Deep learning for analysis of diffusion-MRI based white matter tractometry

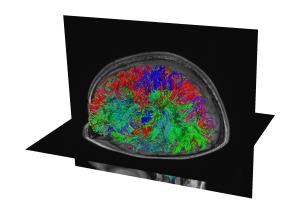
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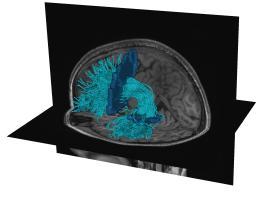
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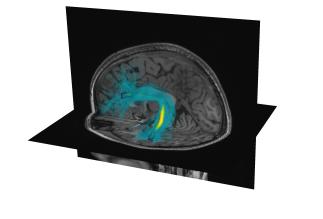


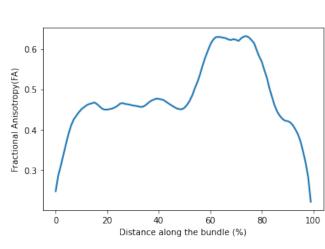
Introduction

- Tractometry uses diffusion MRI (dMRI) to quantify brain tissue properties within white matter connections in vivo [1].
- The Healthy Brain Network Processed Open Derivatives (HBN POD2) is a large (n>2,000) pediatric dMRI dataset that has been processed and automatically QC'd[2,
- The pyAFQ software was used to create tract profiles for statistical analysis [4].
- In previous work, we demonstrated that regularized regression provides accurate predictions of individual age in HBN from tractometry data (WM-based "brain
- These models cannot capitalize on non-linear effects and sequence features, but deep learning models are well-suited to do that.









Whole brain tractography

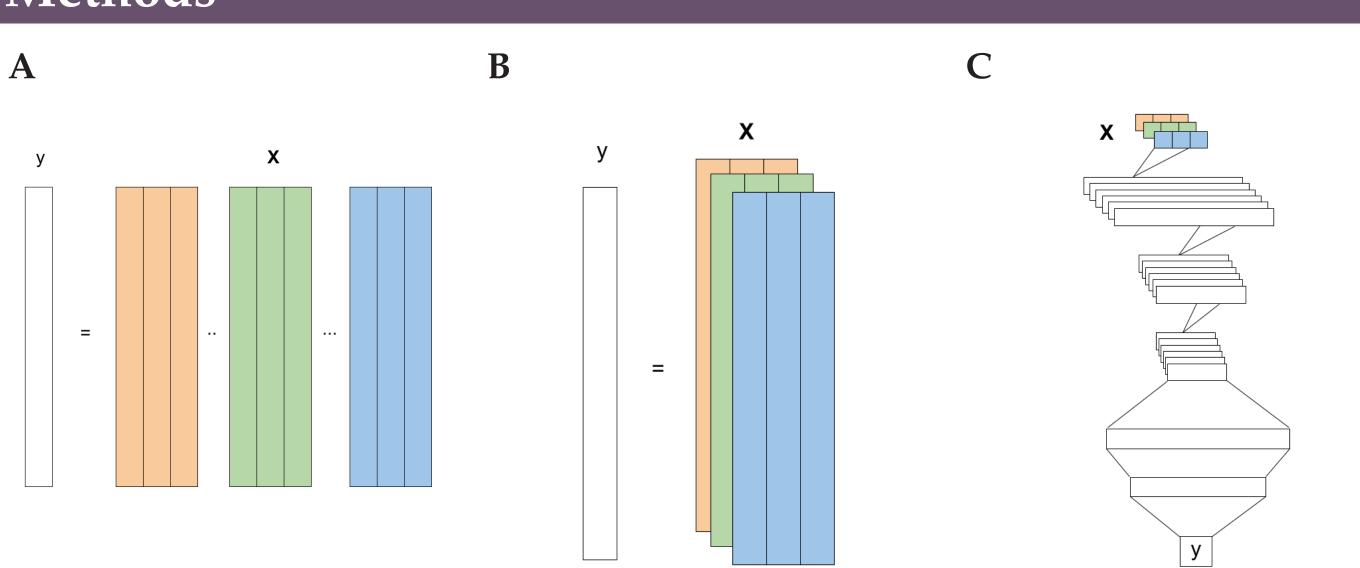
Selecting a bundle with ROIs

Extracting values along the length of the tract

Tract profile

Question: Does deep learning provide improvements in inferences from tractometry?

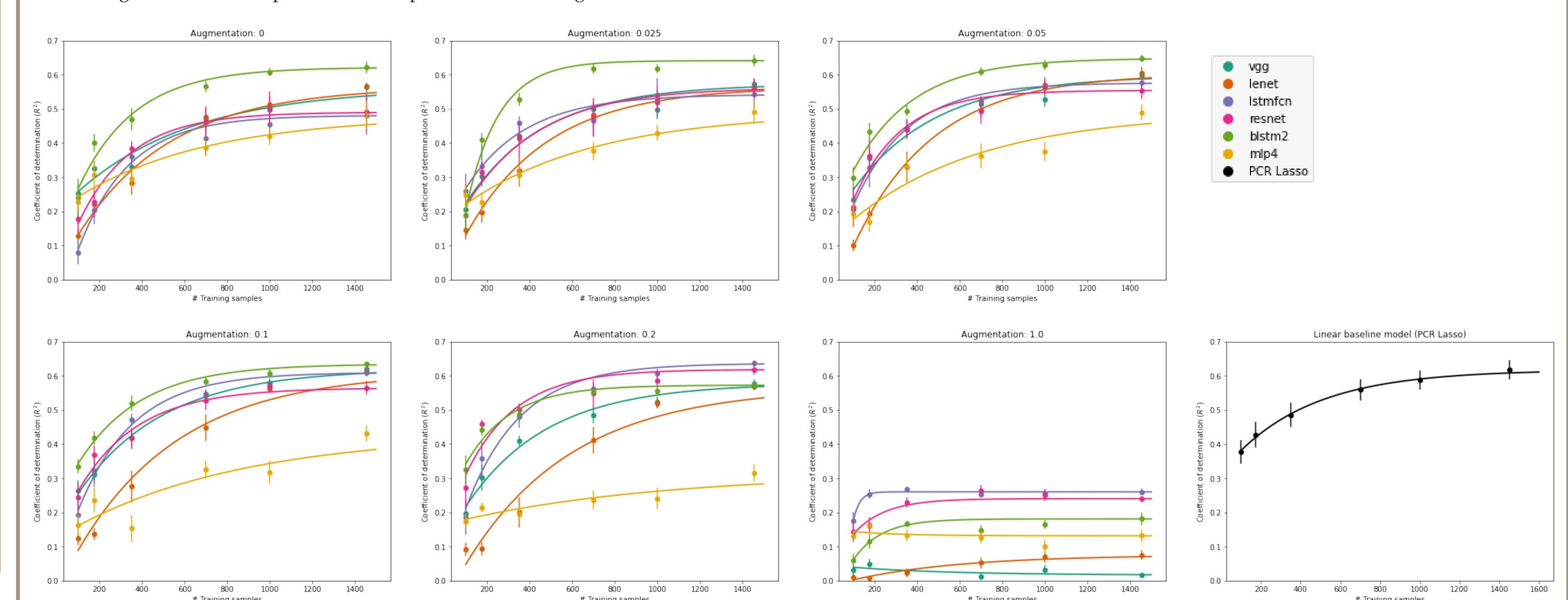
Methods



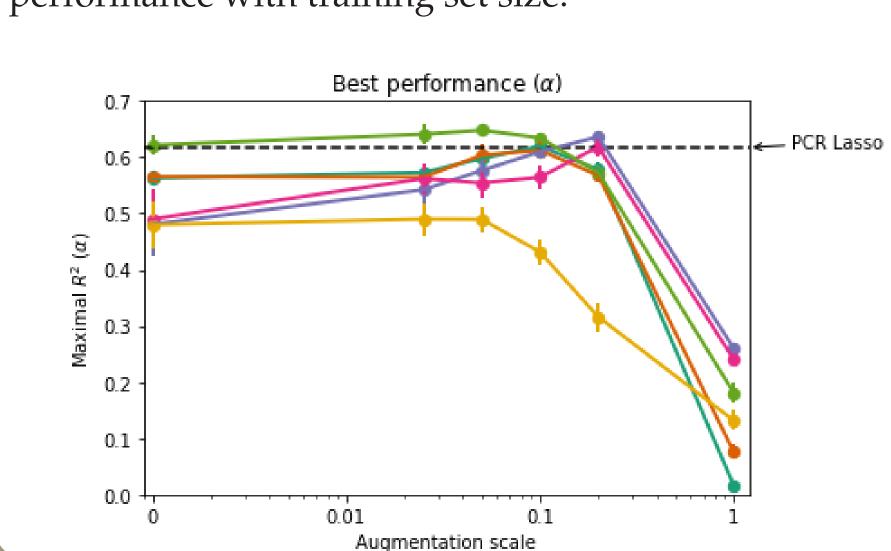
- (A) In a linear tractometry model, $y = \beta X$. (B) To move towards a convolutional neural networks, we stack the data from different tracts and metrics (FA, MD, MK) as different measurement "channels". (C) Training samples are then passed to a network (here as schematic)
- We used the 1817 subjects from HBN POD2 that had passing QC scores and age information.
- A variety of convolutional neural networks were implemented in AFQ-Insight (https://richiehalford.org/AFQ-Insight)
- We trained the models in "brain age" prediction. To evaluate the models, we set aside a test set of 20% of the subjects (363 subjects)
- To compare model dependence on training set size, we trained with variable train set sizes (100, 175, 350, 700, 1000, 1453 subjects) and different augmentation levels
- We compared to a state-of-the-art linear model: PCR Lasso [5]
- Model performance was quantified as the coefficient of determination, R^2 , in predicting the age of the test set subjects.
- R^2 was modeled as: $\alpha (\alpha \beta)e^{-\frac{x-x_{min}}{\kappa}}$, where x is the number of training samples, α is R^2 at the maximal number of training samples, β is R^2 at the smallest number of training samples (x_{min}) and κ is a free parameter that denotes that number of training samples required to achieve R^2 that is 67% of the difference between β and α .

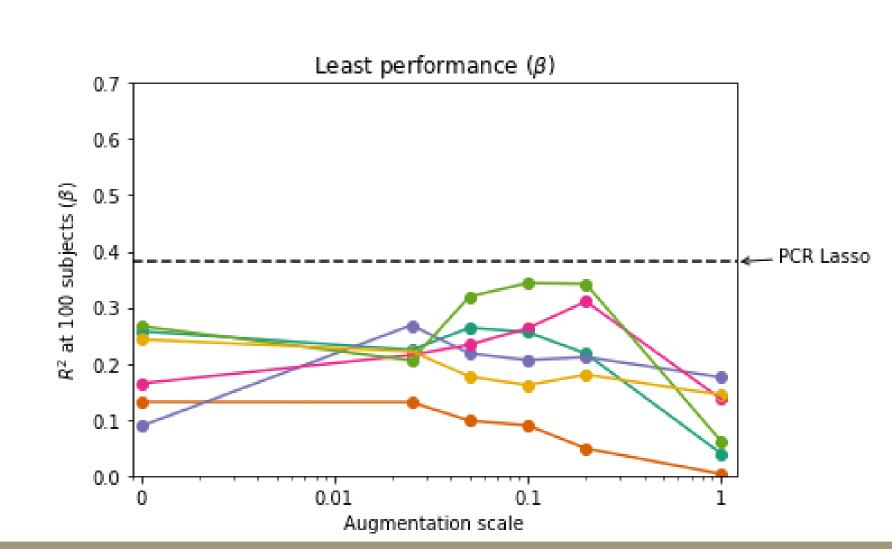
Results

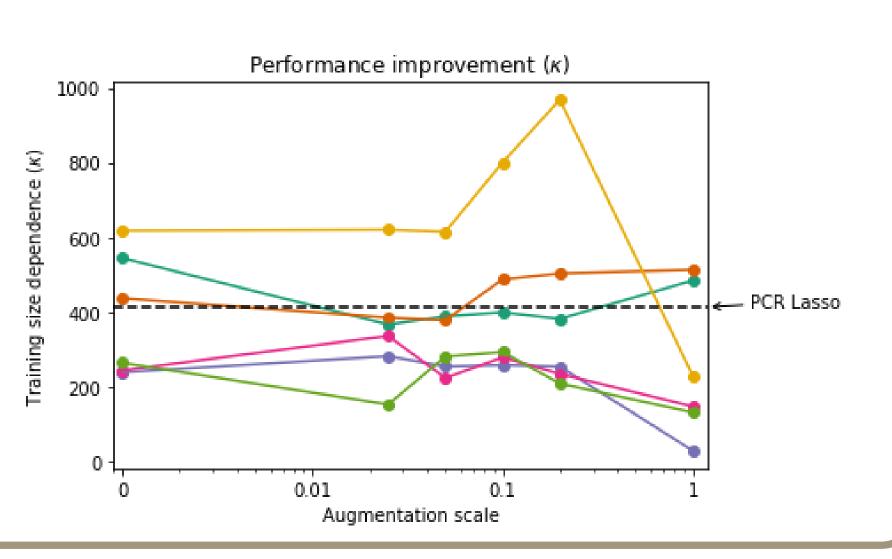
At each augmentation level, performance improves with training set size:



The models' performance at each augmentation level is summarized through three parameters that quantify the maximal and minimal performance levels, and the convergence of performance with training set size:







Conclusion and future work

- Neural network models (NNs) improve accuracy of tractometry analysis
- NNs are very data hungry
- Tuning and training these models is complicated and timeconsuming
- Differences can be much more important in some cases (see poster # XXX)

References

- [1] Jason D Yeatman, Robert F Dougherty, Nathaniel J Myall, Brian A Wandell, and Heidi M Feldman. Tract profiles of white matter properties: automating fiber-tract quantification. PLoS One, 7(11):e49790, November 2012.
- [2] Adam Richie-Halford et al. An analysis-ready and quality controlled resource for pediatric brain white-matter research. Scientific Data, 9(1):1–27, October 2022.
- [3] Alexander et al. An open resource for transdiagnostic research in pediatric mental health and learning disorders. Scientific Data, 4:170181, December 2017.
- John Kruper et al. Evaluating the reliability of human brain white matter tractometry. Aperture, 1:10.52294/e6198273-b8e3-4b63-babb-6e6b0da10669, 2021
- [5] Adam Richie-Halford, Jason D. Yeatman, Noah Simon, and Ariel bf Rokem. Multidimensional analysis and detection of informative features in human brain white matter. *PLoS* Computational Biology, in press(6):1–24, 06 2021. PMC5838108[pmc.

Acknowledgments

