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

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Michael Milham[1], Petros Petrosyan[4], Carinna Torgerson[3], John Van Horn[3], Cameron Craddock[1]

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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
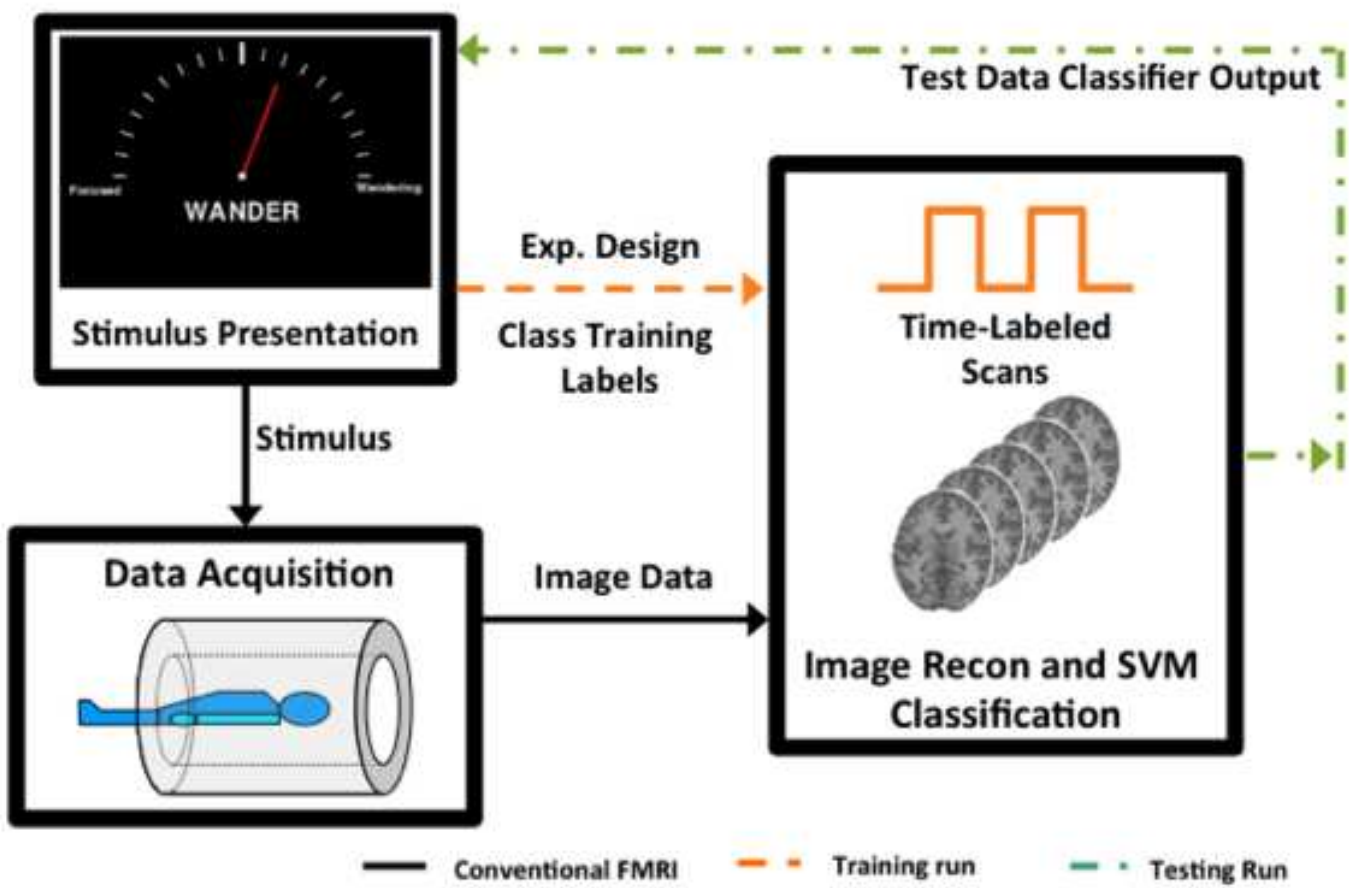
Methods

Figure 1 : Neurofeedback experiment, adapted from S. LaConte[8,9]

Subjects
▶ 13 volunteers participated in accordance with IRB Policy.

Scanning
▶ 3.0T Siemens Magnetom TIM Trio using 12-channel head matrix.
  ▷ T1 weighted 3D MPRAGE anatomical scan (FA$=8°$, TI$=900$ms, TR$=2600$ms, TE$=3.02$ms, GRAPPA $\times2$)
  ▷ Realtime fMRI experiments were performed using an EPI seqeunce that has been customised to export reconstructed image volumes, over a network connection, as they are connected[8,9]
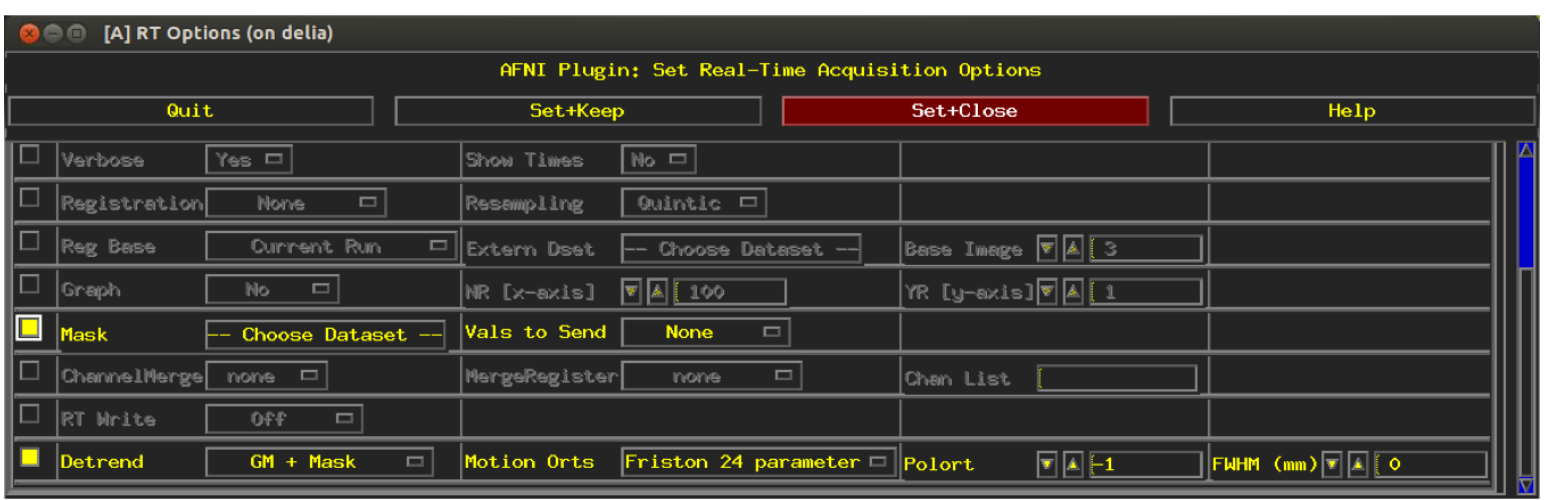   ▸ TR/TE/FA/FOV $= 2000$ ms/30 ms/$90°$/220 mm, in plane resolution $3.44 \times 3.44 \times 4$ mm^3

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

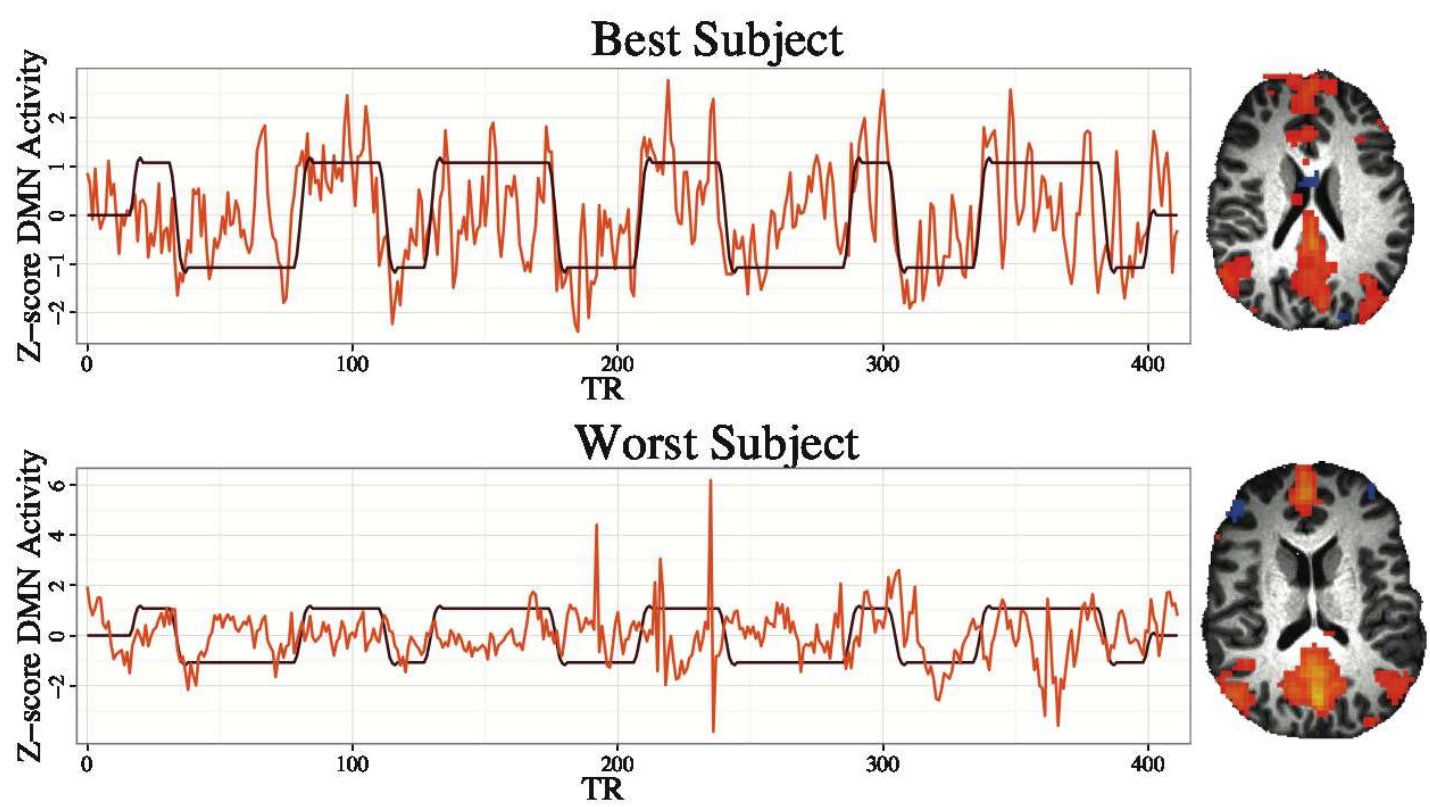Figure 2 : AFNI interface for online denoising.
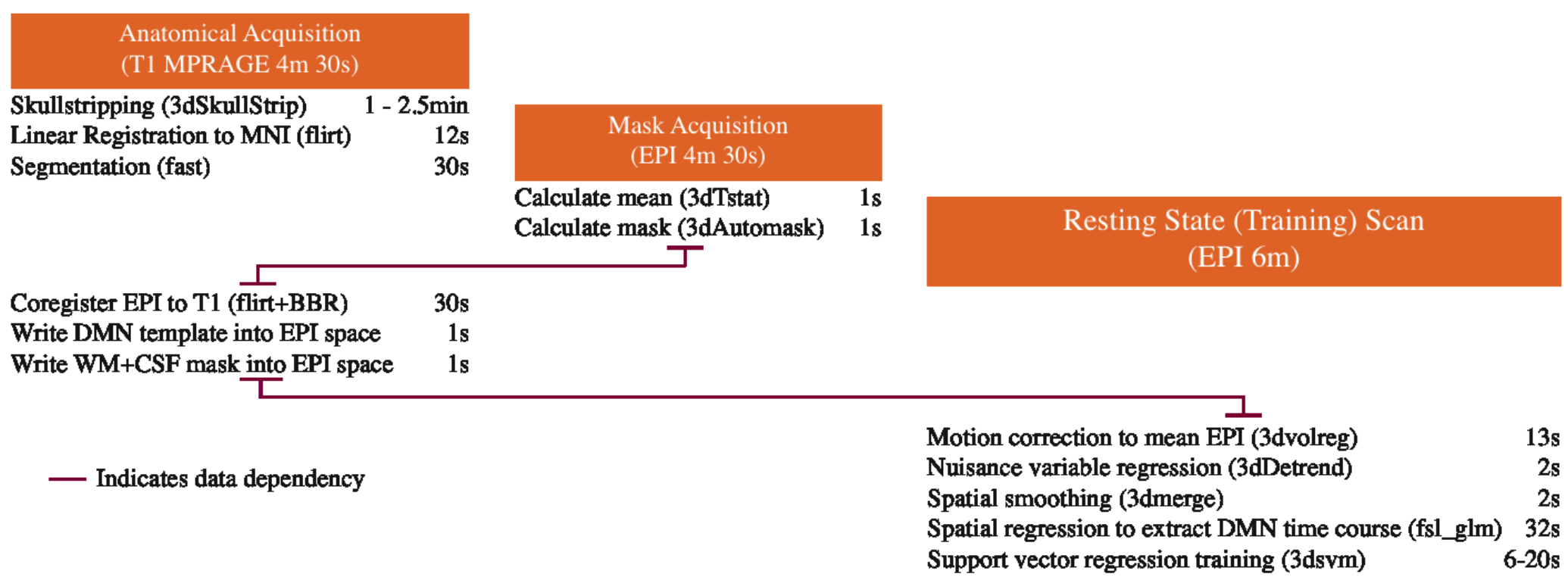
Results

Figure 4 : Example of classifier and feedback timecourse for participants with the best and worst performance.
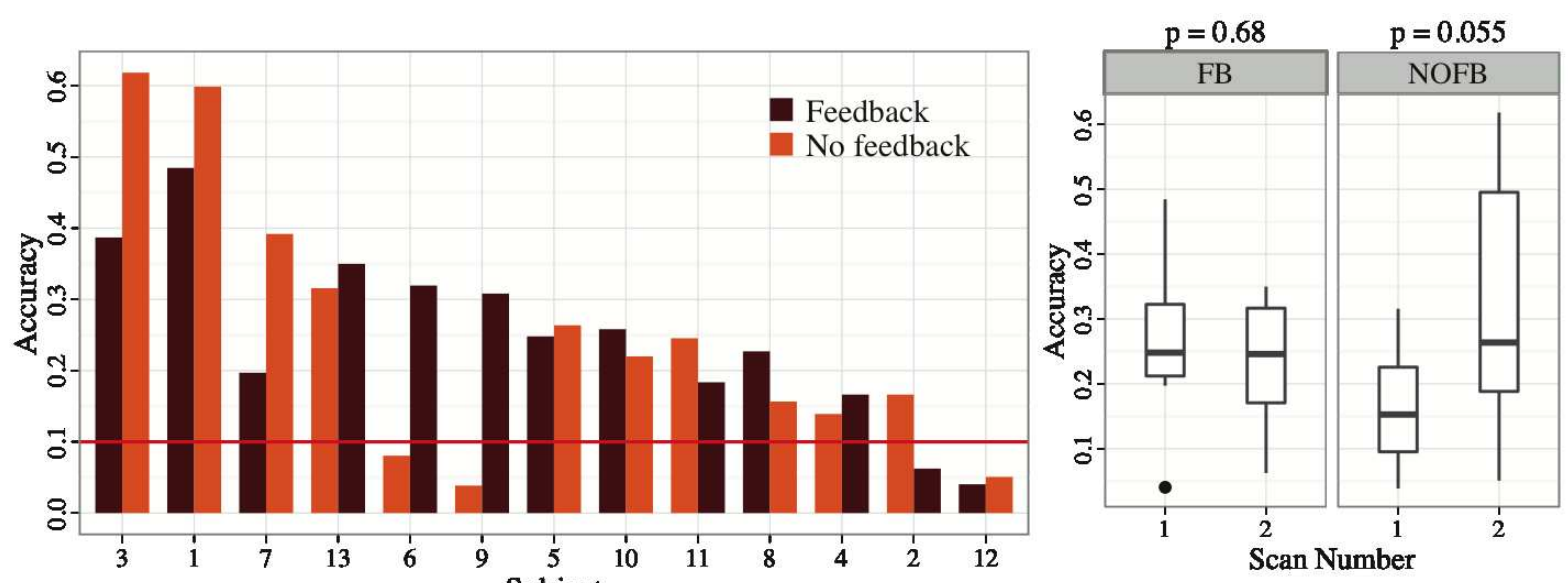

Figure 5 : Performance across particpants (A) differs between feedback and neurofeedback scans as determined by their order (B).
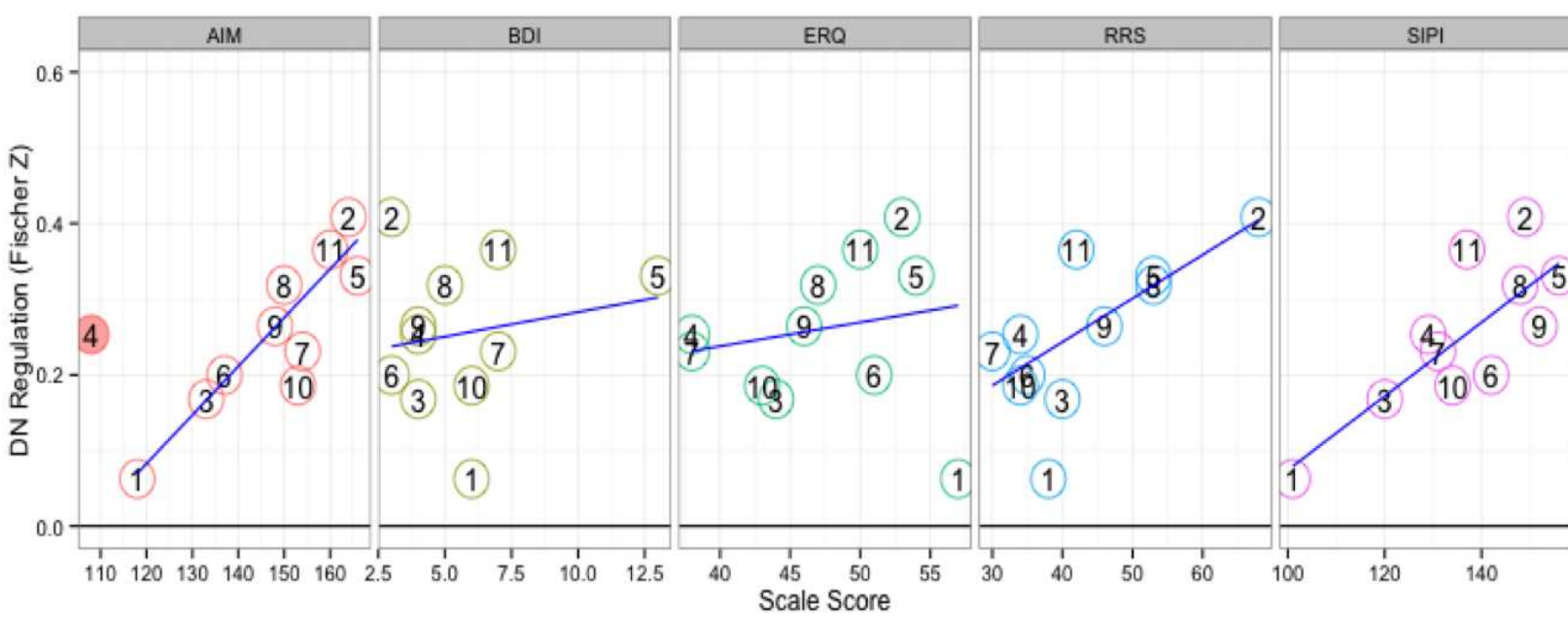

Figure 6 : Inter-individual variation in preformance correlates with behavioral measures.

▶ 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 instructures 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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