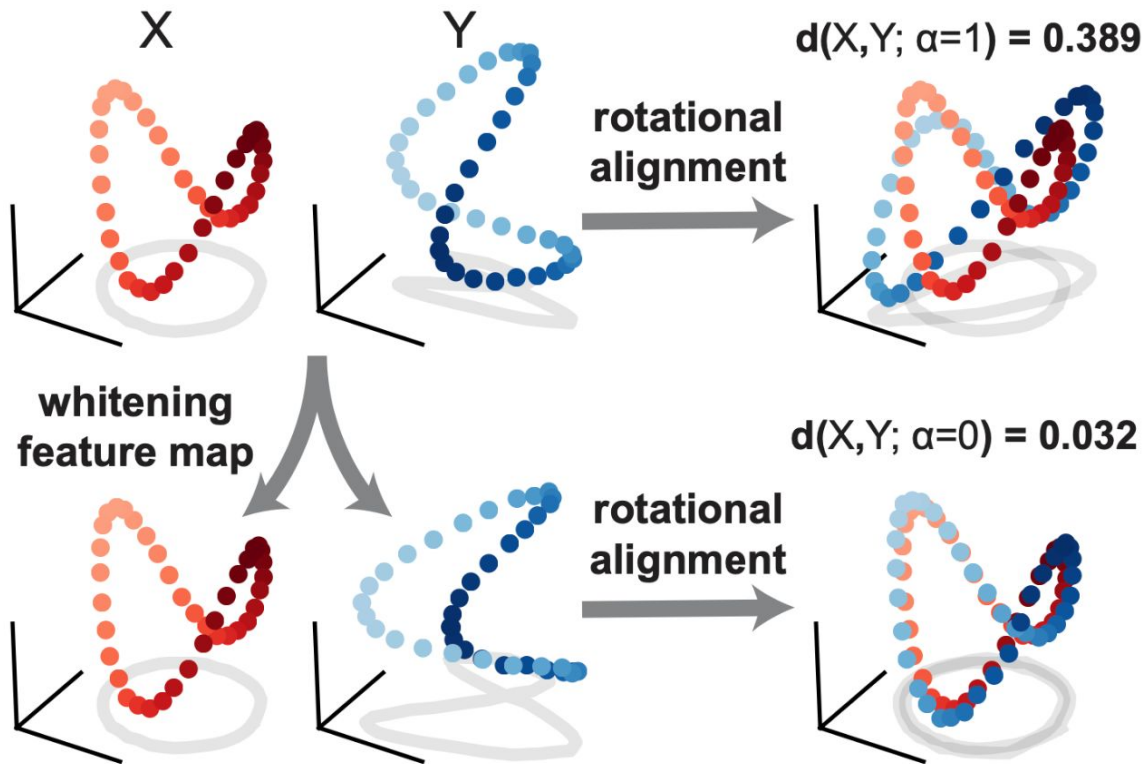
2. Symmetry $A \rightarrow B = A \leftarrow B$

3. Triangle inequality



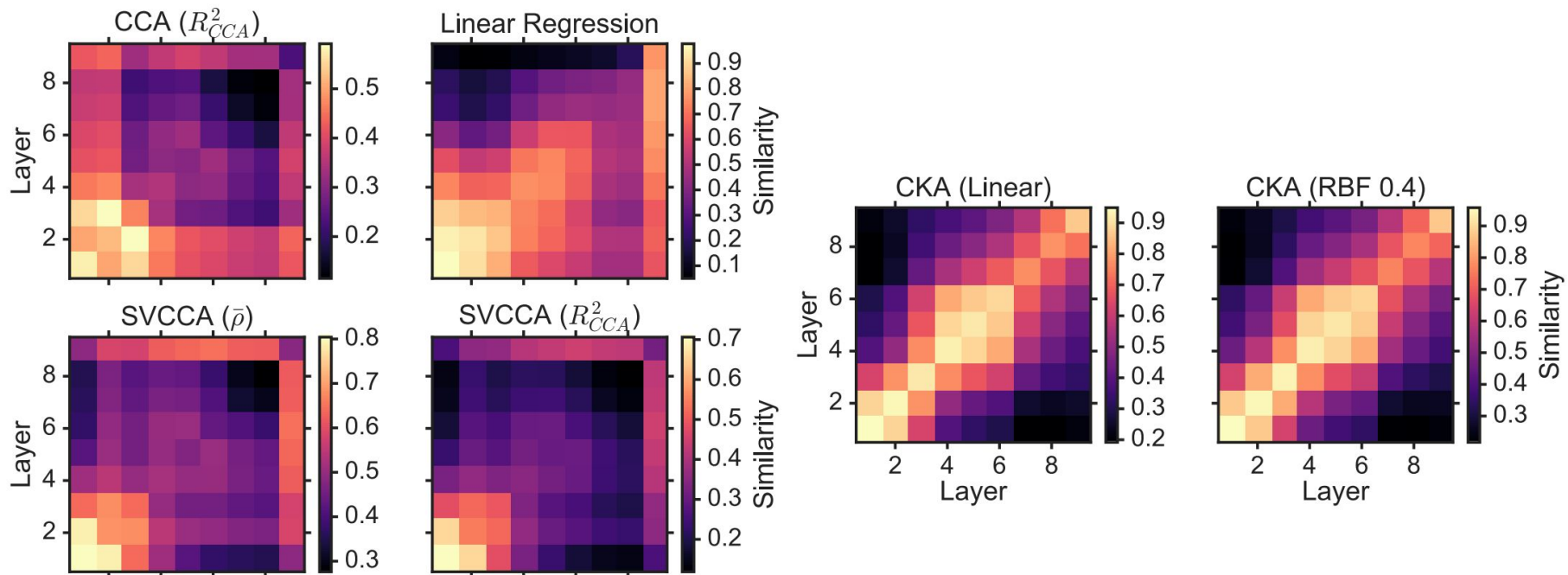
Measuring dissimilarity with metrics

- To quantify differences between individuals or conditions, we can use metrics that measure their dissimilarity
- Each metric provides different insight into the underlying structure or dynamics ([Ostrow et al., 2023](#))



Orthogonal Procrustes distance
(invariant to rotations)

CCA-based distance
(invariant to linear transformations)



More than metrics

- While metric-based results have driven significant research—and work to define rigorous metrics is ongoing; e.g., [Duong et al., 2022](#)—metrics are intended to provide insight at a given level of analysis
- In some contexts, we can also leverage the similarity of the neural systems (e.g., individual brain activations) to improve downstream inferences

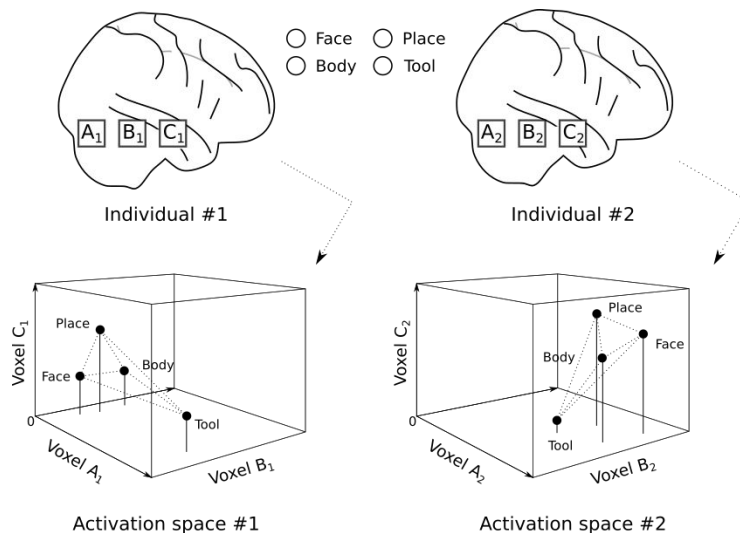
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Using alignment to leverage similarity

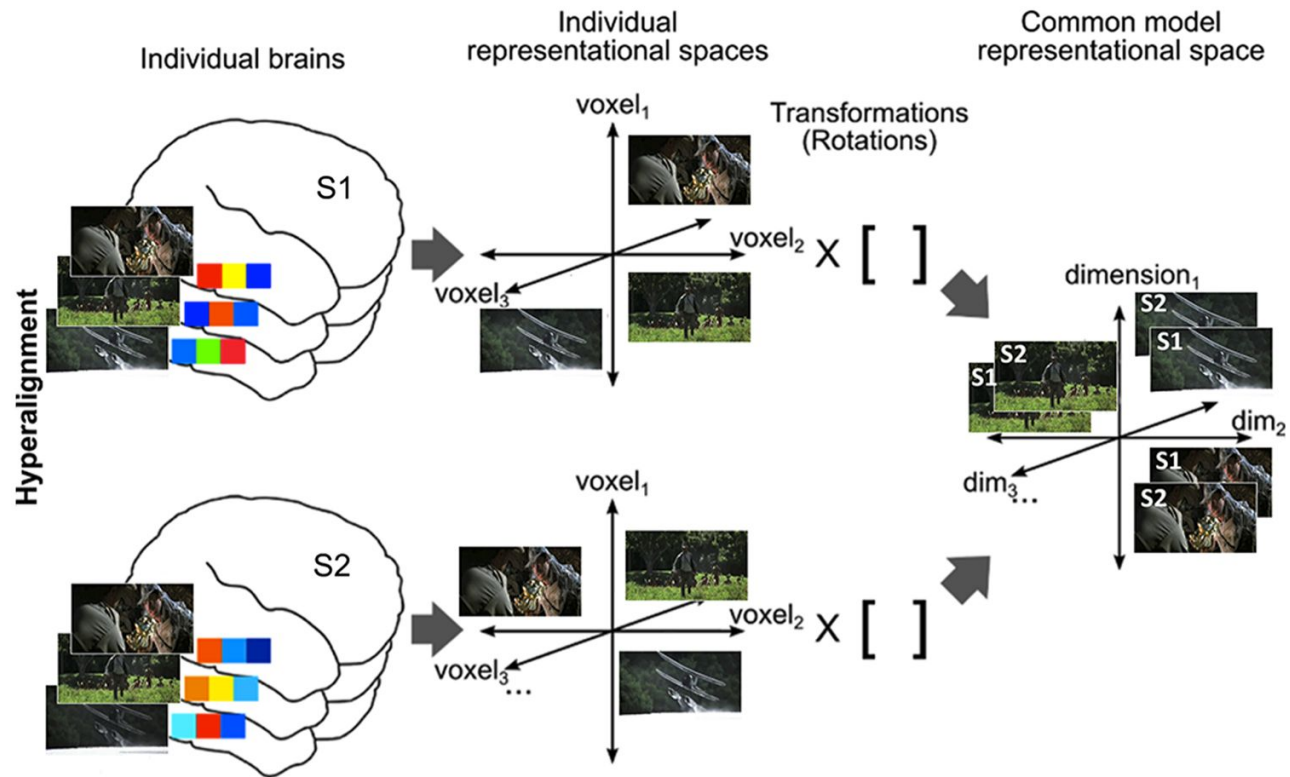
- For a given measure of similarity, we can also calculate transformations that maximize that similarity metric

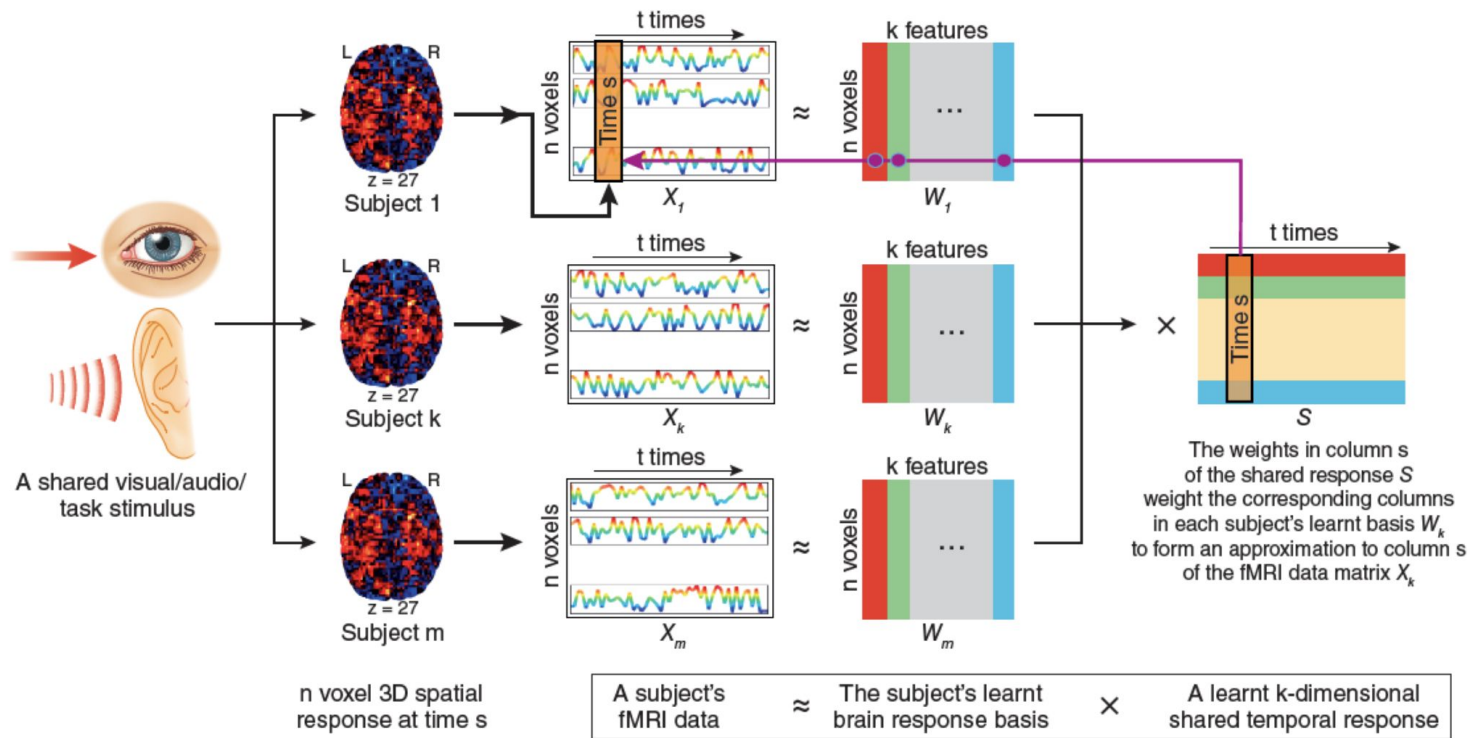


Adapted from [Churchland \(1998\), J.Philo.](#)

Alignment as a rich alternative

- Using alignment, we can directly bring data from different individuals or different experimental conditions into the same functional space
- This can be done:
 - In high- or low-dimensional space
 - Using labelled or or unlabeled experimental data; i.e., with or without knowing correspondence between time points
- These alignments can be re-used in new data





Choosing an alignment method

- Much as for metrics, *which* alignment method to choose is data dependent and remains largely guided by field norms
- In the cases considered thus far, we assume alignment to a real, known target
 - Calculating such a template is an active research area, with initial methods proposing Generalized Procrustes to an inferred average ([Haxby et al., 2020](#)) or Wasserstein barycenters ([Thual et al., 2022](#))

Thank you !



Poldrack Lab



Linderman Lab



Wu Tsai Neuroscience Institute



Let's run some alignments !



Supplementary slides

