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Identifying brain networks in a clinically rich and naturalistic dataset using tensor decomposition

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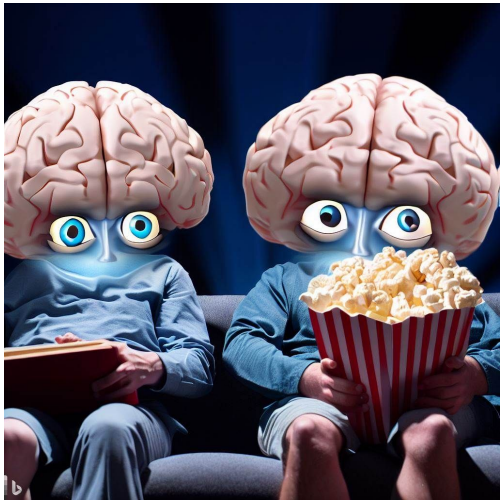
Motivation: Why Naturalistic Stimuli?

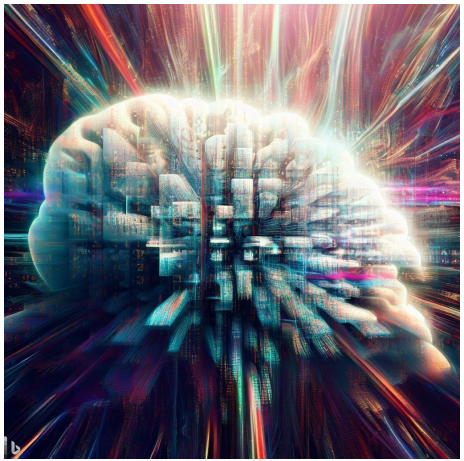
- Ecological validity (Hasson et al., 2004)
- Rich semantic, social, perceptual features (Haxby et al., 2011)
- Engaging, useful in young and clinical populations (Vanderwal et al., 2015)
- Amenable to data-driven approaches (Huth et al., 2016)



(DALL-E: brains watching a movie)

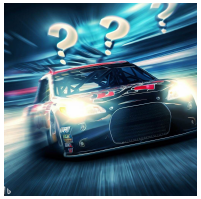
Motivation: Why Tensor Decomposition?

- Data-driven decomposition approaches like PCA, ICA, NMF, etc. are prevalent in neuroimaging research
- **BUT**: many require assumptions like temporal or spatial statistical independence
- These assumptions are not necessarily biologically plausible
  - We know that brain networks can overlap spatially and temporally
- **Tensor Decomposition:**
  - Allows for identification of temporally and spatially overlapping networks
  - Successfully applied to resting state and clinical (ADHD) datasets

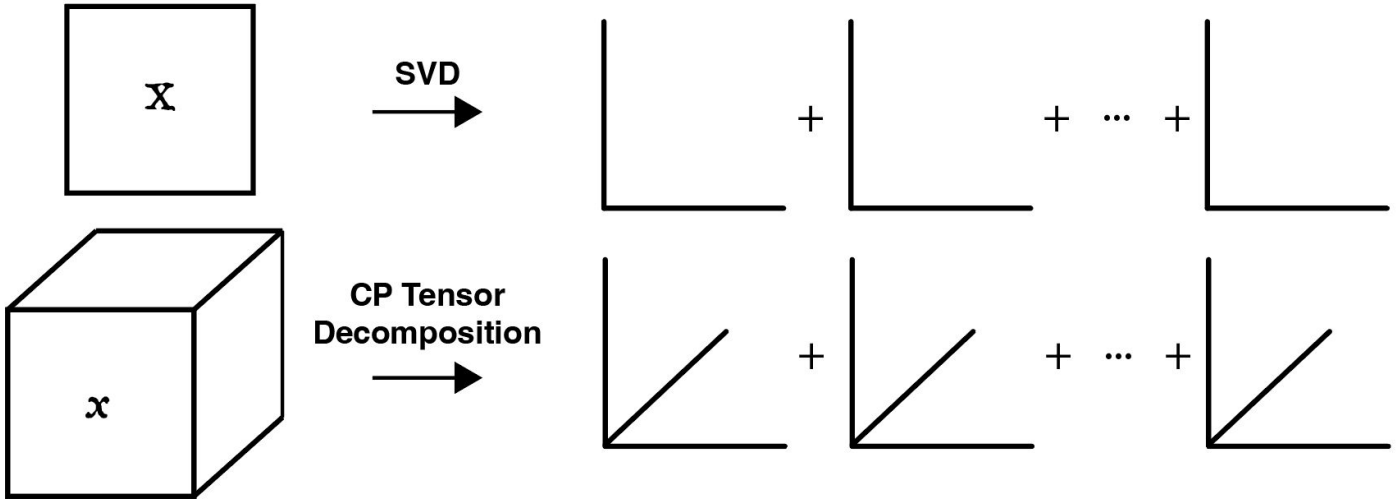


(DALL-E: tensor decomposition brain)

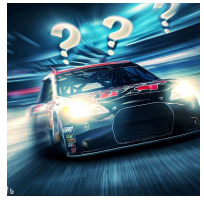
Tensor Decomposition: What is it?

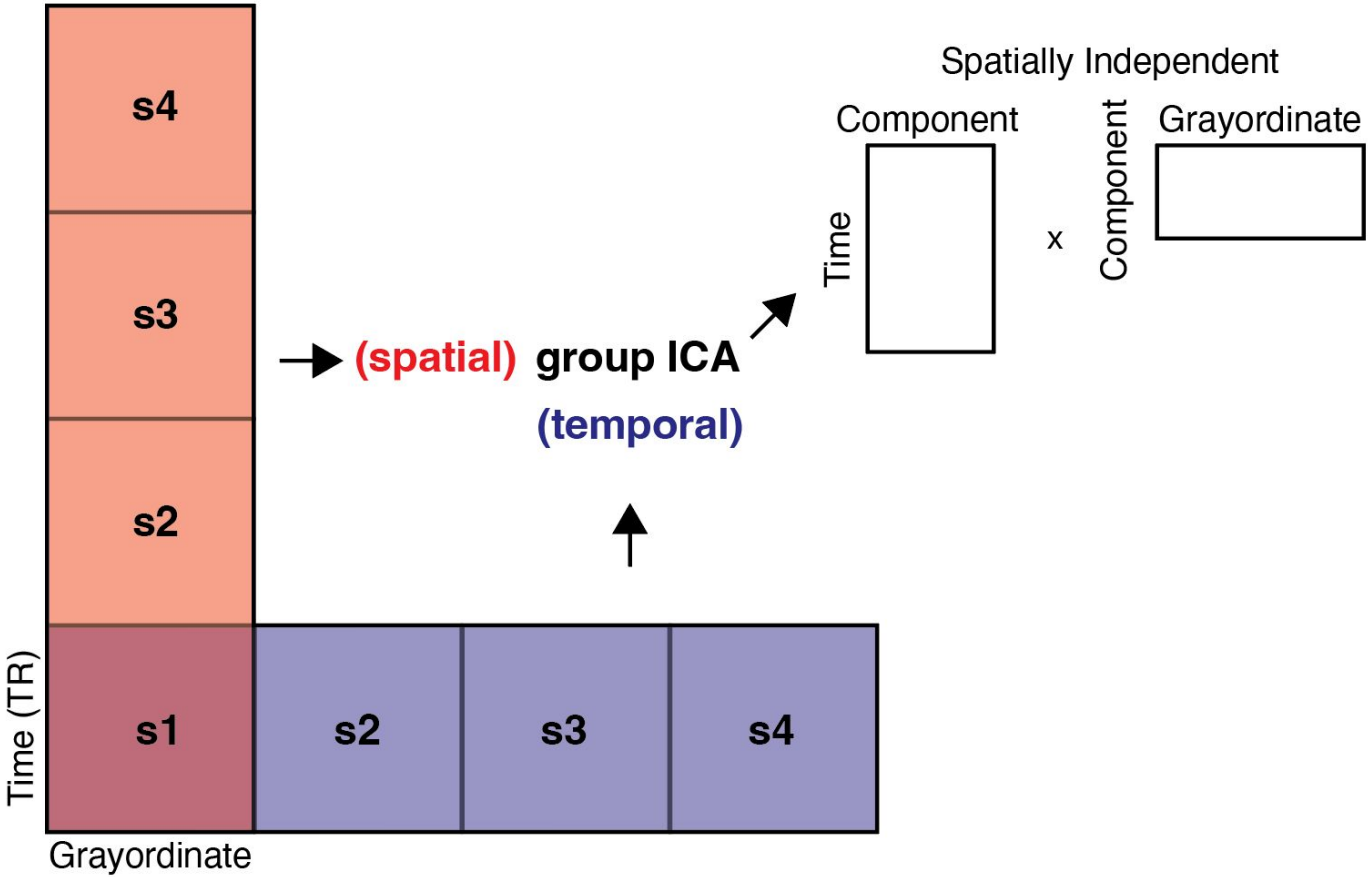


- A method to find low rank representations of a higher dimensional tensor where a tensor can be approximated by a sum of rank-1 components
- A generalization of SVD but without the orthogonality constraint



Tensor Decomposition: What is it not?

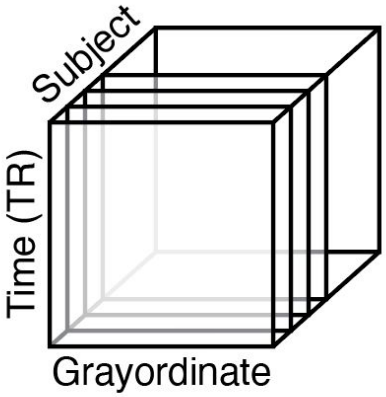




Tensor Decomposition: What is it, in practice?

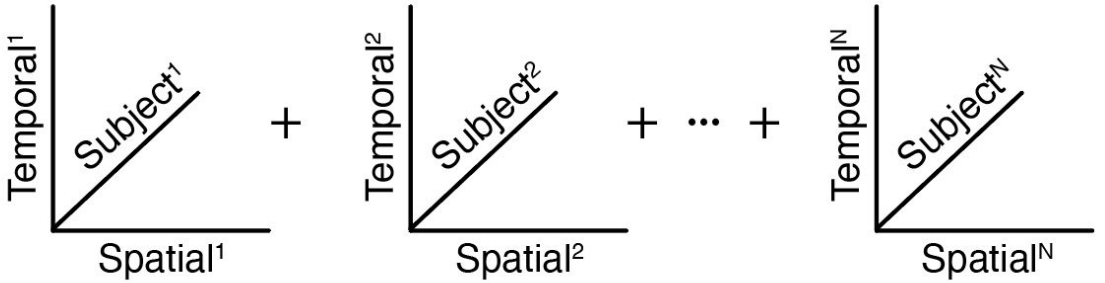
- Nadam-accelerated Scalable and Robust CP Decomposition (**NASCAR**) is a robust way of solving the tensor decomposition problem (Li et al., 2023)

Third-order Tensor



CP Tensor Decomposition

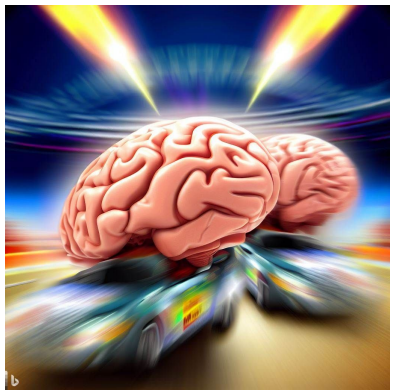
Rank-1 Components



Component 1 **Component 2** **Component N**

Hypotheses

1) NASCAR was previously applied to resting state, by applying NASCAR for the first time to movie viewing data, we predict that we will observe consistent spatio-temporal components compared to rest
2) By applying NASCAR to movie-viewing data, we can map temporal modes of the components to movie features to better understand brain differences in clinical populations like autism
3) We can classify ASD diagnosis from subject contributions



(DALL-E: NASCAR brains

Methods: Dataset

- The Healthy Brain Network (HBN) dataset
  - Small subset: Site 1, Releases 1-8
  - n=212
- fMRI data:
  - 2 Resting state (5 minutes each)
  - 2 Movies (4 minutes, 10 minutes)
  - TR=0.8s

Child Mind Institute
HEALTHY BRAIN NETWORK

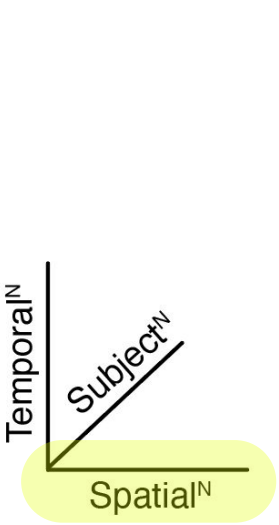
(Alexander et al. 2017)

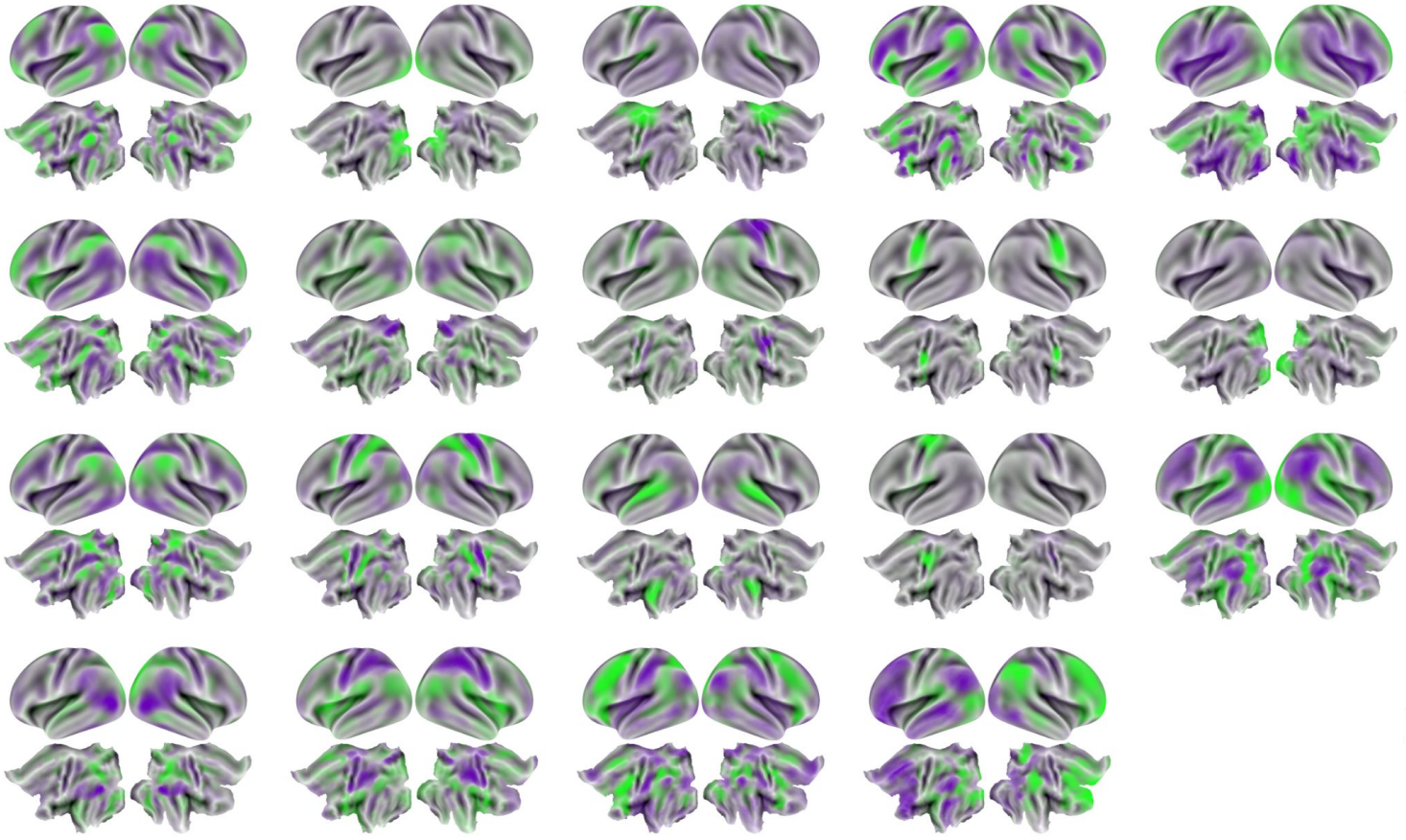
Methods: fMRI Processing

- **fMRIPrep** v23.0 -> CIFTI2 (grayordinates)
  - (Esteban et al., 2017; FreeSurfer: Fischl, 2012)
- **Nilearn:** Remove confounds, detrend
  - (Abraham et al., 2014)
- **Connectome WB:** Gaussian Smooth 2mm FWHM
  - (Marcus et al., 2011)
- StandardScaler()
- **Group BrainSync:** Temporal Synchronization
  - (Akrami et al., 2019)
- **NASCAR**: Nadam-accelerated Scalable and Robust CP Decomposition
  - (Li et al., 2023; 2021; 2019)

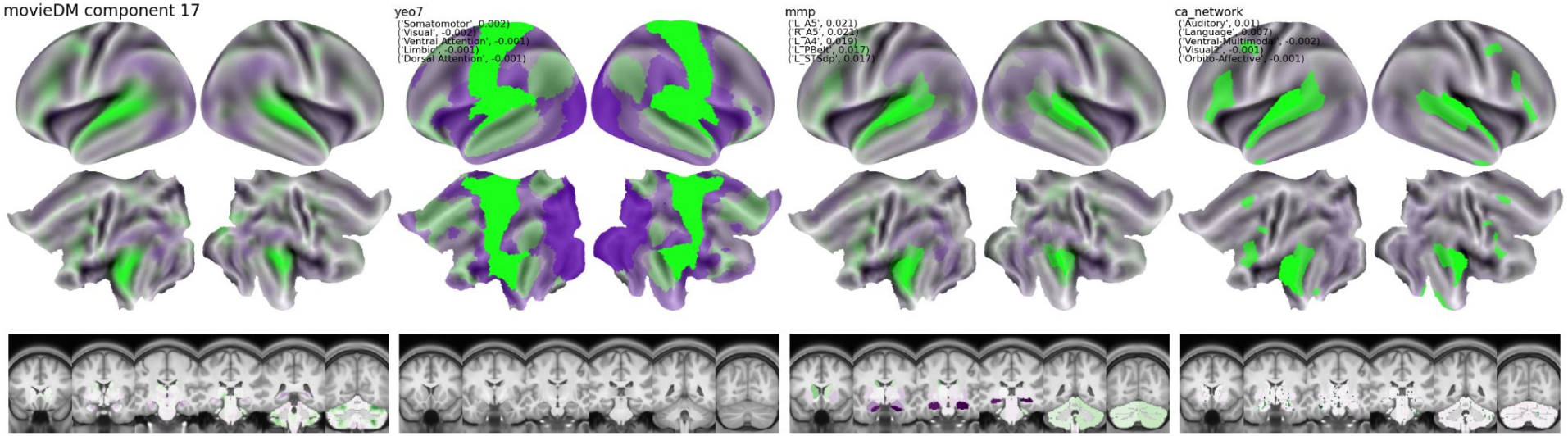
Results: Spatial Modes

Despicable Me: 19 Component, Spatial Modes

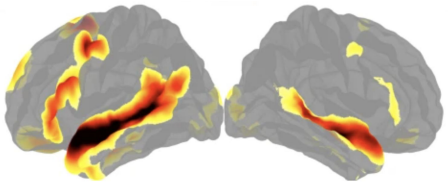




Results: Spatial Modes - Validation



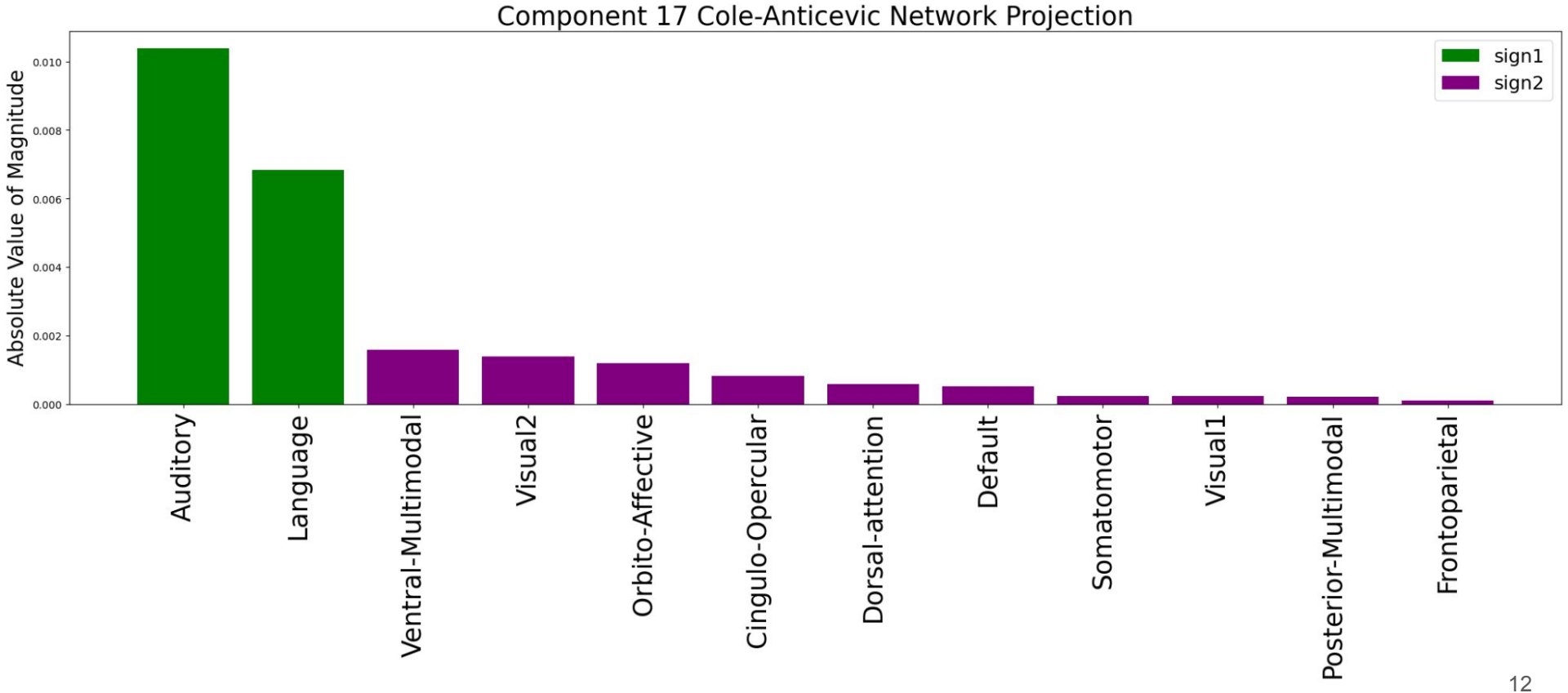
(Yeo et al., 2011) (Glasser et al., 2016) (Ji et al., 2019)



Language Network?

(Lipkin et al. 2022)

Results: Spatial Modes - Validation



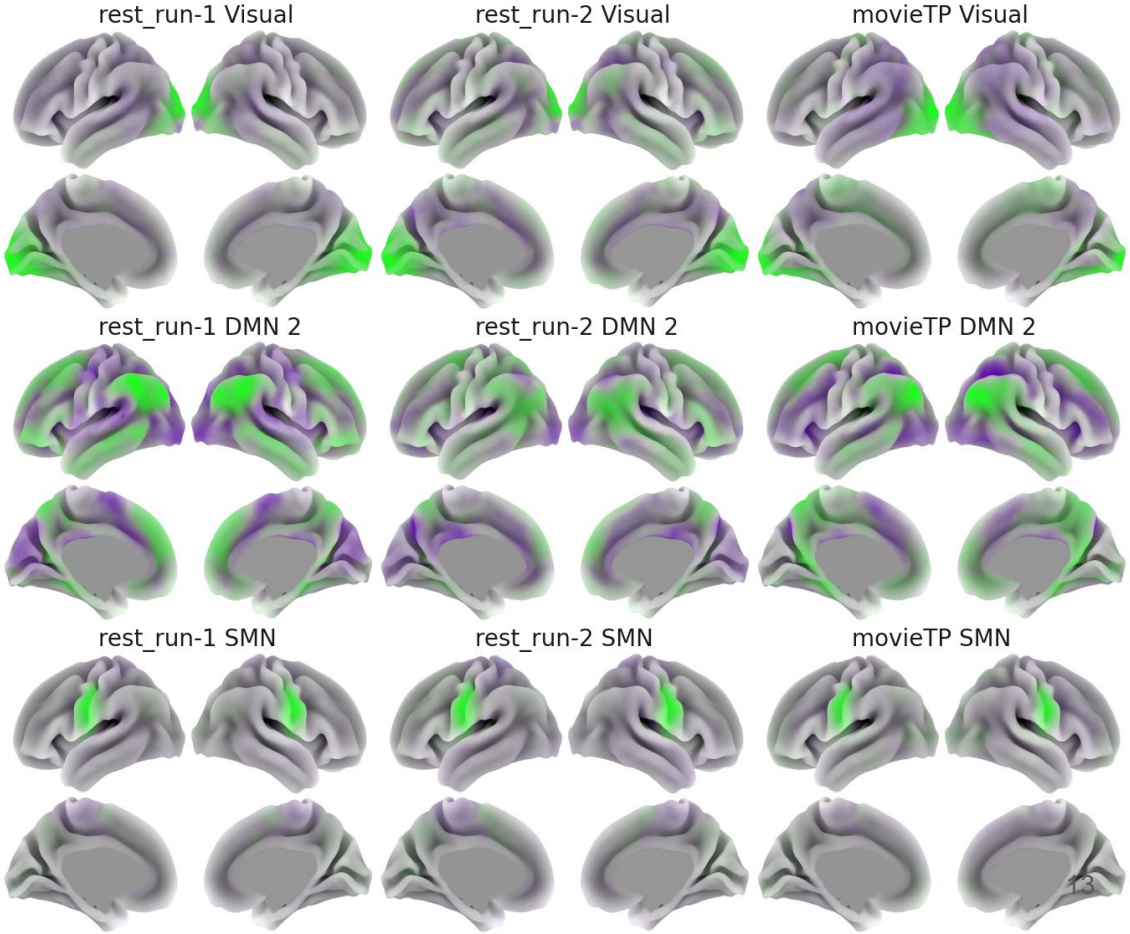
Results: Spatial Modes

1) Are the same components observed across different resting state runs?

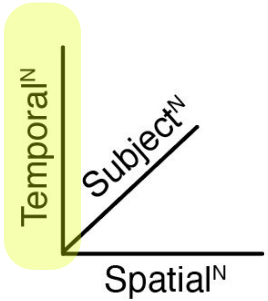
Yes!

2) Are the same components observed across rest and movie-viewing?

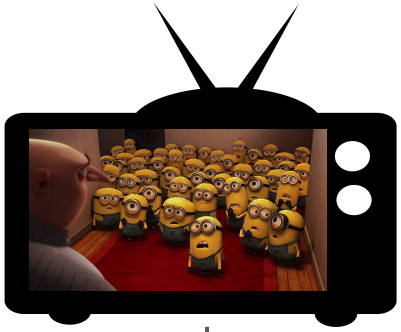
Yes!



Results: Temporal Modes

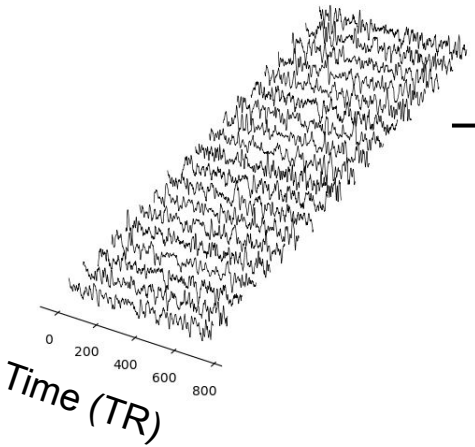


Example Features:
- **Faces**
- **Objects**
- **Speech**
- **Music**
- **Contrast**

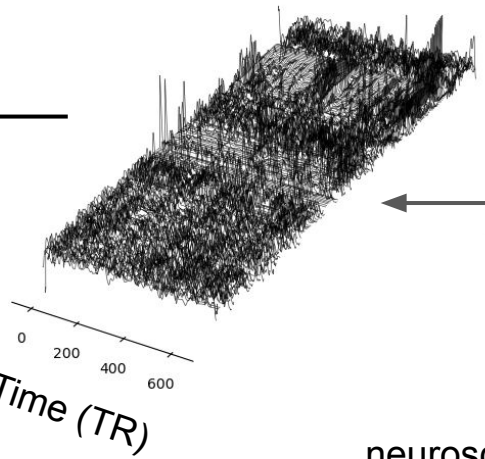


19 Components

215 Movie Features



Corr



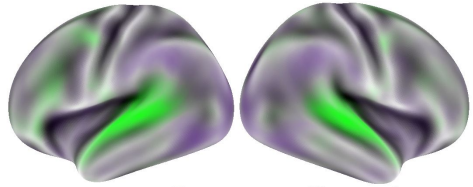
Neuroscout

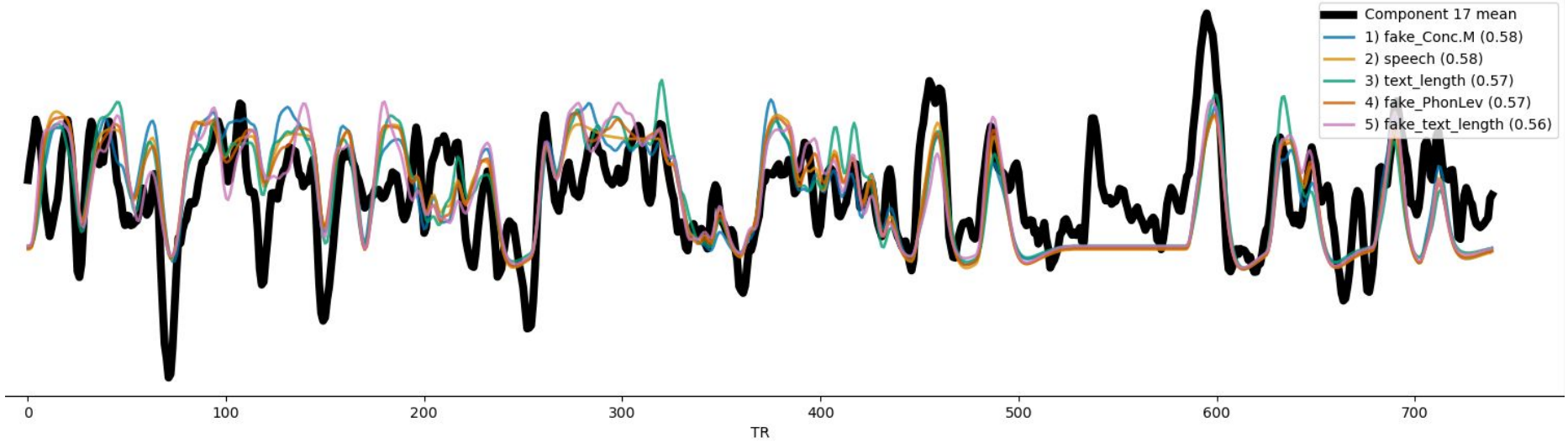
librosa AudioSet Google Cloud Platform TensorFlow Hub Rev clarifai

github.com/tyarkoni/pliers

neuroscout.org (de la Vega et al., 2022)

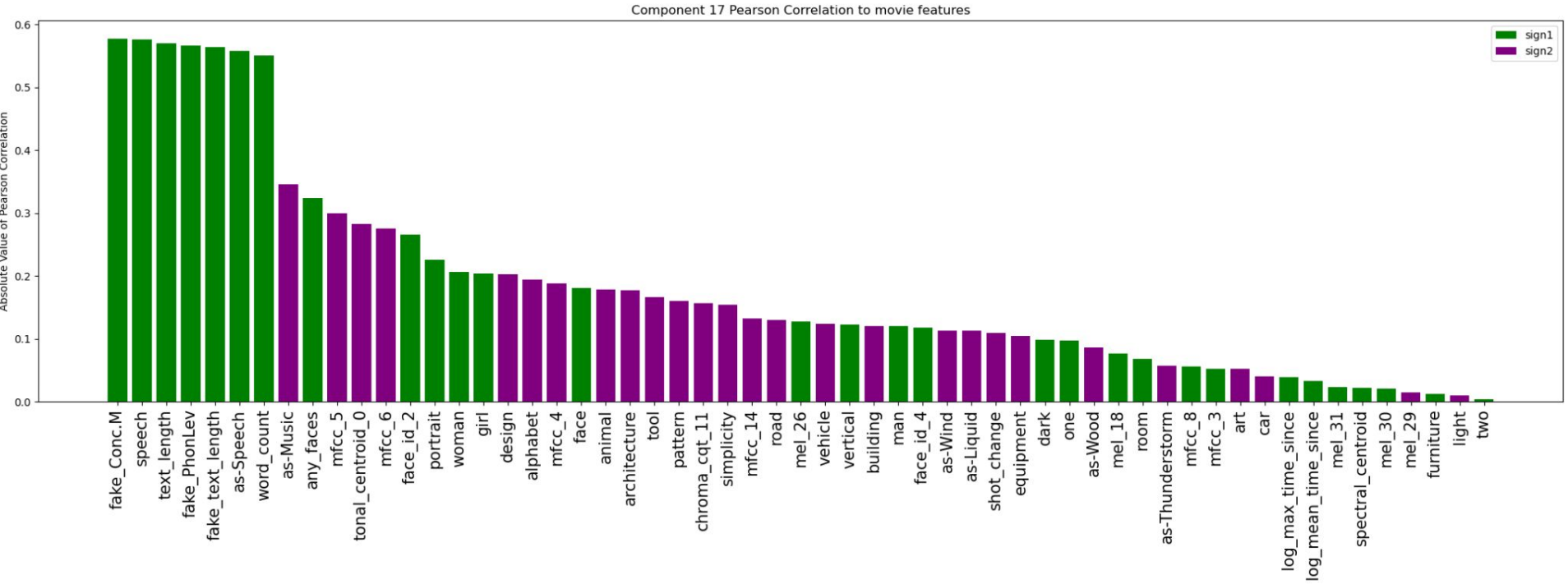
Component 17 Temporal Mode



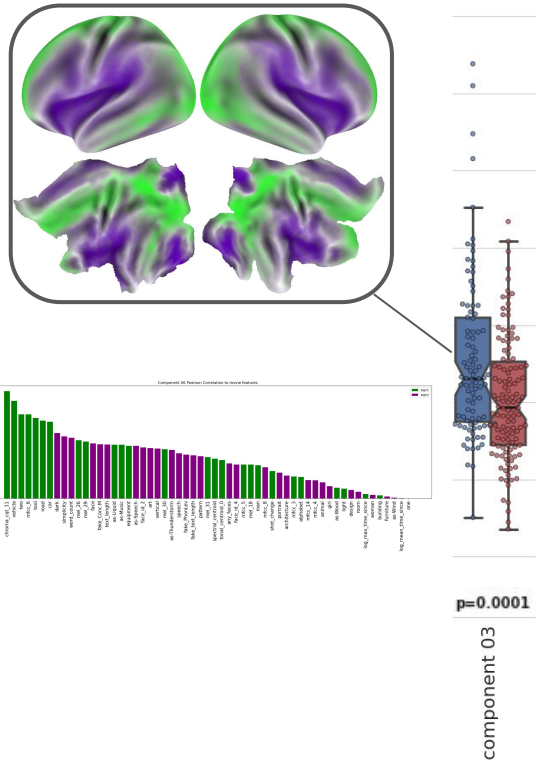


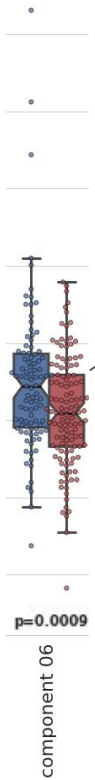
- Speech and movie transcript-related features are most correlated

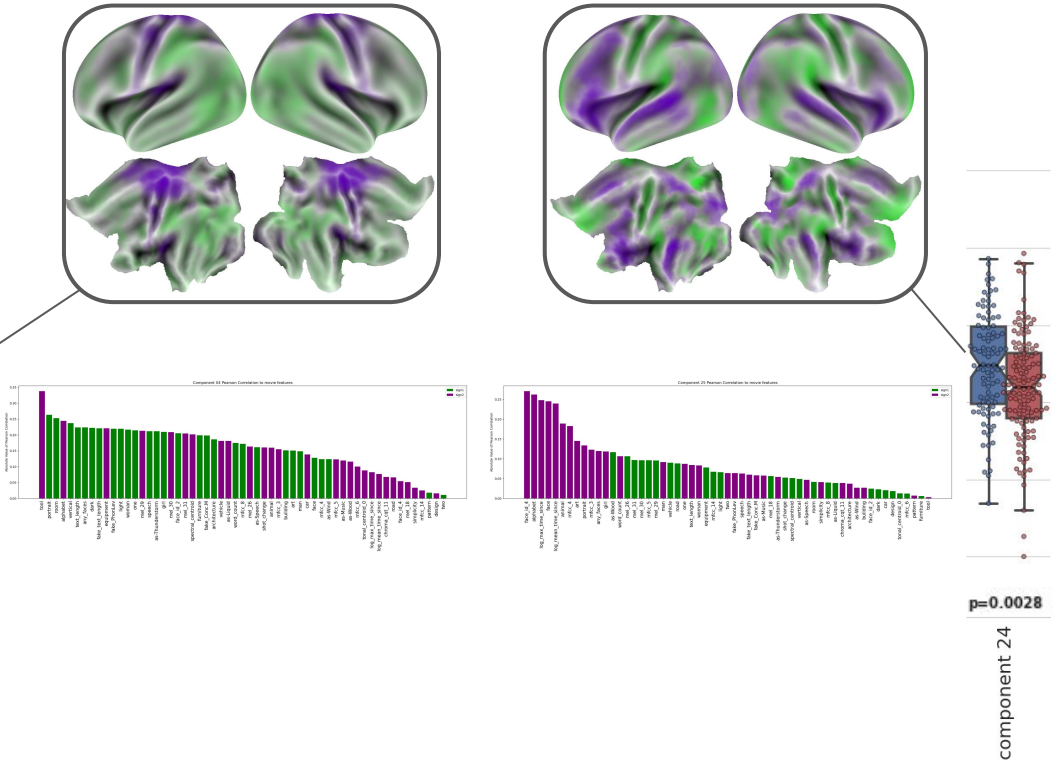
Component 17 Temporal Mode



Results: Subject







Summary

Conclusions:

- Consistent components are identified across both movies and resting state and correspond with known networks
- Temporal modes from movie components can be mapped back to movie features
- Significant differences were observed between ASD and controls in some components
- Classification accuracy ~60%

Future Directions:

- Expand scope of analyses to more subjects and sites
- Implement a left-out-sample model
- Predict clinical measures of interest like Social Responsiveness Scale (SRS)

Thank you!

Find us at poster #589 !

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