

Neuroimaging Statistics in the brisklab

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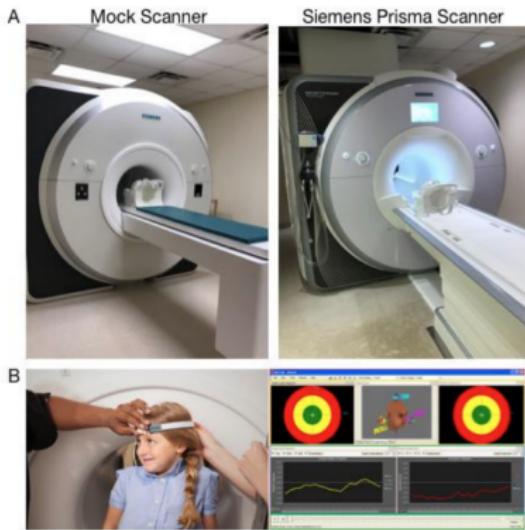


Figure 2. Mock scanner training facilities and equipment at Emory's Center for Systems Imaging Core. **A.** Side-by-side pictures of our mock scanner (left) and the actual Siemens Magnetom Prisma 3T scanner (right). Our mock scanner is equipped with the same façade and head coil as the real scanner, thereby increasing familiarity and sameness of routine for participants. **B.** Motion sensor that measures participant head movement (left) and MoTrak software (right), designed to provide participants with contingent feedback regarding head movement.

One scanner for all MRIs

An MRI scanner is used to collect many different types of images

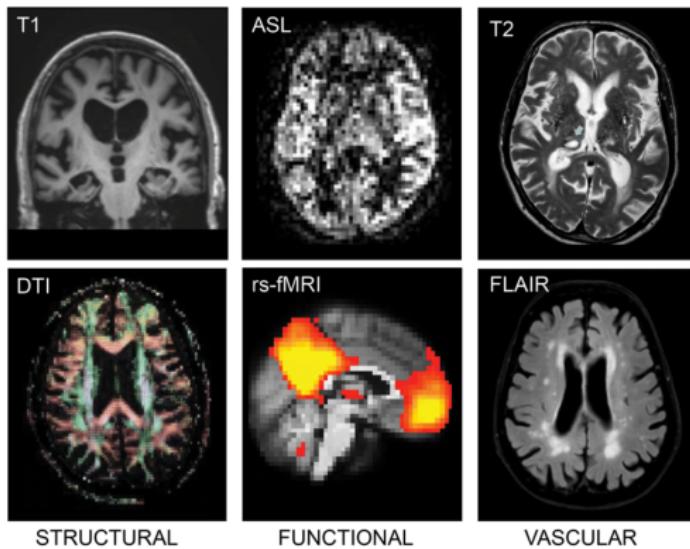
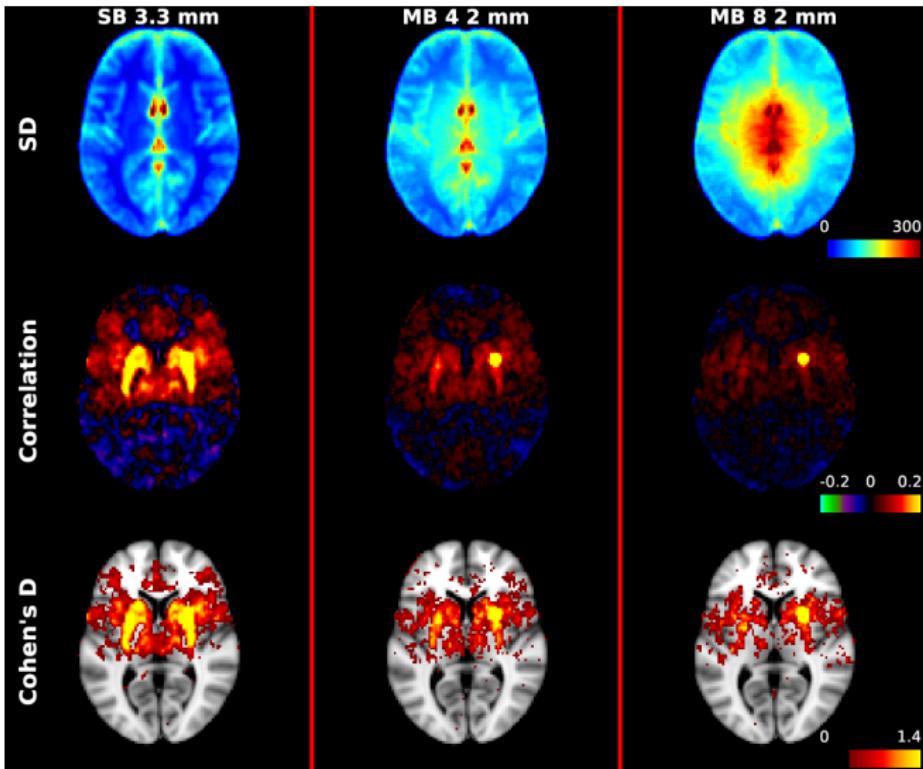


Figure: Ten Kate et al. (2018)

Image acquisition speed

Costs of faster image acquisition



- Multiband impacts in fMRI Risk et al. (2021, 2018)

Data integration studies

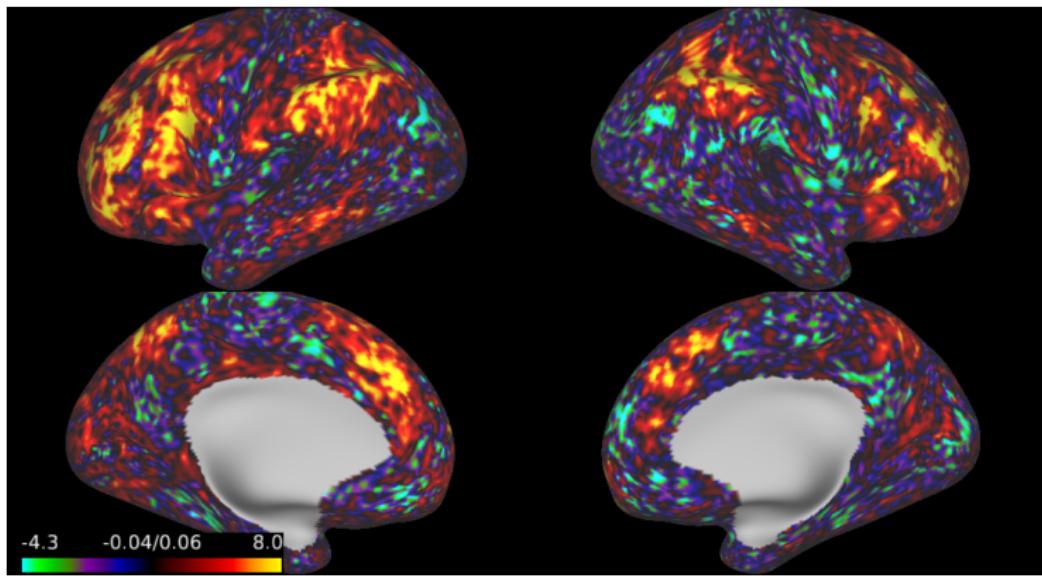
SING: Simultaneous Non-Gaussian Component Analysis

- ▶ Motivating principle: combining information across datasets leads to a more accurate understanding of the underlying biology.
- ▶ **Subject scores**: summarize a subject's brain phenotype from multiple neuroimaging data types.
- ▶ Here, we extract subspaces using information measured by higher order moments, whereas JIVE uses variance.
- ▶ Scientific aim: Data integration in cognition studies of healthy adults [Lerman-Sinkoff et al. \(2017\)](#).

Are cognitive task regions related to spontaneous brain activity?

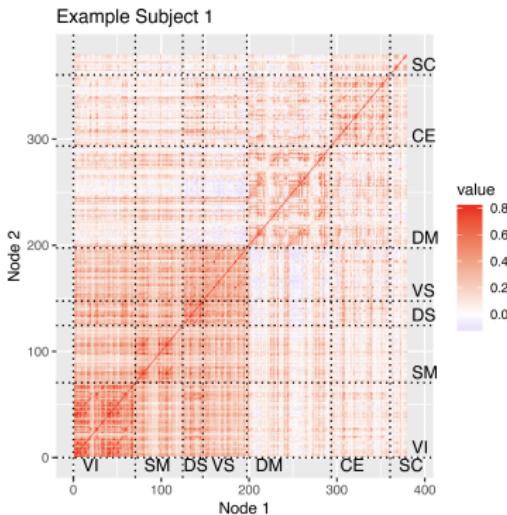
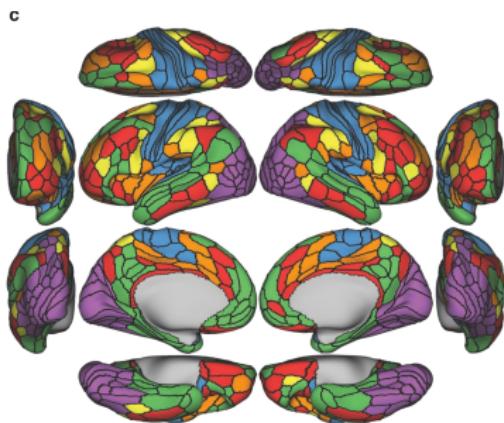
Example activation maps

Input \mathbf{X} : z-stat at each vertex from 2-back versus 0-back task contrast [Barch et al. \(2013\)](#). Vectorized activation maps:
 $p_x \approx 60,000$, $n = 996$.

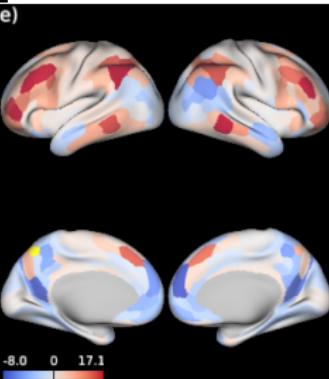
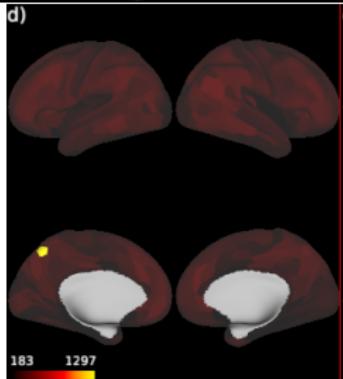
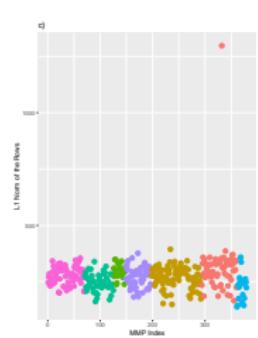
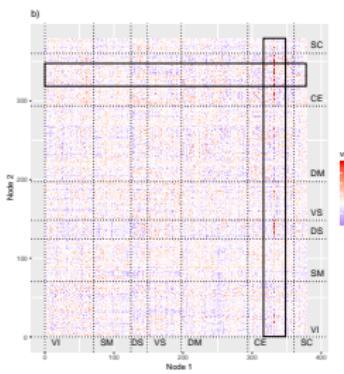
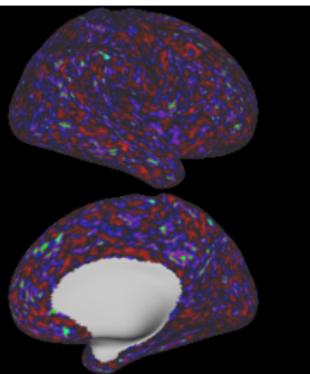
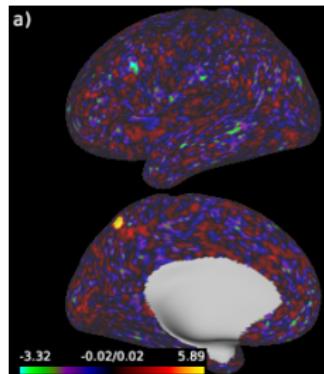


Functional Connectivity: Resting-state correlations

Input **Y**: Fisher-transformed **rs correlations** between regions defined by multi-modal parcellation [Glasser et al. \(2016\)](#); [Akiki and Abdallah \(2018\)](#).



Joint component and fluid intelligence



singR

R package created by Liangkang Wang (MSPH students)
implements the method from [Risk and Gaynanova \(2021\)](#)

- ▶ [singR package on CRAN](#)

The screenshot shows a GitHub repository page for 'thebrisklab/singR'. The main content is the README.md file, which contains R code for generating brain maps. Below the code are two rows of eight brain maps each, labeled 'Component 1 X Estimation' and 'Component 2 X Estimation'. Each row has a color scale at the bottom ranging from -2.43 to 2.82.

```
## README.md
#A_rhoSmall = signchange(2A_rhoSmall)
Sy_rhoSmall = signchange(Sy_rhoSmall)

Estimation plot for X

xii_new <- newdata_xifti(xii_template, cbind(Sxtrue,Sx_rhoSmall))

view_xifti_surface(select_xifti(xii_new,3),zlim = c(-2.43,2.82)) # component1 small rho
view_xifti_surface(select_xifti(xii_new,4),zlim = c(-2.43,2.82)) # component2 small rho
```

Component 1 X Estimation Component 2 X Estimation

Selection bias in functional connectivity studies

Motion quality control causes massive data loss

- ▶ Motion in the scanner produces artifacts ([Power et al., 2012](#)).
- ▶ Lenient criteria: < 5 min data after removing frames with > 3 mm or 3° from previous frame ([Fassbender et al., 2017](#)).
- ▶ Strict criteria: mean framewise displacement > .2 mm or < 5 min data after excluding FD > .25 mm ([Ciric et al., 2017](#)).

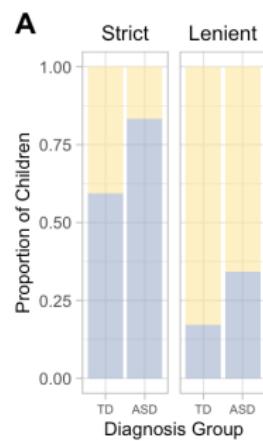


Figure: QC removes 60% and 83% of TD and ASD, respectively, under strict and 16% and 30% under lenient.

The problem: motion exclusion criteria in functional MRI causes selection bias

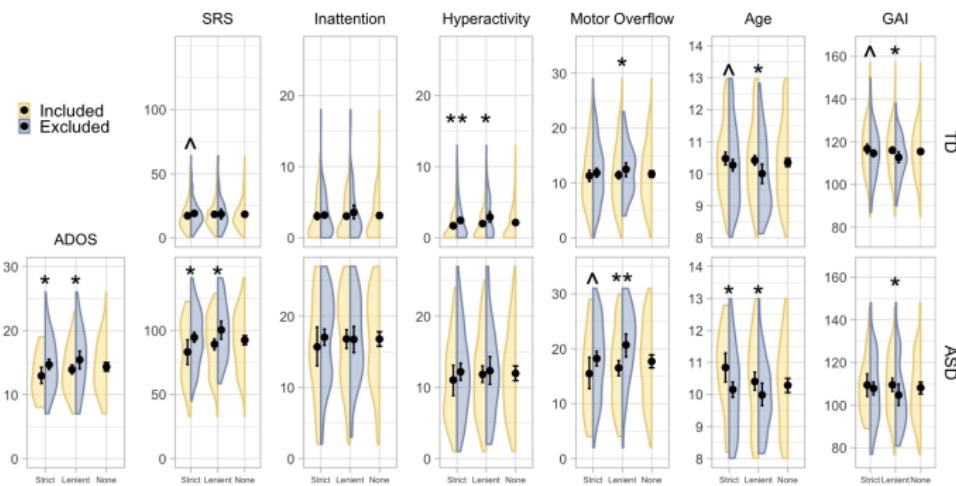
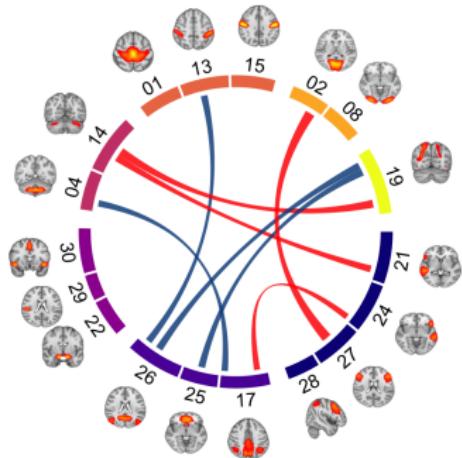
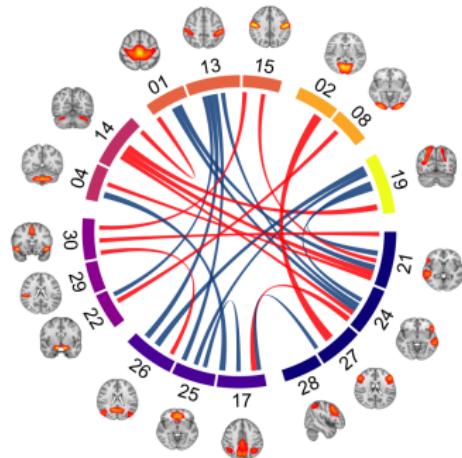


Figure: During quality control, **more severe cases of autism are excluded**. FDR-adjusted p value: ** <0.05 ; * <0.1 ; ^ <0.2 .

Results



(a) Naïve

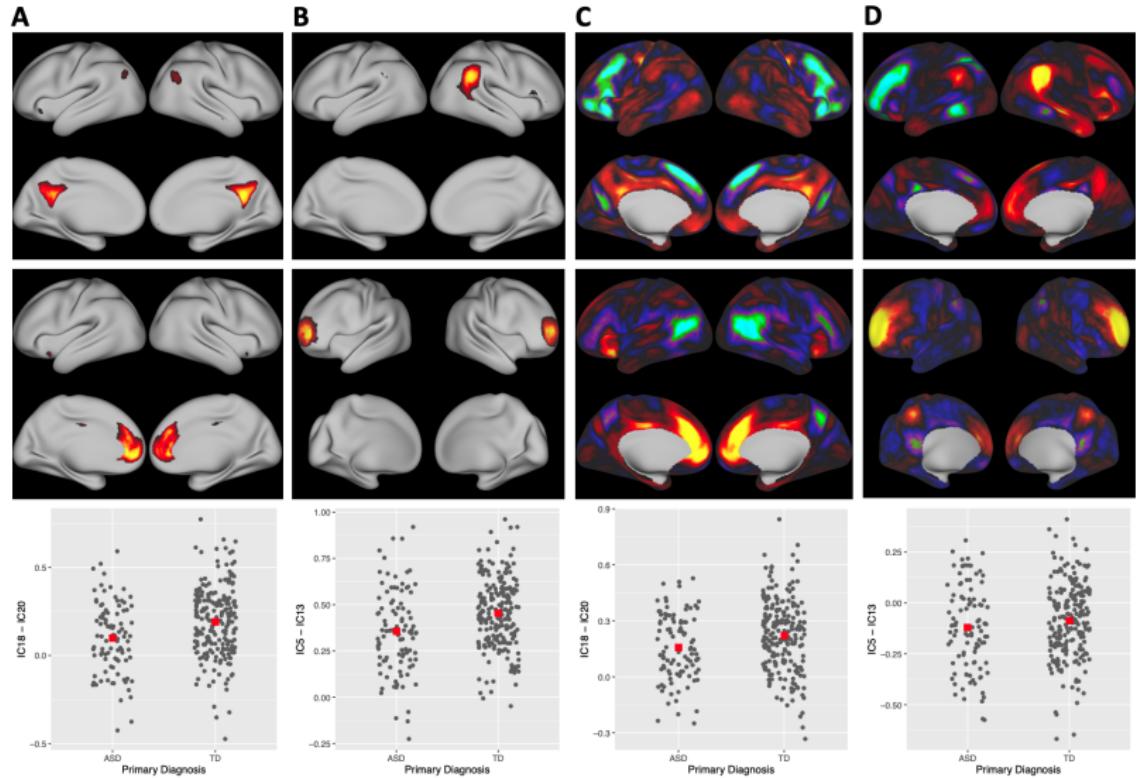


(b) DRTMLE

Figure: Z-stats of ASD-TD difference in partial correlations. Thresholded at FDR=0.20. Blue: ASD>TD. Naïve (left): 8 edges, DRTMLE (right): 25 edges.

Sparse ICA

Sparse ICA



Working in the brisklab

Working in the brisklab

Keys to success:

- ▶ Strong desire to work with complicated data.
- ▶ Ability to independently problem solve.
- ▶ Complete training in fMRI [Lindquist's course in fMRI](#).
- ▶ Volunteer for a semester to see if you like it.

Projects:

1. Examine how engagement during movie watching differs between autistic children and typically developing children.
2. Explore new MRI applications that flexibly model motion artifacts (brain morphometry, longitudinal data).
3. Improving image reconstruction in MRI using convolutional neural networks.
4. Collaborative projects. Areas include Parkinson's disease, calcium imaging in non-human primates, infant brain trajectories, Alzheimer's disease, concussions, and others.

References I

- Akiki, T. J. and Abdallah, C. G. (2018). Determining the Hierarchical Architecture of the Human Brain Using Subject-Level Clustering of Functional Networks. *bioRxiv*, page 350462.
- Barch, D. M., Burgess, G. C., Harms, M. P., Petersen, S. E., Schlaggar, B. L., Corbetta, M., Glasser, M. F., Curtiss, S., Dixit, S., Feldt, C., and others (2013). Function in the human connectome: Task-{fMRI} and individual differences in behavior. *NeuroImage*, 80:169–189.
- Ciric, R., Wolf, D. H., Power, J. D., Roalf, D. R., Baum, G. L., Ruparel, K., Shinohara, R. T., Elliott, M. A., Eickhoff, S. B., Davatzikos, C., Gur, R. C., Gur, R. E., Bassett, D. S., and Satterthwaite, T. D. (2017). Benchmarking of participant-level confound regression strategies for the control of motion artifact in studies of functional connectivity. *NeuroImage*, 154:174–187.
- Fassbender, C., Mukherjee, P., and Schweitzer, J. B. (2017). Reprint of: Minimizing noise in pediatric task-based functional MRI; Adolescents with developmental disabilities and typical development. *NeuroImage*, 154:230–239.
- Glasser, M. F., Coalson, T. S., Robinson, E. C., Hacker, C. D., Harwell, J., Yacoub, E., Ugurbil, K., Andersson, J., Beckmann, C. F., Jenkinson, M., and others (2016). A multi-modal parcellation of human cerebral cortex. *Nature*, 536(7615):171–178.

References II

- Lerman-Sinkoff, D. B., Sui, J., Rachakonda, S., Kandala, S., Calhoun, V. D., and Barch, D. M. (2017). Multimodal neural correlates of cognitive control in the Human Connectome Project. *NeuroImage*, 163.
- Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., and Petersen, S. E. (2012). Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *NeuroImage*, 59(3):2142–2154.
- Risk, B. and Gaynanova, I. (2021). Simultaneous Non-Gaussian Component Analysis (SING) for Data Integration in Neuroimaging. *Annals of Applied Statistics*, 15(3):1431–1454.
- Risk, B., Kociuba, M., and Rowe, D. (2018). Impacts of simultaneous multislice acquisition on sensitivity and specificity in fMRI. *NeuroImage*, 172.
- Risk, B. B., Murden, R. J., Wu, J., Nebel, M. B., Venkataraman, A., Zhang, Z., and Qiu, D. (2021). Which multiband factor should you choose for your resting-state fMRI study? *NeuroImage*, 234:117965.
- Ten Kate, M., Ingala, S., Schwarz, A. J., Fox, N. C., Chételat, G., Van Berckel, B. N., Ewers, M., Foley, C., Gispert, J. D., Hill, D., Irizarry, M. C., Lammertsma, A. A., Molinuevo, J. L., Ritchie, C., Scheltens, P., Schmidt, M. E., Visser, P. J., Waldman, A., Wardlaw, J., Haller, S., and Barkhof, F. (2018). Secondary prevention of Alzheimer's dementia: Neuroimaging contributions. *Alzheimer's Research and Therapy*, 10(1).