Identifying Brain Networks in a Clinically Rich and Naturalistic Dataset using Tensor Decomposition

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Introduction

- **Naturalistic stimuli** have gained increasing attention as a more ecologically valid method of studying the brain
  - Ecological Validity
  - Rich semantic, social, and perceptual features
  - Engaging + less head motion in young and clinical populations
  - Amenable to data-driven approaches
  - An exciting tool to examine conditions like **autism** (characterized by social and perceptual alterations)

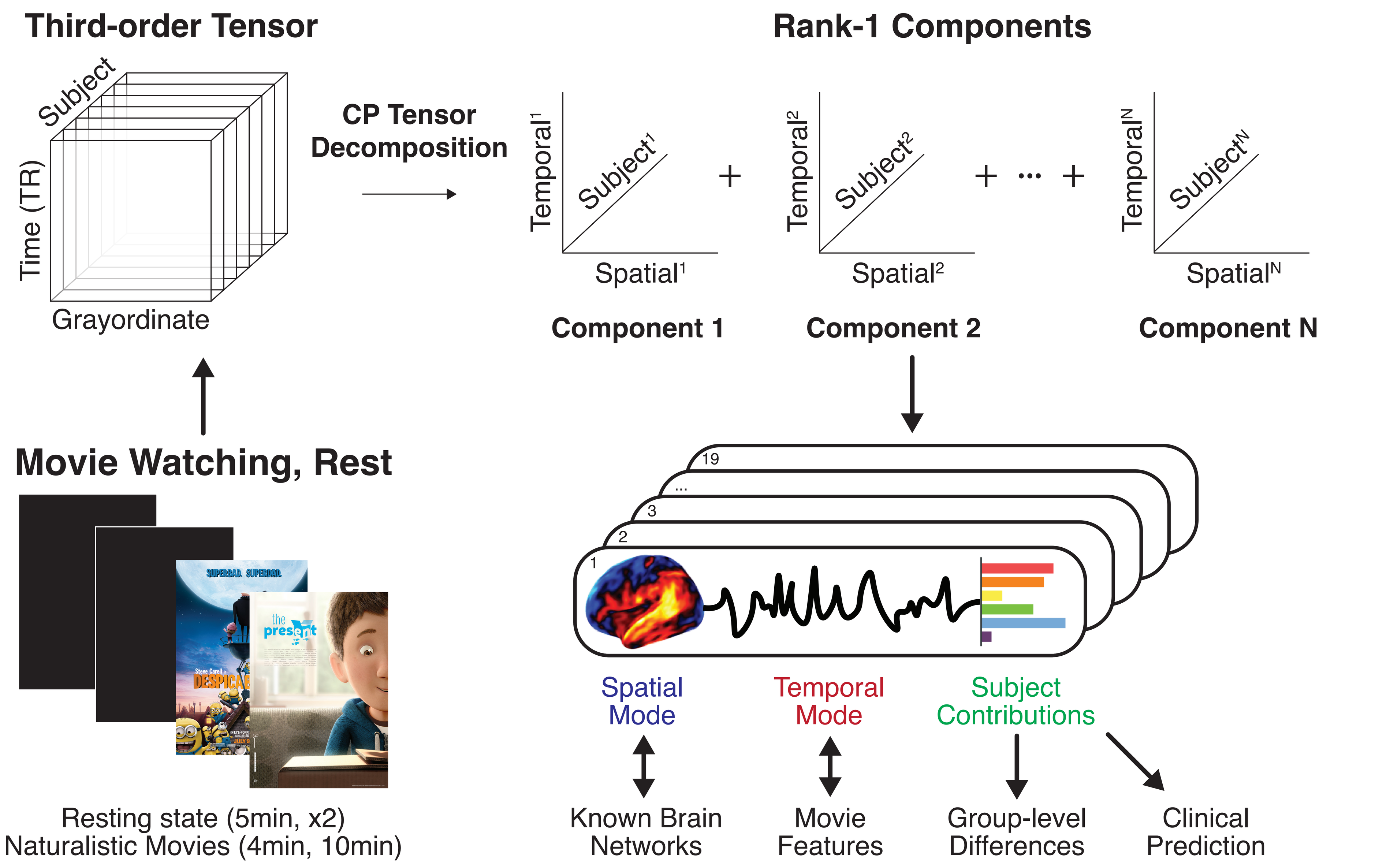
- Data-driven approaches like PCA, ICA, NMF are prevalent but require assumptions that are not always biologically plausible
- **Tensor Decomposition** allows for identification of temporally and spatially overlapping networks
  - Here we apply tensor decomposition to naturalistic movies and an autism population for the first time

Methods

Data:
- A subset of Healthy Brain Network (HBN) subjects were acquired including individuals with autism (n=212; autism=119)
- fMRI data (TR=0.8s) includes 2 resting state runs (5 min each) and 2 movies (4 min and 10 min) (see Alexander et al. 2017 for a full dataset description and acquisition parameters)

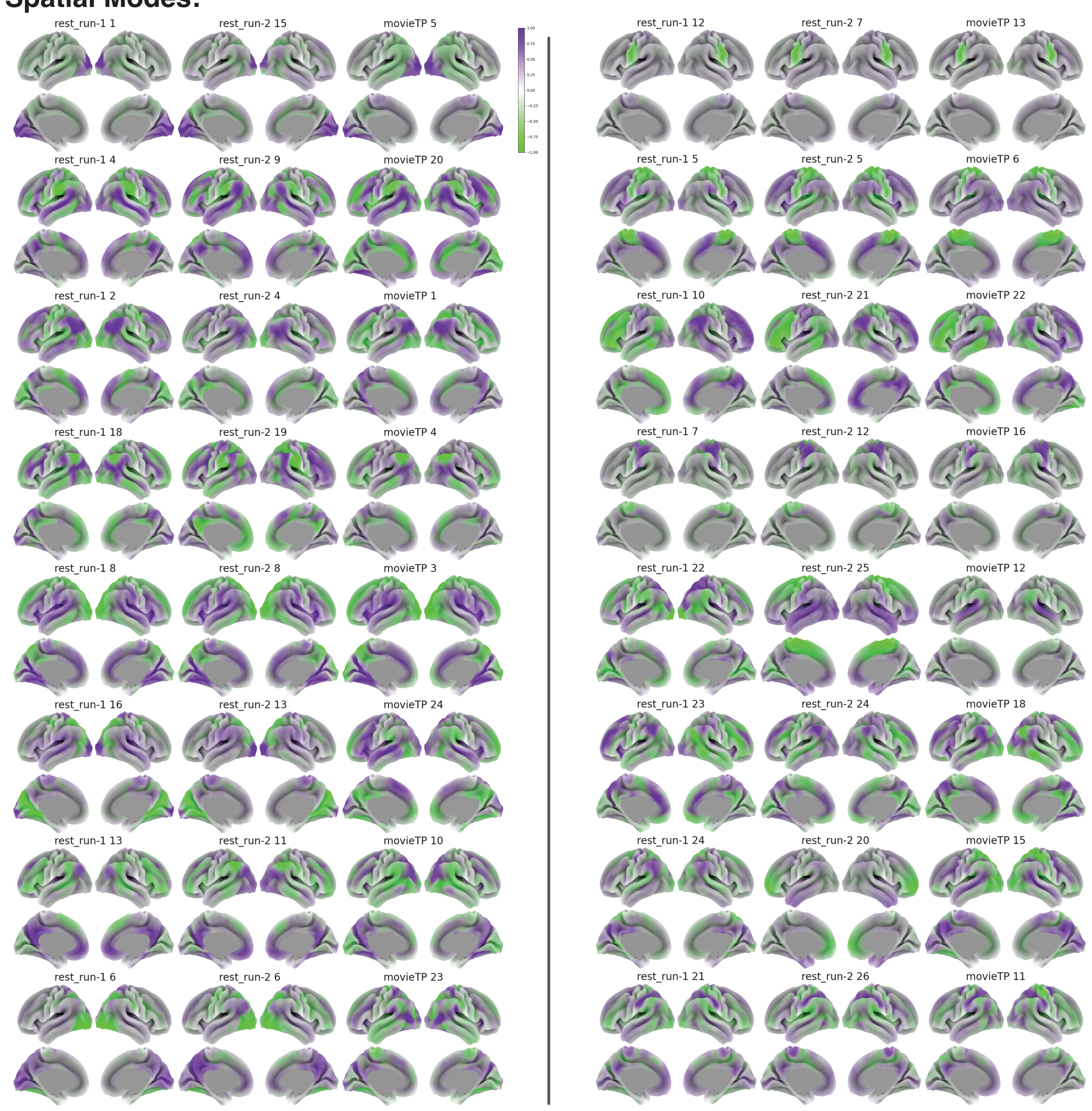
Preprocessing:
- Brain volumes were pre-processed using **fMRIPrep** 23.0.1, which included head-motion estimation, slice time correction, field-map-based distortion correction, EPI to T1 registration and resampling to both MNI volumetric and grayordinate space (Esteban et al., 2017; **FreeSurfer**: Fischl, 2012)
- **Nilearn** was used to remove confounds and for detrending followed by standard scaling (Abraham et al. 2014)
- 2mm FWHM gaussian smoothing was performed using **Connectome Workbench** (Marcus et al. 2011)
- Temporal alignment was performed with **Group BrainSync** (Akrami et al. 2019)

Analysis:
- Temporally aligned fMRI data was mapped to a **3D tensor** (grayordinate x TR x subject)
- Canonical polyadic (CP) tensor decomposition was performed using **NASCAR** to identify brain networks as low rank approximations of the data. (Li et al. 2023)
- Audio and visual features were extracted from the movie using Pliers (McNamara et al., 2017) and HRF convolved for reverse correlation analysis



Results

Spatial Modes:

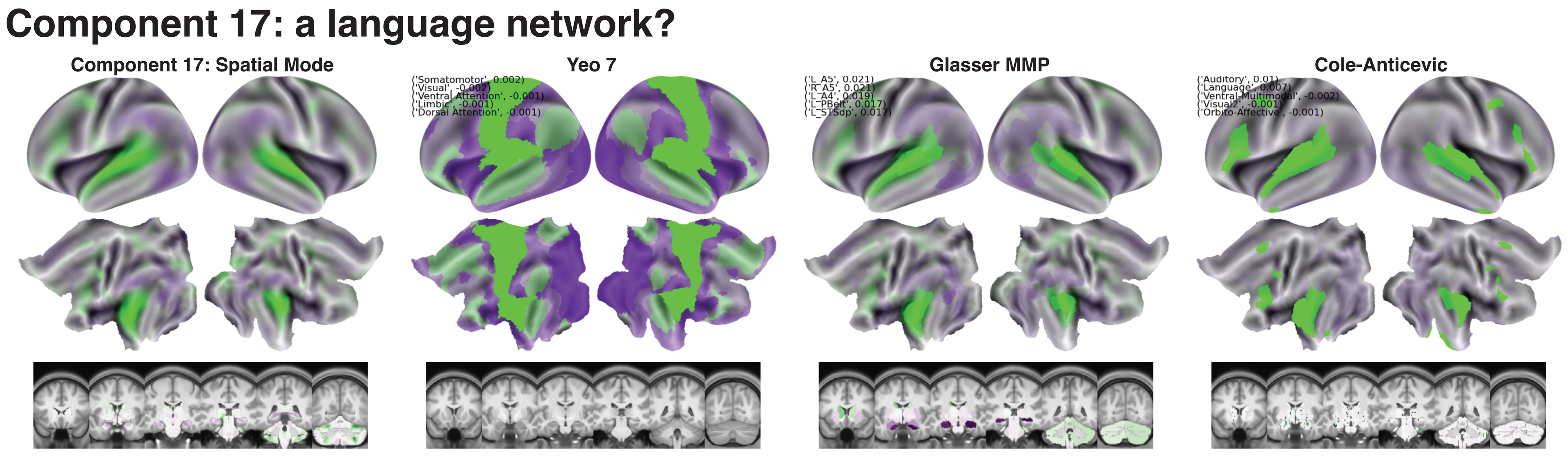


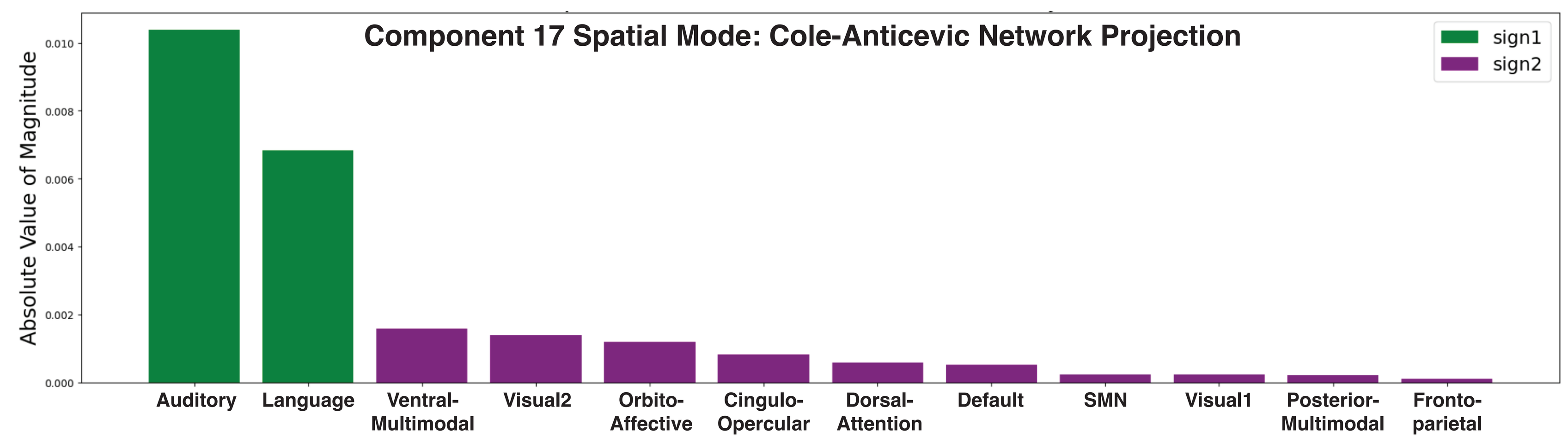
Conclusions

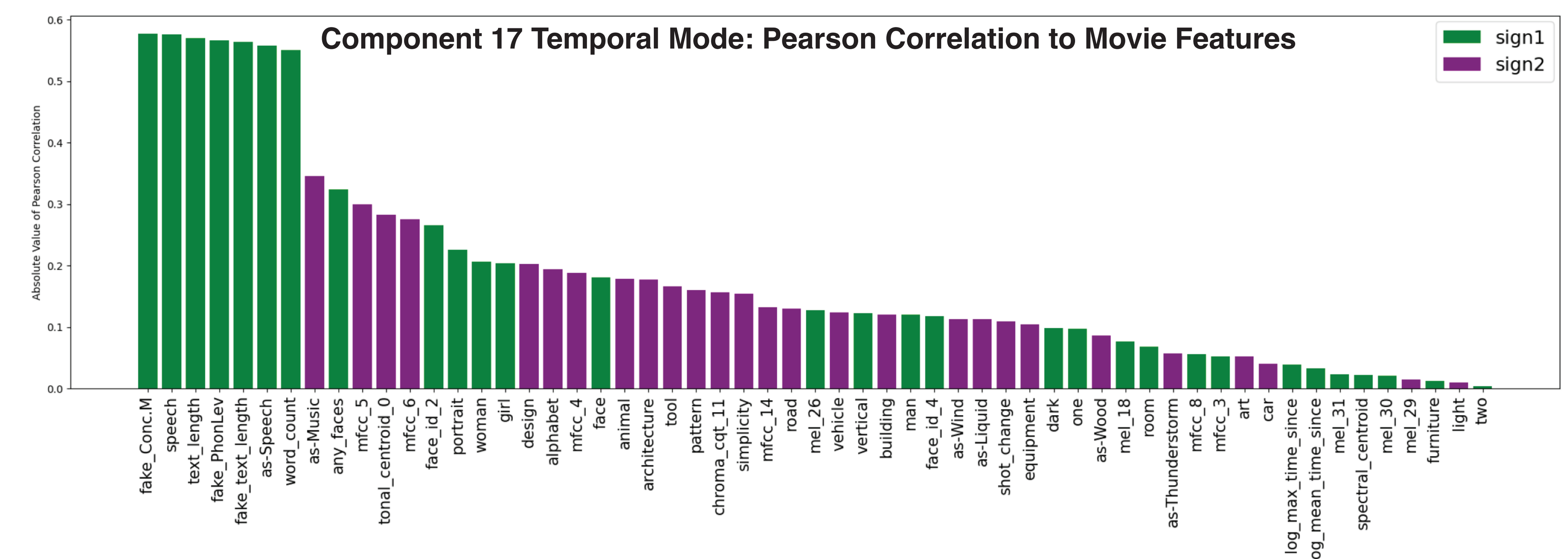
1) Consistent components are identified across both movies and resting state and correspond with known networks
2) Temporal modes from movie components can be mapped back to movie features
3) Significant differences were observed between ASD and controls in some components
4) Subject contribution classification accuracy: ~60%

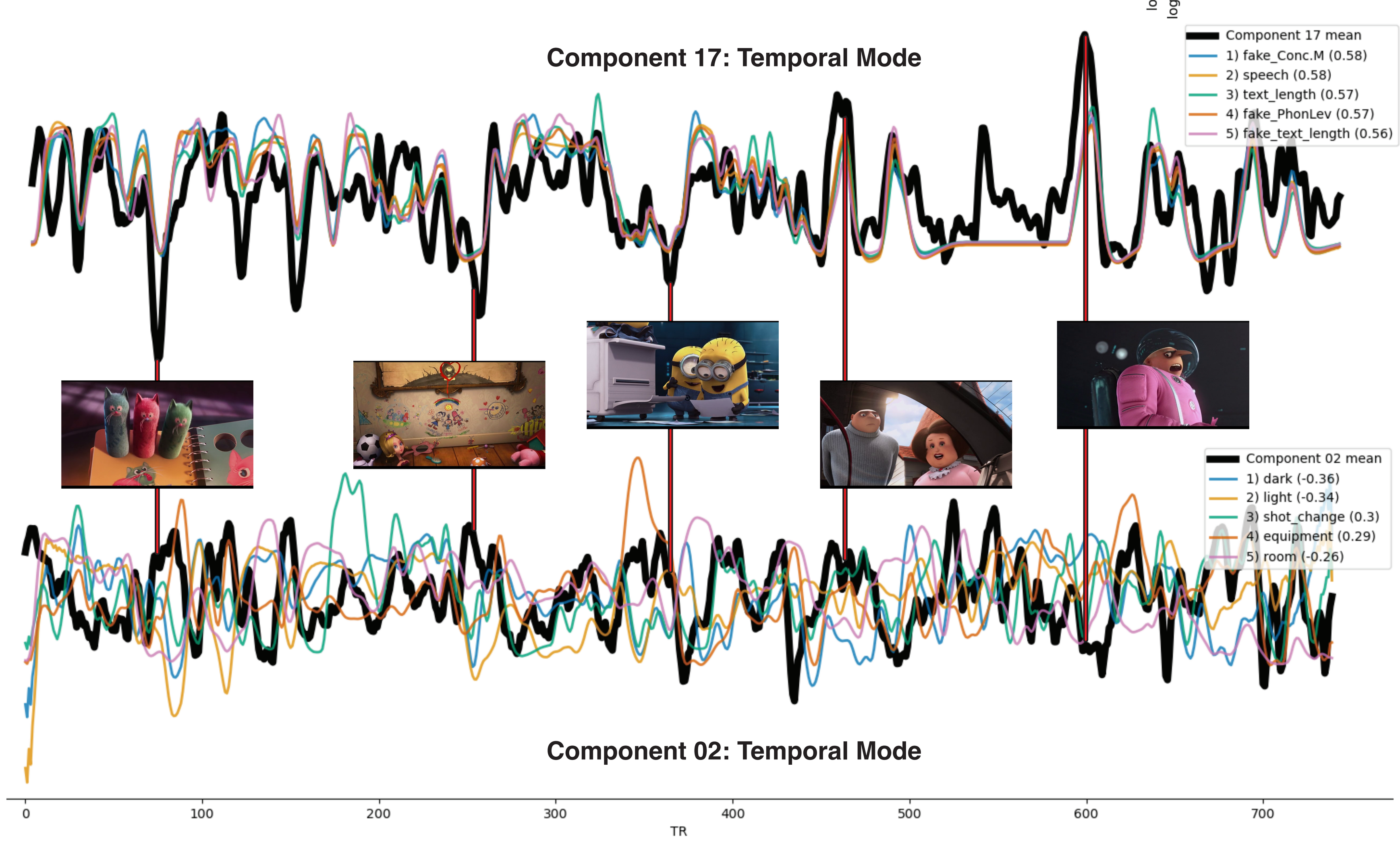
Future Directions: 1) expanding the scope of analyses to more subjects and sites, 2) implementing a left-out-sample model, and 3) predicting clinical measures of interest like Social Responsiveness Scale (SRS)

Component 17: a language network?

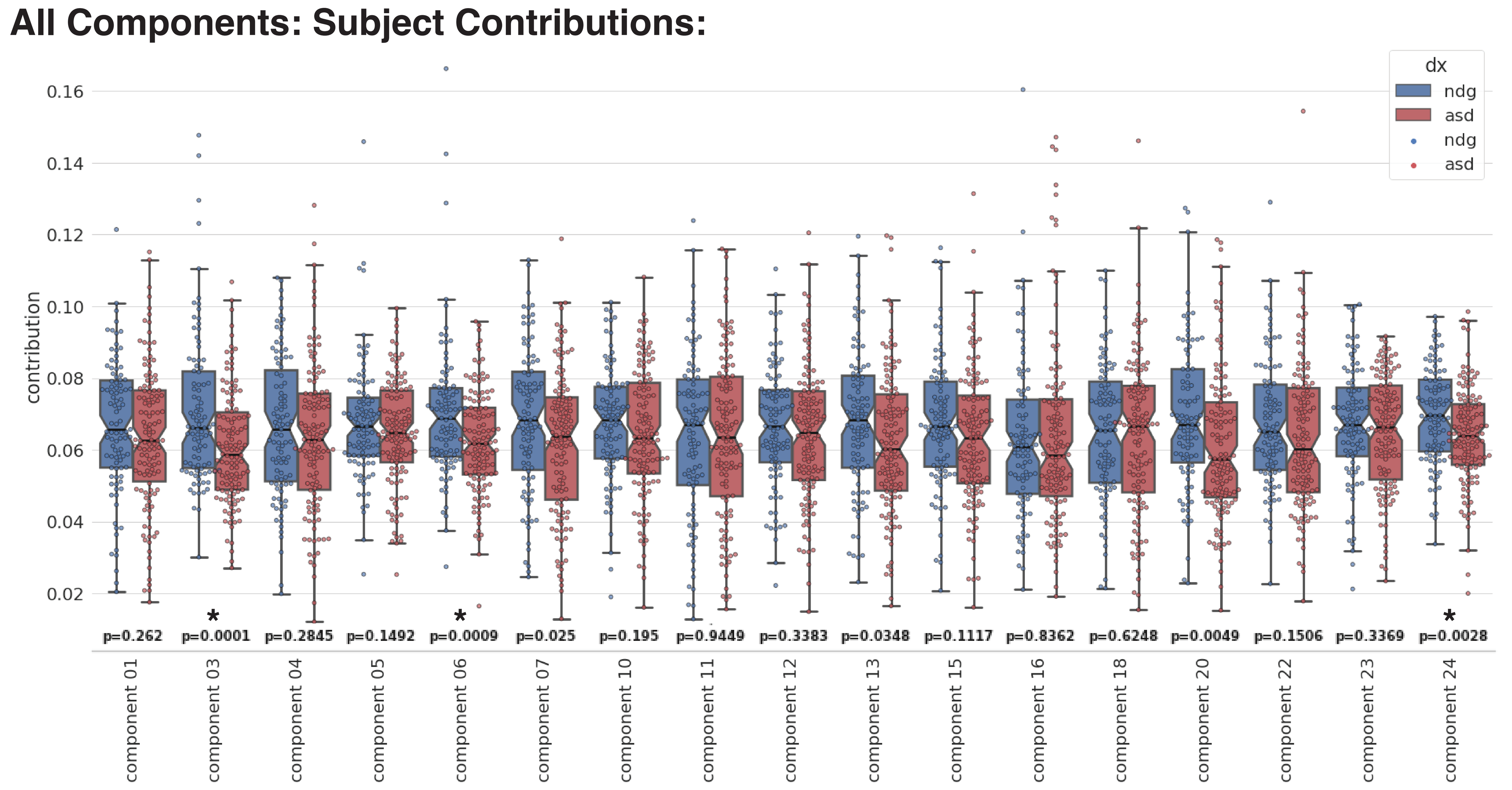








All Components: Subject Contributions:



References

Abraham, A., Pedregosa, F., Eickenberg, M., Gervais, P., Mueller, A., Kossaifi, J., Gramfort, A., Thirion, B., & Varoquaux, G. (2014). **Machine learning for neuroimaging with scikit-learn. Frontiers in Neuroinformatics**, 8, 14.
Alexander, L. M., Escalera, J., Ai, L., Andreotti, C., Febre, K., Mangone, A., Vega-Potler, N., Langer, N., Alexander, A., Kovacs, M., Litke, S., O'Hagan, B., Andersen, J., Bronstein, B., Bui, A., Bushey, M., Butler, H., Castagna, V., Camacho, N., … Milham, M. P. (2017). **An open resource for transdiagnostic research in pediatric mental health and learning disorders. Scientific Data**, 4, 170181.
Calhoun, V. D., Liu, J., & Adali, T. (2009). **A review of group ICA for fMRI data and ICA for joint inference of imaging, genetic, and ERP data**. NeuroImage, 45(1 Suppl), S163–S172.
Joshi, A. A., Chong, M., Li, J., Choi, S., & Leahy, R. M. (2018). **Are you thinking what I'm thinking? Synchronization of resting fMRI time-series across subjects.** NeuroImage, 172, 740–752.
Li, J., Wisnowski, J. L., Joshi, A. A., & Leahy, R. M. (2021). **Robust brain network identification from multi-subject asynchronous fMRI data**. NeuroImage, 227, 117615.
Marcus, D. S., Harwell, J., Olsen, T., Hodge, M., Glasser, M. F., Prior, F., Jenkinson, M., Laumann, T., Curtiss, S. W., & Van Essen, D. C. (2011). **Informatics and data mining tools and strategies for the human connectome project.** Frontiers in Neuroinformatics, 5, 4.
McNamara, Q., De La Vega, A., & Yarkoni, T. (2017). **Developing a Comprehensive Framework for Multimodal Feature Extraction.** Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1567–1574.

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