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Harnessing cloud computing for high capacity analysis of neuroimaging data from NDAR

Daniel Clark[1], Christian Haselgrove[2], David Kennedy[2], Zhizhong Liu[3], Michael Milham[1], Petros Petrosyan[4], Carinna Torgerson[3], John Van Horn[3], Cameron Craddock[1]

[1]Child Mind Institute, New York, NY, [2] University of Massachuttes Medical School, Worcester, MA, [3]University of Souther California, Los Angeles, CA, [4]UCLA, Los Angeles, CA, [5]Nathan S. Kline Institute for Psychiatric Research, Orangeburg, NY

Introduction

- The National Database for Autism Research (NDAR) hosts a vast collection of neuroimaging datasets that can be processed and utilized to yield significant scientific discoveries.
- This amount of resources necessitates a high-performance computing (HPC) infrastructure, which is not always readily available for researchers in-house.
- Amazon Web Services (AWS) Elastic Compute Cloud (EC2) computing service offers a “pay as you go” model that allows researchers to utilize HPC performance without the up-front captial costs and maintenance of an in-house solution.
- The developers of the Laboratory of Neuro Imaging (LONI) Pipeline, the Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC) Computational Environment (CE) and the Configurable Pipeline for the Analysis of Connectomes (C-PAC) have implemented pipelines in EC2 that interface with NDAR

Methods

- Launched an AWS-hosted miNDAR database by querying NDAR website for the data of interest (e.g. from a particular study)
- Built a subject list by querying the database for subjects of interest to pass to our pipeline
- Launch an AWS EC2 HPC cluster using Starcluster
- Log into the cluster and submit a Sun Grid Engine job using our pipeline software and the subject list
- The pipeline software will process the data, store raw outputs in an AWS S3 bucket and insert S3 filepaths and output measures into miNDAR database

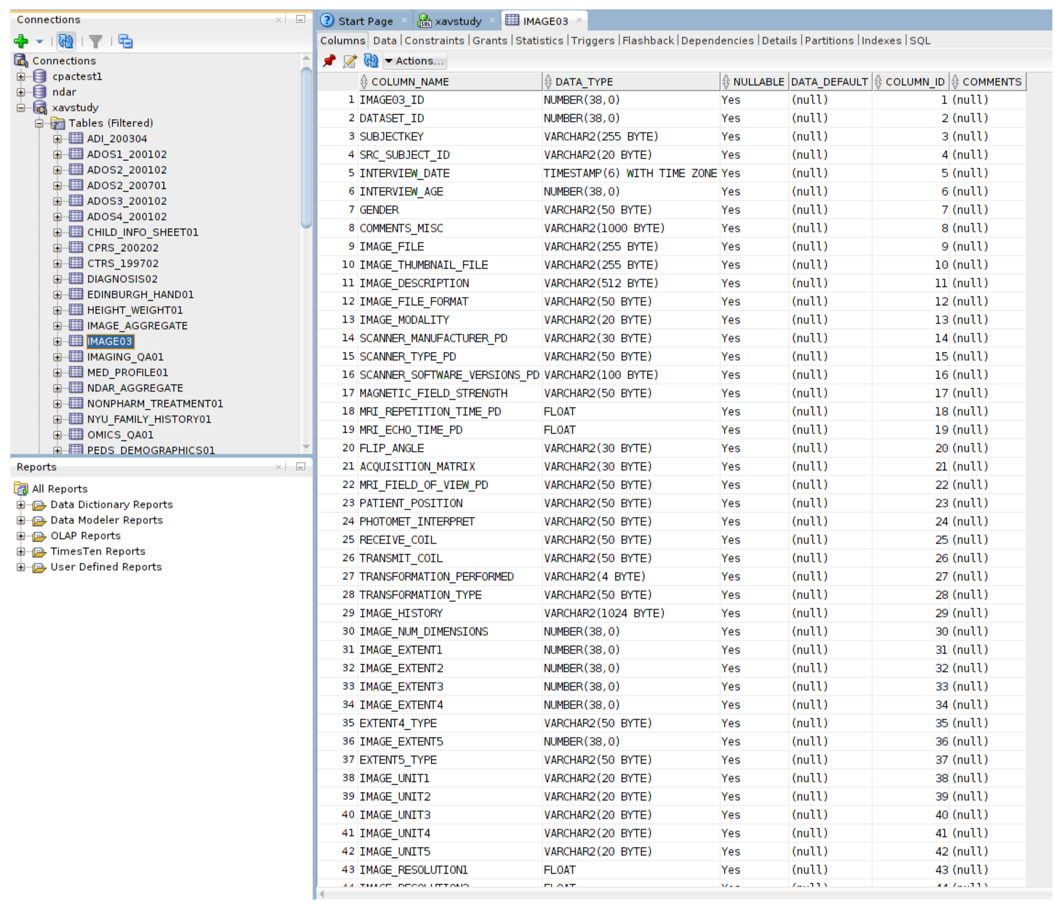


Figure 1 : miNDAR database

Online Preprocessing

- RT denoising implemented in AFNI[10] to remove contributions of confounds (intensity modulations induced by head motion, physiological noise, scanner drift, . . .)
  - N^{th} order polynomial
  - Global mean
  - Mask average time series (i.e. WM, CSF)
  - Motion parameters (6 or 24 regressor models)
  - Spatial smoothing
- Adds < 5 ms of delay

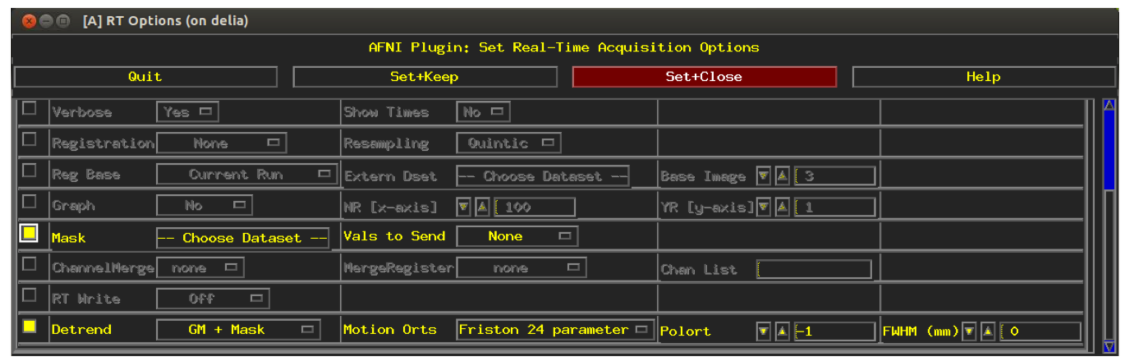
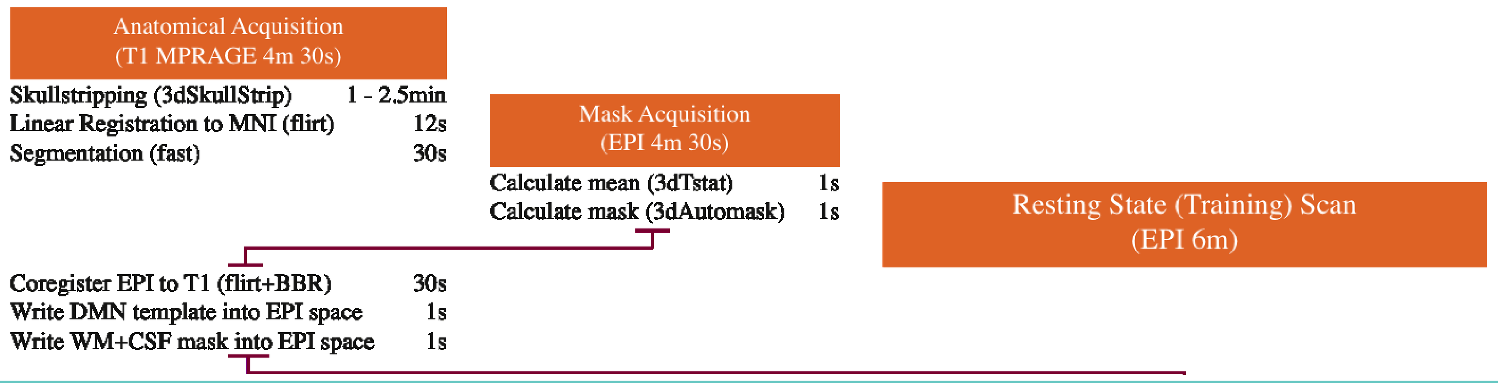


Figure 2 : AFNI interface for online denoising.



Results

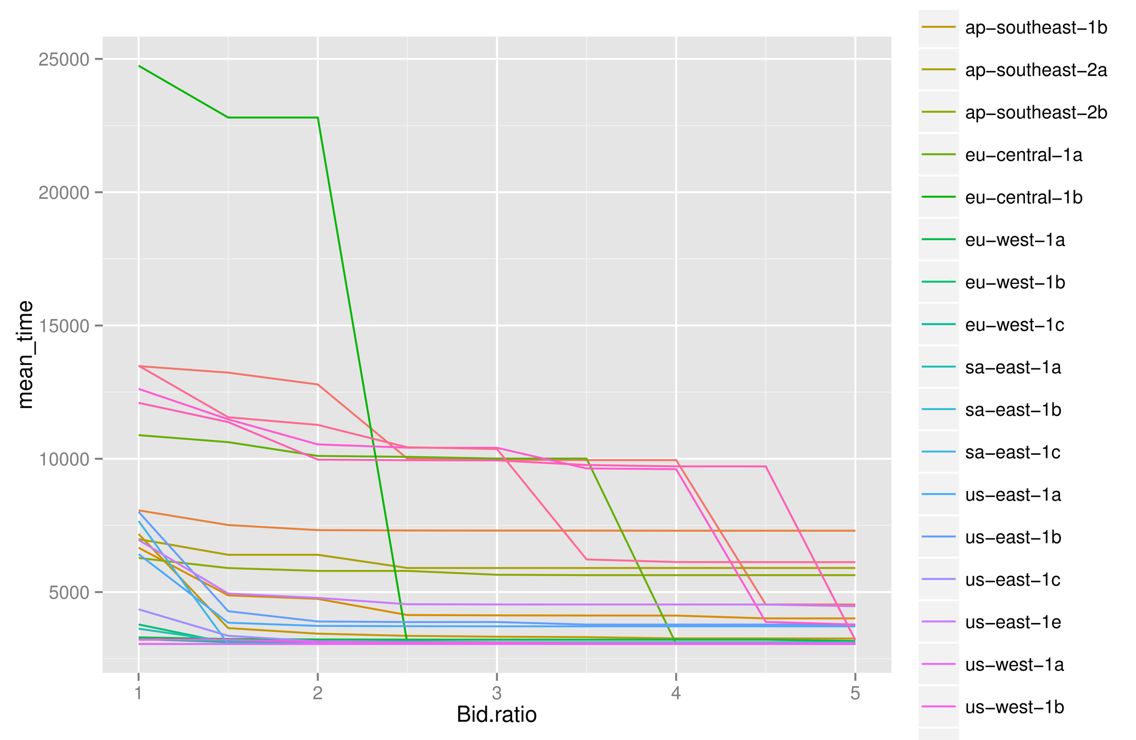


Figure 4 : Bid ratio vs Computation time in minutes for the Freesurfer pipeline

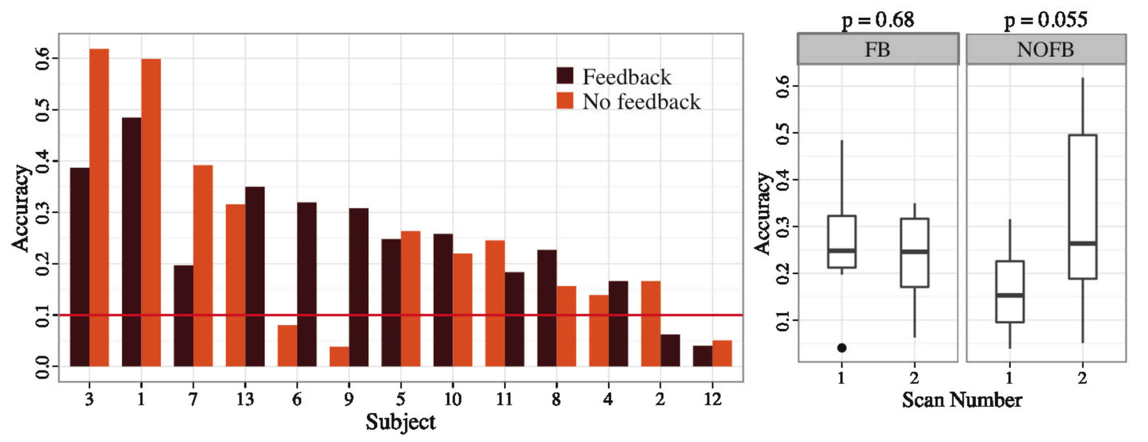


Figure 5 : Performance across particpants (A) differs between feedback and neurofeedback scans as determined by their order (B).

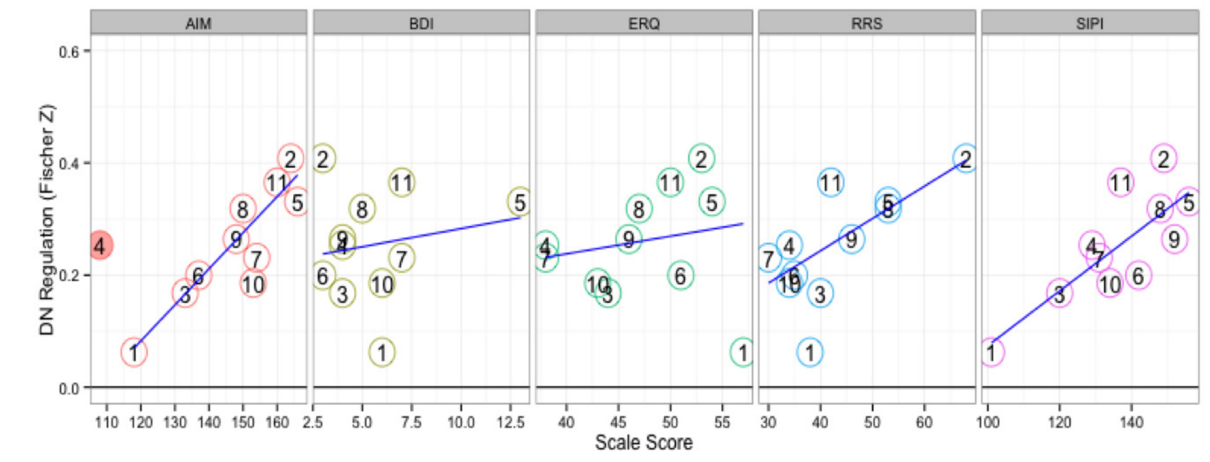


Figure 6 : Inter-individual variation in preformance correlates with behavioral measures.

- As shown in figure 4 models learned for the best and worst performing participants match with the canonical pattern of the default network.
- The best participant was able to follow the instructions very well 4, the worst seems to have been corrupted by noise.
- Figure 5 shows 12 of the subjects were able to modulate the DN at above chance levels, performance on feedback runs is consistent independent of order, but performance on nonfeedback runs improves if they occur after feedback runs.
- Measures that were significantly associated with DN regulation include ($p < 0.05$, FDR corrected): the affect intensity measure (AIM), ruminative responses scale (RRS), and the imaginal processes inventory.

Conclusion

- We developed a system for measuring DN regulation using realtime neurofeedback.
- Participants were able to modulate their DN activity and their ability to do so was correlated with phenotype.
- This system provides a new experimental paradigm for understanding network dysregulation and how it maps to disease states and phenotype.

References and Acknowledgements

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cameron.craddock@childmind.org