Variability of topological features on networks in precision resting-state fMRI.

Juan Carlos Díaz-Patiño[1], Isaac Arelio[2], Sarael Alcauter[1]

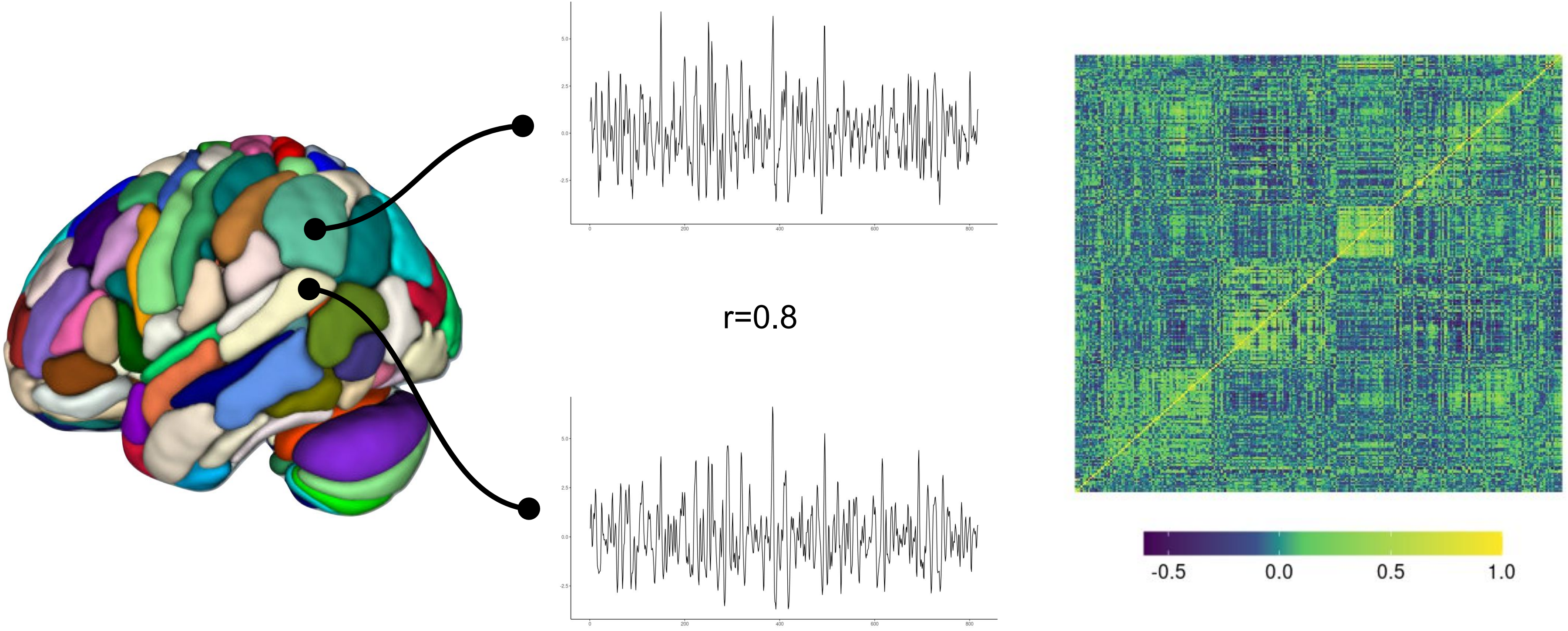
1 Instituto de Neurobiología, UNAM
2 Instituto de Matemáticas, UNAM

Resting state fMRI

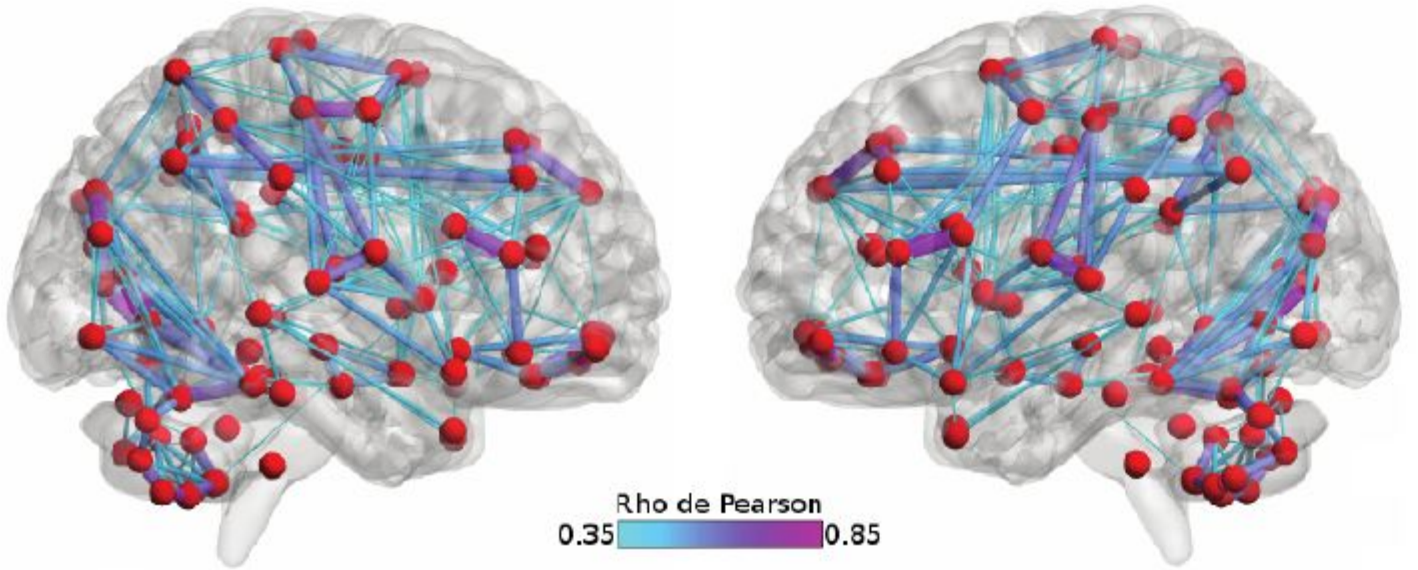
Resting state technique is used to measure spontaneous activity in the BOLD signal (Blood-oxygen-level-dependent).

The instruction for the participants is: don’t sleep, don't close your eyes and don't move during the scanning (around 10 min).

Network construction



Network Construction



Midnight Scanning Club

Is a dataset with 10 pre-processed resting-state fMRI from 10 healthy subjects (100 studies total, 30 min. each study), 5 males, 5 females, ages 24-34.

Subjects MSC08, MSC09 and MSC10 have been reported to close their eyes during sessions and extreme movement (MSC08 possibly was sleeping during sessions).

NeuroResource

Neuron

Precision Functional Mapping of Individual Human Brains

Highlights

- Individual brain organization is qualitatively different from group-average estimates
- Individualized measures of brain function become reliable with large amounts of data
- Individuals exhibit distinct brain network topography and topology
- We release highly sampled, multi-modal fMRI data on ten subjects as a NeuroResource

Authors

Evan M. Gordon, Timothy O. Laumann, Adrian W. Gilmore, ..., Steven E. Petersen, Steven M. Nelson, Nico U.F. Dosenbach

Correspondence

evan.gordon@va.gov (E.M.G.), laumannt@wustl.edu (T.O.L.), steven.nelson1@va.gov (S.M.N.), ndosenbach@wustl.edu (N.U.F.D.)

In Brief

Gordon et al. demonstrate advantages of conducting whole-brain fMRI research in individual humans using large amounts of per-individual data, which greatly increases reliability and specificity. This work illustrates new approaches for fMRI-based neuroscience that allow detailed characterization of individual brain organization.

Network construction

Each correlation matrix is transformed to a distance matrix with the formula d=1-r.

Betti Curves and Minimum Spanning Trees where extracted from each distance matrix by their Vietoris-Rips filtration.

The networks where built using three different atlas.

- Individual cortical Parcellations given in the MSC dataset,
- a priori cortical Parcellation, Gordon 2016,
- Whole brain atlas, Power 2011.

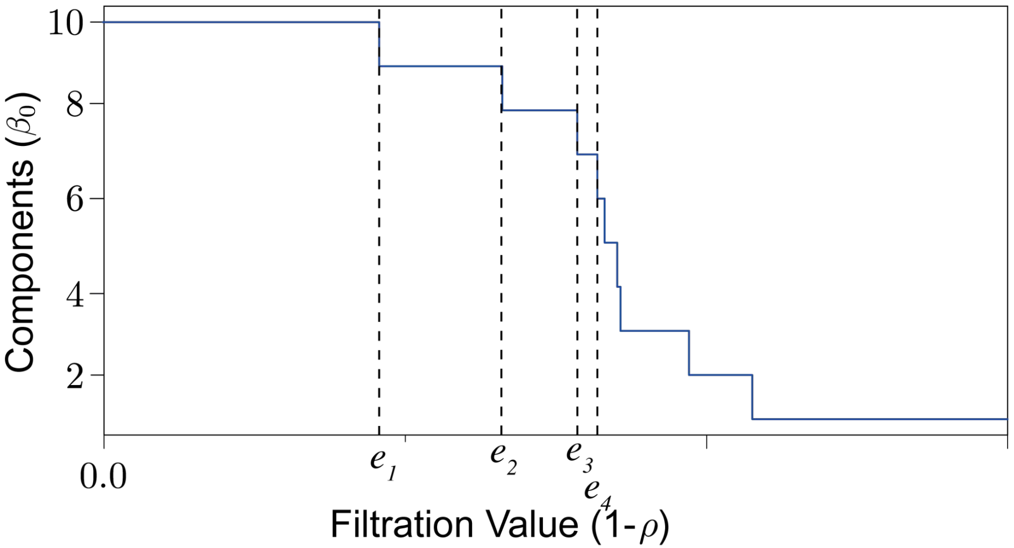
Comparisons between Betti curves are done with the l_p distances and MST's comparisons are done using the L_1 norm and L_2.

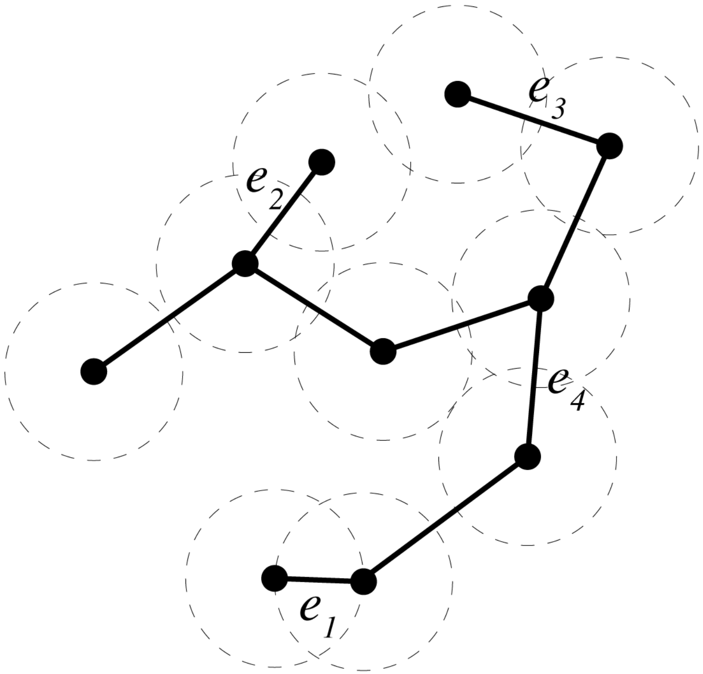
$$l_1(f,g) = \int_0^2 |f-g|dx \qquad l_p(f) = \left(\int_0^2 f^p dx\right)^{1/p}$$

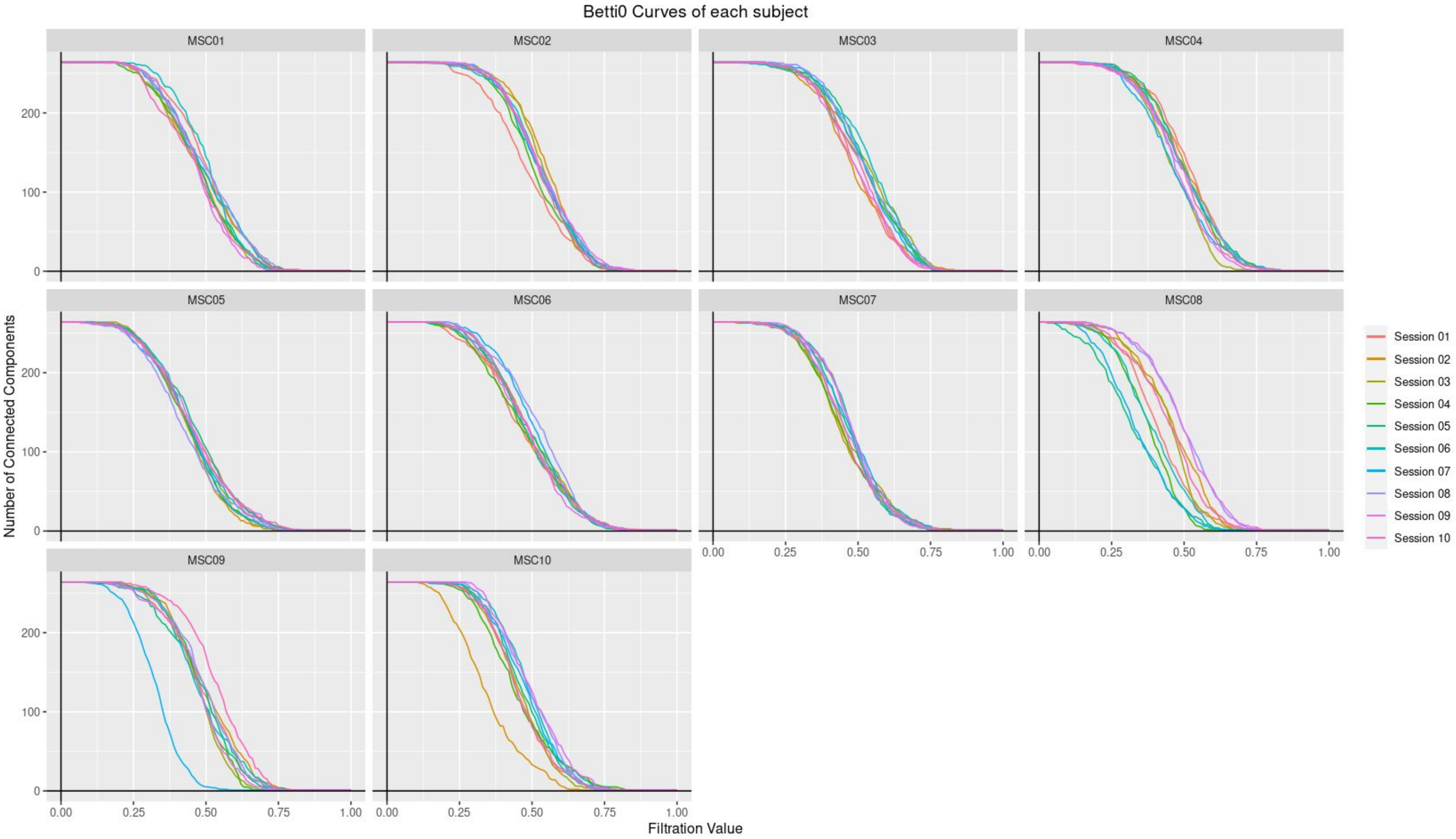
$$L_1(x,y) = \sum^n \{|x_i - y_i|\} \quad L_2(x,y) = \left(\sum^n (x_i - y_i)^2\right)^{1/2}$$

Minimum Spanning Tree

Given a weighted graph with no repeated and positive edge weights, there is an spanning tree with minimum weight.







Betti0 Curves of each subject
MSC01
MSC02
MSC03
MSC04
MSC05
MSC06
MSC07
MSC08
MSC09
MSC10
Number of Connected Components
Filtration Value
0
100
200
0.00
0.25
0.50
0.75
1.00
Session 01
Session 02
Session 03
Session 04
Session 05
Session 06
Session 07
Session 08
Session 09
Session 10

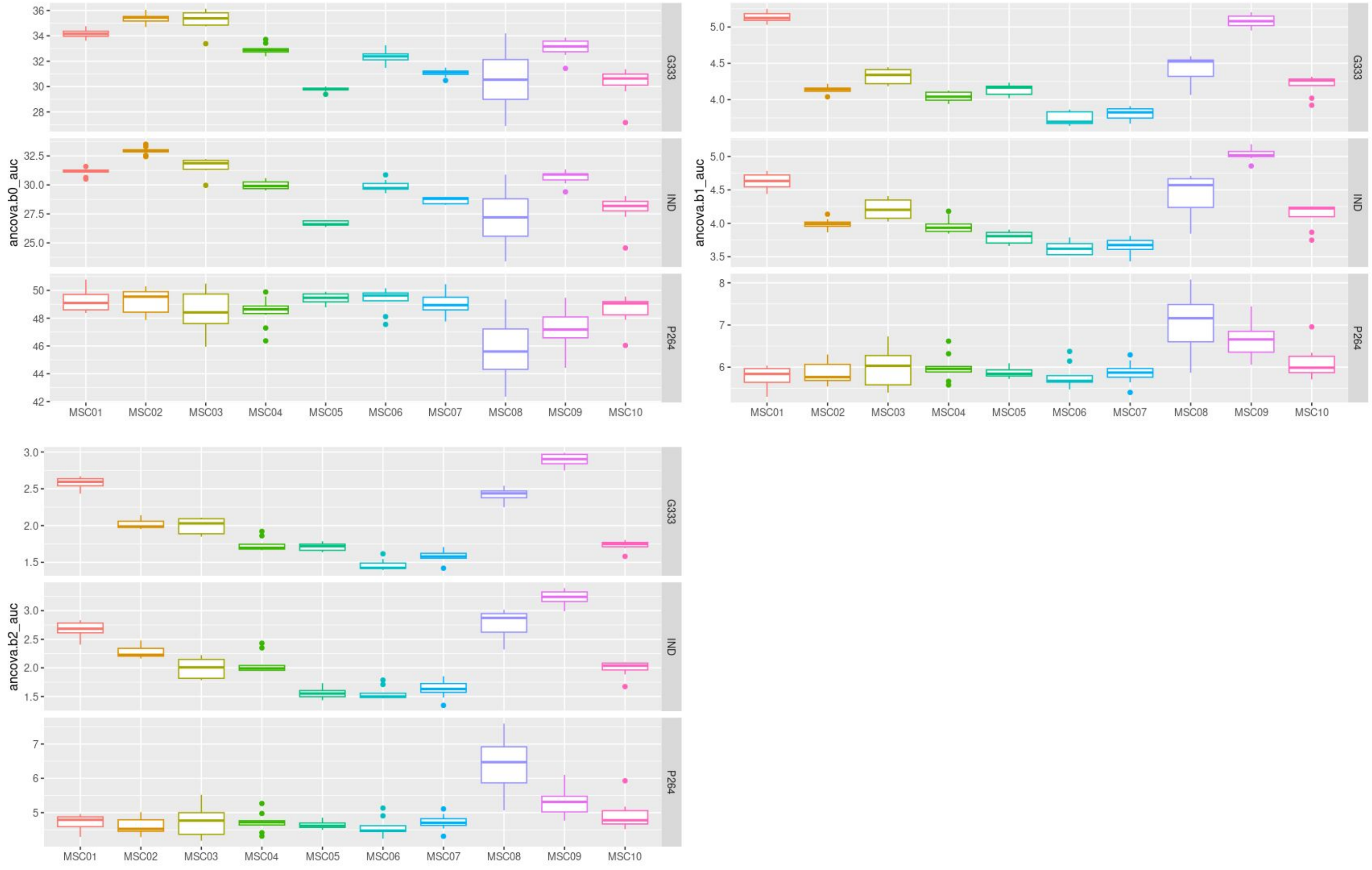
Research Questions.

How reliable is the information obtained from fMRI? do they change a lot between sessions?

What is the variability of the topological and graph features of the networks associated to each individual?

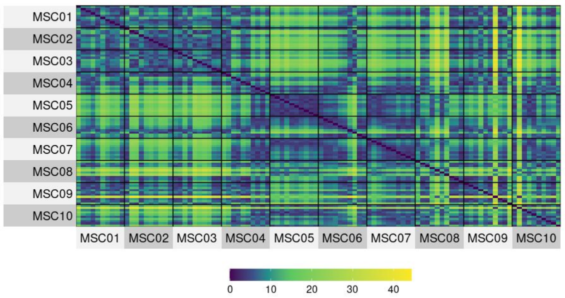
Hypothesis: There is low variability within individuals and greater variability between individuals.

Boxplots of AUC for dimensions 0,1 and 2 (ANCOVA)

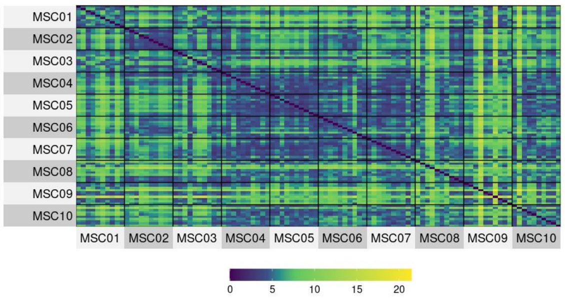


Comparisons between Betti Curves

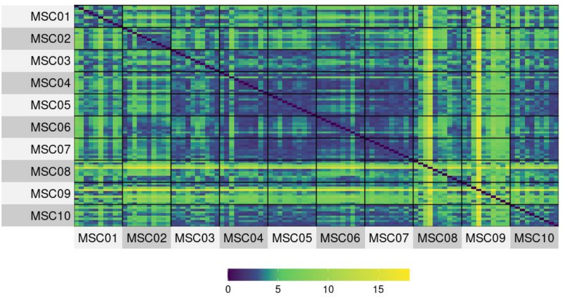
l1-distance Between Betti_0 curves, G333



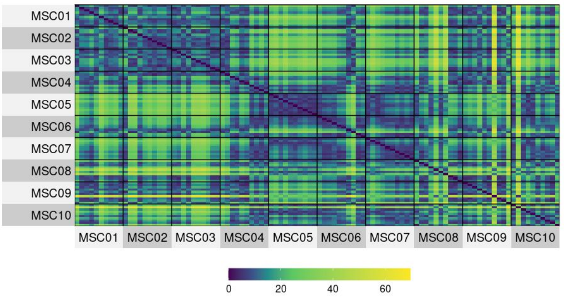
l1-distance Between Betti_1 curves, G333



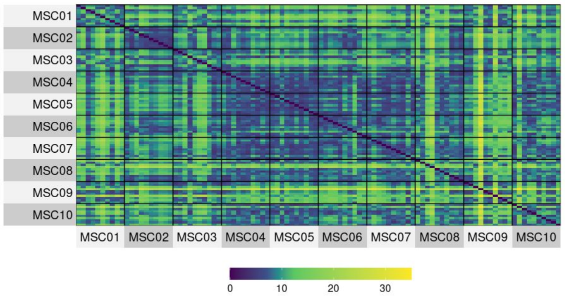
l1-distance Between Betti_2 curves, G333



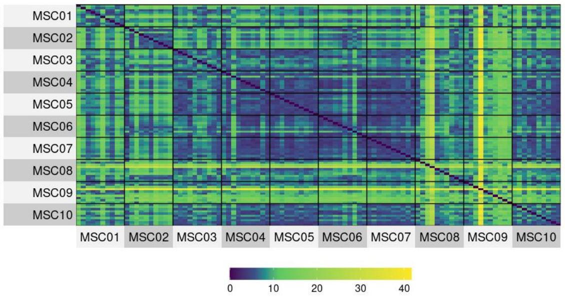
l2-distance Between Betti_0 curves, G333



l2-distance Between Betti_1 curves, G333

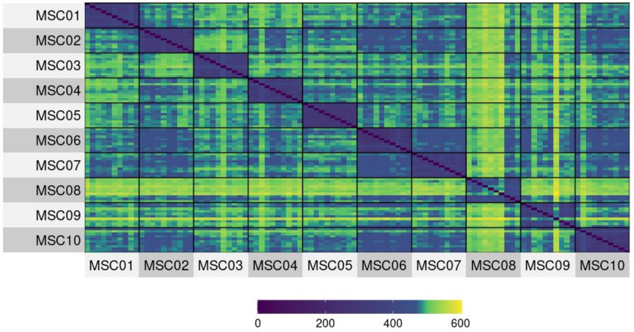


l2-distance Between Betti_2 curves, G333

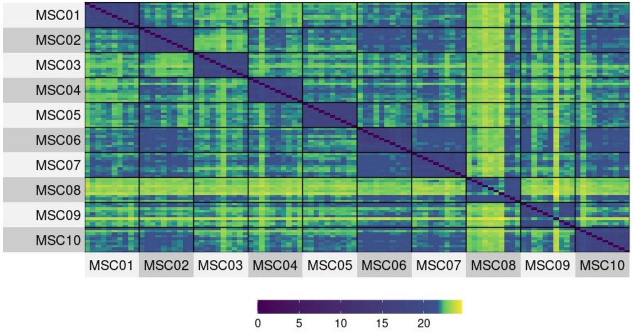


Comparisons between MST’s

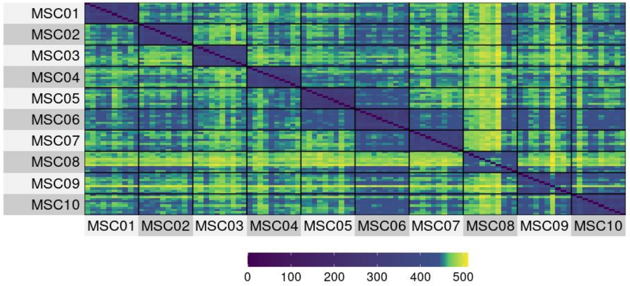
Manhattan Distance Between MST's, G333 Parcellation



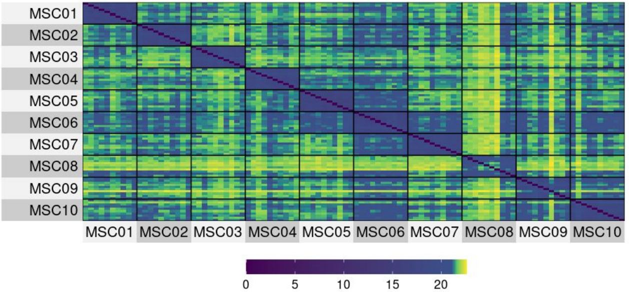
Euclidean Distance Between MST's, G333 Parcellation



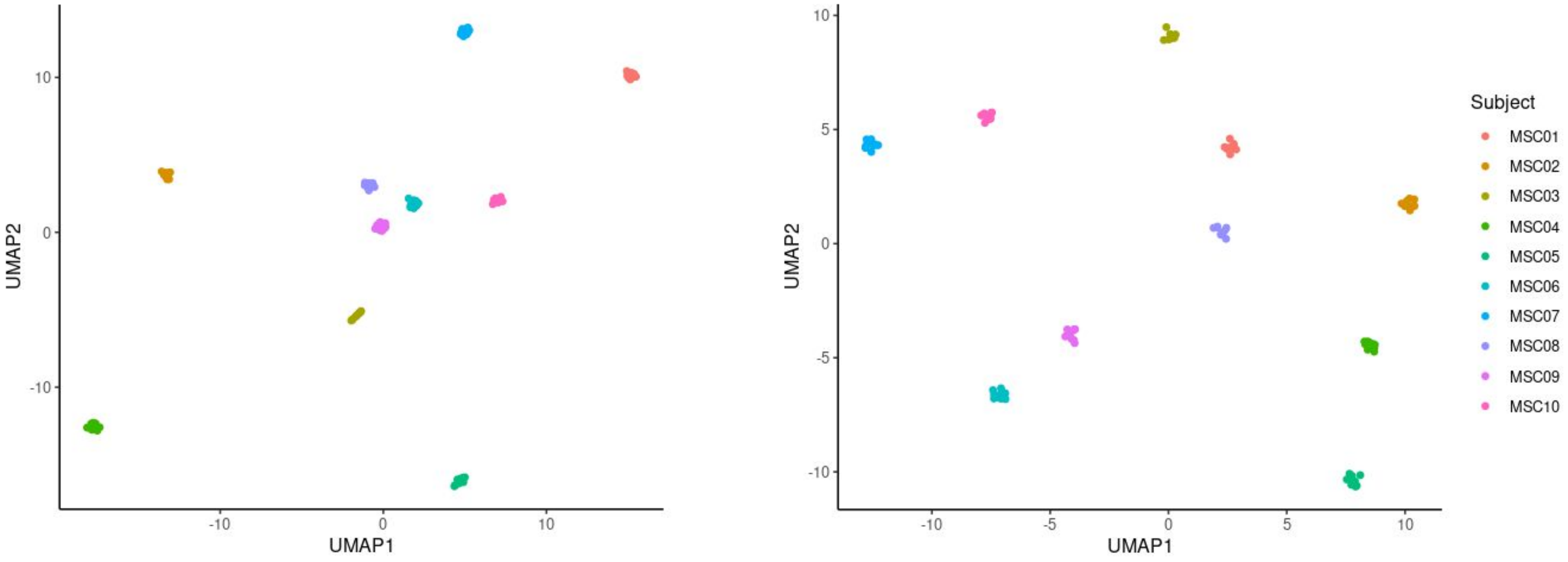
Manhattan Distance Between MST's, P264 Atlas



Euclidean Distance Between MST's, P264 Atlas



UMAP dimension reduction



UMAP projection for atlas G333 and P264 of MST’s

Conclusions

- AUC of Betti Curves showed low variability within subjects and higher variability between subjects with exceptions on MSC08, MSC09 and MSC10.
- L_1 and L_2 distances didn't show the same effect.
- MST is a more specific way to differentiate subjects and showed lower variability within subjects and higher variability between subjects.
- Topological and Graphs Features are relevant (especially the ones that are interconnected).
- Cortical Parcellations gives us a better way to differentiate subjects.

More questions:

- The same effect is detected with other topological/graph constructions? (Landscapes, Scaffolds).
- What is the variability within the same sessions? (Sliding windows).

References

1. Bauer, U. (2021). Ripser: Efficient computation of Vietoris–Rips persistence barcodes. Journal of Applied and Computational Topology, 5(3), 391–423. https://doi.org/10.1007/s41468-021-00071-5
2. Gordon, E. M., Laumann, T. O., Gilmore, A. W., Newbold, D. J., Greene, D. J., Berg, J. J., Ortega, M., Hoyt-Drazen, C., Gratton, C., Sun, H., Hampton, J. M., Coalson, R. S., Nguyen, A. L., McDermott, K. B., Shimony, J. S., Snyder, A. Z., Schlaggar, B. L., Petersen, S. E., Nelson, S. M., & Dosenbach, N. U. F. (2017). Precision Functional Mapping of Individual Human Brains. Neuron, 95(4), 791-807.e7. https://doi.org/10.1016/j.neuron.2017.07.011
3. Gracia-Tabuenca, Z., Díaz-Patiño, J. C., Arelio, I., & Alcauter, S. (2020). Topological Data Analysis Reveals Robust Alterations in the Whole-Brain and Frontal Lobe Functional Connectomes in Attention-Deficit/Hyperactivity Disorder. eNeuro, 7(3), ENEURO.0543-19.2020. https://doi.org/10.1523/ENEURO.0543-19.2020
4. Gracia-Tabuenca, Z., Díaz-Patiño, J. C., Arelio-Ríos, I., Moreno-García, M. B., Barrios, F. A., & Alcauter, S. (2023). Development of the Functional Connectome Topology in Adolescence: Evidence from Topological Data Analysis. eNeuro, 10(2). https://doi.org/10.1523/ENEURO.0296-21.2022
5. Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., Vogel, A. C., Laumann, T. O., Miezin, F. M., Schlaggar, B. L., & Petersen, S. E. (2011). Functional Network Organization of the Human Brain. Neuron, 72(4), 665–678. https://doi.org/10.1016/j.neuron.2011.09.006
6. Package in R, 2022. https://cran.r-project.org/package=TDA

email: juancdp@inb.unam.mx

What do Betti's curves look like?