

# Growth Charting of Brain Connectivity Networks and the Identification of Attention Impairment in Youth

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Daniel Kessler

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# Outline

1 Introduction

2 Methods

3 Results

4 Discussion

# Motivation

## Pediatric Growth Charts

- Long history for height, weight, etc

## Intrinsic Connectivity Networks

- Attention & ADHD connection
- DMN vs TPN balance

# Background

Focus today: processing pipeline, modeling, and analysis

# Sample

- Philadelphia Neurodevelopmental Cohort
- Resting state fMRI
- Penn Continuous Performance Task
- $N = 519$  (after QC & exclusions)

# Task: PCPT

- Penn Continuous Performance Test
- 180 trials
- 1s to respond
- "Go" on digit/letter (varies by phase)
- Measure: Acc (corrected for age with quadratic model)

# Clinical Interview

- Assesses psychopathology dimensions
- ADHD Module
- Symptom endorsement -> pseudo ADHD "diagnosis"

# MRI Measures

- T1-weighted image (structural contrast)
- Resting State fMRI

## T1 Image

- Structural contrast
- Ventricles are black, "gray matter" is darker, "white matter" is brighter

## Resting state fMRI

- 4D Image (Multiple "Volumes"):  $X*Y*Z*time$
- T2\* contrast captures BOLD (blood oxygenation, coupled to neural activity)



# fMRI Preprocessing Overview

Lots of quality-control steps throughout

- 1 Slice-time Correction
- 2 Motion Correction
- 3 Normalization
- 4 Smoothing

# Preproc: Slice-time Correction



- Each fMRI volume is acquired sequentially in slices
- Volume not acquired simultaneously
- Correct (through interpolation) s.t. all slices w/in volume temporally aligned

# Preproc: Motion Correction

- Participants move their head over the scan
- Estimate affine realignment to common volume (e.g.  $V_0$ )
- Alignment is progressive (rigid body transforms)
  - realign  $V_1$  to  $V_0$  using affine matrix  $Q_1$
  - align  $V_2$  to  $V_0$ , initialize solution with  $Q_1$
  - and so on
- Store  $Q_i$
- Process  $Q_i$ 's to capture summary displacement information for each frame
  - this will be used later in preprocessing

# Preproc: Normalization

- Everybody's brain is unique
- This is problematic for group analyses
- Standard Brain/Space: MNI (Montreal Neurological Institute)
- Steps
  - 1 Rigid body registration of T1 scan to T2\* scan
  - 2 Estimate nonlinear warp (affine + splines) b/w T1 and MNI template
  - 3 Apply estimated warp to each volume of T2\* scan

# Preproc: Smoothing

- Normalization isn't perfect
- Brains are plastic and diverse even when perfectly aligned anyway
- Smooth with Gaussian kernel (3D, 8mm FWHM)

# Resting Processing & Connectome Generation

## Processing

- Linearly detrended
- COMPCor: PCA-based nuisance regression (CSF & WM)
- Bandpass Filtering (0.01 to 0.1 Hz)
- Motion Scrubbing: Delete volumes with large displacement/motion

## Connectome Generation

- Isomorphic grid, 12mm spacing
- 1068 Regions of Interest (ROIs)
- Calculate pairwise correlation, then R-to-Z transform
- Vector embedding: Each participant contributes  $\binom{1068}{2}$  edges

# Data Cleansing

- Intersubject nuisance effects may manifest at edge level
- e.g.: left handers have  $>$  connectivity at edge  $i$
- Concatenate vector embeddings into matrix  $X$
- estimate with OLS  $X = Y\hat{\beta} + \hat{\epsilon}$
- Reestimate data as  $X^{\dagger} = Y^{\dagger}\hat{\beta}$
- $Y$  is ideal design matrix where nuisance fx are flat
- Induce eigenvector selection through augmentation: add  $\hat{\beta}$  for fx of interest at each edge

# Independent Components Analysis

- reduce rows of  $X^\dagger$  through PCA ( $DX$ ) (retain top 15 eigenvectors)
- ICA-decomposition using FastICA  $X = AS$
- A: mixing matrix 15 by 15
- S: source matrix: 15 by  $\binom{1068}{2}$
- Unreduce  $A^\dagger = D^{-1}A$
- $A^\dagger$  is # of subjects by 15
- The  $i,j$  element indicates the expression of component  $j$  for subject  $i$



# Network Growth Charting Analyses

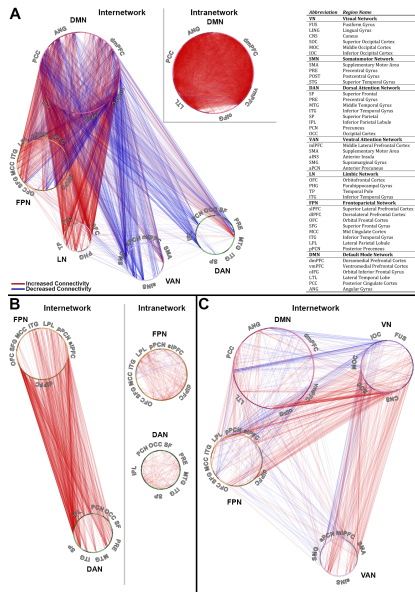
- Growth charts obtained from OLS population-level estimates
- Predict each column of A with OLS  $A_i^\dagger = age + age^2$
- Residuals from these models are **deviation scores** reflecting over- or under- expression of a component relative to age
- Use **deviation scores** to predict
  - Accuracy on PCPT (age-corrected)
  - ADHD status

# Network Growth Charting to Predict Task Accuracy

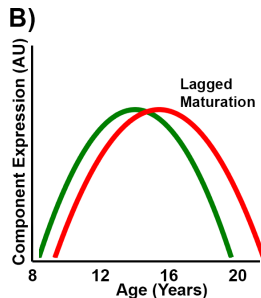
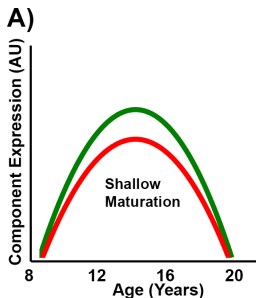
- **Deviation scores** predict accuracy very well ( $R^2 = 0.287$ )
- A subset of just 6 components' **deviation scores** do most of the work ( $R^2 = 0.240$ )
- Of these, 5 show vigorous maturational profiles
- Split half analysis, OLS with all 15 **deviation scores**:  $R^2 = 0.176$



## DMN-TPN Shifts in Maturing Components



# Shallow vs Lagged Dysmaturation and Task Accuracy



## Shallow Dysmaturation

Dysmaturation yields consistent underexpression of components

## Lagged Dysmaturation

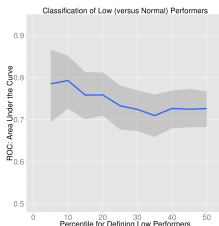
Dysmaturation yields comparable, but right-shifted, peak

Strong Evidence for Shallow Dysmaturation over Lagged

Likelihood Ratio  $> 10^{26}$

# Biomarker of Attention Dysfunction from Network Growth Charting

- Goal: Binary Classification of Attention Dysfunction
- Binarize task performance into *low* and *normal* performers (split by %ile cutoff)
- Vary %ile cutoff for binning
- LOOCV of Logistic Regression, performance assessed with ROC AUC, error bars from permutations



# Biomarker of ADHD from Network Growth Charting

- Goal: Binary Classification of Pseudo ADHD Diagnosis
- Logistic regression predicting dx using 6 components IDED earlier
- Model is significant, but effect size weak compared to attention prediction
- $\chi^2_6 = 13.00; P = 0.043$

- Recent review paper calls for developmental approaches to connectomic imaging
- We link dysmaturation of ICN topology to attention dysfunction
- DMN-TPN intra- and inter-relationships implicated
- Shallow vs lagged dysmaturation provides better predictive fit